THESIS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

Life and AI at NASA

An Ethnography of How Scientists and Engineers Make Tools to Explore Other Worlds

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Cover image: An image of Titan from Cassini-Huygens mission. Source: NASA/JPL/Space Science Institute.
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Abstract

Artificial intelligence (AI) is increasingly introduced into scientific practices, including NASA's missions that explore conditions for life and habitability on other planets and moons. How does the development of new AI tools within these missions transform scientific knowledge production?

Drawing on theories from Science and Technology Studies (STS), this dissertation analyzes science as a cultural practice. It is based on ethnographic research conducted at NASA and within the wider community of planetary scientists and astrobiologists, including interviews and documentary materials.

The dissertation demonstrates how efforts to realize visions of autonomous science beyond Earth already reshape the everyday work of scientists on the ground. It shows how AI is shaped by organizational structures, knowledge infrastructures, and scientific cultures at NASA, while simultaneously feeding back into these dimensions. Boundary work to sustain the legitimacy of planetary missions influences the purposes for which AI can be developed – to identify organic molecules, to explore habitability and potential biosignatures.

The study further shows how field sites, laboratories, and national databases together constitute a knowledge infrastructure that shapes AI by determining which data are available for training. Choices of field sites are influenced by accessibility and symbolic value, rendering some places more popular than others, which skews knowledge production. Digital databases and AI training datasets serve as libraries of knowns against which the unknown is identified. Decisions about anomalies, artifacts, and novelty in data are central to both AI design and scientific discovery. The study highlights the limits of performance metrics and the importance of

negotiations with domain experts, particularly in the emerging use of synthetic data.

Although AI remains at an early stage of development in the cases studied, it already reshapes power relations in scientific knowledge production by introducing new ideals of epistemic order and altering who determines the value and usability of data.

By providing an empirical account of AI development in one of the most impactful scientific institutions, this dissertation contributes to discussions about data-driven solutions in science, and the epistemic consequences of using AI in science on Earth and beyond.

Keywords: space explorations, NASA, AI in science, machine learning, synthetic data, science and technology studies, social studies of outer space, epistemic cultures, epistemic responsibility, truth-spots

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Acknowledgements

As the title of this dissertation implies, this study would not be possible without the generosity of scientists and engineers at NASA Goddard Space Flight Center, who agreed to become study participants and welcomed me to their workplace which became my ethnographic field site. I would therefore like to thank each of you for offering your time, patience, and engagement. A handful of you have been essential for this project. Eric, Victoria, Lu, and Samantha – I cannot capture my gratitude in words.

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I would also like to acknowledge the sources of inspiration for diving into astrobiology. Anna Neubeck's and David Dunér's lectures at SCAS in 2020 made me curious about astrobiology. This interest was then cultivated further in conversations with Erik Persson, and other participants at summer school in astrobiology at Ven. Stéphane Tirard has been an important conversation partner about the history of origins of life studies, as well as life in general. I would also like to thank each scientist and engineer who offered their time for an interview. It provided crucial guidance in planetary science, astrobiology, and the role of AI technologies in space explorations.

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This dissertation is dedicated to the memory of my dad, whose wisdom, curiosity and love for the written word inspired me to write with joy.

Chapter 1 Introduction – Ways of Knowing Other Worlds

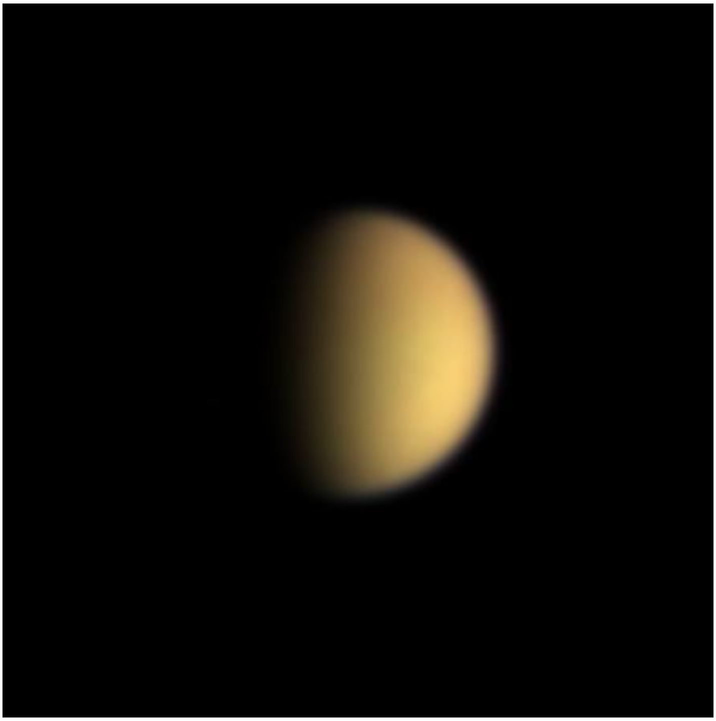

Figure 1. An image of Titan from Cassini-Huygens mission. Source: NASA/JPL/Space Science Institute

This thesis is about how the ways of knowing other worlds change with the introduction of new technological tools. Based on fieldwork at NASA Goddard Space Flight Center, I analyze science behind the scenes at a point in time where new AI tools are introduced for the purposes of "science autonomy" – the ability of scientific instruments to analyze their own data onboard missions to other planets and moons. These missions are one of the ways in which NASA explores conditions for past, present, and future life in the universe. Although these subjects concern intimidatingly big questions, this dissertation focuses on the practices of scientists and engineers, with the hope to make the cosmic, and molecular scales more approachable. The point of departure in this study is that scientists and engineers, as any other groups of people, share a culture – a particular set of meaning-making activities, which constitutes the ways in which they produce knowledge (Knorr Cetina, 1999). Based on this premise, scientific claims about other worlds, and the place of life in the universe, are results of negotiations within, and between particular cultures at NASA. This dissertation discerns these cultures alongside scientists and engineers in the laboratories, during meetings, and breaks, as well as in interviews, strategic documents, and scientific publications.

As we consider science as a cultural practice, we must also keep in mind that science is not just any kind of domain, but a very powerful one. Scientific knowledge claims have an authority in informing and legitimizing future courses of action by individuals, organizations, and states. The purpose here is to make visible how NASA's aspirations to comprehend life as a universal phenomenon derive from local places, and practices that entail particular ways of knowing.

This dissertation provides an empirical account and theoretical formulations about the major actor in explorations of outer space. It offers insights about scientific knowledge production, and more specifically, scientific knowledge production with AI. It does so by showing how the introduction of new AI tools for science autonomy changes the ways in which life is made known in science at NASA.

New Tools To Produce Knowledge about Life

Since the ancient times, humans have gazed up to the sky in wonder about the universe, telling each other stories about our origins and futures. The big questions, previously posed by humans looking up with the naked eye, are rephrased in the scientific objectives of NASA missions. Are other planets habitable? Could they sustain life? One of the destinations of NASA's missions is the largest moon of Saturn, Titan (Figure 1). Beneath a thick orange-brown haze, Titan's surface is covered with dark sand dunes. The temperature is -179 degrees Celsius. Under its icy crust, there might be a liquid ocean of water. Beyond the possible presence of water, often considered one of the necessary conditions for life, Titan is also full of organic molecules – the building blocks of life. To explore environments such as Titan, which is around 1.5 kilometers billions away from Earth, NASA scientists and engineers send robotic missions that collect samples and conduct scientific experiments at the site. In most cases, the robots never come back to Earth. Nor do they send back the samples of rocks, or gases. What they do send back is information. Scientists gaze on the computer screen and the data, which shape the stories about the origins, present, and futures of life on our planet.

Transfer of scientific data across the universe is reminiscent of the science fiction tales, like Star Trek, where objects and people can become immaterialized and teleported from one place to another. Some of the scientists and engineers at NASA are inspired by these imaginaries. However, the material world is posing severe challenges for sending scientific data between planets. First, the amount of data that can be transferred is limited. Because of that, although the miniaturized laboratory instruments on other planets can produce enormous amounts of data with very detailed information, not all of it can be sent back to Earth. Second, throughout the interstellar journey at the speed of light, the signal becomes weaker and weaker, the farther away the planet is. Some of the data become lost on the way. Third, sending data through the immense distances to other planets and moons takes time. The transfer of data between Earth and Titan will take 70 to 90 minutes, which significantly prolongs decision making for teams of scientists and engineers, who operate the spacecraft from Earth.[1] While the data is being transferred between planets, the billion dollar mission stands still and awaits commands.

The solution to the challenges of data transfer, according to a group of scientists and programmers at NASA Goddard Space Flight Center, is what they refer to as “science autonomy.” This group posits that to “maximize” science, data should be analyzed in real-time onboard the instrument, rather than sent back to the human scientists on Earth for review. They suggest that scientific instruments should operate, analyze, tune and direct themselves autonomously. Their idea was acknowledged in the most important strategic document (NASEM, 2023) defining the future activities of NASA, which paves the way for a fundamental shift in decision making in NASA missions. The plan is to train algorithms – AI, machine learning, deep learning, etc – to prioritize which data is valuable in searching for signs of life and habitability on other planets and moons. In future missions, algorithms might make decisions about what is worth knowing about the universe.

The term autonomy comes from the Greek *autonomía*, meaning self-governance. In philosophy, autonomy refers to the capacity of an agent to act on the behalf of their own will. In the case at NASA, autonomy figures as a property of technological systems. *Autonomy* differs from *automation*.[2] Automated systems can act on their own, based on predetermined rules. Autonomous systems can be understood as an

[1] This can be compared to data transfer between Earth and Mars. Mars is on average 225 million kilometers away from Earth. The data transfer takes from just a few up to 20 minutes, depending on where the planet is in its orbit. The moon Titan is much farther away – around 1.5 billion kilometers – which prolongs the data transfer.

[2] Although these terms are used interchangeably by my informants at NASA in their everyday practice.

extension of that – besides acting on their own, they can dynamically "perceive", "learn," and "adapt to" their environment. Anthropologist Lucy Suchman has argued that such vocabulary contributes to the enchantment of these technologies, and it masks the labour it takes to produce them (Suchman, 2007; 2023).

This study makes visible the efforts it takes to develop AI tools, and the ways in which this development alters how scientific knowledge is produced. More specifically, this dissertation asks how the introduction of new AI tools for science autonomy changes the ways in which life is made known in planetary science. To address this question, I conducted an ethnography at NASA Goddard Space Flight Center. Programmers and scientists who suggest the idea of more science autonomy, and their closest colleagues, became my interlocutors. I accompanied them in the laboratories, during meetings, and the breaks in-between, which allowed me to analyze science in the making at NASA. Scientists and engineers whom I observed, speak of the algorithms they develop as "intelligence", "machine learning," "networks," and sometimes, "AI." In this thesis, I use AI as an umbrella term for the various kinds of autonomous technologies.

Technology, Science, Society, and Change

Previous studies in history of science have demonstrated how the societal context and the technological tools available shape life as a research subject in different ways (Dick, 1996; De Chadarevian & Kamminga, 2003; Reinecke & Bimm, 2022). With new technologies, such as the radio or the microscope, emerged new disciplines, and new ways of studying life – through radio waves, or molecular analysis.

New tools open up new ways of knowing, but also, new understandings of what it means to know. Philosopher and historian of science Evelyn Fox Keller articulates this in her book *Making Sense of Life*, where she studies the changes with adoption of computational methods in biology.

> Everyone recognizes that scientific understanding depends on the techniques available for analysis. But the very meaning of understanding also depends on available techniques, albeit less evidently so. Both what counts as knowledge and what we mean by knowing depend on the kinds of data we are able to acquire, on the ways in which those data are gathered, and on the forms in which they are represented. Usually, however, we become aware of this dependence only in times of change, when new techniques noticeably alter our styles of knowing (Keller, 2002, p. 199).

We know little about how the scientific study of life shifts in practice, and ethnography can play an important role here (Praet & Salazar, 2017, p. 317). Anthropologist Sophia Roosth have brought attention to how emergence of the new field of synthetic biology entailed a particular way of studying life, namely, as being made and improved (Roosth, 2019). Anthropologist Stefan Helmreich observed how researchers in the field of Artificial Life make artificial systems in cyberspace, and articulate them as being alive (Helmreich, 1999). Development of new tools – AI – to study life and habitability as universal phenomena is something that calls for ethnographic attention.

Why Study AI at NASA?

Introduction of AI tools in science is part of a larger transformation in society. Autonomous technologies are often spoken of as revolutionizing the world, the ways in which we know things, and how we relate to each other. Since the beginning of the 2020s, AI has been on everyone's lips. Proponents of this technology bring big promises into numerous areas in society. From better car drivers and more accurate medical diagnosis, to liberation from labour-intensive work tasks in general. The rhetoric is often that AI can do more and better.

Nonetheless, AI is also spoken of in terms of problems. Exploitation of workforce to develop AI, the environmental costs it entails, and biased datasets amplifying injustice in society, are among the main issues being raised (Benjamin, 2019; Bolukbasi et al., 2016; Buolamwini & Gebru, 2018; Crawford, 2021; Sumpter, 2018). Although the risks have prompted certain degree of legislation of AI, the technological development keeps accelerating.

As AI tools are being introduced to new areas, there is an urgent need to empirically explore how AI is made, and what consequences this development has in particular contexts (Suchman, 2023) – what can be gained, and what can be lost. It is especially crucial to scrutinize the consequences of introducing AI by powerful actors. NASA is the largest organization exploring outer space, which entails a profound impact on the ways in which humans form an understanding of the world.

Another recent development is that explorations of outer space has gained a new currency. The potential for private companies to extract resources from outer space and the spectacular aspirations of billionaires to establish space tourism has caught a lot of attention. Although the revival of the Space Race emerged out of the competition between a few privileged individuals, NASA remains as the main actor exploring the universe.

Along with detecting more planets outside of our Solar System, NASA has continued the quest to search for life and habitable environments, meaning preconditions for life. This field of research is referred to as astrobiology, which draws on several disciplines, such as astronomy, biology, and chemistry to mention a few. In strategic documents, NASA articulates a link between the missions to other planets, the field of astrobiology, and the big questions.

> Given NASA's focus on the search for planets and life, astrobiology will be the focus of a growing number of Solar System exploration missions. Astrobiology research sponsored by NASA will continuing pushing science closer to answering the Big Questions in space science: Where did we come from? Where are we going? And are we alone? (Hays, 2015, p. xii)

Addressing the big questions captures the outreach rhetoric of astrobiology at NASA, which I focus on in the first empirical chapter. Searching for signs of life is, however, a subject that has a history of struggling with legitimacy. This was evident during my fieldwork at NASA Goddard Space Flight Center. One of my informants used to say humorously that "You'll not find any UFOs at NASA." Yet, during my visit in June 2022, the agency announced a commission dedicated to study unidentified anomalous phenomena (UAPs, previously termed as UFOs, unidentified flying objects), meaning objects that cannot be identified as human-made technology, or natural known phenomena. The regained currency of outer space explorations has revived the interest in posing questions about our place in the universe.

Development of new AI tools at NASA can reshape the knowledge production and impact future discoveries. However, previous works in Social Studies of Outer Space (SSOS) have shown how space explorations shape not only knowledge about outer space, but also social orders on Earth (Armstrong & Klinger, 2025; Salazar & Gorman, 2023). Space activities depend on material infrastructures on Earth, from data centers, and laboratories, to sites for testing robots and launching rockets. Therefore, it is also important to pay attention to how space explorations affect the labor, and distribution of resources, as well as visions of the future that orient current actions on our own planet.

Aim and Research Questions

The aim of this thesis is to understand how scientific knowledge is produced in NASA missions to explore life and habitability on other planets and moons, and how development of new AI tools changes these practices. More specifically, the aim is to understand how the new AI tools change the ways in which life is made known, by scientists and engineers.

The framework for this study is to approach science as a cultural practice, by drawing on theories from Science and Technology Studies (STS). This enables analyzing the process of mutual shaping of the research subject, technological tools, scientific cultures, and the organization in which these are situated. The focus in this study is on investigating which ways of knowing are considered as legitimate, how knowledge claims are accomplished, and how epistemic concerns shift with the development of AI. Therefore, the study analyzes which practices are enabled and not, as well as what is included and excluded, in the context of scientific practice at NASA Goddard.

The analysis is based on material from ethnography at NASA Goddard, and the wider scientific community of planetary scientists and astrobiologists, including interviews and documentary material. Studying the practices ethnographically at the stage of early development of AI tools makes it possible to show the process of science and technology in the making. This research provides an empirical account and theoretical formulations about the major actor in explorations of outer space. It also provides insights to studies about scientific knowledge production, and more specifically, scientific knowledge production with AI. It does so by addressing the following overarching question:

- How does development of AI change the ways of producing scientific knowledge at NASA Goddard?

To address this overarching question, I focus on how development of AI at NASA Goddard is shaped by, and reshapes, the organization, knowledge infrastructure, and scientific culture. I analyze these three dimensions through the following research questions:

1) How does NASA engage in boundary work to sustain legitimacy for missions investigating life and habitability on other planets and moons?

2) How do different knowledge infrastructures enable and constrain data that can be used to train AI?

3) How are AI data practices integrated into scientific cultures at NASA Goddard?

In the following sections, I provide a technical and organizational background for the reader with descriptions that facilitate understanding of the empirical chapters. I describe where it took place and which NASA missions are in the focus of this thesis.

Where This Study Takes Place

In 1958, a year after the launch of Sputnik, the US established a new agency to keep up in the Space Race with the Soviet Union. NASA (National Aeronautics and Space Administration) is the US agency

Figure 2. Aerial view of the NASA Goddard Space Flight Center in Greenbelt, Maryland, US. Credit: NASA.

responsible for the national civil space program, aeronautics and space research. It has ten centers across the country and at the time of doing fieldwork, around 18,000 employees.[3] NASA Goddard Space Flight Center (figure 2), which is where I conducted fieldwork, is the largest of the NASA centers, with over 10,000 employees.[4] It is named after Robert H. Goddard, who constructed the first rocket using liquid fuel. NASA Goddard – as I

[3] This number includes both civil servants and contractors, as off 2023 (National Aeronautics and Space Administration, 2023). However, by 2025, the number is estimated to have decreased by around 20 % due to the Trump Administration resignation program to reduce federal workforce, as part of the DOGE initiative (The Department of Government Efficiency).

[4] This number includes both civil servants and contractors, as off 2023 (NASA Goddard Space Flight Center, 2024), which is when the field work was conducted. As mentioned above, these numbers have been reduced due to the DOGE initiative.

will refer to the location from now on – was established in 1959 as the first NASA space center. The large complex is in Greenbelt, a small city with 24,000 inhabitants. It is around 30 minutes car ride away from Washington DC, which is the location of NASA Headquarters.

During fieldwork at Goddard, I followed programmers and scientists working at the Planetary Environments Laboratory, which is dedicated to studying "the chemistry and astrobiology of the atmospheres and surfaces of planetary bodies (NASA Goddard Space Flight Center, n.d.a)." In this thesis I refer to (AI) programmers, and (software) engineers interchangeably. Among scientists, many informants identify themselves as planetary scientists or astrobiologists. "Planetary scientists" is a more general and representative term, since not all of the scientists identify themselves as "astrobiologists." I use the term "astrobiologist" only when it is relevant, and if the scientist in question has explicitly identified themselves as such. These fields, according to NASA's narrative, aspire to understand life and its origins in the universe. Its large aspirations are reflected in the resources dedicated to this NASA center. The Planetary Environments Laboratory is part of The Sciences and Exploration Directorate, which according to NASA, is the "largest Earth and space science research organization in the world (NASA Goddard Space Flight Center, n.d.b)." In chapter 4, I discuss the history of astrobiology and the politics of its scientific objectives.

What This Study Observes

This thesis concerns robotic missions (not crewed). While the robots conduct scientific experiments *in situ* autonomously, scientists interpret the results and direct the robot in terms of where it should go or what it should do. Three missions, which I will describe in the following sections, were especially relevant for my interlocutors in regard to the development of AI tools for autonomous decision making onboard. All three missions have the same ultimate goal. Namely, to search for signs of life and habitability on other planets and moons.

Mars and Titan as Destinations

One of the destinations for these missions is Mars. It is often called the "Red Planet" because of its surface color. Rather than searching for signs of present life there, scientists search for signs of past life that might have existed billions of years ago, when Mars was wetter and warmer. Observations of river valleys and lakebeds, as well as particular rocks and minerals imply that Mars has a history of liquid water. Currently, the atmosphere of Mars is too thin to sustain liquid water. The only place beyond Earth with bodies of liquids on its surface – that scientists know of – is the moon Titan, which is another destination of the missions I observed. Titan is the largest moon of Saturn. It has rivers, lakes and seas of methane on its surface. However, previous missions have also detected signs of a potential ocean of liquid water under the surface of ice. This is among the criteria that makes it a candidate for a habitable environment. Since NASA scientists study conditions for life and habitability in these conditions, the descriptions of these places have focused on how they resemble our environment on Earth. However, to keep in mind is that the atmospheres on Mars and Titan are very different from ours, which makes design of instruments that can manage these conditions a very complex task. This is reflected in the mission timelines, spanning over decades, at times involving several space agencies where each delivers different parts or services.

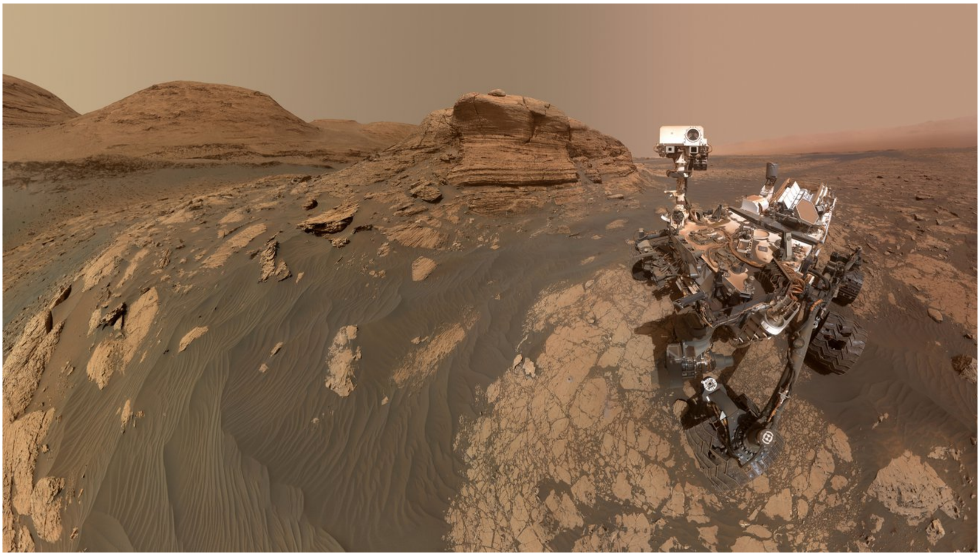

Figure 3. Mars Science Laboratory (MSL) Curiosity rover taking an image of itself on Mars. Credit: NASA/JPL-Caltech/MSSS

Experiments with Mass Spectrometry

NASA missions searching for life and habitability in outer space build on the assumption that life on other planets and moons will most likely be microbial. Scientists believe that molecules can provide important cues about life and habitability. Space robots (for instance, rover in figure 3) are designed to explore molecular composition of samples. Robotic “arms” collect samples from the surface and put it inside its “belly” (space robots are usually spoken of in anthropomorphic terms by NASA mission members).

The instrument in the “belly” of the space robot is a miniaturized version of a mass spectrometer (see figure 4). Scientists and engineers whom I followed at NASA Goddard design and work with this instrument, which plays a central role onboard these missions. Mass spectrometers are used to identify organic molecules and their structure in a sample. In simple terms, mass spectrometers can be explained as a tool that smashes

Figure 4. The copy of Sample Analysis on Mars (SAM) instrument at NASA Goddard Space Flight Center. The instrument is behind a so called "clean tent" that protects it from contamination. Photo from fieldwork.

something into pieces in order to understand it. There are different kinds of mass spectrometers. However, regardless of their type, the process occurs in three stages. First, the sample is converted into ions (charged particles). Second, these ions are sent to a mass analyzer that separates them based on their mass-to-charge ratio (m/z), which means the weight of an ion divided by how many charges it has. Third, the separated ions hit a detector that counts them and produces a mass spectrum image with peaks (Figure 5). Each peak is a group of ions with the same mass-to-charge ratio – the height of the peak indicates how much of this group is present in the sample. To summarize, scientists use mass spectrometers to identify molecules in a sample, which produce images with peaks that scientists

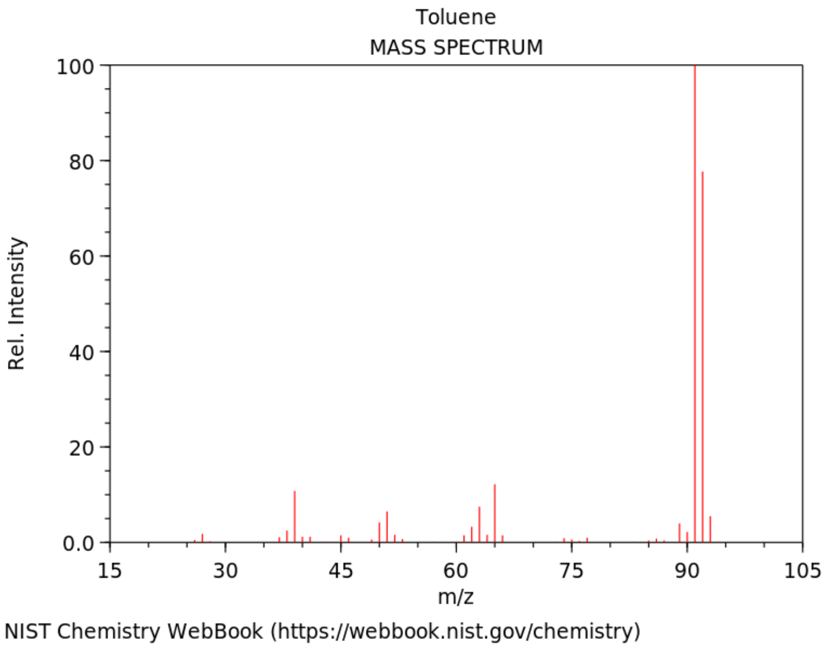

Figure 5. Mass spectrum image of Toluene from National Institute of Standards and Technology (NIST).

interpret with their naked eye, or with the help of an algorithm. The peaks indicate what kind of chemical elements are present in the sample – carbon, oxygen, sulfur or something else – and the present molecular structures. Potential signs of life or habitability in outer space are anticipated to appear as peaks in a mass spectrum.

Scientists and engineers from Goddard design mass spectrometers for NASA missions to outer space. Each of these instruments is unique, as it is constructed to work in a particular extraterrestrial environment. The conditions on Mars for instance, are not the same as on Venus or Titan. To identify as many different kinds of organic molecules as possible, the mass spectrometers in the space instruments discussed here are combined with other techniques, however, these are outside of the scope of this study.

The Role of AI in Mass Spectrometry Experiments

The AI being developed at NASA Goddard will make decisions about which mass spectrum data are the most interesting to send back to Earth. In the following, I will briefly describe each mission and its stage of development during fieldwork, and specify how it relates to the development of AI.

The first of the three missions that I will touch on below, has the goal to explore the habitability of Mars. After landing on Mars in 2012, the Mars Science Laboratory (MSL) mission was still in operation during my visits at NASA Goddard in 2022 and 2023. MSL can be described as a large mobile laboratory. The 899 kilogram, three meters long rover with six wheels, drives across the surface of Mars to conduct experiments (figure 3). It is equipped with ten scientific instruments. One of them, Sample Analysis at Mars (SAM, figure 4) has been developed and tested by researchers at NASA Goddard Space Flight Center. Its role is to investigate the chemistry of Martian surface and atmosphere, which helps scientists to assess the habitability of Mars. SAM (figure 4) is a complex laboratory suite consisting of three miniaturized instruments located inside the Curiosity rover (figure 3). The three instruments, a Gas Chromatograph (GC), a Quadrupole Mass Spectrometer (QMS) and a Tunable Laser Spectrometer (TLS), analyze gases from the atmosphere or powdered rock samples. My informants use the Mars data from SAM to train their AI tools for future missions to Mars and Titan, which I describe below.

The second mission, Exobiology on Mars program (ExoMars), is in collaboration with the European Space Agency (ESA). The aim of the mission is to explore the habitability of Mars. It is the first mission that will be able to drill two meters below the surface, which makes it possible to gather samples that have not been exposed to the radiation and extreme temperatures. NASA Goddard Space Flight Center is providing ExoMars with an instrument for scientific analysis of the samples - Mars Organic Molecule Analyzer (MOMA). It was planned to launch in 2022 but got suspended because of the conflict with Russia, which was supposed to deliver a lander for the mission. A new estimated date for the launch is 2028. The delay provided my informants more time to work on AI tools. They aim to develop a tool that will help scientists on Earth to analyze data from MOMA.

The third mission, Dragonfly, is developed to explore the habitability of Titan. It will consist of a rotorcraft that weights 875 kilograms and is 3.85 meters long. The rotorcraft lander is a new approach to planetary exploration that will allow it to travel and gather samples from diverse sites. NASA Goddard Space Flight Center is providing DraMS, which is a mass spectrometer analyzing chemical components. During my fieldwork, the Dragonfly mission was at the development stage, with an estimated launch in 2028. The billion kilometers distance to this moon poses difficulties for data transfer between the spacecraft and scientists on Earth. Instead of operating the rover by sending all the data back and forth between the spacecraft and scientists on Earth, the plan is to automate decision making onboard the mission, with AI. The AI being developed at Goddard will make decisions about which mass spectra are the most interesting to send to Earth.

To summarize, I have observed work on three NASA missions that search for, or will search for, signs of life and habitability on other planets and moons. Each mission was at a different stage of development. First, the MSL on Mars was still in operation during my fieldwork at NASA Goddard. Second, ExoMars was developed but delayed due to an international conflict. Third, the Dragonfly mission to Titan was at the development stage.

AI for science autonomy has a different role in each of these missions. The MSL mission has operated on Mars for over a decade and programmers use data collected by MSL to train their AI algorithms. For the ExoMars mission, once the data from the space instrument has reached Earth, AI tools will analyze it to facilitate decision making of human scientists, to operate the mission more efficiently. In other words, AI will work on Earth, to help scientists analyze data from Mars. Both missions have Mars as its destination.

Dragonfly will travel all the way to Titan, 1.5 billion kilometers away, which poses challenges for data transfer. Therefore, the plan for Dragonfly is to apply AI tools that will make decisions onboard the spacecraft, autonomously. The last case is a pivotal step in a shift of autonomy in decision making. In future missions, algorithms will be making decisions impacting what we can know about other planets and moons.

AI for science autonomy was still at the development stage during my fieldwork. This means that it has not been used in any missions yet. To become part of a mission, the AI tool has to reach a higher level of maturity, which is estimated in a measurement system called Technology Readiness Level (TRL). A tool is assigned a rating from 1 to 9 TRL by NASA, where 1 refers to the initial research stage and 9 to a tool that has been successfully operated in a mission to space – "flight proven." During fieldwork at NASA, the programmers leading this project estimate the stage of AI development as TRL 3, which means that the technology is feasible based on an experiment on a small scale.

Chapter Outline

How does development of integrate AI change the ways of producing scientific knowledge at NASA Goddard? This dissertation addresses this question by following the practices of planetary scientists and software engineers at NASA Goddard, when they work with missions to other planets and moons in search of signs of life and habitability. **Chapter 2** delves into previous studies, and **chapter 3** is about the method and material that constitute this study.

Addressing the aim and research questions based on the empirical material generated at NASA Goddard required a diverse set of theoretical tools. Therefore, the varying theoretical outlooks are presented in each of the four empirical chapters. AI does not emerge from a blank slate.

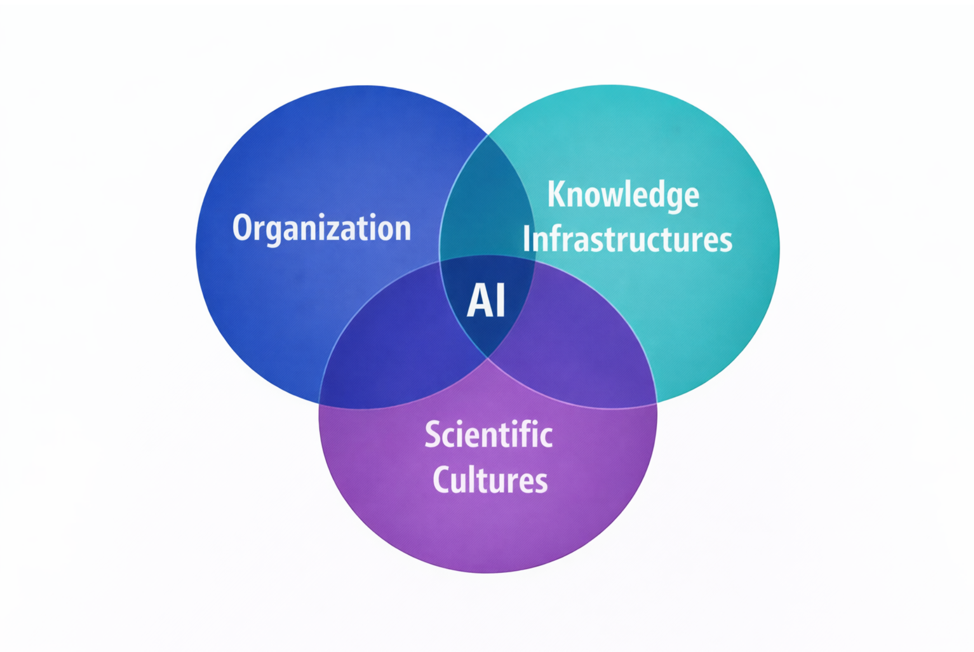

Figure 6. The dimensions foregrounded in the empirical chapters.

Development of AI at NASA Goddard takes place in a particular organization, knowledge infrastructure, and scientific culture. Each of these dimensions enables and constrains particular courses of action, which shapes development of AI. The development of AI in turn, has consequences on these dimensions. Each of the four empirical chapters in the dissertation foregrounds a particular dimension (figure 6).

Chapter 4 situates the search for signs of life in outer space in the organizational context of astrobiology at NASA. It shows what kinds of practices and research subjects are considered as legitimate in life detection, and what kinds of practices and objects are excluded from the spectrum of what potential life elsewhere could be. This process is analyzed in terms of boundary work (Gieryn, 1983). The ways in which NASA demarcates astrobiology enables and constrains actions of scientists and engineers in life detection. This chapter shows how development of AI for life detection can be designed to search for not just any signs of life, but very particular ones, which are considered as legitimate at NASA.

The idea that AI could facilitate the search for life in outer space in NASA missions is the point of departure in **chapter 5**. To develop AI, programmers need large amounts of data. Chapter five is about the knowledge infrastructure it takes for scientists to produce the data, which programmers use to train AI tools to operate on other planets and moons. The focus is on how scientists accomplish credibility in claims about other planets and moons by drawing on different places on Earth – from the Atacama desert and Svalbard, to meteorites, and digital databases. This process is analyzed in terms of truth-spots (Gieryn, 2006; 2018). I argue that digital databases figure as important truth-spots in scientific knowledge production, alongside the laboratory and the field site. Then, the chapter demonstrates how the epistemic concerns shift when programmers take over these data to train AI.

Selection of which data to include and exclude from training AI is a matter of negotiations between planetary scientists and programmers. **Chapter 6** analyzes this in terms of negotiations between two different epistemic cultures (Knorr Cetina 1999; 2007). The chapter shows how each culture has its own way of approaching life detection, and ascribing value to data, which can be challenging to bridge. It shows how presence *versus* absence of negotiations between the cultures has consequences for what I call epistemic responsibility. I argue that organizational arrangements can inscribe data with a biography, or make it ahistorical, which can foster, or hinder, preconditions for epistemic responsibility in programming.

The negotiations discussed above play a crucial role in development of AI. However, the data from the scientists are not enough to train these tools. In **chapter 7**, we find out how programmers make AI work. Production of scientific data moves into the realm of programming, where larger amounts of synthetic data are computationally simulated, in the hope of better algorithmic performance. Based on ethnographic material from NASA Goddard, this chapter provides insights about the creation of synthetic data – a practice that has seen little empirical study in STS. The chapter shows what is at stake in the production of synthetic data in planetary science.

In the final and concluding **chapter 8**, I return to the dimensions illustrated in figure 6, and articulate the main findings of this study. This dissertation demonstrates how AI is shaped by organizational structures, knowledge infrastructures, and scientific cultures. The development of AI, in turn, reshapes these dimensions and the ways in which life is made known in science.

Chapter 2 Previous Works – Scientific Knowledge Production About Life on Earth and Beyond

How life is made known in science, has been a prevalent topic in many disciplines across social science and humanities. In history of science, we can learn about how life has been studied and imagined by astronomers and biologists (De Chadarevian & Kamminga, 2003; Dunér et al., 2013; Kay, 1995; Leicester, 1974; Tirard, 2010). In philosophy, there are vivid discussions about how to define life (Cleland et al., 2002; Gayon, 2010), and the politics of which lives have the conditions to flourish (Arendt, 1958; Agamben, 1998; Butler, 2009; Canguilhem, 2008; Coccia, 2021; Foucault, 1994). In sociology, life has been approached as a subject of political and economic management (Rose, 2006). The discussions in these fields have informed my work. However, the approach I have in this study is closest to anthropology, by observing the work of scientists and engineers in laboratories, to understand how life is shaped in practice (Helmreich, 2009; Roosth, 2019).

Studying science and technology in the making has been one of the main topics of study in Science and Technology Studies (STS), a field at the intersection of sociology, anthropology and history of science. Therefore, STS provides well established theoretical tools to achieve the aim of this study – to understand how scientific knowledge at NASA is produced, and how it changes with the development of AI. The tradition within STS that I draw on – laboratory studies – emerged in the 1970s. Laboratory studies are ethnographic accounts from laboratories, which means that the author observes the work of scientists and engineers. This approach makes it possible to open up the stabilized notions of facts by showing what actions, and assumptions are inscribed in them (Latour & Woolgar, 1986 (1979); Latour, 1987), and how the ways in which knowledge is produced varies, depending on the local culture (Knorr-Cetina, 1999). Following these insights, the point of departure in this study is that scientists and engineers, as any other group of people, share a culture – a particular set of meaning-making activities, which constitutes the ways in which they produce knowledge. Consequently, scientific claims are a result of negotiations within, and between particular cultures. They are not given, but accomplished.

Another key point in STS concerns how knowledge is always situated – scientific claims are made from a particular position (Haraway, 1988). Making scientific claims depends on the laboratory, the instruments needed to conduct experiments, as well as the human bodies who construct these tools and operate them. However, once scientific claims are made, the craftwork and the material dependencies tend to fade away and become transformed into ideas and theories. This paradox – on the one hand dependency and on the other hand forgetfulness, about the material circumstances of knowledge production – is a central feature of science (Latour & Woolgar, 1986 (1979), p. 69). Bruno Latour articulates how the degree of objectivity in science depends on the cascades of transformations from one stabilized object to another. "The more steps there are in between the objects and those who make judgments about them, the more robust those judgments will be." (Latour, 2014, p. 347) In this project, I pay attention to how the material objects are transformed to form chains of references that constitute: scientific knowledge at NASA, and the objects that AI tools are trained on. Although the tradition which I described here is referred to as laboratory studies, my analysis is not limited to what happens within the four walls of the laboratory. I return to this subject in the following sections.

AI as Data with Attachments to Places

To construct AI, large amounts of data are required. The quality and quantity of the data used for training determine how well the AI tools perform. Selecting the right data for training, and having sufficient amounts of them, are among the main challenges in development of AI at NASA. Therefore, to understand the development of AI, we must understand the data it is trained on. This dissertation scrutinizes the process of making and using the objects referred to as data. Data, in the modern understanding of the term, stands for information that can be stored and analyzed. It can serve as evidence to generate knowledge. In that sense, data figure as facts. The etymology of the term from Latin *dare*, "to give", implies that data is something given (Kitchin, 2021, p. 25-26). But data are not given – they are made.

In social studies of data, the point of departure is that data are made across different times and places, and they are enshrined with assumptions stemming from particular situations and their past (Douglas-Jones et al., 2021; Gitelman, 2013; Loukissas, 2019). With access to closely observe the knowledge infrastructure at NASA where data used for training of AI is produced, I illuminate what attachments to people and places are embedded in the data that constitutes these tools. Data is just one part of the process of scientific knowledge production, however, a crucial part. Based on the data, scientists make interpretations, and based on these, scientific facts.

After noticing how the notion of place has been overlooked in social studies of data, scholar Yanni Loukissas has argued for bringing back the focus on attachment of data to places. As Loukissas put it, instead of relying on the terminology of "data sets" implying something stable, contained and portable, we should study the shaping power of "data settings" meaning the local social life of data and their attachments (Loukissas, 2019, p. 1-2, 10). Data emerges from local sites, and is therefore embedded with local values and assumptions, but it can serve to form relations with distant entities. The attachments of data to places "invisibly structure their form and interpretation" (Loukissas, 2019, p. 3). In a world where data is often granted a status of universalism or objectivity, attention to the local settings of data is a crucial sensibility. In the case of NASA, scientific data used to train AI, to interpret unknown phenomena on other planets and moons, stem from numerous local places on Earth. To understand how the data used to train AI are made, it is necessary to analyze these attachments beyond the walls of the laboratory, for instance, by looking at where the laboratory samples come from.

To make the complex attachments of scientific data and places visible, I analyze how certain places serve as *truth-spots* that lend credibility in making claims about the world. Sociologist Thomas Gieryn describes the concept as follows:

> Truth-spots are 'places' in that they are not just a point in the universe, but also and irreducibly: (1) the material stuff agglomerated there, both natural and human-built; and (2) cultural interpretations and narrations (more or less explicit) that give meaning to the spot. (Gieryn, 2006, Footnote 3)

Gieryn has illustrated the concept of truth-spots with diverse cases, in science and beyond. For instance, governmental buildings, like the White House, can serve as a truth-spot, as well as religious sanctuaries, like the oracle in Delphi. In science, Linnaeus could draw upon field visits in Lapland, Sweden, and botanical collections in Netherlands, to render authority to his claims of a classification system for nature in 1700s that stands to this day (Gieryn, 2018). In chapter 5, I analyze how certain field sites on Earth are used as truth-spots to make claims about other planets, for instance, how places like the Atacama desert are narrated as analogous to Mars.

In STS, two places have been identified as especially important in scientific knowledge production: laboratories and field sites (Gieryn, 2006; Knorr-Cetina, 1992; Latour, & Woolgar, 1986 (1979)). Both play an important role in astrobiology and planetary science (Marcheselli, 2022; Messeri, 2011; Vertesi, 2015; 2020). Nevertheless, I argue that digital databases are another important place in scientific knowledge production, which are at least as important as the laboratory and the field site. I build this argument upon Gieryn's concept of "truth-spots," (Gieryn, 2006; 2018) and expand its use to the realm of the digital. I illustrate it in chapter 5, with the case of digital databases, which play just as important a role as laboratories or field sites for lending credibility to scientific claims at NASA.

The role of place-making in planetary science has been studied before. Anthropologist Lisa Messeri has conducted an ethnography of the everyday practices of scientists and engineers across different sites – MIT, NASA, Chile observatory, and a field site in Utah. Messeri shows how making objects in outer space into places is a tool for knowing. For instance, scientists frequently refer to planets as "worlds," which Messeri notes is a more emotive term implying notions of human habitation, in comparison to the technical term "planet." Messeri also provides rich ethnographic illustrations of how scientists use different kinds of proxies – from terrestrial field sites, to digital images – to make sense of extraterrestrial objects and make them into places (Messeri, 2011). As these themes are also present in my ethnographic material, the analysis of how data are made, in the laboratory and beyond, is in close conversation with Messeri's work.

Tools Shaping Knowledge About Outer Space

There is a substantial body of work on the scientific knowledge production about outer space. Many studies have focused on instruments that provide visual depictions: telescopes (Kessler, 2012; Lynch & Edgerton, 1987), cameras taking images of Mars (Vertesi, 2015), or 3D mapping to create a virtual experience of being on Mars (Messeri, 2011). These studies have demonstrated how pictures from a telescope, or a camera on a Mars rover, do not merely show us what outer space looks like. Instead, the images are carefully crafted in line with particular aesthetic ideals. Art historian Elizabeth A. Kessler has studied how the spectacular images of deep space from the Hubble telescope are produced by astronomers who adjust colors, contrast and compose the images – and how they need to balance between creating representations that are scientifically valid, as well as aesthetically pleasing (Kessler, 2012). This can be tied to the seminal work on the history of objectivity, by historians of science Lorraine Daston and Peter Galison, who showed how production of scientific images has been permeated by different epistemic virtues, meaning particular values that scientists adhere to when they produce and evaluate knowledge (Daston & Galison, 1992).

Studies in STS have recognized the power of visual representations in science (Coopmans, Lynch & Woolgar, 2014). With one image, scientists can capture an idea that can travel across different settings. The power of images in scientific knowledge production can also be understood in a wider societal context in the West, where vision serves as the primary source of evidence, over evidence of sound, touch, smell, and taste (Ong, 1991). This indicates how scientific work must be understood as both shaping, and being shaped by, the societal context.

Nevertheless, if we turn to life detection, historical accounts make it clear that scientists searching for extraterrestrial life have not only looked for signs of life in images – they have also listened to radio signals (Dick, 1996; Webb, 2020). What these studies demonstrate is how the object of research in life detection is shaped by the scientific disciplines, their methods and technologies. Historian Steven Dick identifies connections between how the discovery of radio waves and radio communication shaped the development of radioastronomy and SETI (Search for Extraterrestrial Intelligence, described in chapter 4). Microscopes and discovery of DNA shaped the development of origins of life studies. Dick identifies the following shifts in what scientists searched for in life detection: from intelligence (artificial canals), vegetation (dark spots), microbes (extreme environments), to organic molecules (DNA) (Dick, 1996, p. 60-61). The approach to searching for signs of life as organic molecules can be tied to wider developments in life sciences, which has been referred to as the "molecularization of life," a change resulting from technologies working on a new scale (De Chadarevian & Kamminga, 2003; Rose, 2006). Sociologist David Reinecke and historian of science Jordan Bimm (2022) point to the emergence of environmental science and its impact on how astrobiologists at NASA have shifted the methods, scale and object of study, to maintain legitimacy for life detection. To summarize, historical accounts have shown how the societal context and the technological tools available, shape the object of research in the scientific study of life. This implies that the introduction of new AI tools in life detection at NASA is intertwined with new ways of producing knowledge about life as a research subject.

With ethnography at NASA Goddard, I contribute to a deeper understanding of how scientists develop and use two particular instruments in life detection – mass spectrometry and AI. Mass spectrometry plays a central role in generating evidence about the chemistry of other planets in NASA's missions. Despite its central role, in previous ethnographic accounts of scientific knowledge production, mass spectrometry resides rather in the periphery. Mass spectrometry images, which I described in chapter 1, are not as spectacular as images from the Hubble telescope – they do not work for outreach activities but for scientific purposes. To be interpreted, the peaks and numbers in mass spectra images require expertise in chemistry. Due to the importance of this tool in NASA's production of knowledge about other worlds, mass spectrometry needs to be put under the microscope.

Another tool for life detection being developed for future NASA missions is AI for autonomous analysis onboard the scientific instrument. Its novelty resides in that it will make real-time decisions about scientific analysis autonomously onboard the missions, without communicating with scientists on Earth. While there are works studying the decision making involving robotics, software, and communication between human teams and rovers (Mazmanian, Cohn & Dourish, 2014; Mirmalek, 2019; Vertesi, 2015, 2020), to my knowledge, the impact of AI tools on how scientists and engineers explore outer space has not been studied by other social scientists. Given previous discussion on how shifts in life detection are tied to development of new technologies (telescopes, radio, and microscopes), it is crucial to study how the new AI tools can change the ways in which scientists explore life in outer space.

Practices at NASA as Culture

I am not the first to analyze the practices at NASA in terms of a culture (Vaughan, 1996). In her book "Shaping Science", sociologist Janet Vertesi shows how organizational circumstances shape the knowledge produced in NASA laboratories (Vertesi, 2020). Based on observations of two missions with different organizational structures, Vertesi demonstrates how organizational aspects shape scientific knowledge through three principles. The first is that science is produced by organizations with local practices, norms and structures of authority. Second, these organizational practices shape the scientific outcomes, such as data, scientific publications and scientists' careers. It does not necessarily mean that scientific knowledge is foreordained by the organization - but considering that the knowledge is produced in a particular organization, it provides "a texture and contour that is isomorphic with the organization" (Vertesi, 2020, p. 6) from where the knowledge emerges. Third, scientific outcomes feed back into the organization by stabilizing its elements (Vertesi, 2020, p. 5-6, 26-27). My approach to observe the process of mutual shaping between the organization and data is aligned with Vertesi's work. Vertesi's earlier work focuses more on the role of technology, more specifically rovers, in the process of shaping scientific knowledge production (Vertesi, 2015). This dissertation is also focused on the technological tools, as one of the key elements in the shaping of scientific knowledge production. However, it focuses on a particular area of scientific knowledge production at NASA – life detection.

Previous studies by Vertesi and social scientist Zara Mirmalek show that the concepts of life and aliveness at NASA are not reserved to biology – rovers on missions are ascribed agency to see and lead missions on Mars (Mirmalek, 2019; Vertesi, 2015). Anthropomorphizing laboratory equipment is not unique to NASA scientists – it is a common practice in other laboratory settings (Knorr-Cetina, 1999; Kruse, 2006; Suchman, 2007). While these themes were prevalent in my material, the focus in this study is less on anthropomorphism, and more on how scientific cultures shape life as a research subject. Similarly to Vertesi's and Mirmalek's ethnographic studies, my work is also based on observations of the interactions between scientists and engineers who work on NASA missions.

However, previous ethnographies of NASA were conducted before the era of "science autonomy," which was introduced with promises of revolutionizing explorations of other planets. At this stage, the robots on distant planets are provided instructions from scientists and engineers on Earth. This loop is about to be broken by inscribing the decision making about scientific analysis to an autonomous system, onboard distant robots. In this work, I show how realizing the dream of autonomy of scientific work on other planets is bringing actual changes to the work of scientists on the ground. Even though "science autonomy" is at the stage of early development (so called proof of concept), it already shapes the scientific work in new ways and by that, it changes the way the knowledge is produced. I contribute to previous studies of scientific practice at NASA by illuminating how the anticipated autonomy of scientific analysis changes knowledge production about other planets and moons.

Exploring Outer Space, Shaping Conditions on Earth

With the increased interest in outer space in society, and commercialization of space, social scientists have turned more attention to the cultural role of outer space. This study is informed by and contributes to the emerging field of Social Studies of Outer Space (SSOS), which is concerned with how space activities shape and are shaped by social orders on Earth (Armstrong & Klinger, 2025; Salazar & Gorman, 2023).

Future-Oriented Discourse

One significant theme in this body of work is to study the space explorations in terms of a future-oriented discourse. In the context at NASA, Messeri and Vertesi showed how NASA missions that applied for support but were never flown impact anticipation of the future (Messeri &

Vertesi, 2015). Messeri and Vertesi suggest the concept of “sociotechnical projectory”, to show how anticipation of a future and shared goals plays an important “material-discursive role in the production of actors’ cohesive social worlds”, which shapes “technological development, career paths, and community membership.” (Messeri & Vertesi, 2015, p. 56) These theoretical formulations can be tied to work in the sociology of expectations, focusing on innovation and the role of expectations in how they shape change in science and technology (Borup et al., 2006; Brown et al., 2003). Messeri and Vertesi observe how missions are also a part of a larger projectory. For instance, the mission to return samples from Mars is positioned as the next step toward flying humans to Mars, since it enables technological development needed for that. The imagined future plays an important role in shaping scientific communities as well as imposing material constraints for action (Messeri & Vertesi, 2015, p. 74-77). Development of AI at NASA Goddard can be understood in similar terms, as an anticipated tool to be used in the future, while already shaping the current actions of scientists and engineers.

NewSpace, and Distribution of Resources on Earth

Another significant theme in SSOS is studying the impact of private actors in the space domain, also referred to as NewSpace. In their studies of national space activities, space scientist Temidayo Isaiah Oniosun and geographer Julie Michelle Klinger show how space explorations continue to be for the purposes of research or socioeconomic development. However, the distinction between public and private actors in space explorations can be blurry. Agencies outsource parts of space research to private companies (Oniosun & Klinger, 2022; Oniosun, 2025). NASA is engaged with outsourcing certain parts of knowledge production, therefore, it is worthwhile to delve into previous studies about the private actors in space research, to get an idea about the organization and culture in these work environments, as compared to a state agency.

Since the Cold War, state agencies have been leading the space explorations. However, in the early 1990s, entrepreneurs, primarily in the US, entered this arena. Space companies, also called NewSpace, like SpaceX and Blue Origin were formed (Valentine, 2012). Although referred to as “private,” these companies are dependent upon governmental contracts. Based on ethnographic fieldwork in the context of NewSpace, anthropologist David Valentine observes how the government figures as an economic enabler, and the outer space as an enabler of profit. The logic of their business is to work more efficiently to reduce the enormous costs of launches (Valentine, 2012, p. 1055). Drawing on SpaceX as an example, sociologist Richard Tutton brings attention to how faster space exploration occurs at the expense of humans working long hours to meet the deadlines of resolving complex engineering tasks (Tutton, 2021). These conditions are driven by Elon Musk’s vision of changing the world and humans to become a “multi-planetary species.” This future, according to Musk and other Silicon Valley entrepreneurs, are to be led by charismatic individuals inspiring people through techno-optimistic visions, rather than by public institutions (Tutton, 2021, p. 435).

The anticipatory discourse of life as multi-planetary is often understood as future-oriented. But David Young and Niall Docherty point specifically to how these discourses are “also dependent on configurations of power rooted in the past,” and nostalgic narratives where great men and disruptive enterprises figure as heroic protagonists (Young & Docherty, 2024, p. 21). As these narratives succeed in turning the attention of the audience toward the future, Mars, and Man’s mastery over nature, they are also turning the attention away from the present concerns about the environmental state of our own planet. Young and Docherty point to how making life multi planetary is marginalizing questions about distribution of wealth on Earth (Young & Docherty, 2024). This argument echoes public debates from the beginning of the establishment of space program in the US. At the time, public figures questioned whether spending such large amounts of money on space exploration is justifiable in the face of poverty and inequality on Earth (Dick, 1996; Tutton, 2021).

Social scientists have also attended to the injustices tied to production of data about outer space. James Merron and Siri Lamoureaux studied a radio telescope in Ghana used for satellite data transfer (Merron & Lamoureaux, 2024). Drawing on STS, they questioned the narratives of technoscientific modernity for the "common good," given the material infrastructure required for data to be stored and transferred. The demands for cables, servers and bandwidth, the authors argue, compete with satisfying the everyday needs of population in Ghana, such as electricity, clean water and health care (Merron & Lamoureaux, 2024).

Outer space is not just a geographical territory, but a social realm onto which human ideas are projected. It is crucial to study who projects which ideas, since exploration of outer space does affect both material (i.e. labor, distribution of resources) and discursive (visions of the future that orient action) conditions of life on Earth.

Conclusion

Historical accounts have shown how the societal context and the technological tools available, shape the object of research in the scientific study of life. For instance, tools such as the telescope and microscope created new ways of knowing. This implies that introduction of new AI tools in life detection at NASA is intertwined with new ways of producing knowledge about life. This calls for ethnographic attention, to understand how this change occurs in practice.

To address this, this study approaches science and technology as a cultural practice. Drawing on previous work in STS, especially laboratory studies (Knorr Cetina, 1999; Latour & Woolgar, 1986 (1979)), this study will observe the practices of scientists and engineers, to understand science and technology in the making. Nonetheless, the study is not limited to the laboratory – insights from social studies of data underline that understanding data requires an analysis of their attachments to places and people (Loukissas, 2019). I operationalize the attachment to places through the concept of truth-spots (Gieryn, 2006; 2018), and make a theoretical contribution by expanding it to the digital realm.

Studies in the field of SSOS have scrutinized the actors in NewSpace and visions of entrepreneurs for the future of Earth, as they play a powerful material and discursive role in shaping society (Tutton, 2021; Valentine, 2012; Young & Docherty, 2024). Nonetheless, previous studies also show that space explorations continue to be for purposes of research or socioeconomic development (Oniosun & Klinger, 2022). NASA remains as the major actor in exploration of outer space, producing scientific knowledge about the universe. This organization has a profound impact on the ways in which humans imagine the universe and our place in it. It has global impact, and universal aspirations, but as any knowledge claim, it emerges from a particular place (Haraway, 1988). In future missions, knowing might be increasingly mediated through AI. Considering NASA's role in knowledge production, it is crucial to study what is made (un)known and what is (not) inscribed in the algorithms that constitute this knowledge.

In the next chapter, I introduce the method and material used in this study. Subsequently, I turn to the empirical chapters, where I introduce the theoretical tools used for analysis.

Chapter 3 Method and Material – Life in Planetary Science and at NASA

Studying development of AI ethnographically opens up a window to the negotiations, uncertainties and instabilities involved in its development. I am fortunate to have access and have closely observed a group of scientists and engineers at NASA Goddard Space Flight Center, who work with AI for NASA missions searching for life and habitability in outer space. These observations have become the core material of this dissertation.

In this chapter, I provide a thorough discussion of the methods as well as the material generated in this study. I start with briefly describing what is at stake in the ethnographic method. Then, the discussion is organized in accordance with the steps I took during the research process. Beginning with the choice of research problem, I continue with formation of a field site and how I went about generating material for this study. Throughout the chapter, I reflect on the choice of research subject, participants and field sites, my role in the field and the problem of access.

Ethnography as a Method

Ethnography is a method where the researcher spends a period of time with a group of people, observing their daily lives. These observations, inscribed in a notebook or recorded through a digital device, constitute the data that the ethnographer generates. Data generation is mostly unstructured, meaning that there is no fixed research design applied from the start. In order to facilitate an in-depth understanding, it is common to focus on a single setting. During the process of analysis, the ethnographer interprets the "meanings, sources, functions, and consequences of human actions and institutional practices, and how these are implicated in local, and perhaps also wider, contexts" (Hammersley and Atkinson, 2019, p. 3-4). The ethnographic method is an activity of decoding, recoding, distinguishing between order and diversity, as well as inclusion and exclusion. The aim is to study powerful meaning systems and question the boundaries of classifications (Clifford & Marcus, 1986, p. 2). The final product is often a verbal description or explanation of a particular phenomena (Hammersley and Atkinson, p. 22).

The ethnographer is not only describing what is out in the field - the ethnographer is continuously a part of it (Clifford & Marcus, 1986, p. 2). As a fellow human, studying other humans in their natural habitat, the ethnographer entering the field becomes part of the social world being studied. Analysis of a culture is never complete (Geertz, 1973, p. 322). The subjects being studied are not static still lifes and do not live up to the portrait painted by the ethnographer. It is necessary to be conscious of what one includes in and excludes from the picture. Reflexivity about how the ethnographer affects the field, generation of data and analysis, are fundamental in this method (Schwartz-Shea & Yanow, 2012, p. 100).

The ethnographic method is often described as either "emic" or "etic". The aim of "emic" ethnography is to understand the informants' own perspective of the world. On the other hand, the aim of 'etic' ethnography is to explain why people live in a certain way, drawing on theories, history and other empirical studies (Fortun, 2024, p. 126). In this project, I use a combination of emic and etic analysis, by both seeking to understand how my informants understand the world but also seeking for explanations of why they act in certain ways. To do that, I have complemented careful analysis from observation of informants with strategy documents and historical context. This approach draws on Science and Technology Studies, where science is understood as practice shaped by "historical, organizational and social context" (Law, 2004, p. 8).

From the Problem to the Field

Ethnographic research starts with an interest, question or issue that emerges from the literature or other sources (Hammersley & Atkinson, 2019, p. 22). This is what Malinowski referred to as “foreshadowed problem”, stressing it as an essential part in the research process (Malinowski, 1922, p. 8-9). Ethnography is an open-ended approach that initially explores a subject quite broadly and throughout the process, becomes more focused (Hammersley & Atkinson, 2019, p. 4). During the investigation, the “foreshadowed problem” is continuously revisited and reformulated (Hammersley & Atkinson, 2019, p. 22).

The initial curiosity guiding this study was about *how AI changes the understanding of life*. During 2020, in the beginning of this project, AI was on the rise in society. How AI affects society became an urgent question to study for social scientists. This spurred my earlier interest in the effects of digitalization on society. The choice of focusing on how AI changes the understanding of *life* was due to both professional and personal experiences. During the Syrian war in 2015, I was working with immigrants in Sweden and volunteering at a refugee camp on Lesbos, an island in Greece. Witnessing the misery in the camp was indescribable – but what I found most striking was how human lives have such different conditions to flourish depending on their passport. I recall how I did not take any images of humans in the camp because of the risk that the images could be used for *autonomous tools,* used to identify humans by their appearance, with potentially harmful consequences for the legal status of the refugees. Five years later, in the beginning of this research project, I was concerned about how *AI technologies* would affect our understanding of different kinds of lives.

While designing the research project, I was inspired by the approach of Mette Svendsen, Laura Navne, Iben Gjødsbøl and Mia Seest Dam, who studied caregiving in Denmark by looking at lives across different categories. From newborns at neonatal intensive care units and piglets at a research laboratory to elderly people in a dementia nursing home, the authors showed what it takes to constitute “beings with worthy lives” (Svendsen et al., 2018). This shaped my analytical attunement to how entities are *made* into worthy of care or not.

Following this, I was interested in lives across different categories, staying open to study contexts such as border control offices or bioscience laboratories. Drawing on my training in political science, I was inclined to study power relations by looking at decision making in the process of designing AI technologies as well as the organizations where they are implemented. However, in studying powerful institutions or corporations, access can be a major obstacle (Gusterson, 1997; Nader, 2018). I will return to this subject later in the chapter and describe the problem of gaining access to NASA, the largest space agency in the world.

Another challenge that appeared already at the initial stage of the study was the state of the world, being locked down due to Covid-19 pandemic. This posed a severe challenge for getting access to fieldwork beyond the virtual format. In order to adjust to these circumstances, I searched for other sites to observe the astrobiology community. In times of difficulties to get access, “polymorphous engagement” (Gusterson, 1997, p. 116) can be a fruitful strategy. The term derives from anthropologist Hugh Gusterson, who studied the nuclear weapons laboratory. Without having access to the laboratory building, he had to engage in other settings where his participants were present, such as local clubs, bars, churches, and complementing it with reading the newspapers and following the popular culture. This approach, which he referred to as “polymorphous engagement”, means that the ethnographer interacts “with informants across a number of dispersed sites, not just in local communities, and sometimes in virtual form; and it means collecting data eclectically from a disparate array of sources in many different ways." (Gusterson, 1997, p. 116) In line with this strategy, due to lack of access to a physical field site, I engaged with searching for other sites to observe. In the following, I discuss the steps I took to generate material for this dissertation.

Searching for a case study quite broadly brought me to a particular field of study within biosciences: astrobiology. I immediately got curious about its attempts to answer the big, unresolved questions (What is life? How did life emerge?). Intrigued by how AI plays a role in addressing the big questions about life and its origins, I started fieldwork by exploring the scientific community in the field of astrobiology. By then, the aim of the research narrowed down to focus on the field of astrobiology.

Observation of Scientific Conferences

I started to collect material by attending conferences, seminars and lectures. The main purpose was to get insights about astrobiology by paying attention to the currently discussed topics, research questions and methods. Guided by the previously described "foreshadowed problem", I was specifically interested in the use of novel technological tools such as AI or other autonomous systems. Between 2021 and 2022, I observed five online conferences and three online seminars on the subjects related to astrobiology, space research and planetary science. Three of these conferences were the main global conferences in the following research fields: astrobiology, origins of life studies and planetary science. I contacted the organizers to receive permission to observe the events, however, most of the events were publicly accessible online. The majority of the participants were scientists within these fields, some were engineers. Some of the events involved presentations by politicians or were aimed at laymen audience. The events were of varying duration – from a half-day seminar to a two-week-long conference. The majority took place online, during the Covid-19 pandemic. During observations of the conferences and seminars, I generated field notes and photographs. This material has served as an important background for understanding the epistemic community, that my main interlocutors at NASA are situated in.

In May 2021, after the pandemic restrictions were lifted, I joined a summer school in astrobiology, organized by the European Astrobiology Institute. I participated in the summer school in order to experience the community of astrobiology and establish relations with people in the field, both junior and senior researchers, whom I am still in touch with today. The summer school took place at Ven. It is a small island in Sweden, with great historical importance to astronomy – it was the home of Tycho Brahe, whose measurements of stars were the most accurate before the invention of the telescope. Compared to the virtual settings which I explored previously, socializing with researchers was much helped by the physical setting at Ven, the picturesque island in full bloom of May. Nor should the locally brewed beverages be underestimated as a glue in bonding between researchers. This was acknowledged among researchers at several occasions during fieldwork. In an interview with one of the most influential researchers in the origins of life studies, he stated that research happens at the pub. During the pandemic, at a virtual conference in planetary science, the host was explicitly mentioning how unfortunate it is to miss out on the gatherings around dinner and wine with colleagues. Throughout fieldwork, participation in casual settings showed to be important to understand the social world of my informants.

Interviews with Scientists and Engineers

Dependence on the virtual context during the pandemic made it possible to access researchers around the world. Observations of conferences and seminars related to astrobiology enabled me to find relevant interlocutors for initial interviews. Later, I continued with snowball sampling. During the period between fall 2020 and the beginning of 2022, I conducted 21 interviews with one participant at a time. An exception was one interview conducted with two planetary scientists who were working on a project together. Among the 22 participants, 20 were scientists, and two were software engineers. The scientists I reached out to were in some way contributing to the field of astrobiology. The majority of my requests, sent to potential participants through e-mail, led to an interview.

Given that informed consent is a fundamental initial step in conducting interviews (Flick, 2018, p. 140), I informed the participants about the objectives of the study, their right to withdraw from the study at any point, and confidentiality. I also asked for the consent for recording audio. In line with ethical standards of qualitative research to not cause harm to the participants (Flick, 2018, p. 136), I have been considerate about how the data will affect the social situation of the informants. In order to mitigate causing harm by accident, I have involved my informants in the review of quotes and observations, and opened up for revising the material and use of their real names, or pseudonyms before publication. I have not collected any sensitive personal data, such as health condition, religion, etc.

Interviews were semi-structured, in order to balance between allowing participants to express their viewpoints, yet steering the interview in a direction related to the aim of the study (Flick, 2018, p. 216). During interviews, I asked about the researcher's scientific background, their work with astrobiology and their thoughts or work on AI. Interestingly, several interviewees clearly articulated that they are *not astrobiologists per se*, rather, they *contribute* to the field of astrobiology. This turned out to be a key point in my material. It made me wonder why informants working with astrobiological research prefer to call themselves biologists, chemists, physicists, or astronomers. Throughout fieldwork, I noticed that researchers with ties to NASA were more inclined to call themselves astrobiologists. Reading accounts about the history of life detection provided me with explanations to this, which I intertwine with my observations from NASA in the first empirical chapter.

The majority of the interviewees were based in Europe and the US. This reflects the global asymmetry in the infrastructure of knowledge production in astrobiology – rocket launch sites, telescopes and testbeds are often situated in the global South, and used for generation of scientific knowledge in the global North. The choices of sites and languages (English and Swedish) were based on temporal and economic convenience, as well as linguistic abilities. However, the "smoothness" of studying English-speaking and Northern contexts is problematic from the perspective of knowledge production. Being aware of the colonial history and cognitive injustice, it is crucial to remain attentive to how different sites are affected and whose interests are served by particular endeavors. I address these aspects in chapter 5, by folding in alternative narratives of places used by NASA, and engaging with previous studies on sociopolitical consequences of space explorations.

Some interviews turned out as interviews, some as conversations, some were more of me being lectured. By the time of starting this study, I did not have any experience of astrobiology, beside reading a few books and listening to lectures. Pursuing the semi-structured interviews by asking questions with such limited experience of the subject was initially challenging. I was veering between feelings of incompetence, awe and humility. To get rid of the uncomfortable feeling of incompetence, I dedicated a lot of effort to learn the jargon, terminology and the social norms in the field of astrobiology. The fact that the pandemic restrictions resituated my field to the virtual part of our world could have been an advantage in allowing me to learn and increase my competence in astrobiology, thus, entering the physical field with more confidence. Downsides of the virtual format are that some understandings might have got lost in translation - communication with new people can be more challenging when mediated through a flat screen. The mediation can make it difficult to show the participants that they have my full attention - it is impossible to establish eye contact and one does not know what the other looks at or expresses with the body. Nevertheless, post-interview communication with the participants showed that they did have a positive experience. Several participants were grateful and curious about my research, and one even sent me a book with a greeting by post. These gestures became gentle reminders that it is worthwhile to show the authentic self during field work, showing empathy toward the participants. Being challenging, even in difficult situations, is not a good strategy in trying to establish trust with participants (Lähdesmaki, 2020, p. 156).

Literature Review – What Is the Role of AI in Astrobiology?

In order to get a systematic overview of the role of AI in astrobiology or life detection specifically, I conducted a literature review in the spring of 2021. I collected 82 scientific publications of which 62 were from the last ten years. Most of the publications were collected through search engines (Scopus and Google Scholar) and a smaller number directly from journals (Astrobiology Journal and Journal Origins of Life and Evolution of Biospheres). After exploring numerous keyword entries, the combinations that generated the most relevant results for the aim of this study involved "artificial intelligence", "machine learning", "neural networks", "astrobiology", "origin of life." At the stage of collecting 82 papers, I reached a level of saturation. The literature review was conducted with the software NVivo. Initially, I coded the themes manually. Some of the prevalent themes were: “AI as a tool to find life”, “AI as unbiased with minimal assumptions”, “machine learning for prediction”, “questioning Earth-centrism”, “microbial life in outer space”, “life as biology”, “life as carrying information”, “life as ET civilization-intelligence”. Successively, after getting an increased insight about the material, I was able to search for certain keywords that were important.

The most important keyword turned out to be “intelligence,” as it illuminated the multiple understandings of life, as biology or technology. Based on that, I identified multiple roles of AI in the context of astrobiology and life detection. A common depiction of AI within astrobiology, is as a tool to enhance search for life and habitability. However, another narrative prevalent in life detection is understanding of AI as a potential post-biological life form that could be detected in outer space. This finding proved to be crucial for understanding the multiplicity of approaches in life detection. I complemented these insights with historical accounts about how search for life in outer space has been a subject struggling with legitimacy. This opened up important questions about what kinds of life NASA considers as legitimate to search for and with what tools. This topic is discussed in the first empirical chapter and provides an important context for understanding what is at stake for practitioners at NASA.

The steps described above, including observations of conferences, interviews and literature review, provided a solid background for understanding the role of AI in the field of astrobiology. However, access to the field to conduct participant observations of scientists’ everyday work has been difficult due to several reasons. First, it was difficult to interpret the research among natural scientists and decide whether their work is aligned with my research questions. For instance, I got invited to join scientists working with drones in planet analogs on Iceland, but had to kindly decline after a reconsideration. The purposes of their study did not overlap sufficiently with the aim of my research. Second, the pandemic restrictions have limited my possibilities to build relationships with astrobiologists which otherwise might have helped me to navigate through the field. An example of the difficulty of getting access to the field is a conference organized by NASA that I registered for but only got limited access to. I was not able to use the conference material, since I did not apply for a particular consent in time. Instead, I used this as an opportunity to learn about the field of astrobiology, before conducting more in-depth ethnography of conferences later on.

Participant Observation at NASA Goddard Space Flight Center

Now, I will turn to what constitutes the core material for this dissertation – participant observations at NASA Goddard Space Flight Center. Among my interviewees were scientists and engineers at NASA. Two software engineers were working at NASA with developing AI tools for life detection in outer space. Given my “foreshadowed problem” being how AI changes the understanding of life, this was an ideal case. After a period of negotiation, I was able to get access from my interlocutors who let me conduct participant observation of their work at NASA Goddard Space Flight Center in Greenbelt, Maryland.

Being considerate about ethical dilemmas is crucial to legitimate qualitative research. This involves the balance between generating new scientific knowledge and maintaining the dignity and rights of participants. Ethical committees can work as an instrument to assess if a project is complying with good ethical practice (Flick, 2018, p. 139, 147). To conduct ethnography at NASA Goddard Space Flight Center, I applied to NASA’s ethical review board. I submitted a plan of the study, focusing on protection of individuals and mitigating risks of causing harm. After making minor adjustments to the plan, based on several rounds of comments from NASA’s ethical review board, I received ethical approval to conduct fieldwork. The process of applying for ethical approval entailed passing NASA’s course on studies of human subjects.

The main participants in the study have formally consented to be part of the study. All participants were informed about the study in accordance with the guidelines in NASA’s ethical approval. They have been introduced to the objectives of the study and their right to withdraw from the study at any point. I have not recorded any sensitive personal data, such as health condition, religion, etc. Throughout the process of collection of the material as well as analysis and writing up, I have been considerate about not causing harm to the participants. Nevertheless, in order to mitigate causing harm by accident, I have involved my informants in the review of quotes. This opened up for revising whether the material contains any information that could potentially cause discomfort for their social situation at work, as well as discussing concealing their identity in different ways. To summarize, I have taken all the promises made to NASA’s ethical review board and each participant very seriously.

As a foreign national (Swedish and Polish citizenship) at a governmental US agency, I was excluded from witnessing or registering certain information. US regulations do not permit foreign nationals to access technical details about the missions. I complied with these rules and did not witness or record such information. This limitation did not impact the results of the study. Furthermore, in accordance with guidelines for foreign nationals, I was escorted by NASA personnel at all times. In most cases, I was escorted by participants in the study. Instead of being an issue, being escorted was a great opportunity to shadow my informants at all times.

I conducted participant observation at NASA Goddard Space Flight Center on two occasions. First, in June 2022, for four weeks. Then, a follow-up visit with the same interlocutors in July 2023, for three weeks. The length of the visits to the field site were limited by policies at NASA, which allowed me to visit for a maximum of one month. Due to these formal restrictions, the ethnography was executed in what previous ethnographers have termed "compressed time mode", meaning "a short period of intense ethnographic research in which researchers inhabit a research site almost permanently for anything from a few days to a month" (Jeffrey & Troman, 2004, p. 538). In contrast to ethnographies that span over longer periods of time, the "compressed time mode" makes it less likely for researchers to be selective about how they spend time at the field site. Instead, the researcher is fully engaged in the daily routines and has to soak up "every tiny detail" because it might be relevant for later analysis.

The question of time in ethnography regards not only how long the researcher is engaged with the field. It is also a question of choosing the right timing. Dismissing the temporal structures of the social context being studied can lead to misleading conclusions (Hammersley & Atkinson, 2019, p. 39). The right period for fieldwork at NASA was decided based on consultation with informants, in order to choose relatively busy periods at work and at the same time avoid periods when practitioners are away for conferences, field trips or vacation. My first fieldwork was conducted a few weeks after pandemic restrictions were lifted. Practitioners just started to get back to the office. This was celebrated with beer and snacks at a gathering after work during the first week of fieldwork, which was a great opportunity to get acquainted with potential informants.

I spent the majority of fieldwork with one software engineer and accompanied him in meetings with scientists and engineers. I have also spent a substantial amount of time with scientists while they were conducting experiments in laboratories at Goddard, as well as in their meetings. While I have observed dozens of scientists and engineers in their everyday work, a handful were my main interlocutors. They are all engaged in the work with AI for “science autonomy” in different ways (which I described in the introduction chapter). Some are the leading figures introducing the idea to NASA, while others have more of a collaborative role. During my visit, different kinds of AI tools were in development. However, my observations encompassed much more than just AI development, which has provided important insights about the infrastructure of knowledge production at NASA that makes AI possible (or at times impossible, which I will unfold throughout the upcoming chapters). During the visits at Goddard, I wrote field notes, as well as took photographs and made audio and visual recordings, given participants' consent. I have also received additional material from interlocutors, such as presentations, drafts of applications and datasets for AI.

During fieldwork at Goddard, I conducted interviews with six software engineers and eight scientists. Besides that, I interviewed three persons holding managerial positions at Goddard, of which two were scientists and one was an engineer. The majority of the participants were interviewed on several occasions during fieldwork. The boundary between interview and participant observation can be blurry, and moreover, interviews do not always go as planned (Hammersley & Atkinson, 2019, p. 113, 115). In some cases, interviews were successful in terms of being semi-structured and informative, while others were interrupted. Interruptions were not uncommon, as the interviews occurred at the office, in the middle of a workday. On the other hand, having interviews at the office could allow participants to feel comfortable in a familiar setting, in contrast to arranging an interview elsewhere (Hammersley & Atkinson, 2019, p. 122). Each interview with a new participant involved a presentation of the research project, information about the conditions of being studied, such as the right to confidentiality and withdrawal at any point. The interviewees have formally consented to participate in the study and the majority consented to be recorded. Recording has great advantages for the research, by providing accurate data and freeing the researcher to focus on listening and asking questions. However, an over-emphasis on recording audio can turn the attention of the ethnographer toward data that is recordable, focusing on spoken words rather than other forms of action (Hammersley & Atkinson, 2019, 160-1). Bearing in mind that scientific practice is more than what people say, I used other means than audio-recording. This draws on insights from sensory ethnography, as explored in Lähdesmaki and others (2020), who emphasize how the ethnographer is situated in the materialities of the environment through the sensing body. By attending to various sensory experiences, these undermined modes of knowing can become a source of non-verbal notions that play a meaningful role in our everyday lives and interactions (Lähdesmaki, et al., 2020, p. 21, 22). I explored these notions by being present, observing, writing, taking pictures, making videos, registering temperatures, distances versus closeness between entities and aesthetic impressions.

During the fieldwork, at the end of my workdays at NASA, I dedicated some time to write down reflections about what I observed and how it relates to certain theoretical concepts but also, about my role in the field. This part of the process was vital, in order to maintain focus on the aim of the study and plan how I should continue fieldwork – what and whom to observe, what kind of follow-up questions to pose, whom to interview.

My role in the field can be described as coming across as young (28-29 years old) and incompetent, which is common in ethnography and can be an advantage (Hammersley & Atkinson, 2019, p. 80). It is a common practice at NASA to hire interns, who are usually young students. Because of the prevalence of interns during the periods of doing fieldwork, I might have blended in more easily among other young and unexperienced peers. Moreover, due to the character of social research being radically different than practitioners' at NASA, I was less likely to be considered as a threat in the competitive environment at NASA. This identity, of being young and incompetent, allowed me to ask naive questions and search for clarifications without awkwardness. As an example of this role, in post-fieldwork correspondence with one of my main informants, the person described how I have become internalized as a someone who asks questions:

> Or sometimes I sit in my office and think, "How would I explain this to Alicja?"

I arrived at NASA, curious about how scientists and engineers generate knowledge about the world. Once I met them in the field, they turned out to be as curious about my research methods as I was about theirs. While introducing myself as a social scientist and explaining my research, it became evident that our ways of producing knowledge differ. In spite of these differences, I needed to establish a common ground with practitioners in order to build trustworthy relationships with participants, which is a central point in ethnography. As Hammersley and Atkinson stress, ordinary topics of conversation can help to establish an identity of a decent person that can be trusted (Hammersley & Atkinson, 2019, p. 70). I engaged in conversations on topics beyond the aims of the study, such as hobbies, family life, pets and references in popular culture. During fieldwork, I developed closer relationships with core participants. Together, we hosted a celebration upon my departure. I brought with me a selection of beverages and was surprised upon receiving some gifts and a card, which my participants have signed with expressions of gratitude for my visit. After my departure, one of the participants shared that they wish I would work with them at NASA. While staying in touch with my main informant through correspondence, I get updates and pictures about work as well as personal life.

Developing close relationships with informants has the advantages of being able to immerse the self in the social world of others, which helps to unfold an in-depth understanding. On the other hand, the process of disengagement from the field – when sympathetic humans become research material to analyze – can be emotionally difficult (Gobo, 2008). At some points I had to remind myself that I was not one of the astrobiologists, rather, I was studying them. This was difficult due to two reasons. First, as I mentioned, I developed a strong sympathy toward my informants, who turned out to be very likable. Second, I shared the curiosity that my informants have in relation to the big questions that are central in astrobiology. With time passing since my field visit, I was able to get distance and revise my role as an ethnographer, not an astrobiologist addressing the big questions. Anthropologist Clifford James Geertz summarizes this distinction well in the conclusion of his article on thick description:

> The essential vocation of interpretive anthropology is not to answer our deepest questions, but to make available to us answers that others, guarding other sheep in other valleys, have given, and thus to include them in the consultable record of what man has said (Geertz, 1973, p. 323).

Access to NASA Revisited

Access to the field site was not something that I could take for granted. During the first visit in Greenbelt, upon my arrival, I still had not got "the badge" – the permission to enter NASA facilities – despite submitting applications long in advance. Fortunately, this issue resolved quickly and I soon got the right papers in place. My second visit was planned to be for a period of two months. While standing in line to show my passport, just a moment after my flight arrived to the airport in Washington DC, I received an email from my informant. "I just went back and checked the start date and found a terrible mistake. It has you starting AND FINISHING on 3/31/23." This meant that my permit to access NASA facilities was issued for one day, instead of two months. Hoping that the issue would get resolved quickly, with help of my interlocutors, we attempted to get the right papers in place. After almost two weeks of staying in Greenbelt and trying to get access without success, I returned back home to make up a new plan. A few months after, I was in Greenbelt once again, this time for a period of three weeks. The following are my field notes from the first day of returning to NASA.

> Monday 3rd of July 2023
> Went through the formalities without any issues. (…) Long and intense first day. I feel even more grateful to get in, now when I know how bad it can be, after last time. Me and Eric laughed that it might have happened since I applied for a visit starting 1st of April. A very cruel April's fool joke. He's said how sorry he is but I prefer to laugh at the situation by now. Otherwise, it's unbearable. I haven't re-read the notes from the days when I wasn't able to get in, staying in the limbo. Speaking of hardships, me and Eric talked about not only life detection

> missions and AI but turned to our common topic of discussion – running. And family. After having a lunch with a small beer to celebrate my first day in, we continued to talk about Eric's work. I think we were in a constant conversation from 9 AM at his office, until 2 PM after lunch, when I had to go to the bathroom.

The above illustrates the intensity of doing fieldwork and its *ad hoc* nature. Access to the field can be difficult to get to begin with, and it can also easily be taken away. Access can not be taken for granted. Therefore, once getting in, as ethnographer, one has to adjust to the circumstances.

The experience of being denied access was indeed challenging. However, interruptions in fieldwork, such as lack of access, do not have to be dismissed as failures (Fortun, 2024, p. 129). In this case, lack of access generated important analytical points for this dissertation. I was not the only one at NASA without a "badge". Once I conducted fieldwork at Goddard, a frequent problem echoing in the hallways was how X researcher is still waiting to get a "badge" and can therefore not access facilities. Bureaucracy at NASA is impacting preconditions for scientists and engineers to do their work. However, programmers that do not rely on laboratories do not need a "badge" – they can do their work from anywhere. This has two consequences for the infrastructure of knowledge production. First, being able to do the work regardless of the "badge" gives programmers an advantage in comparison with other professions. The work of scientists and engineers is dependent on having access to the unique instruments at NASA laboratories. Programmers can mobilize resources from anywhere in the world. All they need is a computer. Second, access to the facilities and insight into the material work of scientists and engineers at NASA generate a sense of epistemic responsibility. Lack of access to the context of knowledge production does not create a precondition for epistemic responsibility, but rather, for accountability according to metrics. This vantage point is explored further in chapters 6 and 7.

Post-Fieldwork: Transcription, Analysis, Writing Up

After conducting fieldwork, I transcribed the field notes entirely, which entailed two notebooks of 200 A5-pages each. Regarding audio- and video-recordings, I listened through each of them and kept a separate notebook where I identified themes, wrote summaries or noted down relevant quotes. I transcribed only parts of the recordings that were essential in relation to the study. A risk in doing so is missing out what might turn out to be relevant material at an unexpected point. Nonetheless, due to time constrains, full transcription of almost hundred hours of recordings was not feasible (for reference, transcription of one interview can take an entire workday). To prevent overlooking relevant material, I repeatedly revisited the notes with themes, summaries and quotes, and returned to the recordings.

As you may have noticed in the earlier sections of this chapter, the analysis is not a separate period of work, beginning after collection of all material. Analysis occurs throughout the entire research process. Identifying prevalent themes took place already during generation of material and continued afterwards, by revisiting the field notes and transcriptions. In the notebook for field notes, where I already started to inscribe analytical ideas, I clearly separated my analysis from the observations and participants' own descriptions of events by using different colors.

The process of analysis shares traits with the logic of abduction. It is an approach to qualitative data analysis "aimed at generating creative and novel theoretical insights through a dialectic of cultivated theoretical sensitivity and methodological heuristics." (Timmermans & Tavory, 2012, p. 180) Here, the dialectic relates to the notion of continuously revisiting the empirical material and theoretical assumptions, trying out alternative ways of analyzing material. The fundamental aspect of abductive logic that proved to be fruitful in the process of analyzing this project has turned out to be revisiting the phenomena being studied throughout different periods of time. Data that did not appear to be important during fieldwork can become valuable after a period of time, including new empirical and theoretical insights (Timmermans & Tavory, 2012, p. 176). This process made it possible to reevaluate the material and its relevance.

Since the beginning of this research project, I kept an analytical notebook where I noted down ideas throughout the research process. However, after completing participant observation at NASA, I shifted to working closely to the empirical material. After conducting fieldwork, I revised the aim of the study and narrowed it down, from astrobiology to NASA specifically. I continuously revisited the material from participant observation at NASA and searched for themes that related to my research interest, looking for patterns and anomalies in the practices that I observed. After getting a good insight into this core material, I was able to incorporate the earliest interviews and observations from conferences to the analysis, as they provided valuable context to understand the scientific community that my informants are part of. Having qualitative data from a range of different sources enabled triangulation during the analytical process (Flick, 2018, p. 196-197). I was searching for patterns, anomalies and discrepancies between the material generated during conferences, interviews, literature review and the visit at NASA. The data from different levels, such as documents versus everyday practices at a laboratory, showed interesting discrepancies. The outreach rhetoric at NASA and its claims about what kind of knowledge is produced, compared to the everyday practices of researchers and their hesitation in making knowledge claims has constituted a significant theme in the thesis (discussed in chapter 4). Furthermore, by looking at the published literature in the field of astrobiology and comparing it to the practices at NASA, I was able to show how certain actors are excluded from the governmentally funded organization, due to arguments of illegitimacy.

Rather than analyzing the computational code itself, I have focused on what each profession considers crucial to maintain, or change, in negotiations about the data used for training AI. This has enabled me to generate insights about the epistemic concerns, and how they change in development of AI. I have observed the practices of producing scientific knowledge in laboratories at NASA but not beyond – such as field work to collect samples which are analyzed in the laboratories. I rely on interviews, scientific articles, conferences, and other documents, to complement the analysis of how scientists produce data without limiting it to what happens in the laboratory.

At the stages of writing up the dissertation, I realized that I should get more insight into how popular culture impacts the social world at NASA. To do so, I watched movies, TV shows and documentaries about NASA, space research and sci-fi, such as Star Trek, which I observed has had a significant influence on how NASA researchers imagine space exploration.

An important stage for the process of analysis of the material has been a visit with the research group who spiked my initial analytical interest in looking at lives across categories (Svendsen et al., 2018). I am indebted to the MeInWe research group at Copenhagen University for being an extremely stimulating intellectual community to think together with, during the fall term of 2023. Furthermore, I am fortunate to have had a group of researchers whose wisdom, anchored in different scientific backgrounds, has pointed my analytical attention in new directions. My supervisors (STS-scholar Francis Lee and sociologist Shai Mulinari), my mentors (historian of science Sven Widmalm and anthropologist Mette Svendsen) and my final seminar opponent (anthropologist Klaus Høyer) have played important roles by providing invaluable feedback.

Following up with Participants

During the last months of this project, I got back to the participants individually with the material – quotes and descriptions – that I plan to use in the dissertation. Participants were re-informed about their rights as participants in the study, and provided the opportunity to review the material. Some of the participants provided feedback with minor revisions. Most of the comments aimed at achieving more accurate descriptions of the scientific terminology. In two instances, the participants asked to withdraw a particular section of the material. In one case, it was to mitigate the risk of social discomfort. In another case, it was to not reveal data used for AI training which has not been published. Beside these examples, participants provided confirmed consent to use the material for this study. Some of the names of participants are real, and in some cases, they are referred to with pseudonyms. The choices were made based on individual consultation with participants. In some instances, titles or other characteristics that might reveal the identity of a participant are concealed.

I include a list of the participants who figure in the thesis, in the approximate order of how frequently they appear (Figure 7). Two of the participants explicitly identify themselves as astrobiologists, while others prefer other labels (planetary scientists, chemists, geologists). What unities these scientists, and engineers, is that they have in different ways contributed to research on the main questions addressed in astrobiology. Although 14 participants explicitly figure in the thesis, the descriptions of

Participant	*Profession*
Eric	Software engineer
Victoria	Software engineer
Lu	Scientist
Jason	Scientist
Samantha	Scientist
Michelle	Software engineer
Walter	Scientist
Ryan	Scientist
Sandra	Scientist
Michael	Scientist
Paul	Scientist
David	Scientist
Caroline	Scientist
Ashley	Software engineer

Figure 7. Participants who are referred to in the dissertation.

scientific practices are informed by participant observation and interviews with four participants who do not figure in the dissertation – two scientists and two programmers. All participants have ties to NASA, either as present or past employees, or as collaborators.

Regarding interview material used in the dissertation, the quotes that are italicized indicate my own emphasis. When an informant put an emphasis through intonation, I use capital letters. In documents and previous studies cited in the thesis, I include a parenthesis to clarify if parts of the text are italicized by me.

Limitations

The two major strengths of ethnography – appropriateness and methodological flexibility – have enabled me to adapt to the research subjects throughout the process (Flick, 2018, p. 335). However, the use of this method has limitations, such as finding the right timing for observations of events. Even though I have done my best to plan for a fruitful period to visit NASA, "the best period" can never be fully anticipated in advance. Another limitation is my relation to the informants at NASA, whom I avoided challenging, to not come across as a difficult person to be around. During fieldwork, I have aimed for acting respectfully and approach informants with kindness. I already mentioned that I did have a strong feeling of sympathy toward my participants – however, not being challenging during fieldwork was also because my access to the field was dependent on them.

The study provides insights about the development of AI in society in general. However, the implications of this study do not necessarily translate to other contexts and domains where AI is being developed. This dissertation concerns AI tools in the making, at a particular place and point in time, and a particular example in planetary science at NASA Goddard.

Cultures are not a static phenomenon. Along with rapid technological development of AI tools, it is likely that a lot has changed at NASA since the fieldwork was conducted. This is also implied in recent follow-up correspondence with participants. For instance, one participant notes that they currently work with a team that has a different attitude than a few years ago. Furthermore, they state that there are now new kinds of AI, and new ways of simulating data, which contribute to increased robustness and trust in these tools.

Chapter 4 Drawing Boundaries Around Astrobiology to Sustain Legitimacy at NASA

225 million kilometers away from Earth, a three-meters-long, 899-kilogram rover with six wheels drives around on the surface of Mars. It is a dusty, cold desert world. The rover is on a NASA mission to explore whether Mars has ever been capable of supporting life. Through a camera, the rover looks for an interesting spot, drills a hole, picks up a sample with its robotic arms and puts it inside its "belly." It is designed to resemble a human body and do experiments like a human astrobiologist. A human astrobiologist might not put a sample in their belly – but the rover does. To digest the samples, the rover uses several scientific instruments. One of them is called SAM (Sample Analysis at Mars), already introduced in the first chapter. It is a miniaturized laboratory that analyses gases and powdered rock to identify which organic molecules are present on Mars. Scientists at NASA believe that organic molecules can provide important cues about the possibility of life on other planets.

Unlike the Red Planet, the city of Greenbelt is, as the name suggests, full of vegetation. Parts of the green area are framed in a window behind Walter, at his office at NASA Goddard Space Flight Center. I enter his room and ask if he has some time to talk. Sure, he says, after which I sit down on the chair at the other side of his desk. Walter is one of the scientists who developed SAM, the instrument operating on Mars. Given that Walter is engaged in development and operation of the main laboratory instrument on a mission exploring possibilities for life on another planet, I wonder how he understands what life is. In one of my questions, I take NASA's working definition of life as a point of departure. Derived by a panel of scientists in 1992, it reads:

Life is a self-sustaining chemical system capable of Darwinian evolution.

I ask Walter about the notion of Darwinian evolution, "since it is in NASA's working definition of life." Walter raises an eyebrow and asks "Oh, really?" His slightly surprised reaction makes us both amused. But for me, this was also quite stressful. I went into Walter's office with an assumption that he is engaged in a mission for life detection. Yet, he is not even familiar with the official NASA definition of life. I clarify what I refer to by NASA's working definition of life, and then give the question another try by asking Walter if Darwinian evolution is something that he considers in his work. "No, I think that's many, many layers away from us. Like I said, we're looking at not even progenitor molecules of these things, we're just looking at byproducts and fragments."[5] Walter describes the mission that he is engaged in as "not really looking for life, but looking for the byproducts of the progenitor molecules you need, to get to life." He says that the mission he is part of is exploring habitability – not life. He emphasizes that NASA is careful about the distinction between life and habitability. I find this puzzling. In outreach activities, NASA proudly promotes their missions as searching for life in the universe.

The discrepancy in the articulation of what NASA does in their missions is at the heart of the argument in this chapter. The articulation of the research subject at NASA shifts depending on the source of legitimacy.

Life detection at NASA has a history of struggling with legitimacy. Previous studies have shown how scientists adopt different strategies to get continued support, despite the absence of signs of extraterrestrial life (Dick, 1996; Reinecke & Bimm, 2022). Based on documentary and ethnographic

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[5] Progenitor means an ancestor/parent from which something originates. In this case, a progenitor molecule refers to the parent/main molecule from which the fragments measured with SAM came from.

material from NASA, this chapter contributes a more nuanced picture of how NASA draws boundaries to maintain legitimacy for their life detection missions among the public and the scientific community. I unfold how NASA draws the boundaries around astrobiology, shapes life detection as a research subject, and the tools to detect it. As I alluded to in the vignette, these articulations are sometimes in conflict – I argue that the articulation of life detection shifts depending on the source of legitimacy. I also draw attention to how NASA excludes particular approaches from astrobiology to maintain legitimacy for their activities.

To analyze this, I use concepts from previous studies of scientific knowledge production. First, I analyze how scientists construct *doable problems* through the everyday processes of organizing their work (Fujimura, 1987). I focus on how the work of scientists and engineers at NASA is situated in two social worlds, that serve as sources of legitimacy for NASA: the general public, who (financially) support their activities, and the scientific community, who authorize their knowledge claims. I pay attention to how these social worlds play a role as NASA's sources of legitimacy and how it in turn shapes the everyday work of practitioners. I conceptualize this mutual process of shaping as the *rightness* of the research subject, practitioners, and their tools. The rightness refers to appropriateness in a particular social context (Clarke & Fujimura, 1992).

To understand how astrobiology at NASA maintains legitimacy, I also analyze it in terms of *boundary work* that the institution and its practitioners do, meaning the practices demarcating science in ways that justify their "claims to authority or resources" (Gieryn, 1983, p. 781). *Demarcation* is performed through inclusion and exclusion of particular approaches. In this chapter, I discuss the processes of shaping a doable research subject and the rightness of the tools in astrobiology at NASA, in the light of performing boundary work to maintain legitimacy for their activities.

The chapter begins with a description of the most significant strategies to maintain legitimacy in astrobiology, identified by previous studies. It is followed by an analysis based on documentary and ethnographic material from NASA Goddard. The ways in which NASA demarcates astrobiology enable and constrain actions of scientists and engineers in life detection. Consequently, this chapter provides an important foundation to understand for what purposes AI can be developed – to search for very particular kinds of signs of life.

Previous Studies About the Strategies to Sustain Legitimacy for Life Detection at NASA

Life detection and the field of exobiology – today's astrobiology – emerged during the Space Race in the 1950s. It was mobilized at NASA by Joshua Lederberg, a Nobel-Prize winning molecular biologist. Initial life detection campaigns at NASA were driven by the fear of potential microbes in outer space. However, the field of exobiology struggled with scientific credibility and legitimacy to receive governmental support. In a comprehensive historical account of astrobiology at NASA, Steven Dick depicts how prioritization of life detection got criticized by prominent scientists who argued that the scientific goals presuming life in outer space were unreasonable. Moreover, they questioned the extent of public fundings dedicated to explorations of life in outer space, in light of unresolved issues of poverty on Earth (Dick, 1996, p. 143).

To legitimize exobiology, NASA adopted several strategies. Dick (1996) points to how the interest in search for life detection was maintained by creating a link to the big questions of the nature of life in the universe.

Implications of extraterrestrial life for the place of humans in the universe were positioned in line with how Copernicus and Darwin previously redrew the position of Earth and living beings (Dick, 1996, p. 141-142). Sociologist David Reinecke and historian of science Jordan Bimm (2022) bring attention to two other strategies through which exobiologists sought credibility. First, exobiologists drew upon the threat of biological weapons during the Cold War, to legitimize the research on microbial contamination from outer space. The second way of managing credibility was by making connections to existing sciences, such as astronomy and biochemistry, to borrow their scientific legitimacy. To demarcate this image of the field, in the 1990s, NASA changed the name of the field from exobiology to astrobiology. These strategies were used to increase the interest and legitimacy of life detection among the public as well as within the scientific community.

There is one more, and for the sake of this chapter, the most crucial strategy that must be mentioned. Based on documentary material, Reinecke and Bimm (2022) have identified that exobiologists at NASA maintain credibility through purposeful use of ambiguity. By ambiguity, the authors refer to resisting "closure or an experiment's premature end by creating doubt in negative findings and fostering hope for future positive results." (Reinecke & Bimm, 2022, p. 1) This mechanism, they argue, has served to sustain the legitimacy of astrobiology through the periods of non-detection. It takes the shape of different scientific strategies: shifting methods, scales and object of research. For instance, the example of shifting mission objective from "life" to "habitability" that I introduced in the vignette illustrates what Reinecke and Bimm refer to as the strategy of shifting the object of research (Reinecke & Bimm, 2022). Throughout the chapter, I will show how these strategies are present among the practitioners working with life detection missions at NASA. Moreover, I provide insights that add complexity to Reinecke and Bimm's argument, by showing how maintenance of ambiguity can clash with other kinds of boundary work performed by NASA. To make this point, I turn to strategic documents and ethnographic material from fieldwork at NASA Goddard Space Flight Center, and begin by showing how NASA makes life detection into a "publicly appealing" subject.

Shaping the Public Appeal to Maintain Legitimacy for Life Detection

Scientist Paul was previously a director of the Planetary Environments Laboratory, and afterward, a director of the Solar System Exploration Division at Goddard. Even though he just retired, after 43 years of studying other planets in our Solar System, he still comes to the office. Each day since 1979, he has taken a five minute drive to work. Paul lives in Greenbelt, right outside of the vast NASA complex. During our interview, he articulates why NASA is searching for life in outer space.

> The possibility of life outside the Solar System, the discovery of such would be a very profound discovery of course, because you know, many people wonder if life is unique to Earth or developed somewhere else, so it engages a lot of people and has kind of turned into many drivers of the exploration themes of NASA, so it gets a lot of support.

Paul proclaims that NASA's explorations of life in outer space are motivated by the interest of the people. This line of argument echoes the rhetoric prevalent in NASA's strategic documents, where "public appeal" of searching for life in the universe is used as a rationale to support NASA's activities. I exemplify this with an excerpt from the preface of an astrobiology strategy document published in 2019.

> Combining inherent scientific interest and public appeal, the search for life in the solar system and beyond provides a scientific rationale for many current and future activities carried out by the National Aeronautics and Space Administration (NASA) and other national and international agencies and organizations. (NASEM, 2019, p. vii)

The "public appeal" of life detection figures as a justification to support NASA's activities, both in strategic documents and among practitioners. To keep in mind is that life detection endeavors have a history of fluctuating reputation and that NASA is a publicly funded organization. Thus, the public image plays a crucial role in maintenance of NASA's legitimacy and continued support.

I identify maintenance of "public appeal" in life detection as an important strategy in NASA's boundary work. Instead of assuming public appeal as a resource that NASA has, I interpret the public appeal as something that is made and managed. It is an asset managed intensely by NASA through promotion and outreach activities. Online, NASA's astrobiology program is promoted as addressing the big questions – understanding life and its origins in the universe – complimented with romanticizing sublime images of outer space.[6] In popular culture, NASA astronauts are portrayed as brave national heroes. In classrooms, NASA researchers give talks about their work to inspire children to pursue a career

[6] For a more elaborate discussion on the production of images of outer space drawing upon American romanticism, see previous study by Kessler (2012). For a discussion about the production of images of Mars for the public, see Vertesi (2015) or Messeri (2011).

as rocket scientists – a term that has come to stand for the ultimately intelligent person. In fashion, merchandising with large NASA-logotypes is popular among young people. Given these examples, it is apparent that NASA has managed to produce an image of scientific excellence and national pride. I understand these practices as the making and managing of the "public appeal" to legitimize NASA's activities. "Public appeal" is a crucial resource for maintenance of legitimacy, considering that NASA is a publicly funded organization and has a history of struggling with legitimacy for research on life detection. As the fore mentioned efforts illustrate, "public appeal" is not something that NASA has – rather, it takes a lot of work to make and maintain it.

Now, I turn to how NASA's strategy to maintain its appeal for life detection is translated into what is perceived as supported practices, but also how the institutional incentives are translated into abstaining from certain practices. This addresses the aim of the study by analyzing what epistemic practices are included and excluded in the process of shaping life detection in astrobiology at NASA.

Aiming for the Nobel Prize – Shaping Practitioners to Search for Life in Outer Space

Many scientists and engineers whom I interviewed at NASA Goddard Space Flight Center want to be the first to detect life in outer space. The search for life on other planets is expressed as a prestigious endeavor among the practitioners. This is evident when I shadow the software engineer and manager Eric, who develops AI tools for NASA missions to outer space. In meetings with colleagues as well as in our conversations, he frequently refers to detection of life as finding the "Nobel Prize."

The prestige of life detection is also reflected in how practitioners perceive their funding opportunities. I will illustrate this with an account from shadowing astrobiologist Lu. She is very passionate about life detection. At the stage of being an early career researcher, she is very mindful of her future as an astrobiologist. I accompany her during a workday at NASA Goddard Space Flight Center. We enter one of the large buildings and Lu sees a colleague in the hallway. They talk for a moment. Small talk at Goddard spans from catching up on each other's missions, lamenting launch delays, to asking how one's pet is doing. I introduce myself to the colleague and talk about the purpose of my research (observing development of AI for life detection). Then, Lu says to her colleague how "life detection is the sexy stuff" if you want to get funding.[7] On another occasion, Lu refers to life detection as a "hot research topic."[8] This illustrates how searching for life in outer space is a research subject that practitioners are passionate about, while also being perceived as a fundable career strategy.

Besides the choice of career and research subject, the appeal of life detection also has implications for knowledge production about the universe. In an online interview with Sandra, an astrobiologist working with NASA, she says that biological phenomena are surrounded by more prestige than non-biological phenomena.

> There's more prestige in studying the biological, rather than the abiotic cell-like structures.

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[7] To emphasize here: my research project is not funded by NASA and I have not applied for such support.

[8] Planetary science division concerned with explorations of life and habitability does receive a significant share in NASA budgets. However, the NASA budgets are outside of the scope of this study. For a 'follow the money' account of NASA's planetary science, see Reinecke (2021).

In our interview, Sandra maintains that this asymmetry is a problem. She says that if we do not study the abiotic entities, we will have a difficult time to distinguish which objects in outer space are biological. She continues to explain that we can not understand life if we do not study non-life. Sandra's critique shows how knowledge production can be skewed toward studying life, at the expense of making non-living phenomena less interesting as a research subject, which in turn becomes understudied. This becomes a problem in life detection especially in the case of so called "life-like" objects that resemble life but are abiotic – I return to this subject in a later section.

To summarize the discussion so far, after a history of struggling with legitimacy (Dick, 1996; Reinecke & Bimm, 2022), life detection at NASA has re-established prestige. To legitimize their research, NASA makes and maintains "public appeal" through outreach activities. These practices generate interest in the potential of life in outer space, which can shape personal motivations, career choices, and formulations of scientific objectives. Planetary scientists at NASA Goddard consider life detection and the search for biology in outer space as a popular, prestigious and fundable research subject (in contrast to non-biological phenomena). Life detection constitutes the right research subject for planetary scientists at NASA Goddard. Scientists and engineers need to align their practices with the right research subject – life detection and biology – to receive NASA funding. This in turn, feeds into reproduction and maintenance of the attention on studying biology in outer space.

In the above sections, I have discussed how NASA and its practitioners (re)produce the attention on life and biology in outer space. But how do the scientists and engineers study life detection in practice? In the following, I discuss the process of constructing a doable research problem (Fujimura, 1987) in NASA missions. This unfolds how NASA performs boundary work (Gieryn, 1983), and what epistemic consequences it has in terms of what is included and excluded from the study of life at NASA.

Habitability – Constructing the Objectives of NASA Missions

In the vignette, I introduced scientist Walter working with SAM, the instrument identifying molecules on Mars. Walter was clear in stating that the mission he works with is not searching for life. It is exploring habitability. This distinction is reproduced among other scientists and engineers working on NASA missions. One of the scientists is Lu, who works with the data from Mars produced by SAM. In an interview, Lu states that life detection is her "personal desire for any missions but life detection is NOT one of the science objectives" for the missions she works with. When Lu says that "they're not allowed to call it life detection mission," she refers to an organizational imperative. In the history of NASA missions, there has been only one mission designed for the purpose of detecting signs of microbial life.

> In fact, the only *life detection* mission that we've ever sent to another planet is the Viking mission. That was considered life detection because the instruments were literally designed to look for microbes, look for metabolism and all those things. But the mission objectives of Curiosity [current rover on Mars] is to characterize the *habitability* of Mars.

Launched in 1975, Viking is the first NASA mission that landed on Mars. It was designed to search for life and equipped with a biological laboratory. Biological experiments did not provide any evidence of life at the landing sites. Given its scientific objective to search for signs of life on Mars, the absence of evidence of biology deemed this mission as a failure. As a consequence, during the following two decades, there was no funding for further missions to Mars (NASEM, 2019, p. 9). Viking was the first and last NASA mission officially searching for signs of life.

In Janet Vertesi's ethnographic study of practitioners at NASA, the Viking mission and its failure to find evidence of biology on Mars figure as an important reference point in development of new missions (Vertesi, 2019, p. 479). In their historical account of astrobiology, Reinecke and Bimm have observed post-Viking shifts of methods, scope, and object of study, to maintain legitimacy in astrobiology at NASA (Reinecke & Bimm, 2022). Viking’s failure has shaped how scientific objectives of NASA missions are articulated. Since Viking, NASA missions are articulated as exploring habitability. I ask astrobiologist Lu about the crucial difference between searching for life and habitability.

> So searching for habitability or habitable environments can help you understand the *potential for life*. But *you could have a habitable environment and no life in it* because life never began, or life was never put there or brought there or whatever. So understanding habitability allows us to know what are the environments that could harbor life, whereas life detection is actually looking for those signatures, so you have already a predisposed notion, or presumption, that the environment you’re going to is habitable. You could try to do life detection on the Moon but there’s much lower probability that it would exist on the Moon or Mercury or whatever. But if you go to a place like Mars or Europa, or Enceladus, because of our knowledge of life on Earth and our knowledge of extreme

> environments and extreme life, or just basically normal life, normal for the microbes. Our understanding of those environments has pointed us to this increased probability that those places might have life.

When labeling a mission as exploring habitability, the scientific objective turns away from the question whether there is life on Mars or not. Instead, the question is whether Mars is, or ever has been, a planet with an environment that can, or ever could have sustained microbial life. Mission objectives have shifted from life detection to a question of potential or probability of life, which is a much wider scope. The shift from search for life to habitability can be read as a strategy to construct a more doable research problem. To do that, scientists must convince colleagues that the results of one's experiments solve a shared problem (Fujimura, 1987, p. 261). Since the Viking mission, finding signs of life on Mars has been considered as a less credible problem to solve.

This is in line with Reinecke and Bimm's account, who observe how the scope of astrobiology shifted after Viking – from searching for life on Mars to an exploration of planetary conditions for life. In the 1980s, astrobiology aligned with the emerging ecological and environmental sciences, which shifted the position of Mars from a destination for life detection, to a planet with comparable environmental conditions to Earth (Reinecke & Bimm, 2022, p. 14-15).

Scientist Walter who is engaged with the operation of the instrument SAM on Curiosity juxtaposes Mars and Earth, as sharing the planetary history of having liquid water – one of the conditions to sustain life. The shared history with Earth serves as a motivation to continue exploring Mars.

> Curiosity [the current rover on Mars] originally was to determine whether or not Mars was *habitable*, or had conditions that would be conducive to have previous life on Mars. You know, at some point, Mars was wet and warmer. Mars and Earth diverged and we want to understand why.

Walter articulates the objective of NASA missions as exploring habitability, meaning conditions to sustain life. Vertesi has pointed to how the ontological flexibility of a planet can reveal unstable institutional settings (Vertesi, 2019, p. 480). The re-crafting of Mars – from a destination for life detection to exploration of habitability – reveals a shift in the institutional conditions after Viking. To gain support for missions to Mars, after two decades without funding, NASA scientists re-phrased the role of Mars and the objective of their missions.

However, practitioners do not only articulate the mission objectives as searching for habitability. Many are also explicitly distancing their practices from life. Programmer Victoria refers to the mission with the instrument that Walter and Lu are working with as “not a life detection mission, it was more of a habitability and search for organics kind of mission.” Victoria and her colleague Eric are programmers developing AI for instruments on upcoming missions to Mars (MOMA) and Titan (DraMS). According to Victoria, “MOMA and DraMS are not life detection instruments, they will be instruments onboard missions to understand other planets better.” Programmer Eric says that MOMA, the instrument that will be sent to Mars can show “reminiscence of life.” These articulations illustrate how practitioners actively create a distance between life detection and their activities by referring to “habitability” and “organic molecules.” In an interview with scientist Lu, she suggests that the shift away from life detection at the institutional level occurred for political reasons.

> So you COULD really design a mission for life detection. This was just not part of the… *I don't know what the history is but someone in Congress or someone in government or whatever, was not, didn't, wasn't comfortable with calling Curiosity life detection*. Part of it might also have to do with the payload itself. Because life detection is still an open-ended hot research topic. No one has been able to design a mission concept or a series of instruments that is able to say 'oh, if I put all these five instruments onboard and I analyze it and it shows this and this and this and this, you know, I'm very confident about it's life'. That wasn't really what MSL [mission on Mars with instrument SAM], Curiosity, was designed for. So because of that, I think *people weren't comfortable calling it life detection mission, even though it IS capable of finding some biosignatures*.

In line with previous research (Reinecke & Bimm, 2022), I suggest that re-framing the objectives of the missions from life detection to habitability is a strategy to maintain legitimacy for NASA missions. Drawing upon the interviews above, habitability is about studying the environment and its preconditions for the possibility of sustaining life. It is a much broader aim than detection of life itself. To keep in mind is that after Viking – the first mission for life detection – was deemed as a failure, NASA lost funding for missions to Mars for two decades. The move away from life detection and toward habitability can be understood as a demarcation to legitimize NASA's activities and re-gain governmental funding. Exploring habitability is a more doable research problem than life detection. NASA can not fail to find evidence of extraterrestrial life if it is not searching for it. Exploring habitability is a much wider concept that encompasses a long list of molecules prevalent across the universe. Habitability is not just about preconditions for life – it constitutes preconditions for missions less prone to fail.

Biosignatures – Constructing the Research Problem

In spite of the institutional imperative to explore habitability, Lu emphasizes that NASA missions to Mars are “capable of finding some biosignatures.” Biosignatures refers to signs of life. It is a term used in the context of NASA missions. A biosignature is described as “an object, substance, and/or pattern whose origin specifically requires a biological agent.” (NASA Astrobiology, 2003, p. 23) Such a definition includes a wide range of phenomena: “dinosaur fossils, empty candy wrappers, the green haze of a forest too far away to make out the individual trees, or the oxygen we’re all breathing.” (Harman & Domagal-Goldman, 2018) However, in NASA missions to other planets and moons, biosignatures are narrowed down to signs of past or present microbial life, assuming that life beyond Earth will most likely be microbial. The reasoning behind this draws on a history of life on Earth, where single celled organisms might have been the most prevalent kind of life.

One kind of biosignature that instruments on NASA missions are designed to detect are organic molecules. SAM, introduced in the vignette, is an example of such instrument. Astrobiologists recognize that all life on Earth consists of a particular set of chemical elements. The ingredients shared by all life forms are often referred to as CHNOPS (carbon, hydrogen, nitrogen, oxygen, phosphorus and sulfur). These assumptions shape how scientists and engineers at NASA design their instruments. This is articulated in an interview with astrobiologist Sandra who works with the MOMA instrument on NASA’s and ESA’s (European Space Agency) mission to Mars. Her approach is representative for NASA missions, searching for signs of life in terms of organic molecules.

> The core of my research is about searching for organic molecules in rocks. When we search for life on other planets, we usually search for certain things such as liquid water, certain chemical elements like carbon, nitrogen and oxygen, and so on. And then we search for organic molecules. And this is based on the assumption that it is most probable that life is organic. I work with development of methods to detect these organic molecules in different rocks.

The instruments designed to detect organic molecules are mass spectrometers. As I described in chapter 1, mass spectrometers measure the chemical composition of a sample. Scientists put a sample in the instrument. The instrument shoots a laser on the sample which creates a fraction of molecules. The result of this process – a mass spectrum – is displayed visually as a graph with peaks. The peaks are signs of the molecular mass, which indicates what kind of chemical elements are present in the sample – carbon, oxygen, sulfur and so on. Mass spectrometry is used in laboratories at NASA as well as in spacecrafts on other planets, although the latter is in a miniaturized version. Potential signs of life in outer space are anticipated to appear as peaks in a mass spectrum.

Mass spectrometry has a constitutive role in how scientists on NASA missions look at the universe. Astrobiologist Lu, who works with mass spectrometry, describes the universe as full of organics. This outlook shapes how Lu understands her job as an astrobiologist.

> If you just close your eyes and imagine *all the organic matter in the solar system, they're distributed everywhere*. There's some of them that are very simple, like the simple amino acids etcetera. We've seen them by remote observations. We've seen them in extraterrestrial samples that landed on Earth, meteorites. We've gone through the technical steps to confirm that there are amino acids in extraterrestrial samples that isn't coming from biology. So when you have this idea of how much organics are distributed in the solar system, *your job now, if you're an astrobiologist interested in life detection, is to distinguish what organics come from the background, which is space*, whether you're on Titan or Europa or whatever, *and what organics are coming from life*.

This illustrates how mass spectrometry, as the standard tool to use at NASA, constitutes how practitioners understand their object of study and their work. Lu's description of the universe is as full of organic molecules, and her job is to distinguish which ones are signs of life and which are not. Astrobiologists frequently bring up a particular problem with interpreting organic molecules. Organic molecules can be generated biologically, but they can also be generated by non-biological sources (abiotically). There are also certain objects that can look "life-like" although they are abiotic – this phenomenon is also referred to by scientists as "pseudosignatures", "false biosignatures", or "false positives." In an earlier section, I mentioned how astrobiologist Sandra brought to my attention the problem of how non-biological life-like objects are understudied, which poses a problem in life detection. To illustrate the difficulty with interpretation of organic molecules, Lu provides an example of amino acids that are present in both humans and meteorites (rocks from outer space that have fallen to Earth).

> That's the thing too, biosignatures aren't necessarily a binary question either. I have like amino acids in me but so does a meteorite. The amino acids in me are biosignatures. But the same amino acids in a meteorite aren't a biosignature. So finding that isn't necessarily telling you you've detected life but it's more like one piece of evidence that it could be.

Human life has more commonalities with meteorites than we would think. At least in terms of organic molecules. But an organic molecule alone can not tell whether an object is a biosignature (unless we are fine with recognizing rocks as life). Lu articulates that on the one hand, detecting amino acids "isn't necessarily telling you you've detected life" but at the same time, "it could be." Lu insists on how amino acids are just one piece of evidence. According to her – and most astrobiologists I have interviewed – scientists need multiple lines of evidence to identify that an object is a sign of life.

Lu's description of biosignatures as a non-binary question, where interpretation of organic molecules can be a matter of multiple interpretations, is by definition ambiguity. Ambiguity is not only characteristic for interpretation of biosignatures, it is even anticipated in future missions to Mars. In a scientific publication about this subject, entitled "False biosignatures on Mars: anticipating ambiguity," two astrobiologists based in the UK put forward examples of "misleadingly life-like objects and substances." However, they claim that these cases represent only a small set of phenomena relevant to study. That is because the examples that are known have been discovered by chance, rather than during systematic research. The two astrobiologists also point to the problem (which I mentioned earlier, based on the interview with astrobiologist Sandra) of poor understanding of life-like abiotic objects, which makes it difficult to interpret life. Drawing on the examples of "false biosignatures" and how understudied they are, the authors make the argument that "it seems prudent to anticipate more ambiguous results" from missions for life detection on Mars, rather than a discovery of "unequivocal biosignatures" (McMahon & Cosmidis, 2022, p. 17). This articulation makes ambiguity the status quo in life detection.

The rhetorical move to "anticipate ambiguity" can be understood as a strategy to maintain ambiguity, which is in line with Reinecke and Bimm's analysis of astrobiology (2022). However, in the publication by the UK astrobiologists, ambiguity figures also in the sense of an uncertainty, due to unknowns (understudied life-like objects), which affect the ability to interpret phenomena. Scientists frame ambiguity as something that should be anticipated in life detection, however, also as something that can be mitigated. The theme of ambiguity appears explicitly in yet another scientific publication about biosignatures.

In a scientific publication by a group of 14 scientists with background in planetary science, based in European and Canadian universities, the authors argue that biosignature is a vague concept, "intrinsically fraught with ambiguities" (Malaterre et al, 2023, p. 1222). They suggest that the vagueness can serve both positive and negative ends – on the one hand, it can promote interdisciplinarity, and on the other, life detection is a context with particular "public and media scrutiny," and therefore, the terminology should be used with caution (Malaterre et al, 2023, p. 1223). Malaterre and colleagues do not suggest to replace the concept of biosignature, however, they do recommend that scientists working with life detection should mitigate ambiguity through clarity in communication (2023).

Keeping the concept of biosignature in the context of life detection, in spite of its vagueness, can be read as serving the interdisciplinary character of astrobiology, which requires communication and cooperation across many different social worlds. Biosignature can be understood as what science studies scholars Star and Griesemer call a “boundary object”, meaning a scientific object that inhabits many social worlds. A boundary object is both flexible enough to adapt to the local context, yet stable enough to keep a shared identity across the different contexts. Star and Griesemer argue that production and management of boundary objects is central to maintain “coherence across social worlds” (Star & Griesemer, 1989, p. 393). Biosignatures can work as a scientific object that is flexible enough but still maintains a shared identity within astrobiology as an interdisciplinary field.

The use of biosignature as a concept can also be interpreted differently. Before the adoption of “biosignature” as a concept in life detection at NASA in the 1990s, other terminology was prevalent, such as “evidence of life,” “signs of life”, “evidence of living microorganisms” (Malaterre et al, 2023, p. 1216). I want to bring attention to the timing of adoption of the concept of biosignatures at NASA as noteworthy. It was in the late 1990s during the scientific controversy of signs of Martian life on meteorite ALH84001 that the term biosignature was adopted and has since then been part of the vocabulary at NASA (Malaterre et al, 2023). It was also in the 1990s that the field of astrobiology was rebranded, from exobiology to astrobiology, shifting the focus from life detection on Mars to a wider aim of understanding life and its origins in the universe (Reinecke & Bimm, 2022). The vagueness of the concept of biosignature can serve what Reinecke and Bimm refer to as maintenance of ambiguity. Read in this way, the vagueness of biosignature as a term can facilitate “interpretive flexibility” in experiments, to “resist closure or an experiment’s premature end by creating doubt in negative findings and fostering hope for future positive results." (Reinecke & Bimm, 2022, p. 1) Reinecke and Bimm have identified the maintenance of ambiguity as a key strategy in astrobiology, to maintain credibility. In the light of NASA's boundary work, where the focus shifts away from life toward potentialities of signs of present or past life, biosignature can be understood as another facet of this repertoire that maintains legitimacy of astrobiology and the research subject.

After decades of search, without finding credible signs of extraterrestrial life, the astrobiology community has developed arguments and strategies to maintain the search as a legitimate endeavor. We can see how scientists and engineers at NASA Goddard distance their practices from life detection. They do so by shifting attention from "life" to "habitability," "biosignatures," and "organic molecules." This move is taking them a step away from "life" by focusing on its preconditions. I interpret this as demarcation to maintain legitimacy and part of rebranding of the field of astrobiology, after the Viking mission for life detection which was deemed as a failure and led to withdrawal of funding. In line with previous studies by Reinecke and Bimm, I identify maintenance of ambiguity in the results during the periods of non-detection as a prevalent strategy in astrobiology (Reinecke & Bimm, 2022).

Maintenance of ambiguity however, is in conflict with performing boundary work in relation to the general public. This unfolds as I discuss interpretation of data with a group of scientists at NASA. During an early afternoon, me and three scientists take a seat in comfortable armchairs in an open work space at Goddard. When colleagues pass by to leave for the day, we realize that we have been talking for hours. Throughout this long conversation, NASA's public appeal is a recurring subject. For instance, the inspiring role of the space images and the anthropomorphic design of rovers, which helps to make them relatable.[9] But when the three scientists discuss scientific interpretation of data from space missions, communication with the public is expressed with a concern. One of the scientists insists on how scientific interpretations of data cannot be reduced to a binary "yes or no" answer, upon which the colleague counters: "but how do you tell that to the public?" In their discussion, the three scientists articulate a clash between two poles. On the one hand is the human desire to get a "yes or no" answer, and on the other, the multiple scientific interpretations of data. The scientists are concerned about how the framing of scientific results into a binary of life or not life makes the multiple layers of interpretations invisible.

To provide an example of the clash between scientific practice and communication about the missions with the public, I return to the interview with planetary scientist and previous director Paul. He depicts the contrast between scientific interpretations of when methane (an organic molecule) was detected on Mars *versus* how it was reported in media.

> Methane on Earth is mostly produced by biology so the public is always very interested whenever we report methane detection, then the press picks up on it 'Oh, they detected life on Mars!' and we never say that, but it's again, providing the foundation for understanding on what one needs to do next in terms of looking for biosignatures on Mars.

As a NASA scientist, Paul interprets methane as an organic molecule that serves as a cue for further explorations of biosignatures on Mars. However,

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[9] For a discussion about the construction of appealing images at NASA, see Kessler (2012). For a discussion about how humans build relations with rovers, see Vertesi (2015).

the media communicates the findings as signs of life on Mars. To capture attention, several news articles about methane detection relate it to "life" in their headlines: "NASA Rover on Mars Detects Puff of Gas That Hints at Possibility of Life" (Chang, 2019) in The New York Times, and "Methane on Mars: does it mean the Curiosity rover has found life?" (Sample, 2014) in The Guardian. Detection of methane was made into a sensation. Because of the "public appeal" of life in outer space, layers of scientific interpretation of an organic molecule were made invisible.

Communication of scientific findings with the public illustrates how NASA practitioners experience a conflict. I read this as a conflict in performing two different kinds of boundary work. At the institutional level, as a governmentally funded organization, NASA has to maintain a "publicly appealing" image to the citizens. This is prevalent in how NASA creates engagement in life detection through outreach activities. In the scientific practice, astrobiologists at NASA have to maintain scientific credibility. Scientists do so by maintaining distance from life as a research subject and focusing on a more doable problem, namely, by searching for organic molecules. Noteworthy is that publicly, the missions are still promoted as missions searching for signs of life. The distancing from life contradicts the outreach rhetoric, where NASA communicates how it is "searching for signs of life" on other planets. I have shown how the demarcations of NASA's activities to the public are in conflict with how scientists articulate their everyday practices in the laboratories.

This conflict shows how the rightness of the research subject shifts depending on the context – from life, to organic molecules, biosignatures and habitability. This terminology allows practitioners to maintain ambiguity in interpretation of experiments. Rewinding to previous examples of organic molecules, amino acids and methane, they can but do not have to be biosignatures. Reinecke and Bimm have argued that maintaining ambiguity has been a crucial strategy to maintain credibility in astrobiology. Such strategies can entail injecting doubt in negative findings and encouraging hope for the possibility of positive findings in the future. The emphasis on the ambiguity of the results contributes to the endurance of astrobiology as publicly funded research at NASA (Reinecke & Bimm, 2022). However, the maintenance of ambiguity through vague terminology is in clash with NASA's maintenance of "public appeal" through outreach activities promoting missions as searching for life in outer space. Ambiguity does not sell well. For the purposes of communicating with the public, many layers of interpretation of organic molecules can be framed within the binary of life and not-life. Because of the "public appeal" of life detection, "life" is sometimes imposed upon non-conclusive scientific interpretations. The institutional boundary work focusing on life clashes with the boundary work that scientists perform, by distancing their research subject away from life.

The Search for Extraterrestrial Intelligence (SETI) – A Brief History of Boundary Work

The mechanism of ambiguity is an important strategy – however, in analyzing how exobiology at NASA maintains credibility, Reinecke and Bimm (2022) have left out SETI (Search for Extraterrestrial Intelligence), which I argue plays a role of an important Other, in relation to which NASA articulates life detection. Currently in the US, both NASA and SETI promote themselves as organizations searching for life in outer space. However, only one of the two receives governmental support. Gieryn identifies how excluding "rivals from within by defining them as outsiders" (Gieryn, 1983, p. 792) is a common strategy to demarcate scientific authority. Below, I will show how NASA demarcates astrobiology by excluding SETI. To understand the demarcation of astrobiology at NASA, its boundary work must be analyzed in relation to SETI. In the following, I depict how SETI emerged as a field, and then, how it gained and lost its governmental support. Throughout the rest of the chapter, I will show how this history is reenacted by the practitioners at NASA, through articulation of a doable research problem and the right tools.

In the 1960s, a small group of astronomers were interested in listening to signs of intelligent extraterrestrial life through radio signals. According to historian Steven Dick, the group was aware that it would be a controversial research subject, so they agreed to keep it a secret (Dick, 1996, p. 422). A dozen scientists met in Green Bank in 1961. Among them were the molecular biologist Joshua Lederberg, who played a key role in the establishment of exobiology at NASA and the famous astronomer Carl Sagan (in chapter 5, I discuss how Sagan still figures as an admired legend among practitioners at NASA). Astronomer Frank Drake thought that it would be convenient to organize the discussion around the main topics of interest. He formalized the meeting agenda as an equation – now called the Drake equation – which is still used to estimate the probability of existence of extraterrestrial intelligence.[10] The ideas started to spread soon after the Green Bank meeting. In the 1970s, SETI became a part of NASA (Dick, 1996, p. 428, 459). The fact that the participation of the founder of

[10] In The Drake equation, the terms are defined as follows:
N: The number of civilizations in the Milky Way galaxy whose electromagnetic emissions are detectable.
R*: The rate of formation of stars suitable for the development of intelligent life (number per year).
fp: The fraction of those stars with planetary systems.
ne: The number of planets, per solar system, with an environment suitable for life.
fl: The fraction of suitable planets on which life actually appears.
fi: The fraction of life bearing planets on which intelligent life emerges.
fc: The fraction of civilizations that develop a technology that produces detectable signs of their existence.
L: The average length of time such civilizations produce such signs (years).

exobiology at NASA (Joshua Lederberg) was one of the dozen scientists in the Green Bank meeting indicates that the search for life in outer space was initially a common ground between NASA and SETI.

Despite institutional support from NASA, SETI's credibility remained contested. Historian Stephen Garber depicts how SETI has struggled with a so called "giggle factor" – an image of being a pseudoscientific search for little green men – which has posed challenges for maintaining public support (Garber, 1999). In 1978, after almost two decades of listening to radio signals, SETI lost its governmental funding. Astronomer Carl Sagan, who was a public figure and a SETI proponent, managed to influence relevant politicians to provide continued federal support. Nonetheless, it did not last for long. In 1993, SETI lost its governmental funding again. Garber describes that this occurred during a governmental budget deficit and that the "giggle factor" made it an easy target in the political hunting for cuts. Individuals behind the SETI community mobilized private funding and continued listening to radio signals outside of NASA quarters (Garber, 1999). Since 1993, the SETI Institute has been a privately funded organization based in Silicon Valley.

Both NASA and SETI promote themselves as searching for life in outer space. To maintain credibility after decades of searching without evidence of extraterrestrial life, each organization adopts certain strategies. In a study of SETI's boundary work, science studies scholar Valentina Marcheselli shows that since the formulation of the Drake equation in 1961, the rhetoric of probability has been a consistent framing of SETI's enterprise and it has played an important role in keeping SETI afloat (Marcheselli, 2024, p. 445).

As already discussed, one of the ways in which exobiology at NASA has sought credibility is by maintaining the ambiguity of results (Reinecke & Bimm, 2022). However, as I will show in the following section, another important strategy to maintain credibility at NASA is by excluding SETI from astrobiology. By keeping SETI in the periphery, NASA creates distance from the "giggle factor". In the following, I show how this is performed among practitioners at NASA and then, I turn to how it is articulated in strategic documents.

Technosignatures – Demarcating Astrobiology at NASA Through Exclusion

During fieldwork at NASA Goddard Space Flight Center, I meet planetary scientist Michael, whom I recognized from an astrobiology conference that took place a few months earlier. Michael studies habitability of planets outside of the Solar System (exoplanets). When I ask Michael about life detection, he wonders what I mean by life. "When you say life, do you mean biological or technological?" he asks. I want to keep the question as open as possible and let Michael define what life can mean. Instead of answering, I ask him further. "I don't know, what would *you* say?" upon which Michael answers "I would consider both."

In astrobiology, signs of biology are referred to as "biosignatures", while signs of technology are referred to as "technosignatures". A biosignature, discussed earlier in this chapter, is "a detectable sign, e.g., chemical or morphological, that supports the likelihood of the presence of life." (NASEM, 2019, p. 170) As I stated before, what is assumed in the search of biosignatures at NASA is that life in outer space will most likely be microbial. Organic molecules serve as a proxy to detect life. A technosignature is "a detectable sign of technologically advanced life." (NASEM, 2019, p. 170) In the search for technosignatures, the assumption is instead that life in outer space has produced technology. Examples of technosignatures that are searched for are radio or other electromagnetic signals, as well as industrial emissions.

By being explicitly open to the search for both biology and technology in outer space, Michael is not a typical scientist at Goddard. In his personal description at NASA website, he presents himself as a planetary scientist who is dedicated to technosignatures. While Michael articulates this in his presentation, he highlights that technosignatures are as relevant to study as biosignatures. This line of argument is also prevalent in one of his publications, concluding with a justification that technosignatures are as worthy of studying as biosignatures. What this implies is that biosignatures are a more established approach. When I discuss life detection with other scientists at NASA Goddard, technosignatures are rarely brought up. Biosignatures are often assumed as *the* approach in life detection. This illustrates the strength of biosignatures as the right research subject in astrobiology at NASA.

Defending technosignatures, by juxtaposing it to biosignatures, shows the strength of biosignatures as the main approach in life detection at NASA. It can be understood as an attempt to redraw the demarcation between the two approaches in life detection. This rhetoric has to be interpreted further in the context of technosignatures as tied to SETI (Search for Extraterrestrial Intelligence) and its history with NASA. Both NASA and SETI have a history of struggling with scientific legitimacy.

To show how this history is reenacted, I rewind to the interview with planetary scientist and previous director at NASA, Paul. I ask him explicitly about his view on SETI.

> I think it's easier to make the case - there might be microbes somewhere in the Solar System or in the Universe, than for somebody to actually think there will be *humans like us making*

> *radio stations*. (…) SETI was always a bit of a *political controversy* let's say. The senators would say, you're looking for life outside Earth, *he he, do something useful*, so… I think NASA treads carefully there.

Paul's comment about how senators perceive SETI as ridiculous is a reenactment of what Garber calls the "giggle factor" (Garber, 1999). Furthermore, Paul articulates the demarcation of NASA and their search for microbes as legitimate, in contrast to the "political controversy" of SETI, searching for "humans like us making radio stations". According to Gieryn, "monopolization of professional authority and resources" is performed by exclusion of "rivals from within by defining them as outsiders with labels such as "pseudo", "deviant" or "amateur" (Gieryn, p. 792). In order to make the NASA Astrobiology Program the undisputed center of the astrobiology community, NASA keeps SETI at arm's length, creating distance from what Gerber refers to as the "giggle factor" associated with SETI (Gerber, 1999).

In a strategic document from 2015, NASA defines itself as being "the lead agency of astrobiology research in the United States." (Hays, 2015, p. xvi) Noteworthy is that while "biosignatures" are referred to 180 times in that document, "technosignatures" are mentioned three times, and "SETI" four times. This pattern continues in later strategic NASA documents concerning astrobiology. The Decadal Survey (NASEM, 2023) is the most significant strategic document shaping NASA's future "Planetary Science and Astrobiology" activities. Out of the 700 pages of the document, technosignatures are only mentioned in the appendix. However, once NASA did mention SETI in a strategic document published in 2015, it was to explicitly exclude it from the field of astrobiology.

> While traditional Search for Extraterrestrial Intelligence (SETI) is not part of astrobiology, and is currently well-funded by private sources, it is reasonable for astrobiology to maintain strong ties to the SETI community. (Hays, 2015, p. 150)

Considering the history of lack of credibility in search for life in outer space, one interpretation of this statement is that NASA draws boundaries to exclude SETI from "astrobiology," in order to avoid guilt by association, to maintain scientific credibility and funding. This serves as the strongest example of exclusion in NASA's boundary work.

The statement quoted above was met by strong criticism from SETI's proponents. They responded with a number of white papers to NASA. A leading figure at the SETI Institute, Jill Tarter, is the first author in one of the white papers submitted to the National Academies (which provides recommendations about astrobiology research to the government). Tarter and the co-authors directly address NASA's exclusion of SETI from astrobiology in the document from 2015.

> This is an arbitrary distinction that artificially limits the selection of appropriate tools for astrobiology to employ in the search for life beyond Earth, one that is not supported scientifically. The science of astrobiology recognizes life as a continuum from microbes to mathematicians. It is time to remove this artificial barrier, and to re-integrate the community of all those who wish to study the origin, evolution, and *distribution* of life in the universe. [emphasis in original] (Tarter et al., 2018)

In the same year that the white paper referenced above was submitted

(2018), NASA hosted a workshop about technosignatures. The aim of the "Technosignatures Workshop at the Lunar and Planetary Institute" in Houston was to discuss the state of the art of the technosignature field and the role that "NASA partnerships with the private sector and philanthropic organizations" can have for the field of technosignatures.

In a strategic astrobiology document published in 2019, NASA acknowledged that SETI projects lost federal support but the "interest is once again growing in the search for technosignatures." (NASEM, 2019, p. 147) SETI is recognized for their success to generate research through private funding. However, there is no recognition of the value of the technosignatures approach for the field of astrobiology.

Conclusion

Development of AI is situated in an organization that enables and constrains certain courses of action. This chapter focused on how NASA demarcates which practices are considered as legitimate, and not, through the lens of boundary work (Gieryn, 1983). The question of legitimacy is particularly important for NASA missions, due to their history of non-detection. The first life detection mission to Mars in the 1970s was followed by withdrawal of funding.

Drawing on ethnographic material from fieldwork at NASA Goddard, and strategic documents, this chapter shows how NASA's boundary work has been shifting focus away from life, and toward potentialities of signs of present or past life. Widening the scope from life detection to habitability, biosignatures, and organic molecules creates preconditions for organizational survival.

The results are in line with previous work by Reinecke and Bimm, who pointed out that maintenance of ambiguity in interpretation of experiments contributes to the endurance of astrobiology as a publicly funded field of research at NASA (Reinecke & Bimm, 2022). However, the findings in this chapter add more nuance to the understanding of how NASA sustains legitimacy. NASA's boundary work shifts not only across different historical periods, but also across different social worlds. In order to sustain legitimacy, NASA aligns with two social worlds: the scientific community and the public. This study finds that the ambiguity of multiple interpretations of experiments (Reinecke & Bimm, 2022) articulated within the scientific community, is in clash with the outreach rhetoric and public understanding of life as a binary question: life *versus* not-life. Furthermore, this chapter demonstrates how astrobiology at NASA focuses on identifying biosignatures, and excludes technosignatures from the field, as a way to sustain legitimacy.

These organizational preconditions – demarcations of astrobiology at NASA – shape what kind of research subjects and tools are considered as legitimate. Against this background, the AI tools developed for the missions at NASA Goddard are designed to facilitate identification of organic molecules, as potential biosignatures.

Chapter 5 Making Field Sites, Laboratories and AI Datasets into Truth-spots

A group of scientists and software engineers are gathered in a conference room at NASA Goddard Space Flight Center. The room is furnished with functional modern interior, a large white board, a screen and a long table around which everyone is seated. Well, almost everyone. In the middle of the room is a camera for video calls, allowing a few scientists and software engineers to join from anywhere. This impersonal room is designed to feel like anywhere, a space where universal aspirations can flourish. But even universal aspirations are entangled with local places.

The large NASA complex is located in Greenbelt, a small city outside of Washington DC. As usual in July, Greenbelt is unbearably hot and humid. Thankfully, the efficient air conditioner in the conference room is offering protection from the weather during the meeting. Scientists and programmers are brainstorming about automation of a mission to Saturn's largest moon, Titan. The environment on Titan is way colder than the air conditioner in the conference room is simulating. Way colder than the researchers would endure. Way colder than any kind of life as we know it would survive. But – there is a quintessential but – are there possibly other kinds of life forms that could thrive in such conditions? Could such environment be habitable? These are central questions in the future NASA mission to the -179 Celsius degrees cold moon Titan, which is being discussed in the moderately cold conference room at NASA Goddard Space Flight Center.

The 1.5 billion-kilometer distance to Titan poses severe challenges for the NASA team, who has to figure out how to communicate with the spacecraft. The data rates are slow, because of the limited power of a spacecraft and the distance that the signal has to travel. Over the long distance, the signal becomes weaker. Once it gets to Earth, it is very faint. Given these data limitations, only a small portion of all the data from Titan can be sent back to Earth. What scientists and programmers envision, is that an autonomous software on Titan will make decisions about which data is interesting to get back to Earth. This desire is captured in a witty comment made by Desmond, one of the scientists in the conference room.

> Well, anything that can be done manually should be automated. We just have to teach the computer how to think the way that we do.

Automation seems effortless, the way Desmond puts it. Scientists around the table find it funny and provoking at the same time. Ryan, a scientist who sits by the table with his arms crossed says: “Yeah, that’s easily said but it’s true.” The challenge for the scientists resides in deciding how to predetermine which data will be interesting *versus* not. What is at stake is choosing the *right* data to *send back*, to enable new discoveries about other worlds.

After some giggling across the room, programmer Victoria expresses her doubts. “Easy to say, hard to do.” Victoria is the person making automation happen. She needs to transform the idea into practice and sees the challenges in front of her. To train the algorithms, programmers need large amounts of data. But not any kind of data. To perform well, the algorithms have to be *trained* on the *right* data. Ideally, it would be data equivalent to where it will be used – experiments on Titan’s surface. But there is no data from such experiments on Titan. How can programmers train the algorithm without data from Titan? Programmers discussed how to resolve this during an earlier meeting. I rewind to their brainstorming session a month before.

In the same conference room at NASA Goddard, software engineers discuss training of AI. Software manager Eric describes how he envisions development of AI to optimize data transfer from Titan. To fly the spacecraft from Earth to Titan will take almost ten years, Eric says.[11] Nonetheless, instead of articulating the long interstellar journey as a problem, Eric formulates it as an opportunity. A decade of waiting for the spacecraft to land, means a decade of collecting more data to train AI! It is not until the landing on Titan that programmers have to transfer the AI software to the spacecraft. By then, it will have been trained for almost ten years. It sounds promising, given the general premise in the field of AI: the more data for training, the better the algorithmic performance. Noteworthy is that all the training will occur *before* the spacecraft lands on Titan. So where does the data for training of AI come from?

Instead of Titan, the data comes from just across the hallway, a few steps away from the meeting room where the programmers are gathered. Behind the door of the laboratory, scientists use so called "planetary chambers" to simulate the temperature and air pressure of other planets and moons. Scientists put samples in the planetary chamber to analyze their chemical composition and see how they react in a simulated extraterrestrial environment. The samples come from different sources – some are collected from field sites, others are produced synthetically in an industrial facility. Scientists analyze these samples in the laboratory, which in turn becomes data. Data that programmers use to train AI tools for missions to other planets and moons.

With this vignette, I offer a tiny glimpse of the complex process of developing AI for missions to other planets and moons. In the absence of the *right* data for training – from other planets and moons – programmers

[11] 7 years, according to estimations in the mission plan.

train AI on the best data that is available.[12] Data from laboratory experiments at NASA, performed on samples from different sites on Earth. This chapter is about how knowledge infrastructures enable and constrain data, by focusing on these places. Places where data stems from play an important role by forming data's structure and interpretation (Loukissas, 2019, p. 3). To study the role of places in production of data at NASA, I use the concept of truth-spots (Gieryn, 2006). Sociologist Thomas Gieryn understands truth-spots as places that lend credibility in making claims about the world.

> Truth-spots are 'places' in that they are not just a point in the universe, but also and irreducibly: (1) the material stuff agglomerated there, both natural and human-built; and (2) cultural interpretations and narrations (more or less explicit) that give meaning to the spot (Gieryn, 2006, Footnote 3).

In the vignette, I alluded to NASA as a truth-spot that lends credibility in making claims about the universe – the impersonal conference room at NASA Goddard, designed to feel like "anywhere," reflecting the aspirations of making objective decisions. If we consider a spacecraft on Titan as a truth-spot, it reflects the epistemic virtues of both a field site and a laboratory. It is on the one hand a risky exploration of a unique, unknown place. On the other hand, scientists will bring a miniature laboratory, to create controlled experimental conditions. Due to the lack of control and precision associated with fieldwork, the laboratory has become an important site in making scientific claims (Gieryn, 2006).

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[12] Substantial amounts of data from other planets are available, however, it does not correspond to the amount and quality needed for training of AI.

To design a successful truth-spot, NASA thus draws on the epistemic virtues of both the laboratory and the field site. In this chapter, I turn to how scientists at NASA use truth-spots to produce scientific data for missions to other planets and moons. I will expand Gieryn's concept and suggest to understand digital databases as yet another important truth-spot in scientific knowledge production – at least as important as the laboratory and the field site.

The chapter is structured by different truth-spots used in NASA's production of data to explore life and habitability on other planets and moons. Rather than a biography of a particular datapoint, this chapter is an ethnography of the infrastructure that makes it possible to produce data at NASA. It focuses on the stages of transformation of data – starting with the source of samples, continuing to the laboratory, and finally, the AI dataset.

Making and Contesting Planet Analogs

To explore life and habitability in outer space, astrobiologists travel to "planet analogs", which are different places on Earth used as field sites. In these field sites, the scientists collect samples which they bring back to the laboratory. The samples are analyzed in the laboratory, upon which they become data in a spreadsheet. These data are then used to make claims about other planets. How are places on Earth used to make claims about other planets?

Planet analogs are field sites usually depicted as "extreme" environments on Earth. The extremity of these sites - in terms of how dry, cold, hot or salty they are - is argued to resemble conditions on other planets and moons. Conditions in these environments are considered to be harsh for life to survive. Yet, some microbial lives unexpectedly thrive in these environments. Scientists have categorized these life forms as "extremophiles," meaning lovers of the extreme. Astrobiologists suggest that if life can thrive in such harsh environments on Earth, it cannot be ruled out that there are forms of life that could survive in harsh extraterrestrial worlds. To summarize, one way astrobiologists study outer space is by collecting samples from particular places on Earth, which they argue to be analogous to other planets and moons. Moreover, microbial life forms that thrive in planet analogs - the "extremophiles" - are argued to be analogous to potential extraterrestrial life.

Analogies between the terrestrial and extraterrestrial are not only prevalent in choices of field sites - they constitute a fundamental logic of inquiry in astrobiology. NASA scientist Walter, whom I introduced in chapter 4, says the following about the explorations of outer space: "We start with what we know, what is *analogous, familiar* and try to understand it." Walter's formulation is capturing the key logic in astrobiology. Namely, drawing analogies from what is known to what is not known. Historian of science David Dunér goes as far as arguing that "astrobiology as a whole is one single, great analogy," beginning with life as we know it on Earth, to searching for it on other planets (Dunér, 2019, p. 310). Anthropologist Lisa Messeri argues that making things familiar through analogies is the key social dynamic in how scientists make other planets into known places (Messeri, 2011). The use of planet analogs is thus part of a larger narrative in astrobiology, based on drawing analogies between Earth and other planets.

Nonetheless, the epistemic status of these analogies is contested within the discipline. In an interview with a NASA scientist, they articulate how the fundamental assumption of searching for life as we know it on Earth is a potential fallacy. Bringing Earth-bias to explorations of outer space is frequently problematized in scientific publications, conferences, and NASA's strategic documents.[13] While Earth-bias has been problematized, for many researchers, it is understood as the only known way to proceed.

One of the most popular planet analogs for Mars where scientists collect samples is the Atacama desert in Chile. It is recognized as one of the driest places on Earth. Among the qualities that scientists argue to be analogous to Mars are the soil, volcanism, UV radiation, aridity, and presence of extremophiles. Another characteristic that serves as comparison with Mars is that the soil in the Atacama Desert is rich in perchlorate (Preston & Dartnell, 2014, p. 85), a chemical compound which has been detected on Mars but in higher concentrations than on Earth. Scientists have identified that perchlorate has dual implications for the possibility of hosting human life on Mars. On the one hand, perchlorate can be utilized as a resource to produce oxygen. However, in large doses, perchlorate is toxic for humans, which means that it can be hazardous for astronauts (Archer, et al, 2019; Davila, et al, 2013). The significance of perchlorate for experiments on Mars is a subject I return to in later sections.

Besides collecting samples, scientists use planet analogs to prepare for future missions, by testing the instruments and flight protocols. A group of scientists working with an instrument that will be sent to Mars, visited field sites in Svalbard, which they argue are good Mars analogs (Siljeström, et al, 2014, p. 782). The Svalbard archipelago, in the Arctic Ocean, is depicted as a cold and dry climate with minimal vegetation. The group visited two field sites. The first, Colletthøgda, is described as similar to Mars in terms of minerals in sedimentary rocks. These minerals, called

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[13] To address this problem, there have been initiatives in astrobiology to study "life as we don't know it." This approach is often referred to as "agnostic," meaning that scientists try to avoid assumptions about what a potential life form could look like. However, the agnostic approach is rather in the periphery of life detection. The search for life in outer space continues to be about "life as we know it."

evaporites, are produced by evaporation of water. Evaporites have been detected on several places on Mars and Martian meteorites. The group is also making a connection to other studies, showing how this mineral serves for preservation of organic material and suggesting that it could “be a good habitat for microbes in an extreme environment such as the surface of Mars” (Siljeström, et al, 2014, p. 782). The second field site, Botniahalvøya, has basalt rocks which have been weathered by water. Some parts are black and look shiny, reminding the scientists of desert varnish, a coating consisting of clay minerals. They tie this observation to previous studies where others have “suggested that biology is involved in the formation of desert varnish” (Siljeström, et al, 2014, p. 782). Weathered basalts, which could be desert varnish, have been identified on Mars and it has been suggested as a potential habitat for microbes. The two field sites at Svalbard serve as truth-spots lending credibility in preparing for missions to Mars. The sites are an agglomeration of natural material – particular minerals - which scientists narrate as analogous to Mars and the analogy is extended to imply potential habitat for microbial life on Mars.

In an interview with one of the scientists from the Svalbard expedition, Sandra, she describes the Svalbard sites as planet analogs. Nevertheless, she is problematizing the use of terrestrial sites as analogs for other planets.

> There’s not like a lack of samples. People usually have their favorite analog site that they go to and collect samples. But I think that analogs are just analogs. There is no perfect analog.

Sandra’s argument about favoritism in studying certain sites is in line with what Gieryn identifies as a common critique of field sites in science: “emotional attachments to ‘my site’ that introduce subjective biases.”

(Gieryn, 2006, p. 6) However, Sandra's formulation "analogs are analogs," points to acknowledgement of the limitations involved with drawing analogies between Earth and other planets. Still, her excursions to collect samples from planet analogs to explore Mars, indicate that she accepts these limitations. Sandra does not have samples from Mars – so Svalbard is her best available proxy.

Science studies scholar Susan Leigh Star and sociologist Elihu M. Gerson identify how certain "artifacts" can be acceptable in scientific practice, if they are considered as uncontrollable due to "the state of the research art, expense, or political commitments." (Star & Gerson, 1987, p. 151) Bias in analogies in astrobiology can be read as uncontrollable and therefore acceptable, because of the high cost of in-situ experiments on distant planets.

However, a group of scientists tied to a European space project have problematized the vagueness in making analogies between terrestrial and extraterrestrial places. As a solution, the group suggested that the analogy should be made more precisely in relation to how the site or samples are used. For instance, at what stage of the mission is the analog used, for what purposes (astrobiology or engineering) and what kinds of properties are analogous (geological, or biological). The group introduces "functional analogs" as a new term for this practice (Foucher, 2021). They put emphasis on how artifacts in planet analogs can be controlled to some extent and should be managed by the scientists, in order to be accepted as credible claims (Star & Gerson, 1987). The critique and proposed solutions can be understood as an attempt to make field sites more precise and controlled, like the laboratory (Gieryn, 2006, p. 6).

Among the reasons for studying outer space through planet analogs is that places on Earth are more available than the extraterrestrial ones. However, not all of the desirable destinations on Earth are actually accessible to scientists. In a review of planet analogs, planetary scientist Louisa J. Preston and astrobiologist Lewis R. Dartnell have concluded that analogies about habitability between the terrestrial and extraterrestrial sites are not based solely on similarity but also based on accessibility. According to the two scientists:

> It is of no surprise, therefore, that analogue sites most often cited in the literature are those that are easy to get to and can be revisited if needed; are large enough to sustain multiple sampling excursions and teams; and permissions regarding visitation and sampling under most circumstances are obtainable. How many scientifically valuable sites are being understudied or simply overlooked due to a lack of accessibility or available resources? (Preston & Dartnell, 2014, p. 93)

The accessibility of the field sites on Earth has dual implications for the epistemic status of the analogies being made. For instance, if we return to the group of scientists who went on the expedition to Svalbard – they articulated the field sites as having "easy access" for explorations of "martian habitability" (Siljeström, et al, 2014, p. 782). Accessibility enables scientists to adhere to the criteria of reproducibility – scientists in the past and future can visit the site and reproduce the results – which is an important virtue in science (Leonelli, 2018). On the other hand, in the review of planet analogs in astrobiology by Preston and Dartnell (2014), inaccessibility of certain sites is articulated as an uncontrollable artifact, skewing the explorations in the direction of what is accessible and fundable. Accessibility of certain sites on Earth is thus articulated as a virtue, making it possible to reproduce the results – however, inaccessibility of other sites also makes it a problem.

Economic aspects also have an important impact on research in astrobiology (as in all research). Funding is one of the most frequent aspects brought up by my informants at NASA Goddard. Given how expensive it is to conduct research in extreme environments, astrobiology is very dependent on generous financial support. These themes appear during an interview with David, an influential scientist within origins of life studies who has been part of NASA's astrobiology review boards. David travels to various warm ponds around the world to conduct experiments researching the origins of life. He has developed a new hypothesis about life emerging in fresh water, which he is testing by conducting experiments in warm ponds (so-called hydrothermal *fields*). David frames his hypothesis as an "alternative" to the hypothesis about life emerging below the surface of the ocean (in so called hydrothermal *vents*). The hydrothermal *fields* are situated on the surface of Earth, while the hydrothermal *vents* are deep down below the surface of the ocean. In our interview, David is acknowledging that the hydrothermal *fields* on the surface of Earth are much more accessible than working with hydrothermal *vents* deep in the ocean.

> The hydrothermal vent hypothesis does not have an easy test. If you want to work on hydrothermal vents, it's very expensive. You need to rent a submersible and go down to the vent thousands of meters below the surface of the ocean. You have to somehow inject your experiment into the vent and collect the products coming out the top. It's so complicated and so expensive, that nobody has ever done this. It's beyond what we are able to do today, in terms of the cost. My research happens to be cheap. For instance, I can just buy a plane ticket and I can fly to Iceland. In fact, I'm doing that next July, with a field trip

to hydrothermal fields where we'll do experiments.

This case illustrates how the economic aspects and research funding is a significant factor in selection of sites and samples, which in turn has profound consequences for how scientists theorize about life and its origins. The understanding of life is skewed toward what is fundable and geographically convenient – a warm pond on the surface, rather than a hydrothermal vent at the bottom of the ocean.

Now, it is time to return to the question posed earlier: how can places on Earth legitimize knowledge claims about other planets? I have shown how the status of planet analogs as truth-spots is negotiated in astrobiology. The sites on Earth are made into planet analogs through narratives of being "extreme" environments with microbial life forms, unexpectedly thriving in such conditions. Moreover, the narrative of the sites is also aligned with the larger narrative of drawing analogies in astrobiology. Nonetheless, the epistemic status of planet analogs is contested for a number of reasons, such as vagueness and subjectivity.

However, once the scientific analysis of the sample has turned into a datapoint in a spreadsheet, the contestations of assumptions and narratives are rendered invisible – they become black-boxed (Latour, 1987). When the data shifts scale to the planetary level in the study of outer space, it shifts focus away from how data is derived from particular local places on Earth. Places chosen based on *inter alia* accessibility and favoritism.

Making Mars in California

Lu, a young astrobiologist, points to one of the pictures on her desk at NASA Goddard Space Flight Center. The image is of an austere desert environment. In the middle of it is a white spacecraft with a radar and a man standing in front of it, showing his widest smile for the camera. The picture seems like it could have been taken on another planet. However, the man is not wearing any space suit to protect his fragile human body. Lu tells me about how she "went to visit that exact same spot in Death Valley," which is a Californian desert. The man in the picture is Carl Sagan, a famous astronomer who popularized astrobiology during the 1970s. Sagan's book "Pale Blue Dot: A Vision of the Human Future in Space" (Sagan, 1994) made Lu curious about outer space as a teenager. A doctoral degree later, she works as an astrobiologist at NASA. During our conversation, she describes further the image on her desk. Behind Sagan is a white probe. "That's the Viking lander," Lu says. Launched by NASA in 1976, Viking was the first mission that landed on Mars. Moreover, it was the first mission for life detection. Although the image we are looking at was taken in the Californian desert, making space suits superfluous, the Viking spacecraft implies that this place has a connection to Mars. I ask Lu if this place is considered a planet analog for Mars.

> Yes. So Death Valley is huge. It has the lowest elevation in the North American continent. That place is called Badwater Basin in Death Valley and is where the hottest temperature has ever been recorded. It used to be like a biiiiig lake. It's literally like a closed basin, like a big bathtub.

The vivid way in which Lu portrays Death Valley reflects the epistemic virtues characteristic of field work. Scientists become immersed and absorbed in a field site for a period of time, to develop "embodied ways of feeling, seeing, and understanding." (Gieryn, 2006, p. 6) Some field sites are understood as unique places. In those instances, "being there" is "an essential part of claiming authority for an observation or discovery." (Gieryn, 2006, p. 6) However, "being there" in the field site can also be understood as playing a constitutive role in the identity of the researcher (Messeri, 2011, p. 208). While looking at the image on her desk, Lu continues to describe what the field site means to her.

> I don't know exactly if that specific place he [Carl Sagan] is standing on is a Mars analog but the whole park itself [Death Valley] is. I think it holds a pretty special place in astrobiology community because people have studied that. There's a portion of the park that was used to train the Apollo astronauts because it had these volcanic features that are similar to the rocks on the moon. So that was trained there. NASA also did testing of rover traversing through different terrains. So there's parts of Death Valley that has like rocks that look like almost like this, really rubbly (…)

Lu did not collect any samples in Death Valley, but went to this field site as a visitor. I suggest that the above quote illustrates the mutual constitution of three narratives: Lu as an astrobiologist, the park as a NASA field site, and the landscape as Mars. Certain places are made more spectacular or prestigious to study, which can generate more attention, more funding, and more interest of people willing to dedicate their careers to study those places. Geoffrey C. Bowker refers to this dynamic in knowledge production as "feedback loops" with an effect of skewing knowledge about the world in particular directions (Bowker, 2000). Death Valley as a Martian analog clearly illustrates the dynamic of feedback loops in knowledge production. The desert and its history – Apollo astronauts, the Viking mission, more recent rovers, as well as the presence of Carl Sagan – make the site charismatic for astrobiologists and the public through outreach activities, potentially generating more interest and funding to study this kind of phenomena. I will now turn further to the national narrative of this park.

The narrative of Death Valley as a planet analog - with a history of being an analog for Apollo astronauts, the Viking mission, and rovers for more recent missions - is shared beyond the scientific community. The national park has been holding festivals where the public gets to meet NASA scientists and get educated on how this environment resembles Mars. Focusing on the connection between Mars and Death Valley in public events is reinforcing the perception of the environment as an analog for the other planet. In the previous chapter, I discussed how outreach activities to engage the public are an important part of NASA. Branding can maintain the popularity of the organization, legitimize public funding, and inspire people to choose a career within space research. Lu herself was inspired by a public figure, Carl Sagan. Sagan maintains a legendary position in the field of astrobiology and is frequently quoted by my informants at NASA Goddard Space Flight Center. His presence at the site in Death Valley, portrayed in a widely reproduced image together with the Viking spacecraft, enhances the narrative of the field site as a Mars analog.

So far, I have discussed how field sites on Earth, such as Svalbard, Atacama, and Death Valley, serve as important truth-spots in astrobiology. I have described how scientists construct narratives of these places as resembling conditions on other planets, like Mars, extending the analogy to potential microbial life. Certain places are more accessible, more popular, or prestigious to study, which skews the scientific knowledge production in particular directions. It is in these truth-spots that scientists collect samples, which they bring to the laboratory and turn into data. The data that programmers use to train AI tools. Before turning to the next stage in the transformation of the objects used to train AI tools, I provide another significant example of where scientists collect samples from: rocks from outer space.

Asteroids and Meteorites as Archives of the Origins of Life

During one day of fieldwork at NASA, when astrobiologist Lu and I walk across the hallway, we meet scientist Jason. I get introduced to him and in less than a minute, we end up in a discussion about the fundamental question in life detection: what is life? Jason has four decades of experience in studying the origins of life. As a doctoral student, Jason was supervised by Stanley Miller, an influential chemist whose experiment published in 1953 was a key landmark in the modern studies on the origins of life (Lazcano & Bada, 2003). Miller's experiment simulated the conditions of early Earth and provided the first evidence that organic molecules could have been synthesized under those conditions. Over a half-century after the experiment, Miller's former student directs the Astrobiology Analytical Laboratory at NASA Goddard Space Flight Center, where scientists analyze organic molecules in "samples from comets, asteroids, meteorites, and Moon dust, to help determine the origin of life on Earth." (NASA, n. d. a)

We walk over to Jason's office, which is the largest I had seen so far – Jason has his own conference space in his room. Next to the large oval table is a bookcase. But instead of books, one shelf is occupied by rocks and samples. Jason picks one of the rocks - a tiny black meteorite (a rock from outer space that has fallen to Earth) with white blobs. He puts the meteorite in front of me, on the large oval table by which we are seated during our interview. Jason tells me how the meteorite in front of me is 4.567 billion years old – a little older than the Earth. A "little" in this case means approximately 27 million years. The chemistry of this meteorite can be similar to the chemistry of early Earth. "[Meteorites] are witnesses of early solar system," he says.

The bookshelf in Jason's office, full of rocks and other samples, is on the one hand a collection of tokens, meaningful objects that remind him of his field trips. But besides being a diary of his work life, these rocks are also understood as an archive of the history of the universe. This is a narrative I have encountered previously with researchers in origins of life studies. During the main conference of the origins of life community (ISSOL) in 2021, a keynote scientist spoke of asteroids as "archives," while another scientist claimed that "rocks are archives of Earth and history of life." In September 2023, two months after my interview with Jason, a sample return mission landed on Earth, with the first asteroid that NASA has delivered. Jason is anticipating to analyze the samples from the asteroid. According to NASA, "The material gathered from [asteroid] Bennu acts as a time capsule from the earliest days of our solar system and will help us answer big questions about the origins of life and the nature of asteroids."(NASA, n. d. b)

Through the narratives of asteroids as "archives" and "time capsules," they become a truth-spot that lends legitimacy to claims about the history of Earth and the universe. "Places can be like time machines," according to Gieryn, "by providing tangible, resonating, and convincing evidence for assertions about how things were yesterday and how they will be tomorrow." (Gieryn, 2018, p. 172-3) Asteroids are articulated as tangible time machines, lending NASA the powerful epistemic effects of answering "big questions about the origins of life." This material – as a result of a billion dollar mission to bring the samples to Earth – is accessible only to a few scientists in the world. The uniqueness of asteroids as material from outer space provides a high epistemic value in origins of life studies.

The way in which scientists tie objects and places to history of life and the universe can also be interpreted in terms of awe. Awe can be explained as an enchanting experience of being carried away, a moment of connection and consummation (Lorimer, 2007, p. 922). Awe plays a significant role in guiding scientists attention and constituting their motivation for action. For instance, in Linnaeus journal from an expedition to Lapland in the north of Sweden, he noted the experience of being "as if in a new world," and how the "time passed unperceived away" as he "sat down to collect and describe vegetable rarities." (Linnaeus, Carl von, 1811/2021). This immersion reflects the epistemic value of a field site. Gieryn argues that the Lapland expeditions became an important place providing credibility in "the eventual universalization of Linnaeus' system for classifying plants (Gieryn, 2018, p. 52)." While the scientists in the 1700s "discovered" the "new world" on foot or through the sea, astrobiologists "explore the unknown" in outer space. Immersion and awe are characteristic epistemic virtues in addressing the "big questions" through the study of outer space.

With rocks as "archives," scientists can travel through timelines and experience places which they deem as "exotic" and "tantalizing." The narratives of the origins of life tied to asteroids open up portals for meaning-making across vast scales of time and space. A particular sample from an asteroid can be used to make universal claims about history of life.

The concept of truth-spots, which I have used to analyze the making of scientific knowledge claims about other worlds, was introduced by Gieryn 20 years ago. What I suggest, is that truth-spots do not need to be tangible in the ways that field sites, or archives are. They can also be digital. To continue the analysis of what kind of infrastructure it takes to produce data at NASA, I turn to another important truth-spot in scientific knowledge production: digital databases. Scientists refer to these as "databases," "libraries" and "catalogs." While scientists at Goddard use various libraries, sometimes by constructing them on their own, I provide an example of the national database that is often used among scientists working with mass spectrometry for life detection. It is used at the stage of analyzing the samples' chemical composition in the laboratory. This constitutes another transformation of data – which can be used for training AI.

Interpreting Data from Laboratory Experiments with the NIST Database

The physical library full of rocks and other samples in Jason's room is not the only library we discuss. Early on in our conversation, Jason brings up a digital database with mass spectrometry data, which scientists use for comparison with their own laboratory experiments. The database is developed and curated by NIST, which stands for National Institute of Standards and Technology. NIST is an agency of the US Department of Commerce, with a mission to develop standards and measurements to promote national "innovation and industrial competitiveness."

When scientists conduct laboratory experiments with mass spectrometers, they use the NIST database as a reference point to compare the results.[14] Scientist Jason compares a mass spectra result in his laboratory experiments with existing data in the NIST database. When he explains his reasoning as he looks at the images of his own results *versus* NIST, he says "my spectra looks like this and there's a NIST spectrum that looks like that, that's pretty close, so maybe it's a match." Algorithms help Jason with this process but he uses his own eyes to verify the comparison.

I suggest to expand the concept of truth-spots into the realm of the

[14] This thesis considers the NIST library with mass spectra. However, it is worth mentioning that it is not the only NIST library – another one, for example, is the infrared spectra library.

digital, with the NIST database as an example. Digital databases can be understood as a particular kind of truth-spot which Gieryn refers to as "collections," such as libraries, zoos and botanical gardens. Collections sacrifice the context of the object in the field in exchange for powerful epistemic gains. Collections allow "comparisons of specimens no longer separated by ocean or continent, with presumably less privation and risk than in the field, and in a more patient manner" because the scientist "is not a transient in this place (as Linnaeus was in Lapland)." (Gieryn, 2018, p. 45-46)

The digital database consists of agglomerated data from laboratories across different contexts, conducted by various practitioners, spanning across long time scales. It is curated by professionals employed at NIST, which is a governmental agency with aspirations to provide universal standards. The database is used as a yardstick in laboratory experiments - scientists compare their results with the national database - which means that it has an authoritative position in the making of knowledge claims. Therefore, I understand this digital database as a truth-spot. Digital databases are not only mediating relations to non-digital places (for instance, between the results in two different laboratories). They should not be understood as an entirely different kind than analog archives or libraries (whose status as a truth-spot most of us would acknowledge). The digital places are as important (if not more!) as the non-digital, in the current practices of scientific knowledge production, where scientists spend a substantial amount of their time by the computer screen.

At NASA Goddard, and in the wider context of astrobiology, the NIST database serves as a comparison for laboratory results with mass spectrometry, for instance, at several stages of explorations of Mars. We can rewind to the group of scientists who collected samples in Svalbard, the Mars analog, from earlier in the chapter. To validate the results from their

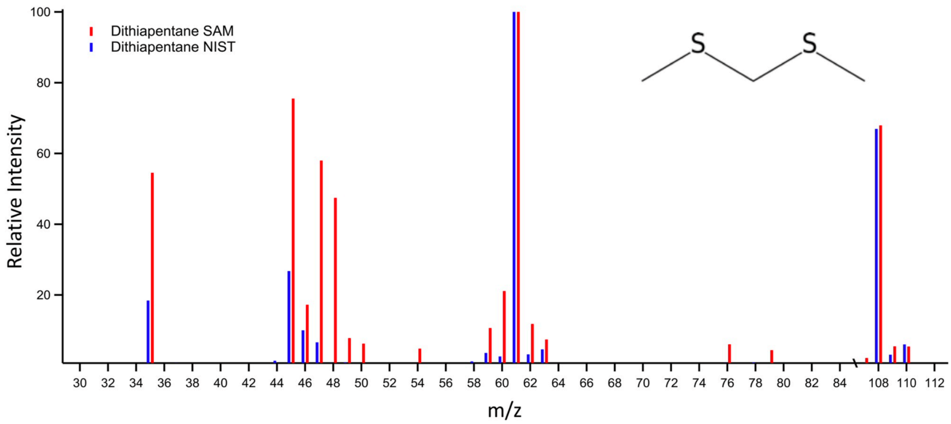

Figure 8. Mass spectra of 2,4-dithiapentane compound with SAM instrument on Mars (red), compared to the mass spectra from the NIST Mass Spectral Database (blue). The image is used in article by Millan and colleagues (2022, p. 15).

experiments, the group compared it with the NIST database (Siljeström, 2014, p. 786). NIST is also used for comparison of samples analyzed onboard the laboratory on Mars spacecraft (Millan et al, 2016, p. 95; Millan et al, 2022, p. 13). In other words, it serves as a reference point in the interpretation of mass spectrometry data from Mars (Figure 8), for instance, the interpretation of whether a particular kind of organic molecule is present on Mars. Moreover, NIST is used as a comparison in experiments testing instruments for future missions. At a Mars conference presentation, a group of scientists testing an instrument that will land on Mars in the future, argues that the mass spectrometry from their experiments are "accurate as their comparison with the reference mass spectrometry database from NIST allows to identify each peak without ambiguity." (Szopa et al, 2019, p. 6227)

However, the interpretation of mass spectrometry from Mars is complex. The comparison with the NIST database does not always provide scientists the confidence to make claims about the presence or absence of particular molecules. One aspect is that NASA's flight instruments are designed particularly for the purposes of the objectives of missions to other planets – detecting organic molecules in particular extraterrestrial environments. The experiments in the NIST database are likely conducted on commercial instruments, standardized for use on Earth. The mass spectra from flight instruments on for instance Mars are therefore not necessarily comparable to the mass spectra in NIST, performed on commercial instruments.

Another aspect that makes the interpretation of Martian mass spectrometry more complex are the unprecedented conditions on other planets, which can alter the experiments in unexpected ways. Instruments on NASA missions are designed based on assumptions about the environments on other planets. Certain conditions can be "partly unknown" and lead to "unexpected behavior of the experiments" (Millan et al, 2016, p. 90). SAM experiments with mass spectra on Mars are one example. A chemical compound called perchlorate was found on Mars, and scientists believe that it might react with the chemicals in the SAM instrument. This might lead to destroying the organic molecules or altering their chemical composition.[15] Such unprecedented aspects add another layer of complexity in interpretation of mass spectrometry from Mars.

When these uncontrolled artifacts (Star & Gerson, 1987) in extraterrestrial conditions become visible, NASA scientists try to manage them by constructing their own comparison for mass spectrometry, in

[15] Detection of perchlorate on Mars in the early 2000s has had significant implications for NASA missions exploring life on Mars – NASA scientists believe that the perchlorate impacted the results of previous experiments on Mars. The instruments onboard the spacecraft were designed to detect organic molecules on Mars, but the chemicals in the instruments reacted with perchlorate, which can either destroy the organic molecules or change their chemical composition (Archer, et al, 2019).

simulated Martian conditions, on instruments that are more flight-like than the commercial ones used in the NIST database.

Scientists' own mass spectra data and the ones from the NIST database are never a perfect match – different mass spectrometers with different ionization sources and ionization energies produce different types of mass spectra. Jason writes in a correspondence that "comparing similar kinds is ok, but you will never get a perfect match." To make knowledge claims, the differences are bracketed, to focus on the similarities (Pinch, 1993, p. 30-31).

NASA scientist Jason acknowledges in an interview that there are further problems with the NIST database. More fundamental problems with the quality of its data. When me and Jason are discussing the databases in the context of potentially using it for AI to detect life, he is mentioning three kinds of problems. One is related to the technological changes, which affects the quality of data. For instance, "oh here's a dataset from the 90s that I took in, so I have to know that the peak shape was poor because of the technology." The second issue identified by Jason is the aspect of different researchers producing different quality of data. "Not every spectrum is the same quality. Some of them are very poor. These are taken from whatever laboratory and as better ones come in they get replaced but you have to be aware of that."

The third issue pointed out by Jason in relation to the NIST database is the systematic bias. To explain this further in correspondence, he brings up the example of Murchison – a famous meteorite named after the Australian city where it landed in 1969. Studies of Murchison meteorite (figure 9), which is older than our solar system, have contributed with knowledge about interstellar chemistry before, or just during the birth of our solar system (Schmitt-Kopplin et al, 2010). Jason explains that there is a small overlap between the millions of compounds in the NIST database,

Figure 9. Samples of Murchison meteorite held by scientist Lu in a laboratory at NASA Goddard Space Flight Center. Photo from fieldwork.

and the ones in Murchison meteorite, which are probably one million unnamed compounds. Jason points out that the NIST database has an inherent bias toward compounds that are important to the US Department of Commerce. And as their Mass Spectrometry Data Center states, they work with mass spectrometry data “for industrially and environmentally important (bio)molecules.” (National Institute of Standards and Technology, n.d.) Jason draws a relation between the database and the impact of funding, which then leans the research toward certain areas with relevance for “medicine, industry, and technology.”

> The NIST database is based on things that people look for. It's based on things where there's money for people to research on. Therefore, it's biomedical. So there's a heavy bias for things that are important for *medicine, industry, technology*, things of that sort. Which is biased heavily toward *Earth* life. And heavily away from chemistry we haven't thought of.

Jason mentions how the NIST database is "biased heavily toward *Earth* life", which relates to the previous discussion about Earth-bias as an uncontrolled artifact. But it is not any just kind of Earth-bias. Jason points to how the NIST database is skewed toward production of knowledge for the purposes of "medicine, industry, technology." After all, as I mentioned earlier, NIST is an agency of the US Department of Commerce, with a mission to develop standards and measurements to promote national "innovation and industrial competitiveness." As a consequence, the unknown in outer space is interpreted in light of what is relevant to conduct research on - for medical, industrial and technological purposes.

Jason contests the epistemic status of the NIST database as a truth-spot in making claims about laboratory results. In Jason's depiction, NIST database is an agglomeration of data tied to particular research areas – medicine, industry, technology. Mass spectra of extraterrestrial phenomena have small overlap with mass spectra in the NIST database, with molecules that are relevant for industrial purposes. Awareness about this issue comes through as important in an interview with Jason, however, without condemning its epistemic status. This implies that the artifacts can be controllable to a certain extent (Star & Gerson, 1987). If used with caution, it can serve as a truth-spot for making knowledge claims.

I wrap up this section with Jason's reflection about the NIST database as "having an *incomplete* knowledge" which is based on "funding, as everything is.” In the previous chapter, I described how AI tools can appeal to ideals of objectivity in science. Could AI have a more *complete* knowledge? We discuss visions of AI as a tool to facilitate understanding of life. AI needs to be trained on a set of data - it needs its own database of knowns, to distinguish the unknown.

> (…) To get better models and back and forth but that bootstrapping is in a direction, that’s not agnostic. It’s toward something that is fundable. That is something relevant to medicine or plastics or petroleum or whatever. It’s all biased. So you can’t totally free your mind from terrestrial influences when you’re looking for something that is unique.

Based on discussion with scientist Jason, terrestrial bias is an uncontrollable artifact in scientific practice, as well as in development of AI tools. The search for the unique in outer space is through analysis of the terrestrial – in this case medicine, plastics or petroleum. Now, I turn to the next stage in the transformations, and new contestations, when programmers take over the scientific data to develop AI tools.

Using Data From Planet Analogs in Datasets for AI

At the start of this chapter, I introduced how NASA scientists and engineers plan a future mission to Titan, the moon of Saturn. However, as I wrote in the introduction, the distance to Titan being over a billion kilometers away from Earth poses severe data limitations. It slows down the communication between the scientists on Earth, and the instrument on Titan. The team argues that this can be addressed with automation of decision making onboard the spacecraft.

The aim of the algorithms developed by the programmers at NASA Goddard is to make real-time decisions onboard the spacecraft, about how to interpret the data from experiments or how to proceed with operations on the landing site. Instead of sending all the data back and forth between the spacecraft and the scientists on Earth, the algorithm will make some of the decisions. In the following section, I discuss how the making of automation for "partly unknown" (Millan et al, 2016, p. 90) worlds is done in practice. I pay particular attention to how the epistemic contestations change, when the programmers take over the data.

In the AI domain, it is often said that AI is only as good as the data it learns from. To make reliable decisions, the tool has to be trained on the *right* data. Ideally, the AI would be trained on the kind of data that it is designed to detect. Following this logic, if the aim of an AI tool is to detect organic molecules on Titan, it should ideally be trained on mass spectra from Titan. However, there is not enough such data and for some unexplored destinations in the universe there is no such data at all. In the absence of enough data from other planets and moons, programmers create datasets based on the data that are available. They use the scarce data from other planets, together with data from planet analogs described in this chapter. For instance, field sites in Svalbard, the Atacama Desert and meteorites. Another kind of data programmers use is from laboratory experiments on samples that are purchased and produced in an industrial facility, which I described in the first chapter. Yet another kind of data used for training of AI are computed simulations, which I focus on in the last empirical chapter.

I accompany programmers Victoria and Eric, and scientist Caroline during a meeting about a mass spectrometry dataset for training algorithms.

Victoria and Eric are among the leading AI developers at NASA Goddard. So, what does a dataset for life detection on Mars look like? I get to see an excerpt, to which programmers Victoria and Eric have to pay close attention. It is a long list with several columns – the first consists of sample labels. It includes labels such as “atacama”, “PaintedDesert”, “terephtalicacid”, “kitkat”, “Snickers” and “Butterfinger.”

While observing, I wonder, how can sample labels such as “kitkat” and “Snickers” facilitate the search for signs of life on Titan or Mars? The planet Mars, not the chocolate bar. I think… A few days before going through the data, I recall Victoria being pleasantly surprised by getting a KitKat, as a friendly gesture from a colleague at the office. Now, I am rather puzzled, by seeing “kitkat” amongst the samples for life detection. In order to make sense of the chocolate bars in data for AI and decide whether they should remain or be deleted from the list, Victoria has to consult the scientist who worked with the samples.

Caroline, the scientist who shared the data with Victoria, was collecting samples in Svalbard. The conditions in Svalbard, which is close to the Earth’s North Pole, are seen as resembling Mars – this time, definitely the planet Mars, not the chocolate bar. While conducting fieldwork in the ice cold, distant, Mars-like site, scientists found themselves hungry, and labeled the samples after what they were longing for – chocolate bars.

This is just one quirky example of Victoria’s detective work, in order to create AI. She needs to investigate much more than which compounds the chocolate bars represent for the scientist. During the consultation with scientist Caroline, other questions rise. Some require Victoria and her programmer colleague Eric, to search for a decade-old notebook across the laboratories at NASA Goddard to find an answer about a particular datapoint. The missing data concerns information about an experiment conducted by the scientist many years ago, documented on paper but not clear in which of the laboratories. A long walk back and forth later – Goddard is a large facility – Victoria and Eric are cheerfully back, with an old notebook, ready to turn it into computer code. What appears as a single datapoint on a list – "Snickers" – requires a lot of effort for scientists to produce, and moreover it requires a lot of detective work for programmers to understand.

What is interesting here is the shift of what is understood as an artifact. Star and Gerson (1987) point out that anomalies can shift status very quickly, depending on the shift of context where the anomaly is situated. In the case above, we can see that planet analogs, previously contested by scientists, are not contested by programmers who include them in the datasets for AI. The analogy is no longer a relevant question. On the other hand, new artifacts arise when the data shifts context from one profession to the other. The chocolate labels for samples from Svalbard were accepted by the scientists in the peer review process - Snickers and Butterfinger made it into the journal publication (Siljeström et al, 2014). However, data labelled after chocolate bars becomes an artifact in the context of programmers who need the data to be standardized for training of AI.

During the meeting about mass spectrometry data for training of AI, programmers Victoria and Eric, together with the scientist, discuss how to categorize the data. The AI will analyze organic molecules based on the categories ascribed to the data it is trained on. In this particular set of data for training, there are nine categories. The categories stand for different kinds of chemical compounds. For instance, mineral, hydrocarbon- or sulfur-bearing compounds. Based on the dataset, the algorithm is trained to ascribe categories of chemical compounds to new data.

Once an experiment on Mars or Titan is executed, the algorithm analyzes the results by distributing probability of what the extraterrestrial sample most likely contains. In other words, it ascribes a certain percentage of how much the sample belongs to each category. Ultimately, when NASA scientists on Earth receive the data analyzed by AI, they will see it on a computer screen with a display of the top categories, suggesting which are the most likely to fit the sample. For instance, minerals or sulfur-bearing compounds. So, the instrument does experiments with the mass spectrometer and the AI categorizes the results. Now, I turn to the question of how to decide which data is interesting in explorations of life and habitability, and how to train an AI to make these decisions.

Interpreting Anomaly in the Data – Potential Life or Error?

What data from missions searching for signs of life and habitability is most interesting? When I pose this question to scientists and programmers at NASA Goddard Space Flight Center, I get almost a unanimous answer. Signs of potential life in outer space are expected to appear as an *anomaly* in the data. Anomalies in the data can be a sign of something *known* but rarely occurring, or something unexpected in a given setting. Anomalies can also be a sign of a completely *unknown* phenomenon. For instance, unique chemistry or biology in outer space.

I ask programmer Eric how an anomaly would appear in the AI tool. Based on how frequently I hear researchers addressing search for life in terms of anomaly detection, I deduced that one of the categories would be labeled precisely as the desired kind of data: anomaly. However, after persistently asking Eric follow up questions, I realized that there is no formal category for an anomaly. Instead, detecting an anomaly is a matter of interpretation of the scores from all categories. Eric imagines that if the algorithm would ascribe low probabilities to categories that it was taught to recognize, the interpretation would be that it can possibly contain an "unknown" object. I ask Eric at what stage something becomes an unknown. He seems troubled and I soon realize why. I have been asking for clarifications about something very unclear. There is no particular threshold, percentage, or category for when an entity becomes an unknown anomaly, a potential sign of extraterrestrial life.

The scientists and engineers I observed at NASA Goddard are searching for life and habitability within our solar system. However, searching for anomalies in outer space is also a prevalent practice amongst astronomers searching for new exoplanets – planets outside of our solar system. In an ethnographic account, Messeri depicts how astronomers search for new planets by searching for anomalies. What Messeri brings attention to is how the declaration of new planets is not about seeing them, but rather about noting the absence of alternative explanations for the anomaly (Messeri, 2011, p. 51). The same logic follows in the case of life detection with AI - detection of an unknown anomaly is not about seeing the anomaly but rather, noting the absence of correlation with the categories of known chemical compounds.

Failing to detect interesting anomalies is the "number one concern," according to Eric. The danger with the use of algorithms is that they can potentially ascribe misleading categories to the samples. As a result, the AI can skew scientists' attention toward false positives – recognizing something common as a novelty – or false negatives – recognizing a novelty as something common. The consequences can be both immediate and long-lasting. AI can drive the course of action of a billion-dollar mission in misleading directions. In such case, it is a loss in terms of economic resources and scientific efforts. Errors in algorithmic performance can steer researchers in life detection missions away from what they are looking for – potential signs of life and habitability.

NASA researchers expect that the AI approach with predetermined categories – the so-called supervised approach – will perform well with detecting *known* anomalies, meaning objects that are known but rarely occurring. For detection of *unknown* anomalies, the researchers expect that a technique called unsupervised training will perform better. The unsupervised approach is about training the algorithm on a dataset that is not labeled, to let the algorithm identify patterns on its own.[16]

I discuss training of AI for anomaly detection with Victoria. In search of refreshment, we are sitting on a bench outside of the office at NASA Goddard, stubbornly, despite the windy weather. In order to focus on asking adequate follow-up questions, I have surrendered to the wind madly twisting my hair all over my face. I want to disentangle what anomaly means in practice. In order to show me how training AI works, Victoria displays graphs on her computer. Scatter plots with plenty of blue dots. The dots are data from experiments with mass spectrometry. I see that all the dots form a clear pattern, a wave-like shape. But there is this one dot that stands out, like a splash from the wave. What does it mean?

While staring at the odd dot during the interview, I recall my conversations with Victoria from last year and how anomalies seemed to have more than one meaning in the context of life detection. She has referred to data as "anomaly", "novelty", "weird" and "outlier". These terms are at times articulated as distinct and at times used interchangeably. At times, anomalous data is desired, at other times avoided. This ambiguity reappears still one year later, when I ask Victoria about what she means by anomaly.

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[16] Similar approach is used on the present Mars mission (ChemCam on MSL) to find scientific targets autonomously. However, in contrast to Mars, there is not as much data from "ocean worlds," like Titan, for training of algorithms. The already mentioned data from planet analogs and synthetic data (chapter 7) serve as a solution.

> A: So in this case, does the anomaly detection refer to fault in experiments or something interesting, potentially, scientifically speaking?
>
> V: That's a great great question. It could be both. An anomaly could be something very weird, compared to all these points, this one doesn't have a lot of signal so maybe this point here is weird because there's no signal. But it could also be maybe this one is like it looks different in the way that there are more peaks and maybe a massive peak that is not somewhere else. So we use anomaly and novelty, these two words, sometimes saying the same thing. But anomaly usually has a negative connotation. If it's an anomaly, it's not great so we should remove it. To me, anomaly is also a way to learn about how your instrument did well or not, and how to learn from it. This is weird data so I really want to look at it.

Recall the scatter plot with blue dots forming a wave-like pattern and the splash. The "weird" dot, in Victoria's terms. Based on Victoria's explanation, a single dot that stands out can be interpreted by programmers as two fundamentally different phenomena.

The first interpretation of anomaly in data can be that it stands for an error. An error in terms of a failed scientific experiment. If an instrument is not calibrated correctly, or breaks altogether, it can result in a datapoint that stands out from the rest. Consequently, programmers remove the datapoints interpreted as failed experiments. Keeping such data in a dataset for AI is perceived as endangering the training process. The intention is to teach the AI on examples of successful experiments, not on the failed ones.

Nevertheless, as Victoria points out, the failures can still be important lessons for the humans involved.

The second interpretation of anomaly in data can be as a novel phenomenon. In one of the articles that Victoria has co-authored, novelty detection is articulated as a matter of both *known* anomalies that are rarely occurring in a particular context or an anomaly that is completely *unknown.* It can stand for something unique that scientists have not encountered before. In the context of life detection in outer space, many scientists expect a sign of life to appear as precisely that: an anomaly in the data. In contrast to anomalies in the data as an error, novelty is desirable.

Star and Gerson describe how anomalies in science usually appear in small research projects involving a small group of people. In most cases, anomalies can be interpreted as either mistakes or controlled artifacts before publishing results. Furthermore, Star and Gerson point to that there is an incentive to interpret the anomalies quickly – extended negotiations delay the work process, funding, as well as career advancement. On the other hand, interpreting anomalies as discoveries is tied to "professional or public honor, funds, and career opportunities." (Star & Gerson, 1987, p. 152)

The two interpretations of anomalies in mass spectrometry data have drastically different consequences. One entails a risk of deviance, which is considered as something to be avoided. The second is a promise of something unique, which is highly desirable. The contrasting interpretation entails opposite consequences for the datapoint - one is to be removed, the other remains in the dataset. If the unique object and failed experiment look the same in a scatter plot… How can you teach an AI to distinguish between these two anomalies? Misinterpreting data is one of the biggest fears amongst programmers. Missing a sign of life could cost you a potential Nobel Prize! (see the discussion in chapter 4)

This uncertainty in the interpretation of data is not experienced just by the programmers. Scientists do recognize this as a fundamental problem in interpretation of data. I rewind to the meeting in the vignette, where scientists and programmers at Goddard discussed automation for a future mission to Titan. Scientist Desmond seemed confident about the capacity of AI tools to select the right data to send back to Earth ("We just have to teach the computer how to think the way that we do.") But after a discussion around the table, Desmond admits that the challenges of automation are serious.

> Yeah, I mean the difficult part of that, you know Ryan is not wrong, I'm trivializing that, right. The typical parts in that is, it's an unknown. You don't know what the heck signal is versus noise, right? So how do you know what to add and what to ignore, right? Obviously, we talked just about ignoring, you know, completely empty spectra and not returning those, that's easy. But how do you, you know, teach and determine what is actual signal and what is actual noise? Blaaah!

All objects in the universe produce background noise. The results of scientific experiments ("signal") are entangled with the background noise generated from spacecraft and all other objects surrounding it. Scientists need to determine what is the signal *versus* noise in the data. Both programmers, and scientists, struggle to operationalize the difference between the interesting and non-interesting data. Data from experiments on field sites which they have not yet accessed.

Conclusion

The development of AI depends on data that is available for training these tools. Which data are available is in turn dependent on the knowledge infrastructure, which enables and constrains the practices in planetary science and astrobiology. This chapter analyzes particular truth-spots (Gieryn, 2006; 2018) in astrobiology, which are places on Earth that lend credibility to making claims about other planets and moons, as well as life and its origins in the universe.

The chapter demonstrates how the choice of field sites is dependent on accessibility and symbolic value, rendering some places more popular than others. As a result, scientific knowledge production about life and its origins is skewed toward the sites that are accessible, or popular. Consequently, this skewness is reflected in the data that is available. These findings are in line with Bowker's study on databases on biodiversity, reflecting similar feedback loops that skew knowledge production in a particular direction (Bowker, 2000). This problem is also prevalent in NIST databases with mass spectrometry, which scientists use to compare results of experiments, from laboratories on Earth as well as on other planets and moons. This database is curated and developed for industrial purposes, which has little overlap with the compounds of interest for astrobiologists, for instance, a meteorite. These truth-spots – the planet analogs, from where scientists collect samples, and the NIST database, which serves as a library of knowns with which to compare the unknown – constitute the knowledge infrastructure that enables and constrains what kind of scientific data is produced. The knowledge infrastructure shapes AI, through the availability of scientific data which can be used for training of these tools.

Development of AI also changes the scientific knowledge production, by black-boxing particular epistemic concerns and introducing new ones, in line with the norms of practice in the field of AI. With development of AI comes a shift in who makes the decisions about the data, which concerns are relevant, and what is interpreted as an artifact.

The samples collected in the extreme field sites and dissected into molecules in the laboratory, are tamed into a pattern in a dataset and the outliers are managed. Although the risks with filtering out interesting data with AI are acknowledged, the performance of life as a pattern in data is successfully coercive in life detection. Standardization and control of anomalies in datasets for AI reflects the epistemic virtues of laboratory work.

AI datasets can also be understood as truth-spots in their own right – they are an agglomeration of huge amounts of data, and in the programming practices, sometimes narrated as "ground-truths" (Jaton, 2021), or being envisioned as an oracle in scientific knowledge production (Messeri & Crockett, 2024). However, in this case, AI is at the early stage of development and has not reached the epistemic status of a truth-spot – yet.

Chapter 6 Negotiating Between Two Epistemic Cultures, Within One Data Economy

On a Monday morning, June 5 2022, by the main gate of NASA Goddard Space Flight Center, me and software manager Eric, are glad to meet for the first time. However, none of us have received any updates about my permission to enter the facilities. The bureaucracy got even worse since the pandemic, Eric says. Trying to maintain a good spirit, we decide to get a coffee a few minutes car ride away from Goddard. As we are chatting at the coffee shop, a man with a face mask walks in with decisive footsteps. Even though half his face is shielded, Eric recognizes the colleague. They wave and say hi to each other. The man continues to walk at a brisk pace to the cashier, makes a quick purchase and before we see him leave, Eric leans in to whisper “that is the smartest guy at NASA”. Eric’s comment could be interpreted as just regular American English, where things tend to be expressed in superlatives. But soon enough, I find out that there is more to the superlative than just embellishment.

During the first weeks of field work at Goddard, I spend a lot of time shadowing a group of software engineers. While discussing how to design AI that would make decisions onboard future missions to outer space, a particular risk is repeatedly brought up. Namely, the fear of missing out interesting data. To illustrate the challenge that programmers are facing, Eric tells me about a particular example of a previous mission to the moon, in which “the smartest guy at NASA” reappears. The following is Eric’s account of what he refers to as “the garbage story,” which he often mentions when discussing AI.

Imagine a satellite orbiting around the moon. To save energy during the long journey around the moon, the instrument is powered up only during the right planetary conditions. Once powered up, it takes the instrument 15 minutes to warm up. Data generated during the warm up period was considered as not interesting for scientific purposes. Instead, it was considered as "garbage," according to Eric. While most scientists focused on what they understood as interesting data, one day, a scientist (the man at the coffee shop, that walked in and out in a hurry) decided to take a look at the "garbage data." Thanks to that, he estimated the amount of water on the moon.[17] In other words, going through the disregarded "garbage data" led him to a new scientific discovery. In Eric's account of this story, "the smartest guy at NASA" figures as a hero. The heroism for Eric, as a software engineer, resides not in launching a rocket but in making data useful. The scientist turned "garbage" into a valuable resource. Understanding and selecting data is a key problem in the development of AI, which makes "the garbage story" an important lesson for programmers. The interesting data can lurk where you least expect it.

Understanding data as garbage is brought up at yet another occasion during my visit at Goddard, in a conversation with Jason, the scientists introduced in the earlier chapter, with decades of experience in research on the origins of life. Right away after I mention AI for life detection, he is turning to the pitfall of "garbage in and garbage out." In the field of computation, this term refers to how low-quality data for training will result in low output. Just like the programmers, Jason is also concerned about the

[17] The scientist found signs of water molecules in the data from the first 15 minutes of getting the instrument ready. Water was present in the data only during the first two seconds of the powering up period, because the warming up of the instrument caused evaporation of the water molecules. As a result, after the first two seconds of turning the instrument on, there were no signs of water molecules in the data.

problem with selecting the right data to train AI. However, his problematization, as a scientist, goes further. It goes back to the fundamental question of (not) understanding what life is. Jason asks, how do you teach an AI for life detection, "if we can't even define life?"

With the vignette, I have introduced what is at stake in choosing the right data. This chapter focuses on how data practices to develop AI tools are integrated into scientific cultures at NASA Goddard. The value of data is negotiated between two groups: the software engineers and the planetary scientists (whom I refer to as scientists, for the sake of brevity). There is a major clash between their ways of approaching data. Broadly speaking, software engineers need specific requirements to design a tool to detect life, while scientists do not know what to look for. In other words, to develop an AI tool, the uncertainty about not knowing what life is has to vanish.

I analyze the negotiations in terms of trading zones (Galison, 1999) between the scientists and programmers. I identify these two groups as two epistemic cultures (Knorr Cetina, 1999), yet, belonging to one data economy (Pinel & Svendsen, 2023). My argument in this chapter is twofold. The first argument is that even though AI is at the stage of early development, it already changes the power relations in scientific knowledge production by imposing new ideals of epistemic order. However, it does not preclude the presence of relations of care, which are fostered through participation in the context of scientific knowledge production. And this is at the heart of my second argument, which can be summarized as follows: organizational arrangements can inscribe data with a biography or make it ahistorical, which in turn has consequences for what I call epistemic responsibility in programming. Without further ado, I dive right into showing how this is the case at NASA Goddard Space Flight Center. In the first part of the chapter, I focus on the relations of power, and toward the end, I unfold the relations of care.

Negotiating Between "Two Worlds" at Goddard

In order to construct an AI for life detection, programmers need to prepare the data to train the algorithms on. As I already alluded to in the previous chapter, programmers rarely do this alone. Often, they consult the scientists, asking about their interpretation of the data. However, the interaction between the professions is challenging. During a brainstorming session about automation of life detection missions, in a meeting room full of software engineers, programmer Victoria clearly articulates a distinction between the two groups and their interests. Software engineers and scientists, as "us" and "them."

> It's a lot about questions about what is interesting for *them* is not the same as what is interesting to *us*. And by *them*, I mean *mass spec experts* and *us*, *software people*.

The challenging distinction between the two groups resides in the differing views on "what is interesting" in life detection. But this distinction resides not only in the context of development of AI tools. It is more fundamental than that. NASA scientists explicitly mention this distinction. In the following, I discuss how this theme appeared during interviews and observations of the everyday work at Goddard. I understand this as two epistemic cultures, meaning "those amalgams of arrangement and mechanisms – bonded through affinity, necessity and historical coincidence – which in a given field, make up how we know what we know" (Knorr Cetina, 2009, p. 1). Afterwards, I will turn to how these two epistemic cultures affect the negotiations about the value of data selected for training of AI.

A major obstacle in the interaction between scientists and engineers is brought up in an interview by scientist Ryan. He works in the field of mass spectrometry and its application to life detection missions. In our interview, he depicts the roles of scientists and engineers as fundamentally different. His descriptions are representative for how practitioners at Goddard speak about their professions. Here, Ryan puts the scientist hat on.

> Most of the time, we don't know what we're looking for. We have an idea about what life looks like here, on Earth. It might not look the same in space and still could be life, right? Just because you don't see a human across Mars, it doesn't mean there's no life there, or a bug, it could look like something else.

In the context of life detection, knowing what to look for is a very difficult question. Scientist Ryan gives a hint of this difficulty by referring to how life in outer space could look like life on Earth, but it could also look completely different.

During the interview, Ryan also puts the engineering hat on. He describes how engineers need to start with "performance specifications, in terms of like how small of an amount of a chemical might be there and what types of chemicals are we trying to look for, to sort of define that life exists." To design missions for outer space, scientists and engineers need to make decisions about what can be searched for, specifically. In spite of not knowing what to look for, designing a life detection mission boils down to specific requirements for what can be searched for. In other words, the obstacle here is the clash between engineers asking for specific measurements to build an instrument and scientists not knowing what to look for.

> I think that for better or for worse, and sort of as defined by their goals and training in some sense you know, *scientists like*

> *to keep things very open ended*. Like 'I wanna detect life on Mars. That's it, I want to do that and however I'm gonna do that.' And engineers on the other side are like 'OK, I want to be able to detect methane, five parts per million, at 20 degree Celsius, at noon on Mars', you know. So those are two totally different starting points, I mean they're the same end result maybe, right? *They're both going to detect life but two totally different ways to approach that*. And there's a reason for why they have those approaches. *Scientists don't know what they need to do necessarily* and they want to do science, they want to get the best outcome. And *the engineer sort of wants to build the instrument to do the one specific thing*.

Scientists and engineers are depicted as having "two totally different ways to approach" life detection grounded in "their goals and training." He speaks of how "based on their goals and their jobs" each profession is also "training sort of their mindset of what they want." This implies that the difference between professions is not merely a matter of title or tradition, but rather a deeply rooted way of approaching the world. I read it as two different epistemic cultures (Knorr Cetina, 1999), which through professional training, shape how they constitute their epistemological goals and needs. It is not necessarily about knowing – take agnosticism as a position for instance – and more about the ideals and practices shaping how knowledge should be produced. It guides which questions should be posed and (im)possible venues for how they could (not) be addressed. In the case at Goddard, both professions strive for the same result – searching for signs of life and habitability – but they approach it through different goals and means. Ryan portrays scientists as "keeping things very open ended," while engineers are about "measurements." While an engineer is determined to get specific information about what to search for, in order to be able to build the tool, the scientists tend to be open about how scientific objectives are formulated and operationalized. I already hinted at this in the vignette by quoting scientist Jason – his formulation about how scientists "can't even define life" on Earth is representative. Scientists are inclined toward a more pluralistic worldview, by not knowing what to search for and staying open in the face of the multitude of possibilities of what life could look like.

Ryan frames the difference as not just a problem but also the essential characteristic of each profession – "they're doing their job." Despite emphasizing how the difference between scientists and engineers is something good, he does acknowledge how the difference in the two approaches creates a gap that needs to be addressed.

> So I think that implicitly based on their goals and their jobs, they're gonna come at two different sides so *there's a gap* there, there has to be and *that's good* in some sense cause *they're doing their job*. But the way that we produce a functioning mission is by *bridging that gap and understanding*. OK, what do we need to actually make that measurement? And what is that measurement then that we're gonna define and then build to. So you have to bridge those *two goals* but then it's also people and they're training sort of their mindset of what they want so I think there's a need for some individuals that understand both sides of the coin.

Bridging the gap between scientists and engineers is crucial for a successful mission, according to Ryan. The "gap" is also articulated in an interview with another engineer at NASA Goddard. They describe the professions as two *languages* in need of "translation" – science and engineering. The engineer explains that the gap and lack of understanding can sometimes lead to frustration on both sides. Frustration can be read as an expression of the clash discussed above – the clash between different epistemic cultures. On the one hand, software engineers being frustrated about how scientists "do not know what they want." On the other hand, scientists being frustrated when they discuss with engineers about how difficult it is to know what to look for when searching for signs of life. I want to emphasize how the differences, described above by Ryan as different "approaches," are expressed by the engineer as different *languages:* "speaking science and speaking engineer." This is important because it takes us further to the use of "translator" as a metaphor for bridging what scientist Ryan depicts as "two worlds."

> Once the specifications can be defined, then we can work with those and say you know, this is how we can produce that sort of measurement and you know *it's always a give and take. It's never just like I want this, period*, and it never changes because sometimes we can make those measurements and sometimes we can't. There's sometimes we can make the measurements but only in certain ways or at certain times. My contribution is also some of that *back and forth* of like 'well, we probably can't achieve this level of sensitivity in this condition but if we get a little bit more sample, or operate under the right temperature constraints, we can achieve that'. *So it's always a back and forth of trading off, you know, I can't quite do this under those conditions but if you give me a little bit here, I can produce that*. So certainly, a lot of my time is spent *negotiating and sort of trading off the best way to achieve a desired science outcome.* And I'll also just say my specific role on a lot of these projects

> is sort of *bridging that science and engineering gap.* And I think that maybe comes from, I don't know if it's just what I like to do, or I'm good at, but also sort of my training. Like I said, I consider myself a scientist, a chemist by training but I do a lot of engineering. And the ability to *understand what the science goal is* and then also how you would do that with the *engineering capabilities* that we have. That sort of *bridges those gaps cause you can't have one without the other.* That's really been my primary role as sort of making that connection and both sort of seeing how it can work and *helping those two worlds kind of mesh.*

In the quote above, Ryan describes how the "two worlds kind of mesh" through the practices of negotiation. He repeats how working on a mission is always a "trade-off", "back-and-forth", "give-and-take." To do so, Ryan is saying that he needs to make the connection between the "two worlds" and "bridge the gap." This reveals a common set of metaphors used by the scientist and the engineer. Metaphors can be understood as upholding structures for how humans perceive and act in the world (Lakoff & Johnson, 1981). The scientist's use of metaphor of *trade-off* between *two worlds* and the engineer's use of metaphors of speaking different *languages* in need of *translation*, can be read as an exchange between two cultures.

This can be tied to the concept of "trading zones" introduced into history of science by Peter Galison (1999) who has studied the context of physics by paying attention to the interactions between different groups: theoreticians, experimentalists and instrumentalists. Borrowing from linguistic anthropology and their observations of trade between different cultures, Galison suggests that we can draw parallels to negotiations between different groups in science. By developing contact languages, different groups can reach local coordination of action and beliefs, despite having global disagreements. In his understanding of science, Galison brings attention to how it is disunity that keeps science stable.

To summarize this discussion, global consensus is not necessary for scientific work – rather, different groups reach local agreements. They can even develop a new mode of communication to prepare for the exchange, yet, without losing their local identity. Now, I turn to how the negotiations between scientists and software engineers occur in the everyday practice of developing AI to detect signs of life in outer space.

Scientists in Authority of Interpreting Causality

When I ask practitioners at Goddard about AI, many of them refer to their colleague Samantha as the person to talk to. She is a planetary scientist working with life detection. On several occasions, I hear her turning AI into a verb, when humorously asking "Can I ML my project?"[18] Described by colleagues as "fun to be around", she is indeed a person with contagious enthusiasm. Once, Samantha presented her ideas about a mission for life detection to a group of engineers. During the meeting, Samantha presented a picture of the process of life detection. She stressed how it is a continuous process of re-evaluation of what life is, based on new discoveries. New discoveries and insights about life are in turn leading to new design of technology for life detection. Samantha described this as an interplay between on the one hand, philosophy (new insights about understanding of life), and on the other hand, operationalization (re-designing of technology to align more with the recent discoveries). Based on this reciprocative

[18] In correspondence, Samantha explains how "Can I ML my project?" is a joke that refers to how some people that have just started working with ML approach it as "a hammer trying to find a nail." She points out that a more robust way to approach AI or ML is by being driven by a hypothesis.

relation, Samantha wanted to suggest a mission that allows for staying flexible in the face of not knowing what to search for and being able to change the goal of the mission during its lifespan.

"It flopped HARD, they were NOT OK with me talking about the agile stuff," Samantha says, emphasizing how much the engineers dismissed her ideas. This "flopped," she says, since the engineers "were like 'just tell me what you need!'". Samantha laughs upon remembering that interaction with engineers. She was the only scientist in the room.

The collision between engineers' requirements and scientists not knowing what they look for is also mentioned in conversations I have with one of the programmers, Victoria, who collaborates a lot with Samantha on AI for life detection. "We [software developers] need to understand what they [scientists] need, but she [Samantha] doesn't always know what she needs." Samantha has even put this very straight during another meeting with a group of software engineers: "I don't know what I want." In later correspondence, Samantha explains that she can not know what she wants the engineers to design, "if we don't know what life looks or acts like." She shifts the question to designing an AI that could search for knowns and unknowns, which relates to detection of anomalies, discussed in the previous chapter.

It is evident that Samantha and the engineers experienced moments of frustration in their interaction – something that Samantha can now laugh about. This echoes what I explained earlier as the clash between two epistemic cultures. What scientist Samantha asks for is "goal re-orientation," in NASA's official terms. It is about opening up for different possibilities of what the goal of a mission could be. When engineers ask for specific requirements to build instruments, it results in a clash. Samantha's suggestions lean toward a more pluralistic thinking, which is in conflict with the engineer's view, who requires clear-cut specifications to develop technological tools. Changing the design of a technology is possible in theory but in practice, institutional requirements can pose challenges for the vision of flexible goals. What this account illustrates is how scientists and engineers have contrasting needs and modes of reasoning throughout the process, which is posing challenges in working toward the same goal – designing a mission to detect signs of life and habitability. Software engineers are eager to understand a setting upon which they can clearly define a problem and address it. Scientists, on the other hand, emphasize the vague nature of the problem and possibilities of having to re-define the problem throughout the process. In the following, I will focus on how these two groups negotiate about data.

To develop AI for life detection missions, Samantha collaborates with Victoria. While working with preparation of data for training of algorithms, in order to try to understand it better, programmer Victoria is using a technique called PCA (Principal Component Analysis). It is a way to explore data through visualizations, displayed as axes in a graph. "This is math, trying to find a linear relationship between the features to best represent the variance of the data," she says. Drawing linear relations between phenomena in a plot, like PCA, is a common practice in data work. However, Victoria pinpoints that linearity is not only a solution but also a problem. It looks for linear relationships, whilst in many scientific problems, the relationship is not linear. Thus, the techniques relying on linearity need to be complemented with other tools, to understand the data. Another key problem with this method of deriving the correlations "is that there's no clear metrics to say if it's a good result or a bad result (…) and that's where the experts come into the picture, they can look at the data and say 'yes, that makes sense, no, we don't care'", Victoria says. Another programmer, Ashley, describes how correlation is just one step during the process of developing algorithms – "this only tells us that they are correlated, not that they are important." The AI techniques are helpful for drawing correlations but interpretation of causality is something that programmers leave to the scientists. Understanding the data, its preparation and creation of algorithms is a continuous process of reiterations between software engineers and scientists. Like much, if not everything at NASA, everything depends on teamwork.

To find out what "makes sense" or what is "important" in the data, programmers Victoria and Ashley ask scientist Samantha. Samantha explains to me how she looks at the data visualizations and wonders, "Is this a blob or are there certain groupings that are meaningful?" She derives meaning by *looking* at the plot. Therefore, to accommodate Samantha's way of understanding the data, Victoria works a lot with visualizations. She is showing me colorful plots with a myriad of tiny figures. Squares, triangles and circles in different colors, where each stands for a variable. Victoria is meticulous with which colors and figures to select. "It might sound stupid, but the colors really help for the analysis of the data," Victoria says.

Making visualizations can be interpreted as helpful in understanding data. But given Victoria's need to collaborate with another profession – a scientist – it can also be read as Victoria's way of establishing a common language. Her expression of how creating colorful visualizations for analyzing the data "might sound stupid" suggests that choices about figures and colors can come across as a simplification. This resembles what Galison refers to as pidginization in "trading zones." Derived from linguistic anthropology, pidgin is a simplified language that arises as a means of contact between different groups that need to reach an agreement about exchange. Galison suggests that such language arises in trading, when a group wants to "withhold its full language either to guard it to preserve their cultural identity, or because they believe that their social inferiors could not learn such a complex structure." (Galison, 1999, p. 154)

Victoria's work with colorful visualizations can be interpreted as preparing for an exchange with another culture, through the means of simplified communication. She admits how this language "might sound stupid." However, it is not because she believes that the other group (NASA scientists) are "social inferiors." Rather the opposite is the case. I interpret Victoria's efforts as reflecting how scientists are social superiors. Scientists are the ones ascribed the power to interpret causality – the authority to decide which data is meaningful and valuable.

So far, I have discussed how scientists are in authority in interpreting the causality in data used to train AI. In the following, I will deepen the discussion about power relations between the two groups at Goddard. In the vignette, I shared accounts where practitioners speak of data in terms of "garbage." I started with the story about how a scientist turned "garbage data" into a valuable resource. Then, I turned to scientist Jason's concern about selection of data for AI, which he refers to as "garbage in, garbage out." A contrary vocabulary is also prevalent amongst programmers – namely, the cleaning of data. That is my next point of departure in the analysis of power relations between scientists and engineers at Goddard.

Ideals of Purity – In the Laboratory and In the Dataset

Power is about imposing a particular order in the world. In their pioneering study "Laboratory Life," Latour and Woolgar argue that scientific practice is essentially about creating a particular order, out of disorder. I suggest focusing on practices of cleaning as a way of establishing an order. Why focus on cleaning practices to depict power relations? In the classic work of anthropologist Mary Douglas, "Purity and Danger: An Analysis of Concepts of Pollution and Taboo" (1966), she shows how hygiene – the rules about dirt – can illuminate a lot about a culture. I follow her argument about how "dirt is essentially disorder. There is no such thing as absolute dirt: it exists in the eye of the beholder." (Douglas, 1966, p. 2) Cleaning can be understood as a positive act of organizing the environment, rather than a negative movement to eliminate dirt. Imposing purity by the practice of cleaning is also tied to power – it imposes a particular order, driven by particular ideals of purity, which controls people's behavior. Whose ideals about hygiene are prioritized in negotiations about data? In other words, whose order is maintained at Goddard? And how?

To analyze this, I rewind to a Monday morning, June 13 2022 – a week after the episode in the vignette. Programmer Victoria comes by Eric's office. The two programmers are very dedicated to spreading the idea of applying AI tools amongst their colleagues, scientists. To convince them, they plan to organize a workshop and let scientists try out different AI tools. Despite their eagerness to introduce AI to the scientists, Victoria and Eric agree on the significance of being cautious. To not overwhelm the scientists, they plan to take it one small step at a time. Currently, the two programmers do not see how they can make time to prepare the AI workshop. They are swamped by other projects. One of the major tasks that programmers are occupied with is testbed. It refers to a process of testing the spacecraft routines and instruments in a simulated environment, before the launch of a mission. The instrument is separated from the rest of the environment in a "clean room", behind closed doors, in order to avoid contamination. Lately, Victoria and Eric have spent a lot of time communicating numerical values on a screen to the scientist in the "clean room". Although sometimes frustrated by how much time these tasks can consume, programmers continue to support this work, sometimes at the expense of working with AI.

Back at Eric's office, after a moment of chatting about work, Eric and Victoria catch up about what they did last weekend. Victoria tells us that she did a lot of cleaning. She cleaned her entire house as well as the folders on her computer. "I love to clean!", she expresses with great satisfaction. Beside cleaning her home and computer folders, there is one more instance that she cleans even more frequently. In our interviews, she describes how creating AI is for her a lot about "cleaning data." After collecting the data from the scientists, she has to "clean" them by removing files that are irrelevant and correcting labels that are inconsistent.

Each group, programmers and scientists, has their own practices of cleaning. Scientists are concerned about not contaminating their space instruments, therefore, they keep them in closed environments in which they wear protective clothing. Programmers are concerned about bad data for AI-training, thus, they want to keep their data consistent. For scientists, hygiene is mainly biochemical. For programmers, hygiene is primarily digital. Each group has their own ideals of order, what to consider as dirt and how to clean it. Yet, it is programmers who sacrifice their time for the sake of scientists and their ideals of "cleaning", rather than the opposite. On several occasions, programmers provide accounts of asking scientists to do favors, but it is rare that scientists sacrifice their time for the programmers on voluntary basis. As Douglas argues, the idea of dirt is constituted by care for hygiene as well as respect for conventions. "The rules of hygiene change, of course, with changes in our state of knowledge. As for the conventional side of dirt-avoidance, these rules can be set aside for the sake of friendship." (Douglas, 1966, p. 6) Instead of dedicating their time to cleaning data in a software, programmers agree to assist scientists' in their practices around the "clean room." Programmers express how wearisome they find it, which suggests that it is a sacrifice on their part. Consequently, the assistance can be understood as an act of respect for the other profession

– programmers set aside working with their own rules of creating order by cleaning data. Noteworthy is that the act is rarely reciprocated, which illustrates a hierarchy between the groups.

The interpretation of engineers as subordinate at Goddard is aligned with Eric's own depiction of Goddard, which he argues is dedicated to science objectives, rather than engineering. The planetary science building, where we are seated, is brand new. One day, Eric takes me on a tour to an engineering building to show me how degraded it is. The prestige of each profession can be read as reflected in the spendings on facilities for each group.

This dynamic can be tied to what historian of science Steven Shapin identified as the hierarchy between the scientists and the invisible technician. Invisible technicians are skilled practitioners doing a lot of manual work (Shapin, 1989). In contrast to Shapin's account, the work of NASA programmers is not invisible, as their names are acknowledged in scientific publications. However, there is a persisting hierarchy between the status of each profession, as mentioned above, where the programmers support the scientists.

Scientists are in authority but that is not to say that programmers are powerless. After my fieldwork visits at Goddard, I find out that programmers have managed to mobilize scientists to help with cleaning data on a regular basis. In the following, I will argue that programmers' cleaning practices have an impact on the scientists by imposing new norms in the process of knowledge production. First, I will describe in more detail what they consider as dirt and how they clean it.

Standardizing for a Machine

To produce an AI tool, programmers rely on digital data, which is an inscription produced by scientists in a laboratory. Data produced by scientists can appear in very heterogeneous formats. From analog notes, lost somewhere at one of the laboratories at Goddard, to a scientist's records from experiments at a university elsewhere, performed by students. The records span over various formats and are documented by various individuals. At times, documentation is fragmentary. At times, it involves labels based on other things that scientists were thinking about during sample collection – such as craving different foods, which I described in previous chapter. For a software developer working with AI, all these aspects pose a problem.

> They [Scientists] used to write really good notes but they're not necessarily *machine readable*. So they might have handwritten very good notes about something, on a certain day, but if it's not online, and if *it's not in a format that we can read, then it's not very useful*.

For the programmers, the problem with the existing data produced by scientists is that it is inconsistent. Eric frequently brings up that the data for AI needs to be "machine readable" to be useful. "Machine readable" refers to data being compatible with a software. If the data do not fit the format that is readable for a machine, "then it's not very useful."

Scientists' data is *made* useful by the programmers, through the practice that they refer to as "data cleaning." It is a set of practices that make the data fit into a standardized system that is compatible with a software. It is a long and meticulous process executed by programmers, manually. Cleaning entails both reiteration with scientists – such as asking which data to keep or remove – and correction of language and punctuation. The prevalence of an additional   space or a CaPital Letter instead of a lower case letter in a dataset, are major disturbances for a machine, requiring flawless consistency. Data cleaning assignments are often met with sighs or eye rolls from the programmers. No wonder, since it has sometimes required sleepless nights of coding, to deliver a dataset on time.

Cleaning, perceived as a time-consuming and sometimes frustrating task by the programmers, has led them to introduce what Eric refers to as "data discipline" amongst the scientists. It is a norm of how scientists during laboratory experiments inscribe everything in a particular digital format – that is "machine readable." Since the previous norms of documentation by scientists were not "machine readable", "data discipline" was brought forth to establish a more consistent system of keeping record of experiments to begin with, amongst the scientists. Eric tells me about how scientists that he collaborates with put all information about the experiment in a particular software, as soon as they touch the instrument. The information that becomes data, makes it possible to keep track of what was put in a certain cup. Thousands of such experiments are conducted and all the information "needs to be computer readable," says Eric. He argues that establishing data discipline has been crucial for development of machine learning. He says that scientists have improved their data discipline "once they saw the value of it."

Programmers' emphasis on the inconsistency of existing data and expressing the urgency to "clean" it, is telling for a clash between the ideas about order by scientists and programmers. When actors have divergent viewpoints, standardization can serve as a means of translation to reach a generalizable result. According to Star and Griesemer, standardization is about "developing, teaching, and enforcing a clear set of methods to 'discipline' the information" obtained by other actors (Star & Griesemer, 1989, p. 186). Development of "data discipline" by programmers can be understood as standardization.

I suggest that another analysis illuminating the power relations at stake here can be made by reflecting upon the metaphor of "cleaning" used by programmers and how it imposes particular ideals of purity. As Douglas argues, the ideas about dirt are not absolute. What is considered clean *versus* dirty is in the eye of the beholder. Moreover, the understanding of dirt is not static. Within this framework, "machine readability" can be interpreted as programmers' ideal of hygiene, where "data cleaning" is their own way of keeping data tidy, and "data discipline" then, is programmers' attempt to impose their ideals of hygiene upon the scientists. These practices are not only changing the routines of how data is recorded but also the perception of *what* kind of data is valuable, and *how* to make it useful. The consequence of introducing "data discipline" is how it shifts *who* recognizes the value in data and *for whom* it is useful. By complying to the new norms of how the data should be recorded, scientists recognize the value of data as perceived by programmers. Part of the process of data production by scientists becomes dedicated to "machine readability" – to programmers' ideals of order, that fits right into a dataset for AI.

In this context at Goddard, AI for life detection is at the development stage. However, its' capacity to change power relations in science should not be disregarded. Even at the stage of early development, AI already works as a mandate to impose new norms for the infrastructure of knowledge production. Previously, it has been up to programmers to make scientists' data useful. With "data discipline," this effort shifts to an earlier stage and to a different group – scientists make data useful in accordance with programmers' ideal of order. The practices of "data discipline" are disciplining both data and practitioners. Most importantly, they shift norms about how data can be made useful and who decides its value.

Selecting Data for the Algorithm – The Taboo of Bad Data

Choosing which data to select and which to exclude plays a crucial role in the development of AI. Decisions made by humans about the value of data are constituting which decisions AI will be able to make. A lot is at stake here. While “data discipline” was not much of a controversy, not all “data cleaning” practices are well received amongst scientists. Something that programmers admit that they need to tip toe around, is removal of data. Before explaining why this is a controversial subject, I describe the practices briefly.

To create a training dataset for AI, programmers need to select which data to keep and which to remove. Some programmers refer to it as choosing between “good” and “bad” data. In order to understand which data is “bad,” programmers use clustering techniques, such as PCA described earlier in this chapter. Through a visual display of data, these techniques help programmers to identify patterns, to which some data does not fit. However, this is just a tool to facilitate programmers’ work, rather than provide a clear categorization by clustering data as “good” or “bad.” Eric says that it is difficult to draw the line between “good” and “bad” data. It can be something scientifically interesting, something novel, or an error during an experiment. The “outliers,” get an extra check to see if they make sense, or if their oddity does not belong in the dataset. To interpret the “outliers”, programmers consult the scientists (which I described earlier in chapter 5).

When speaking about removal of “bad data” with scientists, programmers meet resistance. “When we talk to the scientists and say we throw all this bad data, they’re like ’WOAAH, wait, wait, wait! What’s the bad data?!’”, says Eric and laughs. For Eric, “bad data” stands for data that is “detrimental to the learning, the data that we thought would be deceptive", says Eric. In order to avoid the connotation of what "bad" can entail for the scientists, software engineers are now calling it "deceptive data." At times, I hear Eric use the term "useless data." Scientists' reluctance to throw out data is also a reoccurring topic in my conversations with programmer Victoria. She describes negotiations about data with scientists as scientists wanting to keep as much information as possible. "It took us a year to decide on categories, to get the scientists to tell us what they need, because they need everything," Victoria laughs and continues "if you talk to them, they will need every single thing."

While depicting negotiations with scientists and their reluctance to remove data, Victoria and Eric are laughing. I read their laughters as an emotional reaction to what they find puzzling – namely, the diametrically different understandings on the value of data. This reflects what I described earlier as the clash between the two professions and their epistemic cultures.

"Cleaning data" is essentially about choosing what to keep and what to exclude. For programmers, the removal of data can be a promise of improving the performance of their tool. For scientists, the removal of data can pose a threat of losing precious information. What is at stake in the creation of a dataset for AI is creation of a particular order – it has the potential to become a very powerful one, through its acceleration across time and space.

Thinking about "data cleaning" in terms of ideals of hygiene (Douglas, 1966) illuminates how these practices are a matter of imposing a particular order in the world, by distinguishing between the "clean" and the "dirty." Programmers create an order by distinguishing between "good" and "bad" data. "Bad" data is considered as detrimental for AI training and thus, as something to be excluded. Scientists' reluctance when programmers are about to remove data can be read as fear of losing power of maintaining the scientific order.

Seated by the computer screen and software to train algorithms, programmers are in power over datasets. They could delete whatever they find “deceptive”. All it takes is the push of a button. Nevertheless, programmers do not select the data simply as they wish.

Eric’s move in changing terminology when speaking to the scientists (from “bad” to “deceptive”) can be understood as avoiding a language that discredits the scientists and their gift. Scientists are the producers of the data and the ones with authority in interpretation of what the data means. Programmers adapting to the scientists reflects the power relation between the two professions – programmers serve the scientists. In spite of the clash between each profession’s needs, the needs of scientists’ have higher status. Programmers are the ones sitting by the computer and “cleaning,” but they do not impose their own order – they negotiate the value of data with the scientists.

It is not only programmers who want to delete certain data. In the following account, I discuss how programmers can also be reluctant toward when scientists want to remove data. Programmer Victoria shows me graphs with datasets before and after negotiations with scientists. We look at visual displays of data as dots between two axes. She points my attention to how a few dots stand out from what is otherwise a linear pattern. Then, she shows me a plot that has been “cleaned.” The process of “cleaning” involved continuous iterations between her, as a programmer, and the scientist with whom she develops AI for life detection, Samantha.

> This is a clean one. It’s a lot of iterations. Maybe we did ten iterations on this work, to clean, ’OK, this is cleaner, maybe it was better before, bla, bla, bla’, and then we agreed. And we

> can always clean *more*. It will always be 'Oh, this one is a tiny weird one here! Maybe we should remove it?' But when we're happy enough – because *we don't want to remove data, as a data scientist, I hate having to remove data*, because it's *less* inputs for me, and so, it's harder to train something on *less* inputs. So it's again *a trade-off between the scientists saying 'OK, this is good enough' and me saying 'hey, I still need data, don't remove everything'*.

This is a contradiction with my previous description of the two professions. Earlier, I discussed how programmers who wanted to remove data that is "bad" for AI training, meant that scientists insist on keeping as much information as possible. Here, it is instead programmers who insist on not removing too much data. In the case of this dataset, the extensive cleaning is not Victoria's intention. Rather, it is the scientists that she collaborates with, that require data being "good enough," from the scientific perspective.

Cleaning too much is problematic for Victoria, as a programmer. The less data she has, the less reliable the dataset, and in turn, the less reliable the algorithm. The scientist with whom Victoria collaborates, Samantha, is aware of that she has a very different understanding of data than a programmer. Samantha says:

> I met this [ML/AI] person and said 'I have this *large amount of data*!' But of course, to an ML person, it's nothing.

The interaction between Victoria and Samantha provides a good illustration of the negotiations about the value of data. "We can always clean more" implies that cleaning is a matter of degree, of which there can be more or less. Victoria prefers to remove less data and keep as much as possible, in order to have a large dataset, which implies that programmers are concerned about quantities of data. Her needs are once again in conflict with the scientist, who needs data to be "good enough," which implies a concern about quality of data. What "we can always clean more" and Victoria's emphasis on the "trade-off" between her and the scientist suggest, is that "cleaning" – creating order in data – is a collective act. It is an act of balance between two professions. Interpreted as a trading zone (Galison, 1999), this situation illustrates how scientists and programmers reach local agreements about an exchange of data, despite disagreement about their epistemic value. Scientists see value in having as much information as possible about a single phenomenon, while programmers see value in data as simplified for a machine, but in large quantities. The value of data resides in two different principles about what is worth knowing. Knowing as much as possible about an object versus knowing little about as many objects as possible.

So far, I have discussed how programmers at NASA Goddard negotiate which data to include and exclude from a dataset for training AI. Now, I dig deeper into how the context of where the cleaning takes place impacts how the data is valued. Based on an international competition organized by NASA, I analyze how organizational preconditions affect choices of which data to keep and which data to throw out.

Deleting Negotiations – Deleting Data, Deleting Responsibility

To develop AI, programmers need large quantities of data. The amount of data that is available is not sufficient. Programmers need more. In search of creative solutions to this problem, Victoria and Eric have announced a competition. Anyone in the world – even you – can join and try to train the most accurate algorithm. After a brief introduction to the scientific problem, the competitors receive a dataset to train an AI algorithm. Programmers compete from home and their own computers, situated anywhere in the world. None of the contributors needed a “badge” to enter the NASA facilities.

NASA programmer Eric defines the competition as successful, in terms of how many participated. Over 700 from across the world. I accompany Eric while he is reviewing winners of the competition. Initially, Eric says that he is “having a blast.” I see the joy emanating from him. After a while, his enthusiasm starts to fade. Winners of the contest have chosen to throw out a lot of data to develop the algorithms, which resulted in improved performance, according to an accuracy metric – a way of evaluating the performance of an algorithm (which I will discuss further in the next chapter). Instead of training the AI on the entire dataset, the winner trained it on a number of averages of the data. Eric describes how the winner of the competition “got rid of 3/4 of the data. He reduced it to 1/4 by averaging chunks of the mass spectra.” I ask Eric a follow up question “So basically, simplifying even more for the model?”

> Yeah, *he simplifies even more*. Which is really interesting, cause *we wouldn’t do that*. We would see like, OK, here’s mass, and here’s one, and here’s one… and he’s just taking all of these, taking them all and averaging them. *So you’re losing all this information about these different peaks.* (…) He’s just like ’I don’t care what mass it is, just gonna take the average’. My point of view is that there’s information in there and he’s just like maybe it doesn’t matter. There’s something in there and apparently, to me it’s like, *I’m always worried that mass spec scientists, they’re looking very carefully at the ratio of these and*

> *looking at every peak so carefully and trying to break it up from the bottom-up point of view. And he's just deliberately, like putting on blurry glasses* and looking at it like 'hmmm maybe I see this'.

While discussing the results of the competition, Eric is laughing nervously, which implies that he feels uncomfortable about what the programmers across the world did with the data. The degree to which they reduced the data comes across as drastic to Eric. "Reading the reviews from the other day, they all did stuff like this. *They all blurred the data deliberately*." As Eric squints to illustrate someone not seeing things clearly, we both burst into laughter.

The programmers in the competition are "sacrificing some information to make it easier for the computer and apparently, it works" Eric admits. Then, he brings back scientists into the picture. "But the final test is if it's useful to the scientists." What if the scientists would know that 3/4 of the data is removed? "They [scientists] wouldn't even show up to the meeting!", according to Eric. "*They* [the scientists] *spend their whole life looking at mass spectra in detail and you're just gonna tell them 'oh, we don't really care about these four peaks, we're just gonna throw those out'?*", says Eric humorously. "Like killing darlings?", I ask. "Yeah, exactly. *I would've never have done it, I would just intuitively be like, no we're not gonna lose information*."

Losing information refers to the danger of throwing out important or interesting data. To illustrate what is at stake, Eric often brings up "the garbage story" introduced in the beginning of this chapter. It became a lesson for NASA programmers about the danger of throwing out interesting information that can lead to a discovery. The outsiders of NASA lack the insight about the risks of losing information.

Eric's reaction to the reduction of data is shifting between different emotions. While inspecting the results, he laughs nervously. He is curious about the results but worries about what the scientists would think. While reviewing the winners, Eric is shifting between being impressed and skeptical. Afterwards, he tries to be humorous about it by making a silly face. I interpret this shift of emotions as struggling with a dilemma. Eric is mindful of the value that scientists ascribe to data. While Eric is skeptical about the extensive removal of data in the competition, he admits that it seems to be good for the algorithm. "I'm actually kind of shocked that it seems to work, they're getting better metrics than we did."

Interpreting the value of data at NASA Goddard is tied to its particular data economy. In the pioneering account of trade between different cultures in Western Pacific islands, anthropologist Bronisław Malinowski described how the exchange of objects is not just a practical matter but also a matter of belonging to a particular economy (Malinowski, 1922). The intimate tie between economy and belonging is also acknowledged in a more recent anthropological study of the use of data in laboratories by Pinel and Svendsen (2023). The authors conceptualize data exchange between groups in different laboratories as "economy", referring to the etymology of the word – from the Greek *oikos* and *nomos*, economy means household management. Valuation of data, as Pinel and Svendsen suggest, can be understood as a matter of belonging to a data economy.

> Managing the home means opening the door to the outside to let some data in, while it also entails welcoming and shaping the data that have entered. These insights, we argue, shed an important light on valuation processes in the data economy. (…) we see value creation in the data economy as a matter of belonging. Crucially, we show how rendering data valuable in

> the home means making them belong. This involves crafting and organizing the data's ties to the home, rather than only imposing control and claiming ownership over data that have travelled (Pinel & Svendsen, 2023, p. 19).

Data economy at NASA Goddard is an important organizational boundary. What the competition illuminates is how ideals about the value of data are contingent, depending on whether the practitioner is part of the epistemic cultures involved in the data economy, or a complete outsider. Outside of the data economy at NASA Goddard, the rituals of negotiations between programmers and scientists have no meaning. I suggest that employing outsiders or insiders for evaluation of the data can have an important consequence for the relation of care and implications for epistemic responsibility – which I unfold in the sections below.[19]

While shadowing Eric and trying to understand his reluctance to throw out the same extent of data as participants in the competition, I notice that he frequently mentions how scientists would react if too much information would be removed. At the end of one of our interviews, me and Eric conclude that he and his colleagues feel "sentiment" toward data. How can this "sentiment" to data be interpreted?

Eric's computing world consists of not only data, but the relations he and the data have to the practices beyond the computer screen. A software developer at NASA is creating algorithms *for* a scientist – a dear colleague, toward whom they are responsible. Eric's conscience is stopping him from throwing out too much information, while "these guys [outsiders] are just throwing it out". Knowing how much "blood, sweat and tears" is

[19] By epistemic responsibility, I mean responsibility in knowledge production. Following Barad, I understand responsibility as not a formal obligation, but a sense that emerges in entanglement with others – things, people, and other beings (Barad, 2014).

condensed in the data, how could Eric just throw it away? In the introduction chapter, and chapter 5, I described the efforts it takes for the scientists to produce data. By finding labels named after chocolate bars in the dataset, Victoria became aware of how the scientist had to experience a tough expedition to the Arctic, in order to produce the data. My adventures in the laboratories at NASA, including the experimental trials with Titan conditions by scientists, are inscribed not only in my field notes, but also very strongly in my memory. I suggest that it is precisely the memory, the history of data and the context of its emergence, which is constituting awareness about the scientists' efforts amongst programmers at NASA, that becomes inscribed in the development of AI. Awareness of scientists' efforts is inscribed through the choices of selecting which information should be included and excluded from a dataset. The "sentiment" toward data makes programmers mindful of balancing the record of information valuable to the scientists and the imperative to simplify for AI training.

In their study of data work at a research laboratory, Pinel, Prainsack and McKevitt (2020) have paid attention to the relational aspects constituting value of data. They suggest that "As researchers build relationships with data, they feel connected to the data and responsible for its flourishing and growth, and are thus willing to go at great length to make the data valuable." (Pinel, Prainsack, & McKevitt, 2020, p. 192) In contrast to Pinel, Prainsack, and McKevitt (2020) depicting the relation of care being between researchers and their data, I would emphasize that care occurs between humans. Whilst programmers at NASA do take care of data in a sense, they care about the scientists behind the data, not just the data itself. In previous studies about data work in biosciences by Svendsen and colleagues, they pay attention to substitution of entities and exemplify how data can appear as the extension of humans (Svendsen, Dam, Nave & Gjødsbøl, 2022). Data can appear as the extension of scientists at NASA.

NASA programmer Eric foregrounds the efforts of scientists to produce the data. In the competition, outsiders were able to remove data with ease, since it was produced by an anonymous source. This suggests that the presence or absence of any relationship with the human producing the data is decisive for which information is included and excluded when creating AI. For a programmer at NASA, a datapoint encapsulates not just information for AI but condensed efforts of scientists to produce it. Data has a biography with an emotional and material experience. The effort of scientists is encapsulated in the data. Whether a programmer is aware of these efforts or not can have decisive consequences for which data is included and excluded.

By belonging to the data economy at NASA Goddard, the programmers are attached to the context of data production – and I showed how this attachment has moral implications (Navne, Svendsen & Gammeltoft, 2018; Pinel & Svendsen, 2021) for epistemic responsibility in the development of AI. Without the sense of attachment to the data economy, and room for negotiations with scientists, outsiders make choices in relation to accuracy metrics. They impose a new ideal of order by removing even more data.

Conclusion

This chapter focuses on how data practices to develop AI are integrated into the scientific cultures at NASA Goddard. The development of AI occurs at the intersection of two groups – planetary scientists and software engineers. Each group constitutes an epistemic culture (Knorr Cetina, 1999) with particular ways of approaching life detection. While scientists are open to different kinds of possible life forms, engineers require predetermined parameters for what kind of objects to search for.

Although scientists and programmers constitute two distinct epistemic cultures, they belong to one data economy (Pinel & Svendsen, 2023) in which they negotiate the value of data, and organize them together. Belonging to a data economy shows to be decisive for the evaluation of data. This was especially evident in a competition arranged for programmers outside of NASA – in absence of negotiations with the scientists, outsiders evaluated data differently, and solely in relation to performance metrics. This shows that negotiations with domain experts are decisive for how the data is evaluated, and more specifically, which data is included and excluded from a training dataset. Consequently, whether the programmer belongs to a data economy, or not, plays a crucial role in shaping the AI tools. Relationships between humans become encoded in the algorithms.

This study shows that belonging to a data economy is tied to a sense of epistemic responsibility, which is a sense of care that emerges through entanglement in the context of scientific knowledge production. Organizational arrangements can play an important role in fostering epistemic responsibility, as they can inscribe data with a biography, or make it ahistorical.

Another significant finding is that although AI is at the early stage of development, it is already changing the power relations in scientific knowledge production by imposing new ideals of epistemic order. While algorithms can be helpful for identifying correlations in data, scientists at NASA Goddard remain in authority of interpreting causality, by making claims about which relations in data are meaningful and important. Nonetheless, programmers can use AI as a mandate to impose their own ideals of order on the scientific practices. Standardization practices introduced by programmers are disciplining both data and the scientists. It shifts the norms of how data can be made useful and who decides about its value. The development of AI can play a role as an infrastructuring entity, even when it just at the stage of early development, and not yet working for the intended purposes – which resonates with findings from other social contexts (Gjødsbøl etal, 2024).

Chapter 7 Simulating Synthetic Data for AI and Measuring Their Success

I am sitting with programmer Eric at his office at NASA Goddard. It is a small room with a narrow window high up on the wall that lets the daylight in. A few inches below, on the desk, two rectangular windows allow Eric to enter meeting rooms across the world. He is jumping between meetings, but his physical presence remains unchanged by the two computer screens. Many of his meetings are online. During the breaks, I ask follow up questions about the meetings he just had, we catch up on how our families are doing, share running routines. Regardless of where the conversation starts, sooner or later, there is one problem that always comes up. AI, spoken of as a solution, is also introducing new problems.

> We're training [AI] the best we can here, but you really want to train on the *real* thing. But we'll never ever have *enough* data on the *real* thing. That's one of our biggest problems.

Insufficient amounts of the right data for training is a common problem within the field of AI. Large amounts of data are associated with better performance in algorithmic predictions. For programmers at NASA, this means that to train AI tools, they need millions of data points from scientific experiments. But it is something that they do not have. The manual labor of scientific experiments comes across as too slow, in relation to the massive amounts of data required for AI training. To speed up the process, programmers take the production of data in their own hands. Or rather, computers. Programmers produce more scientific data through computer simulations.

Simulations are not new in planetary science – for example, scientists simulate extraterrestrial conditions in terrestrial laboratories. The novelty with simulations of data for AI resides in introducing particular norms of practice into scientific knowledge production: the standards in the field of AI.

In the field of AI, where programmers never have enough "real-world" data for training, data produced through simulations figure as a solution to build more robust AI tools. The so-called synthetic data can be described as "computer-generated data that mimic and substitute empirical observations without directly corresponding to real-world phenomena." (Offenhuber, 2024, p. 1) Synthetic data has figured as a technical solution and "risk-free" technology (Jacobsen, 2023) but many concerns about its social implications have been raised. Among the risks that scholars point out are inaccurate representations of phenomena (Johnson & Hajisharif, 2024; Lee, Hajisharif & Johnson, 2025), amplification of bias in society (Capasso, 2025), and reduction of the ethical questions to matters of technical concerns (Helm, Lipp & Pujadas, 2024). However, there are few empirical studies about how these data are actually produced in particular domains (Kampania et al 2025). This chapter contributes to a more empirically substantiated discussion about the social implications of synthetic data – it draws on ethnography of how scientists and programmers at NASA Goddard Space Flight Center simulate scientific data for AI.

Simulation, from latin *simulo,* means "to make a thing like another," and stems from *similis*, meaning similar (Perseus Digital Library, n.d.). A lot is at stake in simulations, considering that drawing relationships of similarity and difference is central in the construction of knowledge in science. As science studies scholar Trevor Pinch points out, relationships of similarity and difference are not out there to be found – they depend on classification of things, by selecting what is relevant and bracketing what is not, out of a myriad of possibilities. Drawing these relationships is often taken for granted and embedded in theories and assumptions in a particular scientific or technological context (Pinch, 1993, p. 30-31). Paying attention to how the relationships of similarity and difference are drawn in simulations of data for AI can open up a window to see what kinds of epistemic concerns become embedded in these tools. In this chapter, I show how drawing the relations of similarity and difference is performed differently, depending on which profession performs the simulations. To show how the epistemic concerns shift depending on who performs the simulations, the chapter is divided into two parts, focusing on each profession – beginning with an astrobiologist, and then turning to programmers.

Modeling Polymers to Search for a “Universal Biosignature”

In between sips of coffee, at a cafeteria at NASA Goddard, astrobiologist Lu talks about one of her projects with particular enthusiasm. It is not just the amount of caffeine from the American-size mug that is causing her to speak so passionately. I have become familiar with how the daily work of NASA scientists resembles science-fiction tales, but this research project is different, by pushing the conceptual boundaries of what we imagine life to be.

Lu’s project is about developing a tool following an *agnostic* approach, to search for what Lu and her team call *universal biosignatures*. The agnostic approach is about searching for life without presupposing a particular biochemistry based on life on Earth. For instance, the building blocks of life on other planets and moons could differ from the chemical molecules that constitute the life on Earth (carbon, hydrogen, nitrogen, oxygen, phosphorus, and sulphur). In Lu's work, agnostic biosignatures figure as synonymous to universal biosignatures (Chou, et al, 2020a; 2020b), which are defined as "features that are common to all possible life forms in the universe," including both "terrestrial" and possible "exotic" life forms (Chou, et al, 2021, p. 1).

In the context of astrobiology at NASA, this approach is often referred to as searching for "life as we don't know it." It alludes to another phrase used in astrobiology: searching for "life as we know it," which builds on assumptions that life elsewhere will share characteristics with life on Earth. This relates to what some astrobiologists refer to as Earth bias, discussed earlier in chapter 5.

The term agnostic became especially popular in astrobiology around 2018, when a research project called LAB (Laboratory for Agnostic Biosignatures), which Lu is associated with, was established, after winning a grant from NASA's Astrobiology Program.[20] LAB consists of biologists, chemists, computer scientists, and engineers, among others, scattered across different universities in the US and Europe. Agnostic approach to life detection might be a recent buzzword, but the idea behind it is not entirely new. The notion that potential life on other planets or moons might not necessarily be based on the same biochemistry as life on Earth was for instance supported by Carl Sagan in the 1970s (Sagan & Khare, 1979, p. 107). Nevertheless, the LAB research group has been successful in promoting the idea anew – around 2021, many scientists outside of NASA

[20] 7 million US dollars grant for five years of research, for a group of 15 members (Kaufman, 2019; Steigerwald, 2018).

whom I interviewed were familiar with the agnostic approach.[21]

The tool for agnostic life detection that astrobiologist Lu develops is searching for *polymers*. In conference presentations together with her team, she refers to polymers as a universal biosignature (Chou, et al, 2020a; 2020b). Polymers are larger molecules that consist of repeated sets of molecular building blocks, and some of them, like DNA or proteins, allow life to store and propagate information. Lu and her team argue that the presence of a polymer in a sample from outer space can allude to the presence of life.

However, there is a problem with interpretation of polymers as a biosignature. The issue runs parallel to the ambiguity in interpretation of organic molecules as biosignatures, discussed earlier in chapter 4. Similarly to organic molecules, polymers are also very common in outer space. For instance, they are present in the orange-brown haze on the surface of Titan. Does that mean that there is life on Titan? The mere presence of polymers does not necessarily indicate presence of life. Polymers can be of *biotic* and *abiotic* origin even on Earth.

[21] Agnostic approach to life detection figures in NASA's strategic documents concerning astrobiology since 2018 (NASEM, 2018). In 2021, when I observed conference presentations about astrobiology, the agnostic approach was a quite widely spread concept. Many of the scientists whom I interviewed were familiar with it. The attempt to reduce terrestrial bias about life generates both curious and skeptical responses among scientists studying life and its origins. In one of my interviews, an early career non-NASA scientist who does research in astrobiology in US depicted agnostic life detection as the "cool approach." One researcher had even adopted this approach in their own research on life detection. In another interview, a senior scientist working with origins of life studies in Europe became agitated once I asked about their view on agnostic life detection. They exclaimed that one cannot construct a tool to search for anything.

Training AI to Detect Polymers

The challenge in interpretation of whether polymers are biosignatures or not, can be addressed with data science tools, according to Lu and her colleague Victoria, a programmer who is also associated with LAB. Lu and Victoria are developing an algorithm to automatically identify whether a sample in a mass spectra experiment on another planet contains a polymer that is biotic or abiotic. They train the algorithm to classify the data based on two questions. Is there a polymer, or not? And if the answer is yes, is the polymer biotic or abiotic?

As mentioned in the beginning of this chapter, to train AI, programmers need large amounts of data, which is, paradoxically, a scarce resource at NASA. How do astrobiologist Lu and programmer Victoria resolve this issue? In conference presentations, Lu and Victoria describe the data that their algorithm is trained on as "artificially generated" mass spectrum data, or "*in silico*." *In silico* means in silicon – as in computer chips – and refers to experiments performed in a computer, such as models or simulations. The term in silico is related to the latin terms in life sciences that describe different kinds of experimental settings – *in vivo* and *in vitro*. The *in vivo* experiments are performed inside of a living organism, while *in vitro* experiments are performed outside of the organism's context, for instance, in a glass tube. What this implies is that the mass spectra data of polymers that Lu and Victoria use to develop the ML algorithm are not experiments performed on living organisms, nor on any other samples in laboratories (described in previous chapters). Rather, the ML algorithm is trained on simulations or models performed in a computer.

In our conversation at NASA Goddard, Lu mentions that the algorithm for polymer detection is "trained on this simulated data." I ask what she means by simulated data, upon which she takes over my notebook and fills it with drawings. She illustrates mass spectrometry data and its peaks with patterns of lines (Figure 10). While pointing at this drawing, she explains the data used for training of the ML algorithm.

> The data that we got here [figure 10] is *not the data that we get from these instruments* [laboratory instruments at NASA] at all. *These are data that we mathematically generate ourselves*. We have the data here and we give it a string, and we fragment that string and count the number of masses that adds up here, and the number of masses that adds up there, and form these strings.

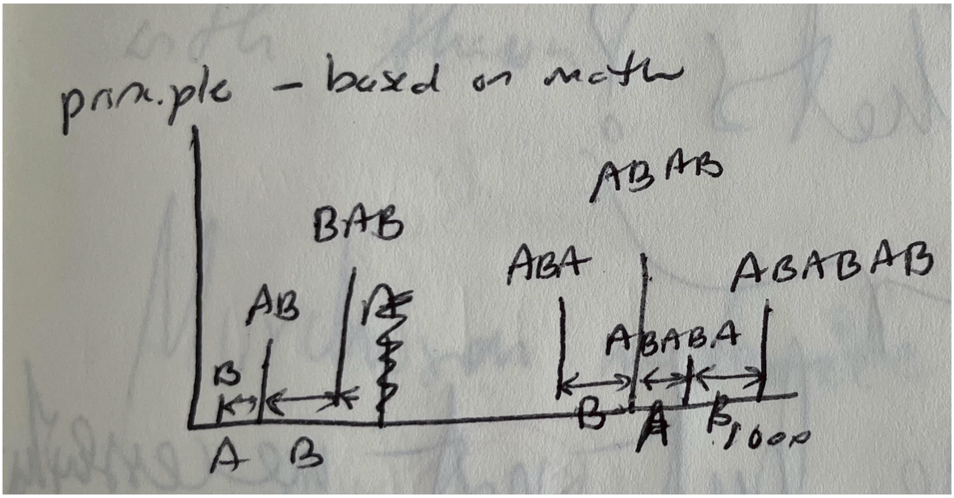

Figure 10. An illustration of simulated mass spectrometry data. Drawing by scientist Lu. Notebook from fieldwork.

Above the graph, Lu notes "principle – based on math." I wonder how the data can be generated mathematically, and what is behind those numbers. "So there's no physical reference beside the computational code? That's what you mean when you say simulated?" I ask, upon which Lu confirms.

> Exactly. *It's almost like a model and it's all built in into the computer code*. And the assumption that the fragmentation happens, these are just assumptions. These are one type of assumptions we're making here for this specific process, that we're trying to use ML to answer.

To construct the data for AI training, scientist Lu makes general assumptions based on previous studies about polymers, for instance, how they fragment in the mass spectrometer. However, simulating the chemical signal of polymers is not enough. Lu and Victoria need to simulate noise too. Both the instrument and outer space generate noise, which is also present as peaks in mass spectra. Based on assumptions about how the noise works, for instance in samples of meteorites, Lu and Victoria simulate the noise and add it to the data they produced.

Then, Lu and Victoria use the method called *supervised* machine learning (ML), which is about training an algorithm based on data that is labeled, to reach a particular prediction goal. Lu and Victoria label the simulated data as polymers of biotic or abiotic origin. They train the algorithm to classify data in accordance with these two categories. The goal is to determine whether a data point – a mass spectra – represents a biotic polymer, or not.

The algorithm is trained on *in silico* data, but to evaluate how well it performs, Lu and Victoria test it on both artificially generated data as well as data from laboratory experiments. The latter are performed on samples with polymers from a prototype MOMA instrument (a laboratory suite with mass spectrometry designed for a mission to Mars, described in chapter 1). The samples from these experiments contain biotic polymers (such as DNA), and abiotic polymers (present in meteorites, or in tholins analogs, which are laboratory analogs of the abiotic polymers on Titan). This entails testing the algorithm on data derived from laboratory experiments on samples of polymers.

In the field of AI, the objects that the algorithms are trained on are often referred to as data, or datasets. In life sciences, data can be understood as durable *traces* of experiments (Rheinberger, 2014, p. 325). However, according to scientist Lu, the data that this particular AI tool is trained on are "almost like a model," which implies that the boundary between data and models is slippery. *Models* – in life sciences – consist of *deliberate configurations* of data (Rheinberger, 2014, p. 325). They are made with the goal of *representing* a phenomenon (Leonelli, 2019, p. 22). The objects produced by Lu and Victoria are configurations of mass spectrometry data from previous experiments on polymers, made with the goal of representing polymers, to make claims about polymers as universal biosignatures. The objects that Lu and Victoria make are not merely data, because they are not strictly traces of experiments in laboratories. These data are *simulations* of such traces, which means that these practices aim at imitation, at making a thing like another. In this case, it is an imitation of the signal and noise in data from laboratory experiments.

If we return to the etymology of simulation, there is yet another meaning of the latin *simulo* that is adequate for this case: "to represent a thing as being which has no existence, to feign a thing to be what it is not" (Perseus Digital Library, n.d.). The simulated data is made to represent polymers based on mathematical constructs, without correspondence to a particular experiment on a sample. What we can observe in computational simulations, is a dynamic of detachment from the terrestrial laboratories and attachment to mathematical abstractions.

Pointing out this dynamic is important, but it would be shortsighted to view the *in silico* data as merely mathematical constructs entirely detached from material circumstances. We must keep in mind the preceding transformations of these objects. The *in silico* data are not made from scratch – they are configured into models based on previous laboratory experiments with polymer samples. Moreover, the astrobiologist evaluates the *in silico* data in relation to laboratory experiments. I am not the first to emphasize the attachment between computational simulations and biological material. Historian of science Soraya De Chadarevian has pointed out that the *in silico* data in biology remains "linked to the biological material from which it is abstracted (even if perhaps by other researchers and in other laboratories) and to which it always refers back." (De Chadarevian, 2018, p. 655-656) The *in silico* data that AI is trained on, to search for "universal biosignatures," maintains a link to samples of organisms on Earth. It is because these objects are constructed based on previous experiments on organisms, and ultimately, they are also evaluated in relation to them.

However, the epistemic status of simulated data is contested amongst the researchers at NASA Goddard. Samantha, a scientist working with life detection and AI, says that simulated data is worth exploring, but there might be many potential biases. "I think we all feel like we have complicated feelings about simulated data and there are some people who are absolutely against it, and I understand that." Software manager Eric says that he does not know of any project where synthetic data has worked successfully, in the context of life detection. Simulated data – creating new data based on mathematical equations, without correspondence to a physical sample – is spoken of with a slight skepticism.[22]

[22] However, three years after the first fieldwork visit, correspondence with scientist Samantha indicates that there might be a shift in the approach to simulated data as more trustworthy: "There are many new approaches to simulating data now, and new methods to make data and ML models more interpretable. I think these new methods are increasing the confidence in both simulating data and in generating ML models." This shows how epistemic cultures are not static but changing and therefore calls for further studies.

Previous studies have discussed the doubt in simulations among scientists. For instance, it is a prevalent concern in Sherry Turkle's ethnographic account of molecular biologists at MIT. Some of the scientists argue that a computed version of the physical reality is always leaving something out. However, Turkle observes that some students are able to understand the physical dimensions better, through simulations, which allows them to feel closer to the reality. Engaging with simulations can indeed lead to new ways of knowing. But molecular biologists are concerned that replacing a particular practice with computational simulations can also lead to new ways of forgetting (Turkle, 2009 p. 19). Now, I will turn to the new ways of knowing, and forgetting, when another profession at NASA Goddard – programmers – simulate data to train AI on their own.

Simulating Data for AI for Science Autonomy

As a child, Victoria's dream was to become an astronaut. Her dream is about to come true, at least in one sense. She might not travel to outer space herself, however, as a programmer, she designs AI tools that can travel onboard future missions to other planets and moons. These AI tools are part of a shared vision of a new way of doing science in outer space at NASA – *science autonomy*. This initiative is led by programmers Victoria and Eric, in collaboration with NASA scientists who work with mass spectrometers. As described in earlier chapters, the idea is to increase autonomy in analysis of scientific experiments onboard missions, by adopting data science tools, such as AI. This entails a profound shift in mission operations – from scientists in the loop, to distributing more agency to AI tools. AI onboard mission to other planets and moons could do a wide range of things. Examples include everything from prioritizing which data from experiments to send back to scientists on Earth, to making real-time decisions about what to do next in the mission (instead of waiting for commands from Earth). The proponents of this approach argue that science autonomy enables more efficient scientific exploration – by prioritizing which data from experiments on other planets and moons are of most value to the scientists.

To develop robust and reliable AI tools, programmers at NASA need much more data for training than they have access to. In previous chapters, I discussed how programmers train AI on data from scientists, and how scientists produce these data in laboratories. Because of how labor-intensive and time-consuming the process behind data production is, it cannot match the quantities needed to train AI. Insufficient amount of data for training AI is one of the major challenges in development of AI tools at NASA. To overcome the obstacle of not having enough data from the scientists, programmers produce data on their own. They do so through different techniques of computer simulations.

Testing Data Augmentation to Make AI Work

To test which techniques are most successful in producing data for AI, programmer Eric – who is also a software manager – hired a programming intern, Michelle. She is a student from a prestigious university in the US, with a background in computer science and molecular biology. During the internship at NASA Goddard, Michelle works with AI tools for autonomous categorization of the mass spectrometry data on Mars, based on which chemical compounds they contain. The main task for Michelle is to test different ways of training the AI tools, to see which techniques improve the performance of AI.

Michelle uses one of the most prevalent methods to generate new data for AI training – a method called data augmentation (Nikolenko, 2021,

p. 88).[23] The point of departure in data augmentation is a set of data that is available. In Michelle's case, it is the mass spectrometry data produced by the scientists. To augment this data means to modify it through different techniques: *stretching*, *shifting*, *intensifying* the high peaks, as well as *adding noise* to the tiny peaks in the bottom of the mass spectra. In an interview, Michelle explains how augmentation of intensity works, while pointing at a list of trials and errors on her laptop.

> M: For some of the graphs, we *multiplied the intensity values across all data points*. In this case, the original intensity was 400, and I increased it by about 50 %, making it 600. So this is an example of multiplying intensity where we increased all the data points and we multiplied it by some value.
>
> A: And do you have an equation for this or what do you rely on?
>
> M: Yeah, so for intensity we had randomized intensity and multiply intensity. So multiply intensity, I took every single value and based on your input, I would ask the user for input, it would *multiply every single value by certain percentage.* So you put in 10 % and it's gonna take every single value and multiply it by 1.1.

[23] In the first book about synthetic data, the author Sergey I. Nikolenko understands data augmentation as the first step in development of synthetic data. However, he admits that the lines between these two techniques are blurry (Nikolenko, 2021, p. 12, 88). I do not take stances on the categorization here, but instead, focus on how programmers use data augmentation to produce more data.

The practice of data augmentation goes in line with the mechanism identified by sociologist Karin Knorr Cetina – scientific work begins with a perceived solution from which practitioners move backwards and try to "make it work" by "tinkering toward success." (Knorr, 1979) By tinkering, Knorr Cetina refers to the practice of striving toward what is good enough to work in a particular context, rather than optimal in a general sense. In contrast to the claims of "truth" as absolute in science, "success" is tied to a structure of interest of an agent in a particular place and time, consisting of resources, instruments and social alignment. The role of a solution resides in driving the research forward and orienting action in a particular direction (Knorr, 1979, p. 364-8).

Recruitment of Michelle to NASA was based on an already defined ultimate solution: AI algorithms for categorization of mass spectra from Mars. With the solution as a starting point, Michelle's actions are oriented toward making AI work. To do so, Michelle tinkers with numerical values to modify the mass spectra peaks in various degrees. The peaks can be amplified by 5, 10 or 15 percent, which intensifies them slightly. A few clicks later, programmer Michelle has new data, generated by multiplying and augmenting values on the computer screen.

Now, let us look at the different means of producing data by rewinding to previous chapters. When scientists produce data in the laboratories, they spend hours on preparations of the sample, the instrument, and then careful analysis. We must also recall that this is preceded by collection of samples in "extreme" field sites, such as lava caves, which entail physically demanding work conditions. It takes a lot of manual effort for the scientists, to produce data in scientific laboratories. Meanwhile, when a programmer produces data, it takes a few clicks to multiply the data and modify their values in a computer. This is a major shift in the pace and mode of data production – from manual effort in field sites and in laboratories, to instant production *in silico*.

However, what we need to keep in mind is that programmers do not produce the data from scratch. The work of the programmers is dependent on the data produced by the scientists – without it, there is nothing to augment. Programmers augment data that are traces of experiments on samples (Rheinberger, 2014, p. 325), performed by scientists in the laboratories. Consequently, even in the augmented data, the link to the biological material is maintained (De Chadarevian, 2018, p. 655-656).

Measuring the Success of Data Augmentation

What is noteworthy in Michelle's account of data augmentation is how manipulating digital values gives countless possibilities to create new data. But is "more data" *per se* leading to better performance of AI? Is that the case regardless if Michelle intensifies the peaks by 5, 10 or 15 percent, adds noise, or stretches the entire graph? Can data be modified without limits?

> So the idea for data augmentation is that we can generate more data to train [AI] models. But it's also very important that the data that we generate should still be… I guess scientifically accurate, because we're generating artificial spectra but we still want this spectra to *be kind of like real*. Anyway, *if it would be super off, it probably wouldn't improve the algorithm anyway.*

While augmenting, Michelle is torn between preserving and modifying data. However, this concern is not expressed in relation to what is contained in the data, but rather, in relation to how well the algorithm performs. After trying different augmentation methods, Michelle concludes that "the more we like got away from the original spectra *the worse the model was doing*." The success of the balance between preservation and modification in data augmentation is interpreted in light of how well the algorithm performs.

To measure the performance of the algorithm, programmer Michelle relies on so called accuracy metrics. It is one kind of performance metrics for machine learning algorithms, which is calculated by dividing the number of correct predictions by total predictions. On the last day of Michelle's internship at NASA, in a presentation of her work for a group of scientists and engineers, she concludes that data augmentation was successful by displaying accuracy metrics reaching over 99 %.

The discussion above tells us about one important implication of data augmentation on the scientific knowledge production. With the shift of profession comes a shift of how the simulations are evaluated – namely, through performance metrics.

The use of performance metrics is a prominent practice in the field of AI – nevertheless, it is also part of a larger discourse at NASA, where scientists and engineers prove the value of the knowledge they produce in terms of metrics. During two brainstorming sessions about science autonomy for a future mission to Titan, I witnessed how one question that programmers and scientists always return to is: How can we *measure* an improvement in the value of science? At one occasion, this question was addressed humorously by a programmer – "Create measurements that make it look good!" – which reflects the struggle to estimate improved value in scientific knowledge production, in terms of performance metrics. Displaying some kind of metric to NASA's review boards comes across as a necessity, to prove the value of what they do – which is also tied to maintaining funding for their missions in a very competitive research environment. This clearly shows that metrics have an epistemic authority in proving the value of scientific work. It also shows how metrics are human constructs, and a result of negotiation. And most importantly, it shows how the value of science is not easy to quantify and fit into performance metrics.

Estimating the value of an object through metrics is characteristic of a modern ontology, “in which the real easily becomes coextensive with what is measurable” (Espeland & Stevens, 2008, p. 432). Sociologists Wendy Nelson Espeland and Mitchell L. Stevens point out that measurements can be productive, by making it possible to see complicated relations – upon which humans and organizations can act. However, measurements can also “narrow our appraisal of value and relevance to what can be measured easily, at the expense of other ways of knowing” (Espeland & Stevens, 2008, p. 432).

High results in performance metrics for AI – such as accuracy metrics used by programmer Michelle – might be interpreted as success. However, metrics can also be misleading. For instance, *overfitting*, a common problem in development of AI, can coincide with high accuracy metrics. Overfitting happens when the algorithm learns the training data too closely, instead of generalizing the patterns. As a consequence, the algorithms can perform very well on training data, but less so on novel data. Algorithms, as well as metrics, have limitations – by being trained on particular datasets, they provide a partial view of the world.

Are there other ways of knowing for the programmers if the augmented data is adequate? In the following section, I describe how programmers Victoria and Eric aspired to use the experts – NASA scientists – as a yardstick to measure the success of augmented data. I rewind to the programmers’ first experiment with data augmentation, which Eric tells me about at his office.

What is at Stake in Data Augmentation

“So Victoria and I had this idea,” programmer Eric recalls from a few years ago. “We made fake data. We made like ten different fake experiments.” He refers to the experiments as the Frankenstein files, because “they were like sewn together pieces from other experiments." Although Eric is currently referred to as "the AI guy" at NASA Goddard, he recalls his initial disbelief toward this method. In our interviews, he describes how it did not make sense to him that an algorithm could be improved by adding "fake data." What Eric refers to as the fake experiments or the Frankenstein files are the initial experiments with data augmentation at NASA Goddard (figure 11).

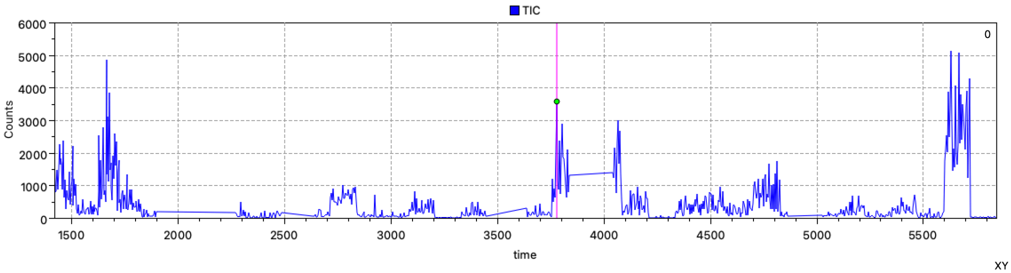

Figure 11. "Frankenstein files" – modified mass spectrometry data.

In popular culture, Frankenstein figures as "a cautionary tale against technology." (Latour, 2011, p. 19) The choice of Frankenstein as the name for the augmented data reflects how the introduction of the new method to produce simulated data entailed ethical dilemmas for programmers. Once the data was augmented, to Eric,

> they [fake experiments] *looked exactly like actual experiments from Mars* but they were these Frankenstein things (…) like sewn together pieces from other experiments.

In the eyes of a programmer, the augmented data looks similar to the data from experiments on Mars. Programmers induce differences in the data, and evaluate whether the data is similar enough, to stand in for real-world data. Considering the significance of drawing the relationships of similarity in the construction of knowledge in science (Pinch, 1993, p. 31), data augmentation can be recognized as an instance where decisions about knowledge production at NASA are being made. Data augmentation moves the space for decision making in scientific knowledge production to the domain of computer science, more specifically, to the standards of good practice in the field of AI.

We can see that even clearer by rewinding to the scientific practices described throughout the thesis. In chapter 5, I described how scientists draw relations of similarity between field sites on Earth, as analogs to extraterrestrial environments. Yet another instance is mass spectrometry data, where scientists compare the data produced in the laboratory experiments, to the existing data in a database. In the beginning of this chapter, I described how a scientist and a programmer together draw relations of similarity between signal and noise in mass spectrometry data – the data produced *in silico*, and the data from laboratory experiments. In data augmentation, solely programmers are the ones who draw relations of similarity between mass spectrometry data: the data produced in scientific laboratories on Mars, and the data simulated by the programmers. Programmers, like Michelle, Eric, and Victoria, make decisions about how to preserve and modify the data, in order to improve algorithmic performance. Data augmentation entails a shift in who makes the decisions in knowledge production, for what purposes, and based on what epistemic grounds. Considering the central role of drawing relations between similarity and difference in scientific knowledge production, a lot is at stake in the augmentation of scientific data.

One of the main risks associated with simulated data is inadequate representation. If we recall the latin etymology of simulation, this risk seems rather inherent. Simulation, from latin *simulo* means "to represent a thing as being which has no existence, to feign a thing to be what it is not."

(Perseus Digital Library, n.d.) Researchers in the field of AI use the metaphor of "hallucinations" to discuss how synthetically produced data can generate representations of phenomena that are not present. For instance, Johnson and Hajisharif show how synthetic data of a population from the 1990s generates "intersectional hallucinations," such as "male wives," and "11-year old doctors." (Johnson & Hajisharif, 2024). These examples can be evaluated as inadequate representations based on common sense. But AI hallucinations in mass spectra data are not as evident. Interpreting the peaks in a mass spectra image requires a particular kind of expertise. Whether the augmented data at NASA contains hallucinations or not is outside of the programmers' area of expertise. At NASA, inadequate representation translates to the risk of missing interesting data and potential discoveries.

Programmers at NASA are well aware of the risks, and therefore, asked the scientists for help. Eric and Victoria prepared a blind test – they have put together a dataset with mass spectra, where some were produced by the scientists, but the majority were augmented by programmers (the so-called Frankenstein files). Without revealing that some of the data were augmented, Eric and Victoria gave this dataset to the scientists. The goal of this test was to see if scientists will find the augmented data meaningful. The underlying question was whether the augmented data that programmers produced can serve as substitutes for the data that scientists produced in laboratories.

Programmer Victoria is expressing what is at stake in this test:

> We changed the intensity of some peaks and then we shifted some peaks (…) It [the test] was supposed to keep track of *the science, the chemistry behind*, that was the test for us, if our *artificially generated data was making sense scientifically or*

> *not* (…) 'Cause we need to know. *If we lose the chemistry, what's the point?* You know.

At stake in augmentation of mass spectra data is "losing chemistry." This utterance reflects the previously discussed act of balance between modifying and preserving the "chemistry" contained in data. The programmers aspired to use the scientists as a yardstick to measure their success in data augmentation. In a previous chapter, I showed how scientists are in authority of interpreting the value of data, and the test of the Frankenstein files confirms this position. So, did programmers find out if the augmented data contain AI hallucinations?

The test constructed by programmers at NASA did not get any response from the scientists, who could not afford to volunteer their time. Without getting any assistance from the scientists, the programmers had to work with other measures of success to evaluate the augmented data. Left to their own devices, the programmers draw relations about similarity between the different kinds of data in relation to performance metrics. This has implications for the decision making in scientific knowledge production, by positioning it in the realm of programming.

Conclusion

Based on ethnographic material from NASA Goddard, this chapter shows how the ways in which synthetic data are made and evaluated can diverge between epistemic cultures. Synthetic data can be evaluated in relation to data from previous experiments, and/or performance metrics.

The reliance on metrics in the field of AI can be understood as part of a larger discourse in society, where the value of objects – across science, governance, and everyday life – is estimated in quantitative measures (Espeland & Stevens, 2008; Porter, 1995). At NASA, a governmental agency, metrics do have an epistemic authority in estimating the value of scientific practices. Practitioners are incentivized to prove the value of what they do in terms of metrics, in order to maintain funding for their missions in a competitive environment. Against this background, using performance metrics for AI fits well into the organizational context at NASA.

Metrics figure as an important way of communicating the results of scientific work – but they provide a partial view, and can hardly capture complex phenomena. The same goes for performance metrics for AI. Previous studies have identified how reliance on metrics in AI can lead to focus on short-term goals and qualities, inadequate proxies for complex phenomena, or gaming the system to improve the metrics (Thomas & Uminsky, 2022). This relates to a general problem with measurements: Goodhart's law, named after the economist Charles Goodhart. It can be summarized as follows: "When a measure becomes a target, it ceases to be a good measure." (Strathern, 1997, as cited in Thomas & Uminsky, 2022)

Programmers at NASA Goddard are mindful of the fact that metrics are a limited yardstick that needs to be complemented with other ways of knowing. To train robust AI tools, there is a need for joint efforts between programmers and domain experts, who can facilitate evaluation of the adequacy of synthetic data that AI tools are trained on. Without collaboration with other professions (relevant domain experts), the decision making in scientific knowledge production will reside in the realm of programming, and the standards of practice in the field of AI rather than science. Moreover, data from scientific experiments, such as mass spectrometry, require a particular kind of expertise to identify whether it contains adequate representations of phenomena.

Synthetic data are computationally simulated. Nevertheless, these practices do not reside merely in the computational realm. In line with previous studies of the introduction of computational methods to life sciences (De Chadarevian, 2018; Keller, 2001), this chapter shows how synthetic data maintain links to material circumstances of biological experiments, as a point of departure, and/or evaluation.

Chapter 8 Conclusion – How NASA Shapes AI, and How AI Shapes NASA

This dissertation examines how the ways of knowing other worlds change with introduction of new technological tools. Although it focuses on the development of AI for life detection on other planets and moons, it demonstrates more broadly how these practices reshape the conditions of scientific knowledge production on Earth. By studying science in practice, this study shows how AI is an outcome of human decisions, situated in a particular organization, knowledge infrastructure, and scientific culture. In this concluding chapter, I synthesize how these three dimensions shape development of AI and vice versa. By doing that, I return to the overarching research question of this thesis: how the development of AI changes the ways in which scientific knowledge at NASA is produced.

First, the development of AI is situated in an organization that both enables and constrains particular courses of action. In the case of NASA missions, the question of legitimacy is particularly important, due to the history of non-detection in the search for extraterrestrial life. To sustain legitimacy for missions to other planets and moons, NASA has been shifting the focus away from life detection, and toward detection of potential signs of present or past life. By widening the scope from life detection to habitability, biosignatures, and organic molecules, NASA creates preconditions for continued exploration and funding. These organizational preconditions – demarcations of astrobiology at NASA – shape what kind of research subjects and tools are considered legitimate. Against this background, the AI tools developed for the missions at NASA Goddard are designed to facilitate analysis of mass spectrometry data, in order to identify organic molecules, as potential biosignatures, or signs of habitability.

Second, the development of AI depends on data that is available for training, which in turn is shaped by the knowledge infrastructure in planetary science and astrobiology. The data used for training AI stem from laboratories, where scientists perform experiments on samples. Scientists collect these samples in field sites. The findings show how the choice of field sites is dependent on accessibility and influenced by symbolic value, rendering some places more popular to study than others. As a result, scientific knowledge production about life and its origins becomes skewed toward the sites that are accessible, popular, or prestigious. Subsequently, this skew is reproduced in the datasets used to train AI. These findings resonate with Bowker's observation that knowledge production in biodiversity databases becomes skewed toward certain charismatic phenomena (Bowker, 2000). Importantly, knowledge production is always shaped by social interests. The critical questions are how, for what purposes, and with what consequences this skew is produced.

At NASA, this dynamic is also prevalent through the use of mass spectrometry databases, which is curated by NIST for industrial purposes. This database serves as a library of known compounds against which new data are compared, despite limited overlap with compounds of interest in astrobiology, such as those found in meteorites. Field sites, laboratories, and databases together constitute a knowledge infrastructure that shapes AI by determining which data are available for training.

These epistemic concerns – such as analogies between places on Earth and another planet or moon – become black-boxed, when the data is used in a dataset for AI. The development of AI introduces new epistemic concerns, in line with norms of practice in the field of AI. With development of AI comes a shift in which concerns are relevant, and who makes the decisions about the data. For example, by determining whether the anomaly in the data is an artifact, or a novel phenomenon – which lays the groundwork for potential discoveries. However, discoveries of novel phenomena facilitated by AI is not necessarily about seeing an anomaly. Rather, it is about noting the absence – the absence of correlation with known chemical compounds that the algorithm has been trained to detect. Datasets used for training AI constitute another library of knowns, against which the unknown is identified.

Third, AI development at NASA Goddard takes place at the intersection of two epistemic cultures (Knorr Cetina, 1999): planetary science and software engineering. Negotiations between these groups play a decisive role in determining which data are included in training datasets and how they are evaluated. Without negotiations, data is evaluated solely in relation to performance metrics. This means that the decision making is executed in the domain of programming, in line with standards of practice in the field of AI, rather than science. This dynamic echoes Leonelli's (2014) observations of the consequences of Big Data in life sciences, moving the decision making about scientific data to the domain of programming (Leonelli, 2014). The findings demonstrate that the presence or absence of negotiations with domain experts is a key factor shaping how AI tools are made.

Performance metrics have an epistemic authority for estimating value in science, society and governance at large (Espeland & Stevens, 2008; Porter, 1995). This study confirms that metrics are also central to evaluating scientific practices within NASA's competitive organizational environment. Practitioners are incentivized to prove the value of what they do in terms of metrics, in order to maintain funding. Against this background, using performance metrics for AI fits well into the organizational context at NASA. One of the problems with reliance on performance metrics is that they do not always reflect the actual performance of the tools (i.e. overfitting).

This issue becomes especially significant in the emergent phenomenon of synthetic data, which are developed for the purposes of training AI. Synthetic data can be produced by programmers computationally, and evaluated solely with performance metrics. However, these simulations are not merely computational. In line with previous studies about *in silico* data in life sciences (De Chadarevian, 2018), synthetic data for AI does maintain a link to material circumstances. How the links to material circumstances are maintained, and broken, and how the data is evaluated, are crucial aspects to pay attention to, while studying the epistemic consequences of synthetic data.

Although AI remains at an early stage of development in the cases studied here, it already reshapes power relations in scientific knowledge production by introducing new ideals of epistemic order. It shifts the norms of how data can be made useful and who decides their value. This shows how AI can work as an infrastructuring entity in an organization, regardless of whether it functions successfully for the intended purposes or not – this role of AI resonates with findings from other social contexts, such as clinical practice (Gjødsbøl etal, 2024).

This dissertation shows that while organizational structures, knowledge infrastructures, and scientific cultures shape AI, the development of AI also feeds back into these dimensions by enabling and constraining particular understandings of life. The development of AI can amplify understandings of life that are manageable through data and algorithms.

Contribution and Future Research

This study adds to previous ethnographic works about the scientific cultures and organization of work at NASA (Messeri, 2011; Mirmalek, 2019; Olson, 2018; Vaughan, 1996; Vertesi, 2015; 2020). It provides knowledge about two important tools that play key roles in explorations of other planets and moons in-situ: mass spectrometry and AI. By focusing on the context of astrobiology, this dissertation offers knowledge about the role of computational methods and simulations in scientific studies of life (Kay, 1995; Keller, 2002; Helmreich, 1999; Roosth, 2019; Turkle, 2009). By focusing on AI at NASA, this study can be relevant for STS discussions about data-driven science (Edwards, 2010; Leonelli, 2014; Leonelli & Tempini, 2020; Messeri & Crockett, 2024; Mulinari, 2023).

One of the dissertation's central empirical contributions lies in its analysis of how synthetic data are produced in practice. Rather than treating synthetic data as a uniform phenomenon, this study shows that their social implications vary across contexts, underscoring the importance of empirical, situated analysis. These findings offer empirical insights to discussions on the social implications of synthetic data (Capasso, 2025; Jacobsen, 2023; Lee, Hajisharif & Johnson, 2025; Offenhuber, 2024).

This study also demonstrates how relations of care impact decision making about data in the development of AI, which is relevant for discussions on the ethics of AI (Capasso, 2025; Dignum, 2019). Drawing on anthropological scholarship about moral implications in data work (Navne, Svendsen & Gammeltoft, 2018; Pinel, Prainsack, & McKevitt, 2020; Pinel & Svendsen, 2021), and based on fieldwork at NASA Goddard, I introduced the term epistemic responsibility to theorize how relations of care and preconditions for responsibility emerge through attachment to the context of knowledge production. Epistemic responsibility is a term that adds a crucial emphasis to the discussions about responsibility in AI development. While there are a lot of discussions on the ethics of AI and formal obligations ascribed top-down to organizations who work with AI, the concept of epistemic responsibility focuses instead on how responsibility emerges bottom-up. Building on the concept of epistemic responsibility introduced here, future studies can examine how it emerges in other contexts, and what consequences it has for data practices.

This dissertation addresses the urgent call for social scientists to scrutinize the increasingly prevalent AI tools (Suchman, 2023). Methodologically, this study demonstrates how ethnography can facilitate an understanding of how AI tools fit into organizational circumstances, and in turn, how these tools change the ways in which we manage and understand the world. It supports the approach to pay attention to “data settings” rather than “data sets” (Loukissas, 2019), as a lot of the work it takes to make AI occurs beyond the data sheets on the computer screen. Moreover, the study provides an example of how to balance describing the matters of concerns of our interlocutors, and attention to practices of marginalization and exclusion in construction of scientific knowledge (Lee, 2023).

The concept of truth-spots (Gieryn, 2006) greatly facilitated the analysis of various places used in scientific knowledge production at NASA. This study expands this concept by showing how digital phenomena, such as databases, can serve as important truth-spots lending legitimacy in scientific knowledge production – alongside the laboratory and the field site. These findings are relevant at the intersection of the studies of place-making in scientific knowledge production (Gieryn, 2006; Messeri, 2011), and the studies of materiality of data (Leonelli & Tempini, 2020; Mazmanian, Cohn & Dourish, 2014).

In chapter 5, I concluded that AI, or AI datasets, can be understood as truth-spots in their own right, given that they are an agglomeration of data, and sometimes narrated as ground-truths (Jaton, 2021), or envisioned as oracles (Messeri & Crockett, 2024). In this study, AI is at the early stage of development and has not reached the epistemic status of a truth-spot.

However, it leads to an avenue that is worthwhile to explore in future studies: to what extent does AI or datasets for AI serve as an important truth-spot that lends credibility to claims about the world? How is it made and used as a truth-spot to make knowledge claims? What epistemic virtues characterize it? In what ways does it relate to the legacy of the laboratory and/or the field site?

This study focuses on one of NASA's ten centers. As studies from STS have shown, epistemic cultures are local and diverse (Knorr Cetina, 1999). This study provides another piece of the puzzle in understanding the local cultures at NASA (Vertesi, 2020). Moreover, cultures are not static entities – they change. This means that the results of this study apply to the specific period of time when fieldwork was conducted (2022 and 2023). Considering the rapid changes and prevalence of new techniques to make AI work – such as synthetic data – there is a need to study this development further. Continued studies of how AI tools for science autonomy are being developed could provide insights about how AI becomes a trusted tool in an organizational context and scientific cultures at a large scientific institution like NASA.

Considering the central role of NASA in the production of scientific knowledge about the universe, this case study provides insights into the dominant ways in which other worlds are made known. This dissertation demonstrates how AI is shaped by organizational structures, knowledge infrastructures, and scientific cultures. The development of AI is in turn reshaping these dimensions and by that, the ways in which life is made known in science.

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