IFIP Networking 2024

TX4Nets 2024

CHALMERS
UNIVERSITY OF TECHNOLOGY

Explainable Reinforcement Learning: Towards Trustworthy Autonomous Network Operations

Carlos Natalino

Researcher, Optical Networks Unit

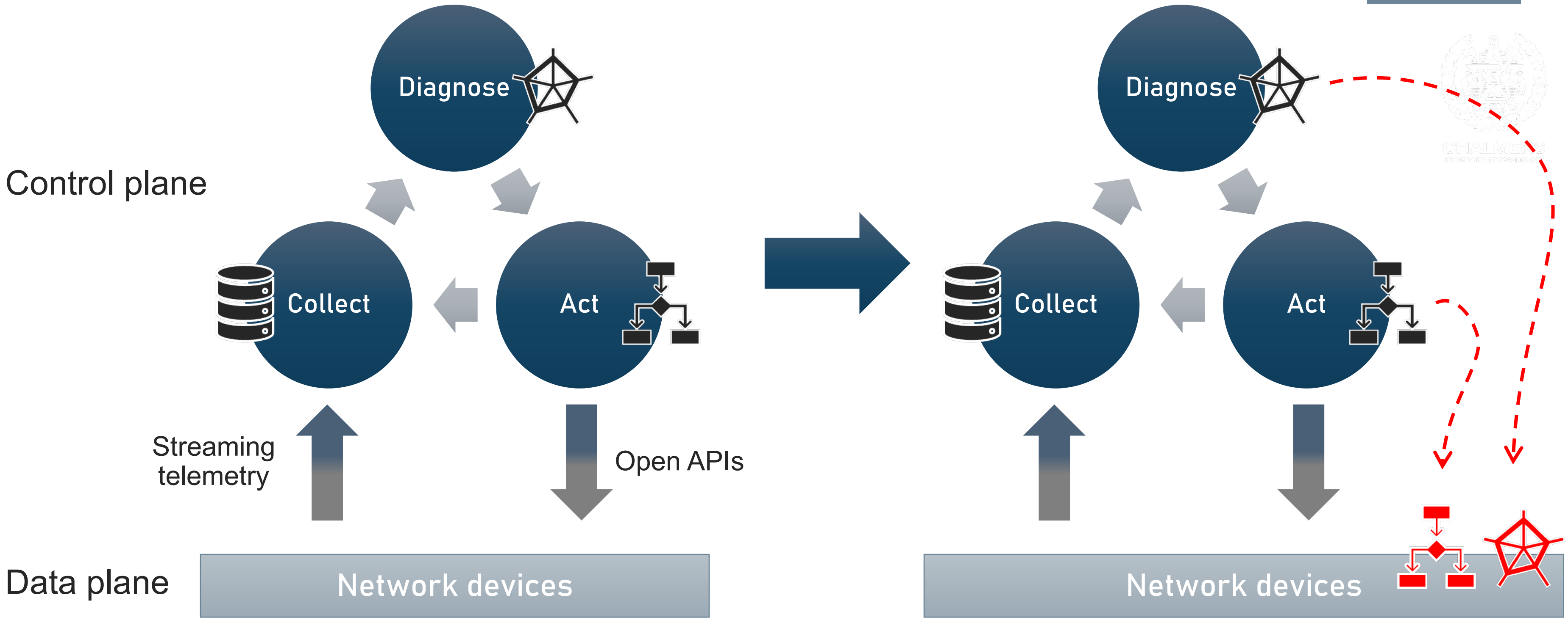
Department of Electrical Engineering

Chalmers University of Technology, Gothenburg, Sweden

Outline

- Network automation & programmability
- Trustworthy AI
- Understanding reinforcement learning
- Representative use case
- Preliminary investigation
- Challenges and opportunities

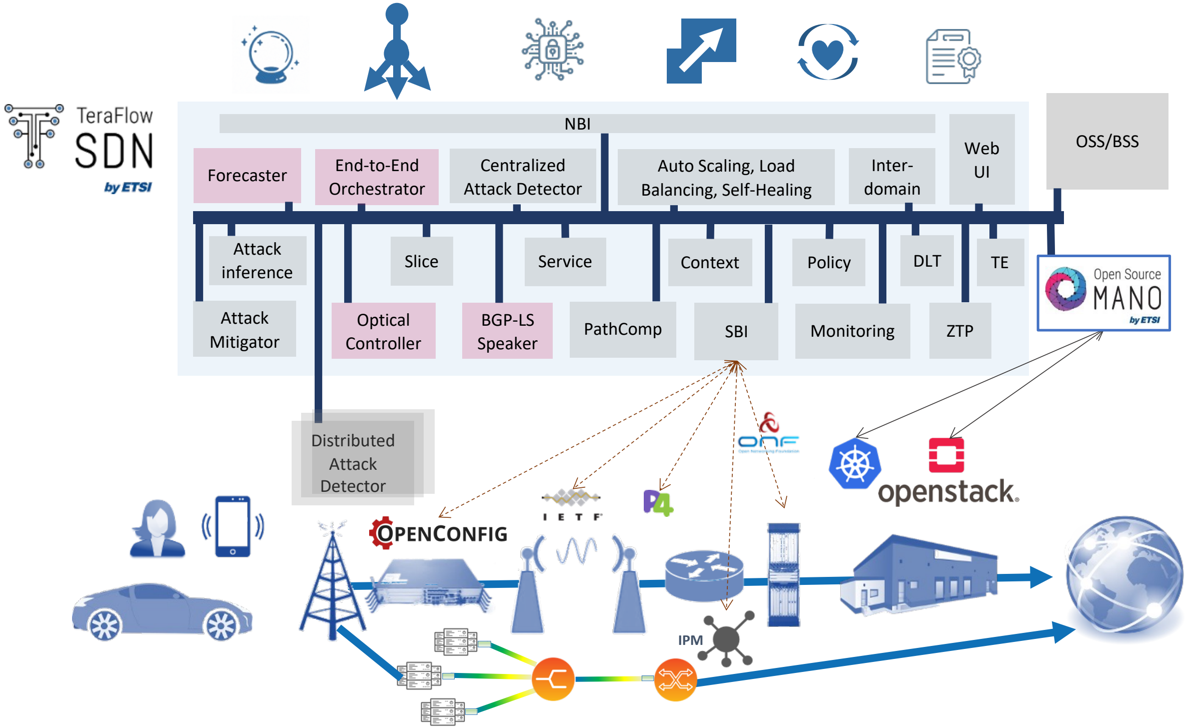
Network automation & programmability



*Achim Autenrieth, “Carrier Grade AI/ML for Network Automation”, invited talk, OFC 2022, 9 March 2022

Fixed networks

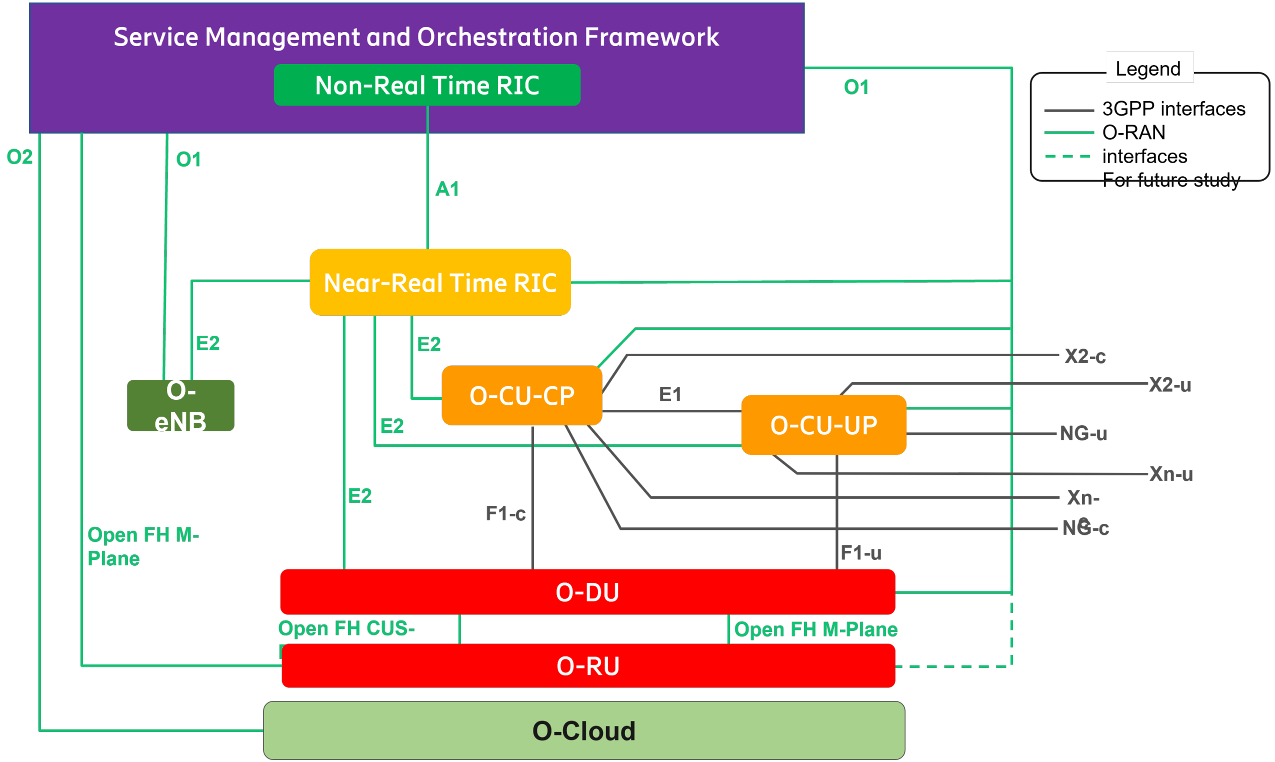
Network automation and programmability



Source: ETSI SDG TFS

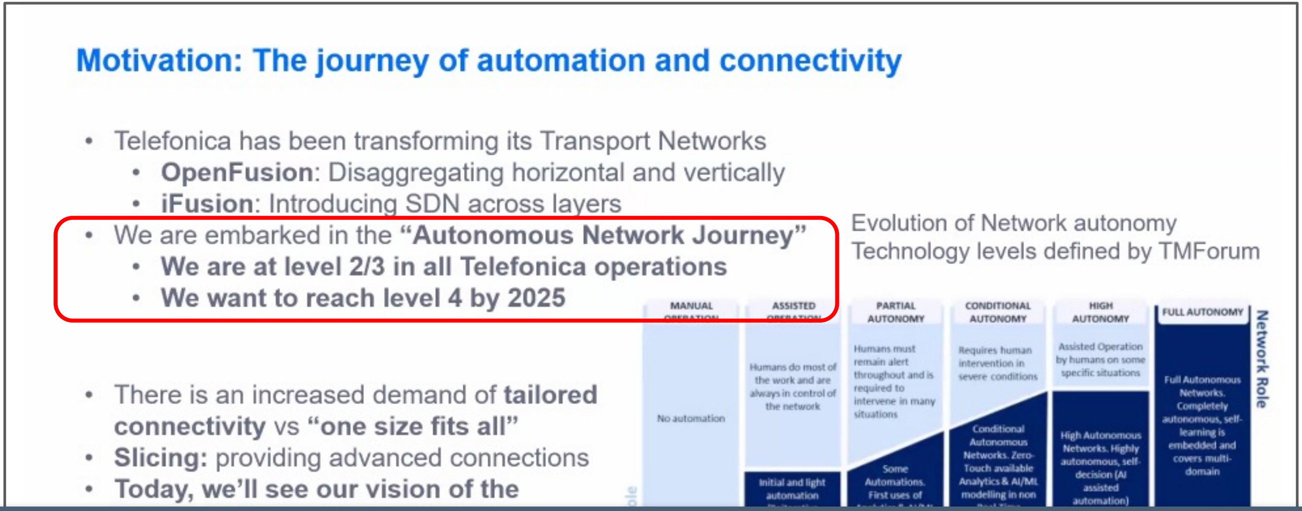
Wireless networks

Network automation and programmability



Source: O-RAN Alliance

Current level of network autonomy



Why are we still experiencing a low level of autonomy?

* Oscar Gonzáles de Dios, "AI-based automation of multi-layer multi-domain transport networks," OFC, pp. W4I.2, March 2024.

Outline

- Network automation & programmability
- **Trustworthy AI**
- Understanding reinforcement learning
- Representative use case
- Preliminary investigation
- Challenges and opportunities

Trustworthy AI

1 Human agency and oversight
- Including fundamental rights, human agency and human oversight

2 Technical robustness and safety
- Including resilience to attack and security, fall back plan and general safety, accuracy, reliability and reproducibility

3 Privacy and data governance
- Including respect for privacy, quality and integrity of data, and access to data

4 Transparency
- Including traceability, explainability and communication

5 Diversity, non-discrimination and fairness
- Including the avoidance of unfair bias, accessibility and universal design, and stakeholder participation

6 Societal and environmental wellbeing
- Including sustainability and environmental friendliness, social impact, society and democracy

7 Accountability
- Including auditability, minimisation and reporting of negative impact, trade-offs and redress.

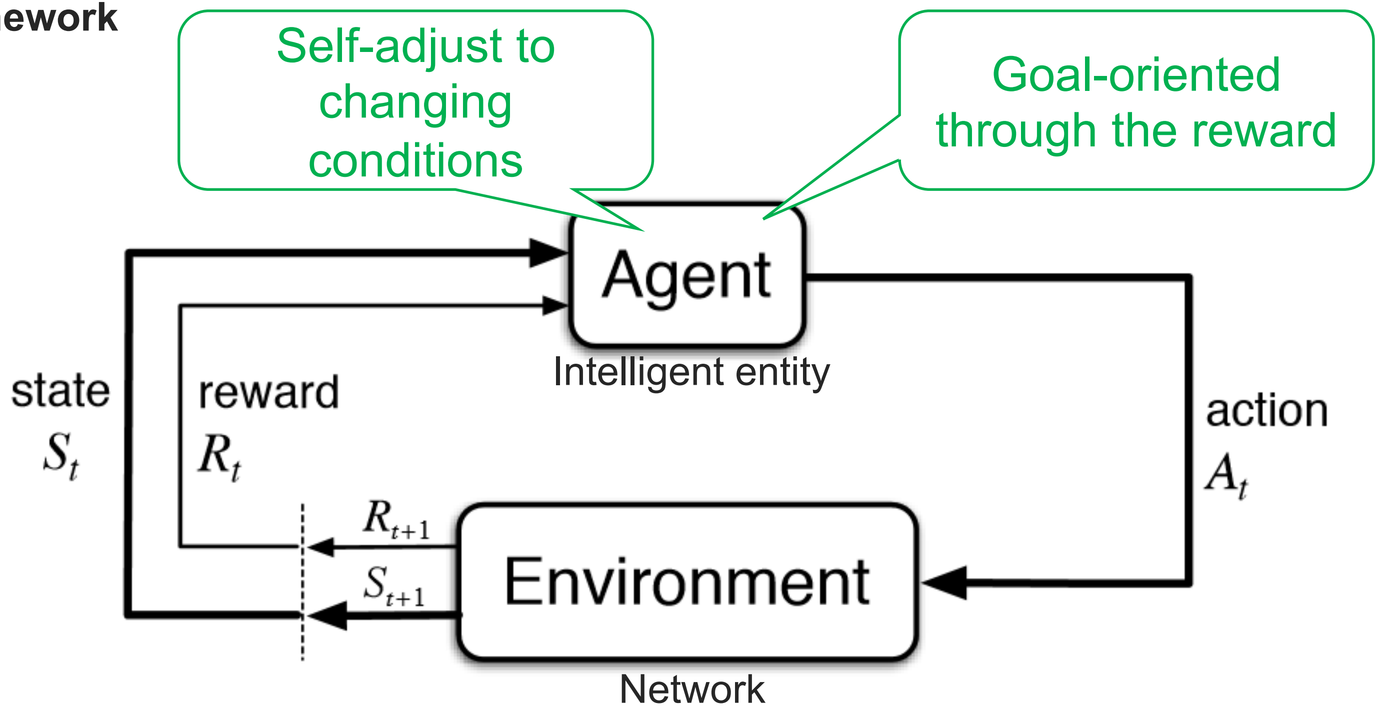
Ethics guidelines for trustworthy AI, EU, April 2019.

Outline

- Network automation & programmability
- Trustworthy AI
- **Understanding reinforcement learning**
- Representative use case
- Preliminary investigation
- Challenges and opportunities

The reinforcement learning loop

RL framework



Discounter reward

RL framework

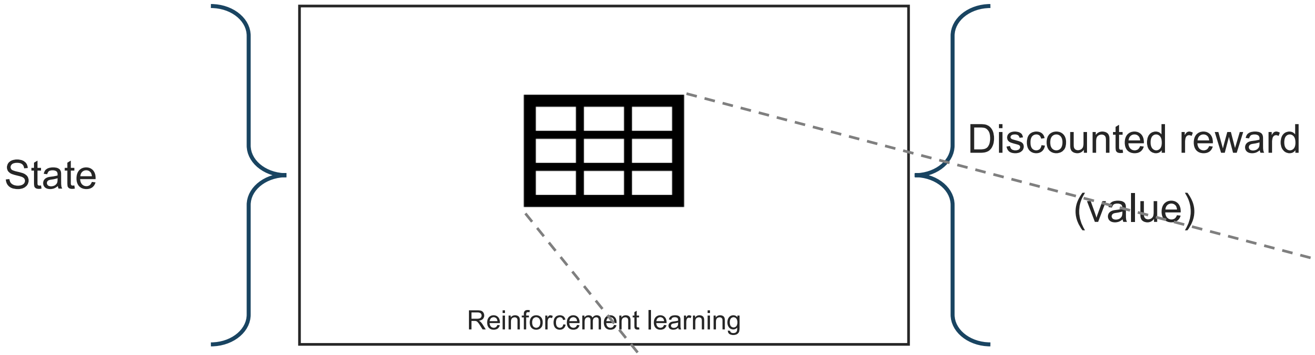
- Long-term value of each state/action pair
- Term γ regulates the value of future rewards to the current action
- Number of interactions depends on the *episode length*

$$R_t = \sum_{k=0}^{\infty} \gamma^k \times R_{t+k+1}$$

$$R_t = R_{t+1} + \gamma \times R_{t+2} + \gamma^2 \times R_{t+3} + \cdots$$

RL vs. DRL

RL framework

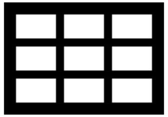


State	Action 1	Action 2	…	Action $\|A\|$
(0, 0, …, 0)	10	5	…	1
(0, 0, …, 1)	3	8	…	4
…	…	…	…	…
(1, 1, …, 1)	6	2	…	11

RL vs. DRL

RL framework

State



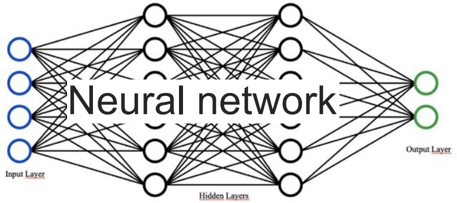
Reinforcement learning

Discounted reward

(value)

State

Neural network



Deep reinforcement learning

Discounted reward (value)

or

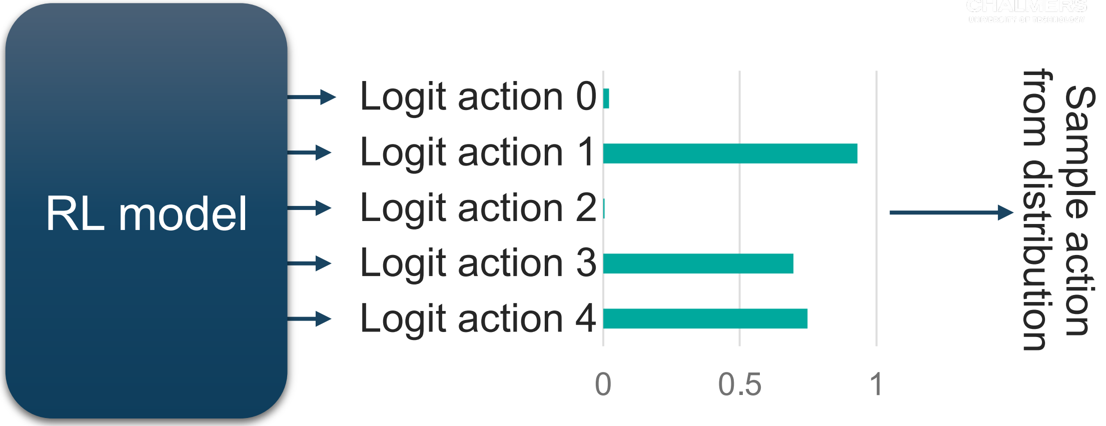
Action probability (policy)

Inference

RL framework

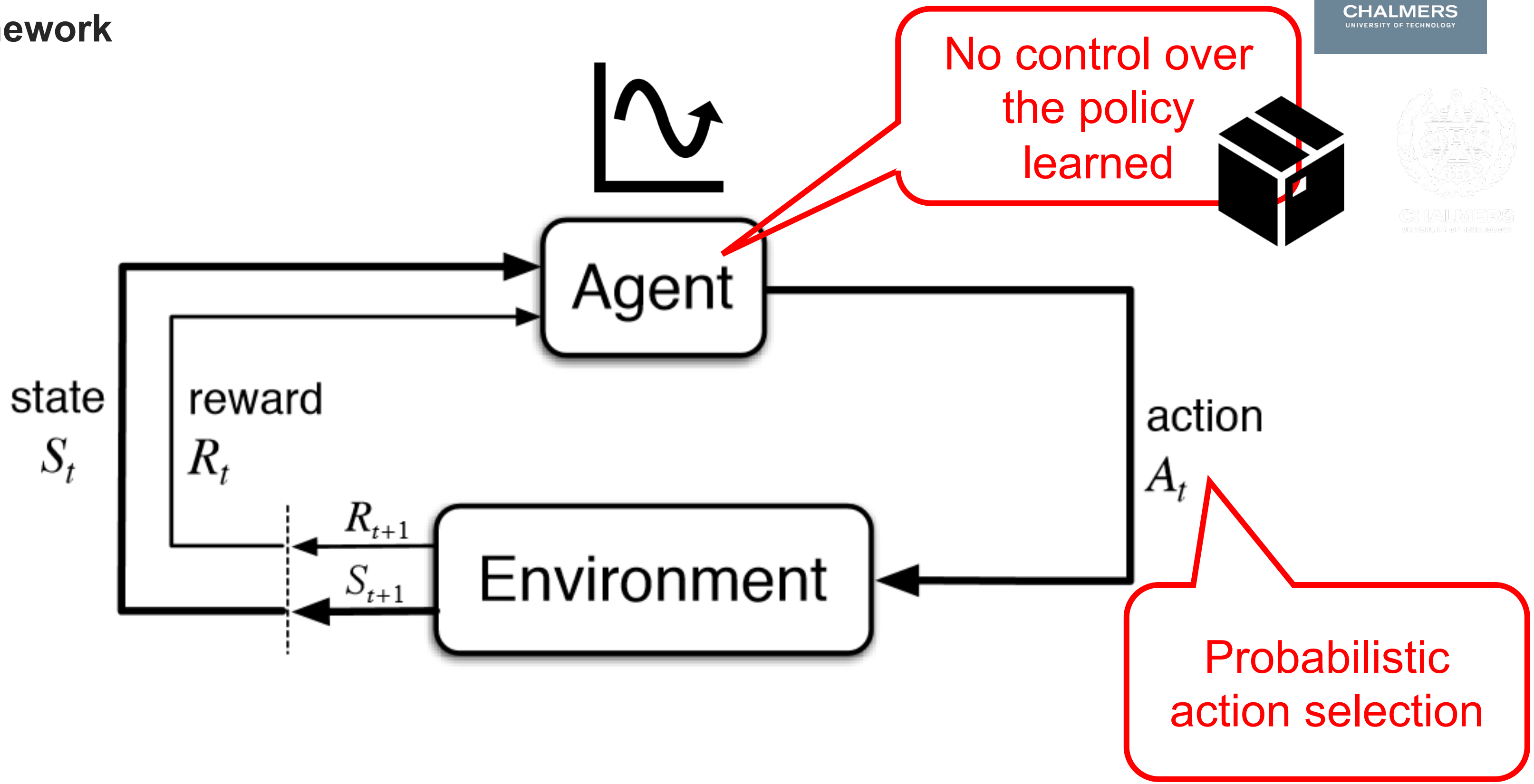
State

- Source
- Destination
- Bit rate
- Block spectrum information
- Path spectrum information
- Etc.



How does RL learn?

RL framework



Outline

- Network automation & programmability
- Trustworthy AI
- Understanding reinforcement learning
- **Representative use case**
- Preliminary investigation
- Challenges and opportunities

Use cases for reinforcement learning

Suitable use cases

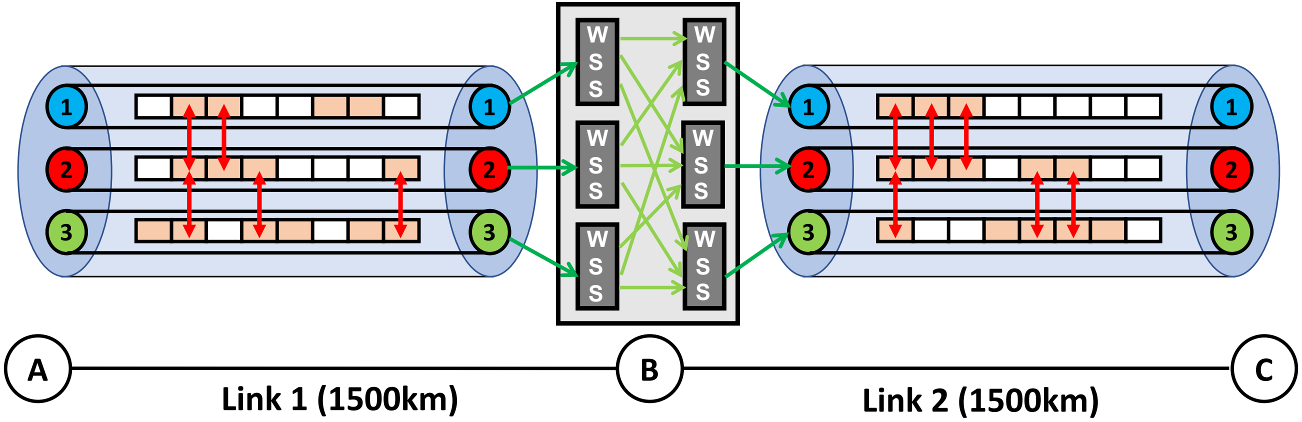
- Complex problems
  - Scenario-specific behavior
  - Need for context-specific thresholds
- Unknown future
  - Random arrivals
  - External events

Unsuitable use cases

- Simple problems
  - Heuristics are sufficient
- Known sequence of steps
  - Concurrent optimization (e.g., linear programming) is a better fit

Problem statement

Routing, modulation, core, and spectrum allocation



Rt (A, C, 35 gbit/s)

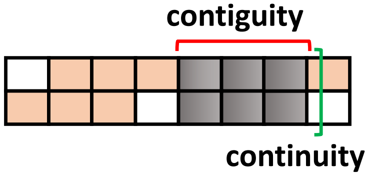
QPSK *s* = 3 slots → Available Core Path

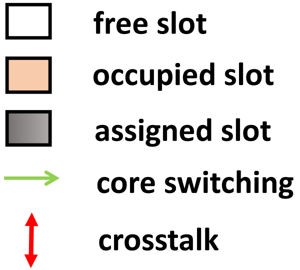
Route: *A-B-C*

CP: [Φ_1^2 , Φ_2^1]

Core2 on *Link1*

Core1 on *Link2*

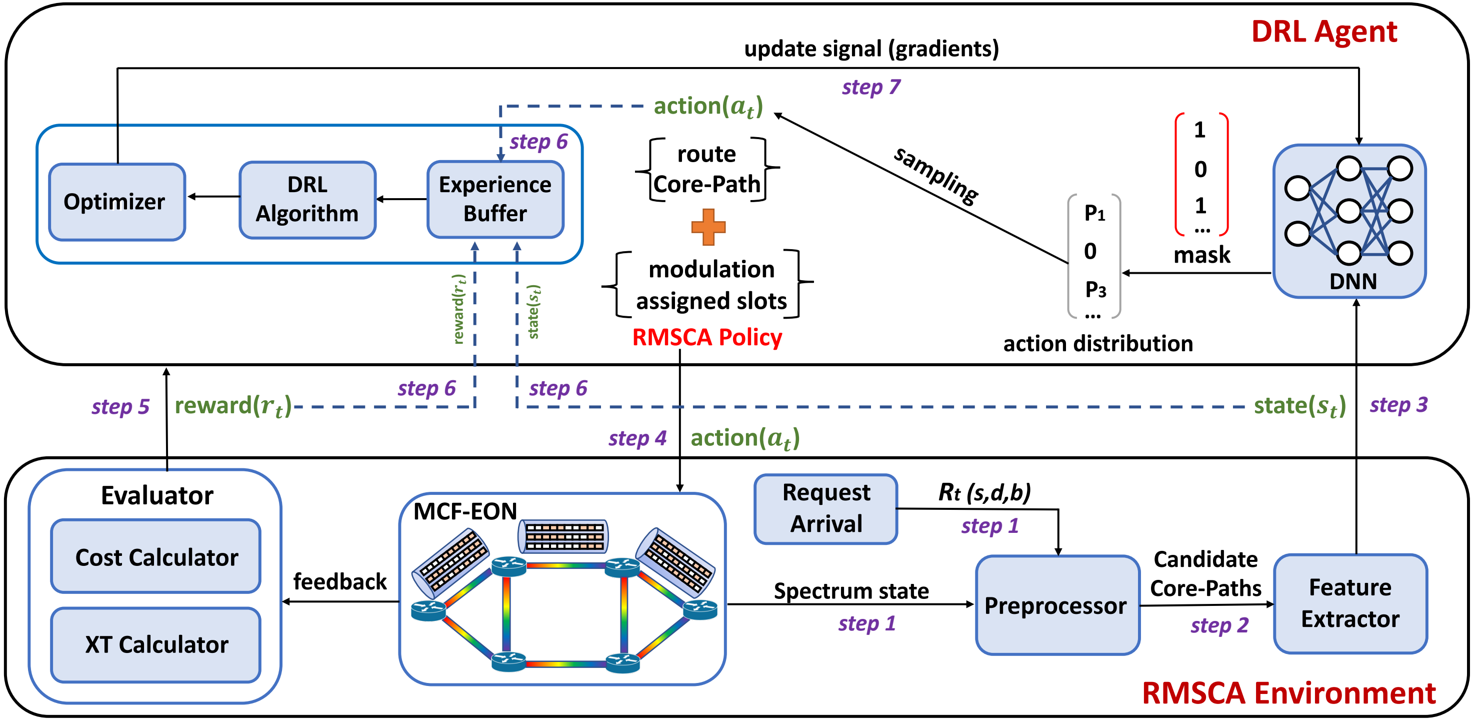




Teng et al., JOCN, 2024

RL modeling

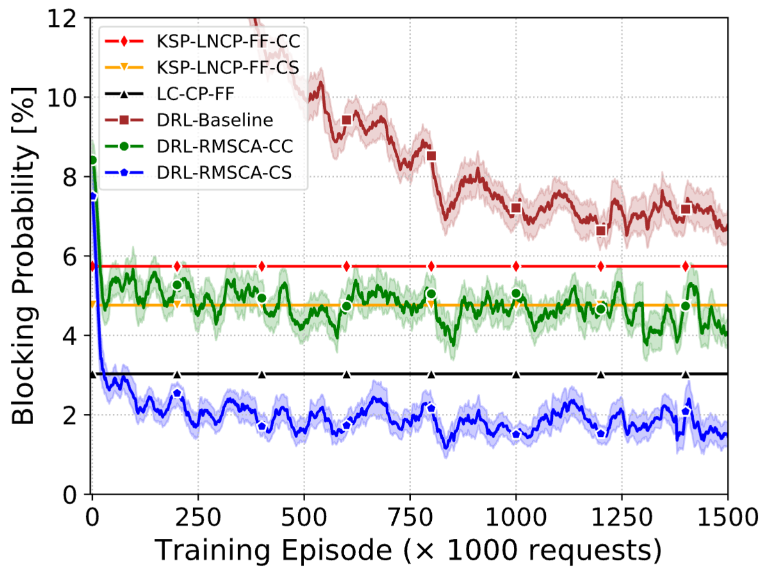
Routing, modulation, core, and spectrum allocation

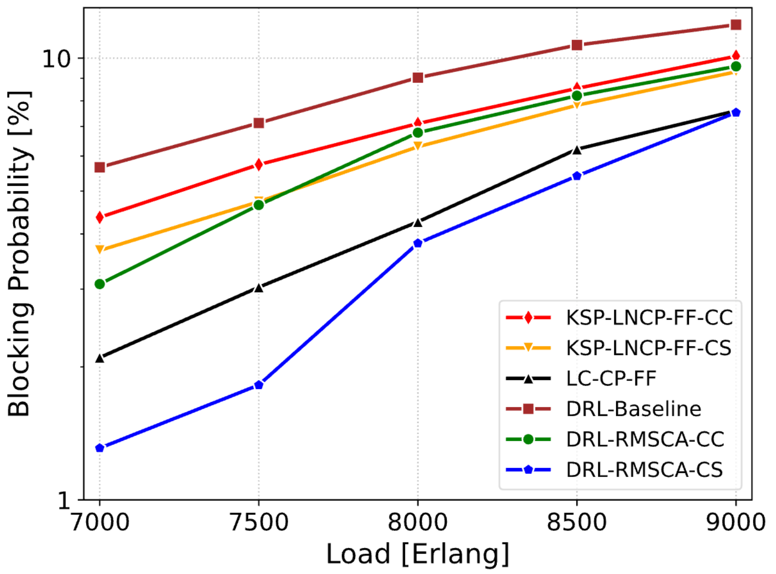


Teng et al., JOCN, 2024

Representative results

Routing, modulation, core, and spectrum allocation





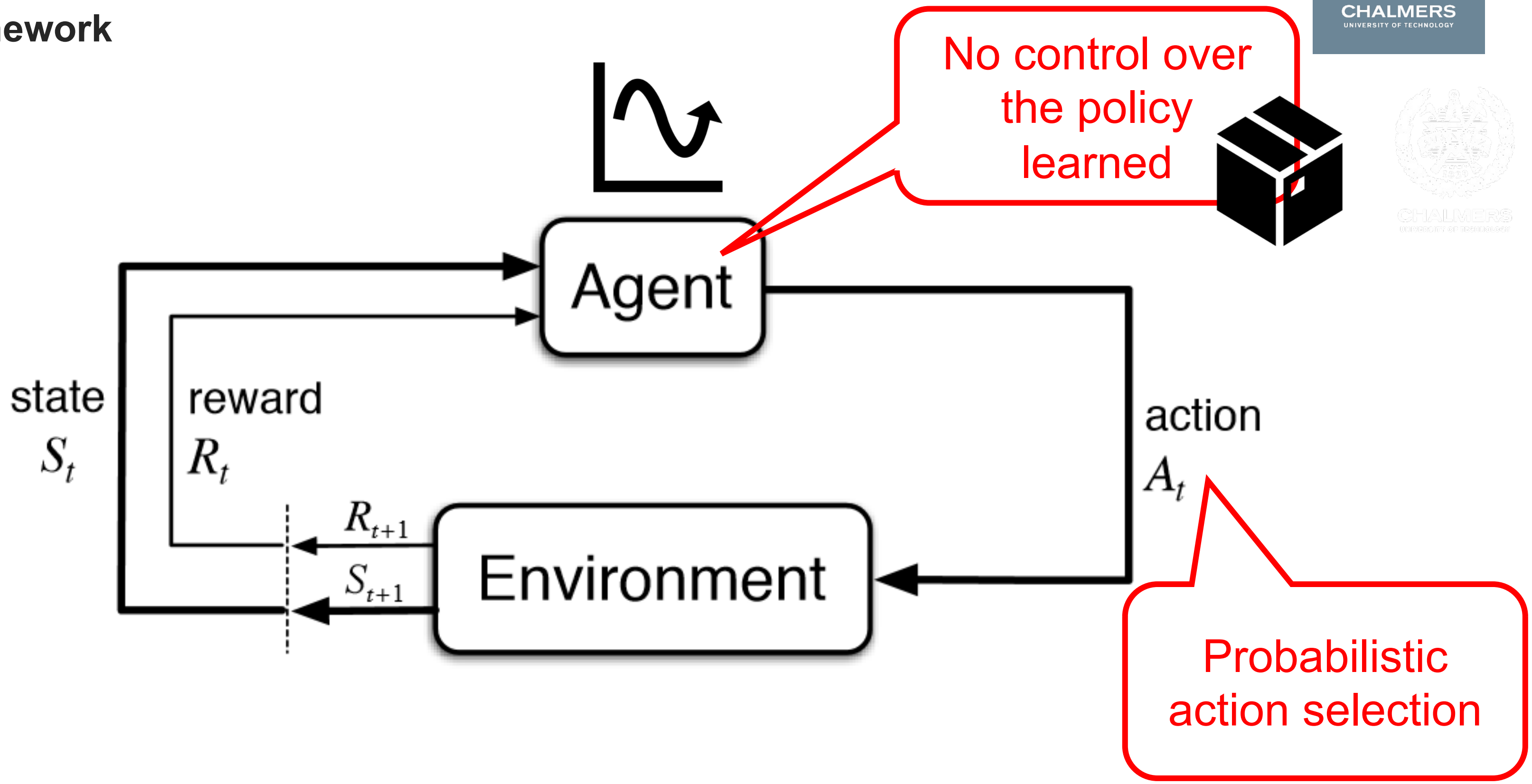
Teng et al., JOCN, 2024

Outline

- Network automation & programmability
- Trustworthy AI
- Understanding reinforcement learning
- Representative use case
- **Preliminary investigation**
- Challenges and opportunities

How does RL learn?

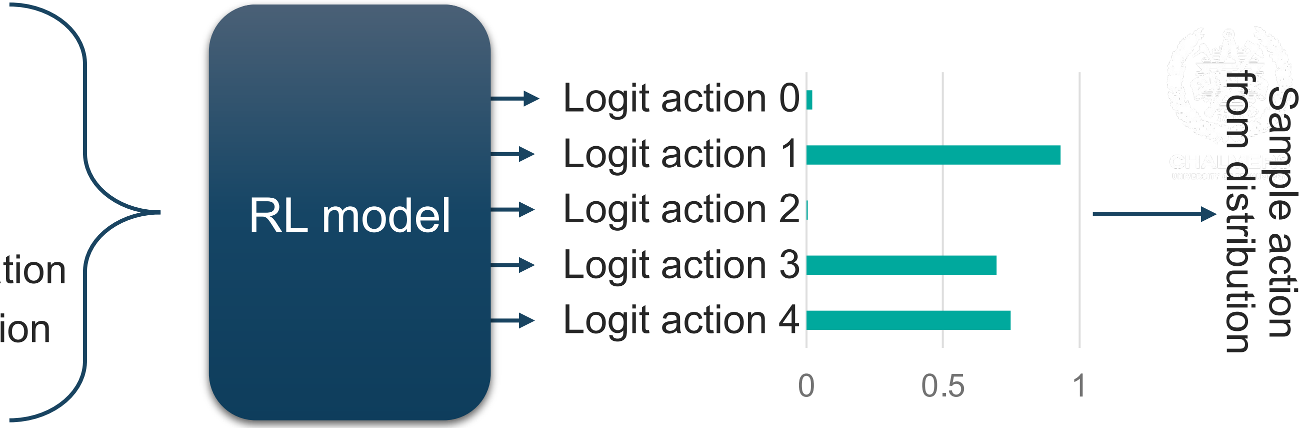
RL framework



Research questions

RL framework

State
- Source
- Destination
- Bit rate
- Block spectrum information
- Path spectrum information
- Etc.



Q1: How do features impact the RL decision?
Q2: How does the impact of features change for different RL scenarios?
Q3: Can we identify unwanted behavior?

Ayoub et al., OFC'24, p. W4I.6

Proposed approach

Train RL → Learn classifier → Assess feature impact

Ayoub et al., OFC’24, p. W4I.6

Proposed approach

Train RL → **Learn classifier** → **Assess feature impact**

- DeepRMSA*
- Maximize acceptance / minimize blocking

- ~ to imitation learning
- Choose the most accurate model
- Accuracy assessed as classification

- Use Shapley Additive exPlanations (SHAP)

SHAP

* Chen et al., JLT 37 (16), 2019.
Ayoub et al., OFC'24, p. W4I.6

RF classifier performance

Results

Model	Infeasible allowed	Infeasible penalized	Infeasible masked
F1-score	0.75-0.85	0.74-0.84	0.77-0.84
Accuracy	0.84-0.94	0.77-0.91	0.84-0.94
Precision (class 5)	0.75-1.00	0.67-0.90	0.75-1.00

Fairly uniform accuracy across scenarios

Ayoub et al., OFC’24, p. W4I.6

Feature importance

Results

Features:

Request:

0. Bit rate
1. Source node
2. Destination node

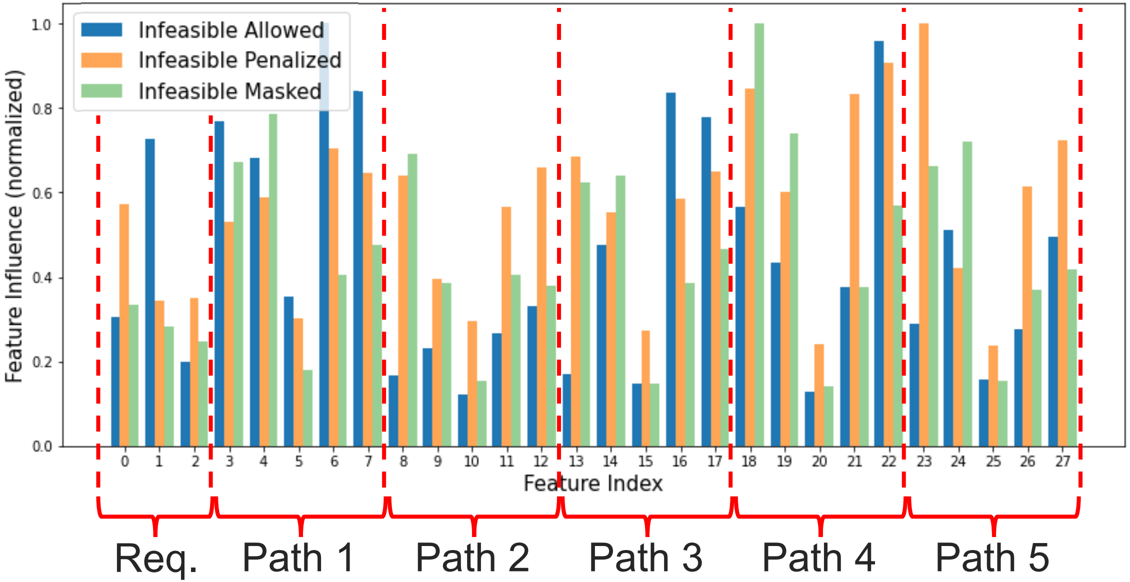
Path/block option:

Block:

3. Initial index
4. Number of free slots

Path:

5. Number of requested slots
6. Total free slots in the path
7. Average free block length



Ayoub et al., OFC'24, p. W4I.6

Feature importance

Results

Features:

Request:

0. Bit rate
1. Source node
2. Destination node

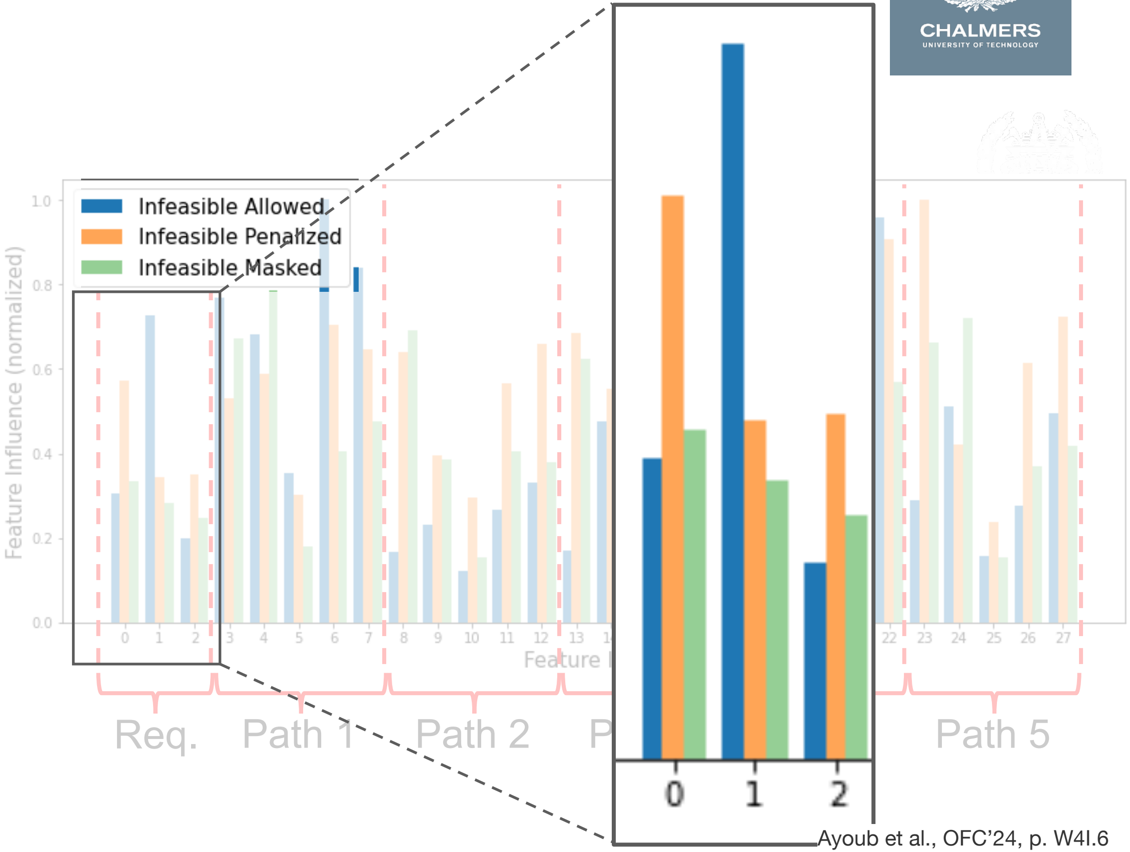
Path/block option:

Block:

3. Initial index
4. Number of free slots

Path:

5. Number of requested slots
6. Total free slots in the path
7. Average free block length



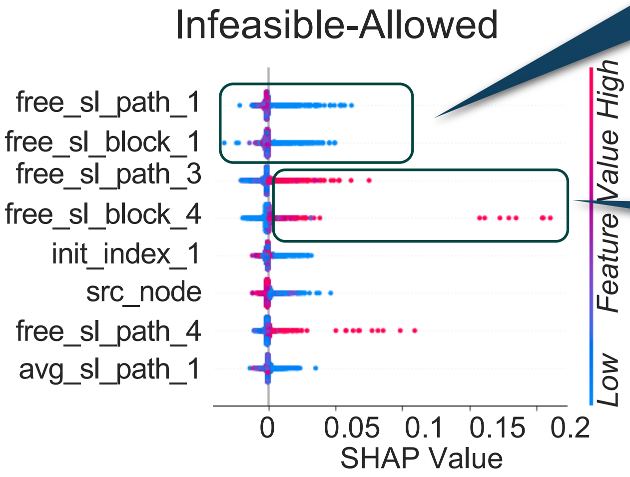
Ayoub et al., OFC'24, p. W4I.6

Feature influence/impact on rejection

Results

Low values in path 0 influence rejection

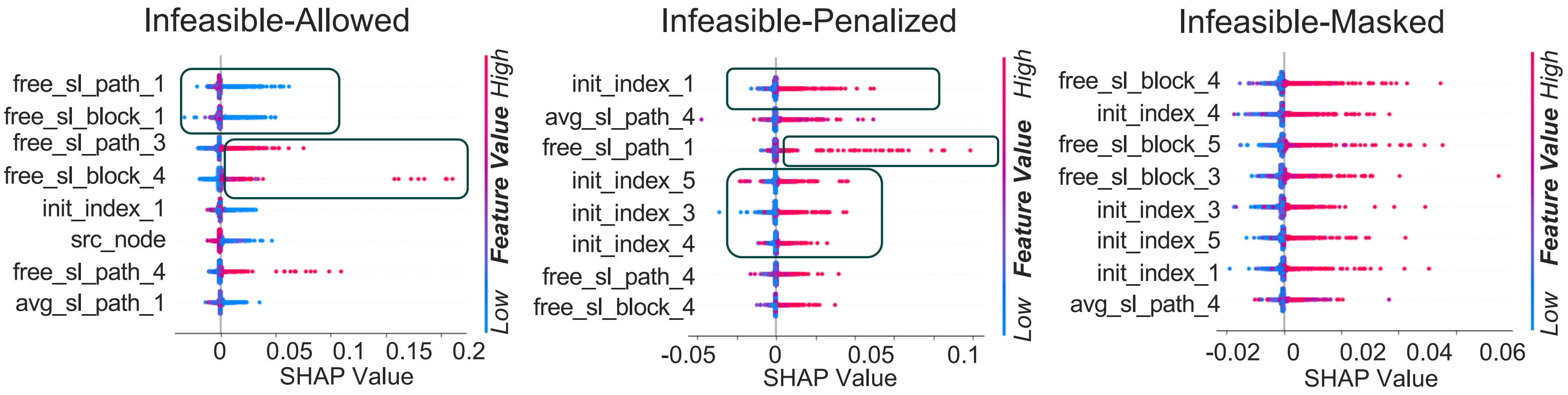
High values in paths 2 and 3 also influence rejection



Ayoub et al., OFC’24, p. W4I.6

Feature influence/impact on rejection

Results



Ayoub et al., OFC’24, p. W4I.6

Outline

- Network automation & programmability
- Trustworthy AI
- Understanding reinforcement learning
- Representative use case
- Preliminary investigation
- **Challenges and opportunities**

Challenges and opportunities

1 Human agency and oversight
- Including fundamental rights, human agency and *human oversight*

2 Technical robustness and safety
- Including resilience to attack and security, fall back plan and general safety, *accuracy*, *reliability* and *reproducibility*

3 Privacy and data governance
- Including respect for *privacy*, *quality and integrity of data*, and *access to data*

4 Transparency
- Including *traceability*, *explainability* and communication

5 Diversity, non-discrimination and fairness
- Including the avoidance of unfair *bias*, accessibility and universal design, and stakeholder participation

6 Societal and environmental wellbeing
- Including *sustainability* and environmental friendliness, social impact, society and democracy

7 Accountability
- Including *auditability*, minimisation and reporting of negative impact, trade-offs and redress.

Ethics guidelines for trustworthy AI, EU, April 2019.

Acknowledgements

- Paolo Monti
- Yiran Teng
- Shuangyi Yan
- Anders Lindgren
- Stefan Melin
- Achim Autenrieth
- Wolfgang John
- Ali Balador

- Celtic-Next project AI-NET-PROTECT
- ECO-eNET

References and further reading

- Y. Teng *et al.*, "Deep-reinforcement-learning-based RMSCA for space division multiplexing networks with multi-core fibers," in *Journal of Optical Communications and Networking*, vol. 16, no. 7, pp. C76-C87, July 2024, doi: 10.1364/JOCN.518685.
- O. Ayoub, C. Natalino and P. Monti, "Towards Explainable Reinforcement Learning in Optical Networks: The RMSA Use Case," *Optical Fiber Communications Conference and Exhibition (OFC)*, San Diego, CA, USA, 2024, pp. W4I.6.
- E. Etezadi et al., "Deep reinforcement learning for proactive spectrum defragmentation in elastic optical networks," in Journal of Optical Communications and Networking, vol. 15, no. 10, pp. E86-E96, October 2023. DOI: 10.1364/JOCN.489577.
- Wolfgang John, "The journey towards 6G: Going beyond connectivity services," IEEE NetSoft, Madrid, Spain, June 2023.
- Achim Autenrieth, "Carrier Grade AI/ML for Network Automation", invited talk, OFC 2022, 9 March 2022.
- Whitepaper, "European Vision for the 6G Network Ecosystem," 5GPPP, 2021. DOI: 10.5281/zenodo.5007671.
- Whitepaper, "Ethics guidelines for trustworthy AI," EU, April 2019. URL: https://digital-strategy.ec.europa.eu/en/library/ethics-guidelines-trustworthy-ai

*In chronological order

Thank you! ☺

Chalmers profile

GitHub page

IFIP Networking 2024

TX4Nets 2024

CHALMERS
UNIVERSITY OF TECHNOLOGY

Explainable Reinforcement Learning: Towards Trustworthy Autonomous Network Operations

Carlos Natalino
Researcher, Optical Networks Unit
Department of Electrical Engineering
Chalmers University of Technology, Gothenburg, Sweden

AVANCEZ

1829

CHALMERS

UNIVERSITY OF TECHNOLOGY