One-Shot Learning for Modulation Format Identification in Evolving Optical Networks

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Abstract: We report on the first successful application of one-shot machine learning scheme that identifies new modulation formats based on a single constellation diagram without re-training. 100% accuracy is achieved when expanding from 2 to 5 supported modulation formats.

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1. Introduction

Coherent receivers in evolving optical networks are expected to quickly adapt their transmission parameters, e.g., modulation format and bit rate, to the changing network status. modulation format identification (MFI) without prior information of the transmitter settings enables the receiver to tune digital signal processing algorithms to these changes in real time [1], which relaxes the requirements on the optical performance monitoring and control message exchange in software-defined optical networks. The potential of machine learning (ML) in optical networking has recently been showcased in several MFI applications [2,3]. Deep learning (DL) models, i.e., convolutional neural networks (CNNs) in particular, show great accuracy in MFI when analyzing visual representations of the optical channels, such as amplitude histograms [2], eye diagrams [4] and constellation diagrams [1,3].

However, these MFI models face two challenging requirements upon introduction of new modulation formats: *(i)* the need to collect and label large datasets for training and validation, which can be lengthy, expensive and energy-consuming [5]; and *(ii)* the need for complex re-training and possibly re-engineering of the ML model. Namely, CNN parameters (e.g. layers and neurons, filters, activation functions) are optimized for a set of supported modulation formats, and the same CNN setup may not be able to classify a new format. Fig. 1(a) shows an example of a CNN used for MFI trained for two modulation formats (i.e., 4- and 16-level quadrature amplitude modulation (QAM)), along with the output probabilities of classifying the input constellation diagram, represented by the blue bars. When 64QAM is introduced, the CNN architecture needs to be changed by adding a new class (denoted with the red dot in the output layer), and re-trained. All these factors may lead to a labor of hours or even days to deploy updated MFI, which limits the network agility in introducing new modulation formats.

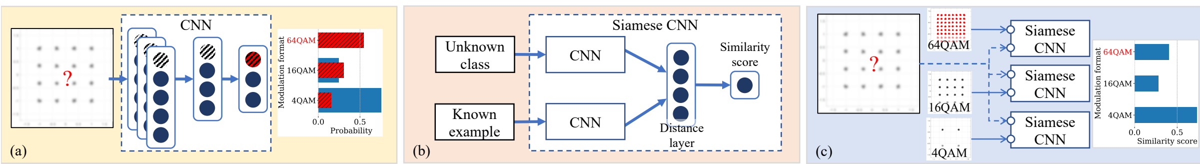

Fig. 1: Traditional MFI vs. one-shot learning: (a) traditional classification-based MFI with two (blue) and three (red) modulation formats; (b) architecture of a Siamese CNN and (c) one-shot learning Siamese CNN.

We propose, for the first time, an one-shot learning (OSL) Siamese CNN [6] constellation-diagram-based MFI approach to mitigate the drawbacks of the existing deep learning-based MFI models. The approach does not require re-training nor re-engineering upon introduction of new modulation formats, and paves the way to seamless adaptive ML models for evolving optical networks. The OSL model is trained over a set of constellation diagrams of known modulation formats, learning the similarity between diagram pairs, as illustrated in Fig. 1(b). Once trained, the model[1] can assess the similarity between any pair of constellation diagrams based on a single example from each modulation format, even if the format was not present in the training dataset.

2. Learning to identify the modulation format in one shot

The DL models, such as the CNN illustrated in Fig. 1(a), learn to extract relevant features in the initial (leftmost) layers, whereas the last (rightmost) layers learn to map the extracted features to particular classes (representing modulation formats in our case), outputting the probability of the input belonging to each class [2,3]. OSL takes a

[1] The implementation is available at https://github.com/carlosnatalino/osa-networks-one-shot-learning.

different approach than CNNs, as illustrated in Fig. 1(b). Instead of learning to extract features and their relation to each class, the model learns a similarity function. The training dataset contains several pairs of constellation diagrams, labelled as instances of the same (defined by a similarity score of 1) or different modulation formats (defined by a similarity value of 0). During training, the CNN parameters are iteratively tuned to match the output to the true similarity value of an input constellation pair. At the inference phase, while a CNN receives one example and generates the probability it belongs to each class, the OSL model receives a pair of examples and computes the similarity score between them. Given that one of the examples is of a known modulation format, the OSL output similarity score indicates whether the unknown input is of the same or a different format. The OSL approach for MFI is illustrated in Fig. 1(c), where only one constellation diagram example of each, even newly introduced, modulation format is needed *a priori* for classification.

3. Results

The simulation setup illustrated in Fig. 2(a) was used to obtain 100 constellation diagrams with 2,000 symbols per diagram. Five modulation formats were analyzed: quadrature phase-shift keying (QPSK), square-shaped 16 and 64QAM (Sq-16/64QAM) as well as circular-shaped 16 and 64 QAM (C-16/64QAM). For each format, we considered two optical signal-to-noise ratio (OSNR) levels: high (45 dB), and low (tailored to each format) emulating noise-impaired system conditions. A dataset with 10 classes total was thus generated, ensuring that the proposed scheme performs accurately for ideal and impaired constellations.

The training dataset was composed of 50 examples of each QPSK and square-shaped 16QAM constellation diagrams, while 64QAM and circular-shaped 16 and 64QAM were used to evaluate the performance of the model for newly introduced modulation formats. Fig. 2(b) shows the training loss and accuracy, where the model takes about 40 iterations (epochs) to converge, achieving 100% accuracy. The test results are shown in Fig. 2(c) for a test dataset composed of 100 samples per class. OSL and nearest neighbor (NN) are provided with one constellation diagram example of each modulation format. Besides achieving 100% accuracy for the formats used during training (denoted with red font color), the OSL model is able to identify the 3 newly introduced formats with the same level of accuracy. The nearest neighbor (NN) algorithm, which guesses the modulation format based on the Euclidean distance between the unknown constellation diagram and the provided examples, performs much worse and for several formats obtains accuracy below 25%, similar to random guessing (Rnd).

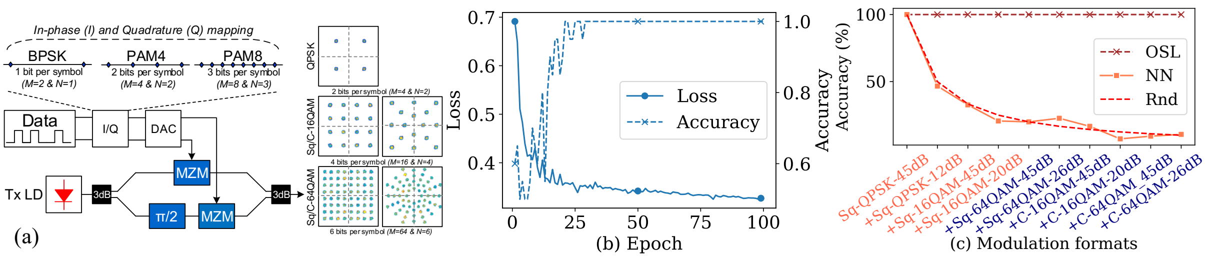

Fig. 2: (a) mQAM modulation format implementation, with transmitter configuration and the modulation alphabet for in-phase (I) and quadrature (Q) components consisting of $M = 2^N$ symbols of N bits each: laser diode (LD), Mach-Zehnder modulator (MZM), digital-to-analog converter (DAC), pulse amplitude modulation (PAM), binary phase-shift keying (BPSK); (b) binary cross-entropy loss and classification accuracy of training; and (c) accuracy over the cumulative modulation formats for one-shot learning (OSL), nearest neighbor (NN) and random (Rnd).

4. Conclusions

We proposed a one-shot learning (OSL) model for efficient modulation format identification (MFI) in evolving optical networks. The model enables immediate and seamless identification of newly introduced modulation formats based on a single constellation diagram example, without the need for costly data gathering or complex model re-engineering and re-training. The proposed model can find beneficial applications in other optical networking common classification tasks, such as bit rate recognition or fault identification.

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