Workshop on Machine Learning for Optical Communication Systems: a summary

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Abstract: A summary and overview of a public workshop on machine learning for optical Communication systems held on August 2nd 2019, by the Communications Technology Laboratory at the National Institute of Standards and Technology in Boulder, CO.

1. Introduction

Expected increased demand and functionality on optical networks to address higher speeds, lower latency, and higher reliability poses opportunities for improvement from both hardware and software infrastructure. However, the complexity and analog nature of the optical network poses challenges for software control. As these demands increase along with the implementation of smarter components and subsystem the use of artificial intelligence (AI) and machine learning (ML) to improve network function and automation makes increasing sense. Over recent years many use case scenarios have been introduced for ML and AI in optical communication systems; however, to date agreement on implementing ML on a larger scale across the industry and for specific applications is still lacking and debated. Many factors both technical and non-technical play a role in the implementation of ML in optical communication systems (MLOCS).

In an effort to expand discussion on the topic of machine learning (ML) and artificial intelligence (AI) in optical communication systems a public workshop was organized and held at the Boulder campus of the National Institute of Standards and Technology (NIST) by the Communications Technology Laboratory (CTL). On August 2nd 2019, members of industry, academia and government convened to participate in talks, panel discussions and breakout session discussions addressing various subtopics of ML in optical communication systems. The workshop was designed to provide opportunities for attendee participation where scheduled talks transitioned to panel discussions followed by an afternoon session of open breakout discussions on specific subtopics. The workshop attempted to address a range of topics related to AI/ML in the context of optical communication systems. These included general approaches of ML and application to optical transport systems, possible training scenarios, types of data, and use cases. For a more a detailed summary of the workshop outcomes we refer the reader to the workshop White Paper [1] and workshop website at [2].

2. Talk Summary

Workshop talk topics spanned general ML approaches such as linear regression and neural networks as well as training scenarios. The topic of data for use in ML algorithms was also broached in the context of what data is important and the limiting cases of an abundance of data as well as too small of data sets. Several use cases were discussed ranging in domain from the device level to the end-to-end network.

The vast amounts of data generated by optical network management and control shows much promise as a mechanism to make use of AI/ML for the purpose of improving the optical network in several ways from management to improved transmission. In particular quality of transmission (QoT) estimation and failure management became a focus of discussions at the workshop [3],[4]. ML was discussed as a means of improving fault identification and traffic management within the network layer and the function of components in the physical layer. Control of amplifiers, mitigation of system nonlinearities, modulation format adaptation and QoT estimation could be addressed with ML. As in most ML approaches these use cases require training data sets, a topic of which was discussed at length during the workshop and deemed a topic requiring ongoing discussion.

Many models were discussed including those for individual devices, network behavior, physical layer impairments, and traffic prediction. Models based either on analytical methods, numerical methods and live monitoring all were considered. Each with advantages and disadvantages, with a tradeoff of accuracy, speed and reliability (e.g. an analytical model may be faster but not as accurate as a complex numerical model, etc.). The use case of nonlinear impairment compensation was a focus of discussion as it is difficult to compute analytically and is a critical factor in many networks, and thus is a scenario wherein ML may prove useful.

Considering the vast amount of data that could be acquired from optical networks the question arises as to "what data matters?". This is an ongoing question [5],[6],[7],[8] and is use case dependent. Non-linearities in the physical layer poses some of the more challenging scenarios for ML with use cases ranging from nonlinearity mitigation, optical performance monitoring and modulation format recognition. Waveforms show promise as input data sets across use cases whereas on the output what data is useful depends on the use case under consideration. Standardization of waveforms could possibly provide a means for determining the effectiveness of ML algorithms and approaches.

One consideration discussed during the workshop was the data starved scenario, wherein there is a limited set of data available for training. Although the amounts of data could potentially be vast, constraints on data availability whether due to technical or non-technical reasons often severely limit the size of training sets. For example, network operators often cannot share data due to customer privacy considerations. This situation suggests that understanding the case where there is possibly too little data as a result of use case dependent data accessibility is also important. The use of ML and AI spans across many disciplines, where lessons learned, and approaches appear unique to one discipline may in fact inform new approaches and open doors in another. On this topic, work was presented at the workshop on the use of data sets that are "too small" in the context of deep learning for application to computer vision when limited annotated data are available. In particular, two common approaches widely used were discussed: 1) data augmentation and 2) transfer learning. The use of label preserving transformations for data augmentation is an efficient process for expanding a data set that is too small. Furthermore, it also allows one to specify what invariance should be present in the trained model. In the practice of model definition, transfer learning could be used to further refine a model that was first trained on large data sets then refined further on smaller sets of domain or application data.

3. Breakout Session Discussion

Three subtopics were addressed during breakout sessions. As there is a multitude of possible subtopics possible these were judiciously chosen in particular because they provided coverage of several main areas relevant to ML in optical communication systems and overarching architectures. Furthermore, these subtopics contain use cases that range in complexity from individual devices such as coherent transponders, to core networks, to multi-layer networking. More specifically, breakout session topics examined data set curation and applications related to:

- Reconfigurable optical add drop multiplexers (ROADM) and optical line system layer
- Coherent transponders
- Cross Layer End-to-end networking

With these three subtopics the optical line systems (OLS), including the ROADM nodes, fibers and amplifiers were considered as well as transponders and networking. Potential focus areas related to OLS wherein ML could make an impact were quality of transmission (QoT) estimation, fault identification, and failure prediction. QoT estimation was identified as the most promising for obtaining data sets that would provide widespread use across the community. Three network use cases wherein ML applied to the OLS could be an enabler were disaggregation, network defragmentation, and faster dynamic operation. All three of these use cases entail a more "dynamic" network either through the network accommodating variability due to changes and variations in hardware (disaggregation) or through the requirement of more dynamic control (faster add/drop and switching of optical signals). Optical parameters generated by coherent modems were discussed as a potential source of data that may prove difficult to obtain in real time otherwise. Data available from coherent modems was explored in the context of both directly measured as well as computed parameters and the possible applications of such data. In particular, applications range from predictive assessment of network health, fiber health, network performance estimation, to remote assessment of fiber integrity. The complexity of the network as a whole poses challenges to cross-domain core/metro/cloud/access and cross-layer IP/Optical performance and coordination. ML could play an important role in assessing performance based on metrics from such cross-domain/layer interactions. For example, using ML for error correlation, probability, and prediction and impact of errors based on such interactions between domains and layers. Executing ML in such a scenario also highlights the needs for more extensive training data sets.

3. References

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