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Abstract *We apply an explainable artificial intelligence framework to interpret quality of transmission predictions produced by a machine learning model. The framework identifies the combinations of features' values relevant to drive the prediction process. ©2022 The Author(s)*

Introduction

Artificial Intelligence (AI) and Machine Learning (ML) are key tools for network operators to achieve zero-touch network management. In optical networks, these tools are being increasingly adopted to tackle a wide range of tasks, including automated fault management and lightpath Quality of Transmission (QoT) estimation[1],[2]. However, the majority of these applications rely on complex ML models, such as ensemble and deep learning models, due to the desired powerful prediction capabilities they possess in contrast to simpler learning methods such as decision trees and linear regression. The drawback of complex ML models is the lack of interpretability[3]. In other words, these models do not expose their internal mechanics nor the decisional processes adopted to associate outputs with the set of feature values provided as input. This hinders model understanding and prevents practitioners from fully interpreting their behavior, and hence, from achieving a reliable zero-touch network management.

To mitigate this shortcoming, eXplainable Artificial Intelligence (XAI) frameworks can be adopted to explain the decision making process, with the final goal of improving the interpretation of the models and enhancing trust in ML-based systems[4],[5]. Specifically, XAI frameworks provide explanations describing the model's behavior, i.e., how the model correlates inputs features to its decisions, based on features' values and their interactions, thus allowing practitioners to debug the model's reasoning[6]. Such explanations also allow extracting useful insights that could be leveraged to better understand the nature of the problem at hand and, in some cases, to reverse-teach domain experts, especially when ML models reveal previously unknown correlations between input features and outputs.

In this paper, we focus on the problem of ML-assisted lightpath QoT estimation and we exploit an XAI framework to explain the ML model's reasoning. We formalize the QoT estimation task as a regression problem, which consists on predicting the value of the Bit Error Rate (BER) associated with the transmission along a perspective lightpath. Additionally, each BER value is associated with a binary class label that indicates whether the BER of the lightpath is above or below the system's acceptability threshold T.

In our previous work[7], we made a first attempt to demonstrate the benefits of applying XAI in optical networking by framing the QoT estimation problem as a classification task. In this work, we take a step forward, by developing supervised ML regression models leveraging eXtreme Gradient Boosting (XGB) to estimate the lightpaths' BER. Then, we use a XAI framework named SHapley Additive exPlanations (SHAP)[6] to explain the decision process of the developed regressors. Our study aims at 1) identifying the main features that drive the decision process; and 2) quantifying to what extent each of the features, on the basis of its value and interactions with the other features, impacts the estimation of the lightpath's BER. Results show that a number of simple classification rules can be extracted from the observation of the models' explanations, which could be leveraged by network operators for future deployments. While the specific outcomes extracted from the application of XAI to BER estimation depend on the model developed and hence, on the characteristics of the dataset used to train it, we argue that our application of XAI opens a new direction in the understanding of automated lightpath QoT problem, which can be generalized to

Tab. 1: Characteristics of the two considered datasets

	Dataset DSA					Dataset DSB									
	Class 0		Class 1			Class 0				Class 1					
	Mod Order		Mod Order			Mod order				Mod order					
	32-QAM	64-QAM	16-QAM	32-QAM	64-QAM	8-QAM	16-QAM	32-QAM	64-QAM	BPSK	QPSK	8-QAM	16-QAM	32-QAM	64-QAM
Nr. Samples	97860	273910	66538	475231	407913	45207	26189	27192	3749	580054	335894	278540	45798	10027	5670
Num Spans	12-20	6-12	12-21	6-14	2-7	48-76	24-39	12-21	6-12	1-105	1-106	1-56	1-28	1-14	1-7
Path Len (km)	668-1313	324-709	668-1382	324-903	84-490	3466-5359	1679-2639	747-1359	365-719	24-7797	24-7797	24-4109	24-2080	24-1070	24-554
Freq (max)	195.7					195.7			194.7	195.7				194.7	193.2

other datasets and network scenarios.

Datasets Description

We used two datasets from the QoT dataset collection made publicly available to the research community[8]. Both datasets comprise an in-depth description of every active lightpath of an emulated optical network with WDM grid and dynamic traffic allocated with First Fit (FF) policy. Each dataset $X \in R^{D \times N}$ includes D samples with N scalar features describing the lightpath and the status of all links the lightpath passes through. The input set of features to the regression algorithm in both datasets includes $N = 35$ different features, among those: lightpath modulation format (*Mod Order*), carrier frequency (*Freq*), length in km (*Path Len*) and number of hops (*Num Hops*) of the path over which the lightpath is provisioned. Each sample is associated with a BER value. Dataset DSA (DSB) consists of around 1.3 (1.4) million samples, with 28% (8%) of them representing lightpaths with BER above T ($T = 0.0038$). For DSA (DSB), 3 (5) modulation formats are used to provision lightpaths. However, in DSA (DSB) no samples for lightpaths with BER above T (indicated by class 0) use 16-QAM (BPSK and QPSK). Indeed, transmission parameters characterizing each sample is not random but reflect the criteria adopted by the network operator. Tab. 1 summarizes the main characteristics of the two datasets (see Ref.[8] for a complete description). The breakdown of the ranges of *Num Spans* and *Path Len*, as well as the maximum *Freq*, per modulation format and lightpath class, is shown in Tab. 1.

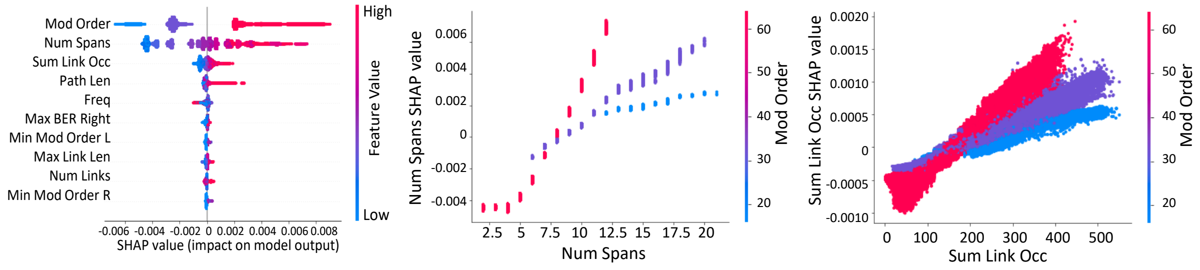
Results and Discussion

ML and XAI Models: We rely on XGB as ML regression model for BER estimation. The SHAP XAI framework is a model-agnostic framework that explains the output of ML models by estimating each feature's contribution (Shapley value, or SHAP value) on the model's output. To this aim, SHAP compares the model's output *without using* vs *when using* the considered feature, while iterating through all permutations of input features. Note that, for the regression problem at hand, the SHAP value of a feature (which can be either positive or negative) indicates how much a feature contributed to model's prediction, by either increasing or decreasing the predicted BER value. The XGB models trained and tested for DSA (DSB)[1] show a regression mean squared error of $2.7 \cdot 10^{-08}$ ($1.05 \cdot 10^{-08}$). Then, we classified each data sample based on estimated BER, i.e., whether it exceeds T, and classification accuracy is 99.3% (99.4%) for DSA (DSB).

Features' Contribution to BER: Focusing first on DSA, in Fig. 1(a) we show *SHAP summary plots*, which correlate features' impact (SHAP value) with features' value and model's prediction. The y-axis lists features in descending order of importance. Each point on the plot represents a given feature and a given data point and is associated to a color that quantifies the feature's value in a low-to-high scale. The plot shows that predictions are mainly driven by *Mod Order* and *Num Spans*, which exhibit a significantly larger ranges of SHAP values than all the other features. Specifically, high values of *Mod Order* and *Num Spans* (red points) increase the BER prediction by up to 0.01 and 0.007, respectively, while low-medium values (blue points) of *Mod Order* and *Num Spans*, decrease the prediction by up to -0.006 and -0.004, respectively.

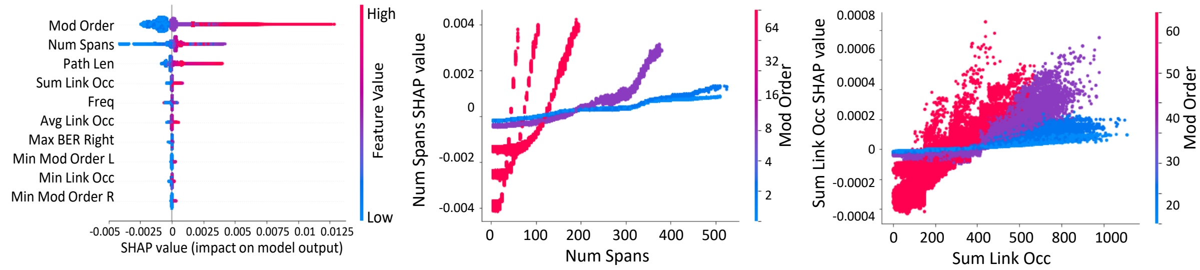
Outcome 1: Since the range of SHAP values of other features is relatively smaller with respect to that of *Mod Order* and *Num Spans*, we can conclude that the estimation of BER for a lightpath with a high *Mod Order* can only be lower than T if characterized by a low *Num Spans*. Similarly, the estimation of BER for a lightpath with a high *Num Spans*, in many cases, can only be lower than T if a low-order modulation format is assigned to the lightpath. To analyze this aspect in more detail, we report in Fig. 1(b) and (c) two *SHAP dependency* plots, which show the SHAP value for *Num Spans* with respect to *Num Spans* feature values (x-axis) and values of *Mod Order* (color scale), and the SHAP value for *Sum Link Occ* with respect to *Sum Link Occ* feature values (x-axis) and values of *Mod Order* (color scale), respectively.

[1]The hyperparameters of the models are: learning rate = 0.2 and maximum depth of tree = 9, while subsample is 0.9 and 0.7 for models of DSA and DSB, respectively.



(a) (b) (c)

Fig. 1: Summary plot and dependence plots for dataset DSA



(a) (b) (c)

Fig. 2: Summary plot and dependence plots for dataset DSB

From Fig. 1(b) the impact of *Num Spans* raises (and hence, the estimated BER increases) as *Num Spans* grows, with different patterns, based on value of *Mod Order*. With high modulation order (red-colored points), medium values of *Num Spans* (around 10) show a high impact on the estimated BER (up to 0.006). On the contrary, with low modulation order (blue-colored points), increasing *Num Spans* increments the estimated BER only mildly.

Regarding *Sum Link Occ* in Fig. 1(c), it increases the estimated BER for increasing values, but its impact is larger with high-order modulation formats than with low-order modulation formats.

Outcome 2: When correlated with high modulation order, high values of *Sum Link Occ* play a significant role in raising the BER estimation, increasing it by up to 0.002. In particular, the impact of *Sum Link Occ* on the BER of lightpaths using 64-QAM is on average 4 times higher than on the BER of lightpaths using 16-QAM. These results hint that wavelength assignment policies tailored per modulation format would be more effective than FF in ensuring acceptable lightpath deployments, e.g., by privileging lightly loaded links to allocate lightpaths with high-order modulation formats. Moreover, useful bounds could be derived to guide the operator in the choice of transmission parameters: for example, when using 16-QAM (associated to a SHAP value ≤ -0.004), the lightpath can be routed on highly-loaded links with an arbitrary number of spans, since the maximum increase to the BER will be around 0.003 (for *Num Spans*, see Fig. 1(b)) plus 0.0006 (for *Sum Link Occ*, see Fig. 1(c)), which ensures that the BER will be lower than T even if the lightpath length is extremely high (as the maximum BER increase given by *Path Len* is 0.003, see Fig. 1(a)).

We now briefly discuss the same set of explanations for the model trained on DSB, which is generated considering a much larger network topology than DSA. Fig. 2(a) is SHAP's *summary plot*, which shows that, similarly to the case of DSA, *Mod Order*, *Num Spans*, *Path Len* and *Sum Link Occ* are the features most impacting the model's prediction, while the rest of features barely having an impact. However, differently from the of DSA, *Mod Order* has a much larger impact than *Num Spans*. In some cases of high *Mod Order* (red-colored points), *Mod Order* contributes by 0.0125 to the BER estimation, while low value of *Num Spans*, in the best cases, decreases model's estimation of BER by 0.004. In Fig. 2(b), it is shown that when 32-QAM (respectively 64-QAM) is used, *Num estimation*, giving a negative a contribution for values below 25 (respectively below 10) and a positive contribution otherwise.

Outcome 3: In a large-sized network topology, the BER estimation provided by the model is largely reliant on lightpath's modulation order, disregarding information provided by most of the rest of the features. As far as *Sum Link Occ* (Fig. 2(c)) is concerned, explanations confirm the same outcomes obtained for the model trained on DSA (see *Outcome 2*).

References

[1] R. Gu, Z. Yang, and Y. Ji, “Machine learning for intelligent optical networks: A comprehensive survey”, *Journal of Network and Computer Applications*, vol. 157, p. 102 576, 2020.

[2] Y. Pointurier, “Machine learning techniques for quality of transmission estimation in optical networks”, *Journal of Optical Communications and Networking*, vol. 13, no. 4, B60–B71, 2021.

[3] S. Chakraborty, R. Tomsett, R. Raghavendra, *et al.*, “Interpretability of deep learning models: A survey of results”, in *2017 IEEE smartworld, ubiquitous intelligence & computing, advanced & trusted computed, scalable computing & communications, cloud & big data computing, Internet of people and smart city innovation (smartworld/SCALCOM/UIC/ATC/CBDcom/IOP/SCI)*, IEEE, 2017, pp. 1–6.

[4] A. Adadi and M. Berrada, “Peeking inside the black-box: A survey on explainable artificial intelligence (xai)”, *IEEE access*, vol. 6, pp. 52 138–52 160, 2018.

[5] M. T. Ribeiro, S. Singh, and C. Guestrin, “” why should i trust you?” explaining the predictions of any classifier”, in *Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining*, 2016, pp. 1135–1144.

[6] S. M. Lundberg and S.-I. Lee, “A unified approach to interpreting model predictions”, *Advances in neural information processing systems*, vol. 30, 2017.

[7] O. Ayoub, A. Bianco, D. Andreoletti, S. Troia, S. Giordano, and C. Rottondi, “On the application of explainable artificial intelligence to lightpath qot estimation”, in *2022 Optical Fiber Communications Conference and Exhibition (OFC)*, 2022, pp. 1–3.

[8] G. Bergk, B. Shariati, P. Safari, and J. K. Fischer, “Ml-assisted qot estimation: A dataset collection and data visualization for dataset quality evaluation”, *Journal of Optical Communications and Networking*, vol. 14, no. 3, pp. 43–55, 2022.