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Quantifying Features’ Contribution for ML-based Quality-of-Transmission Estimation using Explainable AI

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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. 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. 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. 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. 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, 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) 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
other datasets and network scenarios.

Datasets Description
We used two datasets from the QoT dataset collection made publicly available to the research community. 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. 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) 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. 1a) 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. 1b) 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.

1The 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.
From Fig. 1b 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. 1c, 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 $\leq -0.004$), 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. 1b) plus 0.0006 (for Sum Link Occ, see Fig. 1c), 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. 1a).

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. 2a 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. 2b, 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. 2c) is concerned, explanations confirm the same outcomes obtained for the model trained on DSA (see Outcome 2).
References


