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Machine Learning Regression vs. Classification for QoT Estimation of Unestablished Lightpaths

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Abstract: We investigate a Machine Learning regression model for Optical Signal-to-Noise Ratio (OSNR) distribution estimation of unestablished lightpaths. The regressor exposes the estimation uncertainty and how close to a threshold each lightpath resides.

1. Introduction to Machine Learning for QoT estimation

Recent advances in coherent optical transmission allow to adjust huge number of adjustable and interdependent transmission parameters (e.g., routing configurations, modulation format, symbol rate, coding schemes, etc.), thus significantly increasing the alternative scenarios for lightpath deployment. To ensure effective and optimized design and planning of optical networks, accurate prediction of lightpath quality-of-transmission (QoT) prior to deployment is imperative. QoT estimation is currently performed either through exact analytical models (e.g., Split Step Fourier Transform), which provide accurate results but are computationally-heavy, or by using margined formulas (e.g., the GN-model [1]), which are computationally-fast, but introduce link margins leading to compensate inaccurate knowledge of some system parameters, eventually leading to under-utilization of spectral resources. Machine learning (ML) has been proposed as an alternative tool for QoT estimation that overcome these drawbacks by exploiting the historical field measurement from already deployed lightpaths to predict the QoT of unestablished lightpaths. Recently, ML has been investigated as solution for optimization of resource allocation and for QoT prediction in optical networks [2, 3]. In [4], we developed a ML classifier that predicts whether the bit-error-rate (BER) meets the required system threshold. More recent works explore the use of Recurrent Neural Networks for QoT estimation [5] and how ML-based estimators perform depending on different features selections [6]. More in general, several existing works have tackled the ML-based QoT estimation as a classification problem that verifies if a certain lightpath configuration is feasible or not. In this paper, we investigate a ML-based QoT estimation approach based on regression, and we discuss pro's and con's of using a regressor instead of a classifier. The proposed regressor estimates the probability distribution of received Optical Signal-to-Noise Ratio (OSNR), and exposes the uncertainty of the estimation and how close to a threshold each lightpath configuration resides. We show that this regressor allows to make a more informed decision, with respect to classification, about how conservative or aggressive an operator can be when taking network planning choices (i.e, when depolying a new ligthpath).

2. Regression models for estimating OSNR distributions

Most existing work on QoT estimation considers a classification problem: given the features of a lightpath, one predicts whether the OSNR is below or above a pre-defined threshold. Once trained, the resulting classifier returns a numerical score (i.e. the estimated probability that the OSNR is above the pre-defined threshold); and a binary output is obtained by comparing such score with a cutoff probability (P_{cutoff}). By varying P_{cutoff}, one can tune how conservative or aggressive the model should be. A classification-based approach has three main drawbacks: a) it

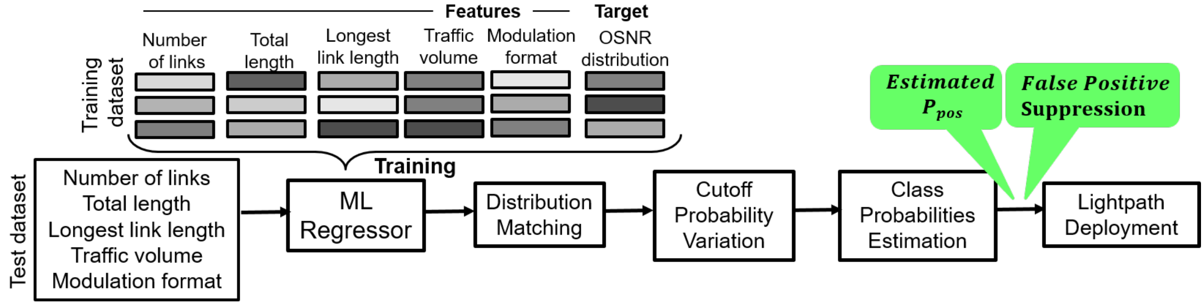

Fig. 1: Main building blocks of the proposed ML-based system

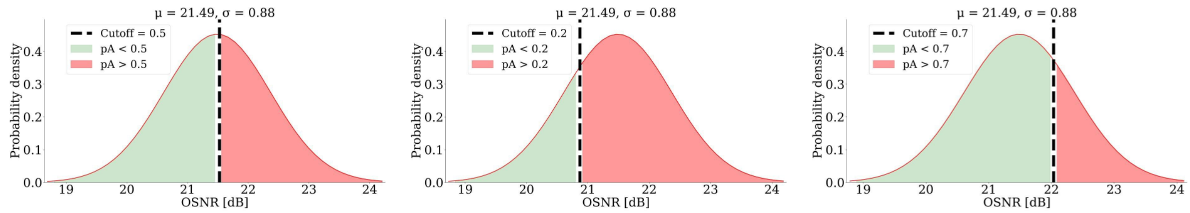

Fig. 2: OSNR distribution and percentile area *(pA)* considering P_{cutoff} equal to 0.5, 0.2 and 0.7

does not convey how close to the threshold the predicted OSNR is; b) it does not return the predicted distribution of the OSNR value; c) during training, no distinction is made between a training sample with an OSNR slightly above threshold, and a training sample that is way above, which leads to a loss of information.

The proposed *regression*-based approach addresses these three issues. Given the unestablished ligthpath' features (traffic volume; modulation format; total length; length of longest link; number of links traversed) a Random Forest regressor returns the mean and variance of a Gaussian distribution representing the OSNR value. Fig. 1 shows the main building blocks of our proposed ML-based system. The *ML regressor* estimates the OSNR distribution of each lightpath which is then matched to a Gaussian distribution (*Distribution Matching*). To each extracted probability distribution, a cutoff probability (P_{cutoff}) is applied to separate the area under the curve (*Cutoff Probability Variation*). To obtain P_{pos}, the percentile area (*pA*) under the curve corresponding to the target OSNR is calculated. If the calculated percentile area (*pA*) is below P_{cutoff}, the lightpath is assigned to the *True* class or to *False* class otherwise (*Class Probability Estimation*). Note that, in this way, the regressor can perform a "distribution-aware" classification considering a variable P_{cutoff}. P_{cutoff} defines the decision boundary to differentiate between *True* and *False* classes. By estimating the OSNR distribution, the regressor is capable of adjusting P_{cutoff} and thus allows a network operator to consider a *conservative* P_{cutoff} (below 0.5), i.e., operate far from threshold, or an *aggressive* P_{cutoff}, i.e., operate near the threshold.

3. Illustrative numerical results

We use of the E-tool in [4] to generate synthetic OSNR data due to unavailability of field data. The E-Tool receives a candidate lightpath and modulation format as the input and estimates distribution of the OSNR. We consider uncompensated transmission over standard single-mode fibers (SSMF) with attenuation coefficient of 0.2 dB/km and that signal power attenuation is restored by identical optical amplifiers with gain G = 20dB and noise figure F = 5dB, equally spaced every 100 km. Optical channels are multiplexed in a flexible grid with standard slice width of 12.5 GHz and elastic transceivers operating at 28 Gbaud with optical bandwidth of 37.5 GHz (i.e., 3 slices). We consider a 14Node-Japan topology [4] and, for generation of training and testing data sets, we consider 25 scenarios (source-destination pairs). For each scenario, the 3 shortest paths are pre-calculated and 6 modulation formats are considered resulting to 450 settings, i.e., one for each scenario, route and modulation format. Each lightpath configuration is generated 100 times (resulting in 45000 data points), each time with an additional exponentially-distributed random margin that emulates fast time-varying physical impairments. In Fig. 2 we show the case when classification is performed considering a default $P_{\text{cutoff}} = 0.5$ (as done by the classifier) compared to the *conservative* and *aggressive* approaches with P_{cutoff} equal to 0.2 and 0.7, respectively. In Tab. 1, we report the confusion matrix for each case and we note that considering a *conservative* approach, we are able to reduce the number of false positives (*FP*) while, when considering an *aggressive* approach, we increase the number of false positives (*FP*) and true positives (*TP*). Note that *FPs* in QoT estimation are highly undesirable, as they could mislead operators to deploy unfeasible lightpath configurations. Moreover, note that the regressor performance is close to optimal with root mean squared error (RMSE) and R2 scores of 0.21 and 0.99. In conclusion, using a regressor for QoT estimation, we enable higher estimation flexibility thanks to the opportunity of setting a variable P_{cutoff}, which allows to operate in an *conservative* regime and suppress the number of *FPs* or in an *aggressive* regime and accept a surge in the number of *FPs*.

Table 1: Confusion matrix for varying P_{cutoff}

P_{cutoff}	TP	FP	FN	TN
0.5	148	2	8	124
0.2	131	0	25	126
0.7	154	9	2	117

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