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Deep Learning Regression vs. Classification for QoT Estimation in SMF and FMF Links

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***Abstract*—We investigate deep learning-based regression and classification for quality of transmission estimation in single-mode and few-mode fiber links. Results show efficiency and low complexity in both methods, however, regression performs better and classification is faster.**

***Index Terms*—Deep learning, single mode fiber, few-mode fiber, quality of transmission estimation.**

I. Introduction

Single-mode fiber (SMF) communication systems are coming close to the capacity crunch due to nonlinear effects. During the last decade, few-mode fiber (FMF) has been proposed as an alternative solution to further increase optical transmission capacity and they have attracted more and more attentions [1].

Precise and fast quality of transmission (QoT) estimation before deployment is important for ensuring the effective and real-time planning of both SMF and FMF networks. Thus, accurate QoT estimation is necessary for decreasing the provisioning margins. In this context, QoT is effectively evaluated by the generalized signal-to-noise ratio (GSNR), which comprises the amplified spontaneous emission (ASE) noise and accumulated effect of nonlinear interference (NLI) noise. The NLI can be estimated by either exact analytical models (e.g., enhanced Gaussian noise (EGN) model [2], [3]) which are accurate but computationally complex, or asymptotic analytical models (e.g., closed-form (CF)-EGN model [4], [5]) which are approximate and computationally light.

Machine learning (ML) is an alternative data-driven QoT estimation approach that has already been proven as an effective tool in different contexts of optical networks. ML-based QoT estimation models can be employed in regression and classification tasks. The regressor-based QoT estimator provides a continuous output and can describe how close or far is the output from the predefined threshold. The classifier-based QoT estimator returns binary output values and it does not care whether the output value is slightly or far above the predefined threshold.

Different ML approaches are presented in [6] for predicting continues GSNR values considering a full-load SMF link. ML is deployed in [7] for classification based on the labels obtained by comparing the bit error rate (BER) with a threshold. It is shown in [8] that artificial neural network is a better QoT estimator than regular ML methods. Deep learning (DL) based on deep neural network (DNN) is suitable for QoT estimation as it is able to learn highly nonlinear input-output relationships [9]. Authors of [10] employed DNN for regression-based GSNR estimation in a full-load SMF link.

In this paper, we develop DL-based regressor and classifier models to predict whether the BER meets the required threshold in SMF and FMF links. We utilize EGN model [2], [3] to generate synthetic datasets considering partial-load for both SMF and FMF links. Performance-complexity comparison of the regressor, classifier, and CF-EGN [4], [5] show accuracy and low complexity of proposed methods, with a little better performs of regressor and higher speed in classifier. In any case both approaches are appropriate for real-time QoT estimation applications such as in autonomous network control and planning.

II. Dataset generation and proposed QoT estimation models

While it is generally not feasible to produce large experimental dataset, DL-models require large training dataset to be applicable in QoT estimation for a variety of system and link characteristics. Thus, we utilize EGN models to generate datasets synthetically [2], [3]. We consider signal propagation in SMF and FMF (3 modes) links with 1 to 8 spans with a uniform length comprised between 80 and 120 km, and an ideal amplifier with 5 dB noise figure after each span for attenuation compensation. We deployed up to 66 channels with 1550 nm center wavelength, 64 $GBaud$ symbol rate, and 75 GHz channel spacing. We randomly employ a modulation format for each channel and mode among polarization multiplexing (PM)-BPSK, PM-QPSK and PM-M-QAM ; $M = \{8, 16, 32, 64\}$. The values for attenuation, chromatic (modal) dispersion, and nonlinear (coupling) coefficient are taken from [1].

We consider a partially-loaded link-state with 50% *randomly ON* channels, however, inclusion of the link-state in our feature space considerably increases the dimension and complexity. To avoid this, inspired from [11], we provide

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datasets on a sub-band basis rather than channel basis. We group each 6 neighboring channels into a sub-band. Therefore, we have 11 sub-bands with 7 possible levels according to their number of ON channels. We produced 60000 train and 6000 test samples for SMF and FMF datasets.

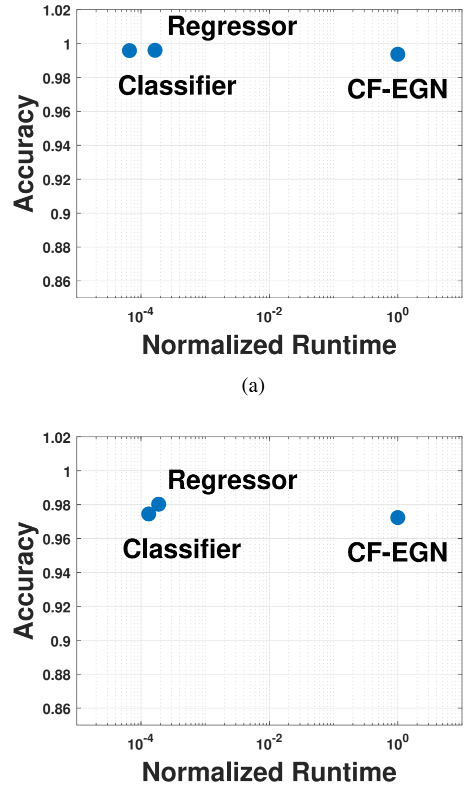
We consider some features for each link configuration. We devote the first 3 features to the indices of channel and mode under test as well as the modulation format. The span length and number of spans are added to the features due to dependency of NLI noise on them. The right and left traffic-volumes as well as the number of right and left empty frequency slots with respect to the channel under test (on the same mode) are also included as features. Likewise, the right and left modulation formats of neighbor channel are added to features. Moreover, we select each sub-band power level as feature. By considering the same features for FMF, we sum up 22 and 48 features for SMF and FMF links, respectively.

For generating the true class labels (i.e. $0, 1$) for each feature, we first calculate the GSNR value at the optimum launch power per channel and mode. We obtain the GSNR of nth channel and pth mode by $GSNR_{n,p} = P_{n,p}/(\sigma^2_{ASE} + P^3_{n,p}\eta_{NLI,n,p})$, where $P_{n,p}$, σ^2_{ASE}, and $\eta_{NLI,n,p}$ are respectively the launched power, ASE noise variance, and the NLI noise variance (EGN model output [2], [3]) of nth channel and pth mode. Then we calculate the BER based on GSNR depending on the modulation format [12]. For defining the class labels, we compare the obtained BER with a predefined threshold BER. We choose 10^{-3} threshold BER according to the selected forward-error code with 28% overhead.

The classifier output is the class label, while the CF-EGN and regressor outputs are continuous predicted $\eta^{pred}_{NLI,n,p}$ values which should be converted to class labels as explained above. To have a fair comparison, we use the same DNN structure for regressor and classifier. The only difference is the type of last layer where we deploy *linear* in regressor and *sigmoid* in classifier. The composed DNN has N_f input neurons where N_f is number of features, one output neuron, 2 hidden layers with N_f and 1000 hidden neurons, respectively, and we train the DNN based on [13]- [16].

III. Simulation results

In this section, we provide the simulation results comparing the regressor, classifier, and CF-EGN models. Fig. 1 demonstrates the accuracy versus normalized runtime. One of the main challenges in training DL-based QoT estimation for SMF and FMF links is providing a large dataset, e.g., in our case it took 3 months consuming 200 parallel computer processing units. Despite that we did not provide such a large dataset for a wide investigation scenario considering different system and link configurations, the obtained results show the effectiveness both of regressor and classifier. Better results can be seen in SMF, as FMF nonlinear interactions are more complex to be learnt, and our generated dataset is not enough to carry all information. Deep transfer learning can help improving performance in FMF case when a huge dataset is collected once for a specific application and used as initial training



(a)

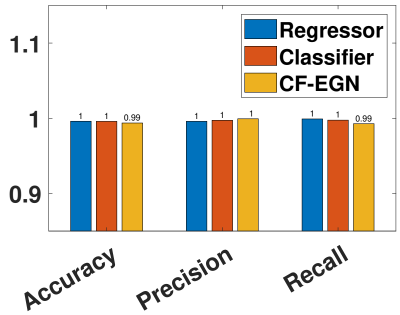
(b)

Fig. 1. Accuracy versus normalized runtime of regressor, classifier, and CF-EGN, for a) SMF and b) FMF.

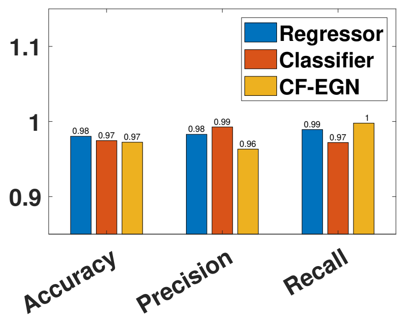
the DL-model for a different application, but we leave this case for future investigations. The binary classification task is simpler than predicting continues values, thereby, the trained classifier structure has less complexity and the classifier is almost 2 times faster than regressor. Moreover, the regressor and classifier are 4 orders of magnitudes faster than CF-EGN.

Fig. 2 plots the accuracy, precision, recall values for regressor, classifier, and CF-EGN. Quite high precision and recall values are obtained for SMF and FMF with a little better performance in SMF which show the effectiveness of proposed methods. Regressor has the same recall and precision values, while classifier has higher precision, and CF-EGN has higher recall value. This shows that classifier has precise but not compact decisions around a specific point, i.e., it is on the safe side, while CF-EGN makes compact decisions which are not precise and is not always on the safe side.

Fig. 3 plots the confusion matrix for regressor (top), classifier (center), and CF-EGN (bottom). SMF has less false decisions (false positive (FP) and false negative (FN)) than FMF which indicates better performance of proposed methods. Considering SMF, FN is more than FP in regressor, classifier, and CF-EGN which indicates that they work on the safe side. Considering FMF, in regressor and classifier FN is more than FP and vice versa for CF-EGN which shows that CF-EGN is not on the safe side.

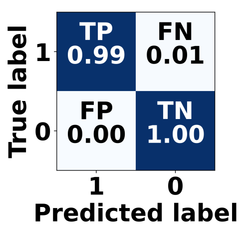


(a)

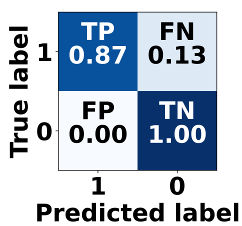


(b)

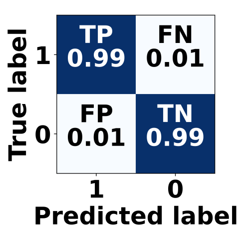
Fig. 2. Accuracy, precision, recall values of regressor, classifier, and CF-EGN, for a) SMF and b) FMF.



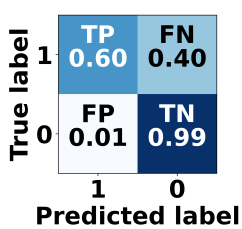
(a)



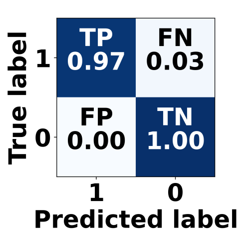
(b)



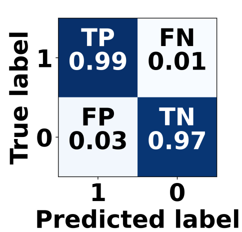
(c)



(d)



(e)



(f)

Fig. 3. Confusion matrix of regressor (top), classifier (center), and CF-EGN (bottom), for a) SMF and b) FMF.

IV. Conclusion

We developed DL-based regressor and classifier for QoT estimation in SMF and FMF links. DL-based regressor, classifier, considering wide range of SMF and FMF system and link configurations. The classifier was 2 times faster than the regressor and 10000 times faster than CF-EGN. In SMF, all methods performed the same while in FMF case, results reported safe classification only for the regressor and classifier.

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