The potential of data augmentation for failure management in optical networks

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Abstract: This paper highlights the benefits of data augmentation in enhancing the accuracy and reducing the complexity of neural networks used for failure identification in optical networks. The obtained results demonstrate significant improvement.

1. Introduction

Machine learning (ML) is being investigated in optical networks for various applications [1–4]. Failure management is one of them, where ML can process monitoring data for identification, localization, or prediction of failures. The imbalance in datasets used for training of ML models is common in failure identification, as different types of failures occur with different probabilities [5, 6]. This leads to limited ML performance, as the model struggles to learn from the imbalanced data.

This paper shows the potential of data augmentation in the context of failure identification. Data augmentation can strongly improve failure identification accuracy and reduce the complexity of the adopted ML model.

2. Data distribution and augmentation

Data augmentation can leverage a variational autoencoder (VAE) [6]. As illustrated in Fig. 1, encoder of VAE first finds the latent distributions by compressing the input data (x) and then the decoder generates synthetic data (x') based on the identified distributions. The Synthetic Samples Selector selects data within (x') that minimize the Euclidean distance from the mean of (x) of each minority class and selects required number of samples achieving class balance. The augmented dataset (x_A) is formed by the union of the original and selected synthetic data, with reduced or no class imbalance.

To evaluate the potential of the proposed data augmentation technique, we used experimental data from a testbed including a 100G commercial coherent transponder, four amplified spans of 80km, and a wavelength selective switch (WSS) placed before the second amplifier. The WSS is exploited to introduce physical layer degradation, thus generating soft failures. In normal operation, the transponder is set to transmit a signal at 192.3 THz, switched in 37.5 GHz. Then, five soft failures are generated through WSS: 1) filter tightening; 2) attenuation; 3) filter tightening plus attenuation; 4) filter tightening plus filter shift; 5) filter shift. We have collected the end-to-end bit error rate (BER) and the optical signal to noise ratio (OSNR) as input data from each scenario. The representation of each failure class within data is shown in Table. 1. It should be noted that the classes are not separable with hard thresholds on BER or OSNR. Data augmentation is then exploited to balance the different classes so that each failure class can have equal representation in this case.

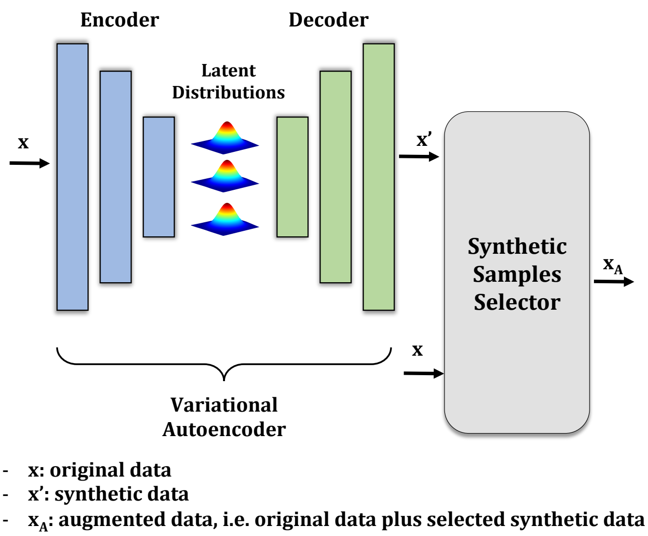

Fig. 1. Data augmentation based on VAE

Table 1. Failures distribution within original data (x)

Filter tightening + Attenuation	Filter shift	Filter tightening + Filter shift	Filter tightening	Attenuation
50%	16.7%	13.2%	11.5%	7.8%

3. Failure identification performance and conclusions

Two dense neural networks are exploited for failure identification by leveraging data from the experimental testbed described in the previous section: NN_{HC} with size $2 \times 20 \times 10 \times 5$ and the comparatively lower complexity NN_{LC} with size $2 \times 15 \times 5$. As in [6], the complexity of these NNs is quantified analytically in terms of number of bit operations. For bit-length of 16, the number of bit operations required to be performed by NN_{HC} and NN_{LC} for a given input are 84592 and 30564, respectively. Both NN_{HC} and NN_{LC} are trained with original unmodified data (UD) and augmented data (AD). Then, the performance is tested on validation and test datasets, which are not augmented. Fig. 2(a) shows the validation accuracy versus training time. First, we observe that data augmentation significantly increases the accuracy i.e., by at least 6% in this case. The same plot also shows that data augmentation can be exploited also to reduce the complexity of NN: NN_{LC} trained with augmented data achieves the similar accuracy as NN_{HC} trained with original data. Fig. 2(b) shows the F1-Score on the test set for the two NNs. F1-score increases for both NNs with augmented training data, demonstrating again a significant improvement.

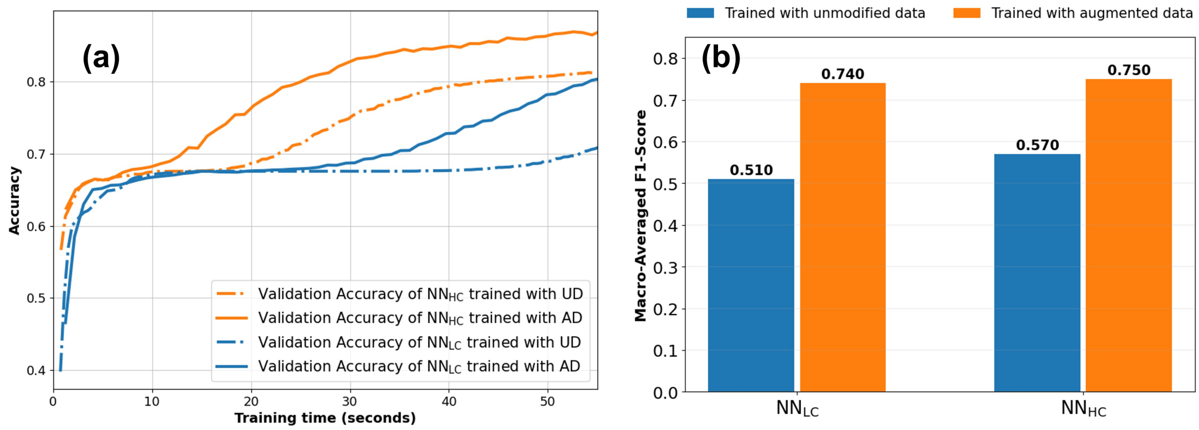

Fig. 2. (a) Accuracy on validation dataset; (b) F1 score on test dataset

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