Optical Network Alarms Classification using Unsupervised Machine Learning

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Abstract: *A deep autoencoder based approach was investigated with experimental data for alarms classification in optical networks. Differently from supervised machine learning techniques, the approach shows promising results without the need of manually labeled data.*

Keywords: *Alarms classification, Optical network failure management, Unsupervised machine learning*

I. INTRODUCTION

Effective failure management emerged to be one of the potential applications of machine learning in optical networks. Prompt failure detection and localization is crucial to avoid outages or complete service disruption in the event of a hard failure, such as a fiber cut. In [1], the authors highlighted numerous machine learning based techniques for failure detection and localization. An alarm prediction method based on cross-layer artificial intelligence was proposed in [2]. Most of the solutions in the available literature utilize supervised machine learning algorithms for optical network failure management (ONFM). As supervised learning needs labeled data, the data extracted from large optical networks may require manual labeling which is costly and time consuming [3]. Moreover, such labeling is prone to error because of the human involvement which suggests that trained machine learning models may only recognize failures identified by human experts [4].

Our work focuses on an unsupervised machine learning approach based on autoencoder technique for classification of alarms received by Network Management System (NMS). As even at the normal operation, NMS has few alarms that are not cleared by operational staff (hereinafter referred to as *uncleared alarms*), so the objective of this study is to distinguish uncleared alarms from alarms received as a result of a failure (hereinafter referred to as *failure alarms*). The obtained results suggest that such alarms classification is indeed possible with unsupervised machine learning.

II. EXPERIMENTAL SETUP AND DATA ACQUISITION

For this investigation, an experimental testbed consisting of an NMS-managed subnetwork shown in Fig.1(a) with an optical service traversing the network components shown in Fig.1(b) was considered. It consisted of four main nodes: N1, N2, N3, N5, and an in-line amplifier N4 was located between N3 and N5. The average distance between two adjacent nodes was nearly 50 km, and the fiber loss was 0.25 dB/km. All nodes were capable of communicating with NMS to update the status of their cards and raise alarms.

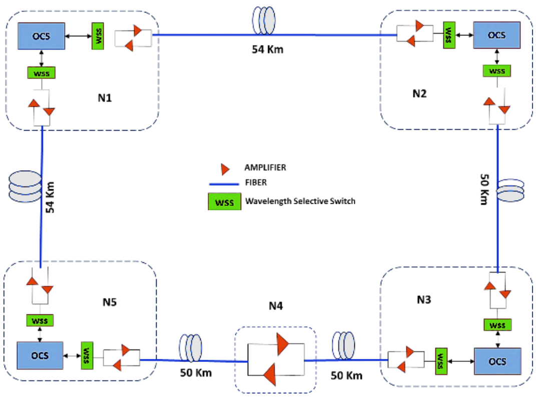

Fig. 1(a). Considered subnetwork (SN) managed by NMS

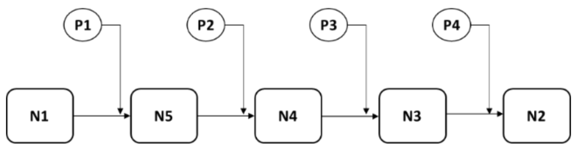

Fig. 1(b). Considered service on subnetwork

Fig. 1. Overview of Experimental Testbed Setup

This testbed was used to produce artificial failures. The data containing the resulting alarms and related performance information was extracted from NMS. A Variable Optical Attenuator (VOA) was used to induce variable attenuation to the optical signal at various positions in the network marked as P1, P2, P3 and P4 in Fig.1(b). The attenuation was changed from the lowest attainable level to the one that caused service disruption. For this study, we assumed that failure events (i.e., different levels of attenuation of an optical signal) are independent of each other and occur one at a time.

III. Data Preprocessing and Architecture of Deep Autoencoder

Most of the extracted data was based on categorical features with many unique values so to avoid curse of dimensionality, hash encoding with 64 bins was performed. As severity of alarms feature was ordinal in nature so it was label encoded. After encoding, data was normalized within [0,1] range using MinMax Scaler. No manual labeling of data was done because the objective of this study was to employ an unsupervised learning approach for alarms classification.

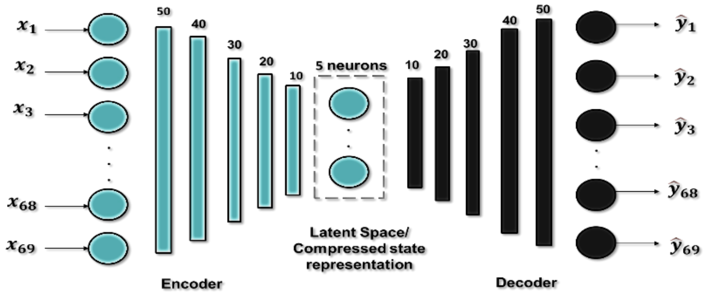

Fig. 2. Architecture of Deep Autoencoder

In our study, we used a deep autoencoder for unsupervised machine learning. A deep autoencoder is a type of deep neural network, which is mainly designed to transform inputs into outputs with the least possible amount of distortion [5]. For our investigation, the deep autoencoder trained to detect failure alarms is shown in Fig.2. On the encoder side, the sixty-nine inputs comprise sixty-four hash encoded features, position, attenuation, service, alarm severity, and impact. The number of neurons in the five hidden layers and the bottleneck layer were determined to be fifty, forty, thirty, twenty, ten, and five, respectively through trial and error analysis. On the decoder side, the number of hidden layers and their dimensions were set to have a shape that is symmetrical to the encoder since the goal was to generate original input data to the best possible extent. For the training of this autoencoder, only uncleared alarms data was used and reconstruction loss i.e., mean squared error between reconstructed input and original input was minimized during training. For testing, unique alarms raised due to an attenuation failure event were provided to autoencoder.

IV. Results

Fig.3(a) depicts a range of reconstruction loss for uncleared alarms incurred by decoder part of autoencoder. The threshold indicated by the red dashed line was chosen to be at the 85th percentile of uncleared alarms reconstruction loss. When failure alarms for 22.1 dB attenuation at position P1 were provided to the trained autoencoder, their reconstruction loss in comparison to that of uncleared alarms is shown in Fig.3(b). As it can be seen that the reconstruction loss for failure alarms exceeds the threshold so these can be distinguished from the already existing alarms in the system.

In our analysis, we considered failure as a positive class and accordingly Table.1 shows the obtained results in terms of recall (i.e., ability of a classifier to find positive observations in the dataset), precision (i.e., ability of a classifier to not misclassify a negative observation as positive) and F1-Score (i.e., harmonic mean of recall and precision). As can be seen, the recall value of 1 was achieved with this specific setting of threshold. The obtained results are also intuitive since by setting the threshold at the 85th percentile, we allow our algorithm to misclassify 15% of uncleared alarms as failure alarms, which refers to False Positive (FP) and it is inversely proportional to precision.

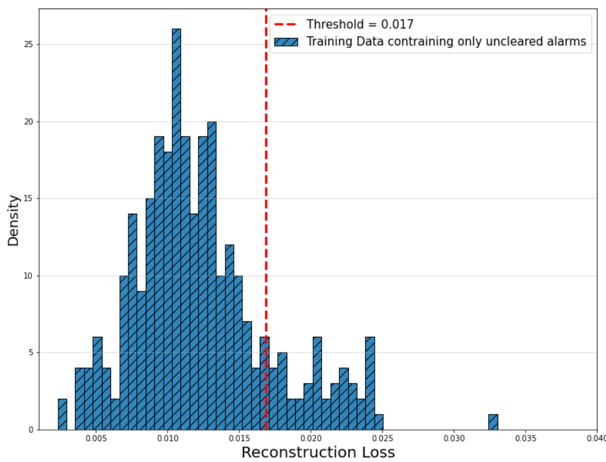

Fig. 3(a). Distribution of reconstruction loss for uncleared alarms and the threshold at 85th percentile

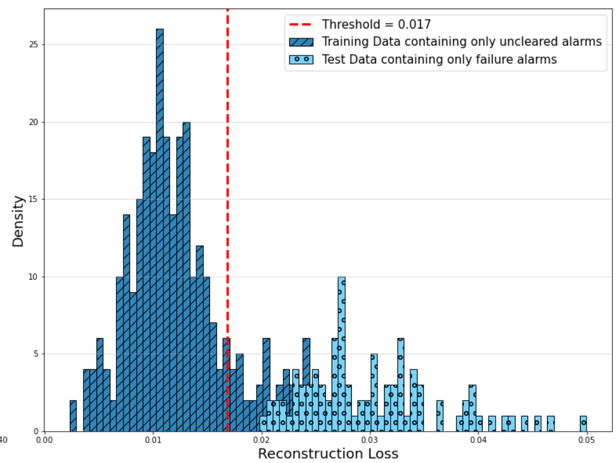

Fig. 3(b). Distribution of reconstruction loss for uncleared alarms, failure alarms and the same threshold

Fig. 3. Histogram based illustration of classification of alarms based on threshold at position P1 of considered service

However, with this threshold, we are not misclassifying any failure alarm as an uncleared alarm, therefore our False Negative (FN) is zero, resulting in a recall of 1 because FN is inversely proportional to recall.

Table. 1. Numerical Results

Metric	Recall	F1-score	Precision
Score	1.0	0.8	0.67

As a second step of this study, we evaluated the performance of our algorithm by varying the threshold. Fig.4 shows the variation of recall, precision, and F1-Scores averaged for all attenuation levels greater than 0 dB at position P1 against different thresholds selected based on n^{th} percentile criteria with n = *75, 76, ..., 100*. It can be inferred that when the threshold moves towards the 100th percentile, FP rate drops, resulting in an increase in precision. On the other hand, FN rises that reduces the recall. At the 100th percentile, FP becomes zero, resulting in a high precision value but it is at the cost of a high FN that results in a sharp decrease of recall and consequently, the F1-Score.

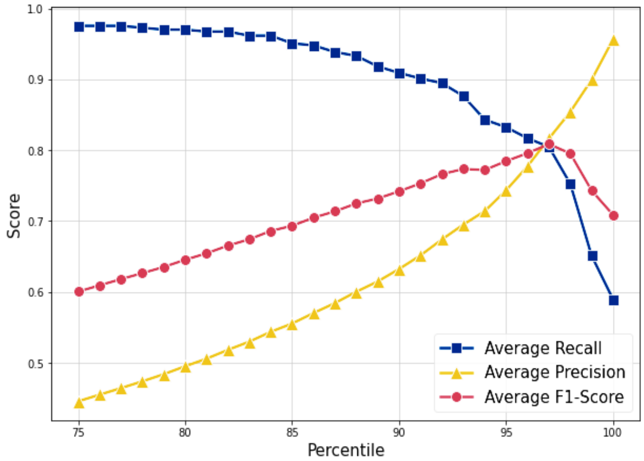

Fig.4. Average Precision, Recall and F1-Score for all failures at position P1

The observed trend in Fig.4 can be generalized for other positions as well, but it does not necessarily mean that for a same threshold value, the best trade-off between recall and precision can be achieved for all positions in a network. Hence, in this case, our findings suggest that we cannot achieve optimum performance throughout the network with a fixed threshold.

V. Conclusions

We investigated a deep autoencoder based unsupervised machine learning approach for optical network alarms classification. The goal was to overcome the fundamental limitation of supervised learning based approaches, i.e., performance dependence on manually labeled data. The obtained results suggest that up to 100% failure alarms can be identified, albeit at the expense of low precision, dependently on the threshold selection. We intend to address the identification of "optimal" thresholds in future research.

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References

[1] F. Musumeci, C. Rottondi, A. Nag, I. Macaluso, D. Zibar, M. Ruffini and M. Tornatore, "An overview on application of machine learning techniques in optical networks," IEEE Communications Surveys & Tutorials, vol. 21, no. 2, pp. 1383-1408, 2018.
[2] B. Zhang, Y. Zhao, S. Rahman, Y. Li, and J. Zhang, "Alarm classification prediction based on cross-layer artificial intelligence interaction in self-optimized optical networks (SOON)," Opt. Fiber Technol., vol. 57, Jul. 2020, Art. no. 102251.
[3] F. Musumeci, L. Magni, O. Ayoub, R. Rubino, M. Capacchione, G. Rigamonti, M. Milano, C. Passera and M. Tornatore, "Supervised and Semi-Supervised Learning for Failure Identification in Microwave Networks," IEEE Transactions on Network and Service Management, vol. 18, no. 2, pp. 1934 - 1945, 2020.
[4] X. Chen, C.-Y. Liu, R. Proietti, J. Yin, Z. Li and S. Yoo, "On Cooperative Fault Management in Multi-domain Optical Networks Using Hybrid Learning," IEEE Journal of Selected Topics in Quantum Electronics (Early Access), 2022.
[5] P. Baldi, "Autoencoders, unsupervised learning, and deep architectures," in Proceedings of ICML workshop on unsupervised and transfer learning, 2012.