Domain Adversarial Adaptation Framework for Few-shot QoT Estimation in Fiber-optic Networks

Zhuojun Cai(1), Qihang Wang(1), Faisal Nadeem Khan(1)

(1) Tsinghua Shenzhen International Graduate School, Tsinghua University, Shenzhen, China, caizj21@mails.tsinghua.edu.cn

Abstract *The data-driven nature of machine-learning-based quality-of-transmission models impedes their application in practical optical networks. We propose a theoretical framework of domain alignment method which generates domain-invariant representations through adversarial training and our experimental results demonstrate that it outperforms conventional transfer learning and neural network-based methods.* ©2023 The Author(s)

Introduction

Machine-learning (ML) based quality of transmission (QoT) estimation models have gained prominence over analytical models like the split-step Fourier method (SSFM) due to their higher tolerance of lightpaths' parameters uncertainty and balance between computational complexity and accuracy. Data efficiency is a key concern for ML-based models' wide deployment, especially when limited data is available in the initial stage of establishing a new lightpath [1]. Transfer learning (TL) is a promising approach to alleviate the burden of new additional data collection by leveraging prior knowledge from source domains into the target domains [2]. Incorporating data from various domains gives rise to domain shift problems that must be addressed to prevent performance degradation Domain shift always exists even without TL in optical networks due to model-agnostic conditions changes like device aging and temperature fluctuations. Fine-tuning-based methods [3,4] and domain adaptation techniques for non-parametric Gaussian predictors (GP) [5] have shown promise. However, these methods have limitations in more general scenarios: the fine-tuning-based approaches merely replace the random initialized model parameters of the neural network (NN) with source domain model parameters which underperforms when the discrepancy between the distributions of the two domains is large; and adaptive GP for QoT metric assume a known posterior, which may not necessarily hold for most real-world data [2]. Faced with the complex mapping between dozens of device parameters and the QoT metrics, a more general solution is expected with more information transferred cross domains and looser assumptions for data distribution.

In this work, we propose an adversarial training-based domain adaptation framework to learn the domain-invariant features of the two domains' data and apply it to transfer signal-to noise ratio (SNR) knowledge from a simulated 15-channel link to our 7-channel experimental link. The framework aiming to realize the minimization of the approximate generalization error bond comprises a feature extractor and a domain discriminator as the domain-invariant representer, followed by a task-related label predictor, i.e., the SNR predictor in our showcase. During training, prediction loss and domain adversarial loss are jointly optimized, enabling the feature extractor to generate domain-invariant features. Therefore, this approach makes efficient utilization of data from different domains by projecting them into a shared space and jointly training the predictor. Compared to the fine-tuning method, our model shows higher adaptability, promising general use cases in optical networks.

Domain Adaptation

We consider regression tasks for QoT estimation where X and Y are the input and label space, and two sets of link data have different distribution over $X \times Y$, we call the one provides external knowledge as source domain $\mathcal{D}_\mathrm{S}$ and the other one to implement prediction as target domain $\mathcal{D}_\mathrm{T}$. $X^S \sim Q(X)$, $X^T \sim P(X)$ denote respectively source and target domain datasets which share the same feature space but follow different marginal data distributions Q and P. Similarly, denote the two empirical distributions $\hat{Q}$ and $\hat{P}$ and $f_Q, f_P: X \to Y$ the QoT estimation task in each domain.

Given a loss function $L: Y \times Y \to R$, which is symmetric and obeys the triangle inequality, the expected loss for any two functions $f, g : X \to Y$ and any distribution Q over X is defined by:

$$\mathcal{L}_Q(f,g) = \mathbb{E}_{x\sim Q}\left[L\big(f(x), g(x)\big)\right] \qquad (1)$$

The domain adaptation goal is to select a hypothesis $h: X \to Y$ out of a hypothesis set $\mathcal{H}$ based on the two datasets with a small expected loss $\mathcal{L}_P(h, f_P)$ over the target distribution P. The generalization bound is given by [6] :

Let $\mathcal{H}$ be a hypothesis set bounded by some $M > 0$ for the loss function L_q: $L_q(h,h') \leq M$, for all

$h, h' \in \mathcal{H}$, for any $\delta > 0$, with probability at least $1-\delta$, the bound holds for any hypothesis $h \in H$:

$$\begin{aligned}\mathcal{L}_P(h, f_P) \le \mathcal{L}_Q\left(h, h_Q^*\right) + \mathrm{disc}_L\left(\hat{P}, \hat{Q}\right) \\ +\mathcal{L}_P\left(h_Q^*, h_P^*\right) + \mathcal{L}_P\left(h_P^*, f_P\right) \\ +4q\left(\widehat{\mathfrak{R}}_{\mathcal{S}}(H) + \widehat{\mathfrak{R}}_{\mathcal{T}}(H)\right) \\ +3M\left(\sqrt{\frac{\log\frac{4}{\delta}}{2n^s}} + \sqrt{\frac{\log\frac{4}{\delta}}{2n^t}}\right)\end{aligned} \quad (2)$$

Where h_Q^*, h_P^* are defined as two minimizers $h_Q^* \in \mathrm{argmin}_{h\in H}\, \mathcal{L}_Q\left(h, f_Q\right)$, $h_P^* \in \arg\min_{h \in H} \mathcal{L}_P(h, f_P)$, $disc_L\left(\hat{P}, \hat{Q}\right) = \max_{h,h' \in H}\left|\mathcal{L}_{\hat{P}}(h', h) - \mathcal{L}_{\hat{Q}}(h', h)\right|$ is the discrepancy distance between distributions $\hat{P}$ and $\hat{Q}$, n^s and n^t are the sample numbers of source and target sets respectively, $\widehat{\mathfrak{R}}_{\mathcal{S}}(H)$ and $\widehat{\mathfrak{R}}_{\mathcal{T}}(H)$ are Rademacher complexity of $\mathcal{H}$, depending on data samples drawn from each distributions.

Only the first two terms on the right contain h in Eq. (2), so optimizing the predictor for target domain is equivalent to minimizing:

$$\mathcal{L}_Q\left(h, h_Q^*\right) + \mathrm{disc}_L\left(\hat{P}, \hat{Q}\right) \quad (3)$$

Observing the following two equations:

$$disc_L\left(\hat{P}, \hat{Q}\right) = \max_{h,h' \in \mathcal{H}}\left|\begin{matrix}\mathbb{E}_{x\sim\hat{P}}\left[L\left(h'(x), h(x)\right)\right] \\ -\mathbb{E}_{x\sim\hat{Q}}\left[L\left(h'(x), h(x)\right)\right]\end{matrix}\right| \quad (4)$$

$$W_1\left(\hat{P}, \hat{Q}\right) = \sup_{\|f\|_L \le 1} \mathbb{E}_{x\sim\hat{P}}[f(x)] - \mathbb{E}_{x\sim\hat{Q}}[f(x)] \quad (5)$$

Eq. (5) is the dual representation of the first Wasserstein distance (WD) [7]. Assume $f(x) = L\left(h'(x), h(x)\right)$ satisfies the Lipschitz constraint, then $disc_L\left(\hat{P}, \hat{Q}\right)$ turns into WD, which is also a reflection of the two domains' discrepancy. Now we get an approximation of the generalization error bound on target domain as the regression error on source domain and the WD between two domains.

Domain Adversarial Adaptation Model

We adopt an adversarial method to learn the domain-invariant representation and minimize the approximation bound to approach the theoretical limit $\mathcal{L}_P(h, f_P)$ as mentioned above. Fig. 1 shows the proposed framework comprising an extractor G to generate feature representation $k = G(x)$, a domain discriminator D and a regressor R, parameterized with $\theta_g, \theta_d, \theta_r$. According to [8], the empirical WD can be approximated then by maximizing the domain discriminative loss $\mathcal{L}_d$ with respect to parameter θ_d, together with a gradient penalty $\mathcal{L}_{grad}$ to enforce the Lipschitz constraint. According to the objective Eq. (3), we still have $\mathcal{L}_Q\left(h, h_Q^*\right)$ to minimize. So, a regressor is added behind the extractor. Now that the final objective function is:

$$\min_{\theta_g, \theta_r}\left\{\mathcal{L}_r + \lambda \max_{\theta_d}\left[\mathcal{L}_d - \gamma\mathcal{L}_{grad}\right]\right\} \quad (6)$$

The overall training process is: (1) train a domain discriminator by updating its parameters with reverse gradient and gradient penalty, approximating the WD; (2) fix the discriminator and minimize the WD by updating the feature extractor, followed by (3) the last step updating the regressor, (4) repeat the above procedures for adequate number of epochs. Note that the min-max process of step (1) and (2) ensures the reduction of domain discrepancy and help align the two different domains by generating domain-invariant representation k. When training completed, $R(G(x))$ is ready for regression task.

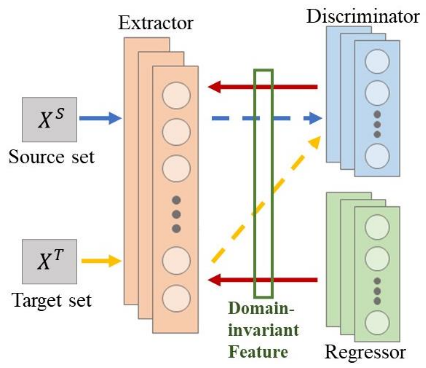

Fig. 1: Domain adversarial adaptation model framework

Experimental Results

In order to thoroughly demonstrate the effectiveness of the proposed framework, we implemented it for a few-shot link SNR regression experiment utilizing 200 training samples, supplemented by additional simulation data.

The simulation data is generated for a 15-channel 28 GBaud polarization-division-multiplexed (PDM) 16-quadrature amplitude modulation (QAM) transmission using VPIphotonics software, and the experimental data is collected employing our 7-channel testbed, whose details can be found in [9]. The simulation only involved nonlinear interference (NLI) and amplified spontaneous emission (ASE) noise while the experiment was conducted with some inevitable uncertainties such as the laser center frequency shift, the noise figure (NF) variation, etc., resulting in the data distribution misalignment.

We choose 27-dimensional input feature vectors **x** including 7 launched power (LPs) including the observed central one and 6 adjacent channels, the gains and NFs of 10 EDFAs in the link, and the SNR as input y. The simulation data which is typically almost free to generate is chosen as source domain data, containing 18000 samples in total. The target domain data is the experimental one which is scarce with a size of 300 only, split to 200,50,50 for training, validation and testing. The training set together with 18000 source data are fed to the model to extract the domain-invariant

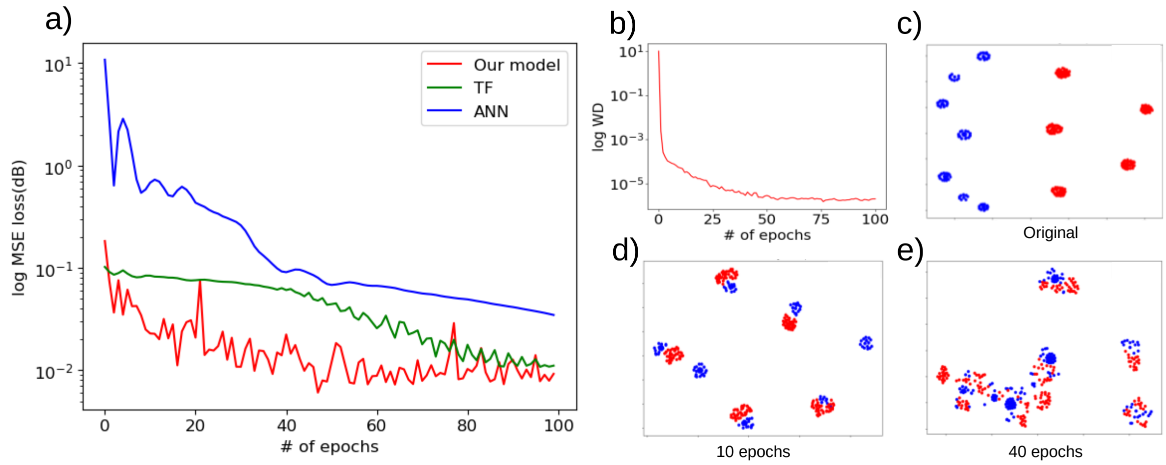

Fig. 2: Training results of the three considered models. a) the validation loss v.s. the numbers of epochs. b) the WD of two distributions. c)-e) are the distribution of two domains (blue for source and red for target) after t-SNE dimension reduction.

representation and to learn the mapping between y and the representation k. The validation set is used to decide whether there is a need to early stop or not. Finally, the trained model is tested on the test set.

For a comparative analysis, fine-tuning-based TL and standard artificial neural network (ANN) are chosen as benchmarks. The regressors of these 3 models as well as the extractor and discriminator modules in our proposed model share the simple structure of 4-layer ANN with 27,128,64,1 neurons for the individual layers and ReLU as activation function. The same 4-layer structure is also adopted for the. The 3 models have been exhaustly trained for 100 epochs and we tuned the hyperparameters based on Bayesian optimization. Mean square error (MSE) and standard deviation (STD) are used to evaluate the prediction accuracy.

As Fig. 2a shows, the validation loss of TL model is lower than ANN at the very beginning due to the pretrained source domain model

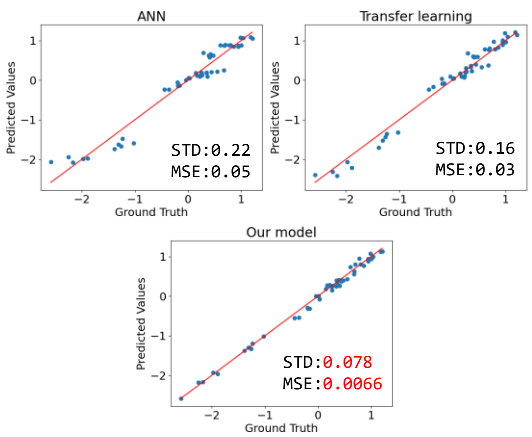

Fig. 3: Testing accuracy of the three considered models

providing a starting point. Nevertheless, our proposed method got even lower MSE. The WD plotted in Fig. 2b, indicates that two distributions are drawn closer during training. A more intuitive representation is given in Fig. 2c-e, presenting the distribution of k projected by a batch of X^S and X^T after t-distributed stochastic neighbour embedding (t-SNE) dimensionality reduction [10]. From original distribution to distribution after 40 epochs, it's obvious that the projection distributions of two domains (in blue and red) are tending to merge. Finally, the testing results in Fig. 3 show that our model outperforms the other two with extremely low STD as 0.078 (dB), presenting more focused scatter points distribution around the prediction-ground truth reference line.

These intermediate and testing results empirically prove that our model can efficiently adapt from source to target domain by explicitly aligning the projected feature k into same distribution. The accurate and stable SNR prediction results promise practical applications in fiber-optic networks.

Conclusions

We proposed a domain alignment method to significantly reduce the data size requirement of ML-based QoT estimation. This is the pioneering study that converts the discrepancy distance of regression domain adaptation into generalization error bound into Wasserstein Distance (WD) and approximate it using a domain adversarial framework. The example adaptation from simulation to experimental data indicates the better performance compared to previous methods, which also testifies great prospects for our method in the future intelligent optical networks.

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