Survey of Utilizing Importance Weights to Improve Transfer Learning

Wenjie Du
Department of Electrical and Computer Engineering
Concordia University
Montreal, Canada
wenjay.du@gmail.com

I. Introduction

Transfer learning is now widely applied in deep learning to improve model performance, especially in cases with small training datasets. Basic steps of transfer learning is firstly training a model on a large dataset which is used as so-called source dataset, such as ImageNet. Secondly, initializing a new model from the pre-trained model and then fine-tuning it on a target dataset. Certainly, the source dataset and the target dataset here are relevant. Or in other words, the source dataset contains information that is also in the target dataset and makes contributions to model learning. During fine-tuning, although parameters of the network are from pre-trained model, a new classification layer will be learned from scratch, based on the target dataset. The reason why transfer learning can help improve models is now that the fine-tuned model is initialized from pre-trained model, relevant information learned by the pre-trained model will be transferred to fine-tuned model.

But how to transfer more relevant information from source datasets to target datasets, from pre-trained models to fine-tuned models? Such as a question proposed in [1], consider a target task where that goal is to classify image of different food items. The straight-forward approach to applying transfer learning is to employ an ImageNet pre-trained model fine-tuned on a food-specific dataset. However, the question is whether the pre-trained model have learned to distinguish dogs from cats would help in current case of food classification? More generally, while pre-training on source datasets, is it more effective to train on all images or just a subset that reflect food-like items? And how to improve the efficiency in transfer learning?

This survey discusses 2 related work tackling the above problems. One is domain adaptive transfer learning (DATL) [1] and the other is learning to transfer learn (L2TL) framework [2].

II. Related Work

A. Domain adaptive transfer learning

In Ngiam's et al. experiments [1], they find that making judicious choices on selecting samples from the source dataset in the pre-training phase results in better performance on the target dataset. Therefore, to solve the problem of improving transfer learning, DATL weights each training example in the source dataset based on their relevancy to the target dataset by comparing data distribution of both datasets.

To compute weights mentioned above, each image in the target dataset will be evaluated by the model pre-trained on the source dataset, then a prediction over all classes in the source dataset will be given. Average these predictions, then get $P_t(y)$ in which P_t means the probability distribution in the target dataset and y means the class in the source dataset. Correspondingly, $P_s(y)$ which means probability distribution of the specify class y in the source dataset is directly obtained by dividing the number of times class y appears in the source dataset by the total number of examples in the source dataset. Finally, the ratio $P_t(y)/P_s(y)$ is the importance weight for class y in the source dataset. $P_t(y)/P_s(y)$ shows how important class y is, and will be used to fine-tuning the pre-trained model on the target dataset.

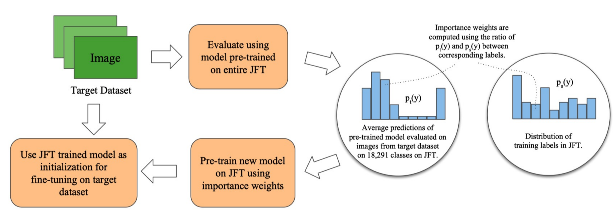

Fig. 1. Main idea in DATL.

There are 3 main findings in Ngiam's et al. paper as following:

- **More pre-training data does not always help.** Sometimes or even most times, it does help, but not always. Ngiam et al. find that the best results are archived while irrelevant examples are discounted.
- **Matching to the target dataset distribution improves transfer learning.** DATL method used to determine relevant examples for pre-training does help improve model performance, and obtain SOTA results in authors' experiments.
- **Fine-grained target tasks require fine-grained pre-training.** Ngiam et al. find that performance of transfer learning is dependent on whether the pre-training data captures similar discriminative factors of variations to the target data.

B. *Learning to transfer learning*

L2TL framework considers joint optimization of strong-shared weights between models of source and target tasks, and utilizes adaptive weights obtained from a policy model based on reinforcement learning to scale constituent loss terms [2]. Different from DATL which uses fixed importance weights, i.e. the ratios of estimated label prior probabilities, L2TL follows the goal of optimizing the target dataset metric directly.

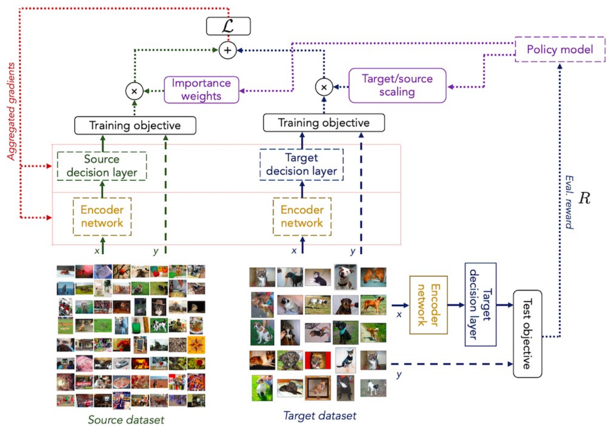

Fig. 2. Idea in L2TL framework.

The above figure [2] clearly illustrates how L2TL framework works. Joint optimization in this frameworks means training of the pre-trained model on the source dataset and the fine-tuned model on the target dataset is at the same time. Learning of the adaptive weights is guided by performance on a held-out target validation dataset. This job is done by the policy model. Then the goal of whole framework is to obtain improvement on the target validation datase, under the guide of policy model. This is a virtuous circle.

One whole learning iteration can be divided into 2 phases. In the 1st phase of learning iteration, the goal is to make models learn on source dataset and target dataset separately to get encoder and classifier layer weights, as shown in figure 2, and the policy model is fixed. In the 2nd phase, the goal is to optimize policy weights, i.e. making the policy model learning to maximize the performance on the target validation dataset based on the encoder weights from the 1st phase. And then update models got in 1st phase under instructions of the policy model.

According to Zhu's et al. experiments, L2TL framework outperforms previous methods a lot while training on small-scale target datasets. And even labels between source datasets and target dataset are mismatched, L2TL can also works fine. This is what methods like DATL cannot obtain.

REFERENCES

[1] J. Ngiam, D. Peng, V . V asudevan, S. Kornblith, Q. V . Le, and R. Pang. Domain adaptive transfer learning with specialist models. arXiv preprint arXiv:1811.07056, 2018.

[2] L.Zhu, S.O.Arik, Y.Yang, T.Pfister. Learning to Transfer Learn. arXiv preprint arXiv:1908.11406, 2019.