# Visual Transfer Learning in the Absence of the Source Data

Image recognition has become one of the most popular topics in machine learning. With the development of Deep Convolutional Neural Networks (CNN) and the help of the large scale labeled image database such as ImageNet, modern image recognition models can achieve competitive performance compared to human annotation in some general image recognition tasks. Many IT companies have adopted it to improve their visual related tasks. However, training these large scale deep neural networks requires thousands or even millions of labeled images, which is an obstacle when applying it to a specific visual task with limited training data. Visual transfer learning is proposed to solve this problem. Visual transfer learning aims at transferring the knowledge from a source visual task to a target visual task. Typically, the target task is related to the source task, and the training data in the target task is relatively small.

In visual transfer learning, the majority of existing methods assume that the source data is freely available and use the source data to measure the discrepancy between the source and target task to help the transfer process. However, in many real applications, source data are often a subject of legal, technical and contractual constraints between data owners and data customers. Beyond privacy and disclosure obligations, customers are often reluctant to share their data. When operating customer care, collected data may include information on recent technical problems which is a highly sensitive topic that companies are not willing to share. This scenario is often called Hypothesis Transfer Learning (HTL) where the source data is absent. Therefore, these previous methods cannot be applied to many real visual transfer learning problems.

In this thesis, we investigate the visual transfer learning problem under HTL setting. Instead of using the source data to measure the discrepancy, we use the source model as the proxy to transfer the knowledge from the source task to the target task. Compared to the source data, the well-trained source model is usually freely accessible in many tasks and contains equivalent source knowledge as well. Specifically, in this thesis, we investigate the visual transfer learning in two scenarios: domain adaptation and learning new categories. In contrast to the previous methods in HTL, our methods can both leverage knowledge from more types of source models and achieve better transfer performance.

In chapter 3, we investigate the visual domain adaptation problem under the setting of Hypothesis Transfer Learning. We propose Effective Multiclass Transfer Learning (EMTLe) that can effectively transfer the knowledge when the size of the target set is small. Specifically, EMTLe can effectively transfer the knowledge using the outputs of the source models as the auxiliary bias to adjust the prediction in the target task. Experiment results show that EMTLe can outperform other baselines under the setting of HTL.

In chapter 4, we investigate the semi-supervised domain adaptation scenario under the setting of HTL and propose our framework Generalized Distillation Semi-supervised Domain Adaptation (GDSDA). Specifically, we show that GDSDA can effectively transfer the knowledge using the unlabeled data. We also demonstrate that the imitation parameter, the hyperparameter in GDSDA that balances the knowledge from source and target task, is important to the transfer performance. Then we propose GDSDA-SVM which uses SVMs as the base classifier in GDSDA. We show that GDSDA-SVM can determine the imitation parameter in GDSDA autonomously. Compared to previous methods, whose imitation parameter can only be determined by either brutal force search or background knowledge, GDSDA-SVM is more effective in real applications.

In chapter 5, we investigate the problem of fine-tuning the deep CNN to learn new food categories using the large ImageNet database as our source. Without accessing to the source data, i.e. the ImageNet dataset, we show that by fine-tuning the parameters of the source model with our target food dataset, we can achieve better performance compared to those previous methods.

To conclude, the main contribution of is that we investigate the visual transfer learning problem under the HTL setting. We propose several methods to transfer the knowledge from the source task in supervised and semi-supervised learning scenarios. Extensive experiments results show that without accessing to any source data, our methods can outperform previous work.

Key Words: Visual Transfer Learning, Hypothesis Transfer Learning, Supervised Learning, Semi-supervised Learning