UNIVERSITY OF TECHNOLOGY SYDNEY
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# DEEP NEURAL NETWORKS FOR MULTI-SOURCE TRANSFER LEARNING

by

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# Certificate of Original Authorship

I, Keqiuyin Li, declare that this thesis is submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the Faculty of Engineering and Information Technology at the University of Technology Sydney. This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

This document has not been submitted for qualifications at any other academic institution.

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# ABSTRACT

Transfer learning is gaining incredible attention due to its ability to leverage previously acquired knowledge from source domain to assist in completing a task in a similar target domain. Many existing transfer learning methods deal with single source and single target transfer learning, but rarely consider the fact that information from a single source can be inadequate to a target domain and there can be multiple source domains. Few multi-source domain adaptations methods adapt all source and target data into a same latent feature space. However, domain shifts can be found among source domains and between each pair of source and target domains, thus, the model fitting all domains well may not exist. In addition, most transfer learning methods assume that the source and target domains share the same label space. But in practice, the source domain(s) sharing the same label space with the target domain may never be found. Third, data privacy and security are being magnificently conspicuous in real-world applications, which means the traditional transfer learning relying on data matching can trigger privacy concerns.

To solve the above-mentioned problems, this thesis develops a series of methods to tackle transfer learning with multiple source domains. Knowledge transfer with and without source data are explored under both homogeneous and heterogeneous label space settings.

To tackle knowledge transfer from multiple source domains, and measure contributions of source domains, multi-source contribution learning and dynamic classifier alignment methods are developed. In multi-source contribution learning method, the similarities and diversities of domains are learned simultaneously by extracting multi-view features. One view represents common features (similarities) among all domains. Other views represent different characteristics (diversities) in a target domain, in which each characteristic is expressed by features extracted in a source domain. Then multi-level distribution matching is employed to improve the transferability of latent features, aiming to reduce misclassification of boundary samples

by maximizing discrepancy between different classes and minimizing discrepancy between the same classes. Concurrently, when completing a target task by combining source predictions, instead of averaging source predictions or weighting sources using normalized similarities, the original weights learned by normalizing similarities between source and target domains are adjusted using pseudo target labels to increase the disparities of weight values, which is desired to improve the performance of the final target predictor if the predictions of sources exist significant difference.

In dynamic classifier alignment method, it aligns classifiers driven from multi-view features via a sample-wise automatic way. As proposed, both the importance of each view and the contribution of each source domain are investigated. To determine the important degrees of multiple views, an importance learning function is built by generating an auxiliary classifier. To learn the source combination parameters, a domain discriminator is developed to estimate the probability of a sample belonging to multiple source domains. Meanwhile, a self-training strategy is proposed to enhance the cross-domain ability of source classifiers with the assistance of pseudo target labels.

To learn similarity of source and target domains to define what to transfer, sample and source distillation method is proposed. It develops a two-step selective strategy to distill source samples and define the importance of source domains. To distill samples, the pseudo-labeled target domain is constructed to learn a series of category classifiers to identify transfer and inefficient source samples. To rank domains, a domain discriminator, which returns the degrees of a target sample belonging to the source domains, is developed based on selected transfer samples. Using the selected samples and ranked domains, transfer between the source and target domains is achieved by adapting multi-level distribution in a latent feature space. Furthermore, to explore more usable target information which is expected to enhance the cross-domain ability of source predictors, an enhancement mechanism is built by matching selected pseudo-labeled and unlabeled target samples. The degrees learned by the domain discriminator are finally employed to combine source predictors when predicting the target task.

To address transfer learning without the access to source data, generally auxiliary model training method is explored. The proposed method fits the source models to the target domain via fine-tuning under the supervision of pseudo target labels rather than matching data distributions. To collect high-quality initial pseudo target labels, both specific and generally auxiliary source models are pre-trained to improve the generality across domains of source models based on auxiliary learning, where source contributions are determined using an automatic way. Besides, the generally auxiliary model can take the benefit of sharing knowledge from multiple source domains without sharing data. Going further, it introduces a class balanced coefficient of each category based on the number of samples to reduce the misclassification caused by data imbalance.

To deal with soft information in transfer learning, fuzzy rule-based deep neural network is proposed to achieve multi-source data-free transfer learning. It takes advantage of a fuzzy system to handle data uncertainty in domain adaptation without source data. To learn source private models with high generality, which is important to collect low noisy pseudo target labels, auxiliary tasks are designed by jointly training source models from multiple domains which share source parameters and fuzzy rules while protecting source data. To transfer fuzzy rules and fit source private parameters to the target domain, self-supervised learning and anchor-based alignment are built to force target data to source feature spaces.

To handle transfer learning where source and target domains have unshared label space, partial and open-set transfer learning with generally auxiliary model training and fuzzy rules are explored under source-free setting. Universal transfer learning method is developed under multi-source-absent setting. In partial source-free transfer learning, a selection method is built to remove source samples from unshared categories, which is expected to eliminate the negative transfer resulting from the source outliers. In open-set transfer learning, a threshold generated from the predictions of the pre-trained source models is defined to identify the unknown target samples, aiming to eliminate the pseudo label noise caused by introducing unshared target samples.

In universal transfer learning, a unified learning model is proposed. The proposed method designs a module that can transfer knowledge from multi-source domains with both homogeneous and heterogeneous label spaces in universal scenario without accessing the source data. To classify known target classes, source anchors are generated to build data-matching between source and target domains via a contrastive method. In addition, class center consistency is adopted to distinguish source private samples when pseudo-labeling the target data to reduce label noise. To detect unknown classes, a clustering strategy which combines global and source local entropy assumptions is adopted to recognize the known and unknown target samples. By removing source private classes and target unknown samples, highly confident target samples are collected to self-supervise the adaptation of the pre-trained source model. At the same time, constraints enlarging the distance among target known classes and between the known and unknown samples are applied based on the pseudo-labels to enhance the performance of the proposed model.

# Dedication

To myself and my family.

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# List of Publications

## Journal Papers

J-1. **Keqiuyin Li**, Jie Lu, Hua Zuo, and Guangquan Zhang, "Multi-source contribution learning for domain adaptation," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 33, no. 10, 2022, pp 5293 - 5307.[A*; Q1]

J-2. **Keqiuyin Li**, Jie Lu, Hua Zuo, and Guangquan Zhang, "Dynamic classifier alignment for unsupervised multi-source domain adaptation," *IEEE Transactions on Knowledge and Data Engineering*, DOI: 10.1109/TKDE.2022.3144423, 2022. [ A*; Q1]

J-3. **Keqiuyin Li**, Jie Lu, Hua Zuo, and Guangquan Zhang, "Multi-domain adaptation with sample and source distillation," *IEEE Transactions on Cybernetics*, DOI 10.1109/TCYB.2023.3236008. [A; Q1]

J-4. **Keqiuyin Li**, Jie Lu, Hua Zuo, and Guangquan Zhang, "Source-free multi-domain adaptation with fuzzy rule based deep neural networks," *IEEE Transactions on Fuzzy System.* Under review. [ A*; Q1]

J-5. **Keqiuyin Li**, Jie Lu, Hua Zuo, and Guangquan Zhang, "Unified Learning for Source-Absent Universal Multi-Domain Adaptation," *IEEE Transactions on Neural Networks and Learning Systems.* Under review. [A*; Q1]

## Conference Papers

C-1. **Keqiuyin Li**, Jie Lu, Hua Zuo, and Guangquan Zhang, "Multi-source domain adaptation with distribution fusion and relationship extraction," *in Proceedings of the International Joint Conference on Neural Networks (IJCNN).* Virtual online: IEEE, July 19 - 24 2020, DOI: 10.1109/IJCNN48605.2020.9207556. [A]

C-2. **Keqiuyin Li**, Jie Lu, Hua Zuo, and Guangquan Zhang, "Multi-source domain adaptation with fuzzy-rule based deep neural networks," *in Proceedings of the IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)*. Virtual Online: IEEE, July 11 - 14 2021, DOI: 10.1109/FUZZ45933.2021.9494586. [A]

C-3. **Keqiuyin Li**, Jie Lu, Hua Zuo, and Guangquan Zhang, "Source-free multi-domain adaptation with generally auxiliary model training," Proceedings of the International Joint Conference on Neural Networks (IJCNN). Padova, Italy, July 18 - 23 2022, DOI: 10.1109/IJCNN55064.2022.9892718. [A]

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