Bridging Theory and Algorithms for Open-Set and Heterogeneous Domain Adaptations

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and
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CERTIFICATE OF ORIGINAL AUTHORSHIP

I, Zhen Fang, 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. This research is supported by the Australian Government Research Training Program.

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*To my loving wife Yueting Peng,
my parents and my son Junlin
Fang.*

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ABSTRACT

The availability of massive labeled datasets results in the successes of supervised learning in many applications such as object detection, speech recognition and natural language processing. However, the curse of domain mismatch arises if the test samples (target samples) and training samples (source samples) are from different domains. To overcome the mismatch between domains, researchers have proposed transfer learning, which aims to leverage knowledge from source samples with abundant labels to help train a classifier for target samples with insufficient labels.

Although many algorithms have been developed to solve transfer learning problem, most algorithms depend on additional assumptions to ensure their effectiveness. Many assumptions are difficult to be satisfied in real-world application. For example, the label sets of source and target samples are assumed to be same, however, in unsupervised setting, it is impossible to check this assumption. Those unrealistic assumptions limit the application of transfer learning.

This thesis mainly studies two important problems faced by many existing transfer learning algorithms: 1) how to transfer knowledge in the unsupervised setting, when the target label set is larger than the source label set; and 2) how to transfer knowledge, when the source and target samples are from different feature spaces.

Before solving problems 1) and 2), we first consider transfer learning which assumes that the feature spaces and label sets are both same. The setting is also called homogeneous domain adaptation. By studying the homogeneous domain adaptation, we aim to understand how the source knowledge can be used to help improve the target's performance under the simplest setting (i.e., homogeneous setting).

To solve problem 1), this thesis considers a challenging task: *unsupervised open-set domain adaptation* (UOSDA). First, to understand why source samples can be used to help target samples achieve good

performance in the open-set setting, we develop Probably approximately correct (PAC) learning theory for OSDA. Then, based on our theory, a kernel-based algorithm is proposed to solve problem 1). As an application of our OSDA theory, we also establish a theoretical foundation for *open-set learning* (OSL), an important sub-field in machine learning.

To solve problem 2), this thesis studies *semi-supervised heterogeneous domain adaptation* (SsHeDA) problem. Motivated by the compatibility condition in semi-supervised PAC theory, we explain the SsHeDA problem by proving its generalization error – why labeled source samples and unlabeled target samples help to reduce the target error. Guided by our theory, we devise a kernel-based algorithm.

List of Publications

Referred journals:

[**1**] **Zhen Fang**, Jie Lu, Feng Liu, Junyu Xuan, and Guangquan Zhang, Open Set Domain Adaptation Theoretical Bound and Algorithm, ***IEEE Transactions on Neural Networks and Learning Systems***, 2020. Published. (ERA **A***)

[**2**] Yiyang Zhang, Feng Liu, **Zhen Fang**, Bo Yuan, Guangquan Zhang and Jie Lu, Learning from a Complementary-label Source Domain: Theory and Algorithms, ***IEEE Transactions on Neural Networks and Learning Systems***, 2021. Accepted for publication. (ERA **A***)

International conferences:

[**1**] **Zhen Fang** and Jie Lu, Anjin Liu, Feng Liu, and Guangquan Zhang, Learning Bounds for Open-Set Learning, ***International Conference on Machine Learning*** (**ICML**), 2021. Accepted for publication. (CORA **A***)

[**2**] **Zhen Fang** and Jie Lu, Feng Liu, and Guangquan Zhang, Unsupervised Domain Adaptation with Sphere Retracting Transformation, ***International Joint Conference on Neural Networks*** (**IJCNN**), 2019. Published. (CORA **A**)

[**3**] Li Zhong, **Zhen Fang**, Feng Liu, Jie Lu, Bo Yuan, and Guangquan Zhang, How does the Combined Risk Affect the Performance of Unsupervised Domain Adaptation Approaches ?, ***Association for the Advancement of Artificial Intelligence*** (**AAAI**), 2020. Published. (CORA **A***)

[**4**] Yiyang Zhang, Feng Liu, **Zhen Fang**, Bo Yuan, Guangquan Zhang and Jie Lu, Clarinet: A One-step Approach Towards Budget-friendly Unsupervised Domain Adaptation, ***International Joint Conference on Artificial Intelligence*** (**IJCAI**), 2020. Published. (CORA **A***)

Papers submitted in referred journals:

[**1**] **Zhen Fang**, Jie Lu, Feng Liu and Guangquan Zhang, Semi-supervised Heterogeneous Domain Adaptation: Theory and Algorithms, ***IEEE Transactions on Pattern Analysis and Machine Intelligence***, 2021 (Revise and Resubmit). Submitted for publication. (ERA **A***)

[**2**] Feng Gu, Jie Lu, **Zhen Fang** and Guangquan Zhang, Neighbor-Searching Discrepancy-based Real Concept Drift, ***IEEE Transactions on Pattern Analysis and Machine Intelligence***, 2020 (Revise and Resubmit). Submitted for publication. (ERA **A***)

[**3**] Li Zhong, **Zhen Fang**, Feng Liu, Bo Yuan, Guangquan Zhang and Jie Lu, Bridging the Theoretical Bound and Deep Algorithms for Open Set Domain Adaptation, ***IEEE Transactions on Neural Networks and Learning Systems***, 2021 (Minor Revision). Submitted for publication. (ERA **A***)

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List of Symbols

$\mathcal{X}$	Feature space
$\mathbf{x}$	Sample from $\mathcal{X}$
$\mathcal{Y}$	Label set
$\mathbf{y}$	Label (one-hot vector) from $\mathcal{Y}$
$\mathcal{X}_s$	Source feature space
$\mathbf{x}_s$	Source sample from $\mathcal{X}_s$
$\mathcal{S}$	Labeled source samples
$\mathcal{X}_t$	Target feature space
$\mathbf{x}_l$	Labeled target sample from $\mathcal{X}_t$
$\mathcal{T}_l$	Labeled target samples
$\mathbf{x}_u$	Unlabeled target sample from $\mathcal{X}_t$
$\mathcal{T}_u$	Unlabeled target samples
$\mathcal{Y}_s$	Source label set
$\mathbf{y}_s$	Label (one-hot vector) from $\mathcal{Y}_s$
$\mathcal{Y}_t$	Target label set
$\mathbf{y}_t$	Label (one-hot vector) from $\mathcal{Y}_t$
P_{XY}	Joint distribution
$P_{X_sY_s}$	Source joint distribution
$P_{X_tY_t}$	Target joint distribution
P_X	Marginal distribution
P_{X_s}	Source marginal distribution
P_{X_t}	Target marginal distribution
$P_{Y\|X}$	Conditional distribution
$P_{Y_s\|X_s}$	Source conditional distribution
$P_{Y_t\|X_t}$	Target conditional distribution

ℓ	Loss function
$\boldsymbol{h}$	Hypothesis function
$\mathcal{H}$	Hypothesis space
$k(\cdot,\cdot), k_s(\cdot,\cdot), k_t(\cdot,\cdot)$	Reproducing kernel (RK), source RK, target RK
$\mathcal{H}_k, \mathcal{H}_{k_s}, \mathcal{H}_{k_t}$	RKHS with kernels $k(\cdot,\cdot), k_s(\cdot,\cdot), k_t(\cdot,\cdot)$
$d^{\ell}_{\mathcal{H}}, d^{\ell}_{\boldsymbol{h},\mathcal{H}}$	$\mathcal{H}\Delta\mathcal{H}$-divergence, disparity discrepancy
$D_{\boldsymbol{h}}, D_{\mathcal{F}}$	Projected MMD distance, MMD distance
χ	Compatibility
$\mathrm{err}, \widehat{\mathrm{err}}$	Transfer error rate, empirical transfer error rate
Λ	Combined risk
$\boldsymbol{T}_s, \boldsymbol{T}_t$	Source and target transformations
$\mathcal{F}_s, \mathcal{F}_t$	Source and target transformation spaces
R^{α}_P, R^{α}_Q	α-risks corresponding to P_{XY}, Q_{XY}
$R_{P,k}$, $R_{Q,k}$	Partial risks for known classes for P_{XY}, Q_{XY}
$R_{P,u}$, $R_{Q,u}$	Partial risks for unknown classes for P_{XY}, Q_{XY}
R_s, R_t	Source risk, target risk risk
$\widehat{R}_s, \widehat{R}_t$	Empirical source risk, empirical target risk
R^*_t	Partial risk on known target classes
R^{K+1}_t	Partial risk on unknown target classes