CS 165 Project Proposal

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1 Introduction

1.1 Background & Problem

With a model learned from source domain, it may fail to achieve good performance in target domain due to the distribution difference, i.e., training samples from data sets and real-world data for testing. Therefore, we need to correct for shifts in order to improve the classification accuracy, which requires the knowledge of both source distribution and target distribution. Under most practical situations, the information of target data may be achievable but with expensive cost, while useful information of such target samples is highly possible to help adapt the model to target domain.

In this project, we plan to apply active learning to choose "useful" target samples to label for more information of $\hat{Q}(Y)$. Therefore, combining $\hat{P}(Y), \hat{P}(X|Y)$, $\hat{Q}(X|Y)$ and $\hat{Q}(Y)$, we could map source domain to target domain more accurately with better importance weights estimation, which promises to improve the performance of classifier.

1.2 Related Topic

1.2.1 Domain Adaption

Domain adaption is often used in the problem where the source domain and the target domain have different but relative data distributions. Domain adaption could be classified to four cases: arbitrary shift, covariate shift, label shift, and no shift. In this project, we are interested in label shift and covariate shift, where the conditional probability does not change while the marginal probability changes.

1.2.2 Active Learning

Active learning is often used in the scenario where manual labelling is expensive. It could help us select the data which includes more information. In this project, active learning will be applied to obtain more information of target domain and thus help improve the model trained from source domain.

2 Intended Approach

The main idea of our project is to apply active learning to domain adaption. For domain adaption under label shift, we are given labeled source and unlabeled target data and make assumptions that $P(Y) \neq Q(Y), P(X|Y) = Q(X|Y)$. Here we plan to obtain small number of samples from target domain with corresponding labels and apply active learning to achieve more information about target distribution so that it could better correct the shift and fit target domain better. Therefore, our project could be mainly divided into two parts: active learning and domain adaption under label shift.

In active learning part, we hope to find an effective query strategy help to choose the "useful" target data should be labeled for smallest cost. Several query strategies, such as random sampling, uncertainty sampling, and pool-based sampling, have already been proposed. We will compare the performance of several strategies under domain adaptation situations and choose the best one or combine them to achieve better performance.

In domain adaption part, we plan to consider label shift which is more reasonable in practice such as diagnosing disease problem and modify regularized learning with additional target data information from active learning, as this approach has lower weight estimation error and higher prediction accuracy as well as in the low sample and large-shift regimes, even with totally unlabeled target data.

3 Data Used

The experiments will be carried on MNIST data set in our project. We will randomly separate entire dataset into two sets of same size and sample the same number of data points from each pool to form the source and target set. We assume source dataset to have uniform distribution over the labels and apply various kinds of shifts on target dataset. Then we train models on source domain together with part of target domain, which is queried by active learning, and finally evaluate on the target domain for the performance of classification accuracy.

4 Group Member & Labor Division

4.1 Group Member

Sha Sha, Master student of Electrical Engineering

Yu Wu, Master student of Electrical Engineering

4.2 Labor Division

Theoretical analysis and experiment on different algorithms: Sha Sha, Yu Wu

Design the final algorithm applied to domain adaption model: Sha Sha

Experiment on the final model: Yu Wu