Active Learning for Cross-domain Sentiment Classification

Shoushan Li, Yunxia Xue, Zhongqing Wang, and Guodong Zhou

Natural Language Processing Lab, School of Computer Science and Technology
Soochow University, Suzhou, China

Introduction

- **Sentiment Classification** is a task of determining the sentimental orientation of a given textual document.
- **Domain Adaptation** use some labeled data from the source domain and a large amount of unlabeled data from the target domain to classify the target domain data.

Negative transfer of cross-domain sentiment classification, the distributions of the source and target domains become too different to make the adaptation algorithm useful.

- **Active Learning**, One possible solution to such dilemma is to annotate a small amount of good labeled data in the target domain to quickly reduce the huge difference between the two domains.

Major challenges of active learning for cross-domain sentiment classification

- ✓ The newly-added labeled data from the target domain may become too weak to affect the **selection** decision.
- ✓ The newly-added labeled data from the target domain are normally too few to quickly affect the **classification** decision.

- **We address these challenges:**

1. We use the newly-added labeled data from the target domain to **train a separate classifier** and apply it in both the sample selection strategy and the classification algorithm
2. We propose a **label propagation (LP)** - based classification algorithm, which leverages both the labeled and unlabeled data, and apply it to both the source and target classifiers.

Symbol definition

Symbol	Definition
L_S	Labeled source-domain data
L_T	Labeled target-domain data
f_S	The source Classifier
f_T	The target Classifier
U_T	Unlabeled target-domain data
$\triangle L_T$	Newly-added data at each iteration
$f_{LP\text{-}S}$	The LP-based source Classifier
$f_{LP\text{-}T}$	The LP-based target Classifier
T_T	Test data in the target domain

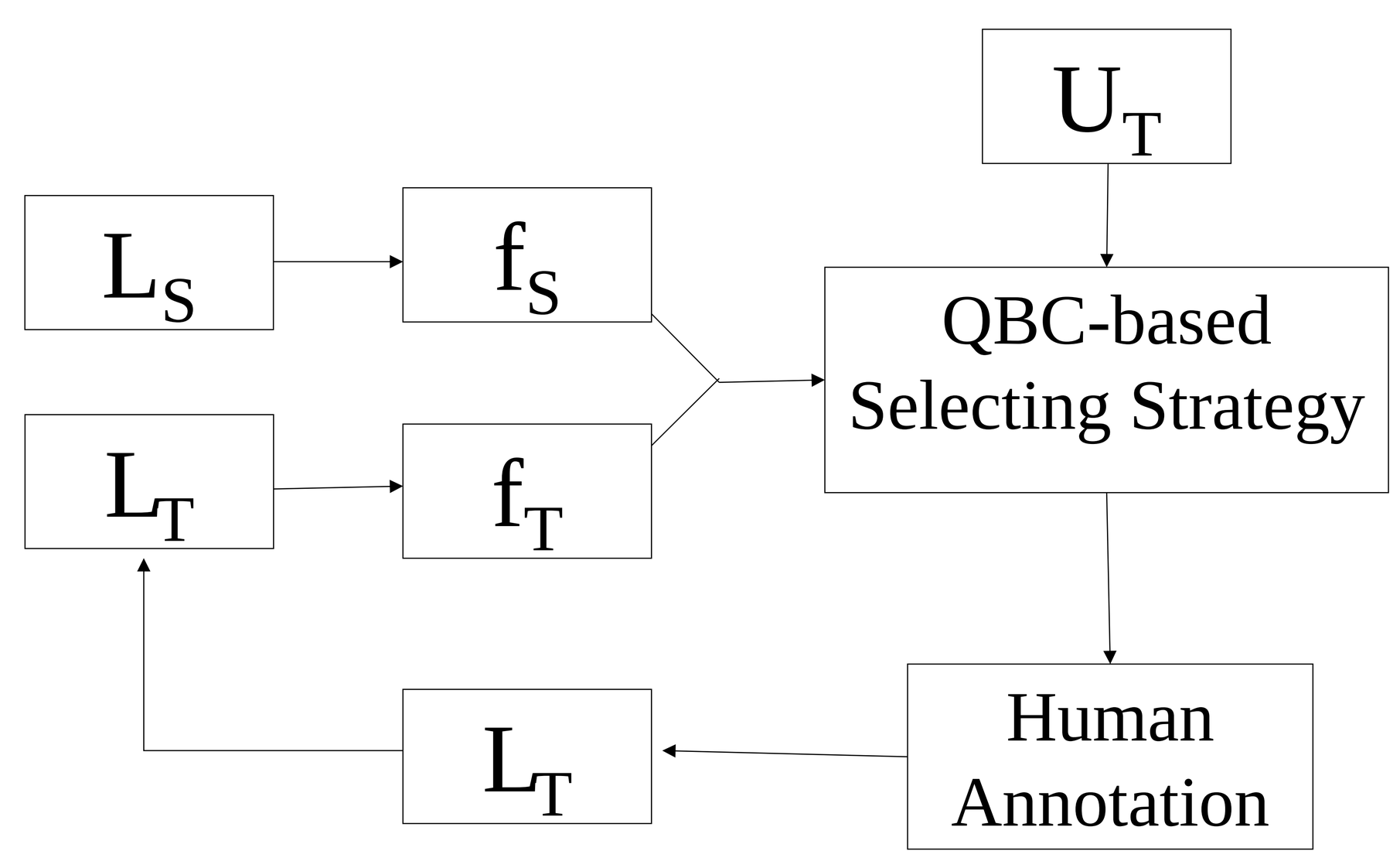
QBC-based Selection Strategy

- **Query by Committee (QBC)** is a group of active learning approaches that employ many copies of "hypotheses" to select an unlabeled example at which their classification predictions are maximally spread.

- **In our approach**,

1. We first use the source classifier and the target classifier to collaboratively select label-disagreed samples as the selection candidates.
2. We then rank the label-disagreed samples according to their uncertainty values by the source classifier.
3. We finally select the top-N uncertainty samples as the newly-added data for human annotation.

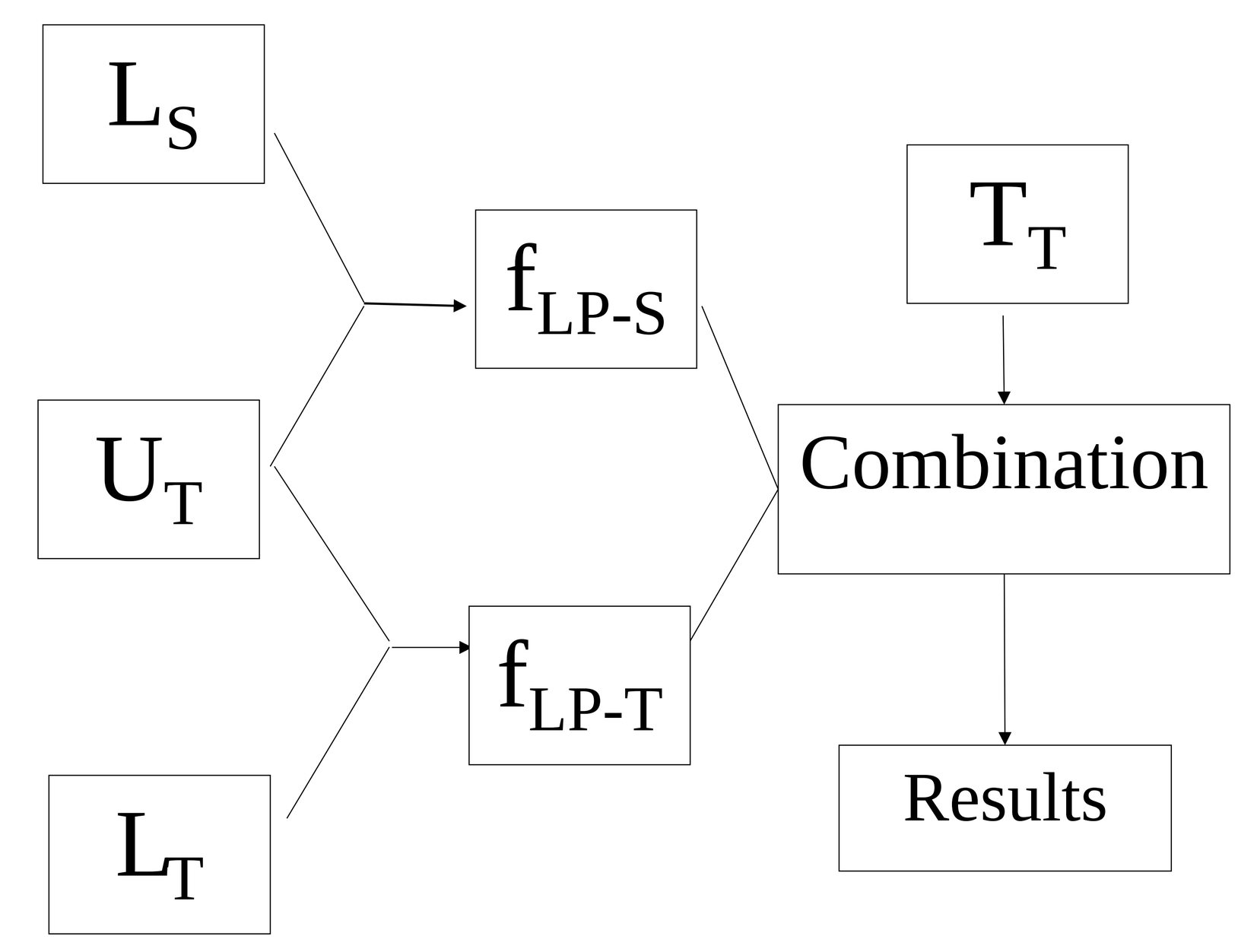
Figure: Sample selection in our approach



LP-based Classification

1. Construct the document-word bipartite graph with both the labeled data and the unlabeled data (in the target domain) and get the transition probability matrix.
2. Run the LP algorithm as shown in following figure to obtain the labels of unlabeled data.
3. Consider the unlabeled data with the predicted labels as pseudo-labeled data.
4. Emerge the labeled data and the pseudo-labeled data to train a classifier.

Figure: Sample classification in our approach



Experimentation

- **Dataset**: Book, DVD, Electronics and Kitchen appliances.
  - ✓ We randomly select 1600 instances from the source domain as labeled data, 1600 instances from the target domain as unlabeled data, and the remaining 400 instances from the target domain are reserved as test data.
- **Classification algorithm**: the maximum entropy classifier implemented with the public tool, Mallet Toolkits.

Figure: Experiment Results