

Corpus Fusion for Emotion Classification

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Abstract

Machine learning-based methods have obtained great progress on emotion classification. However, in most previous studies, the models are learned based on a single corpus which often suffers from insufficient labeled data. In this paper, we propose a corpus fusion approach to address emotion classification across two corpora which use different emotion taxonomies. The objective of this approach is to utilize the annotated data from one corpus to help the emotion classification on another corpus. An Integer Linear Programming (ILP) optimization is proposed to refine the classification results. Empirical studies show the effectiveness of the proposed approach to corpus fusion for emotion classification.

1 Introduction

Emotion classification aims to recognize human emotions, such as *joy*, *anger* or *surprise* in a given text. Emotion classification has a variety of applications including online chatting (Galik and Rank, 2012), news classification (Liu et al., 2013) and stock marketing (Bollen et al., 2011). In recent years, emotion classification in social media has been greatly popular in the Natural Language Processing (NLP) community (Chen et al., 2010; Purver and Battersby, 2012; Li et al., 2015). Because of the popularity of social media today, the analysis of short text on social media becomes more important (Kiritchenko et al., 2014; Wen and Wan, 2014; Wang et al., 2015). Users express their feelings and emotions on various social media platforms.

Existing emotion classification approaches are based on corpus classification methods where human-annotated emotion corpora are leveraged to train a machine learning-based emotion classification models. Recently, several different emotion corpora have been proposed by different researchers, such as Yao et al. (2014) and Huang et al. (2015). However, the size of each existing labeled corpus might be rather limited due to the high cost of data annotation, which results low performance in traditional supervised emotion classification.

In this paper, we propose a novel task, namely corpus fusion for emotion classification, which aims to leverage the data from different emotion corpora so as to alleviate the data deficiency problem. This task is motivated by the fact that although the emotion corpora are from different resources, they have the same objective of emotion classification. So it is easy to enlarge the size of the corpora by mixing the data of the same emotion category from two corpora. However, corpus fusion for emotion classification is challenging due to the following two factors:

First, the emotion taxonomies are often different between two emotion corpora because of the lack of an accepted standard. As a result, similar instances which express similar or same emotion can be categorized into different types of emotions under different taxonomies. An example from two emotion corpora (Yao et al., 2014; Huang et al., 2015) in Figure 1 expresses this problem. These two instances which express close emotion are labeled with different emotion classes under different emotion taxonomies.

Second, the annotation guidelines are often different between two emotion corpora because of different annotators. For example, the instance from Yao et al. (2014) in Figure 1 which contains a positive

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emotion *like* may not be labeled as *positive* under the taxonomy of Huang et al. (2015) because it doesn't contain a strong emotional word to express such a positive emotion. The numbers of emotion labels of each instance in two corpora are also different: some instances in Yao et al. (2014) have both primary emotion and secondary emotion, while most of the instances in Huang et al. (2015) are labeled with only one emotion. Because of the difference between emotion taxonomies, it is difficult to directly use the data from different emotion corpora together.

<p>Yao et al. (2014):</p> <p>“我先是震惊，继而敬重，如同听到冯军哥的裸捐一样。”</p> <p>(English Translation: “I was first shocked, and then respected. Just like when I heard the giving pledge made by Feng Jun.”)</p> <p>Emotion Categories: Like, Surprise</p>
<p>Huang et al. (2015):</p> <p>“创意无处不在！令人感到震惊的街头3D艺术！”</p> <p>(English Translation: “Creativity is everywhere! The shocking 3D street arts!”)</p> <p>Emotion Categories: Neutral Complex</p>

Figure 1: An example for two similar instances being categorized into different emotion categories under two emotion taxonomies

In this paper, we propose a corpus fusion approach to leverage the two emotion corpora, i.e., Yao et al. (2014) and Huang et al. (2015) in order to utilize the annotated data from each other. First, we perform supervised emotion classification on two corpora. Second, we refine the predicted emotion labels via a joint inference method, called Integer Linear Programming (ILP). A global objective function is minimized with the obtained posterior probabilities of the test instances. Two types of constraints, namely intra-corpus constraint and extra-corpus constraint are proposed in the ILP approach to address two challenges mentioned above. We use extra-corpus constraint to overcome the first challenge, and intra-corpus constraint is used for overcoming the second challenge. Results of experiments prove that our model makes a promotion on both classification accuracy and F_1 -measure, and both intra-corpus constraints and extra-corpus constraints are effective for the corpus fusion task.

The remainder of this paper is organized as follows. Section 2 overviews the related studies. Section 3 introduces two corpora used in this paper. Section 4 proposes the approach to corpus fusion for emotion classification. Section 5 illustrates the experiments to evaluate the proposed approach. Section 6 gives the conclusion and future work.

2 Related Work

In last decade, mainstream approaches for emotion analysis are corpus-based machine learning methods. Several studies construct emotion corpus from social media platform such as blog, microblog and news portal. Gilad (2005) collects blog texts from LiveJournal to construct an emotion corpus with 815,494 blog articles. Quan and Ren (2009) build an emotion corpus from blogs with eight types of emotions on three granularity levels. Pak and Paroubek (2010) establish an emotion corpus by capturing tweets on Twitter. Yao et al. (2014) build an emotion corpus with seven emotion types from SINA microblog. Huang et al. (2015) construct an emotion from TENCENT microblog including both simple and complex emotion annotation.

According to the text granularity, emotion analysis works can be generally divided into three levels: document-level, sentence-level, and word-level. Gilad (2005) uses SVM to model a document-level

emotion classifier with blog articles. Yang et al. (2007) identify the emotion types of blog articles based on SVM and CRF with sentiment lexicon. Lin et al. (2007) use the articles on Yahoo! News to analysis the news readers' emotion.

Sentence-level emotion analysis is mainly based on emotion lexicon. Mohammad and Turney (2010) study the effect of word level emotion lexicons for sentence level emotion analysis. They use word level emotion lexicons based on Word Net and NRC-10 to predict the emotion in sentences with Logistic Regression and SVM. Das and Bandyopadhyay (2010) categorize the emotions on Bengali blog. They first identify the emotion of words in a sentence, then judge the emotion of this sentence according to the words' emotion. Aman and Szpakowicz (2007) implement a knowledge-based sentence level emotion recognition method.

Word-level emotion analysis aims to construct emotion lexicon, which plays an important auxiliary role in emotion analysis. Yang et al. (2014) propose Emotion-aware LDA model to build a domain-specific lexicon. Xu et al. (2010) use language resource, such as synonym dictionary, semantic dictionary, and labeled and unlabeled corpus to construct the similarity matrix between words and seed words. They build an emotion lexicon with five emotion classes using graph-based rules. As a special expression of words, emoticons play an important role in emotion analysis due to the explosion in social media. Tang et al. (2013) annotate data from microblog posts with the help of emoticons.

There are several studies to address corpus adaptation problem in NLP field. Gao et al. (2004) do a pioneer work by describing a transformation-based converter to transfer a certain word segmentation result to another annotation guideline. Jiang et al. (2009) investigate the automatic integration of word segmentation knowledge in different annotated corpora. Similar approaches are applied to constituency parsing (Zhu et al., 2011) and word segmentation (Sun and Wan, 2012)

Unlike all above studies, we propose a corpus fusion approach to emotion classification in order to address the corpus fusion problem to combine two corpora with different emotion taxonomies and annotation guidelines. To the best of our knowledge, this is the first attempt to address this task in emotion analysis.

3 Corpus

Two emotion corpora we used are respectively constructed by Yao et al. (2014) and Huang et al. (2015). We simply denote the two corpora as YAO (2014) and HUANG (2015) in the rest of this paper for convenience.

YAO (2014) is constructed from SINA microblog¹. It categorizes emotions into seven classes: *happiness*, *anger*, *sadness*, *fear*, *like*, *surprise* and *disgust*. The corpus consists of 14,000 instances, of which 7,407 instances express emotions. Each instance may include both primary emotion and secondary emotion, or just has one primary emotion. Table 1a illustrates the distribution of primary emotions and secondary emotions in this corpus.

Notation	Emotion Class	Primary Emotion	Secondary Emotion	Notation	Emotion Class	Amount
e_{Y_1}	<i>happiness</i>	1460	359	e_{H_1}	<i>joy</i>	1038
e_{Y_2}	<i>anger</i>	669	203	e_{H_2}	<i>anger</i>	472
e_{Y_3}	<i>sadness</i>	1173	269	e_{H_3}	<i>sadness</i>	581
e_{Y_4}	<i>fear</i>	148	61	e_{H_4}	<i>fear</i>	94
e_{Y_5}	<i>like</i>	2203	546	e_{H_5}	<i>positive</i>	1178
e_{Y_6}	<i>surprise</i>	362	170	e_{H_6}	<i>neutral</i>	1131
e_{Y_7}	<i>disgust</i>	1392	385	e_{H_7}	<i>negative</i>	2175
-	Total	7407	1993	-	Total	6669

(a) YAO (2014)

(b) HUANG (2015)

Table 1: Emotion categories and distribution on two corpora

¹<http://weibo.com>

Huang et al. (2015) propose another emotion taxonomy with both basic emotions and complex emotions. Basic emotions include four emotion classes: *joy*, *anger*, *sadness* and *fear*. Complex emotions contain three emotion classes: *positive*, *neutral* and *negative*. This corpus is constructed from TENCENT microblog², and it consists of 15,540 instances. 6,669 instances express certain emotion. Although there is a very few multi-label annotation on it, we consider this corpus as single-label annotated. Table 1b shows the distribution of emotions in the two corpora.

4 Approach to Corpus Fusion for Emotion Classification

The corpus fusion approach to emotion classification aims to exploit the relationship between two corpora which have similar emotion taxonomies. Figure 2 illustrates the framework of our model. The testing results generated by the supervised emotion classifier are refined by ILP with label constraints.

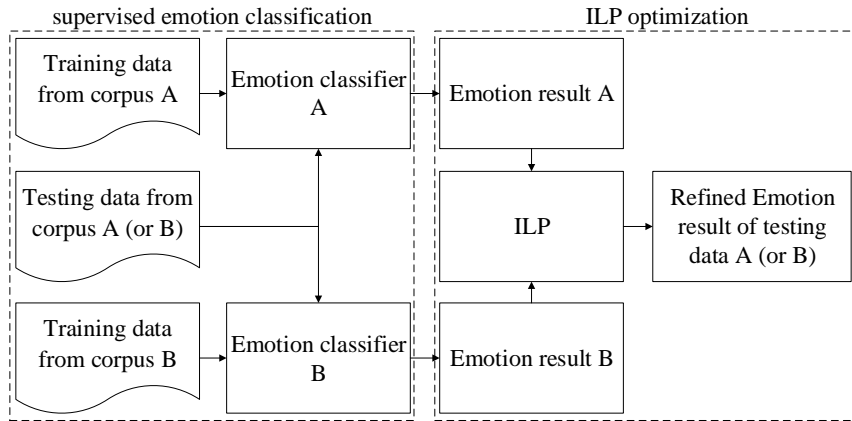


Figure 2: The framework of corpus fusion for emotion classification with ILP

4.1 Supervised Emotion Classification

Supervised classification problem trains a predictor f which maps an input vector x to the corresponding class label y on a set of training data. In emotion classification, a feature vector x is extracted from the instance. Formally, the objective of classification is defined as follows:

$$f(x) \rightarrow y, \quad y \in \{emotion1, emotion2, \dots\} \quad (1)$$

In this task, we train plural binary predictors for each emotion class for the testing set from YAO (2014), and a 7-way predictor for the testing set from HUANG (2015). For one sample instance t_i from the testing set, predicting results r_{Y_i} and r_{H_i} indicating the predicted emotion labels, and we get two sets of probabilities P_{Y_i} and P_{H_i} which contain the probabilities of this sample belonging to each category in two emotion taxonomies:

$$\begin{aligned} P_{Y_i} &= \{p(r_{Y_i} = e_{Y_1}), p(r_{Y_i} = e_{Y_2}) \dots p(r_{Y_i} = e_{Y_7})\}, \\ P_{H_i} &= \{p(r_{H_i} = e_{H_1}), p(r_{H_i} = e_{H_2}) \dots p(r_{H_i} = e_{H_7})\} \end{aligned} \quad (2)$$

where $p(r_{Y_i} = e_{Y_1})$ denotes the probability of t_i belonging to *happiness* under the emotion taxonomy of YAO (2014), and $p(r_{H_i} = e_{H_1})$ denotes the probability of t_i belonging to *joy* under the emotion taxonomy of HUANG (2015). The rest can be done in the same manner.

²<http://t.qq.com/>

4.2 Global Optimization with ILP

ILP optimization aims to refine the label result given the probability result. We design objective function and constraints to exploit the similarity between two emotion taxonomies. Like Roth and Yih (2004), we firstly define following assignment costs:

$$\begin{aligned} c_{Y_i} &= -\log(p(r_{Y_i} = e_{Y_i})) + \log(1 - p(r_{Y_i} = e_{Y_i})), \\ c_{H_i} &= -\log(p(r_{H_i} = e_{H_i})) + \log(1 - p(r_{H_i} = e_{H_i})), \end{aligned} \quad (3)$$

$$1 \leq i \leq 7$$

where c_{Y_i} is the cost of t_i belonging to the i th emotion class under the taxonomy of YAO (2014), and c_{H_i} is the cost of t_i belonging to the i th emotion class under the taxonomy of HUANG (2015). For each sample t_i in testing set there can be two cost vectors C_Y and C_H , and two label vectors L_Y and L_H used on storing the refined labels of t_i :

$$C_Y = [c_{Y_1} \ c_{Y_2} \ \dots \ c_{Y_7}]^T, \quad C_H = [c_{H_1} \ c_{H_2} \ \dots \ c_{H_7}]^T \quad (4)$$

$$L_Y = [y_1 \ y_2 \ \dots \ y_7], \quad L_H = [z_1 \ z_2 \ \dots \ z_7] \quad (5)$$

where y_1 to y_7 indicate the emotion class of t_i under the taxonomy of YAO (2014), and z_1 to z_7 indicate that under the taxonomy of HUANG (2015). For instance, if the label vector $L_Y=[0,1,0,0,0,0,1]$, it indicates that t_i is refined as *anger* and *disgust* under the emotion taxonomy of YAO (2014). The ILP optimization aims to acquire the refined emotion labels which are given by two label vectors.

ILP with Intra-corpus Constraints

We employ ILP with intra-corpus constraints to address the issue on annotation guideline. Note that we don't solely apply this type of constraints on the testing set of HUANG (2015) because it is considered to be single-labeled. On YAO (2014), the objective function can be defined as follows:

$$\begin{aligned} \min t &= |L_Y \times C_Y| \\ &= \sum_{i=1}^7 (c_{Y_i} y_i) \end{aligned} \quad (6)$$

Subject to:

$$y_i \in \{0, 1\}, \quad (7)$$

$$1 \leq \sum_{i=1}^7 y_i \leq 2 \quad (8)$$

where formula (8) implies that one or two labels are chosen from the emotion taxonomy of YAO (2014) after optimization. The objective function above aims to minimize the product of cost vector and label vector. Furthermore, an additional constraint aiming to align the emotion classes between two taxonomies is defined as follows:

(C1) Co-occurrence constraint: We filter the emotion pairs with low co-occurrence frequency in YAO (2014). The filtered pairs all occur below 30 times in the corpus according to statistics. For instance, *happiness* and *disgust* rarely co-occur in the same instance.

$$\begin{aligned} y_1 + y_2 \leq 1, \ y_1 + y_4 \leq 1, \ y_2 + y_4 \leq 1, \ y_2 + y_5 \leq 1, \\ y_2 + y_6 \leq 1, \ y_4 + y_5 \leq 1, \ y_4 + y_6 \leq 1, \ y_4 + y_7 \leq 1 \end{aligned} \quad (9)$$

ILP with Extra-corpus Constraints

We leverage the similarity between two emotion taxonomies with extra-corpus constraints. Firstly, we add specific costs as follows:

$$\begin{aligned} c_{align_H_1} &= c_{H_1} + c_{H_5}, \ c_{align_H_2} = c_{H_2} + c_{H_7}, \\ c_{align_H_3} &= c_{H_3} + c_{H_7}, \ c_{align_H_4} = c_{H_4} + c_{H_7}, \\ c_{align_H_i} &= c_{H_i}, \ 5 \leq i \leq 7 \end{aligned} \quad (10)$$

In formula (10), some costs in the original cost vector defined in formula (4) are added together. For example, c_{H_1} and c_{H_5} are added into $c_{align_H_1}$. It means that we align *happiness* under the taxonomy of YAO (2014) to both *joy* and *positive* under the taxonomy of HUANG (2015) together with the alignment constraint defined below. The cost vector C_H changes to:

$$C'_H = [c_{align_H_1} \ c_{align_H_2} \ \dots \ c_{align_H_7}]^T \quad (11)$$

As a result, the objective function becomes to:

$$\begin{aligned} \min t &= |L_Y \times C_Y| + |L_H \times C'_H| \\ &= \sum_{i=1}^7 (c_{Y_i} y_i + c_{align_H_i} z_i) \end{aligned} \quad (12)$$

Subject to:

$$y_i, z_i \in \{0, 1\}, \quad (13)$$

$$\sum_{i=1}^7 y_i = 1, \quad (14)$$

$$\sum_{i=1}^7 z_i = 1 \quad (15)$$

where formula (14) and (15) unify the number of possible labels on both taxonomies to one because we don't consider any intra-corpus constraints which are derived from the annotation guideline of YAO (2014) when extra-corpus is solely applied. The alignment constraint is defined as follows:

(C2) Alignment constraint: When a sample instance is categorized into a certain emotion e under one taxonomy, it can be categorized into an emotion e' which is same or similar to e under the other taxonomy. For instance, if an instance t is labeled as *disgust* under the taxonomy of YAO (2014), it can be labeled as *negative* under the taxonomy of HUANG (2015).

$$y_i = z_i, \ 1 \leq i \leq 7 \quad (16)$$

ILP with Two Types of Constraints

In this subsection, both intra-corpus and extra-corpus constrains are employed. The objective function is defined as follows:

$$\begin{aligned} \min t &= |L_Y \times C_Y| + |L_H \times C'_H| \\ &= \sum_{i=1}^7 (c_{Y_i} y_i + c_{align_H_i} z_i) \end{aligned} \quad (17)$$

Subject to:

$$y_i, z_i \in \{0, 1\}, \quad (18)$$

$$1 \leq \sum_{i=1}^7 y_i \leq 2, \quad (19)$$

$$\sum_{i=1}^7 z_i = 1 \quad (20)$$

Moreover, constraint C1 and C2 are also employed to restrict the labels in both views of intra-corpus and extra-corpus. Additionally, we make a relaxation on the alignment constraint C2.

(C3) Relaxed Alignment constraint: We make a relaxation on C2 to allow more than one chosen label on YAO (2014). C2 makes the numbers of labels on two corpora be the same so that formula (19) becomes meaningless. We employ the following version to replace C2.

$$y_i \geq z_i, \ 1 \leq i \leq 7 \quad (21)$$

5 Experimentation

5.1 Experimental Setting

Features

Bag-of-words feature is adopted in training supervised emotion classifiers. Each instance is represented as a binary vector indicating the presence or absence of word unigrams.

Evaluation Metrics

We employ the widely used accuracy and F_1 -measure on the multi-class-single-label emotion classification on HUANG (2015). On multi-class-multi-label emotion classification on YAO (2014), we employ two evaluation metrics to measure the performance. These metrics have been popularly used in multi-label classification problems (Godbole and Sarawagi, 2004).

- **Accuracy:** It gives an average degree of the similarity between the predicted and the ground truth label sets of all test examples:

$$Accuracy = \frac{1}{q} \sum_{i=1}^q \frac{|y_i \cap y'_i|}{|y_i \cup y'_i|} \quad (22)$$

where q is the number of all test instances, y'_i is the estimated label and y_i is the true label.

- **F_1 -measure:** It is the harmonic mean between precision and recall. It can be calculated from true positives, true negatives, false positives and false negatives based on the predictions and the corresponding actual values:

$$F_1 = \frac{1}{q} \sum_{i=1}^q \frac{|y_i \cap y'_i|}{|y_i| + |y'_i|} \quad (23)$$

5.2 Experimental Results with ILP Optimization

ILP with Intra-corporis constraints

In this experiment, intra-corporis constraints are applied for refining the predicting results. Note this experiment is only taken place on YAO (2014) in which an instance might have one or two labels. We experimentalize following methods for comparison:

- **Baseline:** We apply Maximum Entropy classifier with BOW feature as one baseline. Seven binary classifiers are trained for each emotion class. We balance the proportion of positive data and negative data for each classifier in order to achieve the best overall performance.
- **ILP with Intra-corporis Constraints:** ILP global optimization approach with defined intra-corporis constraints and objective function.

Table 2 shows the performance of ILP with intra-corporis constraints on the testing set of YAO (2014). According to the results, ILP approach with intra-corporis constraints overcomes the baseline with a 0.050 promotion in accuracy and a 0.013 promotion on F_1 -measure, which demonstrates the effectiveness of proposed intra-corporis constraints.

	Accuracy	F_1
Baseline	0.375	0.243
ILP (Intra-corporis)	0.425	0.256

Table 2: Performance of ILP with intra-corporis constraints on YAO (2014)

ILP with Extra-corpus constraints

In this experiment, we apply extra-corpus constraints on ILP optimization to leverage the annotated data from two corpora. We experimentalize following methods for comparison:

- **Baseline:** Max Entropy classifier with BOW feature serves as baseline. In the experiment on YAO (2014), the baseline is same as the one used in the experiment with intra-corpus constraints. In the experiment on HUANG (2015), a 7-way classifier is trained for baseline. The proportion of training data for each emotion class follows its original proportion.
- **ILP with Intra-corpus Constraints:** ILP global optimization approach with defined extra-corpus constraints and objective function.

Table 3 shows the performance of ILP when extra-corpus constraints are utilized on both testing sets. Extra-corpus constraints improve the accuracy on YAO (2014), but the F_1 -measure reduces. While on HUANG (2015), both accuracy and F_1 -measure improve distinctly, proving the capability of extra-corpus constraints on corpus fusion to leverage the annotated data from other corpus.

	Accuracy	F_1		Accuracy	F_1
Baseline	0.375	0.243	Baseline	0.405	0.359
ILP (Extra-corpus)	0.430	0.231	ILP (Extra-corpus)	0.431	0.386

(a) On YAO (2014) (b) On HUANG (2015)

Table 3: Performance of ILP with extra-corpus constraints

ILP with Both Types of constraints

In this experiment, we apply both intra-corpus and extra-corpus constraints on ILP optimization to implement corpus fusion from both views. Following methods are experimentalized:

- **Baseline:** Same as those used in the experiment with extra-corpus constraints.
- **ILP with Intra-corpus Constraints:** ILP approach with only intra-corpus constraints. This method is only employed on YAO (2014).
- **ILP with Extra-corpus Constraints:** ILP approach with only extra-corpus constraints.
- **ILP with Both Types of Constraints:** ILP approach with both intra-corpus and extra-corpus constraints and defined objective function.

Table 4 shows the performance of ILP approach with both intra-corpus and extra-corpus constraints compared to baselines. From these tables, we can see that employing both constraints further improves accuracy and F_1 -measure on YAO (2014). The joint use of both constraints avoids the decrease on F_1 -measure when only extra-corpus constraints are applied. On HUANG (2015), ILP with both constraints slightly improves the accuracy compared to ILP with only extra-corpus, but the F_1 -measure also decreases slightly. Intra-corpus constraints impact a little on HUANG (2015).

	Accuracy	F_1		Accuracy	F_1
Baseline	0.375	0.243	Baseline	0.405	0.359
ILP (Intra-corpus)	0.425	0.256	ILP (Extra-corpus)	0.431	0.386
ILP (Extra-corpus)	0.430	0.231	ILP (both)	0.435	0.382
ILP (both)	0.440	0.261			

(a) On YAO (2014) (b) On HUANG (2015)

Table 4: Performance of ILP with both types of constraints

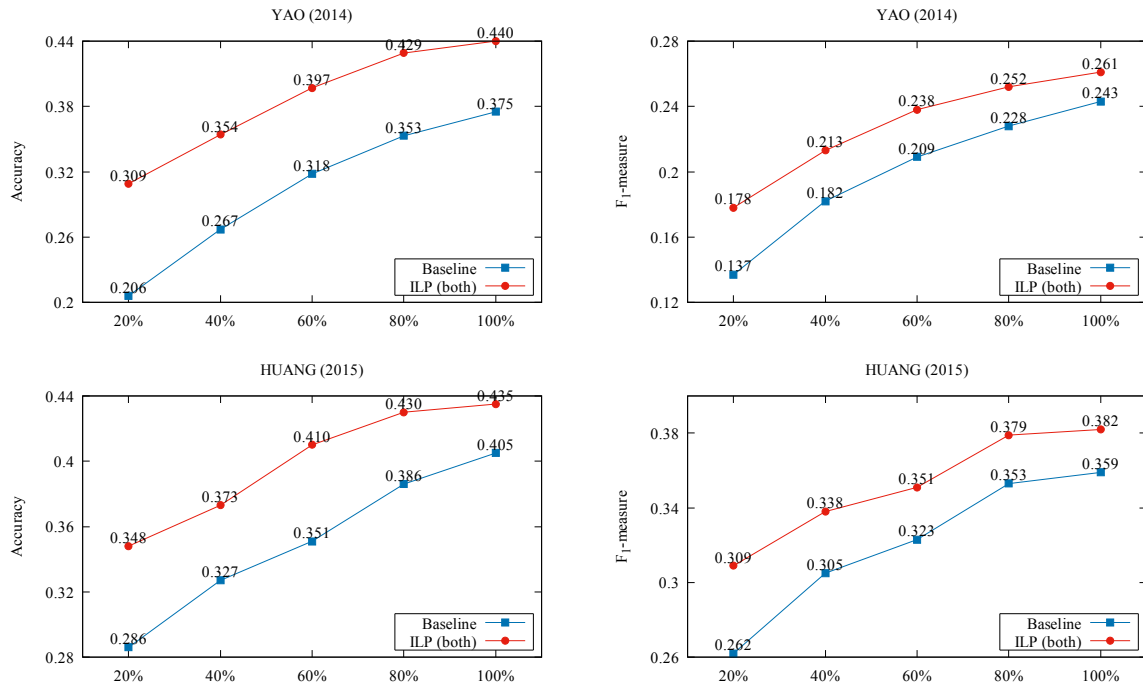


Figure 3: Performance of ILP with both types of constraints with different scales of training set

Figure 3 gives the performance of ILP with both constraints when different scales of training set are used. The improvement of ILP approach decreases with the increase of the scale of training set. It means that a highly performed baseline may reduce the space of promotion achieved by ILP optimization because the amount of error classified instances which can be refined decreases. Even so, ILP approach still improves the performance distinctly when the scale of training set is 100%.

6 Conclusion and Future Work

In this paper, we propose a corpus fusion approach to corpus fusion for emotion classification with ILP optimization. Specifically, we employ intra-task and extra-task constraints to better capture the similarity between two different emotion taxonomies and address the different annotation guidelines. Experiments demonstrate that ILP optimization improves the performance by using annotated data from other corpus, which has a different emotion taxonomy.

In our future work, we would like to seek better modification on ILP for further improvement. Moreover, we will try to adapt this approach to other NLP tasks where two or more corpora are available.

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