Identifying Tweets that Contain a 'Heartwarming Story'

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Abstract: We present a rather new task of detecting and collecting tweets that contain heartwarming stories from a huge amount of tweets on Twitter in this paper. We also present a method for identifying heartwarming tweets. Our prediction method is based on a supervised learning algorithm in SVM along with features from the tweets. We found by comparing the feature sets that adding sentiment features mostly improves the performance. However, simply adding the features for detecting a story in a tweet (past tense and tweet length) cannot contribute to improving the performance, while adding all the features to the baseline feature set mostly yields the best performance from among the feature sets.

1 INTRODUCTION

Since users of social media such as blogs and Twitter have been increasing with the development of the Internet, we now have a huge amount and variety of information on the Web. It is now very common to effectively use such a vast amount of information disseminated from many people worldwide to find out their opinions and feelings. Therefore, the research topics, sentiment analysis, and opinion mining, have recently received more attention(Pang and Lee, 2008; Liu, 2012).

Although a lot of work have recently been conducted on sentiment analysis and opinion mining, most of the work specifically targeted the writer's opinions and feelings. However, only a given few came from the reader's perspective. We believe sentiment analysis and opinion mining from the reader's perspective is also useful in many applications. When we can devise a method for identifying what documents make readers happy, we will then be able to more effectively mine a collection of 'heartwarming stories.' When we can identify what sentences or expressions make readers feel unpleasant, we will be able to develop a system of supporting writing that prevents writers from using rude expressions.

We were able to find the following few work on sentiment analysis from the reader's perspective. Yang et al.(Yang et al., 2009) tried to construct not only a writer-emotion corpus but also a reader-emotion corpus. Furthermore, they tried to statistically analyze the corpus. Lin et al.(Lin et al., 2008) built a reader-emotion classifier that classifies a document into one of eight reader emotion classes. They used Support Vector Machines (SVM) and the following types of features: character bigrams, words, affix similarities, and emotional words. Hasegawa et al.(Hasegawa et al., 2013) tried to predict the emotion of the addressee and to generate a response that elicits a specific emotion in the addressee's mind. They targeted Japanese Twitter posts as a source of dialogue data and automatically built training data for learning the predictors and generators.

Offensive content detection is not a new field, but there are only a small number of existing work. Razavi et al.(Razavi et al., 2010) treated the offensive language detection problem as a machine learning task and adopted three-level classifications with bag-of-words features that are based on an abusive expression dictionary.

In this paper, we first present a rather new task of detecting and collecting documents that contain heartwarming stories from a huge variety of contents on the Web. More specifically, since we target tweets on the social networking site Twitter(https://twitter.com/), our task is to detect tweets that contain heartwarming stories from the huge amount of tweets posted on Twitter. We then present a method for identifying heartwarming tweets. We believe the task for detecting documents (tweets) containing heartwarming stories is new in that they should not only make readers happy (have positive sentiment from the reader's perspective) but contain the writer's actual experiences.

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2 TWEETS THAT CONTAIN HEARTWARMING STORIES

There have been many sites on the Web that are dedicated to heartwarming stories[1]. Those stories on these sites tend to touch the readers' hearts. The visitors of the sites will find a lot of joy in these stories. Heartwarming stories are said to be the stories that will make readers laugh, cry, and smile. However, the stories on these sites are manually collected.

Our task is to detect tweets that contain such heartwarming stories from a huge amount of tweets on Twitter. The following is a sample tweet that is considered heartwarming[2]:

> 「もうくたくたの私．今日はお弁当作れないとコンビニへ．店員さんのさりげない行ってらっしゃいませの一言にぐっときた．」
>
> (I was really tired. I stopped at the convenience store because I could not make a boxed lunch today. I was woken up by the staff's casual words of, 'Have a nice day.')
>
> 「終電逃したと思って，閉まったドアの前ですごいテンション下がってたらまた開けてくださった．駅員さん優しい．」
>
> (I thought I missed the last train when I fell down just in front of the closing door but the st aff kindly opened the door again. He was kind.)

3 COLLECTING HEARTWARMING TWEETS

We tried to construct a corpus of heartwarming tweets. Since it is difficult to collect heartwarming tweets from the vast number of topics on Twitter, we decided to construct a corpus of heartwarming tweets that contain episodes concerning railway and convenience-store staffs. We chose these two groups of individuals because we often come in daily contact with them as customers. We selected two railway companies and a convenience store chain in Japan.

We first retrieved a collection of tweets from Twitter that contained the following query: *Company name* + Keywords indicating company staffs[3]. We then tried to automatically remove the following types of tweets:

- tweets created by bots,
- retweets, and
- tweets considered news articles.

Next, we manually judged whether each tweet contained a heartwarming story by actually reading it. The statistics of the corpus are shown in Table 1. As seen in this table, the ratio of heartwarming tweets is quite small, and therefore, it is challenging to identify them from a complete collection of tweets.

4 DETECTING HEARTWARMING TWEETS

Our method for detecting heartwarming tweets from a collection of tweets is based on a classification model trained by using SVM. We used SVM because the learning algorithms have been successfully used in text classification in the past.

The simplest way to construct a model for detecting heartwarming tweets using supervised learning algorithms is to use a 'bag of words' (BoW) whose parts-of-speech are a verb, a noun, and a suffix in the tweet as the features. We used suffixes because beneficiary expressions such as 「てくれる」 and 「てもらう」 are suffixes.

However, we took into account the following ideas and devised better features to improve the prediction accuracy, because heartwarming tweets should not only contain positive sentiments from the reader's perspective but also contain the actual experiences of the writer:

1. When writers describe their positive feelings in a tweet, readers might empathize and thus become happy. Therefore, we used the lexica of polarity-bearing words and calculate the number of positive and negative words as features.

   We used two sentiment lexica as our lexical resource for the polarity-bearing words. The first is available on the Web[4]. The lexicon was constructed using the method developed by Takamura et al.(Takamura et al., 2005). The second was constructed using the method developed by Suzuki et al.(Suzuki et al., 2007).

2. Since heartwarming tweets should also contain actual experiences, clues for whether a tweet contains a story should be incorporated. Therefore, we used the length of the tweet and whether or not the tweet contained verbs in the past tense as features[5].

[1] For example, http://www.heartwarmingstories.net/.

[2] We manually rephrased original tweets more formally.

[3] For example, 「車掌」 (conductor), 「駅員」 (station staff), 「店員」 (store staff), and so on.

[4] http://www.lr.pi.titech.ac.jp/∼takamura/pndic_en.html

[5] Tweets describing a story might be long.

Table 1: Statistics of heartwarming tweets corpus.

Company	Total No. of tweets	Heartwarming tweets	Non-heartwarming tweets
Family-Mart	691	71	620
JR	657	48	609
Tokyo Metro	664	74	590

3. As noted in Table 1, our data set is severely imbalanced and the heartwarming tweets class has fewer examples than the other. Learning algorithms that do not take into account the class imbalance tend to be overwhelmed by the majority class and ignore the minority one, and the overall accuracy of conventional learning algorithms will thus significantly degrade, since their classifiers are greatly biased towards the majority class. Therefore, under-sampling (Zhang et al., 2010) is used and the training is performed using an equal number of positive and negative examples.

   The sampling came from a class of methods that alters the size of the training sets. Under-sampling is an imbalanced data learning method that uses only a subset of the majority class examples. Under-sampling changes the training sets by randomly sampling the examples from the majority class training set and making it smaller. The level of imbalance is reduced, with the hope that a more balanced training set can provide better results. Among the various class-imbalance learning methods, under-sampling has been commonly used. The under-sampling method we adopted clusters the examples in the majority class first and then randomly selects examples from these clusters.

5 EXPERIMENTS

In this section, we report on the experimental results using our prediction method described in the previous section on our data collection described in Section 3.

We used the standard precision and recall for the positive class of heartwarming tweets, and the F1 measure, which is the harmonic mean between the precision and recall, to evaluate the prediction. We used the libsvm implementation (Fan et al., 2005) for SVM with the linear kernel in the 10-fold cross-validation.

We compared the following different feature sets for the prediction:

1. BoW whose parts-of-speech are a verb, a noun, and a suffix in the tweet (baseline feature set),

Table 2: Prediction performance.

Family-Mart:

Feature	Precision	Recall	F1-measure
Baseline	0.534	0.775	0.632
+ polarity	0.518	0.817	**0.634**
+ tense	0.529	0.775	0.629
+ length	0.417	0.845	0.558
All	0.378	0.789	0.511

JR:

Feature	Precision	Recall	F1-measure
Baseline	0.183	0.625	0.283
+ polarity	0.208	0.729	0.324
+ tense	0.172	0.729	0.278
+ length	0.163	0.792	0.270
All	0.284	0.646	**0.395**

Tokyo Metro:

Feature	Precision	Recall	F1-measure
Baseline	0.384	0.757	0.510
+ polarity	0.341	0.757	0.471
+ tense	0.364	0.797	0.500
+ length	0.290	0.784	0.423
All	0.425	0.838	**0.564**

2. BoW + polarity information (Please see 1. in Section 4),
3. BoW + past tense (Please see 2. in Section 4),
4. BoW + tweet length (Please see 2. in Section 4),
5. BoW + polarity + past tense + tweet length + other features (all features).

'Other features' in the above feature sets indicate whether interjections or quotation marks are in the tweet. The experiments were performed using under-sampling for all the feature sets.

In Table 2, we show the prediction results for the three companies mentioned in Section 3 using our method. The best performance is shown in boldface for each company.

We found by comparing the feature sets that adding sentiment features mostly improves the performance. However, simply adding the features for detecting a story in a tweet (past tense and tweet length) cannot contribute to improving the performance, while adding all the features to the baseline feature set mostly yields the best performance from among the feature sets.

6 CONCLUSIONS

In this paper, we first presented a rather new task of detecting and collecting tweets that contain heartwarming stories from a huge amount of tweets on Twitter. We then presented a method for identifying heartwarming tweets. Our prediction method is based on a supervised learning algorithm in SVM along with the features from the tweets.

We need to improve the prediction performance by devising more intelligent features for future work. Furthermore, we also need to construct larger corpus of heartwarming tweets for the experiments. Trying the task in other languages such as English is also our future work.

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