Semi-supervised Learning Approach for Automatic Emotional Expression Extraction from eBook Text

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***Abstract*—We have developed an approach for the automatic extraction of emotion expression from text data of ebooks, such as novels and short stories. The embedding of the extraction results as metadata allows a text-to-speech system to enable the expressive reading of these texts along with the selection of a dictionary of voices associated with emotions. As a text prefilter for the automatic extraction of emotions, we adopt a complement naive-Bayes-based method to assign emotion labels to the text data and combine this method with an EM algorithm to obtain a semi-supervised method for exploiting unlabeled data. We conducted experiments that assigned to the text data the three pre-defined emotion labels–joy, anger, and sadness–that contribute to effective expressive reading. Using two types of evaluation datasets–International Survey on Emotion Antecedents and Reactions (ISEAR) and the Japanese open ebook library "Blue Sky Library"–we confirmed that the proposed approach exceeded the baseline.**

***Keywords*-Emotion Classification, Complement Naive Bayes, EM algorithm.**

I. Introduction

The popularity of ebooks has increased recently, leading to the development and availability of some unique applications and functions related to ebooks. Text-to-speech (TTS) reading is one such attractive application. Using TTS, users can enjoy the audio versions of various ebooks in a voice of their preference. However, the current TTS readers are not sophisticated and cause discomfort to users when they read novels or tales that contain a considerable number of dialogues, because the TTS speaker and the speaking styles for the dialogues are the same as those for the description parts.

Through the proposed expressive reading approach, we aim to modulate the voice while reading the dialogues in order to convey different emotions such as anger, joy, and sadness, i.e., the automatically extracted labels. Several approaches were previously developed for extracting emotion expression from text [1]. In Stopparava [2], experiments involving various approaches were conducted using a knowledge-based method with the WordNet-Affect database and LDA, and a corpus-based method whose corpus consisted of blog entries. However, the assignment of emotion labels to the dialogues of ebooks is different from that to news headlines or blogs that previous studies used. The ebook dialogues have various kinds of words and expressions and hence cannot always be assigned fixed emotion labels. Moreover, the creation of learning data such as positive examples, a dictionary, and a thesaurus of emotions incurs considerable cost.

II. Automatic Emotional Expression Extraction

In order to resolve the abovementioned issues, we adopted the following approaches:

- Complement naive-Bayes-based approach that is robust to the difference in the volume of each category.
- A combination of the abovementioned method and the EM algorithm; in this combined approach, the classifier can exploit not only labeled data but also unlabeled data.

These details are shown at Fig.1.

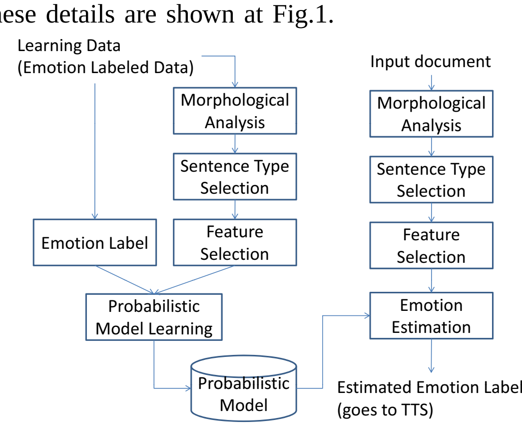

Figure 1. Emotion Estimation using Naive Bayes based approach

In following subsections, two characteristic processings of the proposed approach are explained.

A. Complement naive-Bayes-based classification method

In general, several methods are available for categorizing input data into predefined categories. From among these, we adopt a naive-Bayes-based method because it is easy to maintain in the case of a high number of input documents and because of its component simplicity resulting from the use of a text prefilter. Considering a target sentence s to be the task, we classified this sentence into one of the previously mentioned categories. $C = \{c_1, ..., c_n\}$.

A naive-Bayes classifier is based on the following Bayes theorem: $P(c|s) = \frac{P(c)P(s|c)}{P(s)}$. Further, we also determined a suitable category c_{max} that maximizes the probability of $P(c)P(s|c)$ in equation $c_{max} = argmaxP(c)P(s|c)$.

However, the left part of the equation cannot be calculated in reality; hence, we approximate $P(s|c)$ with (1) by representing words in the learning data as $word_1, ..., word_n$.

$$P(s|c) = P(word_1|c)P(word_2|c)...P(word_n|c) \qquad (1)$$

In order to determine the category that the input sentence belongs to, we extract words and calculate the likelihood of each category. Further, the complement naive-Bayes-based method exploits all data except those in the target category and calculates the least occurring category.

B. EM-combined approach for semi-supervised learning

By utilizing the unlabeled data, we apply the EM algorithm to the complement naive-Bayes-based method. The EM-combined approach is implemented as follows:

1) Calculate the complement naive-Bayes models from each item of emotion-labeled data.
2) Repeat the following steps until the parameters are converge:
   - (E-step) Using the current naive-Bayes model, estimate the probability of the category of unlabeled data.
   - (M-step) Exploiting the estimated results as a post-probability, update and re-generate the probability model.
3) Using optimized parameters, estimate the target label of the unlabeled data.

III. Experiments and Results

We conducted experiments to measure the classification accuracy of the proposed approach. The datasets listed in Table I were used for this evaluation. In the ISEAR dataset, seven kinds of emotion labels are defined, and we define another category set that composes the main emotion labels (joy, anger, and sadness) and others(the other four labels).

Test Set	Joy	Anger	Sadness	others	Total
ISEAR	1094	1096	1096	4380	7666
Blue Sky Library	1388	1831	1232	4149	8600

Table I
Number of sentences for each emotion

In contrast, the BSL dataset consists of approximately 10,000 Japanese ebooks with open access, and from these, we select approximately 1,600 popular books on the basis of the public download ranking. In the preprocessing stage, certain parts of the dialogues are extracted with pattern-match rules formulated by us and emotion labels are assigned manually to each sentence on the basis of a majority vote of five persons. In the experiments, first, we set the baseline accuracy for the most frequently occurring label in each dataset to be assigned all data virtually. The comparison methods were naive Bayes (NB), complement naive Bayes (compNB), and a combination of these methods with EM ((NB+EM) and (compNB+EM)). The experiments were conducted by using 10-fold cross validations. The evaluation results are shown in Fig.2.

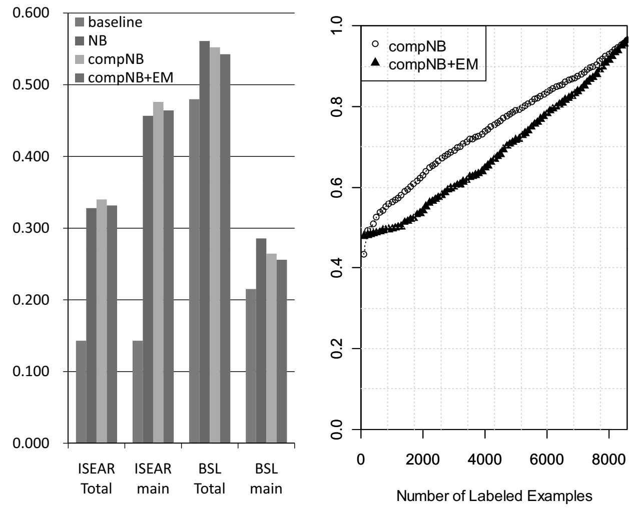

Figure 2. Experimental Result

The bars labeled “ISEAR/BSL Total” denote the average estimation accuracy obtained by using all the labels. Further, the bars marked “ISEAR/BSL main” show the F-value results of the three limited emotion labels. However, both the complement method and the EM-based methods can exceed the baseline. Nevertheless, the combination method (compNB+EM) is not as effective as the NB and compNB methods. As shown on the right side of Fig.2, the EM iteration involving unlabeled data lowers the overall accuracy.

IV. Conclusion

We compared the performances of certain techniques for extraction of emotion expression based on the naive Bayes algorithm and combination of this algorithm and the EM algorithm. As a future work, we intend to improve the proposed approach using relatively large practical dataset and evaluate the user satisfaction of the TTS reading of auto annotated emotion labels.

References

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