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An Emotion Detection System for Cantonese

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Abstract

We present the first study on automatic emotion detection for Cantonese. Our system classifies input text into the eight emotion categories used in the Ren-CECps corpus. While a number of emotion corpora and lexica for Mandarin Chinese have been developed, no emotion dataset is available for Cantonese. Leveraging existing Mandarin Chinese resources, we build the system by integrating Cantonese-Mandarin lexical mappings from a machine translation system, as well as English-Mandarin lexical mappings to handle code-switching in Cantonese input. Evaluation on a set of Cantonese sentences harvested from social media shows promising results.

Introduction

With the explosion of blogs, tweets, and other user-generated web content, there has been increasing interest in automatic analysis of the emotion and sentiment in unstructured text. Researchers have built systems that can perform polarity classification and emotion detection. Polarity classification determines whether an input text is positive, neutral, or negative (Wang and Ku, 2016). Emotion detection assigns the text to an emotion category, such as "happiness", "anger", "sadness", "fear", or "surprise" (Turner, 2000; Lee et al., 2013). It can perform emotion classification at different levels of granularity, e.g., from six to eight emotion categories (e.g., Ekman, 1992; Ren and Quan, 2012).

For commercial applications, emotion detection is useful in identifying the mood of customers. The chatbot or dialogue system can then adjust the emotion in their responses to improve customer experience (Polzin and Waibel, 2000; Hu et al., 2018). For mental health applications, emotion detection can facilitate self-check for users, and guide system recommendations of activities to promote psychological well-being.

This paper presents the first emotion analyzer for Cantonese, the “most widely known and influential variety of Chinese other than Mandarin” (Matthews and Yip, 2011). Spoken by more than 55 million people, Cantonese is the dominant variety of Chinese spoken in Hong Kong. Growing interest in automatic (Mandarin) Chinese emotion analysis has led to shared tasks focusing on emotion analysis in Chinese Weibo text, for example at the Conference on Natural Language Processing and Chinese Computing. A considerable number of emotion lexica and corpora have been developed for automatic emotion analysis in Chinese. Although Cantonese and Mandarin share similar writing systems as well as many cognates, emotion detection systems for Mandarin do not perform well for Cantonese input, since it is often peppered with lexical items that are not used in Mandarin. This is especially the case for casual, informal, low-register Cantonese, which users are likely to use when expressing emotions.

Emotion detection for Cantonese is also challenging because of extensive code-switching, typically with embedded English. Hence, emotion can be expressed in English, Cantonese, or mixed Cantonese-English phrases (Dewaele and Pavlenko, 2002). In the only previous attempt on emotion detection for bilingual or code-switching text (Lee and Wang, 2015), the system applies base classifiers for Mandarin Chinese and English to evaluate the input text, and then uses a sum rule to combine their scores.

To the best of our knowledge, there has not been any reported attempt on compiling emotion corpora and lexica on Cantonese. Following best practices from recent work on exploiting language resources for closely related languages and language variants (Zampieri et al., 2017), we leveraged three kinds of resources to build the system: Mandarin Chinese emotion corpora; Cantonese-Mandarin lexical mappings from a machine translation system (Wong and Lee, 2018); as well as English-Mandarin lexical mappings for handling code-switching. On a test set of Cantonese sentences harvested from social media, our system showed promising performance.

The rest of the paper is organized as follows. We summarize previous work in the next section. Following a description of our datasets, we present our approach and report on results in a preliminary evaluation.

Previous Work

Emotion detection systems can be classified into two main types — statistical or knowledge-based — and can be augmented with bilingual approaches.

Statistical Emotion Detection

Statistical systems are trained with machine learning methods on large emotion-annotated corpus, such as the Ren-CECps corpus (Ren and Quan, 2012) and the Chinese Sentiment Treebank (Li et al., 2014). Various machine learning methods have been applied in previous research. Ren and Quan (2012) trained their system with the Multinomial Naive Bayes algorithm on the Ren-CECps corpus. In an evaluation on eight-way detection of emotions, their system achieved 77.3 F-measure at the sentence level. In more recent work, Su et al. (2014) applied word2vec to learn word embeddings and to learn deep semantic features. An SVM classifier, trained on these semantic features, achieved over 90% accuracy. Odbal and Wang (2014) proposed a segment-based approach for more fine-grained emotion detection. A semi-CRF model, trained on bag-of-words, part-of-speech, dependency and emotion lexicon features, outperformed the SVM and achieved over 65% accuracy.

Knowledge-Based Emotion Detection

A knowledge-based system typically exploits emotion lexica, such as the SenticNet (Cambria et al., 2016) or the Augmented NTU Sentiment Dictionary (ANTUSD) (Wang and Ku, 2016). The ANTUSD contains 26K words annotated with the CopeOpi numerical sentiment score, ranging from -1 to 1, expressing the degrees of the positive and negative polarity. Emotion lexica can also be automatically created. Xu et al. (2010), for example, used a graph-based algorithm to label words that express one of the five primary emotions (Turner, 2000).

Given such a lexicon, an unsupervised system can determine the overall emotion polarity of an input text by considering the score of its words and phrases (e.g., Taboada et al., 2011). Most systems also incorporate syntactic rules to detect emotion negation and intensification: negation of an emotion expression may flip or shift the polarity, while amplifiers (e.g., 'extremely') and downtoners (e.g., 'a little') may increase or decrease it. Quan et al. (2013) used a dependency parser to identify dependency relations involving emotion words and negators or intensifiers, and integrated word similarity scores to broaden the coverage of the sentiment lexicon in HowNet. Lee et al. (2013) developed a linguistically motivated, rule-based system that is able to not only determine the emotion category, but also identify the causes of the emotion. Cambria et al. (2016) proposed a concept-based approach to sentiment analysis to better handle compositional semantics.

Bilingual Approaches

The bilingual approach uses machine translation to exploit existing resources in the source language for a target language. Since English is supported by the largest amount of emotion language resources, researchers have taken bilingual approaches to exploit these resources for other languages. A straightforward approach is to translate the input text into English before performing emotion analysis (Wan, 2008). Likewise, Odbal and Wang (2014) converted the English WordNet Affect lists (Strapparava and Valitutti, 2004) into Chinese. Gao et al. (2015) developed a more accurate model using cross-lingual sentiment lexicon learning with bilingual word graph label propagation.

Data

Our system exploits three kinds of resources: an emotion-annotated corpus for Mandarin Chinese (Ren and Quan, 2012), Cantonese-Mandarin and English-Mandarin lexical mappings from a machine translation system (Wong and Lee, 2018).

Mandarin Emotion Corpus

The Ren-CECps corpus is an emotion-annotated corpus with 35K Chinese sentences from microblogs (Ren and Quan, 2012). It contains 12,742 sentences, and 324,571 Chinese words. Its fine-grained annotations characterize emotion at document, paragraph and sentence levels. At the sentence level, emotions include expectancy (11%), joy (15%), love (22%), surprise (3%), anxiety (19%), sorrow (16%), angry (6%) and hate (10%). An 8-dimension emotion vector encodes the emotion categories and emotion intensities for each keyword and phrase. For each emotion keyword in the corpus, we calculated its average emotion intensity.

Cantonese-Mandarin and English-Mandarin Lexical Mappings

To leverage the Mandarin emotion corpus described above, our system must be able to transform Cantonese input, possibly with embedded English, into Mandarin. For this purpose, we obtained Cantonese-Mandarin and English-Mandarin lexical mappings from an existing machine translation system (Wong and Lee, 2018). The lexical mappings consist of pairs of equivalent Cantonese/Mandarin and English/Mandarin words or phrases, taken from a parallel corpus of transcribed Cantonese speech and Mandarin Chinese subtitles (Lee, 2011). The speech was transcribed from television programs broadcast in Hong Kong within the last decade by Television Broadcasts Limited. The Cantonese and Mandarin texts were manually word-segmented and aligned. The television programs represent a number of genres, including news, current-affairs shows, drama series and talk shows. They therefore exhibit vocabulary from widely different domains, but also a variety of registers in spoken Cantonese, from the formal language in news to the more colloquial kind in drama series and talk shows. We harvested all word alignments from the corpus to create lexical mappings. We further supplemented these mappings with a Cantonese-Mandarin dictionary that is freely available from the Kaifang Cidian website (http://kaifangcidian.com).

Overall, the mappings cover 35,196 distinct Mandarin words. Out-of-vocabulary Mandarin words are likely to be infrequently used words; fortunately, these words tend to be rendered in the same way in Cantonese, and therefore require no translation.

Approach

Given an input text in Cantonese, the system detects emotion by identifying all emotion words, as well as negators and intensifiers. More specifically, it follows the following steps.

(1) Perform word segmentation, part-of-speech tagging and dependency parsing with the Stanford Chinese Parser (Levy and Manning, 2003).

(2) Retrieve the emotion intensity of the eight emotion types for each word, based on the Ren-CECps corpus. If a word is not included in the corpus, we translate it into Mandarin with the Cantonese-Mandarin lexical mappings described above, and attempt again to retrieve its score. Embedded English words or phrases are handled in a similar fashion with the English-Mandarin lexical mappings.

(3) Identify negators (e.g., 唔 'not', etc.), amplifiers and downtoners (e.g., 非常 'very', etc.) that modify the emotion words. We harvested the degree words from the RenCECps corpus, and manually crafted a list of negators. The system ignores the score of a negated emotion word, and boosts the score of an emotion word according to the intensity (low, medium, or high) of the degree word.

(4) Compute the sum of the intensity scores for all eight emotions — expectancy, joy, love, surprise, anxiety, sorrow, angry, and hate — and visualize their relative share in a pie chart. Figure 1 shows an example input sentence and its emotion analysis.

Evaluation

We constructed a test set of 80 sentences from Cantonese social media for evaluation. For each of the eight emotions, we collected 10 Cantonese sentences that exhibit it as the dominant emotion. The system performed automatic emotion analysis for each sentence. The analysis is counted as accurate if the dominant emotion receives the highest score. The task is thus essentially eight-way emotion classification.

The overall accuracy of the system was 62.5%. As shown in Table 1, it performed best in detecting the emotion "joy" (100%), and worst for "surprise" (20%). Among the "surprise" sentences, the system most often mistook them to be "anxiety". Another frequent confusion was between "sorrow" and "surprise".

System performance was somewhat correlated with the frequency of the emotion in the training corpus: the "love" emotion, which is the most frequent in the RenCECps corpus, achieved 90% accuracy, while "surprise", the least frequent, yielded only 20%. Limited coverage of the emotion lexicon and word segmentation errors sometimes prevented the system from retrieving the intended score, and from identifying the negators and intensifiers. The impact was especially severe on short input. Finally, when a sentence expressed multiple emotions, it could be challenging to pinpoint the dominant one.

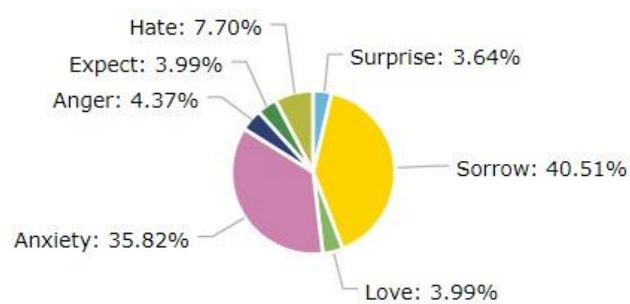

Figure 1: Automatic emotion analysis for the input text 死傷慘重既係香港既樹 "Hong Kong's trees were badly wounded."

Emotion	Accuracy	Emotion	Accuracy
Joy	100%	Anger	60%
Love	90%	Sorrow	50%
Anxiety	70%	Hate	40%
Expectancy	70%	Surprise	20%

Table 1: System accuracy on eight-way emotion classification.

Conclusion and Future Work

We have presented the first study on emotion detection for Cantonese. Our system exploits existing Mandarin emotion resources and lexical mappings between Cantonese, English and Mandarin, and takes negators and intensifiers into account. In a preliminary evaluation on eight-way emotion classification, it performed at 62.5% accuracy.

This research constitutes our first step in building a chatbot for psychological well-being. In the future, we plan to train language models to generate system replies that are appropriate for the user's emotion (cf. Ghosh et al., 2017), and to recommend activities to the user for promoting emotional intelligence and mindfulness.

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