Employing hierarchical Bayesian networks in simple and complex emotion topic analysis[☆]

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Abstract

Traditional emotion models, when tagging single emotions in documents, often ignore the fact that most documents convey complex human emotions. In this paper, we join emotion analysis with topic models to find complex emotions in documents, as well as the intensity of the emotions, and study how the document emotions vary with topics. Hierarchical Bayesian networks are employed to generate the latent topic variables and emotion variables. On average, our model on single emotion classification outperforms the traditional supervised machine learning models such as SVM and Naive Bayes. The other model on the complex emotion classification also achieves promising results. We thoroughly analyze the impact of vocabulary quality and topic quantity to emotion and intensity prediction in our experiments. The distribution of topics such as Friend and Job are found to be sensitive to the documents' emotions, which we call emotion topic variation in this paper. This reveals the deeper relationship between topics and emotions.

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1. Introduction

Emotion analysis aims to reveal the delicate human emotions found in texts, which could help to promote the quality of the human–computer interface, create more accurate review analysis, and diagnose some mental diseases (Ren, 2009, 2010). Traditional emotion models often simplify the problem by assigning a single emotion to each document, while the document could, in fact, have multiple emotions conveyed as a whole. This situation has been found in Ren-CECps (Quan and Ren, 2010) as well as other emotion corpora, and a single-emotion assumption would not only reduce the coverage of emotions but also affect the accuracy of emotion prediction. In this paper, we employ hierarchical Bayesian networks to model the complex emotions found in documents and the emotion intensities, interpreting the significance of each single emotion.

The traditional studies of emotions and topics are distinctly performed. A topic is a particular distribution over the vocabulary, and in most cases represents a cluster of words when only the top *N* possible words in the vocabulary are considered. One of the most discussed problems of the automatically generated topics (Blei et al., 2003) is that we can

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never know the semantic meanings of these topics before generation; we only receive enlightenment by watching the top N words generated from each topic. On the other hand, through a thorough observation of the document emotions in Ren-CECps, we find that people's choice of topics (words) in writing is closely related to their emotional states. For example, the topics of Child and Family are more often observed in the Joy and Love documents than the other documents, while the words under the Job topic are found with higher frequencies in the Hate documents. For the majority of words in a corpus, which although do not directly indicate emotions, could be divided into some emotion indicative latent topics. Following this intuition, in this paper we provide a generative process to jointly encode the choice of words and topics under different emotions in the documents, and try to interpret the latent topics on the emotion level.

To model the emotions and emotion-related topics, we build hierarchical Bayesian networks by incorporating the emotion and emotion intensity variables into the LDA model (Blei et al., 2003). The idea behind this is straightforward: in the emotion topic models, the word generation procedure is determined not only by the document topics that are the core distribution in LDA, but also by the emotions (intensities) of that document. This extension of the LDA model enables us to naturally incorporate topics into the variation of document emotions. In addition to the word variables, the emotion intensity variables are generated from emotion variables. This ensures important parallelism between the existing emotions and the emotion intensities. We claim the emotion topic model is a half-supervised model since the generation of document emotions, emotion intensities, and words needs previous counts that could only be collected from a training set, suggesting a supervised procedure, while the topic generation component is similar to the LDA model, which is an unsupervised procedure.

Two emotion models are studied in the framework of hierarchical Bayesian networks: the simple emotion topic (SET) model for predicting simple emotions and latent topics in documents, which covers the similar task of traditional emotion classification, and the complex emotion topic (CET) model for discovering the complex emotions and topics in documents. As we would discuss in detail later, the imbalance of emotion instances in real blog articles is very common, since some emotions such as Love and Hate are statistically more often than Surprise in people's attitude toward objects. It would be difficult for machine learning algorithms to correctly recognize the infrequent emotions without proper regularizations. In our hierarchical Bayesian networks, we employ Dirichlet and Beta priors on the proportional variables for emotion and word distributions, which in turn leads to the regularization of these distributions given a training set. In this sense, our emotion topic models are expected to be more robust to the real data. We develop different methods for evaluating simple and complex emotion predictions, not only for the accuracies of emotion(s) per document, but also for the quality of single emotions contained in the complex emotions. The emotion topic variation is also examined for both models, which reveals the special emotion distribution among different topics.

The rest of this paper is arranged as follows. Section 2 makes a brief review of the emotion system in Ren-CECps. Section 3 introduces the simple and complex emotion topic models. Section 4 illustrates our Gibbs sampling method for inference. In Section 5 we perform experiments on emotion prediction and emotion topic variation, and discuss the results and models' complexities. Related works are introduced in Section 6. Finally, Section 7 concludes.

2. Emotion system

Our study of text emotions is based on Ren-CECps, which is a collection of totally 1487 Chinese blog articles, with the complex emotions annotated to four text levels including word, phrase, sentence, and document. A complex emotion is represented as the combination of single emotions from eight basic emotion categories: Joy, Love, Expectation, Surprise, Anxiety, Sorrow, Anger, and Hate. To distinguish the strengths of different emotions within a complex emotion, Ren-CECps also labels a decimal score as the emotion intensity between 0.1 and 1.0 to each single emotion. The following are two examples of sentences from Ren-CECps with the complex emotions annotated,[1] which have been translated into English:

Jo:0.3|Lo:0.3 Life was *bitter*(So:0.3|Ax:0.3), but I was *glad*(Jo:0.3|Lo:0.3) to have you around.
Ha:0.3|Ax:0.4 I said *fine*(Jo:0.3|Lo:0.3), but felt extremely *refusal*(So:0.3|Ax:0.3) in heart.

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[1] Emotions are abbreviated using the first few characters: Jo for Joy, Lo for Love, Ex for Expectation, Su for Surprise, Ax for Anxiety, So for Sorrow, Ag for Anger, and Ha for Hate.