Classification for Unmeaning Document using Emotion-Topic Model

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ABSTRACT
Mining social emotions from text and more documents are assigned by social users with emotion labels like happiness, warmness, and amusement. Documents categorized based on emotions and it help for related document selection in online. It can collect document from social users and assign emotion for the words in that document and based on the preference level achieve emotion for the whole document. In the existing approach usually the document model is the bag-of-word and there is no relationship between the words. In proposed work documents collected from online and using emotion-topic model for emotion modeling. It first generates topic from document followed by affective terms and effectively identify emotion for the topic. While in online news collections intimate that the model is not only effective in pull out the meaningful latent topics. Notably it upgrades the performance of social emotion forecasting.

INDEX TERMS*-affective text mining,emotion-term model*

I. INTRODUCTION

Today, very large amounts of information are available in on-line documents. With the growth of Internet, automatically recommendation now has becoming an important role in document collection. The user-generated social emotions provide a new aspect for document categorization, and they cannot only help online users select related documents based on emotional preferences, but also benefit a number of other applications such as contextual music recommendation [1]. Emotion classification allows us to identify the feelings of individuals toward specific events. To use and evaluate the effectiveness of statistical learning methods for emotion classification [4], we need both a training dataset and a testing dataset. Weblog, or simply blog, is a very good dataset, which is collaboratively contributed by users, bloggers, on the web. We investigate the emotion classification of web blog corpora using support vector machine (SVM) and conditional random field (CRF) machine learning techniques. The emotion classifiers are trained at the sentence level and applied to the document level. When applying emotion classification to a blog at the document level, the emotion of the last sentence in a document plays an important role in determining the overall emotion. In here consider the problem of collecting emotions for the online documents and associate it with the latent topic. All words can potentially convey affective meaning. The automatic detection of emotion in texts is becoming increasingly important from an applicative point of view. Text mining, also referred to as *text data mining*, roughly equivalent to text analytics, refers to the process of deriving high-quality information from text. High-quality information is typically derived through the devising of patterns and trends through means such as statistical pattern learning. The "Affective Text" [2] focuses on the classification of emotions and valence (positive/negative polarity) in news headlines. The automatic detection of emotions in texts is becoming increasingly important from an applicative point of view.

In this use an emotion-topic model for associating emotions for the document and latent topics. For selecting topic from the document use an algorithm as latent dirichlet allocation [3] and collect latent topics. Latent Dirichlet allocation (LDA) is a generative probabilistic model of a corpus. The basic idea is that documents are represented as random mixtures over latent topics, where each topic is

characterized by a distribution over words. LDA is a three-level hierarchical Bayesian model, in which each item of a collection is modeled as a finite mixture over an underlying set of topics.

As a complete generative model, the proposed emotion-topic model allows us to infer a number of conditional probabilities for unseen documents, e.g., the probabilities of latent topics given an emotion, and that of terms given a topic. For social emotion prediction, the proposed model outperforms the emotion term model, term-based SVM model, and topic-based SVM model significantly. At the document level, the strategy of picking the last sentence's emotion as the answer outperforms all other strategies. It implies that humans summarize their emotion of the overall document by the last sentence of the document.

II. RELATED WORK

The paper MusicSense: Contextual Music Recommendation using Emotional Allocation Modeling is a novel approach–MusicSense– is to provide contextual music recommendation. The main idea is, to automatically deliver music pieces (or their thumbnails) which are relevant to the context of a Web page when users read it. Thus, it needs a way to properly measure the context relevance between music songs and Web pages.

In MusicSense [1] choose emotion as the bridge for such a relevance matching, as music is all about conveying composers' emotions, and lots of Web pages such as Weblogs also express sentiments of writers. Propose a generative model– *Emotional Allocation Modeling*–in which a collection of word terms is considered as generated with a mixture of emotions. Music songs are also described using textual information extracted from their meta-data and relevant Web pages. Thus, both music songs and Web documents can be characterized as distributions over the emotion mixtures through the emotional allocation modeling. For relevance matching, songs and Web documents are respectively represented by a collection of word terms, based on which their emotion distribution parameters are optimized in an iterative way.

With this model, it could reasonably consider each song (or a Weblog) is generated with a distribution over the mixture of emotions, effectively integrate knowledge discovering from a Web-scale corpus and guidance from psychological studies, and also keep the inference ability of generative model. Emotion acts as a bridge for the relevance matching between blogs and songs. Preliminary experiments indicate that the model work effectively; both the emotion estimation and the music recommendation match subjective preference closely. This paper may have drawback of some implementation details needed to improve the performance, and will also try to utilize more information besides emotion to measure the relevance between music and documents.

In the "Affective Text" [2] task focuses on the classification of emotions and valence (positive/negative polarity) in news headlines, and is meant as an exploration of the connection between emotions and lexical semantics. The "Affective Text" task was intended as an exploration of the connection between lexical semantics and emotions, and an evaluation of various automatic approaches to emotion recognition.

In this description the data set used in the evaluation and the results obtained by the participating systems. They proposed to focus on the emotion classification of news headlines extracted from news web sites. Headlines typically consist of a few words and are often written by creative people with the intention to "provoke" emotions, and consequently to attract the readers' attention. The automatic detection of emotion I texts is becoming increasingly important from an applicative point of view.

Latent Dirichlet allocation (LDA) [3] is a generative probabilistic model of a corpus. The basic idea is that documents are represented as random mixtures over latent topics, where each topic is characterized by a distribution over words. LDA is a three-level hierarchical Bayesian model, in which each item of a collection is modeled as a finite mixture over an underlying set of topics.

They present efficient approximate inference techniques based on variational methods and an EM algorithm for empirical Bayes parameter estimation. The goal is to find short descriptions of the members of a collection that enable efficient processing of large collections while preserving the essential statistical relationships that are useful for basic tasks such as classification, novelty detection, summarization, and similarity and relevance judgments.

The principal advantages of generative models such as LDA include their modularity and their extensibility. LDA is a simple model, and although we view it as a competitor to methods such as LSI and pLSI in the setting of dimensionality reduction for document collections and other discrete

corpora, it is also intended to be illustrative of the way in which probabilistic models can be scaled up to provide useful inferential machinery in domains involving multiple levels of structure.

Emotion classification [4] allows us to identify the feelings of individuals toward specific events. To use and evaluate the effectiveness of statistical learning methods for emotion classification, they need both a training dataset and a testing dataset. Weblog, or simply blog, is a very good dataset, which is collaboratively contributed by users, bloggers, on the web. More and more bloggers wish to share their feelings on blogs, some blog service providers start to allow their users to use non-verbal emotional expressions. Previous works used emoticons from blogs as categories for authors sentiment classification. Emoticons were used to identify emotions associated with textual keywords.

In emotion classification of web blog corpora [4] using support vector machine (SVM) and conditional random field (CRF) machine learning techniques. The emotion classifiers are trained at the sentence level and applied to the document level. When applying emotion classification to a blog at the document level, the emotion of the last sentence in a document plays an important role in determining the overall emotion. A lexicon construction method builds an emotion lexicon, which forms the fundamental features for emotion classification at the sentence level. The emotion information carried by a word can be treated as a kind of semantic orientation or subjectivity.

The paper Capturing Global Mood Levels using Blog Posts [5] is presented the blogosphere, the fast-growing totality of weblogs or blog-related webs, is a rich source of information for marketing professionals, social psychologists. Many blogs function as an online diary, reporting on the blogger's daily activities and surroundings. This leads a large number of bloggers to indicate what their mood was at the time of posting a blog entry. The collection of such mood reports from many bloggers gives a "blogosphere state-of-mind" for each point in time: the intensity of different moods among bloggers at that time.

The models exhibit a strong correlation with the actual moods reported by the bloggers, and significantly improve over a baseline. It is possible to cluster moods or terms according to their temporal behavior. They are not using non-content attributes for mood level prediction. Sentiment values of the individual words and other features are not included.

III. MODEL DESCRIPTIONS

3.1 Emotion-Term Model

A method that is to model the emotion-word association is the emotion-term model, which follows the Naive Bayes method by assuming words are independently generated from social emotion labels. Emotion-term model simply treats terms individually and cannot discover the contextual information within the document.

Emotion is a "positive or negative" experience that is associated with a particular pattern of physiological activity. Emotions are described as "discrete" because they are believed to be distinguishable by an individual's facial expression. The current being is conducted about the concept of emotion involves the development of materials that stimulate and elicit emotion. Emotions have been described as discrete and consistent responses to internal or external events which have a particular significance for the organism.

3.2 Topic Model

A topic model is a type of statistical model for discovering the abstract "topics" that occur in a collection of documents. A topic model captures this intuition in a mathematical framework, which allows examining a set of documents and discovering, based on the statistics of the words.

A "topic" consists of a cluster of words that frequently occur together. Using contextual clues, topic models can connect words with similar meanings and distinguish between uses of words with multiple meanings.

3.3 Emotion-Topic Model

Emotion Topic models are generative models that can be used to analyze the evolution of topics of a collection of documents over time. In LDA, both the order the words appear in a document and the order the documents appear in the corpus are oblivious to the model. Whereas words are still assumed to be exchangeable, in a dynamic topic model the order of the documents plays a fundamental role.

More precisely, the documents are grouped by time slice. With all the parameters derived above, we can apply the emotion-topic model to various applications.

IV. SYSTEM ARCHITECTURE

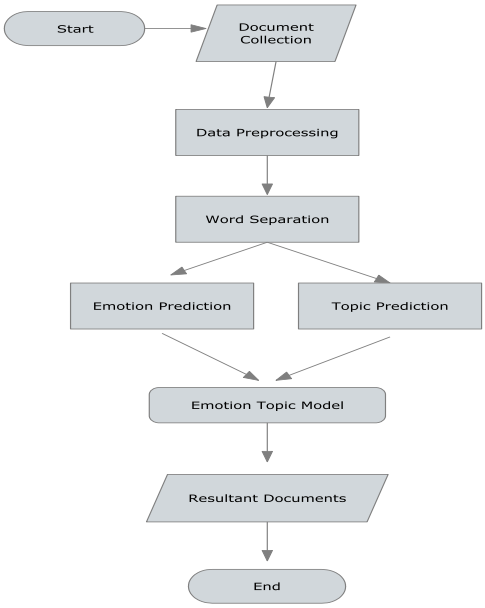

Fig 1: System Architecture

A data set is a collection of data it lists values for each of the variables, such as height and weight of an object. The query used to generate a particular data set from the selected connection or flat file profile. You can create multiple data set definitions for the same profile in order to generate different data set instances. To improve classification accuracy, insignificant parameters and patient data could be deleted from the data set.

In word separation it may use part-of-speech to separate words. Part-of-speech tagging (POS tagging or POST), also called grammatical is the process of marking up a word in a text as corresponding to a particular part of speech. A simplified form of this is commonly the identification of words as nouns, verbs, adjectives, adverbs, etc. Part of speech tags give relevant information about the role of a word in its narrow context. It may also provide information about the inflection of a word. POS tag share a valuable part of a language processing pipeline, they provide useful information to other components such as a parser or a named-entity recognizer.

In the emotion prediction we may use emotion-term model to predict the emotion of the word. Emotion is a "positive or negative" experience that is associated with a particular pattern of physiological activity. Emotions are described as "discrete" because they are believed to be distinguishable by an individual's facial expression. The current being is conducted about the concept of emotion involves the development of materials that stimulate and elicit emotion. Emotions have been described as discrete and consistent responses to internal or external events which have a particular significance for the organism.

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Emotion-term model simply treats terms individually and cannot discover the contextual information within the document. It is more sensible to associate emotions with a specific emotional event/topic instead of only a single term. A sentence is what is being talked about, and the comment is what is being said about the topic. Topic model utilizes the contextual information within the documents it fails to utilize the emotional distribution to guide the topic generation.

V. ALGORITHM

Latent dirichlet allocation

Latent Dirichlet allocation (LDA) is a generative probabilistic model of a corpus. The basic idea is that documents are represented as random mixtures over latent topics, where each topic is characterized by a distribution over words. LDA is a three-level hierarchical Bayesian model, in which each item of a collection is modeled as a finite mixture over an underlying set of topics.

We present efficient approximate inference techniques based on variational methods and an EM algorithm for empirical Bayes parameter estimation. The goal is to find short descriptions of the members of a collection that enable efficient processing of large collections while preserving the essential statistical relationships that are useful for basic tasks such as classification, novelty detection, summarization, and similarity and relevance judgments.

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LDA assumes the following generative process for each document **w** in a corpus *D*:

1. Choose $N \sim$ Poisson (ξ).
2. Choose $\theta \sim$ Dir (α).
3. For each of the N words w_n:

(a) Choose a topic $z_n \sim$ Multinomial(θ).

(b) Choose a word w_n from $p(w_n|z_n,\beta)$, a multinomial probability conditioned on the topic z_n.

The principal advantages of generative models such as LDA include their modularity and their extensibility. LDA is a simple model, and although we view it as a competitor to methods such as LSI and pLSI in the setting of dimensionality reduction for document collections and other discrete corpora, it is also intended to be illustrative of the way in which probabilistic models can be scaled up to provide useful inferential machinery in domains involving multiple levels of structure.

VI. CONCLUSION

In this paper, we present and examine a new problem called social affective text mining, which aims to discover and model the connections between online documents and user-generated social emotions. We proposed to determine our model with a larger scale of online document collections, and apply the model to other applications such as emotion-aware recommendation of advertisements, songs, and so on.

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