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Spatio temporal and aspect features based sentiment analysis on customer reviews

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Abstract

Online reviews are used as a decision support model for the consumers and feedback channel for the business organizations. Sentiment analysis techniques are employed to investigate online reviews. The sentiment expressed in review document is called as overall sentiment. Attribute level like and dislike factors are not represented in the overall sentiment estimation methods. The aspect level sentiment analysis model discovers the unique semantic fact of individual entity. The Aspect based sentiment analysis consists of two major tasks. They are, detect hidden semantic aspect from review document and identify fine-grained sentiments for the aspect. Probabilistic topic models are used for aspect-based sentiment analysis.

The review documents and rating measures are analyzed to discover the semantic aspect level sentiments and overall sentiments. The probabilistic supervised joint aspect and sentiment model (SJASM) is employed to analyze the review documents in an unified framework. SJASM represents each review document in the form of opinion pairs. The aspect terms and opinion words are modeled for hidden aspect and sentiment detection. The overall sentimental rating is estimated with aspect and aspect level sentiments. The collapsed Gibbs sampling-based inference method is used for parameter estimation of SJASM. The aspect distribution is used to select the parameters for the sentiment estimation. The review documents are classified into positive or negative sentiments.

The collaborative sentiment assessment model (CSAM) integrates the aspect and spatio temporal features. The Bayesian nonparametric model is applied to automatically estimate the number of latent topics from review data. The hybrid indexing scheme combines the aspect and spatio temporal parameters to order the review documents. The recommendation process is build with aspect, location and time features.

Index Terms: Sentiment analysis, aspect-based learning, supervised joint topic model, Spatio Temporal Features and Customer Review Analysis.

1. Introduction

The Web has an overwhelming amount of reviews of products, restaurants, books, and many other types of tangibles and intangibles. In those reviews, people praise and criticize a variety of aspects of the target of the review, such as the waiting time of a restaurant or the noise level of a vacuum cleaner. The reviewer evaluates aspects of a laptop such as the price, monitor size, and sound. Although some Websites are specifically designed for user reviews with a predefined evaluation form, most users express their opinion in online communities and personal blogs using plain text without any structure.

One big problem is to find aspects is that users evaluate in reviews. From the perspective of a user reading the reviews to get information about a product, the evaluations of the specific aspects are just as important as the overall rating of the product. A user looking to buy a digital camera may want to know what a review says about the photo quality, brightness of lens, and shutter speed of a Panasonic Lumix, not just whether the review recommends the camera. Al- though sometimes the aspect information is available, it is unlikely to be a comprehensive set of all aspects that are evaluated in the reviews. Another important task in review analysis is discovering how opinions and sentiments for different aspects are expressed [14]. The cell phone's battery lasts “long", a laptop's screen “reects" and a restaurant's server is “attentive". These are sentiment words at the level of the aspect. Previous efforts have mostly focused on sentiment words at the level of the domain.

The problems are tackled with the unified generative model of aspect and sentiment. Probabilistic topic models are suitable for the following two reasons: first, they provide an unsupervised way of discovering topics from documents and second, they result in language models that explain how much a word is related to each topic and possibly to a sentiment. The Latent Dirichlet Allocation (LDA) model is taken to adapt it to match the granularity of the discovered topics to the details of the reviews. In addition, sentiment is incorporated into the unified model so that the resulting language models represent the probability distributions over words for various pairs of aspect and sentiment.

In reviews, one sentence tends to represent one aspect and one sentiment. The review is evaluating several aspects including the price, free upgrade, size, and sound, and each sentence expresses sentiment about one aspect. In the first sentence in the second paragraph, the words “monitor" and “bag" co-occur. In general, these two words are not closely related, but the co-occurrence of them signals that this sentence is evaluating the size of the monitor. Thus, the observations are used in the models.

2. Related Work

Sentiment classification is a fundamental problem in sentiment analysis, which targets at inferring the sentiment label of a document. Pang and Lee cast this problem a classification task, and use machine learning method in a supervised learning framework [1]. Goldberg and Zhu use unlabeled reviews in a graph based semi-supervised learning method. Many studies design effective features, such as text topic, bag-of opinion [6] and sentiment lexicon features. User information is also used for sentiment classification. Gao et al. [11] design user-specific features to capture user leniency. Li et al. incorporate textual topic and user-word factors with supervised topic modeling. Tan et al. [10] and Hu et al. [8] utilize user text and user-user relations for Twitter sentiment analysis. Unlike most previous studies that use hand-crafted features, is discriminative features from data. It differs from Li et al. [4] in that is encoded four kinds of consistencies and use neural network approach. User representation is also leveraged for recommendation [2], web search social media analytics [5].

Neural networks have achieved promising results for sentiment classification. Existing neural network methods can be divided into two groups: word embedding and semantic composition. For learning word embeddings, use local and global contexts, [12] further incorporate sentiment of texts. For learning semantic composition, Glorot et al. [7] use stacked denoising autoencoder, introduce a family of recursive deep neural networks (RNN). RNN is extended with adaptive composition functions, global feed backward [3], feature weight tuning and also used for opinion relation detection. Li et al. compare the effectiveness of recursive neural network and recurrent neural network on five NLP tasks including sentiment classification. [9] Use convolutional neural networks. Le and Mikolov [13] introduce Paragraph Vector. Like existing neural network approaches that only use the semantics of texts, we take consideration of user and product representations and leverage their connections with text semantics for sentiment classification. This work is an extension of our work only takes consideration of user word association.

3. Supervised Joint Topic Modeling Approach

Online user-generated reviews are of great practical use as they have become an inevitable part of decision making process of consumers on product purchases, hotel bookings, etc. and they collectively form a low cost and efficient feedback channel, which helps businesses to keep track of their reputations and to improve the quality of their products and services. As a matter of fact, online reviews are constantly growing in quantity, while varying largely in content quality. To support users in digesting the huge amount of raw review data, many sentiment analysis techniques have been developed for past years.

Generally, sentiments and opinions can be analyzed at different levels of granularity. The sentiments are expressed in a whole piece of text, e.g., review document or sentence and overall sentiment. The task of analyzing overall sentiments of texts is typically formulated as classification problem, e.g., classifying a review document into positive or negative sentiment. Then, a variety of machine learning methods trained using different types of indicators have been employed for overall sentiment analysis [15]. Analyzing the overall sentiment expressed in a whole piece of text alone, does not discover what specifically people like or dislike in the text. In reality, the fine-grained sentiments may very well tip the balance in purchase decisions. For example, savvy consumers nowadays are no longer satisfied with just overall sentiment/rating given to a product in a review, they are often eager to see why it receives that rating, which positive or negative attributes (aspects) contribute to the particular rating of the product.

Recently, there has been a growing interest in analyzing aspect-level sentiment, where an aspect means a unique semantic facet of an entity commented in text documents and is typically represented as a high-level hidden cluster of semantically related keywords. Aspect-based sentiment analysis generally consists of two major tasks, one is to detect hidden semantic aspect from given texts and the other is to identify fine-grained sentiments expressed towards the aspects. Probabilistic topic models, which are typically built on a basic LDA model, have been used for aspect-based sentiment analysis where the semantic aspect can be naturally formulated as one type of latent topics.

Majority of existing probabilistic SJASM models are unsupervised or weakly/partially supervised, meaning that they primarily model user-generated text content, and have not considered overall ratings or labels of the text documents in their frameworks. As a result, though they have captured the hidden thematic structure of text data, the models cannot directly predict the overall sentiments or ratings of text documents, instead, they only rely on document-specific sentiment distribution in approximate the overall sentiments of documents.

Moreover, previous studies usually treat overall sentiment analysis and aspect-based sentiment analysis in isolation, and then introduce a variety of methods to analyze either overall sentiments or aspect-level sentiments, but not both. As per the observation there exists naturally interdependency between the aspect based and overall sentiment analysis problems. Specifically, inferring predictive hidden aspects and sentiments from text reviews can be helpful for predicting overall ratings/sentiments of reviews, while overall ratings/sentiments of text reviews can provide guidance and constraint for inferring fine-grained sentiments on the aspects from the reviews. A carefully designed supervised unification model can benefit from the inter-dependency between the two problems and support them to improve each other. It is thus important to analyze aspect-level sentiments and overall sentiments in one go under a unified framework.

The main focus is on modeling online user generated review and overall rating pairs and aims to identify semantic aspects and aspect-level sentiments from review texts as well as to predict overall sentiments of reviews. Generally, online reviews often come with overall ratings, for example, in the form of one-to-five stars, which can be naturally regarded as sentiment labels of the text reviews. This evidence provides us with pretty good opportunity to develop SJASM model for aspect-based and overall sentiment analysis problems.

In particular, instead of using bag-of-words representation, which is typically adopted for processing usual text data, first each text review is represented as a bag of opinion pairs, where each opinion pair consists of an aspect term and corresponding opinion word in the review. The basic LDA model construct a probabilistic joint aspect and sentiment framework to model the textual bag-of-opinion-pairs data. Then, on top of the probabilistic topic modeling framework, a new supervised learning layer via normal linear model to jointly capture overall rating information is introduced. In addition, the leverage weak supervision data based on pre-compiled sentiment lexicon, which provides sentimental prior knowledge for the model. In this way, a novel SJASM model which is able to cope with aspect-based sentiment analysis and overall sentiment analysis in a unified framework.

Several key advantages of SJASM help it stand out in the probabilistic joint topic models to sentiment analysis:

a. SJASM can simultaneously model aspect terms and corresponding opinion words of each text review for semantic aspect and sentiment detection;
b. It exploits sentimental overall ratings as supervision data, and can infer the semantic aspects and fine-grained aspect-level sentiments that are not only meaningful but also predictive of overall sentiments of reviews; and
c. It leverages sentiment prior information, and can explicitly build the correspondence between detected sentiments and real-world sentiment orientations. Moreover, based on the collapsed Gibbs sampling method a new efficient inference algorithm is presented to estimate the parameters for SJASM. The publicly available real-world review data is used to evaluate SJASM for three typical sentiment analysis tasks, i.e., semantic aspect detection, aspect-level sentiment identification, and overall rating/sentiment prediction. The experimental results demonstrate the superiority of SJASM over seven well established baseline methods.

Next, this work has made the following main contributions:

- This work presents a new supervised joint topic model called SJASM, which forms the prediction for overall ratings/sentiments of reviews via normal linear model based on the inferred hidden aspects and sentiments in the reviews.
- It formulates overall sentiment analysis and aspect-based sentiment analysis in a unified framework, which allows SJASM to leverage the inter dependency between the two problems and to support the problems to improve each other.
- It presents a detailed inference method for SJASM based on collapsed Gibbs sampling.
- This work compares SJASM with seven strong representative baselines, and experimentally

shows the benefits of SJASM over them for the sentiment analysis problems.

4. Issues on Sentiment Analysis Models

The review documents and rating measures are analyzed to discover the semantic aspect level sentiments and overall sentiments. The probabilistic SJASM is employed to analyze the review documents in an unified framework. SJASM represents each review document in the form of opinion pairs. The aspect terms and opinion words are modeled for hidden aspect and sentiment detection. The overall sentimental rating is estimated with aspect and aspect level sentiments. The collapsed Gibbs sampling-based inference method is used for parameter estimation of SJASM. The aspect distribution is used to select the parameters for the sentiment estimation. The review documents are classified into positive or negative sentiments. The following issues are identified from the current sentiment analysis models.

- Spatio temporal sentiment analysis is not supported
- Automatic topic estimation is not provided
- Topic frequency assignment is not supported
- Rating based indexing and recommendation operations are not provided

5. Spatio Temporal and Aspect Feature based Sentiment Analysis

The CSAM integrates the aspect and spatio temporal features. The Bayesian nonparametric model is applied to automatically estimate the number of latent topics from review data. The hybrid indexing scheme combines the aspect and spatio temporal parameters to order the review documents. The recommendation process is built with aspect, location and time features.

The sentiment detection analysis scheme is built to analyze the Hotel review data values. The customer opinion data values are analyzed with location and time details. The indexing and recommendation methods are integrated with the sentiment estimation scheme. The system is divided into six major modules. They are Review Document Management, Topic Extraction Process, SJASM, CSAM, Indexing Review Data and Recommendation Process.

The data preprocessing operations are carried out under the review document management. The topics are derived from the review document using the topic extraction module. The aspects and sentiments are extracted under the SJSAM module. The CSAM module is built to assess the review documents with spatio temporal features. The indexing process is carried out to arrange the review documents based on the rating parameters. The recommendation process is built to provide suggestions to the customers.

5.1. Review Document Management

The review documents are collected from the TripAdvisor web site for hotel review analysis. The Stanford parser is used to parse the review documents in the data set. The aspect terms and opinion words are extracted from the review documents. The opinion pairs are built with the aspect and opinion word collections.

5.2. Topic Extraction Process

The topic detection operations are performed on the preprocessed data values. The topics and parameter identification is carried out with collapsed Gibbs sampling based inference method. The automatic topic extraction process is performed using the Bayesian nonparametric model. The aspect distribution is also performed in the topic extraction process.

5.3. Supervised Joint Aspect and Sentiment Model (SJASM)

The SJASM is used to fetch the aspect level and overall sentiments. The aspect level sentiment-based rating is assigned for each aspect in the review document. The overall rating is estimated for the entire review document. The positive and negative sentiments are identified for the aspects and documents.

5.4. Collaborative Sentiment Assessment Model (CSAM)

The CSAM is built to extract aspect and overall sentiments with location and time parameters. The spatial parameters are used analyze location relationship levels. The time relationships are analyzed with temporal data values. The aspect and sentiment detection operations are carried out with spatio temporal factors.

5.5. Indexing Review Data

The review documents are arranged with its sentiment and rating levels. The rating-based index is applied with aspect and overall sentimental scores. The spatial index is carried out with the location information. The indexed data values are used to produce top level reviews.

5.6. Recommendation Process

The recommendation process is used to suggest the products based on the historical review data values. The recommendations are produced with reference to the user requirements. The aspect and sentiment-based recommendations are prepared with aspect and overall sentimental ratings. The location and time features are integrated in the spatio temporal aspect-based recommendation process.

6. Performance Analysis

The sentiment analysis models are applied to detect the sentiments on the user reviews. The review data values are analyzed with its aspects and rating levels. The aspect rating and overall ratings are combined in the sentiment analysis process. The sentiment analyses operations are carried out with Supervised Joint Aspect and Sentiment Model (SJASM) and Collaborative Sentiment Assessment Model (CSAM). The system is tested with hotel review data sets that are collected from the TripAdvisor web site. The sentiment prediction accuracy parameter is analyzed in the system.

7. Conclusion

Online reviews are used as a communication channel between the consumers and the business organizations. The probabilistic SJASM is used to extract aspect and sentiment levels. The CSAM is built to analyze the review documents with aspect and spatio temporal features. The indexing scheme and recommendation process are combined with the review document analysis. The online review analysis is carried out on aspect level and overall document level.

The spatio temporal parameters supports region-based sentiment estimation process. The index model arranges the review documents with sentiments and score values. The user decision making process is efficiently supported with recommendation process.

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