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Opinion mining with target extraction using word identification

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ABSTRACT

The growth of cloud computing has resulted in uneconomic energy consumption, which has negatively impacted the environment through the generation of carbon emissions. This project proposes a distributed Locust-inspired scheduling algorithm to reduce cloud computing consumed energy (LACE). It schedules and optimizes the allocation of virtual machines (VMs) based on behavior derived from locusts. LACE distributes scheduling among servers; each server is responsible for allocating and migrating its VMs. Therefore, the scheduling load is distributed between servers rather than being centralized in one component. LACE was thoroughly evaluated by equaling it with long-standing VM scheduling algorithms: dynamic voltage–frequency scaling (DVFS), energy-aware scheduling using the workload-aware consolidation technique, and the static threshold with minimum utilization policy. In addition, this project proposes a resource provisioning and scheduling strategy for scientific workflows on Infrastructure as a Service (IaaS) and Platform as services clouds (PaaS). This project presents an algorithm based on the Superior Element Multitude Optimization (SEMO), which aims to minimize the overall workflow execution cost while meeting deadline constraints. The main scope of the project is used to analyze best available resource in the cloud environment depends upon the total execution time and total execution cost which is compare between one process to another process. If the provider satisfies the time least time, then the process becomes to termination.

Keywords: Cloud Computing, Energy Efficiency, Resource Management, Virtualization

INTRODUCTION

In mining the opinion relations between opinion targets and opinion words was the key to collective extraction. To this end, the most-adopted techniques have been nearest-neighbor rules and syntactic patterns Nearest-neighbor rules regard the nearest adjective/verb to a noun/noun phrase in a limited window as its modifier. Clearly, this strategy cannot obtain precise results because there exist long-span modified relations and diverse opinion expressions.

To address this problem, several methods exploited syntactic information, in which the opinion relations among words are decided according to their dependency relations in the parsing tree. Accordingly several heuristic syntactic patterns were designed .However, online reviews usually have informal writing styles, including grammatical errors, typo graphical errors, and punctuation errors.

These existing parsing tools, which are usually trained on formal texts such as news reports, prone to generating errors. Accordingly, these syntax-based methods, which heavily depend on parsing performance, suffer from parsing errors and often do not work well. To improve the performance of these methods, we can specially design exquisite, high-precision patterns. However, with an increase in corpus size, this strategy is likely to miss more items and has lower recall. Therefore, how to precisely detect the opinion relations among words is a considerable challenge in this task.

The collective extraction adopted by most previous methods was usually based on a bootstrapping framework, which has the problem

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of error propagation. If some errors are extracted by an iteration, they would not be filtered out in subsequent iterations. As a result, more errors are accumulated iteratively. Therefore, how to alleviate, or even avoid, error propagation is another challenge in this task.

- To this end, the most adopted techniques have been nearest-neighbor rules and syntactic patterns. Nearest- neighbor rules regard the nearest adjective/verb to a noun/noun phrase in a limited window as its modifier.
- To online reviews usually have informal writing styles, including grammatical errors, typo graphical errors, and punctuation errors
- To improve the performance of these methods, we can specially design exquisite, high-precision patterns.
- To collective extraction adopted by most previous methods was usually based on a bootstrapping framework, which has the problem of error propagation.

RELATED WORKS

News Comments on the web express readers' attitudes or opinions about an event or object in the corresponding news article. And opinion target extraction from news comments is very important for many useful Web applications. However, many sentences in the comments are irregular and informal, and sometimes the opinion targets are implicit. Thus the task is very challenging and it has not been investigated yet. In this paper, we propose a new approach to uniformly extracting explicit and implicit opinion targets from news comments by using Centering Theory.

The approach uses global information in news articles as well as contextual information in adjacent sentences of comments. Our experimental results verify the effectiveness of the proposed approach.

Qiaozhu Mei And Xu Ling, Matthew, we define the problem of topic-sentiment analysis on Weblogs and propose a novel probabilistic model to capture the mixture of topics and sentiments simultaneously. The proposed Topic-Sentiment Mixture (TSM) model can reveal the latent topical facets in a Weblog collection, the subtopics in the results of an ad hoc query, and their associated sentiments. It could also provide general sentiment models that are applicable to any ad hoc topics. With a specifically designed HMM structure, the sentiment models and topic models estimated with TSM can be utilized to extract topic life cycles and sentiment dynamics. Empirical experiments on different Weblog datasets show that this approach is effective for modeling the topic facets and sentiments and extracting their dynamics from Weblog collections.

Wayne Xin Zhao And Jing Jian Discovering and summarizing opinions from online reviews is an important and challenging task. A commonly-adopted framework generates structured review summaries with aspects and opinions. Recently topic models have been used to identify meaningful review aspects, but existing topic models do not identify aspect-specific opinion words. In this paper, we propose a MaxEnt-LDA hybrid model to jointly discover both aspects and aspect-specific opinion words. We show that with a relatively small amount of training data, our model can effectively identify aspect and opinion words simultaneously. We also demonstrate the domain adaptability of our model.

Arjun Mukherjee, Bing Liu Writing comments about news articles, blogs, or reviews have become a popular activity in social media. In this paper, we analyze reader comments about reviews. Analyzing review comments is important because reviews only tell the experiences and evaluations of reviewers about the reviewed products or services. Comments, on the other hand, are readers' evaluations of reviews, their questions and concerns. Clearly, the information in comments is valuable for both future readers and brands. This paper proposes two latent variable models to simultaneously model and extract these key pieces of information.

The results also enable classification of comments accurately. Experiments using Amazon review comments demonstrate the effectiveness of the proposed models.

In sentence-level extraction, the task of opinion target word extraction is to identify the opinion target mentions or opinion expressions in sentences. Thus, these tasks are usually regarded as sequence-labeling problems. Intuitively,

contextual words are selected as the features to indicate opinion targets/words in sentences. Additionally, classical sequence labeling models are used to build the extractor, such as CRFs and HMM . A proposed lexicalized HMM model to perform opinion mining.

However, these methods always need the labeled data to train the model. If the labeled training data are insufficient or come from the different domains than the current texts, they would have unsatisfied extraction performance. Although proposed a method based on transfer learning to facilitate cross domain extraction of opinion targets/words, their method still needed the labeled data from out-domains and the extraction performance heavily depended on the relevance between in-domain and out-domain.

This paper proposes a novel method for co-extracting opinion targets and opinion words by using a word alignment model. The proposed system main contribution is focused on detecting opinion relations between opinion targets and opinion words. To plan to consider additional types of relations between words, such as topical relations, in Opinion Relation Graph.

METHODOLOGY

In this project propose a novel method for co-extracting opinion targets and opinion words by using a word alignment model. To compared previous methods based on nearest neighbor rules and syntactic patterns, in using a word alignment model, and method captures opinion relations more precisely and therefore is more effective for opinion target and opinion word extraction .Estimating candidate confidence with Graph co-ranking model is opinion associations between opinion target candidates and opinion word candidates complete the construction of the Opinion Relation Graph. Graph relation is calculating the confidence of each opinion target/word candidate on this graph, and the candidates with higher confidence than a threshold are extracted as opinion targets or opinion words. To assume that two candidates are likely to belong to a similar category if they are modified by similar opinion words or modify similar opinion targets. If know one of them to be an opinion target/word, the other one has a high probability of being an opinion target/word. Thus, we can forward the confidences among different candidates, which indicate that the graph-based algorithms are applicable.

The proposed word alignment models effectively lessen the negative effects of parsing errors when dealing with informal online texts. In addition, when estimating candidate confidence, it penalizes higher-degree vertices in the graph-based co-ranking algorithm to decrease the probability of error generation. The experimental results show that the approach effectively outperforms state-of-the-art methods

CONFIGURATION DATA SETS

Add stop word

In this module, the words such as a, an, the, is, was and etc., like words which are not important in opinion mining are added into ‘StopWords’ table.

Add adjective word

In this module, the words such as big, colorful and etc., like words which are giving the adjective meaning and used as ‘opinion mining word’ are added into ‘AdjectiveWords’ table

Add noun word

In this module, the words such as screen, mobile and etc., like words which are giving the noun meaning and used as ‘opinion target word’ are added into ‘NounWords’ table. If phrases are to be used as Nouns, then should be in between the words. For example, If ‘Nokia Lumia’ is the noun, then Nokia-Lumia should be the noun phrase.

OPINION RELATION GRAPH

In this module, the given sentence is eliminated with stop words and then the same sentence is written in twice. Then words not connected with opinion words and targets are connected with each other in sentence A and same sentence B. Then adjective words in sentence A are connected with noun words in sentence Band also the adjective words in sentence B are connected with noun words in sentence A.

To precisely mine the opinion relations among words, propose a method based on a monolingual Word Alignment Model (WAM). An opinion target can find its corresponding modifier through word alignment. Compared to previous nearest-neighbor rules, the WAM does not constrain identifying modified relations to a limited window; therefore, it can capture more complex relations, such as long-span modified relations. Compared to syntactic patterns, the WAM is more robust because it does not need to parse informal texts. In addition, the WAM can integrate several intuitive factors, such as word co-occurrence frequencies and word positions, into a unified model for indicating the opinion relations among words.

Capturing opinion relation between opinion targets and opinion words using word alignment

In this module, the constrained Hill-Climbing algorithm is used to implement the capturing of opinion relation.

Capturing opinion relations between Opinion targets and opinion words using word alignment model are to directly apply the standard alignment model to our task, an opinion target candidate (noun/noun phrase) may align with the irrelevant words rather than potential opinion words (adjectives/verbs), such as prepositions and conjunctions. Thus, we introduce some constraints in the alignment model as follows: Nouns/noun phrases (adjectives/verbs) must be aligned with adjectives/verbs (nouns/noun phrases) or a null word. Aligning to a null word means that this word either has no modifier or modifies nothing; Other unrelated words, such as prepositions, conjunctions and adverbs, can only align with themselves. Optimize toward the constraints. This step aims to generate an initial alignment for our alignment model close to the constraints. First, the simpler alignment models are sequentially trained. Second, evidence that is inconsistent with the partial alignment links is eliminated by using the MOVE operator and the SWAP operator. In this module, from the alignment results, we obtain a set of word pairs, each of which is composed of a noun/noun phrase (opinion target candidate) and its corresponding modified word (opinion word candidate). Next, the alignment probabilities between a potential opinion target wt and a potential opinion word wo are estimated usingwhere P (wt|wo) means the alignment probability between these two words. Similarly, we obtain the alignment probability P (wo|wt) by changing the alignment direction in the alignment process. Next, we use the score function to calculate the opinion association OA (wt, wo) between wt and is the harmonic factor used to combine these two alignment probabilities. In this paper, we set = 0.5.

$$P(w_t \mid w_o) = \frac{Count(w_t, w_o)}{Count(w_o)},$$

Estimating candidate confidence with graph co-ranking (local)

After mining the opinion associations between opinion target candidates and opinion word candidates, we complete the construction of the Opinion Relation Graph. We then calculate the confidence of each opinion target/word candidate on this graph, and the candidates with higher confidence than a threshold are extracted as opinion targets or opinion words. We assume that two candidates are likely to belong to a similar category if they are modified by similar opinion words or modify similar opinion targets.

If we know one of them to be an opinion target/word, the other one has a high probability of being an opinion target/word. Thus, we can forward the confidences among different candidates, which indicates that the graph-based algorithms are applicable.

Estimating Candidate Confidence by Using Random Walking Naturally, we can use a standard random walk with restart algorithm to estimate the confidence of each candidate.

Ck are the confidence of an opinion target candidate and opinion word candidate, respectively, in the k iteration AND the confidence

of an opinion target candidate and opinion word candidate, respectively, in the k iteration.

Estimating candidate confidence with graph co-ranking (global)

The Opinion associations between opinion target candidates and opinion word and dates, complete the construction of the Opinion Relation Graph and calculate the confidence of each opinion target/word candidate on this graph, and the candidates with higher confidence than a threshold are extracted as opinion targets or opinion words. Assume that two candidates are likely to belong to a similar category if they are modified by similar opinion words or modify similar opinion targets.

If know one of them to be an opinion target/word, the other one has a high probability of being an opinion target/word and the confidences among different candidates, which indicate that the graph-based algorithms are applicable.

- Salience feature: This feature indicates the salience degree of a candidate in reviews.
- Domain relevance feature: Observe that opinion targets are usually domain-specific and there are remarkable distribution differences between them in different domains.
- Lexical feature: For each candidate, all words having opinion relations with it are selected as lexical features.

CONCLUSION

This project considers mining the opinion relations between opinion targets and opinion words was the key to collective extraction. To this end, the most adopted techniques have been nearest-neighbor rules and syntactic patterns. Nearest neighbor rules regard the nearest adjective/verb to a noun/noun phrase in a limited window as its modifier. Clearly, this strategy cannot obtain precise results because there are long-span modified relations and diverse opinion expressions. In this project the standard word alignment models are often trained in a completely unsupervised manner, which results in alignment quality that may be unsatisfactory. It certainly can improve alignment quality by using supervision and both time consuming and impractical to manually label full alignments in sentences.

Thus, it further employs a partially supervised word alignment model. It is deemed that we can easily obtain a portion of the links of the full alignment in a sentence. These can be used to constrain the alignment model and obtain better alignment results. In addition, additional types of relations between words, such as topical relations are considered. Also multiple words are considered in finding opinion word and opinion target i.e., phrases are used.

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