© 2017 IJSRST | Volume 3 | Issue 2 | Print ISSN: 2395-6011 | Online ISSN: 2395-602X

National Conference on Advances in Engineering and Applied Science (NCAEAS)
16th February 2017
In association with
International Journal of Scientific Research in Science and Technology

Online Reviews Based on the Word Alignment Model

Sayali kothekar, Kalpana Malape, Vijaya Kamble

Department of Computer & Science, GNIET, Nagpur, Maharashtra, India

ABSTRACT

Mining opinion targets and opinion words from online reviews are important tasks for fine-grained opinion mining, the key component of which involves detecting opinion relations among words. To this end, this paper proposes a novel approach based on the partially-supervised alignment model, which regards identifying opinion relations as an alignment process. Then, a graph-based co-ranking algorithm is exploited to estimate the confidence of each candidate. Finally, candidates with higher confidence are extracted as opinion targets or opinion words. Compared to previous methods based on the nearest-neighbor rules, our model captures opinion relations more precisely, especially for long-span relations. Compared to syntax-based methods, our word alignment model effectively alleviates the negative effects of parsing errors when dealing with informal online texts. In particular, compared to the traditional unsupervised alignment model, the proposed model obtains better precision because of the usage of partial supervision. In addition, when estimating candidate confidence, we penalize higher-degree vertices in our graph-based co-ranking algorithm to decrease the probability of error generation. Our experimental results on three corpora with different sizes and languages show that our approach effectively outperforms state-of-the-art methods.

Keywords : Opinion Mining, Opinion Targets Extraction, Opinion Words Extraction

I. INTRODUCTION

With the rapid development of Web 2.0, a huge number of product reviews are springing up on the Web. From these reviews, customers can obtain first-hand assessments of product information and direct supervision of their purchase actions. Meanwhile, manufacturers can obtain immediate feedback and opportunities to improve the quality of their products in a timely fashion. Thus, mining opinions from online reviews has become an increasingly urgent activity and has attracted a great deal of attention from researchers [1], [2], [3], [4].

To extract and analyze opinions from online reviews, it is unsatisfactory to merely obtain the overall sentiment about a product. In most cases, customers expect to find finegrained sentiments about an aspect or feature of a product that is reviewed. For example:

"This phone has a colorful and big screen, but its LCD resolution is very disappointing."

Readers expect to know that the reviewer expresses a positive opinion of the phone's screen and a negative opinion of the screen's resolution, not just the reviewer's overall sentiment. To fulfill this aim, both opinion targets and opinion words must be detected. First, however, it is necessary to extract and construct an opinion target list and an opinion word lexicon, both of which can provide prior knowledge that is useful for fine-grained opinion mining and both of which are the focus of this paper.

An opinion target is defined as the object about which users express their opinions, typically as nouns or noun phrases. In the above example, "screen" and "LCD resolution" are two opinion targets. Previous methods have usually generated an opinion target list from online product reviews. As a result, opinion targets usually are product features or attributes. Accordingly this subtask is also called as product feature extraction [5], [6]. In addition, opinion words are the words that are used to express users' opinions. In the above example, "colorful", "big" and "disappointing" are three opinion words. Constructing an opinion

1) Into a unified model for indicating the opinion relations among words. Thus, we expect to obtain more precise results on opinion relation identification. The alignment model used in [4] has proved to be effective for opinion target extraction. However, for opinion word extraction, there is still no straightforward evidence to demonstrate the WAM's effectiveness.
2) We further notice that standard word alignment models are often trained in a completely unsupervised manner, which results in alignment quality that may be unsatisfactory. We certainly can improve alignment quality by using supervision [11]. However, it is both time consuming and impractical to manually label full alignments in sentences. Thus, we further employ a partially-supervised word alignment model (PSWAM). We believe 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. To obtain partial alignments, we resort to syntactic parsing. Although existing syntactic parsing algorithms cannot precisely obtain the whole syntactic tree of informal sentences, some opinion relations can still be obtained precisely by using high-precision syntactic patterns. A constrained EM algorithm based on hill-climbing is then performed to determine all of the alignments in sentences, where the model will be consistent with these links as much as possible. In this way, some errors induced by completely unsupervised WAMs will be corrected. For example, in Fig. 2, "kindly" and "courteous" are incorrectly identified as modifiers for "foods" if the WAM is performed in a wholly unsupervised manner. However, by using some syntactic patterns, we can assert that "courteous" should be aligned to "services". Through the PSWAM, "kindly" and "courteous" are correctly linked to "services". This model not only inherits the advantages of the word alignment model for opinion relation identification, but it also has a more precise performance because of the use of partial supervision. Thus, it is reasonable to expect that the PSWAM is likely to yield better results compared to traditional methods for extracting opinion targets and opinion words.

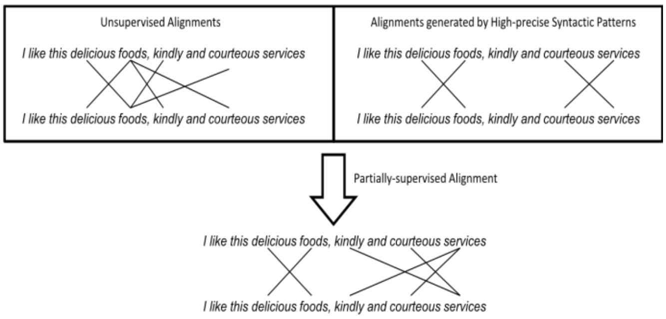

Figure 1. Mining opinion relations between words using partially supervised alignment model.

3) To alleviate the problem of error propagation, we resort to graph co-ranking. Extracting opinion targets/words is regarded as a co-ranking process. Specifically, a graph, named as Opinion Relation Graph, is constructed to model all opinion target/word candidates and the opinion relations among them. A random walk based co-ranking algorithm is then proposed to estimate each candidate's confidence on the graph. In this process, we penalize high-degree vertices to weaken their impacts and decrease the probability of a random walk running into unrelated regions on the graph. Meanwhile, we calculate the prior knowledge of candidates for indicating some noises and incorporating them into our ranking algorithm to make collaborated operations on candidate confidence estimations. Finally, candidates with higher confidence than a threshold are extracted. Compared to the previous methods based on the bootstrapping strategy, opinion targets/words are no longer extracted step by step. Instead, the confidence of each candidate is estimated in a global process with graph co-ranking. Intuitively, the error propagation is effectively alleviated.

To illustrate the effectiveness of the proposed method, we select real online reviews from different domains and languages as the evaluation datasets. We compare our method to several state-of-the-art methods on opinion target/word extraction. The experimental results show that our approach improves performance over the traditional methods.

II. METHODS AND MATERIAL

1. Related Work

Opinion target and opinion word extraction are not new tasks in opinion mining. There is significant effort focused on these tasks [1], [6], [12], [13], [14]. They can be divided into two categories: sentence-level extraction and corpuslevel extraction according to their extraction aims.

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 [13], [14], [15], [16]. 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 [13] and HMM [17]. Jin and Huang [17] proposed a lexicalized HMM model to perform opinion mining. Both [13] and [15] used CRFs to extract opinion targets from reviews. 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 [2] proposed a method based on transfer learning to facilitate crossdomain 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.

In addition, much research focused on corpus-level extraction. They did not identify the opinion target/word mentions in sentences, but aimed to extract a list of opinion targets or generate a sentiment word lexicon from texts. Most previous approaches adopted a collective unsupervised extraction framework. As mentioned in our first section, detecting opinion relations and calculating opinion associations among words are the key component of this type of method. Wang and Wang [8] adopted the co-occurrence frequency of opinion targets and opinion words to indicate their opinion associations. Hu and Liu [5] exploited nearest-neighbor rules to identify opinion relations among words. Next, frequent and explicit product features were extracted using a bootstrapping process. Only the use of cooccurrence information or nearest-neighbor rules to detect opinion relations among words could not obtain precise results. Thus, [6] exploited syntax information to extract opinion targets, and designed some syntactic patterns to capture the opinion relations among words. The experimental results showed that their method performed better than that of [5]. Moreover, [10] and [7] proposed a method, named as Double Propagation, that exploited syntactic relations among words to expand sentiment words and opinion targets iteratively. Their main limitation is that the patterns based on the dependency parsing tree could not cover all opinion relations. Therefore, Zhang et al. [3] extended the work by [7]. Besides the patterns used in [7], Zhang et al. further designed specific patterns to increase recall. Moreover, they used an HITS [18] algorithm to compute opinion target confidences to improve precision. Liu et al. [4] focused on opinion target extraction based on the WAM. They used a completely unsupervised WAM to capture opinion relations in sentences. Next, opinion targets were extracted in a standard random walk framework. Liu's experimental results showed that the WAM was effective for extracting opinion targets. Nonetheless, they present no evidence to demonstrate the effectiveness of the WAM on opinion word extraction.

Furthermore, a study employed topic modeling to identify implicit topics and sentiment words [19], [20], [21], [22]. The aims of these methods usually were not to extract an opinion target list or opinion word lexicon from reviews. Instead, they were to cluster for all words into corresponding aspects in reviews, which was different from the task in this paper. These methods usually adopted coarser techniques, such as frequency statistics and phrase detection, to detect the proper opinion targets/words. They put more emphasis on how to cluster these words into their corresponding topics or aspects.

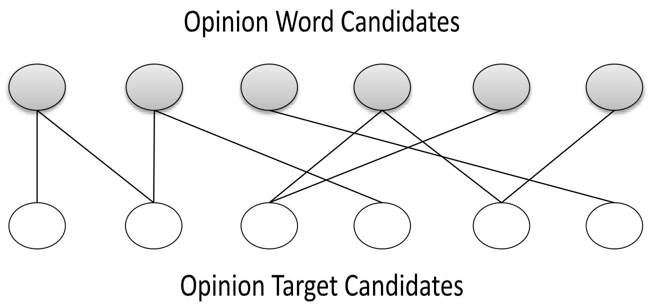

Figure 2. Opinion relation graph.

2. The Overview of Our Method

In this section, we present the main framework of our method. As mentioned in Section 1, we regard extracting opinion targets/words as a co-ranking process. We assume that all nouns/noun phrases in sentences are opinion target candidates, and all adjectives/verbs are regarded as potential opinion words, which are widely adopted by previous methods [4], [5], [7], [8]. Each candidate will be assigned a confidence, and candidates with higher confidence than a threshold are extracted as the opinion targets or opinion words. To assign a confidence to each candidate, our basic motivation is as follows.

If a word is likely to be an opinion word, the nouns/ noun phrases with which that word has a modified relation will have higher confidence as opinion targets. If a noun/noun phrase is an opiniontarget, the word that modifies it will be highly likely to be an opinion word.

We can see that the confidence of a candidate (opinion target or opinion word) is collectively determined by its neighbors according to the opinion associations among them. Simultaneously, each candidate may influence its neighbors. This is an iterative reinforcement process. To model this process, we construct a bipartite undirected graph G ¼ ðV;E;WÞ, named as Opinion Relation Graph. In G, V ¼ V^t [V^o denotes the set of vertices, of which there are two types: v^t2 V^tdenote opinion target candidates (the white nodes in Fig. 3) and v^o2 V^o denote opinion word candidates (the gray nodes in Fig. 3). E is the edge set of the graph, where e_{ij}2 E means that there is an opinion relation between two vertices. It is worth noting that the edges e_{ij}only exist between $v^t$and $v^o$and there is no edge between the two of the same types of vertices. w_{ij}2 W means the weight of the edge e_{ij}, which reflects the opinion association between these two vertices.

Based on our Opinion Relation Graph, we propose a graph-based co-ranking algorithm to estimate the confidence of each candidate. Briefly, there are two important problems: 1) how to capture the opinion relations (e_{ij}2 E) and calculate the opinion associations between opinion targets and opinion words (w_{ij}2 W); 2) how to estimate the confidence of each candidate with graph co-ranking.

For the first problem, we adopt a monolingual word alignment model to capture opinion relations in sentences.

A noun/noun phrase can find its modifier through word alignment. We additionally employ a partially-supervised word

3. Capturing Opinion Relations Between

OPINION TARGETS AND OPINION WORDS USING THE WORD ALIGNMENT MODEL

A. Word Alignment Model

As mentioned in the above section, we formulate opinion relation identification as a word alignment process. We employ the word-based alignment model [23] to perform monolingual word alignment, which has been widely used in many tasks such as collocation extraction [24] and tag suggestion [25]. In practice, every sentence is replicated to generate a parallel corpus. A bilingual word alignment algorithm is applied to the monolingual scenario to align a noun/noun phase (potential opinion targets) with its modifiers (potential opinion words) in sentences.

Formally, given a sentence with n words S ¼ fw$_1$; w $_2$;...;w$_n$g, the word alignment A ¼ fði;a$_i$Þji 2 ½1;n;a$_i$ 2 ½1;ng can be obtained as

A¼ argmaxPðAjSÞ; (1)

whereði;a$_i$Þmeans that a noun/noun phrase at position iis aligned with its modifier at position a$_i$. There are several word alignment models for usage, such as IBM-1, IBM-2 and IBM-3 [23]. We select IBM-3 model in our task, which has been proven to perform better than other models for our task [4]. Thus, we have

n n
P$_{ibm3}$ðAjSÞ / Y nðf$_i$jw$_i$Þ Y tðw$_j$jw$_{aj}$Þdðjja$_j$;nÞ; (2)
i¼1 j¼1

where there are three main factors tðw$_j$jw$_{aj}$Þ, dðjja$_j$;nÞand nðf$_i$jw$_i$Þthat model different information to indicate the opinion relations among words. tðw$_j$jw$_{aj}$Þmodels the co-occurrence information of two words in corpora. If a word frequently modifies a noun (noun phrase), they will have a higher value of tðw$_j$jw$_{aj}$Þ. For example, in reviews of cell phone, "big" often co-occurs with "phone's size"; therefore, "big" has high association with "phone's size". dðjja$_j$;nÞmodels word position information, which describes the probability that a word in position a$_j$is aligned with a word in position j. nðf$_i$jw$_i$Þdescribes the ability of a word for "one-tomany" relation, which means that a word can modify (or be modified by) several words. f$_i$denotes the number of words that are aligned with w$_i$. For example,

"Iphone4 has an amazing screen and software".

In this sentence, "amazing" is used to modify two words: "screen" and "software". Thus, f equals to 2 for "amazing".

Algorithm 1. Constrained Hill-Climbing Algorithm.

Input: Review sentences S$_i$ ¼ fw$_1$;w$_2$;...;w$_n$gOutput:
The calculated alignment a^ for sentences

Initialization: Calculate the seed alignment a$_0$ orderly using simple model (IBM-1, IBM-2, HMM)
Step 1: Optimize toward the constraints
while N$_{ill}$ða^Þ> 0 do
if {a: N$_{ill}$ðaÞ<N$_{ill}$ða^Þ}=Ø then
break
a^ ¼ argmax$_a$2nbða$_\wedge$ÞProðfje;aÞ
end
Step 2: Toward the optimal alignment under the constraint
for i< N and j < N do
M$_{i;j}$¼ 1, if ði;jÞ 2= A^;
end
while M$_{i1}$;j$_1$ > 1 or S$_{j1}$;j$_2$ > 1 do
If ðj$_1$;a$_{j2}$Þ 2= A^ or ðj$_2$;a$_{j1}$Þ 2= A^ then
S$_{j1}$;j$_2$ ¼ 1
end
M$_{i1}$;j$_1$ ¼ argmaxM$_{i;j}$
S$_{j1}$;j$_2$ ¼ argmaxS$_{i;j}$
If M$_{i1}$;j$_1$ > S$_{j1}$;j$_2$ then
Update M$_{i1}$;,M$_{j1}$;,M;i$_1$,M;j$_1$
Update S$_{i1}$;,S$_{j1}$;,S;i$_1$,S;j$_1$
set a^ :¼ M$_{i1}$;j$_1$ðaÞ
end
else
Update M$_{i1}$;,M$_{j2}$;,M;i$_1$,M;j$_2$
Update S$_{j2}$;,S$_{j1}$;,S;j$_2$,S;j$_1$
set a^ :¼ S$_{j1}$;j$_2$ðaÞ
end
end
return a^;

"and", are aligned with themselves. There are no opinion words to modify "Phone" and "has" modifies nothing; therefore, these two words may align with "NULL".

To obtain the optimal alignments in sentences, we adopt an EM-based algorithm [23] to train the model. Specifically, for training the IBM-3 model, the simpler models (IBM-1, IBM-2 and HMM) are sequentially trained as the initial alignments for the subsequent model. Next, the hill-climbing algorithm, a greedy algorithm, is used to find a local optimal alignment.

B. Partially-Supervised Word Alignment Model

As mentioned in the first section, the standard word alignment model is usually trained in a completely unsupervised manner, which may not obtain precise alignment results. Thus, to improve alignment performance, we perform a partial supervision on the statistic model and employ a partially-supervised alignment model to incorporate partial alignment links into the alignment process. Here, the partial alignment links are regarded as constraints for the trained alignment model. Formally, given the partial alignment links ^{A}^ ¼ fði;a$_i$Þji 2 ½1;n;a$_i$ 2 ½1;ng.

4. Estimating Candidate Confidence With Graph Co-Ranking

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.

III. RESULTS AND DISCUSSION

EXPERIMENTS

A. Data Sets and Evaluation Metrics

We select three datasets to evaluate our approach. The first dataset is the Customer Review Datasets (CRD), which includes English reviews of five products. CRD was also used in [5], [7]. The second dataset is COAE 2008 dataset2,[6]which contains Chinese reviews of four types of products: cameras, cars, laptops and phones. The third dataset is Large, which includes three corpora with different languages from three domains including hotels, mp3s and restaurants. For each domain in Large, we randomly crawl

TABLE 2

The Detailed Information of Data Sets

Datset	Domain	Language	#Sentence	#OW	#OT
	Restaurant	Chinese	6,000	451	949
Large	Hotel	English	6,000	398	872
	MP3	English	6,000	503	924
	D1	English	597	175	109
	D2	English	346	182	98
CRD	D3	English	546	261	177
	D4	English	1,716	138	73
	D5	English	740	164	103
	Camera	Chinese	2075	351	892
COAE	Car	Chinese	4,783	622	1,179
2008	Laptop	Chinese	1,034	475	518
	Phone	Chinese	2,644	538	1,125

6,000 sentences. Additionally, the opinion targets and opinion words in Large were manually annotated as the gold standard for evaluations. Three annotators are involved in the annotation process. Two annotators were required to judge whether every noun/noun phrase (adjectives/verbs) is an opinion target (opinion word) or not. If a conflict occurred, a third annotator makes a judgment for the final results. The inter-agreement was 0.72 for opinion target annotation and 0.75 for opinion word annotation. Statistical information of each dataset is shown in Table 2, where #OW and #OT stand for the numbers of annotated opinion words and opinion targets, respectively.

In the experiments, reviews are first segmented into sentences according to punctuation. Next, sentences are tokenized, with part-of-speech tagged using the Stanford NLP tool.[7] We then use the Minipar toolkit to parse English sentences and the Stanford Parsing tool to parse Chinese sentences. The method in [33] is used to identify noun phrases. We select precision (P), recall (R) and F-measure (F) as the evaluation metrics.

B. Our Methods versus State-of-the-art Methods

For comparison, we select the following methods as baselines.

Hu is the method described in [5]. It used nearest neighbor rules to identify opinion relations among words. Opinion targets and opinion words are then extracted iteratively using a bootstrapping process.

DP is the method proposed by [7]. They designed several syntax-based patterns to capture opinion relations in sentences, and used a bootstrapping algorithm (called Double Propagation) to extract opinion targets and opinion words.

Zhang is the method proposed by [3]. It is an extension of DP. Besides the syntactic patterns used in DP, Zhang designed some heuristic patterns to indicate opinion target candidates. An HITS [18] algorithm combined with candidate frequency is then employed to extract opinion targets.

OursWAM uses an unsupervised word alignment model (described in Section 4.1) to mine the associations between words. A standard random walk

IV. CONCLUSIONS AND FUTURE WORK

This paper proposes a novel method for co-extracting opinion targets and opinion words by using a word alignment model. Our main contribution is focused on detecting opinion relations between opinion targets and opinion words. Compared to previous methods based on nearest neighbor rules and syntactic patterns, in using a word alignment model, our method captures opinion relations more precisely and therefore is more effective for opinion target and opinion word extraction. Next, we construct an Opinion Relation Graph to model all candidates and the detected opinion relations among them, along with a graph co-ranking algorithm to estimate the confidence of each candidate. The items with higher ranks are extracted out. The experimental results for three datasets with different languages and different sizes prove the effectiveness of the proposed method.

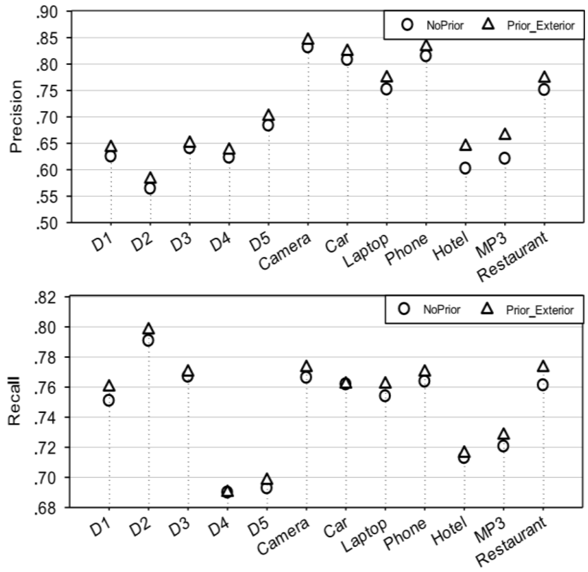

Figure 3. Experimental comparison among different ranking methods for opinion target extraction.

In future work, we plan to consider additional types of relations between words, such as topical relations, in Opinion Relation Graph. We believe that this may be beneficial for co-extracting opinion targets and opinion words.

V. ACKNOWLEDGMENTS

This work was sponsored by the National Basic Research Program of China (No. 2014CB340503), the National Natural Science Foundation of China (No. 61272332, No. 61202329 and No. 61333018), and CCF-Tencent Open Research Fund.

VI. REFERENCES

[1] M. Hu and B. Liu, "Mining and summarizing customer reviews," in Proc. 10th ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining, Seattle, WA, USA, 2004, pp. 168–177.

[2] F. Li, S. J. Pan, O. Jin, Q. Yang, and X. Zhu, "Cross-domain coextraction of sentiment and topic lexicons," in Proc. 50th Annu. Meeting

Assoc. Comput. Linguistics, Jeju, Korea, 2012, pp. 410–419.

[3] L. Zhang, B. Liu, S. H. Lim, and E. O'Brien-Strain, "Extracting and ranking product features in opinion documents," in Proc. 23th Int. Conf. Comput. Linguistics, Beijing, China, 2010, pp. 1462–1470.

[4] target extraction using wordbased translation model," in Proc. Joint Conf. Empirical Methods Natural Lang. Process. Comput. Natural Lang. Learn., Jeju, Korea, Jul. 2012, pp. 1346–1356.

[5] M. Hu and B. Liu, "Mining opinion features in customer reviews," in Proc. 19th Nat. Conf. Artif. Intell., San Jose, CA, USA, 2004, pp. 755–760.

[6] A.-M. Popescu and O. Etzioni, "Extracting product features and opinions from reviews," in Proc. Conf. Human Lang. Technol. Empirical Methods Natural Lang. Process., Vancouver, BC, Canada, 2005, pp. 339–346.

[7] G. Qiu, L. Bing, J. Bu, and C. Chen, "Opinion word expansion and target extraction through double propagation," Comput. Linguistics, vol. 37, no. 1, pp. 9–27, 2011.

[8] B. Wang and H. Wang, "Bootstrapping both product features and opinion words from chinese customer reviews with crossinducing," in Proc. 3rd Int. Joint Conf. Natural Lang. Process., Hyderabad, India, 2008, pp. 289–295.

[9] B. Liu, Web Data Mining: Exploring Hyperlinks, Contents, and Usage Data, series Data-Centric Systems and Applications. New York, NY, USA: Springer, 2007.

[10] G. Qiu, B. Liu, J. Bu, and C. Che, "Expanding domain sentiment lexicon through double propagation," in Proc. 21st Int. Jont Conf. Artif. Intell., Pasadena, CA, USA, 2009, pp. 1199–1204.

[11] R. C. Moore, "A discriminative framework for bilingual word alignment," in Proc. Conf. Human Lang. Technol. Empirical Methods Natural Lang. Process., Vancouver, BC, Canada, 2005, pp. 81–88.

[12] X. Ding, B. Liu, and P. S. Yu, "A holistic lexicon-based approach to opinion mining," in Proc. Conf. Web Search Web Data Mining, 2008 , pp. 231–240.

[13] F. Li, C. Han, M. Huang, X. Zhu, Y. Xia, S. Zhang, and H. Yu, "Structure-aware review mining and summarization." in Proc. 23 th Int. Conf. Comput. Linguistics, Beijing, China, 2010, pp. 653–661.

[14] Y. Wu, Q. Zhang, X. Huang, and L. Wu, "Phrase dependency parsing for opinion mining," in Proc. Conf. Empirical Methods Natural Lang. Process., Singapore, 2009, pp. 1533–1541.

[15] T. Ma and X. Wan, "Opinion target extraction in chinese news comments." in Proc. 23th Int. Conf. Comput. Linguistics, Beijing, China, 2010, pp. 782–790.

[16] Q. Zhang, Y. Wu, T. Li, M. Ogihara, J. Johnson, and X. Huang, "Mining product reviews based on shallow dependency parsing," in Proc. 32nd Int. ACM SIGIR Conf. Res. Develop. Inf. Retrieval, Boston, MA, USA, 2009, pp. 726–727.

[17] W. Jin and H. H. Huang, "A novel lexicalized HMM-based learning framework for web opinion mining," in Proc. Int. Conf. Mach. Learn., Montreal, QC, Canada, 2009, pp. 465–472.

[18] J. M. Kleinberg, "Authoritative sources in a hyperlinked environment," J. ACM, vol. 46, no. 5, pp. 604–632, Sep. 1999.

[19] Q. Mei, X. Ling, M. Wondra, H. Su, and C. Zhai, "Topic sentiment mixture: modeling facets and opinions in weblogs," in Proc. 16 th Int. Conf. World Wide Web, 2007, pp. 171–180.

[20] I. Titov and R. McDonald, "A joint model of text and aspect ratings for sentiment summarization," in Proc. 46th Annu. Meeting Assoc. Comput. Linguistics, Columbus, OH, USA, 2008, pp. 308–316.

[21] W. X. Zhao, J. Jiang, H. Yan, and X. Li, "Jointly modeling aspects and opinions with a MaxEnt-LDA hybrid," in Proc. Conf. Empirical Methods Natural Lang. Process., Cambridge, MA, USA, 2010 , pp. 56–65.

[22] A. Mukherjee and B. Liu, "Modeling review comments," in Proc. 50th Annu. Meeting Assoc. Comput. Linguistics, Jeju, Korea, Jul. 2012, pp. 320–329.

[23] P. F. Brown, V. J. D. Pietra, S. A. D. Pietra, and R. L. Mercer, “The mathematics of statistical machine translation: Parameter estimation,” Comput. Linguist., vol. 19, no. 2, pp. 263–311, Jun. 1993.

[24] Z. Liu, H. Wang, H. Wu, and S. Li, “Collocation extraction using monolingual word alignment method,” in Proc. Conf. Empirical Methods Natural Lang. Process., Singapore, 2009, pp. 487–495.

[25] Z. Liu, X. Chen, and M. Sun, “A simple word trigger method for social tag suggestion,” in Proc. Conf. Empirical Methods Natural Lang. Process., Edinburgh, U.K., 2011, pp. 1577–1588.

[26] Q. Gao, N. Bach, and S. Vogel, “A semi-supervised word alignment algorithm with partial manual alignments,” in Proc. Joint Fifth Workshop Statist. Mach. Translation MetricsMATR, Uppsala, Sweden, Jul. 2010, pp. 1–10.

[27] S. Baluja, R. Seth, D. Sivakumar, Y. Jing, J. Yagnik, S. Kumar, D. Ravichandran, and M. Aly, “Video suggestion and discovery for youtube: taking random walks through the view graph,” in Proc. 17th Int. Conf. World Wide Web, Beijing, China, 2008, pp. 895–904.

[28] P. P. Talukdar, J. Reisinger, M. Pasca, D. Ravichandran, R. Bhagat, and F. Pereira, “Weakly-supervised acquisition of labeled class instances using graph random walks,” in Proc. Conf. Empirical Methods Natural Lang. Process., Honolulu, Hawaii, 2008, pp. 582–590.

[29] K. Liu, H. L. Xu, Y. Liu, and J. Zhao, “Opinion target extraction using partially-supervised word alignment model,” in Proc. 23 rd Int. Joint Conf. Artif. Intell., Beijing, China, 2013, pp. 2134–2140.

[30] K. W. Gan and P. W. Wong, “Annotating information structures in chinese texts using hownet,” in Proc. 2nd Workshop Chin. Lang. Process.: Held Conjunction 38th Annu. Meeting Assoc. Comput. Linguistics, Hong Kong, 2000, pp. 85–92.

[31] Z. Hai, K. Chang, J.-J. Kim, and C. C. Yang, “Identifying features in opinion mining via intrinsic and extrinsic domain relevance,” IEEE Trans. Knowledge Data Eng., vol. 26, no. 3, p. 623–634, 2014.

[32] Z.-H. Zhou and M. Li, “Semi-supervised regression with cotraining,” in Proc. 15th Int. Joint Conf. Artif. Intell., Edinburgh, Scotland, U.K.

[33] J. Zhu, H. Wang, B. K. Tsou, and M. Zhu, “Multi-aspect opinion polling from textual reviews,” in Proc. 18th ACM Conf. Inf. Knowl. Manage., Hong Kong, 2009, pp. 1799–1802.