SAE : Syntactic-based Aspect and Opinion Extraction from Product Reviews

Warih Maharani, Dwi H.Widyantoro, Masayu L. Khodra
School of Electrical Engineering and Informatics
Bandung Indonesia
wmaharani@telkomuniversity.ac.id dwi@stei.itb.ac.id masayu@informatika.org

***Abstract*—Aspect extraction is an important task in sentiment analysis to identify aspects in customer review products. Most existing works defines the pattern set manually or using heuristic approach. In this paper, we propose SAE, a Syntactical-based Aspect Extraction using decision tree and rule learning to generate the pattern set based on sequence labelling. We provide a comprehensive analysis of aspect extraction using pattern-based method and typed-dependency. The patterns will be used to identify and extract aspect term candidates in customer product review. First, we generate pattern set that identify aspect term candidates using decision tree and rule learning such as ID3, J48, Random Tree, Part and Prism, based on sequence labelling. The set of pattern is employed to produced aspect term candidates. We use a list of positive and negative opinion lexicon as aspect term candidates filtering. Finally, we combine the pattern-based method with typed dependency to remove irrelevant aspect term. The results showed that the combination of pattern-based and typed dependency can increase the performance. However, since our work is based on syntactic-based approach, it can be used to other domains, that is expected to include an unlimited domain datasets.**

Keywords*—aspect extraction; Decision Tree; rule learning; sequence labelling, typed dependency

I. INTRODUCTION

The development of Web 2.0 has changed the way people express their opinions in internet. Currently, product reviews that found in the Web became an important source for some parties. The reviews are essential for consumers in considering the decision before they buy the products. These are also essential for the product manufacturers to understand and analyze the response of consumers to their products. As the number of reviews expands, it is difficult for consumers to read all of the reviews.

Aspect extraction is an important task in sentiment analysis because it affects the performance of sentiment analysis. Some research defines aspects as object features or product feature [12], [27]. The purpose of aspect extraction is to identify and extract topics, aspects, objects in the document. Previous works have implemented a pattern-based approach and dependency pattern to extract aspect and opinions, such as Hu and Liu [1], [27], [28], Turney [7], Htay [8], [9], Poria [2], [26]. Nevertheless, an open domain aspect extraction is still a problem and a major challenge in opinion mining.

Liu stated that the most of aspect expressed in noun phrase [1], [12]. It underlies the subsequent study, which adopt noun phrase extraction to build an aspect extraction system [2], [4], [10], [11], [13]. Yi [3] used BNP1 pattern as a base noun phrase for the aspect candidate extraction and ranks them according to a relevance score. While Bross [4] applied BNP1, BNP2, dBNP and bBNP as the base noun phrase pattern. Turney used five pattern sets to extract candidate aspect and opinions [7], and Htay used different pattern consist of eight pattern set [8]. Aspect terms also can be identified by dependency pattern obtained from dependency parsing as the Zhuang and Bancken [5], [10], [11].

However, the majority of existing works defines the pattern set using heuristic approach [5], [6], [11], [17]. In this paper, we discuss our approach to generate pattern using sequence labelling. We apply two aspect extraction approach described above to the dataset from Hu & Liu [27], [28]. A pattern set will be generated automatically using decision tree and rule learning based on bag-of-term sequence labelling. Those patterns will be used to identify and extract aspect-opinion pairs. The aspect terms that already identified will be classified into positive or negative. Our goal was to investigate whether techniques that have been successful in aspect extraction between two approach : pattern-based method and combination of pattern and type dependency-based method. In this paper, we perform a re-annotation to analyze the performance of the aspect extraction of each method.

We use decision trees and rule learning because they are quite powerful. The complex rules can be encoded as decision trees and rules. General pattern set can be used for the extraction of aspect and opinions on unlimited domains, that is expected to include a wider domain datasets.

The rest of this paper is organized as follows : Section 2 presents the related works of this paper. Section 3 describes the proposed method for aspect extraction. Section 4 provide the experiments result. Section 4 also presents the discussion of the result of aspect extraction. Finally, we concludes the paper and challenges as well as opportunities for further research in Section 5.

978-1-4673-8143-7/15/$31.00 ©2015 IEEE

II. RELATED WORKS

This paper focus on aspect extraction in product reviews. In aspect extraction area, aspect is generally expressed in the noun phrase, so [7], [11], [13], [14], [23], [27] focus to extract noun phrases which represents the aspects. Hu and Liu extracted frequently noun phrases as aspect identification, combined with their nearest opinion words [27]. Turney used a pattern set to extract aspects and classify reviews into recommended and not recommended [7]. Turney used pattern-based approach to extract phrases and implemented a pointwise Mutual Information (PMI) to classify opinion based on the word "excellent" and "poor" [7]. Semantic orientation of the document predicted based on the average semantic orientation of the adjective phrases and adverb phrases. Modifications made to the pattern set and candidate filtering to extract aspect and opinions in Zhang and Htay [8], [10], [11]. Htay developed aspect extraction through patterns and opinion seed set [8], [9]. They identified opinion pattern through adjective, adverb, verb and noun [8], [9]. While Zhang identified noun phrase feature to implied opinions [10], [11]. Zhang proposed candidate identification using statistical tests and lexicon-based approach [10], [11]. Existing research commonly used POS tag and parsing techniques because they are relatively simple and produced relatively high accuracy [11], [12].

Riloff proposed bootstrapping algorithm to classify subjective noun [13]. The subjective nouns can be used to extract aspects and opinions using subjectivity clues. Popescu proposed unsupervised technique to extract aspect, which used syntactic dependencies produced by MINIPAR parser [14], [15]. While Qiu proposed double propagation method to extract aspect and their opinion using a seed set of opinion words and syntactic dependencies. The extracted aspect and opinion words are used to extract new aspect and opinion words until no more aspect and opinion words extracted [16].

Meanwhile, Zhuang used the keyword list and dependency relation templates to extract explicit aspect and opinion pairs [17]. They used dependency relations templates to detect path between aspect and opinion words, according to some opinion words that frequently used for movie feature [17]. Bancken build ASPECTATOR which used a handcrafted dependency paths to extract aspect and opinion. Then, they clustered the different mentions of aspects using WordNet-based similarity measure.

Wei [18] proposed a semantic-based product aspect extraction (SPE) method by using list of positive and negative opinion for refinement step. The semantic-based refinement task remove the irrelevant aspect and non-aspect [18]. The SPE method implemented frequency-based and semantic-based extraction for aspect detection. While Bagheri [19] proposed an unsupervised model for detecting aspects in reviews based on heuristic rules and bootstrapping algorithm. Bagheri [19] used frequency-based and inter-connection information between aspects. The FLR methods was proposed to rank the extracted multi-word aspects and select the importance ones. The unsupervised method in Wei [18] and Bagheri [19] did not require any annotated dataset for training step. Breck [20], Yang [21] proposed sequence modelling with syntactic and dictionary-based features for aspect extraction. Zhai [23] extracted opinion features with its positions in document and implemented feature filtering. While Garcia [25] used simple and compound noun phrases as potential aspects and select those which have been modified by opinion words according to some dependency relations. Poria [26] introduced sentic patterns which merge linguistics, common-sense computing, and machine learning for properly deconstructing natural language text into concepts and opinion targets and allow sentiments to flow from concept to concept based on the dependency relation of the sentences. The contribution of this paper is to combine generated pattern from decision tree and rule learning, with typed dependencies pattern.

III. THE PROPOSED APPROACH

For aspect extraction task, we use syntactic-based aspect extraction based on sequence labelling, examining several decision tree algorithm and rule learning. In order to comprehensive analysis on pattern-based method, we experimented several pattern set generated from decision tree and rule learning. The focus of this paper is aspect term extraction which explicitly mentioned in dataset.

A. *Aspect Term Extraction*

For aspect term extraction, we adopted two methods : the pattern-based method and typed dependency-based method. In the pattern-based method, we use sequence labelling to generate pattern that can be used to identify aspect terms in each sentence. The pattern–based method utilize opinion lexicon to filter candidate aspects. In our preliminary experiments, we found that this method did not consider the relations between aspect and opinion, so it produced several invalid aspects. In order to overcome this drawbacks, we combine the pattern-based method with typed dependency, by using the result of pattern-based method as an additional aspect candidate to typed dependency method.

1. *Preprocessing*

The sentences tokenized into tokens, bigram and trigram. We used Stanford Parser Tools[1] to annotate each word with an appropriate POS tag. Here is an example of a sentence with its POStag

Sentence :

```
A larger memory card and extra battery are good things to buy.
```

The annotated sentence after POS tagging :

```
A/DT larger/JJR memory/NN card/NN and/CC extra/JJ battery/NN are/VBP good/JJ things/NNS to/TO buy/VB ./.
```

2. *The pattern-based method*

We use POStag sequence labelling as the target class of each token. For each token, we extract the word, its POS tag,

[1] http://nlp.stanford.edu

its dependency relation, its chunks and whether the word is in head or dependent position. The features used for learning-based aspect extraction derived from current POStag with their N-before and N-after POStag.

Sequential pattern can be generated by varying POS tag length. This paper examined the sequential pattern with 3POStag and 5POStag. The patterns can be used to identify terms as the candidate aspects. Sequential labeling on each token in the dataset will be stored in a csv file, which is used to generate a pattern using decision tree algorithm and rule learning in Weka [22]. We applied ID3, J48, RandomTree, Part and Prism in Weka to generate the pattern sets.

The results of sequence labelling are as showed in Table I.

TABLE I. SEQUENTIAL LABELLING

Token	POS_1	POS_0	POS_1	Label
Larger	DT	JJR	NN	F
Memory	JJR	NN	NN	T
Card	NN	NN	CC	F
Card	NN	NN	CC	F
Extra	CC	JJ	NN	F
Battery	JJ	NN	VBP	T
Battery	JJ	NN	VBP	T
Good	VBP	JJ	NNS	F
Things	JJ	NNS	TO	F
Buy	TO	VB	-	F

Previous research stated that using only pattern-based method produced a lot of terms including some irrelevant aspects. The irrelevant aspects can be pruned by candidate filtering using the specific domain filter. So in this paper, after the pattern set is generated, candidate filtering conducted to select the aspect by utilizing the opinion lexicon corpus [27], [28]. Opinion lexicon corpus contains a list of adjective and adverb which generally represent the positive and negative opinion [27], [28]. For each aspect candidate which is extracted from the pattern set, will be matched with the nearby opinion lexicon, in order to obtain a list of aspects and opinions. For example :

```
Battery##However, sometimes battery can get very hot and become uncomfortably hot to touch.
```

Aspect term candidate "battery" can related to term "hot" with N-term distance before and after current aspect term, in condition that the word "hot" contained in opinion lexicon as positive or negative opinion words.

3. Type dependency-based method

For aspect term extraction, we adopted typed dependency patterns, which used in previous research [23], [24], [26]. The typed dependency consider the relations between aspect and its opinion. So, the irrelevant aspect and opinion pairs can be reduced using typed dependencies. We used Stanford Parser Tools[2] for parsing the sentences. The following typed dependencies are used to extract and construct the opinion phrases inside an opinion sentence [24–26] :

TABLE II. THE TYPED DEPENDENCIES

Dependency relation
NN – Amod – JJ
NN – nsubj – JJ
NN – nsubj – VB – dobj – NN
VB|JJ – Advmod – RB
X – dobj – Y
X – acomp – Y
X – ccomp – Y

Consider the following examples :

```
The good are small size; durable-seeming metal case; easy to use; good picture quality.
```

The result of dependency parser :

```
[det(good-2, The-1), nsubj(size-5, good-2), cop(size-5, are-3), amod(size-5, small-4), root(ROOT-0, size-5), amod(case-9, durable-seeming-7), nn(case-9, metal-8), dep(size-5, case-9), amod(size-5, easy-11), aux(use-13, to-12), xcomp(easy-11, use-13), amod(quality-17, good-15), nn(quality-17, picture-16), dobj(use-13, quality-17), parataxis(use-13, quality-17)]
```

We can extract aspect terms and its related opinion words accoding to typed dependencies in Table II, by using "nsubj", "amod", "advmod". Each of those pairs will become aspect term and opinion candidate, as showed below :

```
[Size – small]
[case – durable-seeming]
[picture quality – good]
```

4. Combination of pattern-based and typed dependency

We combine the above two methods in order to overcome their drawbacks and use their advantages. Figure 1 provides an overview of aspect extraction model.

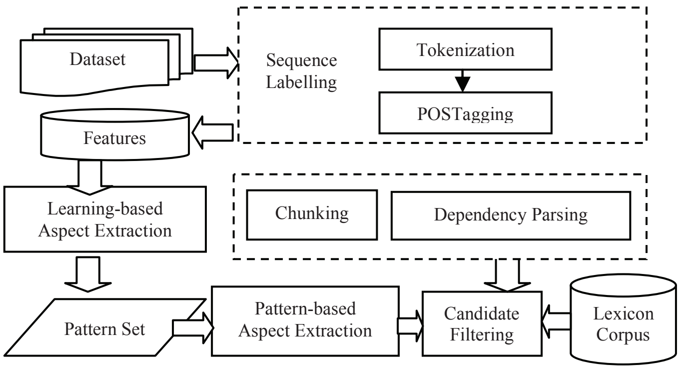

Fig. 1. Architecture of Combination-based Aspect Extraction

IV. EXPERIMENTAL RESULTS AND ANALYSIS

A. Data Collection

We use macro-average Precision, Recall and F-measure to measure the effectiveness of aspect term extraction methods.

[2] http://nlp.stanford.edu

We utilize data sets from Hu & Liu research consists of five different electronic products that are collected from Amazon product review sites [27], [28]. Table III showed descriptive statistics of dataset of Hu & Liu [27] and the revised annotation dataset.

TABLE III. DESCRIPTIVE STATISTICS OF DATASET

Dataset	**No. of sentences**	**Hu & Liu** [27]		**Revised annotation**	
		Distinct aspect	**Total Aspects**	**Distinct aspect**	**Total Aspects**
Canon S100	300	82	135	134	196
Canon SD500	229	76	147	129	171
Canon G3	597	99	286	155	578
Apex	739	110	347	158	522
Jukebox	1716	180	736	228	1005

Hu & Liu defined a product features as a characteristic of the product which customers have expressed an opinion about this products [27], [28]. In this paper, we revised the annotation of several sentence according to the following criteria, for examples :

1) Sentences with explicit or implicit aspect, for instance in this sentence :

   ```
   storage[+3][u]##+ the memory ( 40 gb ) is staggering
   ```

   We revised the annotation :

   ```
   memory[+3][u]##+ the memory ( 40 gb ) is staggering
   ```

2) Sentences with adjective / adverb as an aspect, for instance in these sentences :

   ```
   small[+1]##I want to start off saying that this camera is small for a reason.
   small[+3],durable[2]## it is so small and it is so durable
   fun[+3]##I bought this little guy a few weeks back, and I have to saythat I never had so much fun with a new toy as this.
   play[+2], dvd-r[+1]##what got me to buy was the reviewer that said it would play dvd-rs fill of files ( e., mp3s ).
   ```

   Since we focus on explicit aspects, we consider it necessary to annotate those explicit aspects rather than adjective/adverb as an aspect.

3) Sentences that has not been annotated with explicit aspects, for instance in this sentence :

   ```
   ##Some people, in their reviews, complain about its small size, and how it doesn't compare with larger cameras.
   ```

The aspect “size” has not been annotated in Hu & Liu dataset, but we revised the annotation, so that “size” become an aspect.

Table IV presents the statistics based on the revised annotations schemes. The first column gives the number of sentences that contained implicit aspects. The second column gives the number of sentences that contained adjective/adverb as an aspect. While the third column shows the number of sentences that we added several explicit aspects and the column 4 contain the total number of reannotated sentences.

TABLE IV. STATISTICS OF REVISED ANNOTATION DATASET

Dataset	# Sentences Criteria 1	# Sentences Criteria 2	#Sentences Criteria 3	Total sentences
Canon 100	17	35	52	104
Canon SD500	0	14	23	37
Canon G3	83	56	36	175
Apex	30	23	36	89
Jukebox	112	34	21	167

B. Experiments and Results

As mentioned in section 3 and in order to investigate whether techniques that have been successful in aspect extraction, we implemented pattern-based aspect extraction and combination of pattern-based and typed dependency-based aspect extraction.

Table V shows the results of the above two methods. According to the comparison of the results, we easily find that the combination method outperforms the pattern-based method in terms of precision, recall and F-measure values on 5 dataset.

Since the pattern-based method can extract only aspect that are explicitly mentioned in a sentence, so this paper is focused on extracting explicit aspects. Meanwhile, not all explicit aspects can extracted using this approach. For instance in this sentence :

```
lens##lens has problems
picture quality##the quality of this picture is amazing.
```

This experiment showed that the combination method can produced a significant increase, compared with the pattern-based method. In dataset Canon S100 and Canon SD500, the value of the F-Measure increased by average 5-28%, while for the dataset canon G3 increased 25%, for Apex increased 33.3% and Jukebox increased by 29%. However, both approaches only focus to extract explicit aspects contained in the document, combined with corpus-based candidate aspect filtering.

TABLE V. PRECISION OF THE EXPERIMENTS

Dataset	ID3		J48		RandomTree		Part		Prism	
	Pattern-based	Combination	Pattern-based	Combination	Pattern-based	Combination	Pattern-based	Combination	Pattern-based	Combination
Canon S100	0.51	0.67	0.54	0.69	0.49	0.67	0.43	0.64	0.50	0.61
Canon SD500	0.52	0.65	0.56	0.69	0.52	0.66	0.53	0.60	0.56	0.62
Canon G3	0.46	0.64	0.48	0.68	0.46	0.66	0.40	0.68	0.41	0.64
Apex	0.42	0.66	0.47	0.68	0.44	0.65	0.40	0.66	0.40	0.65
Jukebox	0.46	0.65	0.46	0.71	0.47	0.64	0.42	0.66	0.40	0.64

TABLE VI. RECALL OF THE EXPERIMENTS

Dataset	ID3		J48		RandomTree		Part		Prism	
	Pattern-based	Combination	Pattern-based	Combination	Pattern-based	Combination	Pattern-based	Combination	Pattern-based	Combination
Canon S100	0.65	0.66	0.62	0.73	0.52	0.68	0.50	0.64	0.64	0.73
Canon SD500	0.66	0.66	0.75	0.69	0.59	0.67	0.64	0.68	0.74	0.66
Canon G3	0.59	0.68	0.58	0.71	0.48	0.65	0.44	0.67	0.50	0.66
Apex	0.48	0.66	0.48	0.69	0.47	0.65	0.43	0.68	0.49	0.65
Jukebox	0.67	0.64	0.68	0.71	0.51	0.66	0.47	0.68	0.51	0.66

TABLE VII. F-MEASURE OF THE EXPERIMENTS

Dataset	ID3		J48		RandomTree		Part		Prism	
	Pattern-based	Combination	Pattern-based	Combination	Pattern-based	Combination	Pattern-based	Combination	Pattern-based	Combination
Canon S100	0.65	0.66	0.62	0.73	0.52	0.68	0.50	0.64	0.64	0.73
Canon SD500	0.66	0.66	0.75	0.69	0.59	0.67	0.64	0.68	0.74	0.66
Canon G3	0.59	0.68	0.58	0.71	0.48	0.65	0.44	0.67	0.50	0.66
Apex	0.48	0.66	0.48	0.69	0.47	0.65	0.43	0.68	0.49	0.65
Jukebox	0.67	0.64	0.68	0.71	0.51	0.66	0.47	0.68	0.51	0.66

C. Discussions

As mentioned in section 3, pattern-based method will extract aspect terms according to generated pattern from decision tree and rule learning. While in combination method, for each aspect term candidate, we select as aspect those ones that are modified by some opinion words using typed dependency. This paper used an opinion lexicon corpus that contains a list of words that represent the positive and negative opinions, to extract aspect and opinions pairs [28]. Those combination method can produce a more complete list of aspects, because it can complement the drawbacks of pattern-based and typed dependency-based method.

As outlined in Table V, VI and VII, the two methods have their strength and weakness. The pattern-based method could produce an invalid aspect and opinion pairs because it is not considered the relations between aspect and its opinion. Based on pattern-based method that treats the nearby adjective words of aspect term candidates as opinion words, several adjective do not have subjective implication. So that it produced an irrelevant aspect term. For example :

```
auto setting[+2]##with the automatic settings, i really have n't taken a bad picture yet.
##and with the panoramic "stitch" mode,it guides you through stitching together multiple pictures to build a seamless panoramic image.
##I buy a camera with a panoramic mode.
```

Nevertheless, pattern-based method has not been able to extract all of explicit aspects. For example, there are some aspects that are not in the form of Noun Phrase, for instance *"use","looks", "ease of use"* as contained in the following sentences :

```
Picture quality,Use##Excellent picture quality and so simple to use!!!
Looks##Looks great.
Ease of use##I was looking for something that wasn't too complicated to use and to help the pics I post on Ebay show more detail.
```

While typed dependency-based method can cover this drawbacks. Typed dependencies are used to extract the relations of aspect term candidates and the related opinion words. However, the typed dependency-based approach can not extract the aspect and opinion pairs that are not included in dependency-relation templates in Table II. For example :

```
pictures##The pictures some time turn out blurry.
LCD display##It's great having the LCD display.
```

The combination method that involved pattern-based method and typed dependency, can produced a significant improvement because they are complementary to each other. The pattern-based method depend on the pattern set which used to extract aspect term candidates guided by list of positive and negative opinion words. While typed dependency relies primarily on relation dependency pattern. When they are implemented independently, they have several limitations, but the combination of these two methods, improves the effectiveness of aspect term extraction.

Aspect extraction is critical task in sentiment analysis, because its result affects the performance of sentiment orientation. Table VIII shows a comparison of the results of aspect extraction with some examples sentences using the two experimental scenarios above :

TABLE VIII. COMPARISON OF THE RESULTS

Sentences	Pattern-based	Pattern + typed dependency
use##Excellent picture quality and so simple to use!!!	Picture quality	Picture quality
looks##looks great.	-	Looks
camera##I like this camera.	Camera	Camera
battery life##The battery life is good.	Battery life	Battery life
pictures##I have found that this camera take incredible pictures.	Camera Pictures	Camera Pictures
pictures##The pictures some time turn out blurry.	Time	Pictures

Sentences	Pattern-based	Pattern + typed dependency
movie mode##It has movie mode that works good for a digital camera.	-	Movie mode Camera
LCD display##It's great having the LCD display.	-	LCD
battery,flash,LCD##battery is very good even when using flash and LCD.	-	Battery Flash,LCD
camera##There is a great camera.	Camera	Camera
optical zoom##The optical zoom works great.	Zoom	Optical Zoom
lens##lens has problems	-	Lens
canon g3##i bought my canon g3 about a month ago and i have to say i am very satisfied.	Canon g3	Canon g3
memory card[+1]##the nice thing is that it uses the SD memory card.	Thing	Thing

The experimental results showed that the combination of pattern-based method and typed-dependency based method can cover the drawbacks and use the advantages of each method. The pattern-based method can only extract the aspects in simple sentences, but not in complex sentences.

V. CONCLUSION

In this paper, we provide a comprehensive analysis of aspect extraction based on sequence labelling and dependency relations. The results showed that the generated pattern from decision tree and rule learning combined with typed dependency can improve the effectiveness of aspect term extraction. The pattern-based method could produce an invalid aspect and opinion pairs because it is not considered the relations between aspect and its opinion. While dependency-based approach can cover up these weaknesses.

However, dependency-based method can not extract all of the aspects and opinions pairs that are not on the typed dependency pattern that has been determined. The combination of both approaches can improve the performance average in 20 %. Since our work is based on syntactic-based approach, it can be used to other domains, that is expected to include an unlimited domain datasets.

REFERENCES

[1] B. Liu, M. Hu, and J. Cheng, "Opinion observer: analyzing and comparing opinions on the web," in *Proceedings of the 14th international conference on World Wide Web*, 2005, pp. 342–351.

[2] S. Poria, E. Cambria, L.-W. Ku, C. Gui, and A. Gelbukh, "A rule-based approach to aspect extraction from product reviews," *SocialNLP 2014*, p. 28, 2014.

[3] J. Yi and W. Niblack, "Sentiment mining in WebFountain," in *Data Engineering, 2005. ICDE 2005. Proceedings. 21st International Conference on*, 2005, pp. 1073–1083.

[4] J. Bross and H. Ehrig, "Automatic construction of domain and aspect specific sentiment lexicons for customer review mining," in *Proceedings of the 22nd ACM international conference on Conference on information & knowledge management*, 2013, pp. 1077–1086.

[5] W. Bancken, D. Alfarone, and J. Davis, "Automatically detecting and rating product aspects from textual customer reviews," in *(To appear in) Proceedings of DMNLP Workshop at ECML/PKDD*, 2014.

[6] Z. Zhang, Q. Ye, Z. Zhang, and Y. Li, "Sentiment classification of Internet restaurant reviews written in Cantonese," *Expert Systems with Applications*, vol. 38, pp. 7674–7682, 2011.

[7] P. D. Turney, "Thumbs up or thumbs down?: semantic orientation applied to unsupervised classification of reviews," in *Proceedings of the 40th annual meeting on association for computational linguistics*, 2002, pp. 417–424.

[8] S. S. Htay and K. T. Lynn, "Extracting Product Features and Opinion Words Using Pattern Knowledge in Customer Reviews," *The Scientific World Journal*, vol. 2013, 2013.

[9] S. S. Htay, "Biologically Inspired Opinion Mining: Features Extraction based on Linguistic Patterns for Customer."

[10] L. Zhang, B. Liu, S. H. Lim, and E. O'Brien-Strain, "Extracting and ranking product features in opinion documents," in *Proceedings of the 23rd international conference on computational linguistics: Posters*, 2010, pp. 1462–1470.

[11] L. Zhang and B. Liu, "Identifying noun product features that imply opinions," in *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies: short papers-Volume 2*, 2011, pp. 575–580.

[12] B. Liu, "Sentiment analysis and subjectivity," *Handbook of natural language processing*, vol. 2, pp. 627–666, 2010.

[13] E. Riloff, J. Wiebe, and T. Wilson, "Learning subjective nouns using extraction pattern bootstrapping," in *Proceedings of the seventh conference on Natural language learning at HLT-NAACL 2003-Volume 4*, 2003, pp. 25–32.

[14] A.-M. Popescu, B. Nguyen, and O. Etzioni, "OPINE: Extracting product features and opinions from reviews," in *Proceedings of HLT/EMNLP on interactive demonstrations*, 2005, pp. 32–33.

[15] A.-M. Popescu and O. Etzioni, "Extracting product features and opinions from reviews," in *Natural language processing and text mining*, Springer, 2007, pp. 9–28.

[16] G. Qiu, B. Liu, J. Bu, and C. Chen, "Opinion word expansion and target extraction through double propagation," *Computational linguistics*, vol. 37, pp. 9–27, 2011.

[17] L. Zhuang, F. Jing, and X.-Y. Zhu, "Movie review mining and summarization," in *Proceedings of the 15th ACM international conference on Information and knowledge management*, 2006, pp. 43–50.

[18] C.-P. Wei, Y.-M. Chen, C.-S. Yang, and C. C. Yang, "Understanding what concerns consumers: a semantic approach to product feature extraction from consumer reviews," *Information Systems and E-Business Management*, vol. 8, pp. 149–167, 2010.

[19] A. Bagheri, M. Saraee, and F. de Jong, "An unsupervised aspect detection model for sentiment analysis of reviews," in *Natural Language Processing and Information Systems*, Springer, 2013, pp. 140–151.

[20] E. Breck, Y. Choi, and C. Cardie, "Identifying Expressions of Opinion in Context.," in *IJCAI*, 2007, vol. 7, pp. 2683–2688.

[21] B. Yang and C. Cardie, "Joint Inference for Fine-grained Opinion Extraction.," in *ACL (1)*, 2013, pp. 1640–1649.

[22] I. H. Witten and E. Frank, *Data Mining: Practical machine learning tools and techniques*. Morgan Kaufmann, 2005.

[23] Y. Zhai, Y. Chen, X. Hu, P. Li, and X. Wu, "Extracting Opinion Features in Sentiment Patterns," in *Information Networking and Automation (ICINA), 2010 International Conference on*, 2010, vol. 1, pp. 1–115.

[24] Y. Wu, Q. Zhang, X. Huang, and L. Wu, "Phrase dependency parsing for opinion mining," in *Proceedings of the 2009 Conference on Empirical Methods in Natural Language Processing: Volume 3-Volume 3*, 2009, pp. 1533–1541.

[25] L. Garcıa-Moya, R. Berlanga-Llavori, and M. J. Aramburu-Cabo, "Extraction and Ranking of Product Aspects Based on Word Dependency Relations."

[26] S. Poria, E. Cambria, G. Winterstein, and G.-B. Huang, "Sentic patterns: Dependency-based rules for concept-level sentiment analysis," *Knowledge-Based Systems*, vol. 69, pp. 45–63, 2014.

[27] M. Hu and B. Liu, "Opinion extraction and summarization on the web," in *AAAI*, 2006, vol. 7, pp. 1621–1624.

[28] M. Hu and B. Liu, "Mining and summarizing customer reviews," in *Proceedings of the tenth ACM SIGKDD international conference on Knowledge discovery and data mining*, 2004, pp. 168–177.