# Detecting Opinions and their Opinion Targets in NTCIR-8

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## ABSTRACT
Identifying an opinion target, a primary object of the opinion expression (e.g., the real-world object, event, and abstract entity), is helpful for extracting target-related opinions and detecting user interests. This paper presents a novel framework for target-based opinion analysis, which extracts opinionated sentences and identifies their opinion targets from news articles. To determine whether a sentence includes opinions, we utilize opinion lexicons (i.e., predefined clue words) and linguistic patterns. In identifying the opinion target, candidates are generated and examined for existence of four different features. We attempt to capture the relationship between an object target and opinion clues and utilize a document theme. For evaluation, we used English news articles from New York Times, provided by NTCIR-8 MOAT and annotated opinionated sentences and theirs opinion targets. Experimental results show that our proposed method is promising although many additional issues remain to be studied in the future.

## Categories and Subject Descriptors
H.3.3 [**Information Storage and Retrieval**]: Information Search and Retrieval – *Information Filtering*. I.2.7 [**Artificial Intelligence**]: Natural Language Processing – *Text Analysis.*

## General Terms
Algorithms, Experimentation.

## Keywords
Opinion Analysis, Sentiment Analysis, Opinion Judgment, Opinion Target Identification, Multilingual Opinion Analysis Task (MOAT), NTCIR.

## 1. INTRODUCTION
Deliberating on some problems such as social issues and individual problems or deciding on something such as problems and products, one of the important information is what others are thinking about the same issues [1]. Nowadays, as online opinion resources, such as online news, blogs, online communities, reviews, and forums, grow up, Internet users can easily search for others opinion (or public opinion) about their interest. In fact, 31% of the whole Americans were online for gathering information and exchanging views via email during the 2006 election campaign season. Also, about 14 million people contributed to political discussion and activity through reading and writing Web articles [5].

Opinion analysis is to recognize opinions and their related attributes such as polarity (positive or negative), opinion holder, and opinion target [3]. These opinions and related attributes can be of service to not only individuals but also governments and companies [6]. So, many researchers have been interested in opinion mining from several data such as news articles, blogs and product reviews, and several methods which obtained reasonable performances have been developed [7,8,9]. However, the most of them have focused on identifying subjective or objective sentences, judging polarity values, and extracting opinion holders, not identifying opinion targets.

Opinion data, such as news articles, blogs, and reviews, contain at least one topic and its opinions. Therefore, people are practically interested in opinions relevant to a particular topic, not any opinions. However, almost every previous study has neglected a relevant topic when opinions were decided. Moreover, opinions which contain interesting topics (e.g., popular products and social issues) can be more closed to user interest. For instance, many people are interested in popular movies, political election, and sensational events which obtain many and various opinions from the public [3]. This topic can be defined as the real-world object, event, or abstract entity, which would be the primary subject of the opinion as intended by the opinion holder [10]. As previous studies [3,11] referred such a topic as an opinion target, in this paper, we adopt the same concept.

The opinion target identification would be very useful for several applications such as extracting target-related (or topic-related) opinions, estimating trends (e.g., popular products and issues) and detecting user interests. However, there have been a few research works on the opinion target identification [3,8]. Kim et al. [3] attempted to build an opinion target classifier using syntactic path information between opinion clues and an opinion target and syntactic dependency feature (i.e., syntactic patterns such as "V*erb opinion clues + Target*" and "A*djective opinion clues + Target*"). In another work [8], they used FrameNet semantic role labeling to identify an opinion target.

Although these syntactic features and semantic role labeling make a great contribution to identify an opinion target, they cannot solve completely this problem [11]. With this question in opinion target identification, we are motivated to participate in the 3rd

Multilingual Opinion Analysis Task (MOAT) in NTCIR which has five subtasks: opinionated sentence judgment, relevance sentence judgment, polarity judgment, opinion holder identification, and opinion target identification [2]. Among them, we joined in 2 subtasks: opinionated sentence judgment and opinion holder identification.

In this paper, we focus on the opinion target identification. To judge opinionated sentences, we utilize opinion lexicons, such as "*good*", "*criticize*", and "*death*", and devised linguistic patterns. As lexicons, a sentiment lexicon and a list of appraisal verbs are used. In the opinion target identification, unlike previous works [3,8] applied syntactic paths, syntactic dependencies and semantic roles as features, in this paper, we attempt to detect an opinion target by considering sentence and document information and collocation information between an opinion target and opinion clue words, not syntactic features. We first extract all noun phrases as candidates and build a classifier which determines whether a candidate is suitable for an opinion target or not. Features used for the classifier include the degree to which it is correlated with the document-level theme, collocation information between the candidate and opinion clues, and the opinion score of the candidate.

The rest of our paper is organized as follows. In Section 2, we explain several related works. Section 3 presents our proposed methods, and Section 4 shows and briefly discusses the evaluation results. Finally, we conclude in Section 5.

# 2. Related Work

In this paper, we focus two tasks: opinionated sentence judgment and opinion target identification. There have been a few previous works about opinion target identification, so we also investigate opinion holder identification because they may have similar approaches.

## 2.1 Opinionated Sentence Judgment

Most previous works have adopted statistical classification methods such as Naïve Bayes and Support Vector Machine with lexical features [3]. Early work by Wiebe et al. [12] developed the probabilistic classifier to automatically discriminate the subjective and objective category. The subjective sentence refers to aspects of language used to express opinions. They utilized the Navie Bayes classifier with several features: the presence of a pronoun, an adjective, a cardinal number, a modal other than "*will*", and an adverb other than "*not*", whether the sentence begins a new paragraph, and the co-occurrence of words and punctuation marks. Hatzivassiloglou and Wiebe [13] studied the benefit of dynamic adjectives (oriented adjectives) and gradable adjectives for the sentence-level subjectivity classification. Yu et al. [14] studied separating opinions from facts at the document-level and sentence-level on TREC [1] 8, 9, and 11 collections. They also applied the Naïve Bayes and multiple Naïve Bayes classifier, and the presence of semantically oriented words, the average semantic orientation score of the words, and the N-grams are used for features.

Riloff and Wiebe [15] suggested bootstrapping methods for the subjectivity classifier. From the labeled data, they generated patterns to represent subjective expressions, and these patterns were utilized to identify more subjective sentences. Then, based on these patterns, they classified subjective sentences. In [16], they developed the learning method for the rule-based subjectivity classifier which looks for subjective clues. Stepinski and Mittal [17] also developed the new sentence classification using a Passive-Aggressive algorithm trained on unigram, bigram, and trigram features. Also, the recent work [18] considered relations between word sense disambiguation and subjectivity [1].

## 2.2 Opinion Target Identification

The opinion target identification task newly proposed in NTCIR-7 [22]. There had only one team which participated in this task. Kim et al. [3] proposed the statistical classifier to detect an opinion target. Syntactic paths between a candidate and opinion clues (e.g., "*NP VP VBZ*"), syntactic dependencies based on the part-of-speech of opinion clue words, the presence of topic words, and the named entity type are used for features.

Kim and Hovy [8] attempted to extract an opinion topic (or target) utilizing FrameNet semantic role labeling and manually mapping semantic roles to an opinion topic in news articles. They firstly identified frame elements in a sentence and detect an opinion topic from these. The mapping table to map frame elements to an opinion topic was manually built by them.

## 2.3 Opinion Holder Identification

Kim and Hovy [8] applied FrameNet semantic role labeling to detect an opinion holder. The method was same with the opinion topic identification (we mentioned in Section 2.2), and it had the different mapping table for the opinion holder extraction. Another paper [19] suggested the new approach which used syntactic paths between an opinion holder's candidate and the expression (opinion clue words). They used the Maximum Entropy ranking model to obtain the scores and to rank candidates. Kim et al. [4] used the dependency tree to identify an opinion holder. They extracted the nominal subject of the verb as the opinion holder in an opinionated sentence.

Choi et al. [20] proposed the hybrid approach which used both Conditional Random Fields (CRFs) and extraction patterns. Features for CRFs are lexical and syntactic information and semantic words. Seki et al. [21] suggested the new opinion holder identification method based on a differentiation between the author and authority viewpoints in opinionated sentences. They exploited the named entity and grammatical information and used NTCIR-6 data for evaluation.

# 3. Opinion Mining System

Our proposed system consists of two parts. The first one is for the opinionated sentence judgment which decides whether a given sentence expresses an opinion or not (i.e., subjectivity or objectivity). The other part is for the opinion target identification which detects opinion targets within opinionated sentences.

## 3.1 Opinionated Sentence Judgment

For the goal of this work, classifying a sentence into opinionated or factual (i.e., non-opinionated), we made two assumptions:

- Opinionated sentences contain opinion clue words
- Some patterns may appear in opinionated sentences

[1] TREC, http://trec.nist.gov/.

Based on these assumptions and commonly used methods in the related works, we address our opinionated sentence judgment approach which combines two methods: pattern matching method and opinion scoring method.

For opinion patterns, first, we analyzed NTCIR-8 sample data [2] to devise several patterns to determine the subjectivity of a sentence. In this paper, the pattern means several lexical clues, such as "*believe*", which strongly reveal one's opinion in a sentence. We observed some verbs and auxiliary verbs such as "would" could be strong evidence for the non-factual statement. We finally select 15 opinion patterns through the analysis of sample data (Table 1). These patterns are used to detect the subjectivity.

**Table 1. Opinion patterns frequently shown in sample data**

| | |
|---|---|
| **Main Verb** | "*believe*", "*insist*", "*claim*", "*criticize*", "*think*", "*advise*" |
| **Auxiliary Verb** | "*would*", "*could*", "*may*", "*should*", "*might*", "*will*" |
| **Phrase** | "*in fact*", "*unfortunately*", "*consequently*" |

For other sentences which cannot discover opinion patterns, we employ opinion lexical resources such as SentiWordNet[2] [23], which has 5,321 sentiment words, and Appraisal verbs[3] [24], which has 703 appraisal verbs or adjectives. SentiWordNet is a freely available lexical resource in which each synset of WordNet is associated to two numerical scores, such as positive score and negative score, representing how much the term in the synset has positive value and negative value, respectively. Using these two scores, we get the subjectivity score which can be calculated as follows:

$$SubjScr(t) = \left| PosScr(t) - NegScr(t) \right|$$

where $t$ is each term, and *PosScr(t)* and *NegScr(t)* is a positive score and negative score of a term $t$, respectively. In this case, SentiWordNet has different scores depended on senses, so we apply the maximum score among them [4]. Appraisal lexicon is hand-picked appraisal words from Levin's Verb Classes [25] and adjectives extracted from the NTCIR corpus. However, Appraisal lexicon is just the word set and has no appraisal score. Then, to combine with SentiWordNet, we give an appraisal score to members of Appraisal Verb set. The appraisal score is 0.3, which is empirically set, since a major portion of opinion clue words in SentiWordNet have more than 0.3 as a sentiment score while non-opinion clues or trivial words have less than 0.3. The opinion score of a term is computed to combine the objectivity score and appraisal score, and the opinion score of a sentence is calculated to sum up all opinion scores of the terms in a sentence as follows:

$$OpiScr(t) = SubjScr(t) + AppScr(t)$$
$$OpiScr(S) = \sum_{t \in S} OpiScr(t)$$

where $S$ is a sentence and *AppScr(t)* is an appraisal score of a term $t$.

If a sentence is matched to the opinion patterns, we decide the given sentence is opinionated. Also we determine a correct answer for subjectivity that if the opinion scores of the given sentence is over the certain threshold. We optimize the threshold value using sample data.

## 3.2 Opinion Target Identification

In previous works, syntactic and lexical features or devised syntactic patterns are utilized to identify an opinion target. Furthermore, we can think an opinion target may employ similar features to an opinion holder, and many researchers have also used syntactic and lexical information to detect an opinion holder. However, those are mostly sentence-level features. In this paper, we show the document-level feature and collocation between an opinion target and opinion clue words (corpus-level feature) also are useful.

First, we should decide which parts in a sentence are candidates for an opinion target. As we mentioned above, the opinion target means the real-world object, event, or abstract entity. Therefore, the unit of an opinion target can be confined to be a noun phrase. So, for opinion target's candidates, we extract all atomic noun phrases from each sentence using a parser[4].

For opinion target identification, we have three intuitions:

- Document-level theme can be an opinion target
- An opinion target may contain opinion clue words
- An opinion target will frequently co-occur with several opinion clue words

Based on these, we generate a statistical classifier which decides whether a given candidate is appropriate for an opinion target or not. We consider the four types of features, and they are explained below. In order to incorporate these features, we adopt the linear regression method which works well with a small size of training data (the number of documents in sample data is only 12).

Our first intuition is an opinion target should be related to a document-level theme. Most sentences in a document talk about a document theme (or topic). So, if a sentence expresses an opinion (e.g., positive or negative), it may be close connection between the target of opinion and the document theme. For this, we exploit two features. One is whether or not the given candidate's keyword appears on the title section in a document since most document topics are mentioned on the title section in a document. For example, in a document with the title "*Bohemian Border Town Blues: The Euro's to Blame!*" and the sentence "*Things will get worse, not better, when his country adopts the euro* ...", "*the euro*" can be not only a document theme in this document but also an opinion target in this sentence. The other feature is the

[2] SentiWordNet, http://sentiwordnet.isti.cnr.it.

[3] Appraisal Verbs, http://lingcog.iit.edu/arc/appraisal_lexicon_2007b.tar.gz.

[4] We used Stanford Parser (http://nlp.stanford.edu/software/lex-parser.shtml).

document-level language model. We adopt the unigram language model:

$$P(NP \mid D) = P(t_1, ..., t_n \mid D) = \prod_{i=1}^{n} P(t_i \mid D)$$

where *NP* is a candidate of an opinion target, *D* is a document, *t* is a term, and *n* is the number of terms in a candidate *NP*. Furthermore, the probabilities are estimated as follows:

$$P(t_i \mid D) = \frac{c(t_i, D)}{\sum_{t \in D} c(t, D)}$$

where *c(t, D)* is the number of occurrences of a term *t* in a document *D*.

From the analysis of sample data that the topic is "*Bali Island Terrorist Bombing"* [2], we discover several opinion targets, which have strong opinions, comprehend opinion clue words such as "*bomb*", "*threat*", "*terrorism*", "*attack*", and so on. Also, according to the definition, several events (e.g., social issues, car accidents, and big festivals) can be an opinion target, and sometimes the name of events contains opinion clue words such as "*festival*", "*accident*", "*strike*", etc. So, the opinion score of terms in a candidate are also deliberated.

$$OS(NP) = \frac{\sum_{i=1}^{n} OpiScr(t_i)}{n}$$

where *OpiScr(t)* is the opinion score of term *t* which is estimated as follows:

$$OpiScr(t) = Max[Scr(t \mid POS), Scr(t \mid NEG)]$$

where *Scr(w|POS)* and *Scr(w|NEG)* are positive and negative sentiment score of the term *t*, respectively, which are provided by SentiWordNet. The range of score is $0 \le Scr(.) \le 1$.

The last intuition is an opinion target will co-occur with various opinion clues in several documents (or corpus). The opinion target detected one sentence can also be detected in other sentences. Moreover, opinion targets usually are constructed with manifold opinion clues while others (non opinion targets) are written with a few opinion words. For example, the opinion target "*SARS*" is usually used with opinion clues such as "*threat*", "*worry*", and "*warn*" in several sentences even though the non opinion target "*the network structure*" isn't. Therefore, we utilize collocation information between a candidate and opinion clues as follows:

$$C(NP, OW) = \frac{|S_{NP} \cap S_{OW}|}{\sqrt{|S_{NP}|} \times \sqrt{|S_{OW}|}}$$

where *OW* is the opinion clue set (we use SentiWordNet), $S_{NP}$ and $S_{OW}$ is the set of sentences which contain *NP* and one of opinion clues *OW*, respectively, and |.| is the number of sentences in a set.

Overall, the feature space to identify an opinion target consists of four types: whether the title section contains an opinion target, document-level language model, opinion target's opinion score, and collocation information between an opinion target and opinion clues.

# 4. Experiment

In this section, we present the effectiveness of our proposed method using NTCIR-8 MOAT data which will be explained in Section 4.1. Precision, recall, and F-measure are used to evaluate opinionated sentence judgment and opinion target identification method, which are suggested in [2].

## 4.1 NTCIR-8 MOAT Data Collection

The NTCIR-8 MOAT collection [2] consists of 21 topics (150 articles). They are New York Times articles which had been published in 2002-2005. Among them, one topic containing 12 articles is provided as the sample data, and others (20 topics – 138 articles) are used for test (i.e., formal running data). Each sentence in articles was annotated about opinionatedness, topic-relevance, polarity, opinion holder, and opinion target. We utilize only the sample data (one topic) for training and others (20 topics) for testing.

## 4.2 Experimental Result and Discussion

First, we present the experimental result with the sample data. Based on this experiment, we optimized our system and submitted our result with the formal running data. The result of formal running data will be described in Section 4.2.2.

### *4.2.1 Sample Data*

We got two annotation results (i.e., two annotators participated in the annotation task) about each articles. So, two different gold-standard are existed. One is a lenient standard that an answer is agreed by at least one of two annotators, and the other is a strict standard that an answer is agreed by all two annotators.

**Table 2. Opinion judgment result in sample data**

| *Features* | *Precision* | *Recall* | *F-measure* |
|---|---|---|---|
| Opinion Scoring (OS) | 0.1525 | 0.1244 | 0.1370 |
| Opinion Rules (OR) | 0.3826 | 0.3011 | 0.3369 |
| OS + OR | **0.4625 (0.3612)** | **0.3559 (0.2827)** | **0.4022 (0.3172)** |

Table 2 is opinionated sentence judgment result in sample data. Strict cases represent in parentheses. Performance on the opinion judgment on sample data was best when opinion patterns and opinion scoring method are applied together whereas using only opinion patterns or opinion scoring method could not cover many opinion sentences.

Table 3 shows the result of opinion target identification in sample data. We regard as a correct answer when a detected opinion target is exactly matched with the gold-standard. Document-level language model and collocation information between an opinion target and opinion clues are the most important for the opinion target identification while a feature about the appearance on the title section is not. The opinion score feature is also non-trivial since the effect of using only this feature is not trifling. When those features are combined, we can know all features contribute to identify the opinion target even if the difference is not significant.

**Table 3. Opinion target identification result in sample data**

| *Features* | *Precision* | *Recall* | *F-measure* |
|---|---|---|---|
| Title Section (TS) | 0.1040 | 0.0774 | 0.0887 |
| Opinion Score (OS) | 0.2667 | 0.3333 | 0.2963 |
| Language Model (LM) | 0.3151 | 0.4464 | 0.3695 |
| Collocation (CO) | 0.2972 | 0.4405 | 0.3549 |
| LM + CO | 0.3231 | 0.5000 | 0.3925 |
| LM + CO + OS | 0.3269 | 0.5060 | 0.3972 |
| LM + CO + OS + TS | **0.3282 (0.2744)** | **0.5060 (0.5844)** | **0.3981 (0.3734)** |

### *4.2.2 Formal Running Data*

The result of the formal run is shown in Table 4. Comparing with sample data results, the overall performance is deteriorated because our submitted result is over-fitted to the sample data. The sample data contained only one topic while test collection contained 20 topics. Therefore, the sample data would not embrace all features of opinionated sentences and opinion targets, so we could miss something important.

In the opinion extraction task, our proposed system has higher recall value than NTCIR-7 result [22]. Since we utilized abundant opinion words (e.g., SentiWordNet and Appraisal Verbs), our system detected a lots sentences. Among them, some sentences are extracted because they contain plenty of weak opinion clue words. Also, SentiWordNet had different sentiment score according to senses, but we didn't deliberate on this case and considered only the maximum score about each word. Besides, several non-opinion words also have a sentiment score in SentiWordNet. Therefore, while the precision value is low, the recall is high.

The opinion target identification task has overall better performance than previous work [22]. Then, we can verify the document-level information and collocation information are also useful to detect an opinion target. However, the precision and recall values are still low, partly due to the strict matching criterion. Most notably, inability to handle anaphora gave many incorrect opinion targets. This anaphora can be found very often in news articles. Also, since the gold-standard is made by human annotators, it contains many pronouns (e.g., "*it*", "*them*", and "*him*") as opinion targets. Synonymy problem is also significant. Some opinion targets could occur in other sentences with different surface-level, but these regard as different opinion targets. Another weakness is associated with reliance on the term frequency and the presence of opinion clues in the features. Some opinion targets do not occur very often or sometimes are not connected with opinion clue words.

**Table 4. Formal running result**

| *Task* | *Precision* | *Recall* | *F-measure* |
|---|---|---|---|
| Opinion Extraction | 0.1888 | 0.6526 | 0.2943 |
| Opinion Target Identification | 0.231 | 0.346 | 0.277 |

## 5. Conclusion

This paper presents two tasks, opinionated sentence judgment and opinion target identification, which are subtasks in NTCIR-8 MOAT. For the opinion judgment at the sentence-level, the opinion score and opinion patterns are used. If a sentence is matched to opinion patterns or contains strong or several opinion clue words, it would be detected as an opinionated sentence. For the opinion target identification, we extract noun phrases as candidates and build a classifier, which determines whether a candidate is suitable for an opinion target or not, with four types of features: the appearance on the title section, document-level language model, opinion score of a candidate, and collocation information between a candidate and opinion clues. Although we didn't obtain good performance, we show not only sentence information (e.g., syntactic and lexical features), but also document information and collocation information are helpful to identify an opinion target.

As future works, we should investigate the opinion target boundary detection although we confined it to a noun phrase in this paper. The anaphor and synonym problem are also important issue in natural language processing since almost texts have such problem. Moreover, after analyzing plenty of opinion documents, to discover significant features or characters of the opinion target should be necessary for improvement.

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