

# News Bias Analysis Based on Stakeholder Mining

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**SUMMARY** In this paper, we propose a novel stakeholder mining mechanism for analyzing bias in news articles by comparing descriptions of stakeholders. Our mechanism is based on the presumption that interests often induce bias of news agencies. As we use the term, a “stakeholder” is a participant in an event described in a news article who should have some relationships with other participants in the article. Our approach attempts to elucidate bias of articles from three aspects: stakeholders, interests of stakeholders, and the descriptive polarity of each stakeholder. Mining of stakeholders and their interests is achieved by analysis of sentence structure and the use of RelationshipWordNet, a lexical resource that we developed. For analyzing polarities of stakeholder descriptions, we propose an opinion mining method based on the lexical resource SentiWordNet. As a result of analysis, we construct a relations graph of stakeholders to group stakeholders sharing mutual interests and to represent the interests of stakeholders. We also describe an application system we developed for news comparison based on the mining mechanism. This paper presents some experimental results to validate the proposed methods.

**key words:** stakeholder mining, RelationshipWordNet, relationship structure, bias analysis

## 1. Introduction

Due to intentions of news agencies and their sponsors, in a sense, news is never free from bias. Bias often causes readers to misunderstand the facts of actual events and even the whole story. Although a large number of studies [1]–[3] have been made on analyzing bias by means of comparing related news articles, conventional methods present related articles and ask users to compare them. To the best of our knowledge, models and criteria for bias analysis have not yet been well studied.

There are multiple types of media biases such as subjectivity of description, selectivity of events, and accuracy of information. In this paper, we focus on the relation between media bias and interests, on the presumption that the latter induce the former. Under this presumption, it is possible to make bias overt by analyzing the descriptions on stakeholders and their relationships appearing in news articles. As a bias analysis method, we propose a novel stakeholder mining mechanism to extract stakeholders referred to in news articles and relationships among them. Although the stakeholder mining mechanism can be used for analysis of documents other than news articles, in this paper we give

an explanation using news articles for the purpose of news comparison.

We define a “stakeholder” as a participant in an event described in a news article and who should have some relationships to another participant or participants. We propose a method for comparing analysis results of news articles and attempt to elucidate bias from three descriptive aspects: 1) stakeholders in articles, 2) interests of stakeholders, and 3) the descriptive polarity of each stakeholder.

Stakeholders described in a news article specify the objects to which the article refers. When two articles are compared, some stakeholders are referred to by only one article. In other words, the scope of events that news articles deal with is biased because one article may describe the stakeholder while another does not.

An interest state is represented by a pair of values, one being a positive relationship indicating a degree of corresponding interests and the other being a negative degree indicating that of conflicting interests. Comparisons of these values and the existences or nonexistence of interests also show a bias. For example, although two articles *A* and *B* describe the same event “Obama visits China”, article *A* and article *B* may describe the relation of US and China from negative and positive viewpoints respectively.

Descriptive polarity is represented by two numerical scores indicating how positive or negative the descriptive tendency is. The polarity makes it possible to deal quantitatively with the viewpoints of news articles. For example, for the news event of “Google withdraw from China”, articles *A* and *B* may describe China from negative and positive viewpoints respectively. Thus comparisons of descriptive polarities enable us to understand differences in the perspectives of news articles.

In our approach, participants are extracted by using a named entity recognition tool. Then, some of the participants are identified as stakeholders by analyzing their relationships described in sentences of a news article.

A sentence referring to the relationship among stakeholders includes words that express their interests because stakeholders share interests. This suggests that (1) words that express interests indicate states of the interests and (2) the structure of a sentence specifies the stakeholders in each interest. Therefore, we constructed RelationshipWordNet, a lexical resource in which each word assigns scores indicating a state of relationship, and Relationship Structure, a sentence structure appropriate for extracting relationships. Relationship structure is also used to descriptive polarity anal-

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ysis because the structure is helpful to identify stakeholders that a description expresses.

We propose an opinion mining method based on SentiWordNet [4] for analyzing the polarity of stakeholder descriptions. SentiWordNet is a lexical resource for opinion mining, which assigns to each synset of WordNet sentiment scores. Descriptive polarity is represented by scores indicating the descriptive features of stakeholders. The polarity is calculated with relationship structure and SentiWordNet. By using relationship structure, we discover the descriptions related to a certain stakeholder. Then, we obtain descriptive polarity by analyzing the description with SentiWordNet.

Stakeholders and their interests are represented in the form of a graph we call “Relations Graph”, the vertices of which are stakeholders and the edges of which are interests. We also use the graph for aggregating the stakeholders who share mutual interests.

Based on the stakeholder mining mechanism, we propose a system for comparing news articles. This system enables us to browse related news articles and concurrently compare their mining results for bias analysis.

Experiments and a user study have been carried out. The results demonstrate the efficacy of our methods.

## 2. Related Work

Liu, et al. [2] proposed LocalSavvy, a system that finds and aggregates local news articles published by official and unofficial news sources associated with stakeholders (countries) in an event. Then it presents summarized and highlighted opinions from each local social group for news comparison.

NewsCube [1] provides readers with multiple classified viewpoints on a news event. This system analyzes aspects of news articles and classifies them, then recommends articles with contrasting aspects. It tends to induce deeper understanding about news events on the part of users and more balanced reading for them.

The Comparative Web Browser (CWB) [3] is a system designed to search for articles that are similar to the article a user is currently reading. It enables users to concurrently browse related news articles for comparison.

TVBanc [5] analyzes bias and diversity in Web-news content. The system extracts the topic and viewpoints of news content by using a contents structure consisting of subject, aspect, and state terms. It then groups related news items from various news sources into different clusters and analyzes their viewpoints distribution to estimate the diversity and bias of the news contents.

Opinion analysis of media delivering news articles was conducted by Grefenstette, et al. [6]. They collected articles on an entity by using Google News and then elucidated descriptive tendencies by analyzing words in texts around the entity.

In contrast to the conventional methods, our method enable users to compare news articles from the entity (stake-

holder) level. In other words, we elucidate interests and descriptive polarities of stakeholders for news comparison.

## 3. Stakeholder Mining Mechanism

In this section, at first we overview the stakeholder mining mechanism. Then, we describe the construction methods of RelationshipWordNet and relationship structure used for stakeholder mining. After that, we introduce the details of the stakeholder mining mechanism.

### 3.1 Overview

Stakeholder mining mechanism analyzes stakeholders, including their interests, and their descriptive polarities in a given news article. It outputs a relations graph representing the analysis results.

The overview of this mechanism is shown in Fig. 1. First of all, named entities such as country, person and organization are extracted as stakeholder candidates for each sentence in a given news article. Next, a relationship structure of each sentence is constructed for interests extraction and descriptive polarity analysis. Interests are extracted by using RelationshipWordNet. In addition, stakeholders are extracted in the interests extraction. Descriptive polarity is analyzed for each stakeholders by using SentiWordNet. Finally, a relations graph of stakeholders is constructed to group stakeholders sharing mutual interests and to represent the mining results.

### 3.2 RelationshipWordNet and Relationship Structure

To detect the participants sharing interests in an event, we build a lexical resource named RelationshipWordNet and construct a sentence structure named relationship structure.

#### 3.2.1 RelationshipWordNet

We construct RelationshipWordNet from WordNet [7] to specify words expressing interests. WordNet is a lexical resource that groups terms into sets of cognitive synonyms (synsets), each expressing a distinct concept. RelationshipWordNet assigns all synsets with three numerical scores: “positivity”, “negativity” and “objectivity”. A synset that

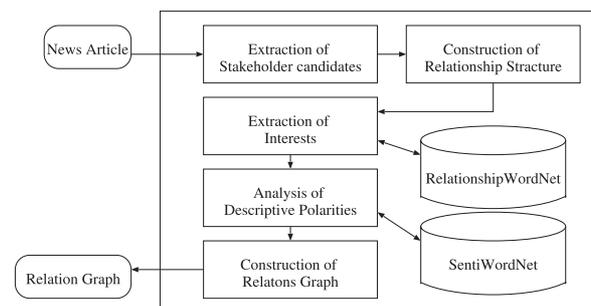


Fig. 1 Overview of stakeholder mining mechanism.

**Table 1** Example of seed sets.

$L_p$	$L_n$	$L_o$
depend	attack	say
comfort	blame	go
favorite	complain	act

express a better relationship has a larger positive score. One that expresses a worse relationship has a larger negative score. The “objective” score indicates the degree of objectivity the corresponding synset has.

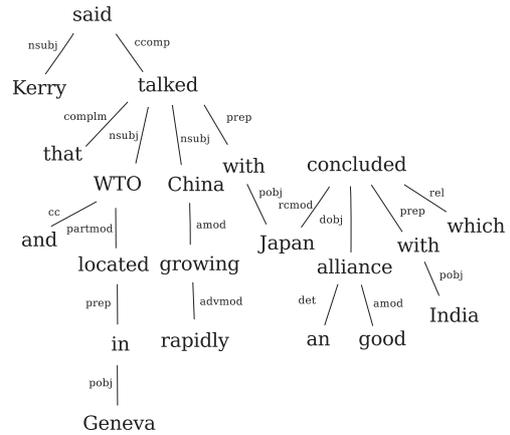
RelationshipWordNet is constructed by modifying the construction method of SentiWordNet [4]. RelationshipWordNet differs from SentiWordNet in that three scores of the former indicate the state of relationships, while those in the latter express the degree of sentiments. For example, the verb “ally” expresses a good relationship, but in SentiWordNet three scores of the synset including the verb are *Pos:0.0*, *Neg:0.0* and *Obj:1.0*. Therefore, we need to assign different scores to synsets for RelationshipWordNet.

**Step 1** We collect synsets that each includes any word in 2193 words of The Longman Definition Vocabulary. Then, we manually classify the synsets into the three kinds of seed sets  $L_p$ ,  $L_n$  and  $L_o$ . The criterion for the classification is: when a word included in a synset is used to express a relationship between two stakeholders, the synset is classified into  $L_p$ ,  $L_n$  or  $L_o$  according to the state of the relationship (positivity, negativity and objectivity) the word expresses. An example of seed sets is shown in Table 1.

**Step 2**  $L_p$ ,  $L_n$  are expanded in  $k$  iterations to obtain a training set  $T^k$  that consists of the three groups  $T_p^k$ ,  $T_n^k$ , and  $T_o^k$ . We use the relations between synsets defined by WordNet for each expansion. The relations we use for expansions are *direct antonymy*, *similarity*, *derived-from*, *pertains-to*, *attribute*, and *also-see*. Two synsets connected by these relations except for *direct antonymy* have the same polarity. On the other hand, two synsets connected by the relation *direct antonymy* have mutually opposite polarity. The expansion for obtaining  $T_p^k$  (resp.  $T_n^k$ ) is conducted in two ways: 1) all the synsets that are connected to synsets in  $T_p^{k-1}$  (resp.  $T_n^{k-1}$ ) by the relations except for *direct antonymy* are added to  $T_p^{k-1}$  (resp.  $T_n^{k-1}$ ), 2) all the synsets that are connected to synsets in  $T_n^{k-1}$  (resp.  $T_p^{k-1}$ ) by the relation *direct antonymy* are added to  $T_p^{k-1}$  (resp.  $T_n^{k-1}$ ). In comparison, a training set  $T_o^k$  equals  $L_o$  in any  $k$ .

**Step 3** To enable learning machines to be used with synsets, we give each synset a vector representation by applying cosine normalized *tf · idf* to the text of its gloss. Then, we obtain eight learning machines by making two learning machines (Rocchio and SVMs<sup>†</sup>) respectively learn four training sets ( $T^k$ ,  $k = 0, 2, 4, 6$ ). Each learning machine classifies all synsets as “positive”, “negative”, or “objective”.

**Step 4** Each synset is given three scores, each indicating

**Fig. 2** Example of relationship structure for the sentence “Kerry said that the WTO, located in Geneva, and the rapidly growing China talked with Japan, which concluded a good alliance with India.”

“positivity”, “negativity”, and “objectivity”, proportional to the ratio of the according categories to which eight classifiers assign them. For instance, given that the eight classification results of a synset are composed such that five are “positive”, one is “negative”, and two are “objective”, the three scores of the synset are  $Pos : 0.625 \left(\frac{5}{8}\right)$ ,  $Neg : 0.125 \left(\frac{1}{8}\right)$ , and  $Obj : 0.250 \left(\frac{2}{8}\right)$ .

Hereinafter, we use the expression *relation word* to refer to a term included in a synset whose “positive” or “negative” score is more than 0, i.e., the objective score is not 1.0.

### 3.2.2 Relationship Structure

We define relationship structure, a sentence structure suitable for identifying stakeholders who share interests. An example of relationship structure is shown in Fig. 2.

Relationship structure is constructed on the basis of Stanford Dependencies [8]. Stanford Dependencies provide grammatical relations in the form defined below.

*type (governor, dependent)*

The *type* is the abbreviated name of a grammatical relation held between a word *governor* and another word *dependent* in a sentence. We can obtain a tree structure of a sentence by identifying *governor* as a parent node and *dependent* as a child node.

It is important to identify positional relations among relation words, verbs, and stakeholder candidates in a sentence structure to specify the relationships among stakeholders. Tree structure operations are necessary due to the need to identify the positional relations on the basis of the sentence structure. Therefore, to construct a relationship structure, we operate a tree structure corresponding to the grammatical relations shown in Table 2.

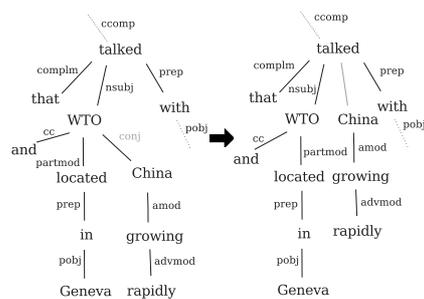
<sup>†</sup>The two learning machines used here are Andrew McCallum’s Bow package (<http://www-2.cs.cmu.edu/mccallum/bow/>) and Thorsten Joachims’ SVM<sup>light</sup> (<http://svmlight.joachims.org/>).

Of the grammatical relations in Table 2, “conj” applies to two elements connected by a coordinating conjunction such as “and” or “or”, “appos” is a noun phrase immediately to the right of the first noun phrase that serves to define or modify that noun phrase, and “rcmod” is a relative clause modifying the noun phrase. The relation points from the head noun of the noun phrase to the head of the relative clause, normally a verb. “cop” is the relation between the complement of a copular verb and the copular verb. For example, in the sentence “Tom is an honest man.”, “cop” indicates the relation between “is” and “man”.

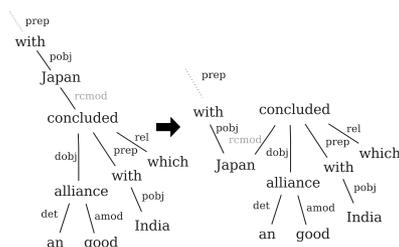
Figure 3 illustrates an example of the operation for “conj” in the sentence used in Fig. 2. In this case, the relation “conj (WTO, China)” is omitted and “talked”, the parent node of “WTO”, is added to the parents of “China”. Figure 4 is an example of the operation for “rcmod”, in which the relation “rcmod (Japan, concluded)” is omitted and the new edge whose parent node is “concluded” and whose child is “Japan” is added to the structure.

**Table 2** Operations for grammatical relations.

Type	Operation
conj appos	Omit this relation from the structure and the parents of the <i>governor</i> are added to the parents of <i>dependent</i> . Furthermore, if both <i>governor</i> and <i>dependent</i> are verbs, the children of <i>governor</i> except <i>dependent</i> is added to those of <i>dependent</i> .
rcmod cop	Interchange <i>governor</i> and <i>dependent</i> .



**Fig. 3** Operation for “conj”.



**Fig. 4** Operation for “rcmod”.

### 3.3 Details of Stakeholder Mining Mechanism

#### 3.3.1 Extraction of Stakeholder Candidates

First of all, we extract the sentences from an input news article. Then, we extract named entities such as country, person and organization from each sentence as stakeholder candidates. In our current work, we use a named entity recognition tool [9] for named entity extraction. If two or more stakeholder candidates have been mentioned in the same sentence and they share interests with each other, they will be considered as stakeholders. Here, the interests between two stakeholders are detected by using RelationshipWordNet and relationship structure.

#### 3.3.2 Extraction of Interests

An interest is represented as  $(\{s_1, s_2\}, P, N)$  where  $s_1$  and  $s_2$  are stakeholders that have an interest and  $P$  and  $N$  are numerical scores ranging from 0.0 to 1.0, in which  $P$  indicates the degree of coincidence between the interests and  $N$  indicates the degree of conflict between them.

The interests extraction procedure is executed for each relation word  $w_R$  in a sentence. Here, in relationship structure of a sentence, we define a “root” as a node that does not have any parent nodes, a “leaf” as a node that does not have any child nodes,  $V(w_R)$  as a set of verbs for which the distance between  $w_R$  and the verb is the smallest on each path from  $w_R$  to a root in ascendants of  $w_R$ , and  $N_e(v)$  as a set of stakeholder candidates for which the distance between a verb  $v$  and the stakeholder candidate is the smallest on each path from  $v$  to a leaf in descendants of  $v$ . In the interests extraction procedure, interests are extracted by referring to the structure types defined in Table 3. A structure type matches a part of the relationship structure of a sentence. That part forms a tree structure. In a structure type,  $V$  matches the root verb of a part of a relationship structure, the symbol to the right of  $V$  means whether stakeholder candidates exist in the subject, and the symbol to the left of  $V$  means whether stakeholder candidates exist in the predicate.  $N_s(v)$  indicates stakeholder candidates in  $N_e(v)$  exist in the subject.  $N_p(v)$  indicates stakeholder candidates in  $N_e(v)$  exist in the predicate.  $N_n$  means there are no stakeholder candidates in the subject or predicate where  $N_n$  is located. The interests extraction procedure for each  $w_R$  in a sentence is described below.

**Step 1** If any stakeholder candidates are on a path from  $w_R$  to a verb  $v$  in  $V(w_R)$ ,  $w_R$  is considered as a modification to the nearest stakeholder candidate to  $w_R$  on that path, and does not represent interests. If  $w_R$  satisfies the condition, the procedure for  $w_R$  stops.

**Step 2** For each  $v$  in  $V(w_R)$ , a set of stakeholder candidate pairs is extracted according to the expression in Table 3 where the structure type matches the tree structure of which  $v$  is the root. If no structure type matches the tree

**Table 3** Structure types for interests extraction.

Structure type	A set of stakeholder candidate pairs
$N_sVN_p$	$\{(s_i, s_j)   s_i \in N_s, s_j \in N_p\}$
$N_sVN_n$	$\{(s_i, s_j)   s_i \in N_s, s_j \in N_s, s_i \neq s_j\}$
$N_nVN_p$	$\{(s_i, s_j)   s_i \in N_p, s_j \in N_p, s_i \neq s_j\}$

structure, a set of candidate pairs is not extracted. Each pair of stakeholder candidates shares interests. We consider those candidates as stakeholders. If no interests are extracted for any  $v$ , the procedure for  $w_R$  stops.

**Step 3** If an extracted interest is obtained the first time, initialize P and N values of the interest to 0. Positive and negative scores of  $w_R$  are respectively added to P and N values of each interest. At this time, if the sentence includes a negation word, the grammatical relations of the sentence include

$$\text{neg}(\text{governor}, v), v \in V(w_R)$$

or

$$\text{neg}(\text{governor}, w_R),$$

and  $w_R$  is handled in the way its positive and negative scores are interchanged because  $w_R$  is used to represent the opposite meaning in this sentence.

We point to a sentence in Fig.2 as an example of a stakeholder extraction. This sentence has two relation words, “talked” and “alliance”. Given that we regard “talked” as  $w_R$ ,  $V(w_R)$  is {talked} and then  $N_e(\text{talked})$  is {WTO, China, Japan}. The structure type of a tree structure whose root is “talked” is  $N_sVN_p$ , which is derived to extract two relationships, {WTO, Japan} and {China, Japan}. The positive and negative scores of “talk” in Relationship-WordNet are added respectively to P and N values of each interest. If “talk” has 0.250 positive and 0.00 negative values, we can obtain interests as follows.

$$(\{\text{WTO}, \text{Japan}\}, 0.250, 0.00)$$

$$(\{\text{China}, \text{Japan}\}, 0.250, 0.00)$$

### 3.3.3 Descriptive Polarities of Stakeholders

Descriptive polarity denotes the opinion of a news agency on a stakeholder. The polarity is represented by two scores, each indicating a degree of positive or negative description of a stakeholder. Descriptive polarities enable us to deal quantitatively with the viewpoints of news articles to stakeholders.

We use relationship structure and a sentiment dictionary to analyze descriptive polarity. Relationship structure is used to identify stakeholders that a description expresses and the sentiment dictionary is used to analyze polarities.

Currently, we use SentiWordNet as the sentiment dictionary. Unlike RelationshipWordNet, SentiWordNet assigns three sentiment scores “positivity”, “negativity”, and “objectivity” to each WordNet synset. Hereinafter, we use

the expression *sentiment word* to refer to a term included in a synset whose “positive” or “negative” scores in SentiWordNet is more than 0.

The procedure of descriptive polarity analysis is executed for each sentiment word  $w_S$  in a sentence. Here, in relationship structure of a sentence, we define  $V(w_S)$  as a set of verbs for which the distance between  $w_S$  and the verb is the smallest on each path from  $w_S$  to a root in ascendants of  $w_S$ , and  $S(v)$  as a set of stakeholders for which the distance between a verb  $v$  and the stakeholder is the smallest on each path from  $v$  to a leaf in  $v$ ’s descendants. The procedure for each  $w_S$  in a sentence is described below.

**Step 1** If any stakeholder is on a path from  $w_S$  to a verb in  $V(w_S)$ ,  $w_S$  is considered as a modification to the nearest stakeholder to  $w_S$  on that path. Therefore, positive and negative scores of  $w_S$  are respectively added to the P and N values of the stakeholder’s descriptive polarity.

**Step 2** If no stakeholder is on each path from  $w_S$  to a verb in  $V(w_S)$ ,  $w_S$  is considered to modify all the stakeholders in  $S(v)$ ,  $v \in V(w_S)$ . Therefore, positive and negative scores of  $w_S$  are respectively added to the P and N values of the stakeholder’s descriptive polarity in  $S(v)$ .

In these two steps, if the sentence has negation words the scores of  $w_S$  are dealt with in the same way as that in the stakeholder extraction process described above.

We consider a sentence in Fig 2 as an example. This sentence has two sentiment words, i.e., “growing” and “good”. Given that we regard “growing” as  $w_S$ , the stakeholder “China” is on the path from  $w_S$  to a verb “talked” in  $V(w_S)$ . This means that the  $w_S$  modifies “China”, and positive and negative scores are respectively added to resultant scores of the descriptive polarity of “China”. Given that we regard “good” as  $w_S$ , no stakeholder is on the path from  $w_S$  to  $V(w_S)$ . This is because the sentiment word “good” is a description of all stakeholders in  $S(v)$ ,  $v \in V(w_S)$ ; the description means that both Japan and India are good because they had a good alliance. Therefore, positive and negative scores are respectively added to corresponding scores of each descriptive polarity of “Japan” and “India”.

### 3.3.4 Construction of Relations Graph

We obtain the interests described in an article as a whole by summing up all the scores of the same interest in each sentence. Similarly, we obtain the descriptive polarities by summing up all the scores of the same stakeholder in each sentence.

Stakeholders and their interests can be represented as a graph. The vertices correspond to stakeholders and the edges correspond to their interests. The label of an edge denotes the interest between the two vertices (stakeholders). The label of a vertex denotes the descriptive polarity of that stakeholder. We call such a graph a “relations graph”. Figure 5 is an example of a relations graph.

We group stakeholders by using the interest types shown in Table 4. The process of relations graph grouping

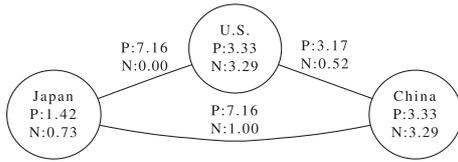


Fig. 5 Example of relations graph.

Table 4 Interest types.

Interest type	State of interest	Explanation
5	$P > 0, N = 0$	Perfect coincidence in interests
4	$P > N > 0$	Although the interests have conflicting and coinciding parts, the degree of coincidence is larger than that of conflicts.
3	$P = N \neq 0$	Although the interests have conflicting and coinciding parts, the degree of coincidence is equivalent to that of conflicts.
2	$N > P > 0$	Although the interests have conflicting and coinciding parts, the degree of conflicts is larger than that of coincidence.
1	$N > 0, P = 0$	Absolute conflict in interests

inputs a relations graph and returns the aggregated graph. We define  $E$  as a set of edges in relations graph and  $V$  as a set of vertices in the graph. The function  $type(e)$  in this procedure returns an interest type of the input edge  $e$ . The grouping process is executed for each edge in an input graph.

**Step 1** If a given edge does not satisfy all the next three conditions, two stakeholders connected by the edge can not merge. Therefore, the procedure for the given edge stops.

For a given edge  $e = (u, t)$ , we suppose that the edges connecting to  $u$  are  $E_u$  and the edges connecting to  $t$  are  $E_t$ . The three conditions are:

1.  $type(e) = 5$ ,
2. for each edge  $e' = (u, u') \in E_u$ , if there is a  $e = (t, u') \in E_t$ ,  $e'$  and  $e''$  satisfy the expression  $type(e') = type(e'')$ , and
3. suppose that the vertices connected by the edges in  $E_u$  are  $U$  and the vertices connected by the edges in  $E_t$  are  $T$ ,  $U$  and  $T$  satisfy the expression  $\{U - u\} = \{T - t\}$ .

**Step 2** Merge the two vertices  $u$  and  $t$  connected by  $e$  into a new vertex  $v$ , and add  $v$  to  $V$ .

**Step 3** Suppose that a vertex connected to both  $u$  and  $t$  is  $u'$ . For each  $u' \in V$ , remove all the edges connecting  $u'$  with  $u$  or  $t$  from  $E$ , and add a new edge connecting  $v$  with  $u'$  to  $E$ .

**Step 4** Remove the two vertices  $u$  and  $t$  from  $V$ .

An interest satisfying the three conditions in Step 1 means that two stakeholders share mutual interests in the event. If an interest type between stakeholders  $u$  and  $t$  is 5, there is no conflict in their interests, and if two interests between  $u$  and

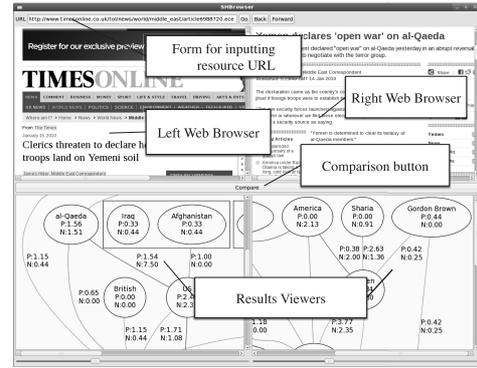


Fig. 6 Screenshot of news comparison system.

$u'$  and between  $t$  and  $u'$  are the same interest type, the two stakeholders  $u$  and  $t$  share interests with another stakeholder  $u'$ . Therefore, we can consider the two stakeholders  $u$  and  $t$  as one stakeholder (group) that shares interests with  $u'$ .

As a consequence, stakeholders and their interests described in an article can be found, and features of its description can be elucidated.

#### 4. Application to News Comparison

In this section, we describe an application system we developed that compares news articles for bias analysis. Figure 6 shows the screenshot of our prototype system. If a resource URL is inputted, the news article will be displayed in the left Web browser, and a list of the related articles obtained from Google News is displayed in the right Web browser. If we select one of the related articles, that article will be displayed in the space. Then, if we click the “Compare” button, stakeholder mining results of the two articles are presented in the results viewers to enables us to compare the news articles for bias analysis. Bias analysis is carried out by comparing the relations graphs from three aspects: 1) stakeholders described in each article, 2) descriptive polarities of stakeholders, and 3) stakeholder interests.

#### 5. Experiments

We carried out the following experiments:

1. an experiment of interests extraction,
2. an experiment of descriptive polarity analysis, and
3. a user evaluation on the news comparison.

We also need to evaluate RelationshipWordNet, but it is difficult to directly evaluate the degree of “positivity”, “negativity” and “objectivity” in a relationship that the three scores assigned to a synset represent. Due to the consideration that the evaluation of interests extraction covers that for RelationshipWordNet, we can assume that RelationshipWordNet is evaluated indirectly.

##### 5.1 Experiment for Interests Extraction

We evaluated whether the mining results of articles could

extract appropriate interests described in the corresponding article. As a dataset, we selected ten news topics. Each topic consisted of five news articles chosen from among related articles that were carried for less than a week on Google News.

Although synset scores in RelationshipWordNet are needed in interests extraction, it is difficult to identify a synset by the context in which a word is used. For this reason, we adopted a different approach in this experiment. That is, we defined a set of synsets included in a term  $w$  as  $S = \{s_1, s_2, \dots, s_n\}$  and  $S$  was grouped into three sets:  $S_P$ ,  $S_N$ , and  $S_O$ . The  $S_P$  scores satisfied  $P > N$ , those of  $S_N$  satisfied  $N > P$ , and those of  $S_O$  satisfied  $P = N = 0$ . The three scores of a term  $w$  are given in Formula 1:

$$Score(w) = m \cdot \Delta \quad (1)$$

where  $m$  and  $\Delta$  are defined as below:

$$m = \max\left(\frac{|S_P|}{n}, \frac{|S_N|}{n}, \frac{|S_O|}{n}\right)$$

$$\Delta = \begin{cases} ave(S_P) \cdot (1, 0, 0)^T & (|S_P| > \max(|S_N|, |S_O|)) \\ ave(S_N) \cdot (0, 1, 0)^T & (|S_N| > \max(|S_P|, |S_O|)) \\ (0, 0, 1) & (Otherwise) \end{cases}$$

where  $ave(S_X)$  is a  $1 \times 3$  matrix whose three elements are P, N, and O in that order, each equal to the average of the corresponding scores in all synsets included in  $S_X$ .

We evaluated the extraction results with recall and precision ratios. Recall ratio is the percentage of well extracted interests within all interests described in an article. Precision is the percentage of well extracted interests within all extracted interests. Here, a well extracted interest is defined as an interest whose state, whether one of conflict or coincidence, is equivalent to the state expressed in an article. We averaged the results of five articles for each topic, and calculated the average of 10 topics. The result showed that recall  $r_l$  was 69.12% and precision  $p_l$  was 65.88%.

## 5.2 Experiment of Descriptive Polarity

We evaluated the analysis method of descriptive polarity with the same dataset used in the experiment of interest extraction. In analyzing descriptive polarity, we used two scores indicating “positivity” and “negativity” defined in SentiWordNet. Due to the difficulty of using the scores according to the context (concept) in which a sentiment word is used, here the two scores of the word are defined as the averages of the corresponding scores in all synsets that include the word. We also evaluated the precision of the analysis results, precision being the percentage of well assigned descriptive polarities within those assigned to all extracted stakeholders. Well assigned descriptive polarity is defined as polarity whose state, whether more positive or more negative, is equivalent to the tendency of an article’s point of view. We averaged the results of five articles for each topic, and calculated the average of 10 topics. The results showed that precision  $p_{DP}$  was 67.26%.

**Table 5** Dataset for user evaluation.

	Topic	Article I	Article II
Same country pair	Yemen Declares War on al-Qaeda	UK	UK
	Human Rights in North Korea	UK	UK
	Google-China Feud	US	US
	UN Aid for Haiti Earthquake	US	US
	Japan Prosecutors Target DPJ Chief	UK	UK
	Different country pair	Developing countries at Climate Change Conference	UK
Sea Shepherd and Japanese Whalers		New Zealand	US
Obama’s Asia Trip		Japan	Russia
Pakistani Taliban Leader Injured in Attack		UK	US
Tension Politics between Turkey and Israel		Turkey	Israel

## 5.3 User Evaluation for News Comparison

We also conducted a user study to validate the bias analysis using stakeholder mining results. The subjects evaluated the method by comparing two articles using the mining results of each article. As a dataset, we selected a pair of articles for each of the ten topics in the dataset used in the experiment of interest extraction. Five of the article pairs were reported by news agencies located in the same countries and the other five pairs were reported by news agencies located in different countries (cf. Table 5). As the subjects, four graduate students in our laboratory participated in the evaluation. A news article pair and the corresponding mining results (i.e. a relations graph) were displayed to the subjects for each topic. They were asked to compare a news article pair while referring to the corresponding mining results and then fill out a questionnaire for each of the ten topics. The questions they were asked are:

- Q1** Were the mining results representative of the bias of the two articles?
- Q2** Did the mining results help you to understand the bias of the two articles?
- Q3-1** Was comparison of the stakeholders helpful to understand the bias?
- Q3-2** Was comparison of the interest states helpful to understand the bias?
- Q3-3** Was comparison of the descriptive polarities helpful to understand the bias?

The subjects gave point-score answers ranging from 1 to 5, with 5 being the best and 1 being the worst.

Figure 7 and Fig. 8 show the results obtained for Question 1 and Question 2 in the form of score percentages corresponding to the same country pairs, different country pairs, and the average for both. Each figure from Fig. 9 to Fig. 11 represents the result obtained from Question 3-1, 3-2 or 3-3

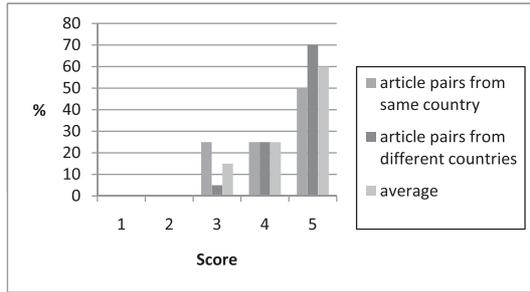


Fig. 7 Question 1 results.

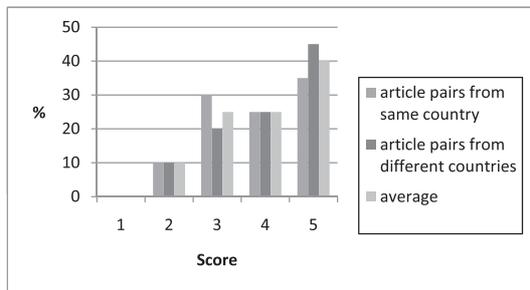


Fig. 8 Question 2 results.

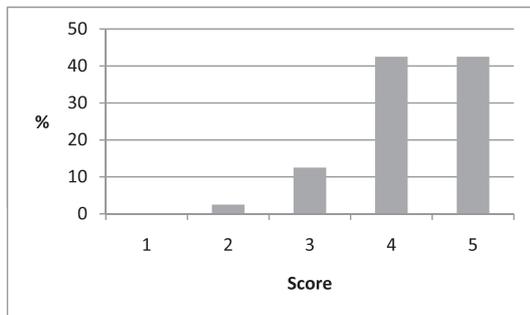


Fig. 9 Question 3-1 results. (helpfulness of comparison using stakeholders)

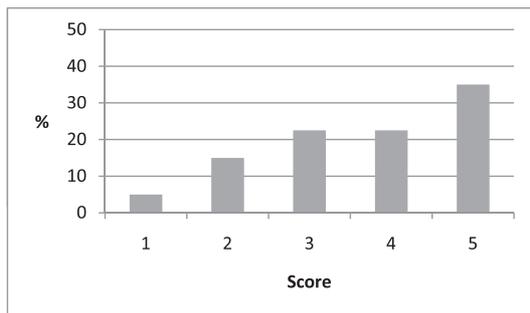


Fig. 10 Question 3-2 results. (helpfulness of comparison using interest states)

in the form of score percentages. Table 6 shows the average scores of each question and the percentages of pairs whose score was 4 or 5.

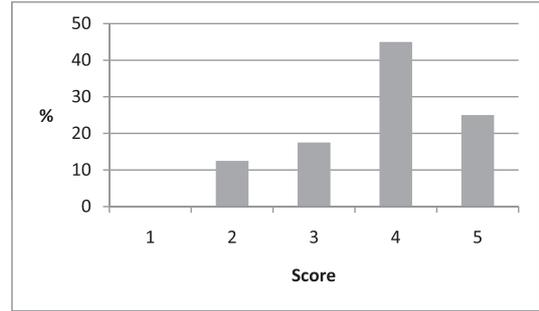


Fig. 11 Question 3-3 results. (helpfulness of comparison using descriptive polarities)

Table 6 User study results.

		Score Average	Score of 4 or 5
Q1	same country pair	4.25	75.0%
	different country pair	4.65	95.0%
	average	4.45	85.0%
Q2	same country pair	3.85	60.0%
	different country pair	4.05	70.0%
	average	3.95	65.0%
Q3-1	-	4.40	85.0%
Q3-2	-	3.30	57.5%
Q3-3	-	3.90	70.0%

### 5.4 Discussion

The recall and precision of interests extraction were 69.12% and 65.88%. The precision of descriptive polarity analysis was 67.3%. From these results, it can be said that our stakeholder mining mechanism can be used to analyze news articles. As an example of failures in interest extraction, experts who did not have a stake were extracted mistakenly because articles included remarks they had made. Mistakes were also incurred as a result of failure to use appropriate synsets for the meanings of words according to context. In addition, in the approach we have used to date, we did not identify identical entities that were referred to using different words. For instance, words such as “U.S.” and “USA” can be used to refer to “America”. Identifying such entities would enable us to achieve improved recall and precision in stakeholder mining. Therefore, further improvements need to be made in the method.

The user study we conducted showed the effectiveness of using mining results to analyze bias in news articles.

As shown in Table 6, the average percentages of the evaluations in which our stakeholder mining mechanism was found to be useful for bias analysis were 85.0% for Question 1 and 65.0% for Question 2. Obvious differences were found in comparing results obtained for article pairs prepared by news agencies in the same country and in different countries, i.e., bias appeared more clearly in the latter case. For Question 1 and 2, 95.0% and 70.0% of the scores were either 4 or 5, respectively. In addition, it can be said that bias is revealed even for article pairs prepared by news agencies in the same country because 75.0% of the scores

for Question 1 were 4 or more.

Questions from 3-1 to 3-3 were asked to reveal effectiveness of the three bias analysis aspects: stakeholders, interest states and descriptive polarities. The average scores of the three questions were 4.40, 3.30 and 3.90 respectively in that order. These results reveals that stakeholders are the most helpful to bias analysis among the three aspects. Descriptive polarities also received a high score. As for interest states, although the average score was the lowest among them, we can conclude that interest states are effective because the scores were distributed and the percentage of either 4 or 5 was 57.5%.

## 6. Conclusion

In this paper, we proposed a stakeholder mining mechanism and described how it can be applied to bias analysis.

The stakeholder mining approach analyzes a news article to extract stakeholders and their interests appearing in the article. To achieve stakeholder mining, we developed the lexical resource RelationshipWordNet and proposed a notion of relationship structure. We also developed a system for comparing mining results and supporting bias analysis by providing objective criteria.

The experimental results obtained indicate that the stakeholder mining mechanism is helpful for discovering news articles' bias.

In future work we will attempt to further improve the stakeholder mining mechanism. We need to identify identical entities that were referred to using different words. It will also be necessary to use lexical resources appropriately to the meanings of words according to context to achieve further improvement. Improvement of the user interface of our prototype system will be also needed.

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