

Opinion Bias Detection Based on Social Opinions for Twitter

A-Rong Kwon* and Kyung-Soon Lee*

Abstract—In this paper, we propose a bias detection method that is based on personal and social opinions that express contrasting views on competing topics on Twitter. We used unsupervised polarity classification is conducted for learning social opinions on targets. The tf-idf algorithm is applied to extract targets to reflect sentiments and features of tweets. Our method addresses there being a lack of a sentiment lexicon when learning social opinions. To evaluate the effectiveness of our method, experiments were conducted on four issues using Twitter test collection. The proposed method achieved significant improvements over the baselines.

Keywords—Social opinion, Personal opinion, Bias detection, Sentiment, Target

1. INTRODUCTION

In recent years, social media has become an attractive source for up-to-date information and a great medium for exploring the types of developments that most matter to a broad audience [1]. With the advancement of information technology, social media has become an increasingly important communication channel for consumers and firms [2]. In the social network, the opinion held by one individual is not static, and can be influenced by others [3]. Twitter is an efficient conduit of information for millions of users around the world. Its ability to quickly spread information to a large number of people makes it an efficient way to shape information and, hence, to shape public opinion [4]. Opinionated social media, such as product reviews, are now widely used by customers for decision making process [5]. Consumer feedback on a company's product is essential to recognize the consumer tendency and to implement appropriate marketing measures [6]. Opinions play a primary role in decision-making processes. Whenever people need to make a choice, they are naturally inclined to listen to the opinions of others. In particular, when the decision involves consuming valuable resources, such as time and/or money, people strongly rely on their peers' past experiences [7].

An important part of our information-gathering behavior has always been to find out what

※ This work was supported by the Basic Science Research Program through the National Research Foundation of Korea (NRF), which is funded by the Ministry of Education, Science, and Technology (MEST) (2012R1A1A2044811).

This research was financially supported by the Ministry of Education, Science, and Technology (MEST) and the Korea Industrial Technology Foundation (KOTEF) through the Human Resource Training Project for Regional Innovation. It was also supported by the second stage of Brain Korea 21.

Manuscript received November 13, 2012; accepted May 12, 2013.

Corresponding Author: Kyung-Soon Lee (selfsolee@chonbuk.ac.kr)

* Dept. of Computer Science & Engineering, CAIT, Chonbuk National University, Jeonju, 561-756, Korea (lifecorrect@naver.com, selfsolee@chonbuk.ac.kr)

other people think. With the growing availability and popularity of opinion-rich resources, such as social network services and personal blogs, challenges have arisen since people can and do actively use information technologies to seek out and understand the opinions of others.

There has been recent work done on opinion mining for event detection and debate-side classification. In this paper, we propose a bias detection method based on personal and social opinions that have been learned from tweets.

Twitter users state opinions on certain issues that can be expressed as sentiments about various targets. The following statement is an example of an expressed opinion on an issue. For example, *X is better than Y*. The *X* and *Y* are competing trends in the market and each is an example of a competing topic. The word *better* is a positive sentiment word that is being used to express an opinion about *X*. As in the above-example, users can express their opinion regarding a topic by employing a sentiment word. *Such personal opinions are not necessarily reflected by social users.*

Even Twitter users express their opinion via a target. The following Tweet is an example of expressing an opinion on competing trends in the market through a target. For example, *X is my favorite one. After trying them you will notice the difference in photo quality and price between X and Y*. Here, *X* and *Y* are the topics, while “picture quality” and “price” are the targets of the associated topics, even though a sentiment word is not used and both targets are supporting *X*. The above example could be interpreted as a positive Tweet about *X*. In addition, targets supporting certain topics in the above example reflect people's preferences. This aspect can be an important feature in detecting bias in a user's opinion.

In this paper, we propose a novel bias detection method based on social preferences of targets learned automatically from Twitter data for the competing topics. Specifically, we are proposing a bias detection method that uses *personal opinions regarding a topic and social opinions pertaining to the target*. The contribution of this research is as listed below.

- Unsupervised polarity classification of tweets to automatically learn social opinions of targets.
- Target extraction based on the Term Frequency-Inverse Document Frequency (tf·idf) algorithm by considering the targets, sentiment words, and Tweet features.
- *A target without a sentiment word can be addressed* with our model. This is important when a sentiment lexicon or context analysis is lacking. By using this feature, we can build a probability table about social opinion.
- A bias detection method by considering social opinions (i.e., one's general preference about a target in social media data), as well as a Tweeter's personal opinion that is *not necessarily reflected by social users*, is developed.

The remainder of this paper is organized as follows: related work is described in Section 2. The unsupervised training process is introduced in Section 3. The bias detection method is presented in Section 4 and the experimental results are given in Section 5. Finally, conclusions and areas for future work are detailed in Section 6.

2. RELATED WORK

Our research is related to previous work on opinion mining, specifically constructing opinion corpus, extracting targets, summarizing opinions on targets, and learning social opinions.

Pak et al. [8] reported on a method that automatically collected a corpus for sentiment analysis and opinion mining purposes. The researchers performed a linguistic analysis of the collected

corpus and explained the phenomena that they discovered. Using the corpus, a sentiment classifier that was able to determine positive, negative, and neutral sentiments for a document was built. Popescu et al. [9] also studied the automatic detection of events involving known entities from Twitter and sought an understanding of both the events as well as the audience's reaction to them. Jindal et al. [10] proposed the mining of comparative sentences and relations using gradable comparatives.

Several studies have been conducted on sentiment analysis and target extraction using a HITS graph by Li [11]. Some research on target extraction has been carried out by Hu et al. [12] in order to extract the target by reviewing an issue using sentiment features. Qui et al. [13] employed syntactic relations for target extraction, while Jakob et al. [14] used Anaphora Resolution to improve opinion target identification in movie reviews.

Zhang et al. [15] proposed a target extraction method based on the HITS algorithm. Zhao et al. [16] proposed the extraction of topical key phrases as a way to summarize Twitter. The researchers proposed a context-sensitive topical PageRank method for keyword ranking and a probabilistic scoring function that considers both the relevance and interestingness of key phrases for ranking them. Target-dependent syntactic features are incorporated for sentiment classification, which generated using words syntactically connected with the given target in the tweet by Jiang et al. [17].

Somasundaran et al. [18] presented an unsupervised opinion analysis method for debate-side classification. The authors used syntactic properties and sentiment words for target extraction on a specific issue. The difference between the approach outlined in Ref. [19] and our proposed method is that we deal with a personal opinion, which is not necessarily reflected by social opinion, and that is mentioned without a sentiment word for the target since there are a lack of insufficient lexical resources or context analysis.

3. THE LEARNING PROCESS FOR BIAS DETECTION

In order to detect a bias, we need to identify targets and learn social opinions as a general preference of the target. We revised the tf-idf algorithm to extract targets. Pattern-based polarity classification is conducted for each tweet in training the Twitter for learning social opinions.

The collection of Tweets used for unsupervised learning is shown in Table 1. We collected tweets using the Korean Twitter Search API. Here, a tweet mentions only one of the two topics. The Tweet is classified as positive and/or negative for the topic. We excluded a Tweet that mentions the two topics, in order to get a high accuracy of training data.

For the *Galaxy Tab vs. iPad* pair in Table 1, *topic_i* refers to a Tweet that only mentioned the topic *Galaxy Tab*, while *topic_j* refers to a Tweet that only mentioned the topic *iPad*.

Using the above data, target extraction is conducted based on the tf-idf algorithm and the probabilities of for social opinions on each target are learned by using specific patterns.

Table 1. Collection of Korean Tweets for learning social opinions

	<i>Topic_i</i>	<i>Topic_j</i>	<i>Total</i>
<i>GalaxyTab vs. iPad</i>	10,814	26,760	37,574
<i>Nikon vs. Canon</i>	13,089	20,565	33,654
<i>Windows vs. Mac</i>	49,844	1,861	51,705

3.1 Unsupervised polarity classification

In order to extract social opinion, tweets are classified as positive or negative based on their specific patterns. There are two types of patterns – explicit and contextual. An *explicit pattern* reflects opinions about the topic explicitly, while a *contextual pattern* needs to reflect the context of the sentiment.

The *explicit pattern*, which a sentiment word comes next to the topic word is described as below. Here, a sentiment can be one of words in the sentiment lexicon.

<topic> <sentiment>

When a sentiment word follows a topic word within a distance of 10 words, Tweets are classified as positive or negative according to the polarity of the sentiment word.

For example, consider the Tweet, *The weight and portability of X are good*. In this sentence, the positive word *good* follows the topic *X*. Thus, this Tweet is classified as a positive tweet.

The *contextual pattern* is used to consider the context such as a comparative, negative, or interrogative word.

<topic> <comparative word> <sentiment>

<topic> <negative word> <sentiment>

<topic> <question word> <sentiment>

When a sentiment word is followed by a comparison word or a negative word within a distance of 1 word, the polarity of the sentiment word is applied to the opposition. When a sentiment word is followed by a question word within a distance of 1 word, the polarity of the sentiment word is not applied.

To evaluate our pattern-based polarity classification method, 400 Tweets were randomly selected and judged by two human assessors. The Tweets in the above patterns are classified as being in a positive, negative, or neutral class. The evaluation result shows 75% precision. Due to the simple pattern classification scheme, little noise is observed.

3.2 Target extraction

A target is frequently mentioned with a topic. The target of the topic isn't mentioned to a target for another topic that often. By applying these features, we can extract the targets.

In this paper, the proposed weight of the target is as follows:

$$weight(t) = \frac{tf_i(t)}{N_i} + \frac{N_j}{tf_j(t) + \alpha \cdot N_j} \quad (1)$$

Where i is the topic, j is another topic, and t is the target candidate. N_i corresponds to the Tweet number for *topic_i*, $tf_i(t)$ corresponds to the term frequency of target candidate t for *topic_i*. The parameter α is set to 0.001. This parameter can be controlled to extract a better target. $Weight(t)$ is the high score of target t when it is frequently mentioned with the topic and when it is not frequently mentioned with another topic.

The pattern for calculation of $tf_i(t)$ is described as follows:

<topic> <target> <verb>

In the above pattern, a target between a topic and a verb is extracted within 2 words distance in front of a verb. This distance can be controlled to clearly extract the target.

Because the number of word of Sentiment lexicon's[20] is too lack to express our thoughts

precisely, we use verbs instead of using sentiment words. The result of the morphological analysis is applied to the distance calculation. Pronouns, adverbs, and conjunctions are ignored. For example, *Galaxy Tab's resolution and speed are good*. The words *resolution* and *speed* are appear in front of the verb word *are*. Both *resolution* and *speed* are 2 words distance in front of a verb *are*.

The top 50 targets are extracted from among the target candidates by the authority scores, $A(t)$. The results of the target extraction are shown in Table 2.

In Table 2, *GalaxyTab vs. iPad* represents a collection of tweets for either *Galaxy Tab* or *iPad*. The targets such as *iPhone*, *application*, and *skill* are extracted and contained in the specifications of the product. But, the targets such as *use*, *launch*, and *price* are extracted since Twitter users frequently mention these even though they are not contained in the specifications about the product. The word *recommendation* is noise. The accuracy of this target extraction was above 90%.

Table 2. Targets that were extracted using the tf-idf weighting

Rank	<i>GalaxyTab vs. iPad</i>	<i>Nikon vs. Canon</i>	<i>Windows vs. Mac</i>	<i>Samsung vs. Apple</i>
1	iPhone	lens	install	product
2	use	camera	Windows7	iPhone
3	application	bag	use	businesses
4	launch	DSLR	computer	price
5	skill	use	mobile	sale
6	price	price	format	use
7	Samsung	NikonD	android	Korea
8	phone	secondhand	support	service
9	charge	<u>recommendation</u>	file	money
10	screen	sony	program	company

3.3 Building Probabilities of social opinions

Social users' general preferences on a target for a topic are calculated by conditional probabilities in the automatically classified tweets.

Twitter users express emotion about the competing topics via the target as a means of stating their opinion. In addition, a simple mentioning of the target without the expression of any feelings may also be used to express an opinion.

In observing social behaviors, we defined that there are two types of patterns, a polarity pattern and a neutral pattern, for extracting social opinions. A *polarity pattern* includes a positive or negative sentiment about a target. In a *neutral pattern*, any sentiment word is not mentioned for a target or it is not detected due to a lack of lexicons. Here, the neutral pattern plays an important role, especially when there is an insufficient amount of sentiment lexicons and when it is difficult to analyze the contexts.

The *polarity pattern for a target* is described as follows:

$\langle \text{topic} \rangle \langle \text{sentiment} \rangle \langle \text{target} \rangle \langle \text{sentiment} \rangle$

Where, the frequency of target_k^\pm is counted for the topic_p^\pm depending on if the sentiment is positive or negative. This is used for calculating the polarity probability of a target for a topic,

$P(topic_p^\pm | target_k^\pm)$.

The **neutral pattern for a target** is described as follows:

$\langle topic \rangle \langle sentiment \rangle \langle target \rangle$

Where, the frequency of $target_k^0$ is counted for the $topic_p^\pm$ depending on if the sentiment is positive or negative. This is used for calculating the neutral probability of a target for a topic, $P(topic_p^\pm | target_k^0)$.

The equation for extracting social probabilities for targets with the polarity pattern is as follows:

$$P(topic_i | target_k^\pm) = P(topic_i^+ | target_k^\pm) + P(topic_i^- | target_k^\pm) \tag{2}$$

Where, the $topic_i^+$ denotes a positive tweet on $topic_i$. The $topic_i^-$ of represents a negative tweet on $topic_i$, which can be considered to be positive opinion for the $target_k^\pm$ on the competing topic $topic_i$. $P(topic_i^+ | target_k^\pm)$ is the probability that $target_k^\pm$ prefers $topic_i$. The probability $P(topic_i^- | target_k^\pm)$ allows for the competing topic to be considered. As such, positive or negative opinions on a topic will result in equivalent values.

The equation for extracting social probabilities for targets with the neutral pattern is as follows:

$$P(topic_i | target_k^0) = P(topic_i^+ | target_k^0) + P(topic_i^- | target_k^0) \tag{3}$$

Where, $P(topic_i^+ | target_k^0)$ is the probability that $target_k$ prefers $topic_i$. The $target_k^0$ means that any sentiment word is not detected for the target.

The social probabilities for each target on the topics are shown in Table 3.

As shown by the target $weight^+$ in Table 3, users' preferences were generally more biased towards *GalaxyTab* when compared to *iPad*.

Table 3. Social probabilities on the target of the topic

$target_k$	$P(GalaxyTab target_k)$	$P(iPad target_k)$
$weight^+$	0.2635	0.125
$weight^-$	0.1666	0.1666
$weight^0$	0.1999	0.0908
$application^+$	0.1178	0.2256
$application^-$	0.2042	0.1239
$application^0$	0.1339	0.1592
$phone^+$	0.111	0.0694
$phone^-$	0.1151	0.1211
$phone^0$	0.1001	0.1152

4. OPINION BIAS DETECTION

When our system is given a tweet to conduct opinion analysis on, it conducts bias detection or polarity detection depending on the topics being dealt with in the tweet.

When a Tweet deals with two competing topics, our system detects the bias. If $P(topic_i) > P(topic_j)$, the opinion of the tweet is biased toward $topic_i$; otherwise, it is biased toward $topic_j$. When the difference of the two probabilities is below the threshold, it is classified as neutral.

When a tweet only mentions one topic, $topic_i$, then our system conducts a polarity classification on the topic. If $P(topic_i) > P(topic_j)$, $topic_i$ will be classified as positive; otherwise $topic_i$ will be classified as negative.

The probability of there being bias about a topic for each tweet is calculated as follows: it is combined with the value of a Tweeter's personal probability on the topic in a tweet and with the social probabilities for targets on the competing topics.

$$P(topic_i) = (1 - \alpha) \cdot P(topic_i^{\pm}) + \alpha \cdot (P(topic_i | target_k^{\pm}) + P(topic_i | target_k^0)) \quad (4)$$

Where, the parameter α is set to 0.5 by training in our experiments. This parameter can be controlled to give higher weight to social or personal opinions. $P(topic_i | target_k^{\pm})$ and $P(topic_i | target_k^0)$ denote the probability of the social opinion on $target_k$, which is calculated from social media data that has been written by other users. $P(topic_i^{\pm})$ denotes the probability of a Tweeter's personal opinion on $topic_i$ in the Tweet. Note that $P(topic_i^{\pm})$ is not extracted from the training data, but this is directly calculated from the tweet to detect the bias.

Twitter users express their opinion directly on a topic by using sentiment words without mentioning targets. Thus, the probability of the $topic_i$ is calculated in a tweet. For example, suppose there is a tweet that states *X and Y are good, but X's lens is better*. Then, $P(X^{\pm}) = 2/3$ and $P(Y^{\pm}) = 1/3$, where two positive sentiment words such as *good* and *better* are expressed for X, and one positive sentiment word is expressed for Y.

Our method is reflects a Tweeter's personal opinion on the tweet and on the social opinions for targets with or without sentiments.

5. EXPERIMENTS

5.1 Korean Twitter test collection

To see the effectiveness of the proposed method, we evaluated it using a test collection of Korean Tweets. Four competing issues were chosen and tweets for the issues were collected by the Korean Twitter Search API (all issues and tweets were written in Korean).

The numbers of tweets related to each issue are shown in Table 4. The answer sets of the test collection were judged by two human assessors.

Words that were nouns, verbs, and sentiments were extracted by a Korean morphological analysis for tweets. The sentiment lexicon from Opinion Finder [20] contains 8,221 words with their polarity and strength. These English words are automatically translated to Korean using the Google translator and manually inspected the translations and removed the words that are not clearly either positive or negative in the Korean context. As a result, we selected 1,192 strong positive and strong negative words, for our Korean sentiment lexicon.

Table 4. A test collection of Korean tweets

Issues	$Topic_i$	$Topic_j$	$Topic_i$ & $Topic_j$	Total
<i>GalaxyTab vs. iPad</i>	100	100	300	500
<i>Nikon vs. Canon</i>	100	100	300	500
<i>Windows vs. Mac</i>	100	100	300	500
<i>Samsung vs. Apple</i>	100	100	300	500

5.2 Comparative methods

In order to prove the effectiveness of our proposed method, comparative experiments are conducted against OpTarget and OpTopic.

- **OpTarget**: This method considers the social opinion about the target as being that of either a positive or negative sentiment. Here, $P(topic_i)$ is calculated as $P(topic_i | target_k^{\pm})$ by Somasundaran et al.[18].
- **OpTopic**: This method considers personal opinion that is directly expressed about the topic. Here, $P(topic_i)$ is calculated as $P(topic_i^{\pm})$.
- **OpTopic & OpTarget[±]**: This is our proposed method based on a Tweeter's personal and social opinions on targets with or without sentiments given by (8).

5.3 Experimental Results

Performance is measured using the following metrics: Accuracy (C/N), Precision (C/S), Recall (C/R), and F_1 measure ($2 \cdot \text{Precision} \cdot \text{Recall} / (\text{Precision} + \text{Recall})$). Where N is the total number of Tweets in the collection of test Tweets, C is the number of relevant tweets detected by the system for a topic, S is the number of tweets detected to the topic by the system, and R is the number of relevant Tweets.

The experimental results for the four competing issues are shown in Tables 5. From the results, the OpTopic method exhibits better performance than OpTarget. This was expected because Tweets are short in length. In other words, OpTopic is useful for Twitter data because users are more straightforward.

But, OpTopic only considers the personal opinion without the social opinion. Because OpTopic & OpTarget[±] consider both the personal and social opinion, the proposed method OpTopic & OpTarget[±] showed significant improvements over the baselines. It achieved a 22.9% improvement in accuracy over the OpTarget, which uses social opinion as the target with sentiment words.

This result shows that a Twitter user's straightforward opinion on a topic and targets without sentiment words are useful.

Table 5. Results from the collection of test Tweets

	OpTarget	OpTopic	OpTopic & OpTarget [±]
Accuracy	0.492 (-)	0.550 (+11.7%)	0.617 (+25.4%)
Precision	0.36 (-)	0.406 (+12.7%)	0.432 (+20.0%)
Recall	0.418 (-)	0.471 (+12.6%)	0.525 (+25.5%)
F_1	0.388 (-)	0.436 (+12.3%)	0.474 (+22.1%)

6. CONCLUSION

In this paper, we presented the bias detection method that uses personal opinion and social opinion from data derived from Twitter.

Targets for the competing topics are extracted based on the revised tf-idf algorithm using targets, Tweets, and sentiment features for considering the strong opinion of a tweet. Targets that

are not the property of a topic could be extracted according to the behavior of users. The polarity of a Tweet is classified as positive, negative, or neutral based on the patterns for training Tweets to learn what the social probabilities for a target are.

Our bias detection method reflects the personal opinion of the Tweet and social opinions on targets with a polar or neutral opinion. The experimental results from a collection of Korean Tweets shows that a Tweeter's straightforward opinion is effective, which is seen from the results of *OpTopic*. It also showed that the social opinion about targets without the use of sentiment words is helpful.

The occurrence of an event may affect social opinion on a target. In future research, we plan to consider time-evolving features for a bias detection.

REFERENCES

- [1] A.-M. Popescu, and M. Pennacchiotti, "Detecting Controversial Events from Twitter," *The 19th ACM international conference on Information and knowledge management, 2010*, pp. 1873-1876.
- [2] Z. Zhang, Z. Li, and Y. Chen, "Deciphering Word-of-Mouth in Social Media: Text-Based Metrics of Consumer Reviews," *ACM Transactions on Management Information Systems*, vol. 3, no. 5, 2012.
- [3] D. Gao, "Opinion Influence and Diffusion in Social Network," *The 35th International ACM SIGIR conference on Research and development in information retrieval, 2012*, pp. 997-997.
- [4] C. Lumezanu, N. Feamster, and H. Klein, "#bias: Measuring the Tweeting Behavior of Propagandists," *The AAAI International Conference on Weblogs and Social Media, 2012*, pp. 210-217.
- [5] A. Mukherjee, B. Liu, and N. Glance, "Spotting Fake Reviewer Groups in Consumer Reviews," *The 21st International conference on World Wide Web, 2012*, pp. 191-200.
- [6] F. Bodendorf, and C. Kaiser, "Detecting Opinion Leaders and Trends in Online Social Networks," *The 2nd ACM workshop on Social Web Search and Mining, 2009*, pp. 65-68.
- [7] IEEE Intelligent Systems, <http://www.computer.org/portal/web/computingnow/iscfp2>.
- [8] A. Pak, and P. Paroubek, "Twitter as a Corpus for Sentiment Analysis and Opinion Mining," *The 7th conference on International Language Resources and Evaluation, 2010*, pp. 1320-1326.
- [9] A.-M. Popescu, M. Pennacchiotti, and D. Paranjpe, "Extracting events and event descriptions from Twitter," *The 20th International conference World Wide Web, 2011*, pp. 105-106.
- [10] N. Jindal, and B. Liu, "Mining Comparative Sentences and Relations," *The 21st national conference on Artificial intelligence, 2006*, pp. 1331-1336.
- [11] B. Li, L. Zhou, S. Feng, and K. Wong, "A Unified Graph Model for Sentence-based Opinion Retrieval," *The 48th Annual Meeting of the Association for Computational Linguistics, 2010*, pp. 1367-1375.
- [12] M. Hu, and B. Liu, "Mining Opinion Features in Customer Reviews," *The 19th National conference on Artificial Intelligence, 2004*, pp. 755-760.
- [13] G. Qui, B. Liu, J. Bu, and C. Chen, "Opinion Word Expansion and Target Extraction through Double propagation," *Computational Linguistics, 2011*, pp. 9-27.
- [14] N. Jakob, and I. Gurevych, "Using Anaphora Resolution to Improve Opinion Target Identification in Movie Reviews," *The 48th Annual Meeting of the Association for Computational Linguistics, 2010*, pp. 263-268.
- [15] L. Zhang, B. Liu, S.-H. Lim, and E. O'Brien-Strain, "Extracting and Ranking Product Features in Opinion Documents," *The 23rd International conference on Computational Linguistics, 2010*, pp. 1462-1470.

- [16] W. Zhao, J. Jiang, J. He, Y. Song, P. Achananuparp, E-P. Lim, and X. Li, "Topical Keyphrase Extraction from Twitter," *The 49th Annual Meeting of the Association for Computational Linguistics*, 2011, pp. 379-388.
- [17] L. Jiang, M. Yu, M. Zhou, X. Liu, and T. Zhao, "Target-dependent Twitter Sentiment Classification," *The 49th Annual Meeting of the Association for Computational Linguistics*, 2011, pp. 151-160.
- [18] S. Somasundaran, and J. Wiebe, "Recognizing Stances in Online Debates," *The 47th Annual Meeting of the Association for Computational Linguistics*, 2009, pp. 226-234.
- [19] J. Kleinberg, "Authoritative sources in a hyperlinked environment," *Journal of the ACM vol. 46*, 1999, pp. 604-632.
- [20] T. Wilson, J. Wiebe, and P. Hoffmann, "Recognizing contextual polarity in phrase-level sentiment analysis," *The conference on Human Language Technology and Empirical Methods in Natural Language Processing*, 2005, pp. 347-354.



A-Rong Kwon

He is currently working toward the MS degree in the Department of Computer Science and Engineering, Chonbuk National University. His research interests include information retrieval and natural language understanding.



Kyung-Soon Lee

She received the PhD degree in computer science from *Korea Advanced Institute of Science and Technology* (KAIST) in 2001. She has been an associate professor in the Department of Computer Science and Engineering, Chonbuk National University since 2004. Her research interests include information retrieval, natural language understanding and social information mining in computer science.