2007 IEEE/WIC/ACM International Conference on Web Intelligence

# Emotion Sensitive News Agent: An Approach Towards User Centric Emotion Sensing from the News

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## Abstract

*This paper describes a character-based system called "Emotion Sensitive News Agent" (ESNA). ESNA is been developed as a news aggregator to fetch news from different news sources chosen by a user, and to categorize the themes of the news into eight emotion types. A small user study indicates that the system is conceived as intelligent and interesting as an affective interface. ESNA exemplifies a recent research agenda that aims at recognizing affective information conveyed through texts. News is an interesting application domain where user may have marked attitudes to certain events or entities reported about. Different approaches have already been employed to "sense" emotion from text. The novelty of our approach is twofold: affective information conveyed through text is analyzed (1) by considering the cognitive and appraisal structure of emotions, and (2) by taking into account user preferences.*

## 1. Introduction

The retrieval and classification of news articles from the Web has been a topic attracting much research effort recently (e.g., [2,6,12,33]). Interestingly, no one has ever considered to sense affective information from news text with the aim to group those into a set of emotions or to associate the affective content of news with the personal opinion of its readers. Available systems (e.g., [1,2,7,8,16,20]) attempt to categorize news mostly into two classes (e.g., pleasant or unpleasant) without having a provision for user centric assessment. The largest drawback of these systems is that they are all based on static corpora of published news articles. Our previously developed system [26] is able to classify news topics according to emotional affinity, but it cannot perform user centric emotion assessment. Hence this paper extends our previous work and focuses on two new features. First, we have integrated the user centric approach to sense affective information from news texts by applying a cognitive theory of emotions, known as the OCC model [18]. Secondly, instead of applying a machine learning algorithm, we utilized a rule-based approach to assess and to assign a numerical valence to each line of text in order to perform categorization of its emotional affinity. Details of the algorithm of textual emotion sensing are provided in [26][27][29].

This paper is organized as follows. Section 2 reports on related work. Section 3 explains our approach and several components of the system. Section 4 reports our preliminary evaluation and finally Section 5 concludes the paper.

## 2. Background and Related Work

The assessment of emotion conveyed by written text is inevitably subjective and thus a hard research problem. Interest in emotion based automated text categorization has increased with the availability of large amount of text on the Internet. The applications range from document organization, automatic document indexing for information retrieval, text or email filtering, word sense disambiguation, categorization of web pages, news-article classification and, most recently, spam filters [24]. It is noticed that all the previous approaches for analyzing texts for affect sensing have employed techniques like keyword spotting [34], lexical affinity [32], statistical methods [19], pre-processed models, a dictionary of affective concepts and lexicon [3] and commonsense knowledgebase [10,11], fuzzy logic [30], a knowledge-base approach [4], machine learning [24,31,33], or domain specific classification [15]. In [26,27] we have discussed about the pros and cons of these techniques.

Another recent active research area is news categorization. There are mainly two tasks involved in such a classification. First, document indexing is needed in order to transform the natural language text into a numerical representation suitable for further processing. The second task is the actual classification. According to the literature, both statistical and knowledge-based techniques have been employed to perform the above tasks. A detailed review of those methods can be found in [26]. Several researches have been conducted with the goal to analyze sentiment expressed through text. For example, Sentiment! [25] is a commercial application that reads news articles and shows if they are positive, negative or neutral, claiming 85% accuracy against human analysts. Affective-News Theory [7] conceptualizes news as having (different) story structures, the inverted pyramid among others, and certain structures meet intuitions on 'storyhood' by evoking specific

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DOI 10.1109/WI.2007.124

emotional reactions (e.g. suspense or curiosity based on event and discourse structure) to different story structures in news. The approach described in [15] used a sentiment analysis dictionary with 3,513 entries. Instead of analyzing the favorability of the whole context, each statement on favorability is extracted, and then presented to the end users so that they can use the results according to their application requirements.

The primary goal for developing the ASNA system described in [26] was to demonstrate the feasibility of categorizing news stories according to their emotional content, using natural language processing techniques for quicker and intuitive understanding of the news through an intelligent user interface. We have utilized RSS [23] feeds as the sources for the news, which enables a more elegant way to determine the domain of a news item than a keyword based method. The approach of ASNA is quite straightforward. First, the user chooses some RSS feeds as the sources of news according to his/her domain of interest. After the news sources are selected, the 'News Fetcher' component collects the news headline and a brief story corresponding to the news headline by parsing the results returned by the RSS feeds. Then these plain texts are classified into eight emotion-types, namely, Happy, Sad, Hopeful, Fearful, Admirable, Shameful, Loveable, and Hatred, plus a Neutral category. Finally, the user can browse the news according to the emotional categories. However, ASNA has some limitations. Specifically, it does not provide for user-centric emotion assessment. Moreover the emotion rules are simplistic because they do not incorporate cognitive variables like 'self appraisal', 'other presumption', etc., which are essential for sophisticated emotion classification according to the OCC emotion model.

## 3. Our Approach

We believe that analysis of favorable or unfavorable emotion-affinity of news is a task requiring emotional intelligence and deep understanding of the textual context, involving commonsense and domain knowledge as well as linguistic knowledge. The interpretation of opinions is usually debatable affair even for humans. Our ESNA system, which is an extension of ASNA, followed a pipelined architecture with the following stages: Parse, Process, Solicit, Assess and Classify.

- The *Parse* stage implements a deep parsing technique to extract different linguistic components (e.g. actor, verb, object etc.) and their relationships within the input sentence(s).
- The *Process* stage assigns contextual valence [21] to the linguistic components (e.g. verb or object) by consulting a linguistic resource, our SenseNet [28]. This stage also creates a list of named entities detected from the news-text.
- The *Solicit* stage presents the list of named entities with preset emotional attitude to the user, and provides the user the option to reset his/her personal feeling towards those. The 'Solicit' phase was not integrated to the ASNA system.
- The *Assess* stage assigns values to the variables underlying the emotion rules by assessing the values obtained from Process stage and consulting user preferences for certain named entities.
- The Classify stage implements the rules to realize a linguistic version of the OCC emotion model for emotion analysis. The OCC model defines 22 emotion types specified by a corresponding set of lexical tokens and rules using cognitive variables. In ESNA we only considered a subset of eight emotional categories. Explanation of these rules can be found in [18,27,29]. According to such a rule, e.g. emotion-type 'Happy', the input "*Italy claim world cup triumph.*" would be classified as a 'happy' news by default processing, but it might be classified as a 'sad' news if someone has already set one's 'negative' or 'dislike' preference towards "Italy" in the genre of sports.

Although some of the modules have been discussed in detail previously in [26][27][28], we will briefly explain some of them for convenience. The architecture of ESNA is explained in Figure 1.

ESNA has ten operational steps. First the user chooses the sources of news according to his/her interest. In this case we used RSS [23] feeds as the sources for the news. The justification of using RSS feeds is given in Section 3.1. After the news sources are selected, News Fetcher collects the news as tuples by parsing the results returned by the RSS feeds. Each tuple contains the news-headline and a brief story corresponding to the headline. Then the text tuples are parsed by a Semantic Parser [13]. We have implemented a semantic parsing technique that performs dependency analysis on the words and outputs triplet(s) of subject, verb, and object according to each semantic verb-frame of the input sentence(s). The output of semantic parser is assessed by a linguistic tool, SenseNet [28], that we have developed employing WordNet [5] and ConceptNet [10]. Section 3.2 gives a summary about SenseNet. SenseNet offers the user a list of named entities that are obtained from the news item and also assigns a prior emotion towards each named entity. A user can change the prior emotion and may setup his/her feeling towards that entity. These two steps (i.e., step 6 and 7) are discussed in Section 3.3. SenseNet outputs a numerical value for each lexical-unit (e.g. sentence) and also assign values to the cognitive variables that deal with the rules for the emotions. Emotion Sensing Engine has implemented rules for the eight OCC-emotion types and these rules are evaluated to classify the news according to the eight emotion types. Section 3.4 will discuss the algorithm of affect sensing using these rules. This module is also an improvement over the ASNA system. Finally a user can browse the news according to the emotion groups and a character agent reads out the news. The news browser is discussed in Section 3.5.

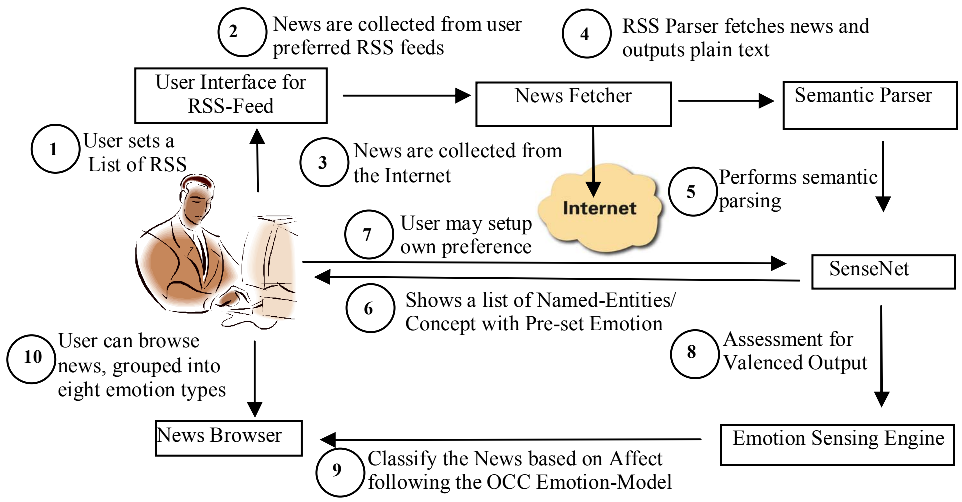


**Figure 1. The architecture of ESNA system.**

### 3.1. RSS Feeds

Most of the systems for news categorization primarily target clustering news according to specific domains (e.g. sports, war, business, technology etc.), but this limitation can be overcome by RSS [23] technology. The RSS 1.0, 2.0 and ATOM standards (for details, see [23]) include categorical information for each news item, which supports an elegant way to determine the domain of a news item. Still, the problem of intelligent filtering of information exists. In general, one can subscribe to a web-site's (e.g. MyYahoo [22]) RSS feed using a desktop news aggregator to receive the news of one's domain of interest. If, for example, 10 RSS news feeds are subscribed by a user, and each news feed delivers 10 news items per day on average, then the user will have to filter through 100 news items in total per day, hence grouping news by studying the relationship between natural language and affective information by a theory of cognitive appraisal for emotion is worthwhile in this case.

### 3.2. SenseNet

SenseNet [28] calculates the contextual valence of the words using rules and prior valence of words. It outputs a numerical value ranging from -15 to +15 flagged as the 'sentence valence' for each input sentence. As examples, SenseNet outputs -11.158 and +10.466 for the inputs, "The attack killed three innocent civilians." and "It is difficult to take bad photo with this camera.", respectively. These values indicate a numerical measure of negative and positive sentiments carried by the sentences. The accuracy of SenseNet to assess sentence-level negative/positive sentiment is about 90% according to our experimental study [28.]. SenseNet's output for each sentence is conceived as a "valenced reaction", which determines whether the emotion category is positive or negative. The algorithm described in Section 3.4 will show how the output of SenseNet output is utilized within the system.

### 3.3. User-Centric Emotion Recognition

The system maintains a list of scored named entities. The information of an entity is stored as the following format: Named-entity [Role, Concept, Genre, General-Sentiment]. The field 'Role' indicates any of the values from the list {Company, Concept, Country, Object, Other, Person, Product, Service, Team} and 'Concept' stores a ConceptNet [10] keyword to represent the concept of the entity. 'Genre' indicates any of the 15 genres (e.g. Politics, Sports, Technology etc.) taken from the news domain [22]. 'General-Sentiment' indicates any of the value from the list {Dislike; Hate; Interested; Like; Love; Negative; Not-Interested; Positive} to indicate pre-set emotion towards the named entity. We did not use any named entity recognizer to identify a named entity, and make the simplifying assumption that anything for which ConceptNet fails to assign valence is a named entity. To assign General-Sentiment we have developed a tool that can extract sentiment from Opinmind [17]. Briefly explain what Opinmind is. For example, ConceptNet fails to assign a valence to “George Bush” or “Asimov”. From Opinmind we get 37% positive, 63% negative and 97% positive, 3% negative votes for those two entities, which is stored as: George Bush {Person, President, Politics, -3}; Asimov {Product, Machine, Science, +4}. The algorithm to assign a negative or positive value to indicate the above enumerated values is:

If (positive vote > negative vote) then
Begin
If $(0\% \le$ positive vote $\le 30\%)$
Pre-set emotion = 1 //indicates ‘Positive’ feeling
Else if $(30\% <$ positive vote $\le 60\%)$
Pre-set emotion = 2 //indicates ‘Interested’
Else if $(60\% <$ positive vote $\le 80\%)$
Pre-set emotion = 3 //indicates ‘Like’
Else if $(80\% <$ positive vote $\le 100\%)$
Pre-set emotion = 4 //indicates ‘Love’
End

Similarly if the negative vote is greater than the positive vote, -1; -2; -3; or -4 is assigned to set negative pre-set emotion towards the input named-entity. The range of the values to decide pre-set emotion has been taken heuristically.

Initially a list of 2000 entries is manually created and scored using Opinmind. Usually the value of ‘General Sentiment’ is idiosyncratic and arguable, and hence these values are shown to the user with the corresponding pre-set emotions. Figure 2 shows the interface where a user can add his or her particular sentiment towards a specific entity. In the text-box the name of the entity is displayed or typed, the preferred role of the entity is selected from any of the values like, Company; Concept; Country; Object; Other; Person; Product; Service; or Team that the drop-down list shows. The preferred genre of the entity is selected from the 15 genres. Finally the sentiment towards that entity can be chosen from the eight pre-set emotions discussed before.


**Figure 2. Customizing the emotion towards a named entity**

## 3.4. Rules of Emotions

In [27,29] we have discussed about the cognitive variables which are the building blocks for the rules of the OCC emotion types. In Table 1 we show the definition of the eight emotions according to the OCC emotion model. In the definition, the single quoted text indicates the values of the cognitive variables as described by the OCC model.

**Table 1. The definitions of the Rules for the eight OCC Emotion types**

| Defining the OCC Emotion Types using the OCC Emotion Variables | |
|---|---|
| **Emotion** | **Definition** |
| Joy/Happy | ‘Pleased’ about a ‘Desirable’ event |
| Distress/Sad | ‘Displeased’ about an ‘Undesirable’ event |
| Hope | ‘Pleased’ about ‘Positive’ Prospect of a ‘Desirable’ ‘Unconfirmed’ event |
| Fear | ‘Displeased’ about ‘Negative’ Prospect of an ‘Undesirable’ ‘Unconfirmed’ event |
| Admiration | ‘Pleased’ for ‘Praiseworthy’ action/event of Other |
| Reproach | ‘Displeased’ for ‘Blameworthy’ action/event of Other |
| Love | ‘Liking’ an ‘Attractive’ entity (e.g. agent or object) |
| Hate | ‘Disliking’ an ‘Unattractive’ entity |

OCC emotion type definitions are implemented as rules using cognitive variables so that the system outputs either a ‘true’ or ‘false’ value for each emotion type. The algorithm of emotion assessment is given below.

**3.4.1. Knowledgebase.** SenseNet maintains a list of prior valenced verbs, adjectives, adverbs and concepts or nouns. The verbs are classified into two groups, affective verb ($AV$) and non-affective verb ($V$) group. The verbs having the tag *<affect>* in the knowledge-base are the members of $AV$. Both $AV$ and $V$ are further partitioned into positive ($AV_{pos}$, $V$pos) and negative ($AV_{neg}$, $V$neg) groups on the basis of their prior valences. Similarly, adjectives ($ADJ$), adverbs ($ADV$), concepts ($CON$) also have positive and negative groups indicated by $ADJ_{pos}$, $ADJ_{neg}$; $ADV_{pos}$, $ADV_{neg}$; and $CON_{pos}$, $CON_{neg}$; respectively.

**3.4.2. Algorithm.** The core algorithm underlying our system can be summarized as follows.
*Input:* $P=\{S_1, S_2, \dots S_n\}$ // a set of sentences. Each $P$ indicates a news story.
*Output:* $E$ // indicates the emotion detected from $P$

*Pseudo Code for Processing:*
Procedure getNewsEmotion ($P$)
Begin
emotionSet ={} //null set
for each $S_i$ in $P$ do //assume $1 \le i \le n$
tripletSet$_i$ = getSemanticParsing ($S_i$)
//output of Parser is a set of Triplets for each sentence.
valencedReaction =
getSentimentFromSenseNet(tripletSet$_i$)
// returns a value between $\pm$ 15

```
  reaction = getSelfReactionOfEvent (tripletSet_i)
  // returns "pleased" or "displeased"
  presumption = getSelfPresumptionOfEvent (tripletSet_i)
  // returns "desirable" or undesirable"
  prospect = getProspectOfEvent (tripletSet_i)
  // returns "positive" or "negative"
  appraisal = getSelfApprisalOfEvent(tripletSet_i)
  // returns "praiseworthy" or "blameworthy"
  eventStatus = getEventStatus (tripletSet_i)
  // returns "present" or "past" or "future"
  objectAppealing=getAppealingnessOfEntity(tripletSet_i)
  // returns "attractive" or "unattractive"
  objectFondness = getFondnessOfEntity(tripletSet_i)
  //returns "liking" or "disliking"
  presetEmotion =getPresentEmotionOfEntity(tripletSet_i)
  // returns a value between ± 4
  emotionOfTheSentence = getSentenceEmotion
(reaction, presumption, prospect, appraisal, eventStatus,
objectAppealing, objectFondness, presetEmotion)
  //return an emotion for the sentence.
  emotionSet = emotionSet ∪ {emotionOfTheSentence}
loop until all sentences are processed
newsEmotion = pickBestEmotion (emotionSet)
 //get the highest emotion from the set
 return newsEmotion
End Procedure
```

Due to space-limitation we cannot provide the details of the functions described in the algorithm. However, in order to explain the idea how user-centric emotion classification is achieved, we present an example rule that is used in the function *getSentenceEmotion()* to decide "happy" or "sad".

- IF valencedReaction > 5.0 and reaction = "pleased" and presumption ="desirable" and presetEmotion >0 THEN sentenceEmotion= sentenceEmotion ∪ {"happy"}
- ELSE IF valencedReaction < -5.0 and reaction = "displeased" and presumption ="undesirable" and presetEmotion < 0 THEN sentenceEmotion= sentenceEmotion ∪ {"sad"}
- ELSE IF valencedReaction > 5.0 and reaction = "pleased" and presumption ="desirable" and presetEmotion < 0 THEN sentenceEmotion= sentenceEmotion ∪ {"sad"}// a positive event may be classified as "sad" based on the user's preference.
- ELSE IF valencedReaction < -5.0 and reaction = "displeased" and presumption ="undesirable" and presetEmotion > 0 THEN sentenceEmotion= sentenceEmotion ∪ {"happy"} // a negative event may be classified as "happy" based on the user's preference.

In the example above, we assume that in order to decide a sentence having affective strength the SenseNet output (i.e., valencedReaction) for the sentence should be either grater than 5 or less than -5. The value for the cognitive variable *self_reaction (sr)* is assessed by the function getSelfReactionOfEvent as "Pleased" or "Displeased" if the valence of the concerned event is assessed either positive or negative by considering the scores of verbs (*V* or *AV*) and concepts (*CON*) stored in the knowledgebase.

### 3.5. News Browser

The news browser enlists the news according to emotion types, and the user can browse news accordingly. Figure 3 shows a snap-shot of the emotion sensitive news browser having 9 buttons (one for each emotion type). Clicking any of the buttons shows a list of news summary corresponding to a specific emotion represented by the caption of the button. For example, clicking on "Happy" button gives the list of the news that is assessed as the "Happy News" for the user. A character agent reads the news summary and a user can also view the full story of the news on this browser by clicking either on the headline or the image associated with the news.

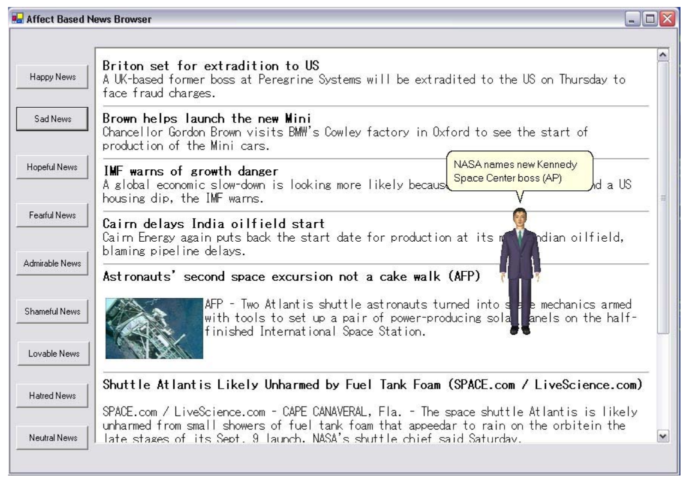


**Figure. 3. The news browser enlists the news according to the emotion category.**

## 4. Preliminary Evaluation

We conducted a small user study with 7 participants (4 females, 3 males; all are university students) to quantitatively measure the performance of the system. In order to do this we developed 4 versions of the system with exactly the same user-interfaces but varying functionalities. For a list of fetched news:

- System A categorizes the news randomly,
- System B categorizes without consulting user-preferential information,
- System C categorizes consulting user-preferential information, and
- System D enlists user-preference reversely (e.g. if someone has set "Love" as a preference towards "David Beckham", system considered it as "Hate").

The participants in the study (using within-subject design) were not informed about the different versions of the system, but they were told that all the four systems do the same things in different ways. Each user interacted with the four systems for 7 days and each time they could select the news sources as well as setup preferences towards certain entities according to their choices. For each day at a particular time (e.g. in morning) a person was given one of the four systems (e.g. System B); in the same day at another time (e.g. before noon) the same person was given another system (e.g. System D) and in the same manner the other systems were assigned to the same user. After every session everyone filled a survey form to assign numerical values (0 to 10) according to one's scoring towards the questions. There were four questions, asking about accuracy of classification, interestingness of the system, interactivity of the system in terms of how obliging the system was to synchronize with the personal preferences in the classification and finally the score for the intelligence of the system. The average score of the user-opinions towards the four characteristics (i.e., Accuracy, Interestingness, Interactivity and Intelligence) of the systems are summarized in Figure 4.

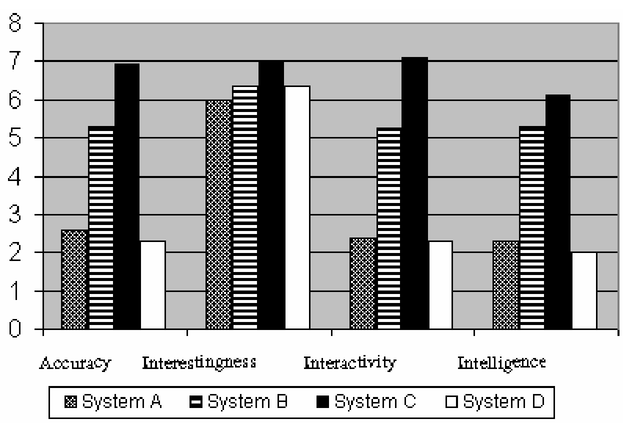


**Figure 4. The summary of user study**

System C (which is our target system) showed the higher score on all the dimensions. System D had the worst scores. At present system C takes several minutes (avg. 240 sec.) to compute an output, mainly because we have to start several underlying systems, such as ConceptNet and SenseNet to load the initial knowledgebase. Therefore, we deliberately inserted delays to the systems A, B and D in order to achieve comparable experimental conditions. Although we performed the comparative usability study of the system over a small-sized group, we believe that the overall assessment of the targeted system would not be much different from the obtained result because the data is normal for each system with respect to the daily scores for those four characteristics given by each individual. Moreover the f-ratio of two-way between groups ANOVA for the interestingness of the System A (i.e., with random classification) and System C (i.e., target system) is not significant; similarly the f-ratio for intelligence between System B and System C is also not significant. But the f-ratios for interactivity and intelligence are significant between System C and System D which again re-established the theory that the people most naturally interact with their computers in a social and affectively meaningful way [22].

## 5. Conclusion

We conclude that the system described in this paper is interesting, interactive, intelligent and accurate to some extent. In the area of personalized affective news, we have found two types of systems: one type classifies news according to taxonomical categories, and the other one considers news topics as story events to assess sentiment (positive or negative or neutral) and limited emotional reactions (suspense or curiosity). But none of those ever considered classifying news articles into a broad range of emotion categories. So the ESNA system described in this paper would definitely help news readers to grasp news articles in a more accurate and more personalized manner. In the future we want to conduct more experiments and usability study of the system. We also plan to compare our system to other similar approaches e.g. [4],[11]. We admit that additional work is necessary to optimize the system so that it can have fast response time. In future we plan to implement the system as a web based system so that anyone can interact with the system.

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