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AMAZING: A sentiment mining and retrieval system

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ABSTRACT

With the rapid growth of e-commerce, there are a great number of customer reviews on the e-commerce websites. Generally, potential customers usually wade through a lot of on-line reviews in order to make an informed decision. However, retrieving sentiment information relevant to customer's interest still remains challenging. Developing a sentiment mining and retrieval system is a good way to overcome the problem of overloaded information in customer reviews. In this paper, we propose a sentiment mining and retrieval system which mines useful knowledge from consumer product reviews by utilizing data mining and information retrieval technology. A novel ranking mechanism taking temporal opinion quality (TOQ) and relevance into account is developed to meet customers' information need. Besides the trend movement of customer reviews and the comparison between positive and negative evaluation are presented visually in the system. Experimental results on a real-world data set show the system is feasible and effective.

1. Introduction

In recent years, the rapid process of internet and web technologies has promoted the development of electronic commerce. Generally speaking, consumers rely on online product reviews, posted online by other consumers, for their purchase decisions (Chevalier & Mayzlin, 2006). So the customer reviews is a powerful source of opinion information. Unfortunately, due to the large number of reviews, it is difficult for a prospective buyer to get efficient opinion information to make an informed decision on whether to purchase the product or not. Moreover, the majority of reviews have a bimodal and non-normal distribution. For these reviews, the average score does not necessarily reveal the product's true quality and may provide misleading recommendations (Hu, Pavlou, & Zhang, 2006). In these situations, prospective buyer has to manually read a few reviews in order to form a decision regarding the product (Ghose & Ipeirotis, 2007). Similarly, manufacturers have to read the reviews to understand consumer behavior.

One way to overcome the above problem is to develop an opinion search system to provide efficient opinion information for potential customers' particular demand. The opinion search system provides an opinion search service. With the help of opinion search system, users can search for opinions on a particular object or feature of an object (Liu, 2006), e.g., customer opinions on a digital camera or the picture quality of a digital camera.

Fortunately, some researches on opinion mining and opinion search are conducted in recent years. (Hu & Liu, 2004a, 2004b; Liu, Hu, & Cheng, 2005; Popescu & Etzioni, 2005) proposed some methods on extracting product features and opinions. Hatzivassiloglou and Wiebe (2000); Kim and Hovy (2004) and Turney (2002) proposed some methods to identify opinion semantic orientation. Liu, Wu, and Yao (2006) studied the problem of opinion searching, whose aim is to search the opinions about specific feature of specific product and locate them in multi-product reviews. Furuse, Hiroshima, Yamada, and Kataoka (2007) implemented a search engine that can extract opinion sentences relevant to an open-domain query from Japanese blog pages.

Although several works have been done on opinion mining and opinion search, there are still some problems to be solved. For example, the search results should be ranked before returning to the user. In many cases, the search results are very long (Liu, 2006), it is hard for potential customers to read all of them in order to obtain an overview of the prevailing sentiments. Some forms of results visualization are desirable. Opinions have a temporal dimension (Liu, 2006). For example, the opinions of people on a particular object, e.g., a product or a topic, may change over time. Displaying the trend movement of sentiments along the time axis can be very useful in many applications.

This paper focuses on a novel ranking mechanism and search results visualization. Our contributions are as follows:

(1) We introduce a ranking mechanism, which is different from general web search engine since it utilizes the quality of each review rather than the link structures for generating review authorities. Most important we incorporate temporal dimension information into the ranking mechanism, and make use of temporal opinion quality (TOQ) and relevance to rank review sentences.

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(2) We monitor customer reviews' changing trends with time, and visualize the changing trends of positive and negative opinion respectively.
(3) We generate visual comparison between positive and negative evaluation of a particular feature which potential customers are interested in.

The remainder of the paper is organized as follows. Section 2 describes literature review, Section 3 introduces the basic terminology, Section 4 gives the architecture of the opinion search system, Section 5 expatiates the implementation methods, Section 6 gives illustrated example, and Section 7 reports the experimental process and the results of the study. Finally the conclusion is given in Section 8.

2. Literature review

Our work is closely related to Minqing Hu and Bing Liu's work in (Hu & Liu, 2004; Liu et al., 2005) on mining product features and determining the polarity of opinion sentences, their work is preformed in three steps: (1) mining the product features and opinions that have been commented on by customers. First, they used association rule mining to find all frequent item sets, after that they did feature pruning or compactness pruning, they extracted the nearby adjective words as opinion words at last; (2) identifying the opinion sentence in each review and deciding whether each opinion sentence is positive or negative, they used WordNet to predict the semantic orientations of opinion words; (3) summarizing the results; Our review sentences translation module is partly based on their work. In Turney (2002) proposed a corpus-based approach PMI-IR. PMI-IR uses pointwise mutual information (PMI) and information retrieval (IR) to measure the similarity of pairs of words or phrases. The semantic orientation of a given phrase is calculated by comparing its similarity to a positive reference word ("excellent") with its similarity to a negative reference word ("poor"). In Yu, Li, and Liu (2004) and Yu, Li, and Liu (2005) Yu et al. studied the temporal dimension of search in the context of research publication. They argued that page rank and HITS algorithms miss the temporal dimension. They added temporal dimension to the PageRank algorithms, and proposed TimePageRank. In Liu et al. (2006) Liu et al. studied the problem of opinion searching. They used PMI to retain the domain-related phrases. For determining on which product a given feature semantically depends, they used machine learning method to build a classifier to predict feature-product dependence. Their work included two steps: opinion indexing and opinion retrieving. Opinion indexing is to mark up all the informative opinions as opinion tuples and opinion retrieval is only to look up the opinion tuples. Our work differs from theirs in three main aspects: (1) our focus is not on opinion indexing but on ranking the search results, our ranking mechanism can return more appropriate results to meet the user's information need. (2) Our work monitors customer reviews' changing trends with time. (3) Our system generates visual comparison of positive and negative evaluation of a particular feature which potential customers are interested in. In Aciar, Zhang, Simoff, and Debenham (2007) created an informed recommender system on consumer product reviews, although they focused on ranking but they did not take the temporal dimension into the rank algorithm. Also they did not monitor customer reviews' changing trends with time. In Furuse et al. (2007) Osamu Furuse's system identified positive, negative and neutral opinions and extracted only explicitly stated writer's opinions at the sentence level. In Miao & Li (2008), they used opinion quality and temporal dimension information to rank reviews, however, they linearly combine the two factors. In this paper, we incorporate opinion quality and temporal information in a unified way, we also analyze the strength of sentiment polarity of opinion words.

3. Terminology

For clearness and disambiguation, here we introduce the important terms (Miao & Li, 2008).

A product P has a set of reviews $R = \{r_1, r_2, \ldots r_m\}$. Each review r_i is a sequence of sentences, $r_i = \{r_{i1}, r_{i2}, \ldots r_{in}, \}$. We represent each review of a product as a tuple including four elements [title, help, date, R-content], where title is the title of the review, help is the number of customers who find the review is helpful, date is the date when the review is commented, R-content is a set of sentences in customer reviews. We adopt the method in (Liu et al., 2006) to represent each sentence of a customer review as a tuple, which includes three elements [feature, sentiment, S-content]. Feature includes a property, a part, a feature of product, a related concept, a property or a part of related concepts. Sentiment is the opinion polarity of the feature in the same sentence, S-content is the content of the sentence. Fig. 1 shows the tuple's general structure. Metadata describes how and when and by whom a particular set of data was collected, and how the data is formatted. The metadata of a review contains title, help and date.

4. System architecture

Fig. 2 shows the architecture of the sentiment mining and retrieval system for customer reviews (Miao & Li, 2008).

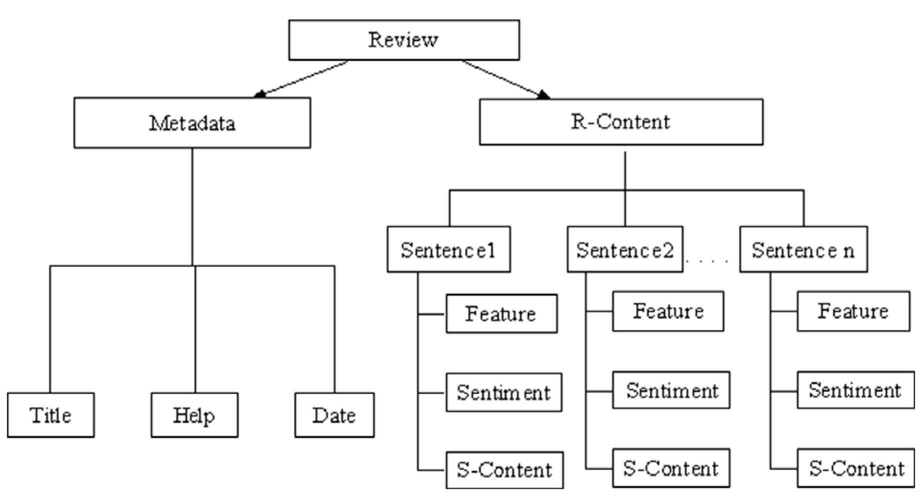


Fig. 1. The structure of the tuple used in the sentiment mining and retrieval system.

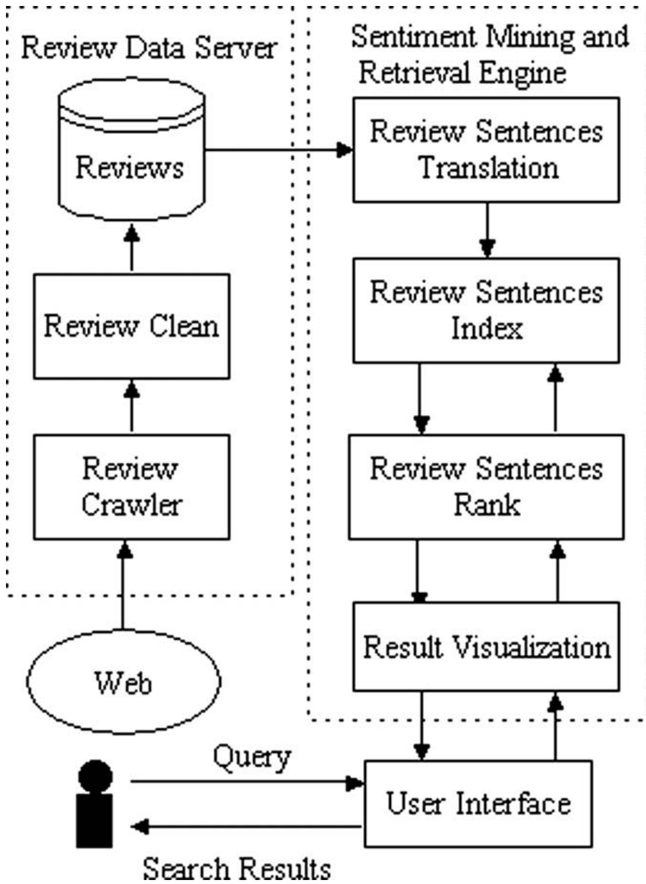


Fig. 2. The Architecture of the opinion search system.

The system consists of three parts: (1) review data server; (2) opinion search engine; (3) user interface.

4.1. Review data server

The review data server collects review pages by periodically crawling the e-commerce websites such as www.Amazon.com. These review documents are then cleaned to remove HTML tags, after that, reduplicate reviews are removed and the rest of the reviews are stored in the review data server.

4.2. Sentiment mining and retrieval engine

Our sentiment mining and retrieval engine receives review pages from the review data server, it consists of four main modules: review sentences translation, review sentences index, review sentences rank and results visualization. The review sentences translation module checks whether each sentence in the crawled review pages contains product feature and determine the sentiment of customer opinion on the feature. Review sentences are then translated to the tuple we defined in Section 3. The review sentences index module index the review sentences and build index files off-line. The review sentences rank module is the core of the ranking mechanism which ranks review sentences according to temporal opinion quality (TOQ) and relevance to the user's query phrases from the index of opinion sentences. This module is processed on-line.

The result visualization module monitor the trend movement of customer reviews and visualize the changing trends of positive and negative reviews, respectively, besides the comparison between positive and negative evaluation of a particular feature which the user is interested in.

4.3. User interface

Fig. 3 shows the user interface of the system. A user inputs a particular object or features of an object, e.g., "Sony W55 size" in the query box and then clicks the search button. The results relevant to the query are presented in a page. The result contains three parts: the top left corner of the page is the visualization of customer reviews' changing trends, the red curve represents the trend movement of positive reviews and the blue one represents the trend movement of negative reviews.[1] The top right corner of the page is the comparison between positive and negative evaluation of a particular feature which the user is interested in. The rest of the page presents customer review sentences which are relevant to the user's query.

5. Implementation methods

We implement our system as follows:

Step 1. Review sentences translation.

To retrieve opinion sentences that are obvious and a user is glad to read, we only extract explicit features at the sentence level and discard the implicational features. First, the NLProcessor linguistic parser (Bourigault, 1995) is used to parse each review to sentences, synchronously generate the POS (part-of-speech) tag for each word (Hu & Liu, 2004). Second, for the hypothesis that product features are usually nouns or noun phrases in review sentences (Hu & Liu, 2004), a file which only includes the identified nouns and noun phrases of the sentences is built. Third, the association miner CBA (Liu, Hsu, & Ma, 1998), which is based on the Apriori algorithm in (Agrawal & Srikant, 1994) is used to extract frequent features, such as size, picture quality, battery, price, et al. We build a feature set which contains all the features we have obtain.

After feature extraction, the sentences which do not contain the features in the feature set are discarded. For the sentences which contain features in the feature set, we extract opinion word about the feature in the sentence and then use the dictionary-based approach (Hu & Liu, 2004) to determine the polarity and strength of sentiment polarity of opinion words. We use the following formula (1) to compute:

$$\arg\max_{c} P(c|w) \cong \arg\max_{c} P(c)\frac{\sum_{i=1}^{n}\text{count}(\text{syn}_i, c)}{\text{count}(c)} \qquad (1)$$

where c is a sentiment category (positive or negative), w is the unseen word, and syn_i is the WordNet synonyms of w.

At last we map the reviews to the tuple mentioned in Section 3.

Step 2. Review sentences index.

In the review sentences index module, Lucene is used to build our index files, which is an open source project of the Apache software foundation. The metadata title, help and date are stored in the index files, and the *R*-content are indexed in the index files.

Step 3. Review sentences rank.

In the review sentences rank module, we computes two measures including temporal opinion quality (TOQ) and Lucene rank (LR). TOQ evaluates opinions' authority according to temporal information and the number of people who find the review is helpful. LR is a relevant rank based on the vector space model, which evaluates the

[1] For interpretation of color in Fig. 3, the reader is referred to the web version of this article.

Fig. 3. User interface of the system.

similarity between opinion sentence and query. The sentiment mining and retrieval system ranks the result sentences in response to a user request on the basis of these measurements. In this section, we describe the calculation of these measures.

5.1. Rating the temporal opinion quality (TOQ)

Reviewers with different experience and skill levels made different reviews. In general, if more people find the review is helpful, more important the review is. Therefore, rather than treating all opinions equally, we should give more helpful reviews higher weight than those of less help.

The opinion quality (OQ) is calculated as formula (2):

$$\mathrm{OQ}_i = \frac{a_i}{b_i} \tag{2}$$

where OQ_i is the opinion quality of sentence i, a_i is the number of people who find the review is helpful, b_i is the number of people who have read the review.

OQ is calculated from the values stored in the corresponding part of the index files.

In general, people want to read the latest reviews because the latest reviews contain more new information than the old ones. Moreover, the helpful votes are accumulated over a long period of time, in such situation OQ, which is defined above is not proper to evaluate the opinion quality.

So we propose temporal opinion quality (TOQ), which takes the temporal dimension into account. Inspired by the idea of the paper (Liu et al., 2005; Yu et al., 2005), we choose to decay the temporal weights of each review exponentially, where the temporal dimension mentioned above is considered.

The Temporal opinion quality (TOQ) is calculated as formula (3):

$$\mathrm{TOQ}_i = \mathrm{OQ}_i \exp\frac{(t_i - t)}{30 * \beta} \tag{3}$$

where TOQ_i is the temporal opinion quality of sentence i, t_i is the date when review i was commented, t is the date user do the search and β is a constant. Note that the value of $(t_i - t)$ is negative.

5.2. Lucene rank (LR)

Lucene rank is calculated as formula (4):

$$\mathrm{LR}_i = \sum_{t \in q} \mathrm{tf}(t) * \mathrm{idf}(t) * b(t.\mathrm{field}) * \mathrm{lN}(t.\mathrm{field}) \tag{4}$$

where tf(t) is the term frequency, idf(t) is the inversed document frequency, b(t.field) is the boost factor of each field and lN(t.field) is the standardized value of field.

5.3. Final rank (FR)

The final rank is calculated as formula (5):

$$\mathrm{FR}_i = \alpha \mathrm{LR} + (1 - \alpha)\mathrm{TOQ}_i \tag{5}$$

where α is a constant between zero and one.

Step 4. Search results visualization.

In the result visualization module, we give two statistics curves to show customer reviews' changing trends with time at a review level and a histogram to show comparison of positive and negative evaluation of a particular feature which the user is interested in.

In order to give product manufacturers the changing trends of customer reviews, we compute the number of positive and negative reviews in each month, a moving average of order 3 is used to smooth the curve. The red curve represents the positive trend movement and the blue one represents the negative trend movement.

For the purpose of giving potential customer the comparison between the positive and negative evaluation, a histogram is presented by computing the polarity strength of positive sentence and negative sentences separately. For opinion sentences, the strength of polarity is different, so we should not treat them equally. We compute the evaluation using formula (6):

$$E(c) = \sum\nolimits_{\substack{i=1\\c}}^{n} s_i \tag{6}$$

where c is a sentiment category (positive or negative), n is the total number of results belonging to c, s_i is the strength of opinion sentence i. The part above x-axis presents positive evaluation and the part below x-axis presents negative evaluation. From the histogram, potential customer can intuitively see the comparison between the positive and the negative evaluation.

6. An illustrated example

An example is presented to show how the system works, a digital camera is regarded as an object. The data is crawled from www.Amazon.com. First, we explain how the reviews are mapped to the tuple.

6.1. Translate the review to the tuple

Fig. 4 shows the review used in illustrated example. Through analyzing the reviews we obtain the product features and sentiment. Fig. 5 shows the analysis results. After analyzing we translate the review to the tuple. Fig. 6 shows the translation of the review to the predefined tuple.

6.2. Review sentences index

In this step the field title = "a very good choice for lots of people - easy to carry, easy to use", help = "257 of 261", date = "March 24 2007" are stored in the index file, and the S-content is indexed in the index file.

6.3. Review sentences rank

In this section, we provide the details of the ranking mechanism for a user query. For simpleness, we suppose that one product only has three reviews.

149 of 198 people found the following review helpful:
A very good Camera
April 5, 2007
It's a very good compact camera, and It is very easy to use and easy to carry. Reasonably priced. Image stabilization will correct your hand movements but will not stop action. Face Detection automatically finds and focuses on faces, and sets the proper exposure. The lenses is good. The 2 1/2 LCD screen is very high resolution. Good lenses.
Image and video quality are very good for such a small camera.

Fig. 4. A review from Amazon.com that we used in our example.

Helpful: 149 of 198
Title: A very good Camera
Date:April 5, 2007
[Camera; +0.9999; It's a very good compact camera,]
[Use; +0.8542; easy to use,]
[Carry; +0.8542; easy to carry,]
[Price; +0.7855; and reasonably priced]
[Lens; +0.9999; good lenses,]
[Image; +0.9999; Image and video quality are very good for such a small camera.]
[LCD; +0.8564; The 2 1/2 LCD screen is very high resolution.]

Fig. 5. The result of review sentences analysis.

6.3.1. Calculating OQ

OQ is computed using formula (2). Table 1 presents the metadata help in row 2. The OQ values for each consumer review in Table 1 are

$$\mathrm{OQ}_1 = \frac{257}{261} = 0.9847$$
$$\mathrm{OQ}_2 = \frac{13}{17} = 0.7647$$
$$\mathrm{OQ}_3 = \frac{12}{18} = 0.6667$$

From the opinion quality perspective, the most helpful review is Review1, Review1 has been read by most people and most of them believe it is helpful. So Review1 has better quality than Review2 and Review3.

6.3.2. Calculating TOQ

TOQ is calculated using formula (3), there we assign $\beta = 10$, $t = 11/1/2007$. Table 1 presents the metadata date in row 3. The TOQ values for each consumer review in Table 1 are

$$\mathrm{TOQ}_1 = \mathrm{OQ}_1 * \exp\left\{-\frac{[30*(11-3)-24]}{30*10}\right\} = 0.4793$$
$$\mathrm{TOQ}_2 = \mathrm{OQ}_2 * \exp\left\{-\frac{[30*(11-4)-5]}{30*10}\right\} = 0.3861$$
$$\mathrm{TOQ}_3 = \mathrm{OQ}_3 * \exp\left\{-\frac{[30*(11-4)-15]}{30*10}\right\} = 0.3480$$

6.3.3. Calculating LR

LR is calculated using formula (4), LR represents the similarity between opinion sentence and query.

$$\mathrm{LR}_1 = 0.87$$
$$\mathrm{LR}_2 = 0.91$$
$$\mathrm{LR}_3 = 0.93$$

6.3.4. Calculating FR

FR is computed using formula (5), there we assign $\alpha = 0.65$. Note that if α is 1, the FR is equal to LR. FR gives the final rank as follows:

$$\mathrm{FR}_1 = 0.65 * 0.87 + 0.35 * 0.4793 = 0.7333$$
$$\mathrm{FR}_2 = 0.65 * 0.91 + 0.35 * 0.3861 = 0.7266$$
$$\mathrm{FR}_3 = 0.65 * 0.93 + 0.35 * 0.3480 = 0.7263$$

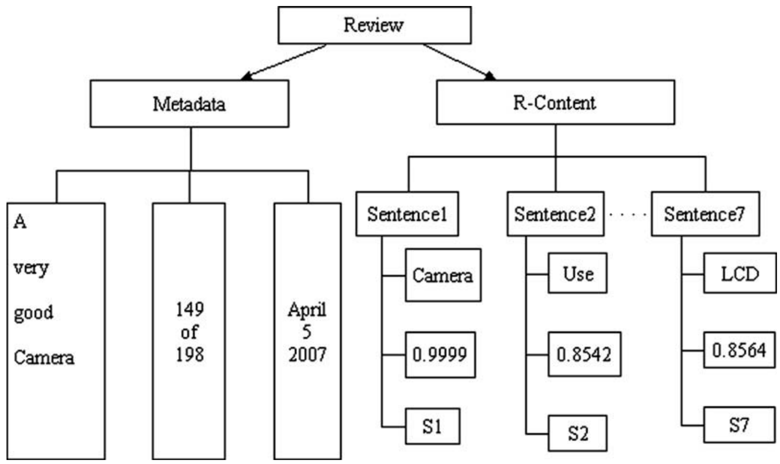


Fig. 6. Translated tuple from a customer review.

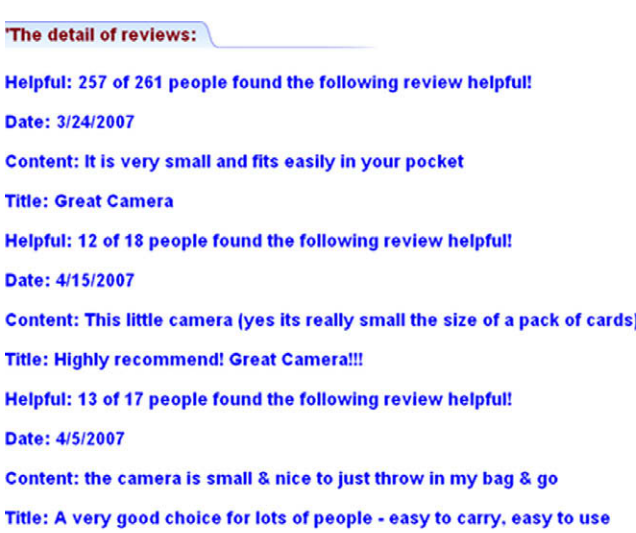
Table 1
Three example reviews on camera Sony W55

	Review1	Review2	Review3
Help	257/261	13/17	12/18
Date	3/24/07	4/5/07	4/15/07

Figs. 7 and 8 show that our ranking mechanism can give more efficient opinion information than lucene, for the most helpful review sentence gets the highest rank in our ranking mechanism, but it gets the lowest rank in Lucene rank.

Fig. 9 shows customer reviews' changing trends with time. From the curve, product manufacturers can easily know the customers' concern about their products.

Fig. 10 shows comparison between positive and negative evaluation of a particular feature which the user is interested in. If the positive evaluation is preponderant, the feature of the product is likely good; otherwise the feature of the product may be bad.


'The detail of reviews:

Helpful: 257 of 261 people found the following review helpful!

Date: 3/24/2007

Content: It is very small and fits easily in your pocket

Title: Great Camera

Helpful: 12 of 18 people found the following review helpful!

Date: 4/15/2007

Content: This little camera (yes its really small the size of a pack of cards)

Title: Highly recommend! Great Camera!!!

Helpful: 13 of 17 people found the following review helpful!

Date: 4/5/2007

Content: the camera is small & nice to just throw in my bag & go

Title: A very good choice for lots of people - easy to carry, easy to use

Fig. 7. Results based on FR.


'The detail of reviews:

Title: Great Camera

Helpful: 12 of 18 people found the following review helpful!

Date: 4/15/2007

Content: This little camera (yes its really small the size of a pack of cards)

Title: Highly recommend! Great Camera!!!

Helpful: 13 of 17 people found the following review helpful!

Date: 4/5/2007

Content: the camera is small & nice to just throw in my bag & go

Title: A very good choice for lots of people - easy to carry, easy to use

Helpful: 257 of 261 people found the following review helpful!

Date: 3/24/2007

Content: It is very small and fits easily in your pocket

Fig. 8. Results based on LR.

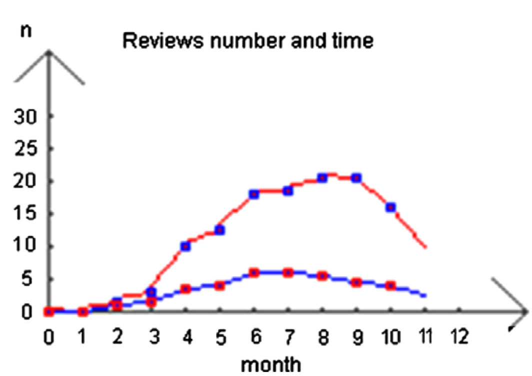


Fig. 9. The changing trend of reviews.

7. Experimental evaluation

The purpose of the experiment is to test the effects of the system in this research. We conducted our experiments in the senti-

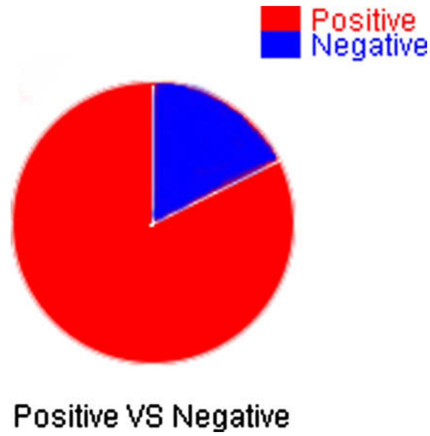


Fig. 10. The comparison of positive and negative evaluation of a particular feature.

Table 2
Parameter definitions of precision, recall

Value	Meaning
Ra	The relevant results which has been retrieved by the system
R	All relevant results about the query
A	All results the system retrieved

Table 3
Experimental results

α = 0.65	Recall (%)	Precision (%)	F (%)
User1	83.2	88.7	85.9
User2	89.3	88.2	88.7
User3	88.6	87.4	88.0
User4	91.5	85.7	88.5
User5	88.1	84.3	86.2
User6	86.4	89.8	88.1
User7	85.8	87.0	86.4
User8	87.6	88.2	87.1
Average	87.6	87.4	87.4

ment mining and retrieval system using the customer reviews of four kinds of electronic products including 20 digital cameras, 20 cell phones, 20 laptops and 20 MP3 players. The reviews were collected from Amazon.com. For each electronic product we crawled top 100 reviews. Eight participants issued their own queries and evaluated the search results, each participant was asked to issue at least 20 queries.

Precision and recall are used as measures to evaluate the effects of the system. F1 is also used to represent the effects of combining precision and recall.

$$\text{Precision } (p) = \frac{\text{Ra}}{A}$$

$$\text{Recall } (r) = \frac{\text{Ra}}{R}$$

$$F = \frac{2rp}{r+p}$$

where the value of Ra, R and A are defined in Table 2.

Table 3 shows the experimental results of our system.

8. Conclusion

Opinion retrieval is intellectually challenging but practically very useful. We have proposed a novel approach for mining and retrieving sentiment information from customer reviews. Temporal opinion quality and relevance are incorporated in a unified ranking way.

Our experimental results indicate that our opinion search system is promising in searching opinion in customer reviews.

In our future work, we plan to further improve and refine our techniques, i.e., extracting implicit opinion and opinions expressed with verbs. Finally we will also address comparison search.

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