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RESEARCH ARTICLE

Online Product Reviews Based on Sentiment Analysis

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ABSTRACT

With the speedy growth of social media on the web, there is a growing amount of information posted to social online services in an audio format, audiovisual format, and textual format in the form of reviews, and comments. People are sharing their views and opinions online. With the rising availability of review sites and blogs, consumers depend on online reviews to make their purchase decisions. A survey found that more than 90% of consumers read online reviews, to judge purchasing decision on consumer products. The sentiment analysis (SA) can be achieved by performing analysis at various levels of the granularity-document level, sentence level, phrase level, and feature level. In this paper, online reviews can be filtered using the SA and repeated incremental pruning to produce error reduction algorithm is presented.

Key words: Classification rules, machine learning, market intelligence, natural language processing, repeated incremental pruning to produce error reduction, sentiment analysis, etc.

INTRODUCTION

Customers' comments about the product are an invaluable asset in business today. Companies can evaluate their customers' satisfaction by analyzing comments from customers. Comment is an unstructured data and includes the noisy data. Opinion mining at sentence level is to identify opinion at the sentence and then classify into positive, negative, or neutral. Opinion mining at document level is to identify a whole review is either a positive, negative or neutral. Main tasks on opinion mining at feature level are to identify and to extract object features from users' comments and then determine opinion from the comment as positive, negative, or neutral. With the growth of the internet, more and more personal comments are coming for the products. The analysis and extraction of the sentiment information have been a burning topic in natural language processing (NLP) and related areas. Among these, the sentiment analysis (SA) for text mining has attracted increasing attention,[41] especially in the product reviews.[42,43] SA has many tasks, such as extraction of sentimental information, classification (polarity or extent), retrieval, and induction.[16,44] Early work in this area includes some machine learning methods to detect the products reviews polarity.[16,11] Reviews represent the so-called user-generated content, and this is of growing attention and a rich resource for marketing teams, sociologists and psychologists, and others who might be concerned with opinions, views, public mood, and general or personal attitudes.[14] The rise of blogs and social networks has fueled a bull market in personal opinion: Reviews, ratings, recommendations, and other forms of online expression.[5] The Financial Times recently introduced News sift, an experimental program that tracks sentiments about business topics in the news, coupled with a specialized search engine that allows users to organize their queries by topic, organization, place, person, and theme. Tweet feel, Twendz and Twitrratr, these sites allow users to take the pulse of Twitter users about particular topics.[5] The term opinion mining first appeared in 2003 in a paper,[28] though some papers had previously addressed the same task.[16,28,30-32] The 2003 paper described opinion mining as the analysis of reviews about entities, and it presented a model for document polarity classification as being either recommended or not

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recommended. This work opened new avenues for applied research in NLP and text mining. A recent and interesting development in this area is the development of a cognitive model based on a natural language concept using an artificial neural network organized in a brain-like universe to mine opinions from customer reviews.[34] The overall goal of this paper is to develop an approach to extracting SA for comments with the expectation of achieving meaningful sentiment words with high precision and close to the topic.

SA

SA (sometimes known as opinion mining or emotion artificial intelligence) refers to the use of NLP, text analysis, computational linguistics, and biometrics to systematically identify, extract, quantify, and study affective states, and subjective information. SA is extensively applied reviews and survey responses, online, and social media.[1] Opinion-summary is produced as a final result. Sentiment mainly refers to feelings, emotions, opinion, or attitude.[26] SA used to get the opinion or attitude of a speaker. SA is the measurement for keywords as positive, negative, or neutral. The advantage of this technology is to know public opinion about a particular product or object. SA helps the market people to know what customers like and dislike about their brands. SA is a hard subject and in some cases impossible for both people and technology to tackle. It helps companies understand what buying customers think of their products, services, buying experience, customer service, and even the competition. It can help organizations to identify issues for help.[6] SA is treated as a classification task as it classifies the orientation of text into either positive or negative. Document-level SA classifies the entire document into either positive or negative.[16] Sentence level classification classifies the sentence into the positive, negative, or neutral category. Machine learning is one of the widely used approaches toward sentiment classification in addition to lexicon based methods and linguistic methods.[15] It has been claimed that these techniques do not perform as well in sentiment classification as they do in topic categorization due to the nature of an opinion at the text which requires more understanding of the text while the occurrence of some keywords could be the key for accurate classification. Machine learning classifiers such as naive Bayes, maximum entropy, and support vector machine (SVM) are used in[16] for sentiment classification to achieve accuracies that range from 75% to 83%, in comparison to a 90% accuracy or higher in topic-based categorization. SA addresses polarity classification, the task aimed at classifying texts as positive, negative, or neutral, at different levels: Document,[7] sentence,[8,9] and feature/aspect.[10] The state-of-the-art approaches for polarity classification can be divided into: Unsupervised, semi-supervised, and supervised. Most unsupervised learning approaches are usually composed of two phases: The first is the creation of a sentiment lexicon in an unsupervised manner and the second is the evaluation of the degree of positivity/negativity of a text unit through some function based on positive and negative indicators.[11] The polarity of a given the word or phrase is determined by considering the difference between the pointwise mutual information of the phrase with the words “poor” and “excellent.” Regarding the semi-supervised learning framework, most of the studies[12,13] address the polarity classification by expanding an initial set of sentiment words through synonyms and antonyms retrieved by thesauruses.[10] The common characteristic of these approaches concerns with the identification of the model which classifies the polarity of text sources with the highest accuracy as possible. In most of the SA works based on supervised learning. This paper deals with the supervised learning techniques to evaluate the sentiment documents.

RELATED WORK

Qiang Ye *et al*.[11] used a supervised method in traveler review sites and found the sentiment based on user reviews and also proved that the SVM outperformed naïve Bayes approach. Deng *et al*.[12] introduced a new term weight method based on two factors; first one being the importance of the document and the second one, the importance of the term for expressing the sentiment. Advantage of this method is that it can make full use of the available labeling information to assign appropriate weights to terms. In[21] polarity prediction model for sentence-level sentiment classification was introduced. Entity and aspect level also known as feature level sentimental analysis gives the summary about which feature of a product does user like or dislike.[22] Mishne and Rijke proposed[23] a system called mood view for tracking and analyzing the mood of bloggers worldwide. Mood view can analyze the temporal change of sentiment. Fukuhara *et al*.[24] proposed a method for analyzing temporal trends of sentiments and topics from documents with timestamps. Das *et al*.[25] proposed a method for finding the contribution of sentiments in determining the event-event relations from text. Usually, event sentiment over time is calculated based on the web content such as tweets, blogs, and normal news article sites. These methods can easily summarize the events based on the time and overall sentiment. Pang *et al*. have considered sentiment classification based on categorization aspect with positive and negative sentiments.[16] They have undertaken the experiment with three different machine learning algorithms, i.e., naive Bayes classification, SVM, and Maximum Entropy classification and are being applied over the n-gram technique.

CLASSIFICATION RULES [FIGURE 1]

Classification is one of the most significant areas in data mining. It is also known as pattern recognition, discrimination, or prediction. A classification rule is a procedure in which the elements of the population set are each assigned to one of the classes. A perfect test is such that every element in the population is assigned to the class it really belongs. An imperfect test is such that some errors appear, and then statistical analysis must be applied to examine the classification. When the classification function is not perfect, false results will show. The example confusion matrix below, of the 8 actual cats, a function predicted that three were dogs, and of the six dogs, it predicted that one was a rabbit and two were cats.[39]

Confusion matrix is generated to tabulate the performance. This matrix shows the relation between correctly and wrongly predicted reviews. In the confusion matrix, true positive represents the number of positive reviews that are correctly predicted whereas false positive gives the value for a number of positive reviews that are predicted as negative by the classifier. Similarly, true negative is number of negative reviews correctly predicted, and false negative is number of negative reviews predicted as positive by the classifier.[27]

From this confusion matrix, different performance evaluation parameter such as precision, recall, F-measure, and accuracy is calculated. The of confusion matrix formation is shown in Table 1.

Precision

It gives the exactness of the classifier. It is the ratio of number of correctly predicted positive reviews to the total number of reviews predicted as positive.

$$\text{Precision-}\frac{TP}{TP+FP}$$

Recall

It measures the completeness of the classifier. It is the ratio of number of correctly predicted positive reviews to the actual number of positive reviews present in the corpus.

$$\text{Recall-}\frac{TP}{TP+NP}$$

The calculation of precision and recall is calculated by forming some rules and predict some unrelavent or uncompleted comments using the rule classifiers.

Classification algorithms

Extract patterns using data files with a set of labeled training examples. Classification algorithms are in the supervised learning group because they build a classifier/model based on supplied classes. It uses classifiers to predict classes. A classifier is a global model which generates a concise and eloquent description for each class using attributes of data files.

Rule learning algorithms

Rule-based machine learner is the identification and utilization of a set of relational rules that collectively represent the knowledge captured by the system.[40]

Table 1: Confusion matrix

	Correct labels	
	Positive	**Negative**
Positive	TP	FP
Negative	FN	TN

TP: True positive, FP: False positive, FN: False negative, TN: True negative

Rule-based mining can be performed through either supervised learning or unsupervised learning techniques.

Rules are a good way of representing information or bits of knowledge. A rule-based classifier uses a set of IF-THEN rules for classification. An IF-THEN rule is an expression of the form.

IF *condition* THEN conclusion.

Direct method

Extract rules directly from data.

e.g.: Repeated incremental pruning to produce error reduction (RIPPER), CN2, Holte's 1R.

Indirect method

Extract rules from other classification models (e.g., decision trees, neural networks).

e.g.: C4.5 rules

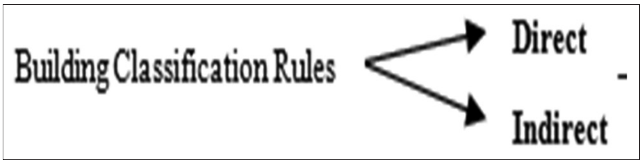

Figure 1: Classification rules

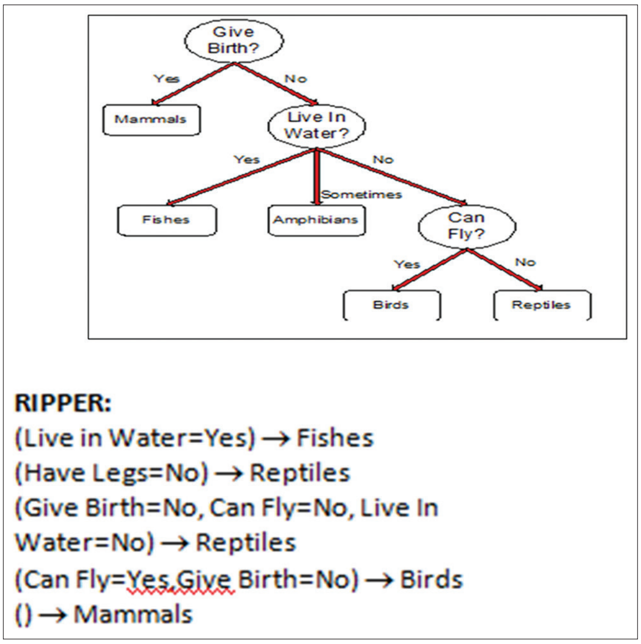

Figure 2: Classification of rules using if then rules

Table 2: Table for the above shown Figure 2

Actual class	Predicated class			
	Amphibians	Fishes	Reptiles	Mammals
Amphibians	0	0	0	2
Fishes	0	3	0	0
Reptiles	0	0	3	1
Birds	0	0	1	1
Mammals	0	2	1	4

RIPPER

RIPPER algorithm was designed by Cohen in 1995. RIPPER is professional on noisy datasets. RIPPER builds a rule set by repeatedly adding rules to an empty rule set until all positive examples are covered. Rules are formed by adding conditions to the antecedent of a rule until no negative examples are covered. After a rule set is constructed, an optimization post passes messages the rule set so as to reduce its size and improve its fit to the training data. A combination of cross-validation and minimum-description length techniques is used to stop overfitting.[35,36] RIPPER algorithm is efficient on large, noisy corpora, running in linear, or nearly linear time. RIPPER algorithm use what could be called a direct representation of text, in which a document is represented as an ordered list of tokens; in particular, it is not necessary to extract from a corpus a small set of informative features. RIPPER algorithm allows the context of a word *w* to influence how the presence or absence of word will contribute to a classification.[37]

RIPPER procedure

1. For 2-class problem, choose one of the classes as positive class, and the other as a negative class:
   - Learn rules for the positive class.
   - Negative class will be default class.
2. For multiclass problem:
   - Order the classes according to increasing class prevalence (fraction of instances that belong to a particular class)
   - Learn the rule set for smallest class first, treat the rest as negative class
   - Repeat with next smallest class as positive class.
3. Growing a rule:
   - Start from the empty rule
   - Add conjuncts as long as they improve FOIL's information gain
   - Stop when rule no longer covers negative examples
   - Prune the rule immediately using incremental reduced error pruning

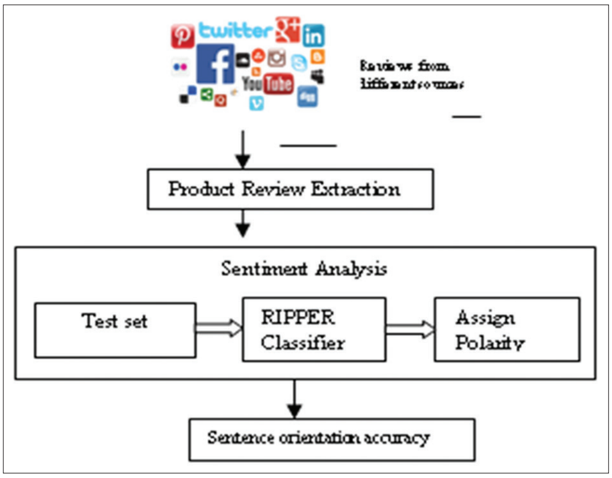

Figure 3: Proposed system

- Measure for pruning: v = (p-n)/(p+n).
- p: Number of positive examples covered by the rule in the validation set.
- n: Number of negative examples covered by the rule in the validation set.
- Pruning method: Delete any final sequence of conditions that maximize v

4. Building a rule set:
   - Use sequential covering algorithm
   - Finds the best rule that covers the current set of positive example
   - Eliminate both positive and negative examples covered by the rule
   - Each time a rule is added to the rule set, compute the new description length stop adding new rules when the new description length is a bits longer than the smallest description length obtained so far.
5. Optimize the rule set:
   - For each rule *r* in the rule set *R:*
   - Consider two alternative rules:
     - Replacement rule (r*): Grow new rule from scratch
     - Revised rule (r'): Add conjuncts to extend the rule *r*
     - Compare the rule set for *r* against the rule set for r* and r'
     - Choose rule set that minimizes minimum description length principle.
     - Repeat rule generation and rule optimization for the remaining positive examples.

Example

Actual Ripper algorithm

Actual ripper algorithm

```
function IREP*(Data)
begin
Data0:=copy(Data);
Ruleset:=an empty ruleset
while 3 positive examples ε Data0 do
/* grow and prune a new rule*/
split Data0 into GrowData ,PruneData
Rule:=GrowRule(GrowData)
Rule:=PruneRule(Rule,PruneData)
add rule to Ruleset
/*check stopping condition*/
if DL(RuleSet)>DL(RuleSetopt )+d
where RuleSetopt has lowest DL
of any RuleSet constructed so far
then
RuleSet:=Compress(RuleSet,Data0)
retrun Ruleset
endif
endwhile
RuleSet:=Compress(RuleSet,Data0)
return RuleSet
end


function Optimize(RuleSet,Data)
begin
for each rule c εRuleSet do
split Data into GrowData,PruneData
c':=GrowRule(GrowData)
c':=PruneRule(c',PruneData)
  guided by error of RuleSet-c+c'
ê:=GrowRuleFrom(c,GrowData)
ê:=PruneRule(ê,PruneData);
  guided by error of RuleSet-c+ ê
replace c in RuleSet with best of c,c', ê
guided by DL(Compress(RuleSet-c+x))
endfor
return RuleSet
end
function RIPPER(Data)
begin
RuleSet:=IREP*(Data)
Repeat 2 times:
RuleSet:=Optimize(RuleSet,Data);
UncovData:=examples in data not
covered by rules in RuleSet
RuleSet:=RuleSet+IREP*(Unov Data)
endrepeat
end
```

Table 3: Calculate sentence orientation accuracy using flipper algorithm

Product item	Opinion sentence extraction		
	Precision	Recall	Sentence orientation accuracy
Digital camera	0.719	0.643	0.927

Table 4: Calculation of precise, recall for different products based on reviews using RIPPER algorithm

Product items	Opinion sentence extraction		
	Precision	Recall	Sentence orientation accuracy
Diaphers	72.73	27.35	48.5456170121766
CVD players	85.14	72.41	78.26070961599492
Phone	0.84	0.75	0.7924528301886792
TV	0.79	0.82	0.8047204968944099
DVD players	70.65	32.99	44.97768236202239
Milk	92.86	69.89	79.75404485407066
Coca cola	44.19	17.76	25.33702663438257
Beer	70.73	87.22	78.11422095599873
Soda	56.11	44.30	49.5104670849517
Flour	93.33	46.67	62.22444428571429
Popcorn	84.38	64.29	72.9776040895944
Laptop	0.65	0.85	0.7366666666666667
Mp3 palyer	0.72	0.84	0.7753846153846154
Ipod	0.81	0.84	0.8247272727272727
PC	0.78	0.84	0.8088888888888889

RIPPER: Repeated incremental pruning to produce error reduction

When to stop building a rule in RIPPER:

- When the rule is perfect.
- When an increase in accuracy gets below a given threshold.
- When the training set cannot be split any further.

PROPOSED SYSTEM [FIGURE 3]

At the document level, sentiment classification of documents into positive, negative, and neutral polarities is done with the assumption made that each document focuses on a single object and contains opinion from a single opinion holder. At the sentence level, identification of subjective or opinion at sentences among the corpus is done by classifying data into objective and subjective or opinionated text. Subsequently, sentiment classification of the aforementioned sentences is done moving each sentence into positive, negative, and neutral classes. At this level assume that a sentence contains only one opinion. An optional task is to consider clauses. At the feature level, the various tasks are determining whether the opinions on the features are positive, negative, or neutral.

Evaluating sentence polarity:

- Extract "opinion sentences" based on the presence of a determined list of product features and adjectives.
- Evaluate the sentences supported on counts of positive and negative polarity words.
- Predict the sentence polarity based on words.

RESULTS AND DISCUSSION

Various types of datasets such as camera, laptop, mobile, and other reviews are used to test RIPPER model.

Lower Recall and precision have a disagreement with humans on opinion sentences. For the set-valued RIPPER is substantially faster than the other learning algorithms. RIPPER would show improvement on a noisy dataset since it includes a pruning mechanism.

CONCLUSION

The appearance of online business has revolutionize the way of customer buys a product and the product reviews posted by customers also can manipulate a potential customer in making a decision whether to buy a product or not. Product review is an unstructured data, and it is integrated with noisy data. Customer expression on product covers many issues about products. Comments by customers may be about general product as a whole, or maybe more toward technical/specific issues; some of the comments are positive or negative, and some of the comments may be neutral. The goal of this paper was to investigate review comments can be used for extracting opinion targets in short product reviews and develop a new approach to successfully extracting opinion targets for noisy data. For future work, we will consider new ways for improving the system performance, by investigating new methods for better segmentation of words, and considering approaches to better using prior knowledge for word representation and automatically learning the weights of opinion targets.

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