Review of Aspect Based Opinion Polling

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ABSTRACT

Any organization needs to conduct surveys and collect reviews, in order to improve their product quality. There are number of websites which deals with product reviews. All these reviews are nothings but the opinions of people all over the world about different products. These reviews are very huge and difficult to analyse. Opinion polling has been traditionally done via customer satisfaction studies in which questions are carefully designed to gather customer opinions about target products or services. This paper deals with review of various aspects of aspect-based opinion polling from unlabelled free-form textual customer reviews without requiring customers to answer any questions.

Keywords: aspect based opinion poling, sentiment analysis, customer review

1. INTRODUCTION

Text Mining is an exciting research area that tries to solve the information overload problem by using techniques from data mining, machine learning, NLP, IR and knowledge management. Text Mining involves the pre-processing of document collections (text categorization, information extraction, and term extraction), the storage of the intermediate representations, the techniques to analyse these intermediate representations (distribution analysis, clustering, trend analysis, association rules etc) and visualization of the results. Sentiment analysis or opinion mining is the computational study of people's opinions, appraisals, and emotions toward entities, events and their attributes. It involves the application of natural language processing, computational linguistics, and text analytics to identify and extract subjective information in source materials. The goal of opinion polling is to give quantitative indications of user's positive or negative opinions about products or business. To achieve this goal, the crucial step is to identify the polarity of each aspect expressed in each review. Figure 1. a) Shows exemplary generation of structured summaries by extracting product aspects and related sentiment expressions from unstructured customer review texts. Figure 1. b) showsa general architecture of a generic sentiment analysis.

Paper can be outlined into seven sections, section II comprises of definitions, tasks and terminologies related to aspect based opinion mining for customers reviews. Section III deals with challenges followed by approaches and current state of art in section IV and V respectively. Section VI deals with datasets and evaluation parameters. The paper is concluded in last concluding section.

2. DEFINITIONS, TASKS, AND TERMINOLOGY

Unfortunately, the relevant literature is quite inconsistent with regard to the use of terminology. By describing the most relevant subtasks in sentiment analysis, this section clarifies some important terms. The goal is to define a uniform terminology that we will use throughout the paper.

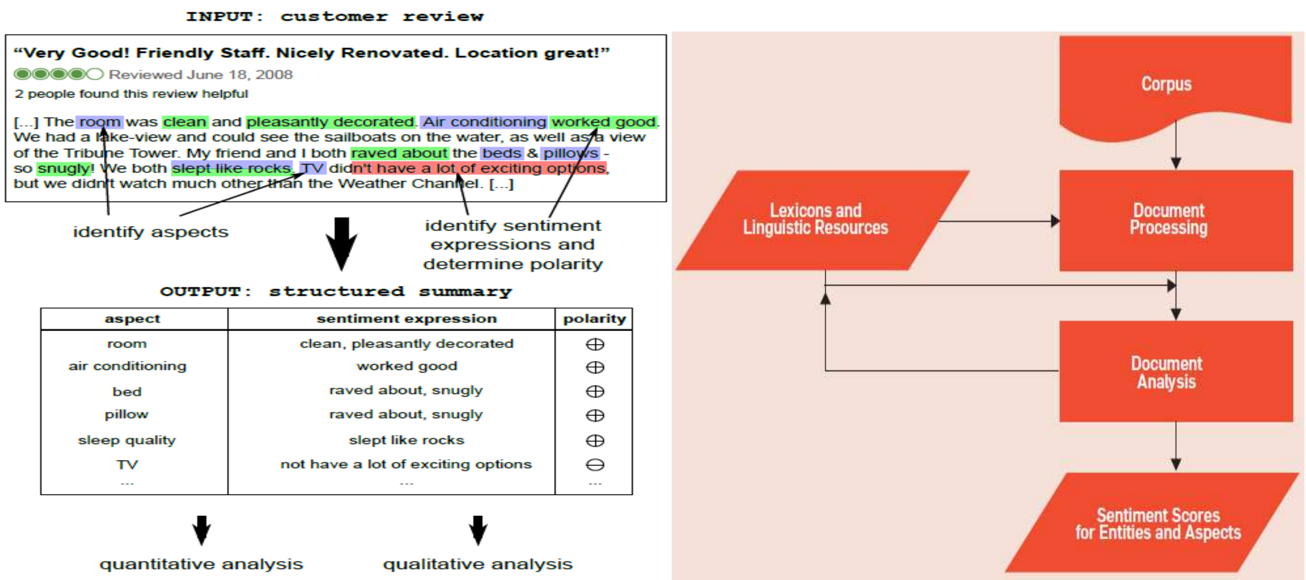

Figure: 1. a)Generating structured summaries by extracting product aspects and related sentiment expressions from unstructured customer review texts. b)A general architecture of a generic sentiment analysis

Sentiment analysis is a field of study that addresses the application of NLP techniques to automatically identify and analyse subjective information in natural language texts. The goal (mentioned in Table 1) is to determine the author’s opinion about a specific target, or more abstract, about a specific topic. Subjective information may become manifest as a judgment or evaluation, the author’s affective state when writing, or the affective state the author wants to evoke in the reader. The author may express his attitude on different levels of granularity, e.g., within individual text passages or as the general tone of the document. Besides pure identification, sentiment expressions are typically associated with different types of semantic categories, e.g., polarity, strength, or type of emotion.

Task	Goal
Sentiment Polarity Classification	Determine whether the general tone of the text is predominantly positive or negative.
Subjectivity Classification	separate subjective from objective information
Emotion Classification	classify a piece of text according to a predefined set of basic emotions
Sentiment Source Detection	identifying the person, the organization, or more general, the entity which is the source of subjective information
Sentiment Target Detection	Determine the subject of a sentiment expression.

Table 1: Different tasks and goals of Sentiment analysis

Task	Goal
Review classification	to determine the general tone of a review
Aspect-oriented review mining and summarization	analyse the reviewers’ sentiment with regard to individual product aspects
Review identification:	determine whether a given document is a review or not
Review helpfulness prediction	rate a review text according to its helpfulness and utility for other readers
Review spam detection	to counteract the proliferation of fake-reviews.

Table2: Different tasks and goals of customer review mining

Among the diverse sources and types of online customer feedback (e.g., in the form of blog entries, comments in social networks, posts to message boards), online customer reviews naturally represent a very valuable resource. Applying sentiment analysis techniques to analyse and summarize this specific type of data is denoted as **customer review mining**. Table 2 represents different tasks and goals of customer review mining**.** There are two aspects of customer review mining as research area and field of application as follows

1. Sources for Online Reviews: Review site, Online shopping site, Web log
2. Formats of Online Reviews: review text, pros and cons, combination

3. CHALLENGES

Here are some of the challenges that are facing the text mining research area:

3.1. Challenge 1: Entity Extraction Most text analytics systems rely on accurate extraction of entities and relations from the documents. Since the systems should work in any domain they must be totally autonomous and require no human intervention.

3.2. Challenge 2: Autonomous Text Analysis Text Analytics systems today are pretty much user guided, and they enable users to view various aspects of the corpus. We would like to have a text analytics system which is totally autonomous and will analyze huge corpuses and come up with truly interesting findings that are not captured by any single document in the corpus and are not known before. The system will get streams of documents from a variety of sources and send emails to relevant people if an "interesting" finding is detected.

Some potential ideas for a grand challenge in data mining include:

• Automatic tagging and classification of 1 billion digital photos on the web. A company called Riya (www.riya.com) is already working on a smaller scale project.

• Identifying all genes and potential therapeutic targets for some specific types of cancer.

• A text-mining and understanding system that can use the web to pass standard tests, e.g. SAT in World History.

• Literature-based discovery of drug X side effects ([Swan86] is one of the earliest examples)

• Fraud detection based on company financial statements – can we find another Enron before it collapses?

4. APPROACHES

Existing approaches to opinion mining and sentiment analysis can be grouped into four main categories:

keyword spotting, in which text is classified according to the presence of fairly unambiguous affect words; lexical affinity, which assigns arbitrary words a probabilistic affinity for a particular emotion or opinion polarity; statistical methods, which calculate the valence of keywords and word co-occurrence frequencies on the base of a large training corpus; finally sentic computing, which uses affective ontologies and common sense reasoning tools for a concept-level analysis of natural language text.

In this paper, authors used a subsumption hierarchy to formally define different types of lexical features and their relationship to one another, both in terms of representational coverage and performance. They used the subsumption hierarchy in two ways: (1) as an analytic tool to automatically identify complex features that outperform simpler features, and (2) to reduce a feature set by removing unnecessary features. It was shown that reducing the feature set improves performance on three opinion classification tasks, especially when combined with traditional feature selection. the results showed that the subsumption process counteracted the negative effect of adding the more complex features. The best accuracy results were 99.0% on the OP data, 83.1% on the Polarity data, and 75.4% on the MPQA data.

The major findings of our survey

- Lexicon-based approaches to product aspect detection show consistently good results in different settings.
- The application of variant aggregation techniques promises only minor improvements in recall.
- The candidate filtering techniques significantly increase the accuracy of the extracted lexicons.

Product aspect extraction with a lexicon mainly suffers from the following problems: false positives, false negatives, and unrecognized part-of-speech patterns of aspects only play a minor role.

5. CURRENT STATE OF ART

Most commercial sentiment analysis approaches seem to rely on simple lexicon-based approaches. They simply aggregate phrase level sentiment scores and ignore more complex linguistic constructs (e.g., sentiment shifters). Some other systems apply natural language parsing and provide a rule engine to model more complex constructs. Machine learning techniques for fine-grained sentiment analysis (e.g., sequence labelling methods such as CRF or HMM) seem to be rather uncommon. We presume that one reason is the cost involved with creating appropriate training datasets. Table 3presents a comprehensive overview of some exemplary systems.

6. DATASETS AND EVALUATION PARAMETERS

In this section we provide an overview of other, publicly available datasets that explicitly target or are closely related to the task of aspect-oriented sentiment analysis. We are particularly interested in gold standard corpora which may serve as reliable evaluation datasets. Following table 4 consists the list of dataset for restaurant, electronics and movie reviews only.

Product name	Type of analysis	Approach
Google Product Search	aspect-oriented sentiment summary	sentiment lexicon, fine &coarsegrained aspect dictionary, machinelearning
Rapid-I RapidSentilyzer	polarity classification	classification model
Repustate Sentiment Analysis API	clause level polarity scores	sentiment lexicon
SAS Sentiment Analysis	aspect-oriented sentiment summary, polarity classification	sentiment lexicon, aspect taxonomy, rule engine

Table 3: Overview of some commercial systems

Granularity	Annotation Scheme	Domain
Sentence	sentiment target/expression tuples (as strings) attributed with polarity and intensity	electronics
Sentence	topic, sentiment polarity	restaurants
sentence	sentiment target/expression tuples (as strings) attributed with polarity	movies

Table 4: Manually annotated corpora (in English) for aspect-oriented sentiment analysis

The consistency of algorithms is validated using certain metrics. They are accuracy, sensitivity, specificity, positive predictive value, and negative predictive value and F measure. These metrics are computed as follows.

i. **Accuracy**: For sentiment analysis, the accuracy is the proportion of true results (both true positive opinions and true negative opinions) generated from the algorithm implemented on the review database. To clear the context by the semantics, it is often referred to as the "Rand Accuracy". It is a parameter used for the test.

   Accuracy = TP + TN / (TP + TN + FP + FN)

   where TP - number of true positive instances in the test dataset, TN – number of true negative instances, FP - number of false positive instances, FN - number of false negatives, -,

ii. **Sensitivity** = TP / (TP + FN)

iii. **Specificity** = TN / (TN + FP)

iv. **Positive predictive value (PPV)**

   PPV = TP / (TP + FP)

v. **Negative predictive value (NPV)**

   NPV = TN / (TN + FN)

vi. **F-measure**: A measure that combines precision and recall is the harmonic mean of precision and recall, the traditional F-measure or balanced F-score

   F Measure = 2PR / P+R

Where, P - precision and R – Recall.

In information retrieval, recall is the fraction of the documents that are relevant to the query that are successfully retrieved. Precision: While retrieving any information, precision is the fraction of retrieved documents that are relevant to search.

7. CONCLUSION

With the emergence of the Internet as a social and interactive platform, an increasing share of public discourse and opinion making is taking place on the Web. Customer reviews represent a very prominent example where people share their opinions and experiences online. For companies and consumers such genuine customer voices represent extremely valuable information and they would like to have tools that automatically analyze and summarize this textual data. This paper can be used as reference for those who want to contribute in the field of customer review polling.

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