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Marketing Research: The Role of Sentiment Analysis

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MARKETING RESEARCH: THE ROLE OF SENTIMENT ANALYSIS

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Abstract: This article promotes sentiment analysis as an alternative research technique for collecting and analyzing textual data on the internet. Sentiment analysis is a data mining technique that systematically evaluates textual content using machine learning techniques. As a research method in marketing, sentiment analysis presents an efficient and effective evaluation of consumer opinions in real time. It allows data collection and analysis from a very large sample without hindrances, obstructions and time delays. Through sentiment analysis, marketers collect rich data on attitudes and opinion in real time, without compromising reliability, validity and generalizability. Marketers also gather feedback on attitudes and opinions as they occur without having to invest in lengthy and costly market research activities. The paper proposes sentiment analysis as an alternative technique capable of triangulating qualitative and quantitative methods through innovative real time data collection and analysis. The paper concludes with the challenges marketers can face when using this technique in their research work.

Keywords: Sentiment analysis; Machine leaning; Marketing research; Triangulation; Qualitative research; Quantitative research.

JEL Codes: M10, M30, M31, M39

1. INTRODUCTION

Consumers use different types of online forums for social engagement including social media alternatives such as Facebook and Twitter. Through social media, consumer engagement occurs in real time. This type of interaction offers an unprecedented opportunity for marketing intelligence. People across nationality, gender, race and class use the internet to share experiences and impressions about almost every facet of their lives. Besides writing e-mails, blogging or leaving comments on corporate websites, millions of people are using social network sites to log opinions, express emotions and disclose details about their daily lives. People write on almost anything including movies, brands, or social activities. These logs circulate throughout online communities and provide an interactive forum where consumers inform and influence others. To the marketer, these logs provide deep insights into consumer behavioral tendencies and present an opportunity to learn about customer feelings and perceptions in real time, as they occur without intrusion or provocation. But, recent explosions of user generated content on social sites are presenting unique challenges in harnessing, analyzing and interpreting textual content since data are dispersed, disorganize, and fragmented (Kaplan and Haenlein, 2010). Sentiment analysis is a tool in data mining that can overcome these challenges by systematically extracting and analyzing online data without incurring any time delays. With sentiment analysis, marketers have the opportunity to learn about consumer feelings and attitudes in real time despite the challenges of data structure and volume.

Our interest in using sentiment analysis as a marketing research tool is twofold. Firstly, marketers and academics alike have recognized the profound influence of social communities on consumer behavior (Gruen, Osmonbekov and Czaplewski, 2006; Park, Lee and Han, 2007). But, the recent explosion in user generated content is presenting enormous challenges for marketers (Stanton and Rogelberg, 2001). Secondly, recent developments in technology have enhanced classification accuracy, and user friendliness. Marketers can collect large body of data in real time, unobstructed or contaminated by the presence of an external researcher. Therefore, we argue that through sentiment analysis market research cost and sampling error are reduced and validity and reliability of research findings are enhanced.

The marketing research literature purports two basic types of research methods: quantitative and qualitative (Newman, 2011). Quantitative research methods are generally used when researchers are interested in verifying research hypotheses. The research design focuses on collecting data from a large sample of respondents from a defined population, and relies on statistical, mathematical and computational techniques for data analysis (Given, 2008). But, quantitative research is criticized as a rigid approach that ignores inherent subjectivity of human social interactions (Holstein and Gubrium, 1995). On the other hand, qualitative research recognizes multiple realities of human social environment, and is used to discover attitudes, beliefs and emotions on identified phenomenon. But, like quantitative research, qualitative research is also criticized. Opponents describe this approach as a subjective, non-scientific method that lacks structural coherence (Poggenpoel and Myburgh, 2005). Despite the ongoing debate, recent development in research methodologies suggest that the two approaches should be integrated in comprehensive research designs in order to improve research rigor and address several of the epistemological and methodological criticisms (Kelle, 2006; Olsen, 2004).

This article contributes to the argument for pluralism in research design by demonstrating how sentiment analysis can be used as a complementary research technique. The paper presents a unique view on the topic of sentiment analysis in social science research by showing how marketers and by extension all stakeholders in the social sciences can benefit from the technique flexibility and scientific rigor. The paper will highlight among other things, the published literature on the topic of sentiment analysis, sentiment analysis methodology, uses of sentiment analysis and the role of sentiment analysis in marketing research.

2. WHAT IS SENTIMENT ANALYSIS

Origins of sentiment analysis are rooted in the disciplines of psychology, sociology and anthropology and flow from the theory of affective stance and appraisal theory which focus on emotions in shaping cognitions. Emotions are feelings generated from both conscious and unconscious processing. An emotional assessment of a situation is a general evaluation of that situation (whether positive or negative) that manifest in mental and bodily responses. The role of emotions in marketing is not new. To the marketer, customer emotions are indirect motivators of purchase behavior. It shapes brand saliency, influences attitudes, beliefs, opinions and perceptions. Links have already been established between emotions and strong brands (Aaker and Keller, 1990, Morrison and Crane, 2007); emotions and consumption; and emotions on product evaluations (Mano and Oliver, 1993).

Sentiment analysis is also not new to market research. Marketers have been analyzing sentiments using old fashion customer comment cards, surveys, interviews and focus groups. Although some of the tools can be adapted to take advantages of the internet interactive environment, their uses are subjected to researcher presence and small sample sizes. Sentiment analysis addresses these problems by systematically collecting and analyzing online sentiments from a very large sample of customers in real time. We conceptualize online sentiments as human convictions or emotions expressed on the internet. It is an attitude towards a situation, event or object, usually expressed through a variety of online media alternatives, with the most popular being social network sites. Examples of online sentiments are:

"I love my new Ipad"
"The movie is the best movie I have ever seen"
"Worst tasting bagels in town"

Sentiment analysis is a systematic analysis of online expressions. Specifically, sentiment analysis focuses on evaluating attitudes and opinions on a topic of interest using machine learning techniques. The definition of sentiment analysis in data mining can be described from two perspectives: functional and operational. The functional aspects focus on practical uses of the method. For instance, Liu (2010) describes sentiment analysis as a process that categorizes a body of textual information to determine feelings, attitude and emotions towards a particular issue or object. The definition points to the way sentiment analysis works and describes the outcome of polar classification. Another aspect of sentiment analysis in data mining focuses on the operations of the technique as a sub-field of computational linguistics. Kumar and Sebastian (2012) describe sentiment analysis as automated subjectivity analysis similar to opinion mining and appraisal extraction which focuses on extracting and classifying texts with machine language and computer programming. Despite the differences in both perspectives, the general narrative is the same. In other words, sentiment analysis is a data mining technique that uses natural language processing, computational linguistic and text analytics to identify and extract content of interest from a body of textual data.

The use of automated extraction tools and techniques has emerged as a commanding research topic. Pang and Lee (2008) presented a detailed and comprehensive review on affective computing and computer technology for emotion and expression recognition. Affective computing technology lends measurability and objectivity to analysis. It adds consistency and control for quality, positively contributing to research credibility, dependability and verifiability. Extracting emotions from automatic processing (generally achieved through natural language processing, computer algorithms and machine learning), is now commanding the attention of researchers and practitioners because of the speed and efficiencies in processing large volumes of data. Through automatic processing, unlimited volume of opinions can be extracted in real time providing timely information to decision makers.

In terms of process, sentiment analysis combines several tasks to produce knowledge from text based data. We conceptualize this process into five stages (see Figure 1) which starts with data collection and ends with presentation of output. In summary, the process involve sourcing data from user generated web content either through social media or any other online forum. The extracted data is cleaned and examined for subjective sentiments. These sentiments are subsequently classified into mutually exclusive categories using a system of polar classification. Finally, the technique ends with the presentation of the results using interactive displays.

3. SENTIMENT ANALYSIS: METHODOLOGY

A graphical description of the processes involve in sentiment analysis is detailed in Figure 1 below.

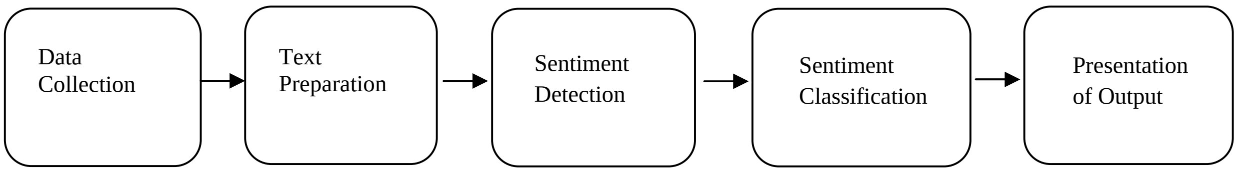

Figure 1: Sentiment analysis process

3.1 Data collection

Sentiment analysis takes advantage of the vast user generated content over the internet. The data source points to queries of user discussions on public forums like blogs, discussion boards and product reviews boards as well as on private logs through social network sites like Twitter and Facebook. Very often, the data log is bulky, disorganized, and disintegrated on multiple portals. Opinions and feelings are expressed in different ways including the amount of details given, type of vocabulary used, context of writing, slangs and lingua variations are just a few examples. This makes manual analysis tedious, and almost impossible. But, with sentiment analysis, innovative text analytics and natural language processing is employed to extract and classify data. Once the data is extracted, it will then be prepared for analysis. An example of the data is presented in Figure 2.

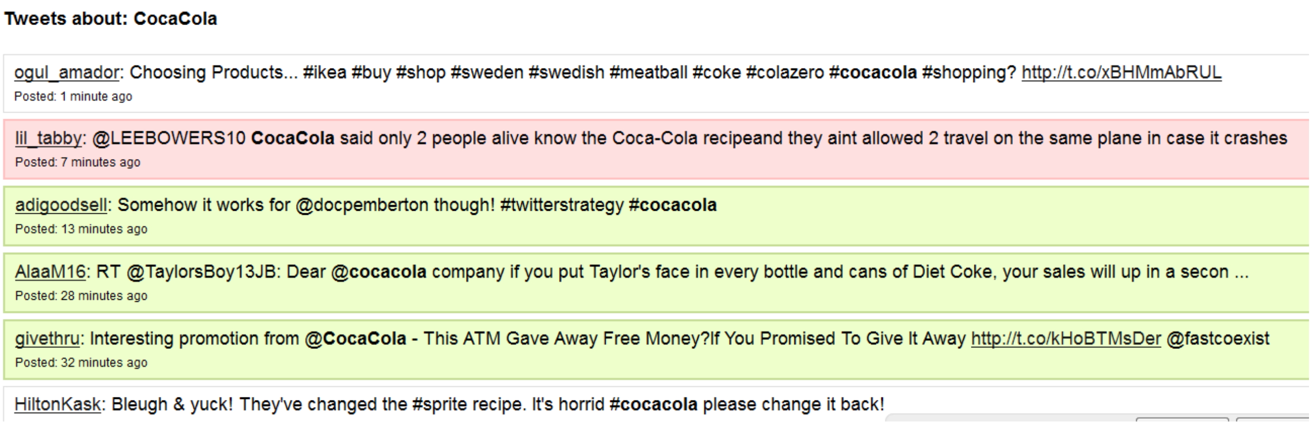

Figure 2: Data extracted from online sources

Source: http://www.sentiment140.com/search?query=CocaCola&hl=en

3.2 Text preparation

Text preparation involves cleaning the extracted data before the analysis is performed. Usually text preparation involves identifying and eliminating non textual content from the textual dataset, and any information that can reveal the identities of reviewers including: reviewer name, reviewer location, review date. In addition, any other content that is not deemed relevant to the area of study is also removed from the textual dataset such as includes stop words or words that are not relevant to the course of analysis.

3.3 Sentiment detection

The third stage is sentiment detection. Sentiment detection requires appraising and extracting reviews and opinions from the textual dataset through the use of computational tasks. Each sentence is examined for subjectivity. Only sentences with subjective expressions are kept in the dataset. Sentences that convey facts and objective communication are discarded from further analysis. Sentiment detection is done at different levels either single term, phrases, complete sentences or complete document with commonly used techniques such as:

- *Unigrams*: This is a classic approach where each element is represented as a feature vector based on frequency of a single word. It is often described as a bag of words approach
- *N-Grams:* In this approach the features of a document is represented by multiple words in sequence (e.g.: words in pairs, triplets) which captures more context
- *Lemmas:* This involves the use of synonyms rather than the literal word. For example: better → good, best → good. This method reportedly makes the classification task easier as well as facilitates generalization. However, Kushal et al. (2003) argued that meanings are not necessarily synonyms and provided evidence through his experiment that suggested that the accuracy of sentiment classification was reduced when words are linked to their thesaurus meanings.
- *Negation:* This is basically an extension to the n-gram methods where the phrases "I like this book" and "I do not like this book" would have considered similar under most classification techniques, but with negation, both terms are forced into opposite groupings. However, negation is not always easy to model. For instance, Pang and Lee (2008) reported that it is difficult to identify negation when sarcasms and ironies are used in a sentence. Additionally, the negation term does not always reverse the polarity. For example, it will be considered incorrect to attach the word *NOT* to *BEST* in the sentence "No wonder this is considered to be the best book".
- *Opinion words*: These are basically words that are used to describe people feelings and opinions (nouns, verbs, adjectives, adverbs). These words are incorporated into a feature vector where they represent the presence of absence of a word. These words are good indicators of subjectivity in a document.

It is not uncommon to find textual sentences making reference to several objects, features and attributes. Through mathematical algorithms, sentiment analysis can be used to extract these objects, features and attributes and form categorize. This assists in the analysis stages and enhances precision in classification and data summarization.

3.4 Sentiment classification

The fourth stage is polarity classification which classifies each subjective sentence in the textual dataset into classification groups. Usually these groups are represented on two extreme points on a continuum (positive, negative; good, bad; like, dislike). However, classification can also involve multiple points similar to the star ratings used by hotels, restaurants and retailers.

A wide variety of machine learning techniques are used in binary and polar classification. Machine learning is linked to the field of artificial intelligence and aims at building computational models from past experiences and observation. It fundamentally promotes the use of computer programming to learn and understand fundamentals a particular data set and then use that knowledge acquired to predict or optimize some future criterion. The general objective is to generate a predictive function capable of predicting a target outcome - y (dependent variable) using predefined input criteria or attributes - x (Gama and Carvalho, 2009). When the target is known, this type of learning is called “supervised learning”. Using a supervised leaning approach in sentiment analysis requires training document of textual content or a data corpus, which serves as a preparation document for classification learning. The three basic functions available for classification includes: Naive Bayes (NB), Support Vector Machines (SVM) and Maximum-Entropy (ME). A Naive Bayes classifier is a probabilistic classifier based on applying Bayes’ theorem assuming that features are independent given the class label. This classifier is constructed based on the frequency of occurrence of each feature per class in the training data set. Support vector machines are based on the statistical learning theory (Vapnik, 1995). Binary classifiers show high generalization capability by looking for a hyperplane that maximizes the separation margin between observations from different classes. The use of kernels allows their use for nonlinear problems. Under ME a number of models are constructed where each feature correspond to a constraint on the model. The model with the maximum entropy over all models is selected for classification.

Although all three classifiers are validated in the literature (Pang and Lee 2008, Li and Liu, 2012), they require pre-tagged training data or a data corpus which is not always available, or will take a considerable amount of resources both in terms of time and human resources to build. In addition, the language of the data cannot be ignored. Most literature, tools and techniques available on sentiment analysis are written in English language. This presents a problem for multilingual translation. While there is a stream of research focusing on aligning other languages to the domain of interest, cross lingual adaptation remains a challenge especially when cultural idiosyncrasies are taken into consideration (Kim and Hovy, 2006; Blitzer et al. 2007).

The most basic is the bag of words method where a score or weight is assigned to each word based on the nature of the word (good or bad) and the frequency of the word in the text document. Once the score for each term is calculated, a score for the whole document is calculated by taking the arithmetic sum or mean. The simplest scoring method involves the subjective assignment of scores to opinion documents from which a "pseudo-expected" value is computed. Although this method is statistically grounded and simple to comprehend, it is criticized as not providing an efficient alternative to categorize large volumes of data. Additionally, because it relies on human categorization, the reliability of the classification has also been questioned given the diverse nature of human beings (Li and Liu, 2012).

Another technique involves the use of lexicons. A lexicon acts as a bridge between a language and the knowledge expressed by that language. It is a list of all words and meanings in a specific language. A variety of lexicons have been created for use in sentiment analysis. WordNet is a lexical database for the English Language. Created in 1985 by Princeton University, this database gives general definitions of words, group words into sets of synonyms known as synsets, and record relationship between synonymy sets through conceptual-semantic and lexical relations. In 2004, Kamps and Marx used this synonym relationship to measure the distance between words based on their similarities and differences based on graph theory. They first classify each adjective on a good-bad (+,-) spectrum and then compute the distance between words based on the length of the spectrum with closer words having shorter distances.

Web Search is another scoring method introduced by Turney (2002). This method recognizes the contextual problems with single word classification. For instance, the word "unpredictable" might have negative reviews in an automobile review but might be a positive review for a movie. To accommodate this problem, Turney (2002) used "tuples" which consist of adjectives combined with nouns, and adverbs combined with verbs. The process of word search involves a series of stages. Firstly, tuples are extracted from reviews. Secondly, semantic orientations of the extracted tuples are determined and finally, the average semantic orientations are calculated for the whole document. To determine the semantic orientation of tuples, Turney (2002) used the search engine AltaVista and ran two queries. One that looked that the number of documents that considered the tuple “excellent” and another with the number of documents that considered the tuple “poor”. If the tuple occurred more times in “excellent” query, than “poor” then it is considered a positive orientation. Likewise, if the tuple occurred more times in “poor” query, then it will be considered to be negative.

3.5 Presentation of output

The general purpose of the analysis is to convert unstructured fragmented text into meaningful information. Once the analysis is completed, a number of conventional options are used to display the result of text analysis. Chief among them is the use of graphical displays such as pie charts, bar charts and line graphs. The polarity is segmented on color, frequencies, percentages and size. The format of presentation depends on the research interest. Examples of each are presented in Figure 3-7 below:

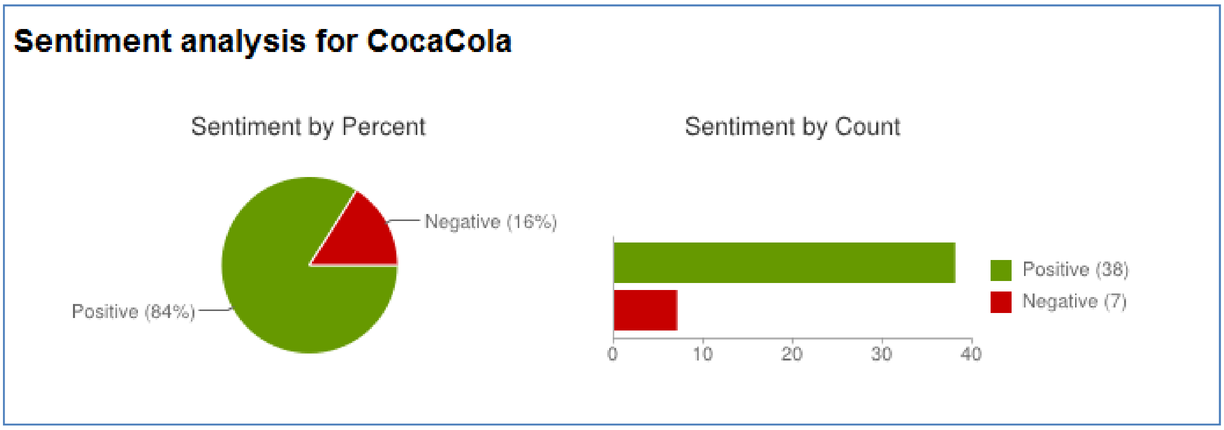

Figure 3: Summary of sentiments on a single product

Source: http://www.sentiment140.com/

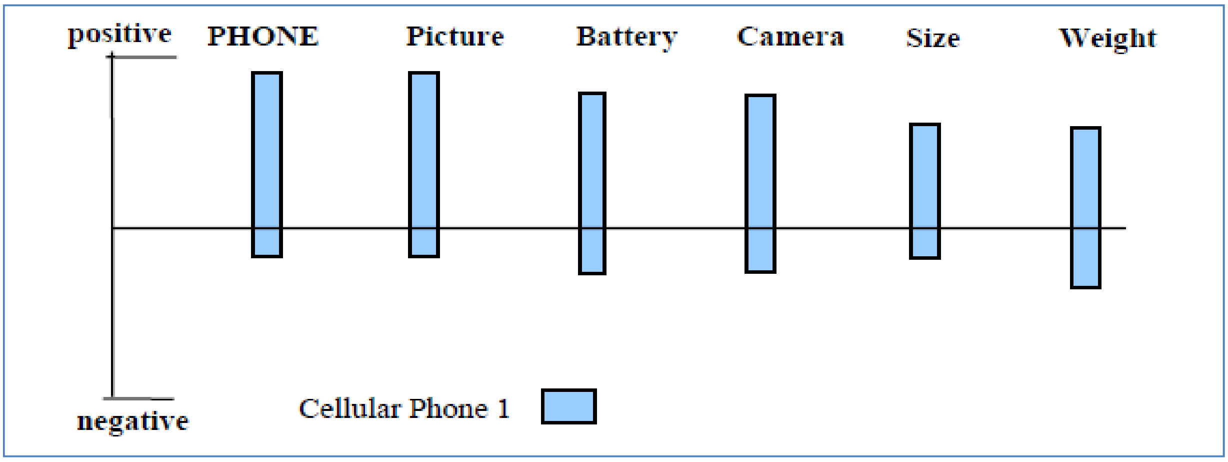

Figure 4: Summary of sentiments on features of a single product

(Source: Lu, 2010 p.8)

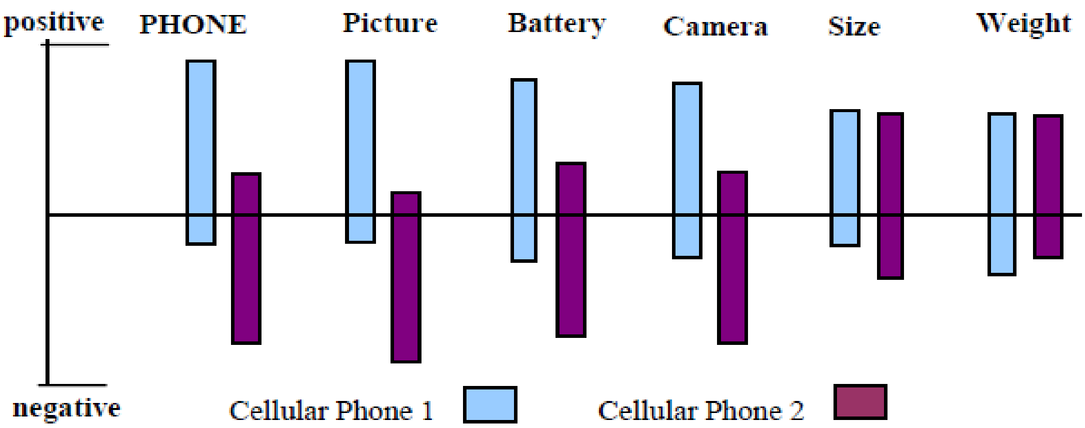

Figure 5: Summary of sentiments comparing two products

(Source: Lu, 2010 p.8)

Ratings are also presented by the number of stars with the number of reviews next to it. This is shown in Figure 6.

Figure 6: Summary of sentiments comparing using stars and ratings
(Source: http://www. amazon.com)

Time can be included in the analysis. Usually, this is graphically displayed through constructing a sentiment time line by plotting the value of the chosen statistic (example frequency, percentages, and averages) over time. This is shown in Figure 7.

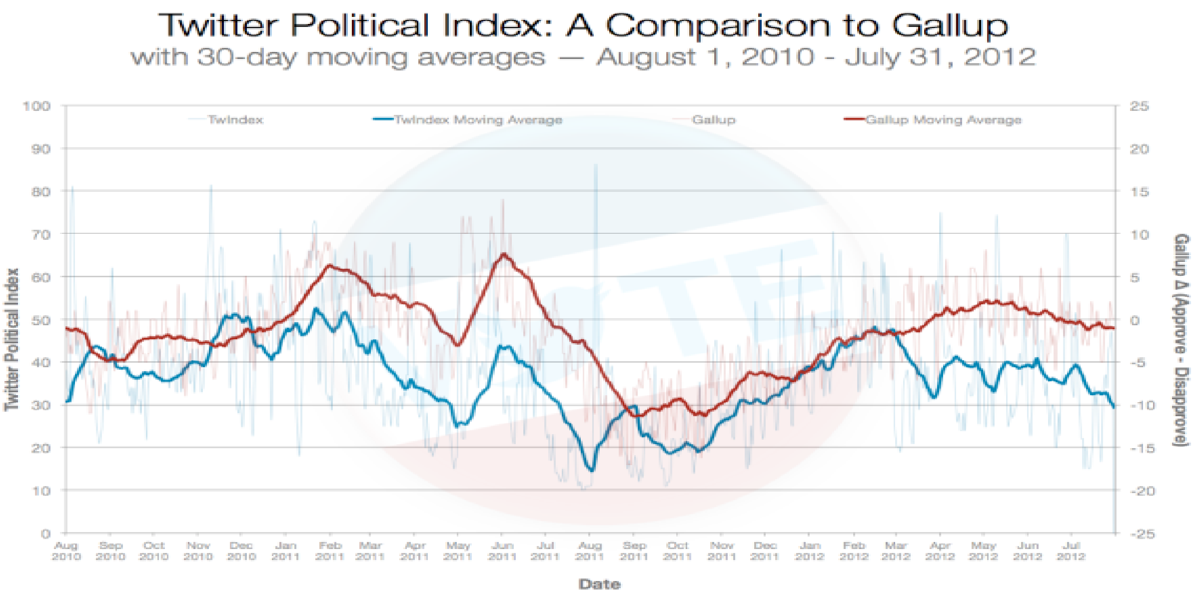

Figure 7: Summary of sentiments over time
(Source: http://techcrunch.com/2012/08/01/twitter-launches-its-own-political-barometer-to-track-u-s-presidential-elections/)

4. USES OF SENTIMENT ANALYSIS

Relative to uses, most published work on sentiment analysis focus on product analysis, i.e. extracting opinions on a specific product like phones, movies, or hotels. However, this interest is being extended to include more abstract areas like product features and attributes i.e "feature extraction". Li (2005) defines features as "components or attributes of a specific object". Feature extraction in sentiment analysis is a process that dissects a product into several features or attributes which are used as topic sentences for extraction and classification. This method gives a detailed analysis of sentiments highlighting aspects of a product a customer are pleased with and aspects they are disenchanted with. It also gives meaningful insights into why customers feel the way they do. Additionally, work is being conducted on analyzing statements from multiple targets. This is called comparative sentences and rank objects based on preference.

Although the concept is relatively new, the use of sentiment analysis in a commercial environment is growing. This is evident in the increasing number of brand tracking and marketing companies offering this service. Some services include:

- Tracking users and non-users opinions and ratings on products and services
- Monitoring issues confronting the company so as to prevent viral effects
- Assessing market buzz, competitor activity and customer trends, fads and fashion
- Measuring public response to an activity or company related issue

Sentiment analysis is useful to government agencies responsible for home land security issues. By monitoring spikes in negative sentiments towards a particular governmental body or authority or even country, agencies can gather useful intelligence about emerging threats. According to the New York Times (2006), the US government spent approximately $2.4 million dollars in funding research that developed software specifically designed to monitor online activities. According to one official:

> "….sentiment analysis is intended to identify potential threats to the nation. We want to understand the rhetoric that is being published and how intense it is, such as the difference between dislike and excoriate." (New York Times, 2006)

Politicians are also using sentiment analysis to gauge their popularity or even public impressions on critical issues. It can help politicians better understand the issues that are important to their voters. For instance the technique was applied in the last UK and US national election campaigns and is expected to make a real breakthrough in the upcoming 2012 US elections. Some examples of the way sentiment analysis is used in politics are (New York Times, 2010):

> "… Crimson Hexagon, a technology company in Massachusetts, analyzed expressions of public sentiment across the country about the oil spill in the Gulf of Mexico. Its analysis showed that people who lived near the gulf had a lower tendency to assign blame, focusing instead on the logistics of the relief efforts..."
>
> "Linguamatics, a British company, analyzed posts from more than 130,000 Twitter accounts to gauge public opinion during the British elections this spring. The company's analysis yielded similar results to traditional political polling, and predicted within one point the percentage of votes the Conservative Party would win."

5. THE ROLE OF SENTIMENT ANALYSIS IN MARKETING RESEARCH

Market research is regarded as a systematic approach that involves data collection and data analysis on any relevant marketing related issues. In marketing, research is used for a variety of purposes including: obtaining insights into customer attitudes and beliefs, measuring customer satisfaction, ascertaining the effectiveness of advertising, etc. Some larger companies have their own market research departments whilst smaller companies usually outsource the function to research specialists (Kotler, 2010). Research is carried out in two basic ways: qualitative and quantitative. In a qualitative approach, the researcher makes knowledge claims based primarily on a constructivist perspectives (i.e. the multiple meanings of individual experiences, meanings socially and historically constructed, with an intent of developing a theory or pattern) or advocacy/participatory perspectives (i.e. political, issue-oriented, collaborative or change oriented) or both (Creswell, 2007, p.18). Qualitative research involves finding out what people think, and how they feel - or at any rate, what they say they think and how they say they feel. This kind of information is subjective. It involves feelings and impressions, rather than numbers. On the other hand, quantitative research focuses on measuring an objective fact. Key to conducting quantitative research is definition of variables of interest and to a large extent a sense of detachment in the data collection by the researcher. Quantitative research analyses data using statistics and relies on large samples to make generalized statements.

The relationship between quantitative and qualitative research has never been a smooth and easy one. In fact, there is a heated debate among scientists as to the scientific validity of qualitative research in promoting the advancement of scientific thought. Proponents of qualitative research challenge the credibility of quantitative research claiming that the focus was on merely reinforcing and validating current paradigms rather than discovering new thought. Although the methodological debate continues, a new trend has emerged in research today - the mixed method research design or plural research designs. Plural research design combines both qualitative and quantitative research methods in market studies and is becoming quite a fashion in social science research. It views qualitative/quantitative techniques are merely tools used in understanding the world we live in. Both tools are united by a shared commitment in knowledge creation, knowledge dissemination and to a rigorous, conscientious research process. Researchers are encouraged to implement plurality through triangulation which involves both qualitative and quantitative approach to data collection and design. However, a recent survey of research papers discovered several methodological deficiencies with triangulated designs given the absence of systematic and scientific guidelines (Kelly, 2006). Triangulation also can be impractical to some research situations given the high research cost of multiple data collection and the time delays in data collection and data analysis.

Sentiment analysis is a useful tool to address triangulation challenges in an online environment. When integrated with qualitative research, sentiment analysis can be used as a tool that promotes rigor and structure to an otherwise flexible and subjective data collection and data analysis process. Alternatively, if integrated with quantitative research sentiment analysis facilitates a deep rich insight into unsolicited opinions and emotions, thus facilitating a more meaningful understanding of any phenomenon. By employing machine learning techniques, sentiment analysis presents an opportunity to lend a systematic approach to mixed method design. We argue that through sentiment analysis, a marketer is presented with a rich option to procure meaningful and insightful feedback into customer feelings, thoughts, opinions and sentiments in real time. Sentiment analysis provides a faster, simpler and less expensive alternative to traditional qualitative market research techniques like observations, interviews and even ethnography as well as provides information in real time. At the same time, it offers the advantages of traditional quantitative methods including measurability and objectivity. Data is also collected in a manner that is entirely unobtrusive as compared to methods used in both qualitative and quantitative research. Sentiment analysis provides an opportunity for marketers to collect data on customers in their natural cyber environment, without the presence of the researcher being felt. Therefore this method eliminates the problem of people reacting differently when they know their responses are being collected.

6. TOOLS AND WORKS IN SENTIMENT ANALYSIS

According to Pang and Lee (2008), researchers have found ways to avoid the use of manual annotation by utilizing existing online textual content generated from sites such as Epinion, Amazon, Rotten Tomatoes, Twitter, Facebook. Several sentiment search engines exist where users run typical queries on any topic of interest, and generate text results. Usually the results are coded and categorized into two or three polar categories. Some examples currently available are:

1. Twitrratr – www.twitrratr.com
2. Sentiment 140 - http://www.sentiment140.com
3. Tweetfeel – www.tweetfeel.com
4. Opinmind – www.opinmind.com
5. Social Mention – www.socialmention.com

Sentiment search engines make sentiment analysis quite easy. But, the online reviews on sites like Amazon and Epinion have been found to be skewed towards the positive which raises questions on validity and reliability of sentiment classification. However, Pang and Lee (2008) admit that although the content might be skewed, the validity of the process is acclaimed. Another tool in sentiment analysis is word lists or annotated databases which categorize words based on their emotions for example -attractive (positive valance) or aversive (negative valance). Some examples include: ANEW, General Inquirer and LIWC. Other tools include sentiment analysis programs that are specifically designed to categorize short textural documents. One example is ***sentistrength***.

7. CONCLUSIONS

Interest in sentiment analysis is growing tremendously. But, although the field is emerging, it is still fairly new and the researcher can be confronted with challenges. One possible challenge relates to the nature of classification. In reality, there is usually a limit to the number of groups and subgroups that can be extracted, with most classification techniques generating two or three groups at most. Also, text based data are usually context specific and domain dependent, valid in specific places at specific times. Although there can be some translation, the validity of the translated text can be compromised by mistranslation. Additionally, postings on the internet can be difficult to analyze given that they often reflect shorter versions of phrases. Other criticisms of sentiment analysis lies on the techniques employed. For instance, machine learning relies on the score generated from a data corpus in order to assign classifications. This can be very expensive and time consuming to develop. In addition, the overall accuracy of classification depends on the classification data, which may not be transferable to other domains. A recent article published by the Academy of Marketing Science (Davis and O'Flaherty, 2012), challenged the reliability of automated sentiment classification. The authors found that companies who use automatic coding were more likely to misclassify sentiments when sentences were long, did not contain keywords or topic statements and have reversed meanings through the negation effect. On the other hand, sentiment classification proved highly accurate (80% and over) when sentences were simple and were clear on the sentiment polarity. Finally, issues of ethical research can surface. The right for voluntary participation, privacy and confidentiality can be questioned with this analysis given that extraction and analysis takes place without writer consent.

In conclusion, sentiment analysis is a relatively new in the context of research. Nevertheless, the contribution to real time conversion of mass volume of textual data into meaningful information can be very useful. Cost, time and processing advantages are enough to support this academic attention. As online purchase, consumption and conversations grown, the marketer tasks of sifting through online textual content also grow. Accelerating Social Sciences for the New Age (ASSANA) is a recent project that aims at developing, refining and disseminating new methodologies for social science (Cougburn, Hansen and Wozniac, 2012). This project recognizes the challenges social science researchers face in using textual based data in analysis. It promotes the use of digital data in social science research. Sentiment analysis can help. It is our belief that sentiment analysis gives the market researcher an opportunity to collect deep rich qualitative information collected from a large number of participants in an unobstructed real world environment without external interferences. We also argue that sentiment analysis provides a systematic alternative in extracting and analyzing a large volume of textual data, in real time. It removes subjectivity, and individual biasness. Sentiment analysis provides a rigorous and comprehensive technique to interpret data in this challenging and new context. If integrated appropriately with existing research design methods, sentiment analysis has the ability to bridge the gap between qualitative and qualitative research debate and provide a richer more integrated perspective into online consumer research.

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