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Consumer Feedback: Does Rating Reflect Reviewers' Feelings?

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ABSTRACT:

Consumer feedbacks have been widely used for product improvement. These consumer reviews reveal customer sentiments (e.g., like/dislike, fulfilled/unfulfilled etc.) about products and the degree of sentiments as well. These reviews are good sources to gauge customer feelings, which are important to make essential business decisions. In this research, we analyzed textual movie reviews semi-automatically using linguistic analysis instead of using manual mechanisms. Generally, adjectives in text reviews express reviewers' feelings about a product while adverbs (gradable) explain the degree of these feelings. Using a well-known movie review database, we analyzed the pattern of adjectives and adverbs that appeared in reviewers' comments. We compared the frequencies of these adjective and adverbial words with the symbolic ratings (A+ to F) of the respective reviews and found strong correlation between the positive/negative terms (adjectives and adverbs) embedded in the text and their corresponding symbolic ratings.

KEYWORDS:

Online Reviews, Information Extraction, Adjectives, Adverbs

INTRODUCTION:

Online communication has significant effects on consumer behavior. Online communication has not only altered the consumer-retailer relationship but also added new dimensions in the relationships among consumers of the same product or service. The use of the Internet has enabled many consumers to come in contact with one another even when they do not know one another. Consumers produce online reviews based on their personal usage experience that in turn develop into "sales assistants" for other customers by helping them to find out the product they are searching (Chen and Xie, 2008). Online reviews, which work as online Word of Mouth, are valuable resources for consumers as well as for producers and retailers. As a consequence, online consumer reviews have become a good source for research on consumer behavior.

Sentiment analysis, which is also called opinion mining, is gaining more importance than the pure economic analysis of online reviews for organizations (Saenz, 2010). As a result, 35% of Wall Street investment firms are now tending towards sentiment analysis of unstructured online reports, editorials, company web sites, and blogs (Bowley, 2010). Previously, online consumer reviews have been analyzed in many ways depending on the goal and type of research. Most of the consumer review formats consist of two parts. The first part is generally symbolic such as star ratings or letter ratings, followed by a textual part of the review (see the Appendix). Therefore, some consumer review studies were based on the symbolic ratings while other studies analyzed the textual part of reviews. In addition, understanding moods of customers is important but difficult. Therefore, understanding how the degree of positive and negative moods lead reviewers to choose the levels of symbolic rating is needed because readers including lurkers (those who do not post a review but read and observe) generally start to read reviews following the symbolic ratings as the symbolic ratings are mostly highlighted separately and easily catch the eyes of readers. The objective of this paper is to compare and contrast symbolic ratings with textual reviews. More specifically, review texts will be automatically extracted and moods that are reflected in the texts will be categorized and analyzed. These mood words will be matched with the symbolic ratings and the study will explore the association between mood words and the level of symbolic ratings.

Thus, this paper contributes to both the managerial interests and the theoretical interests. First, the findings from the sentiment analysis will help the producers of the business organizations to know the public opinion about a product and such information may facilitate profitable business decision making. Secondly, this paper is also contributes to the business intelligence literature. The concept of Business Intelligence requires gathering and storing data, which are analyzed using different tools to produce information for business (Negash, 2004). We gathered consumer feedbacks (text reviews) from a consumer forum and stored them in a database in a structured manner by converting the unstructured text reviews to a set of structured datasets. We performed sentiment analysis on the datasets to reveal consumer sentiment towards a product. The information on consumer sentiment thus generated will be helpful for business decision making by producers.

LITERATURE REVIEW:

Consumer Review and Word of Mouth:

The exchange of views among consumers was very restricted before the advent of the online communication era mainly because of the geographical obstacles and thus predictions about consumer satisfactions were not flawless (Litman and Ahn 1998). The Internet opened up new spaces for consumers where they can exchange their views. In this study, we are considering movie reviews to examine consumers' mood in consumer feedback. The reason behind choosing the movie review database is that in the past people could only access expert reviews that had been mostly published in news papers and magazines and it may be biased by reviewers' own choice. Indeed, online movie forums, such as Yahoo Movies, opened up opportunities for viewers to write their own experiences and thus readers get better chances to inform their decision to watch before viewing movies; thus these reviews reflect emotions and moods of a large pool of viewers about a particular movie. Apart from marketing strategies, consumers' word-of-mouth serves as a very important factor that sets the long-term success of a motion picture (DeVany and Walls, 1996). Online communities maintain a persistent public record of all posted opinions (Dellarocas, Zhang and Awad 2007). Online review research has attracted mainly two groups of professionals. Researchers in marketing and consumer behavior mostly did rigorous textual reviews without utilizing the benefits of technological advancements. The results revealed many important conclusions about customer opinions (see Litman et al, 1998 for a discussion). Researchers in computer science have invented processes and techniques that have the ability to extract and analyze textual reviews automatically without using a vast amount of manual labor (see for example, McDonald, Hannan, Wells, and Reynar, 2007). Unfortunately, in many cases they failed to contribute significantly to the practical world of business. For example, Zuang, Jing, Zhu, and Zang, (2006) discussed about automatic review mining and summarization based on multi-knowledge based approach. However, the authors limited their discussion to the effectiveness of the approach and failed to outline its broader utility and other key information deemed important for the business world. In this study, we will merge both the streams. We will automatically extract reviews from review texts and utilize the extracted information to investigate the effect of consumers' moods and emotions on movie ratings.

Adjective and Adverb words in Sentiment Analysis:

Sentiment analysis is a process of analyzing the underneath sentiment or feeling of a text span (Pang and Lee, 2004). Of late, the understanding of the sentiment and feelings of customers by analyzing the online product reviews has become an important topic in the computer science and business literature. English sentences consist of different types of parts of speech. Adjective, as defined by Oxford Dictionary (Online edition), is "a word or phrase naming an attribute, added to or grammatically related to a noun to modify or describe it." Therefore, the examination of the adjectives that exist in that specific text may help us understand the sentiment underlying a chunk of texts. Many researchers have studied such adjective words in order to explore the underlying sentiments of consumer reviews. For example, Hu and Liu (2004) utilized the text mining technique where they employed the reference of the list of adjectives created by them. Similarly, Zhuang et al (2006) also did review mining considering only the adjective words within the opinion-related words list. Although adjectives are used to express feelings of customers, the adverbs describe the degree of feelings. In other words, adverbs are words or phrases that modify or qualify an adjective (Oxford Dictionary, Online edition). Therefore, as suggested by Benamara, Cesarano, and Reforgiato, (2007), "adjectives and adverbs are better than adjectives alone," which indicates that though the adjectives can be used to express emotion or sentiment, adverbs associated with adjectives are useful to express the degree of emotion. Therefore, in our study, we are going to analyze the adjective words and the respective adverbs to understand the feelings of online reviewers as embedded in the reviews.

Emotions and Mood in Consumer Behavior:

Consumer emotion is a complex construct that is extensively studied in the consumer behavior literature. Laros and Steenkamp (2005) said,

"Emotions are often conceptualized as general dimensions, like positive and negative affect, but there has also been an interest in more specific emotions"

Many previous studies treated consumer emotions as a simple two dimensional construct. For example, Watson and Tellegen (1985) proposed a 'two factor structure' model, which discussed positive and negative effects of consumer affects and extended the concept to high positive-low positive and high negative-low negative emotions. Russell and Carroll (1999) introduced the 'Bipolarity' concept in emotion, such as elated vs. depressed, satisfied vs. dissatisfied and so on. Diener and Emmons (1985) conceptualized the affect words by dividing them in two broad categories such as pleasant and unpleasant. Some authors considered emotions very specifically or divided emotional words vaguely in some subcategories although the divisions were ambiguous and lacked generalizibility.

In addition, researchers contemplated on specific emotions, such as surprise, anger, regret (Laros et al, 2005; Derbaix and Vanhamme, 2003; Inman and Zeelenberg, 2002; Bougie, Pieters, Zeelenberg 2003). In this context, Laros et al (2005) proposed a hierarchical division of consumer emotions (figure 1). The three divisions are ordinate level, basic level, and subordinate level. The extended goal of our project is to divide the review words of our movie dataset into a hierarchical model as proposed by Laros et al. However, in this paper, we will locate the adjective and adverb words (in the review text) which are specifically associated with various explicit ratings specified by the consumers and in future, we will categorize them following the model by Laros et al. as depicted below.

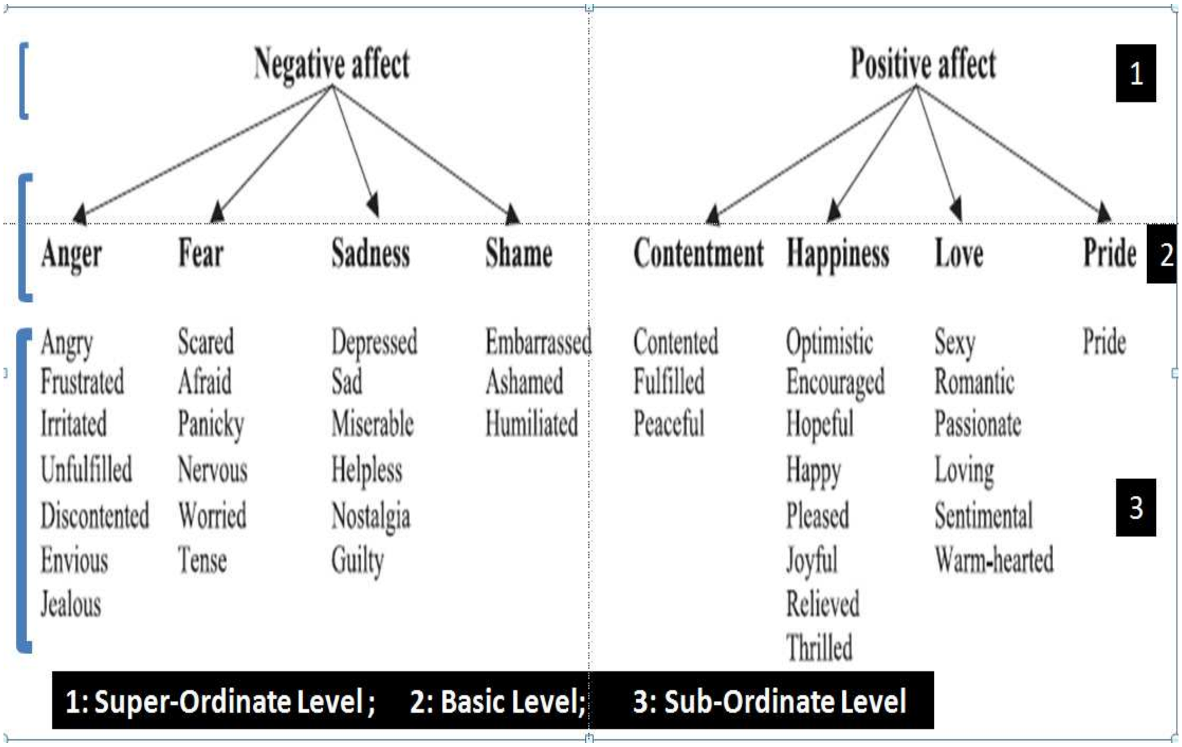


Figure 1: Hierarchical model from Laros et al., (2005)

DATA:

In this study, over 20,000 movie reviews were extracted from an online movie forum (Yahoo Movies). These reviews were assigned to one of the three groups based on their ratings. Thus, three datasets such as A+B+ (for those receiving A+ to B+ ratings), B-C+ (for B- to C+ ratings), and C-F (for C- to F ratings) were created. Then we analyzed the datasets mainly based on adverbs, adjectives, and associated nouns. For the purpose of this current article, we analyzed the dataset of the movie "Balls of Fury" taking it as an example dataset. However, the datasets created from other movie reviews will be included in the future study.

With the help of our extraction system CAINES, which automatically extracts texts from unstructured textual data (here the reviews) to a structured database format, we analyzed consumer's opinions of movies, which revealed consumers' feelings that drove them to use particular words or phrases. Our automated extraction system is less time consuming and has higher reliability than the manual content extraction techniques that have been used in many previous studies (e.g., Litman et al (1998). The extracted adjective and adverb words will be short listed to compare them with symbolic ratings of these reviews. Such comparison will help draw the conclusion about how the intensity and type of reviewers' feelings affects the choice of the levels of symbolic ratings.

METHODOLOGY:

CAINES-The Extraction System:

We built a system called CAINES (Content Analyzer and INformation Extraction System) to perform the data analysis. CAINS is built using Perl as the major programming language and the data are stored using the MySQL relational database management system. CAINES includes several modules available at CPAN (Comprehensive Perl Archive Network) that can be found at http://www.cpan.org/. CPAN includes more than 20,000 modules of software written in Perl (more than 20,000,000 lines of code). The module ligua::en::tagger (available at http://search.cpan.org/~acoburn/Lingua-EN-Tagger/Tagger.pm) is very useful to our project. It can do several syntactic tasks, such as tagging part-of-speech to each word and producing a list of pronouns and noun phrases from sentences.

For example, the paragraph in figure 2, lingua::en::tagger will produce a set of noun phrases as show in figure 3.

> Randy Daytona (Dan Fogler) was a promising ping-pong prodigy when, at the age of 12, he was thoroughly humiliated at the 1988 Summer Olympics in Seoul, South Korea by his showboating German adversary, Karl Wolfschtagg (Thomas Lennon). Now it's been almost two decades since Randy picked up his paddle to play competitively. Ostensibly washed-up, his career has been reduced to performing tricks as a lounge act at a seedy dinner theater in Reno.

Figure 2: A sample paragraph appears in a movie review.

1988 summer olympics in seoul	1	karl wolfschtagg	1	reno	1
act	1	korea	1	seedy dinner theater	1
adversary	1	lennon	1	seoul	1
age	1	lounge	1	showboating german adversary	1
career	1	lounge act	1	south	1
dan	1	olympics	1	south korea	1
dan fogler	1	paddle	1	summer	1
daytona	1	performing tricks	1	summer olympics	1
decades	1	ping-pong	1	theater	1
dinner	1	ping-pong prodigy	1	thomas	1
dinner theater	1	prodigy	1	thomas lennon	1
fogler	1	promising ping-pong prodigy	1	tricks	1
german adversary	1	randy	2	two decades since randy	1
karl	1	randy daytona	1	wolfschtagg	1

Figure 3: a list of noun phrases produced from analyzing the paragraph in Figure

During the sentiment analysis process, we need to see what the movie reviewers wrote. To do so, we put every movie review together in a file and produced a KWIC (Key Word In Context) (Luhn, 1960) file. The sentence "Dan Fogler brings a lot of enthusiasm to his role"for example, appear in the KWIC file as follow:

Dan	Fogler	brings	a	lot	of	enthusiasn	to	his	role
Fogler	brings	a	lot	of	enthusiasn	to	his	role	
brings	a	lot	of	enthusiasm	to	his	role		
a	lot	of	enthusiasm	to	his	role			
lot	of	enthusiasn	to	his	role				
of	enthusiasn	to	his	role					
enthusiasn	to	his	role						
to	his	role							
his	role								
role									

Figure 4: Rows in the KWIC index file containing the sentence "Dan Fogler brings a lot of enthusiasm to his role"

This sentence shows that the reviewer likes Dan Fogler (which is a subject noun phrase in this example) because he "brings" a lot of "enthusiasm to his role."

In general, a sentence consists of a noun phrase and a verb phrase. Each noun phrase can consist of a single word (e.g., "movie," "actor," and "star") or multiple words (e.g., "a good actor," "a long movie," and "great action"). A verb phrase can be a verb with and without noun objects. The sentence, "Dan Fogler brings a lot of enthusiasm to his role" has the following syntactic structure:

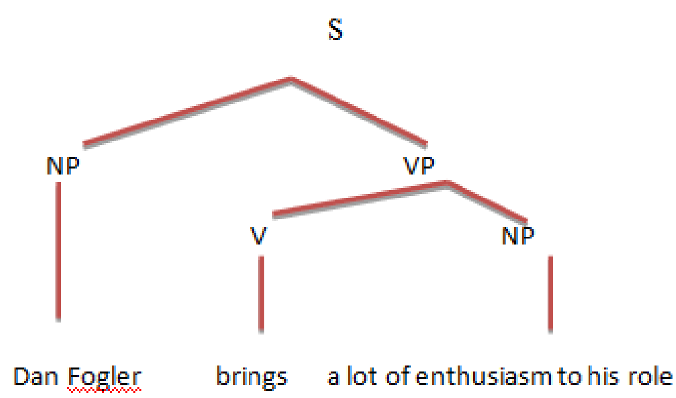


Figure 5: Syntactic structure of a sentence

S- Sentence; NP- Noun Phrase; VP- Verb Phrase; V- Verb;

Thus, to analyze sentiments of a movie, we grouped the reviews according to the ratings they assigned (A+ to B, B- to C, and C- to F). After that, we produced a KWIC file for each category and sorted some columns of the file to see how the words we are interested in appear in sentences. Figure 6 shows a portion of KWIC file containing "very" in columns 4 and some adjectives in column 5

1	2	3	4	5	6	7	8
Dodgeball.	It	Is	very	funny	through	out	the
pretty	good	movie,	very	funny,	and	an	original
this	movie	was	very	funny,	the	only	thing
out	with	friends.	very	funny,	very	entertaining.	thoudg
The	movie	was	very	funny,	with	wierd	quirks
but	hey	still	very	funny.	Go	check	it
This	movie	was	very	funny.	I	will	go
hilarious	and	has	very	good	acting	and	a
players	died.	A	very	good	film.		
sit	and	watch.	Very	good	to	relax	from
Some	good,	some	very	good,	and	some	really
the	movie	wasn\\'t	very	good.			
but	overall	was	very	good.	I	think	the
seem	to	have	very	limited	senses	of	humor
outstanding,	with	some	very	memorable	characters	that	will
Q	is	A	VERY	nice	addition.	Couldn\\'t	really
dont	come	around	very	often.	Look	at	how
but	I	was	very	pleasantly	surprised.	Christopher	Walken
the	plot	was	very	stupid.	but	i	like

Figure 6: Entries in the KWIC file containing the words "very" in columns 4 and some adjectives in column 5

With many of these entries in the database, we are able to analyze sentiments as discussed in the next section.

Thus, the dataset has been generated from textual reviews and is based on the symbolic ratings we extracted from data in different datasets (from N/A to A+, there were 13 categories). To compare and contrast the words/phrases of these categories, we merged them and made three broad categories of datasets, such as A+B+ (for A+ to B+ ratings), B-C+ (for B- to C+ ratings), and C-F (for C- to F ratings). Though we plant to consider reviews of a large number of movies for the final project, we could work with one movie (Balls of Fury) review datasets for this paper.

Content Analysis:

Inductive content analysis, which is done by first examining the patterns of the data and then finding the explanation of those data patterns (Potter and Donnersteinl, 1999), was used to relate the textual words and the symbolic ratings of the reviews.

According to inductive content analysis, to identify the adjectives and adverbs, we needed to look at the words and phrases in the movie review datasets. These words were sorted in some of the columns after generating the KWIC files. In this way we can see the frequencies of the collections of terms that we are interested in.

Data Analysis and Discussion:

The goal of our study is to relate the review ratings and the adjectives/adverbs that express reviewers' feelings inside text reviews. Frequencies of some adjective words are listed in the figure 7 below.

1st Category Words					2nd Category Words			
Adjective	A+B+	B-C+	C- F		Adjective	A+B+	B-C+	C- F
Funny/Funnier	120	74	30		stupid	11	11	43
Like	66	28	0		Better	7	10	20
Good	54	50	30		Dumb	7	7	10
Great	38	26	13		Absurd	1	0	1
Enjoyable	17	9	6		Bad	0	16	40
Best	16	11	9		Boring	0	6	15
Awesome	11	5	1		Disappointing	0	4	12
Cool	10	4	3		Predictable	0	4	0
Nice	8	0	0		Awful	0	2	4
Entertaining	7	12	6		Scary	0	1	0
Amazing	7	0	1		Horrible	0	0	20
Big	7	0	0		Terrible	0	0	9
silly	7	0	0		Unfunny	0	0	5
Favorite	6	0	3		Obvious	0	0	4
Beautiful	4	0	0		Unfortunate	0	0	3
Perfect	3	6	2		Unimaginative	0	0	2
Fantastic	3	1	0		Uninspired	0	0	2
Full	3	1	0		Unoriginal	0	0	2
Damn	2	0	0		Tremendous	0	0	1
					Inexplicable	0	0	1
					Unscrupulous	0	0	1
					Unsettling	0	0	1
TOTAL	389	227	104		TOTAL	26	61	196
	54%	32%	14%			9%	22%	69%

Figure 7: Frequencies of Adjectives

The definition of adjective says, "a word or phrase naming an attribute, added to or grammatically related to a noun to modify or describe it" (Oxford Dictionaries, Online Edition). Therefore, we pointed out the adjectives that were mostly found in our dataset of the movie reviews. All these adjective words can be subdivided into two categories. Firstly, the adjectives occurring most frequently in the higher rated reviews (A+B+) were noted. Secondly, the adjectives that had largest frequencies in the lower rated reviews (C-F) were noted. For example, the word 'awesome' has a frequency 11 for A+B+ rating whereas the frequency for C-F is 1. Therefore, this is an adjective of first category. Similarly, the word 'horrible' has 20 hits in the C-F category whereas there is no entry of this word in A+B+ or B-C+ categories.

1st Category	Amazing, Awesome, Beautiful, Best, Big, Cool, Damn, Enjoyable, Entertaining, Fantastic, Favorite, Good, Like, Nice, Perfect, Funny, Like, Great, Damn
2nd category	Awful, Bad, Boring, Disappointed, Better, Dumb, Horrible, Nothing, Obvious, Predictable, Scary, Stupid, Sucked, Terrible, Tremendous, Inexplicable, unfortunate, Unfunny, Unimaginative, Uninspired, Unoriginal, Unscrupulous, Unsetting

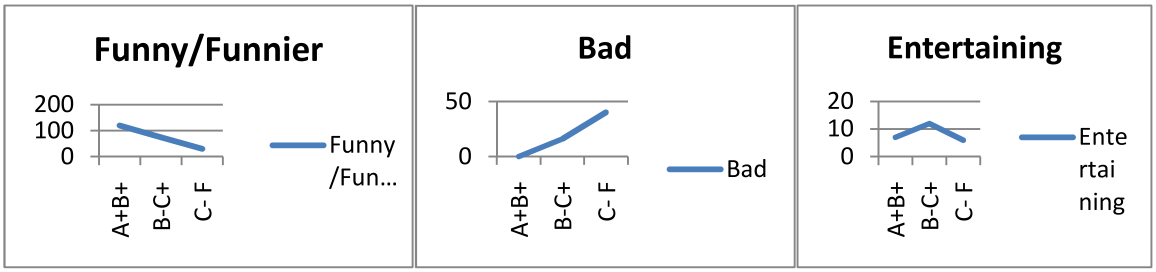
Figure 8: Categories of Adjectives

Another finding from the dataset of figure 7 was that most of the first category adjectives could also be found in lower rated reviews though the frequencies of these adjectives were much lower than their frequencies in the higher rated reviews. However, many second category adjectives did not have even a single entry in the higher rated reviews. For example, the statistics from Figure 7 reveals that the percentages of first category words in A+B+ and C- F groups are 54% and 14% respectively whereas the percentages of second category words in A+B+ and C- F groups are 9% and 69% respectively. Therefore, it can be concluded that the second category adjectives are used more strongly in negative senses than in the positive senses as expressed by the first category adjectives.

Figure 7 also revealed the genre of the movie that we had used. For the current study, we considered the movie 'Balls of Fury,' which is a comedy movie (www.imdb.com). We found that the word 'funny' had the highest frequency of 224that was the highest among the entire list of adjectives. The frequency of 'funny' for the A+B+, B-C+, and C- F category are 120, 74, and 30 respectively, which indicates that the highest rated reviews more strongly support that the movie is a comedy movie.

The slope of frequencies (considering data points for A+B+, B-C+, and C- F rating datasets) for most of the adjective words has monotonously increasing or monotonously decreasing from A+B+ to C-F via B-C+ whereas only 17% of the adjective words have changing slopes (i.e. L pattern) (Figure 9). In other words, the adjectives, which has the highest frequencies for the A+B+ category, also has higher frequency for the B-C+ category than that for the C-F category. This phenomenon implies a monotonously decreasing relationship. For example, the word 'funny' has frequencies of 120, 74, and 30 for the A+B+, B-C+, and C-F category respectively which indicate a steady decrease in frequencies. Similarly, the adjective words, which has the highest frequencies for the C-F category also has higher frequency for the B-C+ category than for the A+B+ category. This reflects a monotonously increasing relationship. Similarly, the word 'bad' has frequencies of 0, 16, and 40 as observed in the A+B+, B-C+, and C-F category respectively, which indicate an increase in frequencies. However, only 17% of adjectives did not follow this pattern and showed a changing L shaped frequency distribution. For example, the word 'entertaining' has frequencies of 7, 12, and 6 for the A+B+, B-

C+, and C- F category respectively. This indicates an increase in frequency first followed by a decrease in frequency. Figure 9 is depicting these features.



Monotonously Decreasing *Monotonously Increasing* *Changing slopes [L]*

Figure 9: Different types of Distribution of Frequencies

As we discussed earlier, adjectives and adverbs are more useful than adjectives alone for the purpose of sentiment analysis because expressed sentiments get stronger when they are associated with adverbs (Benamara et al., 2007). For example, the two chunks of sentences

"… a really stupid plot"

"…. stupid comedy"

express the feeling of stupidity; however in the first sentence, the feeling is much stronger than in the second one. Below are the adjectives and their frequencies from the datasets of the movie "Balls of Fury". It can be noticed that the adverb with negative feelings such as 'not' and 'nothing' were associated more with the lower rated reviews that with the higher rated ones and indeed, there was no entry of this adverbs in the A+B+ rating reviews. Therefore, it can be concluded that adverbial analysis is also useful in order to understand the consumer feedback specifically when it describes the degree of adjectives that define consumer feelings.

Adverb	A+B+	B-C+	C-F
Really	42	21	33
So	31	15	43
Very	26	0	0
Nothing	0	9	11
Not	0	56	10
Definitely	11	5	3
Absolutely	6	2	5

Figure 10: Adverbs and their Frequencies

CONCLUSION:

Content analysis of online consumer reviews is very important to understand the consumer feedback. We were successful in distinguishing between the higher rating related expressions (adjectives and adverbs) and the lower rating related expressions (adjectives and adverbs). Interestingly, we noticed second category adjectives, which had highest frequencies in the C- F group, are more strongly used in negative senses than in the positive senses as expressed by the first category adjectives (having the highest frequencies in A+B+ group). Secondly, adverbs with negative feelings such as 'not' and 'nothing' are associated more with the lower rated reviews (C-F group) and even there is no entry of this adverbs in reviews that obtained A+B+ ratings.

This study contributed to consumer review research by finding interesting facts about consumer reviews. Firstly, the analysis of words contained within text reviews will help to understand sentiments of consumers (here movie watchers). Such analysis will assist the retailers or the producers to understand the consumer behavior. Words may be more expressive and informative than what is reflected by symbolic ratings. Therefore, understanding the association of worded expression with symbolic rating is considered helpful in order to read the psychology of consumers and thus insightful. Moreover, the bulk of textual reviews are difficult to handle while searching for particular patterns of words related to symbolic ratings. In this study, we automatically extracted the bulk of unstructured texts to structured datasets that is a time saving process and will reduce rigorous and continuous work as analyzing the structured data is always easy for scientific investigation.

The limitation of study is that it has used data from only one movie. However, datasets from other movies that we have already extracted will be analyzed in the future to further validate our conclusion. Another limitation of the study is that it analyzed a limited number of words. This study will also be further extended to categorizations and analyses of additional words that specify different types of moods that are associated with different ratings as mentioned in Laros et al. (2005).

CITATION:

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APPENDIX:

Screenshot from Yahoo Movie review database, retrieved on December, 2010