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SENTIMENT RATING ALGORITHM OF PRODUCT ONLINE REVIEWS

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1. Introduction

Spontaneous comments on new products posted by users or customers in the internet are an incredible source of unbiased information. They are testimonies of individual experiences with product usage and/or satisfaction levels. Unbiased feedback has been proven to be unexpectedly hard to obtain. Resulted data from interviews, direct feedbacks, questionnaire, and other similar methods suffer from the influence of the test situation [McGue and Bouchard 1998]. With the rise of Social media, people express themselves without any influence of fear, pressure, intimidation or incentives while giving their opinion. These new media become the center of attention for analytical purposes, both for industrial and academic research, design analytics for example [Lewis and van Horn 2013]. A lot of event specific sentiment analyses have been carried out like stock market trends [Bollen et al. 2010]. Real-time geo-localized tweet analysis has shown to develop efficient and inexpensive applications. For example, they have been effectively used to adapt the emergency situations in the wake of natural disasters [Caragea et al. 2011]. In the same way, an epidemic can be detected based on a certain tweet trend [Palu 2011]. For a designer however, the use of the customer feedback extracted from the internet is still limited.

The other particularity of online product reviews is that the product user motive is either to help others buy the product or make sure no one buys the product in future. So a major part of the review would talk about the salient features of a product linked to its method of usage. Analysing such micro blogs or product reviews carefully may provide a lot of details as to how people uses it, in which scenarios and whether he is satisfied and happy about its usage values and features. Having these as motives, the main objectives of this study are to create a model that:

1. Indicates features a customer is not pleased about
2. Indicates features a customer is pleased about
3. Outlines the overall satisfaction/dissatisfaction
4. Provides keywords of appreciation
5. Provides keywords of criticism
6. Evaluate the modes of usage as described by the customer
7. Detects possibility of sarcasm

The remaining sections in the paper are as follows. Section 2 talks about the related existing works and contributions in this domain. Section 3 explains our proposed framework along with the SENTiment Rating ALgorithm (SENTRAL) which is used to rate the user reviews, isolate the usage scenarios, sacrifices and sarcasm into individual entities. Section 4 is a case study illustrating the use of SENTRAL on a commercial product. Section 5 deals with the validation procedure where the ratings obtained from our system are compared with those obtained from humans before concluding in section 6.

2. Literature review

2.1 Online customers' data analysis

Understanding the customer is a crucial issue for product design. The difficulty of capturing the voice of the customer orally in person can now be compensated with the opinions that customers leave on internet. The analysis of opinions aims to provide professionals and developers with an overview of the customer experience and ideas that provide clues or evidence for designers to better interpret the voice of the customer [Liu 2013]. The first interest is to enrich the customer database, very useful in Customer Relationship Management for example [Buttle 2003]. The first domain using online reviews is the marketing to find the strategic goals and identify the customers [Berry 1997] and customer service [Bennekom 2002]. Increasingly, the design sector employs the webblogs and product review to target relevant information for designer [Kushal 2003], [Tucker 2011]. To analyze these online reviews, computer tools like the General Inquirer [Stone 1966] are essential. Ike and Harway [1974] propose a method attempting to reduce the choice "a priori" word classes.

After a phase of cutting and clean (determiners, prepositions ...), the synonymous words are gathered. Occurrences of the remaining words are calculated and presented as a matrix of correlation between each other. These interactions help to keep the meaning of the text underlining the main topics. In linguistics, POS tagging (part-of-speech tagging) is the process of combining the words of a text as the corresponding part of speech information grammatical, gender, number, etc... using a software tool [Nazarenko 1995]. Syntactic analyzes can then be used to determine the combinations of words or the most frequent grapheme. It may be noticed that in all cases, the structure is similar: (1) Data retrieval and preparation (2) Text processing (3) Analysis.

The freedom given to the online reviewers allows them to express some feelings and sentiments. Particularly on twitter, it is believed that sentiment in public media plays a big role in the decision making process of the end users [OConnor 2010], [Bollen 2011], and hence collective sentiment in social media may induce consumer preferences and impact buying decision.

2.2 Natural language processing (NLP)

Textual information in the world can be broadly categorized into two main types: *facts* and *opinions*. Facts are objective expressions about entities, events and their properties. Opinions are usually subjective expressions that describe people's sentiments, appraisals or feelings toward entities, events and their properties [Liu 2010]. Pak and Paroubek [2010] created a model to classify data as subjective and objective. Sentiment analysis, the process of extracting the feelings expressed in a text, is considered as one of the methods of Natural Language Processing (NLP). This is an area of research that involves the use of computers to analyse and manipulate natural language with minimum human intervention for interpretation. In order to construct a program that understands human language, 3 main bases are required [Chowdary 2003]: Thought Process, Linguistic representation, World Knowledge. NLP is carried out in parts starting from word level to understand the Parts of Speech, then to sentence level in order to understand the word order and meaning of the sentence and then the entire text as whole to lift the underlying context.

Liddy [1998] explained that language is understood in 7 interdependent levels by humans and must be integrated in computer programs to replicate it. They are: (1) Phonetic level (2) Morphological level (3) Lexical level (4) Syntactic level (5) Semantic level (6) Discourse level and Pragmatic level. Phonetics deals with the pronunciation, the smallest parts of a word like suffixes and prefixes are related to the morphology. Lexical level is the parts of speech and syntactic level deals with the structure of the sentence and the order of the words. Meanings of word and sentences are understood at the Semantic level where as knowledge exterior to the document is classified in the pragmatic level. Our system involves 4 of the 7 levels; Morphological, lexical, syntactic and semantic level. Several works had to be studied in order to understand these methodologies.

Though tweets are used for diverse reasons and the context of each tweet is different, they can primarily be grouped into two categories. One category shares personal issues while the other spreads information and creates awareness among the online community [Naman et al. 2010]. A number of biases are possible while conducting an opinion survey. The most prominent of them all is called the

Bradley effect in which the responders are unwilling to provide accurate answers, when they feel such answers may reflect unpopular attitudes or opinions. To overcome this effect, automated polling approaches, known as opinion mining were introduced. These automated polling approaches overcome most of these biases naturally. It was extended to sentiment analysis in [Johan et al. 2011] using POMS (Profile of Mood States) and [Hu and Liu 2004] using POS (Parts of Speech).

3. Methodology

The methodology follows 3 steps:

- Extraction of data from website and pre-processing (reduction of the noise, classification of words) with the aid of Perl script API and Stanford CoreNLP tokenizer,
- Text processing (organised as tree of dependency) with the aid of Stanford Parser and Probabilistic Context Free Grammar (PCFG),
- Extraction and analysis of the sentiments: locally with the aid of DAL (*Dictionary of Affect Language*) and globally with our SENTRAL algorithm.

Each step is described in the following sections.

3.1 Extraction of data from website and pre-processing

Data crawling

Three websites are selected to obtain data: Twitter, Amazon and Flipkart. The main reason is the publicly of their data, available with Perl script API's. Basically 2 types of data are obtained: Tweets and User review data. A tweet is a micro blog, as shown in Figure 1, limited to 140 characters, containing normal text in addition to targets denoted with a "@" symbol, hash tags (#) to group words from different tweets and smileys (emoticons).

@jcdave The iPhone 5 is a waste of money, you end up paying 200 grand more than any other phone with same features ☹ #apple #disappointed	The new sound box by #Bose is an absolute marvel. Crystal clear sound :D I am so happy I decided to invest in this system ☺

Figure 1. Example of tweets that review a product

Another place to express feelings is a product review on commercial websites without character constraint (example hereafter).

Since the maximum number of characters in a tweet is 140, they have a lot of constraints to deal with. This constraint becomes an advantage for textual analysis because the user has no place to ramble, thus expresses quickly and directly his feelings. A tweet consists of the combination of entities: the content, Hash tags, URLS, targets, acronyms and emoticons. Since there is a character constraint, users tends to use a lot of acronyms like "lol" which means "Laugh Out Loud", short forms like "bcoz" in place of "because" and alpha numeric short forms like "p6" instead of "physics" etc. Certain tweets are targeted at specific users and are denoted with the "@" symbol followed by their name. Hash tags are used to group data based on certain user defined topics. They are denoted by "#" followed by the word. URL are provided by certain users to mark references or proofs. Twitter automatically shortens these links to 20 character phrases to minimize character usage. We created thus an acronym/symbolic dictionary from an online resource that contains meaning for all these commonly used acronyms and action of the symbols used.

Unlike tweets, there is no restriction to the size of a product review. The data are extracted with Perl script API from amazon.com and flipkart.com. A user review consists of the following information: the date of the review, the number of stars or rating in a scale of 0 to 5, the location of the user, the content of the review and also a count of the number users agreeing with the review to eliminate plagiarism and misleading customers.

Data pre-processing

As our objective is to find out the sentiments and usage objectives of the customer, there is a lot of noise in the data that is crawled and hence needs to be filtered before it is taken forward in the process. This step is a filtration of the text extracted: each word is categorized thanks to an original list of acronyms (Stanford CoreNLP tokenizer [Manning et al. 2003]). For example, NNP is a singular proper noun, VB is a verb on its basic form, PRP a personal pronoun, RB an adverb. All standard acronyms are expanded using this list and the ones not found in the dictionary are ignored and removed from the sentence. All URLs are removed as they do not help the performance of the system in any way.

Figure 2 illustrates the data pre-processing for the sentence "This product is very good" where one can find a descriptive determiner (ND), a common name (NN), a verb VB2, an adverb RB and an adjective JJ.

Before : `This product is very good http://tinyurl.com/n2hboap`
After: `This/ND product/NN is/VB2 very/RB good/JJ`

Figure 2. Example of pre-processing of a tweet

3.2 Text processing

Parsing and creation of dependency trees

Parsing is the process of breaking down the sentences to words and finding out the grammatical relations between these words. Probabilistic Context Free Grammar (PCFG) is based on the study of language gained from hand-parsed sentences to try to produce the most likely analysis of new sentences. A list of dependencies is obtained and a tree is created. This model proposes 55 kinds of possible grammatical dependencies between words in the English language. A standard dependency is written as: Relation(governor, dependent). For instance, for the sentence “This product is very good”, "This" associated to "product" is a nominal group (NP). "is" is the verbal group (VP) and "very" and "good" is a qualificative group (ADJP). We define grammatical relations defined in a hierarchy so as to arrive at the intended meaning. Using the dependency list and the hierarchy, we are able to create the dependency. The result of the parsing, dependencies and tree is given Figure 3.

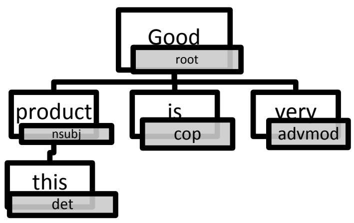
Parsing:	List of dependencies	Dependency tree
(ROOT (S (NP (DT This) (NN product)) (VP (VBZ is) (ADJP (RB very) (JJ good)))))	det(product-2, This-1) nsubj(good-5, product-2) cop(good-5, is-3) advmod(good-5, very-4) root(ROOT-0, good-5)	

Figure 3. The stages of text processing

We want to focus on the feelings and the modes of usages expressed by the user. The full list of relations is reduced for us to acomp (adjective complement), advmod (adverbial modifier), amod (adjectival modifier), neg (negation modifier), aux (auxiliary) and mod (modifier). These are the ones that allow the expression of opinion and physical activities as demonstrated in the sections that follow.

3.3 Extraction and analysis of the sentiments

Local sentiment analysis with DAL

In the dependency list, the relations are binary in nature. To carry out the process of finding the sentiment rating, we propose the SENTRAL algorithm that uses the Dictionary of Affect Language (DAL). The DAL [Whissel 1989] scores each of the 200,000 English words based on the pleasantness it evokes in the human mind. It is on a scale of 1 to 3 where 0 means the most unpleasant and 3 means the most pleasant. We normalize this score on a scale of 0-1 to suit out algorithm. Table 1 presents some words of tweet (Figure 1) with their DAL score. For adjectives, the scores from the DAL can be directly assigned. The meaning of the adjective will change based on the presence of a modifier before or after it. For example, the word "good" and the word-cell "very good" evoke different levels of appreciation. There are basically 2 types of emotions; good and bad. The emotional guidance system [Bryne 2006] of humans indicates that a person is happy and satisfied if he is in alignment with his requirements. After the dependency tree is created, the words with the tags of advmod and amod are assigned the pleasantness score by comparing it with the DAL.

Table 1. Example of the pleasantness rating of words in the Dictionary of affect language

Word	DAL Score
Money	0.8889
Phone	0.4375
Waste	0.0000
Marvel	1.0000
Happy	1.0000
Investment	0.7222

Global sentiment rating with our SENTRAL algorithm

We finally choose a 0-5 scale to globally rate the sentiment of the reviews through our SENTRAL algorithm in order to further compare with customer reviews which are most of the time appraised on such a scale. The SENTRAL algorithm uses the dependency tree, traversing from the last leaf till the root by progressively evaluating the grammatical relations encountered. Each time a dependency relation is considered two words are compared: $S_{governor}$ and $S_{dependent}$ which have their respective DAL scores. For the dependency relation advmod (adverbial modifier), we propose the specific sentiment rating algorithm of Figure 4. We are influenced by the thresholds of segmentation of 0.55 and 0.4 obtained from the guidelines of DAL [Whissel 1989]. A working illustration of this algorithm is shown in Figure 5.

If ($S_{governor} \geq 0.55$ and $S_{dependent} \geq 0.4$)
{ if $S_{governor} \leq S_{dependent}$
$$S_{tag} = \frac{(S_{governor} + S_{dependent})}{2} * 5$$
else $S_{tag} = (S_{governor} + S_{governor} * S_{dependent}) * 5$ }
If ($S_{governor} \geq 0.55$ and $S_{dependent} \leq 0.4$)
{ $S_{tag} = (S_{governor} - S_{governor} * S_{dependent}) * 5$ }
If ($S_{governor} \leq 0.55$ and $S_{dependent} \geq 0.4$)
{ $S_{tag} = (S_{governor} - S_{governor} * S_{dependent}) * 5$ }
If ($S_{governor} \leq 0.55$ and $S_{dependent} \leq 0.4$)
{ if $S_{governor} \geq S_{dependent}$
$$S_{tag} = \frac{(S_{governor} + S_{dependent})}{2} * 5$$
else $S_{tag} = [1 - (S_{governor} - S_{governor} * S_{dependent})] * 5$ }

Figure 4. Sentiment rating algorithm for adverbial modifier relation *advmod(governor,dependent)*

`nsubj(difficult-4, It-1)`
`cop(difficult-4, is-2)`
`advmod(difficult-4, very-3)`
`root(ROOT-0, difficult-4)`
`aux(use-6, to-5)`
`xcomp(difficult-4, use-6)`
`det(control-9, the-7)`
`amod(control-9, remote-8)`
`dobj(use-6, control-9)`
	`advmod(difficult-4, very-3)`
	`(0.1818 , 0.4165)`
	
	$S_{tag} = [S_{governor} - (S_{governor} * S_{dependent})] * 5$
	$S_{tag} = [0.1818 - (0.1818*0.4165)]*5$
	$S_{tag} = [0.1818 - 0.07571]*5 = 0.5304$

Figure 5. Example of sentiment rating for an adverbial modifier relation

The second step is to check if the ROOT word's POS tag is JJ (adjective) or adverb and the DAL scores are assigned directly. If no such tags are found, it means no sentiment has been expressed and the sentence is ignored. After this process we have the separate scores of all the related words, sentences and the paragraph. The score of the jth sentence is given by eq (1).

$$Sentence_j = \frac{\sum Dependency\ tag_{ij}}{i} \quad (1)$$

where "dependency tagij" denotes the score of the ith tag in sentence j.
The score of the entire text is given by eq (2).

$$Sentiment\ score = \frac{\sum Sentence_j}{j} \quad (2)$$

The words that do not figure in the DAL are ignored since almost all words in the WordNet [Miller 1995] dictionary are found in this and the probability of a common word missing is very weak. All nouns that have an adjective close to it are grouped together. Negations words like 'not' 'cannot' 'shouldn't' are dealt in such a way that the scores are inverted for the words. For the non English words, the list of words not found even in the WordNet dictionary is given, with a neutral value of 0.5. Finally, once the score of a sentence calculated, one can consider that the feeling of the customer is approximately given by Table 2.

Table 2. Sentiment score legend

Scores	Conclusion
$0 \le S_{review} < 2$	Sad and unsatisfied
$2 \le S_{review} < 3$	Indifferent, happy to use with sacrifices
$3 \le S_{review} \le 5$	Happy and satisfied

4. Case demonstration

In order to demonstrate the SENTRAL sentiment rating algorithm, a general usage product has been selected from an online product provider with an active feedback forum, in form of text and an overall note from 0 to 5. The selected product is a home theatre system (see Figure 6). 15 reviews (from different reviewers) are crawled from the feedback forum website.

Amazon Product Code: B003B8VBJ2 - **Sony BRAVIA DAV-DZ170 Home Theatre System (Electronics)** Review: Well, Sony definitely let me down on this one. First off this unit was easy to set up. It took longer to run the wires across the room than it did to actually hook it up. But the volume on this was sub-par. Even on the max level volume (35) it still wasn't that loud. The main problem was the amount of bass that it produces. The bass is so overpowering that you can barely even hear people talking in the movie, and there is no way to adjust the levels at all.

Figure 6. A review of a home theatre system

To follow the methodology proposed:

- Step 1- Extraction of data from website and pre-processing. The 15 comments are extracted and sequenced by sentences. Let u take the example of: "It took longer to run the wires across the room than it did to actually hook it up"
- Step 2- Text processing (organised as tree of dependency). The Stanford Parser is used to establish the dependencies network. It gives: “It/PRP took/VBD longer/RB to/TO run/VB the/DT wires/NNS across/IN the/DT room/NN than/IN it/PRP did/VBD to/TO actually/RB hook/VB it/PRP up/RP ./.”. Using this, we obtain the dependency list from the parser again that arranges words in such a way that all grammatical relationships are established between the words. Following this step, we are able to create a dependency tree as shown in Figure 7.
- Step 3: Extraction and analysis of the sentiments in the message. SENTRAL identifies the following tags and assigns them the DAL score and calculates the score of the individual tags as Stag.

advmod(took-2, longer-3): *advmod(0.33,0.4375)* $S_{tag} = 0.94$

advmod(hook-16, actually-15): *advmod(0.55,0.33)* $S_{tag} = 1.84$

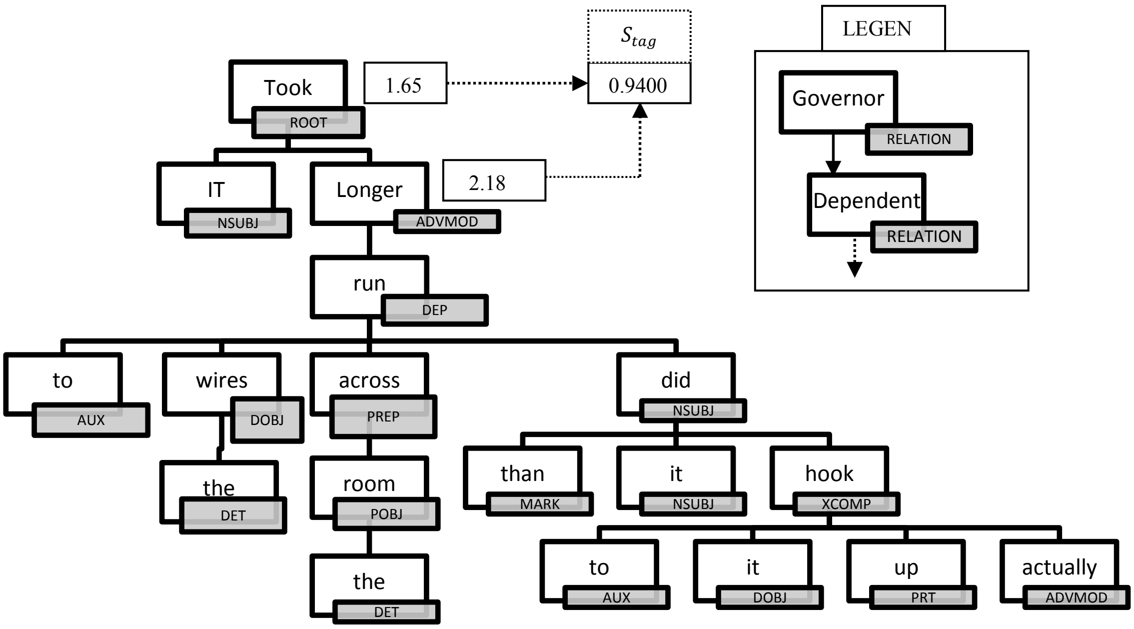


Figure 7. Dependency tree of a sentence for a technical review on the home theatre system. The same procedure is carried out for all sentences iteratively (see scores in Table 3) and the score is obtained for the review as whole using equation 3

Table 3. Scores for the sentences in the review

Sentence	Score
Sentence 1	1.016
Sentence 2	2.325
Sentence 3	1.39
Sentence 4	N/A
Sentence 5	1.8052
Sentence 6	N/A
Sentence 7	1.0675

$$S_{review} = \frac{\sum S_{Sentences}}{Number\ of\ valid\ sentences} = \frac{1.016+2.325+1.39+1.8052+1.0675}{5} = 1.52074 \quad (3)$$

The total score of emotion found by our algorithm is then 1.52 on a scale of 5. According to our values in Table 2, the sentiment expressed by the user is "sad" and "dissatisfied" regarding his experience with the product. On simple reading of the text in Figure 6, we can come to a conclusion that the user is not happy with the usage of the product, our brain recognizes this from words like *"let me down", "overpowering", "the main problem", "it took longer"* etc. The cognitive senses of the human brain put these together and come to a conclusion about the sentiment expressed. Instead, if the sentences like *"I am so happy", "excellent", "flawless"* etc had been used, it would give a very positive outlook to the reader and hence would have obtained a good score in our model (> 3).

5. Validation

The model that we propose basically replaces the human function of understanding and interpreting a text. We propose to validate our model by asking humans to do exactly the same task that our model performs rate reviews on a scale of 0-5. For this, a poll was conducted online. Around 40 respondents from different countries, who had sufficient competence in English language as well as technical knowledge about Home theatres were asked to read all the reviews and rate them on this scale based on what their mind evokes about the satisfaction expressed in the reviews. The question posed was the following: "*This questionnaire contains reviews about a Home Theatre system written by different users. After reading, please rate these reviews on a scale of 0-5 based on what you feel is the satisfaction level of each of these users. I request your kind patience and help me with my thesis. Thanks a lot in advance :)*". The results obtained from the poll are summarized in Table 4.

Table 4. Results from the online questionnaire

Rating number	1	2	3	4	5
1	2	0	17	19	0
2	15	18	2	3	0
3	0	0	2	6	30
4	0	2	4	15	17
5	0	3	19	15	1
6	1	1	13	19	4
7	3	11	10	11	3
8	17	13	5	3	0
9	0	6	10	18	4
10	3	15	14	6	0
11	2	3	18	15	0
12	0	1	6	17	14
13	0	1	14	21	2
14	0	1	9	15	13
15	17	9	4	7	1

In this table, each column denotes the number of persons who have voted for that particular rating, 1 being the least satisfied and 5 being the most satisfied based on their inference after reading the reviews. The scores being well divided (unimodal repartition), the mean is calculated and given in Table 5. The weighted average is then compared with the score obtained from SENTRAL in Figure 8 to find out the MSE between the two. This error is rather weak (see Table 5) since the average of errors is 1.3% and the average of absolute error values is 6.42 %.

Table 5. Weighted scores of the votes

Review Number	Average human ranking	SENTRAL's Score	Error	%Error	SE
1	3.39	3.21	0.181487	3.60%	0.032938

2	1.81	1.07	0.748289	15%	0.559936
3	4.73	4.21	0.523385	10.50%	0.273932
4	4.24	4.05	0.186842	3.70%	0.03491
5	3.37	3.33	0.038439	0.80%	0.001478
6	3.63	3.48	0.154079	3.10%	0.02374
7	3	3.46	-0.45653	-9.10%	0.20842
8	1.84	1.88	-0.03446	-0.70%	0.001187
9	3.53	2.86	0.670878	13.40%	0.450077
10	2.61	2.43	0.172513	3.50%	0.029761
11	3.21	3.47	-0.25704	-5.10%	0.06607
12	4.16	3.95	0.212217	4.20%	0.045036
13	3.63	4.65	-1.0138	-20.30%	1.02779
14	4.05	4.21	-0.15993	-3.20%	0.025578
15	2.11	2.1	0.002916	0.10%	8.5E-06
				MSE	0.185391

Human-computer interaction research often involves experiments with human participants to test one or more hypotheses. We use ANOVA (Table 7) to test the hypothesis of whether the difference between results obtained from SENTRAL and the online poll to rate the sentiments (Table 5 column 2&3) are significant *(H1)* or not *(H0)*. The ANOVA result is reported as an F-statistic and its associated degrees of freedom and p-value. The individual means for SENTRAL and Human rating were 3.29 and 3.22 respectively. The grand mean for both types of sentiment rating is 3.255. As evident from the means, the difference is only 1.92%. The difference is statistically insignificant with ($F_{1,\,28} = 0.034093$, $p > .005$). Hence the null hypothesis *H0* was accepted and *H1* was rejected, which by extension, validates our model.

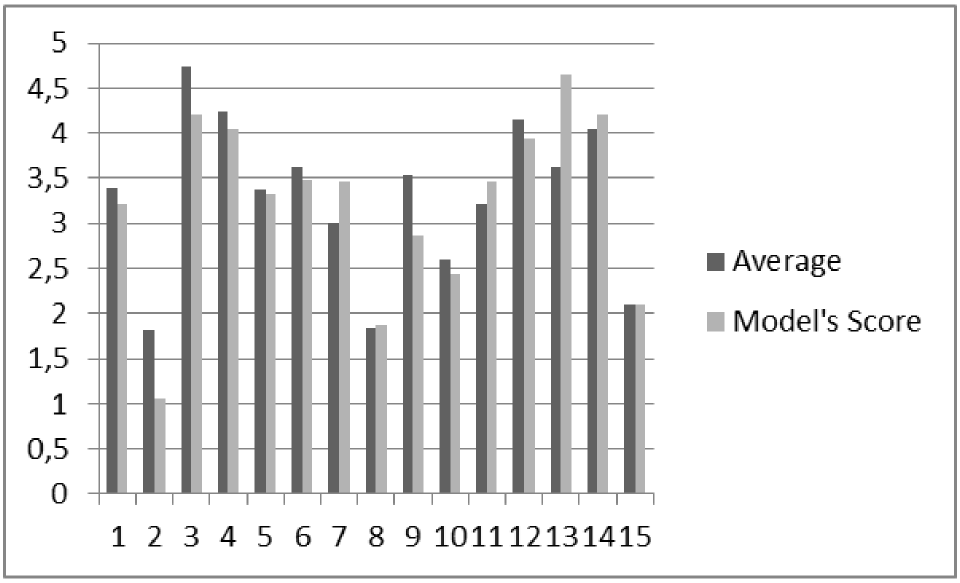


Figure 8. Comparison of weighted values of votes and ratings obtained from SENTRAL

Table 6. Student-t test for correlation

Correlation test(student t test)	
Correlation coefficient	0.896425516
tTab	0.063928134
tcal	7.292754614
Correlation	YES

Table 7. ANOVA table

Anova: Single Factor	*H0:*	The difference between SENTRAL's score & human ratings is not significant
	H1:	The difference is significant.

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
Weighted Average obtained from human ranking	15	49.31	3.287333	0.775278
Model's Score	15	48.36	3.224	0.989483

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	0.030083333	1	0.030083	0.034093	0.854839208	4.195971819
Within Groups	24.70665333	28	0.88238			
Total	24.73673667	29				

ANOVA Result: *F crit (Column 7)> F (Column 5)* Accept hypothesis H0

6. Conclusion

After analysing the results, we conclude that there is a good level of correlation between the results obtained from our SENTRAL algorithm of sentiment rating and customer appraisals. The error obtained might be due to reasons like the lack of quality of English language, improper use of grammar and also typographical errors in the reviews. Overall the model is validated since the errors are extremely small and the results obtained from the model can be of great interest to product designers. A lot of time may be saved since all the reviews are not required to be read by them and they can just easily and quickly obtain a key information from our model that is relevant to their needs and requirements. This model can also be used to find out the global satisfaction of a particular product in the market by comparing the satisfaction scores of similar products. It can possibly be used to find out the trend of a product and be used to predict the performance in the future as well. It also requires certain extensions of the current model to isolate pleasant and unpleasant product features for informing designers with good feedbacks on a recent product of their company or of one competitor's.

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