Improving Review Selection Using Deep Learning

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***Abstract*: -** Visiting any product based or service based website, one can see numerous reviews content on various products and services. Given the proliferation of review content, and therefore the proven fact that reviews are very much descriptive and sometimes irrelevant to the product or service. The reviews must be concise, short and with related to the product being it is written. Our approach is three step approaches: Make a small set of words say Entity set which will help us to find the relation of review and product entity, match the reviews with set of possible words contains in review and formulate the problem to find optimal count using Deep learning Method. The approach of this method to compare two sets of data with the minimal number of comparison and find the similarity between two sets and provide result according to it. The resulted data count of review will be in the set of five possible outcomes viz. Excellent, Good, Neutral, Bad, and Very Bad.

Keywords: Reviews, review selection, deep learning

1. Introduction

Now days, one can find plentiful review content in various web sources. For instance, Amazon.com is a popular ecommerce website which deals in various numbers of products and it also provide facility to customers of feedbacks and reviews regarding of the product. Again, Yelp.com is a popular site for restaurant and hotels reviews, which gives the better suggestion to chalk out dinner plan at restaurant. While useful as well, the deluge of online reviews also poses numbers of challenges. Readers are some time annoyed by the information overload, and it is becoming increasingly harder for them to decide out the reviews that are worthy of their attention or not. This is worsened by the length, verbosity and irrelevant data over of many reviews, whose content may not be completely relevant to the product or service being reviewed. Reviewers often digress, detailing personal anecdotes that do not offer any insight about the item or place being reviewed. Furthermore, it is getting increasingly more difficult to determine whether a review has been written by a genuine customer, or by a spammer [1].

1.1 Identification of Review

Identifying and choosing top quality, authentic reviews could be a exhausting task, and it's bee n the main target of considerable quantity of a nalysis. With the recent growth of social networking and small blogging services, one has a tendency to observe the emergence of a replacement form of online review content. This new style of content, that termed as micro-reviews, will be found in micro-blogging services that permit users to “check-in”, indicating their current location or activity. For example, at Amazon, users login for clothes, daily needs product or jewelry etc. After buying product, a user may choose to write a review up to 200 characters long, about their experience, effectively a micro-review of the place. In addition to Amazon, there also are different sources for micro-reviews in many domains. For instance, Facebook Places, Find My Friends and Favorite feature similar services [1].

In the case of a DSLR camera, reviews are more important when it is talking about quality of picture, brand of camera, camera lenses and price range. Here review or tips are frequently recommendations (e.g., what to order), opinions (what is great or not), or actual "tips". For example, "Nikon has better white balance and vibrant color range than Cannon, but it is expensive". This kind of tip is an actual tip what to buy or not.

1.2 Micro-Review

Micro reviews feature another supply of content to reviews for readers curious about finding info a few places. They need many benefits. First, because of the length restriction, micro-reviews square measure apothegmatic and distilled, distinctive the foremost salient or pertinent points concerning the place. Second, as a result of some micro-reviews square measure written on website, right once the user has checked in, they're spontaneous, expressing the author's immediate and pure reaction to consumer's expertise. Third, as a result of most authors sign up by mobile apps, these authors square measure possible at the place once exploit the information, that makes the information a lot of possible to be authentic. Micro-blogging sites even have the power, if necessary, to filter tips while not associate incidental to sign up therefore, boosting the genuineness of the information. Micro-reviews and reviews nicely complement one another. Whereas reviews square measure extended and prolix, tips square measure short and apothegmatic, specializing in specific aspects of associate item [1]. At a similar time, these aspects can't be properly explored at intervals two hundred characters. This is accomplished in full-blown reviews that elaborate and ponder on the intricacies of a selected characteristic. Marrying these 2 completely different reviewing approaches will yield one thing bigger than the total of their parts: elaborate reviews that specialize in aspects of a venue that square measure of true importance to users that take into account the subsequent downside. Given a set of reviews and a set of tips on an item, one would like to pick out a tiny low range of reviews that best cowl the content of the guidelines. This downside is of interest to any on-line web site or mobile application that desires to showcase a tiny low range of reviews.

1.3 Relevance of Reviews:

Since reviews are used for several decision-making purposes it is important to assess their quality. Reviews are used to access quality of scientific publications, to provide feedback on different products etc.

Apart from containing useful content and a positive tone a review should also be **relevant** to the work being reviewed and **relevant** to and existing well-written and coherent review.

Relevance between two pieces of text can be determined by identifying

i) **Semantic** similarities

ii) **Syntactic** similarities.

- **Semantic Similarity**: - A sentence and a tip may discuss the same concept (e.g., a menu dish), but use different words (e.g., soup vs. broth). In this case one can say that they have high semantic similarity. Latent Dirichlet Allocation: LDA associates each tip t with a probability distribution t over the topics. For each topic as it is learnt from the tips, the system can estimate the topic distribution for T and this topic modeling use for each review sentences [4].
- **Syntactic Similarity**: - Every opinion having their sentiment which reflects from sentence positive, negative or neutral. Hence, in addition to sharing syntactical similar keywords, semantic similarity of word and concepts, the system would also like a matching Review sentence-tip pair to share the same sentiment (positive or negative). The system defines the sentiment similarity between a Review sentence s and a tip t as the product of their polarities: it approaches 1 when the sentence and the tip polarities are similar; it approaches -1 when their polarities are opposite. It approaches 0 when the tip or the sentence polarity is neutral [4].

1.4 Motivation

The motivation of review selection can be describe by an example. A person wants to purchase a product from an e-commerce website. There are various websites which are providing same product for different or same prices. The customer will choose one of the sites and then he will go to the section of reviews. In the review section, sometime there are large no of reviews written and customer may get confuse. Sometime reviewer writes about the product nicely but in the star rating he provides 3 star out of 5. Sometime reviewers gives negative review about product but gave 5 star for the service of the web source. Due to this, the consumer will get confuse to buy that product or not as he can't relate the relation between the star rating and review on the same product. So to overcome this issue, Review selection system is provided that will analyze all the reviews and make them short and easy to understand as well as categories them in five categories like Excellent, Good, Neutral, Bad and Very Bad on the basis of the words written inside the review which helps consumer to understand what exactly reviewer want to say regardless of star rating.

2. Related Work

Evaluation of review starts with text analysis techniques and their targeted consumer to assess the relative effectiveness of different strategies. Evaluation is get started by the lack of annotated corpora for many of the consumer applications and individual text analyses of software. This is mostly due to the need to involve human subjects to judge the output since software engineering is basically a human task. Most studies involve only a few human subjects on a few examples because it is too costly and time consuming to scale up these evaluations.

Here essential focus was on analysis of feature location techniques, FLTs, as client side applications of text analysis. Locating code associated to a targeted feature set is often a software developer's first step in performing a software maintenance goal. Researchers have developed Feature Location Techniques (FLTs) as well as static, dynamic, and hybrid approaches, using various forms of text analysis, to help software professionals to identify relevant code that is often scattered across a large, complex software system. Feature location is one of the key software maintenance tasks used to measure the usefulness of different text analysis techniques for software package [3].

The key challenge in the analysis on usage knowledge rather than skilled judgments is correctly decoding the gathered knowledge through rigorously relating the evident statistics to the standard of the techniques underneath analysis. Once applied to guage web search engines, paired interleaving achieves an internet comparison of result sets related to totally different computer program techniques. the 2 result sets, every from separate computer program technologies, area unit integrated into one interleaved set, that is given to the user such the determined user behavior, within the kind of click through, is indicative of a preference for a selected computer program. It is tend to believe that paired interleaving can even be applied to gauge the relative effectiveness of two FLTs, or FLTs with totally different text analysis or preprocessing. The analysis is conducted by recording implicit feedback (click through data) throughout traditional computer code developer interaction with a feature location tool that embeds and interleaves the responses of various complete approaches to feature location. The relative preference for one approach over another is indicated by a preference for the results of a FLT over another, within the span of a group of queries by variety of developers. [3]

2.1 Semantic and Sentiment Orientation of Customer Reviews

Sentiment analysis or opinion mining could be a sub-division in the text mining, to consider subjectivity, sentiments, affects and other features of emotions within the text found in the other on-line web sources. Opinion mining is in relevance to computational techniques which are utilized to extract, assess, understand and classify the numerous opinions that are expressed in a variety of online social media comments, news sources and other content are also created by the user. Sentiment is a view, feeling, opinion or assessment of a reviewer for some product, entity, event or service [4]. Sentiment Analysis or Mining of Opinion is a challengeful task for the Text Mining and Natural Language Processing (NLP) problem for automatic extraction, classification and making summarization of sentiments and emotions expressed in online text. Sentiment analysis is being replaced the traditional and web based surveys conducted by companies for finding public opinion about entities like products and services. Sentiment Analysis also assists personals and all types of organizations interested in knowing what other people comment about a particular product, service topic, issue and event to find a choice for which they are looking for. Sentiment analysis is of nice worth for business intelligence applications, wherever business analysts will analyze public sentiments regardi ng product, services, and policies. Sentiment Analysis within the context of state Intelligence aims at extracting public views on government policies and selections to infer attainable public reaction on implementation of bound policies [7].

Feature based sentiment analysis embrace feature extraction, sentiment prediction, sentiment classification and elective report modules. Feature extraction identifies those product aspects that area unit being commented by customers, sentiment prediction identifies the text containing sentiment or opinion by deciding sentiment polarity pretty much as good reviews and unhealthy reviews and at last report module aggregates the results obtained from previous 2 steps. Feature extraction method takes text as input and generates the extracted options in any of the forms like rhetorical, syntactical and Discourse primarily based. Sentiment analysis permits for a higher understanding of customers' feelings relating to numerous corporations, their product and services or the manner they handle client services, moreover because the behavior of their individual agents. It may be wont to facilitate in client relationship management, staff coaching, distinguishing and breakdown troublesome issues as they seem [9].

In sentence level sentiment analysis, the text document or reviews are divided to one by one sentences and each sentence is checked for its semantic orientation with the use of lexical or statistical techniques. It can be associated with two tasks. The first of these two steps is to identify since the sentence is subjective or objective. In the second step, subjective sentences get classified into positive sentences, negative sentences or neutral sentences. Which sets the polarity according to that? Sentence level semantic orientation is important because it takes each sentence individually for semantic orientation. Natural Language Processor (NLP) strategies square m easure helpful for such forms of linguistics ori entations. Sentence level analysis decides what the primary or comprehensive semantic orientation of a sentence is while the primary or comprehensive semantic orientation of the entire document is handled by the document level analysis. Many approaches have been adopted for performing sentiment analysis on social media sites. Knowledge primarily based approaches classify the feelings through dictionaries shaping the sentiment polarity of words and linguistic patterns. However, the text documents or reviews are split down into sentences for sentiment analysis at the sentence level. These sentences are then evaluated by utilizing lexical or statistical methods in order to determine their semantic orientation [3].

This method involves in performing; initial is t o see the sound judgment or judgment of a sentence and therefore the next function is of taking the subjective sentences for associate degree opinion orientation[3].

Some existing work involves analysis at completely different levels. Notably, the am ount of linguistics orientation involving words concerning opinion furthermore because the phrase level. Linguistics orientation is accumulated from the words and phrases to seek out the general linguistics orientation of a selected sentence or review. The framework for sound judgment and judgment classification is compatible with each annotated and unannotated dataset. By the considering of the client reviews we'll classify the ways for the strength of sentiments and linguistics sentences. The strength of every sentence in a very review is obtained considering all components of speech [9].

2.2 Methods for the strength of semantics sentences

The following four steps describe the overall process for semantic orientation for different genre and domains using sentence level lexical dictionaries.

1) Collection of data (text), processing and removal of verbose form text data.

2) Developing and using knowledge base which is the collection of lexical dictionaries.

3) Processing of text data at sentence level using Word Sense Disambiguation for extraction of sentence sense.

4) Checking the polarity (positive or negative) of each sentence according to sentence structure and deciding about its opinion orientation.

This method creates a combination of dictionaries called knowledge base which conations SentiWordNet, WordNet and predefined intensifier dictionaries for rule based polarity classification of positive and negative opinions. It combines and interlinks

the lexical dictionaries (WordNet, SentiWordNet, intensifiers etc.) to make a knowledge base and extract the sense of terms, and semantic score. The score can be calculated as below.
1) The WordNet set identifies the pair (POS, offset) uniquely. A numeric ID called offset associated with POS uniquely identified a set in a database.
2)The values PosScore and NegScore are the positive and negative scores assigned by SentiWordNet to the set

Subjective information is based on personal opinions, interpretations, points of view, emotions and judgment. It is often considered ill-suited for scenarios like news reporting or decision making in business or politics. Where, Objective information is fact-based, measurable and observable[9].

A small and concise summary of opinions is generated. The overall summary is helpful for users to filter the relevant reviews from the all the reviews which are posted on the web source. The summaries must be representative to the key opinions and must be in a format so that users can understand it easily. The optimization problem is to search the set of precise and non-redundant text that represents the key opinions in the reviews. The task of generating the textual opinion summaries is difficult. A micro opinion is generally a short phrase that summarizes a key opinion in text. The main objective of review selection is to optimize the representativeness and readability in-order to ensure that the summaries reflect the opinions of the original text and it is also well-formed. Heuristic algorithms are wont to solve this downside that uses the steps like: Generating seed bigrams, scored n-grams and small pinion outline. These methods are used to reduce the redundancies in the document. These shortlists the set of words used to generate the n-grams. It is based on the idea that the words that are not frequent in the selected review document is not considered as a good candidate which can be included in the micro pinion summary. The high frequency words are considered as unigrams. Each unigram is combined with the opposite unigram to create bigrams [1].The depth first search is employed for generating the candidate words. This approach is general and lightweight and does not require any domain knowledge. It can be used in other domains and also in other languages. There is a line of work that deals with the selection of a "good" set of reviews.

3. Working

3.1 Block Diagram:

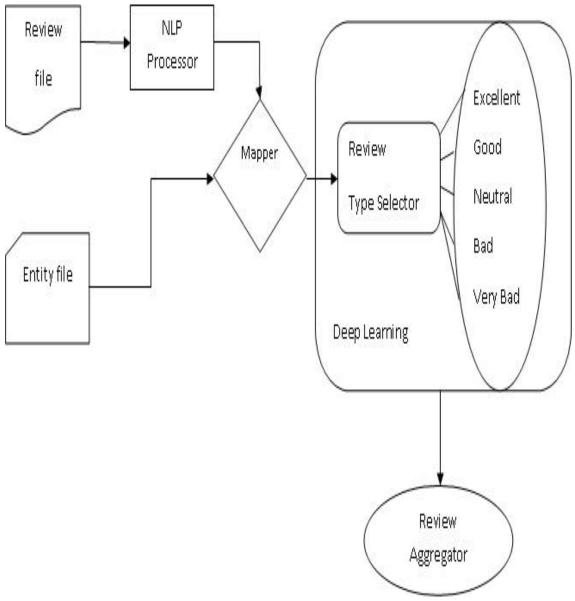

Figure 3.1: Block diagram of Review Selection system

Above block diagram describes overall process of the review selection using Deep learning method.

Review file is a text file contains all the reviews by customer of any product from a web source.

Here reviews are selected one by one. After taking a review, it is given to an NLP possessor which is a Natural Language Processor, which uses Part of speech tagger (POS tagger) to tag each word separately.

Using mapper, map the review with entity file to identify for which product, that review is made.

After mapping the review and entity file, it is given to review type selector in chunk of words. Review type selector uses Temporal Difference algorithm which is Deep Learning method to compare the words with the ontology's.

Review aggregator will give result in the form of review count as excellent, good, neutral, bad and very bad.

3.2 Flow Chart:

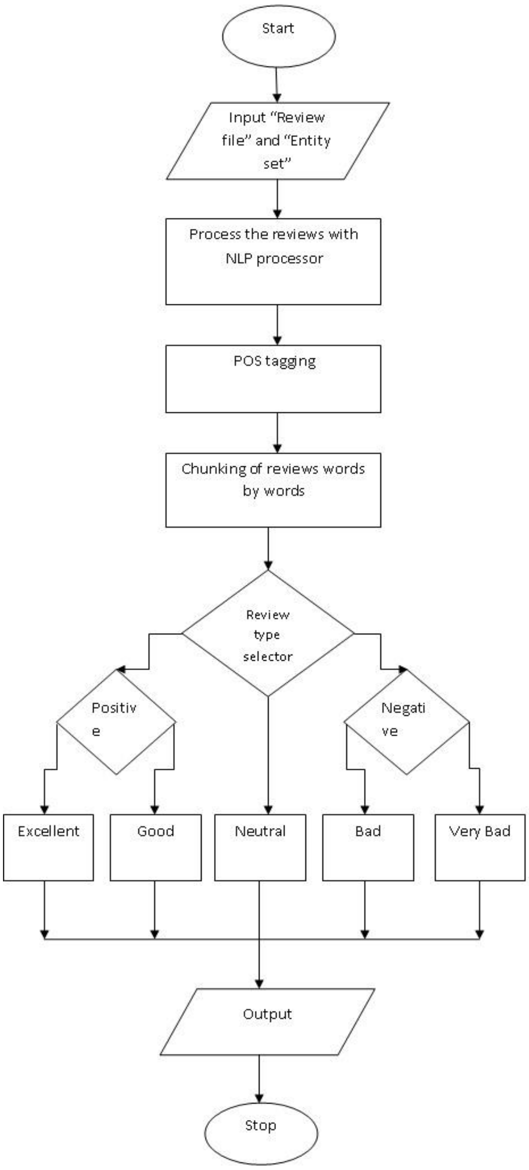

Figure 3.2: Flowchart of the Review selection system

3.3 Algorithm:

INPUT: Document set Review file and Entity file in text file format.

Step 1: Start

Step 2: Apply POS tagging on Review file using Natural Language Processor

Step 3: Separate each word from the sentence by chunking

Step 4: Compare the chunk words form review file with entity words using jaccard distance between chunked words and entity words.

Step 5: Create positive, negative, inversion and more ontology sets.

Step 6: Classify the reviews on the basis of positive, negative, inversion and more ontology using Deep Learning (Temporal difference algorithm).

Step 7: Store the count according to classified reviews.

Step 8: Display the result according to count.

Step 9: Stop

4 Experimental Results

For the experiment purpose, A review file of product 'camera' is taken. This file contains reviews taken randomly from the web sites like Amazon.in, Flipkart.com and ebay.com. The reviews are both subjective type and objective type are taken for the experiment.

An entity file is created for the same experiment purpose which is trained with the words related to camera like picture, cam, megapixel, white balance and many more etc.
Here, e=excellent, g=good, n=neutral, b=bad, vb= very bad

Table 4.1: Comparison of count non Deep learning vs Deep Learning

Review Product	Non Deep Learning [1]					Deep Learning (proposed)				
	E	G	N	B	VB	E	G	N	B	VB
Camera	1	12	26	5	2	2	13	26	6	2
Total= 52	46					50				

4.1 Efficiency Calculation

The efficiency calculation is done by formula,

e= ∑(count {e,g,n,b,vb})/(total count of review)

where, e=excellent, g=good, n=neutral, b=bad, vb= very bad

Table 4.2: Efficiency of non Deep learning vs Deep Learning

Review Product	Efficiency Calculation	
	Non Deep Learning [1]	Deep Learning (proposed)
Camera	0.88	0.96

4.2 Graphs

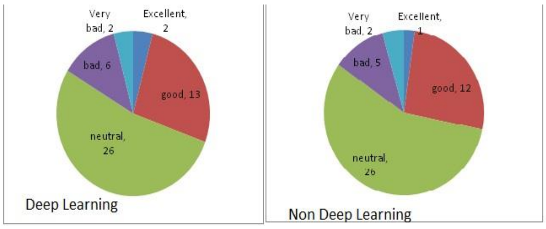

Figure 4.1: Pie chart for comparing results

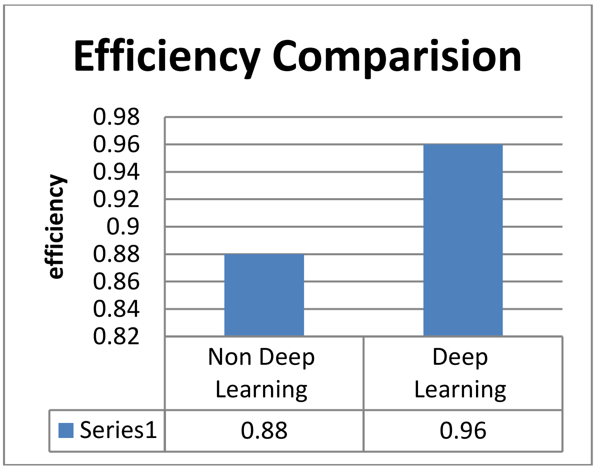

Figure 4.2: Efficiency comparison

5. Conclusion

This paper introduces a method using Deep learning technique to improve the review selection process for the better count of the results in different category. As discussed earlier previous work found out the results in three categories whereas our approach finds the result in five categories. The result has displayed in five categories viz. Excellent, Good, Neutral, Bad, and Very Bad. Then the r esults calculated and plotted graphs in compari son with previous approaches.

As a future scope, with the use of artificial intelligence one can train the entity set stronger rather as all the words for an entity is not possible to enter by their own.

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