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Unsupervised Learning Based Brand Sentiment Mining using Lexicon Approaches – A Study on Amazon Alexa

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***Abstract:** Consumer sentiment analysis has gained immense attention in the recent past. The abundance of data in today's world, especially those generated from the social media platforms, has triggered sentiment exploration like never before. The analysis of consumer sentiments have indeed helped organizations in effective decision making worldwide. In the communication technology domain, voice activated virtual assistants (VAVAs) are one of the latest entrants and they are gaining immense popularity by the time. Brand sentiment studies on VAVAs being limited in number creates an opportunity to explore further. This study fits into the domain of sentiment mining and the purpose of the paper is to review the consumer sentiment towards the global leader brand in the voice activated virtual assistant product segment, Amazon Alexa. Of the various approaches available, the researchers chose unsupervised learning based lexicon approach to estimate the brand sentiment. Three popular lexicon based sentiment classifiers, TextBlob, VADER and AFINN, have been used in the present context for exploration purpose. To the best of the knowledge of the researchers, this research effort includes, for the first time, multiple lexicon based approaches in exploring the sentiment towards the brand Alexa. This study shows consumers to have a significantly positive sentiment towards the chosen brand. The output from the three comparative classifiers reveal similar results which also validates the robustness of the outcomes and that of the chosen methods. The study anticipates a bright sales potential of the brand. Also, the use of alternative lexicon approaches is expected to enrich the existing literature in the sentiment mining domain.*

***Keywords:** AFINN, TextBlob, Unsupervised learning, VADER, Word Cloud.*

I. INTRODUCTION

Brand sentiment refers to the emotions evoked or expressed by the consumer on the mention of a brand. Consumer interactions involving language, emoticons etc. reflect their feelings and opinions which, in many cases appear complex. Understanding brand sentiments have helped organizations with insights which are otherwise almost impossible to decipher. Rather than being fixated on quantitative data such as the number of likes or comments, brand sentiment takes a step further by analyzing the context behind interactions to gain deeper understanding. Mining of brand sentiment allows organizations to make informed decisions and work towards improving business in general. There are various aspects where understanding of brand sentiments has been found to be extremely beneficial, some of which include brand image and performance, brand customer reviews, detecting crisis, performance analysis of campaigns, analyzing competitor activities, identifying key consumer groups for the brand, gaining insights on product design, price and its features to name a few. The present paper focuses on a product that has drawn worldwide attention in the communication technology space where communication between humans being are being increasingly substituted by humans on one side and computers on the other end. One such technology applications include the use of Voice Activated Virtual Assistants (VAVA). Such intelligent devices or agents have found different nomenclature, virtual assistants (Garcia, Lopez and Donis, 2018) are also AI agents (Castelfranchi, 1998), intelligent assistants (Kiseleva et al, 2016). Literature suggest absence of consensus on a common terminology, though different terms refer to the same thing. VAVA's make use of Natural Language Processing (NLP) to communicate and interact with its users. They are gaining immense popularity owing to efforts by corporates in terms of investments in technology, distribution and media penetration. Worldwide, the major players in the VAVA domain are Siri (Apple), Google Assistant (Google), Cortana (Microsoft) and Alexa (Amazon) (Garcia, Lopez and Donis, 2018). While Siri is Apple's VAVA launched in 2011, Alexa is Amazon's VAVA and was launched in 2014. Microsoft's VAVA was named Microsoft Cortana and launched in 2015, while Google's VAVA, Google Assistant, made its debut in 2016. With more than 70% of all intelligent VAVA devices running the Alexa platform (apart from phones), Alexa has emerged as the dominant market leader (Griswold, 2018; Terzopoulos and Satratzemi, 2020). The present study focuses on Amazon Alexa which has the highest global market share (Statista, 2021). Of the various sentiment mining approaches, the researchers chose unsupervised learning strategy based lexicon methods with an aim to explore the brand sentiment and also validate the individual results. The rest of the paper follows a structured approach. Section II focuses on the review of literature. Section III elaborates the methodology used in this study. The analysis and findings are discussed in section IV while section V details the conclusions and recommendations.

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II. REVIEW OF LITERATURE

Literature survey was done to explore the areas of research already done, enables strong foundation of knowledge already available in the desired field and to identify the areas where research is needed and will permit our study. Voice assistants as well as smart speakers have penetrated in daily life and in education (Terzopoulos and Satratzemi, 2020). It is likely that there would be as many virtual assistants as people (Shulevitz, 2018). According to Garcia, Lopez and Donis (2018), the major players in the VAVA domain are Siri by Apple, Google Assistant by Google, Cortana by Microsoft and Alexa from Amazon. Some of the important works conducted on VAVA domain include that of Maita (2018) who conducted an exploratory study on the consumer perception of Amazon Echo and Alexa. Topic modeling and sentiment analysis was done by Kosaka (2020) on Amazon Alexa reviews using Vader, which is a lexicon based sentiment analysis tool. However, the accuracy of sentiment analysis has not been verified with any other well-known APIs like TextBlob, a python library for Natural Language Processing (NLP), or AFINN which is another lexicon approach. Cen (2020) has predicted consumers' Brand Sentiment using text analysis. This research focuses on four brands, Apple, Samsung, Microsoft and Google and then uses a lexicon based sentiment analyzer as well as four supervised learning classifiers (Bernoulli and Complement Naïve Bayes, Logistic regression and Random Forest) to predict brand sentiments for four brand clusters. Another interesting study is on user adoption of Intelligent Personal Assistants (IPAs) like Amazon Alexa, Apple Siri, Google Assistant (Lopatovska et al., 2019). Past research suggests limited work on the sentiment analysis of brand ALEXA. The existing lexicon based studies have primarily focused on VADER. Validation with other lexicon based sentiment mining techniques has not been found. This gap is being addressed in the present study by framing three research objectives:

1. Visualizing Text Data using an exploratory technique.
2. Computing Sentiment scores separately using TextBlob, VADER and AFINN.
3. Comparing the similarity among the outputs obtained from the lexicon based approaches.

III. METHODOLOGY

The present study uses an exploratory method, Word Cloud, to understand the terms that are important to consumers. It also uses lexicon based (unsupervised learning) approaches to comprehend the consumer sentiment. Primary data forms the source of text input.

A. Word Cloud

Word clouds are graphical representations of the frequency of words that appear in a text document. Words with higher frequencies indicate greater prominence to words with lower frequencies in the same source text. A word cloud are also termed as a text cloud, a tag cloud or a weighted list, as they are a visual depiction of the frequency tabulation of the words in a particular text material. A word cloud depicts a collection (cluster) of words in different sizes. The font size is used to indicate frequency, so the larger the font size, the more frequently a word is used in the document(s). An alternative way of interpreting word cloud is that the larger the word in the visual the more common the word is. This visualization technique is exploratory in nature and the importance of words or themes or prominent points may be understood at the initial stage of text analysis. In the present study, Word Cloud Python tools have been used.

B. Lexicon Based Techniques

They form the unsupervised learning techniques (Eisenstein, 2017) for analyzing sentiments. The underlying principle within these techniques include a search for positive and negative words (classification) using a pre-defined dictionary. A collection of words, already labelled as positive or negative are assigned a number. An improved lexicon also features intensity of words that not only considers positivity or negativity but also considers the extent or degree of it and numbers assigned accordingly. Each positive word in the text document augments the overall score, while the negative words reduce it. It is then compared with the threshold values and the overall sentiment assessed for the text document. Lexicon-based classification finds wide applications both in industry and academia, with the applications ranging from sentiment classification and opinion mining (Pang and Lee 2008; Liu 2015) to the psychological and ideological analysis of texts (Laver and Garry 2000; Tausczik and Pennebaker, 2010). There are several lexicons available, however, TextBob, VADER and AFFIN are found to be highly popular.

B1. TextBlob: It is a renowned lexicon based approach used for various natural language processing jobs on raw text documents (Loria, 2018). It is an open source Python library which implements TextBlob Algorithm 1 (Table 2). The TextBlob algorithm for sentiment analysis is a part of the Natural Language Toolkit library and there are around 2918 lexicons in it (Amin et. al. 2019). The output of this method includes the polarity score and subjectivity score (Amin et. al. 2019). The TextBlob sentiment score range is depicted in Table 1.

Table 1: TextBlob sentiment score range

Sentiment	Score
Negative	Polarity score < 0
Neutral	Polarity score = 0
Positive	Polarity score > 0

Source: Adapted from Reshi, 2022

Table 2: Text Blob Algorithm

Algorithm 1 - TextBlob algorithm for sentiment analysis

Input: Consumer reviews on Amazon Alexa
Result: Polarity Score > 0 −→ (Positive)
Polarity Score = 0 −→ (Neutral)
Polarity Score < 0 −→ (Negative) initialization loop (each review in reviews)
Compute Polarity Score TextBlob (review)
condition:
if (Polarity Score > 0) **then**
Tweet Sentiment = Positive;
elseif (Polarity Score = 0) **then**
review Sentiment = Neutral;
else
review Sentiment = Negative;
condition end
loop end

Source: Adapted from Reshi, 2022

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B2. VADER: Valence Aware Dictionary and Sentiment Reasoner (VADER), a popular method used for analyzing human sentiments especially from the social media texts, is written in the Python programming language.

It is sensitive to both polarity and the intensity of human expressions. Further, it also encompasses a collection of libraries and programs for symbolic and statistical natural language processing for English language.

Kirlic and Orhan (2017) opines that the scores projected by the VADER sentiment analyzer are quite alike to that of human analysis. Its corpus includes more than 7500 lexicons collectively (Reshi, 2022). A unique feature of VADER algorithm (Table 4) is that it considers both grammatical rules and syntactical conventions (Reshi, 2022) while computing the sentiment score (Table 3).

Table 3: VADER sentiment score range

Sentiment	Score
Negative	compound score <= −0.05
Neutral	−0.05 < compound score < 0.05
Positive	Polarity score > 0

Source: Adapted from Reshi, 2022

Table 4: VADER Algorithm

Algorithm 2 - VADER algorithm for sentiment analysis

Input: Consumer reviews on Amazon Alexa
Result: Compound Score >= 0.05 → (Positive)
−0.05 < Compound Score < 0.05 → (Neutral)
Compound Score < 0.05 → (Negative) initialization loop (each review in reviews)
Compute Compound Score VADER (review)
condition:
if (Compound Score >= 0.05) **then**
Tweet Sentiment = Positive;
elseif (Compound Score > −0.05 to Compound Score < 0.05) **then**
review Sentiment = Neutral;
elseif (Compound Score <= 0.05) **then**
review Sentiment = Negative;
condition end
loop end

Source: Adapted from Reshi, 2022

B3. AFINN: AFINN is another lexicon based sentiment analyzer for English language (Nielsen, 2017). Like VADER, it covers a broad range of words of the English language and incorporates their respective sentiment scores. The polarity scores are indicated against with each word in this lexicon. The AFINN lexicon is also highly popular and finds large scale application in analyzing sentiments. The AFINN sentiment score range is shown in Table 5 while its algorithm presented in Table 6.

Table 5: AFINN sentiment score range

Sentiment	Score
Negative	Polarity score < 0
Neutral	Polarity score = 0
Positive	Polarity score > 0

Source: Adapted from Reshi, 2022

Table 6: AFINN Algorithm

Algorithm 3 - AFINN algorithm for sentiment analysis

Input: Consumer reviews on Amazon Alexa
Result: Polarity Score > 0 → (Positive)
Polarity Score = 0 → (Neutral)
Polarity Score < 0 → (Negative) initialization loop (each review in reviews)
Compute Polarity Score AFINN (review)
condition:
if (Polarity Score > 0) **then**
Tweet Sentiment = Positive;
elseif (Polarity Score = 0) **then**
review Sentiment = Neutral;
else
review Sentiment = Negative;
condition end
loop end

Source: Adapted from Reshi, 2022

C. Data Sourcing

The study is based on secondary data, reviews of Amazon Alexa. The dataset contains a review of 3150 Amazon customers. The dataset is available at:
https://www.kaggle.com/sid321axn/amazon-alexa-reviews

D. Data Pre-Processing

Pre-processing of data is the process of cleaning and preparing text so as to ready it into a form that can be analyzed for the task. The data was processed before performing the exploratory analysis. It involves a combination of various tasks detailed below. The whole process involves several steps which include:

D1. Tokenization: It is the process by which the text document is split into smaller fragments called “tokens”. Paragraphs are broken into smaller parts called sentences and sentences into yet smaller parts called words.

D2. Conversion to Lowercase: It is an effective form of text preprocessing, which is applicable to most text mining and NLP problems. This enhances the consistency of expected output.

D3. Stopword Removal: Stop words are a collection of words that are used quite commonly in a language. Examples of stop words in English are “a”, “the”, “is”, “are” etc. By removing the Stopword from the text, one is able to focus on the important words.

D4. Removing numbers: Numbers are usually removed from the text since they contain no information about sentiments, in most cases.

D5. Removal of punctuations, white space and special characters: It helps to get rid of that portion of the data, which does not add any value to the sentiment mining process.

IV. FINDINGS AND ANALYSIS

The outcome of the exploratory study, i.e. Word Cloud formation is discussed first. Word Cloud gives the graphical representation of the importance of the words present in the text document. It is then followed by the analysis of sentiments using lexicon based techniques. Also, a comparison between the three outputs are shown and similarity assessed between them subsequently.

IV.A. Analysis of the Exploratory Study

The Word Cloud generated (Figure 1) using Word Cloud Python tools indicates the word 'love' to be of largest font size. This indicates that this word has the highest frequency among all other words in the text review documents. It is followed by the words 'Alexa', 'Echo', 'great', 'device', 'work' etc. Analysis of the most frequently used words indicate a strong possibility of positive sentiment towards Amazon Alexa. However, word cloud being exploratory in nature, a conclusive statement on the consumer sentiment towards the brand cannot be arrived at from this study. Hence, further analysis have been done using Lexicon based techniques.

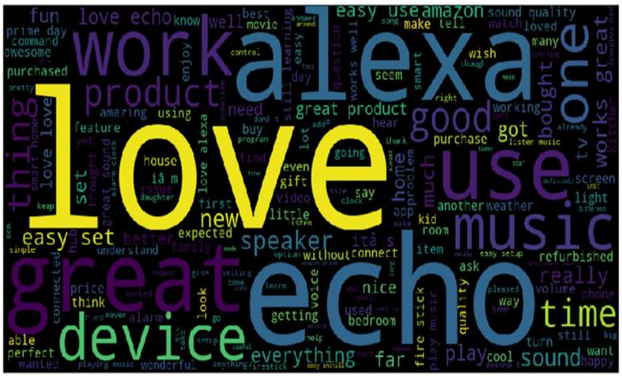

Figure 1: Word Cloud

Source: Author's Computation

IV.B. Sentiment analysis using TextBlob

The output of TextBlob Sentiment Analysis program in Python is shown in Table 7. Of the 3150 consumer reviews, the first five and the last five reviews and their corresponding sentiment properties have been captured. The python program returns polarity and subjectivity. The polarity ranges from -1 to 1, with 0 at the central point (neutral sentiment). Subjectivity is a decimal number which lies in the range of [0, 1]. Subjectivity recognizes the contextual polarity of opinions, attitudes and emotions. The more the subjectivity score, lesser is the objectivity i.e. lesser is the fact content in texts and higher is the opinion content. It is possible to find out the sentiments from polarity measures of individual reviews and the overall sentiment towards the brand is found to be 0.35. This value indicates an overall positive sentiment for brand Alexa, which complements the strong possibility of positive sentiment as found in word cloud. The overall subjectivity value of 0.64 indicates that the reviews or opinions are low in terms of fact based content. In fact this value is indicative of higher emotion content in the statements.

IV.C. Sentiment Analysis using VADER

The output of VADER Sentiment Analysis program in Python is shown in Table 8. Of the 3150 consumer reviews, the first five reviews and their corresponding sentiment properties have been illustrated. VADER not only gives an indication about the Positivity and Negativity score but also specifies how intense is the positive or negative sentiment. The metric named Compound score (comp') computes the sum of all the lexicon ratings which is then normalized between -1 (extremely negative) and +1 (extremely positive). The more the compound score is closer to +1, the higher is the positive sentiment in the text. The overall sentiment score is understood from the compound score which is found to be 0.53, thus indicating an overall positive sentiment. The comp_score indicates if a statement is positive (pos'), negative (neg') or neutral (neu'). The overall comp_score indicates the highest frequency term (among pos', neg' and neu') considering all the reviews. Thus, it may be concluded that the overall sentiment towards Alexa is moderately positive and does not reveal an extremely positive sentiment.

IV.D. Sentiment Analysis using AFINN

The output of TextBlob Sentiment Analysis program in Python is shown in Table 9. The first five and the last five reviews of the 3150 consumer reviews, along with their corresponding sentiment properties are shown. The overall polarity score, 3.85, indicates a fairly positive sentiment towards brand Alexa. Analysis of the all three unsupervised (lexicon) based methods indicate a positive consumer sentiment towards brand Alexa (Table 10). The results have high similarity among them which also validates the robustness of the individual outputs and that of the methods used.

Table 7: TextBlob Sentiment Analysis

Sl.	Variation		Verified_Reviews	Polarity	Subjectivity
0	Charcoal	Fabric	Love my Echo!	0.62500	0.60000
1	Charcoal	Fabric	Loved it!	0.87500	0.80000
2	Walnut	Finish	Sometimes while playing a game, you can answer…	-1.00000	0.51250
3	Charcoal	Fabric	I have had a lot of fun with this thing. My 4 ...	0.35000	0.45000
4	Charcoal	Fabric	Music	0.00000	0.00000
…	…		… … … …	…	…
3145	Black	Dot	Perfect for kids, adults and everyone in betwe...	1.00000	1.00000
3146	Black	Dot	Listening to music, searching locations, check...	0.33333	0.45238
3147	Black	Dot	I do love these things, i have them running my…	0.27662	0.53377
3148	White	Dot	Only complaint I have is that the sound qualit…	0.16667	0.63210
3149	Black	Dot	Good	0.70000	0.60000
			Overall Sentiment	0.34979	0.63944

Source: Author's Computation

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Table 8: VADER Sentiment Analysis

Sl.	Verified_Reviews	neg'	neu'	pos'	comp'	comp_score
0	Love my Echo!	0.000	0.308	0.692	0.670	pos'
1	Loved it!	0.000	0.193	0.807	0.660	pos'
2	Sometimes while playing a game, you can answer…	0.102	0.784	0.114	-0.128	neg'
3	I have had a lot of fun with this thing. My 4 ...	0.000	0.617	0.383	0.917	pos'
4	Music	0.000	1.000	0.000	0.000	pos'
...	... ...	...	...	...	...	...
	Overall Sentiment				0.53	pos'

Source: Author's Computation

Table 9: AFINN Sentiment Analysis

Sl.	Verified_Reviews	Polarity_Score	Sentiment_Type
0	Love my Echo!	3.0	Positive
1	Loved it!	3.0	Positive
2	Sometimes while playing a game, you can answer…	0.0	Neutral
3	I have had a lot of fun with this thing. My 4 ...	9.0	Positive
4	Music	0.0	Neutral
...	... ...	...	...
3145	Perfect for kids, adults and everyone in betwe...	3.0	Positive
3146	Listening to music, searching locations, check...	0.0	Neutral
3147	I do love these things, i have them running my…	13.0	Positive
3148	Only complaint I have is that the sound qualit…	3.0	Positive
3149	Good	3.0	Positive
	Overall Sentiment	3.85	Positive

Source: Author's Computation

Table 10: Comparison of Sentiment based on unsupervised learning methods

Method	Polarity_Score	Subjectivity	Compound Score	Sentiment_Type
TextBlob	0.35	0.64	--	Positive
VADER	--	--	0.53	Positive
AFINN	3.85	--	--	Positive

Source: Author's Computation

V. CONCLUSION AND RECOMMENDATIONS

The present work is a humble attempt aimed at enriching the scholarly contributions in the field of brand sentiment mining. Emphasis has been laid on the theoretical and conceptual aspects involved in the study and the same is expected to augment the intellectual content in this domain further. For the purpose of study, Amazon Alexa, is chosen as it represents of one the most sophisticated product that uses Artificial Intelligence and Natural Language Processing. The present study makes the following contributions. At first, the methods used in analyzing sentiment of brands have been discussed. The analytical study begins with an exploratory approach (Word Cloud) to understand the words that are most frequently used and arrive at a general idea of the possible sentiments out of it. Next, the most popular unsupervised learning based lexicon methods of sentiment classification, i.e. TextBlob, VADER and AFINN have been discussed and implemented using Python programming language. The study reveals positive sentiment towards Amazon Alexa and similar outcome is noted from all the methods used in the study. This substantiates the robustness of the methods used and also validates the study findings. The outcome of this research initiative is expected to serve as a ready reckoner to academicians as well to those in industry. This study has an important managerial implication for the brand in consideration. Future studies may focus on feature based sentiment analysis. Also, supervised learning approaches may be used to further validate the study results. Upcoming studies may consider application of the Naïve Bayesian algorithms, support vector machines, logistic regression and neural network for further exploration and comparison among the methods may be made to understand the precision and accuracy level of the classification task. Use of unsupervised learning approaches, as in the present study, may also be applied to different domains or brands where consumer sentiments keep changing rapidly.

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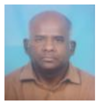

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