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Using Lexicon-Based Opinion Mining to Gauge Customer Satisfaction

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Abstract: The web offers businesses a great tool to get instant feedback from their customers. Decision-makers need to improve the decision quality and increase the business performance, they required applications that provides data analysis and data visualization. In this paper, we will try to test users' reviews about hotels in Europe, they stayed and left a comment expressing their feelings about their experience, by applying opinion mining and sentimental analysis methodology on 515,000 customers reviews to uncover how effective and useful a lexicon-based Sentiment Analysis system will be for business executives to improve the performance and quality of hotels.

We wish to explore key-concepts of sentiment analysis, classification levels, different approaches to Sentiment Analysis. And we will apply step by step SA techniques to preprocess the text, tokenize, lemmatize, analyze text, then produce business intelligence visualization results.

Keywords: Opinion Mining, Sentiment Analysis, Polarity Analysis, Business Intelligence, Support Decision-Making.

I. INTRODUCTION

In the past, companies and organizations used to do costly and time-consuming wide-scale surveys and opinion polls. In order to know the public opinion about their products and services. They used to do these polls by themselves or by paying specialized companies who would perform these tasks for money. The polls used to take weeks sometimes months to complete. Now, in the era of modern web 2.0, anybody can express their opinion, feeling, and share their experience with a product or a service by any company.

Data text mining is the science whose main task is to categorize and summarize those massive loads of text and turn them into easy-to-understand graphs and tables that help business executives make the right decision.

The process of employing classic Text Mining Technique helps businesses, harness the power of reviews written by users expressing their thoughts, comments, and experiences about products they had acquired from e-commerce website.

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In this paper, we went through the process of:
1- Data acquisition and conversion.
2- Data pre-processing.
3- Text analysis.
4- Sentiment analysis and opinion mining.
5- Business Intelligence Visualization.

To extract knowledge from enormous loads of unstructured and schema-less text. We use classical techniques of text-mining that helps businesses to get a clear view of what their users think of their products and services.

In this paper, we wish to argue that Sentiment Analysis also known as Opinion Mining is the right choice to reach the goal of decision-making support. We will try employing Sentiment Analysis in pursuit of knowledge extraction of users' opinions towards the subject the user has given the review for.

II. RELATED WORK

In this section, we will review a few of the papers that discuss problems that fall in the same domain.

To stay competitive in the global market, businesses tend to build customer-centric products and services.

By understanding user-generated content available online companies can turn this information into marketing insights. The authors of this paper employ text-mining combined with semantic network analysis tools. The authors study two cases: users' feedback on Sedan Cars and users' feedback on Diabetes drugs. [1].

Hospitals and medical institutes produce a huge amount of Electronic Medical Records (EMR) which can be redundant, missing some information, diverse and most important, private data. The nature of EMR makes it almost impossible to analyze it without data pre-processing. The authors of this paper focus on the key techniques and carry out a detailed study on applications based on text-mining and challenges and research problems for future use. [2]

III. SENTIMENT ANALYSIS

If Sentiment is the feeling, attitude, and opinion towards a topic, product, event or figure. It is rather subjective which means they differ from person to person.

Sentiment = <Holder, Target, Polarity, Auxiliary>

Holder: the person who articulates the sentiment.
Target: the entity whom the sentiment is directed to.
Polarity: the orientation of the sentiment, it can be (positive, negative, or neutral).
Auxiliary: optional extra information like confidence, date/time, emphasis, summary, etc.

Sentiment Analysis or Opinion Mining – both terms can be used interchangeably - is a computational process that uses Natural Language Processing (NLP) and Data Text Mining techniques to build systems that can extract opinions, feelings, and emotions and identify polarity (binary/n-class) of those opinions about an entity. The entity exemplifies a product, service, event or person. Sentiment Analysis can help us craft schema-less and unstructured data into useful information summarizing public opinions about a given entity [3].

A. Challenges for sentiment analysis systems

The human language is sophisticated with almost inexhaustible diversity in grammatical structures, patterns, idioms, expressions, implicit meaning, deliberate/accidental misspellings, shortcuts, acronyms, emoticons, and slangs. Building a computer system that can understand and manage the data has taken researchers across the globe huge efforts to accomplish. These countless researches have achieved vastly in some areas and still lags in many others. And this is where Natural Language Processing (NLP) comes to tackle these tasks and overcome obstacles to help meet the challenges we discussed above.

B. Polarity vs Subjectivity

Sentences can be either objective or subjective. Objective sentences refer to facts while subjective sentences express opinions. In other words, sentences tagged as subjective sentences should be analyzed so they can further be classified in terms of polarity/orientation. [4]

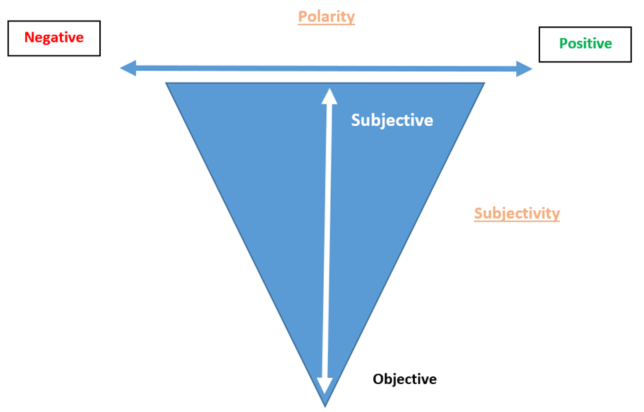

Fig. 1. Polarity vs Subjectivity.

C. Sentiment Classification

Sentiment Analysis is performed on objects on multiple levels of granularity:

1. Document level classification: The entire document is considered as a single unit of information and assumed to be opinionated text thus evaluated and given an overall positive or negative polarity. It is worth mentioning that this classification level is the most studied problem. [5], [6]

2. Sentence level classification: Sentiment classification is performed on the sentence level. However, subjectivity classification should determine if the sentence is opinionated then classifies the sentence's polarity. [7]– [10]

3. Aspect level classification: Aspect-based opinion mining also known as feature-based opinion mining [11]. Note that some researchers do not differentiate between Aspects and Entities and they refer to them all as "Opinion targets" [12]–[14]. While others, use the term "Object" instead of "Entity" and the term "feature" instead of "Aspect". The primary goal of aspect-based opinion mining is to identify and outlines the opinions conveyed by users about entities and aspects of entities. This goal is achieved through three essential tasks:

1. Task1: extracting entities from text.
2. Task2: identifying aspects of extracted entities.
3. Task3: calculating and revealing the polarity of entities and aspects of those entities [15].

As most of the data mining domain, Sentiment Analysis is modeled as a classification to solve two major sub-problems:

1. Classify subjectivity whether is objective or subjective.
2. Classify subjective objects based on polarity which later classified as according to a binary or an n-class polarity classification.

IV. SENTIMENT ANALYSIS APPROACHES

Sentiment Analysis uses mainly three approaches to determine the polarity of a given text.

A. Lexicon-based approach

The system utilizes a form of a dictionary – Lexicon – to look up words and find their polarity based on some sort of n-class based classification. Those words are given a score that ranges from 1 for positive, 0 for neutral and -1 for negative words. The system finds all positive words and increments the positive counter. Then, it does the same for negative words. Finally, it determines the polarity of the text by checking which of the two counters has a higher value [16], [17]. Lexicon-based approach does not require any training data and can be easy to implement. However, it does have its drawbacks though. Many words, expressions, idioms, and clichés may not be included in the lexicons which makes it unable to understand implicit meanings of a sentence. For instance, consider the following sentences taken from users' reviews dataset [18]. A lexicon is a dictionary of words classified and associated with sentiment score according to the polarity of the sentiment they mean whether positive, neutral, or negative. Some lexicons include other features like Objectivity and Subjectivity, others may have dived their content into groups of intensity scores.

The following is a list of most popular lexica with a brief about each:

- Harvard IV General Inquirer: it is the oldest among all lexica. It was developed by Philip Stone of Harvard University and Earl Hunt of the University of Sydney in 1963. It has two major valence categories of Positive and Negative. As well as, other various subcategories and dimensions like "Strong vs Weak", "Active vs Passive", emotions and cognitive orientations. [19]
- Bing Liu's Opinion Lexicon: With a list of ~6800 words compiled over many years Liu's lexicon is one of the most popular lexica. It was first introduced in 2004. [11]
- Multi-perspective Question Answering (MPQA) subjectivity lexicon: It is licensed under the GNU General Public License framework. It contains ~8000 words. [9]

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- NRC Emotion Lexicon: Developed by the National Research Council Canada. It offers downloads for Manually Created and Automatically Generated lexica. It contains a huge number of words ~14000 and still adding more. NRC emotions and sentiment lexicon is often used when analyzing social media. [20]
- AFINN: is a sentiment analysis word-list approach package for Python. It features English, Danish, and Swedish. And the English version of AFINN-165 contains +3300 words. [21]
- SentiWord: It features a massive number of words ~155000 words with their sentiment scores between -1 and 1. The words in this lexicon are
- listed in the form of (Lemma#PoS) format. Part of Speech includes (verbs, nouns, adjectives, and adverbs). Finally, it is licensed under the Creative Common Attribution-ShareAlike 4.0 framework [22].

There are many lexica out there we cannot cover them all in this paper. However, we will list a few more (MPQA, MaxDiff, VADER, TextBlob, and LIWC).

B. Lexicon-based approach

Machine Learning (ML) for short is a branch of Artificial Intelligence (AI), it is a field of research that seeks ways to employ various ML algorithms and techniques to build systems that can identify and extract text expressing Sentiment/Opinion. Those algorithms can further be divided into two categories:

1. Supervised learning: it uses prelabeled datasets as input for training with expected and known output.
2. Unsupervised learning: the algorithm will be fed data for training without expected outcome. This type of learning technique requires huge amounts of data. And the more data you feed into the system, the better result we get when the system makes predictions.

C. Hybrid approach

This approach encompasses semantic rules, fuzzy sets, and unsupervised machine learning techniques usage as well as the use of sentiment lexicons to create a hybrid system able of extracting Sentiments/Opinions from text and define their polarity [23], [24].

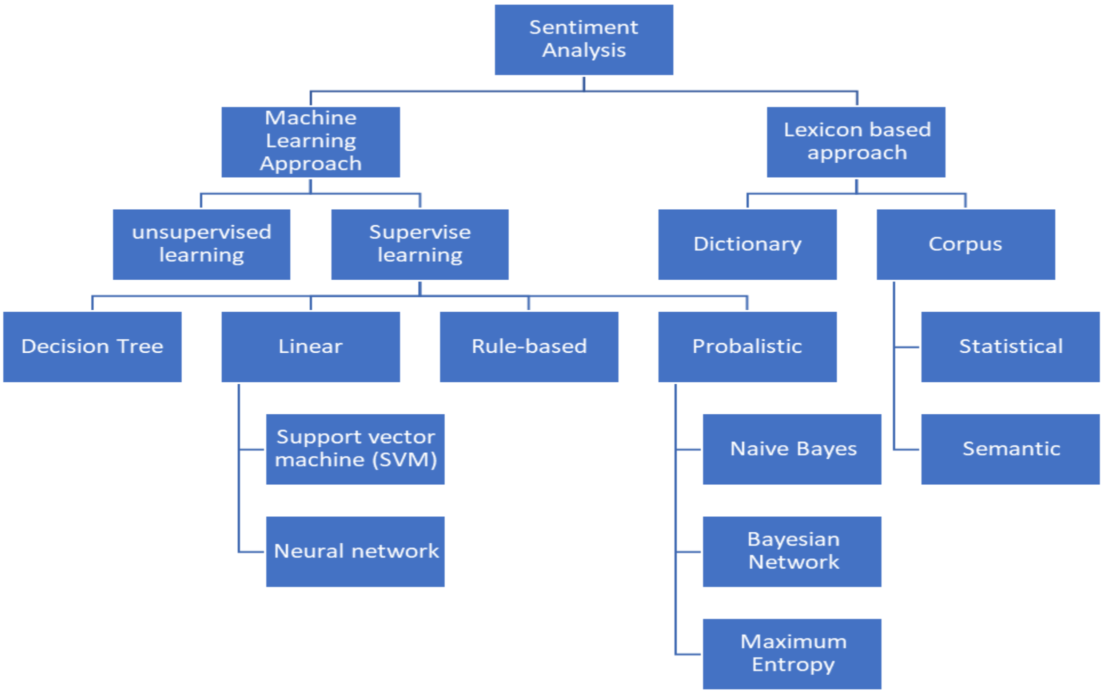

Fig. 2.Sentiment Analysis

V. APPLYING SENTIMENT ANALYSIS METHODOLOGY PROCEDURES.

Like any text mining procedures, Sentiment Analysis requires text preprocessing which involves several steps:

- **Step One Preprocessing text:** we remove numbers, tags, and any special characters or symbols.
- **Step Two Tokenization:** in this step, the text is broken into meaningful chunks of information. A tokenizer first breaks it into sentences then each sentence into individual, often word-tokens and in other cases multi-word phrases. Tokens hold great significance for analysis. It is important to use sentiment-aware tokenizer. A tokenizer that considers isolating emoticons, preserving capitalization where seems meaningful, captures significant multi-word expressions.
- **Step Three Stop-words removal:** removing common most frequent words like (a, an, the, on, etc.).
- **Step Four Stemming/Lemmatization:** Stemming and lemmatizing are similar, they both reduce a given word to its base form. However, there is a profound difference between the two: Let us understand the difference between how stemmers and lemmatizes work. Stemming applies a set of rules without considering any Part of Speech. While lemmatizing cuts down the word to the root after determining the POS and understand the word in the context [25].

Table 1: output sample of stemming and lemmatizing for different stemming & lemmatizing algorithms.

Word	Porter stemmer	Lancaster stemmer	Wordnet lemmatizer
Goes	goe	go	go
Going	go	go	going
Gone	gone	go	gone
Went	went	went	go
Conditions	condit	condit	conditions
Conditioning	condit	condit	conditioning
Conditioned	condit	condit	conditioned
Conditional	condit	condit	conditional
Connects	connect	connect	connects
Connections	connect	connect	connections
Connecting	connect	connect	connecting
Connected	connect	connect	connected
Related	relat	rel	related
Relation	relat	rel	relation
Relational	relat	rel	relational
Friends	friend	friend	friends
Friendship	friendship	friend	friendship
Troubles	troubl	troubl	troubles
Troubled	troubl	troubl	troubled
Troubling	troubl	troubl	troubling
Fill	fill	fil	fill
Filth	filth	fil	filth
Passed	pass	pass	pass
Passionate	passion	pass	Passionate
Competence	compet	compet	competence
Competes	compet	compet	compete
Famous	famou	fam	famous
Famished	famish	fam	famish

- **Step Five Sentiment analysis:** it involves a token valence lookup and calculating the score then, the average of the entities being analyzed. In the following section, we are going to apply Sentiment Analysis using a lexicon-based approach. The dataset used is the booking.com's user reviews.

We used a subset of the dataset titled "515K HOTEL REVIEWS DATA IN EUROPE" published by Kaggle.com. [26]. The dataset is organized in a CSV file, it has 17 Table 2: 515K hotel reviews dataset structure ***table***.

columns. The data consists of +515K rows. Each row represents one review. The good thing about this dataset is that the authors of this dataset have designed in a way that it has two separate columns for each user review. One for negative reviews and the other for positive reviews which makes it easier and clearer to experiment. For detailed information, check

Table 2: 515K hotel reviews dataset structure table.

Column name	Value	Notes
Hotel_Address	String	
Additional_Number_of_Scoring	Numeric	
Review_Date	Date	Date of submitted review
Average_Score	Numeric	Out of 10
Hotel_Name	String	Official name
Reviewer_Nationality	String	
Negative_Review	String	User's negative opinion
Review_Total_Negative_Word_Counts	Numeric	Negative_Review length
Total_Number_of_Reviews	Numeric	
Positive_Review	String	
Review_Total_Positive_Word_Counts	Numeric	Positive_Review length
Total_Number_of_Reviews_Reviewer_Has_Given	Numeric	
Reviewer_Score	Numeric	
Tags	Array[string]	Categories of hotel reservation
days_since_review	Number	
Lat	Numeric	Latitude value of hotel's geo-location
Lng	Numeric	Longitude value of hotel's geo-location

By using the package named "Sentiment Analysis" in R language. We have tested the following statements for users expressing their experiences and opinions and the results of both sentences have come out surprising. "Despite having stood all night in a horribly chaotic queue at this gloomy and unpredictable weather, I am thrilled to get an awesome iPhone on the first day of its release" "I woke up to find out that the weather is lovely. I drove fast to Samsung I got a beautiful gold Galaxy note 7 to discover that its battery has 40% opportunity to blow up and cause me burns ending my beautiful day with a nightmare". The code executed against the first sentence produced the polarity of Negative although the speaker meant to convey their happiness getting a brand-new iPhone although they had endured much to get it.

- **Step Six Calculating Text Polarity:** While the same code executed against the second sentence produces the polarity of Positive although his story tells otherwise. We have also executed the code of the same package "Sentiment Analysis" against a sample of 50k records of the dataset used. We got the following results of the polarity:

Table 3: Results of Polarity.

Negative review column		Positive Review column	
Negative	positive	negative	positive
22889	26777	439	49476

- **Step Seven Calculating Error Ratio:** We have categorized the dataset to study the grouping of the values in a few columns to have a glimpse of what the results will look like. By grouping the column "ReviewerNationality", Check Table 4: Error ratio of the negative reviews text column shows the top15 records of wrong polarity calculations according to the found positive while in fact it was listed in the negative review column.

We have categorized the dataset to study the grouping of the values in a few columns to have a glimpse of what the results will look like. By grouping the Colum.

Table 4: Results of Error ratio of the negative reviews text column.

Reviewer Nationality	Negative	Positive	Ratio
Albania	1	8	0.888889
Bosnia and Herzegovina	1	6	0.857143
Sudan	1	5	0.833333
Libya	1	4	0.8
Namibia	2	8	0.8
Abkhazia Georgia	4	14	0.777778
Bangladesh	3	10	0.769231
Azerbaijan	4	12	0.75
Tunisia	1	3	0.75
Jordan	16	47	0.746032
Qatar	66	155	0.701357
Saudi Arabia	207	480	0.69869
Monaco	5	11	0.6875
Kuwait	115	236	0.672365
Indonesia	41	84	0.672

VI. RESULTS VISUALIZATION

It is said that "a picture is worth a thousand words", putting data into perspective summarizes a huge amount of data and shortens time to understand the data context. We have plotted the following graph for both negative and positive reviews grouped by the "ReviewerNationality" column which has 169 unique nationalities. Above is the graph for positive reviews of the top 35 "reviewerNationality" with its polarity. Below is the polarity outcome of the negative reviews of the same 35 "reviewerNationality" plotted. And for better clarity, we would focus on the top 10 "reviewerNationality" based on the number of negative reviews for each of the nationality in our sample data check Figure 3: Top 35 of the Total number of reviews by reviewer nationality.

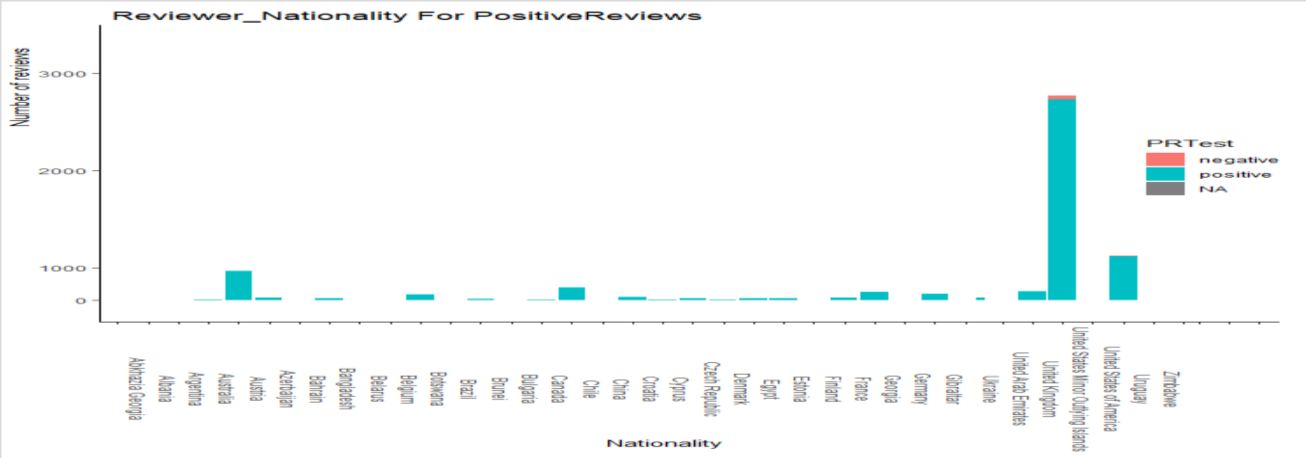

Fig. 3.BI Visualization of Number of Positive reviews by Reviewer's Nationality.

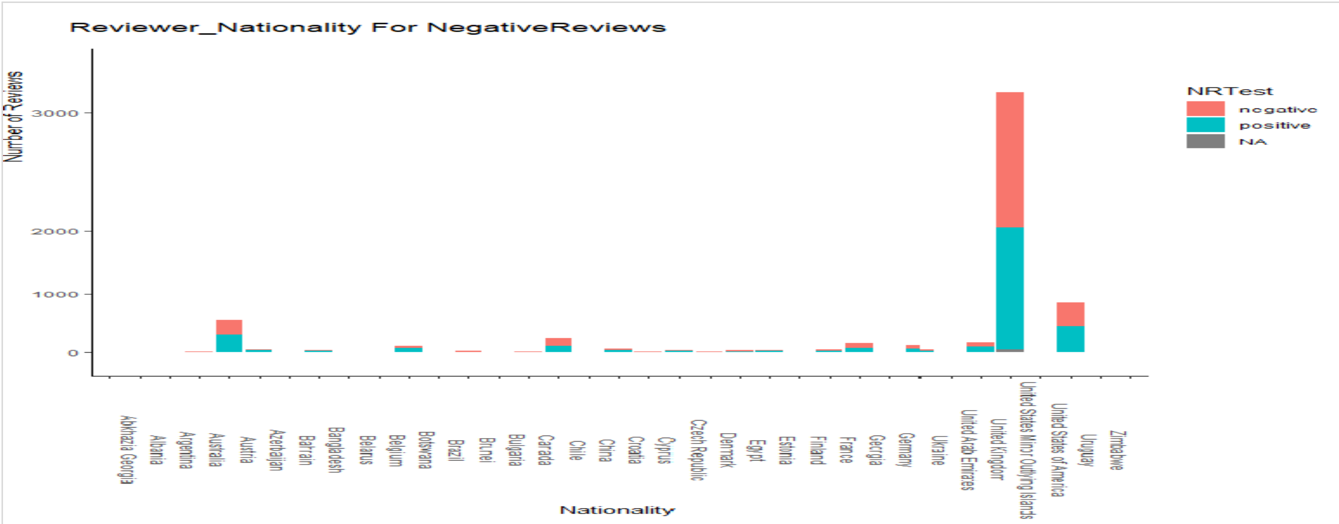

Fig. 4.BI Visualization Number of Negative reviews by Reviewer's Nationality.

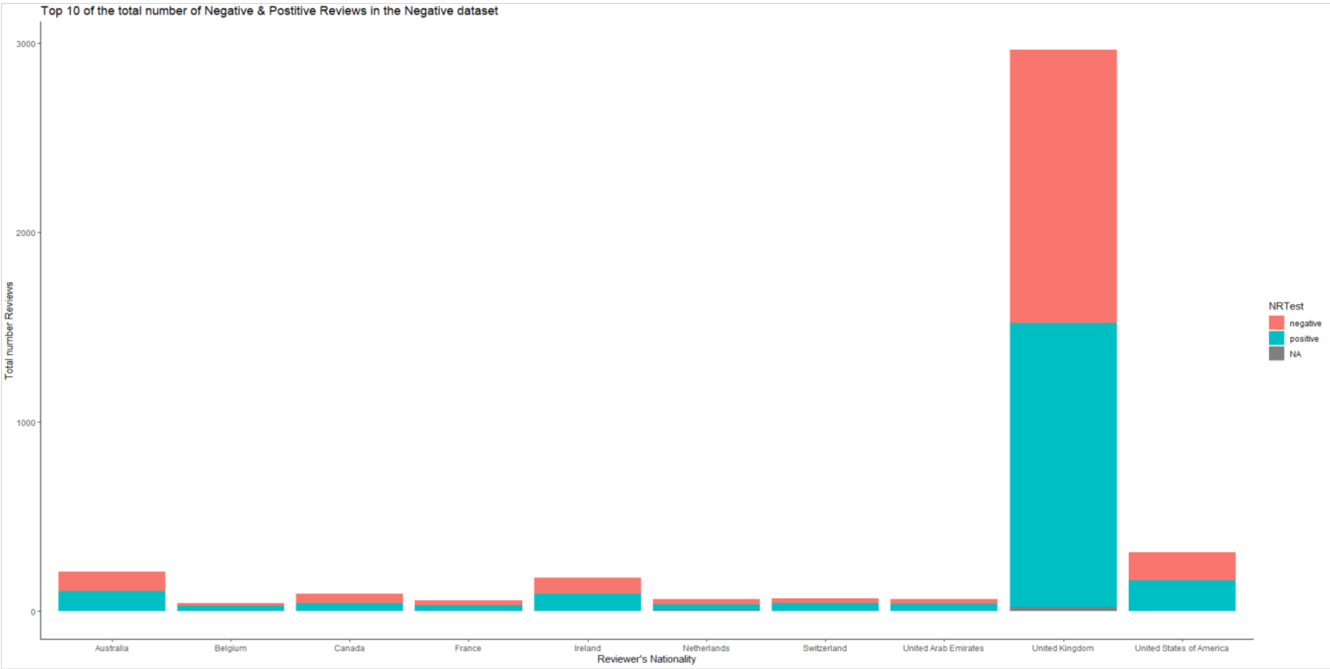

Fig. 5.BI Visualization of Top10 of the Total number of reviews by reviewer nationality.

Using other ways of grouping for categorizable columns, in our case "HotelName" and "ReviewerScore" with the same approach. We plot the polarity of the top10 of each of the above-mentioned categories. Check Figure 4: Total number of reviews by Hotel Name and Figure 5: Top10 of the total number of reviews grouped by the reviewer's score in the Negative Reviews dataset.

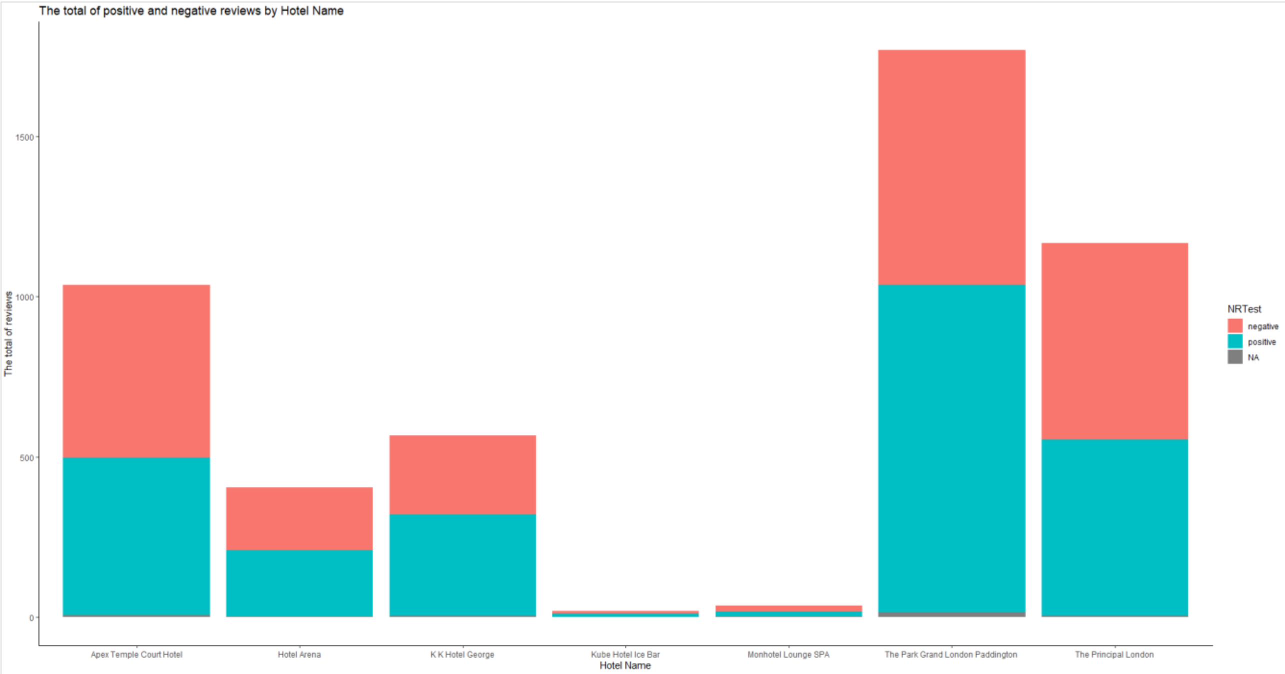

Fig. 6.BI Visualization of Total number of reviews by Hotel Name.

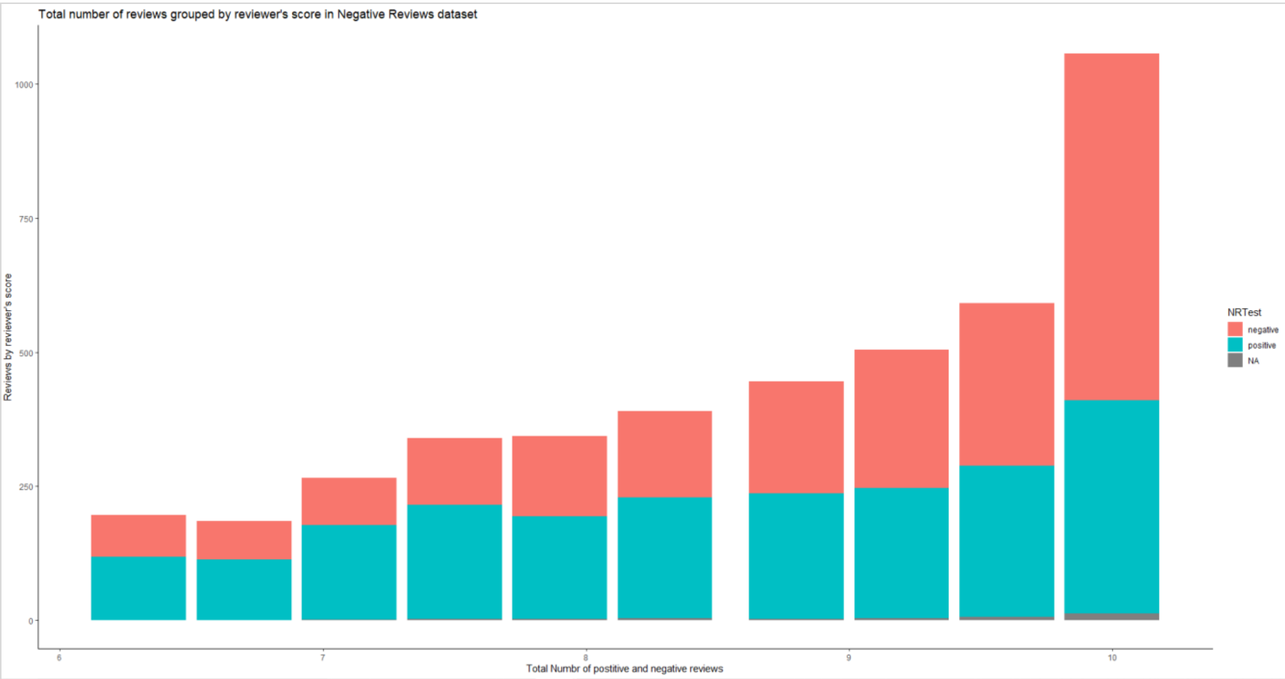

Fig. 7.BI of Top10 of the total number of reviews grouped by the reviewer's score in the Negative Reviews dataset.

VII. CONCLUSION AND FUTURE WORK

By applying sentiment analysis using the Lexicon-based approach on 515,000 customers review related to different European hotel, to extract and calculate the opinion polarity of the reviews and calculate the Error ratio. Then we use the outputs data in business intelligence visualization forms, as we observed above by the charts and results, we founded obviously that the sentiment analysis using the Lexicon-based approach does give us the overall polarity of the opinions. However, it is not clear which aspect the negative or positive opinion is advocating. Besides, the overall accuracy of the results is insufficient to build a system that utilizes such an approach due to language complexity. We would recommend for future work the use of a Machine Learning approach in order to mine opinions and generate a summary of the opinions in a better, understandable format. Also, the use of ML in order to perform SA on any given feature/aspect level.

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