1. INTRODUCTIONS

USA is one of the world's top tourist destinations, and the tourism industry has been expanding quickly in recent years. However, the tourism sector was severely damaged by the coronavirus (Covid-19) outbreak. Timeshare resorts are becoming more and more well-liked among vacationers because of its practicality, accessibility, and adaptability. However, client satisfaction—which can be impacted by a variety of elements like service level, location, and amenities—is crucial to the profitability of the timeshare industry.

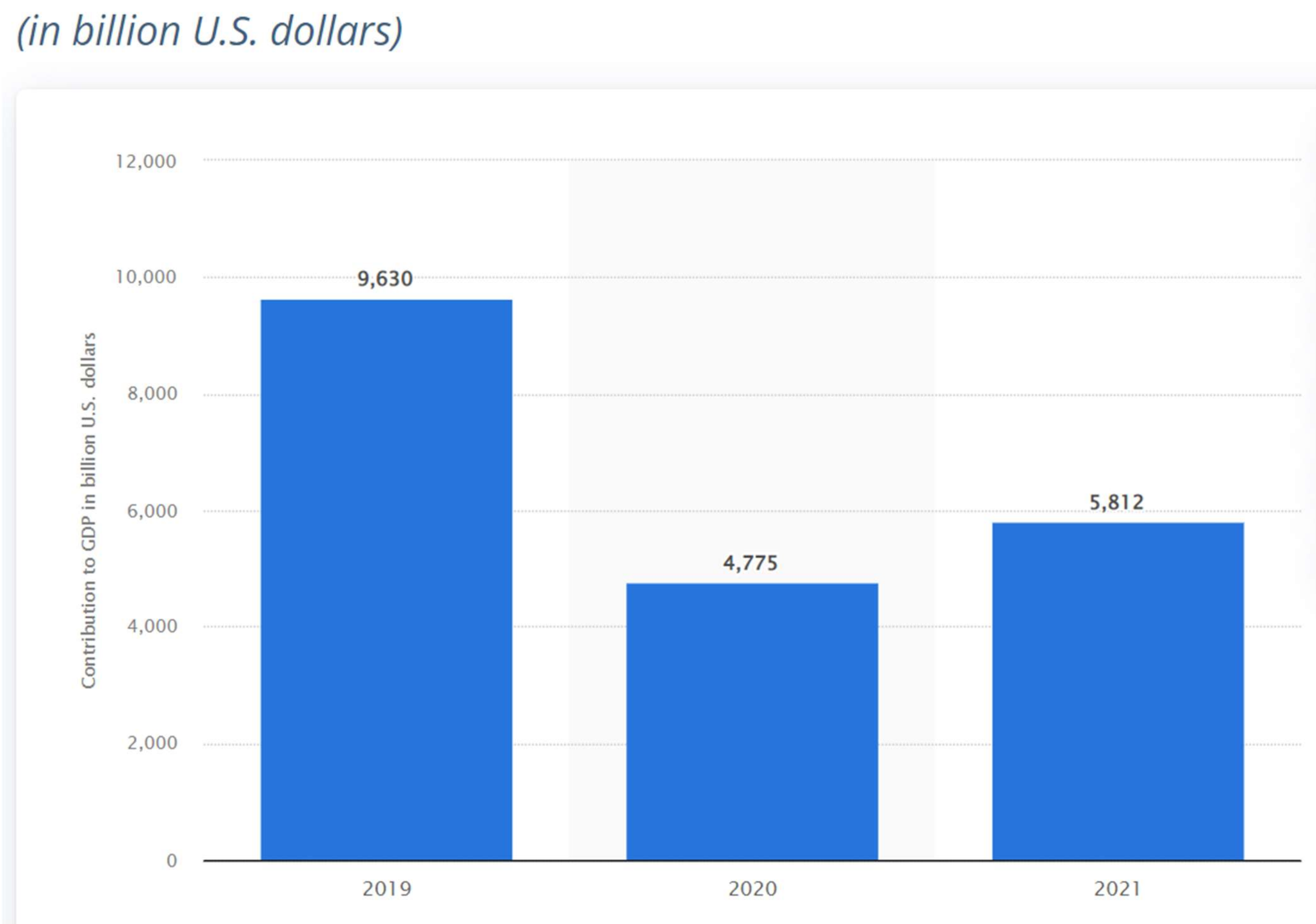


Figure I: T&H's Contribution to GDP in billion U.S 2019-2021

Sources
WTTC; Oxford Economics
Survey by
WTTC; Oxford Economics
Published by
WTTC

The overall contribution of travel and hospitality industry to the global gross domestic product (GDP) has witnessed an increase by 21.7 percent in 2021 compared to the prior years after declining dramatically in 2020 as a result of the coronavirus (COVID-19) pandemic. In 2021, travel and tourism sector added approximately about 5.81 trillion US dollars to the global GDP, which is nearly a trillion more from the previous year but down from levels before to the pandemic.

The worth of all the goods and services produced in a nation in a given year is measured as GDP. Positive changes in GDP are an indication of economic growth and are seen as a key indicator of a nation's economic strength. Based on the total GDP impact of travel and tourism in 2021, the US and China were by far the two largest travel markets. Italy, Germany, and Japan were ranked next in that year's rankings.

The number of foreign visitors arriving worldwide in 2021 climbed somewhat over the previous year but remained significantly lower than the numbers seen before the health crisis. Despite the sharp decline in inbound tourists, France continued to be the nation with the most foreign tourists arriving globally in 2021. The European location had that year welcomed.

The COVID-19 epidemic has influenced the timeshare business, as well as many other industries. There are some signs that the industry may be recovering, though, as travel picks back up and individuals feel more at ease with the thought of taking trips once more.
The rise in domestic travel as more people choose to take road vacations or travel within their own nations rather than travel overseas is one trend that has evolved throughout the pandemic. Given that many timeshare properties are found in well-known domestic holiday spots, this might be advantageous for the timeshare industry.

The advent of remote employment and the "digital nomad" lifestyle is another trend that can be advantageous to the timeshare sector. individuals may be more inclined to think about timeshare ownership as a method to have a "home away from home" in various locations as more individuals have the freedom to work from anyplace.
It's crucial to remember that the timeshare sector has had some difficulties recently, including a decline in customer confidence and heightened competition from other holiday options including vacation rentals and home-sharing websites. How these elements will impact the sector in the post-pandemic era is yet uncertain.

Overall, even though the timeshare market may offer some possibilities for expansion, it is difficult to make firm projections about what the sector will look like after the pandemic. Much will depend on elements like consumer confidence, travel tendencies, and the status of the world economy as a whole.

The COVID-19 pandemic has had a tremendous influence on both customers and companies, with many turning to internet evaluations in the lack of in-person experiences to guide their purchasing decisions. Because it may help businesses understand how their customers are feeling and find areas for development, sentiment analysis of reviews is now more crucial than ever.

Following the pandemic, sentiment analysis of reviews is crucial for the following reasons:
1. Obtaining customer input is crucial for optimizing corporate processes: Businesses can learn a lot about what is functioning well and what needs improvement by looking at the sentiment of consumer evaluations. This can assist companies in identifying areas where they can implement improvements to better serve their clients.

2. Online reviews can have an impact on buying choices: An investigation by BrightLocal found that 87% of consumers check online reviews before making a purchase. The tone and general attitude of customer reviews can have an impact on potential consumers' purchasing decisions, and sentiment analysis can assist firms understand these factors.

3. poor reviews can harm a company's reputation: As more customers rely on online reviews to make purchases, poor reviews can seriously harm a company's reputation. Businesses can avoid reputational harm by identifying bad reviews and taking the required action by using sentiment analysis.

4. The pandemic has altered consumer behaviour. More individuals are now shopping online and relying on online reviews as a result of the outbreak. Due to the necessity for businesses to understand how their customers are feeling in order to adjust to these shifting conditions, sentiment research is now even more crucial.

Overall, sentiment analysis of reviews is critical in the wake of a pandemic because it enables companies to enhance their operations, influence consumer choice, safeguard their reputation, and adjust to shifting consumer preferences. Businesses can provide better service to their clients and prosper in the post-pandemic era by examining consumer feedback and responding properly.

In the study of natural language processing (NLP), concepts of linguistics, artificial intelligence, and computer science inevitably need to be combined and applied.
Computers must process or "understand" natural language in order to perform a variety of tasks that humans individually carry out such as language translation and question-answering. With the increasing popularity of voice interfaces, smart assistants, chatbots etc., NLP has blossomed into one of the most indispensably prominent technologies of the fourth industrial revolution and a favoured area of AI. NLP research has generated an extensive variety of useful applications that are rapidly growing. Also, these research do range from simple to complex.Here are some of them:

- Keyword research, spelling checks, synonym searches, answering complicated queries
- Extracting data from websites, such as items, prices, timestamps, places, names, or dates.
- Machine translation, speech recognition, personal assistants etc.
- Chat bots for customer support, controlling systems, ordering products
- Matching online advertisements, sentiment analysis for marketing or finance
- Identification of financials risks or fraud

The genius behind NLP is a concept called word embedding. Word embeddings are representations of words as vectors, learned by exploiting vast amounts of text. Each word is mapped to one vector and the vector values are learned in a way that resembles an artificial neural network.

Each word is represented by a real-valued vector with often tens or hundreds of dimensions. Here a word vector is a row of real valued numbers where each number is a dimension of the word's meaning and where semantically similar words have similar vectors. Hence certainly, one of the most effective unsupervised learning applications in AI is word embeddings.

There are also additional imperfections such as **conflation deficiency**, which is the failure to distinguish between many word meanings. For instance, the term "bat" can signify either a flying animal or a piece of equipment for sports.
Another difficulty is that a single sentence may express several emotions at once.
However, the good news is that artificial intelligence (AI) can now comprehend sophisticated human language and its intricacies on a large scale and virtually instantly. We began to encounter NLP scenarios in daily life mostly as a result of pre-trained and deep learning driven algorithms.

Sentiment analysis is a subset of natural language processing (NLP) that aims to find and extract opinions from texts spanning across sites, reviews, social media sites, forums, headlines, and others. Sentiment analysis is often referred to as opinion mining as well. With the aid of open source software and NLP, sentiment analysis may well convert the unstructured text that is ever expanding, down to more useful structured data. Online customer review analysis is one of the techniques used in the tourism sector to assess the goods and services provided by companies and comprehend the needs of visitors.

Social media platforms and online storefronts both offer access to these reviews. Utilizing text mining techniques, scientific methodologies are utilized to evaluate customer reviews. Customer reviews for lodging or food & beverage enterprises are utilized in text mining studies in tourism literature. The websites Tripadvisor.com, Booking.com, Expedia.com, Airbnb.com, and Yelp.com are typically used to gather and analyze user reviews.

The main goal of text mining research for the hospitality industry is to ascertain customer happiness and discontent with the provided goods and services.

[1]The all-in-one solution for Java natural language processing is CoreNLP! Users can generate linguistic annotations for text using CoreNLP, such as token and sentence boundaries, parts of speech, named entities, numerical and time values, dependency and constituency parses, coreference, sentiment, quote attributions, and relations.

The centerpiece of CoreNLP is the pipeline. **Pipelines** take in raw text, run a series of NLP annotators on the text, and produce a final set of annotations.

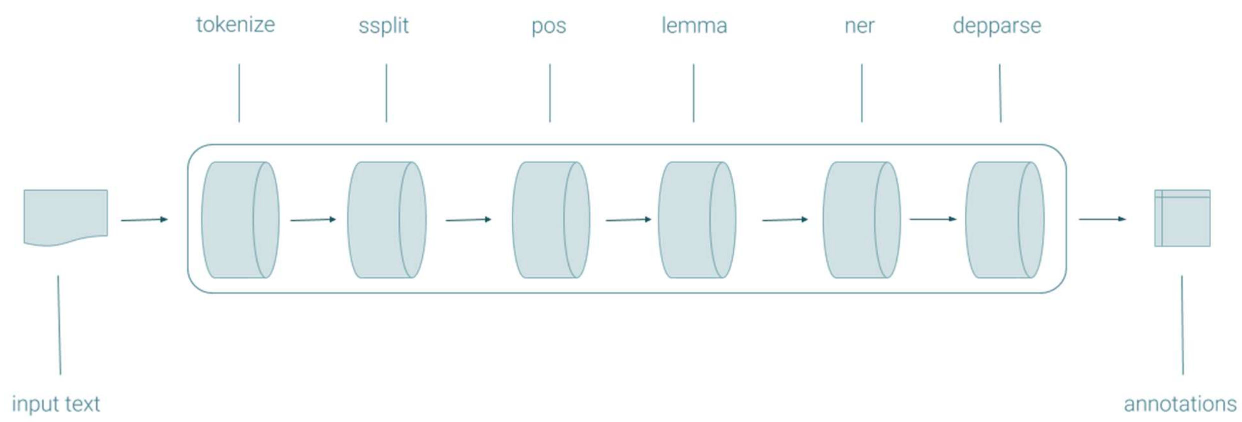


Figure II: Diagrammatic representation of the concept of pipeline in CoreNLP

Pipelines produce **CoreDocuments**, data objects that contain all the annotation information, accessible with a simple API, and serializable to a Google Protocol Buffer.

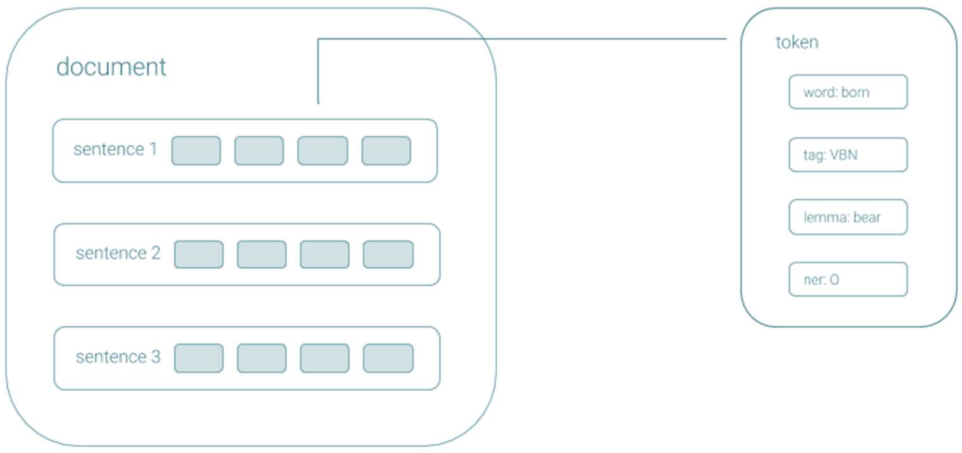


Figure III: Diagrammatic representation of the concept of CoreDocuments.

Annotations

CoreNLP generates a variety of linguistic annotations, including:

PARTS OF SPEECH

Figure IV: Annotations in the context of Parts of Speech generation.

NAMED ENTITIES

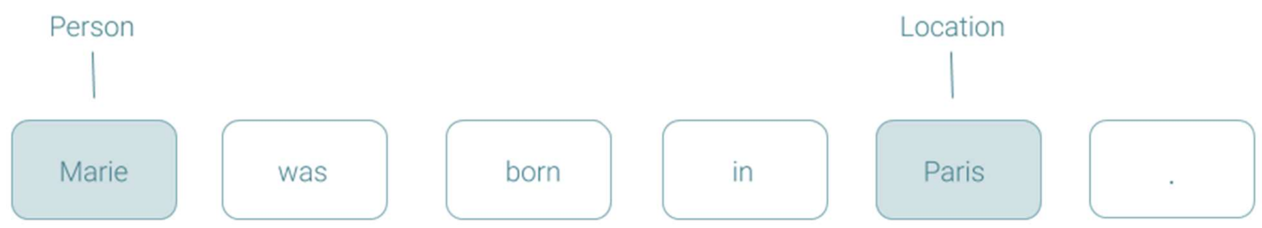


Figure V: Annotations in the context of Named Entities.

DEPENDENCY PARSES

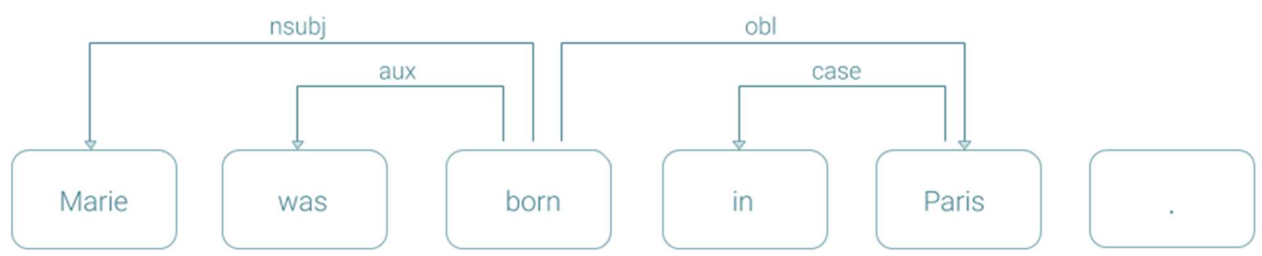


Figure VI: Annotations in the context of Dependency Parsing

COREFERENCE

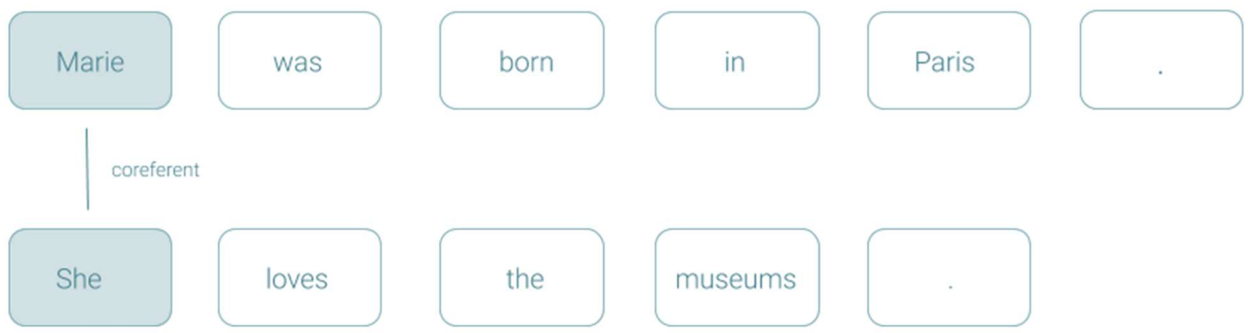


Figure VII: Annotations in the context of Co-Referencing

2. OBJECTIVE

The objective of this dissertation is to:

- Data Scraping from Trip Advisor using Jsoup library for 46 Timeshare properties in USA and Data Analysis of the dataset. This returned the URL to fetch resort specific reviews. Each 46 URLs were scrapped individually for reviews. The final data set was exported in an excel. The JSON to excel conversion was done using Jackson (JSON processing) and Apache POI (for creating EXCEL files) libraries in Java.
- Save the review data, user details and property details in MySQL database for future research and analysis.
- Split each review into sentences to get distinct topics that reviewers mentioned in each sentence.
- Use aspect-based sentiment for timeshare properties using sentiment scoring with Stanford Core NLP.
- Summarize the key insights from the sentiment analysis.
- Present outcomes to client for Business Alignment.

3. LITERATURE REVIEW

3.1 SENTIMENT ANALYSIS

Sentiment analysis examines the emotions that are communicated in a text. It is frequently used to evaluate reviews of products or items, survey outcomes, and customer feedback.

THE APPLICATION OF THE SENTIMENT ANALYSIS

The inception and rapid growth of sentiment analysis coincide with those of social media on the web, such as reviews, forum discussions, blogs, and microblogs, because for the first time in human history, we now have a huge volume of opinion data recorded in digital forms. These data, also called user-generated content, prompted researchers to mine them to discover useful knowledge. This naturally led to the problem of sentiment analysis or opinion mining because these data are full of opinions. That these data are full of opinions is not surprising, because the primary reason why people post messages on social media platforms is to express their views and opinions, and therefore sentiment analysis is at the very core of social media analysis. Since early 2000, sentiment analysis has grown to be one of the most active research areas in natural language processing.[2]

ADVANTAGES

- One can acquire useful brand experience data that might provide you a peek into underlying consumer expectations for his/her brand. These insights are crucial since they help to comprehend market-gap concerns, keep customers, develop a devoted following of clients, and boost sales conversions.

- Emotion mining can provide business owners with insightful information on how to enhance their product so that it reaches more customers from customer feedback data, surveys, news reports and articles, social media listening, and other sources.

- The field of sentiment analysis is growing and there is a lot which is still unexplored. With implementations of newer computations (ML) and (data mining) algorithms, sentiment analysis is overcoming a lot of its downsides.

DISADVANTAGES

- Sentiment analysis mainly focuses on opinions that express or imply positive or negative sentiments, also called positive or negative opinions in everyday language. [3]

- Although sentiment analysis studies opinion text, there was almost no research on it from either the linguistics community or the NLP community before the year 2000.[4] Hence forming insights based on data earlier than that would be incredibly difficult.

- There aren't many resources or tools available in languages other than English that can be utilized to quickly create effective sentiment classifiers for a variety of languages.

- With a huge number of data sets available, more sophisticated or even new kinds of machine learning algorithms should be designed to make major breakthroughs in learning domain–independent and domain-specific knowledge needed for sentiment analysis.[5]

3.2 ASPECT BASED SENTIMENT ANALYSIS(ABSA)

Aspect Based Sentiment Analysis is the task of co-extracting opinion terms and aspect terms (opinion targets) and the relations between them in a given corpus.[6]

This fine-grained level of analysis serves as the foundation for the majority of industrial sentiment analysis and opinion mining systems. Aspect-level analysis directly examines opinion and its target (called the opinion target) rather than looking at language units (documents, paragraphs, sentences, clauses, or phrases). We can comprehend the sentiment analysis issue considerably better by realizing the significance of opinion targets. Here's another illustration: "I still love this restaurant, despite the mediocre service." Although the tone of this line is unmistakably favorable, we cannot conclude that it is fully positive. We can only conclude that while the sentence is favorable toward the eatery (stressed), it is unfavorable for its service (not emphasized). If someone reading the review is particularly concerned about the service, he/she generally won't go to the restaurant.

ADVANTAGES

- In recent years, deep learning (DL) has made breakthroughs and applications in academics and industries, attracting scholars to apply it to ABSA tasks. Instead of machine learning approaches that rely heavily on the quality of the handmade features, deep learning approaches utilize neural networks (NN) to learn the semantic and syntactic features automatically and perform great in the related extensive experiment.[7]

- Granularity: ABSA goes beyond identifying a text's overall sentiment by identifying particular features and the polarities of the sentiments they elicit. This gives a deeper grasp of user opinions on different elements of a good, service, or subject.

- Precision: By concentrating on certain elements rather than the entirety of a text, ABSA enables more precise sentiment analysis. This can lessen misunderstandings brought on by divergent viewpoints on certain textual elements.

DISADVANTAGES

- Because it calls for the identification of aspects and the accompanying sentiment polarity, Aspect Based Sentiment Analysis is more difficult than conventional sentiment analysis methods. It might be more difficult to establish and keep up because of this.
- Aspect Based Sentiment Analysis frequently demands the training of big models and the processing of a lot of data, which can be resource-intensive. Small businesses or researchers with minimal resources may find this difficult.

3.3 PEARSON'S CORRELATION COEFFICIENT

The test statistic that assesses the statistical association, or relationship, between two continuous variables is called Pearson's correlation coefficient. Because it is based on the method of covariance, it is regarded as the best method for determining the relationship between variables of interest.

Pearson's Correlation coefficient is represented as 'r', it measures how strong is the linear association between two continuous variables using the formula:[8]

$$r = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2}}$$

Where,

r = Pearson Correlation Coefficient

x_i = x variable samples y_i = y variable sample

$\bar{x}$ = mean of values in x variable $\bar{y}$ =mean of values in y variable

Figure VIII: Pearson's correlation Coefficient Formula

ADVANTAGES

- The degree and direction of a linear relationship between two variables is measured by the Pearson correlation coefficient, which ranges from -1 (strong negative correlation) to 1 (strong positive correlation), and is simple to comprehend and analyze.
- It is rather simple to calculate Pearson correlation coefficients, and many statistical software programs and programming languages provide built-in methods for this purpose.

- It is straightforward to determine the most important variables in a dataset by comparing the strength of several linear correlations using Pearson correlation coefficients.

DISADVANTAGES

- Pearson correlation is susceptible to outliers, which might have an unjustified influence on the correlation coefficient and produce false results.
- Correlation does not imply causation
- Assumes normally distributed data

4. METHODOLOGY

4.1 <u>DATA COLLECTION</u>:

Data was scrapped from Trip Advisor using Jsoup Library. For the list of 46 Timeshare properties the URL *https://www.tripadvisor.com/Hotels-g191-United_States-Hotels.html* is used. The response was parsed to fetch the list of specific TripAdvisor urls and their respective property names. Thereafter a loop was executed to hit the respective URLs e.g *https://www.tripadvisor.com/Hotel_Review-g45963-d91878-Reviews-Westgate_Las_Vegas_Resort_Casino-Las_Vegas_Nevada.html* to retrieve review lists for individual properties. The response returned was heavy content wise with complicated nested JSON structures. Programmatically unwanted tags were removed and needed JSONs were simplified, for this Jackson a Java based library was used.

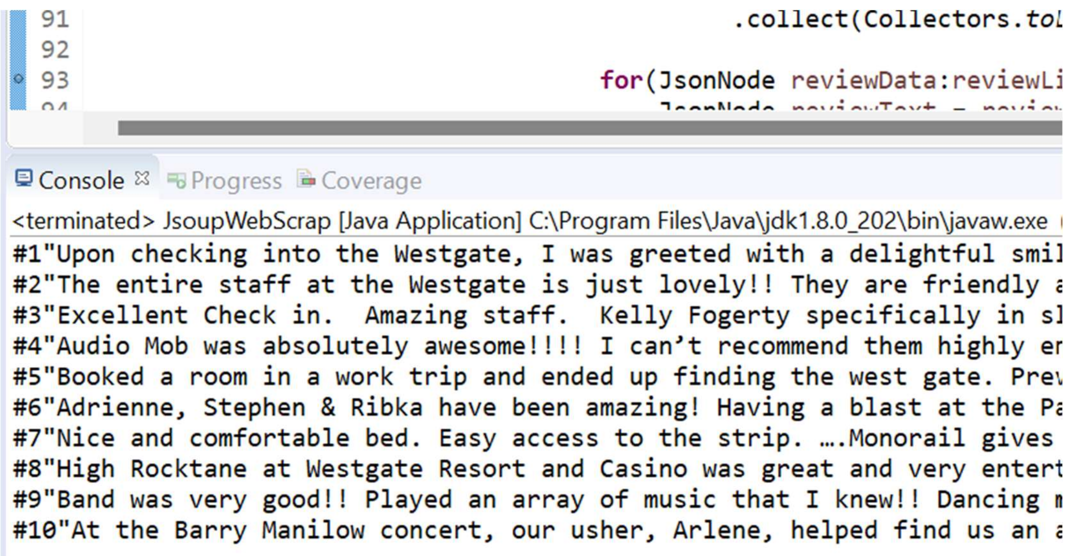


Figure 1: A sample screenshot of few reviews of customers for a timeshare property.

Other key observations include:

1. User profile with details like if user is verified or not, user display name, review published timestamp, etc were also retrieved from the data scrapping from TripAdvisor were available for alongside the actual textual reviews.
2. The textual reviews were filtered for data after 31st March 2021 only to keep the analysis focused on post pandemic customer sentiment.

4.2 SENTIMENT ANALYSIS:

Sentiment analysis (also known as opinion mining or emotion AI) is the use of natural language processing, text analysis, computational linguistics, and biometrics to systematically identify, extract, quantify, and study affective states and subjective information. Sentiment analysis is widely applied to voice of the customer materials such as reviews and survey responses, online and social media, and healthcare materials for applications that range from marketing to customer service to clinical medicine. With the rise of deep language models, such as RoBERTa, also more difficult data domains can be analysed, e.g., news texts where authors typically express their opinion/sentiment less explicitly.[9]

After Data gathering, cleaning and sorting functions from the Stanford Core NLP API were applied (e.g String edu.stanford.nlp.pipeline.CoreSentence.sentiment()) to gather insights about the reviews. Sentiment values are measured on a scale from 0 to 4. Zero indicates a highly negative statement, while four indicates a very positive one. Although some reviews contain difficult terms like "I can't recommend them", CoreNLP successfully identified that they are negated. The simpler sentences were also accurately categorized.

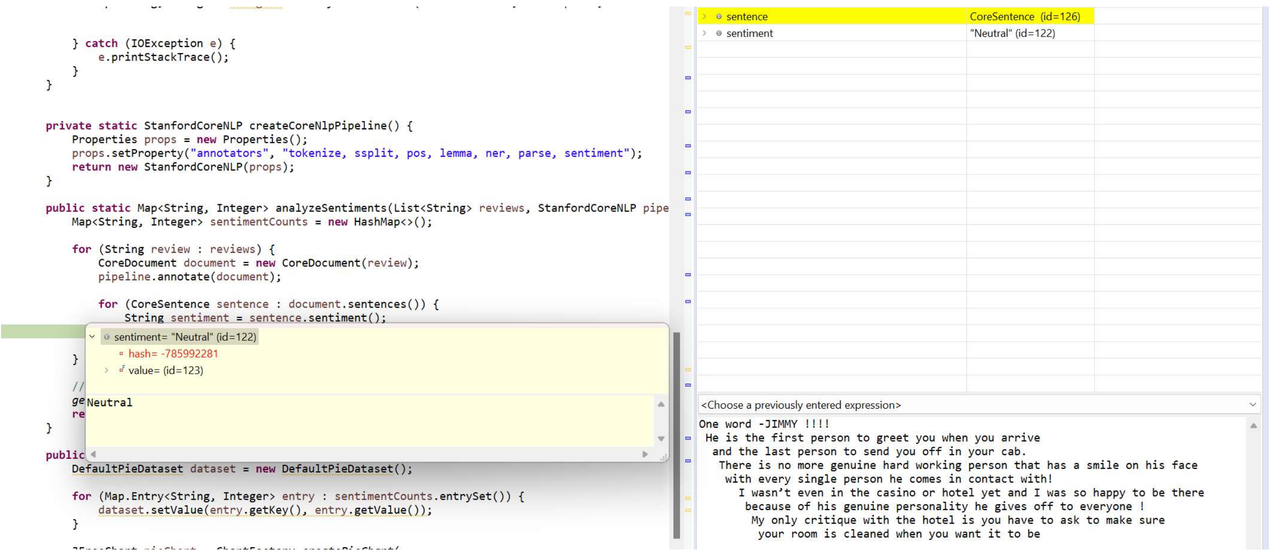


Figure 2: Sentiment Analysis of each review

4.2.1 Visualization

Post sentiment analysis the gathered insights based on the sentiment analysis was charted on pie chart using JFreeChart library.

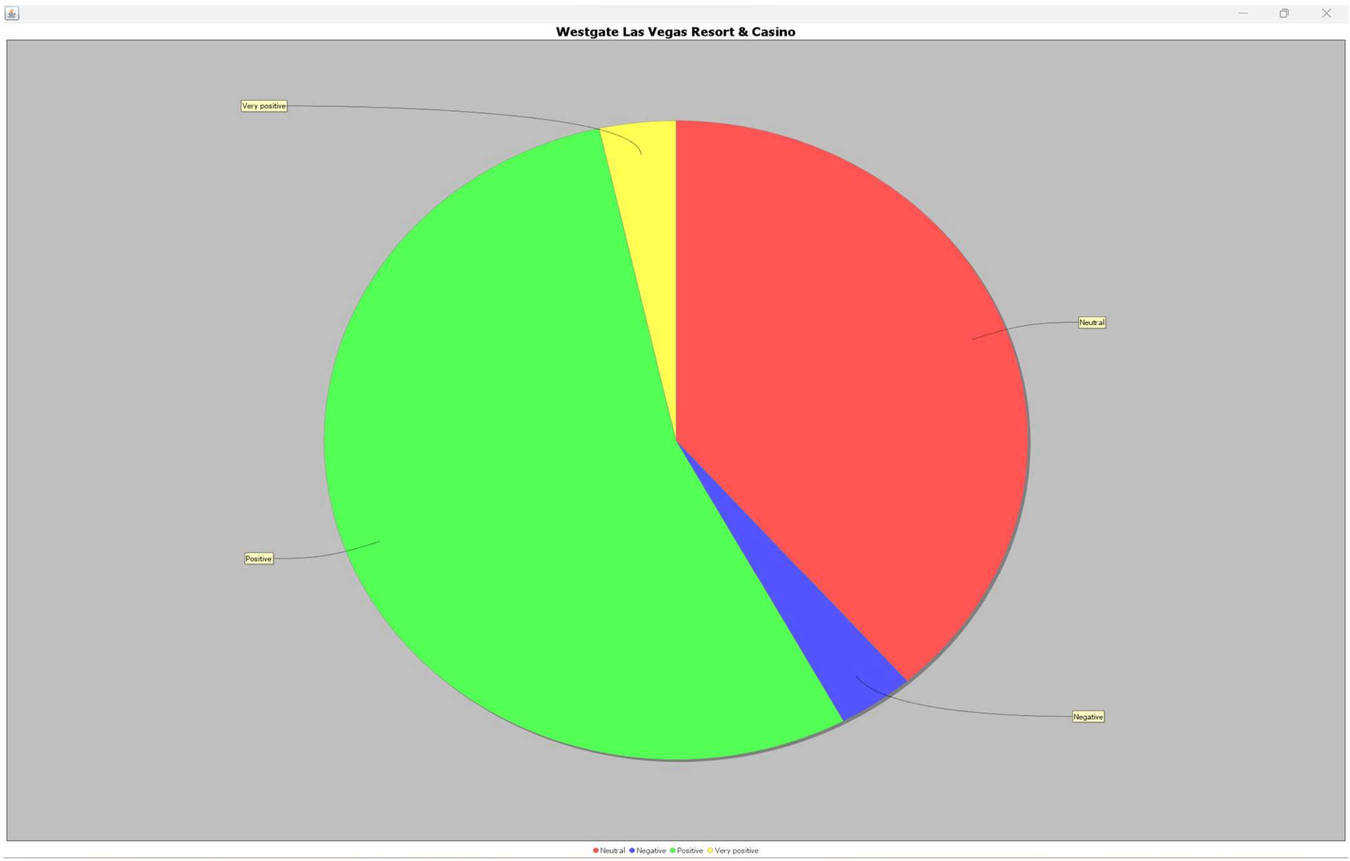


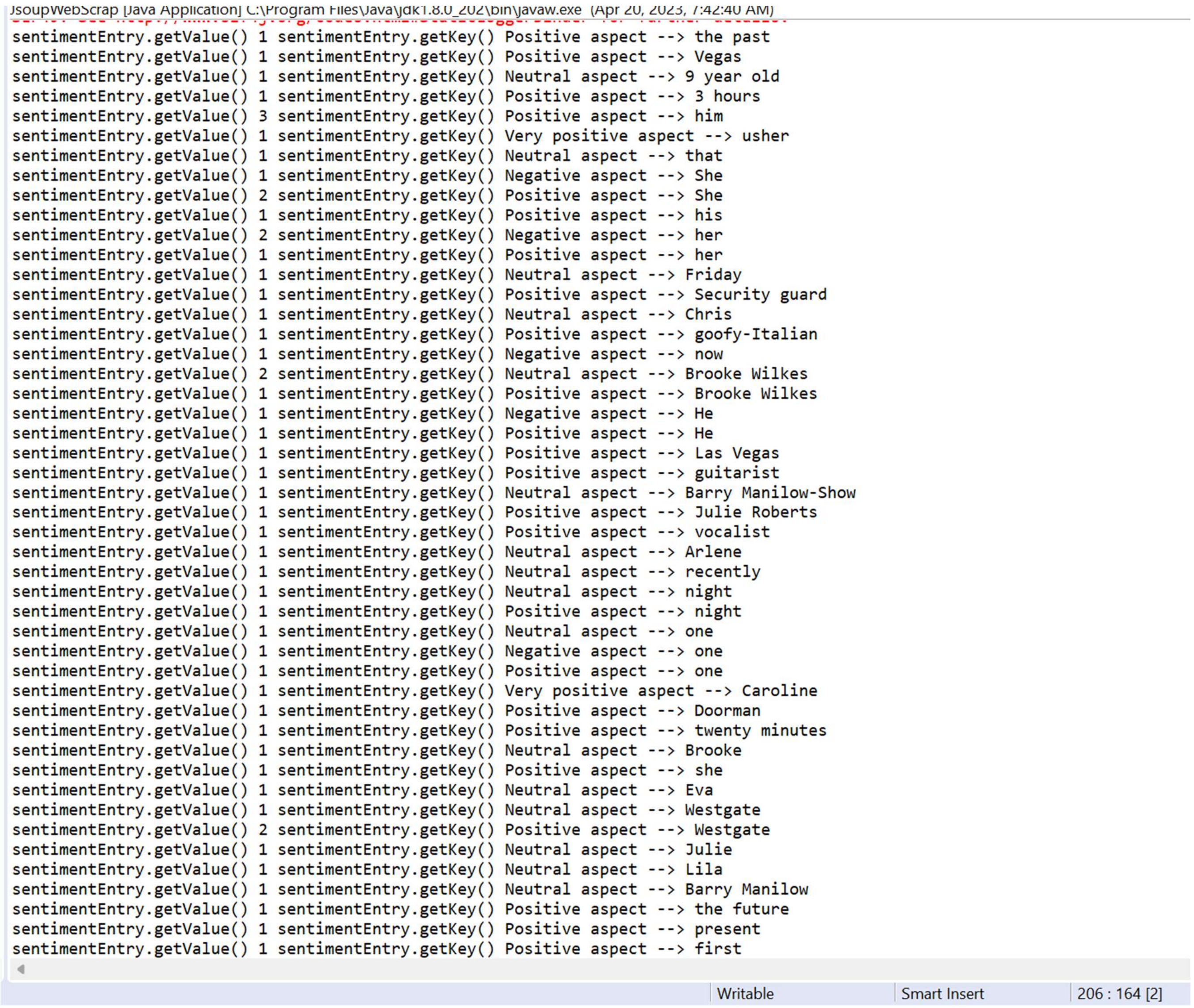
Figure 3: Pie chart plotting using insights from sentiment analysis step

4.3 ASPECT BASED SENTIMENT ANALYSIS: Aspect-Based Sentiment Analysis (ABSA) is a type of text analysis that categorizes opinions by aspect and identifies the sentiment related to each aspect.

An opinion is a quintuple,

$$(e, a, s, h, t)$$

where **e** is the target entity, **a** is the target aspect of entity **e** on which the opinion has been given, **s** is the sentiment of the opinion on aspect a of entity **e**, **h** is the opinion holder, and t is the opinion posting time; s can be positive, negative, or neutral, or a rating (e.g., 1–5 stars). When an opinion is only on the entity as a whole, the special aspect GENERAL is used to denote it. Here e and a together represent the opinion target. Sentiment analysis (or opinion mining) based on this definition is often called aspect-based sentiment analysis.[10]
The pipeline in our program takes care of "annotators", "tokenize”, “ssplit”, “pos”, “lemma”, “ner”, “parse”, “sentiment".


JsoupWebScrap [Java Application] C:\Program Files\Java\jdk1.8.0_202\bin\javaw.exe (Apr 20, 2023, 7:42:40 AM)

```
sentimentEntry.getValue() 1 sentimentEntry.getKey() Positive aspect --> the past
sentimentEntry.getValue() 1 sentimentEntry.getKey() Positive aspect --> Vegas
sentimentEntry.getValue() 1 sentimentEntry.getKey() Neutral aspect --> 9 year old
sentimentEntry.getValue() 1 sentimentEntry.getKey() Positive aspect --> 3 hours
sentimentEntry.getValue() 3 sentimentEntry.getKey() Positive aspect --> him
sentimentEntry.getValue() 1 sentimentEntry.getKey() Very positive aspect --> usher
sentimentEntry.getValue() 1 sentimentEntry.getKey() Neutral aspect --> that
sentimentEntry.getValue() 1 sentimentEntry.getKey() Negative aspect --> She
sentimentEntry.getValue() 2 sentimentEntry.getKey() Positive aspect --> She
sentimentEntry.getValue() 1 sentimentEntry.getKey() Positive aspect --> his
sentimentEntry.getValue() 2 sentimentEntry.getKey() Negative aspect --> her
sentimentEntry.getValue() 1 sentimentEntry.getKey() Positive aspect --> her
sentimentEntry.getValue() 1 sentimentEntry.getKey() Neutral aspect --> Friday
sentimentEntry.getValue() 1 sentimentEntry.getKey() Positive aspect --> Security guard
sentimentEntry.getValue() 1 sentimentEntry.getKey() Neutral aspect --> Chris
sentimentEntry.getValue() 1 sentimentEntry.getKey() Positive aspect --> goofy-Italian
sentimentEntry.getValue() 1 sentimentEntry.getKey() Negative aspect --> now
sentimentEntry.getValue() 2 sentimentEntry.getKey() Neutral aspect --> Brooke Wilkes
sentimentEntry.getValue() 1 sentimentEntry.getKey() Positive aspect --> Brooke Wilkes
sentimentEntry.getValue() 1 sentimentEntry.getKey() Negative aspect --> He
sentimentEntry.getValue() 1 sentimentEntry.getKey() Positive aspect --> He
sentimentEntry.getValue() 1 sentimentEntry.getKey() Positive aspect --> Las Vegas
sentimentEntry.getValue() 1 sentimentEntry.getKey() Positive aspect --> guitarist
sentimentEntry.getValue() 1 sentimentEntry.getKey() Neutral aspect --> Barry Manilow-Show
sentimentEntry.getValue() 1 sentimentEntry.getKey() Positive aspect --> Julie Roberts
sentimentEntry.getValue() 1 sentimentEntry.getKey() Positive aspect --> vocalist
sentimentEntry.getValue() 1 sentimentEntry.getKey() Neutral aspect --> Arlene
sentimentEntry.getValue() 1 sentimentEntry.getKey() Neutral aspect --> recently
sentimentEntry.getValue() 1 sentimentEntry.getKey() Neutral aspect --> night
sentimentEntry.getValue() 1 sentimentEntry.getKey() Positive aspect --> night
sentimentEntry.getValue() 1 sentimentEntry.getKey() Neutral aspect --> one
sentimentEntry.getValue() 1 sentimentEntry.getKey() Negative aspect --> one
sentimentEntry.getValue() 1 sentimentEntry.getKey() Positive aspect --> one
sentimentEntry.getValue() 1 sentimentEntry.getKey() Very positive aspect --> Caroline
sentimentEntry.getValue() 1 sentimentEntry.getKey() Positive aspect --> Doorman
sentimentEntry.getValue() 1 sentimentEntry.getKey() Positive aspect --> twenty minutes
sentimentEntry.getValue() 1 sentimentEntry.getKey() Neutral aspect --> Brooke
sentimentEntry.getValue() 1 sentimentEntry.getKey() Positive aspect --> she
sentimentEntry.getValue() 1 sentimentEntry.getKey() Neutral aspect --> Eva
sentimentEntry.getValue() 1 sentimentEntry.getKey() Neutral aspect --> Westgate
sentimentEntry.getValue() 2 sentimentEntry.getKey() Positive aspect --> Westgate
sentimentEntry.getValue() 1 sentimentEntry.getKey() Neutral aspect --> Julie
sentimentEntry.getValue() 1 sentimentEntry.getKey() Neutral aspect --> Lila
sentimentEntry.getValue() 1 sentimentEntry.getKey() Neutral aspect --> Barry Manilow
sentimentEntry.getValue() 1 sentimentEntry.getKey() Positive aspect --> the future
sentimentEntry.getValue() 1 sentimentEntry.getKey() Positive aspect --> present
sentimentEntry.getValue() 1 sentimentEntry.getKey() Positive aspect --> first
```

Writable | Smart Insert | 206 : 164 [2]

Screenshot of output from console displaying few sample aspects from reviews and the corresponding sentiment scores.

4.3.1 Visualization:

```
("Negative"), Color.RED);
("Positive"), Color.GREEN);
("Very positive"), Color.BLUE);
("Neutral"), Color.YELLOW);
```

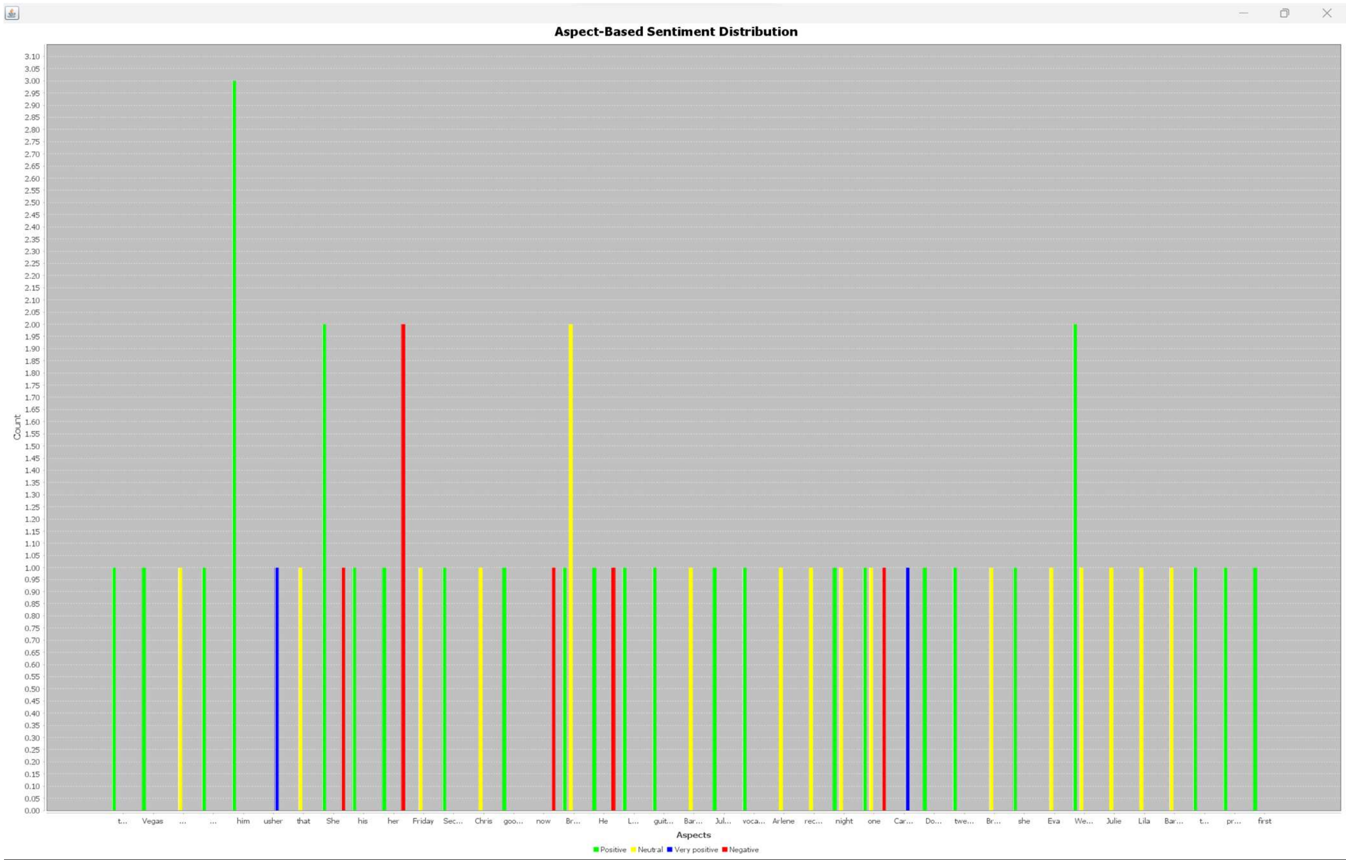


Figure 4: Bar chart representing the Aspect Based Sentiment Distribution

4.4 Correlation Matrix

Returns the correlation matrix.

```java
public static double[][] calculateCorrelationMatrix(double[][] aspectSentimentMatrix) {
    PearsonsCorrelation correlation = new PearsonsCorrelation(aspectSentimentMatrix);
    return correlation.getCorrelationMatrix().getData();
}

public static double[][] createAspectSentimentMatrix(List<Map<String, Double>> aspectSentimentScores, List<String>
```

And the aspectsentimentMatrix was created using following method,

```java
public static double[][] createAspectSentimentMatrix(List<Map<String, Double>> aspectSentimentScores, List<String> aspectNames) {
    int numAspects = aspectNames.size();
    int numReviews = aspectSentimentScores.size();
    double[][] matrix = new double[numReviews][numAspects];

    for (int i = 0; i < numReviews; i++) {
        Map<String, Double> aspectSentimentScore = aspectSentimentScores.get(i);
        for (int j = 0; j < numAspects; j++) {
            String aspect = aspectNames.get(j);
            matrix[i][j] = aspectSentimentScore.getOrDefault(aspect, 0.0);
        }
    }

    return matrix;
}
```

Aspect Sentiment Scores	Aspect Names

```
Arlene: 0.0
He: 1.0
Barry Manilow-Show: 0.0
the past: 1.0
Vegas: 1.0
Eva: 0.0
Westgate: 1.0
Lila: 0.0
Chris: 0.0
recently: 0.0
one: 0.0
present: 1.0
Julie Roberts: 1.0
She: -1.0
Julie: 0.0
her: -1.0
Security guard: 1.0
She: 1.0
that: 0.0
Westgate: 0.0
vocalist: 1.0
her: 1.0
now: -1.0
night: 0.0
Brooke Wilkes: 0.0
Brooke: 0.0
Brooke Wilkes: 0.0
guitarist: 1.0
twenty minutes: 1.0
Westgate: 1.0
goofy-Italian: 1.0
He: -1.0
him: 1.0
Las Vegas: 1.0
Doorman: 1.0
she: 1.0
3 hours: 1.0
Brooke Wilkes: 1.0
night: 1.0
She: 1.0
usher: 0.0
his: 1.0
9 year old: 0.0
her: -1.0
Friday: 0.0
Barry Manilow: 0.0
the future: 1.0
Caroline: 0.0
first: 1.0
```

```
the past
Vegas
9 year old
3 hours
him
She
that
usher
his
her
Security guard
Friday
Chris
now
goofy-Italian
Brooke Wilkes
He
guitarist
Las Vegas
Barry Manilow-Show
Julie Roberts
vocalist
Arlene
recently
one
night
Caroline
Doorman
Brooke
twenty minutes
Eva
Westgate
she
Julie
Lila
Barry Manilow
the future
present
first
```

Table 2: Aspect Sentiment Scores and Aspect Names.

4.4.1 Correlation Matrix output:

	A0	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	A15	A16	A17	A18	A19
A0	1.00	1.00	NaN	-0.11	-0.11	-0.06	NaN	NaN	-0.11	0.06	-0.11	NaN	NaN	0.11	-0.11	-0.11	0.00	-0.11	-0.11	NaN
A1	1.00	1.00	NaN	-0.11	-0.11	-0.06	NaN	NaN	-0.11	0.06	-0.11	NaN	NaN	0.11	-0.11	-0.11	0.00	-0.11	-0.11	NaN
A2	NaN	NaN	1.00	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
A3	-0.11	-0.11	NaN	1.00	-0.11	-0.06	NaN	NaN	-0.11	0.06	-0.11	NaN	NaN	0.11	-0.11	1.00	-0.00	-0.11	-0.11	NaN
A4	-0.11	-0.11	NaN	-0.11	1.00	-0.06	NaN	NaN	-0.11	0.06	-0.11	NaN	NaN	0.11	1.00	-0.11	-0.75	-0.11	1.00	NaN
A5	-0.06	-0.06	NaN	-0.06	-0.06	1.00	NaN	NaN	0.56	0.38	-0.68	NaN	NaN	-0.56	-0.06	-0.06	-0.00	-0.06	-0.06	NaN
A6	NaN	NaN	NaN	NaN	NaN	NaN	1.00	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
A7	NaN	NaN	NaN	NaN	NaN	NaN	NaN	1.00	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
A8	-0.11	-0.11	NaN	-0.11	-0.11	0.56	NaN	NaN	1.00	-0.56	-0.11	NaN	NaN	0.11	-0.11	-0.11	-0.00	-0.11	-0.11	NaN
A9	0.06	0.06	NaN	0.06	0.06	0.38	NaN	NaN	-0.56	1.00	-0.56	NaN	NaN	-0.68	0.06	0.06	-0.00	0.06	0.06	NaN
A10	-0.11	-0.11	NaN	-0.11	-0.11	-0.68	NaN	NaN	-0.11	-0.56	1.00	NaN	NaN	0.11	-0.11	-0.11	0.00	-0.11	-0.11	NaN
A11	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	1.00	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
A12	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	1.00	NaN	NaN	NaN	NaN	NaN	NaN	NaN
A13	0.11	0.11	NaN	0.11	0.11	-0.56	NaN	NaN	0.11	-0.68	0.11	NaN	NaN	1.00	0.11	0.11	-0.00	0.11	0.11	NaN
A14	-0.11	-0.11	NaN	-0.11	1.00	-0.06	NaN	NaN	-0.11	0.06	-0.11	NaN	NaN	0.11	1.00	-0.11	-0.75	-0.11	1.00	NaN
A15	-0.11	-0.11	NaN	1.00	-0.11	-0.06	NaN	NaN	-0.11	0.06	-0.11	NaN	NaN	0.11	-0.11	1.00	-0.00	-0.11	-0.11	NaN
A16	0.00	0.00	NaN	-0.00	-0.75	-0.00	NaN	NaN	-0.00	-0.00	0.00	NaN	NaN	-0.00	-0.75	-0.00	1.00	0.00	-0.75	NaN
A17	-0.11	-0.11	NaN	-0.11	-0.11	-0.06	NaN	NaN	-0.11	0.06	-0.11	NaN	NaN	0.11	-0.11	-0.11	0.00	1.00	-0.11	NaN
A18	-0.11	-0.11	NaN	-0.11	1.00	-0.06	NaN	NaN	-0.11	0.06	-0.11	NaN	NaN	0.11	1.00	-0.11	-0.75	-0.11	1.00	NaN
A19	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	1.00
A20	-0.11	-0.11	NaN	-0.11	-0.11	-0.68	NaN	NaN	-0.11	-0.56	1.00	NaN	NaN	0.11	-0.11	-0.11	0.00	-0.11	-0.11	NaN
A21	-0.11	-0.11	NaN	-0.11	-0.11	0.56	NaN	NaN	-0.11	0.68	-0.11	NaN	NaN	-1.00	-0.11	-0.11	0.00	-0.11	-0.11	NaN
A22	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
A23	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
A24	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
A25	-0.11	-0.11	NaN	-0.11	-0.11	-0.06	NaN	NaN	-0.11	0.06	-0.11	NaN	NaN	0.11	-0.11	-0.11	-0.00	-0.11	-0.11	NaN
A26	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
A27	-0.11	-0.11	NaN	-0.11	1.00	-0.06	NaN	NaN	-0.11	0.06	-0.11	NaN	NaN	0.11	1.00	-0.11	-0.75	-0.11	1.00	NaN
A28	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
A29	-0.11	-0.11	NaN	-0.11	1.00	-0.06	NaN	NaN	-0.11	0.06	-0.11	NaN	NaN	0.11	1.00	-0.11	-0.75	-0.11	1.00	NaN
A30	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
A31	0.67	0.67	NaN	-0.17	0.67	-0.09	NaN	NaN	-0.17	0.09	-0.17	NaN	NaN	0.17	0.67	-0.17	-0.56	-0.17	0.67	NaN
A32	-0.11	-0.11	NaN	1.00	-0.11	-0.06	NaN	NaN	-0.11	0.06	-0.11	NaN	NaN	0.11	-0.11	1.00	-0.00	-0.11	-0.11	NaN
A33	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
A34	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
A35	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
A36	-0.11	-0.11	NaN	-0.11	-0.11	0.56	NaN	NaN	1.00	-0.56	-0.11	NaN	NaN	0.11	-0.11	-0.11	-0.00	-0.11	-0.11	NaN
A37	1.00	1.00	NaN	-0.11	-0.11	-0.06	NaN	NaN	-0.11	0.06	-0.11	NaN	NaN	0.11	-0.11	-0.11	0.00	-0.11	-0.11	NaN
A38	-0.11	-0.11	NaN	-0.11	-0.11	0.56	NaN	NaN	1.00	-0.56	-0.11	NaN	NaN	0.11	-0.11	-0.11	-0.00	-0.11	-0.11	NaN

	A20	A21	A22	A23	A24	A25	A26	A27	A28	A29	A30	A31	A32	A33	A34	A35	A36	A37	A38
A0	-0.11	-0.11	NaN	NaN	NaN	-0.11	NaN	-0.11	NaN	-0.11	NaN	0.67	-0.11	NaN	NaN	NaN	-0.11	1.00	-0.11
A1	-0.11	-0.11	NaN	NaN	NaN	-0.11	NaN	-0.11	NaN	-0.11	NaN	0.67	-0.11	NaN	NaN	NaN	-0.11	1.00	-0.11
A2	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
A3	-0.11	-0.11	NaN	NaN	NaN	-0.11	NaN	-0.11	NaN	-0.11	NaN	-0.17	1.00	NaN	NaN	NaN	-0.11	-0.11	-0.11
A4	-0.11	-0.11	NaN	NaN	NaN	-0.11	NaN	1.00	NaN	1.00	NaN	0.67	-0.11	NaN	NaN	NaN	-0.11	-0.11	-0.11
A5	-0.68	0.56	NaN	NaN	NaN	-0.06	NaN	-0.06	NaN	-0.06	NaN	-0.09	-0.06	NaN	NaN	NaN	0.56	-0.06	0.56
A6	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
A7	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
A8	-0.11	-0.11	NaN	NaN	NaN	-0.11	NaN	-0.11	NaN	-0.11	NaN	-0.17	-0.11	NaN	NaN	NaN	1.00	-0.11	1.00
A9	-0.56	0.68	NaN	NaN	NaN	0.06	NaN	0.06	NaN	0.06	NaN	0.09	0.06	NaN	NaN	NaN	-0.56	0.06	-0.56
A10	1.00	-0.11	NaN	NaN	NaN	-0.11	NaN	-0.11	NaN	-0.11	NaN	-0.17	-0.11	NaN	NaN	NaN	-0.11	-0.11	-0.11
A11	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
A12	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
A13	0.11	-1.00	NaN	NaN	NaN	0.11	NaN	0.11	NaN	0.11	NaN	0.17	0.11	NaN	NaN	NaN	0.11	0.11	0.11
A14	-0.11	-0.11	NaN	NaN	NaN	-0.11	NaN	1.00	NaN	1.00	NaN	0.67	-0.11	NaN	NaN	NaN	-0.11	-0.11	-0.11
A15	-0.11	-0.11	NaN	NaN	NaN	-0.11	NaN	-0.11	NaN	-0.11	NaN	-0.17	1.00	NaN	NaN	NaN	-0.11	-0.11	-0.11
A16	0.00	0.00	NaN	NaN	NaN	-0.00	NaN	-0.75	NaN	-0.75	NaN	-0.56	-0.00	NaN	NaN	NaN	-0.00	0.00	-0.00
A17	-0.11	-0.11	NaN	NaN	NaN	-0.11	NaN	-0.11	NaN	-0.11	NaN	-0.17	-0.11	NaN	NaN	NaN	-0.11	-0.11	-0.11
A18	-0.11	-0.11	NaN	NaN	NaN	-0.11	NaN	1.00	NaN	1.00	NaN	0.67	-0.11	NaN	NaN	NaN	-0.11	-0.11	-0.11
A19	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
A20	1.00	-0.11	NaN	NaN	NaN	-0.11	NaN	-0.11	NaN	-0.11	NaN	-0.17	-0.11	NaN	NaN	NaN	-0.11	-0.11	-0.11
A21	-0.11	1.00	NaN	NaN	NaN	-0.11	NaN	-0.11	NaN	-0.11	NaN	-0.17	-0.11	NaN	NaN	NaN	-0.11	-0.11	-0.11
A22	NaN	NaN	1.00	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
A23	NaN	NaN	NaN	1.00	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
A24	NaN	NaN	NaN	NaN	1.00	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
A25	-0.11	-0.11	NaN	NaN	NaN	1.00	NaN	-0.11	NaN	-0.11	NaN	-0.17	-0.11	NaN	NaN	NaN	-0.11	-0.11	-0.11
A26	NaN	NaN	NaN	NaN	NaN	NaN	1.00	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
A27	-0.11	-0.11	NaN	NaN	NaN	-0.11	NaN	1.00	NaN	1.00	NaN	0.67	-0.11	NaN	NaN	NaN	-0.11	-0.11	-0.11
A28	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	1.00	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
A29	-0.11	-0.11	NaN	NaN	NaN	-0.11	NaN	1.00	NaN	1.00	NaN	0.67	-0.11	NaN	NaN	NaN	-0.11	-0.11	-0.11
A30	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	1.00	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
A31	-0.17	-0.17	NaN	NaN	NaN	-0.17	NaN	0.67	NaN	0.67	NaN	1.00	-0.17	NaN	NaN	NaN	-0.17	0.67	-0.17
A32	-0.11	-0.11	NaN	NaN	NaN	-0.11	NaN	-0.11	NaN	-0.11	NaN	-0.17	1.00	NaN	NaN	NaN	-0.11	-0.11	-0.11
A33	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	1.00	NaN	NaN	NaN	NaN	NaN
A34	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	1.00	NaN	NaN	NaN	NaN
A35	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	1.00	NaN	NaN	NaN
A36	-0.11	-0.11	NaN	NaN	NaN	-0.11	NaN	-0.11	NaN	-0.11	NaN	-0.17	-0.11	NaN	NaN	NaN	1.00	-0.11	1.00
A37	-0.11	-0.11	NaN	NaN	NaN	-0.11	NaN	-0.11	NaN	-0.11	NaN	0.67	-0.11	NaN	NaN	NaN	-0.11	1.00	-0.11
A38	-0.11	-0.11	NaN	NaN	NaN	-0.11	NaN	-0.11	NaN	-0.11	NaN	-0.17	-0.11	NaN	NaN	NaN	1.00	-0.11	1.00

Figure 5: Correlation Matrix

5. CONCLUSION

Customer expectations have changed in line with the market's overall upheaval caused by the pandemic. We could prominently infer that, the reviews by guests were positively influenced majorly by friendly and helpful treatment by staffs or for specific performer's performance. More than materialistic physical services like laundry, pool, casinos etc., positive customer reviews mention about distinctly about ushers, doorman, guitarists, In House Greeter etc.

6. FUTURE WORK

6.1. Incorporate a minimalist and simple UI for end user of the system. The UI will enable user to filter names of timeshare property and the timeframe for review to be sentiment analysed.

6.2. The web-scraping for this project was essential as no dataset is present for the purpose of the analysis which slows down the system significantly. For future enhancement programmatic changes will be needed to omit the data scrapping part and execute data scrapping only when a timeshare property name that is entered is not present in the existing dataset or a time stamp that is beyond the scope of existing dataset.

6.3. The ABSA could be finetuned (for understanding better domain specific aspects better) using insights from existing data set, for better accuracy and efficiency of the system.

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