ANALYSING CUSTOMER SENTIMENTS IN THE HOSPITALITY INDUSTRY: A STUDY OF ONLINE HOTEL REVIEWS

1 INTRODUCTION

Online consumer reviews have become influential sources of information for travellers and businesses in the hospitality industry (Xie, Chen and Wu, 2016). Platforms like TripAdvisor provide volumes of user-generated opinions that reflect guests' experiences, expectations, and satisfaction. Mining these reviews through sentiment analysis helps organizations understand customer perceptions, identify patterns in service quality, and make data-driven decisions to improve guest experience (Singgalen, 2024).

Manually analysing thousands of opinions consumes time, is subjective, and prone to inconsistencies given the availability of large review data (Salehan and Kim, 2016). The dataset used in this task has 10,000 hotel reviews, each with textual feedback from guests. Note that the raw nature of these reviews makes it difficult to extract insights, recognize sentiment trends, or quantify satisfaction without computational techniques (Wankhade, Rao and Kulkarni, 2022). There is a need for automated and reliable methods to classify sentiment and figure out patterns within guest feedback to support informed decision-making in hospitality.

1.1 Research Question

How can sentiment analysis techniques be applied to hotel review data to automatically identify the sentiment expressed by customers and reveal key patterns in guest lived experiences?

2 DATA DESCRIPTION

This dataset was obtained from Data World and has 10,000 entries representing customer reviews for hotels and accommodation related businesses in the United

States. Each row includes business metadata like name, address, geographic coordinates, categories, and website information alongside review-specific details like date, rating, text, title, and reviewer username, with optional reviewer location fields. Businesses appear multiple times because each row corresponds to a single review, while attributes are repeated for each. The dataset combines listing information with user-generated content suitable for analysis of ratings, sentiment, and location-based trends.

2.1 ETHICAL CONSIDERATIONS

There are important ethical and social considerations around safeguarding customer privacy and ensuring responsible data usage. The dataset contains no details that disclose personal identities or sensitive information. There is no legal restriction with respect to its usage as it is available for public use.

3 EXPLORATORY DATA ANALYSES AND DATA PREPROCESSING

The hotel reviews dataset is made up of 10,000 records and 25 variables describing business information, geographical attributes, review metadata, and customer-generated feedback. The dataset is commonly used in sentiment analysis and opinion-mining research to understand customer satisfaction and perceptions within the hospitality industry. Each record represents an individual review associated with a specific hotel.

The independent variables include:

• Business and location attributes: business ID, name, address, city, province, country, postal code, latitude, and longitude
• Categorical descriptors: categories, primary categories, keys, websites, and source URLs
• Review details: review date, date seen, review source URL, review title, and review text
• Reviewer information: username, reviewer city, and reviewer province

The dependent variable for this supervised learning task is:

• Sentiment label**:** the classification of each review as positive, negative, or neutral based on the sentiment expressed in the review text.

Google colab is used to complete this task, and needed packages are imported therein. Dataset is uploaded into Google colab, and the data are read into dataframe and the first 5 rows is printed using head() for initial inspection.

```
[1]
from nltk.stem.snowball import stopwords
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import re
from wordcloud import WordCloud
from collections import Counter
from nltk.sentiment.vader import SentimentIntensityAnalyzer
import nltk
nltk.download(['vader_lexicon', 'stopwords',
               'punkt', 'wordnet',
               'omw-1.4'])
from nltk.probability import FreqDist
```

```
[nltk_data] Downloading package vader_lexicon to /root/nltk_data...
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Unzipping tokenizers/punkt.zip.
[nltk_data] Downloading package wordnet to /root/nltk_data...
[nltk_data] Downloading package omw-1.4 to /root/nltk_data...
```

```
[7]
# Read the dataset into dataframe
# print the first 5 rows
senti_df = pd.read_csv('/content/Datafiniti_Hotel_Reviews.csv')
senti_df.head()
```

	id	dateAdded	dateUpdated	address	categories	primaryCategories	city	country	
0	AVwc252WIN2L1WUfpqLP	2016-10-30T21:42:42Z	2018-09-10T21:06:27Z	5921 Valencia Cir	Hotels,Hotels and motels,Hotel and motel reser...	Accommodation & Food Services	Rancho Santa Fe	US	us/ca/ranc
1	AVwc252WIN2L1WUfpqLP	2016-10-30T21:42:42Z	2018-09-10T21:06:27Z	5921 Valencia Cir	Hotels,Hotels and motels,Hotel and motel reser...	Accommodation & Food Services	Rancho Santa Fe	US	us/ca/ranc
2	AVwc252WIN2L1WUfpqLP	2016-10-30T21:42:42Z	2018-09-10T21:06:27Z	5921 Valencia Cir	Hotels,Hotels and motels,Hotel and motel reser...	Accommodation & Food Services	Rancho Santa Fe	US	us/ca/ranc
3	AVwdOclqIN2L1WUfti38	2015-11-28T19:19:35Z	2018-09-10T21:06:16Z	7520 Teague Rd	Hotels,Hotels and motels,Travel agencies and b...	Accommodation & Food Services	Hanover	US	us/m
4	AVwdOclqIN2L1WUfti38	2015-11-28T19:19:35Z	2018-09-10T21:06:16Z	7520 Teague Rd	Hotels,Hotels and motels,Travel agencies and b...	Accommodation & Food Services	Hanover	US	us/m

5 rows × 25 columns

The dataset has 3 numerical variables, and the rest variables are either string or categorical as seen from the output of info() function.

```
[3]
# provide concise summary of the dataset
senti_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 25 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   id                    10000 non-null  object
 1   dateAdded             10000 non-null  object
 2   dateUpdated           10000 non-null  object
 3   address               10000 non-null  object
 4   categories            10000 non-null  object
 5   primaryCategories     10000 non-null  object
 6   city                  10000 non-null  object
 7   country               10000 non-null  object
 8   keys                  10000 non-null  object
 9   latitude              10000 non-null  float64
 10  longitude             10000 non-null  float64
 11  name                  10000 non-null  object
 12  postalCode            10000 non-null  object
 13  province              10000 non-null  object
 14  reviews.date          10000 non-null  object
 15  reviews.dateSeen      10000 non-null  object
 16  reviews.rating        10000 non-null  float64
 17  reviews.sourceURLs    10000 non-null  object
 18  reviews.text          9999 non-null   object
 19  reviews.title         9999 non-null   object
 20  reviews.userCity      4164 non-null   object
 21  reviews.userProvince  2705 non-null   object
 22  reviews.username      10000 non-null  object
 23  sourceURLs            10000 non-null  object
 24  websites              10000 non-null  object
dtypes: float64(3), object(22)
memory usage: 1.9+ MB
```

Using the dropna() function ensures only rows with review text were kept.

```
[6]
# keep only rows with review text
senti_df = senti_df.dropna(subset=["reviews.text"])
```

A text cleaning function is defined to prepare raw text for sentiment analysis. First, a regular expression tokenizer is used to split the text into words while keeping only alphanumeric characters and apostrophes. All words are converted to lowercase and common English stopwords are removed to reduce noise. Stemming is applied with the Porter Stemmer, which reduces words to their root form to ensure consistency in word representation. The function returns a list of cleaned tokens.

The function is applied to the "review.text" column in the dataframe and a new "cleaned_text" is added therein. The first five rows are returned by the head() function.

```
[11]
# text cleaning function
def clean_text(text):
    tokenize_document = nltk.tokenize.RegexpTokenizer('[a-zA-Z0-9\']+').tokenize(text)
    cleaned_document = [word.lower() for word in tokenize_document if word.lower() not in stopwords.words('english')]
    stemmed_text = [nltk.PorterStemmer().stem(word) for word in cleaned_document]
    return stemmed_text
```

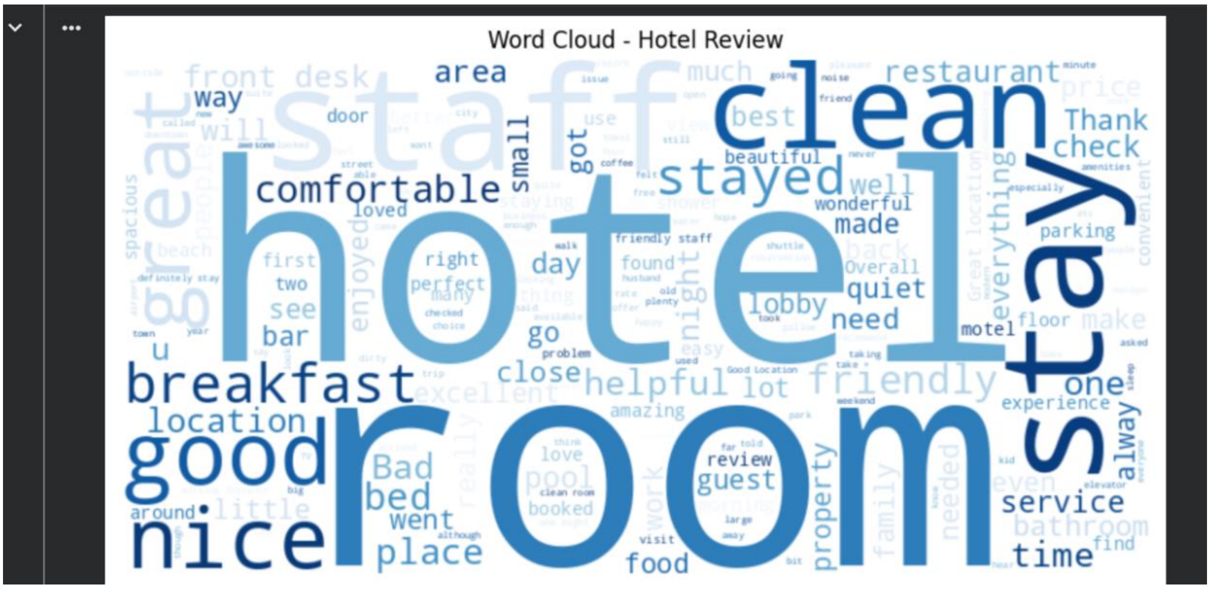
```
[12]
# Apply text cleaning function
senti_df['cleaned_text'] = senti_df['reviews.text'].apply(clean_text)
```

```
[10]
senti_df.head()
```

iews.username	sourceURLs	websites	cleaned_text
Paula	http://www.hotels.com/ho125419/%25252525253Flo...	http://www.ranchovalencia.com	[experi, rancho, valencia, absolut, perfect, b...
D	http://www.hotels.com/ho125419/%25252525253Flo...	http://www.ranchovalencia.com	[amaz, place, everyon, extrem, warm, welcom, s...
Ron	http://www.hotels.com/ho125419/%25252525253Flo...	http://www.ranchovalencia.com	[book, 3, night, stay, rancho, valencia, play,...
jaeem2016	http://www.yellowbook.com/profile/aloft-arunde...	http://www.starwoodhotels.com/alofthotels/prop...	[current, bed, write, past, hr, 1, 2, dog, bar...
MamaNiaOne	http://www.yellowbook.com/profile/aloft-arunde...	http://www.starwoodhotels.com/alofthotels/prop...	[live, md, aloft, home, away, home, stay, 1, n...

Word cloud is generated by combining all the hotel reviews into one large text string. The most frequent words in the text are extracted to form the word cloud which is display as image. Some words of interest include “service”, “time”, “clean”. “nice”, “good”, “bad” etc.

```
[24]
# Combine all reviews into one large string
words_cloud = ' '.join(senti_df['reviews.text'].astype(str))

# Generate the word cloud
wordcloud_pos = WordCloud(
    width=800,
    height=400,
    background_color='white',
    colormap='Blues',
    stopwords=None  # you can add stopwords if needed
).generate(words_cloud)

# Plot the word cloud
plt.figure(figsize=(10, 5))
plt.imshow(wordcloud_pos, interpolation='bilinear')
plt.axis('off')
plt.title("Word Cloud - Hotel Review")
plt.show()
```



4 IMPLEMENTATIONS

VADER (Valence Aware Dictionary and sEntiment Reasoner) is a rule-based sentiment analysis tool used to capture sentiment in text by using a lexicon of words with associated scores (Hutto and Gilbert, 2014). Its use makes sense here as it handles slang, punctuation, capitalization, and emoticons effectively, which is effective for mining user-generated text compared to traditional methods (Moens, Li and Chua, 2014). To use VADER, the analyser needs to be instantiated. The cleaned tokens are joined back into strings for analysis. Sentiment scores are generated for each text using sid.polarity_scores(), which produces values for positive, negative, neutral, and a combined compound score. The compound, negative, neutral and positive scores are extracted from score_dict into new columns.

```
[13]
# Instantiate VADER Analyzer
sid = SentimentIntensityAnalyzer()

[24]
# Generate Sentiment Scores
senti_df['cleaned_text_string'] = senti_df['cleaned_text'].apply(lambda x: ' '.join(x))
senti_df["polarity"] = senti_df["cleaned_text_string"].apply(lambda x: sid.polarity_scores(x))

senti_df["compound"] = senti_df["polarity"].apply(lambda score_dict: score_dict["compound"])
senti_df["neg"] = senti_df["polarity"].apply(lambda score_dict: score_dict["neg"])
senti_df["neu"] = senti_df["polarity"].apply(lambda score_dict: score_dict["neu"])
senti_df["pos"] = senti_df["polarity"].apply(lambda score_dict: score_dict["pos"])
```

5 PRESENTATION, ANALYSIS AND DISCUSSION OF RESULTS

The first 5 rows of the compound, negative, neutral and positive scores are printed.

```
[25] senti_df.head()
```

websites	cleaned_text	cleaned_text_string	polarity	compound	label	neg	neu	pos
http://www.ranchovalencia.com	[experi, rancho, valencia, absolut, perfect, b...	experi rancho valencia absolut perfect begin e...	{'neg': 0.0, 'neu': 0.686, 'pos': 0.314, 'comp...	0.7506	positive	0.000	0.686	0.314
http://www.ranchovalencia.com	[amaz, place, everyon, extrem, warm, welcom, s...	amaz place everyon extrem warm welcom stay top...	{'neg': 0.0, 'neu': 0.723, 'pos': 0.277, 'comp...	0.8225	positive	0.000	0.723	0.277
http://www.ranchovalencia.com	[book, 3, night, stay, rancho, valencia, play,...	book 3 night stay rancho valencia play tenni s...	{'neg': 0.0, 'neu': 0.654, 'pos': 0.346, 'comp...	0.9559	positive	0.000	0.654	0.346
:tarwoodhotels.com/alofthotels/prop...	[current, bed, write, past, hr, 1, 2, dog, bar...	current bed write past hr 1 2 dog bark squeal ...	{'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compound...	0.0000	neutral	0.000	1.000	0.000
:tarwoodhotels.com/alofthotels/prop...	[live, md, aloft, home, away, home, stay, 1, n...	live md aloft home away home stay 1 night 7 7 ...	{'neg': 0.045, 'neu': 0.669, 'pos': 0.287, 'co...	0.8225	positive	0.045	0.669	0.287

5.1 SENTIMENT SCORE DISTRIBUTION

The sentiment scores are predominantly positive. The median compound score is 0.78 meaning that over 50% of the reviews have a compound score of more than 0.78, which suggests strong positive sentiment.

```
[33] # Sentiment scores statistics
senti_df[['compound', 'neg', 'neu', 'pos']].describe()
```

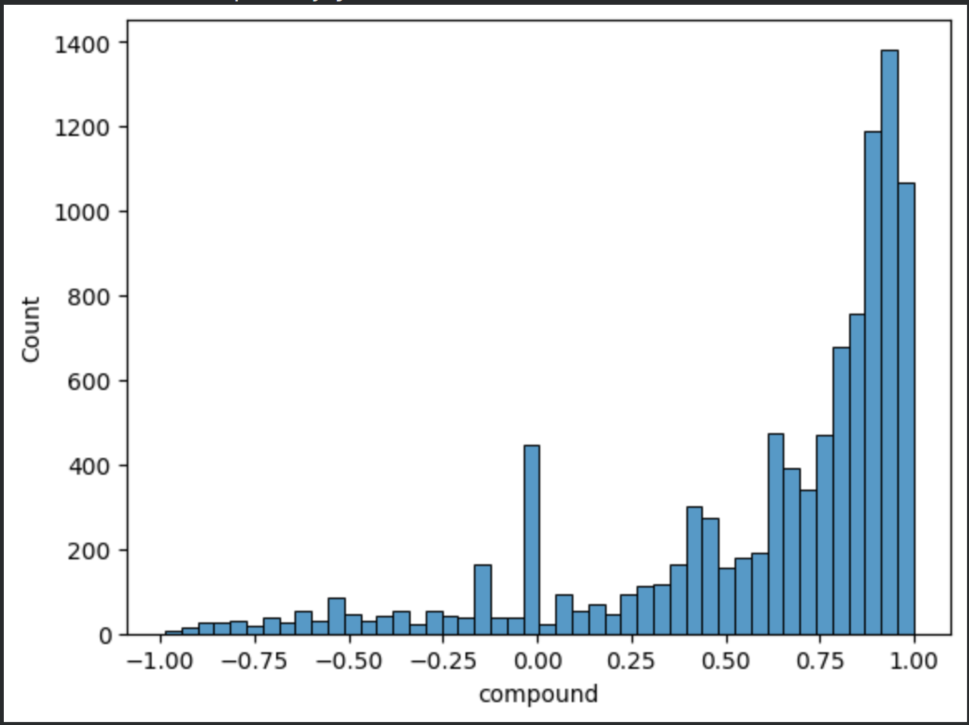
	compound	neg	neu	pos
count	9999.000000	9999.000000	9999.000000	9999.000000
mean	0.607000	0.048588	0.659619	0.291491
std	0.426314	0.087250	0.173804	0.174400
min	-0.987400	0.000000	0.000000	0.000000
25%	0.440400	0.000000	0.561000	0.172000
50%	0.784500	0.000000	0.670000	0.282000
75%	0.911800	0.074000	0.772000	0.395000
max	0.998400	1.000000	1.000000	1.000000

The distributions of the compound, negative, neutral and positive scores are visualized using histplot() function.

[32]
0s

```python
# Histogram distribution of compound scores
sns.histplot(senti_df["compound"])
```

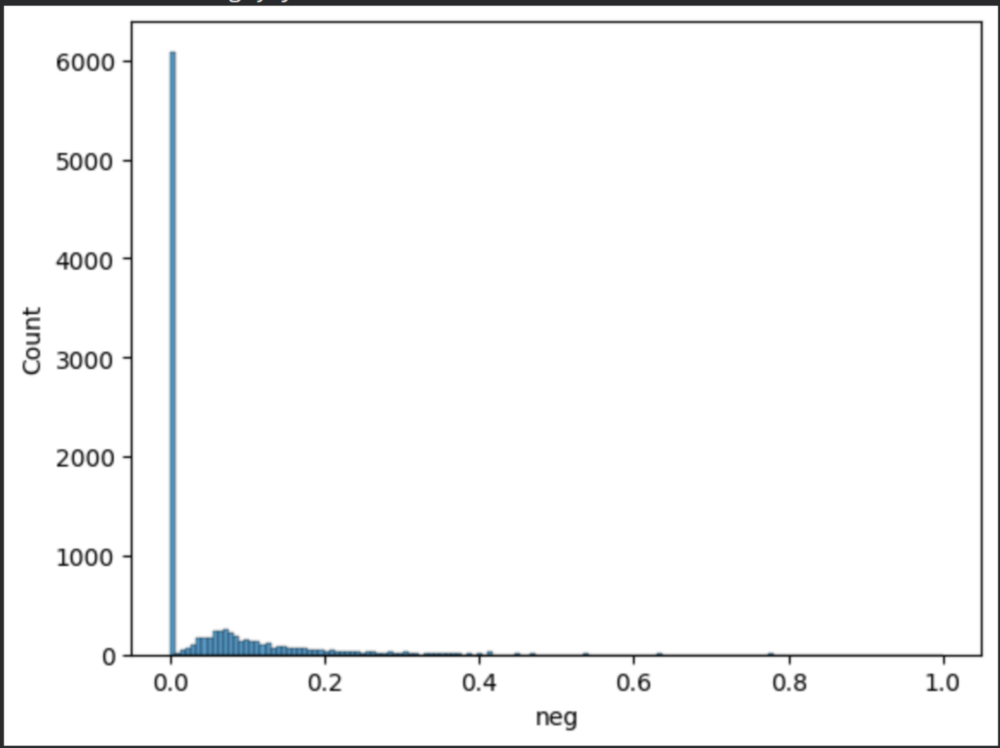
<Axes: xlabel='compound', ylabel='Count'>



[34]
0s

```python
# Histogram distribution of negative scores
sns.histplot(senti_df["neg"])
```

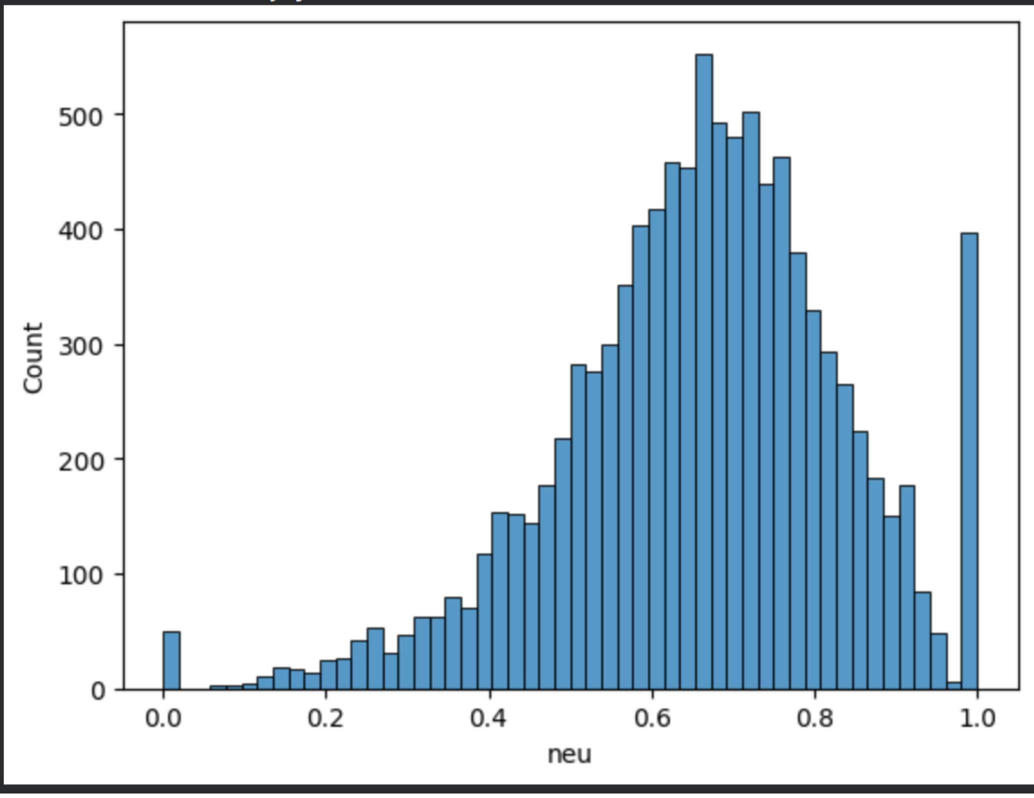
<Axes: xlabel='neg', ylabel='Count'>



[35]
✓ 0s

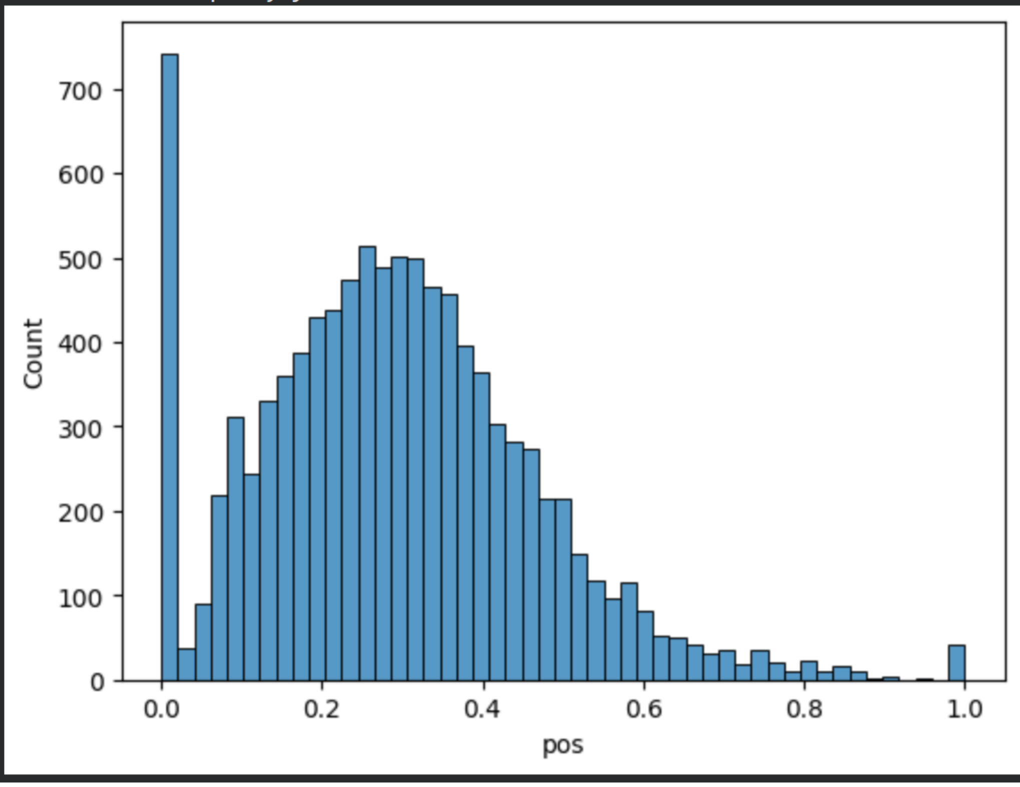
```python
# Histogram distribution of neutral scores
sns.histplot(senti_df["neu"])
```

```
<Axes: xlabel='neu', ylabel='Count'>
```



```
[36]
# Histogram distribution of positive scores
sns.histplot(senti_df["pos"])
```

<Axes: xlabel='pos', ylabel='Count'>



5.2 Sentiment Aggregation by Hotel

Using groupby() function, the total count of negative and positive reviews for each hotel are returned and sorted in descending order.

```
[19]
# Number of negative review per hotel
negative_counts = (senti_df['compound'] <= 0).groupby(senti_df['name']).sum()
negative_counts_sorted = negative_counts.sort_values(ascending=False)
negative_counts_sorted
```

name	compound
The Westin Las Vegas Hotel & Spa	52
Metro Points Hotel-Washington North	44
Fremont Hotel & Casino	34
Kinzie Hotel	25
Ramada BWI Airport/Arundel Mills	22
...	...
Whispering Woods Resort	0
1906 Lodge At Coronado Beach	0
250 Main Hotel	0
Aloft Denver Downtown	0
Yakutat Lodge	0

1670 rows × 1 columns

dtype: int64

```python
# Number of positive review per hotel
positive_counts = (senti_df['compound'] > 0).groupby(senti_df['name']).sum()
positive_counts_sorted = positive_counts.sort_values(ascending=False)
positive_counts_sorted
```

name	compound
Metro Points Hotel-Washington North	158
Best Western Springfield	139
ARIA Resort Casino	127
The Westin Las Vegas Hotel & Spa	119
Kinzie Hotel	113
...	...
Holiday Inn Express and Suites	0
Hotel Prince Spafford	0
Hotel Del Flores	0
Americas Best Value Inn - Medical Center / Lubbock	0
AC Hotel by Marriott Boston Downtown	0

1670 rows × 1 columns

dtype: int64

List comprehension is maintained for both positive and negative words to create word cloud.

```python
# List comprehension of word(positive and negative)
senti_df['hotel_reviews'] = senti_df['reviews.text'].apply(clean_text)
senti_df.head()
positive_review_subset = senti_df.loc[(senti_df['name'] =='The Westin Las Vegas Hotel & Spa') &
                                      (senti_df['compound'] > 0)]
positive_review_subset.head()
negative_review_subset = senti_df.loc[(senti_df['name']=='The Westin Las Vegas Hotel & Spa') &
                                      (senti_df['compound'] <= 0)]
negative_review_subset.head()
```

websites	cleaned_text	cleaned_text_string	polarity	compound	label	neg	neu	pc	
vw.westinvegas.com/	[bad, told, would, get, robe]	bad told would get robe	{'neg': 0.467, 'neu': 0.533, 'pos': 0.0, 'comp...	-0.5423	negative	0.467	0.533	0.000	[bad, told, would, get, robe]
vw.westinvegas.com/	[bad, spa, avail, good, staff, except, friendli]	bad spa avail good staff except friendli	{'neg': 0.307, 'neu': 0.439, 'pos': 0.254, 'co...	-0.1531	negative	0.307	0.439	0.254	[bad, spa, avail, good, staff, except, friendli]
vw.westinvegas.com/	[bad, pre, paid, premium, room, two, doubl, be...	bad pre paid premium room two doubl bed given ...	{'neg': 0.212, 'neu': 0.788, 'pos': 0.0, 'comp...	-0.5423	negative	0.212	0.788	0.000	[bad, pre, paid, premium, room, two, doubl, be...
vw.westinvegas.com/	[bad, first, room, ac, work, hot, water, bathr...	bad first room ac work hot water bathroom seco...	{'neg': 0.139, 'neu': 0.754, 'pos': 0.107, 'co...	-0.2023	negative	0.139	0.754	0.107	[bad, first, room, ac, work, hot, water, bathr...
vw.westinvegas.com/	[bad, cannot, find, book, ticket, arriv, girl,...	bad cannot find book ticket arriv girl serv us...	{'neg': 0.148, 'neu': 0.759, 'pos': 0.093	-0.3182	negative	0.148	0.759	0.093	[bad, cannot, find, book, ticket, arriv, girl,...

5.3 Word Cloud Visualization

I am analysing this sentiment for The Westin Las Vegas Hotel & Spa. Two separate word clouds one for positive reviews and one for negative reviews are created for the hotel. All the cleaned review words are combined into a single string for each sentiment category, WordCloud library is then used to create visual representations of the most frequent words by applying a green colour theme for positive reviews and a red theme for negative reviews. Each word cloud is displayed using Matplotlib, with axes removed and titles showing the review type being visualized.

```
[53]
# Word Cloud for Positive Reviews
positive_words = ' '.join([' '.join(words) for words in positive_review_subset['hotel_reviews']])
wordcloud_pos = WordCloud(width=800, height=400, background_color='white', colormap='Greens').generate(positive_words)

plt.figure(figsize=(10,5))
plt.imshow(wordcloud_pos, interpolation='bilinear')
plt.axis('off')
plt.title("Word Cloud - Positive Reviews (Westin Las Vegas)")
plt.show()

# Word Cloud for Negative Reviews
negative_words = ' '.join([' '.join(words) for words in negative_review_subset['hotel_reviews']])
wordcloud_neg = WordCloud(width=800, height=400, background_color='white', colormap='Reds').generate(negative_words)

plt.figure(figsize=(10,5))
plt.imshow(wordcloud_neg, interpolation='bilinear')
plt.axis('off')
plt.title("Word Cloud - Negative Reviews (Westin Las Vegas)")
plt.show()
```

5.4 Analysis of The Westin Las Vegas Hotel & Spa

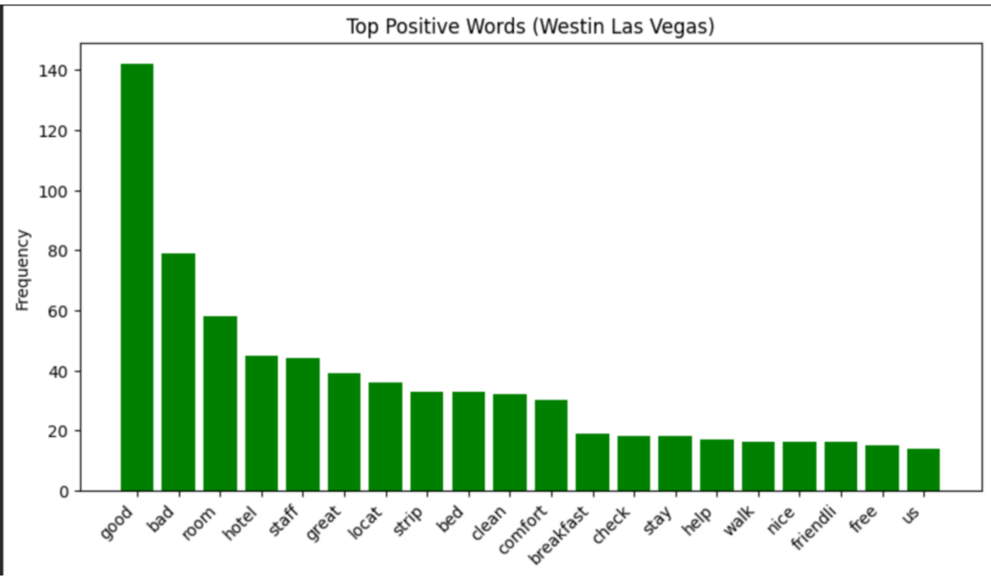
To ease analyses, top 20 most occurring words were extracted from both categories. All positive and negative hotel reviews were flattened into two large strings, then using Counter, the total occurrence of each word is computed. It prints the 20 most common words for both groups to show which terms are most frequently used. Bar charts are used to visualize these top-occurring words.

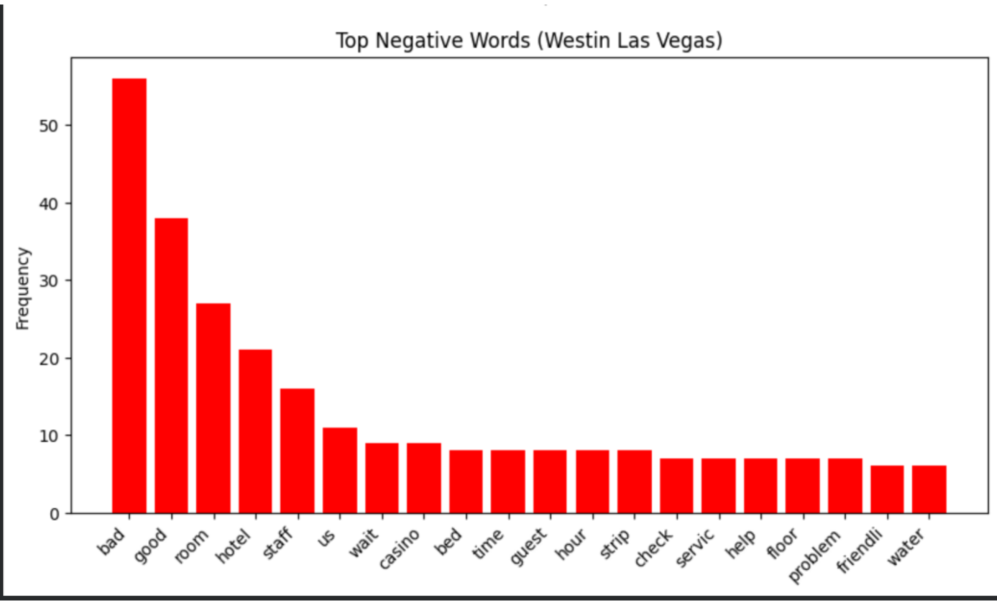
[58]
0s

```python
# Flatten positive reviews into a single string of words
positive_words = ' '.join([' '.join(words) for words in positive_review_subset['hotel_reviews']])
negative_words = ' '.join([' '.join(words) for words in negative_review_subset['hotel_reviews']])

# Count word frequencies
pos_counts = Counter(positive_words.split())
neg_counts = Counter(negative_words.split())

# Display top 20 most common words for positive reviews
print("Top Positive Words:")
for word, freq in pos_counts.most_common(20):
    print(f"{word}: {freq}")

print("\nTop Negative Words:")
for word, freq in neg_counts.most_common(20):
    print(f"{word}: {freq}")

# Visualize with bar charts
def plot_word_freq(counter, title, color):
    words, freqs = zip(*counter.most_common(20))  # top 20
    plt.figure(figsize=(10,5))
    plt.bar(words, freqs, color=color)
    plt.xticks(rotation=45, ha='right')
    plt.title(title)
    plt.ylabel("Frequency")
    plt.show()

plot_word_freq(pos_counts, "Top Positive Words (Westin Las Vegas)", "green")
plot_word_freq(neg_counts, "Top Negative Words (Westin Las Vegas)", "red")
```

```
Top Positive Words:
good: 142
bad: 79
room: 58
hotel: 45
staff: 44
great: 39
locat: 36
strip: 33
bed: 33
clean: 32
comfort: 30
breakfast: 19
check: 18
stay: 18
help: 17
walk: 16
nice: 16
friendli: 16
free: 15
us: 14
```

```
Top Negative Words:
bad: 56
good: 38
room: 27
hotel: 21
staff: 16
us: 11
wait: 9
casino: 9
bed: 8
time: 8
guest: 8
hour: 8
strip: 8
check: 7
servic: 7
help: 7
floor: 7
problem: 7
friendli: 6
water: 6
```





5.5 Business Implications and Recommendations

The analysis of Westin Las Vegas hotel reviews shows strengths and weaknesses in guest experiences. Positive reviews show words like good, room, hotel, staff, great, clean, and comfort which shows guests value the quality of rooms, cleanliness, comfort, and friendly staff interactions. Mentions of location and strip emphasize the hotel's proximity to the Las Vegas Strip, while references to breakfast and free amenities suggest these features contribute positively to guest satisfaction. On the other hand, negative reviews are dominated by words like bad, room, staff, wait, casino, and problem which point out issues with service consistency, delays at check-in, facility maintenance, and dissatisfaction with casino-related experiences. These insights highlight areas where the hotel excels and areas worst at needing improvement.

From a business perspective, these findings can guide decision-making and process improvements. Management can take advantage of positive themes in marketing campaigns, emphasizing cleanliness, comfort, and location to attract new guests, while addressing negative themes through operational changes. Actionable steps include enhancing staff training to ensure consistent service quality, introducing digital check-in options to reduce wait times, and implementing preventive maintenance to resolve water and facility issues. By reinforcing strengths and tackling weaknesses, Westin Las Vegas can improve guest satisfaction, encourage repeat bookings, and strengthen its competitive positioning in the hospitality market.

6 CONCLUSION

Sentiment analysis is an effective method for extracting actionable insights from large volumes of hotel reviews. By applying VADER to the reviews, clear patterns in guest satisfaction and dissatisfaction were identified. The Westin Las Vegas shows strong performance in cleanliness, comfort, and staff service, while issues around wait times, maintenance, and service consistency require attention. To improve performance, the hotel should enhance staff training, optimise check-in, and strengthen preventive maintenance while taking advantage of positive themes in marketing to boost guest satisfaction and competitiveness.

REFERENCES

Hutto, C. and Gilbert, E., 2014, May. Vader: A parsimonious rule-based model for sentiment analysis of social media text. In *Proceedings of the international AAAI conference on web and social media* (Vol. 8, No. 1, pp. 216-225).

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