TEXT MINING AND SENTIMENT ANALYSIS

Title: Using machine learning algorithms to extract text, classify and analyse the sentiment of customer reviews, providing insights on customer satisfaction and potential areas for improvement for restaurant based on rating

4.1 Introduction

Text mining and sentiment analysis are two important components of natural language processing (NLP) that involves extracting insights and understanding sentiments from textual data. These methodologies have become increasingly essential in analysing large volumes of unstructured text data generated from various sources such as social media, customer reviews, news articles, and more. Text mining involves extracting patterns, information, or knowledge from unstructured text data. Sentiment analysis, also known as opinion mining, focuses on determining and understanding sentiments expressed in textual data.

It has become a great tool in the hospitality sector particularly with the growth of online customer reviews and the abundance of available data as restaurants are constantly seeking ways to improve the customer experience and maintain a positive reputation.

The restaurant review dataset used in this research uses the rating and review column to determine the positive and negative reviews gotten from the customers and allowing them to better understand the factors most important to the customers. This could help these businesses to identify areas for improvement and tailor their services to better meet the needs and preferences of their customers.

However, the volume, diversity and unstructured nature of review data on aspects ranging from food to service poses analysis challenges (Johnson et al, 2019). Recent advances in text mining and sentiment classification models show promise for unlocking insights at scale from textual data (Zhong et al, 2020; Wang et al, 2021). The implemented dashboard allows drill-down into aspect-specific sentiments and representative excerpts to diagnose areas of strengths versus weaknesses (Xu et al, 2019).

Through precise text analytics translated into actionable guidelines, the study could significantly enhance data-driven decision making in the restaurant industry plagued by failures.

Text mining is a field of machine learning that involves extracting and analysing large amounts of text data for various purposes, such as identifying patterns and trends (Manning, Raghavan, & Schütze, 2008). Sentiment analysis is a sub field of text mining that involves classifying the sentiment or emotion expressed in a piece of text as positive, negative, or neutral (Pang & Lee, 2008).

Both text mining and sentiment analysis can be used in a variety of applications, including marketing, customer service, and public opinion research, to help organizations better understand their customers and the public.

4.2 Aims and Objectives

To determine the proportion of customers who has given excellent reviews based on the overall rating and visualize these reviews while considering whether they are positive or Negative.

4.3 Exploration and Dataset Analysis

4.31 Description of the dataset:

The Restaurant reviews dataset includes 10000 observations and 8 variables.

4.32 Data preparation:

To prepare the data for analysis, the following steps were taken:

- The tourist accommodation dataset was imported into the python programming language using the read.csv() function.
- The data was checked to ensure that all columns were correctly aligned and had the appropriate data types.
- The data was checked for any duplicate values, missing or null values, irrelevant columns and dropping them.
- Also checking the rating and review column, renaming where needed.

The figures below shows all the steps taken.

```
In [ ]: # Importing all the necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from wordcloud import WordCloud,STOPWORDS
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn import metrics
from sklearn.naive_bayes import MultinomialNB
from nltk.tokenize import word_tokenize
from nltk.corpus import stopwords
from imblearn.under_sampling import RandomUnderSampler
from nltk.sentiment.vader import SentimentIntensityAnalyzer
from nltk.probability import FreqDist
from tabulate import tabulate

import nltk
import string
import warnings
warnings.filterwarnings('ignore')

In [2]: ! pip install WordCloud
```

Figure: Importing all necessary libraries

```
In [3]: # Load the datset
df = pd.read_csv("Restaurant reviews.csv")

In [4]: # View the first 5 rows of the data
df.head()

Out[4]:
```

	Restaurant	Reviewer	Review	Rating	Metadata	Time	Pictures	7514
0	Beyond Flavours	Rusha Chakraborty	The ambience was good, food was quite good . h...	5	1 Review , 2 Followers	5/25/2019 15:54	0	2447.0
1	Beyond Flavours	Anusha Tirumalaneedi	Ambience is too good for a pleasant evening. S...	5	3 Reviews , 2 Followers	5/25/2019 14:20	0	NaN
2	Beyond Flavours	Ashok Shekhawat	A must try.. great food great ambience. Thnx f...	5	2 Reviews , 3 Followers	5/24/2019 22:54	0	NaN
3	Beyond Flavours	Swapnil Sarkar	Soumen das and Arun was a great guy. Only beca...	5	1 Review , 1 Follower	5/24/2019 22:11	0	NaN
4	Beyond Flavours	Dileep	Food is good.we ordered Kodi drumsticks and ba...	5	3 Reviews , 2 Followers	5/24/2019 21:37	0	NaN

Figure: Loading the dataset and viewing the first five rows of the data

```
In [5]: # Check datatset information
        df.info()

        <class 'pandas.core.frame.DataFrame'>
        RangeIndex: 10000 entries, 0 to 9999
        Data columns (total 8 columns):
         #   Column      Non-Null Count  Dtype
        ---  ------      --------------  -----
         0   Restaurant  10000 non-null  object
         1   Reviewer    9962 non-null   object
         2   Review      9955 non-null   object
         3   Rating      9962 non-null   object
         4   Metadata    9962 non-null   object
         5   Time        9962 non-null   object
         6   Pictures    10000 non-null  int64
         7   7514        1 non-null      float64
        dtypes: float64(1), int64(1), object(6)
        memory usage: 625.1+ KB

In [6]: # delete column '7514' as it has only one non-null value

        df.drop(["7514"], axis=1, inplace=True)
```

Figure: Checking the data information and dropping the irrelevant column (7514)

```
In [7]: # Check duplicate data

        print((df.duplicated().sum()))

        36

In [8]: # Delete duplicate data

        df.drop_duplicates(inplace = True)

In [9]: # Null Data
        df.isna().sum()

Out[9]: Restaurant    0
        Reviewer      2
        Review        9
        Rating        2
        Metadata      2
        Time          2
        Pictures      0
        dtype: int64

In [10]: # Let's exclude null values.
         df = df.dropna()
```

Figure: Checking for duplicate and missing or null values and dropping them.

```
In [11]: # Check the unique values and frequency for 'Rating'

         df['Rating'].value_counts()

Out[11]: 5       3826
         4       2373
         1       1735
         3       1192
         2        684
         4.5       69
         3.5       47
         2.5       19
         1.5        9
         Like       1
         Name: Rating, dtype: int64

In [12]: # # Replace string "Like' with '5' as it is the most frequent value in the Rating column.

         df['Rating'] = df['Rating'].replace(['Like'], '5')

In [13]: # Replace column type 'Rating' to 'float'.

         df['Rating'] = df['Rating'].astype(float)
```

```
In [14]: # Check the unique values and frequency for 'Rating'

         df['Rating'].value_counts()

Out[14]: 5.0    3827
         4.0    2373
         1.0    1735
         3.0    1192
         2.0     684
         4.5      69
         3.5      47
         2.5      19
         1.5       9
         Name: Rating, dtype: int64
```

Figure: Modifying the rating column

```
In [15]: # Create a copy of the dataset with only columns Review and Rating
         df=df[['Review','Rating']].copy()

         # Rename columns
         df = df.rename(columns={'Review': 'text', 'Rating': 'text_label'})
         df

Out[15]:
```

	text	text_label
0	The ambience was good, food was quite good . h...	5.0
1	Ambience is too good for a pleasant evening. S...	5.0
2	A must try.. great food great ambience. Thnx f...	5.0
3	Soumen das and Arun was a great guy. Only beca...	5.0
4	Food is good.we ordered Kodi drumsticks and ba...	5.0
...	...	...
9995	Madhumathi Mahajan Well to start with nice cou...	3.0
9996	This place has never disappointed us.. The foo...	4.5
9997	Bad rating is mainly because of "Chicken Bone ...	1.5
9998	I personally love and prefer Chinese Food. Had...	4.0
9999	Checked in here to try some delicious chinese ...	3.5

9955 rows × 2 columns

```
In [16]: print("\n All Data Labels")
         print(df.groupby("text_label").count())

 All Data Labels
             text
text_label
1.0          1735
1.5             9
2.0           684
2.5            19
3.0          1192
3.5            47
4.0          2373
4.5            69
5.0          3827
```

Figure: Checking for our text and text labels (Reviews and Ratings)

4.32 Tokenization and word cleaning:

Tokenization and word cleaning are important steps in natural language processing (NLP) that enables computers to process and understand textual data.

Tokenization is the process of breaking down a text into smaller units called tokens (words, phrases, or symbols) for further analysis. Word cleaning focuses on cleaning and refining tokens for better analysis and modelling. NLTK function is used in this analysis.

```
In [17]: # Tokenization and word cleaning
# Download NLTK stopwords
nltk.download('stopwords')
nltk.download('punkt')

# Lets now create a function to apply all of our data preprocessing steps which we can then use on a corpus

def preprocess_text(text):
    tokenized_document = nltk.tokenize.RegexpTokenizer('[a-zA-Z0-9\'']+').tokenize(text) # Tokenize
    cleaned_tokens = [word.lower() for word in tokenized_document if word.lower() not in stop_words] # Remove
    stemmed_text = [nltk.stem.PorterStemmer().stem(word) for word in cleaned_tokens]
    return stemmed_text

def preprocess_text(text):
    stop_words = set(stopwords.words('english'))
    tokens = word_tokenize(text)
    tokens = [word.lower() for word in tokens if word.isalpha()]
    tokens = [word for word in tokens if word not in stop_words and word not in string.punctuation]
    return ' '.join(tokens)

# Clean text
def clean_text(text):
    text = text.lower()  # Convert text to lowercase
    text = text.translate(str.maketrans('', '', string.punctuation))  # Remove punctuation
    text = ' '.join(text.split())  # Remove extra whitespaces
    return text
```

```
# Preprocess text data
df['preprocessed_text'] = df['text'].apply(preprocess_text)

df['clean_text'] = df['text'].apply(clean_text)

# Tokenization
df['tokens'] = df['clean_text'].apply(word_tokenize)
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\harko\AppData\Roaming\nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package punkt to
[nltk_data]     C:\Users\harko\AppData\Roaming\nltk_data...
[nltk_data]   Package punkt is already up-to-date!
```

```
In [18]: df['text'] = df['text'].apply(preprocess_text)
```

Figure: Tokenization and word cleaning

```
In [19]: # Calculate the class array
# Apply CountVectorizer on preprocessed text
vectorizer = CountVectorizer()
X = vectorizer.fit_transform(df['preprocessed_text'])
X = pd.DataFrame(X.toarray())
X.head()
```

Out[19]:

	0	1	2	3	4	5	6	7	8	9	...	14241	14242	14243	14244	14245	14246	14247	14248	14249	14250
0	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0

5 rows × 14251 columns

Figure: Count Vectorizer

4.33 Class balancing and modelling

The text label was grouped into positive and negative by grouping the ratings above 3.0 as positive and ratings below or equal to 3.0 as negative. Afterwards the data was balanced to avoid overfitting and a classification model (Multinomial) analysis was performed.

In [20]:
```python
# Labelling the class label
# This function returns sentiment value based on:
# text label <= 3.0 -> Negative
# text label > 3.0 -> Positive


def conv(row):

    if row['text_label'] <= 3.0:
        val = 'Negative'
    else:
        val = 'Positive'

    return val

# Applying the function in our dataset
df['text_label'] = df.apply(conv, axis=1)
```

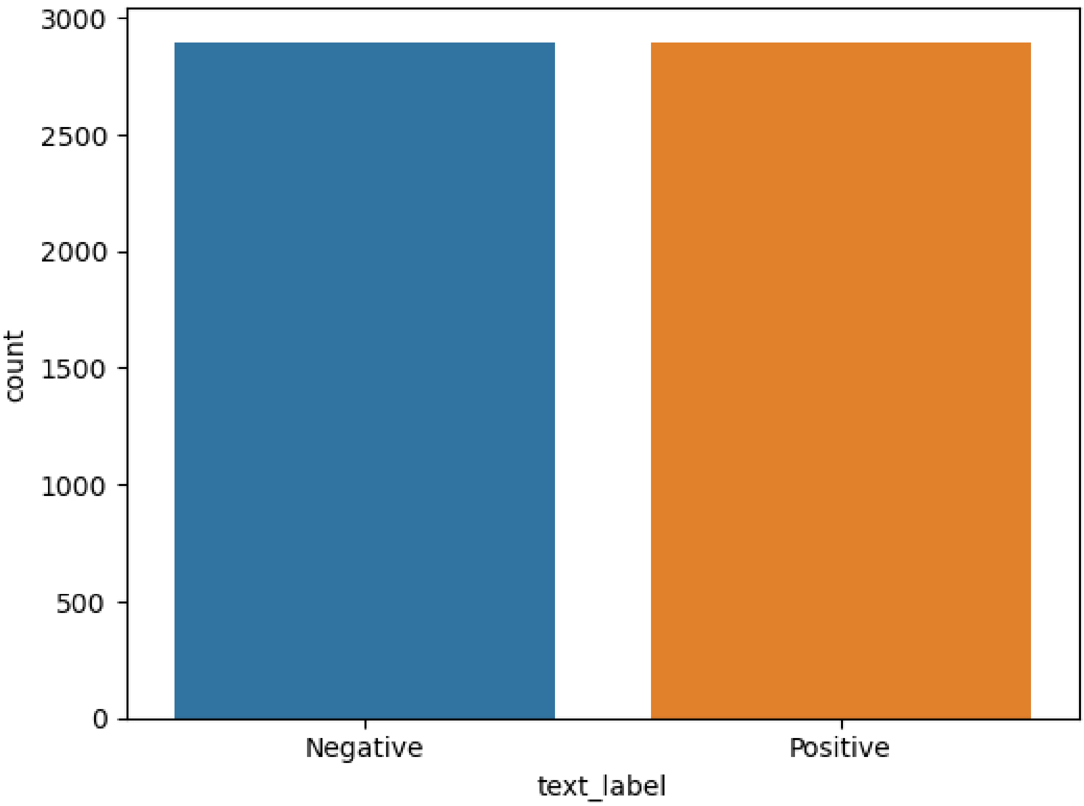
In [21]:
```python
# Splitting and balancing the data

y= df['text_label']

X_train, X_test, y_train, y_test = train_test_split(
X, y, train_size=0.8,test_size=0.2,random_state=99)
```

In [22]:
```python
resampler = RandomUnderSampler(random_state=0)
X_train_undersampled, y_train_undersampled = resampler.fit_resample(X_train, y_train)

sns.countplot(x=y_train_undersampled)
```



```
In [23]: # Modelling the data
         model = MultinomialNB()
         model.fit(X_train_undersampled, y_train_undersampled)

Out[23]: ▾ MultinomialNB
         MultinomialNB()
```

```
In [24]: y_pred = model.predict(X_test)

         # Computing the accuracy and Making the Confusion Matrix
         acc=metrics.accuracy_score(y_test,y_pred)
         print('accuracy:%.2f\n\n'%(acc))
         cm = metrics.confusion_matrix(y_test, y_pred)
         print("Confusion Matrix")
         print(cm, '\n\n')
         print('.......................................................')
         result = metrics.classification_report(y_test, y_pred)
         print("Classification Report:\n",)
         print(result)

accuracy:0.84


Confusion Matrix
[[ 595  145]
 [ 180 1071]]


.......................................................
Classification Report:

              precision    recall  f1-score   support

    Negative       0.77      0.80      0.79       740
    Positive       0.88      0.86      0.87      1251

    accuracy                           0.84      1991
   macro avg       0.82      0.83      0.83      1991
weighted avg       0.84      0.84      0.84      1991
```

Figure: Text label balancing and modelling

4.4 Sentiment Analysis

The SentimentIntensityAnalyser (SIA) in NLTK's VADER module is a is a pre-trained sentiment analysis tool designed to assess the sentiment polarity (positive, negative, neutral) and intensity of text based on a lexicon and a set of rules. It assigns sentiment scores to individual words in a text and generates an overall compound score for the entire text.

```
In [25]: # Performing Sentiment analysis
         # Initialize VADER sentiment analyzer
         sia = SentimentIntensityAnalyzer()

         # Function to get sentiment scores
         def get_sentiment_scores(text):
             sentiment = sia.polarity_scores(text)
             return sentiment['pos'], sentiment['neg'], sentiment['neu'], sentiment['compound']

         # Apply sentiment analysis to each text
         df['positive'], df['negative'], df['neutral'], df['compound'] = zip(*df['clean_text'].map(get_sentiment_scores))

         print("Sample of Sentiment Scores:")
         print(df[['positive', 'negative', 'neutral', 'compound']].head())
```

```
Sample of Sentiment Scores:
   positive  negative  neutral  compound
0     0.418       0.0    0.582    0.9664
1     0.446       0.0    0.554    0.9360
2     0.316       0.0    0.684    0.9186
3     0.292       0.0    0.708    0.8591
4     0.391       0.0    0.609    0.9201
```

```
In [26]: # Calculate summary statistics
         summary_stats = df[['positive', 'negative', 'neutral', 'compound']].describe()

         # Print summary statistics
         print("Summary Statistics:")
         print(summary_stats)
```

```
Summary Statistics:
          positive     negative      neutral     compound
count  9955.000000  9955.000000  9955.000000  9955.000000
mean      0.253180     0.056102     0.688505     0.474117
std       0.233832     0.112885     0.219711     0.583696
min       0.000000     0.000000     0.000000    -0.994200
25%       0.090000     0.000000     0.621000     0.000000
50%       0.208000     0.000000     0.731000     0.764800
75%       0.344000     0.070000     0.820000     0.934900
max       1.000000     1.000000     1.000000     0.999600
```

Figure: Sentiment Analysis

It's apparent that the scores are primarily positive. In fact, we can see that the median compound score is 0.76 – which means that over 50% of the reviews have a compound score of more than 0.76, which suggests strong positive sentiment.

Let's take a look at the distribution of the scores.

```
In [27]: # Plot histogram of compound sentiment scores
         plt.hist(df['compound'], bins=20, color='skyblue', edgecolor='black')  # Adjust color if needed
         plt.xlabel('Compound Sentiment Score')
         plt.ylabel('Frequency')
         plt.title('Distribution of Compound Sentiment Scores')
         plt.show()
```

```
In [28]: # Plot histogram of positive sentiment scores
         plt.hist(df['positive'], bins=20, color='green', edgecolor='black')  # Adjust color if needed
         plt.xlabel('Positive Sentiment Score')
         plt.ylabel('Frequency')
         plt.title('Distribution of Positive Sentiment Scores')
         plt.show()
```

```
In [29]: # Plot histogram of negative sentiment scores
         plt.hist(df['negative'], bins=20, color='purple', edgecolor='black')  # Adjust color if needed
         plt.xlabel('Negative Sentiment Score')
         plt.ylabel('Frequency')
         plt.title('Distribution of Negative Sentiment Scores')
         plt.show()
```

```
In [30]: # Plot histogram of neutral sentiment scores
         plt.hist(df['neutral'], bins=20, color='orange', edgecolor='black')  # Adjust color if needed
         plt.xlabel('Neutral Sentiment Score')
         plt.ylabel('Frequency')
         plt.title('Distribution of Neutral Sentiment Scores')
         plt.show()
```

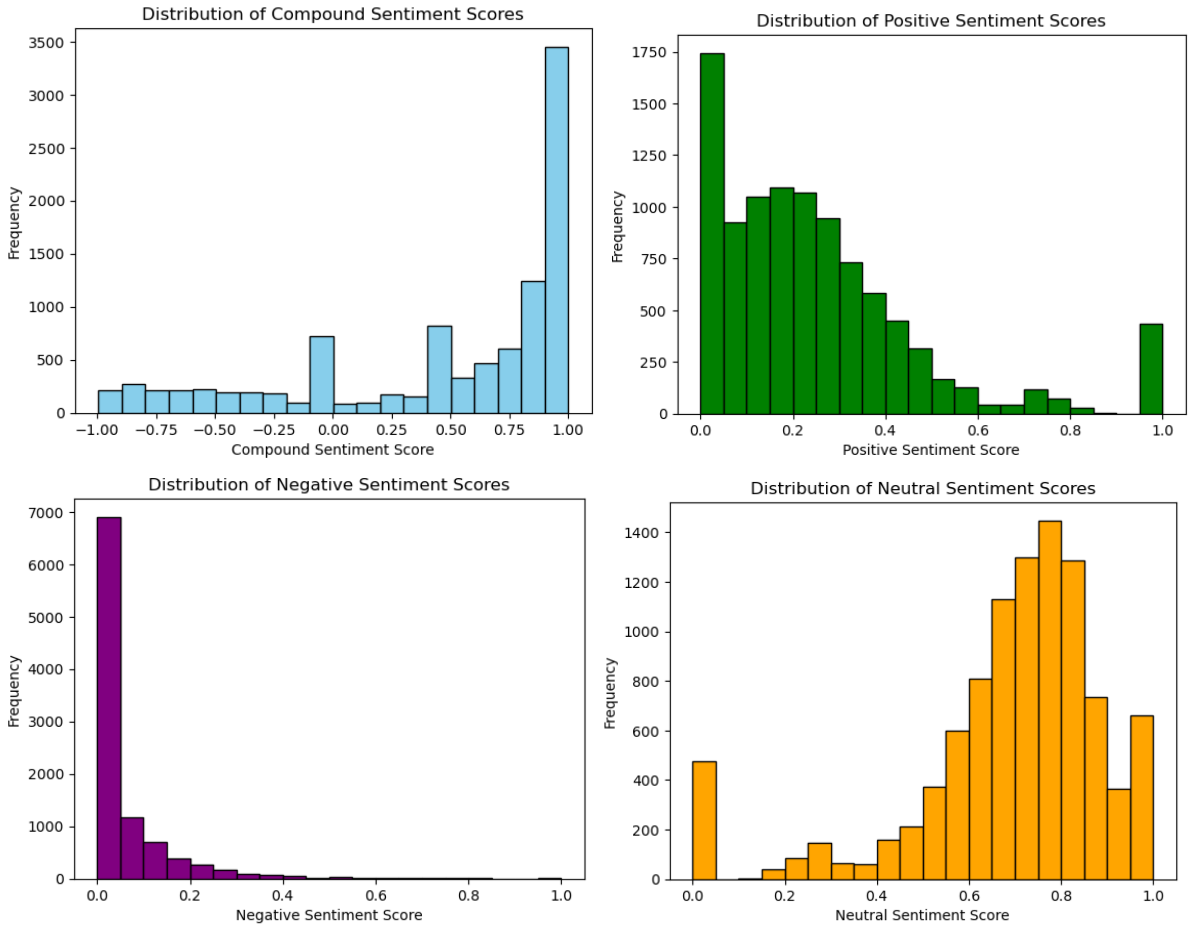


Figure: Sentiment scores

We can also calculate the review percentage from the sentiment score based on the class label(Positive reviews and negative reviews)

In [31]:
```
# Percentage of positive reviews
# Count the number of reviews with a compound score above the threshold
positive_reviews_count = df[df['compound'] > 0].shape[0]

# Total number of reviews
total_reviews = df.shape[0]

# Calculate percentage of positive reviews
percentage_positive = (positive_reviews_count / total_reviews) * 100

print(f"Percentage of Positive Reviews: {percentage_positive:.2f}%")
```

```
Percentage of Positive Reviews: 74.66%
```

In [32]:
```
# Percentage of negative reviews
# Count the number of reviews with a compound score above the threshold
negative_reviews_count = df[df['compound'] < 0].shape[0]

# Total number of reviews
total_reviews = df.shape[0]

# Calculate percentage of negative reviews
percentage_negative = (negative_reviews_count / total_reviews) * 100

print(f"Percentage of Negative Reviews: {percentage_negative:.2f}%")
```

```
Percentage of Negative Reviews: 18.79%
```

Figure: The review percentage

A word cloud visualization was created based on the positive and negative reviews gotten for the sentiment.

In [33]:
```python
# Tokenize words for positive and negative sentiments
positive_words = ' '.join(df[df['compound'] > 0]['clean_text'])
negative_words = ' '.join(df[df['compound'] < 0]['clean_text'])
all_words = ' '.join(df['clean_text'])

# Tokenize all words
tokens_positive = word_tokenize(positive_words)
tokens_negative = word_tokenize(negative_words)
tokens_all = word_tokenize(all_words)
```

In [34]:
```python
# WordCloud - Sentiment Positive

df1 = df[df['text_label']== 'Positive']
words = ' '.join(df1['text'].astype(str))
cleaned_word = ' '.join([word for word in words.split() if not word.startswith('@')])

wordcloud = WordCloud(background_color='white',stopwords=STOPWORDS,
                      width=3000, height=2500).generate(''.join(cleaned_word))
plt.imshow(wordcloud)
plt.axis('off')
plt.show()
```

In [35]:
```python
# WordCloud - Sentiment Negative

df2 = df[df['text_label']=='Negative']
words = ' '.join(df2['text'].astype(str))
cleaned_word = ' '.join([word for word in words.split() if not word.startswith('@')])

wordcloud = WordCloud(background_color='white',stopwords=STOPWORDS,
                      width=3000, height=2500).generate(''.join(cleaned_word))
plt.imshow(wordcloud)
plt.axis('off')
plt.show()
```

Figure: Wordcloud

The common words used for the positive review

Figure: Positive review

The common words used for the negative reviews

Figure: Negative review

4.5 Result Analysis and Conclusion

According to the analysis, 74.66% of the restaurant reviews were positive, 18.79% were negative, and 6.55% were neutral.

While the positive dominance indicates growing customer satisfaction and reputation, the negative reviews indicate areas for improvement. The improvements include staff training, quality control procedures, operational strategies, and food and service quality.

Even though there are more positive sentiments than negative ones, the negative sentiments help to point out areas that could use improvement, which helps the restaurants improve customer satisfaction and service quality.