# A Text Mining Journey through Hotel and Restaurant Reviews in Thailand.

## **Dataset:**

The dataset contains 53,644 rows and 5 columns of customer reviews of hotels and restaurants in 25 different locations in the province of Phuket, Thailand. In this report we'll select reviews of hotels and Restaurants from two major districts in the Phuket province, each representing a customer's experience. We carefully selected 15 hotels/Restaurants located in Choeng thale in Thalang, in the Northern part of Phuket, as well as another 15 hotels/Restaurants in Cape Panwa which is situated in Mueang Phuket in the southern part of Phuket which is also the capital of the province. The dataset used for this task is the tourist accommodation reviews.csv dataset.

## **Explanation and preparation of dataset (Exploratory Data Analysis)**

- 1. Open Jupyter Notebook, either from the Anaconda Prompt or the Anaconda Navigator. Open a new notebook by clicking the New tab button and select Python 3 (ipykernel) to create a new notebook workspace.
- For this report, I will use the Natural Language Toolkit (NLTK) library, which
  provides a range of text-processing tools for tasks such as classification,
  tokenization, stemming, tagging, and sentiment analysis. Run the code below to
  import the libraries.

3. Import data using the read\_csv() function in the pandas library to read the dataset into a pandas data frame, and then analyse and visualise some of the results.

```
In [2]: #importing the dataset
    reviews = pd.read_csv('tourist_review.csv')
```

- 4. To gain a better understanding of the dataset and its columns, execute the following code:
  - (a) reviews.head()

This function retrieves the first few rows of the dataset.



## (b) reviews.tail()

This function retrieves the last few rows of the dataset. To get more rows, simply specify a different number inside the parentheses. Example: "reviews.tail(20)" which would return the last 20 rows.



# (c) reviews.describe()

This function is used to return the summary of the data.



5. To identify and define stop words in the English language, run the following code:

```
stop_words = nltk.corpus.stopwords.words('english')
print(stop_words)

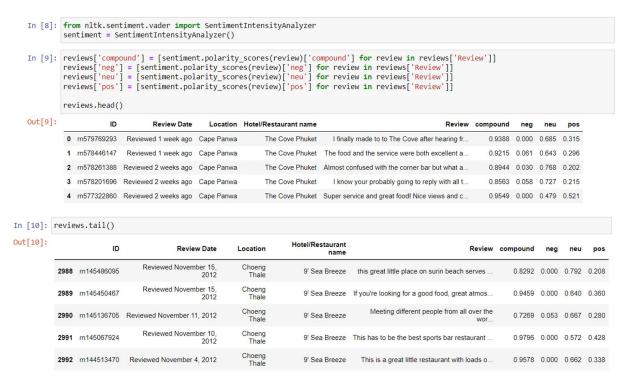
['i', 'me', 'my', 'myself', 'we', 'our', 'ourselves', 'you', "you're", "you've", "you'll", "you'd", 'your', 'yours, 'yourself', 'yourselves', 'he', 'him', 'his', 'himself', 'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'its', 'itself', 'they', 'them', 'their', 'themselves', 'what', 'which', 'whoo', 'whom', 'this', 'that'll", 'these', 'those', 'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have', 'has', 'had', 'having', 'do', 'does', 'did', 'doing', 'a', 'a n', 'the', 'and', 'but', 'if', 'or', 'because', 'as', 'until', 'while', 'of', 'at', 'by', 'for', with', 'about', 'against', 'b', 'each', 'ino', 'or', 'at', 'and', 'having', 'down', 'in', 'out', 'on', 'off', 'over', 'under', 'again', 'further', 'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'all', 'any', 'both', 'each', 'few', 'more', 'most', 'other', 'some', 'such', 'nor', 'not', 'only', 'own', 'same', 'so', 'than', 'too', 'very', 's', 't', 'can', 'will', 'just', 'don', "don't", 'should've", 'now', 'd', 'll', 'm', 'o', 're', 've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", "didn't", 'doesn', "doesn't", 'hadn', "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't", 'mas', "mightn't", 'mustn', "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "should n't", 'wasn', "wasn't", 'weren't", 'won', "won't", 'wouldn't"]
```

6. Having explored the pre-processing steps, the texts were split into two separate parts called tokens and cleaned out by removing the stop words using the below code:

```
In [7]: #preprocessing the texts by splitting them into seperate parts named tokens and cleaning out these tokens by removing the stop wo

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

For **Implementation in Python**, We'll import the **SentimentIntensityAnalyzer** class from **NLTK's VADER**, which returns a dictionary of sentiment scores, including the overall compound score, a positive score, a negative score, and neutral scores, and retrieve the first few rows with *reviews.head()* and *reviews.tail()* for last few rows.



7. To gain more insights into the sentiment scores of the new columns, run the following code:

In [11]:	<pre>#Exploring the new columns for more insights into sentiment scores for review reviews[['compound', 'neg', 'neu', 'pos']].describe()</pre>							
Out[11]:		compound	neg	neu	pos			
	count	2993.000000	2993.000000	2993.000000	2993.000000			
	mean	0.708503	0.022771	0.730721	0.246509			
	std	0.378836	0.045676	0.126106	0.133492			
	min	-0.959400	0.000000	0.286000	0.000000			
	25%	0.662400	0.000000	0.648000	0.147000			
	50%	0.865800	0.000000	0.737000	0.241000			
	75%	0.933600	0.037000	0.819000	0.336000			
	max	0.990900	0.407000	1.000000	0.714000			

8. We will create a function to compute negative, neutral, and positive sentiments.

Then, add a new column named Sentiment to the dataset using the code below:

```
In [12]: #creating a funtion to compute negative, neutral and positive sentiments and add a new colum named sentiment to our dataset

def getAnalysis(score):
    if score < 0:
        return 'Negative'
    elif score == 0:
        return 'Neutral'
    else:
        return 'Positive'

reviews['sentiment'] = reviews['compound'].apply(getAnalysis)</pre>
```

9. View the dataset again to see the new columns.



10. To view the counts for each sentiment type, run the below code.

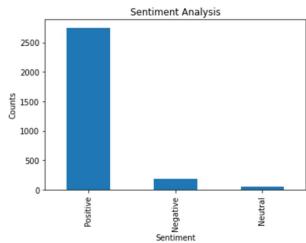
```
In [14]: #Counts for each sentiment type
    reviews['sentiment'].value_counts()

Out[14]: Positive 2749
    Negative 191
    Neutral 53
    Name: sentiment, dtype: int64
```

11. We can visualise the counts for each sentiment type in a bar graph using the following code:

```
In [15]: #visualise the counts for each sentiment type

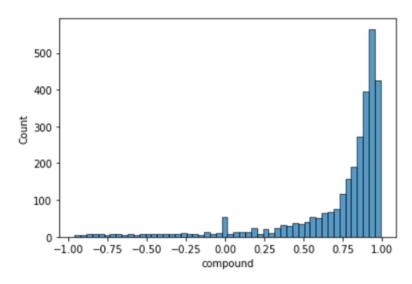
plt.title('Sentiment Analysis')
plt.xlabel('Sentiment')
plt.ylabel('Counts')
reviews['sentiment'].value_counts().plot(kind = 'bar')
plt.show()
```



- 12. We can further view the distribution of compound, positive, and negative scores by executing the codes shown in the images below:
  - (a) Compound score

```
In [16]: #visualise distribution of compound scores
sns.histplot(reviews['compound'])
```

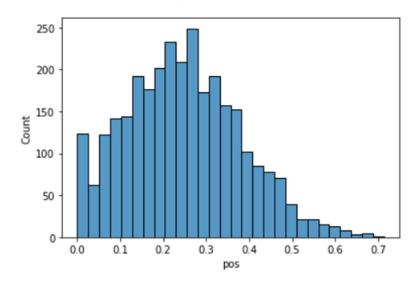
Out[16]: <matplotlib.axes.\_subplots.AxesSubplot at 0x7f22c79bd8b0>



# (b) Positive score

```
In [17]: #visualise distribution of positive scores
sns.histplot(reviews['pos'])
```

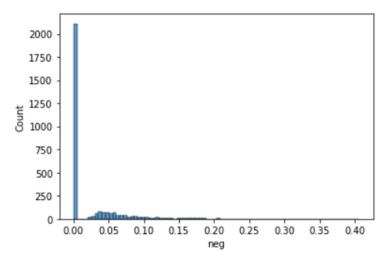
Out[17]: <matplotlib.axes.\_subplots.AxesSubplot at 0x7f22c78cce80>



## (c) Negative score

```
In [18]: #visualise distribution of negative scores
sns.histplot(reviews['neg'])
```

Out[18]: <matplotlib.axes.\_subplots.AxesSubplot at 0x7f22c77ff6a0>



13. Let's look at how many negative reviews there are per hotel/restaurant using the following code below:

```
In [19]: #negative reviews per hotel/Restaurant
         (reviews['compound']<=0).groupby(reviews['Hotel/Restaurant name']).sum()</pre>
Out[19]: Hotel/Restaurant name
         360 ° Bar
                                             5
         9' Sea Breeze
                                            11
         Ann's Kitchen Bar and Grill
                                             5
         Audy Restaurant
         Baan Ra Tree Restaurant
                                            12
         Baba Soul Food
         Bamboo Bar
         Bampot Kitchen & Bar
         Benny's American Bar & Grill
         Black Cat
                                            10
         Bocconcino
                                             7
         Bodega & Grill
                                             9
         Cafe de Bangtao
                                            10
         Chilli Kitchen
                                             7
         Curry Night Indian Restaurant
                                             3
         Cut Grill & Lounge
                                            11
         D Restaurant
                                            11
         DaVinci Restaurant
                                             5
         DeDos
                                             4
         Dino Park
                                            16
         Live India Indian Restaurant
                                            10
         Mali Chic Restaurant
                                            12
         Panwa House
                                             8
         Plum Prime Steakhouse
                                             7
         Sabai Sabai
                                            12
         Sea Breeze
         The Cove Phuket
         The Grill
         Tree Top Restaurant and Bar
                                             6
         Uncle Nan's Italian Restaurant
                                            21
         Name: compound, dtype: int64
```

14. Apparently, we should also look at the number of negative reviews as a proportion of the total number for each hotel/restaurant, unless it's already known. To do this, run the code in the image below:

```
In [20]: #calculate the negative as a percentage of the total reviews
           percent_negative = pd.DataFrame((reviews['compound']<=0).groupby(reviews['Hotel/Restaurant name']).sum()</pre>
                                                 /reviews['Hotel/Restaurant name'].groupby(reviews['Hotel/Restaurant name']).count()*100,
                                                 columns=['% negative reviews']).sort_values(by='% negative reviews')
           percent_negative
Out[20]:
                                        % negative reviews
                  Hotel/Restaurant name
                       The Cove Phuket
                                                 2.000000
            Curry Night Indian Restaurant
                                                 3.000000
                   Bampot Kitchen & Bar
                                                 3.000000
                        Baba Soul Food
                                                 4.000000
                                                 5.000000
                     DaVinci Restaurant
                                                 5.000000
             Benny's American Bar & Grill
                                                 5.000000
                              360 ° Bar
                                                 5.000000
                       Audy Restaurant
                                                 5.000000
              Ann's Kitchen Bar and Grill
                                                 5.000000
             Tree Top Restaurant and Bar
                                                 6.000000
                            Bocconcino
                                                 7.000000
                 Plum Prime Steakhouse
                                                 7.000000
                           Chilli Kitchen
                                                 7.446809
                          Panwa House
                                                 8.000000
                          Bodega & Grill
                                                 9.000000
                             Sea Breeze
                                                 9.000000
                           Bamboo Bar
                                                 9.000000
              Live India Indian Restaurant
                                                 10.000000
                              Black Cat
                                                 10.000000
                        Cafe de Bangtao
                                                 10.101010
                           D Restaurant
                                                 11.000000
                      Cut Grill & Lounge
                                                 11.000000
                           9' Sea Breeze
                                                 11.000000
                    Mali Chic Restaurant
                                                 12.000000
                            Sabai Sabai
                                                 12.000000
                Baan Ra Tree Restaurant
                                                 12.000000
                              Dino Park
                                                 16.000000
            Uncle Nan's Italian Restaurant
                                                 21.000000
```

15. We can further plot the above percentage as a horizontal barplot using seaborn.

```
In [21]: #we can also plot the above percentages as a horizontal barplot

sns.barplot(data=percent_negative, x='% negative reviews', y=percent_negative.index, color='c')

Out[21]: <a href="mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:mailto:ma
```

10.0 12.5 15.0 17.5

% negative reviews

Mali Chic Resta Sabai Baan Ra Tree Resta Din Uncle Nan's Italian Resta 16. We also look into understanding what words appeared more frequently in positive or negative reviews for a particular hotel/restaurant. Then use the Wordcloud to visualise it. In this report, we will focus on Uncle Nan's Italian restaurant as this got the most negative reviews among the restaurants in the Cape Panwa location. To achieve this, execute the codes as shown in the image below.

```
In [22]: #process the text data ready for wordcloud visualisation using the function defined earlier
           #We'll focus on Uncle Nan's Italian restaurant as this got most negative reviews among the restaurants in cape panwa location
           reviews['processed_review'] = reviews['Review'].apply(preprocess_text)
           reviews_positive_subset = reviews.loc[(reviews['Hotel/Restaurant name']=='Uncle Nan\'s Italian Restaurant')
                                                  & (reviews['compound']>0),:]
           reviews_negative_subset = reviews.loc[(reviews['Hotel/Restaurant name']=='Uncle Nan\'s Italian Restaurant')
                                                  & (reviews['compound']<=0),:]
           reviews_positive_subset.head()
Out[22]:
                                                           Hotel/Restaurant
                                 Review Date Location
                                                                                                                           pos sentiment
                                                                                                                                                   processed_review
                                                                                          Review compound neg neu
                                                                     name
                                                                             Needed some non Thai
                                                                                                                                            [need, non, thai, food, one,
                                                           Uncle Nan's Italian
                                  Reviewed 3
                                                  Cape
            1300 rn576095102
                                                                                                      0.7878 0.000 0.655 0.345
                                                                                                                                   Positive
                                                                              food one evening and
                                   weeks ago
                                                                  Restaurant
                                                                                                                                                   even, went, certa.
                                                           Uncle Nan's Italian
                                  Reviewed 4
                                                  Cape
                                                                            This restaurant is at the
                                                                                                                                            [restaur, kantari, bay, hotel,
            1301 rn575028373
                                                                                                      0.8495 0.030 0.796 0.174
                                                                                                                                   Positive
                                                                 Restaurant
                                                                              Kantary Bay Hotel. I.
                                                                                I think my daughter
                                                           Uncle Nan's Italian
                                                                                                                                                Ithink, daughter, made,
                                Reviewed April
                                                  Cape
            1302 m572806144
                                                                               made a better pizza when s...
                                                                                                      0.0258 0.129 0.737 0.134
                                                                                                                                   Positive
                                                                 Restaurant
                                                                                                                                                 better, pizza, 6yr, ol..
                                                                              Food and setting was
                                    Reviewed
                                                  Cape
                                                           Uncle Nan's Italian
                                                                                                                                              ffood, set, love, downsid.
            1306 rn564703288
                                                                                                      0.5106 0.033 0.861 0.106
                                                                                                                                   Positive
                                                                                                                                                   portion, could, big..
                                March 5, 2018
                                                                 Restaurant
                                                                                      downside .
                                    Reviewed
                                                                                We booked through
                                                  Cape
                                                           Uncle Nan's Italian
                                                                                                                                             [book, cape, panwa, hotel,
            1307 m563337120
                                 February 28,
                                                                                                      0.9501 0.000 0.656 0.344
                                                                                                                                   Positive
                                                                              cape panwa hotel .we
                                                                 Restaurant
                                                                                                                                                   excel, meal, staff...
                                                                                        had an
```

17. We can now generate a Wordcloud using the Wordcloud library for negative reviews at Uncle Nan's Italian Restaurant using the code below.

```
In [23]: # Wordcloud of words from negative reviews for Uncle Nan's Italian Restaurant

neg_tokens = [word for review in reviews_negative_subset['processed_review'] for word in review]

wordcloud = WordCloud(background_color='white').generate_from_text(' '.join(neg_tokens))

plt.figure(figsize=(12,12))
 plt.imshow(wordcloud, interpolation='bilinear')
 plt.axis("off")
 plt.show()
```



We can see that some of the words aren't particularly informative. for example: 'food', 'pizza', 'Italian, and 'pasta' are all references to the restaurant menu. But we can also see words like 'disappoint', 'worst', 'expensive', and 'taste' have been mentioned a few times — Maybe these are issues that require further investigation.

18. We can also generate a wordcloud from the positive reviews using the code below.



- 19. Wordclouds do provide a way to visualise word frequencies, but sometimes it might be difficult to explain. we can also use the tabulate method to understand the most frequent words, and the number of occurrences in each with the use of FreqDist from **NLTK** using the code below:
  - (a) Positive Reviews

```
In [25]: #using FreqDist from NLTK to show the frequeny of words in a tabular form for positive reviews
         from nltk.probability import FreqDist
         pos_freqdist = FreqDist(pos_tokens)
         pos freqdist.tabulate(10)
                                                                                     hotel
            food
                     good italian
                                    pizza servic
                                                     nice
                                                             staff restaur
                                                                              meal
              59
                       34
                               31
                                       26
                                               21
                                                       19
                                                                18
                                                                        17
                                                                                17
                                                                                        16
```

## (b) Negative Reviews

```
In [26]: #using FreqDist from NLTK to show the frequeny of words in a tabular form for negative reviews

from nltk.probability import FreqDist

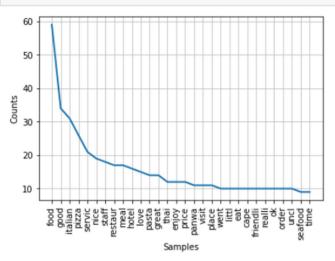
neg_freqdist = FreqDist(neg_tokens)

neg_freqdist.tabulate(10)

food italian pizza restaur servic order went pasta disappoint slow
18 10 9 7 7 6 6 6 6 5 5
```

- 20. We can also use the frequency distribution graph to show word frequency in both positive and negative reviews using the following codes below:
  - (a) Positive reviews

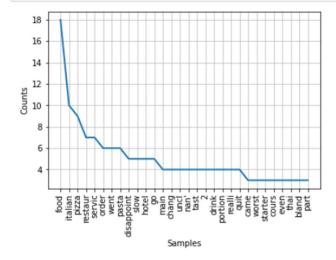
In [27]: #Frequency distribution graph to show word frequency for postive reviews
pos\_freqdist.plot(30)



Out[27]: <matplotlib.axes.\_subplots.AxesSubplot at 0x7f22c7fb9fd0>

(b) Negative reviews

In [28]: #Frequency distribution graph to show word frequency for negative reviews
 neg\_freqdist.plot(30)



Out[28]: <matplotlib.axes.\_subplots.AxesSubplot at 0x7f22c795cee0>

## Results analysis and discussion

Our dataset did not require any pre-processing as we used the implementation of VADER, which takes care of the process. We utilised tokenization, stopword removal, and stemming to generate a wordcloud that visualises the distribution of words and word count. This helped to identify the main words that contribute to positive and negative reviews at Uncle Nan's Italian Restaurant. The management can use this information to investigate and improve specific areas.

# **Conclusions**

For the implementation of this analysis, we chose VADER due to its efficiency, ease of use, and clear, compelling results. This report aims to assist restaurants and hotels in Thailand in identifying their strengths and weaknesses, allowing them to improve their quality of service in the right areas and ultimately leading to higher positive scores.