https://www.kaggle.com/datasets/arushchillar/disneyland-reviews
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The dataset includes 42,000 reviews of 3 Disneyland branches - Paris, California and Hong Kong, posted by visitors on Trip Advisor.

Column Description:

```
Review_ID: unique id given to each review
Rating: ranging from 1 (unsatisfied) to 5 (satisfied)
Year_Month: when the reviewer visited the theme park
Reviewer_Location: country of origin of visitor
Review_Text: comments made by visitor
Branch: location of Disneyland Park
```

Reading Data

Importing Packages

In [1]:
```
from IPython.display import Image # Inserting Images
import re #Regex functions
import contractions
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
from matplotlib import pyplot as plt # creating Visualizations
```

Reading CSV File

In [2]:
```
df = pd.read_csv(r'C:\Users\stanl\OneDrive\Desktop\New folder\Disneyland_Revie
```

1. Data Preparation

1.1 Renaming columns

In [3]:
```
df = df.rename(columns = {'Review_Text':'Review','Branch':'Location'})
df.columns
```

Out[3]:
```
Index(['Review_ID', 'Rating', 'Year_Month', 'Reviewer_Location', 'Review',
       'Location'],
      dtype='object')
```

For Year_Month na or null values are not showing up but value_counts show that data used 'missing' to indentify null or na values

1.1 Missing Values

In [4]:
```
print(df.Year_Month.isna().sum())
print(df.Year_Month.isnull().sum())
```

```
0
0
```

After inspection of all rows, only column Year_Month has missing values fo 2613 labled as 'missing'

In [5]:
```
print(df.Year_Month.value_counts())
```

```
missing    2613
2015-8      786
2015-7      759
2015-12     701
2015-6      692
           ...
2010-8        7
2010-5        4
2019-5        2
2010-3        2
2010-4        1
Name: Year_Month, Length: 112, dtype: int64
```

Replace 'missing' with np.nan so pandas can identify null/na values

In [6]:
```
df['Year_Month'] = df['Year_Month'].replace('missing', np.nan)
```

Pandas now can recognize nan values

In [7]:
```
df['Year_Month'].isna().sum()
```

Out[7]:
```
2613
```

1.2 Duplicate Values

Considering removing duplicate reviews more important than duplicate Review_ID since duplicate reviews are not useful.

```
Duplicate reviews = text is all the same
```

24 Duplicate Reviews Found

In [8]:
```
df.duplicated(subset=['Review']).value_counts()
```

Out[8]:
```
False    42632
True        24
dtype: int64
```

Keeps first occurence of review and removes duplicates from original dataframe

In [9]:
```
df.drop_duplicates(subset='Review', inplace=True, keep='first')
```

All duplicate reviews have been removed

In [10]:
```
df.duplicated(subset=['Review']).value_counts()
```

Out[10]:
```
False    42632
dtype: int64
```

2. Text Preprocessing

2.1 Splitting Year Month into seperate columns

In [11]:
```
df['Year'] = df['Year_Month'].str.split('-').str.get(0)
df['Month'] = df['Year_Month'].str.split('-').str.get(1) # Splits column by de
df['Year'].fillna('NaN', inplace=True)
df['Month'].fillna('NaN', inplace=True)
# df = df.drop(columns='Year_Month') # drops old column after creating new colu
```

2.2 Cleaning up Location Column

```
In [12]: df.Location = df.Location.str.replace("Disneyland_","") # Removes string "Disn
         df.Location = df.Location.str.replace("HongKong","Hong Kong") # Add space
         df
```

Out[12]:

	Review_ID	Rating	Year_Month	Reviewer_Location	Review	Location	Year	Month
0	670772142	4	2019-4	Australia	If you've ever been to Disneyland anywhere you...	Hong Kong	2019	4
1	670682799	4	2019-5	Philippines	Its been a while since d last time we visit HK...	Hong Kong	2019	5
2	670623270	4	2019-4	United Arab Emirates	Thanks God it wasn t too hot or too humid wh...	Hong Kong	2019	4
3	670607911	4	2019-4	Australia	HK Disneyland is a great compact park. Unfortu...	Hong Kong	2019	4
4	670607296	4	2019-4	United Kingdom	the location is not in the city, took around 1...	Hong Kong	2019	4
...	...	...	...	...	...	...	...	...
42651	1765031	5	NaN	United Kingdom	i went to disneyland paris in july 03 and thou...	Paris	NaN	NaN
42652	1659553	5	NaN	Canada	2 adults and 1 child of 11 visited Disneyland ...	Paris	NaN	NaN
42653	1645894	5	NaN	South Africa	My eleven year old daughter and myself went to...	Paris	NaN	NaN
42654	1618637	4	NaN	United States	This hotel, part of the Disneyland Paris compl...	Paris	NaN	NaN
42655	1536786	4	NaN	United Kingdom	I went to the Disneyparis resort, in 1996, wit...	Paris	NaN	NaN

42632 rows × 8 columns

2.3 Creating a Quarter Column

In [13]:
```
def convert_to_int(value):
    try:
        return float(value)
    except (ValueError, TypeError):
        return np.nan

df['Year'] = df['Year'].apply(convert_to_int)
df['Month'] = df['Month'].apply(convert_to_int)

df['Quarter'] = df.apply(lambda row: round((row['Month'] - 1) / 3) + 1 if not
df
```

Out[13]:

	Review_ID	Rating	Year_Month	Reviewer_Location	Review	Location	Year	Month
0	670772142	4	2019-4	Australia	If you've ever been to Disneyland anywhere you...	Hong Kong	2019.0	4.0
1	670682799	4	2019-5	Philippines	Its been a while since d last time we visit HK...	Hong Kong	2019.0	5.0
2	670623270	4	2019-4	United Arab Emirates	Thanks God it wasn t too hot or too humid wh...	Hong Kong	2019.0	4.0
3	670607911	4	2019-4	Australia	HK Disneyland is a great compact park. Unfortu...	Hong Kong	2019.0	4.0
4	670607296	4	2019-4	United Kingdom	the location is not in the city, took around 1...	Hong Kong	2019.0	4.0
...	...	...	...	...	...	...	...	...
42651	1765031	5	NaN	United Kingdom	i went to disneyland paris in july 03 and thou...	Paris	NaN	NaN
42652	1659553	5	NaN	Canada	2 adults and 1 child of 11 visited Disneyland ...	Paris	NaN	NaN
42653	1645894	5	NaN	South Africa	My eleven year old daughter and myself went to...	Paris	NaN	NaN
42654	1618637	4	NaN	United States	This hotel, part of the Disneyland Paris compl...	Paris	NaN	NaN
42655	1536786	4	NaN	United Kingdom	I went to the Disneyparis resort, in 1996, wit...	Paris	NaN	NaN

42632 rows × 9 columns

2.4 Noise Removal of Review Column

The actual raw text of disneylands reviews needs to be process to allow better performance of NLP techniques (Faster Performance)

Common cleaning methods

- Lowercasing the data
- Removing Puncuatations
- Removing Numbers
- Removing extra space
- Replacing the repetitions of punctations
- Removing Emojis
- Removing emoticons
- Removing Contractions

For this dataset steps taken for Preprocessing:

- Seperate Contractions
- Remove Special Characters
- Remove Single Characters
- Remove Multiple Spaces
- Replace multiple Spaces with Single Space
- Remove URLS
-

Seperate Contractions

In [14]:
```
# Define a function to fix contractions
def fix_contractions(text):
    return contractions.fix(text)

df['Review'] = df['Review'].apply(fix_contractions)
```

Removing Special Characters and Lowercase Conversion

In [15]:
```
df.Review = df.Review.apply(lambda x: re.sub(r'\W'," ",x)) # special character
df.Review = df.Review.apply(lambda x: re.sub(r'\s+[a-zA-Z]\s+'," ",x)) # singl
df.Review = df.Review.apply(lambda x: re.sub(r'\^[a-zA-Z]\s+'," ",x)) # multip
df.Review = df.Review.apply(lambda x: re.sub(r'\s+'," ",x)) # replace multiple
df.Review = df.Review.apply(lambda x: re.sub(r'(https?://\S+)',"",x)) # remove
df.Review = df.Review.apply(lambda x: re.sub(r'^b\s+',"",x)) # string b at beg
```

Lowercase Conversion

In [16]:
```
df.Review = df.Review.str.lower() # Lowercase review
```

What about Stop Words?

- In the case for sentiment analysis. Keeping stop words could be useful as it only affects computational speed. For other methods of Text Preprocessing such as Bag-of-Words or TF-IDF, it could be useful and will be done later for other NLP Methods.

2.5 Word Normalization

There are 3 common techniques for normalization:

- Lemmatization
- Stemming
- Tokenization

For each NLP Technique, I will apply these methods but not at this moment.

3. Sentiment Analysis Using VADER

Vader and Textblob are packages that were trained to determined sentiment on text data and have their own use cases but I will apply sentiment analysis using Vader.

- Vader was designed to run sentiment analysis on social media text (commonly short) so more informal and is trained to understand punuactions, slang, emojis, captialization and intensifiers in social media conversation.
- Textblob is considered more versatitle for wide range of texts (long or short)
- Vader provides compound score of negative and positive polarity while Textblob provides polarity of negative and positive sentitments seperately
- Subjectivity is percentage of review that contains personal opinion vs factual information
- Polarity refers to how postive, neutral, or negative sentiment text is where <0 is Negative, 0 is Neutral, >0 is Postive

What about Tokenization of the Reviews?

- Both Vader and Textblob will tokenize text in its pipeline.

3.1 Determine Sentiment

Importing Vader Package and creating Function

In [17]:
```
from vaderSentiment.vaderSentiment import SentimentIntensityAnalyzer
import nltk
nltk.download('vader_lexicon')



# VADER Sentiment Analysis
def analyze_sentiment(text):
    analyzer = SentimentIntensityAnalyzer()
    sentiment_scores = analyzer.polarity_scores(text)
    return sentiment_scores
```

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

In [18]:
```
# Vader Results
sentiments_results = df

sentiments_results['sentiment_scores'] = df['Review'].apply(analyze_sentiment)

sentiments_results['compound_sentiment'] = sentiments_results['sentiment_score
```

```
In [19]: sentiments_results.head(5)
```

Out[19]:

	Review_ID	Rating	Year_Month	Reviewer_Location	Review	Location	Year	Month	Qua
0	670772142	4	2019-4	Australia	if you have ever been to disneyland anywhere y...	Hong Kong	2019.0	4.0	
1	670682799	4	2019-5	Philippines	its been while since last time we visit hk dis...	Hong Kong	2019.0	5.0	
2	670623270	4	2019-4	United Arab Emirates	thanks god it wasn too hot or too humid when w...	Hong Kong	2019.0	4.0	
3	670607911	4	2019-4	Australia	hk disneyland is great compact park unfortunat...	Hong Kong	2019.0	4.0	
4	670607296	4	2019-4	United Kingdom	the location is not in the city took around 1 ...	Hong Kong	2019.0	4.0	

Based on the compound sentiment, we can see that it provides a level or degree of sentiment to each review that otherwise would be difficult to see based on just the Rating of 1-5 stars alone.

A compound sentiment is an aggregation of negative, neutral and positive polarity scores for a more nuanced sentiment where:

- 1 = most positive
- 0 = neutral
- 2 = most negative

Luckily, Vader helps calculate this compound sentiment for easy analysis.

How can this be used for the business for park improvement?

An approach to these could be first seperating the reviews based on location of park since visitors are so vastly different and not every park has the same attractions, restaurants, services, etc.

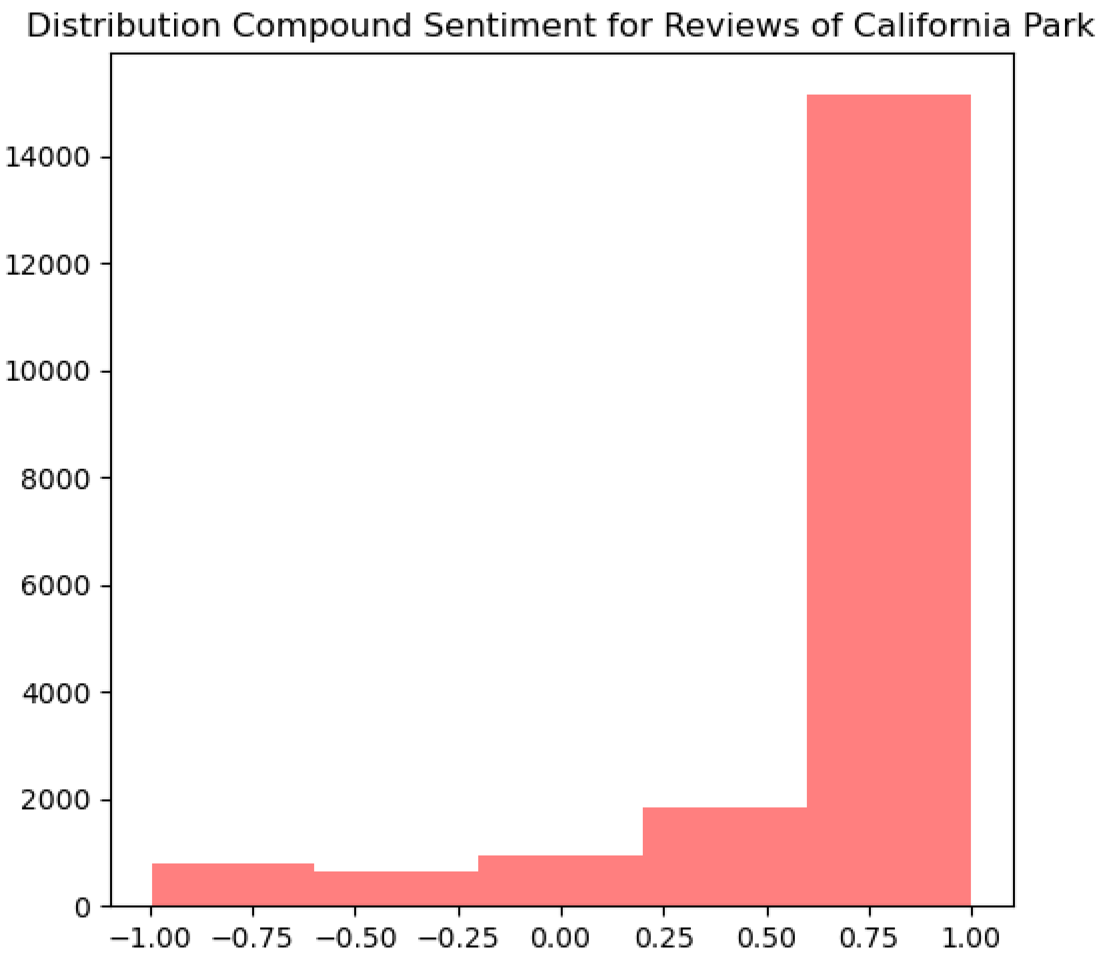
3.2 Subsetting Data based on Park

```
In [20]: sentiments_results_california = sentiments_results.loc[sentiments_results['Loca
sentiments_results_paris = sentiments_results.loc[sentiments_results['Location
sentiments_results_hong_kong =sentiments_results.loc[sentiments_results['Locat
```

Once the reviews are subsetted based on location. I can then focus on another subset of reviews where sentiment is below 0 indicating negative sentiment.

3.3 Graphing Distribution of Reviews by Compound Sentiment

```
In [21]: plt.figure(figsize=(10, 5))
plt.subplot(1, 2, 2)
plt.hist(sentiments_results_california['compound_sentiment'], bins=5, color='r
plt.title('Distribution Compound Sentiment for Reviews of California Park')

plt.tight_layout()
plt.show()
```



3.4 Analysis and Conclusion

If I was inovlved with trying to improve the California Park, I would maybe first determine which reviews to analyze first so I could set a threshold of compound sentiment to subset reviews negative or positive. Example:

- Analyzing positive reviews where compound sentiment is between 0.25 and .75 to find out how to make happy visitors even more satisfied with their visit to the park.
- Analyzing negative reviews between -1 and -0.75 to understand what visitors are frustrated with during their visits and hopefully implement features to avoid recurring frustrations.

Next, Lets try to analyze all negative sentiment reviews that have to determine what can be done to improve the California park.

4. Named Entity Recognition

Named Entity Recognition is a way for us to categorize or group words within text. Some categories are:

- Person
- Organization
- Place/Location
- Date
- Ordinal
- Numerical

The Spacy package allows to perform quick NER over NTLK's packages

In [22]:
```
import spacy
from collections import Counter
spacy.load('en_core_web_sm')
```

Out[22]:
```
<spacy.lang.en.English at 0x161dd8e4350>
```

4.1 Preprocessing Reviews of Negative Reviews

- There will be a need to tokenize our negative reviews of the California Park since the ngrams function does not perform this for us.
- Tokenization seperates each word in our review by a delimiter usually ',' for better peformance.
- NER from Spacy tokenizes the review for us in its pipeline

Subset to include only negative reviews where compund sentiment < 0

In [23]:
```
sentiments_results_california_negative_ner = sentiments_results_california.loc
sentiments_results_paris_negative_ner = sentiments_results_paris.loc[sentiment
sentiments_results_hong_kong_negative_ner =sentiments_results_hong_kong.loc[se
```

4.2 Run NER and group entities frequenies by entity category

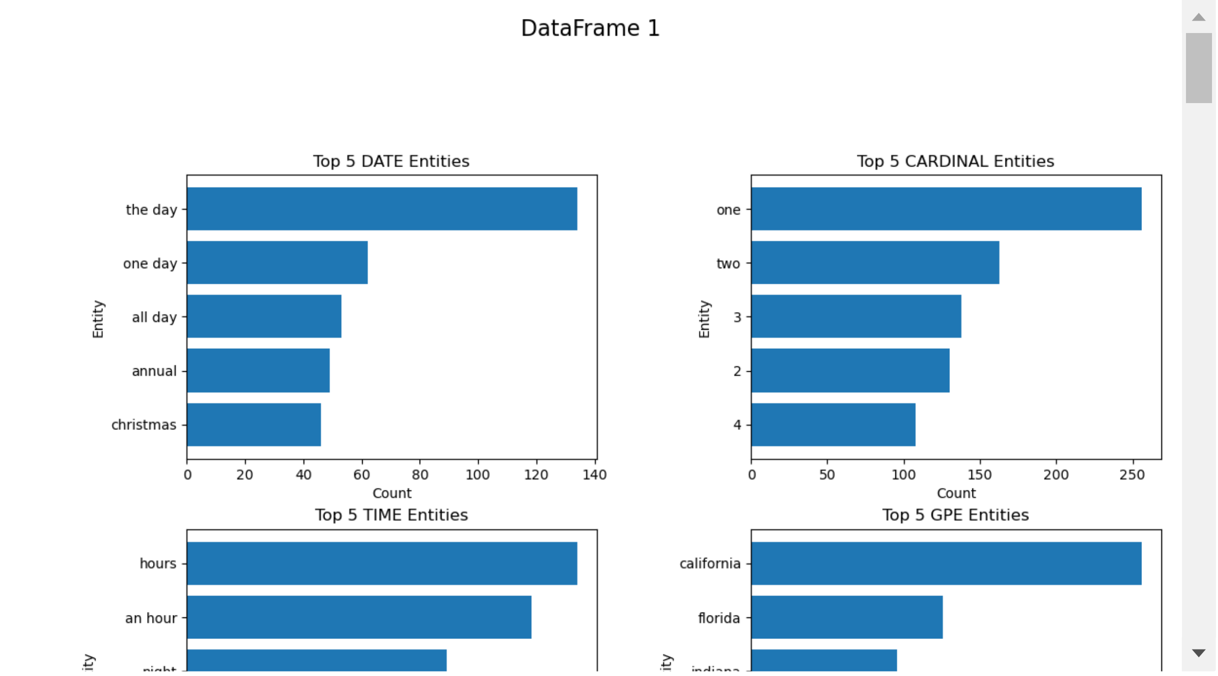
In [24]:
```
# Load the English NER model
nlp = spacy.load("en_core_web_sm")

sentiments_results_california_negative_ner['ner_results'] = sentiments_results_
sentiments_results_paris_negative_ner['ner_results'] = sentiments_results_pari
sentiments_results_hong_kong_negative_ner['ner_results'] = sentiments_results_
```

```
C:\Users\stanl\AppData\Local\Temp\ipykernel_15288\186426782.py:4: SettingWith
CopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/s
table/user_guide/indexing.html#returning-a-view-versus-a-copy (https://panda
s.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-ver
sus-a-copy)
  sentiments_results_california_negative_ner['ner_results'] = sentiments_resu
lts_california_negative_ner['Review'].apply(lambda text: [(ent.text, ent.labe
l_) for ent in nlp(text).ents])
C:\Users\stanl\AppData\Local\Temp\ipykernel_15288\186426782.py:5: SettingWith
CopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/s
table/user_guide/indexing.html#returning-a-view-versus-a-copy (https://panda
s.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-ver
sus-a-copy)
  sentiments_results_paris_negative_ner['ner_results'] = sentiments_results_p
aris_negative_ner['Review'].apply(lambda text: [(ent.text, ent.label_) for en
t in nlp(text).ents])
C:\Users\stanl\AppData\Local\Temp\ipykernel_15288\186426782.py:6: SettingWith
CopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/s
table/user_guide/indexing.html#returning-a-view-versus-a-copy (https://panda
s.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-ver
sus-a-copy)
  sentiments_results_hong_kong_negative_ner['ner_results'] = sentiments_resul
ts_hong_kong_negative_ner['Review'].apply(lambda text: [(ent.text, ent.label
_) for ent in nlp(text).ents])
```

4.3 Function to Create Subplots

4.4 Visualize Top 5 Entities for Each Entity Category for each Park

In [25]:
```
# List of DataFrames
dataframes = [sentiments_results_california_negative_ner, sentiments_results_pa

# Function to extract and plot top 5 entities for each category
def plot_top_entities(df, ax, top_n_categories=10, top_n_entities=5):
    if df['ner_results'].apply(lambda x: isinstance(x, list)).all():
        # Combine all entities from all categories
        combined_entities = {}
        for ner_results in df['ner_results']:
            for entity, category in ner_results:
                if category not in combined_entities:
                    combined_entities[category] = {}
                if entity not in combined_entities[category]:
                    combined_entities[category][entity] = 0
                combined_entities[category][entity] += 1

        # Sort categories by total entity count in descending order
        sorted_categories = sorted(combined_entities.keys(), key=lambda x: sum

        # Limit the number of categories to the top_n_categories
        sorted_categories = sorted_categories[:top_n_categories]

        for i, category in enumerate(sorted_categories):
            # Sort entities within the category by count in descending order
            sorted_entities = sorted(combined_entities[category].items(), key=
            entities, counts = zip(*sorted_entities) if sorted_entities else (

            ax[i].barh(entities, counts)
            ax[i].set_xlabel('Count')
            ax[i].set_ylabel('Entity')
            ax[i].set_title(f'Top {top_n_entities} {category} Entities')
            ax[i].invert_yaxis()

# Create a figure with subplots (5 rows and 2 columns) for each DataFrame
for i, df in enumerate(dataframes, start=1):
    num_categories = 10  # Number of categories to display
    num_entities = 5     # Number of entities to display per category
    num_rows = min(num_categories, len(df['ner_results']))

    fig, axes = plt.subplots(5, 2, figsize=(12, 20))
    fig.subplots_adjust(hspace=0.5, wspace=0.5)

    # Flatten the axes array for easy indexing
    axes = axes.flatten()

    # Call the function to plot top entities for each DataFrame
    plot_top_entities(df, axes, top_n_categories=num_categories, top_n_entitie

    # Hide any unused subplots
    for j in range(num_rows, len(axes)):
        fig.delaxes(axes[j])

    # Adjust layout and display the subplots
    plt.tight_layout()
    plt.suptitle(f'DataFrame {i}', fontsize=16)
    plt.subplots_adjust(top=0.9)
    plt.show()
```



Dataframe 1 = California Dataframe 2 = Paris Dataframe 3 = Hong Kong

4.4 Analysis and Conclusion

What inferencees can we make based on these entities?

California Disneyland

- For Time Entity, it seems like there are some visitors where it takes hours(probably refering to rides) and
- For organization Entity, it seems like Indiana Jones Ride has some negative reviews. Based on some news articles, it seemed like the ride based on 2019 was due for a refurbishment. It seems the ride had some mechanical issues which could have led to visitors leaving negative reviews about the ride.
- For Person Entity, seems like Peter Pan ride is getting some negative reviews as well.

Paris Disneyland

- For Location Entity, carribbean which is refering to the ride is mentioned in negative reviews
- For Person Entity, seems like Peter Pan ride in Paris also is being mentioned in negative reviews.
- For Organization Entity, it is showing a couple of reviews mentioning crockett which may refer to the Disney Davy Crockett Ranch.

Hong Kong Disneyland

- It seems like for Hong Kong, not much inferences or conclusions can be made which is fine, which is why other NLP techniques available and not all is lost.
- One most notable thing is with the Person Entity where Cinderella is mentioned which can refer to the Cinderella Carousel.

After analyzing the results of the NER, we can see that NER is useful to point us into the right direction of how each park can be improved though we are under the assumption that the