# Exploring Disneyland Visitor Reviews

Natural Language Processing

Xuefei Wang

## Table of Contents



## Introduction

One of the most well-known amusement parks, Disneyland, has several locations across the world, each providing a unique and different experience. As with any business, reviews are essential to **understand visitors' sentiment and the elements that most influence a positive or negative experience**. Using sentiment analysis, businesses can determine how customer feedback influences customer satisfaction and decision-making (Kauffman et al., 2019). Using 1-star to 5-star visitor reviews and natural language processing, this study analyzes the factors that contribute to visitor's positive and negative experiences. Considering negative reviews will help **identify areas for improvement** at Disneyland parks, whereas looking at positive reviews will provide **insights into factors that make Disneyland parks memorable and enjoyable for the visitors**.

This analysis will focus on the following research question:

***How can the NLP analysis of visitor reviews help improve customer experience at Disneyland?***

To analyze this, the "Disneyland Reviews" Kaggle dataset (Chillar, 2021) was used, which consists of **42.656 customer reviews** posted by visitors in Tripadvisor from three Disneyland locations:

- Disneyland Hong Kong
- Disneyland Paris
- Disneyland California

The review distribution is as follows:

| Location | Number of reviews | % of Total Reviews |
|---|---|---|
| Disneyland_HongKong | 9,620 | 22.55% |
| Disneyland_Paris | 13,630 | 31.95% |
| Disneyland_California | 19,406 | 45.49% |

The dataset includes review ID, rating scores (1-5 stars), year and month the review was written, review location, review text, and Disneyland branch. This analysis primarily focuses on reviews of 1 and 5 stars to identify patterns in language that indicate either a good or a bad experience.

**For successful analysis of this data the following steps were taken:**

1. **Data Retrieval:** The dataset was downloaded first to analyze each column in more depth and then imported directly into Google Collab using "import from kaggle" to conduct the entire analysis.

2. **Relevant Data Filtering:** Positive and negative reviews were separated by extracting only reviews with one star and five stars. Monthly trends were also analyzed to see if there were any relevant differences among the three branches.
3. **Segmentation by Location:** To analyze unique trends for each of the three Disneyland parks (Hong Kong, Paris, and California), reviews were classified by their respective locations.
4. **Text Preprocessing:** The following preprocessing methods were used before performing NLP analysis:
    a. **Text Cleaning:** Removing punctuation marks, special characters, and unnecessary spaces.
    b. **Stopword Removal:** The words “Disneyland”, “Disney”, “Hong Kong”, “Paris” and “California” were removed from the study, since they add nothing to the sentiment analysis. Other frequently words such as “the”, “and”, and “is” were also removed.
    c. **Lemmatization:** Standardizing vocabulary by reducing words to their root forms (e.g., “running” to “run”). Lemmatization was preferred because it allows more comprehensible words to appear in the word clouds and is more accurate.
5. **Topic Modelling:** Uncover key topics using topic modeling (LDA), to address customer experience, park logistics and common topics in reviews.
6. **Sentiment Analysis:** To understand more deeply the emotions behind the negative reviews and compare them among the different locations.

By implementing the outlined process, it was possible to identify common words and gain insights into what factors lead to a positive Disneyland experience versus those that lead to a negative one. The business relevance of this analysis is the positive changes that Disneyland can implement in their operation to enhance customer satisfaction and guest experiences.

## Analysis and Interpretations

### ***<u>Word clouds, frequency charts and monthly analysis</u>***

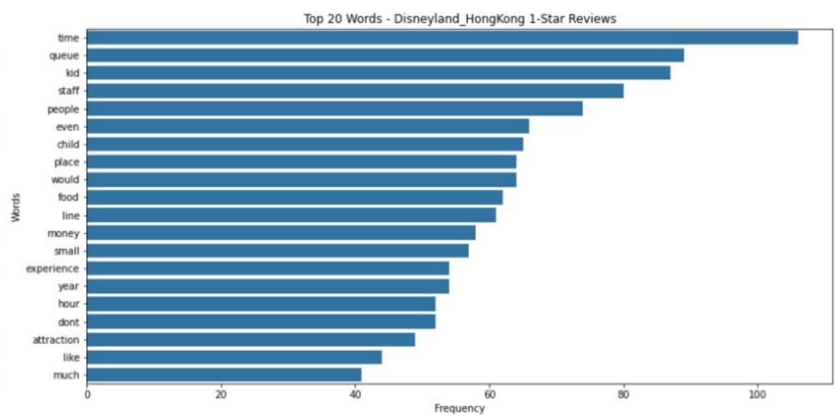
The analysis of word clouds and frequency charts for each Disneyland parks focused on the most common words and phrases visitors used to describe their experiences. The visualizations revealed factors that influence positive and negative experiences. To improve the analysis, it was decided to include standard word clouds composed of singular words and bigram word cloud. After analyzing the results of the standard ones, it was seen that some words did not make sense without the appropriate form. In other words, the forms: adjective + noun and adverb + noun were missing from the word clouds and in this way more value was added to the word clouds and to the interpretation.

For this analysis, the sizes of the datasets were as follows:

| Location | Number of 1-star reviews | % of total branch reviews | Number of 5-star reviews | % of total branch reviews |
|---|---|---|---|---|
| Hong Kong | 172 | 1,80% | 4517 | 47,00% |
| Paris | 828 | 6,10% | 6111 | 44,80% |
| California | 499 | 2,60% | 12518 | 64,50% |

## 1. Hong Kong

### a. 1-star reviews

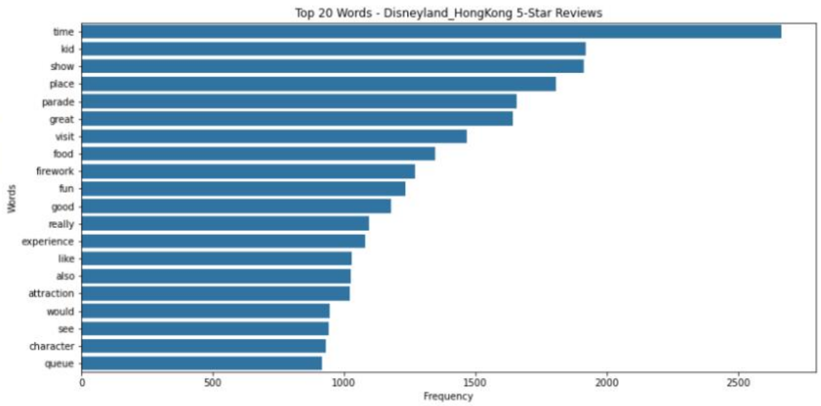




**Key Insights:**

Waiting time, overcrowding, and perceived value for money are among the major frustrations highlighted in 1-star reviews:

- **Queueing and Waiting Time** rank high on the list of major concerns, with a lot of mentions "queue", "time", and "long wait".
- **Crowding and Space** Issues contribute to dissatisfaction, with words like "people" and "place" expressing overcrowding concerns.
- **Customer Service and Value** are criticized for high costs and staffing issues.
- **Attraction and Rides** received negative reviews, with "Space Mountain" and "Small World"

### b. 5-star reviews

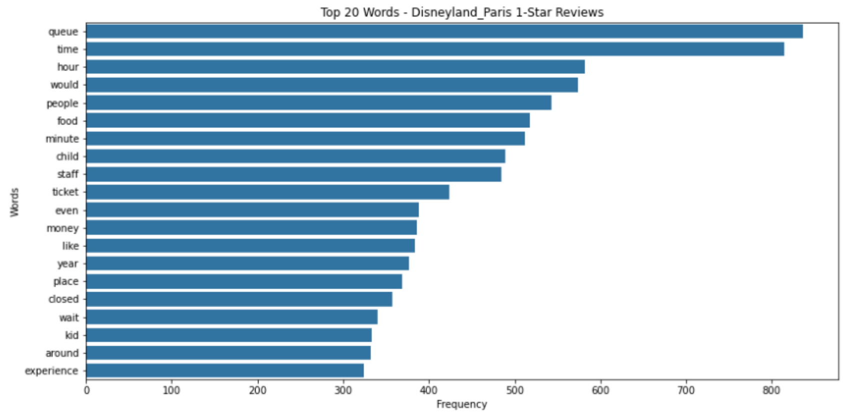

**Key Insights:**

In 5-star reviews, guests are clearly satisfied, especially with entertainment, attractions, and the family-friendly environment.

- **Entertainment and Shows** rated highly, particularly “show”, “fun”, “Lion King”, and “Toy Story”.
- **Attraction and Rides** have received positive reviews. Keywords such as “Mystic Manor”, “Space Mountain”, and “Small World” are frequently used.
- **Family-Friendly Experience** reinforces the park’s appeal to families with words like “kid”, “great”, and “visit”.
- Overall **Satisfaction** has been expressed in the form of “amazing”, “good”, and “must visit”, indicating visitors had an enjoyable experience.

## 2. Paris

### a. 1-star reviews

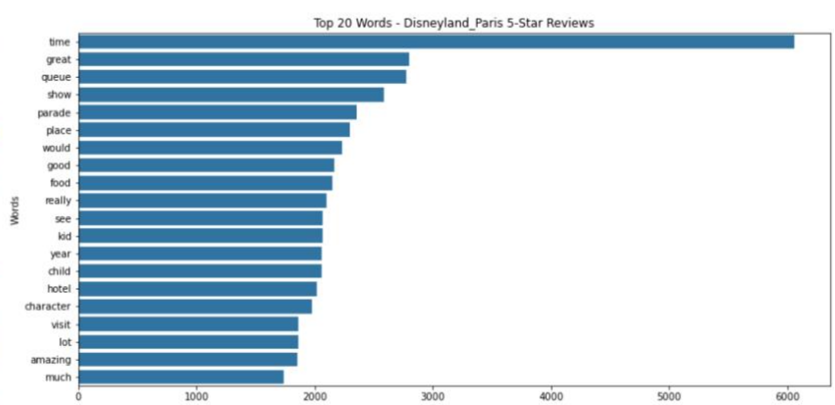




**Key Insights:**

Long wait times, overcrowding and poor customer service are all major frustrations found in 1-star reviews.

- **Queueing and Waiting Time** are common complaints, with frequent references to "queue", "time", and "long wait".
- **Crowding and Space Issues** are a major contributing factor to dissatisfaction. Words like "people", "place", and "many" shows concern about overcrowding.
- **Customer Service and Fast Pass have** received criticism due to the mentions of "staff", "customer service", and "fast pass", which suggests that guest interaction and Fast Pass effectiveness can be improved.
- **Attractions and Ride Experience** are mentioned with phrases like "Thunder Mountain", and "Space Mountain", which suggests that some rides did not meet visitors' expectations.

**b. 5-star reviews**

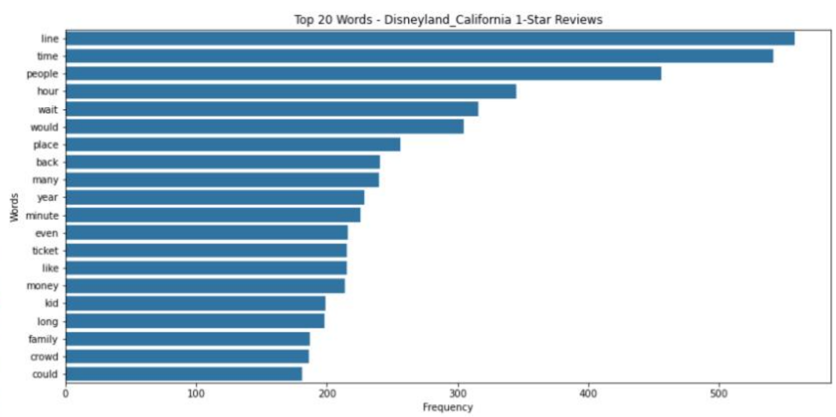

**Key Insights:**

Five-star reviews reveal guests' satisfaction with attractions, entertainment, and overall experience.

- **Entertainment and Shows** receive high ratings, with mention of "parade", "character", and "main street" indicating strong appreciation.
- **Attractions and Ride** reviews are consistently positive, with frequent mentions of "Space Mountain", "Thunder Mountain", and "Peter Pan", indicating these attractions are among the most enjoyable.
- **Family-Friendly Experience** features words such as "child", "great", and "visit", highlighting the park's appeal.

### 3. California

#### a. 1-star reviews

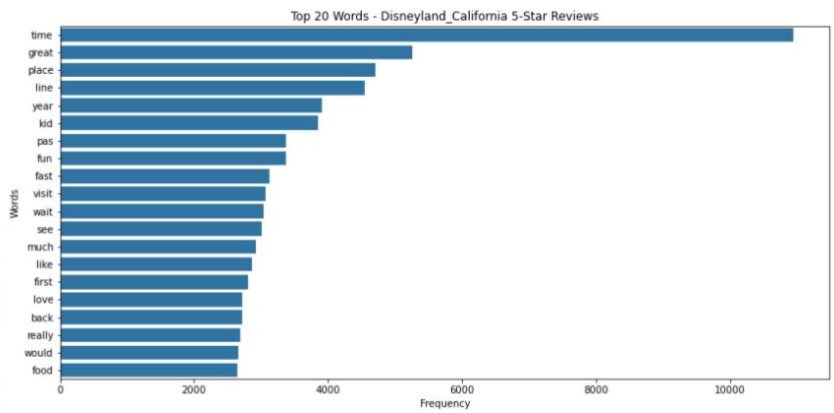

**<u>Key Insights:</u>**

In 1-star reviews, guests express frustration with long wait times, overcrowding, and customer service.

- **Queues and Crowds** frequently feature among visitors' complaints, with references to "line", "people", "wait time", and "crowded".
- **Customer Service and Staff** are criticized, specifically "cast members", and "staff", suggesting guest interaction issues.
- **Fast Pass Concerns** are frequently raised, indicating that they are dissatisfied with how effective Fast Pass is at reducing wait times.

- **Value for Money** seems to be questioned, as “ticket” and “money” are mentioned, suggesting high prices.

b. **5-star reviews**


**Key Insights:**

In 5-star reviews, guests describe their satisfaction with attractions, the overall experience, and the family-friendly environment.

- **Entertainment and Attractions** were highly rated, including “adventure”, “Indiana Jones” and “Main Street”, indicating strong preference for themed activities.
- **Family-Friendly Experience** emphasizes words like “kid”, “great”, and “visit”, highlighting the park’s appeal to families.
- **Overall Enjoyment** indicates a highly positive guest experience that includes the words like “happiest place”, “best”, and “love”.
- **Fast Pass and Convenience** have been highly rated by visitors, with frequent mentions of “Fast pass”.

This analysis provided us with some insights that enabled us to gain a deeper understanding of the guest experiences inside each of the three Disneyland parks. When it comes to negative reviews, queues, waiting times, crowds, expensive, and customer service are the main pain points. Guests expressing positive experiences use words like magical, amazing, family-friendly, shows, and attractions.

## ***Monthly Analysis***

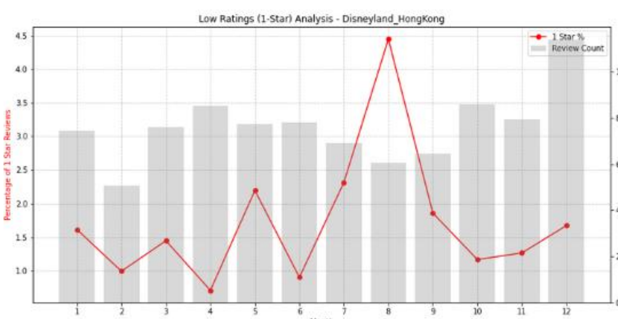
The three Disneyland locations were analyzed monthly to gain a deeper understanding of customer satisfaction and dissatisfaction. As shown by reviews:

- Disneyland Hong Kong has rather stable ratings:

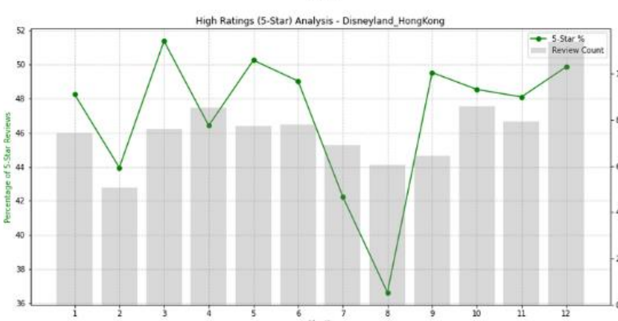
- 1-star reviews range between 0.7% and 4.5%
    - 5-star reviews range between 36.6% to 51.4%
    - August has the highest 1-star reviews – hotter weathers lead to less patience
- **Disneyland Paris is the worst-performing location:**
    - 1-star reviews varied between 3.4% and 8%
    - 5-star reviews varied between 37.8% and 53.2%
    - March, June and August were the worst months to visit
- **Disneyland California had by far the best performance:**
    - with 5-star ratings average of 61.6% to 70.5%
    - and an average of 1-star reviews ranging between 1.7% and 3%.
    - The few months to improve are March, October, and December

All locations show some kind of **seasonal patterns in rating distribution**. These could be due to **popular holidays** like Halloween and Christmas and therefore many people visiting the parks for their attractions and decorations, resulting in longer waiting times, higher ticket prices and fewer interactions with cast members/characters. Another reason could also be linked to **weather** as extreme weather often leads to less patience.

1. **Hong Kong:**

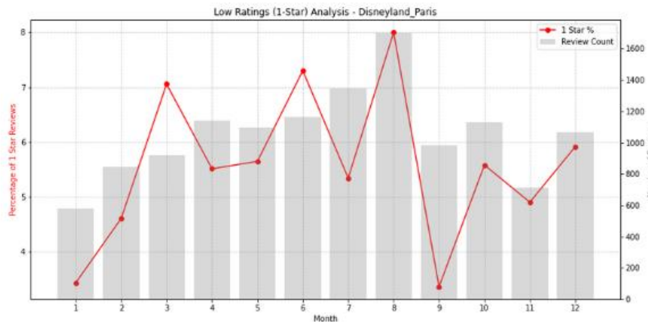



```
Low Ratings Analysis (1-Star) for Disneyland_HongKong:
Month 1: 1.6% 1-star reviews(total reviews: 744)
Month 2: 1.0% 1-star reviews(total reviews: 505)
Month 3: 1.4% 1-star reviews(total reviews: 761)
Month 4: 0.7% 1-star reviews(total reviews: 853)
Month 5: 2.2% 1-star reviews(total reviews: 774)
Month 6: 0.9% 1-star reviews(total reviews: 779)
Month 7: 2.3% 1-star reviews(total reviews: 691)
Month 8: 4.5% 1-star reviews(total reviews: 606)
Month 9: 1.9% 1-star reviews(total reviews: 646)
Month 10: 1.2% 1-star reviews(total reviews: 859)
Month 11: 1.3% 1-star reviews(total reviews: 792)
Month 12: 1.7% 1-star reviews(total reviews: 1137)
```

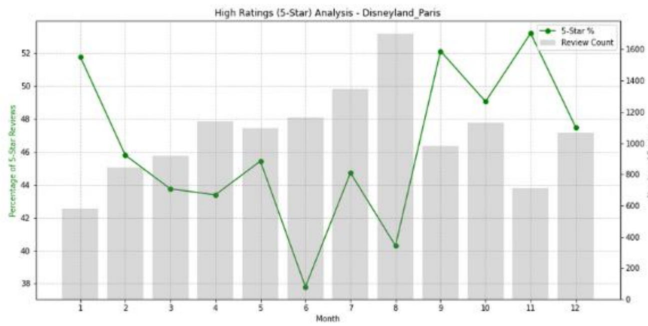



```
High Ratings Analysis (5 Stars) for Disneyland_HongKong:
Month 1: 48.3% 5-star reviews (total reviews: 744)
Month 2: 44.0% 5-star reviews (total reviews: 505)
Month 3: 51.4% 5-star reviews (total reviews: 761)
Month 4: 46.4% 5-star reviews (total reviews: 853)
Month 5: 50.3% 5-star reviews (total reviews: 774)
Month 6: 49.0% 5-star reviews (total reviews: 779)
Month 7: 42.3% 5-star reviews (total reviews: 691)
Month 8: 36.6% 5-star reviews (total reviews: 606)
Month 9: 49.5% 5-star reviews (total reviews: 646)
Month 10: 48.5% 5-star reviews (total reviews: 859)
Month 11: 48.1% 5-star reviews (total reviews: 792)
Month 12: 49.9% 5-star reviews (total reviews: 1137)
```

2. **Paris:**

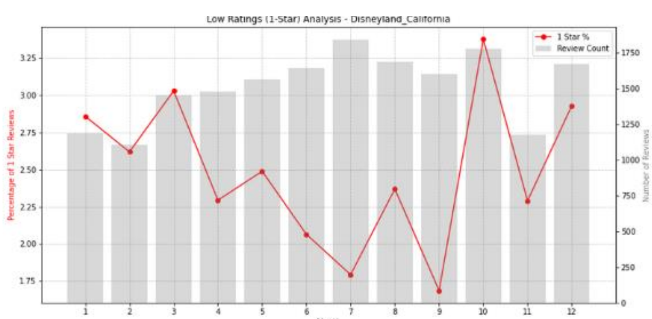



```
Low Ratings Analysis (1-Star) for Disneyland_Paris:
Month 1: 3.4% 1-star reviews(total reviews: 583)
Month 2: 4.6% 1-star reviews(total reviews: 847)
Month 3: 7.1% 1-star reviews(total reviews: 921)
Month 4: 5.5% 1-star reviews(total reviews: 1143)
Month 5: 5.6% 1-star reviews(total reviews: 1098)
Month 6: 7.3% 1-star reviews(total reviews: 1164)
Month 7: 5.3% 1-star reviews(total reviews: 1348)
Month 8: 8.0% 1-star reviews(total reviews: 1700)
Month 9: 3.4% 1-star reviews(total reviews: 982)
Month 10: 5.6% 1-star reviews(total reviews: 1129)
Month 11: 4.9% 1-star reviews(total reviews: 714)
Month 12: 5.9% 1-star reviews(total reviews: 1065)
```

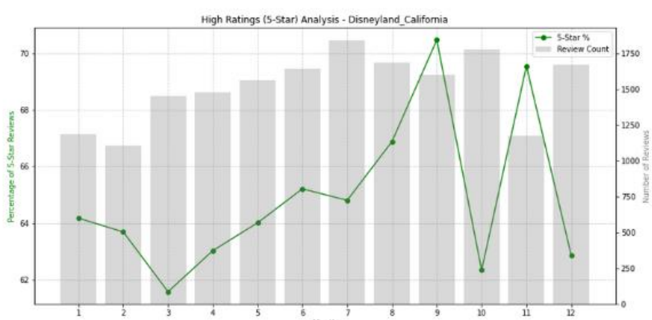



```
High Ratings Analysis (5 Stars) for Disneyland_Paris:
Month 1: 51.8% 5-star reviews (total reviews: 583)
Month 2: 45.8% 5-star reviews (total reviews: 847)
Month 3: 43.8% 5-star reviews (total reviews: 921)
Month 4: 43.4% 5-star reviews (total reviews: 1143)
Month 5: 45.4% 5-star reviews (total reviews: 1098)
Month 6: 37.8% 5-star reviews (total reviews: 1164)
Month 7: 44.7% 5-star reviews (total reviews: 1348)
Month 8: 40.3% 5-star reviews (total reviews: 1700)
Month 9: 52.1% 5-star reviews (total reviews: 982)
Month 10: 49.1% 5-star reviews (total reviews: 1129)
Month 11: 53.2% 5-star reviews (total reviews: 714)
Month 12: 47.5% 5-star reviews (total reviews: 1065)
```

3. **California:**




```
Low Ratings Analysis (1-Star) for Disneyland_California:
Month 1: 2.9% 1-star reviews(total reviews: 1189)
Month 2: 2.6% 1-star reviews(total reviews: 1107)
Month 3: 3.0% 1-star reviews(total reviews: 1452)
Month 4: 2.3% 1-star reviews(total reviews: 1482)
Month 5: 2.5% 1-star reviews(total reviews: 1567)
Month 6: 2.1% 1-star reviews(total reviews: 1647)
Month 7: 1.8% 1-star reviews(total reviews: 1841)
Month 8: 2.4% 1-star reviews(total reviews: 1688)
Month 9: 1.7% 1-star reviews(total reviews: 1602)
Month 10: 3.4% 1-star reviews(total reviews: 1776)
Month 11: 2.3% 1-star reviews(total reviews: 1179)
Month 12: 2.9% 1-star reviews(total reviews: 1672)
```




```
High Ratings Analysis (5 Stars) for Disneyland_California:
Month 1: 64.2% 5-star reviews (total reviews: 1189)
Month 2: 63.7% 5-star reviews (total reviews: 1107)
Month 3: 61.6% 5-star reviews (total reviews: 1452)
Month 4: 63.0% 5-star reviews (total reviews: 1482)
Month 5: 64.0% 5-star reviews (total reviews: 1567)
Month 6: 65.2% 5-star reviews (total reviews: 1647)
Month 7: 64.8% 5-star reviews (total reviews: 1841)
Month 8: 66.9% 5-star reviews (total reviews: 1688)
Month 9: 70.5% 5-star reviews (total reviews: 1602)
Month 10: 62.3% 5-star reviews (total reviews: 1776)
Month 11: 69.6% 5-star reviews (total reviews: 1179)
Month 12: 62.9% 5-star reviews (total reviews: 1672)
```

By analyzing these, Disneyland could identify **when each park receives the most negative reviews and start focusing on these to improve customer service, waiting times, and other factors** as illustrated in the word clouds and frequency charts.

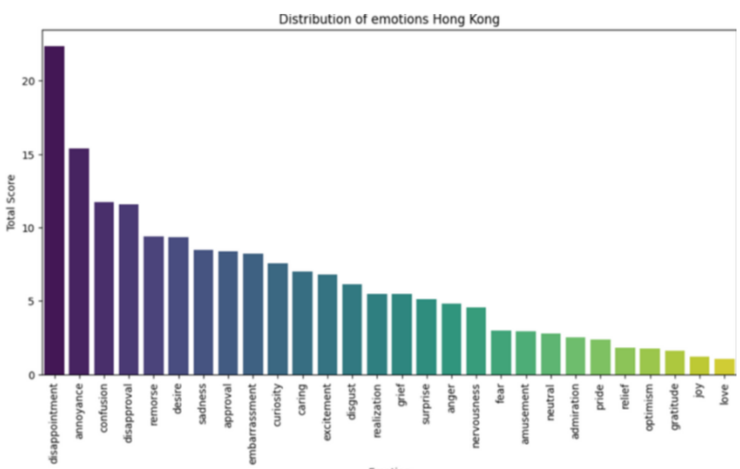
## ***Sentiment Analysis***

The algorithm used for this analysis is a distillation of **Google's GoEmotion** made by Joe Davison and publicly available at Hugging Face (Davison, 2021). A distillation is a smaller model that mimics the big model's predictions. It was selected because it allows not only differentiation between positive and negative reviews, but deep diving into the emotions that are found in the documents.

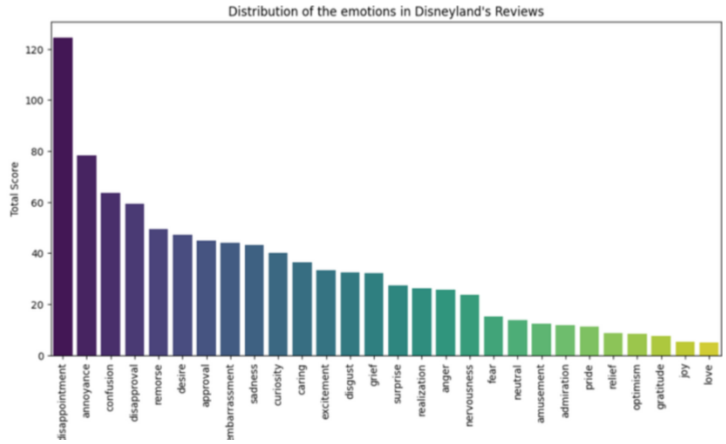
It is based on "a human-annotated dataset of 58k Reddit comments extracted from popular English-language subreddits and labeled with 27 emotion categories (…) Reddit comments from 2005 (the start of Reddit) to January 2019, sourced from subreddits with at least 10k comments, excluding deleted and non-English comments" (Alon et al, 2021). The algorithm "does multi-label classification, meaning one sentence can have multiple emotions at the same time. It assigns a score (probability) between 0 and 1 to each emotion. A higher score means the model is more confident that the sentence expresses that emotion." (ChatGPT, 2025)

Running the student version of the algorithm in the dataset for the worst reviews (rating score = 1) allows the examination of the overall sentiment of negative reviews from all different locations. This was done to **test if different emotions where present across the three locations, allowing to tailor the proposed solutions accordingly:**

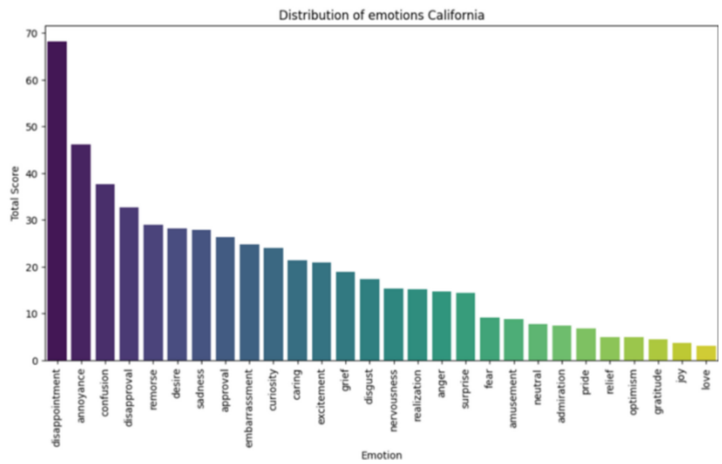
1. Hong Kong:




2. Paris:




3. California:




Contrary to what was expected, most common feelings identified, which included: **"disappointment", "annoyance", "confusion", "remorse"**, are similar for all locations. Now, analyzing the first negative feeling, disappointment, implies that the customer has expectations that are not fulfilled with the actual experience in the parks. This relates to the findings across all the analysis, as it has been shown that the customers complain about customer service and value. Also, it is latent the cost of the visit as expensive, this relates to the feeling of "remorse" as the customer is not perceiving the value that he should be getting in return from the prices at the parks.

Annoyance and confusion reflect the frustration of the customer with the issues identified as the queues and waiting times, the crowding and the space management inside parks. **This analysis will be useful to train staff on how to answer visitors' complaints and learn to acknowledge their feelings.**

## ***Topic modeling***

**Overview**

- The topic modeling is for extracting insights of 1 rating reviews, in order to know where and how to improve.
- The model is trained with **6 topics** (num_topics=6).
- Preprocessing includes **lemmatization, stopword removal, and filtering frequent/infrequent words**.
- The dictionary and corpus have been filtered to improve topic coherence.

Based on the **LDA** topic modeling analysis of Disneyland reviews, the following key themes have been identified:

1. **Topic 0 - Crowds and Long Queues**
    a. **Keywords**: "people", "park", "get", "rides", "queue", "ride", "go", "day", "one", "disneyland"
    b. **Possible Interpretation**: Visitors are frustrated with the **large crowds and long queues** at Disneyland. Words like "people," "queue," and "rides" suggest complaints about overcrowding and extended wait times for attractions.
2. **Topic 1 - Waiting Time for Rides**
    a. **Keywords**: "park", "line", "ride", "day", "minutes", "one", "time", "disney"
    b. **Possible Interpretation**: This topic focuses on the **time spent waiting in line**. The presence of words like "minutes" and "time" indicates that long waiting times are a significant issue for visitors.
3. **Topic 2 - Staff, Food, and Overall Experience**
    a. **Keywords**: "disney", "park", "staff", "food", "rides", "disneyland", "like", "go", "paris", "people"
    b. **Possible Interpretation**: Visitors complain about **staff behavior, food quality, and overall park experience**. Words like "staff" and "food" suggest dissatisfaction with customer service and dining options.
4. **Topic 3 - Closed Attractions and Value for Money**
    a. **Keywords**: "rides", "disney", "park", "closed", "day", "disneyland", "paris", "one", "money", "go"
    b. **Possible Interpretation**: Many complaints revolve around **rides being closed**, making visitors feel they did not get their money’s worth. The presence of "money" and "closed" indicates concerns over spending on an experience that did not meet expectations.
5. **Topic 4 - Visitors' Willingness to Return**

    a. **Keywords**: "disney", "us", "would", "disneyland", "get", "told", "park", "one", "could", "back"
    b. **Possible Interpretation**: This topic is related to **whether visitors would return** to Disneyland. Words like "would" and "back" suggest that many reviewers stated they **would not visit again**.
6. **Topic 5 - Waiting, Cost, and Overall Dissatisfaction**
    a. **Keywords**: "wait", "rides", "time", "line", "park", "go", "money", "ride", "get", "lines"
    b. **Possible Interpretation**: Complaints in this topic combine **waiting time and the high cost of entry**. Visitors feel that the park is too expensive considering the long queues and the overall experience.

## Key Insights

From the analysis of these topics, we can conclude that the most common complaints in Disneyland's 1-star reviews are:

1. **Long waiting times and overcrowding** (Topics 0, 1, 5)
2. **High cost vs. value perception** (Topics 3, 5)
3. **Closed rides reducing visitor satisfaction** (Topic 3)
4. **Poor staff service and food quality** (Topic 2)

## Recommendations for Disneyland

To improve visitor satisfaction and reduce negative reviews, Disneyland could:

- **Implement better crowd control measures**, such as virtual queues or limiting ticket sales.
- **Improve ride availability** to avoid complaints about closures.
- **Enhance customer service and food quality** to improve the overall experience.
- **Offer better value for money**, such as more affordable ticket options or fast-track solutions.

## Bibliography

- **Chillar, A.** (2021). *Disneyland Reviews* [Data set]. Kaggle. https://www.kaggle.com/datasets/arushchillar/disneyland-reviews

- **Davison, J.** (2021, February). *distilbert-base-uncased-go-emotions-student* [Machine learning model]. Hugging Face. https://huggingface.co/joeddav/distilbert-base-uncased-go-emotions-student

- **Alon, D., & Ko, J**. (2021, October 28). *GoEmotions: A dataset for fine-grained emotion classification*. Google Research Blog. https://research.google/blog/goemotions-a-dataset-for-fine-grained-emotion-classification/

- **ChatGPT**. (2025, February 14). *Explanation of Google's GoEmotions model*. OpenAI. Retrieved from https://chat.openai.com

- **Gordeliy, I**. 2025. *Frequency distribution and wordclouds*. GitHub. URL: 02_Frequncy_distribution_and_Wordclouds.ipynb - Colab

- **Kauffmann, E., Peral, J., Gil, D., Ferrández, A., Sellers, R., & Mora, H**. (2019). Managing marketing decision-making with sentiment analysis: An evaluation of the main product features using text data mining. *Sustainability, 11*(4235). https://doi.org/10.3390/su11154235