Universal Studio Visitors Satisfaction

Group: Elizaveta Gorshkova 47574
Dariia Marchuk 47623
Ivan Potieiev 47480

1. Introduction

Business Problem

Universal Studios operates multiple theme parks worldwide, and customer reviews play a crucial role in understanding visitor experiences. This analysis aims to extract insights from online reviews to assess customer sentiment, identify common complaints, and recommend improvements for enhancing visitor satisfaction.

Project Questions:

- What are the primary complaints that guests have about the theme parks at Universal Studios?
- Are there differences between the scores obtained from the sentiment analysis and the ratings given?
- What are the most commonly mentioned topics in reviews?

Objectives

- Analyze sentiment trends over time and across different Universal Studios branches.
- Identify key themes in customer reviews using NLP techniques.
- Develop a sentiment classification model to predict review sentiment.
- Provide recommendations for improving customer experience.

2. Dataset Overview

Description of Dataset

The dataset primarily consists of textual reviews provided by visitors of Universal Studios locations. The dataset consists of 50,904 reviews with the following key columns:

- “Reviewer” - Name of the person who left the review (text).
- “Rating” - A numerical score (1-5) given by the reviewer.
- “Written Date” - Date the review was written.
- “Title” - Review title. (Textual data)
- “Review Text” - Full text of the review. (Textual data)
- “Branch” - Universal Studios branches (Florida, Japan, Singapore).

Source of Data & Method of Collection

- The dataset was collected from an open-access source - Kaggle.

Data Access

- The dataset used in this analysis is stored in CSV format.
- Access to the dataset and the full codebase used for the analysis is available via GitHub, as is this report.

3. Analytical Methods

Data Cleaning and Preprocessing

- **Text cleaning:** Removal of punctuation, special characters, and stopwords.
- **Lemmatization:** Standardizing words to their root form using NLP techniques.
- **Sentiment labeling:** Assigning a polarity score using Vader Sentiment Analysis.
- **Handling missing data:** Missing values in ratings were filled with the average rating. Missing review text entries were replaced with empty strings.
- Converted “written_date” to DateTime format.

Descriptive Analysis

- **Sentiment distribution:** Analyzing the proportion of positive vs. negative reviews.
- **Common words in reviews:** Visualizing frequent terms using Word Clouds.
- **Sentiment trends over time:** Plotting historical sentiment trends by month and year.
- **Sentiment vs Rating comparison:** Examining the correlation between sentiment scores and user ratings.
- **Branch-wise sentiment comparison:** Comparing sentiment and ratings across different locations.

Predictive Modeling

- **Text vectorization:** Converting text reviews into numerical format using TF-IDF.
- **Class balancing:** SMOTE (Synthetic Minority Over-sampling Technique) was used to handle class imbalance, ensuring that negative and positive reviews had comparable representation in the training set.
- A **GridSearchCV** approach was used to optimize the regularization parameter C of Logistic Regression.
- The best-performing hyperparameter was **C = 10**, which was chosen based on cross-validation results.
- **Model training:**
    - Logistic Regression for sentiment classification.
    - Hyperparameter tuning using GridSearchCV.
    - Performance evaluation using accuracy, precision, recall, and F1-score.
    - Confusion matrix visualization for classification performance assessment.

Topic Modeling

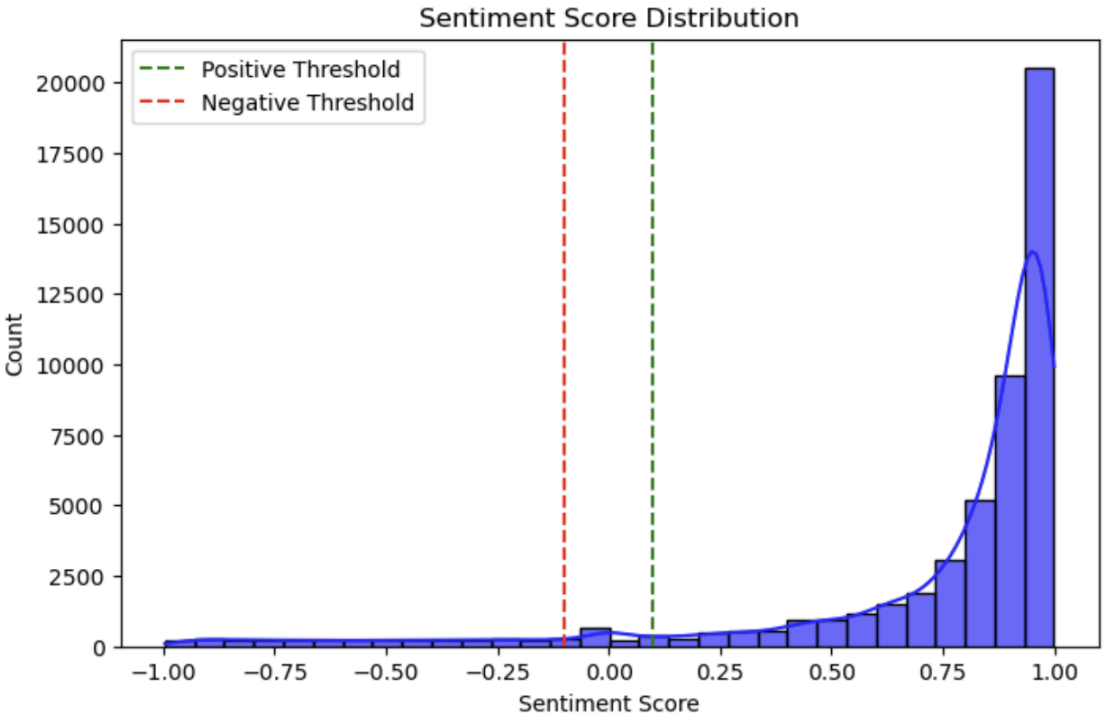
- **Latent Dirichlet Allocation (LDA):** Identifying common discussion topics in customer reviews.
- **Keyword correlation analysis:** Analyzing the most influential words in positive and negative reviews.

4. Analysis of the Data

In this section, a detailed analysis of the obtained data is presented to address the business problem.

Sentiment Distribution Overview

The sentiment analysis provides a general understanding of customer feedback across all branches of Universal Studios. The Sentiment Score Distribution Histogram presented below provides insight into the overall distribution of sentiment scores in the dataset. Below is a detailed breakdown of the key observations:



- The histogram shows that most sentiment scores are highly skewed toward positive values.
- There is a sharp peak near 1.0, indicating that a majority of reviews have high sentiment scores.
- A smaller distribution exists for neutral and negative sentiments, but they are significantly less frequent.
- The green dashed line (positive threshold at 0.1) and the red dashed line (negative threshold at -0.1) mark the boundaries used for categorizing sentiment.
- Smoe number of reviews fall into the negative sentiment range (< -0.1), which suggests that negative feedback is minimal in the dataset.

Key Findings:

- The concentration of scores near 1.0 suggests that the sentiment analysis model (VADER) is assigning highly positive scores to some of the reviews, possibly overestimating positivity. This may not accurately reflect nuanced opinions within the dataset, leading to an overly optimistic sentiment distribution.
- The Sentiment Distribution across all Universal Studios branches chart reveals that the majority of reviews across all locations have positive sentiment. However, there

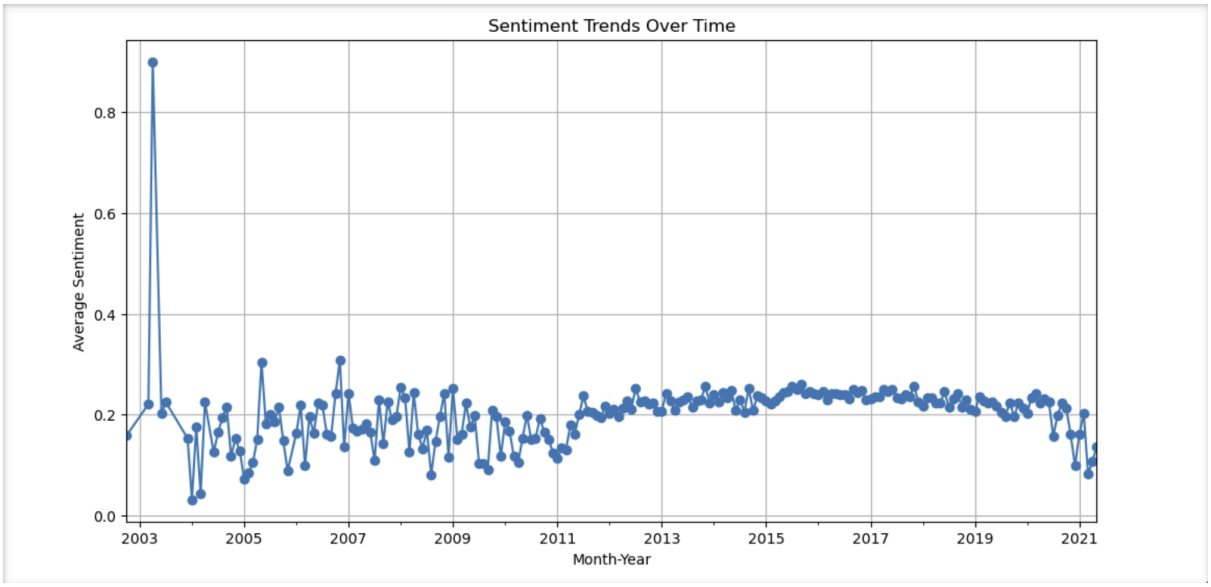
are still notable negative reviews. This indicates that while most customers had a favorable experience, there are areas where improvements can be made.

- Despite the fact that the above graph shows a very positive situation and suggests that the Universal Studio Theme Parks have no problems with visitor experience and feedback, based on personal experience and social media observation, our group still continued the analysis to identify the specific weak points.

Sentiment and Rating Trends Over Time

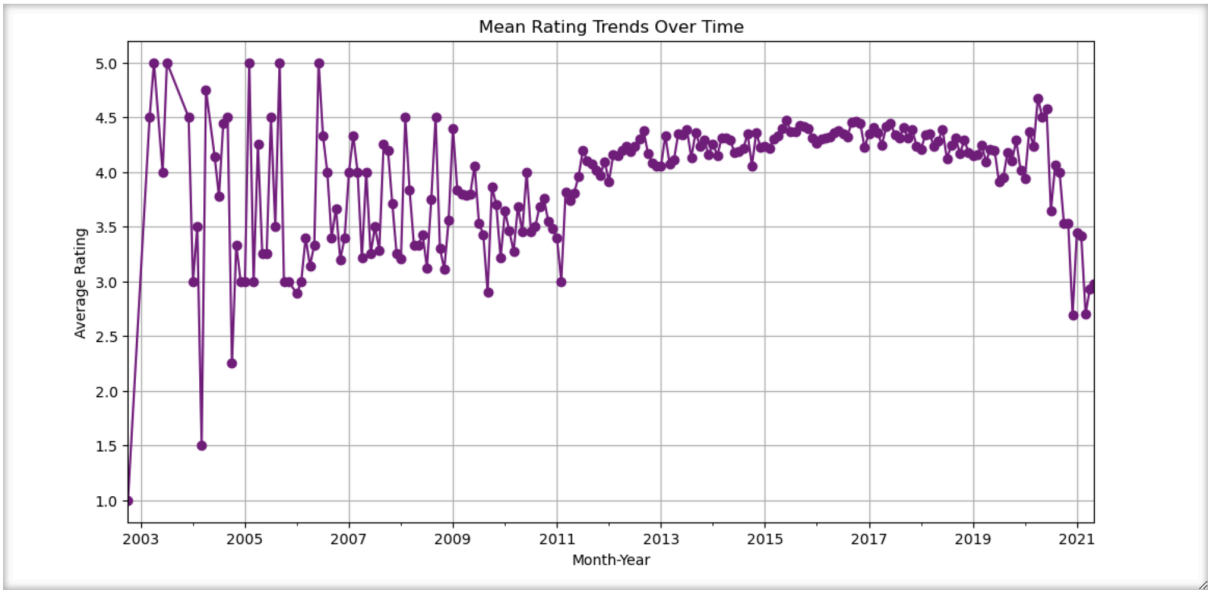
To conduct a comparative analysis of sentiment and ratings from Universal Studio customers, we first visualize and analyze the average trends in sentiment and ratings from 2003 to 2021.

Sentiment Trends Over Time



The sentiment trend graph shows that the average sentiment score remains consistently low over time, mostly below 0.2, indicating that many reviews contain neutral or slightly negative sentiment. However, this contradicts the previous sentiment distribution chart, which suggested a highly positive sentiment overall. This disagreement highlights that the graph reflects only an average, i.e. a large amount of positive feedback exists, but its impact is mixed with neutral and negative sentiment, however it affects a lot. From 2005 to 2013, fluctuations indicate different customer experiences, followed by relative stability from 2013 to 2019. After 2019, sentiment drops significantly, likely due to the impact of the COVID-19 pandemic on the theme park visitor experience.

Mean Rating Trends Over Time



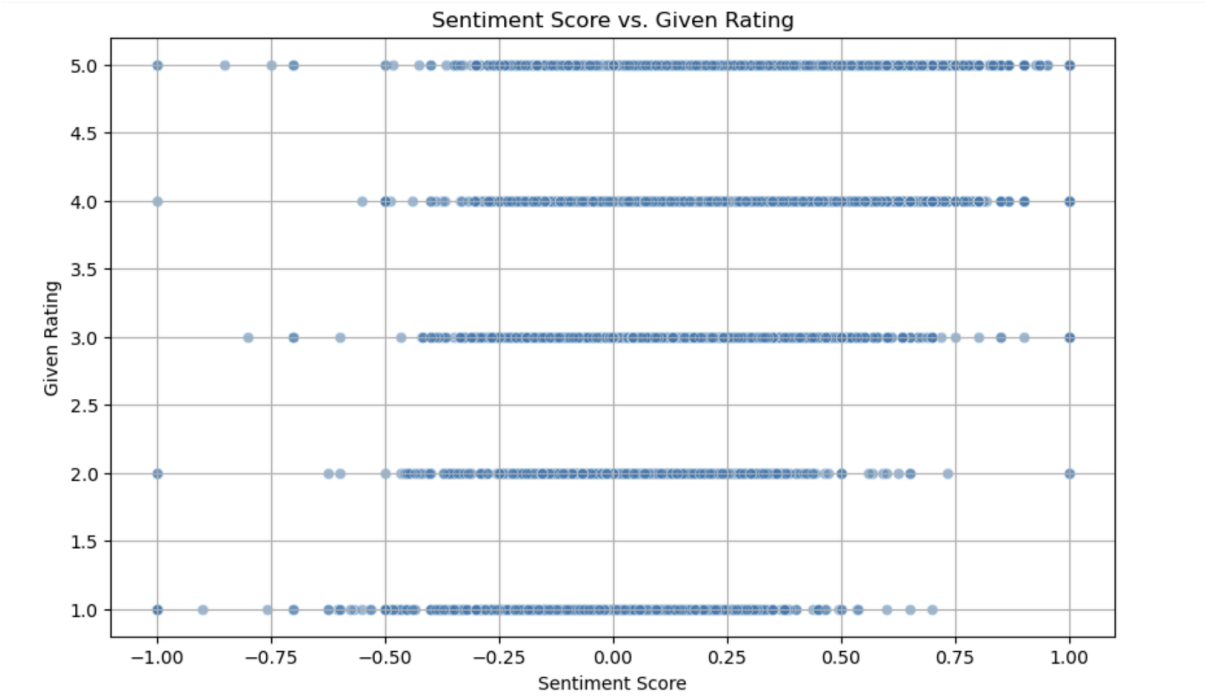
In contrast, the graph of rating trends remains consistently high, with values above 3.5 and often going above 4.0, indicating that customers continue to rate the park highly even though there is negative sentiment in their written opinions. While there are some fluctuations until 2011, the ratings stabilise in subsequent years, reflecting overall satisfaction. However, the sharp decline after 2019, mirroring the sentiment dynamic, suggests that customer perceptions have been negatively impacted by a significant external factor - most likely COVID-19 restrictions.

- The contrast between sentiment scores and ratings suggests that many customers give high ratings despite expressing dissatisfaction in their feedback. This may be due to rating bias, where people avoid very low ratings unless their experience is not so good. In addition, the sentiment analysis model may sometimes misclassify neutral or slightly negative reviews, making sentiment scores appear lower than they actually are.

This comparison suggests that while ratings provide a broad view of satisfaction, sentiment analysis reveals hidden dissatisfaction, so both metrics are necessary to fully understand the customer experience.

Relationship Between Sentiment and Ratings

To validate the relationship between sentiment scores and actual ratings, a scatter plot was generated:



X-axis: Measures the sentiment polarity of review text, where:

- Negative values indicate negative sentiment.
- Values near zero indicate neutral sentiment.
- Positive values indicate positive sentiment.

Y-axis: Represents the actual rating given by users on a scale of 1 to 5.

Key Findings:

- Ratings Represent Discrete Values (1 to 5). This causes the horizontal bands in the scatter plot, as each rating is a distinct integer, while sentiment scores are continuous.
- Lower sentiment scores mostly align with 1-star and 2-star ratings, confirming that highly critical reviews correspond to low ratings.
- Higher sentiment scores tend to align with 4-star and 5-star ratings, showing that strongly positive reviews correspond to higher ratings.
- Mismatched Cases**:**

- Some negative sentiment scores appear in 4-star or 5-star ratings, indicating potential cases where users gave a high rating despite a relatively critical review. Similarly, some reviews with high sentiment scores (0.5 or above) still have low ratings (1-2 stars), suggesting discrepancies where the review text sounds positive, but the rating is low.

- At approximately a sentiment score of 0.0, reviews are distributed across multiple rating levels. This suggests that neutral or mixed reviews are rated differently by different users.

This scatter plot helps validate the sentiment analysis model because there is a general correlation between sentiment and ratings. However, not all reviews perfectly align, which suggests that some reviews have mixed sentiments.

Mismatched Reviews (High ratings but negative sentiment)

In order to identify inconsistencies in the reviews of customers, we sorted out feedback in which the sentiment scores were negative but the rating was 4 or 5 stars.

```
Total number of mismatched reviews: 1203
```

```
Mismatched Reviews (Negative Sentiment but High Rating):
                                          review_text  rating  sentiment
95   We flew in from California after we were vacci...     4.0  -0.096548
145  This was our first time at Universal and I was...     5.0  -0.166667
238  If you want to walk around all day and not rid...     5.0  -0.015000
252  The only way to do Universal is with the Expre...     4.0  -0.006944
292  Let me begin by saying they should keep the sa...     4.0  -0.054167
```

An example of this type of review:

```
Selected Review Text:
The only way to do Universal is with the Express Pass! It hit capacity every day of our trip by 9a
m. Some rides, we waited 10 minutes, some we waited 30 minutes. THE MOST difficult ride to get on
is Hagrid's Motorbike Adventure. This ride doesn't take Express Pass. We tried the Virtual Line an
d were never successful until after 7pm! One day, guest services helped put us on the ride because
it was our last day. We made dinner reservations 24 hours in advance. We felt that we did not need
a dining plan. We did the breakfast at The Leaky Cauldron and food was decent. There is minimal se
rvice there due to Covid. During our trip, we also went to Epcot one day (we had never been), and
Universal has managed the whole Covid thing WAY better than Disney. Lines were long there 90-120 m
inutes waiting time for rides and NO fast passes!
```

Key Findings:

- Some visitors provided high ratings despite writing negative reviews.
- This inconsistency may be due to factors like brand loyalty, specific positive experiences, or rating habits where people avoid giving low scores. Also rating behavior may be influenced by factors beyond textual sentiment, such as a generally positive overall experience or appreciation for specific attractions.
- Addressing this inconsistency is important for ensuring that rating-based insights accurately reflect customer sentiment.

The finding demonstrates that there were a lot of these kinds of reviews. As a result, it highlights that even with the high rating, there are particular factors that frustrate people and lead them to be dissatisfied therefore these should be taken into consideration as well.

Accordingly, the next step in the analysis is to explore the topics of complaints in more detail and identify similarities in people's complaints in order to recognise and highlight key areas that Universal Studios could improve further

Common Complaints Analysis

To better understand the negative sentiment, a Word Cloud was generated. This visualization highlights the most frequently occurring words in customer complaints.

Key Findings:

- **“Universal”, “ride”, “park”, “time”** and **“ticket”** are some of the most frequently mentioned words, indicating that general experiences at the theme park, rides, and ticketing are common sources of complaints.
- Waiting time is a major issue, as words like **“wait”, “line”, “queue”, “minute”, “hour”,** and **“long”** appear in a visible position, signalling that customers are frustrated by overly long waiting times.
- Cost-related concerns are evident, with words like **“money”, “price”, “paid”** and **“expensive”** suggesting dissatisfaction with pricing, value for money, or additional charges.
- Service-related issues may also be present, as words like **“staff”** and **“customer”** appear, possibly hinting at customer service dissatisfaction.
- Food and family experiences might be factors in complaints, as **"food," "child,"** and **"family"** are present in the word cloud.

Topic Modeling Analysis

The LDA model extracted five key topics from the Universal Studios visitor reviews, based on commonly occurring words:

```
Top Topics in Reviews:
Topic 1:  pas , disney , line , time , harry , potter , universal , day , ride , park
Topic 2:  year , time , new , simpson , universal , great , harry , potter , park , ride
Topic 3:  family , visit , studio , day , fun , universal , park , great , ride , place
Topic 4:  singapore , queue , time , day , roller , coaster , park , mummy , transformer , ride
Topic 5:  hour , queue , line , day , park , ticket , time , express , pas , ride
```

Topic 1: Popular Attractions and Time Factors

- Visitors frequently comment on theme park queues, time management and specific attractions such as Harry Potter. The mention of the word ‘Disney’ suggests a comparison between Universal Studios and the Disney parks.

Topic 2: Experience and New Attractions

- This topic involves discussion of new attractions (The Simpsons, Harry Potter) and general visitor experiences over the years.

Topic 3: Family-Friendly and Enjoyment Factors

- Multiple visitors connect Universal Studios to family vacations, focusing a high priority on enjoyment, visits, and the whole experience.

Topic 4: Location-Specific Rides and Logistics

- This topic is particularly related to Universal Studios Singapore, as it centers on queues for roller coasters, rides, and specific rides like Transformers and The Mummy.

Topic 5: Time, Waiting, Tickets

- The topic refers to ticketing systems, waiting times, and express passes, meaning that guests value express choices and queue management highly.

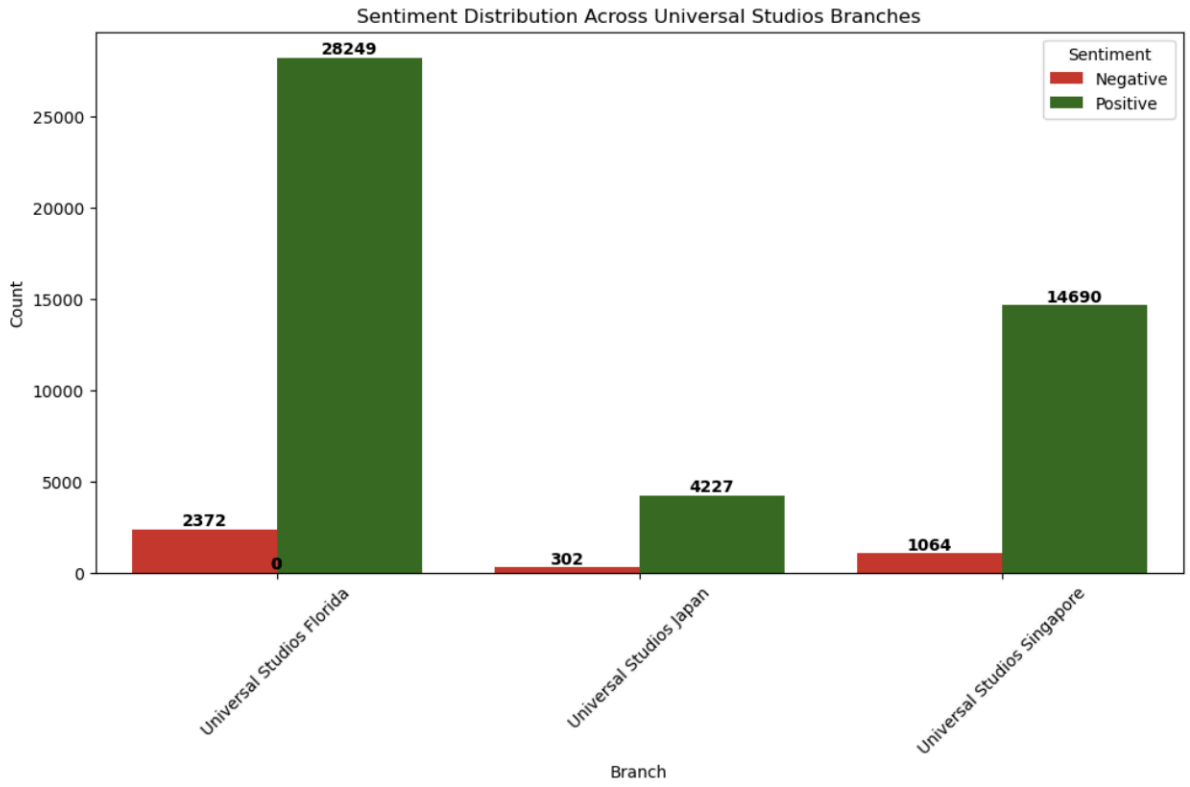
Key Findings:

- Long wait times and queues are a major concern, as seen in Topics 1, 4, and 5. Operational improvements in queue management and fast-track passes could enhance visitor satisfaction
- Universal Studios Singapore has distinct feedback, mentioning Transformers, Mummy, and roller coasters.
- There are comparisons with Disney parks, suggesting competition in visitor satisfaction.

In addition to the overall analysis of the Universal Studio theme parks, the different branches were also evaluated separately to explore the issues a bit deeper and highlight the pain points that need attention in each location.

Sentiment and Ratings Comparison Across Different Universal Studios Locations

The bar chart displays sentiment distribution across different Universal Studios locations (Florida, Japan, and Singapore):

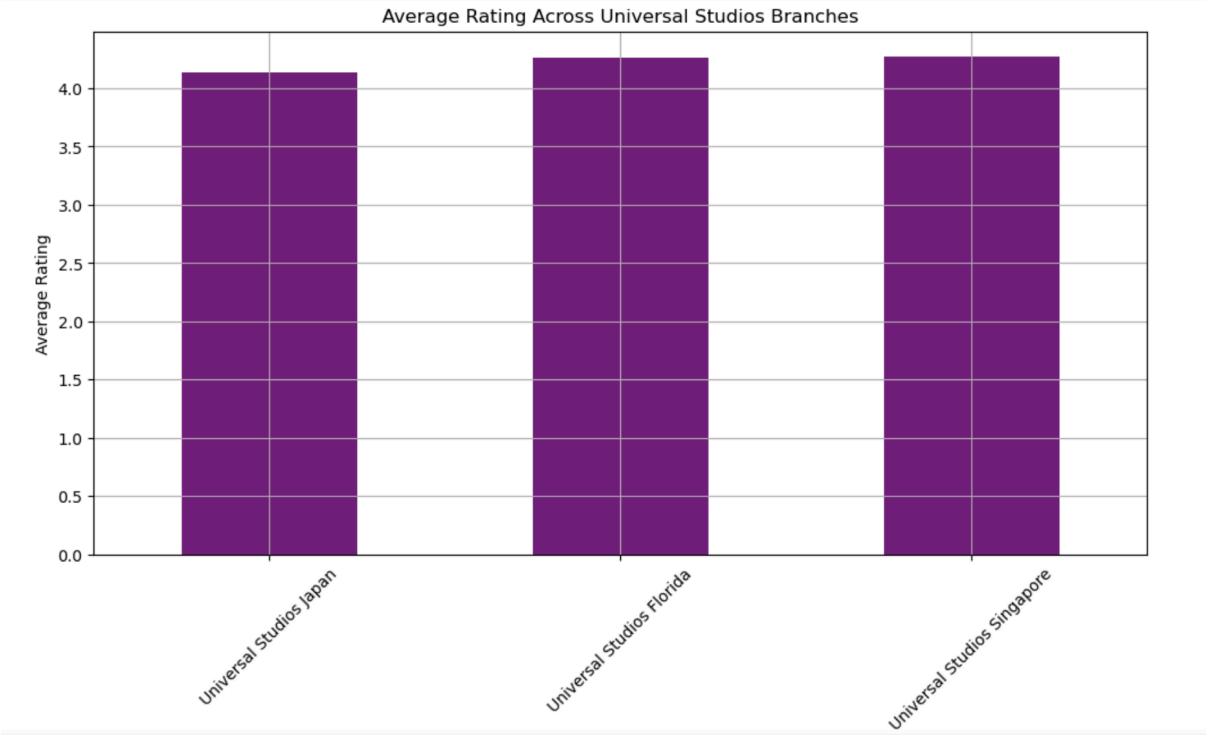


Key Findings:

- Florida has the highest number of reviews, which suggests it receives the most customer feedback. However, its complaint ratio (7.75%) is also the highest among the three branches, meaning that a higher proportion of visitors express dissatisfaction compared to Japan (6.67%) and Singapore (6.75%).
- Japan has the lowest complaint ratio (6.67%), indicating a relatively more positive visitor experience or fewer complaints per total reviews.
- Singapore's complaint ratio (6.75%) is slightly lower than Florida but higher than Japan, suggesting an intermediate level of dissatisfaction.

All locations have a higher number of positive reviews than negative, indicating general customer satisfaction. However, the volume of negative reviews, especially in Florida, could indicate that Florida's branch might have more operational challenges or higher visitor expectations, leading to a relatively higher share of complaints. Japan may require further investigation to understand why it has a comparatively higher proportion of negative reviews.

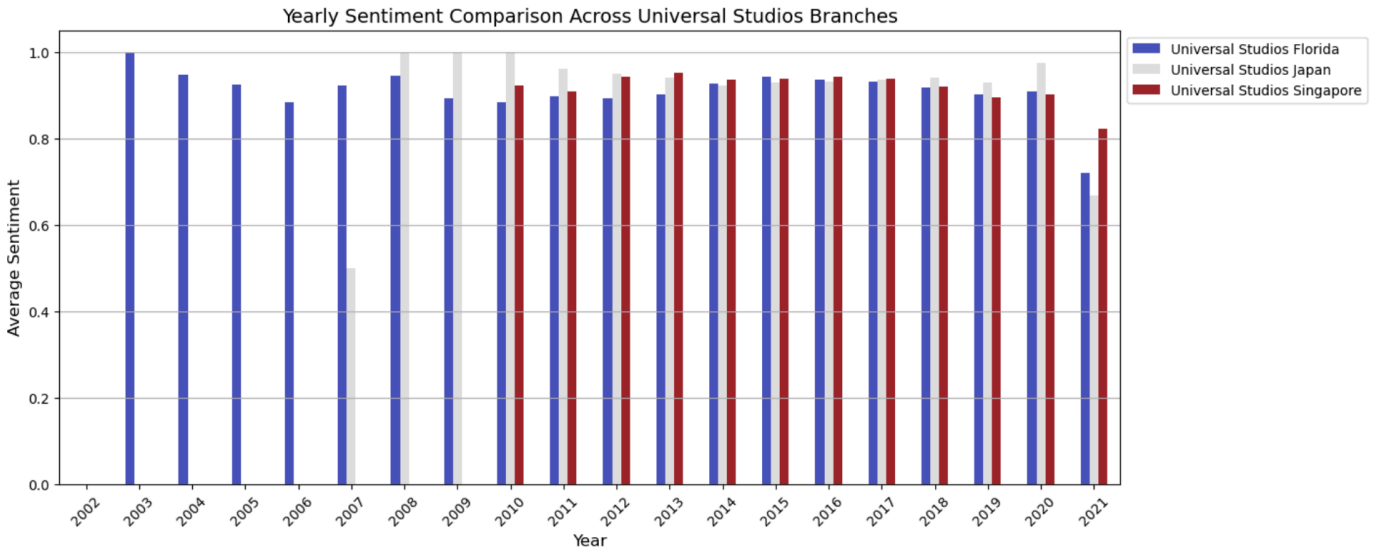
<u>Average Ratings Across Universal Studios Branches:</u>



Key Findings:

- The chart shows that all three Universal Studios branches—Japan, Florida, and Singapore—have very similar average ratings, all slightly above 4.0.
- The ratings suggest that, on average, customers are satisfied with their experiences at these parks. A rating above 4.0 implies that most visitors rate their experiences positively, with only minor variations between locations.
- <u>Comparison with Sentiment Analysis:</u>
    - When compared with the sentiment distribution from previous analyses, this high rating contrasts with the presence of negative sentiment in customer reviews. This suggests that while visitors may express dissatisfaction with specific elements as was discovered in previous sections of the report, their overall experience remains favorable enough to warrant high ratings.
- Given the relatively low sentiment scores seen in the sentiment trend analysis, this high average rating may indicate a bias where visitors tend to give high ratings despite mixed or even negative textual feedback. This aligns with findings from the mismatched reviews, where some visitors rated their experience highly despite negative sentiment in their review text.

Also, we examined sentiment trends over time for each Universal Studios branch:

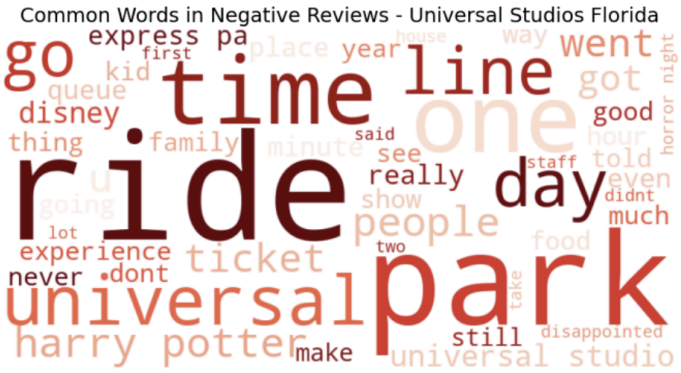


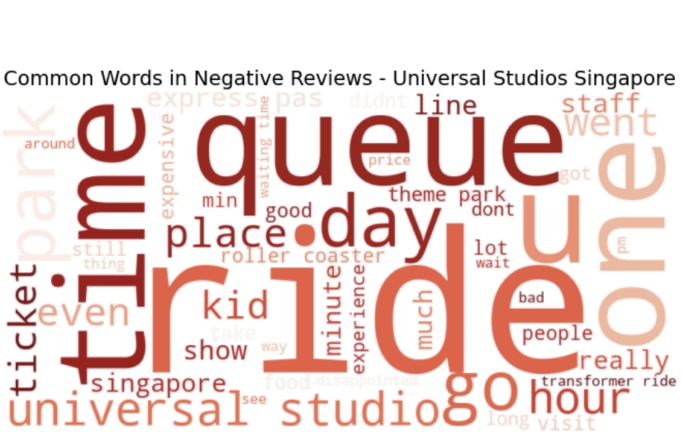
Key Findings:

- Across all branches (Florida, Japan, and Singapore), the average sentiment remains consistently high, generally above 0.8.
- Consistency Across Locations:
    - Universal Studios Singapore (brown bars) maintains a very stable sentiment trend, with minimal fluctuations.
    - Universal Studios Japan (gray bars) shows a slight dip in some early years (2007-2008), suggesting a temporary period of lower satisfaction.
    - Universal Studios Florida (blue bars) displays slightly more variation over the years, especially a notable drop in 2021.
- Decline in Sentiment in Recent Years (2020-2021):
    - The noticeable drop in sentiment in 2021, especially in Universal Studios Florida, could be linked to pandemic-related challenges such as operational restrictions, service limitations, and crowd control issues.
    - While Singapore and Japan maintain relatively stable sentiment even during the pandemic, Florida experiences the largest decline.
- There is no data available for Japan in the early years (2002-2006), although parks there have been open since 2001, which may indicate fewer surveys or data gaps in sentiment tracking.

The Yearly Sentiment Comparison Across Universal Studios Branches highlights that while sentiment has remained high across all locations, Universal Studios Florida has experienced more fluctuations compared to Singapore and Japan. This suggests that operational or experiential factors may vary more significantly in Florida, leading to periodic sentiment shifts.

WordClouds for Universal Studios Branches:





Key Findings and Observations:

- Common themes across all parks:
  - Common negative words include “ride”, “queue”, “time”, “line”, “day” and “ticket”, indicating that long wait times, crowded queues, and the overall time-consuming experience are significant concerns.
  - The frequent mention of “universal” and “studio” suggests that general expectations and reality could be contributing to dissatisfaction.
- Universal Studios Florida

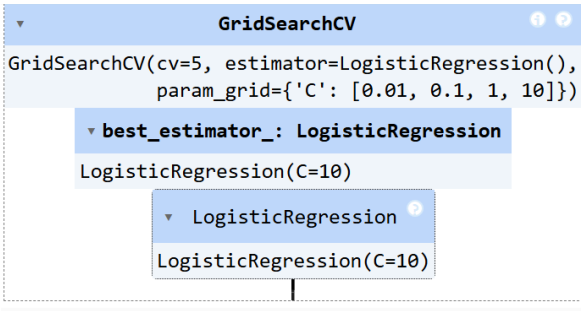
- Highlighted among the complaints are “time”, “queue”, “people” and “Harry Potter”, demonstrating that attractions in high demand like Harry Potter rides can be the cause of long queues.

- Universal Studios Japan
  - Similar to Florida, "Harry Potter" is highly mentioned, confirming the strong appeal of the franchise across different markets.
  - The word “Japanese” appearing in complaints may suggest language barriers or cultural differences in service.
- Universal Studios Singapore
  - The most frequent words include “ride”, “queue”, “time” and "staff," implying that waiting times and service quality issues might be the biggest problems at this location.

- Wait times are a major concern. The frequent mentions of “queue”, “line” and ”hour” across all locations suggest that long waiting periods significantly impact visitor satisfaction.
- The word “ride” appears dominant in all branches, meaning ride availability, breakdowns, or long waits might be a key factor driving negative reviews.
- Since “Harry Potter” appears in both Florida and Japan, it is likely that high visitor demand, long lines, and potential capacity limits contribute to visitor frustration.

Machine Learning Model for Sentiment Classification

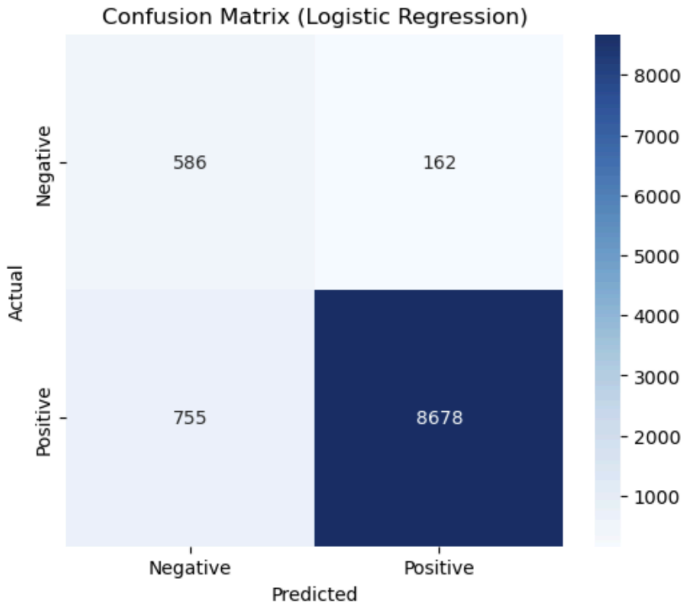
The main idea of sentiment classification model is to categorise user reviews into positive and negative based on textual content. This helps in understanding the tendencies of customer feedback.



Performance Evaluation

```
Best Hyperparameters: {'C': 10}

Classification Report:
              precision    recall  f1-score   support

           0       0.44      0.78      0.56       748
           1       0.98      0.92      0.95      9433

    accuracy                           0.91     10181
   macro avg       0.71      0.85      0.76     10181
weighted avg       0.94      0.91      0.92     10181

Accuracy Score: 0.9099302622532168
```

- The classification report showed that the model achieved an overall accuracy of 90.9%.
- Positive Sentiment: Precision of 98%, Recall of 92% – indicating strong reliability in predicting positive reviews.
- Negative Sentiment: Precision of 44%, Recall of 78% – suggesting the model struggles with identifying negative reviews accurately.
- Confusion Matrix Insights:



- The model correctly classified 8678 positive reviews but misclassified 755 positive reviews as negative.
- Among negative reviews, 586 were correctly identified, but 162 were misclassified as positive.

- This suggests that reviews classified as positive in some contexts represent small margins of error. The model misclassified some negative feedback as positive, as weak critique was interpreted as neutral or positive.

Key Findings:

- The model is highly effective at capturing positive sentiments, but has some difficulties in categorising negative sentiments in particular cases.
- The model can be further improved by including extra linguistic features such as negative statements, sarcasm identification and a contextual analysis of sentiment.

5. Description, Strategies, and Conclusion

- **Description of a problem**

A sentiment analysis of feedback provided by consumers from several Universal Studios locations highlighted several notable concerns. Even though the majority of the reviews are positive there are some important to point out complaints regarding long waits, interaction with employees, and the visit charges. Which are highlighted vividly and consistently among the negative reviews.

- **Strategies and Action plan**

To enhance customer experience and address these challenges, Universal Studios can implement the following strategies:

- Virtual Queue System Expansion – implement and optimize virtual queueing for the most popular attractions across more branches, as for nowadays this feature exists only in the US, allowing guests to reserve time slots and enjoy other rides instead of waiting in long lines.
- AI-Powered Line Management – employing crowd forecasting systems powered by AI to regulate the availability of attractions, increase the amount of staff members, and send out mobile phone alerts in the mobile application to guide visitors to less crowded locations.
- Customer Service Training with Gamification – regular professional development in hospitality involving realistic simulations, role-playing, and

performance-based rewards helps to ensure that employees create amazing experiences for guests.

- Off-Season Discounts – create more varied pricing models that make visits more affordable by allowing guests to pay less at times of low demand or off-seasons.

- **Conclusion**

Despite the overall positive tone in the reviews, the analysis of feedback from guests from Universal Studios branches indicates several significant issues. Long wait times, inconsistent customer service, and costly ticket prices are the primary complaints identified. Queues were a major source of dissatisfaction especially for popular attractions. Visitors' experiences with customer service varied, with some complaining about poor or disinterested personnel. In addition, quite a number of guests felt that the total price of entrance, plus additional charges, did not always align with the quality of what they received.

Universal Studios should concentrate on increasing perceived value, enhancing client satisfaction, and strengthening their operational effectiveness in order to guarantee continued profitability and avoid customer unhappiness. Wait times could be significantly lowered by upgrading virtual queue systems and implementing AI-powered crowd management into reality. Regular employee development activities with bonuses could raise the general level of service and make the location more attractive to people. Affordability can be addressed by introducing flexible pricing alternatives such as packaged offers and discounts during non-peak hours. Furthermore, for those who can afford to pay more, premium experiences and exclusive after-hours events may improve the value.

By addressing the detected customer complaints, Universal Studios will be able to maintain a high level of customer satisfaction without losing its client base. It will also encourage repeat visits and strengthen its competitive advantage in the theme park industry.