Summative Capstone

Data Analysis of Universal Studios Theme Parks

Contents:

1. Introduction

- Who are you? :
  - Ex-Operations Team Member in Universal Studios Singapore
  - Analyst for Universal Studios Theme Parks

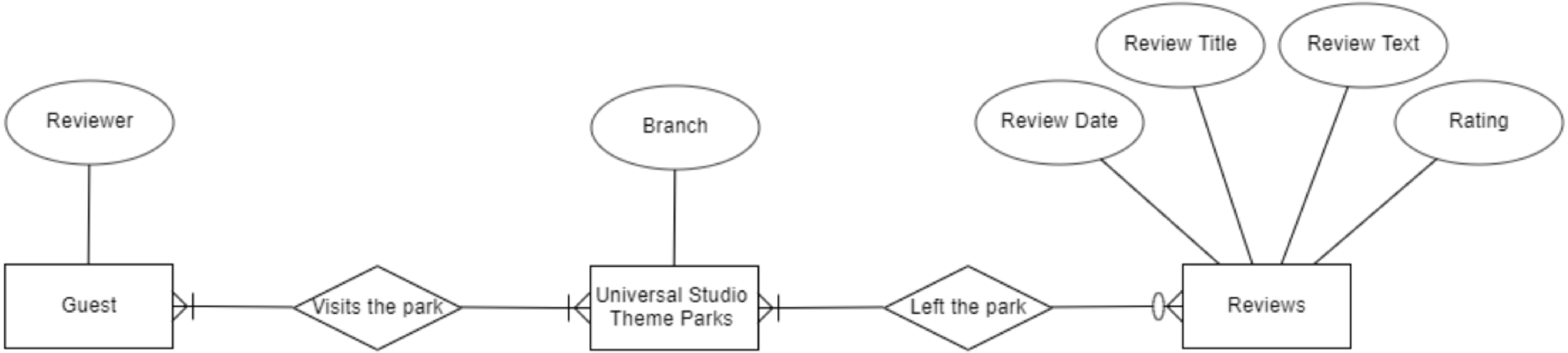
2. Objective

- Target audience:
  - Business Development Managers
  - Guest Service Managers

- Business case and Goals:
  - Constantly improve theme park quality
    - To continue attract visitors
  - Increase financial profit
    - To know which park merchandise is currently popular

- How will your prediction work help?
  - Give insights by analysing guest reviews and their links to higher or lower rating results

3. ER Diagram:



Review Title
Review Text
Reviewer
Branch
Review Date
Rating
Guest
Visits the park
Universal Studio Theme Parks
Left the park
Reviews

4.1. Methodology

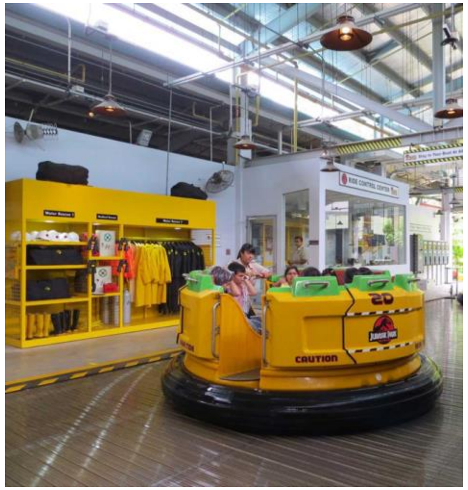
- Datasets:
  - Kaggle
    - https://www.kaggle.com/dwiknrd/reviewuniversalstudio
    - 50,000+ reviews
    - 3 Universal Studios branches (Florida, Singapore and Japan)

- Data Analysis Tools:
  - MS SQL
  - Python
  - Power BI

4.2. Methodology

- Models:
    - Supervised Machine Learning Model
        - Random Forest
        - Logistic Regression
        - Support Vector Machines (SVM)
        - Naive Bayes
        - Decision Tree

- Metrics:
    - F1 - Score

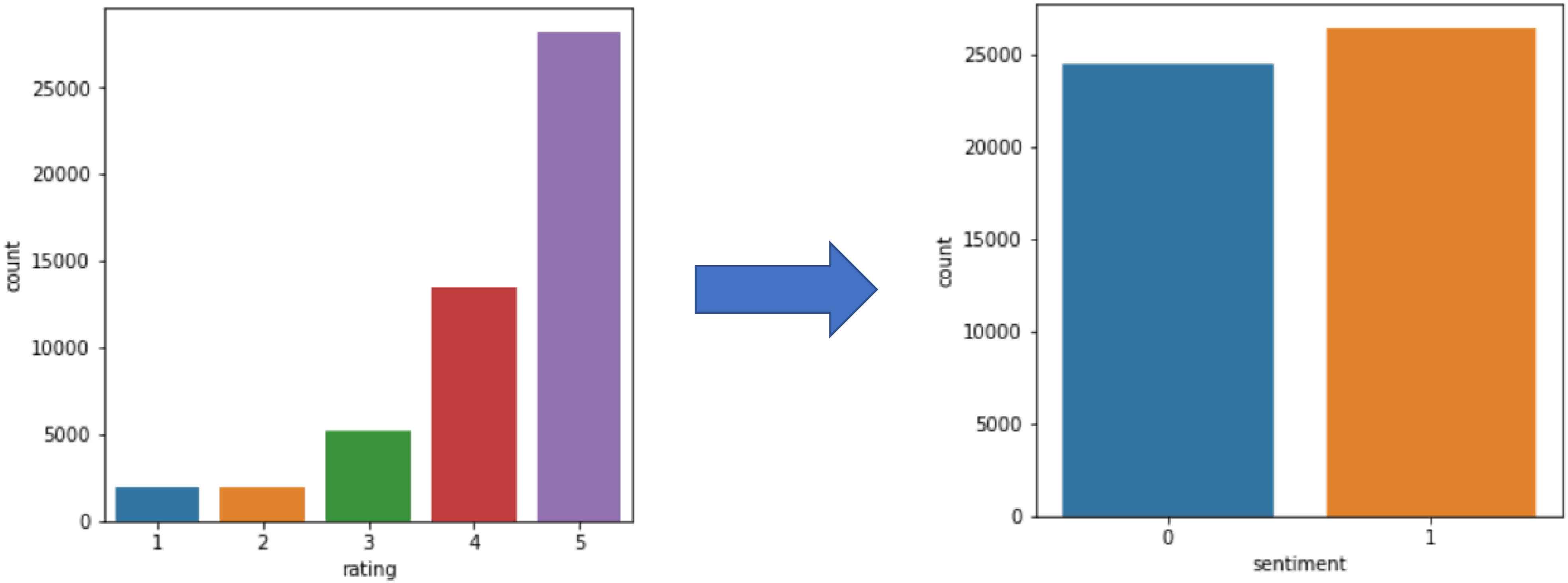


5.1. Process Workflow

- Data Preparation
  - Data Pre-Processing and Cleaning
    - Remove punctuations, rare and common occurring words, etc
  - Natural Language Process (NLP)
    1. **Tokenizing**
       - Break text into sentences, words, or other units
    2. **Removing Stop Words**
       - e.g. “if,” “but,” “or,” etc
    3. **Normalizing words**
       - Condensing all forms of word into a single form
       - Using Stemming or Lemming method
    4. **Vectorizing**
       - Turning text into numerical representation

5.2. Process Workflow

- EDA
  - Guest rating are very skewed
  - Conducted sentiment analysis
  - Used mean polarity score from sentiment analysis to split and decrease skewness



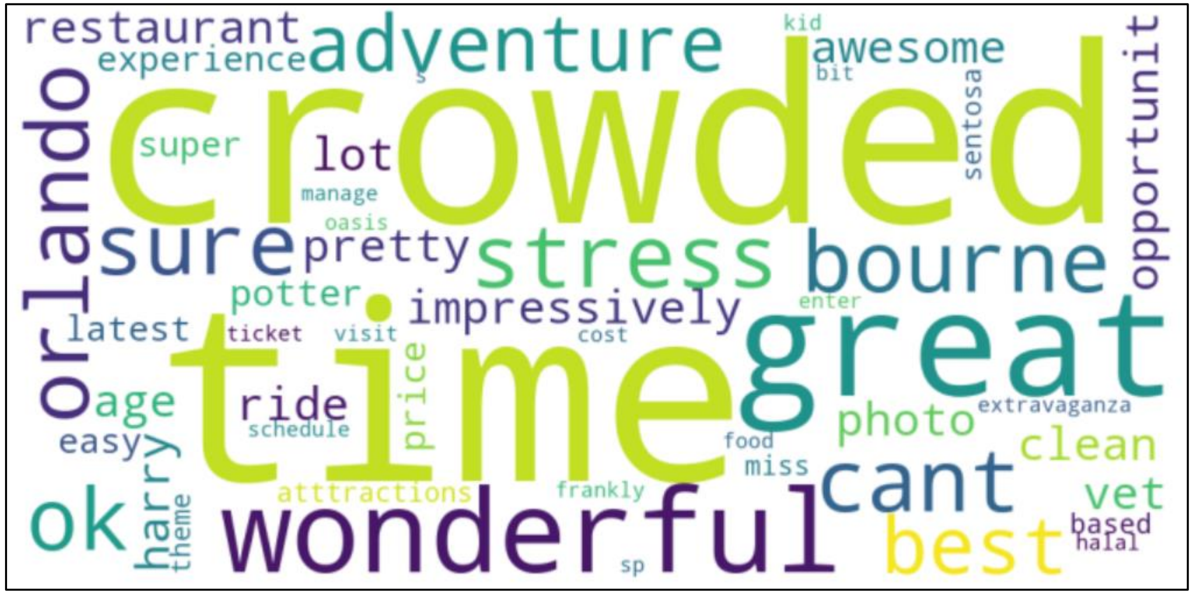
- 0 = Negative Sentiment
- 1 = Positive Sentiment

5.3. Process Workflow

- Data Analysis (Word Cloud)

Negative Sentiment:

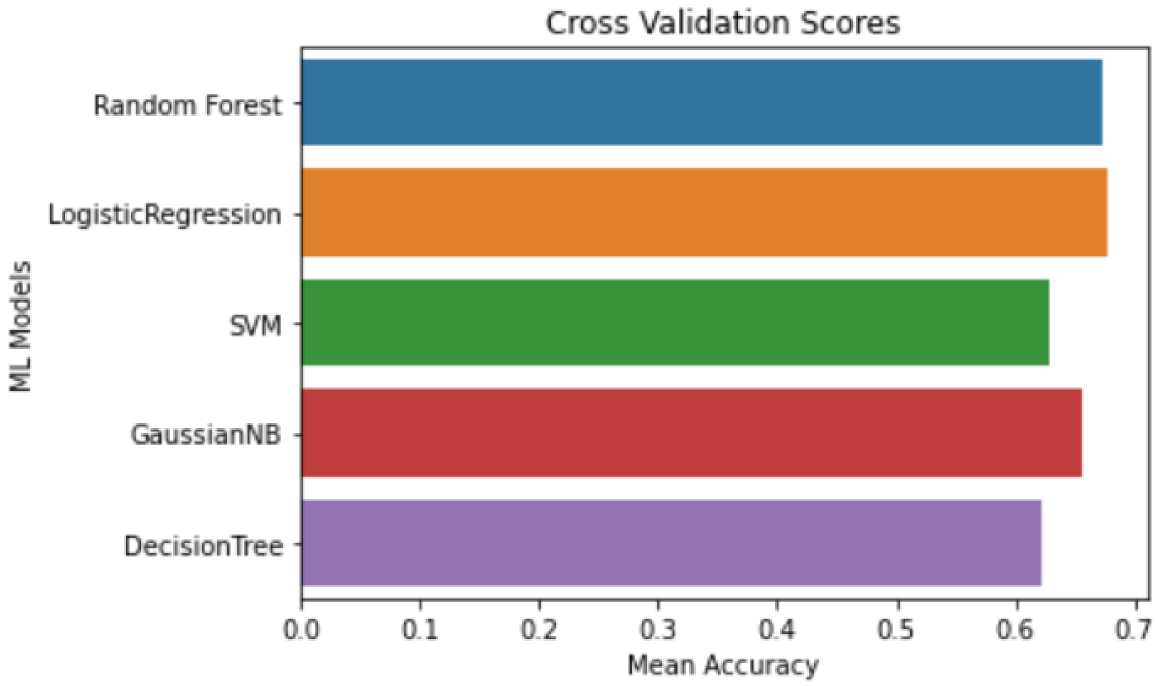
Positive Sentiment:



5.4. Process Workflow

- ML Model Training & Rvaluation

  - **Logistic Regression** - Best Model



	Score
Random Forest	0.673081
LogisticRegression	0.676659
SVM	0.628023
GaussianNB	0.656906
DecisionTree	0.621227

5.5. Process Workflow

- Hyperparameter fine-tuning for Logistic Regression:

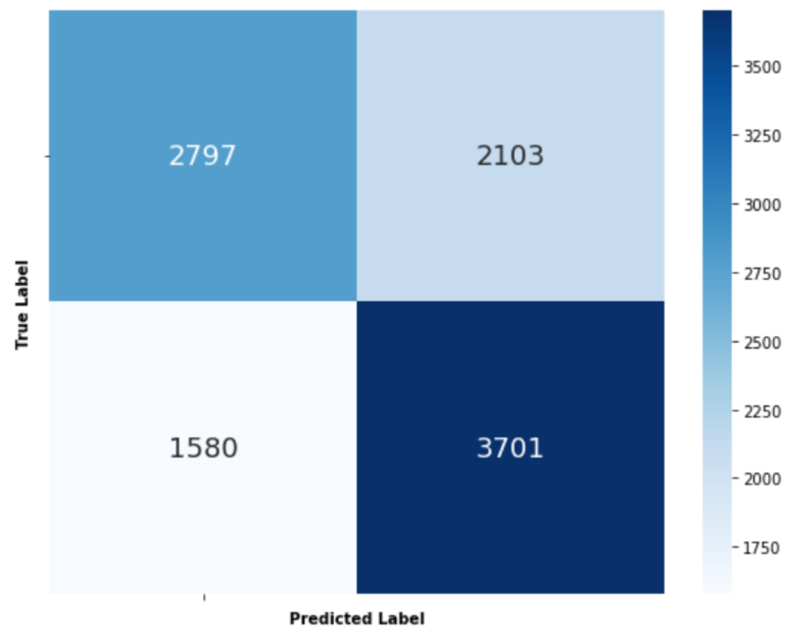
```
# Hyperparameter fine-tuning for Logistic Regression on multi-class dataset
parameters = {'penalty': ['l1', 'l2', 'elasticnet', 'none'],
              'C': np.logspace(-2, 2, 5)}

gs_clf = RandomizedSearchCV(LogisticRegression(multi_class='ovr', max_iter= 100000),
                      parameters,
                      cv=5,
                      # scoring='f1_macro',
                      scoring='roc_auc_ovr',
                      n_jobs=-1)
_ = gs_clf.fit(X_test_clean, y_test)

print(gs_clf.best_estimator_)
print(gs_clf.best_params_)
print(gs_clf.best_score_)

print("'{}' gives the best F1-score at: {:.2%}".format(gs_clf.best_params_, gs_clf.best_score_))
```

6.1. Results

- ML model Test & Evaluation
  - F1 - Score: **68.09 %**

```
LogisticRegression(C=0.1, max_iter=100000, multi_class='ovr', penalty='none')
{'penalty': 'none', 'C': 0.1}
0.6809420490856961
'{'penalty': 'none', 'C': 0.1}' gives the best F1-score at: 68.09%
```

```
Classification report:

              precision    recall  f1-score   support

           0       0.64      0.57      0.60      4900
           1       0.64      0.70      0.67      5281

    accuracy                           0.64     10181
   macro avg       0.64      0.64      0.64     10181
weighted avg       0.64      0.64      0.64     10181


Confusion Matrix:

array([[2797, 2103],
       [1580, 3701]], dtype=int64)
```



6.2. Results

- Prediction using observations from Test Model

	Desired Output (Actuals)	Predicted Output
40686	1	1
14285	0	1
25004	0	0
38742	1	1
16573	1	0
5748	0	0
15714	1	1
34726	0	0
21394	0	1
18968	1	1
50064	1	1
33921	1	1
43051	1	0
9798	1	1
7515	1	1
33942	0	1

```
In [131]: x = ['unfortunate weekend stressful experience horrible food worst service outdated park']

          x = clean_text(x)

          vec = Tfidf.transform([x])

          gs_clf.predict(vec)

Out[131]: array([0], dtype=int64)

In [132]: x = ['Best wonderful park']

          x = clean_text(x)

          vec = Tfidf.transform([x])

          gs_clf.predict(vec)

Out[132]: array([1], dtype=int64)
```

7.1. Conclusions

- What are the results and insights from the data analysis?
  - Rides are the main draw for all parks
  - In Florida and Japan, the Harry Potter themed area is most popular
  - In Singapore, Transformer ride is most popular
  - Main reason for low rating is long wait time in queues and lines

7.2. Conclusions

- Recommendations :
  - Constant update, revamp of rides
  - Higher prices and more variety of Harry Potter and Transformer merchandises
  - Live entertainment and Hai Di Lao restaurant style customer services for long queue

8. Appendix

- Power BI Dashboards screenshots: