

# Tripadvisor Reviews

w/ Natural Language
Processing

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## 01 Business Problem

- Categorize reviews as "poor", "average", and "excellent"
- Helps consumers and business owners get a better summary of each product or service
- Helpful for systems that do not already have preset review or rating system





## Tripadvisor

- ♦ World's largest travel guidance platform
- Helps travelers plan, book & take trips
- Assists travelers discover where to stay, eat & sleep
- ♦ 884M+ reviews of ~8M businesses globally



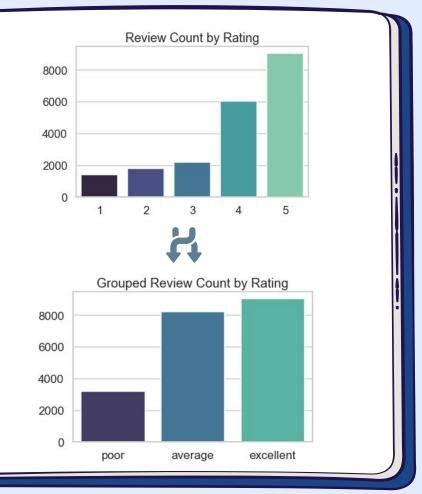


### Dataset

- Pre-scraped Kaggle dataset
- **♦** 20K+ hotel reviews
- Rating based on 1-5 scale

## 02 Exploratory Data Analysis

- Due to class imbalance in original data set, we grouped rating scores together
  - > 1 & 2 -- 'poor'
  - > 3 & 4 -- 'average'
  - > 5 -- 'excellent'



#### Word Clouds

- Shows how common certain words are for each category
  - "best", "nice", "deceptive"

```
reason package rainy deal good rd husband room say city of western wonderful hotel loyal awesome wee affordable night choice western wonderful hotel
```

excellent

```
kimpton late price augus hotel
late price augus hotel
location monaco clean value
loca
```

average

```
par Monaco

horrible

chargegues

seattle

chargegues

seattle

chargegues

seattle

chargegues

seed

chargegues

seed

say

need

phighin

location

seed

say

seet

solve

so
```

poor

#### NOUN ADV ADJ 0.025 0.15 0.020 0.015 0.010 WORD 1500 10000 0.15 1000 poor average excellent SENT 1500

#### Violin Plot

- Frequency of nouns, adjectives, verbs are fairly even across all three review types
- Word count, character count and average length of sentences tend to be higher for 'poor' reviews







# Preprocessing & Vectorizing

#### Preprocessing

- removing punctuation
- > lower-cased words
- ➤ removing stop-words
- assigned part of speech tags
- > lemmatizing words
- tokenized remaining words

#### **❖** TF-IDF Vectorizer

- Better results than Countvectorizer
- $\rightarrow$  Min df = .10
- $\rightarrow$  Max\_df = .80
- > uni-grams

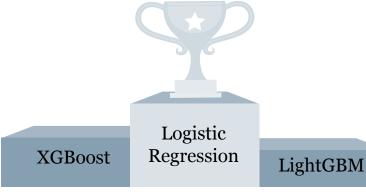
## 04 Modeling

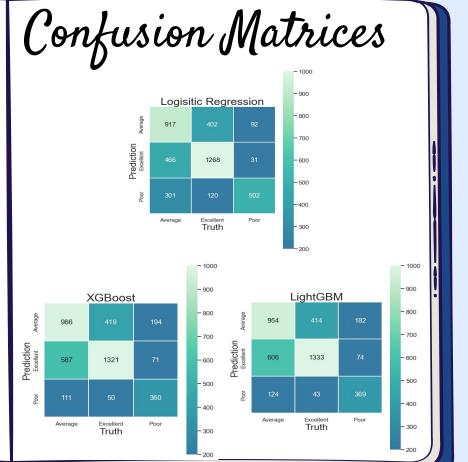
	accuracy score	f1 score
name		
Naive Bayes	0.624787	0.604537
Logistic Regression	0.655526	0.653858
Logistic Regression (PCA)	0.650159	0.653858
Decision Tree	0.572091	0.571000
Decision Tree (PCA)	0.595755	0.593609
Random Forest	0.616004	0.599506
XGBoost	0.650646	0.648684
Light GBM	0.647963	0.645438
KNN	0.601610	0.592157

- All models were grid-searched to determine optimal hyperparameters
- Focused on accuracy score
- **❖** Top model: Logistic Regression
- ❖ Accuracy score: .655
- **♦** F1 score: .653



- \* Top 3 Models: Logistic Regression, XGBoost, & LightGBM
- Logistic Regression model did the best at identifying the 'poor' reviews
- 'average' and 'excellent' were relatively similar across the three models





### 05 Conclusion & Next Steps



Per our business problem, Logistic Regression model is best model for taking in text data and accurately categorizing the user review sentiment

#### **♦** Next Steps:

- Utilize deep-learning to create potentially more accurate models
- ➤ Incorporate n-grams
- > Try different preprocessing techniques
- Bring in new unseen data to assess our model performance
- Resample "poor" reviews to even out classes
- Include exogenous features

# Thank you!

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- Ryan Lewis https://github.com/rylewww