Ryanair: Better Service through AI

Team 4:

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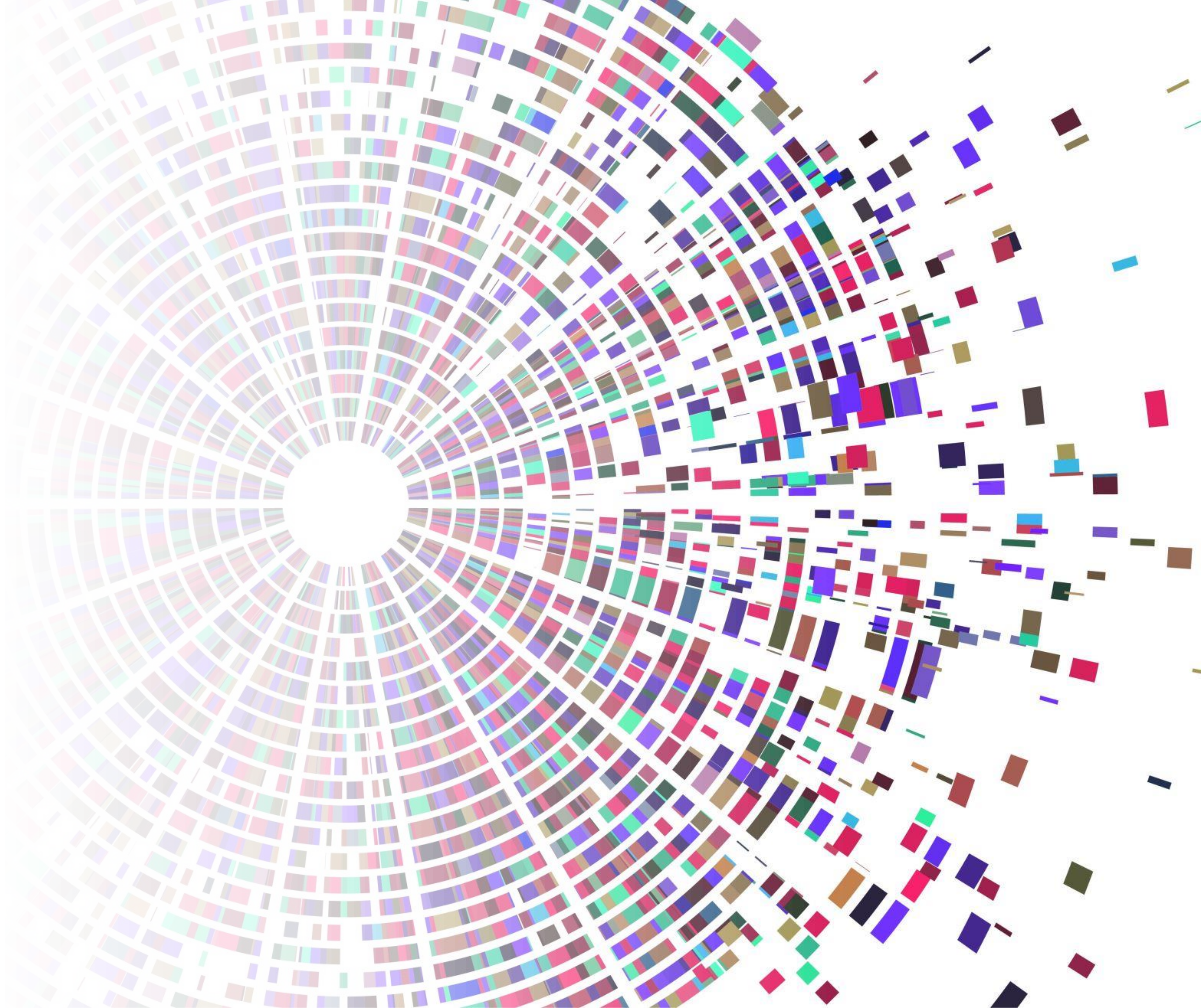


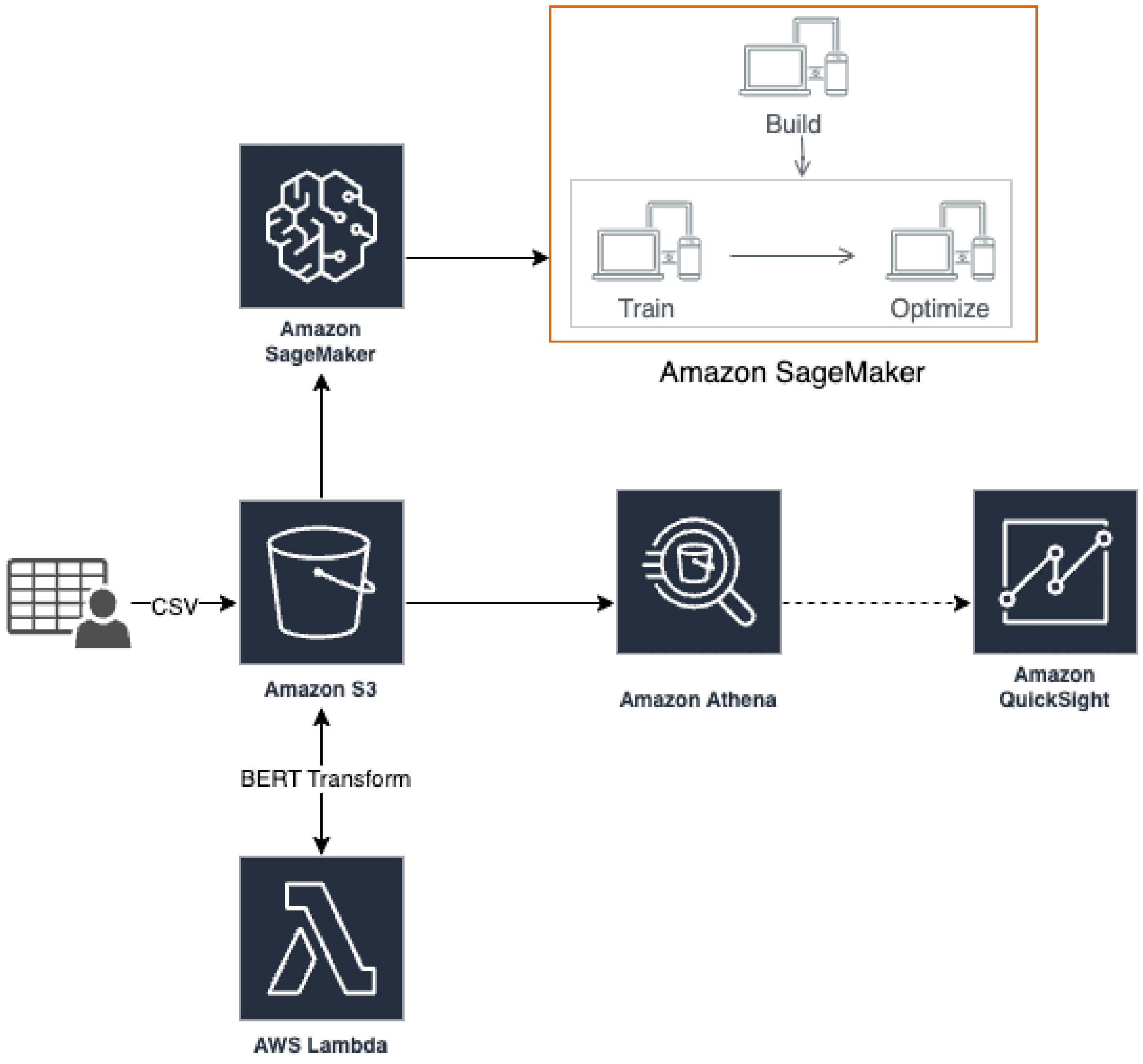
Introduction

Predicting customer satisfaction by analyzing historical customer feedback involves leveraging data analytics and machine learning techniques to gain insights into customer sentiments, preferences, and areas of concern. This proactive approach allows businesses to anticipate future issues, enabling them to react promptly and enhance overall customer experience.

For this project, our team used AWS to process, analyze, and build a model that would accurately predict customer recommendation by looking Ryanair customers in reviews.

We utilized AWS and the Ryanair dataset to determine if there are other insights that can be generated to help improve customer experience.

Architecture



Dataset

Ryanair – Passenger Experience Reviews

- CSV source file, published on Kaggle
- 2249 records, 21 columns
- Flight data from 2012-2024
- Various useful metadata e.g., "Seat Type", "Inflight Entertainment", "Wi-Fi & Connectivity"

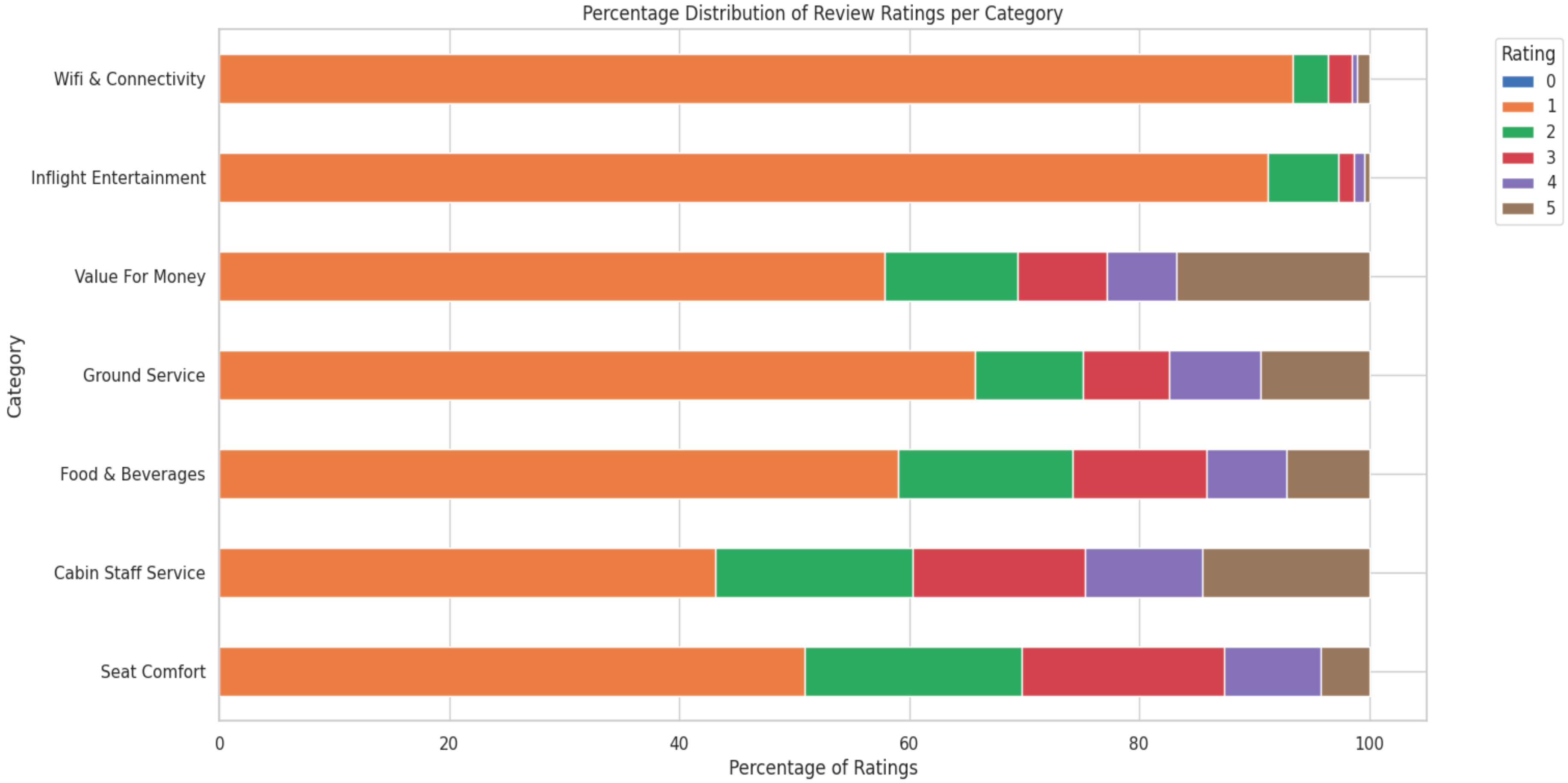
Dataset Columns

Date Published
Overall Rating
Passenger Country
Trip_verified
Comment title
Comment
Aircraft
Type Of Traveller
Seat Type
Origin
Destination
Date Flown
Seat Comfort
Cabin Staff Service
Food & Beverages
Ground Service
Value For Money
Recommended
Inflight Entertainment
Wifi & Connectivity

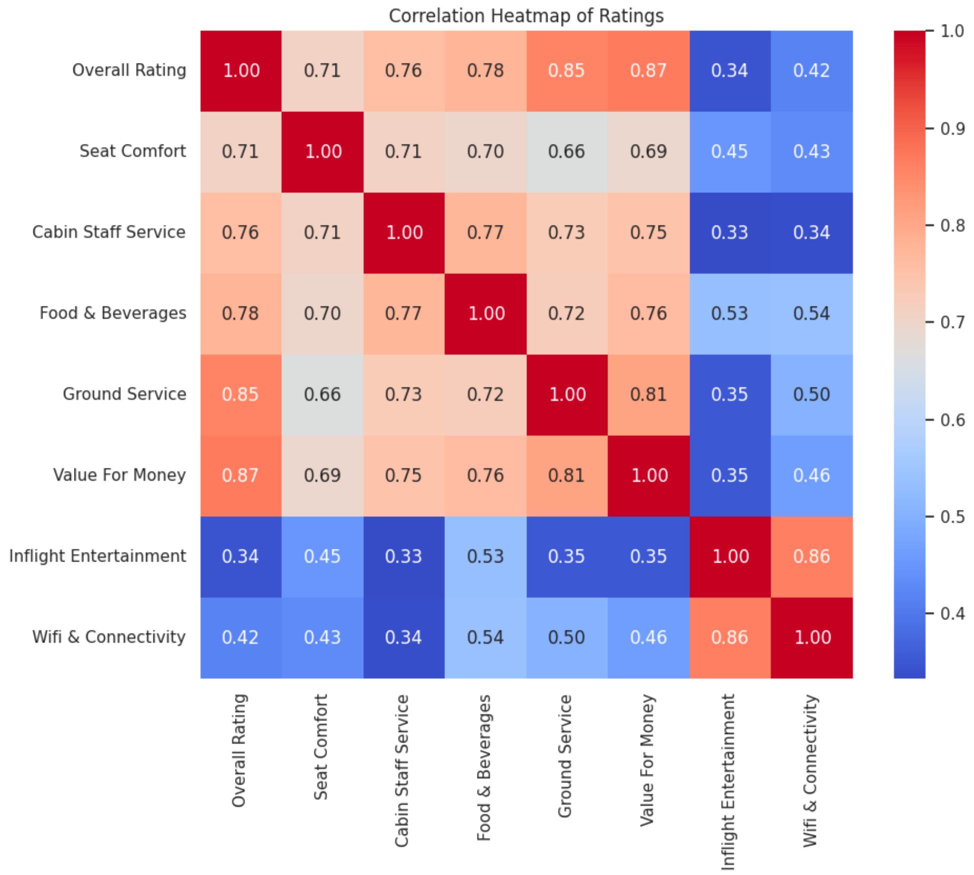
Data Pre-processing

- No outliers were identified/removed
- Transformed raw customer feedback to BERT embeddings by performing:
  - **Tokenization**
    - Break raw text into tokens (words, sub-words, or characters).
    - BERT typically uses WordPiece tokenization.
  - **Vocabulary Creation**
    - BERT has a fixed-size vocabulary of common tokens.
    - Tokens not in the vocabulary are split into sub-word units.
  - **Token ID Mapping**
    - Map each token to a unique integer ID in the BERT vocabulary.
  - **Special Tokens**
    - Add special tokens ([CLS], [SEP]) to indicate sentence boundaries.
  - **Padding and Truncation**
    - Adjust tokenized text to fit BERT's fixed input length.
  - **Attention Mask**
    - Create a mask to indicate which tokens are words and which are padding.

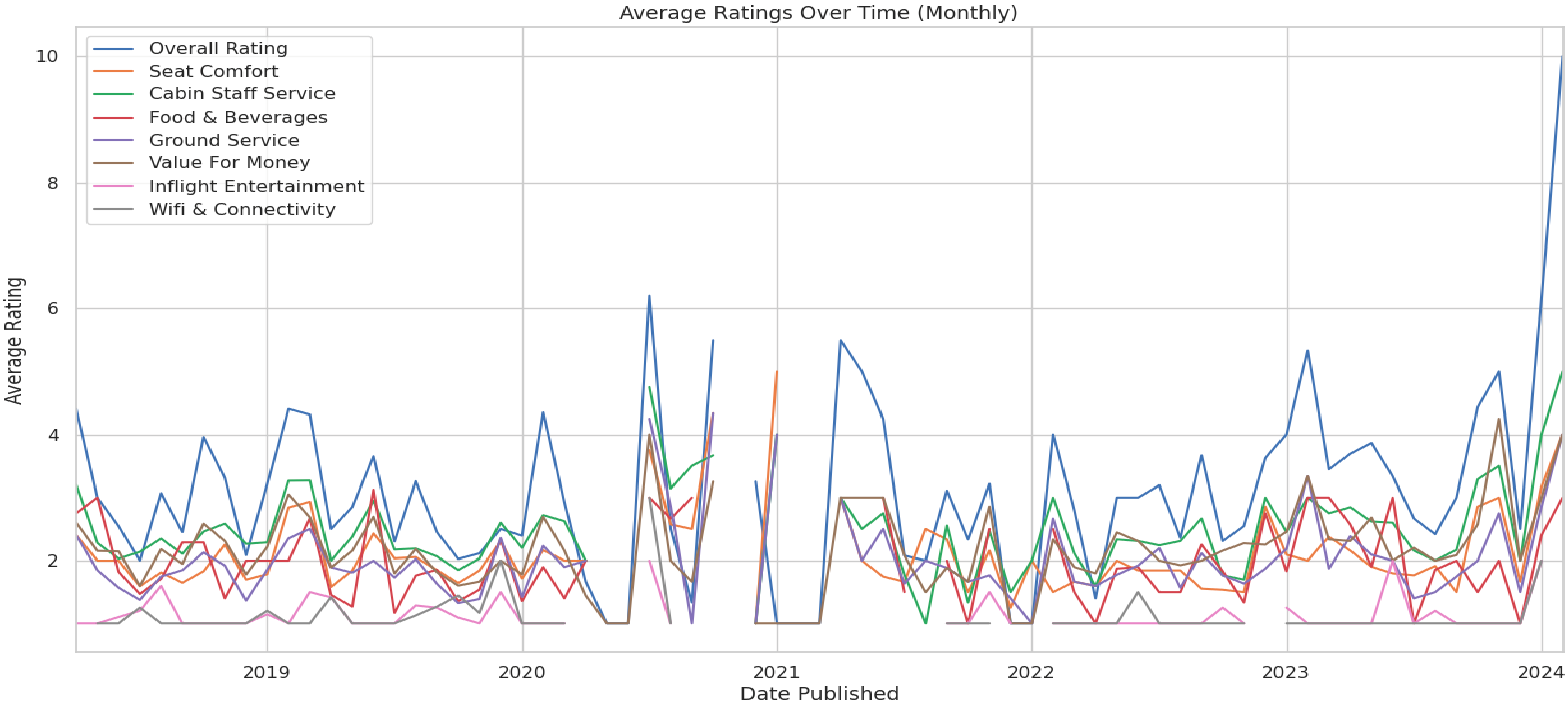
Exploratory Data Analysis: Comparative Overview of Airline Service Ratings



Unpacking Passenger Feedback: Key Terms and Rating Correlations in Airline Reviews



Trends in Airline Service Quality Over Time



Training and Testing

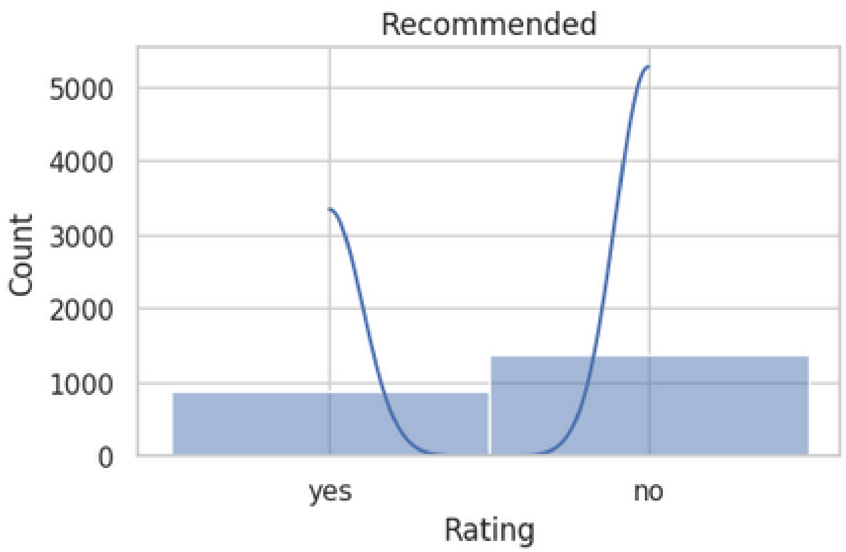
- Used pre-trained BERT model and measured train/val/test loss and accuracy
- Fit Random Forest classifier and generated permutation importance metrics (sklearn)

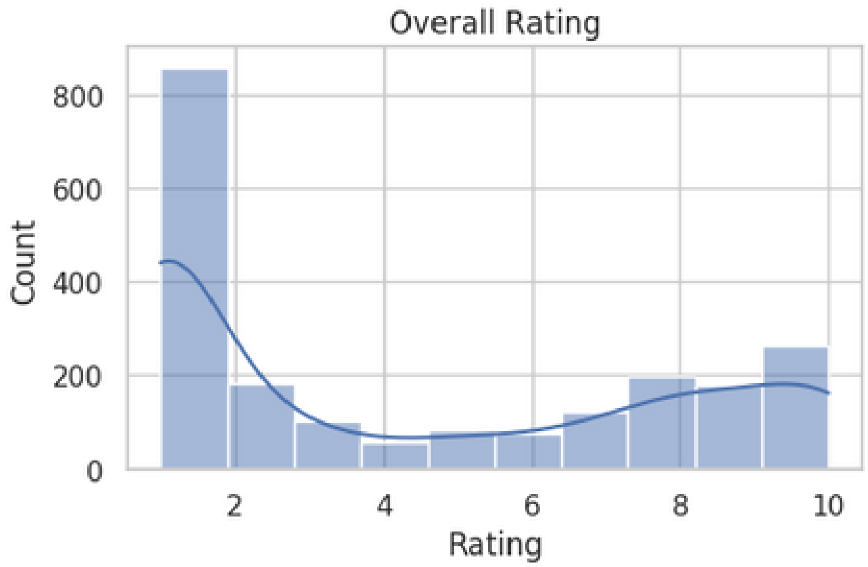
Results

Metrics	"Overall Rating"	"Recommended"
Training Accuracy	0.93	0.91
Validation Accuracy	0.21	0.89
Test Accuracy	N/A	0.91
Most important fields	Food & Beverages, Cabin Staff Service, Ground Service, Seat Comfort, Value For Money	

Conclusion

- 10 labels is a more complex task than 2
    - Reviews tend to be polarized
- Maximizing customer satisfaction is important
- Next steps: identifying customer pain points in comment text





Cost Analysis

No.	Metrics	Name	Value	AWS Cost
1	Input Data Amazon Simple Storage Service Amazon Simple Storage Service Requests-Tier1 Amazon Simple Storage Service Requests-Tier2 Data Transfer	Size /Request	<50 TB / month <1,000 PUT, COPY, POST, or LIST requests <10,000 GET and all other requests	$4.59 $1.15 $0.31 $0.49
2	Data Loading Amazon Athena AWS Lambda	Size	<10 TB / month data transfer out beyond the global free tier	$0.03
3	Model Inference Hosting ml.m5.large hour in US East (N. Virginia) Processing ml.m5.large hour in US East (N. Virginia)	Time	1.214 Hrs 3.029 Hrs	$0.14 $0.35
4	Visualization Google Labs (non-AWS)	Time	N/A	N/A
5	Debugging/Testing Amazon SageMaker CreateVolume Workspace Instance (Session-Hrs):RunInstance in US East (N. Virginia)	Size /Time	<10GB ~15 Hrs	$1.12 $28.6
6	Total			$36.78 (<$100)

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