Sentiment Analysis on Airlines reviews

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Introduction

The airline organization seeks to implement sentiment analysis on customer feedback data to gain insights into passenger satisfaction and identify areas for improvement. Customer satisfaction is paramount in the fiercely competitive airline industry. High satisfaction fosters loyalty and positive marketing, while dissatisfaction risks customer loss and reputation damage. Understanding passenger sentiment is crucial for maintaining a strong market position.

Data Collection

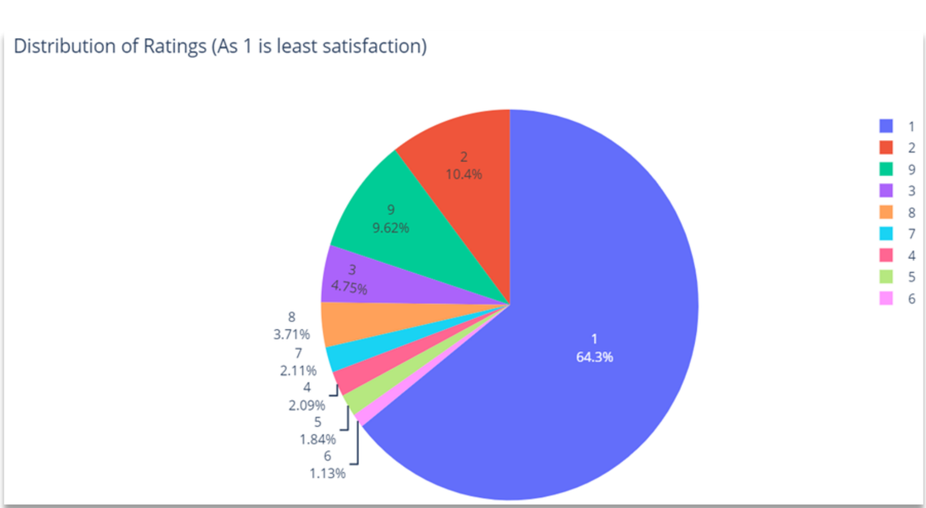
The dataset has been imported by a web scraping script that targets a webpage (*https://www.airlinequality.com*) pertaining to each airline. The script was designed to scrape airline reviews from a website and organize them into a structured format using Python libraries such as requests, BeautifulSoup, and pandas.

Data Cleaning

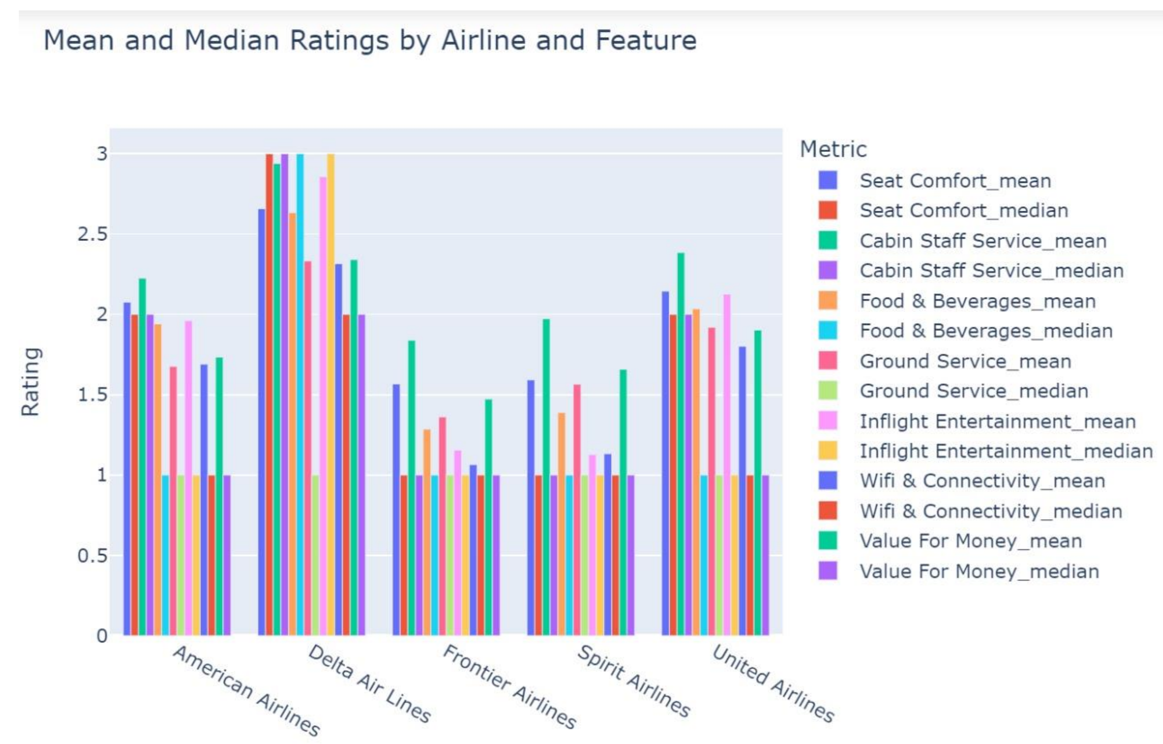
Our dataset comprises two type of reviews, Numerical ratings for various airline services and Descriptive reviews providing qualitative insights.
To address missing values in the rating data, we adopted a pragmatic approach by imputing null values with the median rating. This ensures a fair representation of service quality without unduly influencing the overall rating.
The choice of median imputation is strategic, as it is less sensitive to extreme values and maintains the integrity of the overall rating.

Exploratory Data Analysis

Rating Distribution in the Dataset:64.3% of customers rated their experience as 1, indicating a trend of dissatisfaction.
Significant Dissatisfaction at Moderate Levels:
10.4% of customers gave a rating of 2, representing a noteworthy dissatisfaction beyond the lowest rating.
Surprising Positive Sentiment:
9.62% of customers rated their experience as 9, showcasing a smaller but significant group with highly satisfactory experiences**.**



Describing the Features of the Airlines

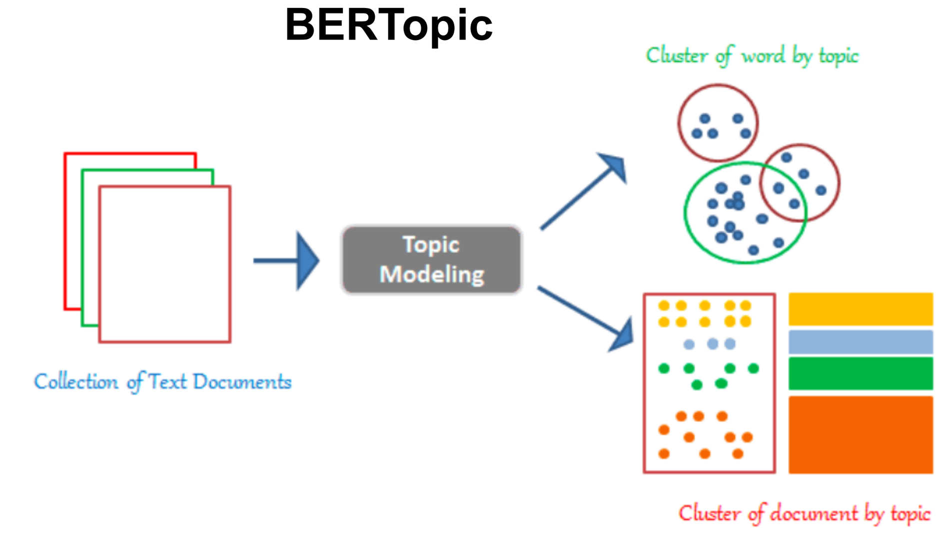


Topic Modeling

Used the following models with 5 data sets with several iterations of
hypertuning:

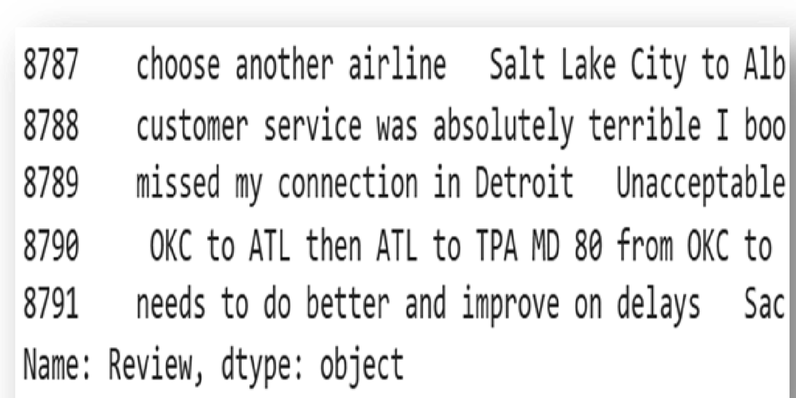
BERTopic starts by transforming text data into numerical representations using a Sentence transformer model.

BERTopic



Llama2

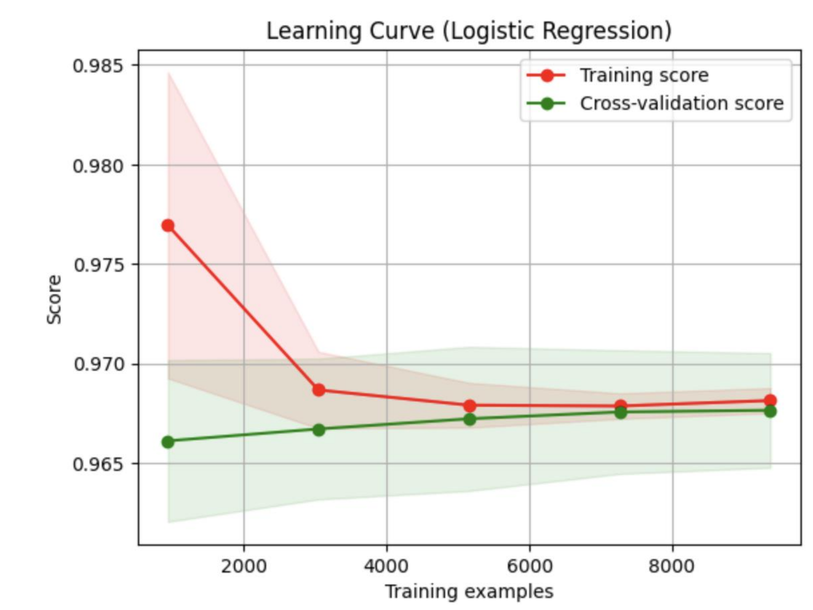
Llama 2 is used to generate labels for these topics, potentially providing more intuitive or coherent topic names. The labels or summaries generated by Llama 2 make it easier for users to understand what each topic is about without needing to delve into the technical details of the keywords.



```
8787    choose another airline   Salt Lake City to Alb
8788    customer service was absolutely terrible I boo
8789    missed my connection in Detroit   Unacceptable
8790     OKC to ATL then ATL to TPA MD 80 from OKC to
8791    needs to do better and improve on delays   Sac
Name: Review, dtype: object
```

Model Building

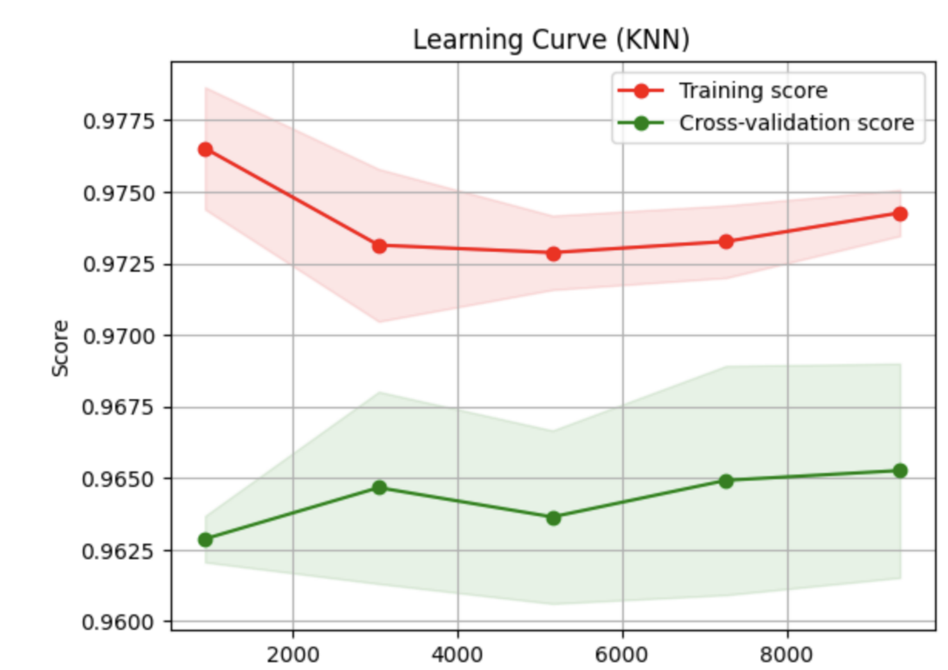
Logistic Regression



Performance Metrics for dataset :

Precision	Recall	F1-score
0.966	0.967	0.967

KNN



Precision	Recall	F1-score
0.964	0.964	0.964

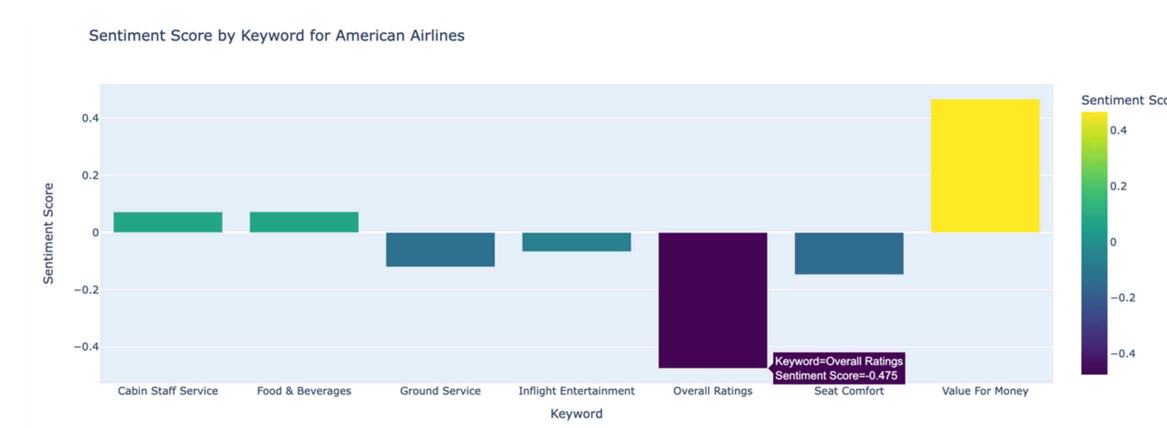
Results

ML Model	Precision	Recall	F1-Score
Logistic Regression	0.966	0.967	0.967
KNN	0.964	0.964	0.964

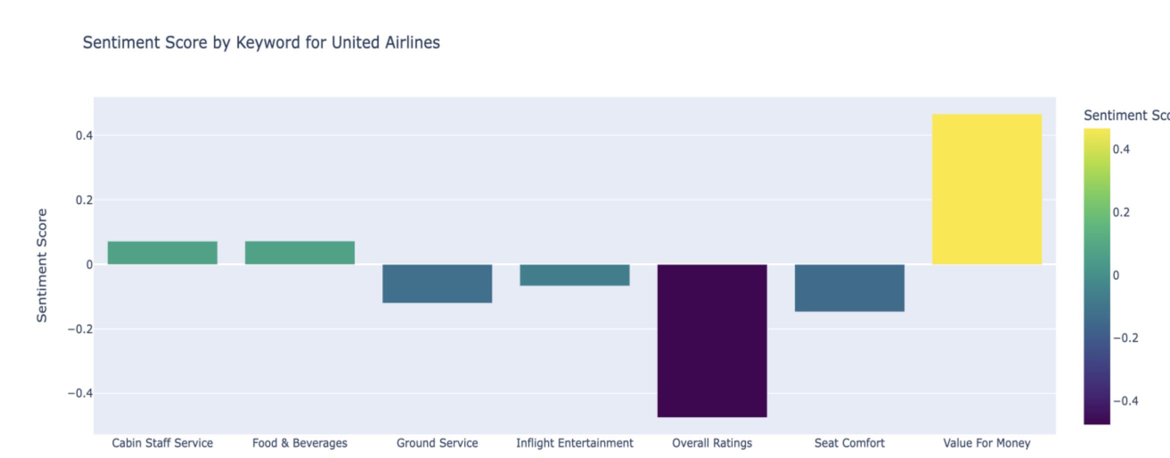
Conclusions

The topic we obtained from topic modeling has been applied into sophisticated data analysis of customer sentiments towards American Airlines and United Airlines, using datasets from 'AmericanACS.xlsx' and UnitedA.xlsx'. The analysis focused on key service aspects by selecting specific topics and keywords, such as 'Flight Time', 'Staff Behavior', 'Customer Service', and 'Seat Comfort'.

For American Airlines, the analysis identified topics like flight delays, staff unprofessionalism, poor customer service at gates, quality of lounge services, and issues with seating arrangements. Keywords like 'rude attendant' and 'terrible customer service' were prominent, indicating areas needing improvement. The sentiment scores, calculated based on key phrases and representative documents, suggested mixed feelings among customers, with some areas scoring neutrally or negatively.



In the case of United Airlines, common topics included general flight experiences, problems with luggage handling, customer service quality, seat comfort, and food selection. Keywords such as 'lost luggage', 'terrible customer service', and 'comfortable seating' highlighted the varied aspects of the airline service. Sentiment scores again provided a nuanced view, showing a mix of negative and slightly positive customer experiences.



In summary, the project offered comprehensive insights into how customers perceive various aspects of American and United Airlines' services, revealing crucial areas for enhancement and highlighting aspects that are well-received. The approach effectively transformed complex data into clear, actionable insights.