Airline Project

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Introduction & Motivation

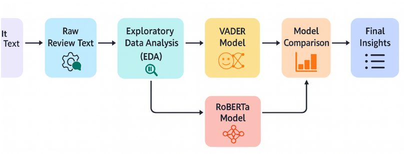
- Passenger reviews provide valuable insights into overall airline service quality.
- These reviews capture real customer experiences across multiple service dimensions.
- The scale and variability of online feedback make manual analysis inefficient.
- **Motivation:**
  - Need a reliable, scalable method to interpret customer sentiment.
  - NLP enables consistent extraction of opinions from unstructured text.
  - Sentiment patterns help identify service strengths and operational gaps.
  - Comparing **VADER** and **RoBERTa** supports selecting an effective analytical approach.

Project Objectives

- Preprocess and clean airline review text to enable accurate sentiment analysis.
- Conduct exploratory data analysis (EDA) to understand customer opinions and service patterns.
- Apply and compare two sentiment analysis approaches:
  - **VADER** — lexicon-based sentiment model.
  - **RoBERTa** — transformer-based contextual sentiment model.
- Evaluate which model better captures sentiment trends in real-world airline reviews.
- Identify key insights related to passenger satisfaction and areas of concern.
- Support data-driven recommendations for improving airline service quality.

Methodology Overview

- Structured workflow to analyse airline passenger reviews.
- Text preprocessing to clean and normalize reviews.
- Exploratory Data Analysis (EDA) to surface patterns and trends.
- Two sentiment approaches implemented:
  - **VADER** — lexicon-based, fast baseline.
  - **RoBERTa** — transformer-based, context-aware.
- Compare model outputs to derive actionable insights.



Raw Review Text (Input) → Text Preprocessing → EDA → VADER Model & RoBERTa Model → Model Comparison → Final Insights

Dataset & Preprocessing

- Dataset contains 1300+ passenger reviews with both text feedback and structured ratings.
- **Key attributes include:**
  - **Basic Information:** aircraft, traveller_type, seat_type, route, date_flown
  - **Verification & Recommendation:** trip_verified, recommended
  - **Overall Metric:** rating
  - **Service Ratings:** seat_comfort, cabin_staff_service, food_beverages, ground_service, value_for_money, entertainment
- **Preprocessing steps:**
  - Removal of HTML tags, URLs, emojis, special characters
  - Lowercasing, tokenization, stopword removal
  - Lemmatization for word normalization

Exploratory Data Analysis (EDA)

- Correlation matrix was used to study relationships between sentiment outputs and service ratings.
- **Positive sentiment (roberta_pos)** shows strong correlation with:
  - Recommendation (0.79)
  - Seat comfort
  - Cabin staff service
  - Value for money
- **Negative sentiment (roberta_neg)** correlates strongly with lower service ratings.
- EDA highlights which service features drive passenger satisfaction the most.

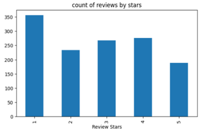
▸ Find correlation between positive, negative emotions and other factors

	roberta_neg	roberta_neu	roberta_pos	rating	seat_comfort	cabin_staff_service	food_beverages	ground_service	value_for_money	entertainment	recomendation_bin
roberta_neg	1.000000	-0.042108	-0.927694	-0.005067	-0.641812	-0.656334	-0.588935	-0.590056	-0.755307	-0.226165	-0.788237
roberta_neu	-0.042108	1.000000	-0.333946	-0.002729	-0.111343	-0.116671	-0.229953	-0.109890	-0.121896	-0.128532	-0.145705
roberta_pos	-0.927694	-0.333946	1.000000	0.005800	0.647110	0.662801	0.641545	0.597739	0.758127	0.261399	0.798092
rating	-0.005067	-0.002729	0.005800	1.000000	-0.014026	-0.000519	-0.023138	0.037645	0.007009	0.025536	-0.009975
seat_comfort	-0.641812	-0.111343	0.647110	-0.014026	1.000000	0.626678	0.553229	0.551421	0.691872	0.316689	0.653460
cabin_staff_service	-0.656334	-0.116671	0.662801	-0.000519	0.626678	1.000000	0.654637	0.509738	0.662671	0.232070	0.644050
food_beverages	-0.588935	-0.229953	0.641545	-0.023138	0.553229	0.654637	1.000000	0.457083	0.626677	0.408918	0.601566
ground_service	-0.590056	-0.109890	0.597739	0.037645	0.551421	0.509738	0.457083	1.000000	0.614198	0.242097	0.577848
value_for_money	-0.755307	-0.121896	0.758127	0.007009	0.691872	0.662671	0.626677	0.614198	1.000000	0.288547	0.779993
entertainment	-0.226165	-0.128532	0.261399	0.025536	0.316689	0.232070	0.408918	0.242097	0.288547	1.000000	0.227408
recomendation_bin	-0.788237	-0.145705	0.798092	-0.009975	0.653460	0.644050	0.601566	0.577848	0.779993	0.227408	1.000000

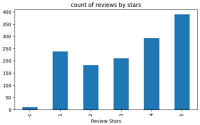
Service Rating Comparisons

- Bar chart analysis reveals clear differences across service components.
- **Value for Money** shows the highest negative ratings, indicating dissatisfaction.
- **Cabin Staff Service** receives consistently positive feedback.
- **Seat Comfort** exhibits mixed ratings with noticeable neutral/negative responses.
- **Food & Beverages** shows significant variation, including lower ratings.
- These comparisons help identify priority areas for service improvement.

1. Value for money

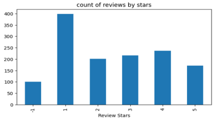


2. Cabin staff service



3. Seat comfortability

4. Food beverages



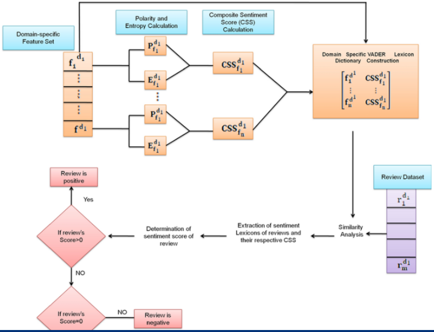
Model Overview & Architecture

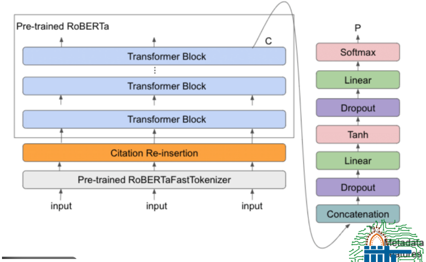
VADER Architecture (Rule-Based Pipeline)

- Lexicon-based model using predefined polarity scores.
- Heuristic rules handle negation, intensity, punctuation, and emphasis.
- Outputs: Positive, Negative, Neutral and Compound sentiment score.

RoBERTa Architecture (Transformer-Based Pipeline)

- Based on Transformer encoder with multi-head self-attention.
- Uses contextual embeddings to capture semantic meaning.
- Fine-tuned classification head predicts sentiment labels.





Results & Sentiment Insights

Model Performance Highlights

- RoBERTa sentiment predictions align strongly with user rating trends.
- Key positive correlations:
  - Seat comfort (**0.647**)
  - Cabin staff service (**0.662**)
  - Value for money (**0.758**)
- Key negative correlations:
  - Food & beverages (-**0.589**)
  - Seat comfort (-**0.641**)
  - Ground service (-**0.590**)

Recommendation Correlation

- Positive sentiment → higher recommendation (**0.798**)
- Negative sentiment → lower recommendation (-**0.788**)

```
results_df.corr()
```

Python

```
<ipython-input-93-419e2a40607f>:1: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select only valid co
  results_df.corr()
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Conclusion & Future Scope

Conclusion

- Passenger sentiment is strongly influenced by key service factors such as **seat comfort**, **cabin staff service**, and **value for money**.
- **RoBERTa outperforms VADER** by providing deeper contextual understanding and more accurate polarity separation.
- VADER serves as a fast, interpretable baseline but struggles with nuanced or mixed sentiment expressions.
- Positive sentiment (RoBERTa_pos) strongly predicts recommendation, while negative sentiment aligns with low service ratings.

Future Work

- Improve service areas linked to negative sentiment:
  - Food & beverages quality
  - Seat comfort
  - Ground service responsiveness
- Implement **RoBERTa-based sentiment monitoring** for continuous customer feedback analysis.
- Use sentiment insights to support data-driven operational decision-making.
- Perform periodic EDA and sentiment analysis as customer expectations

Thank You!

Your attention is appreciated.