#### **United Airlines**

Customer Calls prediction

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October 10, 2024

**NSUT** 

# **United Airlines Call Center Optimization**

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- Objective: Improve Average Handle Time (AHT) and Average Speed to Answer (AST)
- Focus: Enhance customer satisfaction and operational efficiency

## **Problem Statement**

#### **Key Metrics**

- Average Handle Time (AHT): Time from when the agent picks up the call to when they hang up
  - Formula: AHT = Total Handle Time Total Number of Calls
- Average Speed to Answer (AST): Time spent by the customer in queue till the agent answers the call
  - Formula:  $AST = \frac{Total \ Waiting \ Time}{Total \ Number \ of \ Calls}$

## **Data Overview**

#### **Datasets Used**

- calls.csv: Call details
- **customers.csv**: Customer information
- reason.csv: Call reasons
- sentiment\_statistics.csv: Sentiment analysis
- **test.csv**: Test data for predictions

## **Data Analysis**

#### **Initial Data Exploration**

- Loaded datasets using Pandas
- Displayed basic information about each dataset

```
Calls Dataset:
Data columns (total 7 columns):
    Column.
                             Non-Null Count Dtupe
    call id
                             71810 non-null
                                             int64
    customer id
                             71810 non-null
                                             int64
    agent id
                             71810 non-null int64
    call_start_datetime
                             71810 non-null
                                             object
    agent assigned datetime
                            71810 non-null
                                             object
    call end datetime
                             71810 non-null
                                             object
    call transcript
                             71810 non-null
                                             object
dtypes: int64(3), object(4)
Customers Dataset:
RangeIndex: 71810 entries, 0 to 71809
Data columns (total 3 columns):
                      Non-Null Count Dtupe
     Column.
    customer id
                      71810 non-null int64
    customer name
                      71810 non-null
                                      object
```

## **Factors Contributing to Long AHT**

#### **Analysis of Call Durations**

- The Average Handle Time (AHT) for a call is  $\approx 697.05$  seconds.
- The Average Speed to Answer (AST) for a call is  $\approx 437.07$  seconds .

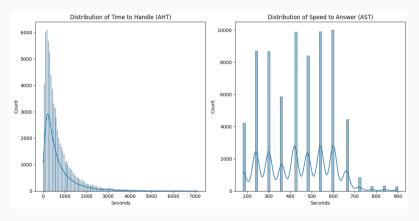
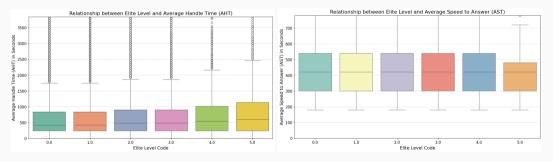


Figure 1: AHT Analysis

## Analysis of Elite level of customers

#### Analysis of Elite level of customers

- Had discrete values (NaN were filled with zeroes) [0, 1, 2, 3, 4, 5]
- Note the outliers



### **Analysis of Silence and Sentiment**

• Silence Percentage: Average silence in calls is  $\approx 0.29\%$ 

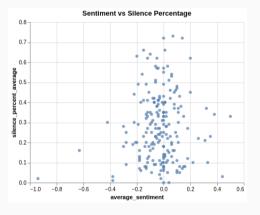
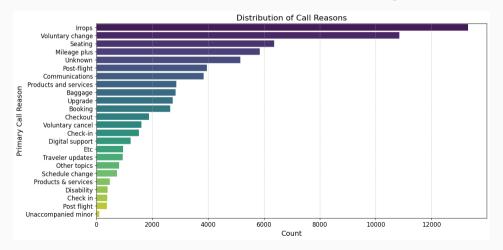


Figure 2: Silence Analysis

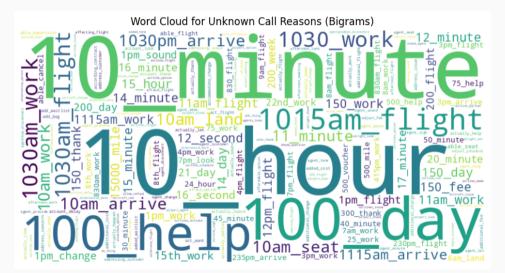
#### **Categorizing Call Reasons**

- Analyzed dataset to uncover patterns in call reasons
- Cleaned and normalized data for feature identification to categorize call reasons



### Bigram Wordcloud

Extracted and created a bigram wordcloud



#### **Topic Modeling**

#### Used Latent Dirichlet Allocation (LDA) to identify topics in call transcripts

```
Topic 0:
looks like today customer youre welcome agent youre help today agent problem customer hi agent okay let pull im calling Topic 1:
looks like understand frustration agent understand customer ugh earlier flight let know let check customer hi today customer contains agent youre
Topic 2:
agent youre youre welcome looks like agent problem let look san francisco customer hi today customer im calling let pull
Topic 3:
looks like understand frustration agent youre today customer im sorry travel voucher customer yeah help today let know contains customer service
Topic 4:
chance fee looks like agent youre voure welcome really appreciate let look let know rest day agent understand customer hi
```

#### Reason Investigation

 Utilized Gemini-1.5-pro-preview to infer an actionable summary of call reasons for each category

```
**Irrops Call Driver Analysis:** ...
Customers frequently contact support due to disruptions (Irrops) stemming from:
- **Flight Schedule Changes: **
- **Baggage Issues:**
- **Compensation and Refunds:** ...
**Recommended Actions:**
- **Proactive Communication: ** Implement automated notifications for flight
 changes and delays with clear rebooking options.
- **Streamlined Rebooking: ** Develop a user-friendly online rebooking system
 with flexible search options for alternative flights and seat selection. ...
```

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## **Model Predictions**

#### **Predicting Primary Call Reasons**

- Used Meta Llama-3.2-1B-Instruct model to predict primary call reasons
- Utilized a prompt-based approach for inference with refined conversation context for better predictions
- 5157 predictions with ~.45s latency

## Recommendations

#### **Actionable Insights**

- Reduce AHT: Streamline processes and improve agent training
- Enhance IVR System: Implement self-service options for recurring issues
- Categorize Call Reasons: Improve call routing and reduce manual tagging through automation using SOTA ML models.

#### **Further Investigation**

- Explore additional data sources
- Conduct deeper sentiment analysis
- Implement finetuned models for better predictions

## Q&A

#### **Questions?**

- Thank you for your attention!
- Feel free to ask any questions.