# United Airlines

Customer Calls prediction

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# United Airlines Call Center Optimization & Prediction

# United Airlines Call Center Optimization & Prediction

- **Objective**: Improve Average Handle Time (AHT) and Average Speed to Answer (AST)
- **Focus**: Enhance customer satisfaction and operational efficiency
- Key Metrics
  - Average Handle Time (AHT): $\frac{\text{Total Handle Time}}{\text{Total Number of Calls}}$
  - Average Speed to Answer (AST): $\frac{\text{Total Waiting Time}}{\text{Total Number of Calls}}$

## 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

# Initial Data Exploration

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

```
Calls Dataset:
Data columns (total 7 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   call_id                 71810 non-null  int64
 1   customer_id             71810 non-null  int64
 2   agent_id                71810 non-null  int64
 3   call_start_datetime     71810 non-null  object
 4   agent_assigned_datetime 71810 non-null  object
 5   call_end_datetime       71810 non-null  object
 6   call_transcript         71810 non-null  object
dtypes: int64(3), object(4)

Customers Dataset:
RangeIndex: 71810 entries, 0 to 71809
Data columns (total 3 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   customer_id     71810 non-null  int64
 1   customer_name   71810 non-null  object
```

# 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 .

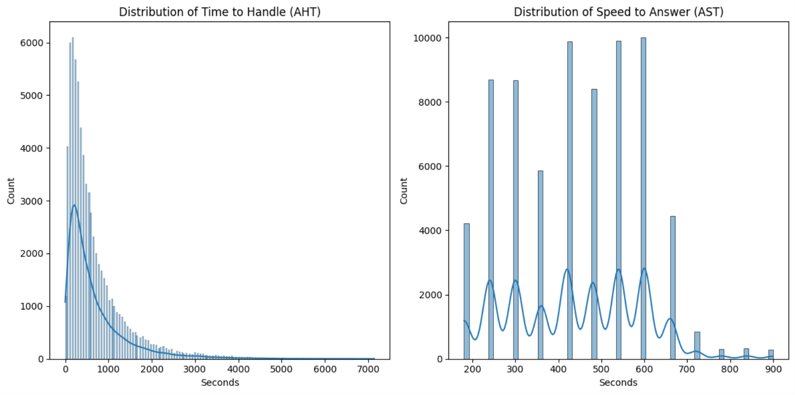
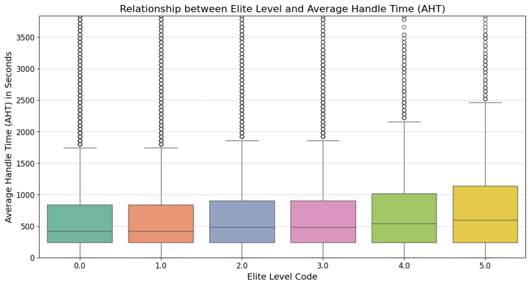


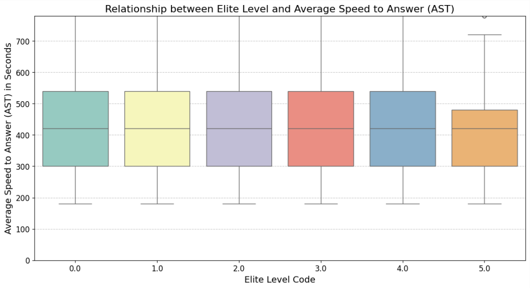

**Figure 1:** AHT Analysis

# Analysis of Elite level of customers

# Analysis of Elite level of customers

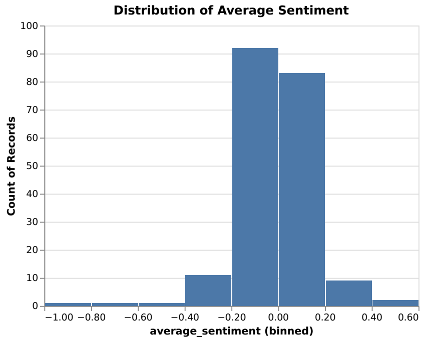
- Had discrete values (NaN were filled with zeroes) `[0, 1, 2, 3, 4, 5]`
- Note the outliers

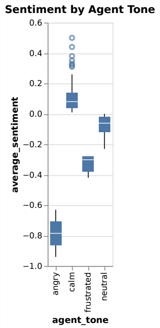


# Analysis of Silence and Sentiment

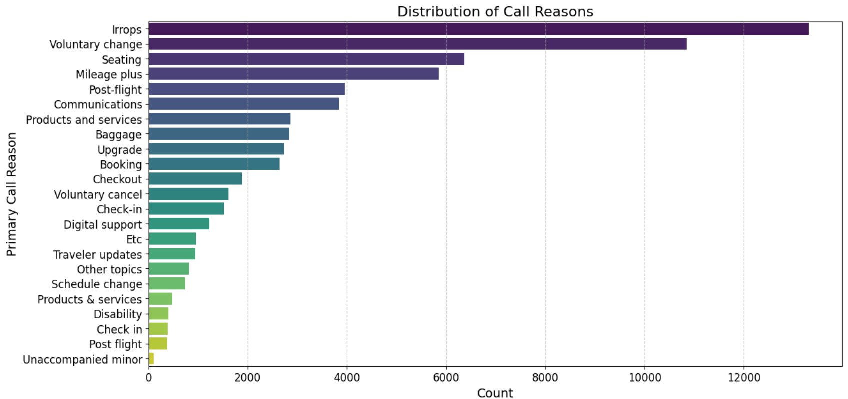
- **Silence Percentage**: Average silence in calls is $\approx 0.29\%$

# Categorizing Call Reasons

- Analyzed dataset to uncover patterns in call reasons
- Extracted the training data from the calls dataset
- Preprocessed the transcript data using stop word removal for LDA and Bigram analysis. Reason categories were normalized for feature identification.



# Bigram Wordcloud

- Extracted and created a bigram wordcloud for each primary call reason

# Bigram Wordcloud

# Topic Modeling

- Used Latent Dirichlet Allocation (LDA) to identify topics in call transcripts
- Identify recurring problems that could be resolved via self-service options
- Preprocessed call transcripts and extracted key phrases using TF-IDF and NMF.
- Displayed the top words for each topic and mapped topics to primary call reasons.
- Identified recurring problems that could be resolved via self-service options.

```
Topic 1:
looks like understand frustration agent understand customer ugh earlier flight let know let check customer hi today customer
↪ 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
↪ customer service
Topic 4:
change fee looks like agent youre youre welcome really appreciate let look let know rest day agent understand customer hi
...
```

# Recurring Problems

The following are the top words for each topic:

```
Refund, Monday, Lost, Sunday, Voucher, Return, Frustration,
Dates, Class, Bag, Wanted, La, San, Sf, Hours, Day, Francisco, Thursday, Took,
Returning, Seat, Check, Friday, London, Missed, Aisle, Tonight, Date, York,
Schedule, Delay, Smith, Standby, Delays, 500, Upgrade, Tuesday, Denver, Seats,
Need, Days, Tomorrow, Instead, Fee, Earlier, Meeting, Economy, Work,
Confirmation, Experience, Saturday, Ugh, Checked, Row, Waive, Chicago, Booked,
Delivered, Baggage, Booking, Weather, Sir, New, Change, Time, Delayed, Luggage,
Bags, Reservation, Scheduled, Travel, Sfo, Following, Wednesday, Claim, Fare,
Forecast, 150, Double, American, Assignment, Legroom
```

# Reason Investigation

- Utilized Gemini-1.5-pro-preview to infer an actionable summary of call reasons for *each* category
- Please refer to the detailed report in the submitted `reasons.md` file

```
**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. ...

...
```

# Model Predictions

# Predicting Primary Call Reasons

- Split into testing and training datasets

```
Training Data Shape: (66653, 10)
Testing Data Shape: (5157, 9)
```

- We use the Meta Llama-3.2-1B Instruct Fine-Tuned model to predict primary call reasons
- Utilized a prompt-based approach for inference with refined conversation context for better predictions
- 5157 predictions with ~.45s/inference latency
- All of the training and inference was done on 2 notebooks on Kaggle with 2xT4 GPUs ran parallelly.
- Due to time constraints we are still in the process of fine-tuning the model on the training dataset.

# 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

Please find the source code at **GitHub**: github.com/KorigamiK/calls.

# Thank You!