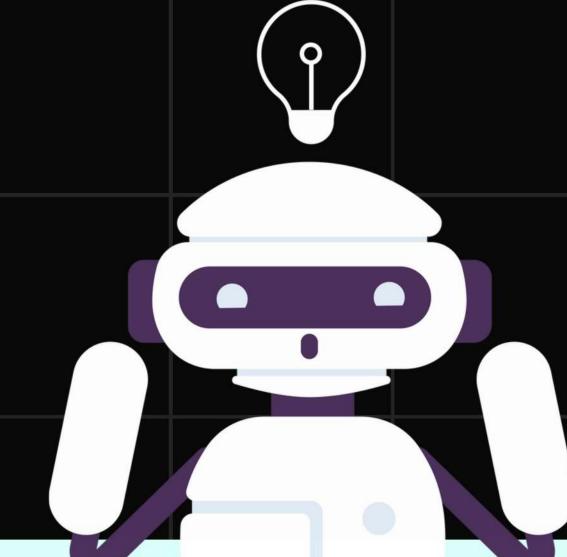




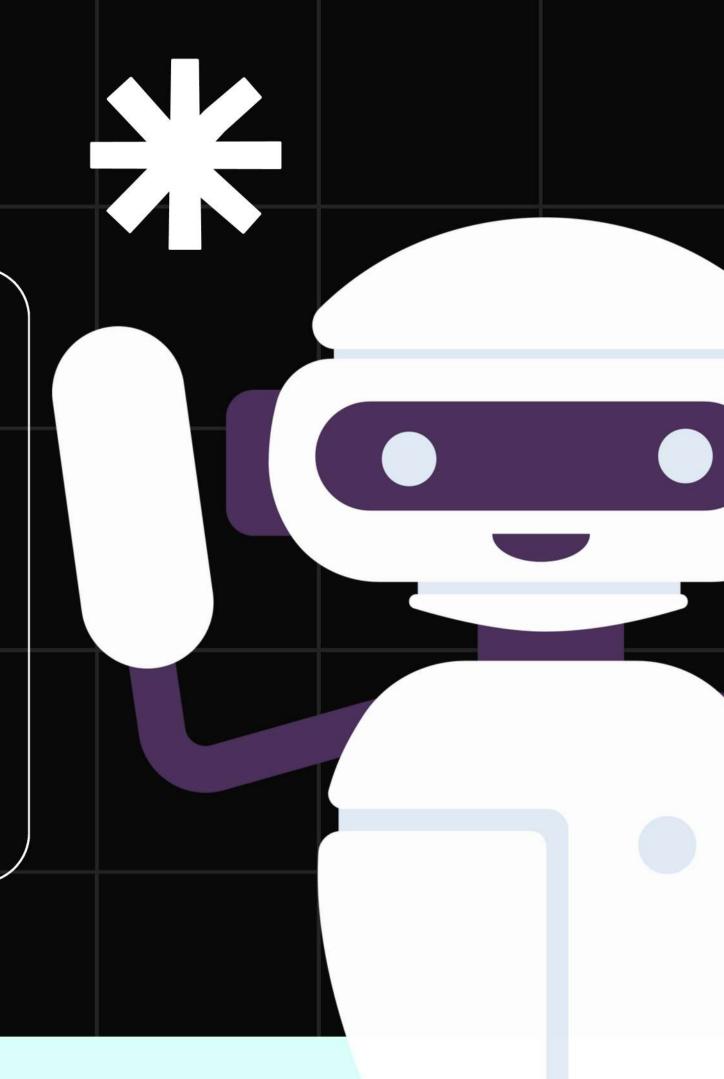
Quick Answers, Happy Customers: Revolutionizing United Airlines' Call Center

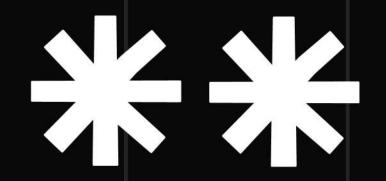
Submitted By: Team ChanduChampion



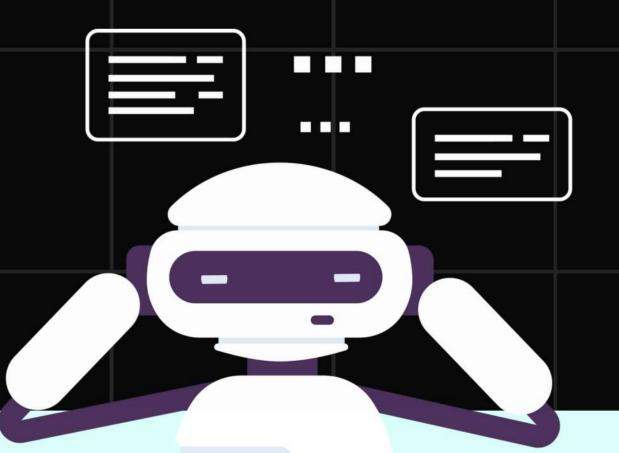
Problem Statement

United Airlines aims to optimize its call center operations by reducing Average Handle Time (AHT) and Average Speed to Answer (AST), improving customer service efficiency and satisfaction. Through data analysis, we will identify inefficiencies, key drivers of extended call durations, and areas where self-service options can reduce agent workload. The goal is to streamline call handling processes, enhance resource allocation, and elevate the overall customer experience while maintaining high service quality.





Data Description



Calls Data

Customers call transcript and duration with agents.

Customer Data

Customer insights

Call Reasons Data

Call reasons of conversation

Sentiments Data

Customer conversations sentiments

Deliverables

• Analyze AHT and AST data to identify inefficiencies and key drivers of long call times.

• Quantify percentage difference between most frequent and least frequent call reasons' AHT.

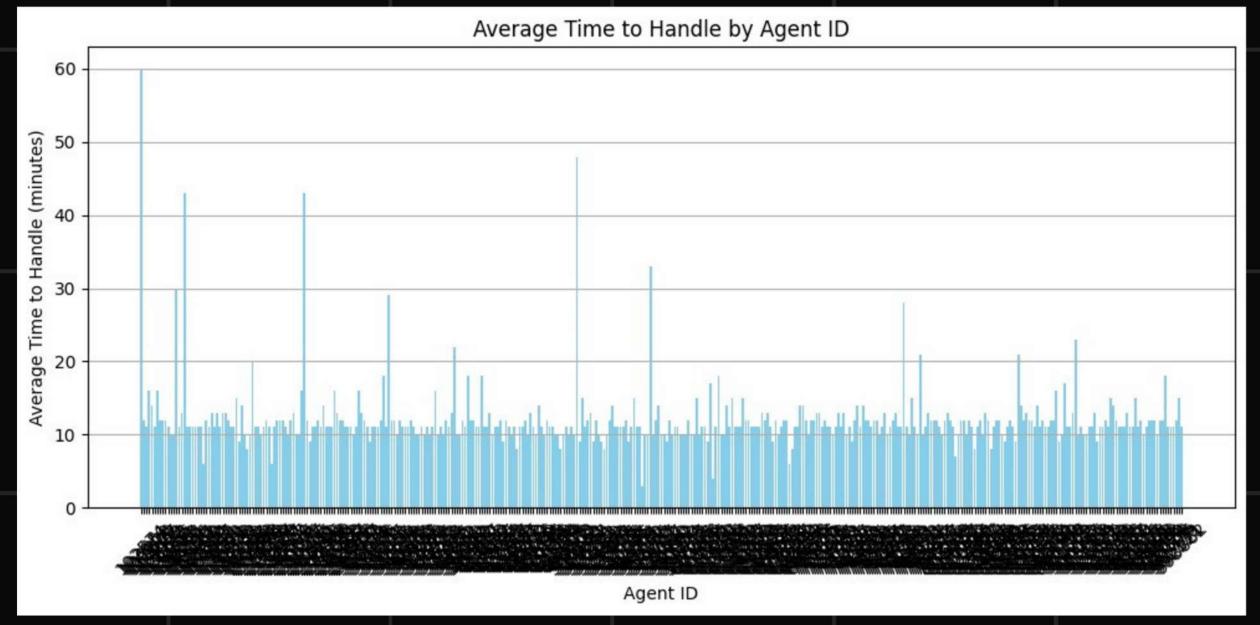
• Identify self-solvable issues escalating to agents and recommend IVR improvements.

 Categorize primary call reasons to streamline processes and reduce manual efforts.

Provide actionable recommendations to optimize call center performance.



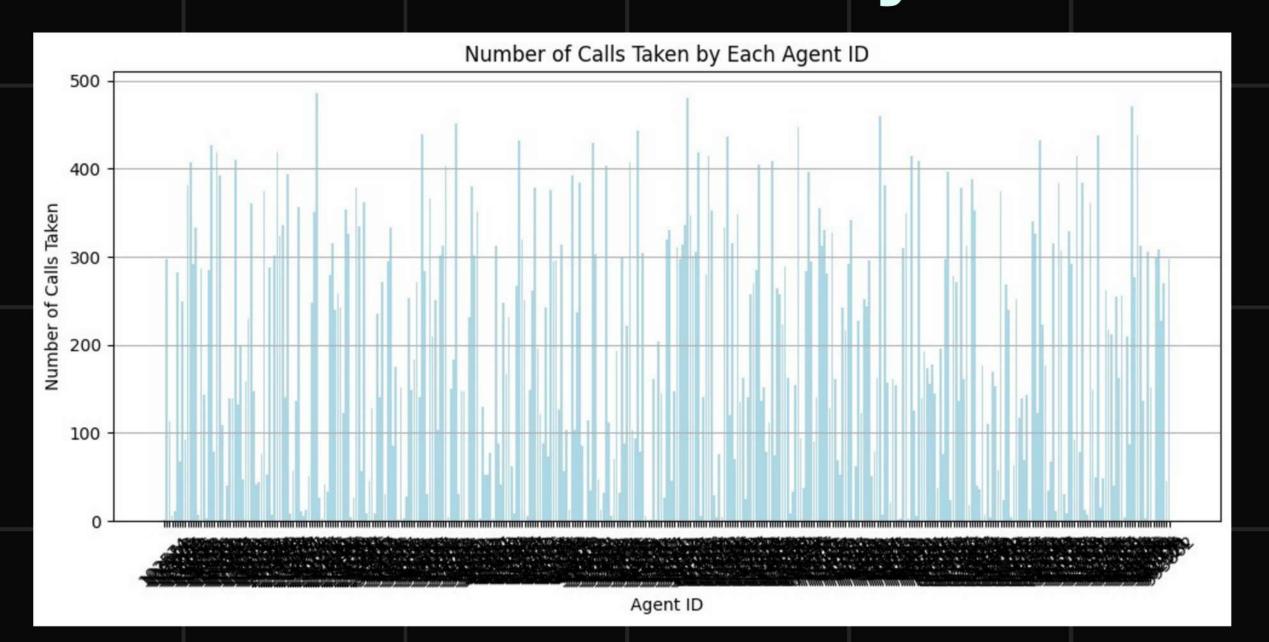


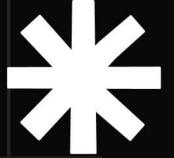


Value
-+========+ 383
0 days 00:12:06.579634464
0 days 00:04:46.525582134
0 days 00:03:00
0 days 00:11:00
0 days 00:11:00
0 days 00:12:00
0 days 01:00:00

The graph illustrates each agent's Average Handle Time (AHT). To enhance customer experience, AHT should ideally remain low, but certain agents exhibit significantly higher times. These outliers need to be reviewed, and appropriate steps should be taken to understand and address the reasons behind their longer call durations.

Agents with higher AHT should be monitored and coached to optimize their performance and improve overall efficiency.





Metric	Value
Count	383
Mean	187.493
Std Dev	137.938
Min	1
25th Percentile	54.5
Median (50th Percentile)	161
75th Percentile	302.5
Max	486

The graph displays the number of calls handled by each agent. Agents handling fewer calls should be assessed to understand why they are less occupied. If an agent has more available time, they should be handling more calls to reduce customer queueing time and improve the Average Speed to Answer (AST). This can help optimize resource allocation and enhance overall call center efficiency.

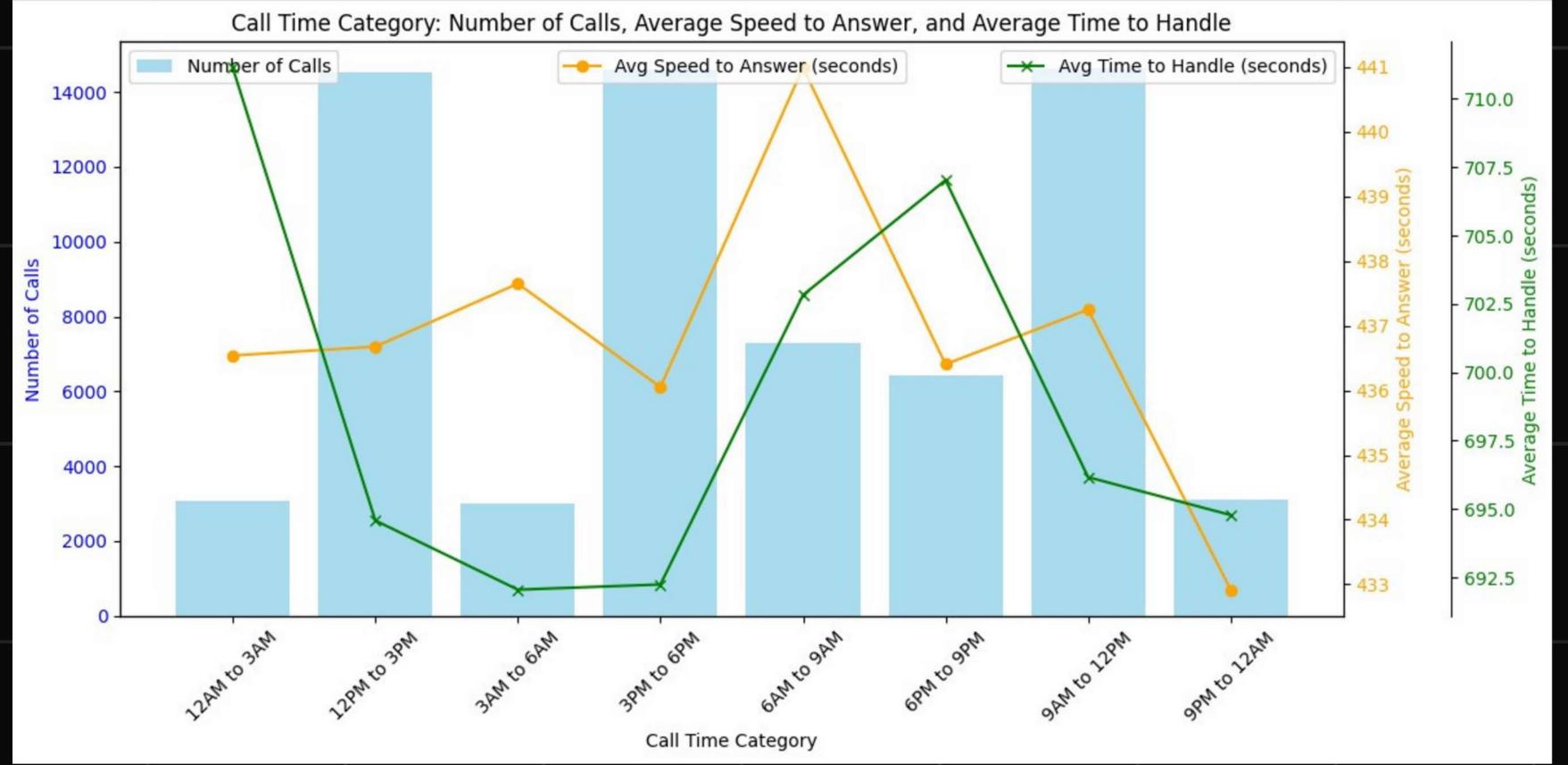


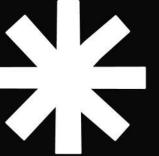
Agents that must be reviewed:

Number of agents that need to be revised (High AHT > 12.00 minutes and Low Calls < 54.50): 48

The thresholds of 12.00 minutes for high average handle time (AHT) and 54.50 for low call volume are derived from statistical analysis using percentiles. The 12.00 minutes represents the 75th percentile of AHT, indicating that agents exceeding this time are performing slower than 75% of their peers. The 54.50 reflects the 25th percentile of total calls taken, meaning that agents handling fewer than this number may be underperforming in engagement. Together, these metrics highlight agents needing revision for potential performance improvements.



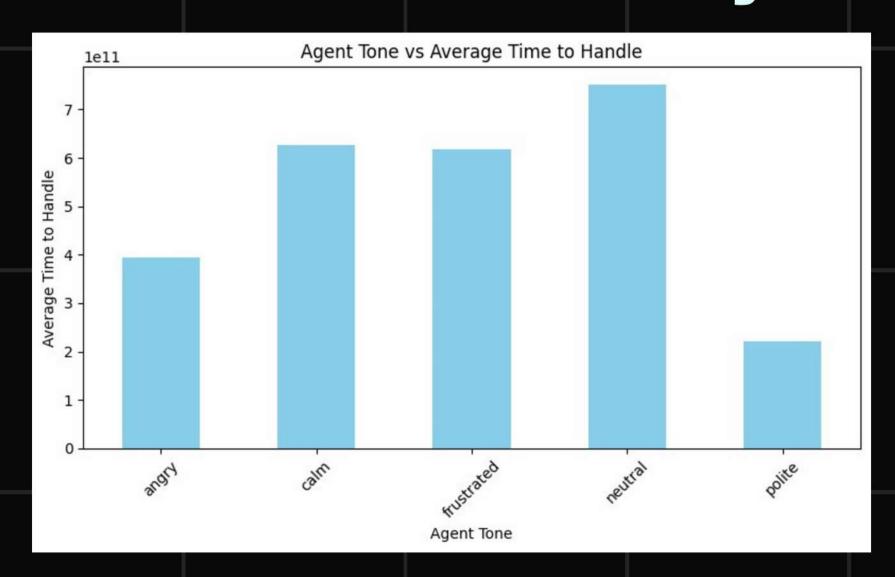


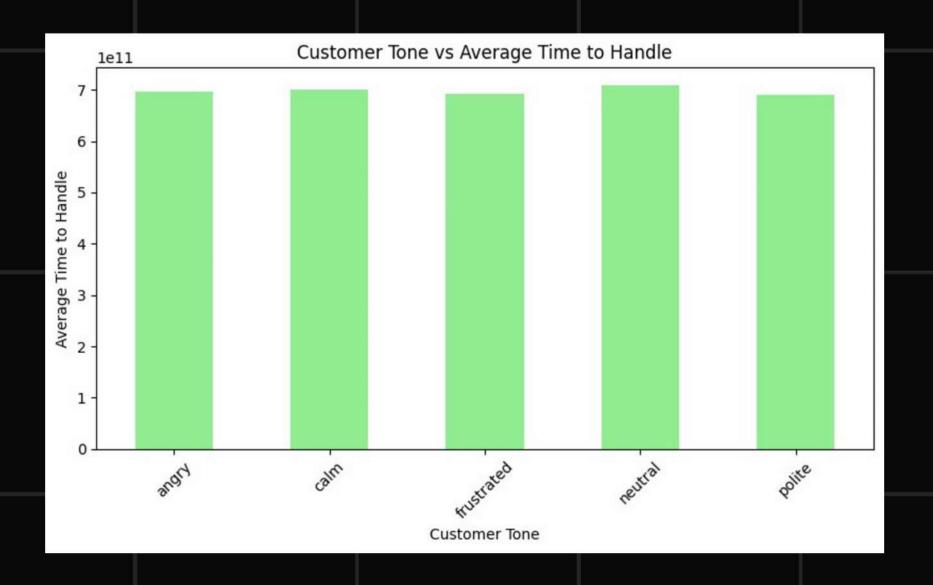


This graph in the previous slide shows call volume across 3-hour slots, along with Average Speed to Answer (AST) and Average Handle Time (AHT).

- **High AST During Low Traffic (9 PM 12 AM):** Despite fewer calls, AST remains high, indicating inefficiency during low traffic hours.
- Consistent AST Despite High Traffic (6 AM 9 AM): Even with higher call volumes, AST is not reduced, suggesting inefficiency during peak hours.
- Actionable Insight: AST should be reduced to decrease waiting time, particularly during low-traffic periods. AHT improvements can enhance call handling and overall efficiency.

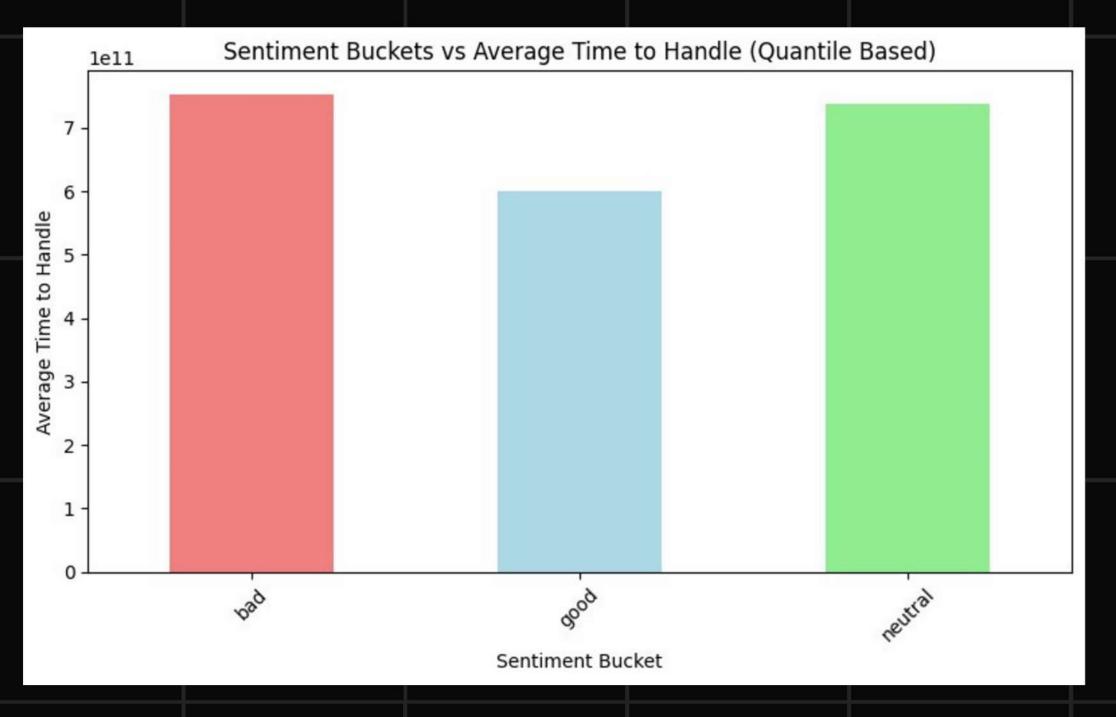
Sentiment Analysis





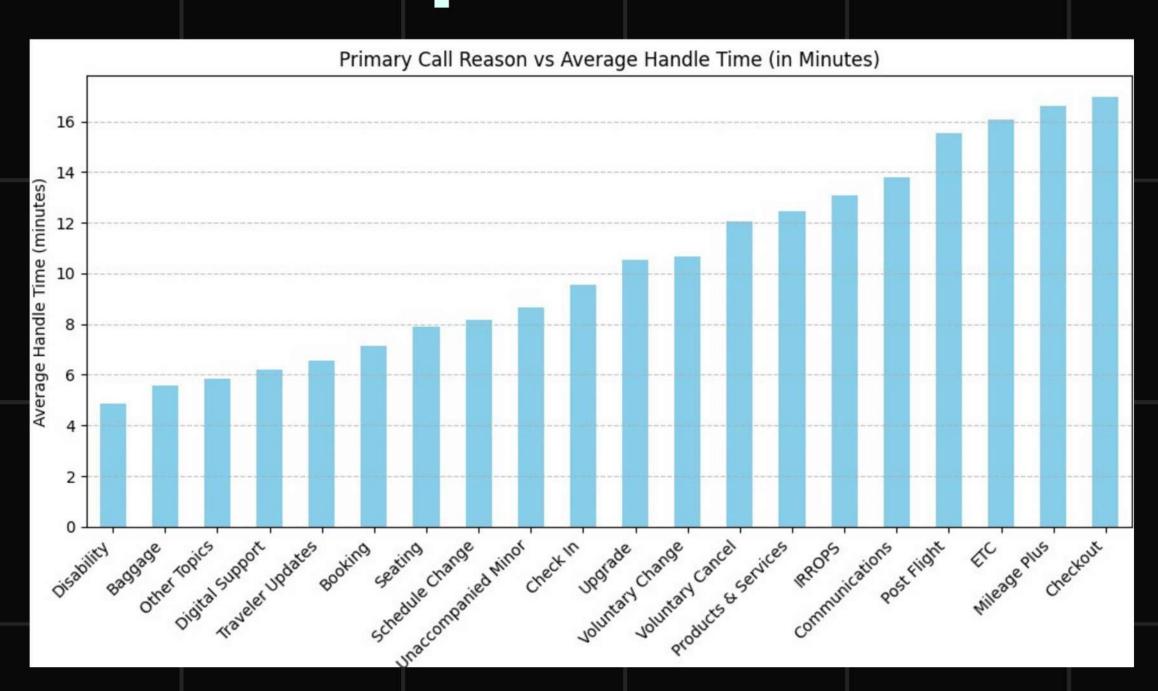
Observation: The graph doesn't reveal clear patterns or behaviors that directly explain the impact on call durations. Therefore, we can't precisely predict how different factors are affecting call times from this data alone.

Sentiment Analysis



The graph divides sentiment into three buckets (bad, neutral, good) based on quantiles. The "bad" sentiment bucket shows a higher Average Handling Time (AHT), indicating that negative sentiment correlates with longer handling times. To improve efficiency, we should aim to maintain more positive sentiment during calls, which can help reduce AHT.

Difference in AHT b/w most frequent and least frequent call reasons



- Most Frequent Reason: IRROPS
- Least Frequent Reason:
 Unaccompanied Minor
- Average Handle Time (AHT):
 - IRROPS: 00:13:05
 - Unaccompanied Minor:00:08:39
- Percentage Difference in AHT:
 51.21%

Self-solvable Issues Analysis

IRROPS	13311	
Voluntary Change	10848	
Seating	6365	
Mileage Plus	5851	
Post Flight	4330	
Communications	3840	
Products & Services	3332	
Baggage	2832	
Upgrade	2738	
Booking	2637	
Check In	1904	
Checkout	1888	
Voluntary Cancel	1607	
Digital Support	1225	
ETC	952	
Traveler Updates	937	
Other Topics	818	
Schedule Change	731	
Disability	403	
Unaccompanied Minor	104	
Name: primary_call_	reason, dtype:	int64

Key Insights:

- Self-Solvable Reasons (49% of total calls):
 - Voluntary Cancel, Booking, Seating, Mileage Plus, Checkout,
 Voluntary Change, Check In, Schedule Change, Digital
 Support, Traveler Updates
- Agent-Required Reasons (28% of total calls):
 - o IRROPS, Upgrade, Baggage, Disability, Unaccompanied Minor
- Mixed/Complex Reasons (23% of total calls):
 - Other Topics, Communications, ETC

Recommendation:

Automate common tasks to reduce agent interactions by up to 49%, improving efficiency and customer satisfaction.

Designing the Model

Data Preprocessing

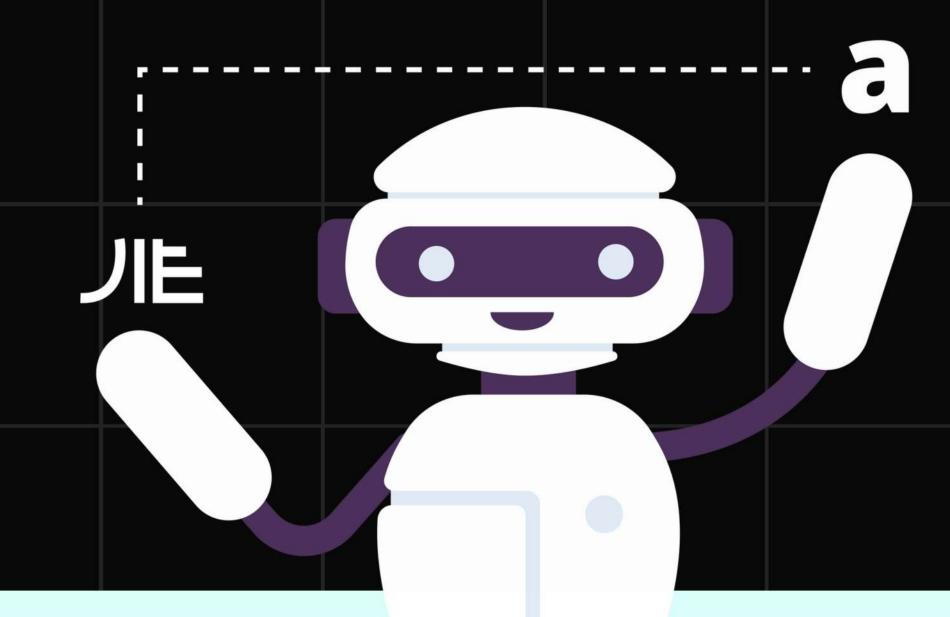
- Tokenize Call Transcripts
- Generate Embeddings
 - Using Normal Tokenizer
 - Using Universal Sentence Encoder

Modeling

- Pass Embeddings to Models
 - ANN (Artificial Neural Network)
 - ANN with LSTM (Long Short-Term Memory)

Training

- Train Models on Dataset
- Predict Call Reasons



Proposed Architecture

Layer (type)	Output Shape	Param #
lstm_6 (LSTM)	(None, 1, 256)	787,456
dropout_16 (Dropout)	(None, 1, 256)	0
lstm_7 (LSTM)	(None, 128)	197,120
dropout_17 (Dropout)	(None, 128)	0
dense_55 (Dense)	(None, 256)	33,024
dense_56 (Dense)	(None, 128)	32,896
dense_57 (Dense)	(None, 20)	2,580

Total params: 1,053,076 (4.02 MB)

Trainable params: 1,053,076 (4.02 MB)

Non-trainable params: 0 (0.00 B)

This architecture consists of:

- LSTM Layers: Two LSTMs with 256 and 128 units, learning sequential patterns.
- Dropout Layers: Added after each LSTM to prevent overfitting.
- Dense Layers: Three fully connected layers (256, 128, and 20 units) for classification.
- Total Parameters: 1,053,076 (all trainable).

nankyou

