Documentary Note: Full Process of AHT and AST Analysis

This document outlines the entire process we have undertaken to analyze and optimize **Average Handle Time (AHT)** and **Average Speed to Answer (AST)** for the call center operations of United Airlines, based on the provided data and task requirements.

1. Problem Understanding

The task was to:

- **Optimize key call center metrics** such as AHT and AST.
- **Identify inefficiencies** leading to long AHT and AST.
- **Suggest improvements** to enhance customer satisfaction and operational efficiency.
- **Analyze transcripts and call data** to propose solutions that can be automated via IVR.

2. Data Exploration

We were provided with multiple datasets, including:

- **Calls Dataset**: Containing call information such as `call_id`, `agent_id`, `call_start_datetime`, `call_end_datetime`, and more.
- **Customer Dataset**: Containing customer details such as `customer_id` and loyalty status.
- **Reasons Dataset**: Detailing the primary reason for each call.
- **Sentiment Dataset**: Including sentiment scores for both the agent and customer during each call.

3. Data Cleaning and Preparation

We merged the datasets to create a consolidated view of the calls, which allowed us to:

- Calculate **Average Handle Time (AHT)** as the time between when the agent picked up the call and when the call ended.
- Calculate **Average Speed to Answer (AST)** as the time between when the customer entered the queue and when the call was answered.

Missing values were handled using appropriate techniques, such as filling numerical columns with the **mean** and categorical columns with the **mode**.

4. Key Analysis Insights

4.1 Factors Contributing to Long AHT and AST

- **Call Reason**: IRROPS (Irregular Operations) was the most time-consuming call type, with an AHT of **13.09 minutes**, while the least time-consuming was Unaccompanied Minor, with an AHT of **3.0 minutes**.
- **Agent and Customer Sentiment**: Calls with negative or frustrated customer tones tend to last longer.
- **Silence Percentage**: Calls with a high percentage of silence between the agent and customer resulted in higher AHT (e.g., calls with more than 60% silence had an AHT of **21+ minutes**).
- **Call Volume**: High call volumes during peak periods led to longer **AST**, as customers spent more time in the queue.

4.2 Quantifying the Difference Between Most and Least Frequent Call Reasons

We compared the AHT for the most frequent and least frequent call reasons:

- **Most Frequent Call Reason (IRROPS)**: 13.09 minutes.
- **Least Frequent Call Reason (Unaccompanied Minor)**: 3.00 minutes.
- **Percentage Difference**: The AHT for IRROPS was **336% higher** than that for Unaccompanied Minor.

5. IVR Improvement Suggestions

Based on the analysis, we identified several self-solvable issues that could be automated through IVR, which would help reduce the call load and AHT:

- **Seating**: Automating seat selection and modifications.
- **Baggage**: Providing real-time baggage tracking and resolving baggage-related inquiries via IVR.
- **Booking**: Enabling customers to manage flight bookings and make minor modifications without speaking to an agent.
- **Check-In**: Providing automated assistance for customers seeking help with online check-in or printing boarding passes.

6. Suggested Operational Improvements

- **Agent Training**: Improving agent efficiency through training on how to handle common call types and complex calls like IRROPS more effectively.
- **Real-Time AI Assistance**: Implementing AI-driven tools to suggest resolutions to agents during live calls.

- **Silence Reduction**: Reducing the percentage of silence during calls by providing agents with better tools for retrieving information more quickly.

7. Proactive Communication

To further reduce call volume and enhance customer experience, we recommended proactive communication:

- **Flight updates**: Notify customers of flight changes, cancellations, or delays via SMS or email to prevent them from needing to call.
- **Baggage Tracking**: Providing real-time updates on baggage status to reduce inquiries related to lost or delayed baggage.

8. Visualization and Reporting

We generated several key visualizations to support our analysis:

- **Bar Chart**: Comparing AHT for each call reason.
- **Pie Chart**: Showing the distribution of call volumes for each call type.
- **Trend Line**: Displaying trends in AHT over different call periods.

9. Machine Learning Models

We explored the potential for machine learning (ML) to predict key outcomes:

- **AHT Prediction**: A regression model (Random Forest Regressor) was trained to predict AHT based on call details, sentiment, and customer loyalty status.
- **Call Escalation Prediction**: A classification model (Random Forest Classifier) was used to predict whether a call would escalate based on call features such as call reason, sentiment, and customer tone.