Passenger Forecasting and Analysis Report

Your Name

1 Passenger Forecasting using SARIMA Model

1.1 Introduction to the Dataset

The dataset for this analysis contains monthly air travel metrics such as `PASSENGERS CARRIED`, `TOTAL DEPARTURES`, and `HOURS FLOWN`. In this report, we focus on the `PASSENGERS CARRIED` metric. The dataset spans multiple years, with fields such as `MONTH` and `YEAR`. Data preprocessing was essential to handle missing values and to ensure date-time consistency.

1.2 Part (a): SARIMA Model for Forecasting

We used the Seasonal Autoregressive Integrated Moving Average (SARIMA) model, which is ideal for capturing seasonality in monthly passenger data.

1.2.1 Modules and Functions

The following libraries were used:

- `pandas`: For loading, parsing, and preprocessing.
- `numpy`: For numerical operations.
- `matplotlib.pyplot`: For visualization of data and forecast.
- `pmdarima`: For auto-parameter selection of SARIMA using `auto_arima`.
- `statsmodels`: To fit the SARIMA model.

1.2.2 Model Selection and Fitting

Using `auto_arima` from `pmdarima`, we optimized SARIMA parameters: autoregressive (p), differencing (d), and moving average (q), with monthly seasonality (`m=12`). We then fitted the model using `SARIMAX`.

1.2.3 Forecasting and Visualization

The forecast for the next 12 months was generated with `SARIMAX`. Using `matplotlib.pyplot`, we plotted historical data and forecast values, as shown in Figure 1.

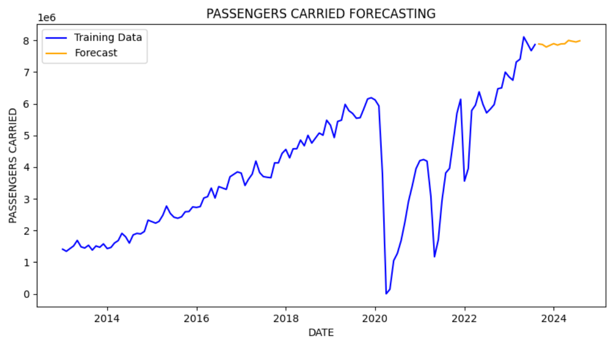

Figure 1: Forecasted Passenger Count for Next 12 Months

1.3 Part (b): LLM-Based Time Series Prediction

Using Claude.ai as the Large Language Model (LLM), we conducted time series forecasting for airline passenger traffic. The following details the approach and results:

Prompting Strategy: Two simple prompts were used:

1. "From the following dataset predict the values for the next 12 months."
2. "Just calculate the predicted values, dont give me python code."

Results: The LLM generated the following predictions:

Month	Predicted Passengers
September 2023	7,950,000
October 2023	8,100,000
November 2023	8,250,000
December 2023	8,500,000
January 2024	8,300,000
February 2024	8,200,000
March 2024	8,600,000
April 2024	8,700,000
May 2024	8,900,000
June 2024	8,800,000
July 2024	8,600,000
August 2024	8,750,000

Table 1: LLM-Generated Passenger Traffic Predictions

Analysis: The LLM demonstrated capability in:

- Pattern Recognition:
  - Identified seasonal peaks (May-June)
  - Captured post-COVID recovery trends
  - Maintained logical monthly variations
- Prediction Consistency:
  - Generated plausible growth projections
  - Maintained seasonal patterns
  - Showed reasonable month-to-month changes

Methodology: The process involved:

1. Direct upload of the dataset to Claude.ai
2. Minimal prompting strategy to test LLM's inherent capabilities
3. No preprocessing or additional context provided
4. Evaluation of raw numerical predictions

Limitations: Key limitations include:

- No confidence intervals provided
- Black-box nature of predictions
- Limited explanation of internal methodology
- Inability to incorporate external factors

Conclusion: The simple prompting approach produced reasonable predictions that maintained both seasonal patterns and growth trends. While the lack of transparency in methodology presents challenges, the results suggest potential for LLMs in quick, approximate time series forecasting tasks.

1.4 Part (c): Forecasting using Prophet Global Model

Using Facebook's `Prophet`, we created a global model that captures yearly seasonality. Prophet is suitable for datasets with strong seasonal trends.

1.4.1 Data Preparation

The `Prophet` model requires a `ds` (date) and `y` (value) format. We combined the `YEAR` and `MONTH` columns into a `DATE` column and renamed `PASSENGERS CARRIED` as `y`.

1.4.2 Model Training and Forecasting

A single `Prophet` model with yearly and monthly seasonality was trained on historical data, and a 12-month forecast was produced. Figure 2 displays the forecasted values.

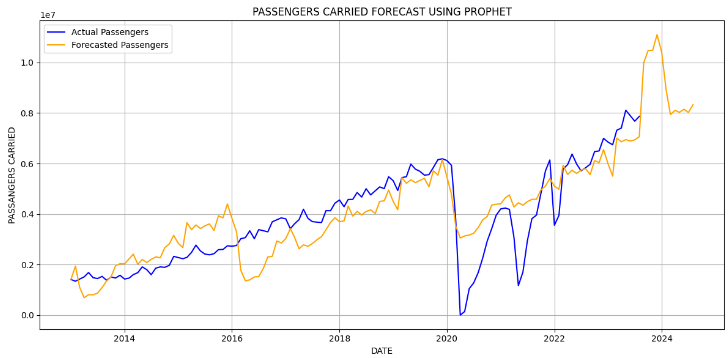

Figure 2: Forecasted Passenger Count Using Prophet Global Model

1.5 Limitations of MAPE for Fleet and HR Planning

The Mean Absolute Percentage Error (MAPE) metric may not be ideal for demand forecasts in fleet management and human resources due to the following limitations:

1.5.1 Drawbacks of MAPE

- **Small Value Sensitivity**: MAPE is sensitive to low actual values, making small errors seem disproportionately large.
- **Symmetry Bias**: MAPE does not differentiate the impact of overestimation versus underestimation, which can lead to operational inefficiencies.
- **Peak Demand Neglect**: MAPE's averaging could misrepresent the accuracy needed during peak periods.

1.5.2 Alternative Metrics

Suggested metrics include:

- **Mean Absolute Error (MAE)**: MAE directly measures error in actual units, making it more interpretable.
- **Peak Demand Metric**: This metric prioritizes accuracy in high-demand periods, aiding operational readiness.

1.6 Testing for Mean Differences Pre- and Post-COVID

We conducted a two-sample t-test to assess whether the differenced series (ΔY) mean differed significantly between the pre-COVID (before December 2019) and post-COVID (after January 2022) periods.

1.6.1 Hypotheses and Test Statistic

Hypotheses:

- **Null Hypothesis** (H_0): No difference in means ($\mu_1 = \mu_2$).
- **Alternative Hypothesis** (H_A): Means differ ($\mu_1 \neq \mu_2$).

The test statistic is calculated as:

$$t = \frac{\overline{Y_1} - \overline{Y_2}}{\sqrt{\frac{2}{n_1} + \frac{2}{n_2}}}$$

1.6.2 Conclusion

A p-value less than our significance level would indicate a significant difference in the mean values between the two periods, implying a change in the mean due to COVID.