DATA ANALYSIS AND FORECASTING TASK AT KOVAI.CO

KEY INSIGHTS :

1. Rapid and Local Routes Drive Overall Ridership: Rapid Route posts the highest average (12,597) and peak (28,678) ridership, making it the backbone of the transit system. Local Routes also contribute significantly but show high variability (standard deviation: 6,120), requiring flexible scheduling and targeted forecasting.

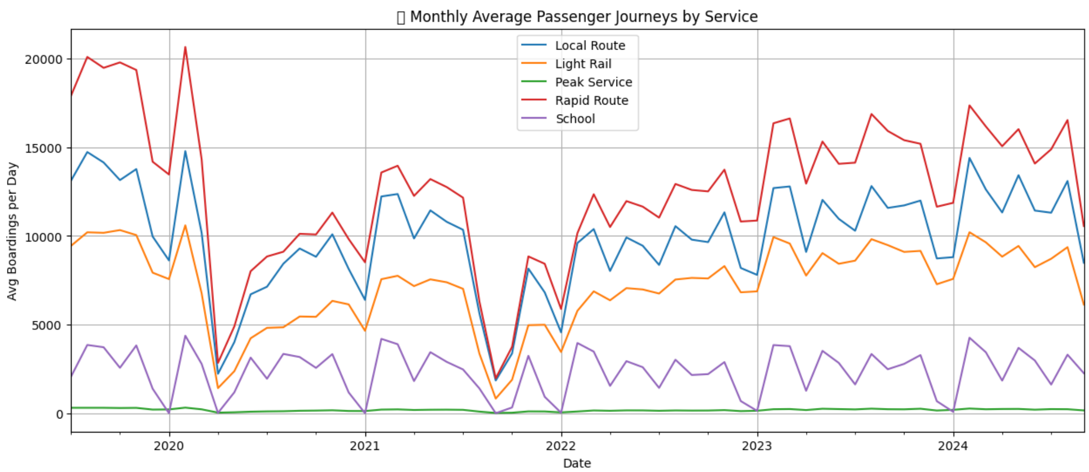
2. Peak Service and School Transport Are Highly Variable : Peak Service has low average numbers but experiences sharp mid-week spikes (standard deviation: 156.5). Similarly, School Transport shows strong weekday and academic term patterns, with usage dropping to zero during holidays—demanding seasonal and weekday-based planning.

3. "Other" Transit Modes and Light Rail Reflect Unique Patterns : The "Other" category has a low average (43) but can spike up to 1,105, often driven by events or seasonal factors—highlighting the need for contingency strategies. Light Rail, on the other hand, shows more stable and gradually increasing usage, suggesting long-term growth potential.

4. COVID-19 Caused Sharp Temporary Disruptions : A significant dip in ridership across all services between 2020–2021 reveals the clear impact of COVID-related disruptions, offering valuable context for anomaly detection in forecasting models.

5. Total Ridership Is Rising Over Time : The consistent increase in median and peak values across transit types indicates a clear upward trend, underscoring the need for scalable infrastructure and forward-looking transit investments.

MONTHLY AVERAGE PASSENGER JOURNEYS BY SERVICE:



2.FORECASTING FOR NEXT 7-DAYS:

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...
Forecasted Data for All Columns:
       Local Route   Light Rail  Peak Service   Rapid Route       School  \
1534  9842.985784  6939.768567    154.560774  12097.212712  2990.054209
1535  9260.151703  6470.858985    135.237966  11356.235769  2934.715617
1536  8068.058335  6087.932337    108.127338  10258.180077  2548.210537
1537  7878.931207  6228.900935    101.309524  10440.007260  2442.290655
1538  6993.635788  6088.435051     85.027732   9787.462282  1860.375327
1539  7635.466574  6374.216157     95.184726  10428.784264  2062.004735
1540  8249.724362  6359.826605    112.183031  10715.696714  2476.230217

          Other
1534  53.242998
1535  53.802276
1536  48.863794
1537  46.234821
1538  46.778438
1539  45.740840
1540  48.676740
```

ARIMA Model and Its Parameters

1. Introduction

The ARIMA (Autoregressive Integrated Moving Average) model is widely used for forecasting non-seasonal time-series data by capturing trends and past patterns.

2. ARIMA(p, d, q)

p: Lag order (past values)

d: Differencing order (for stationarity)

q: Moving average order (past errors)

3. Parameter Selection

p: Based on PACF plot

d: Chosen via stationarity tests (e.g., ADF test)

q: From ACF plot

Auto-ARIMA or manual tuning can be used. In this case, GridSearchCV was applied to find the optimal (p, d, q) combination by minimizing error metrics (e.g., AIC or RMSE).

4. Model Optimization

Checked stationarity and applied differencing

Used GridSearchCV for systematic hyperparameter tuning

5. Accuracy Evaluation & Improvements

The final **optimized ARIMA(3,0,2)** model was evaluated using:

- **MAE:** Measures absolute errors.
- **RMSE:** Quantifies overall error magnitude.
- **MAPE:** Assessed the forecasting accuracy across different dataset columns

6.Challenges include:

Poor handling of non-linear or highly volatile patterns

Needs sufficient historical data for accurate modeling

7. Conclusion

ARIMA is a reliable forecasting model when properly tuned. With techniques like GridSearchCV, prediction accuracy can be significantly improved. Future work can explore hybrid models for better performance on complex datasets.

THANK YOU!