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8/20/2025

1. **Understanding the Data**

a) Identify the most and least trafficked routes

Some of the most trafficked routes included the following (Jan 1985 - June 1989):

- Sydney and Auckland (2.96 million total passengers, 126.71k tonnes of freight, 3,280.77 tonnes of mail)
- Sydney and Singapore (1.44 million total passengers, 69.31k tonnes of freight, 1,147.66 tonnes of mail)
- Sydney and Tokyo (1.29 million total passengers, 79.16k tonnes of freight, 2,423.64 tonnes of mail)
- Sydney and Hong Kong (1.15 million total passengers, 51.61k tonnes of freight, 494.55 tonnes of mail)
- Perth and Singapore (952.93k total passengers, 53.57k tonnes of freight, 383.26 tonnes of mail)

Some of the least trafficked routes included:

- Brisbane and Chicago (0 total passengers, 0 tonnes of freight, 0.009 tonnes of mail)
- Adelaide and Harare (0 total passengers, 0 tonnes of freight, 0 tonnes of mail)
- Brisbane and Colombo (0 total passengers, 0.2 tonnes of freight, 0 tonnes of mail)
- Perth and Bandar Seri Begawan (0 total passengers, 149.46 tonnes of freight, 0 tonnes of mail)
- Melbourne and Denver (0 total passengers, 0.054 tonnes of freight, 0 tonnes of mail)

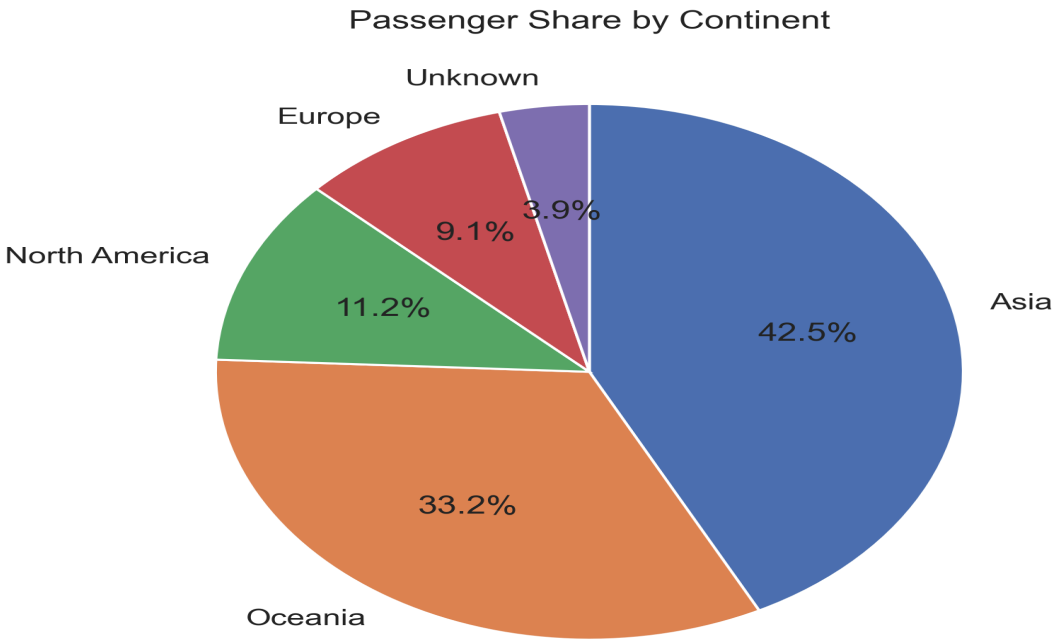
b) Analyze trends and/or geographical patterns

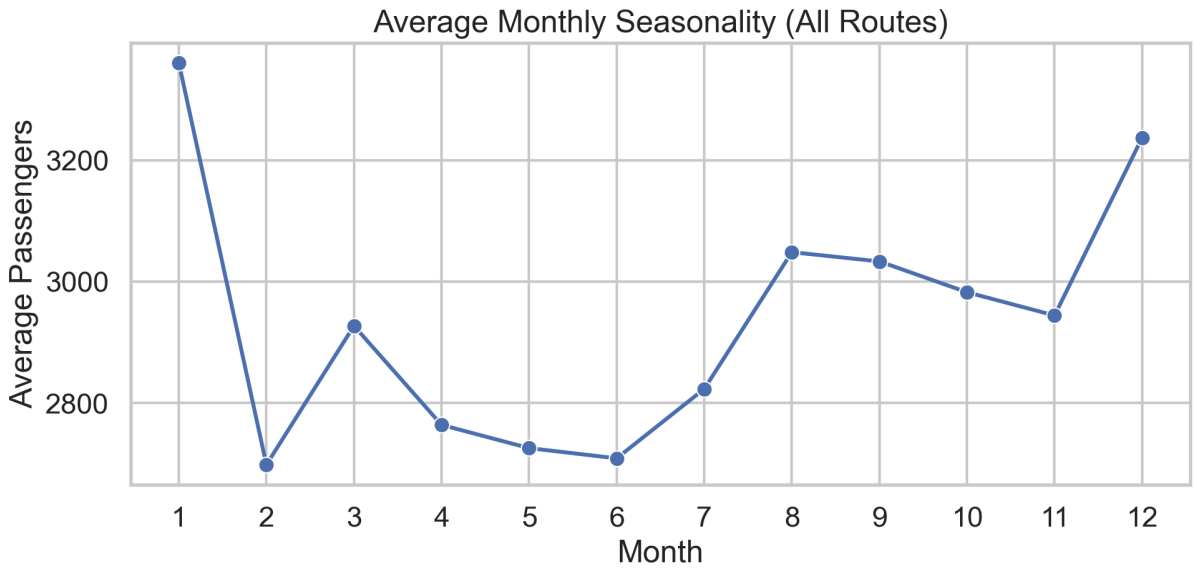
I noticed that most of the passenger traffic came from Asia and Oceania, continents that are close in proximity to Australia. Due to this, some of the most popular foreign ports included Singapore, Auckland, Tokyo, Hong Kong, and Christchurch. Additionally, across all the Australian port passenger totals, I found that months December and January were the most busiest due to the holidays and weather in Australia, making it an extremely great tourist location then. Additionally, lots of boxing day (day after Christmas) sports games happen in this area, so many tourists love to travel for those occasions. Most of the time, by February, we usually observe a local minimum (hype dips), then in March it spikes again slightly for it to stagnate usually until around July. The pattern here stays somewhat consistent across the 4.5 years of data given, until we reach 1989, where the local minimums and maximums aren't reflective of the pattern observed in the previous 4 years.

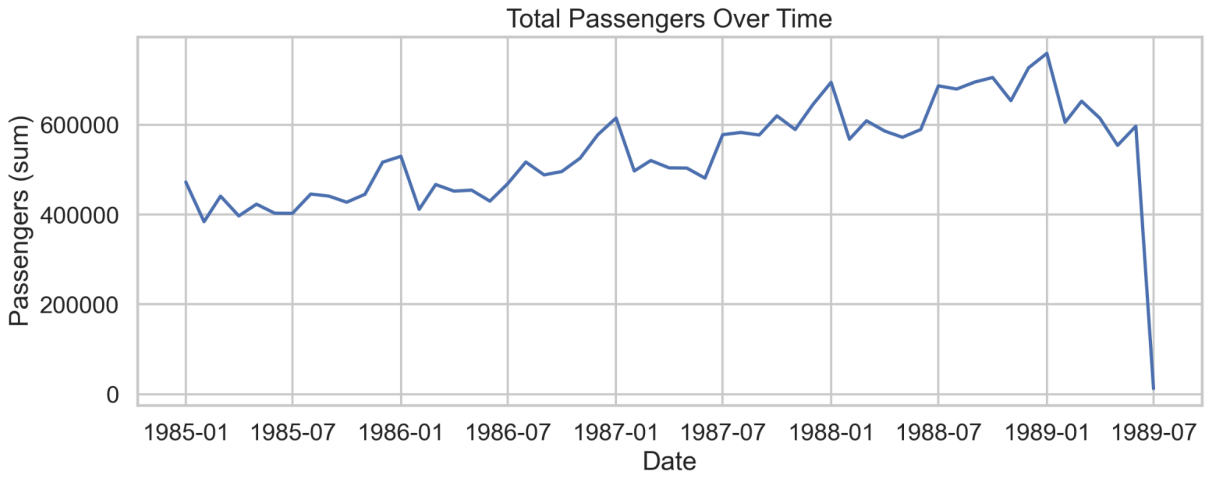
Looking at some of the city pairs, I realized that even though Sydney and Auckland had high passenger traffic coming in and out of it, the peaks and valleys were much more inconsistent compared to other Australian ports and Singapore. Routes connected to Singapore,

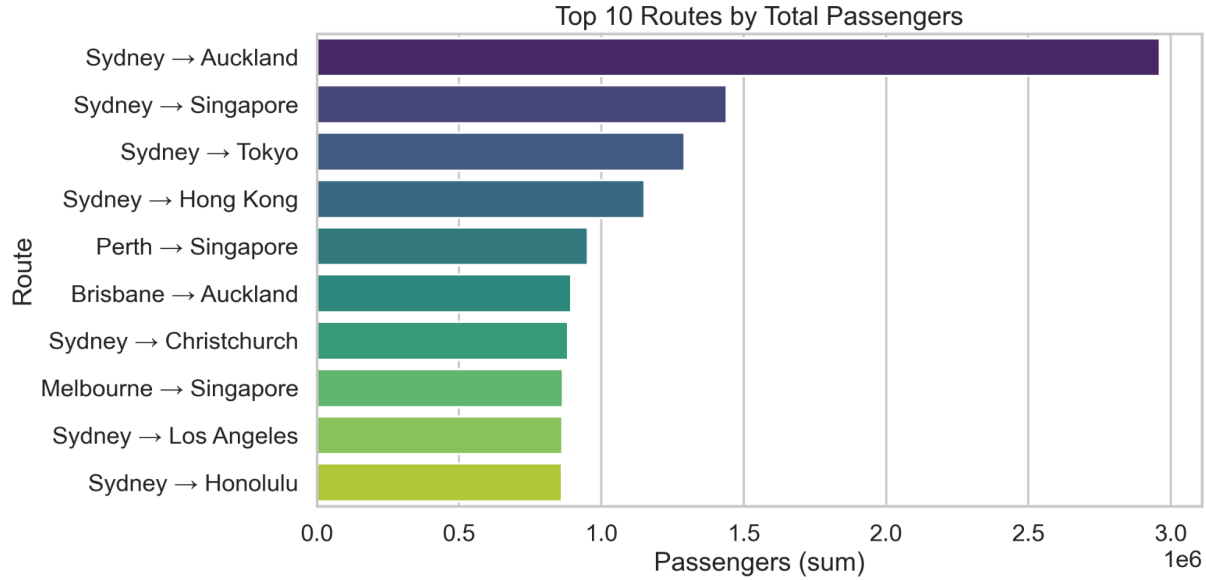
for example, displayed steadier growth patterns with smaller fluctuations, while Sydney and Auckland tended to swing up and down with sharper highs and lows. This suggests that while these two hubs were major traffic drivers, their demand was more volatile, whereas other ports maintained a more stable passenger flow.

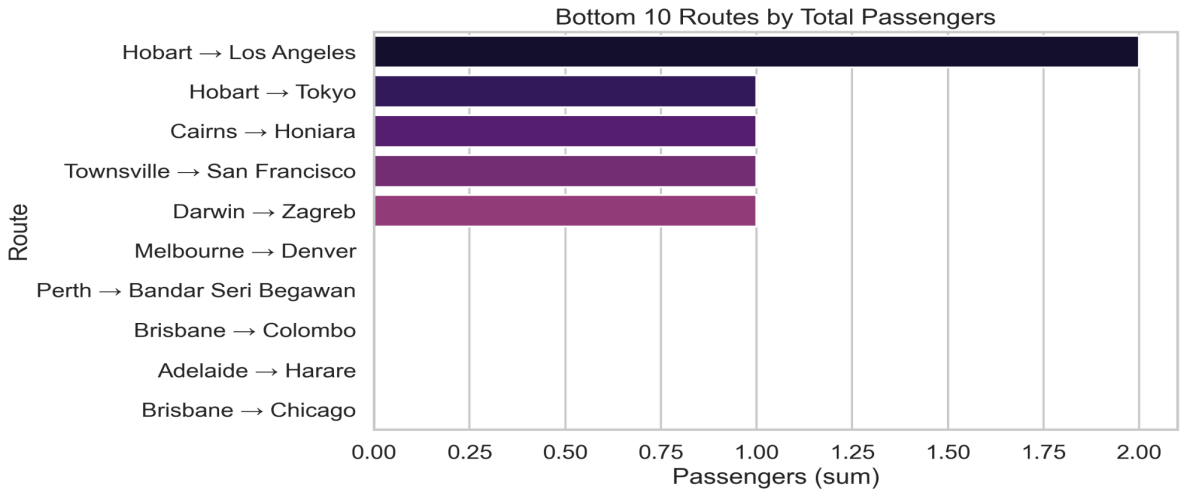
c) Create visualizations to demonstrate trends & patterns determined in part b



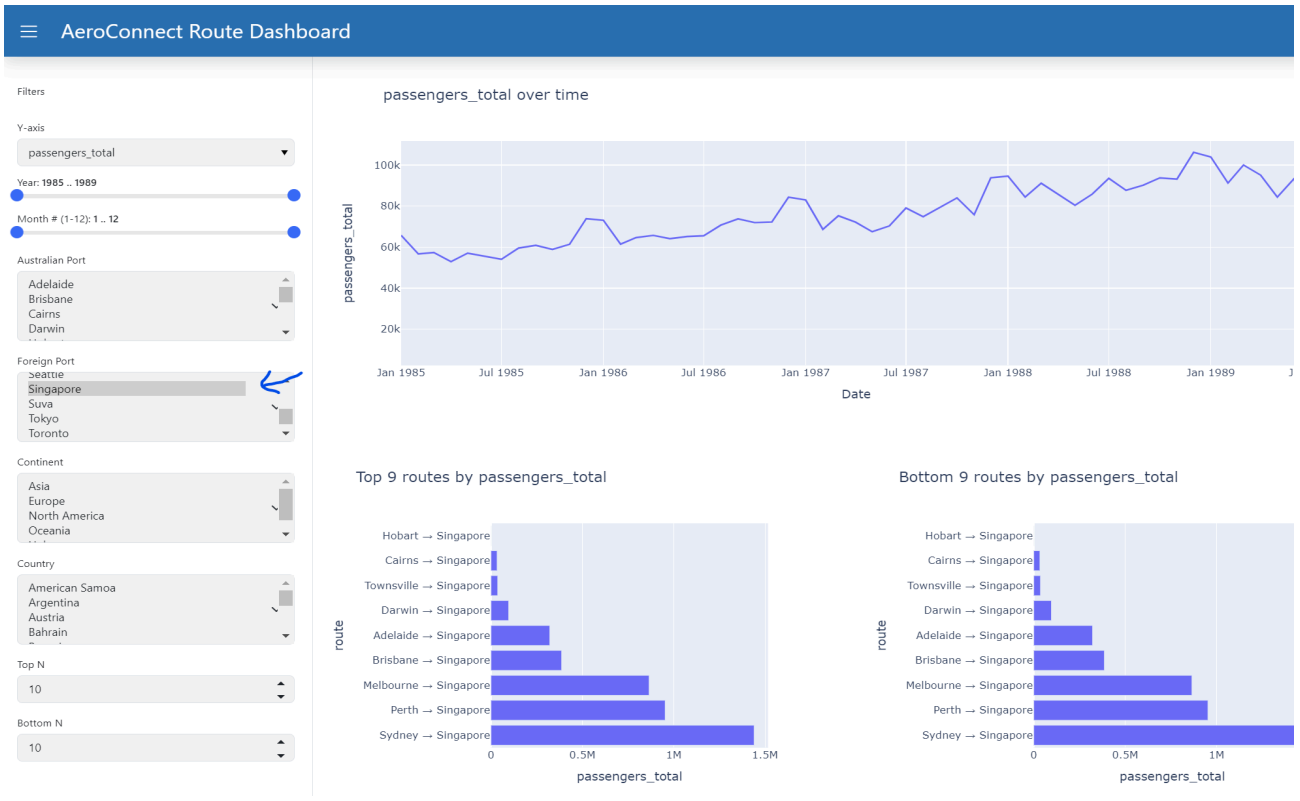



Total Passengers Over Time
Passengers (sum)
600000
400000
200000
0
1985-01
1985-07
1986-01
1986-07
1987-01
1987-07
1988-01
1988-07
1989-01
1989-07
Date

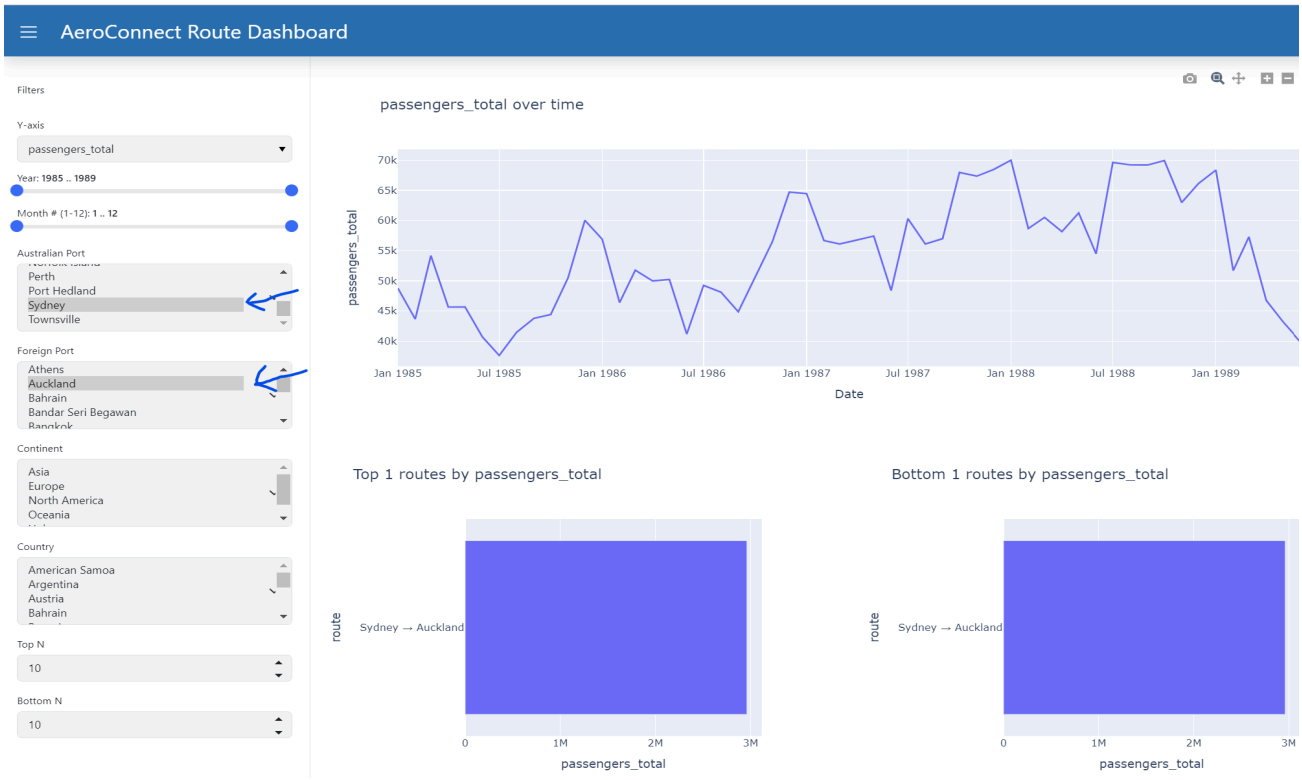

Top 10 Routes by Total Passengers
Route
Sydney → Auckland
Sydney → Singapore
Sydney → Tokyo
Sydney → Hong Kong
Perth → Singapore
Brisbane → Auckland
Sydney → Christchurch
Melbourne → Singapore
Sydney → Los Angeles
Sydney → Honolulu
0.0
0.5
1.0
1.5
2.0
2.5
3.0
1e6
Passengers (sum)



From my Dashboard:



(Shows passenger totals overtime when foreign port is just Singapore)



(Shows passenger totals overtime when australian port is Sydney and foreign port is Auckland)

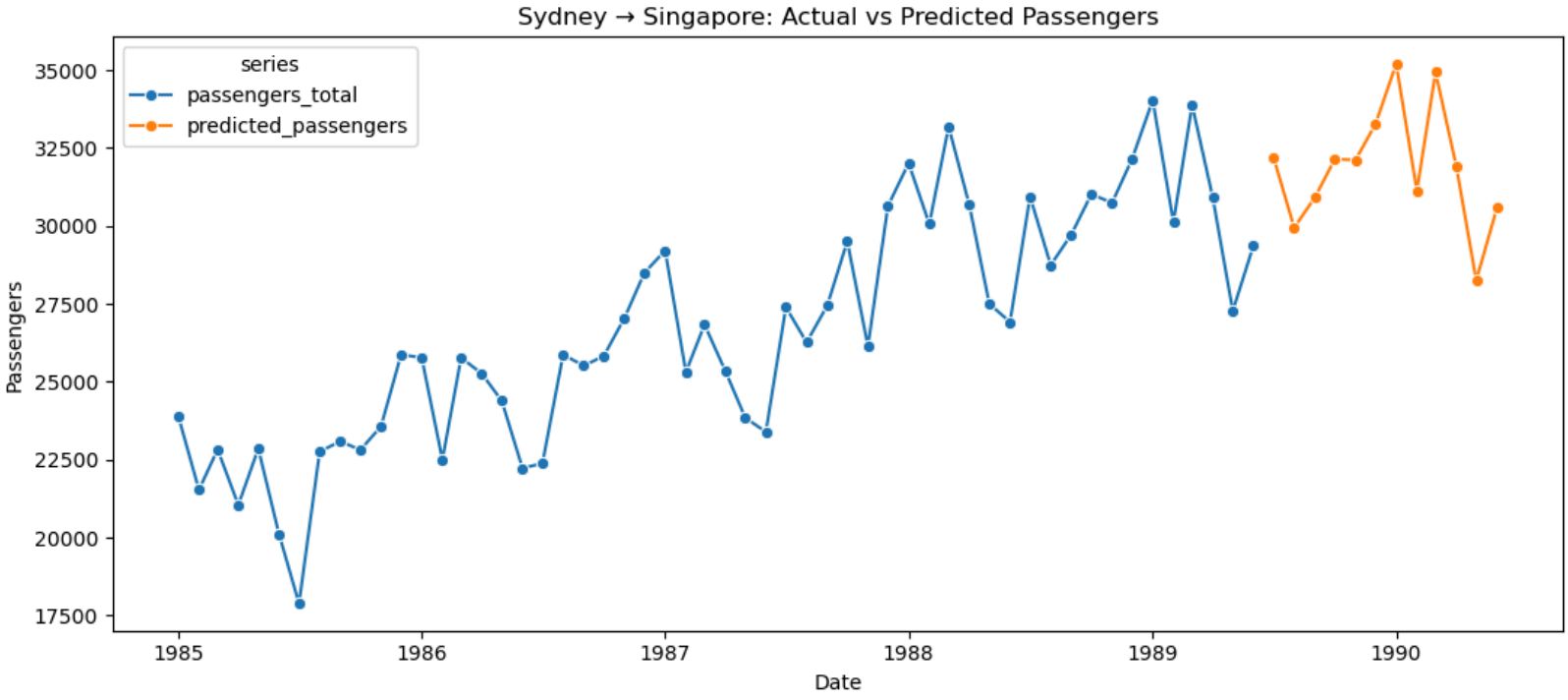
2. Build a Model

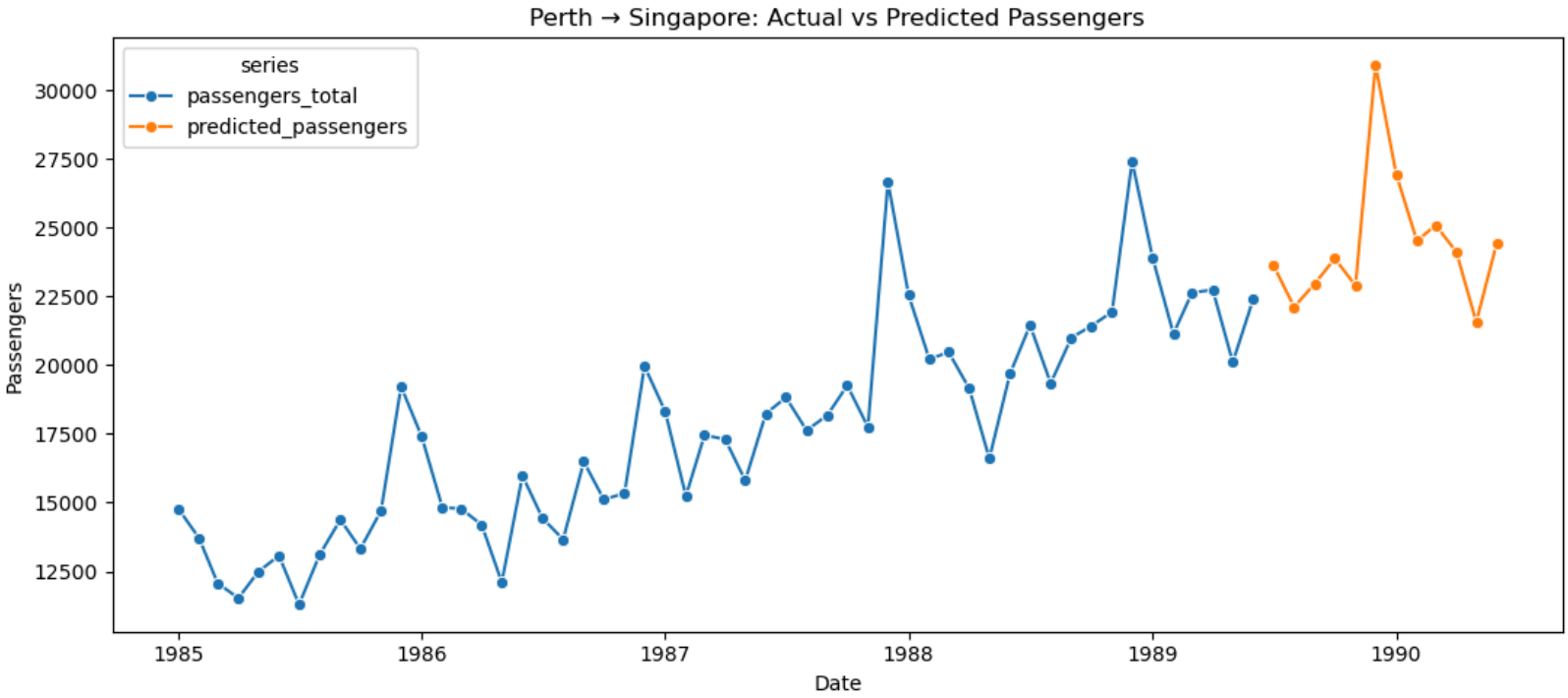
a) Your model should predict passenger traffic for the next 6–12 months on at least 1 city pair

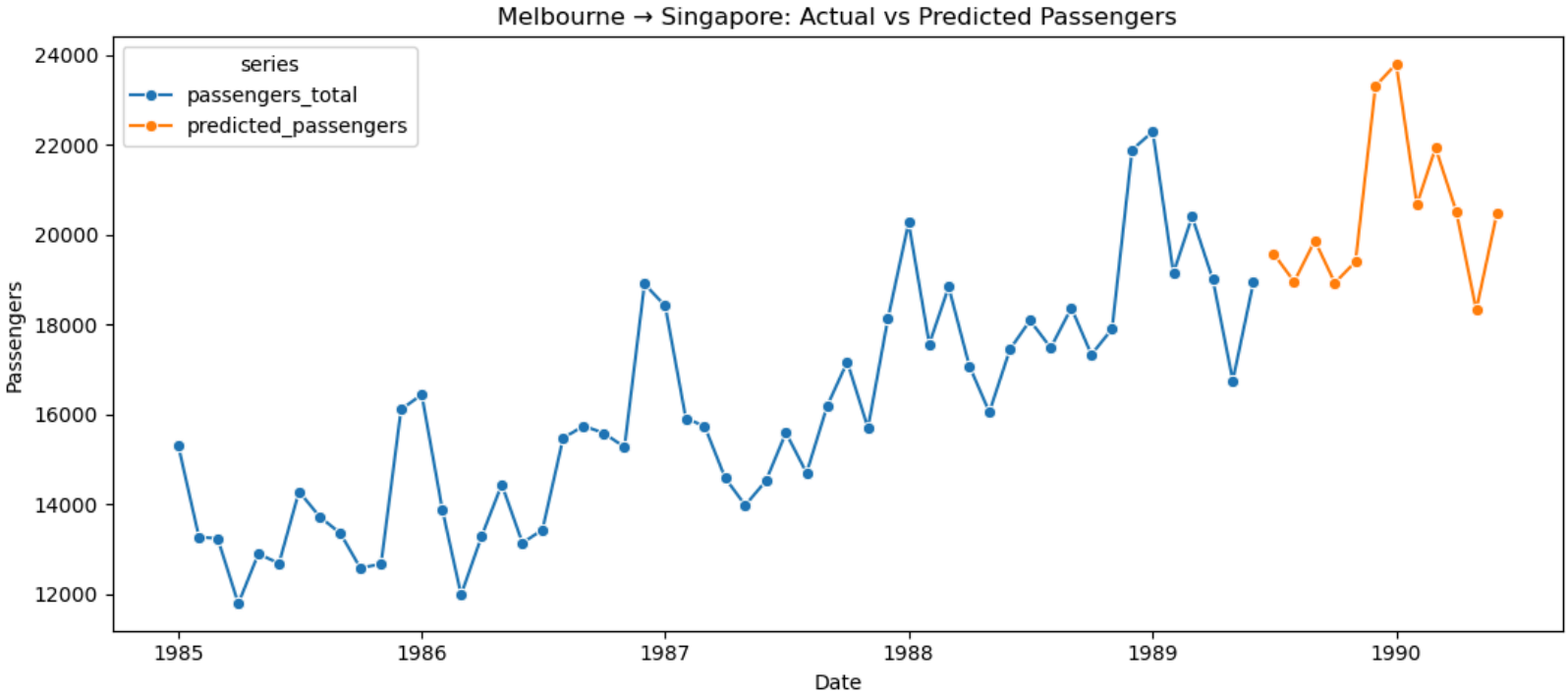
Route	Predicted Values

Sydney → Singapore	date,predicted_passengers 1989-07-01,32214.94978365379 1989-08-01,29946.52182835597 1989-09-01,30914.875699718177 1989-10-01,32144.011213272002 1989-11-01,32119.40948811096 1989-12-01,33271.43043930177 1990-01-01,35203.398531082596 1990-02-01,31125.65066205877 1990-03-01,34938.40685201779 1990-04-01,31928.49870923276 1990-05-01,28255.009916558243 1990-06-01,30576.39882423147
Perth → Singapore	date,predicted_passengers 1989-07-01,23635.24694511035 1989-08-01,22119.1472940862 1989-09-01,22973.9846010786 1989-10-01,23884.19797783349 1989-11-01,22894.209824491398 1989-12-01,30932.616970102787 1990-01-01,26957.72063424316 1990-02-01,24524.268311174546 1990-03-01,25098.250808383484 1990-04-01,24136.848722573646 1990-05-01,21573.40742096973 1990-06-01,24461.113379907718

Melbourne → Singapore	date,predicted_passengers 1989-07-01,19586.15555620497 1989-08-01,18957.834204548155 1989-09-01,19874.15192767809 1989-10-01,18931.6935209761 1989-11-01,19405.4885926266 1989-12-01,23314.531613760228 1990-01-01,23807.06062815905 1990-02-01,20679.79186770392 1990-03-01,21935.519381369024 1990-04-01,20524.813789733027 1990-05-01,18329.285088366396 1990-06-01,20482.91493940039







3. **Evaluate your model**

   a) Explain your model choices — why did you choose the elements you did

   Since the dataset was related to time series and each point update on a monthly basis, I knew that a model that accounts for seasonal change needed to be employed for this data. I knew linear regression wasn't going to work here since it doesn't account for volatile

peaks and valleys in seasonal data like this and only tries its best to fit the data based on the standard deviation, outliers, and residuals of the data. So I decided SARIMA was the best fit here, especially for city pairs with Singapore since the general trend each year is very stable.

The parameters I used in this model for the non-seasonal order was (1,1,1), where **p=1** (first parameter) was for one autoregressive term, meaning that the current value depends partly on the most recent month. For **d=1** (second parameter), since the time series plot had a general upward trend, I wanted to use first differencing to remove any long-term trend that could distort the stationarity of the series (since the mean is continually increasing). Finally, **q=1** (third parameter) accounted for one moving average term, which allowed the model to capture and correct patterns in the residual errors from prior time steps.

For the seasonal order, the explanations are very similar to non-seasonal order, and I used (1,1,1,12). Here, **P=1** (first parameter) included one seasonal autoregressive term, which lets the model use the same month of the prior year as a predictor. **D=1** (second parameter) applied seasonal differencing, which helps remove repeating yearly cycles and stabilizes the mean across seasons. **Q=1** (third parameter) introduced one seasonal moving average term, so the model could account for error terms from the same season in the past. Lastly, **s=12** (fourth parameter) was chosen because the dataset was monthly and clearly had annual seasonality, with consistent peaks during December/January and dips in February.

Since I was able to use the short term (p,d,q) and seasonal (P, D, Q, s) components, the SARIMA model was able to capture the month to month fluctuations and the larger yearly patterns observed in the past, making stable seasonal trends extremely accurate.

b) Evaluate the model's performance & report the accuracy of the model

Overall, the model did an excellent job in predicting the city pairs of Melbourne, Perth, and Sydney with Singapore. Their mean average percent error (MAPE) was between 2 to 4%, which means that the predicted monthly passenger counts were, on average, only slightly off from the actual values. This shows how accurate the model is when there's a consistent seasonal trend shown. I found this value by splitting the data by training the first four years of the data (1985-1988) and testing the first six months of 1989.

While the Singapore tests were successful, this model wasn't as accurate when predicting the passenger traffic for Sydney to Auckland as the relative maximums and minimums did not occur on the same months each year, and 1989 showed unusual volatility for this specific route that the model couldn't unfortunately account for. Overall, the model will perform well on time series trends where seasonality is stable and repeats across multiple years and might struggle slightly when there's not a consistent pattern each season.