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Airline Demand Forecasting

Summary

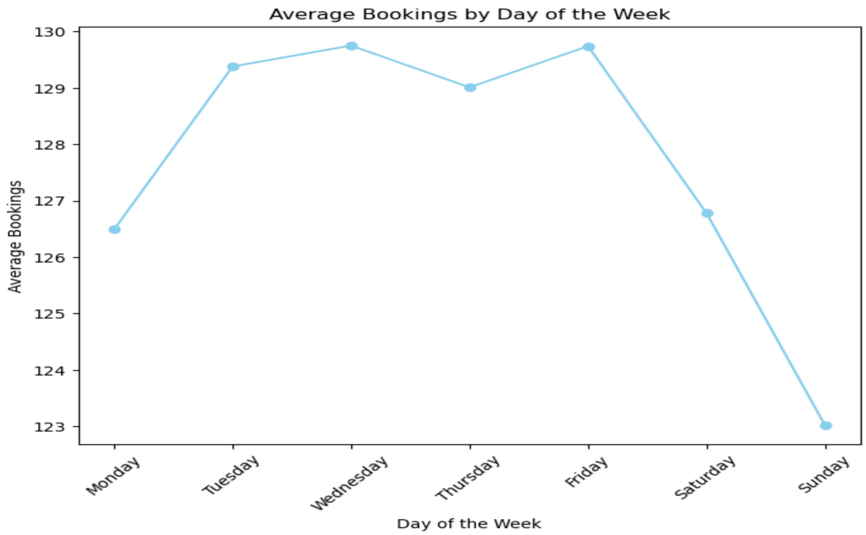
In this analysis, we used two different forecasting approaches to evaluate the performance of booking predictions for an airline. The first approach involved a basic model, which did not account for the day of the week, while the second model incorporated the day of the week to adjust forecasts based on booking patterns observed throughout the week.

The second forecasting method incorporates several strategic steps that collectively contribute to a lower MASE (Mean Absolute Scaled Error) of 0.634 especially for the additive model. The key improvement comes from introducing the day-of-week variation, which is a significant factor in booking behavior. Through the code, after converting the date columns and calculating days' prior, the final demand was determined based on bookings confirmed on the day of departure. This was crucial for understanding the real-time booking situation and served as the reference point for forecasting future demand. By using historical data averages for each day of the week (as calculated by grouping by days prior), the model could adjust its predictions more accurately, factoring in known trends. This is particularly important because booking behavior is not uniform and can vary significantly depending on the day, time of the week, or season.

The additive forecast method further improved the accuracy by adding the remaining demand to the cumulative bookings, which proved to be a better fit for the data in this case. By considering the variation in demand across the days of the week, the additive model was able to provide a more precise forecast, as it adjusted the predicted booking curve to reflect these fluctuations. The incorporation of day-of-week effects allowed the additive forecast to adapt to periods of higher or lower demand, such as the higher bookings observed on Fridays and Wednesdays.

In contrast, the multiplicative forecast, which used the average booking rate, did not fully capture these fluctuations and was less accurate, resulting in a higher MASE of 1.63**.** This indicates that while the multiplicative model accounted for overall booking trends, it missed out on the more nuanced day-of-week patterns that the additive model could leverage.

The booking curve by day of the week illustrates the average cumulative bookings across different days, providing insights into how booking behavior varies throughout the week. From the graph, we can observe that bookings are generally higher towards the middle of the week, particularly on **Friday**, **Thursday**, and **Wednesday**, suggesting that customers tend to finalize their bookings more frequently as the week progresses. In contrast, bookings are lower at the beginning of the week, particularly on **Sunday** and **Monday**, which might indicate that customers tend to book later in the week, possibly closer to the departure date. This pattern could be influenced by factors such as weekend planning or last-minute booking behavior. The shape of this curve is useful for understanding booking trends and can aid in demand forecasting, helping airlines optimize their capacity and pricing strategies. By recognizing peak booking days, airlines can adjust their marketing and pricing strategies to maximize bookings during these high-demand periodsBy recognizing that bookings fluctuate depending on the day of the week—higher on Fridays and Wednesdays, and lower on Sundays—the model is able to capture the natural cyclical patterns of demand that were missed by a more simplistic approach.



Thus, by incorporating day-of-week patterns, and using the additive method, the model was able to better fit the data and generate forecasts that closely matched the actual booking behavior, which in turn resulted in a lower MASE. This explains why the second model, especially with the additive method**,** outperforms the first one, providing more reliable and accurate predictions