1. Method

What was your approach?

The original dataset is duplicated and partitioned at various points to facilitate randomized testing at a later stage. The AutoARIMA algorithm is employed to identify the optimal parameters for the predictive model. Subsequently, cross-validation is performed using a rolling forecast approach, where forecasts are generated over a horizon of seven time steps. The rolling mechanism advances in increments of four steps, with an initial training window size set to 180 observations (6 months) prior to the dataset's end. This approach ensures that model performance is systematically evaluated across the dataset.

Guided by the optimal parameters determined by AutoARIMA, a refined rolling forecast procedure is implemented to assess the performance of various hyperparameter combinations within a defined range around the AutoARIMA-selected values. Given the high volatility of the dataset, root mean squared error (RMSE) is chosen as the evaluation metric to compare parameter effectiveness. Once the most suitable hyperparameters are identified, they are incorporated into the final model, which is then tested against the previously generated random test data. The model's performance is subsequently recorded and stored for further analysis.

1. Project Results

Outcome

The absolute mean error (AME) of the final time series model is 14,681, while the root mean squared error (RMSE) is 18,678. The mean absolute percentage error (MAPE) is 11.35%. To derive meaningful insights, these metrics must be compared with those obtained from the two alternative forecasting approaches—machine learning and deep learning.

Problems

The primary drawback of AutoARIMA is that its computational time and resource consumption increase significantly with the length of the seasonal period. This is due to the algorithm's exhaustive search through all possible parameter combinations to determine the optimal model configuration. For extended forecasting horizons, such as 30 days (one month) or 365 days (one year), the seasonal period must be appropriately scaled, further amplifying computational demands.

1. Conclusion

Areas of improvement

Cross-validation using a rolling forecast across the entire dataset is ideal but is constrained by limited computational resources. With sufficient computational capacity, the range of hyperparameters tested for RMSE evaluation could be expanded beyond the typical range of 0 to 2, allowing for a more comprehensive search. Additionally, the step size of the rolling forecast could be reduced below 4, enabling more frequent sampling and improving the accuracy of cross-validation results.

Future Work/ Outlook

Alternative time series analysis methods, such as Exponential Smoothing and SARIMAX, should be explored to identify the most effective model. With increased computational power, the seasonal period could be extended up to 365 days, potentially improving forecasting accuracy for longer time horizons.