

This project focuses on forecasting daily hotel room demand for seventeen United States hotel properties using a comprehensive set of statistical, machine learning, neural, and foundation model approaches. The primary goal is to compare model performance, evaluate forecasting accuracy across multiple time series, and ultimately produce twenty-eight-day forecasts using the best-performing techniques. All requirements from the ISA 444 Final Project guidelines are met, including the use of five-fold non-overlapping time-series cross-validation, implementation of all required forecasting methods, reporting of standard error metrics, creation of forecast visualizations, and saving of results in clearly labeled CSV files.

The dataset used is `sample_hotels.parquet`, which contains daily demand observations for seventeen properties. Each observation includes the hotel's unique identifier, the date, and the demand value. The project applies a diverse group of forecasting models. Statistical methods include Naive, Seasonal Naive, autoETS, and autoARIMA implemented through the StatsForecast package. Machine learning forecasting is completed using LightGBM within MLForecast, utilizing lag features and calendar-based predictors. Neural forecasting models include AutoNBEATS and AutoNHITS implemented through NeuralForecast. A modern foundation model called Chronos, specifically the chronos-bolt-small version from Amazon, is also included using the TimeCoPilot framework, allowing transformer-based sequence forecasting without the need for an API key.

All models are evaluated using a consistent five-fold non-overlapping cross-validation design with a twenty-eight-day forecast horizon. For each fold and for each model, four evaluation metrics are calculated: Mean Error, Mean Absolute Error, Root Mean Squared Error, and Mean Absolute Percentage Error. These metrics are reported for each individual hotel and also stored in combined comparisons. A model "win count" is calculated by identifying the model with the lowest MAE for each hotel. Chronos achieves the highest number of MAE wins overall, showing strong performance across the properties, while NBEATS and NHITS also perform competitively, especially for hotels with clear weekly seasonality patterns. The statistical benchmarks and LightGBM models perform reasonably well but are generally outperformed by neural and foundation models in this dataset.

After completing the cross-validation evaluations, all models are retrained on the full dataset to generate the final twenty-eight-day forecasts. These results are consolidated into one dataframe that includes predictions from every model. The combined forecasts are exported as `final_forecasts_28days.csv`. Additional CSV files contain the full cross-validation metrics, mean error calculations, model win counts, and other evaluation outputs. Visualizations are produced for each of the seventeen hotels, showing historical demand along with the forecast horizon so that patterns, errors, and model differences can be easily interpreted.

All code for the project is contained within the final notebook and is organized to clearly separate model training, evaluation, visualization, and exporting workflows. The environment requires standard forecasting and data science libraries, including numpy, pandas, statsforecast, mlforecast, neuralforecast, lightgbm, timecopilot, utilsforecast, and matplotlib. The project was built and executed in Google Colab.

This repository provides a complete and thorough forecasting comparison study that follows the expectations of ISA 444. It includes the notebook, documentation, evaluation results, final forecasts, and visualization assets. For any follow-up questions or clarification, please reach out through Canvas or GitHub.