Electricity Consumption Forecasting

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Outlines

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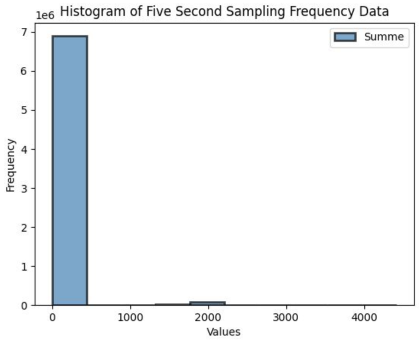
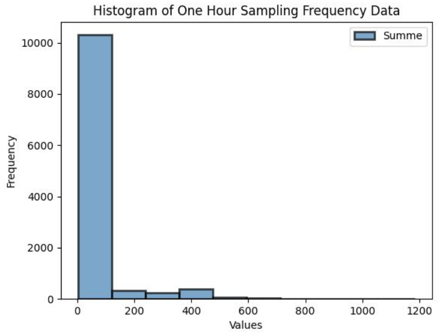
Problem statement

The goal of this project is to develop a system that analyzes energy consumption patterns and forecasts future energy peaks. The system aims to identify devices, such as smart washing machines or pool pumps, that can be rescheduled to lower-priced time slots to save energy costs. By leveraging historical consumption data and real-time energy price charts, the system provides personalized recommendations to optimize device usage and promote energy efficiency. The system empowers users to make informed decisions, reducing costs and conserving energy.

Data Analysis

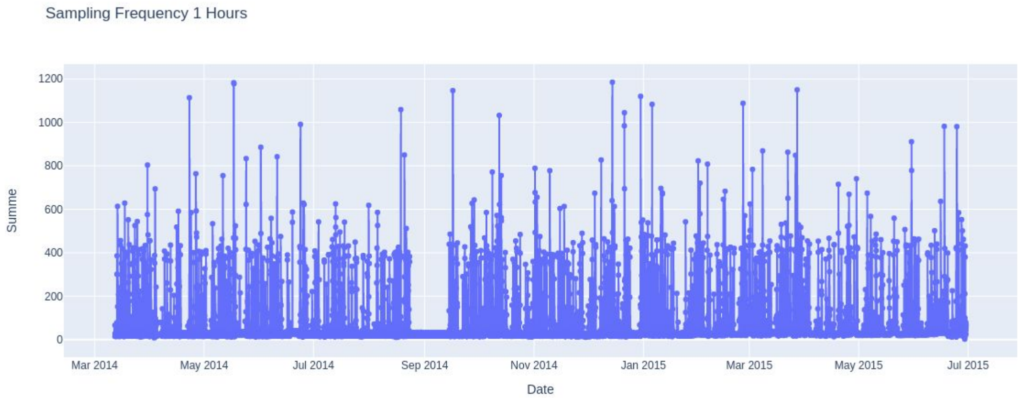
- Data Available:
  - From 2014-03-12 07:52:42 to 2015-06-29 21:49:14 have 5 second sample Frequency.
- Data Distribution
  - The histogram plot provides information about the distribution of values in the dataset. It visualizes the frequency or count of values falling into different bins or intervals. From the histogram, you can observe the shape, central tendency, and spread of the data. It helps in understanding the data's overall pattern and identifying any potential outliers or unusual behavior

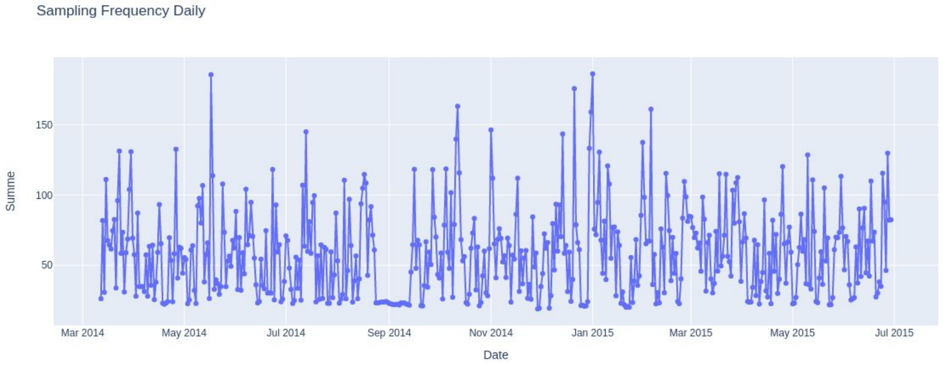




Data Visualization

By analyzing plots with different sampling frequencies allows us to understand the data at various levels of detail, identify different patterns and trends, and assess the data's stability and noise characteristics. This information helps in making informed decisions about data analysis, modeling, and forecasting





Models : ARIMA

SARIMA (Seasonal AutoRegressive Integrated Moving Average)

SARIMA is a popular and widely used model for time series forecasting. It is an extension of the ARIMA model that incorporates seasonality into the analysis. SARIMA takes into account the **autoregressive (AR)**, **moving average (MA)**, and **differencing (I)** components of the time series data. It can handle both trend and seasonality in the data, making it suitable for capturing complex patterns. SARIMA requires tuning of hyperparameters such as the order of autoregressive, moving average, and seasonal components, as well as the seasonal period.

Models : XGBoost (Extreme Gradient Boosting)

XGBoost (Extreme Gradient Boosting)

XGBoost is a powerful and versatile machine learning algorithm that has gained popularity in time series forecasting tasks. It is an ensemble learning method that combines multiple decision trees to make accurate predictions. XGBoost is known for its excellent performance, scalability, and ability to handle complex feature interactions. It can capture both linear and nonlinear relationships in the data. XGBoost requires tuning of hyperparameters such as the number of trees, learning rate, and maximum tree depth

Models: LSTM (Long Short-Term Memory)

LSTM (Long Short-Term Memory)

LSTM is a type of recurrent neural network (RNN) that is particularly effective for modeling and predicting sequential data, including time series. LSTM networks are designed to overcome the limitations of traditional RNNs by incorporating memory cells and gates that selectively retain and forget information over long sequences. This allows LSTM to capture long-term dependencies in the data and handle vanishing or exploding gradients. LSTM can automatically learn relevant features from the data and is suitable for handling complex temporal patterns. However, LSTM models can be computationally expensive and require careful tuning of hyperparameters such as the number of LSTM layers, hidden units, and dropout rates

Evaluation Metrics : MAE (Mean Absolute Error)

- MAE (Mean Absolute Error)
  - MAE measures the average absolute difference between the predicted values and the actual values. It represents the average magnitude of the errors without considering their direction. MAE is calculated by taking the average of the absolute differences between each predicted value and its corresponding actual value. A lower MAE indicates better accuracy and closer alignment between the predicted and actual values.
  - **Interpretation**: An MAE of, for example, 10 means that, on average, the predictions deviate from the actual values by 10 units. It provides a measure of the absolute prediction error magnitude.

Evaluation Metrics : RMSE (Root Mean Squared Error)

- RMSE (Root Mean Squared Error)
  - RMSE is a commonly used error metric that measures the square root of the average squared difference between the predicted values and the actual values. RMSE gives higher weight to larger errors, making it more sensitive to outliers or large deviations. It is calculated by taking the square root of the average of the squared differences between each predicted value and its corresponding actual value. A lower RMSE indicates better accuracy and closer alignment between the predicted and actual values.
  - **Interpretation**: An RMSE of, for example, 15 means that, on average, the predictions deviate from the actual values by 15 units, taking into account the squared errors

Evaluation Metrics : MAPE (Mean Absolute Percentage Error)

- MSE (Mean Squared Error)
  - MAPE measures the average percentage difference between the predicted values and the actual values. It calculates the absolute percentage difference for each prediction and takes the average of these values. MAPE is often used when dealing with relative errors or when the scale of the data varies significantly.
  - **Interpretation**: An MAPE of, for example, 5% means that, on average, the predictions deviate from the actual values by 5% of the actual values. It provides a measure of the relative prediction error percentage.

Evaluation Metrics : MSE (Mean Squared Error)

- MSE (Mean Squared Error)
  - MSE measures the average squared difference between the predicted values and the actual values. It is calculated by taking the average of the squared differences between each predicted value and its corresponding actual value. MSE is commonly used as it amplifies larger errors more than MAE and provides a measure of the prediction error variance.
  - **Interpretation**: An MSE of, for example, 225 means that, on average, the predictions deviate from the actual values by 225 units, considering the squared errors.

When interpreting these error metrics, it's important to consider the context and scale of the data. Lower values for MAE, RMSE, and MSE indicate better accuracy, while lower values for MAPE indicate better relative accuracy. These metrics help assess the performance of the forecasting models and can guide the selection and evaluation of the best model for the given time series dataset.

Results

No	ModelName	MAE	RMSE	MAPE (Error in %)	Interactive Plots
1	ARIMA	51.85	100.344	110.97	plots
2	Prophet	48	98.22	96.54	plots
3	XGBOOST	73.00	120.83	184	plots
3	LSTM	30.08	93.46	29	plots

From these results, we can make the following observations:

- The LSTM model outperforms the other models in terms of MAE, RMSE, and MAPE. It has the lowest values for these error metrics, indicating better accuracy in forecasting the time series data.
- The ARIMA and Prophet models have similar performance, with relatively higher errors compared to LSTM. They show higher MAE, RMSE, and MAPE values, suggesting less accurate predictions
- The XGBoost model has the highest errors among the four models, indicating the least accuracy in forecasting the time series data.
- Considering both accuracy and interpretability, the LSTM model seems to be the most suitable for forecasting the time series data in this scenario.

Why LSTM is better than other models?

The logical reasons why LSTM (Long Short-Term Memory) models can be considered better than ARIMA, Facebook Prophet, and XGBoost models in certain scenarios are as follows:

1. **Capturing Complex Patterns**: LSTM models, as a type of recurrent neural network (RNN), are designed to capture long-term dependencies and intricate patterns in sequential data. Unlike ARIMA, which assumes linearity and struggles with non-linear data, LSTM models excel at capturing complex non-linear relationships. This makes LSTM models suitable for datasets with intricate patterns and non-linear trends.

2. **Handling Long-Term Forecasts**: ARIMA and XGBoost models can sometimes struggle with long-term forecasts due to their limited memory and inability to capture long-range dependencies effectively. LSTM models, on the other hand, are specifically designed to address this limitation by maintaining a memory of past information over long sequences. Consequently, LSTM models can often provide more accurate long-term forecasts compared to ARIMA and XGBoost.

3. **Handling Multiple Input Features**: While ARIMA is a univariate model, Facebook Prophet and XGBoost can handle multiple input features to incorporate external factors. However, LSTM models are inherently designed to handle and learn from multiple input features. By considering the interactions between various features, LSTM models can potentially capture more complex relationships and improve forecasting accuracy.

4. **Handling Non-Stationary Data**: ARIMA assumes that the data is stationary, meaning its statistical properties remain constant over time. If the data is non-stationary, ARIMA may produce inaccurate forecasts. In contrast, LSTM models can handle non-stationary data as they can learn and adapt to changing patterns over time. This makes LSTM models more suitable for datasets with evolving trends and irregularities.

Why LSTM is better than other models?

The logical reasons why LSTM (Long Short-Term Memory) models can be considered better than ARIMA, Facebook Prophet, and XGBoost models in certain scenarios are as follows:

5. **Adaptability to Data Characteristics**: LSTM models are highly flexible and can be trained on a wide variety of data types, including time series with irregular intervals or missing values. They can handle outliers and noise in the data, making them robust in the presence of data imperfections. This adaptability allows LSTM models to be applied to a broader range of forecasting scenarios compared to ARIMA, Facebook Prophet, and XGBoost.

It is important to note that the superiority of LSTM models over other models may not be absolute and depends on various factors, including the specific dataset, data characteristics, and modeling objectives.