Predicting Electricity Usage: Deliverable 2

Data Extraction, Processing, Initial Modeling, Model Comparison, Error Reports

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Agenda

Introduction

Data

Variables

Pre-Modeling

Modeling

Results




Introduction

Problem

What will energy consumption look like after 2014?

Objective

Predict energy consumption after 2014 using data from 2011-2014

From:

Raw uncleaned dataset 'LD2011_2014.txt'

To:

Trained models with performance analysis

Value Creation

Evaluate the accuracy of a forecasting model on the data

Predict post-2014 energy consumption

Clean raw dataset so it is usable for other forecasting models

Data

Data Extraction

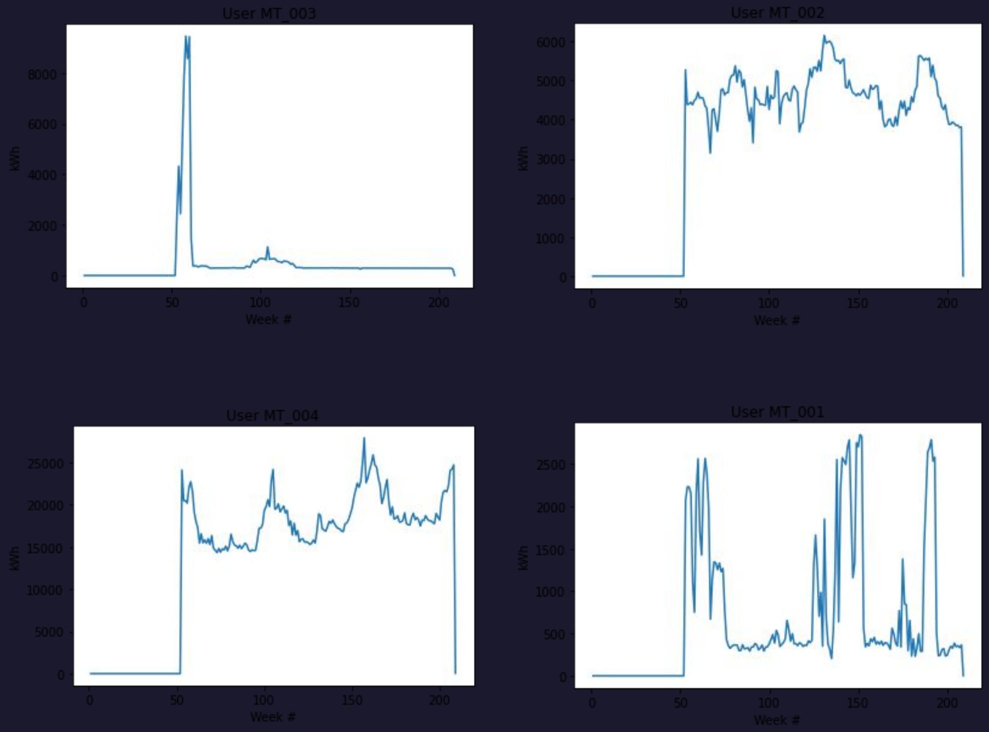
- Source: https://archive.ics.uci.edu/ml/datasets/ElectricityLoadDiagrams20112014#
    - Dataset is in a .zip file; extraction yields a .txt file
    - Text file delimited by ";"
    - Decimal values encoded as 0,00
    - Values in kW per 15 minutes - to convert to kWh, values must be divided by 4
    - Missing values ie) accounts created during the timeframe are encoded with zeros
    - Biannual time change results in either one hour of zeros or aggregation, depending on the season

- Shape of (140256, 370), or 140,256 rows and 371 columns (one for Datetime, 370 accounts)
- Head of raw data:

	Datetime	MT_001	MT_002	MT_003	MT_004	MT_005	MT_006	MT_007	MT_008	MT_009	...	MT_365	MT_366	MT_367	MT_368	MT_369	MT_370
0	2011-01-01 00:15:00	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0
1	2011-01-01 00:30:00	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0
2	2011-01-01 00:45:00	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0
3	2011-01-01 01:00:00	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0
4	2011-01-01 01:15:00	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0

Data Processing

- Data Extraction Process
  - Read entire dataset delimited by “;” into pandas DataFrame object
- Data Diagnostics
  - Dataset is clean (i.e. no duplicates, missing values, etc.)
  - Time change assumed not to affect overall trend (occurs every year)
- Modeling Preprocessing
  - Transform data into long pivot form
  - Divide all values by 4 to arrive at kWh, a unit of energy
  - Aggregate the dataset by account ID, year and week






Variables

Variables Overview

Target Variables	*Predictive Variables*

• Variable that is predicted in the forecasting model.
• Weekly usage of electricity in kWh is our "y."
• Denoted in DataFrame as *value*
	• Variables that predict target variable
	• Organized into direct or derived variables
	  ○ Direct variable: Directly from dataset
	  ○ Derived variable: Created by manipulating direct variables
	• All variables are direct

Predictive Variables Overview

- Initial model fit (SARIMA) does not use any exogenous variables
- SARIMA components (Autoregressive, Moving Average) use target variables at different lags, and weighted average forecast errors, as predictor variables, as well as a seasonal component.
- SARIMAX uses exogenous variables
    - ie) Holiday Week indicator, weather, additional seasonality component ie) quarterly, monthly
- The FB Prophet models trained did not use exogenous variables either



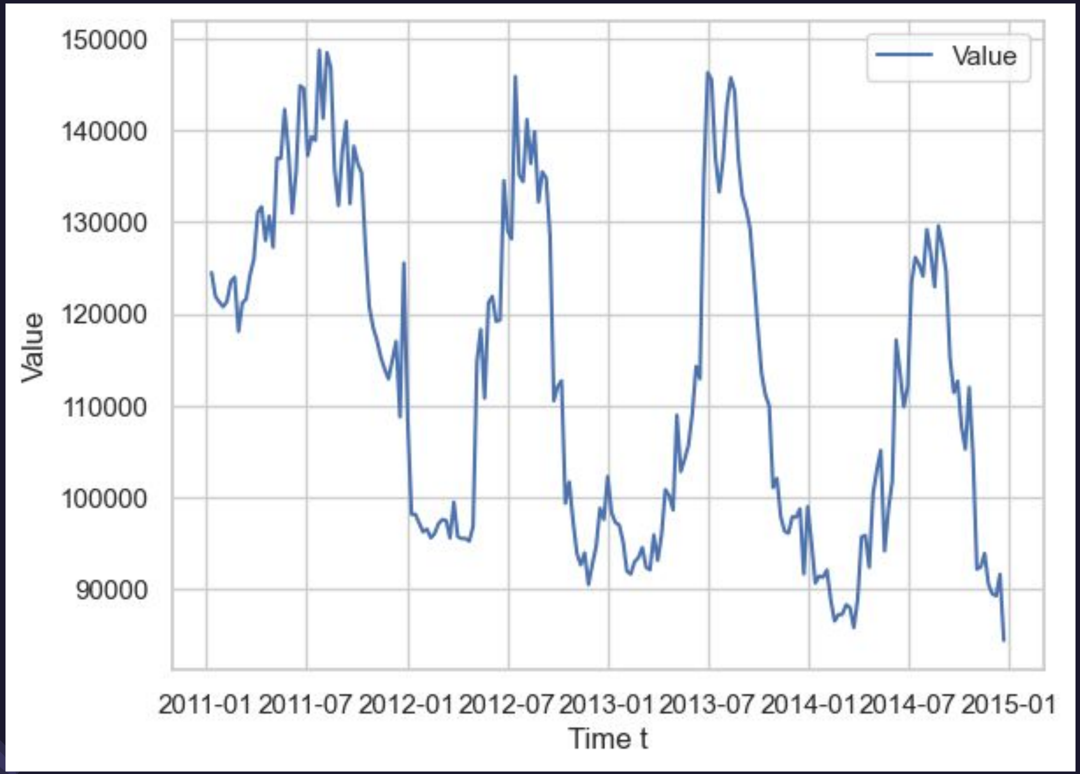

Pre-Modeling

Pre-Modeling

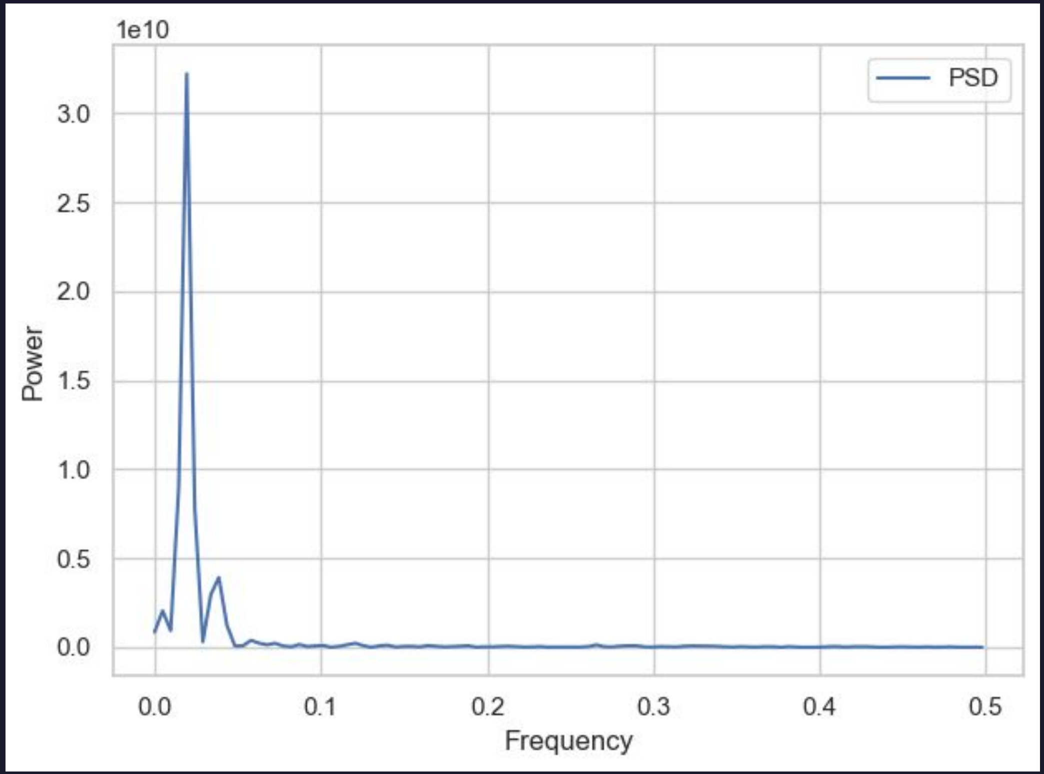
- Exploratory Data Analysis
  - Identify trend and seasonality in the data for initial modeling
  - Perform this exercise on all accounts aggregated, then apply the chosen model to each individual account
- Pre-Modeling Utility Functions
  - Create utility functions for train-validation-test split, MAPE, walk-forward validation, etc.

Pre-Modeling
Trend / Seasonality

Average Energy Use (kWh) - All Accounts

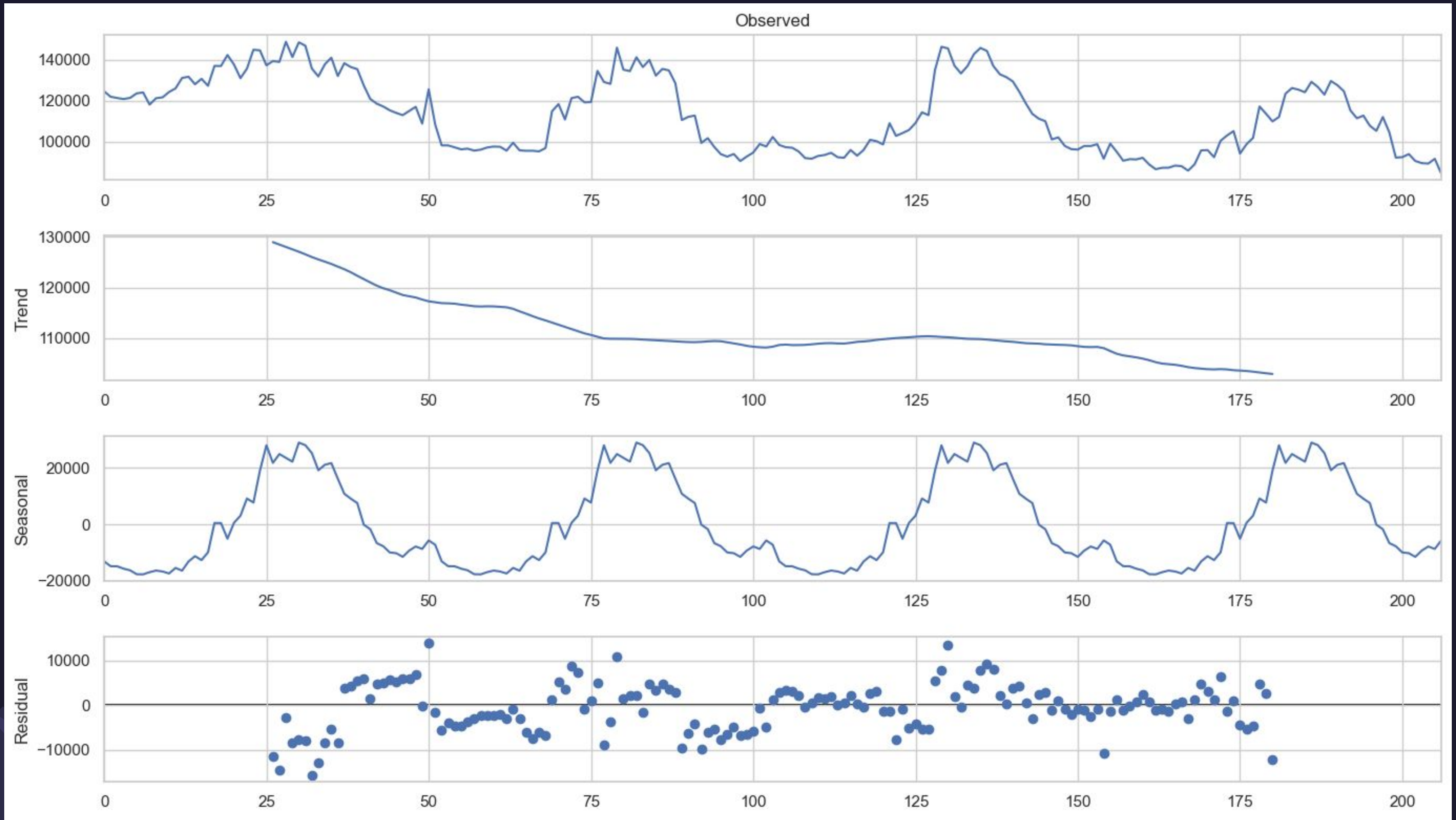


PSD of Average Energy Use



Time series plot and PSD indicate a first-order downward trend and yearly seasonality
Maximum power corresponds to a period of 51.75

Pre-Modeling
Seasonal Decomposition



- First order-trend indicates first-order differencing / integration component likely fits best on aggregated dataset
- Seasonal component appears to have a yearly period
- Initial choice for model parameters: SARIMA(0, 1, 1)(0, 1, 1)$_{52}$
- Hyperparameter tuning will be done




Modeling

Modeling

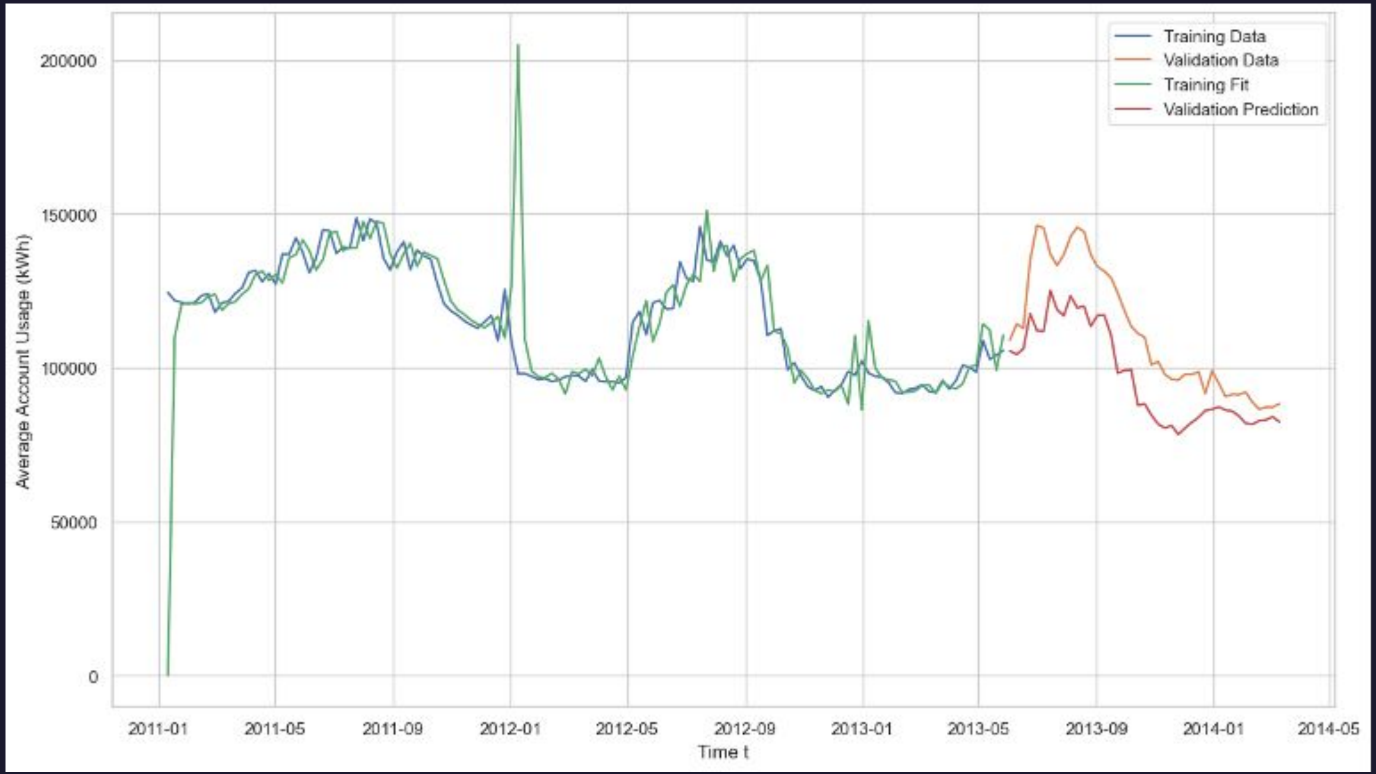
- Algorithmic Solution Design
  - Fit an initial model with SARIMA, Facebook Prophet
  - Evaluate MAPE on complete dataset and individual accounts
- Evaluation Metric
  - Mean Absolute Percentage Error (MAPE)
- Algorithmic Solution Finalization
  - Compare Predictions vs. Actual data to test the SARIMA model, Facebook Prophet, MAPE calculations by account
  - Report MAPE by 3 test regions for each model, compare the errors with box plots.
- Train-Validation-Test Split
  - Training Set: First 60% of Timeframe
  - Validation Set: Middle 20% of Timeframe
  - Test Set: Last 20% of Timeframe
  - Test set was divided into three equally sized regions




Results

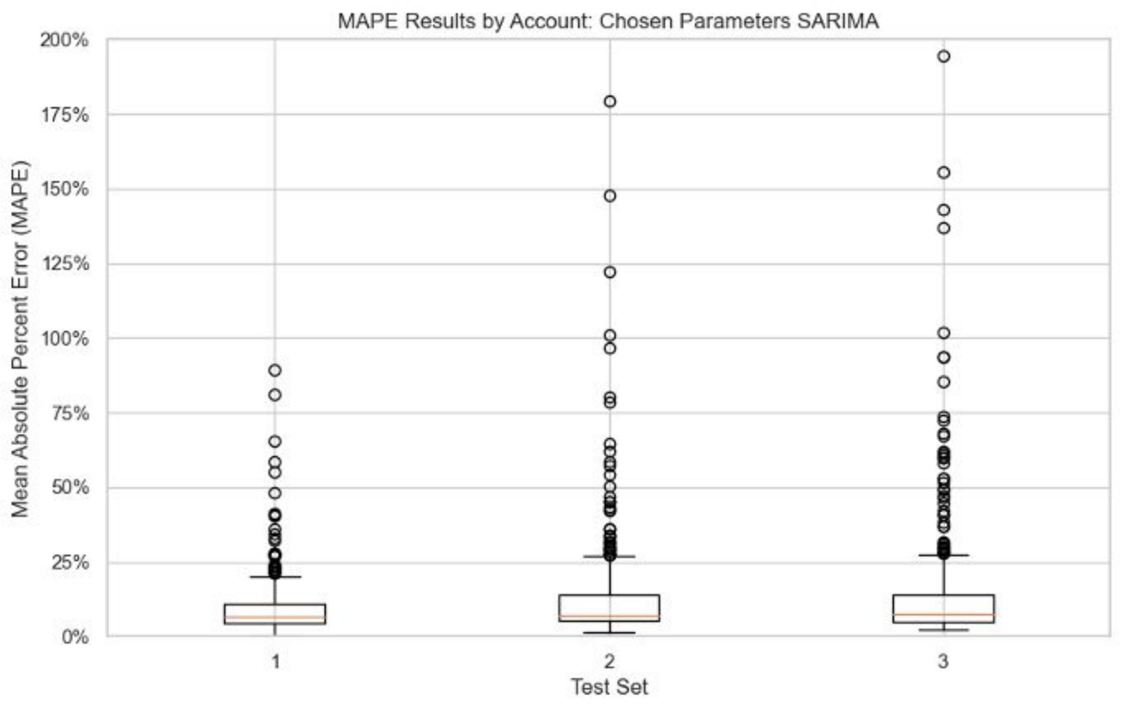
Results: SARIMA(0, 1, 1)(0, 1, 1)$_{52}$

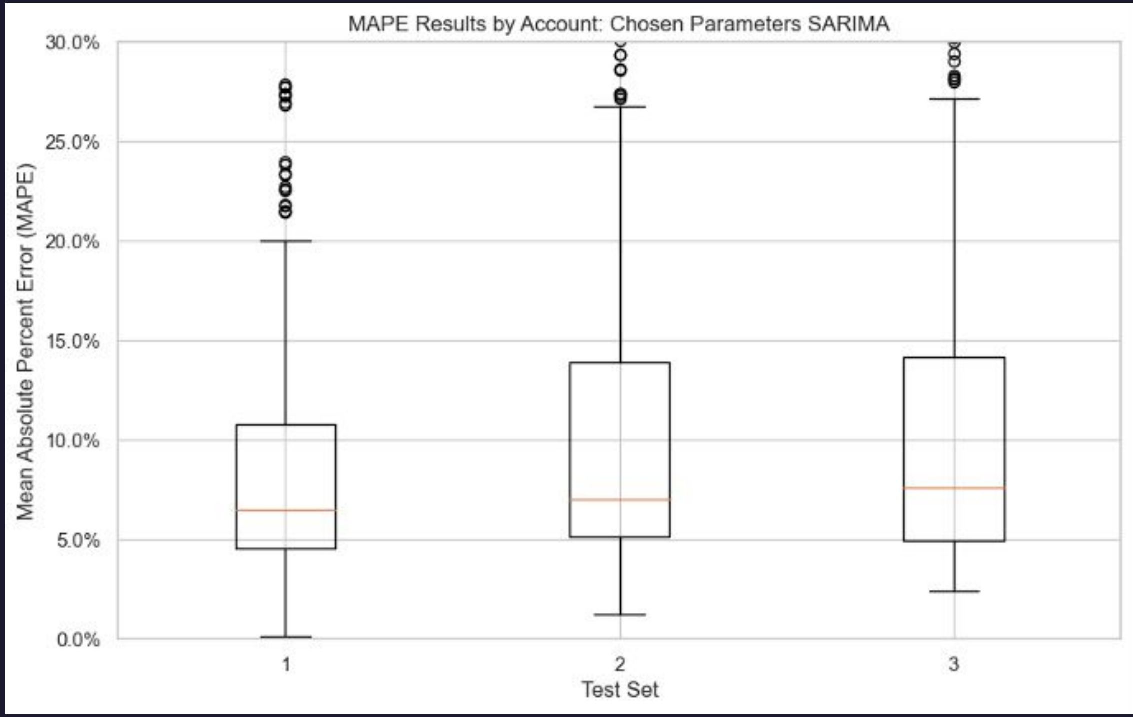
- Train-Validation-Test Split
  - Training Set: First 60% of Timeframe
  - Validation Set: Next 20% of Timeframe
  - Test Set: Last 20% of Timeframe
- Validation Set MAPE =12.8%



Results: SARIMA(0, 1, 1)(0, 1, 1)$_{52}$

- Test set was divided into three equal regions
- Median MAPE on Test Set:
- Region 1: 6.5%; Region 2: 7.0%; Region 3: 7.6%

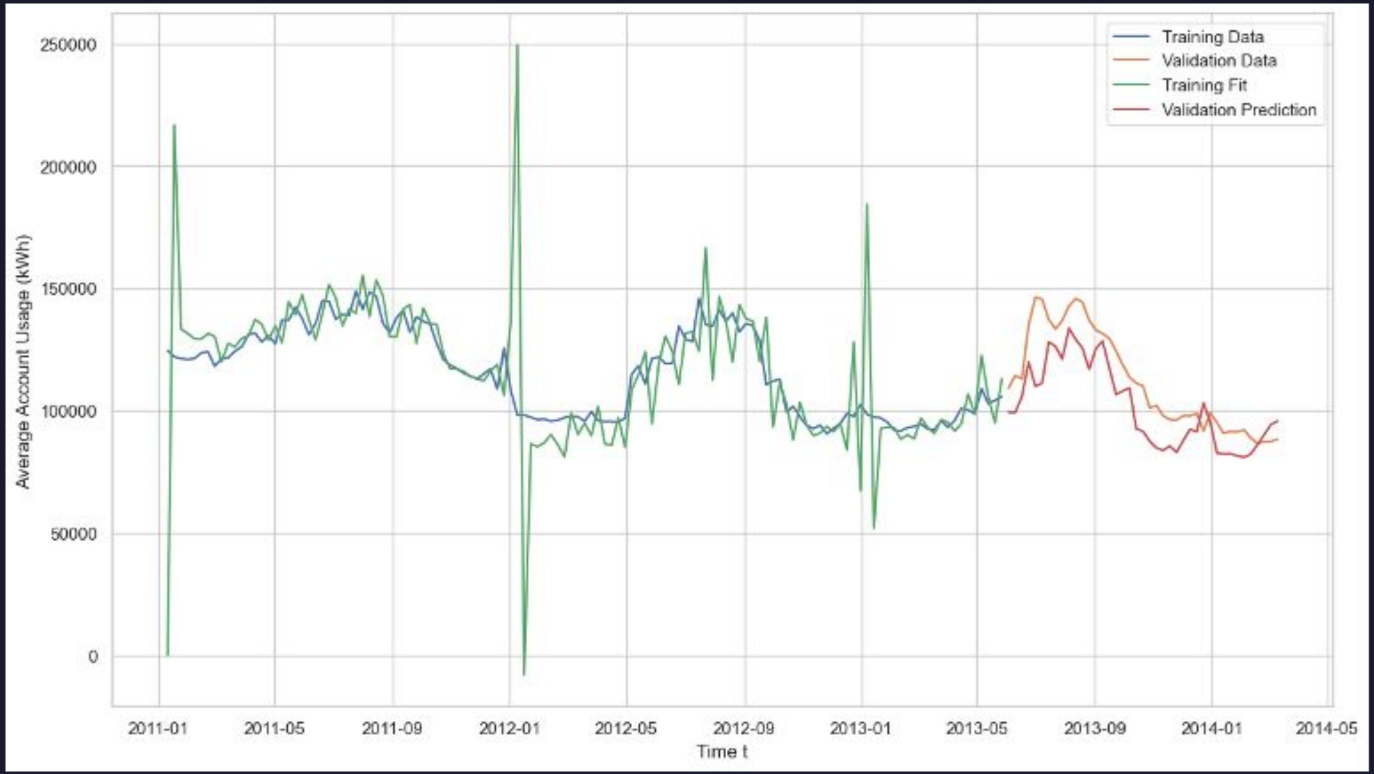




Results: Hyperparameter-Tuned SARIMA

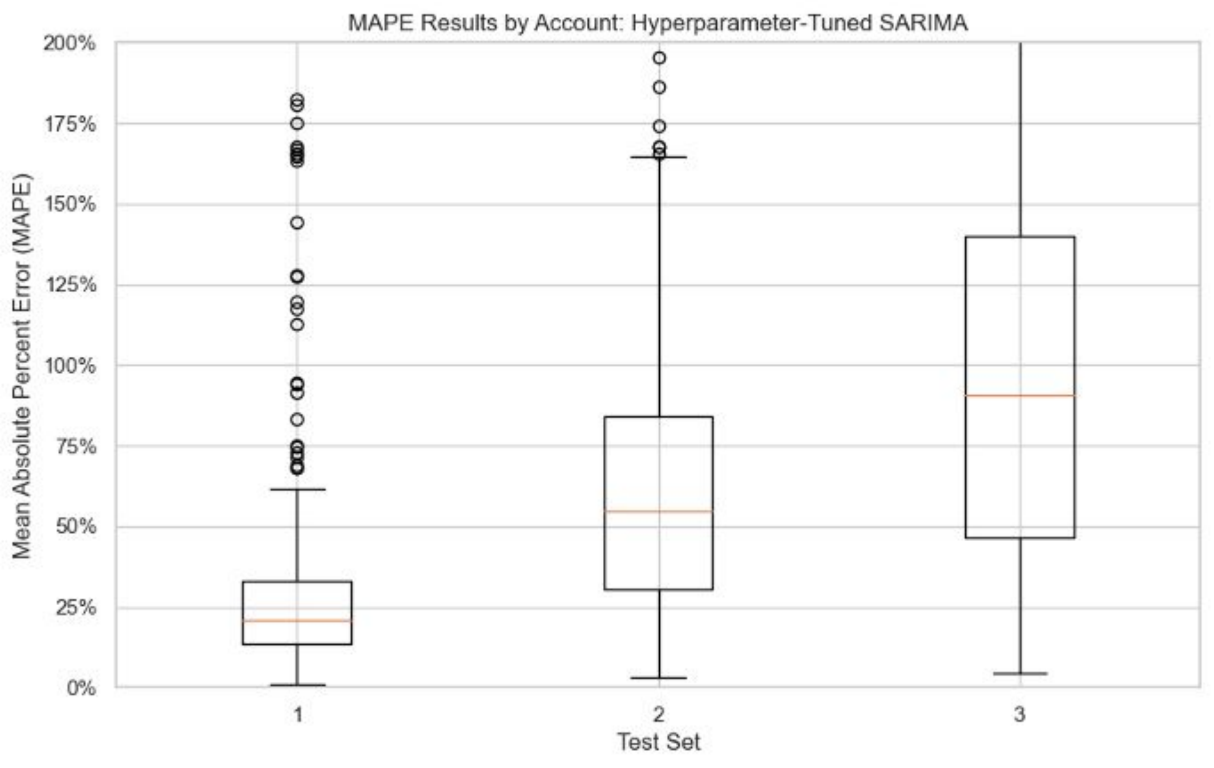
- Train-Validation-Test Split
  - Training Set: First 60% of Timeframe
  - Validation Set: Next 20% of Timeframe
  - Test Set: Last 20% of Timeframe
- Optimized Validation Set

  MAPE =10.4%



Results: Hyperparameter-Tuned SARIMA

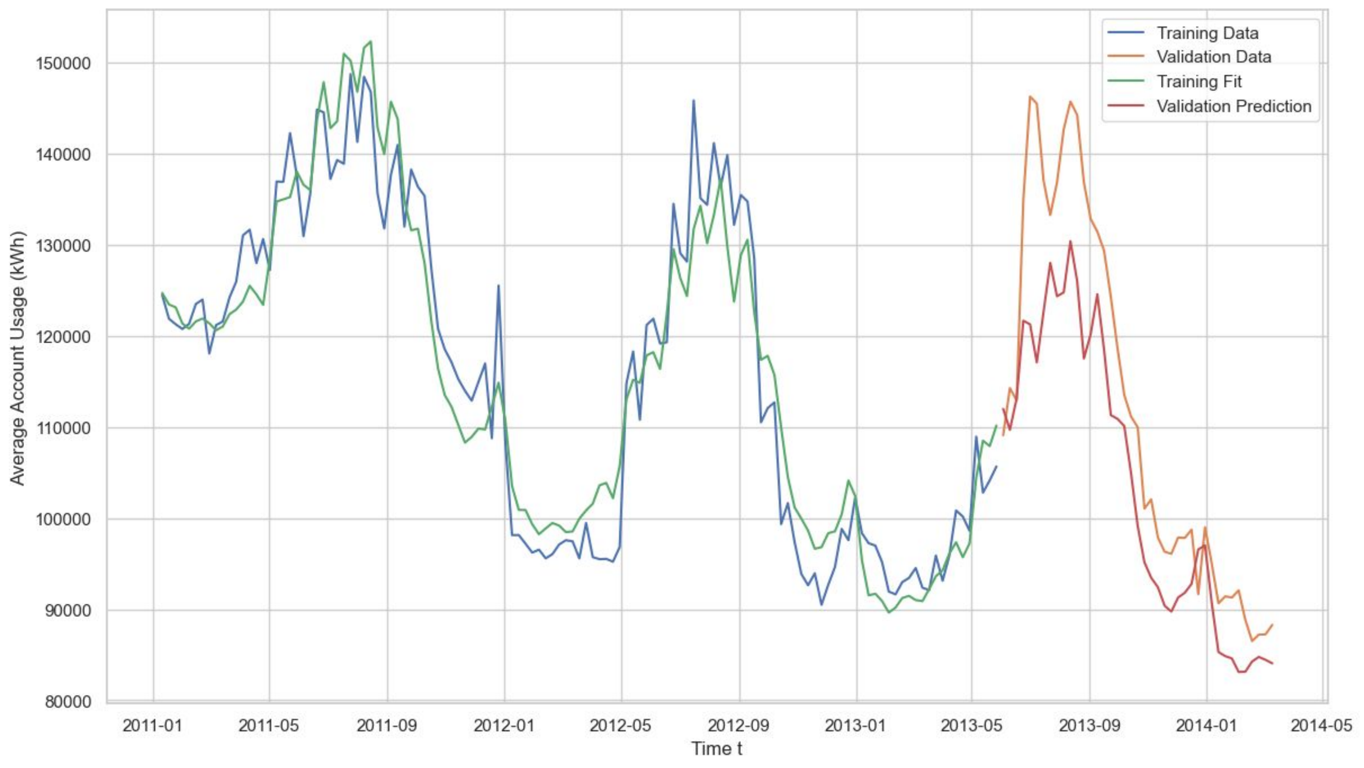
- Test set was divided into three equal regions
- Model: SARIMA(1, 2, 1)(1, 2, 1)$_{52}$
- Median MAPE on Test Set:
- Region 1: 21.1%
- Region 2: 54.8%
- Region 3: 90.6%



Results: FB Prophet - Chosen Parameters

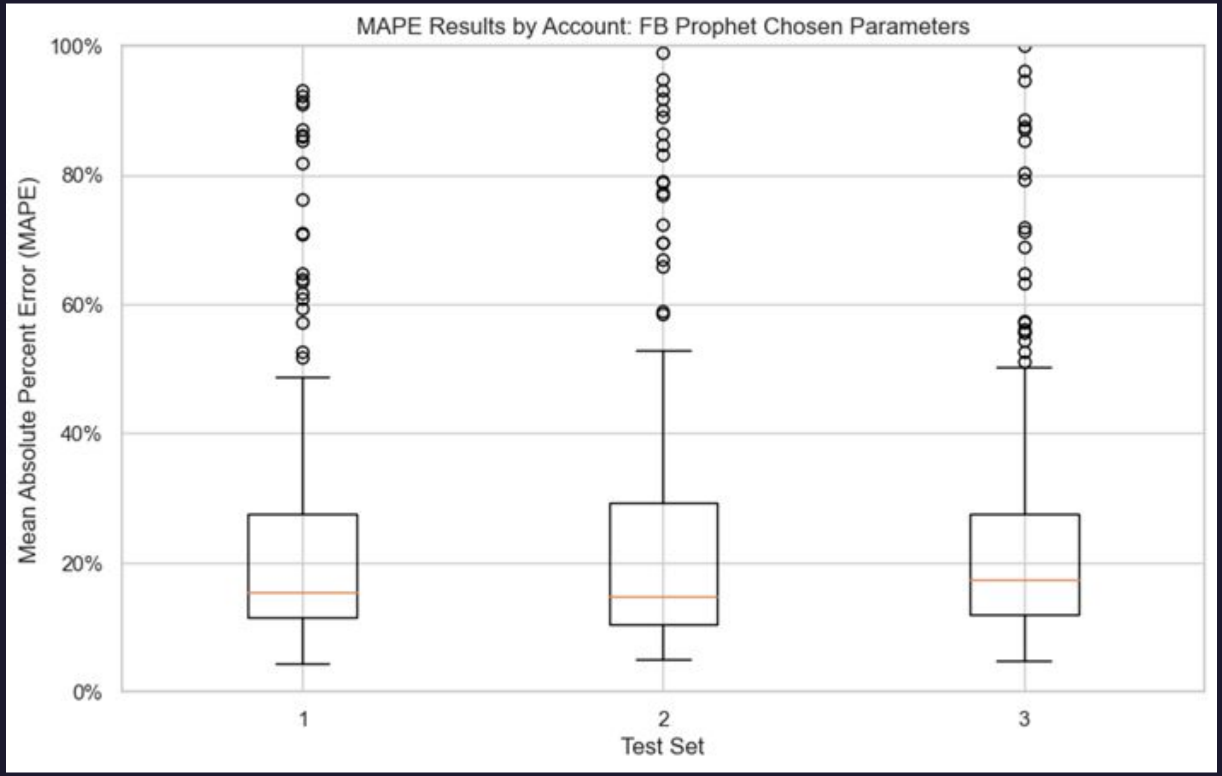
Model: Facebook Prophet
(period=365.25,
fourier_order=12,
monthly=False)

- Train-Validation-Test Split
  - Training Set: First 60% of Timeframe
  - Validation Set: Next 20% of Timeframe
  - Test Set: Last 20% of Timeframe
- Validation Set MAPE = 18.9%



Results: FB Prophet - Chosen Parameters

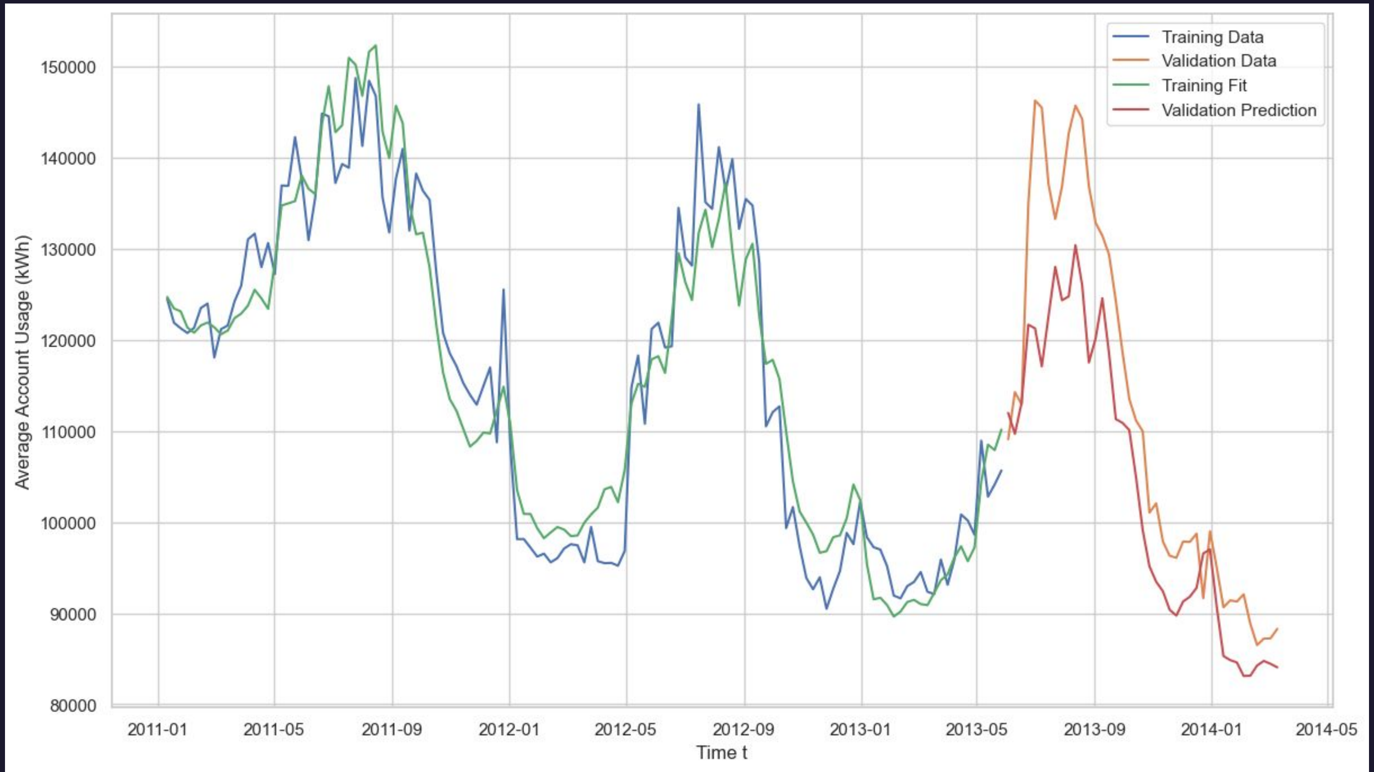
- Test set was divided into three equal regions
- Median MAPE on Test Set:
- Region 1: 15.4%
- Region 2: 14.8%
- Region 3: 17.4%



Results: Hyperparameter-Tuned FB Prophet

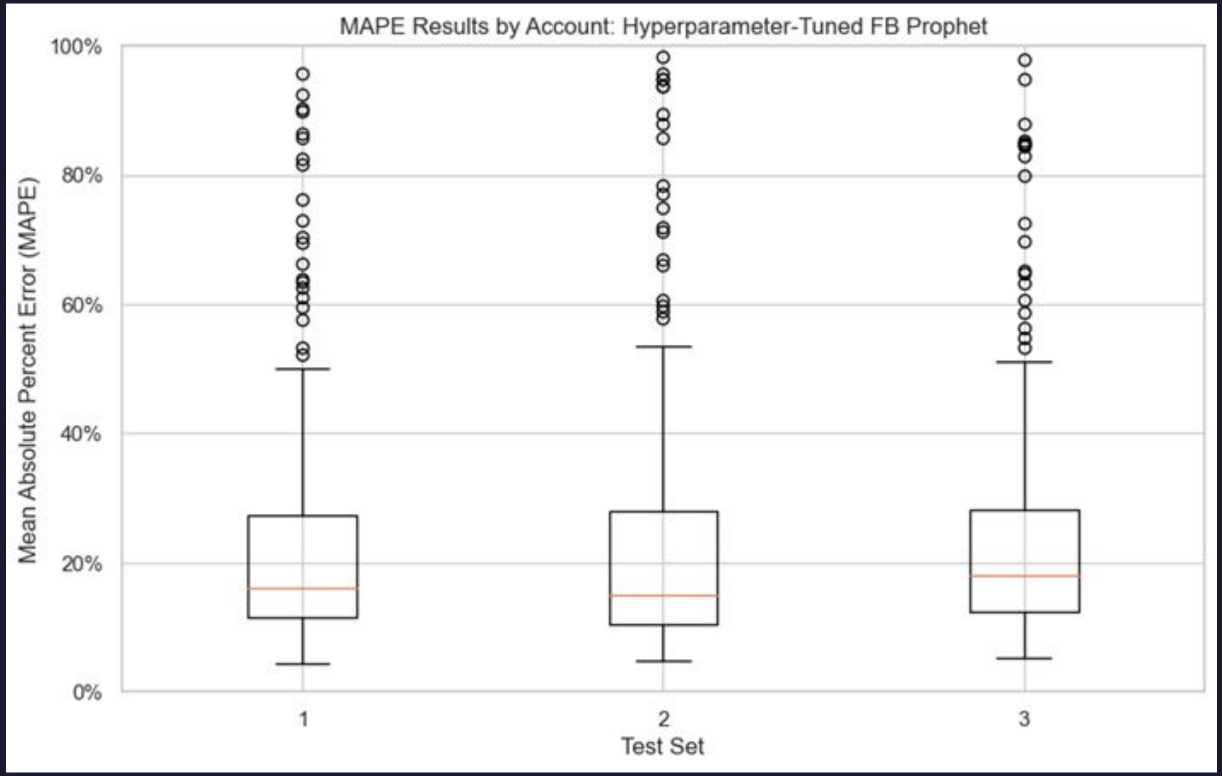
Model: Tuned FB Prophet

- Train-Validation-Test Split
  - Training Set: First 60% of Timeframe
  - Validation Set: Next 20% of Timeframe
  - Test Set: Last 20% of Timeframe
- Validation Set MAPE = 18.79%



Results: Hyperparameter-Tuned FB Prophet

- Test set was divided into three equal regions
- Model: Tuned Facebook Prophet
- Median MAPE on Test Set:
- Region 1: 16.02%
- Region 2: 14.91%
- Region 3: 18.11%



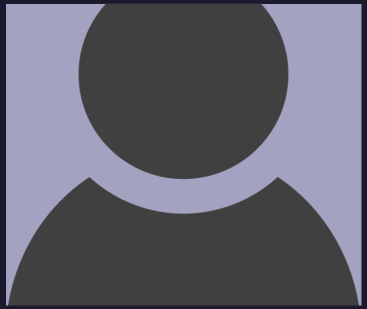
Results Summary

Model	Aggregated Data Cross-Validation MAPE	Test Set 1 MAPE	Test Set 2 MAPE	Test Set 3 MAPE
SARIMA $(0, 1, 1)x(0, 1, 1)_{52}$	12.8%	6.5%	7.0%	7.6%
SARIMA $(1, 2, 1)x(1, 2, 1)_{52}$	10.4%	21.1%	54.8%	90.6%
FB Prophet: Chosen Parameters	18.9%	15.4%	14.8%	17.4%
FB Prophet: Hyperparameters Tuned by Account	N/A	16.0%	14.9%	18.1%

Future Ideas

- Incorporation of Exogenous Variables to Transform SARIMA -> SARIMAX:
  - Since the SARIMA model performed the best on the test set, continuing with this model would be wise. Creation of time-based features such as holiday indicators, or other exogenous variables such as average monthly temperature, could help improve model performance.
- Other Models:
  - Trying other models on the data, including neural networks, could improve the performance of the model on the test set.

Team



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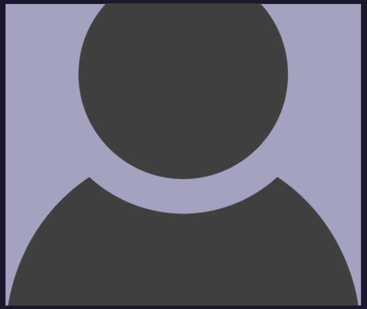

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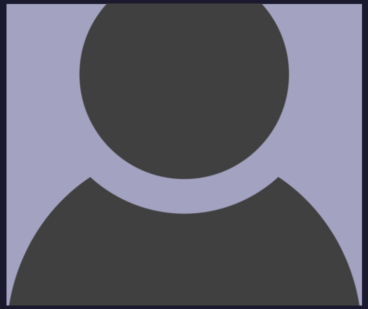

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