GILEAD
Creating Possible

GnA DNA Intern Project

Forecasting SPARC Request Volumes

Meeting Agenda

Things I Learned

Regression, SQL, Starburst, Time Series Models

Project Overview

Forecasting SPARC Service Request Volume

Data Analysis and Model Selection

EDA (Exploratory Data Analysis), Regression, Fourier series modeling & final model selection

Model Tuning

Hyperparameter Tuning

Results

Accuracy and performance on historicals and 90-day forecast windows

Things I learned

Regression, SQL, Starburst, Time Series Models

- *Time Series Models*
  - *Trend, Seasonality, Confidence Intervals*
- *Data Analysis*
  - *Periodogram, Seasonality, Trends, Volumes*
- *Querying Data via SQL*
- *Data Cleaning*
- *Hyperparameters and Impacts Thereof,*
- *Evaluating Model performance*
  - *MAPE, Percent Error, Accuracy across windows (90-days, etc.)*

High Level Project Overview

Impetus

- A value proposition to demonstrate the potential benefits of a demand forecast for SPARC request volumes

Problem

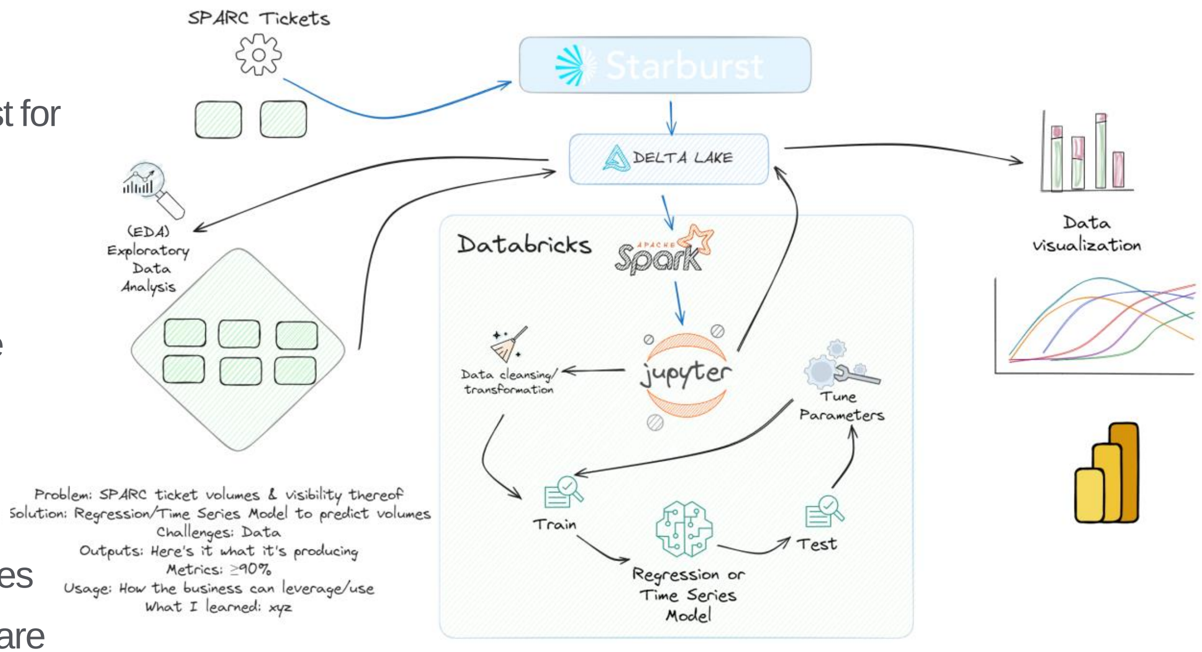
- SPARC ticket volumes can fluctuate based on system outages, new software offerings, organization changes and hiring patterns

Proposed Solution

- Build a demand forecast model to help inform the business of potential volumes
- Provide a solution that can incorporate external variables such as user hardware updates, software launches, new country rollouts, shifts in work patterns (*remote vs office*), etc.

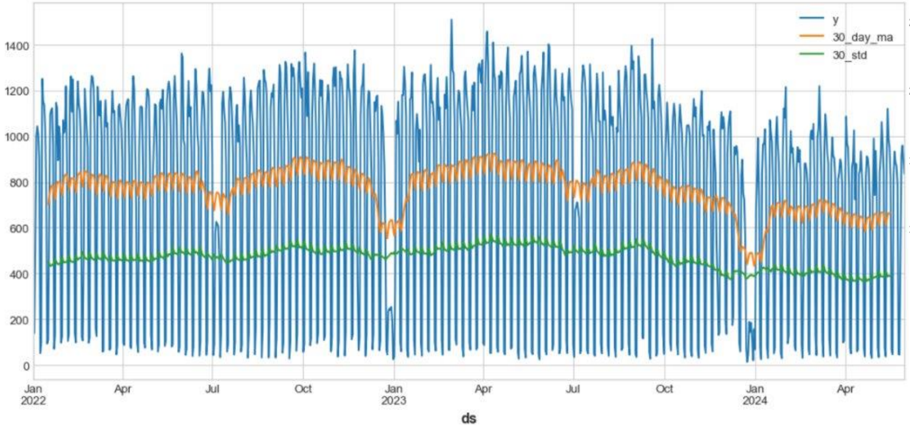
Potential Benefits

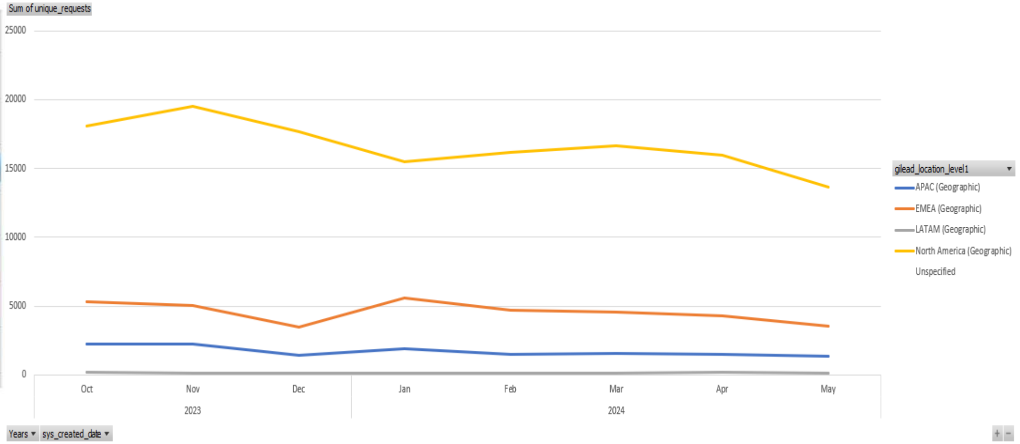
- Headcount projections (*required personnel to handle volume*) and business cost calculations thereof
- Accommodate what-if scenarios by correlating ticket inflow with external factors and applying them to projections

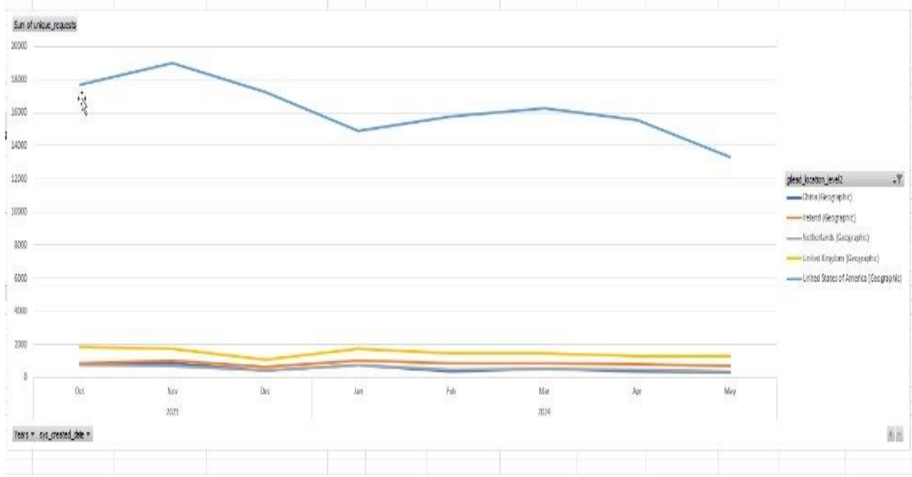


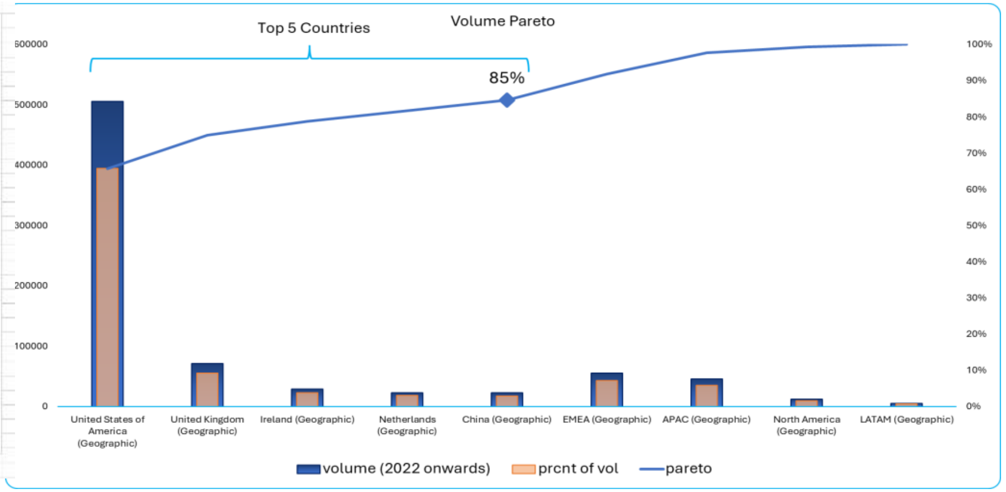
Exploratory Data Analysis

- *Pulled data down from Starburst via SQL*
- *Removed duplicates*
- *Broke down data into regions*
- *Analyzed Gilead vs Kite*
- *Cleaned data by removing spikes/ outliers*
- *The top 5 countries by volume represented 86% of the overall volume*

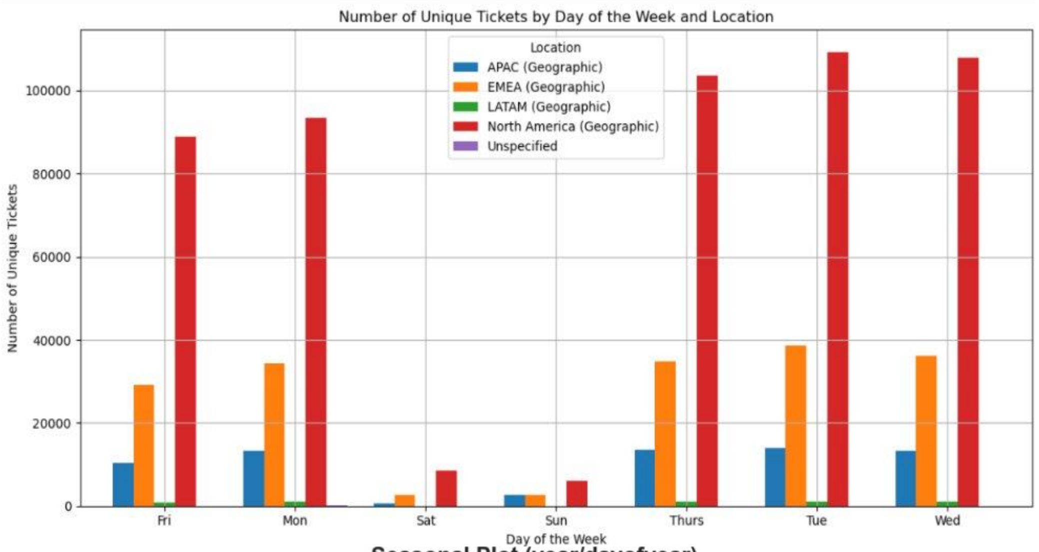


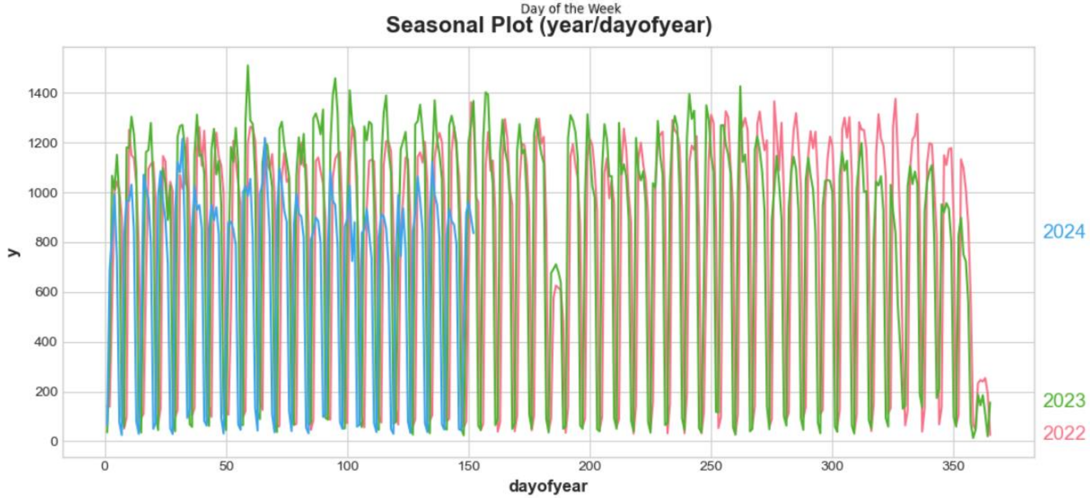




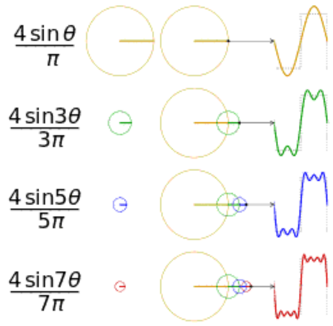


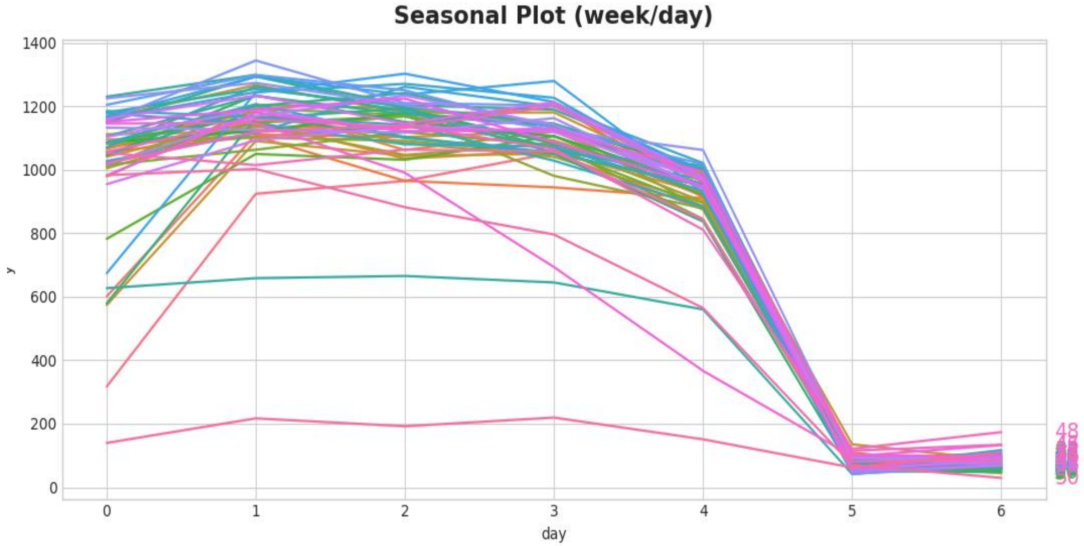
Exploratory Data Analysis, cont.
Seasonality (Month, Week, Day)





- *Examined seasonality across all significant intervals*
  - *Quarters, Months, Weeks*
- *As well as across the top 5 countries and 4 regions*

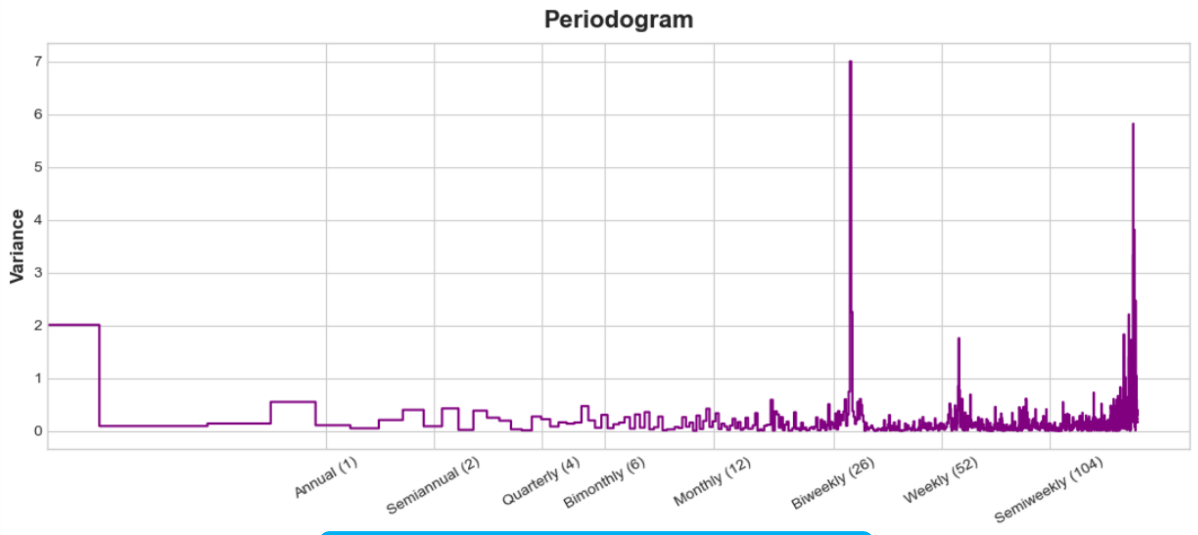




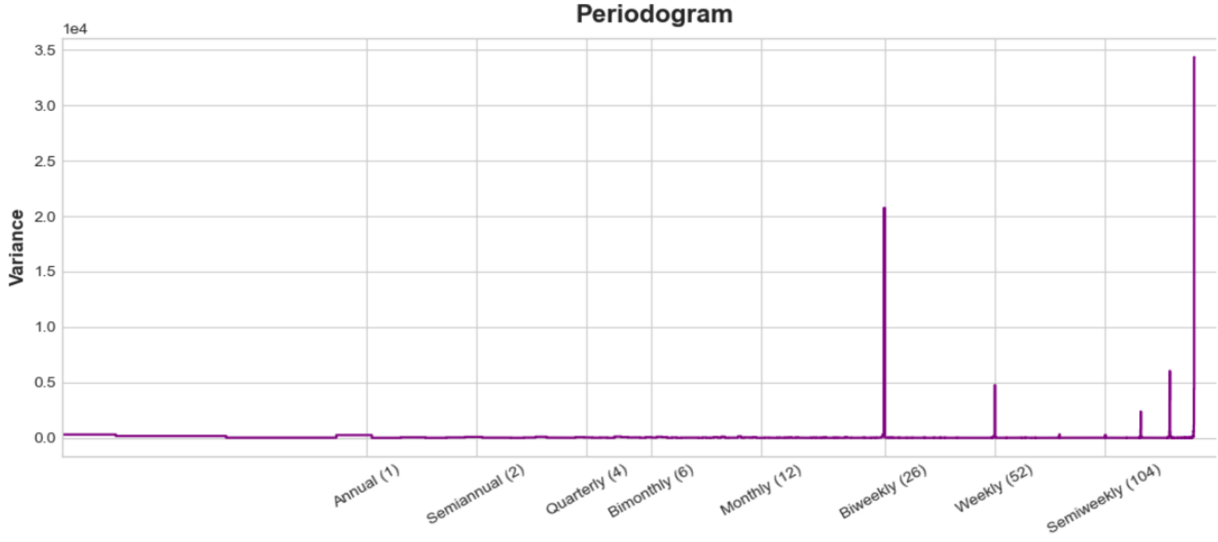
Exploratory Data Analysis, cont.
Periodicity

- *The variance in the data by country/region indicated a model would be required that could accommodate more than simple trend and growth factors for SPARC tickets*
- *Examining the unique seasonality patterns within the data's subsets helped identify that segregating the data by the top 5 countries, and remaining countries by region would compensate for the unique seasonality patterns within regions that would impact demand*
  - *Some areas had unique periodicity, i.e Netherlands*
  - *Netherlands and US pictured*

Netherlands



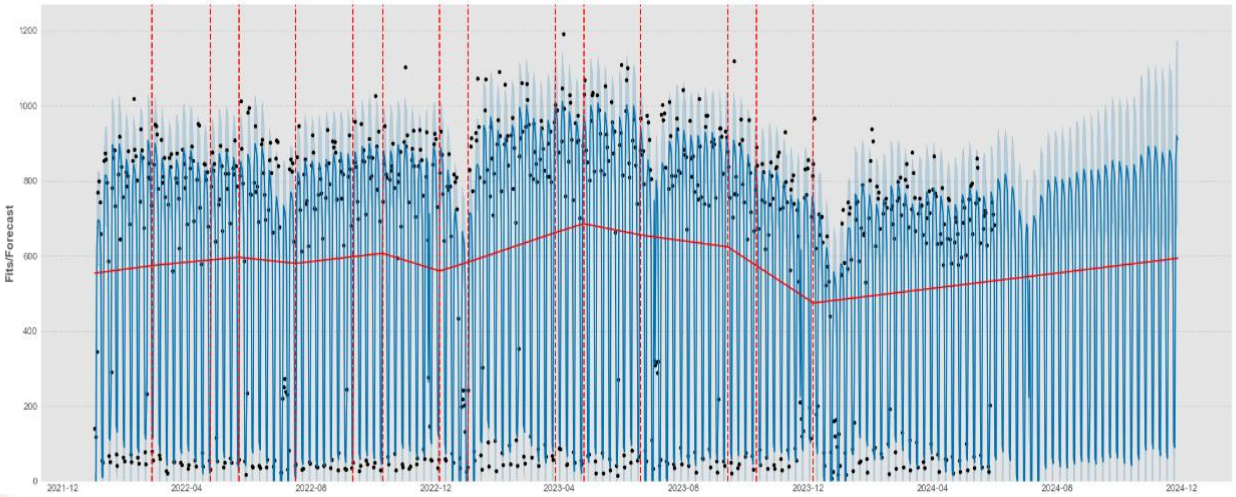
US

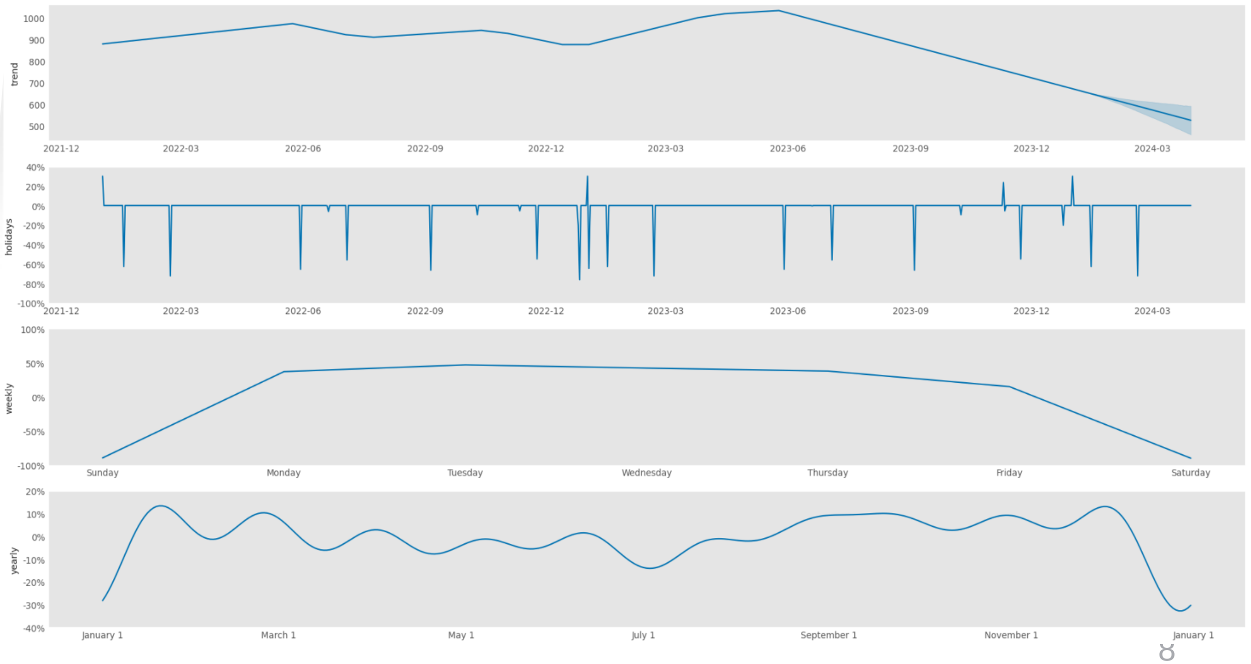


Model Selection

- *Tested 9 Different Algorithms*
- *All model testing leveraged Fourier weights for seasonality (month, week and day of year) informed by the EDA using a deterministic process*
  - *AutoARIMA*
  - *Croston Classic*
  - *Dynamic Optimized Theta*
  - *Generalized Additive (GAM)*
  - *Historic Average*
  - *Holt Winters*
  - *Linear Regression*
  - *Random Forest Regression*
  - *Seasonal Naïve*
- *Highest Performance (MAPE) was with:*
  - *GAM model (prophet model from Meta)*
  - *Benefits:*
    - Robust seasonality
    - Accommodates exogeneous regressors (holidays, etc.)
    - Robust trend weights with changepoint inflection markers
    - Numerous hyper-parameters for tuning

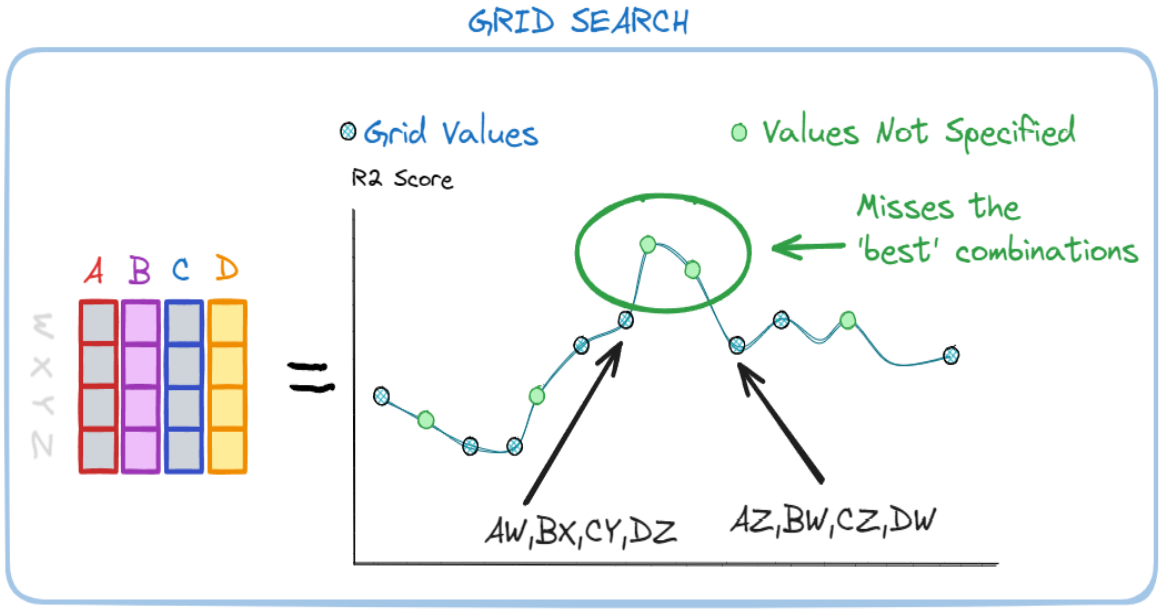
GAM (*prophet*)





Hyperparameter Optimization

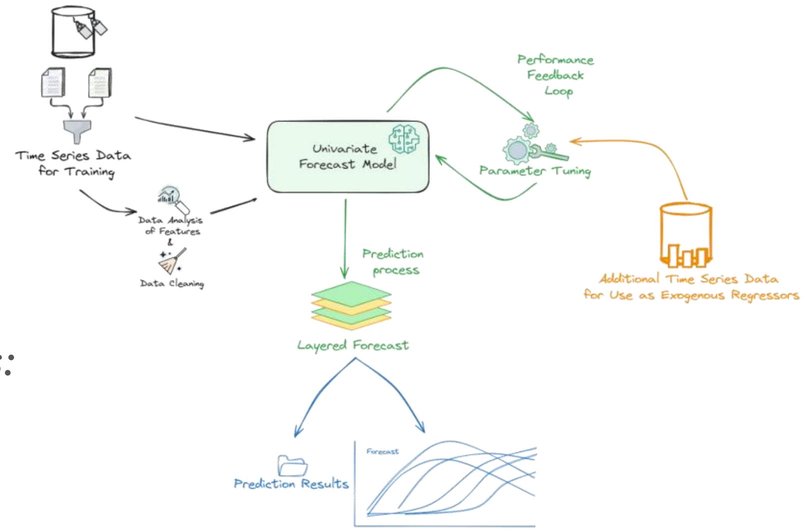
- *Method: Bayesian Optimization*
  - *Faster model tuning as well as potentially improved accuracy for the model compared to traditional methods (e.g., random or grid searching)*
  - *Treats tuning like a regression problem by iterating through value combinations*
    - *Each run uses values incrementally close to the best previous or far removed to explore the range of values*
    - *Concentrates on trying combinations of 'good' values across the individual parameters*
  - *Other methods are limited by either:*
    - *A finite number of suggested values we enter – and the more values we suggest, the longer the run time*
    - *Random selection of values (i.e., not concentrating on combinations near previous good values)*
  - *Allows us to re-train the model quickly while still maximizing accuracy*



Results and Evaluating Model Performance

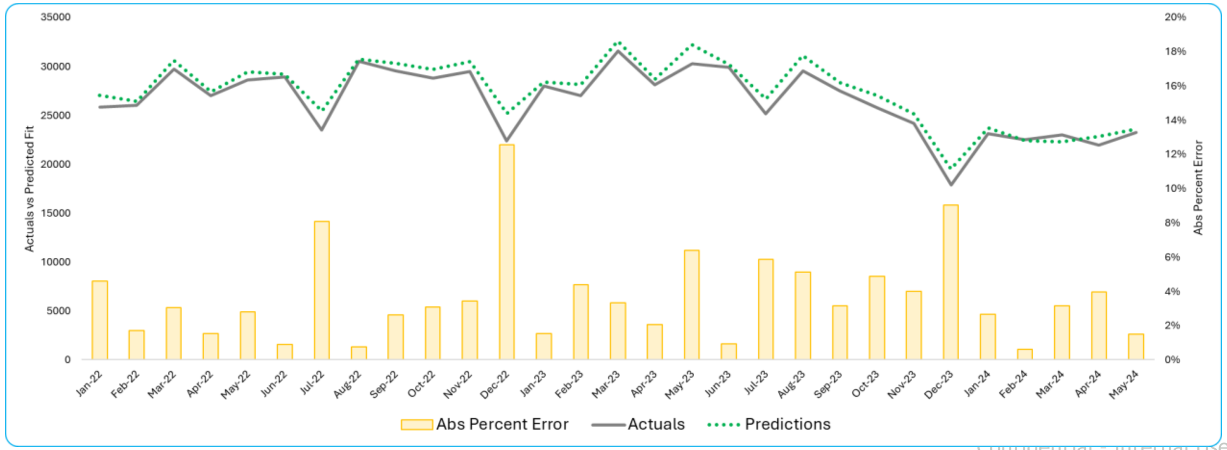
The layered (9 variable) forecast resulted in performance of:

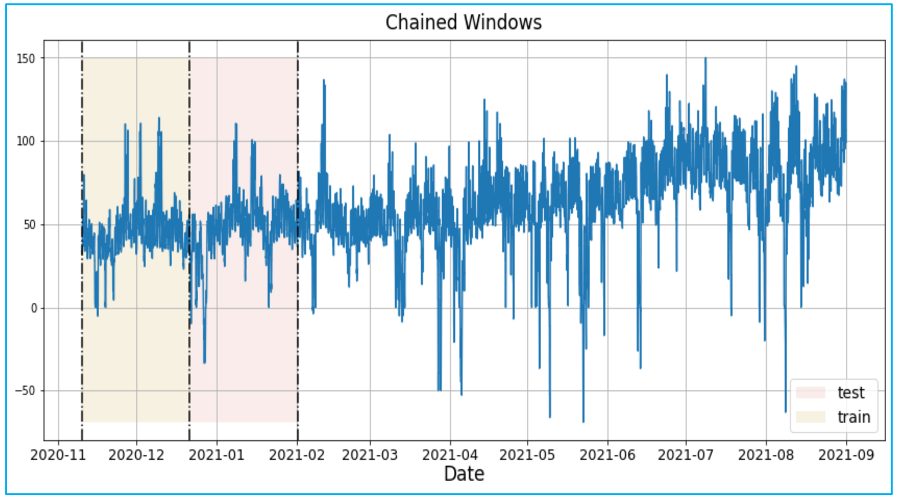
- *Tuned Model:*
  - *Fit w/ MAPE of 3.7%*
    - *St Dev of 2.7%*
- *Forecast results on a 90-day Horizon measured across chained windows:*
  - *E.g. when predicting a month's volume a quarter ahead from historicals (actuals through Dec, predict Mar)*
  - *Mean accuracy 92.5%, St Dev 3.2%*



Chained Window Forecasts

Tuned Model





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