DS 5500 - Fall 2021

Capstone: Applications in Data Science

Walmart Sales Forecasting

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Agenda

- Summary
- Data Overview
- Methodology
- Initial Results
- Modeling Phase
- Key Learnings

Summary

Context :

- Ecommerce has been an ever-growing industry with projected revenue growth of **$4.9 trillion** in 2021.

- Sales forecasting will help businesses understand changing customer demands, manage inventories and create a pricing strategy that reflects demand.

Problem Goals :

- This project will present the right methodologies to analyze time-series sales data and predict **28 days** ahead point forecasts for Walmart to help take strategic decisions.

- We plan to leverage the traditional time series forecasting methods(**Phase 1**) as well as the modern forecasting methods(**Phase 2**), to analyze Walmart's sales data.

Data Overview

The dataset contains **5 year historical sales** from 2011- 2016 for various products and stores.

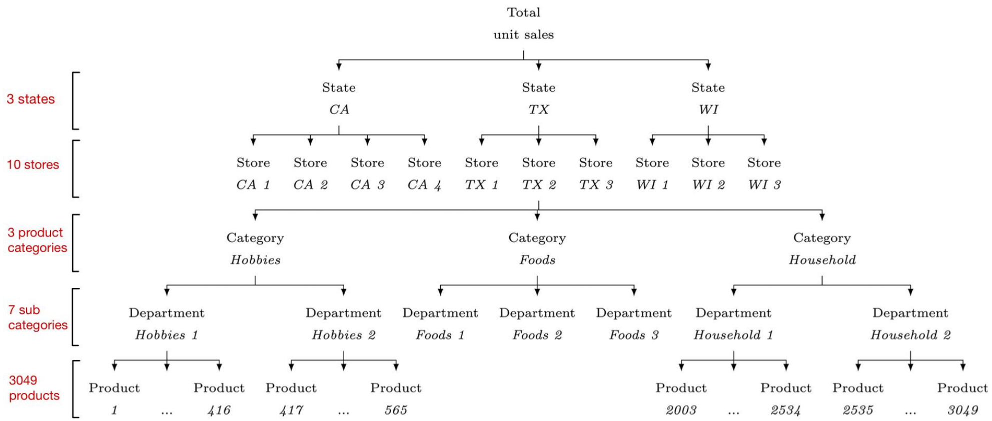
Data is hierarchically organized: stores are divided into 3 states, and products are grouped by categories and sub-categories

The dataset is organized in 3 CSV files :

calendar.csv - Contains dates on which the products are sold and events held on that day.

Sales_train_evaluation.csv: Contains historical daily unit sales of each product on each store

Sell_prices.csv: price of products each week



M5 Competition: https://mofc.unic.ac.cy/m5-competition/

Methodology

Standard statistical time-series forecasting strategies are important to establish a baseline for the model performance, which is our **primary goal for Phase 1**.

Phase 1

Traditional Time Series Models

- Involves historical analysis, finding dynamics of the data like cyclical patterns, trends, and growth rates.
- Three general ideas to tackle the forecasting problem would be Repeating/Static Patterns and Seasonal Trends.
- Exponential Smoothing(EA), ARIMA (Autoregressive integrated moving average) and SARIMA (Seasonal ARIMA) are some examples.

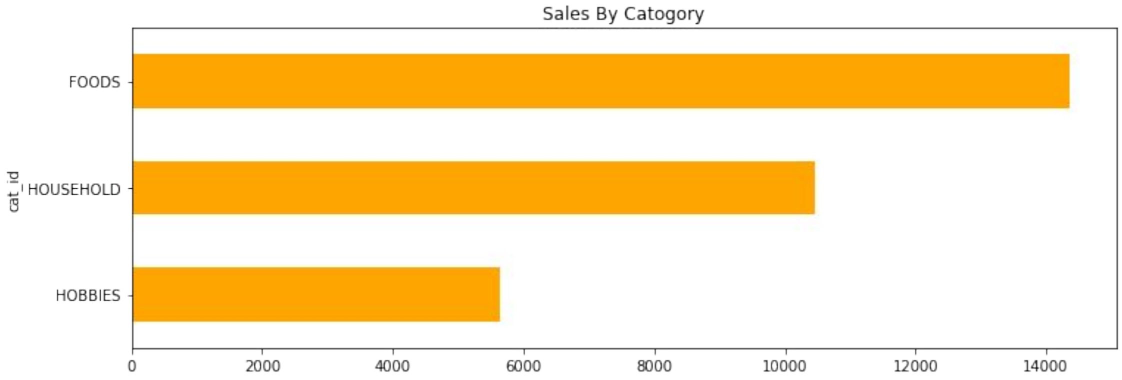
Causal Forecasting

- Assumes the variable to be forecasted has a cause-effect relationship with one or more independent variables.
- For sales, it can be used to forecast at a much granular level i.e., by product, product category, subclass etc.
- Regression model and Econometric model are some examples we will explore.

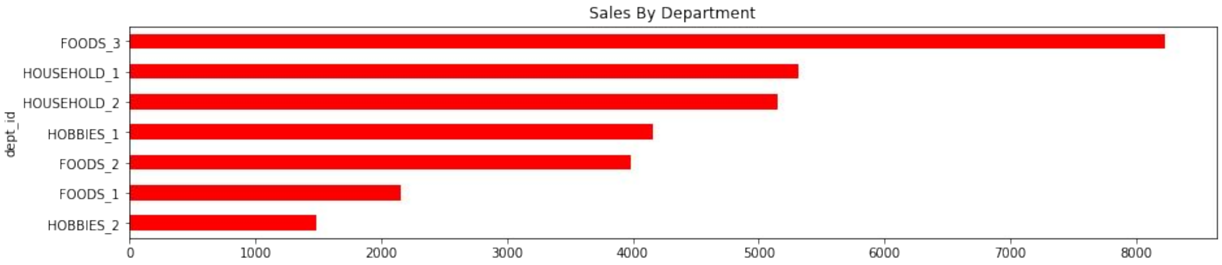
Deep Learning/Ensemble Models

- Neural Networks can learn inherent patterns in different time series without bothering about breaking up the trend and seasonality patterns.
- Forecasting can also be significantly improved using techniques like Gradient Boosted Trees.
- DeepVanilla LSTM (Long Short Temporal Memory), XGBoost and LightGBM are some examples.

Initial Analysis: FOODS is the Top Category

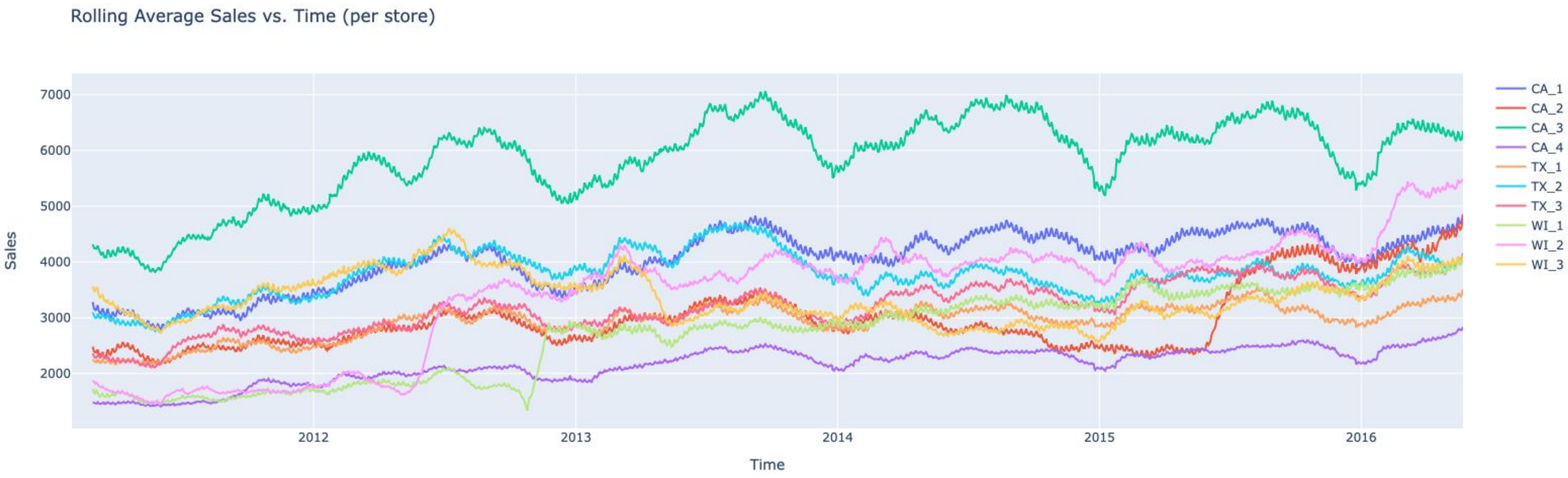


- FOODS category has the highest sales
- Precise forecasting on FOODS could be most beneficial



- Top 3 departments based on sales are FOODS_3, HOUSEHOLD_1 & HOUSEHOLD_2

Initial Analysis: CA has the highest overall sales



- Rolling average Sales with time for the store CA_3 situated in California is the highest amongst all
- We can also observe some seasonal high and lows in sales across all the stores

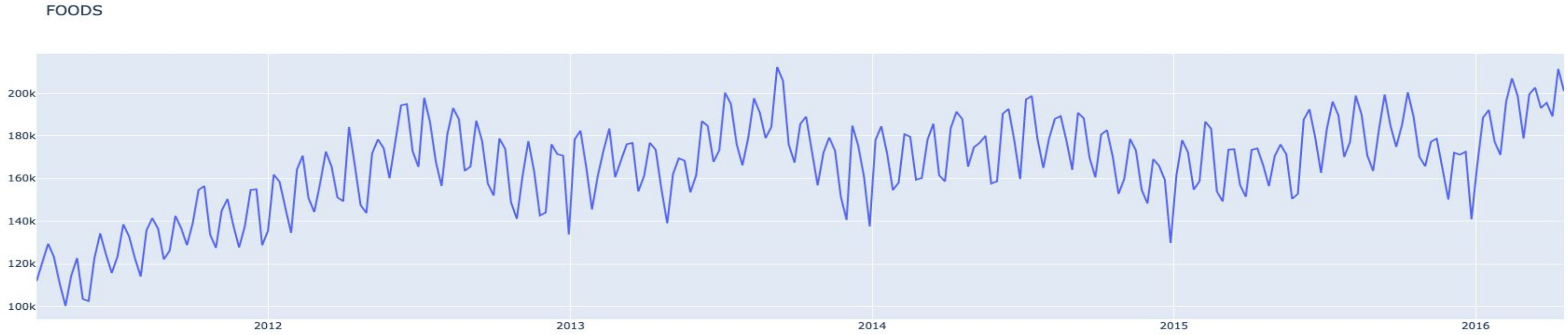
Modeling Initiation: Aggregated Weekly for Baseline

- Sales data is grouped by the different categories i.e FOODS, HOBBIES, HOUSEHOLD

- To reduce memory footprint, downcasting was performed along with weekly aggregation of sales

- Exogenous variables like holidays, weekends and paydays were created leveraging the calendar data

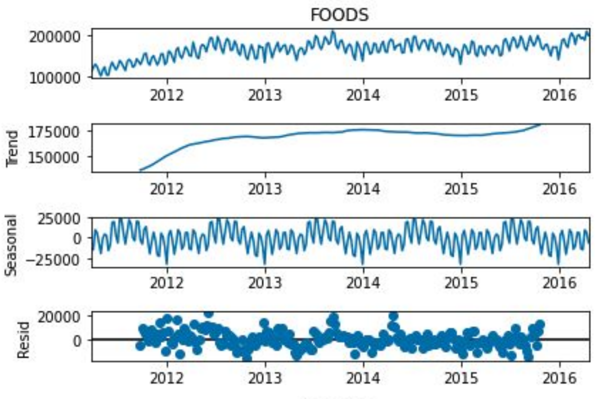
cat_id	FOODS	HOBBIES	HOUSEHOLD
d_1	23178	3764	5689
d_2	22758	3357	5634
d_3	17174	2682	3927
d_4	18878	2669	3865
d_5	14603	1814	2729

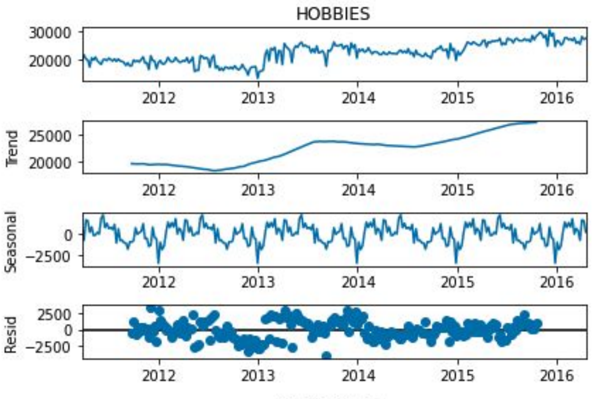


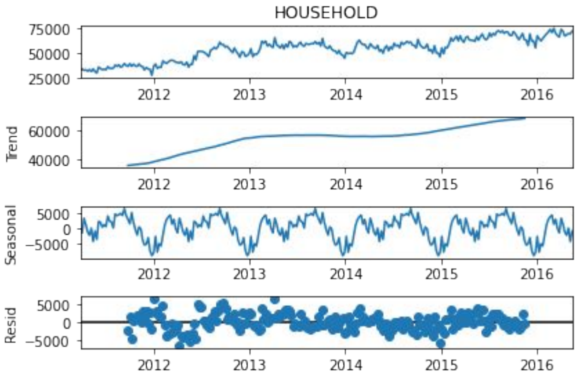
Total sales of the FOODS category across the entire timeline - Aggregated Weekly

Time series Decompose: Highlights Trend & Seasonality

Based on Trend and Seasonality plots, we hypothesize that data is **non-stationary**







Statistical Tests: Augmented Dickey-Fuller Stationarity Test

P-value of **<0.05** indicates data is stationarized and **suited for forecasting**

```
Results of Dickey-Fuller Test for :  FOODS
Test Statistic                  -2.521061
p-value                          0.110434
#Lags Used                      16.000000
Number of Observations Used    248.000000
Critical Value (1%)             -3.460000
Critical Value (5%)             -2.870000
Critical Value (10%)            -2.570000
dtype: float64
++++++++++++++++++++++++++++++++++++++
```

```
Results of Dickey-Fuller Test for :  FOODS
Test Statistic                  -4.734638
p-value                          0.000072
#Lags Used                      13.000000
Number of Observations Used    249.000000
Critical Value (1%)             -3.460000
Critical Value (5%)             -2.870000
Critical Value (10%)            -2.570000
dtype: float64
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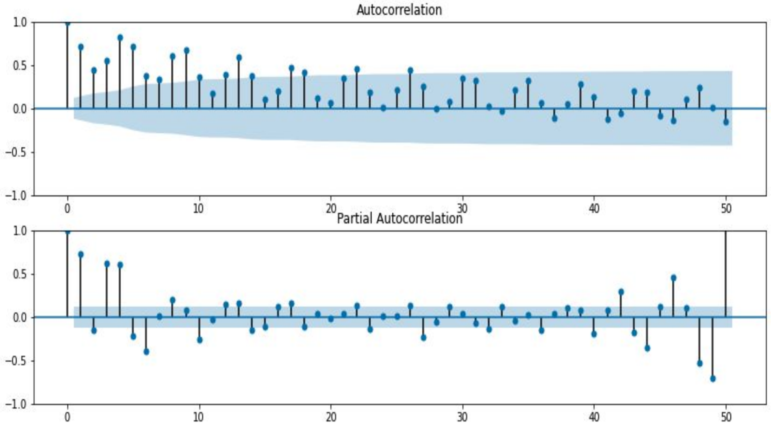
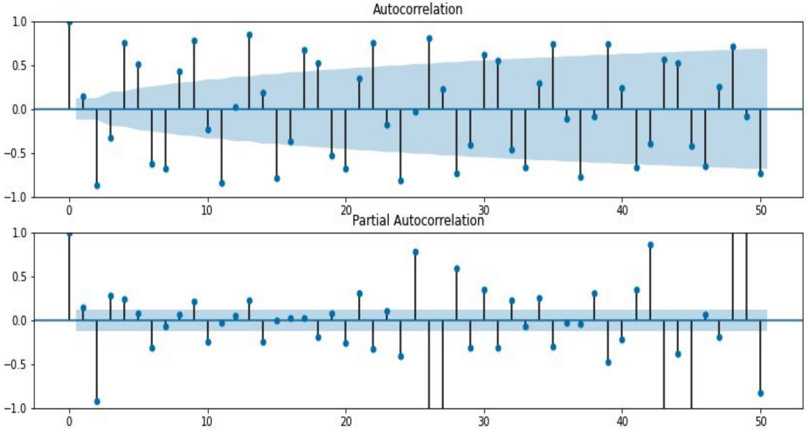
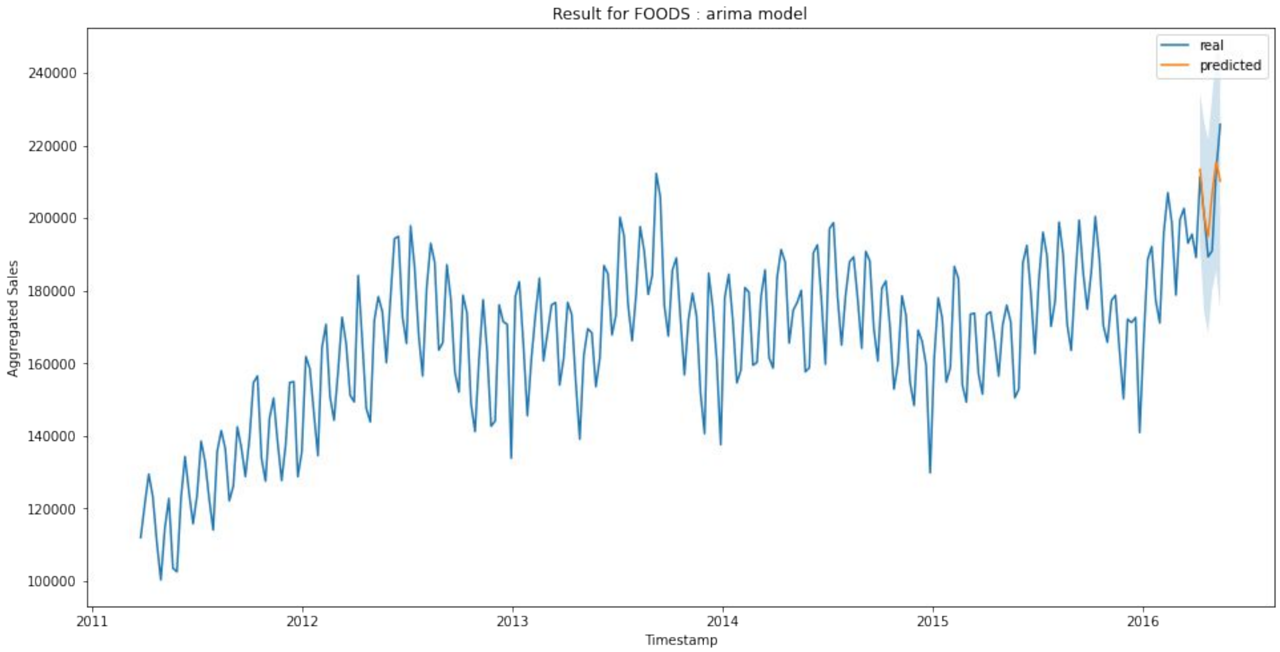


ACF/PACF plots before differencing



ACF/PACF plots after differencing

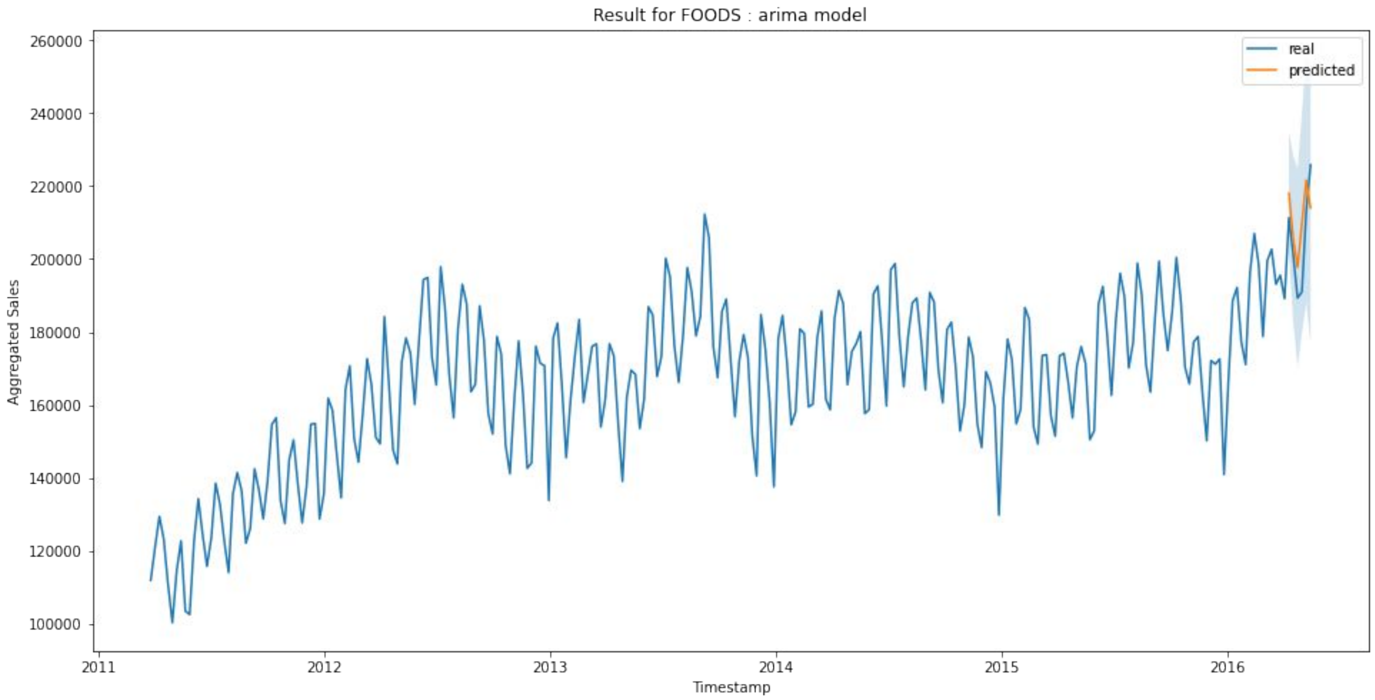
FOODS: Baseline ARIMA performance was not optimal



Results:

- Model tuning was performed using **Auto ARIMA.**
- The test size was kept at 6 weeks to be closer to 28 days forecast.

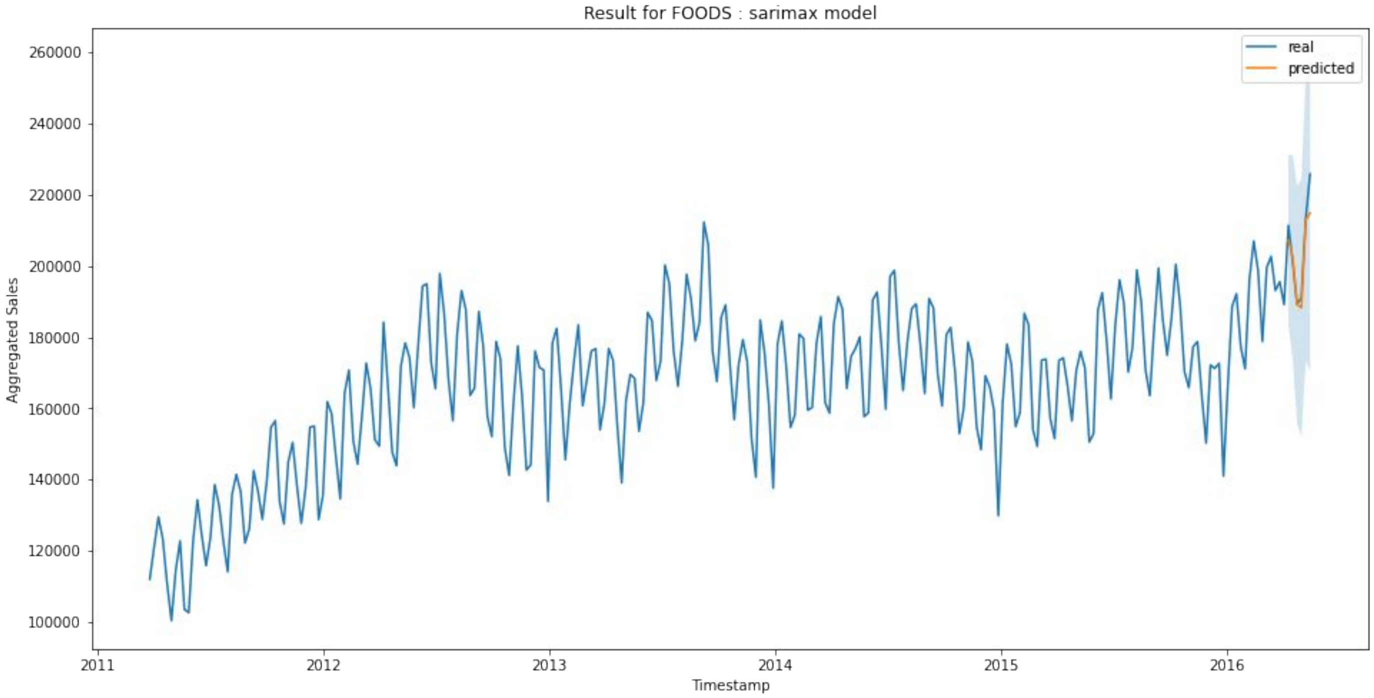
FOODS: Gridsearch optimized Baseline ARIMA by 36%



Results:

- The test size was kept at 6 weeks to be closer to 28 days forecast.
- As an alternative to k-fold CV, **Walk Forward validation** was used to perform backtesting.
- GridSearch gave RMSE of 6217.83, a **~36.5%** improvement over baseline ARIMA

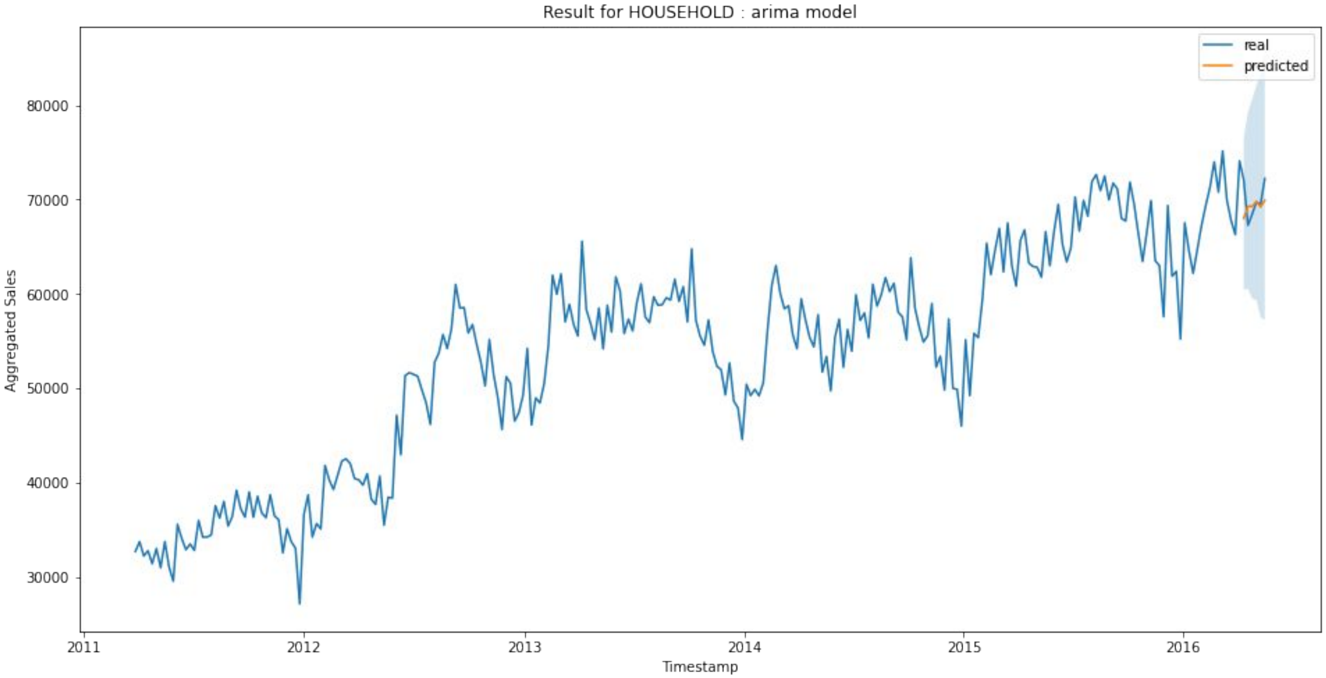
FOODS: SARIMAX improved ARIMA model by further 20%



Results:

- **Exogenous variables** like holidays, paydays and weekend were modeled to improve trend capture.
- Improved RMSE score of 4969.28, further improved the forecasting RMSE by **~20.1%.**

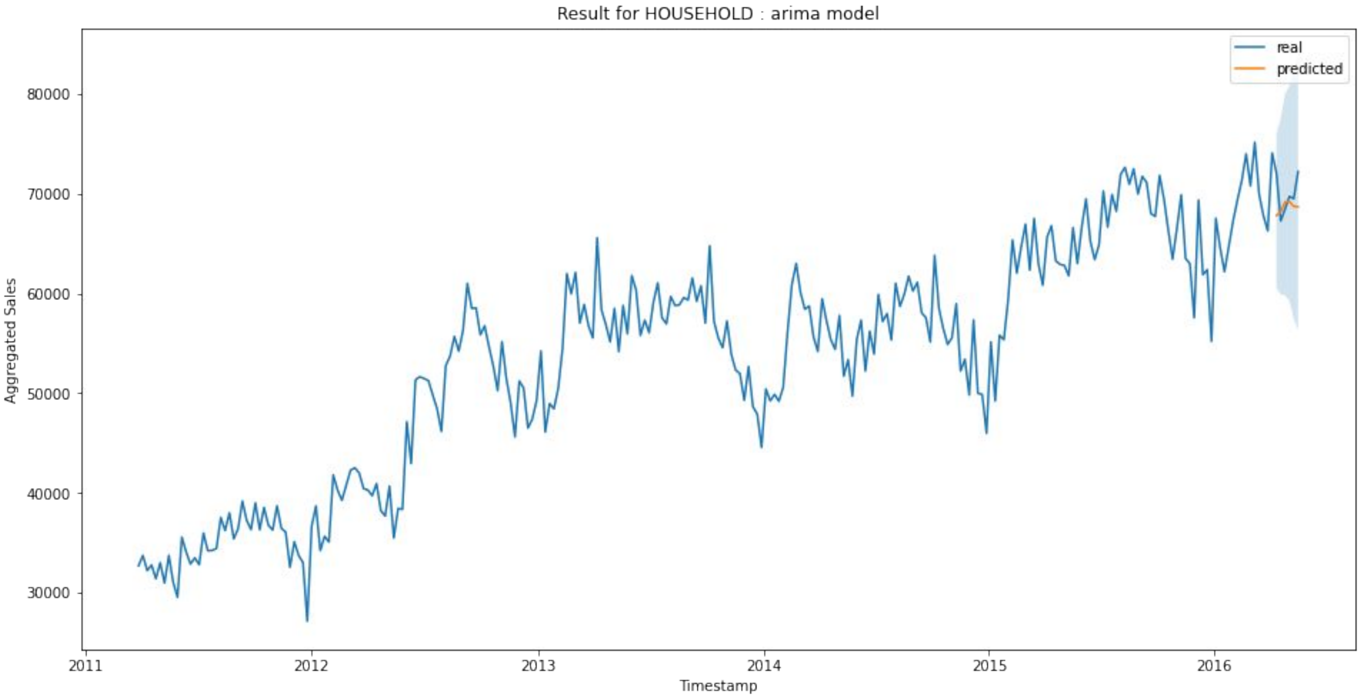
HOUSEHOLD: Baseline ARIMA model showed a poor fit



Results:

- Model tuning was performed using Auto ARIMA.
- **Log Transformation** was applied to account for variance
- The test size was kept at 6 weeks to be closer to 28 days forecast.

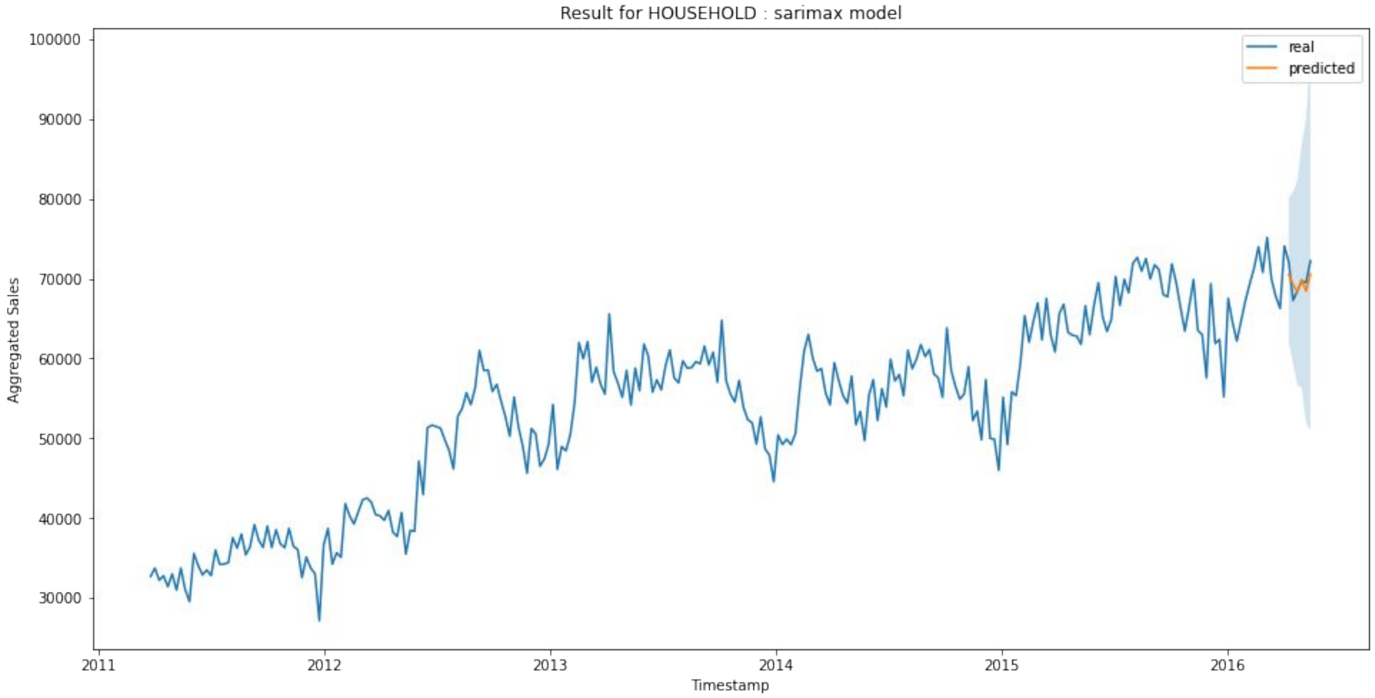
HOUSEHOLD: ARIMA model shows poor fit despite gridsearch



Results:

- The test size was kept at 6 weeks and backtesting was performed using Walk Forward validation.
- **Log Transformation** was applied to account for variance
- RMSE of 2130.08 after gridsearch, only showed a minor **~15.9%** improvement over baseline ARIMA.

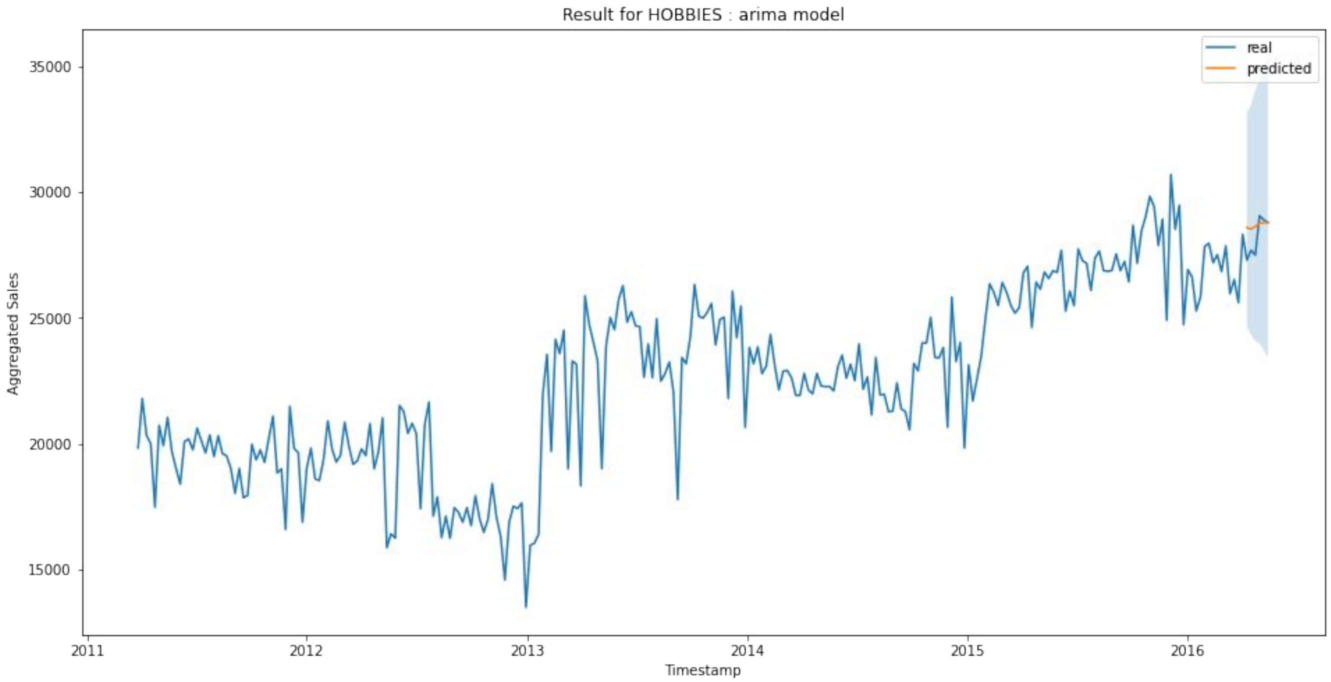
HOUSEHOLD: SARIMAX improved ARIMA model fit by 38%



Results:

- **Exogenous variables** like holidays, paydays and weekend were modeled to improve trend capture.
- RMSE score of 1314.61 after gridsearch optimization, showed a significant improvement of **~38%** over best ARIMA model.

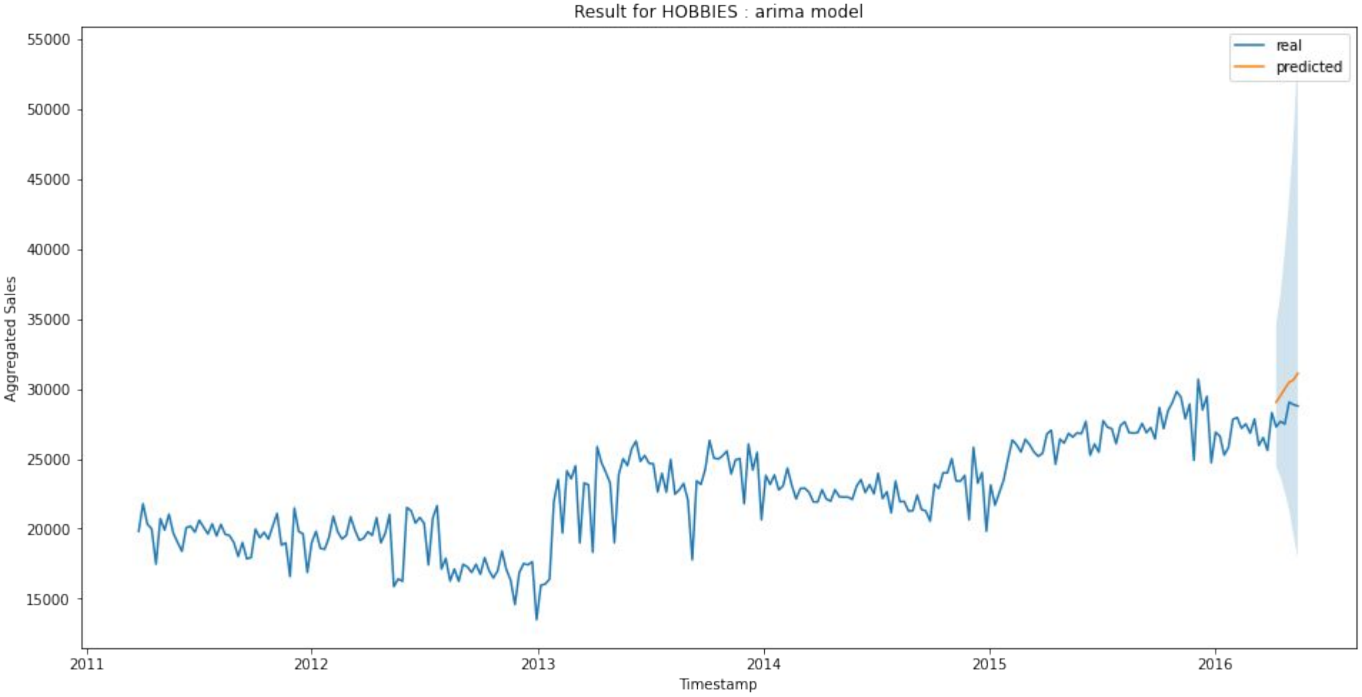
HOBBIES: Baseline ARIMA model showed almost no trend capture



Results:

- Model tuning was performed using **Auto ARIMA.**
- **Log Transformation** was applied to account for variance
- The test size was kept at 6 weeks to be closer to 28 days forecast.

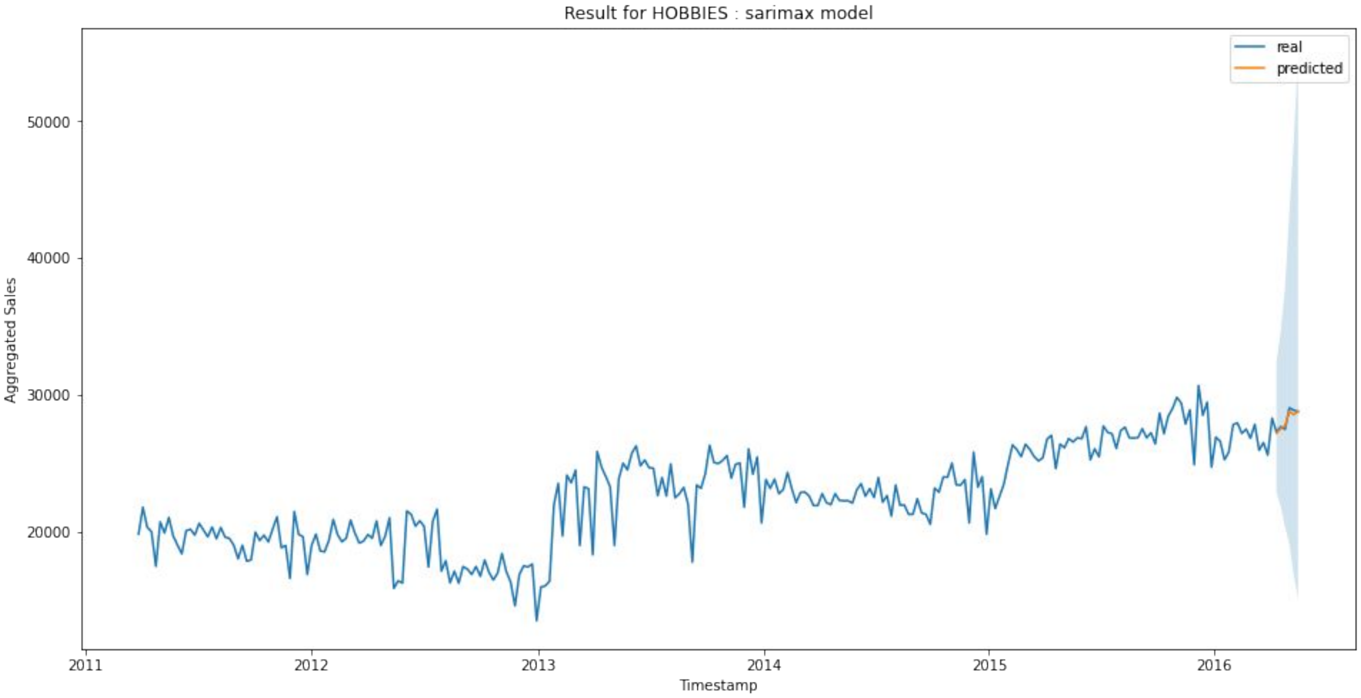
HOBBIES: ARIMA showed a very poor fit despite Gridsearch



Results:

- The test size was kept at 6 weeks and backtesting was performed using Walk Forward validation.
- Log Transformation was applied to account for variance.
- ARIMA model was unable to show a good fit even after applying gridsearch based optimizations.

HOBBIES: SARIMAX improved ARIMA model fit by 53%



Results:

- Exogenous variables like holidays, paydays and weekend were modeled to improve trend capture.
- RMSE score of 215.28 after gridsearch optimization, showed an impressive **~53%** improvement over best ARIMA model.

Phase 1 Goals were successfully met

Key Learnings

- ➔ Downcasting is a good alternative to Spark and other Cloud based architecture when training on larger data.
  - ◆ Reduced memory usage by almost ~80%.
- ➔ Walk Forward Validation is a good alternative to k-fold CV for backtesting.
- ➔ SARIMAX performed better than ARIMA across all the categories, due to better Trend and Seasonality capture.
- ➔ Log Transformation is a good step when the data has lot of variance (eg: in case of HOBBIES and HOUSEHOLD).
- ➔ While Gridsearch performs much slower than Auto ARIMA, it showcased much better results on almost all the 3 categories.

Despite lower RMSE, larger confidence interval in SARIMAX results is a compelling reason to try modern forecasting techniques, which will be the primary goal for Phase 2.