

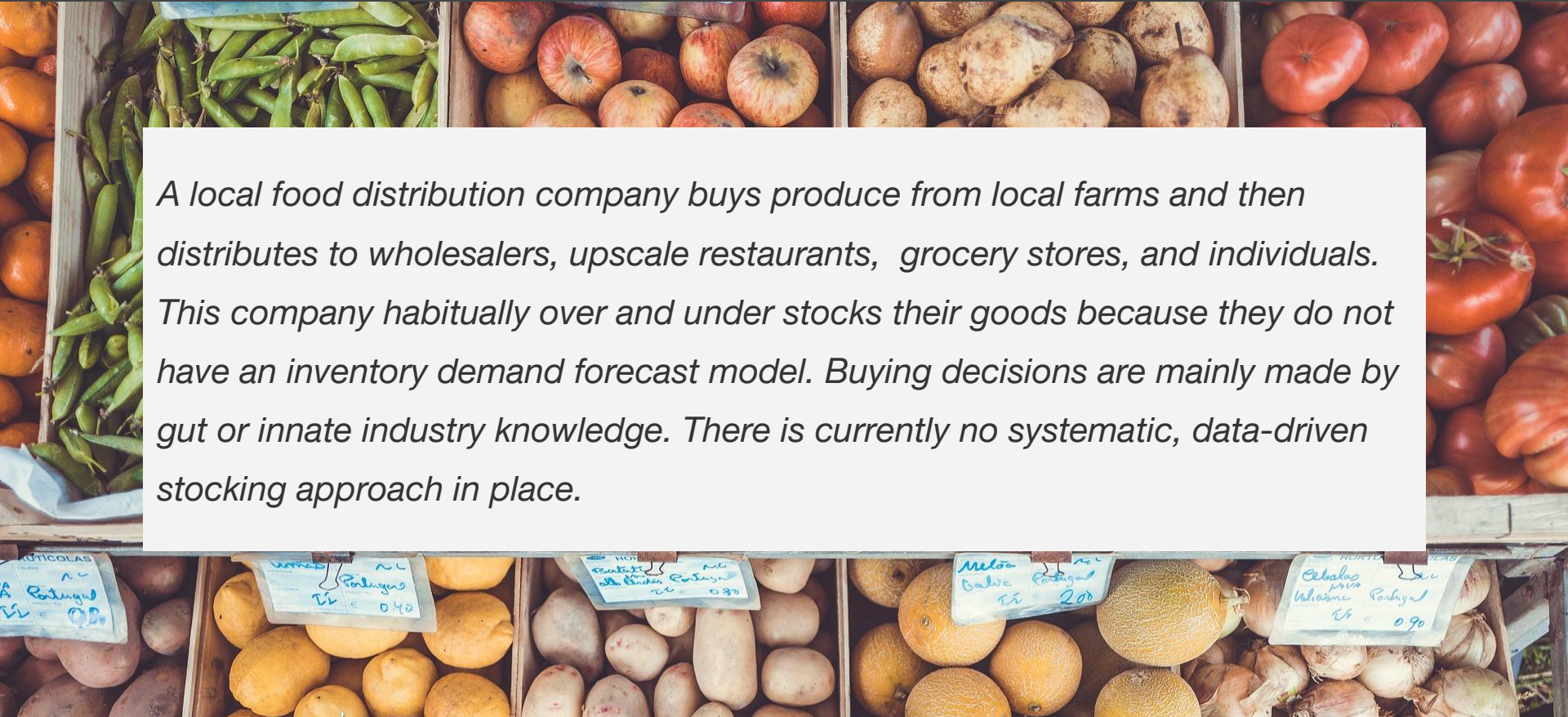


Forecasting Weekly Grocery Product Demand

Capstone 2 By: Kristen Colley

Why?

A local food distribution company buys produce from local farms and then distributes to wholesalers, upscale restaurants, grocery stores, and individuals. This company habitually over and under stocks their goods because they do not have an inventory demand forecast model. Buying decisions are mainly made by gut or innate industry knowledge. There is currently no systematic, data-driven stocking approach in place.



Method

Predicting Weekly SKU's

1

Model each of the 3,000
different items

2

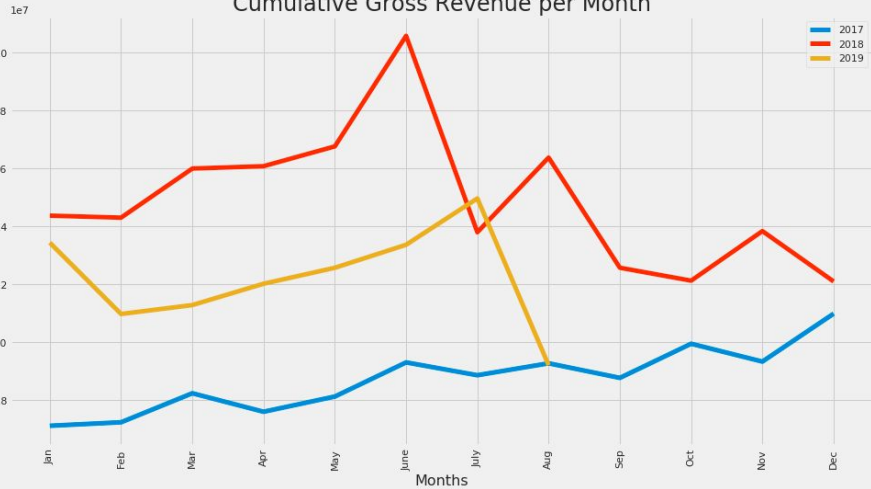
Create 10-15 Broad
Categories, and
customize models for
each of those
categories

Models

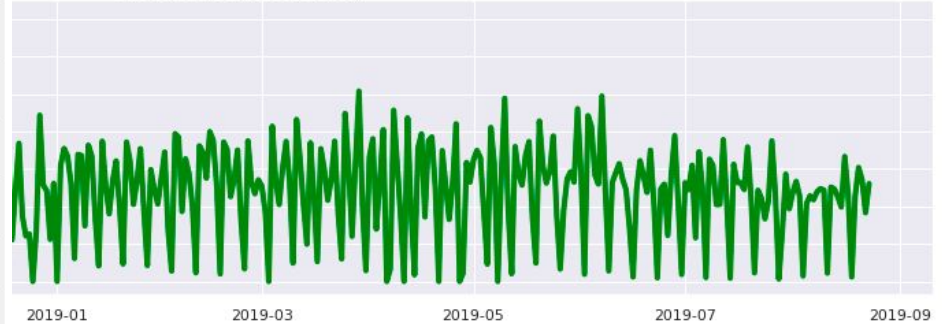
1. Naive Model
2. Classical Models (SMA, SES, HLT, HWM)
3. Prophet (Facebook)
4. Random Forest Regression
5. Light Gradient Boost model

EDA

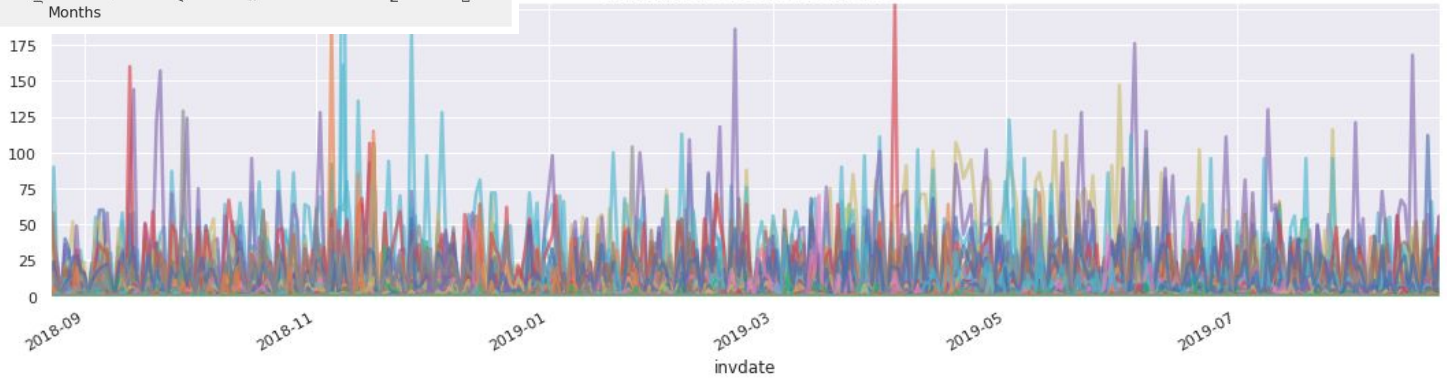
Cumulative Gross Revenue per Month



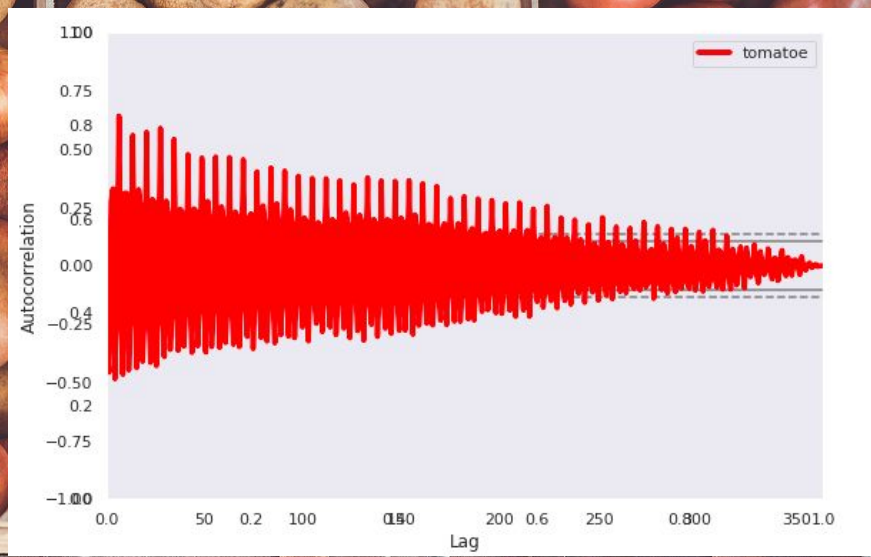
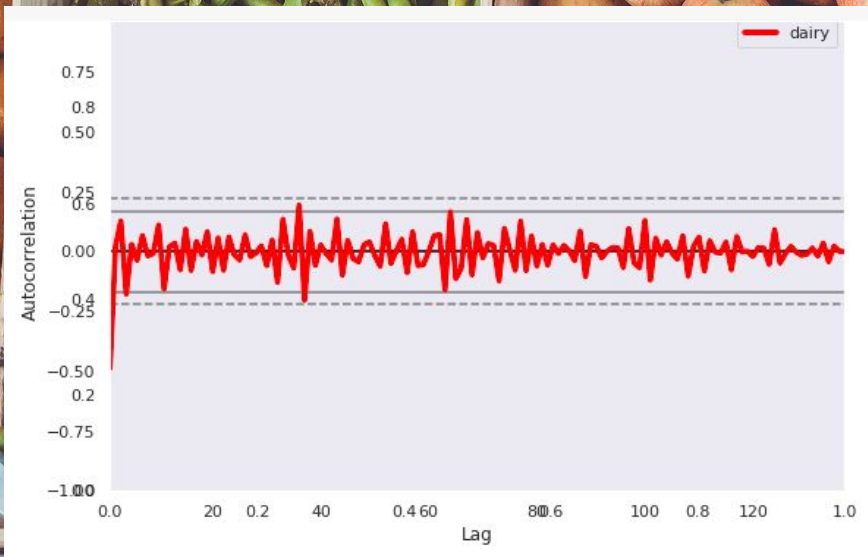
Overall Greens Category



Individual Greens Products



Random Walk Process



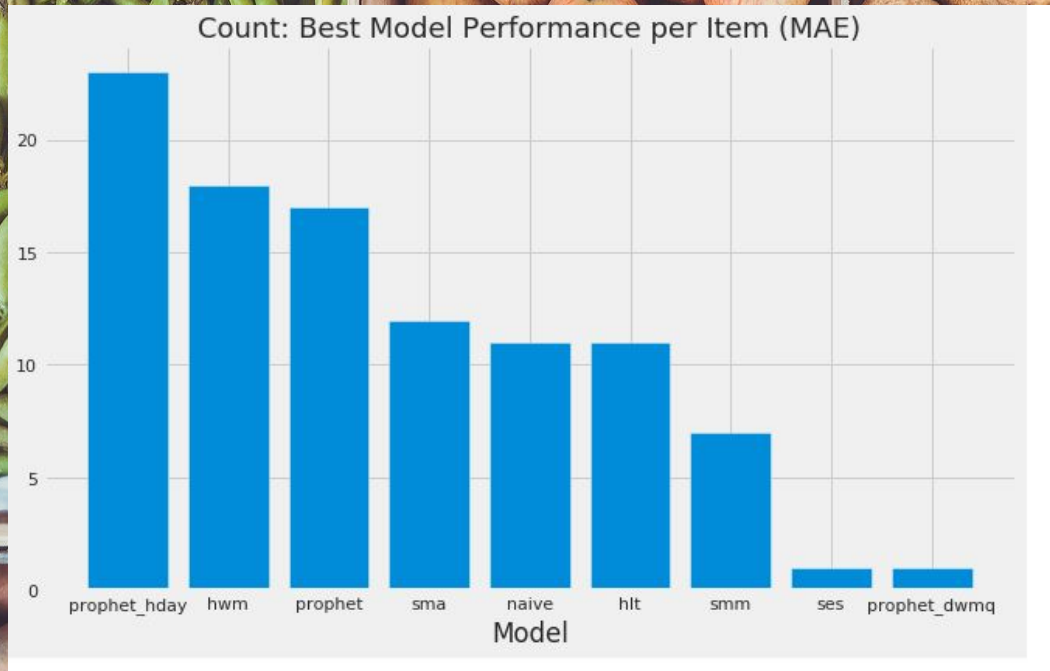
WINNER: ONE YEAR WEEKLY DATA

How to Measure Success

Baseline = *Naive Model*

- **MAPE-** *Mean Absolute Percentage Error*
- **RMSE-** *Root Mean Squared Error*
- **MAE-** *Mean Absolute Error*

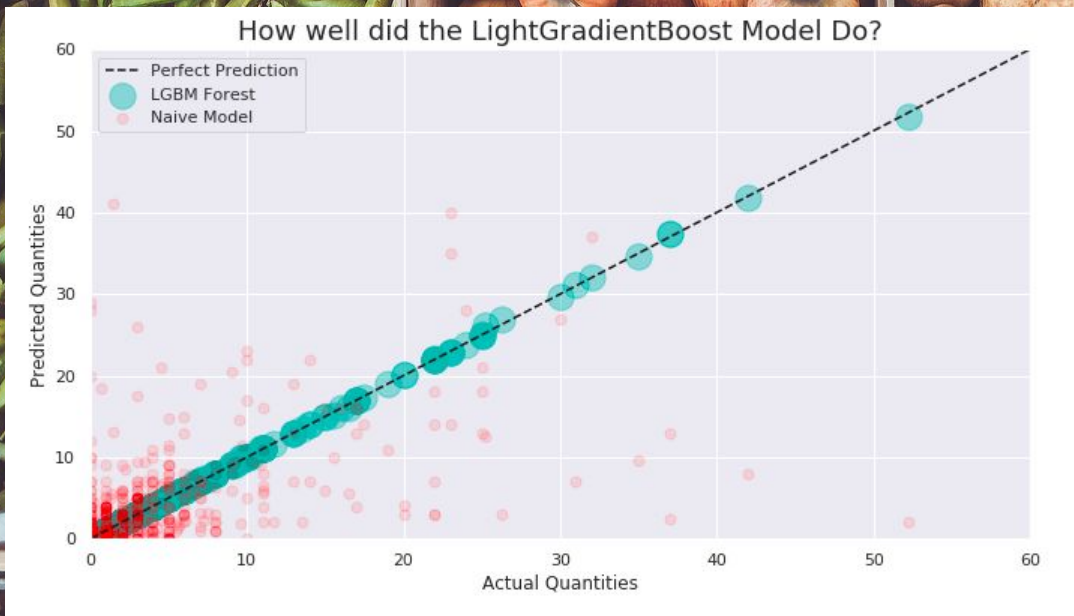
Classical Models + Prophet



IMPROVEMENT
OVER NAIVE
MODEL=
43%-50%

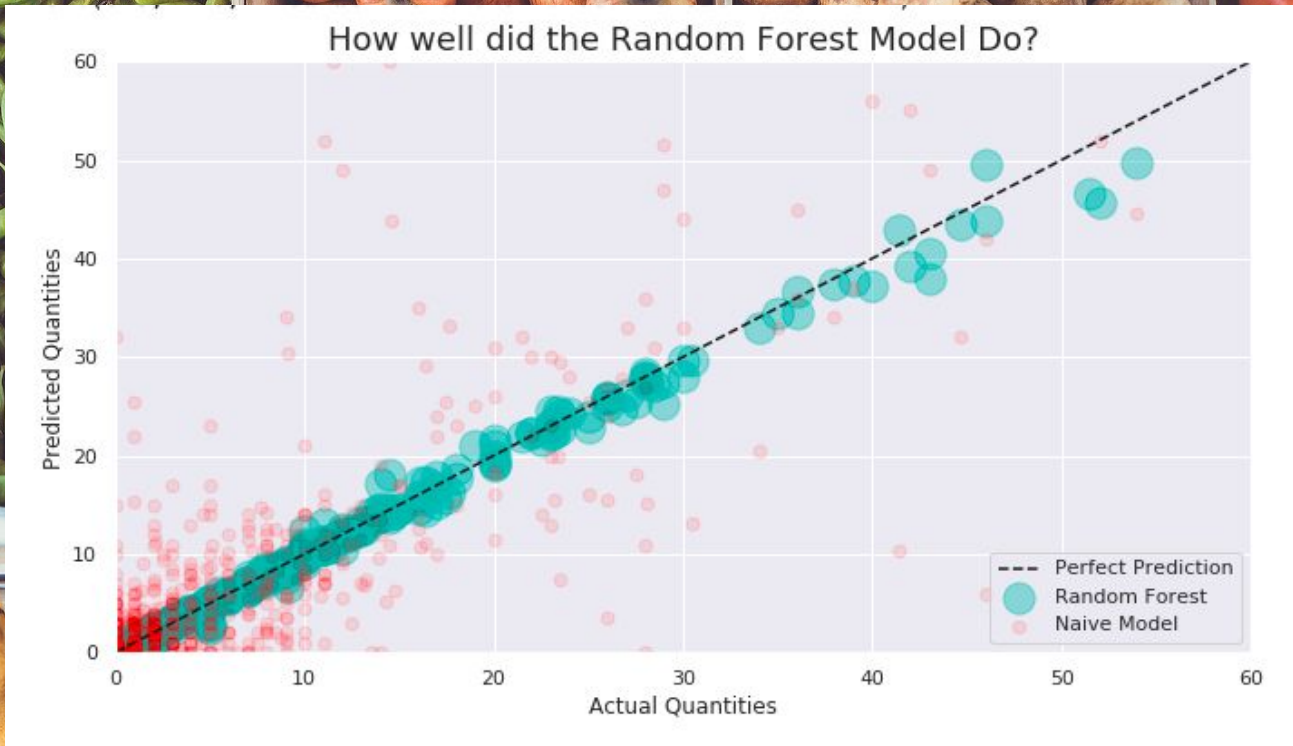
**11% STILL
NOT BEATING
NAIVE MODEL**

Trees- LGBM, Random Forest

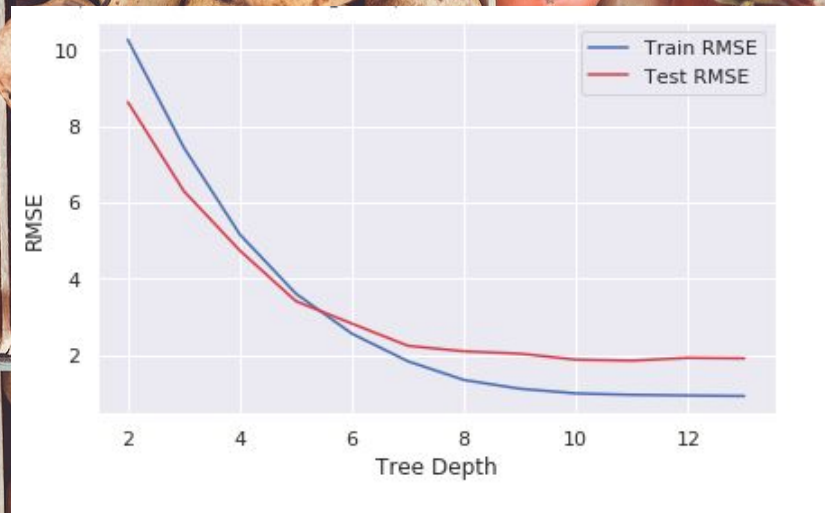
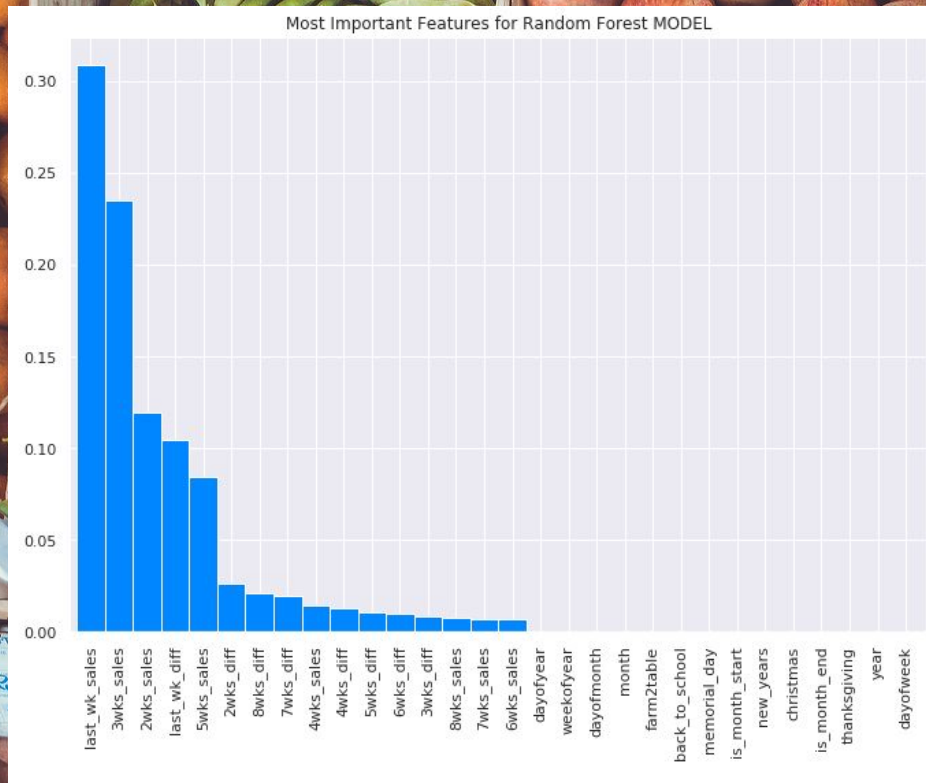


- **Best Models**
- **Beating Naive**
 - 60-88%
- **Can Handle Lots of zeros**
- **LGBM overfitting**

WINNER = Random Forest Regression



Feature Engineering & Parameter Tuning



Conclusion

The Random Forest Regression model was able to beat the customers current naive model by 60-88% (depending on the week). This is a great result for the forecasting modeling space where you don't really see incredibly accurate results. Also, the most recent sales were the biggest factor influencing the prediction in the RFR model.

