Improving Demand Forecasting

A Study in Data Science by Juichia Che Holland

Define

The Problem

What is the seasonality of products in a store? How does demand compare across different stores for the same item? What about seasonally? What will the demand for a product be in the next few months? Accurate forecasting of sales and demand is an important part to managing the supply chain for both online and physical retail.

This time series study analyzes the sales of 50 different items at 10 stores in a span of 5 years and goes through a process of fine tuning the forecasts in demand.

The Data

The dataset comes from Kaggle's store item demand forecasting challenge. It describes the daily sales numbers over 5 years of 50 items across 10 stores each and comes in 2 csv files, train.csv and test.csv. This analysis assumes that the stores are from the US.

	date	store	item	sales
0	2013-01-01	1	1	13
1	2013-01-02	1	1	11
2	2013-01-03	1	1	14
3	2013-01-04	1	1	13
4	2013-01-05	1	1	10

0 - 913,000

1 - 10 per item

1 - 50

0 - 231

2013-01-01 to 2017-12-31 per item per store

The Process

Explore the descriptive statistics, density, distribution, trend, and seasonality of overall and individual item sales

Explore

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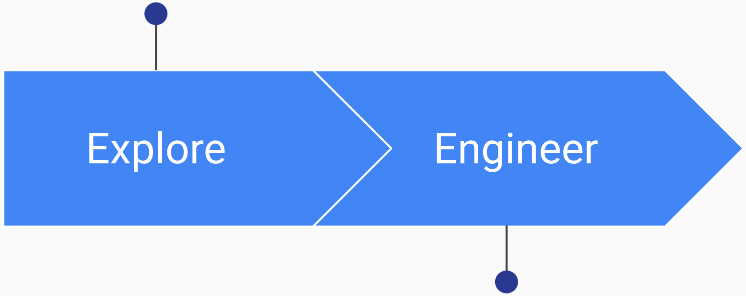

Extend the dataset with descriptive features for the dates. Determine feature importances based on predictive modeling using tree based learning algorithm.

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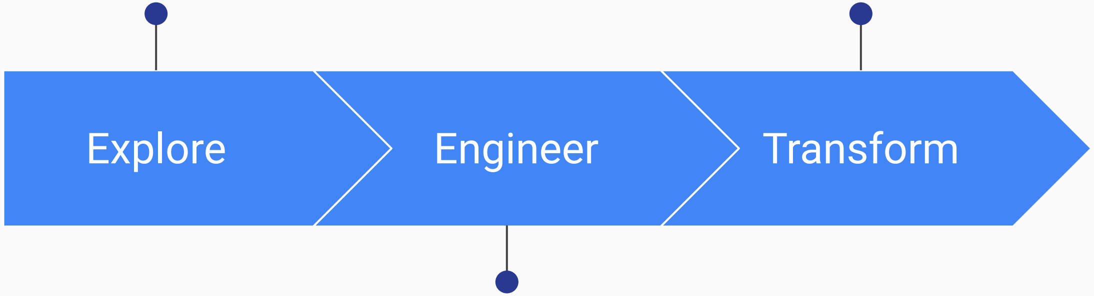
Test and transform the time series for stationarity.



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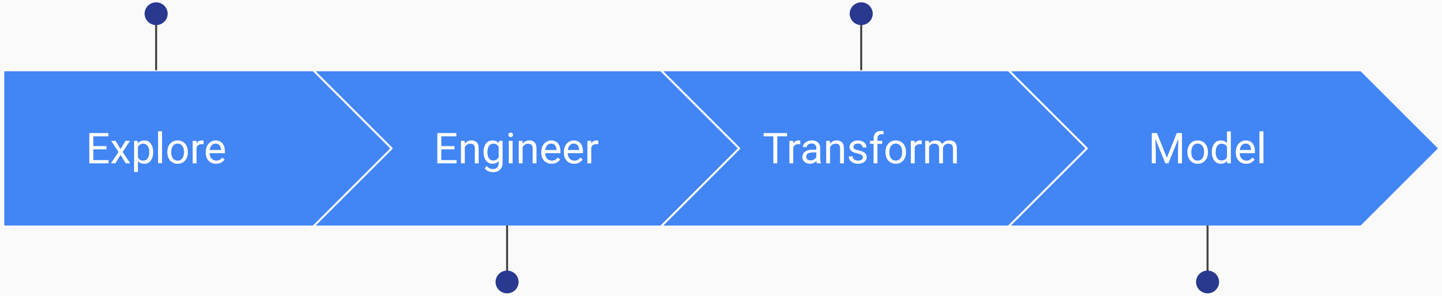

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Forecast item sales using a variety of models. Evaluate and compare the results of prediction.

The Process

Explore the descriptive statistics, density, distribution, trend, and seasonality of overall and individual item sales

Test and transform the time series for stationarity.

Fine tune the seasonal orders of the predictive models and iterate.

Explore

Engineer

Transform

Model

Tune

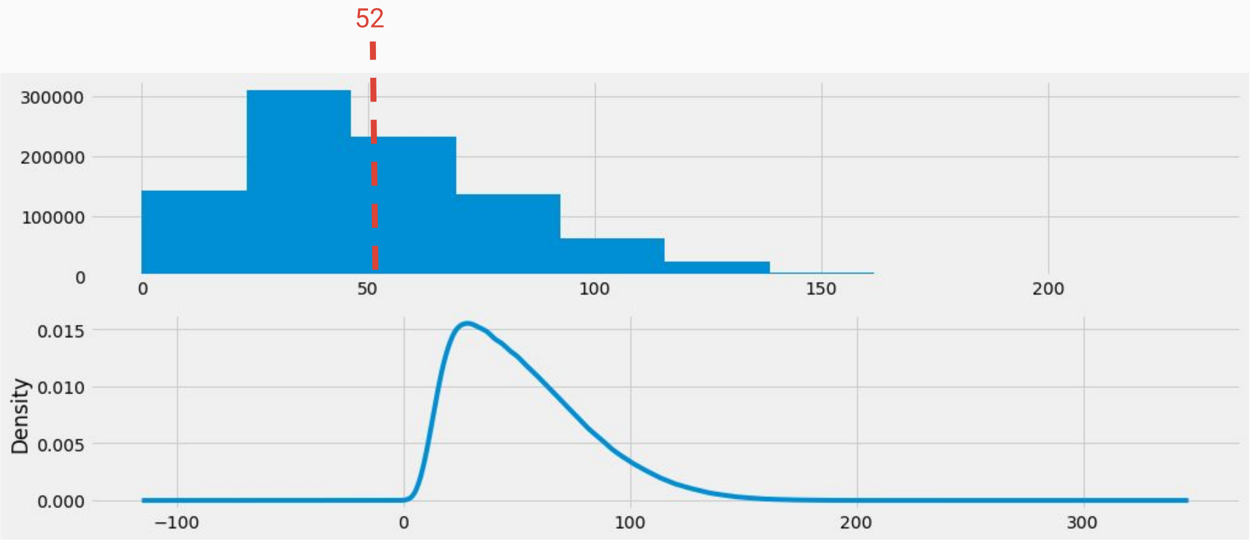
Extend the dataset with descriptive features for the dates. Determine feature importances based on predictive modeling using tree based learning algorithm.

Forecast item sales using a variety of models. Evaluate and compare the results of prediction.

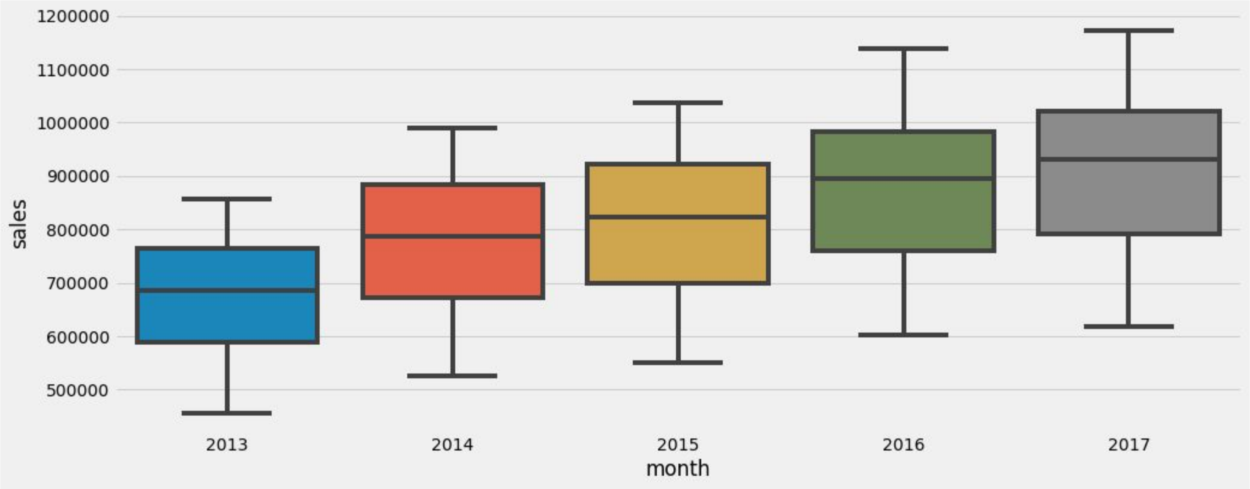
Explore

Overall Sales

Daily sales numbers range from 0 to 231 with a mean of 52. The majority, or middle 50%, of daily item sales numbers fall between 30 and 70, and there are the least number of observations above 100. Density of the sales observations shows the data has non-normal distribution and is slightly left shifted.

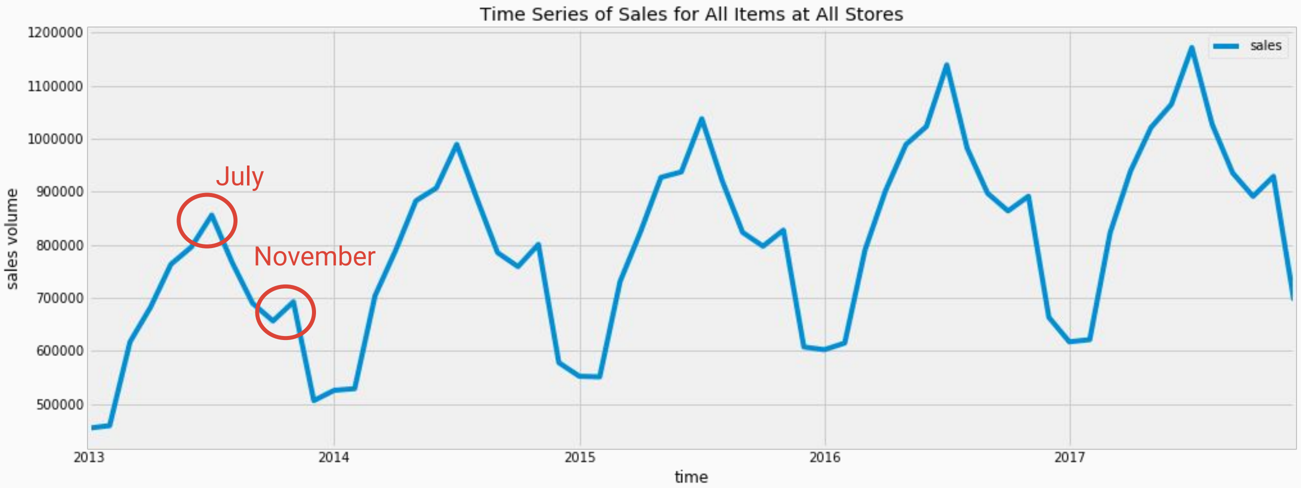


Overall Sales



Median sales values have an upward trend over time. Total annual sales volume increased slightly each year, and there is also an increase in the spread, or middle 50% of the data, over time.

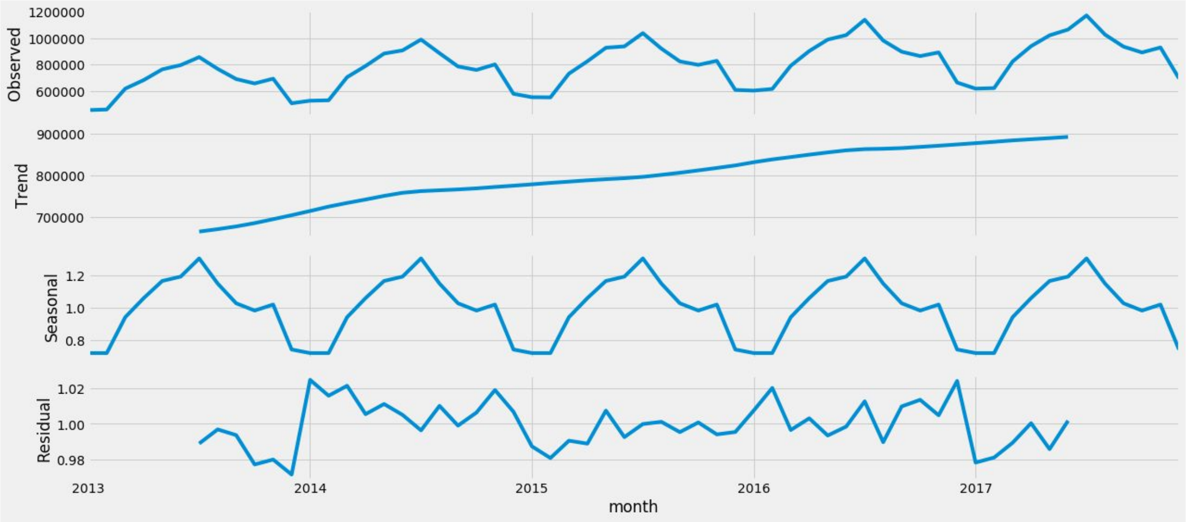
Overall Sales



Each year, total sales climbs to a peak in July from January, and then goes back down to a trough with a slight peak in November. Reviewing the total sales numbers over time for all items in all stores reveals a time series with yearly seasonality and an upwards trend.

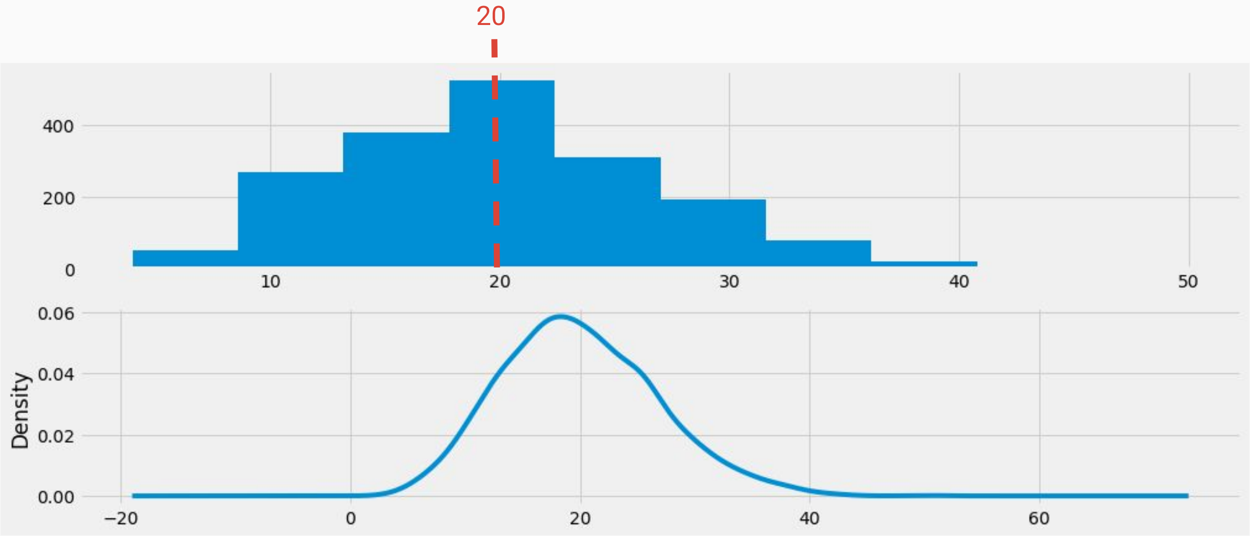
Decomposition

An upwards trend and strong seasonality are visible with decomposition of the time series for the sales totals of all items at all stores. This indicates that transformations might be required prior to modeling, and that models which take seasonality into consideration should be utilized when making forecasts.

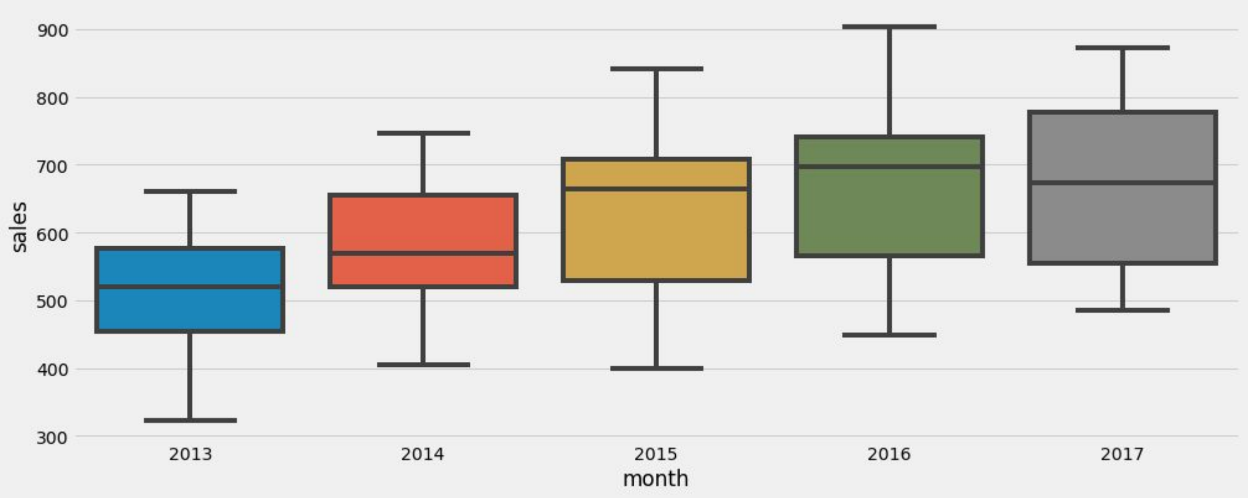


Individual Sales

For item 1 at store 1, daily sales numbers range from 4 to 50 with a mean of 20. The majority, or middle 50%, of daily sales numbers fall between 15 and 24, with the least number of observations below 8 and above 35. Unlike overall sales, density of individual item sales observations at one store shows the data is normally distributed.

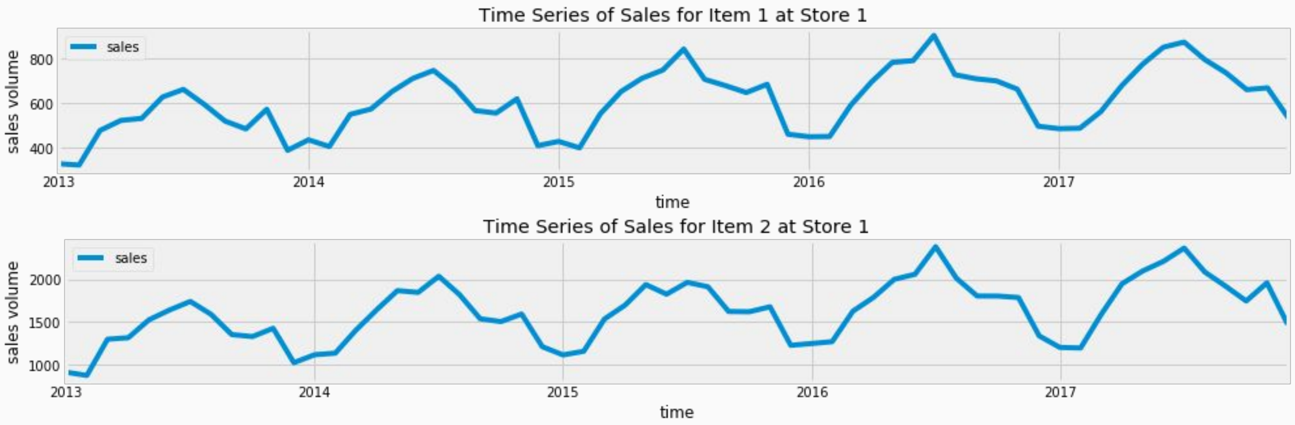


Individual Sales



Both the median and total volume of annual sales for item 1 at store 1 decreased from 2016 to 2017. There is an overall increase in the spread over time.

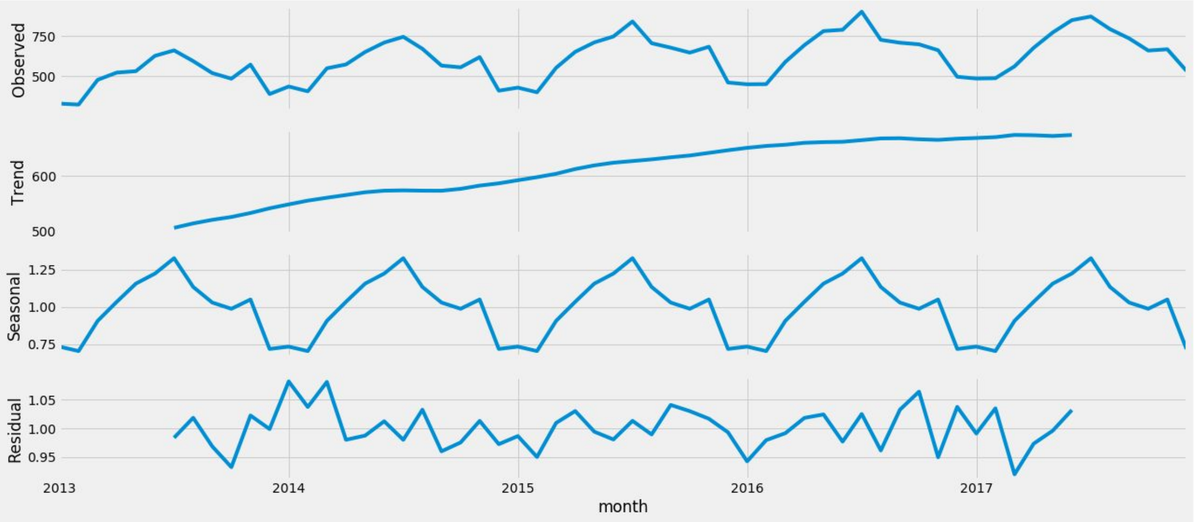
Individual Sales



For both item 1 and item 2 at store 1, the peaks and troughs are irregular throughout the years. The trends and seasonality of the time series are less pronounced.

Decomposition

An upwards trend and strong seasonality became more visible with decomposition of the time series for the sales of item 1 at store 1. This indicates that transformations might be required prior to modeling, and that models which take seasonality into consideration should be utilized when making forecasts.



Engineer

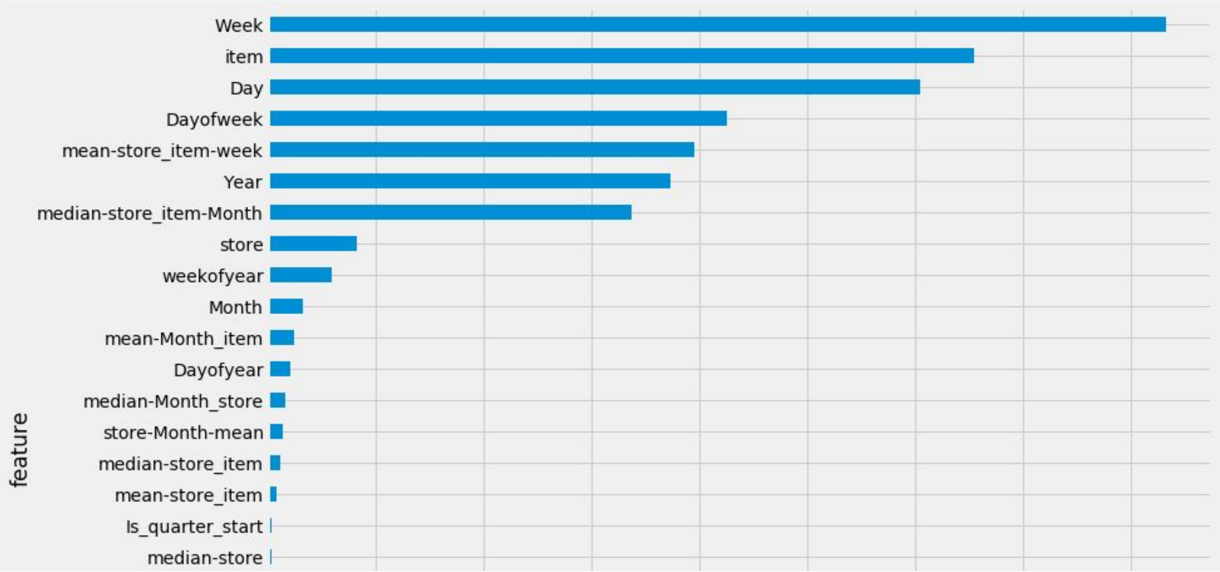
Extending Date Features

date	store	item	sales	month	Year	Month	Week	Day	Dayofweek	Dayofyear	weekofyear	Is_month_end	Is_month_start	Is_quarter_end	Is_quarter_start	Is_year_end	Is_year_start
2013-01-01	1	1	13	2013-01	2013	1	1	1	1	1	1	FALSE	TRUE	FALSE	TRUE	FALSE	TRUE
2013-01-02	1	1	11	2013-01	2013	1	1	2	2	2	1	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
2013-01-03	1	1	14	2013-01	2013	1	1	3	3	3	1	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
2013-01-04	1	1	13	2013-01	2013	1	1	4	4	4	1	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
2013-01-05	1	1	10	2013-01	2013	1	1	5	5	5	1	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE

Feature Importances

Tree based learning algorithms from the LightGBM framework are used to determine feature importances.

The week, item, and day are the top 3 most important features having the biggest impact on sales numbers. Conversely, the store, day of year, and month are among the least important features



Transform

Test for Stationarity

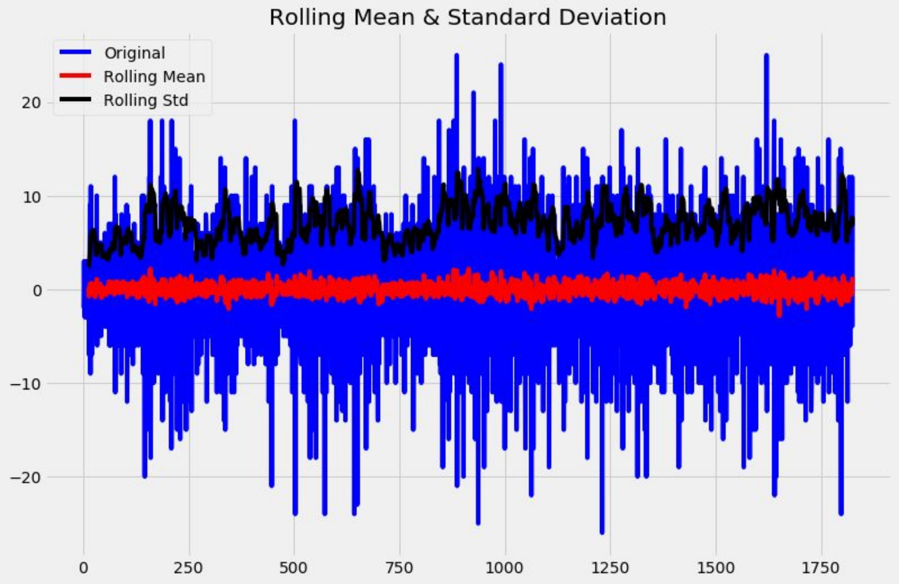
Stationarity of an individual time series (for item 1 at store 1) is checked using the augmented Dickey-Fuller Test. Here the null hypothesis is that the time series is non-stationary.

Since the series has a strong upward trend, we will use the strictest 1% critical value to test the hypothesis. We accept the null hypothesis and the time series of item 1 at store 1 is non-stationary. Transformations of individual time series are necessary prior to modeling using ARMA models.

Results of Dickey-Fuller Test:

Test Statistic	-3.157671
p-value	0.022569
#Lags Used	23.000000
Number of Observations Used	1802.000000
Critical Value (1%)	-3.433984
Critical Value (5%)	-2.863145
Critical Value (10%)	-2.567625

Differencing



To transform the series of sales numbers of each item at each store, we take the difference of the observation at a particular instant with that at the previous instant using first order differencing in Pandas. The transformed time series shows constant variance over time.

This is the most important takeaway that everyone has to remember.

Thanks!

juichiaholland@gmail.com
www.juichiacheholland.com