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Predict 413 – Time Series & Forecasting
Midterm – Summer 2018

Forecasting 1C Company Total Sales for Every Product and Store in Next Month

Introduction

All companies with stores and products to sell need to know if their stores are profitable, or if they're lagging in certain areas either due to product loss, product popularity, seasonal changes in the needs and wants of their customers, lack of products, etc. Maybe some stores do better in certain geographies versus other geographical areas. Maybe the customer base is significantly larger or smaller in some areas versus others.

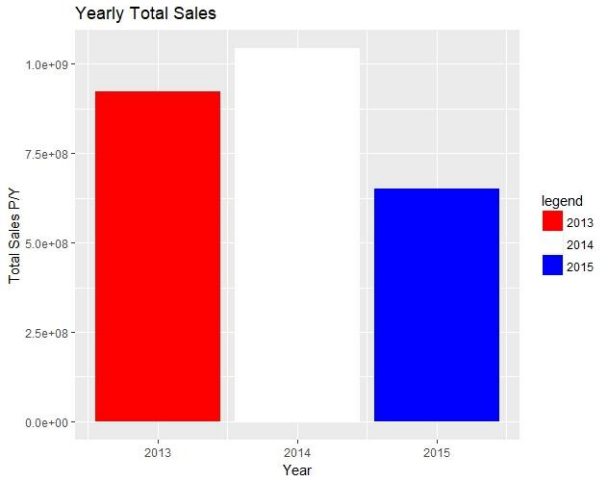
This competition is to predict the total sales for every product and store for the next month in 2015, which was November. Since November is practically the start of the holiday season, depending on where the store is located, it's important to know whether or not you'll need more of a certain product or products, and whether or not the stores can improve on sales during the holidays, or if they can find ways to cut back and not take a profit loss – i.e.: shutting down the stores earlier instead of later to save on money; not keeping products that aren't selling on the shelves.

I didn't think about getting ahead of this midterm and starting weeks earlier, which is showing to be detrimental because the difficult part of this problem set is the actual data analysis and cleansing. I could not open the csv.gz files, even with a winZip converter because it either came out as nothing but odd characters, or corrupt files. I needed to be able to pull the "item_cnt_month" data from the *sample submission* but it too was a csv.gz file that I had issues with. The dataset was the biggest set I've ever worked with, and my computer couldn't even handle such a large set of data when I tried to merge the *sample submission* data into the *sales training* data.

Data

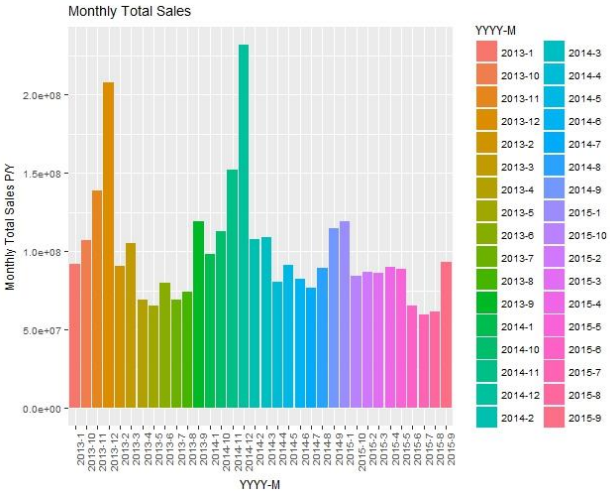
To start this analysis of the data, I read in each of the provided datasets: *sales_train.csv.gz, test.csv.gz, shops.csv, items.csv, item_categories.csv,* and *sample_submission.csv.gz*. I reviewed the top 20 rows of each set, as well as looked at descriptions about each set to see the number of observations and variable counts. I decided to join a few columns from the items, shops, and item_category files into the sales_train data set, and then confirmed they were merged. I then added "year", "day", "weekday", and "month" columns to the sales_train dataset.

In reviewing the dataset, I started with the yearly sales from 2013-2015.

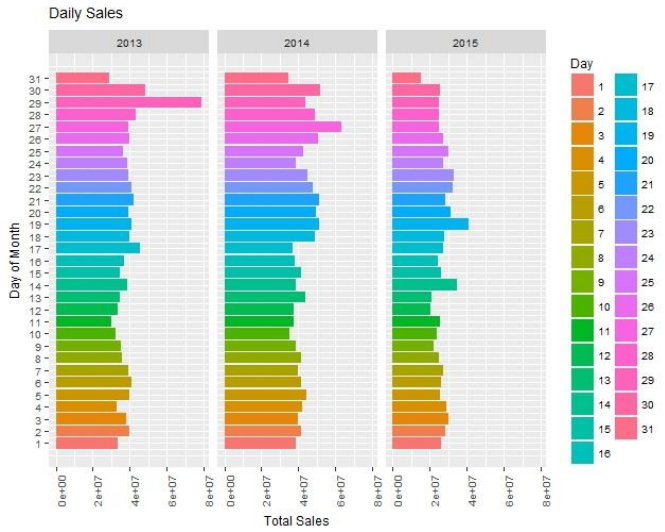


We can see that sales went up by $122 million in 2014 in comparison to 2013; however, in 2015, sales fell by about $393 million.

Next, we look at monthly sales. There's a significant spike in November for both 2013 and 2014, probably due to the holidays. It is likely that November in 2015 will show a spike as well, but not has much as 2014 due to the lack of sales occurring in 2015 prior to November.



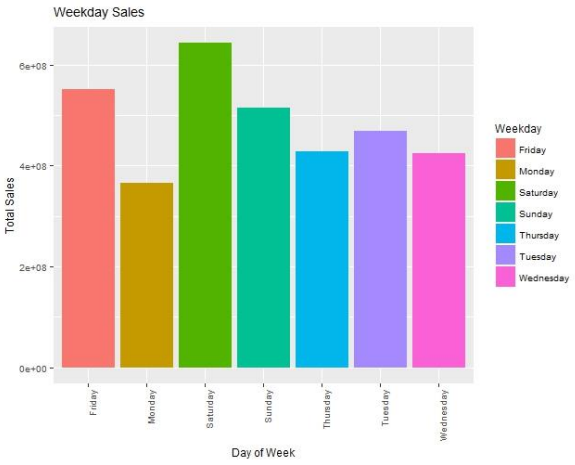
Next, we see which day of the month had the highest sales.

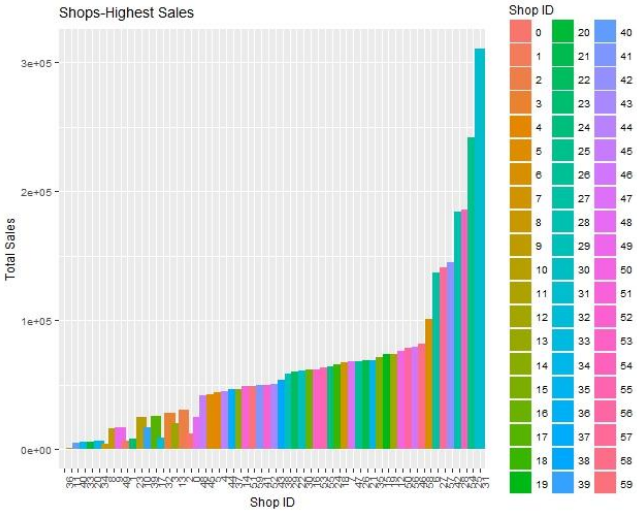


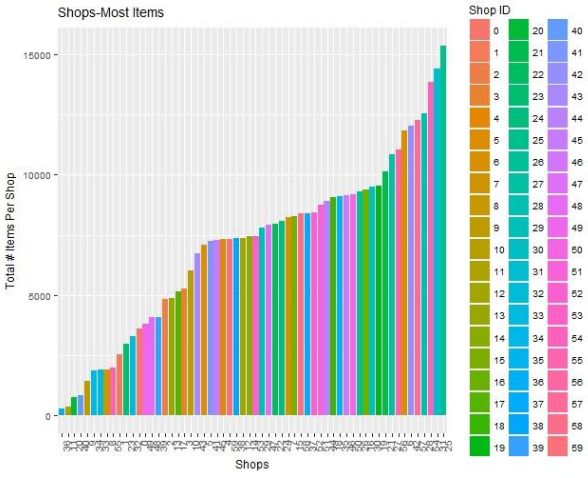
2013 shows a spike near the end of the month, 2014 shows as nearly equal from the middle to the end of the month, and 2015 shows a decrease as the end of the month with a small increase in the middle.

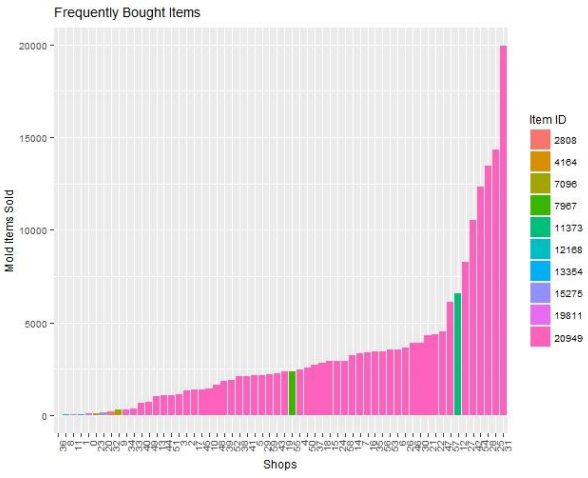
Next we look at more descriptive graphs for:

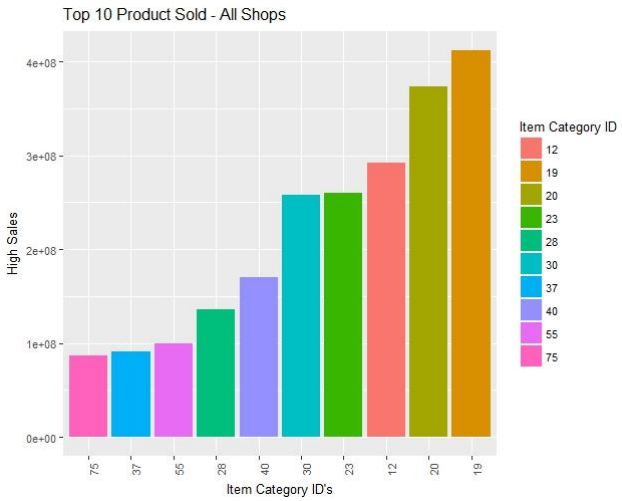
- Weekday with highest sales
- Shops with highest sales
- Shops with most items
- Frequently bought items per store
- Top 10 sold products – all stores
- Top 10 sold products – within each category

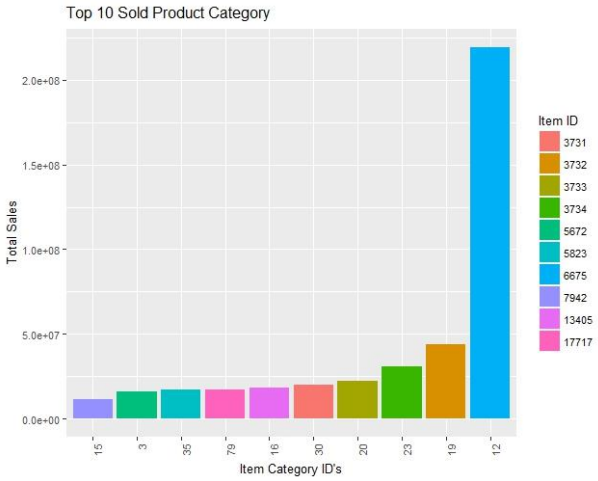






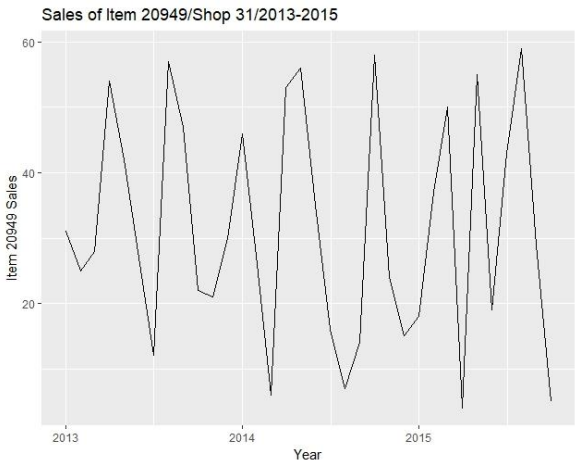


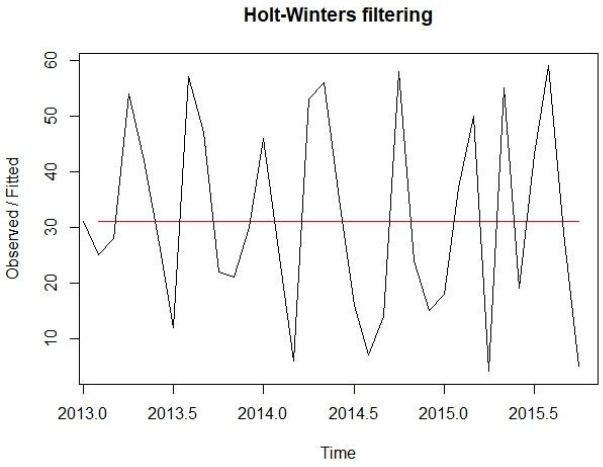




Models / Formulation / Performance / Limitations

I created a plot and model for frequently bought items because I felt as though this would have significant impact on sales for each store. In plotting this time series, it looks like nothing but white noise. I then ran a Holt-Winters SES on this data and it shows a straight, smooth line for prediction.





I ran three different methods on this time series: ETS, ETS with “ZZZ”, and an Auto.Arima. Out of the three, ETS and ETS with “ZZZ” were better (and were the same RMSE values. So, I chose to fit and forecast with the above model. The forecast doesn’t seem that great:

	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
Nov 2015	31.45705	8.886689	54.02741	-3.061339	65.97544
Dec 2015	31.45705	8.886689	54.02741	-3.061339	65.97544
Jan 2016	31.45705	8.886689	54.02741	-3.061339	65.97544
Feb 2016	31.45705	8.886689	54.02741	-3.061339	65.97544
Mar 2016	31.45705	8.886689	54.02741	-3.061339	65.97544

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Apr 2016        31.45705 8.886689 54.02741 -3.061340 65.97544
May 2016        31.45705 8.886689 54.02741 -3.061340 65.97544
Jun 2016        31.45705 8.886688 54.02741 -3.061340 65.97544
Jul 2016        31.45705 8.886688 54.02741 -3.061340 65.97544
Aug 2016        31.45705 8.886688 54.02741 -3.061340 65.97544
Sep 2016        31.45705 8.886688 54.02741 -3.061340 65.97544
Oct 2016        31.45705 8.886688 54.02741 -3.061341 65.97544
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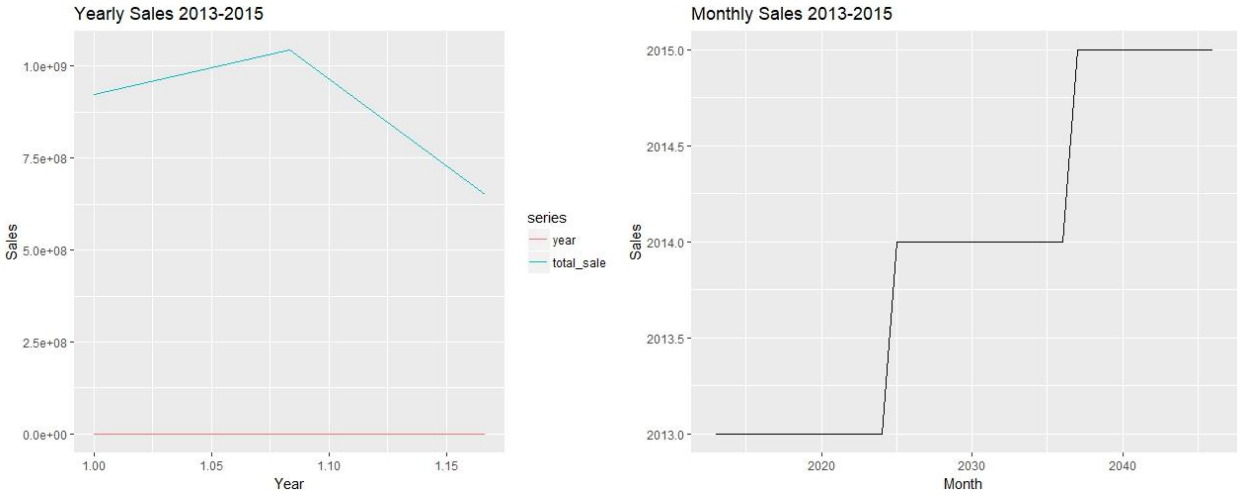
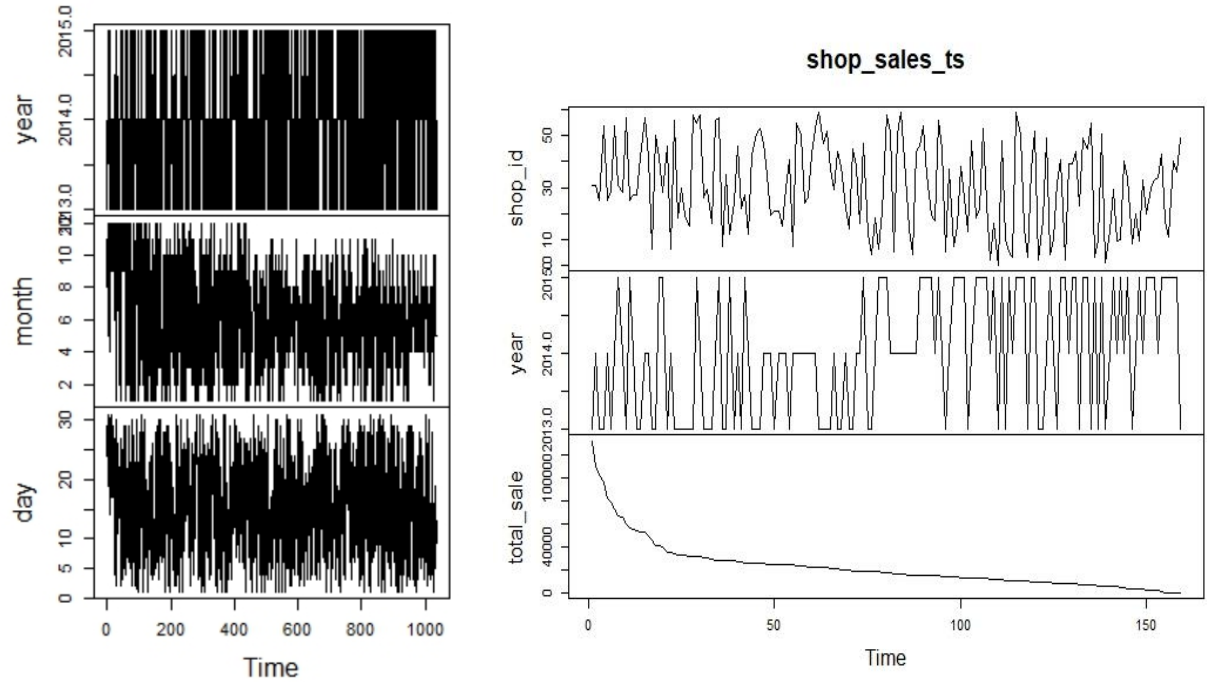
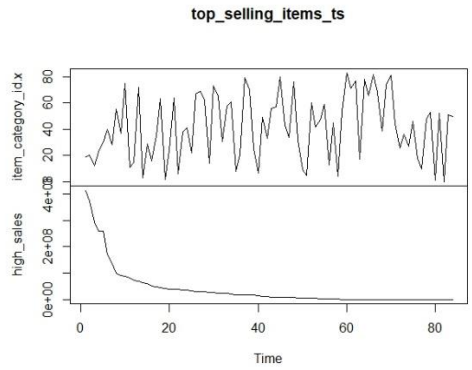
I tried plotting the yearly and monthly sales, but the plots look odd:



I tried to plot and forecast a couple other variables with SES, but they looked odd as well, or didn't work. It's probably because some things weren't seasonal data:





I believe had I given more time to the data cleansing portion, I would've been able to utilize what I initially planned on trying out from what we've learned so far in class: *meanf*, *naïve*, *snaive*, and *drift* methods to see which would work best. I would then move on to transformation/adjustments with residual diagnostics before moving on to accuracy. Time series decompositions would've also been helpful, especially STL decomp because of the below:

- Unlike SEATS and X11, STL will handle any type of seasonality, not only monthly and quarterly data. [1]
- The seasonal component is allowed to change over time, and the rate of change can be controlled by the user. [1]
- The smoothness of the trend-cycle can also be controlled by the user. [1]
- It can be robust to outliers (i.e., the user can specify a robust decomposition), so that occasional unusual observations will not affect the estimates of the trend-cycle and seasonal components. They will, however, affect the remainder component. [1]

Future Work

For future work (and the final) I plan on starting the data cleansing process immediately (weeks ahead of time) since I struggled with this piece a lot. At this point, anything I do in the future should improve this competition if I were to come back to it since this didn't turn out so well.

Learning

For me, the biggest issue was data cleansing. I can follow the book's models and other resource methods for forecasting my data, but I must get past the initial cleansing first. I would like to incorporate xboosting and poisson methods as some of the other students did to see how those options would work against the data.

Literature

Kapoor, S.G., Madhok, P., Wu, S.M. *Journal of Marketing Research*. Modeling and Forecasting Sales Data by Time Series Analysis, 1981. https://www.jstor.org/stable/3151318?seq=1#page_scan_tab_contents Accessed 27 July 2018.

Nunnari, Giuseppe & Nunnari, Valeria. (2017). Forecasting Monthly Sales Retail Time Series: A Case Study. 1-6. 10.1109/CBI.2017.57. https://www.researchgate.net/publication/319224544_Forecasting_Monthly_Sales_Retail_Time_Series_A_Case_Study Accessed 28 July 2018.

Sanwlani, Monica & Murlidhar, Vijayalakshmi. (2013). Forecasting Sales Through Time Series Clustering. International Journal of Data Mining & Knowledge Management Process. 3. 39-56. 10.5121/ijdkp.2013.3104. https://www.researchgate.net/publication/269803515_Forecasting_Sales_Through_Time_Series_Clustering Accessed 28 July 2018.

Shafik, Engy. *JTATM*. Predictive Modeling of US Winter Apparel Sales Using Time Series Forecasting Method, 2016. ojs.cnr.ncsu.edu/index.php/JTATM/article/download/9858/4923 Accessed 27 July 2018.

Ugiliweneza, Beatrice. Use of ARIMA Time Series and Regressors to Forecast the Sale of Electricity. https://analytics.ncsu.edu/sesug/2007/PO10.pdf Accessed 29 July 2018.