FORECASTING PRODUCT DEMAND FOR A RETAIL CHAIN TO REDUCE COST OF UNDERSTOCKING AND OVERSTOCKING

FCAS1 FINAL PROJECT REPORT

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Executive Summary

Bad inventory planning can have a negative impact leading to loss of sales at the retailer end (understocking) or an inventory build-up across the chain (overstocking). This can result in potential losses to all stakeholders in the chain. Forecasting can help demand planners of retail chains make better decisions regarding the right quantity of products to stock on retail shelves.

Our forecasting goal is to manage inventory better by forecasting demand and determining the right amount of product to stock. We will also look to forecast how the demand varies based on seasonality. We studied store level sales data for a particular SKU, to identify trends across stores with high, medium or low growth rates for the SKU. The stores were c

hosen to include those samples with the highest, intermediate and least annual sales. The data was taken from Kaggle. The data is relatively clean and covers daily sales for a period of 5 years and has seasonality. The methodologies used were Naïve Forecasts, Holt-Winters Smoothing (Additive/Multiplicative) and Linear Regression (Additive/Multiplicative).

Holt Winter's exponential smoothing method provided the least MAPE value and was chosen as the model for forecasting demand for the next quarter. Holt Winter's smoothing is used when trend and seasonality is present in the data. The appropriate Level(α), Trend(β) and Seasonality(γ) values were arrived at for each store either iteratively or by choosing the optimize function in XLMiner.

Holt Winter's MAPE values compared to Naïve benchmark values are as shown below:

MAPE values	Holt Winter's	Naïve model
Store 1	30.3%	31.3%
Store 2	24.8%	24.6%
Store 3	25.4%	27.1%
Store 4	26.8%	27.3%
Store 6	30.9%	30.9%
Store 7	22.7%	26.8%

Conclusion & Recommendations:

By evaluating different models and their error measures using the 2 years of training data and 1 year of validation, the Holt Winter's model is used to forecast demand for the next 3 months. The demand from the stores for the next 3 months can be used by demand planners within the company to better manage inventory and ensure no stockouts and overstocking. The recommendations for various stakeholders within the retail ecosystem are as follows:

1) Retailers can incentivize sales on weekdays to make demand smooth and predictable, additionally retailers with low sale volumes can rent out temporary storage facilities to replenish shelf space when needed.
2) Warehouses can consolidate shipments by retail outlets to reduce shipping cost/ vehicle and in case of highly variable demand, increase order frequency.
3) Production and manpower planning can be done with the demand forecast, shifts can be increased during peaks and SKU batch runs can be scheduled on production lines based on demand forecasts.

II. Technical Summary

i) Data Preparation and Issues

The original dataset contained daily data for 10 stores and 50 SKUs, from January 1, 2013 to December 31, 2017. As mentioned earlier, we used this data to forecast sales for SKU-1 across 6 stores(Store # 1,2,3,4,6,7). The following steps were taken to clean data:

- Scanned data for missing dates, improper values in sales column
- Checked for outliers in sales (e.g. values >200% or <200% the nearest value)
- Removed data for 29th February 2016 (due to additional record in leap years)

No other data-related issues were detected.

ii) Analysis

a) Naive Forecast:

The time series plot of the data featured level, noise, trend (linear), and seasonality (multiplicative in stores 1,2,3, and 6 while additive in stores 4 and 7).

We considered MAPE to be the rightful metric to judge the effectiveness of the model. Also, the plot of the obtained forecast is used to understand if the model is effective.

Thus the MAPE values for Naïve forecasts, mentioned below, set the benchmark for each store.

With training data taken as actual sales of year 2015 and 2016, and validation on sales of year 2017, following is the benchmark MAPE of naïve forecast for validation period -

Store #	MAPE (Validation Period - Naive)
1	31.25%
2	24.59%
3	27.14%
4	27.27%
6	30.91%
7	26.76%

b) Holt Winter's Smoothing:

Due to the presence of trend and seasonality in the data, Holt-Winter's smoothing method was used. The smoothing was done on both additive and multiplicative with a period of 365. Due to Limitations of 1000 data set by XLMiner, the recent years i.e 2015 and 2016 (731 data points) was chosen as the training set and year 2017 (365 data points) was chosen as the validation set.

The optimize option helped us get an initial estimate of values for Alpha, Beta and Gamma. The additive or multiplicative seasonality was confirmed over better values observed in MAPE. The forecasts and residuals were plotted in a time series to observe the components of the series not captured by the model. The values of alpha, beta and gamma were tuned accordingly to capture the components of level, trend and seasonality missed by the model to optimize the MAPE. The final values are as follows.

	Alpha	Beta	Gamma	Training MAPE	Validation MAPE
Store 1	0.2	0.15	0.1	17.59	30.65
Store 4	0.01	0.01	0.45	18.94	26.79
Store 2	0	0.15	0.05	13.992	25.37
Store 6	0.2	0.15	0.05	17.87	29.14
Store 3	0	0.2	0	13.26	24.76
Store 7	0	0.01	0.08	17.59	22.65

In our pursuit for better values of MAPE, we switch from a data driven method to model driven method with the assumption of global pattern and the expectation that the model will remain same in the future.

c) Linear regression:

Linear regression was done with t as time index (due to presence of linear trend) and dummy variables based on each month of the calendar year. Following were the MAPE obtained of the validation period. Though, the MAPE is slightly better than Holt Winter's Smoothing method for a few stores but since in the plot, it is visible that this forecast is not capturing seasonality, hence this was discarded.

Store #	MAPE (Validation Period - Linear Regression)
1	24.54%
2	20.45%
3	18.59%
4	22.18%
6	22.90%
7	33.44%

d) ARIMA Model:

ARIMA lag analysis was done to find the ACF and PACF charts. Multiple points of correlation was found between 1-7 and was found to be different for different stores. The Auto-regressive model was then applied with maximum of 7 and the consequent MAPE was calculated. Though there was marginal improvement over the Naïve forecasts, we did not use it due to the presence of partial auto correlation in both positive and negative direction (refer to Exhibit 1) and the requirement of longer forecast (90 days) made the model unworthy of business objective.

iii) Conclusion

Holt-Winters multiplicative smoothing method turns out to be the best way to forecast store-level daily sales for SKU-1 (based on MAPE comparison and plot). While the results are not a significant improvement over Naïve forecast, they are better than ARIMA and Linear Regression. Refer exhibit 3 for the final forecast.

iv) Recommendations:

The retailers as well as the suppliers can implement several measures based on the forecast to reduce overall costs

- Inventory Decisions
    - Given the demand forecasts for the next 3 months, retailers should place orders for peak days in advance in order to avoid stock out situations.

    - Low volume retailers can consider renting a temporary storage space/godown near the store. This can lead to consolidation of orders from the distribution centre and replenishment of shelves on an as needed basis.
    - Sales on weekdays can be incentivized to make demand smooth and more predictable.
- **Logistics cost**
    - Given demand forecasts, the warehouse can consolidate shipments to the retail outlets. Order frequency can be increased in case of highly variable demand as seen in store 6 to remain flexible.
- **Production & Manpower**
    - By aggregating demand at a weekly/monthly level across all stores, production should be planned for the SKU at pre-defined intervals.
    - Manpower can be planned for peak periods by adding additional shifts as required as per demand forecasts

v) Limitations, Possible Improvements and Next Steps:

A few limitations to the process highlighted above are –

- Risk of over-fitting is high if the values of α, β, γ are optimized
- There may be unknown seasonality (e.g. holidays, festivals) which may not be captured through this process, as peaks and troughs are not accurately predicted by ARIMA
- Holt-Winters is not a major improvement on the Naïve Forecast

Possible improvements to the above process are -

- Instead of predicting only daily sales, it might be more feasible to predict aggregate sales (e.g. weekly, monthly or quarterly)
- An ensemble approach might yield better results in terms of capturing weekly/monthly seasonality and also, predicting daily variations more accurately
- A more exhaustive process, where multiple SKUs are evaluated across the 6 stores can provide information on product bundles, and thus offer more insight into the trends followed by SKU-1
- Another approach where SKU-1 is observed across all 10 stores can be used to gauge spatial information – e.g. location of the store

Next Steps:

Forecast should be updated after every month to capture latest trend and seasonality, and hence, to obtain better accuracy

Appendix

Exhibit 1:

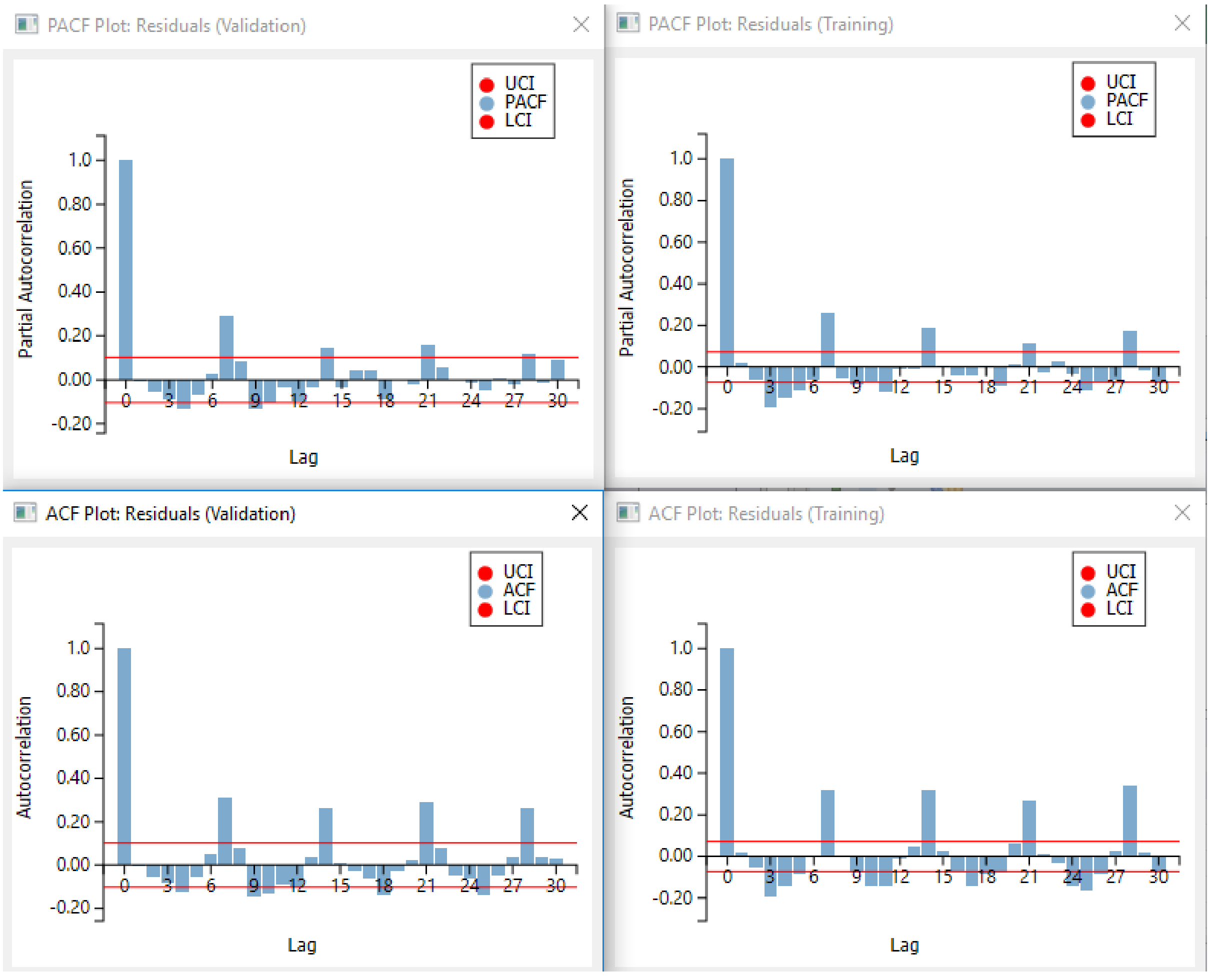
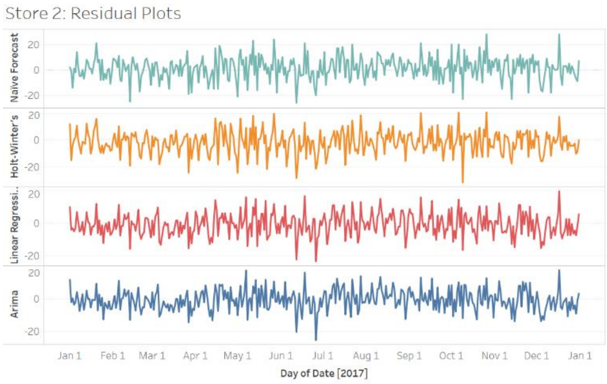


Exhibit 2

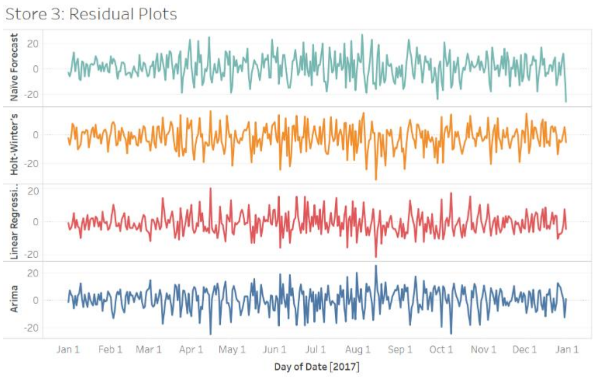
Comparison of methods: Residual Plots across methods

In general there was no trend in the residuals for any of the stores, irrespective of the method used, which is a good sign. However, based on the method, residuals changed for each store. Marked differences can be seen. For instance, for Store 2 we can clearly see that smoothing techniques could better capture some peaks and troughs better than a regression based forecast. However, this being said, in general, a linear regression based forecast produced a lower MAPE.

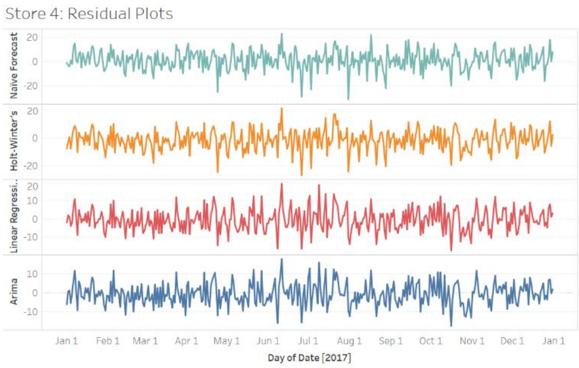
The trends of Naïve, Holt-Winter's, Linear Regression and Arima for Date Day. Color shows details about Naïve, Holt-Winter's, Linear Regression and Arima.



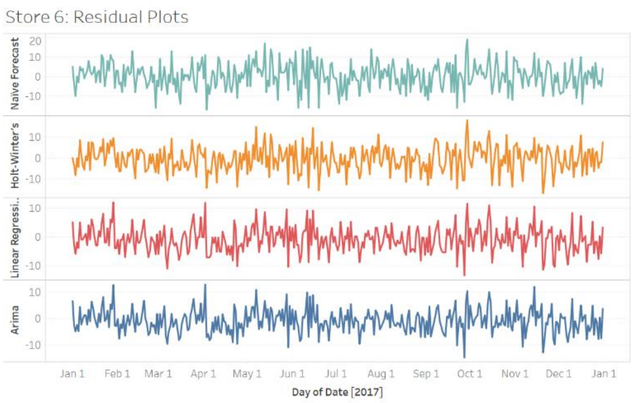
The trends of Naïve Forecast, Holt-Winter's, Linear Regression and Arima for Date Day. Color shows details about Naïve Forecast, Holt-Winter's, Linear Regression and Arima.



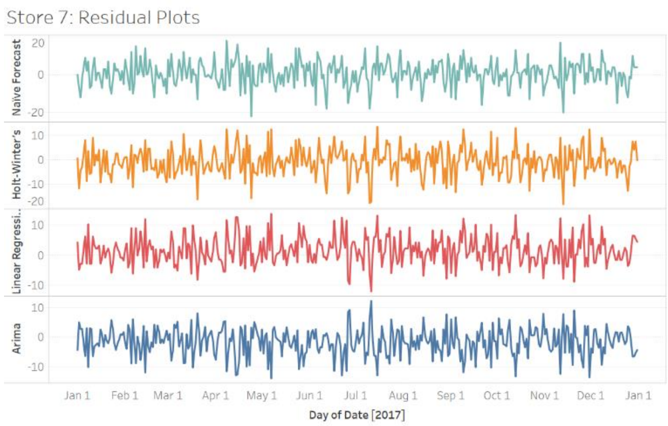
The trends of Naïve Forecast, Holt-Winter's, Linear Regression and Arima for Date Day. Color shows details about Naïve Forecast, Holt-Winter's, Linear Regression and Arima.



The trends of Naïve Forecast, Holt-Winter's, Linear Regression and Arima for Date Day. Color shows details about Naïve Forecast, Holt-Winter's, Linear Regression and Arima.



The trends of Naïve Forecast, Holt-Winter's, Linear Regression and Arima for Date Day. Color shows details about Naïve Forecast, Holt-Winter's, Linear Regression and Arima.



The trends of Naïve Forecast, Holt-Winter's, Linear Regression and Arima for Date Day. Color shows details about Naïve Forecast, Holt-Winter's, Linear Regression and Arima.

Exhibit 3: Final Forecast (using Holt Winter Smoothing)

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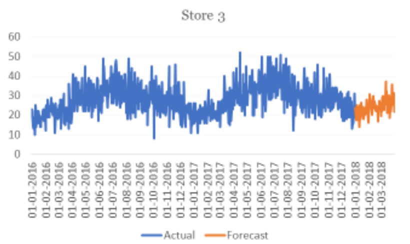
Holt Winter's smoothing model had the least MAPE based on 2 years of training data and 1 year of validation data

α = 0 β = 0.3 γ = 0

α = 0 β = 0.15 γ = 0.05



- Method Used: Holt-Winters Smoothing (Multiplicative)
- Training Period: 1/1/2015 – 31/12/2016 | MAPE: 13.992
- Validation Period: 1/1/2017 – 31/12/2017 | MAPE: 25.37
- Forecast Period: 1/1/2018 – 31/3/2018
- Naïve model – MAPE – 27.14

- Method Used: Holt-Winters Smoothing (Multiplicative)
- Training Period: 1/1/2015 – 31/12/2016 | MAPE: 13.26
- Validation Period: 1/1/2017 – 31/12/2017 | MAPE: 24.76
- Forecast Period: 1/1/2018 – 31/3/2018
- Naïve model – MAPE – 24.59

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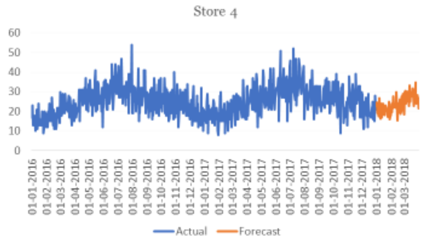
Holt Winter's smoothing model had the least MAPE based on 2 years of training data and 1 year of validation data

α = 0.01 β = 0.01 γ =0.45

α = 0.2 β = 0.15 γ = 0.1



- Method Used: Holt-Winters Smoothing (Additive)
- Training Period: 1/1/2015 – 31/12/2016 | MAPE: 18.94
- Validation Period: 1/1/2017 – 31/12/2017 | MAPE: 26.79
- Forecast Period: 1/1/2018 – 31/3/2018
- Naïve model – MAPE – 27.27

- Method Used: Holt-Winters Smoothing (Multiplicative)
- Training Period: 1/1/2015 – 31/12/2016 | MAPE: 17.59
- Validation Period: 1/1/2017 – 31/12/2017 | MAPE: 30.65
- Forecast Period: 1/1/2018 – 31/3/2018
- Naïve model – MAPE – 31.25

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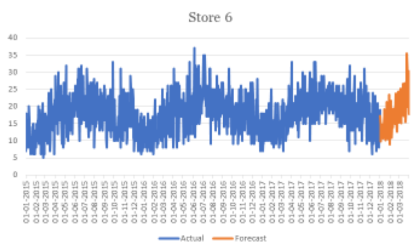
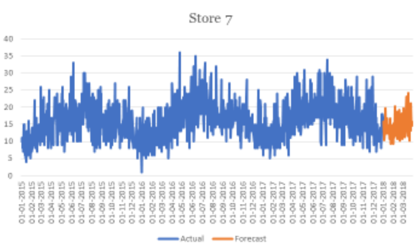
Holt Winter's smoothing model had the least MAPE based on 2 years of training data and 1 year of validation data

α = 0.2 β = 0.15 γ = 0.05

α = 0 β = 0.01 γ = 0.08





- Method Used: Holt-Winters Smoothing(Multiplicative)
  Training period – 1/1/2015 to 31/12/2016 |MAPE: 29
- Validation period – 1/1/2017 to 31/12/2017
- Forecast period – Jan 1, 2018 to March 31, 2018
- Naïve model – MAPE – 30.91

- Method Used: Holt-Winters Smoothing (Additive)
- Training Period: 1/1/2015 – 31/12/2016 | MAPE: 17.59
- Validation Period: 1/1/2017 – 31/12/2017 | MAPE: 22.65
- Forecast Period: 1/1/2018 – 31/3/2018
- Naïve Model – MAPE – 26.76

Exhibit 4:

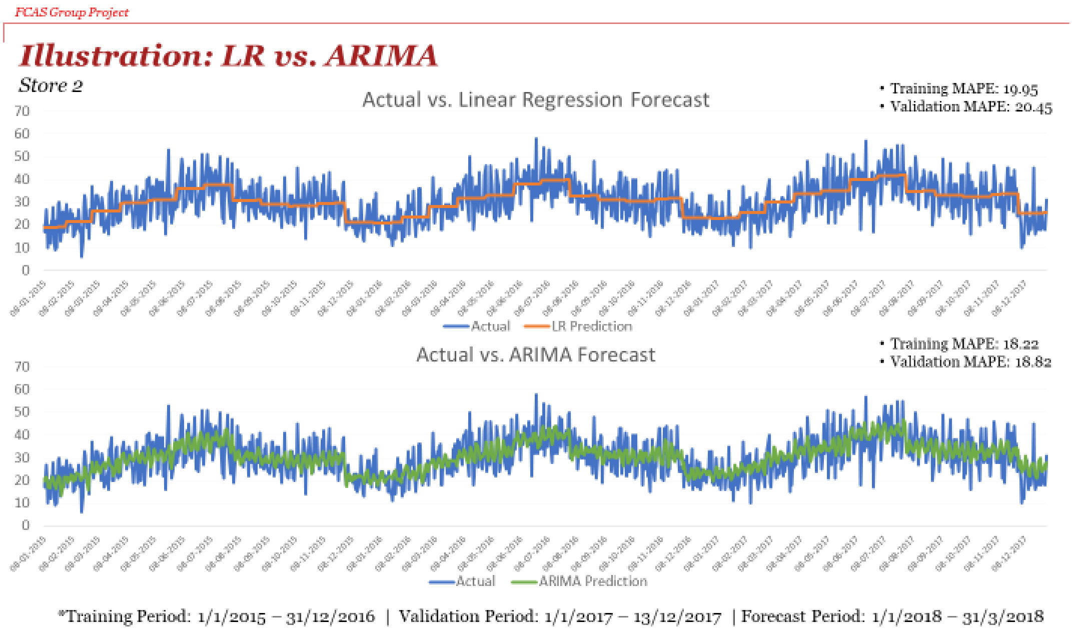

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Illustration: LR vs. ARIMA
Store 2
Actual vs. Linear Regression Forecast
• Training MAPE: 19.95
• Validation MAPE: 20.45
Actual
LR Prediction
Actual vs. ARIMA Forecast
• Training MAPE: 18.22
• Validation MAPE: 18.82
Actual
ARIMA Prediction
*Training Period: 1/1/2015 – 31/12/2016 | Validation Period: 1/1/2017 – 13/12/2017 | Forecast Period: 1/1/2018 – 31/3/2018