Sales Forecast OffSup Inc

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Problem Statement

OffSup Inc. is a multinational conglomerate that sells supplies, furniture and technology essential to offices. OffSup had a tie up with a certain logistics provider which spanned across the United States, France, Germany, Mexico, Australia and China. The contract is close to expiry and OffSup must negotiate new terms for the future.

OffSup's analysts are tasked with forecasting the total demand for the next year for each of these countries, to help OffSup negotiate the delivery services for the right expected demand.

Data Description

The data we use for this analysis is called "Global Superstore 2016" which is known as a sample dataset released by Tableau. The dataset contains over 50,000 observations and 24 variables.
We have data from different countries at a product-day level, but for our analysis we aggregate data to a country-month level.

Goals

In this project, we will focus on the sales in the US, which is the largest market among the countries in this dataset. Our analysis will first identify the best ARIMA model for the US market and then forecast for the future. Alongside the report, we have also built an R shiny app. In this app, we will give the user the flexibility to change the country and use separate pre-determined models for each country.

Exploratory Analysis

The most relevant EDA plots are the time series plots.

Monthly time series of demand in the US:

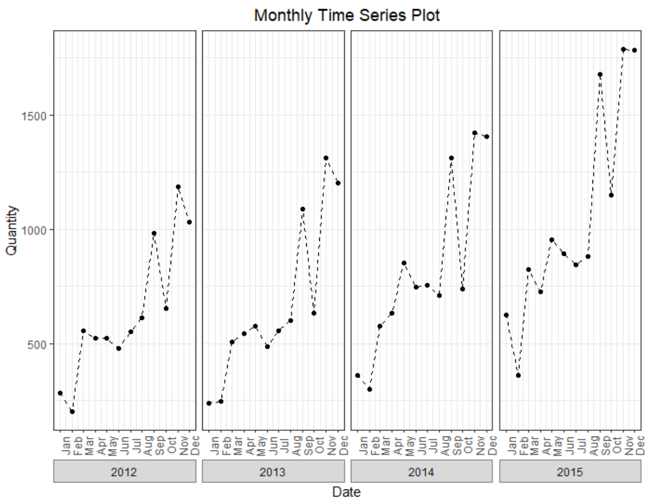


Figure 2.1.1

In these plots, we demonstrate the monthly patterns for each year. We can see an obvious seasonal pattern and an increasing trend in these plots.

Monthly time series of demand by Category in the US:

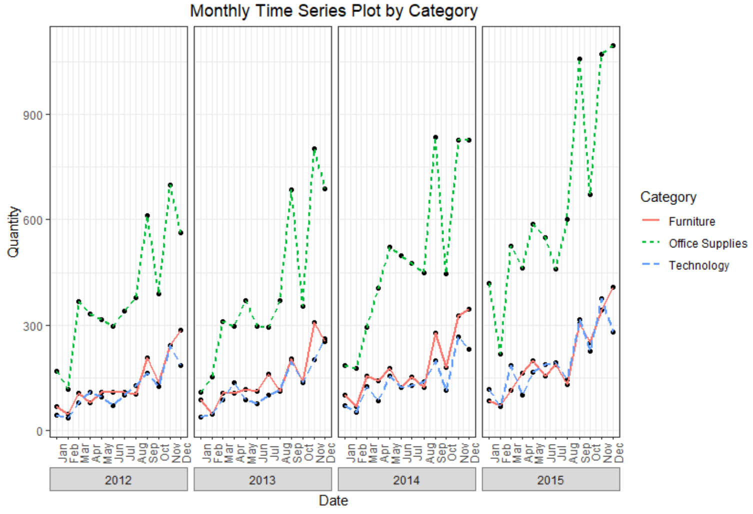
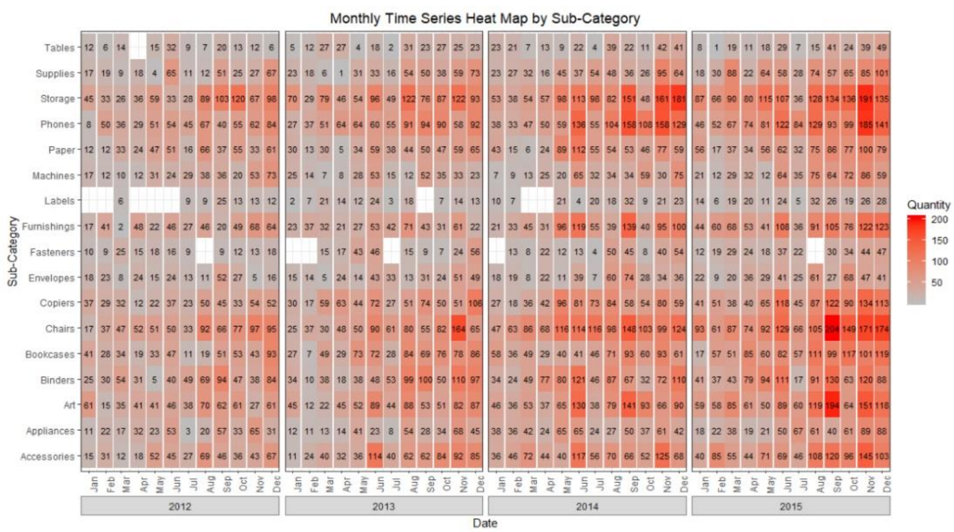


Figure 2.2.1

Findings of fig 2.2.1

- Office supplies bought are considerably higher in volume than Furniture and Technology.
- Office supplies also begin at a similar point in the beginning of the year, but rise in volume much faster.
- Furniture and technology volumes and patterns are very close to each other.

Heatmap of demand by sub-category in the US:



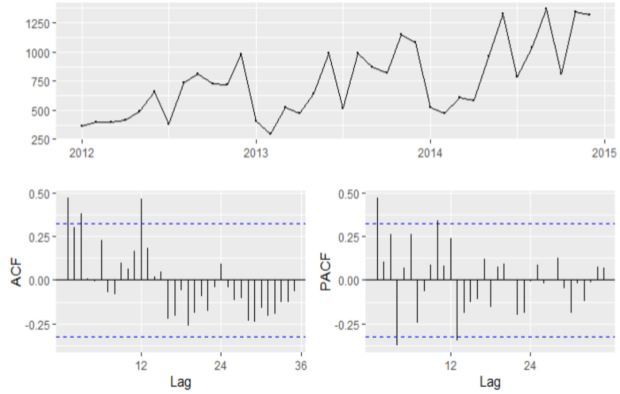
Findings of Heatmap

Most sub-categories seem to follow a similar demand pattern each month.

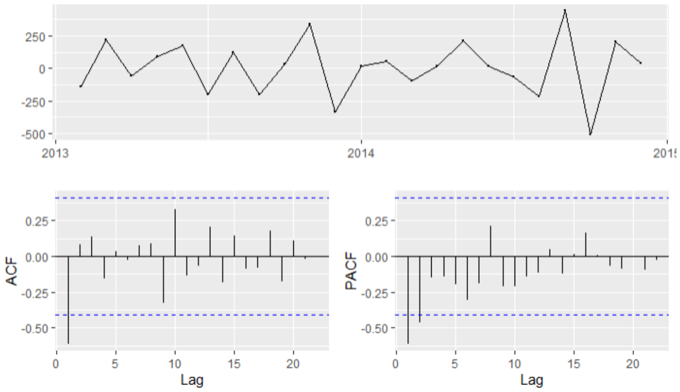
Modeling

Model Identification

In the model fitting section, we used the time period from 01/2012 to 12/2014 as training data, 01/2015 to 12/2015 as testing data. We started with plotting the original time series, ACF and PACF plots



The large spike at 12 means there is a high correlation with the 12th lag element, indicating seasonality. We could take a seasonal 1st order differencing and a normal differencing. Upon differencing and performing the adf test, we achieved a p-value < 0.05 indicating the series is stationary. After differencing, we get the following plots:

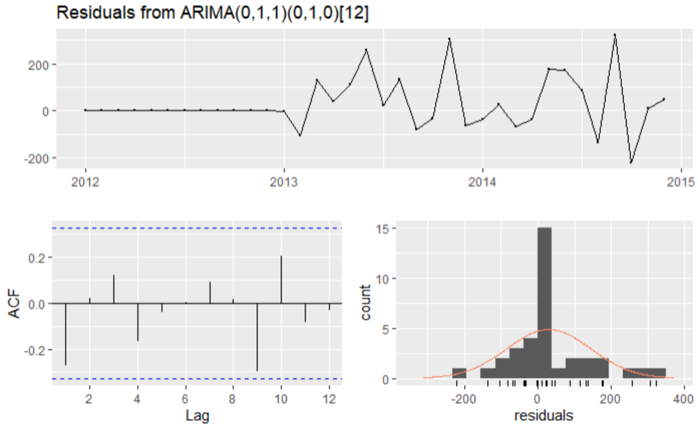


We see a spike at 1 in ACF, indicating the presence of an MA(1) component. Our current guess at the model is ARIMA(0,1,1)(0,1,0)[12] .

It turns out the Auto ARIMA model is ARIMA(0,0,0)(0,1,0)[12].
On comparing AIC value, we get that our model has 299.81 and the auto Arima model has 308.72, so we go with our model.

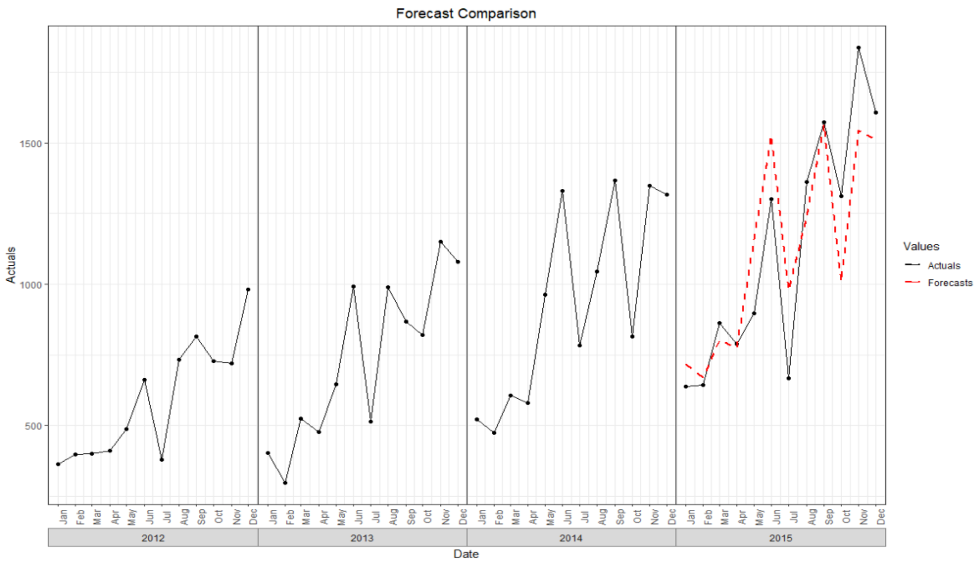
Model Fitting

The ma1 coefficient is -0.8812, and the SE is 0.1337, the t-statistic for this component is -6.59, thus the component is significant.



Upon analyzing the residuals, we see no spikes in the ACF, no obvious pattern in the residuals, and we see that the residuals are normally distributed around the mean. This means our model seems adequate. In the Ljung-Box test, we see that the p-value is > 0.05 which means we cannot reject the null hypothesis. Thus, the model is adequate.

Forecasting



Here is the time series plot with our model prediction marked in red dashed curve. As we can see, our model can well predict the sales pattern and the result is very close to the actual data. Therefore, we believe, our model is ready to be used. After training the data for the US market, we have also built 5 independent models for other 5 countries in the same workflow. All these models can be selected in our shiny app dashboard.

Shiny App

In the shiny app dashboard, users can first choose the region they want to predict. Then users can see the EDA for the market they have selected. Users can then move to the “Forecasting” tab. By selecting the forecasting duration, users would be able to see the prediction from the model we have built specifically for the selected country. Because we believe the models we provided to the shiny app are fine-tuned and optimal, we do not offer users the privilege to change other model parameters.

Conclusion

In this analysis, we started from exploratory data analysis, and found a seasonality pattern of the sales volume in the US market. We then followed the workflow of: Model Identification—Testing stationarity— Fitting Model—Model diagnosis—Forecasting to build our final model. There are two models we have established during the workflow. One is manually fitted Model 1: ARIMA (0,1,1)(0,1,0)[12], the other is what we obtained from “autoarima” function which is Model 2: ARIMA (0,0,0)(0,1,0)[12]. Model 1 has slightly lower MAE=149.41 where Model 2 has a higher MAE=153.68. Model 1 also has a lower AIC score=302.08, the AIC score for Model 2=311.08. The R^2 for Model 1= 0.7846, Model 2= 0.7808. Here is a summary data compares these statistical criteria between these 2 models:

Criteria	Model 1 (Manually Built)	Model 2 (auto arima)	Which one is better?
MAE	149.41	153.68	Model 1
AIC	302.08	311.08	Model 1
$\mathbf{R^2}$	0.7846	0.7808	Model 1

Therefore, we used Model 1 that we built manually. The final model performs very well with a MAPE as low as 14.34.