



Demand and Sales Forecasting using Time Series Algorithm Case Study

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Retail-Giant Sales Forecasting



GLOBAL MART is an online retail company with worldwide operations in 147 countries grouped into 7 Global Market Regions. The customers are spread across three major segments Consumer, Corporate and Home Office and it product categories are technology, furniture and office supplies.

Business Problem:

Global Mart needs to plan for Operations and Logistics. They need to finalize the plan for the next 6 months and forecast the sales and the demand for the next 6 months, that would help to manage the revenue and inventory accordingly.

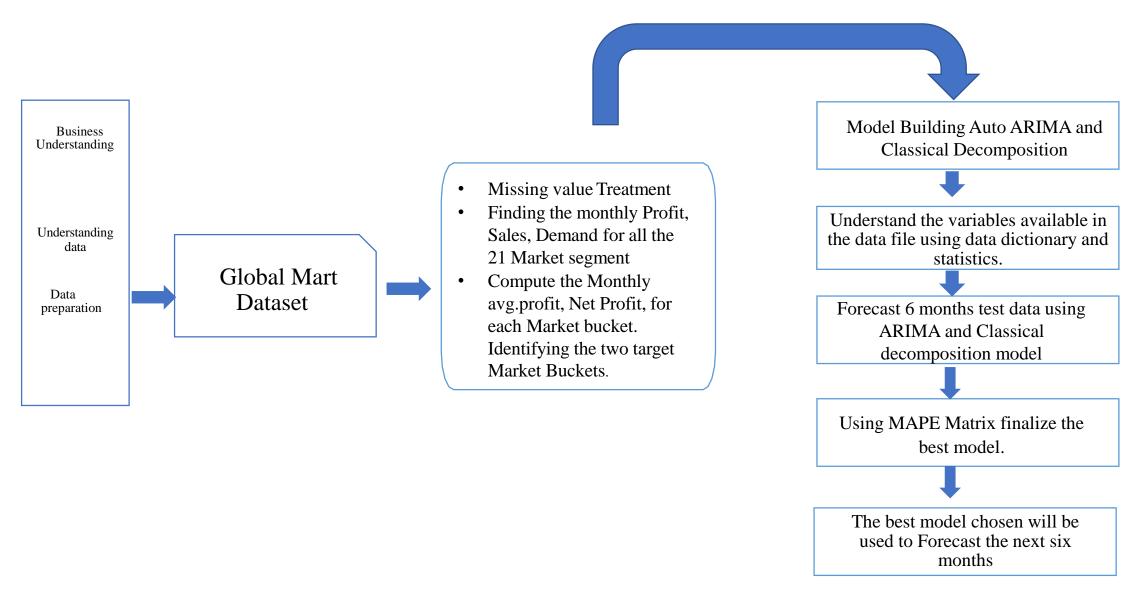
Our Objective

- The store caters to 7 different market segments and in 3 major categories. We need to forecast at this granular level, so we subset our data into 21 (7*3) buckets before analyzing these data.
- Not all of these 21 market buckets are important from the store's point of view. So we need to find out 2 most profitable (and consistent) segment from these 21 and forecast the sales and demand for these segments.
- We need to build a Classical decomposition model and time series auto ARIMA model on sales & demand. Then we need to evaluate the best model to forecast sales and demand for each market buckets



Data Analysis Methodology









- 1. Month.Number: We have 48 months ranging from 1st Jan 2011 to 31st Dec 2014. Hence we have derived a new metric called Month.Number ranging from 1 to 48 to determine number of months passed since Jan 2011.
- 2. US postal codes are missing and hence we will not use postal codes in our model. We are not imputing the column as we are going to ignore this column in our analysis anyway.
- 3. There are few outliers in our data. However we are not removing them since these are actual demand and sales for products & they reflect the real-life data. While doing classical decomposition we are smoothing out the series which would any way take care of any extreme values present in the series.
- 4. Multiplicative model has been trained for the global trend component for both the segments since the amplitude of sales and demand is increasing with time.
- 5. There are peaks and troughs in the series which resembles to a sinusoidal pattern. Hence we are also training multiplicative sinusoidal model to replicate the global trend.

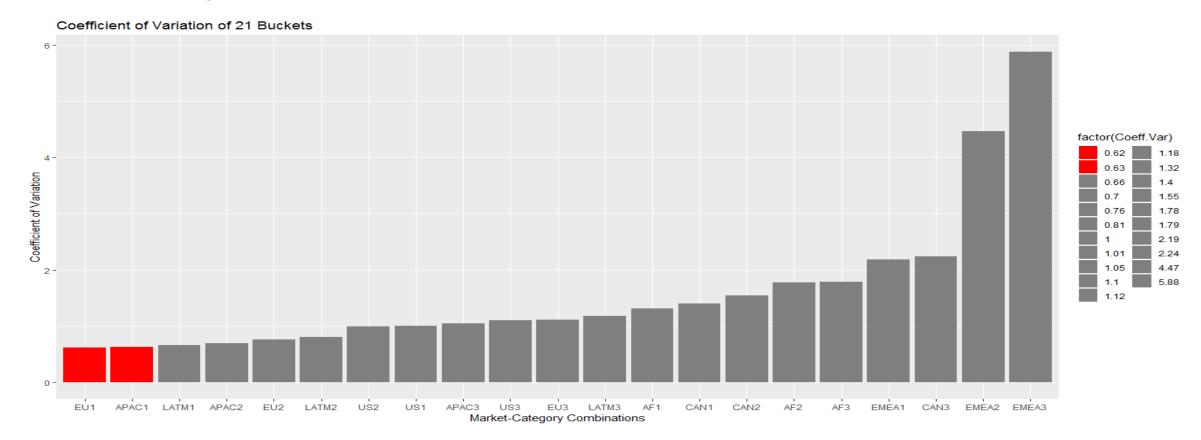




We have identified most profitable Market-Consumer Segment combination using coefficient of variation. Lower is the coefficient of variation lesser is the fluctuation is series and the more consistent the profit will be.

Based on the above definition we found out our **top two segments** which are

- **❖** APAC Consumer Segment
- **❖** EU Consumer Segment

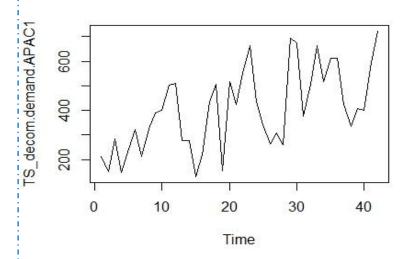


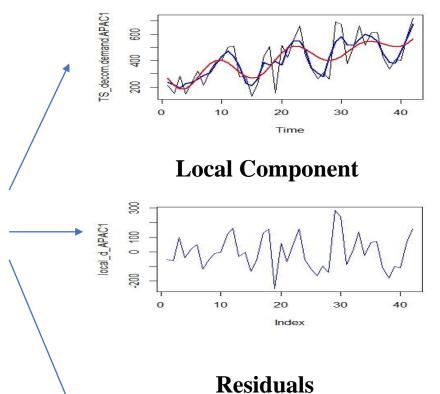


APAC Consumer Demand Curve

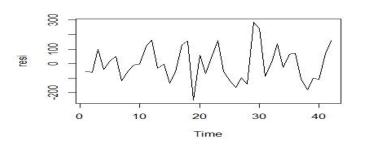


Actual APAC Demand Series

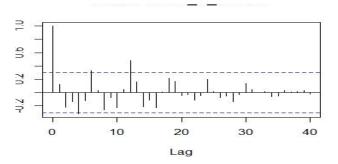


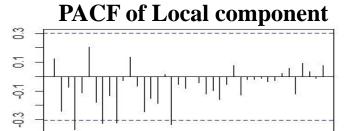


Global trend: In red



ACF of Local component





20

Lag

30

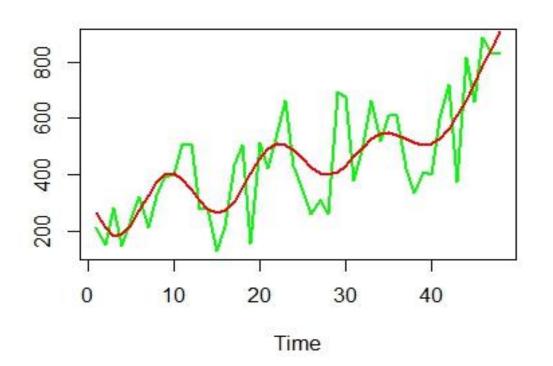
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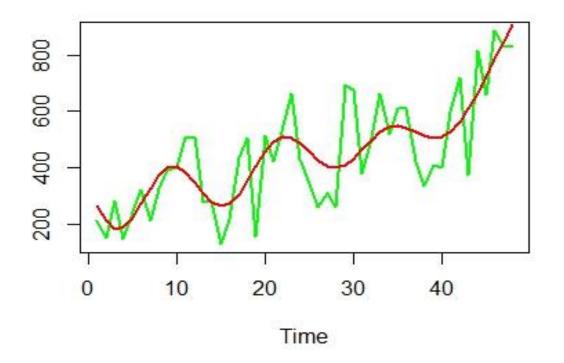
- From ACF and PACF plots we see local component is almost stationary (<5% data pts. Cross 95% CF line)
- Residuals are stationary as per DF test and KPSS test





Comparing Auto ARIMA and Classical Decomposition Models for Demand- APAC





Forecasting using classical decomposition method

MAPE: 18.79196

Forecasting using Auto Arima Method

MAPE: 26.24458

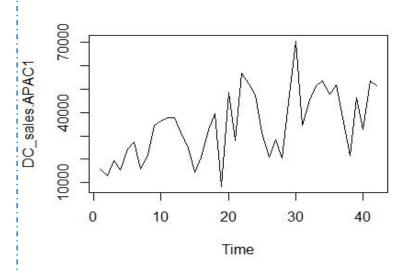
Classical decomposition is doing a better job at forecasting as compared to Auto Arima.

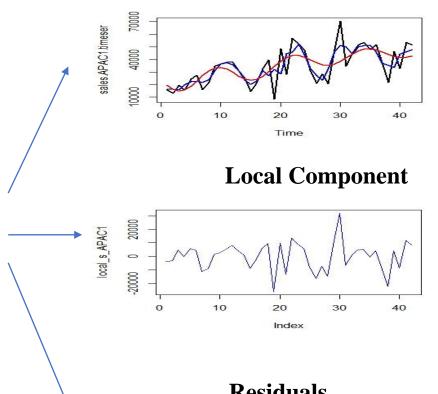


APAC Consumer Sales Curve



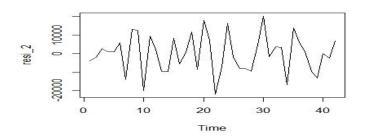
Actual APAC Sales Series



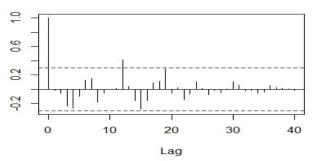


Residuals

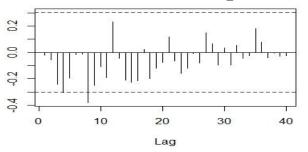
Global trend: In red



ACF of Local Component



PACF of Local Component

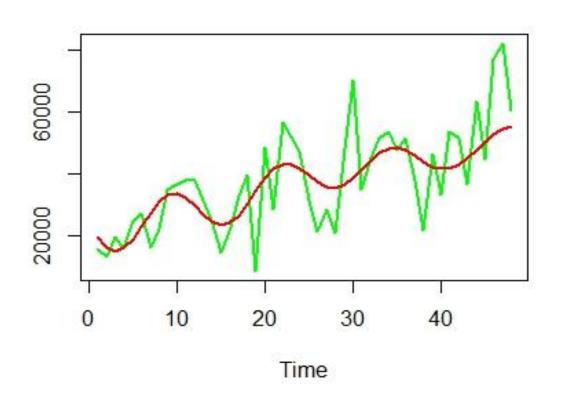


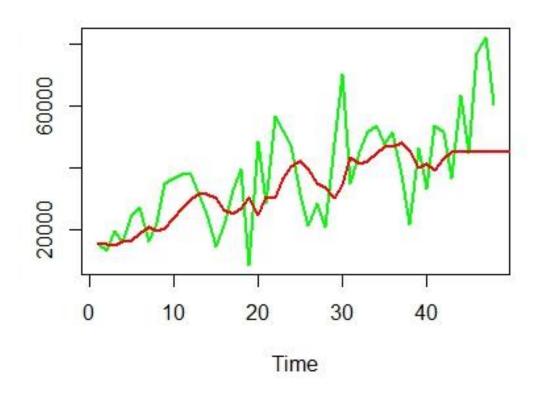
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Comparing Auto ARIMA and Classical Decomposition Models for Sales- APAC





Forecasting using classical decomposition method

MAPE: 22.53589

Forecasting using Auto Arima Method

MAPE: 27.68952

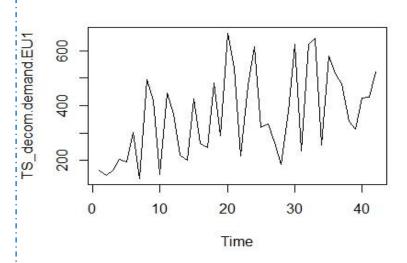
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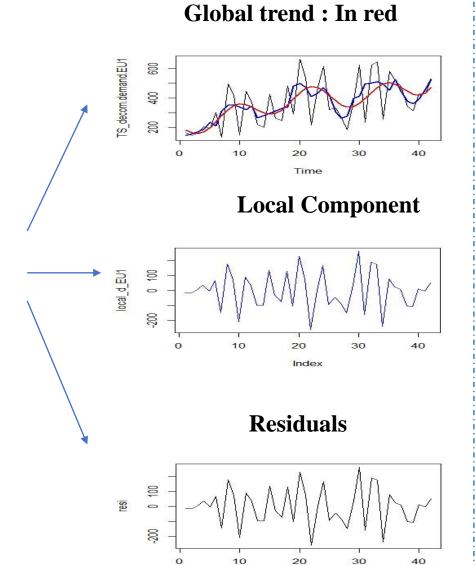


EU Consumer Demand Curve

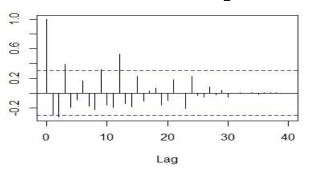


Actual EU Demand Series

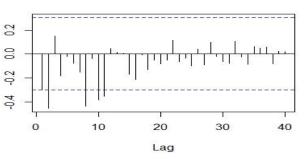




ACF of Local Component



PACF of Local Component

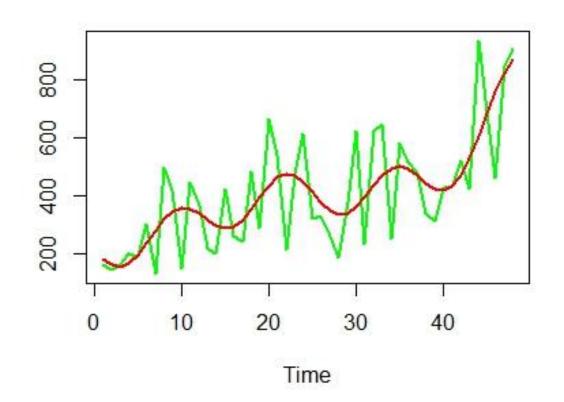


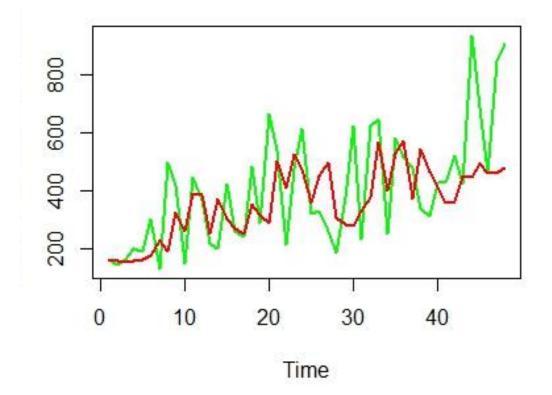
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Comparing Auto ARIMA and Classical Decomposition Models for Demand - EU





Forecasting using classical decomposition method

MAPE: 22.18186

Forecasting using Auto Arima Method

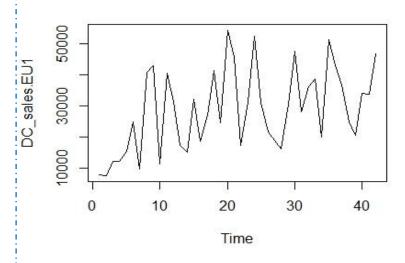
MAPE: 30.13319

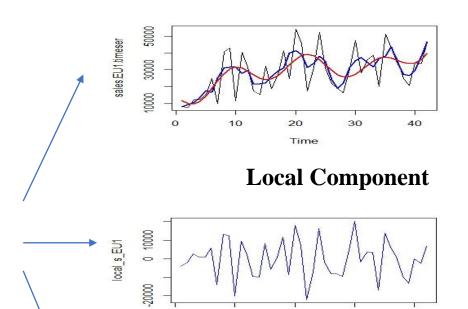
Classical decomposition is doing a better job at forecasting as compared to Auto Arima.











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Residuals

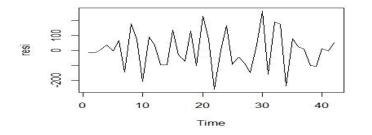
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Index

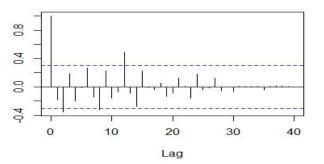
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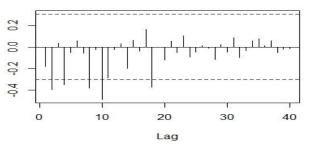
Global trend: In red



ACF of Local Component



PACF of Local Component

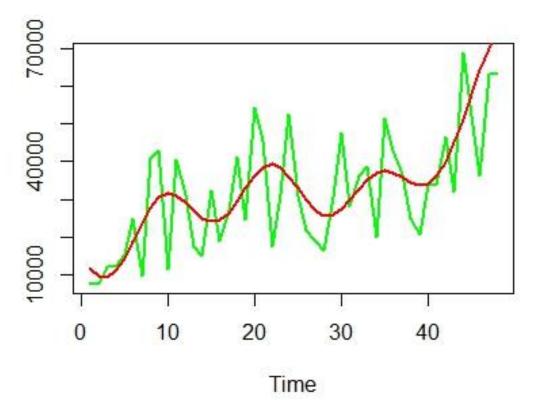


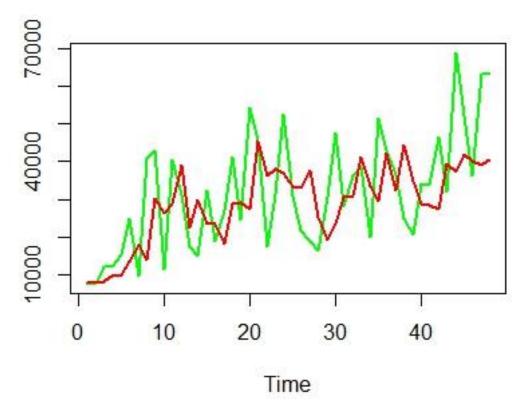
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Comparing Auto ARIMA and Classical Decomposition Models for Sales - EU





Forecasting using classical decomposition method

MAPE: 30.69751

Forecasting using Auto Arima Method

MAPE: 28.9226

Auto Arima is doing a better job in forecasting as compared to Classical Decomposition.





- The two most profitable buckets out of 21 are EU Consumer and APAC Consumer segment.
- The MAPE values of all the predictions are in moderately acceptable range.
- Classical decomposition Method is doing a better forecast in most of the cases.
- For both the segments sales and demand follow a seasonal pattern and show an overall increasing trend.
- The ACF,PACF plots for all the segments shows that the local component of the series are weakly stationary (<5% of the lines are crossing the confidence interval boundary) and residuals for all the segments are pure white noise.