Forecasting of Consumer Goods Appliances

By Optimal forecast reconciliation method for hierarchical and grouped time series through trace minimization

Submitted towards partial fulfilment of the requirements for award of Post Graduate Program in Business Analytics and Business Intelligence by Great Lakes Institute of Management

Capstone Project Report

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CERTIFICATE

This is to certify that the participants Sharmistha Mondal, Sramana Sengupta, Suryanarayana Reddy Yarrabothula & Taranum Shohel Haji Mohammed who are the students of Great Lakes Institute of Management, has successfully completed their project on ***Forecasting Model for Consumer Goods Appliances by Optimal forecast reconciliation method for hierarchical and grouped time series through trace minimization***

This project is the record of authentic work carried out by them during the academic year 2019- 2020.

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Name: Dr. Srabashi Basu

Date:

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ABSTRACT

Forecasting modelling is one of the biggest issues faced by consumer appliances industry. It has a cascading effect as unsold items will contribute to the losses in the form of inventory costs, resource wastage and capital investment. The design of good forecast model is key to avoid these losses and more and more modelling approaches are being developed to solve this challenge. In this capstone project, we have proposed a forecasting model using hierarchical time series approach by using tidyverse tools and implemented one of advanced algorithms available to date to achieve better forecast results. Accuracy metrics are used to validate our proposed model.

Keywords: *Hierarchical Time Series, Forecasting, Optimal Reconciliation method, Marketing & Retail Analytics, RMSE, MAE, MAPE, Accuracy, ETS, ARIMA, SNAIVE.*

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ABBREVIATIONS

KAP: Kitchen Appliance Product

DAP: Domestic Appliance Product

F&L: Fans & Lights

MFR: Modern Format Retail.

SECF: Sub-economy ceiling fans

TPWF: Table pedestrial wall fans

LED: LED bulbs & Tubes

CFL: Compact Fluorescence Light

ECF: Economy Ceiling Fans

PCF: Premium Ceiling Fans

DEF: Domestic Exhaust Fan

Ahmd: Ahmedabad

BHB: Bhubaneshwar

TS: Time Series

HTS: Hierarchical Time Series

ME: Mean Error

MAE: Mean Absolute Error

RMSE: Root Mean Square Error

MASE: Mean Absolute Scaled Error

MAPE: Mean Absolute Percentage Error

MPE: Mean Percentage Error

EXECUTIVE SUMMARY

Demand and Sales Forecasting is a complex business problem that requires design of efficient forecasting models. Developing a model that gives accurate point and distribution forecast results is challenging. Specifically, for a consumer appliances company with distribution channels in multiple cities and selling large range products, it is very much necessary to do the demand forecasting in order make the production planning.

In this capstone project, we have attempted to investigate how hierarchical time series models can be implemented to address these forecasting challenges and have formalized a framework that reproduces the working conditions of real-world demand forecasting methodologies. We focussed on the design of framework that can forecast sales in product wise and segment wise and aggregate them into single forecasting model. We also demonstrated practicality of our approach my evaluating our model on actual sale data.

Since we are dealing with real-time data from industry, the data consist of overall sales values, negative sales where the products are returned and zero sales where the products are unsold. In this project we tried to understand the various patterns in data about product returns and unsold products and evaluated how issues such as seasonal effects, manufacturing defects or better products are causing them. We also tried to evaluate the how the seasonal effects are on a particular product or in a particular city and which of the cities or products are showing upward trend in sales.

Our approach in the project is to implement hierarchical time series forecasting methods because of their ability handle multiple series of data into single model. We implemented advanced tidyverse approach to get the better forecast results and improve the computational efficiency. For better understanding of the model and to display the results, we limited our model development to only top 10 cities and top 10 products. We explored three techniques of forecasting ETS, ARIMA and SNAIVE and also did an ensemble forecasting model of these three methods. To further improve the performance of model we implemented a research paper on optimal forecast reconciliation through trace minimization by Wickaramsuriya et al (2019). The model performance was measure by measures such as MAPE, MAE, ME and RMSE. We also showed the accuracy metric will be different to each series and no one metric would be enough to evaluate the performance of final model. In conclusion, our report presents that use of forecasting methods to forecast the sales city wise and product to make informed decisions about product planning and to make business decisions about future course of action.

Key Recommendations:

A. Pune, Guwahati, Lucknow, Chandigarh & Raipur are having sales degrowth. To revive the sales in these cities following products to be promoted:

City	Proposed products
Pune	Food processor,Water Heater, LED
Guwahati	Water Heater, Induction cooker & Microwave Oven
Lucknow	Coolers, Water Heater, Induction cookers
Chandigarh	Mixers, SECF , Water Heater
Raipur	Mixers, Coolers, Water Heater, LED

B. Pressure Cookers sold in Noida city during the year have high negative sales throughout year. This issue needs to be further examined.

C. In West region except Mumbai, Water heaters are among top selling product. This shows the market potential for this. Thus, water heaters to be relaunched with marking backup to establish in Mumbai market.

D. Juice Extractor & Pressure cooker are becoming dead products of KAP category. These products require realignment with the latest technology & competitive pricing to ensure a share in market demand.

E. In East region, sales dependency on Mixers to be spread over other products such as Rice cookers, Water heaters, Induction cookers, Toasters etc. to ensure even sales growth.

F. Light category is almost nil in east region cities of Bhubaneshwar, Guwahati & Patna. LED could be introduced in these cities.

G. Degrowing sales trend products (Non-Electrical Kitchen products, CFL & Down light) to discontinued and dropped from product list.

1. INTRODUCTION

Bajaj Electricals Ltd is an Indian consumer electrical equipment manufacturing company based in Mumbai, Maharashtra. Bajaj's network of 20 branch offices, 478 distributors and more than 2,00,000 retail outlets fortifying the dominant presence in consumer product segment. Employee strength of over 3,000 people and a dedicated consumer care team spread across more than 500 consumer care centres in India showcases the Company's ethos of putting customer first and thereby strengthening brand loyalty quotient. Indian electrical appliances industry heavily competitive with both international (CG, Philips, LG) and domestic players (Prestige, SURYA). With large product portfolio and geographical presence, it is essential for Bajaj to accurately forecast the sales to improve the profitability. It also helps to improve the supply chain efficiency and make effective production planning. Regional wise and product wise forecasting also help the company to bridge gaps between sales targets and actual sales made. It also helps to understand the short comings the in the sales figures and effective planning of advertisement and promotional campaigns to address the shortfalls.

For decades, companies have built supply chains focused on cost optimization, using inventory as a buffer to meet customer service objectives and since forecasting customer demand can be challenging, companies often add inventory to protect against inaccurate forecasts. From a profit-and-loss perspective, they think of this inventory as "free," creating little incentive for efficiency. Such problems are the result of an underperforming supply chain, often resulting from poor forecasting accuracy, ineffective planning processes, and production capabilities that are slow to respond to changing market demand.

Companies can leverage a more analytical based forecast to understand gaps between financial performance targets and sales and operating plans early in the planning cycle, when actions can be taken to address them. Sales executives can leverage bottom-up forecasting to evaluate the impact of specific planned activities - such as promotions and merchandising events—compared with the top-down targets established in their overall plans.

1.1. Problem Statement

The problem at hand is forecasting the sales for Bajaj Electricals Ltd which sells products in three different segments namely Kitchen Appliances, Domestic Appliances and Lights & Fans category. The company asked us to understand the patterns of seasonality and overall performance of sales of different products across cities. Also, as part of the exercise, we wanted to analyse the negative sales (Returned products due to manufacturing defects or service complaints) and zero sales in different product segments to identify what are the products that are having highest number of return sales and where are returned.

Further, we were asked to developed a forecasting model of production quality and evaluate the forecasting accuracies with respect to final model. Given the nature of business it is important to forecast across products and cities along with overall sales.

1.2. Objectives & Scope of Project:

Objective:

The Objectives of this project are

a. Study and understand the patterns in sales performance of data across the products and segments or geographic regions to give business insights.
b. Studying and understanding the Negative Sales and Zero Sales across products and cities.
c. Developing a forecasting model using hierarchical time series techniques to forecast the sales for various cities and products.
d. Exploring the possibility of improving the model accuracy by applying the Ensemble approaches

Scope:

a. The scope of this project is limited to forecasting of sales for top 10 highest products and top 10 highest selling cities due to nature of data and presence of huge number of cities and products.
b. The data used in the study covers four years span from April’14 to March’18 to ensure the seasonality of sales is captured.
c. Tidyverse approach is followed due to its ability to give distribution forecasts along with point forecasts and computational efficiency. Majority of the tools for hierarchical time series using this approach are still under development and highly experimental.
d. Residual diagnostics and Stationality checks for ARIMA are not considered as the transformations to data to bring Stationality might give non-gaussian distributions and are not supported at present.

e. New research paper for calculating the forecasts using trace minimization and optimal reconciliation approach is implemented and the results might be highly experimental.

1.3. Model Flow Chart

The analytics approach and model flow in building the forecasting model is as displayed below.

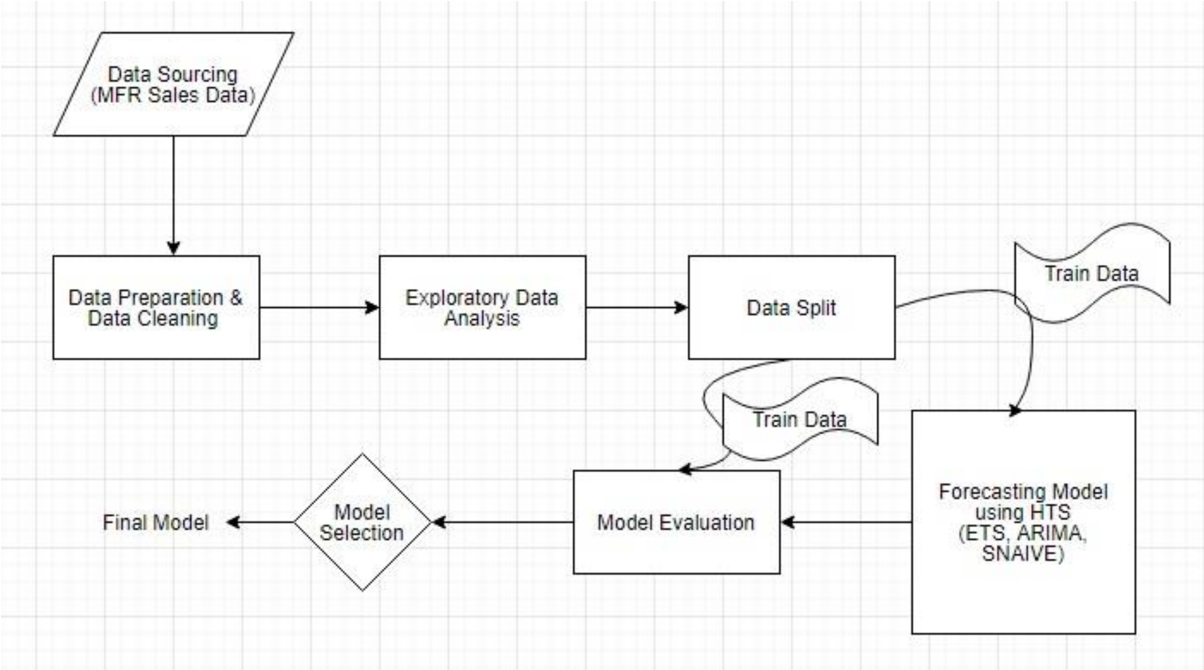


Fig 1.3.1 Flow Chart for Model Building Process

1.4. Tools & Techniques

Analytical Tools:

Languages: R – Programming Language

Algorithms: ARIMA, ETS, SNAIVE, Optimal Reconciliation for hierarchical and grouped time series through Trace minimization(minT)

2. <u>DATA DESCRIPTION & PREPARATION</u>

2.1. Data Description:

We have received Year on Year sales data of different products of Four product verticals of **Bajaj Electricals Pvt. Ltd.** Company from a company source.

The time period of the data is monthly data of four financial years i.e. FY 14-15 to FY 17-18. The sales data is for Pan India Sales Value of Modern Trade Channel only. Here Modern Trade Channel refers to all the regional as well as Pan India retail chain stores such as Big Bazaar, Reliance retail, Spencer & Next retail etc.

Following are the Product verticals and products:

KAP- Kitchen Appliance Products: Mixers, Juicers, Food Processor, Choppers & Hand blenders, Rice Cooker, Pressure cooker, OTG (Oven Toaster Griller), Microwave Oven, Induction cooktop etc.

DAP-Domestic Appliance Products: Dry Iron, Wet Iron, Coolers, Room heaters, Water heaters etc.

Lights: CFL bulbs & Tubes, LED etc.

Fans: Economy & Premium Ceiling Fans, Pedestal Fan, Domestic Exhaust Fans.

2.2. Data Preparation

In the given dataset, we have total of 3 sheets and each sheet for one segment. The available segments are referred as KAP – Kitchen Appliance Products, DAP – Domestic Appliance Products and F&L – Fans and Lights. Henceforth, in this document the abbreviations and the full forms will be used alternatively depending upon the context. Each sheet contains 4 variables. Product Name, Date / Month, City and Sales. The explanation for each of these variables is as follows.

Product Name – Name of the Appliance

Date / Month – Month & Year of Sales in YYYY-MM format

City – City Names in India

Sales – Sales figure for that product for that month

2.3. Data Quality

Outlier Analysis:

We will carry out the outlier analysis for these 3 data sets. In statistics, an outlier is a data point that differs significantly from other observations. An outlier may be due to variability in the measurement or it may indicate experimental error; the latter are sometimes excluded from the data set.

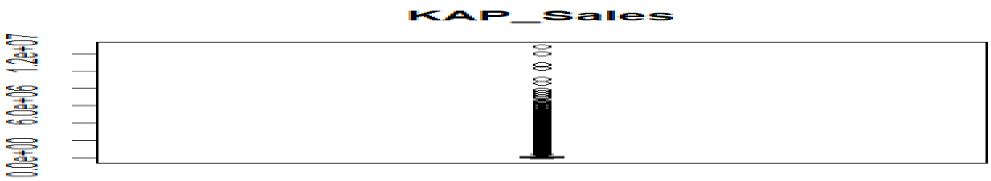


Fig 2.3.1 Box Plot of Sales in KAP Segment

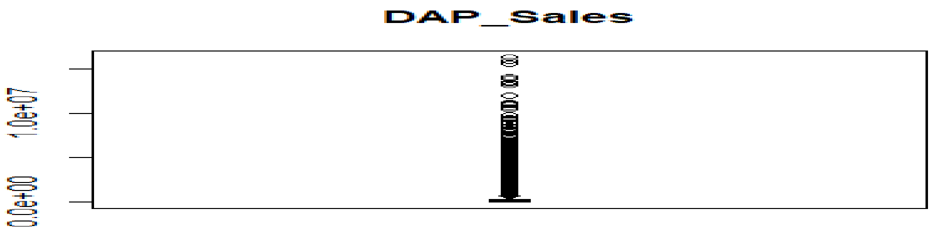


Fig 2.3.2 Box Plot of Sales in DAP Segment

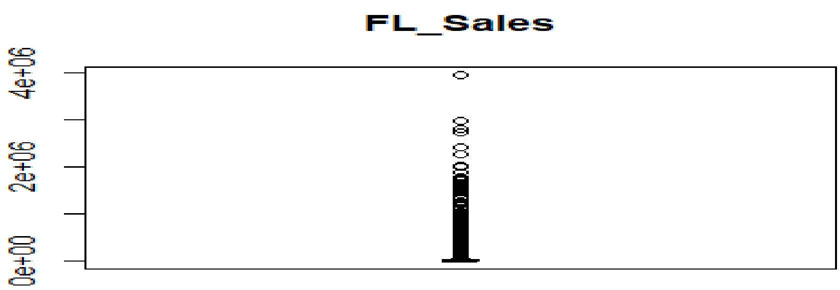


Fig 2.3.3 Box Plot of Sales in Fans & Lights Segment

In this data, for the domestic appliances data we have 694 values as outliers. Similarly, for kitchen appliance data, fans & lights data we have 1622 and 1236 values as outliers respectively. These are not the wrong data points or experimental errors, but real data points and sales figures of products or cities that have outperformed the others. Hence, we will carry out our analysis without treating these outliers.

Missing Value Analysis

No missing values are present in the data set.

Zero or Negative Values

As this is a sales data, there is a possibility of presence of zero sales or negative sales. Zero sales mean that, either the product is not sold or the product is discontinued in that region. Negative sales mean that return of the sold items against previous sales value. In this data, for the domestic appliances data we have 27 negative values. Similarly, for kitchen appliance data, fans & lights data we have 72 and 140 values respectively. In this data, for the domestic appliances data we have 1033 records as zero sales. Similarly, for kitchen appliance data, fans & lights data we have 1287 and 2734 values respectively.

3. EXPLORATORY DATA ANALYSIS

3.1 DAP Products Analysis – Domestic Appliances

Product Wise & City Wise Analysis:

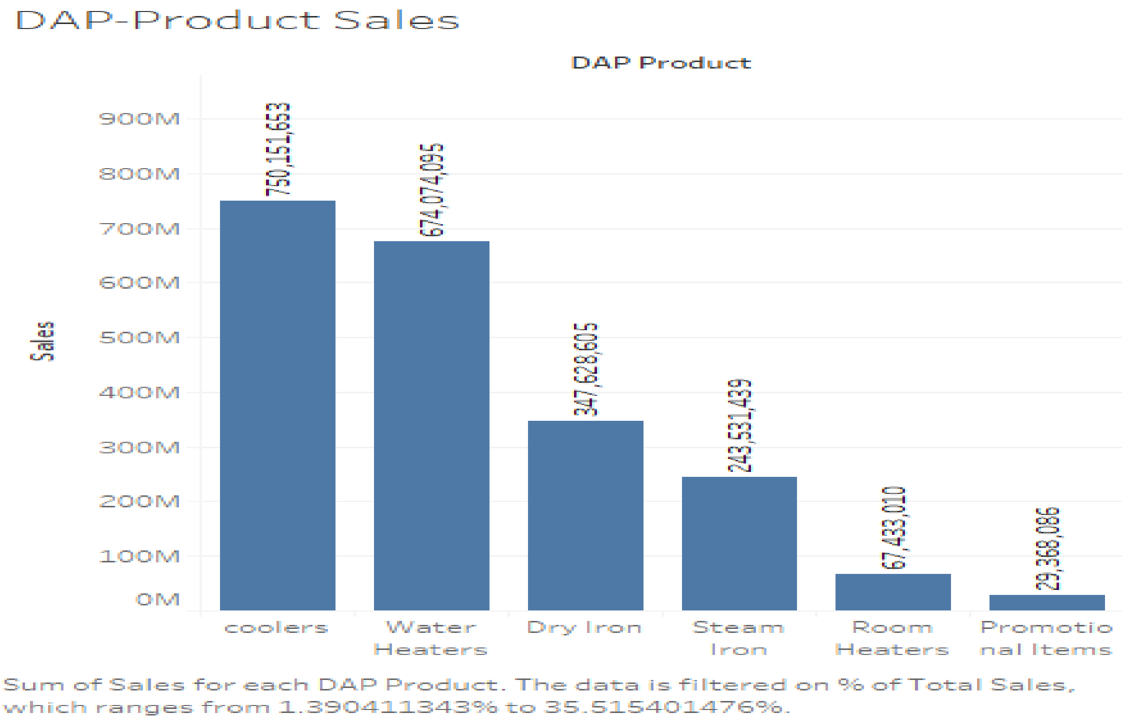


Fig 3.1.1 Product Wise Sales in DAP

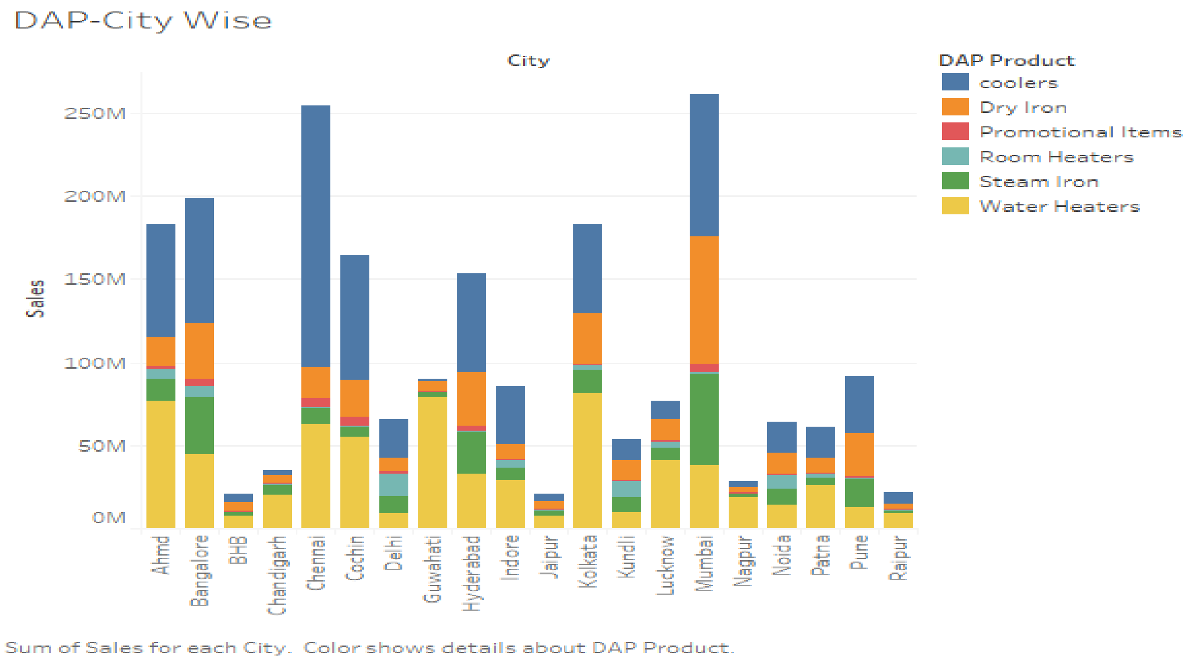


Fig 3.1.2 City Wise Sales Analysis for DAP products

1. Coolers having the maximum sales with a whopping 750,151,653 sales followed by water heaters, dry irons and steam irons.
2. Chennai is maximum sales of coolers of 157,377,026 sales in total. Kolkata has the maximum sales of water heaters of about 81,194,619. Mumbai has the highest sale of steam irons with 55,167,447 sales. Bangalore has the highest sale of dry iron with 33,246,566 sales.
3. Top performing cities are Mumbai, Chennai and Bangalore. While the sales of Chennai and Bangalore are majorly driven by water heaters and coolers, Mumbai has sales presence in Dry Iron and Steam Iron.
4. In all the Top 5 high performing cities, Water Heaters is in Top 3 seller list except in Mumbai and it needs to be examined.
5. Coolers is in list of Top 3 selling items in all the Top 5 performing areas.

Top Performing Cities & Products

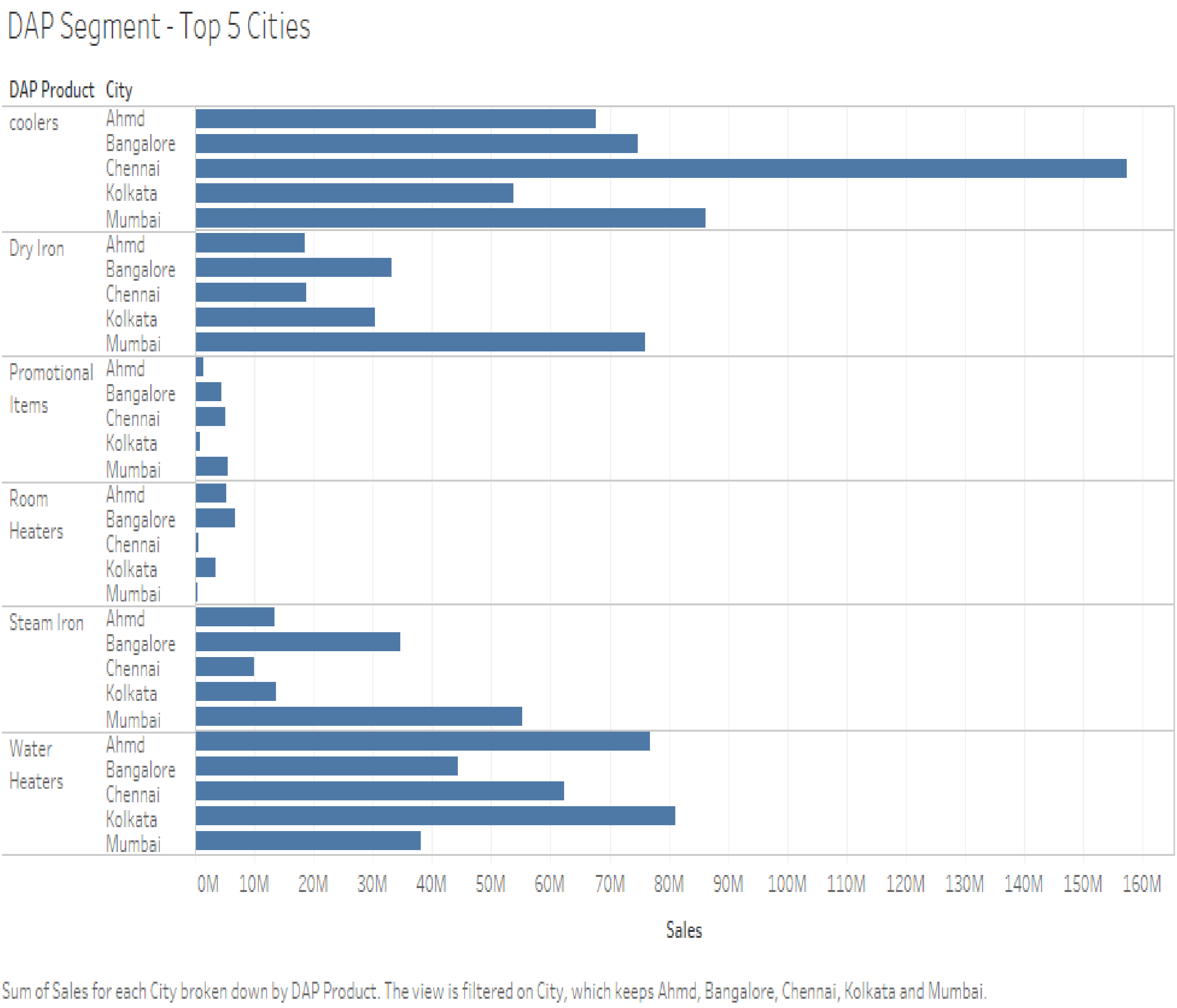


Fig 3.1.3 Top 5 Cities (Sales Wise) in Each Product

Sales Seasonality & Trend Analysis

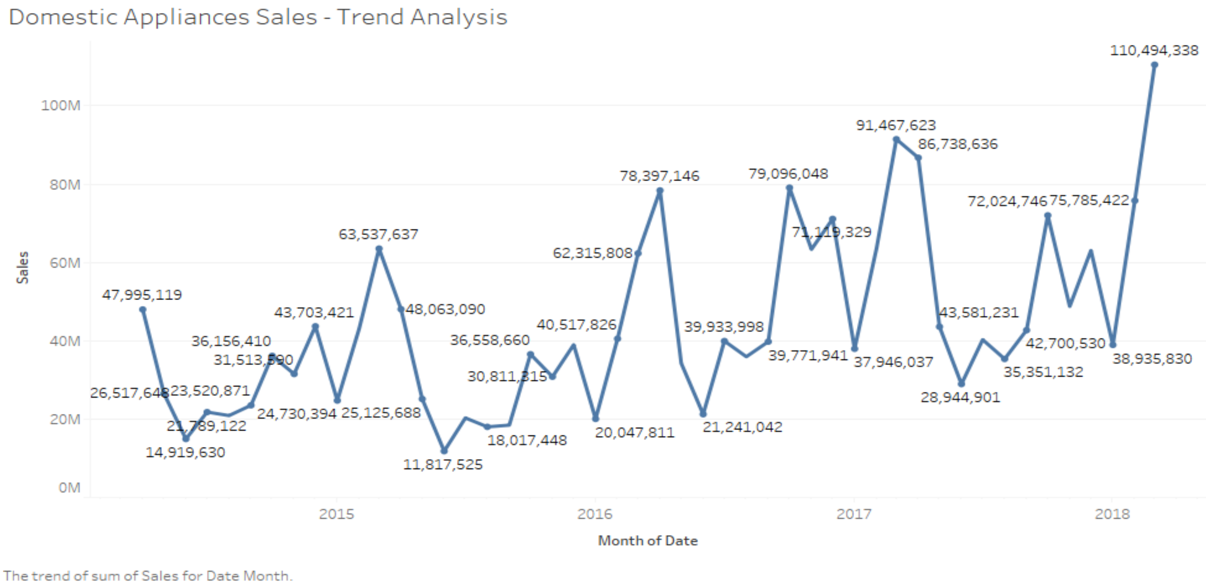


Fig 3.1.4 Sales Trend Analysis of DAP Products

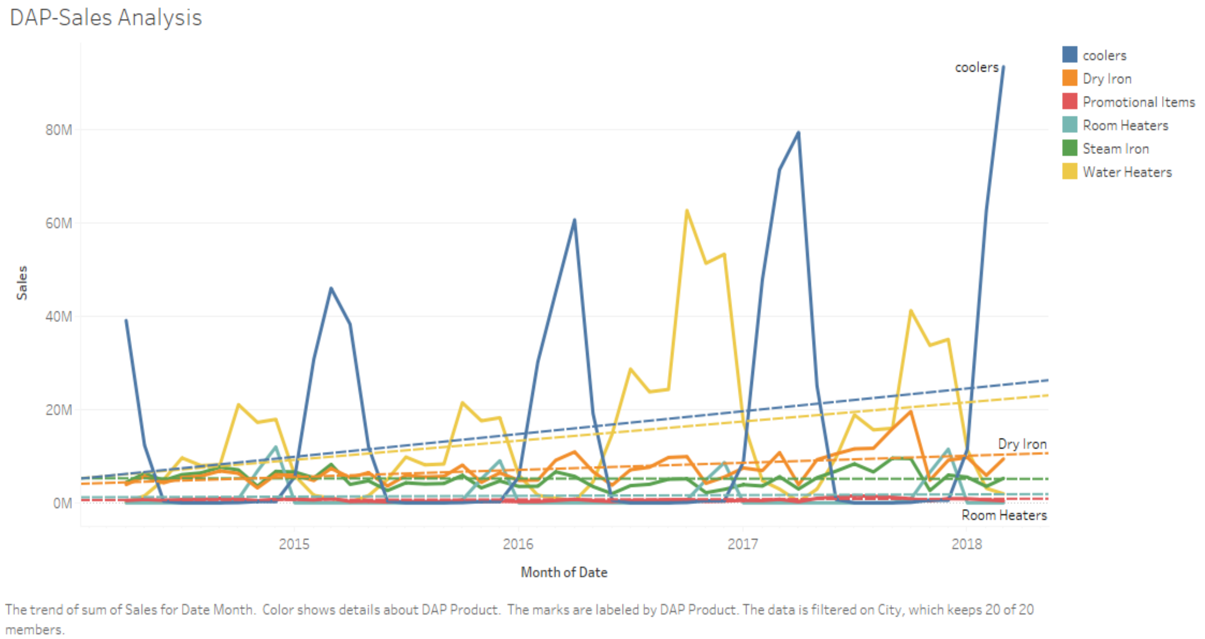


Fig 3.1.5 Product Wise Sales Trend Analysis

1. From the forecast results, we can clearly see the trend for coolers and seasonality component also visible.
2. For Water heaters, the sales suddenly spiked during Q3 winter and in the next winter even though sales are better than 2015 and 2016 years, they are less than 2017. Over all, the trend is positive.
3. For the Dry Iron and Steam Iron, the trend is almost zero except in Q3 of 2017, where there is a spike.

4. We can see the opposite effect for winter and summer seasons. In winters, the Water heaters are selling better and where as in summer the sales of Coolers are good.

3.2 KAP - Kitchen Appliance Products - Analysis

Product Wise and City Wise Analysis:

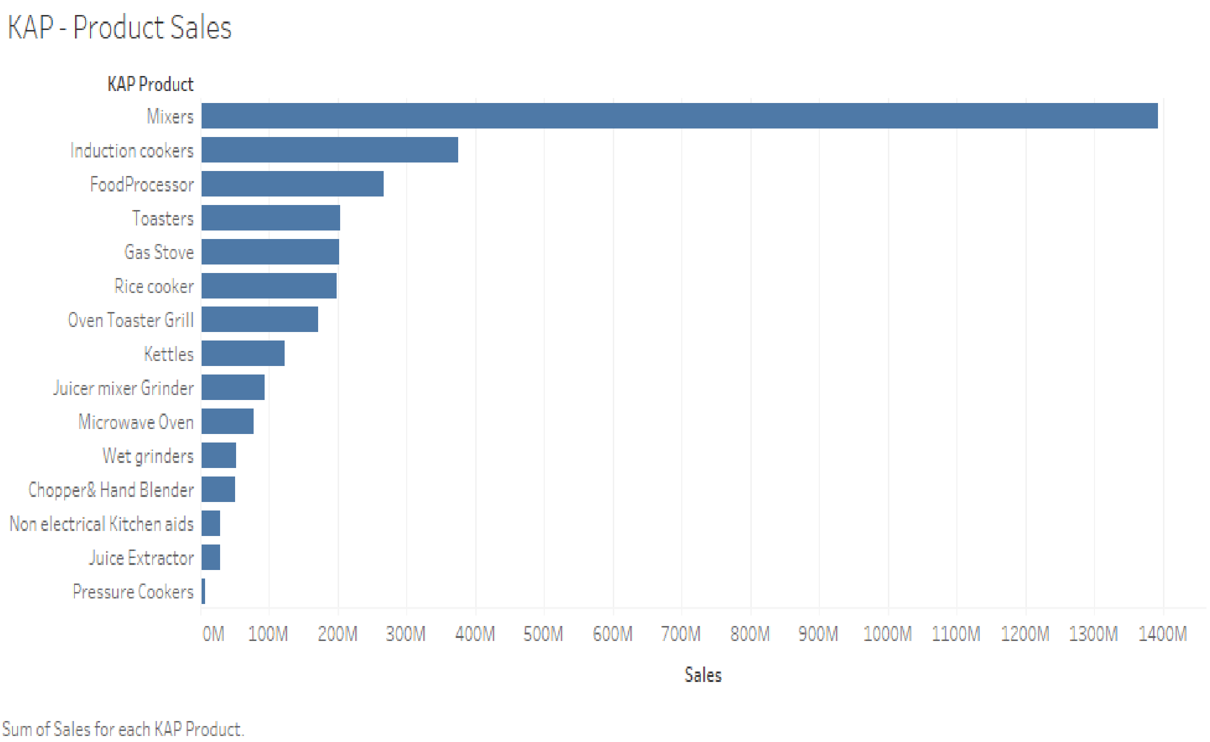


Fig 3.2.1 Product Wise Sales Analysis - KAP

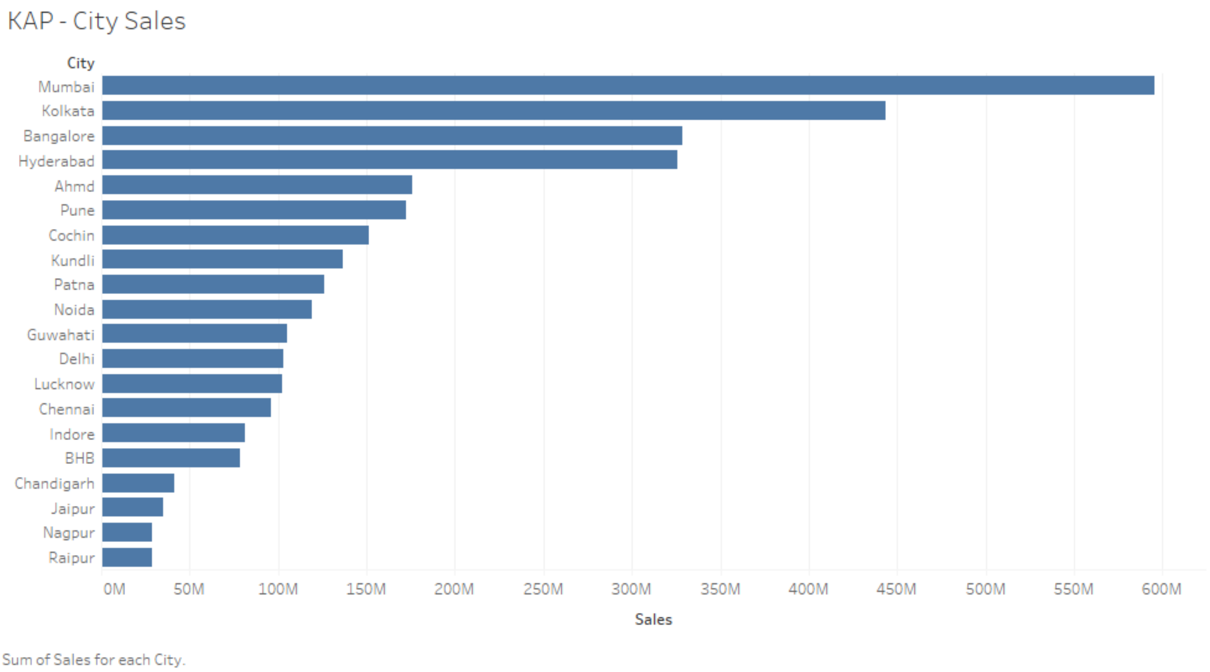


Fig 3.2.2 City Wise Sales Analysis – KAP Data

1. Top selling cities in the Kitchen appliance segment are Ahmedabad, Bangalore, Hyderabad, Kolkata and Mumbai. Product wise sales of these cities are shown in the above figure.
2. In the KAP segment, Mixers are the highest selling product followed by Induction Cookers and Food Processors.
3. The Top 5 are Mixers, Induction Cookers, Food Processor, Toasters and Gas Stoves
4. In the KAP segment the highest selling cities is Mumbai followed by Kolkata. For Bangalore and Hyderabad, the sales are almost similar.

Top Performing Products & Cities

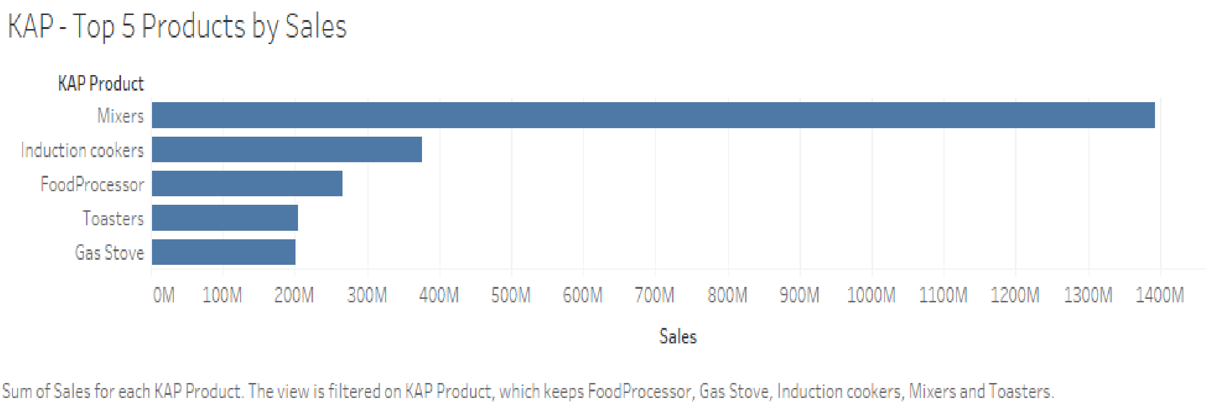
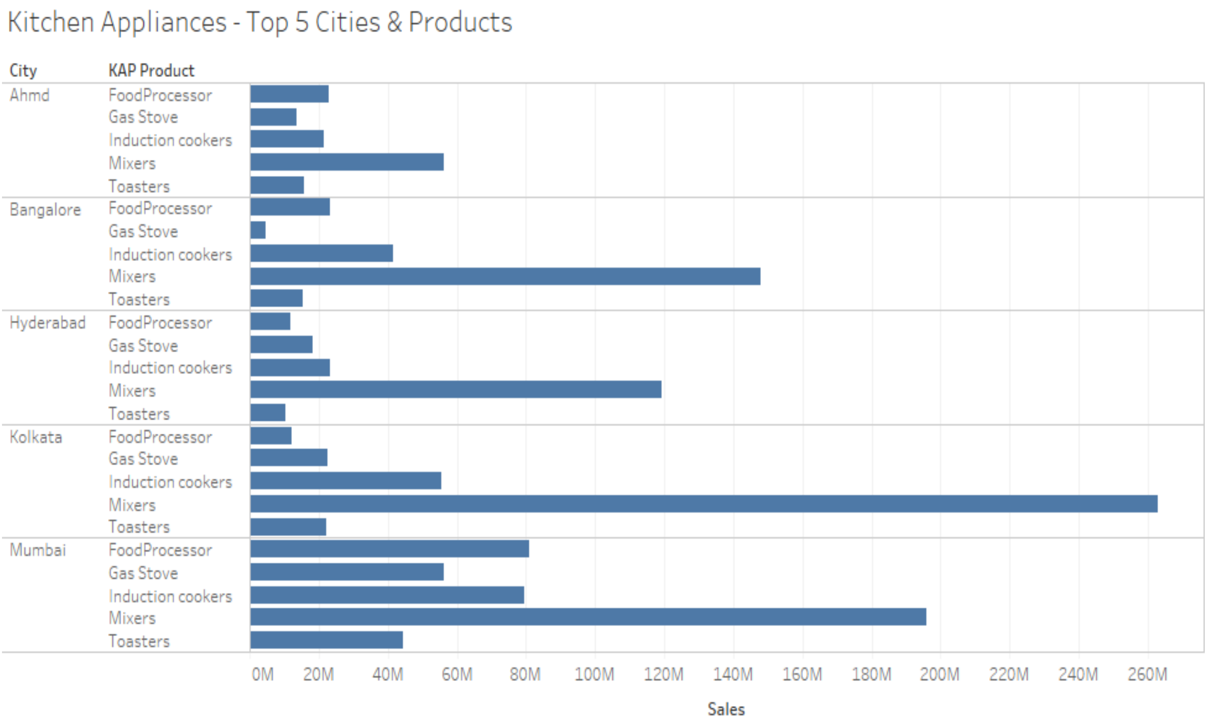


Fig 3.2.3 Top 5 Products by Sales - KAP

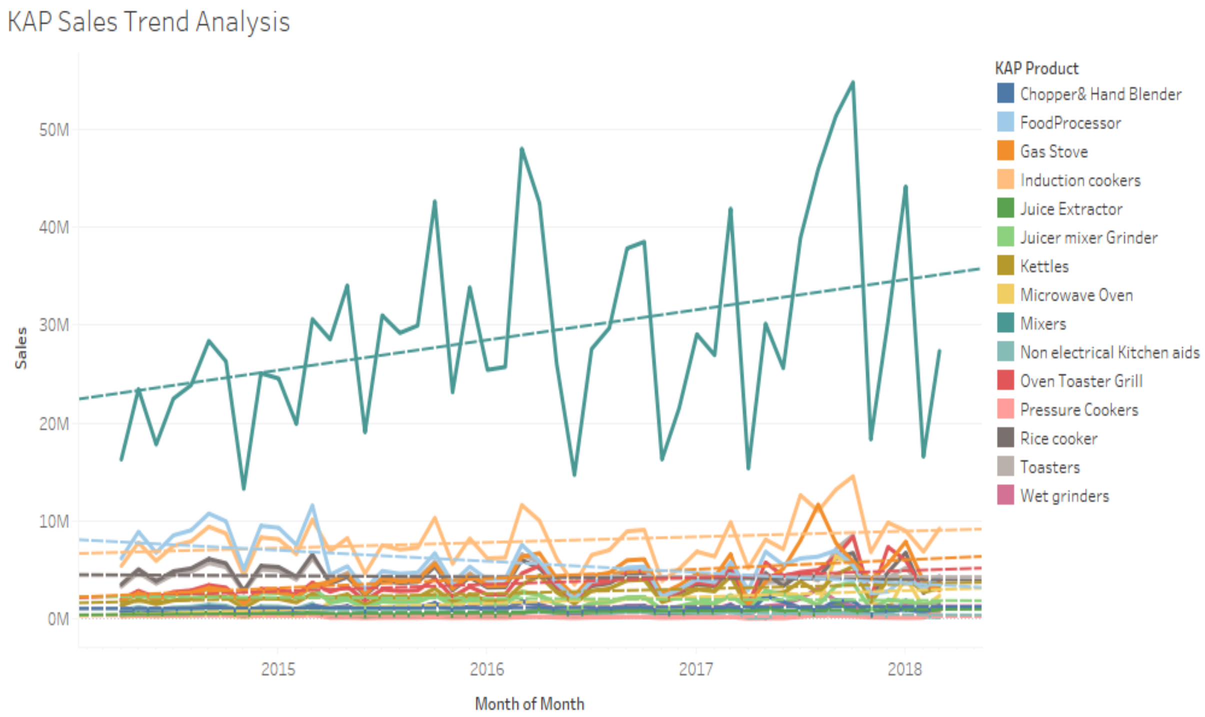
1. In all the Top 5 performers in Sales, Mixers is the leading seller. Highest sales in Mixers are contributed by Kolkata following Mumbai
2. Rice Cooker is in Top 3 selling products list in Southern States (Hyderabad & Bangalore) because of habit of eating Rice in the culture.
3. Except Mixers, all most all the product in Ahmedabad are not selling well and Ahmedabad is in list of Top 5 cities in sales performance.
4. Wet Grinders are sold in Southern Cities only and in all the remaining cities the sales are either negligible or zero.
5. In all cities, the sales of Juice Extractor and Pressure Cooker are either zero or negligible.



Sum of Sales for each KAP Product broken down by City. The view is filtered on City and KAP Product. The City filter has multiple members selected. The KAP Product filter keeps FoodProcessor, Gas Stove, Induction cookers, Mixers and Toasters.

Fig 3.2.4 Top 5 Cities Analysis – KAP Data

KAP Products – Sales Trend Analysis



The trend of sum of Sales for Month Month. Color shows details about KAP Product.

Fig 3.2.5 Sales Trend Analysis Product Wise - KAP

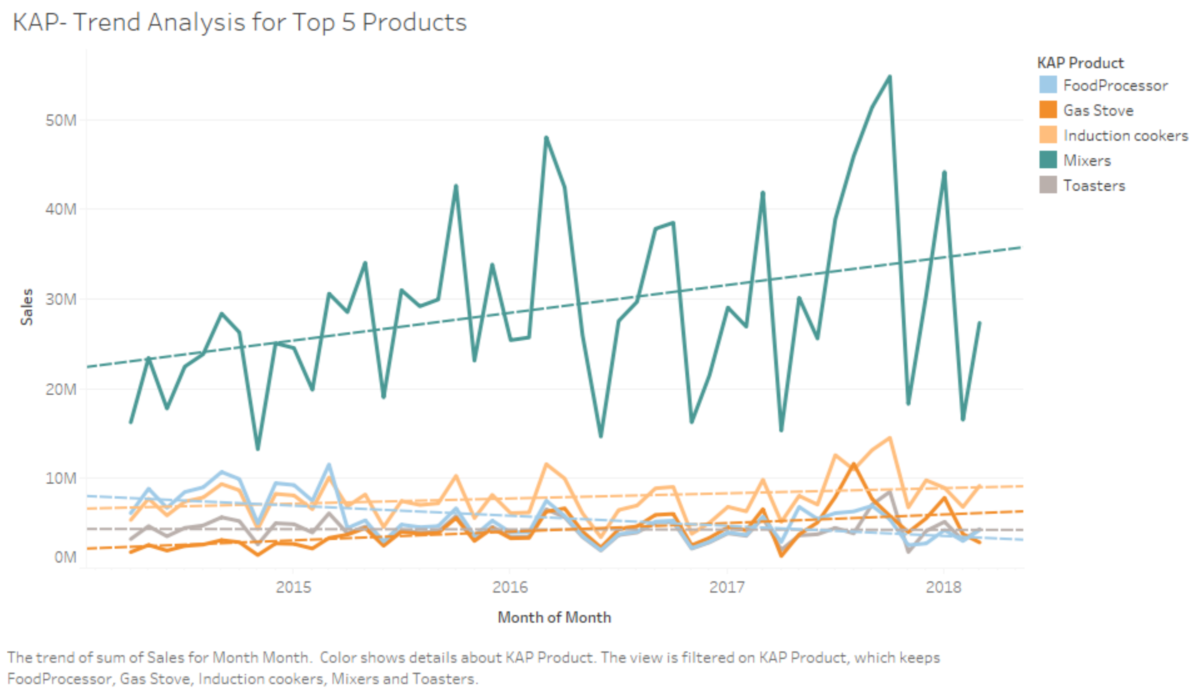


Fig 3.2.6 KAP Sales Trend Analysis - Top 5 Products

1. All the products have some kind of seasonality exhibiting and trend is not visible over the time.
2. The averaged sales are almost same and trend is flat over the years for all the products except for Mixers.
3. There is a steep increase in sales of Mixers, Induction cookers and gas stoves in the Q3 of 2017. 2016 and 2017 are best performing years of the lot.
4. From the forecasting figures we can see the visible changes in mixers sales in Kolkata during 2016 and 2017. Mixers performed well in all the top selling cities in 2017.

3.3 Fans & Lights Products Analysis

Product Wise and City Wise Analysis

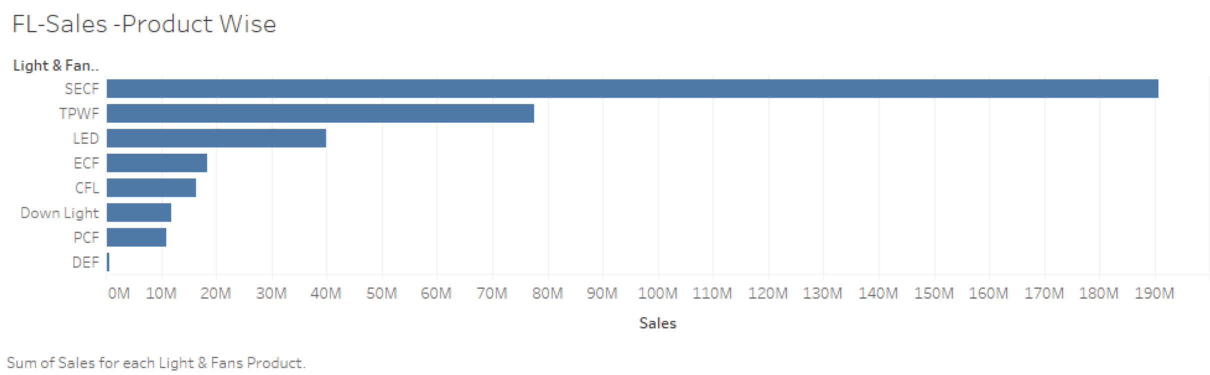


Fig 3.3.1 Product Wise Sales Analysis – F&L

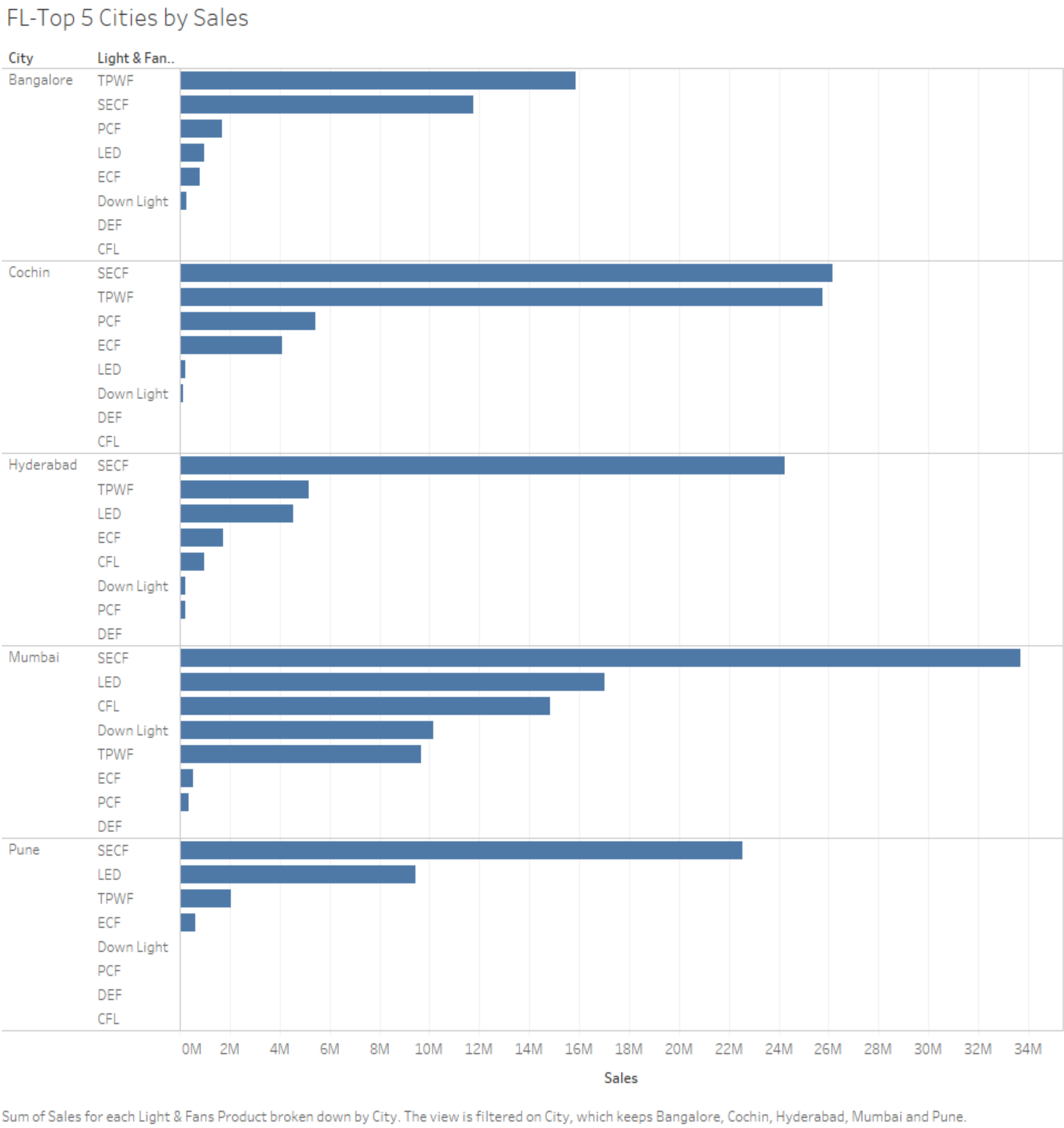


Fig 3.3.2 City Wise Sales Analysis – F&L

1. In the Fans & Lights segment SECF, TPWF & LED are highest selling products. They make up almost 80% of total sales.
2. In City, Mumbai is the leading performer followed by Cochin. Top 5 are Mumbai, Cochin, Hyderabad, Pune and Bangalore.
3. The Sales of DEF are either negligible or zero over the years.
4. The performance of TPWF is very good in Bangalore, Cochin and Hyderabad (*Southern States) which indicate weather might have contributed to the increased sales of this product.

5. Another product in Fans category SECF also performed very well in all the states and specifically in west zone i.e. Mumbai and Pune (Maharashtra State).
6. Sales of TPWF are average in Mumbai, however in Pune the sales of TPWF are very low. It needs to be further examined.
7. There is a sudden spike in LED bulbs sales in Mumbai, Pune and Hyderabad. However, the same is not the case in Bangalore and Cochin. It needs to be addressed.

Top Performing Cities & Products

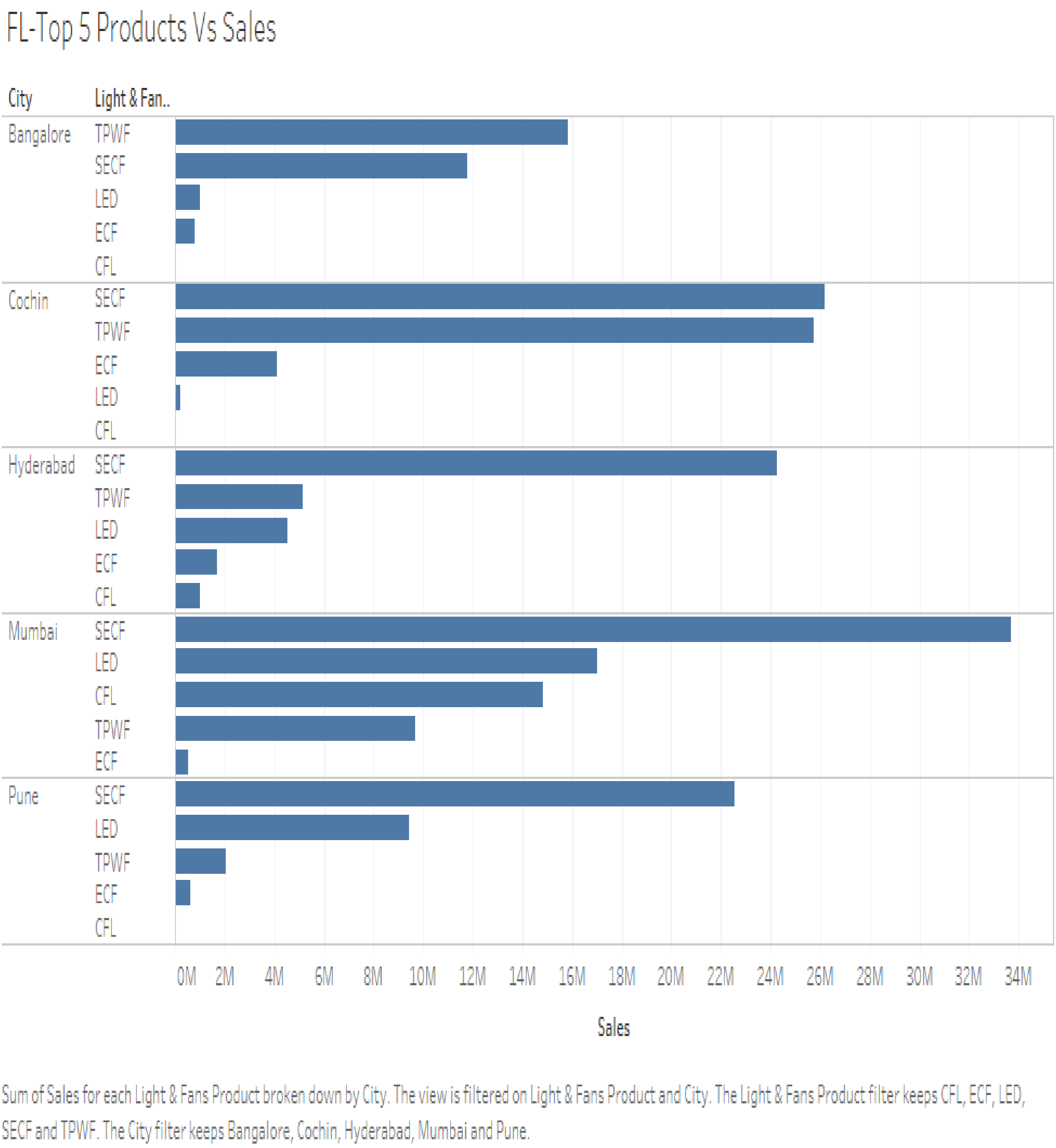


Fig 3.3.3 Top 5 Cities Sales Analysis - F&L

Sales Trend Analysis for F&L Products

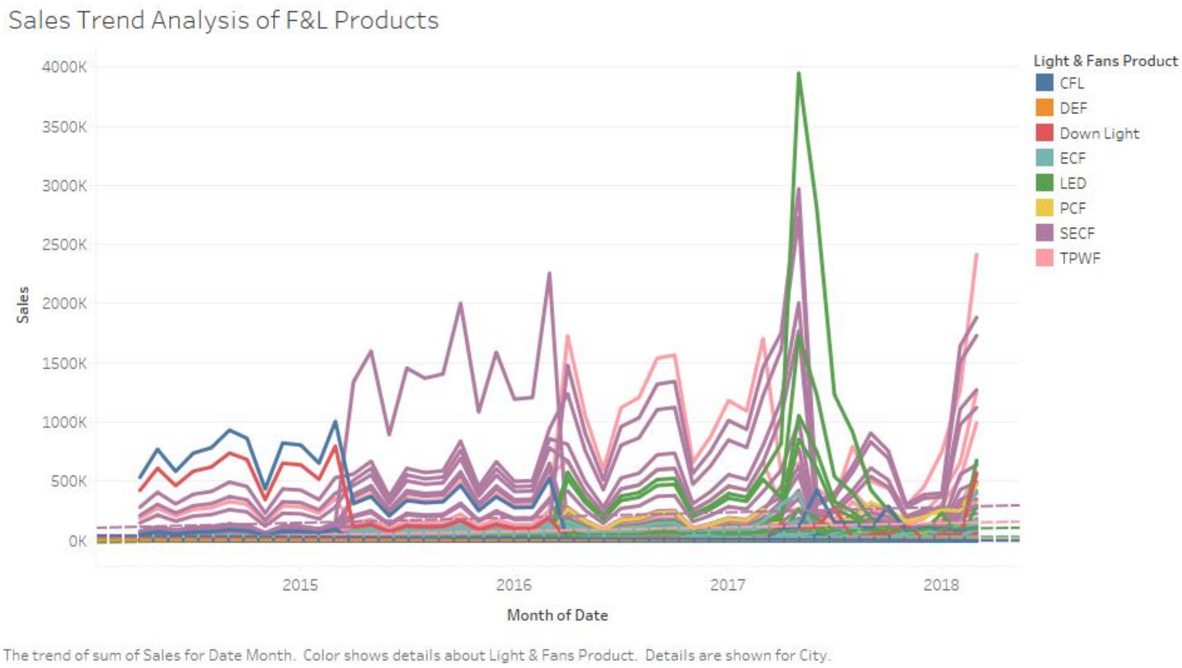


Fig 3.3.4 Sales Trend Analysis for Products- F&L

1. The only place where CFL is doing good in Mumbai. Apart from Mumbai, in all the other places CFL is having either zero or negligible sales.
2. Apart from Maharashtra (Mumbai, Nagpur and Pune) and Hyderabad LED bulbs also have very negligible or zero sales.
3. From both the results, we can say that Fan's segment is performing much better than lights segment aided by Southern States and Maharashtra region.
4. The forecasts for these products are given below. For all the products in this segment, there is neither trend nor seasonality and the sales have been almost consistent across the years.

3.4. Negative & Zero Sales Analysis

Negative Sales:

Some of the reasons for negative sales or sales return are:

A. Operational Issue: Purchase orders expire and delayed goods delivery. Due to which retail stores deny the products into warehouse and those are return back.
B. Logistics delay
C. Technical / Manufacturing issue in the products like quality and performance problems

In the year 2014-15, PCF in Delhi recorded highest negative sales followed by downlight in Kolkata. There is a sudden increase in negative sales in the year 2015-16 with pressure cookers in Noida city recording highest returns. After 2016, gas stoves in Jaipur are having highest negative returns followed by downlights. Overall, downlights showed consistent negative sales across the years and pressure cookers and gas stoves returned in one particular city.

In KAP, Pressure cooker has either negative sales or zero sales in some of the cities. On the other hand, the Rice cooker sales have increased in those cities. This indicates that Bajaj Rice cookers are more preferred over pressure cookers. This may be more brand consciousness among consumer for pressure cookers of Prestige, Futura etc. In DAP, Room heaters is replaced by water heaters in region like Mumbai. In F& L, PCF is replaced by SECF IN Delhi & Indore whereas Down light is replaced by LED in Noida.

Zero Sales:

Zero sales may have majorly following reasons:

A. Product is not listed for that geographic region like Wet grinders listed in West and South but not in North Zone.

B. Product is replaced by similar featured upgraded different product. For example, Down light is replaced by LED in many regions. And Mixers are more preferred over Wet Grinders.

C. Seasonality of the product – Seasonality may be due to weather condition / local festivals etc. Here Coolers, Room heaters are showing seasonality in specific season months and thus showing zero sales in other months.

3.5. Time Series Features

Measuring Strength of Trend & Seasonality Components:

We can measure the strength of seasonality and trend with respect to each product in individual cities.

From the below picture,

1. Water Heaters and Coolers are having very strong seasonal components in almost all the cities
2. Seasonality has very minimal effect in Kolkata and it is having very strong upward trend in sales across all the products.
3. Kolkata and Patna along with all the southern cities (Hyderabad, Bangalore, Cochin) are showing positive trend in sales across all the segments.

4. In southern cities the sales of OTG are very flat.

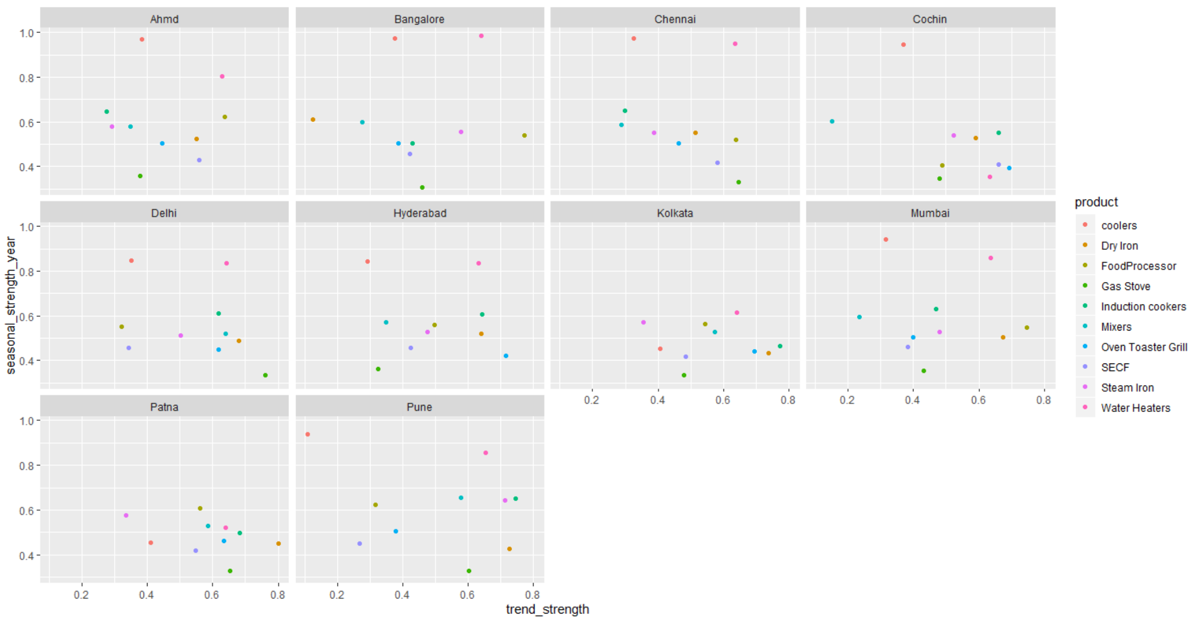


Fig 3.5.1 Strength of Trend Vs Strength of Seasonality Graph

5. Out of entire product segment Dry Iron & Water Heater sales have improved by good numbers over the years. Kitchen Appliances section also has shown good positive trend.

4. FORECAST MODEL DEVELOPMENT

The proposed model in this project report is based on hierarchical time series as the data set contains multiple products and multiple cities. The given time series is disaggregated on basis of product such as mixers, coolers, lights and city such as Hyderabad, Mumbai, Kolkata..etc. As we have large number of products and cities, the forecasting is limited to top ten cities and top 110 products. Out of 4 of monthly data given to us, we selected 3 years as test set and 1 year as validation set. We applied ETS, ARIMA, SNAIVE algorithms and forecasting model was developed. The model validation process was performed using metrics such as MAPE, MASE, RMSE. In order to produce better forecasts, we implemented Optimal forecast reconciliation for hierarchical and grouped time series through trace minimization approach by Wickramasuriya et al. (2019).

4.1. Tidy Forecasting Approach:

The first step in forecasting is to prepare data in the correct format. This process may involve loading in data, identifying missing values, filtering the time series and other pre-processing tasks. The functionality provided by "tsibble" and other packages in the "tidyverse" substantially simplifies this step. In tidy approach, models in are specified using model functions, which each use a formula (y ~ x) interface. The response variable(s) are specified on the left of the formula, and the structure of the model is written on the right. The left side of the formula also supports many transformations, which can be useful in simplifying the time series patterns or constraining the forecasts to be between specific values. When forecasting from a model with transformations, the appropriate back-transformation will be applied to ensure forecasts are on the correct scale.

Once an appropriate model is specified, we next train the model on some data. One or more model specifications can be estimated using the model () function. The resulting object is a model table or a "mable". With an appropriate model specified, estimated and checked, it is time to produce the forecasts using forecast (). In tidyverse approach we can use natural language in specifying the forecasting period like "2 Years" or "10 months". This is a forecasting table, or "fable". Each row corresponds to one forecast period. This table contains both the point forecasts and distribution forecasts and the point forecast is the mean (or average) of the forecasting distribution.

Accuracy Evaluation:

We can measure the forecast accuracy by summarizing forecast accuracy in different ways.

Scale Dependent Errors:

The forecast errors are on the same scale as the data. Accuracy measures that are based only on et are therefore scale-dependent and cannot be used to make comparisons between series that involve different units. Two most commonly used scale-dependent measures are based on the absolute errors or squared errors

$$\text{Mean absolute error (MAE)= } \mathbf{mean}\ (|\boldsymbol{e_t}|),$$

$$\text{Root mean squared error (RMSE)=}\sqrt{\boldsymbol{mean}(\boldsymbol{e_t^2})}$$

When comparing forecast methods applied to a single time series, or to several time series with the same units, the MAE is popular as it is easy to both understand and compute. A forecast method that minimises the MAE will lead to forecasts of the median, while minimising the RMSE will lead to forecasts of the mean. Consequently, the RMSE is also widely used, despite being more difficult to interpret.

Percentage Errors:

The percentage error is given by $P_t = 100 \times e_t/y_t$. Percentage errors have the advantage of being unit-free, and so are frequently used to compare forecast performances between data sets. The most commonly used measure is

$$\text{Mean absolute percentage error: MAPE= mean } (|P_t|).$$

Measures based on percentage errors have the disadvantage of being infinite or undefined if y_t=0 for any t in the period of interest, and having extreme values if any y_t is close to zero.

4.2. Optimal Forecast Reconciliation:

Large collections of time series often have aggregation constraints due to product or geographical groupings. The forecasts for the most disaggregated series are usually required to add-up exactly to the forecasts of the aggregated series, a constraint we refer to as "coherence". Forecast reconciliation is the process of adjusting forecasts to make them coherent. Optimal forecast reconciliation approach incorporates the information from a full covariance matrix of forecast errors in obtaining a set of coherent forecasts.

This approach frames the problem in terms of finding a set of minimum variance unbiased estimates of future values of all time series across the entire collection. That is, we minimize the sum of variances of the reconciled forecast errors under the property of unbiasedness. This is called as MinT (minimum trace) reconciliation. An interesting feature of the MinT approach is that resulting coherent forecasts are guaranteed to be at least as good the base forecasts. Furthermore, this method allows for greater computational efficiency in obtaining a set of reconciled forecasts for very large collections of time series.

4.3.ETS Modelling:

Forecasts produced using exponential smoothing methods are weighted averages of past observations, with the weights decaying exponentially as the observations get older. In other words, the more recent the observation the higher the associated weight. A fable is a forecasting table. In the table, sales column represents the point forecast and distribution represents the distribution of forecast. The forecasting was done for a period of 12 months. In the result, only the 10 rows in the result table are displayed. The table contains all the product in "product" column and all the cities in "city" column. The total table will have m*n+(m+n)+1 series for forecast. Where m is the no. of products and n is the no. of cities. In this example we have total of 1452 results when we forecast for 12 months and as we applied both "ETS" and ETS Minimum Trace Approach algorithm we have a total of 2904 rows in final table.

```
# A fable: 2,904 x 6 [1M]
# Key:     product, city, .model [242]
   product city  .model    month    sales .distribution
   <chr>   <chr> <chr>     <mth>    <dbl> <dist>
 1 coolers Ahmd  ets    2017 Apr 5508044. N(5508044, 1.5e+11)
 2 coolers Ahmd  ets    2017 May 2606775. N(2606775, 2.2e+11)
 3 coolers Ahmd  ets    2017 Jun 1190679. N(1190679, 3.0e+11)
 4 coolers Ahmd  ets    2017 Jul 1144479. N(1144479, 3.7e+11)
 5 coolers Ahmd  ets    2017 Aug 1120899. N(1120899, 4.5e+11)
 6 coolers Ahmd  ets    2017 Sep 1071220. N(1071220, 5.2e+11)
 7 coolers Ahmd  ets    2017 Oct 1196010. N(1196010, 6.0e+11)
 8 coolers Ahmd  ets    2017 Nov 1186952. N(1186952, 6.7e+11)
 9 coolers Ahmd  ets    2017 Dec 1176473. N(1176473, 7.5e+11)
10 coolers Ahmd  ets    2018 Jan 1728170. N(1728170, 8.2e+11)
# ... with 2,894 more rows
```

We can see the forecasting for product wise, city wise and total sales in the figures

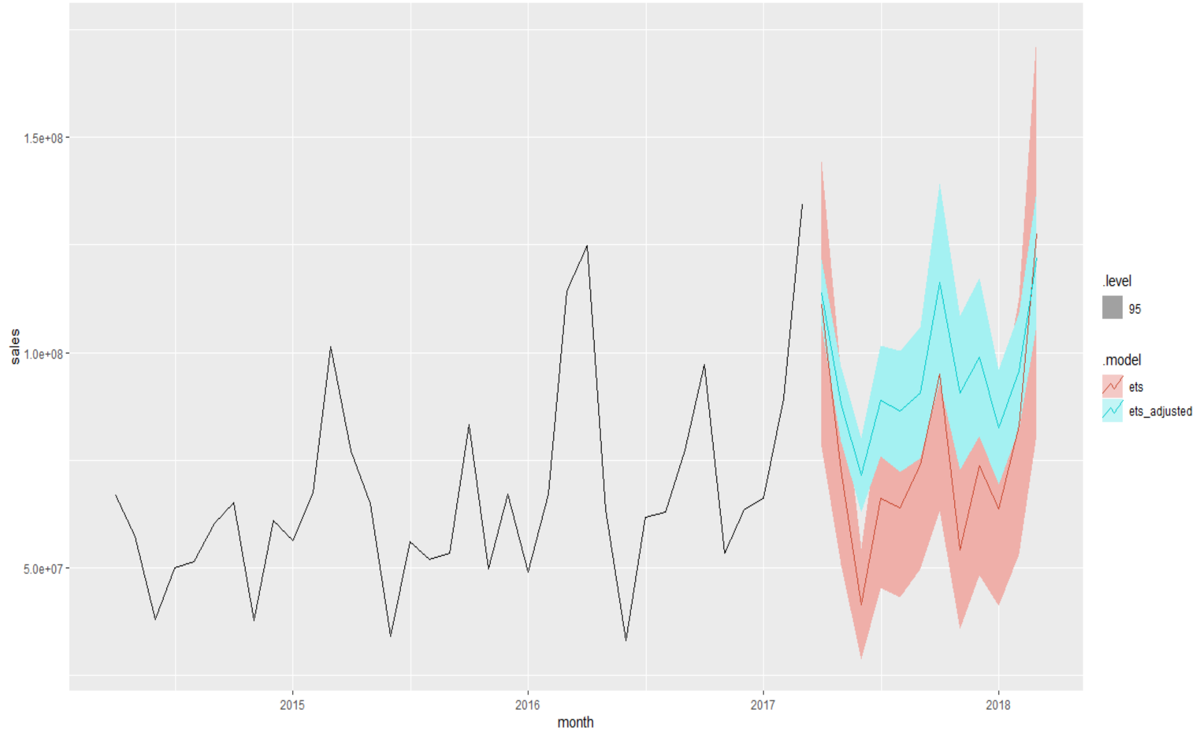


Fig 4.3.1– Overall Sales Forecast - ETS

Fig 4.3.2– Sales Forecast for the City of Kolkata - ETS

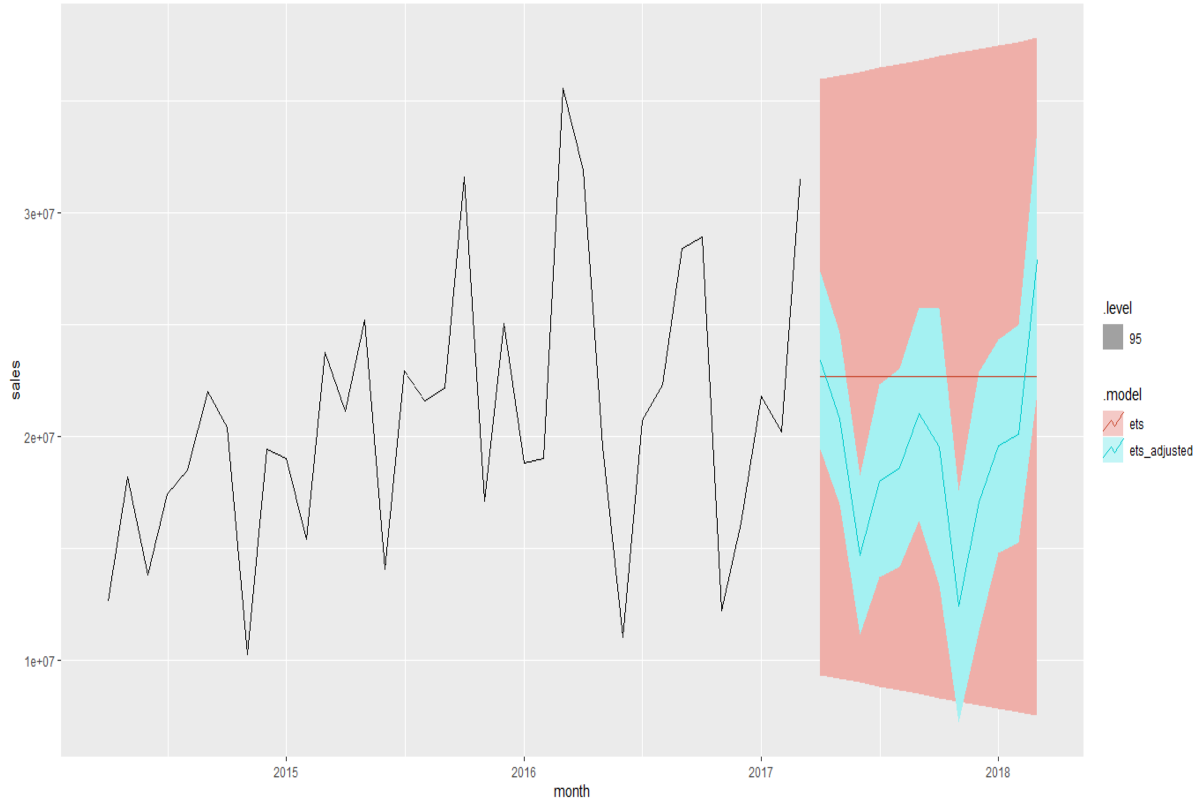


Fig 4.3.3– Sales Forecast for Product Mixers - ETS

Accuracy Evaluation:

We will calculate the average error for all the series forecasts as the large number of series are present. We can see from the below table that ETS_adjusted through minimum trace approach is giving better accuracy measures when compared with ETS. We are getting the value of MAPE as "Infinity" because of presence of sales as "Zero" or near "Zero" values as the sales figures for any value of previous observations. Also, the value of MASE (Mean Absolute Scaled Error) are NaN because to calculate the MASE we should have test data of more than 12 observations (at least 13) if the data set is a monthly data.

Parameter (Mean value)	**ETS**	**ETS_Adjusted**
RMSE	1638783	1528802
MAPE	Inf	Inf
MASE	NaN	NaN
ME	91591	17830
MAE	1396718	1289956

Table 4.3.1– Accuracy Evaluation for ETS

4.4. ARIMA Modelling:

One of the fundamental features of ARIMA modelling is to check for Stationality and by removing the trend and seasonal components making the series stationary. However, due to the present of large number of series in the dataset and it is not possible to enforce on single type of transformation in the overall series. For ARIMA the forecasts are as given below. In the ARIMA modelling we applied no data transformations has been done because transformations like log or differentiation can present us a non-gaussian distributions and "tidyverse" approach still doesn't support the forecasting for these distributions. Also, due to the presence of zero or negative sales makes the log transformation application non-feasible. However, as discovered in the EDA most of the products in the data set don't have any clear trend pattern and removal seasonality or variance with respect to time can be taken care of by optimal reconciliation approach. Hence, even without the transformation of data to gain the Stationality we can still get some good forecast results. The below table has point and distribution forecasts for dataset when forecasted for 12 months and applied ARIMA and ARIMA through optimal reconciliation approaches.

```
# A fable: 2,904 x 6 [1M]
# Key:     product, city, .model [242]
   product city  .model    month    sales .distribution
   <chr>   <chr> <chr>     <mth>    <dbl> <dist>
 1 coolers Ahmd  arima  2017 Apr 6352033. N(6352033, 1.9e+11)
 2 coolers Ahmd  arima  2017 May 2340689. N(2340689, 2.7e+11)
 3 coolers Ahmd  arima  2017 Jun  473923. N( 473923, 3.0e+11)
 4 coolers Ahmd  arima  2017 Jul  271973. N( 271973, 3.2e+11)
 5 coolers Ahmd  arima  2017 Aug  173957. N( 173957, 3.2e+11)
 6 coolers Ahmd  arima  2017 Sep  111265. N( 111265, 3.2e+11)
 7 coolers Ahmd  arima  2017 Oct   78378. N(  78378, 3.2e+11)
 8 coolers Ahmd  arima  2017 Nov   84688. N(  84688, 3.2e+11)
 9 coolers Ahmd  arima  2017 Dec   65273. N(  65273, 3.2e+11)
10 coolers Ahmd  arima  2018 Jan  784918. N( 784918, 3.2e+11)
# ... with 2,894 more rows
```

Accuracy Evaluation:

Parameter(Mean value)	ARIMA	ARIMA_adjusted
RMSE	1354859	1387081
MAPE	Inf	Inf
MASE	NaN	NaN
ME	430148	431921
MAE	1127788	1164003

Table 4.4.1– Accuracy Evaluation for ARIMA

Similar to ETS, we will calculate the average error for all the series forecasts as the large number of series are present. We can see from the below table that simple ARIMA is giving better accuracy measures when compared with Optimal reconciliation approach. We are getting the value of MAPE as “Infinity” because of presence of sales as “Zero” or near “Zero” values as the sales figures for any value of previous observations. Also, the value of MASE (Mean Absolute Scaled Error) are NaN because to calculate the MASE we should have test data of more than 12 observations (at least 13) if the data set is a monthly data. The forecasts are displayed in the below figures

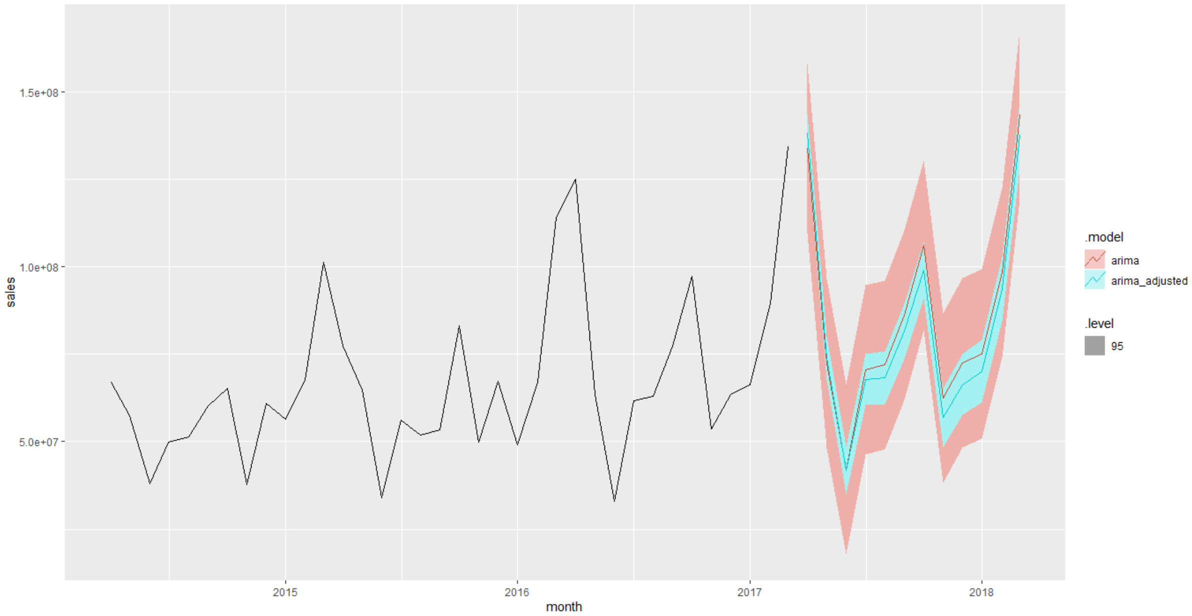


Fig 4.4.1 – Overall Sales Forecast - ARIMA

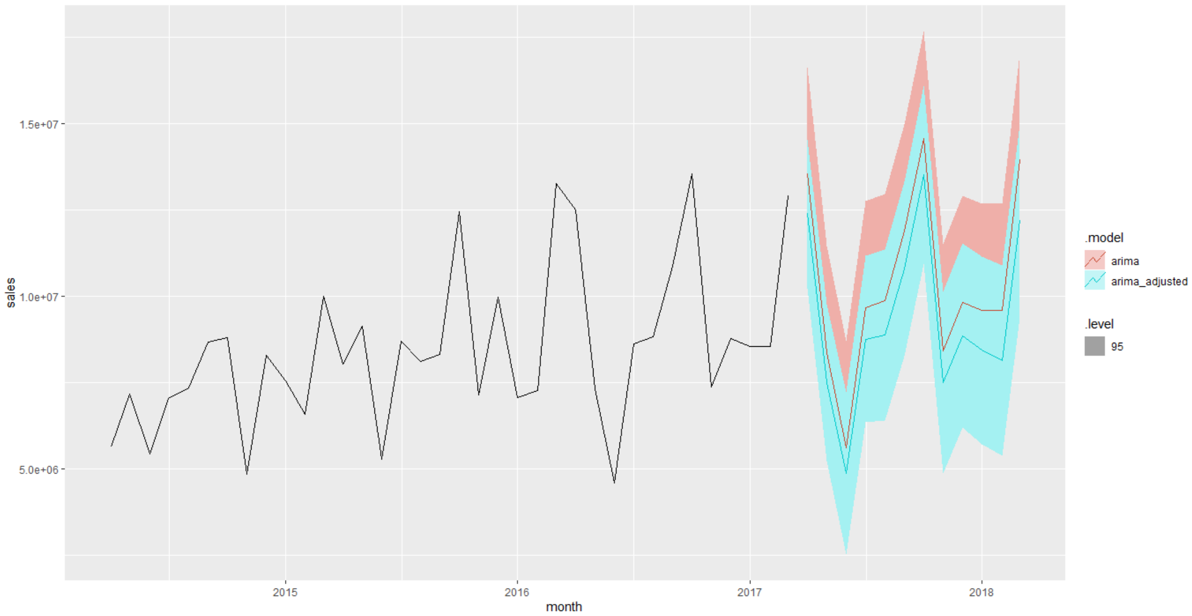


Fig 4.4.2– Sales Forecast for the City of Kolkata - ARIMA

Fig 4.4.3– Sales Forecast for the product Mixers - ARIMA

4.5 SNAIVE Modelling:

A similar method is useful for highly seasonal data. In this case, we set each forecast to be equal to the last observed value from the same season of the year (e.g., the same month of the previous year). However, this is a simple model and can't account for any sudden changes in sales in the corresponding previous observation or current observation. In our data set, in most of the times SNAIVE might give a better forecast results because of presence of high seasonality and lack of trend for most of the products. The below table has point and distribution forecasts for dataset when forecasted for 12 months and applied ARIMA and ARIMA through optimal reconciliation approaches. Like ETS and ARIMA, it also has total of 2904 results in the table.

```
# A fable: 2,904 x 6 [1M]
# Key:     product, city, .model [242]
   product city  .model    month    sales .distribution
   <chr>   <chr> <chr>     <mth>    <dbl> <dist>
 1 coolers Ahmd  snaive 2017 Apr 5312646 N(5312646, 2.5e+11)
 2 coolers Ahmd  snaive 2017 May 1675885 N(1675885, 2.5e+11)
 3 coolers Ahmd  snaive 2017 Jun   48707 N(  48707, 2.5e+11)
 4 coolers Ahmd  snaive 2017 Jul       0 N(      0, 2.5e+11)
 5 coolers Ahmd  snaive 2017 Aug       0 N(      0, 2.5e+11)
 6 coolers Ahmd  snaive 2017 Sep       0 N(      0, 2.5e+11)
 7 coolers Ahmd  snaive 2017 Oct    7212 N(   7212, 2.5e+11)
 8 coolers Ahmd  snaive 2017 Nov   39169 N(  39169, 2.5e+11)
 9 coolers Ahmd  snaive 2017 Dec   36159 N(  36159, 2.5e+11)
10 coolers Ahmd  snaive 2018 Jan  766296 N( 766296, 2.5e+11)
# ... with 2,894 more rows
```

We can see from the above forecast table some times why SNAIVE is a better approach. Both ETS and ARIMA approached forecasted values of sales for cooler products in after summer season is over as positive. However, we can see from our data set these values are zero for almost all the years. We can see the city wise forecast for Kolkata and Product wise forecast for “Mixers” using SNAIVE forecasting approach in the below figures.

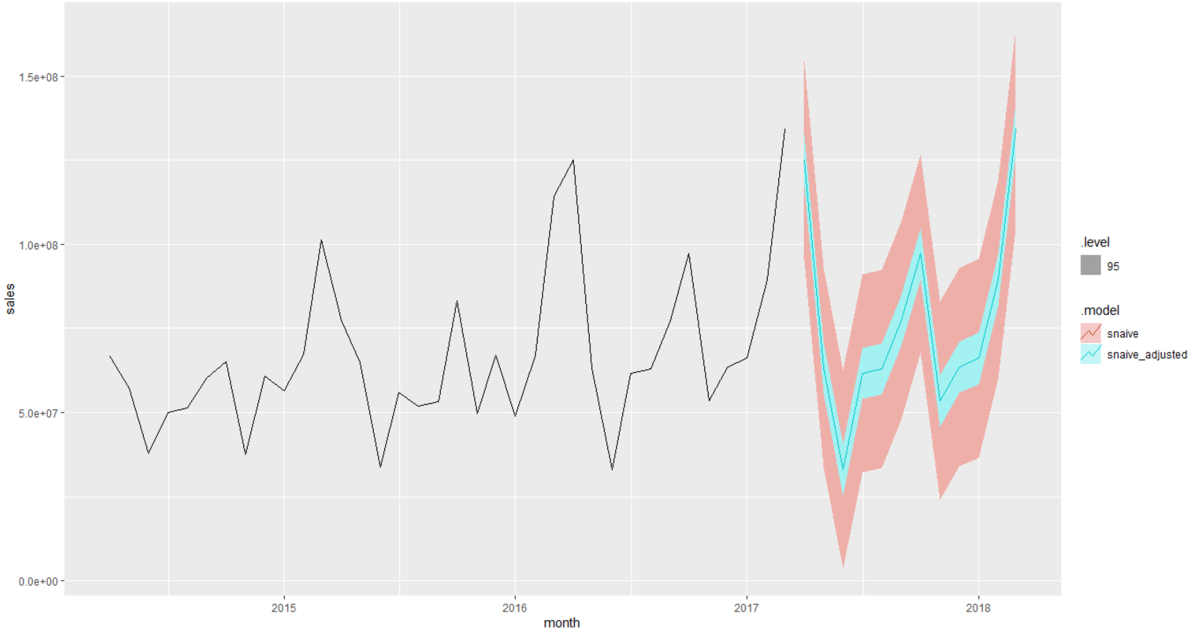


Fig 4.5.1 – Overall Sales Forecast using SNAIVE

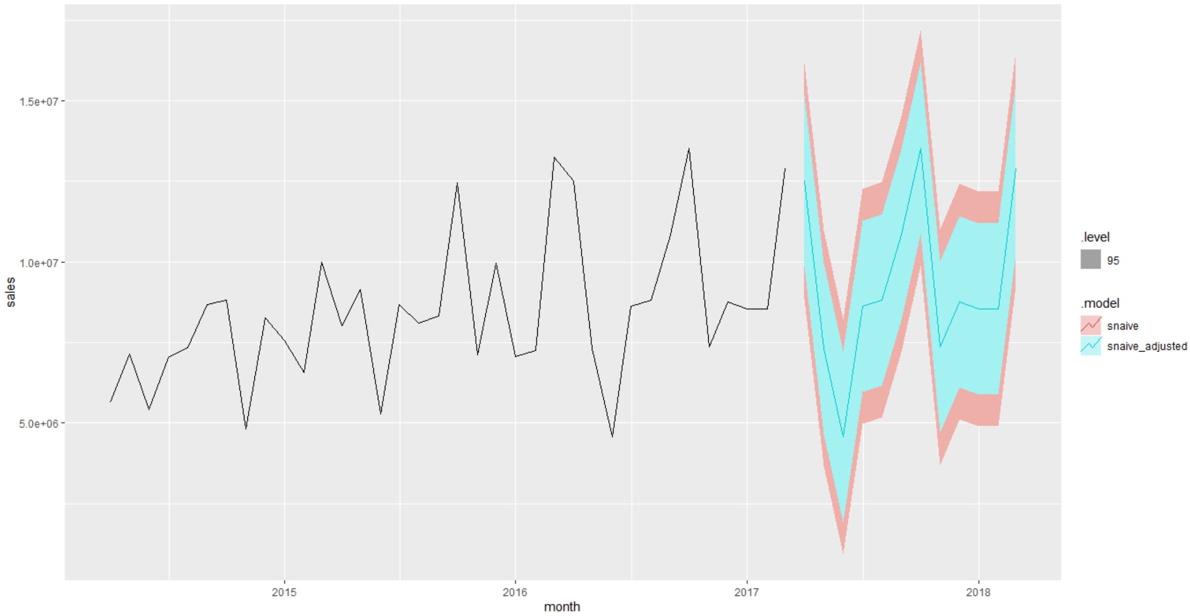


Fig 4.5.2– Sales Forecast for the City of Kolkata using SNAIVE

Fig 4.5.3– Sales Forecast for Mixture Product using SNAIVE

Accuracy Evaluation:

Similar to ETS, we will calculate the average error for all the series forecasts as the large number of series are present. We can see from the below table that simple SNAIVE and Optimal reconciliation approach are giving the same accuracy measures because both the approaches simply takes the previous values in same period as forecasted values. Even, in the forecasted charts we can see that SNAIVE and SNAIVE adjusted forecasting closely follows each other. The values of MASE (Mean Absolute Scaled Error) are NaN because to calculate the MASE we should have test data of more than 12 observations (at least 13) if the data set is a monthly data.

Parameter(Mean value)	**SNAIVE**	**SNAIVE_adjusted**
RMSE	1366817	1366817
MAPE	67.0	Inf
MASE	NaN	NaN
ME	617333	617333
MAE	1127574	1127574

Table 4.5.1 – Accuracy Evaluation for SNAIVE

We will compare the evaluations and select the best forecasting method for our data set. Because of presence of multiple series in our data set some times having forecasting for individual series might give better forecast errors. However, the call needs to be taken depends on the cost of Forecast Error. If we want to minimize the forecast error along the median, we choose to minimize MAE. But it might give undesirable results if we don’t have data symmetry. Similarly, if we choose to minimize the error along the mean we might choose RMSE.

4.6 Ensemble Forecast:

We tried to introduce ensemble forecast by combining all the above three forecasts. Sometimes, an ensemble approach might give the better forecast results. In the approach implemented in this project we choose an ensemble of simple averages of ETS, ARIMA and SNAIVE forecasts. We can also choose ensemble like weighted averages if we fell that one forecasting method is always giving better accuracy results than others. The below table has average point and distribution forecasts for dataset when forecasted for 12 months and also ensemble through optimal reconciliation approach.

```
# A fable: 11,616 x 6 [1M]
# Key:     product, city, .model [968]
   product city  .model    month     sales .distribution
   <chr>   <chr> <chr>     <mth>     <dbl> <dist>
 1 coolers Ahmd  ets    2017 Apr 5508044. N(5508044, 1.5e+11)
 2 coolers Ahmd  ets    2017 May 2606775. N(2606775, 2.2e+11)
 3 coolers Ahmd  ets    2017 Jun 1190679. N(1190679, 3.0e+11)
 4 coolers Ahmd  ets    2017 Jul 1144479. N(1144479, 3.7e+11)
 5 coolers Ahmd  ets    2017 Aug 1120899. N(1120899, 4.5e+11)
 6 coolers Ahmd  ets    2017 Sep 1071220. N(1071220, 5.2e+11)
 7 coolers Ahmd  ets    2017 Oct 1196010. N(1196010, 6.0e+11)
 8 coolers Ahmd  ets    2017 Nov 1186952. N(1186952, 6.7e+11)
 9 coolers Ahmd  ets    2017 Dec 1176473. N(1176473, 7.5e+11)
10 coolers Ahmd  ets    2018 Jan 1728170. N(1728170, 8.2e+11)
# ... with 11,606 more rows
```

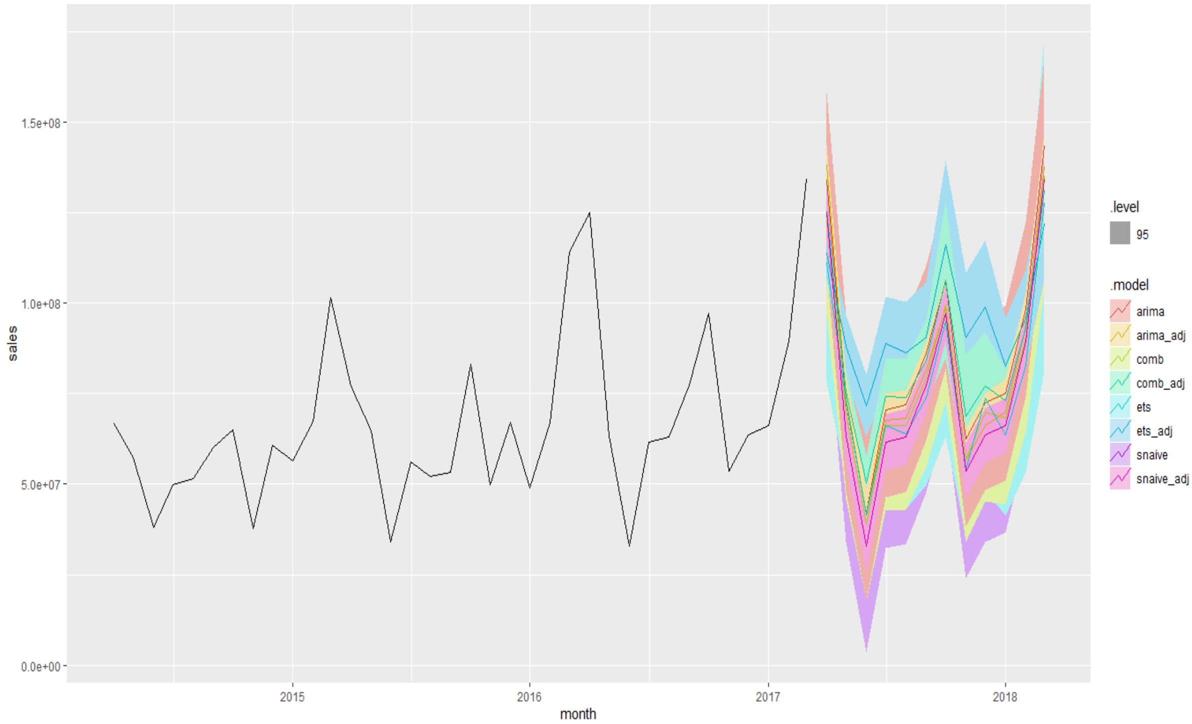


Fig 4.6.1– Overall Forecast through Ensemble Approach

Fig 4.6.2 – Sales Forecast for Kolkata City – Ensemble Approach

Fig 4.6.3– Sales Forecast for Mixtures – Ensemble Approach

Accuracy Evaluation:

Similar to other models, we will calculate the average error for all the series forecasts as the large number of series are present. We can see from the below table that simple Ensemble and Optimal reconciliation approach are giving the same accuracy measures except for RMSE. The values of MASE (Mean Absolute Scaled Error) are NaN because to calculate the MASE we should have test data of more than 12 observations (at least 13) if the data set is a monthly data.

Parameter (Mean value)	Combined	Combined_adjusted
RMSE	1367792	1327512
MAPE	Inf	Inf
MASE	NaN	NaN
ME	617333	617333
MAE	379691	379691

Table 4.6.1– Accuracy Evaluation for Ensemble Forecast

4.7. Model Selection:

Until this point we implemented a total of 3 modelling techniques ETS, ARIMA and SNAIVE and we applied Optimal Reconciliation Approach for all the above three methods. In addition to this, we also implemented an ensemble model by taking simple average of point forecasts of three models and applied Optimal Reconciliation Approach to this also. We now need to compare the accuracy measures of all these forecasts and select the best model for our data set. All these forecasts are done for a 12-month period to capture the seasonality in the forecast.

Parameter	RMSE	ME	MAE	MAPE	MASE
ARIMA	1354859	430148	1127788	Inf	NaN
ARIMA_ADJUSTED	1387081	431921	1164003	Inf	NaN
COMBINED	1367792	617333	379691	Inf	NaN
COMBINED_ADJUSTED	1327512	617333	379691	Inf	NaN
ETS	1638783	91591	1396718	Inf	NaN
ETS_ADJUSTED	1528802	17830	1289956	Inf	NaN
SNAIVE	1366817	617333	1127574	67	NaN
SNAIVE_ADJUSTED	1366817	617333	1127574	Inf	NaN

Table 4.7.1 – Accuracy Evaluation Metrics all models

From the above table, we can say that if we would like to minimize error from the mean (RMSE), then Ensemble of all models with Optimized Reconciliation Approach is giving better results. If our point of concern is minimization of error from medium value, then we will be choosing MAE as our evaluation metric. Even in this case, Ensemble of all models with Optimized Reconciliation Approach is giving better results. Mean Error is not an ideal choice because of the presence of negative sales in the data. In both the cases we can see that Ensemble of all models applied through Optimized Reconciliation Approach is better choice of modelling. We can't interpret the values of MAPE as they are showing infinity because of presence of zero sales for some products in the data. Similarly, the MASE values are calculated as NaN due to availability of only 1 year of data as the validation set.

In order to understand and interpret the forecasting results in the better way, we randomly selected 4 products and 4 city combinations and implemented the ensemble approach for the selected combination. The selected series are Kolkata – Mixers, Mumbai – Coolers, Bangalore – Dry Iron and Hyderabad – Water Heaters. The point forecasts for the above combinations are given the excel file attached. We will here focus on model evaluation of these series.

Parameter	RMSE	ME	MAE	MAPE	MPE	ACF1
ARIMA	4207430	3781391	4207430	52.2	40.3	0.229
ARIMA_ADJUSTED	3817853	2963681	3817853	49.2	27.5	0.242
COMBINED	3615220	3113374	3615220	43.5	29.6	0.214
COMBINED_ADJUSTED	3861354	3216345	3861354	47.9	31	0.27
ETS	3258668	2669597	3258668	37.4	22	0.164
ETS_ADJUSTED	4563194	4248567	4563194	54.1	45.5	0.374
SNAIVE	3656750	2889134	3656750	46.7	26.6	0.229
SNAIVE_ADJUSTED	3656750	2889134	3656750	46.7	26.6	0.229

Table 4.7.2– Accuracy Evaluation: Kolkata - Mixers

Parameter	RMSE	ME	MAE	MAPE	MPE	ACF1
ARIMA	602920	315909	315909	Inf	Inf	0.496
ARIMA_ADJUSTED	614047	360933	360933	Inf	Inf	0.497
COMBINED	949504	513287	540530	Inf	Inf	0.469
COMBINED_ADJUSTED	952608	581771	586816	Inf	Inf	0.485
ETS	1569150	817373	910745	Inf	Inf	0.436
ETS_ADJUSTED	1549095	887273	924707	NaN	NaN	0.46
SNAIVE	721996	406581	406581	17	17	0.427
SNAIVE_ADJUSTED	721996	406581	406581	NaN	NaN	0.427

Table 4.7.3– Accuracy Evaluation: Mumbai – Coolers

Parameter	RMSE	ME	MAE	MAPE	MPE	ACF1
ARIMA	341000	-133269	237000	54.6	-43.9	0.193

ARIMA_ADJUSTED	342000	-128576	237000	54.4	-43.2	0.194
COMBINED	294000	-58652	222000	47.1	-31.2	0.194
COMBINED_ADJUSTED	296000	-55467	223000	47.1	-30.6	0.2
ETS	293000	-9810	217000	41.3	-23.2	0.149
ETS_ADJUSTED	285000	805	216000	40.5	-20.8	0.187
SNAIVE	316000	-32876	231000	48.3	-26.5	0.193
SNAIVE_ADJUSTED	316000	-32876	231000	48.3	-26.5	0.193

Table 4.7.4– Accuracy Evaluation: Bangalore – Dry Iron

Parameter	**RMSE**	**ME**	**MAE**	**MAPE**	**MPE**	**ACF1**
ARIMA	1220000	937000	937000	105	105	0.557
ARIMA_ADJUSTED	1210000	939000	939000	114	114	0.556
COMBINED	1210000	929000	929000	89.2	89.2	0.559
COMBINED_ADJUSTED	1220000	933000	933000	90.9	90.9	0.558
ETS	1220000	933000	933000	82.1	82.1	0.559
ETS_ADJUSTED	1230000	936000	936000	82.2	82.2	0.559
SNAIVE	1200000	917000	917000	80.5	80.5	0.56
SNAIVE_ADJUSTED	1200000	917000	917000	80.5	80.5	0.56

Table 4.7.5– Accuracy Evaluation: Hyderabad – Water Heaters

For the series Kolkata – Mixers, we can see that we are able to deduce the values of MAPE because of non-presence of zero sales in any month which is not the case with Mumbai – Coolers data. As the coolers are highly seasonal, there are zero sales recorded during the months from Jul – Sep. For the Kolkata – Mixers series, simple ETS model is performing better than ensemble or reconciliation approach. Similarly, for the Mumbai – Coolers series ARIMA performed better because of its ability to capture the seasonality in a good way and Coolers in Mumbai has shown strong seasonality. For Bangalore – Dry Iron series, ETS with reconciliation approach gave the better forecast results. Finally, for the Hyderabad – Water Heaters series, Seasonal Naïve gave a better forecast accuracy in almost all the metrics. However, in our initial discussion we concluded that Ensemble of all models is performing better for the entire data set rather than individual series and even in the ensemble, Optimal Reconciliation Approach is giving much better results. Hence, it is reasonable to imply that not a single forecasting model or a forecasting error metric is enough to decide the better model and we need to understand the Cost of Forecast Error to decide the approach. Even in the individual series also, presence of near zero or zero sales gives the extreme error values or infinity as error if we calculate MAPE as metric. The forecast visualization for individual series are displayed below.

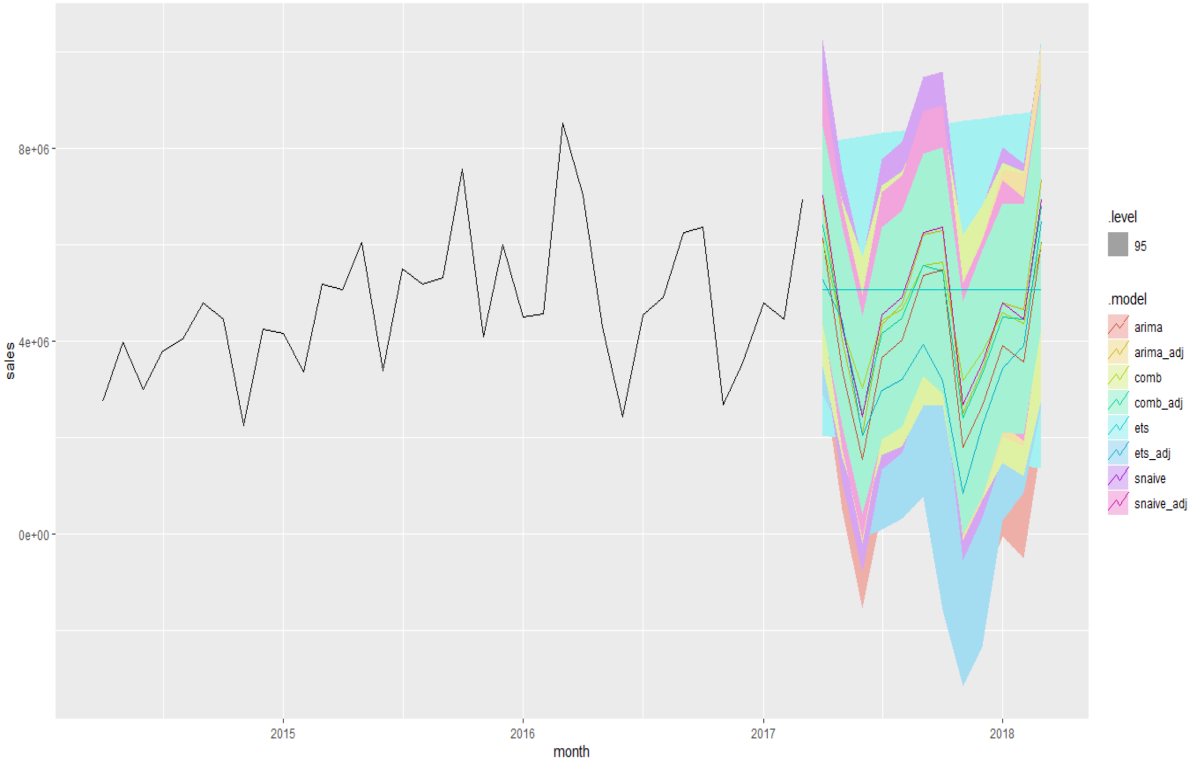


Fig 4.7.1– Mixture Sales Forecast for Kolkata

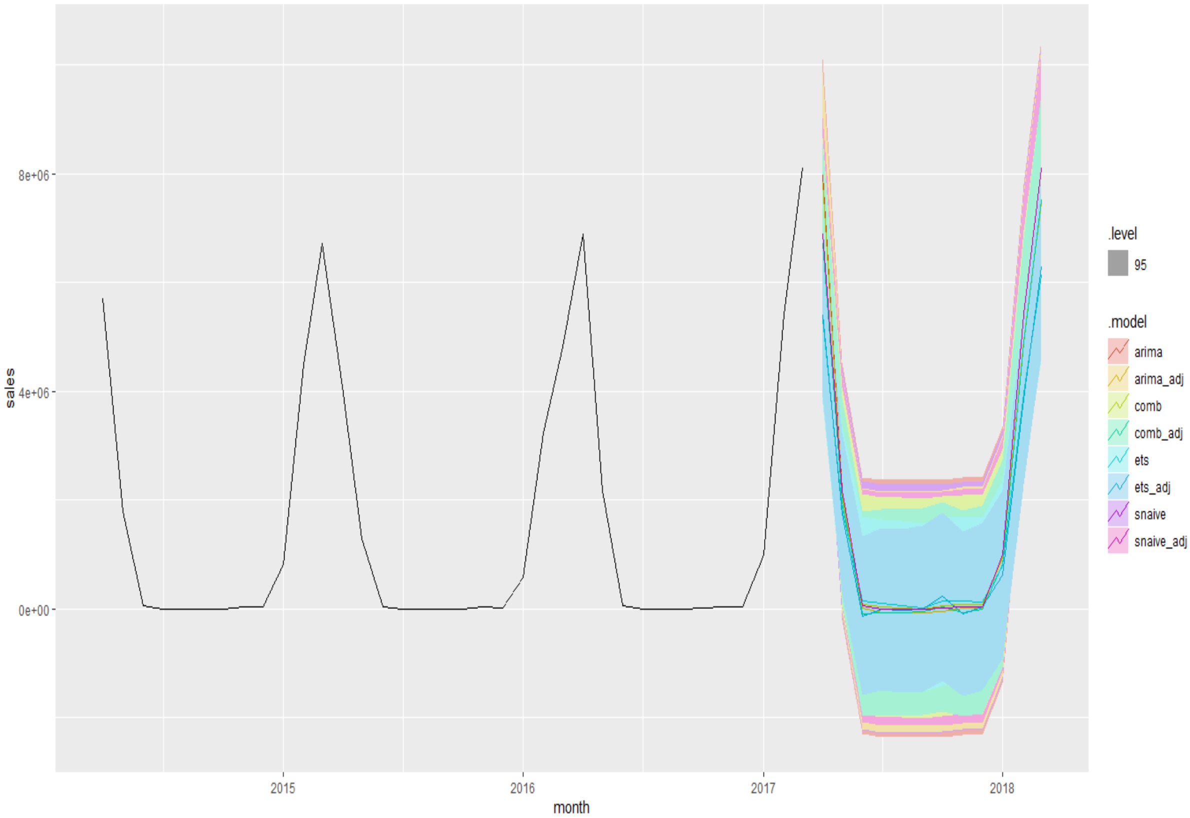


Fig 4.7.2– Cooler Sales Forecast for Mumbai

Fig 4.15– Dry Iron Sales Forecast for Bangalore

5. CONCLUSION & RECOMMENDATIONS

To conclude, in this project, we analysed the data of an electrical consumer appliances company and built a sales forecasting model to aid the production planning. As the dataset also consists of negative and zero sales, we tried to identify the patterns among these for certain products and made recommendations accordingly. As the data set contains multiple cities and multiple products, we implemented hierarchical time series forecasting with tidyverse tools and package to get better forecasting results. The model was further improved by applying optimal reconciliation approach through trace minimization to aggregate the forecasts at base level. Finally, we evaluated our model with accuracy metrics and proposed final forecasting model as ensemble of ETS, ARIMA and SNAIVE approaches. In conclusion, our report presents that use of forecasting methods to forecast the sales city wise and product to make informed decisions about product planning and to make business decisions about future course of action.

Business Recommendations:

A. To avoid Negative sales / Sales return following to be considered:

- Proper coordination within Operation and Sales department to avoid last minute expiry of Purchase orders and thus rejection from the subsequent Warehouses.
- More stringent quality checks at factory level to avoid defects in Finished goods.
- End to End Supply chain& Logistics plan to ensure least product damage during transit and product delivery within the time frame.

B. Pune, Guwahati, Lucknow, Chandigarh & Raipur are having sales degrowth. To revive the sales in these cities following products to be promoted:

City	Proposed products
Pune	Food processor,Water Heater, LED
Guwahati	Water Heater, Induction cooker & Microwave Oven
Lucknow	Coolers, Water Heater, Induction cookers
Chandigarh	Mixers, SECF , Water Heater
Raipur	Mixers, Coolers, Water Heater, LED

C. Water heaters have moved from seasonal product to a regular usage product thus marketing plan for this has to be aligned with this.

D. In West region except Mumbai, Water heaters are among top selling product. This shows the market potential for this. Thus, water heaters to be relaunched with marking backup to establish in Mumbai market.

E. In KAP category, Food processor is the second highest selling product in West & North zone cities but least preferred in East & South Zone. This to be checked with Market facts.

F. Juice Extractor & Pressure cooker are becoming dead products of KAP category. These products require realignment with the latest technology & competitive pricing to ensure a share in market demand.

G. Wet Grinder & Rice cooker could be promoted in combo offer in Southern region cities.

F. In East region, sales dependency on Mixers to be spread over other products such as Rice cookers, Water heaters, Induction cookers, Toasters etc. to ensure even sales growth.

H. Light category is almost nil in east region cities of Bhubaneshwar, Guwahati & Patna. LED could be introduced in these cities.

I. Degrowing sales trend products (Non-Electrical Kitchen Products, CFL & Down light) to discontinued and dropped from product list.

J. In Eastern Region – Kolkata, Patna showed good upward trend in sales. Similarly, except Bangalore all the southern cities are showing good sales growth.

K. Pressure Cookers sold in Noida during the year 2015-16 has huge negative sales. Whether it is an operational issue or quality issue needs to be further examined.

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