FORECASTING OF CONSUMER GOODS APPLIANCES

-Optimal Reconciliation through trace minimization approach(minT)

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What we want to talk about..

- Problem statement, Objectives & Scope of the Project
- Analytical Approach
- Exploratory Data Analysis
- Forecast Modelling – HTS & GTS
- Model Evaluation & Selection
- Business Recommendations & conclusion.

What is the issue..

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. Also Evaluating the effects of seasonality in various cities and products. We were also asked to build a forecasting model of production quality and evaluate its performance.

What we wanted to achieve..

- Analyse Overall Sales Performance – City & Product
- Analyse Negative and Zero Sales
- Developing Forecasting Model - Hierarchical or Grouped Time Series
- Model Evaluation & Performance Enhancement

What are our limitations..

- Limited to Top 10 Cities and Top 10 Products
- 4 Years of data at hand
- Assumed forecasts are normal and unbiased
- Packages are still under development –fable, fable tools

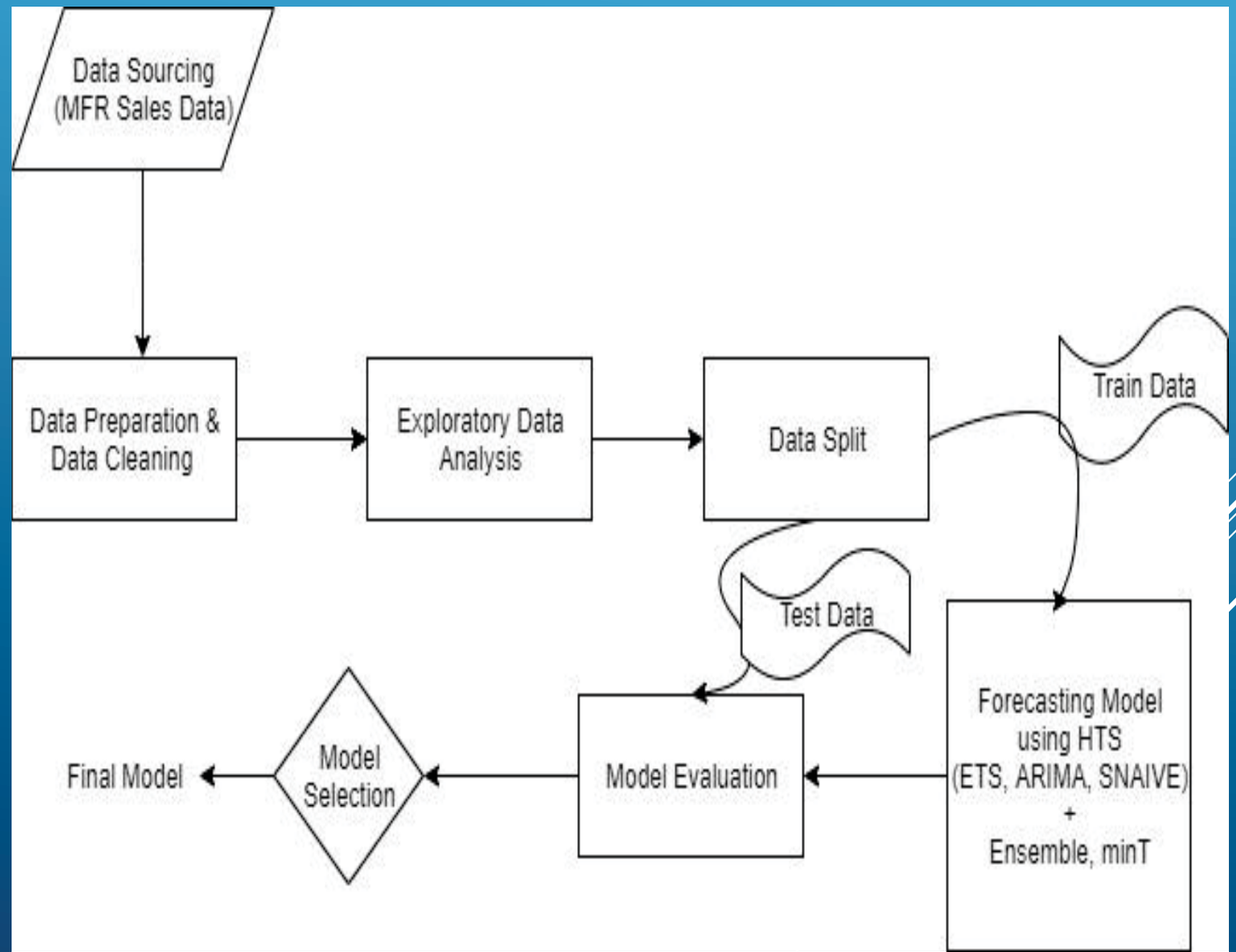
How we did..

TOOLS & TECHNIQUES

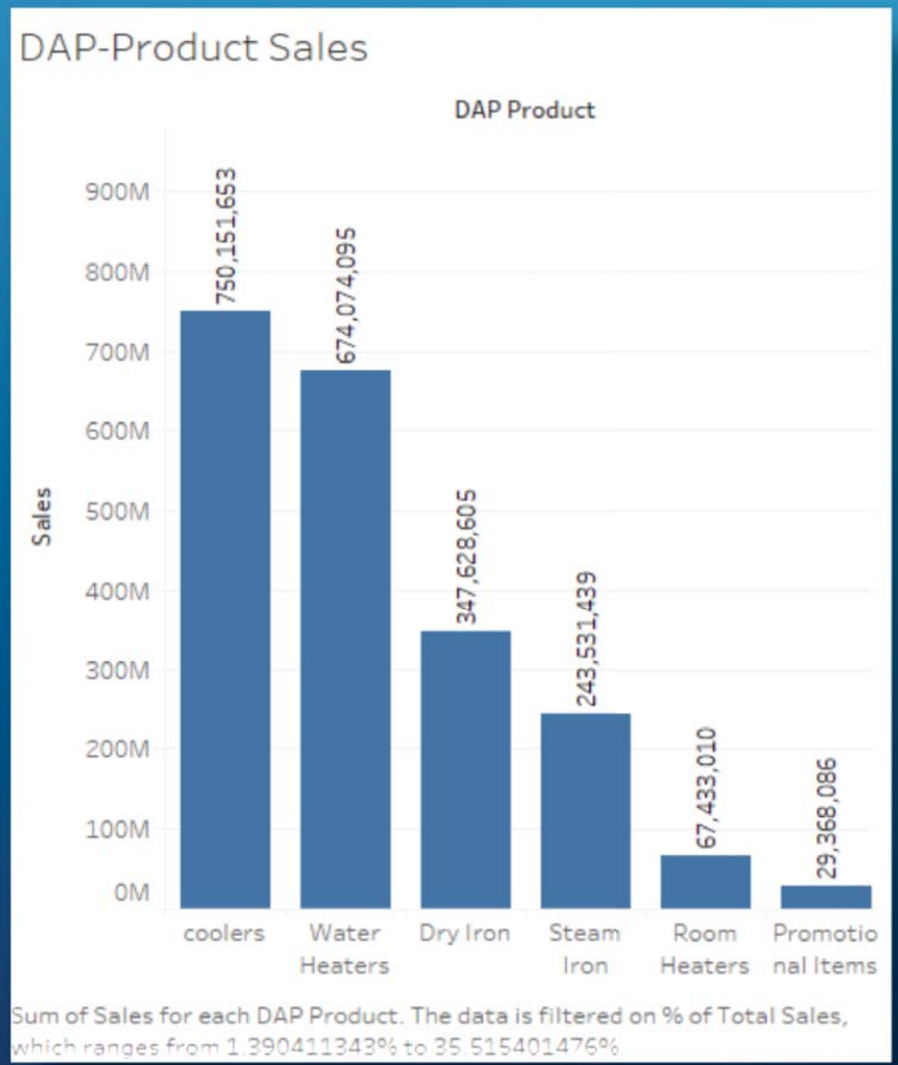
Algorithms:

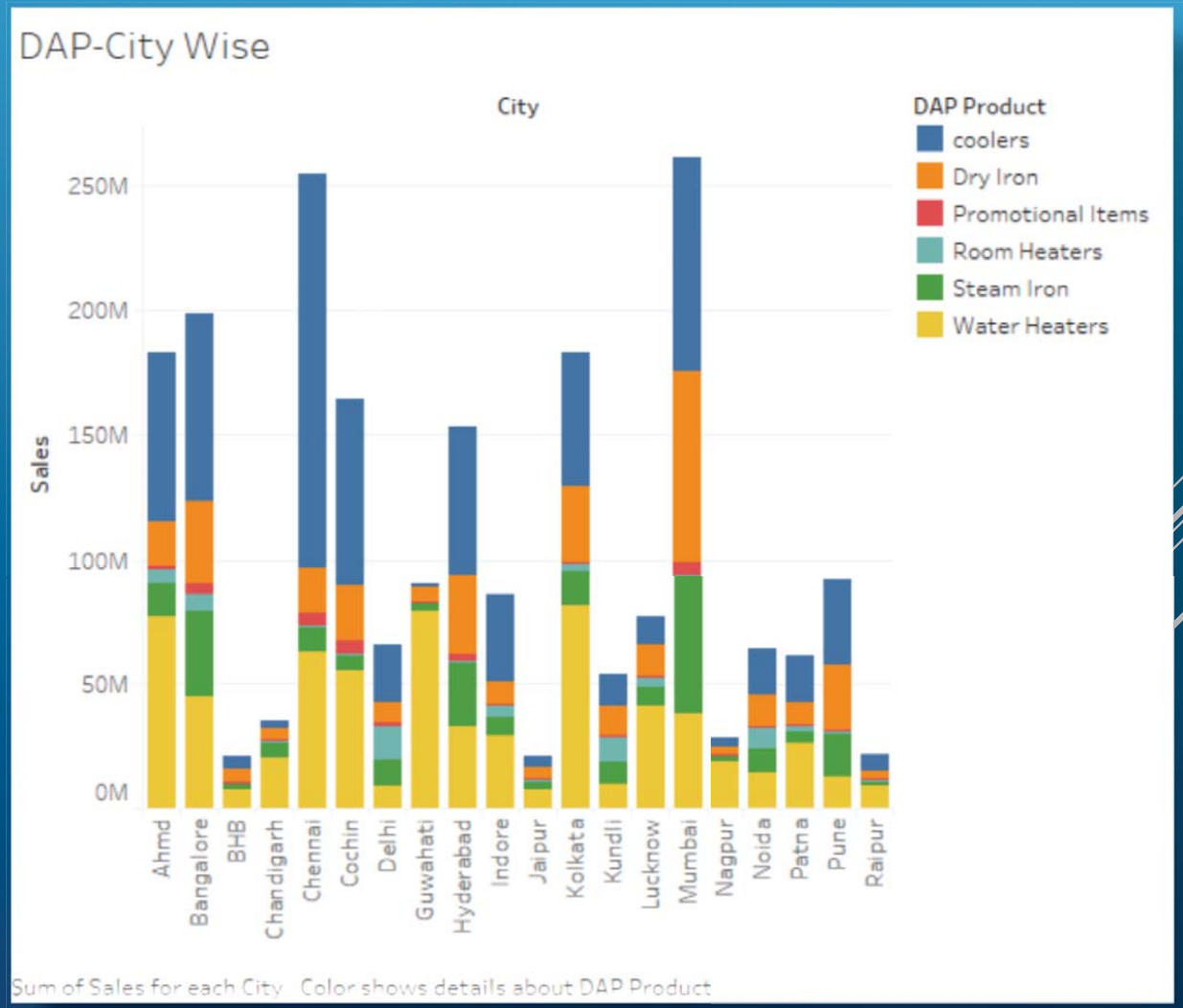
- ARIMA, ETS, SNAIVE
- Ensemble
- Reconciliation through minT

Analytical Tools:

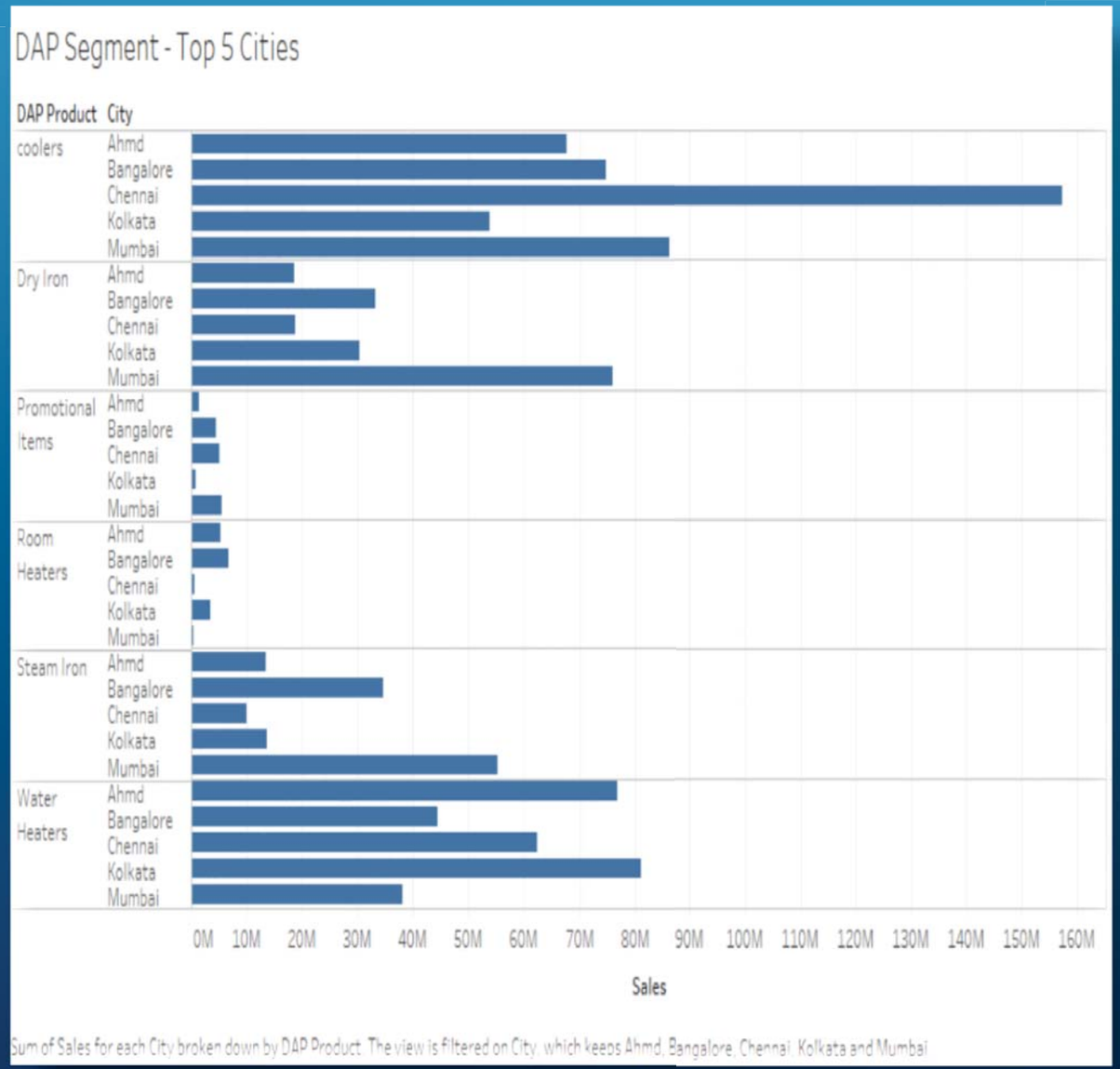


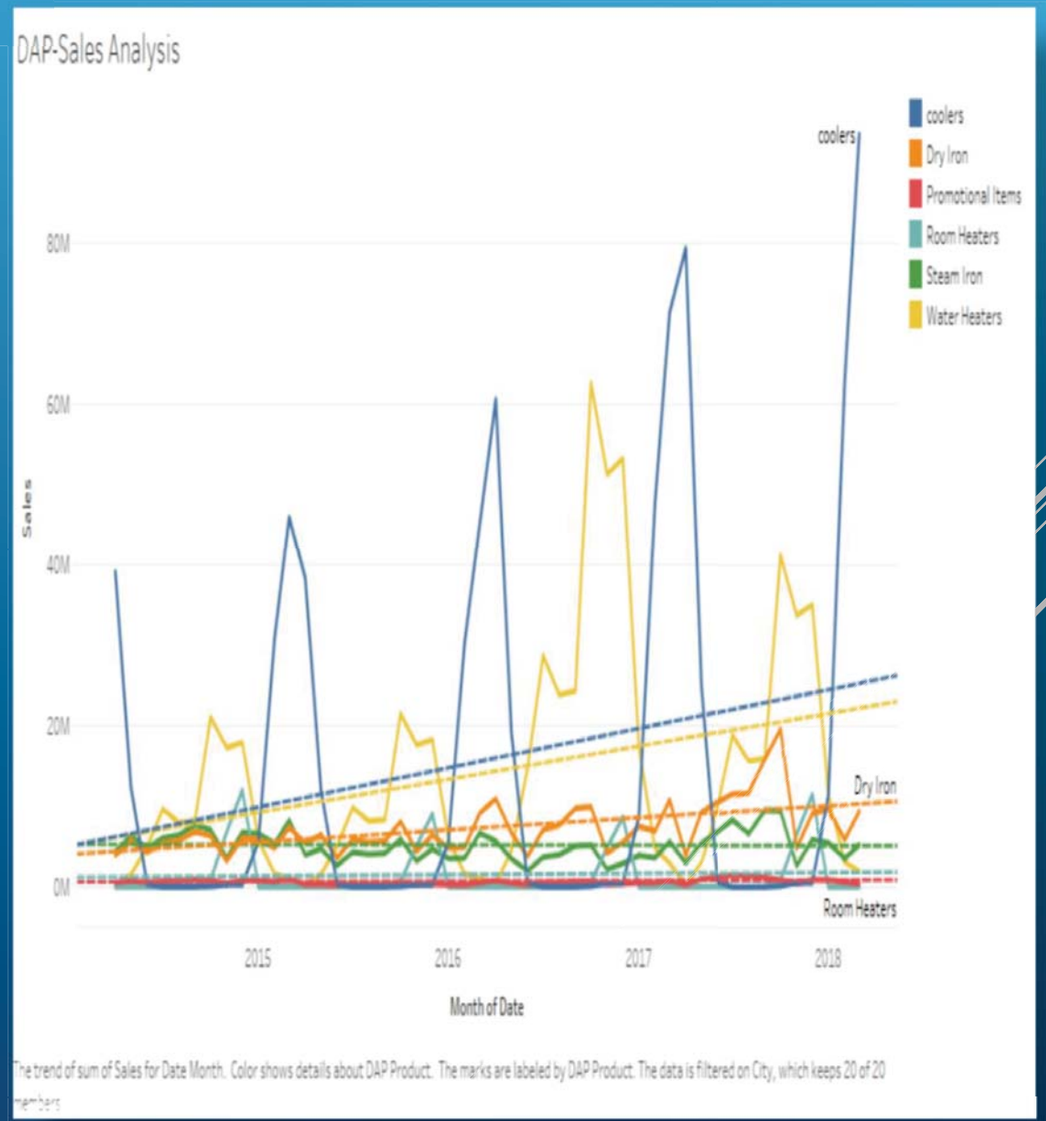
Insights & Visualizations- DAP



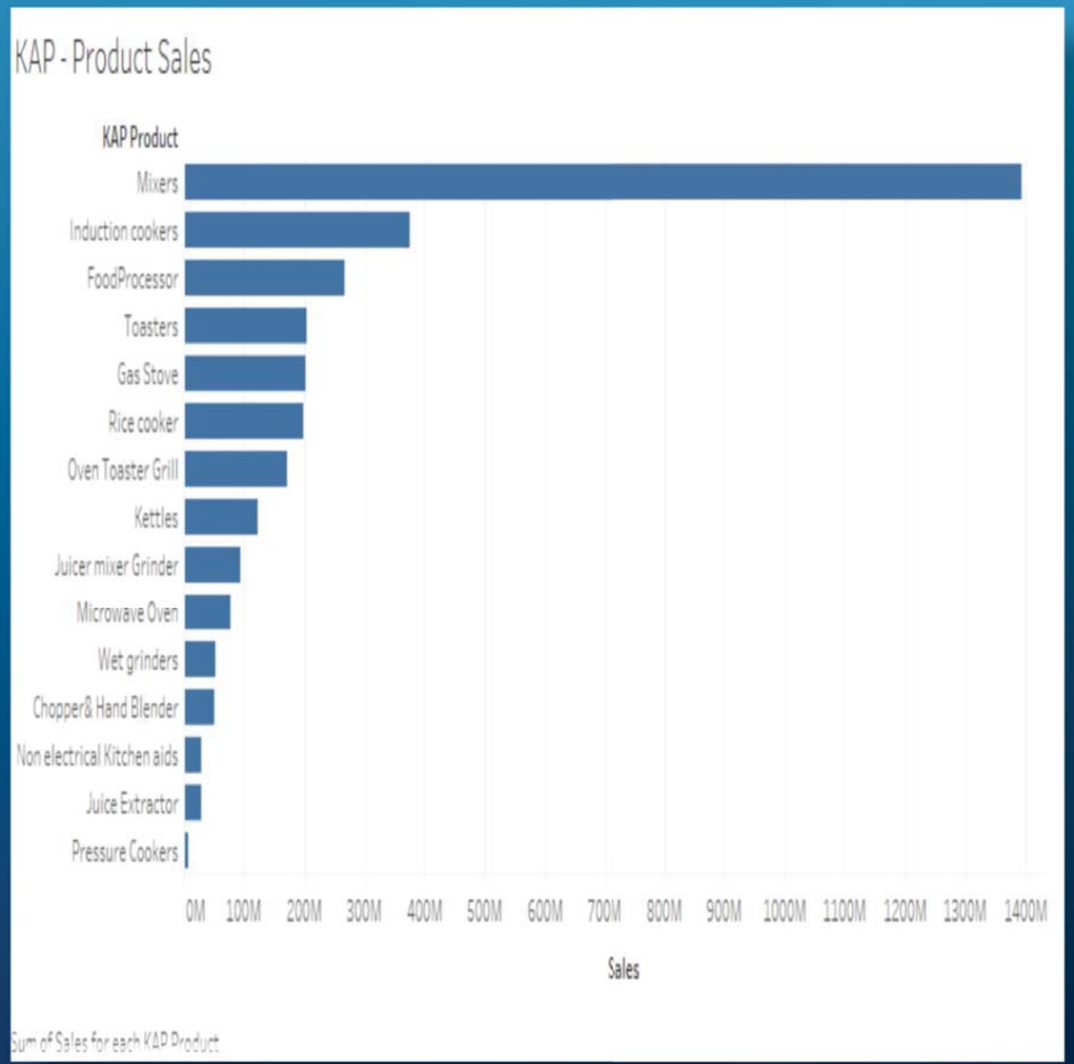


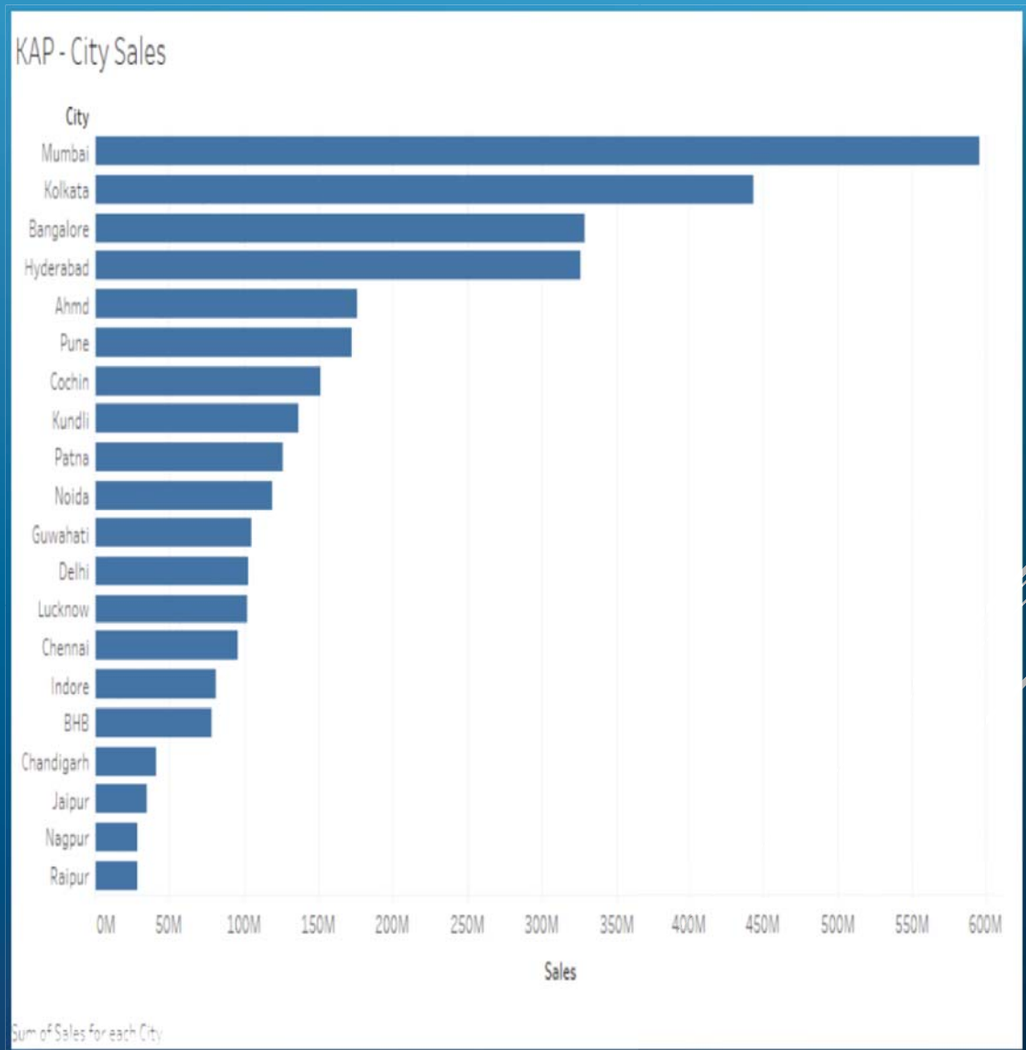
Insights & Visualizations- DAP



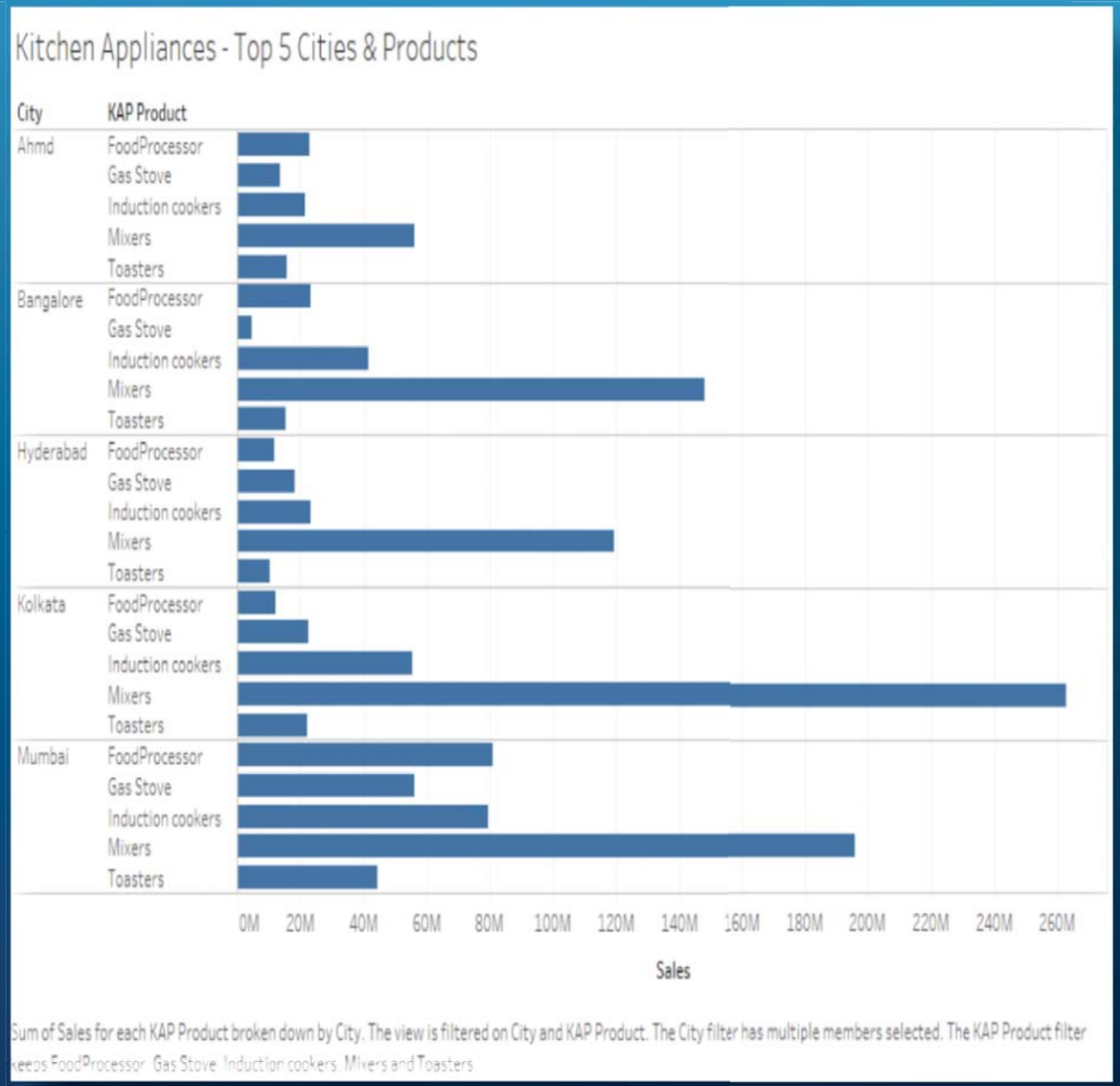


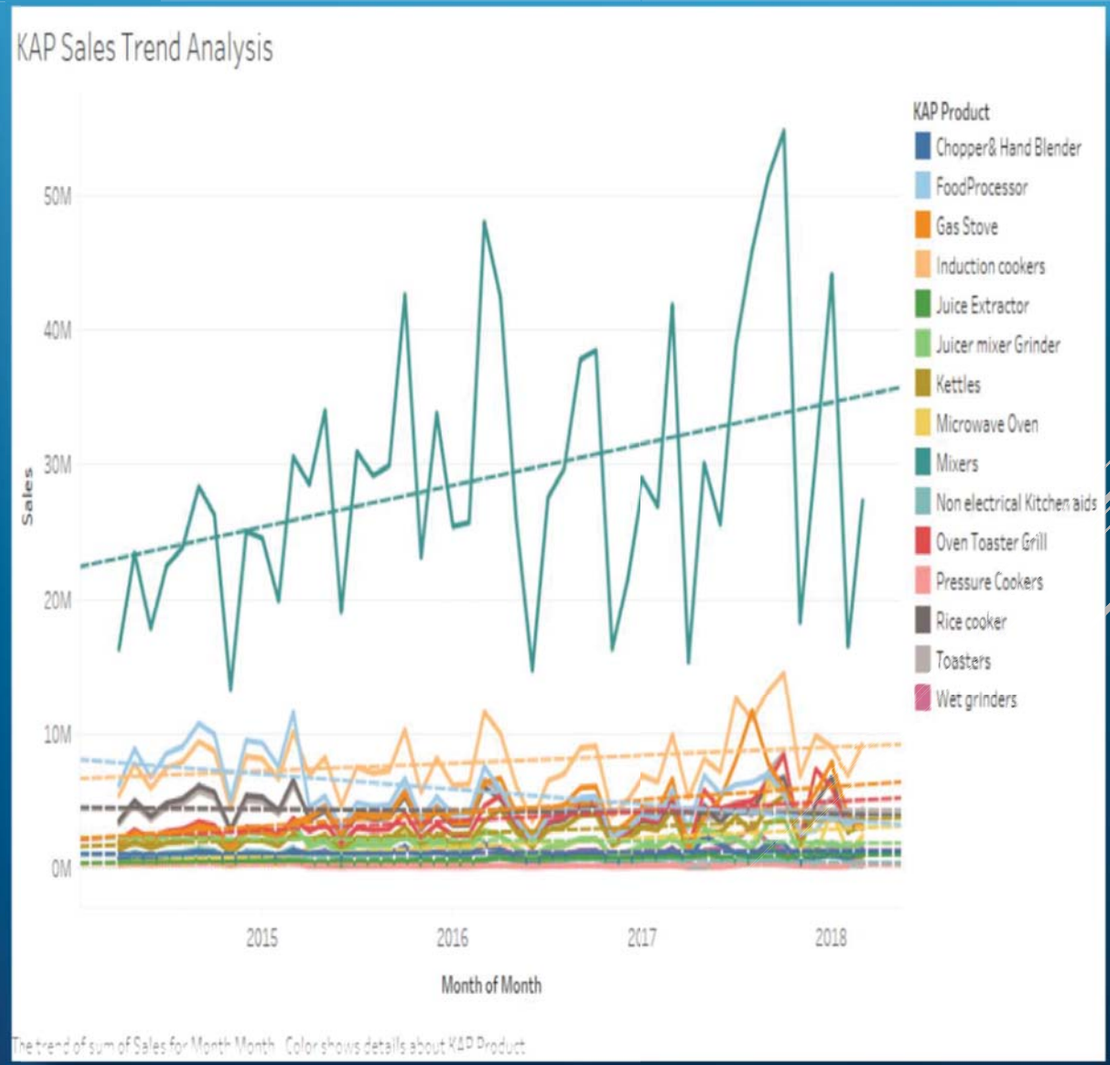
Insights & Visualizations - KAP



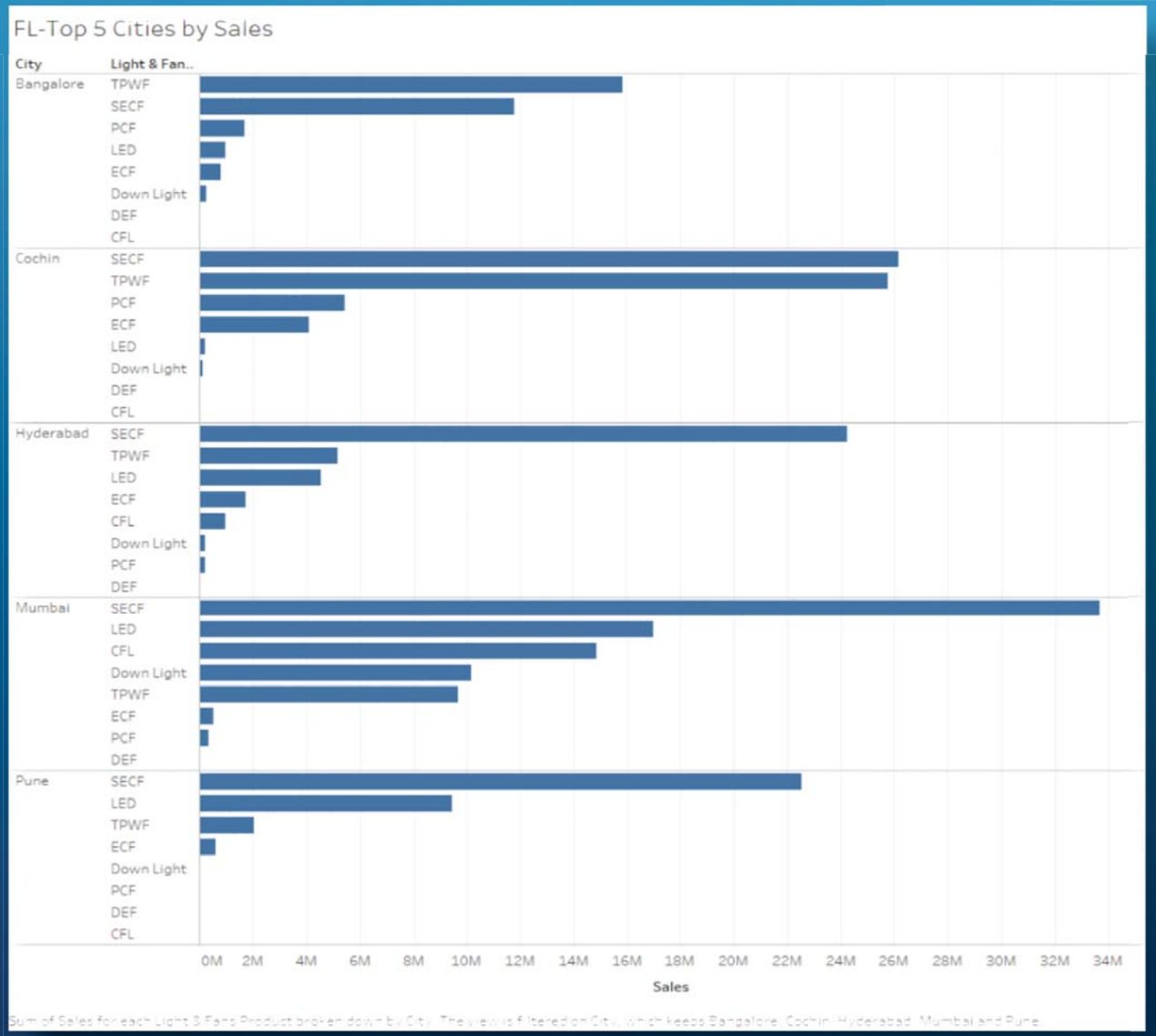


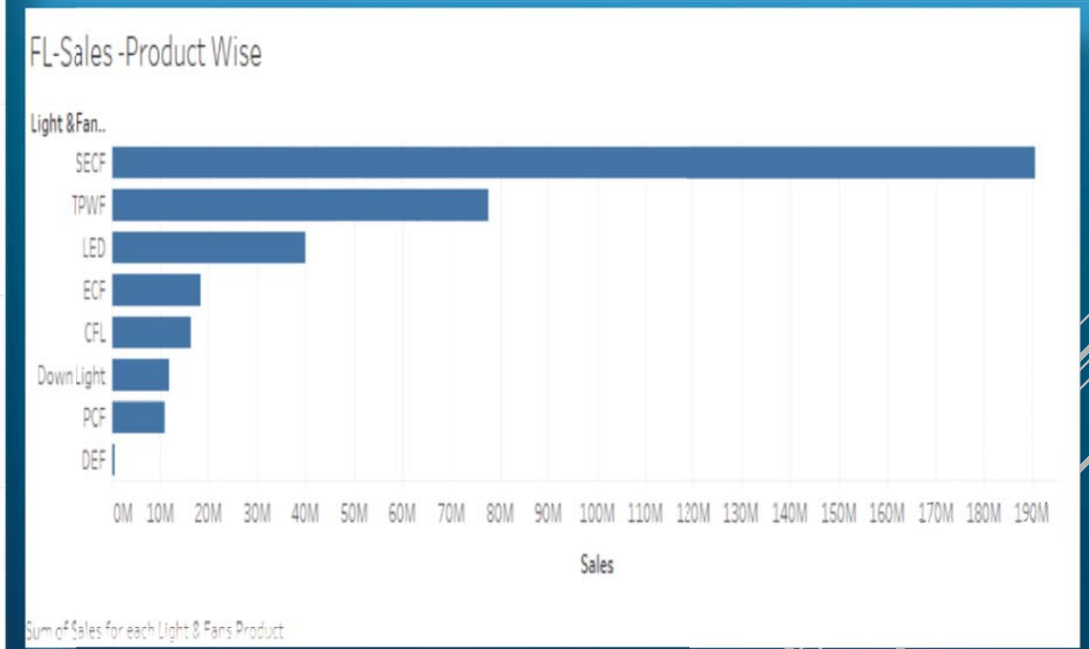
Insights & Visualizations- KAP



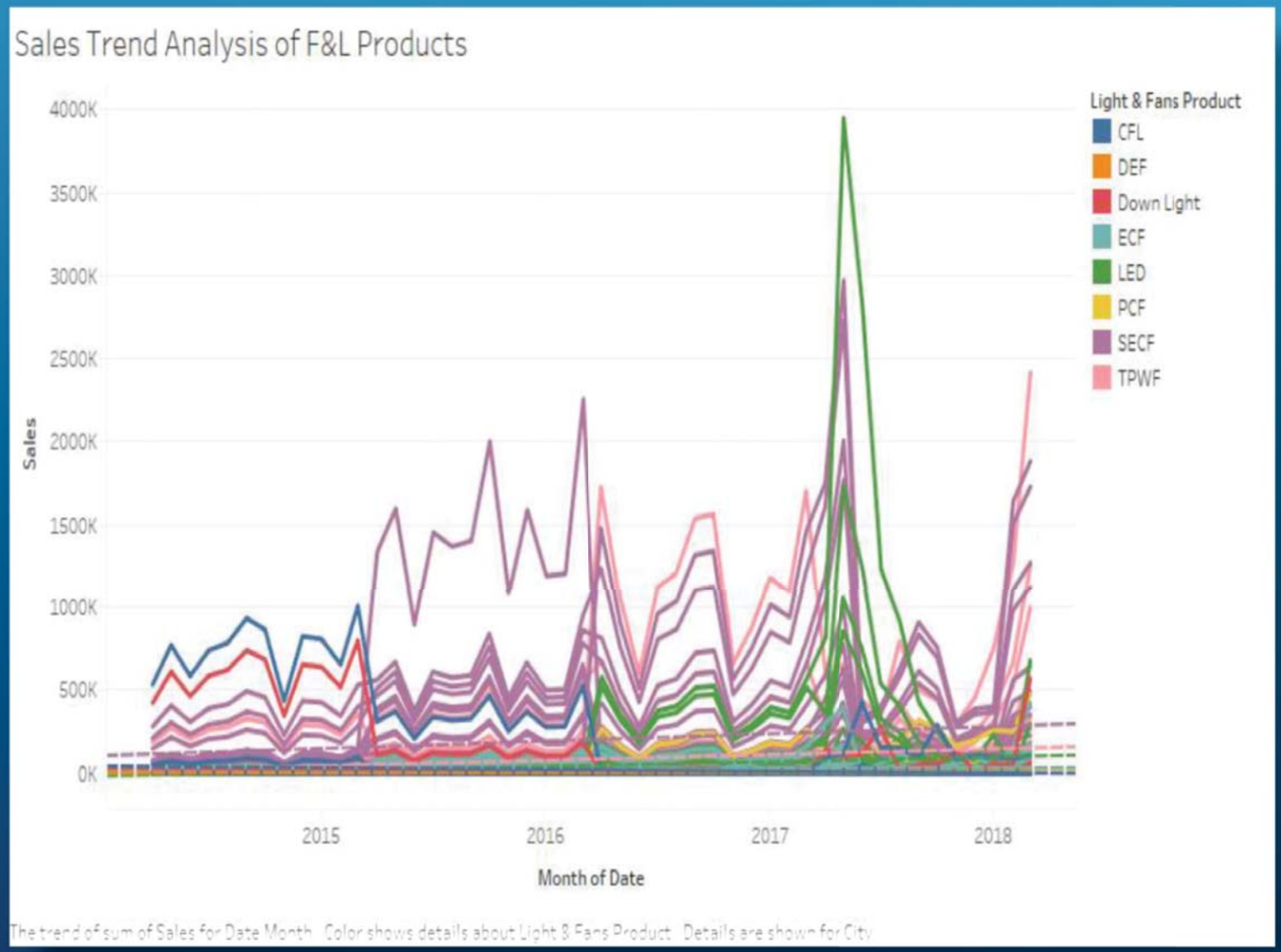


Insights & Visualizations– F&L





Insights & Visualizations– F&L



Insights & Visualizations – Negative & Zero Sales

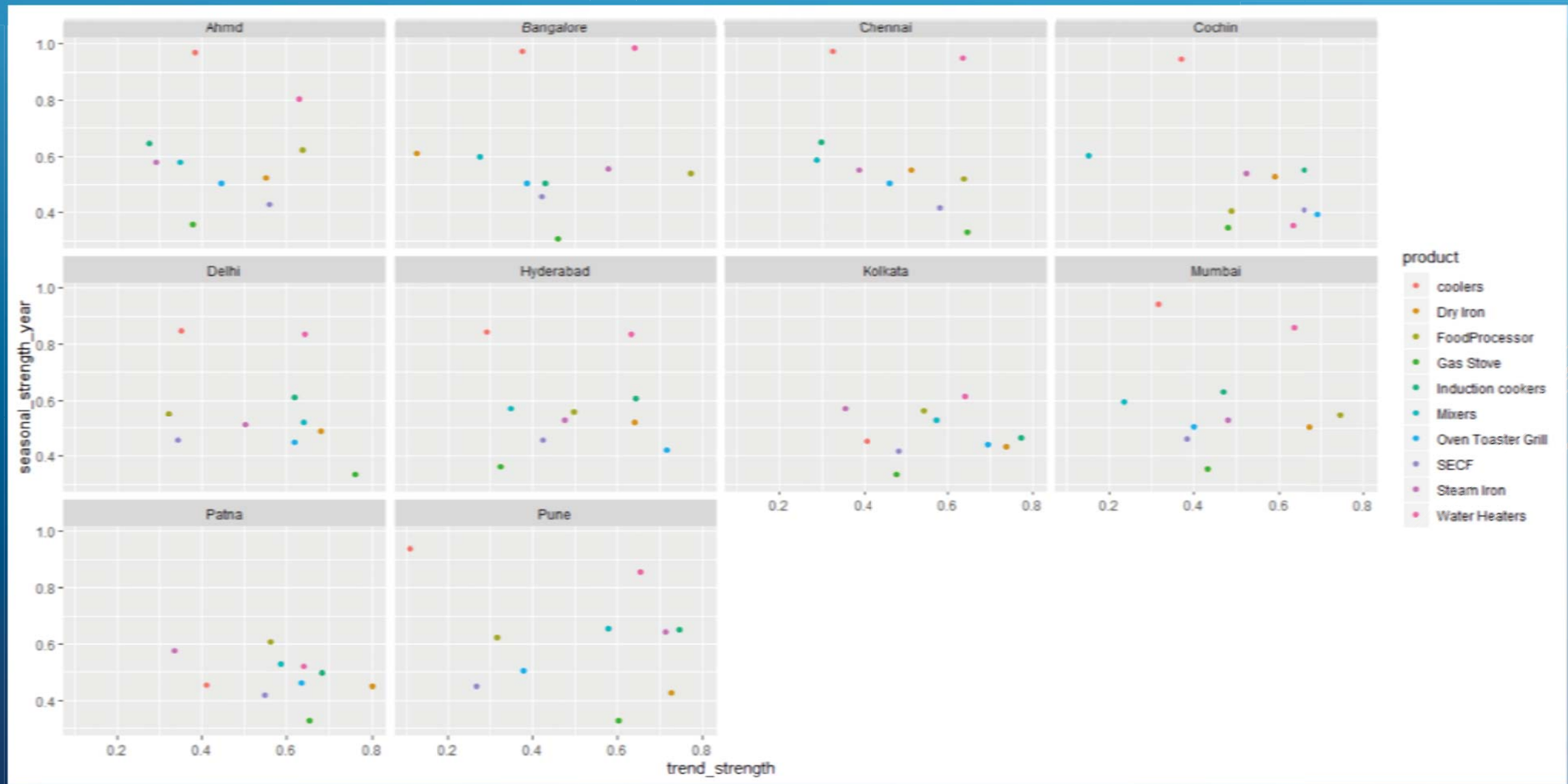
Negative Sales:

- 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 Downlights showed consistent negative sales across the years.
- Pressure cooker has either negative sales – Highest in Noida. Similarly Gas stoves in Jaipur

Zero Sales:

- Product is not listed - Wet grinders listed in West and South but not in North Zone.
- Product is discontinued – Downlights by LED's
- High Seasonality- Coolers after Summer

Insights & Visualizations– Trend & Seasonality



Insights & Visualizations– Trend & Seasonality

Product - Seasonality & Trend Strength

Product	Avg_Trend_Str	Avg_Season_Str
coolers	0.334	0.834
Dry Iron	0.604	0.503
FoodProcessor	0.553	0.554
Gas Stove	0.521	0.338
Induction cookers	0.56	0.581
Mixers	0.402	0.577
Oven Toaster Grill	0.543	0.468
SECF	0.467	0.437
Steam Iron	0.465	0.559
Water Heaters	0.638	0.761

City - Trend Strength

City	Avg_Trend_Str
Ahmd	0.45
Bangalore	0.447
Chennai	0.478
Cochin	0.525
Delhi	0.548
Hyderabad	0.499
Kolkata	0.57
Mumbai	0.477
Patna	0.585
Pune	0.509

Forecast Model Development

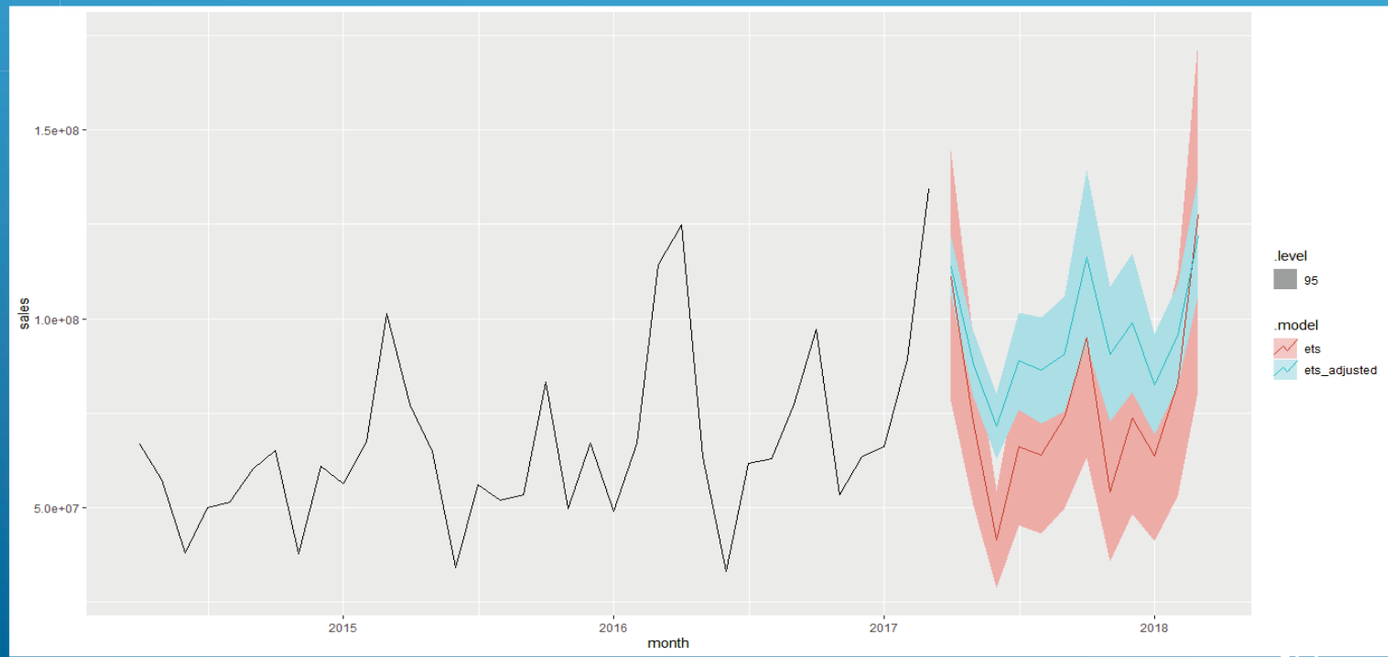
- Hierarchical or Grouped Time Series Approach
- ETS, ARIMA, SNAIVE Algorithms
- Ensemble Approach – Simple Average of above three
- Optimal Reconciliation through Trace Minimization Approach(minT)

Forecast Model – ETS

1. Weighted average of past observations; The more recent the observation is the more weight it gets.

2. A fable is a forecasting table. Sales column represents the point forecast and distribution represents the distribution of forecast.

3. 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.



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

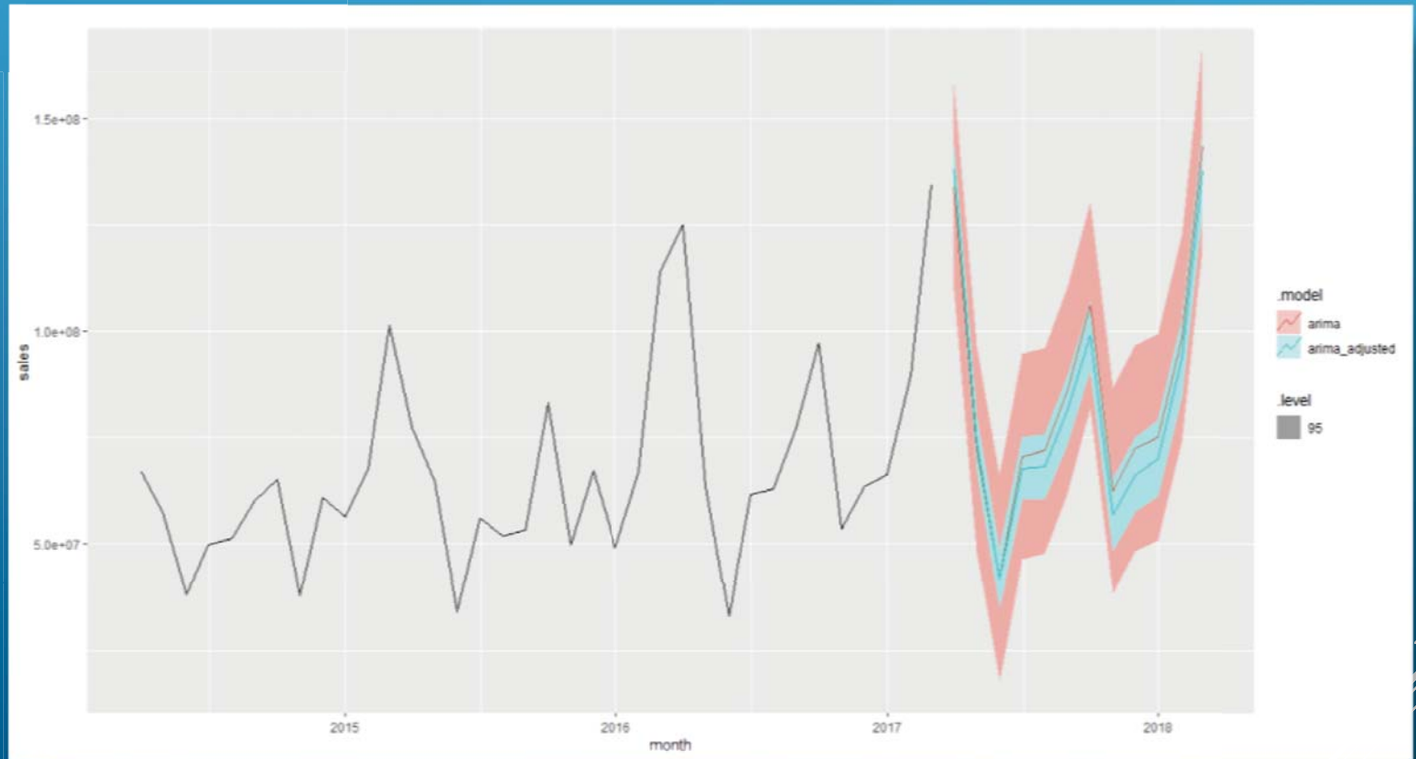
Table 4.3.1– Accuracy Evaluation for ETS

Forecast Model – ARIMA

1. Stationality & residual analysis is not done

2. No general trend as such is observed and seasonality is taken care of optimal reconciliation process

3. Presence of negative and zero values makes log or other data transformations not feasible



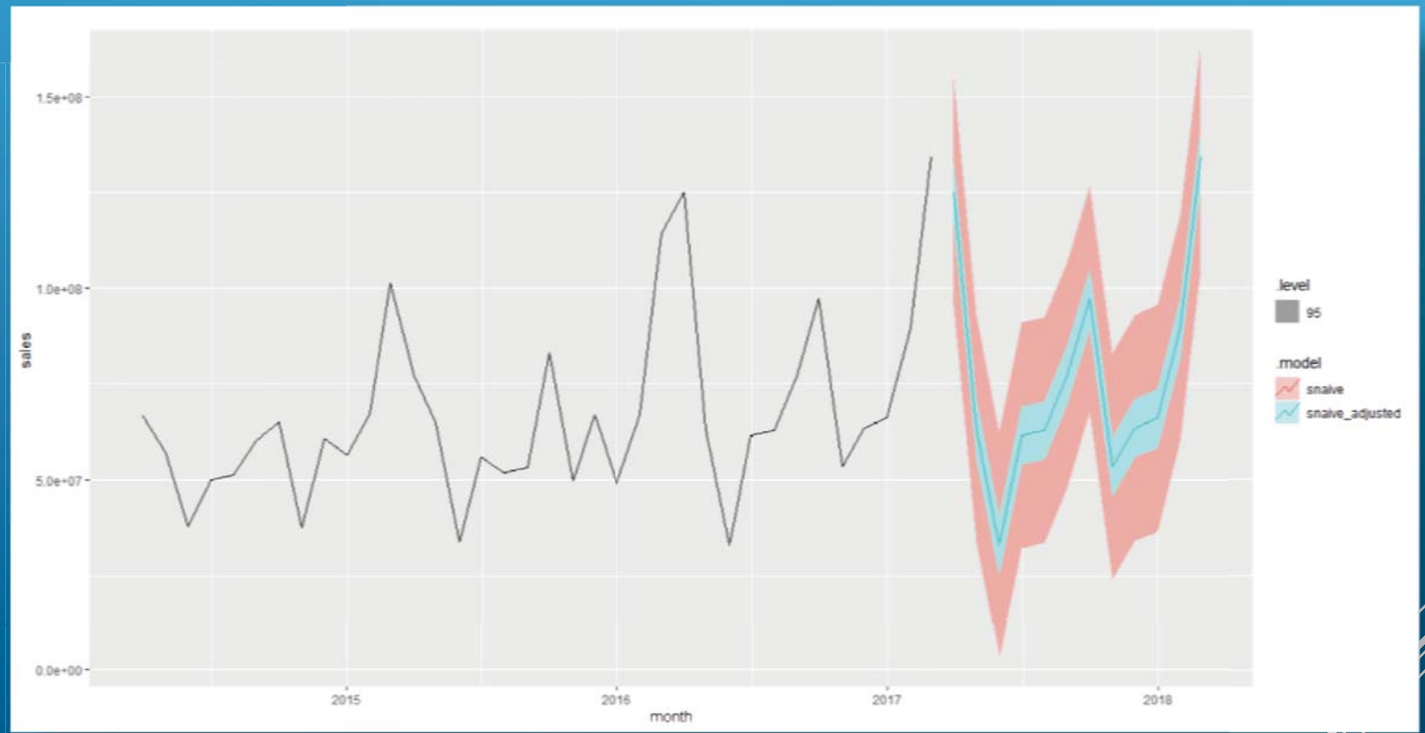
Parameter(Mean value)	ARIMA	ARIMA_adjusted
RMSE	1354859	1387081
MAPE	Inf	Inf
MASE	NaN	NaN
ME	430148	431921
MAE	1127788	1164003

Table 4.4.1– Accuracy Evaluation for ARIMA

Forecast Model – SNAIVE

1. Forecast to be equal to the last observed value from the same season of the year (The same month of the previous year).

2. 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.



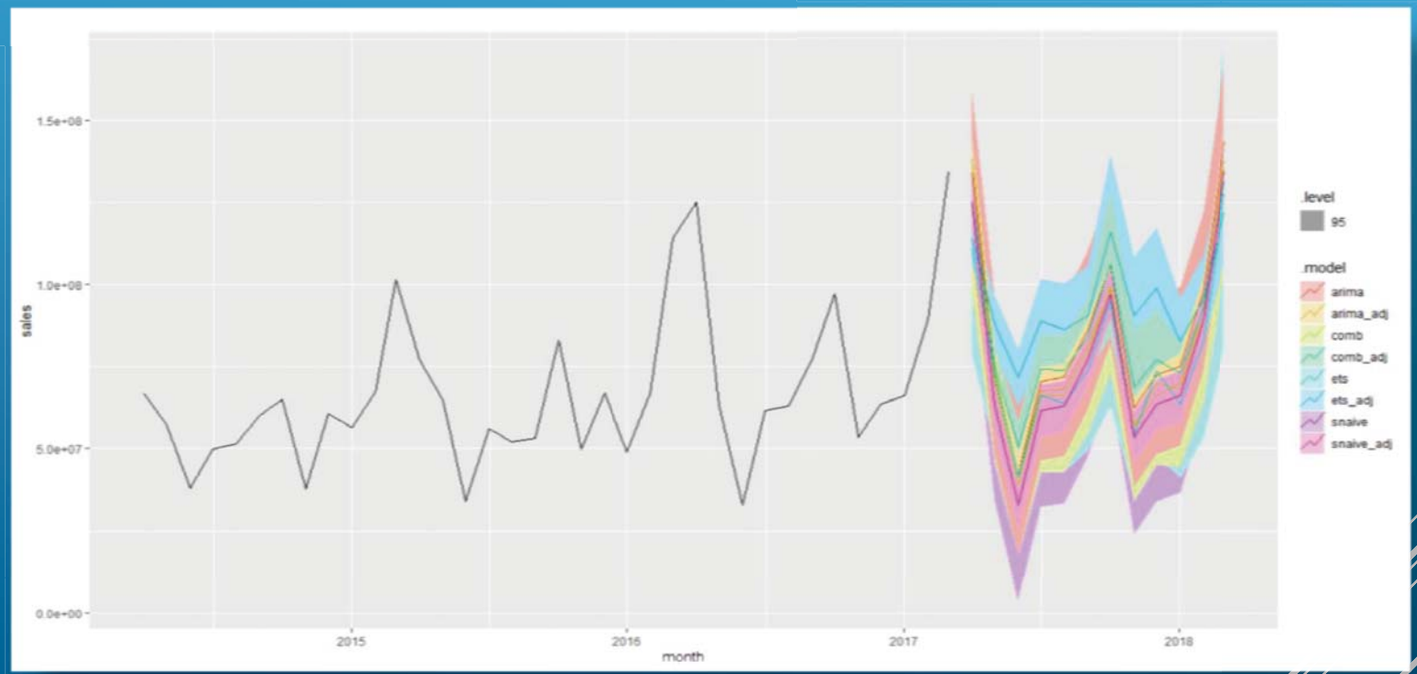
Parameter(Mean value)	SNAIVE	SNAIVE_adjusted
RMSE	1366817	1366817
MAPE	67.0	Inf
MASE	NaN	NaN
ME	617333	617333
MAE	1127574	1127574

Table 4.5.1 – Accuracy Evaluation for SNAIVE

Forecast Model – Ensemble Approach

Simple Average of 3 models

```
fc_comb <- train_agg %>%
  model(
    ets = ETS(sales),
    arima = ARIMA(sales),
    snaive = SNAIVE(sales)
  ) %>%
  mutate(
    comb = (ets+arima+snaive)/3
  ) %>%
  reconcile(
    ets_adj = min_trace(ets),
    arima_adj =
min_trace(arima),
    snaive_adj =
min_trace(snaive),
    comb_adj = min_trace(comb)
  ) %>%
  forecast(h = 12)
```



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

Model Evaluation & Selection..

MAPE

Effected by Zero Sales

MASE

min of 13 months of Test Data

MAE

Error minimized towards median
Biased forecasts

RMSE

Error minimized towards mean
Easy to interpret

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

Model Evaluation & Selection – Contd..

*4 city combinations - Kolkata – Mixers, Mumbai – Coolers, Bangalore – Dry Iron and Hyderabad – Water Heaters.

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

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	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	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

Conclusion & Recommendations

- 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

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

- 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.
- 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.
- 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.
- Light category is almost nil in east region cities of Bhubaneshwar, Guwahati & Patna. LED could be introduced in these cities.
- Degrowing sales trend products (Non-Electrical Kitchen products, CFL & Down light) to discontinued and dropped from product list.

Thanks for your Patience. We are Done. Now your Turn..