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An Intelligent Approach to Demand Forecasting

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Abstract Demand Forecasting, undeniably, is the single most important component of any organizations Supply Chain. It determines the estimated demand for the future and sets the level of preparedness that is required on the supply side to match the demand. It goes without saying that if an organization does not get its forecasting accurate to a reasonable level, the whole supply chain gets affected. Understandably, Over/Under-forecasting has deteriorating impact on any organizations Supply Chain and thereby on P and L. Having ascertained the importance of Demand Forecasting, it is only fair to discuss about the forecasting techniques which are used to predict the future values of demand. The input that goes in and the modelling engine which it goes through are equally important in generating the correct forecasts and determining the Forecast Accuracy. Here, we present a very unique model that not only pre-processes the input data, but also ensembles the output of two parallel advanced forecasting engines which uses state-of-the-art Machine Learning algorithms and Time-Series algorithms to generate future forecasts. Our technique uses data-driven statistical techniques to clean the data of any potential errors or outliers and impute missing values if any. Once the forecast is generated, it is post processed with Seasonality and Trend corrections, if required. Since the final forecast is the result of statistically pre-validated ensemble of multiple models, the forecasts are stable and accuracy variation is very minimal across periods and forecast horizons. Hence it is better at estimating the future demand than the conventional techniques.

Keywords Supply chain · Demand forecasting · Time series · Machine learning Ensemble · Optimization · Cognitive analysis · Outliers

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1 Introduction

Demand Forecasting is the key activity which more or less controls all other activities of Supply Chain Management. It is the key driving factor in planning and decision making in Supply Chain Management as well as Enterprise level. All major firms truly depend on the efficiency of demand forecasting to take major decisions such as capacity building, resource allocation, expansion and forward or backward integration, etc. Forecasting is a prediction or an estimation of an actual value in a future time period. It is usual that there might be forecast error as actual results differ from the projected value, long time horizon has chance of more error. This is important to measure the forecast error for adapting corrective action plan. The development of advanced technology enables the Supply Chain Management stakeholders to share real time data and information across the network which helps dual benefit to inventory and customer service. This underlying result of the process is accuracy of forecast which firmly ensures the successful and sustainable business operations. This is called Collaborative Planning, Forecast, and Replenishment. Sales and Operations Planning (S&OP) is an integration process used in business organization to ensure efficient coordination among cross functional units to align company strategy with Supply Chain planning. Globalization, new opportunities and Supply Chain Management differentiation compel the organization even struggle further as the integration process among suppliers, market, and stakeholders become complex and data intensive. Various forecasting models are used to predict what the demands on the system will be in the future so that appropriate designs and operating plans can be devised. Ironically, the basic premise behind generating forecasts is that they are mostly wrong. Forecasts must include analysis of their potential errors. The longer the forecast horizon, the less accurate the forecast will generally be. Benefits can often be obtained from transforming a forecasted quantity into a known quantity. The information systems play a key role mainly in operative planning and management. It is the requirement of almost all the companies to start run their business without having relevant information from ERP (Enterprise Resource Planning) systems. In consequence of more efficient information use through ERP, the partial planning methods as MRP II (Manufacturing Resource Planning), Sales and Operations Planning (S&OP) or APS (Advanced Planning and Scheduling) are developed. To maximize the effect of accessible methods for any internal company processes, the company must be built on an objective and evaluated demand forecasts. The choice of optimum forecasting procedures and following use of obtained forecasts may become a competitive advantage. Together with other modern methods it accelerates other company processes, reduces the costs and increases the value for the customer. The demand forecast determines the volume of products, place and time horizon in which they will be needed. In relation with the demand forecast it is necessary to deal not only with the quantitative aspect of the needs (the volume demanded by customers) but also their qualitative aspect (the type of customer's needs). The accurate demand forecast is thus important for the production and distribution management but also for, e.g., areas of marketing (distribution of sales forces, communication, promotion and planning of new products), finance (current need of money, budgets and calculations), investment designs (production facilities, workshops and warehouses), research and development (innovations) and human resources (structure and labour force volume planning, training). Demand planning represents a set of methodologies and information technologies for the use of demand forecasts in the process of planning. The aim is to accelerate the flow of raw materials, materials and services beginning with the suppliers through transforming to products in the company and to their distribution to their final consumers. The demand planning process is done to help the business understand its profit potential. Indirectly it sets the stage for capacity, financing, and stakeholder confidence. The implementation of the demand planning enables to determine the closest possible forecast to the planning horizon and decide the volume of production, stock and sources capacity distribution among particular products to maximize the profits of the whole company. The key requirement for efficient company management is sharing the mutual forecast. However, the research carried in production companies showed individual departments of the company in some cases draw up forecasts on their own and thus they base their planning on different figures. This provokes conflicts among the resulting activities of in-company plans. This kind of situation happens in case when the company prefers to approve the financial plan which does not correspond with the updated forecast results. The forecasting should always be the process which is essential and determining for other company processes, including financial planning. The financial plan often represents the main motivation source for the company managers as this reflects the requirements of the company top management and company's strategic goals.

A variety of modelling techniques are available for producing forecasts. Based on data patterns, forecasting horizon, data availability and business requirements the choice of technique differs [1]. Through appropriate combining of the forecasting techniques it is possible to estimate quantitative influences of the identified factors and set the demand forecast [2]. The most frequently used statistical forecasting method is the time-series technique. It uses historical data sequenced by time and projects future demand by the same time sequence [3]. POS data is rich in information for building forecast models. Building a good forecasting model with POS data is demonstrated in many case studies. It is important to realize that demand planning used in practice is not a mere creation of a perfect system to carry out the demand and sales forecast. The objective of forecasting is to predict demand while the aim of demand planners is to shape the demand and produce a resource requirement plan [4]. Without the right forecast planning system integration, it is not possible to use efficiently the information provided in the forecasts.

2 Existing Procedure

2.1 Demand Planning Process

The objective of Demand planning is to make reliable demand plans as base for the S&OP process. Game-playing, the intentional manipulation of the forecasting process to gain personal, group, or corporate advantage, is clearly not allowed. Examples of such games:

- Sandbagging: underestimating sales in order to set expectations lower than the demand actually anticipated
- Hedging: overestimating sales in order to secure additional product or production capacity
- Enforcing: maintaining a higher forecast than the anticipated sales, in order to keep forecasts in line with the organizations sales or financial goals
- Spinning: manipulating forecasts to obtain the most favourable reaction from individuals or departments in the organization

Demand plans should reflect what we really think what we will sell in the future.

2.2 Statistical Forecast

The ambition of the business in using the statistical forecast is to minimize the sales planner work load and, in the meantime, give a good forecast that will benefit the organization. Statistical forecasting might not be suitable for every product, but it is proven successful for products with a fairly stable sales history and a large number of lighting products fit this description. Statistical forecasting significantly reduces the number of products that will have to be touched by every individual sales planner every week/month.

- Data pre-processing: Outlier alerts are used as input for the stat forecast manager to do history cleaning. All individual alerts will be listed, which means that if a certain product has more than one outlier, all these events will be specified. A value is considered an outlier if:
  (1) Value is higher than (average + 3*standard_deviation) which is the upper limit or the
  (2) Value lower than (average - 3*standard_deviation)
- Algorithms: Based on the chosen statistical model, the existing business model will calculate a forecast. Available statistical forecast models are listed as:
  (1) *Moving Average* The moving average model is used to exclude irregularities in the history pattern. The model calculates the average of all historical values.

All values are weighted equally. It does not take leading zero values into account.

(2) *SES Model* The SES model will also calculate an average, but instead of weighting all historical values equally, the SES model will give more weight to the more recent history. Within the SES model the smoothing factor (alpha) will determine how quickly the forecast reacts to a change in the history pattern. The higher the alpha factor, the more weight will be assigned to the most recent history, the quicker the forecast reacts to the recent history.

(3) *Croston Model* The Croston model is used for products with intermittent demand. It consists of exponential smoothing calculation, together with an average interval between demands. These two inputs will then be used in a form of a constant model to predict future demand. In case no zero values exist in the history pattern, Croston model will have exactly the same result as the SES model (in case of an equal alpha factor).

(4) *Seasonal Linear Regression* Seasonal linear regression will automatically determine trend values and seasonal indices. The system will first try to find a seasonal pattern. In case the system cannot find a seasonal pattern, it will calculate a forecast using linear regression. In case it can find a seasonal pattern, it will first correct the historical values using calculated seasonal indices. A linear regression will calculate a forecast using these corrected historical values. Last step is to apply the seasonal indices to the calculated linear regression.

(5) *Double Exponential Smoothing* Double exponential smoothing uses the same technique as the single exponential smoothing but will also apply a trend. As in the single exponential smoothing, an alpha factor will determine the weight to determine how quickly the forecast reacts to a change in recent history. The beta will determine how quickly the forecast picks up a trend in history.

- Forecast Corrections:

(1) A manually maintained seasonality can be applied to SES and moving average models. The system will first de-seasonalize the history using seasonality factors as put in by the regional planning manager. It will then calculate a forecast using SES or moving average. The result of the forecast will be re-seasonalized again using the seasonality factors.

(2) A workday correction will be applied to all stat forecasts that do not use the manual seasonality or statistical forecasts that are using SLR.

(3) A manually maintained trend can be applied to SES and moving average models. After calculating a forecast using SES or moving average, it will apply the trend values to the result.

3 Demand Forecasting Procedure

The following set of procedures describes the demand forecasting process, quality control and exceptions management process for forecasts.

3.1 Extraction of Corrected Baseline History (CBH) with Links

(1) The Data in the real world has the life-cycle which varies a lot. The correct linking to the new product introduction, sister SKU and de-cleaning SKU is very important in the forecasting methodology.
(2) The Data which the model forecasts is CBH (Corrected Baseline History), which has the correct linking with the sister SKU or correction of the sales taking out the effect of the external driving factors like promotions, stockouts, etc. If the corrections of the data is not done or maintained, then the model will correct the data as required using the outliers correction and missing value imputation.

3.2 Validation

The first step of the validation should be done by checking for the availability of the lowest Characteristics Vector Code (CVC) elements. For each Market, comparison of the sum for last three months with that of the Month-wise Sum for the data downloaded in the previous month should be done. This is done to have a validation on the actual which is downloaded is matching the figures that is going into the model for forecast.

3.3 Data Shaping

The Data should be aggregated or dis-aggregated to the level in which the forecast should be generated. This helps in making the generalization capability of the forecasting to a better level. The cost function for the time-series forecasting in this domain differs for different organization.

Some common cost functions used are

1. $\text{Accuracy} = 1 - \frac{\sum_{i=1}^{N} \left|\sum_{j=1}^{3} (y_p - y_a)\right|}{\sum_{j=1}^{3} y_p}$
2. $\text{Accuracy} = 1 - \frac{\sum_{i=1}^{N} \left|\sum (y_p - y_a)\right|}{\sum_{j=1}^{3} y_a}$

3. Accuracy $= 1 - \frac{\sum_{i=1}^{N} \left|\sum (y_p - y_a)\right|}{\sum_{j=1}^{3} y_a}$,

where N is the total SKU's present for a market and y_p and y_a are the predicted forecast for a month and actual for that month respectively. j varies for the forecasted done for the consecutive months. The first equation is to evaluate the accuracy in the three months of forecast against the actuals and the last two for evaluating the accuracy for one month.

3.4 Data Quality Assurance

(1) Once the CBH data with Links is prepared as per markets requirement, the CBH data is now required to be analysed and the quality of the data is to be ensured before it is used for forecasting demand. The demand forecasting for each market is done from different stand points, as per market needs. Some of the examples are sales region wise, SKU wise, Channel level and material level.
(2) It is mandate to validate the data sets used for the purpose of generating Baseline Statistics Forecast. If some garbage data is put into the model the result will be garbage in itself.
(3) The Data complete description is made which makes it important and easy to validate the data which input and output from the model.
(4) The Data needs to be validated by the market demand planners to find if the forecast follows the trend, pattern and level along with the actual. In case of any discrepancy, the forecast will be modified with the intelligence of the market.

3.5 Models Used for Generating the Forecast

Once the Data Quality is assured then the data is uploaded in the forecasting model prepared on R and Python.

(1) *Outliers Detection, Data Treatment and Data Pre-processing* The most important part for any data analysis is the data processing. If there are ambiguities in the data, the forecast will also be ambiguous and un-useful. Outlier detection and removal or correction of the data are a part of the model [5–7]. Each Market requires the forecast at different level.
(2) *Model Selection* The forecast done for each SKU, is done using the time-series and machine learning algorithms. Then each of the SKU is matched with the results given by time-series, machine learning and a model with the ensemble of the outputs of time-series and machine learning.

    (1) Time-Series Algorithms: The actual data is fed into the model consisting of the time-series algorithms. For different SKU's different algorithms are

selected based on the *mse* in the validation or testing data. Before passing the data into the model, it is pre-processed [8].

- Data Pre-processing: The actual sales do have great impact with the *promotions*, *stockouts* and *dumping*, etc. These behave as the outlier in the system and need to be removed or treated. The values which are more than 40% or less than 10% for a particular month in a range of 12-month are replaced with the mean of the actual sales data or if the sales for a particular month is above the *particular limit Inter Quartile Range* is treated and imputed with the accepted sales for that month. *Particular limit* varies SKU to SKU. Also, the sparse SKU, i.e., the actual data containing more number of zeros are either passed into *croston model* [9, 10] else the zero sales data in a month is replaced with mean of the data.
- Algorithms: The algorithms which are used in the time-series algorithms are Weighted Moving Average, Simple moving average, Autoregressive integrated moving average (ARIMA) and Holts Winter [11–15]. For Weighted Moving Average 0.5, 0.3 and 0.2 weights are given starting from the most recent observation to the 3rd last observation whereas equal weights are assign to the last n (no of dependent variables) observations to find out the new forecast. On the basis of residuals, we are finding out the value of n. To find out the order of the Arima model we have used Arima optimization function ML and CSS and then using residuals RMSE and MSE. To find out the value of α, β and γ of Holt's Winter, the optimization functions L-BFGS-B and Nelder-Mead and for finding the residuals RMSE and MSE is used. In case the model gives 0 in the middle of the forecast [16] value is replaced with the mean of the whole vector. In the validation set, the algorithm which gives the minimum *mse* is selected for the future forecast [17].

(2) Regression-Based Algorithms: There is a bit of difference in the data that is fed into the models containing machine learning regression algorithms. This regression-based model contains the following steps to be done to take care of the forecasting of sales data.

- Data Processing: The sales of a particular period (day, week, month or year) is matched with the actual data and the values or the sales which contribute to more than 40% or less than 10% of the total sales for 7 days (if the data is weekly), 53 weeks (data is weekly) or 12 months (data is monthly) is treated as the outlier and is either brought down/up to the mean/median based on maximizing the cost function of the organization. This basically means that each SKU will have a different set of the outlier treatment. The missing value is nothing but to find out whether the "sales zero" in a particular data is actually the case or not. If the zero sales are not possible for the SKU, then the missing value is imputed with mean of the actual data. For getting the seasonal pattern of the data, the data is transformed into the lags of the months for finding a relationship between the current actual sales. The problem of forecasting

is a regression problem. The regressors are the lags of the actual data. Here to find a seasonality pattern in the data, each yearly data is taken as a lag. The two-important constraint are taken into the consideration:
  - *Time Constraint* It takes a lot of time to find the correct hyper-parameter settings.
  - *Seasonality Pattern* It was found that if the lag of 12 for monthly data and 53 for weekly data was taken into the consideration, the accuracy [cost function] increased.
- Algorithms: There is a lot of constraints for the forecasting using machine learning.
  - The hyper-parameters for each SKU for different algorithms will be different all the time. This takes a lot of time to optimized to the required parameters settings.
  - Seasonality capturing is very less when used machine learning algorithms.

  The algorithms that are used are Support Vector Regression [18–20], Decision Trees Regression [21], Linear Regression, Ridge Regression [22] and Random Forest Regression [23]. Random Forest Regression is used for the selection of important features out of the lag training set [24]. Other feature selection techniques can be used which is the future implementation and research for our work. As the dataset is a time-series dataset, the sequence of the data or the training examples is important. The training and testing sets are divided into the 70.30% using the holdout method. For the optimizing the hyper-parameters, Grid Search and Random search methods are used. Bayesian Search and other evolutionary optimization search methods are the future work. The best algorithm which results in the minimum mse in the validation set is selected for the future prediction of the sku. Out of all the algorithms the one which gives the minimum mse is matched again with the ensemble of the algorithms. Ensemble is done with the averaging of the error in the validation set.

$$\begin{aligned}\text{model} &= \left[\text{algorithm}_1, \text{algorithm}_2, \ldots, \text{algorithm}_n\right]\\ \text{error}_i &= \left|y_p - y_a\right|,\end{aligned}$$

  where y_p is the predicted value and y_a is actual. Also, the weights assigned to each model/algorithm [algoritm$_i$] is given by

$$\text{weight}_i = \frac{\frac{1}{\text{error}_i}}{\sum_{i=1}^{n} \frac{1}{\text{error}_i}},$$

  where $i \in (1, n)$, n varies in the model set.
- Future Forecast Generation: Once the forecast is done, then the forecast results are validated and different methodology are taken into the account

to see which all process can be taken into the account for improving the accuracy. The comparison is required to be done at the level at which the forecast is generated. Identify the Models [algorithm with hyper-parameter settings] producing SKU wise best results and separate the SKUs as per the models giving best results consistently in the validation phase. Once the Model for specific variable is identified, initiate the run to forecast for future 18 months. Seasonality factor is applied to the model if required. This depends on the pattern in which the result is produced.

Algorithm for the Proposed Model

- *Input the Data*
- *for sku 1:N*, where $N =$ total number of SKU for a market
  - *Data Pre-process* Outlier treatment, Missing value treatment
  - *Dataset Creation* Convert the Actual data to 12-lag dataset
  - *Train, Test Subset* Holdout method is used and time sequence for the data is maintained [As the data is time-series]
  - *Feature Selection* Transform the dataset to the most correlated dataset
  - *Training the Algorithms* Pass the Data through different algorithms
  - *Algorithm Selection* Based on the MSE in the validation/test period the model which results in the minimum error is selected [25, 26]
  - *Future Prediction* Generate the future forecast

(3) Ensemble of the Algorithms: The results/forecast generated by the time-series and regression-based algorithms can either be over-forecasting or under-forecasting. To achieve higher accuracy 100%, the forecast should be very much near to the actual sales or the error in the forecasting should minimize. Here, the term that defines the error is *deviation*.

$$\text{deviation} = \sum_{j=1}^{k} \begin{pmatrix} y_{\text{actual}_j} \\ -y_{\text{predicted}_j} \end{pmatrix},$$

where k is the time period for the calculation of the deviation. Thus, if the deviation is minimum, the generalization capability of the model increases. Here, we used averaging of the time-series and regression-based model results to give an ensemble forecast which brings the deviation near to zero or minimum of the deviation of time-series output and regression-based model output. Hence, this more enhances the generalization capability of the model. The weights that is calculated for the two kinds of models is by calculating the deviation from the validation period of the data.

$$\text{model} = [\text{model}_{\text{time-series}}, \mathit{model}_{\text{machine-learning}}]$$

$$\text{weight}_i = \frac{\frac{1}{\text{deviation}_i}}{\sum_{i=1}^{k} \frac{1}{\text{deviation}_i}}$$

here, k varies in the model dataset. The model that is selected in case of the ensemble is through the *greedy selection*. Here the algorithms that gives better results consistently is selected to use in the ensemble of the results [27, 28].

(4) Market Intelligence or Cognitive Approach: After the results are generated, the forecasts are plotted against the history actual and level, trend and seasonality pattern of the SKU is observed. If the forecast for the SKU doesn't follow any pattern with the history sales, it is changed or tweaked a bit. The following are some of the market intelligent inputs that are implemented in the model:

- *Zero Forecast* If the actual sales for a SKU is zero for the consecutive 2 months, its converted into zero forecast for the forecasting periods. This case will not be valid for the SKU having sparse data.
- *Trend Imbalance* If the trend of the forecast doesn't follow the trend of the history of the sales, the trend is corrected. If the mean of the initial forecast value is 4 times or 0.25 time of the mean of the last 6 months then the forecast value is replaced with the last 3 months weighted moving average.
- *Level Correction* There will be some SKU's which are going to have a change in the level due to some promotional impacts and other external conditions. This information which is externally present is input to the model and the level is shifted for the future forecast for that many number of periods which the market Demand Planner have informed.
- *Seasonality Correction* Some of the months will have lower peaks or depths in the forecast data than expected. This can be externally corrected before the forecast is submitted.
- *PIPO* Phase-In and Phase-Out SKU's are clustered and the forecast is changed in that manner. The Phase-In products are basically the NPI or New Products Introduced and will have a higher or lower sale which are difficult to predict. In case of those SKU's having only one data point, are either used Naive Forecast or done the same result as the forecasting output. Mostly Market Demand Planner's intelligence helps a lot to take care of this.

4 Results

The model comprising of the methods discussed above is used to generate the forecast for the different markets of Philips and the results are compared with the tool which is mostly used in the forecasting for different organization, Incumbent Business Model(I-B-M). For generating the forecasts two different platforms are used R (Version 1.0.136) and Python (Version 2.7). The results are generated for different markets and for different consecutive months to check the validity and the stability of the models. Two different terminology which are used are "$t-1$" and "$t-5$"

forecast accuracy. "$t-1$" is the accuracy generated after two months of the current month the forecast is generated and "$t-5$" is after 5 months of the current month.

Dataset Description: This data set contains the information of 7 markets. Due to confidentiality, actual names of the markets are masked with $market-$ "no". In this section, first the comparison of the I-B-M is done with the developed model with different statistical measures followed by the result improvement comparison of *ensemble method* over the *Regression based model* and *time-series methods*.

4.1 Forecast Comparison for the Month April-2017 Using the Actual Data till February-2017

Market-name	Total SKU's	Model FACC (%)	I-B-M (%)
Market-1	3256	53	43
Market-2	982	36	28
Market-3	1806	29	31
Market-4	923	64	62
Market-5	1078	30	51.1
Market-6	2620	48	48
Market-7	2301	49	50

Total number of SKU's that has been forecasted is 12966. Using the model developed by us, the overall average accuracy that has been achieved is 44.14% and the overall accuracy that has been achieved by Incumbent Business Model is 44.72%. In checking the market-wise accuracy comparison, our model is equivalent to Incumbent Business Model. This comparison is the overall comparison of the total SKU's for each market in the month of April-2017.

4.2 Forecast Comparison for the Month May-2017 Using the Actual Data till March-2017

Total number of SKU's that has been forecasted is 16422. Using the model developed by us, the overall average accuracy that has been achieved is 52% and the overall accuracy that has been achieved by Incumbent Business Model is 49%. In checking the market-wise accuracy comparison, our model is better than Incumbent Business Model in five markets out of seven markets. This comparison is the overall comparison of the total SKU's for each market in the month of May-2017.

Market-name	Total SKU's	Model FACC (%)	I-B-M (%)
Market-1	2999	54	45
Market-2	1164	49	49
Market-3	2007	49	39
Market-4	1446	56	58
Market-5	3265	58	56
Market-6	3026	47	43
Market-7	2515	51	53

4.3 Forecast Comparison for the Month June-2017 Using the Actual Data till April-2017

Market-name	Total SKU's	Model FACC (%)	I-B-M (%)
Market-1	3480	55	38
Market-2	1391	39	33
Market-3	2685	48	41
Market-4	480	58	68
Market-5	3262	58	59
Market-6	3028	49	50
Market-7	2549	54	56

Total number of SKU's that has been forecasted is 16875. Using the model developed by us, the overall average accuracy that has been achieved is 51.57% and the overall accuracy that has been achieved by Incumbent Business Model is 49.28%. This comparison is the overall comparison of the total SKU's for each market in the month of June-2017. If we check the above two table, we can find that our model is consistently beating Incumbent Business Model by 3%.

If we take the above three results, our model is stable and giving good results. In case of the April-2017, the results of our model is comparable to that of the Incumbent Business Model.

Below are the results for the comparison of the individual models for different markets.

4.4 Forecast Comparison for Different Algorithms in the Model for Different Markets

Market-1:

Month	Time-series (%)	Regression models (%)	Ensemble (%)
April'17	66	63	66
May'17	68	64	69
June'17	65	63	66

Market-5:

Month	Time-series (%)	Regression models (%)	Ensemble (%)
April'17	60	58	62
May'17	62	59	64
June'17	60	59	62

Market-3:

Month	Time-series (%)	Regression models (%)	Ensemble (%)
April'17	53	48	53
May'17	45	46	49
June'17	49	47	51

Market-7:

Month	Time-series (%)	Regression models (%)	Ensemble (%)
April'17	49	53	54
May'17	41	38	42
June'17	55	50	55

The above table tells about the comparison of the different algorithms that we are using in out model. We can see that the ensemble of the results produces better results than the individual algorithms in consecutive three months of April'17, May'17 and June'17. The weights for the ensemble is found out from the previous months and the average weight is assigned for the final month.

5 Conclusion

The model which we have presented has all the state-of-art statistical methods used in the demand forecasting fields. In the results above, we see that ensemble of the results of time-series model and regression-based model gives a better result due to the fact of nullifying the over-forecasting and under-forecasting and bringing the forecast values near to the actual. These results are far better than considering individual algorithms used in the two models.

Accurate forecast is very important for the demand planning team. The data used in this research and building the model is using the sales-in data for different markets. The important factor to be considered is the stability of the model and removing the *game-playing*. Two open-source platforms are used to build the model. Time-series model is developed in R-Studio and Regression-Based model using the data mining algorithms developed in Python. After the results are generated, Ensemble of results is validated and generated using the Microsoft Excel. In the future work, different techniques will be considered and researched. Time-Series and Machine Learning to be built in one platform and check how the minimization of mse produces the forecast.

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