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# DEVELOPMENT OF DEMAND FORECASTING MODEL FOR RETAIL OUTLET

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## ABSTRACT:
A main objective of the paper is improving the demand forecasting in shops. This paper presents a use case of linear regression for sales forecasting in retail demand and sales prediction. Forecasting helps the retailer to meet the demands of the customer by understanding consumer purchase patterns better. It is also known to assist in more efficient use of shelf and display space within the retail establishment, in addition to optimal use of inventory space. The forecast of potential sales is based on a mixture of temporal and economical features including prior sales data, store promotions, retail competitors, school and state holidays, location and accessibility of the store as well as the time of year. Using these data to improve the sales among the customer. It helps you make smart decisions about your product offering, inventory, staffing, and marketing.

Keywords: Forecasting, Retail, Linear Regression, Prediction, ANOVA

## INTRODUCTION
Demand forecasting is, in essence, developing the best possible understanding of future demand. In practice, this means analyzing the impact of a range of variables that affect demand—from historical demand patterns to internal business decisions and even external factors—to increase the accuracy of these predictions. Accurate demand forecasts can be leveraged throughout retail operations to improve decision-making and outcomes in areas such as store and distribution center replenishment, capacity planning, and resource planning.
Demand forecasts can be developed on different levels of granularity—monthly, weekly, daily, or even hourly—to support different planning processes and business decisions, but highly granular forecasts are always extremely valuable. The benefits of a granular forecast are obvious when thinking of fresh food products whose short shelf-lives sometimes call for intra-day forecasts at the product-location level to prevent spoilage.
Why, then, would slow-moving items that sell only a couple units per location per day, if even that, require the same level of forecast granularity? Even if the day-product-location level forecast for a slow-moving item is itself somewhat inaccurate, forecasting at this level of granularity ultimately makes it easier to aggregate demand—whether for different periods of time, across products (for example, total demand per product per distribution center), or by total order lines per DC per day, etc. To effectively execute store replenishment, capacity planning, and other business decisions, retailers need multiple forecasts with different levels of granularity that look at different time spans. This is why flexible aggregation across products or over different planning horizons is critical to a retailer’s ability to leverage the same demand forecast in all their retail planning.

## OBJECTIVE OF THE STUDY
- To predict the demand for upcoming months using predictive analysis
- Objectives of Demand Forecasting in retail store for inventory or stock management.

## NEED AND SCOPE
- Demand forecasting helps reduce risks and make efficient financial decisions that impact profit margins, cash flow, allocation of resources, opportunities for expansion, inventory accounting, operating costs, staffing, and overall spend. All strategic and operational plans are formulated

around forecasting demand.

- Sales forecasting allows companies to efficiently allocate resources for future growth and manage its cash flow. Sales forecasting also helps businesses to estimate their costs and revenue accurately based on which they are able to predict their short-term and long-term performance.

**LITERATURE REVIEW**

**2.1 BALANCING SUPPLY AND DEMAND**

Businesses need to balance their supply and demand for a more competitive value. A company will need to increase the supply if their demand is high or lower demand if their supply is high. Low demand coupled with low supply would also suggest that a business looks into optimization and efficiency. One tool that companies could use to maintain the equilibrium is the concept of marginal-cost pricing. Marginal cost is the extra cost to produce one other unit of output. If a business uses marginal costing, it will price its product higher when supply is high and lower when supply is low. Companies also need to be aware that pricing too high may sacrifice sales volume while pricing too low can result in a lost profit margin. Businesses should consider what will happen if their strategies are ineffective in maintaining balance through their economic decisions. They should be aware of which methods are optimal for maximizing profit and minimizing losses; however, they should also understand why these choices were optimal for them. The economic decisions should be carefully thought out and well-informed, not based on spur-of-moment situations. A business should keep its strategy as flexible as possible to allow for further adjustments because as the levels of supply and demand change, so too must a company's pricing strategies. In economics, an equilibrium price is when the quantity supplied equals the quantity demanded by a product or service in a competitive market. Equilibrium generally implies an ideal state that doesn't often occur "in real life." The word "equilibrium" is used in several related senses. It can be defined that there is some price at which the quantity demanded and the amount supplied is equal at any given moment. However, this is much more difficult to achieve or detect in the competitive market.

Despite the critical nature or need to balance the demand and supply of the goods or products from the company to the market, many companies still face significant challenges in managing this aspect. A company can maintain a healthy balance of demand and supply by ensuring that its output or supply matches the amount demanded by consumers or the demand, producing enough products to meet consumer needs, but not too much. It ensures that producers' costs are kept at a minimum and minimizes excess inventory. However, it can be challenging to maintain this balance when external factors like changes in demand or changes in price affect the situation [1]. For example, suppose there's a sudden increase in demand due to an anticipated drought during the summer months. In that case, it may be impossible for manufacturers to meet this increased consumer need without significantly increasing production costs. Therefore, it is a challenge for companies that usually experience a decrease in demand during the summer months.

In marketing, one of these challenges is managing price and promotional strategies to balance demand and supply without affecting profitability, as this involves marketing techniques like pricing strategies, promotions, and distribution methods. The key here is to match the proper marketing technique with each product's demand curve. Another example will be if the company has an agreement with its suppliers that prevents it from changing prices unless other companies' prices vary. In the above example, the company may have to absorb higher costs for increased production costs. The challenge here would be to find ways to reduce those production costs without breaking the agreement with its suppliers. This balancing act is essential for a company's long-term financial health and success. A common situation occurs when a company does not have enough inventory to meet the expected demand or the supply. This is common in retail environments where retailers make decisions based on anticipated sales volume each week. When demand exceeds the retailer's supply, retailers usually experience higher-than-expected loss and overstocking costs [2]. Retailers may be unable to quickly buy enough new products to fill their customers' needs. Thus, they might have to cancel orders, lower prices, pay employees more overtime, or some combination of these things.

This oversupply situation can cause retailers to be cash poor. To avoid or minimize these losses, retailers must be flexible and adapt well to changing demand conditions. Retailers must always adopt flexible and adaptable strategies for every stage or process. Another factor that plays a significant role in balancing supply and demand is the manufacturer's ability to produce products quickly and efficiently. This production ability is essential because manufacturers can control supply, leading to overstocking at ret ail stores. If the supply exceeds demand, the manufacturer will sell the excess inventory at a lower price and possibly retail. Reselling inventory results in a revenue loss for both the retailer and manufacturer.

**2.2 RETAIL AND DEMAND MANAGEMENT**

Retail is a tricky business, even in the best of times. Merchants are faced with the challenge of balancing supply and demand through careful inventory management. Retailers are constantly faced with the risk of not having enough stock to meet customer demand while also trying to avoid having too much stock on hand, leading to excess inventory costs. Demand management happens when the company manages customer demand for its products. This process includes forecasting the amount of product the company needs on hand, fulfilling orders or requests at the right time, and making sure available stock meets customers' needs [3].

Retailers have tools to help them meet customer demand, including sophisticated data analytics programs that can use purchase history data to forecast future customer needs. However, even if inventory is managed optimally, other factors can still produce poor demand management performance. These include the cost of storing inventory, the price that the customer pays for products, and management of product loss. In addition, bottlenecks in supply chain processes can lead to delays in fulfilment, which will upset customers and negatively impact sales[4]. Retailers can use several inventory management practices to help their stores meet demand. The optimal inventory levels for a store depend on local market conditions and the type of products offered by the retailer.

Just-in-time production in manufacturing plants is one of the ways through which this aspect is achieved within the business. This strategy can be used when the company does not want to store extra product but instead produce more only when the demand arises. Another strategy is the reorder point. With this strategy, managers establish a trigger level for reordering products used up or sold out. For example, if the company wants to reorder a product at $10 per unit, they would study their purchasing history to establish what price levels indicate that more stock is needed. Such practice may result from poor forecasting or increased customer demand for their products or services. Therefore, the company can manage its inventory even better.

**2.3 DEMAND FORECASTING**

Demand forecasting is essential for large e-commerce companies because they can neither afford understocking nor overstocking. Understocking affects direct sales, customers start to lose interest in the product, and overstocking causes money loss due to wastage of products because there is not enough demand. Demand forecasting models cater to the overstocking and understocking cases and forecast when the demand increases or decreases [5]. For example, Amazon sells way more products on Christmas than on other regular days; the same is the case for Black Friday. This kind of forecasting is crucial because of how big an impact it can create on a company financially and save companies money if done right.

Forecasting is a time-consuming and challenging process, but it's also essential to any business. With the advent of artificial intelligence, many companies have been exploring this technology to simplify forecasting processes. When competition is fierce, and businesses are always looking to maintain an edge over their competitors, AI seems promising. After evaluating the value of artificial intelligence in forecasting processes, many companies look upon this computing power to make their businesses worth the competition [6].

Knowing and understanding the importance of such a model, companies have invested vast amounts of financial and human resources in improving the model and increasing demand forecasting accuracy. Researchers have developed several approaches to build a model which can work on a wide variety of data. With the start of the internet age, we now have a considerable amount of data that we can work on. Recent work in this field proposed an approach known as computational intelligence to predict the newly published books' sales [7]. Another strategy for forecasting daily food sales is using a hybrid seasonal approach using the moving average technique[8].

Statistical forecasting is one of the most widely used approaches, if not the most commonly used approach, for building predictive models where the effects don't co-occur. It also addresses many other problems such as seasonality, secular trends, and cyclical patterns that aren't easily described by a simple linear equation. Many different techniques fall under the umbrella of statistical forecasting. The first is simple linear regression, which attempts to find the best linear function for describing that data. This forecast is almost always a poor choice because it assumes that all periods have an equal effect on the outcome. This assumption is often not valid, so one must first normalize each of the periods or be unable to compare it to other periods [9]. The following approach is called "time series analysis," and it's generally used with data that has timestamps attached to every observation in the data set. This analysis is also a practical approach to implementing the machine learning algorithms and techniques but has its fair share of problems in forecasting.

## DATA ANALYSIS AND INTERPERTATION

Linear regression analysis is used to predict the value of a variable based on the value of another variable. Linear regression is a linear approach for modelling the relationship between a scalar response and one or more explanatory variables (also known as dependent and independent variables). The case of one explanatory variable is called simple linear regression; for more than one, the process is called multiple linear regression. This term is distinct from multivariate linear regression, where multiple correlated dependent variables are predicted, rather than a single scalar variable.

**AIR CAP:**

**Table 4.1 REGRESSION STATISTICS FOR AIR CAP**

| | |
|---|---|
| Multiple R | 0.354594 |
| R Square | 0.125737 |
| Adjusted R Square | 0.10273 |
| Standard Error | 1.942308 |
| Observations | 40 |

The above table indicates the R square value as 0.1257 for the AIR CAP. Similarly, the adjusted R square value is 0.1027 and standard error is 1.942.

**TABLE 4.2 ANOVA FOR AIRCAP**

| | Df | SS | MS | F | Significance F |
|---|---|---|---|---|---|
| Regression | 1 | 20.61768 | 20.61768 | 5.465169 | 0.024765 |
| Residual | 38 | 143.3573 | 3.772561 | | |
| Total | 39 | 163.975 | | | |

The p-value for the above mentioned model is 0.0247. This results in acceptance of alternative hypothesis i.e., the overall model is acceptable at the significance level of 0.05.

**TABLE4.3 REGRESSION ESTIMATION FOR AIRCAP**

| | Coefficients | Standard Error | t Stat | P-value | Lower 95% | Upper 95% | Lower 95.0% | Upper 95.0% |
|---|---|---|---|---|---|---|---|---|
| Intercept | 11 | 0.625912 | 17.57435 | 7.69E-20 | 9.732907 | 12.26709 | 9.732907 | 12.26709 |
| Time | -0.0622 | 0.026604 | -2.33777 | 0.024765 | -0.11605 | -0.00834 | -0.11605 | -0.00834 |

**TABLE4.4PREDICTED AND RESIDUAL VALUE FOR AIR CAP**

| Observation | Predicted Y | Residuals |
|---|---|---|
| 1 | 10.9378 | 1.062195 |
| 2 | 10.87561 | -3.87561 |
| 3 | 10.81341 | 1.186585 |
| 4 | 10.75122 | -0.75122 |
| 5 | 10.68902 | 1.310976 |
| 6 | 10.62683 | -3.62683 |
| 7 | 10.56463 | 1.435366 |
| 8 | 10.50244 | -0.50244 |
| 9 | 10.44024 | 1.559756 |
| 10 | 10.37805 | -3.37805 |
| 11 | 10.31585 | 1.684146 |
| 12 | 10.25366 | -0.25366 |
| 13 | 10.19146 | 1.808537 |
| 14 | 10.12927 | -2.12927 |
| 15 | 10.06707 | -0.06707 |
| 16 | 10.00488 | 0.995122 |
| 17 | 9.942683 | 2.057317 |
| 18 | 9.880488 | -1.88049 |
| 19 | 9.818293 | 0.181707 |
| 20 | 9.756098 | 1.243902 |
| 21 | 9.693902 | 2.306098 |
| 22 | 9.631707 | -1.63171 |
| 23 | 9.569512 | 0.430488 |
| 24 | 9.507317 | 1.492683 |
| 25 | 9.445122 | 2.554878 |
| 26 | 9.382927 | -1.38293 |
| 27 | 9.320732 | 0.679268 |
| 28 | 9.258537 | 1.741463 |
| 29 | 9.196341 | 0.803659 |
| 30 | 9.134146 | 2.865854 |
| 31 | 9.071951 | -0.07195 |
| 32 | 9.009756 | 0.990244 |
| 33 | 8.947561 | -0.94756 |
| 34 | 8.885366 | 0.114634 |
| 35 | 8.823171 | -3.82317 |
| 36 | 8.760976 | -4.76098 |
| 37 | 8.69878 | -0.69878 |
| 38 | 8.636585 | 1.363415 |

| | | |
|---|---|---|
| 39 | 8.57439 | 0.42561 |
| 40 | 8.512195 | -0.5122 |

**ATLAS PIPE:**
**TABLE 4.5 REGRESSION STATISTICS FOR ATLAS PIPE**

| Regression Statistics | |
|---|---|
| Multiple R | 0.04818 |
| R Square | 0.002321 |
| Adjusted R Square | -0.01488 |
| Standard Error | 3.916507 |
| Observations | 60 |

The above table indicates the R square value as 0.0023 for the ATLAS PIPE. Similarly the adjusted R square value is -0.0148 and standard error is 3.9165.

**TABLE4.6 ANOVA FOR ATLAS PIPE**

| | DF | SS | MS | F | Significance F |
|---|---|---|---|---|---|
| Regression | 1 | | | 0.134948 | 0.714693 |
| Residual | 58 | 889.6634 | 15.33902 | | |
| Total | 59 | 891.7333 | | | |

The p-value for the above mentioned model is 0.7146. This results in acceptance of alternative hypothesis i.e., the overall model is rejected at the significance level of 0.05.

**TABLE 4.7 REGRESSION ESTIMATION FOR ATLAS PIPE**

| | Coefficients | Standard Error | t Stat | P-value | Lower 95% | Upper 95% | Lower 95.0% | Upper 95.0% |
|---|---|---|---|---|---|---|---|---|
| Intercept | 18.73955 | 1.024012 | 18.30013 | 9.06E-26 | 16.68977 | 20.78933 | 16.68977 | 20.78933 |
| Time | 0.010725 | 0.029196 | 0.367352 | 0.714693 | -0.04772 | 0.069167 | -0.04772 | 0.069167 |

**TABLE4.8 PREDICTED AND RESIDUAL VALUE FOR ATLAS PIPE**

| Observation | Predicted Y | Residuals |
|---|---|---|
| 1 | 18.75027 | -3.75027 |
| 2 | 18.761 | -3.761 |
| 3 | 18.77172 | -8.77172 |
| 4 | 18.78245 | 1.217551 |
| 5 | 18.79317 | 1.206826 |
| 6 | 18.8039 | 11.1961 |
| 7 | 18.81462 | 1.185376 |
| 8 | 18.82535 | 1.17465 |
| 9 | 18.83607 | 1.163925 |
| 10 | 18.8468 | 1.1532 |
| 11 | 18.85753 | -3.85753 |

| | | |
|---|---|---|
| 12 | 18.86825 | -3.86825 |
| 13 | 18.87898 | -8.87898 |
| 14 | 18.8897 | 1.110299 |
| 15 | 18.90043 | 1.099574 |
| 16 | 18.91115 | 11.08885 |
| 17 | 18.92188 | 1.078124 |
| 18 | 18.9326 | 1.067398 |
| 19 | 18.94333 | 1.056673 |
| 20 | 18.95405 | 1.045948 |
| 21 | 18.96478 | -4.96478 |
| 22 | 18.9755 | 0.024498 |
| 23 | 18.98623 | -6.98623 |
| 24 | 18.99695 | -0.99695 |
| 25 | 19.00768 | -0.00768 |
| 26 | 19.0184 | 10.9816 |
| 27 | 19.02913 | 0.970872 |
| 28 | 19.03985 | 0.960146 |
| 29 | 19.05058 | 0.949421 |
| 30 | 19.0613 | 0.938696 |
| 31 | 19.07203 | -4.07203 |
| 32 | 19.08275 | -1.08275 |
| 33 | 19.09348 | 0.90652 |
| 34 | 19.1042 | -2.1042 |
| 35 | 19.11493 | 0.88507 |
| 36 | 19.12566 | 5.874345 |
| 37 | 19.13638 | 0.86362 |
| 38 | 19.14711 | 0.852894 |
| 39 | 19.15783 | 0.842169 |
| 40 | 19.16856 | 0.831444 |
| 41 | 19.17928 | -4.17928 |
| 42 | 19.19001 | -1.19001 |
| 43 | 19.20073 | -0.20073 |
| 44 | 19.21146 | -2.21146 |
| 45 | 19.22218 | 0.777818 |
| 46 | 19.23291 | 5.767093 |
| 47 | 19.24363 | 0.756368 |
| 48 | 19.25436 | 0.745642 |
| 49 | 19.26508 | 0.734917 |
| 50 | 19.27581 | 0.724192 |
| 51 | 19.28653 | -4.28653 |
| 52 | 19.29726 | -1.29726 |
| 53 | 19.30798 | -1.30798 |
| 54 | 19.31871 | -2.31871 |
| 55 | 19.32943 | -1.32943 |

| | | |
|---|---|---|
| 56 | 19.34016 | 5.659841 |
| 57 | 19.35088 | -1.35088 |
| 58 | 19.36161 | 0.63839 |
| 59 | 19.37233 | -5.37233 |
| 60 | 19.38306 | 0.61694 |

**BRASS REDUCER:**

**TABLE 4.9 REGRESSION STATISTICS FOR BRASS REDUCER**

| | |
|---|---|
| Multiple R | 0.43553 |
| R Square | 0.189686 |
| Adjusted R Square | 0.169428 |
| Standard Error | 2.132125 |
| Observations | 42 |

The above table indicates the R square value as 0.1896 for the BRASS REDUCER. Similarly the adjusted R square value is 0.1694 and standard error is 2.1321.

**DEPTH BOX:**

**4.10 REGRESSION STATISTICS FOR DEPTH BOX**

| Regression | Statistics |
|---|---|
| Multiple R | 0.440428 |
| R Square | 0.193977 |
| Adjusted R Square | 0.179051 |
| Standard Error | 3.73365 |
| Observations | 56 |

The above table indicates the R square value as 0.19397 for the DEPTH BOX. Similarly, the adjusted R square value is 0.1939 and standard error is 3.7336.

**TABLE 4.11 ANOVA FOR DEPTH BOX**

| | df | SS | MS | F | Significance F |
|---|---|---|---|---|---|
| Regression | 1 | 181.1609 | 181.1609 | 12.99563 | 0.000681 |
| Residual | 54 | 752.7677 | 13.94014 | | |
| Total | 55 | 933.9286 | | | |

The p-value for the above mentioned model is 0.000681. This results in acceptance of alternative hypothesis i.e., the overall model is acceptable at the significance level of 0.05.

**TABLE 4.12 REGRESSION ESTIMATION FOR DEPTH BOX**

| | Coefficients | Standard Error | t Stat | P-value | Lower 95% | Upper 95% | Lower 95.0% | Upper 95.0% |
|---|---|---|---|---|---|---|---|---|
| Intercept | 15.7928 | 1.01137 | 15.6152 | 1.13E-21 | 13.76517 | 17.8205 | 13.7651 | 17.8204 |

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| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Time | 0.11127 | 0.03086 | 3.604 94 | 0.0006 81 | 0.049391 | 0.17316 | 0.04939 | 0.17315 |

**TABLE 4.13 PREDICTED AND RESIDUAL VALUE FOR DEPTH BOX**

| Observation | Predicted Y | Residuals |
|---|---|---|
| 1 | 15.90414 | -5.90414 |
| 2 | 16.01541 | -6.01541 |
| 3 | 16.12669 | -1.12669 |
| 4 | 16.23797 | -1.23797 |
| 5 | 16.34925 | -6.34925 |
| 6 | 16.46053 | -1.46053 |
| 7 | 16.5718 | -4.5718 |
| 8 | 16.68308 | -3.68308 |
| 9 | 16.79436 | 5.205639 |
| 10 | 16.90564 | 0.094361 |
| 11 | 17.01692 | 4.983083 |
| 12 | 17.1282 | 2.871805 |
| 13 | 17.23947 | -0.23947 |
| 14 | 17.35075 | 8.649248 |
| 15 | 17.46203 | -3.46203 |
| 16 | 17.57331 | 2.426692 |
| 17 | 17.68459 | 4.315414 |
| 18 | 17.79586 | -0.79586 |
| 19 | 17.90714 | 4.092857 |
| 20 | 18.01842 | 1.981579 |
| 21 | 18.1297 | -1.1297 |
| 22 | 18.24098 | 7.759023 |
| 23 | 18.35226 | -4.35226 |
| 24 | 18.46353 | 1.536466 |
| 25 | 18.57481 | 1.425188 |
| 26 | 18.68609 | -0.68609 |
| 27 | 18.79737 | 4.202632 |
| 28 | 18.90865 | 1.091353 |
| 29 | 19.01992 | -1.01992 |
| 30 | 19.1312 | 5.868797 |
| 31 | 19.24248 | -5.24248 |
| 32 | 19.35376 | -0.35376 |
| 33 | 19.46504 | 0.534962 |
| 34 | 19.57632 | -1.57632 |
| 35 | 19.68759 | 3.312406 |
| 36 | 19.79887 | 0.201128 |
| 37 | 19.91015 | -1.91015 |
| 38 | 20.02143 | 4.978571 |
| 39 | 20.13271 | -6.13271 |
| 40 | 20.24398 | -1.24398 |

| | | |
|---|---|---|
| 41 | 20.35526 | 1.644737 |
| 42 | 20.46654 | -0.46654 |
| 43 | 20.57782 | 3.42218 |
| 44 | 20.6891 | 1.310902 |
| 45 | 20.80038 | -0.80038 |
| 46 | 20.91165 | 3.088346 |
| 47 | 21.02293 | -7.02293 |
| 48 | 21.13421 | -1.13421 |
| 49 | 21.24549 | 0.754511 |
| 50 | 21.35677 | -1.35677 |
| 51 | 21.46805 | 2.531955 |
| 52 | 21.57932 | 0.420677 |
| 53 | 21.6906 | -1.6906 |
| 54 | 21.80188 | 2.19812 |
| 55 | 21.91316 | -7.91316 |
| 56 | 22.02444 | -2.02444 |

## FINDING & SUGGESTIONS

### FINDING

- The September 2024 the AIR CAP forecast value using liner regression is 8
  - $AIRCAP \ = 3.44 + 0.156 * time$
- The September 2024 the ATLAS PIPE forecast value using linear regression is 19
  - $ATLAS\ PIPE = 18.73 + 0.010 * time$
- The September 2024 the DEPTH BOX MERRAKUNJ forecast value using linear regression is 9
  - $DEPTH\ BOX\ MERRAKUNJ = \ 7.790 + \ 0.019 * time$

### SUGGESTIONS

- This forecasting process helps for Inventory or stock management in the retails stores.
- This helps to decrease the cost which involved in the inventory
- This mainly used for sales planning for forthcoming month
- This helps to frame the marketing strategies for improvise the sales
- The most of the forecasted values are similar to the expert opinion. So based on this automatic forecasting process may be carried out to improvise the Inventory planning process.

## CONCLUSION

This study mainly focused on demand forecasting for retail stores. To achieve this objective, one of the most popular forecasting technique linear regression is used for model building. The data are collected for various products and liner regression model is developed for each product. After the model building the forecasting for the next period is performed. Finally, the expert opinion is performed to evaluate the performance of the model. This retail demand forecasting helps for effective stock management or inventory planning process. In future this could be extended with nonlinear and time series model to improve the accuracy of the forecasting technique. Only linear regression is adopted for model building and forecasting process. Models like nonlinear models, moving average and exponential models to be considered for further study to improve the forecasting accuracy.

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