Examining the Effect of Forecast Accuracy on a Dynamic Inventory Optimization Model for Spares

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Abstract

This study describes an optimization solution to minimize costs at the inventory system by the retailer. In the past, all demands were forecasted yearly and information regarding item distribution was not used. The retailer used weekly and monthly demand forecasts by just dividing yearly forecast with specific numbers. Therefore, the retailer purchased items in bulk to prepare for unexpected demand from vendors, which generated huge holding costs. If we approach the distribution of each item, then a dynamic economic order quantity model would be possible. We solved this problem by using diverse distributions for each item. Then, we built up formulas to calculate costs and service levels. Then we optimized our model to minimize the cost, while meeting several business requirements, such as minimum service level, for each item type. Lastly, we show the impact that the quality of the demand forecast has on the business.

Introduction

Retailers continue to develop data-driven decision-support solutions to help improve inventory management decisions. If retailers can better handle inventory that will be more successful at fulfilling customer needs, while simultaneously managing the firm's cash flows for more efficient operations and opportunities. It has been stated in the literature that increasing the accuracy of demand forecasts can save retailers millions of dollars a year in lost sales and inventory holding costs. The research question in this study is: how does demand forecast accuracy translate to additional inventory costs when using a dynamic inventory optimization model for replenishment of spare-type items?

Methodology

Data Source
The dataset used in this study was inventory records from 2016 to 2017 obtained from a spare item distributor. They reviewed item quantity on a weekly basis and placed orders based on their demand forecast. Other features of the dataset include inventory on hand, actual shipping quantity, purchase price, lead time, minimum order level, and item class. Item class is the parameter used to divide the items in inventory based on the expected service level.

Data Preparation
The sparse items inventory data was first cleaned to remove items which had one or two data points. We cannot optimize orders based on very few data points and hence they were ignored from the model. The cleaned data was then subset on spare patterns observed in the data. We did this two ways:
  I. Algorithmic: used an unsupervised learning algorithm to cluster the data and provide grouped inventory items.
  II. Segmentation: partitioned data based on the Item Class that was known to us.

The objective of this step is to have all homogenous data together and then apply a model to those groups.
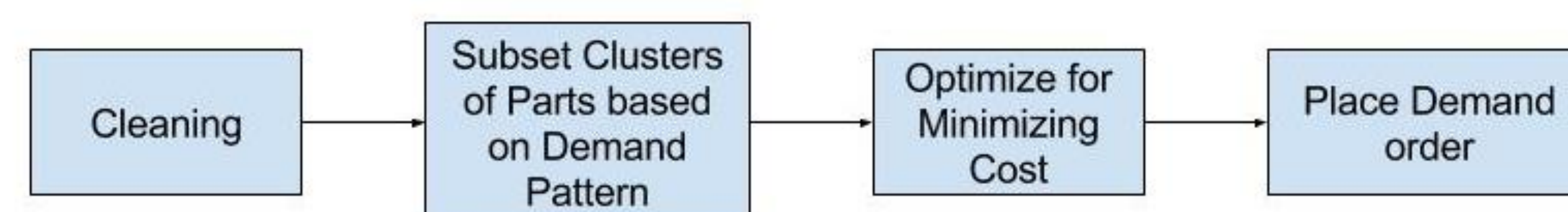

Demand Forecast
To explore the impact of demand forecast accuracy on cost, we designed three sets of demand forecasts as the input for modeling.
  I. Predicted demand by retailer's model
  II. Actual shipping quantity as actual demand
  III. Based on the demand distribution pattern. We used a random ±1 of actual shipping quantity as our forecast set.

Fixed-time Period Ordering Model

In Fixed-time Period Ordering Model, the order is placed only after a fixed time period, and the order quantity can be varied based on expected demand. Initially, we are in idle state and when demand occurs, we satisfy the demand based on the current inventory position. In a Fixed-time Period model, we wait till review time occurs. When the time occurs, we compute the inventory position based on the formula below. Then we compute the order quantity level up to which the distributor should place an order, and orders are placed.
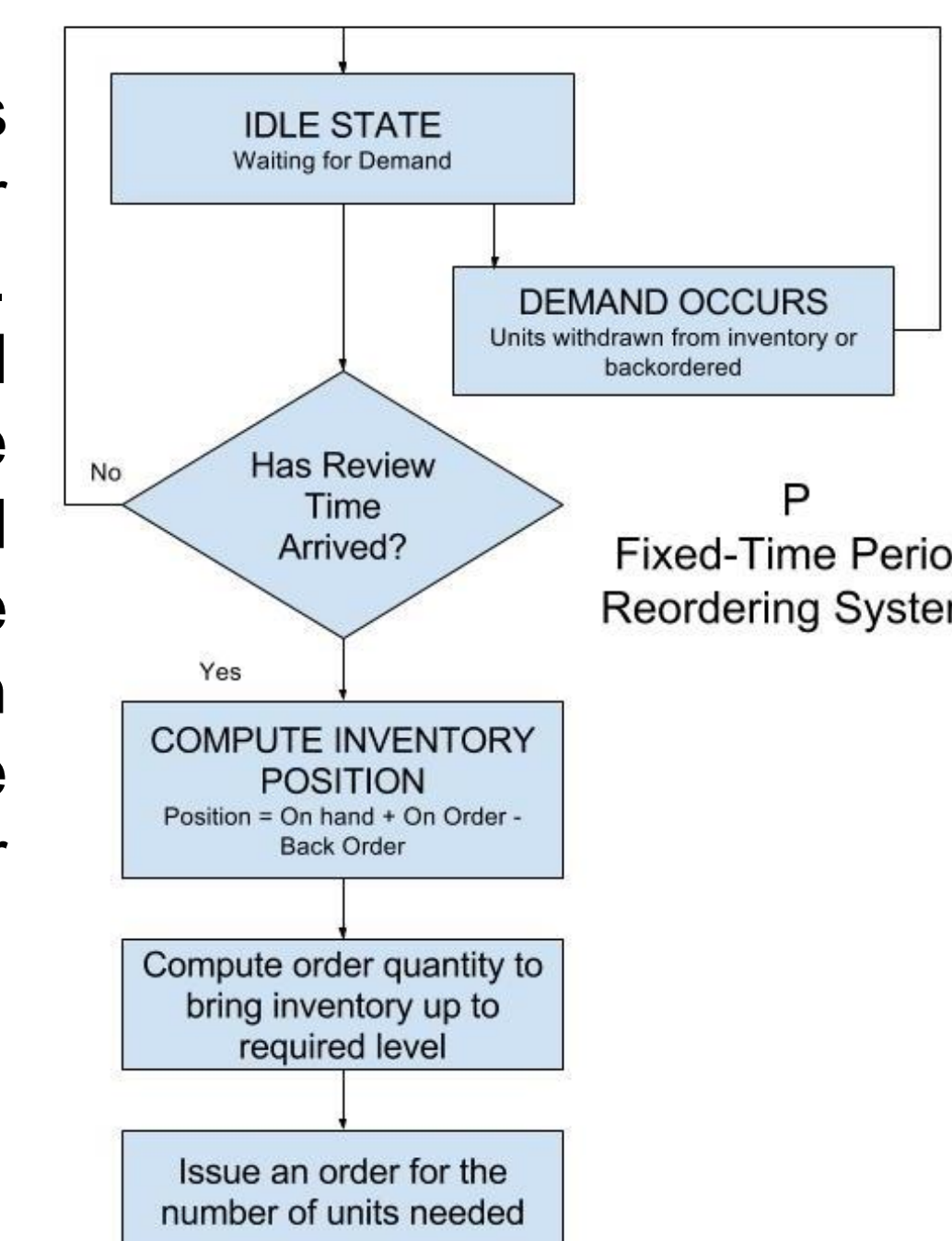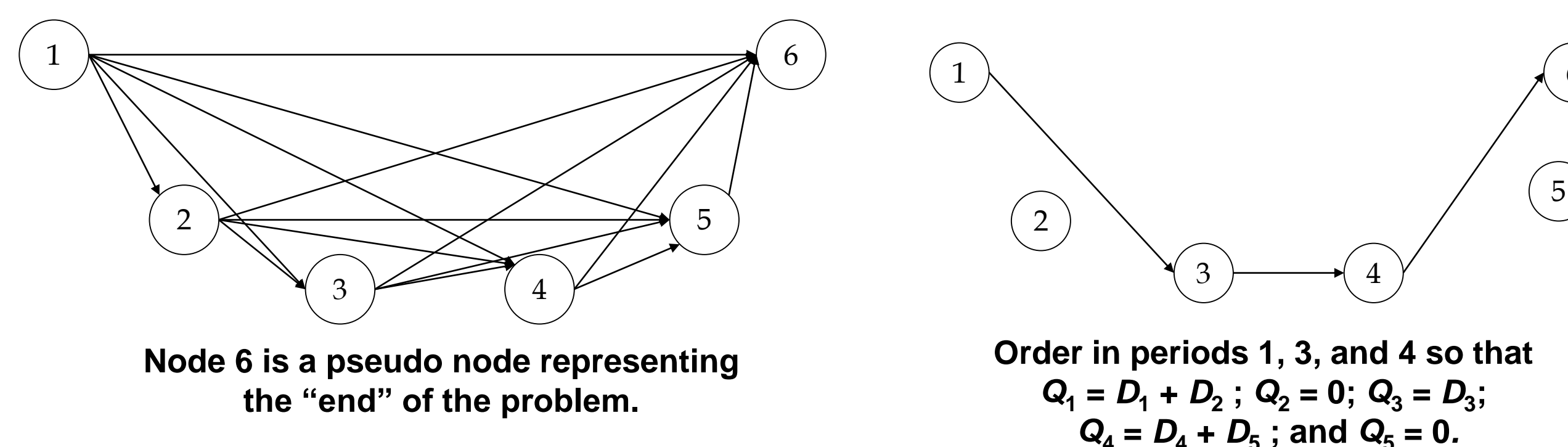
$$Position(P) = On\ hand + On\ Order - Back\ Order$$

where
- $On\ hand$ refers to the inventory for the items available at the distributor
- $On\ Order$ refers to the order for items made to the vendor expected to be delivered in a lead time agreed with the vendor
- $Back\ Order$ refers to the order for items which is to be delivered to the customer as soon as it is available at the distributor


Dynamic Programming model
Dynamic Programming was coined by Richard Bellman in the 1940s when creating solutions to solving sequential decision problems. The model is for solving a series of smaller sub-problems such as an N period problem, where the solution to each sub-problem is used in solving the next subproblem.

Node 6 is a pseudo node representing the "end" of the problem.

Order in periods 1, 3, and 4 so that $Q_1 = D_1 + D_2$; $Q_2 = 0$; $Q_3 = D_3$; $Q_4 = D_4 + D_5$; and $Q_5 = 0$.

Model Building and Comparison
We compared total cost computed by the two models after considering 3 sets of demand forecasts.
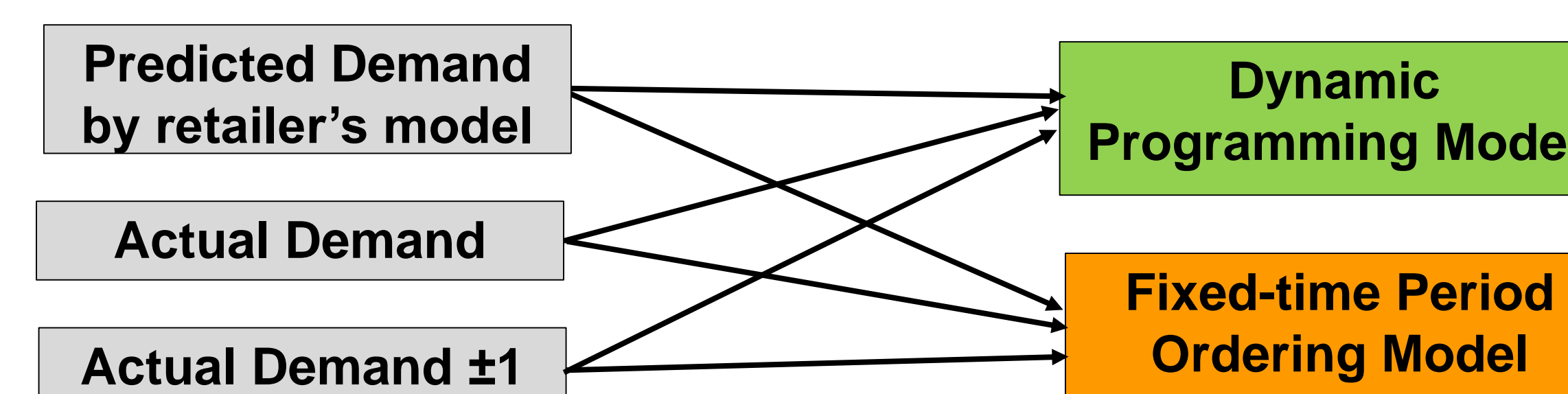
Results

Exploratory Data Analysis
Inventory management should consider demand distribution, cost factors, service level, minimum order quantity, and inventory capability. In our dataset, we only focus on studying the demand distribution of spare item and held other factors as constant. We found that the predicted demand computed by the established model did not consider seasonality and did not match with the trend of actual demand. In fact, when we visualized the distribution of actual quantity demanded of each item class, we found that some classes showed higher deviation than others. For instance, class A, which requires the most demanding service level, and fluctuates significantly more than other classes.
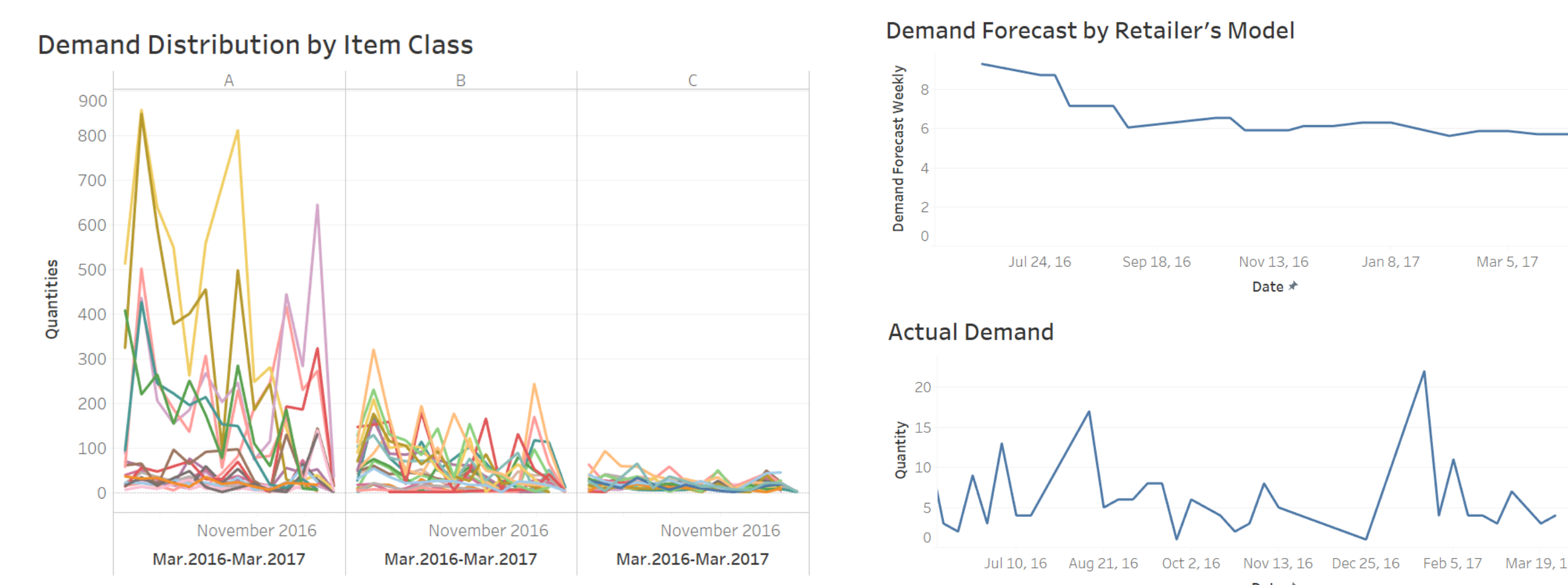
Decision Model

Decision variables
The variables that would be required to be decided are the Order Quantity and the Frequency of Order. From our model we can predict when you need to order. The quantity to be ordered is based on predicted demand.

Parameters
TC = Total cost over a period of time t
Q = Total demand over time t
P = Ordering price of the item
V = Vendor request minimum order quantity
O = Order up to level in units
M = Minimum Order Level
SL = Service Level
SOQ = Suggested Order Quantity
I = Inventory on hand
PoS = Percentage of Stock-outs

Objective Function
Min {TC} = Q*P + I*R*P

Constraints
SOQ > V
SOQ < O
SOQ > M
PoS (when I < D) < 1 − SL

We also included other constraints in our model such as the maximum order quantity (O) that can be placed for every item at a time. This quantity will depend on the size of warehouse and what the dimensions of the item are.

Dynamic Programming model
We construct a Dynamic Programming Model, which allows us to order based on the objective to minimize the Total cost of fulfilling demand over a period. The model aim helps to determine whether or not to order at time t and the quantity that is to be ordered. If we order, then the order quantity should be just enough to cover demand until the next period in which we order. Here are the steps to find out Least Costly Path for fulfilling demand predicted over a period of time.

Algorithm

Step 1: $t = 1$, $z_t^* = 0$

Step 2: $t = t+1$. If $t > T+1$, stop. Otherwise go to step 3.

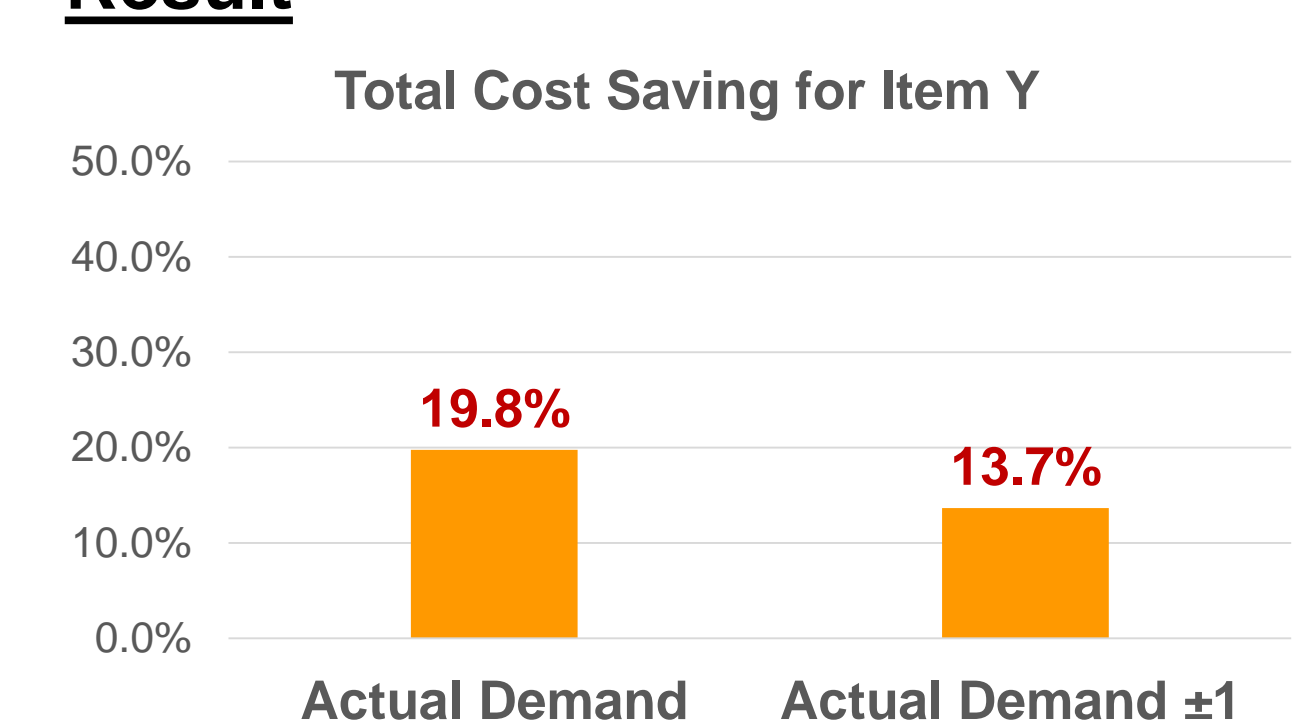**Step 3:** For all $t' = 1, 2, …, t - 1$,

$$c_{t',t} = A_{t'} + c_{t'}·(D_{t'} + ... + D_{t-1}) + h_{t'}(D_{t'+1} + ... + D_{t-1}) + h_{t'+1}(D_{t'+2} + ... + D_{t-1}) + ... + h_{t-2}D_{t-1}$$

Step 4: Compute
$$z_t^* = \min_{t'=1,2,...,t-1} \{z_{t'}^* + c_{t',t}\}$$

Parameters
t = week number
T = week for window
z_t = optimum cost at time t
D_t = Demand at time t
A_t = min cost till the previous week
h_t = inventory holding cost
c_t = total cost at time t

Result

Total Cost Saving for Item Y

Actual Demand: 19.8%
Actual Demand ±1: 13.7%

Conclusions

We compare the results from our model for the three predicted demands to see which one performed better based on the accuracy of demand. We used total cost incurred during the period under consideration including the cost of stock-outs as a metric to compare the performance. We found that the client's predicted demand had the highest total cost associated with it due to poor forecasted demand accuracy. Our attempt to use exponential smoothing technique to simulate predicted demand did not yield an accurate forecast. As the model with highly accurate predicted demand showed least total cost, we suggest the client to focus their efforts in improving the accuracy of their demand forecasts.

Acknowledgements