Inventory Forecasting - Proof of Concept

Chetak Chauhan

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APPROACH

Exploratory Data Analysis

- Price, Orders & Revenue trend
- Revenue vs Orders split
- Inventory Replenishments
- Surplus Inventory
- Revenue loss due to stockout

Inventory Forecasting Model

- Model key points
- Potential savings
- Caveats

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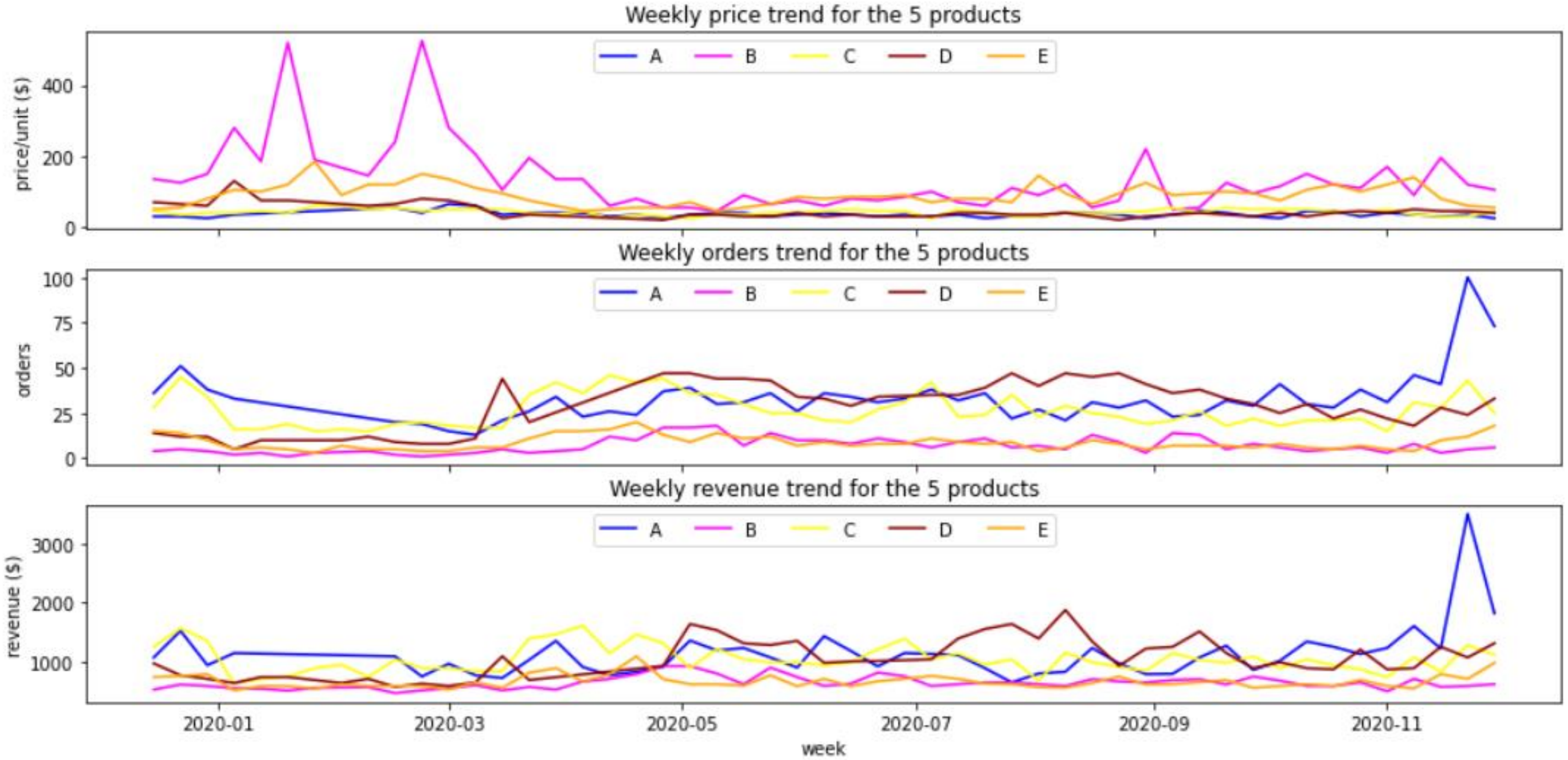
- Data Dictionary

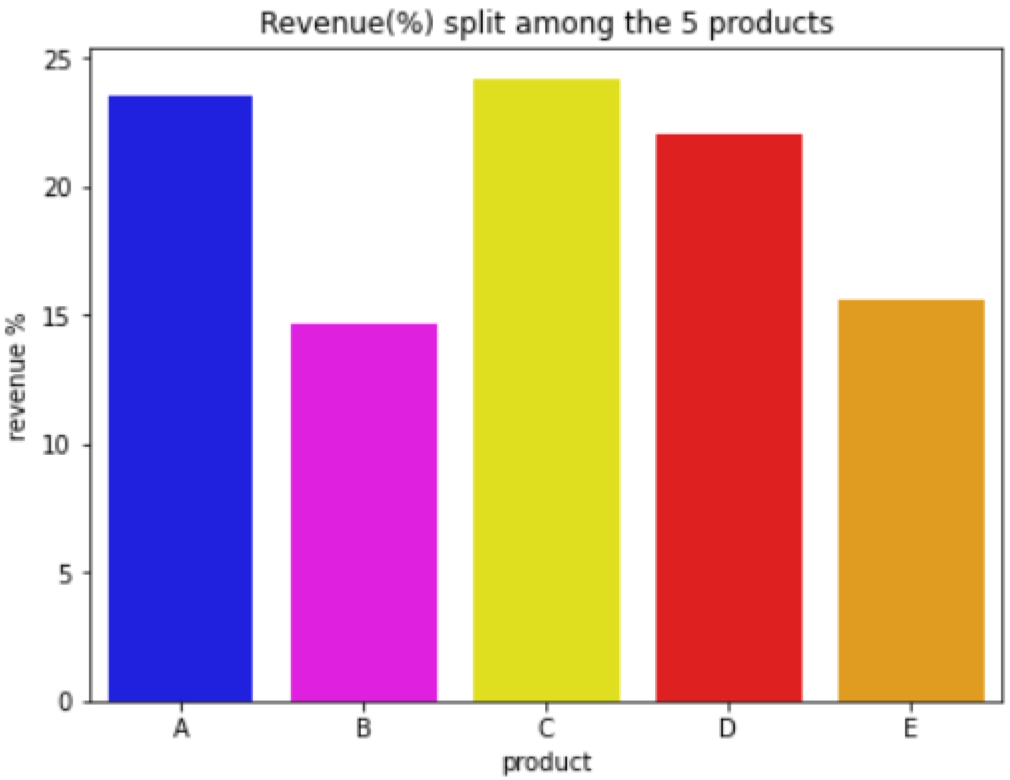
EXPLORATORY DATA ANALYSIS

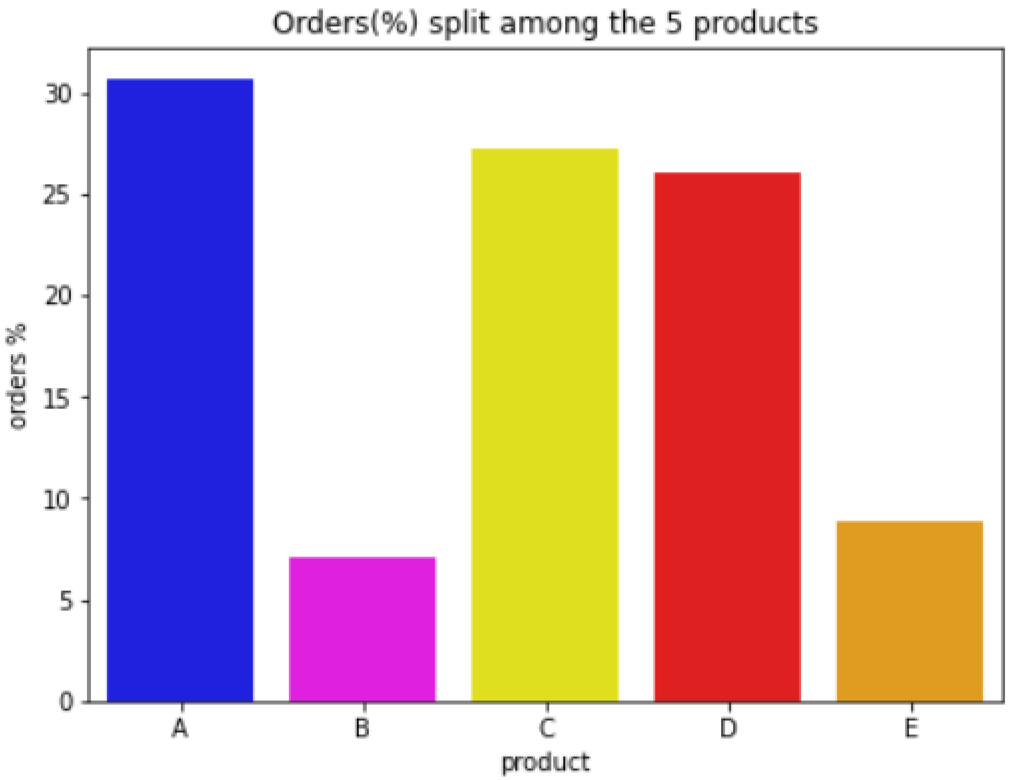
Price, Orders & Revenue trend for the 5 products



- ➢ Product B & E have been more expensive throughout the year, and both had significant price swings
- ➢ Even though prices for A, C & D tend to be steady(post Q1 2020), we see swings in quantity of orders, and this could be due to factors like seasonal demand peak, holiday sale etc.
- ➢ Product A, C & D were the major contributors to revenue throughout the year.

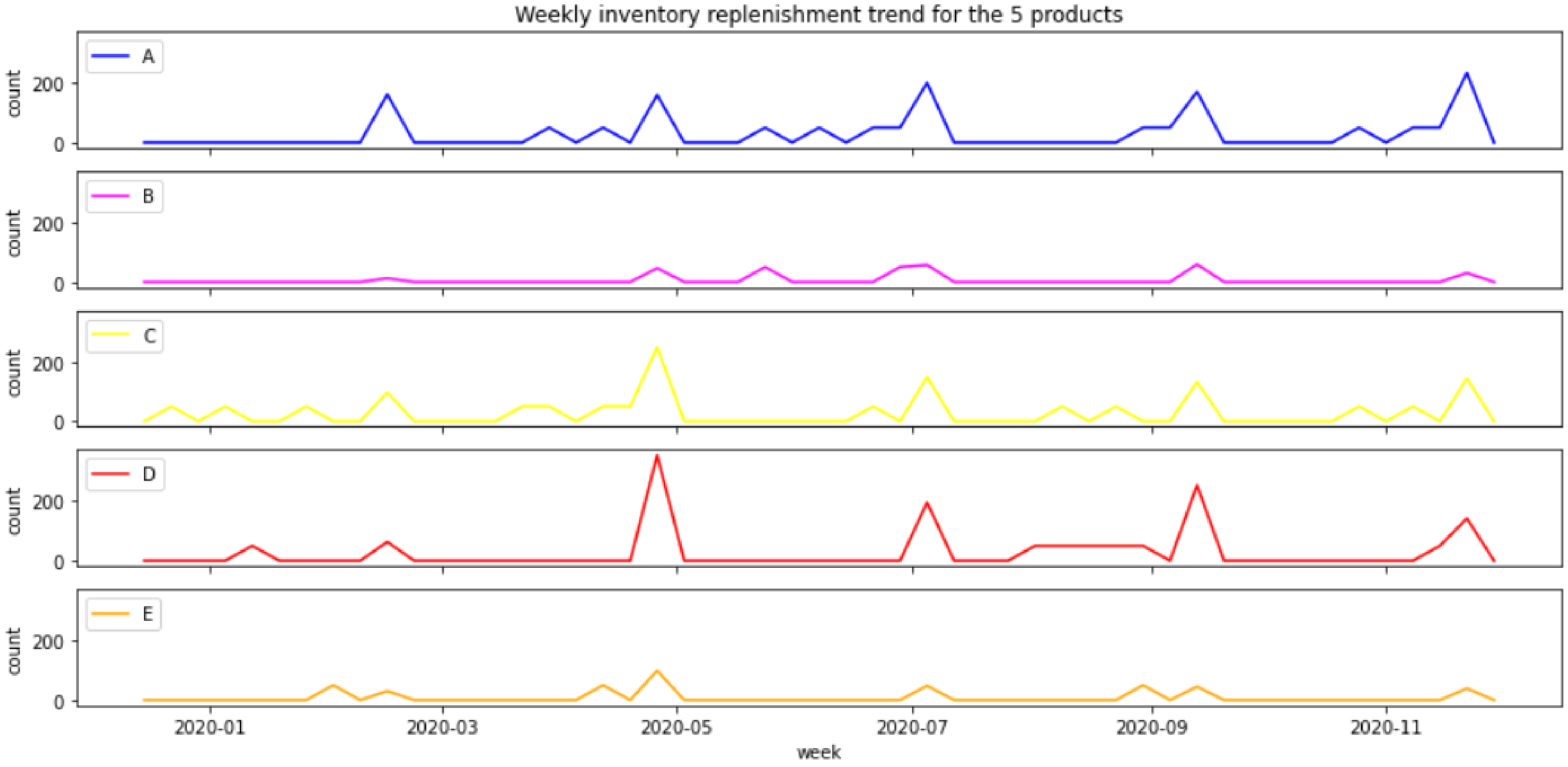
Revenue vs Orders split among the 5 products





- Products A, C & D contribute approx. 70% to the overall revenue and account for approx. 85% of total orders.
- As top performers A, C & D need more attention through better inventory control and avoiding stock-outs.
- For products, B & E, stocking too much of these will result in unwanted inventory carrying costs.

Inventory Replenishments



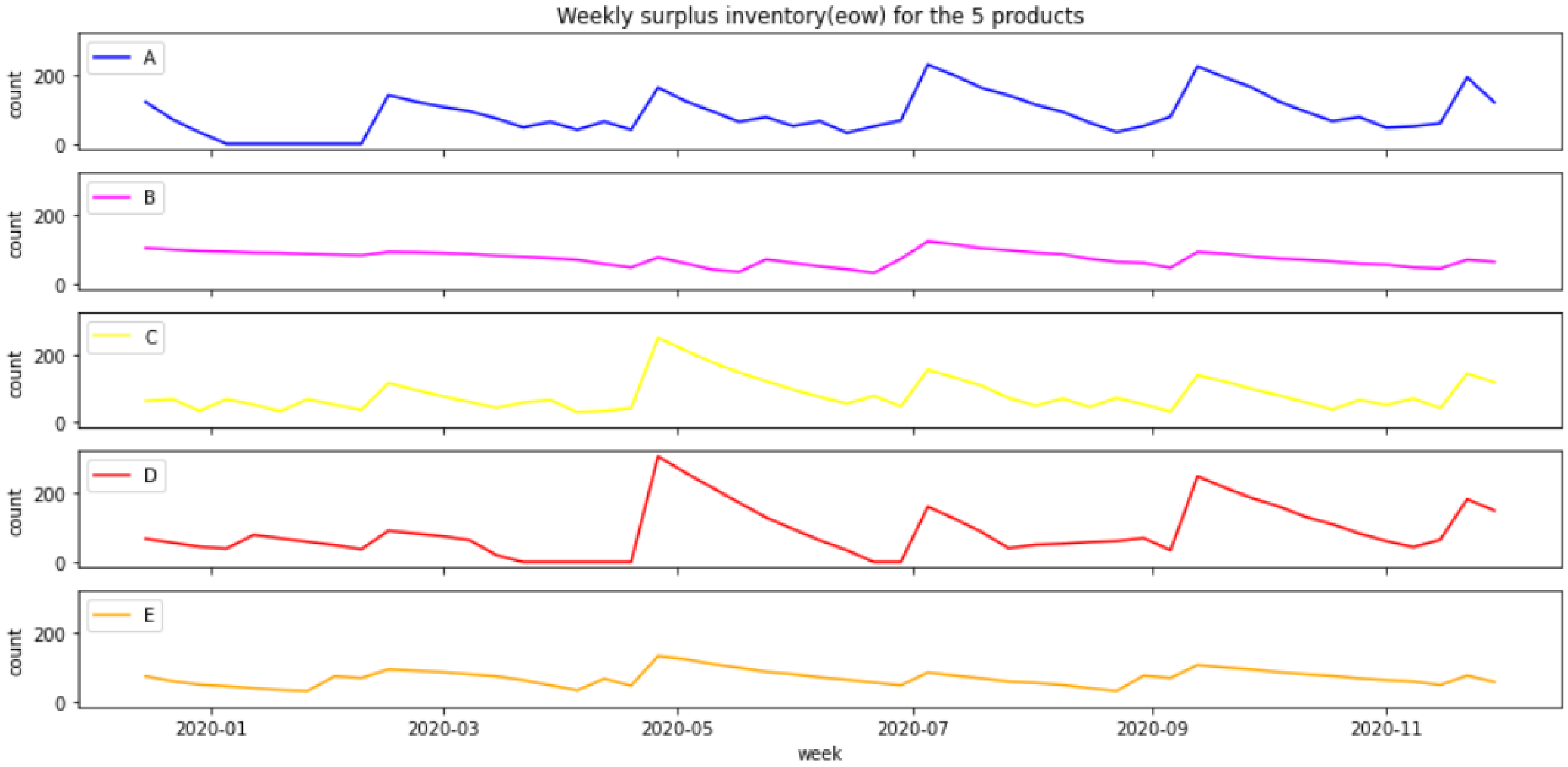
product	replenish_freq	max	median	min
A	16	234	50	50
B	7	59	50	12
C	17	249	50	50
D	12	355	50	50
E	8	99	49	30

	week
1	2020-02-16
2	2020-04-26
3	2020-07-05
4	2020-09-13
5	2020-11-22

- Family Day week
- My assumption 2 & 3 are summer sales
- Fall school opening
- Black Friday week

- Products A, C & D had replenishment approx. twice many times when compared to B & E.
- The min & max replenishment quantity for A, C & D is significantly larger than that of B & E.
- During the above listed 5 weeks, all products had significantly larger replenishments, probably this was in anticipation of the seasonal demand peak and/or holiday sale cycle for these products.

Surplus Inventory (end of week)



product	surplus_inv_cost($)	surplus_inv_cost(%)
A	15866.0	12.0
B	52276.0	39.0
C	16836.0	13.0
D	18652.0	14.0
E	30871.0	23.0
Total	134501.0	100.0

#I have assumed same inventory holding cost of 10% of the potential revenue (if the inventory did sell) for all the 5 products

- For most part of the year, products A, C & D have maintained more end of week inventory then B & E.
- Even though B & E had lower inventory, but they contributed over 60% towards the inventory holding cost.
- This is an area that needs improvement, a better inventory forecast can help in reducing the overall inventory holding cost.

Revenue loss due to stockout/limited Inventory

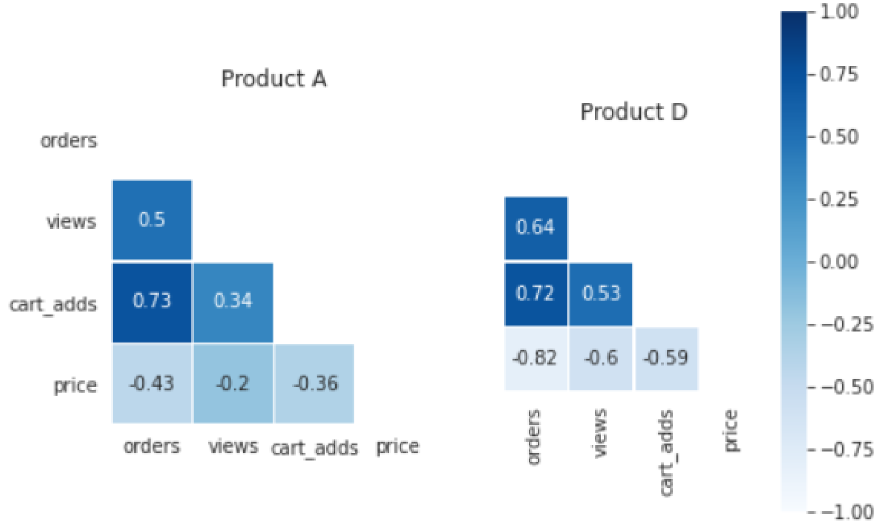
week	product	orders	brand	views	cart_adds	price	inventory	inv_sow	inv_rep	inv_cost	revenue
2020-01-12	A	0	Big Cable Brand	2091	0	44.99	0	0	0	0.0	0.0
2020-01-19	A	0	Big Cable Brand	4476	0	29.99	0	0	0	0.0	0.0
2020-01-26	A	0	Big Cable Brand	1466	0	34.99	0	0	0	0.0	0.0
2020-02-02	A	0	Big Cable Brand	3829	0	54.99	0	0	0	0.0	0.0
2020-02-09	A	0	Big Cable Brand	3215	0	29.99	0	0	0	0.0	0.0
2020-03-29	D	0	Little Cable Brand	4338	0	19.99	0	0	0	0.0	0.0
2020-04-05	D	0	Little Cable Brand	7615	0	24.99	0	0	0	0.0	0.0
2020-04-12	D	0	Little Cable Brand	5764	0	19.99	0	0	0	0.0	0.0
2020-04-19	D	0	Little Cable Brand	2771	0	34.99	0	0	0	0.0	0.0
2020-06-28	D	0	Little Cable Brand	2746	0	44.99	0	0	0	0.0	0.0

- Products A & D had zero orders for 5 weeks each.
- There was no inventory at start of week and neither there were any replenishment, resulting in zero orders.
- This is potential revenue loss due to unavailability of in-demand products and needs better inventory planning.

week	product	orders	brand	views	cart_adds	price	inventory	inv_sow	inv_rep	inv_cost	revenue
2020-01-05	A	33	Big Cable Brand	5970	66	34.99	0	33	0	0.0	1154.67
2020-03-22	D	20	Little Cable Brand	9138	91	34.99	0	20	0	0.0	699.80
2020-06-21	D	34	Little Cable Brand	1547	66	29.99	0	34	0	0.0	1019.66

- There were 3 weeks for products A & D when the orders were same as the available inventory(start of week).
- Interestingly both A & D were having substantial views & cart adds, signifying demand among the consumers.
- Its possible that we could have seen more orders if additional inventory was available for those weeks.

Estimating Revenue loss due to stockout



week	product	views	cart_adds	price	ord_pred	rev_loss
2020-01-12	A	2091	0	44.99	27	1214.73
2020-01-19	A	4476	0	29.99	36	1079.64
2020-01-26	A	1466	0	34.99	29	1014.71
2020-02-02	A	3829	0	54.99	16	879.84
2020-02-09	A	3215	0	29.99	32	959.68

week	product	views	cart_adds	price	ord_pred	rev_loss
2020-03-29	D	4338	0	19.99	33	659.67
2020-04-05	D	7615	0	24.99	33	824.67
2020-04-12	D	5764	0	19.99	33	659.67
2020-04-19	D	2771	0	34.99	30	1049.70
2020-06-28	D	2746	0	44.99	30	1349.70

- From the plot we can see that product orders has strong correlation with views, cart adds & price.
- Built a model (Random Forest) to predict orders for the weeks which had zero orders due to inventory stockout.

- Based on the weekly price, estimated the potential revenue loss due to inventory stockout for products A & D.
  - potential revenue loss for product A: $5149
  - potential revenue loss for product D: $4543
- Potential Total Revenue loss: $9692

INVENTORY FORECASTING MODEL

Inventory Forecasting model key points

Objective: Forecast start of week (sow) inventory to meet the order demand[1] during the week.

Data provided: Products weekly order data for the time period Dec-2019 to Nov-2020.

Data transformation: Zero order weeks for products A & D were updated with predicted[2] orders

Forecasting model: Built a timeseries model to capture the pattern of the orders.

Model inputs: Model considered trend, seasonality, holidays[3] and brand[4].

Output: Forecasted sow inventory, based on which potential savings for each product is estimated.

Considerations / Assumptions:

1. Aim is to order just the right number of products to arrive at the right time to minimize inventory carrying costs.

- *Inventory replenishment cost & lead time is insignificant, and replenishment can be done at start of week as per the inventory forecast.*

2. Zero order weeks are due to inventory stockout and is not a true representation of product demand, hence a predicted order value is used for such instances.

3. Major holidays provide a window for higher demand due to sales & promotions. Have considered the following holidays as inputs to the model.

- *New Year's Day, Family Day, Good Friday, Victoria Day, Canada Day, Civic Holiday, Labour Day, Thanksgiving, Christmas Day, Boxing Day.*

4. The 5 products are from two brands namely, Big Cable Brand & Little Cable Brand. Probably these are similar kind of products with different quality/functionality. To factor in whether, the brand itself impacts the demand (and thereby the required inventory) I have considered it as an additional input in the model.

Potential savings

week	product	orders	price	inventory	inv_sow	inv_cost	revenue	ord_ts	rev_loss	inv_sow_pred	inv_eow_pred	inv_cost_pred	rev_loss_pred
2019-12-15	A	36	29.99	122	158	365.88	1079.64	36	0.00	38	2	6.00	0.00
2019-12-22	A	51	29.99	71	122	212.93	1529.49	51	0.00	36	0	0.00	449.85
2019-12-29	A	38	24.99	33	71	82.47	949.62	38	0.00	35	0	0.00	74.97
2020-01-05	A	33	34.99	0	33	0.00	1154.67	33	0.00	33	0	0.00	0.00
2020-01-12	A	0	44.99	0	0	0.00	0.00	27	1214.73	32	5	22.50	0.00
2020-01-19	A	0	29.99	0	0	0.00	0.00	36	1079.64	30	0	0.00	179.94
2020-01-26	A	0	34.99	0	0	0.00	0.00	29	1014.71	29	0	0.00	0.00
2020-02-02	A	0	54.99	0	0	0.00	0.00	16	879.84	27	11	60.49	0.00
2020-02-09	A	0	29.99	0	0	0.00	0.00	32	959.68	26	0	0.00	179.94
2020-02-16	A	20	54.99	142	0	780.86	1099.80	20	0.00	24	4	22.00	0.00

Per original data

Per model prediction

- Snapshot of the model output for product A.
- Forecasted start of week inventory (inv_sow_pred) is better aligned with weekly orders (ord_ts).

product	inv_cost	inv_cost_pred	rev_loss	rev_loss_pred	potential_saving
A	15865	599	5148	5453	14961
B	52275	952	0	5254	46069
C	16836	821	0	6508	9507
D	18652	672	4543	5128	17395
E	30871	659	0	4559	25653
Total	134499	3703	9691	26902	113585

- Based on forecasted inventory, we see huge savings in inventory holding cost.
- Some revenue loss is also seen because of stockout during certain weeks but it is more than compensated by the inventory cost savings.

Caveats

- The analysis was done on the data for the time period between Dec-2019 to Nov-2020. This will be having impacts of COVID-19 pandemic. For a more robust forecasting model, we should also analyze previous years data when the business would have been operating in normal/expected environment.

- For inventory holding cost, I have taken an assumption of 10% of potential revenue, however there are factors like warehouse storage cost, depreciation cost, shrinkage cost, etc. that need to be analyzed to get the inventory holding cost.

- Not considered Safety Stock which is important to mitigate stock outs. This needs business inputs to be incorporated.

- I have assumed zero lead time and no minimum order requirement for inventory replenishments which is generally not the case. The business considers various factors to decide on the frequency & quantity of inventory Reorder Points.

- The analysis is done considering the product revenues, but equally important is the product profit margin. A slow-moving product can offer a high margin, on the other hand a low margin product may be extremely popular with the consumers, and the business will carry it to engage more with consumers and possibly cross-sell.

- The POC was done on small dataset but if this needs to be expanded to large dataset in the realm of Bigdata, necessary code tweaks will be needed to take advantage of Spark distributed cluster computing.

APPENDIX

Data Dictionary

Original Data		
	Variable	**Description**
	week	Starting date of the week represented in MM/DD/YYYY
	product	Name of the product
	orders	Number of orders placed for that product in that week
	brand	Brand of the product
	views	Number of page views for the product
	cart_adds	Number of customers who added the product to their cart
	price	Price of the product listed for that week
	inventory	Available inventory of the product at the end of that week

Calculated / Forecasted Data		
	Variable	**Description**
	inv_sow	Inventory at the start of the week as per the original data
	inv_rep	Quantity of inventory replenished as per the original data
	inv_cost	Surplus inventory holding cost as per the original data
	revenue	Product revenue as per the original data
	ord_ts	Zero order weeks for products A & D were updated with predicted orders
	rev_loss	Estimated Revenue loss for the original data
	inv_sow_pred	Forecasted start of the week inventory
	inv_eow_pred	Predicted inventory at the end of week
	inv_cost_pred	Predicted surplus inventory (end of week) holding cost
	rev_loss_pred	Potential revenue loss if the forecasted inventory results in a shortfall

BEST BUY