ME 308 Project Report

Group 28: Thread Keepers

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Topic : Mapping Inventory Model with Discounting for a T-Shirt Business in IITB

Introduction:

Optimization in inventory management can help businesses to better manage their inventory levels and reduce costs by using data-driven decision-making. Optimization models can analyze historical data and market trends, optimize ordering processes, determine safety stock levels, and prioritize inventory management efforts. The result is improved service levels, reduced costs, and increased profitability for businesses.

In a t-shirt business, inventory management is a critical aspect of operations. An effective inventory management strategy can help ensure that the right products are available when customers want to buy them, while also reducing the costs associated with holding too much inventory. This also ensures a uniformly followed pricing despite the seasonal demand of the product.

Managing inventory levels can be a big problem in the t-shirt business for several reasons. First, t-shirts come in various sizes, colors, and designs, which can make it difficult to forecast demand accurately. Second, trends and fashion preferences change quickly, which can result in excess inventory if not managed properly. Finally, managing inventory can be costly, as excess inventory ties up capital and takes up valuable warehouse space. To overcome these challenges, t-shirt businesses need to develop effective inventory management strategies that allow them to balance supply and demand, reduce costs, and improve customer satisfaction.

One way to manage inventory in a t-shirt business is by using inventory models that incorporate discounting. These models can help to optimize inventory levels based on expected demand and the cost of holding inventory. Hence, we wish to explore various inventory models incorporating discounting, to optimize the inventory costs for such a business.

Motivation:

We knew the ME308 Optimisation Project was an opportunity for us to create a real-world impact and help someone who could benefit directly from what we study as part of our curriculum. We explored various domains that needed optimisation in and around the institute and one of the sectors which grabbed our attention directly was the IIT Bombay Merchandise area.

IIT Bombay has many local small players in the merchandise Tshirt business, none of whom have properly organized inventories and hence run into a lot of 'dead stock' or 'unavailability' issues. In a t-shirt business, inventory management is a critical aspect of operations. An effective inventory management strategy can help ensure that the right products are available when customers want to buy them, while also reducing the costs associated with holding too much inventory.

As a group, we witnessed a variety of merchandise available for IIT Bombay students at a variety of prices - even the same products being sold at very different prices at different points of time! On interacting with a few suppliers, we quickly understood the problems involved in this business: competition, sourcing, and trends, logistics, etc. However, the most important of these problems is - inventory management due to manufacturers' different policies, variable demand throughout the year and automation of methods minimizing cost and maximizing profit.

We realize that a uniformly priced and trendy shop that has supply throughout the year can prove to be useful for the students across all years (and even non-IITB students). For this, we need to optimize order splitting. It refers to the practice of dividing a customer's large order into smaller ones for the purpose of fulfilling the order most efficiently i.e. distribution of order placed to different vendors . It can be done by using various inventory models incorporating discounting.

It was also important to make the solution easy to understand and use by any layman vendor and hence automation of the proposed solution is what we aimed to focus on, as well. We aimed to keep the solution very general, while also being dynamically modern wherein the vendor could keep updating the order levels based on actual demand curves.

The Problem

Multiple TShirt Vendors have a non-professional way of managing their TShirt inventories, which causes stock-outs as well as dead-stock problems multiple times throughout the year. Their current approach is based on rough guesstimates through manual guessing approach, based on previous data. This makes storage of t-shirts very uneconomical and overpriced for the vendors. Furthermore, to balance a randomly maintained stock level, they have to vary prices (sometimes a lot) throughout the year.

The Solution

The need for a simple optimisation model that helps predict the demand of stock very accurately (based on past trends), as well as helps them know how much to order when - in the most economical manner. Taking into account real-life scenarios of seasonality of ordering costs as well as bulk discounting is essential. Automation and Ease-of-Use of such a model would be preferable.

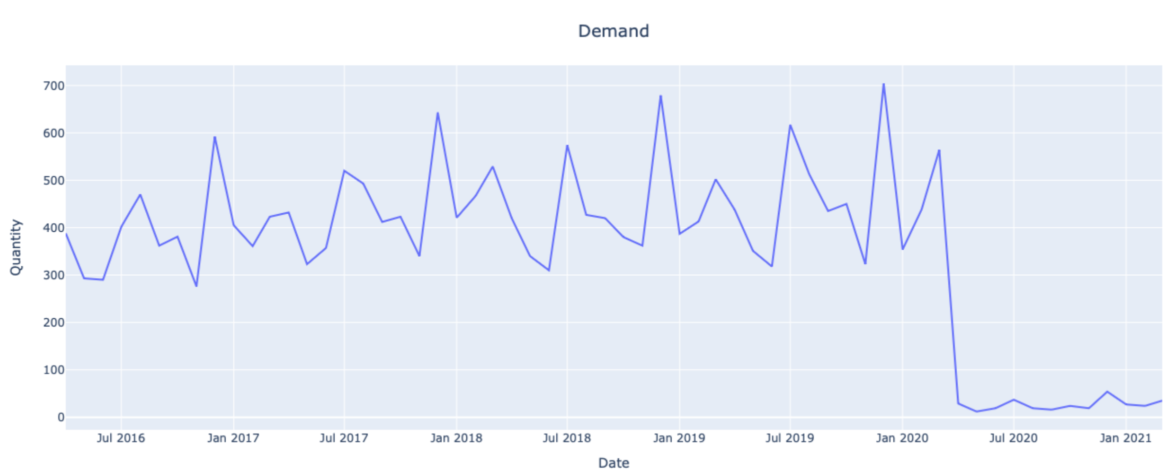
A. Data Acquisition and Understanding the Demand

Any exercise in optimisation of ordering for an optimal stock needs to predict data as a primary step. For this, it was important to acquire data from the vendor for as many years as we could.

We received data from Apr'16 to Apr'22.

Data obtained:

ME 308_Data



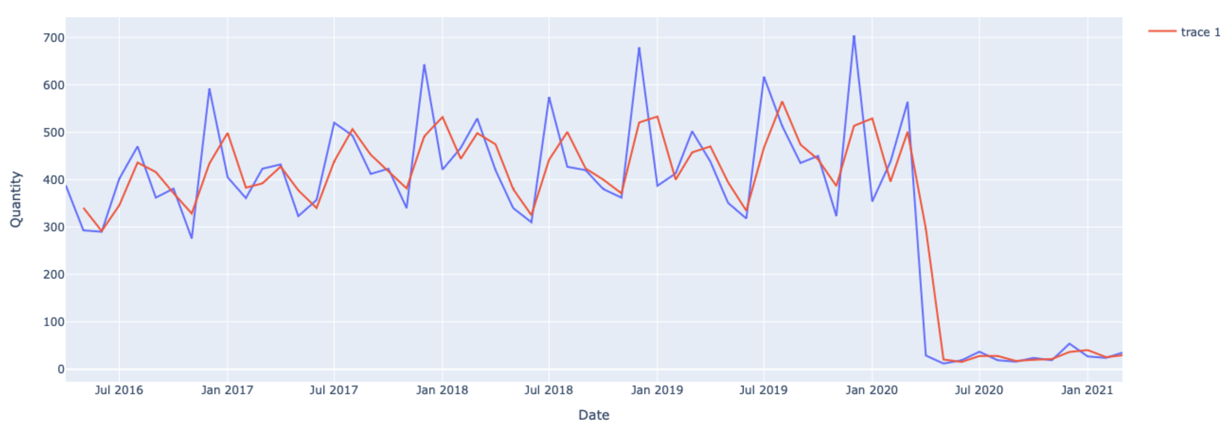
- Peaks of demand observed in December in 2017, 2018, 2019
- A comparable smaller peak observed in March
- Huge dip in demand in month of June and November
    - Due to Vacating of campus
    - Onset of winter, sales of t-shirts go down as compared to winter clothes
- 2020 shows a steep decline in demand due to COVID-19

B. Demand Prediction

The COVID-19 data for the year 2020-2021 created anomalies in data prediction. Hence it was removed for prediction analysis and the data for the year 2022 was considered as 2021 data which was quite normal. The training of data was performed on 2016-2020 and 2021 data was used as the testing data. Then using all of the data from 2016-2021, predictions were made for the year 2022 which are actually for 2023.

Forecasting Models

Moving Average:



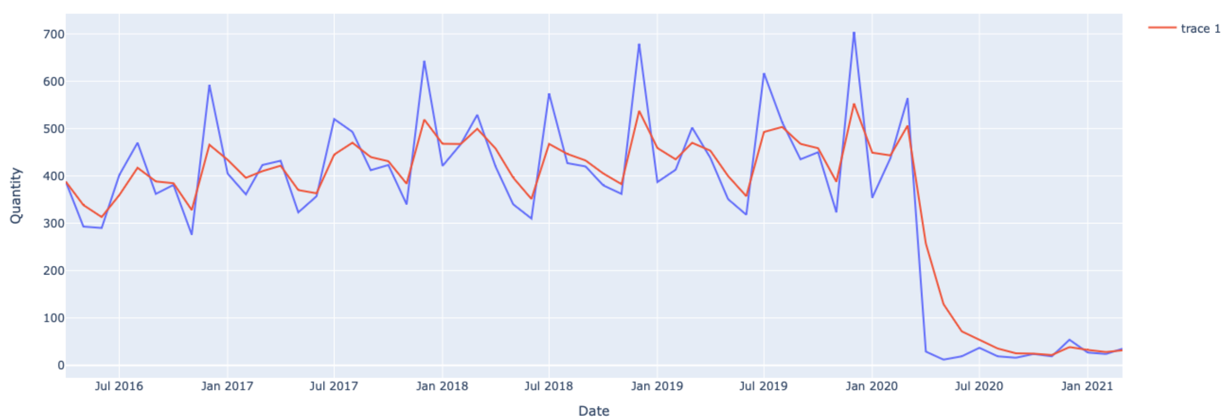
- The moving average uses a window size to compute average for the next reading
- Various window sizes were used and their errors were calculated:

Window	Error

2	2497.5
3	3159.5
4	3197.5
5	3378.6
6	3432.83
7	3796.85

- Error is minimum for window size = 2
- As visible in the graph, this isn't able to catch the peaks very clearly
- Even the peaks occur at a lag

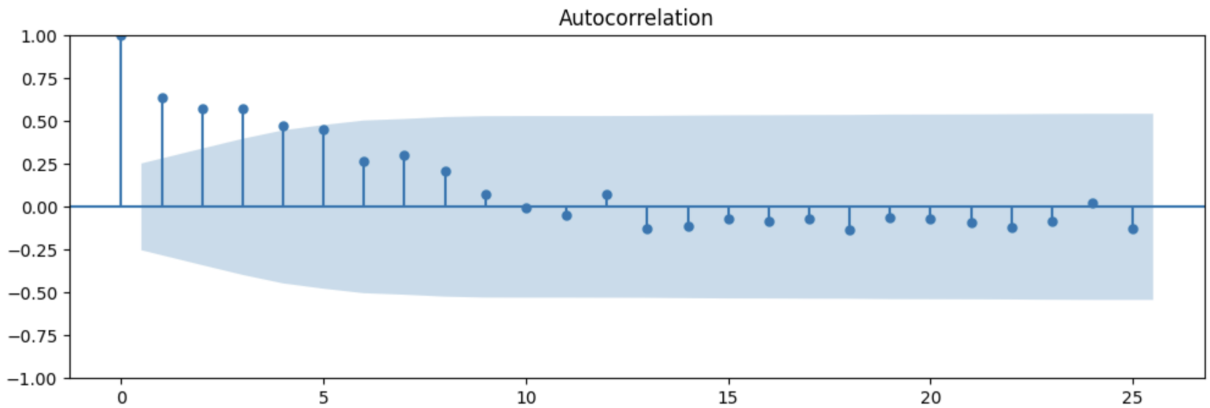
Exponential Moving Average:
Since we expect a repetition of 12 months, the parameter COM can be related as 1/(1-COM) = 12 => COM = 0.916

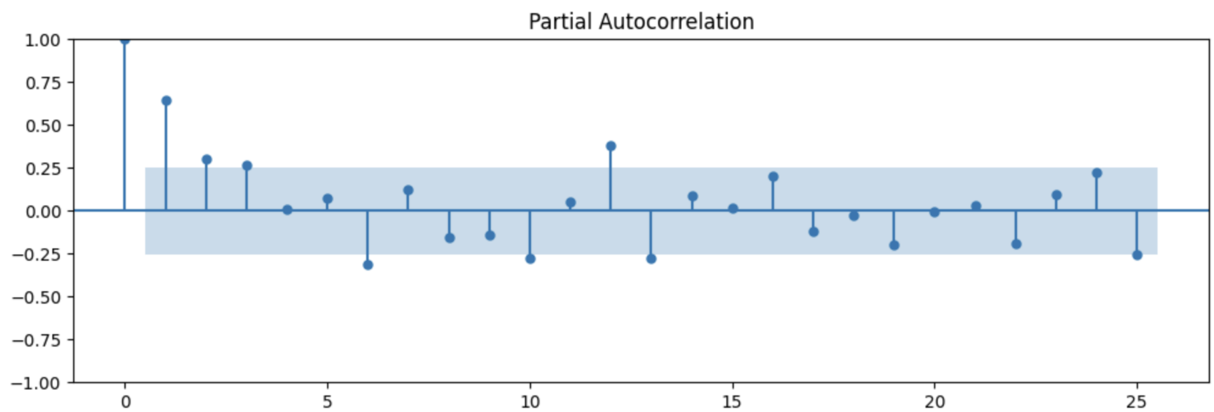


- As it can be seen, the EMA corrects the lags as compared to MA but the peaks aren't being captured properly.

ARIMA:
Adfuller test:
- Indicated that the data is non-stationary.
- Even after doing the seasonal first difference, it remained stationary.

The data during the COVID-19 peak year was removed to carry out the forecasting.
- Data became stationary on the first hand itself.





The autocorrelation and partial autocorrelation plots were used to find out the p (AR value), d (differencing), q(MA value) values to fit into the ARIMA model.

Results: The optimization results failed to converge leading to failure of the model

```
/usr/local/lib/python3.9/dist-packages/statsmodels/base/model.py:604: ConvergenceWarning:
Maximum Likelihood optimization failed to converge. Check mle_retvals
```

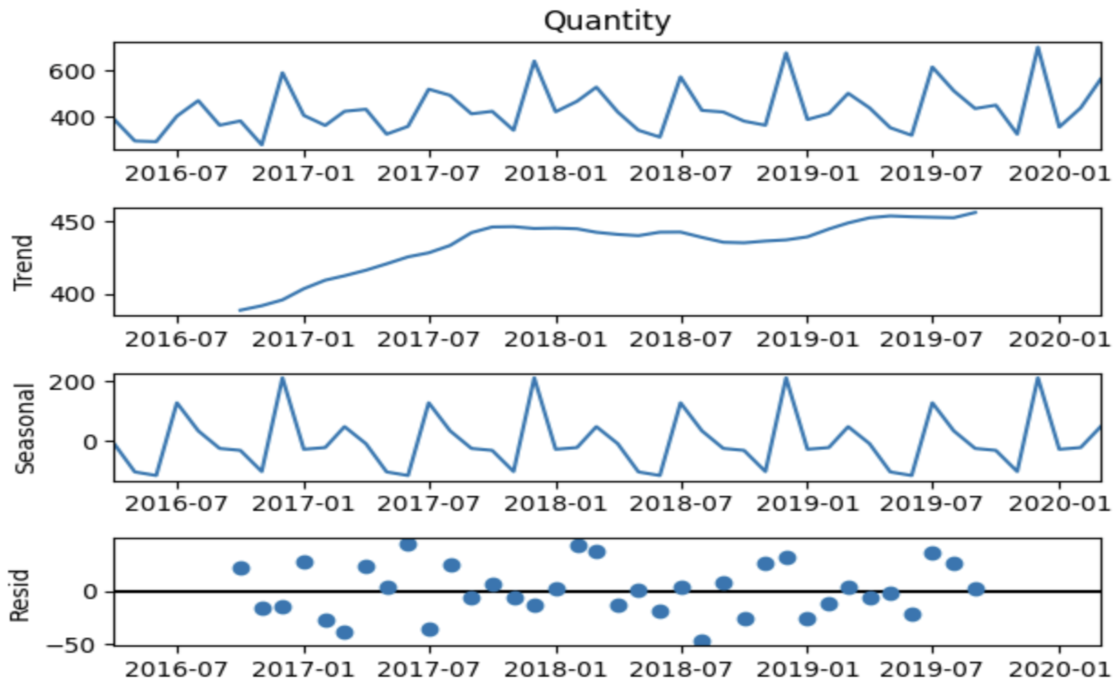
Since regressive models weren't working to carry out forecasting with problems such as identification of peaks, lags, convergence failure. We turned to Deep Learning.

Colab link of the analysis:
https://colab.research.google.com/drive/1nstXQRrHQNTEk-9-DD3I6bghPPk5hZuS?usp=sharing

LSTM:

LSTM stands for long short-term memory networks, used in the field of Deep Learning. It is a variety of recurrent neural networks (RNNs) that are capable of learning long-term dependencies, especially in sequence prediction problems.

<u>Seasonal decomposition:</u>



- Trend : Increasing
- Seasonality: Present

Adam Optimizer along with MSE error was used in the model for convergence.

<u>Training loss</u>:

The error reduced significantly after training for 50 epochs.

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[<matplotlib.lines.Line2D at 0x7fbeb52efb20>]
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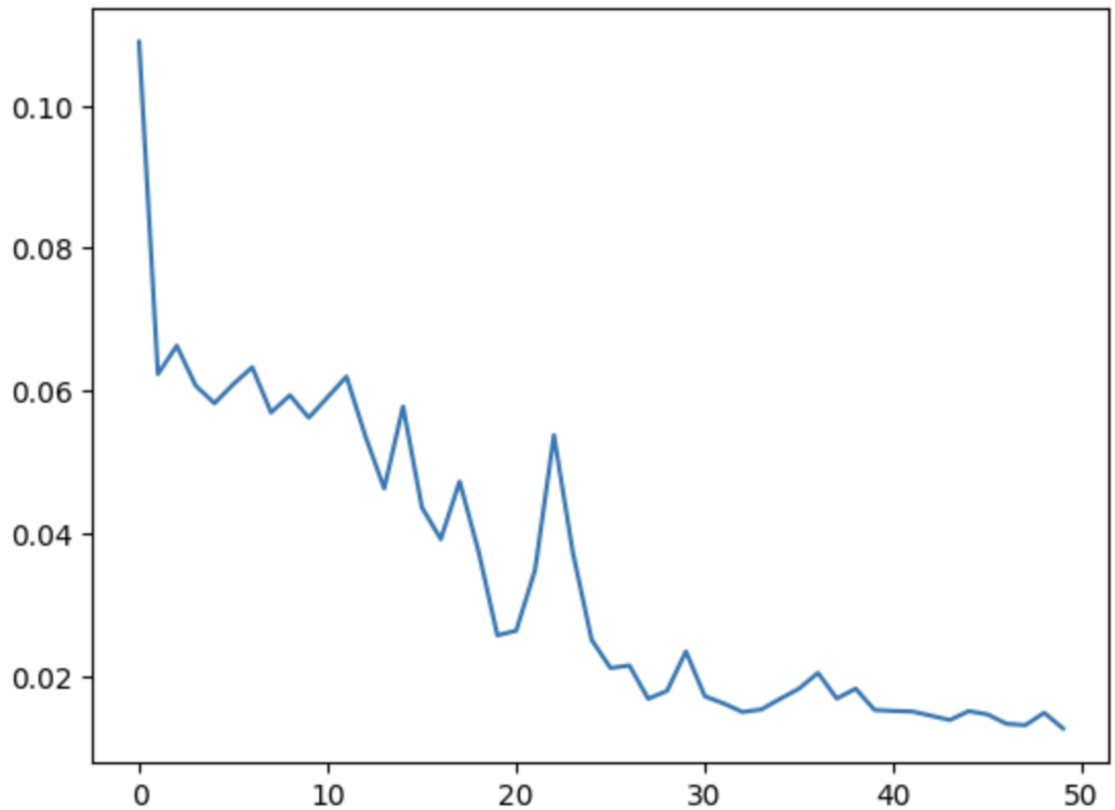
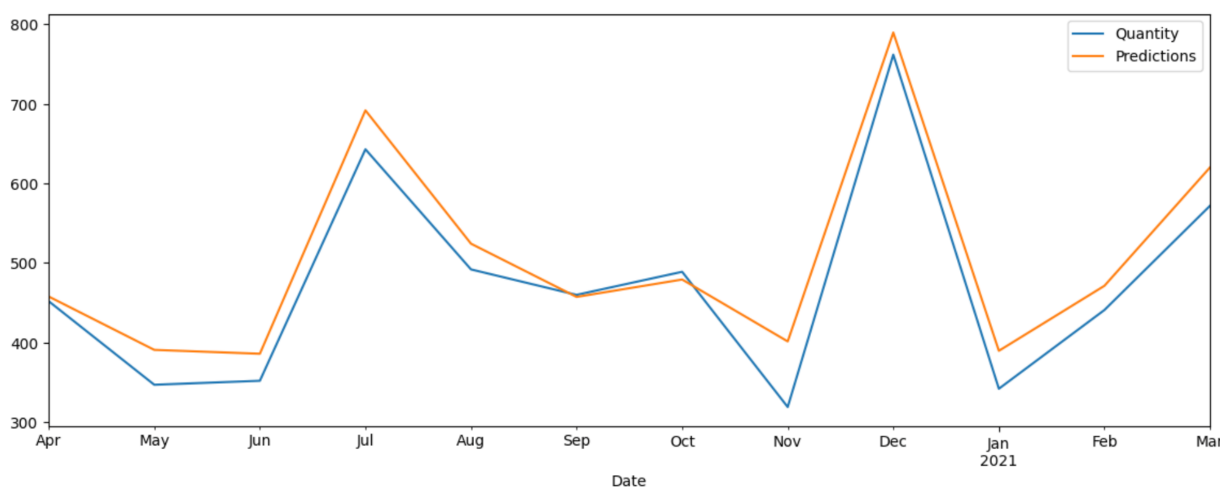


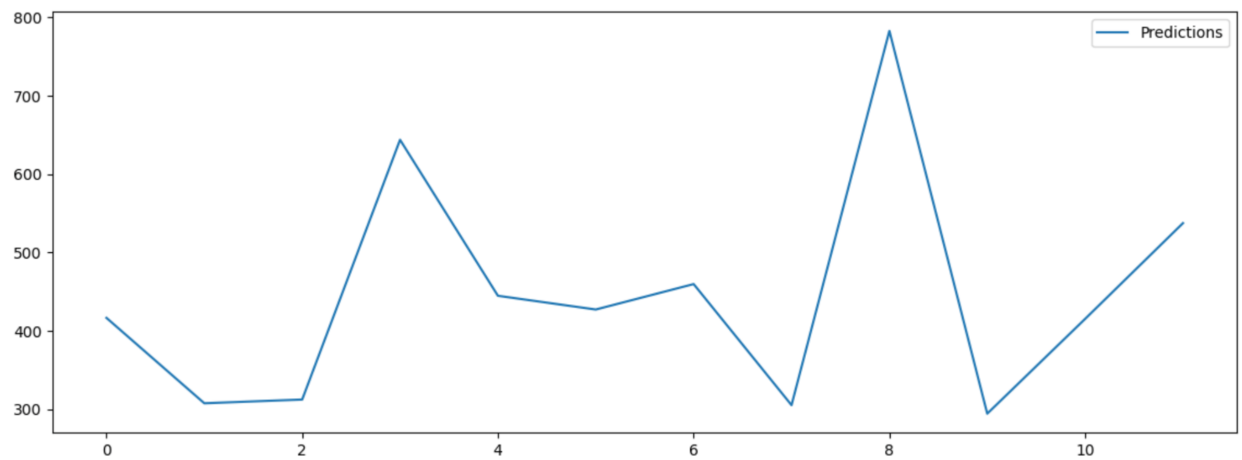
Results:



- The LSTM model seems to work very accurately, it is able to identify the peaks very closely.
- Hence we choose this model for forecasting our t-shirt business.

- A factor of safety of 5% was used since the predicted demand was over the actual quantity in most of the months.

<u>Demand Prediction for 2023:</u>



<u>Colab link of the LSTM analysis:</u>
https://colab.research.google.com/drive/1j1QvJwDy9U_XcpulQUWSky2oOKslEN9h?usp=sharing

C. Choosing an Appropriate Optimisation Model

Once the data has been predicted accurately by our LSTM model, and the vendor knows a very good guess of how much Tshirt demand is expected in the upcoming 12 months, it is important to choose an optimisation model that uses this data to determine how much and when orders should be placed for t-shirts so that the total holding costs are minimized (and there is no deadstock either!) A detailed study of many models was performed, some standard ones of which are summarized below :-

- **Economic Order Quantity (EOQ)**: A model that determines the optimal order quantity that minimizes total inventory costs.
- **Reorder Point (ROP)**: A model that calculates minimum inventory level at which a new order should be placed for no stockout.
- **Just-in-Time (JIT)**: A model that focuses on reducing inventory levels by synchronizing production and delivery with demand.

- **Periodic Review**: A model that orders inventory at fixed intervals based on inventory levels at the time of review.

However, these methods are usually applicable to industries where the product demand is more or less uniform throughout the year. The T-Shirt business, as we discovered through data analysis, is very seasonal in its demand.

'Part Period Balancing' can be a useful inventory optimization model to consider for seasonal demands. Seasonal businesses often experience fluctuating demand and may require higher inventory levels during peak periods to avoid stockouts, while minimizing excess inventory during off-seasons to avoid carrying costs. Part period balancing takes into account these demand fluctuations by dividing the seasonal period into smaller intervals and balancing inventory levels across them. This approach can help ensure that inventory levels are optimized for both high and low demand periods, reducing the risk of stockouts and excess inventory. Additionally, part period balancing can help businesses maintain better control over cash flow by reducing the need to tie up capital in excess inventory during off-seasons.

D. Part Period Balancing as a Solution

The Part Period Balancing Model is a scheduling technique used in manufacturing or production contexts to optimize the allocation of production resources such as labor, machinery, and materials in order to reduce production costs while increasing efficiency.

It's a form of inventory control system that's used to figure out the best order amounts and reorder points for products with fluctuating demand and lead times. It is a lot-sizing strategy that minimizes the absolute difference between ordering and carrying expenses for a single item. It determines the order interval to be the number of periods that best match the overall carrying expenses with the fixed ordering cost of that period.

A fundamental unit of PP (Part-Period) is employed in this technique. When one component is saved for one period, the value is one PP, and the sum of all PP values determined for each period is an accumulated PP. When the carrying cost of accumulated inventory exceeds the order cost, the amount of scheduling order is determined.

To simplify these computations, a common figure for lot sizing known as EPP (Economic Part-Period) is employed. This value, meaning that the accumulated PP is over the order cost, is calculated by means of the following formula:

$$\text{EPP Value} = \frac{\text{Order Cost}}{\text{Inventory Carrying Cost}} = \frac{\text{Order Cost}}{\text{Inventory Carrying Rate} \times \text{Unit Cost}}$$

Example illustrating the application of a PPB Model :

Week no.	**Demand**
Week 1	18
Week 2	30
Week 3	42
Week 4	5
Week 5	20

Set up cost =$ 80/order
Holding cost = $ 2/item/week
Economic part period = Set up cost / Holding cost = 80/2 = 40

Week no.	**Part period**
Week 1	0
Week 1 , 2	0 + (30*1) = 30
Week 1 ,2,3	0 + (30*1) + (42*2) = 114

Since the absolute difference of the accumulated part period and economic part period for 3 weeks (1,2,3) is greater than the absolute difference for 2 weeks (1,2), 1st lot will be of week 1 , 2 and demand = 18 + 30 = 48.

Week no.	Part period
Week 3	0
Week 4	0 + (5*1) = 5
Week 5	0 + (5*1) + (20*2) = 45

Since the absolute difference of accumulated part period and economic part period for 3 weeks (3,4,5) is less as compared to absolute difference for 2 weeks (3,4) , 2nd lot will be of week 3 , 4 and 5 and demand = 42+5+20 = 67.

Thus , according to PPB Model , order will be placed for 2 lots :

- Order 1 of 48 (Fulfilling demand of week 1 ,2)
- Order 2 of 67 (Fulfilling demand of week 3 ,4 and 5)

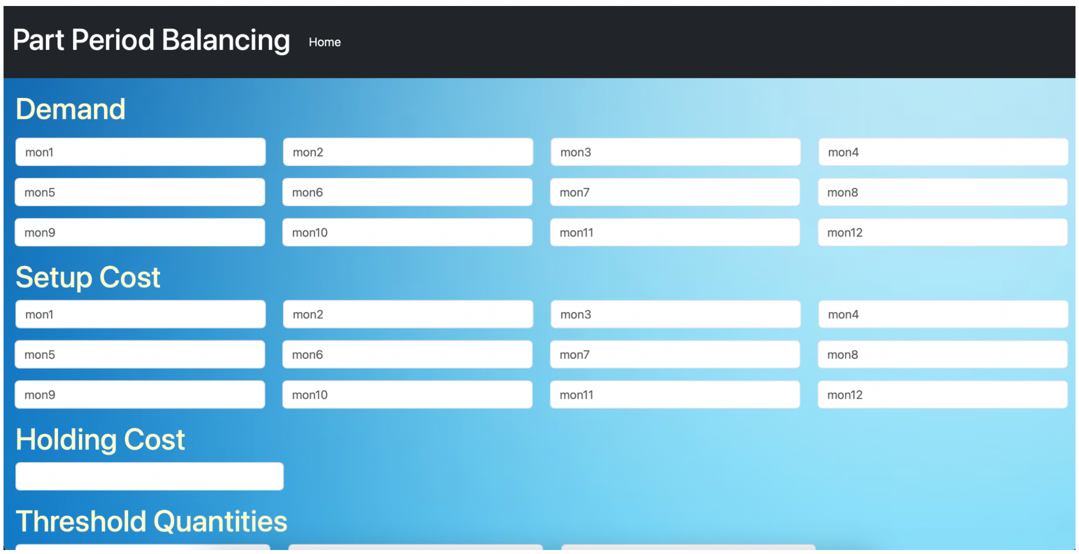
E. Modifications to Part Period Balancing

We had adjusted the Part Period Balancing Model to include the variable SETUP COST and DISCOUNTS provided by the manufacturer to vendors for a big order of T-shirts. This has been accomplished by specifying a dynamic holding cost for the computation of EPP. We have also added the notion of order-based discounts. The more the number of T-Shirts bought in a single order, the greater the discount. This is seen in the code snippet image attached to the report. This makes the code more realistic and easier to use for the real-world vendor, allowing them to lower total holding costs and maximize sales and earnings.

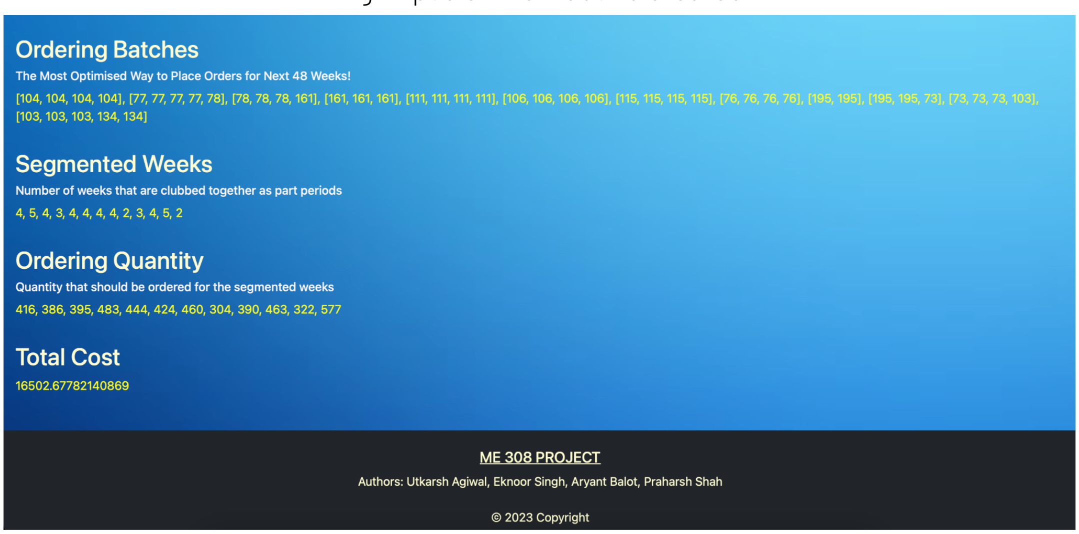
Along with the Part Period Balancing explained in the above section, the discounting model was incorporated with everything being automated.
Colab link of the code:
https://colab.research.google.com/drive/1xYsF7kbAn-aJE_L6FEssNZQv4C26B3jx?usp=sharing

F. Automation and Web Application

The process of Part Period Balancing (with Discounting) for the Mapping Inventory model for T-Shirt business was automated using a Python script, which was utilized to create our basic web application, which vendors may easily use. It takes as inputs the setup cost (cost per order), holding cost (cost to store a t-shirt per unit time), and predicted demand to provide a simple order summary (quantity and time) for the whole year ahead. The algorithm-based online software also considers bulk order discounts provided by manufacturers. This decreases the cost of storing even a big stock and must thus be included when running the PPB model for stock inventory computation.



A glimpse of the website created



Github link of the application: https://github.com/UtkarshAIITB/ME-308_Project

Impact and Limitations - Inventory model in t - shirt business can have a no. of impact on the financial performance of the business. Some of them are listed below:

- Better inventory management - An inventory model in a t-shirt business can manage its inventory levels more effectively. Using various forecasting techniques, the business can predict demand and adjust its inventory levels accordingly, reducing the risk of stockouts or overstocking.
- Lower cost - Effective inventory management can also assist the t-shirt business in lowering its costs. Avoiding overstocking allows the company to avoid tying up cash in extra inventory, while avoiding stock outs allows the company to avoid lost sales and the costs associated with fast delivery or hastened manufacture.
- Improved cash flow - Using inventory model in a t-shirt business can also help improve the cash flow thus enabling the business to reinvest in growth initiatives, pay down debt, or return capital to shareholders.
- Improved customer service - Using the right inventory model in a t - shirt business can help fulfill the customers requirements and lead to customers satisfaction thus leading to repeat business and positive word-of-mouth referrals.
- Improved forecasting - A t-shirt business can increase its forecasting accuracy over time by utilizing an inventory model. This allows the company to better predict demand trends and modify its production and inventory levels accordingly, resulting in more efficient operations and improved financial performance.performance.

Limitations - Optimising t-shirt inventory management problem can be challenging for a no. of reasons including:

- Forecasting demand - Accurately predicting demand (based on historical data and/or guesstimation) for t-shirt designs and sizes can be difficult, especially when dealing with seasonal trends or sudden changes in consumer behavior.
- Adapting change - Rapid changes in consumer demand or the introduction of new products can require quick adjustments to inventory levels, which can be challenging for businesses with limited resources. Outdated designs can go unsold creating problems leading to stocking of the inventory.

- Data accuracy - A t-shirt business must have access to precise and trustworthy data regarding sales, inventory levels, and manufacturing capacity in order to properly execute an inventory model. The model may not be useful if the company lacks this data or has erroneous data.
- Inventory obsolescence - Using an inventory model can increase the risk of inventory obsolescence. If the company overestimates demand or fails to sell specific designs, the extra inventory may become obsolete or unsellable, resulting in increased expenditures and revenue loss.

Results and Conclusions

- Oftentimes, the local vendors order for their inventory at the end of the month without any proper forecasting predictions or sort, which boosts up their cost, excess stocks due to discount offerings and such problems. What we did to solve this problem was to break the demand for each month into weeks and make a lot of sizing for weeks.
- As visible in the segmented weeks section of the website, optimized solutions require vendors to order after 3 or 4 or 5 weeks and so on.
- Discounting often leads to a lot of reduction in costs, we observed that discounting conditions presented by default provide a cost reduction of around 50%.
- The LSTM model was able to capture the demand seasonality very well.
- Lead time is often of physical significance rather than it being of mathematical significance.

Future Scope of Work

1. Incorporation of multiple manufacturers:
   Different manufacturers with different lead times and set-up costs can increase the complexity, but with accurate predictions, the manufacturer with the lowest set-up cost will always win because lead time isn't an important factor if predictions are accurate. As a result, we seldom see manufacturers with varied set-up costs across marketplaces, and PPB is often done for a single manufacturer. It is advisable to use linear programming for this. At present, there are almost no papers dedicated to multiple manufacturers in PPB.

2. Incorporating sustainability and social costs:
   Researchers might investigate how the PPB model can be updated to integrate environmental and social costs associated with inventory management as sustainability becomes an increasingly significant factor for corporations.
3. Incorporating vendor to consumer discounts:
   Large sales or discounts (which are presently not available to IITB students) have an impact on the vendor's total profit and put pressure on inventories. As a result, such instances must be factored into the model, which may be accomplished by employing a probabilistic demand model.
4. Empirical Studies:
   More empirical studies are needed to test the effectiveness of PPB models in real-world settings. Case studies and tests can be conducted by researchers to assess the efficacy of the PPB model in various sectors and settings. Typically, due to the market's set-up and holding costs for a specific good, the PPB produces results that demonstrate that the naive method of ordering every month by local vendors is correct. What is not considered is that splitting the month into weeks and then clubbing orders is useful, as done in the project.

References

1. Production and operation analysis by Steven Nahmias and Tava Lennon Olsen
2. https://intellipaat.com/blog/what-is-lstm/
3. https://plotly.com/
4. https://studylib.net/doc/9681314/lot-sizing—part-period-balancing
5. https://hrcak.srce.hr/file/427729

Project code and files:

https://github.com/UtkarshAIITB/ME-308_Project.git

Contribution

- Data Collection : Praharsh(200100143), Aryant Balot(200100035)
- Forecasting : Utkarsh Agiwal (200020154)
- Model Research : Praharsh(200100143), Aryant Balot(200100035)

- PPB and its automation with discounting: Eknoor Singh(200020051), Utkarsh Agiwal (200020154)
- Web Application : Eknoor Singh(200020051), Utkarsh Agiwal (200020154)
- Future Scope Research : Eknoor Singh(200020051), Utkarsh Agiwal (200020154)
- Poster : Utkarsh Agiwal(200020154), Eknoor Singh(200020051), Aryant Balot(200100035), Praharsh(200100143)
- Report : Utkarsh Agiwal(200020154), Eknoor Singh(200020051), Aryant Balot(200100035), Praharsh(200100143)