Inventory Pooling (Risk Pooling): A Centralized Warehouse Approach to Inventory Optimization.

By Group 02:

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Executive Summary:

This project investigates inventory optimization for a meal delivery company that operates across multiple cities with various fulfillment centers. The primary objective is to address challenges related to stockouts and overstocking while efficiently managing perishable raw materials. Given the high uncertainty in demand patterns, the project explores the potential of inventory pooling (risk pooling) as a solution to reduce these issues, improve procurement planning, and enhance operational efficiency.

The company faces significant challenges in inventory management due to unpredictable demand, especially considering that raw materials are replenished weekly and are perishable. Effective inventory management is crucial for maintaining a balance between supply and demand while minimizing costs, such as storage and waste.

The study focuses on three key areas:

1. ABC Classification – To categorize and prioritize high-value products.
2. Risk Pooling – To explore the benefits of centralized inventory management across multiple locations.

Key findings include:

- ABC Classification Analysis: Identified high-revenue products (A category) that require closer attention in terms of stock levels and placement. Approximately 78.98% of revenue comes from 43.14% of SKUs in the A category.
- Risk Pooling (Inventory Pooling): By consolidating inventories across all locations, we observed a significant reduction in maximum stock levels and safety stock. For Meal ID 1062 (beverages, Italian cuisine), the combined inventory policy reduced the stock level from 1,23,946.2 to 1,15,689.5, and the safety stock from 28,901.41 to 18,183.37. This reduction highlights the benefits of inventory pooling in a high-uncertainty demand environment. The overall efficiency of the supply chain improves when demand uncertainty across locations is mitigated by pooling inventories.
- Advantages of Centralized Inventory: Centralized inventory pooling reduces inventory holding costs, minimizes the risk of overstocking or stockouts, and improves operational efficiency by simplifying procurement and distribution processes.
- Service Levels and Risk Management: The client set a target service level of 95%, ensuring adequate stock levels to meet customer demand while maintaining cost-efficiency.

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INTRODUCTION:

The client is a meal delivery company that operates in multiple cities. They have various fulfillment centers in these cities for dispatching meal orders to their customers. The client wants to order inventory which reduces stock outs and stock over. The replenishment of most raw materials is done on a weekly basis and since the raw material is perishable, procurement planning is of utmost importance. The Client is facing problems with inventory management due to high uncertainty in demand distribution or patterns. Inventory management plays a crucial role in the supply chain by balancing demand and supply while minimizing costs. Businesses often face challenges such as overstocking, stockouts, and managing uncertainties in demand. Centralized warehousing, coupled with inventory pooling, is a solution to these problems. This project examines the role of inventory pooling for a meal delivery service business.

The scope and study of project are:

- To perform ABC classification to identify high-priority items.
- To implement a risk pooling strategy for inventory optimization.

Research questions:

- How can ABC classification be used to optimize product placement within a warehouse to reduce picking time and improve operational efficiency and identify High priority, low priority items?
- What is the effect of risk pooling on optimum stock level and safety stock?

LITERATURE REVIEW:

Managing inventory is vital for businesses to balance supply and demand, reduce costs, and avoid issues like overstocking or running out of stock. Poor inventory management can lead to increased expenses, unsatisfied customers, and reduced profits. Based on the Pareto Principle, the ABC analysis is a widely used method to improve inventory management. This principle suggests that a small number of items (Category A) often account for most of the revenue. ABC analysis divides inventory into three groups: **Category A** (high-value items requiring close attention), **Category B** (medium-value items needing moderate focus), and **Category C** (low-value items that are simpler to manage). By focusing on high-priority items, businesses can allocate their resources more efficiently and ensure better inventory control.

Advances in technology and data analysis have made inventory management more effective. Businesses can predict demands and improve decision-making by studying sales data and customer trends. ABC analysis has been shown to help companies identify key products, reduce storage costs, and avoid losses from slow-moving or low-profit items. This method enables businesses to focus on high-value products, optimize their operations, and remain competitive. Overall, the ABC approach provides a simple and effective way to improve inventory performance and profitability.

Model/Methodology:

1. Downloaded the data set
2. Data cleaning
3. Data Exploration
4. Feature engineering
5. ABC classification
6. Risk pooling – Inventory pooling

Results:

Data source:

Kaggle **[Meal Demand Forecasting]**

Data cleaning:

there is meal information data which is having different meal id's information, fulfilment centre information data which is having different locations id's information and train data which is number of orders per week from past 145 weeks.

We merged all data sets for data exploration. Then we checked duplicated rows. We found that there were no duplicated rows in merged dataset.

```
# Check for duplicate rows in the merged_data DataFrame
duplicate_rows = merged_data[merged_data.duplicated()]

# Print the number of duplicate rows
print("Number of duplicate rows:", len(duplicate_rows))
```

```
Number of duplicate rows: 0
```

We checked missing values in all columns, and we found that there were no missing values in each column.

```python
# Check for missing values in the merged_data DataFrame
missing_values = merged_data.isnull().sum()

# Print the number of missing values for each column
print("Missing values per column:\n", missing_values)
```

```
Missing values per column:
 id                     0
week                   0
center_id              0
meal_id                0
checkout_price         0
base_price             0
emailer_for_promotion  0
homepage_featured      0
num_orders             0
category               0
cuisine                0
city_code              0
region_code            0
center_type            0
op_area                0
dtype: int64
```

We checked the data types in all columns and found every column in the correct data type format.

```
merged_data.info() #checking data/variable type
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 456548 entries, 0 to 456547
Data columns (total 15 columns):
 #   Column                 Non-Null Count   Dtype  
---  ------                 --------------   -----  
 0   id                     456548 non-null  int64  
 1   week                   456548 non-null  int64  
 2   center_id              456548 non-null  int64  
 3   meal_id                456548 non-null  int64  
 4   checkout_price         456548 non-null  float64
 5   base_price             456548 non-null  float64
 6   emailer_for_promotion  456548 non-null  int64  
 7   homepage_featured      456548 non-null  int64  
 8   num_orders             456548 non-null  int64  
 9   category               456548 non-null  object 
 10  cuisine                456548 non-null  object 
 11  city_code              456548 non-null  int64  
 12  region_code            456548 non-null  int64  
 13  center_type            456548 non-null  object 
 14  op_area                456548 non-null  float64
dtypes: float64(3), int64(9), object(3)
memory usage: 52.2+ MB
```

Dropped unnecessary columns for analysis like id, city code, region code, operation area.

```
# Dropping  the unnecessary colums from merged data
merged_data = merged_data.drop(['id', 'city_code', 'region_code','op_area'], axis=1)

# Display the first few rows of the updated dataset
merged_data.head()
```

	week	center_id	meal_id	checkout_price	base_price	emailer_for_promotion	homepage_featured	num_orders	category	cuisine	center_type
0	1	55	1885	136.83	152.29	0	0	177	Beverages	Thai	TYPE_C
1	1	55	1993	136.83	135.83	0	0	270	Beverages	Thai	TYPE_C
2	1	55	2539	134.86	135.86	0	0	189	Beverages	Thai	TYPE_C
3	1	55	2139	339.50	437.53	0	0	54	Beverages	Indian	TYPE_C
4	1	55	2631	243.50	242.50	0	0	40	Beverages	Indian	TYPE_C

We checked data size. There are 4,56,548 rows or samples and 11 columns.

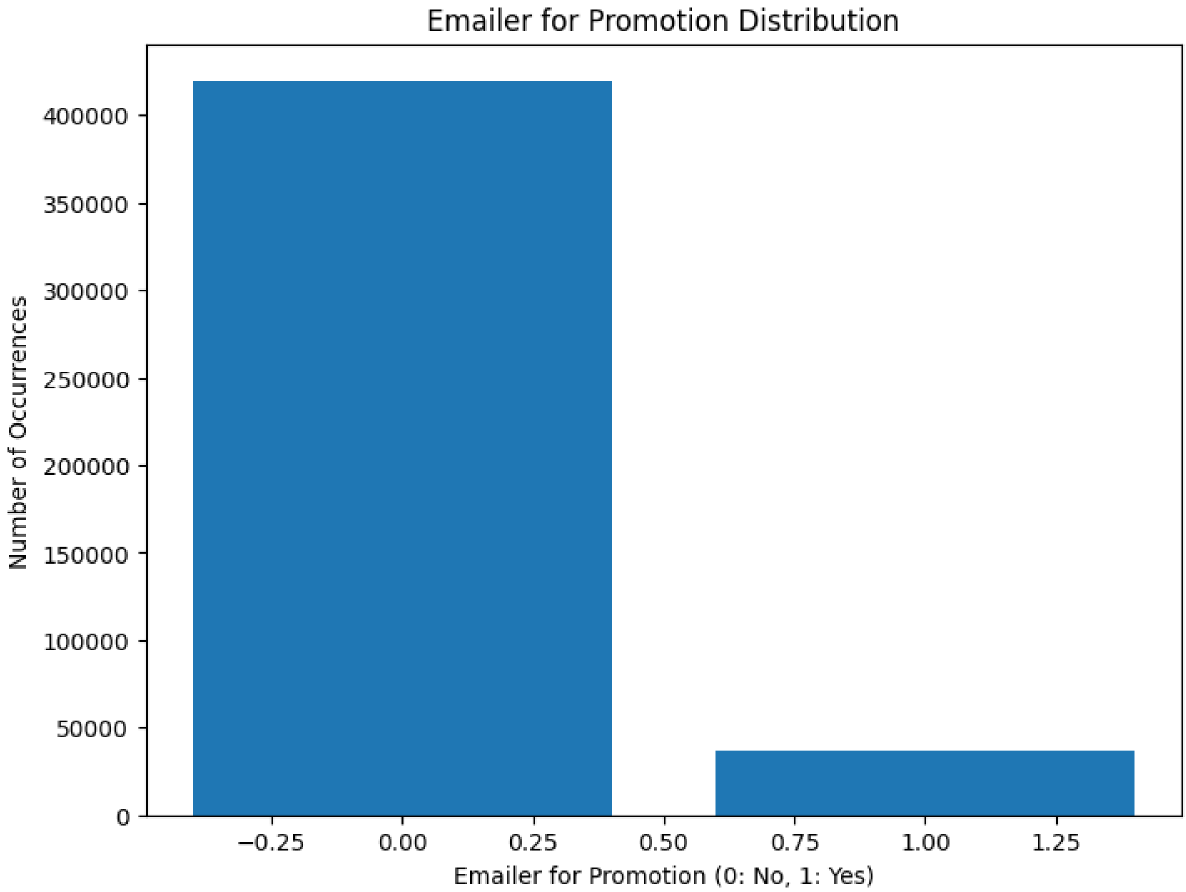
```
merged_data.shape
```

```
(456548, 11)
```

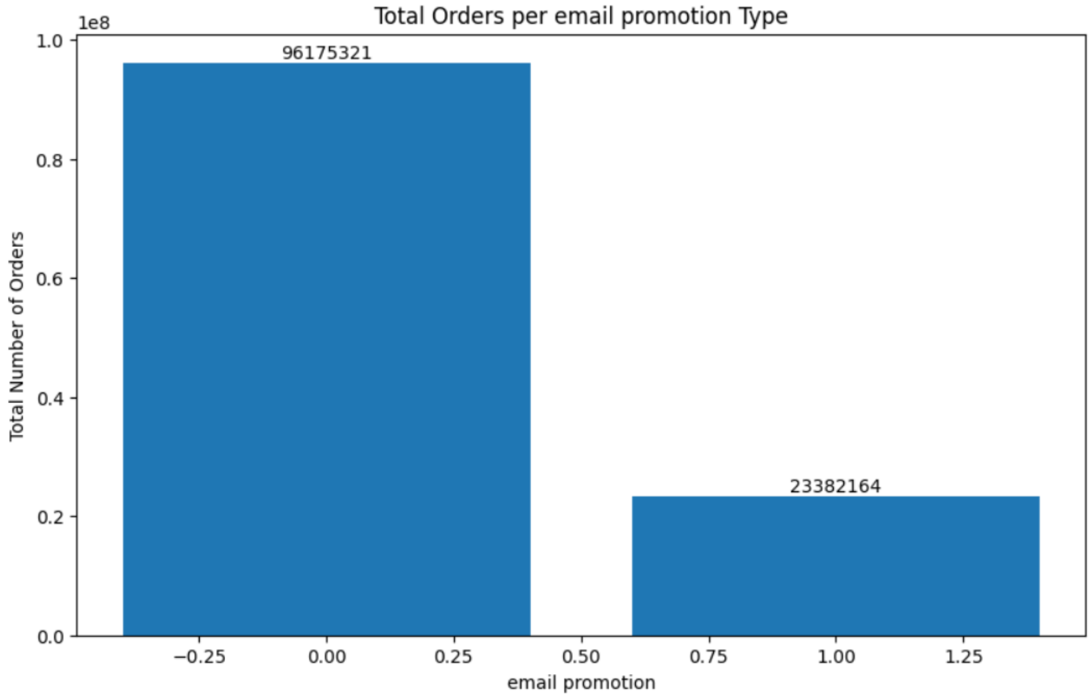
EXPLORATORY DATA ANALYSIS:

Client sent emails to 419498 customers to get orders as marketing promotion and did not send emails to 37050 for promotion. We observed that for most of the customers, client sent emails for promotion.

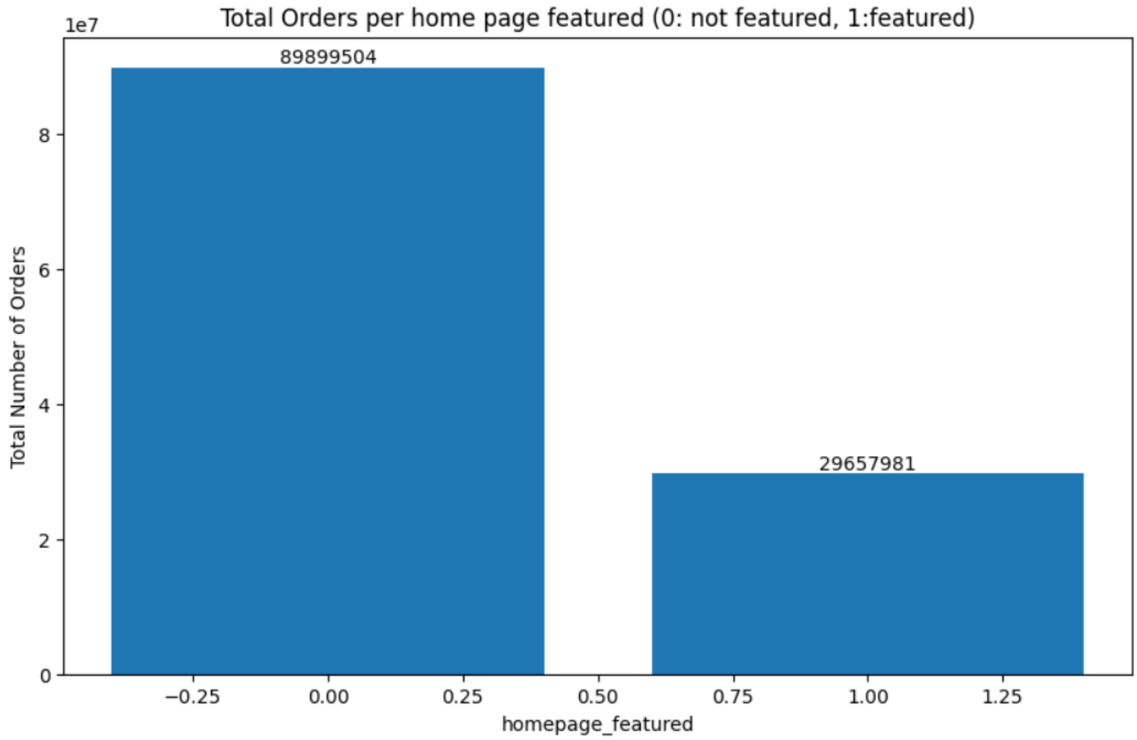
emailer_for_promotion	count
0	419498
1	37050



We observed that most of the orders around 96175321 orders come from email promotion and 23382164 orders got from no email promotion. This indicates that email promotion plays a crucial role to get meal orders from customers.

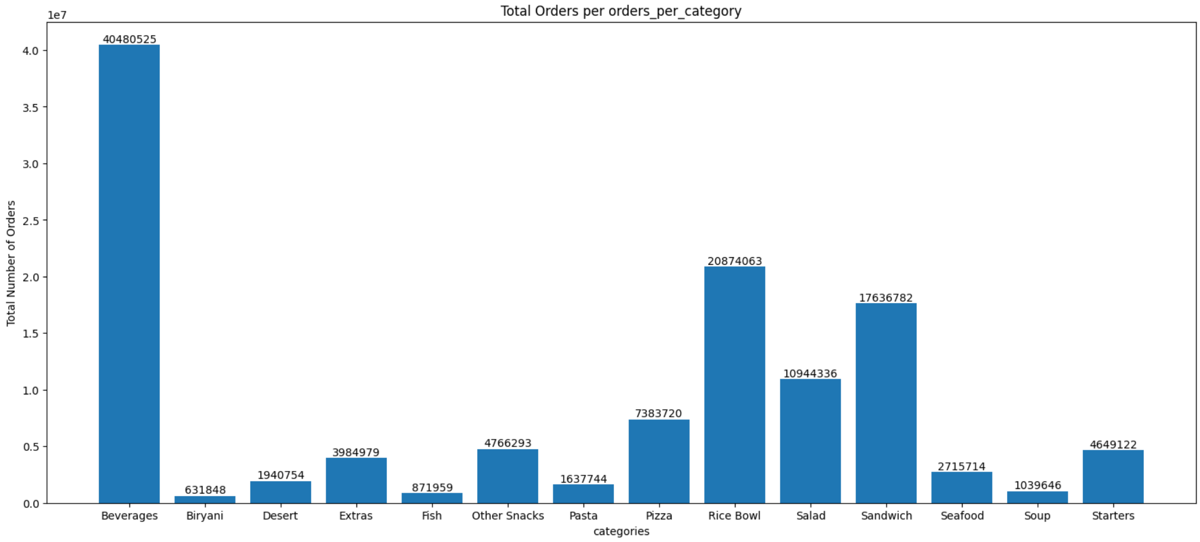


The client added some meal on website as home page featured. We observed that most of the orders 89899504 from non-home page features meals , which indicates this home page feature did not effect to get orders from customers.



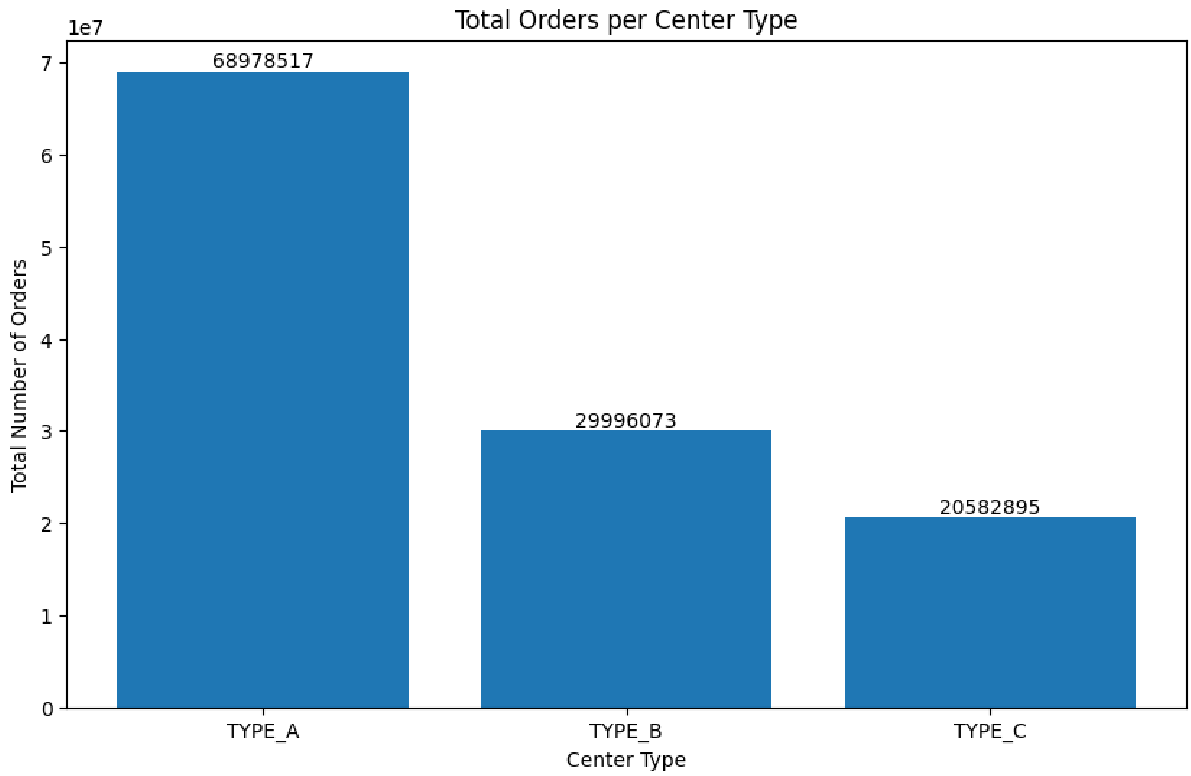
We can see from below chart that most of client orders came from beverages as top category. Rice bowl is the second most popular item. Sandwich is third most popular item in our menu. Salad is the fourth most popular item.

Biryani, Fish and soup is the least popular items in our menu.

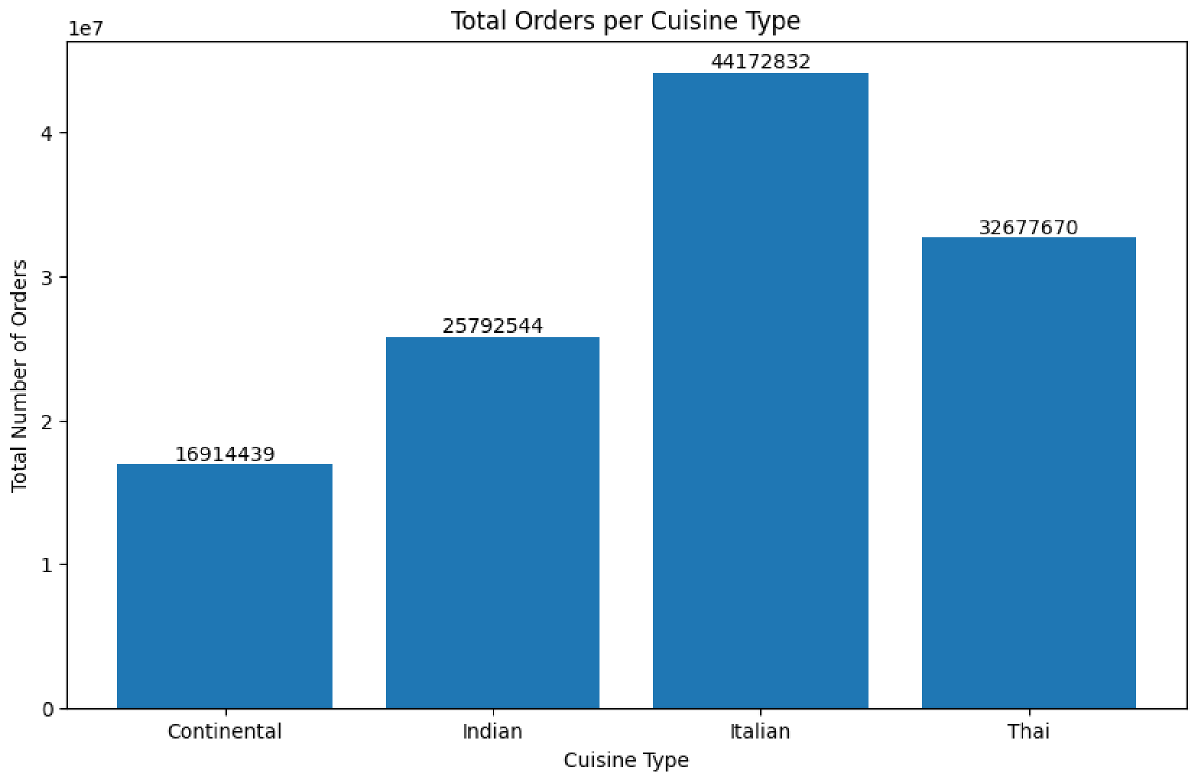


Client categorised centres based on some condition or assumption, but we are not sure about this and could not found in meta data.

We can see type-A centre is the top one in getting orders from customers.

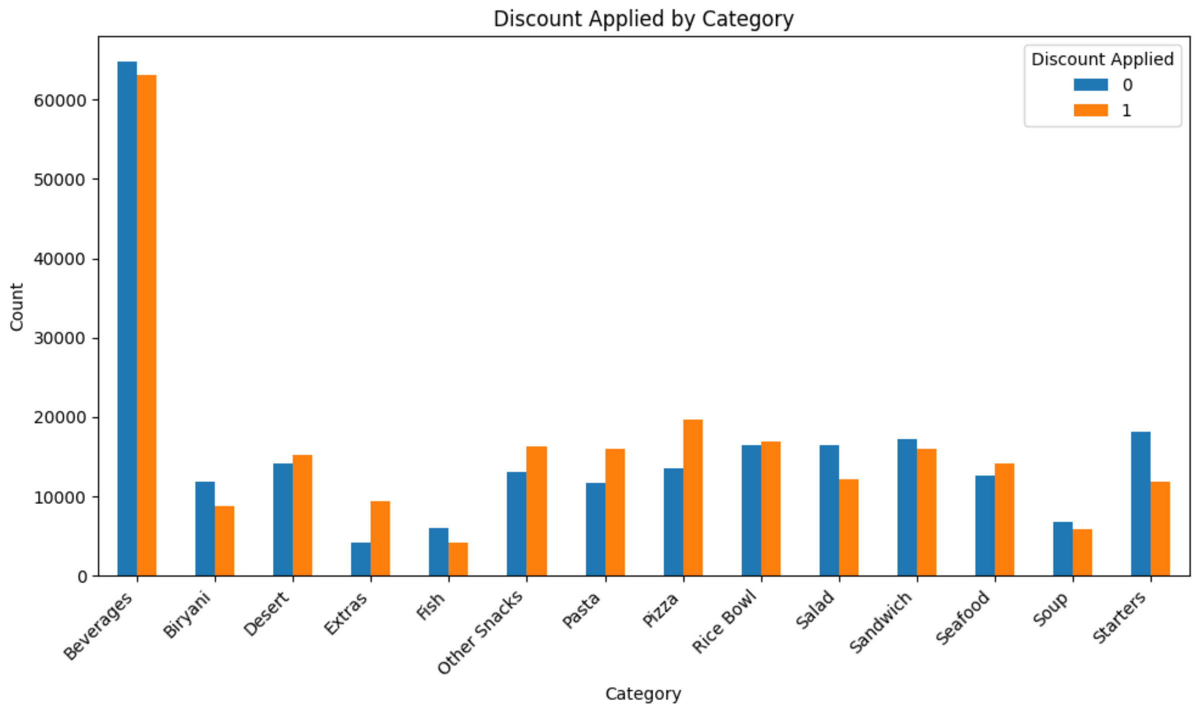


We observed that most of client orders 44172832 are from Italian cuisine type and least orders from continental cuisine type.



We got more orders in dessert, extras, other snacks, pasta, pizza categories for giving discounts. It indicates that giving discounts to these categories, can increase orders or get more orders in future.

Sandwich, salad, biryani and starters are not affected by discounts much but still significant to increase orders from customers.



Feature engineering:

we created new variable called discount, which is initially not given in dataset. But we understand data and difference between checkout price and base price, that is wherever the checkout price is less than base price in row, which indicates that client had given some discount to customers.

We created new column called revenue by multiplying checkout column with number of orders. This is for ABC classification analysis purpose.

ABC CLASSIFICATION ANALYSIS:

We performed ABC classification analysis on SKUs to see what the highest revenue SKU's and lowest revenue SKUs are.

A category: We got 22 SKUs which is around 43.14 % out of 51 SKUs indicating that these are most important and high revenues SKUs for client business. Total revenue from A category is 25211570413, Which is around 78.98 % of total revenue.

B CATEGORY: We got 15 SKUs which is around 29.41 % out of 51 SKUs indicating that these are normal and medium revenue SKUs for client business. Total revenue from B category is 5058644162, which is just 15.85 % of total revenue.

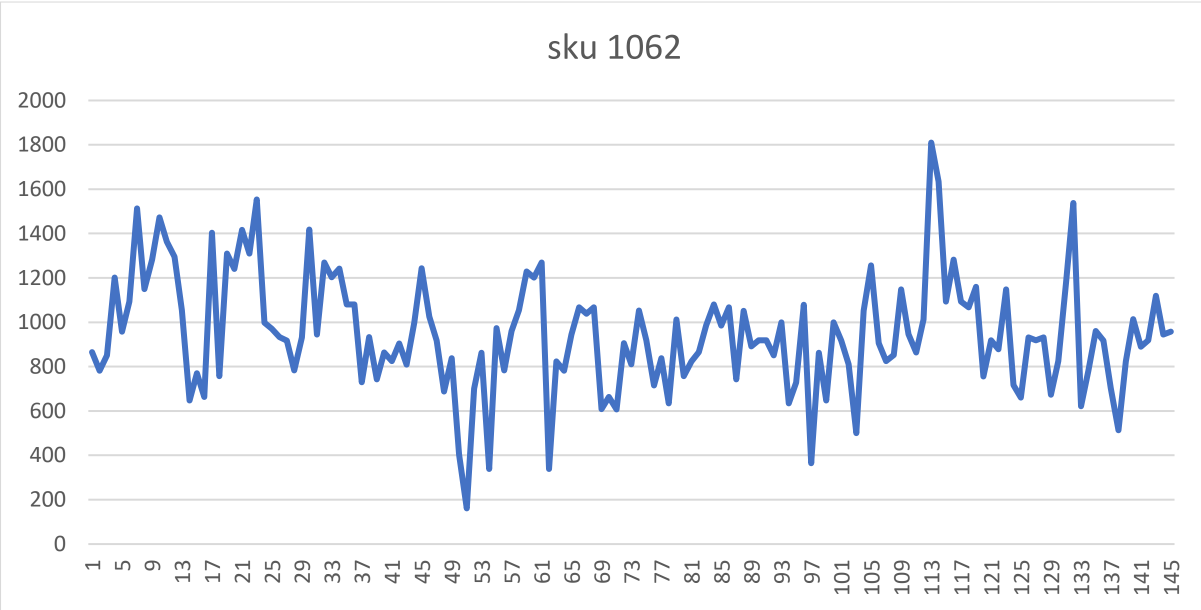
C CATEGORY: We got 14 SKUs which is around 27.445 % out of 51 SKUs indicating that these are not important and very small revenue SKUs for client business. Total revenue from B category is 1652556464, which is just 5.18 % of total revenue.

Total revenue is 31922771040.

Place A category products in warehouse where we can move easily for pick up and load, because this is high revenue and most frequent items. Rest items place after A category.

RISK POOLING ANALYSIS:

We identified that all SKUs demand pattern is High uncertainty and stationery.



So, ordering Inventory by forecasting is not appropriate method as data is having high uncertainty patterns. ordering inventory by simply historical distribution of each SKUs is not suggested. In this scenario, we are suggesting risk- pooling (inventory pooling) is appropriate method for order or materials or inventory management. We have total 51 SKUs and 77 locations. So, for simplicity, we have taken one SKU which is meal id - 1062 (Beverage's category – Italian cuisine) for risk pooling effect analysis.

The replenishment of raw materials is done on weekly basis and since the raw material is perishable in nature and business has continuity which means multiple periods for inventory policy required.

Assumption: client did not provide information for lead time and periodic review of inventory in weeks and order placing. So, we assumed that lead time is 1 week, review period is 2 weeks and target service level is 95% as most of the companies target this service level.

Lead time	1
Review period	2
Working days	52
Service level	95%

Calculations:

Combined inventory policy for meal id 1062:

Maximum stock level is 1,15,689.5 and safety stock level is

18183.37 for combined demand for all locations -1062.

S (order level upto S)	115689.5
Safety stock	18183.37

Independent locations inventory policy:

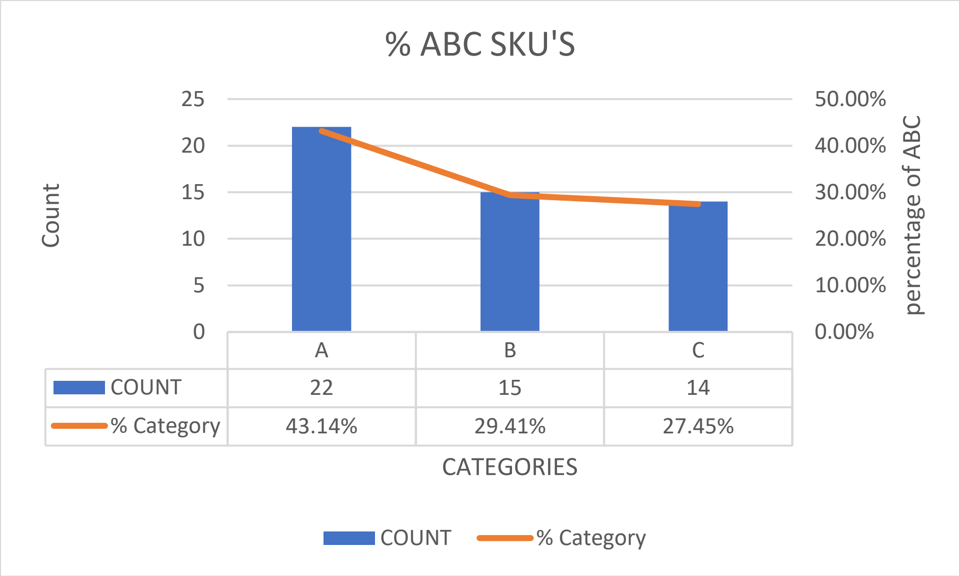
Total Location wise inventory policy for meal id 1062, for S(maximum stock level) is 1,23,946.2 and safety stock is 28901.41

Total S	123946.2
Total SS	28901.41

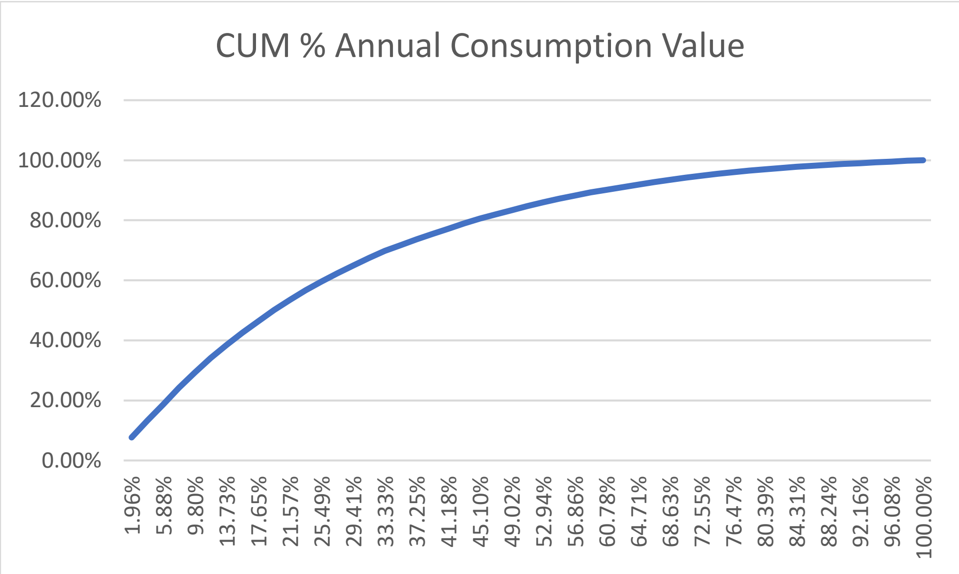
We clearly observed that maximum stock level from 123946.2 is reduced to 115689.5, which is almost 97,506.13 difference between them, when we did combine inventory policy calculation.

We clearly observed that safety stock is also reduced from 28901.41 to 18183.37, which is almost 95044.79 difference between them, when we did combine inventory policy calculation.

It is indicating that risk pooling is the most effective way for inventory management and order management when demand pattern is high uncertainty and stationery.



	A	B	C
COUNT	22	15	14
% Category	43.14%	29.41%	27.45%



Future research:

Perform risk pooling analysis on all other SKUs and see results.
Perform Machine learning or deep learning for demand forecasting

Conclusion:

Finally, we concluded that ABC classification analysis to know what are high revenue SKUs in an organization and placing which SKUs in warehouses are crucial for any organization. When demand is high uncertainty risk pooling-inventory pooling is most efficient for inventory policy or order policy or inventory management.

References:

Silaen, B. R., Nasution, M., & Muti'ah, R. (2023). Implementation of the ABC Analysis to the Inventory Management.

Appendices:

Meta data

Weekly Demand data (train.csv):

Variable	**Definition**
id	**Unique ID**
week	**Week No**
center_id	**Unique ID for fulfillment center**
meal_id	**Unique ID for Meal**

Variable	Definition
checkout_price	Final price including discount, taxes & delivery charges
base_price	Base price of the meal
emailer_for_promotion	Emailer sent for promotion of meal
homepage_featured	Meal featured at homepage
num_orders	(Target) Orders Count

fulfilment_center_info.csv:

Variable	Definition
center_id	Unique ID for fulfillment center
city_code	Unique code for city
region_code	Unique code for region

Variable	Definition
center_type	Anonymized center type
op_area	Area of operation (in km^2)

meal_info.csv:

Variable	Definition
meal_id	Unique ID for the meal
category	Type of meal (beverages/snacks/soups….)
cuisine	Meal cuisine (Indian/Italian/…)