# A Quantitative Study to Analyse and Optimise the Inventory and Sales for an Automobile Parts Retailing Shop

## A Mid-Term Report for the BDM capstone Project


Submitted by

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# Contents

# 1 Executive Summary and Title

This capstone project focuses on Kusum Enterprise (KE Henceforth), a Tata Motors Authorised Retailer situated at Chandrakona Road (CKR Henceforth) in West Bengal. Owned by Mr Joy Prakash Loadha, this B2C business deals with motor parts of automobiles. Situated at a place which is not only positioned along the convergence of NH 14 and NH 116B and the Kharagpur-Bankura-Adra railway line, CKR is also a hotspot of timber and potato business on a large scale. Thus, shops like KE will always be in demand at such a position to serve heavy vehicles/vehicles.

However, there are some major challenges faced by KE. An immediate concern is the problem of less profitability even after the location being, aforementioned, hotspot. Another issue that affects KE is poor inventory management. This has lead to a significant amount of dead stocks and impacts the demand fullfilment. Thus, these issues seem to be intertwined with each other.

To address these issues, various analytical approaches shall be used. Using descriptive statistics can help us understand the summary of the attributes in the dataset. Methods utilising Python packages shall be important to examine the trends in purchases and sales. Pattern and correlation detection amongst various attributes and categories of products can help us asses the demand and turnover rates in order to find which particular categories are adding the most to the sales; also tell us about the stocks which can be compromised with.

The expected outcome could significantly improve the efficiency of stock inventory management. By aligning the available stock with the demand for goods, KE can reduce deadstocks and heighten profitability.

# 2 Proof of Originality of Data

## 2.1 Letter from the Organisation

**KUSUM ENTERPRISE**

-: AUTHORISED RETAILER :-
TATA Motors Spare Parts, T.V.S., JPSL, G.S., Banco etc.
-: UNDER TAKING :-
Cabine & Load Body Building & Repair.
Chassis Frame, Front Axlebeam
& Engine Overhauling & Repair etc.

TATA MOTOR

*Prop.- Joy Prakash Lodha*
CHANDRAKONA ROAD
Satbankura
Paschim Medinipur
STD : 03227 283101
Mob.- 9434000839 / 9474444703
email-kusum_enterprise@hotmil.com

Ref. No. ..........................

Date. 08/01/2024.

Subject: Proof of Originality of data for BDM Project

I, Joy Prakash Lodha, confirm that the data provided to Satyaki Goswami for his BDM project is original, authentic, and consensual. The data has been collected from our business, "Kusum Enterprise".

I have personally overseen the data collection process and can vouch for its accuracy and confidentiality. The data reflects the actual state of our business operations.

Thank You,
Regards

KUSUM ENTERPRISE
TATA
TATA RETAILER

*Figure 1: Letter of Consent from Mr Lodha, Owner of KE*

## 2.2 Images from the Organisation


*Fig 2: Mr Lodha was kind enough to provide multiple appointments from his busy schedul*


*Fig 3 : Multiple visits were made to collect data over the time*

*Fig 4: Interaction with Mr Lodha on the first visit*

2.3 Interaction video with the Owner

For LINK: **Click Here**

## 3 Metadata and Descriptive Statistics

For Dataset LINK: **Click Here**

The collected data spreads over April, 2023 to December, 2023. The data was computerised and was provided by the owner over time. The dataset consists of Product Particulars, Category, Opening Balance (including Quantity, Cost, Total Value), Inwards (Purchase; including Quantity, Cost, Total Value), Outwards (Sale; including Quantity, Cost, Total Value), Closing Balance (including Quantity, Cost, Total Value), and Month of Sale.

Further, the dataset was divided into two separate sub-datasets - one where only those items are kept which were sales is not zero and another where only those items which where purchase value over the time of April-December, 2023 is not zero. Going by the first dataset (DS1 Henceforth), the Outwards Value ranges from ₹12.72 to ₹2252756.52 with a mean of ₹21543.36. (Fig 5).

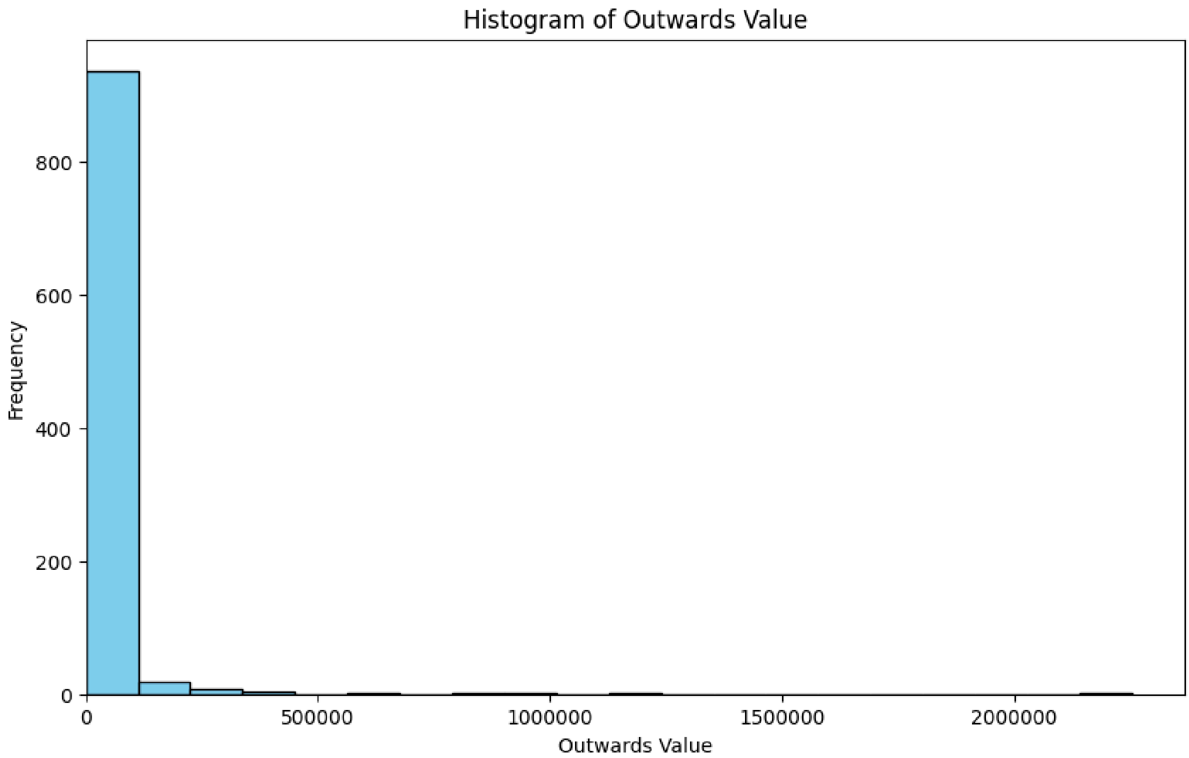



*Figure 5: Histogram of Outwards Value; the frequencies past ₹500000 are low*

Considering the second dataset (items with Inwards Value is not equal to zero; DS2 Henceforth), the expenditure ranges from ₹32 to ₹2086043.02 with a mean of ₹21983.23. (Fig 6). Python package Matplotlib was used for plotting. All the plots and analysis will be cross-verified using LibreOffice as well to maintain the integrity of inferences.

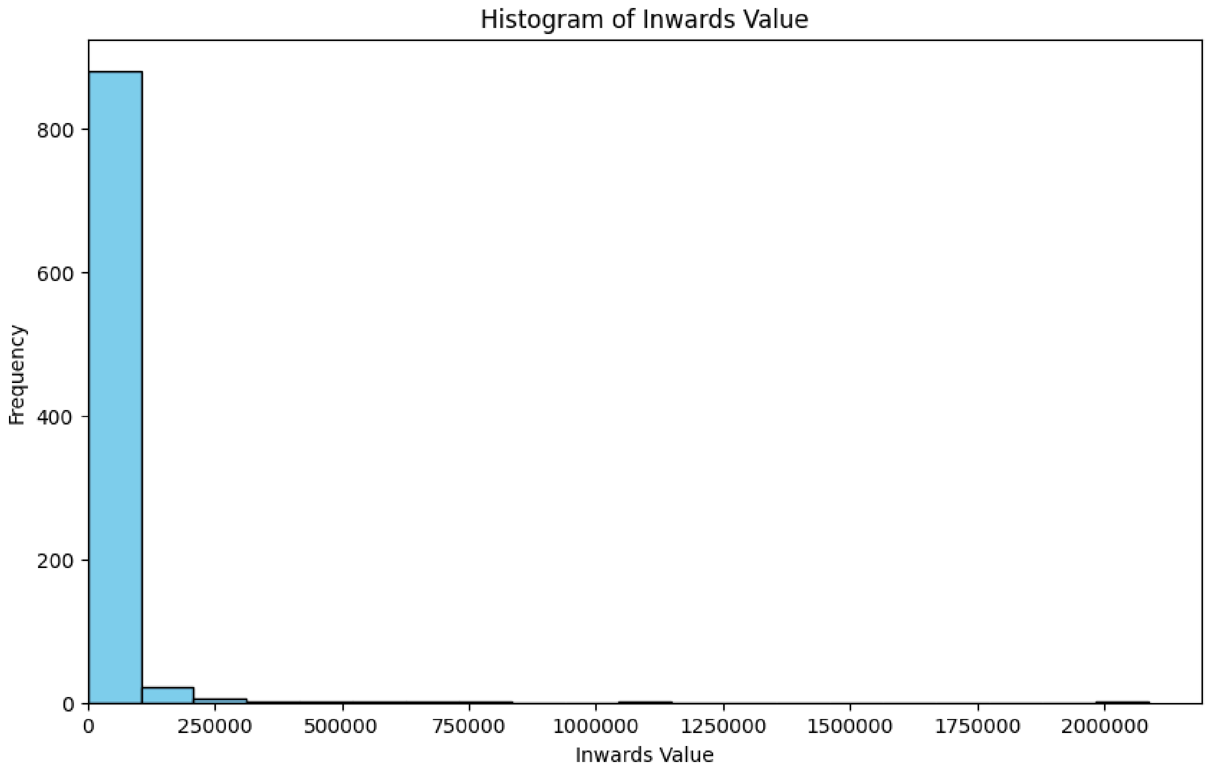
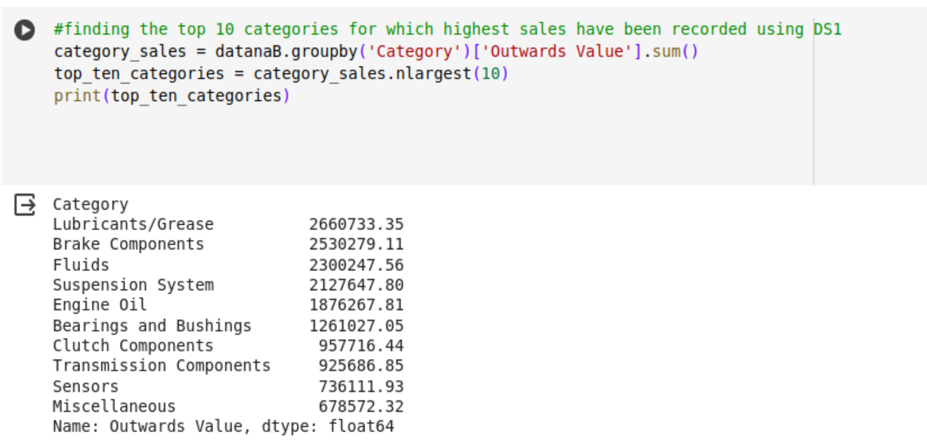



*Figure 6: Histogram of Inwards Value; the frequencies past ₹250000 are low*

Anaysing DS1, it was found that the top five categories that have added the most to sales (not profit) are Lubricants/Grease (₹2660733.35), Brake Components (₹2530279.11), Fluids (₹ 2300247.56), Suspension System (₹2127647.80), and Engine Oil (₹1876267) respectively. (Fig 7).



```
#finding the top 10 categories for which highest sales have been recorded using DS1
category_sales = datanaB.groupby('Category')['Outwards Value'].sum()
top_ten_categories = category_sales.nlargest(10)
print(top_ten_categories)
```

```
Category
Lubricants/Grease          2660733.35
Brake Components           2530279.11
Fluids                     2300247.56
Suspension System          2127647.80
Engine Oil                 1876267.81
Bearings and Bushings      1261027.05
Clutch Components           957716.44
Transmission Components     925686.85
Sensors                     736111.93
Miscellaneous               678572.32
Name: Outwards Value, dtype: float64
```

*Figure 7: Top Ten Categories adding to sales from DS1 (Python Code with results)*

From DS2, we found that Suspension System (₹2594128.95), Brake Components (₹2321475.10), Fluids (₹2127343.08) Lubricants/Grease (₹1904282.18), and Engine Oil (₹1540386.02) respectively. (Fig 8).

```
#finding the top 10 categories for which the most expenditure was made using DS2

category_sales2 = datanaC.groupby('Category')['Inwards Value'].sum()
top_ten_categories2 = category_sales2.nlargest(10)
print(top_ten_categories2)
```

```
Category
Suspension System          2594128.95
Brake Components           2321475.10
Fluids                     2127343.08
Lubricants/Grease          1904282.18
Engine Oil                 1540386.02
Bearings and Bushings      1305513.73
Clutch Components           880509.38
Miscellaneous               879937.19
Transmission Components     760809.60
Filters                     695695.49
Name: Inwards Value, dtype: float64
```

*Figure 8: Top Ten Categories adding to Expenditure from DS2 (Python Code with results):*

Another important factor that was obtained from the main data set is that the top five categories which add the most to deadstocks are Suspension System (with 465 unsold particulars), Transmission Components (with 206 unsold particulars), Bearings and Bushings ( with 177 unsold particulars), Clutch Components (with 148 unsold particulars), and Engine Components (with 148 unsold particulars).

## 4 Detailed Explanation of Analysis Method

The dataset was collected over several visits and contains data from April-December, 2023. Majorly Python Notebooks have been used for the analysis. An overview of analysis steps are as follows:

1) The data was first imported into google sheets, followed by its conversion to csv format in order to upload and use it in the Python notebook. The original data was cleaned and organised in a new dataset; which since then has been divided into many subsets based on the nature of analysis. Each dataset is kept safe along with copies.
2) Each attribute has been organised properly and separately. Each column is thoroughly checked for mistakes and each operation on them has been annoted in the Python notebook.

3) EDA has been done in order to understand the nature of; to see which category has the highest sales, which has the lowest. It also helps one understand about the spread of purchase and sale, depicting the most frequently occurring price ranges for both. Not only does it give the idea of the average, but also tells a little bit about the demand. Python notebook has been used to plot the frequency distribution in the form of histogram by resorting to the matplotlib and pandas packages.
4) The ongoing process to study the relationships between various columns has resorted to scatterplots as of now. Scatter plots help us to visulaise the correlations better where we can identify clusters and outliers. Python Package titled matplotlib has come handy in doing these plottings. Line graphs have also helped in depicting trends as of now. More methods are being used for further analysis.
5) Although major analysis is still ongoing, there have been a few interesting insights that has shown up in the initial steps which can help to form final conclusions by the end of this project. Certain findings and insights are presented in the next section.

# 5 Results and Findings

1) It can be seen from (Fig 9). that the scatterplot of top five most profitable components, namely Lubricants/Grease, Engine Oil, Break Components, Transmission Components, and Fluids, form a cluster near the origin. The major components of the custer are Transmission Components, Brake Components, and Engine Oil.
2) One of the proabable inferences could be that there exists a cross-selling opportunity for Transmission Components, Brake Components, and Engine Oil.
3) This cluster might help in better marketing strategies for these three products, given that there sale is also very high.
4) Transmission Components, Brake Components, and Engine Oil might share similar supply chain requirements which can add to better inventory management.
5) Such a clustering can indicate similar market dynamics which influence profitability across diverse product categories. But at the same time, further analysis is needed to make sure that this cluster (and further clusters) are not a result of human error in data analysis.
6) It is also observed that the category Fluids adds to Outlier. There is a chance that outlying product of this category might have a premium pricing compared to others of the same category. Further analysis will add to this inference.

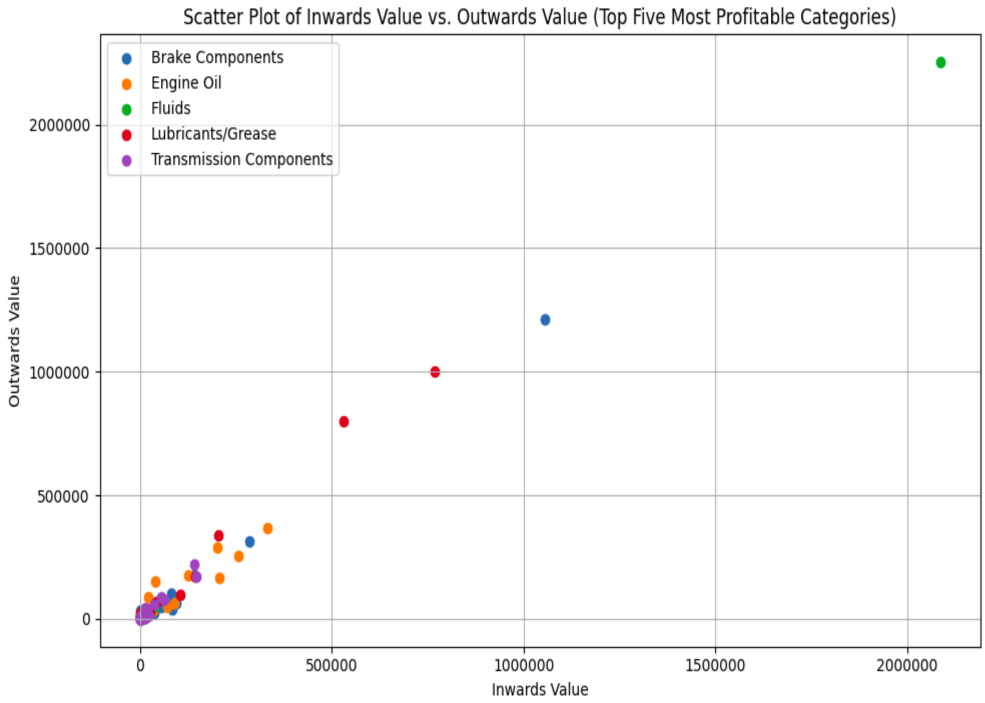



*Fig 9: Scatterplot of five most profitable product categories from KE*

7) From (Fig 10)., we can see that the most profitable months are September, April, October, June, and August respectively. July, on the other hand, goes opposite and takes a huge dip.
8) One possible inference regarding profit being at peak during September could be the fact that September serves as the advent of the festive season. The region celebrates Viswakarma Puja and Durga Puja, among other major festivals like Diwali, in the months of September-December. This might add to higher sales.
9) Another probable inference might be the fact that CKR is a hotspot for Potato business. The sowing period is from mid-September to November while the harvesting starts from December. The whole system would be needing an early preparation and lot of heavy transportation which might add to the sales.
10) The loss in July has to be studied better. Rectifying it can add to the overall profit in future.

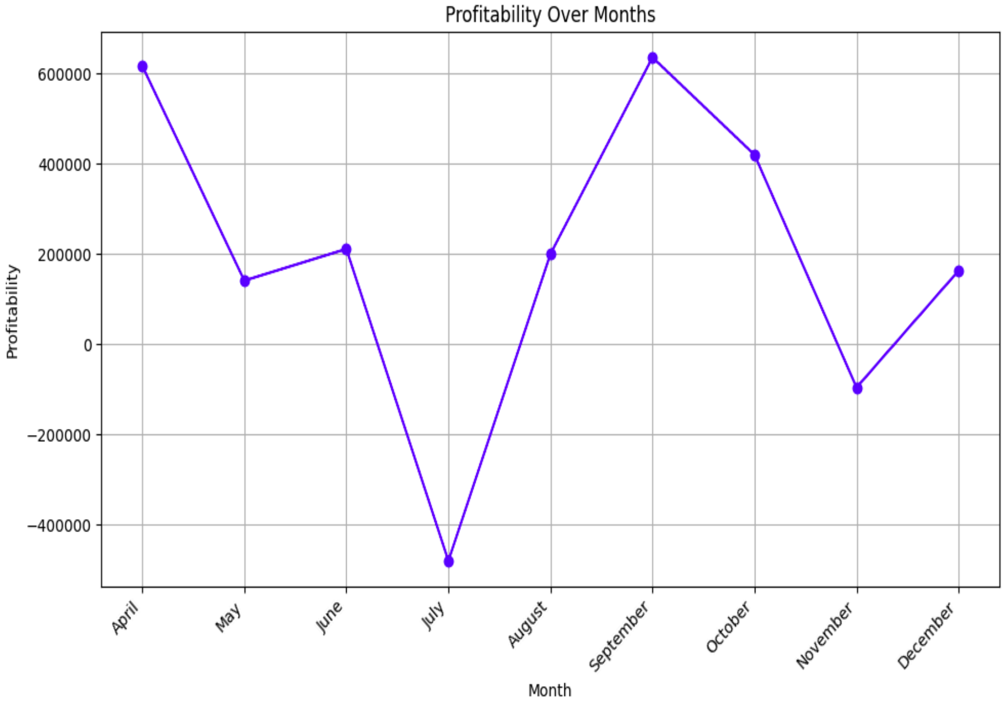



*Fig 10: While September, April, October, June, and Auguts see most profit, July sees the most loss*

Note: The analysis is ongoing and better and more refined inferences as well as concrete conclusions would be provided in the Final Report.