Superstore Sales & Customer Analytics

Objectives:-

The goal of this project is to study sales and customer behavior to understand what drives business performance and where growth opportunities lie. The project begins with **data cleaning** to ensure accuracy and consistency before moving into analysis, forecasting, and customer segmentation. Then, **exploratory data analysis (EDA)** is used to check how sales and profits vary across different customer segments, regions, and shipping modes. Next, a **sales forecast using Prophet** predicts the trend for the next 6 months to help with planning. Finally, **RFM customer segmentation** groups customers based on how recently, how often, and how much they buy. This helps in creating focused marketing and customer retention strategies. Additionally, relevant **business KPIs** were queried using SQL and an **interactive dashboard** was created for visualization and decision-making support. Overall, the project combines data insights with business recommendations to improve profits and strengthen customer relationships.

Data Source:-

The dataset used for this project was obtained from Kaggle – Superstore Dataset. Each row in the dataset represents a unique customer transaction, containing details such as order date, product purchased, quantity, sales value, profit, customer information, shipping mode, segment, and region.

Data Cleaning:-

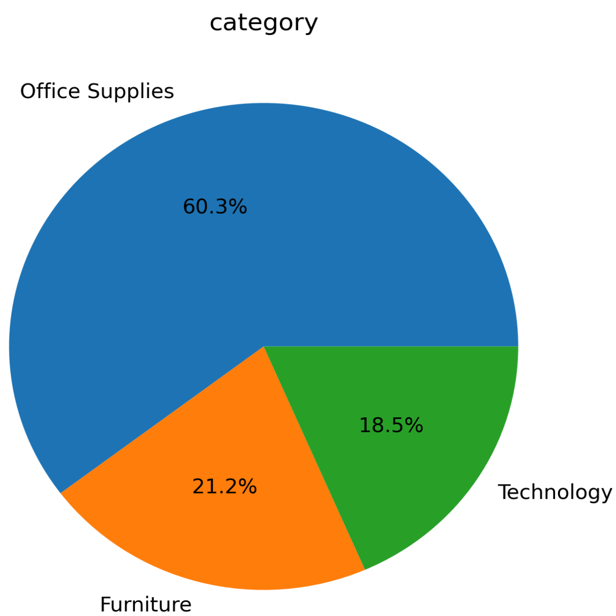
i) Standardization of column names
ii) Checking for null values and duplicates
iii) Checking and fixing incorrect datatypes

The dataset was mostly clean with no missing or duplicate values. There were a few inaccuracies with column datatypes which got fixed. For ensuring consistency, the column names were standardized.

Exploratory Data Analysis (EDA):- (Univariate)

i) Univariate analysis of Categorical columns:-

1. category



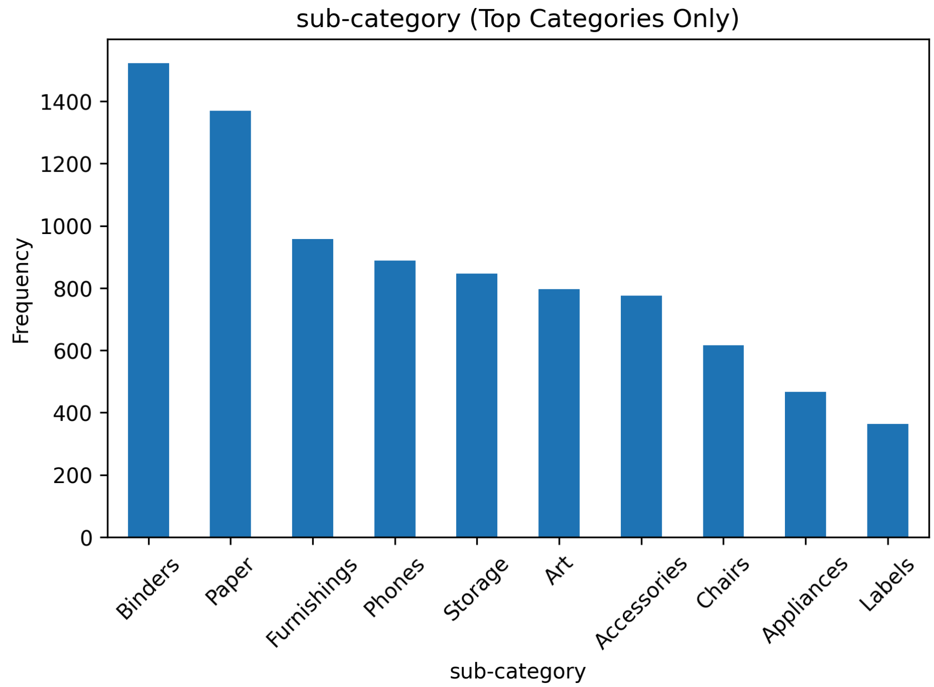
- This feature shows which category a product bought by the customer belongs to.
- There are just 3 unique categories.
- 60.3% of all the products bought throughout the dataset belong to the office supplies category, followed by 21.2% from furniture and the rest 18.5% from technology. This shows that the category distribution has imbalance and is skewed where the office supplies category dominates. It suggests that things like stationary and other accessories which are used in office as well as in everyday life, might be categorised under office supplies possibly explaining why its contribution is the highest. Furniture and technology products might be bought less as people who do online shopping might be skeptical about what is shown and what it will turn out to be.
- There are no missing values
  Recommendations:
  As majority sales are from the office supplies category, it indicates that the promotional strategies like campaigns are already doing its job well. But,

simultaneously if growth efforts are also put in furniture and technology, it will diversify the revenue streams.

Modeling consideration:

One hot encoding shall be done as order doesn't matter here and the cardinality is also low, hence less sparsity.

2. <u>sub-category</u>



- It represents the sub-domain of the category in which the product bought by a customer belongs to.
- There is a moderate cardinality (17) and hence for analysis point of view, top 10 frequent sub-categories are kept and the rest are grouped into 'other'.
- binders are bought the highest number of times (15.2%), followed by paper (13.7%). As there are no sub-categories which are clearly and overly dominating, the distribution appears to be balanced. Binders and paper being the top most sold products conform with office supply category domination. Many of the top 10 sub-categories are those which could come under office supplies, possibly explaining its domination.
- There are 0 missing values

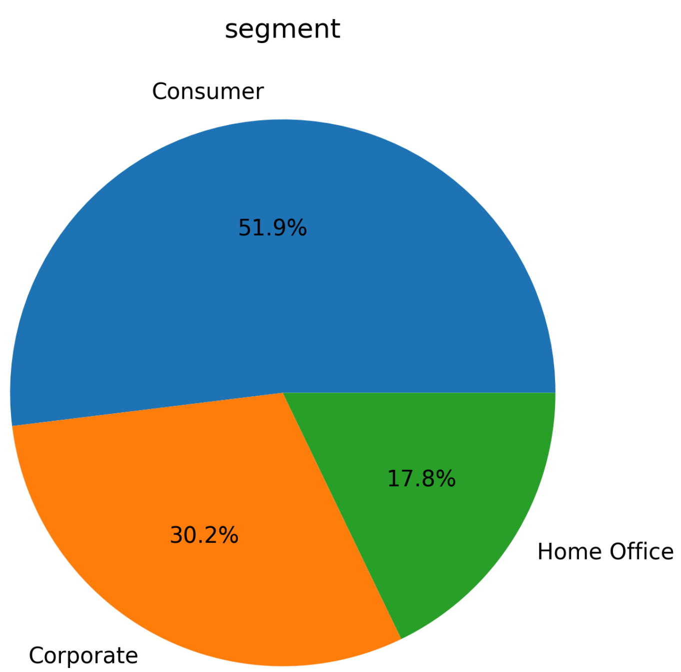
  Recommendations:

  There are 7 categories which were grouped under 'other' suggesting they are less frequently bought. For products in those sub-categories, keeping an eye might help us find the relevant pain points which are stopping their growth and hence, may help us find the exact solutions to such problems helping their sales grow.

Modeling considerations:

Due to moderate cardinality, label encoding could be done if tree based modeling was done as it won't create sparsity. For linear models, one hot encoding is still a safe option as cardinality is not too high.

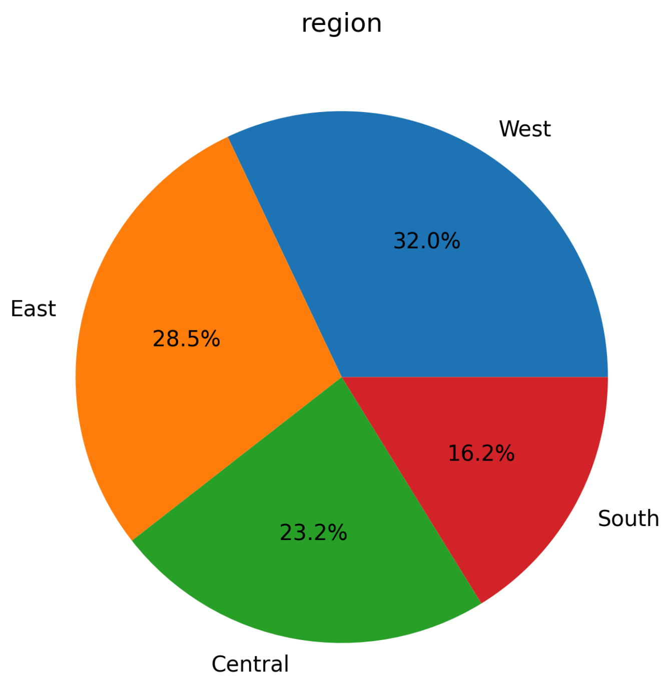
3. segment:



- It represents the customer type
- There are just 3 unique categories indicating low cardinality
- The consumer segment dominates with about 51% of the customers being consumers followed by corporate (30.2%) and home office (17.8%). as most of the buyers are consumers, it contradicts with office supplies category domination. It could suggest that there are many everyday products which could have been classified under office supplies thereby increasing its contribution. The next highest share being of corporate customers still aligns with office supply domination. The home office segment has the least share of products bought, indicating either some home office products might have been classified under consumer as home office is small scale or not many customers of superstore are interested in small scale businesses. The distribution is skewed.
- There are no missing values

Recommendations:
As the consumer segment shows dominance, it shall be targeted with loyalty offers. Corporate segment and home office segment might be targeted with ad campaigns, offers, and discounts in order to increase their engagement.
Modeling considerations:
With cardinality being very low, one hot encoding could be executed safely.

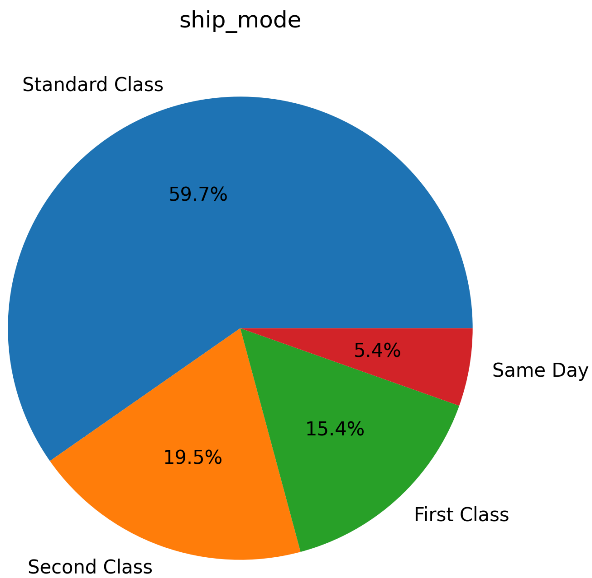
4. <u>Region</u>



- It represents the region in which the order took place. It gives us insight about which region generated the highest sales.
- it has low cardinality (4)
- highest sales were done in the west region (32%) followed by east (28%). lowest sales were done in the south (16%). West region shows no over domination and south region doesn't show negligible amount of sales done there. Hence, overall, the distribution could be said to be balanced, with no clear domination.
- there are no missing values

Recommendations:
The south region, showing the lowest amount of sales done, could be targeted with ad and marketing campaigns. Customers ordering from that region could be given limited time offers and discounts to increase engagement.
Modeling considerations:
One hot encoding could be done as low cardinality ensures no sparsity issues.

5. ship mode



- It represents the mode of shipping a customer prefers
- The cardinality is low (4 unique shipping types)
- Standard class shipping dominates here showing that 59% of the customers prefer it followed by second class (19.4%). a very less number of customers (5.4%) prefer delivery on the same day, which indicates that not too many of the customers would be able to afford same day shipping. The cheapest shipping mode, being standard shipping, is preferred by the majority of customers which could also suggest that the majority of people are okay waiting for longer periods to receive their purchased products. higher the shipping mode, lower it is preferred among the customers.
- There are 0 missing values.

  Recommendations:

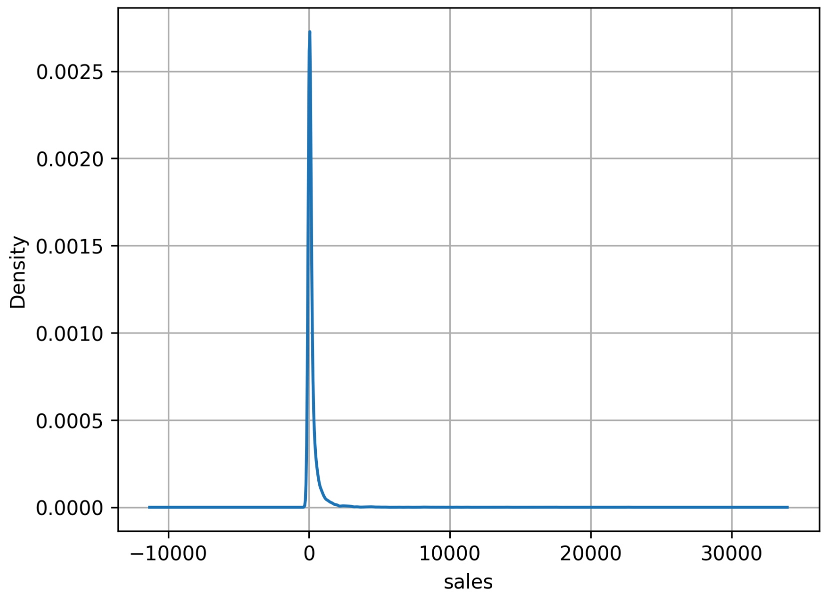
  There could be limited time offers and first time incentives for the rest of the shipping mode in order to encourage the customer to try a different shipping mode at least once.

  Modeling considerations:

  Ordinal encoding shall be done as order matters from cheapest to most expensive, or order on the basis of which mode takes how much time.

ii) Univariate analysis of Numerical columns:-

1. Sales



- It represents the amount of sales done that day by a customer who bought products from the superstore
- The distribution of sales is heavily right skewed (12.97), which indicates that most of the sales are small with very few sales being huge pushing the mean upwards. This aligns with 75% sales below 209.94 dollars. With the upper bound of sales (above which any sales are classified as outliers) being 498.93 dollars, there are 11.67% of sales which are classified as outliers. There is a significant difference between mean (229.85) and median (54.49) suggesting that this small segment of large sales is pushing the mean upwards. These stats suggest there are 2 types of transactions. Many low values and few high values.
- all the outliers are valid indicating that there might have been huge sales (max = 22.6k dollars) from a customer on a particular day.
- there are no missing values.

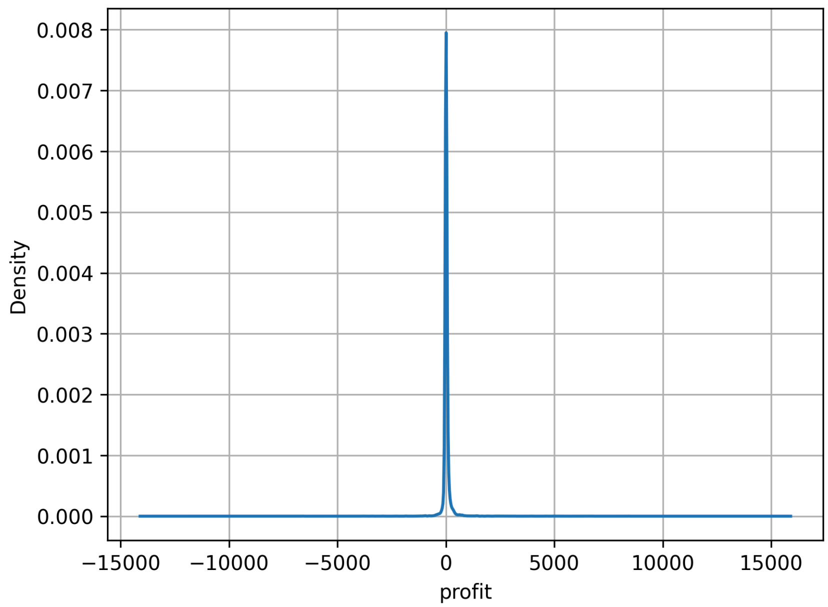
  Recommendations:

  For the group of sales that are unusually high, the transaction history of the customer and products bought by the customer needs to be checked.

  Modeling considerations:

For outlier treatment, use transforms like log, box-cox, yeo-johnson. If the transformation does not solve the problem, go for binning if required for business. Scale the values (standardization or min-max scaling) before using any models.

2. profit



- It represents the profit the superstore makes for each customer's sales it does on a particular day.
- Profit distribution is highly positively skewed (7.56) representing that majority sales gave low profit and 18.8% of sales gave high profit. with 75% of sales giving profit below 30 dollars, and an upper bound being 70.81 dollars, it suggests that some sales got a very huge profit (max = 8399 dollars). It demonstrates that those high profits could be arising from unusually high sales done that day. It could be due to bulk buying or buying of expensive items. Such high profit sales are pushing the mean (28.65) upwards away from the median (8.66).
- There aren't just huge profits but also heavy losses with min value of -6599.97 dollars suggesting that it's a high unusual loss, which could have also occurred due to bulk orders (huge sales) with heavy discounts causing cost prices to outweigh selling prices.
- All the outliers (18% of them) are valid.
- There are no missing values.

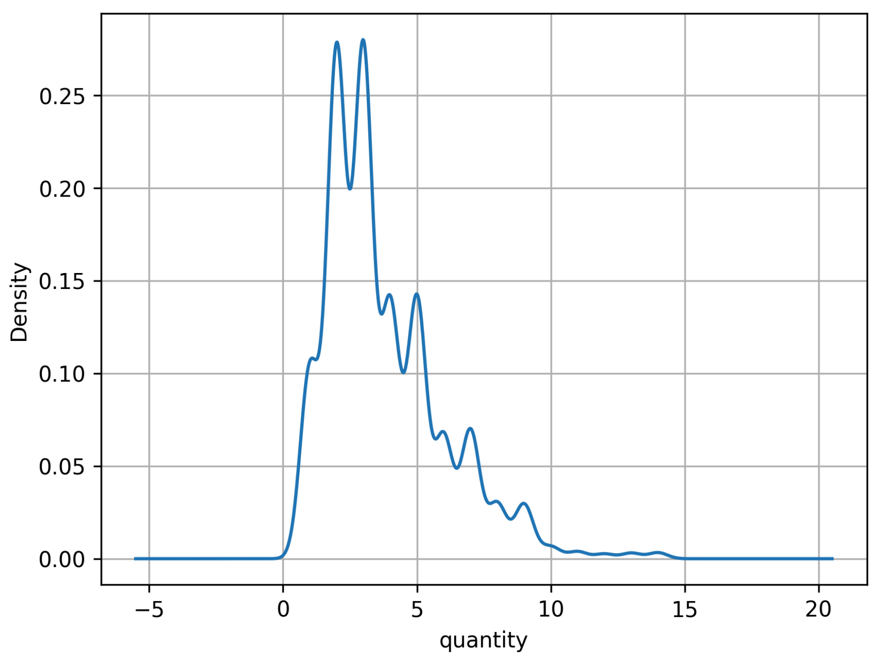
  Recommendations:

  days where profits are unusually high and losses are unusually low require inspection on whether they are occurring due to buying expensive items, or due to rare bulk buying of products which may have heavy discounts. If they are customers who buy frequently, their transaction history needs a check to see if they bought expensive items before or are just going with cheap products. These checks could give us an idea whether the profits/losses were falsely noted or have really occurred.

Modeling considerations:

Log, box-cox, yeo-johnson transforms could be applied for treating outliers. If the skewness persists, go for binning if required. Scale values by checking the overall distribution type of all features. If normal, go for standardization else go for min-max.

3. quantity



- It represents the quantity of products bought by the customer of a particular category
- The lightly right skewed distribution (skew = 1.278) suggests that most of the customers bought quantities of a category close to what an average customer (quantity = 3.78) bought. With 75% of customers buying less than 6 products of a particular category and the upper bound for outlier being 9.5, 1.7% of customers have bought more than 9.5 products on average. This very small segment of customers suggest that there are very few (1.7%) of customers who have bought an unusually high number of quantities indicating there might be a very few customers who are bulk buying if we consider the upper bound to be the normal maximum a customer could go.

- All outliers are valid (no negative quantity)
- There are no missing values

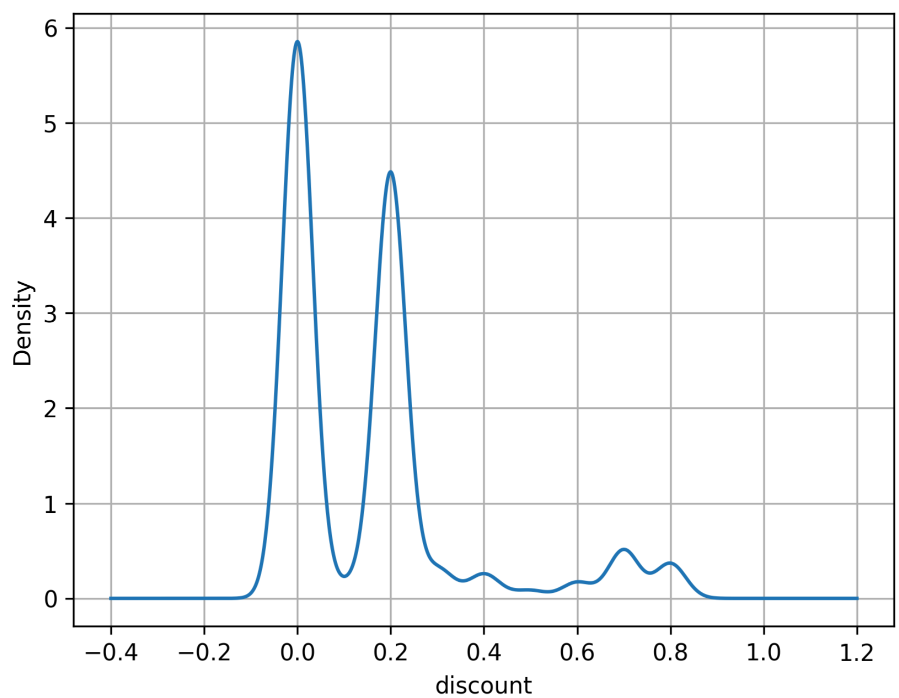
  Recommendations:

  If we are to segment the customers as retail or bulk buyers, there is a need to inspect the transaction history for 1.7% of the customers who bought unusually high amounts of quantities. This could give an idea whether the superstore also has bulk buying customers or not and are they the ones driving heavy profits and heavy losses.

  Modeling considerations:

  As the skewness is low, log or box-cox transform could eliminate it. If it still persists, do binning if required. Scale it before modeling.

4. <u>discount</u>



- This feature represents the discount given for a product bought by the customer
- The distribution of discounts is moderately right skewed, with 25% of the people receiving no discount, the other 25% of people receiving a discount of 20%. Another quarter received a discount of less than 20% and the rest got a discount of more than 20%. As a significant number of customers (25% of them) got 20% discount, it sounds like a standard seasonal offer as another significant chunk (25%) got no discounts. With the upper bound value of discount being 50%, 8.5% of customers received discounts more than 50%. This indicates that high discounts might be a possible cause for heavy losses. As customers receiving

discounts more than 20% also form a significant chunk (25%), suggesting it could be for stock clearance where majority of losses might have had happened.

- There are no invalid outliers present.
- no missing values are there.

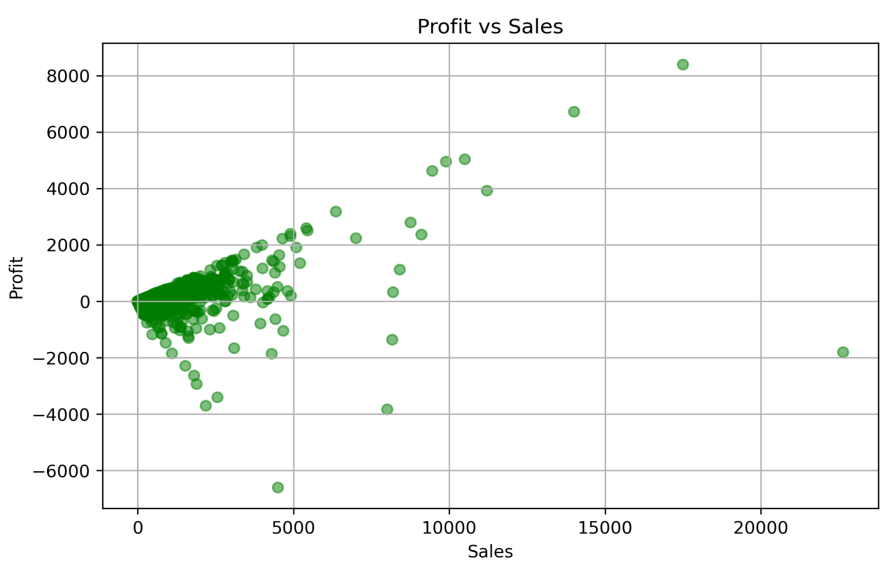
Recommendations:
For 20+ discount tier, sales and corresponding profits/losses should be inspected. If losses outweigh profits, it could suggest that discount policies are linked with negative margins.
Modeling considerations:
As the skewness is low, log or box-cox transform could eliminate it. If it still persists, do binning if required. Scale it before modelling.

Exploratory Data Analysis (EDA):- (Bivariate)

NOTE: The target variable is 'profit'.

i) Numerical-Numerical Bivariate Analysis:

1. Profit vs Sales



- A moderate positive correlation (0.54) is seen, making the relationship moderately linear. This suggests that when the sales increase, there are good chances of profit increasing too (but not a strong chance as strong correlation is not seen).
- There are a few extreme points, some having high sales and equitably high profit and some showing the exact opposite property of high sales and a small loss that

superstore suffered. This indicates that there are some high sales which might have offered less discounts even for bulk buying, thereby extracting high profits. high sales but loss suggests that high discounts could have been given to bulk buyers due to which the margin could have been compromised.

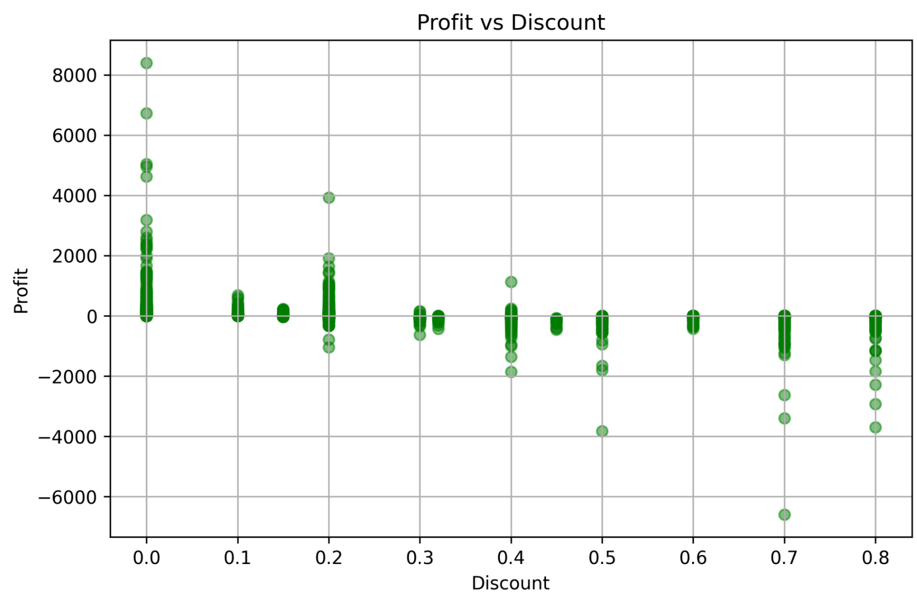
- The majority of points are in a single big cluster (around 75% of them), indicating the majority of the points are having low sales and low profit, indicating most of the orders done by the customer are generating less sales, and this might be the reason for less profit generation.
- The relationship is moderately stable and hence moderately predictable.
  Business implication:
  As the relationship is not too strong, relying on high sale high profit ideas might not guarantee high profits even for very high sales.

2. <u>Profit vs Quantity</u>

- There is almost no correlation existing between these 2 features (corr = 0.07). It indicates that most of the time, change in quantity is not influencing profit.
- When 5 quantities are sold in a particular purchase, extreme outliers are prevalent. There are high profits (over $8000) and high losses (over $6000) occurred.
- Overall, regardless of any quantity sold, there are equitable profits and losses, suggesting that when a customer buys too many quantities, it is not necessary that he/she will generate high/low profits in that purchase.
- The relationship between these 2 quantities is highly volatile, leading to profit being almost unpredictable with changes in quantities.

Business implication:
Encouraging the customers to buy a higher number of quantities through any targeted campaigns may not guarantee high profitability.

3. Profit vs Discount

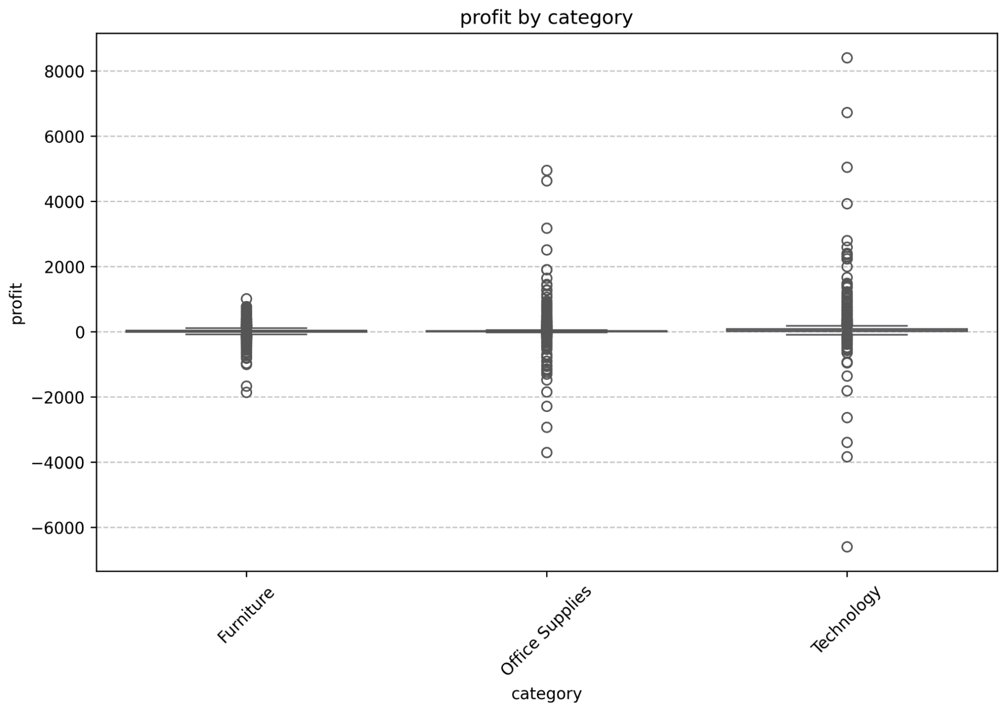


- Mild negative correlation (-0.21) is seen between these two features. It indicates that with increasing discounts, there are some chances of decreasing the profit and increasing the losses.
- There are some extremely high profits observed when 0 discount is given, which indicates no harm to the margin when a company sells products at retail price. The profits dip and losses rise after the discount tier of 20%, indicating that the company had kept discounts less than 20% for 75% of sales possibly to avoid hurting the profit margins. The highest number of losses are seen at the discount tier of 80%, which indicates the company could be emptying the old stocks and is okay to bear with the losses.
- There are no cluster formations at any discount tier, suggesting that there are no huge sales done at any discount tier, be is low or high discount
- The relationship is mildly stable and more on the volatile side, offering mild predictability.

Business implication:
Because losses start to occur if exceeding the discount tier of 20%, it suggests that going for discounts > 20 is not preferable as it may harm the profit margin, leading to lesser profits or even losses.

ii) Categorical-Numerical Bivariate Analysis:

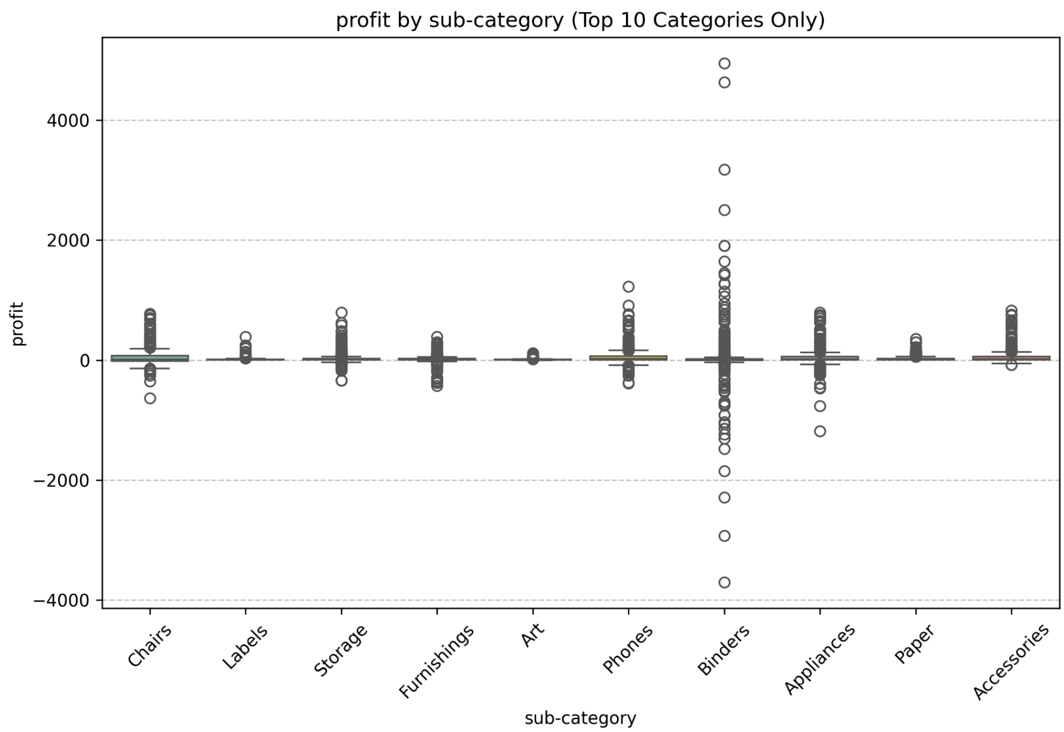
1. Category vs Profit



- Leaders - technology generates the highest average profit, indicating the margin for products in this segment might be higher comparatively. However, products in this segment are least sold in the superstore. This is followed by office supplies, which are sold the most but the average profit it generates is much lower (20.33) when compared to the technology segment.
- Laggards - Furniture category generates the lowest average profit, but more products are sold here than in the technology segment.
- Volatility and Outliers - while technology is the leading segment when it comes to average profit, it has also seen unusually highest profits and unusually highest losses too. There is a vast difference between its mean (78.75) and median (25.02) which suggests a significant amount of sales do generate low profit/loss and there are some sales which generate huge profits, pushing the mean upwards. A considerable difference between mean and median is also seen in office supplies also indicating that most of the profits done are low with some being high.
- Stability - furniture profits show a minor difference between mean (8.7) and median (7.7) indicating that the profits here are relatively much stable with much lesser profits/losses being extreme and majority of them lying close to mean/median value.

- Risk Profile - technology and office supplies show high profits as well as high losses showing increased variability.
  Recommendations:
  As technology products, despite being sold the least, are generating higher average profits, could be marketed aggressively via marketing and ad campaigns. As some products have shown high losses too, considering a change in discount policy to keep them within safer limits could save the margins. Office supplies, which are sold the most yet yield less average profit. Discounts could be reduced while preserving the traffic in order to extract more profit.

2. <u>Sub-category vs Profit</u>



- Leaders - Products belonging to accessories show the highest mean profit (54.11) followed by Phones (50.07) and Chairs (43.10). These sub-categories have significant sales counts. With sale count being high, it could indicate that products in these categories have lower discounts comparatively.
- Laggards - Labels, furnishings and art are the sub-categories generating lowest average profit among all sub-categories. It suggests that products from these sub-categories could have higher discounts leading to compromising of the profit margin and hence leading to lesser value of average profit being generated.
- Volatility and Outliers - the leader sub-categories have a vast difference between their mean and median with median being less than mean. This suggests that there are less sales of the products with huge profits generated and more sales

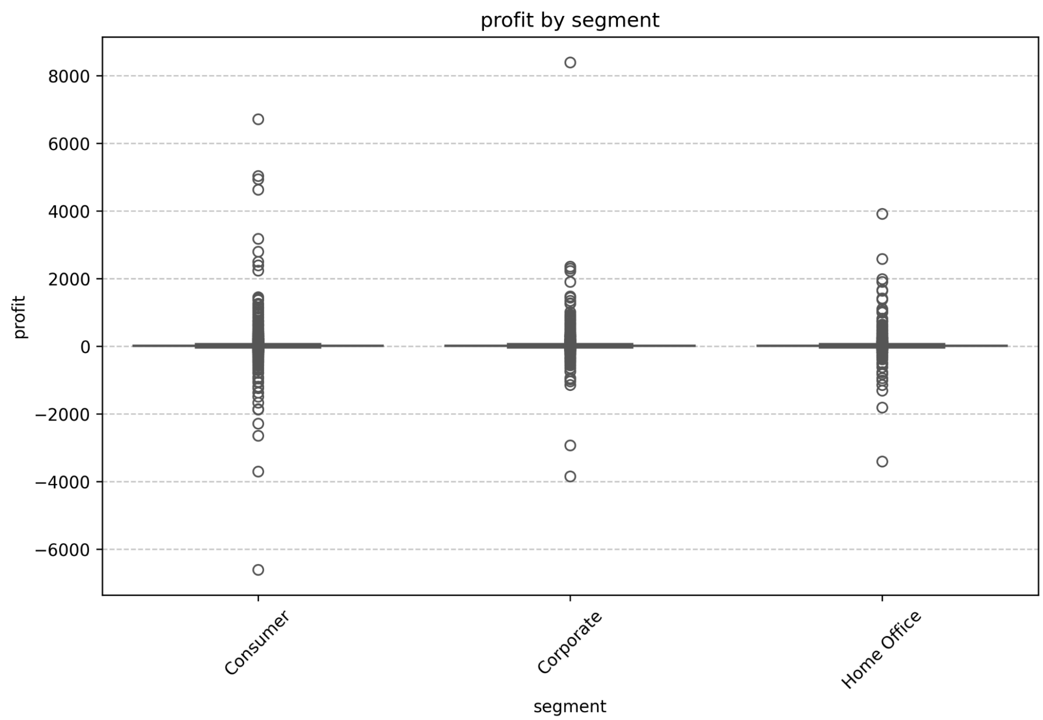
where less profit was generated. This indicates there are occasional large deals with most sales remaining low-margin.

- Stability - the laggard sub-categories have seen less difference between their mean and median relatively, which suggests they are more stable. Though there are unusual losses and profits, there aren't too many of them.
- Risk Profile - Accessories, phones and chairs have relatively more products having unusual losses and profits and due to that, the variability is too high (std > 120)

  Recommendations:

  For accessories, phones, and chairs, the products could have controlled discounts even during emptying of warehouses in order to extract higher profits even during bulk orders. If there are more offers and discounts while selling products from labels, furnishings and art, they could be reduced in a way that still maintains the usual traffic, in order to compromise less with the profit margins.

3. <u>Segment vs Profit</u>



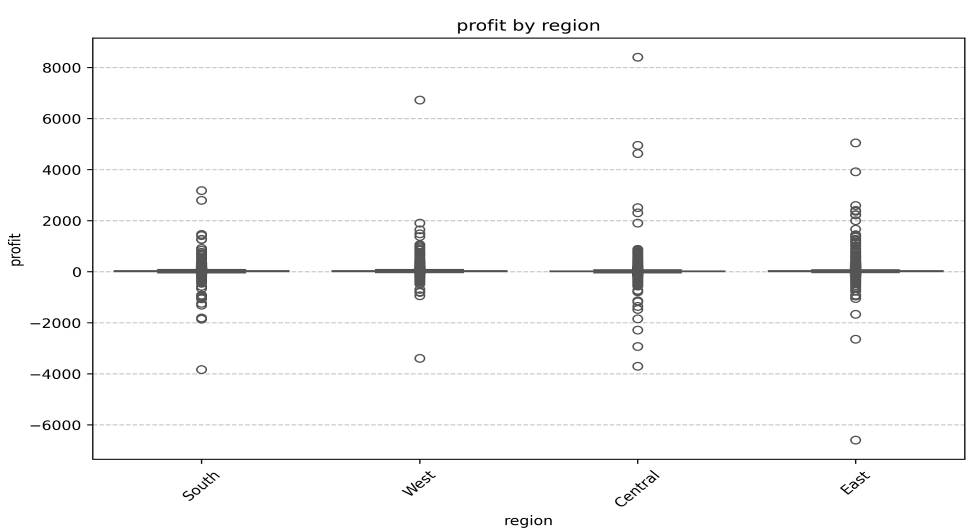
- Leaders - While the least number of sales are done in the home office segments, the average profit is highest here (33.82). While it is high, it isn't an overly dominating segment as the other 2 segments have average profits close to it (30.46 and 25.84). all the 3 segments have median profits more or less the same.

- Laggards - While the highest number of sales are done in the Consumer segment, it generates the lowest mean profit (25.84).
- Volatility and Outliers - all the 3 segments have differences between mean and median being high where mean > median. But, the leader segment, home office, shows the highest difference only due to mean profit being high as median profit for all the 3 segments is almost similar. This suggests that the home office segment has occasionally generated high unusual profits while most of the products the customers belonging to this segment buy have generated less profits.
- Stability - None of the 3 segments show stability in the profits and all the 3 segments have high variability (std > 210)
- Risk Profile - Due to high variability in profits, none of the 3 segments show stable profits but show high volatility.

  Recommendations:

  Highest profit is seen in the corporate segment. with proper pricing and discounts, the average profit generated from this segment could be pushed upwards. If high discounts are set for the consumer segment in order to encourage more sales (as it shows the highest number of sales), then discounts could be lowered in such a way that the usual traffic is preserved. This segment could then become more profitable as with highest sales happening here, higher profits can further push the average profit generated from this segment. Customers from the home office segment could be encouraged to buy more by doing targeted campaigns (aggressive marketing, ads, etc). Discount policy could also be changed for home offices (lowering the discount).

4. Region vs Profit

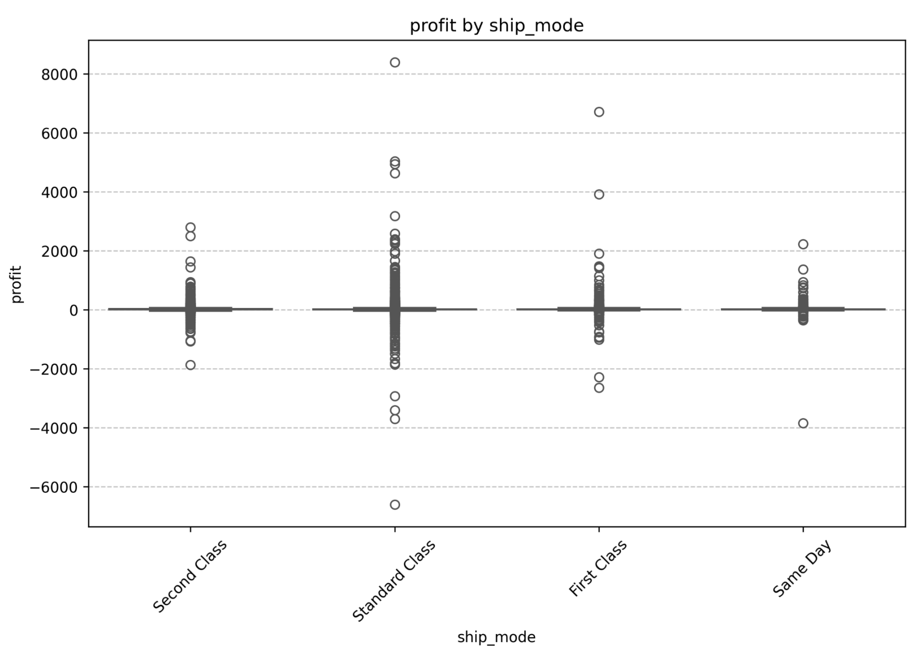


- Leaders - West and east regions have seen the highest number of sales as well as higher average profits followed by the south region.
- Laggards - Lowest average profit is seen in the Central region.
- Volatility and Outliers - all the 4 regions have vast difference between mean and median, indicating most of the sales could have been low margin while a few occasional ones generating high profit/high loss. The Central and West region have seen highest variability in profits.
- Stability - West region, though having lowest variability, the variability is still considerably high (std = 174) suggesting profits generated in all the 4 regions aren't stable but fluctuating.
- Risk Profile - highest variability is seen in the central region, being the one with lowest average profit generated. in the central region, the highest profit sale is also seen. This indicates that more sales done here are relatively low profit when compared with other regions with a very few high profit sales.

  Recommendations:

  Marketing and ad campaigns could be done in the south region in order to increase the sale count there, which could possibly increase profit generation in the south. For the west and east, as most of the sales have low profit generation, pricing and discount policy could change in order to extract more profits.

5. Ship Mode vs Profit



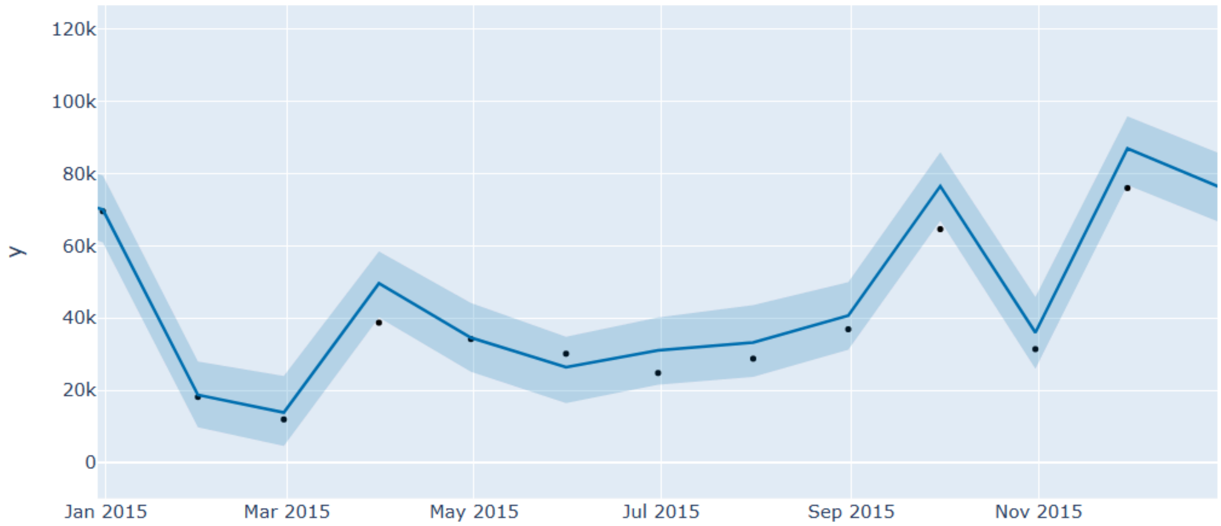
- Leaders - First class, though not preferred most of the times, generates an average profit of 31.84. despite being the highest, it is not overly dominating. The distribution of all the 4 shipping modes on the basis of average profit and median profit is quite balanced. Shipping modes show an inverse proportionality with their costs, with same day shipping being the most expensive, preferred the least, and whereas standard class, being the cheapest, preferred by the most.
- Laggards - Standard class, being the most preferred, generates lowest average profit (27.49). However, it isn't considerably low relative to the leader mode (first class).
- Volatility and Outliers - all the shipping modes show vast difference between mean and median, suggesting their charges could be closer to the margins most of the time, affecting the profits, with only a few times where the charge is much lower than the margin extracting high profits. First Class and Standard Class are the most volatile, with Second Class relatively more stable.
- Stability - Lowest variability is seen in second class shipping mode with std = 152. despite it being relatively stable, overall its variability is still high.
- Risk Profile - all the shipping modes have high variability making profits/losses hard to predict.

  Recommendations:

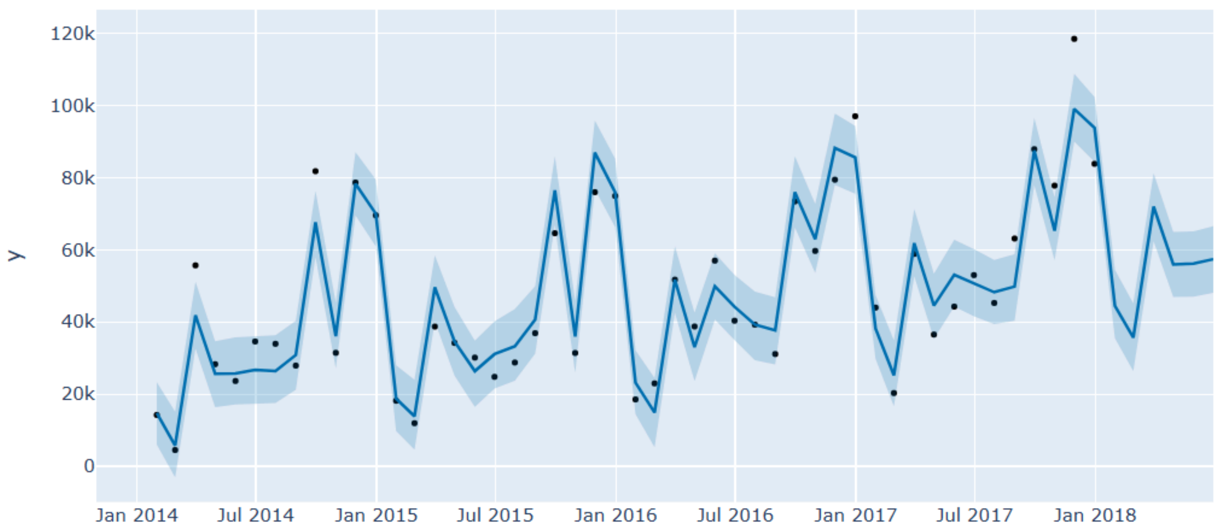
  Standard class, being the cheapest option, shows highest profit as well as highest losses. If the pricing is done effectively in a way that won't hurt the margins, more profits could be extracted as it is the most preferred. with first class generating high profits and relatively lower loss, it could be promoted via targeted campaigns. All the shipping modes are generating unusual losses which could suggest the cost the company faces for delivering is outweighing the charges they take from customers. A proper revision of delivery cost and charges could save the margins.

Time Series Analysis and Sales Forecasting:-

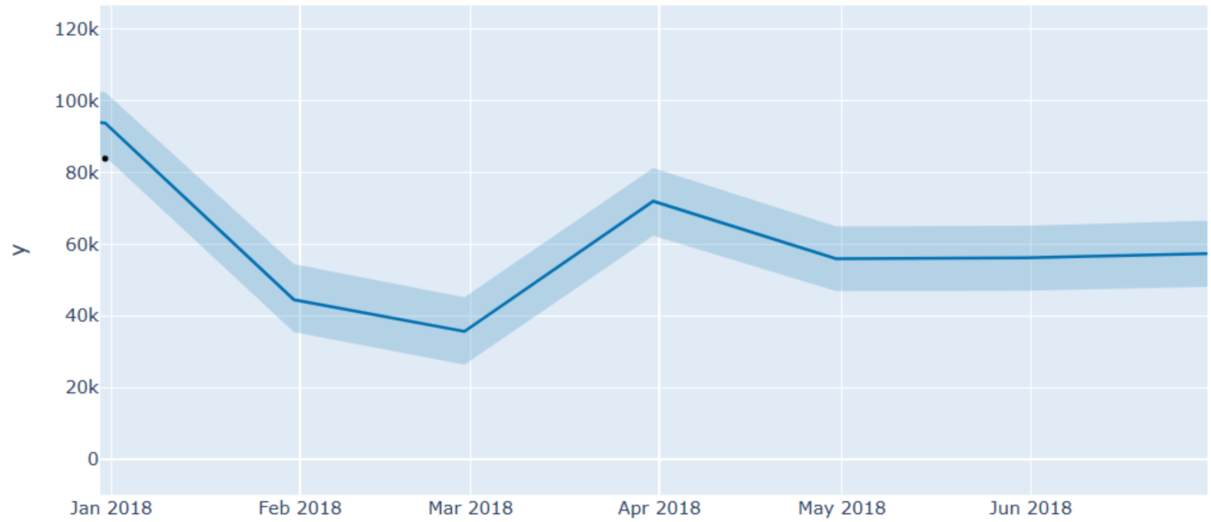
Time series analysis is done where historical sales are used. The Prophet model is used for forecasting sales for the next 6 months.



The above graph shows the sales trends over a year.



The above graph shows the sales trend for all the years, including the forecasted 6 months.



The above graph shows only the 6 month sales forecast.

<u>Insights</u>

1. **Overall Growth**
   - There is a steady upward year by year seen. This suggests that the customer demand and market presence is growing.
2. **Seasonality & Cyclic Behavior**
   - Clear seasonal spikes are observed in Q4 (Oct-Dec) which suggests that the increase in sales are likely holiday driven.
   - Early Q1 (Jan) also shows strong performance, possibly due to new year sales.
   - Early Q2 (April) shows sales recovery spike after the dip in Q1 (Feb-Mar). This could possibly be due to spring sales and promotions.
   - Rest of the Q2 and Q3 show a consistent dip, which indicates that it might be due to off-season market slowdown in sales.
3. **Volatility**
   - Peaks have wide confidence intervals, suggesting uncertainty in sales in high demand months.
4. **Forecast (Next 6 months)**
   - The next 6 months are expected to follow the same general trend as previous years — a dip during the early months (Jan–Mar) followed by a recovery in April and stable sales through mid-year.

Recommendations

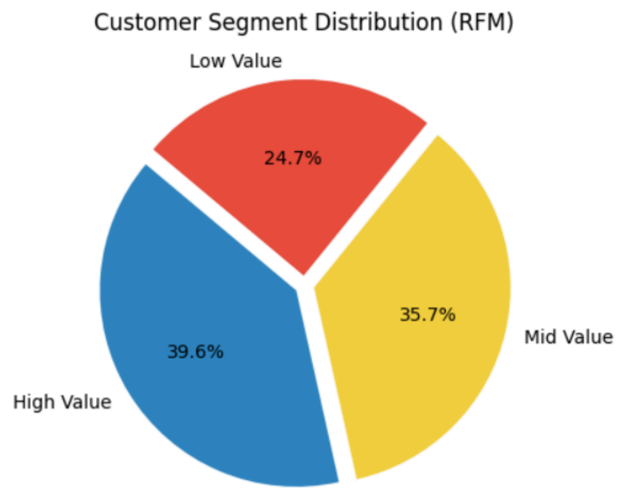
1. **Seasonal demand planning**
   - Preparing to have enough stocks in the inventory during the Q4 and Jan spikes could avoid stockouts.
   - Increasing workforce and logistics during this period could also help making the products reachable
2. **Off-season sales strategy**
   - During Q2-Q3, where the decline of sales is seen, targeted marketing campaigns, discounts, loyalty rewards, and offers could be introduced.
3. **Pricing and Marketing**
   - Customers are less concerned about prices during the holiday season (Q4). The pricing could be revisited and increased in such a way in which it still attracts usual traffic. This way, higher profit could be extracted.
   - Advertising could be done heavily during Q4 and early Q1 period which could increase more sales in such a way that sales could outweigh the marketing spend.

RFM Customer Segmentation:-

The Recency-Frequency-Monetary Segmentation is done in order to segment the customer on the basis of:

1. **Recency value:** How recently a customer did a purchase
2. **Frequency value:** How frequently does a customer purchase from the superstore
3. **Monetary value:** How much does a customer spend on average.

All the 3 values are added in order to get the RFM score of each customer. The customers with RFM score greater than or equal to 9 are classified under High Value customers. For the score being less than 9 but greater than or equal to 6, the customer gets classified under Mid Value. Rest of the customers go under Low Value.



The above graph represents the percentage of customers belonging to each segment.

Insights:

1. **High Value (39.6%):**
   - These are the group of customers who spend higher, purchase more often and show recent purchases done.
   - This segment indicates a group of highly loyal customers
   - Retaining them is much cheaper than acquiring new ones.
2. **Mid Values (35.7%):**
   - This group indicates moderate spending and purchase moderately often.
   - This group has moderately loyal customers but could be pushed to the highly loyal customer segment if more engagement via targeted campaigns is encouraged.
3. **Low Value (24.7%):**
   - This group of customers show least engagement, with least amount spent and infrequent purchases.
   - They could be at a high risk of churning and could be just one-time buyers, thereby not contributing much to the overall revenue and profit.

Recommendations:

- **High Value:** Loyalty could be maintained via exclusive offers and loyalty rewards for keeping them from churning.
- **Mid Value:** Targeting them via the marketing campaigns might boost the engagement. Timely offers and discounts could also increase the frequency of purchase.
- **Low Value:** Timely reminders, limited time offers, and rewards linked with purchase frequency could increase their engagement and purchases. This group could be targeted with retention strategies.

Relevant KPIs:-

Following are the relevant KPIs which are queried in MySQL and then used for dashboarding:

1. Average Order Value (AOV)
   It shows the average revenue generated per order.

2. Overall Profit Margin
   It shows the percentage of total profit generated from the total sales done.

3. Top 5 Products by Profit
   It shows the 5 products which gave the highest profit

4. Total Sales vs Total Profit by Region
   It shows the comparison between sales and profit generated by region to understand the nuance between them.

5. Total Sales by Category and Sub-Category
   It shows the overall sales done per category and sales done for major sub-categories.

6. Yearly Profit and YoY Growth(%)
   It shows profit generated each year and the growth percentage of profit each year.

7. Monthly sales by Year
   It shows the total sales done per month and for each month, it shows the sale contribution by year.

8. Average Profit by Discount Range
   It shows the profit generated at each discount tier.

9. Profit Contribution(%) by Category
   It shows how much profit each category contributes in percentage of total profit.

Conclusion:-

This end-to-end analysis of sales and customer data provided both insights and actionable recommendations. Data cleaning ensured reliable inputs, followed by exploratory analysis that revealed key drivers of profit. Time-series forecasting indicated that future sales are likely to follow the same seasonal trend observed historically, with peaks around Q4 and recoveries in early Q2 (April).

RFM segmentation showed a balanced customer base with nearly 40% high-value customers, but also highlighted disengaged segments requiring retention strategies. SQL-based KPI extraction and dashboarding allowed tracking of core business metrics in a structured, real-time way.

Overall, the study highlights that profitability has shown volatility, customer engagement is uneven, and seasonality strongly influences sales. Revisiting pricing and discount policy, strengthening targeted marketing, and focusing on customer retention can together drive sustainable growth in the upcoming months.