```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from scipy.stats import norm
from sklearn.preprocessing import StandardScaler
from scipy import stats
import warnings
warnings.filterwarnings('ignore')
```

```
df=pd.read_excel("/content/drive/MyDrive/sample_-_superstore.xls")
df.head()
```

	Row ID	Order ID	Order Date	Ship Date	Ship Mode	Customer ID	Customer Name	Segment	Country	Cit
0	1	CA-2016-152156	2016-11-08	2016-11-11	Second Class	CG-12520	Claire Gute	Consumer	United States	Henderso
1	2	CA-2016-152156	2016-11-08	2016-11-11	Second Class	CG-12520	Claire Gute	Consumer	United States	Henderso
2	3	CA-2016-138688	2016-06-12	2016-06-16	Second Class	DV-13045	Darrin Van Huff	Corporate	United States	Lc Angele
3	4	US-2015-108966	2015-10-11	2015-10-18	Standard Class	SO-20335	Sean O'Donnell	Consumer	United States	Fo Lauderdal
4	5	US-2015-108966	2015-10-11	2015-10-18	Standard Class	SO-20335	Sean O'Donnell	Consumer	United States	Fo Lauderdal

5 rows × 21 columns

```
df.shape
```

```
(9994, 21)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9994 entries, 0 to 9993
Data columns (total 21 columns):
```

```
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Row ID         9994 non-null   int64
 1   Order ID       9994 non-null   object
 2   Order Date     9994 non-null   datetime64[ns]
 3   Ship Date      9994 non-null   datetime64[ns]
 4   Ship Mode      9994 non-null   object
 5   Customer ID    9994 non-null   object
 6   Customer Name  9994 non-null   object
 7   Segment        9994 non-null   object
 8   Country        9994 non-null   object
 9   City           9994 non-null   object
 10  State          9994 non-null   object
 11  Postal Code    9994 non-null   int64
 12  Region         9994 non-null   object
 13  Product ID     9994 non-null   object
 14  Category       9994 non-null   object
 15  Sub-Category   9994 non-null   object
 16  Product Name   9994 non-null   object
 17  Sales          9994 non-null   float64
 18  Quantity       9994 non-null   int64
 19  Discount       9994 non-null   float64
 20  Profit         9994 non-null   float64
dtypes: datetime64[ns](2), float64(3), int64(3), object(13)
memory usage: 1.6+ MB
```

1. Top 3 Selling Categories by Total Units Problem: Given a CSV with Category, Sales, find top 3 categories by total units sold.

1. What is the total profit made in each region?

```
df.describe()
```

	Row ID	Order Date	Ship Date	Postal Code	Sales	
count	9994.000000	9994	9994	9994.000000	9994.000000	99
mean	4997.500000	2016-04-30 00:07:12.259355648	2016-05-03 23:06:58.571142912	55190.379428	229.858001	
min	1.000000	2014-01-03 00:00:00	2014-01-07 00:00:00	1040.000000	0.444000	
25%	2499.250000	2015-05-23 00:00:00	2015-05-27 00:00:00	23223.000000	17.280000	
50%	4997.500000	2016-06-26 00:00:00	2016-06-29 00:00:00	56430.500000	54.490000	
75%	7495.750000	2017-05-14	2017-05-18	90008.000000	209.940000	

Insights:

**Sales Mean = ₹229.86, but max = ₹22,638 → huge spread

Std Dev = ₹623 → high variation

Right-skewed (mean > median)

** Profit Negative min profit: -₹6599 → some orders lead to major losses!

High std deviation → unstable profitability

** Discount Max = 0.8 → 80% discounts exist!

Median = 20%, but 25% of orders have 0% discount

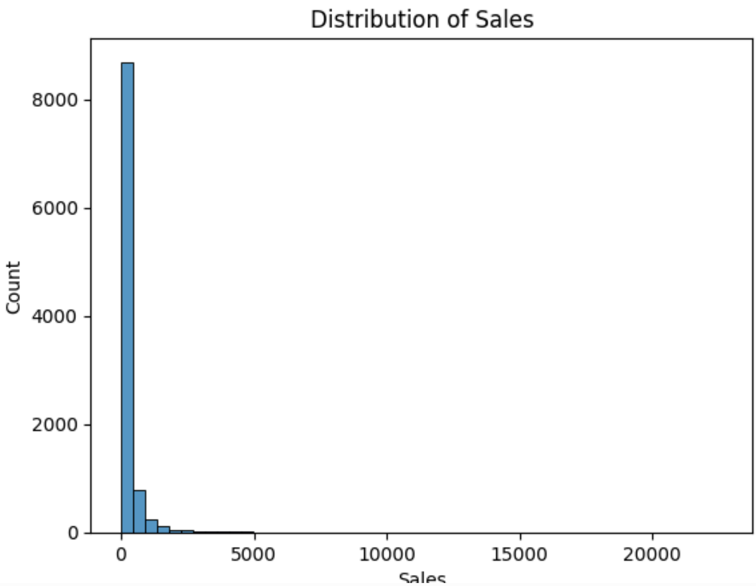
There is high variability in profit values.

min = -6599.97 , max = 8399.97 , mean = 28.6, std = 234.26

Some orders even incur losses as large as ₹6599, while others reach profits of ₹8399. Despite a positive average, the business needs to investigate loss-making orders.

Histograms to See Distributions

```
sns.histplot(df['Sales'],bins=50)
plt.title("Distribution of Sales")
plt.show()
```



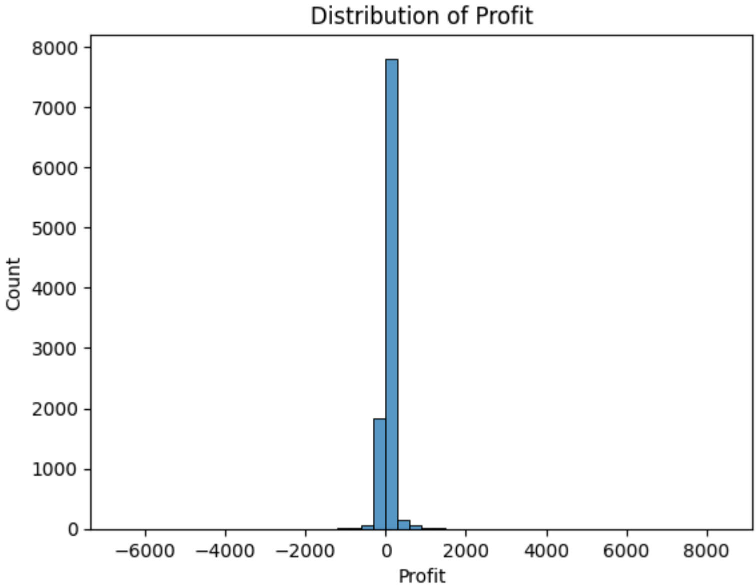
Insight from Distribution of Sales

** The sales distribution is highly right-skewed, with most orders having low sales values (below ₹1000), and a few very high-value sales going up to ₹22,000.

** This suggests that the company relies heavily on a large volume of small sales.

** Recommendation: Focus on increasing average order value or encouraging upselling in low-ticket items.

```
sns.histplot(df['Profit'],bins = 50)
plt.title("Distribution of Profit")
plt.show()
```



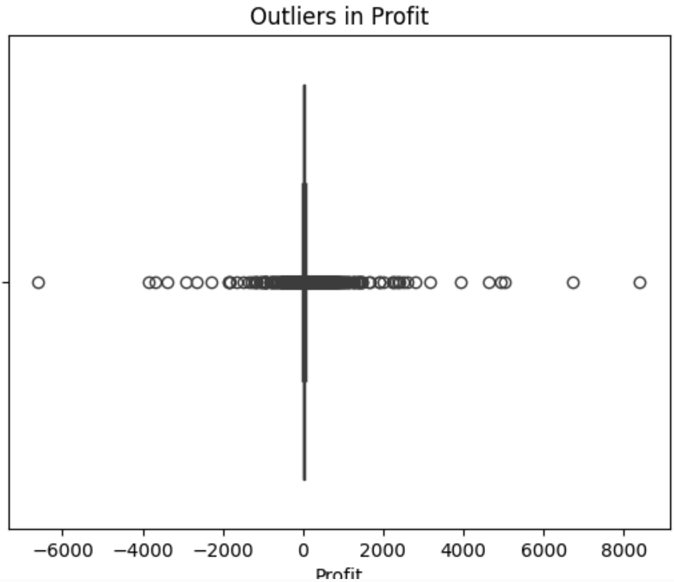
Insight from Distribution of Profit

**The profit distribution appears centered around 0, but has a long tail on both the loss and gain side. Many orders fall near zero profit, and a noticeable number of transactions show negative profit, going as low as ₹-6599.

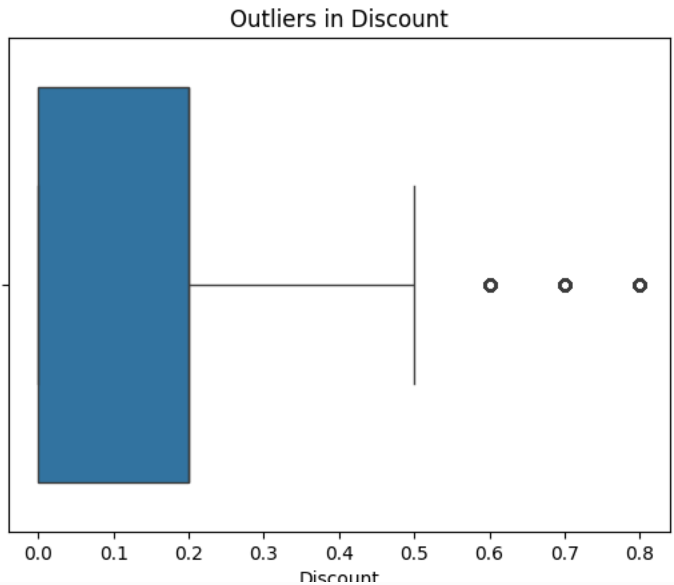
** This indicates that the business is experiencing both profitable and loss-making orders.

** Recommendation: Identify the loss-making products or regions, especially where discounts are high, to reduce the negative profit margin.

```
sns.boxplot(x=df['Profit'])
plt.title("Outliers in Profit")
plt.show()
```




```
sns.boxplot(x=df['Discount'])
plt.title("Outliers in Discount")
plt.show()
```



```
df.isnull().sum()
```

	0
Row ID	0
Order ID	0
Order Date	0
Ship Date	0
Ship Mode	0
Customer ID	0
Customer Name	0
Segment	0
Country	0
City	0
State	0
Postal Code	0
Region	0
Product ID	0
Category	0
Sub-Category	0
Product Name	0
Sales	0
Quantity	0
Discount	0
Profit	0

There is no null values in data

Use Grouping to Summarize

```
region_profit=df.groupby('Region')['Profit'].sum().reset_index()
region_profit
```

	Region	Profit
0	Central	39706.3625
1	East	91522.7800
2	South	46749.4303
3	West	108418.4489

Next steps: Generate code with region_profit | View recommended plots | New interactive sheet

Insights:

" West " and " East " Regions are generate the highest profits compare to " South and Central".while central is poor region performance.

CITIES With Highest Loss

```
df.groupby('City')['Profit'].sum().sort_values().head(5)
```

	Profit
City	
Philadelphia	-13837.7674
Houston	-10153.5485
San Antonio	-7299.0502
Lancaster	-7239.0684
Chicago	-6654.5688

Insight:

The City "Philadelphia" is most loss making Location,which may be due to low sales volume or deep discounts,Investigating this city can help over all reduces.

Double-click (or enter) to edit

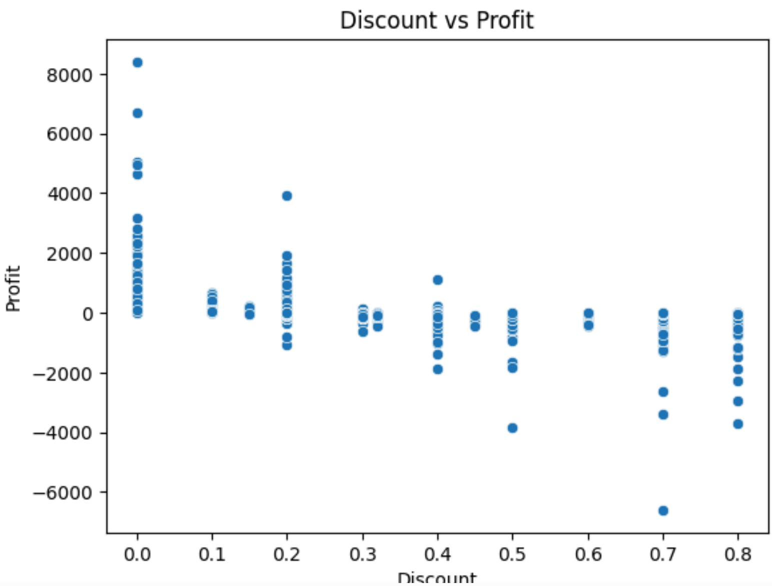
```
top3=df.groupby('Category')['Sales'].sum().nlargest(3)
top3
```

	Sales
Category	
Technology	836154.0330
Furniture	741999.7953
Office Supplies	719047.0320

Double-click (or enter) to edit

Explore Correlation

```
sns.scatterplot(data=df,x="Discount",y="Profit")
plt.title("Discount vs Profit")
plt.show()
```



Insights:

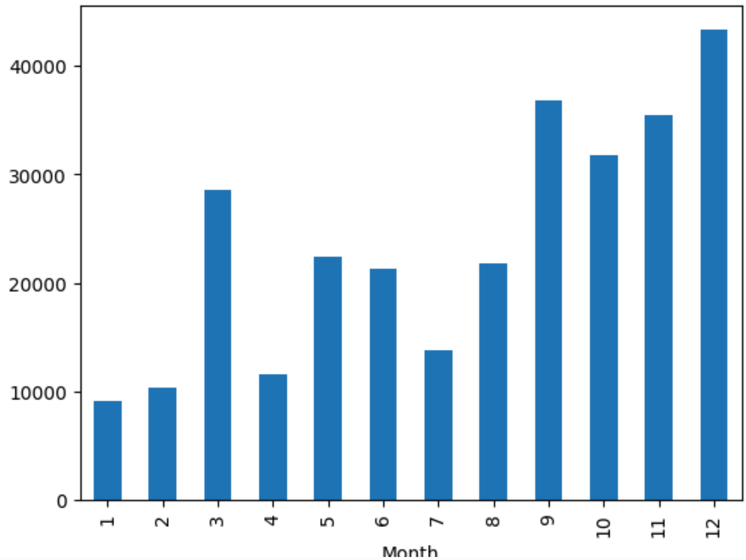
A Scatter Plot negtive trend between discount and profit as the discount increases,the profit trends to decrease.

Many orders with discount 40% in losses,the highest profit observed no discounts.

This suggests that aggressive discounting may be hurting profitability. The business should re-evaluate high-discount strategies, especially for categories where discounts do not drive profitable sales.

```
df['Order Date']=pd.to_datetime(df['Order Date'])
df['Month'] = df['Order Date'].dt.month
df['Year'] = df['Order Date'].dt.year
df.groupby('Month')['Profit'].sum().plot(kind='bar')
```

```
<Axes: xlabel='Month'>
```



The monthly sales trend shows a significant peak in December, followed by high sales in September and November.

This pattern suggests that Q4 (October to December) is the most profitable quarter, likely due to holiday season, year-end purchases, and promotional campaigns.

The business should consider strategically increasing marketing and inventory in these months to maximize revenue

The data shows that [month/quarter] has the highest [sales/profit/volume], while [other months] are comparatively lower.

This indicates [seasonal behavior / customer pattern], possibly driven by [reason like holidays, festivals, etc.].

The business should [plan promotions / stock inventory / run offers] during this period to optimize performance.

Segment Analysis

Which customer segment is most profitable? Bonus: What actions would you recommend based on this?

```
df.groupby('Segment')['Profit'].sum().nlargest()
```

Segment	Profit
Consumer	134119.2092
Corporate	91979.1340
Home Office	60298.6785

Sub-Category Loss

Which sub-category consistently shows negative profit, even if sales are good?

The Consumer segment is the most profitable, contributing over ₹1.34 lakh in total profit.

The business should continue to target consumers with personalized offers and consider cross-selling within this group.

```
df.groupby('Sub-Category')['Profit'].sum().sort_values().head(5)
```

Sub-Category	Profit
Tables	-17725.4811
Bookcases	-3472.5560
Supplies	-1189.0995
Fasteners	949.5182
Machines	3384.7569

State-Level Insight Identify top 3 states by total profit and bottom 3 by total loss.

```
total_profit_state_smallest=df.groupby('State')['Profit'].sum().nsmallest()
total_profit_state_smallest
```

State	Profit
Texas	-25729.3563
Ohio	-16971.3766
Pennsylvania	-15559.9603
Illinois	-12607.8870
North Carolina	-7490.9122

```
total_profit_state_highest=df.groupby('State')['Profit'].sum().nlargest()
total_profit_state_highest
```

State	Profit
California	76381.3871
New York	74038.5486
Washington	33402.6517
Michigan	24463.1876
Virginia	18597.9504

Ship Mode Impact

Analyze if Ship Mode affects delivery time or profit.

```
ship_mode_profit=df.groupby('Ship Mode')['Profit'].sum()
ship_mode_profit
```

Ship Mode	Profit
First Class	48969.8399
Same Day	15891.7589
Second Class	57446.6354
Standard Class	164088.7875

Customer Insights

Are repeat customers buying more often, or just once? (Hint: Count Customer ID frequency)

```
df['Customer ID'].value_counts().head(100)
```

Customer ID	count
WB-21850	37
MA-17560	34
JL-15835	34
PP-18955	34
CK-12205	32
...	...
JK-15730	20
HW-14935	20
BP-11095	20
MP-17965	20
CJ-12010	20

100 rows × 1 columns

Time Series + Strategy

```
df['Order Date'] = pd.to_datetime(df['Order Date'])
df['Month'] = df['Order Date'].dt.month
df['Year'] = df['Order Date'].dt.year

monthly_sales = df.groupby(['Year' , 'Month'])['Sales'].sum()
monthly_sales.plot()
```

```
<Axes: xlabel='Year,Month'>
```