

# Sales\_Analytics using Python

## 1.cumulative sales

```
import pandas as pd
data=pd.read_csv("sales_data.csv")
df=pd.DataFrame(data)
df['CumSales'] = df['Sales_Amount'].cumsum()
print(df["CumSales"].head())
```

```
0      5053.97
1      9437.99
2     14069.22
3     16237.16
4     19987.36
Name: CumSales, dtype: float64
```

## 2. Percentage of Total

```
print(df["Sales_Amount"].dtype)
df['Sales_Amount'] = df['Sales_Amount'].fillna(0)
df['SalesPct']=df['Sales_Amount']/df['Sales_Amount'].sum()*100
df['SalesPct']=df['SalesPct'].round(2)
print(df[['Sales_Amount','SalesPct']].head())
```

```
float64
   Sales_Amount  SalesPct
0      5053.97      0.10
1      4384.02      0.09
2      4631.23      0.09
3      2167.94      0.04
4      3750.20      0.07
```

## 3. Quartile Segmentation

```
import pandas as pd
df['SalesGroup']=pd.qcut(df['Sales_Amount'],q=4,labels=['low','mediam','high','top'])
print(df['SalesGroup'].head(5))
```

```
0      high
1    mediam
2    mediam
3      low
4    mediam
Name: SalesGroup, dtype: category
Categories (4, object): ['low' < 'mediam' < 'high' < 'top']
```

## 4. Running Average (Rolling)

```
df['7D_Avg'] = df['Sales'].rolling(7).mean()
```

```

0      NaN
1      NaN
2      NaN
3      NaN
4      NaN
5      NaN
6    3480.974286
7    3858.824286
8    3835.877143
9    4351.355714
10   5258.571429
11   5036.934286
12   5443.598571
13   6037.495714
14   6196.728571
Name: Sales_Amount, dtype: float64

```

## 5. Customer Recency

```

print(df['Sale_Date'].dtype)
df['Sale_Date'] = pd.to_datetime(df['Sale_Date'])
df['Recency']=(df['Sale_Date'].max() - df['Sale_Date']).dt.days
print(df[['Sale_Date','Recency']].head())

```

```

datetime64[ns]
Sale_Date  Recency
0 2023-02-03      332
1 2023-04-21      255
2 2023-09-21      102
3 2023-08-24      130
4 2023-03-24      283

```

## 6. Cumulative % (Pareto 80/20)

```

df_sorted=df.sort_values('Sales_Amount',ascending=False)
df['CumPct']=df_sorted['Sales_Amount'].cumsum()/df['Sales_Amount'].sum() *100
print(df['CumPct'].head())

```

```

0    74.273497
1    80.460660
2    78.409732
3    95.406976
4    85.530313
Name: CumPct, dtype: float64

```

## 7. Sales Growth %

```

df['Growth'] = df['Sales_Amount'].pct_change() * 100
df['Growth'].head()

```

```

0      NaN
1   -13.255916
2    5.638889
3   -53.188678
4    72.984492
Name: Growth, dtype: float64

```

## 8. Profit Margin %

```

df['Actual_Amount']=df['Sales_Amount']*df['Discount']
df['Profit']=df['Sales_Amount']-df['Actual_Amount']
df['ProfitMargin']= df['Profit'] / df['Sales_Amount'] * 100
df.sort_values('ProfitMargin',ascending=False).head(10)
df.head()

```

| _Category   | Unit_Cost | Unit_Price | Customer_Type | Discount | Payment_Method | Sales_Channel | Region_and_Sales_Rep | Month | Actual_Amount | Profit    | ProfitMargin |
|-------------|-----------|------------|---------------|----------|----------------|---------------|----------------------|-------|---------------|-----------|--------------|
| Furniture   | 152.75    | 267.22     | Returning     | 0.09     | Cash           | Online        | North-Bob            | 2     | 454.8573      | 4599.1127 | 91.0         |
| Furniture   | 3816.39   | 4209.44    | Returning     | 0.11     | Cash           | Retail        | West-Bob             | 4     | 482.2422      | 3901.7778 | 89.0         |
| Food        | 261.56    | 371.40     | Returning     | 0.20     | Bank Transfer  | Retail        | South-David          | 9     | 926.2460      | 3704.9840 | 80.0         |
| Clothing    | 4330.03   | 4467.75    | New           | 0.02     | Credit Card    | Retail        | South-Bob            | 8     | 43.3588       | 2124.5812 | 98.0         |
| Electronics | 637.37    | 692.71     | New           | 0.08     | Credit Card    | Online        | East-Charlie         | 3     | 300.0160      | 3450.1840 | 92.0         |

## 9. Correlation Check

```
df[['Discount','Profit','Sales']].corr()
```

|              | Discount  | Sales_Amount | Profit   |
|--------------|-----------|--------------|----------|
| Discount     | 1.000000  | 0.023153     | -0.15690 |
| Sales_Amount | 0.023153  | 1.000000     | 0.97841  |
| Profit       | -0.156900 | 0.978410     | 1.00000  |

## 10. Top N Products

```
top_products = df.groupby('Product')['Sales'].sum().nlargest(5)
```

```
Product_Category
Clothing      1313474.36
Furniture     1260517.69
Name: Sales_Amount, dtype: float64
```

## 11. Bottom N Products

```
low_products = df.groupby('Product')['Sales'].sum().nsmallest(5)
```

```
Product_Category
Food          1201773.54
Electronics   1243499.64
Name: Sales_Amount, dtype: float64
```

## 12. Monthly Sales Pivot

```
import datetime as dt
df['Sale_Date']=pd.to_datetime(df['Sale_Date'])
df['Month']=df['Sale_Date'].dt.month
df.pivot_table(values='Sales_Amount',index='Month',aggfunc='sum')
```

|       | Sales_Amount |
|-------|--------------|
| Month |              |
| 1     | 495420.37    |
| 2     | 368919.36    |
| 3     | 402638.77    |
| 4     | 438992.61    |
| 5     | 389078.76    |
| 6     | 418458.34    |
| 7     | 374242.88    |
| 8     | 443171.28    |
| 9     | 367837.60    |
| 10    | 460378.78    |
| 11    | 467482.90    |
| 12    | 392643.58    |

### 13. Region-Category Mix

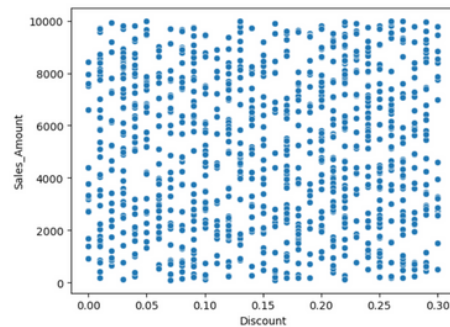
```
pd.crosstab(df['Region'], df['Category'], values=df['Sales'], aggfunc='sum', normalize='index')
```

| Product_Category | Clothing | Electronics | Food     | Furniture |
|------------------|----------|-------------|----------|-----------|
| Region           |          |             |          |           |
| East             | 0.283118 | 0.240596    | 0.258665 | 0.217620  |
| North            | 0.272323 | 0.250192    | 0.189094 | 0.288391  |
| South            | 0.233500 | 0.254420    | 0.260938 | 0.251143  |
| West             | 0.254376 | 0.246088    | 0.255530 | 0.244006  |

### 14. Discount Impact

```
import seaborn as sns
```

```
sns.scatterplot(x='Discount',y='Sales_Amount',data=df)
```



### 15. Product Value (PV)

```
df.groupby('Product_ID')['Sales_Amount'].sum().sort_values(ascending=False).nlargest(5)
```

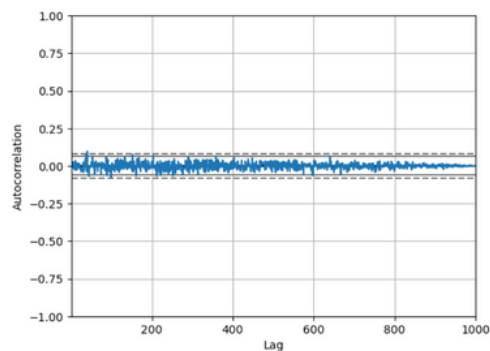
| Product_ID |           |
|------------|-----------|
| 1099       | 101773.87 |
| 1092       | 90615.62  |
| 1033       | 89130.41  |
| 1090       | 88043.25  |
| 1086       | 82269.71  |

Name: Sales\_Amount, dtype: float64

### 16. Seasonality Detection

```
from pandas.plotting import autocorrelation_plot
```

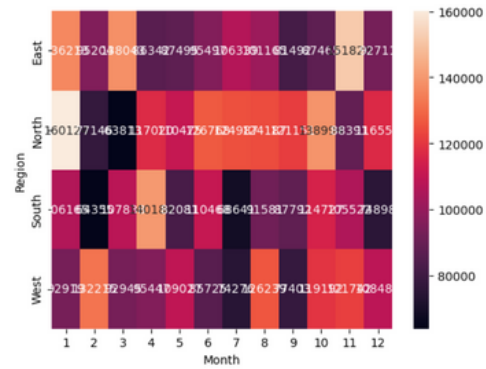
```
autocorrelation_plot(df['Sales_Amount'])
```



### 17. Heatmap of Sales by Region & Month

```
sales_matrix = df.pivot_table(values='Sales_Amount', index='Region', columns='Month', aggfunc='sum')
```

```
sns.heatmap(sales_matrix, annot=True, fmt='.0f')
```



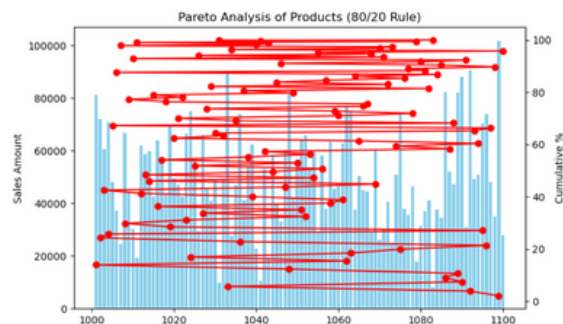
## 18. Plot Pareto chart

```
import matplotlib.pyplot as plt
df_sorted = df.groupby('Product_ID')['Sales_Amount'].sum().sort_values(ascending=False)
cum_pct = df_sorted.cumsum() / df_sorted.sum() * 100
```

```
fig, ax1 = plt.subplots(figsize=(8,5))
```

```
ax1.bar(df_sorted.index, df_sorted, color="skyblue")
ax2 = ax1.twinx()
ax2.plot(df_sorted.index, cum_pct, color="red", marker="o")
```

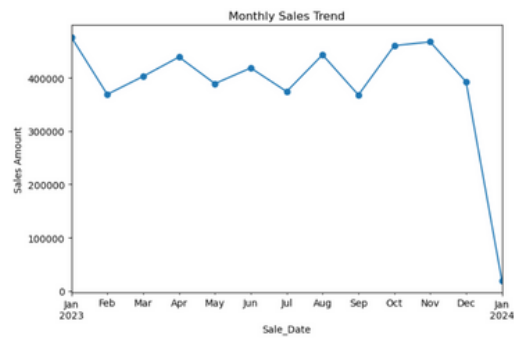
```
ax1.set_ylabel("Sales Amount")
ax2.set_ylabel("Cumulative %")
ax1.set_title("Pareto Analysis of Products (80/20 Rule)")
plt.xticks(rotation=90)
plt.show()
```



## 19. Monthly Sales

```
monthly = df.groupby(df['Sale_Date'].dt.to_period("M"))['Sales_Amount'].sum()
```

```
monthly.plot(kind="line", marker="o", figsize=(8,5), title="Monthly Sales Trend")
plt.ylabel("Sales Amount")
plt.show()
```



## 20. Recency Distribution (RFM Analysis Start)

import seaborn as sns

```
df['Sale_Date'] = pd.to_datetime(df['Sale_Date'])
df['Recency'] = (df['Sale_Date'].max() - df['Sale_Date']).dt.days
```

```
sns.histplot(df['Recency'], bins=20, kde=True)
plt.title("Distribution of Customer Recency")
plt.xlabel("Days Since Last Purchase")
plt.show()
```

