```python
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

# Load data

Amason_sales_data = pd.read_csv(r"C:\Users\steph\OneDrive\Documents\
Desktop\Amazon sales data\amazon_sales_data 2025.csv")

# Show first few rows

Amason_sales_data.head()
```

```
  Order ID        Date         Product     Category  Price  Quantity  \
0  ORD0001  14-03-2025  Running Shoes     Footwear     60         3
1  ORD0002  20-03-2025     Headphones  Electronics    100         4
2  ORD0003  15-02-2025  Running Shoes     Footwear     60         2
3  ORD0004  19-02-2025  Running Shoes     Footwear     60         3
4  ORD0005  10-03-2025     Smartwatch  Electronics    150         3

   Total Sales  Customer Name Customer Location Payment Method
Status
0          180     Emma Clark          New York     Debit Card
Cancelled
1          400  Emily Johnson     San Francisco     Debit Card
Pending
2          120       John Doe            Denver     Amazon Pay
Cancelled
3          180  Olivia Wilson            Dallas    Credit Card
Pending
4          450     Emma Clark          New York     Debit Card
Pending
```

```python
# Dataset Summary

Amason_sales_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 250 entries, 0 to 249
Data columns (total 11 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Order ID           250 non-null    object
 1   Date               250 non-null    object
 2   Product            250 non-null    object
 3   Category           250 non-null    object
 4   Price              250 non-null    int64
 5   Quantity           250 non-null    int64
 6   Total Sales        250 non-null    int64
 7   Customer Name      250 non-null    object
 8   Customer Location  250 non-null    object
```

```
 9   Payment Method     250 non-null    object
 10  Status             250 non-null    object
dtypes: int64(3), object(8)
memory usage: 21.6+ KB

## Checking the correct Date format

Amason_sales_data["Date"] =
pd.to_datetime(Amason_sales_data["Date"],format="%d-%m-%Y")

## Rename Columns for Clarity

Amason_sales_data.rename(columns={Amason_sales_data.columns[1]:"Order_
Date"},inplace=True)

Amason_sales_data["Order_Date"] =
pd.to_datetime(Amason_sales_data["Order_Date"],errors = "coerce")

# Converts string to datetime object. errors="coerce" replaces invalid
formats with NaT (null),
# which is then dropped in step 1.

Amason_sales_data["Order_Date"].head()

0   2025-03-14
1   2025-03-20
2   2025-02-15
3   2025-02-19
4   2025-03-10
Name: Order_Date, dtype: datetime64[ns]

#  Strip Whitespaces from All Object Columns
# Why: Removes leading/trailing whitespace that may cause grouping
errors or
# mismatched filtering in Power BI.


Amason_sales_data=Amason_sales_data.apply(lambda x:x.str.strip() if
x.dtype== "object" else x)

    Order ID Order_Date        Product     Category  Price
Quantity  \
0    ORD0001 2025-03-14  Running Shoes     Footwear     60         3

1    ORD0002 2025-03-20     Headphones  Electronics    100         4

2    ORD0003 2025-02-15  Running Shoes     Footwear     60         2

3    ORD0004 2025-02-19  Running Shoes     Footwear     60         3

4    ORD0005 2025-03-10     Smartwatch  Electronics    150         3
```

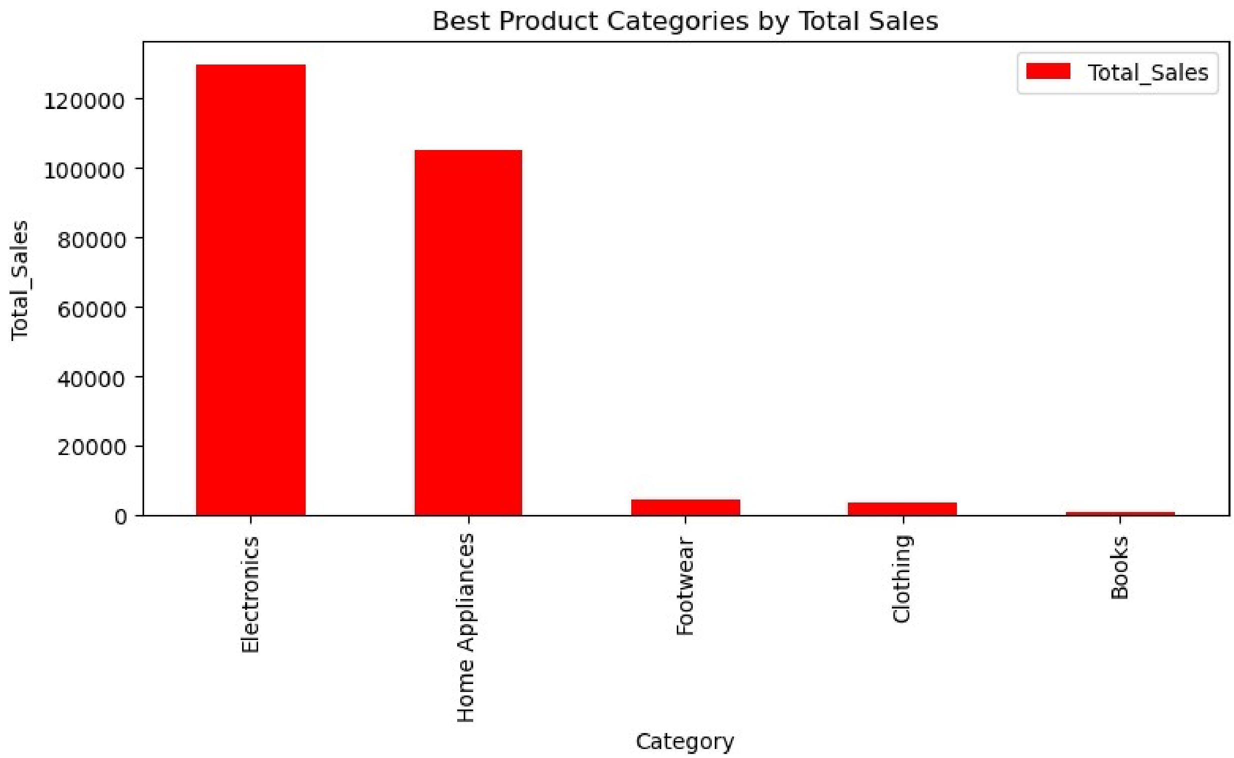
```
..       ...        ...            ...          ...    ...       ...
245  ORD0246 2025-03-17        T-Shirt     Clothing     20         2
246  ORD0247 2025-03-30          Jeans     Clothing     40         1
247  ORD0248 2025-03-05        T-Shirt     Clothing     20         2
248  ORD0249 2025-03-08     Smartwatch  Electronics    150         3
249  ORD0250 2025-02-19     Smartphone  Electronics    500         4

     Total Sales  Customer Name Customer Location Payment Method
Status
0            180     Emma Clark          New York     Debit Card
Cancelled
1            400  Emily Johnson     San Francisco     Debit Card
Pending
2            120       John Doe            Denver     Amazon Pay
Cancelled
3            180  Olivia Wilson            Dallas    Credit Card
Pending
4            450     Emma Clark          New York     Debit Card
Pending
..           ...            ...               ...            ...
...
245           40  Daniel Harris             Miami     Debit Card
Cancelled
246           40  Sophia Miller            Dallas     Debit Card
Cancelled
247           40    Chris White            Denver     Debit Card
Cancelled
248          450  Emily Johnson          New York     Debit Card
Cancelled
249         2000  Emily Johnson           Seattle     Amazon Pay
Completed

[250 rows x 11 columns]

# Standardize Column Names
# Result: Avoids syntax errors in Power BI and Python due to
inconsistent or
# space-containing column headers.

Amason_sales_data.columns =
Amason_sales_data.columns.str.strip().str.replace(" ","_") # for
column name

Amason_sales_data.columns
```

```
Index(['Order_ID', 'Order_Date', 'Product', 'Category', 'Price',
'Quantity',
       'Total_Sales', 'Customer_Name', 'Customer_Location',
'Payment_Method',
       'Status'],
      dtype='object')
```

```
# Dropping Null/Empty Rows
# Reason: These are essential columns for time series, sales
aggregation,
# and trend visualization. Missing values here would disrupt EDA and
Power BI integration.

Amason_sales_data.dropna(subset=['Order_Date', 'Price', 'Quantity',
'Total_Sales'], inplace=True)

Amason_sales_data.to_csv("cleaned_amazon_sales.csv",index=False) #
this cleaned data  for PowerBI Analysis

## Exploratory Data Analysis (EDA)

import pandas as pd

import matplotlib.pyplot as plt

import seaborn as sns

## 1.best performing product categories

best_product_categories = Amason_sales_data.groupby("Category")
[["Total_Sales"]].sum().sort_values(by =
"Total_Sales",ascending=False)

best_product_categories
```

Category	Total_Sales
Electronics	129950
Home Appliances	105000
Footwear	4320
Clothing	3540
Books	1035

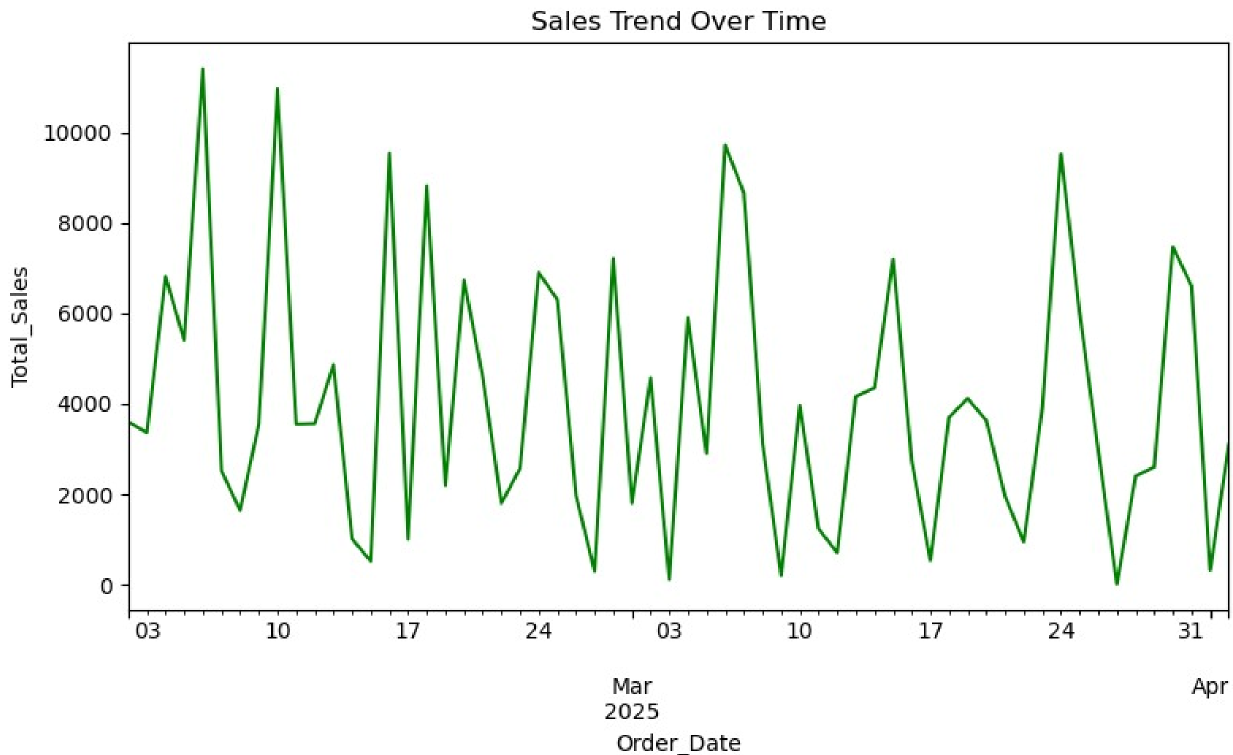
```
best_product_categories.plot(kind = "bar",color ="Red",figsize=(8,5))
plt.xlabel("Category")
plt.ylabel("Total_Sales")
plt.title("Best Product Categories by Total Sales")
plt.tight_layout()
plt.show()
```




```
## 2.Sales Trend Over Time

daily_sales = Amason_sales_data.groupby("Order_Date")
["Total_Sales"].sum().sort_index()

daily_sales

Order_Date
2025-02-02     3600
2025-02-03     3360
2025-02-04     6815
2025-02-05     5400
2025-02-06    11400
2025-02-07     2520
2025-02-08     1640
2025-02-09     3550
2025-02-10    10965
2025-02-11     3550
2025-02-12     3560
2025-02-13     4860
2025-02-14     1015
2025-02-15      520
2025-02-16     9540
2025-02-17     1005
2025-02-18     8810
2025-02-19     2195
2025-02-20     6730
```

```
2025-02-21     4600
2025-02-22     1800
2025-02-23     2570
2025-02-24     6900
2025-02-25     6300
2025-02-26     1980
2025-02-27      300
2025-02-28     7210
2025-03-01     1800
2025-03-02     4575
2025-03-03      120
2025-03-04     5900
2025-03-05     2900
2025-03-06     9720
2025-03-07     8660
2025-03-08     3125
2025-03-09      200
2025-03-10     3965
2025-03-11     1240
2025-03-12      710
2025-03-13     4160
2025-03-14     4350
2025-03-15     7190
2025-03-16     2735
2025-03-17      540
2025-03-18     3700
2025-03-19     4115
2025-03-20     3630
2025-03-21     1960
2025-03-22      950
2025-03-23     3900
2025-03-24     9520
2025-03-25     6015
2025-03-26     2970
2025-03-27       15
2025-03-28     2400
2025-03-29     2600
2025-03-30     7465
2025-03-31     6600
2025-04-01      320
2025-04-02     3100
Name: Total_Sales, dtype: int64
```

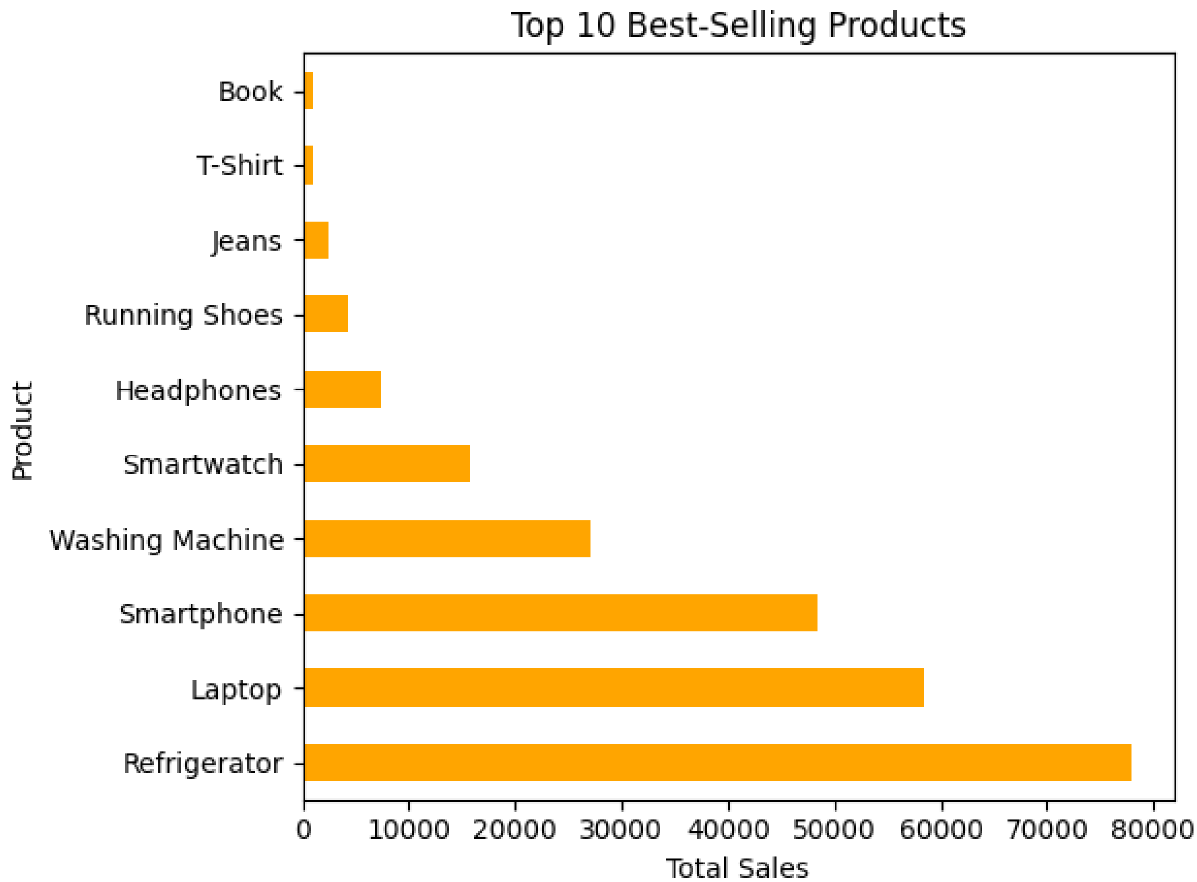
```
daily_sales.plot(kind = "line",color = "Green",figsize= (8,5))
plt.xlabel("Order_Date")
plt.ylabel("Total_Sales")
plt.title("Sales Trend Over Time")
plt.tight_layout()
plt.show()
```



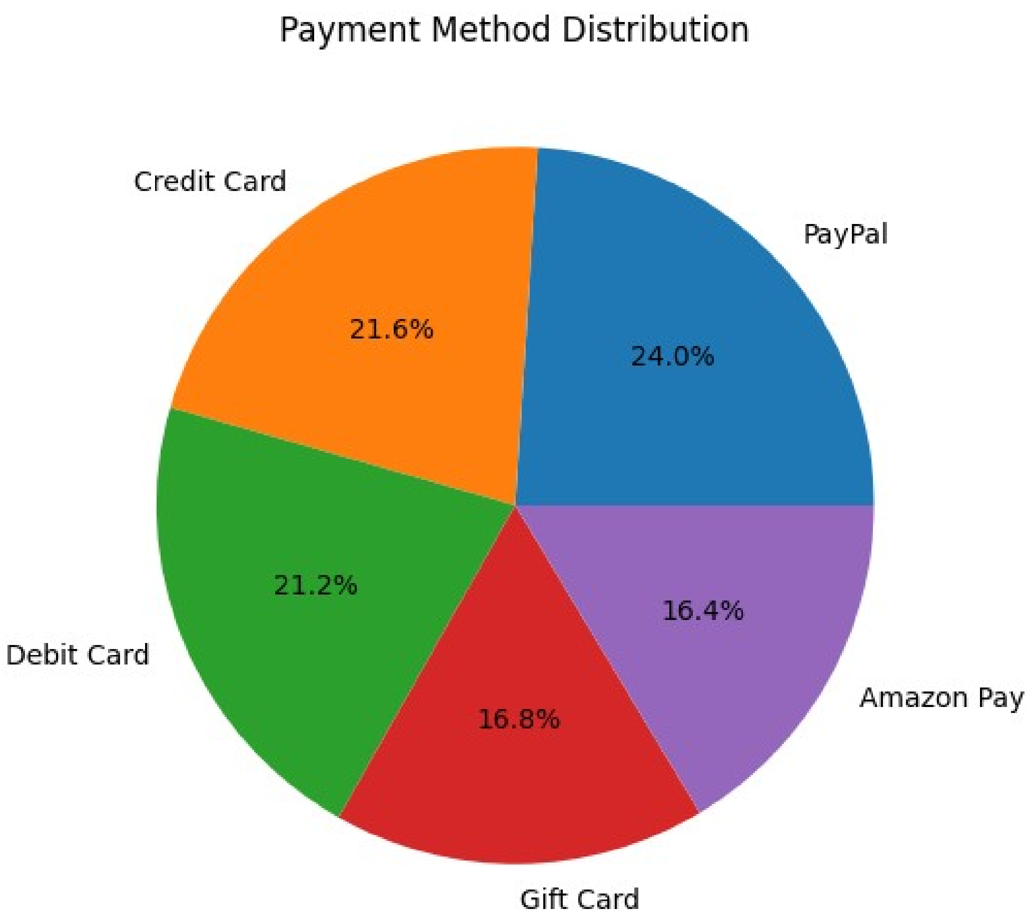

```
## 3.Sales By location

 Amason_sales_data.columns

Index(['Order_ID', 'Order_Date', 'Product', 'Category', 'Price',
'Quantity',
       'Total_Sales', 'Customer_Name', 'Customer_Location',
'Payment_Method',
       'Status'],
      dtype='object')

sales_location =  Amason_sales_data.groupby("Customer_Location")
[["Total_Sales"]].sum().sort_values("Total_Sales",ascending=False)

sales_location

                   Total_Sales
Customer_Location
Miami                    31700
Denver                   29785
Houston                  28390
Dallas                   27145
Seattle                  26890
Boston                   26170
Chicago                  20810
New York                 18940
```

```
Los Angeles                 17820
San Francisco               16195

sales_location.plot(kind = "bar",color = "salmon",figsize=(8,5))
plt.xlabel("Customer_location")
plt.title("Sales BY Customer Location")
plt.ylabel("Total_Sales")
plt.tight_layout()
plt.show()
```

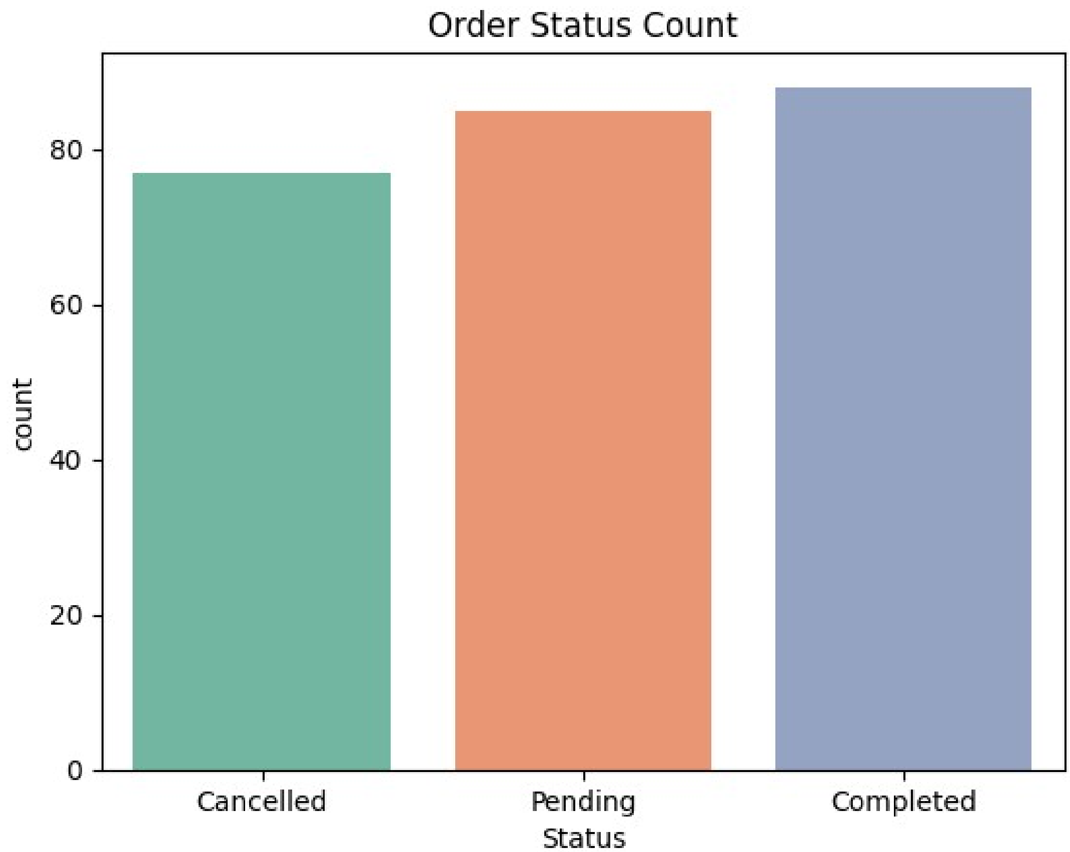

```
## 4.Top Products by Sales:

top_products = Amason_sales_data.groupby("Product")
["Total_Sales"].sum().sort_values(ascending=False).head(10)
top_products.plot(kind="barh", color="orange")
plt.title("Top 10 Best-Selling Products")
plt.xlabel("Total Sales")
plt.tight_layout()
plt.show()
```




```
# 5.Payment Method Preference:

Amason_sales_data["Payment_Method"].value_counts().plot(kind="pie",
autopct='%1.1f%%', figsize=(6,6))
plt.title("Payment Method Distribution")
plt.ylabel("")
plt.show()
```

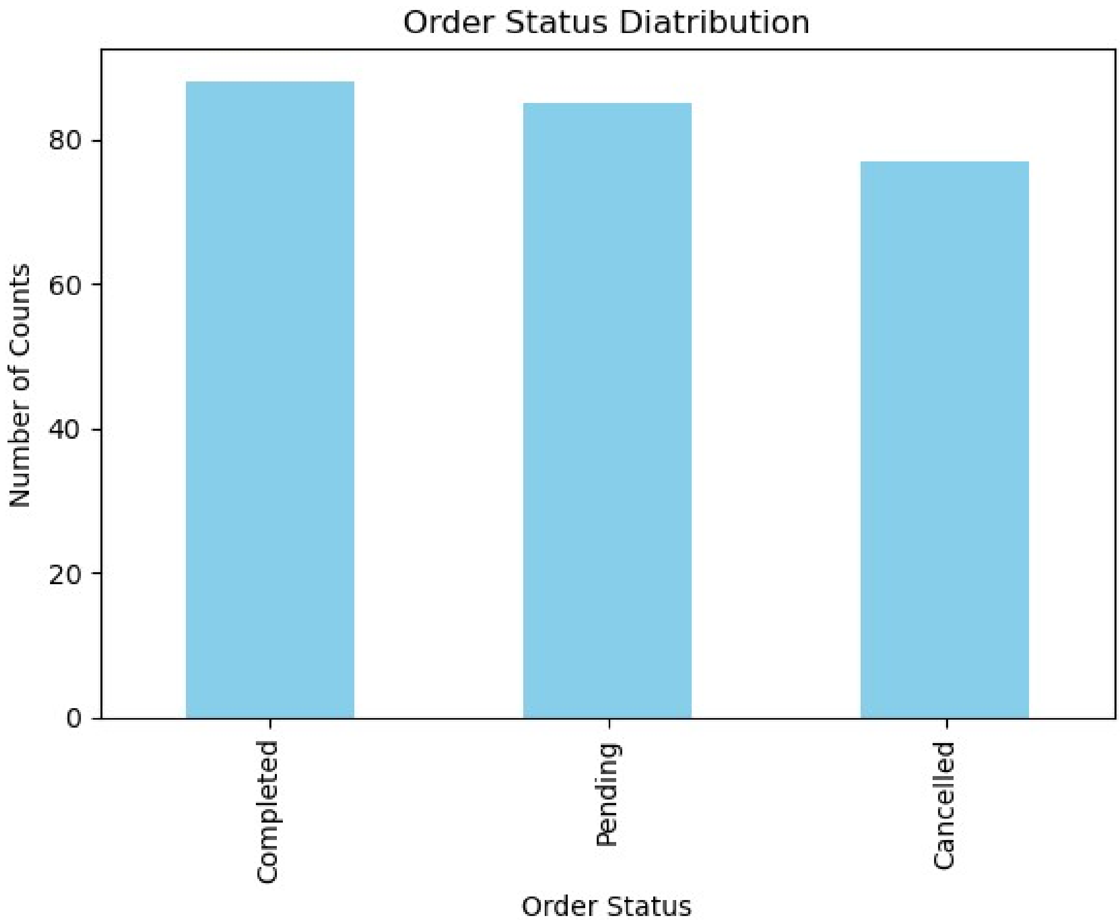



```
# 6.Order Status Breakdown:

import seaborn as sns

sns.countplot(data=Amason_sales_data, x="Status", hue="Status",
palette="Set2", legend=False)
plt.title("Order Status Count")
plt.show()
```




```
## 7.Order Status Distribution

Amason_sales_data.columns

Index(['Order_ID', 'Order_Date', 'Product', 'Category', 'Price',
'Quantity',
       'Total_Sales', 'Customer_Name', 'Customer_Location',
'Payment_Method',
       'Status'],
      dtype='object')

Amason_sales_data["Status"].value_counts()

Status
Completed    88
Pending      85
Cancelled    77
Name: count, dtype: int64

Amason_sales_data["Status"].value_counts().plot(kind =
"bar",figsize=(6,5),color ="skyblue")
plt.xlabel("Order Status")
plt.ylabel("Number of Counts")
plt.title("Order Status Diatribution")
```

```
plt.tight_layout()
plt.show()
```




```
### Statistical Insights with scipy and statsmodels

import pandas as pd

import seaborn as sns

import matplotlib.pyplot as plt

### correlation Matrix

cor = Amason_sales_data[["Price", "Quantity", "Total_Sales"]].corr()

cor
```

	Price	Quantity	Total_Sales
Price	1.000000	-0.010858	0.846673
Quantity	-0.010858	1.000000	0.332444
Total_Sales	0.846673	0.332444	1.000000

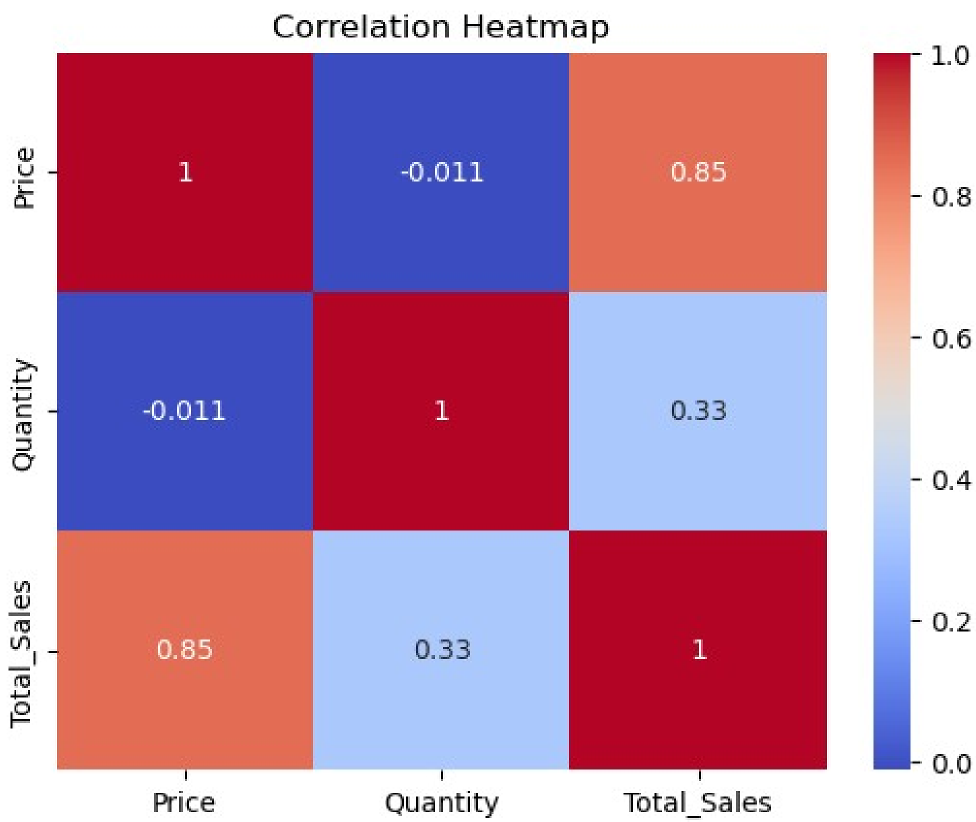
+1 = Perfect Positive Correlation,As price increases, total sales also tend # to increas. logical, because Total_Sales = Price × Quantity

0 = No Correlation

–1 = Perfect Negative Correlation

Price and Quantity aren't related A product's price doesn't influence how many are bought in this dataset

```
#In this data, Total Sales depends more on Price than Quantity, and
Price doesn’t affect Quantity bought.

# by heat map we can see clearly

sns.heatmap(cor,annot=True,cmap="coolwarm") #  annot=True   This means
annotate the cells — display the numeric values (correlation
coefficients) inside each box.
plt.title("Correlation Heatmap")
plt.show()
```




```
# ANOVA: Are Total Sales significantly different between categories?

from scipy import stats

# Grouping sales by category

Amason_sales_data.columns

Index(['Order_ID', 'Order_Date', 'Product', 'Category', 'Price',
'Quantity',
       'Total_Sales', 'Customer_Name', 'Customer_Location',
'Payment_Method',
       'Status'],
      dtype='object')

sales_category = [group["Total_Sales"].values for name,group in
Amason_sales_data.groupby("Category")]

sales_category

[array([30, 15, 75, 15, 15, 15, 75, 45, 15, 75, 75, 75, 45, 15, 60,
15, 15,
        15, 75, 75, 15, 75, 30, 60, 15], dtype=int64),
 array([ 20,  60, 160,  20,  20, 100,  80,  40, 100, 120,  80, 100,
200,
         40, 200,  40,  60, 120, 200,  20,  60, 200,  80,  20,  80,
```

```
40,
        200,  40, 100,  20, 160, 160, 200,  80,  80,  80,  40,  40,
40,
         40], dtype=int64),
 array([ 400,  450,  600,  500,  500, 1600,  600, 1000,  400,  300,
100,
         500,  500, 2000, 2400,  300, 2400, 1600,  150,  300,  150,
2000,
        2400,  450,  300,  500,  500,  300, 4000, 2500,  300,  300,
100,
         750, 2400, 2500,  200,  200,  300,  300, 1500, 2500,  750,
750,
        3200, 1000,  600,  450,  300, 1000,  200, 2500, 3200, 3200,
500,
        1000, 4000,  500, 2400,  500,  300,  750, 1000,  800, 2500,
450,
         750, 1600,  300, 1000, 1500,  300,  300,  400,  150,  750,
200,
         600, 1500, 2400,  100, 1000,  750, 4000,  800,  300,  300,
1500,
        2400, 2400,  300, 1500,  500, 3200, 1500, 1000,  200, 2400,
500,
         800,  750,  400,  300,  450,  500,  400, 4000, 2500,  300,
100,
         750,  150, 2000, 2000, 2000,  800,  450, 2000], dtype=int64),
 array([180, 120, 180, 180, 120, 240, 120, 240, 300, 300,  60,  60,
180,
        300, 180, 120, 120,  60, 120, 300,  60, 120, 240,  60, 180,
60,
        120], dtype=int64),
 array([1800, 1200, 4800, 3600,  600, 1800, 2400, 3600, 1200, 4800,
4800,
        4800,  600, 2400, 2400, 6000, 3000, 1200, 6000, 2400, 2400,
2400,
        4800, 1800, 2400, 2400, 2400, 1200, 3600,  600, 2400, 3600,
3000,
         600, 3600, 1200, 1200, 1200, 3600, 1200], dtype=int64)]
```

```
f_stat,p_val = stats.f_oneway(*sales_category)      # Or anova_result
= stats.f_oneway(*category_groups)
                                                    # print("ANOVA F-
statistic:", anova_result.statistic)
                                                    # print("ANOVA p-
value:", anova_result.pvalue)

print("f_statistics:",f_stat)
print("p_value:",p_val)
```

```
f_statistics: 53.463921351737696
p_value: 2.4079237572585064e-32
```

```
if p_val<0.05:
    print("Significant difference found between categories.")
else:
    print("no Significant difference found between categories.")
```

```
Significant difference found between categories.
```

```
import statsmodels.api as sm

 #  Linear Regression: Predict Total Sales using Price & Quantity

# Predicting sales from price and quantity linear Regression is useful

X = Amason_sales_data[["Price","Quantity"]]

Y = Amason_sales_data["Total_Sales"]

X = sm.add_constant(X) ## Add Constant(intercept)

model = sm.OLS(Y,X).fit()

print(model.summary())
```

```
                            OLS Regression Results

======================================================================
========
Dep. Variable:            Total_Sales   R-squared:
0.834
Model:                            OLS   Adj. R-squared:
0.832
Method:                 Least Squares   F-statistic:
618.6
Date:                Fri, 30 May 2025   Prob (F-statistic):
6.56e-97
Time:                        21:43:36   Log-Likelihood:
-1913.2
No. Observations:                 250   AIC:
3832.
Df Residuals:                     247   BIC:
3843.
Df Model:                           2

Covariance Type:            nonrobust

======================================================================
========
                 coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------
--------
```

```
const        -840.4835     78.556    -10.699      0.000    -995.208
-685.759
Price           2.7974      0.085     32.760      0.000       2.629
2.966
Quantity      299.2809     22.737     13.163      0.000     254.498
344.064
======================================================================
========
Omnibus:                      17.219   Durbin-Watson:
2.259
Prob(Omnibus):                 0.000   Jarque-Bera (JB):
53.569
Skew:                          0.018   Prob(JB):
2.33e-12
Kurtosis:                      5.267   Cond. No.
1.28e+03
======================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The condition number is large, 1.28e+03. This might indicate that
there are
strong multicollinearity or other numerical problems.

#I used linear regression to predict Total Sales based on Price and
Quantity.
#The model had high accuracy (R² = 0.834),
# showing that these two features strongly influence sales.
# I used statsmodels in Python to find this and both variables were
statistically significant.
```