Online Retail Analysis Project

Start coding or generate with AI.

Installing Necessary Modules

```
!pip install openpyxl
```

```
Requirement already satisfied: openpyxl in /usr/local/lib/python3.11/dist-packages (3.1.5)
Requirement already satisfied: et-xmlfile in /usr/local/lib/python3.11/dist-packages (from openpyxl) (2.0.0)
```

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

```
!wget https://archive.ics.uci.edu/static/public/352/online+retail.zip
```

```
--2025-05-04 00:47:59--  https://archive.ics.uci.edu/static/public/352/online+retail.zip
Resolving archive.ics.uci.edu (archive.ics.uci.edu)... 128.195.10.252
Connecting to archive.ics.uci.edu (archive.ics.uci.edu)|128.195.10.252|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: unspecified
Saving to: 'online+retail.zip'

online+retail.zip       [    <=>             ]  22.62M  31.5MB/s    in 0.7s

2025-05-04 00:48:00 (31.5 MB/s) - 'online+retail.zip' saved [23715478]
```

```
!unzip online+retail.zip
```

```
Archive:  online+retail.zip
  extracting: Online Retail.xlsx
```

```
dfx = pd.read_excel('Online Retail.xlsx')
dfx.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 541909 entries, 0 to 541908
Data columns (total 8 columns):
 #   Column       Non-Null Count   Dtype
---  ------       --------------   -----
 0   InvoiceNo    541909 non-null  object
 1   StockCode    541909 non-null  object
 2   Description  540455 non-null  object
 3   Quantity     541909 non-null  int64
 4   InvoiceDate  541909 non-null  datetime64[ns]
 5   UnitPrice    541909 non-null  float64
 6   CustomerID   406829 non-null  float64
 7   Country      541909 non-null  object
dtypes: datetime64[ns](1), float64(2), int64(1), object(4)
memory usage: 33.1+ MB
```

```
dfx[['InvoiceNo', 'StockCode', 'Description', 'Country']] = dfx[['InvoiceNo', 'StockCode', 'Description', 'Country']].astype('string')
```

```
dfx.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 541909 entries, 0 to 541908
Data columns (total 8 columns):
 #   Column       Non-Null Count   Dtype
---  ------       --------------   -----
 0   InvoiceNo    541909 non-null  string
 1   StockCode    541909 non-null  string
 2   Description  540455 non-null  string
 3   Quantity     541909 non-null  int64
 4   InvoiceDate  541909 non-null  datetime64[ns]
 5   UnitPrice    541909 non-null  float64
 6   CustomerID   406829 non-null  float64
 7   Country      541909 non-null  string
dtypes: datetime64[ns](1), float64(2), int64(1), string(4)
memory usage: 33.1 MB
```

```
dfx.head()
```

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	2010-12-01 08:26:00	2.55	17850.0	United Kingdom
1	536365	71053	WHITE METAL LANTERN	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	2010-12-01 08:26:00	2.75	17850.0	United Kingdom
[illegible]	[illegible]	[illegible]	KNITTED UNION FLAG HOT WATER	[illegible]	2010-12-01	[illegible]	[illegible]	United

```
dfx.shape
```

```
(541909, 8)
```

Start coding or generate with AI.

Data Cleaning : Handling the Missing Values

```
dfx.isnull().sum()
```

	0
InvoiceNo	0
StockCode	0
Description	1454
Quantity	0
InvoiceDate	0
UnitPrice	0
CustomerID	135080
Country	0

dtype: int64

```
dfx[dfx.Description.isnull()]
```

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
622	536414	22139	<NA>	56	2010-12-01 11:52:00	0.0	NaN	United Kingdom
1970	536545	21134	<NA>	1	2010-12-01 14:32:00	0.0	NaN	United Kingdom
1971	536546	22145	<NA>	1	2010-12-01 14:33:00	0.0	NaN	United Kingdom
1972	536547	37509	<NA>	1	2010-12-01 14:33:00	0.0	NaN	United Kingdom
1987	536549	85226A	<NA>	1	2010-12-01 14:34:00	0.0	NaN	United Kingdom
...	...	...	...	...	...	...	...	...
535322	581199	84581	<NA>	-2	2011-12-07 18:26:00	0.0	NaN	United Kingdom
535326	581203	23406	<NA>	15	2011-12-07 18:31:00	0.0	NaN	United Kingdom
535332	581209	21620	<NA>	6	2011-12-07 18:35:00	0.0	NaN	United Kingdom
536981	581234	72817	<NA>	27	2011-12-08 10:33:00	0.0	NaN	United Kingdom
538554	581408	85175	<NA>	20	2011-12-08 14:06:00	0.0	NaN	United Kingdom

1454 rows × 8 columns

```
dfx[dfx.StockCode=="22139"] ## checking other valid Description with the same code to match
```

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
106	536381	22139	RETROSPOT TEA SET CERAMIC 11 PC	23	2010-12-01 09:41:00	4.25	15311.0	United Kingdom
622	536414	22139	<NA>	56	2010-12-01 11:52:00	0.00	NaN	United Kingdom
6392	536942	22139	amazon	15	2010-12-03 12:08:00	0.00	NaN	United Kingdom
6885	536982	22139	RETROSPOT TEA SET CERAMIC 11 PC	10	2010-12-03 14:27:00	11.02	NaN	United Kingdom
7203	537011	22139	<NA>	-5	2010-12-03 15:38:00	0.00	NaN	United Kingdom
...	...	...	...	...	...	...	...	...
538411	581405	22139	RETROSPOT TEA SET CERAMIC 11 PC	1	2011-12-08 13:50:00	4.95	13521.0	United Kingdom
539531	581439	22139	RETROSPOT TEA SET CERAMIC 11 PC	1	2011-12-08 16:30:00	10.79	NaN	United Kingdom

```
dfx[dfx.StockCode=="22139"].Description.mode()
```

	Description
0	RETROSPOT TEA SET CERAMIC 11 PC

dtype: string

```
df_freq=dfx[['StockCode','Description']].value_counts().reset_index()
df_freq
```

	StockCode	Description	count
0	85123A	WHITE HANGING HEART T-LIGHT HOLDER	2302
1	22423	REGENCY CAKESTAND 3 TIER	2200
2	85099B	JUMBO BAG RED RETROSPOT	2159
3	47566	PARTY BUNTING	1727
4	20725	LUNCH BAG RED RETROSPOT	1638
...	...	...	...
4787	21491	SET OF THREE VINTAGE GIFT WRAPS	1
4788	84876D	damaged	1
4789	20827	damages	1
4790	20832	check	1
4791	21578	?	1

4792 rows × 3 columns

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

```
df_freq[df_freq.StockCode=='85123A'] ## suppose to take the most frequent description for the particular StockCode
```

	StockCode	Description	count
0	85123A	WHITE HANGING HEART T-LIGHT HOLDER	2302
3320	85123A	CREAM HANGING HEART T-LIGHT HOLDER	9
4283	85123A	?	1
4284	85123A	wrongly marked carton 22804	1

```
most_freq =df_freq.groupby('StockCode').head(1)
most_freq
```

	StockCode	Description	count
0	85123A	WHITE HANGING HEART T-LIGHT HOLDER	2302
1	22423	REGENCY CAKESTAND 3 TIER	2200
2	85099B	JUMBO BAG RED RETROSPOT	2159
3	47566	PARTY BUNTING	1727
4	20725	LUNCH BAG RED RETROSPOT	1638
...	...	...	...
4755	37503	TEA TIME CAKE STAND IN GIFT BOX	1
4773	37461	FUNKY MONKEY MUG	1
4775	37474	SET/4 2 TONE EGG SHAPE MIXING BOWLS	1
4782	22145	CHRISTMAS CRAFT HEART STOCKING	1
4787	21491	SET OF THREE VINTAGE GIFT WRAPS	1

3958 rows × 3 columns

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

```
most_freq.columns = ['StockCode', 'Freq_Description', 'freq']
dfx1 = pd.merge(dfx, most_freq, on='StockCode', how='left')
dfx1.head()
```

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country	Freq_Description	freq
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	2010-12-01 08:26:00	2.55	17850.0	United Kingdom	WHITE HANGING HEART T-LIGHT HOLDER	2302.0
1	536365	71053	WHITE METAL LANTERN	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom	WHITE METAL LANTERN	328.0
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	2010-12-01 08:26:00	2.75	17850.0	United Kingdom	CREAM CUPID HEARTS COAT HANGER	293.0

```
dfx1['Description']=dfx1['Freq_Description']
```

```
dfx1.isnull().sum()
```

	0
InvoiceNo	0
StockCode	0
Description	112
Quantity	0
InvoiceDate	0
UnitPrice	0
CustomerID	135080
Country	0
Freq_Description	112
freq	112

dtype: int64

```
dfx1[dfx1.Description.isnull()]
```

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country	Freq_Description	freq
1970	536545	21134	<NA>	1	2010-12-01 14:32:00	0.0	NaN	United Kingdom	<NA>	NaN
1987	536549	85226A	<NA>	1	2010-12-01 14:34:00	0.0	NaN	United Kingdom	<NA>	NaN
1988	536550	85044	<NA>	1	2010-12-01 14:34:00	0.0	NaN	United Kingdom	<NA>	NaN
2024	536552	20950	<NA>	1	2010-12-01 14:34:00	0.0	NaN	United Kingdom	<NA>	NaN
2026	536554	84670	<NA>	23	2010-12-01 14:35:00	0.0	NaN	United Kingdom	<NA>	NaN
...	...	...	...	...	...	...	...	...	...	...
280754	561498	21610	<NA>	-14	2011-07-27 14:10:00	0.0	NaN	United Kingdom	<NA>	NaN
281615	561555	37477B	<NA>	-11	2011-07-28 10:21:00	0.0	NaN	United Kingdom	<NA>	NaN

```
dfx1.dropna(subset=['Description'], inplace=True)
dfx1.isnull().sum()
## It is acceptable to go with the null on CustmerID in this scenario
```

	0
InvoiceNo	0
StockCode	0
Description	0
Quantity	0
InvoiceDate	0
UnitPrice	0
CustomerID	134968
Country	0
Freq_Description	0
freq	0

dtype: int64

```
dfx1.drop(columns=['Freq_Description', 'freq'], inplace=True)
```

```
dfx1.describe() # Here Quantity and Unitprice Should not be zero.So kept it for further analysis and will go further with rest of the da
```

	Quantity	InvoiceDate	UnitPrice	CustomerID
count	541797.000000	541797	541797.000000	406829.000000
mean	9.555919	2011-07-04 14:06:48.671255296	4.612067	15287.690570
min	-80995.000000	2010-12-01 08:26:00	-11062.060000	12346.000000
25%	1.000000	2011-03-28 11:36:00	1.250000	13953.000000
50%	3.000000	2011-07-20 08:59:00	2.080000	15152.000000
75%	10.000000	2011-10-19 11:41:00	4.130000	16791.000000
max	80995.000000	2011-12-09 12:50:00	38970.000000	18287.000000
std	218.103428	NaN	96.769831	1713.600303

```
df=dfx1[(dfx1.Quantity > 0) & (dfx1.UnitPrice > 0)]
df.describe()
```

	Quantity	InvoiceDate	UnitPrice	CustomerID
count	530104.000000	530104	530104.000000	397884.000000
mean	10.542037	2011-07-04 20:16:05.225087744	3.907625	15294.423453
min	1.000000	2010-12-01 08:26:00	0.001000	12346.000000
25%	1.000000	2011-03-28 12:22:00	1.250000	13969.000000
50%	3.000000	2011-07-20 12:58:00	2.080000	15159.000000
75%	10.000000	2011-10-19 12:39:00	4.130000	16795.000000
max	80995.000000	2011-12-09 12:50:00	13541.330000	18287.000000
std	155.524124	NaN	35.915681	1713.141560

```
df[df.duplicated()]
```

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
517	536409	21866	UNION JACK FLAG LUGGAGE TAG	1	2010-12-01 11:45:00	1.25	17908.0	United Kingdom
527	536409	22866	HAND WARMER SCOTTY DOG DESIGN	1	2010-12-01 11:45:00	2.10	17908.0	United Kingdom
537	536409	22900	SET 2 TEA TOWELS I LOVE LONDON	1	2010-12-01 11:45:00	2.95	17908.0	United Kingdom
539	536409	22111	SCOTTIE DOG HOT WATER BOTTLE	1	2010-12-01 11:45:00	4.95	17908.0	United Kingdom
555	536412	22327	ROUND SNACK BOXES SET OF 4 SKULLS	1	2010-12-01 11:49:00	2.95	17920.0	United Kingdom
...	...	...	...	...	...	...	...	...
541675	581538	22068	BLACK PIRATE TREASURE CHEST	1	2011-12-09 11:34:00	0.39	14446.0	United Kingdom
541689	581538	23318	BOX OF 6 MINI VINTAGE CRACKERS	1	2011-12-09 11:34:00	2.49	14446.0	United Kingdom

```
df1=df.drop_duplicates()
df1.shape
```

```
(524876, 8)
```

```
start_date = df1['InvoiceDate'].min()
end_date = df1['InvoiceDate'].max()

print("Start Date:", start_date)
print("End Date:", end_date)
```

```
Start Date: 2010-12-01 08:26:00
End Date: 2011-12-09 12:50:00
```

```
df1['Country'].unique()
```

```
<StringArray>
[      'United Kingdom',               'France',            'Australia',
          'Netherlands',              'Germany',               'Norway',
                 'EIRE',          'Switzerland',                'Spain',
               'Poland',             'Portugal',                'Italy',
              'Belgium',            'Lithuania',                'Japan',
              'Iceland',      'Channel Islands',              'Denmark',
               'Cyprus',               'Sweden',              'Finland',
              'Austria',              'Bahrain',               'Israel',
               'Greece',            'Hong Kong',            'Singapore',
              'Lebanon', 'United Arab Emirates',         'Saudi Arabia',
       'Czech Republic',               'Canada',          'Unspecified',
               'Brazil',                  'USA',   'European Community',
                'Malta',                  'RSA']
Length: 38, dtype: string
```

Start coding or generate with AI.

Outlier Interpretation:

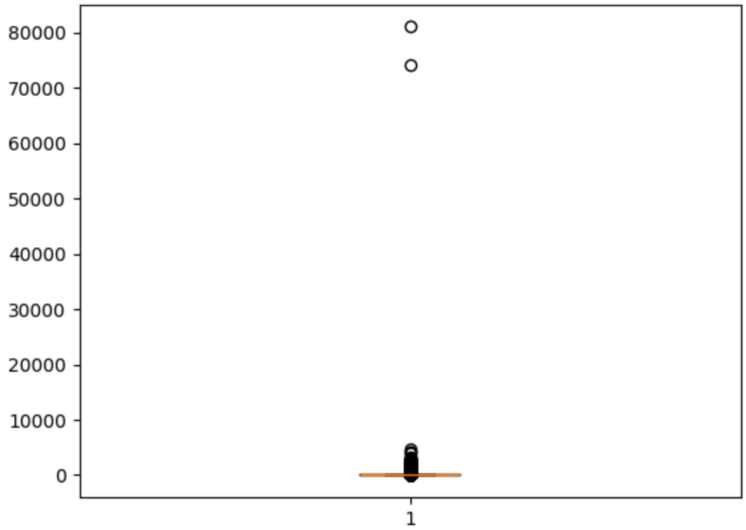
```
# We can notice HUGE values in both Quantity and UnitPrice.
# Outliers in this project are not errors — they represent valid bulk purchases (as confirmed by the business context).
# So, instead of removing them, we showcase them in a separate plot to retain insight without distorting the main view.
```

Box Plot 1: Full Range View (No Limit) ---

```
#  Shows full data including large-scale outliers
#  Useful for transparency and understanding outlier impact
#  Note: Extreme values (e.g., 80,000+) will shrink the box and make it harder to see the main distribution
```

```
plt.boxplot(df1.Quantity)
```

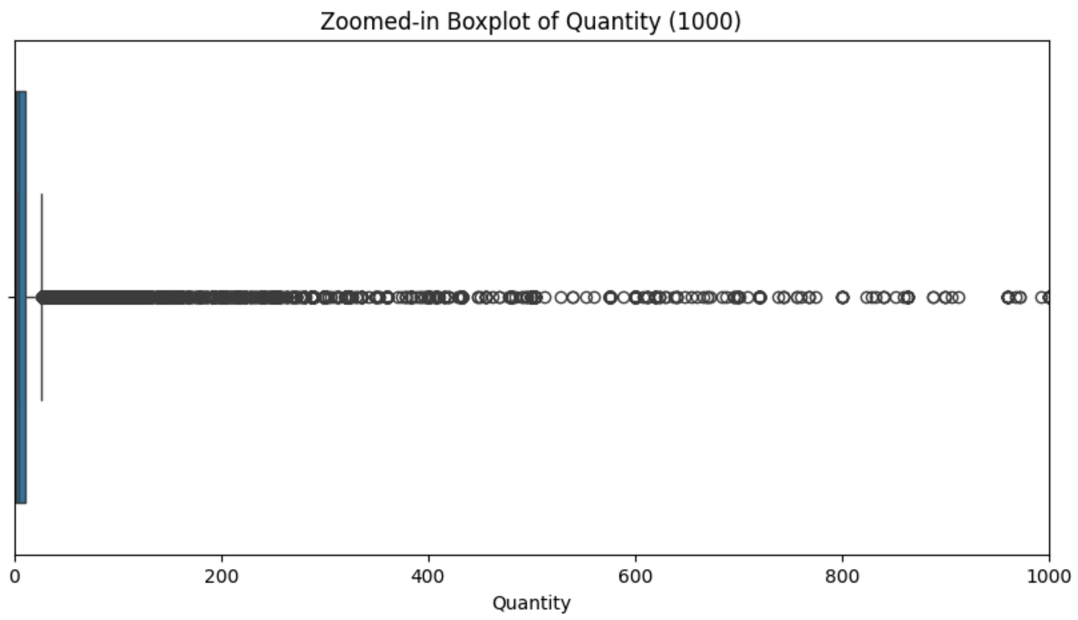
```
{'whiskers': [<matplotlib.lines.Line2D at 0x7a2a3bd4eb10>,
  <matplotlib.lines.Line2D at 0x7a2a3b64aed0>],
 'caps': [<matplotlib.lines.Line2D at 0x7a2a3b649150>,
  <matplotlib.lines.Line2D at 0x7a2a3b64bad0>],
 'boxes': [<matplotlib.lines.Line2D at 0x7a2a3d9cffd0>],
 'medians': [<matplotlib.lines.Line2D at 0x7a2a3b648e50>],
 'fliers': [<matplotlib.lines.Line2D at 0x7a2a3b64ad10>],
 'means': []}
```



Box Plot 2: Medium-Range View (0–1000)

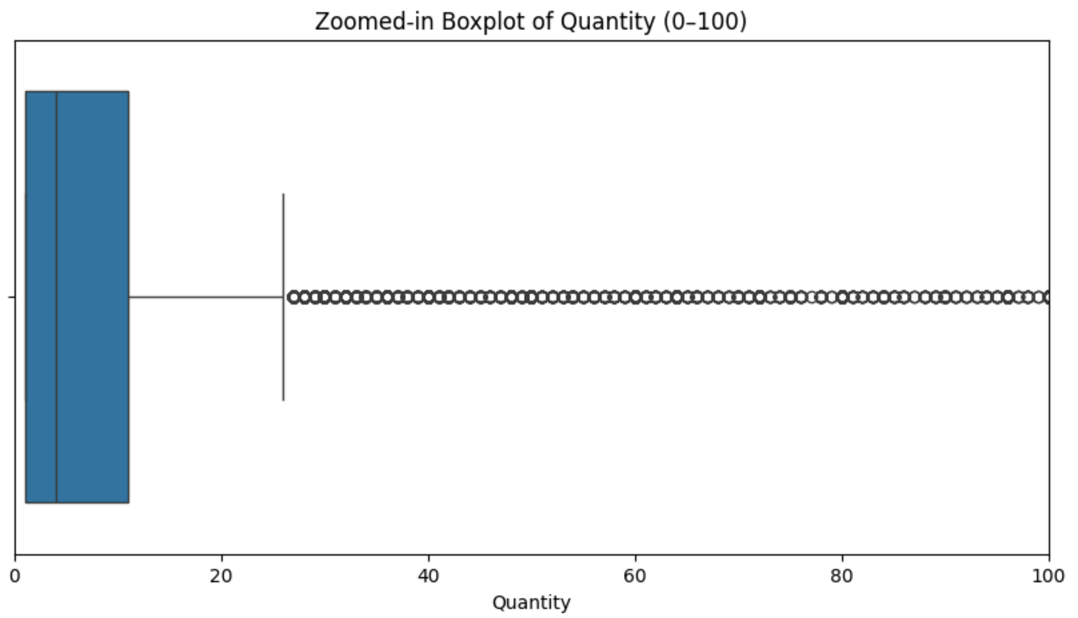
```
#  Reveals medium-size bulk purchases
#  Highlights behavior of small businesses or distributors
#  Smooths the transition from regular to bulk
```

```
plt.figure(figsize=(10, 5))
sns.boxplot(x=df1['Quantity'])
plt.xlim(0, 1000)
plt.title("Zoomed-in Boxplot of Quantity (1000)")
plt.show()
```



Box Plot 3: Zoomed-In View (0–100)

```
#  Captures small retail purchases (which make up the majority of orders)
#  Helps identify most common buying behavior (typically under 20 units)
#  Useful for customer segmentation and pattern spotting


plt.figure(figsize=(10, 5))
sns.boxplot(x=df1['Quantity'])
plt.xlim(0, 100)  # Zoom into normal range
plt.title("Zoomed-in Boxplot of Quantity (0–100)")
plt.show()
```




```
df1.UnitPrice.quantile(0.9999)
```

```
np.float64(1012.8652499996452)
```

```
#  For now, we are not going to worry about extreme values because these can be legitimate values
```

Start coding or generate with AI.

Start coding or generate with AI.

Feature Engineering : Creating New columns

```
df2=df1.copy()
df2['Total_Price']=df2['Quantity']*df2['UnitPrice']
df2.head()
```

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country	Total_Price
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	2010-12-01 08:26:00	2.55	17850.0	United Kingdom	15.30
1	536365	71053	WHITE METAL LANTERN	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom	20.34
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	2010-12-01 08:26:00	2.75	17850.0	United Kingdom	22.00
			KNITTED UNION FLAG HOT		2010-12-01			United	

```
df2.describe()
```

	Quantity	InvoiceDate	UnitPrice	CustomerID	Total_Price
count	524876.000000	524876	524876.000000	392690.000000	524876.000000
mean	10.616064	2011-07-04 15:30:02.360900608	3.922575	15287.855925	20.274425
min	1.000000	2010-12-01 08:26:00	0.001000	12346.000000	0.001000
25%	1.000000	2011-03-28 12:13:00	1.250000	13955.000000	3.900000
50%	4.000000	2011-07-20 11:22:00	2.080000	15150.000000	9.920000
75%	11.000000	2011-10-19 11:41:00	4.130000	16791.000000	17.700000
max	80995.000000	2011-12-09 12:50:00	13541.330000	18287.000000	168469.600000
std	156.279818	NaN	36.093096	1713.535580	271.693148

```
df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 524876 entries, 0 to 541908
Data columns (total 9 columns):
 #   Column       Non-Null Count   Dtype
---  ------       --------------   -----
 0   InvoiceNo    524876 non-null  string
 1   StockCode    524876 non-null  string
 2   Description  524876 non-null  string
 3   Quantity     524876 non-null  int64
 4   InvoiceDate  524876 non-null  datetime64[ns]
 5   UnitPrice    524876 non-null  float64
 6   CustomerID   392690 non-null  float64
 7   Country      524876 non-null  string
 8   Total_Price  524876 non-null  float64
dtypes: datetime64[ns](1), float64(3), int64(1), string(4)
memory usage: 40.0 MB
```

```
df2['month'] = df2['InvoiceDate'].dt.month
df2.head(3)
```

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country	Total_Price	month
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	2010-12-01 08:26:00	2.55	17850.0	United Kingdom	15.30	12
1	536365	71053	WHITE METAL LANTERN	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom	20.34	12

Start coding or generate with AI.

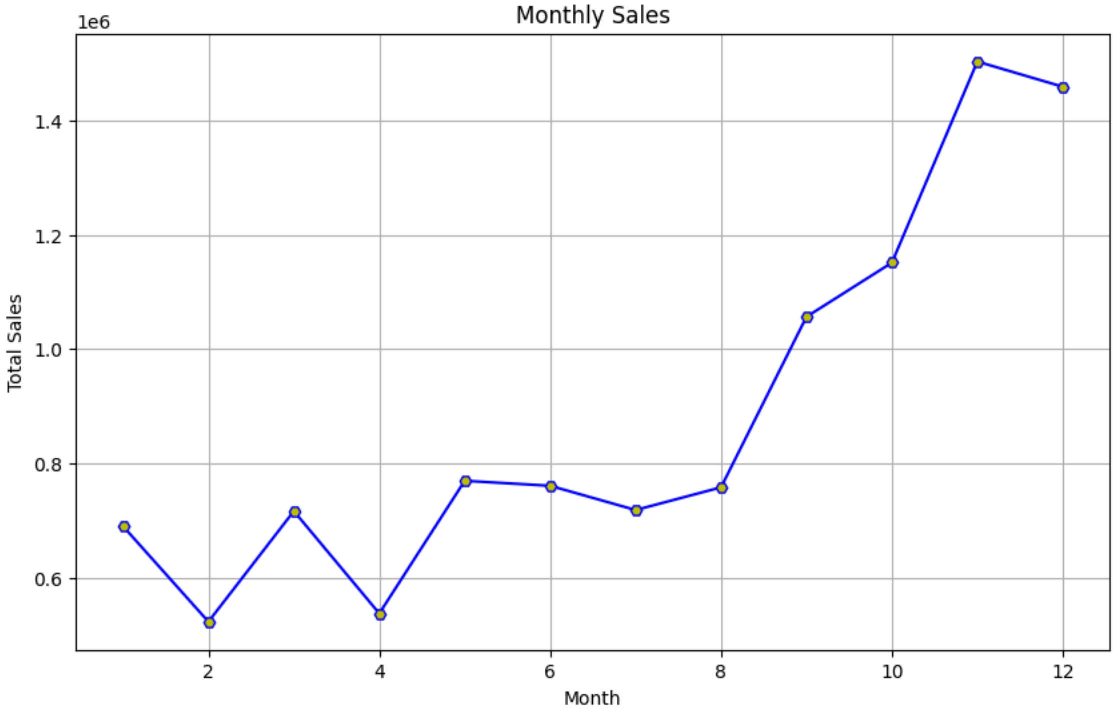
Start coding or generate with AI.

Visualization and EDA

1) Plot Monthly Sales

```
monthly_sales = df2.groupby('month')['Total_Price'].sum()
monthly_sales.plot(kind='line',color='b',marker='H',mfc='y',figsize=(10, 6))
plt.title('Monthly Sales')
plt.xlabel('Month')
```

```
plt.ylabel('Total Sales')
plt.grid()
plt.show()
```



Insights

Total sales started rising up in August having a peek in November. This is likely due to the holiday season at the end of the year

Start coding or generate with AI.

2) Top 5 countries based on total sales

```
top_5_countries = df2.groupby('Country')['Total_Price'].sum().nlargest(5)
top_5_countries
```

Country	Total_Price
United Kingdom	9001192.244
Netherlands	285446.340
EIRE	283140.520
Germany	228678.400
France	209625.370

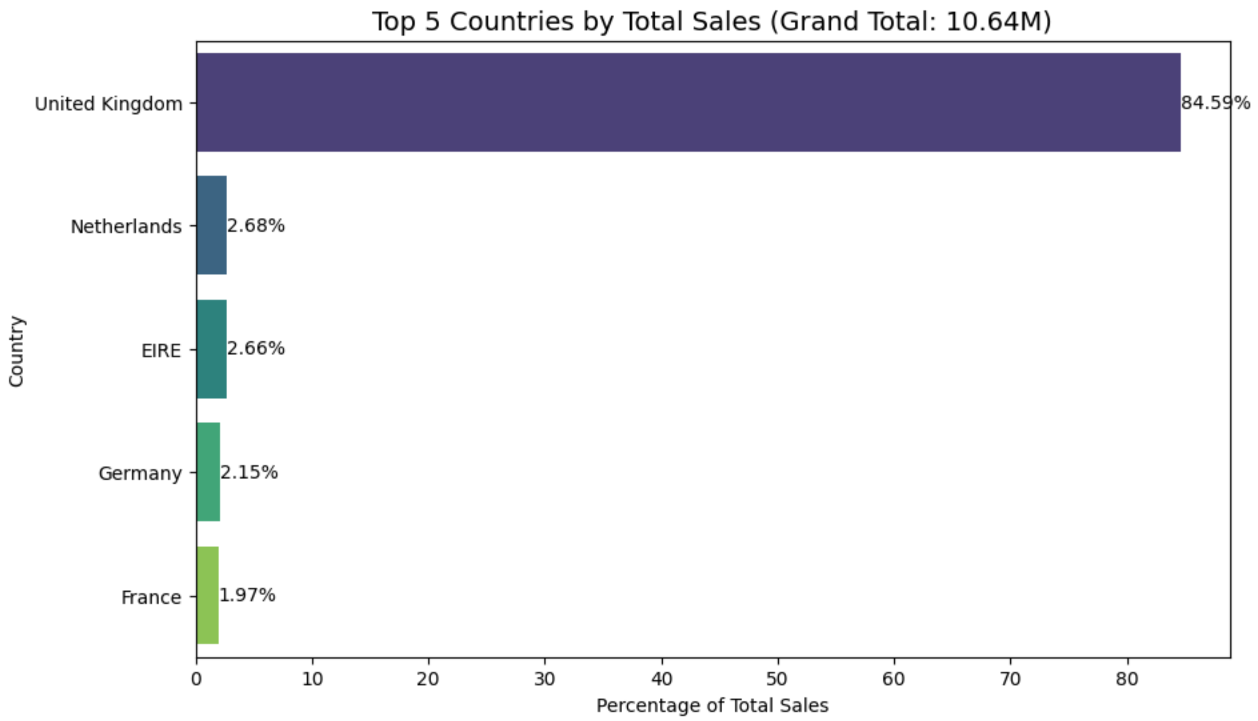
dtype: float64

```
Total_sales = df2['Total_Price'].sum()
gtm = Total_sales / 1_000_000
gtm
```

```
np.float64(10.641558954000006)
```

```
# Calculate the total percentage for each
percentages = (top_5_countries / Total_sales) * 100

# Create the horizontal bar plot with percentages
plt.figure(figsize=(10, 6))
bars = sns.barplot(x=percentages, y=percentages.index, palette="viridis")

# Add percentage labels to the bars
for bar, percentage in zip(bars.patches, percentages):
    width = bar.get_width()
    plt.text(width, bar.get_y() + bar.get_height() / 2, f"{percentage:.2f}%", ha='left', va='center')
```

```
plt.title(f"Top 5 Countries by Total Sales (Grand Total: {gtm:.2f}M)", fontsize=14)
plt.xlabel('Percentage of Total Sales')
plt.ylabel('Country')
plt.show()
```



Insights

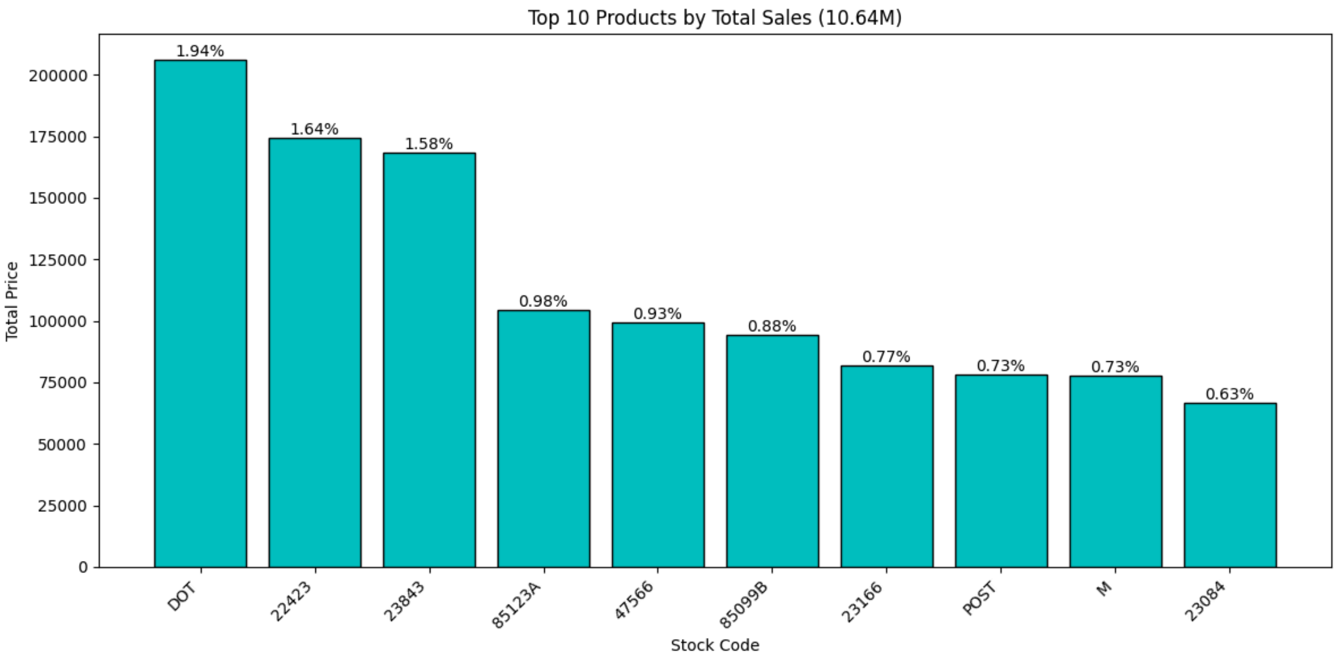
1) United Kingdom alone contributes ~84.6% of the total sales — an overwhelming majority.

2) A business overly reliant on one region (like the UK here) faces high regional concentration risk. Any disruptions (economic, political, or regulatory) in that country could impact revenue significantly.

Start coding or generate with AI.

3. Top 5 products based on sales

```
import matplotlib.pyplot as plt

# Calculate total price for each product
product_sales = df2.groupby('StockCode')['Total_Price'].sum().sort_values(ascending=False).head(10)

# Calculate percentages
total_sales = df2['Total_Price'].sum()
percentages = (product_sales / total_sales) * 100

# Create the bar plot
plt.figure(figsize=(12, 6))
bars = plt.bar(product_sales.index, product_sales.values,color= 'c',edgecolor='k')

# Add percentage labels
for bar, percentage in zip(bars, percentages):
    yval = bar.get_height()
    plt.text(bar.get_x() + bar.get_width()/2, yval + 5, f'{percentage:.2f}%', ha='center', va='bottom')

plt.xlabel('Stock Code')
plt.ylabel('Total Price')
plt.title(f"Top 10 Products by Total Sales ({gtm:.2f}M)")
plt.xticks(rotation=45, ha='right')  # Rotate x-axis labels for better readability
plt.tight_layout()
plt.show()
```



Insights

1) The product with Stock Code 'DOT' ranks #1, contributing ~1.93% of the grand total sales.

2) This product alone generates over 200K, indicating high customer demand or frequent bulk orders

Start coding or generate with AI.

4) RFM Analysis

```
current_date=df2['InvoiceDate'].max()+pd.Timedelta(days=1)
current_date
```

```
Timestamp('2011-12-10 12:50:00')
```

```
rfm= df2.groupby('CustomerID').agg({
    'InvoiceDate': lambda x: (current_date - x.max()).days,
    'InvoiceNo': 'count',
    'Total_Price': 'sum'})
rfm.columns = ['Recency', 'Frequency', 'Monetary']
rfm.head()
```

	Recency	Frequency	Monetary
CustomerID			
12346.0	326	1	77183.60
12347.0	2	182	4310.00
12348.0	75	31	1797.24
12349.0	19	73	1757.55
12350.0	310	17	334.40

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

```
## To check
df2[df2.CustomerID==12347]['Total_Price'].sum()
```

```
np.float64(4310.000000000001)
```

```
## Segment Customers based on RFM
rfm['R_Score'] = pd.qcut(rfm['Recency'], 4, labels=[4, 3,2,1])
```

```
rfm['F_Score'] = pd.qcut(rfm['Frequency'], 4, labels=[1,2,3,4])
rfm['M_Score'] = pd.qcut(rfm['Monetary'], 4, labels=[1,2,3,4])
rfm['RFM_Score'] = rfm[['R_Score','F_Score','M_Score']].sum(axis=1)
rfm
```

	Recency	Frequency	Monetary	R_Score	F_Score	M_Score	RFM_Score
CustomerID							
12346.0	326	1	77183.60	1	1	4	6
12347.0	2	182	4310.00	4	4	4	12
12348.0	75	31	1797.24	2	2	4	8
12349.0	19	73	1757.55	3	3	4	10
12350.0	310	17	334.40	1	1	2	4
...	...	...	...	...	...	...	...
18280.0	278	10	180.60	1	1	1	3
18281.0	181	7	80.82	1	1	1	3
18282.0	8	12	178.05	4	1	1	6
18283.0	4	721	2045.53	4	4	4	12
18287.0	43	70	1837.28	3	3	4	10

4338 rows × 7 columns

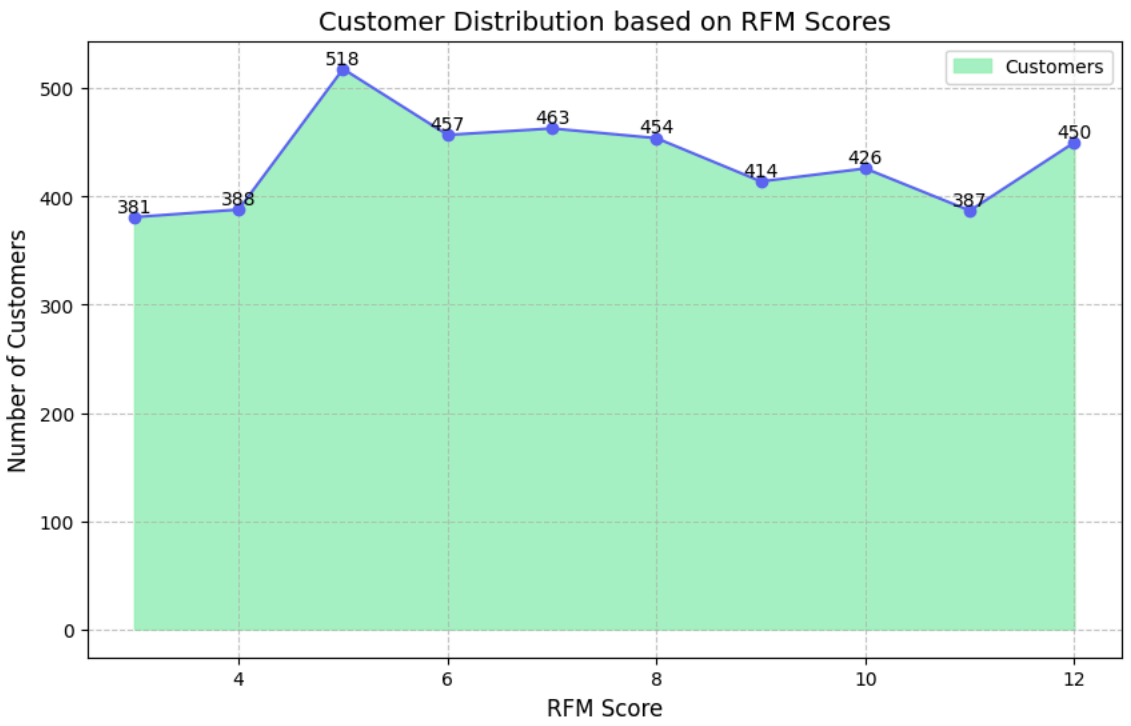
Next steps: Generate code with rfm | View recommended plots | New interactive sheet

```
rfm.sort_values(by='RFM_Score', ascending=False)
```

	Recency	Frequency	Monetary	R_Score	F_Score	M_Score	RFM_Score
CustomerID							
18283.0	4	721	2045.53	4	4	4	12
18245.0	7	175	2567.06	4	4	4	12
18241.0	10	104	2073.09	4	4	4	12
18229.0	12	164	7276.90	4	4	4	12
18225.0	3	269	5504.96	4	4	4	12
...	...	...	...	...	...	...	...
14962.0	271	5	126.70	1	1	1	3
14964.0	247	13	206.21	1	1	1	3
14981.0	246	8	102.12	1	1	1	3
16226.0	203	8	255.12	1	1	1	3
18224.0	264	10	158.95	1	1	1	3

4338 rows × 7 columns

```
rfm_counts = rfm['RFM_Score'].value_counts().sort_index()

plt.figure(figsize=(10, 6))
plt.fill_between(rfm_counts.index, rfm_counts.values, alpha=0.8, color='#94F2B5', label='Customers')  # Filled area
plt.plot(rfm_counts.index, rfm_counts.values, marker='o', linestyle='-', color='#5C64F2')  # Line with markers
plt.xlabel("RFM Score", fontsize=12)
plt.ylabel("Number of Customers", fontsize=12)
plt.title("Customer Distribution based on RFM Scores", fontsize=14)

# Add labels for each data point
for x, y in zip(rfm_counts.index, rfm_counts.values):
    plt.text(x, y + 1, str(y), ha='center', va='bottom', fontsize=10)

plt.legend()
plt.grid(True, linestyle='--', alpha=0.7)
plt.show()
```



Insights:

1) Score 5 has the highest customer count (516) – these are moderately engaged customers with good potential to convert into loyal buyers.

2) Score 12 also has a strong count (447) – these are likely your most loyal and high-value customers. Prioritize them for exclusive offers.

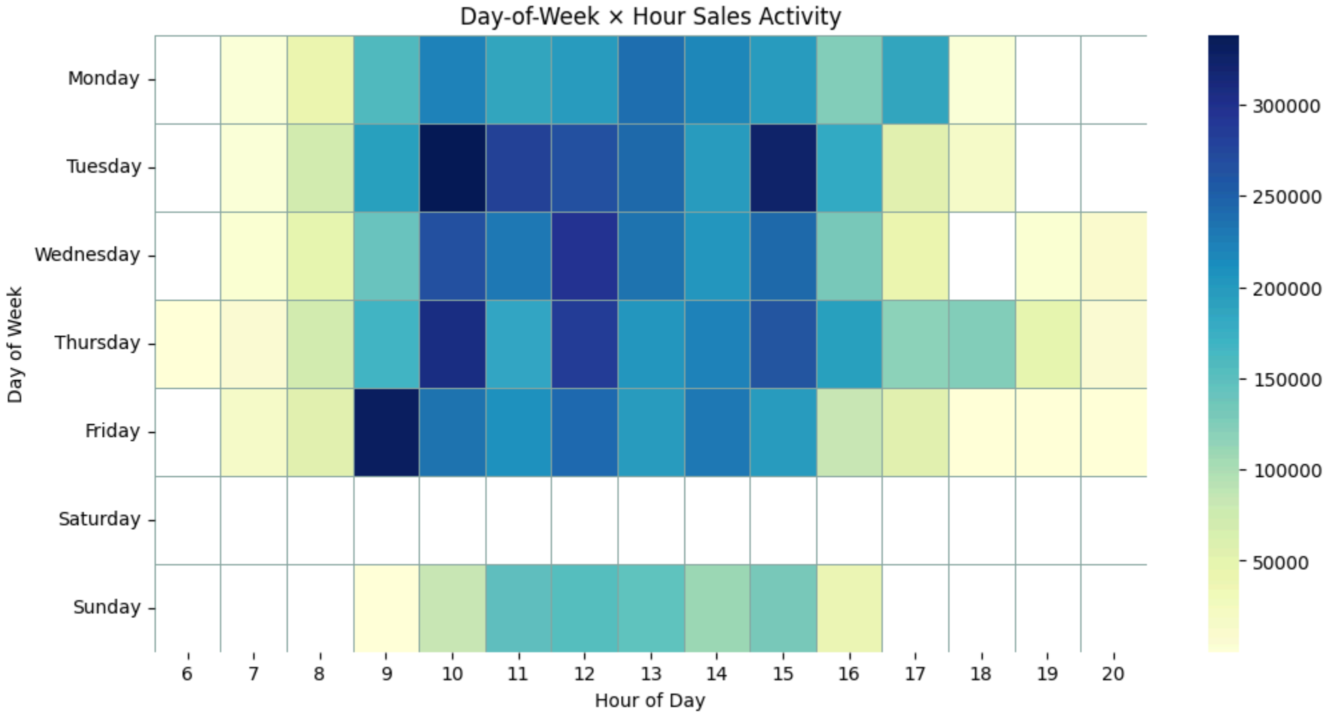
3) Drop at Scores 4 and 11 – these segments may need re-engagement or targeted promotions to boost activity.

Start coding or generate with AI.

Start coding or generate with AI.

5) Hourly Sales Distribution Across the Week

```
import calendar
df2['DayOfWeekName'] = df2['InvoiceDate'].dt.day_name()
df2['Hour'] = df2['InvoiceDate'].dt.hour

sales_activity_named = df2.groupby(['DayOfWeekName', 'Hour'])['Total_Price'].sum().unstack()
# Optional: Order the days correctly
ordered_days = list(calendar.day_name)
sales_activity_named = sales_activity_named.reindex(ordered_days)

plt.figure(figsize=(12, 6))
sns.heatmap(sales_activity_named, cmap='YlGnBu', annot=False, fmt=".0f", linewidths=.5,linecolor='#8AA6A3')
plt.title('Day-of-Week × Hour Sales Activity')
plt.xlabel('Hour of Day')
plt.ylabel('Day of Week')
plt.show()
```



Insights

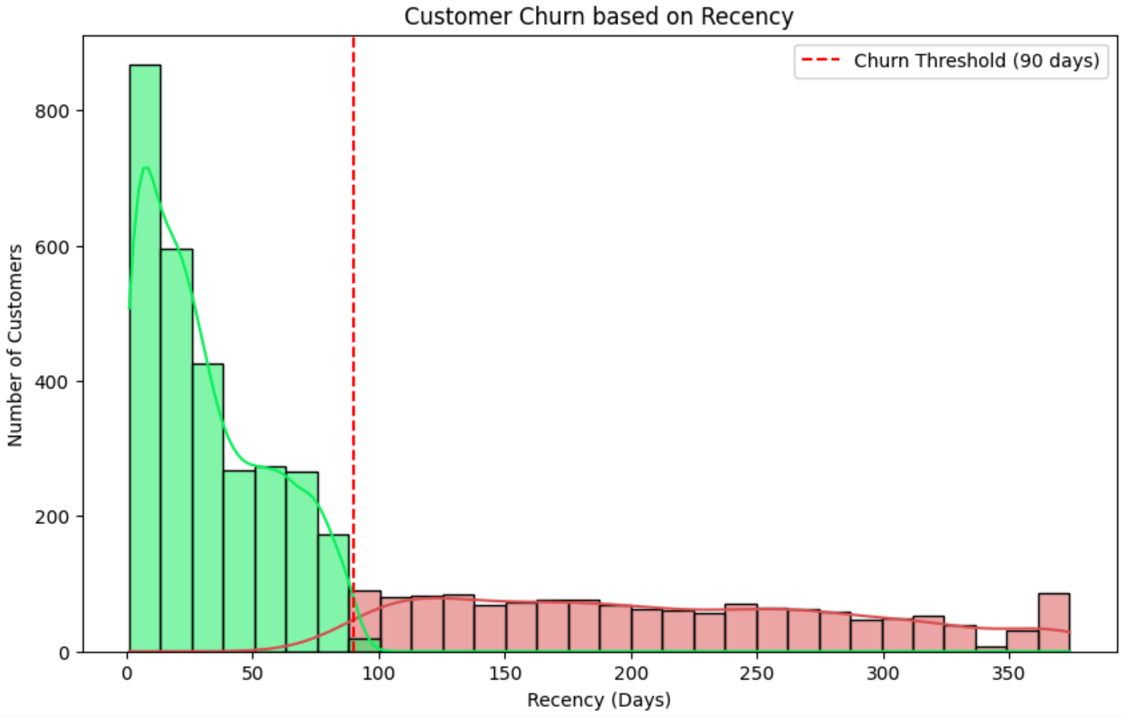
1) Sales are highest during midday hours (11 AM to 2 PM) across most weekdays, indicating a strong buyer presence during business hours.

2) A noticeable dip in sales occurs on Saturday and Sunday, possibly indicating **reduced** B2B activity or business hours.

Start coding or generate with AI.

6) Customer Churn Analysis

```
churn_threshold = 90  # Define churn threshold in days

# Create a new column indicating churn status
rfm['Churned'] = rfm['Recency'] > churn_threshold

# Prepare the DataFrame for seaborn (long-form data)
plt.figure(figsize=(10, 6))
sns.histplot(data=rfm, x='Recency', kde=True, hue='Churned', bins=30, palette=['#0CF25D', '#D95252'])

# Add the threshold line
plt.axvline(churn_threshold, color='red', linestyle='--', label=f'Churn Threshold ({churn_threshold} days)')

# Add labels
plt.xlabel('Recency (Days)')
plt.ylabel('Number of Customers')
plt.title('Customer Churn based on Recency')
plt.legend()
plt.show()
```



Insights

1) Churn Identification: Customers who haven't made a purchase in the last 90 days or more are considered churned. This segment makes up a significant portion, highlighting a need for re-engagement strategies.

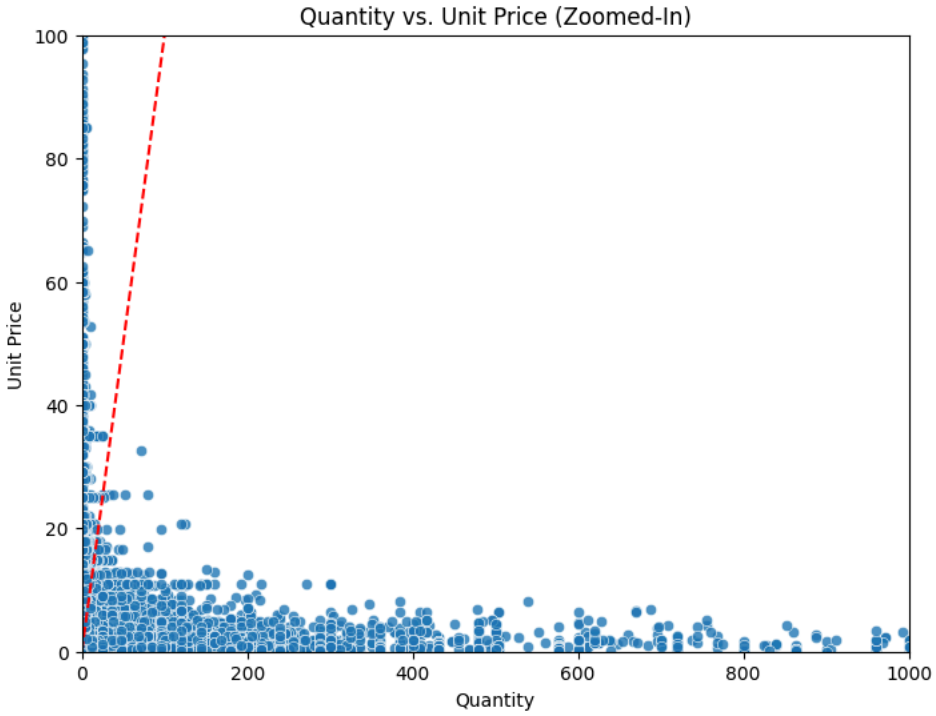
2) Distribution Observation: The majority of customers fall below the 90-day recency mark, suggesting strong engagement overall—but the right tail indicates a growing risk of churn among long-inactive users.

3) Actionable Threshold: The 90-day churn threshold acts as a valuable benchmark for retention campaigns. Targeting users nearing or just past this mark can reduce churn effectively.

Start coding or generate with AI.

7) Transaction Density: Quantity vs. Unit Price (Zoomed-In)

```
plt.figure(figsize=(8, 6))
sns.scatterplot(data=df2, x='Quantity', y='UnitPrice', alpha=0.8)
plt.plot([0, 1000], [0, 1000], color='red', linestyle='--')  # Diagonal reference line
plt.xlim(0, 1000)  # Focus on the main part (adjust limits as needed)
plt.ylim(0, 100)   # Focus on the main part (adjust limits as needed)
plt.title('Quantity vs. Unit Price (Zoomed-In)')
plt.xlabel('Quantity')
plt.ylabel('Unit Price')
plt.show()
```



Insights

1) High Volume of Low-Value Transactions: Most purchases involve low quantities and low unit prices, indicating a large number of everyday