Bike Store Sales

October 30, 2025

Bike Store Sales

Hands on!

[4]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

%matplotlib inline
```

Loading the data:

[6]:
```
sales = pd.read_csv(r"C:\Users\Admin\Downloads\sales_data.csv",␣
↪parse_dates=["Date"])
```

The data glance:

[7]:
```
sales.head()
```

[7]:
```
        Date  Day     Month  Year  Customer_Age       Age_Group  \
0 2013-11-26   26  November  2013            19     Youth (<25)
1 2015-11-26   26  November  2015            19     Youth (<25)
2 2014-03-23   23     March  2014            49  Adults (35-64)
3 2016-03-23   23     March  2016            49  Adults (35-64)
4 2014-05-15   15       May  2014            47  Adults (35-64)

  Customer_Gender    Country             State Product_Category Sub_Category  \
0               M     Canada  British Columbia      Accessories   Bike Racks
1               M     Canada  British Columbia      Accessories   Bike Racks
2               M  Australia   New South Wales      Accessories   Bike Racks
3               M  Australia   New South Wales      Accessories   Bike Racks
4               F  Australia   New South Wales      Accessories   Bike Racks

              Product  Order_Quantity  Unit_Cost  Unit_Price  Profit  Cost  \
0  Hitch Rack - 4-Bike               8         45         120     590   360
1  Hitch Rack - 4-Bike               8         45         120     590   360
2  Hitch Rack - 4-Bike              23         45         120    1366  1035
3  Hitch Rack - 4-Bike              20         45         120    1188   900
4  Hitch Rack - 4-Bike               4         45         120     238   180
```

```
   Revenue
0      950
1      950
2     2401
3     2088
4      418
```

[8]:
```
sales.shape
```

[8]:
```
(113036, 18)
```

[9]:
```
sales.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 113036 entries, 0 to 113035
Data columns (total 18 columns):
 #   Column            Non-Null Count   Dtype
---  ------            --------------   -----
 0   Date              113036 non-null  datetime64[ns]
 1   Day               113036 non-null  int64
 2   Month             113036 non-null  object
 3   Year              113036 non-null  int64
 4   Customer_Age      113036 non-null  int64
 5   Age_Group         113036 non-null  object
 6   Customer_Gender   113036 non-null  object
 7   Country           113036 non-null  object
 8   State             113036 non-null  object
 9   Product_Category  113036 non-null  object
 10  Sub_Category      113036 non-null  object
 11  Product           113036 non-null  object
 12  Order_Quantity    113036 non-null  int64
 13  Unit_Cost         113036 non-null  int64
 14  Unit_Price        113036 non-null  int64
 15  Profit            113036 non-null  int64
 16  Cost              113036 non-null  int64
 17  Revenue           113036 non-null  int64
dtypes: datetime64[ns](1), int64(9), object(8)
memory usage: 15.5+ MB
```

[10]:
```
sales.describe()
```

[10]:
```
                                Date            Day           Year  \
count                         113036  113036.000000  113036.000000
mean   2014-11-23 12:14:55.063519232      15.665753    2014.401739
min              2011-01-01 00:00:00       1.000000    2011.000000
25%              2013-12-22 00:00:00       8.000000    2013.000000
50%              2014-06-27 00:00:00      16.000000    2014.000000
75%              2016-01-09 00:00:00      23.000000    2016.000000
```

```
max            2016-07-31 00:00:00      31.000000    2016.000000
std                            NaN       8.781567       1.272510

        Customer_Age  Order_Quantity      Unit_Cost     Unit_Price  \
count  113036.000000   113036.000000  113036.000000  113036.000000
mean       35.919212       11.901660     267.296366     452.938427
min        17.000000        1.000000       1.000000       2.000000
25%        28.000000        2.000000       2.000000       5.000000
50%        35.000000       10.000000       9.000000      24.000000
75%        43.000000       20.000000      42.000000      70.000000
max        87.000000       32.000000    2171.000000    3578.000000
std        11.021936        9.561857     549.835483     922.071219

              Profit           Cost        Revenue
count  113036.000000  113036.000000  113036.000000
mean      285.051665     469.318695     754.370360
min       -30.000000       1.000000       2.000000
25%        29.000000      28.000000      63.000000
50%       101.000000     108.000000     223.000000
75%       358.000000     432.000000     800.000000
max     15096.000000   42978.000000   58074.000000
std       453.887443     884.866118    1309.094674
```

Numerical analysis and visualization

We'll analyze the Unit_Cost column:

[11]:
```
sales['Unit_Cost'].describe()
```

[11]:
```
count    113036.000000
mean        267.296366
std         549.835483
min           1.000000
25%           2.000000
50%           9.000000
75%          42.000000
max        2171.000000
Name: Unit_Cost, dtype: float64
```

[12]:
```
sales['Unit_Cost'].mean()
```

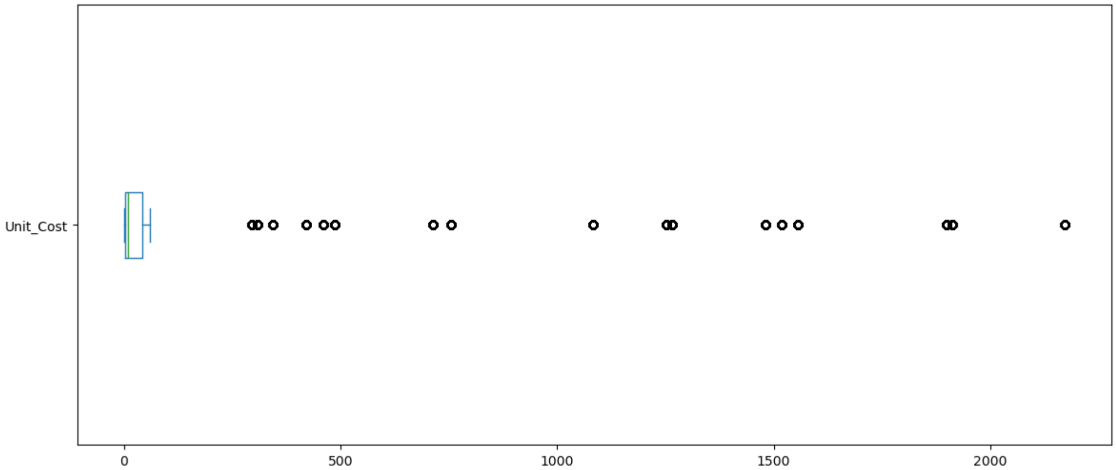
[12]:
```
np.float64(267.296365759581)
```

[13]:
```
sales['Unit_Cost'].median()
```

[13]:
```
9.0
```

[14]:

```
sales['Unit_Cost'].plot(kind='box', vert=False, figsize=(14,6))
plt.show()

# What I can see ?
# The Unit_Cost distribution is right-skewed - most products are low-cost,
# with a few high-cost outliers. The median represents the typical cost better␣
↪than the mean.
# Outliers may indicate premium products or data issues.
# A log transformation could help normalize the data for further analysis.
```

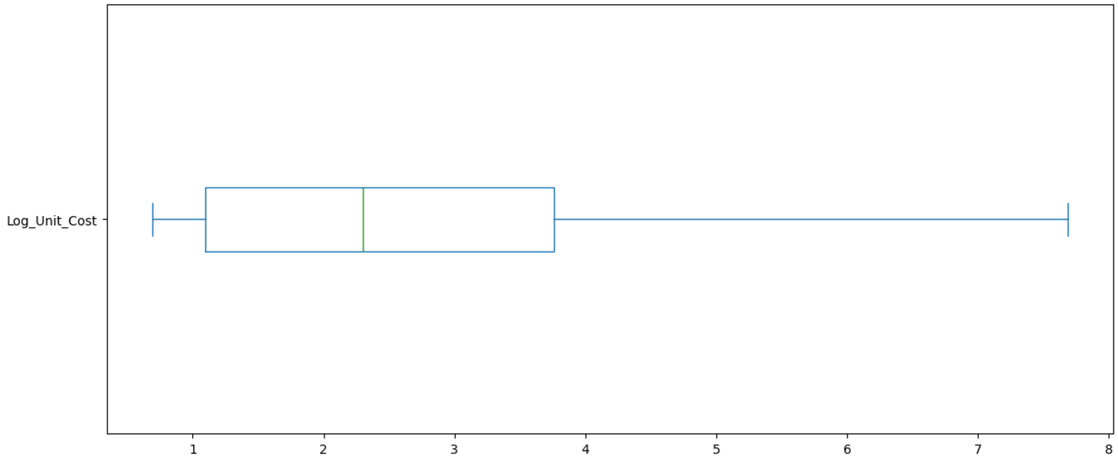


[15]:

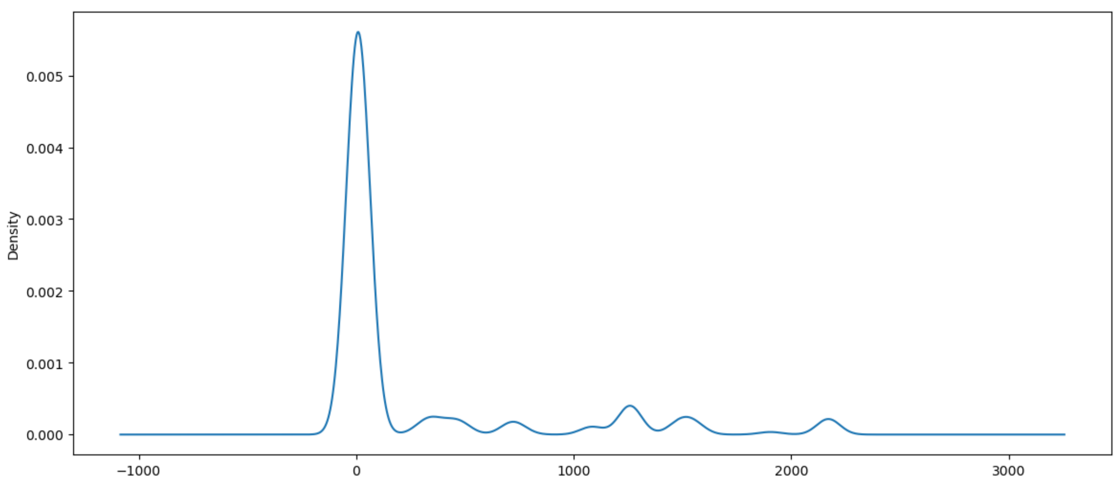
```
sales['Log_Unit_Cost']=np.log(sales['Unit_Cost']+1)
```

[16]:

```
sales['Log_Unit_Cost'].plot(kind='box' , vert = False , figsize =(14,6))
plt.show()

# Applied log transformation to reduce right skewness in Unit_Cost.
# This helps compress large values, making the distribution more symmetrical.
# It improves visibility of lower-cost products and prepares the data for␣
↪accurate statistical analysis
```



[17]:
```
sales['Unit_Cost'].plot(kind = 'density' , figsize =(14,6)) # kde (Kernel␣
 ↪Density Estimation plot)
plt.show()

# The KDE curve shows the distribution of Unit_Cost values.
# Most products have low costs, with a long right tail indicating a few␣
 ↪expensive items.
```

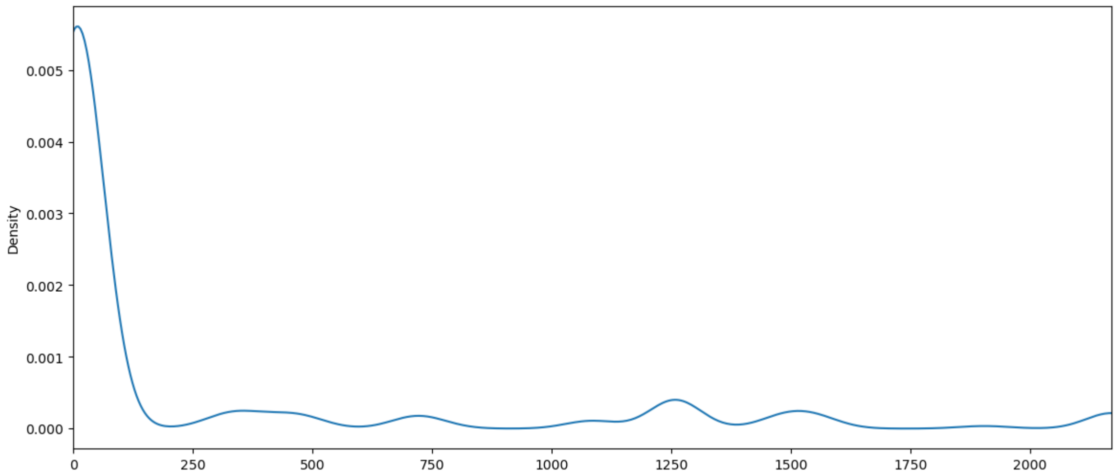


[18]:
```
sales[sales['Unit_Cost'] < 0]
# The curve near -1000 is just a smoothing side effect, not an actual data␣
 ↪problem.
```

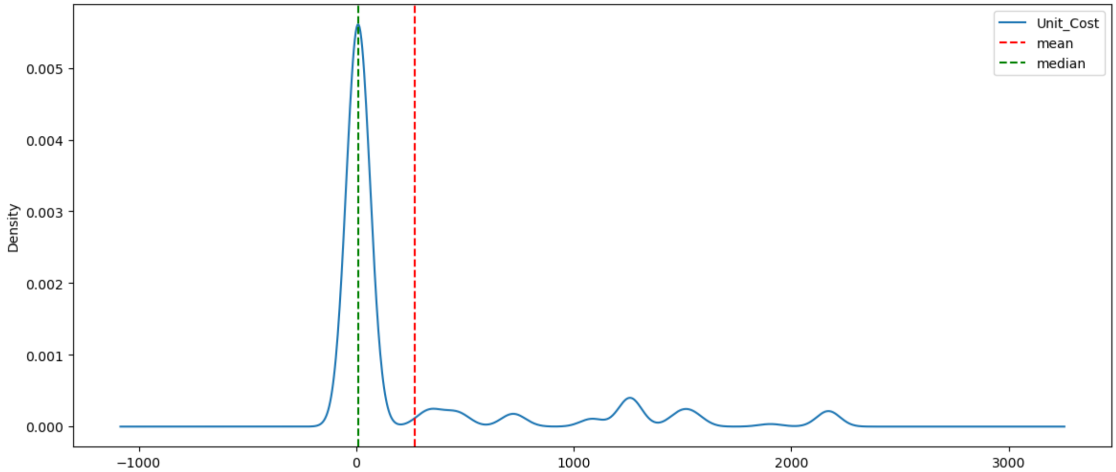
[18]:
```
Empty DataFrame
Columns: [Date, Day, Month, Year, Customer_Age, Age_Group, Customer_Gender,
```

```
Country, State, Product_Category, Sub_Category, Product, Order_Quantity,
Unit_Cost, Unit_Price, Profit, Cost, Revenue, Log_Unit_Cost]
Index: []
```

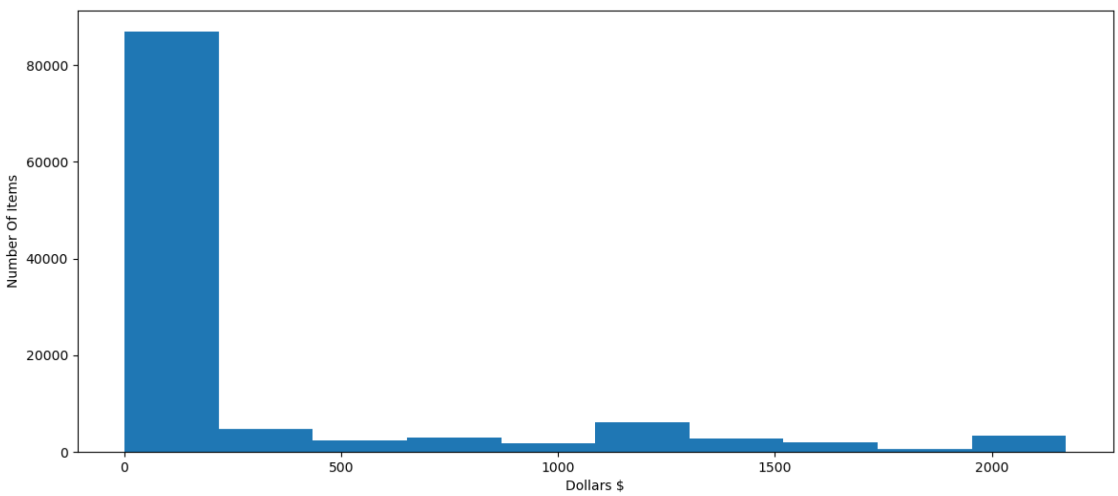
[19]:
```
ax = sales['Unit_Cost'].plot(kind='density', figsize=(14,6))
ax.set_xlim(0, sales['Unit_Cost'].max())  # start from 0  | remove negative␣
↪areas
plt.show()
```



[20]:
```
ax = sales['Unit_Cost'].plot(kind='density', figsize=(14,6))
ax.axvline(sales['Unit_Cost'].mean(),color='red',linestyle ='--',label='mean')
ax.axvline(sales['Unit_Cost'].median(),color='green',linestyle ='--',label =␣
↪'median')
ax.legend()
plt.show()

#The KDE chart shows a right-skewed distribution, where most unit costs are low␣
↪with a few high-cost outliers.
#The mean (red line) is slightly higher than the median (green line).
#This indicates that the average cost is influenced by a small number of␣
↪expensive products.
```



[21]:
```
ax = sales['Unit_Cost'].plot(kind='hist', figsize=(14,6))
ax.set_ylabel('Number Of Items')
ax.set_xlabel('Dollars $')
plt.show()

#Tall bars on the left => many cheap items.
#Long tail on the right => few expensive items
```



Categorical analysis and visualization

We'll analyze the Age_Group column:

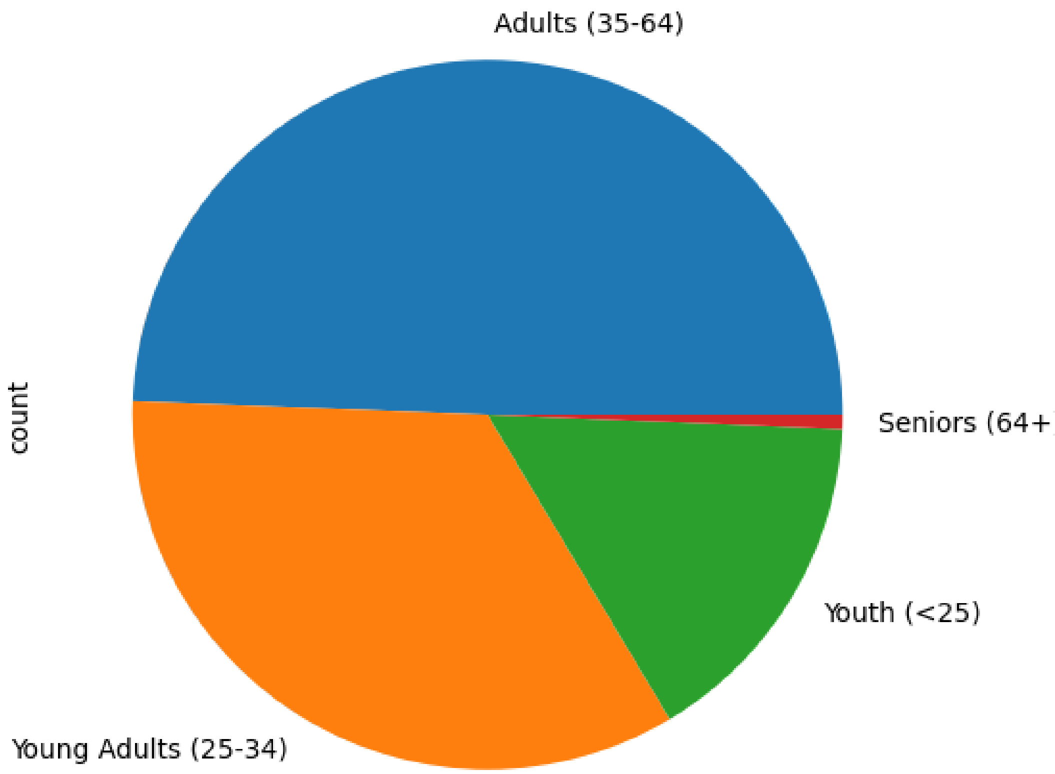
[22]:
```
sales.head()
```

[22]:
```
         Date  Day     Month  Year  Customer_Age       Age_Group  \
0  2013-11-26   26  November  2013            19     Youth (<25)
1  2015-11-26   26  November  2015            19     Youth (<25)
2  2014-03-23   23     March  2014            49  Adults (35-64)
3  2016-03-23   23     March  2016            49  Adults (35-64)
4  2014-05-15   15       May  2014            47  Adults (35-64)

  Customer_Gender    Country             State Product_Category Sub_Category  \
0               M     Canada  British Columbia      Accessories   Bike Racks
1               M     Canada  British Columbia      Accessories   Bike Racks
2               M  Australia   New South Wales      Accessories   Bike Racks
3               M  Australia   New South Wales      Accessories   Bike Racks
4               F  Australia   New South Wales      Accessories   Bike Racks

              Product  Order_Quantity  Unit_Cost  Unit_Price  Profit  Cost  \
0  Hitch Rack - 4-Bike               8         45         120     590   360
1  Hitch Rack - 4-Bike               8         45         120     590   360
2  Hitch Rack - 4-Bike              23         45         120    1366  1035
3  Hitch Rack - 4-Bike              20         45         120    1188   900
4  Hitch Rack - 4-Bike               4         45         120     238   180

   Revenue  Log_Unit_Cost
0      950       3.828641
1      950       3.828641
2     2401       3.828641
3     2088       3.828641
4      418       3.828641
```

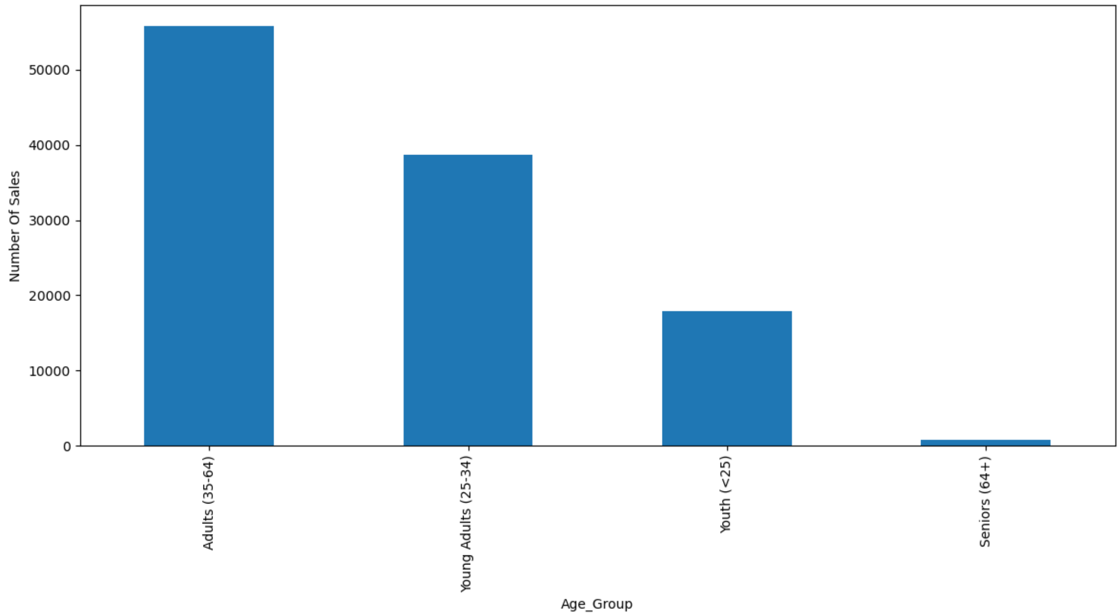
[23]:
```python
sales['Age_Group'].value_counts()
```

[23]:
```
Age_Group
Adults (35-64)          55824
Young Adults (25-34)    38654
Youth (<25)             17828
Seniors (64+)             730
Name: count, dtype: int64
```

[24]:
```python
sales['Age_Group'].value_counts().plot(kind='pie' ,figsize=(6,6))
plt.show()

# Pie Chart Displays the percentage distribution of Age_Group
```



[25]:
```
ax = sales['Age_Group'].value_counts().plot(kind='bar' ,figsize=(14,6))
ax.set_ylabel('Number Of Sales')
plt.show()

# Bar Chart identify which customer age group contributes most to total sales
```



Relationship between the columns?

Can we find any significant relationship?

[26]:
```python
sales.drop(columns=['Log_Unit_Cost'] , inplace=True)
```

[27]:
```python
correlation = sales.select_dtypes(include=['number']).corr()
correlation

#   What I Found ?
# - Unit_Cost and Unit_Price are high positive correlated (~0.99), meaning
↪prices rise with cost.
# - Profit shows a strong positive correlation with both Revenue (~0.96) and
↪Cost (~0.90),
#   means that higher sales increase both costs and profits
# - Order_Quantity has a moderate negative correlation with Unit_Cost and
↪Unit_Price (~-0.5),
#   suggesting bulk purchases come with lower unit prices.
# - Customer_Age, Day, and Year show weak correlations with other variables,
#   indicating little linear relationship with sales metrics.
```

[27]:

	Day	Year	Customer_Age	Order_Quantity	Unit_Cost \
Day	1.000000	-0.007635	-0.014296	-0.002412	0.003133
Year	-0.007635	1.000000	0.040994	0.123169	-0.217575
Customer_Age	-0.014296	0.040994	1.000000	0.026887	-0.021374
Order_Quantity	-0.002412	0.123169	0.026887	1.000000	-0.515835
Unit_Cost	0.003133	-0.217575	-0.021374	-0.515835	1.000000

```
Unit_Price       0.003207 -0.213673     -0.020262        -0.515925    0.997894
Profit           0.004623 -0.181525      0.004319        -0.238863    0.741020
Cost             0.003329 -0.215604     -0.016013        -0.340382    0.829869
Revenue          0.003853 -0.208673     -0.009326        -0.312895    0.817865

                Unit_Price    Profit      Cost   Revenue
Day               0.003207  0.004623  0.003329  0.003853
Year             -0.213673 -0.181525 -0.215604 -0.208673
Customer_Age     -0.020262  0.004319 -0.016013 -0.009326
Order_Quantity   -0.515925 -0.238863 -0.340382 -0.312895
Unit_Cost         0.997894  0.741020  0.829869  0.817865
Unit_Price        1.000000  0.749870  0.826301  0.818522
Profit            0.749870  1.000000  0.902233  0.956572
Cost              0.826301  0.902233  1.000000  0.988758
Revenue           0.818522  0.956572  0.988758  1.000000
```

[28]:
```python
fig = plt.figure(figsize=(8,8))
plt.matshow(corr, cmap='RdBu', fignum=0)
plt.xticks(range(len(corr.columns)), corr.columns, rotation='vertical');
plt.yticks(range(len(corr.columns)), corr.columns);
plt.show()

# In this heatmap
#  Blue => Positive correlation (variables increase together)
#  Red => Negative correlation (one increases while the other decreases)
#  Light color => Weak or no correlation (little relationship)

# The heatmap shows strong positive correlations among Profit, Revenue, and␣
 ↪Cost -
# meaning profitability rises with higher sales and expenses.
# Order_Quantity is negatively correlated with Unit_Price/Cost, suggesting bulk␣
 ↪discounts.
# Time and Customer_Age have little direct impact on financial metrics.
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
Cell In[28], line 2
      1 fig = plt.figure(figsize=(8,8))
----> 2 plt.matshow(corr, cmap='RdBu', fignum=0)
      3 plt.xticks(range(len(corr.columns)), corr.columns, rotation='vertical')
      4 plt.yticks(range(len(corr.columns)), corr.columns);

NameError: name 'corr' is not defined
```

[ ]:
```python
sales.plot(kind='scatter' , x='Customer_Age' , y='Revenue' , figsize=(6,6))
plt.show()
```

```
# The scatter plot shows that most revenue comes from customers aged 20-50.
# Older customers (60+) generate less revenue, and there's no clear correlation
# between age and spending. A few high-value outliers exist around age 50.
```

[ ]:
```
sales.plot(kind='scatter' , x='Revenue' , y='Profit' , figsize=(6,6))
plt.show()

# The scatter plot shows a clear positive relationship between Revenue and␣
↪Profit -
# higher sales generally lead to higher profits. A few outliers may indicate
# exceptional or unprofitable transactions.
```

[ ]:
```
ax = sales[['Profit','Age_Group']].boxplot(by='Age_Group',figsize=(10,6))
ax.set_ylabel('Profit')
plt.show()

# This box plot compares Profit distribution across different Age_Groups.
# It helps identify which age segment generates the most profit
# and highlights variations or outliers within each group.
```

[ ]:
```
boxplot_cols = ['Year', 'Customer_Age', 'Order_Quantity', 'Unit_Cost',␣
↪'Unit_Price', 'Profit']
sales[boxplot_cols].plot(kind='box' , subplots=True , layout=(2,3) ,␣
↪figsize=(14,8))
plt.show()
```

[ ]:
```
sales['Customer_Age'].value_counts()
```

[ ]:
```
sales[sales['Profit']<0]
```

Column wrangling

We can also create new columns or modify existing ones.

Add and calculate a new Revenue_per_Age column by dividing Revenue by Customer_Age for each entry in the dataset.

[ ]:
```
sales['Revenue_Per_Age'] = sales['Revenue'] / sales['Customer_Age']
sales['Revenue_Per_Age'].head()
```

[ ]:
```
sales['Revenue_Per_Age'].plot(kind='density'  , figsize=(14,6))
plt.show()

# The sharp peak indicates that most customers contribute a similar amount of␣
↪revenue relative to their age,
# suggesting a dominant customer segment or consistent pricing model.
```

```
# The smooth curve helps identify the central tendency and spread, while any␣
↪skew or tail could point to outliers-
# such as older customers with unusually high revenue impact.
```

Add and calculate a new `Calculated_Cost` column

Use This Formula

Calculated_Cost = Order_Quantity * Unit_Cost

[ ]:
```
sales['Calculated_Cost'] = sales['Order_Quantity'] * sales['Unit_Cost']
sales['Calculated_Cost'].head()
```

[ ]:
```
sales.head(30)
```

[ ]:
```
(sales['Calculated_Cost'] != sales['Cost']).sum()
```

Add and calculate a new `Calculated_Revenue` column

Use This Formula

Calculated_Revenue = Profit + Cost

[ ]:
```
sales['Calculated_Revenue'] = sales['Profit'] + sales['Cost']
sales['Calculated_Revenue'].head()
```

[ ]:
```
(sales['Calculated_Revenue'] != sales['Revenue']).sum()
```

[ ]:
```
sales.head()
```

[ ]:
```
sales['Revenue'].plot( kind='hist' , bins=100 , figsize=(14,6))
plt.show()
```

[ ]:
```
# Define thresholds using quantiles
low_threshold = sales['Revenue'].quantile(0.33)
high_threshold = sales['Revenue'].quantile(0.66)

# Create a segmentation function
def segment_customer(revenue):
    if revenue <= low_threshold:
        return 'Low Revenue'
    elif revenue <= high_threshold:
        return 'Medium Revenue'
    else:
        return 'High Revenue'

# Apply segmentation
sales['Revenue_Segment'] = sales['Revenue'].apply(segment_customer)

# Preview the result
```

```
sales[['Revenue', 'Revenue_Segment']].head()
```

[ ]:
```
sales.head()
```

[ ]:
```
# Count customers in each segment
segment_counts = sales['Revenue_Segment'].value_counts().sort_index()

# Plot the bar chart
plt.figure(figsize=(8, 5))
plt.bar(segment_counts.index, segment_counts.values, color=['#e74c3c',␣
↪'#f1c40f', '#2ecc71'])
plt.title('Customer Distribution by Revenue Segment')
plt.xlabel('Revenue Segment')
plt.ylabel('Number of Customers')
plt.tight_layout()
plt.show()
```

Modify all Unit_Price values adding 3% tax to them

new price=original price+(original price×3%)

[ ]:
```
sales['Unit_Price_Tax'] = sales['Unit_Price'] * 1.03
sales['Unit_Price_Tax'].head()
```

[ ]:
```
sales.head()
```

Selection & Indexing:

Get all the sales made in the state of Kentucky

[ ]:
```
sales.loc[sales['State'] == 'Kentucky']
```

[ ]:
```
sales.loc[sales['State'] == 'Kentucky'].shape
```

[ ]:
```
sales.loc[sales['State'] == 'Kentucky', 'Customer_Gender'].value_counts()
```

Get the mean revenue of the sales group Adults (35-64)

[ ]:
```
sales.loc[sales['Age_Group'] == 'Adults (35-64)','Revenue'].mean().round(2)
```

How many records belong to Age Group Youth (<25) or Adults (35-64) ?

[ ]:
```
sales.loc[(sales['Age_Group'] == 'Youth (<25)') | (sales['Age_Group'] ==␣
↪'Adults (35-64)')].shape[0]
```

Get the mean revenue of the sales group Adults (35-64) in United States ?

[ ]:
```
sales.loc[(sales['Age_Group'] == 'Adults (35-64)') & (sales['Country'] ==␣
↪'United States'),'Revenue'].mean().round(2)
```

Increase the revenue by 10% to every sale made in France

[ ]:
```
sales.loc[sales['Country'] == 'France','Revenue'].head()
```

[ ]:
```
sales.loc[sales['Country'] == 'France','Revenue'] *=1.1

# Increasing France's revenue by 10% to simulate a pricing or growth strategy.
# This helps analyze potential profit impact or forecast future performance.
```

[ ]:
```
sales['Revenue'] = sales['Revenue'].astype(float)
```

[ ]:
```
sales.loc[sales['Country'] == 'France','Revenue'].head()
```

[29]:
```
sales['Product'].unique()
```

[29]:
```
array(['Hitch Rack - 4-Bike', 'All-Purpose Bike Stand',
       'Mountain Bottle Cage', 'Water Bottle - 30 oz.',
       'Road Bottle Cage', 'AWC Logo Cap', 'Bike Wash - Dissolver',
       'Fender Set - Mountain', 'Half-Finger Gloves, L',
       'Half-Finger Gloves, M', 'Half-Finger Gloves, S',
       'Sport-100 Helmet, Black', 'Sport-100 Helmet, Red',
       'Sport-100 Helmet, Blue', 'Hydration Pack - 70 oz.',
       'Short-Sleeve Classic Jersey, XL',
       'Short-Sleeve Classic Jersey, L', 'Short-Sleeve Classic Jersey, M',
       'Short-Sleeve Classic Jersey, S', 'Long-Sleeve Logo Jersey, M',
       'Long-Sleeve Logo Jersey, XL', 'Long-Sleeve Logo Jersey, L',
       'Long-Sleeve Logo Jersey, S', 'Mountain-100 Silver, 38',
       'Mountain-100 Silver, 44', 'Mountain-100 Black, 48',
       'Mountain-100 Silver, 48', 'Mountain-100 Black, 38',
       'Mountain-200 Silver, 38', 'Mountain-100 Black, 44',
       'Mountain-100 Silver, 42', 'Mountain-200 Black, 46',
       'Mountain-200 Silver, 42', 'Mountain-200 Silver, 46',
       'Mountain-200 Black, 38', 'Mountain-100 Black, 42',
       'Mountain-200 Black, 42', 'Mountain-400-W Silver, 46',
       'Mountain-500 Silver, 40', 'Mountain-500 Silver, 44',
       'Mountain-500 Black, 48', 'Mountain-500 Black, 40',
       'Mountain-400-W Silver, 42', 'Mountain-500 Silver, 52',
       'Mountain-500 Black, 52', 'Mountain-500 Silver, 42',
       'Mountain-500 Black, 44', 'Mountain-500 Silver, 48',
       'Mountain-400-W Silver, 38', 'Mountain-400-W Silver, 40',
       'Mountain-500 Black, 42', 'Road-150 Red, 48', 'Road-150 Red, 62',
       'Road-750 Black, 48', 'Road-750 Black, 58', 'Road-750 Black, 52',
       'Road-150 Red, 52', 'Road-150 Red, 44', 'Road-150 Red, 56',
       'Road-750 Black, 44', 'Road-350-W Yellow, 40',
       'Road-350-W Yellow, 42', 'Road-250 Black, 44',
       'Road-250 Black, 48', 'Road-350-W Yellow, 48',
       'Road-550-W Yellow, 44', 'Road-550-W Yellow, 38',
       'Road-250 Black, 52', 'Road-550-W Yellow, 48', 'Road-250 Red, 58',
       'Road-250 Black, 58', 'Road-250 Red, 52', 'Road-250 Red, 48',
```

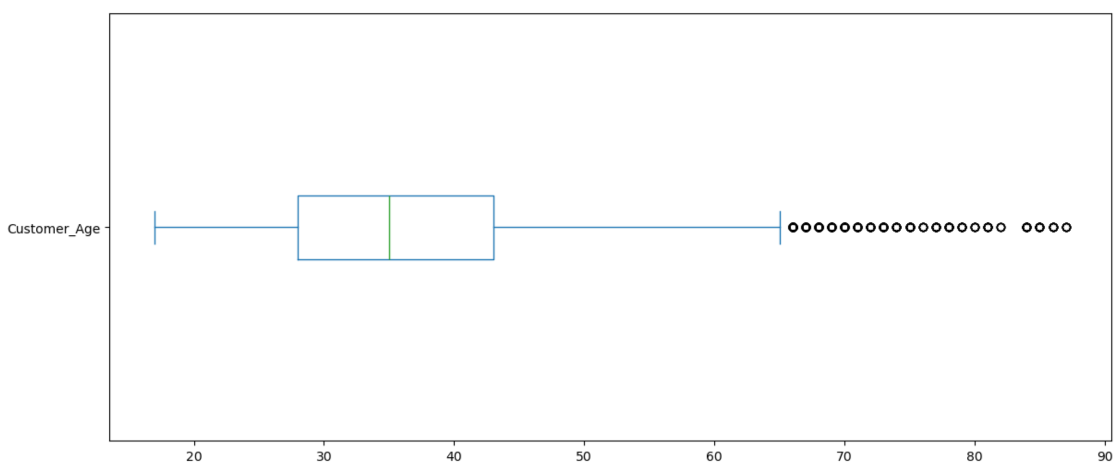
```
 'Road-250 Red, 44', 'Road-550-W Yellow, 42',
 'Road-550-W Yellow, 40', 'Road-650 Red, 48', 'Road-650 Red, 60',
 'Road-650 Black, 48', 'Road-350-W Yellow, 44', 'Road-650 Red, 52',
 'Road-650 Black, 44', 'Road-650 Red, 62', 'Road-650 Red, 58',
 'Road-650 Black, 60', 'Road-650 Black, 58', 'Road-650 Black, 52',
 'Road-650 Black, 62', 'Road-650 Red, 44',
 "Women's Mountain Shorts, M", "Women's Mountain Shorts, S",
 "Women's Mountain Shorts, L", 'Racing Socks, L', 'Racing Socks, M',
 'Mountain Tire Tube', 'Touring Tire Tube', 'Patch Kit/8 Patches',
 'HL Mountain Tire', 'LL Mountain Tire', 'Road Tire Tube',
 'LL Road Tire', 'Touring Tire', 'ML Mountain Tire', 'HL Road Tire',
 'ML Road Tire', 'Touring-1000 Yellow, 50', 'Touring-1000 Blue, 46',
 'Touring-1000 Yellow, 60', 'Touring-1000 Blue, 50',
 'Touring-3000 Yellow, 50', 'Touring-3000 Blue, 54',
 'Touring-3000 Blue, 58', 'Touring-3000 Yellow, 44',
 'Touring-3000 Yellow, 54', 'Touring-3000 Blue, 62',
 'Touring-3000 Blue, 44', 'Touring-1000 Blue, 54',
 'Touring-1000 Yellow, 46', 'Touring-1000 Blue, 60',
 'Touring-3000 Yellow, 62', 'Touring-1000 Yellow, 54',
 'Touring-2000 Blue, 54', 'Touring-3000 Blue, 50',
 'Touring-3000 Yellow, 58', 'Touring-2000 Blue, 46',
 'Touring-2000 Blue, 50', 'Touring-2000 Blue, 60',
 'Classic Vest, L', 'Classic Vest, M', 'Classic Vest, S'],
dtype=object)
```

What's the mean of Customers_Age ?

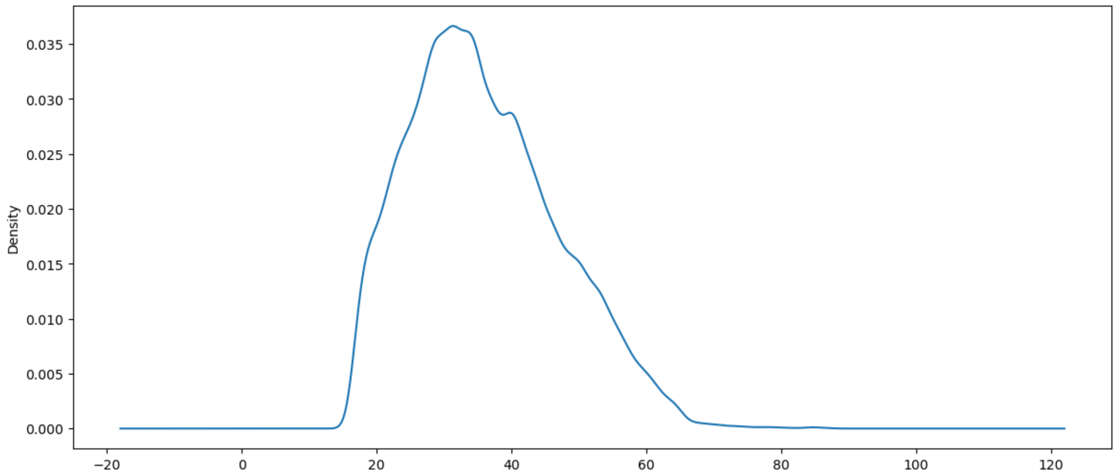
[38]:
```
sales['Customer_Age'].mean().round(0)
```

[38]:
```
np.float64(36.0)
```

[42]:
```
sales['Customer_Age'].plot(kind='box',vert=False,figsize=(14,6))
plt.show()
```



[45]:
```
sales['Customer_Age'].plot(kind='kde',figsize=(14,6))
plt.show()
```



[46]:
```
sales['Year'].value_counts()
```

[46]:
```
Year
2014    29398
2016    29398
2013    24443
2015    24443
2012     2677
2011     2677
Name: count, dtype: int64
```

Can you see any relationship between Unit_Cost and Unit_Price ?

[48]:
```
sales['Month'].value_counts()
```

[48]:
```
Month
June         11234
December     11200
May          11128
April        10182
March         9674
January       9284
February      9022
October       8750
November      8734
August        8200
```

```
September     8166
July          7462
Name: count, dtype: int64
```

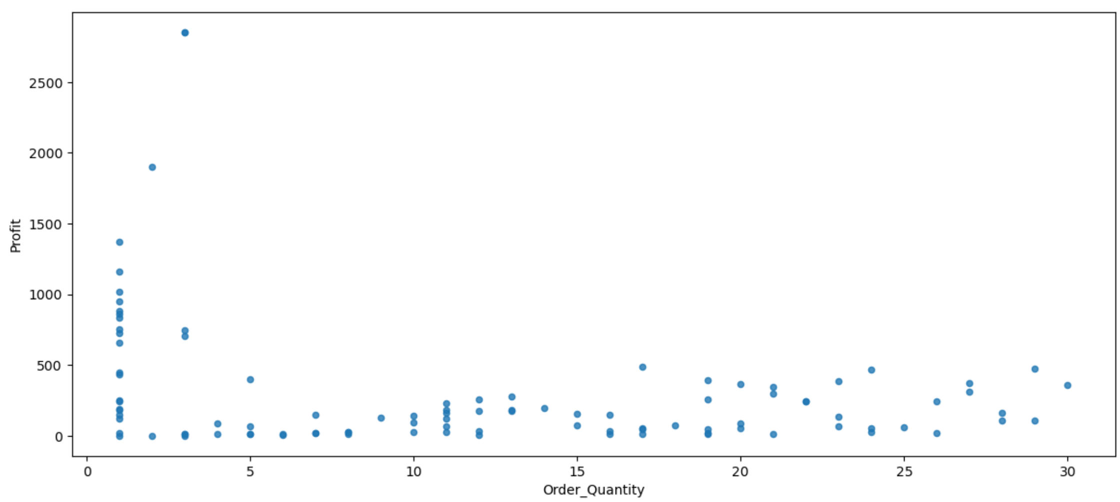
Can you see any relationship between Order_Quantity and Profit?

[63]:
```
sales[['Order_Quantity', 'Profit']].corr()
# Negative Correlation
```

[63]:

	Order_Quantity	Profit
Order_Quantity	1.000000	-0.238863
Profit	-0.238863	1.000000

[64]:
```
sales.sample(100,random_state=1).plot(kind='scatter', x='Order_Quantity',␣
↪y='Profit',alpha=0.8,figsize=(14,6))
plt.show()
```

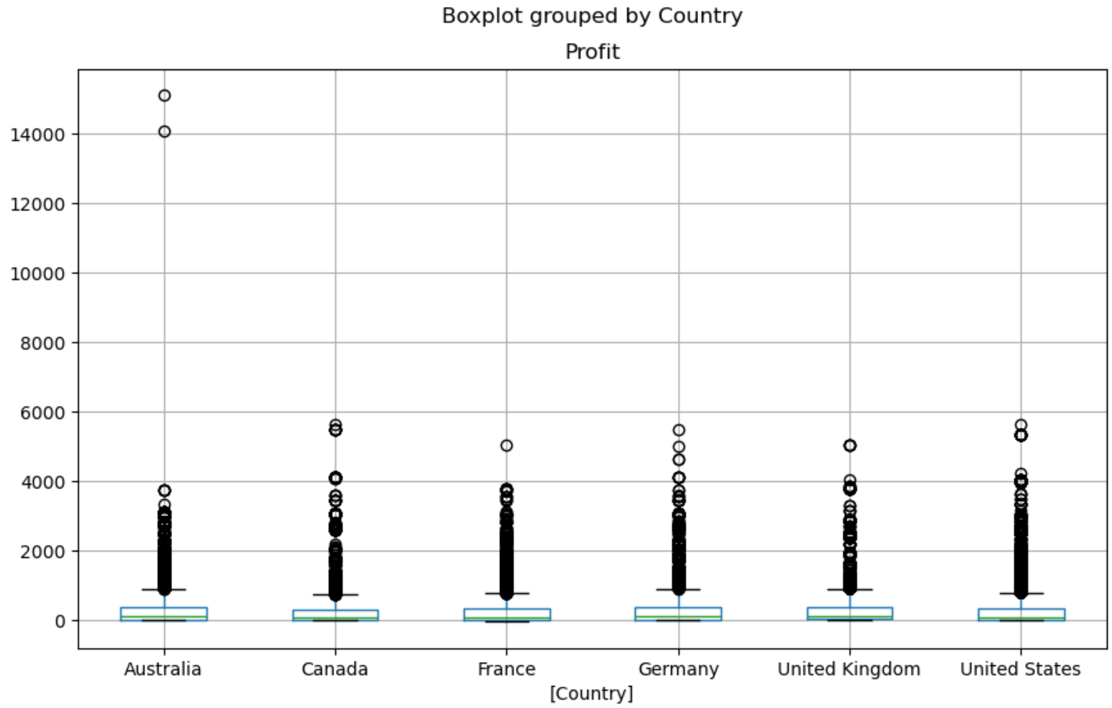


Can you see any relationship between Profit and Country?

[73]:
```
sales.groupby('Country')['Profit'].sum()
```

[73]:
```
Country
Australia         6776030
Canada            3717296
France            2880282
Germany           3359995
United Kingdom    4413853
United States    11073644
Name: Profit, dtype: int64
```

[72]:
```
sales[['Profit', 'Country']].boxplot(by='Country', figsize=(10,6))
plt.show()
```



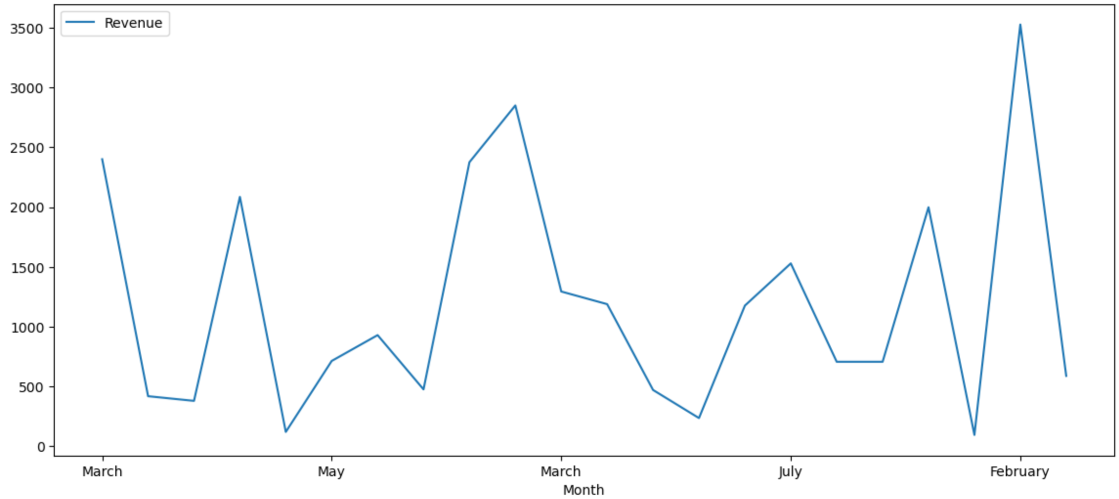
[76]:
```
sales['Calculated_Date'] = sales[['Year','Month','Day']].apply(lambda x :␣
↪'{}-{}-{}'.format(x[0],x[1],x[2]),axis=1)
sales['Calculated_Date']= pd.to_datetime(sales['Calculated_Date'])
sales['Calculated_Date'].head()
```

```
C:\Users\Admin\AppData\Local\Temp\ipykernel_7472\2011521891.py:1: FutureWarning:
Series.__getitem__ treating keys as positions is deprecated. In a future
version, integer keys will always be treated as labels (consistent with
DataFrame behavior). To access a value by position, use `ser.iloc[pos]`
  sales['Calculated_Date'] = sales[['Year','Month','Day']].apply(lambda x :
'{}-{}-{}'.format(x[0],x[1],x[2]),axis=1)
```

[76]:
```
0   2013-11-26
1   2015-11-26
2   2014-03-23
3   2016-03-23
4   2014-05-15
Name: Calculated_Date, dtype: datetime64[ns]
```

[93]:
```
sales.head(100).loc[sales['Year']== 2014].
↪plot(kind='line',x='Month',y='Revenue',figsize=(14,6))
```

```
plt.show()
```



How many Bike Racks orders were made from Canada?

[88]:
```
sales.loc[(sales['Country'] == 'Canada') |(sales['Sub_Category'] == 'Bike␣
↪Rack')].shape[0]
```

[88]: 14178

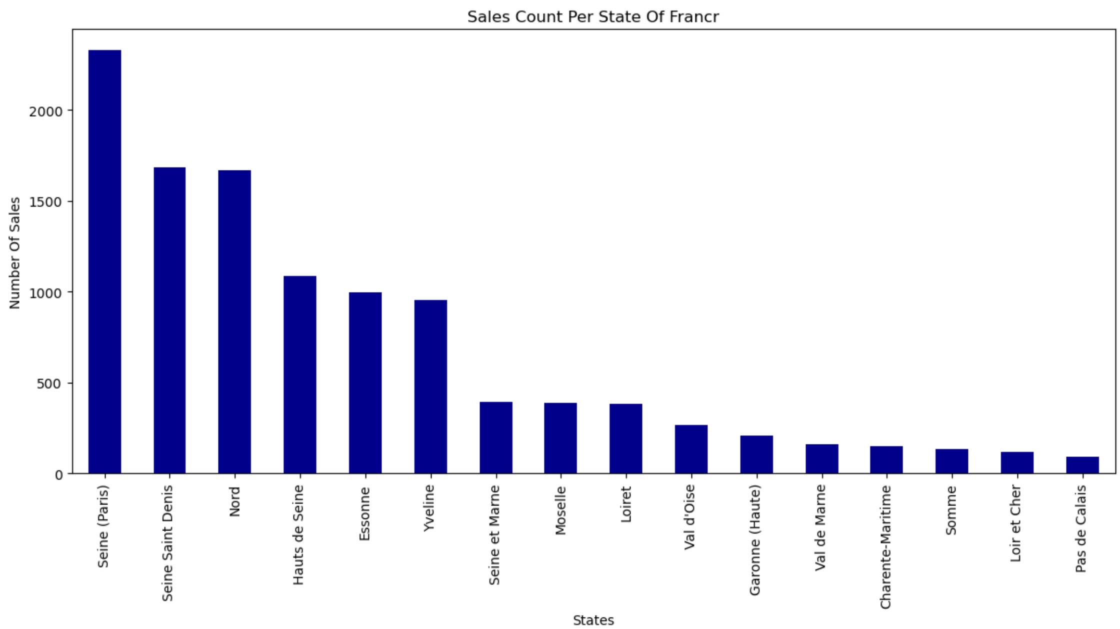
0.0.1 How many orders were made in each region (state) of France?

[95]:
```
france_states = sales.loc[sales['Country'] == 'France','State'].value_counts()
france_states
```

[95]:
```
State
Seine (Paris)         2328
Seine Saint Denis     1684
Nord                  1670
Hauts de Seine        1084
Essonne                994
Yveline                954
Seine et Marne         394
Moselle                386
Loiret                 382
Val d'Oise             264
Garonne (Haute)        208
Val de Marne           158
Charente-Maritime      148
Somme                  134
Loir et Cher           120
```

```
Pas de Calais          90
Name: count, dtype: int64
```

[102]:
```
france_states.plot(kind='bar', figsize=(14,6),color='darkblue')
plt.title('Sales Count Per State Of Francr')
plt.xlabel('States')
plt.ylabel('Number Of Sales')
plt.show()
```



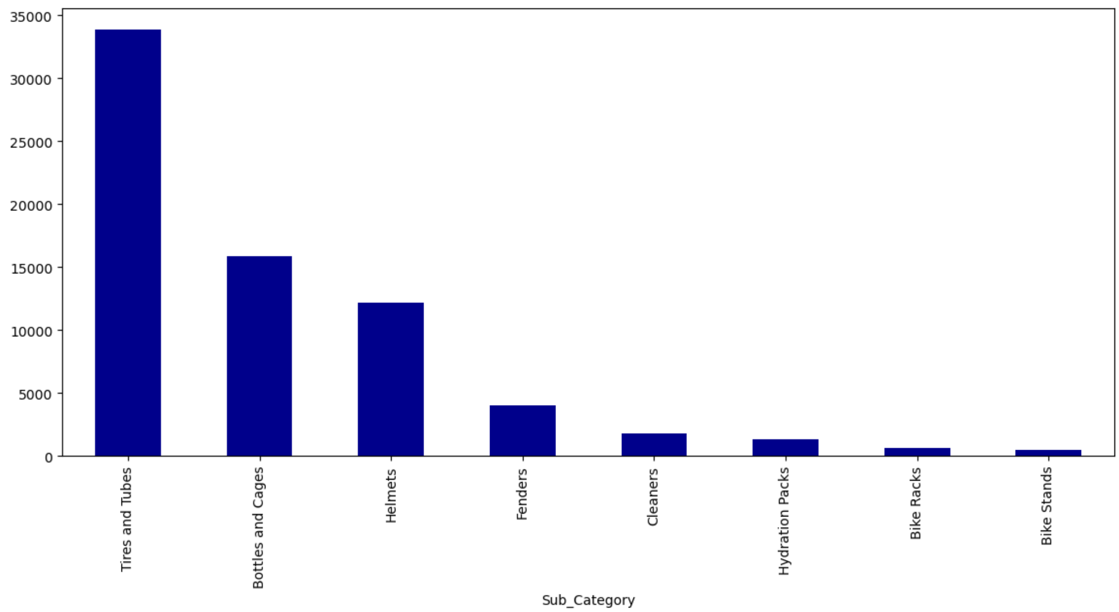
0.1 How many orders were made per accessory sub-categories?

[104]:
```
accessories = sales.loc[sales['Product_Category']==
↪'Accessories','Sub_Category'].value_counts()
accessories
```

[104]:
```
Sub_Category
Tires and Tubes      33870
Bottles and Cages    15876
Helmets              12158
Fenders               4032
Cleaners              1802
Hydration Packs       1334
Bike Racks             592
Bike Stands            456
Name: count, dtype: int64
```

[105]:

```
accessories.plot(kind='bar', figsize=(14,6),color='darkblue')
plt.show()
```



0.2 How many orders were made per bike sub-categories?

[117]:

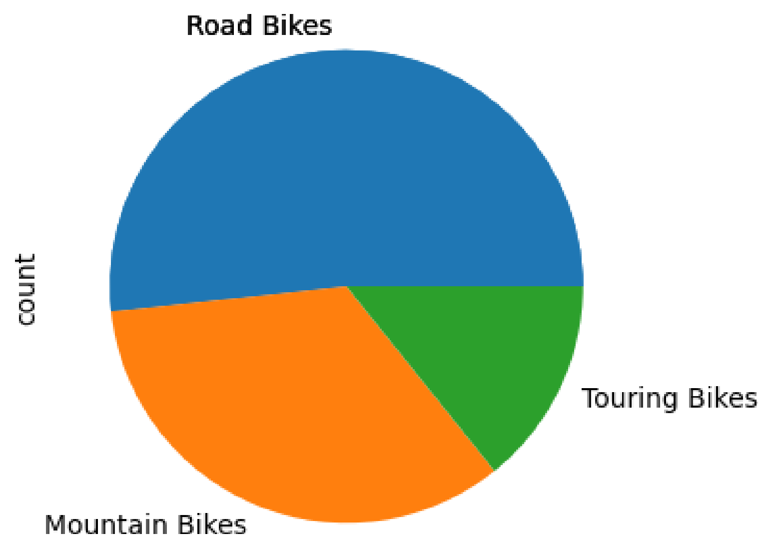
```
bikes = sales.loc[sales['Product_Category'] == 'Bikes','Sub_Category'].
    ↪value_counts()
bikes
```

[117]:

```
Sub_Category
Road Bikes        13430
Mountain Bikes     8854
Touring Bikes      3698
Name: count, dtype: int64
```

[122]:

```
bikes.plot(kind='pie',figsize=(8,4))
plt.show()
```

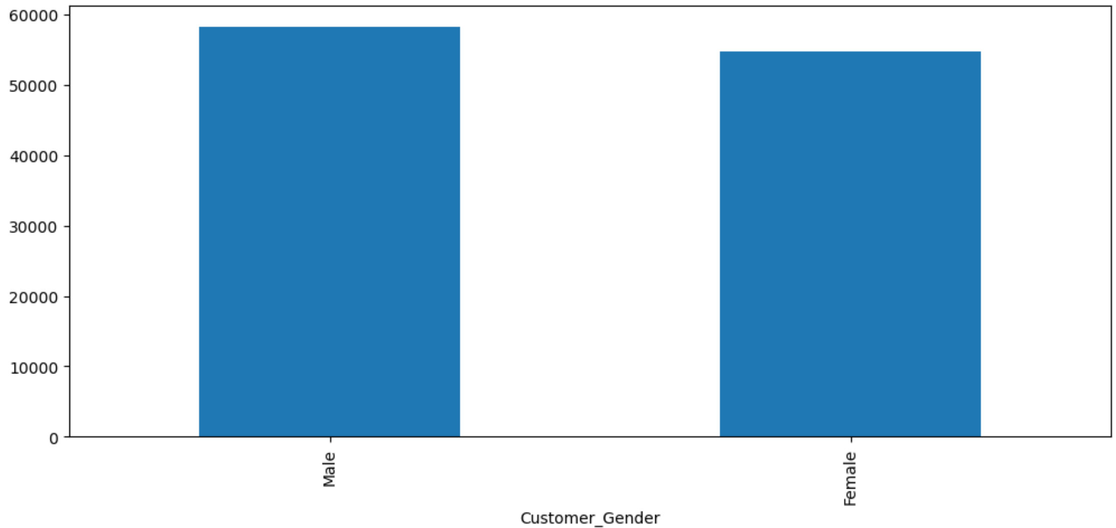


[130]:
```
def Gender(Gen):
    if Gen == 'M':
        return 'Male'
    else:
        return 'Female'
```

[135]:
```
sales['Customer_Gender'].apply(Gender).value_counts()
```

[135]:
```
Customer_Gender
Male      58312
Female    54724
Name: count, dtype: int64
```

[132]:
```
sales['Customer_Gender'].apply(Gender).value_counts().
 ↪plot(kind='bar',figsize=(12,5))
plt.show()
```



0.3 How many sales with more than 500 in Revenue were made by men?

[140]:
```
sales.loc[(sales['Customer_Gender']=='M') & (sales['Revenue'] > 500) ].shape[0]
```

[140]: 21773

0.4 Get the *top-5 sales* with the highest revenue

[147]:
```
sales.sort_values(['Revenue'], ascending= False ) .head()
```

[147]:
```
              Date  Day      Month  Year  Customer_Age       Age_Group  \
112073 2015-07-24   24       July  2015            52  Adults (35-64)
112072 2013-07-24   24       July  2013            52  Adults (35-64)
71129  2011-07-08    8       July  2011            22     Youth (<25)
70307  2011-04-30   30      April  2011            44  Adults (35-64)
70601  2011-09-30   30  September  2011            19     Youth (<25)

       Customer_Gender    Country             State Product_Category  \
112073               M  Australia        Queensland         Clothing
112072               M  Australia        Queensland         Clothing
71129                M     Canada           Alberta            Bikes
70307                M     Canada  British Columbia            Bikes
70601                F     Canada  British Columbia            Bikes

       Sub_Category                  Product  Order_Quantity  Unit_Cost  \
112073        Vests  Touring-1000 Yellow, 50              29       1482
112072        Vests  Touring-1000 Yellow, 50              27       1482
71129    Road Bikes           Road-150 Red, 48               4       2171
70307    Road Bikes           Road-150 Red, 62               4       2171
```

```
70601     Road Bikes         Road-150 Red, 62              4       2171

        Unit_Price  Profit   Cost  Revenue Calculated_Date
112073        2384   15096  42978    58074      2015-07-24
112072        2384   14055  40014    54069      2013-07-24
71129         3578    5628   8684    14312      2011-07-08
70307         3578    5485   8684    14169      2011-04-30
70601         3578    5485   8684    14169      2011-09-30
```

0.5 What is the mean Order_Quantity of orders with more than 10K in revenue?

[152]:
```
sales.loc[sales['Revenue']> 10000 , 'Order_Quantity'].mean()
```

[152]:
```
np.float64(3.7218934911242605)
```

0.6 How many orders were made in May of 2016?

[155]:
```
sales.loc[(sales['Year'] == 2016) &(sales['Month'] == 'May')].shape[0]
```

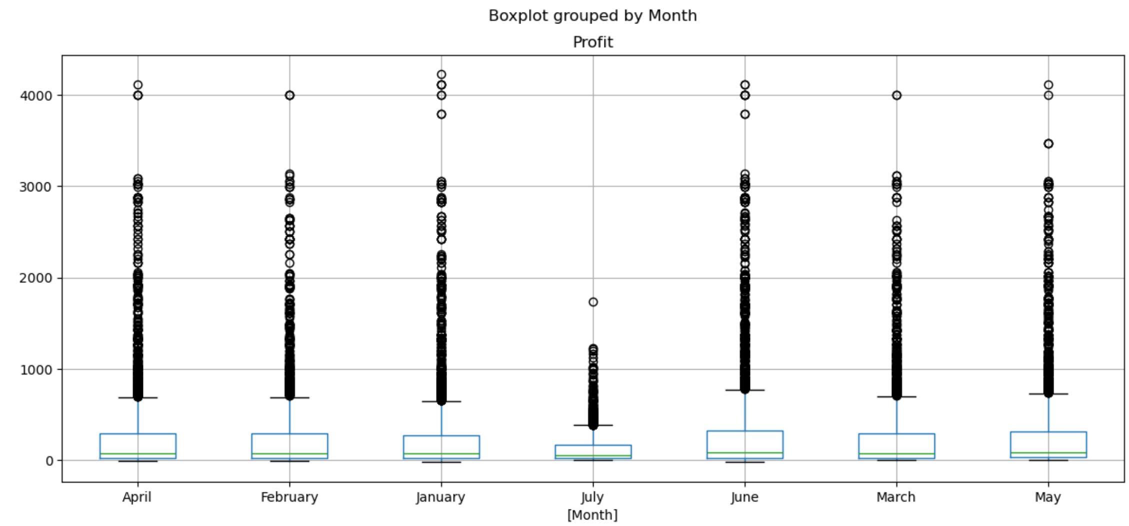
[155]:
```
5015
```

0.7 How many orders were made between May and July of 2016?

[158]:
```
cond = (sales['Year']== 2016 ) & (sales['Month'].isin(['May','June','July']))
sales.loc[cond].shape[0]
```

[158]:
```
12164
```

[162]:
```
profit_2016 = sales.loc[sales['Year'] == 2016, ['Profit', 'Month']]

profit_2016.boxplot(by='Month', figsize=(14,6))
plt.show()
```


Boxplot grouped by Month
Profit
4000
3000
2000
1000
0
April
February
January
July
June
March
May
[Month]

```
[ ]:
```