MSCS-634: Lab assignment: Lab Report: Data Visualization, Data Preprocessing, and Statistical Analysis Using Python in Jupyter Notebook

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MSCS-634 Advanced Big Data and Data Mining

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1. Introduction

This report documents the complete process of Lab 1 for the course MSCS-634 - Advanced Big Data and Data Mining.
The lab involved the use of Python (via Jupyter Notebook) for data preprocessing, visualization, and statistical analysis.
In addition to the analysis itself, this report also includes environment setup, challenges faced, and decisions made.

2. Environment Setup

The lab was performed on a Mac system using a Python virtual environment created using `python3 -m venv venv`.
Jupyter Notebook was run from within the virtual environment to ensure package isolation and dependency management.
The following packages were installed manually due to missing module errors encountered during the lab execution:

- pandas
- matplotlib
- scikit-learn

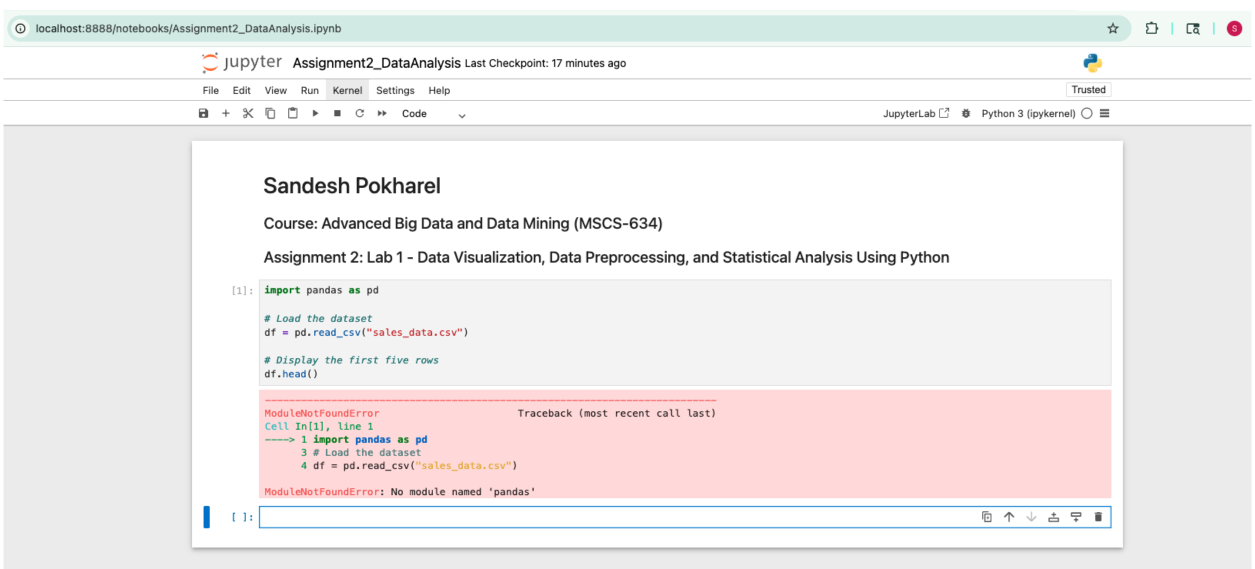
Each package was installed using pip from within the activated virtual environment:

```
$ source venv/bin/activate
$ pip install pandas matplotlib scikit-learn
```

Screenshot Placeholder: Terminal showing venv activation and pip install commands

```
/Users/mac/Sandesh_Cumberlands_Assignments/Advanced_Big_Data_And_Data_Mining/MSCS-634-Assignment2 % source venv/bin/activate
(venv) /Users/mac/Sandesh_Cumberlands_Assignments/Advanced_Big_Data_And_Data_Mining/MSCS-634-Assignment2 % pip install pandas
Collecting pandas
  Using cached pandas-2.3.0-cp313-cp313-macosx_11_0_arm64.whl.metadata (91 kB)
Collecting numpy>=1.26.0 (from pandas)
  Using cached numpy-2.3.1-cp313-cp313-macosx_14_0_arm64.whl.metadata (62 kB)
Requirement already satisfied: python-dateutil>=2.8.2 in ./venv/lib/python3.13/site-packages (from pandas) (2.9.0.post0)
Collecting pytz>=2020.1 (from pandas)
  Using cached pytz-2025.2-py2.py3-none-any.whl.metadata (22 kB)
Collecting tzdata>=2022.7 (from pandas)
  Using cached tzdata-2025.2-py2.py3-none-any.whl.metadata (1.4 kB)
Requirement already satisfied: six>=1.5 in ./venv/lib/python3.13/site-packages (from python-dateutil>=2.8.2->pandas) (1.17.0)
Using cached pandas-2.3.0-cp313-cp313-macosx_11_0_arm64.whl (10.7 MB)
Using cached numpy-2.3.1-cp313-cp313-macosx_14_0_arm64.whl (5.1 MB)
Using cached pytz-2025.2-py2.py3-none-any.whl (509 kB)
Using cached tzdata-2025.2-py2.py3-none-any.whl (347 kB)
Installing collected packages: pytz, tzdata, numpy, pandas
Successfully installed numpy-2.3.1 pandas-2.3.0 pytz-2025.2 tzdata-2025.2
(venv) /Users/mac/Sandesh_Cumberlands_Assignments/Advanced_Big_Data_And_Data_Mining/MSCS-634-Assignment2 % open ./
(venv) /Users/mac/Sandesh_Cumberlands_Assignments/Advanced_Big_Data_And_Data_Mining/MSCS-634-Assignment2 % pip install matplotlib
Collecting matplotlib
  Using cached matplotlib-3.10.3-cp313-cp313-macosx_11_0_arm64.whl.metadata (11 kB)
Collecting contourpy>=1.0.1 (from matplotlib)
  Using cached contourpy-1.3.2-cp313-cp313-macosx_11_0_arm64.whl.metadata (5.5 kB)
Collecting cycler>=0.10 (from matplotlib)
  Using cached cycler-0.12.1-py3-none-any.whl.metadata (3.8 kB)
Collecting fonttools>=4.22.0 (from matplotlib)
  Downloading fonttools-4.58.5-cp313-cp313-macosx_10_13_universal2.whl.metadata (106 kB)
Collecting kiwisolver>=1.3.1 (from matplotlib)
  Using cached kiwisolver-1.4.8-cp313-cp313-macosx_11_0_arm64.whl.metadata (6.2 kB)
Requirement already satisfied: numpy>=1.23 in ./venv/lib/python3.13/site-packages (from matplotlib) (2.3.1)
Requirement already satisfied: packaging>=20.0 in ./venv/lib/python3.13/site-packages (from matplotlib) (25.0)
Collecting pillow>=8 (from matplotlib)
  Downloading pillow-11.3.0-cp313-cp313-macosx_11_0_arm64.whl.metadata (9.0 kB)
Collecting pyparsing>=2.3.1 (from matplotlib)
  Using cached pyparsing-3.2.3-py3-none-any.whl.metadata (5.0 kB)
Requirement already satisfied: python-dateutil>=2.7 in ./venv/lib/python3.13/site-packages (from matplotlib) (2.9.0.post0)
Requirement already satisfied: six>=1.5 in ./venv/lib/python3.13/site-packages (from python-dateutil>=2.7->matplotlib) (1.17.0)
Using cached matplotlib-3.10.3-cp313-cp313-macosx_11_0_arm64.whl (8.1 MB)
Using cached contourpy-1.3.2-cp313-cp313-macosx_11_0_arm64.whl (255 kB)
Using cached cycler-0.12.1-py3-none-any.whl (8.3 kB)
Downloading fonttools-4.58.5-cp313-cp313-macosx_10_13_universal2.whl (2.7 MB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 2.7/2.7 MB 35.7 MB/s eta 0:00:00
Using cached kiwisolver-1.4.8-cp313-cp313-macosx_11_0_arm64.whl (65 kB)
Downloading pillow-11.3.0-cp313-cp313-macosx_11_0_arm64.whl (4.7 MB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 4.7/4.7 MB 83.7 MB/s eta 0:00:00
Using cached pyparsing-3.2.3-py3-none-any.whl (111 kB)
Installing collected packages: pyparsing, pillow, kiwisolver, fonttools, cycler, contourpy, matplotlib
Successfully installed contourpy-1.3.2 cycler-0.12.1 fonttools-4.58.5 kiwisolver-1.4.8 matplotlib-3.10.3 pillow-11.3.0 pyparsing-3.2.3
(venv) /Users/mac/Sandesh_Cumberlands_Assignments/Advanced_Big_Data_And_Data_Mining/MSCS-634-Assignment2 % pip install scikit-learn
Collecting scikit-learn
  Using cached scikit_learn-1.7.0-cp313-cp313-macosx_12_0_arm64.whl.metadata (31 kB)
Requirement already satisfied: numpy>=1.22.0 in ./venv/lib/python3.13/site-packages (from scikit-learn) (2.3.1)
Collecting scipy>=1.8.0 (from scikit-learn)
  Using cached scipy-1.16.0-cp313-cp313-macosx_14_0_arm64.whl.metadata (61 kB)
Collecting joblib>=1.2.0 (from scikit-learn)
  Using cached joblib-1.5.1-py3-none-any.whl.metadata (5.6 kB)
Collecting threadpoolctl>=3.1.0 (from scikit-learn)
```

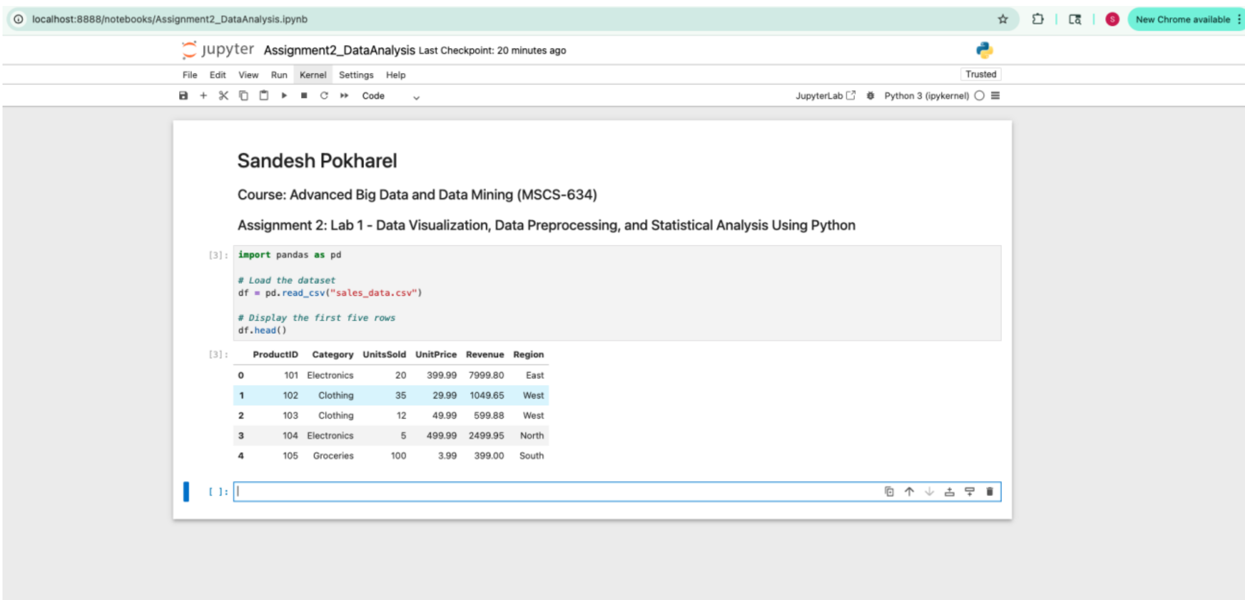
Screenshot Placeholder: Jupyter Notebook errors (e.g., ModuleNotFoundError) and resolutions



3. Dataset Loading and Preview

The dataset used for this lab is a small CSV file named `sales_data.csv`, containing retail sales data.
It includes both numerical and categorical columns suitable for preprocessing and analysis.
The dataset was loaded using pandas and previewed using the `.head()` method.

Screenshot Placeholder: Output of df.head()



4. Data Preprocessing

The following preprocessing steps were performed:
- Missing Values: Simulated missing data in UnitsSold and Region columns, filled using mean and mode.
- Outlier Detection: Used IQR method to detect and demonstrate outlier removal.
- Data Reduction: Sampled 50% of data and dropped irrelevant columns like ProductID.
- Data Scaling: Applied Min-Max Scaling to normalize UnitPrice.
- Discretization: Converted UnitsSold into categorical bins (Low, Medium, High).

Screenshot Placeholder: Missing values simulation and handling

[8]:
```python
# Check for missing values in each column
df.isnull().sum()
```

[8]:
```
ProductID    0
Category     0
UnitsSold    0
UnitPrice    0
Revenue      0
Region       0
dtype: int64
```

[ ]:

[9]:
```python
# Simulate missing values in 'UnitsSold' and 'Region'
df.loc[1, 'UnitsSold'] = None
df.loc[3, 'Region'] = None

# Show dataset with missing values (screenshot this)
df
```

[9]:

	ProductID	Category	UnitsSold	UnitPrice	Revenue	Region
0	101	Electronics	20.0	399.99	7999.80	East
1	102	Clothing	NaN	29.99	1049.65	West
2	103	Clothing	12.0	49.99	599.88	West
3	104	Electronics	5.0	499.99	2499.95	None
4	105	Groceries	100.0	3.99	399.00	South
5	106	Groceries	85.0	2.49	211.65	South
6	107	Clothing	22.0	59.99	1319.78	East
7	108	Electronics	10.0	299.99	2999.90	North
8	109	Groceries	95.0	4.49	426.55	South
9	110	Clothing	18.0	39.99	719.82	East

[ ]:

```python
[10]: # Fill missing numeric value with mean
df['UnitsSold'].fillna(df['UnitsSold'].mean(), inplace=True)

# Fill missing categorical value with mode
df['Region'].fillna(df['Region'].mode()[0], inplace=True)

# Show updated dataset (screenshot this too)
df
```

```
/var/folders/bx/n0b8n8wd0ss985_pj3z33n780000gn/T/ipykernel_91721/781268429.py:2: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform the operation inplace on the original object.


  df['UnitsSold'].fillna(df['UnitsSold'].mean(), inplace=True)
/var/folders/bx/n0b8n8wd0ss985_pj3z33n780000gn/T/ipykernel_91721/781268429.py:5: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform the operation inplace on the original object.


  df['Region'].fillna(df['Region'].mode()[0], inplace=True)
```

[10]:

	ProductID	Category	UnitsSold	UnitPrice	Revenue	Region
0	101	Electronics	20.000000	399.99	7999.80	East
1	102	Clothing	40.777778	29.99	1049.65	West
2	103	Clothing	12.000000	49.99	599.88	West
3	104	Electronics	5.000000	499.99	2499.95	East
4	105	Groceries	100.000000	3.99	399.00	South
5	106	Groceries	85.000000	2.49	211.65	South
6	107	Clothing	22.000000	59.99	1319.78	East
7	108	Electronics	10.000000	299.99	2999.90	North
8	109	Groceries	95.000000	4.49	426.55	South
9	110	Clothing	18.000000	39.99	719.82	East

[ ]:

Screenshot Placeholder: Outlier detection and removal

```python
[11]: # Step 1: Calculate Q1, Q3 and IQR
Q1 = df['UnitsSold'].quantile(0.25)
Q3 = df['UnitsSold'].quantile(0.75)
IQR = Q3 - Q1

# Step 2: Calculate bounds
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

print(f"Q1: {Q1}, Q3: {Q3}, IQR: {IQR}")
print(f"Lower Bound: {lower_bound}, Upper Bound: {upper_bound}")

# Step 3: Identify outliers
outliers = df[(df['UnitsSold'] < lower_bound) | (df['UnitsSold'] > upper_bound)]
print("\nDetected Outliers in 'UnitsSold':")
print(outliers)
```

```
Q1: 13.5, Q3: 73.94444444444444, IQR: 60.44444444444444
Lower Bound: -77.16666666666666, Upper Bound: 164.6111111111111

Detected Outliers in 'UnitsSold':
Empty DataFrame
Columns: [ProductID, Category, UnitsSold, UnitPrice, Revenue, Region]
Index: []
```

[ ]:

Screenshot Placeholder: Sampled data and reduced columns

```
[12]: # Remove rows that are outliers (just for demonstration)
      df_no_outliers = df[(df['UnitsSold'] >= lower_bound) & (df['UnitsSold'] <= upper_bound)]

      # Display cleaned dataset
      df_no_outliers
```

[12]:

	ProductID	Category	UnitsSold	UnitPrice	Revenue	Region
0	101	Electronics	20.000000	399.99	7999.80	East
1	102	Clothing	40.777778	29.99	1049.65	West
2	103	Clothing	12.000000	49.99	599.88	West
3	104	Electronics	5.000000	499.99	2499.95	East
4	105	Groceries	100.000000	3.99	399.00	South
5	106	Groceries	85.000000	2.49	211.65	South
6	107	Clothing	22.000000	59.99	1319.78	East
7	108	Electronics	10.000000	299.99	2999.90	North
8	109	Groceries	95.000000	4.49	426.55	South
9	110	Clothing	18.000000	39.99	719.82	East

[ ]:

Screenshot Placeholder: Scaled and discretized columns

```
[15]: from sklearn.preprocessing import MinMaxScaler
      import pandas as pd

      # Copy the reduced DataFrame to preserve original
      scaled_df = reduced_df.copy()

      # 1. Min-Max Scaling for 'UnitPrice'
      scaler = MinMaxScaler()
      scaled_df['UnitPrice_Scaled'] = scaler.fit_transform(scaled_df[['UnitPrice']])

      # 2. Discretization of 'UnitsSold' into 3 bins
      scaled_df['UnitsSold_Category'] = pd.cut(scaled_df['UnitsSold'],
                                               bins=3,
                                               labels=['Low', 'Medium', 'High'])

      # Display updated DataFrame
      scaled_df
```

[15]:

	Category	UnitsSold	UnitPrice	Revenue	Region	UnitPrice_Scaled	UnitsSold_Category
2	Clothing	12.0	49.99	599.88	West	0.116162	Low
9	Clothing	18.0	39.99	719.82	East	0.090909	Low
6	Clothing	22.0	59.99	1319.78	East	0.141414	Low
4	Groceries	100.0	3.99	399.00	South	0.000000	High
0	Electronics	20.0	399.99	7999.80	East	1.000000	Low

[ ]:

5. Data Visualization

Multiple visualizations were created to explore and interpret the dataset:
- Bar Chart: Total Revenue by Category
- Pie Chart: Sales distribution by Region
- Histogram: Distribution of numeric features
- Boxplot: Detection of outliers in key numeric columns

Screenshot Placeholders: All visualizations with observations jupyter Assignment2_DataAnalysis Last Checkpoint: 23 minutes ago

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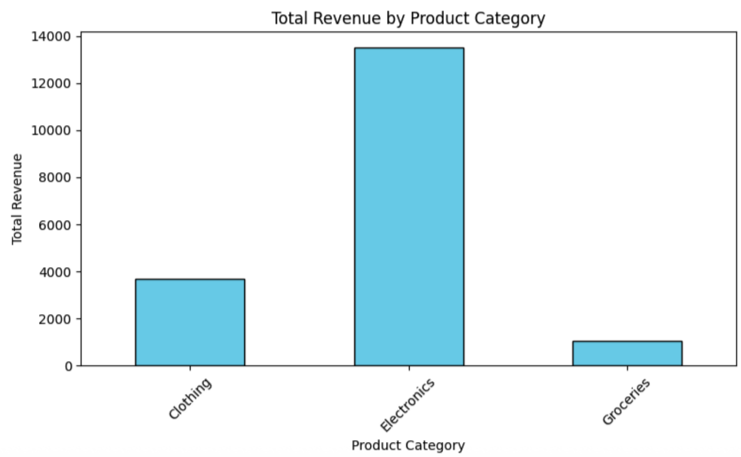
Code JupyterLab Python 3 (ipykernel)

```
# Group by Category and sum the revenue
category_revenue = df.groupby('Category')['Revenue'].sum()

# Plot the bar chart
plt.figure(figsize=(8, 5))
category_revenue.plot(kind='bar', color='skyblue', edgecolor='black')

plt.title('Total Revenue by Product Category')
plt.xlabel('Product Category')
plt.ylabel('Total Revenue')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



[ ]:

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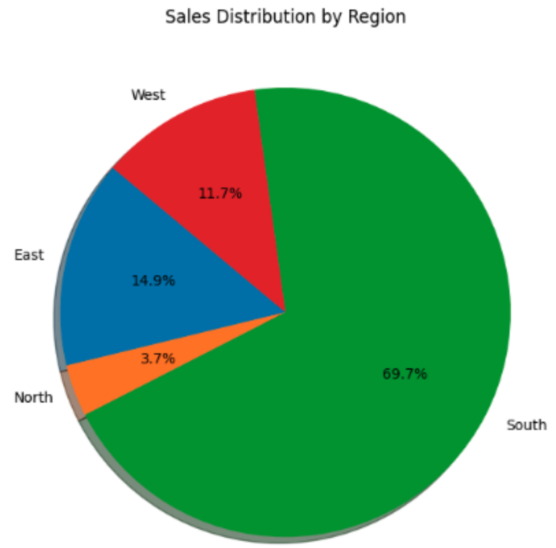
[7]:

```python
# Group by Region and sum the UnitsSold
region_sales = df.groupby('Region')['UnitsSold'].sum()

# Plot the pie chart
plt.figure(figsize=(6, 6))
region_sales.plot(kind='pie', autopct='%1.1f%%', startangle=140, shadow=True)

plt.title('Sales Distribution by Region')
plt.ylabel('')  # Hides the y-axis label
plt.tight_layout()
plt.show()
```

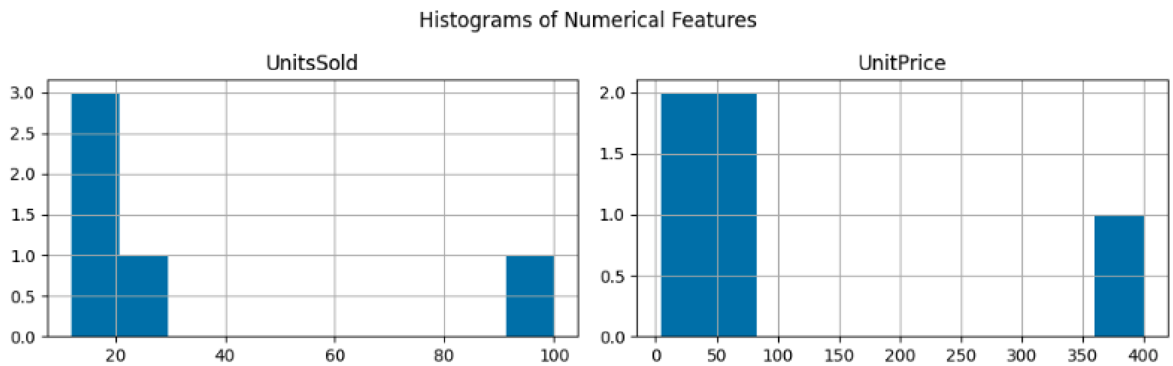


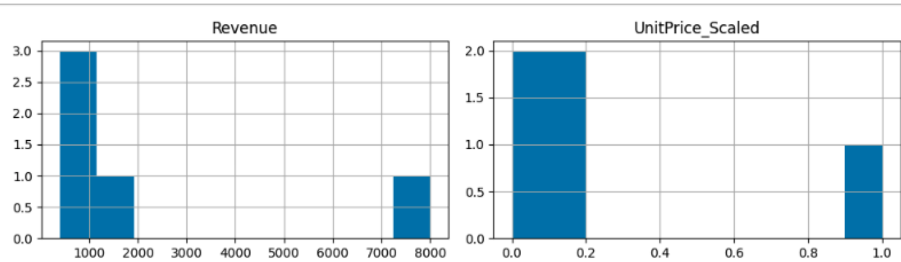
Insight: Pie Chart – Sales Distribution by Region

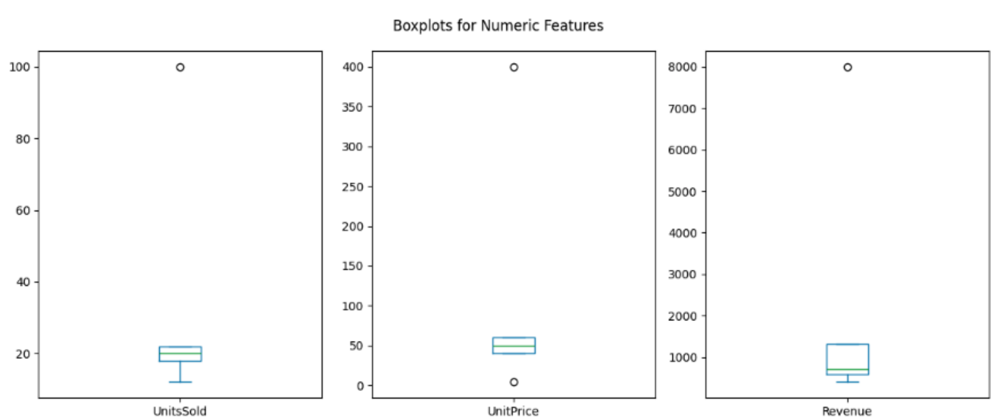
This pie chart shows the proportion of total units sold in each region.
It helps visualize where most of the product sales activity is occurring.
Regions with larger segments indicate stronger sales presence, which may suggest higher demand or market penetration.

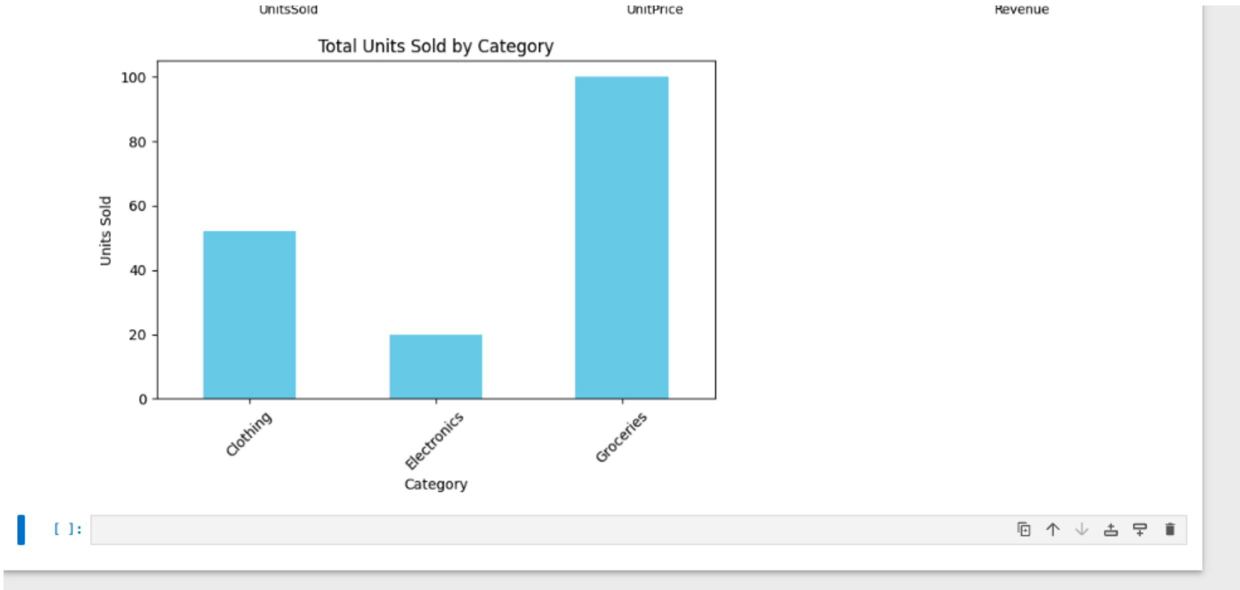
[ ]:

```python
import matplotlib.pyplot as plt

# 1. Histograms
scaled_df.hist(figsize=(10, 6))
plt.suptitle("Histograms of Numerical Features")
plt.tight_layout()
plt.show()

# 2. Boxplots
scaled_df[['UnitsSold', 'UnitPrice', 'Revenue']].plot(kind='box', subplots=True, layout=(1, 3), figsize=(12, 5))
plt.suptitle("Boxplots for Numeric Features")
plt.tight_layout()
plt.show()

# 3. Bar chart of UnitsSold by Category
scaled_df.groupby('Category')['UnitsSold'].sum().plot(kind='bar', color='skyblue')
plt.title("Total Units Sold by Category")
plt.ylabel("Units Sold")
plt.xlabel("Category")
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```









6. Statistical Analysis

Performed a series of statistical calculations including:
- General Overview using `.info()` and `.describe()`
- Central Tendency: Mean, Median, Mode, Min, Max
- Dispersion: Standard Deviation, Variance, Range
- Correlation and Covariance matrices for numeric attributes

Screenshot Placeholders: Info, Describe, Central Tendency, Dispersion, Correlation, Covariance

[16]:

```python
# General info about dataset
print("=== Dataset Info ===")
scaled_df.info()

# Statistical summary of numerical columns
print("\n=== Statistical Summary ===")
scaled_df.describe()
```

```
=== Dataset Info ===
<class 'pandas.core.frame.DataFrame'>
Index: 5 entries, 2 to 0
Data columns (total 7 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Category           5 non-null      object
 1   UnitsSold          5 non-null      float64
 2   UnitPrice          5 non-null      float64
 3   Revenue            5 non-null      float64
 4   Region             5 non-null      object
 5   UnitPrice_Scaled   5 non-null      float64
 6   UnitsSold_Category 5 non-null      category
dtypes: category(1), float64(4), object(2)
memory usage: 417.0+ bytes

=== Statistical Summary ===
```

[16]:

	UnitsSold	UnitPrice	Revenue	UnitPrice_Scaled
count	5.000000	5.000000	5.000000	5.000000
mean	34.400000	110.790000	2207.656000	0.269697
std	36.861904	163.043552	3256.036397	0.411726
min	12.000000	3.990000	399.000000	0.000000
25%	18.000000	39.990000	599.880000	0.090909
50%	20.000000	49.990000	719.820000	0.116162
75%	22.000000	59.990000	1319.780000	0.141414
max	100.000000	399.990000	7999.800000	1.000000

[ ]:

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[17]:

```python
# Central Tendency Measures
print("=== Central Tendency Measures ===")

# Mean
print("\nMean:\n", scaled_df.mean(numeric_only=True))

# Median
print("\nMedian:\n", scaled_df.median(numeric_only=True))

# Mode
print("\nMode:\n", scaled_df.mode(numeric_only=True).iloc[0])  # First mode row

# Minimum
print("\nMinimum:\n", scaled_df.min(numeric_only=True))

# Maximum
print("\nMaximum:\n", scaled_df.max(numeric_only=True))
```

```
=== Central Tendency Measures ===

Mean:
 UnitsSold            34.400000
UnitPrice           110.790000
Revenue            2207.656000
UnitPrice_Scaled      0.269697
dtype: float64

Median:
 UnitsSold           20.000000
UnitPrice           49.990000
Revenue            719.820000
UnitPrice_Scaled     0.116162
dtype: float64

Mode:
 UnitsSold           12.00
UnitPrice            3.99
Revenue            399.00
UnitPrice_Scaled     0.00
Name: 0, dtype: float64

Minimum:
 UnitsSold           12.00
UnitPrice            3.99
Revenue            399.00
UnitPrice_Scaled     0.00
dtype: float64

Maximum:
 UnitsSold          100.00
UnitPrice          399.99
Revenue           7999.80
UnitPrice_Scaled     1.00
dtype: float64
```

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[ ]:

```
[18]: # Dispersion Measures
print("=== Dispersion Measures ===")

# Standard Deviation
print("\nStandard Deviation:\n", scaled_df.std(numeric_only=True))

# Variance
print("\nVariance:\n", scaled_df.var(numeric_only=True))

# Range = Max - Min
range_vals = scaled_df.max(numeric_only=True) - scaled_df.min(numeric_only=True)
print("\nRange:\n", range_vals)
```

```
=== Dispersion Measures ===

Standard Deviation:
 UnitsSold            36.861904
UnitPrice           163.043552
Revenue            3256.036397
UnitPrice_Scaled      0.411726
dtype: float64

Variance:
 UnitsSold           1.358800e+03
UnitPrice          2.658320e+04
Revenue            1.060177e+07
UnitPrice_Scaled   1.695184e-01
dtype: float64

Range:
 UnitsSold             88.0
UnitPrice            396.0
Revenue             7600.8
UnitPrice_Scaled       1.0
dtype: float64
```

```
[ ]:
```

```
[19]: # Correlation and Covariance
print("=== Correlation Matrix ===")
print(scaled_df.corr(numeric_only=True))

print("\n=== Covariance Matrix ===")
print(scaled_df.cov(numeric_only=True))
```

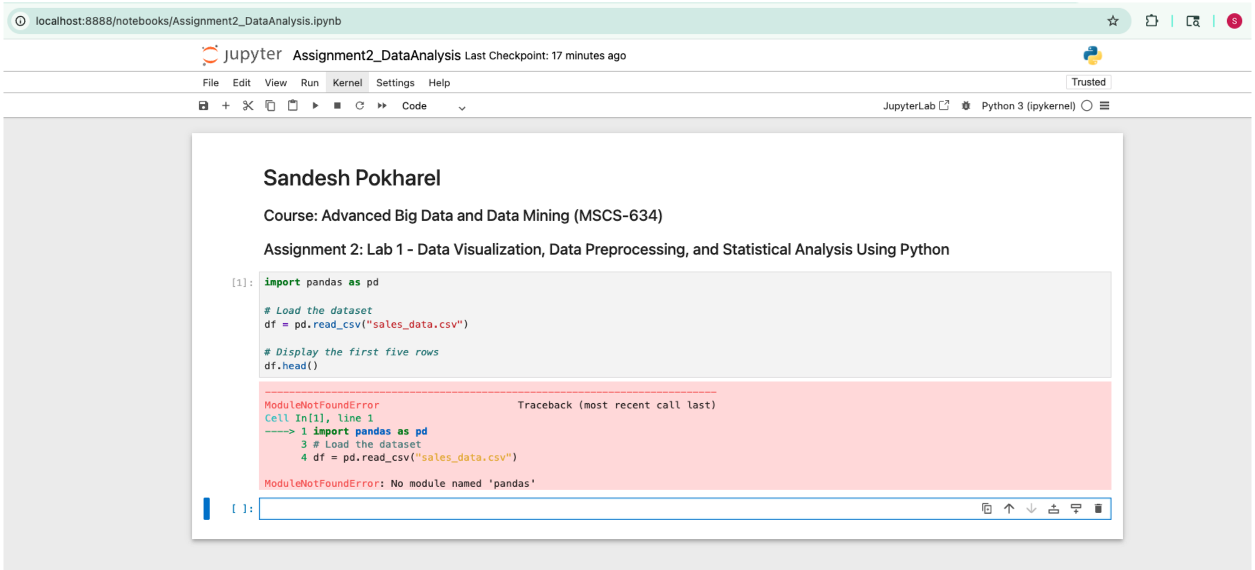
```
=== Correlation Matrix ===
                  UnitsSold  UnitPrice   Revenue  UnitPrice_Scaled
UnitsSold          1.000000  -0.333505 -0.272093         -0.333505
UnitPrice         -0.333505   1.000000  0.996678          1.000000
Revenue           -0.272093   0.996678  1.000000          0.996678
UnitPrice_Scaled  -0.333505   1.000000  0.996678          1.000000

=== Covariance Matrix ===
                     UnitsSold      UnitPrice       Revenue  UnitPrice_Scaled
UnitsSold          1358.800000   -2004.400000 -3.265759e+04         -5.061616
UnitPrice         -2004.400000   26583.200000  5.291120e+05         67.129293
Revenue          -32657.588000  529112.044000  1.060177e+07       1336.141525
UnitPrice_Scaled     -5.061616      67.129293  1.336142e+03          0.169518
```

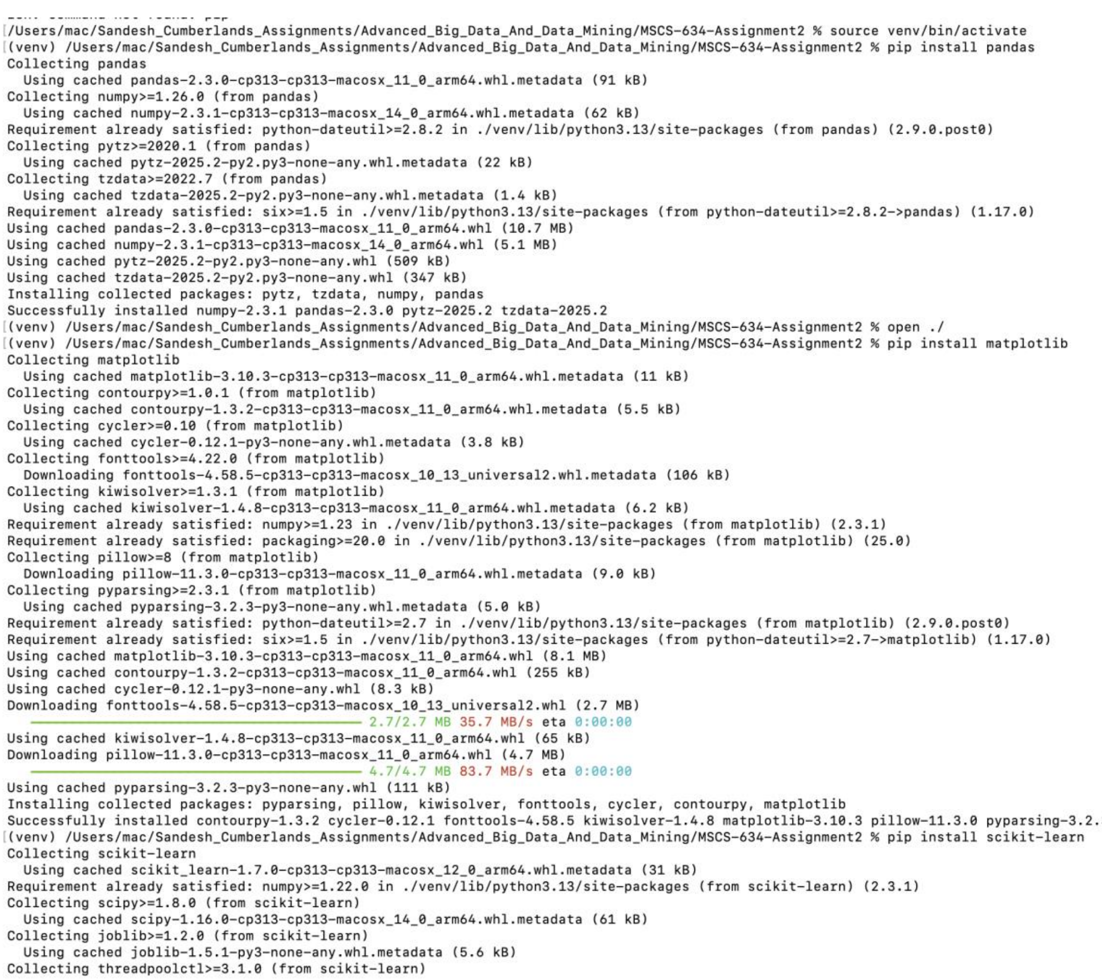
```
[ ]:
```

7. Challenges and Decisions Made

- Encountered `pip` not found error initially due to not activating the virtual environment.
- Jupyter was unable to detect packages unless installed from within the virtual environment.
- Identified and resolved module import errors via console traceback.
- Learned to capture and interpret terminal + Jupyter feedback to guide debugging.
- Ensured screenshots were taken throughout all required and additional stages.

Screenshot Placeholder: Error messages and fixed outputs





8. Conclusion

This lab provided practical experience with preprocessing, visualization, and statistical analysis in Python.
It also reinforced environment management using virtual environments and troubleshooting real-time errors.
The techniques used in this lab lay a foundation for deeper data mining and machine learning tasks.