Exploratory_Data_Analysis_on_SampleSuper_Store_dataset

Task 3-- The Spark Foundation

Adarsh Dubey

The goal is to gain valuable insights into customer behavior and optimize the store's operations based on the findings.

1. The project revolves around leveraging machine learning techniques to analyze the Superstore dataset, perform Exploratory Data Analysis (EDA), and implement clustering algorithms.
2. Using Python
3. Dataset : [https://bit.ly/3i4rbWI (https://bit.ly/3i4rbWI)](https://bit.ly/3i4rbWI)
4. The project contributes to optimizing customer satisfaction, increasing sales, and ultimately enhancing the overall success of the Superstore..

Setting up the environment

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sn
import warnings
warnings.filterwarnings("ignore")
```

In [2]:
```
data = pd.read_csv("SampleSuperstore.csv")
```

In [3]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9994 entries, 0 to 9993
Data columns (total 13 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   Ship Mode     9994 non-null   object 
 1   Segment       9994 non-null   object 
 2   Country       9994 non-null   object 
 3   City          9994 non-null   object 
 4   State         9994 non-null   object 
 5   Postal Code   9994 non-null   int64  
 6   Region        9994 non-null   object 
 7   Category      9994 non-null   object 
 8   Sub-Category  9994 non-null   object 
 9   Sales         9994 non-null   float64
 10  Quantity      9994 non-null   int64  
 11  Discount      9994 non-null   float64
 12  Profit        9994 non-null   float64
dtypes: float64(3), int64(2), object(8)
memory usage: 1015.1+ KB
```

In [4]:
```
data.columns
```

Out[4]:
```
Index(['Ship Mode', 'Segment', 'Country', 'City', 'State', 'Postal Code',
       'Region', 'Category', 'Sub-Category', 'Sales', 'Quantity', 'Discount',
       'Profit'],
      dtype='object')
```

Exploratory-Data-Analysis

In [5]:
```
data.head()
```

Out[5]:

	Ship Mode	Segment	Country	City	State	Postal Code	Region	Category	Sub-Category	Sales	Quantity	Discount	Profit
0	Second Class	Consumer	United States	Henderson	Kentucky	42420	South	Furniture	Bookcases	261.9600	2	0.00	41.9136
1	Second Class	Consumer	United States	Henderson	Kentucky	42420	South	Furniture	Chairs	731.9400	3	0.00	219.5820
2	Second Class	Corporate	United States	Los Angeles	California	90036	West	Office Supplies	Labels	14.6200	2	0.00	6.8714
3	Standard Class	Consumer	United States	Fort Lauderdale	Florida	33311	South	Furniture	Tables	957.5775	5	0.45	-383.0310
4	Standard Class	Consumer	United States	Fort Lauderdale	Florida	33311	South	Office Supplies	Storage	22.3680	2	0.20	2.5164

In [6]:
```
data.describe()
```

Out[6]:

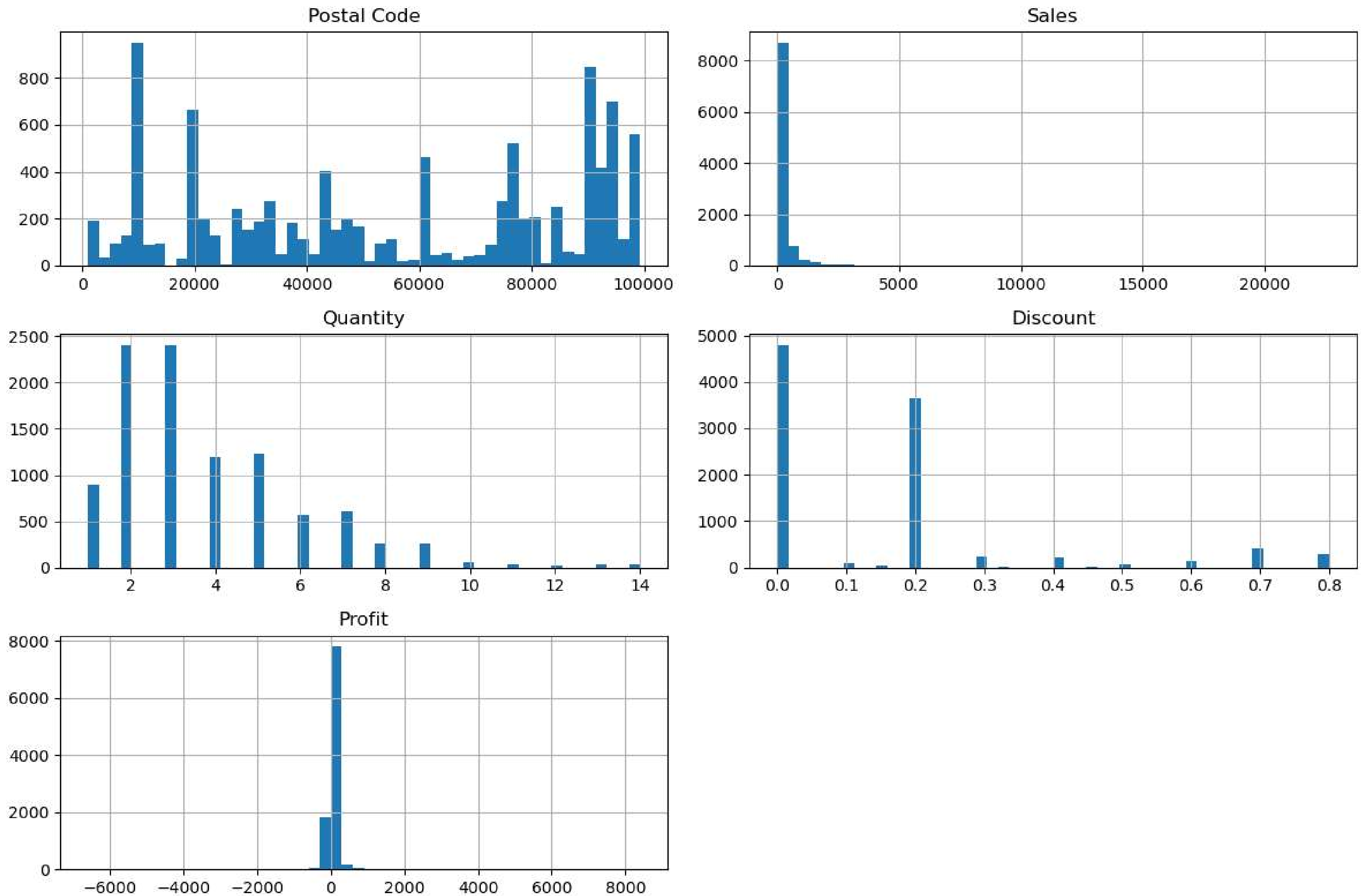
	Postal Code	Sales	Quantity	Discount	Profit
count	9994.000000	9994.000000	9994.000000	9994.000000	9994.000000
mean	55190.379428	229.858001	3.789574	0.156203	28.656896
std	32063.693350	623.245101	2.225110	0.206452	234.260108
min	1040.000000	0.444000	1.000000	0.000000	-6599.978000
25%	23223.000000	17.280000	2.000000	0.000000	1.728750
50%	56430.500000	54.490000	3.000000	0.200000	8.666500
75%	90008.000000	209.940000	5.000000	0.200000	29.364000
max	99301.000000	22638.480000	14.000000	0.800000	8399.976000

In [7]:
```
data.isnull().sum()
```

Out[7]:
```
Ship Mode       0
Segment         0
Country         0
City            0
State           0
Postal Code     0
Region          0
Category        0
Sub-Category    0
Sales           0
Quantity        0
Discount        0
Profit          0
dtype: int64
```

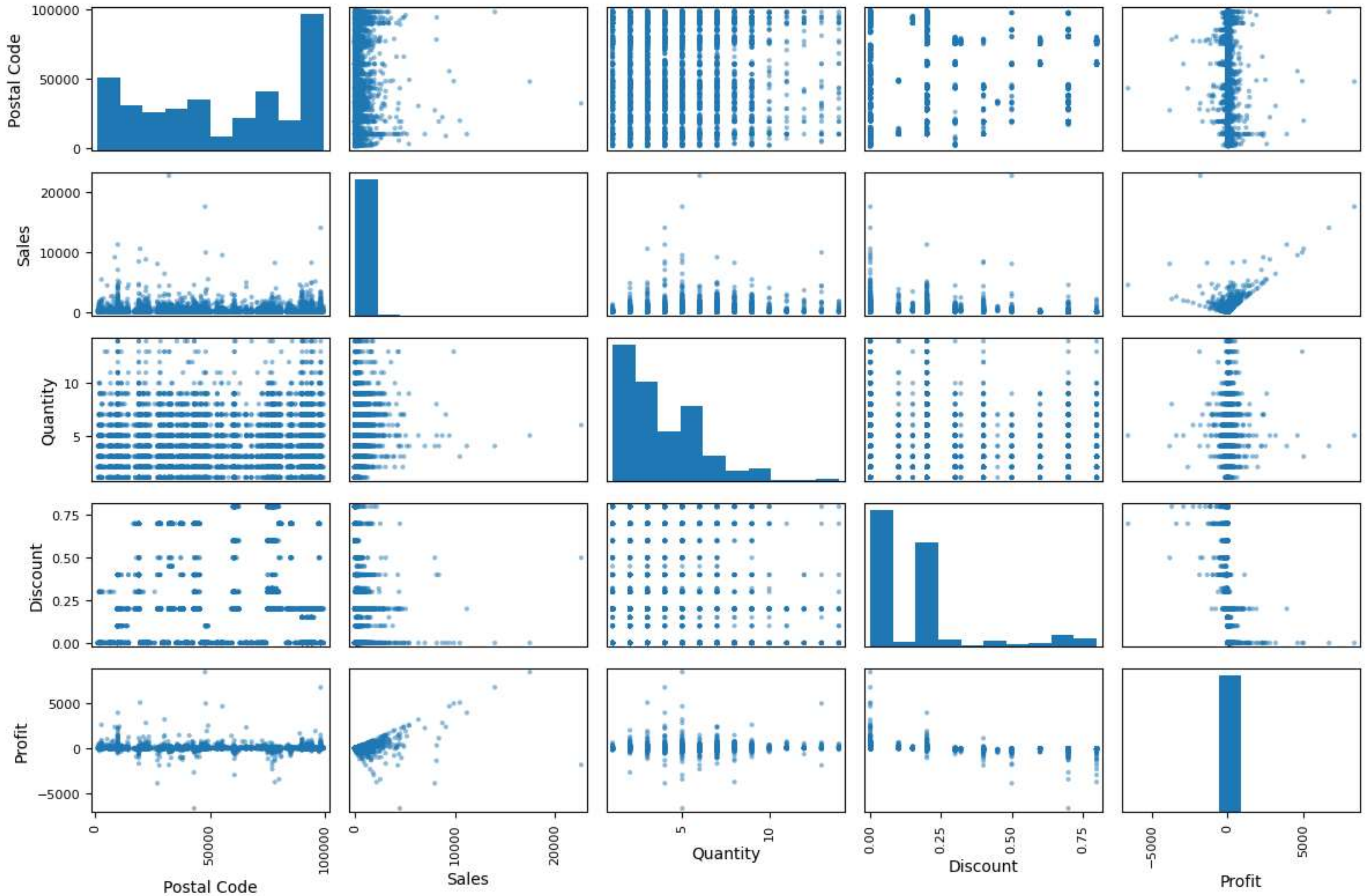
Understanding Numerical variables

In [8]:
```
data.hist(bins=50 , figsize=(12,8))
plt.tight_layout()
plt.show()
```



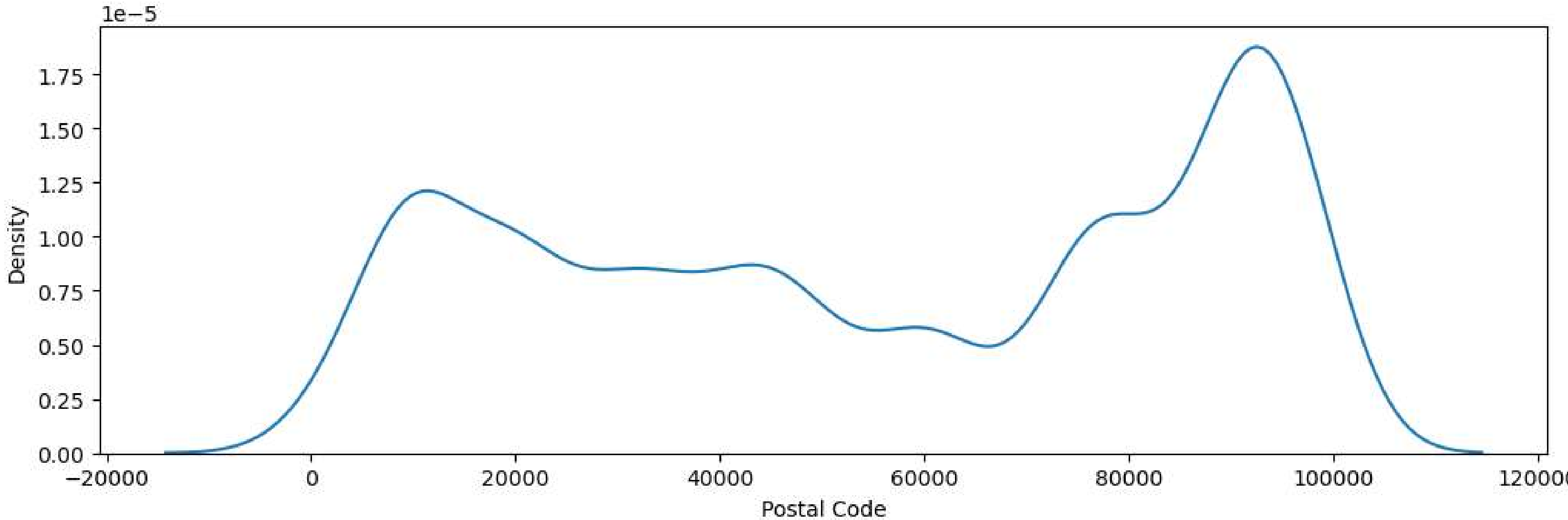
In [9]:
```
from pandas.plotting import scatter_matrix

attributes = [i for i in data.columns]
scatter_matrix(data[attributes] , figsize=(12,8))
plt.tight_layout()
plt.show()
```



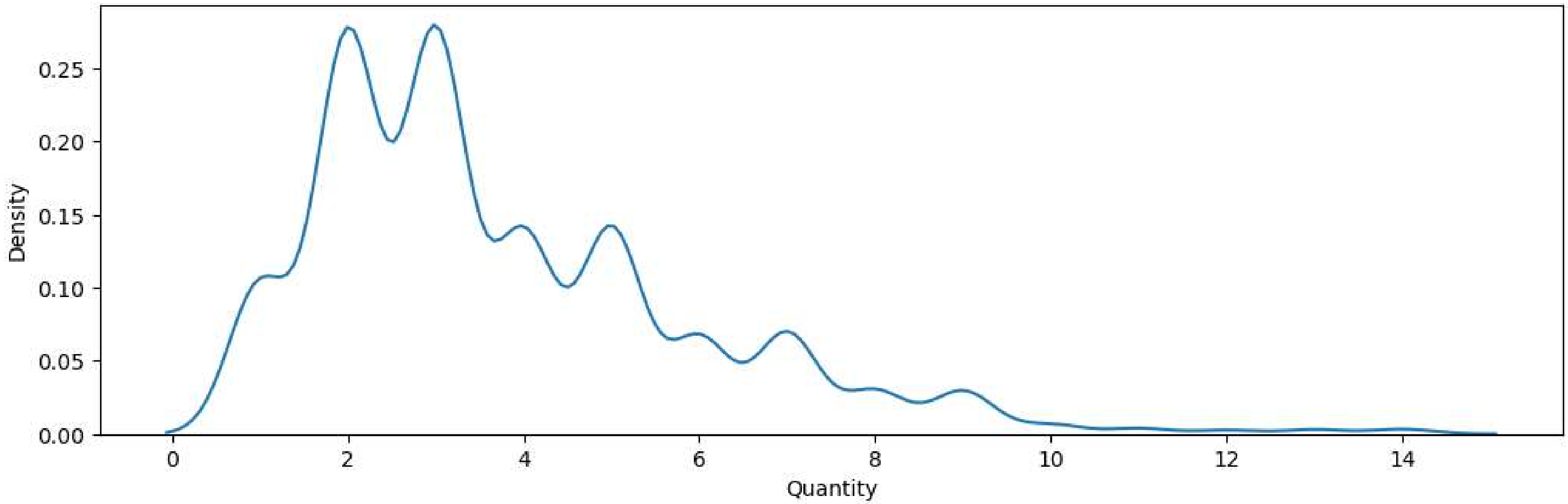
In [10]:
```
plt.figure(figsize=(20,30))
ax = plt.subplot(9, 2,1)
sn.kdeplot(data['Postal Code'], ax=ax)
plt.tight_layout()
plt.xlabel('Postal Code')

plt.show()
```



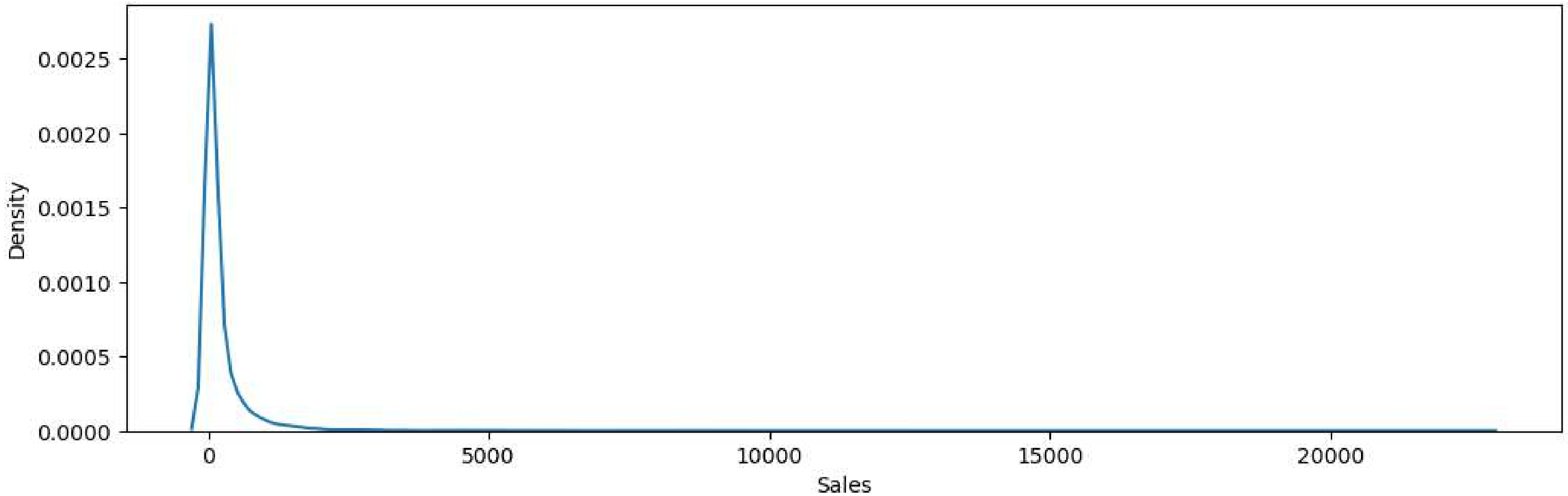
In [11]:
```
plt.figure(figsize=(20,30))
ax = plt.subplot(9, 2,1)
sn.kdeplot(data['Quantity'], ax=ax)
plt.tight_layout()
plt.xlabel('Quantity')

plt.show()
```



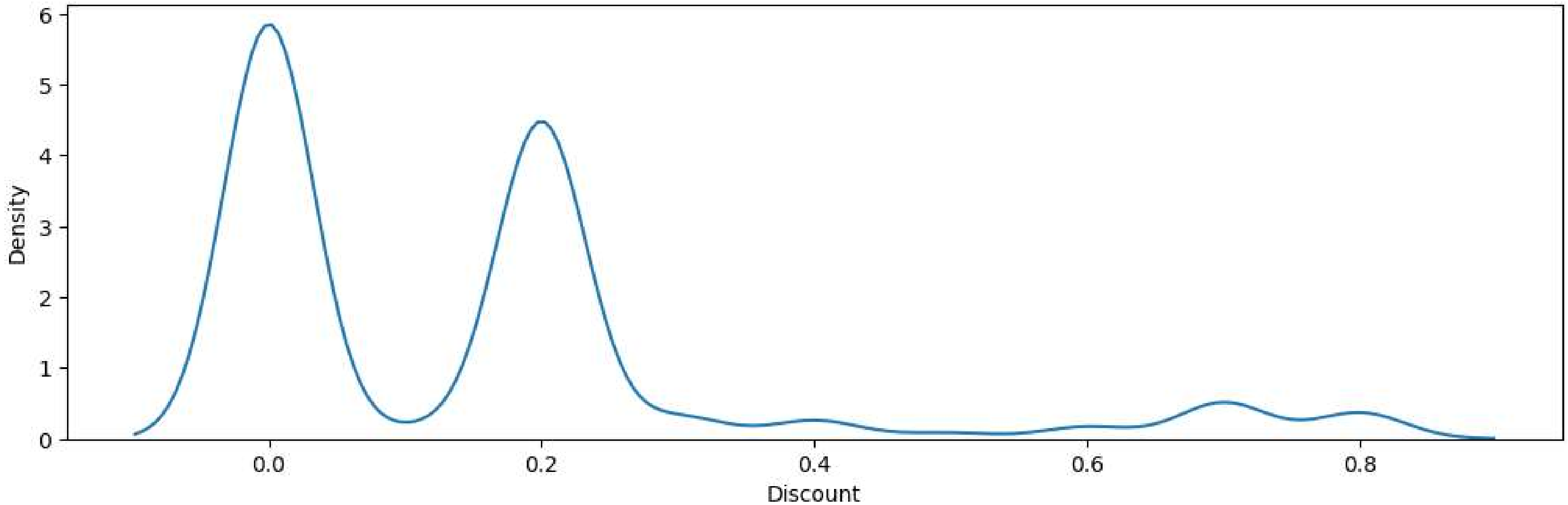
In [12]:
```
plt.figure(figsize=(20,30))
ax = plt.subplot(9, 2,1)
sn.kdeplot(data['Sales'], ax=ax)
plt.tight_layout()
plt.xlabel('Sales')

plt.show()
```



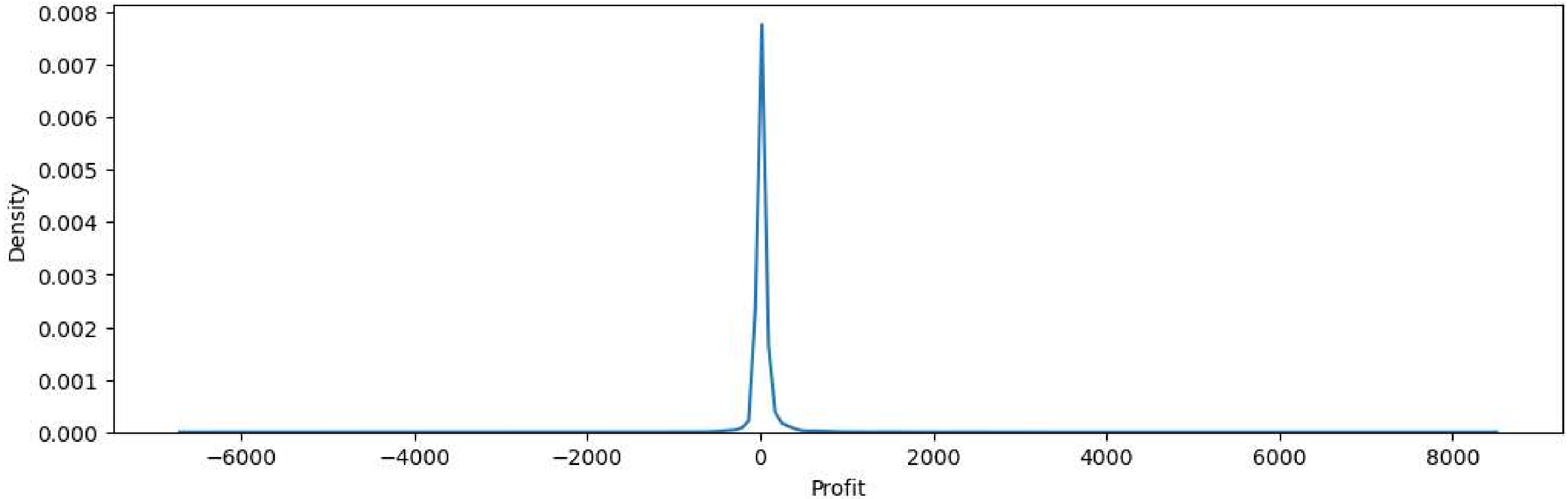
In [13]:
```
plt.figure(figsize=(20,30))
ax = plt.subplot(9, 2,1)
sn.kdeplot(data['Discount'], ax=ax)
plt.tight_layout()
plt.xlabel('Discount')

plt.show()
```



In [14]:
```
plt.figure(figsize=(20,30))
ax = plt.subplot(9, 2,1)
sn.kdeplot(data['Profit'], ax=ax)
plt.tight_layout()
plt.xlabel('Profit')

plt.show()
```

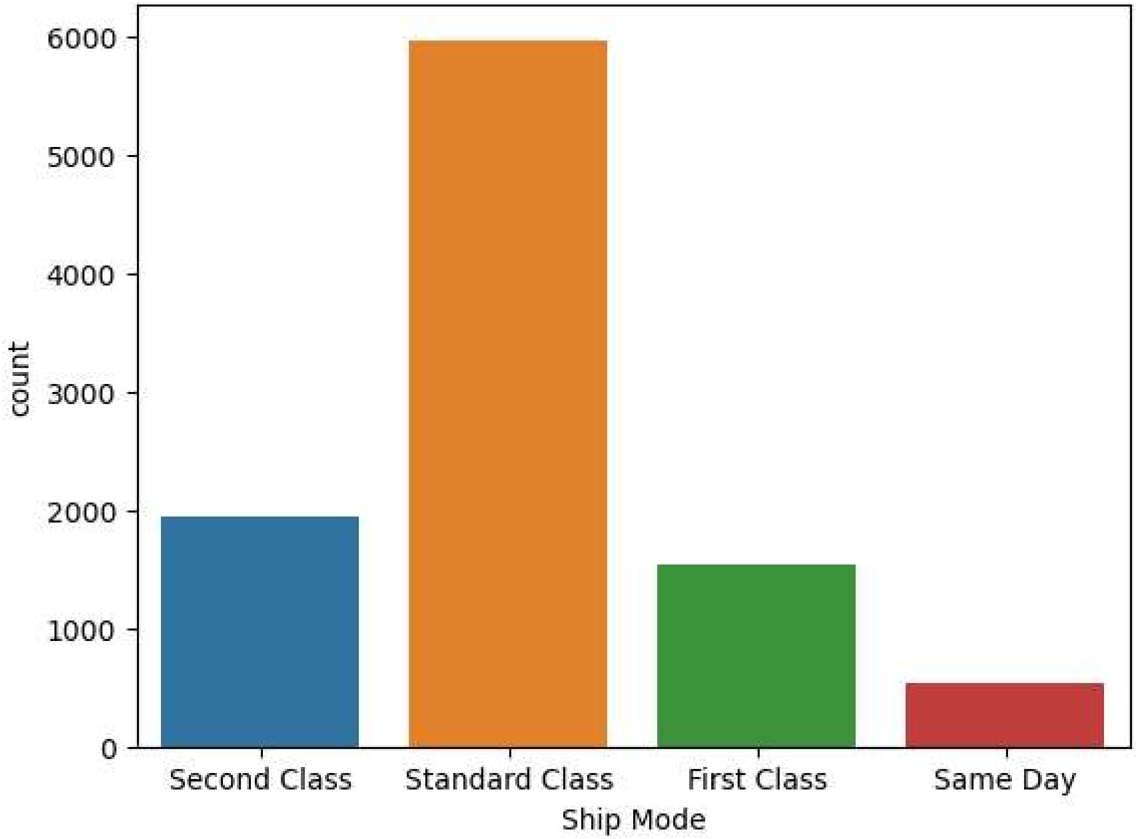


Understanding Categorical variables

In [15]:
```
data.info()
```

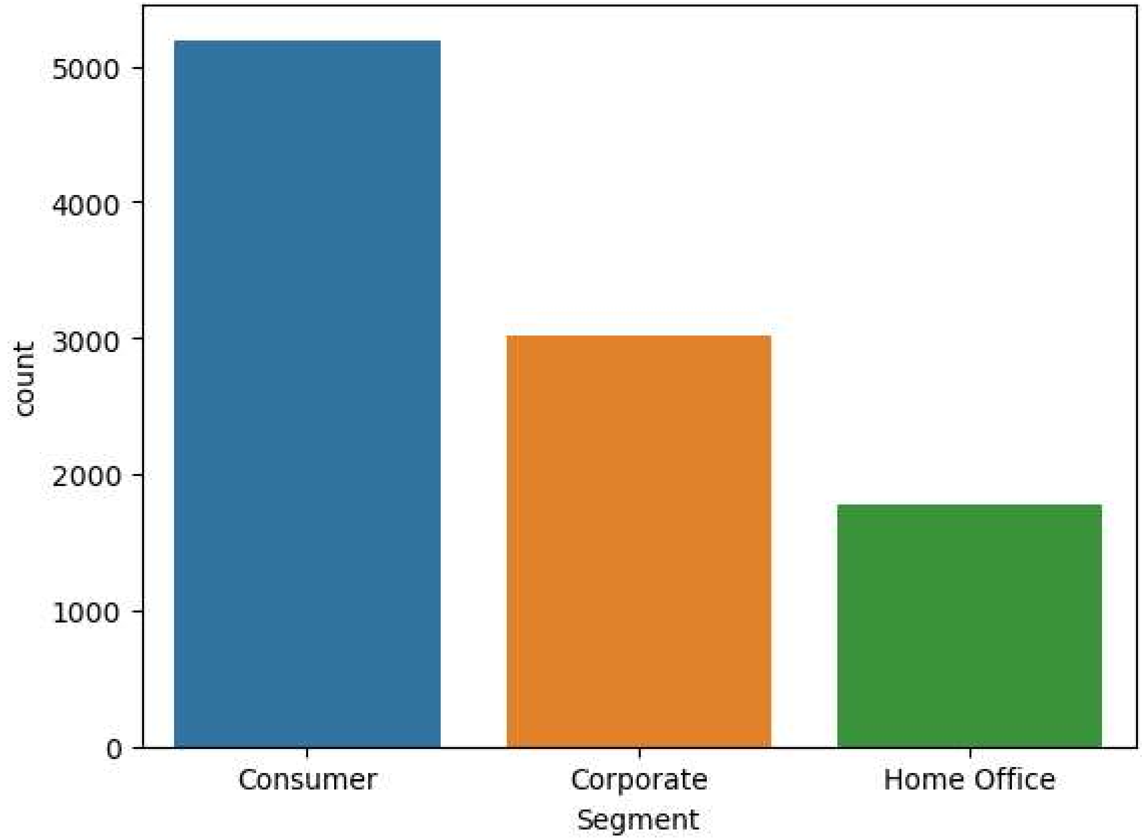
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9994 entries, 0 to 9993
Data columns (total 13 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   Ship Mode     9994 non-null   object 
 1   Segment       9994 non-null   object 
 2   Country       9994 non-null   object 
 3   City          9994 non-null   object 
 4   State         9994 non-null   object 
 5   Postal Code   9994 non-null   int64  
 6   Region        9994 non-null   object 
 7   Category      9994 non-null   object 
 8   Sub-Category  9994 non-null   object 
 9   Sales         9994 non-null   float64
 10  Quantity      9994 non-null   int64  
 11  Discount      9994 non-null   float64
 12  Profit        9994 non-null   float64
dtypes: float64(3), int64(2), object(8)
memory usage: 1015.1+ KB
```

In [16]:
```
ax = sn.countplot(x='Ship Mode',data=data)
```

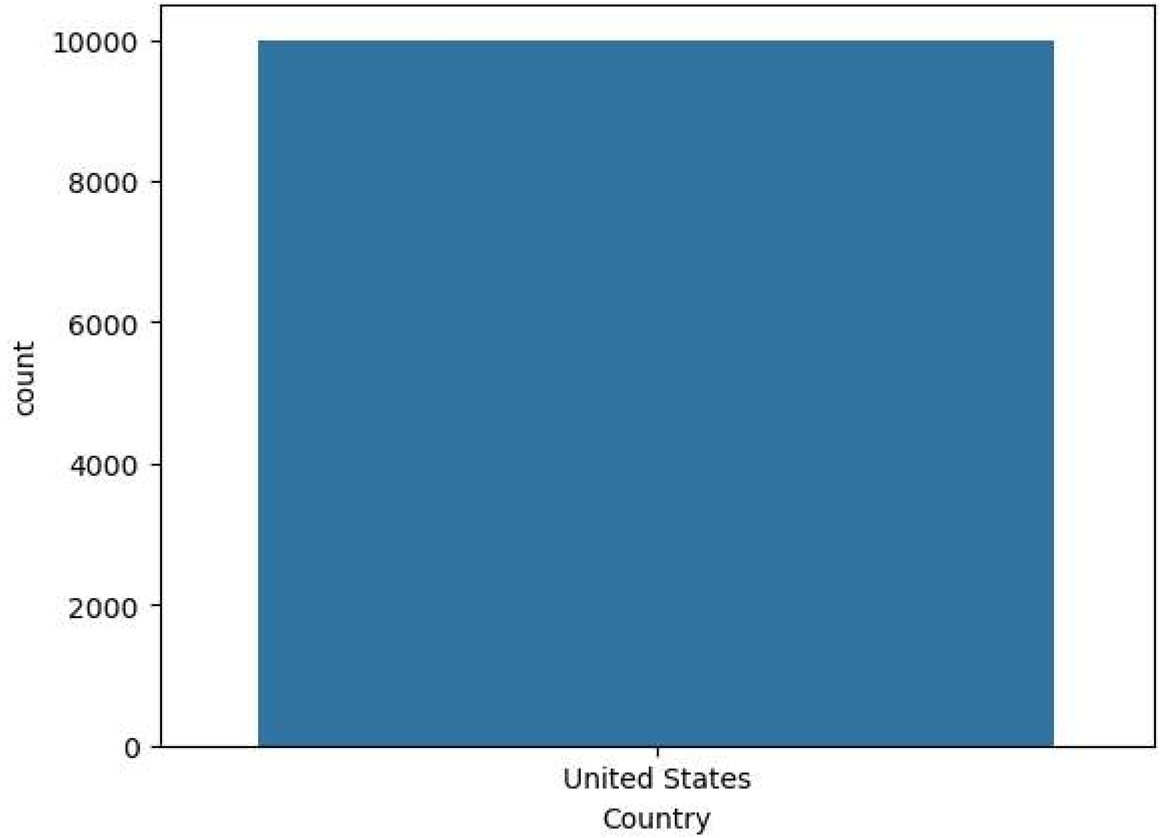


In [17]:

```
ax = sn.countplot(x='Segment',data=data)
```



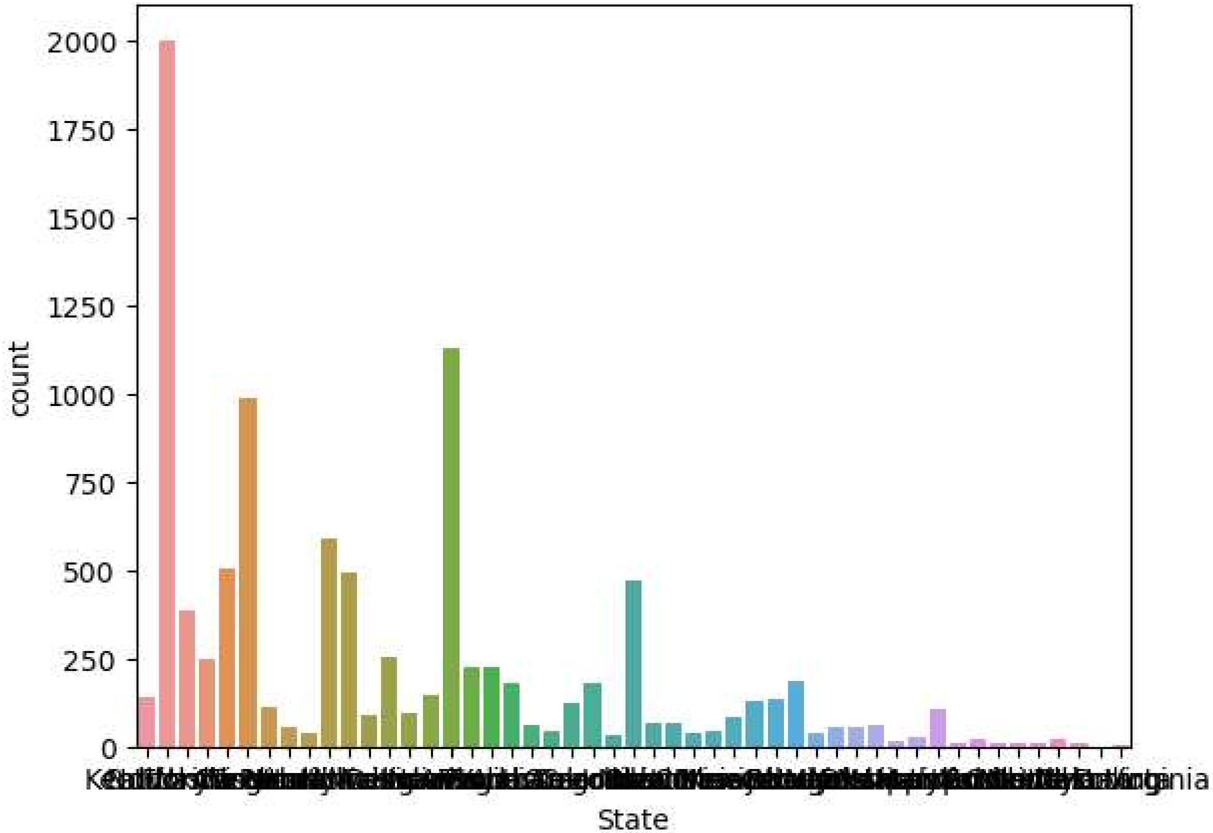
In [18]:
```
ax = sn.countplot(x='Country',data=data)
```



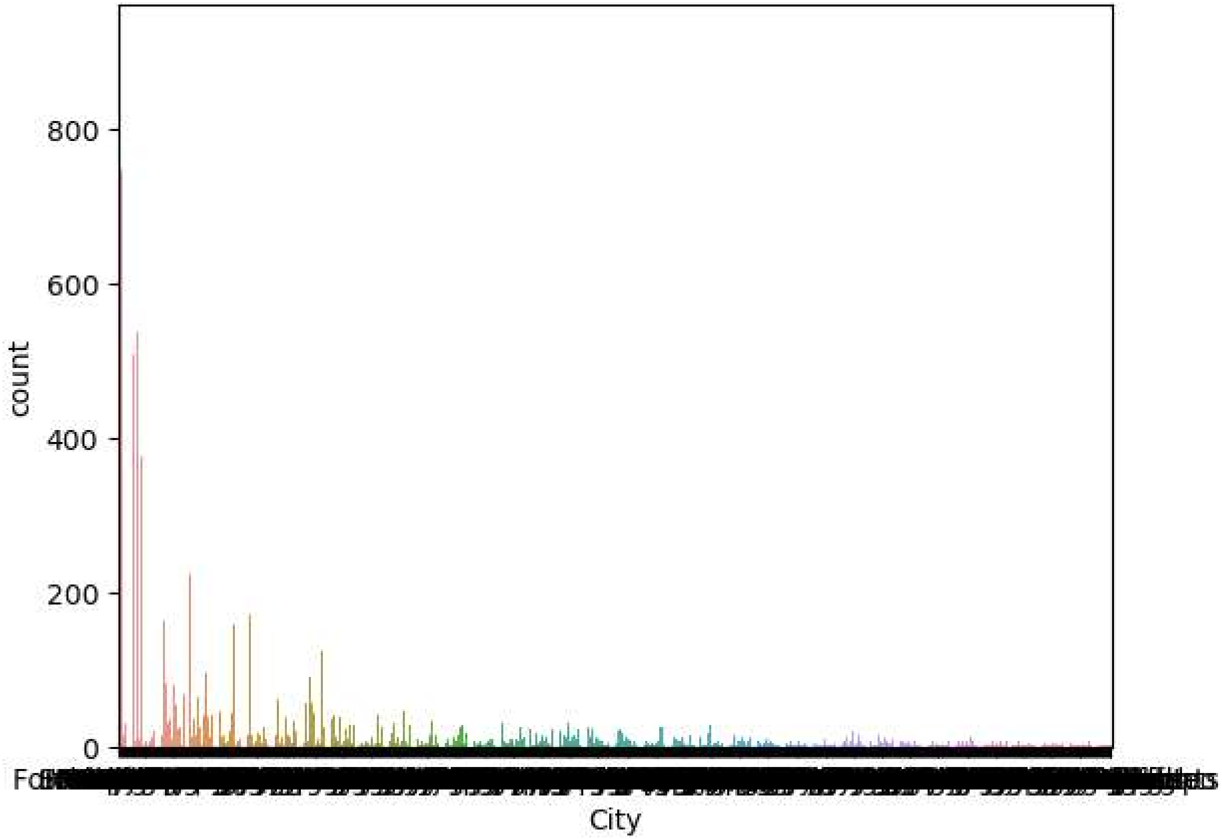
In [19]:
```
data = data.drop(['Country'],axis=1)
```

In [20]:
```
#data['City'].value_counts()
```

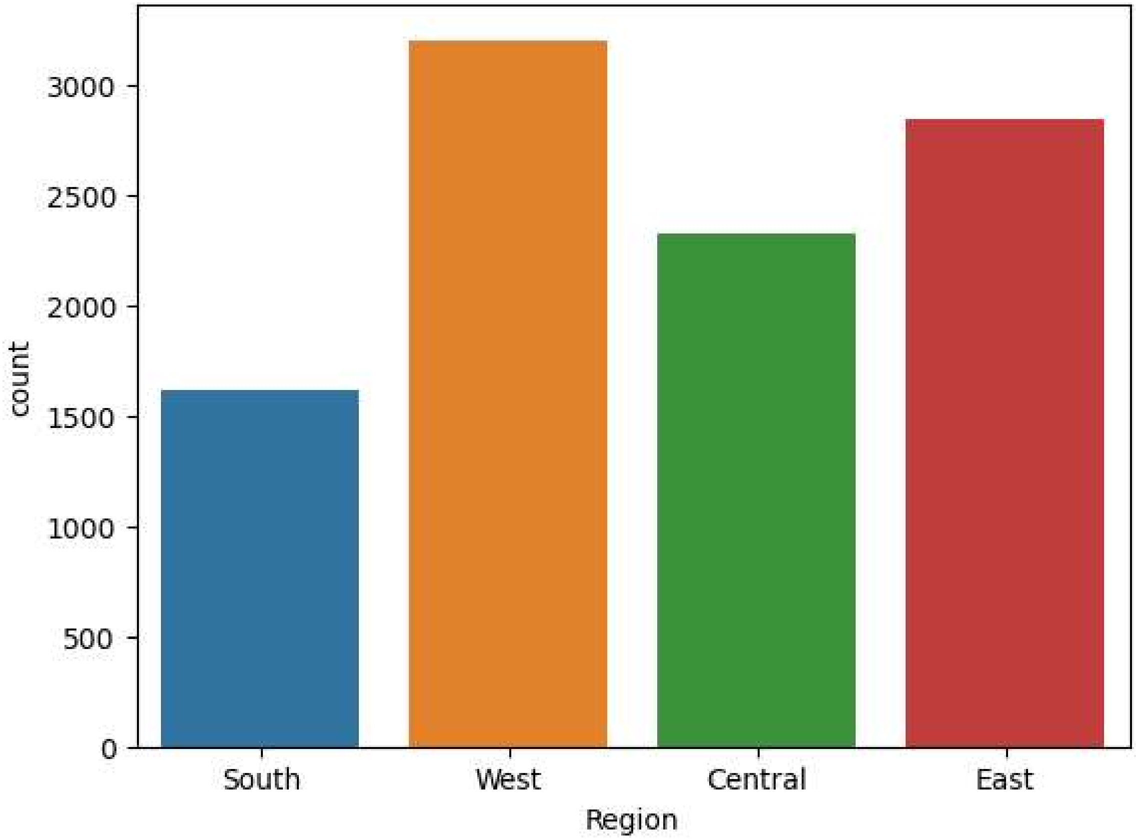
In [21]:
```python
ax = sn.countplot(x='State',data=data)
```



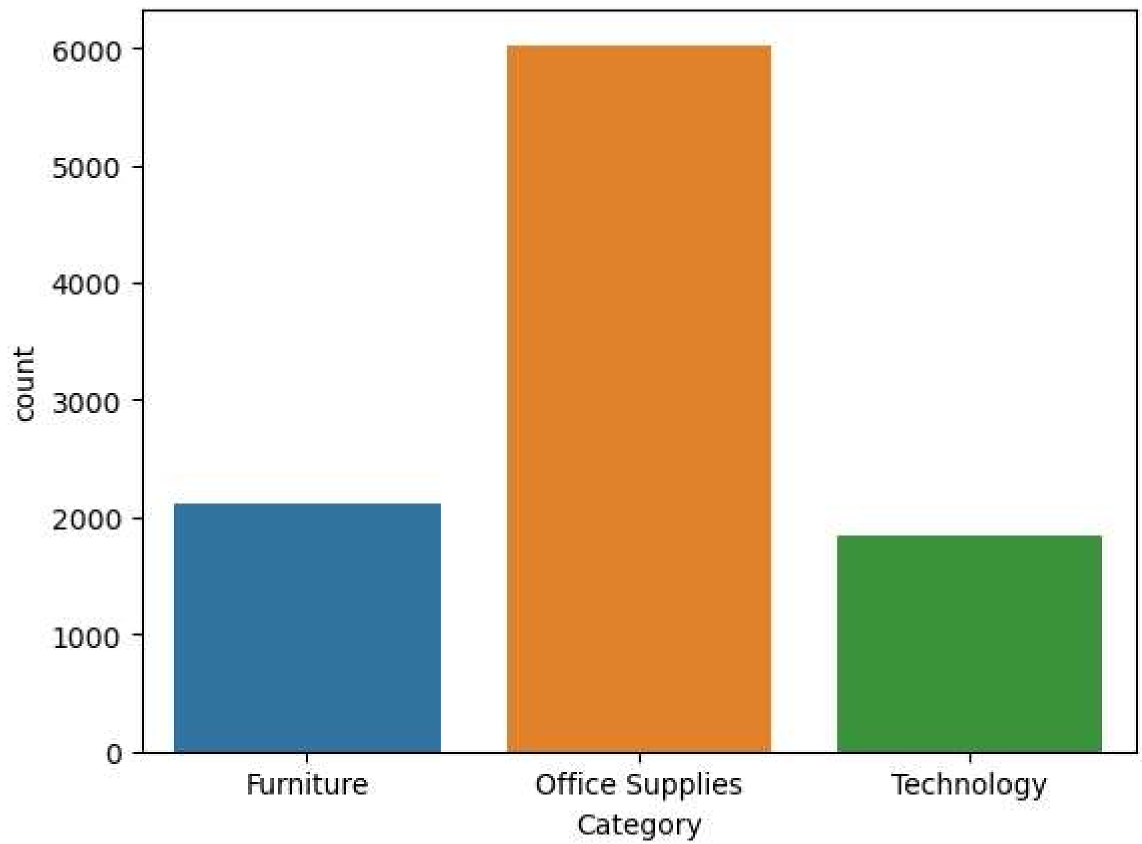
In [22]:
```
ax = sn.countplot(x='City',data=data)
```



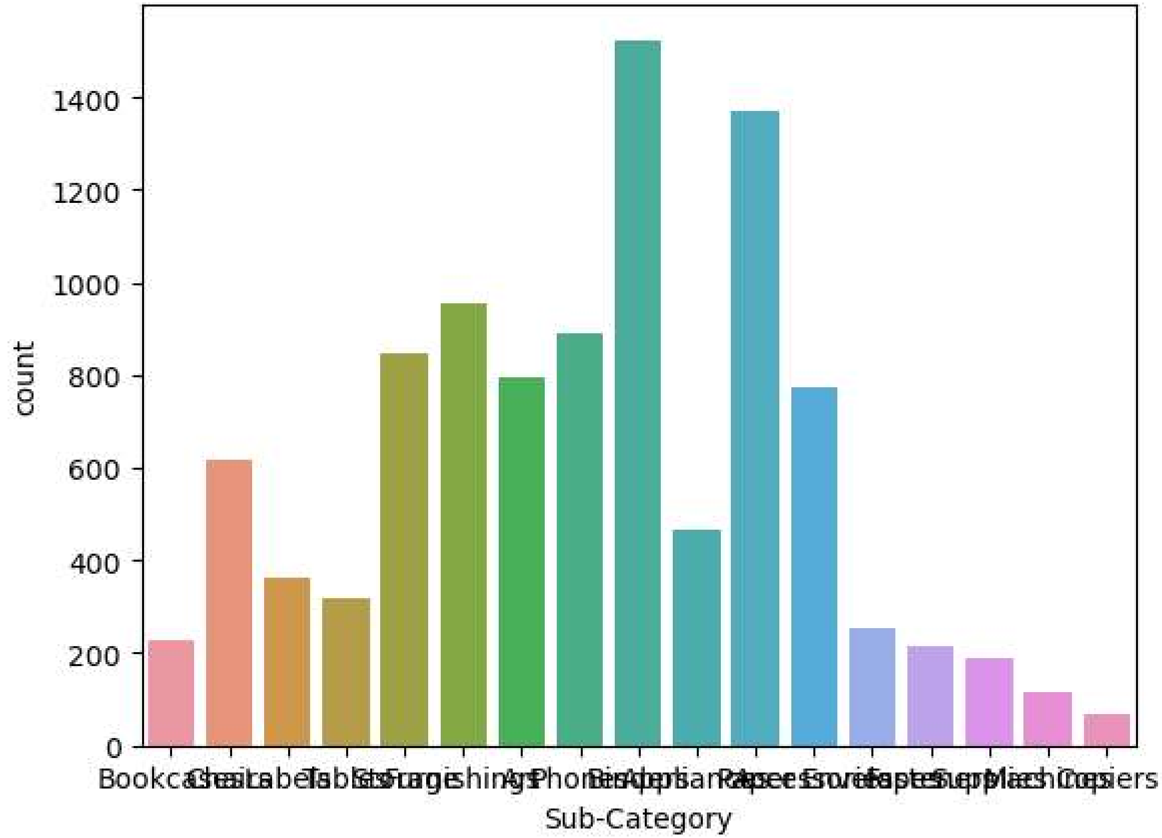
In [23]:
```
ax = sn.countplot(x='Region',data=data)
```



In [24]:
```
ax = sn.countplot(x='Category',data=data)
```



```
In [25]: ax = sn.countplot(x='Sub-Category',data=data)
```



Finding the most profitable states

In [26]:
```
state_profit=pd.DataFrame(data.groupby("State")["Profit"].sum())
state_profit.reset_index(inplace=True)
state_profit=state_profit.sort_values(by="Profit",ascending=False)
state_profit.head(10)
```

Out[26]:

	State	Profit
3	California	76381.3871
30	New York	74038.5486
45	Washington	33402.6517
20	Michigan	24463.1876
44	Virginia	18597.9504
12	Indiana	18382.9363
9	Georgia	16250.0433
15	Kentucky	11199.6966
21	Minnesota	10823.1874
6	Delaware	9977.3748

Finding the most profitable cities

In [27]:
```
cities_profit=pd.DataFrame(data.groupby("City")["Profit"].sum())
cities_profit.reset_index(inplace=True)
cities_profit=cities_profit.sort_values(by="Profit",ascending=False)
cities_profit.head(10)
```

Out[27]:

	City	Profit
329	New York City	62036.9837
266	Los Angeles	30440.7579
452	Seattle	29156.0967
438	San Francisco	17507.3854
123	Detroit	13181.7908
233	Lafayette	10018.3876
215	Jackson	7581.6828
21	Atlanta	6993.6629
300	Minneapolis	6824.5846
437	San Diego	6377.1960

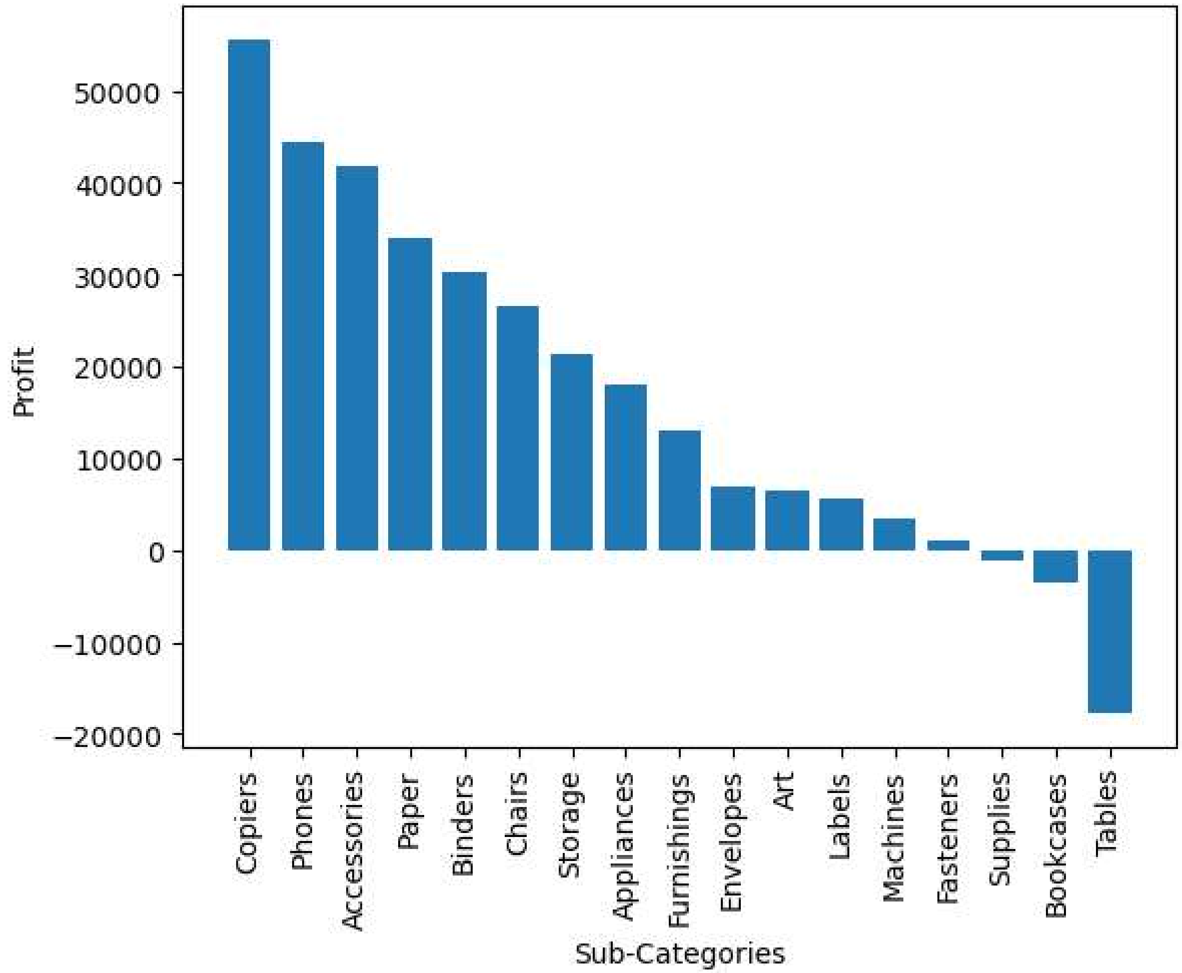
Finding the most profitable sub-categories

In [28]:
```
sub_categories_info=pd.DataFrame(data.groupby("Sub-Category")["Profit"].sum())
sub_categories_info.reset_index(inplace=True)
sub_categories_profit=sub_categories_info.sort_values(by="Profit",ascending=False)
sub_categories_profit.head(10)
```

Out[28]:

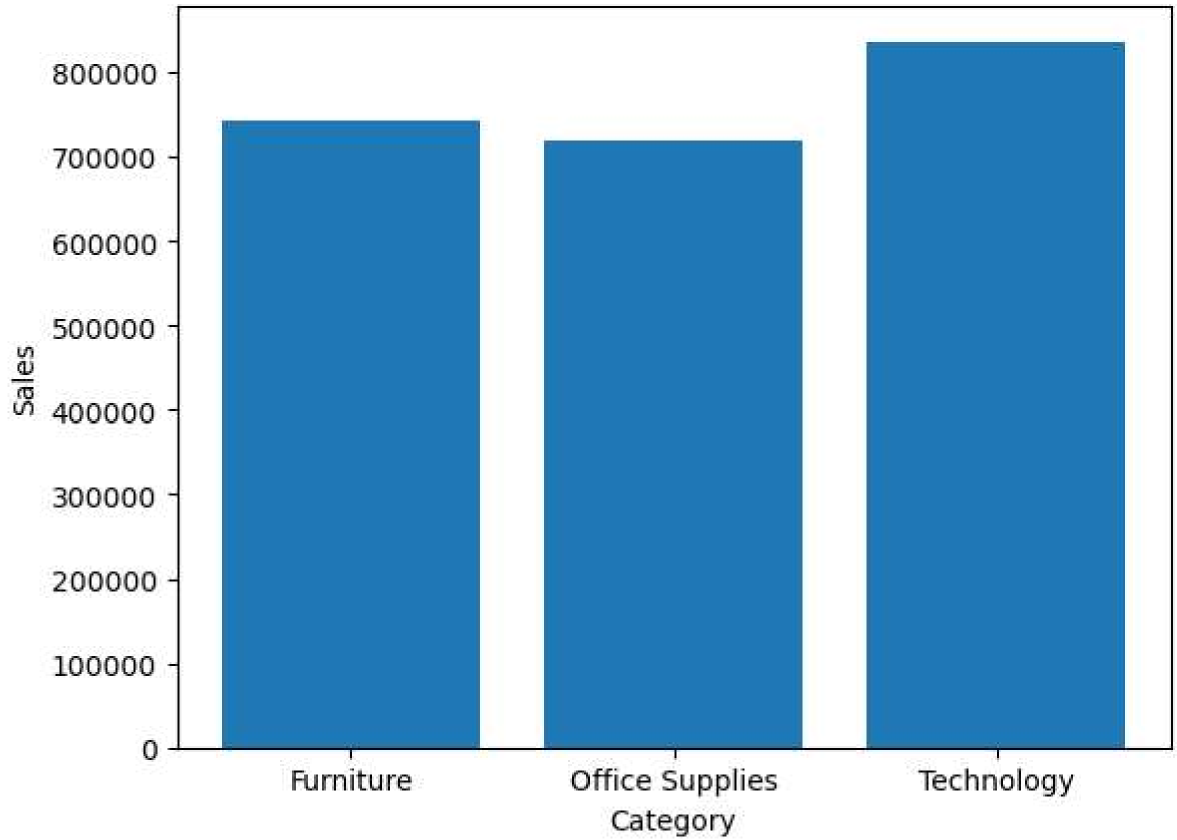
	Sub-Category	Profit
6	Copiers	55617.8249
13	Phones	44515.7306
0	Accessories	41936.6357
12	Paper	34053.5693
3	Binders	30221.7633
5	Chairs	26590.1663
14	Storage	21278.8264
1	Appliances	18138.0054
9	Furnishings	13059.1436
7	Envelopes	6964.1767

In [29]:
```
plt.bar(sub_categories_profit["Sub-Category"],sub_categories_profit["Profit"])
plt.xticks(sub_categories_profit['Sub-Category'] , rotation = "vertical")
plt.xlabel("Sub-Categories")
plt.ylabel("Profit")
plt.show()
```



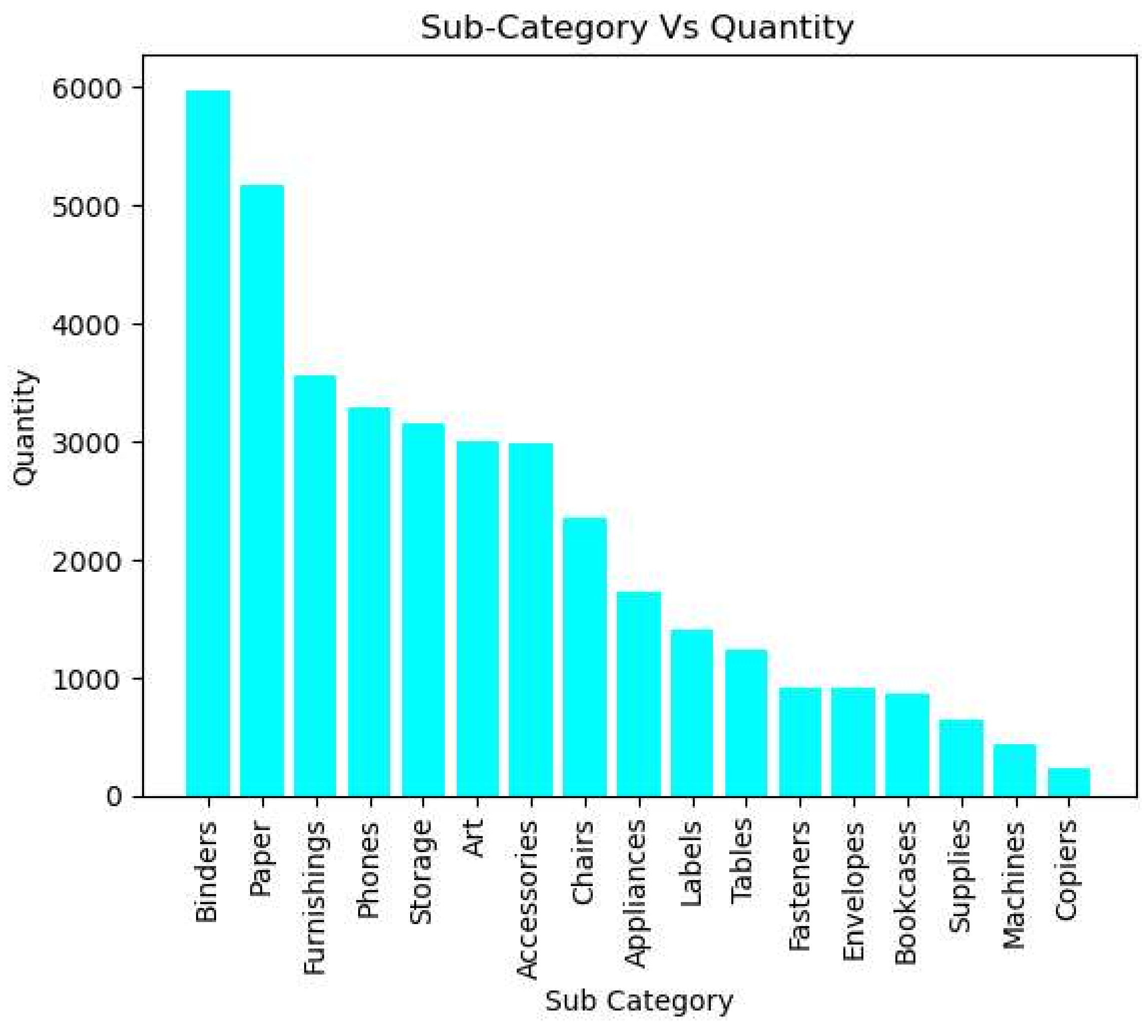
Finding the most profitable categories

In [30]:
```
categories_sales=data.groupby("Category").sum()
categories_sales.reset_index(inplace=True)
plt.bar(categories_sales["Category"], categories_sales['Sales'])
plt.xticks(categories_sales.index)
plt.xlabel("Category")
plt.ylabel("Sales")
plt.show()
```



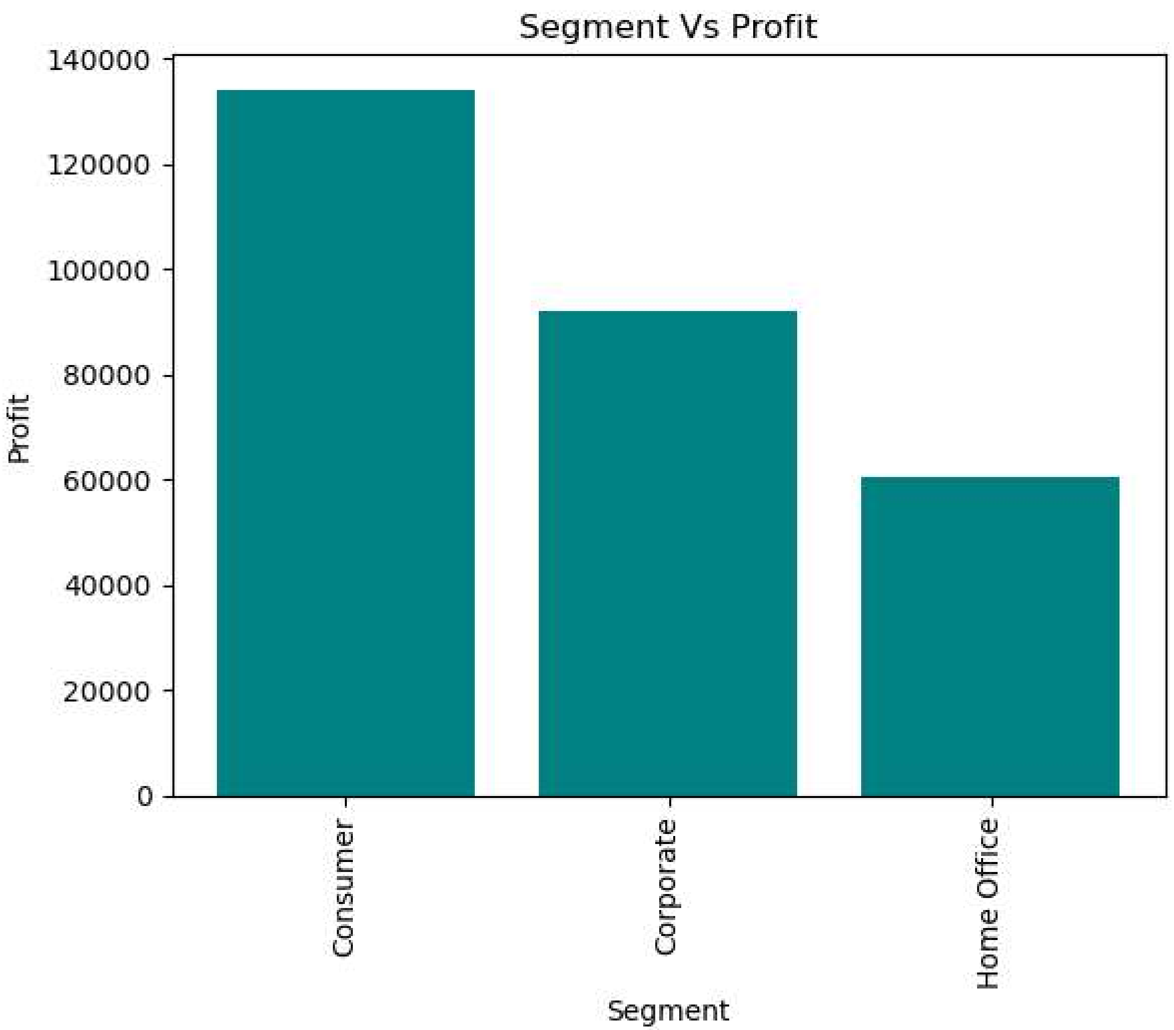
Finding the most popular sub-category

In [31]:
```
popular_sub_category=pd.DataFrame(data.groupby("Sub-Category")["Quantity"].sum())
popular_sub_category.reset_index(inplace=True)
popular_sub_category=popular_sub_category.sort_values(by="Quantity",ascending=False)
plt.bar(popular_sub_category["Sub-Category"],popular_sub_category["Quantity"],color="cyan")
plt.xticks(popular_sub_category["Sub-Category"],rotation="vertical")
plt.title("Sub-Category Vs Quantity")
plt.xlabel("Sub Category")
plt.ylabel("Quantity")
plt.show()
```



Finding the most profitable customer segment

In [32]:
```
customer_segment=data.groupby("Segment").sum()
customer_segment.reset_index(inplace=True)
plt.bar(customer_segment["Segment"],customer_segment["Profit"],color="teal")
plt.xticks(customer_segment["Segment"],rotation="vertical")
plt.title("Segment Vs Profit")
plt.xlabel("Segment")
plt.ylabel("Profit")
plt.show()
```



Finding the most profitable region

In [33]:
```
profitable_region=pd.DataFrame(data.groupby("Region")["Profit"].sum())
profitable_region.reset_index(inplace=True)
profitable_region
```

Out[33]:

	Region	Profit
0	Central	39706.3625
1	East	91522.7800
2	South	46749.4303
3	West	108418.4489

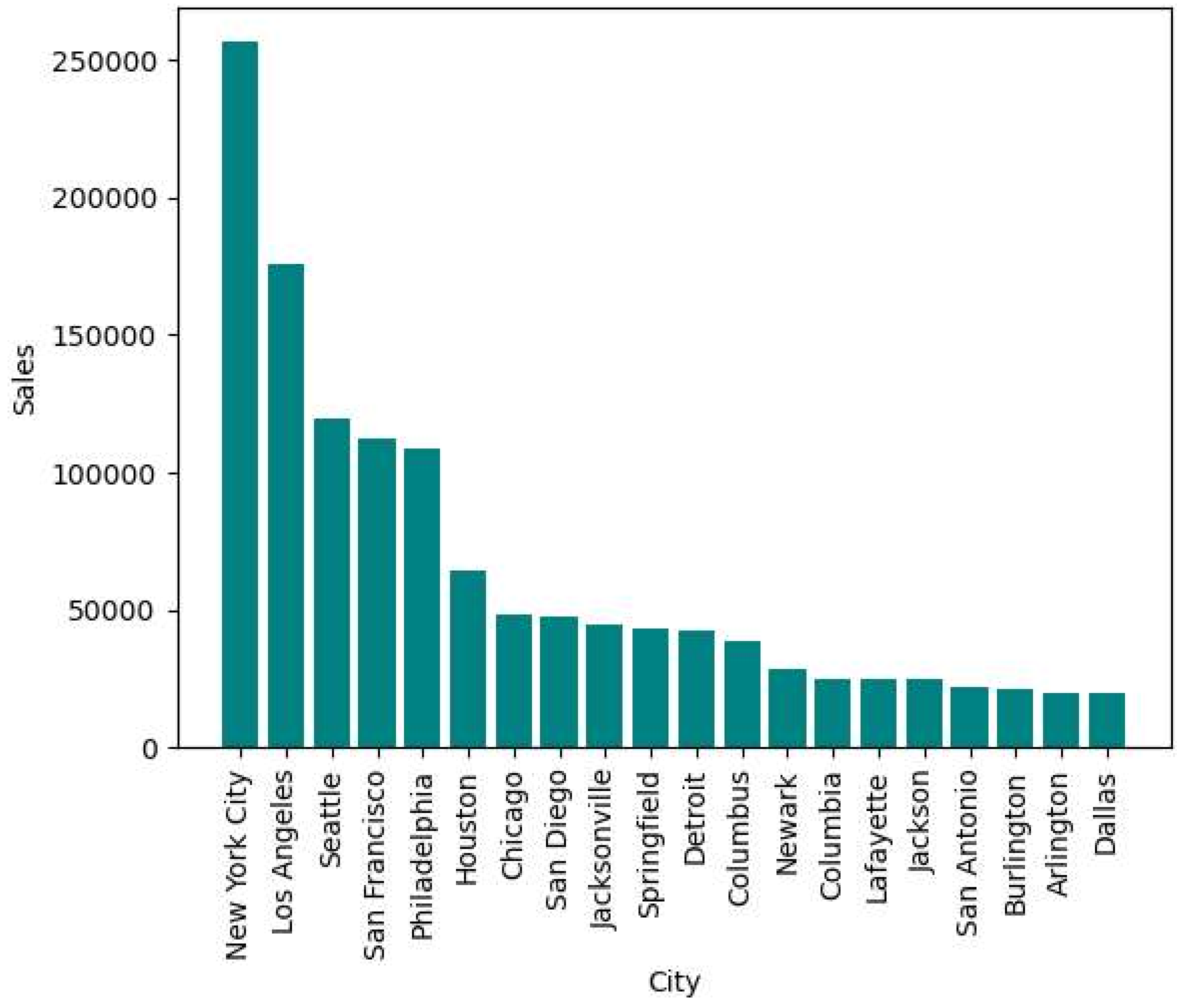
Finding the city with the highest sales volume

In [34]:
```
city_volume = pd.DataFrame(data.groupby('City')['Sales'].sum())
city_volume =city_volume.sort_values(by="Sales",ascending=False)
city_volume.head()
```

Out[34]:

	Sales
City	
New York City	256368.161
Los Angeles	175851.341
Seattle	119540.742
San Francisco	112669.092
Philadelphia	109077.013

In [35]:
```
plt.bar(city_volume.index[0:20], city_volume['Sales'][0:20],color="teal")
plt.xticks(city_volume.index[0:20],rotation = 'vertical')
plt.xlabel("City" )
plt.ylabel("Sales")
plt.show()
```



FEATURE ENGINEERING

In [36]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9994 entries, 0 to 9993
Data columns (total 12 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   Ship Mode     9994 non-null   object 
 1   Segment       9994 non-null   object 
 2   City          9994 non-null   object 
 3   State         9994 non-null   object 
 4   Postal Code   9994 non-null   int64  
 5   Region        9994 non-null   object 
 6   Category      9994 non-null   object 
 7   Sub-Category  9994 non-null   object 
 8   Sales         9994 non-null   float64
 9   Quantity      9994 non-null   int64  
 10  Discount      9994 non-null   float64
 11  Profit        9994 non-null   float64
dtypes: float64(3), int64(2), object(7)
memory usage: 937.1+ KB
```

In [37]:
```
data = data.drop(['Postal Code'],axis=1)
```

In [38]:
```
data.columns
```

Out[38]:
```
Index(['Ship Mode', 'Segment', 'City', 'State', 'Region', 'Category',
       'Sub-Category', 'Sales', 'Quantity', 'Discount', 'Profit'],
      dtype='object')
```

In [39]:
```
from sklearn.preprocessing import OrdinalEncoder

encoder = OrdinalEncoder()
data[['Ship Mode', 'Segment', 'City', 'State', 'Region','Category', 'Sub-Category']] = encoder.fit_transform(d
```

In [40]:
```
data.head()
```

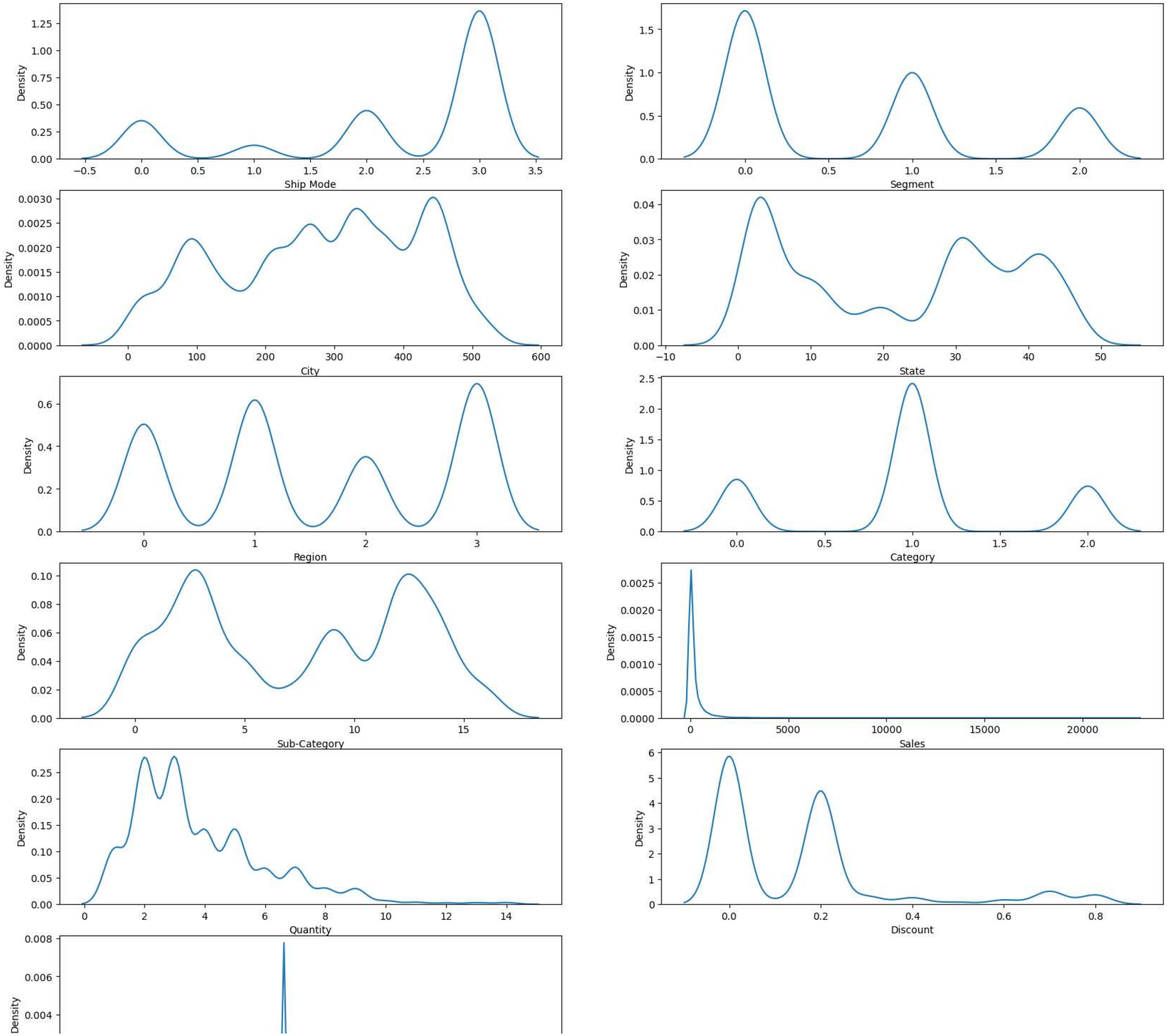
Out[40]:

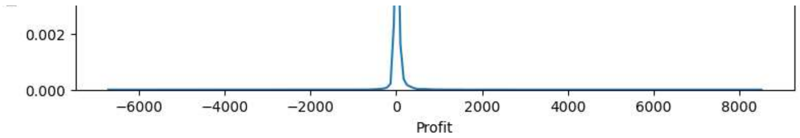
	Ship Mode	Segment	City	State	Region	Category	Sub-Category	Sales	Quantity	Discount	Profit
0	2.0	0.0	194.0	15.0	2.0	0.0	4.0	261.9600	2	0.00	41.9136
1	2.0	0.0	194.0	15.0	2.0	0.0	5.0	731.9400	3	0.00	219.5820
2	2.0	1.0	266.0	3.0	3.0	1.0	10.0	14.6200	2	0.00	6.8714
3	3.0	0.0	153.0	8.0	2.0	0.0	16.0	957.5775	5	0.45	-383.0310
4	3.0	0.0	153.0	8.0	2.0	1.0	14.0	22.3680	2	0.20	2.5164

In [41]:

```
plt.figure(figsize=(20,30))
for i, col in enumerate(data.columns):
    if data[col].dtype != 'object':
        ax = plt.subplot(9, 2, i+1)
        sn.kdeplot(data[col], ax=ax)
        plt.xlabel(col)

plt.show()
```

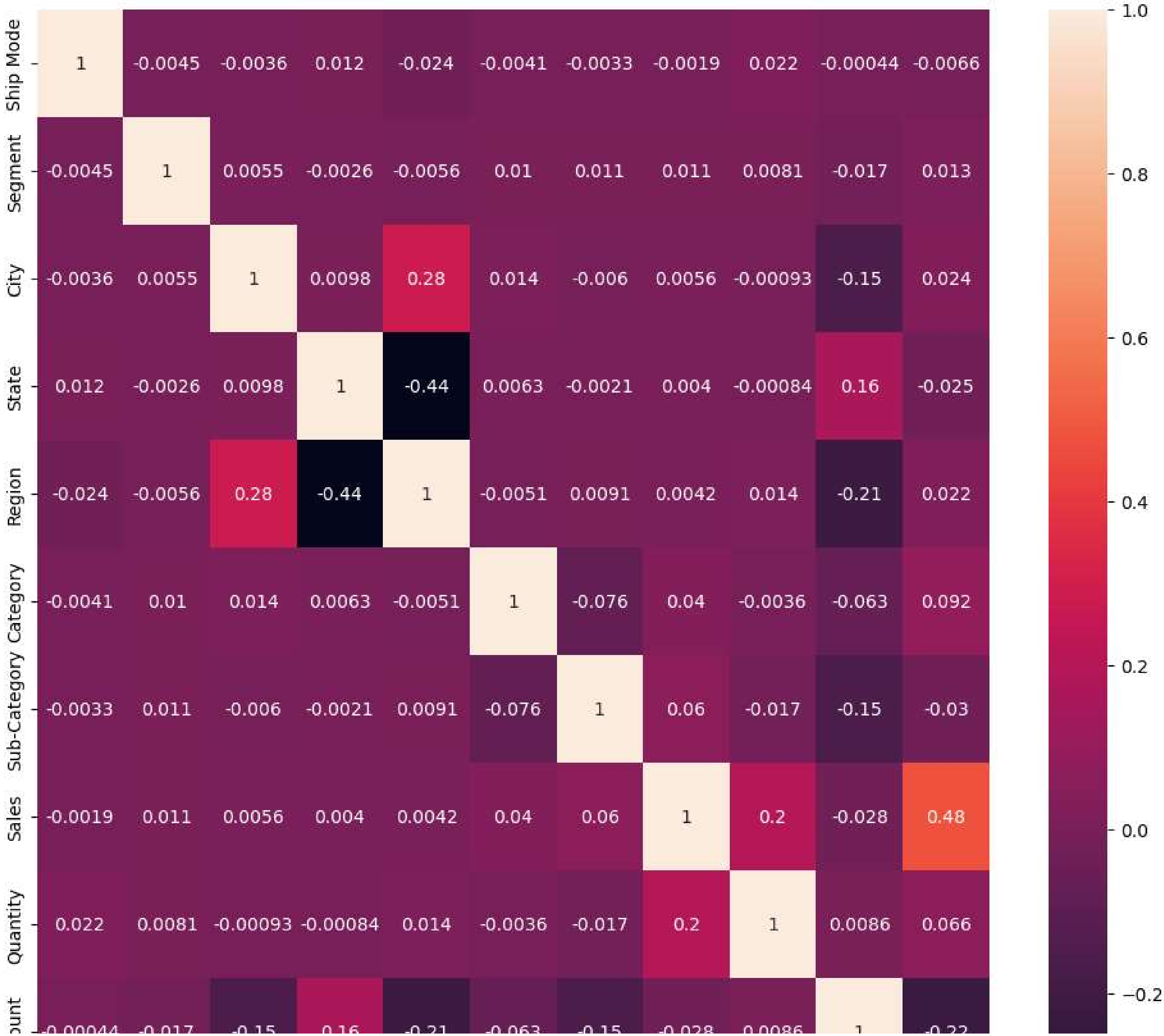

Density
Ship Mode
−0.5 0.0 0.5 1.0 1.5 2.0 2.5 3.0 3.5
0.00 0.25 0.50 0.75 1.00 1.25
Segment
0.0 0.5 1.0 1.5 2.0
City
0 100 200 300 400 500 600
0.0000 0.0005 0.0010 0.0015 0.0020 0.0025 0.0030
State
−10 0 10 20 30 40 50
0.00 0.01 0.02 0.03 0.04
Region
0 1 2 3
0.0 0.2 0.4 0.6
Category
0.0 0.5 1.0 1.5 2.0 2.5
Sub-Category
0 5 10 15
0.00 0.02 0.04 0.06 0.08 0.10
Sales
0 5000 10000 15000 20000
0.0000 0.0005 0.0010 0.0015 0.0020 0.0025
Quantity
0 2 4 6 8 10 12 14
0.00 0.05 0.10 0.15 0.20 0.25
Discount
0.0 0.2 0.4 0.6 0.8
0 1 2 3 4 5 6
0.004 0.006 0.008



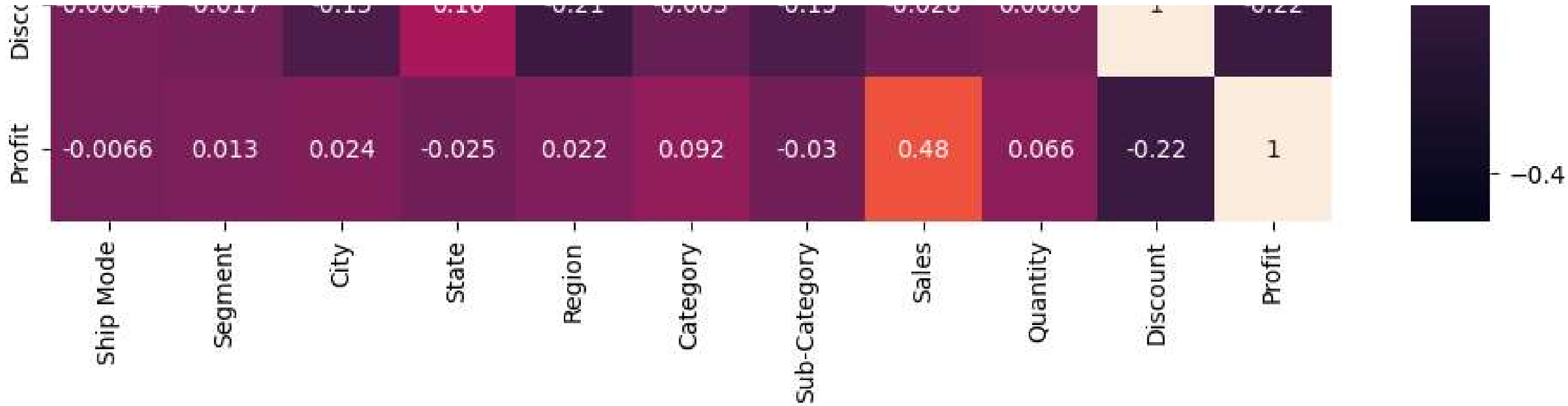
0.002
0.000
−6000
−4000
−2000
0
2000
4000
6000
8000
Profit

In [42]:

```
plt.figure(figsize=(12,12))
sn.heatmap(data.corr(), annot=True)
plt.show()
```



Ship Mode
Segment
City
State
Region
Category
Sub-Category
Sales
Quantity
1.0
0.8
0.6
0.4
0.2
0.0
−0.2



In [43]:
```
X = data.drop(['Profit'],axis=1)
y = data['Profit']
```

In [44]:
```
from sklearn.decomposition import PCA

pca = PCA(n_components=0.95)
X_transformed = pca.fit_transform(X)
```

In [45]:
```
pca.n_components_
```

Out[45]: 1

In [46]:
```
from sklearn.model_selection import train_test_split

X_train , X_test , y_train , y_test = train_test_split(X_transformed , y , test_size=0.20 , random_state=42)
```

Estimation of profit by modelling

In [47]:
```
from sklearn.metrics import mean_squared_error
from sklearn.linear_model import TweedieRegressor

reg = TweedieRegressor()
reg.fit(X_train , y_train)
y_pred = reg.predict(X_test)

rmse = np.sqrt(mean_squared_error(y_test , y_pred))
print(f"Root mean squared error of the model : {rmse} ")
```

```
Root mean squared error of the model : 295.02101189313186
```

In [48]:
```
from sklearn.linear_model import BayesianRidge

reg = BayesianRidge()
reg.fit(X_train , y_train)
y_pred = reg.predict(X_test)

rmse = np.sqrt(mean_squared_error(y_test , y_pred))
print(f"Root mean squared error of the model : {rmse} ")
```

```
Root mean squared error of the model : 294.99641009841633
```

In [49]:
```
from sklearn.linear_model import ElasticNet

reg = ElasticNet()
reg.fit(X_train , y_train)
y_pred = reg.predict(X_test)

rmse = np.sqrt(mean_squared_error(y_test , y_pred))
print(f"Root mean squared error of the model : {rmse} ")
```

```
Root mean squared error of the model : 295.02045026656293
```

In [50]:
```
from sklearn.ensemble import ExtraTreesRegressor

reg = ExtraTreesRegressor()
reg.fit(X_train , y_train)
y_pred = reg.predict(X_test)

rmse = np.sqrt(mean_squared_error(y_test , y_pred))
print(f"Root mean squared error of the model : {rmse} ")
```

```
Root mean squared error of the model : 340.17009758417976
```

In [51]:
```
import xgboost as xgb

reg = xgb.XGBRegressor(n_estimators=100, max_depth=10 , random_state=42)
reg.fit(X_train , y_train)
y_pred = reg.predict(X_test)

rmse = np.sqrt(mean_squared_error(y_test , y_pred))
print(f"Root mean squared error of the model : {rmse} ")
```

```
Root mean squared error of the model : 356.92509363338894
```

In [52]:
```python
from sklearn.ensemble import StackingRegressor

stacking_reg = StackingRegressor(
    estimators = [
        ('Tweedie Regressor ',TweedieRegressor()),
        ('Bayesian Ridge ',BayesianRidge()),
        ('Elastic Net ', ElasticNet())
    ],
    final_estimator = BayesianRidge() , cv = 5
)
stacking_reg.fit(X_train , y_train)
```

Out[52]:
```
StackingRegressor(cv=5,
                  estimators=[('Tweedie Regressor ', TweedieRegressor()),
                              ('Bayesian Ridge ', BayesianRidge()),
                              ('Elastic Net ', ElasticNet())],
                  final_estimator=BayesianRidge())
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [53]:
```python
y_pred = stacking_reg.predict(X_test)
rmse = np.sqrt(mean_squared_error(y_test , y_pred))
print(f"Root mean squared error of the model : {rmse} ")
```

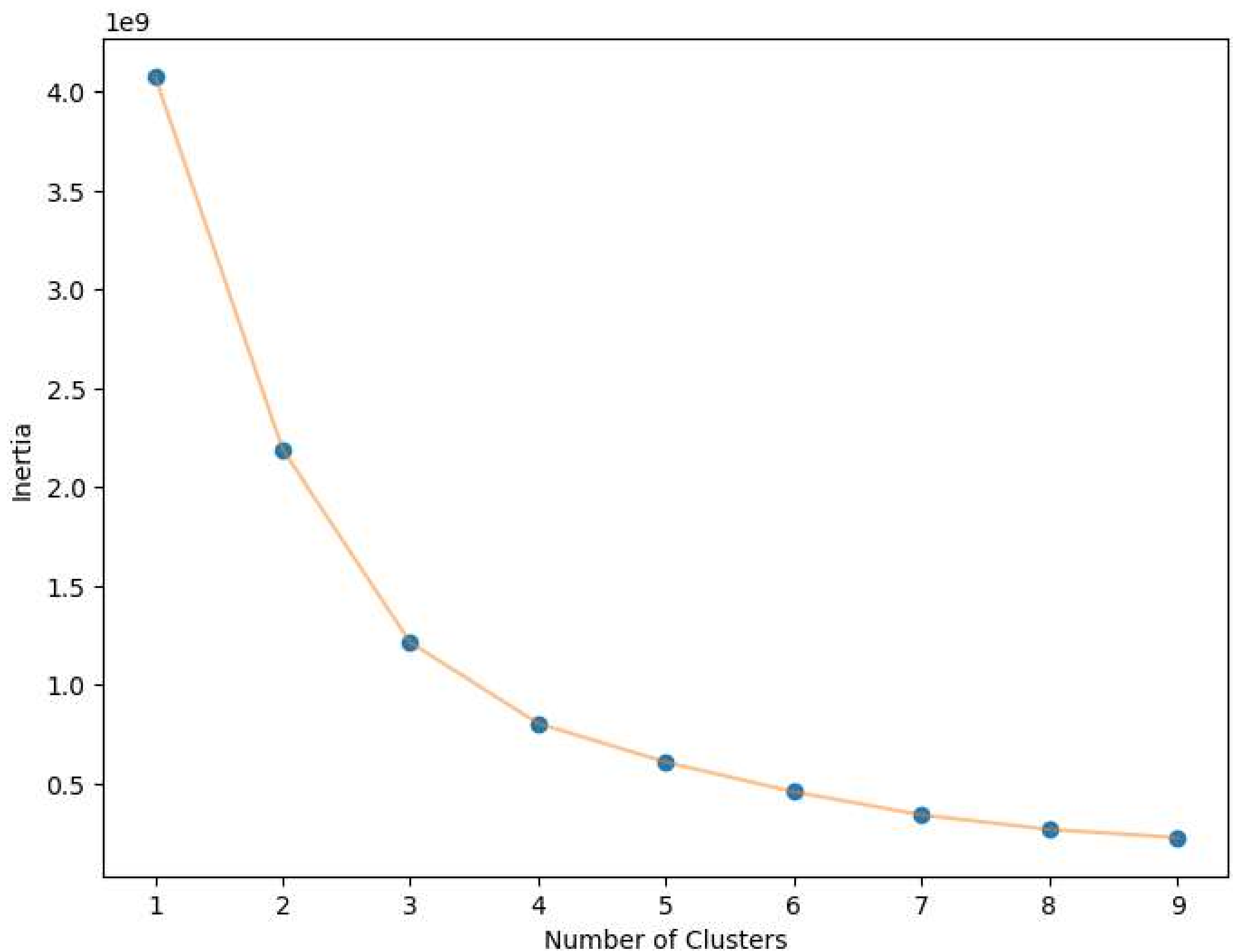
```
Root mean squared error of the model : 294.0254139784906
```

Clustering

In [54]:
```
from sklearn.cluster import KMeans

n_clusters=10
inertia=[]
for i in range(1,n_clusters):
    kmeans= KMeans(n_clusters=i,random_state=42)
    kmeans.fit(X)
    inertia.append(kmeans.inertia_)
```

In [55]:
```
plt.figure(1 , figsize = (8 ,6))
plt.plot(np.arange(1 , n_clusters) , inertia , 'o')
plt.plot(np.arange(1 , n_clusters) , inertia , '-' , alpha = 0.5)
plt.xlabel('Number of Clusters') , plt.ylabel('Inertia')
plt.show()
```



In [56]:
```
kmeans= KMeans(n_clusters=4,random_state=42)
kmeans.fit(X)
```

Out[56]:
```
KMeans(n_clusters=4, random_state=42)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [57]:
```
labels=kmeans.labels_
labels
```

Out[57]:
```
array([3, 0, 3, ..., 3, 3, 3], dtype=int32)
```

In [58]:
```
clusters=pd.concat([data, pd.DataFrame({'CLUSTER':labels})], axis=1)
clusters.head()
```

Out[58]:

	Ship Mode	Segment	City	State	Region	Category	Sub-Category	Sales	Quantity	Discount	Profit	CLUSTER
0	2.0	0.0	194.0	15.0	2.0	0.0	4.0	261.9600	2	0.00	41.9136	3
1	2.0	0.0	194.0	15.0	2.0	0.0	5.0	731.9400	3	0.00	219.5820	0
2	2.0	1.0	266.0	3.0	3.0	1.0	10.0	14.6200	2	0.00	6.8714	3
3	3.0	0.0	153.0	8.0	2.0	0.0	16.0	957.5775	5	0.45	-383.0310	0
4	3.0	0.0	153.0	8.0	2.0	1.0	14.0	22.3680	2	0.20	2.5164	3

In [59]:
```
clusters['CLUSTER'].unique()
```

Out[59]:
```
array([3, 0, 1, 2], dtype=int32)
```

In [60]:
```
clusters['CLUSTER'].value_counts()
```

Out[60]:
```
3    8869
0     998
1     114
2      13
Name: CLUSTER, dtype: int64
```

In [61]:
```
from sklearn.metrics import silhouette_score
print(f"Silhouette Coefficient: {silhouette_score(X, labels):.3f}")
```

```
Silhouette Coefficient: 0.693
```