Project 1

November 10, 2023

[ ]:
```
#conda install psycopg2
```

TOPICS: 1. Predict the future sales volume and price of brands in different locations(states), in order to provide stocking and pricing strategies. 2. Seasonality of the store sales in different state saledate, supply chain management, in different type of product 3. Return and purchase rate of different products 4. Inflation trends through years in stores by different products

[1]:
```
import psycopg2
import pandas as pd

# Connection parameters
host = "pg.analytics.northwestern.edu"
port = "5432"
database = "everything2023"
user = ""
password = ""

# Establish a connection to the database
conn = psycopg2.connect(
    host=host,
    port=port,
    database=database,
    user=user,
    password=password
)
```

[2]:
```
cursor = conn.cursor()
sql_query = "SELECT * FROM group_13.deptinfo;"
cursor.execute(sql_query)
deptinfo = pd.read_sql_query(sql_query, conn)

cursor = conn.cursor()
sql_query2 = "SELECT * FROM group_13.trnsact TABLESAMPLE SYSTEM(10);"
cursor.execute(sql_query2)
trnsact = pd.read_sql_query(sql_query2, conn)

cursor = conn.cursor()
sql_query3 = "SELECT * FROM group_13.skstinfo;"
```

```
cursor.execute(sql_query3)
skstinfo = pd.read_sql_query(sql_query3, conn)
skstinfo.head()

cursor = conn.cursor()
sql_query4 = "SELECT * FROM group_13.strinfo;"
cursor.execute(sql_query4)
strinfo = pd.read_sql_query(sql_query4, conn)

cursor = conn.cursor()
sql_query5 = "SELECT * FROM group_13.skuinfo2;"
cursor.execute(sql_query5)
skuinfo = pd.read_sql_query(sql_query5, conn)

conn.close()
```

[3]:
```
skstinfo
```

[3]:
```
              SKU  STORE    COST  RETAIL  unknown
0               3    102  123.36  440.00        0
1               3    103  123.36  440.00        0
2               3    104  123.36  440.00        0
3               3    202  123.36  440.00        0
4               3    203  123.36  440.00        0
…             …     …      …      …       …
39230141  9999997   2007   15.00   19.50        0
39230142  9999997   2707   15.00    9.75        0
39230143  9999997   3307   15.00   19.50        0
39230144  9999997   7507   15.00   19.50        0
39230145  9999997   7907   15.00   19.50        0

[39230146 rows x 5 columns]
```

[4]:
```
skuinfo.head()
```

[4]:
```
  SKU  DEPT CLASSID           UPC        STYLE         COLOR        SIZE  \
0   0     1       2             3            4             5           6
1   3  6505     113  400000003000  00     F55KT2  WHISPERWHITE  P8EA
2   4  8101     002  400000004000  22     615CZ4  SPEARMI       S
3   5  7307     003  400000005000  7LBS   245-01  34 SILVER     KING
4   8  3404     00B  400000008000  622    F05H84  MORNING MI    2T

   PACKSIZE   VENDOR      BRAND
0         7        8          9
1         1  5119207  TURNBURY
2         1  3311144  C A SPOR
3         1  5510554  BEAU IDE
```

```
4          1  2912827  HARTSTRI
```

[5]:
```
deptinfo.head()
```

[5]:
```
   DEPT  DEPTDESC  Unknow
0   800  CLINIQUE       0
1   801  LESLIE         0
2  1100  GARY F         0
3  1107  JACQUES        0
4  1202  CABERN         0
```

[6]:
```
trnsact
```

[6]:
```
              SKU  STORE  REGISTER  TRANNUM        SEQ    SALEDATE STYPE  \
0             387   9806       823    77700  191100910  2005-01-14     P
1             391    203       360     6100  109800320  2004-09-03     P
2             391    503       250      600          0  2004-08-16     P
3             397    303       910     6100  544100323  2004-08-21     P
4             398   6902       140     3000  220804694  2005-08-27     P
…               …     …        …        …          …         …   …
12097396  9999974   7002       420     3300          0  2005-07-01     P
12097397  9999974   7102       130     3300          0  2005-05-19     P
12097398  9999974   7202       210     1400  479607345  2005-08-03     P
12097399  9999974   7202       210     2200  479607345  2005-08-11     R
12097400  9999974   7302       480     1100  157308035  2005-08-18     P

          QUANTITY  ORGPRICE  SPRICE     AMT    INTERID  MIC  Unknow
0                1      79.0   79.00   79.00  360700007  696       0
1                1      56.0   56.00   56.00  687600007  680       0
2                1      56.0   14.00   14.00  222900004  680       0
3                1      32.5    8.13    8.13  557900008  205       0
4                1     100.0  100.00  100.00  102000018  661       0
…                …       …      …       …      …   …       …
12097396         1      82.0   59.99   59.99  567200116  290       0
12097397         1      82.0   82.00   82.00   70200069  290       0
12097398         1      82.0   41.00   41.00  853800085  290       0
12097399         1      82.0   41.00   41.00  509100090  290       0
12097400         1      82.0   41.00   41.00  196800081  290       0

[12097401 rows x 14 columns]
```

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

[7]:
```
   store                 city state    zip  x
0      2  ST. PETERSBURG          FL  33710  0
1      3  ST. LOUIS               MO  63126  0
2      4  LITTLE ROCK             AR  72201  0
```

3	7	FORT WORTH	TX	76137	0
4	9	TEMPE	AZ	85281	0

0.1 Clean Data

Drop the last column:

[8]:
```python
# Drop unknow column (the last column):
deptinfo.drop(columns=["Unknow"],inplace=True)
deptinfo.head()
```

[8]:

	DEPT	DEPTDESC
0	800	CLINIQUE
1	801	LESLIE
2	1100	GARY F
3	1107	JACQUES
4	1202	CABERN

[9]:
```python
# Drop the last unknown column:
trnsact.drop(columns=["Unknow"],inplace=True)
trnsact
```

[9]:

	SKU	STORE	REGISTER	TRANNUM	SEQ	SALEDATE	STYPE	\
0	387	9806	823	77700	191100910	2005-01-14	P	
1	391	203	360	6100	109800320	2004-09-03	P	
2	391	503	250	600	0	2004-08-16	P	
3	397	303	910	6100	544100323	2004-08-21	P	
4	398	6902	140	3000	220804694	2005-08-27	P	
…	…	…	…	…	…	…	…	
12097396	9999974	7002	420	3300	0	2005-07-01	P	
12097397	9999974	7102	130	3300	0	2005-05-19	P	
12097398	9999974	7202	210	1400	479607345	2005-08-03	P	
12097399	9999974	7202	210	2200	479607345	2005-08-11	R	
12097400	9999974	7302	480	1100	157308035	2005-08-18	P	

	QUANTITY	ORGPRICE	SPRICE	AMT	INTERID	MIC
0	1	79.0	79.00	79.00	360700007	696
1	1	56.0	56.00	56.00	687600007	680
2	1	56.0	14.00	14.00	222900004	680
3	1	32.5	8.13	8.13	557900008	205
4	1	100.0	100.00	100.00	102000018	661
…	…	…	…	…	…	…
12097396	1	82.0	59.99	59.99	567200116	290
12097397	1	82.0	82.00	82.00	70200069	290
12097398	1	82.0	41.00	41.00	853800085	290
12097399	1	82.0	41.00	41.00	509100090	290
12097400	1	82.0	41.00	41.00	196800081	290

```
[12097401 rows x 13 columns]
```

[10]:
```python
# Drop the last unknown column:
skstinfo.drop(columns=["unknown"],inplace=True)
skstinfo
```

[10]:
```
               SKU  STORE    COST  RETAIL
0                3    102  123.36  440.00
1                3    103  123.36  440.00
2                3    104  123.36  440.00
3                3    202  123.36  440.00
4                3    203  123.36  440.00
…              …      …       …       …
39230141   9999997   2007   15.00   19.50
39230142   9999997   2707   15.00    9.75
39230143   9999997   3307   15.00   19.50
39230144   9999997   7507   15.00   19.50
39230145   9999997   7907   15.00   19.50

[39230146 rows x 4 columns]
```

[11]:
```python
# Drop the last unknown column:
strinfo.drop(columns=['x'],inplace=True)
strinfo
```

[11]:
```
     store                  city state   zip
0        2  ST. PETERSBURG          FL  33710
1        3  ST. LOUIS               MO  63126
2        4  LITTLE ROCK             AR  72201
3        7  FORT WORTH              TX  76137
4        9  TEMPE                   AZ  85281
..     …                       …    …     …
448   9808  GILBERT                 AZ  85233
449   9812  METAIRIE                LA  70006
450   9900  LITTLE ROCK             AR  72201
451   9906  LITTLE ROCK             AR  72201
452   9909  CHEYENNE                WY  82009

[453 rows x 4 columns]
```

[12]:
```python
strinfo.columns = ['STORE','CITY','STATE','ZIP']
strinfo
```

[12]:
```
     STORE                  CITY STATE   ZIP
0        2  ST. PETERSBURG          FL  33710
1        3  ST. LOUIS               MO  63126
2        4  LITTLE ROCK             AR  72201
```

```
3       7  FORT WORTH           TX  76137
4       9  TEMPE                AZ  85281
..    …                …   …    …
448  9808  GILBERT              AZ  85233
449  9812  METAIRIE             LA  70006
450  9900  LITTLE ROCK          AR  72201
451  9906  LITTLE ROCK          AR  72201
452  9909  CHEYENNE             WY  82009

[453 rows x 4 columns]
```

Check Missing Value:

[13]:
```
strinfo.isna().sum()
```

[13]:
```
STORE    0
CITY     0
STATE    0
ZIP      0
dtype: int64
```

[14]:
```
deptinfo.isna().sum()
```

[14]:
```
DEPT        0
DEPTDESC    0
dtype: int64
```

[15]:
```
trnsact.isna().sum()
```

[15]:
```
SKU         0
STORE       0
REGISTER    0
TRANNUM     0
SEQ         0
SALEDATE    0
STYPE       0
QUANTITY    0
ORGPRICE    0
SPRICE      0
AMT         0
INTERID     0
MIC         0
dtype: int64
```

[16]:
```
skstinfo.isna().sum()
```

[16]:
```
SKU      0
STORE    0
```

```
COST       0
RETAIL     0
dtype: int64
```

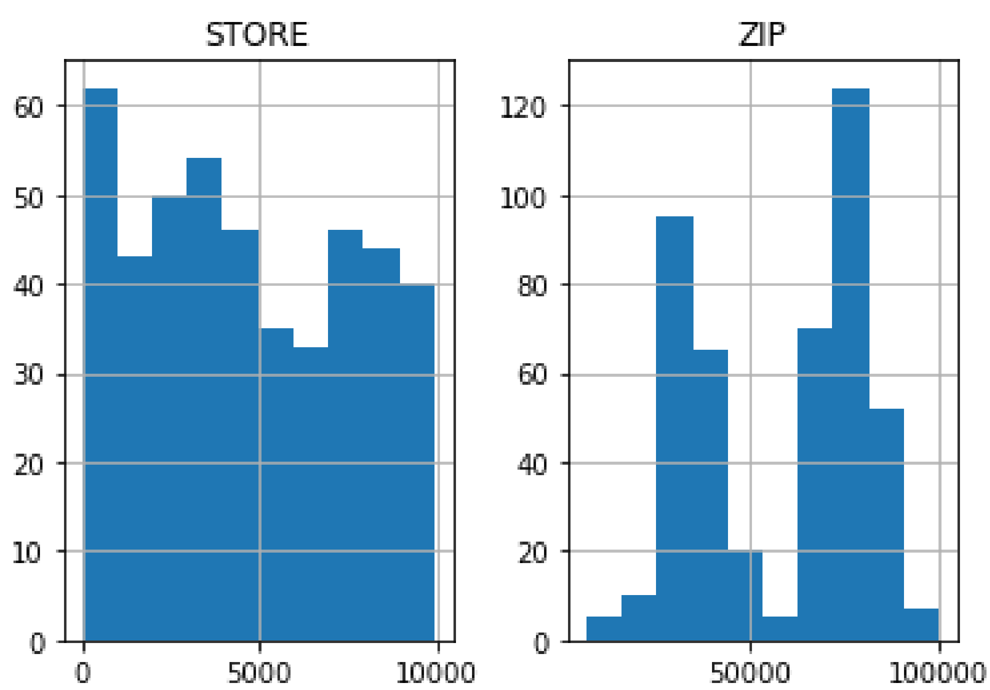
[17]:
```
skuinfo.isna().sum()
```

[17]:
```
SKU         0
DEPT        0
CLASSID     0
UPC         0
STYLE       0
COLOR       0
SIZE        0
PACKSIZE    0
VENDOR      0
BRAND       0
dtype: int64
```

0.1.1 strinfo:

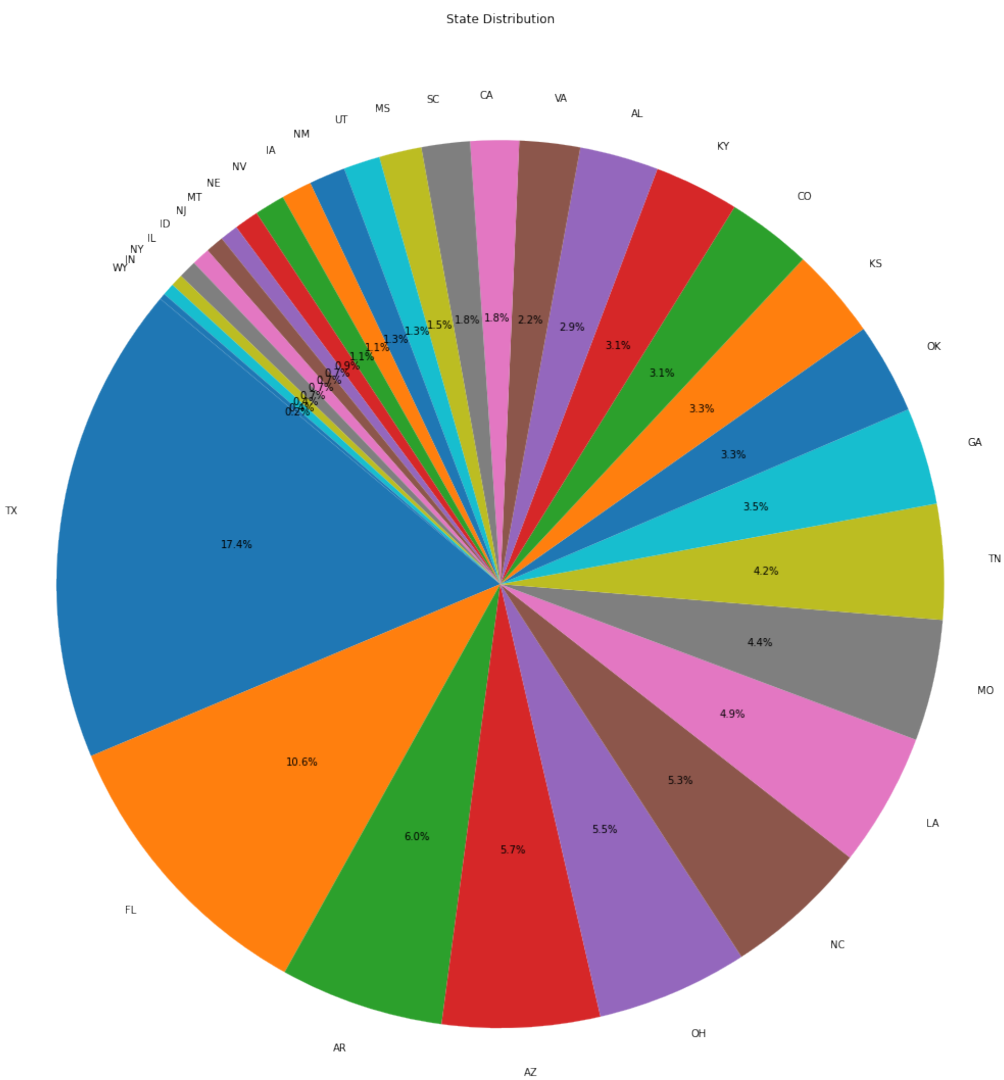
[18]:
```
strinfo.hist()
```

[18]:
```
array([[<AxesSubplot:title={'center':'STORE'}>,
        <AxesSubplot:title={'center':'ZIP'}>]], dtype=object)
```



[19]:
```python
import matplotlib.pyplot as plt

state_counts = strinfo['STATE'].value_counts()
plt.figure(figsize=(20, 20))  # Optional: Set the figure size
plt.pie(state_counts, labels=state_counts.index, autopct='%1.1f%%',␣
↪startangle=140)
plt.title('State Distribution')
```

[19]:
```
Text(0.5, 1.0, 'State Distribution')
```



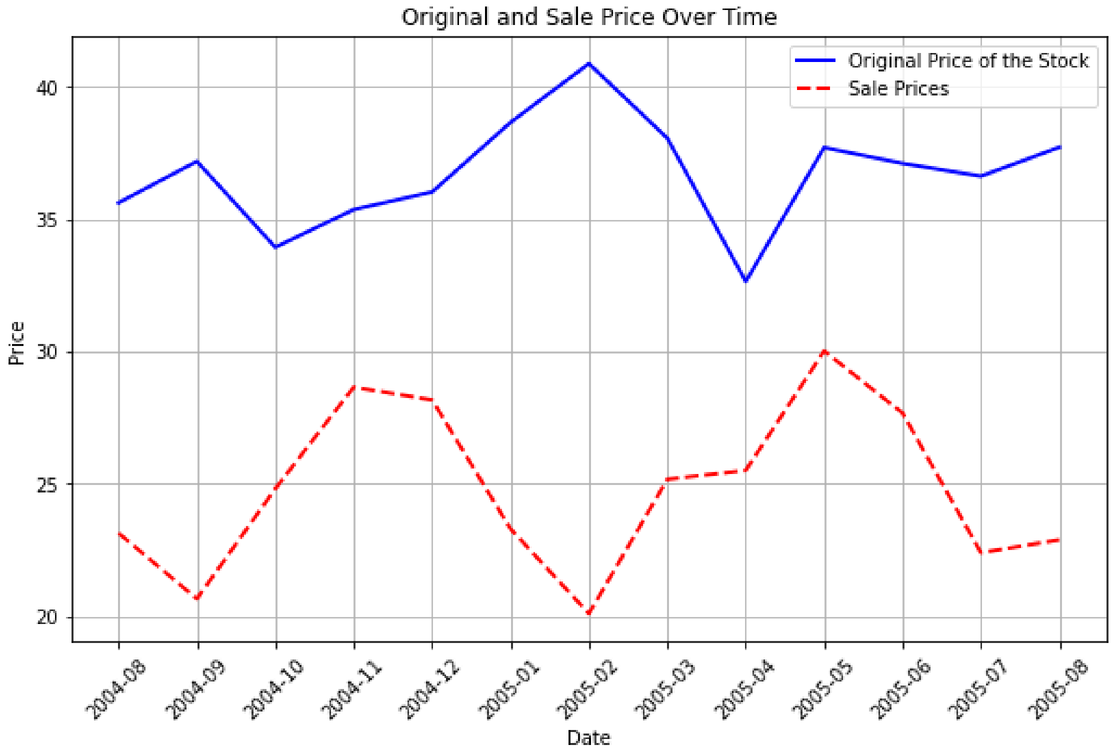
0.1.2 trnsact:

[20]:
```
trnsact.dtypes
```

[20]:
```
SKU            int64
STORE          int64
REGISTER       int64
TRANNUM        int64
SEQ            int64
SALEDATE      object
STYPE         object
QUANTITY       int64
ORGPRICE     float64
SPRICE       float64
AMT          float64
INTERID        int64
MIC            int64
dtype: object
```

[21]:
```
# Assuming 'SALEDATE' is in a datetime format
trnsact['SALEDATE'] = pd.to_datetime(trnsact['SALEDATE'])

# Extract year and month from 'SALEDATE'
trnsact['Year'] = trnsact['SALEDATE'].dt.year
trnsact['Month'] = trnsact['SALEDATE'].dt.month

# Group by year and month and calculate the mean
trnsact_group_price = trnsact.groupby(['Year', 'Month']).mean()

plt.figure(figsize=(10, 6))  # Optional: Set the figure size

# Assuming 'Year' and 'Month' are now separate columns
date_labels = [f"{year}-{month:02d}" for year, month in zip(trnsact_group_price.
 ↪index.get_level_values('Year'), trnsact_group_price.index.
 ↪get_level_values('Month'))]

plt.plot(date_labels, trnsact_group_price['ORGPRICE'], label='Original Price of␣
 ↪the Stock', color='blue', linestyle='-', linewidth=2)
plt.plot(date_labels, trnsact_group_price['SPRICE'], label='Sale Prices',␣
 ↪color='red', linestyle='--', linewidth=2)

# Add labels and a legend
plt.xlabel('Date')
plt.ylabel('Price')
plt.title('Original and Sale Price Over Time')
plt.legend()
```

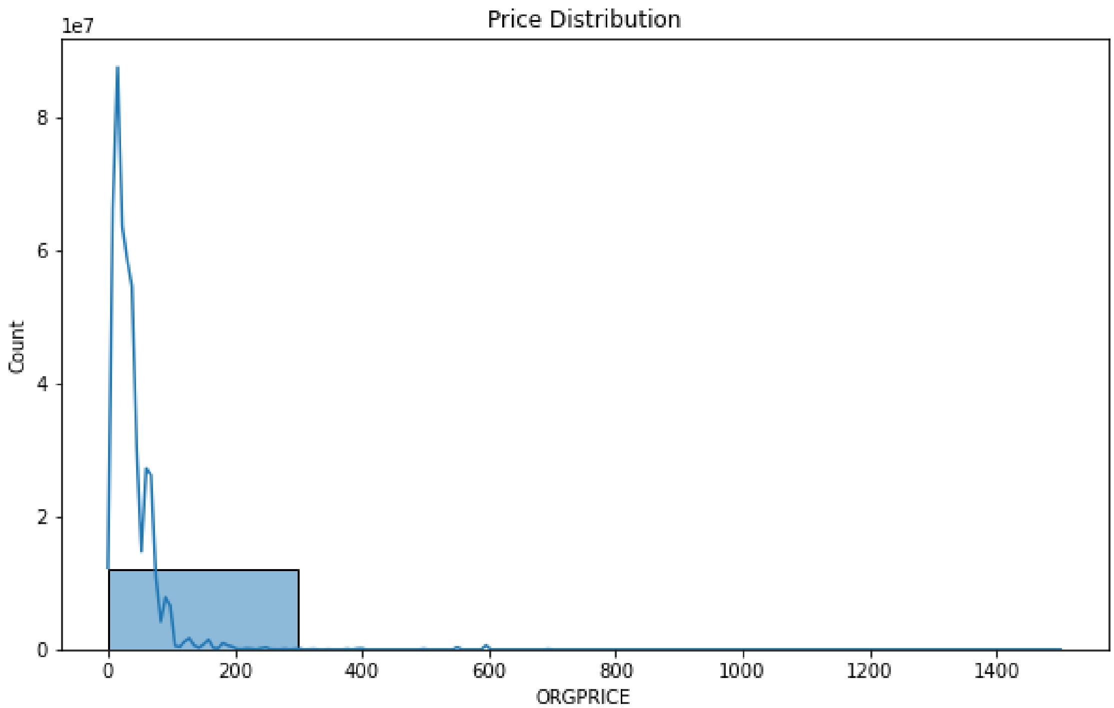
```
# Display the line chart
plt.grid(True)  # Optional: Display grid lines
plt.xticks(rotation=45)  # Optional: Rotate x-axis labels for better readability
plt.show()
```

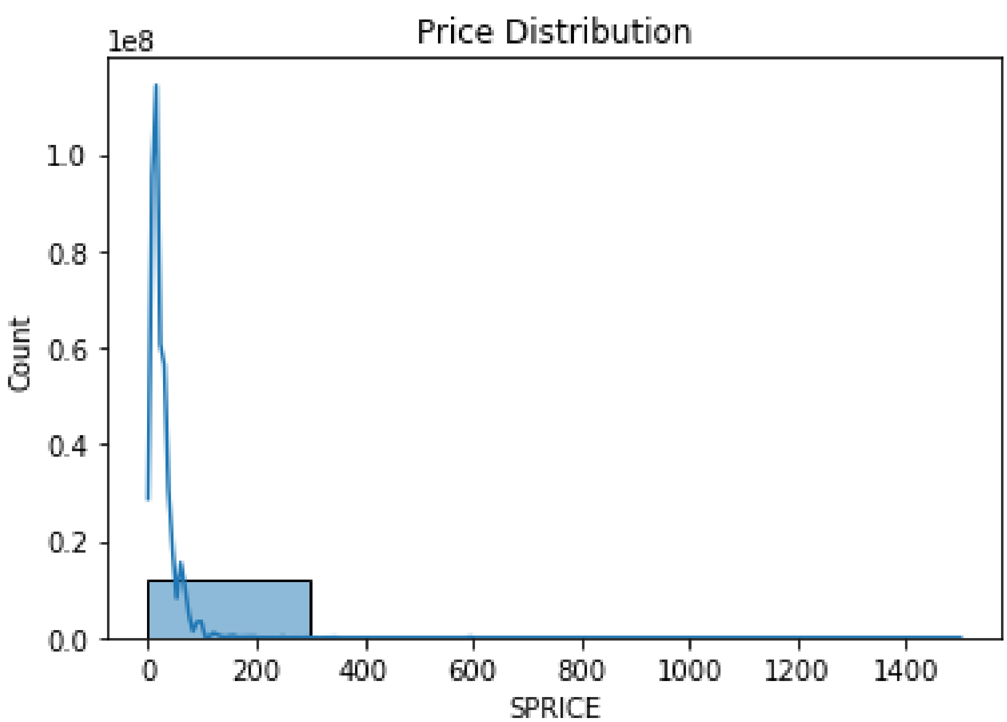


[22]:
```
trnsact.columns
```

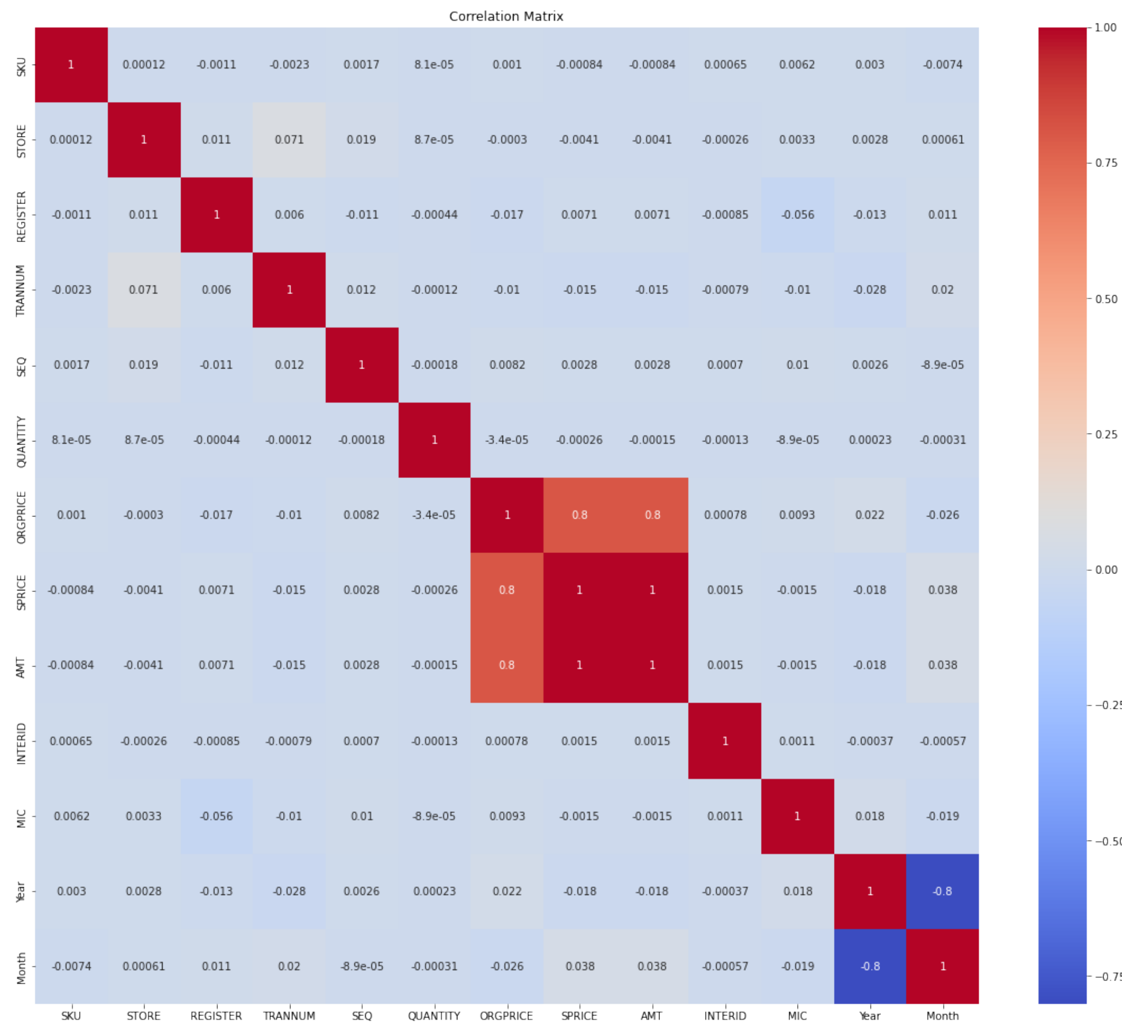
[22]:
```
Index(['SKU', 'STORE', 'REGISTER', 'TRANNUM', 'SEQ', 'SALEDATE', 'STYPE',
       'QUANTITY', 'ORGPRICE', 'SPRICE', 'AMT', 'INTERID', 'MIC', 'Year',
       'Month'],
      dtype='object')
```

[23]:
```
import seaborn as sns
# Data Distribution and Visualization
plt.figure(figsize=(10, 6))
sns.histplot(trnsact['ORGPRICE'], bins=5, kde=True)
plt.title('Price Distribution')
plt.show()
sns.histplot(trnsact['SPRICE'], bins=5, kde=True)
plt.title('Price Distribution')
plt.show()
```


Price Distribution
1e7
Count
ORGPRICE
0
2
4
6
8
0
200
400
600
800
1000
1200
1400


Price Distribution
1e8
Count
SPRICE
0.0
0.2
0.4
0.6
0.8
1.0
0
200
400
600
800
1000
1200
1400

```
[24]: # Correlation Analysis
correlation_matrix = trnsact.corr()
plt.figure(figsize=(20, 17))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()
```




```
[ ]:
```

0.1.3 Merge Datasets Based on Topic 1:

```
[25]: skuinfo['SKU'] = skuinfo['SKU'].astype(int)
skuinfo['DEPT'] = skuinfo['DEPT'].astype(int)
skuinfo['UPC'] = skuinfo['UPC'].astype(int)
skuinfo['PACKSIZE'] = skuinfo['PACKSIZE'].astype(int)
```

```python
skuinfo['VENDOR'] = skuinfo['VENDOR'].astype(int)

skuinfo.dtypes
```

[25]:
```
SKU          int64
DEPT         int64
CLASSID     object
UPC          int64
STYLE       object
COLOR       object
SIZE        object
PACKSIZE     int64
VENDOR       int64
BRAND       object
dtype: object
```

[26]:
```python
merge_table = pd.merge(trnsact, skuinfo, on='SKU', how='inner')
merge_table = pd.merge(merge_table, skstinfo, on=['SKU', 'STORE'], how='inner')
merge_table
```

[26]:
```
             SKU  STORE  REGISTER  TRANNUM        SEQ   SALEDATE STYPE  \
0            387   9806       823    77700  191100910 2005-01-14     P
1            391    203       360     6100  109800320 2004-09-03     P
2            398   6902       140     3000  220804694 2005-08-27     P
3            418   1502       290     1400  631706034 2004-10-06     R
4            418   1502       740     3200          0 2005-02-17     P
…            …     …         …        …         …        …   …
6853729  9999974   7002       420     3300          0 2005-07-01     P
6853730  9999974   7102       130     3300          0 2005-05-19     P
6853731  9999974   7202       210     1400  479607345 2005-08-03     P
6853732  9999974   7202       210     2200  479607345 2005-08-11     R
6853733  9999974   7302       480     1100  157308035 2005-08-18     P

         QUANTITY  ORGPRICE  SPRICE  …  CLASSID          UPC          STYLE  \
0               1      79.0   79.00  …      913  400000387000          74017
1               1      56.0   56.00  …      002  400000391000   30    EJMU49
2               1     100.0  100.00  …      354  400000398000         939053
3               1      39.0    9.75  …      224  400000418000         306L44
4               1      39.0    5.99  …      224  400000418000         306L44
…             …       …      …   …      …          …
6853729         1      82.0   59.99  …      726  400009974999         G50171
6853730         1      82.0   82.00  …      726  400009974999         G50171
6853731         1      82.0   41.00  …      726  400009974999         G50171
6853732         1      82.0   41.00  …      726  400009974999         G50171
6853733         1      82.0   41.00  …      726  400009974999         G50171

                COLOR         SIZE  PACKSIZE   VENDOR       BRAND   COST  RETAIL
```

```
0        BROWN        110M                1  5016699  TIMBERLA   38.00   79.00
1        N RDSE/ONX   M                   1  3313116  EMMA JAM   22.14   56.00
2        ROYAL        16                  1  6913116  K STUDIO   46.75  100.00
3        NAVY FABRI   085M                1    10903  BROWN SH   14.00    5.99
4        NAVY FABRI   085M                1    10903  BROWN SH   14.00    5.99
…            …         …       …     …         …     …     …
6853729  NAVY MULTI   10                  1  9212766  GABAR IN   18.00   41.00
6853730  NAVY MULTI   10                  1  9212766  GABAR IN   18.00   41.00
6853731  NAVY MULTI   10                  1  9212766  GABAR IN   18.00   20.50
6853732  NAVY MULTI   10                  1  9212766  GABAR IN   18.00   20.50
6853733  NAVY MULTI   10                  1  9212766  GABAR IN   18.00   41.00

[6853734 rows x 26 columns]
```

[27]:
```python
merge_table = pd.merge(merge_table, deptinfo, on = 'DEPT', how='inner')
merge_table = pd.merge(merge_table, strinfo, on = 'STORE', how='inner')
merge_table
```

[27]:
```
             SKU  STORE  REGISTER  TRANNUM        SEQ   SALEDATE STYPE  \
0            387   9806       823    77700  191100910 2005-01-14     P
1         317373   9806       673     8800          0 2005-08-01     P
2         317373   9806       893     7100  462300308 2005-06-20     P
3         513268   9806        23    95200  504708135 2005-01-28     P
4         513268   9806       413    67900          0 2005-02-22     P
…            …    …        …       …        …          …   …
6853729  5689840   1404       160     1100          0 2004-09-18     P
6853730  5689840   1404       160     1200  646500209 2005-03-28     P
6853731  5689840   1404       160     1300          0 2004-12-17     P
6853732  5689840   1404       160     1400          0 2004-10-09     P
6853733  5689840   1404       160     1500  726308853 2004-10-01     P

         QUANTITY  ORGPRICE  SPRICE  …        SIZE  PACKSIZE   VENDOR  \
0               1      79.0    79.0  …  110M              1  5016699
1               1      99.0    89.0  …  110M              1  7510902
2               1      99.0    89.0  …  110M              1  7510902
3               1      49.0    49.0  …  115W              1    86288
4               1      49.0    49.0  …  115W              1    86288
…             …        …       …   …          …        …       …
6853729         1      47.5    47.5  …  4.2 OZ.           3  6011254
6853730         1      47.5    47.5  …  4.2 OZ.           3  6011254
6853731         1      47.5    47.5  …  4.2 OZ.           3  6011254
6853732         1      47.5    47.5  …  4.2 OZ.           3  6011254
6853733         1      47.5    47.5  …  4.2 OZ.           3  6011254

             BRAND  COST  RETAIL  DEPTDESC                    CITY STATE    ZIP
0        TIMBERLA   38.0   79.00  SPERRY    MABELVALE                  AR  72103
1        H.H. BRO   42.5   89.00  SPERRY    MABELVALE                  AR  72103
```

```
2        H.H. BRO   42.5   89.00  SPERRY    MABELVALE             AR  72103
3        SPERRY T   28.0   39.99  SPERRY    MABELVALE             AR  72103
4        SPERRY T   28.0   39.99  SPERRY    MABELVALE             AR  72103
…             …  …     …       …                 …   …      …
6853729  LIZ CLAI   28.5   47.50  BORA      VICKSBURG             MS  39180
6853730  LIZ CLAI   28.5   47.50  BORA      VICKSBURG             MS  39180
6853731  LIZ CLAI   28.5   47.50  BORA      VICKSBURG             MS  39180
6853732  LIZ CLAI   28.5   47.50  BORA      VICKSBURG             MS  39180
6853733  LIZ CLAI   28.5   47.50  BORA      VICKSBURG             MS  39180

[6853734 rows x 30 columns]
```

[28]:
```python
# Export DataFrame to a CSV file (which can be saved with a .css extension)
merge_table.to_csv('merge_table.csv', index=False)
```

[29]:
```python
import pandas as pd
merge_table = pd.read_csv("merge_table.csv")
```

Analysis of Highest Profit and Discount per Brand within Each State and Store:

[65]:
```python
# Calculate profit (SPRICE - RETAIL) for each group of 'STATE', 'STORE', and␣
↪'BRAND'
merge_table['PROFIT'] = merge_table['SPRICE'] - merge_table['COST']
merge_table['discount'] = merge_table['ORGPRICE'] - merge_table['SPRICE']

# Group the data by 'STATE', 'STORE', and 'BRAND', and calculate the total␣
↪profit for each group
grouped_state_store_brand = merge_table.groupby(['STATE', 'STORE',␣
↪'BRAND'])[['SPRICE', 'PROFIT','QUANTITY','discount']].sum().reset_index()

# Find the group with the highest profit within each 'BRAND' and each 'STATE'␣
↪and 'STORE' combination
highest_profit_per_brand_state_store = grouped_state_store_brand.
↪groupby(['BRAND', 'STATE', 'STORE']).apply(
    lambda x: x.loc[x['PROFIT'].idxmax()]
).reset_index(drop=True)

highest_profit_per_brand_state_store = highest_profit_per_brand_state_store.
↪sort_values(by=['STATE', 'PROFIT'], ascending=[True, False])
highest_profit_per_brand_state_store
```

[65]:

	STATE	STORE	BRAND	SPRICE	PROFIT	QUANTITY	discount
17636	AL	4102	CLINIQUE	82088.40	31811.40	4939	8.60
17642	AL	7102	CLINIQUE	48180.90	18488.10	3039	29.60
55140	AL	4102	LANCOME	43621.00	16916.20	1509	7.50
17635	AL	3902	CLINIQUE	43358.50	16582.60	2646	-246.50
17644	AL	7302	CLINIQUE	42223.50	16346.92	2561	1.50

```
...      ...   ...     ...       ...       ...       ...       ...
18275    WY    9909    CM SHAPE  1287.79   -104.21    80       2465.21
93438    WY    9909    SUSAN BR   265.65   -143.52    14        825.35
2030     WY    9909    AGB       1468.59   -258.41   104       2728.41
91141    WY    9909    SPODE      284.81   -342.19    19       1026.19
76704    WY    9909    POLO FAS  7379.84   -362.41   220       8306.16

[107402 rows x 7 columns]
```

[66]:

```python
# Summary Statistics
summary_stats = highest_profit_per_brand_state_store[['SPRICE', 'PROFIT',␣
↪'QUANTITY', 'discount']].describe()
summary_stats
```

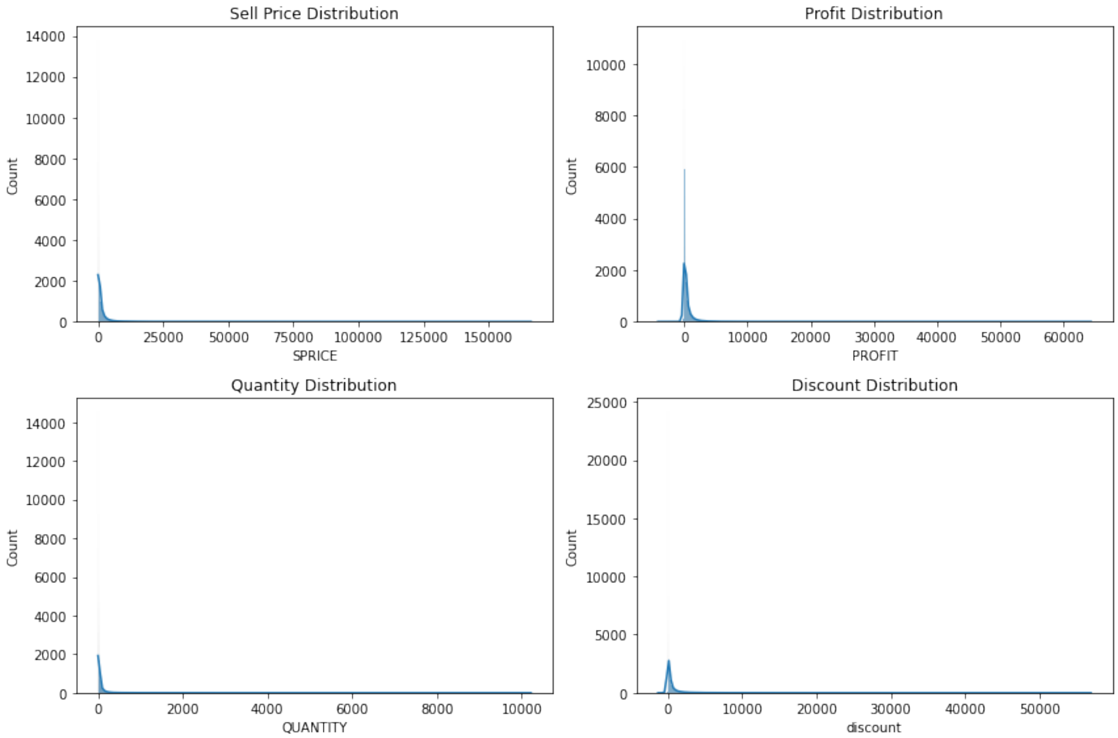
[66]:

	SPRICE	PROFIT	QUANTITY	discount
count	107402.000000	107402.000000	107402.000000	107402.000000
mean	1584.504464	621.572042	63.813840	607.182941
std	5107.580673	1973.796900	242.788685	1786.902817
min	0.000000	-4167.740000	1.000000	-1338.990000
25%	100.642500	31.430000	5.000000	17.000000
50%	351.880000	129.875000	16.000000	116.210000
75%	1193.497500	485.195000	46.000000	456.922500
max	166285.500000	64319.100000	10222.000000	56927.800000

[73]:

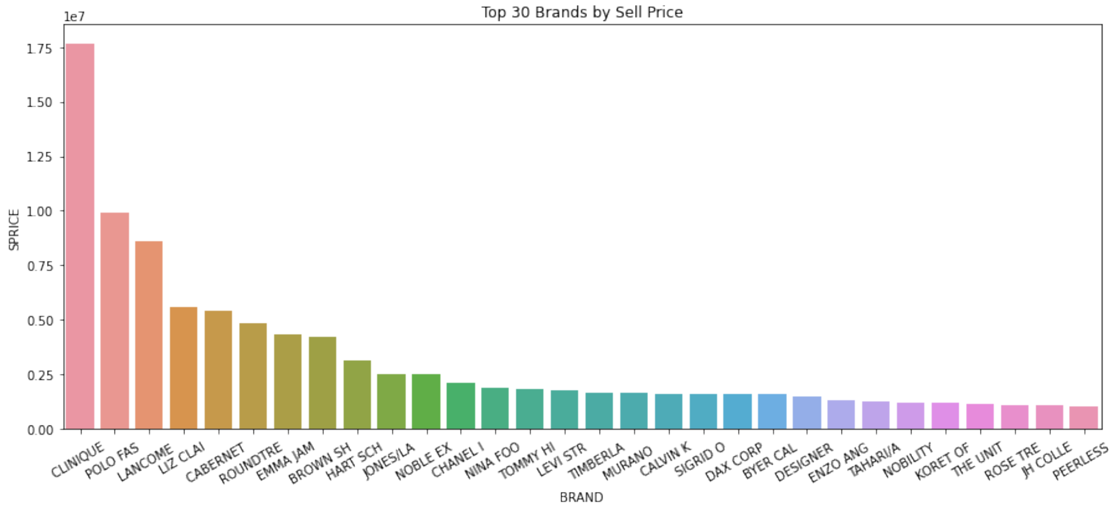
```python
import matplotlib.pyplot as plt
import seaborn as sns

# Distribution Plots
plt.figure(figsize=(12, 8))  # Adjusted the figure size for better layout

plt.subplot(221)  # Subplot in the first row, first column
sns.histplot(highest_profit_per_brand_state_store['SPRICE'], kde=True)
plt.title('Sell Price Distribution')

plt.subplot(222)  # Subplot in the first row, second column
sns.histplot(highest_profit_per_brand_state_store['PROFIT'], kde=True)
plt.title('Profit Distribution')

plt.subplot(223)  # Subplot in the second row, first column
sns.histplot(highest_profit_per_brand_state_store['QUANTITY'], kde=True)
plt.title('Quantity Distribution')

plt.subplot(224)  # Subplot in the second row, second column
sns.histplot(highest_profit_per_brand_state_store['discount'], kde=True)
plt.title('Discount Distribution')

plt.tight_layout()
```

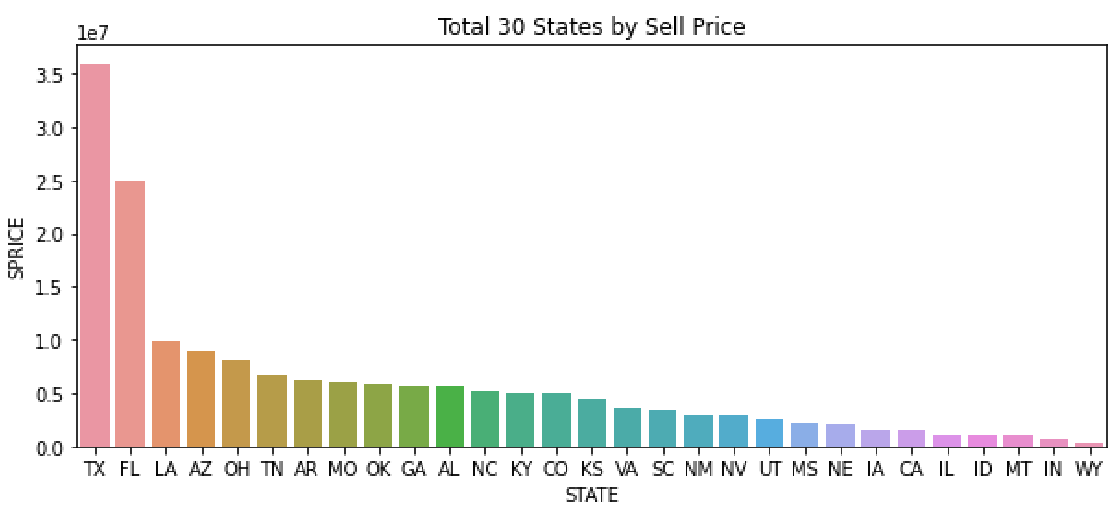
```
plt.show()
```



[74]:
```
# Bar Plot: Top 30 Brands by Sell Price
brand_discount = highest_profit_per_brand_state_store.
↪groupby('BRAND')['SPRICE'].sum().reset_index()
brand_discount = brand_discount.nlargest(30, 'SPRICE')  # Select the top 30␣
↪brands by discount

plt.figure(figsize=(15, 6))
sns.barplot(x='BRAND', y='SPRICE', data=brand_discount)
plt.title('Top 30 Brands by Sell Price')
plt.xticks(rotation=30)
plt.show()

# Bar Plot: Total Discount by State
state_discount = highest_profit_per_brand_state_store.
↪groupby('STATE')['SPRICE'].sum().reset_index()
state_discount = state_discount.nlargest(30, 'SPRICE')  # Select the top 30␣
↪brands by discount
plt.figure(figsize=(10, 4))
sns.barplot(x='STATE', y='SPRICE', data=state_discount)
plt.title('Total 30 States by Sell Price')
plt.show()
```

```
# Bar Plot: Top 30 Stores by Total Discount
store_discount = highest_profit_per_brand_state_store.
 ↪groupby('STORE')['SPRICE'].sum().reset_index()
store_discount = store_discount.nlargest(30, 'SPRICE')  # Select the top 30␣
 ↪stores by discount
plt.figure(figsize=(12, 6))
sns.barplot(x='STORE', y='SPRICE', data=store_discount,␣
 ↪order=store_discount['STORE'])
plt.title('Top 30 Stores by Sell Price')
plt.xticks(rotation=30)
plt.show()
```

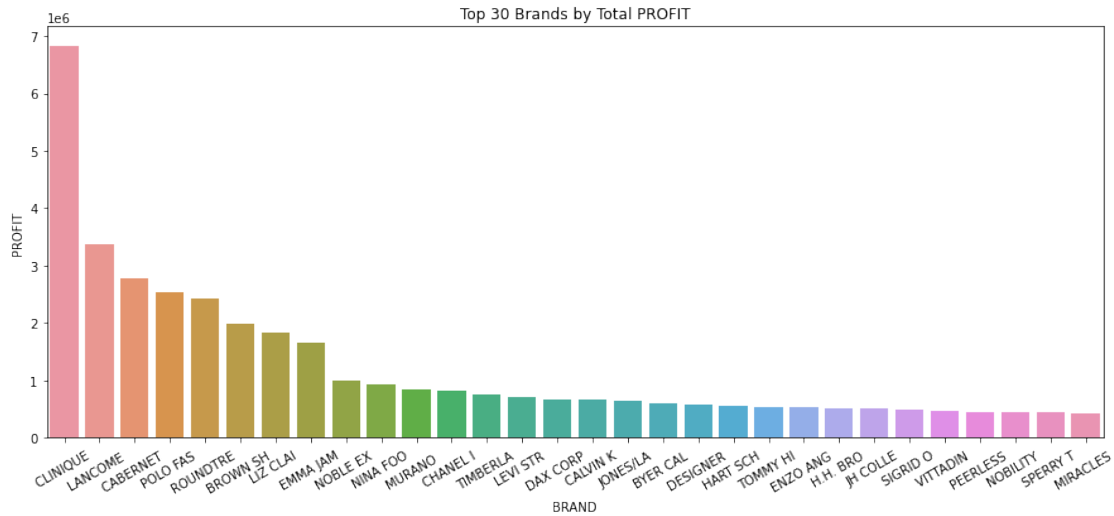


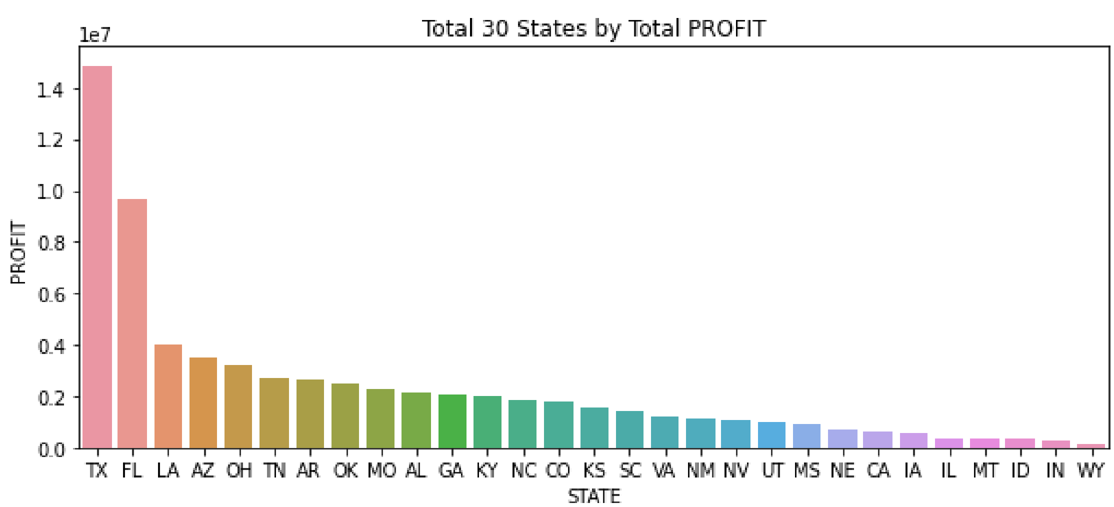


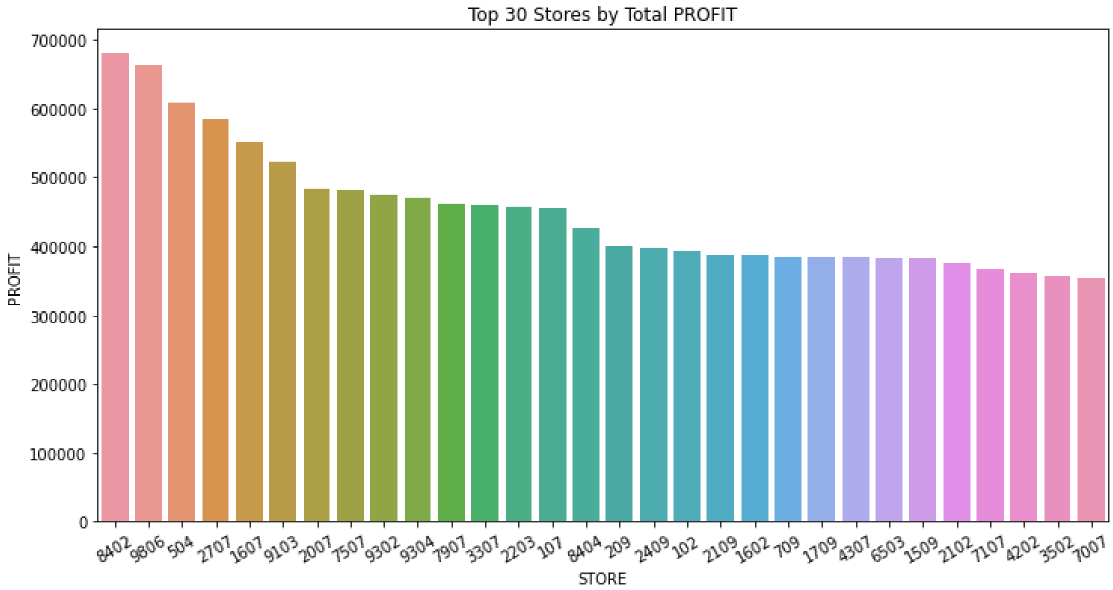
[75]:

```
# Bar Plot: Top 30 Brands by Total Profit
brand_discount = highest_profit_per_brand_state_store.
 ↪groupby('BRAND')['PROFIT'].sum().reset_index()
brand_discount = brand_discount.nlargest(30, 'PROFIT')  # Select the top 30␣
 ↪brands by discount

plt.figure(figsize=(15, 6))
sns.barplot(x='BRAND', y='PROFIT', data=brand_discount)
plt.title('Top 30 Brands by Total PROFIT')
plt.xticks(rotation=30)
plt.show()

# Bar Plot: Total Discount by State
state_discount = highest_profit_per_brand_state_store.
 ↪groupby('STATE')['PROFIT'].sum().reset_index()
state_discount = state_discount.nlargest(30, 'PROFIT')  # Select the top 30␣
 ↪brands by discount
plt.figure(figsize=(10, 4))
sns.barplot(x='STATE', y='PROFIT', data=state_discount)
plt.title('Total 30 States by Total PROFIT')
plt.show()

# Bar Plot: Top 30 Stores by Total Discount
store_discount = highest_profit_per_brand_state_store.
 ↪groupby('STORE')['PROFIT'].sum().reset_index()
```

```python
store_discount = store_discount.nlargest(30, 'PROFIT')  # Select the top 30␣
↪stores by discount
plt.figure(figsize=(12, 6))
sns.barplot(x='STORE', y='PROFIT', data=store_discount,␣
↪order=store_discount['STORE'])
plt.title('Top 30 Stores by Total PROFIT')
plt.xticks(rotation=30)
plt.show()
```



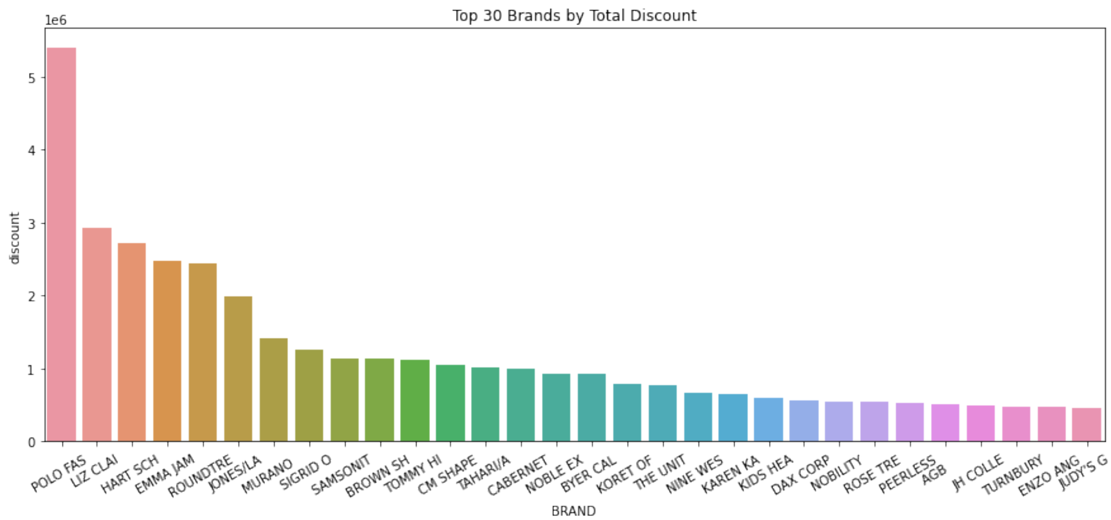


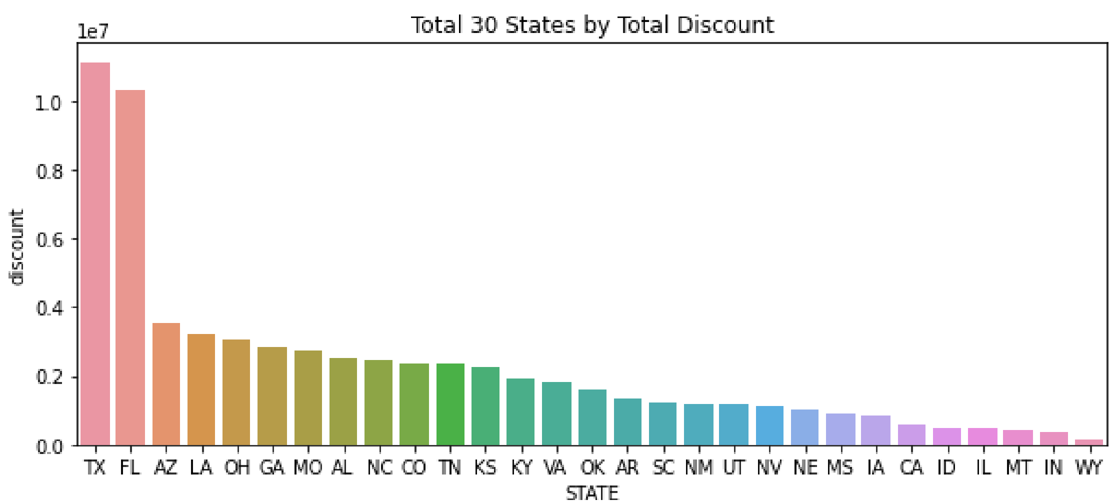


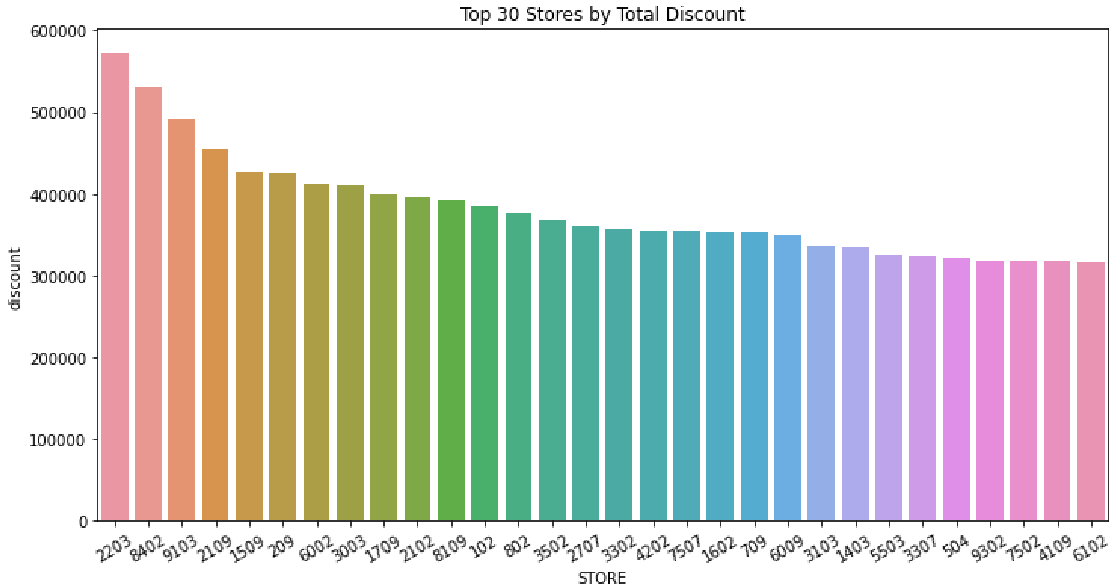
[76]:

```
# Bar Plot: Top 30 Brands by Total Discount
brand_discount = highest_profit_per_brand_state_store.
 ↪groupby('BRAND')['discount'].sum().reset_index()
brand_discount = brand_discount.nlargest(30, 'discount')  # Select the top 30␣
 ↪brands by discount

plt.figure(figsize=(15, 6))
sns.barplot(x='BRAND', y='discount', data=brand_discount)
plt.title('Top 30 Brands by Total Discount')
plt.xticks(rotation=30)
plt.show()

# Bar Plot: Total Discount by State
state_discount = highest_profit_per_brand_state_store.
 ↪groupby('STATE')['discount'].sum().reset_index()
state_discount = state_discount.nlargest(30, 'discount')  # Select the top 30␣
 ↪brands by discount
plt.figure(figsize=(10, 4))
sns.barplot(x='STATE', y='discount', data=state_discount)
plt.title('Total 30 States by Total Discount')
plt.show()

# Bar Plot: Top 30 Stores by Total Discount
store_discount = highest_profit_per_brand_state_store.
 ↪groupby('STORE')['discount'].sum().reset_index()
store_discount = store_discount.nlargest(30, 'discount')  # Select the top 30␣
 ↪stores by discount
```

```
plt.figure(figsize=(12, 6))
sns.barplot(x='STORE', y='discount', data=store_discount,␣
↪order=store_discount['STORE'])
plt.title('Top 30 Stores by Total Discount')
plt.xticks(rotation=30)
plt.show()
```

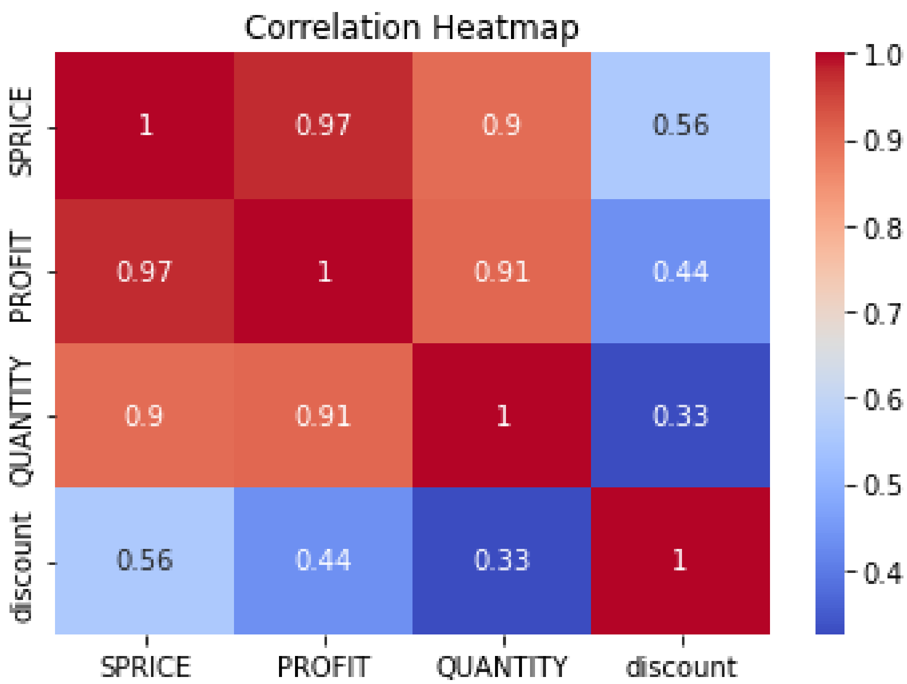






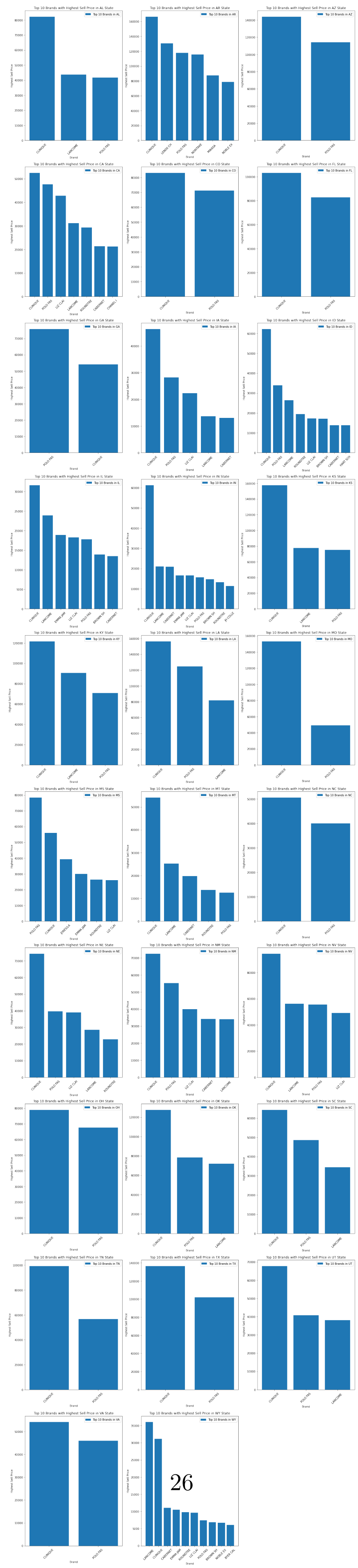
[77]:

```
# Heatmap
corr_matrix = highest_profit_per_brand_state_store[['SPRICE', 'PROFIT', 
 ↪'QUANTITY', 'discount']].corr()
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm')
plt.title('Correlation Heatmap')
plt.show()
```



[78]:
```
# Top brands with highest sell price in each state

# Get a list of unique states
states = highest_profit_per_brand_state_store['STATE'].unique()

# Define the number of subplots per row
subplots_per_row = 3

# Calculate the number of rows needed
num_rows = int(np.ceil(len(states) / subplots_per_row))

# Create a figure and a grid of subplots
fig, axes = plt.subplots(num_rows, subplots_per_row, figsize=(18, 8 * num_rows))

# Flatten the axes array
axes = axes.flatten()

for i, state in enumerate(states):
    state_data =␣
↪highest_profit_per_brand_state_store[highest_profit_per_brand_state_store['STATE']␣
↪== state]

    # Select the top 10 brands with the highest profit within the state
    top_brands = state_data.nlargest(10, 'SPRICE')

    # Plot the highest profit for each of the top 10 brands within the state
    ax = axes[i]
    ax.bar(top_brands['BRAND'], top_brands['SPRICE'], label=f'Top {10} Brands␣
↪in {state}')

    # Set labels and title
    ax.set_xlabel('Brand')
    ax.set_ylabel('Highest Sell Price')
    ax.set_title(f'Top {10} Brands with Highest Sell Price in {state} State')

    # Rotate x-axis labels for better readability
    ax.tick_params(axis='x', rotation=45)

    # Add a legend
    ax.legend()

# Hide empty subplots
for i in range(len(states), num_rows * subplots_per_row):
    fig.delaxes(axes[i])
```

```python
# Adjust layout and spacing
plt.tight_layout()
plt.show()
```

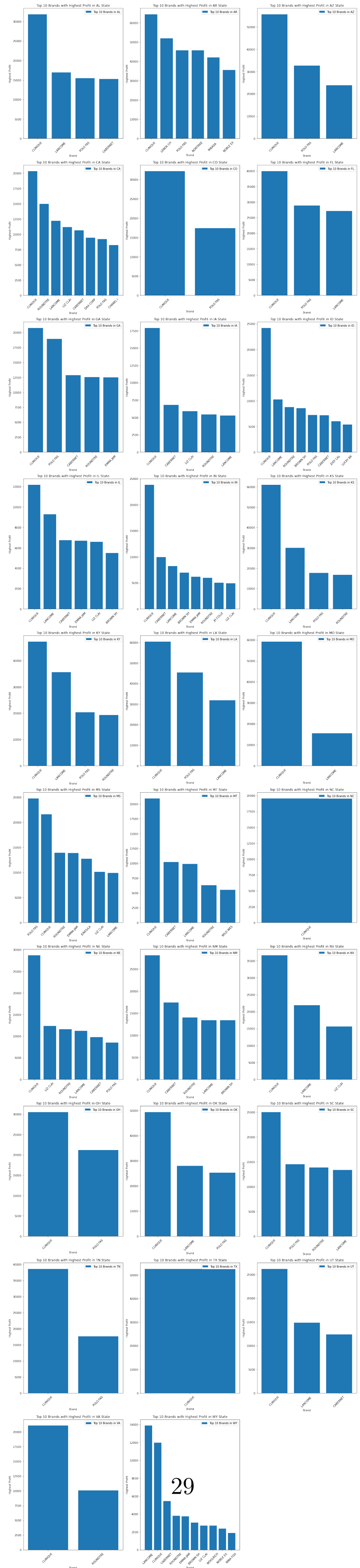


[79]:
```
from collections import Counter

# Create a dictionary to store the top 10 brands with the highest Sell Price␣
↪for each state
state_top_brands = {}

for state in states:
    state_data =␣
↪highest_profit_per_brand_state_store[highest_profit_per_brand_state_store['STATE']␣
↪== state]
    top_brands = list(state_data.nlargest(10, 'SPRICE')['BRAND'])
    state_top_brands[state] = top_brands

# Find the common brands among all states
common_brands = set(state_top_brands[states[0]])  # Initialize with the brands␣
↪from the first state

# Iterate through the states and find the common brands
for state in states:
    common_brands = common_brands.intersection(state_top_brands[state])

# Count the occurrences of each brand in the common brands set
brand_counts = Counter(brand for state in states for brand in␣
↪state_top_brands[state])

# Find the most common brands
most_common_brands = [brand for brand, _ in brand_counts.most_common(5)]

# Print the first five most common brands
print("Most Common Brands That Have High Sell Price:")
for rank, brand in enumerate(most_common_brands, start=1):
    print(f"{rank} - {brand}")
```

```
Most Common Brands That Have High Sell Price:
1 - CLINIQUE
2 - POLO FAS
3 - LANCOME
4 - LIZ CLAI
5 - CABERNET
```

[39]:
```
import numpy as np
# Top brands with highest PROFIT in each state

# Get a list of unique states
states = highest_profit_per_brand_state_store['STATE'].unique()
```

```python
# Define the number of subplots per row
subplots_per_row = 3

# Calculate the number of rows needed
num_rows = int(np.ceil(len(states) / subplots_per_row))

# Create a figure and a grid of subplots
fig, axes = plt.subplots(num_rows, subplots_per_row, figsize=(18, 8 * num_rows))

# Flatten the axes array
axes = axes.flatten()

for i, state in enumerate(states):
    state_data =␣
 ↪highest_profit_per_brand_state_store[highest_profit_per_brand_state_store['STATE']␣
 ↪== state]

    # Select the top 10 brands with the highest profit within the state
    top_brands = state_data.nlargest(10, 'PROFIT')

    # Plot the highest profit for each of the top 10 brands within the state
    ax = axes[i]
    ax.bar(top_brands['BRAND'], top_brands['PROFIT'], label=f'Top {10} Brands␣
 ↪in {state}')

    # Set labels and title
    ax.set_xlabel('Brand')
    ax.set_ylabel('Highest Profit')
    ax.set_title(f'Top {10} Brands with Highest Profit in {state} State')

    # Rotate x-axis labels for better readability
    ax.tick_params(axis='x', rotation=45)

    # Add a legend
    ax.legend()

# Hide empty subplots
for i in range(len(states), num_rows * subplots_per_row):
    fig.delaxes(axes[i])

# Adjust layout and spacing
plt.tight_layout()
plt.show()
```


Top 10 Brands with Highest Profit in AL State
Top 10 Brands with Highest Profit in AR State
Top 10 Brands with Highest Profit in AZ State
Top 10 Brands with Highest Profit in CA State
Top 10 Brands with Highest Profit in CO State
Top 10 Brands with Highest Profit in FL State
Top 10 Brands with Highest Profit in GA State
Top 10 Brands with Highest Profit in IA State
Top 10 Brands with Highest Profit in ID State
Top 10 Brands with Highest Profit in IL State
Top 10 Brands with Highest Profit in IN State
Top 10 Brands with Highest Profit in KS State
Top 10 Brands with Highest Profit in KY State
Top 10 Brands with Highest Profit in LA State
Top 10 Brands with Highest Profit in MO State
Top 10 Brands with Highest Profit in MS State
Top 10 Brands with Highest Profit in MT State
Top 10 Brands with Highest Profit in NC State
Top 10 Brands with Highest Profit in NE State
Top 10 Brands with Highest Profit in NM State
Top 10 Brands with Highest Profit in NV State
Top 10 Brands with Highest Profit in OH State
Top 10 Brands with Highest Profit in OK State
Top 10 Brands with Highest Profit in SC State
Top 10 Brands with Highest Profit in TN State
Top 10 Brands with Highest Profit in TX State
Top 10 Brands with Highest Profit in UT State
Top 10 Brands with Highest Profit in VA State
Top 10 Brands with Highest Profit in WY State

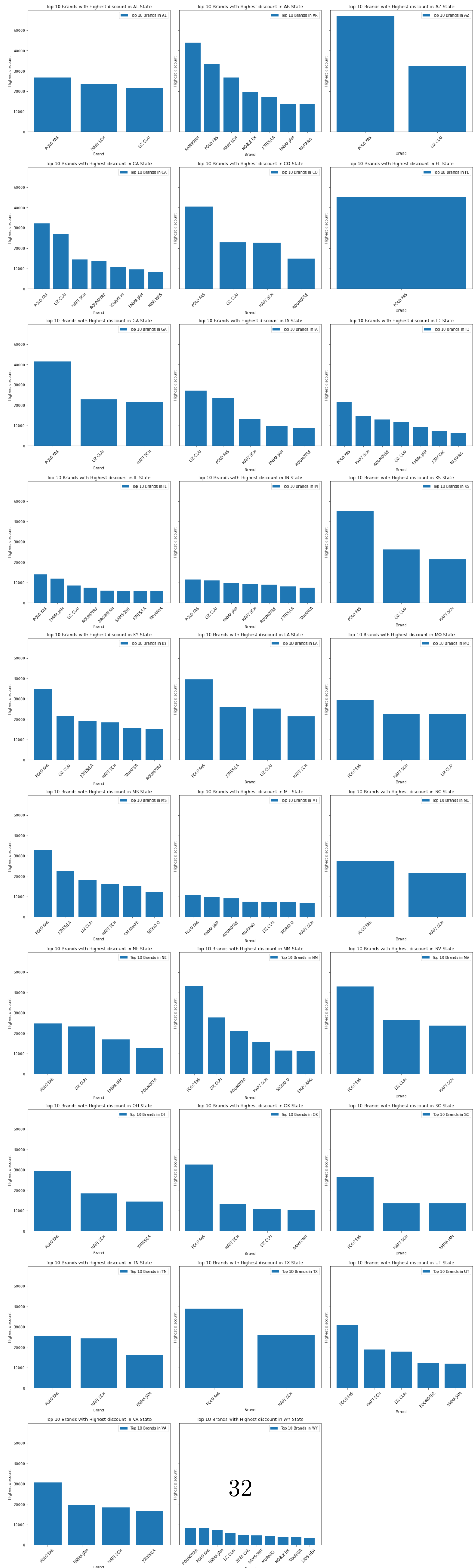
[40]:
```python
from collections import Counter

# Create a dictionary to store the top 10 brands with the highest profit for␣
↪each state
state_top_brands = {}

for state in states:
    state_data =␣
↪highest_profit_per_brand_state_store[highest_profit_per_brand_state_store['STATE']␣
↪== state]
    top_brands = list(state_data.nlargest(10, 'PROFIT')['BRAND'])
    state_top_brands[state] = top_brands

# Find the common brands among all states
common_brands = set(state_top_brands[states[0]])  # Initialize with the brands␣
↪from the first state

# Iterate through the states and find the common brands
for state in states:
    common_brands = common_brands.intersection(state_top_brands[state])

# Count the occurrences of each brand in the common brands set
brand_counts = Counter(brand for state in states for brand in␣
↪state_top_brands[state])

# Find the most common brands
most_common_brands = [brand for brand, _ in brand_counts.most_common(5)]

# Print the first five most common brands
print("Most Common Brands That Have High Profit:")
for rank, brand in enumerate(most_common_brands, start=1):
    print(f"{rank} - {brand}")
```

```
Most Common Brands That Have High Profit:
1 - CLINIQUE
2 - LANCOME
3 - POLO FAS
4 - CABERNET
5 - ROUNDTRE
```

In AL, CLINIQUE, LANCOME, POLO FAS, and CABERNET are the brands that have top profit. In AR, CLINIQUE, LENOX CH, POLO FAS, NORITAKE, MIKASA, and NOBEL EX have high profits compare to other brands. In AZ, LANCOME, POLO FAS, and CLINIQUE have high profits. … The first five common brands that have high profit are CLINIQUE, LANCOME, POLO FAS, CABERNET, ROUNDTRE.

[41]:

```python
# Top brands with highest discount in each state

# Define the number of subplots per row
subplots_per_row = 3

# Calculate the number of rows needed
num_rows = int(np.ceil(len(states) / subplots_per_row))

# Create a figure and a grid of subplots
fig, axes = plt.subplots(num_rows, subplots_per_row, figsize=(18, 6 *␣
↪num_rows), sharey=True)

for i, state in enumerate(states):
    state_data =␣
↪highest_profit_per_brand_state_store[highest_profit_per_brand_state_store['STATE']␣
↪== state]

    # Select the top 10 brands with the highest discount within the state
    top_brands = state_data.nlargest(10, 'discount')

    # Calculate the row and column index for the subplot
    row_index, col_index = divmod(i, subplots_per_row)

    # Plot the highest discount for each of the top 10 brands within the state
    ax = axes[row_index, col_index]
    ax.bar(top_brands['BRAND'], top_brands['discount'], label=f'Top {10} Brands␣
↪in {state}')

    # Set labels and title
    ax.set_xlabel('Brand')
    ax.set_ylabel('Highest discount')
    ax.set_title(f'Top {10} Brands with Highest discount in {state} State')

    # Rotate x-axis labels for better readability
    ax.tick_params(axis='x', rotation=45)

    # Add a legend
    ax.legend()

# Hide empty subplots
for i in range(len(states), num_rows * subplots_per_row):
    fig.delaxes(axes.flatten()[i])

# Adjust layout and spacing
plt.tight_layout()
plt.show()
```

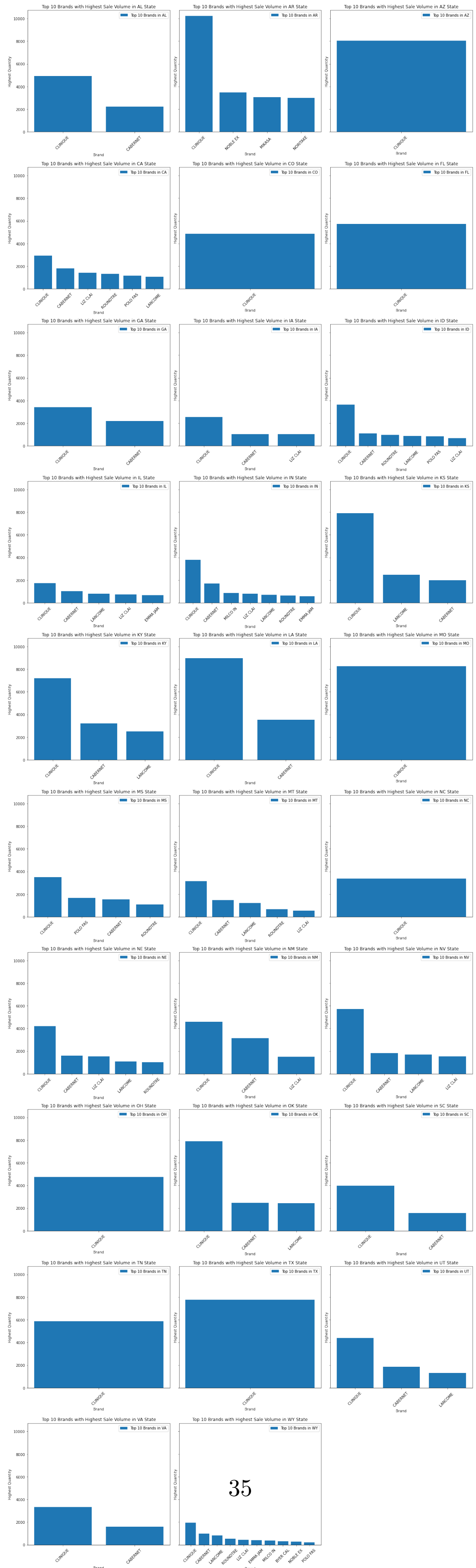

Top 10 Brands with Highest discount in AL State
Top 10 Brands with Highest discount in AR State
Top 10 Brands with Highest discount in AZ State
Top 10 Brands with Highest discount in CA State
Top 10 Brands with Highest discount in CO State
Top 10 Brands with Highest discount in FL State
Top 10 Brands with Highest discount in GA State
Top 10 Brands with Highest discount in IA State
Top 10 Brands with Highest discount in ID State
Top 10 Brands with Highest discount in IL State
Top 10 Brands with Highest discount in IN State
Top 10 Brands with Highest discount in KS State
Top 10 Brands with Highest discount in KY State
Top 10 Brands with Highest discount in LA State
Top 10 Brands with Highest discount in MO State
Top 10 Brands with Highest discount in MS State
Top 10 Brands with Highest discount in MT State
Top 10 Brands with Highest discount in NC State
Top 10 Brands with Highest discount in NE State
Top 10 Brands with Highest discount in NM State
Top 10 Brands with Highest discount in NV State
Top 10 Brands with Highest discount in OH State
Top 10 Brands with Highest discount in OK State
Top 10 Brands with Highest discount in SC State
Top 10 Brands with Highest discount in TN State
Top 10 Brands with Highest discount in TX State
Top 10 Brands with Highest discount in UT State
Top 10 Brands with Highest discount in VA State
Top 10 Brands with Highest discount in WY State

```
[42]: # Create a dictionary to store the top 10 brands with the highest discount for␣
 ↪each state
state_top_brands = {}

for state in states:
    state_data =␣
 ↪highest_profit_per_brand_state_store[highest_profit_per_brand_state_store['STATE']␣
 ↪== state]
    top_brands = list(state_data.nlargest(10, 'discount')['BRAND'])
    state_top_brands[state] = top_brands

# Find the common brands among all states
common_brands = set(state_top_brands[states[0]])  # Initialize with the brands␣
 ↪from the first state

# Iterate through the states and find the common brands
for state in states:
    common_brands = common_brands.intersection(state_top_brands[state])

# Count the occurrences of each brand in the common brands set
brand_counts = Counter(brand for state in states for brand in␣
 ↪state_top_brands[state])

# Find the most common brands
most_common_brands = [brand for brand, _ in brand_counts.most_common(5)]

# Print the first five most common brands
print("Most Common Brands That Have High Discount:")
for rank, brand in enumerate(most_common_brands, start=1):
    print(f"{rank} - {brand}")
```

```
Most Common Brands That Have High Discount:
1 - POLO FAS
2 - HART SCH
3 - LIZ CLAI
4 - EMMA JAM
5 - ROUNDTRE
```

In AL, POLO FAS, HART SCH, and LIZ CLAI are the brands that have highest discount. In AR, SAMSONIT, POLO FAS, HART SCH, JONES/LA, EMMA JAM, and MURANO have high discounts compare to other brands. In AZ, POLO FAS and LIZ CLAI have high discounts. … The first five most common brands that have high discount are POLO FAS, HART SCH, IZ CLAI, EMMA JAM, and ROUNDTRE.

[43]:
```python
# Top brands with highest sale volume in each state

# Define the number of subplots per row
subplots_per_row = 3

# Calculate the number of rows needed
num_rows = int(np.ceil(len(states) / subplots_per_row))

# Create a figure and a grid of subplots
fig, axes = plt.subplots(num_rows, subplots_per_row, figsize=(18, 6 *␣
↪num_rows), sharey=True)

for i, state in enumerate(states):
    state_data =␣
↪highest_profit_per_brand_state_store[highest_profit_per_brand_state_store['STATE']␣
↪== state]

    # Select the top 10 brands with the highest sale volume within the state
    top_brands = state_data.nlargest(10, 'QUANTITY')

    # Calculate the row and column index for the subplot
    row_index, col_index = divmod(i, subplots_per_row)

    # Plot the highest sale volume for each of the top 10 brands within the␣
↪state
    ax = axes[row_index, col_index]
    ax.bar(top_brands['BRAND'], top_brands['QUANTITY'], label=f'Top {10} Brands␣
↪in {state}')

    # Set labels and title
    ax.set_xlabel('Brand')
    ax.set_ylabel('Highest Quantity')
    ax.set_title(f'Top {10} Brands with Highest Sale Volume in {state} State')

    # Rotate x-axis labels for better readability
    ax.tick_params(axis='x', rotation=45)

    # Add a legend
    ax.legend()

# Hide empty subplots
for i in range(len(states), num_rows * subplots_per_row):
    fig.delaxes(axes.flatten()[i])

# Adjust layout and spacing
plt.tight_layout()
plt.show()
```


Top 10 Brands with Highest Sale Volume in AL State
Top 10 Brands with Highest Sale Volume in AR State
Top 10 Brands with Highest Sale Volume in AZ State
Top 10 Brands with Highest Sale Volume in CA State
Top 10 Brands with Highest Sale Volume in CO State
Top 10 Brands with Highest Sale Volume in FL State
Top 10 Brands with Highest Sale Volume in GA State
Top 10 Brands with Highest Sale Volume in IA State
Top 10 Brands with Highest Sale Volume in ID State
Top 10 Brands with Highest Sale Volume in IL State
Top 10 Brands with Highest Sale Volume in IN State
Top 10 Brands with Highest Sale Volume in KS State
Top 10 Brands with Highest Sale Volume in KY State
Top 10 Brands with Highest Sale Volume in LA State
Top 10 Brands with Highest Sale Volume in MO State
Top 10 Brands with Highest Sale Volume in MS State
Top 10 Brands with Highest Sale Volume in MT State
Top 10 Brands with Highest Sale Volume in NC State
Top 10 Brands with Highest Sale Volume in NE State
Top 10 Brands with Highest Sale Volume in NM State
Top 10 Brands with Highest Sale Volume in NV State
Top 10 Brands with Highest Sale Volume in OH State
Top 10 Brands with Highest Sale Volume in OK State
Top 10 Brands with Highest Sale Volume in SC State
Top 10 Brands with Highest Sale Volume in TN State
Top 10 Brands with Highest Sale Volume in TX State
Top 10 Brands with Highest Sale Volume in UT State
Top 10 Brands with Highest Sale Volume in VA State
Top 10 Brands with Highest Sale Volume in WY State

[44]:
```python
# Create a dictionary to store the top 20 brands with the highest sale volume␣
↪for each state
state_top_brands = {}

for state in states:
    state_data =␣
↪highest_profit_per_brand_state_store[highest_profit_per_brand_state_store['STATE']␣
↪== state]
    top_brands = list(state_data.nlargest(10, 'QUANTITY')['BRAND'])
    state_top_brands[state] = top_brands

# Find the common brands among all states
common_brands = set(state_top_brands[states[0]])  # Initialize with the brands␣
↪from the first state

# Iterate through the states and find the common brands
for state in states:
    common_brands = common_brands.intersection(state_top_brands[state])

# Count the occurrences of each brand in the common brands set
brand_counts = Counter(brand for state in states for brand in␣
↪state_top_brands[state])

# Find the most common brands
most_common_brands = [brand for brand, _ in brand_counts.most_common(5)]

# Print the first five most common brands
print("Most Common Brands That Have High Sale Volume:")
for rank, brand in enumerate(most_common_brands, start=1):
    print(f"{rank} - {brand}")
```

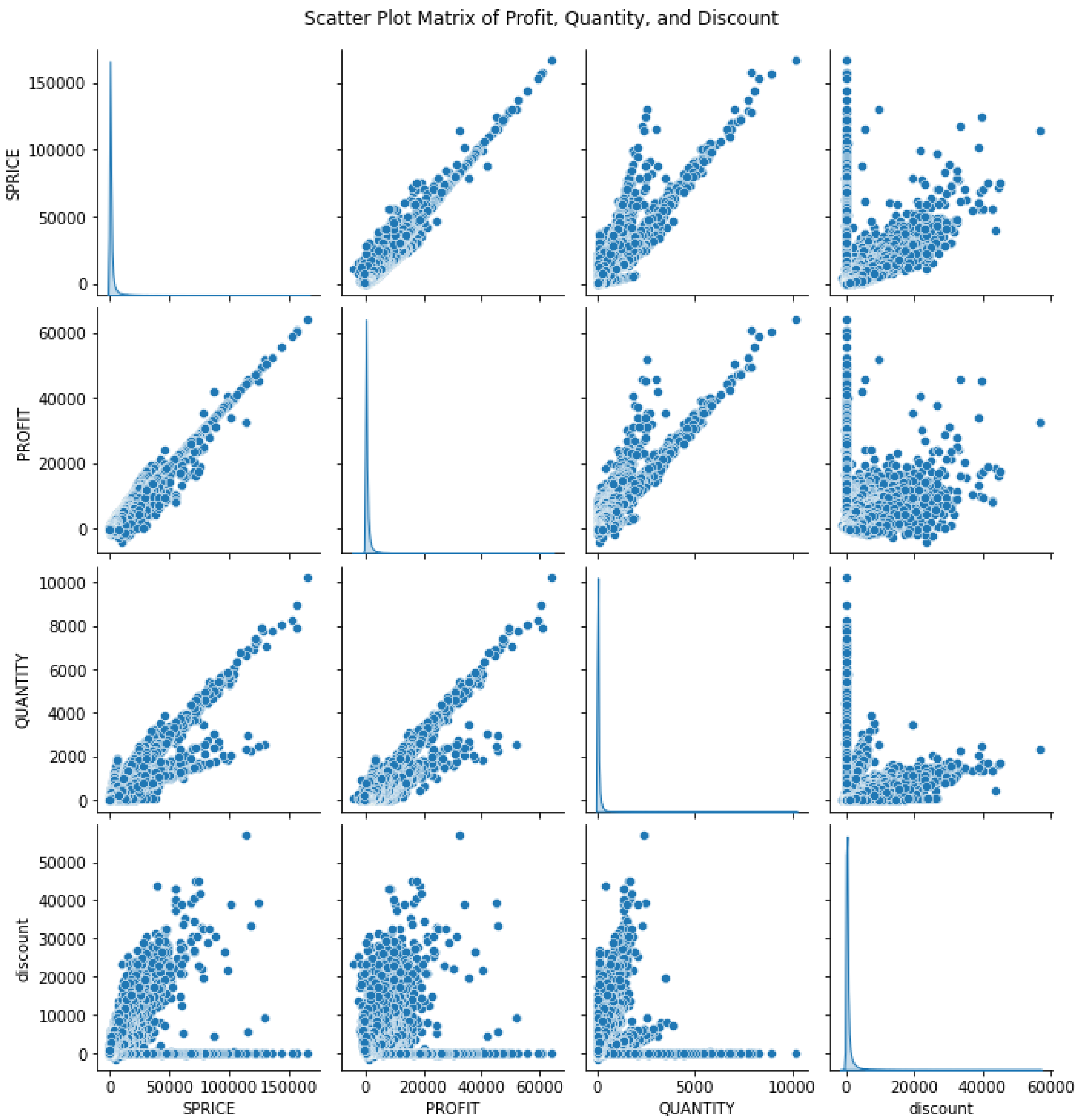
```
Most Common Brands That Have High Sale Volume:
1 - CLINIQUE
2 - CABERNET
3 - LANCOME
4 - LIZ CLAI
5 - ROUNDTRE
```

The first five most common brands that have high sale volumes are CLINIQUE, CABERNET, LANCOME, LIZ CLAI, and ROUNDTRE.

Scatter Plot Matrix:

[80]:
```python
import seaborn as sns

# Select the relevant columns from your DataFrame
```

```
data_to_plot = highest_profit_per_brand_state_store[['SPRICE', 'PROFIT',␣
↪'QUANTITY', 'discount']]

# Create a Scatter Plot Matrix using Seaborn
scatter_plot_matrix = sns.pairplot(data_to_plot, diag_kind='kde', markers='o')

# Add a title to the Scatter Plot Matrix
scatter_plot_matrix.fig.suptitle("Scatter Plot Matrix of Profit, Quantity, and␣
↪Discount", y=1.02)

# Display the plot
plt.show()
```



As quantity increases, profit increases.

[ ]:

0.2 Models

Prediction for sell price based on QUANTITY, discount, BRAND, and STATE:

[83]:
```
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
from sklearn.model_selection import GridSearchCV

# Assuming you have a DataFrame named 'highest_profit_per_brand_state_store'␣
↪with your data
X = highest_profit_per_brand_state_store[['QUANTITY', 'discount', 'BRAND',␣
↪'STATE']]
y = highest_profit_per_brand_state_store['SPRICE']

# Define which features need one-hot encoding
categorical_features = ['BRAND', 'STATE']
numeric_features = ['QUANTITY', 'discount']

# Create a transformer that will apply one-hot encoding to categorical features
categorical_transformer = Pipeline(steps=[
    ('onehot', OneHotEncoder(handle_unknown='ignore'))
])

# Create a column transformer to apply transformations to different feature sets
preprocessor = ColumnTransformer(
    transformers=[
        ('cat', categorical_transformer, categorical_features)
    ],
    remainder='passthrough'  # Pass through the numeric features
)

# Split your data into a training set and a testing set
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

# Create and train the linear regression model within a pipeline
regression_model = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('regressor', LinearRegression())
```

```
])

# Define a parameter grid for hyperparameter tuning
param_grid = {
    'regressor__fit_intercept': [True, False],
    'regressor__normalize': [True, False]
}

# Create a GridSearchCV object
grid_search = GridSearchCV(estimator=regression_model, param_grid=param_grid,␣
 ↪cv=5, scoring='neg_mean_squared_error', n_jobs=-1)
grid_search.fit(X_train, y_train)

# Get the best model
best_model = grid_search.best_estimator_

# Make predictions on the testing set
y_pred = best_model.predict(X_test)

# Evaluate the best model's performance
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)

print(f"Best Model Mean Squared Error: {mse}")
print(f"Best Model R-squared: {r2}")
print(f"Best Model Mean Absolute Error: {mae}")
```

```
Best Model Mean Squared Error: 1391879.7457001992
Best Model R-squared: 0.9472890235803216
Best Model Mean Absolute Error: 476.2383594656255
```

[84]:
```
from sklearn.ensemble import GradientBoostingRegressor

# Create a column transformer to apply transformations to different feature sets
preprocessor = ColumnTransformer(
    transformers=[
        ('cat', categorical_transformer, categorical_features),
        ('num', 'passthrough', numeric_features)
    ]
)

# Split your data into a training set and a testing set
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)

# Define hyperparameters to tune
```

```
param_grid = {
    'regressor__n_estimators': [100, 200, 300],
    'regressor__learning_rate': [0.1, 0.01, 0.001],
    'regressor__max_depth': [3, 4, 5]
}

# Create a GradientBoostingRegressor with the preprocessor
gradient_boosting_model = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('regressor', GradientBoostingRegressor())
])

# Create a GridSearchCV object to search for the best hyperparameters
grid_search = GridSearchCV(estimator=gradient_boosting_model,␣
↪param_grid=param_grid, cv=5, scoring='neg_mean_squared_error', n_jobs=-1)
grid_search.fit(X_train, y_train)

# Get the best model
best_model = grid_search.best_estimator_

# Make predictions on the testing set
y_pred = best_model.predict(X_test)

# Evaluate the model's performance
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)

print(f"Best Model Mean Squared Error: {mse}")
print(f"Best Model R-squared: {r2}")
print(f"Best Model Mean Absolute Error: {mae}")
```

```
Best Model Mean Squared Error: 690705.4828516493
Best Model R-squared: 0.9738427399838191
Best Model Mean Absolute Error: 330.5421972796953
```

[85]:

```
from sklearn.ensemble import RandomForestRegressor

# Create and train the Random Forest Regressor model within a pipeline
random_forest_model = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('regressor', RandomForestRegressor(n_estimators=100, random_state=42))
])

random_forest_model.fit(X_train, y_train)

# Make predictions on the testing set
```

```
y_pred = random_forest_model.predict(X_test)

# Evaluate the model's performance
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)

print(f"Mean Squared Error: {mse}")
print(f"R-squared: {r2}")
print(f"Mean Absolute Error: {mae}")
```

```
Mean Squared Error: 623077.1446247447
R-squared: 0.9764038489823462
Mean Absolute Error: 210.79702847105818
```

Prediction for discount based on QUANTITY, PROFIT, BRAND, and STATE:

[57]:
```
# Assuming you have a DataFrame named 'highest_profit_per_brand_state_store'␣
↪with your data
X = highest_profit_per_brand_state_store[['QUANTITY', 'PROFIT', 'BRAND',␣
↪'STATE']]
y = highest_profit_per_brand_state_store['discount']

# Define which features need one-hot encoding
categorical_features = ['BRAND', 'STATE']
numeric_features = ['QUANTITY', 'PROFIT']

# Create a transformer that will apply one-hot encoding to categorical features
categorical_transformer = Pipeline(steps=[
    ('onehot', OneHotEncoder(handle_unknown='ignore'))
])

# Create a column transformer to apply transformations to different feature sets
preprocessor = ColumnTransformer(
    transformers=[
        ('cat', categorical_transformer, categorical_features)
    ],
    remainder='passthrough'  # Pass through the numeric features
)

# Split your data into a training set and a testing set
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

# Create and train the linear regression model within a pipeline
regression_model = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('regressor', LinearRegression())
```

```
])

# Define a parameter grid for hyperparameter tuning
param_grid = {
    'regressor__fit_intercept': [True, False],
    'regressor__normalize': [True, False]
}

# Create a GridSearchCV object
grid_search = GridSearchCV(estimator=regression_model, param_grid=param_grid,␣
↪cv=5, scoring='neg_mean_squared_error', n_jobs=-1)
grid_search.fit(X_train, y_train)

# Get the best model
best_model = grid_search.best_estimator_

# Make predictions on the testing set
y_pred = best_model.predict(X_test)

# Evaluate the best model's performance
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)

print(f"Best Model Mean Squared Error: {mse}")
print(f"Best Model R-squared: {r2}")
print(f"Best Model Mean Absolute Error: {mae}")
```

```
Best Model Mean Squared Error: 893925.1438350071
Best Model R-squared: 0.7080161134946139
Best Model Mean Absolute Error: 346.3126794717499
```

[59]:

```
# Assuming you have a DataFrame named 'highest_profit_per_brand_state_store'␣
↪with your data
X = highest_profit_per_brand_state_store[['QUANTITY', 'PROFIT', 'BRAND',␣
↪'STATE']]
y = highest_profit_per_brand_state_store['discount']

# Define which features need one-hot encoding
categorical_features = ['BRAND', 'STATE']
numeric_features = ['QUANTITY', 'PROFIT']

# Create a transformer that will apply one-hot encoding to categorical features
categorical_transformer = Pipeline(steps=[
    ('onehot', OneHotEncoder(handle_unknown='ignore'))
])
```

```python
# Create a column transformer to apply transformations to different feature sets
preprocessor = ColumnTransformer(
    transformers=[
        ('cat', categorical_transformer, categorical_features),
        ('num', 'passthrough', numeric_features)
    ]
)

# Split your data into a training set and a testing set
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

# Define hyperparameters to tune
param_grid = {
    'regressor__n_estimators': [100, 200, 300],
    'regressor__learning_rate': [0.1, 0.01, 0.001],
    'regressor__max_depth': [3, 4, 5]
}

# Create a GradientBoostingRegressor with the preprocessor
gradient_boosting_model = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('regressor', GradientBoostingRegressor())
])

# Create a GridSearchCV object to search for the best hyperparameters
grid_search = GridSearchCV(estimator=gradient_boosting_model,␣
↪param_grid=param_grid, cv=5, scoring='neg_mean_squared_error', n_jobs=-1)
grid_search.fit(X_train, y_train)

# Get the best model
best_model = grid_search.best_estimator_

# Make predictions on the testing set
y_pred = best_model.predict(X_test)

# Evaluate the model's performance
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)

print(f"Best Model Mean Squared Error: {mse}")
print(f"Best Model R-squared: {r2}")
print(f"Best Model Mean Absolute Error: {mae}")
```

```
Best Model Mean Squared Error: 199329.71633173432
Best Model R-squared: 0.9348926857333166
```

```
Best Model Mean Absolute Error: 198.91569294163224
```

[60]:
```python
# Create and train the Random Forest Regressor model within a pipeline
random_forest_model = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('regressor', RandomForestRegressor(n_estimators=100, random_state=42))
])

random_forest_model.fit(X_train, y_train)

# Make predictions on the testing set
y_pred = random_forest_model.predict(X_test)

# Evaluate the model's performance
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)

print(f"Mean Squared Error: {mse}")
print(f"R-squared: {r2}")
print(f"Mean Absolute Error: {mae}")
```

```
Mean Squared Error: 135508.0321631375
R-squared: 0.9557388421652983
Mean Absolute Error: 117.86812573844139
```

Prediction for QUANTITY based on dicount, PROFIT, BRAND, and STATE:

[61]:
```python
# Assuming you have a DataFrame named 'highest_profit_per_brand_state_store'␣
↪with your data
X = highest_profit_per_brand_state_store[['discount', 'PROFIT', 'BRAND',␣
↪'STATE']]
y = highest_profit_per_brand_state_store['QUANTITY']

# Define which features need one-hot encoding
categorical_features = ['BRAND', 'STATE']
numeric_features = ['PROFIT', 'discount']

# Create a transformer that will apply one-hot encoding to categorical features
categorical_transformer = Pipeline(ste ps=[
    ('onehot', OneHotEncoder(handle_unknown='ignore'))
])

# Create a column transformer to apply transformations to different feature sets
preprocessor = ColumnTransformer(
    transformers=[
        ('cat', categorical_transformer, categorical_features)
    ],
```

```
    remainder='passthrough'  # Pass through the numeric features
)

# Split your data into a training set and a testing set
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

# Create and train the linear regression model within a pipeline
regression_model = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('regressor', LinearRegression())
])

# Define a parameter grid for hyperparameter tuning
param_grid = {
    'regressor__fit_intercept': [True, False],
    'regressor__normalize': [True, False]
}

# Create a GridSearchCV object
grid_search = GridSearchCV(estimator=regression_model, param_grid=param_grid,␣
↪cv=5, scoring='neg_mean_squared_error', n_jobs=-1)
grid_search.fit(X_train, y_train)

# Get the best model
best_model = grid_search.best_estimator_

# Make predictions on the testing set
y_pred = best_model.predict(X_test)

# Evaluate the best model's performance
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)

print(f"Best Model Mean Squared Error: {mse}")
print(f"Best Model R-squared: {r2}")
print(f"Best Model Mean Absolute Error: {mae}")
```

```
Best Model Mean Squared Error: 3832.479124333375
Best Model R-squared: 0.9380416912485268
Best Model Mean Absolute Error: 22.77668318652504
```

[62]:
```
# Create a transformer that will apply one-hot encoding to categorical features
categorical_transformer = Pipeline(steps=[
    ('onehot', OneHotEncoder(handle_unknown='ignore'))
])
```

```
# Create a column transformer to apply transformations to different feature sets
preprocessor = ColumnTransformer(
    transformers=[
        ('cat', categorical_transformer, categorical_features),
        ('num', 'passthrough', numeric_features)
    ]
)

# Split your data into a training set and a testing set
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

# Define hyperparameters to tune
param_grid = {
    'regressor__n_estimators': [100, 200, 300],
    'regressor__learning_rate': [0.1, 0.01, 0.001],
    'regressor__max_depth': [3, 4, 5]
}

# Create a GradientBoostingRegressor with the preprocessor
gradient_boosting_model = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('regressor', GradientBoostingRegressor())
])

# Create a GridSearchCV object to search for the best hyperparameters
grid_search = GridSearchCV(estimator=gradient_boosting_model,␣
↪param_grid=param_grid, cv=5, scoring='neg_mean_squared_error', n_jobs=-1)
grid_search.fit(X_train, y_train)

# Get the best model
best_model = grid_search.best_estimator_

# Make predictions on the testing set
y_pred = best_model.predict(X_test)

# Evaluate the model's performance
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)

print(f"Best Model Mean Squared Error: {mse}")
print(f"Best Model R-squared: {r2}")
print(f"Best Model Mean Absolute Error: {mae}")
```

```
Best Model Mean Squared Error: 829.2310035057027
```

```
Best Model R-squared: 0.9865941212268345
Best Model Mean Absolute Error: 11.86027240332083
```

[63]:

```
# Create and train the Random Forest Regressor model within a pipeline
random_forest_model = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('regressor', RandomForestRegressor(n_estimators=100, random_state=42))
])

random_forest_model.fit(X_train, y_train)

# Make predictions on the testing set
y_pred = random_forest_model.predict(X_test)

# Evaluate the model's performance
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)

print(f"Mean Squared Error: {mse}")
print(f"R-squared: {r2}")
print(f"Mean Absolute Error: {mae}")
```

```
Mean Squared Error: 879.055550428493
R-squared: 0.9857886257338405
Mean Absolute Error: 7.956133210391705
```

[ ]: