hppg3dg3m

July 29, 2025

1 Importing Libraries

[4]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
import sqlite3
from scipy.stats import ttest_ind
import scipy.stats as stats
warnings.filterwarnings('ignore')
```

2 Loading the Dataset

[9]:
```
# creating database connection
conn = sqlite3.connect('inventory.db')

# fetching vendor summary data
df = pd.read_sql_query("select * from vendor_sales_summary",conn)
df.head()
```

[9]:
```
   VendorNumber                 VendorName  Brand              Description  \
0          1128          BROWN-FORMAN CORP   1233  Jack Daniels No 7 Black
1          4425      MARTIGNETTI COMPANIES   3405    Tito's Handmade Vodka
2         17035           PERNOD RICARD USA   8068         Absolut 80 Proof
3          3960  DIAGEO NORTH AMERICA INC   4261    Capt Morgan Spiced Rum
4          3960  DIAGEO NORTH AMERICA INC   3545           Ketel One Vodka

   PurchasePrice  ActualPrice  Volume  TotalPurchaseQuantity  \
0          26.27        36.99  1750.0                 145080
1          23.19        28.99  1750.0                 164038
2          18.24        24.99  1750.0                 187407
3          16.17        22.99  1750.0                 201682
4          21.89        29.99  1750.0                 138109

   TotalPurchaseDollars  TotalSalesQuantity  TotalSalesDollars  \
```

```
0          3811251.60          142049.0         5101919.51
1          3804041.22          160247.0         4819073.49
2          3418303.68          187140.0         4538120.60
3          3261197.94          200412.0         4475972.88
4          3023206.01          135838.0         4223107.62

   TotalSalesPrice  TotalExciseTax  FreightCost  GrossProfit  ProfitMargin  \
0        672819.31       260999.20     68601.68   1290667.91     25.297693
1        561512.37       294438.66    144929.24   1015032.27     21.062810
2        461140.15       343854.07    123780.22   1119816.92     24.675786
3        420050.01       368242.80    257032.07   1214774.94     27.139908
4        545778.28       249587.83    257032.07   1199901.61     28.412764

   StockTurnover  SalesToPurchaseRatio
0       0.979108              1.338647
1       0.976890              1.266830
2       0.998575              1.327594
3       0.993703              1.372493
4       0.983556              1.396897
```

[11]:
```
df.to_csv('vendor_sales_summary.csv',index  = False)
```

3 Exploratory Data Analysis

- Previously, we examined the various tables in the database to identify key variables, understand their relationships, and determine which ones should be included in the final analysis.
- In this phase of EDA, we will analyze the resultant table to gain insights into the distribution of each column. This will help us understand data patterns, identify anomalies, and ensure data quality before proceeding with further analysis.

[14]:
```
# Summary statistics for numerical columns
summary_stats = df.describe().T
display(summary_stats)
```

```
                        count          mean            std     min  \
VendorNumber          10692.0  1.065065e+04   18753.519148    2.00
Brand                 10692.0  1.803923e+04   12662.187074   58.00
PurchasePrice         10692.0  2.438530e+01     109.269375    0.36
ActualPrice           10692.0  3.564367e+01     148.246016    0.49
Volume                10692.0  8.473605e+02     664.309212   50.00
TotalPurchaseQuantity 10692.0  3.140887e+03   11095.086769    1.00
TotalPurchaseDollars  10692.0  3.010669e+04  123067.799627    0.71
TotalSalesQuantity    10692.0  3.077482e+03   10952.851391    0.00
TotalSalesDollars     10692.0  4.223907e+04  167655.265984    0.00
TotalSalesPrice       10692.0  1.879378e+04   44952.773386    0.00
TotalExciseTax        10692.0  1.774226e+03   10975.582240    0.00
```

```
FreightCost             10692.0  6.143376e+04   60938.458032      0.09
GrossProfit             10692.0  1.213238e+04   46224.337964 -52002.78
ProfitMargin            10692.0          -inf            NaN      -inf
StockTurnover           10692.0  1.706793e+00       6.020460      0.00
SalesToPurchaseRatio    10692.0  2.504390e+00       8.459067      0.00

                                 25%           50%           75%           max
VendorNumber             3951.000000   7153.000000   9552.000000  2.013590e+05
Brand                    5793.500000  18761.500000  25514.250000  9.063100e+04
PurchasePrice               6.840000     10.455000     19.482500  5.681810e+03
ActualPrice                10.990000     15.990000     28.990000  7.499990e+03
Volume                    750.000000    750.000000    750.000000  2.000000e+04
TotalPurchaseQuantity      36.000000    262.000000   1975.750000  3.376600e+05
TotalPurchaseDollars      453.457500   3655.465000  20738.245000  3.811252e+06
TotalSalesQuantity         33.000000    261.000000   1929.250000  3.349390e+05
TotalSalesDollars         729.220000   5298.045000  28396.915000  5.101920e+06
TotalSalesPrice           289.710000   2857.800000  16059.562500  6.728193e+05
TotalExciseTax              4.800000     46.570000    418.650000  3.682428e+05
FreightCost             14069.870000  50293.620000  79528.990000  2.570321e+05
GrossProfit                52.920000   1399.640000   8660.200000  1.290668e+06
ProfitMargin               13.324515     30.405457     39.956135  9.971666e+01
StockTurnover               0.807229      0.981529      1.039342  2.745000e+02
SalesToPurchaseRatio        1.153729      1.436894      1.665449  3.529286e+02
```

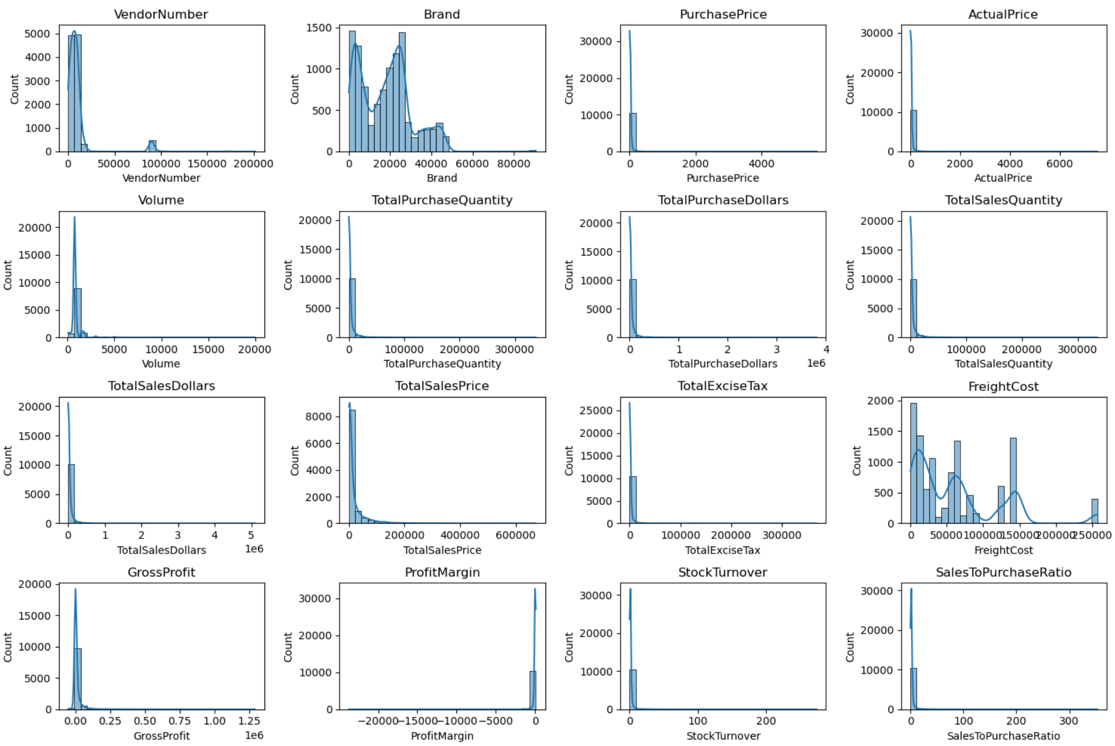
[16]:

```python
# Mode for each numerical column
mode_values = df.mode().iloc[0]
print("\nMode Values:\n\n", mode_values)
```

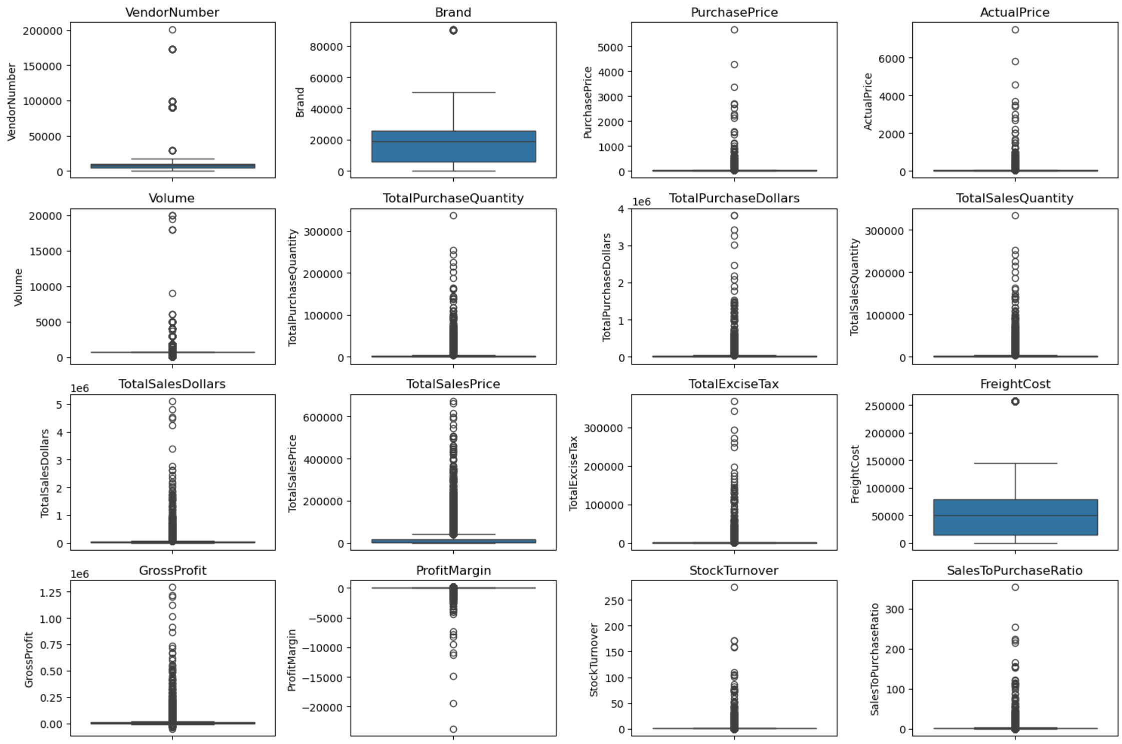
```
Mode Values:

 VendorNumber                              4425.0
VendorName               MARTIGNETTI COMPANIES
Brand                                      809
Description                   Southern Comfort
PurchasePrice                             6.53
ActualPrice                               9.99
Volume                                   750.0
TotalPurchaseQuantity                     12.0
TotalPurchaseDollars                     95.28
TotalSalesQuantity                        12.0
TotalSalesDollars                          0.0
TotalSalesPrice                            0.0
TotalExciseTax                             0.0
FreightCost                          144929.24
GrossProfit                             -106.8
ProfitMargin                              -inf
StockTurnover                              1.0
```

```
SalesToPurchaseRatio                          0.0
Name: 0, dtype: object
```

[18]:
```python
# Distribution Plots for Numerical Columns
numerical_cols = df.select_dtypes(include=np.number).columns

plt.figure(figsize=(15, 10))
for i, col in enumerate(numerical_cols):
    plt.subplot(4, 4, i+1)  # Adjust grid layout as needed
    sns.histplot(df[col], kde=True, bins=30)
    plt.title(col)
plt.tight_layout()
plt.show()
```



[20]:
```python
# Outlier Detection with Boxplots
plt.figure(figsize=(15, 10))
for i, col in enumerate(numerical_cols):
    plt.subplot(4, 4, i+1)
    sns.boxplot(y=df[col])
    plt.title(col)
plt.tight_layout()
plt.show()
```



3.1 Summary Statistics Insights:

Negative & Zero Values:

- Gross Profit: Minimum value is -52,002.78, indicating losses. Some products or transactions may be selling at a loss due to high costs or selling at discounts lower than the purchase price..
- Profit Margin: Has a minimum of -∞, which suggests cases where revenue is zero or even lower than costs.
- Total Sales Quantity & Sales Dollars: Minimum values are 0, meaning some products were purchased but never sold. These could be slow-moving or obsolete stock.

Outliers Indicated by High Standard Deviations:

- Purchase & Actual Prices: The max values (5,681.81 & 7,499.99) are significantly higher than the mean (24.39 & 35.64), indicating potential premium products.
- Freight Cost: Huge variation, from 0.09 to 257,032.07, suggests logistics inefficiencies or bulk shipments.
- Stock Turnover: Ranges from 0 to 274.5, implying some products sell extremely fast while others remain in stock indefinitely. Value more than 1 indicates that Sold quantity for that product is higher than purchased quantity due to either sales are being fulfilled from older stock.

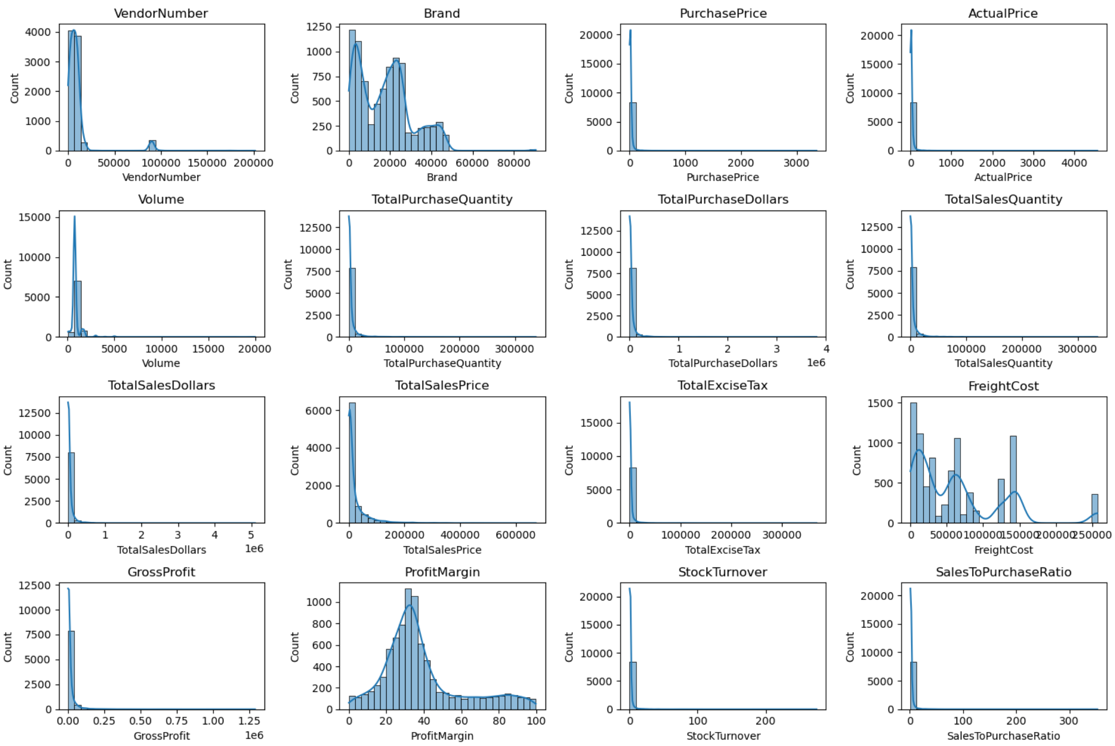
[29]:
```
# let's filter the data by removing inconsistencies
df = pd.read_sql_query("""SELECT *
```

```
FROM vendor_sales_summary
WHERE GrossProfit > 0
AND ProfitMargin > 0
AND TotalSalesQuantity > 0""",conn)
```

[31]:
```
df.shape
```

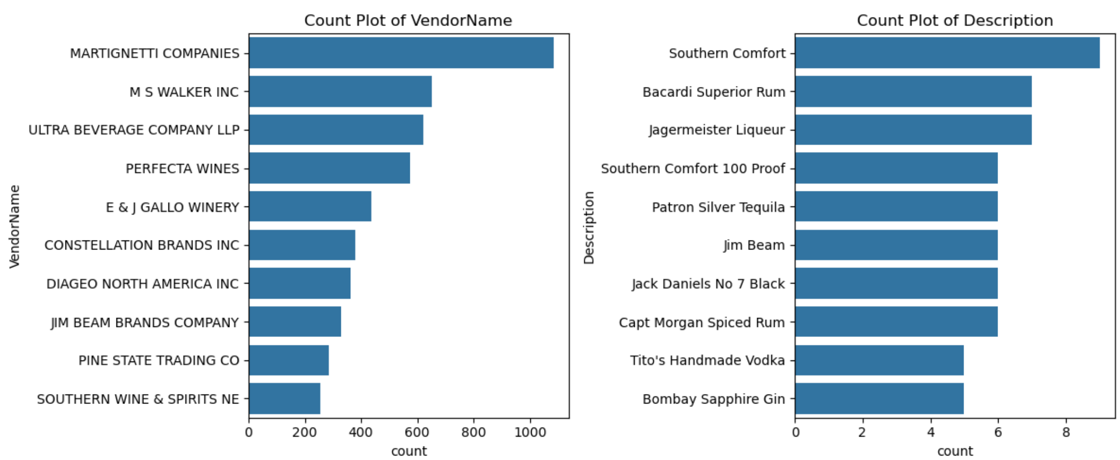
[31]: (8564, 18)

[33]:
```
# Distribution Plots for Numerical Columns
numerical_cols = df.select_dtypes(include=np.number).columns

plt.figure(figsize=(15, 10))
for i, col in enumerate(numerical_cols):
    plt.subplot(4, 4, i+1)  # Adjust grid layout as needed
    sns.histplot(df[col], kde=True, bins=30)
    plt.title(col)
plt.tight_layout()
plt.show()
```

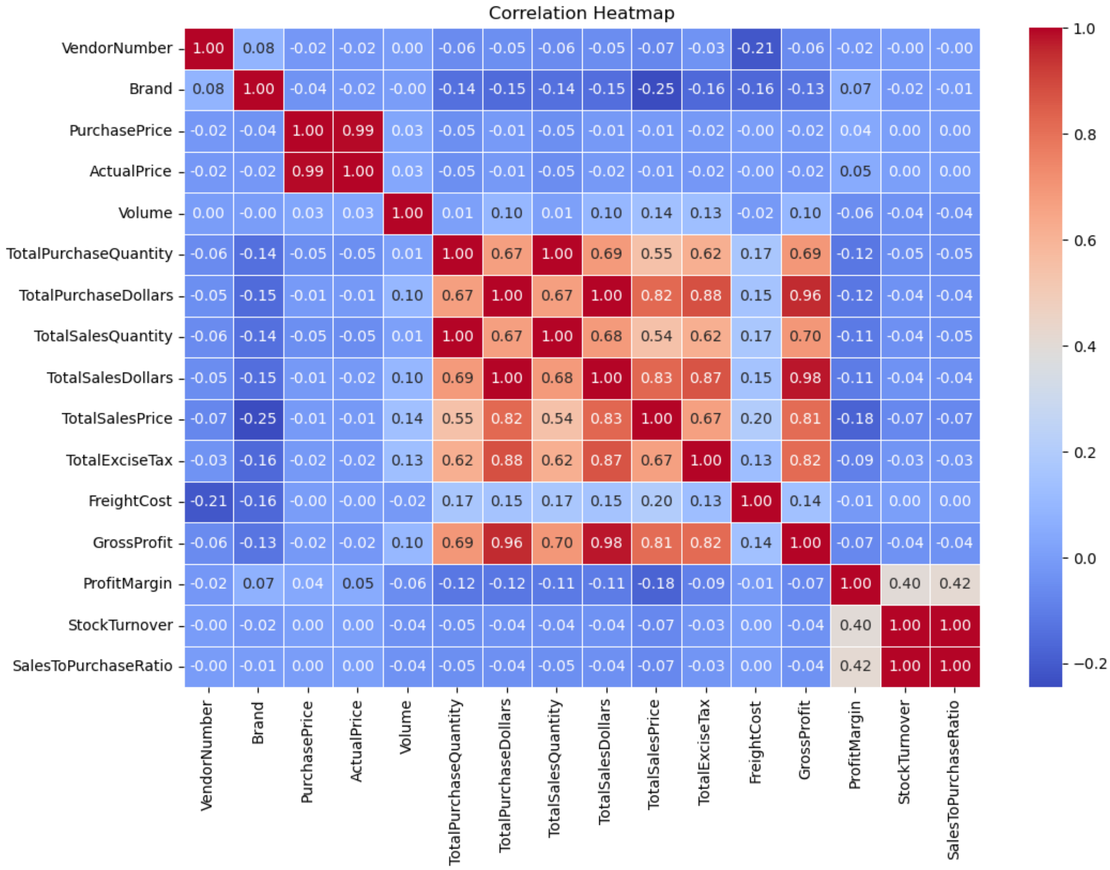


[35]:
```
# Count Plots for Categorical Columns
categorical_cols = ["VendorName", "Description"]
```

```
plt.figure(figsize=(12, 5))
for i, col in enumerate(categorical_cols):
    plt.subplot(1, 2, i+1)
    sns.countplot(y=df[col], order=df[col].value_counts().index[:10])  # Top 10␣
↪categories
    plt.title(f"Count Plot of {col}")
plt.tight_layout()
plt.show()
```



[37]:
```
# Correlation Heatmap
plt.figure(figsize=(12, 8))
correlation_matrix = df[numerical_cols].corr()
sns.heatmap(correlation_matrix, annot=True, fmt=".2f", cmap="coolwarm",␣
↪linewidths=0.5)
plt.title("Correlation Heatmap")
plt.show()
```



3.2 Correlation Insights

- PurchasePrice has weak correlations with TotalSalesDollars (-0.012) and GrossProfit (-0.016), suggesting that price variations do not significantly impact sales revenue or profit.
- Strong correlation between total purchase quantity and total sales quantity (0.999), confirming efficient inventory turnover.
- Negative correlation between profit margin & total sales price (-0.179) suggests that as sales price increases, margins decrease, possibly due to competitive pricing pressures.
- StockTurnover has weak negative correlations with both GrossProfit (-0.038) and ProfitMargin (-0.055), indicating that faster turnover does not necessarily result in higher profitability.

3.3 Data Analysis

Identify Brands that needs Promotional or Pricing Adjustments which exhibit lower sales performance but higher profit margins.

[46]:
```
brand_performance = df.groupby('Description').agg({
    'TotalSalesDollars': 'sum',   # Sales performance metric
    'ProfitMargin': 'mean'        # Average profit margin
}).reset_index()
```

```python
brand_performance.sort_values('ProfitMargin')
```

[46]:

```
                         Description  TotalSalesDollars  ProfitMargin
5485          Pepperjack Barossa Red             191.92      0.020842
2954    Flint & Steel Svgn Bl Napa V             119.92      0.033356
2179               Croft Tawny Porto             191.84      0.041701
2561             Douglass Hill Merlot            143.76      0.083472
5385     Parducci 13 True Grit Chard           24927.81      0.121190
…                                …                 …           …
4568               M Chiarlo Gavi Wh            1208.90     99.393664
657             Beniotome Sesame Shochu         4768.41     99.534226
6449       Skinnygirl Tangerine Vodka           2368.42     99.544844
2411               DiSaronno Amaretto           4781.16     99.553246
5528     Pezzi King Svgn Bl Dry Creek           2221.29     99.604734

[7707 rows x 3 columns]
```

[48]:

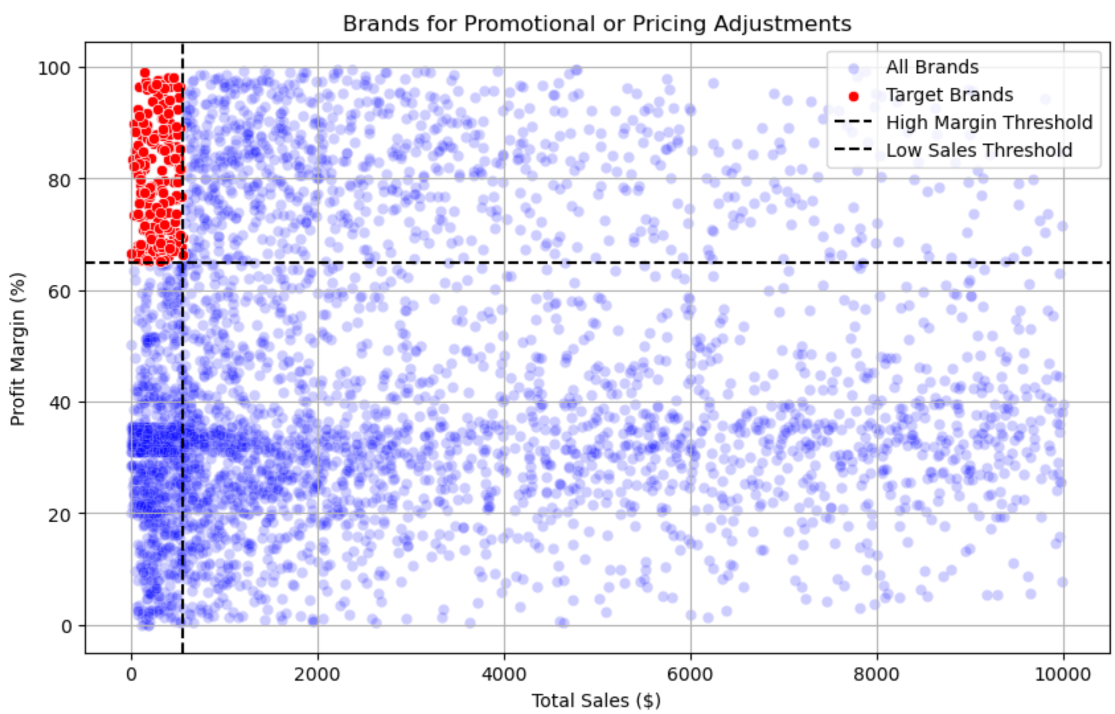
```python
# threshold for "low sales" (bottom 15%) and "high margin" (top 15%)
low_sales_threshold = brand_performance['TotalSalesDollars'].quantile(0.15)
high_margin_threshold = brand_performance['ProfitMargin'].quantile(0.85)

# Filter brands with low sales but high profit margins
target_brands = brand_performance[
    (brand_performance['TotalSalesDollars'] <= low_sales_threshold) &
    (brand_performance['ProfitMargin'] >= high_margin_threshold)
]
print("Brands with Low Sales but High Profit Margins:")
display(target_brands.sort_values('TotalSalesDollars'))
```

```
Brands with Low Sales but High Profit Margins:

                         Description  TotalSalesDollars  ProfitMargin
6199      Santa Rita Organic Svgn Bl               9.99     66.466466
2369                Debauchery Pnt Nr              11.58     65.975820
2070     Concannon Glen Ellen Wh Zin              15.95     83.448276
2188                Crown Royal Apple              27.86     89.806174
6237    Sauza Sprklg Wild Berry Marg               27.96     82.153076
…                                …                 …           …
5074     Nanbu Bijin Southern Beauty             535.68     76.747312
2271             Dad's Hat Rye Whiskey           538.89     81.851584
57          A Bichot Clos Marechaudes            539.94     67.740860
6245        Sbragia Home Ranch Merlot            549.75     66.444748
3326        Goulee Cos d'Estournel 10            558.87     69.434752

[198 rows x 3 columns]
```

Brands with Low Sales but High Profit Margins:

[51]:
```
brand_performance = brand_performance[brand_performance['TotalSalesDollars']<10000] # for better visualization
```

[53]:
```
plt.figure(figsize=(10, 6))
sns.scatterplot(data=brand_performance, x='TotalSalesDollars', y='ProfitMargin', color="blue", label="All Brands", alpha = 0.2)
sns.scatterplot(data=target_brands, x='TotalSalesDollars', y='ProfitMargin', color="red", label="Target Brands")

plt.axhline(high_margin_threshold, linestyle='--', color='black', label="High Margin Threshold")
plt.axvline(low_sales_threshold, linestyle='--', color='black', label="Low Sales Threshold")

plt.xlabel("Total Sales ($)")
plt.ylabel("Profit Margin (%)")
plt.title("Brands for Promotional or Pricing Adjustments")
plt.legend()
plt.grid(True)
plt.show()
```



Which vendors and brands demonstrate the highest sales performance?

[56]:
```python
def format_dollars(value):
    if value >= 1_000_000:
        return f"{value / 1_000_000:.2f}M"
    elif value >= 1_000:
        return f"{value / 1_000:.2f}K"
    else:
        return str(value)
```

[58]:
```python
# Top Vendors & Brands by Sales Performance
top_vendors = df.groupby("VendorName")["TotalSalesDollars"].sum().nlargest(10)
top_brands = df.groupby("Description")["TotalSalesDollars"].sum().nlargest(10)
top_vendors
```

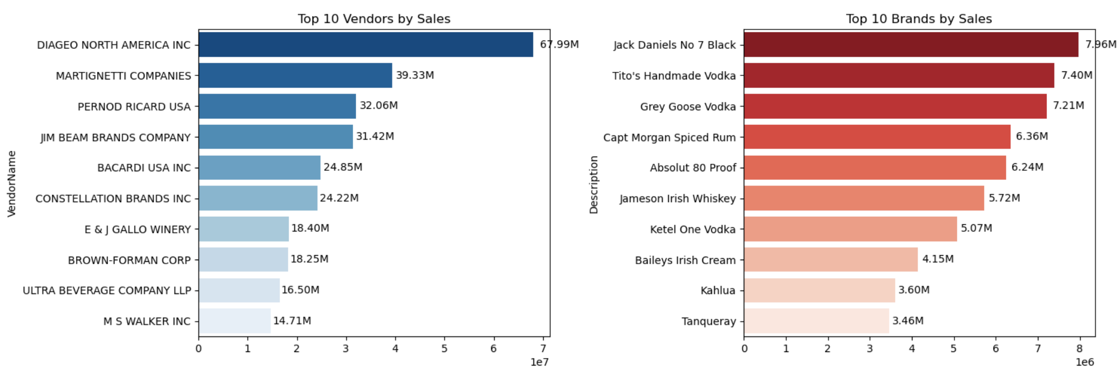
[58]:
```
VendorName
DIAGEO NORTH AMERICA INC      67990099.42
MARTIGNETTI COMPANIES         39330359.36
PERNOD RICARD USA             32063196.19
JIM BEAM BRANDS COMPANY       31423020.46
BACARDI USA INC               24854817.14
CONSTELLATION BRANDS INC      24218745.65
E & J GALLO WINERY            18399899.46
BROWN-FORMAN CORP             18247230.65
ULTRA BEVERAGE COMPANY LLP    16502544.31
M S WALKER INC                14706458.51
Name: TotalSalesDollars, dtype: float64
```

[60]:
```python
top_vendors.apply(lambda x:format_dollars(x))
```

[60]:
```
VendorName
DIAGEO NORTH AMERICA INC      67.99M
MARTIGNETTI COMPANIES         39.33M
PERNOD RICARD USA             32.06M
JIM BEAM BRANDS COMPANY       31.42M
BACARDI USA INC               24.85M
CONSTELLATION BRANDS INC      24.22M
E & J GALLO WINERY            18.40M
BROWN-FORMAN CORP             18.25M
ULTRA BEVERAGE COMPANY LLP    16.50M
M S WALKER INC                14.71M
Name: TotalSalesDollars, dtype: object
```

[62]:
```python
plt.figure(figsize=(15, 5))

# Plot for Top Vendors
plt.subplot(1, 2, 1)
ax1 = sns.barplot(y=top_vendors.index, x=top_vendors.values, palette="Blues_r")
plt.title("Top 10 Vendors by Sales")
```

```python
for bar in ax1.patches:
    ax1.text(bar.get_width() + (bar.get_width() * 0.02),
             bar.get_y() + bar.get_height() / 2,
             format_dollars(bar.get_width()),
             ha='left', va='center', fontsize=10, color='black')

# Plot for Top Brands
plt.subplot(1, 2, 2)
ax2 = sns.barplot(y=top_brands.index.astype(str), x=top_brands.values,
 ↪palette="Reds_r")
plt.title("Top 10 Brands by Sales")

for bar in ax2.patches:
    ax2.text(bar.get_width() + (bar.get_width() * 0.02),
             bar.get_y() + bar.get_height() / 2,
             format_dollars(bar.get_width()),
             ha='left', va='center', fontsize=10, color='black')

plt.tight_layout()
plt.show()
```



3.3.1 Which vendors contribute the most to total purchase dollars?

[67]:
```python
# Rank Vendors by Total Purchase Dollars
vendor_performance = df.groupby("VendorName").agg({
    "TotalPurchaseDollars": "sum",
    "GrossProfit": "sum",
    "TotalSalesDollars":"sum"
}).reset_index()

# Calculate Contribution % to Overall Procurement
```

```python
vendor_performance["Purchase_Contribution%"] = (vendor_performance["TotalPurchaseDollars"] / vendor_performance["TotalPurchaseDollars"].sum()) * 100

# Rank Vendors by Total Purchase Dollars & Profitability
vendor_performance = round(vendor_performance.sort_values(by="TotalPurchaseDollars", ascending=False),2)

# Display Top 10 Vendors
top_vendors = vendor_performance.head(10)
top_vendors['TotalSalesDollars'] = top_vendors['TotalSalesDollars'].apply(format_dollars)
top_vendors['TotalPurchaseDollars'] = top_vendors['TotalPurchaseDollars'].apply(format_dollars)
top_vendors['GrossProfit'] = top_vendors['GrossProfit'].apply(format_dollars)
top_vendors
```

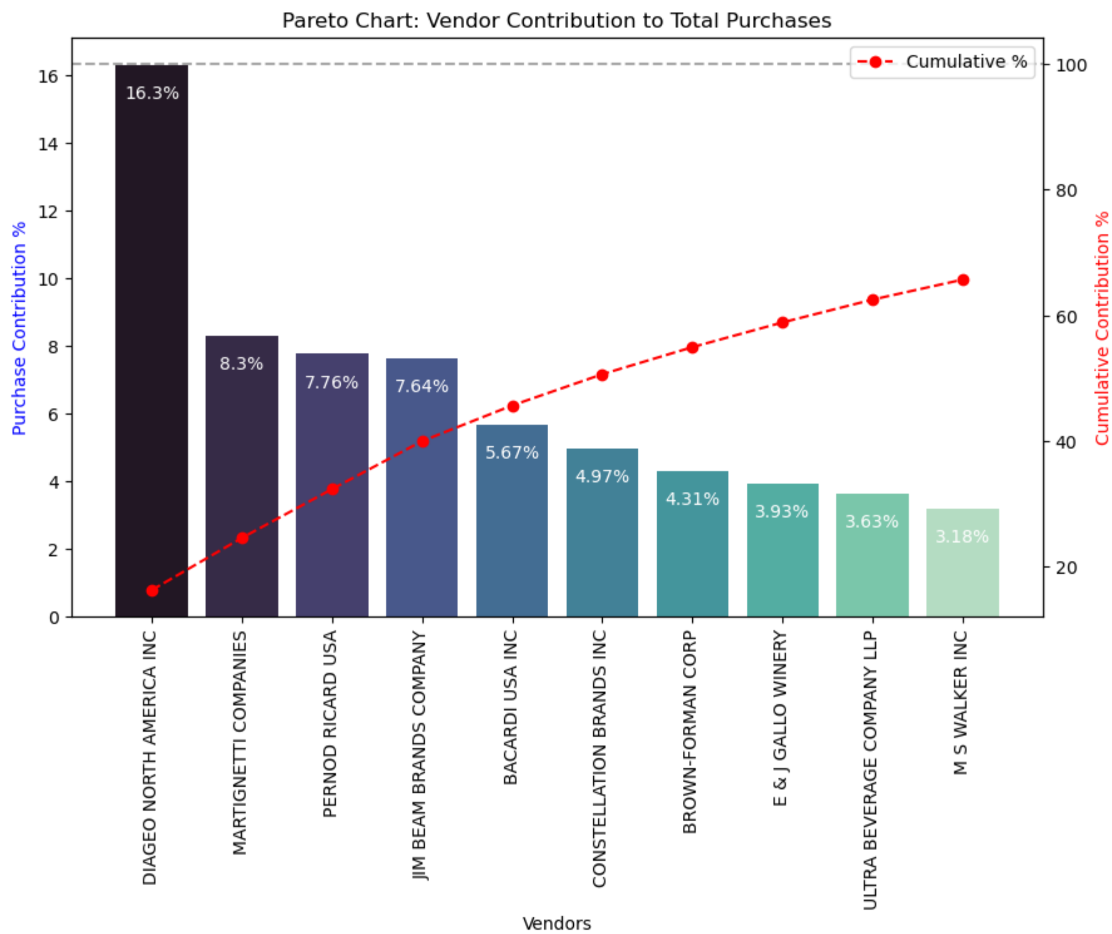
[67]:

```
                       VendorName TotalPurchaseDollars GrossProfit  \
25     DIAGEO NORTH AMERICA INC               50.10M      17.89M
57        MARTIGNETTI COMPANIES               25.50M      13.83M
68             PERNOD RICARD USA              23.85M       8.21M
46       JIM BEAM BRANDS COMPANY              23.49M       7.93M
6                 BACARDI USA INC             17.43M       7.42M
20      CONSTELLATION BRANDS INC              15.27M       8.95M
11              BROWN-FORMAN CORP             13.24M       5.01M
30             E & J GALLO WINERY             12.07M       6.33M
106  ULTRA BEVERAGE COMPANY LLP               11.17M       5.34M
53                 M S WALKER INC              9.76M       4.94M

    TotalSalesDollars  Purchase_Contribution%
25             67.99M                   16.30
57             39.33M                    8.30
68             32.06M                    7.76
46             31.42M                    7.64
6              24.85M                    5.67
20             24.22M                    4.97
11             18.25M                    4.31
30             18.40M                    3.93
106            16.50M                    3.63
53             14.71M                    3.18
```

[69]:

```python
top_vendors['Cumulative_Contribution%'] = top_vendors['Purchase_Contribution%'].cumsum()

fig, ax1 = plt.subplots(figsize=(10, 6))

# Bar plot for Purchase Contribution%
```

```python
sns.barplot(x=top_vendors['VendorName'],␣
↪y=top_vendors['Purchase_Contribution%'],  palette="mako", ax=ax1)

for i, value in enumerate(top_vendors['Purchase_Contribution%']):
    ax1.text(i, value - 1, str(value)+'%', ha='center', fontsize=10,␣
↪color='white')

# Line Plot for Cumulative Contribution%
ax2 = ax1.twinx()
ax2.plot(top_vendors['VendorName'], top_vendors['Cumulative_Contribution%'],␣
↪color='red', marker='o', linestyle='dashed', label='Cumulative %')

ax1.set_xticklabels(top_vendors['VendorName'], rotation=90)
ax1.set_ylabel('Purchase Contribution %', color='blue')
ax2.set_ylabel('Cumulative Contribution %', color='red')
ax1.set_xlabel('Vendors')
ax1.set_title('Pareto Chart: Vendor Contribution to Total Purchases')

ax2.axhline(y=100, color='gray', linestyle='dashed', alpha=0.7)
ax2.legend(loc='upper right')

plt.show()
```



3.3.2 How much of total procurement is dependent on the top vendors?

[104]:
```
print(f"Total Purchase Contribution of top 10 vendors is␣
↪{round(top_vendors['Purchase_Contribution%'].sum(),2)} %")

vendors = list(top_vendors['VendorName'].values)
purchase_contributions = list(top_vendors['Purchase_Contribution%'].values)
total_contribution = sum(purchase_contributions)
remaining_contribution = 100 - total_contribution

# Append "Other Vendors" category
vendors.append("Other Vendors")
purchase_contributions.append(remaining_contribution)

# Donut Chart
fig, ax = plt.subplots(figsize=(8, 8))
```

```
wedges, texts, autotexts = ax.pie(purchase_contributions, labels=vendors,␣
↪autopct='%1.1f%%',
                                  startangle=140, pctdistance=0.85, colors=plt.
↪cm.Paired.colors)

# Draw a white circle in the center to create a "donut" effect
centre_circle = plt.Circle((0, 0), 0.70, fc='white')
fig.gca().add_artist(centre_circle)

# Add Total Contribution annotation in the center
plt.text(0, 0, f"Top 10 Total:\n{total_contribution:.2f}%", fontsize=14,␣
↪fontweight='bold', ha='center', va='center')

plt.title("Top 10 Vendor's Purchase Contribution (%)")
plt.show()
```

```
---------------------------------------------------------------------------
KeyError                                  Traceback (most recent call last)
File ~\anaconda3\Lib\site-packages\pandas\core\indexes\base.py:3805, in Index.
↪get_loc(self, key)
   3804 try:
-> 3805     return self._engine.get_loc(casted_key)
   3806 except KeyError as err:

File index.pyx:167, in pandas._libs.index.IndexEngine.get_loc()

File index.pyx:175, in pandas._libs.index.IndexEngine.get_loc()

File pandas\\_libs\\index_class_helper.pxi:70, in pandas._libs.index.Int64Engine.
↪_check_type()

KeyError: 'Purchase_Contribution%'

The above exception was the direct cause of the following exception:

KeyError                                  Traceback (most recent call last)
Cell In[104], line 1
----> 1 print(f"Total Purchase Contribution of top 10 vendors is␣
↪{round(top_vendors['Purchase_Contribution%'].sum(),2)} %")
      3 vendors = list(top_vendors['VendorName'].values)
      4 purchase_contributions = list(top_vendors['Purchase_Contribution%'].
↪values)

File ~\anaconda3\Lib\site-packages\pandas\core\series.py:1121, in Series.
↪__getitem__(self, key)
   1118     return self._values[key]
   1120 elif key_is_scalar:
```

```
-> 1121     return self._get_value(key)
   1123 # Convert generator to list before going through hashable part
   1124 # (We will iterate through the generator there to check for slices)
   1125 if is_iterator(key):

File ~\anaconda3\Lib\site-packages\pandas\core\series.py:1237, in Series.
 ↪_get_value(self, label, takeable)
   1234     return self._values[label]
   1236 # Similar to Index.get_value, but we do not fall back to positional
-> 1237 loc = self.index.get_loc(label)
   1239 if is_integer(loc):
   1240     return self._values[loc]

File ~\anaconda3\Lib\site-packages\pandas\core\indexes\base.py:3812, in Index.
 ↪get_loc(self, key)
   3807     if isinstance(casted_key, slice) or (
   3808         isinstance(casted_key, abc.Iterable)
   3809         and any(isinstance(x, slice) for x in casted_key)
   3810     ):
   3811         raise InvalidIndexError(key)
-> 3812     raise KeyError(key) from err
   3813 except TypeError:
   3814     # If we have a listlike key, _check_indexing_error will raise
   3815     #  InvalidIndexError. Otherwise we fall through and re-raise
   3816     #  the TypeError.
   3817     self._check_indexing_error(key)

KeyError: 'Purchase_Contribution%'
```

The remaining vendors contribute only 34.31%, meaning they are not utilized effectively or may not be as competitive. If vendor dependency is too high, consider identifying new suppliers to reduce risk.

Does purchasing in bulk reduce the unit price, and what is the optimal purchase volume for cost savings?

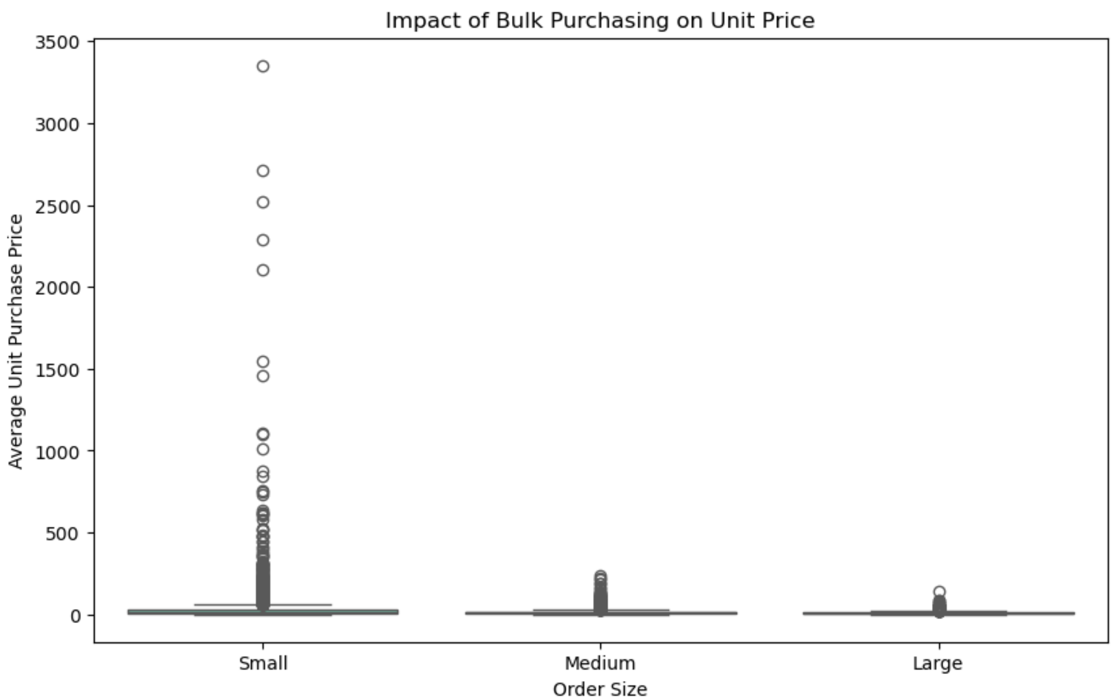
[78]:
```
# Calculate Unit Purchase Price per Vendor & Volume Group
df["UnitPurchasePrice"] = df["TotalPurchaseDollars"] /␣
 ↪df["TotalPurchaseQuantity"]

# Group by Order Sizes (e.g., Small, Medium, Large Purchases)
df["OrderSize"] = pd.qcut(df["TotalPurchaseQuantity"], q=3, labels=["Small",␣
 ↪"Medium", "Large"])

# Analyze Cost Savings per Order Size
bulk_purchase_analysis = df.groupby("OrderSize")["UnitPurchasePrice"].mean().
 ↪reset_index()
```

```python
print(bulk_purchase_analysis)
```

```
  OrderSize  UnitPurchasePrice
0     Small          39.068186
1    Medium          15.486414
2     Large          10.777625
```

[80]:

```python
plt.figure(figsize=(10, 6))
sns.boxplot(data=df, x="OrderSize", y="UnitPurchasePrice", palette="Set2")
plt.title("Impact of Bulk Purchasing on Unit Price")
plt.xlabel("Order Size")
plt.ylabel("Average Unit Purchase Price")
plt.show()
```



- Vendors buying in bulk (Large Order Size) get the lowest unit price ($10.78 per unit), meaning higher margins if they can manage inventory efficiently.
- The price difference between Small and Large orders is substantial (~72% reduction in unit cost)
- This suggests that bulk pricing strategies successfully encourage vendors to purchase in larger volumes, leading to higher overall sales despite lower per-unit revenue.

Which vendors have low inventory turnover, indicating excess stock and slow-moving products?

[86]:
```python
# Identify Low Inventory Turnover Vendors
low_turnover_vendors = df[df["StockTurnover"] < 1].
 ↪groupby("VendorName")["StockTurnover"].mean().reset_index()

# Sort by Lowest Turnover
low_turnover_vendors = low_turnover_vendors.sort_values(by="StockTurnover",␣
 ↪ascending=True)
low_turnover_vendors.head(10)
```

[86]:

	VendorName	StockTurnover
0	ALISA CARR BEVERAGES	0.615385
36	HIGHLAND WINE MERCHANTS LLC	0.708333
60	PARK STREET IMPORTS LLC	0.751306
19	Circa Wines	0.755676
26	Dunn Wine Brokers	0.766022
15	CENTEUR IMPORTS LLC	0.773953
78	SMOKY QUARTZ DISTILLERY LLC	0.783835
90	TAMWORTH DISTILLING	0.797078
91	THE IMPORTED GRAPE LLC	0.807569
101	WALPOLE MTN VIEW WINERY	0.820548

- Slow-moving inventory increases holding costs (warehouse rent, insurance, depreciation)
- Identifying vendors with low inventory turnover is critical for business efficiency, cost reduction, and profitability

How much capital is locked in unsold inventory per vendor, and which vendors contribute the most to it?

[92]:
```python
# Calculate Unsold Inventory Value
df["UnsoldInventoryValue"] = (df["TotalPurchaseQuantity"] -␣
 ↪df["TotalSalesQuantity"]) * df["PurchasePrice"]
print('Total Unsold Capital:', format_dollars(df["UnsoldInventoryValue"].sum()))

# Aggregate Capital Locked per Vendor
inventory_value_per_vendor = df.groupby("VendorName")["UnsoldInventoryValue"].
 ↪sum().reset_index()

# Sort Vendors with the Highest Locked Capital
inventory_value_per_vendor = inventory_value_per_vendor.
 ↪sort_values(by="UnsoldInventoryValue", ascending=False)
inventory_value_per_vendor['UnsoldInventoryValue'] =␣
 ↪inventory_value_per_vendor['UnsoldInventoryValue'].apply(format_dollars)
inventory_value_per_vendor.head(10)
```

```
Total Unsold Capital: 2.71M
```

[92]:

	VendorName	UnsoldInventoryValue
25	DIAGEO NORTH AMERICA INC	722.21K

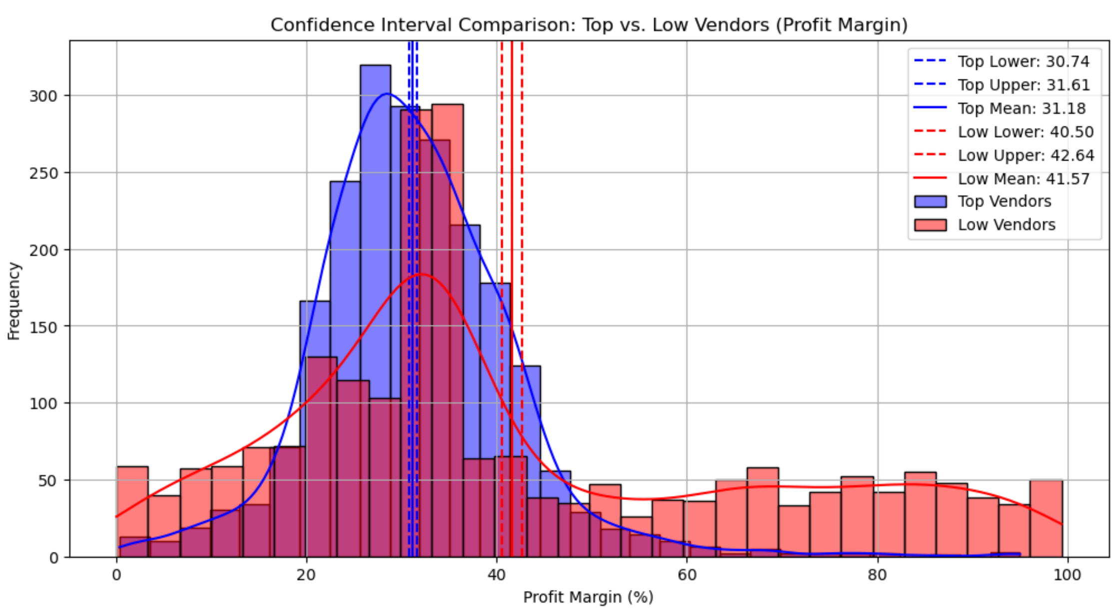
```
46     JIM BEAM BRANDS COMPANY              554.67K
68           PERNOD RICARD USA              470.63K
116  WILLIAM GRANT & SONS INC               401.96K
30           E & J GALLO WINERY             228.28K
79               SAZERAC CO INC             198.44K
11           BROWN-FORMAN CORP              177.73K
20   CONSTELLATION BRANDS INC               133.62K
61       MOET HENNESSY USA INC              126.48K
77     REMY COINTREAU USA INC               118.60K
```

What is the 95% confidence intervals for profit margins of top-performing and low-performing vendors.

[95]:
```
# Define top and low vendors based on Total Sales Dollars (Top 25% & Bottom 25%)
top_threshold = df["TotalSalesDollars"].quantile(0.75)
low_threshold = df["TotalSalesDollars"].quantile(0.25)

top_vendors = df[df["TotalSalesDollars"] >= top_threshold]["ProfitMargin"].
 ↪dropna()
low_vendors = df[df["TotalSalesDollars"] <= low_threshold]["ProfitMargin"].
 ↪dropna()

# Function to compute confidence interval
def confidence_interval(data, confidence=0.95):
    mean_val = np.mean(data)
    std_err = np.std(data, ddof=1) / np.sqrt(len(data))  # Standard error
    t_critical = stats.t.ppf((1 + confidence) / 2, df=len(data) - 1)
    margin_of_error = t_critical * std_err
    return mean_val, mean_val - margin_of_error, mean_val + margin_of_error

# Compute confidence intervals
top_mean, top_lower, top_upper = confidence_interval(top_vendors)
low_mean, low_lower, low_upper = confidence_interval(low_vendors)

print(f"Top Vendors 95% CI: ({top_lower:.2f}, {top_upper:.2f}), Mean: {top_mean:
 ↪.2f}")
print(f"Low Vendors 95% CI: ({low_lower:.2f}, {low_upper:.2f}), Mean: {low_mean:
 ↪.2f}")

plt.figure(figsize=(12, 6))

# Top Vendors Plot
sns.histplot(top_vendors, kde=True, color="blue", bins=30, alpha=0.5,␣
 ↪label="Top Vendors")
plt.axvline(top_lower, color="blue", linestyle="--", label=f"Top Lower:␣
 ↪{top_lower:.2f}")
```

```
plt.axvline(top_upper, color="blue", linestyle="--", label=f"Top Upper: {top_upper:.2f}")
plt.axvline(top_mean, color="blue", linestyle="-", label=f"Top Mean: {top_mean:.2f}")

# Low Vendors Plot
sns.histplot(low_vendors, kde=True, color="red", bins=30, alpha=0.5, label="Low Vendors")
plt.axvline(low_lower, color="red", linestyle="--", label=f"Low Lower: {low_lower:.2f}")
plt.axvline(low_upper, color="red", linestyle="--", label=f"Low Upper: {low_upper:.2f}")
plt.axvline(low_mean, color="red", linestyle="-", label=f"Low Mean: {low_mean:.2f}")

# Finalize Plot
plt.title("Confidence Interval Comparison: Top vs. Low Vendors (Profit Margin)")
plt.xlabel("Profit Margin (%)")
plt.ylabel("Frequency")
plt.legend()
plt.grid(True)
plt.show()
```

```
Top Vendors 95% CI: (30.74, 31.61), Mean: 31.18
Low Vendors 95% CI: (40.50, 42.64), Mean: 41.57
```



- The confidence interval for low-performing vendors (40.48% to 42.62%) is significantly higher than that of top-performing vendors (30.74% to 31.61%).

- This suggests that vendors with lower sales tend to maintain higher profit margins, potentially due to premium pricing or lower operational costs.
- For High-Performing Vendors: If they aim to improve profitability, they could explore selective price adjustments, cost optimization, or bundling strategies.
- For Low-Performing Vendors: Despite higher margins, their low sales volume might indicate a need for better marketing, competitive pricing, or improved distribution strategies.

Is there a significant difference in profit margins between top-performing and low-performing vendors? Hypothesis:

H (Null Hypothesis): There is no significant difference in the mean profit margins of top-performing and low-performing vendors.

H (Alternative Hypothesis): The mean profit margins of top-performing and low-performing vendors are significantly different.

[99]:

```
top_threshold = df["TotalSalesDollars"].quantile(0.75)
low_threshold = df["TotalSalesDollars"].quantile(0.25)

top_vendors = df[df["TotalSalesDollars"] >= top_threshold]["ProfitMargin"].
 ↪dropna()
low_vendors = df[df["TotalSalesDollars"] <= low_threshold]["ProfitMargin"].
 ↪dropna()

# Perform Two-Sample T-Test
t_stat, p_value = ttest_ind(top_vendors, low_vendors, equal_var=False)

# Print results
print(f"T-Statistic: {t_stat:.4f}, P-Value: {p_value:.4f}")
if p_value < 0.05:
    print("Reject H : There is a significant difference in profit margins␣
 ↪between top and low-performing vendors.")
else:
    print("Fail to Reject H : No significant difference in profit margins.")
```

```
T-Statistic: -17.6695, P-Value: 0.0000
Reject H : There is a significant difference in profit margins between top and
low-performing vendors.
```

[101]:

```
# Use this script to save csv files into database with their filename as␣
 ↪tablename
import pandas as pd
import os
from sqlalchemy import create_engine
import logging
import time
```

```python
logging.basicConfig(
    filename="logs/ingestion_db.log",
    level=logging.DEBUG,
    format="%(asctime)s - %(levelname)s - %(message)s",
    filemode="a"
)

engine = create_engine('sqlite:///inventory.db')

def ingest_db(df, table_name, engine):
    '''this function will ingest the dataframe into database table'''
    df.to_sql(table_name, con = engine, if_exists = 'replace', index = False)

def load_raw_data():
    '''this function will load the CSVs as dataframe and ingest into db'''
    start = time.time()
    for file in os.listdir('data'):
        if '.csv' in file:
            df = pd.read_csv('data/'+file)
            logging.info(f'Ingesting {file} in db')
            ingest_db(df, file[:-4], engine)
    end = time.time()
    total_time = (end - start)/60
    logging.info('--------------Ingestion Complete------------')

    logging.info(f'\nTotal Time Taken: {total_time} minutes')

if __name__ == '__main__':
    load_raw_data()
```

[ ]:

```python

```