vendor-inventory

July 10, 2025

#Importing the CSV files into Database

[1]:
```
import pandas as pd
import os
from sqlalchemy import create_engine
import logging
import time
```

[2]:
```
logging.basicConfig(
    filename="content/logs/ingestion_db.log",
    format="%(asctime)s - %(levelname)s - %(message)s",
    level=logging.DEBUG,
    filemode="a"
)
```

[3]:
```
engine = create_engine('sqlite:///inventor.db')
```

[4]:
```
'''This function will ingest Data Frame into Database'''
def ingest_db(df, table_name, engine):
  df.to_sql(table_name, con = engine, if_exists='replace', index=False)
```

[5]:
```
def load_raw_data():
    start_time = time.time()
    for file in os.listdir('/content'):
        if '.csv' in file:
            table_name = file[:-4]
            logging.info(f'Attempting to process file: {file}')
            try:
                logging.info(f'Starting ingestion of {file} into table␣
 ↪{table_name}')
                # Read CSV in chunks
                chunk_size = 10000 # Reduced chunk size
                for i, chunk in enumerate(pd.read_csv(file,␣
 ↪chunksize=chunk_size)):
                    logging.info(f'Ingesting chunk {i} of {file}')
                    try:
                        chunk.to_sql(table_name, con=engine, if_exists='append'␣
 ↪if i > 0 else 'replace', index=False)
```

```
                        logging.info(f'Chunk {i} of {file} ingested␣
↪successfully')
                    except Exception as db_error:
                        logging.error(f'Error ingesting chunk {i} of {file}␣
↪into database: {db_error}')
                        # Consider breaking or continuing based on severity of␣
↪db error
                logging.info(f'{file} fully ingested successfully into table␣
↪{table_name}')
                print(f'{file} fully ingested successfully into table␣
↪{table_name}')
            except Exception as read_error:
                logging.error(f'Error reading or processing file {file}:␣
↪{read_error}')

    end_time = time.time()
    total_time = (end_time - start_time) / 60
    logging.info(f'Total time taken for ingestion: {total_time:.2f} minutes')
    print(f'Total time taken for ingestion: {total_time:.2f} minutes')
```

[6]:
```
if __name__ == "__main__":
    load_raw_data()
```

```
end_inventory.csv fully ingested successfully into table end_inventory
purchases.csv fully ingested successfully into table purchases
sales.csv fully ingested successfully into table sales
vendor_invoice.csv fully ingested successfully into table vendor_invoice
purchase_prices.csv fully ingested successfully into table purchase_prices
begin_inventory.csv fully ingested successfully into table begin_inventory
Total time taken for ingestion: 6.83 minutes
```

[ ]:
```
'''This is failng due to Memory issue'''
def load_raw_data():
    start_time = time.time()
    for file in os.listdir('//content'):
        if '.csv' in file:
          df = pd.read_csv(file)
          ingest_db(df, file[:-4], engine)
          print(df.shape)
    end_time = time.time()
    total_time = (end_time - start_time) / 60
    logging.info(f'Total time taken for ingestion: {total_time:.2f} minutes')
```

```
'logs' directory already exists.
```

1 Bsaic Exploratory Data Analysis

Understanding the dataset to explore how the data is present in the database and and if there is a need of creating some aggregated tables that can help with: * Vendor selection for profitability * Product pricing Optimization

[7]:
```
import pandas as pd
import sqlite3
```

[8]:
```
#creating database connection
conn = sqlite3.connect('inventor.db')
print("Opened database successfully")
```

```
Opened database successfully
```

[ ]:
```
#checking tables present in the database
tables = pd.read_sql_query("SELECT name FROM sqlite_master WHERE type='table';
 ↪", conn)
tables
```

[ ]:
```
              name
0  begin_inventory
1   vendor_invoice
2    end_inventory
3  purchase_prices
4            sales
5        purchases
```

Let's check the total records present in each table and display few records.

[ ]:
```
for table in tables['name']:
  print("-"*50,table,"-"*50)
  print("Count of Records",pd.read_sql(f"SELECT count(*) AS count FROM␣
 ↪{table}", conn)['count'][0])
  display(pd.read_sql(f"SELECT * FROM {table} LIMIT 5", conn))
```

```
-------------------------------------------------- begin_inventory
--------------------------------------------------
Count of Records 206529
```

	InventoryId	Store	City	Brand	Description	Size	onHand	Price	startDate
0	1_HARDERSFIELD_58	1	HARDERSFIELD	58	Gekkeikan Black & Gold Sake	750mL	8	12.99	2024-01-01
1	1_HARDERSFIELD_60	1	HARDERSFIELD	60	Canadian Club 1858 VAP				
2	1_HARDERSFIELD_62	1	HARDERSFIELD	62	Herradura Silver Tequila				
3	1_HARDERSFIELD_63	1	HARDERSFIELD	63	Herradura Reposado Tequila				
4	1_HARDERSFIELD_72	1	HARDERSFIELD	72	No. 3 London Dry Gin				

```
1  750mL       7  10.99  2024-01-01
2  750mL       6  36.99  2024-01-01
3  750mL       3  38.99  2024-01-01
4  750mL       6  34.99  2024-01-01

-------------------------------------------------- vendor_invoice
--------------------------------------------------
Count of Records 5543

   VendorNumber                   VendorName InvoiceDate  PONumber  \
0           105  ALTAMAR BRANDS LLC           2024-01-04      8124
1          4466  AMERICAN VINTAGE BEVERAGE    2024-01-07      8137
2           388  ATLANTIC IMPORTING COMPANY   2024-01-09      8169
3           480  BACARDI USA INC              2024-01-12      8106
4           516  BANFI PRODUCTS CORP          2024-01-07      8170

       PODate     PayDate  Quantity    Dollars  Freight Approval
0  2023-12-21  2024-02-16         6     214.26     3.47     None
1  2023-12-22  2024-02-21        15     140.55     8.57     None
2  2023-12-24  2024-02-16         5     106.60     4.61     None
3  2023-12-20  2024-02-05     10100  137483.78  2935.20     None
4  2023-12-24  2024-02-12      1935   15527.25   429.20     None

-------------------------------------------------- end_inventory
--------------------------------------------------
Count of Records 224489

         InventoryId  Store          City  Brand                  Description  \
0  1_HARDERSFIELD_58      1  HARDERSFIELD     58  Gekkeikan Black & Gold Sake
1  1_HARDERSFIELD_62      1  HARDERSFIELD     62     Herradura Silver Tequila
2  1_HARDERSFIELD_63      1  HARDERSFIELD     63   Herradura Reposado Tequila
3  1_HARDERSFIELD_72      1  HARDERSFIELD     72         No. 3 London Dry Gin
4  1_HARDERSFIELD_75      1  HARDERSFIELD     75    Three Olives Tomato Vodka

    Size  onHand  Price     endDate
0  750mL      11  12.99  2024-12-31
1  750mL       7  36.99  2024-12-31
2  750mL       7  38.99  2024-12-31
3  750mL       4  34.99  2024-12-31
4  750mL       7  14.99  2024-12-31

-------------------------------------------------- purchase_prices
--------------------------------------------------
Count of Records 12261

   Brand                  Description  Price   Size Volume  Classification  \
0     58  Gekkeikan Black & Gold Sake  12.99  750mL    750               1
1     62     Herradura Silver Tequila  36.99  750mL    750               1
2     63   Herradura Reposado Tequila  38.99  750mL    750               1
3     72         No. 3 London Dry Gin  34.99  750mL    750               1
4     75    Three Olives Tomato Vodka  14.99  750mL    750               1
```

```
   PurchasePrice  VendorNumber                 VendorName
0           9.28          8320  SHAW ROSS INT L IMP LTD
1          28.67          1128  BROWN-FORMAN CORP
2          30.46          1128  BROWN-FORMAN CORP
3          26.11          9165  ULTRA BEVERAGE COMPANY LLP
4          10.94          7245  PROXIMO SPIRITS INC.
```

---------- sales ----------

Count of Records 12825363

```
           InventoryId  Store  Brand                 Description        Size  \
0  1_HARDERSFIELD_1004      1   1004  Jim Beam w/2 Rocks Glasses       750mL
1  1_HARDERSFIELD_1004      1   1004  Jim Beam w/2 Rocks Glasses       750mL
2  1_HARDERSFIELD_1004      1   1004  Jim Beam w/2 Rocks Glasses       750mL
3  1_HARDERSFIELD_1004      1   1004  Jim Beam w/2 Rocks Glasses       750mL
4  1_HARDERSFIELD_1005      1   1005     Maker's Mark Combo Pack  375mL 2 Pk

   SalesQuantity  SalesDollars  SalesPrice   SalesDate  Volume  \
0              1         16.49       16.49  2024-01-01   750.0
1              2         32.98       16.49  2024-01-02   750.0
2              1         16.49       16.49  2024-01-03   750.0
3              1         14.49       14.49  2024-01-08   750.0
4              2         69.98       34.99  2024-01-09   375.0

   Classification  ExciseTax  VendorNo                  VendorName
0               1       0.79     12546  JIM BEAM BRANDS COMPANY
1               1       1.57     12546  JIM BEAM BRANDS COMPANY
2               1       0.79     12546  JIM BEAM BRANDS COMPANY
3               1       0.79     12546  JIM BEAM BRANDS COMPANY
4               1       0.79     12546  JIM BEAM BRANDS COMPANY
```

---------- purchases ----------

Count of Records 2372474

```
           InventoryId  Store  Brand                   Description   Size  \
0    69_MOUNTMEND_8412     69   8412     Tequila Ocho Plata Fresno  750mL
1     30_CULCHETH_5255     30   5255  TGI Fridays Ultimte Mudslide  1.75L
2    34_PITMERDEN_5215     34   5215  TGI Fridays Long Island Iced  1.75L
3  1_HARDERSFIELD_5255      1   5255  TGI Fridays Ultimte Mudslide  1.75L
4    76_DONCASTER_2034     76   2034     Glendalough Double Barrel  750mL

   VendorNumber                    VendorName  PONumber      PODate  \
0           105  ALTAMAR BRANDS LLC               8124  2023-12-21
1          4466  AMERICAN VINTAGE BEVERAGE        8137  2023-12-22
2          4466  AMERICAN VINTAGE BEVERAGE        8137  2023-12-22
3          4466  AMERICAN VINTAGE BEVERAGE        8137  2023-12-22
4           388  ATLANTIC IMPORTING COMPANY       8169  2023-12-24
```

```
  ReceivingDate InvoiceDate     PayDate  PurchasePrice  Quantity  Dollars  \
0    2024-01-02  2024-01-04  2024-02-16          35.71         6   214.26
1    2024-01-01  2024-01-07  2024-02-21           9.35         4    37.40
2    2024-01-02  2024-01-07  2024-02-21           9.41         5    47.05
3    2024-01-01  2024-01-07  2024-02-21           9.35         6    56.10
4    2024-01-02  2024-01-09  2024-02-16          21.32         5   106.60

   Classification
0               1
1               1
2               1
3               1
4               1
```

[ ]:
```
#Checking the datasets for the random vendor number 4466
vendor_invoice = pd.read_sql("SELECT * FROM vendor_invoice WHERE VendorNumber =␣
↪4466",conn)
purchase_prices = pd.read_sql("SELECT * FROM purchase_prices WHERE VendorNumber␣
↪= 4466",conn)
purchases = pd.read_sql("SELECT * FROM purchases WHERE VendorNumber =␣
↪4466",conn)
sales = pd.read_sql("SELECT * FROM sales WHERE VendorNo = 4466",conn)
```

[ ]:
```
purchases.groupby(['Brand','PurchasePrice'])[['Quantity','Dollars']].sum()
```

[ ]:
```
                     Quantity   Dollars
Brand PurchasePrice
3140  11.19              4640  51921.60
5215  9.41               4923  46325.43
5255  9.35               6215  58110.25
```

[ ]:
```
sales.groupby(['Brand'])[['SalesPrice','SalesQuantity','SalesDollars']].sum()
```

[ ]:
```
       SalesPrice  SalesQuantity  SalesDollars
Brand
3140     30071.85           3890      50531.10
5215     41542.02           4651      60416.49
5255     51180.60           6096      79187.04
```

- The purchases table contains actual purchase data, including the date of purchase, products(brands) purchased by vendors, the amount paid (in dollars), and the quantity purchased.
- The purchase price column is derived from the purchase_prices table, which provides product-wise actual and purchase prices. The combination of vendor and brand is unique in this table.
- The vendor_invoice table aggregates data from the purchases table, summarizing quantity and dollar amounts, along with and additional column for freight. This table maintains uniqueness based on vendor and PO number.

- The sales table captures actual sales transactions, detailing the brands purchased by vendors, the quantity sold, the selling price, and the revenue earned.

As the data that we need for the analysis is distributed in different tables, we need to create a summary table containing: * purchase transactions made by vendors * sales transaction data * freight costs for each vendor. * actual product prices from vendors.

[ ]:
```
vendor_invoice.columns
```

[ ]:
```
Index(['VendorNumber', 'VendorName', 'InvoiceDate', 'PONumber', 'PODate',
       'PayDate', 'Quantity', 'Dollars', 'Freight', 'Approval'],
      dtype='object')
```

[ ]:
```
pd.read_sql('''SELECT VendorNumber, SUM(Quantity) AS total_quantity,
SUM(Dollars) AS total_dollars, SUM(Freight) AS total_freight
FROM vendor_invoice GROUP BY VendorNumber''', conn)
```

[ ]:
```
     VendorNumber  total_quantity  total_dollars  total_freight
0               2             328        5630.88          27.08
1              54               1         105.07           0.48
2              60            4732       76770.25         367.52
3             105             332       11706.20          62.39
4             200             132        1205.16           6.19
..            …             …             …             …
121         98450           10463      168993.61         856.02
122         99166            1212       25961.04         130.09
123        172662            1629       34708.03         178.34
124        173357            1990       41036.44         202.50
125        201359               1          17.00           0.09

[126 rows x 4 columns]
```

[ ]:
```
purchase_prices.columns
```

[ ]:
```
Index(['Brand', 'Description', 'Price', 'Size', 'Volume', 'Classification',
       'PurchasePrice', 'VendorNumber', 'VendorName'],
      dtype='object')
```

[ ]:
```
purchases.columns
```

[ ]:
```
Index(['InventoryId', 'Store', 'Brand', 'Description', 'Size', 'VendorNumber',
       'VendorName', 'PONumber', 'PODate', 'ReceivingDate', 'InvoiceDate',
       'PayDate', 'PurchasePrice', 'Quantity', 'Dollars', 'Classification'],
      dtype='object')
```

[ ]:
```
pd.read_sql('''SELECT p.VendorNumber, p.VendorName,
p.Brand, p.PurchasePrice,
pp.Volume AS volume, pp.Price AS actual_price,
```

```
SUM(p.Quantity) AS total_purchase_quantity,
SUM(p.Dollars) AS total_purchase_dollars
FROM purchases p
JOIN purchase_prices pp ON p.Brand = pp.Brand
WHERE p.PurchasePrice > 0
GROUP BY p.VendorNumber, p.VendorName, p.Brand''', conn)
```

[ ]:

	VendorNumber	VendorName	Brand	PurchasePrice	volume	actual_price	total_purchase_quantity	total_purchase_dollars
0	2	IRA GOLDMAN AND WILLIAMS, LLP	90085	23.86	750	36.99	8	190.88
1	2	IRA GOLDMAN AND WILLIAMS, LLP	90609	17.00	162.5	24.99	320	5440.00
2	54	AAPER ALCOHOL & CHEMICAL CO	990	105.07	3750	134.49	1	105.07
3	60	ADAMBA IMPORTS INTL INC	771	11.44	750	14.99	39	446.16
4	60	ADAMBA IMPORTS INTL INC	3401	11.10	1750	14.99	6	66.60
…	…	…	…	…	…	…	…	…
10687	173357	TAMWORTH DISTILLING	2804	32.14	750	44.99	210	6749.40
10688	173357	TAMWORTH DISTILLING	3666	18.79	375	24.99	520	9770.80
10689	173357	TAMWORTH DISTILLING	3848	23.30	750	30.99	28	652.40
10690	173357	TAMWORTH DISTILLING	3909	19.37	750	24.99	1232	23863.84
10691	201359	FLAVOR ESSENCE INC	90609	17.00	162.5	24.99	1	17.00

[10692 rows x 8 columns]

[ ]:
```
sales.columns
```

[ ]:
```
Index(['InventoryId', 'Store', 'Brand', 'Description', 'Size', 'SalesQuantity',
       'SalesDollars', 'SalesPrice', 'SalesDate', 'Volume', 'Classification',
       'ExciseTax', 'VendorNo', 'VendorName'],
      dtype='object')
```

[ ]:
```
pd.read_sql('''SELECT VendorNo, Brand,
SUM(SalesPrice) AS total_sales_price,
SUM(SalesQuantity) AS total_sales_quantity,
SUM(SalesDollars) AS total_sales_dollars,
SUM(ExciseTax) AS total_ExciseTax
FROM sales GROUP BY VendorNo, Brand''', conn)
```

[ ]:

	VendorNo	Brand	total_sales_price	total_sales_quantity	total_sales_dollars	total_ExciseTax
0	2	90085	295.92	18	665.82	2.00
1	2	90609	449.82	24	599.76	0.52
2	60	771	494.67	47	704.53	37.01
3	60	3979	41682.51	3931	66871.69	7224.06
4	105	2529	59.98	12	359.88	9.44
…	…	…	…	…	…	…
11267	173357	2804	3194.29	140	6298.60	110.33
11268	173357	3666	4873.05	360	8996.40	141.19
11269	173357	3848	92.97	6	185.94	4.71
11270	173357	3909	14469.21	982	24540.18	773.87
11271	201359	90609	1324.47	59	1474.41	1.24

[11272 rows x 6 columns]

[9]:
```
#Taking the entire tables
vendor_invoice = pd.read_sql("SELECT * FROM vendor_invoice",conn)
purchase_prices = pd.read_sql("SELECT * FROM purchase_prices",conn)
purchases = pd.read_sql("SELECT * FROM purchases",conn)
```

```
chunk_size = 1000000  # Defined a suitable chunk size
all_sales_chunks = [] # Initialize an empty list to store the chunks

# Iterate over chunks of the sales table
for i, sales_chunk in enumerate(pd.read_sql("SELECT * FROM sales", conn,␣
 ↪chunksize=chunk_size)):
    print(f"Processing chunk {i+1}, containing {len(sales_chunk)} rows.")

    # Append the current chunk to the list
    all_sales_chunks.append(sales_chunk)

# Concatenate all the chunks into a single DataFrame after the loop
# Be aware that this step will still require enough memory to hold the final␣
 ↪DataFrame
try:
    sales = pd.concat(all_sales_chunks, ignore_index=True)
    print("\nSuccessfully combined all chunks into the 'sales' DataFrame.")
    print(f"Shape of the final sales DataFrame: {sales.shape}")
except Exception as e:
    print(f"\nError concatenating chunks: {e}")
    print("This might still be a memory issue if the combined DataFrame is too␣
 ↪large.")
```

```
Processing chunk 1, containing 1000000 rows.
Processing chunk 2, containing 1000000 rows.
Processing chunk 3, containing 1000000 rows.
Processing chunk 4, containing 1000000 rows.
Processing chunk 5, containing 1000000 rows.
Processing chunk 6, containing 1000000 rows.
Processing chunk 7, containing 1000000 rows.
Processing chunk 8, containing 1000000 rows.
Processing chunk 9, containing 1000000 rows.
Processing chunk 10, containing 1000000 rows.
Processing chunk 11, containing 1000000 rows.
Processing chunk 12, containing 1000000 rows.
Processing chunk 13, containing 825363 rows.

Successfully combined all chunks into the 'sales' DataFrame.
Shape of the final sales DataFrame: (12825363, 14)
```

[ ]:
```
#This query is taking lot of time to execute so we will optimize this query
final_table = pd.read_sql_query('''
SELECT pp.VendorNumber,
pp.Brand,
pp.Price AS ActualPrice,
pp.PurchasePrice,
SUM(s.SalesQuantity) AS TotslSalesQuantity,
```

```
SUM(s.SalesDollars) AS TotalSalesDollar,
SUM(s.SalesPrice) AS TotalSalesPrice,
SUM(s.ExciseTax) AS TotalExciseTax,
SUM(vi.Quantity) AS TotalPurchaseQuantity,
SUM(vi.Dollars) AS TotalPurchaseDollars,
SUM(vi.Freight) AS TotalFreightCost
FROM purchase_prices pp
JOIN sales s
ON pp.VendorNumber = s.VendorNo
AND pp.Brand = s.Brand
JOIN vendor_invoice vi
ON pp.VendorNumber = vi.VendorNumber
GROUP BY pp.VendorNumber, pp.Brand, pp.Price, pp.PurchasePrice
''',conn)
```

[10]:
```
import time
start_time = time.time()
vendor_sales_summary = pd.read_sql_query('''WITH FreightSummary AS (
    SELECT VendorNumber, SUM(Freight) AS FreightCost
    FROM vendor_invoice
    GROUP BY VendorNumber
),

PurchaseSummary AS (
    SELECT p.VendorNumber,
    p.VendorName,
    p.Brand,
    p.Description,
    p.PurchasePrice,
    pp.Price AS ActualPrice,
    pp.Volume AS Volume,
    SUM(p.Quantity) AS TotalPurchaseQuantity,
    SUM(p.Dollars) AS TotalPurchaseDollars
    FROM purchases p
    JOIN purchase_prices pp ON p.Brand = pp.Brand
    WHERE p.PurchasePrice > 0
    GROUP BY p.VendorNumber, p.VendorName, p.Brand, p.Description, p.
 ↪PurchasePrice, pp.Price, pp.Volume),

SalesSummary AS (
  SELECT VendorNo, Brand,
  SUM(SalesPrice) AS TotalSalesPrice,
  SUM(SalesQuantity) AS TotalSalesQuantity,
  SUM(SalesDollars) AS TotalSalesDollars,
  SUM(ExciseTax) AS TotalExciseTax
  FROM sales
  GROUP BY VendorNo, Brand
```

```
)

SELECT
ps.VendorNumber,
ps.VendorName,
ps.Brand,
ps.Description,
ps.PurchasePrice,
ps.ActualPrice,
ps.Volume,
ps.TotalPurchaseQuantity,
ps.TotalPurchaseDollars,
ss.TotalSalesPrice,
ss.TotalSalesQuantity,
ss.TotalSalesDollars,
ss.TotalExciseTax,
fs.FreightCost
FROM PurchaseSummary ps
LEFT JOIN SalesSummary ss ON ps.VendorNumber = ss.VendorNo AND ps.Brand = ss.
 ↪Brand
LEFT JOIN FreightSummary fs ON ps.VendorNumber = fs.VendorNumber
ORDER BY ps.TotalPurchaseDollars DESC
''',conn)

end_time = time.time()
total_time = (end_time - start_time) / 60
print(f'Total time taken for ingestion: {total_time:.2f} minutes')
```

```
Total time taken for ingestion: 0.95 minutes
```

[ ]:
```
vendor_sales_summary
```

[ ]:
```
       VendorNumber                  VendorName  Brand  \
0              1128  BROWN-FORMAN CORP             1233
1              4425        MARTIGNETTI COMPANIES   3405
2             17035  PERNOD RICARD USA             8068
3              3960  DIAGEO NORTH AMERICA INC      4261
4              3960  DIAGEO NORTH AMERICA INC      3545
…               …                             …    …
10687          9815  WINE GROUP INC                8527
10688          8004  SAZERAC CO INC                5683
10689          3924  HEAVEN HILL DISTILLERIES      9123
10690          3960  DIAGEO NORTH AMERICA INC      6127
10691          7245  PROXIMO SPIRITS INC.          3065

                      Description  PurchasePrice  ActualPrice Volume  \
0          Jack Daniels No 7 Black          26.27        36.99   1750
```

```
1            Tito's Handmade Vodka          23.19        28.99   1750
2                 Absolut 80 Proof          18.24        24.99   1750
3           Capt Morgan Spiced Rum          16.17        22.99   1750
4                  Ketel One Vodka          21.89        29.99   1750
…                              …             …          …     …
10687  Concannon Glen Ellen Wh Zin           1.32         4.99    750
10688  Dr McGillicuddy's Apple Pie           0.39         0.49     50
10689              Deep Eddy Vodka           0.74         0.99     50
10690  The Club Strawbry Margarita           1.47         1.99    200
10691     Three Olives Grape Vodka           0.71         0.99     50

       TotalPurchaseQuantity  TotalPurchaseDollars  TotalSalesPrice  \
0                     145080            3811251.60        672819.31
1                     164038            3804041.22        561512.37
2                     187407            3418303.68        461140.15
3                     201682            3261197.94        420050.01
4                     138109            3023206.01        545778.28
…                        …                     …                …
10687                      2                  2.64            10.96
10688                      6                  2.34             1.47
10689                      2                  1.48             0.99
10690                      1                  1.47            77.61
10691                      1                  0.71            33.66

       TotalSalesQuantity  TotalSalesDollars  TotalExciseTax  FreightCost
0                142049.0       5.101920e+06       260999.20     68601.68
1                160247.0       4.819073e+06       294438.66    144929.24
2                187140.0       4.538121e+06       343854.07    123780.22
3                200412.0       4.475973e+06       368242.80    257032.07
4                135838.0       4.223108e+06       249587.83    257032.07
…                     …                  …               …            …
10687                5.0       1.595000e+01            0.55     27100.41
10688              134.0       6.566000e+01            7.04     50293.62
10689                2.0       1.980000e+00            0.10     14069.87
10690               72.0       1.432800e+02           15.12    257032.07
10691               86.0       8.514000e+01            4.46     38994.78

[10692 rows x 14 columns]
```

This query generates a vendor-wise sales and purchase summary, which is valuable for:

Performance Optimization: * The query invloves heavy joins and aggregations on large datasets like sales and purchases. * Storing the pre-aggregated results avoids repeated expensive computations. * Helps in analyzing sales, purchases, and pricing for different vendors and brands. * Future Benifits of Storing this data for faster Dashboarding & reporting. * Instead of running expensive queries each time, dashboards can fetch data quickly from vendor_sales_summary.

Now let's check if there is any incomsistancy in our final Dataset

[ ]:
```
vendor_sales_summary.shape
```

[ ]:
```
(10692, 14)
```

[ ]:
```
vendor_sales_summary.dtypes
```

[ ]:
```
VendorNumber               int64
VendorName                object
Brand                      int64
Description               object
PurchasePrice            float64
ActualPrice              float64
Volume                    object
TotalPurchaseQuantity      int64
TotalPurchaseDollars     float64
TotalSalesPrice          float64
TotalSalesQuantity       float64
TotalSalesDollars        float64
TotalExciseTax           float64
FreightCost              float64
dtype: object
```

Volume column should be integer/float but in the dataset it is object. So we will change it.

[ ]:
```
vendor_sales_summary['Volume'] = vendor_sales_summary['Volume'].
↪astype('float64')
```

[ ]:
```
vendor_sales_summary.dtypes
```

[ ]:
```
VendorNumber               int64
VendorName                object
Brand                      int64
Description               object
PurchasePrice            float64
ActualPrice              float64
Volume                   float64
TotalPurchaseQuantity      int64
TotalPurchaseDollars     float64
TotalSalesPrice          float64
TotalSalesQuantity       float64
TotalSalesDollars        float64
TotalExciseTax           float64
FreightCost              float64
dtype: object
```

[ ]:
```
vendor_sales_summary['VendorName'].unique()
```

```
[ ]: array(['BROWN-FORMAN CORP          ', 'MARTIGNETTI COMPANIES',
             'PERNOD RICARD USA          ', 'DIAGEO NORTH AMERICA INC   ',
             'BACARDI USA INC            ', 'JIM BEAM BRANDS COMPANY    ',
             'MAJESTIC FINE WINES        ', 'ULTRA BEVERAGE COMPANY LLP ',
             'STOLI GROUP,(USA) LLC      ', 'PROXIMO SPIRITS INC.       ',
             'MOET HENNESSY USA INC      ', 'CAMPARI AMERICA            ',
             'SAZERAC CO INC             ', 'CONSTELLATION BRANDS INC   ',
             'M S WALKER INC             ', 'SAZERAC NORTH AMERICA INC. ',
             'PALM BAY INTERNATIONAL INC ', 'REMY COINTREAU USA INC     ',
             'SIDNEY FRANK IMPORTING CO  ', 'E & J GALLO WINERY         ',
             'WILLIAM GRANT & SONS INC   ', 'HEAVEN HILL DISTILLERIES   ',
             'DISARONNO INTERNATIONAL LLC', 'EDRINGTON AMERICAS         ',
             'CASTLE BRANDS CORP.        ', 'SOUTHERN WINE & SPIRITS NE ',
             'STE MICHELLE WINE ESTATES  ', 'TRINCHERO FAMILY ESTATES   ',
             'MHW LTD                    ', 'WINE GROUP INC             ',
             'PERFECTA WINES             ', 'LUXCO INC                  ',
             'TREASURY WINE ESTATES      ', 'DIAGEO CHATEAU ESTATE WINES',
             'SHAW ROSS INT L IMP LTD    ', 'PINE STATE TRADING CO      ',
             'PHILLIPS PRODUCTS CO.      ', 'CALEDONIA SPIRITS INC      ',
             'STATE WINE & SPIRITS   ', 'KOBRAND CORPORATION        ',
             'BANFI PRODUCTS CORP        ', 'VINEYARD BRANDS INC        ',
             'DELICATO VINEYARDS INC     ', 'FABRIZIA SPIRITS LLC       ',
             'DUGGANS DISTILLED PRODUCTS ', 'Serralles Usa LLC          ',
             'SEA HAGG DISTILLERY LLC    ', 'OLE SMOKY DISTILLERY LLC   ',
             'VRANKEN AMERICA            ', 'KLIN SPIRITS LLC           ',
             'LAIRD & CO                 ', 'ADAMBA IMPORTS INTL INC    ',
             'LATITUDE BEVERAGE COMPANY  ', 'FREDERICK WILDMAN & SONS   ',
             'MCCORMICK DISTILLING CO    ', 'CHARLES JACQUIN ET CIE INC ',
             'WESTERN SPIRITS BEVERAGE CO', 'MARSALLE COMPANY           ',
             'AMERICAN VINTAGE BEVERAGE  ', 'MANGO BOTTLING INC         ',
             'SWEET BABY VINEYARD        ', 'NICHE W & S                ',
             'LABELLE VYDS AND WINERY    ', 'FLAG HILL WINERY & VINEYARD',
             'SMOKY QUARTZ DISTILLERY LLC', 'PREMIUM PORT WINES, INC.   ',
             'Russian Standard Vodka     ', 'Dunn Wine Brokers          ',
             'WEIN BAUER INC             ', 'BULLY BOY DISTILLERS       ',
             'ATLANTIC IMPORTING COMPANY ', 'PREMIER DISTRIBUTORS       ',
             'VINILANDIA USA             ', 'PARK STREET IMPORTS LLC    ',
             'TAKARA SAKE USA INC        ', 'SEA BREEZE CELLARS LLC     ',
             'STARK BREWING COMPANY      ', 'TY KU LLC                  ',
             'PSP WINES ', 'TAMWORTH DISTILLING        ',
             'ZORVINO VINEYARDS          ', 'SOUTHERN GLAZERS W&S OF NE ',
             'HOOD RIVER DISTILLERS, Inc.', 'CRUSH WINES                ',
             'POVERTY LANE ORCHARDS      ', 'DJINN SPIRITS LLC          ',
             'MOONLIGHT MEADERY          ', 'TALL SHIP DISTILLERY LLC   ',
             'FORTUNE WINE BROKERS LLC   ', 'BLACK COVE BEVERAGES       ',
             'VINEXTRA INC               ', 'SURVILLE ENTERPRISES CORP  ',
             'JEWELL TOWNE VINEYARDS     ', 'SWEETWATER FARM         ',
```

```
'MARTIGNETTI COMPANIES ', 'ALTAMAR BRANDS LLC         ',
'CANDIA VINEYARDS           ', 'INCREDIBREW INC            ',
'ALISA CARR BEVERAGES          ', 'STELLAR IMPORTING CO LLC   ',
'FULCHINO VINEYARD INC      ',
'IRA GOLDMAN AND WILLIAMS, LLP          ',
'Circa Wines                ', 'VINEDREA WINES LLC         ',
'BLACK PRINCE DISTILLERY INC', 'VINEYARD BRANDS LLC        ',
'THE IMPORTED GRAPE LLC     ', 'WALPOLE MTN VIEW WINERY    ',
'GILMANTON WINERY & VINEYARD', 'HAUNTING WHISPER VYDS      ',
'STAR INDUSTRIES INC.       ', 'LOYAL DOG WINERY           ',
'R.P.IMPORTS INC            ', 'THE PIERPONT GROUP LLC     ',
'APPOLO VINEYARDS LLC       ', 'BLACK ROCK SPIRITS LLC     ',
'CENTEUR IMPORTS LLC        ', 'HIGHLAND WINE MERCHANTS LLC',
'AMERICAN SPIRITS EXCHANGE  ', 'UNCORKED       ',
'BRONCO WINE COMPANY        ', 'MILTONS DISTRIBUTING CO    ',
'TRUETT HURST               ', 'LAUREATE IMPORTS CO        ',
'FANTASY FINE WINES CORP    ', 'AAPER ALCOHOL & CHEMICAL CO',
'SILVER MOUNTAIN CIDERS     ', 'CAPSTONE INTERNATIONAL     ',
'FLAVOR ESSENCE INC         '], dtype=object)
```

There are some extra spaces in the "VendorName" column so we will remove it.

[ ]:
```
vendor_sales_summary['VendorName'] = vendor_sales_summary['VendorName'].str.
↪strip()
```

[ ]:
```
vendor_sales_summary.isnull().sum()
```

[ ]:
```
VendorNumber               0
VendorName                 0
Brand                      0
Description                0
PurchasePrice              0
ActualPrice                0
Volume                     0
TotalPurchaseQuantity      0
TotalPurchaseDollars       0
TotalSalesPrice          178
TotalSalesQuantity       178
TotalSalesDollars        178
TotalExciseTax           178
FreightCost                0
dtype: int64
```

We will fill the null values with 0

[ ]:
```
vendor_sales_summary.fillna(0, inplace=True)
```

[ ]:
```
vendor_sales_summary.isnull().sum()
```

[ ]:
```
VendorNumber              0
VendorName                0
Brand                     0
Description               0
PurchasePrice             0
ActualPrice               0
Volume                    0
TotalPurchaseQuantity     0
TotalPurchaseDollars      0
TotalSalesPrice           0
TotalSalesQuantity        0
TotalSalesDollars         0
TotalExciseTax            0
FreightCost               0
dtype: int64
```

Let's create some new features for our further Analysis

[ ]:
```
vendor_sales_summary['GrossProfit'] = vendor_sales_summary['TotalSalesDollars']␣
↪- vendor_sales_summary['TotalPurchaseDollars']
```

[ ]:
```
vendor_sales_summary['ProfitMargin'] = (vendor_sales_summary['GrossProfit'] /␣
↪vendor_sales_summary['TotalSalesDollars']) * 100
```

[ ]:
```
vendor_sales_summary['StockTrunover'] =␣
↪vendor_sales_summary['TotalPurchaseQuantity'] /␣
↪vendor_sales_summary['TotalSalesQuantity']
```

[ ]:
```
vendor_sales_summary['SalesToPurchaseRatio'] =␣
↪vendor_sales_summary['TotalSalesQuantity'] /␣
↪vendor_sales_summary['TotalPurchaseQuantity']
```

[ ]:
```
vendor_sales_summary
```

```
/usr/local/lib/python3.11/dist-
packages/google/colab/_dataframe_summarizer.py:57: UserWarning: Could not infer
format, so each element will be parsed individually, falling back to `dateutil`.
To ensure parsing is consistent and as-expected, please specify a format.
  pd.to_datetime(column, errors="raise")
```

[ ]:

	VendorNumber	VendorName	Brand	\
0	1128	BROWN-FORMAN CORP	1233	
1	4425	MARTIGNETTI COMPANIES	3405	
2	17035	PERNOD RICARD USA	8068	
3	3960	DIAGEO NORTH AMERICA INC	4261	
4	3960	DIAGEO NORTH AMERICA INC	3545	
…	…	…	…	

```
10687          9815            WINE GROUP INC   8527
10688          8004            SAZERAC CO INC   5683
10689          3924  HEAVEN HILL DISTILLERIES   9123
10690          3960  DIAGEO NORTH AMERICA INC   6127
10691          7245      PROXIMO SPIRITS INC.   3065

                      Description  PurchasePrice  ActualPrice  Volume  \
0          Jack Daniels No 7 Black          26.27        36.99  1750.0
1            Tito's Handmade Vodka          23.19        28.99  1750.0
2                 Absolut 80 Proof          18.24        24.99  1750.0
3           Capt Morgan Spiced Rum          16.17        22.99  1750.0
4                  Ketel One Vodka          21.89        29.99  1750.0
…                              …              …          …      …
10687  Concannon Glen Ellen Wh Zin           1.32         4.99   750.0
10688  Dr McGillicuddy's Apple Pie           0.39         0.49    50.0
10689              Deep Eddy Vodka           0.74         0.99    50.0
10690  The Club Strawbry Margarita           1.47         1.99   200.0
10691     Three Olives Grape Vodka           0.71         0.99    50.0

       TotalPurchaseQuantity  TotalPurchaseDollars  TotalSalesPrice  \
0                     145080            3811251.60        672819.31
1                     164038            3804041.22        561512.37
2                     187407            3418303.68        461140.15
3                     201682            3261197.94        420050.01
4                     138109            3023206.01        545778.28
…                      …                   …                …
10687                      2                2.64            10.96
10688                      6                2.34             1.47
10689                      2                1.48             0.99
10690                      1                1.47            77.61
10691                      1                0.71            33.66

       TotalSalesQuantity  TotalSalesDollars  TotalExciseTax  FreightCost  \
0                142049.0       5.101920e+06       260999.20     68601.68
1                160247.0       4.819073e+06       294438.66    144929.24
2                187140.0       4.538121e+06       343854.07    123780.22
3                200412.0       4.475973e+06       368242.80    257032.07
4                135838.0       4.223108e+06       249587.83    257032.07
…                    …                  …               …            …
10687                5.0       1.595000e+01            0.55     27100.41
10688              134.0       6.566000e+01            7.04     50293.62
10689                2.0       1.980000e+00            0.10     14069.87
10690               72.0       1.432800e+02           15.12    257032.07
10691               86.0       8.514000e+01            4.46     38994.78

       GrossProfit  ProfitMargin  StockTrunover
0       1290667.91     25.297693       1.021338
```

```
1        1015032.27     21.062810       1.023657
2        1119816.92     24.675786       1.001427
3        1214774.94     27.139908       1.006337
4        1199901.61     28.412764       1.016718
…              …              …              …
10687        13.31     83.448276       0.400000
10688        63.32     96.436186       0.044776
10689         0.50     25.252525       1.000000
10690       141.81     98.974037       0.013889
10691        84.43     99.166079       0.011628

[10692 rows x 17 columns]
```

Now we will insert the data into DB

[ ]:
```
vendor_sales_summary.columns
```

[ ]:
```
Index(['VendorNumber', 'VendorName', 'Brand', 'Description', 'PurchasePrice',
       'ActualPrice', 'Volume', 'TotalPurchaseQuantity',
       'TotalPurchaseDollars', 'TotalSalesPrice', 'TotalSalesQuantity',
       'TotalSalesDollars', 'TotalExciseTax', 'FreightCost', 'GrossProfit',
       'ProfitMargin', 'StockTrunover'],
      dtype='object')
```

[ ]:
```
cursor = conn.cursor()
```

[ ]:
```
cursor.execute('''
  CREATE TABLE vendor_sales_summary (
        VendorNumber INTEGER,
        VendorName VARCHAR(255),
        Brand INT,
        Description VARCHAR(255),
        PurchasePrice DECIMAL(10, 2),
        ActualPrice DECIMAL(10, 2),
        Volume DECIMAL(10, 2),
        TotalPurchaseQuantity INT,
        TotalPurchaseDollars DECIMAL(15, 2),
        TotalSalesPrice DECIMAL(15, 2),
        TotalSalesQuantity INT,
        TotalSalesDollars DECIMAL(15, 2),
        TotalExciseTax DECIMAL(15, 2),
        FreightCost DECIMAL(15, 2),
        GrossProfit DECIMAL(15, 2),
        ProfitMargin DECIMAL(15, 2),
        StockTrunover DECIMAL(15, 2),
        SalesToPurchaseRatio DECIMAL(15, 2),
        PRIMARY KEY (VendorNumber, Brand)
```

```
    )
''')
```

[ ]:
```
<sqlite3.Cursor at 0x79ad1ffc5ec0>
```

[ ]:
```
#Write the data into the table
vendor_sales_summary.to_sql('vendor_sales_summary', conn, if_exists='replace',␣
 ↪index=False)
```

[ ]:
```
10692
```

[ ]:
```
#Checking the final table
pd.read_sql("SELECT * FROM vendor_sales_summary", conn)
```

[ ]:

	VendorNumber	VendorName	Brand	\
0	1128	BROWN-FORMAN CORP	1233	
1	4425	MARTIGNETTI COMPANIES	3405	
2	17035	PERNOD RICARD USA	8068	
3	3960	DIAGEO NORTH AMERICA INC	4261	
4	3960	DIAGEO NORTH AMERICA INC	3545	
…	…	…	…	
10687	9815	WINE GROUP INC	8527	
10688	8004	SAZERAC CO INC	5683	
10689	3924	HEAVEN HILL DISTILLERIES	9123	
10690	3960	DIAGEO NORTH AMERICA INC	6127	
10691	7245	PROXIMO SPIRITS INC.	3065	

	Description	PurchasePrice	ActualPrice	Volume	\
0	Jack Daniels No 7 Black	26.27	36.99	1750.0	
1	Tito's Handmade Vodka	23.19	28.99	1750.0	
2	Absolut 80 Proof	18.24	24.99	1750.0	
3	Capt Morgan Spiced Rum	16.17	22.99	1750.0	
4	Ketel One Vodka	21.89	29.99	1750.0	
…	…	…	…	…	
10687	Concannon Glen Ellen Wh Zin	1.32	4.99	750.0	
10688	Dr McGillicuddy's Apple Pie	0.39	0.49	50.0	
10689	Deep Eddy Vodka	0.74	0.99	50.0	
10690	The Club Strawbry Margarita	1.47	1.99	200.0	
10691	Three Olives Grape Vodka	0.71	0.99	50.0	

	TotalPurchaseQuantity	TotalPurchaseDollars	TotalSalesPrice	\
0	145080	3811251.60	672819.31	
1	164038	3804041.22	561512.37	
2	187407	3418303.68	461140.15	
3	201682	3261197.94	420050.01	
4	138109	3023206.01	545778.28	
…	…	…	…	

```
10687                      2                 2.64            10.96
10688                      6                 2.34             1.47
10689                      2                 1.48             0.99
10690                      1                 1.47            77.61
10691                      1                 0.71            33.66

       TotalSalesQuantity  TotalSalesDollars  TotalExciseTax  FreightCost  \
0                142049.0       5.101920e+06       260999.20     68601.68
1                160247.0       4.819073e+06       294438.66    144929.24
2                187140.0       4.538121e+06       343854.07    123780.22
3                200412.0       4.475973e+06       368242.80    257032.07
4                135838.0       4.223108e+06       249587.83    257032.07
…                     …                  …               …            …
10687                5.0       1.595000e+01            0.55     27100.41
10688              134.0       6.566000e+01            7.04     50293.62
10689                2.0       1.980000e+00            0.10     14069.87
10690               72.0       1.432800e+02           15.12    257032.07
10691               86.0       8.514000e+01            4.46     38994.78

       GrossProfit  ProfitMargin  StockTrunover
0       1290667.91     25.297693       1.021338
1       1015032.27     21.062810       1.023657
2       1119816.92     24.675786       1.001427
3       1214774.94     27.139908       1.006337
4       1199901.61     28.412764       1.016718
…              …             …              …
10687        13.31     83.448276       0.400000
10688        63.32     96.436186       0.044776
10689         0.50     25.252525       1.000000
10690       141.81     98.974037       0.013889
10691        84.43     99.166079       0.011628

[10692 rows x 17 columns]
```

#Get Vendor Summary Function

[11]:
```python
import pandas as pd
import os
from sqlalchemy import create_engine
import logging
import time

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

```
)

def create_vendor_summary(conn):
  '''This function will merge the different tables to get the overall vendor␣
 ↪summary and adding new columns in the resultant data'''
  start_time = time.time()
  vendor_sales_summary = pd.read_sql_query('''WITH FreightSummary AS (
    SELECT VendorNumber, SUM(Freight) AS FreightCost
    FROM vendor_invoice
    GROUP BY VendorNumber
),

PurchaseSummary AS (
    SELECT p.VendorNumber,
    p.VendorName,
    p.Brand,
    p.Description,
    p.PurchasePrice,
    pp.Price AS ActualPrice,
    pp.Volume AS Volume,
    SUM(p.Quantity) AS TotalPurchaseQuantity,
    SUM(p.Dollars) AS TotalPurchaseDollars
    FROM purchases p
    JOIN purchase_prices pp ON p.Brand = pp.Brand
    WHERE p.PurchasePrice > 0
    GROUP BY p.VendorNumber, p.VendorName, p.Brand, p.Description, p.
 ↪PurchasePrice, pp.Price, pp.Volume),

SalesSummary AS (
  SELECT VendorNo, Brand,
  SUM(SalesPrice) AS TotalSalesPrice,
  SUM(SalesQuantity) AS TotalSalesQuantity,
  SUM(SalesDollars) AS TotalSalesDollars,
  SUM(ExciseTax) AS TotalExciseTax
  FROM sales
  GROUP BY VendorNo, Brand
)

SELECT
ps.VendorNumber,
ps.VendorName,
ps.Brand,
ps.Description,
ps.PurchasePrice,
ps.ActualPrice,
ps.Volume,
ps.TotalPurchaseQuantity,
```

```
ps.TotalPurchaseDollars,
ss.TotalSalesPrice,
ss.TotalSalesQuantity,
ss.TotalSalesDollars,
ss.TotalExciseTax,
fs.FreightCost
FROM PurchaseSummary ps
LEFT JOIN SalesSummary ss ON ps.VendorNumber = ss.VendorNo AND ps.Brand = ss.
 ↪Brand
LEFT JOIN FreightSummary fs ON ps.VendorNumber = fs.VendorNumber
ORDER BY ps.TotalPurchaseDollars DESC
''',conn)

  end_time = time.time()
  total_time = (end_time - start_time) / 60
  print(f'Total time taken for ingestion: {total_time:.2f} minutes')
  return vendor_sales_summary

def clean_data(vendor_sales_summary):
  '''This function will clean the data'''

  #Changing data type to float
  vendor_sales_summary['Volume'] = vendor_sales_summary['Volume'].
 ↪astype('float64')

  #Removing sapces from categorical columns
  vendor_sales_summary['VendorName'] = vendor_sales_summary['VendorName'].str.
 ↪strip()
  vendor_sales_summary['Description'] = vendor_sales_summary['Description'].str.
 ↪strip()

  #Filling missing values with zero
  vendor_sales_summary.fillna(0, inplace=True)

  #creating new features for better analysis
  vendor_sales_summary['GrossProfit'] =␣
 ↪vendor_sales_summary['TotalSalesDollars'] -␣
 ↪vendor_sales_summary['TotalPurchaseDollars']
  vendor_sales_summary['ProfitMargin'] = (vendor_sales_summary['GrossProfit'] /␣
 ↪vendor_sales_summary['TotalSalesDollars']) * 100
  vendor_sales_summary['StockTrunover'] =␣
 ↪vendor_sales_summary['TotalPurchaseQuantity'] /␣
 ↪vendor_sales_summary['TotalSalesQuantity']
  vendor_sales_summary['SalesToPurchaseRatio'] =␣
 ↪vendor_sales_summary['TotalSalesQuantity'] /␣
 ↪vendor_sales_summary['TotalPurchaseQuantity']
```

```
  return vendor_sales_summary


if __name__ == "__main__":
  #Creating Database connection
  conn = sqlite3.connect('inventor.db')
  print("Opened database successfully")

  logging.info("Creating vendor_sales_summary table.....")
  print("Creating vendor_sales_summary table.....")
  summary_df = create_vendor_summary(conn)
  logging.info("Vendor_sales_summary table created successfully")
  print("Vendor_sales_summary table created successfully")
  logging.info(summary_df.head())
  print(summary_df.head())

  summary_df = clean_data(summary_df)

  logging.info('Cleaning Data....')
  print("Cleaning Data....")
  clean_df = clean_data(summary_df)
  logging.info("Data cleaned successfully")
  print("Data cleaned successfully")
  logging.info(clean_df.head())
  print(clean_df.head())

  logging.info("Inserting data into vendor_sales_summary table....")
  print("Inserting data into vendor_sales_summary table....")
  #Write the data into the table
  clean_df.to_sql('vendor_sales_summary', conn, if_exists='replace',␣
 ↪index=False)
  logging.info("Data inserted into vendor_sales_summary table successfully")
  print("Data inserted into vendor_sales_summary table successfully")
```

```
Opened database successfully
Creating vendor_sales_summary table…
Total time taken for ingestion: 0.94 minutes
Vendor_sales_summary table created successfully
   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                145080
1          23.19        28.99   1750                164038
2          18.24        24.99   1750                187407
3          16.17        22.99   1750                201682
4          21.89        29.99   1750                138109

   TotalPurchaseDollars  TotalSalesPrice  TotalSalesQuantity  \
0            3811251.60        672819.31            142049.0
1            3804041.22        561512.37            160247.0
2            3418303.68        461140.15            187140.0
3            3261197.94        420050.01            200412.0
4            3023206.01        545778.28            135838.0

   TotalSalesDollars  TotalExciseTax  FreightCost
0       5.101920e+06       260999.20     68601.68
1       4.819073e+06       294438.66    144929.24
2       4.538121e+06       343854.07    123780.22
3       4.475973e+06       368242.80    257032.07
4       4.223108e+06       249587.83    257032.07
Cleaning Data…
Data cleaned successfully
   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  TotalSalesPrice  TotalSalesQuantity  \
0            3811251.60        672819.31            142049.0
1            3804041.22        561512.37            160247.0
2            3418303.68        461140.15            187140.0
3            3261197.94        420050.01            200412.0
4            3023206.01        545778.28            135838.0

   TotalSalesDollars  TotalExciseTax  FreightCost  GrossProfit  ProfitMargin  \
0       5.101920e+06       260999.20     68601.68   1290667.91     25.297693
1       4.819073e+06       294438.66    144929.24   1015032.27     21.062810
2       4.538121e+06       343854.07    123780.22   1119816.92     24.675786
3       4.475973e+06       368242.80    257032.07   1214774.94     27.139908
4       4.223108e+06       249587.83    257032.07   1199901.61     28.412764
```

```
   StockTrunover  SalesToPurchaseRatio
0       1.021338              0.979108
1       1.023657              0.976890
2       1.001427              0.998575
3       1.006337              0.993703
4       1.016718              0.983556
Inserting data into vendor_sales_summary table…
Data inserted into vendor_sales_summary table successfully
```

[ ]:
```
vendor_sales_summary
```

[ ]:
```
       VendorNumber                VendorName  Brand  \
0              1128         BROWN-FORMAN CORP   1233
1              4425     MARTIGNETTI COMPANIES   3405
2             17035         PERNOD RICARD USA   8068
3              3960  DIAGEO NORTH AMERICA INC   4261
4              3960  DIAGEO NORTH AMERICA INC   3545
…               …                         …    …
10687          9815            WINE GROUP INC   8527
10688          8004            SAZERAC CO INC   5683
10689          3924  HEAVEN HILL DISTILLERIES   9123
10690          3960  DIAGEO NORTH AMERICA INC   6127
10691          7245      PROXIMO SPIRITS INC.   3065

                       Description  PurchasePrice  ActualPrice  Volume  \
0          Jack Daniels No 7 Black          26.27        36.99  1750.0
1            Tito's Handmade Vodka          23.19        28.99  1750.0
2                 Absolut 80 Proof          18.24        24.99  1750.0
3           Capt Morgan Spiced Rum          16.17        22.99  1750.0
4                  Ketel One Vodka          21.89        29.99  1750.0
…                              …              …            …      …
10687  Concannon Glen Ellen Wh Zin           1.32         4.99   750.0
10688  Dr McGillicuddy's Apple Pie           0.39         0.49    50.0
10689              Deep Eddy Vodka           0.74         0.99    50.0
10690  The Club Strawbry Margarita           1.47         1.99   200.0
10691     Three Olives Grape Vodka           0.71         0.99    50.0

       TotalPurchaseQuantity  TotalPurchaseDollars  TotalSalesPrice  \
0                     145080            3811251.60        672819.31
1                     164038            3804041.22        561512.37
2                     187407            3418303.68        461140.15
3                     201682            3261197.94        420050.01
4                     138109            3023206.01        545778.28
…                      …                      …                …
10687                      2                  2.64            10.96
10688                      6                  2.34             1.47
```

```
10689                      2                1.48            0.99
10690                      1                1.47           77.61
10691                      1                0.71           33.66

       TotalSalesQuantity  TotalSalesDollars  TotalExciseTax  FreightCost  \
0                142049.0       5.101920e+06       260999.20     68601.68
1                160247.0       4.819073e+06       294438.66    144929.24
2                187140.0       4.538121e+06       343854.07    123780.22
3                200412.0       4.475973e+06       368242.80    257032.07
4                135838.0       4.223108e+06       249587.83    257032.07
…                     …                  …               …            …
10687                5.0       1.595000e+01            0.55     27100.41
10688              134.0       6.566000e+01            7.04     50293.62
10689                2.0       1.980000e+00            0.10     14069.87
10690               72.0       1.432800e+02           15.12    257032.07
10691               86.0       8.514000e+01            4.46     38994.78

       GrossProfit  ProfitMargin  StockTrunover
0       1290667.91     25.297693       1.021338
1       1015032.27     21.062810       1.023657
2       1119816.92     24.675786       1.001427
3       1214774.94     27.139908       1.006337
4       1199901.61     28.412764       1.016718
…              …             …               …
10687        13.31     83.448276       0.400000
10688        63.32     96.436186       0.044776
10689         0.50     25.252525       1.000000
10690       141.81     98.974037       0.013889
10691        84.43     99.166079       0.011628

[10692 rows x 17 columns]
```

2 Final 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 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.

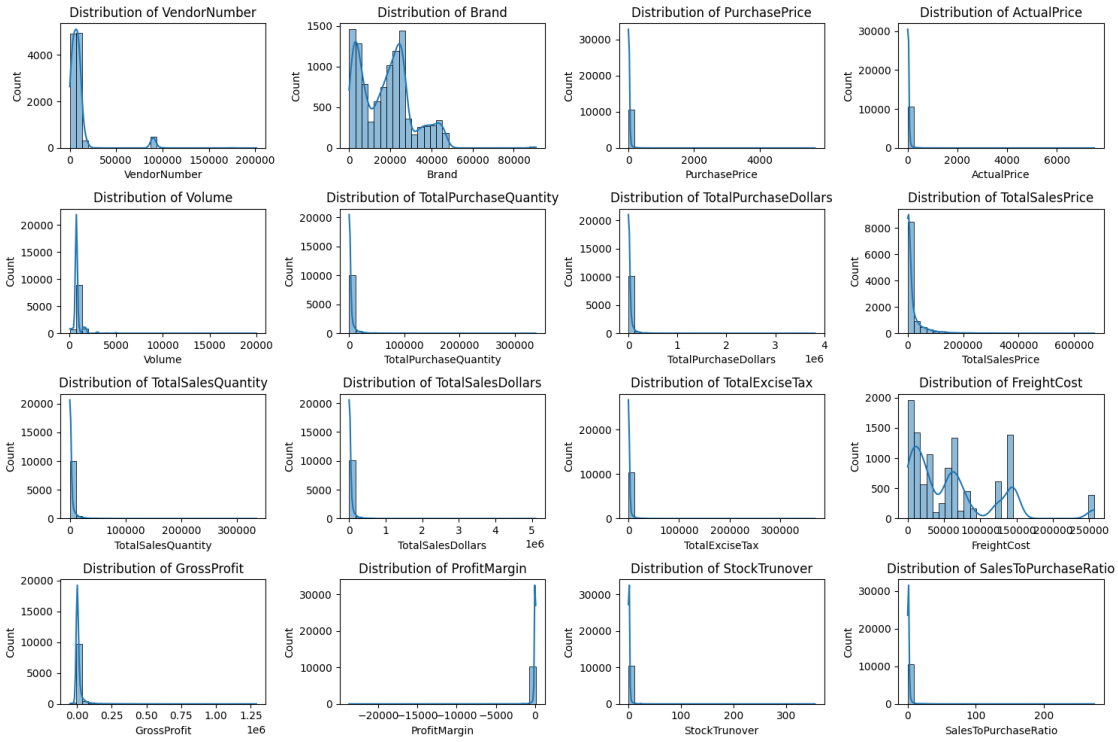
[133]:
```
#summary statistics
summary_df.describe().T
```

[133]:
```
                     count          mean            std           min  \
VendorNumber       10692.0  1.065065e+04   18753.519148  2.000000e+00
Brand              10692.0  1.803923e+04   12662.187074  5.800000e+01
PurchasePrice      10692.0  2.438530e+01     109.269375  3.600000e-01
```

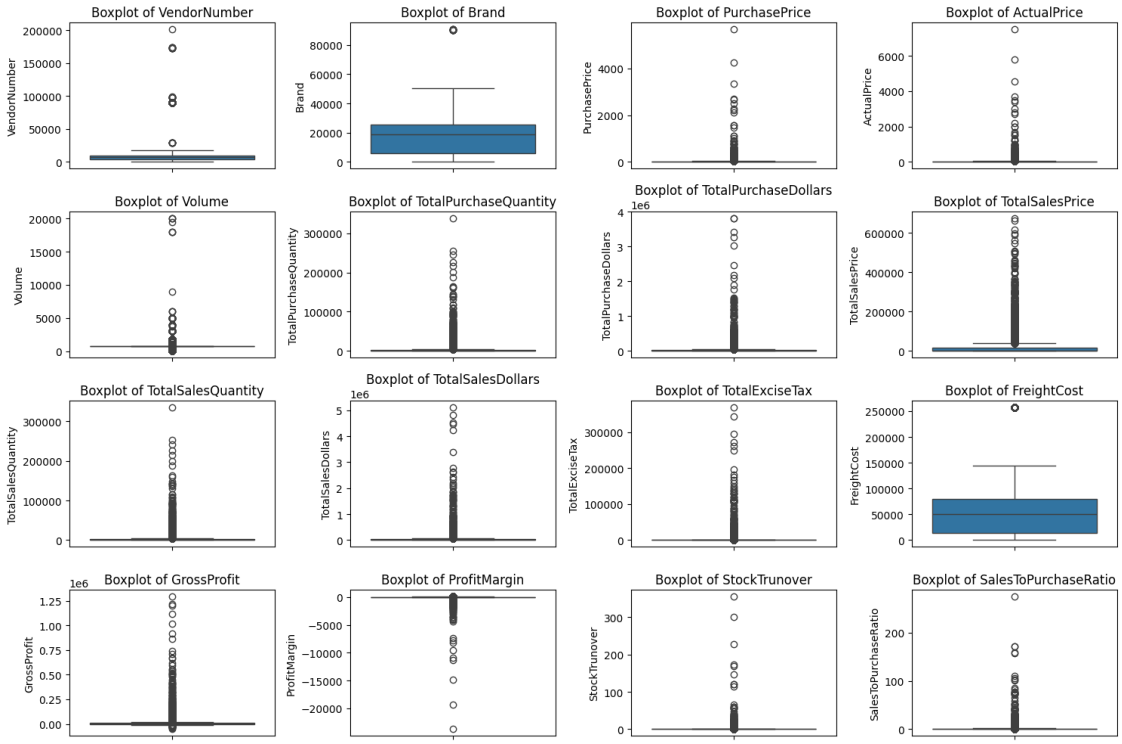
ActualPrice	10692.0	3.564367e+01	148.246016	4.900000e-01
Volume	10692.0	8.473605e+02	664.309212	5.000000e+01
TotalPurchaseQuantity	10692.0	3.140887e+03	11095.086769	1.000000e+00
TotalPurchaseDollars	10692.0	3.010669e+04	123067.799627	7.100000e-01
TotalSalesPrice	10692.0	1.879378e+04	44952.773386	0.000000e+00
TotalSalesQuantity	10692.0	3.077482e+03	10952.851391	0.000000e+00
TotalSalesDollars	10692.0	4.223907e+04	167655.265984	0.000000e+00
TotalExciseTax	10692.0	1.774226e+03	10975.582240	0.000000e+00
FreightCost	10692.0	6.143376e+04	60938.458032	9.000000e-02
GrossProfit	10692.0	1.213238e+04	46224.337964	-5.200278e+04
ProfitMargin	10692.0	-inf	NaN	-inf
StockTrunover	10692.0	inf	NaN	3.642987e-03
SalesToPurchaseRatio	10692.0	1.706793e+00	6.020460	0.000000e+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
TotalSalesPrice	289.710000	2857.800000	16059.562500	6.728193e+05
TotalSalesQuantity	33.000000	261.000000	1929.250000	3.349390e+05
TotalSalesDollars	729.220000	5298.045000	28396.915000	5.101920e+06
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
StockTrunover	0.962147	1.018819	1.238806	inf
SalesToPurchaseRatio	0.807229	0.981529	1.039342	2.745000e+02

[15]:
```
#Distribution plots for numerical columns
import matplotlib.pyplot as plt
import seaborn as sns

numerical_columns = summary_df.select_dtypes(include=['int64', 'float64']).
 ↪columns

plt.figure(figsize=(15, 10))
for i, column in enumerate(numerical_columns):
    plt.subplot(4, 4, i+1)
    sns.histplot(summary_df[column], kde=True, bins=30)
    plt.title(f'Distribution of {column}')
plt.tight_layout()
plt.show()
```



[17]:
```
#Outlier Detection with Boxplots
plt.figure(figsize=(15, 10))
for i, column in enumerate(numerical_columns):
    plt.subplot(4, 4, i+1)
    sns.boxplot(y=summary_df[column])
    plt.title(f'Boxplot of {column}')
plt.tight_layout()
plt.show()
```



#Summary Statistics Insights

Negative & Zero Values:

- Gross Profit: Minimun value is -52,002.78 indicating losses. Some products or transactions may be selling at a loss due to hight costs or selling at discounts lower than the purchase price.
- Prodit Margin: Has a minimun of -infinity, which suggests cases where revenue is zero even lower than costs.
- Total Sales Quantity & Sales Dollars: Minimun 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 inefficient or bulk shipments.
- Stock Trunover: Ranges from 0 to 274.5, implying some products sell extremely fast while other remain in stock indefinitely. Value more than 1 indicates that Sold quantity for that product is higher than purchased quantity due to earlier sales are being fullfilled from the older stock.

[131]:
```
vendor_sales_summary
```

[131]:

	VendorNumber	VendorName	Brand	\
0	1128	BROWN-FORMAN CORP	1233	
1	4425	MARTIGNETTI COMPANIES	3405	
2	17035	PERNOD RICARD USA	8068	
3	3960	DIAGEO NORTH AMERICA INC	4261	
4	3960	DIAGEO NORTH AMERICA INC	3545	
…	…	…	…	
10687	9815	WINE GROUP INC	8527	
10688	8004	SAZERAC CO INC	5683	
10689	3924	HEAVEN HILL DISTILLERIES	9123	
10690	3960	DIAGEO NORTH AMERICA INC	6127	
10691	7245	PROXIMO SPIRITS INC.	3065	

	Description	PurchasePrice	ActualPrice	Volume	\
0	Jack Daniels No 7 Black	26.27	36.99	1750	
1	Tito's Handmade Vodka	23.19	28.99	1750	
2	Absolut 80 Proof	18.24	24.99	1750	
3	Capt Morgan Spiced Rum	16.17	22.99	1750	
4	Ketel One Vodka	21.89	29.99	1750	
…	…	…	…	…	
10687	Concannon Glen Ellen Wh Zin	1.32	4.99	750	
10688	Dr McGillicuddy's Apple Pie	0.39	0.49	50	
10689	Deep Eddy Vodka	0.74	0.99	50	
10690	The Club Strawbry Margarita	1.47	1.99	200	
10691	Three Olives Grape Vodka	0.71	0.99	50	

	TotalPurchaseQuantity	TotalPurchaseDollars	TotalSalesPrice	\
0	145080	3811251.60	672819.31	
1	164038	3804041.22	561512.37	
2	187407	3418303.68	461140.15	
3	201682	3261197.94	420050.01	
4	138109	3023206.01	545778.28	
…	…	…	…	
10687	2	2.64	10.96	
10688	6	2.34	1.47	
10689	2	1.48	0.99	
10690	1	1.47	77.61	
10691	1	0.71	33.66	

	TotalSalesQuantity	TotalSalesDollars	TotalExciseTax	FreightCost
0	142049.0	5.101920e+06	260999.20	68601.68
1	160247.0	4.819073e+06	294438.66	144929.24
2	187140.0	4.538121e+06	343854.07	123780.22
3	200412.0	4.475973e+06	368242.80	257032.07
4	135838.0	4.223108e+06	249587.83	257032.07
…	…	…	…	…
10687	5.0	1.595000e+01	0.55	27100.41

```
10688               134.0       6.566000e+01            7.04     50293.62
10689                 2.0       1.980000e+00            0.10     14069.87
10690                72.0       1.432800e+02           15.12    257032.07
10691                86.0       8.514000e+01            4.46     38994.78

[10692 rows x 14 columns]
```

[20]:
```
#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
)
```

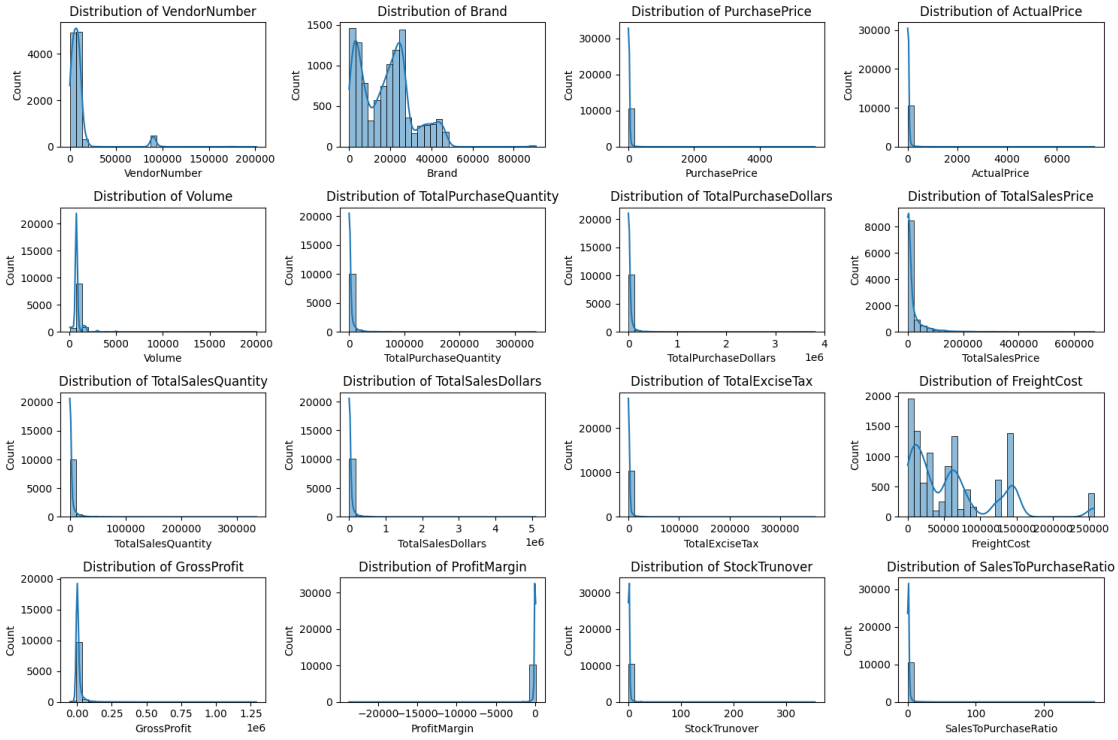
[21]:
```
df
```

[21]:
```
      VendorNumber                VendorName  Brand  \
0             1128          BROWN-FORMAN CORP   1233
1             4425      MARTIGNETTI COMPANIES   3405
2            17035          PERNOD RICARD USA   8068
3             3960   DIAGEO NORTH AMERICA INC   4261
4             3960   DIAGEO NORTH AMERICA INC   3545
…              …                          …     …
8560          9815             WINE GROUP INC   8527
8561          8004             SAZERAC CO INC   5683
8562          3924   HEAVEN HILL DISTILLERIES   9123
8563          3960   DIAGEO NORTH AMERICA INC   6127
8564          7245       PROXIMO SPIRITS INC.   3065

                      Description  PurchasePrice  ActualPrice  Volume  \
0          Jack Daniels No 7 Black          26.27        36.99  1750.0
1            Tito's Handmade Vodka          23.19        28.99  1750.0
2                 Absolut 80 Proof          18.24        24.99  1750.0
3           Capt Morgan Spiced Rum          16.17        22.99  1750.0
4                 Ketel One Vodka          21.89        29.99  1750.0
…                             …              …            …      …
8560  Concannon Glen Ellen Wh Zin           1.32         4.99   750.0
8561  Dr McGillicuddy's Apple Pie           0.39         0.49    50.0
8562              Deep Eddy Vodka           0.74         0.99    50.0
8563  The Club Strawbry Margarita           1.47         1.99   200.0
8564     Three Olives Grape Vodka           0.71         0.99    50.0

      TotalPurchaseQuantity  TotalPurchaseDollars  TotalSalesPrice  \
0                    145080            3811251.60        672819.31
1                    164038            3804041.22        561512.37
```

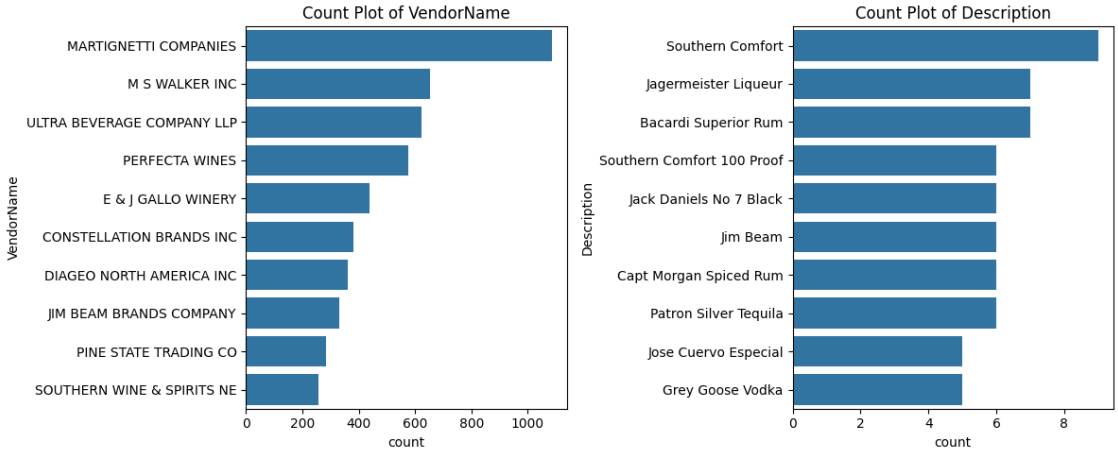
```
2                    187407            3418303.68        461140.15
3                    201682            3261197.94        420050.01
4                    138109            3023206.01        545778.28
…                       …                    …                …
8560                    2                 2.64             10.96
8561                    6                 2.34              1.47
8562                    2                 1.48              0.99
8563                    1                 1.47             77.61
8564                    1                 0.71             33.66

      TotalSalesQuantity  TotalSalesDollars  TotalExciseTax  FreightCost  \
0                142049.0       5.101920e+06       260999.20     68601.68
1                160247.0       4.819073e+06       294438.66    144929.24
2                187140.0       4.538121e+06       343854.07    123780.22
3                200412.0       4.475973e+06       368242.80    257032.07
4                135838.0       4.223108e+06       249587.83    257032.07
…                    …                  …               …            …
8560                5.0       1.595000e+01            0.55     27100.41
8561              134.0       6.566000e+01            7.04     50293.62
8562                2.0       1.980000e+00            0.10     14069.87
8563               72.0       1.432800e+02           15.12    257032.07
8564               86.0       8.514000e+01            4.46     38994.78

      GrossProfit  ProfitMargin  StockTrunover  SalesToPurchaseRatio
0      1290667.91     25.297693       1.021338              0.979108
1      1015032.27     21.062810       1.023657              0.976890
2      1119816.92     24.675786       1.001427              0.998575
3      1214774.94     27.139908       1.006337              0.993703
4      1199901.61     28.412764       1.016718              0.983556
…             …             …              …                     …
8560        13.31     83.448276       0.400000              2.500000
8561        63.32     96.436186       0.044776             22.333333
8562         0.50     25.252525       1.000000              1.000000
8563       141.81     98.974037       0.013889             72.000000
8564        84.43     99.166079       0.011628             86.000000

[8565 rows x 18 columns]
```

[22]:
```python
#Distribution plots for numerical columns after cleaning the data
import matplotlib.pyplot as plt
import seaborn as sns

numerical_columns = summary_df.select_dtypes(include=['int64', 'float64']).
 ↪columns

plt.figure(figsize=(15, 10))
for i, column in enumerate(numerical_columns):
```

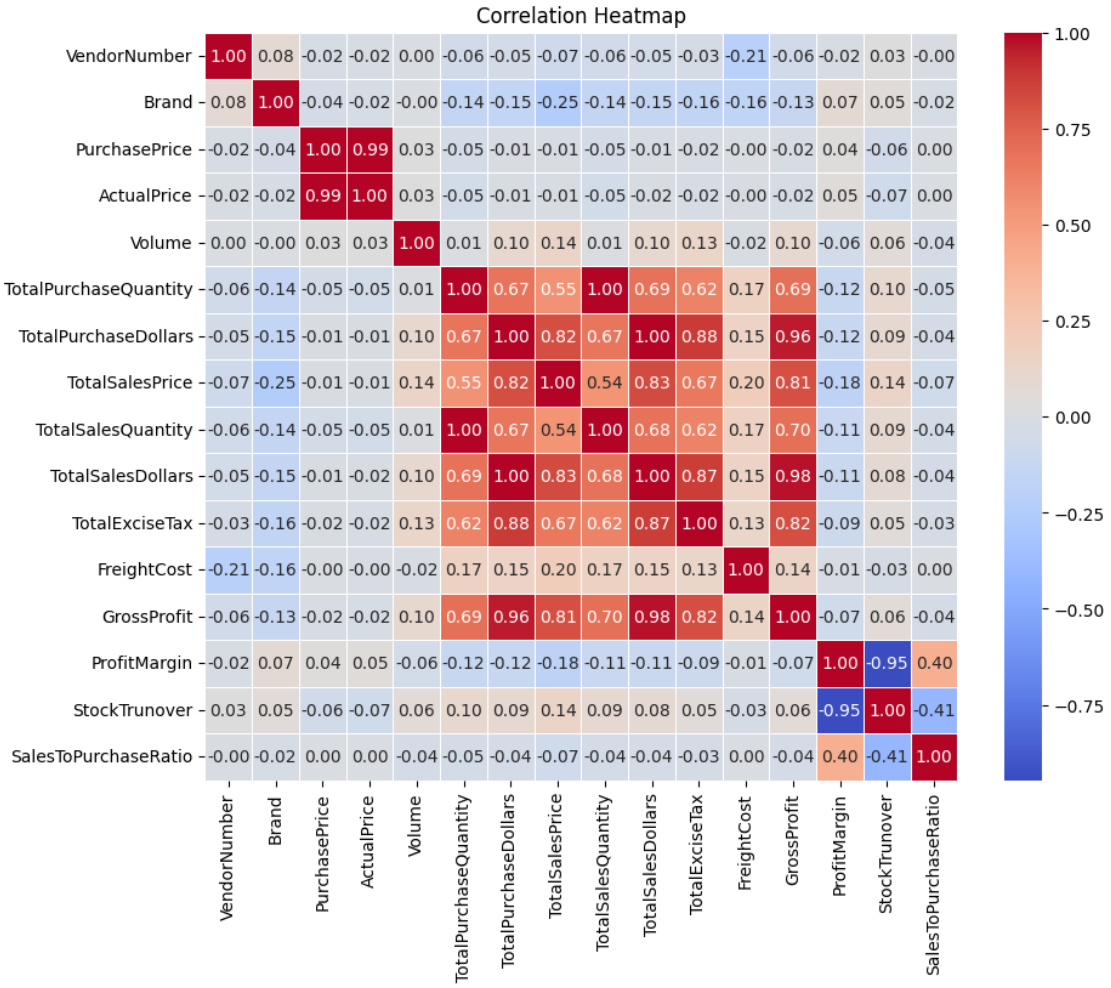
```
    plt.subplot(4, 4, i+1)
    sns.histplot(summary_df[column], kde=True, bins=30)
    plt.title(f'Distribution of {column}')
plt.tight_layout()
plt.show()
```



[24]:
```
# Count plots for Categorical Columns
categorical_columns = ['VendorName','Description']

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



[27]:
```
#Correlation Heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(df[numerical_columns].corr(), fmt = ".2f", annot=True,␣
 ↪cmap='coolwarm', linewidths=0.5)
plt.title('Correlation Heatmap')
plt.show()
```



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(0.99), confirming efficient inventory turnover.
- Negative correlation between proft marign & total sales price(-0.179) suggests that as sales price increases, margin decreases, possibly due to competitive pricing pressure.
- StockTrunover has weak negative correlations with both GrossProfit (-0.38) and ProfitmArgin(-0.055), indicating that fastest turnover dies not necessarily result in higher profitabilty.

#Data Analysis

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

[31]:
```
brand_performance = df.groupby('Description').agg({
    'TotalSalesDollars':'sum',
    'ProfitMargin':'mean',
}).reset_index()
```

[32]:
```
low_sales_threshold = brand_performance['TotalSalesDollars'].quantile(0.15)
high_margin_threshold = brand_performance['ProfitMargin'].quantile(0.85)

low_sales_threshold,high_margin_threshold
```

[32]:
```
(np.float64(560.299), np.float64(64.97017552750111))
```

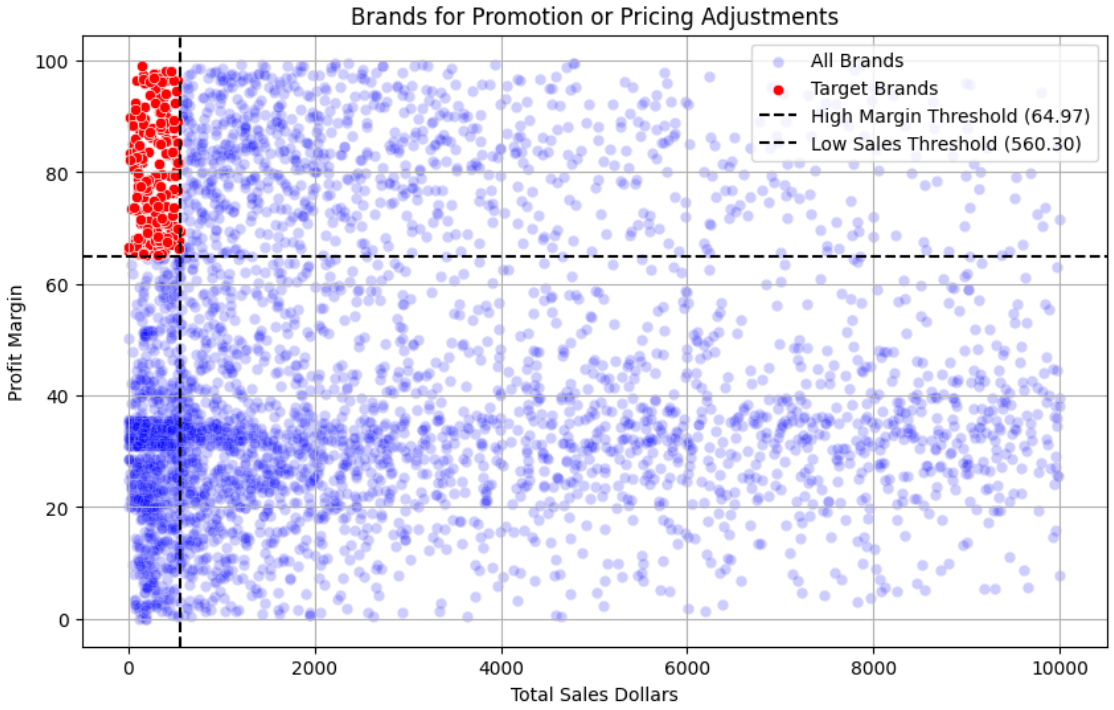
[33]:
```
#Filter brands with low sales but high profit margins
target_brands = brand_performance[
    (brand_performance['TotalSalesDollars'] < low_sales_threshold) &
    (brand_performance['ProfitMargin'] > high_margin_threshold)
]

print("Brands with low sales but high profit margins:")
print(target_brands)
```

```
Brands with low sales but high profit margins:
                      Description  TotalSalesDollars  ProfitMargin
6       12 Days of Pearls Gift Set             309.69     97.678323
45                   4 Orange Vodka             483.78     85.902683
57       A Bichot Clos Marechaudes              539.94     67.740860
59          A Bichot Merc Champs M              515.88     94.552997
96      Absolut Orient Apple Vodka              119.94     87.652159
…                              …                   …             …
7588  Woodford Rsv Master Coll Pnt              489.95     73.760588
7663   Zardetto Pros di Coneg Brut              345.86     88.758457
7677         Zerran Tinto Montsant              139.91     77.592738
7686         Zhenka Vodka 80 Proof              240.39     87.303964
7696                    Zorah Red              417.81     67.559417

[198 rows x 3 columns]
```

[37]:
```
brand_performance = brand_performance[brand_performance['TotalSalesDollars'] <␣
↪10000] # For better visulization
```

[38]:
```
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=f'High␣
 ↪Margin Threshold ({high_margin_threshold:.2f})')
plt.axvline(low_sales_threshold, linestyle='--', color='Black', label=f'Low␣
 ↪Sales Threshold ({low_sales_threshold:.2f})')
plt.title('Brands for Promotion or Pricing Adjustments')
plt.xlabel('Total Sales Dollars')
plt.ylabel('Profit Margin')
plt.legend()
plt.grid(True)
plt.show()
```



Which vendors and brands demonstrate the highest sales performance?

[60]:
```
#Top vendors and brands by sales performance
top_vendors = df.groupby('VendorName')['TotalSalesDollars'].sum().nlargest(10)
top_brands = df.groupby('Description')['TotalSalesDollars'].sum().nlargest(10)
top_vendors,top_brands
```

[60]:
```
(VendorName
 DIAGEO NORTH AMERICA INC      6.799010e+07
 MARTIGNETTI COMPANIES         3.933036e+07
 PERNOD RICARD USA             3.206320e+07
 JIM BEAM BRANDS COMPANY       3.142302e+07
 BACARDI USA INC               2.485482e+07
```

```
CONSTELLATION BRANDS INC      2.421875e+07
E & J GALLO WINERY            1.839990e+07
BROWN-FORMAN CORP             1.824723e+07
ULTRA BEVERAGE COMPANY LLP    1.650254e+07
M S WALKER INC                1.470646e+07
Name: TotalSalesDollars, dtype: float64,
Description
Jack Daniels No 7 Black    7964746.76
Tito's Handmade Vodka      7399657.58
Grey Goose Vodka           7209608.06
Capt Morgan Spiced Rum     6356320.62
Absolut 80 Proof           6244752.03
Jameson Irish Whiskey      5715759.69
Ketel One Vodka            5070083.56
Baileys Irish Cream        4150122.07
Kahlua                     3604858.66
Tanqueray                  3456697.90
Name: TotalSalesDollars, dtype: float64)
```

[102]:
```python
def format_dollars(value):
  if value >= 1000000:
    return f'{value/1000000:.2f}M'
  elif value >= 1000 and value < 1000000:
    return f'{value/1000:.2f}K'
  elif value >= 1000:
    return f'{value:,.2f}'
  else:
    return str(value)
```

[62]:
```python
top_brands = top_brands.apply(format_dollars)
top_vendors = top_vendors.apply(format_dollars)
```

[63]:
```python
top_brands
```

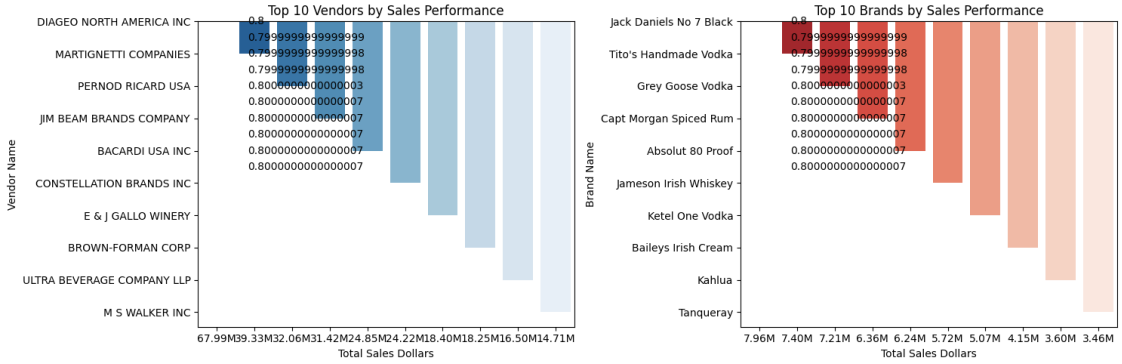
[63]:
```
Description
Jack Daniels No 7 Black    7.96M
Tito's Handmade Vodka      7.40M
Grey Goose Vodka           7.21M
Capt Morgan Spiced Rum     6.36M
Absolut 80 Proof           6.24M
Jameson Irish Whiskey      5.72M
Ketel One Vodka            5.07M
Baileys Irish Cream        4.15M
Kahlua                     3.60M
Tanqueray                  3.46M
Name: TotalSalesDollars, dtype: object
```

[64]:
```
top_vendors
```

[64]:
```
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
```

[65]:
```
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',␣
 ↪hue=top_vendors.values, legend=False)
plt.title('Top 10 Vendors by Sales Performance')
plt.xlabel('Total Sales Dollars')
plt.ylabel('Vendor Name')


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()),
             va='center',ha='left', fontsize = 10, color="black")

#Plot top 10 brands
plt.subplot(1, 2, 2)
ax2 = sns.barplot(y=top_brands.index, x=top_brands.values, palette='Reds_r',␣
 ↪hue=top_brands.values, legend=False)
plt.title('Top 10 Brands by Sales Performance')
plt.xlabel('Total Sales Dollars')
plt.ylabel('Brand Name')

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()),
             va='center',ha='left', fontsize = 10, color="black")

plt.tight_layout()
```

```
plt.show()
```



Which vendors contibute the most to total purchase dollars?

[70]:
```
vendor_performance = df.groupby('VendorName').agg({
    'TotalPurchaseDollars':'sum',
    'GrossProfit':'sum',
    'TotalSalesDollars':'sum'
}).reset_index()
```

[73]:
```
vendor_performance['PurchaseContribution'] =␣
 ↪(vendor_performance['TotalPurchaseDollars'] /␣
 ↪vendor_performance['TotalPurchaseDollars'].sum()) * 100
```

[76]:
```
round(vendor_performance.sort_values('PurchaseContribution', ascending=False),2)
```

[76]:

	VendorName	TotalPurchaseDollars	GrossProfit	TotalSalesDollars	PurchaseContribution
25	DIAGEO NORTH AMERICA INC	50097226.16	17892873.26	67990099.42	16.30
57	MARTIGNETTI COMPANIES	25502095.83	13828263.53	39330359.36	8.30
68	PERNOD RICARD USA	23851164.17	8212032.02	32063196.19	7.76
46	JIM BEAM BRANDS COMPANY	23494304.32	7928716.14	31423020.46	7.64
6	BACARDI USA INC	17432020.26	7422796.88	23854816.74	5.67
..	…	…	…	…	…
33	FANTASY FINE WINES CORP	128.64	198.95	327.59	0.04
107	UNCORKED	118.74	58.20	176.94	0.04
85	SILVER MOUNTAIN CIDERS	77.18	265.33	342.51	0.03
16	CAPSTONE INTERNATIONAL	54.64	192.23	246.87	0.02
35	FLAVOR ESSENCE INC	17.00	1457.41	1474.41	0.01

```
6          24854817.14                  5.67
..                 …                   …
33              327.59                  0.00
107             176.94                  0.00
85              342.51                  0.00
16              246.87                  0.00
35             1474.41                  0.00

[119 rows x 5 columns]
```

[77]:
```
#Display top 10 Vendors
top_vendors = vendor_performance.nlargest(10, 'PurchaseContribution')
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
```

[77]:
```
                    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  PurchaseContribution
25             67.99M             16.300334
57             39.33M              8.297719
68             32.06M              7.760548
46             31.42M              7.644435
6              24.85M              5.671926
20             24.22M              4.969667
11             18.25M              4.307606
30             18.40M              3.926789
106            16.50M              3.633478
53             14.71M              3.177053
```

[79]:
```
top_vendors['PurchaseContribution'].sum()
```

[79]:
```
np.float64(65.68955597053622)
```

[80]:
```
top_vendors['Cumulative_Contribution%'] = top_vendors['PurchaseContribution'].
 ↪cumsum()
top_vendors
```

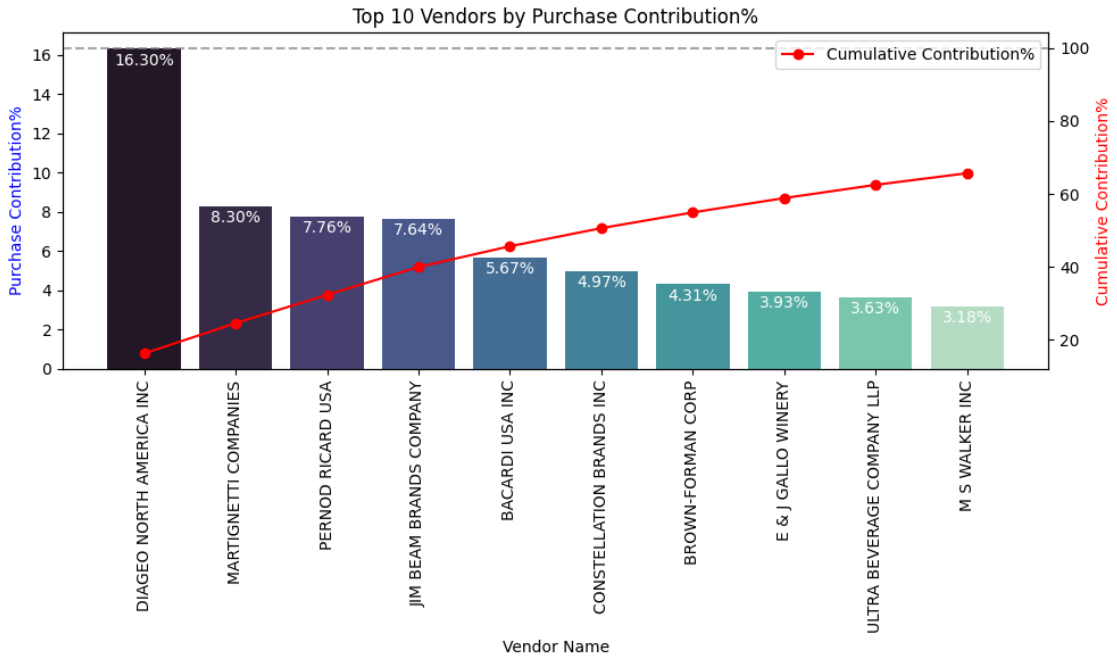
[80]:

	VendorName	TotalPurchaseDollars	GrossProfit	TotalSalesDollars	PurchaseContribution	Cumulative_Contribution%
25	DIAGEO NORTH AMERICA INC	50.10M	17.89M	67.99M	16.300334	16.300334
57	MARTIGNETTI COMPANIES	25.50M	13.83M	39.33M	8.297719	24.598053
68	PERNOD RICARD USA	23.85M	8.21M	32.06M	7.760548	32.358601
46	JIM BEAM BRANDS COMPANY	23.49M	7.93M	31.42M	7.644435	40.003037
6	BACARDI USA INC	17.43M	7.42M	24.85M	5.671926	45.674962
20	CONSTELLATION BRANDS INC	15.27M	8.95M	24.22M	4.969667	50.644630
11	BROWN-FORMAN CORP	13.24M	5.01M	18.25M	4.307606	54.952236
30	E & J GALLO WINERY	12.07M	6.33M	18.40M	3.926789	58.879025
106	ULTRA BEVERAGE COMPANY LLP	11.17M	5.34M	16.50M	3.633478	62.512503
53	M S WALKER INC	9.76M	4.94M	14.71M	3.177053	65.689556

[83]:
```
fig, ax1 = plt.subplots(figsize=(10, 6))

#Bar plot for purchase Contribution%
sns.barplot(x=top_vendors['VendorName'], y =␣
 ↪top_vendors['PurchaseContribution'], palette='mako', ax=ax1)

for i, value in enumerate(top_vendors['PurchaseContribution']):
  ax1.text(i, value - 1, f'{value:.2f}%', ha='center', va='bottom',color =␣
 ↪"white")

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

ax1.set_xticklabels(top_vendors['VendorName'], rotation=90)
ax1.set_xlabel('Vendor Name')
ax1.set_ylabel('Purchase Contribution%', color='blue')
ax2.set_ylabel('Cumulative Contribution%', color='red')
```

```
ax1.set_title('Top 10 Vendors by Purchase Contribution%')

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

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

```
/tmp/ipython-input-83-819876523.py:4: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.barplot(x=top_vendors['VendorName'], y =
top_vendors['PurchaseContribution'], palette='mako', ax=ax1)
/tmp/ipython-input-83-819876523.py:13: UserWarning: set_ticklabels() should only
be used with a fixed number of ticks, i.e. after set_ticks() or using a
FixedLocator.
  ax1.set_xticklabels(top_vendors['VendorName'], rotation=90)
```

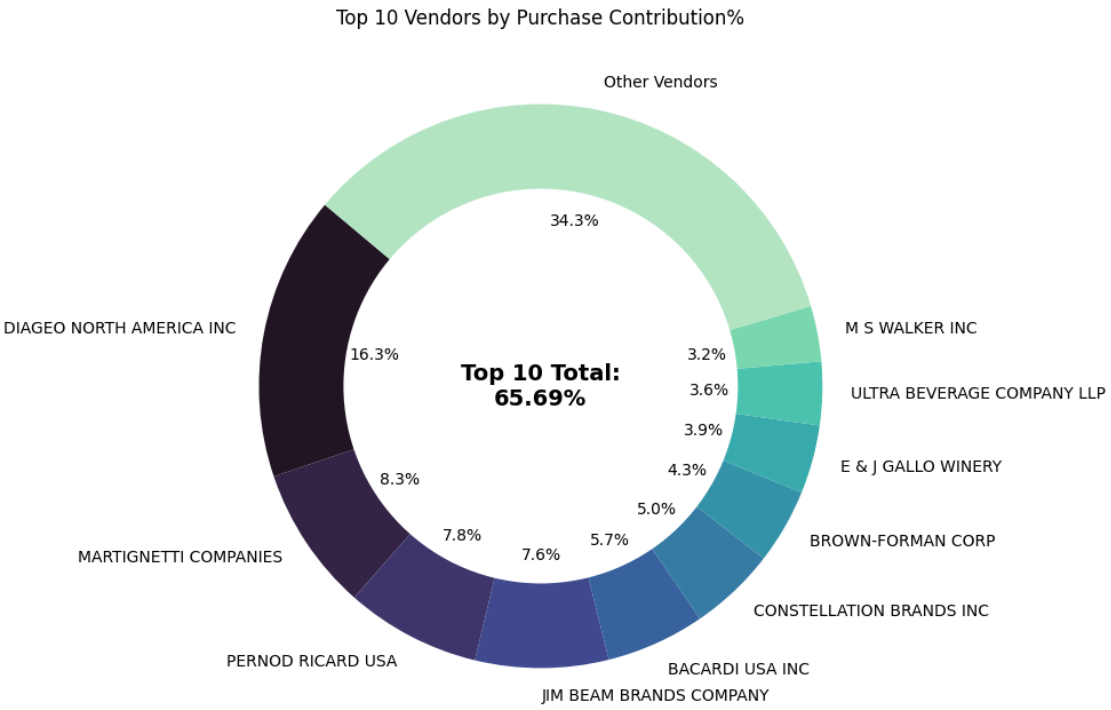


How much of total procurement is dependent on the top vendors?

[84]:
```
print(f'Total Purchase Contribution of top 10 vendors:␣
↪{round(top_vendors["PurchaseContribution"].sum(),2)}%')
```

```
Total Purchase Contribution of top 10 vendors: 65.69%
```

[86]:
```
vendors = list(top_vendors['VendorName'].values)
purchase_contributions = list(top_vendors['PurchaseContribution'].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, colors=sns.
 ↪color_palette('mako', n_colors=len(vendors)))

#Draw a white circle in the center to create a "donut" effect
center_circle = plt.Circle((0, 0), 0.70, fc='white')
fig.gca().add_artist(center_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 Vendors by Purchase Contribution%")
plt.show()
```



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

[87]:
```
df['UnitPurchasePrice'] = df['TotalPurchaseDollars'] /␣
↪df['TotalPurchaseQuantity']
```

[88]:
```
df
```

[88]:

	VendorNumber	VendorName	Brand	\
0	1128	BROWN-FORMAN CORP	1233	
1	4425	MARTIGNETTI COMPANIES	3405	
2	17035	PERNOD RICARD USA	8068	
3	3960	DIAGEO NORTH AMERICA INC	4261	
4	3960	DIAGEO NORTH AMERICA INC	3545	
…	…	…	…	
8560	9815	WINE GROUP INC	8527	
8561	8004	SAZERAC CO INC	5683	
8562	3924	HEAVEN HILL DISTILLERIES	9123	
8563	3960	DIAGEO NORTH AMERICA INC	6127	
8564	7245	PROXIMO SPIRITS INC.	3065	

	Description	PurchasePrice	ActualPrice	Volume	\
0	Jack Daniels No 7 Black	26.27	36.99	1750.0	

```
1           Tito's Handmade Vodka          23.19        28.99  1750.0
2                Absolut 80 Proof          18.24        24.99  1750.0
3          Capt Morgan Spiced Rum          16.17        22.99  1750.0
4                 Ketel One Vodka          21.89        29.99  1750.0
…                             …            …          …      …
8560  Concannon Glen Ellen Wh Zin           1.32         4.99   750.0
8561  Dr McGillicuddy's Apple Pie           0.39         0.49    50.0
8562              Deep Eddy Vodka           0.74         0.99    50.0
8563  The Club Strawbry Margarita           1.47         1.99   200.0
8564     Three Olives Grape Vodka           0.71         0.99    50.0

      TotalPurchaseQuantity  TotalPurchaseDollars  TotalSalesPrice  \
0                    145080            3811251.60        672819.31
1                    164038            3804041.22        561512.37
2                    187407            3418303.68        461140.15
3                    201682            3261197.94        420050.01
4                    138109            3023206.01        545778.28
…                     …                   …                …
8560                      2                2.64            10.96
8561                      6                2.34             1.47
8562                      2                1.48             0.99
8563                      1                1.47            77.61
8564                      1                0.71            33.66

      TotalSalesQuantity  TotalSalesDollars  TotalExciseTax  FreightCost  \
0                142049.0       5.101920e+06       260999.20     68601.68
1                160247.0       4.819073e+06       294438.66    144929.24
2                187140.0       4.538121e+06       343854.07    123780.22
3                200412.0       4.475973e+06       368242.80    257032.07
4                135838.0       4.223108e+06       249587.83    257032.07
…                   …               …               …          …
8560                5.0       1.595000e+01            0.55     27100.41
8561              134.0       6.566000e+01            7.04     50293.62
8562                2.0       1.980000e+00            0.10     14069.87
8563               72.0       1.432800e+02           15.12    257032.07
8564               86.0       8.514000e+01            4.46     38994.78

      GrossProfit  ProfitMargin  StockTrunover  SalesToPurchaseRatio  \
0      1290667.91     25.297693       1.021338              0.979108
1      1015032.27     21.062810       1.023657              0.976890
2      1119816.92     24.675786       1.001427              0.998575
3      1214774.94     27.139908       1.006337              0.993703
4      1199901.61     28.412764       1.016718              0.983556
…           …            …             …                    …
8560        13.31     83.448276       0.400000              2.500000
8561        63.32     96.436186       0.044776             22.333333
8562         0.50     25.252525       1.000000              1.000000
```

```
8563       141.81     98.974037       0.013889             72.000000
8564        84.43     99.166079       0.011628             86.000000

      UnitPurchasePrice
0                 26.27
1                 23.19
2                 18.24
3                 16.17
4                 21.89
…                 …
8560               1.32
8561               0.39
8562               0.74
8563               1.47
8564               0.71

[8565 rows x 19 columns]
```

[89]:
```
df['OrderSize'] = pd.qcut(df['TotalPurchaseQuantity'], q=3, labels=['Small',␣
↪'Medium', 'Large'])
```

[90]:
```
df
```

[90]:
```
      VendorNumber                VendorName  Brand  \
0             1128         BROWN-FORMAN CORP   1233
1             4425     MARTIGNETTI COMPANIES   3405
2            17035         PERNOD RICARD USA   8068
3             3960  DIAGEO NORTH AMERICA INC   4261
4             3960  DIAGEO NORTH AMERICA INC   3545
…              …                        …     …
8560          9815            WINE GROUP INC   8527
8561          8004            SAZERAC CO INC   5683
8562          3924  HEAVEN HILL DISTILLERIES   9123
8563          3960  DIAGEO NORTH AMERICA INC   6127
8564          7245      PROXIMO SPIRITS INC.   3065

                      Description  PurchasePrice  ActualPrice  Volume  \
0         Jack Daniels No 7 Black          26.27        36.99  1750.0
1           Tito's Handmade Vodka          23.19        28.99  1750.0
2                Absolut 80 Proof          18.24        24.99  1750.0
3          Capt Morgan Spiced Rum          16.17        22.99  1750.0
4                 Ketel One Vodka          21.89        29.99  1750.0
…                             …              …            …      …
8560  Concannon Glen Ellen Wh Zin           1.32         4.99   750.0
8561  Dr McGillicuddy's Apple Pie           0.39         0.49    50.0
8562              Deep Eddy Vodka           0.74         0.99    50.0
8563  The Club Strawbry Margarita           1.47         1.99   200.0
```

```
8564     Three Olives Grape Vodka           0.71         0.99    50.0

      TotalPurchaseQuantity  TotalPurchaseDollars  TotalSalesPrice  \
0                    145080            3811251.60        672819.31
1                    164038            3804041.22        561512.37
2                    187407            3418303.68        461140.15
3                    201682            3261197.94        420050.01
4                    138109            3023206.01        545778.28
…                     …                    …                …
8560                      2                  2.64            10.96
8561                      6                  2.34             1.47
8562                      2                  1.48             0.99
8563                      1                  1.47            77.61
8564                      1                  0.71            33.66

      TotalSalesQuantity  TotalSalesDollars  TotalExciseTax  FreightCost  \
0                142049.0       5.101920e+06       260999.20     68601.68
1                160247.0       4.819073e+06       294438.66    144929.24
2                187140.0       4.538121e+06       343854.07    123780.22
3                200412.0       4.475973e+06       368242.80    257032.07
4                135838.0       4.223108e+06       249587.83    257032.07
…                     …                  …               …            …
8560                5.0       1.595000e+01            0.55     27100.41
8561              134.0       6.566000e+01            7.04     50293.62
8562                2.0       1.980000e+00            0.10     14069.87
8563               72.0       1.432800e+02           15.12    257032.07
8564               86.0       8.514000e+01            4.46     38994.78

      GrossProfit  ProfitMargin  StockTrunover  SalesToPurchaseRatio  \
0      1290667.91     25.297693       1.021338              0.979108
1      1015032.27     21.062810       1.023657              0.976890
2      1119816.92     24.675786       1.001427              0.998575
3      1214774.94     27.139908       1.006337              0.993703
4      1199901.61     28.412764       1.016718              0.983556
…           …             …              …                     …
8560        13.31     83.448276       0.400000              2.500000
8561        63.32     96.436186       0.044776             22.333333
8562         0.50     25.252525       1.000000              1.000000
8563       141.81     98.974037       0.013889             72.000000
8564        84.43     99.166079       0.011628             86.000000

      UnitPurchasePrice OrderSize
0                 26.27     Large
1                 23.19     Large
2                 18.24     Large
3                 16.17     Large
4                 21.89     Large
```

```
…                  …       …
8560               1.32     Small
8561               0.39     Small
8562               0.74     Small
8563               1.47     Small
8564               0.71     Small

[8565 rows x 20 columns]
```

[91]:
```
df.groupby('OrderSize')[['UnitPurchasePrice']].mean()
```

```
/tmp/ipython-input-91-1505448859.py:1: FutureWarning: The default of
observed=False is deprecated and will be changed to True in a future version of
pandas. Pass observed=False to retain current behavior or observed=True to adopt
the future default and silence this warning.
  df.groupby('OrderSize')[['UnitPurchasePrice']].mean()
```

[91]:

OrderSize	UnitPurchasePrice
Small	39.057543
Medium	15.486414
Large	10.777625

[92]:
```
#Plotting box plot
plt.figure(figsize=(10, 6))
sns.boxplot(x='OrderSize', y='UnitPurchasePrice', data=df, palette='mako')
plt.title('Box Plot of Unit Purchase Price by Order Size')
plt.xlabel('Order Size')
plt.ylabel('Unit Purchase Price')
plt.show()
```

```
/tmp/ipython-input-92-1601371551.py:3: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.boxplot(x='OrderSize', y='UnitPurchasePrice', data=df, palette='mako')
```

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

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

[97]:
```
df[df['StockTrunover'] < 1].groupby('VendorName')[['StockTrunover']].mean().
↪sort_values('StockTrunover', ascending=True).head(10)
```

[97]:

VendorName	StockTrunover
FLAVOR ESSENCE INC	0.016949
DUGGANS DISTILLED PRODUCTS	0.230769
ATLANTIC IMPORTING COMPANY	0.295581
MOONLIGHT MEADERY	0.295652
CAPSTONE INTERNATIONAL	0.307692
THE PIERPONT GROUP LLC	0.315516
ALISA CARR BEVERAGES	0.324730
STAR INDUSTRIES INC.	0.328744
MILTONS DISTRIBUTING CO	0.333333
SILVER MOUNTAIN CIDERS	0.346939

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

[100]:
```
df['UnsoldInventoryValue'] = (df['TotalPurchaseQuantity'] -␣
 ↪df['TotalSalesQuantity']) * df['PurchasePrice']
print(f'Total Unsold Inventory Value:',␣
 ↪format_dollars(df['UnsoldInventoryValue'].sum()))
```

```
Total Unsold Inventory Value: 2.71M
```

[104]:
```
#Aggregate Capital Locked per Vendor
inventory_value_per_vendor = df.groupby('VendorName')['UnsoldInventoryValue'].
 ↪sum().reset_index()

#Sort vendors with the highest locked capitals
inventory_value_per_vendor = inventory_value_per_vendor.
 ↪sort_values('UnsoldInventoryValue', ascending=False)
inventory_value_per_vendor['UnsoldInventoryValue'] =␣
 ↪inventory_value_per_vendor['UnsoldInventoryValue'].apply(format_dollars)
inventory_value_per_vendor.head(10)
```

[104]:

	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.

[119]:
```
top_threshold = df['TotalSalesDollars'].quantile(0.75)
low_threshold = df['TotalSalesDollars'].quantile(0.25)
```

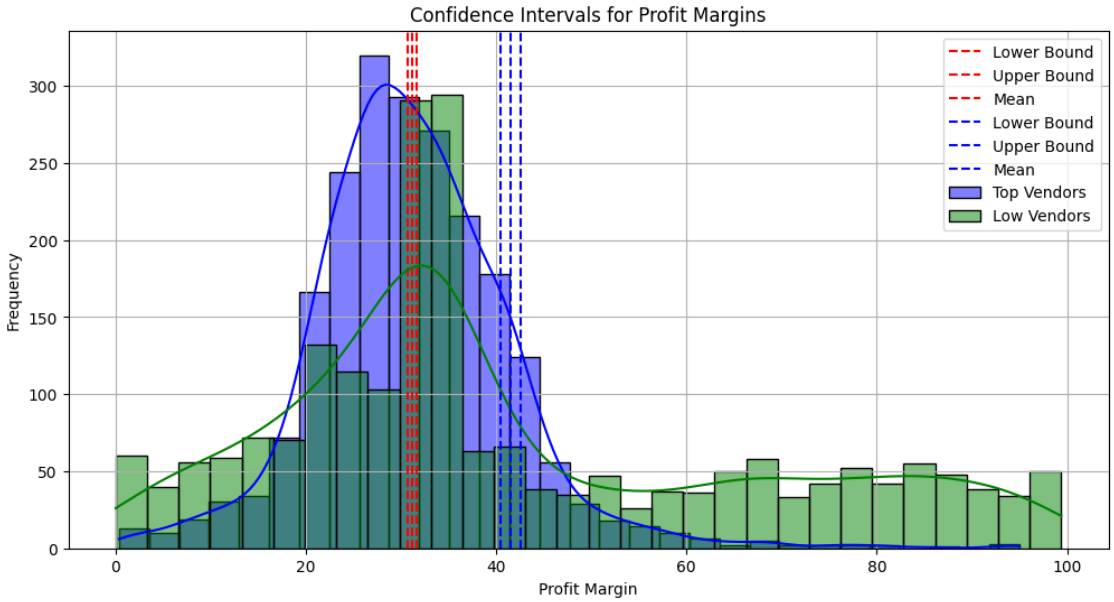
[120]:
```
top_vendors = df[df['TotalSalesDollars'] >= top_threshold]['ProfitMargin'].
 ↪dropna()
low_vendors = df[df['TotalSalesDollars'] <= low_threshold]['ProfitMargin'].
 ↪dropna()
```

[121]:
```
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
  lower_bound = mean_val - margin_of_error
  upper_bound = mean_val + margin_of_error
  return mean_val, lower_bound, upper_bound
```

[122]:
```
import numpy as np
import scipy.stats as stats

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% Confidence Interval: {top_lower:.2f}, {top_upper:.2f},␣
 ↪Mean: {top_mean: .2f}")
print(f"Low Vendors 95% Confidence Interval: {low_lower:.2f}, {low_upper:.2f}, ␣
 ↪Mean: {top_mean: .2f}")

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

#Top vendors plot
sns.histplot(top_vendors, kde=True, bins=30, color='blue', label='Top Vendors')
plt.axvline(top_lower, color='red', linestyle='--', label='Lower Bound')
plt.axvline(top_upper, color='red', linestyle='--', label='Upper Bound')
plt.axvline(top_mean, color='red', linestyle='--', label='Mean')

#low vendor plot
sns.histplot(low_vendors, kde=True, bins=30, color='green', label='Low Vendors')
plt.axvline(low_lower, color='blue', linestyle='--', label='Lower Bound')
plt.axvline(low_upper, color='blue', linestyle='--', label='Upper Bound')
plt.axvline(low_mean, color='blue', linestyle='--', label='Mean')

#Finializing plot
plt.title('Confidence Intervals for Profit Margins')
plt.xlabel('Profit Margin')
plt.ylabel('Frequency')
plt.legend()
plt.grid(True)
plt.show()
```

```
Top Vendors 95% Confidence Interval: 30.74, 31.61, Mean:  31.17
Low Vendors 95% Confidence Interval: 40.48, 42.62,  Mean:  31.17
```



- The CI for low-performing vendors (40.48% to 42.62%) is significantly higher than that of the 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 optimizations, or building 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:

- Ho(Null Hypothesis): There is no significat difference in the mean profit margins of top-performing and low-performing vendors.
- Ha(Alternative Hypothesis): The mean profit margins of top-performing and low-performing vendors are significantly different.

[123]:
```
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_statistic, p_value = stats.ttest_ind(top_vendors, low_vendors,␣
 ↪equal_var=False)

#Print results
print(f"T-statistic: {t_statistic:.4f} P-value: {p_value:.4f}")
if p_value < 0.05:
  print("Reject Null Hypothesis: There is a significant difference in profit␣
 ↪margins between top and low-performing vendors.")
else:
  print("Fail to reject the Null Hypothesis: No Signifiact difference in profit␣
 ↪Margin.")
```

```
T-statistic: -17.6440 P-value: 0.0000
Reject Null Hypothesis: There is a significant difference in profit margins
between top and low-performing vendors.
```

#Final Insights for Business

1. **Optimizing Inventory and Capital Allocation**
   - **Insight:** A significant portion of capital is tied up in unsold inventory, especially with key vendors.
   - **Metric:** Total unsold inventory is valued at 2.71M Dollars, with top contributors including DIAGEO NORTH AMERICA INC 722K Dollars, JIM BEAM BRANDS COMPANY 555K Dollars, and PERNOD RICARD USA 471K Dollars.
   - **Business Impact:** Enables targeted stock reduction strategies to free up capital, improve inventory turnover, and enhance cash flow efficiency.
2. **Strategic Vendor Management for Procurement Efficiency**
   - **Insight:** A large share of procurement spending is concentrated among a few key vendors.
   - **Metric:** The top 10 vendors account for ~65.7% of total purchase value.
   - **Business Impact:** Emphasizes the need to strengthen vendor relationships to negotiate better terms, reduce costs, and build a resilient supply chain.
3. **Leveraging Bulk Purchasing for Cost Savings**
   - **Insight:** Larger purchase orders result in significant reductions in unit cost.
   - **Metric:** ~72% reduction in unit cost for bulk orders ($10.78) versus small orders 39.06 dollars.
   - **Business Impact:** Supports a strategy to prioritize bulk procurement, driving cost savings and improving profit margins.
4. **Targeted Sales & Marketing for High-Margin, Low-Sales Brands**
   - **Insight:** Some brands offer high margins but suffer from low sales volumes.
   - **Metric:** Identified 198 brands below the 15th percentile in sales and above the 85th percentile in profit margin.

- **Business Impact:** Focused marketing on these brands can boost profitability without needing high sales volume, optimizing ROI.

5. Differentiated Strategies for Vendor Profitability

- **Insight:** Profit margins vary significantly between low- and high-sales vendors.
- **Metric:** Low-performing vendors show higher profit margins (40.5%–42.6%) compared to high-performing ones (30.7%–31.6%) at 95% confidence.
- **Business Impact:** Recommends segmented vendor strategies—optimize volume and ops for high-sales vendors; explore pricing or promotion levers for low-sales, high-margin ones.