Forward
School

Program Code: J620-002-4:2020

Program Name: FRONT-END SOFTWARE DEVELOPMENT

Title : P09 Sample Data Analysis and Exploration

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Introduction : Exploring more on data analysis and plotting different graph variants.

Conclusion : This exercise helped me to understand the data analysed and get better at plotting graphs with the data.

Module P9 - Sample Data Analysis and Exploration

In this module, you will try your hand at performing some data analysis on some data. Before that, you should also try to prepare the data as well as you can by doing some data cleaning and preparation. And finally, your analysis can be better captured in the form of some data visualizations.

First, let's import all the necessary packages.

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib
import matplotlib.pyplot as plt

# This line configures matplotlib to show figures embedded in the Jupyter r
# instead of opening a new window for each figure.
%matplotlib inline
```

The data that we are going to use contains some sample sales data, and it is taken from [Kaggle (https://www.kaggle.com/kyanyoga/sample-sales-data)](https://www.kaggle.com/kyanyoga/sample-sales-data). It's not a very big dataset, having only ~2,800 rows of data.

In [41]:

```
df = pd.read_csv("../../data_samples/sales_data_sample.csv", encoding='windo
df.head(10)
```

3	10145	45	83.26	6	3746.70
4	10159	49	100.00	14	5205.27
5	10168	36	96.66	1	3479.76
6	10180	29	86.13	9	2497.77
7	10188	48	100.00	1	5512.32
8	10201	22	98.57	2	2168.54
9	10211	41	100.00	14	4708.44

10 rows × 25 columns

In [3]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2823 entries, 0 to 2822
Data columns (total 25 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   ORDERNUMBER       2823 non-null   int64  
 1   QUANTITYORDERED   2823 non-null   int64  
 2   PRICEEACH         2823 non-null   float64
 3   ORDERLINENUMBER   2823 non-null   int64  
 4   SALES             2823 non-null   float64
 5   ORDERDATE         2823 non-null   object 
 6   STATUS            2823 non-null   object 
 7   QTR_ID            2823 non-null   int64  
 8   MONTH_ID          2823 non-null   int64  
 9   YEAR_ID           2823 non-null   int64  
 10  PRODUCTLINE       2823 non-null   object 
 11  MSRP              2823 non-null   int64  
 12  PRODUCTCODE       2823 non-null   object 
 13  CUSTOMERNAME      2823 non-null   object 
 14  PHONE             2823 non-null   object 
 15  ADDRESSLINE1      2823 non-null   object 
 16  ADDRESSLINE2      302 non-null    object 
 17  CITY              2823 non-null   object 
 18  STATE             1337 non-null   object 
 19  POSTALCODE        2747 non-null   object 
 20  COUNTRY           2823 non-null   object 
 21  TERRITORY         1749 non-null   object 
 22  CONTACTLASTNAME   2823 non-null   object 
 23  CONTACTFIRSTNAME  2823 non-null   object 
 24  DEALSIZE          2823 non-null   object 
dtypes: float64(2), int64(7), object(16)
memory usage: 551.5+ KB
```

Here are some questions that you would be interested to uncover when you perform an exploratory data analysis (or 'EDA' in short) on some sample data.

1. Identify **where** customers are coming from.
2. Find out their **yearly retail performance** (in terms of total revenue).
3. What **product categories** are the most and least popular?
4. Who are their **most valuable customers** (basically we define this as those who purchased the most from them) ?

Feel free to refine these questions in more detailed (if you wish), or define other interesting questions that you want to find out from this data.

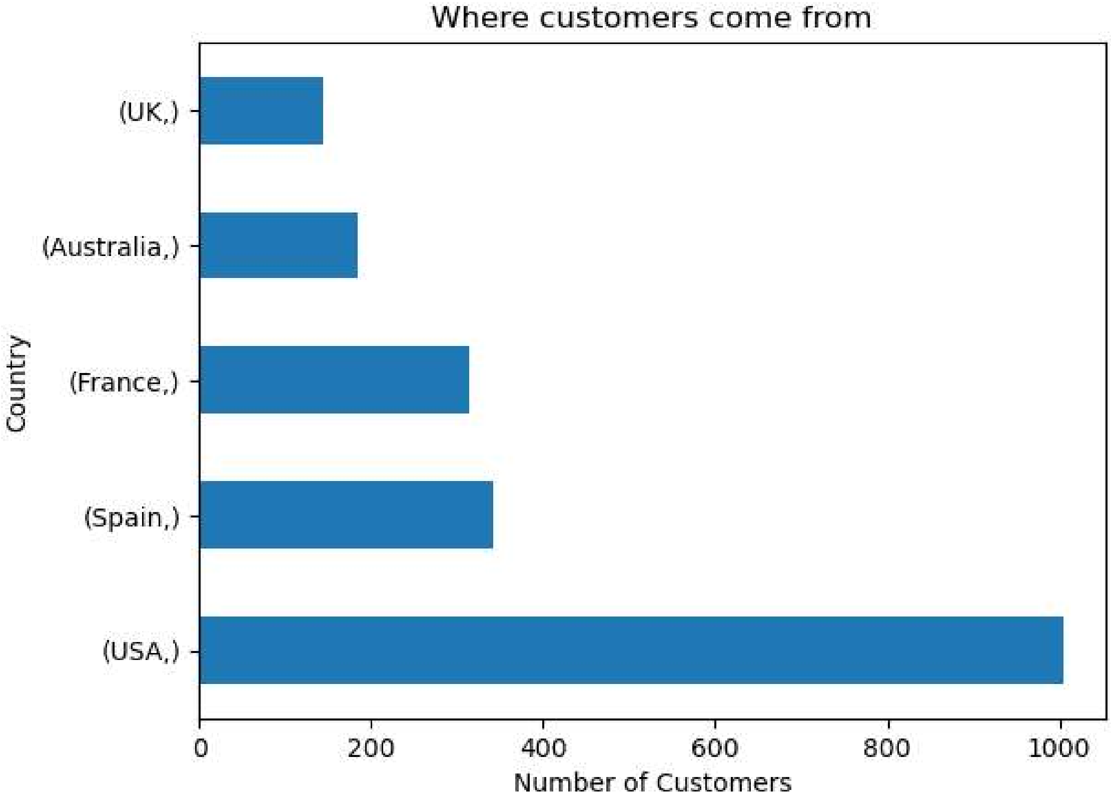
There are some interesting "catches" to consider as well. For example, the 'Status' for most entries are mostly "Shipped", but there are other statuses, i.e. "In Process", "Disputed", "Cancelled", etc. It is up to you to define which of these entries (based on their statuses) that should be considered in your analysis and which should be left out.

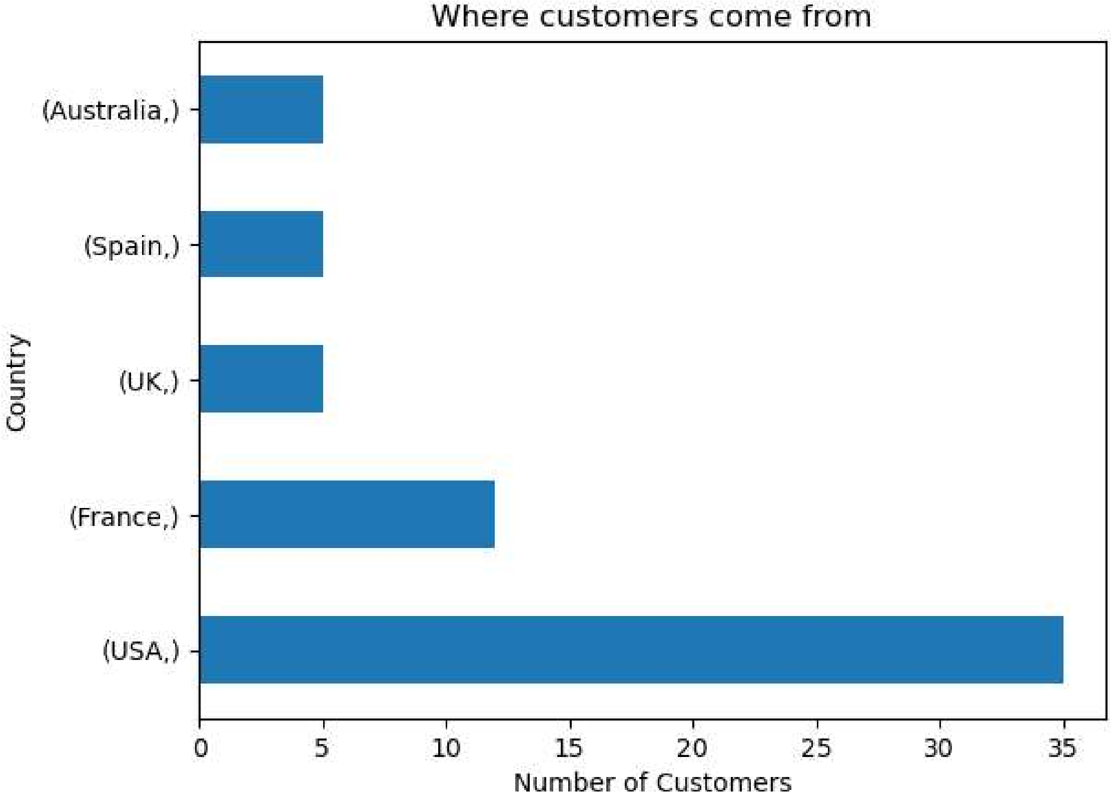
Note: You can do your prototyping here (and transfer relevant lines of code to your source file later), or directly work on the source file using Spyder.

In [48]:

```
# 1
unique_df = df.copy()
unique_df.drop_duplicates(subset=['CONTACTLASTNAME', 'CONTACTFIRSTNAME'],

print(df[['COUNTRY']].value_counts())
print(unique_df[['COUNTRY']].value_counts())

df[['COUNTRY']].value_counts().head().plot.barh()
plt.title("Where customers come from")
plt.xlabel('Number of Customers')
plt.ylabel('Country')
plt.show()

unique_df[['COUNTRY']].value_counts().head().plot.barh()
plt.title("Where customers come from")
plt.xlabel('Number of Customers')
plt.ylabel('Country')
plt.show()
```

```
COUNTRY
USA            1004
Spain           342
France          314
Australia       185
UK              144
Italy           113
Finland          92
Norway           85
Singapore        79
Canada           70
Denmark          63
Germany          62
Sweden           57
Austria          55
Japan            52
Belgium          33
Switzerland      31
Philippines      26
Ireland          16
Name: count, dtype: int64
COUNTRY
USA            35
France         12
UK              5
Spain           5
Australia       5
Finland         3
Germany         3
Norway          3
Canada          3
Italy           3
Denmark         2
Austria         2
Japan           2
Singapore       2
Sweden          2
Belgium         2
Ireland         1
Philippines     1
Switzerland     1
Name: count, dtype: int64
```

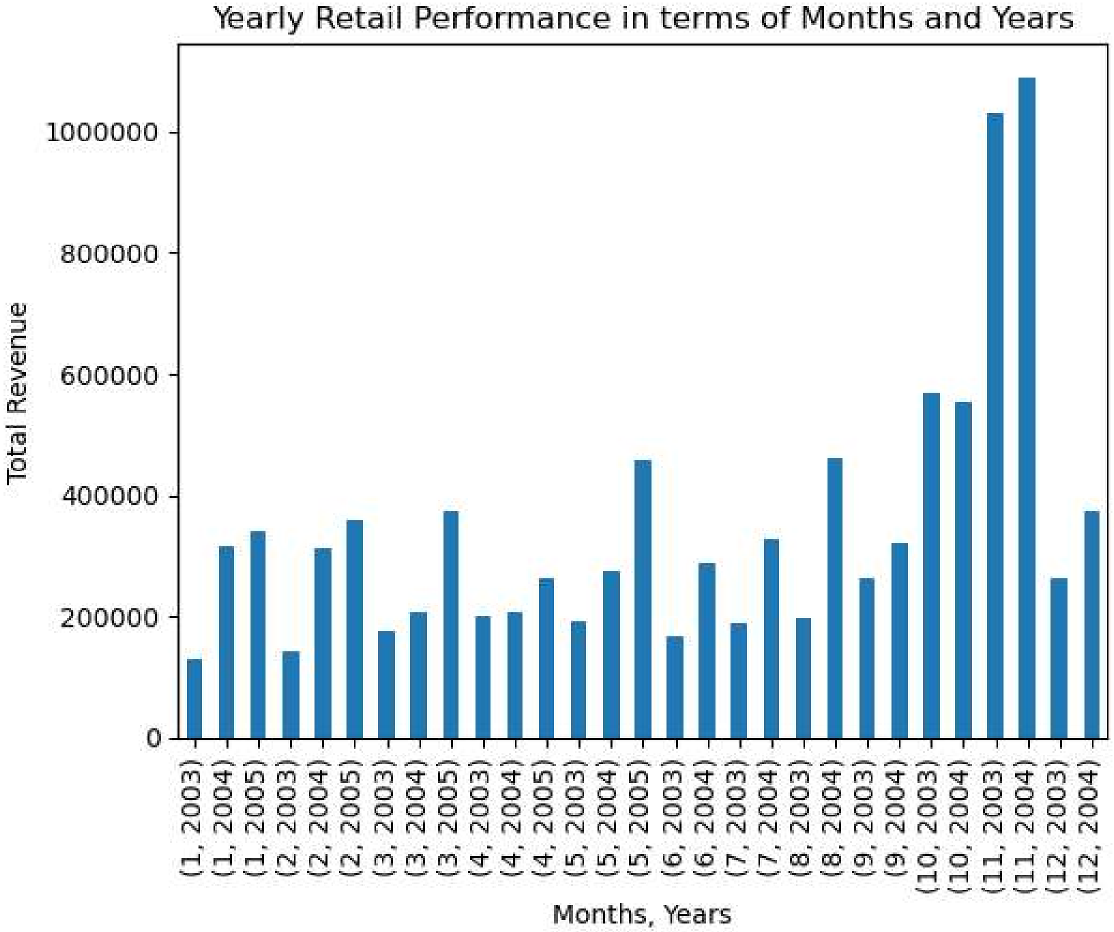

Where customers come from
(UK,)
(Australia,)
(France,)
(Spain,)
(USA,)
Country
0
200
400
600
800
1000
Number of Customers

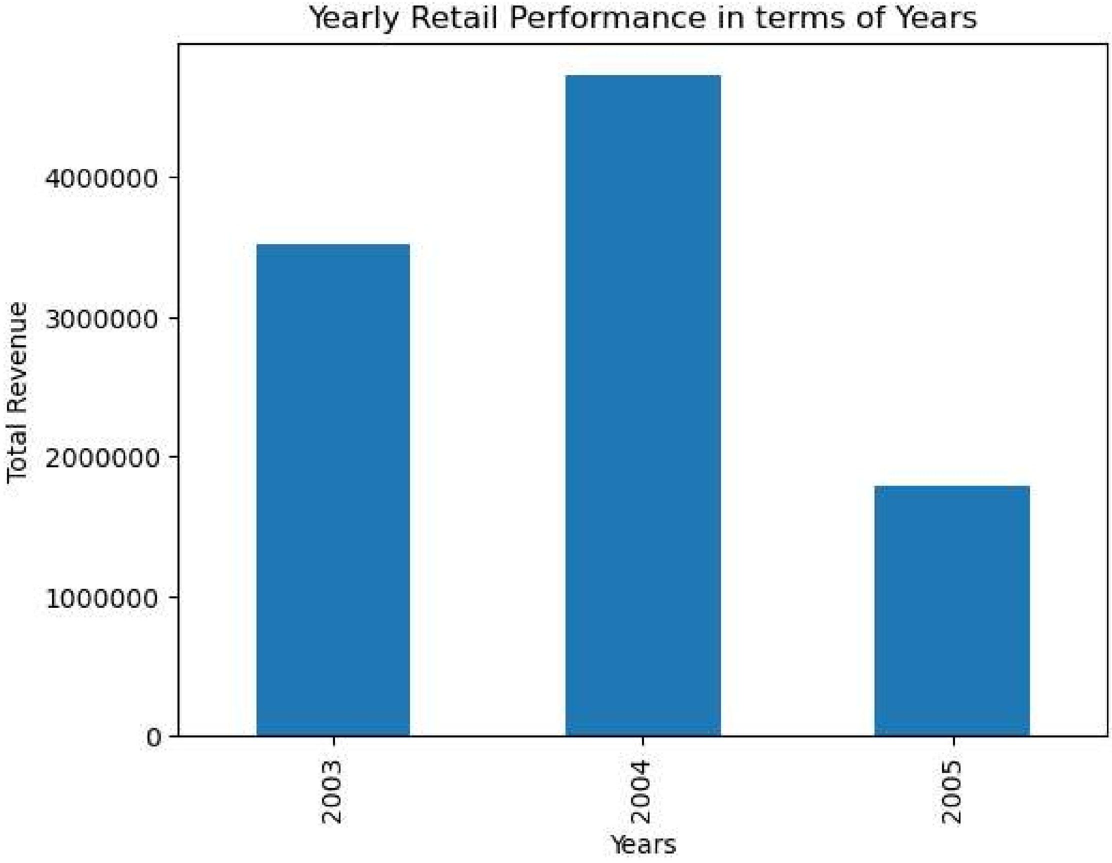

Where customers come from
(Australia,)
(Spain,)
(UK,)
(France,)
(USA,)
Country
0
5
10
15
20
25
30
35
Number of Customers

In [135]:

```
# 2
yearly_revenue = df.groupby(['YEAR_ID', 'MONTH_ID'])['SALES'].sum()
print(yearly_revenue)
yearly_in_months_revenue = df.groupby(['MONTH_ID', 'YEAR_ID'])['SALES'].sur
annual_revenue = df.groupby(['YEAR_ID'])['SALES'].sum()
print(annual_revenue)

yearly_in_months_revenue.plot.bar()
plt.title("Yearly Retail Performance in terms of Months and Years")
plt.ticklabel_format(useOffset = False, style = 'plain', axis = 'y')
plt.xlabel('Months, Years')
plt.ylabel('Total Revenue')
plt.show()

annual_revenue.plot.bar()
plt.title("Yearly Retail Performance in terms of Years")
plt.ticklabel_format(useOffset = False, style = 'plain', axis = 'y')
plt.xlabel('Years')
plt.ylabel('Total Revenue')
plt.show()
```

```
YEAR_ID  MONTH_ID
2003     1            129753.60
         2            140836.19
         3            174504.90
         4            201609.55
         5            192673.11
         6            168082.56
         7            187731.88
         8            197809.30
         9            263973.36
         10           568290.97
         11          1029837.66
         12           261876.46
2004     1            316577.42
         2            311419.53
         3            205733.73
         4            206148.12
         5            273438.39
         6            286674.22
         7            327144.09
         8            461501.27
         9            320750.91
         10           552924.25
         11          1089048.01
         12           372802.66
2005     1            339543.42
         2            358186.18
         3            374262.76
         4            261633.29
         5            457861.06
Name: SALES, dtype: float64
YEAR_ID
2003    3516979.54
2004    4724162.60
2005    1791486.71
Name: SALES, dtype: float64
```

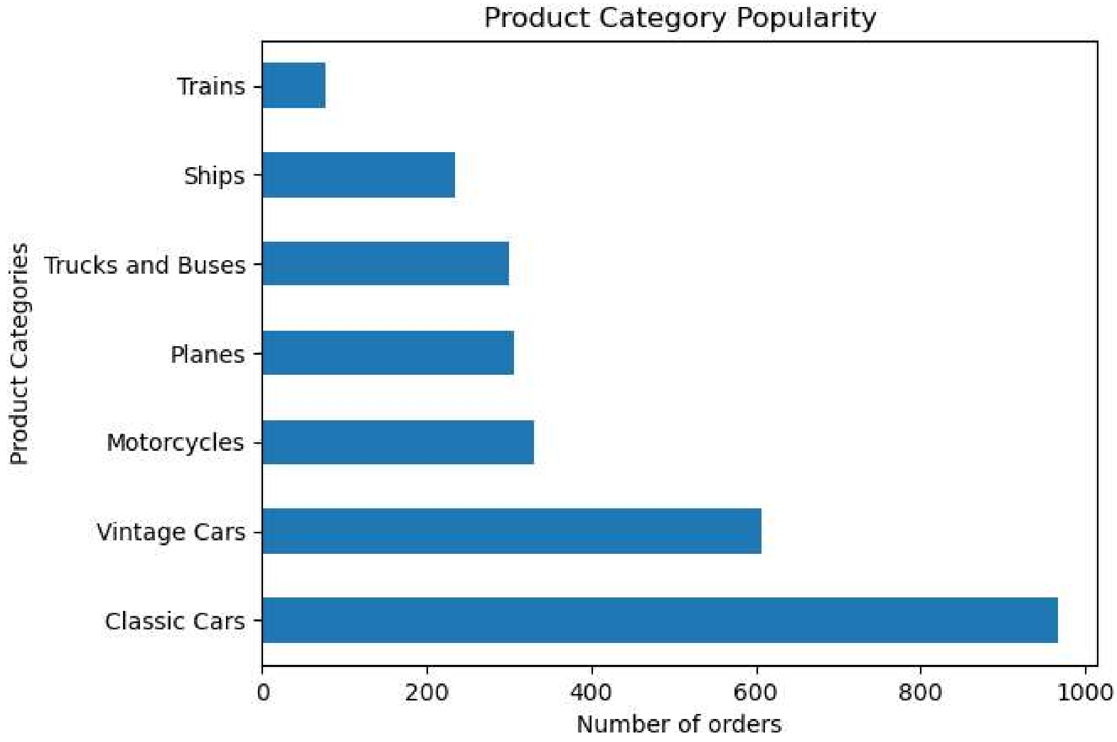

Yearly Retail Performance in terms of Months and Years
Total Revenue
0
200000
400000
600000
800000
1000000
(1, 2003)
(1, 2004)
(1, 2005)
(2, 2003)
(2, 2004)
(2, 2005)
(3, 2003)
(3, 2004)
(3, 2005)
(4, 2003)
(4, 2004)
(4, 2005)
(5, 2003)
(5, 2004)
(5, 2005)
(6, 2003)
(6, 2004)
(7, 2003)
(7, 2004)
(8, 2003)
(8, 2004)
(9, 2003)
(9, 2004)
(10, 2003)
(10, 2004)
(11, 2003)
(11, 2004)
(12, 2003)
(12, 2004)
Months, Years


Yearly Retail Performance in terms of Years
Total Revenue
0
1000000
2000000
3000000
4000000
2003
2004
2005
Years

In [130]:

```
# 3
product_popularity = df['PRODUCTLINE'].value_counts()

print("Most popular product category")
print(product_popularity.head(1))
print()
print("Least popular product category")
print(product_popularity.tail(1))

product_popularity.plot.barh()
plt.title("Product Category Popularity")
plt.xlabel('Number of orders')
plt.ylabel('Product Categories')
plt.show()
```

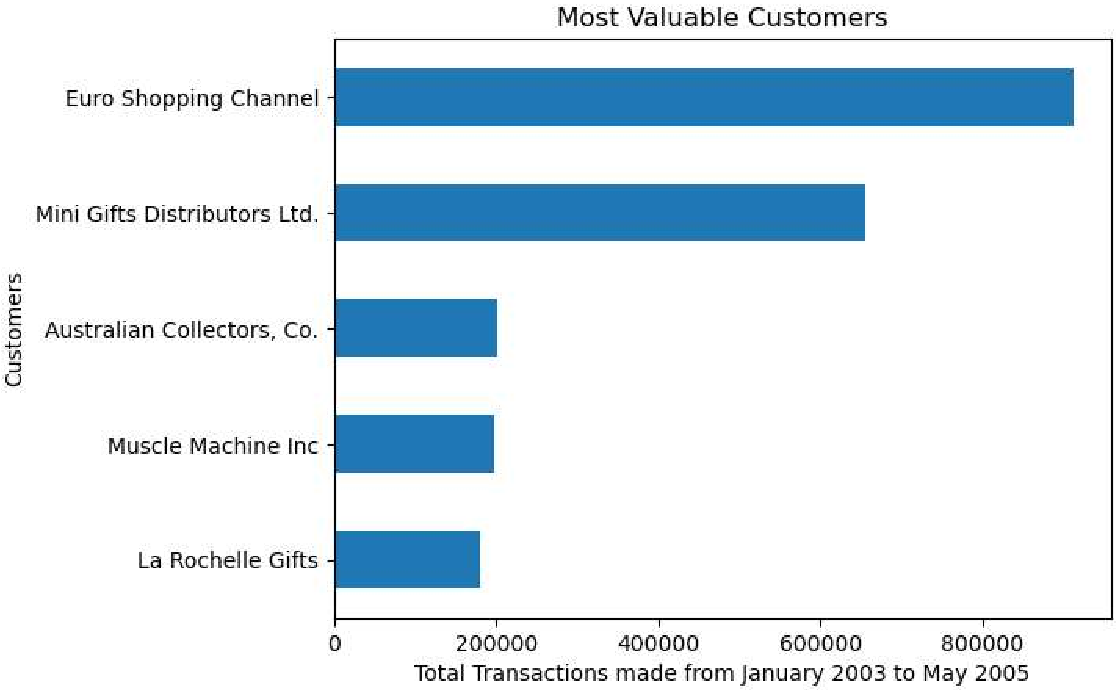
```
Most popular product category
PRODUCTLINE
Classic Cars    967
Name: count, dtype: int64

Least popular product category
PRODUCTLINE
Trains    77
Name: count, dtype: int64
```



In [179]:

```
# 4
most_valuable_customers = df.groupby(['CUSTOMERNAME'])['SALES'].sum()
most_valuable_customers = most_valuable_customers.sort_values(ascending=Tru
print(most_valuable_customers)

most_valuable_customers.plot.barh()
plt.title("Most Valuable Customers")
plt.xlabel('Total Transactions made from January 2003 to May 2005')
plt.ylabel('Customers')
plt.show()
```

```
CUSTOMERNAME
La Rochelle Gifts                 180124.90
Muscle Machine Inc                197736.94
Australian Collectors, Co.        200995.41
Mini Gifts Distributors Ltd.      654858.06
Euro Shopping Channel             912294.11
Name: SALES, dtype: float64
```


Most Valuable Customers
Customers
Euro Shopping Channel
Mini Gifts Distributors Ltd.
Australian Collectors, Co.
Muscle Machine Inc
La Rochelle Gifts
Total Transactions made from January 2003 to May 2005