Stores Sales Preprocessing and Analysis

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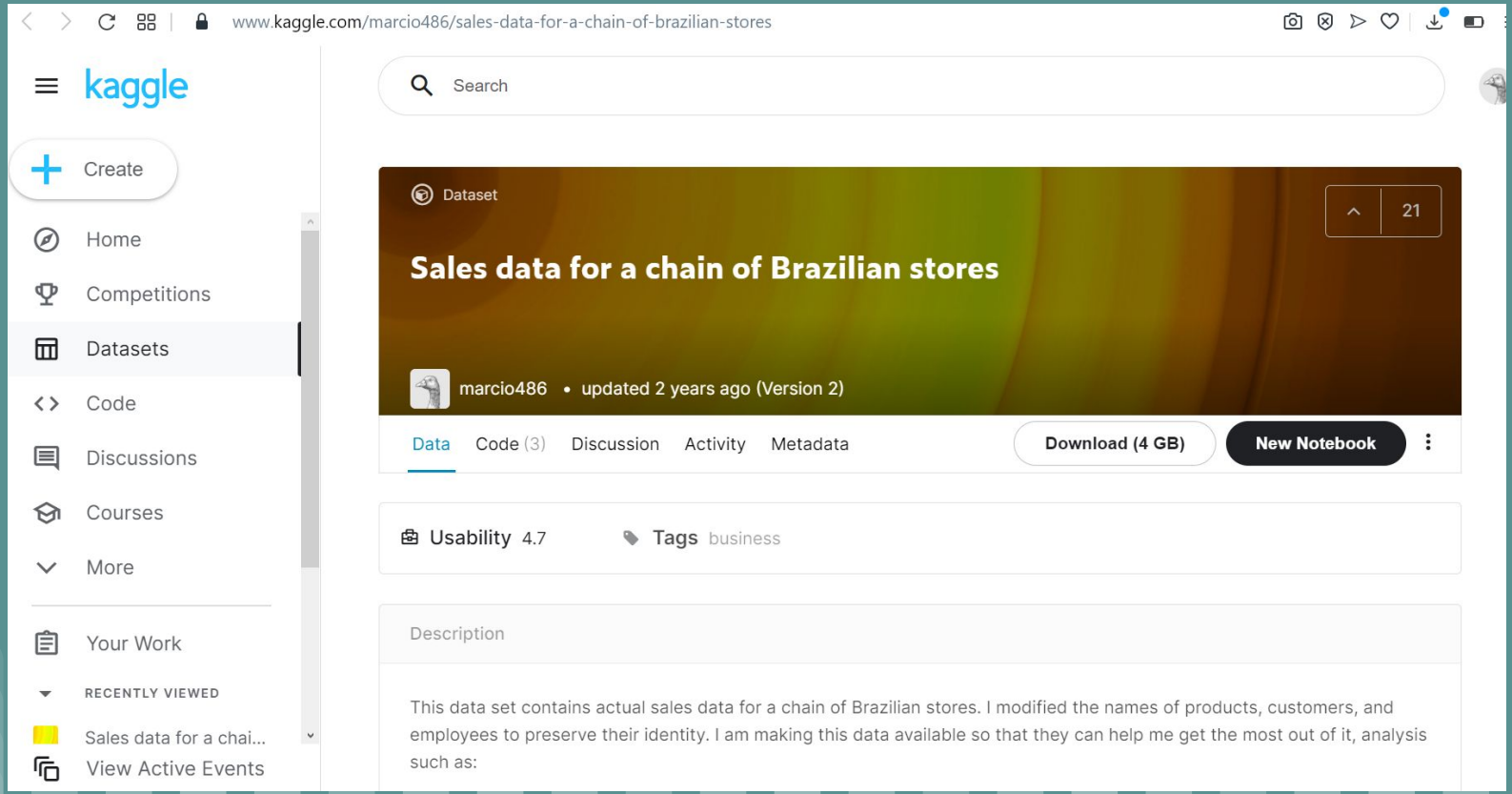
The Database



The Database

	Company Code	Order Number	Employee	Product	Product Category	Client	Client City	Sale Date Time	Product Cost	Discount Amount	Amount	Total	Form of payment
0	39000	12	Stacy Day	Special Gasoline	Fuel	Customer not informed	No City	2017-03-31 04:10:00	3.050	0.0	5.642	20.02	Money
1	39000	21	Olive Stevenson	Special Diesel	Fuel	Customer not informed	No City	2017-03-31 04:13:00	2.510	0.0	125.045	350.00	Debit Card
2	39000	38	Stacy Day	Special Diesel	Fuel	Customer not informed	No City	2017-03-31 04:25:00	2.510	0.0	35.699	99.92	Money
3	39000	39	Olive Stevenson	Lubricant 1108	Lubricant	Customer not informed	No City	2017-03-31 04:26:00	7.409	0.0	1.000	13.00	Money
4	39000	39	Olive Stevenson	Diesel Auto Clean	Fuel	Customer not informed	No City	2017-03-31 04:26:00	2.560	0.0	42.162	120.96	Money
...	...	...	...	...	...	...	...	...	...	...	...	...	...
1048570	39000	312686	Terri Massey	Special Gasoline	Fuel	Customer not informed	No City	2017-09-05 21:04:00	3.187	0.0	35.499	131.31	Money
1048571	1420000	312214	Gerardo Moore	Special Gasoline	Fuel	Customer not informed	No City	2017-09-05 21:04:00	3.215	0.0	27.035	100.00	Credit Card
1048572	1312000	312191	Phillip Fletcher	Gasoline	Fuel	Penny Burns	Krafdale	2017-09-05 21:04:00	3.163	0.0	11.692	45.00	Money
1048573	39000	312687	Rodney Patton	Gasoline	Fuel	Customer not informed	No City	2017-09-05 21:05:00	3.177	0.0	30.160	111.56	Money
1048574	11848000	312058	Robin Johnston	Special Gasoline	Fuel	Customer not informed	No City	2017-09-05 21:05:00	3.227	0.0	27.405	100.00	Money

1048575 rows × 13 columns

Index:

1- data Preprocessing and cleaning.

null values
datatypes readability
finding outliers and removing them

2- sales statistics

max and min products sold and product prices

3- data visualization

numerical and categorical
product cost, amount, total, form of payment, company code

1- Data Preprocessing and cleaning

a- Checking for Null Values

By Checking for Null values there were no null values found

```
Company Code          0
Order Number          0
Employee              0
Product               0
Product Category      0
Client                0
Client City           0
Sale Date Time        0
Product Cost          0
Discount Amount       0
Amount                0
Total                 0
Form of payment       0
dtype: int64
```

b- checking Data Types

By checking data types the time and date was not recognized therefore it's recognized by code as shown

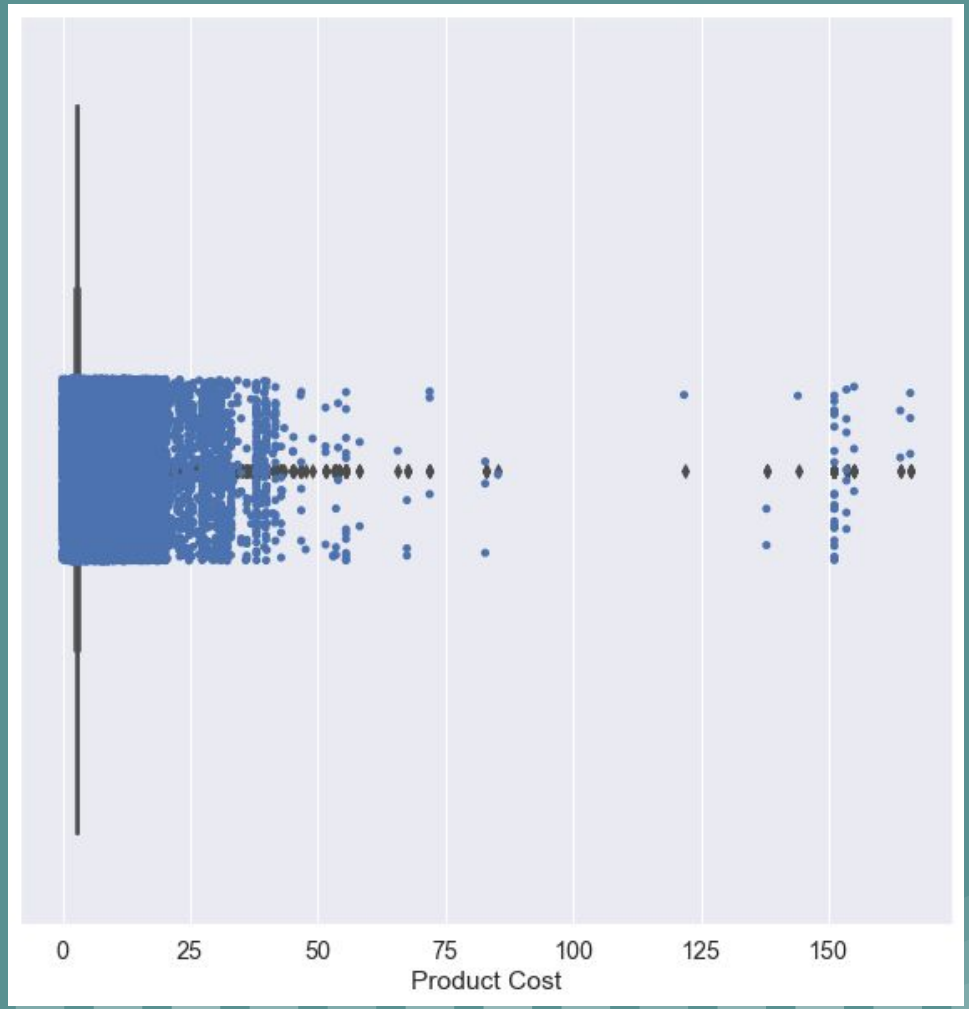
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1048575 entries, 0 to 1048574
Data columns (total 13 columns):
 #   Column            Non-Null Count    Dtype
---  ------            --------------    -----
 0   Company Code      1048575 non-null  int64
 1   Order Number      1048575 non-null  int64
 2   Employee          1048575 non-null  object
 3   Product           1048575 non-null  object
 4   Product Category  1048575 non-null  object
 5   Client            1048575 non-null  object
 6   Client City       1048575 non-null  object
 7   Sale Date Time    1048575 non-null  object
 8   Product Cost      1048575 non-null  float64
 9   Discount Amount   1048575 non-null  float64
 10  Amount            1048575 non-null  float64
 11  Total             1048575 non-null  float64
 12  Form of payment   1048575 non-null  object
dtypes: float64(4), int64(2), object(7)
memory usage: 104.0+ MB
```

```
stores_df['Sale Date Time']=pd.to_datetime(stores_df['Sale Date Time'], format='%Y/%m/%d %H:%M:%S')
stores_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1048575 entries, 0 to 1048574
Data columns (total 13 columns):
 #   Column            Non-Null Count    Dtype
---  ------            --------------    -----
 0   Company Code      1048575 non-null  int64
 1   Order Number      1048575 non-null  int64
 2   Employee          1048575 non-null  object
 3   Product           1048575 non-null  object
 4   Product Category  1048575 non-null  object
 5   Client            1048575 non-null  object
 6   Client City       1048575 non-null  object
 7   Sale Date Time    1048575 non-null  datetime64[ns]
 8   Product Cost      1048575 non-null  float64
 9   Discount Amount   1048575 non-null  float64
 10  Amount            1048575 non-null  float64
 11  Total             1048575 non-null  float64
 12  Form of payment   1048575 non-null  object
dtypes: datetime64[ns](1), float64(4), int64(2), object(6)
memory usage: 104.0+ MB
```

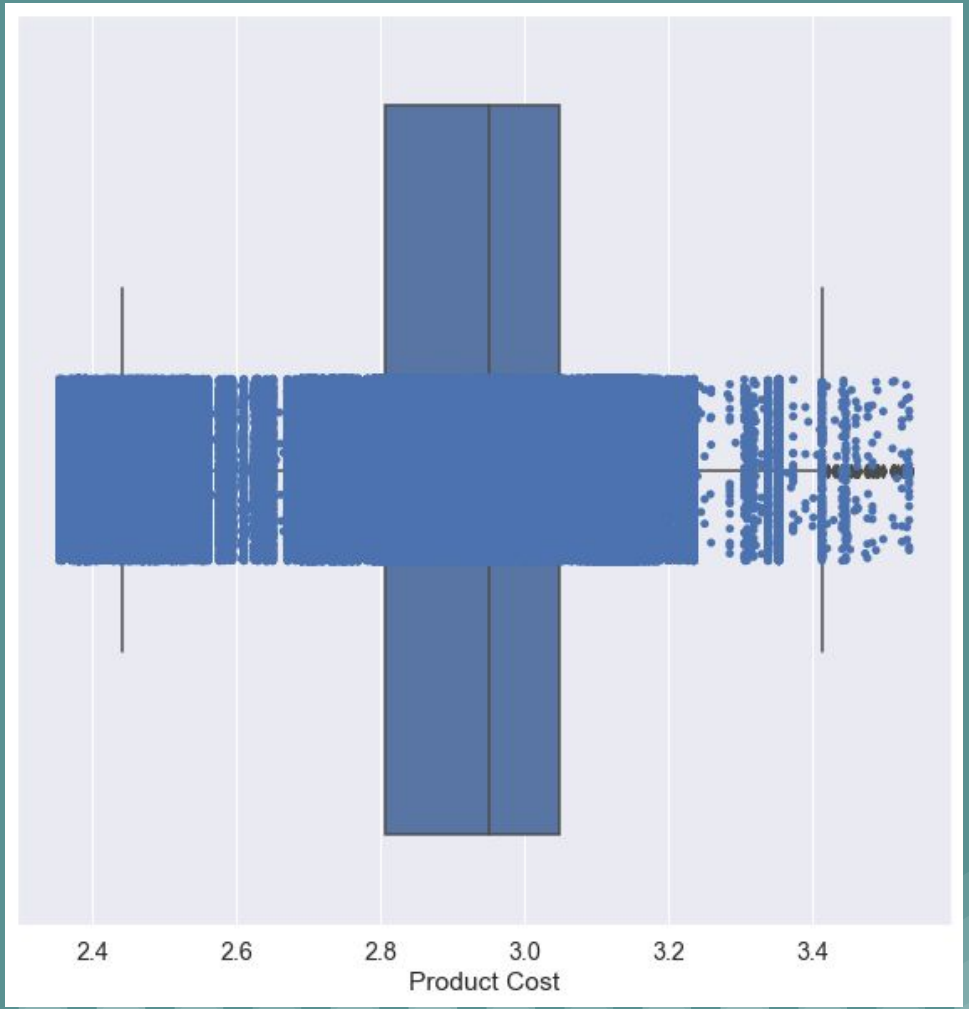
c-checking for outliers and removing them

The box plot for the “Product cost” feature showing outliers

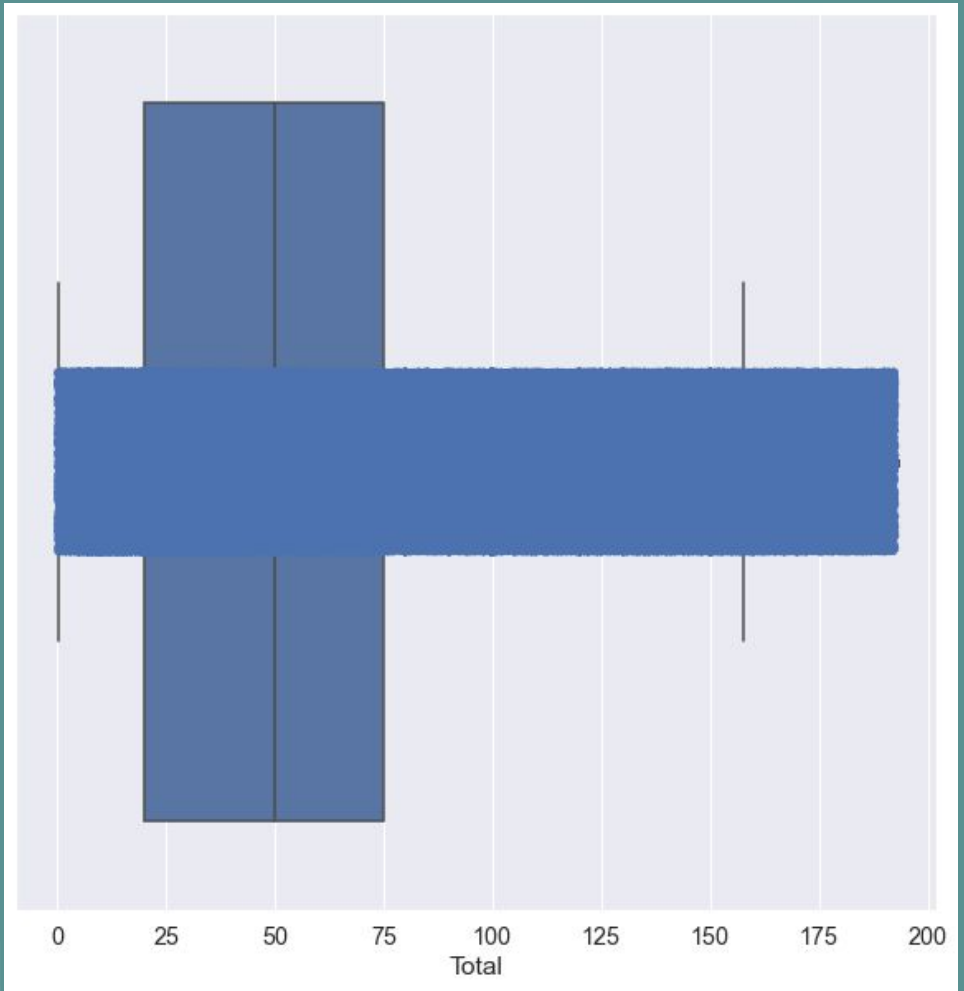


After Removing outliers from “Product Cost” feature

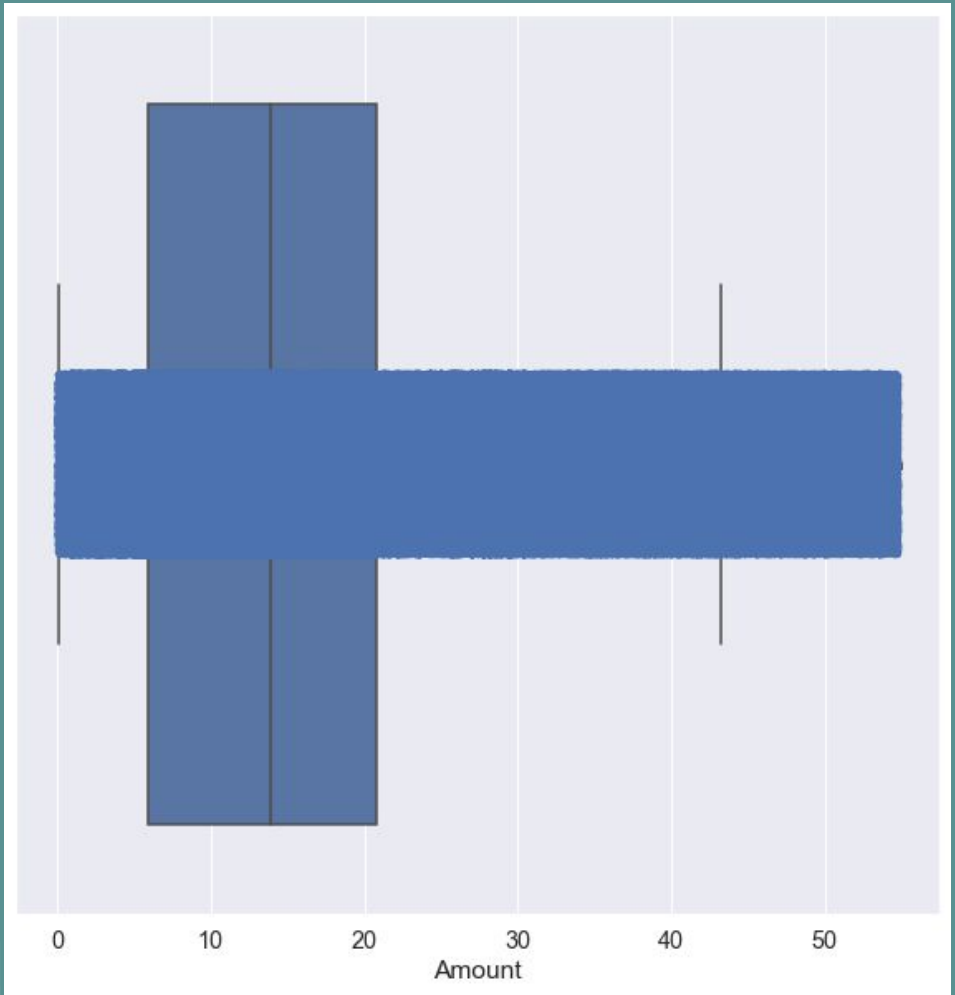
```
# Replacing outliers in Product Cost

from datasist.structdata import detect_outliers

#detecting outliers in "Total Calories" column
outlier_indices=detect_outliers(stores_df,0,['Product Cost'])

#removing outliers and setting them to the median
stores_df.loc[outlier_indices,['Product Cost']]= stores_df['Product Cost'].median()

#rechecking ...
sns.boxplot(x='Product Cost',data=stores_df)
sns.stripplot(x='Product Cost',data=stores_df)
```



After Removing outliers from “Total” feature



After Removing outliers from “Amount” feature



Replacing outliers in 'Discount amount' would ruin the data since most of it is zero therefore the real values are the outliers

Discount Amount
0.0
0.0
0.0
0.0
0.0
...
0.0
0.0
0.0
0.0
0.0

2- Checking the Sales Statistics

Using the describe function

```
stores_df[['Product Cost','Discount Amount','Amount','Total']].describe()
```

	Product Cost	Discount Amount	Amount	Total
count	1.048575e+06	1.048575e+06	1.048575e+06	1.048575e+06
mean	2.917386e+00	2.935126e-04	1.569439e+01	5.557508e+01
std	1.802976e-01	3.516798e-02	1.239711e+01	4.284051e+01
min	2.354000e+00	0.000000e+00	3.800000e-02	1.300000e-01
25%	2.806000e+00	0.000000e+00	5.885000e+00	2.001000e+01
50%	2.950000e+00	0.000000e+00	1.389300e+01	5.000000e+01
75%	3.049000e+00	0.000000e+00	2.084000e+01	7.502000e+01
max	3.534000e+00	2.249000e+01	5.475000e+01	1.925100e+02

Showing most sold products

```
stores_df.loc[stores_df['Total'] == 192.51]['Product'].unique()
```

```
array(['Special Gasoline', 'Diesel Auto Clean'], dtype=object)
```

Showing least sold products

```
stores_df.loc[stores_df['Total'] == .13]['Product'].unique()
```

```
array(['Gasoline'], dtype=object)
```

Showing most expensive products

```
stores_df.loc[stores_df['Product Cost'] ==3.534]['Product'].unique()
```

```
array(['Several 351'], dtype=object)
```

Showing cheapest products

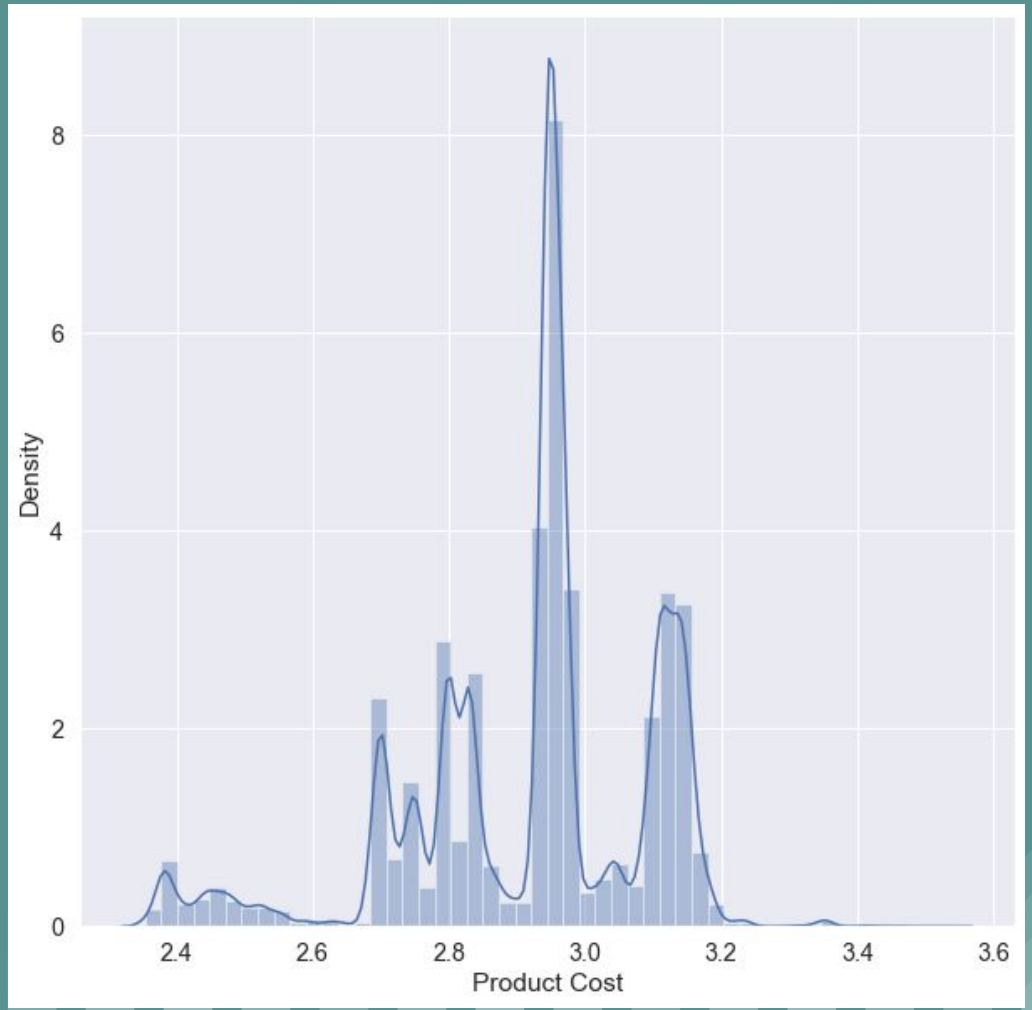
```
stores_df.loc[stores_df['Product Cost'] == 2.354]['Product'].unique()
```

```
array(['Special Diesel'], dtype=object)
```

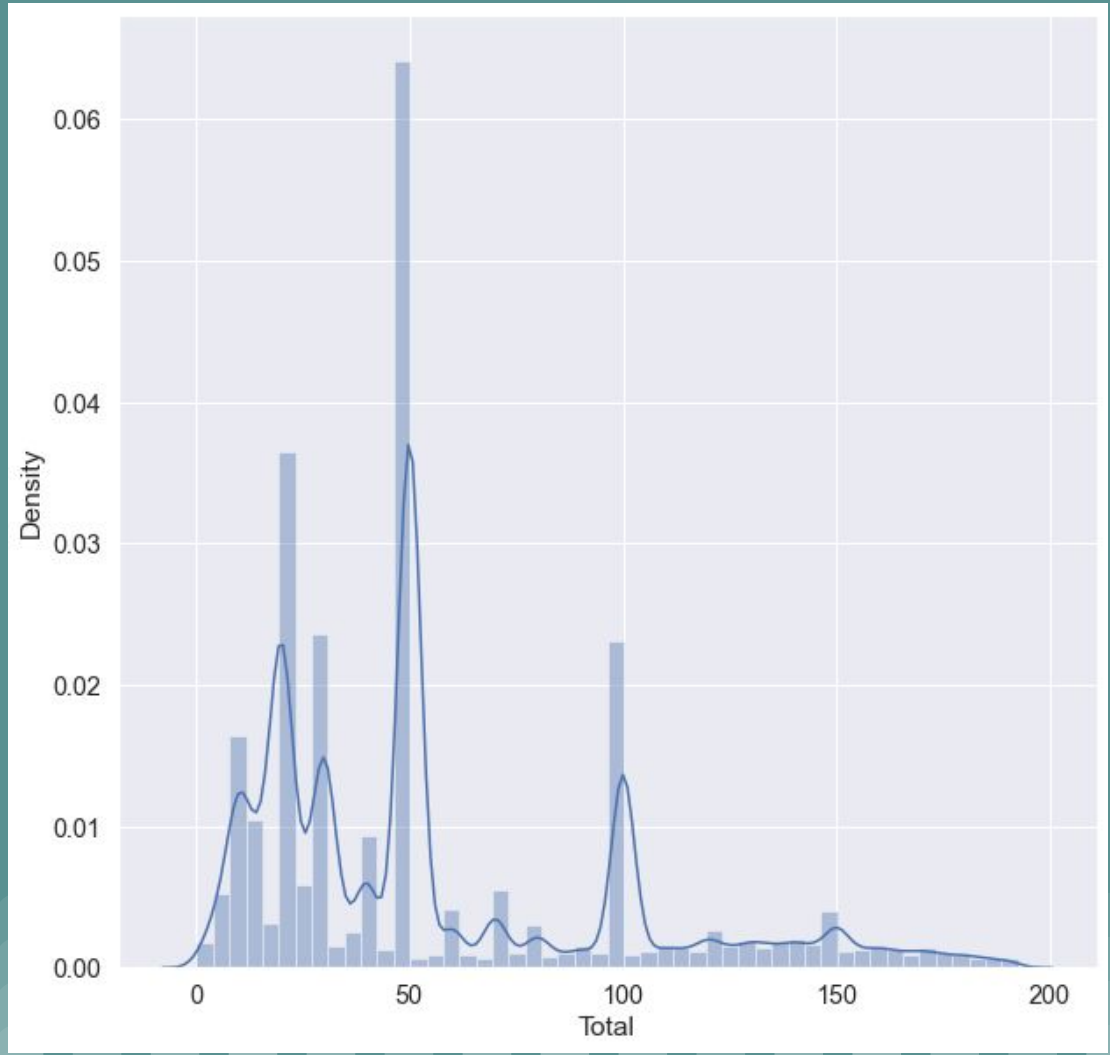
3- Data Visualization

a- Numerical Data Visualization

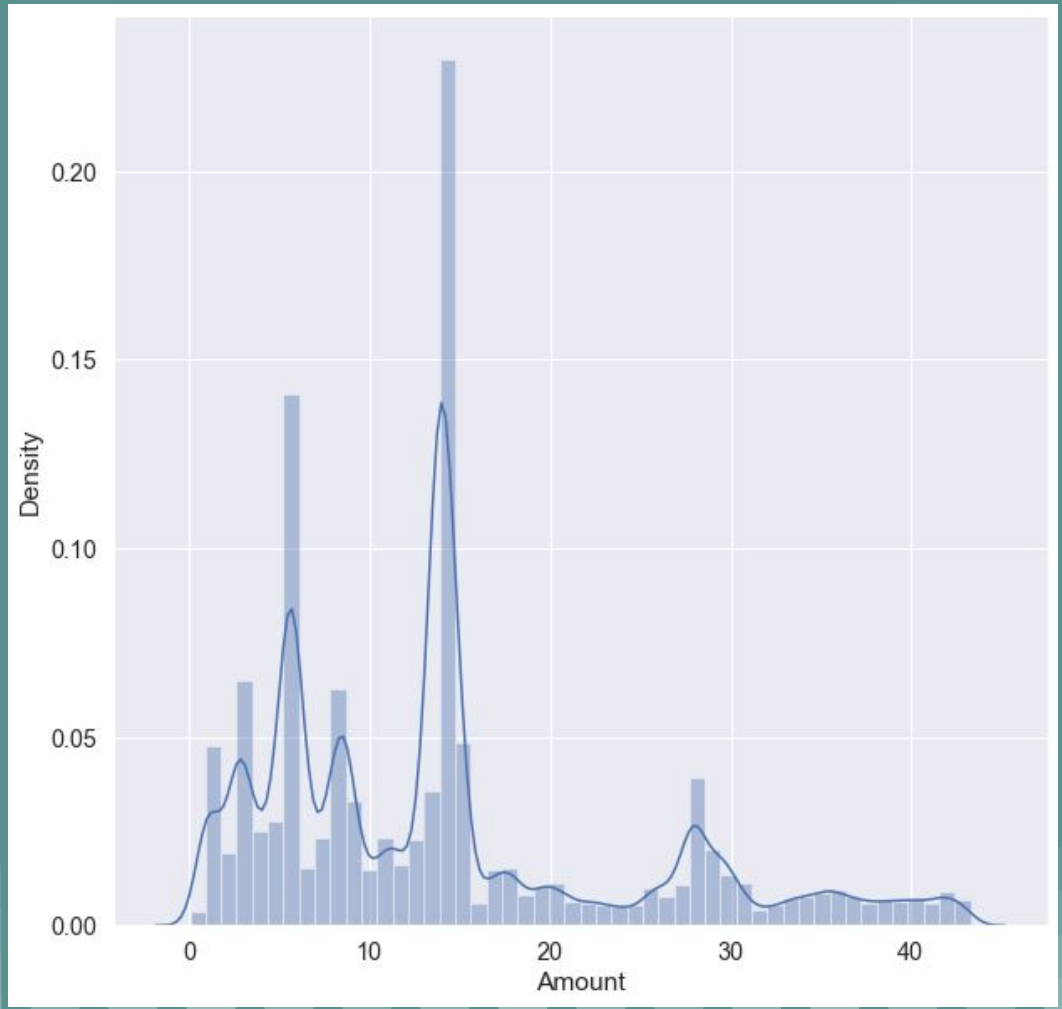
Product Cost



Total Cost

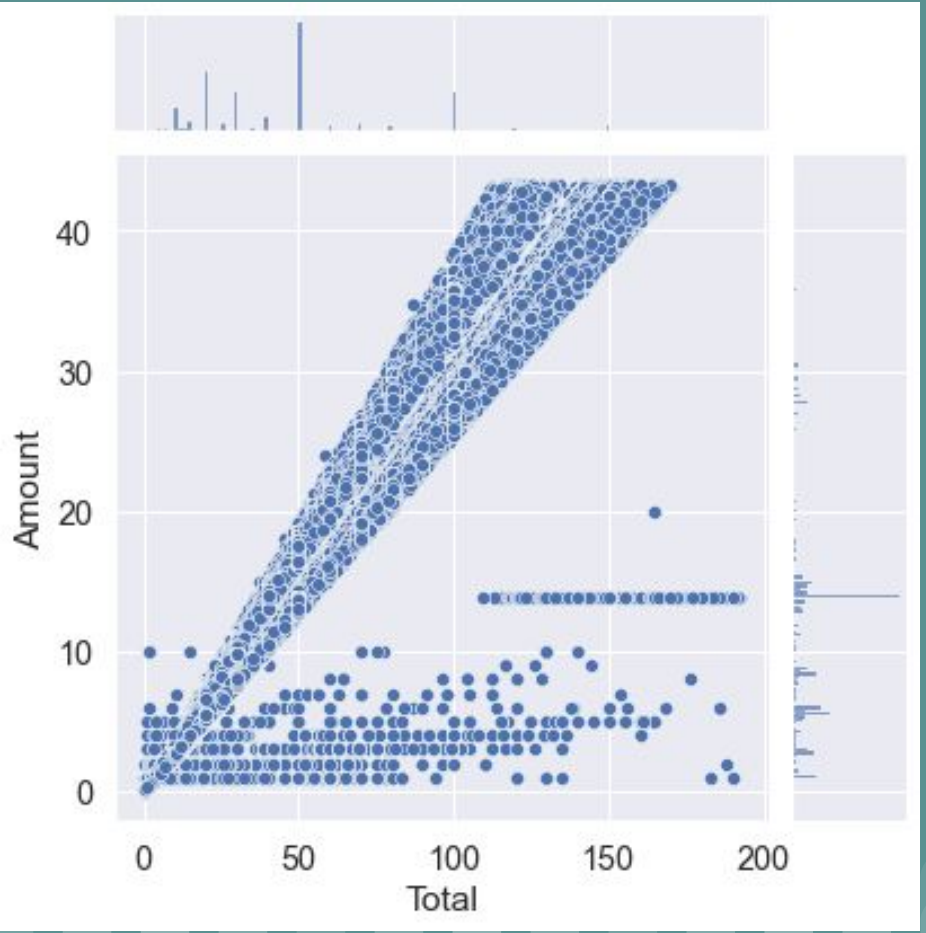


Amount sold



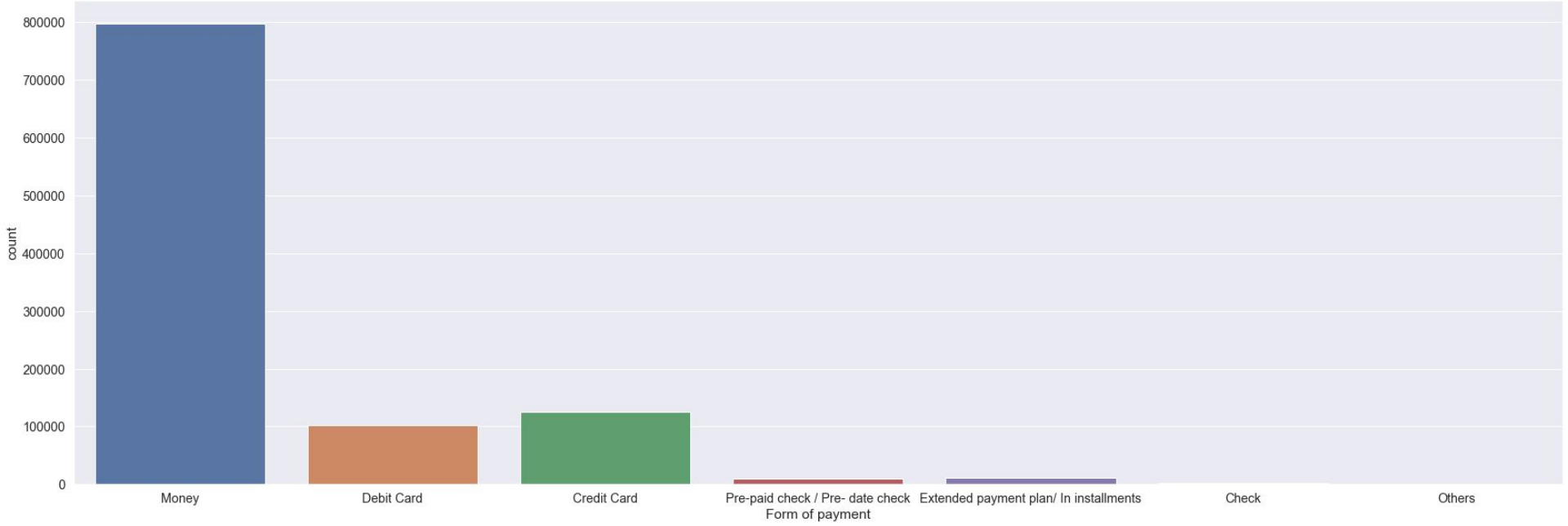
Total sold vs Amount sold

Most data is showing a directly proportional relationship as expected

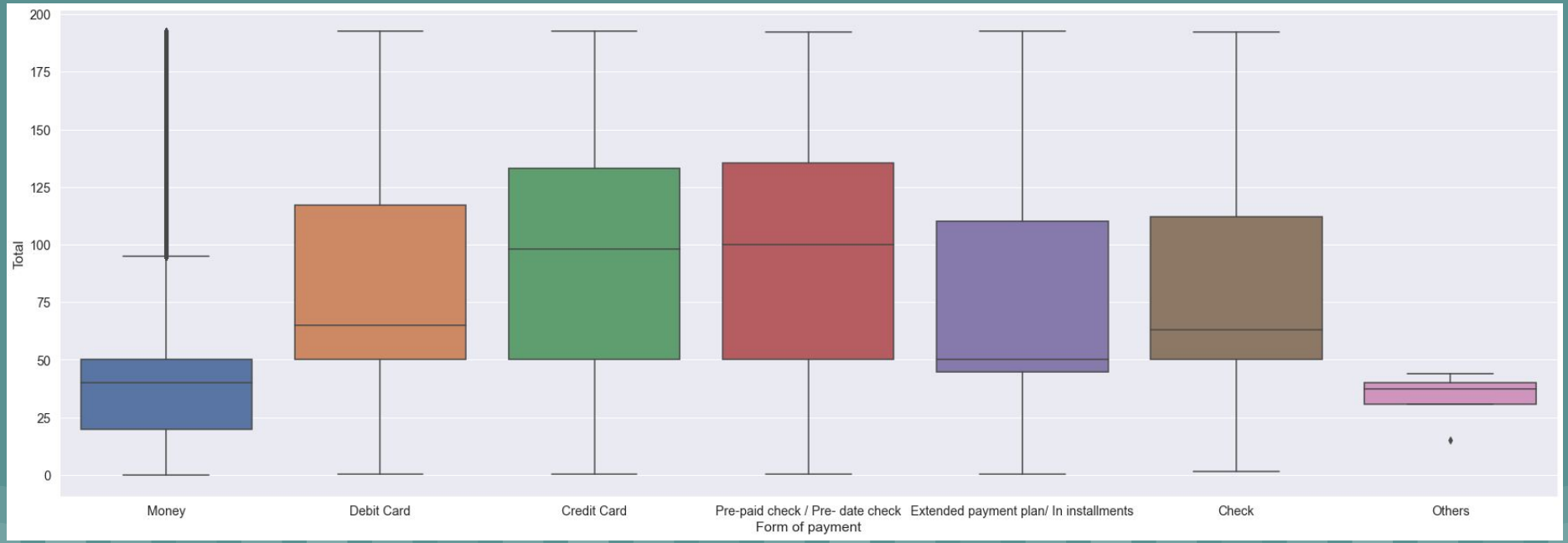


b- Categorical analysis

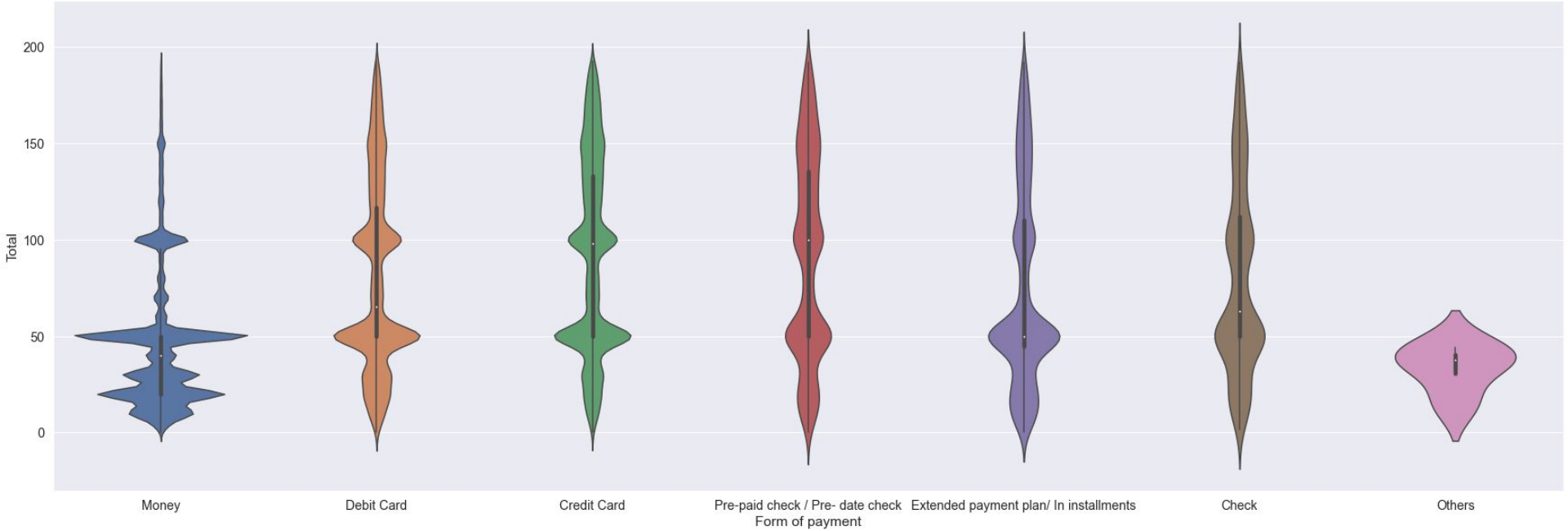
frequency of usage of each form of payment



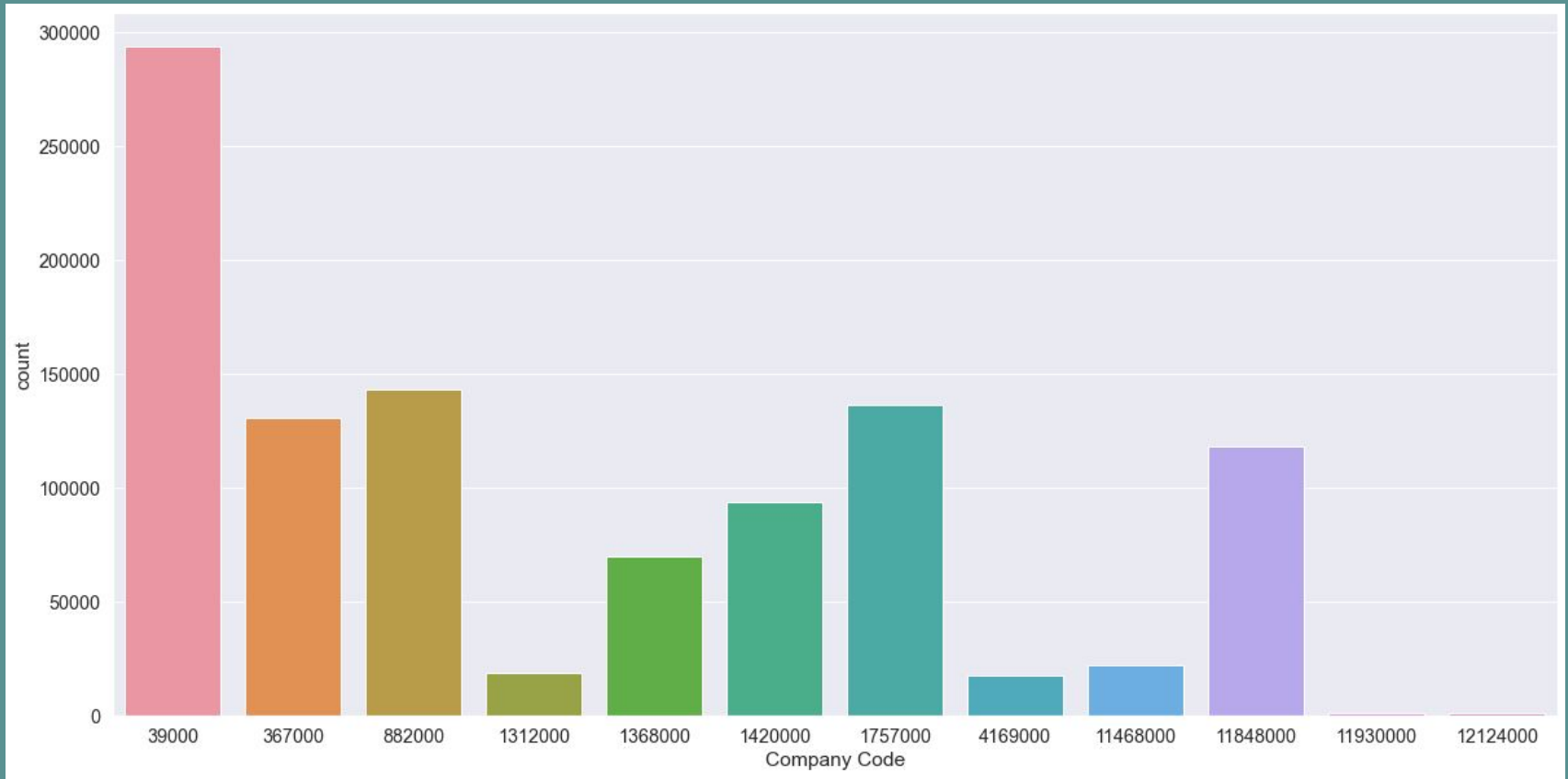
The 5 number theory with the forms of payment with the total cost of products (box plot)



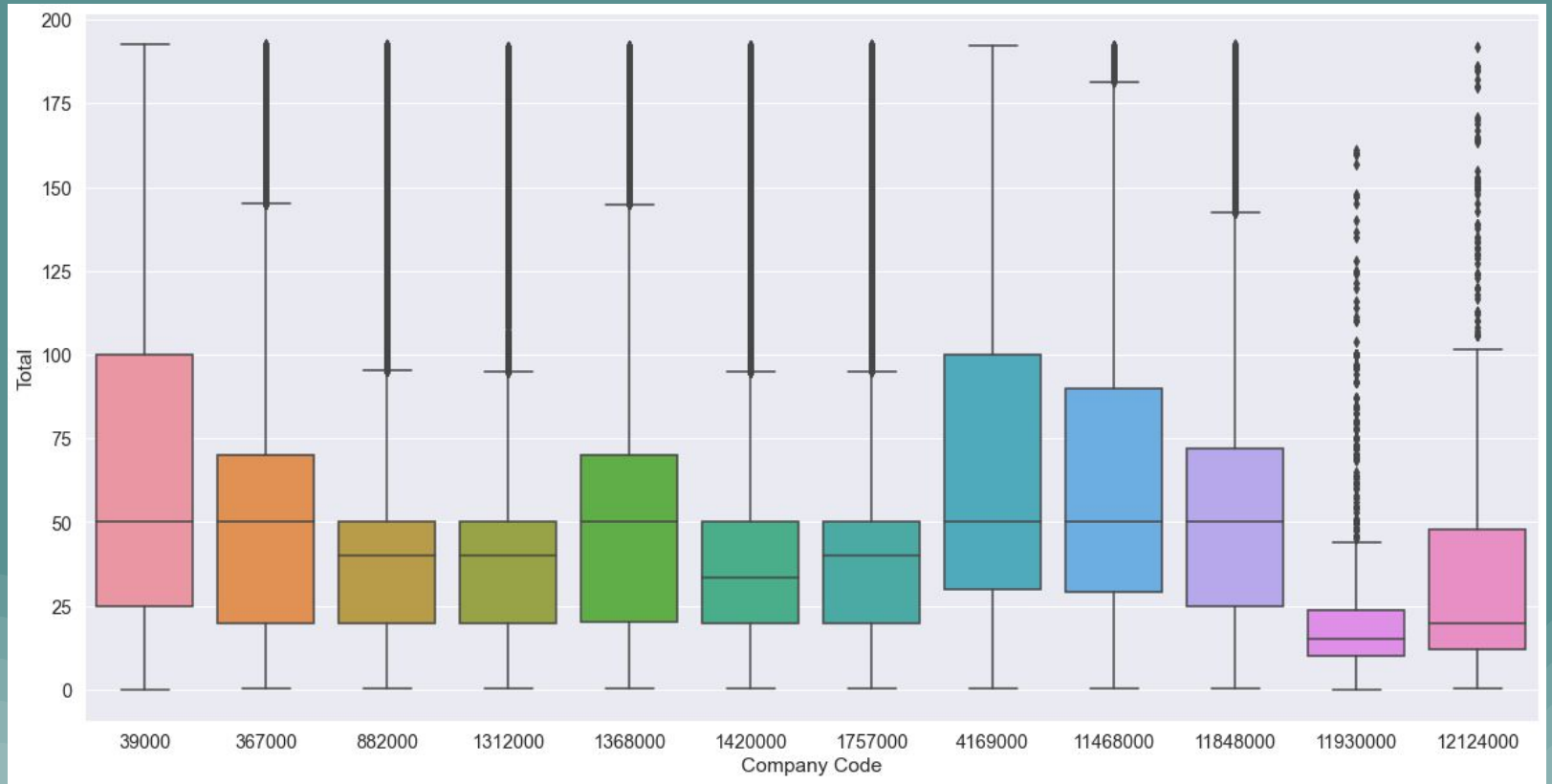
The 5 number theory with the forms of payment with the total cost of products with distribution (violin plot)



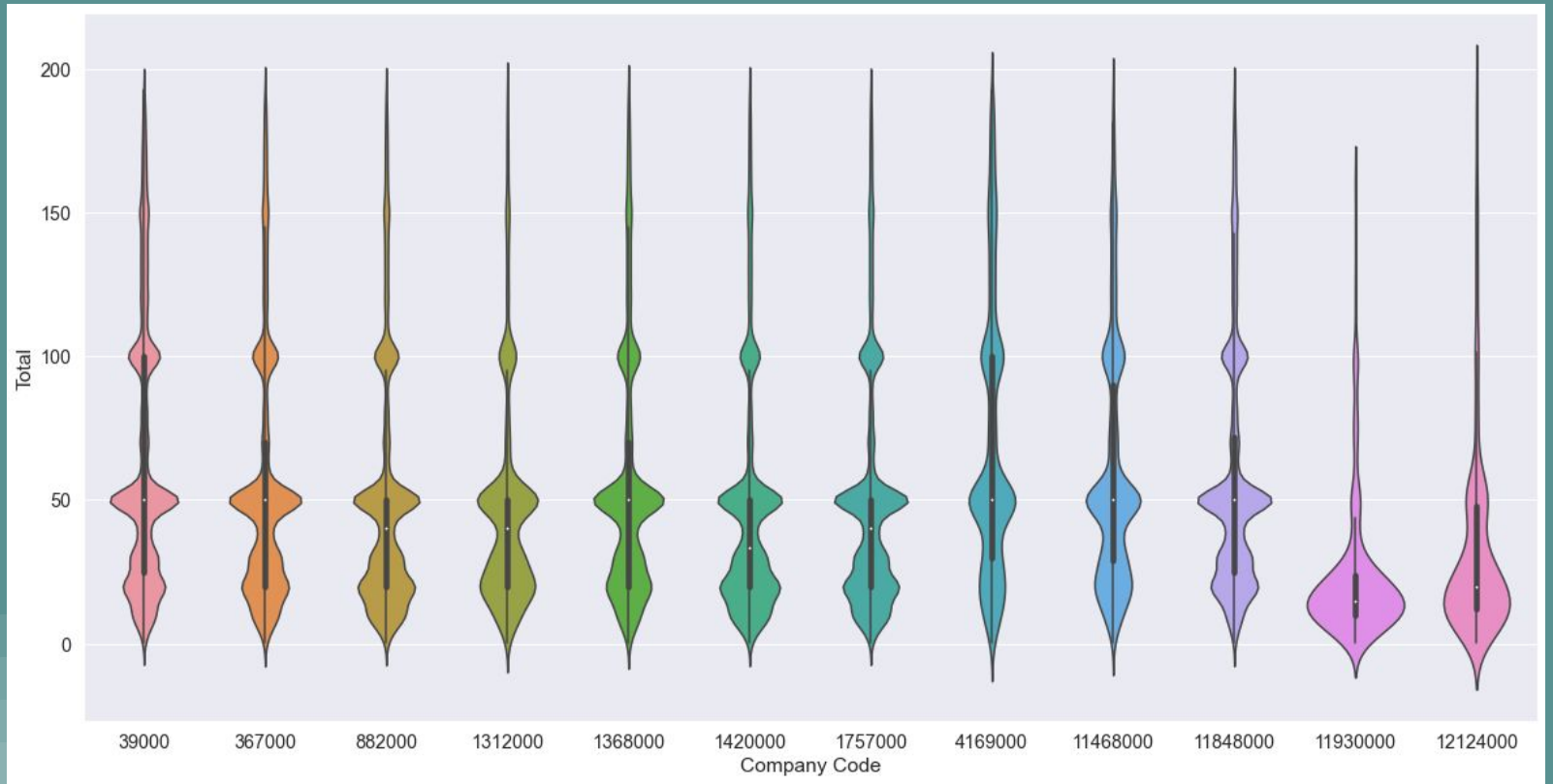
frequency of usage of each company code



The 5 number theory with the company code with the total cost of products (box plot)



The 5 number theory with the company code with the total cost of products with distribution (violin plot)



Recommendation:

Recommending companies with company codes: 1312000, 4169000, 11930000, 12124000 to increase their sellings and look into products and average cost.