DSC680_CPJP_EDA

January 8, 2022

1 Data Preprocessing

[1]:
```
from ipynb.fs.full.DSC680_CPJP_Data_Preprocessing import *
```

```
********* November 2000 data****************
```

```
  transaction_dt customer_id age_group pin_code product_subclass    product_id ␣
 ↪amount asset sales_price
1    2000-11-01      00046855         D         E          110411       4710085120468 ␣
 ↪  3        51          57
2    2000-11-01      00539166         E         E          130315       4714981010038 ␣
 ↪  2        56          48
3    2000-11-01      00663373         F         E          110217       4710265847666 ␣
 ↪  1       180         135
```

```
********* December 2000 data****************
```

```
  transaction_dt customer_id age_group pin_code product_subclass    product_id ␣
 ↪amount asset sales_price
1    2000-12-01      00207423         C         E          530101       4710054134403 ␣
 ↪  1       92          99
2    2000-12-01      00329002         F         E          590514       4710049000973 ␣
 ↪  1       41          49
3    2000-12-01      01657951         E         E          120103       4710011401135 ␣
 ↪  1       23          29
```

```
********* January 2021 data****************
```

```
  transaction_dt customer_id age_group pin_code product_subclass   product_id  ␣
↪amount asset sales_price
1    2001-01-01     00141833        F          F          130207        4710105011011 ␣
 ↪  2       44        52
2    2001-01-01     01376753        E          E          110217        4710265849066 ␣
 ↪  1      150       129
3    2001-01-01     01603071        E          G          100201        4712019100607 ␣
 ↪  1       35        39
```

*********** Feb 2021 data******************

```
  transaction_dt customer_id age_group pin_code product_subclass   product_id  ␣
↪amount asset sales_price
1    2001-02-01     00557818        H          E          500210        4710114105046 ␣
 ↪  1      123       135
2    2001-02-01     01677683        C          B          711310        4902520163103 ␣
 ↪  6      840       894
3    2001-02-01     01900910        A          D          500206        4710036003598 ␣
 ↪  1       26        33
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 817741 entries, 0 to 817740
Data columns (total 12 columns):
 #   Column            Non-Null Count   Dtype
---  ------            --------------   -----
 0   transaction_dt    817741 non-null  datetime64[ns]
 1   customer_id       817741 non-null  object
 2   age_group         817741 non-null  object
 3   pin_code          817741 non-null  object
 4   product_subclass  817741 non-null  object
 5   product_id        817741 non-null  object
 6   amount            817741 non-null  object
 7   asset             817741 non-null  object
 8   sales_price       817741 non-null  object
 9   age_label         817741 non-null  object
 10  age_int           817741 non-null  int64
 11  pin_code_int      817741 non-null  int64
dtypes: datetime64[ns](1), int64(2), object(9)
memory usage: 74.9+ MB
```

```
None
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 817741 entries, 0 to 817740
Data columns (total 29 columns):
```

```
 #   Column             Non-Null Count   Dtype
---  ------             --------------   -----
 0   transaction_dt     817741 non-null  datetime64[ns]
 1   customer_id        817741 non-null  object
 2   product_subclass   817741 non-null  int64
 3   product_id         817741 non-null  int64
 4   amount             817741 non-null  int64
 5   asset              817741 non-null  int64
 6   sales_price        817741 non-null  int64
 7   age_label          817741 non-null  object
 8   age_int            817741 non-null  int64
 9   pin_code_int       817741 non-null  int64
 10  age_group_A        817741 non-null  int32
 11  age_group_B        817741 non-null  int32
 12  age_group_C        817741 non-null  int32
 13  age_group_D        817741 non-null  int32
 14  age_group_E        817741 non-null  int32
 15  age_group_F        817741 non-null  int32
 16  age_group_G        817741 non-null  int32
 17  age_group_H        817741 non-null  int32
 18  age_group_I        817741 non-null  int32
 19  age_group_J        817741 non-null  int32
 20  age_group_K        817741 non-null  int32
 21  pin_code_A         817741 non-null  int32
 22  pin_code_B         817741 non-null  int32
 23  pin_code_C         817741 non-null  int32
 24  pin_code_D         817741 non-null  int32
 25  pin_code_E         817741 non-null  int32
 26  pin_code_F         817741 non-null  int32
 27  pin_code_G         817741 non-null  int32
 28  pin_code_H         817741 non-null  int32
dtypes: datetime64[ns](1), int32(19), int64(7), object(2)
memory usage: 121.7+ MB
```

```
None
```

```
<pandas.io.formats.style.Styler at 0x18e3f9366a0>
```

```
<pandas.io.formats.style.Styler at 0x18e3f986940>
```

2 Exploratory Data Analysis

[2]:

```python
# Import packages
```

[3]:

```python
import matplotlib.pyplot as plt
import seaborn as sns
sns.set_theme(style="whitegrid")
from scipy import stats
```

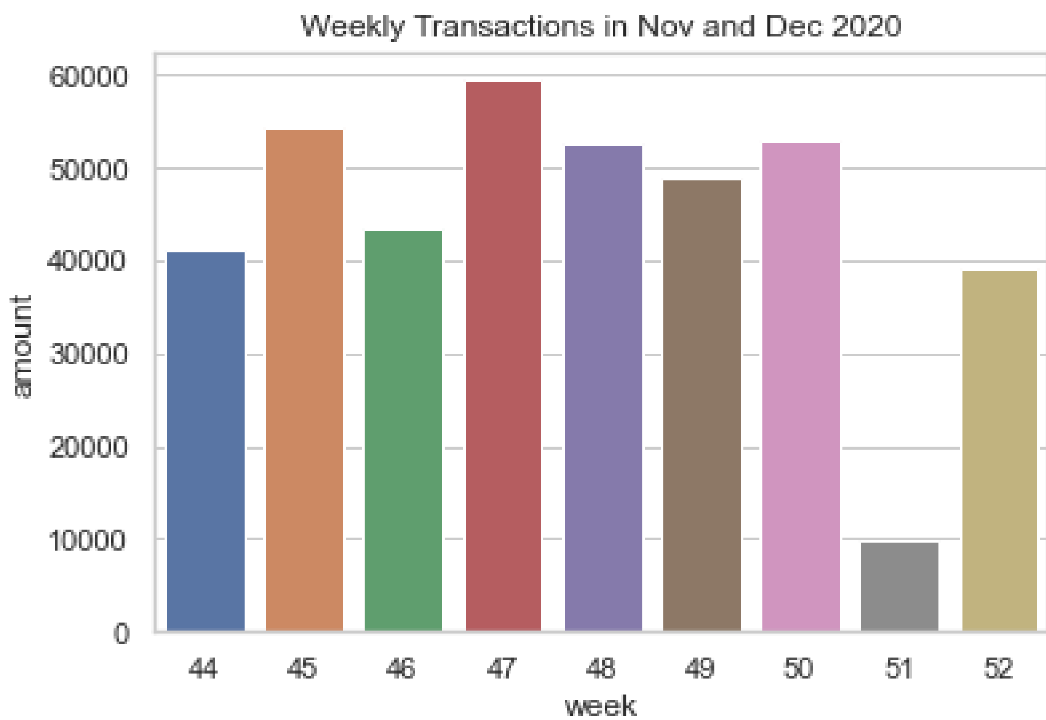
```
from scipy.stats import truncnorm
import statsmodels.api as sm
import pylab
```

1. Count of transactions by weeks

[4]:
```
wk_set=cust_data_subset[['year','week','amount']]
wk_set=wk_set.groupby(['year','week']).count()
wk_set=wk_set.reset_index()
wk_set_2k_df=wk_set[wk_set['year']==2000][['week','amount']]
wk_set_2k1_df=wk_set[wk_set['year']==2001][['week','amount']]
```

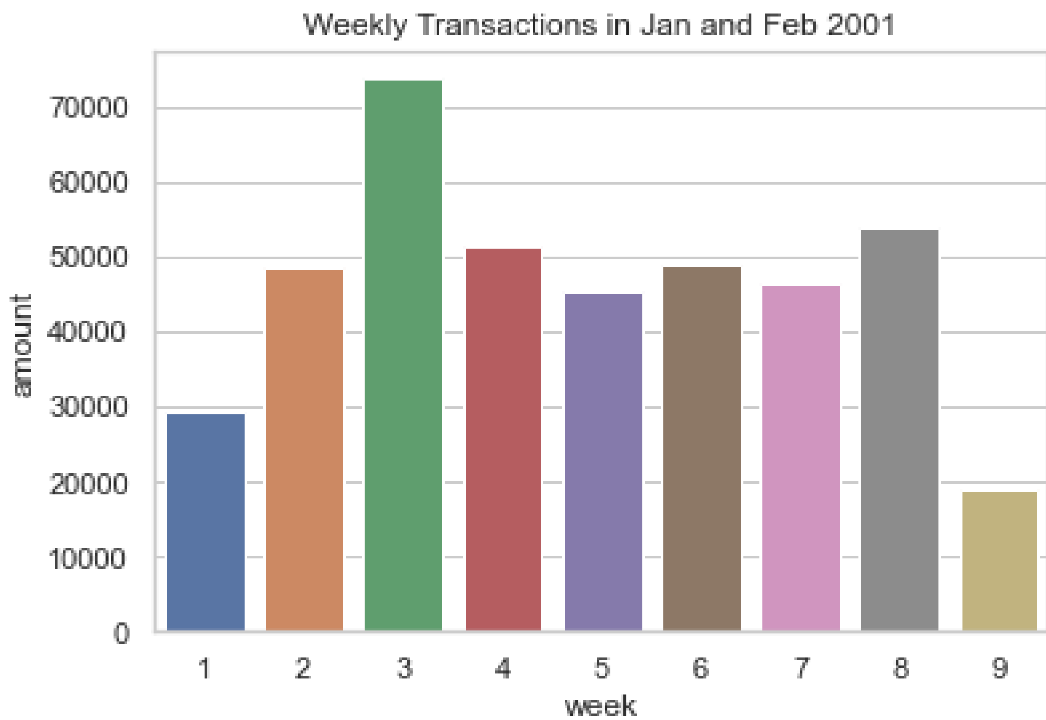
[5]:
```
sns.barplot(x="week", y="amount", data=wk_set_2k_df).set_title('Weekly␣
↪Transactions in Nov and Dec 2020')
```

[5]:
```
Text(0.5, 1.0, 'Weekly Transactions in Nov and Dec 2020')
```



[6]:
```
sns.barplot(x="week", y="amount", data=wk_set_2k1_df).set_title('Weekly␣
↪Transactions in Jan and Feb 2001')
```

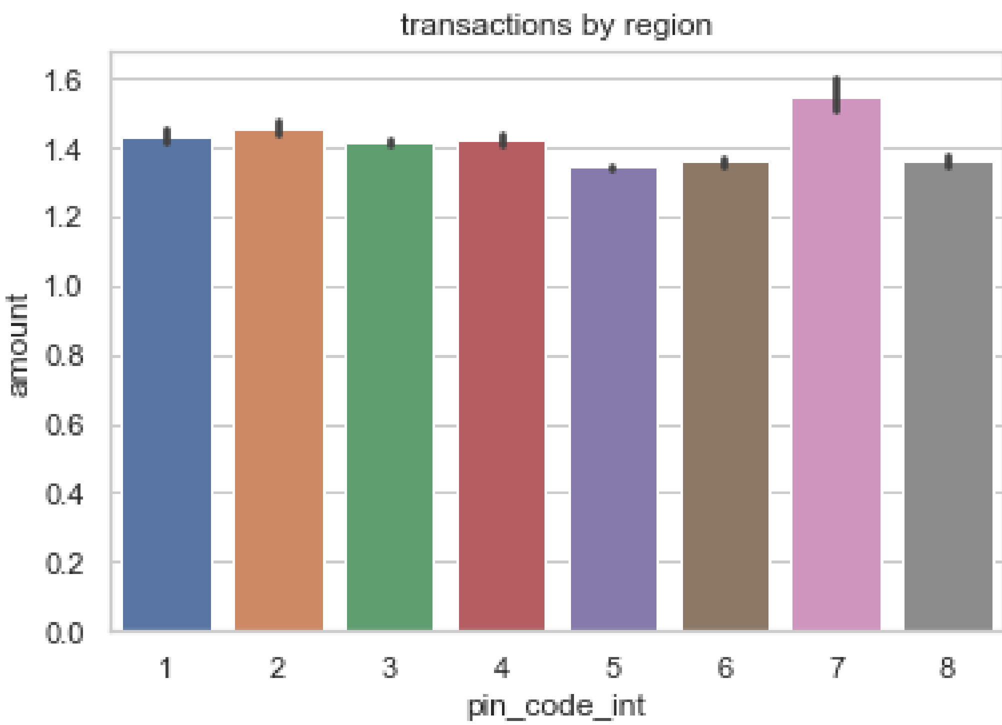
[6]:
```
Text(0.5, 1.0, 'Weekly Transactions in Jan and Feb 2001')
```



2. Transactions per region

[7]:
```
sns.barplot(x="pin_code_int", y="amount", data=cust_data_subset).
 ↪set_title('transactions by region')
```

[7]: Text(0.5, 1.0, 'transactions by region')



3. purchase routines based on age groups

[8]:
```
def row_percent(df,col):
    col_sum=df[col].sum()
    return df[col]/col_sum
```

[9]:
```
age_grps=pd.DataFrame(cust_data_subset.age_int.value_counts()).reset_index()
age_grps.columns=['Age_Class','Counts']

age_grps['Age_Class']=age_grps['Age_Class'].map(inv_age_dict_int)
age_grps['Age_Class']=age_grps['Age_Class'].map(age_dict_class)
age_grps['Percent']=row_percent(age_grps,'Counts')
age_grps
```

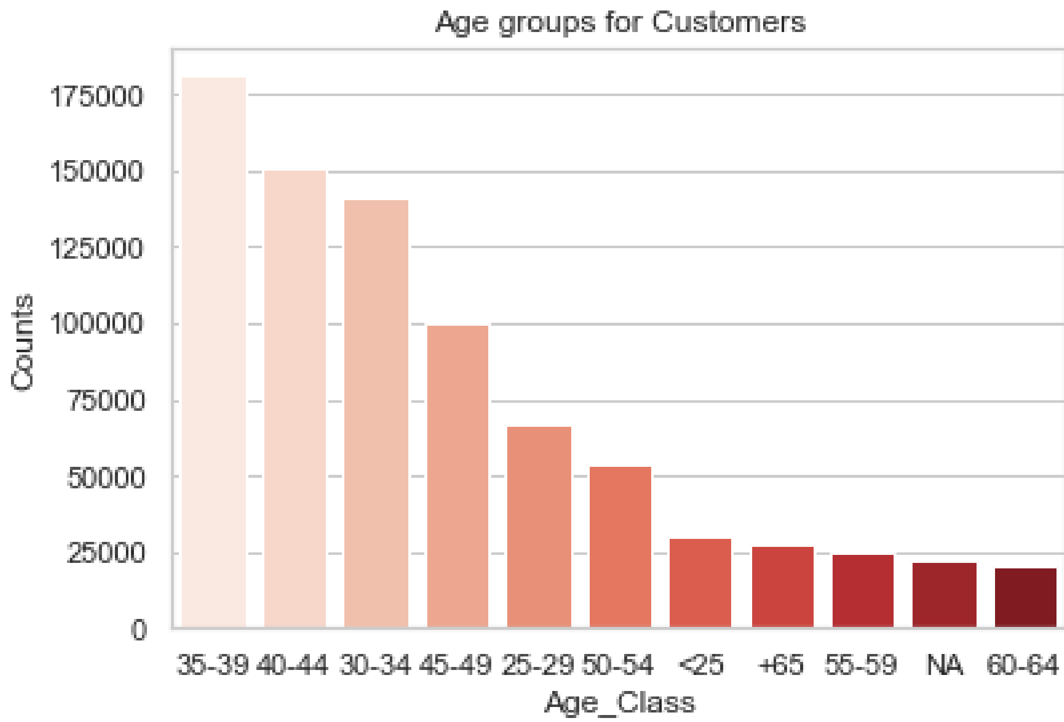
[9]:

	Age_Class	Counts	Percent
0	35-39	181213	0.222
1	40-44	151023	0.185
2	30-34	140805	0.172
3	45-49	99719	0.122
4	25-29	66432	0.081
5	50-54	53719	0.066
6	<25	30070	0.037
7	+65	27353	0.033
8	55-59	24743	0.030

```
9         NA    22362   0.027
10     60-64    20302   0.025
```

[10]:
```
sns.barplot(x="Age_Class", y="Counts", data=age_grps, palette='Reds').
↪set_title('Age groups for Customers')
```

[10]:
```
Text(0.5, 1.0, 'Age groups for Customers')
```



the frequent shoppers belong to age group 35-39 and 40-44 followed by 30-34.

4. large purchase orders

This is a plot showing the number of purchases been mase by customers. Since the data is organized by transaction date we can see that certain dates/days received dramatically more purchases than other days. i am more interested in holiday seasons of 2000 and 2001 we should expect to see increases in purchase activity.

[11]:
```
def boxPlot(variable):
    sns.boxplot(x=variable)
    return plt.show(),plt.clf()
```

[12]:
```
def CDFPlot(variable):
    lower,upper=variable.min(),variable.max()
    mu,sigma = variable.mean(),variable.std()
```

```python
    values = stats.truncnorm((lower - mu) / sigma, (upper - mu) / sigma, loc=mu, scale=sigma)
    sns.kdeplot(variable,cumulative=True,label=variable.name+" CDF",color='b')
    sns.kdeplot(values.rvs(1000),cumulative=True,label="Gaussian CDF",color='r')
    plt.suptitle("Cumulative Distribution Frequency of purchase amount Against Normal Gaussian distribution.")
    plt.figure()
    return plt.show(),plt.clf()
```

[13]:
```python
def Large_Purchase_Order(x):
    if x>99: # Arbitrary threshold of 100
        x=1
    else:
        x=0
    return x
```

[14]:
```python
cust_data['Large_Order']=cust_data.amount.apply(Large_Purchase_Order)
```

[15]:
```python
print('Number of Large Orders',len(cust_data[cust_data['Large_Order']==1]))
cust_data[cust_data['Large_Order']==1].head()
```

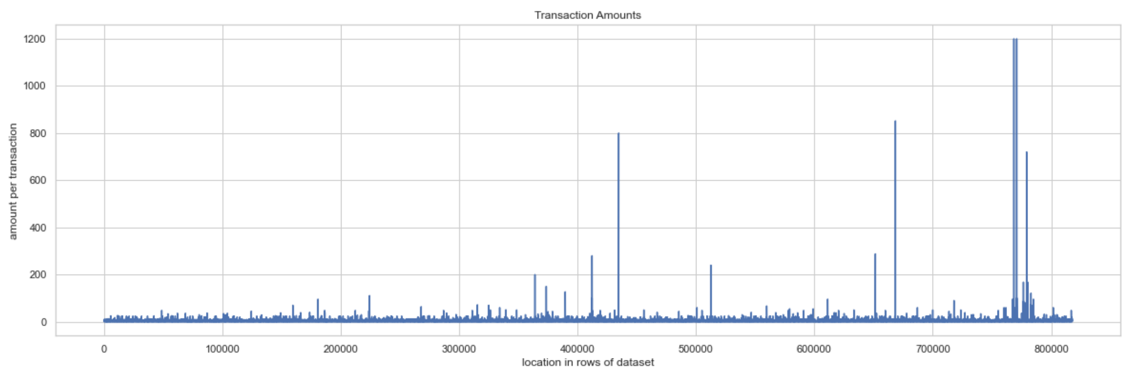
```
Number of Large Orders 23
```

[15]:
```
       transaction_dt customer_id  product_subclass   product_id    amount
asset  sales_price age_label  age_int  pin_code_int  age_group_A  age_group_B
age_group_C  age_group_D  age_group_E  age_group_F  age_group_G  age_group_H
age_group_I  age_group_J  age_group_K  pin_code_A  pin_code_B  pin_code_C
pin_code_D  pin_code_E  pin_code_F  pin_code_G  pin_code_H  Large_Order
224250   2001-01-03     01062489        560402       4710628119010    111
43290     45554        25-29      2            7            0            1
0            0            0            0            0            0            0
0            0            0           0           0            0            0
0           1           0            1
363947   2000-11-25     01515749        100504       4710085104116    200
16200     16920        35-39      4            6            0            0
0            1            0            0            0            0            0
0            0            0           0           0            0            0
1           0           0            1
363948   2000-11-26     01515749        500201       4710114128038    150
22500     21870        35-39      4            6            0            0
0            1            0            0            0            0            0
0            0            0           0           0            0            0
1           0           0            1
373505   2000-11-26     01533705        500201       4710114128038    150
22500     21870        25-29      2            6            0            1
0            0            0            0            0            0            0
0            0            0           0           0            0            0
1           0           0            1
```

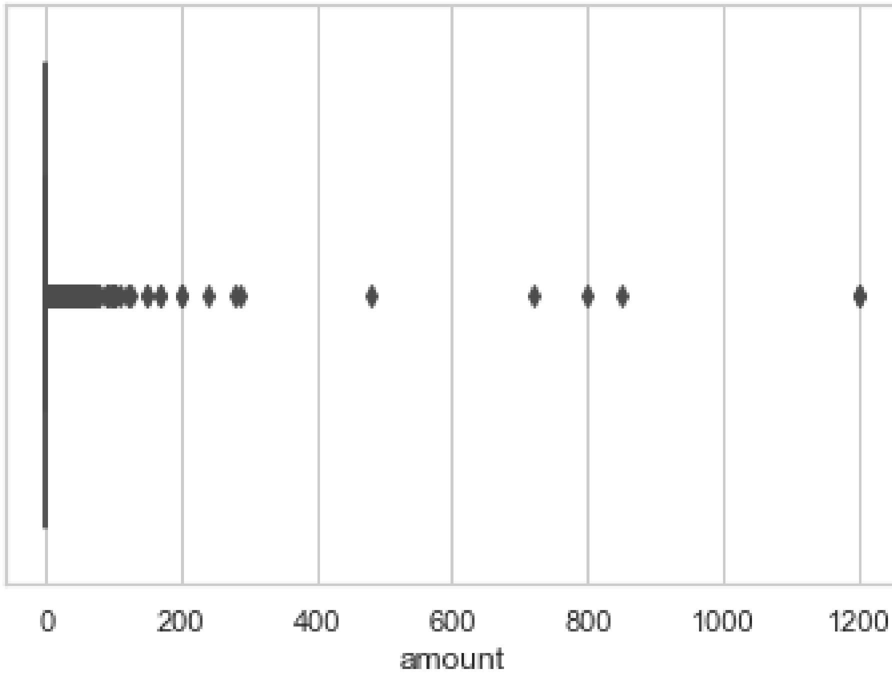
389531 2000-11-27 01558418 560402 4710628131012 127
49403 49172 35-39 4 6 0 0
0 1 0 0 0 0 0
0 0 0 0 0 0 0
1 0 0 1

[16]:
```
fig, axs = plt.subplots(figsize = (20,6))
plt.plot(cust_data.amount)
plt.title('Transaction Amounts')
plt.ylabel('amount per transaction')
plt.xlabel('location in rows of dataset')
```

[16]: Text(0.5, 0, 'location in rows of dataset')



[17]:
```
boxPlot(cust_data_subset['amount'])
```

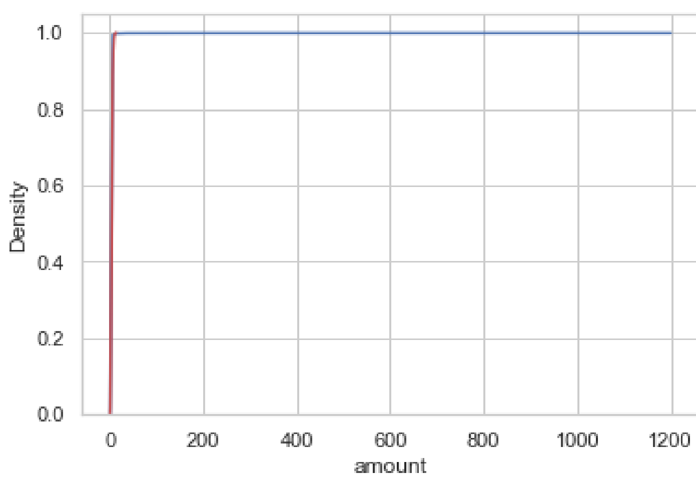


[17]: (None, None)

<Figure size 432x288 with 0 Axes>

[18]:
```
CDFPlot(cust_data_subset['amount'])
```

Cumulative Distribution Frequency of purchase amount Against Normal Gaussian distribution.

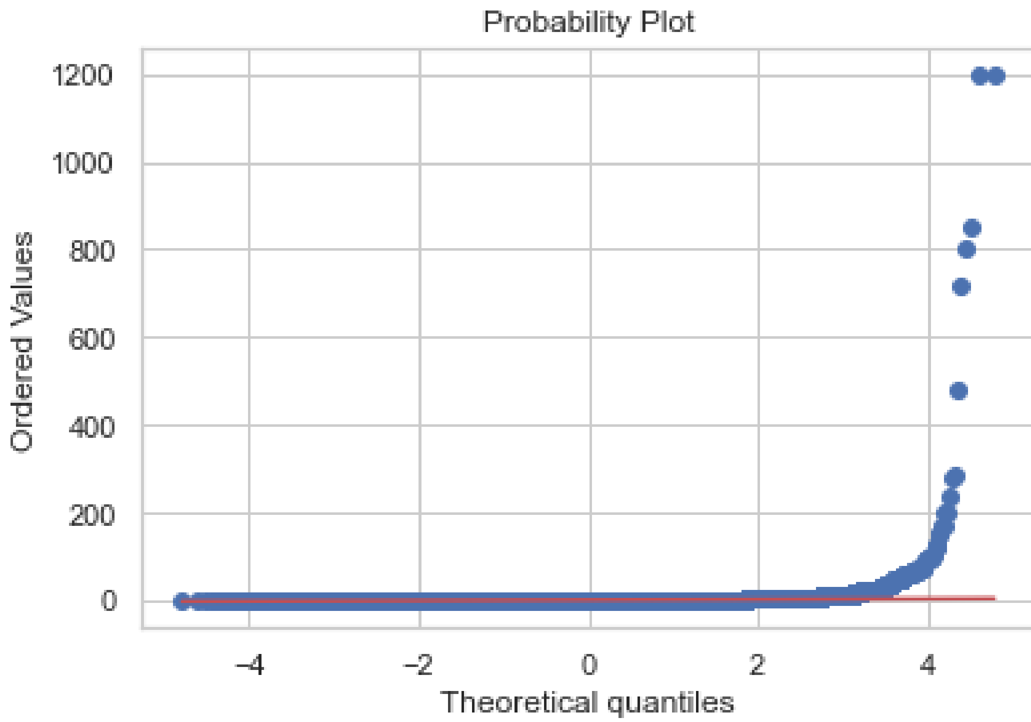


<Figure size 432x288 with 0 Axes>

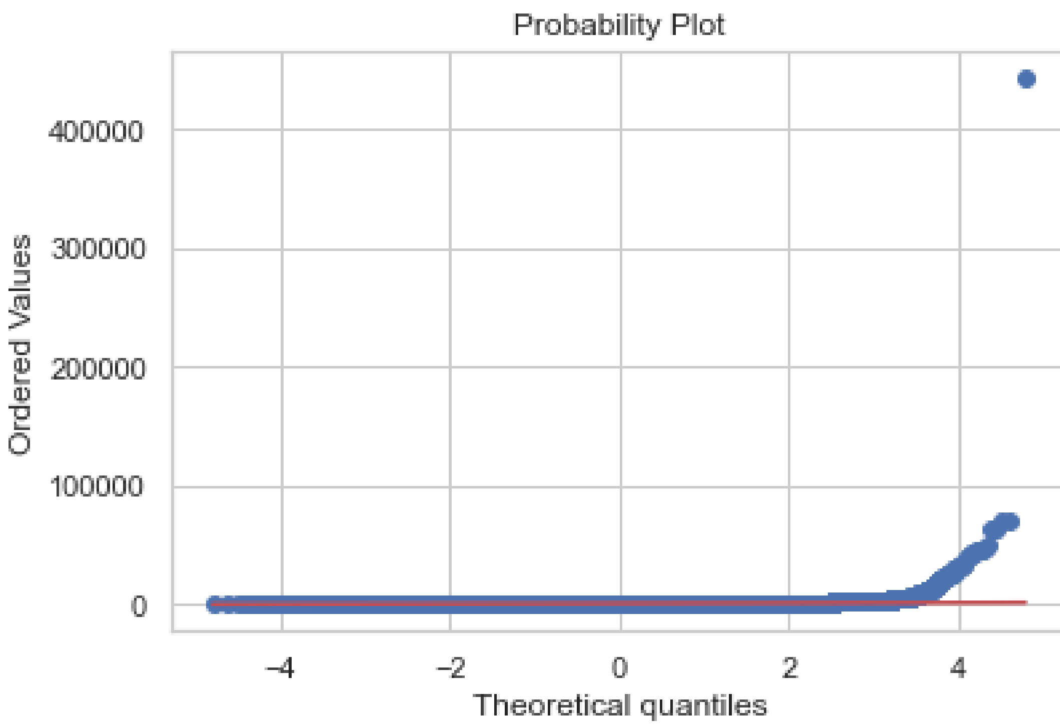
[18]: (None, None)

<Figure size 432x288 with 0 Axes>

[19]:
```
stats.probplot(cust_data_subset['amount'], dist="norm", plot=pylab)
pylab.show()
```



[20]:
```
stats.probplot(cust_data_subset['sales_price'], dist="norm", plot=pylab)
pylab.show()
```




```
[21]: from scipy import stats
#https://docs.scipy.org/doc/scipy/reference/generated/scipy.stats.normaltest.
 ↪html
norm=stats.normaltest(cust_data_subset.sales_price)
print('test statistic: ',norm[0])
if(norm[1] < 0.055):
    print("P-value: ",norm[1],"\nConclusion: Not a normal distribution.")
else:
    print("P-value: ",norm[1],"\nConclusion: A normal distribution.")
```

```
test statistic:  4963437.687618293
P-value:  0.0
Conclusion: Not a normal distribution.
```

```
[22]: from scipy import stats
#https://docs.scipy.org/doc/scipy/reference/generated/scipy.stats.normaltest.
 ↪html
norm=stats.normaltest(cust_data_subset.amount)
print('test statistic: ',norm[0])
if(norm[1] < 0.055):
    print("P-value: ",norm[1],"\nConclusion: Not a normal distribution.")
else:
    print("P-value: ",norm[1],"\nConclusion: A normal distribution.")
```

```
test statistic:  4310127.30717614
P-value:  0.0
Conclusion: Not a normal distribution.
```

For sales prices and amount we can see that they range from 1 to 444000 (not in dollars.. currency is unkown) and furthermore are clearly NOT normally distributed and contain many, many outliers. Its pretty clear that sales price and amount are not a trusted metrics to consider.

[23]:
```
cust_data_subset.amount.describe()
```

[23]:
```
count    817741.000
mean          1.382
std           2.897
min           1.000
25%           1.000
50%           1.000
75%           1.000
max        1200.000
Name: amount, dtype: float64
```

[24]:
```
cust_data_subset.sales_price.describe()
```

[24]:
```
count    817741.000
mean        131.876
std         631.058
min           1.000
25%          42.000
50%          76.000
75%         132.000
max      444000.000
Name: sales_price, dtype: float64
```

After doing statistical tests of both 'sales_price' and 'amount' we find that they are not normally distributed; which also means that I cannot run a pearson-r correlation test to check for associations.

3 Outliers identification

[25]:
```
Observed_Column=cust_data_subset.sales_price
quartile_1=np.percentile(Observed_Column, 25)
quartile_3=np.percentile(Observed_Column, 75)
inter_quartile_range=quartile_3-quartile_1
Inner_fence=1.5*(inter_quartile_range)
Outer_fence=3*inter_quartile_range
#Fences for viewing outliers
#mild outliers
inner_lower_fence=quartile_1-Inner_fence
inner_upper_fence=quartile_3+Inner_fence
#strong outliers
```

```
outer_lower_fence=quartile_1-Outer_fence
outer_upper_fence=quartile_3+Outer_fence
```

[26]:
```
print('Median:',cust_data_subset.amount.median())
print('Outer Fence:',outer_lower_fence,'&',outer_upper_fence)
outliers_df=(cust_data_subset['sales_price']<outer_lower_fence) | (cust_data_subset['sales_price']>outer_upper_fence)
print('Number of Strong Outliers:',len(cust_data_subset[outliers_df]))
cust_data_subset[outliers_df].head()
```

```
Median: 1.0
Outer Fence: -228.0 & 402.0
Number of Strong Outliers: 34788
```

[26]:
```
       transaction_dt customer_id  age_int  product_subclass   product_id
pin_code_int  asset  amount  sales_price  year  month  week  day  unit_price
608898    2000-11-01     01848564      11          320402            20546601
8         905        1       1129       2000    11      44     1    1129.000
608897    2000-11-01     01848564      11          320501            20564131
8         329        1        410       2000    11      44     1     410.000
608896    2000-11-01     01848564      11          320402            20564100
8         946        1       1180       2000    11      44     1    1180.000
212091    2000-11-01     01004373       5          110411       4710199011775
5         372       12        434       2000    11      44     1      36.167
212093    2000-11-01     01004373       5          110401       4710008290056
5         460       10        540       2000    11      44     1      54.000
```

[27]:
```
print('Median:',cust_data_subset.amount.median())
print('Inner Fence:',inner_lower_fence,'&',inner_upper_fence)
outliers_df=(cust_data_subset['sales_price']<inner_lower_fence) | (cust_data_subset['sales_price']>inner_upper_fence)
print('Number of Mild Outliers:',len(cust_data_subset[outliers_df]))
cust_data_subset[outliers_df].head()
```

```
Median: 1.0
Inner Fence: -93.0 & 267.0
Number of Mild Outliers: 69184
```

[27]:
```
       transaction_dt customer_id  age_int  product_subclass   product_id
pin_code_int  asset  amount  sales_price  year  month  week  day  unit_price
43018     2000-11-01     00166324       9          100514       4710626521716
5         276        2        310       2000    11      44     1      155.0
43020     2000-11-01     00166324       9          110217       4719090900058
5         290        2        298       2000    11      44     1      149.0
43029     2000-11-01     00166324       9          100505       4710594124001
5         266        1        300       2000    11      44     1      300.0
400793    2000-11-01     01576146       5          110217       4710265849066
5         360        2        270       2000    11      44     1      135.0
```

```
165041    2000-11-01      00841771       5           110507          723125488095
5         210        2          270        2000     11       44      1         135.0
```

4 Recency, Frequency, Monetary (RFM) Segmentation

1. Recency (R)
   - How many days since customer's last purchase
   - the lower the better
2. Frequency (F)
   - How many purchases the customer has done
3. Monetary Value (M)
   - Measures how much the customer has spent RFM variables are useful for beginning to classify users based on their behavior over time.

[28]:
```python
#setting day units from last day of dataset by adding a day to the␣
↪transaction_dt
snapshot_date=max(rmf_cust_data_subset.transaction_dt)+dt.timedelta(days=1)

#Aggregate data on a customer level
rmf_df=rmf_cust_data_subset.groupby(['customer_id']).agg({
    'transaction_dt': lambda x: (snapshot_date-x.max()).days,'product_id':
↪'count','total_sum':'sum'})

#Rename columns for easier interpretation
rmf_df.rename(columns={'transaction_dt':'Recency',
                        'product_id':'Frequency','total_sum':
↪'Monetary'},inplace=True)

rmf_df.sort_values(by='Monetary',ascending=False).head(15)
```

[28]:
```
             Recency  Frequency  Monetary
customer_id
01622362          12         65  459771.0
01558418          13        141  203498.0
02131269          80         10  197191.0
02119083           6         59  183002.0
00020459           1       1246  160961.0
02112589           1        879  152279.0
02138107          31         24  145572.0
01851588           3         33  138104.0
00842419           2        133  120146.0
02112596           1        822  118900.0
02134819          31          4  118027.0
02133874           1        462  116401.0
01062489           2        357  107177.0
02141282          31          9  106885.0
02132402          17         32  105131.0
```

- Observation: Here we can see the Recency, Frequency, and Monetary values have been created and I have sorted the values descending by the Monetary column. The above dataset makes it clear to understand the valuable customers of an organization.
- For example: We can see customer 02112589 has bought a merchandisea day ago, often buys a product 879 and has spent significantly large amount of 152279.0 when compared to the other customers.

[29]:
```
r_labels=range(10,0,-1) #<reversed lower recency is better
#higher labels higher values
f_labels=range(1,5)
m_labels=range(1,5)

r_quartiles=pd.qcut(rmf_df['Recency'],10,labels=r_labels)
f_quartiles=pd.qcut(rmf_df['Frequency'],4,labels=f_labels)
m_quartiles=pd.qcut(rmf_df['Monetary'],4,labels=f_labels)

rmf_df=rmf_df.assign(R=r_quartiles.values)
rmf_df=rmf_df.assign(F=f_quartiles.values)
rmf_df=rmf_df.assign(M=m_quartiles.values)
rmf_df.head()
```

[29]:

customer_id	Recency	Frequency	Monetary	R	F	M
00001069	19	11	1944.0	6	2	3
00001113	54	18	2230.0	3	3	3
00001250	19	14	1583.0	6	2	2
00001359	87	3	364.0	2	1	1
00001823	36	14	2607.0	5	2	3

[30]:
```
rmf_df['RFM_Score']=rmf_df[['R','F','M']].sum(axis=1)#Sum across columns
rmf_df.sort_values(by='Monetary',ascending=False).head(15)
```

[30]:

customer_id	Recency	Frequency	Monetary	R	F	M	RFM_Score
01622362	12	65	459771.0	7	4	4	15
01558418	13	141	203498.0	7	4	4	15
02131269	80	10	197191.0	2	2	4	8
02119083	6	59	183002.0	9	4	4	17
00020459	1	1246	160961.0	10	4	4	18
02112589	1	879	152279.0	10	4	4	18
02138107	31	24	145572.0	5	3	4	12
01851588	3	33	138104.0	10	4	4	18
00842419	2	133	120146.0	10	4	4	18
02112596	1	822	118900.0	10	4	4	18
02134819	31	4	118027.0	5	1	4	10
02133874	1	462	116401.0	10	4	4	18
01062489	2	357	107177.0	10	4	4	18

```
02141282        31          9     106885.0   5   2   4      11
02132402        17         32     105131.0   7   3   4      14
```

[31]:
```
def RFM_Segmentation(df):
    if df['RFM_Score']>=10:
        return 'First segment customers'
    elif (df['RFM_Score']>=5) and (df['RFM_Score']<10):
        return 'Second segment customers'
    else:
        return 'Third segment customers'
```

[32]:
```
rmf_df['RMF_Segment']=rmf_df.apply(RFM_Segmentation,axis=1)
```

[33]:
```
rmf_df.head(10)
```

[33]:

customer_id	Recency	Frequency	Monetary	R	F	M	RFM_Score	RMF_Segment
00001069	19	11	1944.0	6	2	3	11	First segment customers
00001113	54	18	2230.0	3	3	3	9	Second segment customers
00001250	19	14	1583.0	6	2	2	10	First segment customers
00001359	87	3	364.0	2	1	1	4	Third segment customers
00001823	36	14	2607.0	5	2	3	10	First segment customers
00002189	57	62	14056.0	3	4	4	11	First segment customers
00003667	21	13	11509.0	6	2	4	12	First segment customers
00004282	47	9	967.0	4	2	2	8	Second segment customers
00004381	103	11	701.0	1	2	1	4	Third segment customers
00004947	81	36	3363.0	2	4	3	9	Second segment customers

[34]:
```
display(rmf_df.groupby('RMF_Segment').agg({'Recency':'mean','Frequency':
→'mean','Monetary':['mean','count']}).round(1))
```

	Recency	Frequency	Monetary	
	mean	mean	mean	count
RMF_Segment				
First segment customers	15.7	37.4	4906.3	18796
Second segment customers	59.9	9.8	1364.5	10647
Third segment customers	97.6	3.6	387.6	2823

[ ]:

```

```