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Matric Number: 17201091/1

1. You are required to write code to implement either time-series clustering or density-based clustering model using the above dataset (Question 1). If you select density-based clustering approach to achieve the task, you are going to cover the following steps:
    - Importing required libraries
    - Load the dataset (Question 1) into a DataFrame object
    - Visualize the data, use only two of these attributes at the time
    - You may need to normalise the attribute if necessary
    - Show positive correlation between attributes if necessary
    - Construct a density-based clustering model and extract cluster labels and outliers to plot your results.

Importing required libraries

In [1]:

```
import pandas as pd
import seaborn as sns, numpy as np

import matplotlib.pyplot as plt

from sklearn import preprocessing

from sklearn.cluster import DBSCAN

from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler

from collections import Counter
```

Load the dataset (Question 1) into a DataFrame object

In [2]:

```
# In question 1, we have crawled the datasets and stored in csv files
customer=pd.read_csv("customer.csv",header=0,index_col=0)
transactions=pd.read_csv("transactions.csv",header=0,index_col=0)
product=pd.read_csv("product.csv",header=0,index_col=0)
```

In [3]:

```
# we need to merge the data sets

#1 merge "product" and "transactions" table and create the table "prod_tran"
product=product.rename(columns={"pro_cat_code":"prod_cat_code"})
prod_tran = pd.merge(left=transactions, right=product,
                     on=["prod_cat_code","prod_subcat_code"],how="left")
```

In [4]:

```
#2 merge "prod_tran" and "customer" table and create the table "df"
df= pd.merge(left=prod_tran, right=customer,right_on="customer_id",
             left_on="customer_id", how="left").drop_duplicates()
```

In [5]:

```
#calculate the customers's age column using tran_date(transaction date) and DOB
 attributes(Date or birth)

df['transaction_date'] = pd.to_datetime(df['transaction_date'], errors='coerce')
df.insert(loc=3, column='Tran_year', value= df.transaction_date.dt.year)


df['DOB'] = pd.to_datetime(df['DOB'], errors='coerce')
df.insert(loc=4, column='Birth_year', value= df.DOB.dt.year)



df['Tran_year']=df['Tran_year'].astype(int)
df['Birth_year']=df['Birth_year'].astype(int)

df["age"]=df['Tran_year'] -df['Birth_year']

df= df.drop(['Tran_year','Birth_year'],axis=1)

# check the new age column value
df.age.head()
```

Out[5]:

```
0    33
1    41
2    22
3    33
4    22
Name: age, dtype: int64
```

In [6]:

```
# remove null value
df = df.dropna()

#drop duplicate value
df =df.drop_duplicates()


print("total numer of value:",len(df))
df.head()
```

```
total numer of value: 5952
```

Out[6]:

	transaction_id	customer_id	transaction_date	prod_cat_code	prod_subcat_code	Quantity
0	80712190438	270351	2014-02-28	1	1	-5
1	29258453508	270384	2014-02-27	5	3	-5
10	29258453508	270384	2014-02-20	5	3	5
14	36554696014	269345	2014-02-20	3	5	3
17	25963520987	274829	2014-02-20	4	4	3

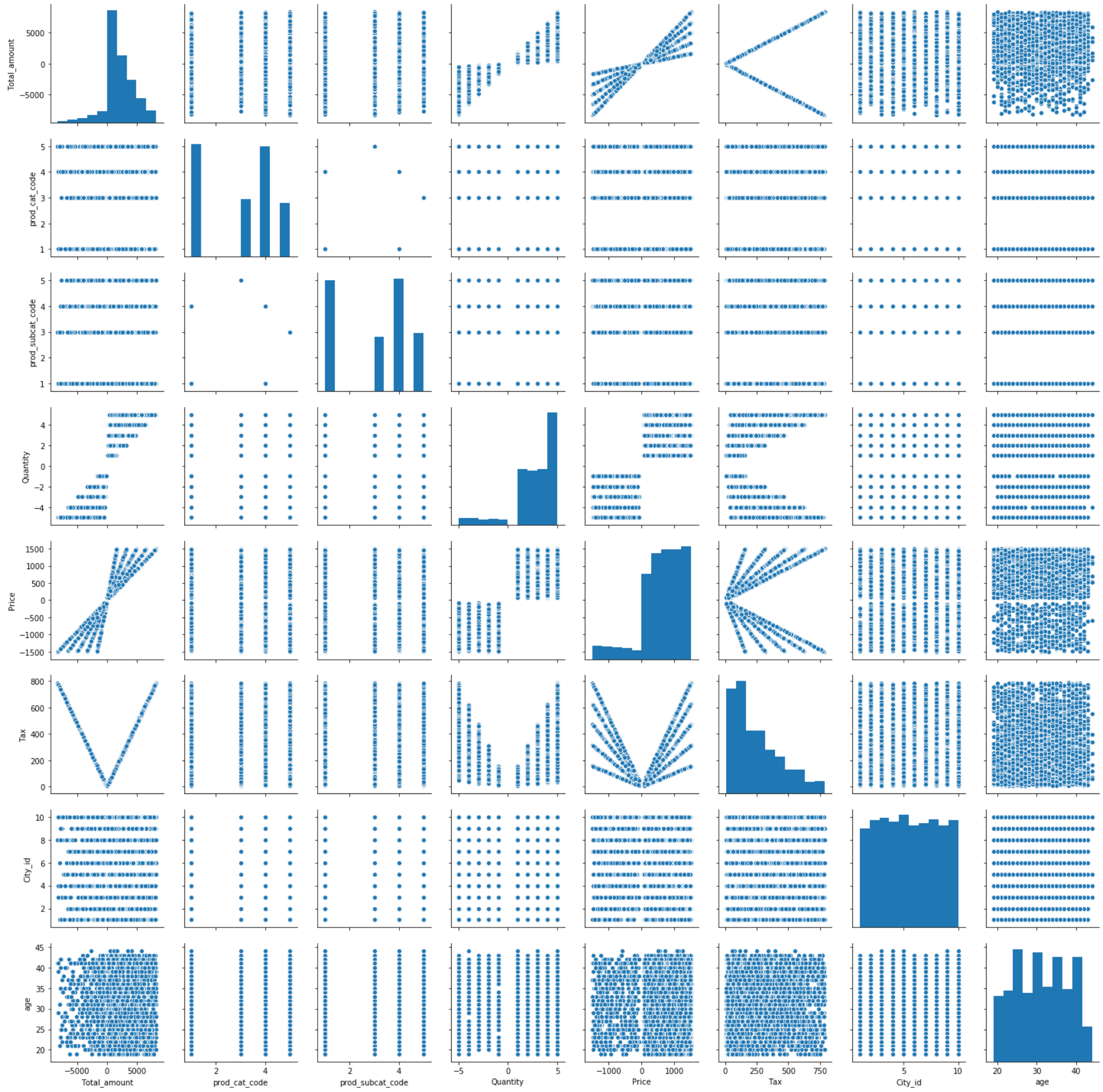
Visualize the data, use only two of these attributes at the time

In [7]:

```
Features=["Gender","Total_amount","prod_cat_code","prod_subcat_code","Quantity"
          ,"Price","Tax","Store_type","City_id","age"]
```

In [8]:

```
#  use pairplot, we could found the relationship between any of two attributes.
ax = sns.pairplot(df[Features])
```



In [9]:

```
#for more detail, we could use lmplot to visualize any two attributes from the a
bove abservation.
#e.g. Prive vs Tax
sns.lmplot('Price','Tax', data=df,fit_reg=False)
plt.title('Price vs Tax')
```

Out[9]:

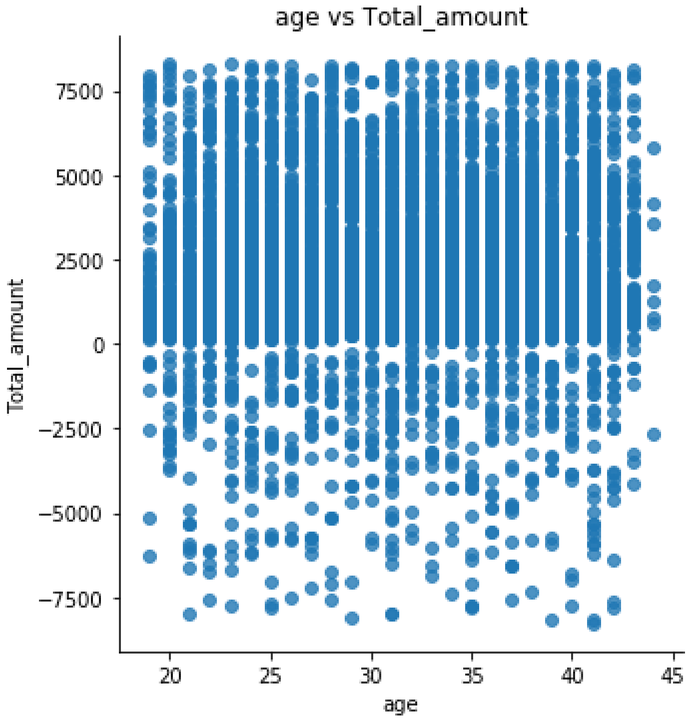
```
Text(0.5, 1, 'Price vs Tax')
```

In [10]:

```
#e.g. age vs Total_amount
sns.lmplot('age','Total_amount', data=df,fit_reg=False)
plt.title('age vs Total_amount')
```

Out[10]:

```
Text(0.5, 1, 'age vs Total_amount')
```

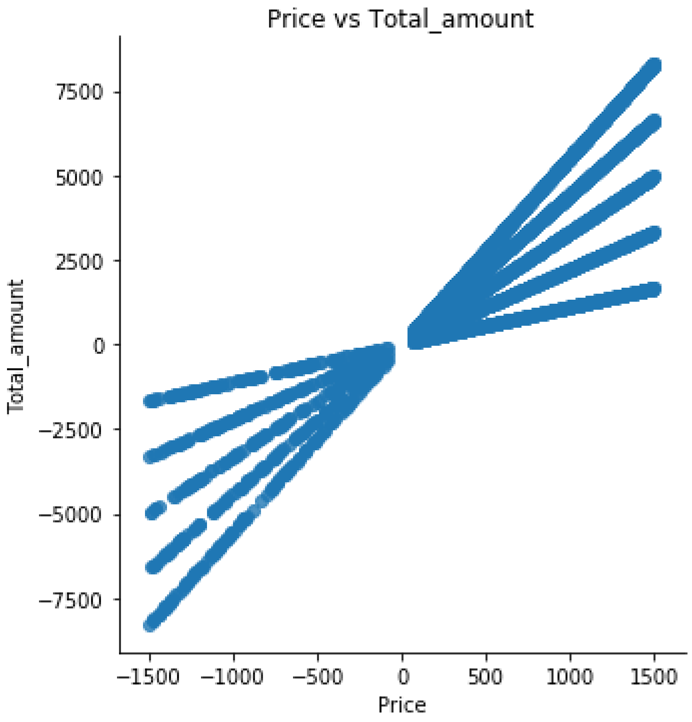


In [11]:

```
#e.g. Price vs Total_amount
sns.lmplot('Price','Total_amount', data=df,fit_reg=False)
plt.title('Price vs Total_amount')
```

Out[11]:

```
Text(0.5, 1, 'Price vs Total_amount')
```



You may need to normalise the attribute if necessary

In [12]:

```
X=df[Features]

# format the categorical features
X= pd.get_dummies(X)
column = X.columns
X.head()
```

Out[12]:

	Total_amount	prod_cat_code	prod_subcat_code	Quantity	Price	Tax	City_id	age
0	-4265.300	1	1	-5	-772	405.300	5.0	33
1	-8270.925	5	3	-5	-1497	785.925	8.0	41
10	8270.925	5	3	5	1497	785.925	8.0	41
14	4153.695	3	5	3	1253	394.695	10.0	44
17	1664.130	4	4	3	502	158.130	2.0	30

In [13]:

```
# we need normalise the attributes to rescale the data into a range of [0;1]
# normalise the data
data=preprocessing.scale(X)

print(data)
```

```
[[-2.47808294 -1.29827201 -1.31706169 ... -0.5106367  -0.49411249
   1.22637541]
 [-4.03926621  1.32850287 -0.01271041 ... -0.5106367  -0.49411249
   1.22637541]
 [ 2.40788237  1.32850287 -0.01271041 ... -0.5106367  -0.49411249
   1.22637541]
 ...
 [ 1.67703326  0.67180915  0.63946523 ... -0.5106367  -0.49411249
   1.22637541]
 [-0.57796139  1.32850287 -0.01271041 ... -0.5106367  -0.49411249
   1.22637541]
 [-0.52412749  0.67180915 -1.31706169 ... -0.5106367  -0.49411249
   1.22637541]]
```

In [14]:

```
normalized = pd.DataFrame(data,columns=column)
```

In [15]:

```
#normalizased results
normalized.head()
```

Out[15]:

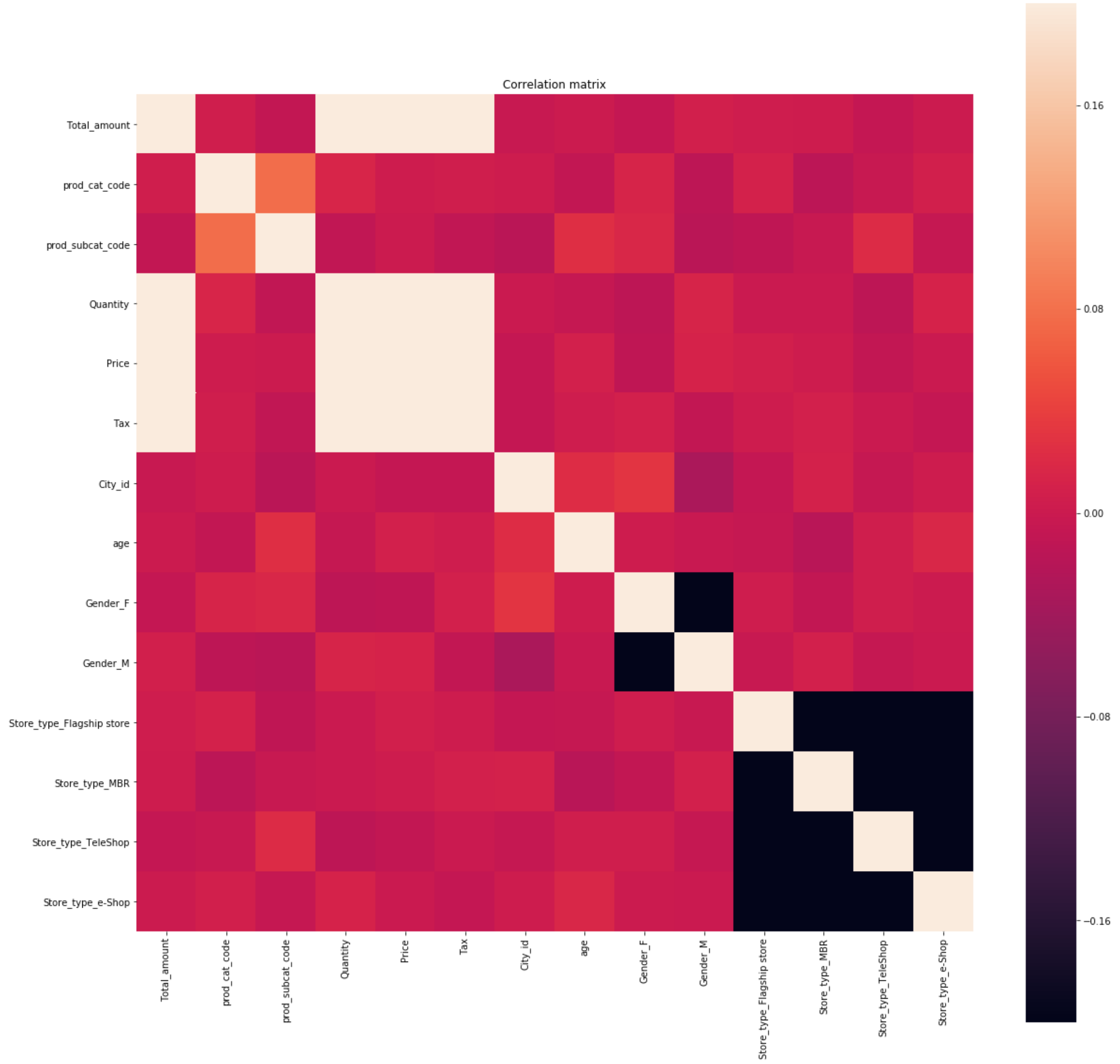
	Total_amount	prod_cat_code	prod_subcat_code	Quantity	Price	Tax	City_id
0	-2.478083	-1.298272	-1.317062	-3.202390	-2.217420	0.813484	-0.176899
1	-4.039266	1.328503	-0.012710	-3.202390	-3.363152	2.824340	0.873901
2	2.407882	1.328503	-0.012710	1.121807	1.368326	2.824340	0.873901
3	0.803201	0.015115	1.291641	0.256967	0.982728	0.757457	1.574434
4	-0.167101	0.671809	0.639465	0.256967	-0.204092	-0.492325	-1.227698

Show positive correlation between attributes if necessary

In [16]:

```
# Show positive correlation between attributes if necessary
plt.figure(figsize=(20,20))
corr = normalized.corr()
mask = np.zeros_like(corr)
sns.heatmap(corr, mask=mask, square=True, vmin=-.20, vmax=.20)
plt.title('Correlation matrix')
Quantity = normalized['Quantity']
Total_amount= normalized['Total_amount']
Price= normalized['Price']
Tax = normalized['Tax']
print("The positive correlation Quantity and Total_amount is {}".format((np.corr
coef(Quantity,Total_amount)[0][1])))
print("The positive correlation Price and Total_amount is {}".format((np.corrcoe
f(Price,Total_amount)[0][1])))
print("The positive correlation Tax and Total_amount is {}".format((np.corrcoef(
Tax,Total_amount)[0][1])))
```

```
The positive correlation Quantity and Total_amount is 0.800321911548
8281
The positive correlation Price and Total_amount is 0.834057874087224
5
The positive correlation Tax and Total_amount is 0.6004325840445992
```

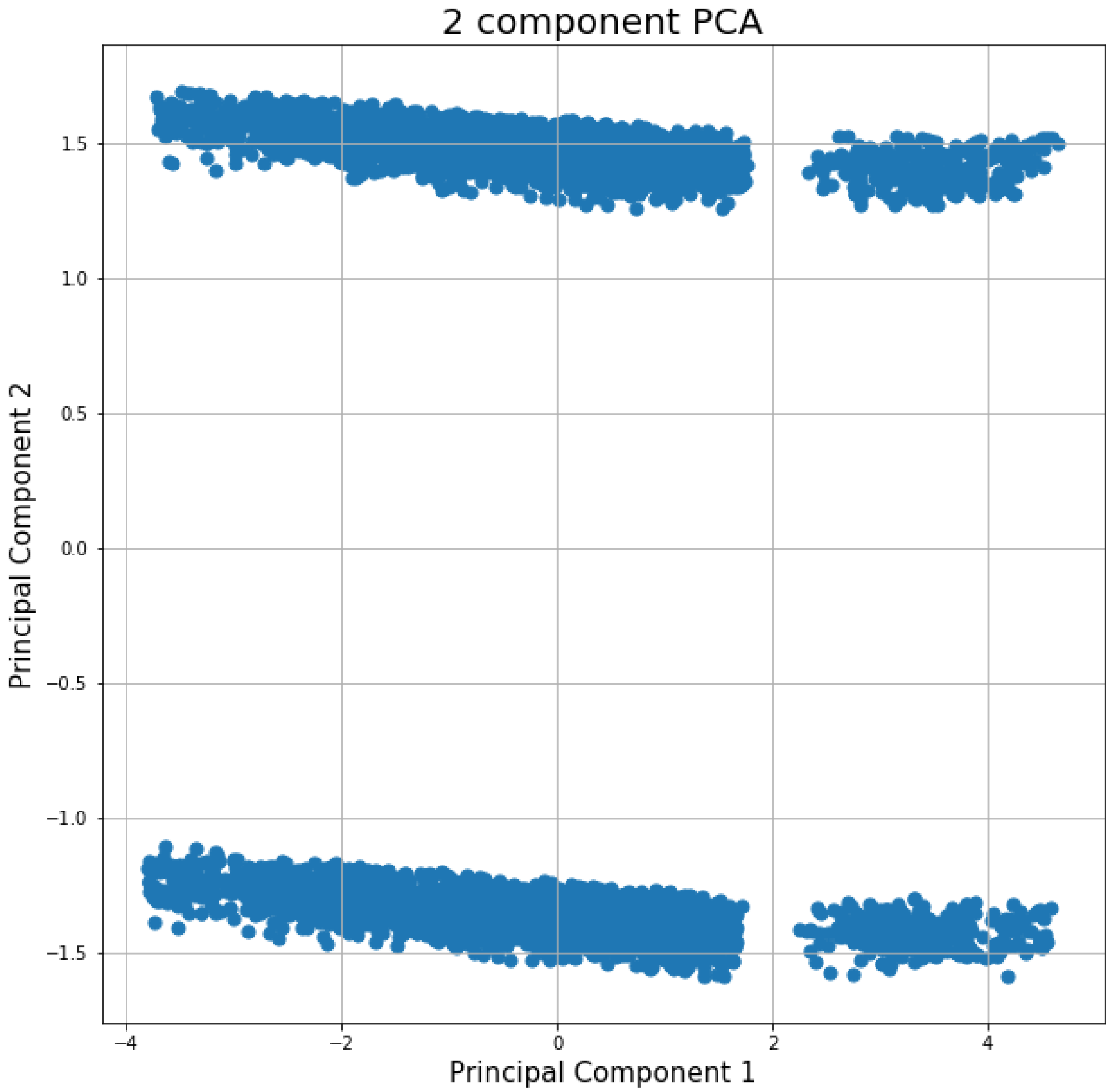


Construct a density-based clustering model and extract cluster labels and outliers to plot your results.

data attributes reduction using PCA

In [19]:

```
pca = PCA(n_components=2)
principalComponents = pca.fit_transform(normalized)
Df = pd.DataFrame(data = principalComponents
             , columns = ['principal component 1', 'principal component 2'])


fig = plt.figure(figsize = (10,10))

ax = fig.add_subplot(1,1,1)

ax.set_xlabel('Principal Component 1', fontsize = 15)
ax.set_ylabel('Principal Component 2', fontsize = 15)
ax.set_title('2 component PCA', fontsize = 20)


ax.scatter(Df.loc[:, 'principal component 1']
               , Df.loc[:, 'principal component 2']
               , s = 50)

ax.grid()
```


2 component PCA
Principal Component 2
Principal Component 1
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−4
−2
0
2
4

Construct a density-based clustering model

In [20]:

```
from sklearn.cluster import DBSCAN
model = DBSCAN(eps=0.2, min_samples=30).fit(Df)
print(model)
```

```
DBSCAN(algorithm='auto', eps=0.2, leaf_size=30, metric='euclidean',
       metric_params=None, min_samples=30, n_jobs=None, p=None)
```

In [21]:

```
model.labels_
```

Out[21]:

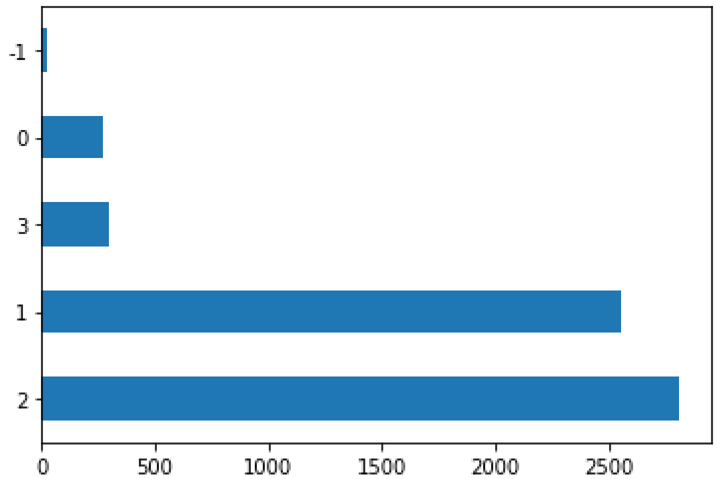
```
array([ 0, -1,  1, ...,  2,  1,  2])
```

In [22]:

```
label = pd.Series(model.labels_)
label.value_counts().plot('barh')
```

Out[22]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1a22cfc8d0>
```



extract cluster labels and outliers

In [23]:

```
# Separate outliers from clustered data
labels = model.labels_
# outlier label
outlier_label = labels[labels == -1]

# outlier datasets
outliers = Df[model.labels_==-1]

print("outlier label",outlier_label)
print("outlier datasets",outliers)
```

```
outlier label [-1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1
-1 -1 -1]
outlier datasets        principal component 1  principal component 2
1                   4.650896               1.500162
185                 2.439860              -1.424890
320                 2.316771              -1.422262
1061                4.578399               1.524293
1147                2.350315              -1.414885
1155                2.518166              -1.475661
1244                4.583476              -1.331115
1655                2.438717              -1.347964
2176                2.463997               1.335942
2520                2.405861              -1.533217
2785                2.425541               1.455934
3003                2.254496              -1.414128
3178                2.534400              -1.572072
3726                2.443787              -1.352899
3841                2.434725              -1.467377
3871                2.410285               1.414323
4119                4.601857               1.521610
4941                2.347162              -1.489985
5282                2.411298              -1.329126
5518                2.375528              -1.416984
5781                2.331870               1.395956
```

In [24]:

```
#normal data's labels
clusters_label = labels[labels!= -1]

#normal data sets
data_points =  Df[model.labels_!=-1]


print("normal data's labels",clusters_label)

print("normal data sets",data_points)
```

```
normal data's labels [0 1 1 ... 2 1 2]
normal data sets       principal component 1  principal component 2
0                   3.833851              -1.479378
2                  -3.716450               1.674018
3                  -1.342601               1.620884
4                   0.287023               1.447791
5                  -1.223904               1.571504
6                   1.768253               1.419171
7                  -1.520127              -1.376995
8                   2.762943               1.386558
9                  -2.561002              -1.241520
10                  0.737773              -1.318933
11                  0.704626               1.537232
12                 -2.644574               1.549945
13                  1.544028              -1.404997
14                  0.372688              -1.400864
15                 -1.195361              -1.311780
16                  1.247473              -1.479391
17                 -1.444831               1.594930
18                  0.242744              -1.268978
19                  0.527809              -1.382531
20                 -2.396445               1.649386
21                  0.912675               1.304450
22                 -1.129268               1.549576
23                 -0.929945              -1.371287
24                  0.093728              -1.313934
25                  0.454388              -1.434172
26                 -0.536417              -1.249801
27                  1.171072              -1.336222
28                  0.988943               1.373907
29                 -0.295258               1.488479
30                  1.100090               1.391778
...                      ...                    ...
5922               -0.498905              -1.326297
5923               -0.281540               1.518223
5924               -1.707831              -1.214814
5925                0.645674              -1.339981
5926               -3.309461              -1.228903
5927               -0.877910               1.467363
5928               -0.090613               1.488045
5929                0.397906              -1.285681
5930                1.240929               1.440722
5931                0.834693               1.523426
5932                0.197655              -1.353849
5933                1.535566              -1.445709
5934                1.105822              -1.388963
5935               -1.485524               1.530579
5936                0.079019              -1.380419
5937               -0.570548              -1.341192
5938               -1.048834              -1.316716
5939               -0.622548              -1.275640
5940                0.125982              -1.316052
5941               -0.011186               1.417807
5942                0.505051              -1.387822
5943                0.363127              -1.299721
5944                0.517653              -1.384982
5945               -1.839322              -1.218784
5946               -2.061561              -1.271842
5947               -2.750490               1.570738
5948                1.348746              -1.307186
5949               -2.747945              -1.289531
```

```
5950            1.125234            1.433190
5951            0.884598           -1.359647

[5931 rows x 2 columns]
```

Outlier label: -1

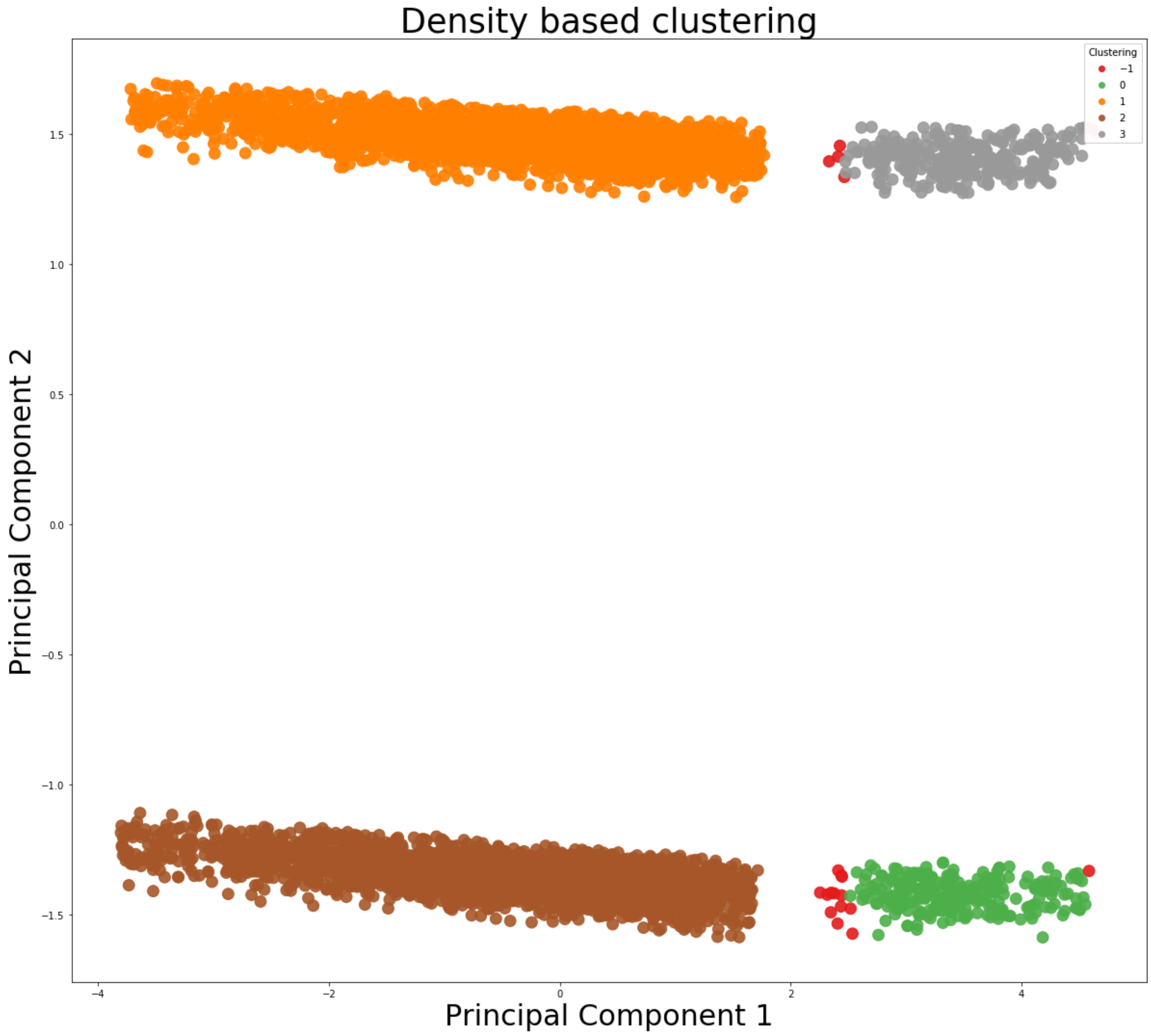
Normal data sets label: 0, 1, 2, 3,

plot your results

In [25]:

```
fig, ax = plt.subplots(figsize=(20,18))
scatter = ax.scatter(Df.iloc[:,0],Df.iloc[:,1],c=model.labels_,s =140,alpha=0.9,
cmap=plt.cm.Set1)

ax.set_xlabel("Principal Component 1",fontsize= 30)
ax.set_ylabel("Principal Component 2",fontsize= 30)

plt.title("Density based clustering",fontsize= 35)


legend = ax.legend(*scatter.legend_elements(),
                    loc="upper right", title="Clustering")

ax.add_artist(legend)

fig.show()
```

```
/Users/liuhongyang/anaconda3/lib/python3.7/site-packages/ipykernel_l
auncher.py:15: UserWarning: Matplotlib is currently using module://i
pykernel.pylab.backend_inline, which is a non-GUI backend, so cannot
show the figure.
  from ipykernel import kernelapp as app
```



Base on the model, there are five different clustering,

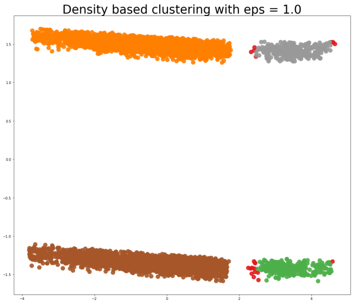
- the labeled - represents outliers
- the other four clustering represents normal data sets

configure the eps to find more results

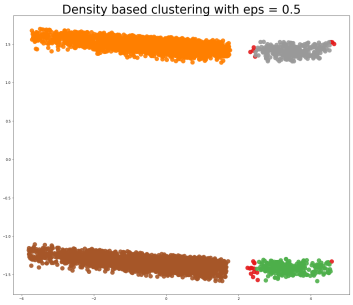
In [26]:

```
fig = plt.figure(figsize=(60, 60))
fig.subplots_adjust(hspace=.5, wspace=.2)
i = 1
for x in range(10, 1, -1):
    eps = 1/(11-x)
    db = DBSCAN(eps=eps, min_samples=20).fit(Df)

    core_samples_mask = np.zeros_like(model.labels_, dtype=bool)

    core_samples_mask[db.core_sample_indices_] = True

    ax = fig.add_subplot(3, 3, i)

    plt.title("Density based clustering with eps = {}".format(round(eps, 3)),fon
tsize= 35 )


    sctr = ax.scatter(principalDf.iloc[:,0],principalDf.iloc[:,1],c=model.labels
_, s=140,alpha=0.9,cmap=plt.cm.Set1)

    i += 1
```

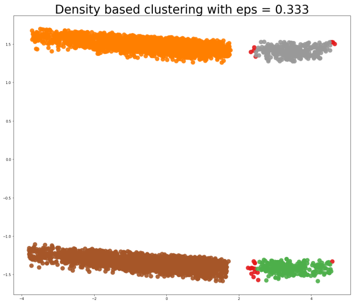
Density based clustering with eps = 1.0



Density based clustering with eps = 0.5

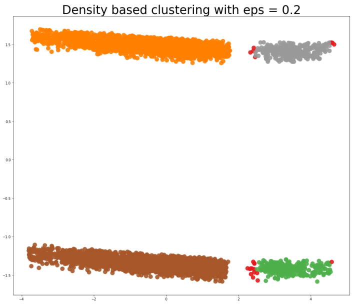


Density based clustering with eps = 0.333

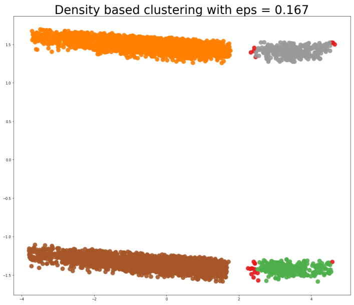


Density based clustering with eps = 0.25

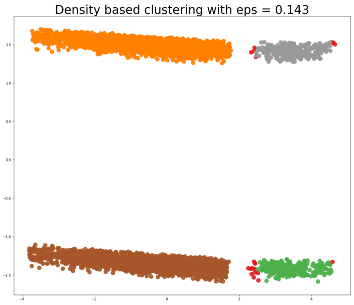
Density based clustering with eps = 0.2



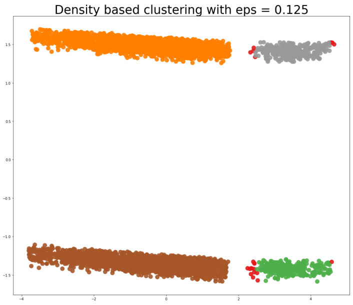
Density based clustering with eps = 0.167



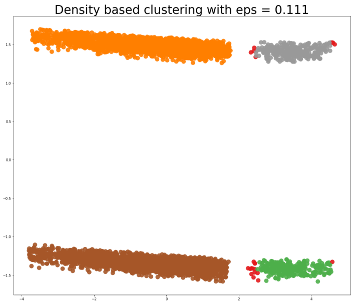
Density based clustering with eps = 0.143



Density based clustering with eps = 0.125



Density based clustering with eps = 0.111



In [ ]:

```

```