Clustering Credit Card Customer

Data preparation

Import library

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")

%matplotlib inline
```

In [104]:
```
ds = pd.read_csv('BankChurners.csv')
ds.head()
```

Out[104]:

	CLIENTNUM	Attrition_Flag	Customer_Age	Gender	Dependent_count	Education_Level	Marital_Status	Income_Category	Card_Category	Months_
0	768805383	Existing Customer	45	M	3	High School	Married	60K−80K	Blue	
1	818770008	Existing Customer	49	F	5	Graduate	Single	Less than $40K	Blue	
2	713982108	Existing Customer	51	M	3	Graduate	Married	80K−120K	Blue	
3	769911858	Existing Customer	40	F	4	High School	Unknown	Less than $40K	Blue	
4	709106358	Existing Customer	40	M	3	Uneducated	Married	60K−80K	Blue	

5 rows × 23 columns

In [4]:
```
ds.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10127 entries, 0 to 10126
Data columns (total 23 columns):
 #   Column
Non-Null Count  Dtype
---  ------
--------------  -----
 0   CLIENTNUM
10127 non-null  int64
 1   Attrition_Flag
10127 non-null  object
 2   Customer_Age
10127 non-null  int64
 3   Gender
10127 non-null  object
 4   Dependent_count
10127 non-null  int64
 5   Education_Level
10127 non-null  object
 6   Marital_Status
10127 non-null  object
 7   Income_Category
10127 non-null  object
 8   Card_Category
10127 non-null  object
 9   Months_on_book
10127 non-null  int64
 10  Total_Relationship_Count
10127 non-null  int64
 11  Months_Inactive_12_mon
10127 non-null  int64
 12  Contacts_Count_12_mon
10127 non-null  int64
 13  Credit_Limit
10127 non-null  float64
 14  Total_Revolving_Bal
10127 non-null  int64
 15  Avg_Open_To_Buy
10127 non-null  float64
```

```
 16  Total_Amt_Chng_Q4_Q1
10127 non-null  float64
 17  Total_Trans_Amt
10127 non-null  int64
 18  Total_Trans_Ct
10127 non-null  int64
 19  Total_Ct_Chng_Q4_Q1
10127 non-null  float64
 20  Avg_Utilization_Ratio
10127 non-null  float64
 21  Naive_Bayes_Classifier_Attrition_Flag_Card_Category_Contacts_Count_12_mon_Dependent_count_Education_Level_Months_I
nactive_12_mon_1  10127 non-null  float64
 22  Naive_Bayes_Classifier_Attrition_Flag_Card_Category_Contacts_Count_12_mon_Dependent_count_Education_Level_Months_I
nactive_12_mon_2  10127 non-null  float64
dtypes: float64(7), int64(10), object(6)
memory usage: 1.8+ MB
```

In [6]:
```
ds = ds.iloc[:,1:-2]
ds
```

Out[6]:

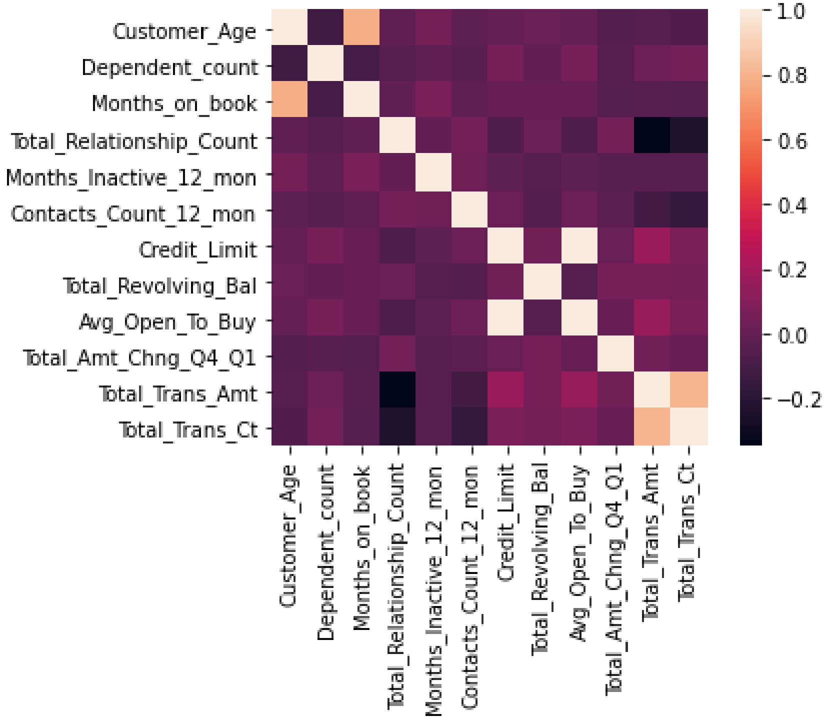
Months_Inactive_12_mon	Contacts_Count_12_mon	Credit_Limit	Total_Revolving_Bal	Avg_Open_To_Buy	Total_Amt_Chng_Q4_Q1	Total_Trans_Amt	Tot
1	3	12691.0	777	11914.0	1.335	1144	
1	2	8256.0	864	7392.0	1.541	1291	
1	0	3418.0	0	3418.0	2.594	1887	
4	1	3313.0	2517	796.0	1.405	1171	
1	0	4716.0	0	4716.0	2.175	816	
...	...	...	...	...	...	...	
2	3	4003.0	1851	2152.0	0.703	15476	
2	3	4277.0	2186	2091.0	0.804	8764	
3	4	5409.0	0	5409.0	0.819	10291	
3	3	5281.0	0	5281.0	0.535	8395	
2	4	10388.0	1961	8427.0	0.703	10294	

Clustering

K Means

In [8]:
```
corr = ds.corr()
sns.heatmap(corr, square=True)
```

Out[8]: <AxesSubplot:>



In [10]:
```
ds.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10127 entries, 0 to 10126
Data columns (total 18 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   Attrition_Flag            10127 non-null  object 
 1   Customer_Age              10127 non-null  int64  
 2   Gender                    10127 non-null  object 
 3   Dependent_count           10127 non-null  int64  
 4   Education_Level           10127 non-null  object 
 5   Marital_Status            10127 non-null  object 
 6   Income_Category           10127 non-null  object 
 7   Card_Category             10127 non-null  object 
 8   Months_on_book            10127 non-null  int64  
 9   Total_Relationship_Count  10127 non-null  int64  
 10  Months_Inactive_12_mon    10127 non-null  int64  
 11  Contacts_Count_12_mon     10127 non-null  int64  
 12  Credit_Limit              10127 non-null  float64
 13  Total_Revolving_Bal       10127 non-null  int64  
 14  Avg_Open_To_Buy           10127 non-null  float64
 15  Total_Amt_Chng_Q4_Q1      10127 non-null  float64
 16  Total_Trans_Amt           10127 non-null  int64  
 17  Total_Trans_Ct            10127 non-null  int64  
dtypes: float64(3), int64(9), object(6)
memory usage: 1.4+ MB
```

In [12]:
```
X = ds.iloc[:,[16,17]].values
```

These are the attributes that I will be using to seperate the client into cluster:

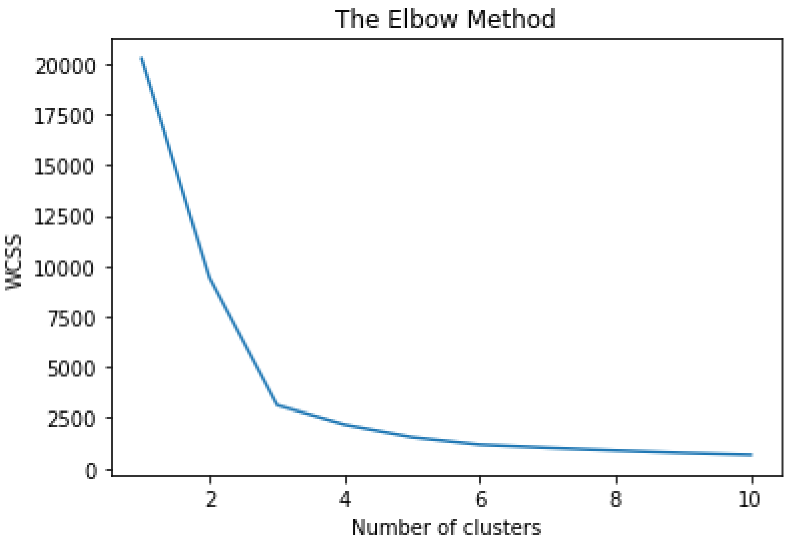
- Total_Trans_Amt - Total amount of transactions made in the last year.
- Total_Trans_Ct - Number of transactions made in the last year.

In [13]:
```
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score
from sklearn.preprocessing import StandardScaler
```

In [14]:
```
ss = StandardScaler()
XX = ss.fit_transform(X)
XX
```

Out[14]:
```
array([[-0.95970657, -0.97389518],
       [-0.91643261, -1.35734038],
       [-0.74098169, -1.91120566],
       ...,
       [ 1.73299393, -0.20700479],
       [ 1.17484807, -0.12179474],
       [ 1.73387707, -0.16439977]])
```

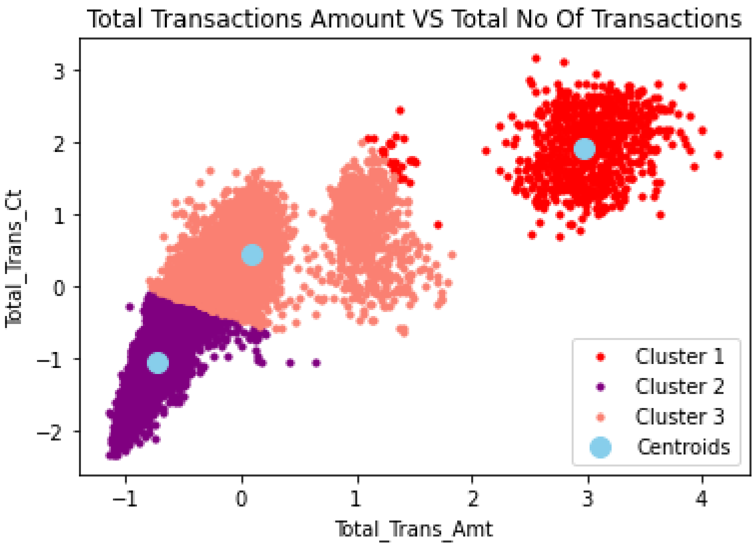
In [71]:
```
wcss = []
for i in range(1,11):
    kmeans = KMeans(n_clusters = i, init = 'k-means++', random_state = 42)
    kmeans.fit(XX)
    wcss.append(kmeans.inertia_)
plt.plot(range(1,11), wcss)
plt.title('The Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.show()
```



In [72]:
```
kmeans = KMeans(n_clusters = 3, init = 'k-means++', random_state = 42)
y_kmeans = kmeans.fit_predict(XX)
y_kmeans
```

Out[72]:
```
array([1, 1, 1, ..., 2, 2, 2])
```

In [73]:
```
plt.scatter(XX[y_kmeans == 0, 0], XX[y_kmeans == 0, 1], s = 10, c = 'red', label = 'Cluster 1')
plt.scatter(XX[y_kmeans == 1, 0], XX[y_kmeans == 1, 1], s = 10, c = 'purple', label = 'Cluster 2')
plt.scatter(XX[y_kmeans == 2, 0], XX[y_kmeans == 2, 1], s = 10, c = 'salmon', label = 'Cluster 3')
plt.scatter(kmeans.cluster_centers_[:,0], kmeans.cluster_centers_[:,1], s = 100, c = 'skyblue', label = 'Centroids')
plt.title('Total Transactions Amount VS Total No Of Transactions')
plt.xlabel('Total_Trans_Amt')
plt.ylabel('Total_Trans_Ct')
plt.legend()
plt.show
plt.savefig("Credit_Card_Kmeans.png", dpi=300)
```



In [74]:
```
score = silhouette_score(XX, kmeans.labels_, metric = 'euclidean')
print(score)
```

```
0.6110049517629068
```

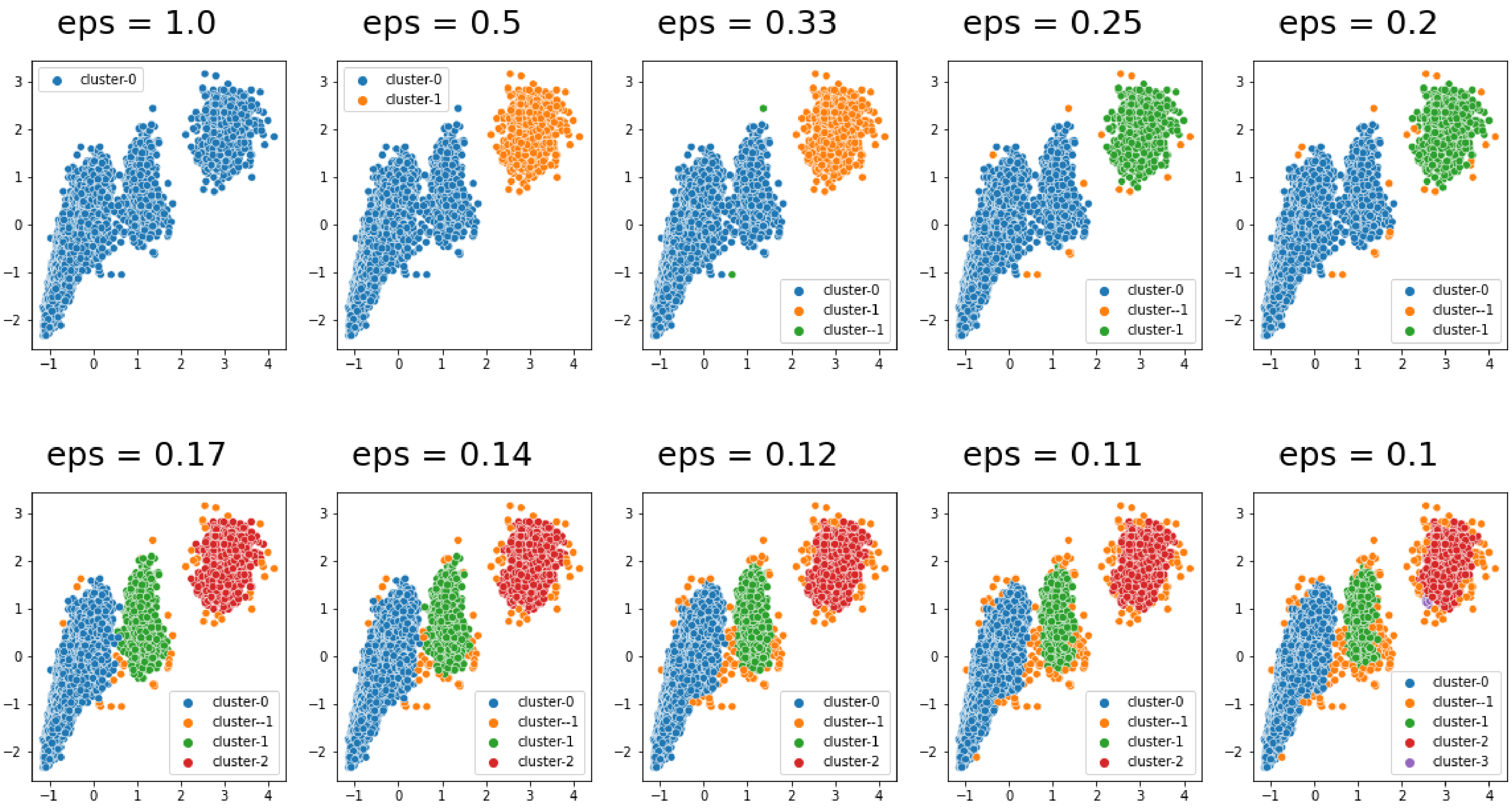
DBSCAN

Option 1: Plot all eps

In [99]:
```
from sklearn.cluster import DBSCAN
from sklearn.neighbors import NearestNeighbors
from kneed import KneeLocator
```

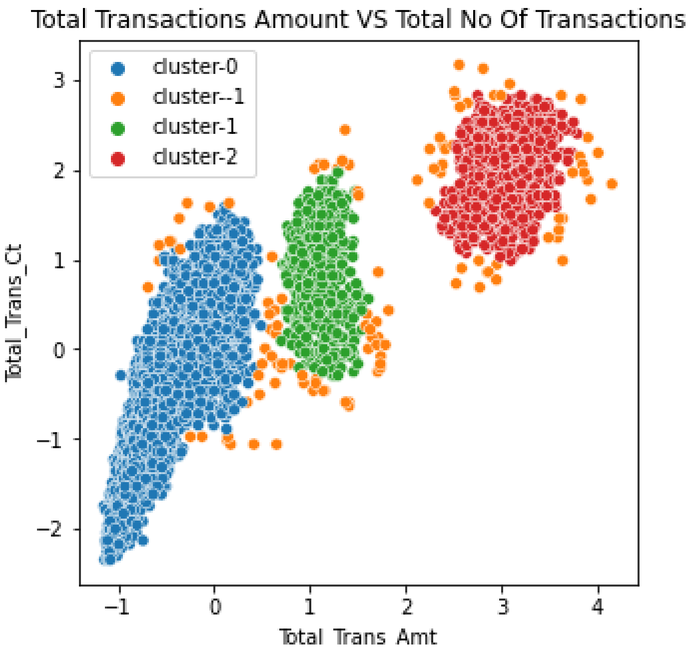
In [100]:

```
fig = plt.figure(figsize=(20, 10))
fig.subplots_adjust(hspace=.5, wspace=.2)
i= 1
for x in range(10, 0, -1):
    eps = 1/(11-x)
    db= DBSCAN(eps=eps, min_samples=8).fit(XX)
    core_samples_mask= np.zeros_like(db.labels_, dtype=bool)
    core_samples_mask[db.core_sample_indices_] = True
    labels = db.labels_
    ax = fig.add_subplot(2, 5, i)
    ax.text(1, 4, "eps = {}".format(round(eps, 2)), fontsize=25, ha="center")
    sns.scatterplot(XX[:,0], XX[:,1], hue=["cluster-{}".format(x) for x in labels])
    i+= 1
```


eps = 1.0
cluster-0
eps = 0.5
cluster-0
cluster-1
eps = 0.33
cluster-0
cluster-1
cluster--1
eps = 0.25
cluster-0
cluster--1
cluster-1
eps = 0.2
cluster-0
cluster--1
cluster-1
eps = 0.17
cluster-0
cluster--1
cluster-1
cluster-2
eps = 0.14
cluster-0
cluster--1
cluster-1
cluster-2
eps = 0.12
cluster-0
cluster--1
cluster-1
cluster-2
eps = 0.11
cluster-0
cluster--1
cluster-1
cluster-2
eps = 0.1
cluster-0
cluster--1
cluster-1
cluster-2
cluster-3

In [101]:

```
db= DBSCAN(eps=0.13, min_samples=8).fit(XX)
labels = db.labels_
fig = plt.figure(figsize=(5, 5))
sns.scatterplot(XX[:,0], XX[:,1], hue=["cluster-{}".format(x) for x in labels])
plt.title('Total Transactions Amount VS Total No Of Transactions')
plt.xlabel('Total_Trans_Amt')
plt.ylabel('Total_Trans_Ct')
plt.legend()
plt.savefig("Credit_Card_DBSCAN(1).png", dpi=300)
```

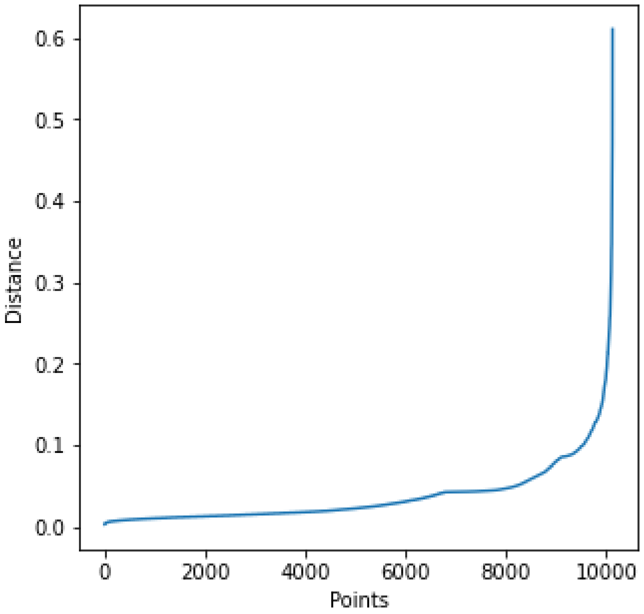


In [107]:
```
clusters = db.labels_
ds['cluster'] = clusters
DBSCAN1 = ds.groupby('cluster')['CLIENTNUM'].sum()
```

Option 2: Knee knee locater

In [89]:
```
nearest_neighbors= NearestNeighbors(n_neighbors=11)
neighbors = nearest_neighbors.fit(XX)
distances, indices = neighbors.kneighbors(XX)
distances = np.sort(distances[:,10], axis=0)
i= np.arange(len(distances))
knee = KneeLocator(i, distances, S=1, curve='convex', direction='increasing', interp_method='polynomial')
fig = plt.figure(figsize=(5, 5))
plt.plot(distances)
plt.xlabel("Points")
plt.ylabel("Distance")
```

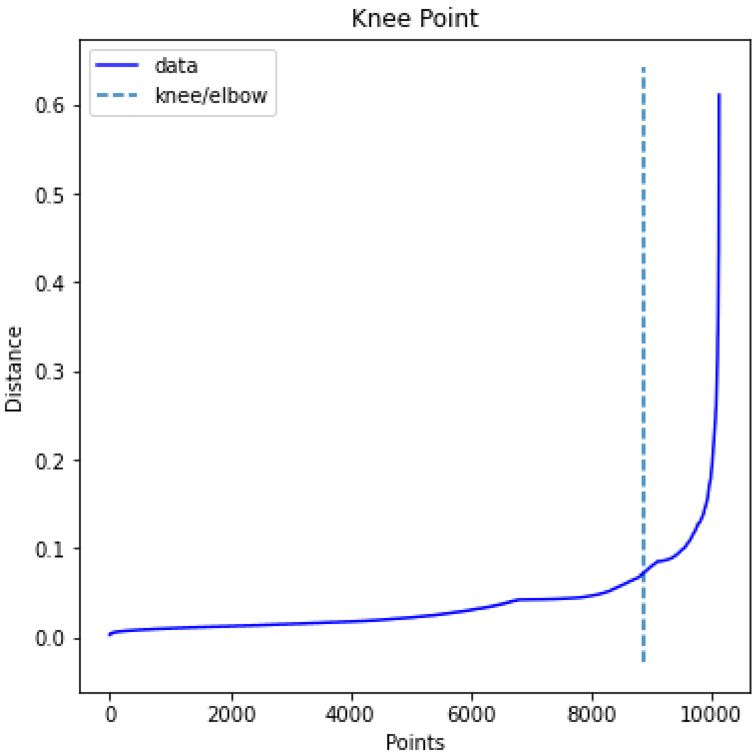
Out[89]:
```
Text(0, 0.5, 'Distance')
```



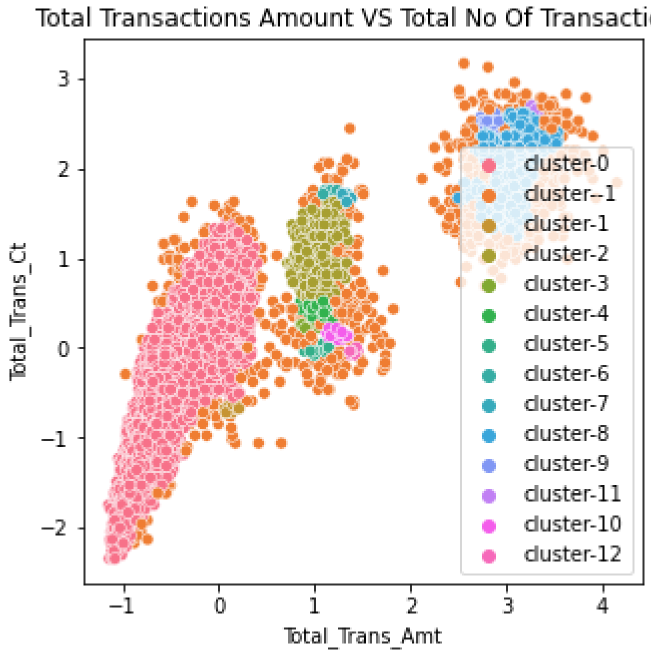
In [90]:
```
fig = plt.figure(figsize=(5, 5))
knee.plot_knee()
plt.xlabel("Points")
plt.ylabel("Distance")
print(distances[knee.knee])
```

```
0.07243625486760386

<Figure size 360x360 with 0 Axes>
```



In [91]:
```
db= DBSCAN(eps=distances[knee.knee], min_samples=8).fit(XX)
labels = db.labels_
fig = plt.figure(figsize=(5, 5))
sns.scatterplot(XX[:,0], XX[:,1], hue=["cluster-{}".format(x) for x in labels])
plt.title('Total Transactions Amount VS Total No Of Transactions')
plt.xlabel('Total_Trans_Amt')
plt.ylabel('Total_Trans_Ct')
plt.legend()
plt.savefig("Credit_Card_DBSCAN(2).png", dpi=300)
```



From all the clustering model that has been conducted, DBSCAN option 1 is the most suitable clustering model for this type of dataset. Its able to distinguish the cluster correctly and can be seperated into 4 cluster. Cluster 0 is credit card client that is low spender, Cluster 1 is credit card client that is medium spender and Cluster 2 is credit card client that is high spender.

Updated dataset with no of cluster:

In [108]:
```
ds.head(10)
```

Out[108]:

	CLIENTNUM	Attrition_Flag	Customer_Age	Gender	Dependent_count	Education_Level	Marital_Status	Income_Category	Card_Category	Months_
0	768805383	Existing Customer	45	M	3	High School	Married	$60K - $80K	Blue	
1	818770008	Existing Customer	49	F	5	Graduate	Single	Less than $40K	Blue	
2	713982108	Existing Customer	51	M	3	Graduate	Married	$80K - $120K	Blue	
3	769911858	Existing Customer	40	F	4	High School	Unknown	Less than $40K	Blue	
4	709106358	Existing Customer	40	M	3	Uneducated	Married	$60K - $80K	Blue	
5	713061558	Existing Customer	44	M	2	Graduate	Married	$40K - $60K	Blue	
6	810347208	Existing Customer	51	M	4	Unknown	Married	$120K +	Gold	
7	818906208	Existing Customer	32	M	0	High School	Unknown	$60K - $80K	Silver	
8	710930508	Existing Customer	37	M	3	Uneducated	Single	$60K - $80K	Blue	
9	719661558	Existing Customer	48	M	2	Graduate	Single	$80K - $120K	Blue	

10 rows × 24 columns

No of customer with each cluster:

In [109]:
```
DBSCAN1
```

Out[109]:
```
cluster
-1      83181383862
 0    6405671819880
 1     478001522100
 2     518796893499
Name: CLIENTNUM, dtype: int64
```

In [ ]:
```

```