Clustering Algorithms:

- KMeans
- Kmeans++ (do smart intialization)
- GMM (Kmeans cant be used when the cluster shape is not globular)

In [1]:
```
import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
import seaborn as sns
```

In [59]:
```
df = pd.read_csv(r"C:\Users\kanwar\Downloads\E-commerce.csv")
df.head()
```

Out[59]:

	ID	n_clicks	n_visits	amount_spent	amount_discount	days_since_registration	profile_information
0	1476	130	65	213.905831	31.600751	233	235
1	1535	543	46	639.223004	5.689175	228	170
2	1807	520	102	1157.402763	844.321606	247	409
3	1727	702	83	1195.903634	850.041757	148	200
4	1324	221	84	180.754616	64.283300	243	259

In [60]:
```
df.shape
```

Out[60]:
```
(2500, 7)
```

In [61]:
```
df_copy=df.copy()
```

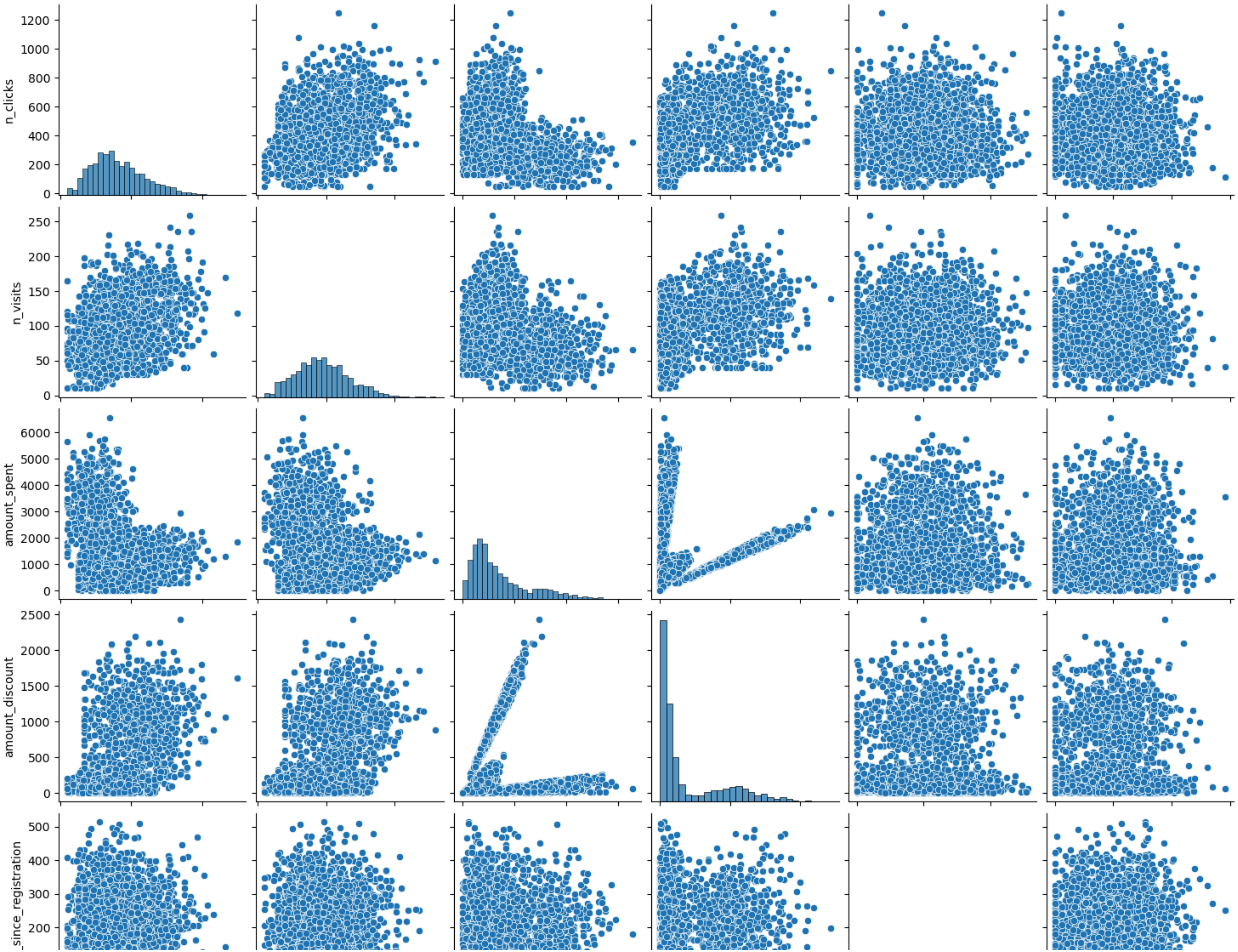
KMeans Animation

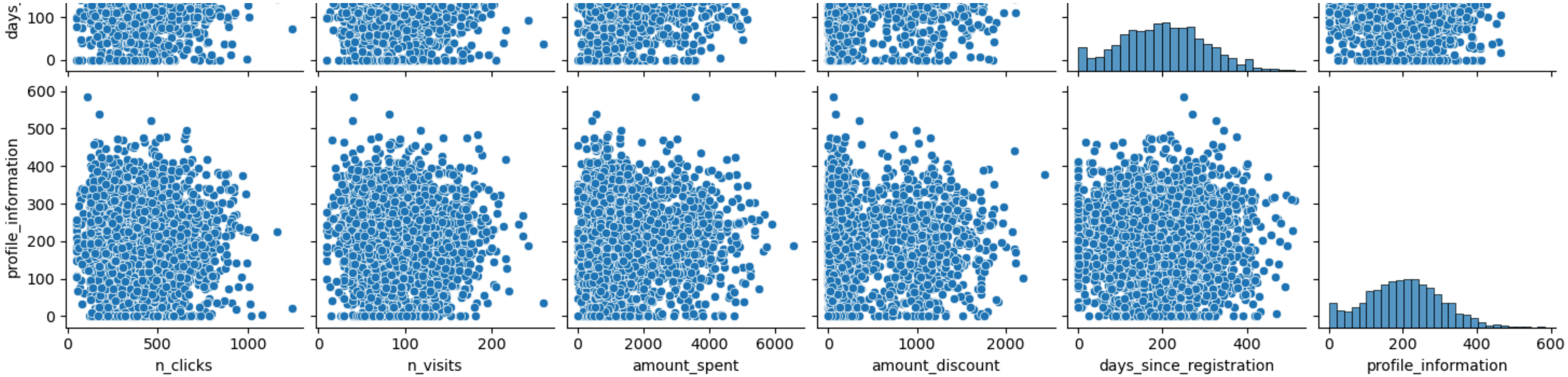
- http://tech.nitoyon.com/en/blog/2013/11/07/k-means/

- https://www.naftaliharris.com/blog/visualizing-k-means-clustering/

In [5]:
```
sns.pairplot(df.drop(columns='ID'))
```

Out[5]:
```
<seaborn.axisgrid.PairGrid at 0x17aa79cacf0>
```


n_clicks
0
200
400
600
800
1000
1200
n_visits
0
50
100
150
200
250
amount_spent
0
1000
2000
3000
4000
5000
6000
amount_discount
0
500
1000
1500
2000
2500
_since_registration
200
300
400
500



In [62]:
```
df = df.drop(columns = ['ID'])
df.head()
```

Out[62]:

	n_clicks	n_visits	amount_spent	amount_discount	days_since_registration	profile_information
0	130	65	213.905831	31.600751	233	235
1	543	46	639.223004	5.689175	228	170
2	520	102	1157.402763	844.321606	247	409
3	702	83	1195.903634	850.041757	148	200
4	221	84	180.754616	64.283300	243	259

In [63]:
```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
X = scaler.fit_transform(df)
X.shape
```

Out[63]: (2500, 6)

In [64]:
```
X = pd.DataFrame(X,columns=df.columns)

X.head()
```

Out[64]:

	n_clicks	n_visits	amount_spent	amount_discount	days_since_registration	profile_information
0	-1.495250	-0.758535	-1.054611	-0.732800	0.323118	0.339192
1	0.720691	-1.247488	-0.690292	-0.786002	0.272672	-0.310034
2	0.597285	0.193635	-0.246428	0.935872	0.464365	2.077120
3	1.573801	-0.295317	-0.213449	0.947616	-0.534456	-0.010392
4	-1.006992	-0.269583	-1.083008	-0.665697	0.424009	0.578906

In [65]:

```
from sklearn.decomposition import PCA
pca = PCA(n_components = 2)

X_embedded = pca.fit_transform(X)


print(X_embedded.shape)
```

```
(2500, 2)
```

In [66]:

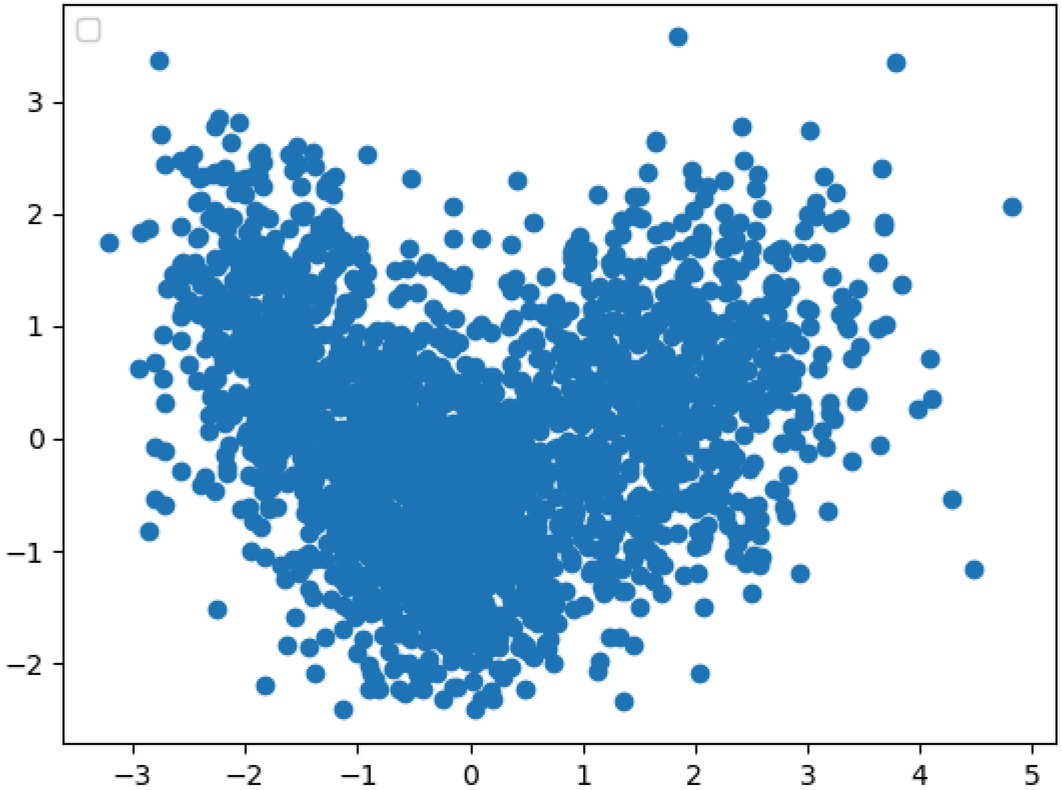
```
plt.set_cmap('tab10')

fig, ax = plt.subplots()
scatter = ax.scatter(X_embedded[:,0],X_embedded[:,1])

legend = ax.legend(*scatter.legend_elements(),loc="upper left")
ax.add_artist(legend)

plt.show()
plt.close()
```

```
C:\Users\kanwar\anaconda3\Lib\site-packages\matplotlib\collections.py:1121: UserWarning: Collection without array used. Make su
re to specify the values to be colormapped via the `c` argument.
  warnings.warn("Collection without array used. Make sure to "
<Figure size 640x480 with 0 Axes>
```



In [67]:
```
from sklearn.manifold import TSNE

X_embedded = TSNE().fit_transform(X)

print(X_embedded.shape)
```

(2500, 2)

plt.set_cmap('tab10')

fig, ax = plt.subplots() scatter = ax.scatter(X_embedded[:,0],X_embedded[:,1])

legend = ax.legend(*scatter.legend_elements(),loc="upper left") ax.add_artist(legend)

plt.show() plt.close()

In [19]:
```
### 3 Clusters looks good to start with
```

In [68]:
```
from sklearn.cluster import KMeans

kmeans = KMeans(n_clusters=4, random_state=0)
kmeans.fit(X)  # centroid location....
```

Out[68]:
```
KMeans
KMeans(n_clusters=4, random_state=0)
```

In [37]:
```
kmeans.cluster_centers_
```

Out[37]:
```
array([[-0.84489356, -0.69074277,  1.53258215, -0.6338525 , -0.03015834,
         0.14114355],
       [-0.152689  , -0.13332478, -0.68014351, -0.50785254,  0.00457148,
        -0.05584233],
       [ 1.12538466,  1.38032559, -0.17703977,  1.20693675,  0.02635991,
         0.6705825 ],
       [ 0.82695384,  0.27435098,  0.02897407,  1.62630936,  0.0081634 ,
        -0.66345728]])
```

In [29]:
```
kmeans.labels_ # (X)
```

Out[29]:
```
array([0, 0, 3, ..., 1, 2, 3], dtype=int32)
```

In [69]:
```
labels = kmeans.labels_
```

In [70]:
```python
df['kmeans'] = labels
df.head()
```

Out[70]:

	n_clicks	n_visits	amount_spent	amount_discount	days_since_registration	profile_information	kmeans
0	130	65	213.905831	31.600751	233	235	1
1	543	46	639.223004	5.689175	228	170	1
2	520	102	1157.402763	844.321606	247	409	2
3	702	83	1195.903634	850.041757	148	200	3
4	221	84	180.754616	64.283300	243	259	1

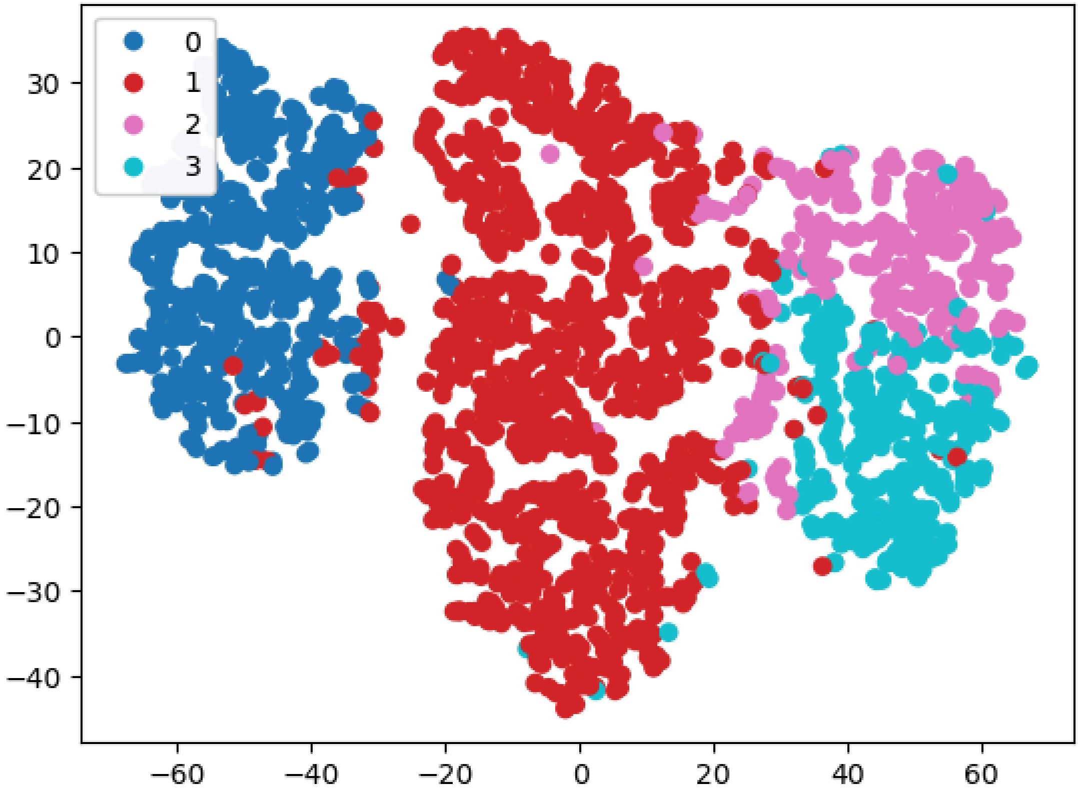
In [71]:
```python
plt.set_cmap('tab10')

fig, ax = plt.subplots()
scatter = ax.scatter(X_embedded[:,0],X_embedded[:,1],c= labels)

legend = ax.legend(*scatter.legend_elements(),loc="upper left")
ax.add_artist(legend)

plt.show()
plt.close()
```

```
<Figure size 640x480 with 0 Axes>
```



In [42]:
```
df['kmeans'].value_counts()
```

Out[42]:
```
kmeans
1    1228
0     577
3     359
2     336
Name: count, dtype: int64
```

In [41]:
```
df.groupby('kmeans').mean()
```

Out[41]:

kmeans	n_clicks	n_visits	amount_spent	amount_discount	days_since_registration	profile_information
0	251.211438	67.634315	3234.272996	79.792978	197.984402	215.171577
1	380.222313	89.294788	651.070865	141.160821	201.426710	195.449511
2	618.425595	148.113095	1238.409226	976.342993	203.586310	268.178571
3	562.805014	105.136490	1478.915938	1180.596965	201.782730	134.615599

In [35]:
```
## As group 0 and group 1 seems very similar can be grouped together hence we can go with n_clusters=3
```

In [ ]:
```
# for k in range(1, 11):
    # check the dunn index
    # https://scikit-learn.org/1.5/modules/generated/sklearn.metrics.davies_bouldin_score.html
```

In [39]:
```
from sklearn.metrics import davies_bouldin_score as dbc
```

In [40]:
```
dbc(X,df['kmeans'])
```

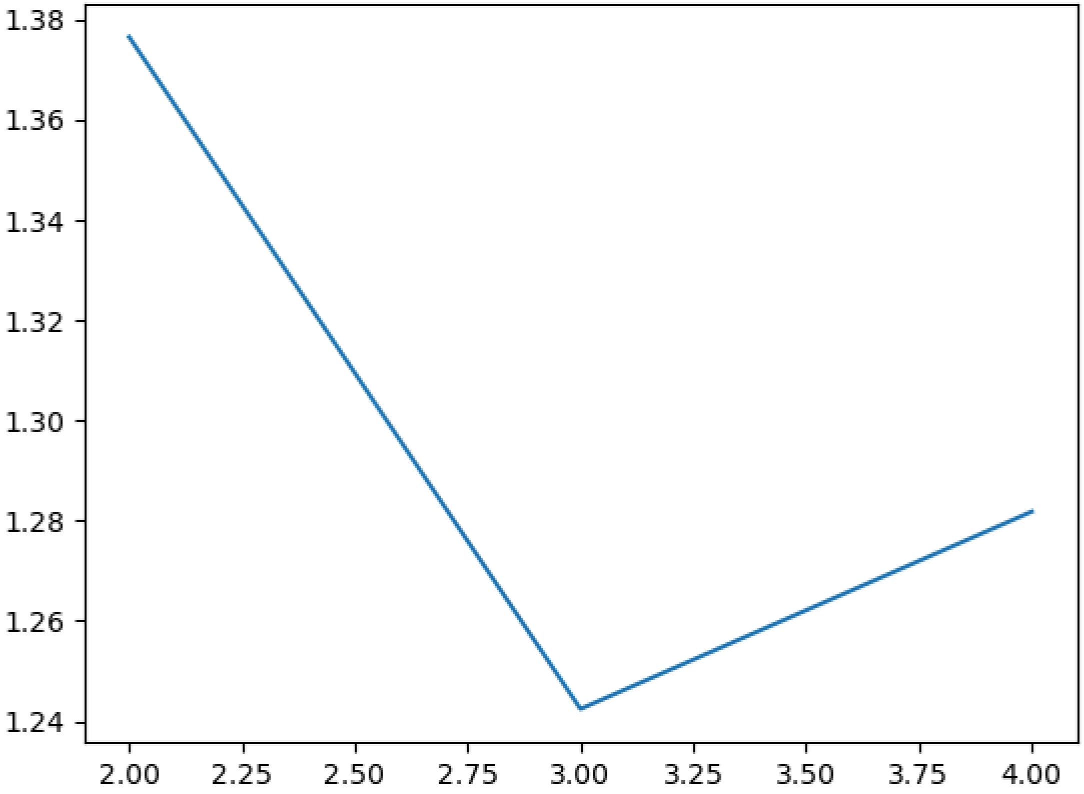
Out[40]:
```
np.float64(1.2817957869735137)
```

In [41]:
```
#The minimum score is zero, with lower values indicating better clustering.
# dun_index=min(inter cluster distance)/max(intra cluster distance)
```

In [46]:
```
score=[]
for i in range(2,5):
    kmeans = KMeans(n_clusters=i, random_state=0)
    kmeans.fit(X)  # centroid location....
    labels = kmeans.labels_
    score.append(dbc(X,labels))
```

In [47]:
```
plt.plot(range(2,5),score)
```

Out[47]:
```
[<matplotlib.lines.Line2D at 0x17aafb7d310>]
```

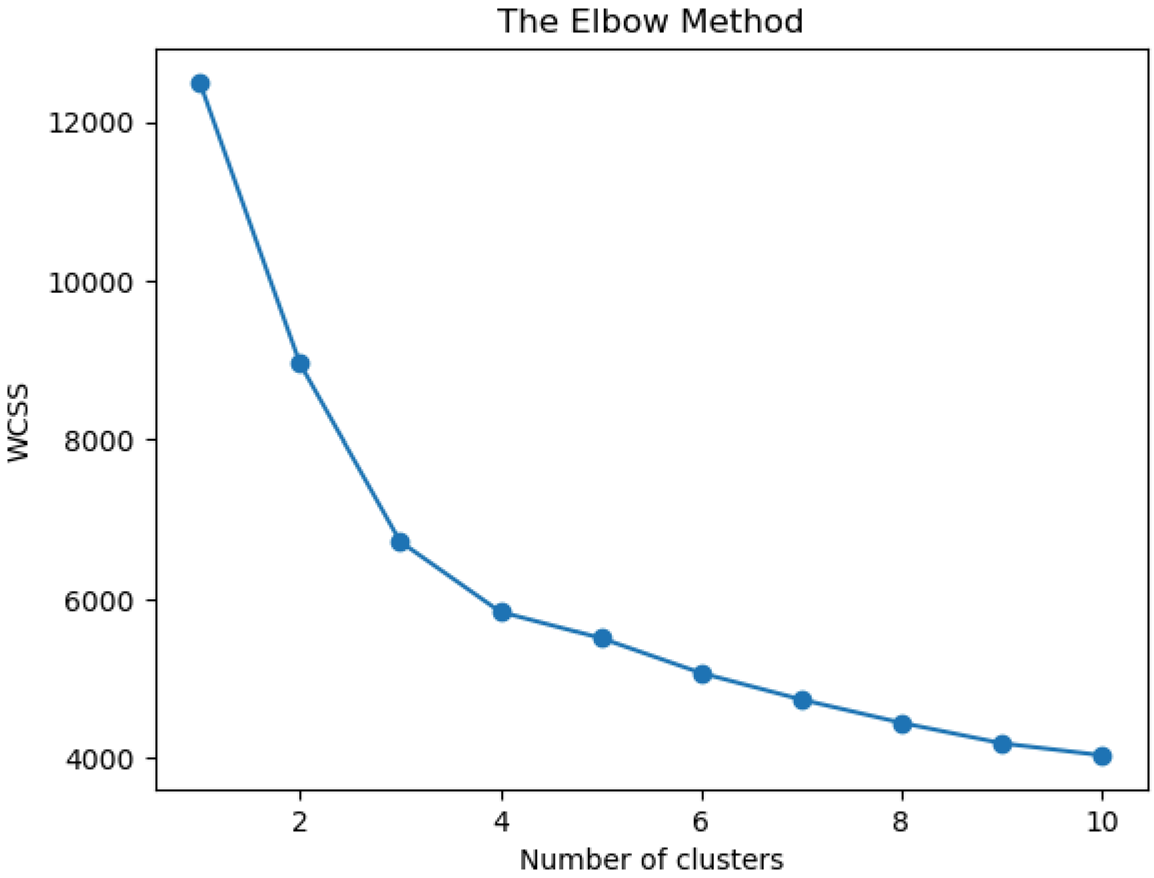


In [48]:
```
score
```

Out[48]:
```
[np.float64(1.3764241480294046),
 np.float64(1.2424428121012676),
 np.float64(1.2817957869735137)]
```

In [49]:
```
### Elbow Plot: WCSS- Within Cluster sum of squares
wcss=[]
for i in range(1,11):
    kmeans = KMeans(n_clusters=i, random_state=0)
    kmeans.fit(X)  # centroid location....
    labels = kmeans.labels_
    wcss.append(kmeans.inertia_)
```

In [54]:
```
plt.plot(range(1,11),wcss,'-o')
plt.xticks()
plt.title('The Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS');
```



In [55]:
```
## There is no significant difference in the wcss after numb of clusters=3
```

In [43]:
```
from sklearn.manifold import TSNE
tsne = TSNE()
```

```python
X_embedded = tsne.fit_transform(X)
X_embedded.shape
```

Out[43]: (2500, 2)

In [44]:
```python
clusters = pd.DataFrame(X_embedded, columns = ['x1', 'x2' ])
clusters.head()
```

Out[44]:

	x1	x2
0	-15.922939	5.951376
1	-9.185535	12.756983
2	34.746590	10.703995
3	46.636509	-22.345158
4	-9.349136	5.257360

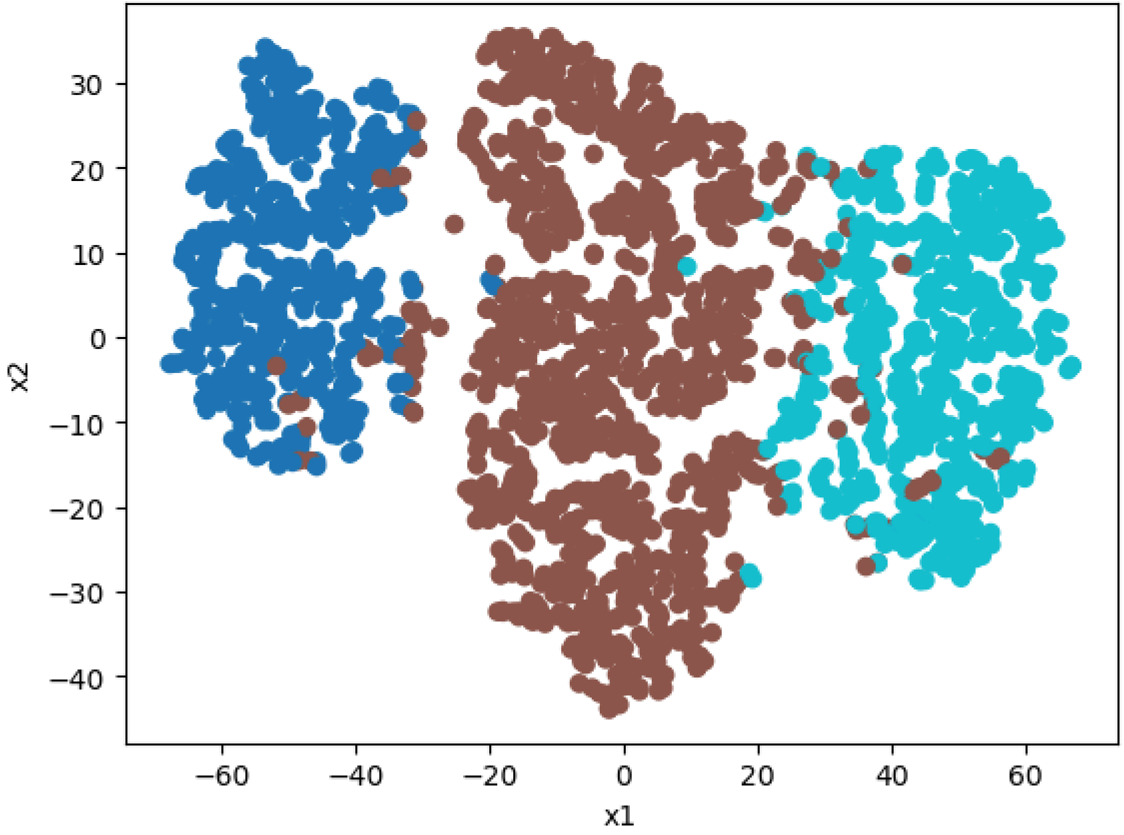
In [72]:
```python
    kmeans = KMeans(n_clusters=3, random_state=0)
    kmeans.fit(X)  # centroid location....
    labels = kmeans.labels_
```

In [73]:
```python
clusters['kmeans'] = labels
clusters.head()
```

Out[73]:

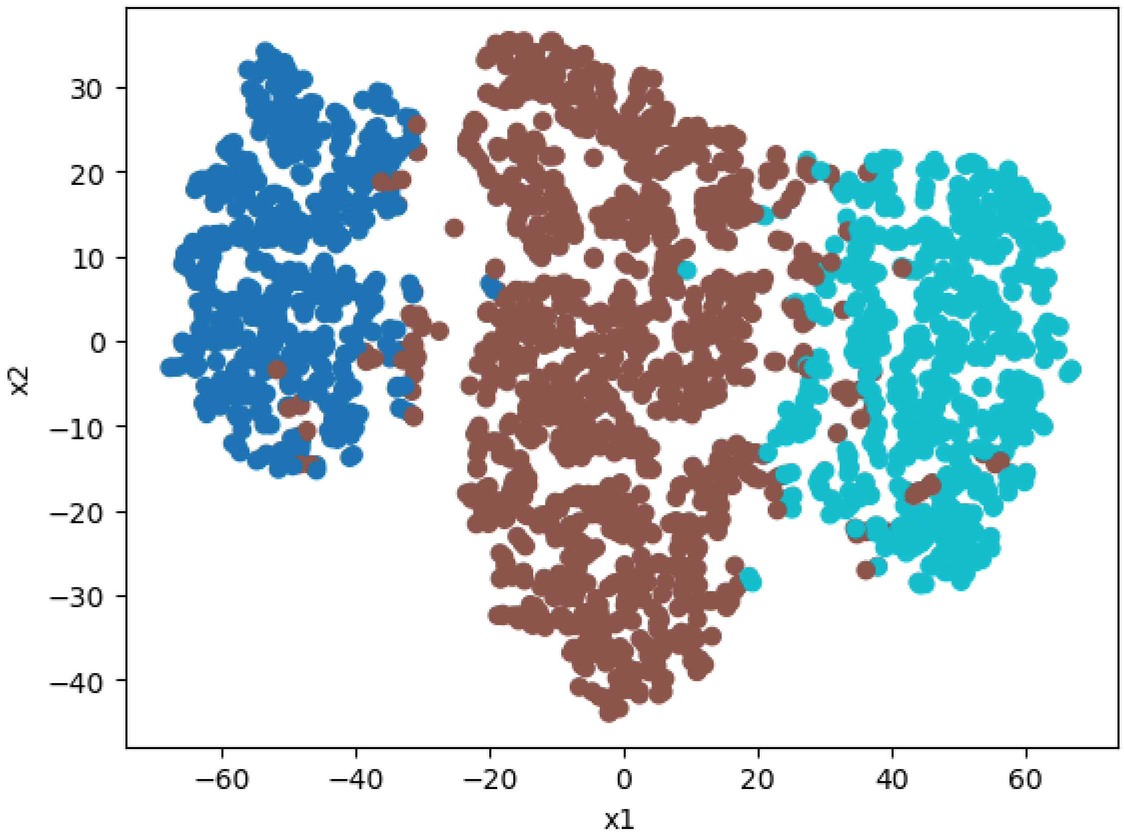
	x1	x2	kmeans
0	-15.922939	5.951376	1
1	-9.185535	12.756983	1
2	34.746590	10.703995	2
3	46.636509	-22.345158	2
4	-9.349136	5.257360	1

In [74]:
```
plt.scatter(clusters['x1'], clusters['x2'], c=clusters['kmeans'])
plt.xlabel('x1')
plt.ylabel('x2');
```



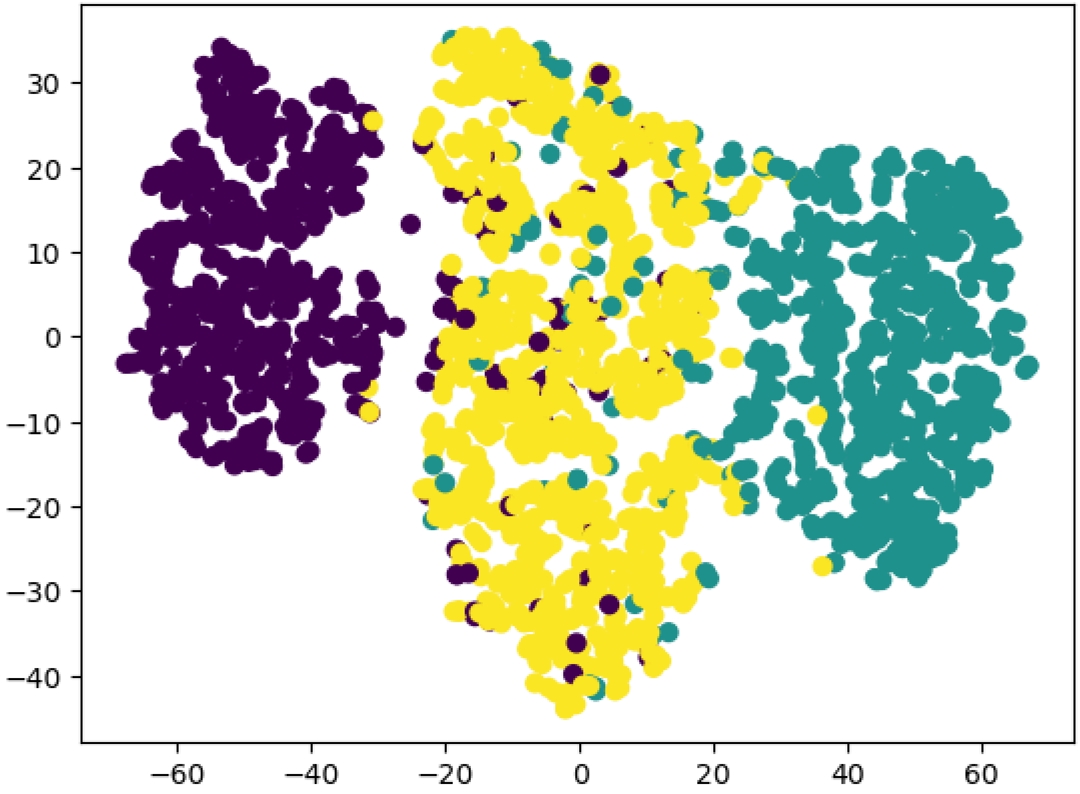
In [75]:
```
    kmeans = KMeans(n_clusters=3, init='k-means++',random_state=0)
    kmeans.fit(X)  # centroid location....
    labels = kmeans.labels_
```

In [76]:
```
plt.scatter(clusters['x1'], clusters['x2'], c=clusters['kmeans'])
plt.xlabel('x1')
plt.ylabel('x2');
```

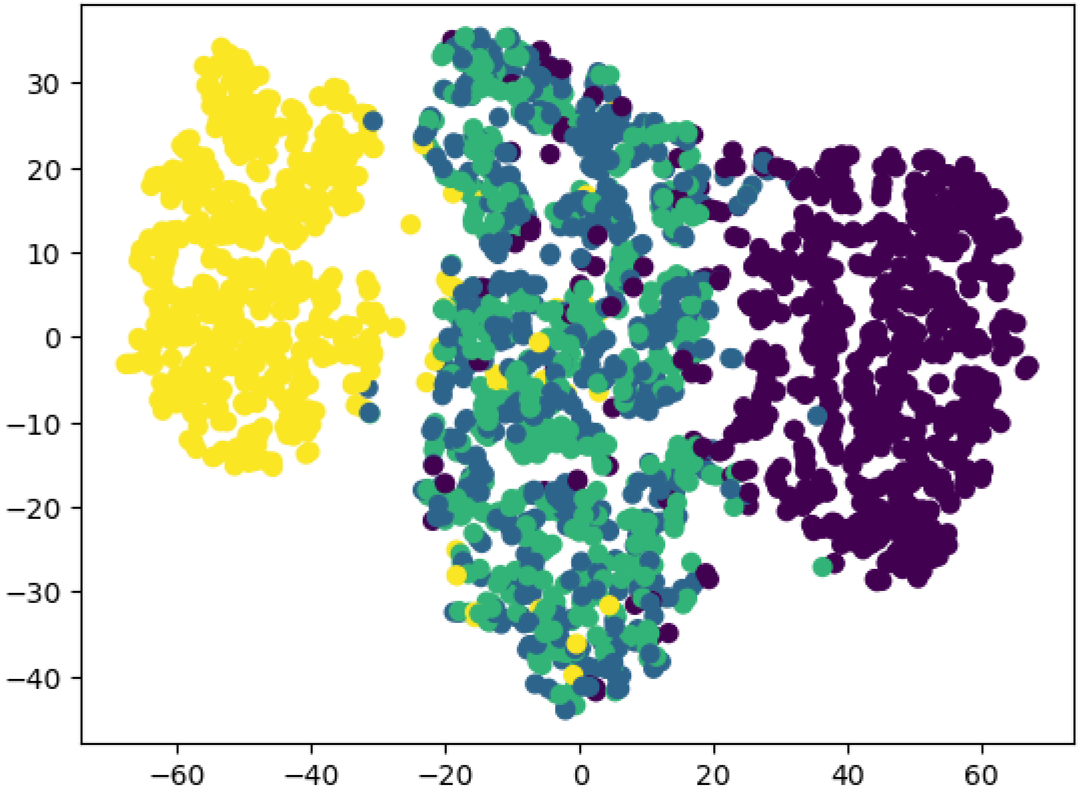


k-means++ do smart initialization: ist centroid is random, the next centroid are selected based on their distance from the centroid. Not just the farthest point is selected but the point with more cumulative probability

In [77]:
```
from sklearn.mixture import GaussianMixture
gmm = GaussianMixture(n_components=3)
gmm.fit(X)
labels = gmm.predict(X)
plt.scatter(clusters['x1'], clusters['x2'], c  = labels, s = 40, cmap = 'viridis');
```



In [78]:
```
from sklearn.mixture import GaussianMixture
gmm = GaussianMixture(n_components=4)
gmm.fit(X)
labels = gmm.predict(X)
plt.scatter(clusters['x1'], clusters['x2'], c  = labels, s = 40, cmap = 'viridis');
```



In [ ]: