Assignment-07-Clustering_Airline_data

In [5]:
```
# Import Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import scipy.cluster.hierarchy as sch
from sklearn.cluster import AgglomerativeClustering
```

In [6]:
```
# Import Dataset
airline=pd.read_excel('EastWestAirlines.xlsx', sheet_name ='data')
airline
```

Out[6]:

	ID#	Balance	Qual_miles	cc1_miles	cc2_miles	cc3_miles	Bonus_miles	Bonus_trans	Flight_miles
0	1	28143	0	1	1	1	174	1	
1	2	19244	0	1	1	1	215	2	
2	3	41354	0	1	1	1	4123	4	
3	4	14776	0	1	1	1	500	1	
4	5	97752	0	4	1	1	43300	26	
...	...	...	...	...	...	...	...	...	
3994	4017	18476	0	1	1	1	8525	4	
3995	4018	64385	0	1	1	1	981	5	
3996	4019	73597	0	3	1	1	25447	8	
3997	4020	54899	0	1	1	1	500	1	
3998	4021	3016	0	1	1	1	0	0	

3999 rows × 12 columns

In [7]:
```
airline.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3999 entries, 0 to 3998
Data columns (total 12 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   ID#                3999 non-null   int64
 1   Balance            3999 non-null   int64
 2   Qual_miles         3999 non-null   int64
 3   cc1_miles          3999 non-null   int64
 4   cc2_miles          3999 non-null   int64
 5   cc3_miles          3999 non-null   int64
 6   Bonus_miles        3999 non-null   int64
 7   Bonus_trans        3999 non-null   int64
 8   Flight_miles_12mo  3999 non-null   int64
 9   Flight_trans_12    3999 non-null   int64
 10  Days_since_enroll  3999 non-null   int64
 11  Award?             3999 non-null   int64
dtypes: int64(12)
memory usage: 375.0 KB
```

In [8]:

```python
airline2=airline.drop(['ID#'],axis=1)
airline2
```

Out[8]:

	Balance	Qual_miles	cc1_miles	cc2_miles	cc3_miles	Bonus_miles	Bonus_trans	Flight_miles_12ı
0	28143	0	1	1	1	174	1	
1	19244	0	1	1	1	215	2	
2	41354	0	1	1	1	4123	4	
3	14776	0	1	1	1	500	1	
4	97752	0	4	1	1	43300	26	2(
...	...	...	...	...	...	...	...	
3994	18476	0	1	1	1	8525	4	2
3995	64385	0	1	1	1	981	5	
3996	73597	0	3	1	1	25447	8	
3997	54899	0	1	1	1	500	1	5
3998	3016	0	1	1	1	0	0	

In [9]:

```python
# Normalize heterogenous numerical data using z-score (x-mean/std) or custom defined fur
# Normalization function - here custom defined
def norm_func(i):
    x = (i-i.min())/(i.max()-i.min())
    return (x)
```

In [10]:

```python
# Normalized data frame (considering the numerical part of data)
airline2_norm = norm_func(airline2)
airline2_norm
```

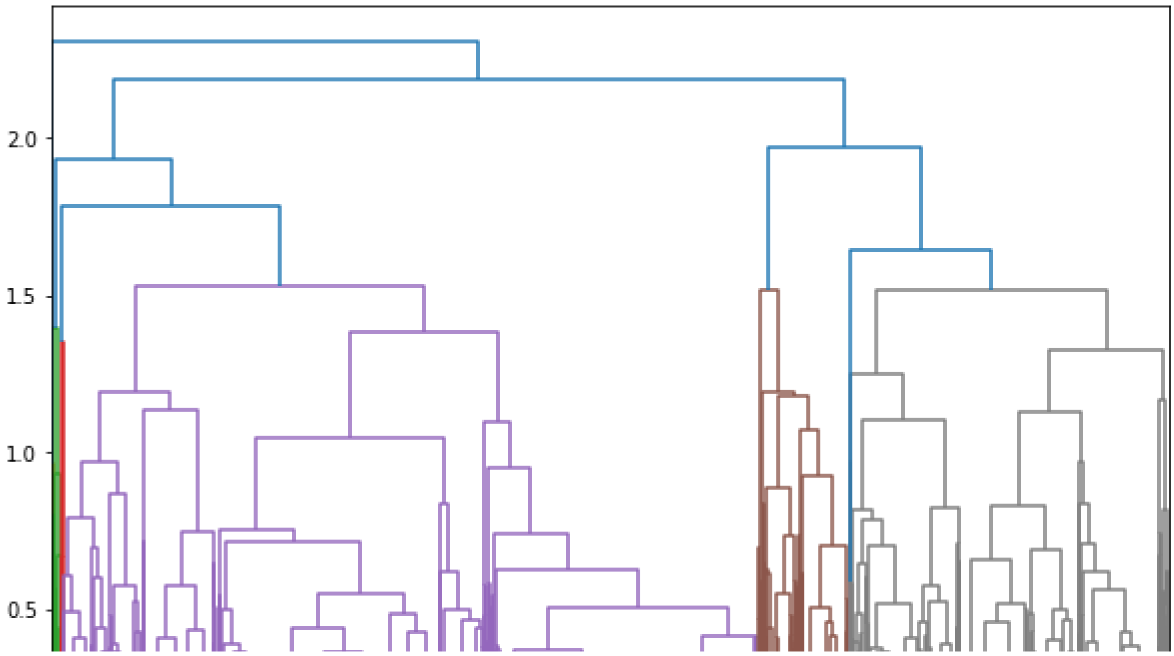
Out[10]:

	Balance	Qual_miles	cc1_miles	cc2_miles	cc3_miles	Bonus_miles	Bonus_trans	Flight_miles_12mo
0	0.016508	0.0	0.00	0.0	0.0	0.000660	0.011628	0.00000(
1	0.011288	0.0	0.00	0.0	0.0	0.000815	0.023256	0.00000(
2	0.024257	0.0	0.00	0.0	0.0	0.015636	0.046512	0.00000(
3	0.008667	0.0	0.00	0.0	0.0	0.001896	0.011628	0.00000(
4	0.057338	0.0	0.75	0.0	0.0	0.164211	0.302326	0.06739ŧ
...	...	...	...	...	...	...	...	..
3994	0.010837	0.0	0.00	0.0	0.0	0.032330	0.046512	0.00649(
3995	0.037766	0.0	0.00	0.0	0.0	0.003720	0.058140	0.00000(
3996	0.043169	0.0	0.50	0.0	0.0	0.096505	0.093023	0.00000(
3997	0.032202	0.0	0.00	0.0	0.0	0.001896	0.011628	0.01622ŧ
3998	0.001769	0.0	0.00	0.0	0.0	0.000000	0.000000	0.00000(

3999 rows × 11 columns

Hierarchical Clustering

In [11]:
```
# Create Dendrograms
plt.figure(figsize=(10, 7))
dendograms=sch.dendrogram(sch.linkage(airline2_norm,'complete'))
```



In [12]:
```
# Create Clusters (y)
hclusters=AgglomerativeClustering(n_clusters=5,affinity='euclidean',linkage='ward')
hclusters
```

Out[12]:
```
AgglomerativeClustering(n_clusters=5)
```

In [13]:
```
y=pd.DataFrame(hclusters.fit_predict(airline2_norm),columns=['clustersid'])
y['clustersid'].value_counts()
```

Out[13]:
```
1    1011
0     946
2     808
4     699
3     535
Name: clustersid, dtype: int64
```

In [14]:
```
# Adding clusters to dataset
airline2['clustersid']=hclusters.labels_
airline2
```

Out[14]:

	Balance	Qual_miles	cc1_miles	cc2_miles	cc3_miles	Bonus_miles	Bonus_trans	Flight_miles_12mo
0	28143	0	1	1	1	174	1	0
1	19244	0	1	1	1	215	2	0
2	41354	0	1	1	1	4123	4	0
3	14776	0	1	1	1	500	1	0
4	97752	0	4	1	1	43300	26	2077
...	...	...	...	...	...	...	...	...
3994	18476	0	1	1	1	8525	4	200
3995	64385	0	1	1	1	981	5	0
3996	73597	0	3	1	1	25447	8	0
3997	54899	0	1	1	1	500	1	500
3998	3016	0	1	1	1	0	0	0

3999 rows × 12 columns

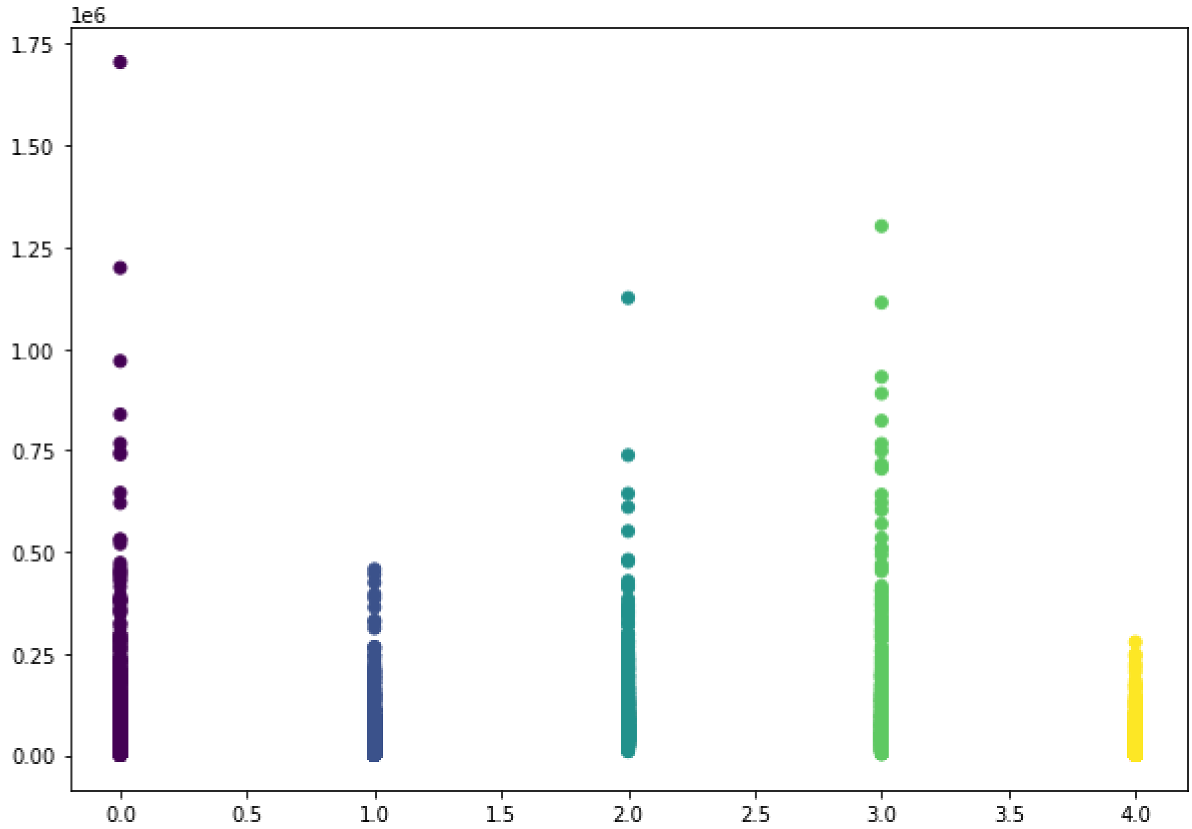
In [15]:
```
airline2.groupby('clustersid').agg(['mean']).reset_index()
```

Out[15]:

	clustersid	Balance	Qual_miles	cc1_miles	cc2_miles	cc3_miles	Bonus_miles	Bonus_trans	Flig
		mean	mean	mean	mean	mean	mean	mean	mea
0	0	79848.233615	285.097252	1.699789	1.024313	1.000000	12079.774841	12.133192	
1	1	43313.653808	21.506429	1.000000	1.033630	1.000989	2562.614243	5.474777	
2	2	106221.111386	161.262376	3.198020	1.001238	1.025990	26458.257426	16.363861	
3	3	127475.028037	160.801869	4.362617	1.000000	1.050467	58656.919626	22.235514	
4	4	30013.416309	98.054363	1.000000	1.000000	1.000000	2552.569385	6.101574	

In [16]:
```
# Plot Clusters
plt.figure(figsize=(10, 7))
plt.scatter(airline2['clustersid'],airline2['Balance'], c=hclusters.labels_)
```

Out[16]: <matplotlib.collections.PathCollection at 0x2032063aac0>

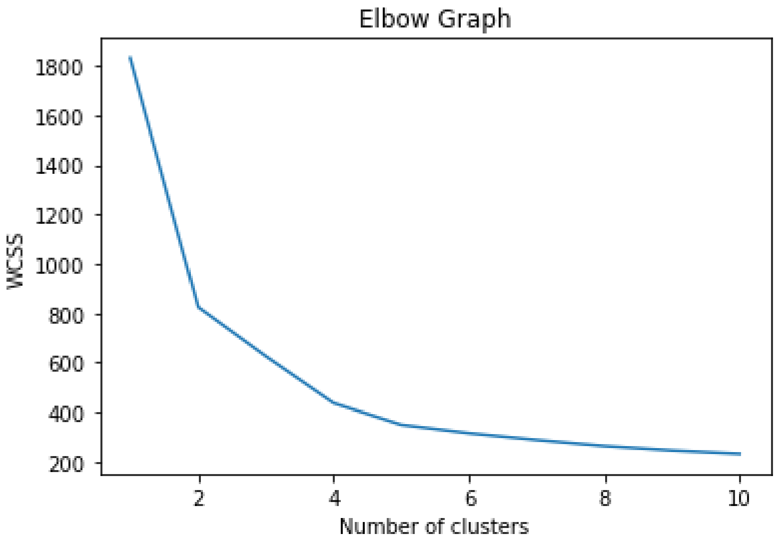


K Means Clustering

In [17]:
```
# Use Elbow Graph to find optimum number of  clusters (K value) from K values range
# The K-means algorithm aims to choose centroids that minimise the inertia, or within-cl
# random state can be anything from 0 to 42, but the same number to be used everytime,sc
from sklearn.cluster import KMeans
from sklearn.preprocessing import normalize
```

In [18]:
```
# within-cluster sum-of-squares criterion
wcss=[]
for i in range (1,11):
    kmeans=KMeans(n_clusters=i,random_state=2)
    kmeans.fit(airline2_norm)
    wcss.append(kmeans.inertia_)
```

In [19]:
```
# Plot K values range vs WCSS to get Elbow graph for choosing K (no. of clusters)
plt.plot(range(1,11),wcss)
plt.title('Elbow Graph')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.show()
```



Build Cluster algorithm using K=4

In [20]:
```
# Cluster algorithm using K=4
clusters4=KMeans(4,random_state=30).fit(airline2_norm)
clusters4
```

Out[20]:
```
KMeans(n_clusters=4, random_state=30)
```

In [21]:
```
clusters4.labels_
```

Out[21]:
```
array([0, 0, 0, ..., 3, 0, 0])
```

In [22]:
```python
# Assign clusters to the data set
airline4=airline2.copy()
airline4['clusters4id']=clusters4.labels_
airline4
```

Out[22]:

	Balance	Qual_miles	cc1_miles	cc2_miles	cc3_miles	Bonus_miles	Bonus_trans	Flight_miles_12mo
0	28143	0	1	1	1	174	1	0
1	19244	0	1	1	1	215	2	0
2	41354	0	1	1	1	4123	4	0
3	14776	0	1	1	1	500	1	0
4	97752	0	4	1	1	43300	26	2077
...	...	...	...	...	...	...	...	...
3994	18476	0	1	1	1	8525	4	200
3995	64385	0	1	1	1	981	5	0
3996	73597	0	3	1	1	25447	8	0
3997	54899	0	1	1	1	500	1	500
3998	3016	0	1	1	1	0	0	0

3999 rows × 13 columns

In [23]:
```python
# Compute the centroids for K=4 clusters with 11 variables
clusters4.cluster_centers_
```

Out[23]:
```
array([[ 2.39011667e-02,  8.28362120e-03,  2.31945177e-02,
         8.96151819e-03,  1.05429626e-03,  1.26482465e-02,
         7.54496083e-02,  7.35308092e-03,  1.24327389e-02,
         4.36111859e-01,  3.27515792e-15],
       [ 4.89953609e-02,  2.60542873e-02,  3.90044577e-02,
         1.63447251e-02,  2.22882615e-03,  3.35642727e-02,
         1.21825219e-01,  3.34267751e-02,  5.94073285e-02,
         5.22892182e-01,  1.00000000e+00],
       [ 6.92335936e-02,  6.55837114e-03,  6.44122383e-01,
         8.05152979e-04,  5.63607085e-03,  1.18636504e-01,
         2.00595439e-01,  7.31260853e-03,  1.19405706e-02,
         5.34640411e-01, -3.88578059e-16],
       [ 6.35352962e-02,  1.77912301e-02,  7.28960396e-01,
         6.18811881e-04,  6.49752475e-03,  1.72970238e-01,
         2.34903868e-01,  2.31602349e-02,  4.04212591e-02,
         5.86139300e-01,  1.00000000e+00]])
```

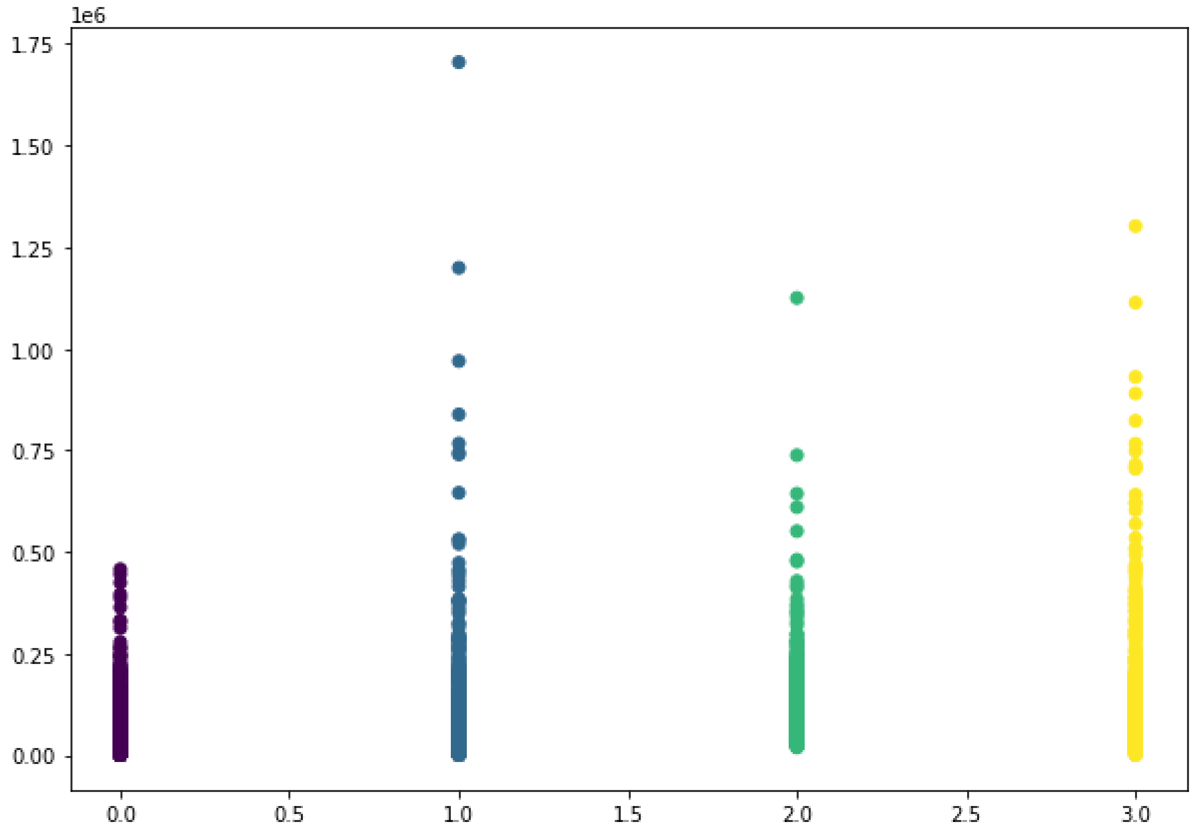
In [24]:
```python
# Group data by Clusters (K=4)
airline4.groupby('clusters4id').agg(['mean']).reset_index()
```

Out[24]:

	clusters4id	Balance	Qual_miles	cc1_miles	cc2_miles	cc3_miles	Bonus_miles	Bonus_trans	Fli
		mean	mean	mean	mean	mean	mean	mean	me
0	0	40747.617290	92.345809	1.092778	1.017923	1.004217	3335.152873	6.488666	
1	1	83529.153046	290.453195	1.156018	1.032689	1.008915	8850.395245	10.476969	
2	2	118032.061192	73.112721	3.576490	1.001610	1.022544	31282.666667	17.251208	
3	3	108317.387376	198.336634	3.915842	1.001238	1.025990	45609.657178	20.201733	

In [25]:
```python
# Plot Clusters
plt.figure(figsize=(10, 7))
plt.scatter(airline4['clusters4id'],airline4['Balance'], c=clusters4.labels_)
```

Out[25]: <matplotlib.collections.PathCollection at 0x2031f4887c0>



Build Cluster algorithm using K=5

In [26]:
```python
# Cluster algorithm using K=5
clusters5=KMeans(5,random_state=30).fit(airline2_norm)
clusters5
```

Out[26]: KMeans(n_clusters=5, random_state=30)

In [27]:
```python
clusters5.labels_
```

Out[27]: array([4, 4, 4, ..., 1, 0, 0])

In [28]:
```python
# Assign clusters to the data set
airline5=airline2.copy()
airline5['clusters5id']=clusters5.labels_
airline5
```

Out[28]:

	Balance	Qual_miles	cc1_miles	cc2_miles	cc3_miles	Bonus_miles	Bonus_trans	Flight_miles_12mo
0	28143	0	1	1	1	174	1	0
1	19244	0	1	1	1	215	2	0
2	41354	0	1	1	1	4123	4	0
3	14776	0	1	1	1	500	1	0
4	97752	0	4	1	1	43300	26	2077
...	...	...	...	...	...	...	...	...
3994	18476	0	1	1	1	8525	4	200
3995	64385	0	1	1	1	981	5	0
3996	73597	0	3	1	1	25447	8	0
3997	54899	0	1	1	1	500	1	500
3998	3016	0	1	1	1	0	0	0

3999 rows × 13 columns

In [29]:
```python
# Compute the centroids for K=5 clusters with 11 variables
clusters5.cluster_centers_
```

Out[29]:
```
array([[ 1.94137515e-02,  8.44382696e-03,  1.76841085e-02,
         8.23643411e-03,  1.69573643e-03,  1.23045313e-02,
         7.17842978e-02,  6.90692719e-03,  1.13902296e-02,
         2.39980966e-01,  3.94129174e-15],
       [ 6.35352962e-02,  1.77912301e-02,  7.28960396e-01,
         6.18811881e-04,  6.49752475e-03,  1.72970238e-01,
         2.34903868e-01,  2.31602349e-02,  4.04212591e-02,
         5.86139300e-01,  1.00000000e+00],
       [ 4.89953609e-02,  2.60542873e-02,  3.90044577e-02,
         1.63447251e-02,  2.22882615e-03,  3.35642727e-02,
         1.21825219e-01,  3.34267751e-02,  5.94073285e-02,
         5.22892182e-01,  1.00000000e+00],
       [ 6.93891884e-02,  6.59020789e-03,  6.46035599e-01,
         8.09061489e-04,  5.66343042e-03,  1.19022293e-01,
         2.00383834e-01,  7.27197078e-03,  1.18458814e-02,
         5.32620376e-01, -4.99600361e-16],
       [ 2.92823328e-02,  8.06451613e-03,  3.05299539e-02,
         9.79262673e-03,  2.88018433e-04,  1.31485480e-02,
         8.03906334e-02,  7.91232441e-03,  1.37379358e-02,
         6.71078504e-01,  1.16573418e-15]])
```

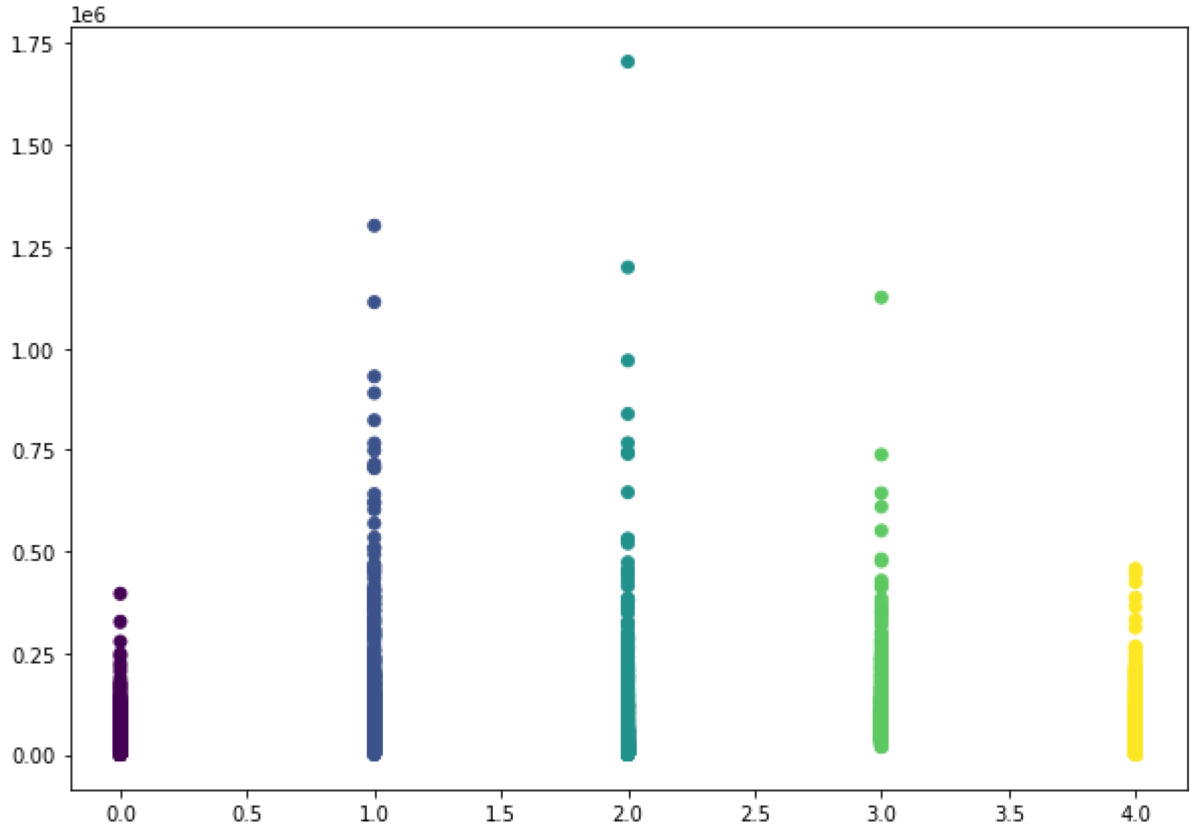
In [30]:
```
# Group data by Clusters (K=5)
airline5.groupby('clusters5id').agg(['mean']).reset_index()
```

Out[30]:

	clusters5id	Balance	Qual_miles	cc1_miles	cc2_miles	cc3_miles	Bonus_miles	Bonus_trans	Fli
		mean	mean	mean	mean	mean	mean	mean	me
0	0	33097.301357	94.131783	1.070736	1.016473	1.006783	3244.520349	6.173450	
1	1	108317.387376	198.336634	3.915842	1.001238	1.025990	45609.657178	20.201733	
2	2	83529.153046	290.453195	1.156018	1.032689	1.008915	8850.395245	10.476969	
3	3	118297.325243	73.467638	3.584142	1.001618	1.022654	31384.393204	17.233010	
4	4	49921.633641	89.903226	1.122120	1.019585	1.001152	3467.074885	6.913594	

In [31]:
```
# Plot Clusters
plt.figure(figsize=(10, 7))
plt.scatter(airline5['clusters5id'],airline5['Balance'], c=clusters5.labels_)
```

Out[31]: <matplotlib.collections.PathCollection at 0x2031f48f460>



DBSCAN Clustering

In [32]:
```
from sklearn.cluster import DBSCAN
```

In [33]:
```
min_samples=2 #n
```

In [34]:
```
dbs=DBSCAN(min_samples=5,eps=0.2)
claas_pr=dbs.fit_predict(airline5.iloc[:,:2])
```

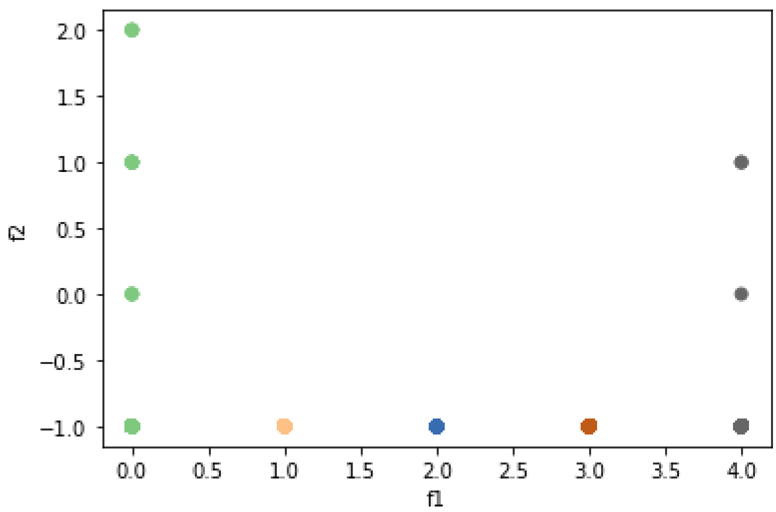
In [35]:
```
claas_pr
```
Out[35]:
```
array([-1, -1, -1, ..., -1, -1, -1], dtype=int64)
```

In [36]:
```
airline5["class_pr"]=claas_pr
airline5
```
Out[36]:

	Balance	Qual_miles	cc1_miles	cc2_miles	cc3_miles	Bonus_miles	Bonus_trans	Flight_miles_12mo
0	28143	0	1	1	1	174	1	0
1	19244	0	1	1	1	215	2	0
2	41354	0	1	1	1	4123	4	0
3	14776	0	1	1	1	500	1	0
4	97752	0	4	1	1	43300	26	2077
...	...	...	...	...	...	...	...	...
3994	18476	0	1	1	1	8525	4	200
3995	64385	0	1	1	1	981	5	0
3996	73597	0	3	1	1	25447	8	0
3997	54899	0	1	1	1	500	1	500
3998	3016	0	1	1	1	0	0	0

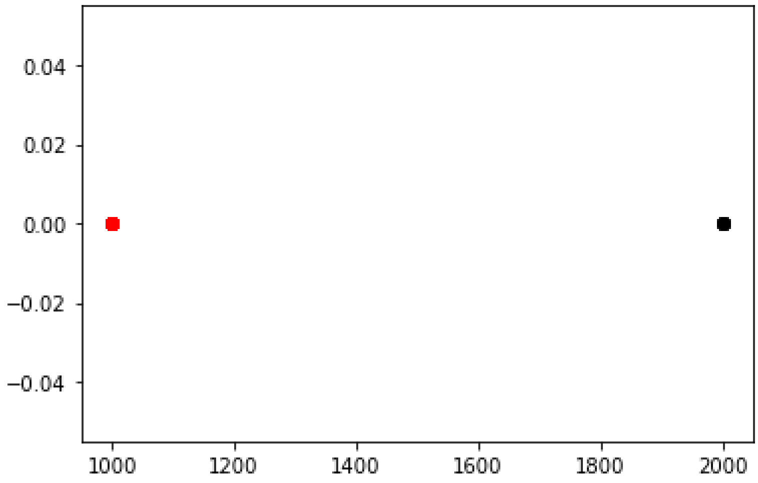
3999 rows × 14 columns

In [43]:
```
import matplotlib.pyplot as plt
plt.scatter(airline5['clusters5id'],airline5['class_pr'], c=clusters5.labels_,cmap=plt.c
plt.xlabel("f1")
plt.ylabel("f2")
```
Out[43]:
```
Text(0, 0.5, 'f2')
```



In [38]:
```
plt.scatter(airline5[airline5["class_pr"]==1].iloc[:,0],airline5[airline5["class_pr"]==1
plt.scatter(airline5[airline5["class_pr"]==0].iloc[:,0],airline5[airline5["class_pr"]==0
```

Out[38]: <matplotlib.collections.PathCollection at 0x2031f453190>



In [ ]: