In [1]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from sklearn.preprocessing import normalize
```

In [3]:
```python
# Import Dataset
airline = pd.read_csv('EastWestAirlines.csv')
airline
```

Out[3]:

| | ID# | Balance | Qual_miles | cc1_miles | cc2_miles | cc3_miles | Bonus_miles | Bonus_trans | Fli |
|---|---|---|---|---|---|---|---|---|---|
| **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 [4]:
```
airline2 = airline.drop(['ID#'],axis=1)
airline2
```

Out[4]:

| | Balance | Qual_miles | cc1_miles | cc2_miles | cc3_miles | Bonus_miles | Bonus_trans | Flight_mil |
|---|---|---|---|---|---|---|---|---|
| **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 | |
| **...** | ... | ... | ... | ... | ... | ... | ... | |
| **3994** | 18476 | 0 | 1 | 1 | 1 | 8525 | 4 | |
| **3995** | 64385 | 0 | 1 | 1 | 1 | 981 | 5 | |
| **3996** | 73597 | 0 | 3 | 1 | 1 | 25447 | 8 | |
| **3997** | 54899 | 0 | 1 | 1 | 1 | 500 | 1 | |
| **3998** | 3016 | 0 | 1 | 1 | 1 | 0 | 0 | |

3999 rows × 11 columns

In [5]:
```
airline2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3999 entries, 0 to 3998
Data columns (total 11 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Balance            3999 non-null   int64
 1   Qual_miles         3999 non-null   int64
 2   cc1_miles          3999 non-null   int64
 3   cc2_miles          3999 non-null   int64
 4   cc3_miles          3999 non-null   int64
 5   Bonus_miles        3999 non-null   int64
 6   Bonus_trans        3999 non-null   int64
 7   Flight_miles_12mo  3999 non-null   int64
 8   Flight_trans_12    3999 non-null   int64
 9   Days_since_enroll  3999 non-null   int64
 10  Award?             3999 non-null   int64
dtypes: int64(11)
memory usage: 343.8 KB
```

In [6]:
```
# Normalize heterogenous numerical data
airline2_norm = pd.DataFrame(normalize(airline2),columns=airline2.columns)
airline2_norm
```

Out[6]:

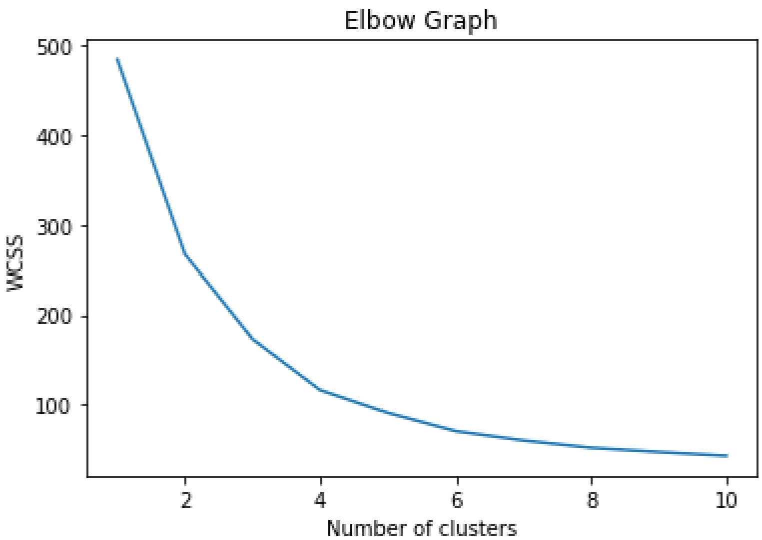
| | Balance | Qual_miles | cc1_miles | cc2_miles | cc3_miles | Bonus_miles | Bonus_trans | Flight_mi |
|---|---|---|---|---|---|---|---|---|
| **0** | 0.970414 | 0.0 | 0.000034 | 0.000034 | 0.000034 | 0.006000 | 0.000034 | |
| **1** | 0.940209 | 0.0 | 0.000049 | 0.000049 | 0.000049 | 0.010504 | 0.000098 | |
| **2** | 0.981113 | 0.0 | 0.000024 | 0.000024 | 0.000024 | 0.097817 | 0.000095 | |
| **3** | 0.904428 | 0.0 | 0.000061 | 0.000061 | 0.000061 | 0.030605 | 0.000061 | |
| **4** | 0.912226 | 0.0 | 0.000037 | 0.000009 | 0.000009 | 0.404078 | 0.000243 | |
| **...** | ... | ... | ... | ... | ... | ... | ... | |
| **3994** | 0.905810 | 0.0 | 0.000049 | 0.000049 | 0.000049 | 0.417949 | 0.000196 | |
| **3995** | 0.999649 | 0.0 | 0.000016 | 0.000016 | 0.000016 | 0.015231 | 0.000078 | |
| **3996** | 0.944948 | 0.0 | 0.000039 | 0.000013 | 0.000013 | 0.326726 | 0.000103 | |
| **3997** | 0.999592 | 0.0 | 0.000018 | 0.000018 | 0.000018 | 0.009104 | 0.000018 | |
| **3998** | 0.907271 | 0.0 | 0.000301 | 0.000301 | 0.000301 | 0.000000 | 0.000000 | |

3999 rows × 11 columns

In [7]:
```
# Use Elbow Graph to find optimum number of  clusters (K value) from K values rar
# The K-means algorithm aims to choose centroids that minimise the inertia, or wi
# random state can be anything from 0 to 42, but the same number to be used every
```

In [8]:
```
# 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 [9]: # 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 [11]: # Cluster algorithm using K=4
clusters4=KMeans(4,random_state=30).fit(airline2_norm)
clusters4
```

```
Out[11]: KMeans(n_clusters=4, random_state=30)
```

```
In [12]: clusters4.labels_
```

```
Out[12]: array([0, 0, 0, ..., 3, 0, 0])
```

In [13]:
```
# Assign clusters to the data set
airline4=airline2.copy()
airline4['clusters4id']=clusters4.labels_
airline4
```

Out[13]:

| | Balance | Qual_miles | cc1_miles | cc2_miles | cc3_miles | Bonus_miles | Bonus_trans | Flight_mil |
|---|---|---|---|---|---|---|---|---|
| **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 | |
| **...** | ... | ... | ... | ... | ... | ... | ... | |
| **3994** | 18476 | 0 | 1 | 1 | 1 | 8525 | 4 | |
| **3995** | 64385 | 0 | 1 | 1 | 1 | 981 | 5 | |
| **3996** | 73597 | 0 | 3 | 1 | 1 | 25447 | 8 | |
| **3997** | 54899 | 0 | 1 | 1 | 1 | 500 | 1 | |
| **3998** | 3016 | 0 | 1 | 1 | 1 | 0 | 0 | |

3999 rows × 12 columns

In [14]:
```
# Compute the centroids for K=4 clusters with 11 variables
clusters4.cluster_centers_
```

Out[14]:
```
array([[9.82878899e-01, 3.71612347e-03, 4.15057209e-05, 3.77179195e-05,
        3.76205578e-05, 8.06914054e-02, 1.57453088e-04, 6.65079627e-03,
        2.12921781e-05, 1.03324885e-01, 4.81770304e-06],
       [5.23653977e-01, 2.37603195e-03, 9.13653056e-05, 4.56081254e-05,
        4.45095230e-05, 7.97866700e-01, 5.07019477e-04, 1.75075997e-02,
        5.89123100e-05, 1.31443994e-01, 3.00837174e-05],
       [6.28081328e-01, 9.30359261e-04, 2.06331617e-04, 2.06128767e-04,
        2.05879951e-04, 1.23980626e-01, 4.76413717e-04, 6.66146530e-03,
        2.24385615e-05, 6.89106611e-01, 2.58980762e-05],
       [8.99048678e-01, 2.03403471e-03, 5.68074076e-05, 3.01913199e-05,
        2.95156437e-05, 4.03089039e-01, 4.02398112e-04, 7.62262675e-03,
        2.24052643e-05, 8.50654942e-02, 9.73901648e-06]])
```

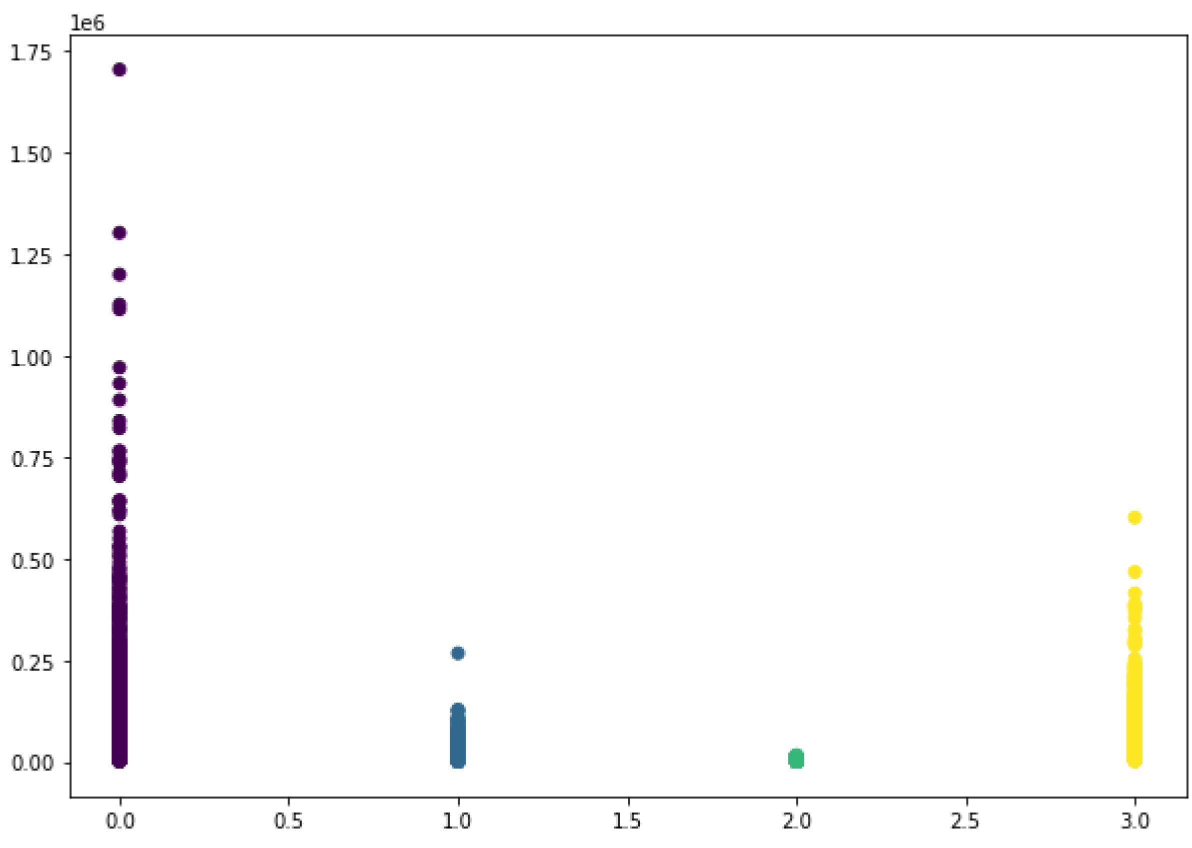
In [15]:
```
# Group data by Clusters (K=4)
airline4.groupby('clusters4id').agg(['mean']).reset_index()
```

Out[15]:

| | clusters4id | Balance | Qual_miles | cc1_miles | cc2_miles | cc3_miles | Bonus_miles | Bonus_tr |
|---|---|---|---|---|---|---|---|---|
| | | mean | mean | mean | mean | mean | mean | mean |
| **0** | 0 | 88484.857577 | 175.062961 | 1.495441 | 1.008250 | 1.001737 | 8110.131568 | 8.770 |
| **1** | 1 | 28617.579670 | 112.000000 | 3.280220 | 1.030220 | 1.068681 | 42166.565934 | 17.634 |
| **2** | 2 | 5129.247934 | 8.285124 | 1.004132 | 1.004132 | 1.000000 | 891.388430 | 3.012 |
| **3** | 3 | 72378.903670 | 119.606422 | 3.077982 | 1.024771 | 1.018349 | 31486.477982 | 17.476 |

In [16]:
```
# Plot Clusters
plt.figure(figsize=(10, 7))
plt.scatter(airline4['clusters4id'],airline4['Balance'], c=clusters4.labels_)
```

Out[16]: <matplotlib.collections.PathCollection at 0x274f0bcb220>




## Build Cluster algorithm using K=5

In [17]:
```
# Cluster algorithm using K=5
clusters5=KMeans(5,random_state=30).fit(airline2_norm)
clusters5
```

Out[17]: `KMeans(n_clusters=5, random_state=30)`

In [18]:
```
clusters5.labels_
```

Out[18]: `array([0, 3, 0, ..., 4, 0, 3])`

In [19]:
```
# Assign clusters to the data set
airline5=airline2.copy()
airline5['clusters5id']=clusters5.labels_
airline5
```

Out[19]:

| | Balance | Qual_miles | cc1_miles | cc2_miles | cc3_miles | Bonus_miles | Bonus_trans | Flight_mil |
|---|---|---|---|---|---|---|---|---|
| **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 | |
| **...** | ... | ... | ... | ... | ... | ... | ... | |
| **3994** | 18476 | 0 | 1 | 1 | 1 | 8525 | 4 | |
| **3995** | 64385 | 0 | 1 | 1 | 1 | 981 | 5 | |
| **3996** | 73597 | 0 | 3 | 1 | 1 | 25447 | 8 | |
| **3997** | 54899 | 0 | 1 | 1 | 1 | 500 | 1 | |
| **3998** | 3016 | 0 | 1 | 1 | 1 | 0 | 0 | |

3999 rows × 12 columns

In [20]:
```
# Compute the centroids for K=5 clusters with 11 variables
clusters5.cluster_centers_
```

Out[20]:
```
array([[9.87581993e-01, 3.39051837e-03, 3.51053916e-05, 3.03791237e-05,
        3.02652033e-05, 9.01709733e-02, 1.53701634e-04, 6.66013521e-03,
        2.09767345e-05, 7.53291184e-02, 3.94536689e-06],
       [5.14758999e-01, 2.45703304e-03, 9.55752981e-05, 5.00781670e-05,
        4.87710513e-05, 8.02358706e-01, 5.20472068e-04, 1.80244812e-02,
        6.06430623e-05, 1.36539353e-01, 3.06234744e-05],
       [4.14644791e-01, 1.30104261e-18, 2.28611980e-04, 2.27627266e-04,
        2.27627266e-04, 1.50766683e-01, 5.97513433e-04, 7.35401490e-03,
        2.84888383e-05, 8.48268382e-01, 3.91049405e-05],
       [8.93103634e-01, 4.45303855e-03, 1.23796982e-04, 1.23612826e-04,
        1.23612826e-04, 7.60122618e-02, 2.95169039e-04, 6.30476783e-03,
        2.07480658e-05, 4.07515394e-01, 1.35161631e-05],
       [8.91833807e-01, 2.00098101e-03, 5.80553278e-05, 3.01489923e-05,
        2.94377607e-05, 4.20637046e-01, 4.04859493e-04, 7.68892416e-03,
        2.27011475e-05, 8.30834166e-02, 1.00407121e-05]])
```

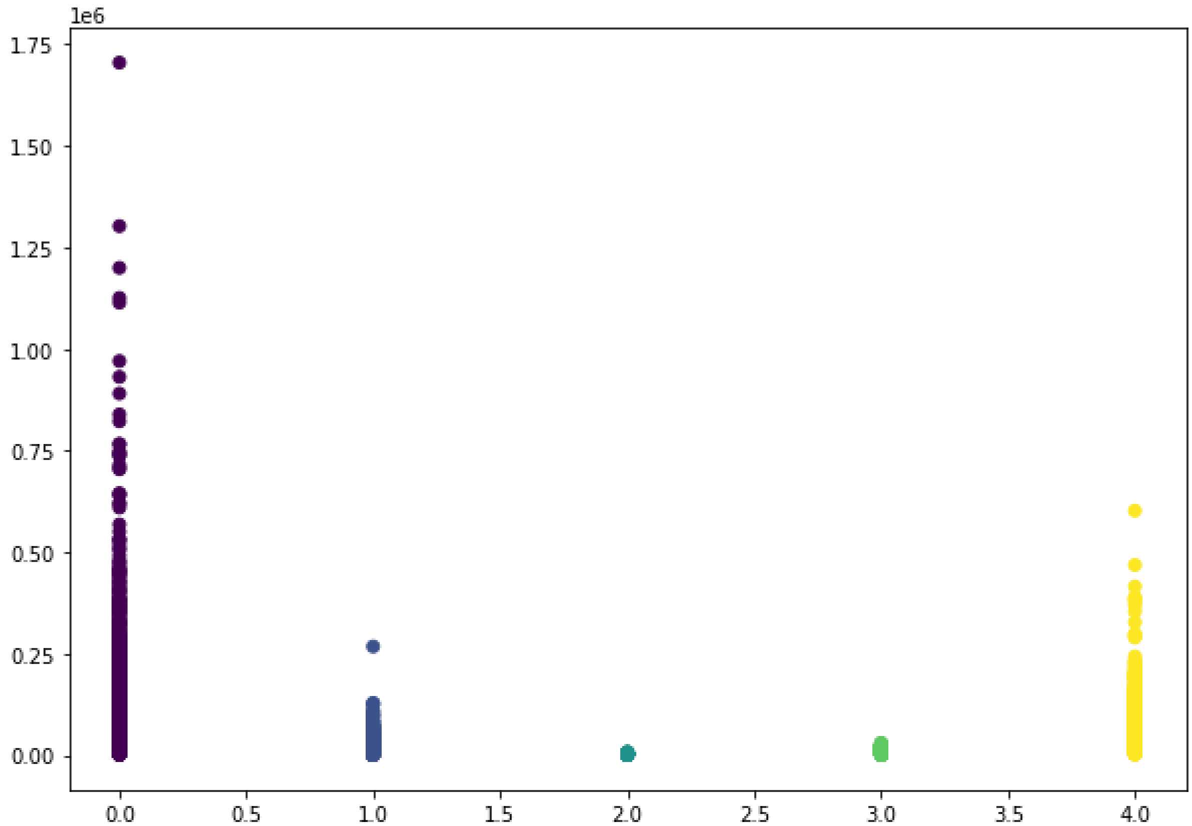
In [21]:
```
# Group data by Clusters (K=5)
airline5.groupby('clusters5id').agg(['mean']).reset_index()
```

Out[21]:

| | clusters5id | Balance | Qual_miles | cc1_miles | cc2_miles | cc3_miles | Bonus_miles | Bonus_tr |
|---|---|---|---|---|---|---|---|---|
| | | mean | mean | mean | mean | mean | mean | mean |
| **0** | 0 | 97404.121382 | 185.499533 | 1.604575 | 1.009337 | 1.001867 | 9636.360411 | 9.704 |
| **1** | 1 | 27526.798295 | 115.818182 | 3.247159 | 1.034091 | 1.071023 | 41812.809659 | 17.599 |
| **2** | 2 | 2415.576577 | 0.000000 | 1.009009 | 1.000000 | 1.000000 | 850.189189 | 3.036 |
| **3** | 3 | 11768.858247 | 55.121134 | 1.005155 | 1.000000 | 1.000000 | 984.778351 | 3.469 |
| **4** | 4 | 70743.739563 | 116.122266 | 3.135189 | 1.025845 | 1.019881 | 32531.393638 | 17.626 |

In [22]:
```
# Plot Clusters
plt.figure(figsize=(10, 7))
plt.scatter(airline5['clusters5id'],airline5['Balance'], c=clusters5.labels_)
```

Out[22]: <matplotlib.collections.PathCollection at 0x274f09d2850>




In [ ]: