In [4]:

```python
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
import pandas as pd
import numpy as np
from sklearn import decomposition
from sklearn import preprocessing
from sklearn.decomposition import TruncatedSVD
```

In [13]:

```python
df = pd.read_csv(r"C:\Users\zhaoe\OneDrive\Documents\ratings.csv")

table = pd.pivot_table(df, values='rating', columns=['movieId'], index=['userId'])
table = table.fillna(0)

sliced_table = table.head(10)
sliced_table = sliced_table.append(table.tail(10))
print(sliced_table)
```

```
movieId  1       2       3       4       5       6       7       8       \
userId
1            4.0     0.0     4.0     0.0     0.0     4.0     0.0     0.0
2            0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
3            0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
4            0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
5            4.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
6            0.0     4.0     5.0     3.0     5.0     4.0     4.0     3.0
7            4.5     0.0     0.0     0.0     0.0     0.0     0.0     0.0
8            0.0     4.0     0.0     0.0     0.0     0.0     0.0     0.0
9            0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
10           0.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
601          4.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
602          0.0     4.0     0.0     0.0     0.0     3.0     0.0     0.0
603          4.0     0.0     0.0     0.0     0.0     4.0     0.0     0.0
604          3.0     5.0     0.0     0.0     3.0     3.0     0.0     0.0
605          4.0     3.5     0.0     0.0     0.0     0.0     0.0     0.0
606          2.5     0.0     0.0     0.0     0.0     0.0     2.5     0.0
607          4.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
608          2.5     2.0     2.0     0.0     0.0     0.0     0.0     0.0
609          3.0     0.0     0.0     0.0     0.0     0.0     0.0     0.0
610          5.0     0.0     0.0     0.0     0.0     5.0     0.0     0.0

movieId  9       10       ...    193565  193567  193571  193573  193579  \
userId                    ...
1            0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
2            0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
3            0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
4            0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
5            0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
6            0.0     3.0  ...       0.0     0.0     0.0     0.0     0.0
7            0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
8            0.0     2.0  ...       0.0     0.0     0.0     0.0     0.0
9            0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
10           0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
601          0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
602          0.0     3.0  ...       0.0     0.0     0.0     0.0     0.0
603          0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
604          0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
605          0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
606          0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
607          0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0
608          0.0     4.0  ...       0.0     0.0     0.0     0.0     0.0
609          0.0     4.0  ...       0.0     0.0     0.0     0.0     0.0
610          0.0     0.0  ...       0.0     0.0     0.0     0.0     0.0

movieId  193581  193583  193585  193587  193609
userId
1            0.0     0.0     0.0     0.0     0.0
2            0.0     0.0     0.0     0.0     0.0
3            0.0     0.0     0.0     0.0     0.0
```

```
4           0.0     0.0     0.0     0.0     0.0
5           0.0     0.0     0.0     0.0     0.0
6           0.0     0.0     0.0     0.0     0.0
7           0.0     0.0     0.0     0.0     0.0
8           0.0     0.0     0.0     0.0     0.0
9           0.0     0.0     0.0     0.0     0.0
10          0.0     0.0     0.0     0.0     0.0
601         0.0     0.0     0.0     0.0     0.0
602         0.0     0.0     0.0     0.0     0.0
603         0.0     0.0     0.0     0.0     0.0
604         0.0     0.0     0.0     0.0     0.0
605         0.0     0.0     0.0     0.0     0.0
606         0.0     0.0     0.0     0.0     0.0
607         0.0     0.0     0.0     0.0     0.0
608         0.0     0.0     0.0     0.0     0.0
609         0.0     0.0     0.0     0.0     0.0
610         0.0     0.0     0.0     0.0     0.0

[20 rows x 9724 columns]
```

In [ ]:

```
# The complete dataframe has 610 rows so I've printed just the first and last 10 rows instead.
```

In [ ]:

```
u, c = np.unique(table, return_counts=True)
u[c.argmax()]
```

In [ ]:

```
# The most common entry is 0
# Matrices with this property are called sparse matrices.
```

In [15]:

```
transposed_t = table.T
X_scaled = transposed_t.apply(lambda x: x-x.mean())

sliced = X_scaled.head(10)
sliced = sliced.append(X_scaled.tail(10))
print(sliced)
```

```
userId         1          2         3         4         5         6         7    \
movieId
1         3.895825 -0.011775 -0.00977 -0.07898  3.983546 -0.112814  4.449506
2        -0.104175 -0.011775 -0.00977 -0.07898 -0.016454  3.887186 -0.050494
3         3.895825 -0.011775 -0.00977 -0.07898 -0.016454  4.887186 -0.050494
4        -0.104175 -0.011775 -0.00977 -0.07898 -0.016454  2.887186 -0.050494
5        -0.104175 -0.011775 -0.00977 -0.07898 -0.016454  4.887186 -0.050494
6         3.895825 -0.011775 -0.00977 -0.07898 -0.016454  3.887186 -0.050494
7        -0.104175 -0.011775 -0.00977 -0.07898 -0.016454  3.887186 -0.050494
8        -0.104175 -0.011775 -0.00977 -0.07898 -0.016454  2.887186 -0.050494
9        -0.104175 -0.011775 -0.00977 -0.07898 -0.016454 -0.112814 -0.050494
10       -0.104175 -0.011775 -0.00977 -0.07898 -0.016454  2.887186 -0.050494
193565   -0.104175 -0.011775 -0.00977 -0.07898 -0.016454 -0.112814 -0.050494
193567   -0.104175 -0.011775 -0.00977 -0.07898 -0.016454 -0.112814 -0.050494
193571   -0.104175 -0.011775 -0.00977 -0.07898 -0.016454 -0.112814 -0.050494
193573   -0.104175 -0.011775 -0.00977 -0.07898 -0.016454 -0.112814 -0.050494
193579   -0.104175 -0.011775 -0.00977 -0.07898 -0.016454 -0.112814 -0.050494
193581   -0.104175 -0.011775 -0.00977 -0.07898 -0.016454 -0.112814 -0.050494
193583   -0.104175 -0.011775 -0.00977 -0.07898 -0.016454 -0.112814 -0.050494
193585   -0.104175 -0.011775 -0.00977 -0.07898 -0.016454 -0.112814 -0.050494
193587   -0.104175 -0.011775 -0.00977 -0.07898 -0.016454 -0.112814 -0.050494
193609   -0.104175 -0.011775 -0.00977 -0.07898 -0.016454 -0.112814 -0.050494

userId         8          9         10      ...          601      602        603  \
movieId                                     ...
1        -0.017277 -0.015426 -0.047203     ...     3.954031 -0.0471  3.659811
2         3.982723 -0.015426 -0.047203     ...    -0.045969  3.9529 -0.340189
3        -0.017277 -0.015426 -0.047203     ...    -0.045969 -0.0471 -0.340189
4        -0.017277 -0.015426 -0.047203     ...    -0.045969 -0.0471 -0.340189
5        -0.017277 -0.015426 -0.047203     ...    -0.045969 -0.0471 -0.340189
```

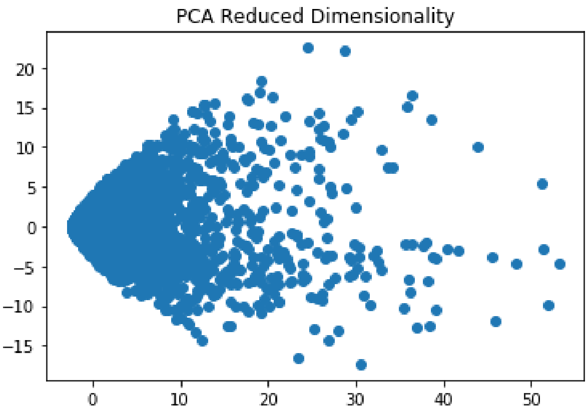
```
6         -0.017277 -0.015426 -0.047203    ...    -0.045969  2.9529  3.659811
7         -0.017277 -0.015426 -0.047203    ...    -0.045969 -0.0471 -0.340189
8         -0.017277 -0.015426 -0.047203    ...    -0.045969 -0.0471 -0.340189
9         -0.017277 -0.015426 -0.047203    ...    -0.045969 -0.0471 -0.340189
10         1.982723 -0.015426 -0.047203    ...    -0.045969  2.9529 -0.340189
193565    -0.017277 -0.015426 -0.047203    ...    -0.045969 -0.0471 -0.340189
193567    -0.017277 -0.015426 -0.047203    ...    -0.045969 -0.0471 -0.340189
193571    -0.017277 -0.015426 -0.047203    ...    -0.045969 -0.0471 -0.340189
193573    -0.017277 -0.015426 -0.047203    ...    -0.045969 -0.0471 -0.340189
193579    -0.017277 -0.015426 -0.047203    ...    -0.045969 -0.0471 -0.340189
193581    -0.017277 -0.015426 -0.047203    ...    -0.045969 -0.0471 -0.340189
193583    -0.017277 -0.015426 -0.047203    ...    -0.045969 -0.0471 -0.340189
193585    -0.017277 -0.015426 -0.047203    ...    -0.045969 -0.0471 -0.340189
193587    -0.017277 -0.015426 -0.047203    ...    -0.045969 -0.0471 -0.340189
193609    -0.017277 -0.015426 -0.047203    ...    -0.045969 -0.0471 -0.340189

userId          604        605        606       607        608        609        610
movieId
1          2.964212  3.927036  2.080625  3.92719  2.232158  2.987557  4.506119
2          4.964212  3.427036 -0.419375 -0.07281  1.732158 -0.012443 -0.493881
3         -0.035788 -0.072964 -0.419375 -0.07281  1.732158 -0.012443 -0.493881
4         -0.035788 -0.072964 -0.419375 -0.07281 -0.267842 -0.012443 -0.493881
5          2.964212 -0.072964 -0.419375 -0.07281 -0.267842 -0.012443 -0.493881
6          2.964212 -0.072964 -0.419375 -0.07281 -0.267842 -0.012443  4.506119
7         -0.035788 -0.072964  2.080625 -0.07281 -0.267842 -0.012443 -0.493881
8         -0.035788 -0.072964 -0.419375 -0.07281 -0.267842 -0.012443 -0.493881
9         -0.035788 -0.072964 -0.419375 -0.07281 -0.267842 -0.012443 -0.493881
10        -0.035788 -0.072964 -0.419375 -0.07281  3.732158  3.987557 -0.493881
193565    -0.035788 -0.072964 -0.419375 -0.07281 -0.267842 -0.012443 -0.493881
193567    -0.035788 -0.072964 -0.419375 -0.07281 -0.267842 -0.012443 -0.493881
193571    -0.035788 -0.072964 -0.419375 -0.07281 -0.267842 -0.012443 -0.493881
193573    -0.035788 -0.072964 -0.419375 -0.07281 -0.267842 -0.012443 -0.493881
193579    -0.035788 -0.072964 -0.419375 -0.07281 -0.267842 -0.012443 -0.493881
193581    -0.035788 -0.072964 -0.419375 -0.07281 -0.267842 -0.012443 -0.493881
193583    -0.035788 -0.072964 -0.419375 -0.07281 -0.267842 -0.012443 -0.493881
193585    -0.035788 -0.072964 -0.419375 -0.07281 -0.267842 -0.012443 -0.493881
193587    -0.035788 -0.072964 -0.419375 -0.07281 -0.267842 -0.012443 -0.493881
193609    -0.035788 -0.072964 -0.419375 -0.07281 -0.267842 -0.012443 -0.493881

[20 rows x 610 columns]
```

In [16]:

```
pca = decomposition.PCA(n_components=2)
pca.fit(X_scaled)
X_trans = pca.transform(X_scaled)
plt.scatter(X_trans[:,0],X_trans[:,1])
plt.title("PCA Reduced Dimensionality")
plt.show()
```



In [17]:

```
var = pca.explained_variance_ratio_
print(var)
```

```
[0.17620942 0.04189505]
```

In [ ]:

```
# 17.620942% of the variance is explained by the first component and 4.189505% of the variance is
explained by the second.
# The difference between them is observable in the plot.
```

In [18]:

```
i = 0
while i < 610:
    pca = decomposition.PCA(n_components=i)
    pca.fit(X_scaled)
    var = pca.explained_variance_ratio_
    if sum(var) >= 0.8:
        print(i)
        break
    i = i + 1
```

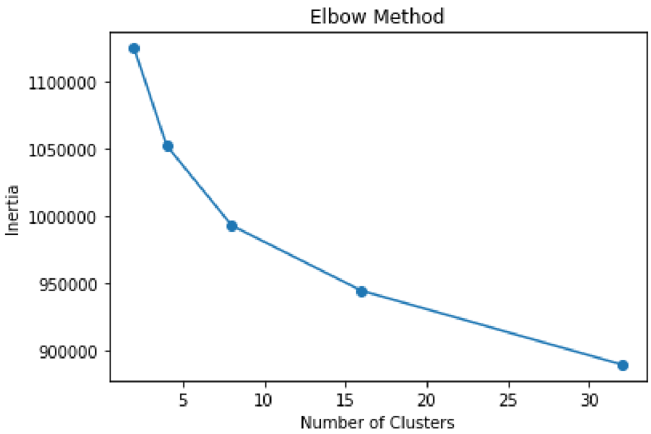
```
154
```

In [ ]:

```
# 154 principle components are needed to to explain 80% of the variance of the data.
```

In [19]:

```
k = [2, 4, 8, 16, 32]
inertia = []
for i in k:
    kmeans = KMeans(n_clusters=i)
    a = kmeans.fit(transposed_t)
    inertia.append(a.inertia_)
plt.plot(k, inertia, marker='o')
plt.title("Elbow Method")
plt.xlabel("Number of Clusters")
plt.ylabel("Inertia")
plt.show()
```



In [ ]:

```
# # The most appropriate choice for k is 8 because the point of the plot is to minimize the number
of clusters and inertia and to do this we have to identify the best elbow point. In this case it i
s k = 8.
```

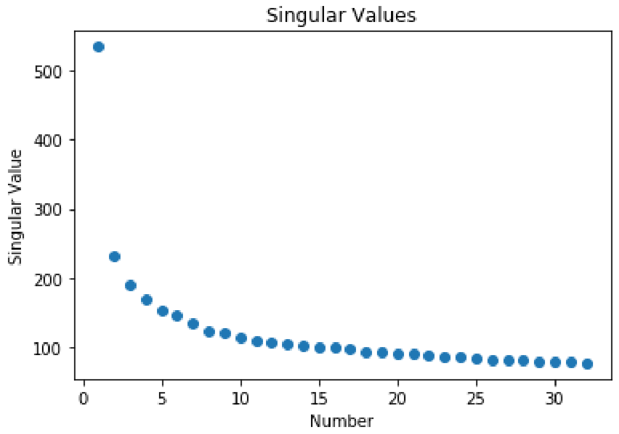
In [ ]:

```
# The movies clustered together likely have similar ratings.
```

In [20]:

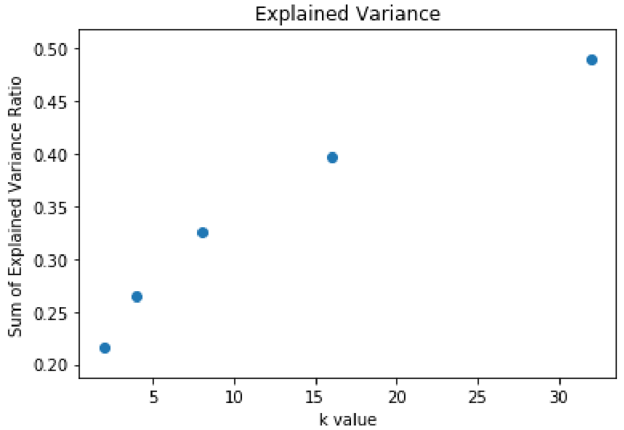
```
svd = TruncatedSVD(n_components = 32)
```

```
y = svd.fit(transposed_t)
plt.scatter(range(1, 33), y.singular_values_)
plt.title("Singular Values")
plt.xlabel("Number")
plt.ylabel("Singular Value")
plt.show()
```



In [27]:

```
k = [2, 4, 8, 16, 32]
sum_evr = []
for i in k:
    svd = TruncatedSVD(n_components = i)
    a = svd.fit(transposed_t)
    sum_evr.append(sum(a.explained_variance_ratio_))
plt.scatter(k, sum_evr)
plt.title("Explained Variance")
plt.xlabel("k value")
plt.ylabel("Sum of Explained Variance Ratio")
plt.show()
```



In [ ]:

```
# The explained variance graph shows that k = 8 is that ideal value because there's an elbow formi
ng at around k = 8 and also it has a high amount of explained variance and a low amount of cluster
s. It's the inverse compared to the inertia values above. This supports my choice of k.
```

In [30]:

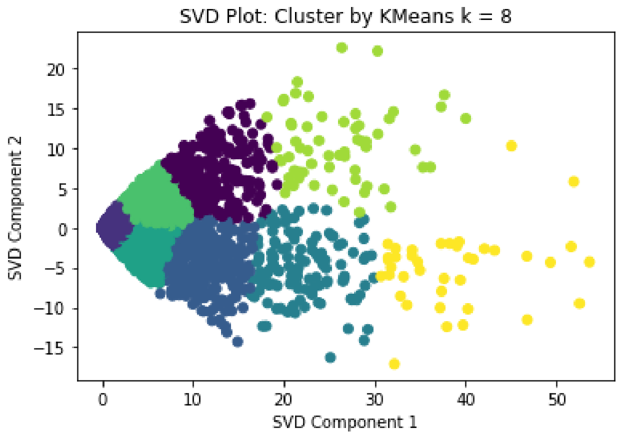
```
svd = TruncatedSVD(n_components = 2)
arr = svd.fit_transform(transposed_t)
print(arr)
```

```
[[ 3.76498261e+01 -6.37363667e+00]
 [ 2.05961905e+01 -4.66199626e-01]
 [ 8.50418300e+00 -5.71765709e+00]
 ...
 [ 3.45681586e-02  1.38364823e-01]
```

```
[ 3.45681586e-02  1.38364823e-01]
[ 1.45217586e-01  2.94093154e-01]]
```

In [31]:

```
kmeans = KMeans(n_clusters = 8)
kmeans.fit(arr)
y_means = kmeans.predict(arr)
plt.scatter(arr[:,0], arr[:,1], c=y_means)
plt.title("SVD Plot: Cluster by KMeans k = 8")
plt.xlabel("SVD Component 1")
plt.ylabel("SVD Component 2")
plt.show()
```



In [ ]:

```
# The clusters are close together and show very similar values. k = 8 is a good choice because the
points in a similar area are clustered together.
```