# K Means Clustering Project

Cluster Universities into to two groups, Private and Public.

**Note: we actually have the labels for this data set, but we will NOT use them for the KMeans clustering algorithm, since that is an unsupervised learning algorithm.**

# About the Data

We will use a data frame with 777 observations on the following 18 variables.

- Private A factor with levels No and Yes indicating private or public university
- Apps Number of applications received
- Accept Number of applications accepted
- Enroll Number of new students enrolled
- Top10perc Pct. new students from top 10% of H.S. class
- Top25perc Pct. new students from top 25% of H.S. class
- F.Undergrad Number of fulltime undergraduates
- P.Undergrad Number of parttime undergraduates
- Outstate Out-of-state tuition
- Room.Board Room and board costs
- Books Estimated book costs
- Personal Estimated personal spending
- PhD Pct. of faculty with Ph.D.'s
- Terminal Pct. of faculty with terminal degree
- S.F.Ratio Student/faculty ratio
- perc.alumni Pct. alumni who donate
- Expend Instructional expenditure per student
- Grad.Rate Graduation rate

In [1]:
```
### Import Libs
```

In [2]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

In [3]:
```
### Load Data set
```

In [4]:
```
Data_org = pd.read_csv('data/College_Data', index_col =0)
```

In [5]:
```
print(Data_org.shape)
Data_org.head(4)
```

(777, 18)

Out[5]:

| | Private | Apps | Accept | Enroll | Top10perc | Top25perc | F.Undergrad | P.Undergrad | Out |
|---|---|---|---|---|---|---|---|---|---|
| **Abilene Christian University** | Yes | 1660 | 1232 | 721 | 23 | 52 | 2885 | 537 | |
| **Adelphi University** | Yes | 2186 | 1924 | 512 | 16 | 29 | 2683 | 1227 | 1 |
| **Adrian College** | Yes | 1428 | 1097 | 336 | 22 | 50 | 1036 | 99 | 1 |
| **Agnes Scott College** | Yes | 417 | 349 | 137 | 60 | 89 | 510 | 63 | 1 |

In [ ]:

In [6]:
```
Data_org.describe()
```

Out[6]:

| | Apps | Accept | Enroll | Top10perc | Top25perc | F.Undergrad | P.Under |
|---|---|---|---|---|---|---|---|
| **count** | 777.000000 | 777.000000 | 777.000000 | 777.000000 | 777.000000 | 777.000000 | 777.00 |
| **mean** | 3001.638353 | 2018.804376 | 779.972973 | 27.558559 | 55.796654 | 3699.907336 | 855.29 |
| **std** | 3870.201484 | 2451.113971 | 929.176190 | 17.640364 | 19.804778 | 4850.420531 | 1522.43 |
| **min** | 81.000000 | 72.000000 | 35.000000 | 1.000000 | 9.000000 | 139.000000 | 1.00 |
| **25%** | 776.000000 | 604.000000 | 242.000000 | 15.000000 | 41.000000 | 992.000000 | 95.00 |
| **50%** | 1558.000000 | 1110.000000 | 434.000000 | 23.000000 | 54.000000 | 1707.000000 | 353.00 |
| **75%** | 3624.000000 | 2424.000000 | 902.000000 | 35.000000 | 69.000000 | 4005.000000 | 967.00 |
| **max** | 48094.000000 | 26330.000000 | 6392.000000 | 96.000000 | 100.000000 | 31643.000000 | 21836.00 |

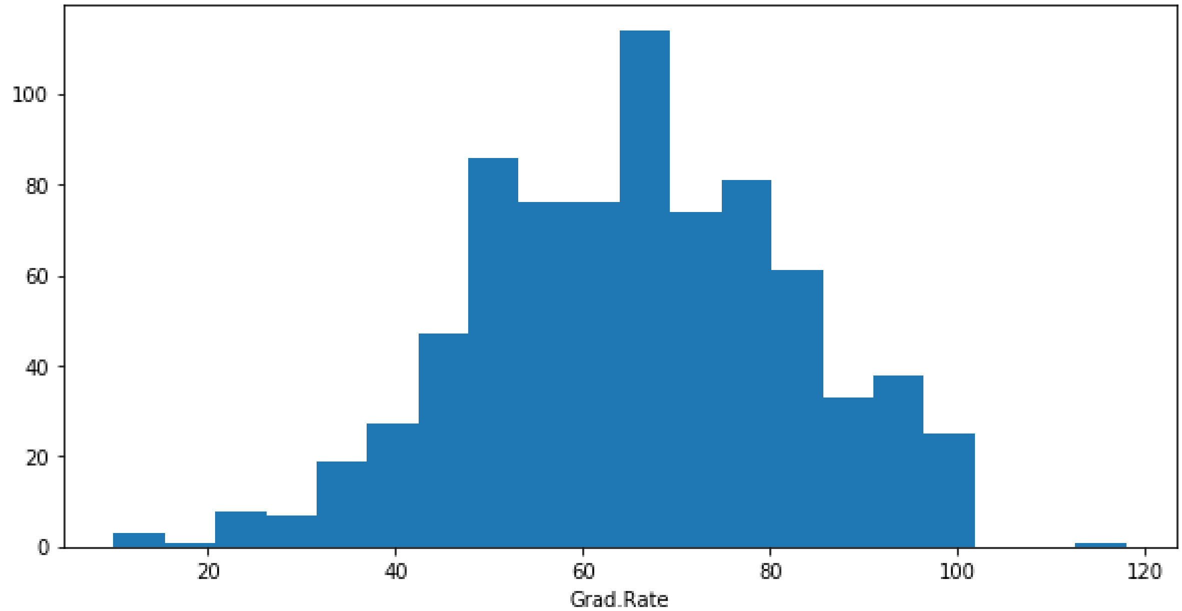
Note that in "Grad.Rate" column, graduation rate of higher than 100%. max value of "Grad.Rate = 118

In the follwoing we replace that with 100%

In [7]:
```
# make a copy of data
Data = Data_org.copy()
```

In [8]:
```python
plt.figure(figsize=(10,5))
plt.hist(Data_org['Grad.Rate'], bins=20)
plt.xlabel('Grad.Rate')
```

Out[8]:
```
Text(0.5, 0, 'Grad.Rate')
```




In [9]:
```python
Data_org[Data_org['Grad.Rate']>100]
```

Out[9]:

| | Private | Apps | Accept | Enroll | Top10perc | Top25perc | F.Undergrad | P.Undergrad | Out |
|---|---|---|---|---|---|---|---|---|---|
| **Cazenovia College** | Yes | 3847 | 3433 | 527 | 9 | 35 | 1010 | 12 | |

In [10]:
```python
# replace 'Grad.Rate'>100 by 100
Index = Data_org[Data_org['Grad.Rate']>100].index
print(Index)
Data.loc[Index, 'Grad.Rate'] = 100
```

```
Index(['Cazenovia College'], dtype='object')
```

In [11]:
```python
Data[Data['Grad.Rate'] > 100]['Grad.Rate'].any()
```

Out[11]:
```
False
```

## Make data reday

In [12]:
```python
X = Data.drop(columns=['Private'], axis=1)
# Note: we will note use y in algorithm
y = Data['Private']
```

In [13]:
```python
from sklearn.cluster import KMeans
```

In [14]:
```
kmeans = KMeans(n_clusters=2)
```

In [15]:
```
kmeans.fit(X)
```

Out[15]:
```
KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
    n_clusters=2, n_init=10, n_jobs=None, precompute_distances='auto',
    random_state=None, tol=0.0001, verbose=0)
```

In [16]:
```
#cluster center vectors
print(X.shape)
print(kmeans.cluster_centers_.shape)
kmeans.cluster_centers_
```

```
(777, 17)
(2, 17)
```

Out[16]:
```
array([[1.81323468e+03, 1.28716592e+03, 4.91044843e+02, 2.53094170e+01,
        5.34708520e+01, 2.18854858e+03, 5.95458894e+02, 1.03957085e+04,
        4.31136472e+03, 5.41982063e+02, 1.28033632e+03, 7.04424514e+01,
        7.78251121e+01, 1.40997010e+01, 2.31748879e+01, 8.93204634e+03,
        6.50926756e+01],
       [1.03631389e+04, 6.55089815e+03, 2.56972222e+03, 4.14907407e+01,
        7.02037037e+01, 1.30619352e+04, 2.46486111e+03, 1.07191759e+04,
        4.64347222e+03, 5.95212963e+02, 1.71420370e+03, 8.63981481e+01,
        9.13333333e+01, 1.40277778e+01, 2.00740741e+01, 1.41705000e+04,
        6.75925926e+01]])
```

In [51]:
```
kmeans.labels_[0:50]
```

Out[51]:
```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1,
       0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0])
```

In [52]:
```
#Sum of squared distances(SSE) of samples to their closest cluster center.
kmeans.inertia_
```

Out[52]:
```
48356200684.31276
```

# Evaluation

Since we have the label of the data, we can use it just to compare

In [18]:
```
# To convert Label {Yes, No} into numerical value
def convertor(cluster):
    if cluster == 'Yes':
        return 1
    else:
        return 0
```

In [19]:
```
y_value = y.apply(convertor)
y_value[0:10]
```

Out[19]:
```
Abilene Christian University    1
Adelphi University              1
Adrian College                  1
Agnes Scott College             1
Alaska Pacific University       1
Albertson College               1
Albertus Magnus College         1
Albion College                  1
Albright College                1
Alderson-Broaddus College       1
Name: Private, dtype: int64
```

In [20]:
```
from sklearn.metrics import classification_report, confusion_matrix
```

In [21]:
```
print(confusion_matrix(y_value, kmeans.labels_))
print(classification_report(y_value,kmeans.labels_))
```

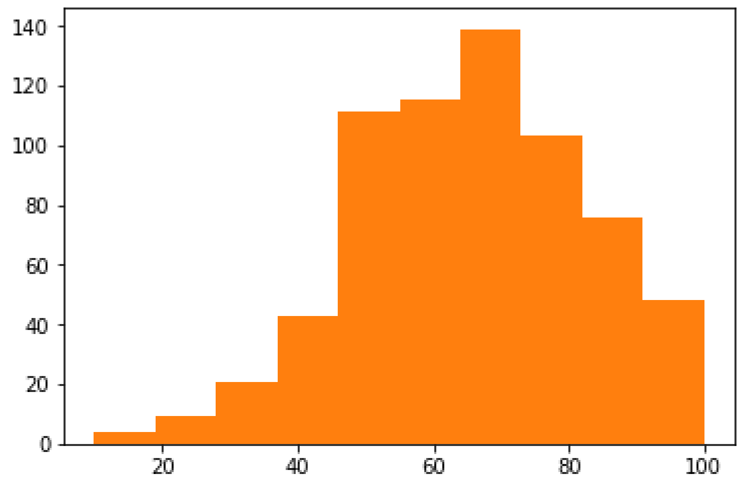
```
[[138  74]
 [531  34]]
              precision    recall  f1-score   support

           0       0.21      0.65      0.31       212
           1       0.31      0.06      0.10       565

   micro avg       0.22      0.22      0.22       777
   macro avg       0.26      0.36      0.21       777
weighted avg       0.29      0.22      0.16       777
```

## Some visualization on Clusters

In [41]:
```
centroids = kmeans.cluster_centers_
```

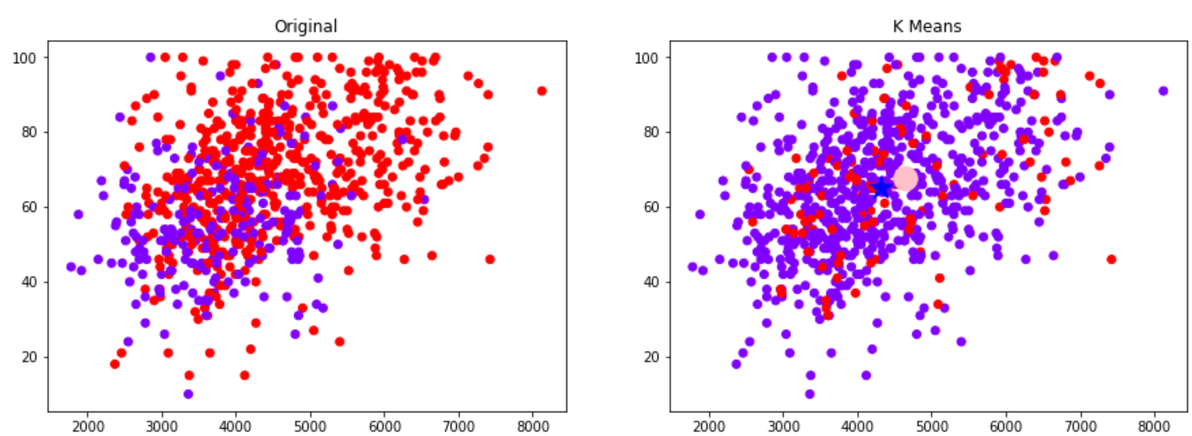
```
In [22]: plt.hist(X[kmeans.labels_ == 1]['Grad.Rate'])
         plt.hist(X[kmeans.labels_ == 0]['Grad.Rate'])
```

```
Out[22]: (array([  4.,   9.,  21.,  43., 111., 115., 139., 103.,  76.,  48.]),
          array([ 10.,  19.,  28.,  37.,  46.,  55.,  64.,  73.,  82.,  91., 100.]),
          <a list of 10 Patch objects>)
```



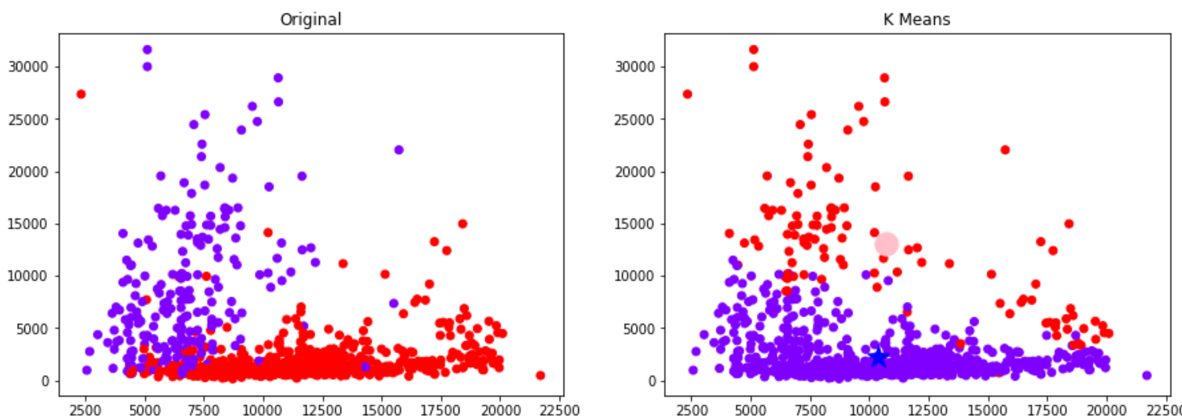

```
In [43]: f, ax = plt.subplots(1, 2, figsize=(15,5))

         ax[0].scatter(x=Data['Room.Board'], y=Data['Grad.Rate'], c=y_value, cmap = 'ra
         inbow')
         ax[1].scatter(x=Data['Room.Board'], y=Data['Grad.Rate'], c=kmeans.labels_, cma
         p = 'rainbow')

         ax[0].set_title("Original")
         ax[1].set_title('K Means')

         ax[1].scatter(centroids[0, 8], centroids[0, 16], marker='*', s=300,
                     c='blue', label='centroid')
         ax[1].scatter(centroids[1, 8], centroids[1, 16], marker='o', s=300,
                     c='pink', label='centroid')
```

```
Out[43]: <matplotlib.collections.PathCollection at 0x24a311f07f0>
```



In [40]:
```
f, ax = plt.subplots(1, 2, figsize=(15,5))

ax[0].scatter(x=Data['Outstate'], y=Data['F.Undergrad'], c=y_value, cmap = 'ra
inbow')
ax[1].scatter(x=Data['Outstate'], y=Data['F.Undergrad'], c=kmeans.labels_, cma
p = 'rainbow', )

ax[0].set_title("Original")
ax[1].set_title('K Means')



ax[1].scatter(centroids[0, 7], centroids[0, 5], marker='*', s=300,
            c='blue', label='centroid')
ax[1].scatter(centroids[1, 7], centroids[1, 5], marker='o', s=300,
            c='pink', label='centroid')

#plt.legend()
```

Out[40]: <matplotlib.collections.PathCollection at 0x24a314f89e8>




In [44]:
```
X.head(2)
```

Out[44]:

| | Apps | Accept | Enroll | Top10perc | Top25perc | F.Undergrad | P.Undergrad | Outstate | Ro |
|---|---|---|---|---|---|---|---|---|---|
| **Abilene Christian University** | 1660 | 1232 | 721 | 23 | 52 | 2885 | 537 | 7440 | |
| **Adelphi University** | 2186 | 1924 | 512 | 16 | 29 | 2683 | 1227 | 12280 | |

In [ ]:

# Calculate Silhouette Coefficient

Silhouette analysis can be used to determine the degree of separation between clusters.

For each sample

- Compute the average distance from all data points in the same cluster ($a_i$).
- Compute the average distance from all data points in the closest cluster ($b_i$).
- Compute the coefficient for the i-th example:

$$s_i = \frac{b_i - a_i}{max(a_i, b_i)}$$

The coefficient can take values in the interval [-1, 1].

- If it is 0 –> the sample is very close to the neighboring clusters.
- It it is 1 –> the sample is far away from the neighboring clusters.
- It it is -1 –> the sample is assigned to the wrong clusters.

Therefore, we want the coefficients to be as big as possible and close to 1 to have a good clusters.

In [48]:
```
from sklearn.metrics import silhouette_score
silhouette_score(X,kmeans.labels_)
```

Out[48]:
```
0.5599267973651544
```

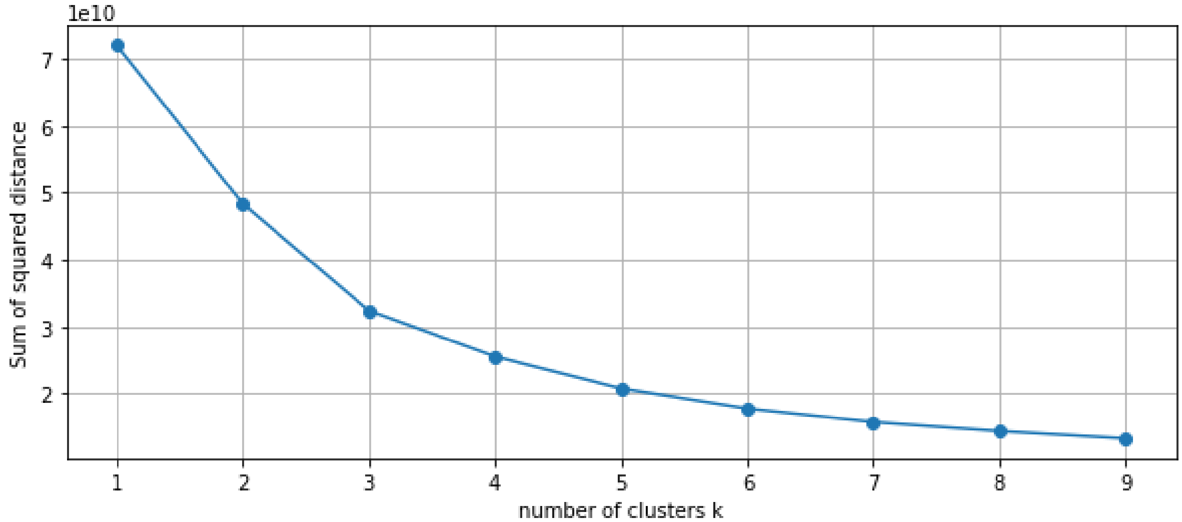
In [ ]:

# Elbow Method to find best K value

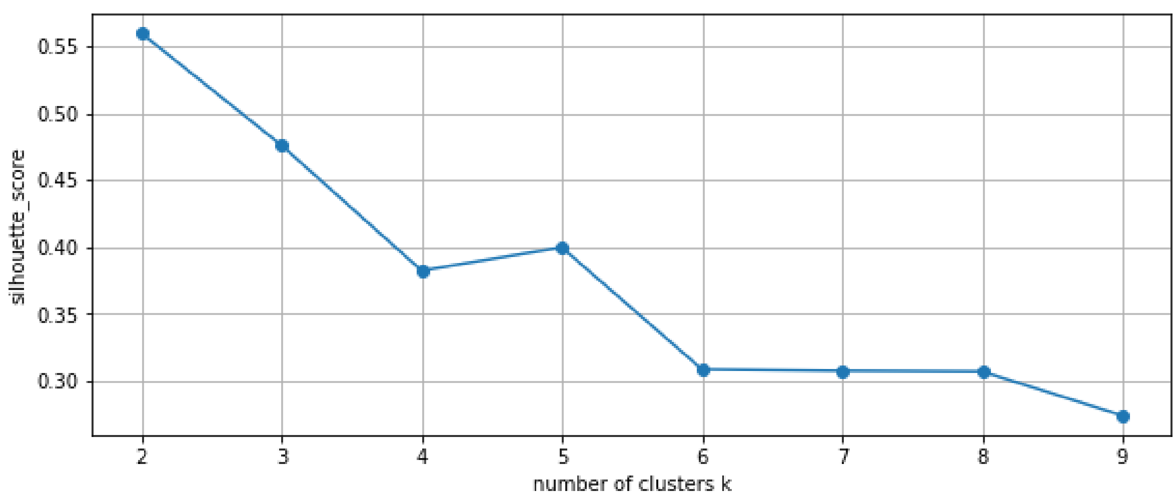
In [81]:
```
SSE =[]
silh_score =[]
list_k = list(range(1,10))
print(list_k)
for k in list_k:
    model = KMeans(n_clusters=k)
    model.fit(X)
    SSE.append(model.inertia_)
    if k>1:
        silh_score.append(silhouette_score(X, model.labels_))
```

```
[1, 2, 3, 4, 5, 6, 7, 8, 9]
```

In [83]:
```
## plot SSE against K
plt.figure(figsize=(10,4))
plt.plot(list_k, SSE, marker ='o')
plt.xlabel('number of clusters k')
plt.ylabel('Sum of squared distance')
plt.grid(True)
```




In [86]:
```
## plot silhouette_score against K
plt.figure(figsize=(10,4))
plt.plot(list_k[1:], silh_score, marker ='o')
plt.xlabel('number of clusters k')
plt.ylabel('silhouette_score')
plt.grid(True)
```




we want the coefficients to be as big as possible and close to 1 to have a good clusters.