Principal Component Analysis for predicting salaries for baseball players

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

In [3]:
```
import rpy2.robjects as robjects
from rpy2.robjects import pandas2ri, r
from rpy2.robjects.packages import importr

pandas2ri.activate()

# load your file
robjects.r['load']('Hitters.rda')

# retrieve the matrix that was loaded from the file
matrix = robjects.r['Hitters']

# turn the R matrix into a numpy array
a = np.array(matrix)
```

```
/anaconda3/lib/python3.7/site-packages/rpy2/robjects/pandas2ri.py:191: FutureWarning: from_items is de
precated. Please use DataFrame.from_dict(dict(items), ...) instead. DataFrame.from_dict(OrderedDict(it
ems)) may be used to preserve the key order.
  res = PandasDataFrame.from_items(items)
```

In [4]:

```
base = importr('base')
base.load('Hitters.rda');
rdf = base.mget(base.ls())

df = {}
for i,f in enumerate(base.names(rdf)):
    df[f] = pandas2ri.ri2py_dataframe(rdf[i])

for k,v in df.items():
    print(v.head())
```

```
   AtBat  Hits  HmRun  Runs  RBI  Walks  Years  CAtBat  CHits  CHmRun  CRuns  \
0    293    66      1    30   29     14      1     293     66       1     30
1    315    81      7    24   38     39     14    3449    835      69    321
2    479   130     18    66   72     76      3    1624    457      63    224
3    496   141     20    65   78     37     11    5628   1575     225    828
4    321    87     10    39   42     30      2     396    101      12     48

   CRBI  CWalks League Division  PutOuts  Assists  Errors  Salary NewLeague
0    29      14      A        E      446       33      20     NaN         A
1   414     375      N        W      632       43      10   475.0         N
2   266     263      A        W      880       82      14   480.0         A
3   838     354      N        E      200       11       3   500.0         N
4    46      33      N        E      805       40       4    91.5         N
```

In [5]:

```
df = pd.DataFrame(df['Hitters'])
df.head()
```

Out[5]:

	AtBat	Hits	HmRun	Runs	RBI	Walks	Years	CAtBat	CHits	CHmRun	CRuns	CRBI	CWalks	League	Division	PutOuts	Assists
0	293	66	1	30	29	14	1	293	66	1	30	29	14	A	E	446	33
1	315	81	7	24	38	39	14	3449	835	69	321	414	375	N	W	632	43
2	479	130	18	66	72	76	3	1624	457	63	224	266	263	A	W	880	82
3	496	141	20	65	78	37	11	5628	1575	225	828	838	354	N	E	200	11
4	321	87	10	39	42	30	2	396	101	12	48	46	33	N	E	805	40

In [6]:

```
indicators=['AtBat','Hits','HmRun','Runs','RBI','Walks','Years','CAtBat','CHits','CHmRun','CRuns',
            'CRBI','CWalks','PutOuts','Assists','Errors','Salary']
```

In [7]:

```
clean = df.dropna()
print(clean.shape)
clean.head()
```

```
(263, 20)
```

Out[7]:

	AtBat	Hits	HmRun	Runs	RBI	Walks	Years	CAtBat	CHits	CHmRun	CRuns	CRBI	CWalks	League	Division	PutOuts	Assists
1	315	81	7	24	38	39	14	3449	835	69	321	414	375	N	W	632	43
2	479	130	18	66	72	76	3	1624	457	63	224	266	263	A	W	880	82
3	496	141	20	65	78	37	11	5628	1575	225	828	838	354	N	E	200	11
4	321	87	10	39	42	30	2	396	101	12	48	46	33	N	E	805	40
5	594	169	4	74	51	35	11	4408	1133	19	501	336	194	A	W	282	421

In [8]:

```
df = df.loc[:, indicators]
df = df.dropna()
print(df.shape)
df.head()
```

```
(263, 17)
```

Out[8]:

	AtBat	Hits	HmRun	Runs	RBI	Walks	Years	CAtBat	CHits	CHmRun	CRuns	CRBI	CWalks	PutOuts	Assists	Errors	Salary
1	315	81	7	24	38	39	14	3449	835	69	321	414	375	632	43	10	475.0
2	479	130	18	66	72	76	3	1624	457	63	224	266	263	880	82	14	480.0
3	496	141	20	65	78	37	11	5628	1575	225	828	838	354	200	11	3	500.0
4	321	87	10	39	42	30	2	396	101	12	48	46	33	805	40	4	91.5
5	594	169	4	74	51	35	11	4408	1133	19	501	336	194	282	421	25	750.0

In [9]:

```
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
```

In [10]:
```
x = StandardScaler().fit_transform(df)
```

```
/anaconda3/lib/python3.7/site-packages/sklearn/preprocessing/data.py:625: DataConversionWarning: Data with input dtype int32, float64 were all converted to float64 by StandardScaler.
  return self.partial_fit(X, y)
/anaconda3/lib/python3.7/site-packages/sklearn/base.py:462: DataConversionWarning: Data with input dtype int32, float64 were all converted to float64 by StandardScaler.
  return self.fit(X, **fit_params).transform(X)
```

In [11]:
```
from array import *

pca = PCA()
pca.fit(x)
variance = pca.explained_variance_ratio_ #calculate variance ratios

var=np.cumsum(np.round(pca.explained_variance_ratio_, decimals=3)*100)
pc = np.array(list(range(1,18)))
eigensum = pd.DataFrame(var, index=pc, columns=['Cumulative % of PC of var'])
eigensum.T
```

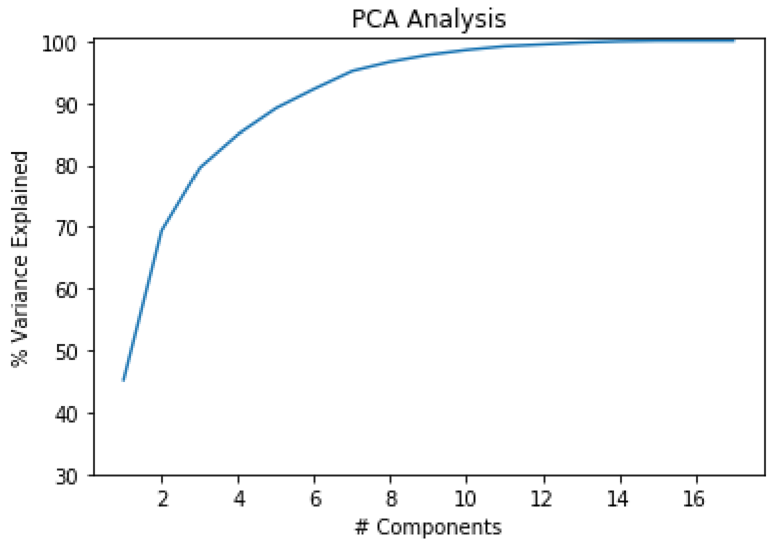
Out[11]:

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Cumulative % of PC of var	45.2	69.4	79.6	85.0	89.2	92.3	95.2	96.7	97.8	98.6	99.2	99.5	99.8	100.0	100.1	100.1	100.1

In [12]:

```
plt.ylabel('% Variance Explained')
plt.xlabel('# Components')
plt.title('PCA Analysis')
plt.ylim(30,100.5)
plt.style.context('seaborn-whitegrid')

plt.plot(list(range(1,18)),var);
```



In [13]:

```
from sklearn.decomposition import PCA
pca = PCA(n_components=2)
principalComponents = pca.fit_transform(x)
principalDf = pd.DataFrame(data = principalComponents
             , columns = ['principal component 1', 'principal component 2'])
```

In [14]:

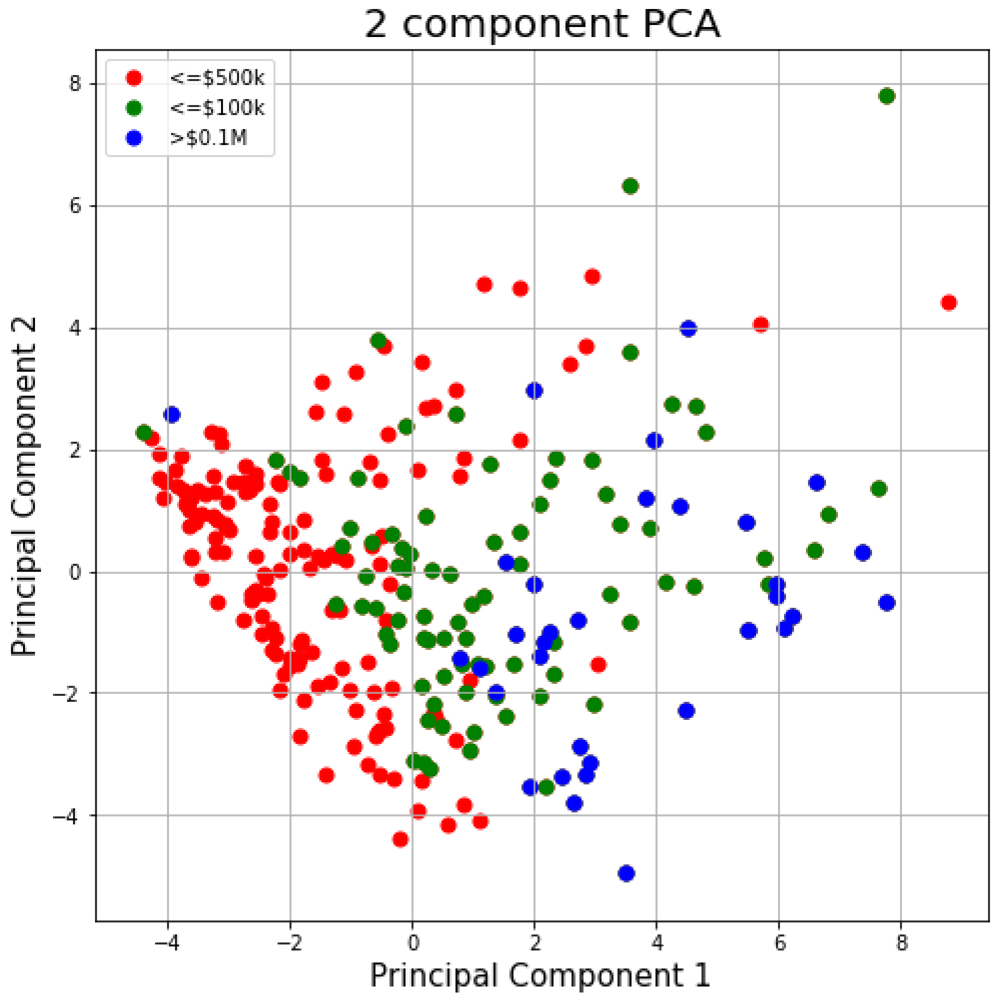
```
finalDf = pd.concat([principalDf.reset_index(),
                     df.reset_index()[['Salary']]],
                     axis = 1).drop('index',axis=1)
finalDf.head()
```

Out[14]:

	principal component 1	principal component 2	Salary
0	0.076848	1.653525	475.0
1	0.337127	-2.320560	480.0
2	3.408362	0.755757	500.0
3	-2.642221	-0.361486	91.5
4	1.071681	-1.511674	750.0

In [15]:

```
fig = plt.figure(figsize = (8,8))
ax = fig.add_subplot(1,1,1)
ax.set_xlabel('Principal Component 1', fontsize = 15)
ax.set_ylabel('Principal Component 2', fontsize = 15)
ax.set_title('2 component PCA', fontsize = 20)
salaries = [0, 500, 1000]
colors = ['r', 'g', 'b']
for salary, color in zip(salaries,colors):
    indicesToKeep = finalDf['Salary'] >= salary
    ax.scatter(finalDf.loc[indicesToKeep, 'principal component 1']
               , finalDf.loc[indicesToKeep, 'principal component 2']
               , c = color
               , s = 50)
ax.legend(['<=$500k', '<=$100k', '>$0.1M'])
ax.grid()
```


2 component PCA
<=$500k
<=$100k
>$0.1M
Principal Component 1
Principal Component 2
8
6
4
2
0
−2
−4
−4
−2
0
2
4
6
8

In [16]:
```
pca = PCA(n_components=4)
principalComponents = pca.fit_transform(x)
loading =np.transpose(pca.components_)
chart = pd.DataFrame(loading,columns =['PC 1','PC 2','PC 3','PC 4'],
                     index=indicators)
chart
```

Out[16]:

	PC 1	PC 2	PC 3	PC 4
AtBat	0.195064	-0.384078	0.073262	-0.077338
Hits	0.194100	-0.377645	0.052328	-0.068722
HmRun	0.196905	-0.228663	-0.335869	-0.233200
Runs	0.194913	-0.374591	-0.061105	-0.126861
RBI	0.229566	-0.310265	-0.165085	-0.160202
Walks	0.206737	-0.231158	-0.064313	0.069321
Years	0.271085	0.268204	0.099577	-0.018776
CAtBat	0.319705	0.196413	0.128697	-0.002258
CHits	0.320773	0.185897	0.124966	0.012231
CHmRun	0.308101	0.133864	-0.114866	-0.086805
CRuns	0.327615	0.176929	0.090643	-0.011355
CRBI	0.329774	0.172834	0.017574	-0.018780
CWalks	0.305731	0.196983	0.058216	0.019782
PutOuts	0.083038	-0.162952	-0.154233	0.876219
Assists	0.001592	-0.176246	0.653316	-0.002904
Errors	-0.005293	-0.209783	0.570491	0.066107
Salary	0.249142	-0.054526	-0.026280	0.327562

Conclusion

Career stats (C*) is most significant for PC1 while AtBat and Hits are major attributes for PC2 in latest season.

Reasons/ Numerical Attributes of Dataset-clustering

Cluster	Pros	Cons
Centroid-based	central vector represents grouping	doesn't account for density/ noise
Distribution-based	assumes Gaussian distribution	limited to known distribution
Connectivity-based	distance	different shaped clusters
Density-based (DBScan)	mitigates noise	arbitrary radial distance; star-coordinates

```
### Choosing the best distribution
Judging from the plot with the two greatest components marked with categorical coloring of the salary, a centroid-based clustering alone doesn't account for the spread of salaries.  A DB-scan here is too complex for a 6-dimensional dataset. We are using linear regression as a simple method for principal component analysis, so our distribution for the dataset is unknown—a Distribution clustering would be inappropriate. The Connectivity-based can identify different shapes of clustering from the categorical data to compare to the flattened data set.  Ultimately a connectivity-centroid based cluster can best explain the combination of behaviors.
```

Applying K-means clustering as a combination of connectivity-centroid based clustering

In [17]:
```python
from sklearn.cluster import KMeans
```

In [18]:
```python
Z=finalDf[['principal component 1','principal component 2']]
X=finalDf[['principal component 1']]
Y=finalDf[['principal component 2']]
```

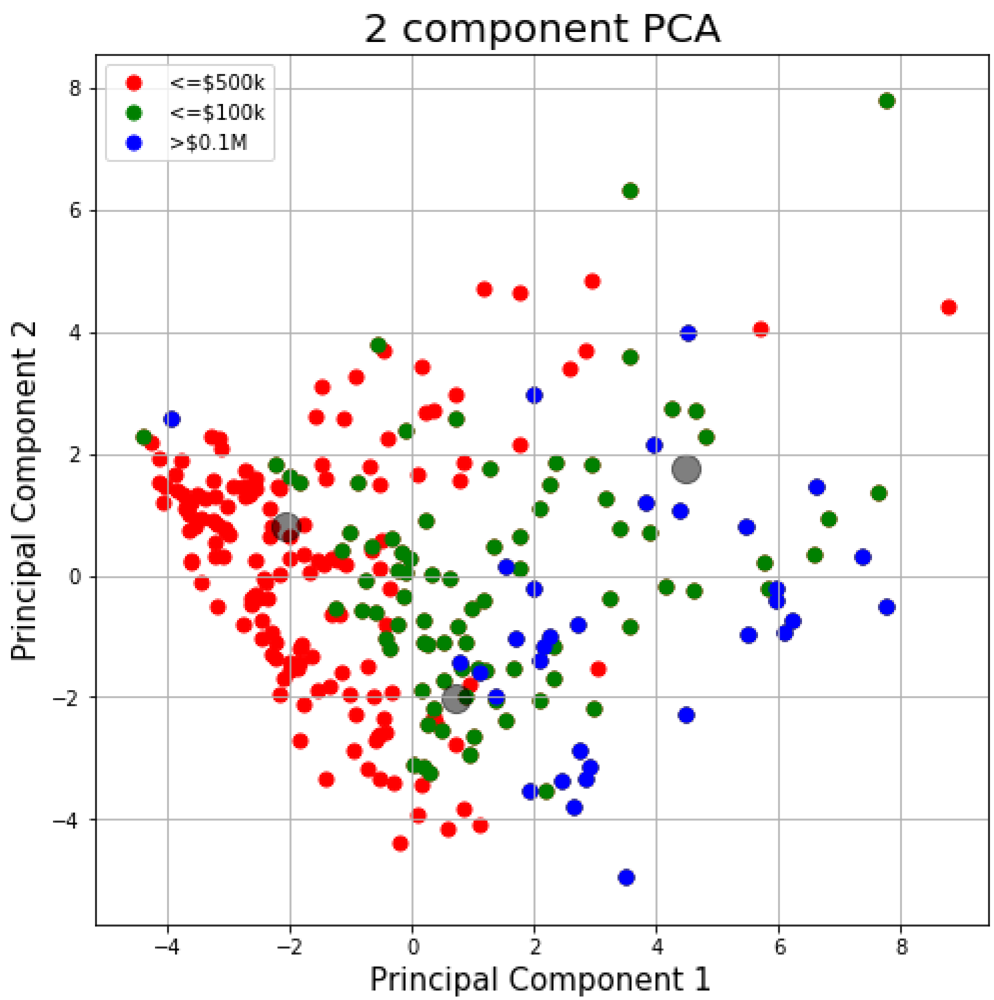
In [19]:
```python
connectivity_centroid=KMeans(n_clusters=3)
connectivity_centroid.fit(Z)
y_kmeans = connectivity_centroid.predict(Z)
```

In [20]:
```python

fig = plt.figure(figsize = (8,8))
ax = fig.add_subplot(1,1,1)
ax.set_xlabel('Principal Component 1', fontsize = 15)
ax.set_ylabel('Principal Component 2', fontsize = 15)
ax.set_title('2 component PCA', fontsize = 20)
salaries = [0, 500, 1000]
colors = ['r', 'g', 'b']
for salary, color in zip(salaries,colors):
    indicesToKeep = finalDf['Salary'] >= salary
    ax.scatter(finalDf.loc[indicesToKeep, 'principal component 1']
               , finalDf.loc[indicesToKeep, 'principal component 2']
               , c = color
               , s = 50)
ax.legend(['<=$500k', '<=$100k', '>$0.1M'])
ax.grid()

#plt.scatter(X, Y, c='b', s=50, cmap='viridis')

centers = connectivity_centroid.cluster_centers_
ax.scatter(centers[:, 0], centers[:, 1], c='black', s=200, alpha=0.5);
```



Results

As we can see, the K-mean clustering of 3 produces overlaid on the categorical marking produces a plausible result to represent connectivity and centroid clustering.

```
1 ### Discussion
```

```
The clustering technique was applied to a 2D PCA result. For a dataset with high dimensionality, a
scatter matrix of a pairwise comparison of the dimensions is generally used for exploratory
visualization.  Applying dimension reduction is meaningful in capturing all the data relationships
in one plot. Notice that principal components 1 and 2 only account for under 70% of the data. A
strong 2D plot is one where the first two components account for at least 85% of the data. We
achieve this at 4 principal components. For a 4D plot, visualizing in star coordinates is
appropriate.
```

Cardata

In [176]:

```
car_data = pd.read_csv('cars_multi.csv')
```

In [177]:

```
print(car_data.shape)
car_data.head()
```

```
(398, 10)
```

Out[177]:

	ID	mpg	cylinders	displacement	horsepower	weight	acceleration	model	origin	car_name
0	1	18.0	8	307.0	130	3504	12.0	70	1	chevrolet chevelle malibu
1	2	15.0	8	350.0	165	3693	11.5	70	1	buick skylark 320
2	3	18.0	8	318.0	150	3436	11.0	70	1	plymouth satellite
3	4	16.0	8	304.0	150	3433	12.0	70	1	amc rebel sst
4	5	17.0	8	302.0	140	3449	10.5	70	1	ford torino

In [178]:

```
df = car_data[(car_data!= '?')].dropna()
df.shape
```

Out[178]:

```
(392, 10)
```

In [179]:

```
dimensions = ['mpg','cylinders','displacement','horsepower','weight','acceleration']
df = df[dimensions]
print(df.shape)
df.head()
```

```
(392, 6)
```

Out[179]:

	mpg	cylinders	displacement	horsepower	weight	acceleration
0	18.0	8	307.0	130	3504	12.0
1	15.0	8	350.0	165	3693	11.5
2	18.0	8	318.0	150	3436	11.0
3	16.0	8	304.0	150	3433	12.0
4	17.0	8	302.0	140	3449	10.5

In [230]:

```
x = StandardScaler().fit_transform(df)
pca = PCA()
pca.fit(x)
variance = pca.explained_variance_ratio_ #calculate variance ratios
```

```
/anaconda3/lib/python3.7/site-packages/sklearn/preprocessing/data.py:625: DataConversionWarning: Data
with input dtype int64, float64, object were all converted to float64 by StandardScaler.
  return self.partial_fit(X, y)
/anaconda3/lib/python3.7/site-packages/sklearn/base.py:462: DataConversionWarning: Data with input dty
pe int64, float64, object were all converted to float64 by StandardScaler.
  return self.fit(X, **fit_params).transform(X)
```

In [232]:

```
var=np.cumsum(np.round(pca.explained_variance_ratio_, decimals=3)*100)
eigensum = pd.DataFrame(var, index=[['PC_1','PC_2','PC_3','PC_4','PC_5','PC_6']], columns=['Cumulat
eigensum.T
```

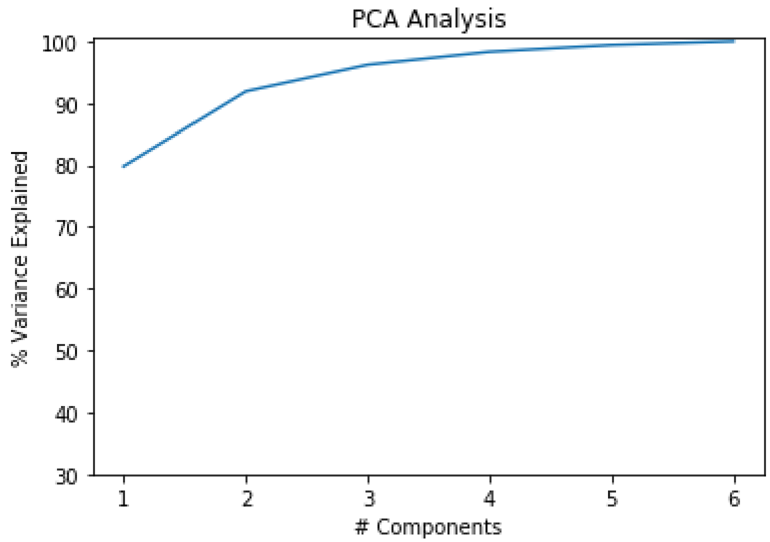
Out[232]:

	PC_1	PC_2	PC_3	PC_4	PC_5	PC_6
Cumulative % of PC of var	79.8	91.9	96.2	98.3	99.4	100.0

In [182]:

```
plt.ylabel('% Variance Explained')
plt.xlabel('# Components')
plt.title('PCA Analysis')
plt.ylim(30,100.5)
plt.style.context('seaborn-whitegrid')

plt.plot(list(range(1,len(dimensions)+1)),var);
```



In [183]:

```
pca = PCA(n_components=2)
principalComponents = pca.fit_transform(x)
principalDf = pd.DataFrame(data = principalComponents
             , columns = ['principal component 1', 'principal component 2'])
```

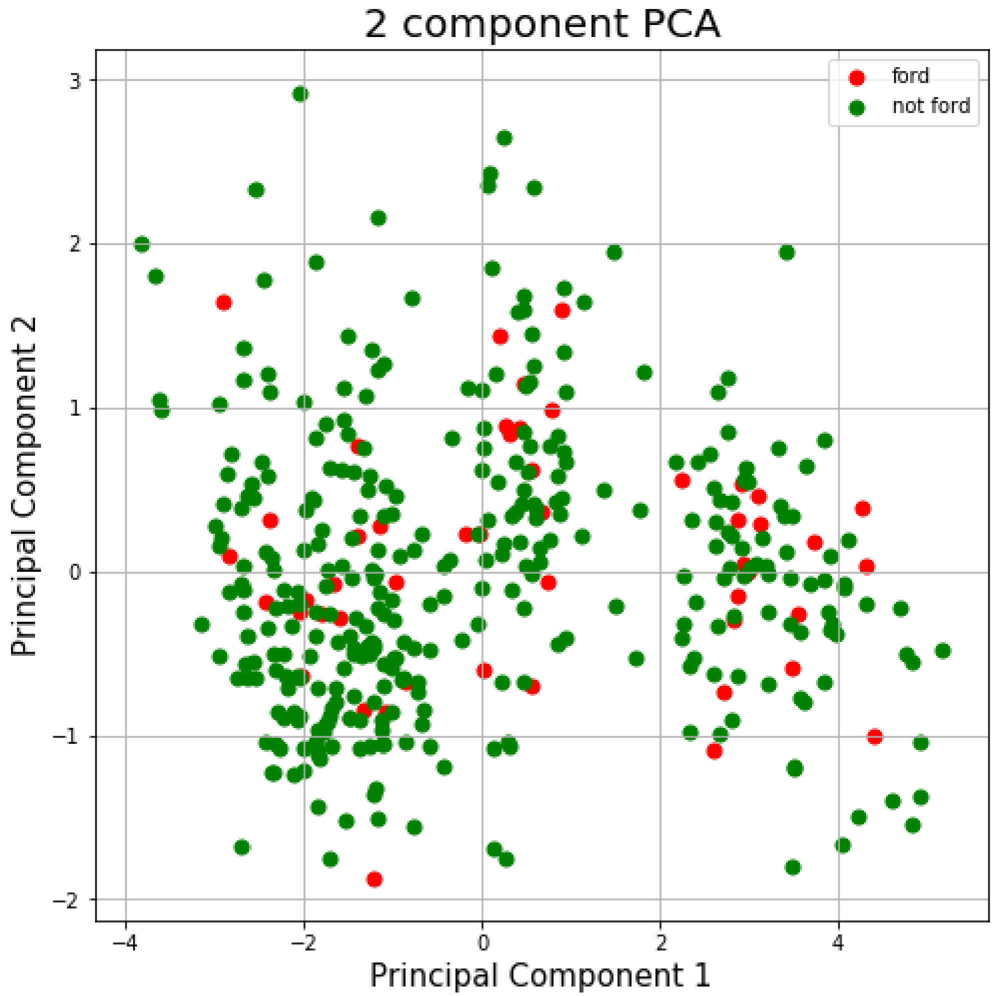
In [185]:
```
finalDf = pd.concat([principalDf.reset_index(),
                     car_data.reset_index()[['car_name']]],
                     axis = 1).drop('index',axis=1)
finalDf.head()
```

Out[185]:

	principal component 1	principal component 2	car_name
0	2.325970	-0.572082	chevrolet chevelle malibu
1	3.206057	-0.682741	buick skylark 320
2	2.669984	-0.994013	plymouth satellite
3	2.605465	-0.622770	amc rebel sst
4	2.599901	-1.093593	ford torino

In [210]:

```
fig = plt.figure(figsize = (8,8))
ax = fig.add_subplot(1,1,1)
ax.set_xlabel('Principal Component 1', fontsize = 15)
ax.set_ylabel('Principal Component 2', fontsize = 15)
ax.set_title('2 component PCA', fontsize = 20)
fav_name = ['ford','not ford']
colors = ['r', 'g']
for fav, color in zip(fav_name,colors):
    if fav == 'ford':
        indicesToKeep = finalDf['car_name'].apply(lambda x: 'ford' in x)
    else:
        indicesToKeep = finalDf['car_name'].apply(lambda x: 'ford' not in x)
    ax.scatter(finalDf.loc[indicesToKeep, 'principal component 1']
               , finalDf.loc[indicesToKeep, 'principal component 2']
               , c = color
               , s = 50)
ax.legend(fav_name)
ax.grid()
```


2 component PCA
ford
not ford
Principal Component 1
Principal Component 2
−4
−2
0
2
4
−2
−1
0
1
2
3

In [211]:
```python
interest = finalDf[finalDf['car_name'].apply(lambda x: 'ford' in x)]
print(interest.shape)
interest.head()
```

```
(51, 3)
```

Out[211]:

	principal component 1	principal component 2	car_name
4	2.599901	-1.093593	ford torino
5	4.401453	-1.010783	ford galaxie 500
17	-0.184110	0.229623	ford maverick
25	4.271642	0.389443	ford f250
32	0.565130	-0.695237	ford pinto

In [212]:
```python
pca = PCA(n_components=2)
principalComponents = pca.fit_transform(x)
loading =np.transpose(pca.components_)
chart = pd.DataFrame(loading,columns =['PC 1','PC 2'],
                     index=dimensions)
chart
```

Out[212]:

	PC 1	PC 2
mpg	-0.398973	-0.244835
cylinders	0.430615	0.148314
displacement	0.443531	0.108497
horsepower	0.434122	-0.166158
weight	0.430103	0.286095
acceleration	-0.291926	0.892652

Conclusion

Acceleration by far is the most significant attribute for the principal component 2. For principal component 1, non acceleration, numerical attributes share medium significance.

Reasons/ Numerical Attributes of Dataset-clustering

The six parameters were chosen, because they are quantitative. The dropped columns were categorical. Two principal components describe almost 92% of the quantitative data.

Choosing the best clustering distribution

I would have imagined that car companies build within a certain expertise and refactor on those models to be modeled by connectivity based-clustering. A performance based model would be hypothesized to have most perform in a dense mediocre range. From the plot there seems to be 3 general regions of density, but we apply 6 k-mean clusters to see how the quantitative dimensions may be represented.

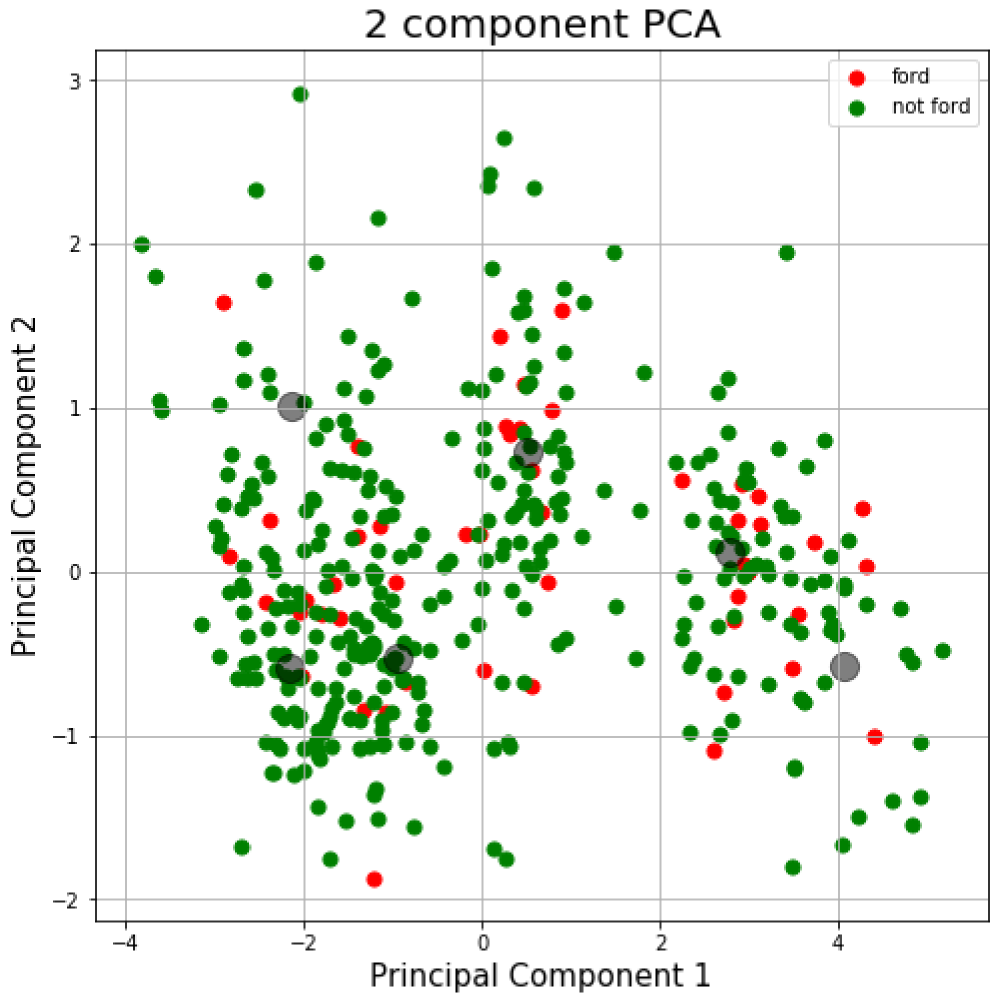
In [237]:
```
Z=principalDf[['principal component 1','principal component 2']]
connectivity_centroid=KMeans(n_clusters=6)
connectivity_centroid.fit(Z)
y_kmeans = connectivity_centroid.predict(Z)
```

In [238]:

```
fig = plt.figure(figsize = (8,8))
ax = fig.add_subplot(1,1,1)
ax.set_xlabel('Principal Component 1', fontsize = 15)
ax.set_ylabel('Principal Component 2', fontsize = 15)
ax.set_title('2 component PCA', fontsize = 20)
fav_name = ['ford','not ford']
colors = ['r', 'g']
for fav, color in zip(fav_name,colors):
    if fav == 'ford':
        indicesToKeep = finalDf['car_name'].apply(lambda x: 'ford' in x)
    else:
        indicesToKeep = finalDf['car_name'].apply(lambda x: 'ford' not in x)
    ax.scatter(principalDf.loc[indicesToKeep, 'principal component 1']
               , principalDf.loc[indicesToKeep, 'principal component 2']
               , c = color
               , s = 50)
ax.legend(fav_name)
ax.grid()

#plt.scatter(X, Y, c='b', s=50, cmap='viridis')

centers = connectivity_centroid.cluster_centers_
ax.scatter(centers[:, 0], centers[:, 1], c='black', s=200, alpha=0.5);
```



Discussion

We can deduce that the 2nd right most centroid represents acceleration, because the acceleration attribute is expected to rest near the mean of PC_2 and far from the mean on PC_1.

```
In [ ]: 1
```