

# pca\_gene\_data

December 5, 2019

## 1 Data Cleaning

```
In [1]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline

In [2]: df= pd.read_csv('../input/data_set_ALL_AML_train.csv')
df.head()
df1 = [col for col in df.columns if "call" not in col]
df = df[df1]
df = df.T
df2 = df.drop(['Gene Description','Gene Accession Number'],axis=0)
df2.index = pd.to_numeric(df2.index)
df2.sort_index(inplace=True)
df2['cat'] = list(pd.read_csv('../input/actual.csv')[:38]['cancer'])
dic = {'ALL':0,'AML':1}
df2.replace(dic,inplace=True)

In [3]: test = pd.read_csv('../input/data_set_ALL_AML_independent.csv')
test1 = [col for col in test.columns if "call" not in col]
test = test[test1]
test = test.T
test2 = test.drop(['Gene Description','Gene Accession Number'],axis=0)
test2.index = pd.to_numeric(test2.index)
test2.sort_index(inplace=True)
test2['cat'] = list(pd.read_csv('../input/actual.csv')['cancer'][38:])

In [4]: df_combined = pd.concat([df2, test2])
dic = {'ALL':0,'AML':1}
df_combined.replace(dic,inplace=True)
df_combined.cat.mean()

Out[4]: 0.3472222222222222

In [5]: from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA as sklearnPCA
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scalar = StandardScaler()
scalar.fit(df_combined.drop('cat',axis=1))
X_std = scalar.transform(df_combined.drop('cat',axis=1))

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sklearn_pca = sklearnPCA(n_components=30)
sklearn_pca.fit(X_std)
cat = df_combined.cat
pc_x = sklearn_pca.transform(X_std)

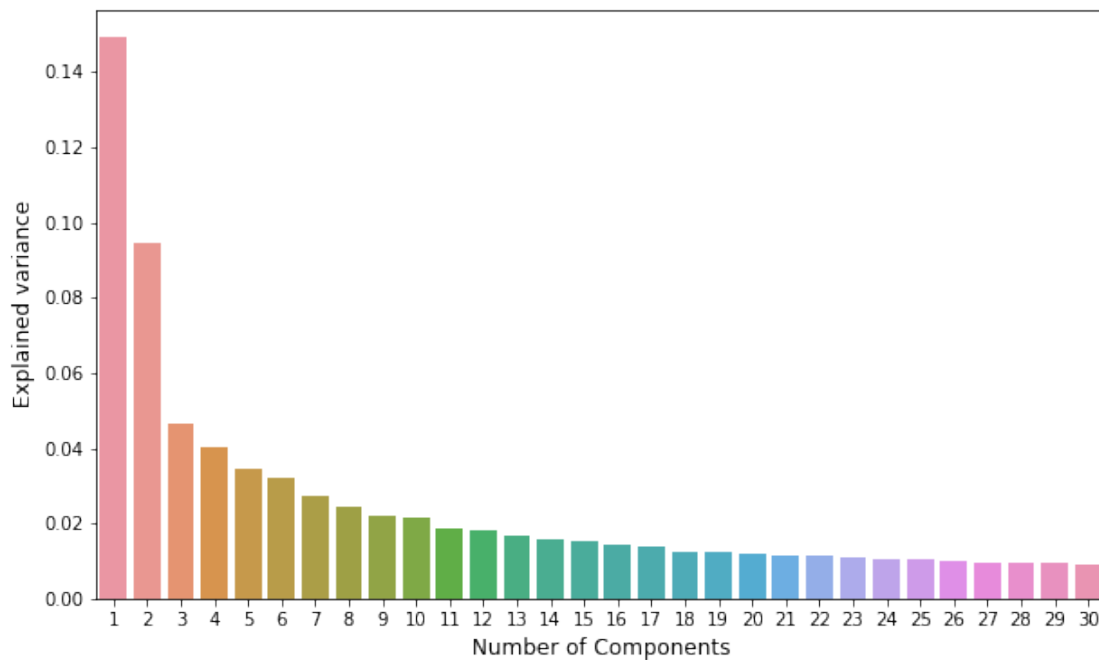
```

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In [6]: import seaborn as sns
plt.rcParams['figure.figsize'] = [10, 6]

sns.barplot(np.arange(1, len(sklearn_pca.explained_variance_ratio_)+1),\
            sklearn_pca.explained_variance_ratio_)
plt.xlabel('Number of Components', size=12)
plt.ylabel('Explained variance', size=12)
plt.savefig('variance_bar.png');

```

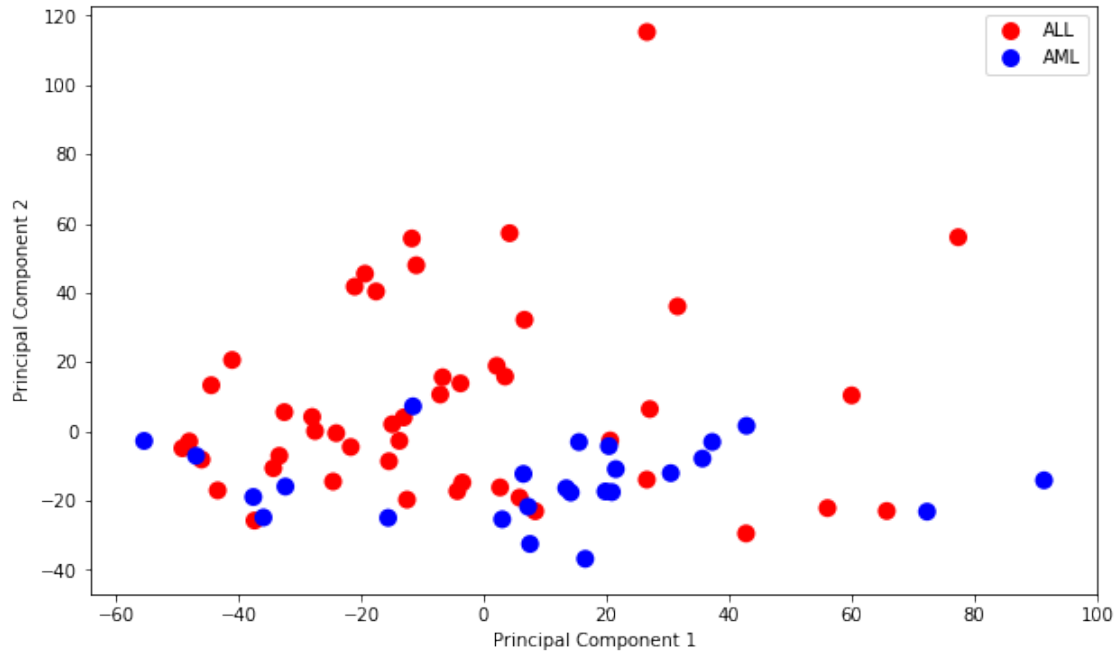


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In [7]: plt.rcParams['figure.figsize'] = [10, 6]
plt.scatter(pc_x[cat==0, 0], pc_x[cat==0, 1],
            c='red', edgecolor='none', s=100, label='ALL')
plt.scatter(pc_x[cat==1, 0], pc_x[cat==1, 1],
            c='blue', edgecolor='none', s= 100, label='AML')

```

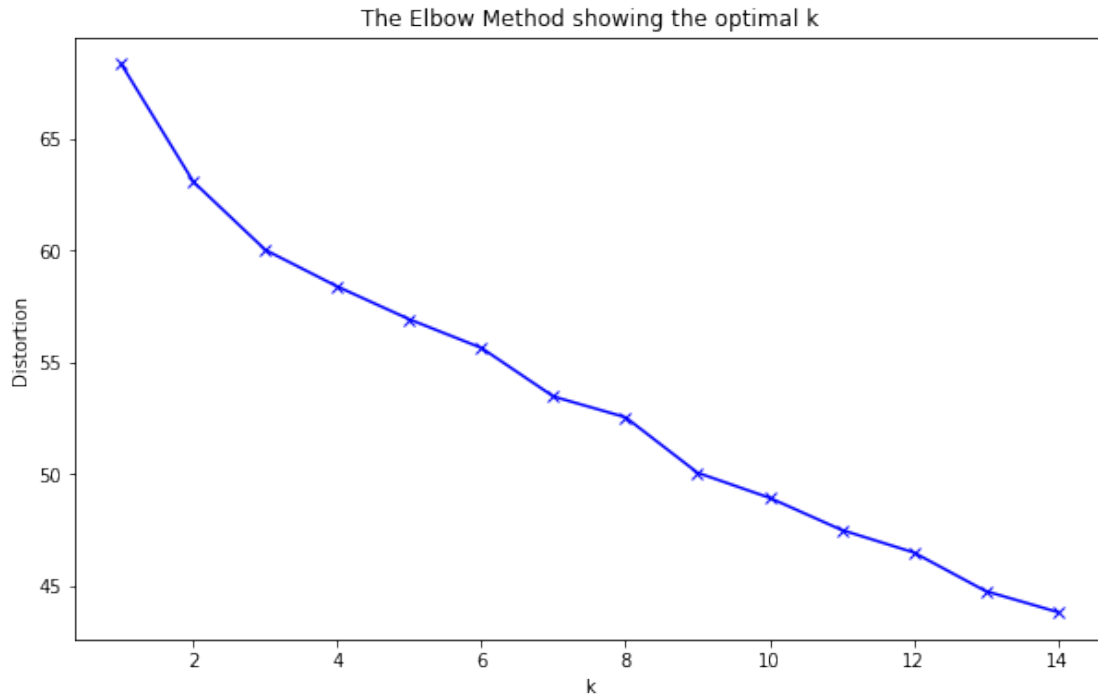
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plt.xlabel('Principal Component 1', size=10)
plt.ylabel('Principal Component 2', size=10)
plt.legend()
plt.savefig('scatter.png')
```



```
In [8]: # k means determine k
from scipy.spatial.distance import cdist
from sklearn.cluster import KMeans

distortions = []
K = range(1,15)
for k in K:
    kmeanModel = KMeans(n_clusters=k).fit(pc_x)
    kmeanModel.fit(pc_x)
    distortions.append(sum(np.min(cdist(pc_x, kmeanModel.cluster_centers_,\
                                        'euclidean'), axis=1)) / pc_x.shape[0])

# Plot the elbow
plt.plot(K, distortions, 'bx-')
plt.xlabel('k')
plt.ylabel('Distortion')
plt.title('The Elbow Method showing the optimal k')
plt.show()
plt.savefig('elbow.png')
```

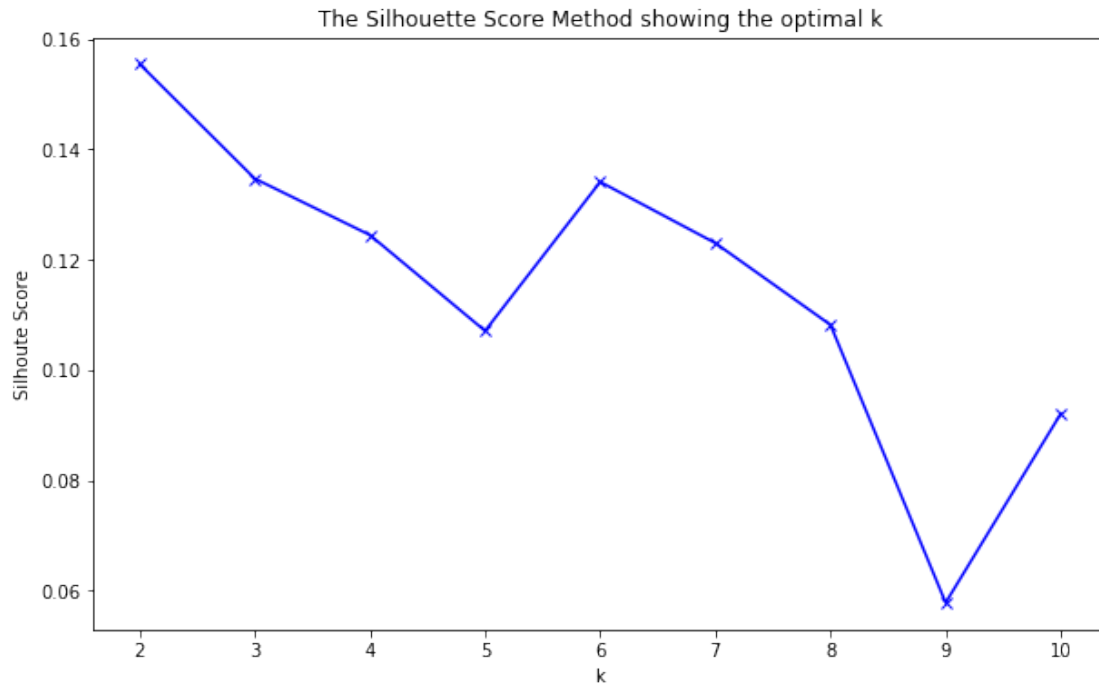


<Figure size 720x432 with 0 Axes>

```
In [9]: from sklearn.metrics import silhouette_score

sil = []
kmax = 10
# dissimilarity would not be defined for a single cluster,\
# thus, minimum number of clusters should be 2
for k in range(2, kmax+1):
    kmeans_1 = KMeans(n_clusters = k).fit(pc_x)
    labels = kmeans_1.labels_
    sil.append(silhouette_score(pc_x, labels, metric = 'euclidean'))

# Plot the elbow
plt.plot(range(2, kmax+1), sil, 'bx-')
plt.xlabel('k')
plt.ylabel('Silhouette Score')
plt.title('The Silhouette Score Method showing the optimal k')
plt.show()
plt.savefig('silhouette.png')
```



<Figure size 720x432 with 0 Axes>

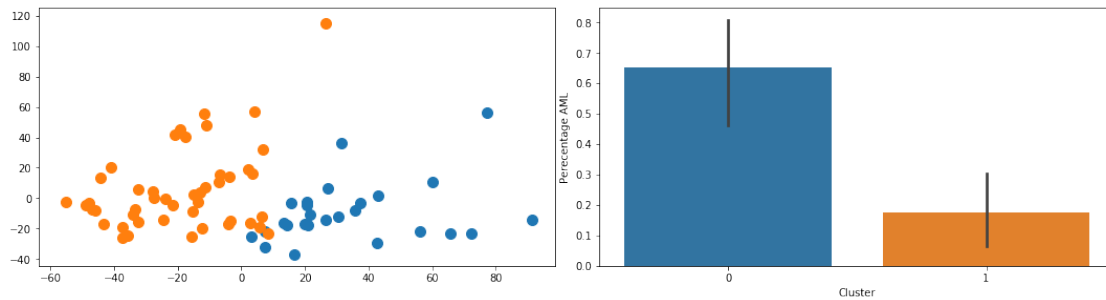
```
In [10]: from sklearn.cluster import KMeans

kmeans = KMeans(n_clusters=2)
kmeans.fit(pc_x)
y_kmeans = kmeans.predict(pc_x)

fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(15, 4))
fig.tight_layout()

for i in np.unique(y_kmeans):
    axes[0].scatter(pc_x[y_kmeans == i, 0], pc_x[y_kmeans == i, 1],\
                    s=100, label=str(i))
plt.xlabel('Principal Component 1', size=10)
plt.ylabel('Principal Component 2', size=10)
#plt.legend(title='Cluster')

axes[1] = sns.barplot(y_kmeans, cat)
plt.ylabel('Percentage AML', size=10)
plt.xlabel('Cluster', size=10)
plt.savefig('cluster_bar.png')
plt.savefig('kmeans_2.png')
```



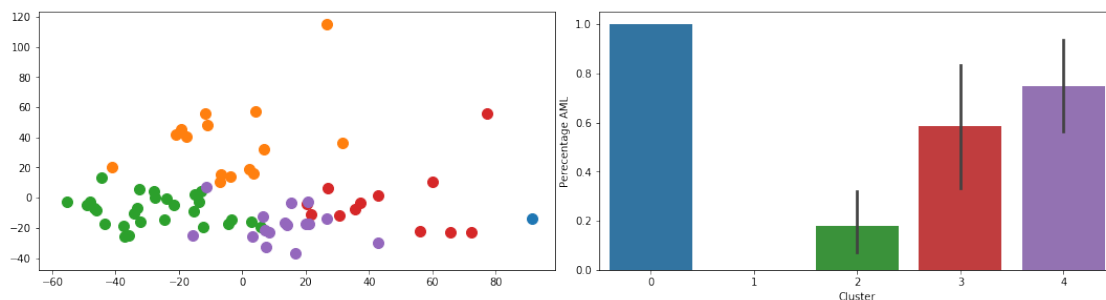
```
In [11]: kmeans = KMeans(n_clusters=5)
kmeans.fit(pc_x)
y_kmeans = kmeans.predict(pc_x)

fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(15, 4))
fig.tight_layout()

for i in np.unique(y_kmeans):
    axes[0].scatter(pc_x[y_kmeans == i, 0],\
                    pc_x[y_kmeans == i, 1], s=100, label=str(i))
plt.xlabel('Principal Component 1', size=10)
plt.ylabel('Principal Component 2', size=10)
#plt.legend(title='Cluster')

axes[1] = sns.barplot(y_kmeans, cat)
plt.ylabel('Percentage AML', size=10)
plt.xlabel('Cluster', size=10)
plt.savefig('cluster_bar.png')

plt.savefig('kmeans_5.png')
```



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In [12]: kmeans = KMeans(n_clusters=7)
kmeans.fit(pc_x)
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y_kmeans = kmeans.predict(pc_x)

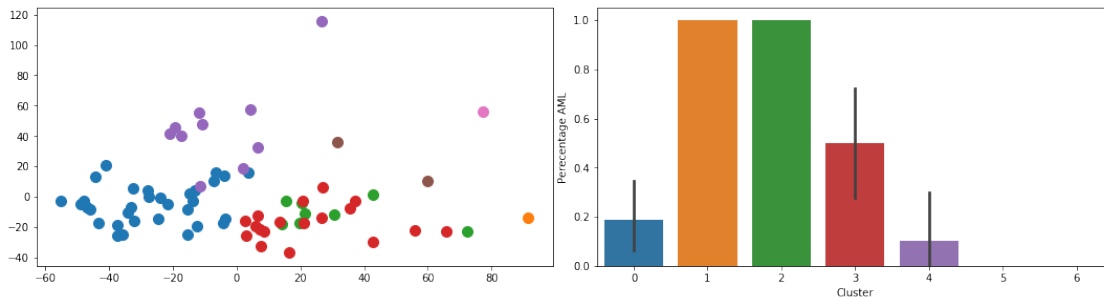
fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(15, 4))
fig.tight_layout()

for i in np.unique(y_kmeans):
    axes[0].scatter(pc_x[y_kmeans == i, 0],\
                    pc_x[y_kmeans == i, 1], s=100, label=str(i))
plt.xlabel('Principal Component 1', size=10)
plt.ylabel('Principal Component 2', size=10)
#plt.legend(title='Cluster')

axes[1] = sns.barplot(y_kmeans, cat)
plt.ylabel('Percentage AML', size=10)
plt.xlabel('Cluster', size=10)
plt.savefig('cluster_bar.png')

plt.savefig('kmeans_7.png')

```



```

In [13]: import numpy as np
import pandas as pd
import random

def sample(data):
    sample = [random.choice(data) for _ in range(len(data))]
    return sample

def bootstrap_t_test(treatment, control, nboot = 1000, direction = "less"):
    ones = np.vstack((np.ones(len(treatment)), treatment))
    treatment = ones.conj().transpose()
    zeros = np.vstack((np.zeros(len(control)), control))
    control = zeros.conj().transpose()
    Z = np.vstack((treatment, control))
    tstat = np.mean(treatment[:,1]) - np.mean(control[:,1])
    tboot = np.zeros(nboot)

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for i in range(nboot):
    sboot = sample(Z)
    sboot = pd.DataFrame(np.array(sboot), columns=['treat', 'vals'])
    tboot[i] = np.mean(sboot['vals'][sboot['treat'] == 1])\
        - np.mean(sboot['vals'][sboot['treat'] == 0]) - tstat
    if direction == "greater":
        pvalue = np.sum(tboot>=tstat-0)/nboot
    elif direction == "less":
        pvalue = np.sum(tboot<=tstat-0)/nboot
    else:
        print('Enter a valid arg for direction')

print('The p-value is %f' % (pvalue))

```

```

In [14]: kmeans = KMeans(n_clusters=2)
         kmeans.fit(pc_x)
         y_kmeans = kmeans.predict(pc_x)

         bootstrap_t_test(cat[y_kmeans == 0], cat[y_kmeans == 1],\
                           nboot = 1000, direction = "greater")

```

The p-value is 0.000000