Assignment5

November 25, 2018

1. [차원변환] 첨부된 데이터를 이용하여 아래의 과업을 수행하고 결과들을 확인하세요.(Hint: scikit-learn 사용)

(1) [PCA] 2차원 변환하는 주성분 분석을 수행한 결과를 확인하고, 시각화하세요 (7점)

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
%matplotlib inline


features=["feature1", "feature2", "feature3", "feature4"]

# load dataset into pandas DataFrame
url = "data/assignmet5_data.csv"

df = pd.read_csv(url, names=features)

df.head()
```

Out[1]:

	feature1	feature2	feature3	feature4
0	feature 1	feature 2	feature 3	feature 4
1	5.1	3.5	1.4	0.2
2	4.9	3	1.4	0.2
3	4.7	3.2	1.3	0.2
4	4.6	3.1	1.5	0.2

In [2]:
```
# Separating out the features
x = df.loc[1:, features].values

# test proportion of the features
print(x[0:2])

# Standardizing the features, N(0, 1)
x = StandardScaler().fit_transform(x)
```

```
standardDf = pd.DataFrame(data=x, columns = features)

standardDf.head()
```

```
[['5.1' '3.5' '1.4' '0.2']
 ['4.9' '3' '1.4' '0.2']]


/home/hyunyoung2/.local/lib/python3.5/site-packages/sklearn/utils/validation.py:475: DataConve
  warnings.warn(msg, DataConversionWarning)
```

Out[2]:

	feature1	feature2	feature3	feature4
0	-0.900681	1.032057	-1.341272	-1.312977
1	-1.143017	-0.124958	-1.341272	-1.312977
2	-1.385353	0.337848	-1.398138	-1.312977
3	-1.506521	0.106445	-1.284407	-1.312977
4	-1.021849	1.263460	-1.341272	-1.312977

In [3]:

```
pcaComponent=["principal component 1", "principal compoent 2"]

pca = PCA(n_components=2)

principalComponents = pca.fit_transform(x)

# checking variance
print("varince : {}".format(pca.explained_variance_ratio_))

pricivpalDf = pd.DataFrame(data = principalComponents, columns = pcaComponent)


pricivpalDf.head()
```

```
varince : [0.72770452 0.23030523]
```

Out[3]:

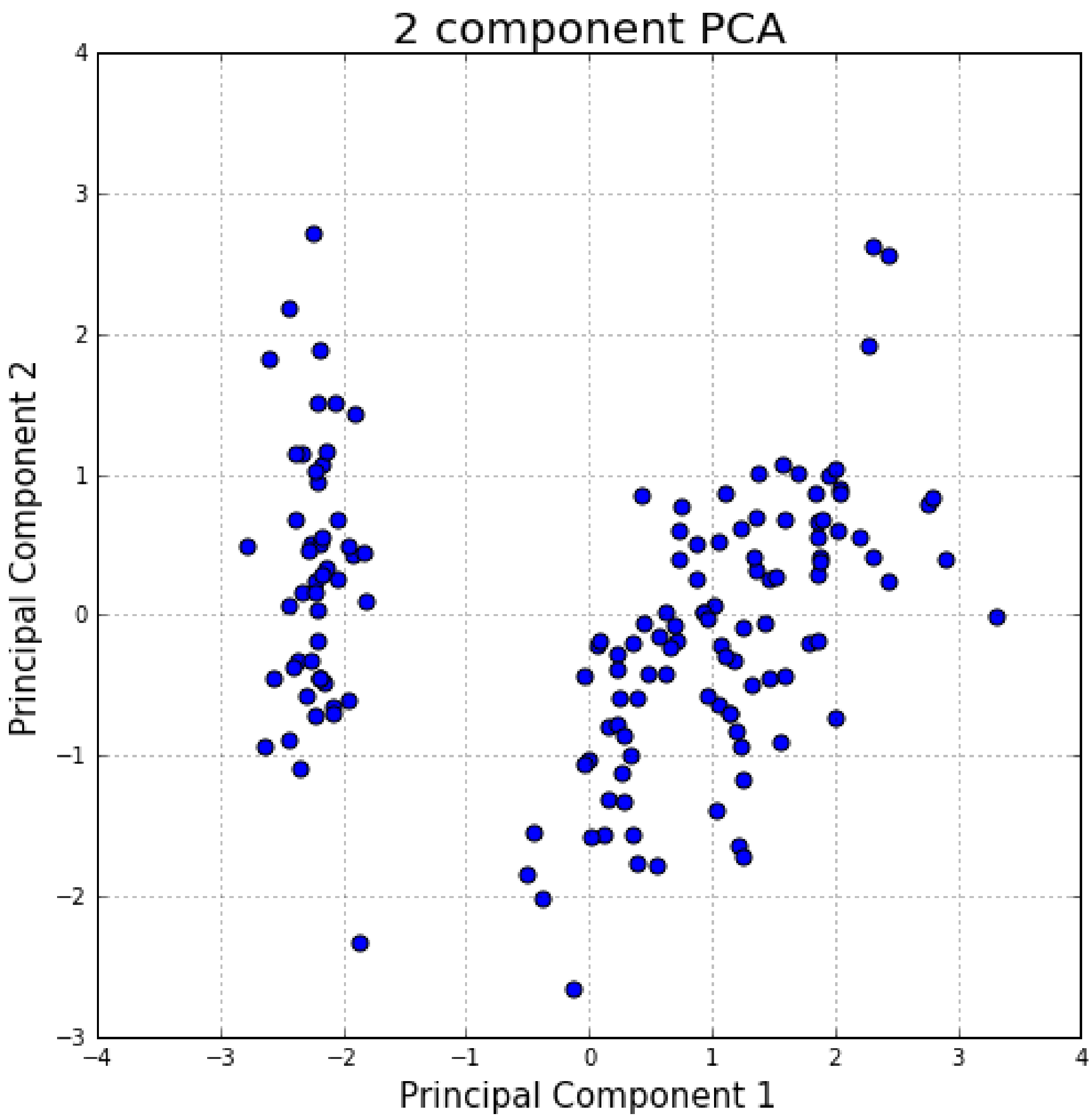
	principal component 1	principal compoent 2
0	-2.264542	0.505704
1	-2.086426	-0.655405
2	-2.367950	-0.318477
3	-2.304197	-0.575368
4	-2.388777	0.674767

In [4]:

```
# visualize 2D Projection
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)
```

```
ax.scatter(pricivpalDf.loc[:, pcaComponent[0]],
           pricivpalDf.loc[:, pcaComponent[1]],
           c ="b",
           s=50)

ax.grid()
```



(2) [t-SNE] 2차원 변환하는 t-SNE 수행한 결과를 확인하고, 시각화하세요.(7점)

```
In [5]: import time
```

```python
from sklearn.manifold import TSNE

time_start = time.time()
tsne = TSNE(n_components = 2, verbose = 1, perplexity = 40, n_iter = 300)
tsne_results = tsne.fit_transform(x)

print("t-SNE done! Time elapsed: {} seconds".format(time.time() - time_start))

tsneComponent=["x", "y"]

tsneDf = pd.DataFrame(data = tsne_results, columns = tsneComponent)

tsneDf.head()
```

```
[t-SNE] Computing 121 nearest neighbors…
[t-SNE] Indexed 150 samples in 0.000s…
[t-SNE] Computed neighbors for 150 samples in 0.002s…
[t-SNE] Computed conditional probabilities for sample 150 / 150
[t-SNE] Mean sigma: 0.868185
[t-SNE] KL divergence after 250 iterations with early exaggeration: 48.752071
[t-SNE] Error after 300 iterations: 0.130219
t-SNE done! Time elapsed: 0.6002943515777588 seconds
```

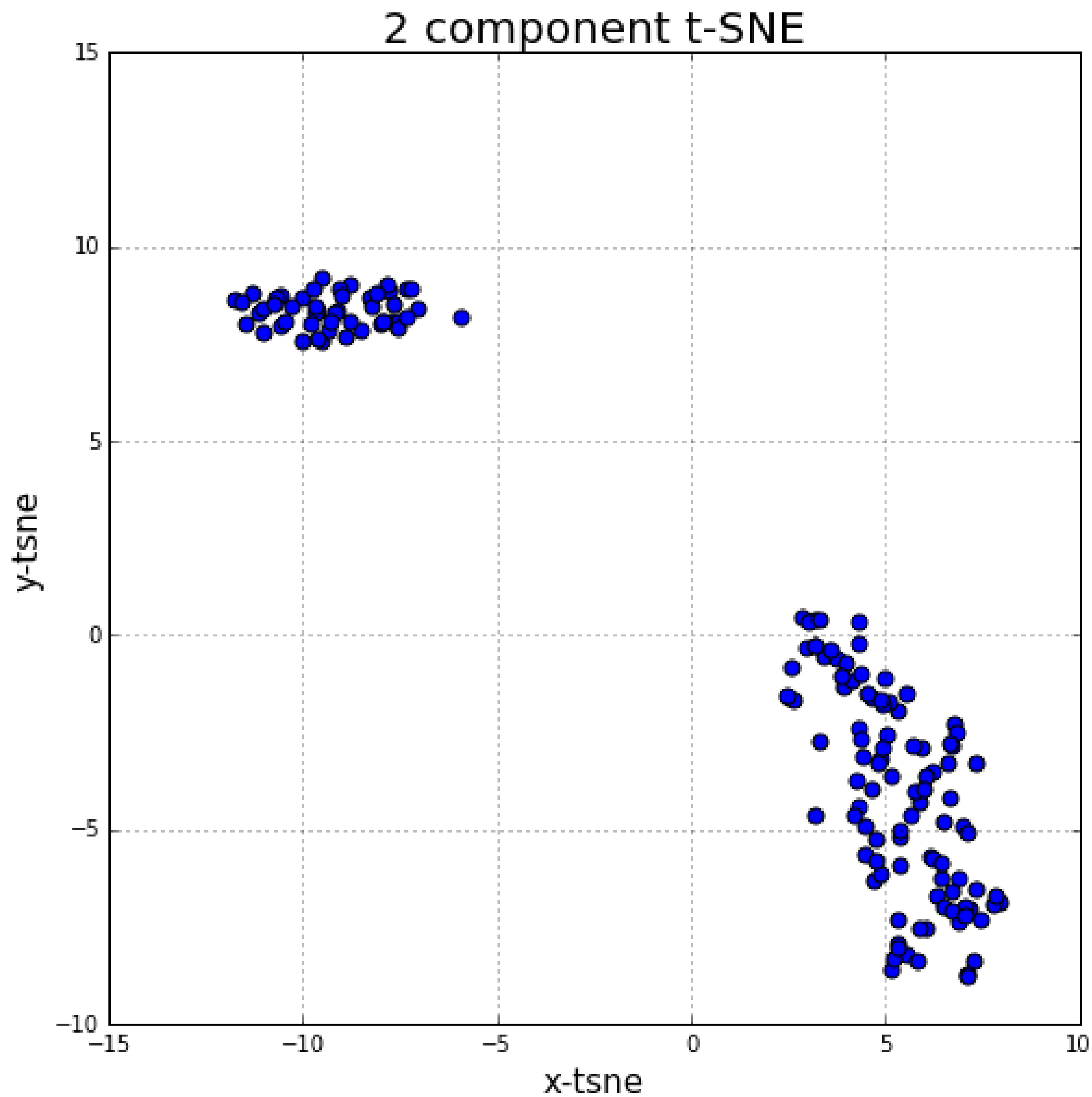
Out[5]:

	x	y
0	-9.636526	8.384428
1	-7.725962	8.092324
2	-8.282676	8.690121
3	-7.805793	8.870246
4	-10.013817	8.682937

In [6]:
```python
# visualize 2D Projection
fig = plt.figure(figsize = (8,8))
ax = fig.add_subplot(1,1,1)
ax.set_xlabel("x-tsne", fontsize=15)
ax.set_ylabel("y-tsne", fontsize=15)
ax.set_title("2 component t-SNE", fontsize=20)

ax.scatter(tsneDf.loc[:, tsneComponent[0]],
           tsneDf.loc[:, tsneComponent[1]],
           c ="b",
           s=50)

ax.grid()
```



2. [군집화] 첨부된 데이터를 이용하여 아래의 과업을 수행하고 결과들을 확인하세요.(Hint: scikit-learn 사용)

In [7]:
```
features=["feature1", "feature2", "feature3", "feature4"]

# load dataset into pandas DataFrame
url = "data/assignmet5_data.csv"

df = pd.read_csv(url, names=features)

df.head()
```

Out[7]:

	feature1	feature2	feature3	feature4
0	feature 1	feature 2	feature 3	feature 4

```
1         5.1        3.5        1.4        0.2
2         4.9          3        1.4        0.2
3         4.7        3.2        1.3        0.2
4         4.6        3.1        1.5        0.2
```

In [8]:
```python
# Separating out the features
x = df.loc[1:, features].values

# test proportion of the features
print(x[0:2])

# Standardizing the features, N(0, 1)
x = StandardScaler().fit_transform(x)

standardDf = pd.DataFrame(data=x, columns = features)

standardDf.head()
```

```
[['5.1' '3.5' '1.4' '0.2']
 ['4.9' '3' '1.4' '0.2']]


/home/hyunyoung2/.local/lib/python3.5/site-packages/sklearn/utils/validation.py:475: DataConve
  warnings.warn(msg, DataConversionWarning)
```

Out[8]:

	feature1	feature2	feature3	feature4
0	-0.900681	1.032057	-1.341272	-1.312977
1	-1.143017	-0.124958	-1.341272	-1.312977
2	-1.385353	0.337848	-1.398138	-1.312977
3	-1.506521	0.106445	-1.284407	-1.312977
4	-1.021849	1.263460	-1.341272	-1.312977

(1) [K-means] K-평균 군집화(K=4)를 수행한 결과를 확인하세요.(7점)

In [9]:
```python
# import KMeans
from sklearn.cluster import KMeans

# create kmeans object
# fit Kmeans object to data
kmeans = KMeans(n_clusters=4).fit(x)
# print location of clusters learned by kmeans object
print("kmeans cluster centers:")
print(kmeans.cluster_centers_)
print("kmeans labels")
print(kmeans.labels_)

standardDf = pd.DataFrame(data=x, columns = features)

standardDf.head()
```

```
kmeans cluster centers:
[[-1.28213558  0.22643209 -1.30968035 -1.29836862]
 [-0.01139555 -0.87288504  0.37688422  0.31165355]
 [ 1.16743407  0.15377779  1.00314548  1.02963256]
 [-0.70049078  1.56529014 -1.29924123 -1.20436862]]
kmeans labels
[3 0 0 0 3 3 0 0 0 0 3 0 0 0 3 3 3 3 3 3 3 3 0 0 0 0 3 0 0 0 3 3 3 0 0 3
 0 0 0 3 0 0 3 3 0 3 0 3 0 2 2 2 1 1 1 2 1 1 1 1 1 1 1 1 2 1 1 1 1 2 1 1 1
 1 2 2 2 1 1 1 1 1 1 1 2 2 1 1 1 1 1 1 1 1 1 1 1 1 1 2 1 2 2 2 2 1 2 1 2 2
 1 2 1 1 2 2 2 2 1 2 1 2 1 2 2 1 1 2 2 2 2 2 1 1 2 2 2 1 2 2 2 1 2 2 2 1 2
 2 1]
```

```
Out[9]:    feature1  feature2  feature3  feature4
        0 -0.900681  1.032057 -1.341272 -1.312977
        1 -1.143017 -0.124958 -1.341272 -1.312977
        2 -1.385353  0.337848 -1.398138 -1.312977
        3 -1.506521  0.106445 -1.284407 -1.312977
        4 -1.021849  1.263460 -1.341272 -1.312977
```

```
In [10]: kmeanslabelDf = pd.DataFrame(data=kmeans.labels_, columns = ["label"])

         kmeanslabelDf.head()
```

```
Out[10]:    label
         0      3
         1      0
         2      0
         3      0
         4      3
```

```
In [11]: kmeansFinalDf = pd.concat([standardDf, kmeanslabelDf], axis = 1)

         kmeansFinalDf.head()
```

```
Out[11]:    feature1  feature2  feature3  feature4  label
         0 -0.900681  1.032057 -1.341272 -1.312977      3
         1 -1.143017 -0.124958 -1.341272 -1.312977      0
         2 -1.385353  0.337848 -1.398138 -1.312977      0
         3 -1.506521  0.106445 -1.284407 -1.312977      0
         4 -1.021849  1.263460 -1.341272 -1.312977      3
```

(2) [K-medoid] K-중심 군집화(K=4)를 수행한 결과를 확인하세요.(7점)

```
In [12]: from pyclustering.cluster.kmedoids import kmedoids
         import random
         # load list of points for cluster analysis
         sample = x
```

```
# set random initial medoids
init_int = list(range(0,150))
init_medoids = random.sample(init_int, 4)
print("init_medoids: {}".format(init_medoids))

# create instance of K-Medoids algorithm
kmedoids_instance = kmedoids(sample, init_medoids)

# run cluster analysis and obtain results
kmedoids_instance.process();
clusters = kmedoids_instance.get_clusters()
medoids = kmedoids_instance.get_medoids()
# show allocated clusters
print("medodis: {}".format(medoids))
print(clusters[0][0:5])
```

```
init_medoids: [96, 131, 70, 71]
medodis: [7, 105, 147, 94]
[7, 0, 1, 2, 3]
```

In [13]:
```
labels_idx = []

for idx in range(0, 150):
    if idx in clusters[0]:
        labels_idx.append(0)
    elif idx in clusters[1]:
        labels_idx.append(1)
    elif idx in clusters[2]:
        labels_idx.append(2)
    elif idx in clusters[3]:
        labels_idx.append(3)

print("labels_idx: {}, len-{}".format(labels_idx[0:5], len(labels_idx)))

kmeanslabelDf = pd.DataFrame(data=labels_idx, columns = ["label"])

kmeanslabelDf.head()
```

```
labels_idx: [0, 0, 0, 0, 0], len-150
```

Out[13]:

	label
0	0
1	0
2	0
3	0
4	0

```
In [14]: kmedoidsFinalDf = pd.concat([standardDf, kmeanslabelDf], axis = 1)

         kmedoidsFinalDf.head()
```

```
Out[14]:    feature1  feature2  feature3  feature4  label
         0 -0.900681  1.032057 -1.341272 -1.312977      0
         1 -1.143017 -0.124958 -1.341272 -1.312977      0
         2 -1.385353  0.337848 -1.398138 -1.312977      0
         3 -1.506521  0.106445 -1.284407 -1.312977      0
         4 -1.021849  1.263460 -1.341272 -1.312977      0
```

(3) [Affine propagation] 친밀도 전파 군집화를 수행한 결과를 확인하세.(7점)

```
In [15]: from sklearn.cluster import AffinityPropagation

         model = AffinityPropagation(preference=-50).fit(x)

         cluster_centers_indices = model.cluster_centers_indices_
         labels = model.labels_
         n_clusters_ = len(cluster_centers_indices)

         from sklearn import metrics

         print('Estimated number of clusters: %d' % n_clusters_)
         print("Silhouette Coefficient: %0.3f" % metrics.silhouette_score(x,
                                                                           labels,
                                                                   metric='sqeuclidean'))

         standardDf = pd.DataFrame(data=x, columns = features)

         standardDf.head()
```

```
Estimated number of clusters: 3
Silhouette Coefficient: 0.627
```

```
Out[15]:    feature1  feature2  feature3  feature4
         0 -0.900681  1.032057 -1.341272 -1.312977
         1 -1.143017 -0.124958 -1.341272 -1.312977
         2 -1.385353  0.337848 -1.398138 -1.312977
         3 -1.506521  0.106445 -1.284407 -1.312977
         4 -1.021849  1.263460 -1.341272 -1.312977
```

```
In [16]: affinityPropagationlabelDf = pd.DataFrame(data=labels, columns = ["label"])
         affinityPropagationlabelDf.head()
```

```
Out[16]:    label
         0      0
         1      0
```

```
2      0
3      0
4      0
```

In [17]:
```python
affineFinalDf = pd.concat([standardDf, affinityPropagationlabelDf], axis = 1)

affineFinalDf.head()
```

Out[17]:

	feature1	feature2	feature3	feature4	label
0	-0.900681	1.032057	-1.341272	-1.312977	0
1	-1.143017	-0.124958	-1.341272	-1.312977	0
2	-1.385353	0.337848	-1.398138	-1.312977	0
3	-1.506521	0.106445	-1.284407	-1.312977	0
4	-1.021849	1.263460	-1.341272	-1.312977	0

(4) 위의 3가지 군집결과를 비교하세요.(7점)

In [18]:
```python
pcaComponent=["principal component 1", "principal compoent 2"]

pca = PCA(n_components=2)

principalComponents = pca.fit_transform(x)

# checking variance
print("varince : {}".format(pca.explained_variance_ratio_))

pricivpalDf = pd.DataFrame(data = principalComponents, columns = pcaComponent)

pricivpalDf.head()
```

```
varince : [0.72770452 0.23030523]
```

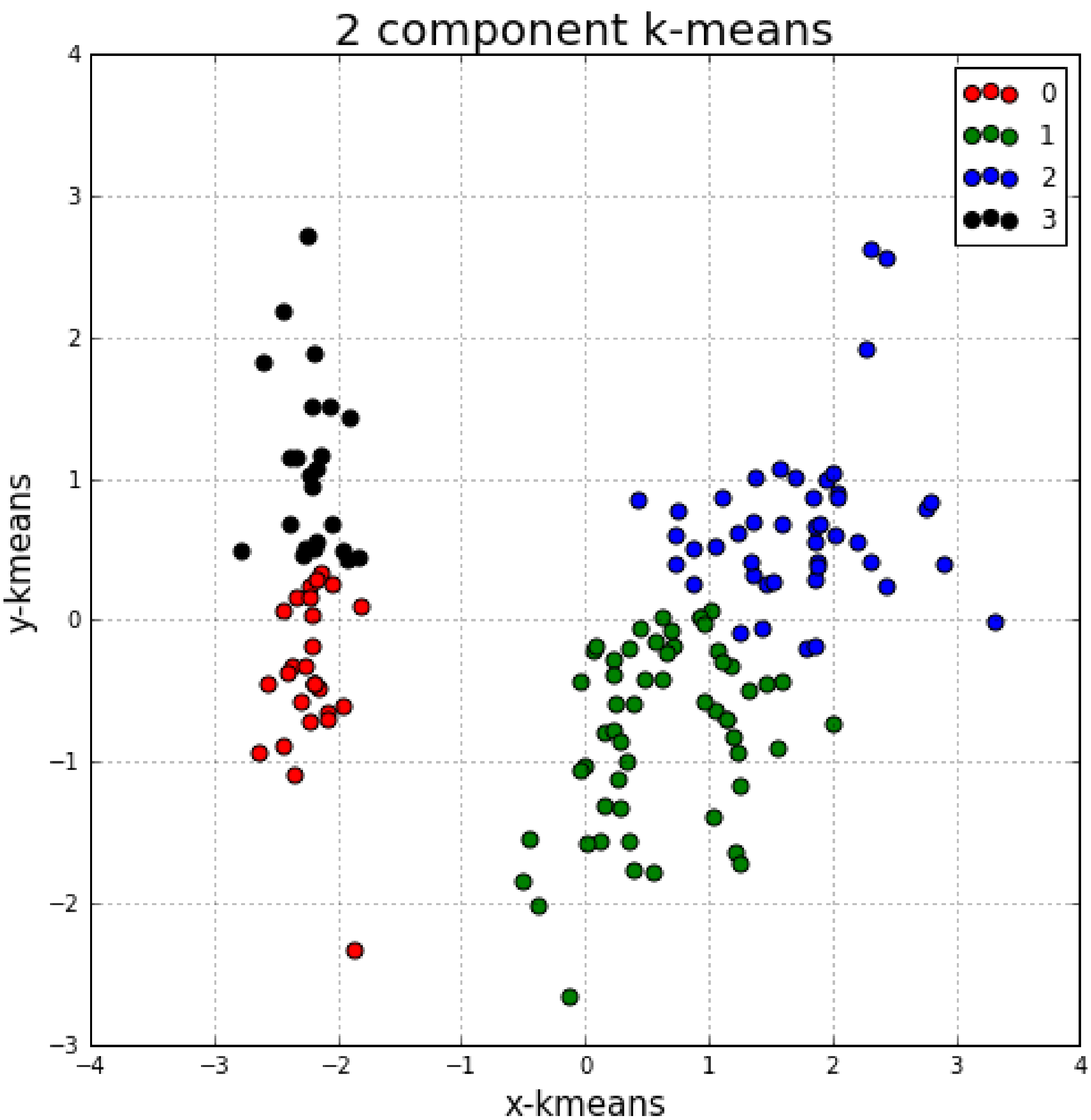
Out[18]:

	principal component 1	principal compoent 2
0	-2.264542	0.505704
1	-2.086426	-0.655405
2	-2.367950	-0.318477
3	-2.304197	-0.575368
4	-2.388777	0.674767

In [19]:
```python
# k- means figure
targets = [0, 1, 2, 3]
colors =['r', 'g', 'b', 'black']
# visualize 2D Projection
fig = plt.figure(figsize = (8,8))
ax = fig.add_subplot(1,1,1)
ax.set_xlabel("x-kmeans", fontsize=15)
ax.set_ylabel("y-kmeans", fontsize=15)
ax.set_title("2 component k-means", fontsize=20)
```

```
for target, color in zip(targets, colors):
    indicesToKeep = kmeansFinalDf['label'] == target
    ax.scatter(pricivpalDf.loc[indicesToKeep, pcaComponent[0]],
               pricivpalDf.loc[indicesToKeep, pcaComponent[1]],
               c =color,
               s=50)

ax.legend(targets)
ax.grid()
```

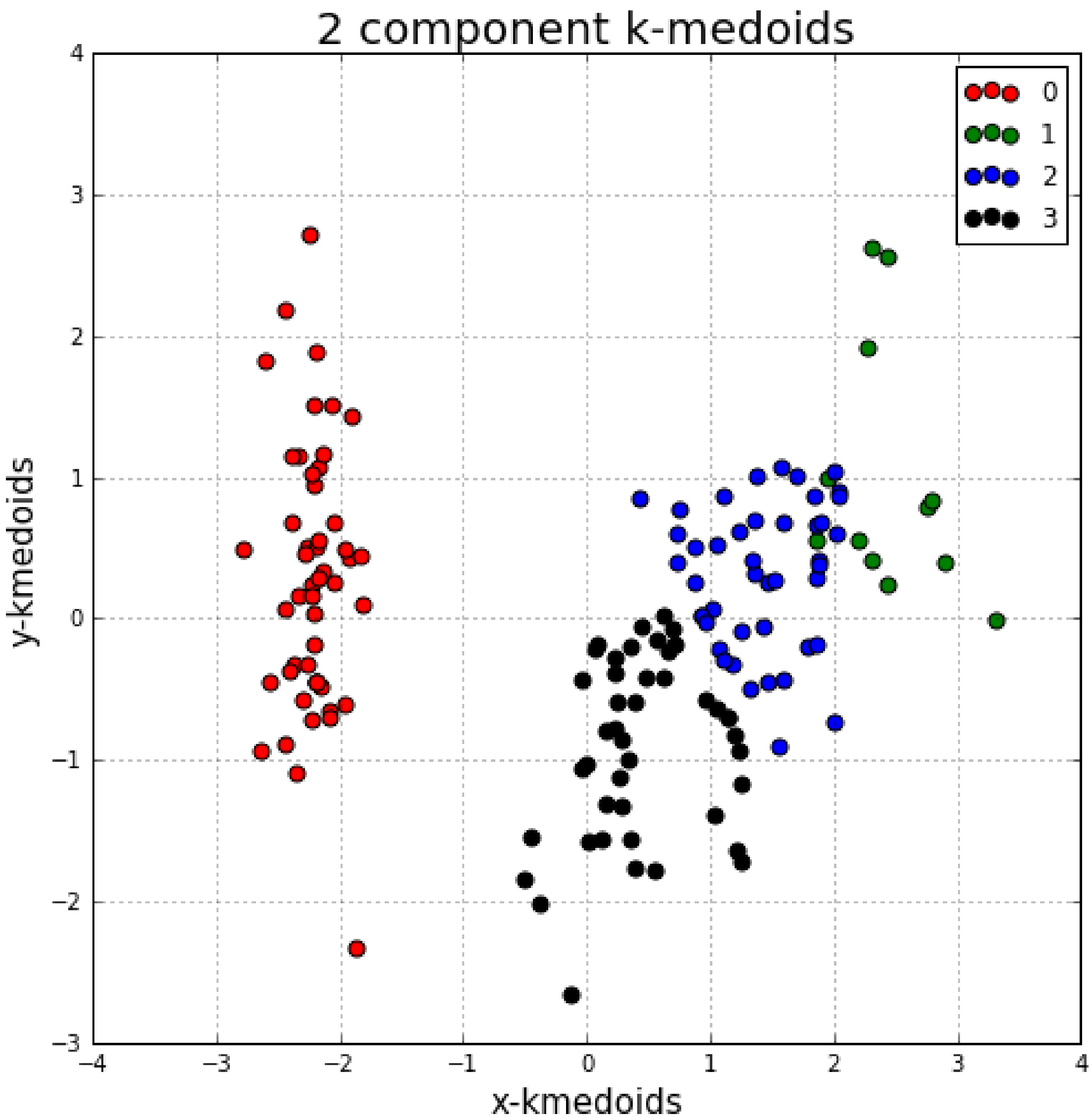



```
In [20]: # k-medoids figure
         targets = [0, 1, 2, 3]
```

```python
colors =['r', 'g', 'b', 'black']
# visualize 2D Projection
fig = plt.figure(figsize = (8,8))
ax = fig.add_subplot(1,1,1)
ax.set_xlabel("x-kmedoids", fontsize=15)
ax.set_ylabel("y-kmedoids", fontsize=15)
ax.set_title("2 component k-medoids", fontsize=20)

for target, color in zip(targets, colors):
    indicesToKeep = kmedoidsFinalDf['label'] == target
    ax.scatter(pricivpalDf.loc[indicesToKeep, pcaComponent[0]],
               pricivpalDf.loc[indicesToKeep, pcaComponent[1]],
               c =color,
               s=50)

ax.legend(targets)
ax.grid()
```

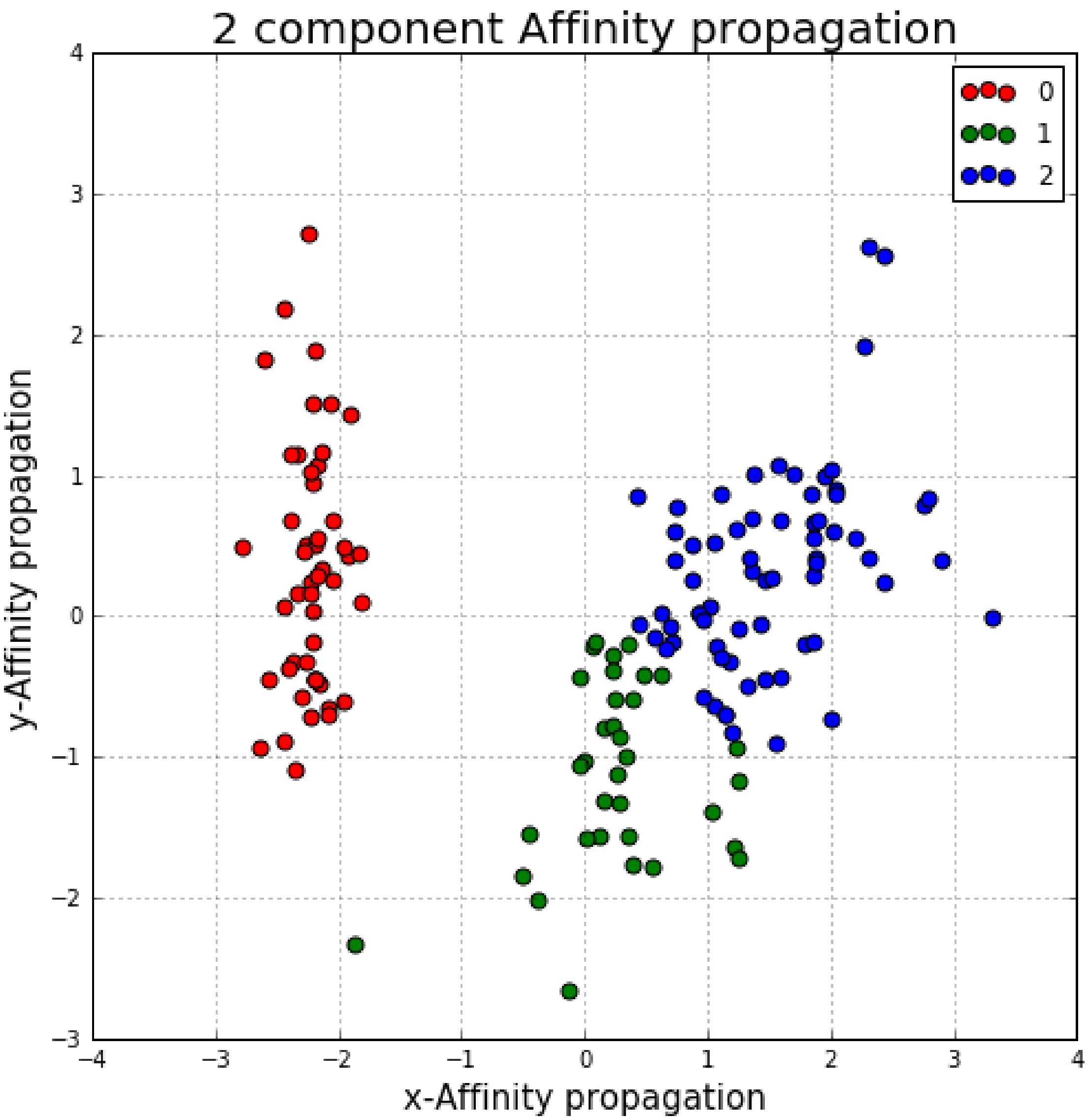



```
In [21]: # Affinity propagtaion figure
         targets = [0, 1, 2]
         colors =['r', 'g', 'b']
         # visualize 2D Projection
         fig = plt.figure(figsize = (8,8))
         ax = fig.add_subplot(1,1,1)
         ax.set_xlabel("x-Affinity propagation", fontsize=15)
         ax.set_ylabel("y-Affinity propagation", fontsize=15)
         ax.set_title("2 component Affinity propagation", fontsize=20)

         for target, color in zip(targets, colors):
             indicesToKeep = affineFinalDf['label'] == target
```

```
    ax.scatter(pricivpalDf.loc[indicesToKeep, pcaComponent[0]],
               pricivpalDf.loc[indicesToKeep, pcaComponent[1]],
               c =color,
               s=50)

ax.legend(targets)
ax.grid()
```



3. [순환신경망][예제 8-1]에서 y'^(2), y'^(3), y'^(4) 를 구하는 과정을 보이세요. 또한, X^(5) = (0.1, 0.1), X^(6) = (0.1, 0.0) 이 추가되어 샘플의 길이가 4에서 6이 되었다면 y'^(5), y'^(6) 을 구하세요.(14점)

```
In [22]: import numpy as np
```

```python
u = [[0.1, 0.1],
    [0.0, 0.0],
    [0.0, -0.1],]

w = [[0.1, 0.1, 0.0],
    [0.0, 0.0, 0.0],
    [0.2, -0.1, -0.1]]

v = [[0.0, 0.1, 0.0],
     [-0.2, 0.0, 0.0]]

b = [0.0, 0.0, 0.2]

c = [0.2, 0.1]

h0 = [0.0, 0.0, 0.0]

x1 = [0.0, 1.0]

H0 = np.array(h0)

X1 = np.array(x1)

U = np.array(u)

W = np.array(w)

V = np.array(v)

B = np.array(b)

C = np.array(c)

def a_(x, h):
    return np.dot(W, h) + np.dot(U, x) + B

def h_(a):
    return np.tanh(a)

def softmax(x):
    scoreMatEx = np.exp(x)
    return scoreMatEx / scoreMatEx.sum(0)

def y_(h):
    return softmax(np.dot(V, h) + C)

def rnn(x, h):
    hidden = h_(a_(x , h))
```

```python
        return y_(hidden), hidden

    x2 = [0.0, 0.1]

    x3 = [0.1, -0.2]

    x4 = [0.5, 0.0]

    x5 = [0.1, 0.1]

    x6 = [0.1, 0.0]

    X2 = np.array(x2)

    X3 = np.array(x3)

    X4 = np.array(x4)

    X5 = np.array(x5)

    X6 = np.array(x6)

    Y1, H1 = rnn(X1, H0)

    print("y1: {}".format(Y1))

    Y2, H2 = rnn(X2, H1)

    print("y2: {}".format(Y2))

    Y3, H3 = rnn(X3, H2)

    print("y3: {}".format(Y3))

    Y4, H4 = rnn(X4, H3)

    print("y4: {}".format(Y4))

    Y5, H5 = rnn(X5, H4)

    print("y5: {}".format(Y5))

    Y6, H6 = rnn(X6, H5)

    print("y6: {}".format(Y6))
```

```
y1: [0.52994751 0.47005249]
y2: [0.5259748 0.4740252]
```

```
y3: [0.52458 0.47542]
y4: [0.52743043 0.47256957]
y5: [0.52622146 0.47377854]
y6: [0.52560211 0.47439789]
```

4. [순환신경망] $ y^{(t)} = (0, 1)^{T} $일 때 식 (8.16)을 유도하세요. 또한 식 (8.19)는 식 (8.16)을 일반화한 것인데 일반화 과정을 설명하세요.(14점)

1 Reference

- PCA using python on Towards Data Science
- Visualising high-dimensional datasets using PCA and T-SNE in python
- K-Means Clusterring with Scikit-learn
- clustering_with scikit with GIFs
- scikit-learn plot affinity propagtion
- pyclustering github for k-medoids
- pyclustering documentation