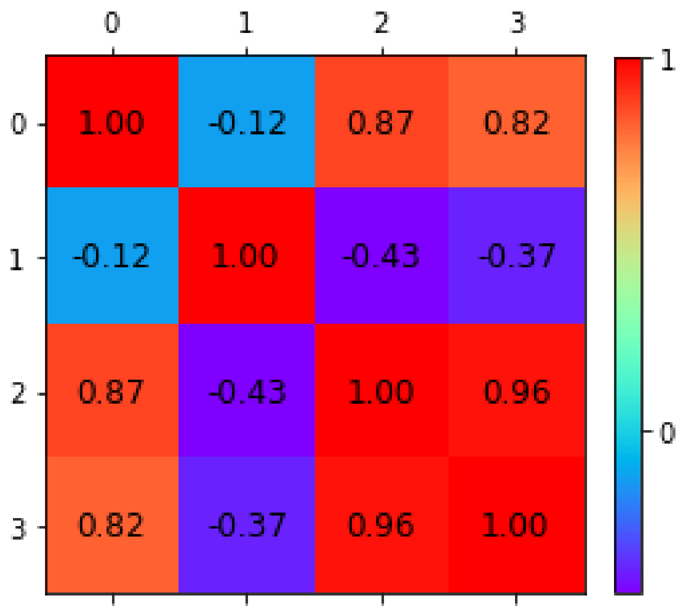
Dimension_reduction

January 13, 2019

In [1]:
```
# covariance matrix
from sklearn import datasets
import numpy as np
iris = datasets.load_iris()
cov_data = np.corrcoef(iris.data.T)
print(iris.feature_names)
print(cov_data)
```

```
['sepal length (cm)', 'sepal width (cm)', 'petal length (cm)', 'petal width (cm)']
[[ 1.         -0.11756978  0.87175378  0.81794113]
 [-0.11756978  1.         -0.4284401  -0.36612593]
 [ 0.87175378 -0.4284401   1.          0.96286543]
 [ 0.81794113 -0.36612593  0.96286543  1.        ]]
```

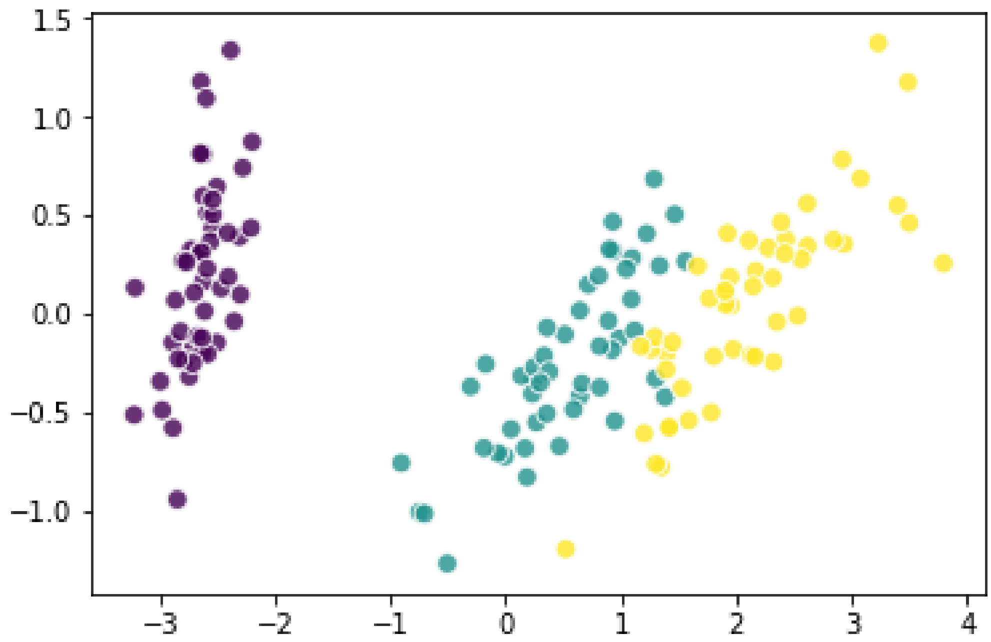
In [16]:
```
# covariance matrix vizaliaztion (thermal map)
import matplotlib.pyplot as plt
img = plt.matshow(cov_data, cmap = plt.cm.rainbow)
plt.colorbar(img, ticks = [-1,0,1],fraction=0.045)
for x in range(cov_data.shape[0]):
    for y in range(cov_data.shape[1]):
        plt.text(x, y, "%0.2f" % cov_data[x,y],
            size=12, color='black', ha='center', va='center')
plt.show()
```



In [3]:
```
#PCA Principal Component Analysys, 2 demensions
from sklearn.decomposition import PCA
pca_2c = PCA(n_components = 2) # reduction to 2 demensions
X_pca_2c = pca_2c.fit_transform(iris.data)
X_pca_2c.shape
```

Out[3]: (150, 2)

In [4]:
```
plt.scatter(X_pca_2c[:,0], X_pca_2c[:,1], c=iris.target, alpha=0.8, s=60, marker='o', 
plt.show()
pca_2c.explained_variance_ratio_.sum()
```



Out[4]: 0.977685206318795

```
In [5]: #PCA - Principal Component Analysys, 3 demensions
        from sklearn.decomposition import PCA
        pca_3c = PCA(n_components = 3) # reduction to 3 demensions
        X_pca_3c = pca_3c.fit_transform(iris.data)
        X_pca_3c.shape
```

Out[5]: (150, 3)

```
In [6]: pca_3c.explained_variance_ratio_.sum()
```

Out[6]: 0.9947878161267247

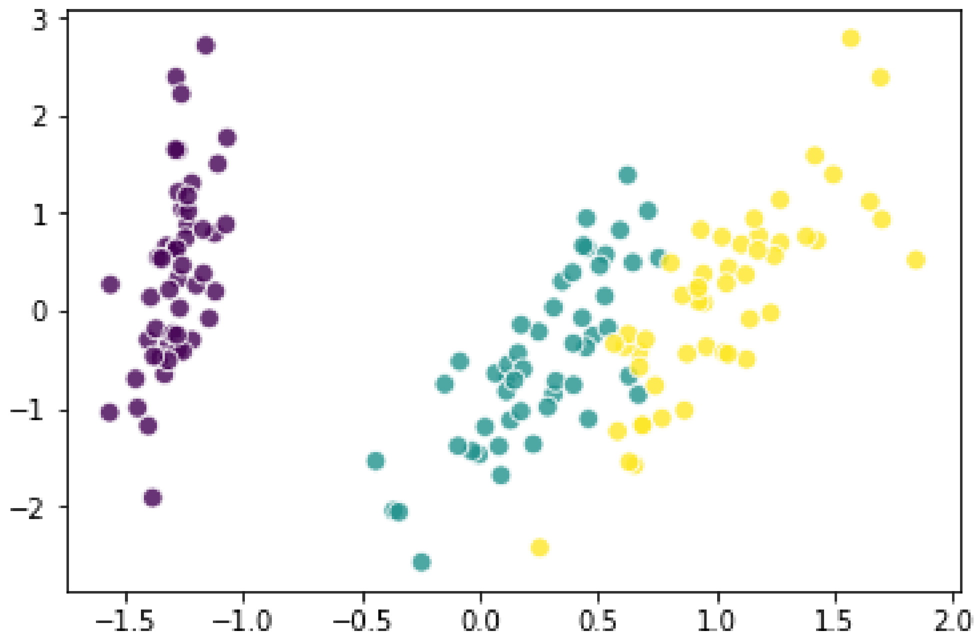
```
In [7]: #PCA Principal Component Analysys, 4 demensions
        from sklearn.decomposition import PCA
        pca_4c = PCA(n_components = 4) # reduction to 4 demensions
        X_pca_4c = pca_4c.fit_transform(iris.data)
        X_pca_4c.shape
```

Out[7]: (150, 4)

```
In [8]: pca_4c.explained_variance_ratio_.sum()
```

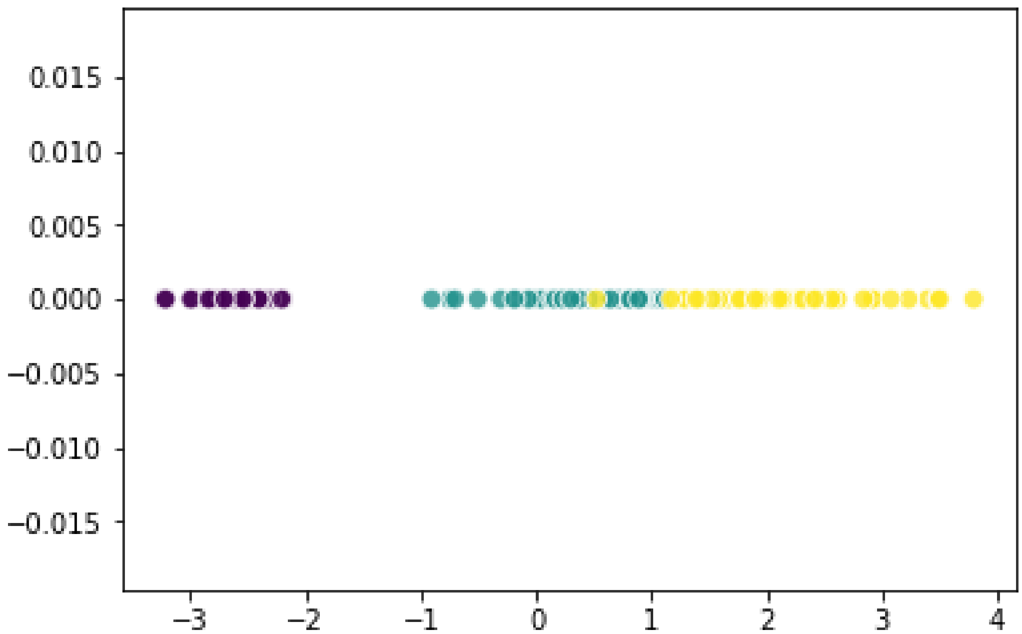
Out[8]: 1.0

In [9]:
```
#PCA with whitewash
pca_2cw = PCA(n_components=2, whiten=True)
X_pca_1cw = pca_2cw.fit_transform(iris.data)
plt.scatter(X_pca_1cw[:,0], X_pca_1cw[:,1],c=iris.target,alpha=0.8, s=60, marker='o', e
plt.show()
pca_2cw.explained_variance_ratio_.sum()
```



Out[9]: 0.977685206318795

In [10]:
```
#PCA 1 dimension
pca_1c = PCA(n_components=1)
X_pca_1c = pca_1c.fit_transform(iris.data)
plt.scatter(X_pca_1c[:,0], np.zeros(X_pca_1c.shape),c=iris.target,alpha=0.8, s=60, ma
plt.show()
pca_1c.explained_variance_ratio_.sum()
```

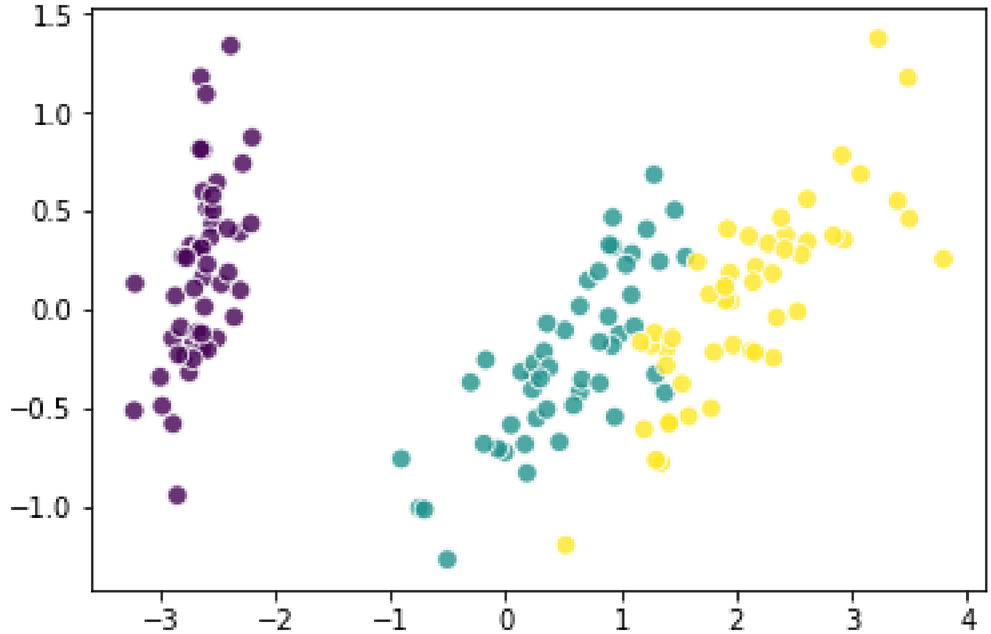



```
Out[10]: 0.9246187232017272
```

```
In [11]: #PCA at least 95% "energy" (explained_variance_ratio_)
         pca_95pc = PCA(n_components=0.95)
         X_pca_95pc = pca_95pc.fit_transform(iris.data)
         print(pca_95pc.explained_variance_ratio_.sum())
         print(X_pca_95pc.shape) # 2 dimension are the best in that case
```

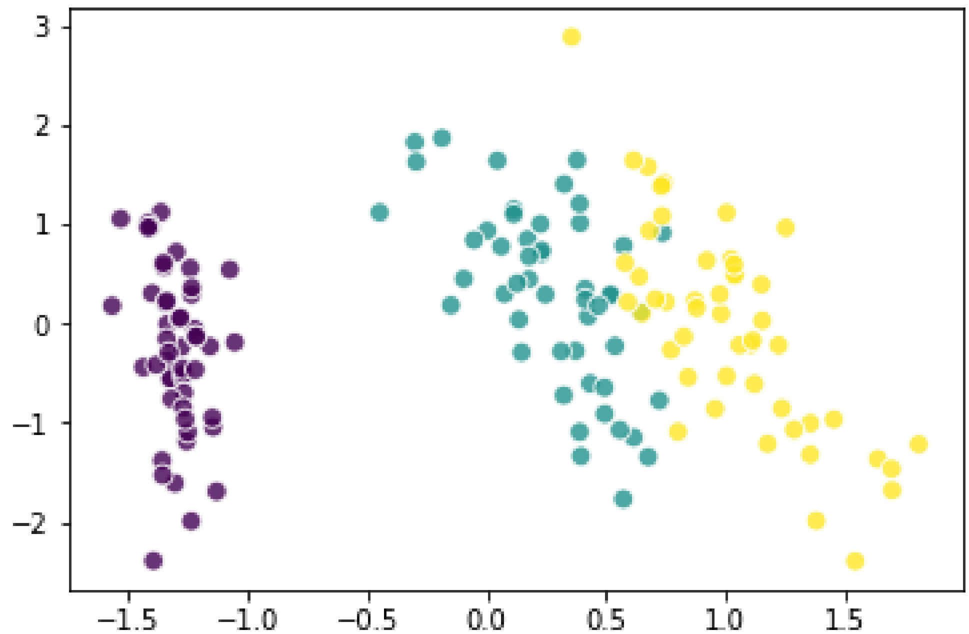
```
0.977685206318795
(150, 2)
```

```
In [12]: # Randomized PCA, mutch faster but less accurate (god for Big Data)
         from sklearn.decomposition import PCA
         rpca_2c = PCA(n_components=2, svd_solver='randomized')
         X_rpca_2c = rpca_2c.fit_transform(iris.data)
         plt.scatter(X_rpca_2c[:,0], X_rpca_2c[:,1],c=iris.target,alpha=0.8, s=60, marker='o',
         plt.show()
         print(rpca_2c.explained_variance_ratio_.sum())
         print(X_rpca_2c.shape)
```



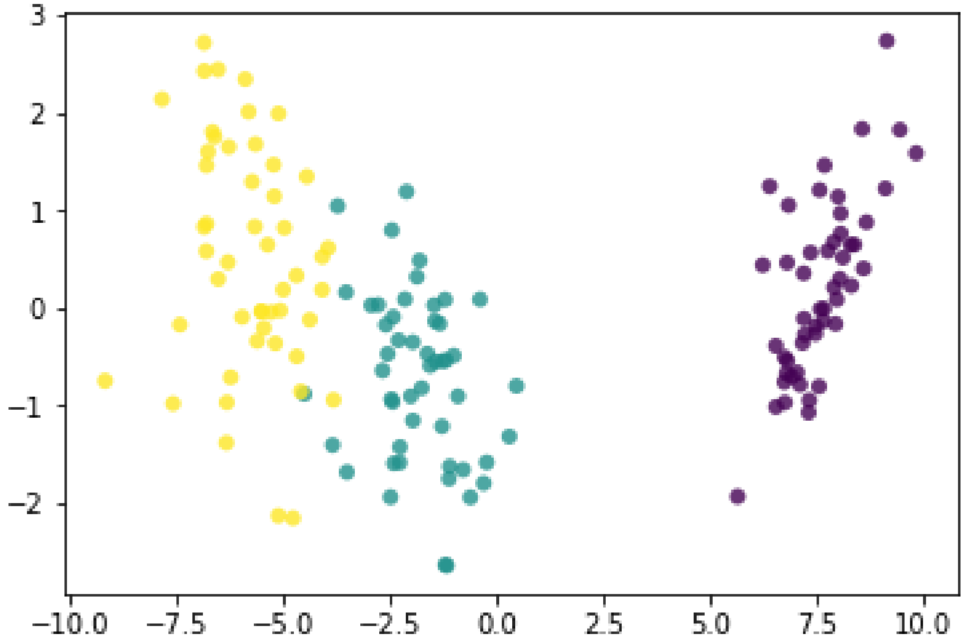

```
0.9776852063187952
(150, 2)
```

```
In [13]: # LFA - Latent Factor Analysis
         from sklearn.decomposition import FactorAnalysis
         fact_2c = FactorAnalysis(n_components=2) # We assume there is 2 latent factors
         X_factor = fact_2c.fit_transform(iris.data)
         plt.scatter(X_factor[:,0], X_factor[:,1],c=iris.target,alpha=0.8, s=60, marker='o', ec
         plt.show()
         print(rpca_2c.explained_variance_ratio_.sum())
```




```
0.9776852063187952
```

```
In [15]: # LDA - Linear Discriminant Analysis
         from sklearn.discriminant_analysis import LinearDiscriminantAnalysis  as LDA
         lda_2c = LDA(n_components = 2)
         X_lda_2c = lda_2c.fit_transform(iris.data, iris.target)
         plt.scatter(X_lda_2c[:,0], X_lda_2c[:,1],c=iris.target,alpha=0.8, edgecolors='none')
         plt.show()
         print(lda_2c.explained_variance_ratio_.sum())
```




```
0.9999999999999999
```

In [ ]: