In [1]:

```
%matplotlib inline
```

In [2]:

```
import pandas as pd
import numpy as np
```

In [3]:

```
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
# importing ploting libraries
import matplotlib.pyplot as plt
from scipy.stats import zscore
from sklearn import datasets
```

In [4]:

```
iris = datasets.load_iris()
X = iris.data

X_std = StandardScaler().fit_transform(X)
```

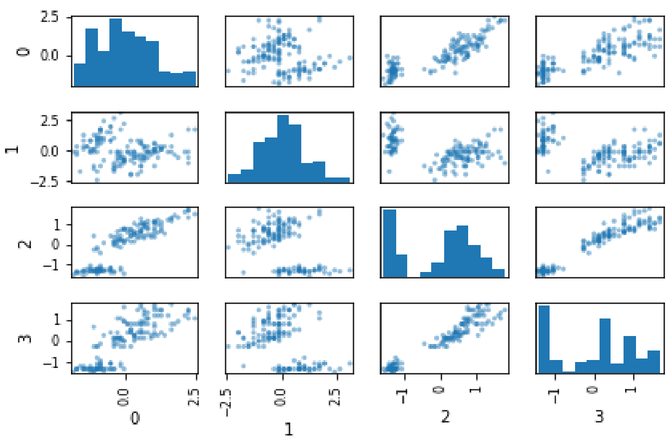
In [5]:

```
cov_matrix = np.cov(X_std.T)
print('Covariance Matrix \n%s', cov_matrix)
```

```
Covariance Matrix
%s [[ 1.00671141 -0.11835884  0.87760447  0.82343066]
 [-0.11835884  1.00671141 -0.43131554 -0.36858315]
 [ 0.87760447 -0.43131554  1.00671141  0.96932762]
 [ 0.82343066 -0.36858315  0.96932762  1.00671141]]
```

In [6]:

```
X_std_df = pd.DataFrame(X_std)
axes = pd.plotting.scatter_matrix(X_std_df)
plt.tight_layout()
```



In [7]:

```
eig_vals, eig_vecs = np.linalg.eig(cov_matrix)
```

In [8]:

```
print('Eigen Vectors \n%s', eig_vecs)
```

```
print('Eigen Vectors \n%s', eig_vecs)
print('\n Eigen Values \n%s', eig_vals)
```

```
Eigen Vectors
%s [[ 0.52106591 -0.37741762 -0.71956635  0.26128628]
 [-0.26934744 -0.92329566  0.24438178 -0.12350962]
 [ 0.5804131  -0.02449161  0.14212637 -0.80144925]
 [ 0.56485654 -0.06694199  0.63427274  0.52359713]]

 Eigen Values
%s [2.93808505 0.9201649  0.14774182 0.02085386]
```

In [15]:

```
eigen_pairs = [(np.abs(eig_vals[i]), eig_vecs[ :, i]) for i in range(len(eig_vals))]
eigen_pairs
```

Out[15]:

```
[(2.9380850501999927,
  array([ 0.52106591, -0.26934744,  0.5804131 ,  0.56485654])),
 (0.9201649041624892,
  array([-0.37741762, -0.92329566, -0.02449161, -0.06694199])),
 (0.1477418210449476,
  array([-0.71956635,  0.24438178,  0.14212637,  0.63427274])),
 (0.020853862176462064,
  array([ 0.26128628, -0.12350962, -0.80144925,  0.52359713]))]
```

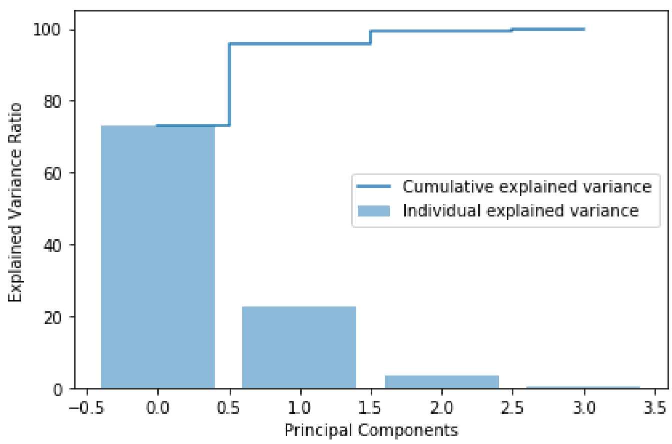
In [10]:

```
tot = sum(eig_vals)
var_exp = [( i /tot ) * 100 for i in sorted(eig_vals, reverse=True)]
cum_var_exp = np.cumsum(var_exp)
print("Cumulative Variance Explained", cum_var_exp)
```

```
Cumulative Variance Explained [ 72.96244541  95.8132072   99.48212909 100.        ]
```

In [11]:

```
plt.figure(figsize=(6 , 4))
plt.bar(range(4), var_exp, alpha = 0.5, align = 'center', label = 'Individual explained variance')
plt.step(range(4), cum_var_exp, where='mid', label = 'Cumulative explained variance')
plt.ylabel('Explained Variance Ratio')
plt.xlabel('Principal Components')
plt.legend(loc = 'best')
plt.tight_layout()
plt.show()
```

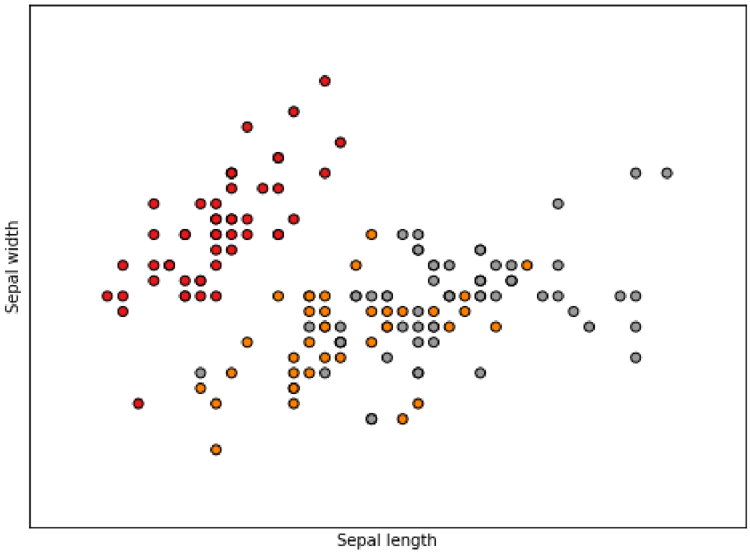


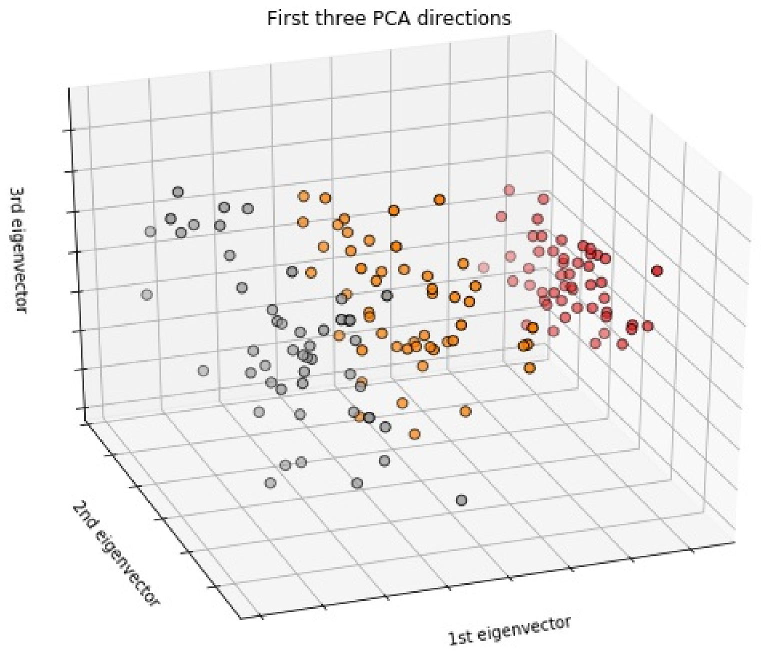
In [12]:

```
# First three principal components explain 99% of the variance in the data. The first three PCA is
shown below
# The three PCA will have to be named because they represent composite of original dimensions
```

In [13]:

```
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D
from sklearn import datasets
from sklearn.decomposition import PCA

# import some data to play with
iris = datasets.load_iris()
X = iris.data[:, :2]  # we only take the first two features.
y = iris.target

## Get the min and max of the two dimensions and extend the margins by .5 on both sides to get the
data points away
## from the origin in the plot
x_min, x_max = X[:, 0].min() - .5, X[:, 0].max() + .5
y_min, y_max = X[:, 1].min() - .5, X[:, 1].max() + .5

## plot frame size
plt.figure(2, figsize=(8, 6))
plt.clf()

# Plot the training points (scatter plot, all rows first and second column only)
plt.scatter(X[:, 0], X[:, 1], c=y, cmap=plt.cm.Set1,
            edgecolor='k')
plt.xlabel('Sepal length')
plt.ylabel('Sepal width')


## plotting the axes with ticks
plt.xlim(x_min, x_max)
plt.ylim(y_min, y_max)
plt.xticks(())
plt.yticks(())

# To getter a better understanding of interaction of the dimensions
# plot the first three PCA dimensions
fig = plt.figure(1, figsize=(8, 6))
ax = Axes3D(fig, elev=-150, azim=110)
X_reduced = PCA(n_components=3).fit_transform(iris.data)
ax.scatter(X_reduced[:, 0], X_reduced[:, 1], X_reduced[:, 2], c=y,
           cmap=plt.cm.Set1, edgecolor='k', s=40)
ax.set_title("First three PCA directions")
ax.set_xlabel("1st eigenvector")
ax.w_xaxis.set_ticklabels([])
ax.set_ylabel("2nd eigenvector")
ax.w_yaxis.set_ticklabels([])
ax.set_zlabel("3rd eigenvector")
ax.w_zaxis.set_ticklabels([])

plt.show()
```





In [0]:

```
# Source - http://scikit-learn.org/stable/auto_examples/datasets/plot_iris_dataset.html
```