LA03_Ex1_GausHist

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1 Hochschule Bonn-Rhein-Sieg

2 Learning and Adaptivity, SS18

3 Assignment 03 (24-April-2018)

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3.2 Task 1

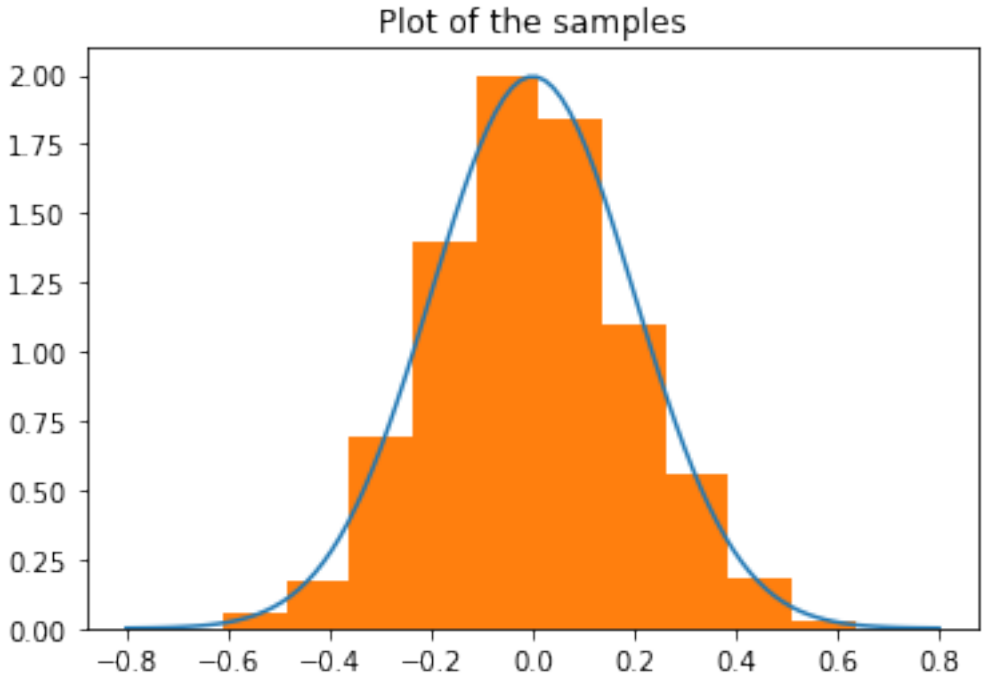
Use NumPy function to draw random samples from a normal (Gaussian) distribution. - Create a set of 2000 samples using NumPy function. This data set should be distributed as a Gaussian with mean=0 and standard deviation (std)=0.2 - For the created data set verify the mean and the variance - Display/plot the histogram of the samples, along with the probability density function using matplotlib.pyplot and np functions

```
In [1]: import numpy as np
        import matplotlib.pyplot as plt
        import scipy.stats as stats
        from scipy.stats import gaussian_kde
        from sklearn.neighbors import KernelDensity
        from matplotlib import mlab
        from __future__ import print_function
```

```
In [2]: mu = 0
        sigma = 0.2
        samples = 2000
        np.random.seed(0)
        data = np.random.normal(mu, sigma, samples)
        esstimated_mu, estimated_sigma = stats.norm.fit(data)
        print ('Difference between actual and estimated mean is {}'.format(
            abs(mu - esstimated_mu)))
        print ('Difference between actual and estimated variance is {}'.format(
            abs(mu - esstimated_mu)))
```

```
Difference between actual and estimated mean is 0.0031639767174031813
Difference between actual and estimated variance is 0.0031639767174031813
```

```
In [3]: x = np.linspace(mu - 4*sigma, mu + 4*sigma, 100)
        plt.plot(x, mlab.normpdf(x, mu, sigma))
        plt.hist(data, normed= True)
        plt.title('Plot of the samples')
        plt.show()
```



3.3 Task 2

Two-dimensional kernel density estimate: comparing scikit-learn and scipy
Reference: daleroberts Githubgist

```
In [4]: def kernel_density_estimation(N1, N2, ax, using= 'scipy'):

            x = N1+N2
            y = N1-N2

            data = np.vstack((x, y))
            x_min, x_max = x.min(), x.max()
            y_min, y_max = y.min(), y.max()

            X, Y = np.mgrid[x_min:x_max:100j, y_min:y_max:100j]
            positions = np.vstack([X.ravel(), Y.ravel()])

            if using == 'scipy':
                scipy_kernel = gaussian_kde(data)
```

```
            Z = np.reshape(scipy_kernel(positions).T, X.shape)

        elif using == 'scikit-learn':
            d, n = data.shape
            bw = (n * (d + 2) / 4.)**(-1. / (d + 4)) # silverman
            #bw = n**(-1./(d+4)) # scott

            kde = KernelDensity(bandwidth=bw, metric='euclidean',
                                kernel='gaussian', algorithm='ball_tree')
            kde.fit(data.T)
            Z = np.reshape(np.exp(kde.score_samples(positions.T)), X.shape)

        ax.imshow(np.rot90(Z), cmap=plt.cm.coolwarm,
                  extent=[x_min, x_max, y_min, y_max])
        ax.scatter(x, y, c='k', s=4, edgecolor='')
        ax.set_title(using)
        ax.set_xlabel('x')
        ax.set_ylabel('y')
```

In [5]:
```
np.random.seed(1)
N1 = np.random.normal(0, scale= np.random.random(), size= 1000)
N2 = np.random.normal(0, scale= np.random.random(), size= 1000)

fig, subplots = plt.subplots(1, 2)
fig.set_figheight(10)
fig.set_figwidth(10)
kernel_density_estimation(N1, N2, ax= subplots[0], using= 'scipy')
kernel_density_estimation(N1, N2, ax= subplots[1], using= 'scikit-learn')
plt.tight_layout()
plt.show()
```