LA03_Ex1_GausHist

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0.1 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 [2]: import numpy as np
        import matplotlib.pyplot as plt
        import matplotlib.mlab as mlab
        from scipy import stats
        import math
        from scipy.optimize import minimize
        %matplotlib inline
```

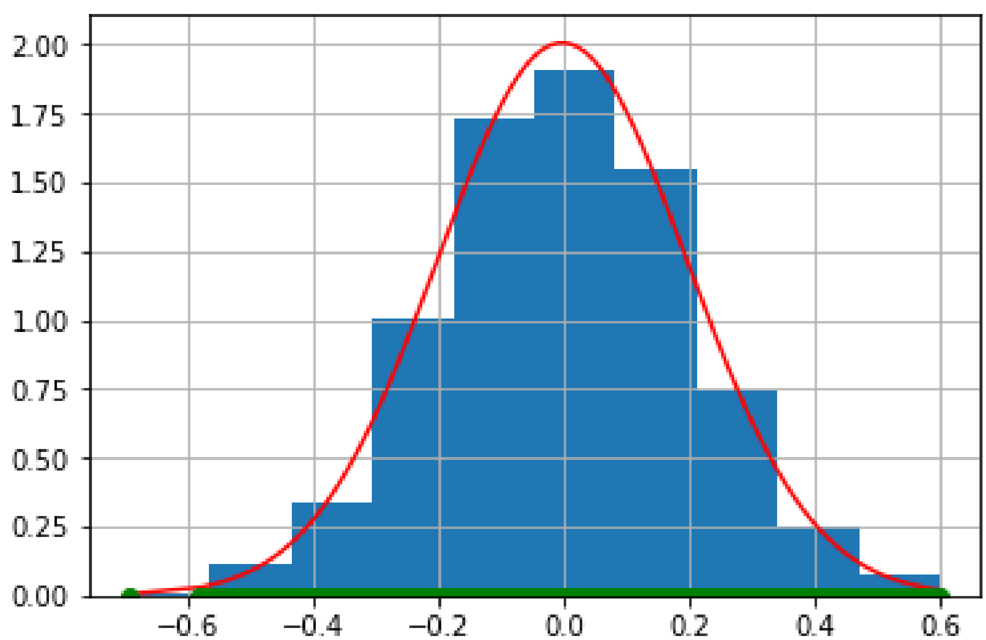
```
In [6]: N = 2000
        mu = 0
        var = 0.2
        sigma = math.sqrt(var)
        X_axis = np.linspace(-20,20,N)
        X = np.random.normal(mu,var,N)
        n, bins, patches = plt.hist(X, normed=True)
        y = mlab.normpdf( bins, mu, sigma)
        X.sort()
        plt.plot(X, stats.norm.pdf(X, np.mean(X), np.std(X)),'r')
        plt.plot(X, [0.001]*len(X), 'go')
        plt.grid()
        plt.show()

        #verifying the mean and variance using minimize function
        def minimize_function(x, args):
```

```
    #mean and sigma values
    m = x[0]
    sig = x[1]
    X_ = args[0]
    pdf = args[1]
    #computing pdf from the formula
    y_ = (np.exp(-1*((X_-m)**2)/(2*sig**2)))/(sig*np.sqrt(2*np.pi))
    #compare the above pdf with the gaussian pdf, Use stats.norm.logpdf
    #sum the difference in pdf values which should result to zero.
    compared = -np.sum(stats.norm.logpdf(y_, loc=pdf))
    return compared

#initialize mean and variance
x0 = [1,2]
pdf_ = stats.norm.pdf(X, np.mean(X), np.std(X))
args = [X, pdf_]
result = minimize(minimize_function, x0, args = args, tol=0.001, method='BFGS')
print "Actual mean:", np.mean(X)
print "Actual standard deviation:", np.std(X)
print "Verified mean:", result.x[0]
print "Verified standard deviation:", result.x[1]
```

```
/home/sushma/anaconda2/envs/my_env/lib/python2.7/site-packages/ipykernel_launcher.py:8: Matplotl
```



```
Actual mean: -0.0026209598040138216
Actual standard deviation: 0.19875059797559141
Verified mean: -0.0026209670551669015
Verified standard deviation: 0.19875059046327503
```

0.2 Task 2

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

0.2.1 Kernel Density Estimation

Kernel density estimation is a non-parametric way of estimating probability density function of a random variable X. Kernels are used for this purpose. The kernel functions are typically smooth functions with a single mode at x=0. There are several options in computing kernel density estimates in python. The task is to compare two of those options: scikit-learn and scipy.

0.2.2 Comparison of scikit-learn and scipy methodologies for KDE

scikit-learn	scipy
1) Implemented using sklearn.neighbors.KernelDensity estimator	1) Implemented using scipy.stats.gaussian_kde
2) Contains six kernels: gaussian, tophat, exponential, linear and cosine.	2) Contains only gaussian kernel.
3) Uses Ball tree or KD tree for efficient queries.	3) No Tree-based computation
4) Emperical approach namely cross validation is used for bandwidth selection.	4) The common reference rule namely Silverman's rule is used for selection of bandwidth.
5) Estimates different charecterstics since it has six kernels.	5) Can estimate only based on gaussian kernel.
6) Results in a very flexible range of effective kernel shapes.	6) It has only one gaussian kernel shape.

Citation

1. https://jakevdp.github.io/blog/2013/12/01/kernel-density-estimation/
2. http://scikit-learn.org/stable/modules/density.html
3. https://docs.scipy.org/doc/scipy-0.15.1/reference/generated/scipy.stats.gaussian_kde.html
4. http://www.mvstat.net/tduong/research/seminars/seminar-2001-05/