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Gaussian (normal) distribution

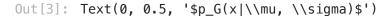
```
In [1]: import numpy as np
import matplotlib.pyplot as plt
from scipy import stats
```

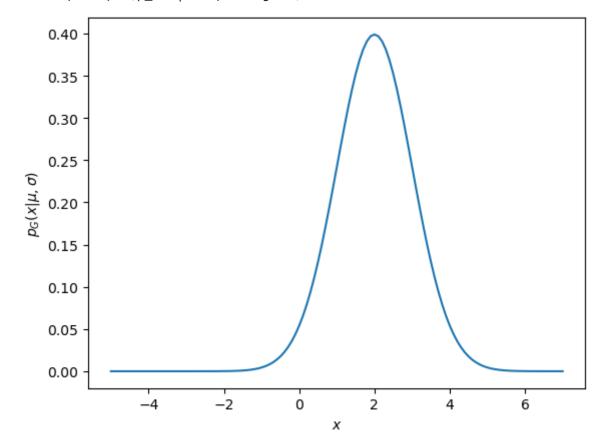
A gaussian distribution is characterized by the mean μ and standard deviation σ . See:

https://docs.scipy.org/doc/scipy/reference/generated/scipy.stats.norm.html

```
In [2]: # mean = 2, sigma = 1
    mu = 2.0
    sig = 1.0
    x = np.arange(-5.0, 7.1, 0.1)
    p = stats.norm.pdf(x, loc=mu, scale=sig)
#print(x, p)

In [3]: plt.plot(x, p)
    plt.xlabel('$x$')
    plt.ylabel('$p_G(x|\mu, \sigma)$')
```





As with other PDFs, you can sample \boldsymbol{x} values from a gaussian PDF with np.random.normal .

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```
In [4]: np.random.seed(12345)

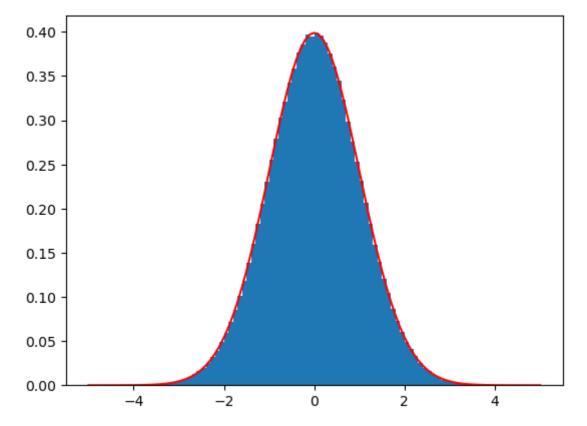
# Let's sample from a Gaussian distribution with mean=0, sigma=1
mean = 0.0
std = 1.0
d1 = np.random.normal(loc=mean, scale=std, size=1000000)

# Create bins of x values
nx = np.arange(-5.0, 5.1, 0.1)

# Let's plot the normalized histogram of the samples
n1, bins1, patches1 = plt.hist(d1, bins=nx, density=True)

# and overplot the analytical Gaussian PDF.
ny = stats.norm.pdf(nx, mean, std)
plt.plot(nx, ny, color='r')
```

Out[4]: [<matplotlib.lines.Line2D at 0x1c2f79150>]



Now let's see what happens with we sample from two different gaussians (μ_1 , σ_1) and (μ_2 , σ_2) and plot the distribution of the difference $\mu_1 - \mu_2$. You can see that the result is a new gaussian with a mean of $\mu_1 - \mu_2$ and standard deviation of $\sqrt{\sigma_1^2 + \sigma_2^2}$.

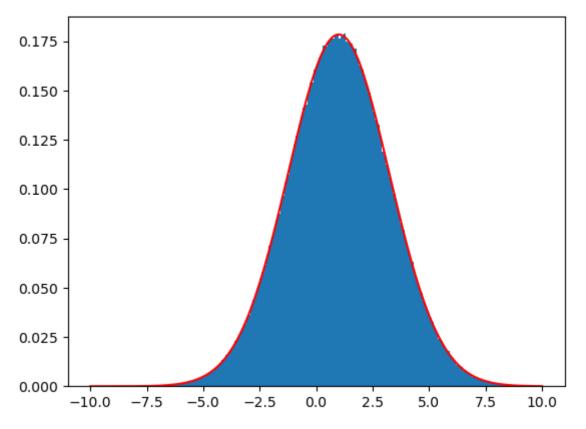
```
In [5]: np.random.seed(12345)

mean1 = 2.0
std1 = 1.0
d1 = np.random.normal(loc=mean1, scale=std1, size=1000000)

mean2 = 1.0
std2 = 2.0
```

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Out[5]: [<matplotlib.lines.Line2D at 0x1c309a3b0>]



In []: