

02_Exercise1_MaxL

April 22, 2018

0.1 Team members

Swaroop Bhandary K

Supriya Vadiraj

Vajra Ganeshkumar Let's suppose we have a set of observations $x = (x_1, \dots, x_N)^T$, that are drawn independent and identically distributed (i.i.d) from a Gaussian distribution with unknown mean μ and variance σ^2

For this example, we are going to assume that the unknown parameters are $\mu=2$ and $\sigma^2=25$ and the number of samples $N=100$.

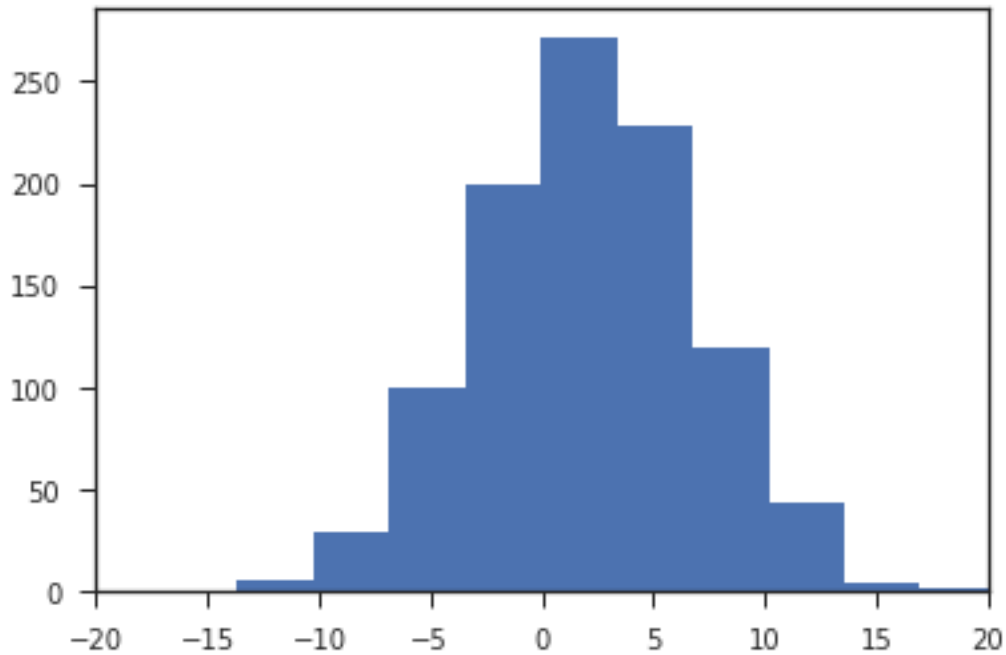
```
In [7]: import numpy as np
import matplotlib.pyplot as plt
from scipy.stats import norm
from mpl_toolkits.mplot3d import Axes3D
from scipy.stats import multivariate_normal
import seaborn as sb
```

1 Task1:

Plot this (unknown) distribution together with the samples in the range $[-20, 20]$.

```
In [54]: normal_samples = np.random.normal(2,5,1000)
plt.xlim(xmin=-20, xmax=20)

plt.hist(normal_samples)
plt.show()
```



2 Task2:

- Implement the likelihood function in python (you can simply use the existing python implementations)
- Use a general optimization method to find the values for μ and σ^2 .

```
In [8]: value = norm.fit(normal_samples)
```

```
print value
```

```
(2.1647298401520207, 4.8342003076518925)
```

3 Task3:

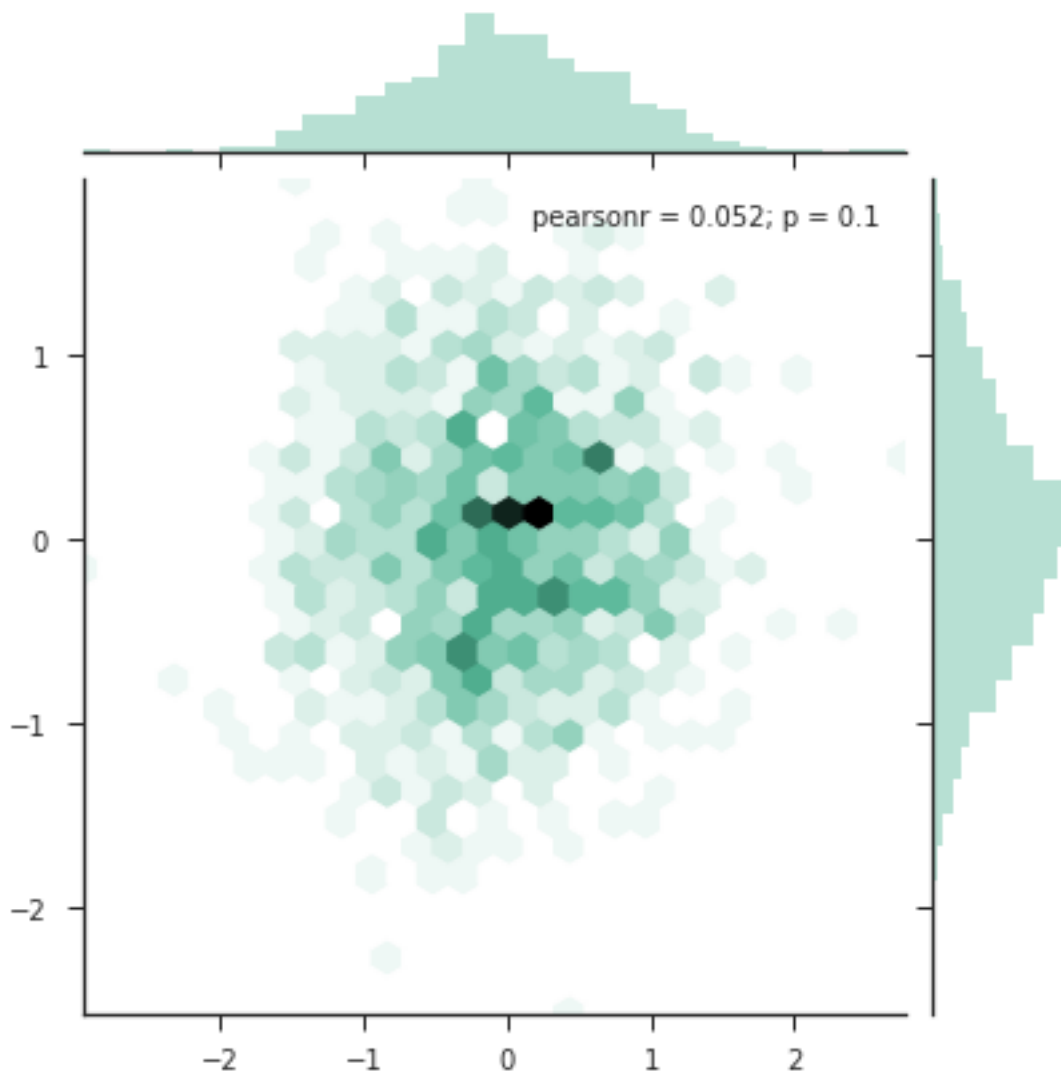
Given: $\mu = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$ $\Sigma = \begin{bmatrix} 0.5 & 0 \\ 0 & 0.5 \end{bmatrix}$ 1. Visualise a Gaussian with the given parameters. 2. Visualise a marginal Gaussian. 3. Visualise a slice of Gaussian.

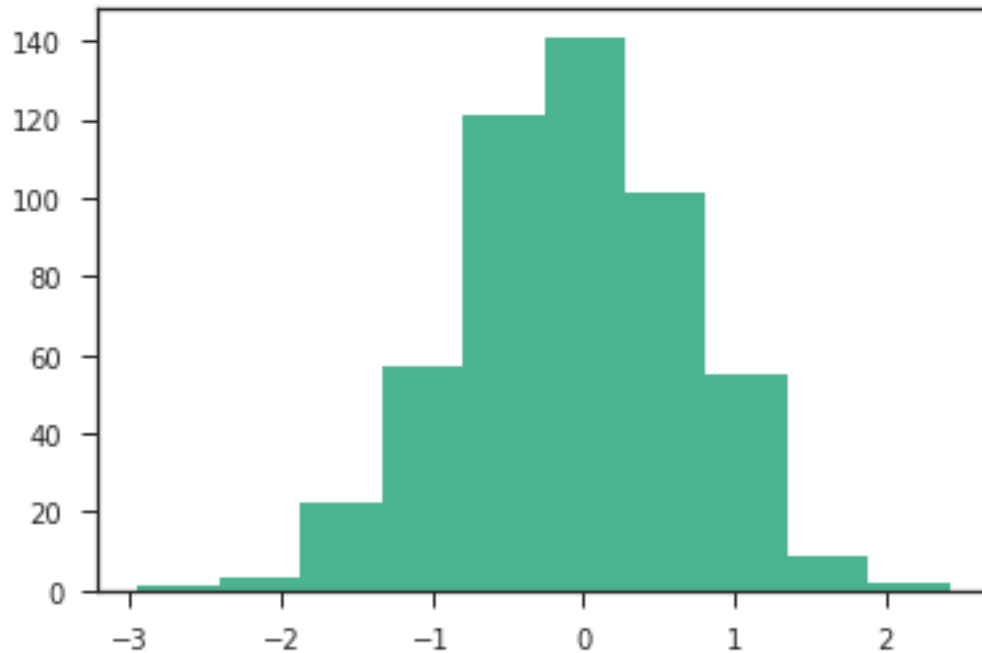
```
In [37]: mean = np.array([0,0])
         covariance = np.array([[0.5,0],[0,0.5]])
```

```
x,y = np.random.multivariate_normal(mean, covariance, 1000).T
```

```
sb.set(style="ticks")
sb.jointplot(x, y, kind="hex", color="#4CB391")
plt.show()

#visualising slice of guassian by setting y to be 0.02
plt.hist(x[np.where(y-0.02 < 1e-5)], color="#4CB391")
plt.show()
```





4 Task4:

Given: Number of samples is 1000 from them 330 samples are labeled as class A and 670 samples are labeled as class B. There are 2 features X1 and X2. It is observed that $p(A, X1)=248$, $p(A, X2)=82$, $p(B, X1)=168$, $p(B, X2)=502$ Compute: Prior $p(A)$, $p(B)$ Likelihood $p(X1|A)$, $p(X1|B)$ Posterior $p(A|X1)$

$$p(A) = 330/1000 = 0.33$$

$$p(B) = 670/1000 = 0.67$$

Likelihood:

$$p(x1|A) = p(x1, A)/p(A) = \frac{248/1000}{0.33} = 0.7515$$

$$p(x2|A) = p(x2, A)/p(A) = \frac{82/1000}{0.33} = 0.248$$

Posterior:

We will first need to find $p(x1)$

$$p(x1|B) = \frac{p(x1, B)}{p(B)} = \frac{168/1000}{670/1000} = 0.251$$

$$\begin{aligned} p(x1) &= p(x1|A) * p(A) + p(x1|B) * p(B) \\ &= 0.7515 * 0.33 + 0.251 * 0.67 \end{aligned}$$

$$= 0.4161$$

$$p(A|x1) = \frac{p(x1|A) * p(A)}{p(x1)} = \frac{0.7515 * 0.33}{0.4161} = 0.5959$$