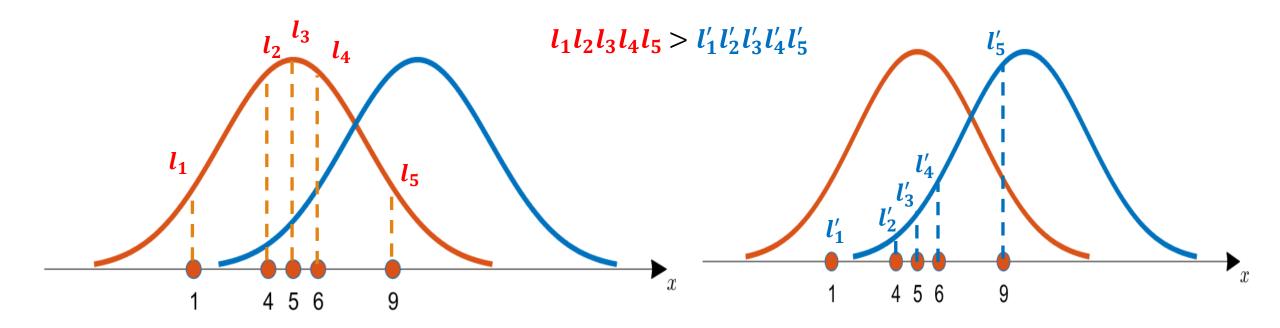
Maximum Likelihood Estimation (MLE)

20201181 JIHWAN OH

Given data $x = \{ 1, 4, 5, 6, 9 \}$

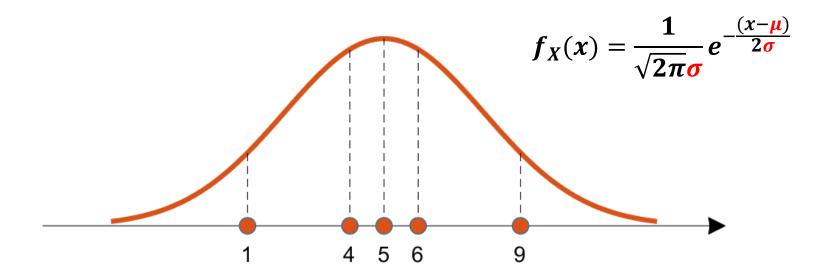
$$f_X(x) = \frac{1}{\sqrt{2\pi}\sigma_1} e^{\frac{(x-\mu_1)}{2\sigma_1}} \qquad f_X(x) = \frac{1}{\sqrt{2\pi}\sigma_2} e^{\frac{(x-\mu_2)}{2\sigma_2}}$$

Given data $x = \{ 1, 4, 5, 6, 9 \}$



Given data $x = \{ 1, 4, 5, 6, 9 \}$

Q. What is best parameter $\theta = (\mu, \sigma)$ that explain the given data well?



Definition:
$$L(heta) = p(X| heta)$$
 (Likelihood function)
$$= \prod_{n=1}^N p(x_n| heta) \quad ext{x_n are independent}$$

In Gaussian distribution, $\theta = (\mu, \sigma)$

$$p(x_n | \theta) = \frac{1}{\sqrt{2\pi}\sigma} \exp\{-\frac{(x_n - \mu)^2}{2\sigma^2}\}$$

Maximum Likelihood Estimation

We want to maximize
$$L(heta) = p(X| heta) = \prod_{n=1}^N p(x_n| heta)$$
 (Likelihood)

Objective: Minimize
$$E(\theta) = -\ln L(\theta) = -\sum_{n=1}^{N} \ln p(x_n|\theta)$$
 ($-\log Likelihood$)

Find parameter $oldsymbol{ heta}$ that minimize -Log Likelihood

$$\frac{\partial}{\partial \theta} E(\theta) = -\frac{\partial}{\partial \theta} \sum_{n=1}^{N} \ln p(x_n | \theta) = -\sum_{n=1}^{N} \frac{\frac{\partial}{\partial \theta} p(x_n | \theta)}{p(x_n | \theta)} \stackrel{!}{=} 0$$

Maximum Likelihood Estimation

In Gaussian distribution :
$$p(x_n|\mu,\sigma) = \frac{1}{\sqrt{2\pi}\sigma}e^{-\frac{||x_n-\mu||^2}{2\sigma^2}}$$

$$\frac{\partial}{\partial \mu} E(\mu, \sigma) = -\sum_{n=1}^{N} \frac{\frac{\partial}{\partial \mu} p(x_n | \mu, \sigma)}{p(x_n | \mu, \sigma)}$$

$$= -\sum_{n=1}^{N} -\frac{2(x_n - \mu)}{2\sigma^2}$$

$$= \frac{1}{\sigma^2} \sum_{n=1}^{N} (x_n - \mu)$$

$$= \frac{1}{\sigma^2} \left(\sum_{n=1}^{N} x_n - N\mu\right)$$

Estimated parameters

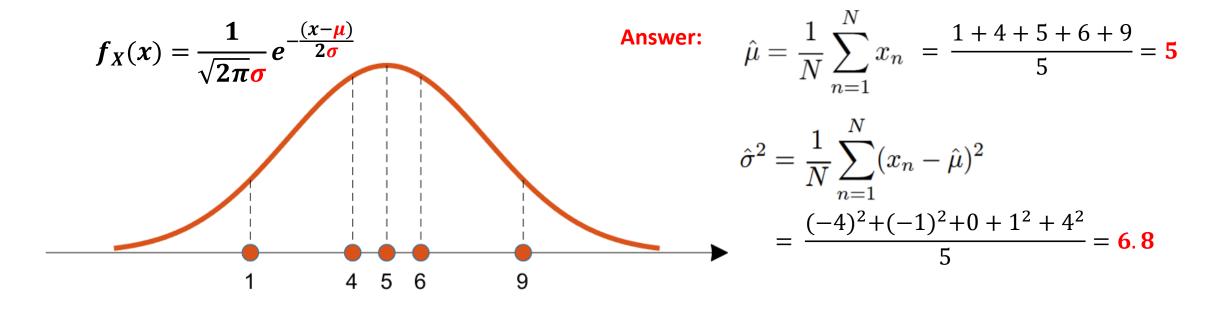
$$\hat{\mu} = \frac{1}{N} \sum_{n=1}^{N} x_n$$

$$\hat{\sigma}^2 = \frac{1}{N} \sum_{n=1}^{N} (x_n - \hat{\mu})^2$$

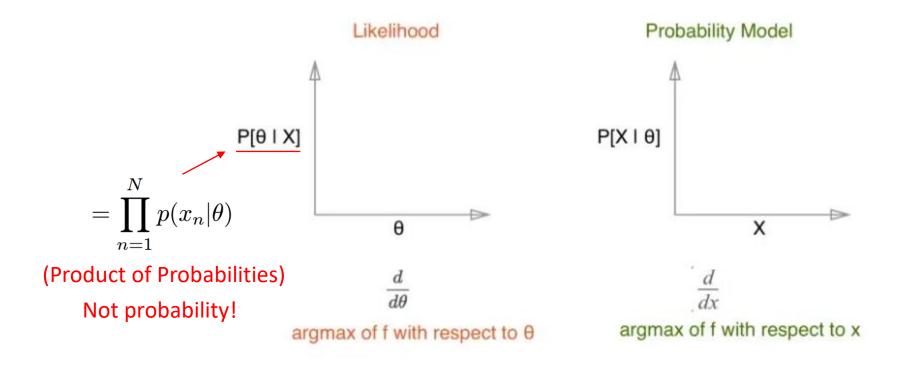
Maximum Likelihood Estimation

Given data $x = \{ 1, 4, 5, 6, 9 \}$

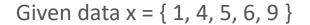
Q. What is best parameter $\theta = (\mu, \sigma)$ that explain the given data well?

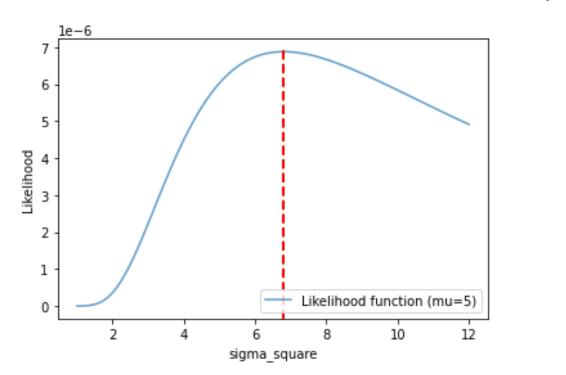


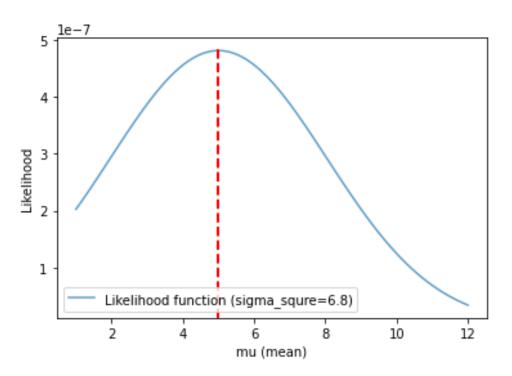
Likelihood ≠ Probability



MLE in Python







Conclusion: We can estimate the parameters of distribution using MLE.

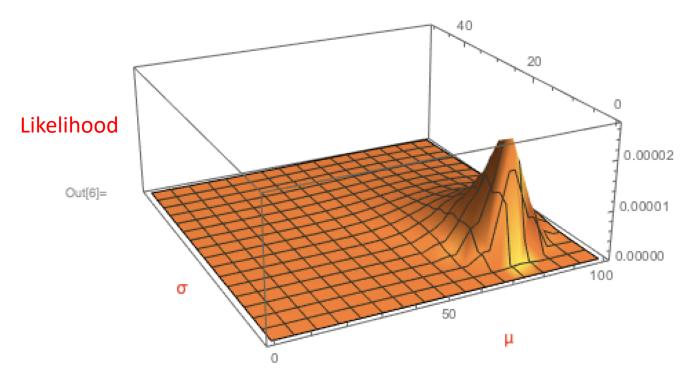
Code

```
[1] 1 import numpy as np
2 import matplotlib.pyplot as plt
3 from scipy.special import erf

1 mu = 5
2 list1 = []
3 for i in np.linspace(1, 12, 100):
4 sigma2 = i
5 Product = 1
6 for x in [1,4,5,6,9]:
7
8 y = (1 / np.sqrt(2 * np.pi * sigma2)) * np.exp(-(x-mu)**2 / (2 * sigma2))
9
10 Product = Product * y
11
12 list1.append(Product)
13 print(Product)
14

[43] 1 plt.plot(np.linspace(1, 12, 100), list1, alpha=0.7, label='Likelihood function (mu=5)')
2 plt.xlabel('sigma_square')
3 plt.ylabel('Likelihood')
4 plt.legend(loc='lower right')
5 plt.axvline(6.8, 0, 0.97, color='red', linestyle='---', linewidth=2)
6 plt.show()
```

3D Likelihood function (Gaussian Dist.)



Reference: https://towardsdatascience.com/bayes-classifier-with-maximum-likelihood-estimation-4b754b641488

Thank you