## Maths

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The PDF of a normal distribution is  $\frac{1}{\sigma\sqrt{2\pi}}*e^{-\frac{1}{2}(\frac{x-\mu}{\sigma})^2}$ . The Likelihood then becomes

$$L=(\tfrac{1}{2\pi\sigma^2})^{n/2}*exp(\tfrac{-\sum_{i=1}^n(x_i-\mu)^2}{2\sigma^2}) \text{ after multiplying the PDF over i=1 to n.}$$

The log-likehood is then  $-\frac{n}{2}log(\frac{1}{2\pi\sigma^2}) - \frac{1}{2\sigma^2}\sum_{i=1}^n(x_i-\mu)^2$  after taking the log of the likelihood. for this expression, we want to find how to pick  $\mu$  and  $\sigma$  so that we maximize it. The derivative of the log-likelihood is calculated with regards to  $\mu$  and  $\sigma$  and set = 0 to find the optimal values.

$$\frac{dL}{d\mu} = \frac{2n(\bar{x}-\mu)}{2\sigma^2} = 0$$

$$\frac{dL}{d\sigma} = -\frac{n}{\sigma} + \frac{1}{\sigma^3} \sum_{i=1}^{n} (\bar{x} - \mu)^2 = 0$$

This produces an MLE estimator for  $\mu$  which is  $\hat{\mu} = \bar{x}$ , the sample mean. The MLE estimator for  $\sigma$  is  $\hat{\sigma}^2 = \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2$ .