

## MLE estimates for a Gaussian distribution

1/1 point (graded)

In this problem, we will derive the maximum likelihood estimates for a Gaussian model.

Let  $X$  be a Gaussian random variable in d-dimensional real space ( $R^d$ ) with mean  $\mu$  and standard deviation  $\sigma$ .

Note that  $\mu, \sigma$  are the parameters of a Gaussian generative model.

Recall from the lecture that, the probability density function for a Gaussian random variable is given as follows:

$$f_X(x|\mu, \sigma^2) = \frac{1}{(2\pi\sigma^2)^{d/2}} e^{-\|x-\mu\|^2/2\sigma^2}$$

Let  $S_n = \{X^{(1)}, X^{(2)}, \dots, X^{(t)}\}$  be i.i.d. random variables following a Gaussian distribution with mean  $\mu$  and variance  $\sigma^2$ .

Then their joint probability density function is given by

$$\prod_{t=1}^n P(x^{(t)}|\mu, \sigma^2) = \prod_{t=1}^n \frac{1}{(2\pi\sigma^2)^{d/2}} e^{-\|x^{(t)}-\mu\|^2/2\sigma^2}$$

Taking logarithm of the above function, we get

$$\log\{\prod_{t=1}^n \frac{1}{(2\pi\sigma^2)^{d/2}} e^{-\|x^{(t)}-\mu\|^2/2\sigma^2}\}$$

$$= \sum_{t=1}^n \log \frac{1}{(2\pi\sigma^2)^{d/2}} + \sum_{t=1}^n \log e^{-\|x^{(t)}-\mu\|^2/2\sigma^2}$$

$$= \sum_{t=1}^n -\frac{d}{2} \log (2\pi\sigma^2) + \sum_{t=1}^n \log e^{-\|x^{(t)}-\mu\|^2/2\sigma^2}$$

$$\log P(S_n|\mu,\sigma^2) = -\frac{nd}{2} \log (2\pi\sigma^2) - \frac{1}{2\sigma^2} \sum_{t=1}^n \|x^{(t)} - \mu\|^2$$

Compute the partial derivative  $\frac{\partial \log P(S_n|\mu,\sigma^2)}{\partial \mu}$  using the above derived expression for  $P(S_n|\mu,\sigma^2)$ .

Choose the correct expression from options below.

- ☐
 $\frac{\partial \log P(S_n|\mu,\sigma^2)}{\partial \mu} = -\frac{1}{\sigma^2} \sum_{t=1}^n (x^{(t)} - \mu)$
- ☒
 $\frac{\partial \log P(S_n|\mu,\sigma^2)}{\partial \mu} = \frac{1}{\sigma^2} \sum_{t=1}^n (x^{(t)} - \mu) \checkmark$
- ☐
 $\frac{\partial \log P(S_n|\mu,\sigma^2)}{\partial \mu} = \frac{1}{\mu^2} \sum_{t=1}^n (x^{(t)} - \mu)$
- ☐
 $\frac{\partial \log P(S_n|\mu,\sigma^2)}{\partial \mu} = -\frac{1}{\mu^2} \sum_{t=1}^n (x^{(t)} - \mu)$

Solution:

$$\frac{\partial}{\partial \mu} \log P(S_n|\mu,\sigma^2)$$

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

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

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You have used 1 of 2 attempts

**i** Answers are displayed within the problem

### MLE for the mean

1/1 point (graded)  
 Use the answer from the previous problem in order to solve the following equation

$$\frac{\partial \log P(S_n | \mu, \sigma^2)}{\partial \mu} = 0$$

Compute expression for  $\hat{\mu}$  that is a solution for the above equation.

Choose the correct expression from options below

☐  $\hat{\mu} = \prod_{t=1}^n x^{(t)}$

☐  $\hat{\mu} = \frac{\prod_{t=1}^n x^{(t)}}{n}$

☐  $\hat{\mu} = \sum_{t=1}^n x^{(t)}$

☒  $\hat{\mu} = \frac{\sum_{t=1}^n x^{(t)}}{n}$  ✓

### Solution:

Recall from the previous solution that

$$\frac{\partial \log P(S_n | \mu, \sigma^2)}{\partial \mu} = \frac{1}{\sigma^2} \sum_{t=1}^n \|x^{(t)} - \mu\|$$

Setting the above expression to zero, we get:

$$\frac{1}{\sigma^2} \sum_{t=1}^n \|x^{(t)} - \hat{\mu}\| = 0$$

$$\sum_{t=1}^n \|x^{(t)} - \hat{\mu}\| = 0$$

$$\sum_{t=1}^n (x^{(t)}) - n\hat{\mu} = 0$$

Resulting in the final expression for  $\hat{\mu}$  as follows:

$$\hat{\mu} = \frac{\sum_{t=1}^n x^{(t)}}{n}$$

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## MLE for the variance

1/1 point (graded)

Compute the partial derivative  $\frac{\partial \log P(S_n | \mu, \sigma^2)}{\partial \sigma^2}$  using the above derived expression for  $P(S_n | \mu, \sigma^2)$  which is restated below as well:

$$\log P(S_n|\mu,\sigma^2) = -\frac{nd}{2}\log(2\pi\sigma^2) - \frac{1}{2\sigma^2}\sum_{t=1}^n\|x^{(t)}-\mu\|^2$$

Choose the correct expression from options below.

- ☐
 $\frac{\partial \log P(S_n|\mu,\sigma^2)}{\partial \sigma^2} = \frac{nd}{2\sigma^2} + \frac{\sum_{t=1}^n\|x^{(t)}-\mu\|^2}{2(\sigma^2)^2}$
- ☒
 $\frac{\partial \log P(S_n|\mu,\sigma^2)}{\partial \sigma^2} = -\frac{nd}{2\sigma^2} + \frac{\sum_{t=1}^n\|x^{(t)}-\mu\|^2}{2(\sigma^2)^2}$ 

- ☐
 $\frac{\partial \log P(S_n|\mu,\sigma^2)}{\partial \sigma^2} = \frac{nd}{2\sigma^2} - \frac{\sum_{t=1}^n\|x^{(t)}-\mu\|^2}{2(\sigma^2)^2}$
- ☐
 $\frac{\partial \log P(S_n|\mu,\sigma^2)}{\partial \sigma^2} = \frac{\sum_{t=1}^n\|x^{(t)}-\mu\|^2}{2(\sigma^2)^2}$

Solution:

$$\frac{\partial \log P(S_n|\mu,\sigma^2)}{\partial \sigma^2} = \frac{\partial}{\partial \sigma^2}\{-\frac{nd}{2}\log(2\pi\sigma^2)\} - \frac{\partial}{\sigma^2}\{\frac{1}{2\sigma^2}\sum_{t=1}^n\|x^{(t)}-\mu\|^2\}$$

$$\frac{\partial \log P(S_n|\mu,\sigma^2)}{\partial \sigma^2} = -\frac{nd}{2\sigma^2} + \frac{\sum_{t=1}^n\|x^{(t)}-\mu\|^2}{2(\sigma^2)^2}$$

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### MLE for the variance

1/1 point (graded)  
Using the answer from the previous problem in order to solve the equation

$$\frac{\partial \log P(S_n|\mu,\sigma^2)}{\partial \sigma^2} = 0$$

Compute expression for  $\hat{\sigma}^2$  that is a solution for the above equation.

Choose the correct expression from options below

- ☒
 $\hat{\sigma}^2 = \frac{\sum_{t=1}^n(x^{(t)}-\mu)^2}{nd}$ 

- ☐
 $\hat{\sigma}^2 = -\frac{\sum_{t=1}^n(x^{(t)}-\mu)^2}{nd}$
- ☐
 $\hat{\sigma}^2 = -\frac{\sum_{t=1}^n(x^{(t)}-\mu)^2}{n}$
- ☐
 $\hat{\sigma}^2 = -\frac{\Pi_{t=1}^n(x^{(t)}-\mu)^2}{nd}$

**Solution:**

Recall from the previous solution that

$$\frac{\partial \log P(S_n | \mu, \sigma^2)}{\partial \sigma^2} = -\frac{nd}{2\sigma^2} + \frac{\sum_{t=1}^n \|x^{(t)} - \mu\|^2}{2(\sigma^2)^2}$$

Setting the above expression to zero, we get:

$$-\frac{nd}{2\sigma^2} + \frac{\sum_{t=1}^n \|x^{(t)} - \mu\|^2}{2(\sigma^2)^2} = 0$$

$$nd = \frac{\sum_{t=1}^n \|x^{(t)} - \mu\|^2}{\sigma^2}$$

The above equation leads us to our final expression for  $\hat{\sigma}^2$ :

$$\hat{\sigma}^2 = \frac{\sum_{t=1}^n (x^{(t)} - \mu)^2}{nd}$$

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**i** Answers are displayed within the problem

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## Discussion

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**Topic:** Unit 4 Unsupervised Learning (2 weeks) :Lecture 15. Generative Models / 10. MLEs for Gaussian distribution