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### 3. EM Algorithm

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Homework due Apr 19, 2023 08:59 -03 Completed

Consider the following mixture of two Gaussians:

$$p(x; \theta) = \pi_1 \mathcal{N}(x; \mu_1, \sigma_1^2) + \pi_2 \mathcal{N}(x; \mu_2, \sigma_2^2)$$

This mixture has parameters  $\theta = \{\pi_1, \pi_2, \mu_1, \mu_2, \sigma_1^2, \sigma_2^2\}$ . They correspond to the mixing proportions, means, and variances of each Gaussian. We initialize  $\theta$  as  $\theta_0 = \{0.5, 0.5, 6, 7, 1, 4\}$ .

We have a dataset  $\mathcal{D}$  with the following samples of  $x$ :  $x^{(0)} = -1, x^{(1)} = 0, x^{(2)} = 4,$

We want to set our parameters  $\theta$  such that the data log-likelihood  $l(\mathcal{D}; \theta)$  is maximized.

$$\operatorname{argmax}_{\theta} \sum_{i=0}^4 \log p(x^{(i)}; \theta).$$

Recall that we can do this with the EM algorithm. The algorithm optimizes a lower bound, thus iteratively pushing the data likelihood upwards. The iterative algorithm is specified successively:

1. E-step: infer component assignments from current  $\theta_0 = \theta$  (complete the data)

$$p(y = k | x^{(i)}) := p(y = k | x^{(i)}; \theta_0), \text{ for } k = 1, 2, \text{ and } i = 0, \dots, 4.$$

2. M-step: maximize the expected log-likelihood

$$\tilde{l}(\mathcal{D}; \theta) := \sum_i \sum_k p(y = k | x^{(i)}) \log \frac{p(x^{(i)}, y = k; \theta)}{p(y = k | x^{(i)})}$$

with respect to  $\theta$  while keeping  $p(y = k | x^{(i)})$  fixed.

To see why this optimizes a lower bound, consider the following inequality:

$$\log p(x; \theta) = \log \sum_y p(x, y; \theta)$$

*Limit Theorems and Classical Statistics, Additional Theoretical Material, 2. Jensen's Ine*

## Likelihood Function

0/1 point (graded)

What is the log-likelihood of the data given the initial setting of ? Please round

*Note:* You will want to write a script to calculate this, using the natural log (np.log) and

2.13



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You have used 3 of 3 attempts

## E-Step

1/1 point (graded)

What is the formula for ? Write in terms of , , , , , and ).

$$\pi_k * N_k / (\pi_1 * N_1 + \pi_2 * N_2)$$


? STANDARD NOTATION

Submit

You have used 1 of 3 attempts

## E-Step Weights

5/5 points (graded)

For each of the given data points say which Gaussian (1 or 2) they are given more weight in the E-step using the given setting of . This is, answer 2 if otherwise.

2



2



Fixing  $\hat{\mu}$ , we want to update  $\gamma_i$  such that our lower bound is maximized.

What is the optimal  $\gamma_i$ ? For simplicity, assume we only have two data points  $x_1$  and  $x_2$  and question. Answer in terms of  $x_1$ ,  $x_2$ , and  $\gamma_1$ ,  $\gamma_2$ , which are defined to be

(For ease of input, use subscripts instead superscripts, i.e. type  $x_i$  for  $x_i$ . Type  $\gamma_i$  for  $\gamma_i$ .)

$$(\gamma_{k1} * x_1 + \gamma_{k2} * x_2) / (\gamma_{k1} + \gamma_{k2})$$




What is the optimal  $\hat{\mu}$ ? Answer in terms of  $x_1$ ,  $x_2$ , and  $\gamma_1$ ,  $\gamma_2$ , which are defined as above to  $\gamma_i$ , and  $\hat{\mu}$ .

(Type  $\hat{\mu}_k$  for  $\hat{\mu}_k$ . As above, for ease of input, use subscripts instead superscripts, i.e. type  $\gamma_i$  for  $\gamma_i$ .)

$$(\gamma_{k1} * (x_1 - \hat{\mu}_k)^2 + \gamma_{k2} * (x_2 - \hat{\mu}_k)^2) / (\gamma_{k1} + \gamma_{k2})$$




What is the optimal  $\hat{\mu}$ ? Answer in terms of  $x_1$  and  $x_2$ , which are defined as above to  $\gamma_i$ , and  $\hat{\mu}$ .

(As above, type  $\gamma_i$  for  $\gamma_i$ .)

Note: that you must account for the constraint that  $\gamma_i \geq 0$  where  $\gamma_i$  is the weight of  $x_i$ .

Note: If you know that some aspect of your formula equals an exact constant, simplify it to that constant.

$$(\gamma_{k1} + \gamma_{k2}) / 2$$



You have used 1 of 1 attempt

## Training 2

0/1 point (graded)

In the first M-step, which Gaussian's variance will increase more (relatively)?

☒ Gaussian 1☐ Gaussian 2

You have used 1 of 1 attempt

## Training 3

0/1 point (graded)

After convergence, which variance will be larger?

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You have used 1 of 1 attempt

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✓ Likelihood Function: which one should we calculate?

? In the first part, where should I use np.float64?

where should I use np.float64? I started my script with import numpy as np from scipy.stats import norm dtype

? Training 3 - after convergence

I don't really see how to qualitatively answer this question. Do we need to run EM to see how the variance ch

? M - step (why not drop the denominator?)

In the M - step described above, why don't we drop the denominator inside the log function, which is assum

💬 "hatmu\_k" is not accepted as a variable in the formula

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