测验, 4个问题

✔ 恭喜!您通过了!

下一项



1/1分

1.

Recall the derivation of EM algorithm. In our notation, X is observable data, Z is latent variable and θ is a vector of model parameters. We introduced q(Z) — an arbitrary distribution over the latent variable. Choose the correct expressions for the marginal log-likelihood $\log p(X\mid\theta)$:

$$\int q(Z)\lograc{p(X,Z| heta)}{q(Z)}\,dZ + \int q(Z)\lograc{q(Z)}{p(Z|X, heta)}\,dZ$$

正确

$$egin{aligned} &\int q(Z)\lograc{p(X,Z| heta)}{q(Z)}\,dZ + \int q(Z)\lograc{q(Z)}{p(Z|X, heta)}\,dZ = \ &\int q(Z)\log p(X,Z| heta)dZ - \int q(Z)\log q(Z)dZ + \ &+ \int q(Z)\log q(Z)dZ - \int q(Z)\log p(Z|X, heta)dZ = \ &= \int q(Z)\lograc{p(X,Z| heta)}{p(Z|X, heta)}\,dZ = \int q(Z)\log p(X| heta)dZ = \log p(X| heta) \end{aligned}$$

$$\log \int p(X,Z|\theta)dZ$$

正确

Z is integrated out:

$$\log \int p(X, Z|\theta) dZ = \log p(X|\theta)$$

$$oxed{egin{array}{c} oxed{\mathbb{E}_{q(Z)} \log p(X,Z| heta)} - \mathbb{E}_{q(Z)} \log p(Z|X, heta)}$$

正确

$$egin{aligned} \mathbb{E}_{q(Z)} \log p(X,Z| heta) &- \mathbb{E}_{q(Z)} \log p(Z|X, heta) = \ &= \mathbb{E}_{q(Z)} \log rac{p(X,Z| heta)}{p(Z|X, heta)} = \mathbb{E}_{q(Z)} \log p(X| heta) = \log p(X| heta) \end{aligned}$$

 $\int q(Z) \log p(X| heta) dZ$

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正确

 $\log p(X|\theta)$ does not depend on Z.

$$\int q(Z) \log p(X|\theta) dZ = \log p(X|\theta)$$



1/1分

2。

In EM algorithm, we maximize variational lower bound $\mathcal{L}(q,\theta) = \log p(X|\theta) - \mathrm{KL}(q|p)$ with respect to q (E-step) and θ (M-step) iteratively. Why is the maximization of lower bound on E-step equivalent to minimization of KL divergence?



Because uncomplete likelihood does not depend on q(Z)

正确

Revise E-step details video

Because we cannot maximize lower bound w.r.t. $q(Z)$
Because posterior becomes tractable
Because of Jensen's inequality



1/1分

3。

Select correct statements about EM algorithm:

E-step can always be performed analytically

未选择的是正确的

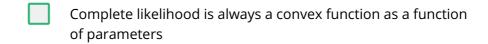
M-step can always be performed analytically

未选择的是正确的

4/4 分 (100%)

测验, 4个问题

Revise M-step details video



未选择的是正确的

EM algorithm always converges to a global optimum

未选择的是正确的



1/1分

4。

Consider $p(x) = \mathcal{N}(\mu, \sigma_1)$ and $q(x) = \mathcal{N}(\mu, \sigma_2)$. Calculate KL divergence between these two gaussians $\mathsf{KL}(p||q)$ (hint: note that KL divergence is an expectation):

$$\log \frac{\sigma_2}{\sigma_1} - \frac{1}{2} + \frac{\sigma_1^2}{2\sigma_2^2}$$

正确

$$KL(p||q) = \mathbb{E}_p \log rac{\mathcal{N}(x|\mu,\sigma_1^2)}{\mathcal{N}(x|\mu,\sigma_2^2)} = \mathbb{E}_p \log rac{\left(\sqrt{2\pi\sigma_1^2}
ight)^{-1} \exp\left(-rac{(x-\mu)^2}{2\sigma_1^2}
ight)}{\left(\sqrt{2\pi\sigma_2^2}
ight)^{-1} \exp\left(-rac{(x-\mu)^2}{2\sigma_2^2}
ight)} =$$

$$=\mathbb{E}_p \Big[\log \frac{\sigma_2}{\sigma_1} + \log \frac{\exp\left(-\frac{(x-\mu)^2}{2\sigma_1^2}\right)}{\exp\left(-\frac{(x-\mu)^2}{2\sigma_2^2}\right)}\Big] = \mathbb{E}_p \Big[\log \frac{\sigma_2}{\sigma_1} - \frac{(x-\mu)^2}{2\sigma_1^2} + \frac{(x-\mu)^2}{2\sigma_2^2}\Big] =$$

$$=\log \tfrac{\sigma_2}{\sigma_1} - \tfrac{\mathbb{E}p(x-\mu)^2}{2\sigma_1^2} + \tfrac{\mathbb{E}p(x-\mu)^2}{2\sigma_2^2} = \log \tfrac{\sigma_2}{\sigma_1} - \tfrac{\sigma_1^2}{2\sigma_1^2} + \tfrac{\sigma_1^2}{2\sigma_2^2} = \log \tfrac{\sigma_2}{\sigma_1} - \tfrac{1}{2} + \tfrac{\sigma_1^2}{2\sigma_2^2}$$

$$\log \frac{\sigma_1}{\sigma_2} + \frac{\sigma_1^2 - \sigma_2^2}{\sigma_1^2 + \sigma_2^2}$$

$$\log \frac{\sigma_1}{\sigma_2} + \frac{\sigma_2^2}{\sigma_1^2}$$

$$\log rac{\sigma_2^2}{\sigma_1^2} - rac{\sigma_1^2}{2\sigma_2^2}$$

EM algorithm

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4/4 分 (100%)

