

Principal Component Analysis

Principal Component Analysis

E-step

$$\begin{aligned} q(t_i) = p(t_i \mid x_i, \theta) &= \frac{p(x_i \mid t_i, \theta)p(t_i)}{Z} \\ &= \mathcal{N}(\tilde{\mu}_i, \tilde{\Sigma}_i) \end{aligned}$$

Principal Component Analysis

M-step

$$\begin{aligned} & \max_{\theta} \mathbb{E}_{q(T)} \sum_i \log p(x_i \mid t_i, \theta) p(t_i) \\ &= \sum_i \mathbb{E}_{q(t_i)} \log \left(\frac{1}{Z} \exp(\dots) \exp(\dots) \right) \end{aligned}$$

(as defined in
previous slide
- likelihood)

Principal Component Analysis

M-step

$$\begin{aligned} & \max_{\theta} \mathbb{E}_{q(T)} \sum_i \log p(x_i \mid t_i, \theta) p(t_i) \\ &= \sum_i \log \frac{1}{Z} \\ &+ \sum_i \mathbb{E}_{q(t_i)} \log (\exp(\dots) \exp(\dots)) \end{aligned}$$

Z doesn't depend on theta. So we can just separate it as follows:

Principal Component Analysis

M-step

$$\max_{\theta} \mathbb{E}_{q(T)} \sum_i \log p(x_i \mid t_i, \theta) p(t_i)$$

$$= \sum_i \log \frac{1}{Z}$$

$$+ \sum_i \mathbb{E}_{q(t_i)} \log \left(\exp(\dots) \exp \left(-\frac{t_i^2}{2} \right) \right)$$

in the one dimensional case. This is just standard normal pdf.

Principal Component Analysis

This is the squared distance from the actual point x_i and the projection of t_i into the multidimensional space as a linear function $Wt_i + b$.

Smart!

We defined it as the probability that x_i is equal to something given the parameters θ (I believe W and b are included in this θ), and latent variable t_i . If the probability is high, that means the distance shouldn't be that far. They gotta be close to each other.

M-step

$$\begin{aligned} & \max_{\theta} \mathbb{E}_{q(T)} \sum_i \log p(x_i \mid t_i, \theta) p(t_i) \\ &= \sum_i \log \frac{1}{Z} \\ &+ \underbrace{\sum_i \mathbb{E}_{q(t_i)} \log \left(\exp \left(-\frac{(x - Wt_i - b)^2}{2\sigma^2} \right) \exp \left(-\frac{t_i^2}{2} \right) \right)}_{at_i^2 + ct_i + d} \end{aligned}$$

And this is because we take the log of the exp. Aha! ^^

And we can compute this analytically because it is quadratic. Simple equation.

Summary

Probabilistic formulation of PCA

- Allows for missing values
- Straightforward iterative scheme for large dimensionalities
- Can do mixture of PPCA
- Hyperparameter tuning (number of components or choose between diagonal and full covariance)