

23/9/19

EES301: Representation Learning

- Review
- GMM
- EM for GMM

Review: • Recall the example of a latent/hidden random variable from the coin example.

- Also recall the GMM distribution:

$$p(\underline{x}; \underline{\theta}) = \sum_{k=1}^K \pi_k \mathcal{N}(\underline{x}; \underline{\mu}_k, \Sigma_k);$$

$$\underline{\theta} = \{ \pi_k, \underline{\mu}_k, \Sigma_k \}_{k=1}^K; \quad \sum_{k=1}^K \pi_k = 1; \quad 0 \leq \pi_k \leq 1$$

Goal: Express $p(\underline{x})$ as a marginal distribution of $p(\underline{x}, \underline{z})$ where \underline{z} is a latent random variable

$$p(\underline{x}) = \sum_{\underline{z}} p(\underline{x}, \underline{z})$$

$$= \sum_{\underline{z}} p(\underline{z}) \cdot p(\underline{x} | \underline{z}). \quad - \textcircled{0}$$

Soln: Defn $\underline{z} \equiv [0, \dots, 1, \dots, 0]^T$ is a one hot vector ^{of length K}, $\Rightarrow \underline{z}$ is zero everywhere except at the k^{th} index.

- Let $p(z_k = 1) \equiv \pi_k$.
- observation: \underline{z} can take K different values

- Now, $p(\underline{z}) = \prod_{k=1}^K \pi_k^{z_k}$ — (1)

- Let us define $p(x | z_k = 1) = \mathcal{N}(x; \mu_k, \Sigma_k)$

$$p(x | \underline{z}) = \prod_{k=1}^K \mathcal{N}(x; \mu_k, \Sigma_k)^{z_k}$$
 — (2)

Plug in (1) & (2) into (0). Note that \underline{z} can take K possible values.

$$\begin{aligned} \Rightarrow \sum_{\underline{z}} p(\underline{z}) \cdot p(x | \underline{z}) &= \sum_{k=1}^K \left[\prod_{i=1}^K \pi_k^{z_i} \prod_{j=1}^K \mathcal{N}(x; \mu_j, \Sigma_j)^{z_j} \right] \\ &= \sum_{k=1}^K \pi_k \cdot \mathcal{N}(x; \mu_k, \Sigma_k) \end{aligned}$$

Q OK, where is this helpful?

A: (1) We can now work with $p(\underline{z})$, $p(x | \underline{z})$ instead of with $p(x)$.

(2) Log likelihood function: $L(\underline{x}; \underline{\theta})$

$$= \sum_{i=1}^N \log p(x_i; \underline{\theta})$$

$$= \sum_{i=1}^N \log \left[\sum_{k=1}^K \pi_k \mathcal{N}(x_i; \mu_k, \Sigma_k) \right]$$

let us suppose we have 1d data
 $p(x; \theta)$

