
Exercise 12 of Machine Learning [IN 2064]

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Problem 1

To be seen in the end.

Problem 2

According to [1], let the linear encoder be

$$\mathbf{h} = f(\mathbf{x}) = \mathbf{W}^T(\mathbf{x} - \boldsymbol{\mu}) \quad (1)$$

The encoder computes a low-dimensional representation of \mathbf{h} . With the autoencoder view, we have a decoder computing the reconstruction:

$$\hat{\mathbf{x}} = g(\mathbf{h}) = \mathbf{b} + \mathbf{V}\mathbf{h} \quad (2)$$

The choice of linear encoder and decoder that minimize reconstruction error $\mathbb{E}[\|\mathbf{x} - \hat{\mathbf{x}}\|^2]$ correspond to $\mathbf{V} = \mathbf{W}$, $\boldsymbol{\mu} = \mathbb{E}[\mathbf{x}]$ and the columns of \mathbf{W} form an orthogonal basis which spans the same subspace as the principle eigenvectors of the covariance matrix

$$\mathbf{C} = \mathbb{E}[(\mathbf{x} - \boldsymbol{\mu})(\mathbf{x} - \boldsymbol{\mu})^T] \quad (3)$$

what we've already known is that the eigenvalue λ_i of \mathbf{C} corresponds to the variance of \mathbf{x} in the direction of eigenvector $\mathbf{v}^{(i)}$. If $\mathbf{x} \in \mathbb{R}^D$ and $\mathbf{h} \in \mathbb{R}^d$ with $K < D$, then the optimal reconstruction error(choosing $\boldsymbol{\mu}$, \mathbf{b} , \mathbf{W} and \mathbf{V} as above) is

$$\min \mathbb{E}[\|\mathbf{x} - \hat{\mathbf{x}}\|^2] = \sum_{i=K+1}^D \lambda_i \quad (4)$$

- So only on the condition that the covariance has rank K , the eigenvalues λ_{K+1} to λ_D are 0 and reconstruction error is 0.
- Thus, it is usually impossible to get zero reconstruction error in the setting that $K < D$.

Problem 3

For expected value, using iterated expectations, we have:

$$\begin{aligned} \mathbb{E}[\mathbf{x}] &= \mathbb{E}_{p(z)}[\mathbb{E}_{p(\mathbf{x}|z)}[\mathbf{x}|z]] \\ &= \sum_{k=1}^K \pi_k \mathbb{E}_{p(\mathbf{x}|z)}[\mathbf{x}|z] \\ &= \sum_{k=1}^K \pi_k \boldsymbol{\mu}_k \end{aligned} \quad (5)$$

For covariance, since

$$\begin{aligned}
\mathbb{E}[\mathbf{x}\mathbf{x}^T] &= \mathbb{E}_{p(z)}[\mathbb{E}_{p(\mathbf{x}\mathbf{x}^T|z)}[\mathbf{x}\mathbf{x}^T|z]] \\
&= \sum_{k=1}^K \pi_k \mathbb{E}_{p(\mathbf{x}|z)}[\mathbf{x}\mathbf{x}^T|z] \\
&= \sum_{k=1}^K \pi_k (\sigma_k + \boldsymbol{\mu}_k \boldsymbol{\mu}_k^T)
\end{aligned} \tag{6}$$

So we have

$$\begin{aligned}
Cov[\mathbf{x}] &= \mathbb{E}[\mathbf{x}\mathbf{x}^T] - \mathbb{E}[\mathbf{x}]\mathbb{E}[\mathbf{x}]^T \\
&= \sum_{k=1}^K \pi_k (\sigma_k + \boldsymbol{\mu}_k \boldsymbol{\mu}_k^T) - \sum_{i=1}^K \sum_{j=1}^K \pi_i \pi_j \boldsymbol{\mu}_i \boldsymbol{\mu}_j^T
\end{aligned} \tag{7}$$

Problem 4

a) The generative process is showed as below:

- Draw k from the categorical distribution on $1, \dots, K_x$ with probability from $\boldsymbol{\pi}^x$
- Draw $\tilde{\mathbf{x}}$ from the normal distribution $\mathcal{N}(\boldsymbol{\mu}_k^x, \boldsymbol{\Sigma}_k^x)$
- Draw l from the categorical distribution on $1, \dots, K_y$ with probability from $\boldsymbol{\pi}^y$
- Draw $\tilde{\mathbf{y}}$ from the normal distribution $\mathcal{N}(\boldsymbol{\mu}_l^y, \boldsymbol{\Sigma}_l^y)$
- Return $\tilde{\mathbf{z}} := \tilde{\mathbf{x}} + \tilde{\mathbf{y}}$

b) The sum of a two Gaussian distribution is still a Gaussian distribution

c) The distribution of \mathbf{z} is showed below:

$$p(\mathbf{z}|\boldsymbol{\theta}^x, \boldsymbol{\theta}^y) = \sum_{k=1}^{K_x} \sum_{l=1}^{K_y} \pi_k^x \pi_l^y \mathcal{N}(\mathbf{z}|\boldsymbol{\mu}_k^x + \boldsymbol{\mu}_l^y, \boldsymbol{\Sigma}_k^x + \boldsymbol{\Sigma}_l^y) \tag{8}$$

Problem 5

To be seen in the end.

References

- [1] Ian J. Goodfellow, Yoshua Bengio, and Aaron Courville. *Deep Learning*. MIT Press, Cambridge, MA, USA, 2016. <http://www.deeplearningbook.org>.