

Homework W2

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1 Multivariate Gaussian Distribution

The distribution is normalized if the area under the curve is equal to 1.

Assume

$$I = \int_{-\infty}^{+\infty} p(x|\mu, \sigma^2) = \int_{-\infty}^{+\infty} \frac{1}{(2\pi)^{\frac{D}{2}} |\Sigma|^{\frac{1}{2}}} \exp(-\frac{1}{2}(x-\mu)^{\top} \Sigma^{-1} (x-\mu)) dx$$

Set

$$\begin{aligned} \Delta^2 &= -\frac{1}{2}(x-\mu)^{\top} \Sigma^{-1} (x-\mu) \\ &= -\frac{1}{2}(x^{\top} - \mu^{\top}) \Sigma^{-1} (x-\mu) \\ &= -\frac{1}{2}x^{\top} \Sigma^{-1} x + \frac{1}{2}x^{\top} \Sigma^{-1} \mu + \frac{1}{2}\mu^{\top} \Sigma^{-1} x - \frac{1}{2}\mu^{\top} \Sigma^{-1} \mu \end{aligned} \quad (1)$$

With

$$-\frac{1}{2}\mu^{\top} \Sigma^{-1} \mu$$

is a constant, so we will mark it as "const."

Now, we proof that:

$$\frac{1}{2}x^{\top} \Sigma^{-1} \mu = \frac{1}{2}\mu^{\top} \Sigma^{-1} x$$

Firstly, we have

$$\frac{1}{2}x^{\top} \Sigma^{-1} \mu \in R \Rightarrow (\frac{1}{2}x^{\top} \Sigma^{-1} \mu)^{\top} = \frac{1}{2}x^{\top} \Sigma^{-1} \mu \quad (2)$$

Secondly, we have

$$\left(\frac{1}{2}x^T \Sigma^{-1} \mu = \frac{1}{2} \mu^T \Sigma^{-1} x \text{ (because } (a^T b)^T = b^T a)\right) \quad (3)$$

From (2), (3)

$$\Rightarrow \frac{1}{2}x^T \Sigma^{-1} \mu = \frac{1}{2} \mu^T \Sigma^{-1} x$$

Continue from (1), we have

$$\Delta^2 = -\frac{1}{2}x^T \Sigma^{-1} x + x^T \Sigma^{-1} \mu + \text{const.} \quad (4)$$

Equation (4) will be used later for conditional Gaussian distribution proof.

Consider eigenvalues λ and eigenvectors u of Σ :

$$\Sigma u_i = \lambda u_i$$

PROOF: If A is a symmetric matrix then its eigenvectors are orthogonals. For any real matrix A and any vectors x and y , we have

$$\langle Ax, y \rangle = \langle x, A^T y \rangle$$

Now assume that A is symmetric, and x and y are eigenvectors of A corresponding to distinct eigenvalues λ and μ , then

$$\lambda \langle x, y \rangle = \langle \lambda x, y \rangle = \langle Ax, y \rangle = \langle x, A^T y \rangle = \langle x, Ay \rangle = \langle x, \mu y \rangle = \mu \langle x, y \rangle.$$

Therefore, $(\lambda - \mu) \langle x, y \rangle = 0$. Since $\lambda - \mu \neq 0$, then $\langle x, y \rangle = 0$, i.e., $x \perp y$.

Σ can be written as follows

$$\Sigma = \sum_{i=1}^D \lambda_i u_i u_i^T \Rightarrow \Sigma^{-1} = \sum_{i=1}^D \frac{1}{\lambda_i} u_i u_i^T$$

PROOF (HAVE NOT BEEN ABLE TO PROOF IT YET):

If

$$\Sigma = \sum_{i=1}^D \lambda_i u_i u_i^T$$

then

$$\Sigma^{-1} = \sum_{i=1}^D \frac{1}{\lambda_i} u_i u_i^T$$

With Σ and Σ^{-1} , we have the new Δ^2

$$\begin{aligned}
\Delta^2 &= -\frac{1}{2}(x - \mu)^\top \Sigma^{-1}(x - \mu) \\
&= -\frac{1}{2} \sum_{i=1}^D \frac{1}{\lambda_i} (x - \mu)^\top u_i u_i^\top (x - \mu) \\
&= -\frac{1}{2} \sum_{i=1}^D \frac{y_i^2}{\lambda_i}, \text{ with } y_i = u_i^\top (x - \mu)
\end{aligned} \tag{5}$$

And

$$|\Sigma|^{\frac{1}{2}} = \left(\prod_{i=1}^D \lambda_i \right)^{\frac{1}{2}} \tag{6}$$

We have

$$p(x) = \frac{1}{(2\pi)^{\frac{D}{2}} |\Sigma|^{\frac{1}{2}}} \exp\left(-\frac{1}{2}(x - \mu)^\top \Sigma^{-1}(x - \mu)\right) dx$$

From $p(x)$, (5) and (6), we have the new $p(y)$

$$p(y) = \prod_{i=1}^D \frac{1}{(2\pi\lambda_i)^{\frac{1}{2}}} \exp^{-\frac{y_i^2}{2\lambda_i}}$$

Then we have the new I equals to

$$\begin{aligned}
\Rightarrow I &= \int_{-\infty}^{+\infty} p(y) dy \\
&= \prod_{i=1}^D \int_{-\infty}^{+\infty} \frac{1}{(2\pi\lambda_i)^{\frac{1}{2}}} \exp^{-\frac{y_i^2}{2\lambda_i}} dy_i
\end{aligned} \tag{7}$$

Leave equation (7) aside for a bit, we have a well-known equation

$$\int \exp^{-\frac{1}{2}at^2} = \left(\frac{2\pi}{a}\right)^{\frac{1}{2}} \tag{8}$$

Going back to equation (7), we have

$$I = \prod_{i=1}^D \frac{1}{(2\pi\lambda_i)^{\frac{1}{2}}} \int_{-\infty}^{+\infty} \exp^{-\frac{y_i^2}{2\lambda_i}} dy_i$$

Apply equation (8) with $a = \frac{1}{\lambda_i}$

$$= \prod_{i=1}^D \frac{1}{(2\pi\lambda_i)^{\frac{1}{2}}} (2\pi\lambda_i)^{\frac{1}{2}}$$

$$\Rightarrow I = 1$$