



Bài 1:

a) $f(x) = \exp\left(-\frac{1}{2\sigma^2}(x-\mu)^2\right)$

Let $\int_{-\infty}^{\infty} f(x) dx = I$

We have:

$$I = \int_{-\infty}^{+\infty} \exp\left(-\frac{1}{2\sigma^2}(x-\mu)^2\right) dx$$

Suppose that, we shift the distribution where $\mu = 0$, so the area stays the same.

$$I = \int_{-\infty}^{+\infty} \exp\left(-\frac{1}{2\sigma^2}x^2\right) dx$$

Squaring both side:

$$I^2 = \int_{-\infty}^{+\infty} \exp\left(-\frac{1}{2\sigma^2}x^2\right) dx \cdot \int_{-\infty}^{+\infty} \exp\left(-\frac{1}{2\sigma^2}y^2\right) dy$$

$$I^2 = \int_{-\infty}^{+\infty} \exp\left(-\frac{1}{2\sigma^2}x^2\right) dx \cdot \int_{-\infty}^{+\infty} \exp\left(-\frac{1}{2\sigma^2}y^2\right) dy$$

\Rightarrow 2 tọa độ và tích phân giống nhau \Rightarrow areas same

$$I^2 = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} \exp\left(-\frac{1}{2\sigma^2}x^2\right) \exp\left(-\frac{1}{2\sigma^2}y^2\right) dx dy$$

$$= \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} \exp\left(-\frac{1}{2\sigma^2}(x^2+y^2)\right) dx dy$$



Then, conversion to polar coordinates leads to

$$I^2 = \int_0^{2\pi} \int_0^{\infty} e^{-\frac{r^2}{2\sigma^2}} r dr d\theta$$

$$x = r \cos \theta$$

$$y = r \sin \theta$$

We have:

$$\cos^2 \theta + \sin^2 \theta = 1$$

$$x^2 + y^2 = r^2$$

$$\Rightarrow I^2 = \int_0^{2\pi} \int_0^{\infty} \exp\left(-\frac{1}{2\sigma^2} r^2\right) \cdot r \cdot dr d\theta$$

We antiderivative : $\exp\left(-\frac{1}{2\sigma^2} r^2\right)$

$$\Rightarrow \int_0^{2\pi} \left[-\sigma^2 \cdot \exp\left(-\frac{1}{2\sigma^2} r^2\right) \right]_0^{\infty} d\theta$$

$$\Rightarrow \int_0^{2\pi} (-\sigma^2 \cdot 0 - (-\sigma^2 \cdot 1)) d\theta$$

$$\Rightarrow \int_0^{2\pi} \sigma^2 d\theta = \sigma^2 \cdot 2\pi$$

$$\Rightarrow I = \sigma \sqrt{2\pi}$$

To prove the case when mean is non zero, we suppose $t = x - \mu$
so that:

$$\int_{-\infty}^{\infty} P(x | \mu, \sigma^2) dx = \frac{1}{\sqrt{2\pi\sigma^2}} \int_{-\infty}^{\infty} \exp\left(-\frac{t^2}{2\sigma^2}\right) dt$$

$$= \frac{1}{\sqrt{2\pi}\sigma^2}$$

$$= \frac{\sigma\sqrt{2\pi}}{\sigma\sqrt{2\pi}}$$

$$= 1.$$

is normalized.

b, We have probability density function of X variable:

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$$

And, the expected value is:

$$E(X) = \int_{-\infty}^{\infty} x f(x) dx$$

$$= \frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{\infty} x \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right) dx$$

Let $t = \frac{x-\mu}{\sqrt{2}\sigma}$ and we have $x = t\sigma\sqrt{2} + \mu$

$$\Rightarrow dt = \frac{1}{\sqrt{2}\sigma} dx$$

$$\Rightarrow dx = \sigma\sqrt{2} dt$$

Substitute t to $E(X)$.

$$E(X) = \frac{1}{\sigma\sqrt{2}\pi} \int_{-\infty}^{\infty} (\sigma\sqrt{2}t + \mu) \cdot \exp(t^2) \cdot \sigma\sqrt{2} dt$$



$$\begin{aligned}
 &= \frac{1}{\sqrt{\pi}} \left[\sqrt{2}\sigma \int_{-\infty}^{\infty} t \cdot \exp(-t^2) dt + \mu \int_{-\infty}^{\infty} \exp(-t^2) dt \right] \\
 &= \frac{1}{\sqrt{\pi}} \left(\sqrt{2}\sigma \left[-\frac{1}{2} \exp(-t^2) \right]_{-\infty}^{\infty} + \mu \sqrt{\pi} \right) \\
 &= \frac{\mu \sqrt{\pi}}{\sqrt{\pi}} \\
 &= \mu
 \end{aligned}$$

c, Similarly to the expectation, from the ^{Probability} density junction, the Variance:

$$\text{Var}(X) = \int_{-\infty}^{\infty} x^2 f(x) dx - (E[X])^2$$

$$= \frac{1}{\sigma \sqrt{2\pi}} \int_{-\infty}^{\infty} x^2 \cdot \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right) dx - \mu^2$$

$$\text{Let } t = \frac{x-\mu}{\sqrt{2}\sigma} \Rightarrow dt = \frac{1}{\sqrt{2}\sigma} dx \Rightarrow dx = \sigma \sqrt{2} dt$$

$$\Rightarrow \text{Var}(X) = \cancel{\frac{(x-\mu)^2}{2\sigma^2}}$$

$$\Rightarrow \text{Var}(X) = \cancel{\frac{1}{\sigma \sqrt{2\pi}}} \cdot \int_{-\infty}^{\infty} \cancel{\frac{(x-\mu)^2}{2\sigma^2}} \cdot \exp(t^2) dt$$

$$\Rightarrow \text{Var}(X) = \frac{1}{\sigma \sqrt{2\pi}} \int_{-\infty}^{\infty} (\sigma \sqrt{2} t + \mu)^2 \cdot \exp(t^2) \cdot \sigma \sqrt{2} dt - \mu^2$$

$$= \frac{1}{\sqrt{\pi}} \left[2\sigma^2 \int_{-\infty}^{\infty} t^2 \exp(-t^2) dt + 2\sqrt{2}\sigma\mu \int_{-\infty}^{\infty} t \exp(-t^2) dt \right]$$

$$+ \mu^2 \int_{-\infty}^{\infty} \exp(-t^2) dt - \mu^2$$

$$= \frac{1}{\sqrt{\pi}} \left[2\sigma^2 \int_{-\infty}^{+\infty} t^2 \cdot \exp(-t^2) dt + 2\sqrt{2}\sigma\mu \left[-\frac{1}{2} \exp(-t^2) \right]_{-\infty}^{\infty} \right.$$

$$\left. + \mu^2 \sqrt{\pi} \right] - \mu^2$$

$$= \frac{1}{\sqrt{\pi}} \left[2\sigma^2 \int_{-\infty}^{\infty} t^2 \exp(-t^2) dt + 2\sqrt{2}\sigma\mu \cdot 0 \right] + \mu^2 - \mu^2$$

$$= \frac{2\sigma^2}{\sqrt{\pi}} \int_{-\infty}^{\infty} t^2 \exp(-t^2) dt.$$

$$= \frac{2\sigma^2}{\sqrt{\pi}} \left(\left[-\frac{t}{2} \exp(-t^2) \right]_{-\infty}^{\infty} + \frac{1}{2} \int_{-\infty}^{\infty} \exp(-t^2) dt \right)$$

$$= \frac{2\sigma^2}{\sqrt{\pi}} \cdot \frac{1}{2} \int_{-\infty}^{\infty} \exp(-t^2) dt$$

$$= \frac{2\sigma^2 \sqrt{\pi}}{2\sqrt{\pi}}$$

$$= \sigma^2$$

Problem 2:

a, Let x is a Dimensional vector:

$$x = \begin{pmatrix} x_a \\ x_b \end{pmatrix}$$

And the mean vector μ :

$$\mu = \begin{pmatrix} \mu_a \\ \mu_b \end{pmatrix}$$

And the covariance matrix Σ given by:

$$\Sigma = \begin{pmatrix} \Sigma_{aa} & \Sigma_{ab} \\ \Sigma_{ba} & \Sigma_{bb} \end{pmatrix}$$

where $\Sigma^T = \Sigma$, Σ_{aa} and Σ_{bb} are symmetric, $\Sigma_{ba} = \Sigma_{ab}^T$

$$\Rightarrow A = \Sigma^{-1} = \begin{pmatrix} A_{aa} & A_{ab} \\ A_{ba} & A_{bb} \end{pmatrix}$$

We are looking for conditional distribution $p(x_a | x_b)$

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

$$= -\frac{1}{2} (x - \mu)^T A (x - \mu)$$

$$= -\frac{1}{2} (x_a - \mu_a)^T A_{aa} (x_a - \mu_a) - \frac{1}{2} (x_a - \mu_a)^T A_{aa} (x_b - \mu_b)$$

$$- \frac{1}{2} (x_b - \mu_b)^T A_{aa} (x_a - \mu_a) - \frac{1}{2} (x_b - \mu_b)^T A_{bb} (x_b - \mu_b)$$

$$= -\frac{1}{2} x_a^T A_{aa}^{-1} x_a + x_a^T (A_{aa} \mu_a - A_{ab} (x_b - \mu_b)) + \text{const}$$

It is quadratic form of x_a hence conditional distribution $p(x_a | x_b)$ will be Gaussian, because this distribution is characterized by its mean and its variance, so, compare with Gaussian distribution

$$\Delta^2 = -\frac{1}{2} x^T \Sigma^{-1} x + x^T \Sigma^{-1} \mu + \text{const}$$

$$\Sigma_{a|b} = A_{aa}^{-1}$$

$$\begin{aligned}\mu_{a|b} &= \Sigma_{a|b} (A_{aa}\mu_a - A_{ab}(x_b - \mu_b)) \\ &= \mu_a - A_{aa}^{-1} A_{ab} (x_b - \mu_b)\end{aligned}$$

By using Schur complement.

$$\Rightarrow A_{aa} = \left(\Sigma_{aa} - \Sigma_{ab} \Sigma_{bb}^{-1} \Sigma_{ba} \right)^{-1}$$

$$A_{ab} = - \left(\Sigma_{aa} - \Sigma_{ab} \Sigma_{bb}^{-1} \Sigma_{ba} \right)^{-1} \Sigma_{ab} \Sigma_{bb}^{-1}$$

As a result:

$$\mu_{a|b} = \mu_a + \Sigma_{ab} \Sigma_{bb}^{-1} (x_b - \mu_b)$$

$$\Sigma_{a|b} = \Sigma_{aa} - \Sigma_{ab} \Sigma_{bb}^{-1} \Sigma_{ba}$$

$$\Rightarrow p(x_a | x_b) = N(x_{a|b} | \mu_{a|b}, \Sigma_{a|b})$$