

Homework week 2.

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a) Gaussian distribution is normalized.

Gaussian distribution function is

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

Normalization is given by

$$\int_{-\infty}^{\infty} N(x|\mu, \sigma^2) dx = 1.$$

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

assume mean equals to 0, so we have

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

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

Let

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

Take square of both sides on the above function

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

then we will change from (x, y) coordinate to (r, θ) coordinate, assume that

$$x = r \cos \theta$$

$$y = r \sin \theta$$

Based on the fact that

$$\int_0^\infty \exp\left(-\frac{r^2}{2\sigma^2}\right) r dr \\ = -\sigma^2 \exp\left(-\frac{r^2}{2\sigma^2}\right) \Big|_0^{+\infty} = -\sigma^2(0-1) = \sigma^2$$

therefore:

$$I^2 = \int_0^{2\pi} \sigma^2 d\theta = 2\pi\sigma^2, \Rightarrow I = \sqrt{2\pi\sigma^2}$$

prove normalize:

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

$$= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left\{-\frac{1}{2\sigma^2} y^2\right\} dy$$

$$\text{Since } y = x - \mu$$

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

$$= 1$$

b) expectation of Gaussian distribution is μ
 probability density function is

$$f_x(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

Expected value formula

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

so

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

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

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

$$= \frac{1}{\pi} (\sqrt{2}\sigma \cdot \left(-\frac{1}{2} \exp(-t)\right) \Big|_{-\infty}^{\infty} + \mu\sqrt{\pi})$$

$$= \frac{\mu\sqrt{\pi}}{\sqrt{\pi}}$$

$$= \mu$$

and Cov matrix Σ given by

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

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

Σ is symmetric so Σ_{aa} and Σ_{bb} are sym.
while $\Sigma_{ab} = \Sigma_{ba}$

We're looking for conditional dist $p(x_a | x_b)$.

$$\begin{aligned} -\frac{1}{2}(x - \mu)^T \Sigma^{-1} (x - \mu) &= -\frac{1}{2}(x - \mu)^T A (x - \mu) \\ &= -\frac{1}{2}(x_a - \mu_a)^T A_{aa} (x_a - \mu_a) - \frac{1}{2}(x_a - \mu_a)^T A_{ab} (x_b - \mu_b) \\ &\quad - \frac{1}{2}(x_b - \mu_b)^T A_{ba} (x_a - \mu_a) - \frac{1}{2}(x_b - \mu_b)^T A_{bb} (x_b - \mu_b) \\ &= -\frac{1}{2} x^T A_{aa} x_a + x_a^T (A_{aa} \mu_a - A_{ab} (\mu_b - \mu_b)) + \text{const} \end{aligned}$$

It's quadratic form of x_a hence cond dist $p(x_a | x_b)$ will be Gaussian, because this dist is characterized by its mean and its variance. Compare with Gauss dist.

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

$$\Sigma_{ab} = A_{aa}^{-1}$$

$$\mu_{ab} = \Sigma_{ab}^{-1} (A_{aa} \mu_a - A_{ab} (\mu_b - \mu_b))$$

$$= \mu_a - A_{aa}^{-1} A_{ab} (x_b - \mu_b)$$

using Schur

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

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

As a result

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

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

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

b)

The marginal dist

$$p(x_a) = \int p(x_a, x_b) dx_b$$

integrate out x_b by looking the quadratic form
relate to x_b

$$- \frac{1}{2} x_b^T A_{bb} x_b + x_b^T m$$

$$= - \frac{1}{2} (x_b - A_{bb}^{-1} m)^T A_{bb} (x_b - A_{bb}^{-1} m)$$

$$+ \frac{1}{2} m^T A_{bb}^{-1} m$$

with $m = A_{bb}b - A_{ba}(x_a - m_a)$, integrate over unnormalized Gaussian.

$$\int \exp\left(-\frac{1}{2}(x_b - A_{bb}^{-1}m)^T A_{bb} (x_b - A_{bb}^{-1}m)\right) dx_b$$

remaining term

$$-\frac{1}{2} x_a^T (A_{aa} - A_{ab} A_{bb}^{-1} A_{ba}) x_a + x_a^T (A_{aa} - A_{ab} A_{bb}^{-1} A_{ba})$$

$$x_a m_a + \text{const.}$$

Similarly

$$E(x_a) = m_a$$

$$\text{Cov}(x_a) = \Sigma_{aa}$$

$$\rightarrow p(x_a) = N(x_a | m_a, \Sigma_{aa})$$