

Any Single Gaussian

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How to summarize data?

x^1, x^2, \dots, x^m

- mean $\mu = \frac{1}{m} \sum_i x^i$

- Variance $\sigma^2 = \frac{1}{m} \sum_i (x^i - \mu)^2$

What about in higher dim? mean is still average.

Variance?

Variance along direction (unit vector v):

Variance of $x^1 \cdot v, x^2 \cdot v, \dots, x^m \cdot v$

$$\sigma_v^2 = \frac{1}{m} \sum_i (x^i \cdot v - \mu \cdot v)^2$$

$$= \frac{1}{m} \sum_i ((x^i - \mu) \cdot v)^2$$

$$= v^T \left(\frac{1}{m} \sum_i (x^i - \mu) (x^i - \mu)^T \right) v$$

$$\sum_{ii} = E((X_i - \mu_i)^2)$$

$$\sum_{ij} = E((X_i - \mu_i)(X_j - \mu_j)).$$

Σ : covariance matrix

Probability distribution

$$P_2(X=a)$$

Probability density function
(continuous densities)

$$\text{pdf}(x=a)$$

e.g. Uniform in $[a, b]$

$$p(x=t) = \begin{cases} \frac{1}{|b-a|} & t \in [a, b] \\ 0 & t \notin [a, b] \end{cases}$$

Can have $p(x) = f(x)$ where

$$f(x) \geq 0$$

nonnegative, integrable.

$$\int f < \infty.$$

Most important example

Gaussian Density.

1-dim

$$-\frac{x^2}{2}$$

Gaussian derivation.

1-dim
$$p(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}$$

Q. Why $\frac{1}{\sqrt{2\pi}}$?

— $x \in \mathbb{R}^d$
$$p(x) = \frac{1}{(\sqrt{2\pi})^d} e^{-\frac{\|x\|^2}{2}}$$

$$\|x\|^2 = \sum_i x_i^2 = \prod_{i=1}^d \frac{1}{\sqrt{2\pi}} e^{-\frac{x_i^2}{2}}$$

Product of 1-dim Gaussians along each coordinate.

F1. for any unit vector v , $x \sim N(0, I_d)$
 $x \cdot v \sim N(0, 1)$

$$p(x \cdot v = t) = \int \frac{1}{(\sqrt{2\pi})^d} e^{-\frac{\|x\|^2}{2}} dx$$

$$x: x \cdot v = t$$

write x in the basis $\{v, v_2, \dots, v_d\}$

$$\|x\|^2 = \sum (x \cdot v_i)^2$$

$$= \frac{t^2}{2} + \dots + e^{-\frac{\sum_{i=2}^d (x \cdot v_i)^2}{2}}$$

$$= \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}} \int \frac{1}{(\sqrt{2\pi})^{d-1}} e^{-\frac{(x-v)^2}{2}}$$

$$= \frac{e^{-\frac{t^2}{2}}}{\sqrt{2\pi}} \int \frac{1}{(\sqrt{2\pi})^{d-1}} e^{-\frac{\|y\|^2}{2}} dy$$

$$= \frac{e^{-\frac{t^2}{2}}}{\sqrt{2\pi}}$$

$$y = (x-v_1, \dots, x-v_d)$$

$$dy = |\det [v_2, \dots, v_d]| dx$$

F2. $\frac{1}{\sqrt{2\pi}} \int e^{-\frac{x^2}{2}} dx = 1$

Let $p(x)$ $p(x,y) = \frac{1}{2\pi} e^{-\frac{x^2+y^2}{2}}$

$$\frac{1}{2\pi} \int e^{-\frac{(x^2+y^2)}{2}} dx dy = \frac{1}{2\pi} \int_{r=0}^{\infty} 2\pi r \cdot e^{-\frac{r^2}{2}} dr$$

$$= \int_u e^{-u} du = 1$$

$u = \frac{r^2}{2} \quad du = r dr$

$$\int p(x,y) = \left(\int p(x) \right)^2 \Rightarrow \int p(x) = 1$$

General Gaussian $N(\mu, \sigma^2)$

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

Multivariate $N(\mu, \Sigma)$

$$= \frac{1}{(\sqrt{2\pi})^d |\det(\Sigma)|} e^{-\frac{(x-\mu)^T \Sigma^{-1} (x-\mu)}{2}}$$

$$X \rightarrow Ax + b$$

$$N(0, I_d) \rightarrow N(b, AA^T)$$

$$X \sim N(\mu, \Sigma) \Rightarrow \Sigma^{-\frac{1}{2}}(X - \mu) \sim N(0, I_d)$$

P1. Estimate Gaussian given random iid samples.

$$x^1, x^2, \dots, x^m$$

Natural choices: $\tilde{\mu} = \frac{1}{m} \sum_i x^i$

$$\tilde{\Sigma} = \frac{1}{m} \sum_i (x^i - \tilde{\mu})(x^i - \tilde{\mu})^T$$

$$\tilde{\Sigma} = \frac{1}{m} \sum_i (x^i - \tilde{\mu})(x^i - \tilde{\mu})'$$

Something better?

Goal. Find $\tilde{\mu}$, $\tilde{\Sigma}$ s.t.

likelihood $N(\tilde{\mu}, \tilde{\Sigma})$ generates $x^1 \dots x^m$ is maximized.

Thm. Empirical mean, covariance give max likelihood estimates.

Pf. Consider the case when $\Sigma = \sigma^2 I$.

$$P(\text{data}) = \prod_{j=1}^m \frac{1}{(\sqrt{2\pi}\sigma)^d} e^{-\frac{\|x^j - \mu\|^2}{2\sigma^2}}$$

$$\log(P(\text{data})) = -\log(\sqrt{2\pi}\sigma) - \sum_j \frac{\|x^j - \mu\|^2}{2\sigma^2}$$

$$\frac{\partial}{\partial \sigma} = -\frac{m d}{\sigma} + \frac{1}{\sigma^3} \sum_j \|x^j - \mu\|^2 = 0$$

$$-m \dots \sigma^2$$

$$\Rightarrow \sigma^2 = \frac{1}{d} \cdot \frac{1}{m} \sum_j \|x^j - \mu\|^2$$

$$\frac{d}{d\mu_i} = 0 \Rightarrow$$

$$-\frac{1}{2\sigma^2} \cdot 2 \sum_j (x_i^j - \mu_i) = 0$$

$$m \mu_i = \sum_j x_i^j$$

$$\mu_i = \frac{1}{m} \sum_j x_i^j$$

$$\mu = \frac{1}{m} \sum_j x^j$$

Thm [Central Limit Theorem] X_1, X_2, \dots, X_n

i.i.d random variables from some distribution
with bounded variance $\text{Var}(X_1) < \infty$.

$$\text{Let } Y_n = \frac{1}{n} \sum_i X_i$$

$$\text{Then } Y_n \rightarrow N(\mathbb{E}(X_1), \frac{1}{n} \text{Var}(X_1))$$

Then $Y_n \rightarrow N(E(Y_n), \frac{1}{n} \text{var}(Y_n))$
(converges in distribution)

This can be made more qualitative -

Thm. [Berry-Esseen] X_1, \dots, X_n independent R.V.

$$Y_n = \sum_{i=1}^n X_i \quad Z_n \sim N(E(Y_n), \text{Var}(Y_n))$$

Then, for any $t \in \mathbb{R}$,

$$|P_{X_n}(Y_n \leq t) - P_{Z_n}(Z_n \leq t)| \leq c \cdot \frac{\sum_{i=1}^n E(|X_i|^3)}{\text{Var}(Y_n)^{3/2}}$$

$$c \in [0, 1].$$

Example $X_i = \begin{cases} -1 & \text{w.p. } \frac{1}{2} \\ 1 & \text{w.p. } \frac{1}{2} \end{cases}$

$$E(|X_i|^3) = 1$$

$$\text{Var}(Y_n) = n \text{Var}(X_1) = n \cdot \left(\frac{1}{2} \cdot 1 + \frac{1}{2} \cdot 1\right) = n$$

$$\therefore \forall t \quad Z_n \sim (0, n)$$

$$|P_n(Y_n \leq t) - P_n(Z_n \leq t)| \leq \frac{c \cdot n}{n^{3/2}} \leq \frac{c}{\sqrt{n}}$$

"Invariance" Principle.

Note, bound also holds for $P_n(Y_n > t)$

$$\begin{aligned} |P_n(Y_n > t) - P_n(Z_n > t)| &= |(1 - P_n(Y_n \leq t)) - (1 - P_n(Z_n \leq t))| \\ &= |P_n(Y_n \leq t) - P_n(Z_n \leq t)| \end{aligned}$$
