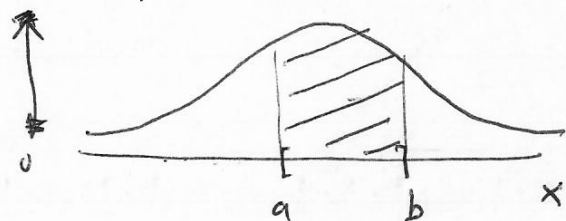


< Probability >

- random variable

X : outcome $\rightarrow \mathbb{R}$

- density. $P[a \leq X < b] = \int_a^b \underline{p(x)} dx$



$$p(x) \geq 0$$

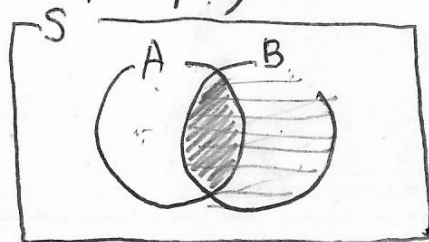
$$\int_{-\infty}^{\infty} p(x) dx = 1$$

- independent

$$p(A, B) = p(A) p(B)$$

- cond.

$$p(A|B) = \frac{p(A, B)}{p(B)}$$



$$* p(A) = \frac{(\text{area of } A)}{(\text{" } S \text{")}}$$

$$p(A, B) = p(A|B) p(B)$$

$$= p(B|A) p(A)$$

$$p(A|B) = \frac{p(B|A) p(A)}{p(B)} \quad \text{Bayes rule}$$

• Properties of r.v

- mode: value of X that max. $p(x)$

- median: 50% percentile

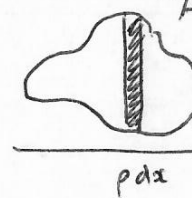
$$P[X \geq \text{med}] = P[X \leq \text{med}] = 0.5$$

- mean

$$E[X] = \bar{X} = \int_{-\infty}^{\infty} \textcircled{x} p(x) dx \quad \left(\begin{array}{l} \text{c.g of} \\ \text{prob.} \end{array} \right)$$

expected value

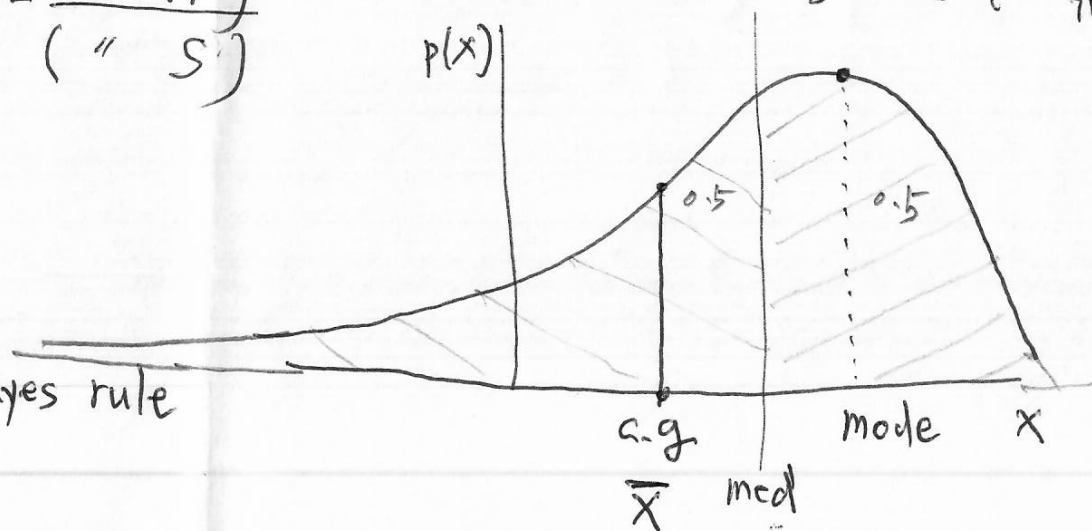
$$* \int_A p(x) dx = \text{mass}$$



mass density, $\rho = \frac{m}{\text{area}}$

$$\int x p(x) dx = \text{c.g}$$

$$\int (x - \text{c.g})^2 p dx = \text{inertial}$$



- variance.

$$V[X] = \int_{-\infty}^{\infty} (x - \bar{x})^2 p(x) dx \quad \left(\begin{array}{l} \text{moment of} \\ \text{inertia} \end{array} \right) \subseteq E[(X - \bar{x})^2]$$

$X \in \mathbb{R}^n$ co-variance

$$\text{Var}[X] = E[(X - \bar{x})(X - \bar{x})^T]$$

* Mean is linear

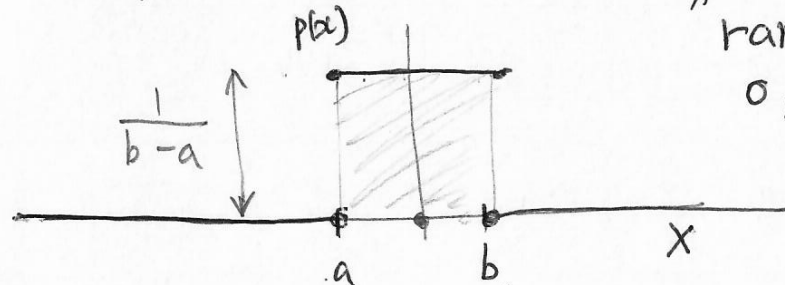
$$E[aX + b] = \int_{-\infty}^{\infty} (ax + b) p(x) dx$$

$$= a \int_{-\infty}^{\infty} x p(x) dx + b \int_{-\infty}^{\infty} p(x) dx$$

$$= a E[X] + b$$

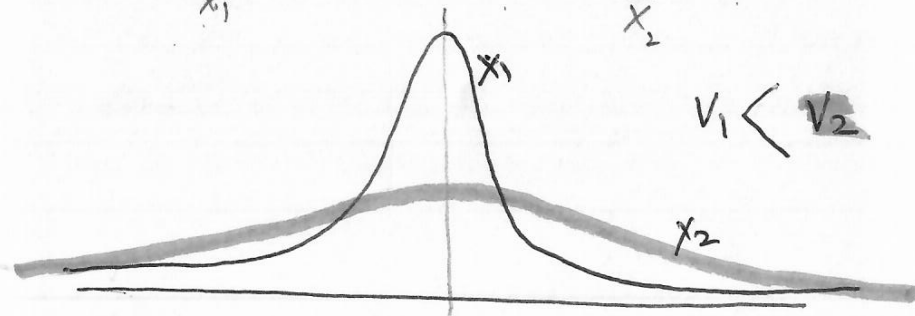
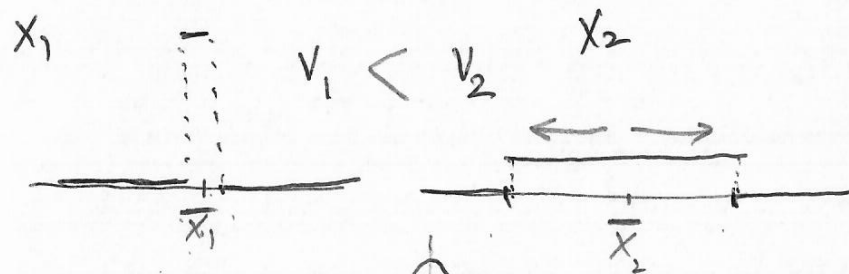
$$\begin{aligned} \text{Var}[X] &= E[(X - \bar{x})(X - \bar{x})^T] \\ &= E[XX^T - X\bar{x}^T - \bar{x}X^T + \bar{x}\bar{x}^T] \\ &= E[XX^T] - E[X]\bar{x}^T - \bar{x}E[X^T] + \bar{x}\bar{x}^T \\ &= E[XX^T] - \bar{x}\bar{x}^T \end{aligned}$$

ex) uniform dist on $[a, b]$ * rand 0, 1



$$\begin{aligned} \bar{x} &= \int_{-\infty}^{\infty} x p(x) dx = \int_a^b x \cdot \frac{1}{b-a} dx \\ &= \frac{1}{b-a} \cdot \frac{x^2}{2} \Big|_a^b = \frac{b+a}{2} \end{aligned}$$

$$V[X] = \frac{1}{3} \left(\frac{b-a}{2} \right)^3 = \frac{1}{3} \left(\frac{b-a}{2} \right)^3$$



covariance

$$\begin{aligned}\text{cov}(X, Y) &= E[(X - \bar{X})(Y - \bar{Y})^T] \\ &= E[XY^T] - \bar{X}\bar{Y}^T \\ \text{cov}(Y, X) &= E[YX^T] - \bar{Y}\bar{X}^T \quad \left. \begin{array}{l} \text{trans} \\ \text{pos.} \end{array} \right\}\end{aligned}$$

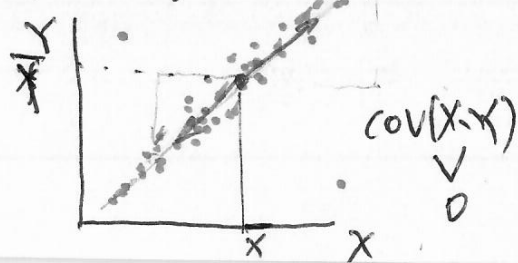
def. X, Y independent $p(X, Y) = p(X)p(Y)$

def. \parallel uncorrelated if $\text{cov}(X, Y) = 0$
or $E[XY^T] = \bar{X}\bar{Y}^T$.

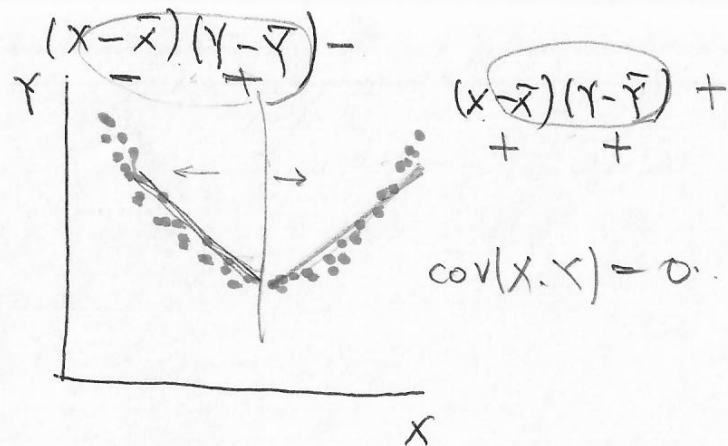
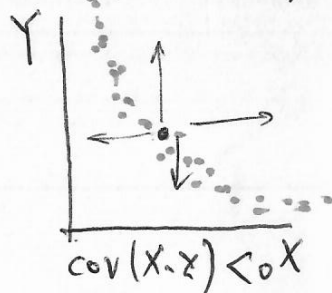
$$\begin{aligned}\text{X, Y independent} &\Rightarrow \begin{cases} E[X|Y] = E[X] \\ E[Y|X] = E[Y] \end{cases} \Rightarrow \begin{cases} \text{cov}(X, Y) = 0 \\ \text{un cor.} \end{cases}\end{aligned}$$

(ave.) linear rel. btw X, Y

X : weight
 Y : height

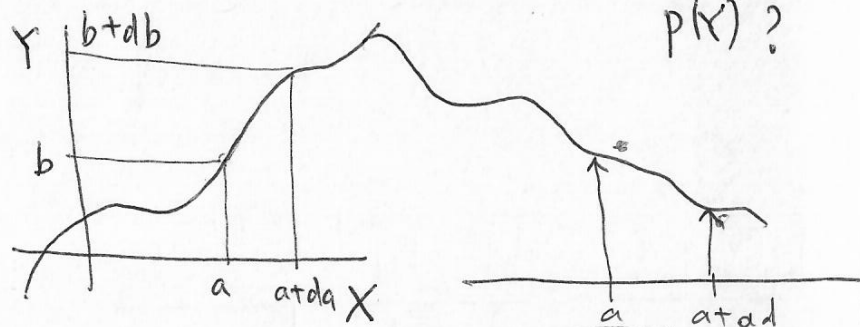


X : alt
 Y : density



• func. of r.v

Given $X, p(X)$ let $Y = f(X)$



$$P[a \leq X \leq a+da] = P[b \leq Y \leq b+db]$$

$$p_X(x)dx = p_Y(y)dy$$

since

$$y = f(x)$$

$$x = f^{-1}(y)$$

$$dx = \frac{df^{-1}}{dy} dy$$

$$p_Y(y) dy = p_X(f^{-1}(y)) \left| \frac{df^{-1}}{dy} \right| dy$$

$X, Y \in \mathbb{R}^n$

$$p_Y(y) = p_X(f^{-1}(y)) \left| \det \left(\frac{df^{-1}}{dy} \right) \right|$$

ex) $X \sim N(\mu, \Sigma)$

Quad. form
 \downarrow
 $x^T Q x$

$$p(x) = \frac{1}{\sqrt{(2\pi)^n \det \Sigma}} \exp \left[-\frac{1}{2} (x - \mu)^T \Sigma^{-1} (x - \mu) \right]$$

$$y = Ax \quad x = A^{-1}y \quad y?$$

$$p_Y(y) = p_X(f^{-1}(y)) \left| \det \left(\frac{df^{-1}}{dy} \right) \right|$$

$$= p_X(A^{-1}y) \left| \det(A^{-1}) \right|$$

$$\propto \exp \left[-\frac{1}{2} (A^{-1}y - \mu)^T \Sigma^{-1} (A^{-1}y - \mu) \right]$$

$$= \exp \left[-\frac{1}{2} (y - A\mu)^T A^{-T} \Sigma^{-1} A^{-1} (y - A\mu) \right]$$

$$Y \sim N(A\mu, A\Sigma A^T) \quad \uparrow \quad Y = AX$$

$$X \sim N(\mu, \Sigma)$$

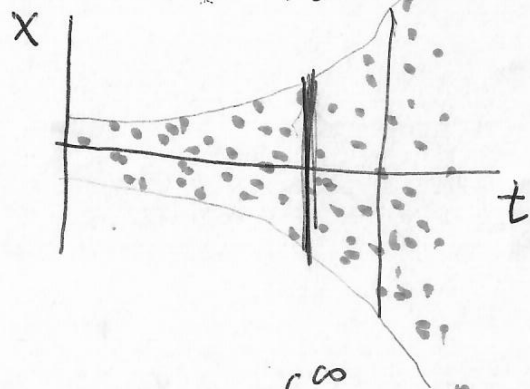
< Random Process >

det. $X: (\text{outcome}) \rightarrow \mathbb{R}^n$ (r.v)

det. r.p. $X(t)$ is a family of r.v indexed by t .

ex) $X = tW$. $W \sim N(0, 1^2)$

$$X \sim N(0, t^2)$$



$$E[X(t)] = \bar{X}(t) = \int_{-\infty}^{\infty} x p_X(t, x) dx.$$

$$\text{Var}[X(t)] = \dots$$

$$\text{Cov}[X(t)Y(t)] = E[(X(t) - \bar{X}(t))(Y(t) - \bar{Y}(t))^T]$$

cross cov.

$$E[(X(t) - \bar{X}(t))(Y(\tau) - \bar{Y}(\tau))^T]$$

def. stationary process.

$X(t)$ is stationary if

$X(t)$ and $X(\tau)$ have the same statistics.

* density is invariant under time shift.

def. Markov process

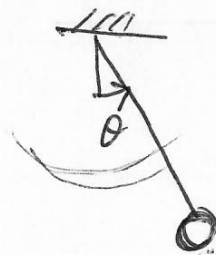
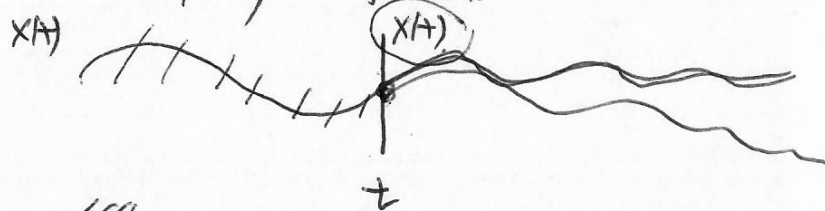
* recall: state of a dyn. sys

$$\dot{x} = f(t, x, u)$$

control input

Given $X(t)$ at t , $u(t)$.

the future behavior can be uniquely defined.



$$[\theta, \dot{\theta}] = x.$$

A random process.
~~duc.~~

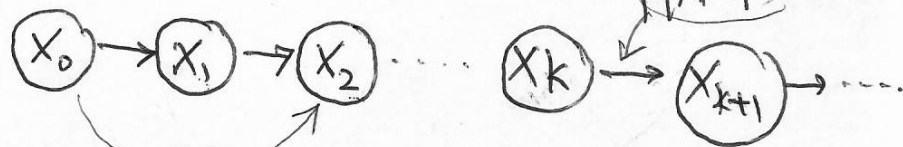
$X(0), X(1), \dots, X(N)$.

is Markov if

$$P[X(k+1) | \underbrace{X(k), X(k-1), \dots, X(0)}_{\text{past}}]$$

future current past

$$= P[X(k+1) | X(k)]$$



$$P[X_N | X_{N-1}, \dots, X_0]$$

$$(* P(A, B) = P(A|B) \times P(B))$$

$$= P[X_N | X_{N-1}, \dots, X_0] P[X_{N-1}, \dots, X_0]$$

$$= P[X_N | X_{N-1}] \cdot \dots$$

$$= P[X_N | X_{N-1}] P[X_{N-1} | X_{N-2}] \times \dots \times P[X_1 | X_0] P[X_0]$$

state transition prob $P[X_{k+1} | X_k]$

< Parameter Estimation >

We wish to determine $x \in \mathbb{R}^n$
 using

① prior guess $x \sim N(\bar{x}, M)$

② sensor measurement

$$z = Hx + v \quad H \in \mathbb{R}^{p \times n}$$

$p \times 1 \quad p \times n \quad n \times 1 \quad p \times 1$

$v \sim N(0, R)$
 (independent of x)

Objective : $x | z$

$$\begin{bmatrix} x \\ z \end{bmatrix} = \begin{bmatrix} I_n & 0 \\ H & I_p \end{bmatrix} \begin{bmatrix} x \\ v \end{bmatrix}$$

$\underbrace{\quad}_{A} \quad \underbrace{\quad}_{R \times n} \quad \underbrace{\quad}_n$

$\text{cov}(x, v)$

$$\begin{bmatrix} x \\ v \end{bmatrix} \sim N \left(\begin{bmatrix} \bar{x} \\ 0 \end{bmatrix}, \begin{bmatrix} M & 0 \\ 0 & R \end{bmatrix} \right)$$

\downarrow
 $\underbrace{\quad}_{\Sigma}$

$$\begin{bmatrix} x \\ z \end{bmatrix} \sim N \left(A \begin{bmatrix} \bar{x} \\ 0 \end{bmatrix}, A \Sigma A^T \right)$$