

3) $N = 200$ here EXC - 7

Chernoff Bound:

$$P(X \geq k) \leq \min_{\alpha > 0} \{ e^{-\alpha k} E(e^{\alpha X}) \}$$

When,

$$X = \sum_{i=1}^N X_i$$

X_i are iid.

$$\begin{aligned} E(e^{\alpha X}) &= E(e^{\alpha \sum_{i=1}^N X_i}) = E(e^{\alpha X_1} e^{\alpha X_2} \dots e^{\alpha X_N}) \\ &= E(e^{\alpha X_1}) E(e^{\alpha X_2}) \dots E(e^{\alpha X_N}) \end{aligned}$$

iid

$$X_i = \begin{cases} 1 & \text{with prob } p \\ 0 & \text{with prob } (1-p) \end{cases}$$

$$Y_i = e^{\alpha X_i} = \begin{cases} e^{\alpha} & \text{with prob } p \\ 1 & \text{with prob } (1-p) \end{cases}$$

$e^y \geq 1 + y \quad \forall y \in \mathbb{R}$

For any i : $E(e^{\alpha X_i}) = p e^{\alpha} + (1-p) e^{\alpha \cdot 0}$
 $\forall i \in [N]$ $= p e^{\alpha} + (1-p)$

$$E(e^{\alpha X_i}) = p(e^{\alpha} - 1) + 1 \quad \text{--- ①}$$

define : $y = p(e^{\alpha} - 1)$

$$p(e^{\alpha} - 1) + 1 \leq e^{p(e^{\alpha} - 1)} \quad (\text{Bounding})$$

From ①

$$E(e^{\alpha X_i}) \leq e^{p(e^{\alpha} - 1)}$$

$$E(e^{\alpha X}) \leq e^{p(e^{\alpha} - 1)} e^{p(e^{\alpha} - 1)} \dots e^{p(e^{\alpha} - 1)} \quad \text{N times}$$

$$E(e^{\alpha X}) \leq e^{N p(e^{\alpha} - 1)}$$

$$e^{-\alpha k} E(e^{\alpha X}) \leq e^{-\alpha k} e^{N p(e^{\alpha} - 1)} \quad \forall \alpha > 0$$

$$\min_{\alpha} \{ e^{-\alpha k} E(e^{\alpha X}) \} \leq \min_{\alpha} \{ e^{N p(e^{\alpha} - 1) - \alpha k} \}$$

$$P(X \geq k) \leq \min_{\alpha > 0} \{ e^{N p(e^{\alpha} - 1) - \alpha k} \}$$

$$\Leftrightarrow \min_{\alpha > 0} N p(e^{\alpha} - 1) - \alpha k$$

Use calculus. (Derivative)

$$\alpha = \log \frac{K}{np}$$

holds when $K \geq np$.

Substitute back and we will get bound.

$$i) E(X) = \mu_X < \infty ; \text{Var}(X) = \sigma_X^2 < \infty$$

a) Chebyshev Centred at some other value (Not at mean)

$$a \geq b$$

$$a, b \in \mathbb{R}^+$$

$$\Rightarrow a^2 \geq b$$

$$P(|X - c| \geq K)$$

$K > 0$ and $|X - c| \geq 0$, Now we can square

$$|X - c| \geq K \iff (X - c)^2 \geq K^2$$

(Don't use Markov for non negative random variables)

$$P[(X - c)^2 \geq K^2] \leq \frac{E[(X - c)^2]}{K^2}$$

$$(X - c)^2 = X^2 + c^2 - 2Xc + \mu^2 - 2X\mu - \mu^2 + 2X\mu$$

$$b) P(a < X < b) = P\left(|X - \left(\frac{a+b}{2}\right)| < \frac{b-a}{2}\right)$$

$$\left|X - \left(\frac{a+b}{2}\right)\right| < \frac{b-a}{2}$$

$$X - \left(\frac{a+b}{2}\right) < \frac{b-a}{2}$$

$$\Rightarrow X < b$$

$$X - \left(\frac{a+b}{2}\right) > -\left(\frac{b-a}{2}\right)$$

$$\Rightarrow X > a$$

In a) we centred at c .

But;

$$P(a < x < b) = P\left(\left|x - \left(\frac{a+b}{2}\right)\right| < \frac{b-a}{2}\right) = 1 - P\left(\left|x - \frac{a+b}{2}\right| \geq \frac{b-a}{2}\right)$$

$$5) E(x) = \mu < \infty$$

$$\text{Var}(x) = \sigma_x^2 < \infty$$

Let $Y = x - \mu_x$ and $a > 0$.

$$a) E(Y) = 0.$$

$$\text{Var}(Y) = \sigma_x^2.$$

b) $t > 0$; is this true?

$$P(Y \geq a) = P(Y + t \geq a + t) \leq P((Y + t)^2 \geq (a + t)^2).$$

$$Y + t \geq a + t \stackrel{?}{\Rightarrow} (Y + t)^2 \geq (a + t)^2$$

No true Y may not be non negative.

$$|Y + t| \geq |a + t| \quad ; a > 0, t > 0$$

$$|Y + t| \geq a + t.$$

$$a + t > 0.$$

$$|a + t| = a + t$$

$$(Y + t) \geq (a + t) \quad | \quad (Y + t) \leq -(a + t)$$

But Since $(a + t) > 0$ hence $(Y + t) > 0$.

$$|Y + t| \geq (a + t) \Leftrightarrow (Y + t)^2 \geq (a + t)^2$$

$$P[(Y + t)^2 \geq (a + t)^2] = P[(Y + t \geq a + t) \cup (Y + t \leq -(a + t))] \\ \geq P(Y + t \geq a + t).$$

$$P(Y \geq a) \leq \frac{\sigma_x^2 + t^2}{(a+t)^2}$$

$$P(Y \geq a) \stackrel{b)}{\leq} P[(Y+t)^2 \geq (a+t)^2]$$

using Chebyshev from 4a)

$$\leq \frac{\sigma_Y^2 + (\mu_Y - t)^2}{(a+t)^2}$$

$$\begin{aligned} \text{From 5@ } \sigma_Y^2 &= \frac{\sigma_x^2}{\mu_Y} = 0 \\ &= \frac{\sigma_x^2 + t^2}{(a+t)^2} \end{aligned}$$

$$d) t = \frac{\sigma_x^2}{a}$$

minimize

$$g''(t) = \frac{2a^2 + 8at - 6\sigma_x^2}{(a+t)^4}$$

$$t = \frac{\sigma_x^2}{a} \Rightarrow 8at = 8\sigma_x^2$$

$$= \frac{2a^2 + 8\sigma_x^2 - 6\sigma_x^2}{(a+t)^4}$$

e) Substituting.

f) $a < 0$ define $b = -a$. Since a is -ve ; b = +ve

$$P(Y \geq a) = 1 - P(Y < a)$$

$$P(Y < a) = P(Y < -b)$$

$$= P(-Y > b)$$

b is positive.

$$\sigma_{-Y}^2 = \sigma_x^2$$

Using previous part.

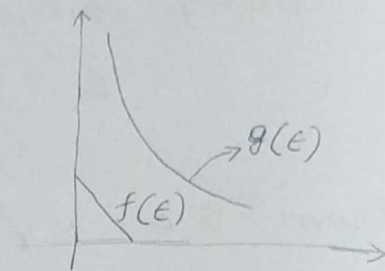
$$\leq \frac{\sigma_y^2}{\sigma_y^2 + b^2} = \frac{\sigma_x^2}{\sigma_x^2 + a^2}.$$

8) X is n.v; $\forall \epsilon > 0$

$$f(\epsilon) = P(X \geq \epsilon).$$

$$f(\epsilon) = 1 - F_X(\epsilon).$$

$$g(\epsilon) = \frac{E(X)}{\epsilon}$$



$$g(\epsilon) > f(\epsilon)$$

How markov inequality behaves in various distribution.

c) Define $y = \frac{t^2}{2\alpha^2}.$

$$y dy = \frac{t}{\alpha^2} dt.$$

g)

b) $f_X(x) = \frac{\lambda}{2} \exp(-\alpha|x|)$

Split for $x < 0$ and $x > 0.$

$$\lim_{n \rightarrow \infty} P(\omega \in \Omega : |X_n(\omega) - X(\omega)| \geq \epsilon) = 0 ; \forall \epsilon > 0$$

$$\lim_{n \rightarrow \infty} P(|X_n(\omega) - X(\omega)| \geq \epsilon) = 0, \text{ converge in probability}$$

$$2) X_n \sim \text{Exp}(n)$$

$$E(X_n) = \frac{1}{n}$$

$$P(|X_n(\omega) - X(\omega)| \geq \epsilon) = P(|X_n(\omega)| \geq \epsilon)$$

Apply Markov.

$$\leq \frac{E(X_n)}{\epsilon} = \frac{1}{n\epsilon}$$

$$\forall \epsilon > 0, \lim_{n \rightarrow \infty} \frac{1}{n\epsilon} \rightarrow 0 ; \forall \epsilon > 0$$

$$3) X_n \sim N(0, \frac{1}{n})$$

$$f_{X_n} = \frac{\sqrt{n}}{\sqrt{2\pi}} \exp\left(-\frac{nx^2}{2}\right)$$

Let $\alpha_n > 0$; s.t $\alpha_n \rightarrow +\infty$.

$$a) P(X_n \leq x) = P(\alpha_n X_n \leq \alpha_n x) ?$$

True α_n is positive

$$\begin{aligned} b) F_{X_n}(x) &= P(X_n \leq x) \\ &= P(\alpha_n X_n \leq \alpha_n x) \end{aligned}$$

$$\lim_{n \rightarrow \infty} F_{X_n}(x) = \lim_{n \rightarrow \infty} P(\alpha_n X_n \leq \alpha_n x)$$

$$x > 0, \alpha_n x > 0$$

$$\lim_{n \rightarrow \infty} \alpha_n x \rightarrow \infty$$

$$= P(\lim_{n \rightarrow \infty} d_n x_n \leq \underbrace{\lim_{n \rightarrow \infty} d_n x}_\infty)$$

$$= 1$$

When $x < 0$, $d_n x < 0$

$$\lim_{n \rightarrow \infty} d_n x \rightarrow -\infty$$

$$P(\text{---} \leq -\infty) = 0.$$

(By definition).

$$F_{x_n}(x) \rightarrow F_x(x)$$

$$F_x(x) = \begin{cases} 1 & \text{if } x > 0 \\ 0 & \text{if } x \leq 0 \end{cases}$$

At 0 it doesn't matter.

NOTE:

$$X(\omega) = K \quad \forall \omega \in \Omega$$

$$P(X=K) = 1$$

$$P(X \leq x) = \begin{cases} 0 & \forall x < K \\ 1 & \forall x \geq K \end{cases}$$

$$F_x(x) = \begin{cases} 0 & \forall x < K \\ 1 & \forall x \geq K \end{cases}$$

$$5) F_{x_n}(x) = \begin{cases} \frac{e^{n(x-1)}}{1+e^{n(x-1)}} & \text{if } x \geq 1 \\ 0 & \text{if } x < 1 \end{cases}$$

$$\downarrow$$

$$\frac{1}{e^{-n(x-1)} + 1}$$

as $\lim_{n \rightarrow \infty}$

6) adjust things as shown above.

Exc 7.

9) It $\lim_{n \rightarrow \infty} \mathbb{E}(|X_n - x|^K) = 0 \Rightarrow X_n \xrightarrow{P} x$

$$P(|X_n - x| > \epsilon) = P(|X_n - x|^K > \epsilon^K) \leq \frac{\mathbb{E}(|X_n - x|^K)}{\epsilon^K}$$

using Markov.

Exc 8.

9) $(\Omega, \mathcal{B}, P) \text{ --- } \{X_n\}$

$$f_{X_n}(x) = \begin{cases} \frac{1}{nx^2} & \text{if } x > \frac{1}{n} \\ 0 & \text{if } x < \frac{1}{n} \end{cases}$$

now, $X_n \xrightarrow{P} 0 \rightarrow \int_{1/n}^x \frac{1}{nx^2} dx$

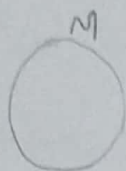
$$F_{X_n}(x) = \begin{cases} 1 - \frac{1}{nx} & \text{if } x > \frac{1}{n} \\ 0 & \text{elsewhere} \end{cases}$$

$$\begin{aligned} P(|X_n - 0| > \epsilon) &= P(X_n > \epsilon) = 1 - F_X(\epsilon) \\ &= 1 - (1 - \frac{1}{n\epsilon}) \\ &= \frac{1}{n\epsilon} \end{aligned}$$

10) $X_n(\omega) = Y_n(\omega) \cdot (\text{ii} \text{ no})$

Linear algebra

Subspace: non empty set of vectors

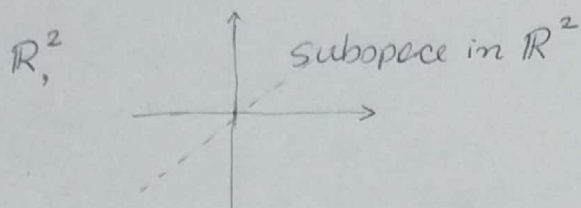


$$x, y \in M \text{ (vectors)}$$

$$x + y \in M$$

$$\alpha \in \mathbb{R} \text{ and } x \in M, \text{ then } \alpha x \in M$$

closed under addition Scalar multiplication.



Spanning set for a subspace:

$$S = \{u_1, u_2, u_3, \dots, u_n\}$$

$$\text{iff i) } u_1, u_2, u_3, \dots, u_n \in M$$

$$\text{ii) } m = \alpha_1 u_1 + \alpha_2 u_2 + \dots + \alpha_n u_n$$

$$m \in M$$

Linear independent set:

$$S = \{u_1, u_2, u_3, \dots, u_n\} \quad \mathbb{R}^k$$

$$\sum_{j=1}^n \alpha_j u_j = \mathbf{0}_k ; \alpha_j = 0 \quad \forall j.$$

Basis:

Spanning set which is linearly independent.

$$S_1 = \left\{ u_1 = \begin{pmatrix} 1 \\ 1 \end{pmatrix} \quad u_2 = \begin{pmatrix} 1 \\ -1 \end{pmatrix} \right\}$$

$$0u_1 + 0u_2 = \mathbf{0}_2$$

orthonormal Basis:

$$S = \{u_1, u_2, \dots, u_n\} \in \mathbb{R}^n.$$

conditions: i) $\langle u_i, u_j \rangle = 0 \quad \forall i \neq j$ — orthogonal.

$$\text{ii) } \langle u_i, u_j \rangle = 1 \quad \forall i=j$$

$$\|u_i\|^2 = 1 \quad (\text{length } 1).$$

Gram Schmidt's process:

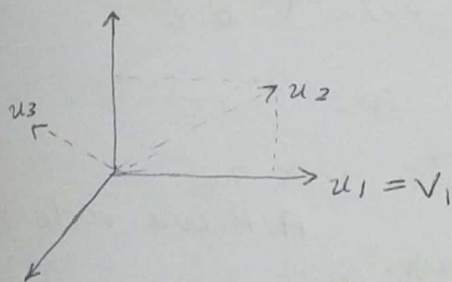
$$(u_1, u_2, \dots, u_n)$$

\Downarrow orthogonalization

$$(v_1, v_2, \dots, v_n)$$

\Downarrow Normalization

$$(a_1, a_2, \dots, a_n)$$



$$v_1 = u_1$$

$$a_1 = \frac{v_1}{\|v_1\|}$$

$$v_2 = u_2 - \frac{\langle u_2, v_1 \rangle}{\|v_1\|^2} v_1$$

$$v_3 = u_3 - \frac{\langle u_3, v_1 \rangle}{\|v_1\|^2} v_1$$

$$a_2 = \frac{v_2}{\|v_2\|}$$

$$a_3 = \frac{v_3}{\|v_3\|}$$

$$\text{Ex: } u_1 = \begin{pmatrix} 3 \\ 3 \\ 6 \end{pmatrix}$$

$$S = \left\{ u_1 = \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix}, u_2 = \begin{pmatrix} 1 \\ 2 \\ 3 \end{pmatrix} \right\}$$

$$v_1 = \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix}, v_2 = \begin{pmatrix} 1 \\ 2 \\ 3 \end{pmatrix}$$

$$a_1 = \frac{v_1}{\|v_1\|} = \frac{1}{\sqrt{3}} \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix}$$

$$a_2 = \frac{1}{\sqrt{14}} \begin{pmatrix} 1 \\ 1 \\ 3 \end{pmatrix}$$

$$\text{Ex: } u_1 = \begin{pmatrix} 3 \\ 3 \\ 6 \end{pmatrix} \quad u_2 = \begin{pmatrix} 1 \\ 1 \\ -7 \end{pmatrix} \quad u_3 = \begin{pmatrix} 3 \\ -1 \\ 8 \end{pmatrix}$$

$$v_1 = u_1 = \begin{pmatrix} 3 \\ 3 \\ 6 \end{pmatrix}$$

$$a_{v_1} = \frac{1}{\sqrt{54}} \begin{pmatrix} 1 \\ 1 \\ -7 \end{pmatrix} = \begin{pmatrix} 1/\sqrt{6} \\ 1/\sqrt{6} \\ -7/\sqrt{6} \end{pmatrix}$$

$$a_3 = \frac{1}{\sqrt{74}} \begin{pmatrix} 3 \\ -1 \\ 8 \end{pmatrix}$$

$$v_2 = u_2 - \frac{\langle u_2, v_1 \rangle}{\|v_1\|^2} v_1 = \begin{pmatrix} 1 \\ 1 \\ -7 \end{pmatrix} - \frac{(-36)}{54} \begin{pmatrix} 3 \\ 3 \\ 6 \end{pmatrix} = \begin{pmatrix} 3 \\ 3 \\ -3 \end{pmatrix}$$

$$v_3 = \begin{pmatrix} 2 \\ -2 \\ 0 \end{pmatrix} \quad a_3 = \frac{1}{2\sqrt{2}} \begin{pmatrix} 2 \\ -2 \\ 0 \end{pmatrix} = \begin{pmatrix} 1/\sqrt{2} \\ -1/\sqrt{2} \\ 0 \end{pmatrix}$$

QR factorization:

$A = QR$ \uparrow upper Δ^u matrix.
orthonormal matrix

A, R are vectors

$$A = [u_1 \ u_2 \ u_3]$$

$$A = \begin{pmatrix} 3 & 1 & 3 \\ 3 & 1 & -1 \\ 6 & -7 & 8 \end{pmatrix}$$

$$r_{ij} = \frac{\langle u_j, v_i \rangle}{\|v_i\|} v_i$$

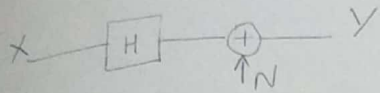
$$r_{jj} = \|v_j\| \quad i > j$$

$$r_{ij} = 0$$

$$R_3 = \begin{pmatrix} r_{11} & r_{12} & r_{13} \\ 0 & r_{22} & r_{23} \\ 0 & 0 & r_{33} \end{pmatrix}$$

$$A = QR.$$

communication system:



$$Y = HX + N.$$

$$H = QR.$$

$$H^{-1}(Y - N) = \hat{X}$$

H^{-1} is computationally intensive.

$$H = QR.$$

↑
orthonormal.

$$Q^* = Q^T, \quad R \text{ is upper } \Delta^k.$$

$$Q^* Y = Q^* \underbrace{QR}_H X + Q^* N.$$

$$\tilde{Q}^* Y = RX + Q^* N.$$

$$\tilde{Y} = RX + \tilde{N}.$$

$$H = UDV^*$$

$$Y = HX + N$$

$$Y = (UDV^H)X + N$$

$$U^* Y V = U^* U D V^H V X + N$$

$$U^* Y V = DX + N$$