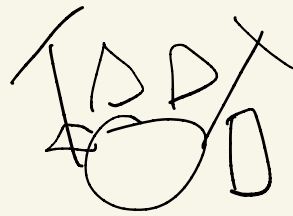
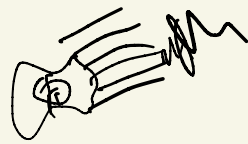


Pb. 1

(a)



$$10 \cdot 9 \cdot 8$$

---

(b)

$$10 \cdot 9 \cdot 8 \cdot 7$$

---

2

(c)

$$P(X = Y)$$

$$= \sum_{i=1}^{100} P(X = Y | Y = i)$$

$\left( \begin{array}{l} i \\ i \end{array} \right)$

$$\frac{1}{100}$$

$$P(Y = i)$$

$$\uparrow \sum_{i=1}^{100}$$

$$P(X = i | \cancel{Y = i}) P(Y = i)$$

$$\uparrow \cancel{100} \cdot \frac{1}{\cancel{100}} \frac{1}{100} = \frac{1}{100} \left( \frac{1}{100} \right)$$

(A) A = event picked coin is unfair

B = event of 10 heads

Quest.  $P(A|B)$

$$= \frac{P(B|A)P(A)}{P(B)}$$

$\frac{1}{1000}$

$\frac{1}{1000}$

$$\rightarrow P(B|A)P(A) + P(B|A^c)P(A^c)$$

$\frac{1}{1000}$        $\left(\frac{1}{2}\right)^{10}$        $\frac{999}{1000}$

$1000 \cdot 2^{10}$

$2^{10} + 999$

$\approx \frac{1}{2}$

Prob. 2

(a)

$$\begin{pmatrix} W \\ X_2 \end{pmatrix}$$

=

$$\begin{pmatrix} \sqrt{2} & -1 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} X_1 \\ X_2 \end{pmatrix}$$

$$\begin{aligned} \text{Cov}(W, X_2) &= \text{Cov}(\sqrt{2}X_1 - X_2, X_2) \\ &= \sqrt{2} \text{Cov}(X_1, X_2) \\ &= \text{Var}(X_2) = 0 \end{aligned}$$

→ indep!

$$(b) \begin{pmatrix} X_+ \\ X_- \end{pmatrix} = \begin{pmatrix} 1 & 1 \\ 1 & -1 \end{pmatrix} \begin{pmatrix} X_1 \\ X_2 \end{pmatrix}$$

$$\left\{ \begin{array}{l} X_1, X_2 \text{ iid } \sim N(0,1) \end{array} \right.$$

$$\left\{ \begin{array}{l} \begin{pmatrix} X_1 \\ X_2 \end{pmatrix} \sim N_2 \left( \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \right) \end{array} \right.$$

$\perp$ .  $X_+, X_-$  is multivariate  $N$

$$\perp \text{ Cov}(X_+, X_-) = \text{Cov}(X_1 + X_2, X_1 - X_2)$$

$$\left\{ \begin{array}{l} = \text{Var}(X_1) - \text{Var}(X_2) \end{array} \right.$$

$$= 0$$

$\rightarrow$  indep

b(i) : not always dep.

counter - ~~ex~~ :

b(ii) : not always indep

counter - ~~ex~~ : iid Bernoulli

$$X_1, X_2 \stackrel{iid}{\sim} \text{Ber}\left(\frac{1}{2}\right) \quad \begin{array}{c|c} \frac{1}{2} & \frac{1}{2} \\ \hline 0 & 1 \end{array}$$

$$\text{if } X_+ = 2$$

$$\Rightarrow X_1 = X_2 = 1$$

$$\Rightarrow X_- = 0$$

$\Rightarrow$  dependent

$$(c) \begin{pmatrix} X_1 \\ X_2 \\ X_3 \end{pmatrix} \sim N_3 \left( \begin{pmatrix} \vdots \\ \vdots \\ \vdots \end{pmatrix}, \begin{pmatrix} * & 0 & 0 \\ 0 & * & 0 \\ 0 & 0 & * \end{pmatrix} \right)$$

No

$$f_{X_1, X_2, X_3} = f_{X_1} f_{X_2} f_{X_3}$$

$\Rightarrow$  independence

$$A) \quad X_1 \perp\!\!\!\perp X_2$$

$$X_1 \perp\!\!\!\perp X_3$$

$$X_2 \perp\!\!\!\perp X_3$$

but  $(X_1, X_2, X_3)$  not mutually  
indep

" given  $X_1, X_2$   
we can infer  $X_3$  differently  
than its marginal "

$$X_1, X_2 \stackrel{\text{iid}}{\sim} \text{Ber}\left(\frac{1}{2}\right)$$

yes!

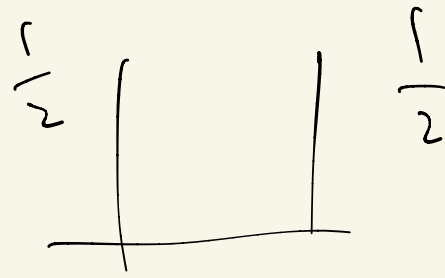
$$X_3 = X_1 \oplus X_2 \sim \text{Ber}\left(\frac{1}{2}\right)$$

$X_1, X_3$  are indep!

$$P(X_1 \oplus X_2 = y \mid X_1 = x) = P(X_2 = y \oplus x)$$

$$P(X_2 = y \oplus x) = \frac{1}{2}$$

Pb. 3



(a) show:

$$P\left(\frac{1}{n} \sum_{i=1}^n X_i > \frac{1}{100}\right)$$

$$\leq P\left(\left|\frac{1}{n} \sum_{i=1}^n X_i\right|^2 > \left(\frac{1}{100}\right)^2\right)$$

$$\leq \frac{E\left(\frac{1}{n} \sum_{i=1}^n X_i\right)^2}{\left(\frac{1}{100}\right)^2}$$

$$= \frac{\frac{1}{n} \text{Var}(X_i) \left(\frac{1}{100}\right)^2}{\left(\frac{1}{100}\right)^2} = \frac{1}{n^2} n \text{Var}(X_i)$$

(b)

$$\frac{1}{\sqrt{n}} \sum_{i=1}^n X_i = \tilde{S}_n$$

$$M_{\tilde{S}_n}(t) = E e$$

$$= E e^{t \frac{1}{\sqrt{n}} \sum_{i=1}^n X_i}$$

$$= E e^{t \frac{X_i}{\sqrt{n}}}$$

$$= \left( E e^{t \frac{X_i}{\sqrt{n}}} \right)^n$$

$$= \left( \frac{e^{2t/\sqrt{n}} + e^{-2t/\sqrt{n}}}{2} \right)^n = e^{2t\sqrt{n}} \frac{1 + e^{-4t/\sqrt{n}}}{2}$$

(c)

$$M_{\tilde{S}_n} \rightarrow e^{2t^2}$$

$$N(0, 4)$$

therefore  $\tilde{\Sigma}_n \xrightarrow{D} N(0, 4)$

(b4)  $X_1, \dots, X_n \stackrel{iid}{\sim} \text{Poi}(\theta)$

(a)  $E X_1 = \theta$   $\leftarrow$

$$\bar{X} = \frac{1}{n} \sum_{i=1}^n X_i = \theta$$

$\hat{\theta} = \bar{X}$   
Mom

(b)  $L(\theta) = \prod_{i=1}^n P(X_i = x_i)$   
 $\log \uparrow$   
 $\log \uparrow$   
 $\log \uparrow$   
 $= A \prod_{i=1}^n \frac{e^{-\theta} \theta^{x_i}}{x_i!}$

$$= \sum_{i=1}^n (x_i \log \theta - \theta = \log x_i!)$$

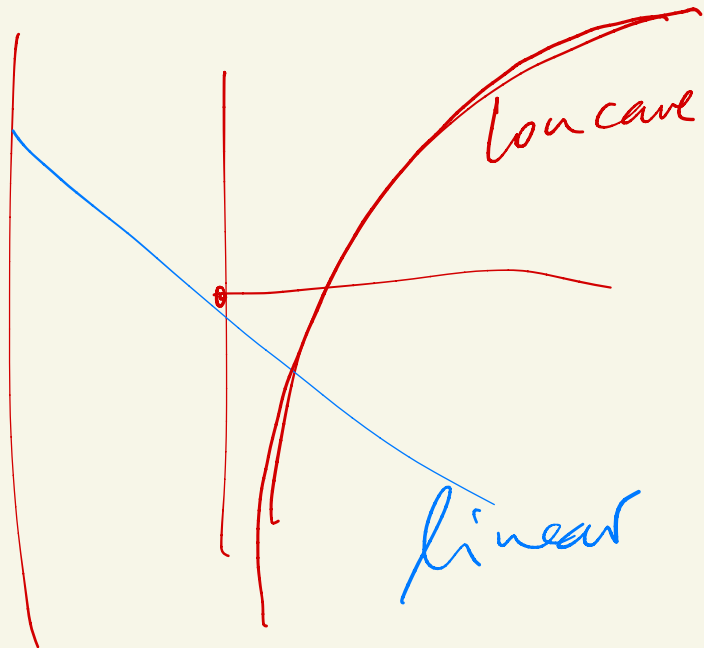
log concave

$$= \log \theta \left( \sum_{i=1}^n x_i \right) - n\theta + C$$

Maximize  $\uparrow$  over  $\theta$

$$\frac{\partial}{\partial \theta} (\ ) = 0$$

$$\frac{\partial^2}{\partial \theta^2} (\ ) < 0$$



$$\left( \sum x_i \right) \frac{1}{\theta_{MLE}} = n$$

$$\hat{\theta}_{MLE} = \frac{1}{X}$$

$$\frac{\partial^2}{\partial \theta^2} : - \sum_{i=1}^n \frac{x_i}{\theta^2} < 0$$

$$\begin{aligned}
 (c) \quad b(\theta) &= E(\hat{\theta}) - \theta \\
 &= E\left(\frac{1}{n} \sum X_i\right) - \theta \\
 &= \frac{1}{n} \sum E X_i - \theta \\
 &= \theta - \theta = 0
 \end{aligned}$$

$$\begin{aligned}
 \text{Var}(\hat{\theta}) &= \text{Var}\left(\frac{1}{n} \sum_{i=1}^n X_i\right) \\
 &= \frac{1}{n^2} \sum_{i=1}^n \text{Var}(X_i) \\
 &= \frac{1}{n} \sigma^2
 \end{aligned}$$

$$\text{MSE} = \text{var}(\hat{\theta}) + b(\theta)^2$$

$$E(\hat{\theta} - \theta)^2 = \underbrace{\text{Var}(\hat{\theta})}_{\text{red}} + \underbrace{\text{Bias}^2}_{\text{red}}$$

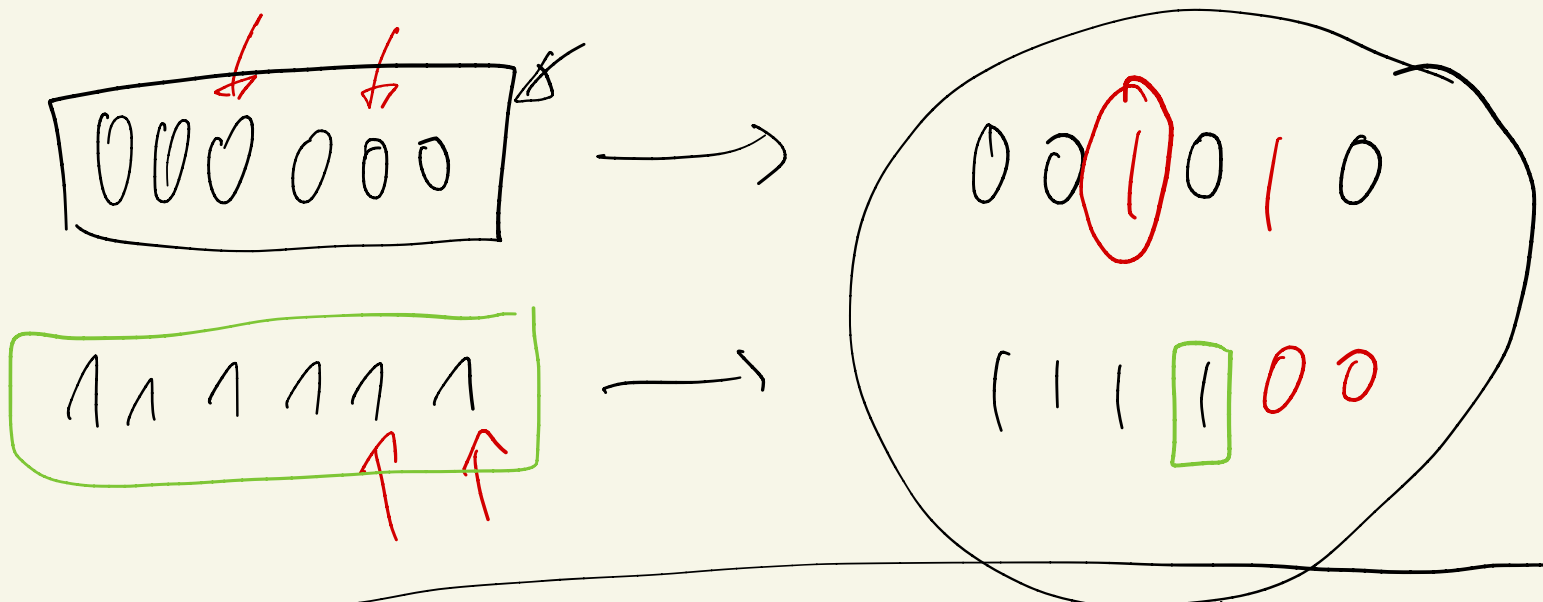
$\wedge$   
 $+ E\hat{\theta} - \theta$

$$\approx \frac{\theta}{n}$$

---

Pb(5)

---



$$\begin{array}{l}
 Y^n \\
 \sim \begin{cases}
 H_0 : Y^n \stackrel{\text{iid}}{\sim} \text{Ber}(P) \\
 H_1 : Y^n \stackrel{\text{iid}}{\sim} \text{Ber}(1-P)
 \end{cases}
 \end{array}$$

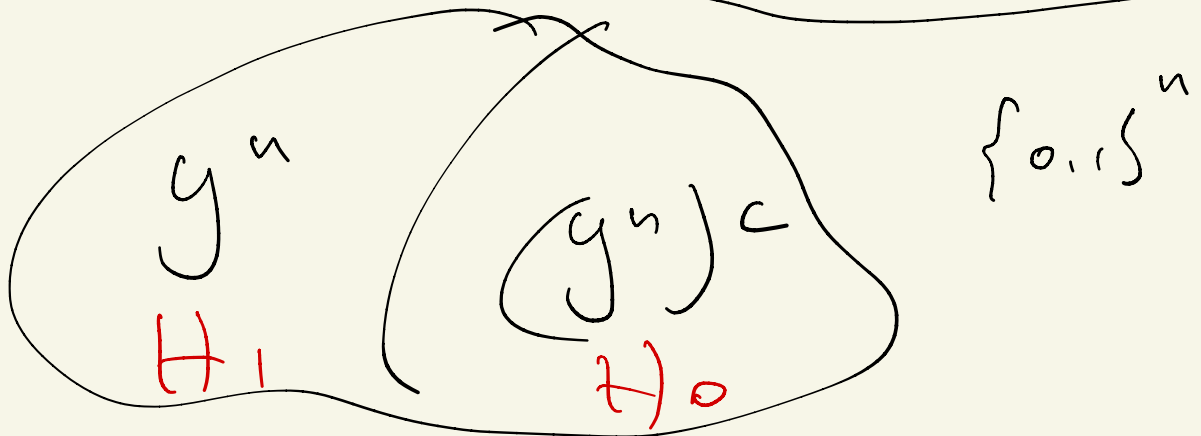
$$\phi \in (0, \frac{1}{2})$$

False positive :

1

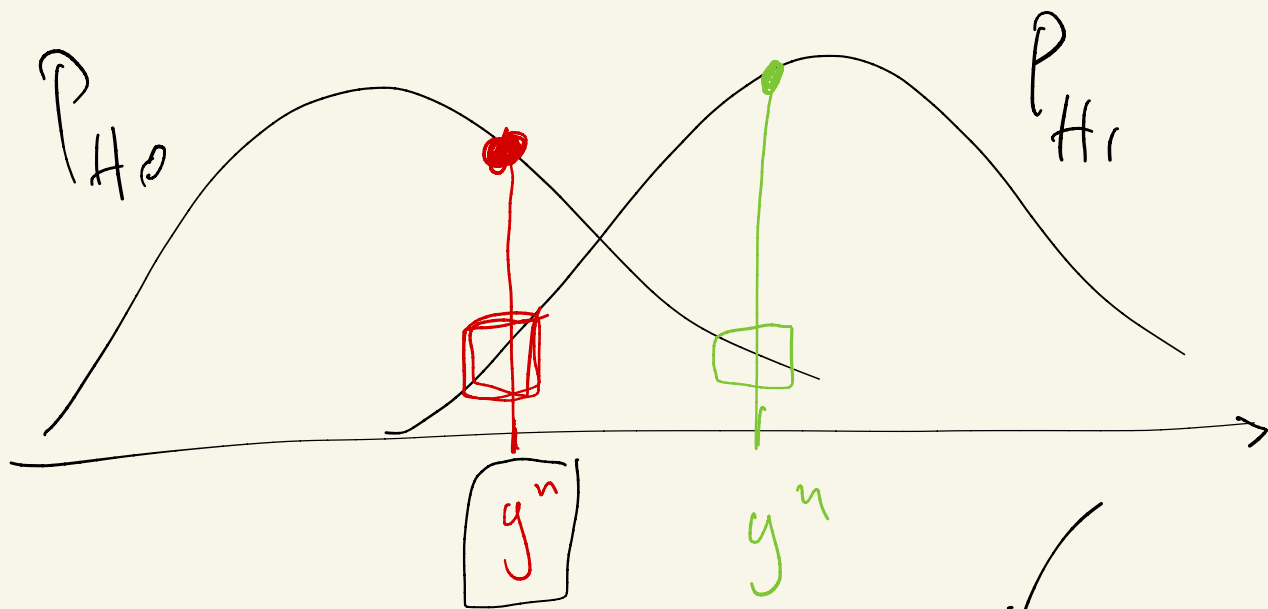
Let

$g^n$  = Set of values of  $Y^n$  where we declare  $H_1$



$$P(\underbrace{Y^n \in g^n}_{\text{declare } H_1} \mid \underbrace{Y^n \sim H_0}_{\text{true } H_0})$$

$$+ P(\underbrace{Y^n \notin g^n}_{\text{declare } H_0} \mid \underbrace{Y^n \sim H_1}_{\text{true } H_1})$$



$$y^n = \left\{ y^n \in \{0,1\}^n : P_{H_1}(y^n) > P_{H_0}(y^n) \right\}$$

$$= \left\{ y^n \in \{0,1\}^n : \frac{1}{n} \sum_{i=1}^n y_i > \frac{1}{2} \right\}$$

$$P_{H_0}(y^n) = \prod_{i=1}^n p^{y_i} (1-p)^{1-y_i}$$

$$p \in (0, \frac{1}{2})$$

$$= p^{\sum y_i} (1-p)^{n - \sum y_i}$$

$$= \left( \frac{p}{1-p} \right)^{\sum y_i} (1-p)^n$$

$$\left(\frac{p}{1-p}\right)^{\sum y_i} (1-p)^n < \left(\frac{1-p}{p}\right)^{\sum y_i} p^n$$

$(\Rightarrow)$

$$\sum y_i < \frac{n}{2}$$

$$\left(\frac{p}{1-p}\right)^{2 \sum y_i} < \left(\frac{p}{1-p}\right)^n$$

$$2 \sum y_i < n$$

$$\left\{ \begin{array}{l} \sum y_i > \frac{n}{2} \Rightarrow H_1 \\ \sum y_i \leq \frac{n}{2} \Rightarrow H_0 \end{array} \right.$$

( $\Rightarrow$ ) majority rule

$$\textcircled{b) } P\left(\sum_{i=1}^n Y_i > \frac{n}{2} \mid Y^n \sim H_0\right) + P\left(\sum_{i=1}^n Y_i \leq \frac{n}{2} \mid Y^n \sim H_1\right)$$

$$P\left(\sum Y_i > \frac{n}{2} \mid Y^n \sim H_0\right) \rightarrow$$

$z_1, \dots, z_n \stackrel{iid}{\sim} \text{Ber}(p)$

$$P\left(\sum_{i=1}^n z_i > \frac{n}{2}\right) \rightarrow 0$$

$$= P\left(\sum_{i=1}^n z_i - np > \frac{n}{2} - np\right)$$

$$\leq P\left(\left|\sum_{i=1}^n z_i - np\right| > \frac{n}{2} - np\right)$$

$$= P\left(\left|\sum_{i=1}^n z_i - np\right|^2 > \left(\frac{n}{2} - np\right)^2\right)$$

Markov

$$\leq \frac{\text{Var}\left(\sum_{i=1}^n z_i\right)}{\left(\frac{n}{2} - np\right)^2} \quad n \cdot c$$

$$\sim \frac{1}{n} \rightarrow 0 \quad \left(\frac{n}{2} - np\right)^2 \leftarrow n^2 \cdot c$$

$$(c) \quad \hat{p} = \frac{1}{2} - \frac{1}{\log(n)}$$

$$\frac{n \operatorname{Var}(Z_1)}{\left(\frac{n}{2} - n\hat{p}\right)^2} \xrightarrow{\log(n)^2} 0$$

*Annotations:*  
- A green circle highlights  $\operatorname{Var}(Z_1)$ .  
- A green arrow points from  $\log(n)^2$  to the denominator.  
- A red arrow points from the denominator to 0.

$$\hat{p} = \frac{1}{2} - \frac{1}{\log(n)}$$

*Annotation:*  
- A green circle highlights the entire equation.

yes