

• Some properties of sum of random variables:
 ← identical independent distributed.

• Say X_1, \dots, X_n are i.i.d R.V.

• $S = X_1 + \dots + X_n$, $\bar{X} = S/n$.
 ↑ sample mean

• let's denote: $\mathbb{E}(X_i) = \mu$
 $\text{Var}(X_i) = \sigma^2$. $\text{Var}(X) = \mathbb{E}(\underline{(X-\mu)^2})$.

$$\mathbb{E}(S) = \mathbb{E}(X_1 + \dots + X_n) = \mathbb{E}(X_1) + \mathbb{E}(X_2) + \dots + \mathbb{E}(X_n)$$

$$= n \cdot \mu.$$

$$\mathbb{E}(\bar{X}) = \mathbb{E}(S)/n = \mu.$$

$$\text{Var}(S) = \mathbb{E}((S - n\mu)^2)$$

$$= \mathbb{E}\left(\left[\sum_{i=1}^n (X_i - \mu)\right]^2\right)$$

$$= \mathbb{E}\left(\sum_{i=1}^n \sum_{j=1}^n (X_i - \mu)(X_j - \mu)\right)$$

$$= \sum_{i=1}^n \sum_{j=1}^n \mathbb{E}\left((X_i - \mu)(X_j - \mu)\right).$$

$i \neq j$, then $\mathbb{E}\left((X_i - \mu)(X_j - \mu)\right) = \mathbb{E}(X_i - \mu) \cdot \mathbb{E}(X_j - \mu) = 0 \cdot 0 = 0$.

because X_i and X_j are indep.
 or rather, $X_i - \mu$ and $X_j - \mu$ are indep.

$$= \sum_{i=1}^n \mathbb{E}\left((X_i - \mu)^2\right) = \sum_{i=1}^n \text{Var}(X_i)$$

$$= n \cdot \sigma^2$$

In fact, if all X_i are indep, then

$$\star \text{Var}(\sum_i X_i) = \sum_i \text{Var}(X_i).$$

$$\text{Var}(\bar{X}) = \text{Var}(S/n) = \text{Var}(S)/n^2$$

$$= (n \cdot \sigma^2)/n^2 = \sigma^2/n$$

Thm: (Law of large numbers).

say X_1, X_2, \dots a seq of iid R.V.

then. " $\lim_{n \rightarrow \infty} \underbrace{\frac{X_1 + \dots + X_n}{n}}_{\text{R.V.}} \stackrel{M_n}{=} \underbrace{\mu}_{\text{constants}}$ " or a R.V. that $= \mu$ with probability one..

(?) what does it mean, for a sequence of R.V. μ_n to converge?

• Thm: (Central Limit Thm).

Say X_1, X_2, \dots iid R.V. $E(X_i) = \mu$, $\text{Var}(X_i) = \sigma^2$.

$$\mu_n = \frac{X_1 + \dots + X_n}{n} \quad (\text{again, } \mu \text{ is a R.V.})$$

Then $\left(\frac{\mu_n - \mu}{\sqrt{\text{Var}(\mu_n)}} \right) = \left(\frac{\mu_n - \mu}{\sigma/\sqrt{n}} \right) \xrightarrow{?} N(0, 1)$
 \uparrow mean \uparrow std dev = $\sqrt{\text{Var}}$

informally: the sample average $\mu_n \sim N(\mu, \frac{\sigma}{\sqrt{n}})$.

Hypothesis Testing and p-value.

- Setup: $\left\{ \begin{array}{l} \cdot \text{observe certain data} \\ \cdot \text{want to figure out the mechanism that generate these data.} \end{array} \right.$

• we assume there is a fixed model that produces these data, but with some unknown parameters.

$\theta \in \Theta$
 \uparrow parameter space.

[for example, normal distribution, $N(\mu, \sigma)$, it has 2 parameters μ, σ . $\theta = (\mu, \sigma)$ $\Theta = \mathbb{R} \times \mathbb{R}_{>0}$.]

- For each $\theta \in \Theta$, we have a probability \mathbb{P}_θ
 given an events $E \subset \Omega$, we can ask $\mathbb{P}_\theta(E)$ probability of E.
 it is a fan of θ .

[Ex: $X \sim N(\mu, \sigma)$. $\mathbb{P}_{\mu, \sigma}(X < 1) = \int_{-\infty}^1 \frac{1}{\sqrt{2\pi} \cdot \sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}} dx$]

- Given the output (data), try to infer what the input (parameters) are like. ----- "Inferences"

- Hypothesis: H_0 : null hypothesis $\theta \in \Theta_0$
 (Statement about the param.) H_1 : alternative hypothesis. $\theta \in \Theta$, $\Leftrightarrow \theta \notin \Theta_0$.

$$\Theta = \Theta_0 \sqcup \Theta_1 \quad \text{decomposition into 2 disjoint sets.}$$

"possible values"

let \mathcal{X} denote the range of R.V. X , then

- Test:
 (about data, or R.V.) a test is a subset $R \subset \mathcal{X}$,
 R is known as the "rejection region"

- We say, the test rejects the null hypothesis, if $X \in R$.

- power function:

$$\beta(\theta) = \mathbb{P}_\theta(X \in R).$$

= if we had model param θ , the probability we reject H_0 .

- level α : $\alpha = \max_{\theta \in \Theta_0} \beta(\theta)$. (maximum false rejection rate.)

(the smaller α is, the better the test)

$\theta \in \Theta_0$

