

## Inequalities

- many important models are too complex to analyze exactly
- help us prove important limiting theorems

We will discuss Markov, Chebyshev & Hoeffding's bound  
EE178 simplest example of a concentration map.

### Markov's Inequality:

For any non-negative r.v.  $X$  and  $t > 0$ , we have

$$\mathbb{P}\{X \geq t\} \leq \frac{\mathbb{E}[X]}{t}$$

↳ tail probability (one-sided)

e.x. average height of Stanford students is 165 cm  
5 feet 5 inches.  
fraction of students that are above 180 cm  
5 feet 11 inches

$$\mathbb{P}\{X \geq 180\} \leq \frac{165}{180}$$

$$\mathbb{1}_{\{X \geq t\}} = \begin{cases} 1 & X \geq t \\ 0 & X < t \end{cases}$$

$$X = X \mathbb{1}_{\{X \geq t\}} + X \mathbb{1}_{\{X < t\}}$$

$$\mathbb{E}[X] = \mathbb{E}[X \mathbb{1}_{\{X \geq t\}}] + \mathbb{E}[X \mathbb{1}_{\{X < t\}}]$$

$$= \int x \mathbb{1}_{\{x \geq t\}} f_X(x) dx + \int x \mathbb{1}_{\{x < t\}} f_X(x) dx$$

$$= \int_t^{\infty} x f_X(x) dx + \int_0^t x f_X(x) dx$$

$$\geq t \int_t^{\infty} f_X(x) dx = t \mathbb{P}\{X \geq t\}$$

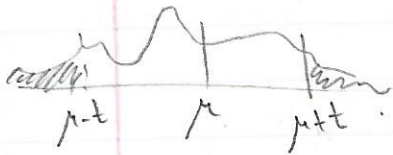
$$\Rightarrow P\{X \geq t\} \leq \frac{E[X]}{t}$$

Chebyshev's inequality:

→ better quadratic dependence on  $t$ .  
 • quantifies concentration of  $X$  about mean, (controls both tails)

Let  $X$  be a r.v. with mean  $\mu$  and variance  $\sigma^2$ . Then for any  $t > 0$ , we have

$$P\{|X - \mu| \geq t\} = P\{(X - \mu)^2 \geq t^2\} \leq \frac{E[(X - \mu)^2]}{t^2} = \frac{\sigma^2}{t^2}$$



Limit Theorems:

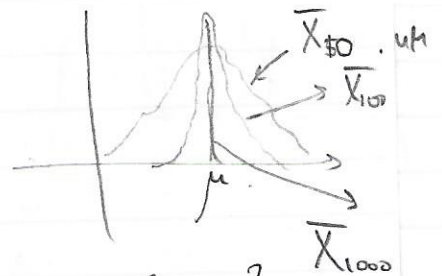
1) The Weak Law of Large Numbers (WLLN)

Let  $X_1, X_2, \dots, X_n$  iid r.v.'s with mean  $\mu = E[X_1] = \dots = E[X_n]$

$$S_n = \sum_{i=1}^n X_i \quad \bar{X}_n = \frac{1}{n} S_n \quad \bar{X}_n \rightarrow \mu \text{ as } n \rightarrow \infty \text{ LLN}$$

WLLN:

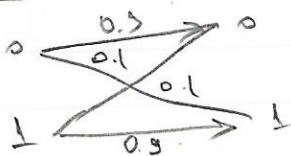
$$\forall \epsilon > 0 \quad P\{|\bar{X}_n - \mu| > \epsilon\} \xrightarrow{n \rightarrow \infty} 0$$



Ex:  $X_i$  independent flips of a coin with  $P\{X_i = 1\} = 0.3$

Ex: Statistics / survey sampling

Ex: Reliable communication



Codebook = { a collection of binary strings that are well separated from each other }

$$C = \{ \overset{\text{codewords}}{00000}, 00111, 11100, 11011 \}$$

use a codebook with codewords of length  $n$  for large  $n$  and make sure all codewords are separated from each other with a distance  $\geq (0.1 + \epsilon)n$  for some small  $\epsilon$

$$\frac{\# \text{ of errors}}{n} \rightarrow 0.1$$

e.x. Monte Carlo Integration

$$I(f) = \int_0^1 f(x) dx$$

numerical mt. rieman sum.

generate  $X_1, \dots, X_n$  iid uniform  $[0,1]$

$$\hat{I}(f) = \frac{1}{n} \sum_{i=1}^n f(X_i)$$

$$\hat{I}(f) \xrightarrow{n \rightarrow \infty} \mathbb{E}[f(X_1)] = \int_0^1 f(x) dx$$

Proof:

$$\text{Var}(\bar{X}_n) = \text{Var}\left(\frac{1}{n} \sum_{i=1}^n X_i\right)$$

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

$$= \frac{1}{n^2} \sum_{i=1}^n \text{Var}(X_i) \quad \text{because } X_1, \dots, X_n \text{ are ind.}$$

$$= \frac{1}{n^2} \cdot n \cdot \sigma^2 = \frac{\sigma^2}{n}$$

Chebyshev's Inequality

$$P\left\{ |\bar{X}_n - \mu| > \epsilon \right\} \leq \frac{\text{Var}(\bar{X}_n)}{\epsilon^2}$$

$$= \frac{\sigma^2}{n\epsilon^2} \rightarrow 0 \text{ as } n \rightarrow \infty$$

$$S_n = \sum_{i=1}^n X_i$$

$$\frac{S_n}{n} - \mu = \frac{S_n - n\mu}{n}$$

$$\text{Var} \left[ \frac{S_n - n\mu}{n} \right] = \frac{1}{n} \sigma^2$$

$$W_n = \frac{\sqrt{n}}{\sigma} \left( \frac{S_n - n\mu}{n} \right)$$

$$\text{Var}(W_n) = n \cdot \frac{1}{n} \frac{\sigma^2}{\sigma^2} = 1$$

$$= \frac{S_n - n\mu}{\sigma \sqrt{n}} \xrightarrow{n \rightarrow \infty} \mathcal{N}(0, 1)$$

$$\mathbb{E}[W_n] = 0$$

$$\text{Var}(W_n) = 1$$

Central Limit Theorem: Let  $X_1, X_2, \dots, X_n$  iid with mean  $\mu$  and variance  $\sigma^2$ .

$$\text{Let } W_n = \frac{\sum_{i=1}^n X_i - n\mu}{\sqrt{n} \sigma}$$

be their standardized sum last row

then

$$F_{W_n}(w) = P\{W_n \leq w\} \xrightarrow{n \rightarrow \infty} P\{W \leq w\}$$

$\uparrow$  convergence in distribution.

for every  $w$ ; where  $W \sim \mathcal{N}(0, 1)$ .

CLT: some justification for Gaussian models.

noise = sum of many independent small noise sources.  
 ex. thermal noise.