

lab report by Nov 10]

## Convergence of random variables & limit Theorems

### Probability inequalities

#### 1. Boole's Inequality (Union Bound)

$(\Omega, \mathcal{F}, P)$

$E_1, E_2, \dots$

$$P\left(\bigcup_{i=1}^n E_i\right) \leq \sum_{i=1}^n P(E_i)$$

Proof:  $E_1$  and  $E_2$

$$P(E_1 \cup E_2) = \underbrace{P(E_1)}_{\geq 0} + \underbrace{P(E_2)}_{\geq 0} - \underbrace{P(E_1 \cap E_2)}_{\geq 0}$$

$n=2$

$$\leq P(E_1) + P(E_2)$$

Proceed by induction to prove the general case.  
let us assume that this theorem holds for  
 $n = n-1$

$$P\left(\bigcup_{i=1}^{n-1} E_i\right) \leq \sum_{i=1}^{n-1} P(E_i)$$

$$P\left(\bigcup_{i=1}^n E_i\right) = P\left(\left(\bigcup_{i=1}^{n-1} E_i\right) \cup (E_n)\right)$$

$$\leq P\left(\bigcup_{i=1}^{n-1} E_i\right) + P(E_n)$$

$$\leq \sum_{i=1}^{n-1} P(E_i) + P(E_n)$$

$$= \sum_{i=1}^n P(E_i)$$

2. Markov Inequality: Suppose  $X$  is a <sup>positive</sup> random

variable

$$P(X \geq a) \leq \frac{E[X]}{a}$$

Proof:

$$\begin{aligned} E[X] &= \int_0^{\infty} x \cdot f_X(x) dx \\ &= \underbrace{\int_0^a x \cdot f_X(x) dx}_{\geq 0} + \int_a^{\infty} x \cdot f_X(x) dx \\ &\geq \int_a^{\infty} \underset{\uparrow}{x} \cdot f_X(x) dx \\ &\geq \int_a^{\infty} a \cdot f_X(x) dx \\ &= a \boxed{\int_a^{\infty} f_X(x) dx} \\ &\quad P(X \geq a) \end{aligned}$$

$$P(X \geq a) \leq \frac{E[X]}{a}$$

Example:  $X \sim \text{Bin}(n, p)$

$$P(X \geq q \cdot n)$$

$$\leq \frac{E[X]}{q \cdot n} = \frac{np}{q \cdot n} = \frac{p}{q}$$

$$p = \frac{1}{3}, \quad q = \frac{2}{3}$$

$$P(X \geq \frac{2}{3}n) \leq \frac{1}{2}$$

↑

### 3. Chebychev Inequality.



Suppose  $X$  is a random variable, then for any  $b > 0$

$$P(|X - E[X]| \geq b) \leq \frac{\text{Var}(X)}{b^2}$$

Proof:

$$Y = (X - E[X])^2$$

$$P(Y \geq b^2) \leq \frac{E[Y]}{b^2} \quad \text{Markov Ineq.}$$

$$E[Y] = E[(X - E[X])^2] = \text{Var}(X)$$

$$= \frac{\text{Var}(X)}{b^2} \quad \text{✓}$$

### 4. Chernoff Bound

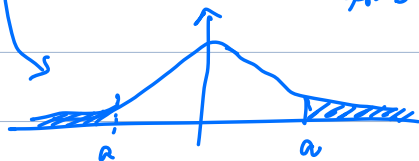
Suppose  $X$  is a random variable, for any  $a$

$$P(X \geq a) \leq \min_{t > 0} e^{-ta} M_X(t)$$

"upper tail prob"

$$P(X \leq a) \leq \min_{t < 0} e^{-ta} M_X(t)$$

"lower tail prob"



Proof:

$$P(X \geq a) = P(tX \geq ta) \quad t > 0$$

$$= P(\underbrace{e^{tX}}_{\text{"exponential transform"}} \geq e^{ta})$$

"exponential transform"

positive random variable

$$\text{Markov} \leq \frac{\mathbb{E}[e^{tx}]}{e^{ta}} = e^{-ta} M_X(t) \quad \text{"MGF of X"}$$

$$\underbrace{P(X \geq a)}_h \leq \underbrace{e^{-ta} M_X(t)}_{f(t)} \leq \min_{t>0} e^{-ta} M_X(t)$$

|               |                        |
|---------------|------------------------|
| $h \leq f(t)$ | $h \leq 10$            |
| $t=1$         | $h \leq 5$             |
| $t=2$         | $h \leq 2$             |
| $t=3$         | $\Rightarrow h \leq 2$ |

2 = min of all upper bounds.

$$h \leq \min_t f(t)$$

Example:  $X \sim \text{Bin}(n, p)$

$$P(X \geq qn) \leq \min_t e^{-tqn} M_X(t)$$

$$(pe^t + (1-p))^n$$

$$\frac{d}{dt} [e^{-tqn} (pe^t + (1-p))^n] \Big|_{t=t^*} = 0$$

$$e^{t^*} = \frac{q(1-p)}{(1-q)p}$$

$$P(X \geq qn) \leq e^{-t^*qn} (e^{t^*} p + (1-p))^n$$

$$q = \frac{2}{3}, \quad p = \frac{1}{3} \quad = \left( \frac{p}{q} \right)^{2n} \left( \frac{1-p}{1-q} \right)^{(1-q)n}$$

$$P(X \geq 2/3 n) \leq \frac{1}{2}$$

$$P(X \geq 2/3 n) \leq 2^{-n/3}$$

"tail bounds in terms of  
"n" "