

Probability and Random Process (SWE3026)

Multiple Random Variables

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Probability Bounds

- 1) Union Bound and its Extensions
- 2) Markov and Chebyshev's Inequalities
- 3) Chernoff Bounds
- 4) Cauchy-Schwarz Inequality
- 5) Jensen's Inequality

Probability Bounds

Usefulness:

- 1) Generality
- 2) When exact computation is not possible.

Probability Bounds

Remember:

$$\begin{aligned} P(A \cup B) &= P(A) + P(B) - P(A \cap B) \\ &\leq P(A) + P(B). \end{aligned}$$

More generally:

$$P(A \cup B \cup C \cup \dots) \leq P(A) + P(B) + P(C) + \dots$$

Probability Bounds

The Union Bound

For any events A_1, A_2, \dots, A_n , we have

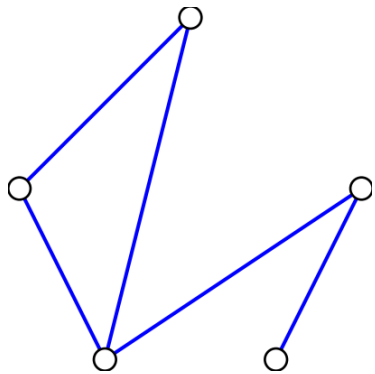
$$P\left(\bigcup_{i=1}^n A_i\right) \leq \sum_{i=1}^n P(A_i).$$

Probability Bounds

Example. Random Graphs: $G(n, p)$.

n : The number of nodes

p : Probability of connection between two nodes (independent from other edges).



$$n = 5$$

Probability Bounds

Example. Let B_n be the event that a graph randomly generated according to $G(n, p)$ model has at least one isolated node (a node that is not connected to any other nodes). Show that

$$P(B_n) \leq n(1 - p)^{n-1}.$$

b) And conclude that for any $\epsilon > 0$, if $p = p_n = (1 + \epsilon) \frac{\ln(n)}{n}$ then

$$\lim_{n \rightarrow \infty} P(B_n) = 0.$$

Probability Bounds

It is an interesting exercise to calculate $P(B_n)$ exactly using the inclusion-exclusion principle:

$$\begin{aligned} P\left(\bigcup_{i=1}^n A_i\right) &= \sum_{i=1}^n P(A_i) - \sum_{i < j} P(A_i \cap A_j) \\ &\quad + \sum_{i < j < k} P(A_i \cap A_j \cap A_k) - \cdots + (-1)^{n-1} P\left(\bigcap_{i=1}^n A_i\right). \end{aligned}$$

Probability Bounds

Generalization of the Union Bound: Bonferroni Inequalities

For any events A_1, A_2, \dots, A_n , we have

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

$$P\left(\bigcup_{i=1}^n A_i\right) \geq \sum_{i=1}^n P(A_i) - \sum_{i < j} P(A_i \cap A_j);$$

$$P\left(\bigcup_{i=1}^n A_i\right) \leq \sum_{i=1}^n P(A_i) - \sum_{i < j} P(A_i \cap A_j) + \sum_{i < j < k} P(A_i \cap A_j \cap A_k).$$

⋮

Probability Bounds

Markov's Inequality

If X is any **nonnegative** random variable, then

$$P(X \geq a) \leq \frac{EX}{a}, \quad \text{for any } a > 0.$$

Probability Bounds

Let X be any positive continuous random variable, we can write

$$\begin{aligned} EX &= \int_0^{\infty} x f_X(x) dx \geq \int_a^{\infty} x f_X(x) dx && \text{(for any } a > 0 \text{ and } x > a) \\ &\geq \int_a^{\infty} a f_X(x) dx = a \underbrace{\int_a^{\infty} f_X(x) dx}_{P(X \geq a)} \end{aligned}$$

$$\Rightarrow P(X \geq a) \leq \frac{EX}{a}, \quad \text{for any } a > 0.$$

Probability Bounds

Chebyshev's Inequality

If X is any random variable, then for any $b > 0$, we have

$$P(|X - EX| \geq b) \leq \frac{\text{Var}(X)}{b^2}.$$

Probability Bounds

Let X be any random variable. If $Y = (X - EX)^2$, then Y is a nonnegative random variable.

$$P(Y \geq b^2) \leq \frac{EY}{b^2} = \frac{\text{Var}(X)}{b^2},$$

$$P((X - EX)^2 \geq b^2) = P(|X - EX| \geq b).$$

Probability Bounds

Chernoff Bounds

$$P(X \geq a) \leq e^{-sa} M_X(s), \quad \text{for all } s > 0$$

$$P(X \leq a) \leq e^{-sa} M_X(s), \quad \text{for all } s < 0$$

Probability Bounds

For $s > 0$, we can write

$$\begin{aligned} P(X \geq a) &= P(e^{sX} \geq e^{sa}) \\ &\leq \frac{E[e^{sX}]}{e^{sa}}, \quad \text{by Markov's inequality.} \\ &= \frac{M_X(s)}{e^{sa}} \end{aligned}$$

Comparison between Bounds

Let's find upper bounds on $P(X \geq \alpha n)$ for $X \sim \text{Binomial}(n, p)$ where $p = \frac{1}{2}, \alpha = \frac{3}{4}$.

1) Markov Inequalities
$$P(X \geq a) \leq \frac{EX}{a}, \text{ for any } a > 0.$$

2) Chebyshev's Inequalities
$$P(|X - EX| \geq b) \leq \frac{\text{Var}(X)}{b^2}.$$

3) Chernoff Bounds
$$P(X \geq a) \leq e^{-sa} M_X(s), \text{ for all } s > 0$$

Probability Bounds

Cauchy-Schwarz Inequality

For any two random variables X and Y , we have


$$|E XY| \leq \sqrt{E[X^2]E[Y^2]},$$

where equality holds if and only if $X = \alpha Y$, for some constant $\alpha \in \mathbb{R}$.

Probability Bounds

$$|\rho(X, Y)| \leq 1 :$$

assuming $EX = EY = 0$


$$|\rho(X, Y)| = \left| \frac{\text{Cov}(X, Y)}{\sqrt{\text{Var}(X)\text{Var}(Y)}} \right| = \left| \frac{EXY}{\sqrt{E[X^2]E[Y^2]}} \right| \leq 1$$

$$\Rightarrow |EXY| \leq \sqrt{E[X^2]E[Y^2]}.$$

Probability Bounds

Jensen's Inequality

Remember

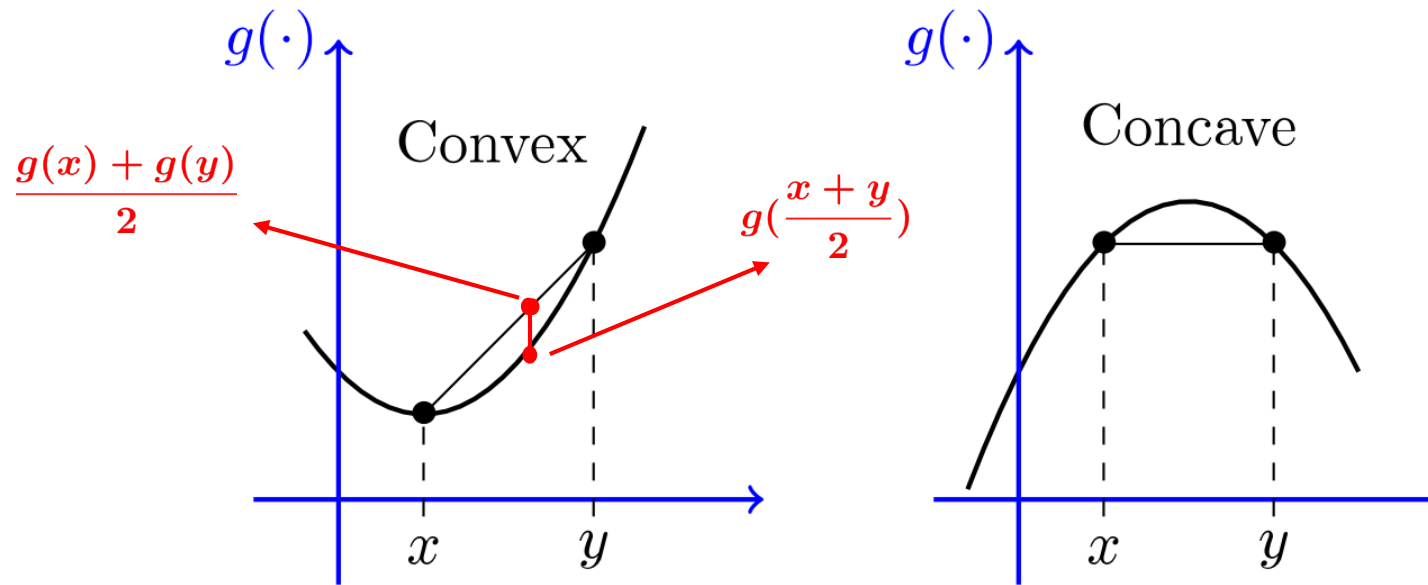
$$\text{Var}(X) = EX^2 - (EX)^2 \geq 0 \Rightarrow EX^2 \geq (EX)^2.$$

If $g(x) = x^2$,

$$E[g(X)] \geq g(E[X]).$$

Probability Bounds

Jensen's Inequality



$$\Rightarrow \text{Convex : } \frac{g(x) + g(y)}{2} \geq g\left(\frac{x+y}{2}\right)$$

Probability Bounds

Definition. Consider a function $g : I \rightarrow \mathbb{R}$, where I is an interval in \mathbb{R} . We say that g is a **convex** function if, for any two points x and y in I and any $\alpha \in [0, 1]$, we have

$$g(\alpha x + (1 - \alpha)y) \leq \alpha g(x) + (1 - \alpha)g(y).$$

We say that g is **concave** if

$$g(\alpha x + (1 - \alpha)y) \geq \alpha g(x) + (1 - \alpha)g(y).$$

Probability Bounds

Jensen's Inequality

If $g(x)$ is a convex function on R_X , and $E[g(X)]$ and $g(E[X])$ are finite, then

$$E[g(X)] \geq g(E[X]).$$

Probability Bounds

A twice-differentiable function $g : I \rightarrow \mathbb{R}$ is convex if and only if $g''(x) \geq 0$ for all $x \in I$.