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LECTURE #6Review: Probability Theory.Random Variable:  $X: \Omega \rightarrow \mathbb{R}$ A real valued function on  
a sample space,  $\Omega$ 

↳ A set of possible outcomes.

Random Outcome

⇒ Property or measurements on  
the random outcomes.Probability Space  $(\Omega, \mathcal{F}, \mathcal{P})$  $\Omega$  = Set of possible outcomes [No Additional Structure] $\mathcal{F}$  =  $\sigma$ -field of subsets of  $\Omega$  [Nonempty, closed under complement<sup>!!</sup> & Countable union.] $\mathcal{P}$  = Measure on  
the measurable space  $(\Omega, \mathcal{F})$ .

$$\mathcal{P}(\Omega) = 1 \Rightarrow \mathcal{P}(\emptyset) = 0$$

$$A \in \mathcal{F} \Rightarrow \mathcal{P}(A) \in [0, 1]$$

$\{\omega \in \Omega : X(\omega) < a\} \in \mathcal{F} \leftarrow \text{Event.}$

$B = \text{Borel subset of the real line.}$

$$P_x(B) \triangleq P(X^{-1}(B))$$

HISTORY. a) Hilbert's SIXTH PROBLEM (1900)

b) Borel's Paradox

(Related to Baye's Theorem).

c) Banach-Tarski Paradox.

(Also Axiom of Choice).

d) Savage's Utility Problem.

Solution  $\rightarrow$  Kolmogorov

1) Kolmogorov's 0-1 Law

"Events in the asymptotic  $\sigma$ -field  
has probability 0 or 1."

2) Law of Large Numbers //

Strong Law of Large Numbers.

$\{X_n, n \geq 1\} = \text{Sequence of centered independent r.v.s.}$

$$S_n = X_1 + X_2 + \dots + X_n$$

$$\sum_{n \geq 1} \frac{E(X_n^2)}{n^2} < \infty \Rightarrow \frac{S_n}{n} \rightarrow 0 \text{ a.s.}$$

$$\left\{ \begin{array}{l} E(|X_1|) < \infty \Rightarrow \frac{S_n}{n} \rightarrow E(X_1) \text{ a.s.} \\ E(|X_1|) = \infty \Rightarrow \limsup_{n \rightarrow \infty} \frac{|S_n|}{n} = +\infty \text{ a.s.} \end{array} \right.$$

# Probability Distribution Function (PDF)

$$P_x(B) = P(X^{-1}(B)) \leftarrow \text{PDF.}$$

$$P[a < x < b] = P_x(a, b) = P\left\{\omega \in \Omega \mid a < x(\omega) < b\right\}$$

Open Interval = Borel.

Sample Space,  $\Omega$  = Set of outcomes of a  
\* Probability Experiment

Example

$$n: \text{coin tosses} \rightarrow (H+T)^n$$

=  $2^n$   $n$ -long strings over  
the alphabet  $\Sigma = \{H, T\}$

$$\text{random genomes of length } n \rightarrow (a+t+c+g)^n$$

=  $4^n$   $n$ -long strings over  
the alphabet  $\Sigma = \{a, t, c, g\}$

Real Random Variable  $X: \Omega \rightarrow \mathbb{R}$

Real-valued functions on  $\Omega$ .

Example: Number of heads among the  
 $n$ -coin tosses

$$X = k \quad \binom{n}{k} \text{ possibilities}$$

$$\frac{n!}{k!(n-k)!} \left\{ \binom{n}{k} = \binom{n-1}{k-1} + \binom{n-1}{k} \right.$$

$$\begin{array}{ll} k = \text{Head} & k = \text{Tail} \\ X = k-1 & X = k \end{array}$$

Event: Subset of  $\Omega$ .  $\left\{ \begin{array}{l} \text{In the } \sigma\text{-field,} \\ \text{if } \Omega \text{ is not finite.} \end{array} \right.$

Example: A specific subset of 3-tosses with even number of heads.

$\{ TTT, HHT, HTH, THH \}$

#  $\binom{3}{0} + \binom{3}{2} = 1 + 3 = 4$ .

Conditional Probability. (of events F conditional on event G).

$Pr(F|G)Pr(G) = Pr(F \cap G)$

Baye's Rule:

$$Pr(F|G) = \frac{Pr(F \cap G)}{Pr(G)} = \frac{Pr(F \cap G)}{Pr(G|F) + Pr(G|\neg F)}$$
$$= \frac{Pr(G|F) Pr(F)}{Pr(G|F) Pr(F) + Pr(G|\neg F) Pr(\neg F)}$$

Independence (of events F and G)

$Pr(F|G) = Pr(F)$

$Pr(F \cap G) = Pr(F|G) \cdot Pr(G)$   
 $= Pr(F) \cdot Pr(G)$ .

Mutual Independence (of events  $F_1, F_2, \dots, F_n$ )

$$\begin{aligned} \Pr(F_1 \wedge F_2 \wedge \dots \wedge F_n) \\ &= \Pr(F_1 | F_2 \wedge \dots \wedge F_n) \Pr(F_2 | F_3 \wedge \dots \wedge F_n) \dots \Pr(F_n) \\ &= \Pr(F_1) \Pr(F_2) \dots \Pr(F_n) \end{aligned}$$

Indicator Variable

$$\mathbb{1}_{\text{Event}} = \begin{cases} 1 & \text{if event happens} \\ 0 & \text{otherwise.} \end{cases}$$

Independence of Random Variables  $X$  &  $Y$ .

$$\forall A, B \subseteq \mathbb{R} \quad \Pr(X \in A \wedge Y \in B) = \Pr(X \in A) \Pr(Y \in B)$$

$$\forall a, b \in \mathbb{R} \quad \Pr(X = a \wedge Y = b) = \Pr(X = a) \Pr(Y = b)$$

Mutual Independence of r.v.s.  $X_1, \dots, X_n$ .

$$\forall A_1, A_2, \dots, A_n$$

$$\begin{aligned} \Pr(X_1 \in A_1 \wedge X_2 \in A_2 \wedge \dots \wedge X_n \in A_n) \\ &= \Pr(X_1 \in A_1) \Pr(X_2 \in A_2) \dots \Pr(X_n \in A_n) \end{aligned}$$

$$\forall a_1, a_2, \dots, a_n$$

$$\begin{aligned} \Pr(X_1 = a_1 \wedge X_2 = a_2 \wedge \dots \wedge X_n = a_n) \\ &= \Pr(X_1 = a_1) \Pr(X_2 = a_2) \dots \Pr(X_n = a_n) \end{aligned}$$

## General Random Variable

Function from  $\Omega$  to any arbitrary Set.

$$X: \Omega \rightarrow S$$

Example:

Random Graph

$G(n, p)$ :  $\binom{n}{2}$  coin tosses  $\rightarrow$

$$G = (V, E); \quad |V| = n$$

$$A_G = \begin{cases} a_{ij} = a_{ji} = 1 & i < j \text{ and } \\ & (i, j)\text{th coin toss} = H \\ 0 & \text{otherwise.} \end{cases}$$

Probability Density Function - pdf  $p(x)$

such that

$$\Pr(a < x < b) = \int_a^b p(x) dx.$$

Cumulative Density Function cdf  $c(a)$

$$f(a) = \int_{-\infty}^a p(x) dx = \Pr(x \leq a).$$

Mean or Expectation.  $E(X)$  of a r.v.  $X$ .

$$E(X) = \int_{-\infty}^{\infty} x p(x) dx = \mu(x)$$

$$\left\{ \text{or } \sum x p(x) \text{ if } \Omega = \text{finite} \right\}$$

$$\begin{aligned} E(\mathbb{1}_{a < x < b}) &= \int_{-\infty}^{\infty} \mathbb{1}_{a < x < b} p(x) dx \\ &= \int_a^b p(x) dx = \Pr[a < x < b]. \end{aligned}$$

Let  $x$  be a nonnegative r.v. Then.

$$t \leq x \iff 1 \leq \frac{x}{t}$$

$$\mathbb{1}_{x \geq t} \leq \frac{x}{t}$$

$$E(\mathbb{1}_{x \geq t}) \leq E\left(\frac{x}{t}\right) = \frac{E(x)}{t}$$

$$\Pr[x \geq t] \leq \frac{E(x)}{t} \quad \left\{ \begin{array}{l} \text{Markov} \\ \text{Inequality.} \end{array} \right.$$

Variance  $\text{Var}(X) = E(X - E(X))^2 = \sigma^2(X)$

k<sup>th</sup> Moment  $\mu_k(X) = E(X^k)$

$$\begin{aligned}\text{Var}(X) &= \mu_2(X) - \mu_1(X)^2 \\ &= E(X^2) - E(X)^2 = \sigma^2.\end{aligned}$$

$$P_r[(X - \mu)^2 \geq a^2 \sigma^2] \leq \frac{E[(X - \mu)^2]}{a^2 \sigma^2} = \frac{1}{a^2}$$

(by Markov Ineq)

$$P_r[|X - \mu| \geq a\sigma] \leq \frac{1}{a^2} \quad \left\{ \begin{array}{l} \text{Chebyshev} \\ \text{Inequality.} \end{array} \right.$$

### Linearity of Expectations

(No independence assumed.)

$$E(\sum x_i) = \sum E(x_i)$$

Expectation of sum of r.v.'s is sum of expectations.

But.

$$\text{Var}(\sum x_i) = \sum \text{Var}(x_i) \quad \text{if } x_i\text{'s are pairwise independent r.v.s.}$$



# Probability Distributions.

## ◊ Bernoulli

$$X \sim \text{Bernoulli}(p)$$

$$X \in \{0, 1\}$$

$$\Pr[X = 1] = p$$

$$\Pr[X = 0] = q = 1 - p$$

## ◊ Binomial

$$X \sim B(n, p)$$

$$X \in \{0, 1, 2, \dots, n\}$$

$$\Pr[X = k] = \binom{n}{k} p^k (1-p)^{n-k}$$

In  $n$  independent trials, exactly  $k$  successes are observed:

$$\mu = np \quad \sigma^2 = npq$$

## ◊ Poisson

$$X \sim \text{Poisson}(\lambda)$$

$$\Pr(X = k) = e^{-\lambda} \frac{\lambda^k}{k!}$$

Average rate of an event per unit time =  $\lambda$   
Exactly  $k$  events are observed in a unit time.

$$X \sim B(n, \frac{\lambda}{n})$$

$$\Pr[X = k] = \binom{n}{k} \left(\frac{\lambda}{n}\right)^k \left(1 - \frac{\lambda}{n}\right)^{n-k}$$

$$= \frac{n(n-1)\dots(n-k+1)}{k!} \frac{\lambda^k}{n^k} \left(1 - \frac{\lambda}{n}\right)^{n-k} = \frac{n(n-1)\dots(n-k+1)}{n^k} \frac{\lambda^k}{k!} \left(1 - \frac{\lambda}{n}\right)^{n-k}$$

$$= \frac{e^{-\lambda} \lambda^k}{k!} \frac{n(n-1)\dots(n-k+1)}{n^k} \frac{1}{\left(1 - \frac{\lambda}{n}\right)^k}$$

$$\lim_{n \rightarrow \infty} \left( \frac{n(n-1)\dots(n-k+1)}{n^k} \frac{1}{\left(1 - \frac{\lambda}{n}\right)^k} \right) \rightarrow e^{-\lambda} \frac{\lambda^k}{k!} \quad \left. \vphantom{\lim} \right\} \mu = \lambda, \sigma^2 = \lambda$$

Let  $x_1, x_2, \dots, x_n$  be independent Bernoulli random variables

$$x_i \sim \text{Bernoulli}(p)$$

Random Walk.

$$S_n = \sum_{i=1}^n x_i \quad m_n = \mu(S_n) = np$$

Chernoff Bound:

$$\forall \delta > 0 \quad \text{Prob}[S_n > (1+\delta)m_n] \leq \left[ \frac{e^\delta}{(1+\delta)^{(1+\delta)}} \right]^{m_n}$$

$$\forall \delta > 2e^{-1} \quad \text{Prob}[S_n > (1+\delta)m_n] \leq \left( \frac{e}{1+\delta} \right)^{(1+\delta)m_n}$$

$$\forall 0 < r \leq 1 \quad \text{Prob}[S_n < (1-r)m_n] < \left[ \frac{e^{-r}}{(1+r)^{(1+r)}} \right]^{m_n} < e^{-r^2 m / 2}$$

Hoeffding Bounds

$$\text{Prob}[S_n - m_n \geq \epsilon] < e^{-2\epsilon^2/n}$$

Gaussian

$$X \sim \mathcal{N}(\mu, \sigma^2)$$

$$p(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

$$\mu = \mu, \sigma^2 = \sigma^2$$

CLT (Central Limit Theorem)

$x_1, x_2, \dots, x_n$  iid with  $E(x_i) = \mu$   
 $Var(x_i) = \sigma^2$

Then

$$\frac{\sum_{i=1}^n x_i - n\mu}{\sqrt{n}\sigma} \sim \mathcal{N}(0, 1)$$

Random Graph

$G(n, p)$  Model  
{ Erdős-Renyi }

A graph  $G = (V, E)$  is constructed by connecting every pair of nodes uniformly randomly.

$$\forall u, v \in V \quad [(u, v) \in E] \sim \text{Bernoulli}(p) \text{ iid.}$$

For every pair of nodes  $u, v \in V$ , an edge  $(u, v) \in E$  is included in the graph with probability  $p$  independent from every other edge.

$$|V| = n \quad \langle |E| \rangle = \binom{n}{2} p$$

Expected number of edges.

Expected degree of a  $G \in G(n, p)$

$$\langle d \rangle = \frac{2 \langle |E| \rangle}{\langle |V| \rangle} = \frac{2 \binom{n}{2} p}{n} = (n-1)p$$

$d(v) \sim \text{Binomial}(n-1, p)$

$$\Pr[d(v) = k] = \binom{n-1}{k} p^k (1-p)^{n-k-1}$$

$$\approx \frac{(np)^k}{k!} e^{-np}$$

if expected degree  $\bar{d}$  is held constant  
(independent of  $n$ ):  $n = \text{large}$ ,  $np = \text{const.}$   
 $= \lambda$

$$d(v) \sim \text{Poisson}(\lambda) \quad \lambda = \bar{d} = np.$$

Poisson Approximation.

Phase Transition: 0.1 Laws.

Small  $p$       $p < \frac{(1-\epsilon) \ln n}{n}$       $G(n, p) = \text{Disconnected a.s.}$

Large  $p$       $p > \frac{(1+\epsilon) \ln n}{n}$       $G(n, p) = \text{Connected a.s.}$