

Random variables

Objectives

1. To learn the definition of a random variable
2. To learn the definition of a probability mass function
3. Discrete random variables

Random Variables

[Definition] A Random Variable is a real-valued function of the elements of a sample space, S .

- Given an experiment, E , with sample space, S , the random variable X maps each possible outcome $\zeta \in S$, to a real number $f(\zeta)$ as specified by some rule
- We cannot describe a random variable X by stating its value; rather, we must give it a probabilistic description by stating the probabilities that the variable X takes on a specific value or values.
→ $P(X = 3), P(X > 8)$
- Example 2.1: Tossing two dice
 - › X : the sum of two dice
 - › $P(X = 7) = P((1,6), (2,5), \dots, (6,1)) = \frac{6}{36}$

Random Variables – example

- Example 2.3: Suppose that we toss a coin having a probability p of coming up heads until the first head appears. Let N denote the number of flips required.
 - › $P(N = 1) = P\{H\} = p$
 - › $P(N = 2) = P\{T, H\} = (1 - p)p$
⋮
 - › $P(N = n) = P\{T, T, \dots, T, H\} = (1 - p)^{n-1}p$

 $n-1$

Discrete random variables

- Discrete random variables: Random variables on either a finite or a countable number of possible values
- The **Probability Mass Function** (PMF), $p(a) = P(X = a)$ of a random variable, X , is a function that assigns a probability to each possible value of the random variable, X .
- Example
 - › Let X be a random variable for the number of times tails occur in n coin-flipping trials. Then

$$P(X = k) = \binom{n}{k} \left(\frac{1}{2}\right)^n$$

Cumulative distribution function (cdf)

- ❖ $F(a) = P(X \leq a) = \sum_{\text{all } x_i \leq a} p(x_i)$
- ❖ Example:
 - › Probability mass function for X : $p(1) = \frac{1}{2}$, $p(2) = \frac{1}{3}$, $p(3) = \frac{1}{6}$
 - › The cumulative distribution function F of X

Bernoulli Random Variable

- ❖ Experiments with 2 possible outcomes
- ❖ $P(0) = 1 - p, P(1) = p$
- ❖ Example ?

Binomial Random Variable

- ❖ Repeating a Bernoulli trial n times

Where the outcome of each trial is **independent**

- ❖ $P(X = k) = \binom{n}{k} p^k (1 - p)^{n-k}, k = 0, 1, 2, \dots, n$

- ❖ $\sum_{k=0}^n P_X(k) = \sum_{k=0}^n \binom{n}{k} p^k (1 - p)^{n-k} = 1$

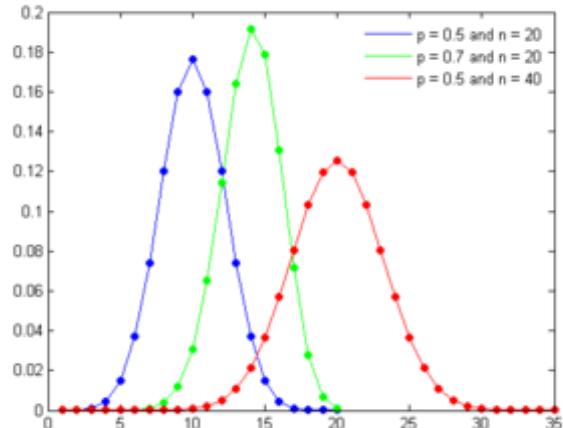
› Theorem of Binomial Coefficients

$$(x + y)^n = \sum_{k=0}^n \binom{n}{k} x^k y^{n-k}$$

- ❖ Example 2.7

› For a binomial random variable X with $p = 0.1, n = 3$

› $P(X \leq 1) =$

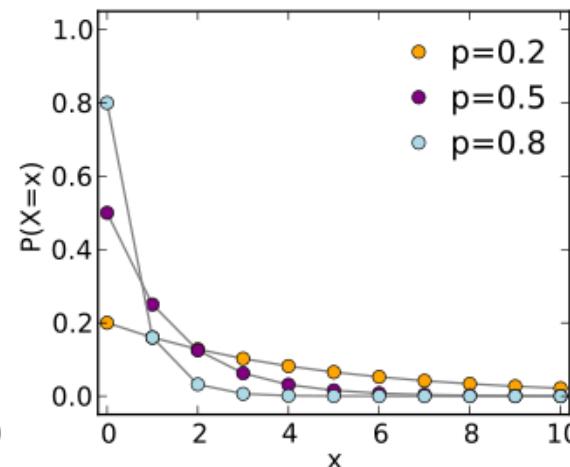
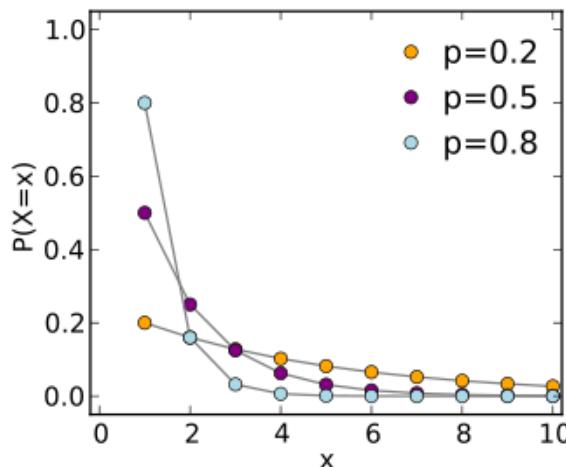


Geometric Random Variable

- ❖ X with parameter p
 - › the number of trials required until the first success
- Example 2.3: Suppose that we toss a coin having a probability p of coming up heads until the first head appears. Let N denote the number of flips required.
 - › $P(N = 1) = P\{H\} = p$
 - › $P(N = 2) = P\{T, H\} = (1 - p)p$
⋮
 - › $P(N = n) = P\{T, T, \dots, T, H\} = \underbrace{(1 - p)}_{n-1} p$

Geometric Random Variable - cdf

- ❖ Cumulative distribution function of a geometric random variable X
 - › $F(x) = P(X \leq x) = 1 - (1 - p)^x$
- ❖ Probability mass functions



Negative binomial

- ❖ X with parameter (p, r)
 - › the number of trials required until the r^{th} success
 - › $P(X = n) = \binom{n-1}{r-1} p^{r-1} (1-p)^{n-r} p = \binom{n-1}{r-1} p^r (1-p)^{n-r}$

Poisson Random Variable

- ❖ X with parameter λ
 - › $P(X = i) = e^{-\lambda} \frac{\lambda^i}{i!}, \ i = 0, 1, \dots$
- ❖ May be used to approximate a binomial random variable when n is large and p is small.

Approximation of a binomial random variable

$$\lim_{n \rightarrow \infty} np = \lambda$$

$$\lim_{n \rightarrow \infty} \left(1 - \frac{\lambda}{n}\right)^n = e^{-\lambda}$$

$$\begin{aligned}\lim_{n \rightarrow \infty} P(X = i) &= \lim_{n \rightarrow \infty} \binom{n}{i} p^i (1-p)^{n-i} = \lim_{n \rightarrow \infty} \frac{n!}{(n-i)! i!} \left(\frac{\lambda}{n}\right)^i \left(1 - \frac{\lambda}{n}\right)^{n-i} \\ &= \lim_{n \rightarrow \infty} \underbrace{\left(\frac{n}{n}\right) \left(\frac{n-1}{n}\right) \left(\frac{n-2}{n}\right) \cdots \left(\frac{n-i+1}{n}\right)}_{\approx 1} \underbrace{\left(\frac{\lambda^i}{i!}\right) \left(1 - \frac{\lambda}{n}\right)^n \left(1 - \frac{\lambda}{n}\right)^{-i}}_{\approx 1}\end{aligned}$$

$$P(X = i) = \frac{\lambda^i}{i!} e^{-\lambda}, \quad i = 0, 1, 2, \dots$$

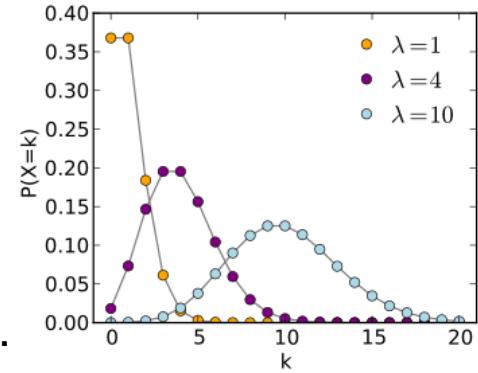
Poisson Random Variable - applications

❖ $P(k) = \frac{\lambda^k}{k!} e^{-\lambda}, \ k = 0, 1, 2, \dots$

› $\sum_{k=0}^{\infty} P(k) = 1$; From Taylor Series $e^x = \sum_{k=0}^{\infty} \frac{x^k}{k!}$

❖ Describes the behavior of many physical phenomena.

- › The number of cars that pass through a certain point on a road (sufficiently distant from traffic lights) during a given period of time.
- › The number of spelling mistakes one makes while typing a single page.
- › The number of phone calls at a call center per minute.
- › The number of times a web server is accessed per minute.
- › The number of mutations in a given stretch of DNA after a certain amount of radiation.



Poisson Random Variable - examples

- Example 2.12: average 3.2 α -particles are given off per second (λ).
 - › $P(X \leq 2) =$