Random Variables - Expectation

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Expectation of a function of a random variable







Expectation

Expectation of a function of a random variable









- Expectation
- Expectation of a function of a random variable
- Linearity of Expectation



Random Variables Expectation Expectation of a function of a random variable Linearity of Expectation Conditional Expectation



Main points

Random experiment,

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Random experiment, sample spaces,

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Random experiment, sample spaces, events, combining events, conditional probability,

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Main points

Random experiment, sample spaces, events, combining events, conditional probability, independence.

Random Variables

Motivation

Subramani Probability Theory

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Example

Let X denote the random variable that is defined as the sum of two fair dice.

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$$P\{X=1\} =$$

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$$P\{X = 1\} = 0$$

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$$P\{X = 1\} = 0$$

$$P\{X = 2\} = \frac{1}{36}$$

$$\vdots$$

$$P\{X = 12\} = \frac{1}{36}$$

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$$P\{Y = 0\} =$$

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$$P\{Y=0\} = \frac{1}{4}$$

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Consider the experiment of tossing two fair coins; let Y denote the random variable that counts the number of heads. What values can Y take?

 $P\{Y = 0\} = \frac{1}{4}$ $P\{Y = 1\} = \frac{1}{2}$ $P\{Y = 2\} = \frac{1}{4}$

Definition

A random variable that can take on only a countable number of possible values is said to be *discrete*.

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Definition

A random variable that can take on only a countable number of possible values is said to be *discrete*. For a discrete random variable *X*, the probability mass function (pmf) p(a) is defined as:

$$p(a) = P\{X = a\}.$$

The Bernoulli Random Variable

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Consider an experiment which has exactly two outcomes;

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Consider an experiment which has exactly two outcomes; one is labeled a "success" and the other a "failure". If we let the random variable X assume the value 1, if the experiment was a success and 0, if the experiment was a failure, then X is said to be a Bernoulli random variable.

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$$p(1) = P\{X = 1\} = p$$

$$p(0) = P\{X = 0\} = 1 - p$$

where $0 \le p \le 1$ is the probability that the experiment results in a success.

The Binomial Random Variable

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Consider an experiment which consists of n independent Bernoulli trials, with the probability of success in each trial being p. If X is the random variable that counts the number of successes in the n trials, then X is said to be a Binomial Random Variable.

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$$p(i) = P\{X = i\} = C(n, i) \cdot p^{i} \cdot (1 - p)^{n-i}, i = 0, 1, 2, \dots n$$

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$$= \frac{3}{8}$$

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$$p(i) = P\{X = i\} = (1 - p)^{i-1} \cdot p, i = 1, 2, \dots$$

Recap Random Variables Expectation

Expectation of a function of a random variable Linearity of Expectation Conditional Expectation



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$$= p$$

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$$= n \cdot p \sum_{i=1}^{n} \frac{(n-1)!}{(i-1)!(n-i)!} \cdot p^{i-1} \cdot (1-p)^{n-i}$$

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Expectation of a Binomial Random Variable (contd.)

Example

$$E[X] = n \cdot p \sum_{k=0}^{n-1} \frac{(n-1)!}{k! \cdot (n-k-1)!} \cdot p^k \cdot (1-p)^{n-k-1}$$

Expectation of a Binomial Random Variable (contd.)

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$$= n \cdot p \sum_{k=0}^{n-1} \frac{(n-1)!}{k! \cdot ((n-1)-k)!} \cdot p^k \cdot (1-p)^{(n-1)-k}$$

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$$E[X] = n \cdot p \sum_{k=0}^{n-1} \frac{(n-1)!}{k! \cdot (n-k-1)!} \cdot p^k \cdot (1-p)^{n-k-1}$$

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= $n \cdot p \sum_{k=0}^{n-1} C(n-1,k) \cdot p^k \cdot (1-p)^{(n-1)-k}$
= $n \cdot p \cdot [p+(1-p)]^{n-1}$, Binomial theorem
= $n \cdot p \cdot 1$

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$$[X] = \sum_{i=1}^{\infty} i \cdot p(i)$$
, by definition

Expectation of a Geometric Random Variable

Example

Let X denote a Geometric Random Variable with parameters n and p. What is E[X]? Solution:

$$\begin{aligned} \mathbf{F}[X] &= \sum_{i=1}^{\infty} i \cdot p(i), \text{ by definition} \\ &= \sum_{i=1}^{\infty} i \cdot (1-p)^{i-1} \cdot p \end{aligned}$$

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Let X denote a Geometric Random Variable with parameters n and p. What is E[X]? Solution:

$$\mathbb{E}[X] = \sum_{i=1}^{\infty} i \cdot p(i), \text{ by definition}$$
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$$= \sum_{i=1}^{\infty} i \cdot q^{i-1} \cdot p, \text{ where } q = 1 - 1$$

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$$= p \cdot \sum_{i=1}^{\infty} i \cdot q^{i-1}$$

$$= p \cdot \sum_{i=1}^{\infty} \frac{d}{dq} [q^{i}]$$

p

Expectation of a Geometric Random Variable

Example

Let X denote a Geometric Random Variable with parameters n and p. What is E[X]? Solution:

$$[X] = \sum_{i=1}^{\infty} i \cdot \rho(i), \text{ by definition}$$
$$= \sum_{i=1}^{\infty} i \cdot (1-\rho)^{i-1} \cdot \rho$$
$$= \sum_{i=1}^{\infty} i \cdot q^{i-1} \cdot \rho, \text{ where } q = 1 - 1$$
$$= \rho \cdot \sum_{i=1}^{\infty} i \cdot q^{i-1}$$
$$= \rho \cdot \sum_{i=1}^{\infty} \frac{d}{dq} [q^{i}]$$

p

Expectation of a Geometric Random Variable (contd.)

Example

$$E[X] = p \cdot \frac{d}{dq} [\sum_{i=1}^{\infty} q^{i}]$$

Expectation of a Geometric Random Variable (contd.)

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$$E[X] = p \cdot \frac{d}{dq} [\sum_{i=1}^{\infty} q^{i}]$$
$$= p \cdot \frac{d}{dq} [\frac{q}{1-q}]$$

Expectation of a Geometric Random Variable (contd.)

Example

$$\begin{aligned} \mathbf{F}[X] &= \rho \cdot \frac{d}{dq} \left[\sum_{i=1}^{\infty} q^i \right] \\ &= \rho \cdot \frac{d}{dq} \left[\frac{q}{1-q} \right] \\ &= \rho \cdot \frac{(1-q) \cdot \frac{d}{dq} [q] - q \cdot \frac{d}{dq} [1-q]}{(1-q)^2} \end{aligned}$$

Expectation of a Geometric Random Variable (contd.)

Example

$$\begin{aligned} \mathbf{F}[X] &= \rho \cdot \frac{d}{dq} [\sum_{i=1}^{\infty} q^{i}] \\ &= \rho \cdot \frac{d}{dq} [\frac{q}{1-q}] \\ &= \rho \cdot \frac{(1-q) \cdot \frac{d}{dq} [q] - q \cdot \frac{d}{dq} [1-q]}{(1-q)^{2}} \\ &= \rho \cdot \frac{(1-q) \cdot 1 - q \cdot (-1)}{(1-q)^{2}} \end{aligned}$$

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Recap Random Variables Expectation

Expectation of a function of a random variable Linearity of Expectation Conditional Expectation



Exercises

Example

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Consider yet another variation to the initial game:

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Example

Consider yet another variation to the initial game: The die is tossed ten times. For each toss that turns up an even number, *A* gets 5 dollars. For tosses turning up an odd number, *A* loses 4 dollars. How much money can *A* expect to make from this game?

Expectation of a function of a random variable

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$$E[Y] = E[X^2] = 0 \cdot 0.3 + 1 \cdot 0.5 + 4 \cdot 0.2 = 1.3$$

Expectation of functions - The Direct Approach

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If X is a random variable with pmf p(), and g() is any real-valued function, then,

$$E[g(X)] = \sum_{x} g(x) \cdot p(x)$$

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Linearity of Expectation

Proposition

Subramani Probability Theory

Linearity of Expectation

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Lemma

Let X and Y denote two random variables. Then, E[X + Y] = E[X] + E[Y].

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Lemma

Let X and Y denote two random variables. Then, E[X + Y] = E[X] + E[Y].

Lemma

Let X denote a random variable and let c denote a constant. Then, $E[c \cdot X] = c \cdot E[X]$.

Linearity of Expectation (contd.)

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Note

Note that linearity of expectation holds even when the random variables are **not** independent.

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Example

What is the expected value of the sum of the upturned faces, when two fair dice are tossed?

Another Application

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Compute the expected value of the Binomial random variable.

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Solution

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Accordingly, the Binomial random variable (say X) can be expressed as:

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What is the relation between $E[X^2]$ and $(E[X])^2$?

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If $f : \Re \to \Re$ is a convex function, and X is a random variable, then

 $f(E[X]) \leq E[f(X)]$

Conditional Expectation

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Definition

Let *X* and *Y* denote two random variables. The conditional expectation of *X*, given that Y = y, is defined as follows:

$$E[X \mid Y = y] = \sum_{x} x \cdot Pr(X = x \mid Y = y).$$

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Example

Let X_1 and X_2 denote the random variables monitoring the upturned faces of two tossed dice and let $X = X_1 + X_2$.

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Theorem

Let X and Y denote two random variables. Then,

$$E[X] = \sum_{y} Pr(Y = y) \cdot E[X \mid Y = y]$$

Conditional Expectation (contd.)

Proof.

Subramani Probability Theory

Conditional Expectation (contd.)

Proof.

$$\sum_{y} Pr(Y = y) \cdot E[X \mid Y = y] =$$

Conditional Expectation (contd.)

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$$= \sum_{x} x \cdot Pr(X = x)$$
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Conditional Expectation (contd.)

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The expression E[X | Y] is a random variable and takes on the values E[X | Y = y], when Y = y.

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