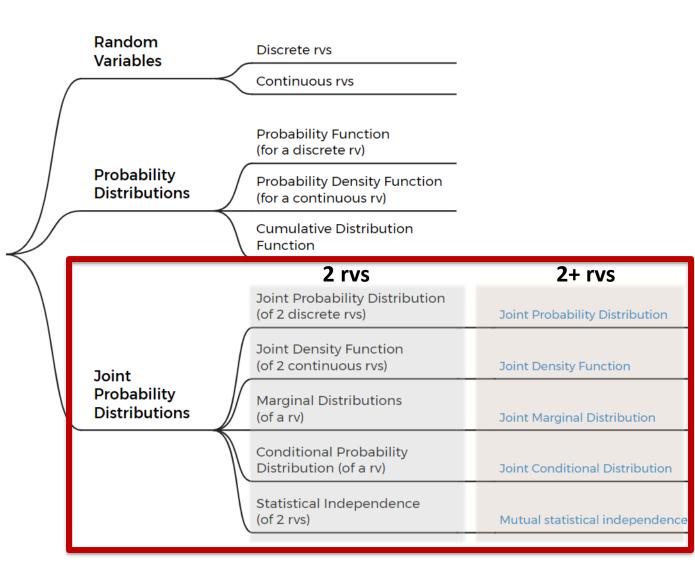
STAT 1151 Introduction to Probability

Lecture 5 Mathematical Expectation

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Last Lecture

Chapter 3. Random Variables & Probability Distributions



Outline

- Chapter 4 Mathematical Expectation
 - Mean of A Random Variable
 - Mean of A Function
 - Mean of Joint Random Variables
 - Means of Linear Combinations of Random Variables

Quiz scores of five students: 10, 10, 9, 8, 8

• Arithmetic mean:
$$\frac{10+10+9+8+8}{5} = 9$$

• Geometric mean:
$$\sqrt[5]{10 \times 10 \times 9 \times 8 \times 8} = 8.96$$

• Harmonic mean:
$$\frac{5}{\frac{1}{10} + \frac{1}{10} + \frac{1}{9} + \frac{1}{8} + \frac{1}{8}} = 8.91$$

These measures are used to show the **central tendency** of a set of observations.

Quiz scores of five students: 10, 10, 9, 8, 8

• Mean:
$$\frac{10+10+9+8+8}{5} = \frac{(10)(2)+9+(8)(2)}{5} = 9$$

Quiz scores of five students: 10, 10, 9, 9, 8

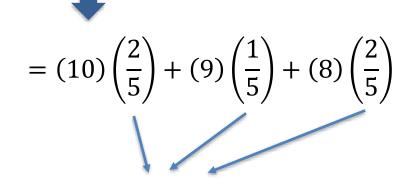
• Mean:
$$\frac{10+10+9+9+8}{5} = \frac{(10)(2)+(9)(2)+8}{5} = 9.2$$

The mean, or average, is not necessarily a possible outcome for the experiment.

Quiz scores of five students: 10, 10, 9, 8, 8

• Mean:
$$\frac{10+10+9+8+8}{5} = \frac{(10)(2)+9+(8)(2)}{5} = 9$$

We can calculate the **mean**, or average, of a set of data by knowing the <u>distinct</u> values that occur and their relative frequencies, without any knowledge of the total number of observations.



Fractions of total observations resulting in each outcome

This method of relative frequencies can be used to calculate the **mean of a random variable X**, or the **mean of the probability distribution X**, denoted by μ_x or simply μ .

It is also common to refer to this mean as the **mathematical expectation**, or the **expected value** of the random variable X, denoted by E(X).

Example:

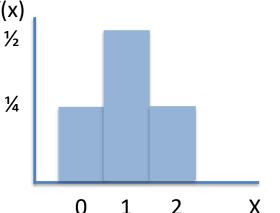
Assuming that two fair coins (red and green) were tossed, the sample space for the experiment is $S = \{HH, HT, TH, TT\}$. Define X as a random variable for the number of heads. f(x)

$$P(X=0) = P(TT) = \frac{1}{4}$$

$$P(X=2) = P(HH) = \frac{1}{4}$$

$$P(X=I) = P(HT) + P(TH) = \frac{1}{2}$$

$$\mu_X = E(X) = (0)\left(\frac{1}{4}\right) + (1)\left(\frac{1}{2}\right) + (2)\left(\frac{1}{4}\right) = 1$$



Definition:

Let X be a random variable with probability distribution f(x). The **mean**, or **expected value**, of X is

$$\mu = E(X) = \sum_{x} x f(x)$$
 (if X is discrete)
$$\mu = E(X) = \int_{x}^{\infty} x f(x) dx$$
 (if X is continuous)

The mean, or expected value, of a rv describes where the probability distribution is centered.

Mean of A Discrete RV

Example:

Suppose we are buying some new microphones from a local store. They have 4 good and 3 defective microphones. We need to randomly buy 3 from the store. What is the expected value of the number of good microphones that we buy from this store?

Let X represent the number of good components in the sample.

- Possible values of X:
- The probability distribution of X is:
- The expected value of X is:

Mean of A Discrete RV

Example:

A company produces some simple pens which are composed by the cap of the pen and the body of the pen. The probability of being defective for the cap and the body are 0.1 and 0.2, respectively. Rework a defective cap or pen body costs \$1 and \$2, respectively. Find the expected cost to rework a random pen.

Let X be the cost to rework a random pen.

- Possible values of X:
- The probability distribution of X:
- The expected value of X is:

Mean of A Continuous RV

Example:

An engineer is interested in the *mean life* of a certain type of electronic device. It is an important parameter for its evaluation. Let X be the random variable that denotes the life in hours of a certain electronic device, with the probability density function:

$$f(x) = \begin{cases} \frac{20,000}{x^3}, & x > 100\\ 0, & elsewhere \end{cases}$$

Find the expected life of this type of device.

Consider a new random variable g(X), which depends on X.

- Ex. $g(x) = X^2$
- Whenever X assumes the value 2, g(X) assumes the value g(2)=4.
- For a discreate rv X with probability distribution f(x), for x = -1, 0, 1, 2
- Possible values of g(X):

x	0	- 1	1	2
$g(x) = x^2$	0	1	1	4

- Probability distribution of g(X):

$$P[g(X) = 0] = P(X = 0) = f(0)$$

$$P[g(X) = 1] = P(X = -1) + P(X = 1) = f(-1) + f(1)$$

$$P[g(X) = 4] = P(X = 2) = f(2)$$

- Expected value of g(X):

$$\mu_{g(X)} = E[g(x)] = (0)f(0) + (1)[f(-1) + f(1)] + (4)f(2) = \sum_{x} g(x)f(x)$$

Theorem:

Let X be a random variable with probability distribution f(x). The **expected value** of a random variable g(X) is

$$\mu_{g(X)} = E[g(X)] = \sum_{x} g(x)f(x)$$
 (if X is discrete)

$$\mu_{g(X)} = E[g(X)] = \int_{-\infty}^{\infty} g(x)f(x)dx$$
 (if X is continuous)

Example:

Suppose that the number of cars X that pass through a car wash between 4 PM and 5 PM on any sunny Friday has the following probability distribution:

Let g(X) = 10(X+5) represent the amount of money, in RMB, paid to the attendant by the manager. Find the attendant's expected earnings for this particular time period.

Example:

Let X be a random variable with density function:

$$f(x) = \begin{cases} \frac{x^2}{3}, & -1 < x < 2\\ 0, & elsewhere \end{cases}$$

Find the expected value of g(X) = 4X+3.

Definition:

Let X and Y be random variables with joint probability distribution f(x, y). The **mean**, or **expected value**, of the random variable j(X,Y) is

$$\mu_{j(X,Y)} = E[j(X,Y)] = \sum_{x} \sum_{y} j(x,y) f(x,y)$$
 (if X and Y are discrete)

$$\mu_{j(X,Y)} = E[j(X,Y)] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} j(x,y)f(x,y)dxdy \quad \text{(if X and Y are continuous)}$$

*The definition can be generalized to calculate the mathematical expectations of functions of 2+ random variables.

Expected Value of Joint Discrete RVs

Example:

Let X and Y be the random variables with joint probability distribution indicated in the table below. Find the expected value of j(X,Y) = XY.

		x			Row
	f(x,y)	0	1	2	Totals
	0	$\frac{3}{28}$	$\frac{9}{28}$	$\frac{3}{28}$	$\frac{15}{28}$
y	1	$\frac{3}{28}$ $\frac{3}{14}$	$\frac{3}{14}$	0	$\frac{\overline{28}}{\frac{3}{7}}$
	2	$\frac{1}{28}$	0	0	$\frac{1}{28}$
Column Totals		$\frac{5}{14}$	$\frac{15}{28}$	$\frac{3}{28}$	1

Expected Value of Joint Continuous RVs

Example:

Find E(Y/X) for the density function

$$f(x,y) = \begin{cases} \frac{x(1+3y^2)}{4}, & 0 < x < 2, 0 < y < 1\\ 0, & elsewhere \end{cases}$$

Special case:

If j(X,Y) = X, we have

$$g(x) = \sum_{y} f(x, y)$$

$$\mu_{j(X,Y)} = E(X) = \sum_{x} \sum_{y} x f(x,y) = \sum_{x} x g(x)$$

(if X and Y are discrete)

$$\mu_{j(X,Y)} = E(X) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x f(x,y) dy dx = \int_{-\infty}^{\infty} x g(x) dx \quad \text{(if X and Y are continuous)}$$

$$g(x) = \int_{-\infty}^{\infty} f(x, y) dy$$

where g(x) is the marginal distribution of X.

Special case:

Similarly, if j(X,Y) = Y, we have

$$h(y) = \sum_{x} f(x, y)$$

$$\mu_{j(X,Y)} = E(Y) = \sum_{x} \sum_{y} y f(x,y) = \sum_{y} y h(y)$$

(if X and Y are discrete)

$$\mu_{j(X,Y)} = E(Y) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} y f(x,y) dx dy = \int_{-\infty}^{\infty} y h(y) dy \quad \text{(if X and Y are continuous)}$$

$$h(y) = \int_{-\infty}^{\infty} f(x, y) dx$$

where h(y) is the marginal distribution of Y.

*To calculate E(Y) over a two-dimensional space, we can use either the joint probability distribution of X and Y or the marginal distribution of Y.

Revisit example:

Let X and Y be the random variables with joint probability distribution indicated in the table below. Find E(X).

		x			Row
	f(x,y)	0	1	2	Totals
	0	$\frac{3}{28}$	$\frac{9}{28}$	$\frac{3}{28}$	$\frac{15}{28}$
y	1	$\frac{\frac{3}{28}}{\frac{3}{14}}$	$\frac{3}{14}$	0	$\frac{\overline{28}}{\frac{3}{7}}$
	2	$\frac{1}{28}$	0	0	$\frac{1}{28}$
Column Totals		$\frac{5}{14}$	$\frac{15}{28}$	$\frac{3}{28}$	1

Useful properties to simplify calculations (valid for both discrete and continuous rvs):

Theorem:

If a and b are constants, then E(aX + b) = aE(X) + b

Proof (for the continuous case):

$$E(aX + b) = \int_{-\infty}^{\infty} (ax + b)f(x)dx = a \int_{-\infty}^{\infty} xf(x)dx + b \int_{-\infty}^{\infty} f(x)dx$$

E(X)

Corollaries:

Setting a = 0, then
$$E(b) = b$$

Setting b = 0, then E(aX) = aE(X)

Revisit example:

Suppose that the number of cars X that pass through a car wash between 4 PM and 5 PM on any sunny Friday has the following probability distribution:

Let g(X) = 10(X+5) represent the amount of money, in RMB, paid to the attendant by the manager. Find the attendant's expected earnings for this particular time period.

Revisit example:

Let X be a random variable with density function:

$$f(x) = \begin{cases} \frac{x^2}{3}, & -1 < x < 2\\ 0, & elsewhere \end{cases}$$

Find the expected value of g(X) = 4X+3.

Theorem:

The expected value of the sum or difference of two or more functions of a random variable X is the sum or difference of the expected values of the functions. That is,

$$E(r_1(X) \pm r_2(X)) = E[r_1(X)] \pm E[r_2(X)]$$

Proof (for the continuous case):

$$E[r_1(X) \pm r_2(X)] = \int_{-\infty}^{\infty} [r_1(x) \pm r_2(x)] f(x) dx$$
$$= \int_{-\infty}^{\infty} r_1(x) f(x) dx \pm \int_{-\infty}^{\infty} r_2(x) f(x) dx$$
$$E[r_1(X)] \qquad E[r_2(X)]$$

Example:

Let X be a random variable with probability distribution as follows:

Find the expected value of $Y = (X - I)^2$.

Example:

The weekly demand for a certain drink, in thousands of liters, at a chain of convenience stores is a continuous random variable $g(X) = X^2 + X - 2$, where X has the density function:

 $f(x) = \begin{cases} 2(x-1), & 1 < x < 2\\ 0, & elsewhere \end{cases}$

Find the expected value of the weekly demand for the drink.

Theorem:

The expected value of the sum or difference of two or more functions of the random variables X and Y is the sum or difference of the expected values of the functions. That is,

$$E[r_1(X,Y) \pm r_2(X,Y)] = E[r_1(X,Y)] \pm E[r_2(X,Y)]$$

Corollaries:

Setting
$$r_1(X,Y) = g(X)$$
 and $r_2(X,Y) = h(Y)$, we see that,

$$E[g(X) \pm h(Y)] = E[g(X)] \pm E[h(Y)]$$

Setting
$$r_1(X,Y) = X$$
 and $r_2(X,Y) = Y$, we see that,

$$E(X \pm Y) = E(X) \pm E(Y)$$

Theorem:

Let X and Y be two independent random variables. Then,

$$E(XY) = E(X)E(Y)$$

Proof (for the continuous case):

$$E(XY) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} xy f(x, y) dx dy$$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} xy g(x) h(y) dx dy$$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} xy g(x) dx \int_{-\infty}^{\infty} y h(y) dy$$

$$E(X) \qquad E(Y)$$

$$X \text{ and Y are independent}$$

$$f(x, y) = g(x) h(y)$$

Example:

Let X and Y be two independent random variables with the joint density function:

$$f(x) = \begin{cases} \frac{x(1+3y^2)}{4}, & 0 < x < 2, 0 < y < 1\\ 0, & elsewhere \end{cases}$$

Show that E(XY) = E(X)E(Y).