

Expected Value and Variance

MATH 472 *Financial Mathematics*

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Objectives

In this lesson we will learn:

- ▶ the definition of expected value,
- ▶ how to calculate the expected value of a random variable,
- ▶ the properties of expected value,
- ▶ the definition of variance,
- ▶ the properties of variance.

Expected Value of a Random Variable

Definition

If X is a discrete random variable with probability mass function $f_X(x)$ then the **expected value of X** is denoted $\mathbb{E}(X)$ and defined as

$$\mathbb{E}(X) = \sum_{x \in \Omega} (x \cdot f_X(x)).$$

Example

What is the expected value of the number of female children in a family of 5 children?

Example

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If X represents the number of female children in a family with five children then

$$\begin{aligned}\mathbb{E}(X) &= \sum_{x \in \Omega} (x \cdot f_X(x)) \\ &= \sum_{x=0}^5 \left(x \cdot \binom{5}{x} \left(\frac{1}{2}\right)^x \left(\frac{1}{2}\right)^{5-x} \right) \\ &= \frac{5!}{32} \sum_{x=0}^5 \frac{x}{(x!)(5-x)!} \\ &= 2.5\end{aligned}$$

Expected Value of a Function of a Random Variable

Definition

If G is a function of the random variable X , then the **expected value of G** is

$$\mathbb{E}(G(X)) = \sum_{x \in \Omega} G(x) f_X(x).$$

Example

What is the expected value of the square of the number of female children in a family of 5 children?

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What is the expected value of the square of the number of female children in a family of 5 children?

If X represents the number of female children in a family with five children then

$$\begin{aligned}\mathbb{E}(X^2) &= \sum_{x \in \Omega} (x^2 \cdot f_X(x)) \\ &= \sum_{x=0}^5 \left(x^2 \cdot \binom{5}{x} \left(\frac{1}{2}\right)^x \left(\frac{1}{2}\right)^{5-x} \right) \\ &= 7.5\end{aligned}$$

Linearity of Expected Value

Theorem

If X is a random variable and a is a constant, then

$$\mathbb{E}(aX) = a\mathbb{E}(X).$$

Linearity of Expected Value

Theorem

If X is a random variable and a is a constant, then

$$\mathbb{E}(aX) = a\mathbb{E}(X).$$

Proof.

$$\mathbb{E}(aX) = \sum_{x \in \Omega} ((ax) \cdot f_X(x)) = a \sum_{x \in \Omega} (x \cdot f_X(x)) = a\mathbb{E}(X).$$



Joint Probability Function

Definition

If X and Y are discrete random variables the **joint probability mass function** of X and Y is denoted $f_{X,Y}(x, y)$ where

$$f_{X,Y}(x, y) = \mathbb{P}(X = x, Y = y) = \mathbb{P}((X = x) \cap (Y = y)).$$

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A joint probability mass function has the properties:

1. $0 \leq f_{X,Y}(x, y) \leq 1$,
2. $\sum_{(x,y) \in \Omega} f_{X,Y}(x, y) = 1$.

Marginal Probability

Definition

If the joint probability mass function of (X, Y) is $f_{X,Y}(x, y)$ then the function

$$f_X(x) = \sum_{y \in \Omega} f_{X,Y}(x, y)$$

is called the **marginal probability distribution of X** .

We may define a **marginal probability distribution for Y** similarly.

Expected Value of a Sum (1 of 2)

Theorem

If X_1, X_2, \dots, X_k are random variables then

$$\mathbb{E}(X_1 + X_2 + \cdots + X_k) = \mathbb{E}(X_1) + \mathbb{E}(X_2) + \cdots + \mathbb{E}(X_k).$$

Expected Value of a Sum (2 of 2)

Proof.

If $k = 2$ then

$$\begin{aligned}\mathbb{E}(X + Y) &= \sum_x \sum_y ((x + y)f_{X,Y}(x, y)) \\ &= \sum_x \sum_y x f_{X,Y}(x, y) + \sum_y \sum_x y f_{X,Y}(x, y) \\ &= \sum_x x \sum_y f_{X,Y}(x, y) + \sum_y y \sum_x f_{X,Y}(x, y) \\ &= \sum_x x f_X(x) + \sum_y y f_Y(y) \\ &= \mathbb{E}(X) + \mathbb{E}(Y).\end{aligned}$$

The general case then holds by induction on k . □

Expected Value of a Sum of Functions

Corollary

Let X_1, X_2, \dots, X_k be random variables and let F_i be a function of X_i for $i = 1, 2, \dots, k$ then

$$\mathbb{E}(F_1(X_1) + \dots + F_k(X_k)) = \mathbb{E}(F_1(X_1)) + \dots + \mathbb{E}(F_k(X_k)).$$

Expected Value of Binomial Random Variable

If X_i is a Bernoulli random variable then

$$\mathbb{E}(X_i) = (1)(p) + (0)(1 - p) = p.$$

Expected Value of Binomial Random Variable

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If the binomial random variable $X = X_1 + \cdots + X_n$ where each X_i is a Bernoulli random variable, then

$$\mathbb{E}(X) = \mathbb{E}(X_1) + \cdots + \mathbb{E}(X_n) = np.$$

Expected Value of a Geometric RV

- ▶ The probability mass function of a geometric RV is given by

$$\mathbb{P}(X = n) = f_X(n) = (1 - p)^{n-1} p \text{ for } n \in \mathbb{N}.$$

- ▶ Recall the geometric series summation,

$$\sum_{n=0}^{\infty} z^n = \frac{1}{1 - z} \text{ for } |z| < 1.$$

- ▶ Differentiate the summation and replace z by $1 - p$.

Expected Value of a Geometric RV

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$$\sum_{n=0}^{\infty} z^n = \frac{1}{1 - z} \text{ for } |z| < 1.$$

- ▶ Differentiate the summation and replace z by $1 - p$.

$$\begin{aligned} \sum_{n=1}^{\infty} n z^{n-1} &= \frac{1}{(1 - z)^2} \\ \sum_{n=1}^{\infty} n (1 - p)^{n-1} p &= \frac{p}{(1 - (1 - p))^2} \\ \mathbb{E}(X) &= \frac{1}{p} \end{aligned}$$

Independent Random Variables (1 of 2)

If X and Y are **independent** random variables then

$$f_{X,Y}(x,y) = f_X(x)f_Y(y)$$

where $f_X(x)$ is the marginal probability distribution of X and $f_Y(y)$ is the marginal probability distribution of Y .

Independent Random Variables (1 of 2)

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where $f_X(x)$ is the marginal probability distribution of X and $f_Y(y)$ is the marginal probability distribution of Y .

Theorem

Let X_1, X_2, \dots, X_k be pairwise independent random variables, then

$$\mathbb{E}(X_1 X_2 \cdots X_k) = \mathbb{E}(X_1) \mathbb{E}(X_2) \cdots \mathbb{E}(X_k).$$

Independent Random Variables (2 of 2)

Proof.

Now let X and Y be independent random variables with joint probability distribution $f_{X,Y}(x, y)$.

$$\begin{aligned}\mathbb{E}(XY) &= \sum_{(x,y) \in \Omega} xy f_{X,Y}(x, y) \\ &= \sum_x \sum_y xy f_X(x) f_Y(y) \\ &= \sum_x x f_X(x) \sum_y y f_Y(y) \\ &= \mathbb{E}(X) \mathbb{E}(Y)\end{aligned}$$

The general case holds by induction on k .



Variance (1 of 2)

Definition

If X is a random variable, the **variance** of X is denoted $\text{Var}(X)$ and

$$\text{Var}(X) = \mathbb{E} \left((X - \mathbb{E}(X))^2 \right).$$

The **standard deviation** of X is denoted $\sigma(X) = \sqrt{\text{Var}(X)}$.

Variance (2 of 2)

Theorem

Let X be a random variable, then the variance of X is

$$\text{Var}(X) = \mathbb{E}(X^2) - \mathbb{E}(X)^2.$$

Variance (2 of 2)

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Let X be a random variable, then the variance of X is

$$\text{Var}(X) = \mathbb{E}(X^2) - \mathbb{E}(X)^2.$$

Proof.

$$\begin{aligned}\text{Var}(X) &= \mathbb{E}\left((X - \mathbb{E}(X))^2\right) \\ &= \mathbb{E}\left(X^2\right) - \mathbb{E}\left(2X\mathbb{E}(X)\right) + \mathbb{E}\left(\mathbb{E}(X)^2\right) \\ &= \mathbb{E}\left(X^2\right) - 2\mathbb{E}(X)\mathbb{E}(X) + \mathbb{E}(X)^2 \\ &= \mathbb{E}\left(X^2\right) - \mathbb{E}(X)^2.\end{aligned}$$



Example (1 of 2)

What is the variance in the number of female children in a family of 5 children?

Example (1 of 2)

What is the variance in the number of female children in a family of 5 children?

If X represents the number of female children in a family of five children, then

$$\text{Var}(X) = \mathbb{E}(X^2) - (\mathbb{E}(X))^2 = 7.5 - (2.5)^2 = 1.25.$$

Example (2 of 2)

Find the variance of a Bernoulli random variable for which the probability of success is p .

Example (2 of 2)

Find the variance of a Bernoulli random variable for which the probability of success is p .

If X represents the outcome of a Bernoulli trial, then

$$\begin{aligned}\text{Var}(X) &= \mathbb{E}(X^2) - (\mathbb{E}(X))^2 \\ &= [1^2(p) + 0^2(1-p)] - p^2 \\ &= p - p^2 \\ &= p(1-p).\end{aligned}$$

Variance of a Sum (1 of 3)

Theorem

Let X_1, X_2, \dots, X_k be pairwise independent random variables, then

$$\text{Var}(X_1 + X_2 + \dots + X_k) = \text{Var}(X_1) + \text{Var}(X_2) + \dots + \text{Var}(X_k).$$

Variance of a Sum (2 of 3)

Take the case when $k = 2$.

$$\begin{aligned}\text{Var}(X + Y) &= \mathbb{E}\left(\left((X + Y) - \mathbb{E}(X + Y)\right)^2\right) \\ &= \mathbb{E}\left(\left((X - \mathbb{E}(X)) + (Y - \mathbb{E}(Y))\right)^2\right) \\ &= \mathbb{E}\left(\left(X - \mathbb{E}(X)\right)^2\right) + \mathbb{E}\left(\left(Y - \mathbb{E}(Y)\right)^2\right) + \\ &\quad 2\mathbb{E}\left(\left(X - \mathbb{E}(X)\right)\left(Y - \mathbb{E}(Y)\right)\right) \\ &= \text{Var}(X) + \text{Var}(Y) \\ &\quad + 2\mathbb{E}\left(\left(X - \mathbb{E}(X)\right)\left(Y - \mathbb{E}(Y)\right)\right)\end{aligned}$$

Variance of a Sum (2 of 3)

Since we are assuming that random variables X and Y are independent, then

$$\begin{aligned}\mathbb{E}((X - \mathbb{E}(X))(Y - \mathbb{E}(Y))) &= \mathbb{E}(X - \mathbb{E}(X))\mathbb{E}(Y - \mathbb{E}(Y)) \\ &= (\mathbb{E}(X) - \mathbb{E}(X))(\mathbb{E}(Y) - \mathbb{E}(Y)) \\ &= 0,\end{aligned}$$

and thus

$$\text{Var}(X + Y) = \text{Var}(X) + \text{Var}(Y).$$

The result can be extended to any finite value of k by induction.

Example

Find the variance of a Binomial random variable with n trials when the probability of success on a single trial is p .

Example

Find the variance of a Binomial random variable with n trials when the probability of success on a single trial is p .

Each trial of a binomial experiment is a Bernoulli experiment with probability of success p . Since the n trials of a binomial experiment are independent

$$\text{Var}(X) = np(1 - p).$$

Variance of a Geometric RV (1 of 2)

- ▶ The probability mass function of a geometric RV is given by

$$\mathbb{P}(X = n) = f_X(n) = (1 - p)^{n-1} p \text{ for } n \in \mathbb{N}.$$

- ▶ Recall the geometric series summation,

$$\sum_{n=0}^{\infty} z^n = \frac{1}{1 - z} \text{ for } |z| < 1.$$

- ▶ Differentiate the summation twice.

$$\sum_{n=1}^{\infty} n(n - 1) z^{n-2} = \frac{2}{(1 - z)^3}$$

Variance of a Geometric RV (2 of 2)

$$\sum_{n=1}^{\infty} n(n-1)z^{n-2} = \frac{2}{(1-z)^3}$$

Replace z by $1-p$.

$$\sum_{n=1}^{\infty} n^2(1-p)^{n-2} - \sum_{n=1}^{\infty} n(1-p)^{n-2} = \frac{2}{(1-(1-p))^3}$$

$$\sum_{n=1}^{\infty} n^2(1-p)^{n-1}p - \sum_{n=1}^{\infty} n(1-p)^{n-1}p = \frac{2(1-p)p}{(1-(1-p))^3}$$

$$\mathbb{E}(X^2) - \frac{1}{p} = \frac{2(1-p)}{p^2}$$

$$\mathbb{E}(X^2) - \mathbb{E}(X)^2 = \frac{2(1-p)}{p^2} + \frac{1}{p} - \left(\frac{1}{p}\right)^2$$

$$\text{Var}(X) = \frac{1-p}{p^2}$$

Variance of a Product (1 of 2)

Theorem

Let X_1, X_2, \dots, X_k be pairwise independent random variables, then

$$\begin{aligned}\text{Var}(X_1 X_2 \cdots X_k) &= \mathbb{E}(X_1^2) \mathbb{E}(X_2^2) \cdots \mathbb{E}(X_k^2) \\ &\quad - (\mathbb{E}(X_1) \mathbb{E}(X_2) \cdots \mathbb{E}(X_k))^2.\end{aligned}$$

Variance of a Product (2 of 2)

Proof.

$$\begin{aligned}\text{Var}(X_1 X_2 \cdots X_k) &= \mathbb{E}\left((X_1 X_2 \cdots X_k)^2\right) - (\mathbb{E}(X_1 X_2 \cdots X_k))^2 \\ &= \mathbb{E}\left(X_1^2 X_2^2 \cdots X_k^2\right) - (\mathbb{E}(X_1) \mathbb{E}(X_2) \cdots \mathbb{E}(X_k))^2 \\ &= \mathbb{E}\left(X_1^2\right) \mathbb{E}\left(X_2^2\right) \cdots \mathbb{E}\left(X_k^2\right) \\ &\quad - (\mathbb{E}(X_1) \mathbb{E}(X_2) \cdots \mathbb{E}(X_k))^2\end{aligned}$$

□

Homework

- ▶ Read Sections 2.6, 2.7
- ▶ Exercises: 16, 18–25

Credits

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An Undergraduate Introduction to Financial Mathematics,
3rd edition, (2012).

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