

Economics 103 – Statistics for Economists

Francis J. DiTraglia

University of Pennsylvania

Lecture # 8

Random Variables

A random variable is neither random nor a variable.

Random Variable (RV): X

A deterministic (i.e. non-random) function that assigns a numeric value to each basic outcome of a random experiment.

Realization: x

A particular numeric value that an RV could take on. We write $\{X = x\}$ to refer to the *event* that the RV X took on the value x .

Support Set (aka Support)

The set of all possible realizations of a RV.

Random Variables (continued)

Notation

Capital latin letters for RVs, e.g. X , Y , Z , and the corresponding lowercase letters for their realizations, e.g. x , y , z .

Intuition

You can think of an RV as a machine that spits out random numbers: although the machine is deterministic, its inputs, the outcomes of a random experiment, are not.

Example: Coin Flip Random Variable

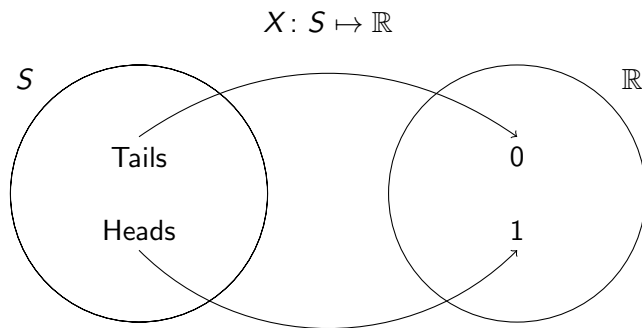


Figure : This random variable assigns numeric values to the random experiment of flipping a fair coin once: Heads is assigned 1 and Tails 0.

Which of these is a realization of the Coin Flip RV?



- (a) Tails
- (b) 2
- (c) 0
- (d) Heads
- (e) $1/2$

What is the support set of the Coin Flip RV?



- (a) {Heads, Tails}
- (b) $1/2$
- (c) 0
- (d) $\{0, 1\}$
- (e) 1

Let X denote the Coin Flip RV



What is $P(X = 1)$?

- (a) 0
- (b) 1
- (c) $1/2$
- (d) Not enough information to determine

Two Kinds of RVs: Discrete and Continuous

Discrete support set is finite or countable , e.g. $\{0, 1\}$,
 $\{\dots, -2, -1, 0, 1, 2, \dots\}$

Continuous support set is *uncountable* e.g. $[-1, 1]$, \mathbb{R} .

Start with the discrete case since it's easier, but most of the ideas we learn will carry over to the continuous case.

Discrete Random Variables I

Probability Mass Function (pmf)

A function that gives $P(X = x)$ for any realization x in the support set of a discrete RV X . We use the following notation for the pmf:

$$p(x) = P(X = x)$$

Plug in a realization x , get out a probability $p(x)$.

Probability Mass Function for Coin Flip RV

$$X = \begin{cases} 0, \text{Tails} \\ 1, \text{Heads} \end{cases}$$

$$p(0) = 1/2$$

$$p(1) = 1/2$$

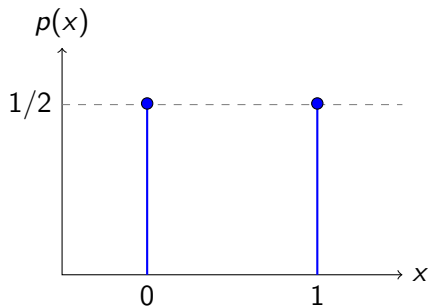


Figure : Plot of pmf for Coin Flip Random Variable

Important Note about Support Sets

Whenever you write down the pmf of a RV, it is **crucial** to also write down its Support Set. Recall that this is the set of *all possible realizations for a RV*. Outside of the support set, all probabilities are zero. In other words, the pmf is **only defined** on the support.

Properties of Probability Mass Functions

If $p(x)$ is the pmf of a random variable X , then

(i) $0 \leq p(x) \leq 1$ for all x

(ii) $\sum_{\text{all } x} p(x) = 1$

where “all x ” is shorthand for “all x in the support of X .”

Cumulative Distribution Function (CDF)

This Def. is **the same** for continuous RVs.

The CDF gives the probability that a RV X **does not exceed** a specified threshold x_0 , as a function of x_0

$$F(x_0) = P(X \leq x_0)$$

Important!

The threshold x_0 is allowed to be *any real number*. In particular, it doesn't have to be in the support of X !

Discrete RVs: Sum the pmf to get the CDF

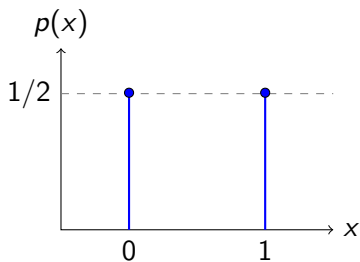
$$F(x_0) = \sum_{x \leq x_0} p(x)$$

Why?

The events $\{X = x\}$ are mutually exclusive, so we sum to get the probability of their union for all $x \leq x_0$:

$$F(x_0) = P(X \leq x_0) = P\left(\bigcup_{x \leq x_0} \{X = x\}\right) = \sum_{x \leq x_0} P(X = x) = \sum_{x \leq x_0} p(x)$$

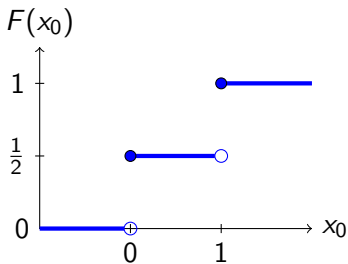
Probability Mass Function



$$p(0) = 1/2$$

$$p(1) = 1/2$$

Cumulative Dist. Function



$$F(x_0) = \begin{cases} 0, & x_0 < 0 \\ \frac{1}{2}, & 0 \leq x_0 < 1 \\ 1, & x_0 \geq 1 \end{cases}$$

Properties of CDFs

These are also true for continuous RVs.

1. $\lim_{x_0 \rightarrow \infty} F(x_0) = 1$
2. $\lim_{x_0 \rightarrow -\infty} F(x_0) = 0$
3. Non-decreasing: $x_0 < x_1 \Rightarrow F(x_0) \leq F(x_1)$
4. Right-continuous (“open” versus “closed” on prev. slide)

Since $F(x_0) = P(X \leq x_0)$, we have $0 \leq F(x_0) \leq 1$ for all x_0

Bernoulli Random Variable – Generalization of Coin Flip

Support Set

$\{0, 1\}$ – 1 traditionally called “success,” 0 “failure”

Probability Mass Function

$$p(0) = 1 - p$$

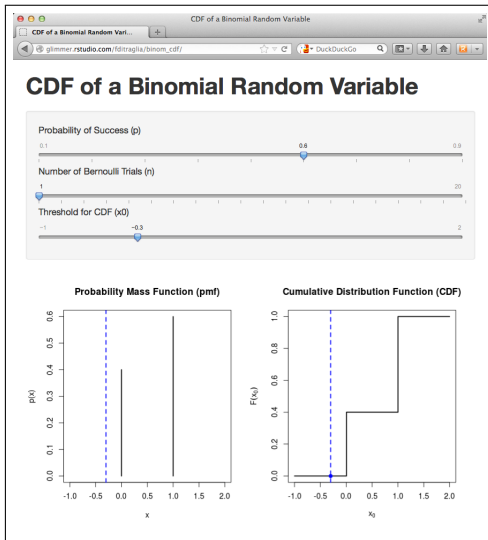
$$p(1) = p$$

Cumulative Distribution Function

$$F(x_0) = \begin{cases} 0, & x_0 < 0 \\ 1 - p, & 0 \leq x_0 < 1 \\ 1, & x_0 \geq 1 \end{cases}$$

http://glimmer.rstudio.com/fditraglia/binom_cdf/

Set the second slider to 1 and play around with the others.



Average Winnings Per Trial



If the realizations of the coin-flip RV were **payoffs**, how much would you expect to win per play *on average* in a long sequence of plays?

$$X = \begin{cases} \$0, \text{ Tails} \\ \$1, \text{ Heads} \end{cases}$$

Expected Value (aka Expectation)

The expected value of a discrete RV X is given by

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

In other words, the expected value of a discrete RV is the *probability-weighted average of its realizations*.

Notation

We sometimes write μ as shorthand for $E[X]$.

Expected Value of Bernoulli RV

$$X = \begin{cases} 0, \text{Failure: } 1 - p \\ 1, \text{Success: } p \end{cases}$$

$$\sum_{\text{all } x} x \cdot p(x) = 0 \cdot (1 - p) + 1 \cdot p = p$$

Your Turn to Caculate an Expected Value



Let X be a random variable with support set $\{1, 2, 3\}$ where $p(1) = p(2) = 1/3$. Calculate $E[X]$.

$$E[X] = \sum_{\text{all } x} x \cdot p(x) = 1 \times 1/3 + 2 \times 1/3 + 3 \times 1/3 = 2$$

Random Variables and Parameters

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

Means X is a Bernoulli RV with $P(X = 1) = p$ and $P(X = 0) = 1 - p$. The tilde is read “distributes as.”

Parameter

Any constant that appears in the definition of a RV, here p .

Constants Versus Random Variables

This is a crucial distinction that students sometimes miss:

Random Variables

- ▶ Suppose X is a RV – the values it takes on are random
- ▶ A function $g(X)$ of a RV is itself a RV as we'll learn today.

Constants

- ▶ $E[X]$ is a constant (you should convince yourself of this)
- ▶ Realizations x are constants. What is random is *which* realization the RV takes on.
- ▶ Parameters are constants (e.g. p for Bernoulli RV)
- ▶ Sample size n is a constant

The St. Petersburg Game

How Much Would You Pay?



How much would you be willing to pay for the right to play the following game?

Imagine a fair coin. The coin is tossed once. If it falls heads, you receive a prize of \$2 and the game stops. If not, it is tossed again. If it falls heads on the second toss, you get \$4 and the game stops. If not, it is tossed again. If it falls heads on the third toss, you get \$8 and the game stops, and so on. The game stops after the first head is thrown. If the first head is thrown on the x^{th} toss, the prize is $\$2^x$

X = Trial Number of First Head

x	2^x	$p(x)$	$2^x \cdot p(x)$
1	2	$1/2$	1
2	4	$1/4$	1
3	8	$1/8$	1
\vdots	\vdots	\vdots	\vdots
n	2^n	$1/2^n$	1
\vdots	\vdots	\vdots	\vdots

$$E[Y] = \sum_{\text{all } x} 2^x \cdot p(x) = 1 + 1 + 1 + \dots = \infty$$

Functions of Random Variables are Themselves Random Variables

Example: Function of Bernoulli RV

Let $Y = e^X$ where $X \sim \text{Bernoulli}(p)$

Support of Y

$$\{e^0, e^1\} = \{1, e\}$$

Probability Mass Function for Y

$$p_Y(y) = \begin{cases} p & y = e \\ 1 - p & y = 1 \\ 0 & \text{otherwise} \end{cases}$$

Expectation: Function of Bernoulli RV

Let $Y = e^X$ where $X \sim \text{Bernoulli}(p)$

Probability Mass Function for Y

$$p_Y(y) = \begin{cases} p & y = e \\ 1 - p & y = 1 \\ 0 & \text{otherwise} \end{cases}$$

Expectation of $Y = e^X$

$$\sum_{y \in \{1, e\}} y \cdot p_Y(y) = (1 - p) \cdot 1 + p \cdot e = 1 + p(e - 1)$$

Expectation: Function of Bernoulli RV

Let $Y = e^X$ where $X \sim \text{Bernoulli}(p)$

Expectation of the Function

$$\sum_{y \in \{1, e\}} y \cdot p_Y(y) = (1 - p) \cdot 1 + p \cdot e = 1 + p(e - 1)$$

Function of the Expectation

$$e^{E[X]} = e^p$$

$$E[g(X)] \neq g(E[X])$$

(Expected value of Function \neq Function of Expected Value)

Expectation of a Function of a Discrete RV

Let X be a random variable and g be a function. Then:

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

This is how we proceeded in the St. Petersburg Game Example

Your Turn: Calculate $E[X^2]$



X has support $\{-1, 0, 1\}$, $p(-1) = p(0) = p(1) = 1/3$.

$$\begin{aligned} E[X^2] &= \sum_{\text{all } x} x^2 p(x) = \sum_{x \in \{-1, 0, 1\}} x^2 p(x) \\ &= (-1)^2 \cdot (1/3) + (0)^2 \cdot (1/3) + (1)^2 \cdot (1/3) \\ &= 1/3 + 1/3 \\ &= 2/3 \approx 0.67 \end{aligned}$$