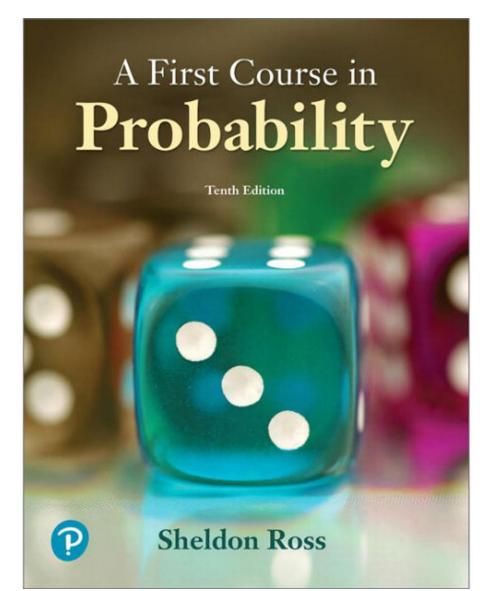
Lecture 6.2

(Real-valued) random variables



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Today's reading: 4.1+4.2

Next class: 4.3

No HW this week. HW5 will be made available soon.

I will do my best to return graded MT1 in class on Monday.



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(Real-valued) random variables

Definition (more-or-less from the book):

Let *S* be a sample space. A <u>(real-valued)</u> random variable on *S* is a function

 $X: S \to \mathbb{R}$

Comments:

- REMEMBER ALL OF THIS ASAP.
- Notice that the definition has NOTHING to do with any choice of probability measure on S. (Recall: a given sample space S typically has many different probability measures on it.) More on this momentarily.
- If *T* is any set, we could talk about an "*T*-valued random variable on *S*". This would simply be a function X: S → T.



Random variables – why do we care?

Let S be a sample space. A <u>(real valued)</u> random variable on S is a function

 $X: S \to \mathbb{R}$

Practically:

We often don't care about the specifics of events in *S*, but instead have some way of associating a real number to every outcome in *S*. E.g., if we roll two dice but only care about their sum, then we really only care about a single real number between 2 and 12 (rather than a pair of numbers, each between 1 and 6). Formally/mathematically:

If we have a random variable X: $S \to \mathbb{R}$ <u>and</u> we have a probability measure P on S, then we can use X to "pushforward" P and define a probability measure on \mathbb{R} . (By a small "abuse of notation," we often denote this measure on \mathbb{R} by P, even though we should really call it something like X_*P .)

[general construction on chalkboard (*I'm showing* you this for your benefit, but you do not need to remember it!)]

Intuitively: real-valued random variables allow us to convert probability measures on "weird" sample spaces S into probability measures on something we know and love, namely, the real line \mathbb{R} .



Cumulative distribution functions

Let S be a sample space. A <u>(real valued)</u> random variable on S is a function

 $X: S \to \mathbb{R}$

Definition:

Fix a sample space S with a probability measure P and let $X: S \to \mathbb{R}$ be a random variable. The <u>cumulative distribution</u> <u>function</u> of X is the function $F: \mathbb{R} \to \mathbb{R}$ defined by

 $F(x) = P(\{X \le x\})$

Comments:

- The definition of the cumulative distribution function of *X* depends on *X*, *S* and *P*, even though the notation does not make this clear. *Sorry, but get used to it!*
- We often refer to the cumulative distribution function as the "CDF," or drop the word "cumulative" and just say "distribution function."
- If I had my druthers, I would denote the CDF by $CDF_{S,P,X}$
- The CDF is monotone increasing. (Why?)
- We will see later why this is useful.



THE VIEW FROM 10,000 FEET: A FUNDAMENTAL FACT ABOUT PROBABILITY MEASURES ON $\mathbb R$

Every probability measure on \mathbb{R} is a "mixture" of a "discrete probability measure" and a "continuous probability measure."



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Comments:

- This is called the "Lebesgue decomposition theorem" (I haven't stated it precisely, but I think it is helpful to see, since it gives some understanding of why we care so much about "discrete" vs "continuous" random variables.
- We won't prove this theorem (take MA 538 or MA 544 if you want to).
- We will define "discrete probability measures" momentarily (and, more importantly, "discrete random variables").
- Chapter 4 only considers discrete random variables. (Thus, we will only consider discrete random variables for the next 3 weeks.)

Discrete probability measures on ${\mathbb R}$

Definition (NOT in the book, but hopefully helpful):

A probability measure P on \mathbb{R} is <u>discrete</u> if there exists a finite or atmost countably infinite set of real numbers $x_1, x_2, x_3, ... \in \mathbb{R}$ with the two following properties:

•
$$P(x_i) > 0$$

•
$$\sum_{i=1}^{\infty} P(x_i) = 1$$

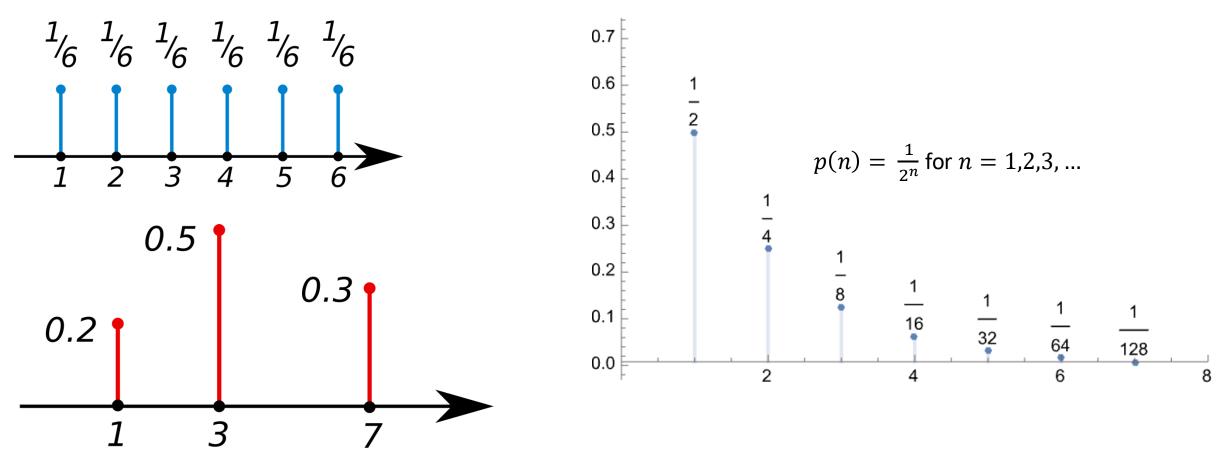
Intuition/equivalently: a probability measure P on \mathbb{R} is discrete if the probability of an event $E \subset \mathbb{R}$ is the sum of the probabilities of the individual outcomes in E. That is: $P(E) = \sum_{e \in E} P(\{e\})$

If *P* is discrete, then its <u>probability</u> <u>mass function (or PMF)</u> is the function $p: \mathbb{R} \to \mathbb{R}$ defined as $p(x) = P(\{x\})$. Being discrete guarantees that *P* is entirely determined by its probability mass function.



Discrete probability measures on \mathbb{R} *:* examples

We specify these examples by their PMFs





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Looking ahead: an example of a continuous probability measure on $\mathbb R$

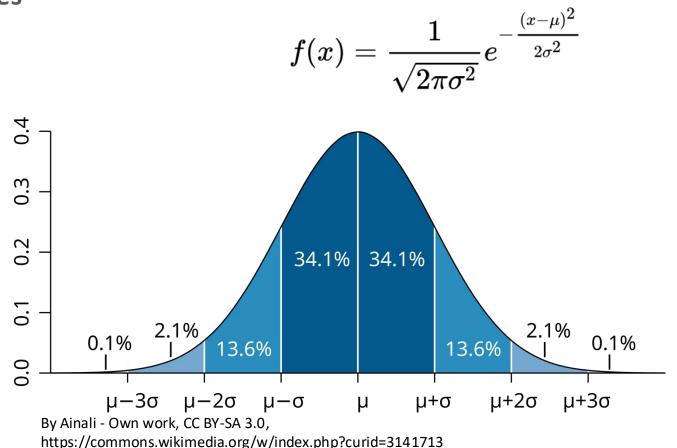
"Absolutely continuous" probability measures on $\mathbb R$ are specified by a "probability density function" (PDF).

If the PDF is $f : \mathbb{R} \to \mathbb{R}$, then the probability of an event $E \subset \mathbb{R}$ is

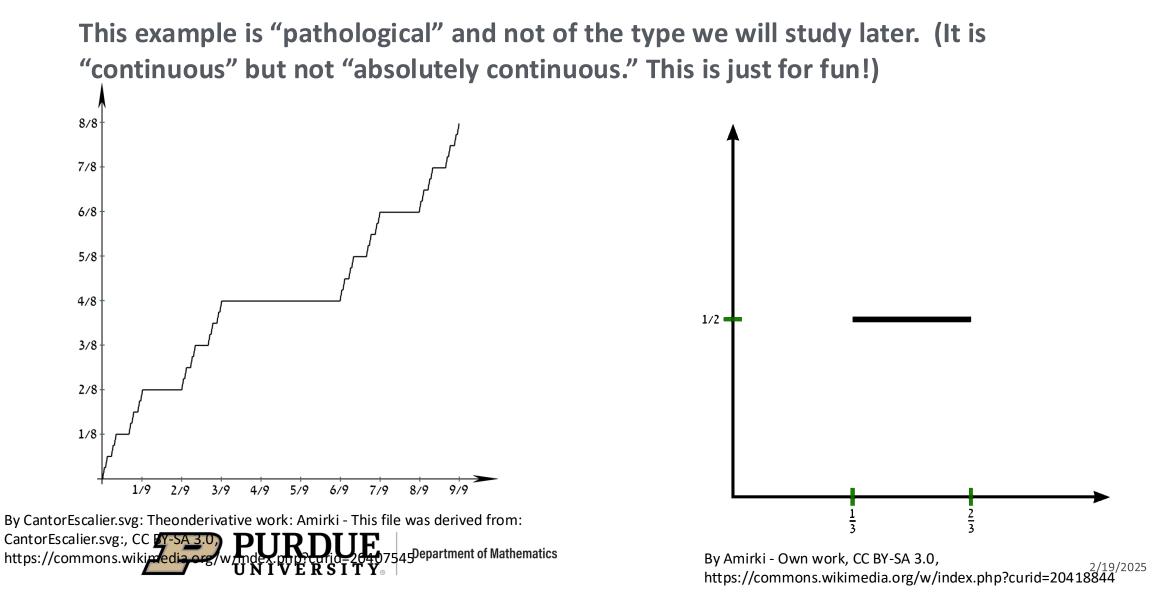
$$P(E) = \int_{x \in E} f(x) \, dx$$

In particular, for a continuous probability measure, the probability of a single outcome is always 0. (Contrast with discrete measures!)





Cantor distribution: a continuous probability measure on \mathbb{R} with a CDF but no PDF



10

Discrete random variables

Definition:

A (real-valued) random variable $X: S \to \mathbb{R}$ is <u>discrete</u> if it takes on at most countably infinitely many different values in \mathbb{R} .

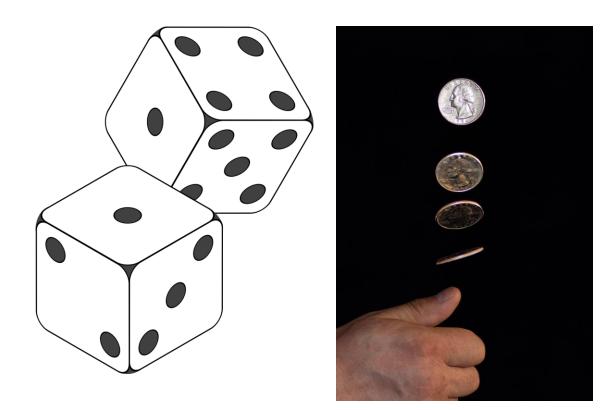
Equivalently, $X: S \to \mathbb{R}$ is discrete if for every probability measure P on S, the induced probability measure on \mathbb{R} is discrete.

We will see many, many examples in the next 3 weeks.



Friday's draft problem

To be presented by Friday's draftee.



Two fair dice are rolled and one fair coin is tossed. Let X be the product of the two dice outcomes together with +1 if the coin was heads or -1 if the coin was tails. Compute $P\{X = i\}$ for each $i = \pm 1, \pm 2, ..., \pm 36$.

