Week 2: Random Variables

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Princeton

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[1]These slides are heavily influenced by Adam Glynn, Justin Grimmer, Jens Hainmueller and Ian Lundberg. Many illustrations by Shay O'Brien.

Where We've Been and Where We're Going...

- Last Week

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  - welcome and outline of course
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  - probability $\rightarrow$ inference $\rightarrow$ regression $\rightarrow$ causal inference

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We will do this by introducing a random variable X to be Barack Obama's position on the 2008 New Hampshire primary ballot.

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We will generally suppress the function notation and just refer to X.

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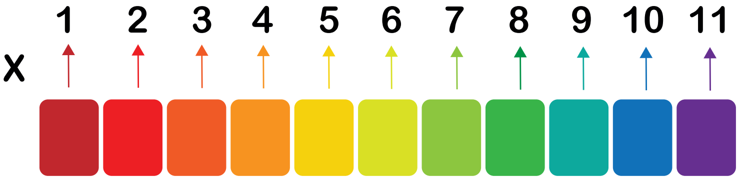

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- Other times the sample space is already numeric so its more obvious (e.g. how many minutes until the train arrives).

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  random variables are about bridging the abstract math and the concrete world. that can be hard, but it is super important and better than the alternative!

NH Ballot Order Example

Candidates:

- Joe Biden
- Hillary Clinton
- Chris Dodd
- John Edwards
- Mike Gravel
- Dennis Kucinich
- Barack Obama
- Bill Richardson

$$X = \left\{ \right.$$

A,B,C,D,E,F,G,H,I,J,K,L,M,N,O,P,Q,R,S,T,U,V,W,X,Y,Z

X is a random variable indicating Obama's position on the ballot. Highlighted letters are those leading to a given ballot position. Highlighted individual is first.

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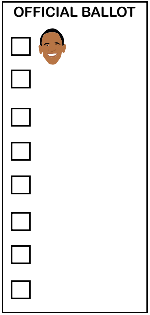

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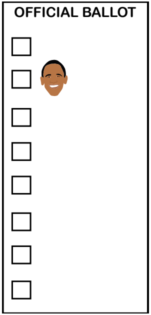

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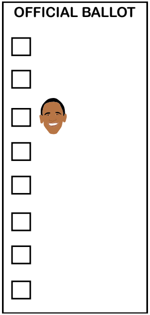
$$X = \begin{cases} 1 \\ 2 \\ 3 \\ \\ \\ \\ \\ \end{cases}$$



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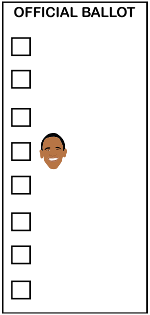
$$X = \begin{cases} 1 \\ 2 \\ 3 \\ 4 \\ \\ \\ \\ \end{cases}$$



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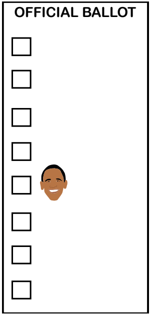
$$X = \begin{cases} 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{cases}$$



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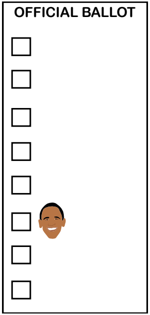
$$X = \begin{cases} 1 \\ 2 \\ 3 \\ 4 \\ 5 \\ 6 \end{cases}$$



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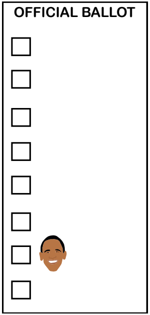
$$X = \begin{cases} 1 \\ 2 \\ 3 \\ 4 \\ 5 \\ 6 \\ 7 \\ \end{cases}$$



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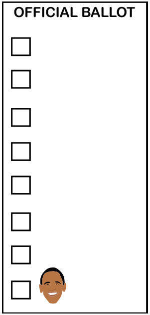

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- A probability mass function (PMF) and a cumulative distribution function (CDF) are two common ways to define the probability distribution for a discrete random variable.
- Probability mass functions provide a compact way to represent information about how likely various outcomes are.

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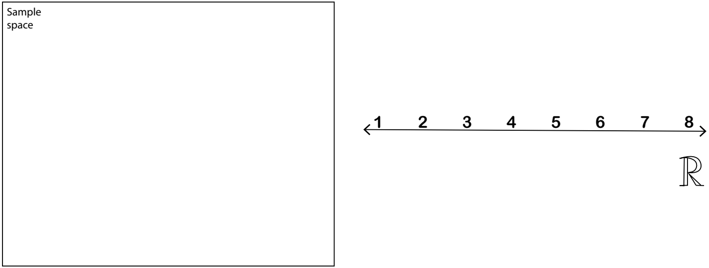

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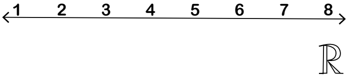

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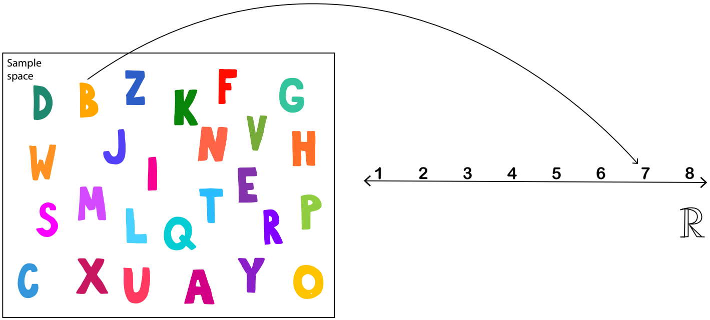

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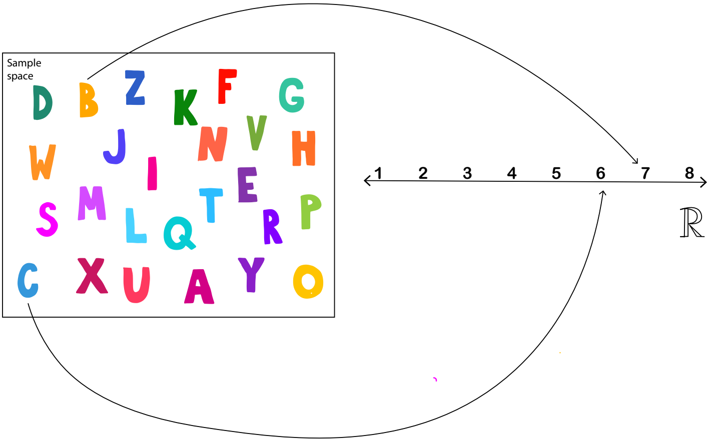

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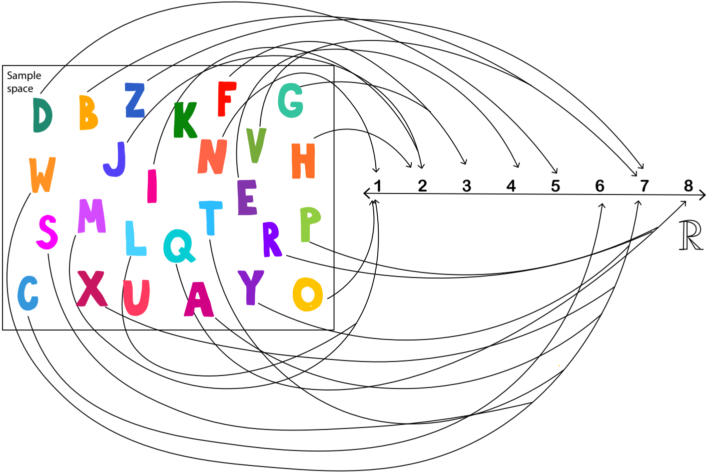

Example: New Hampshire

Candidates:

- Joe Biden
- Hillary Clinton
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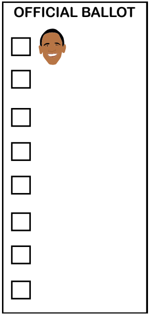
$$p_X(x) = \begin{cases} 4/26 & x = 1 \end{cases}$$



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Probability of the random variable equaling a number is just the probability of the underlying event (subset of the sample space).

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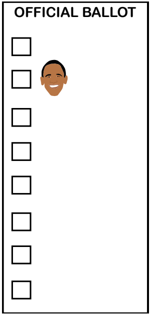

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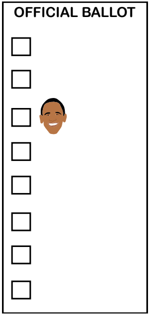

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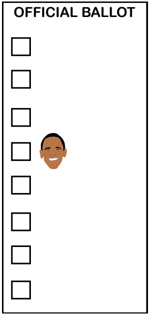

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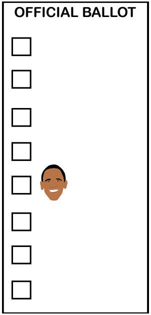

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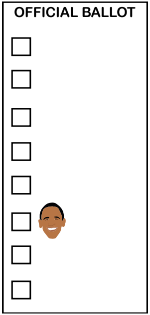

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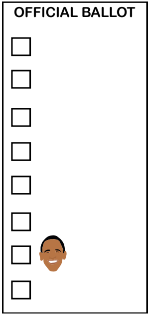

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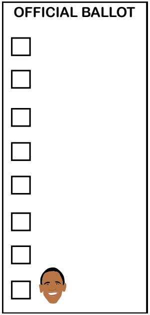
Probability of the random variable equaling a number is just the probability of the underlying event (subset of the sample space).

Example: New Hampshire

Candidates:

- Joe Biden
- Hillary Clinton
- Chris Dodd
- John Edwards
- Mike Gravel
- Dennis Kucinich
- Barack Obama
- Bill Richardson

$$p_X(x) = \begin{cases} 4/26 & x = 1 \\ 4/26 & x = 2 \\ 2/26 & x = 3 \\ 1/26 & x = 4 \\ 1/26 & x = 5 \\ 1/26 & x = 6 \\ 10/26 & x = 7 \\ 3/26 & x = 8 \end{cases}$$



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Discrete Probability Mass Functions

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Understanding the Notation:

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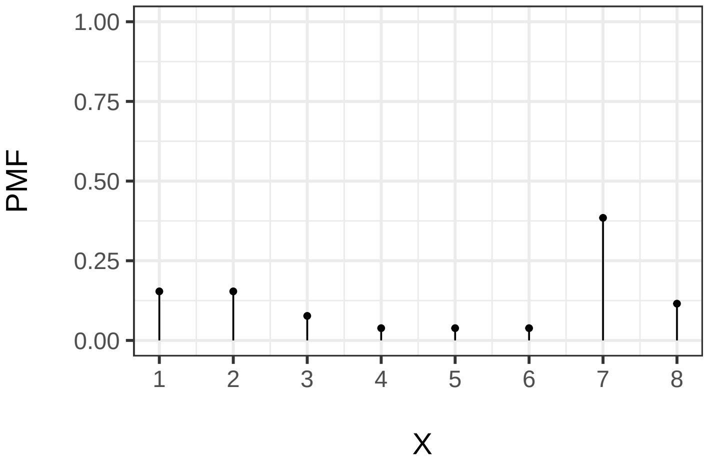
- $\sum_x p_X(x) = 1$.

NH Obama Ballot Position PMF Plot



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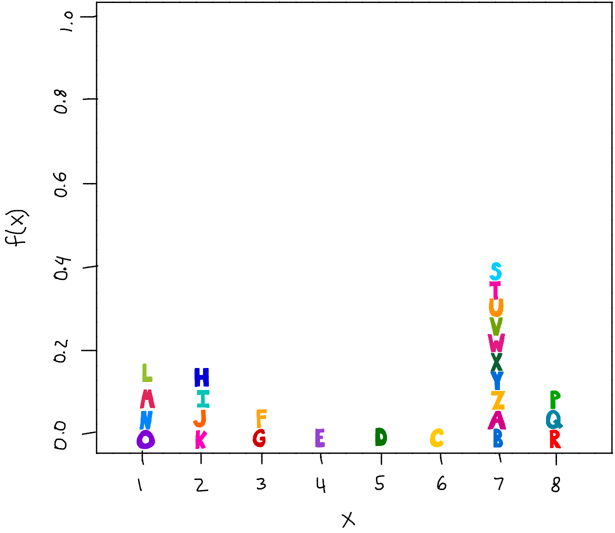

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Key properties:

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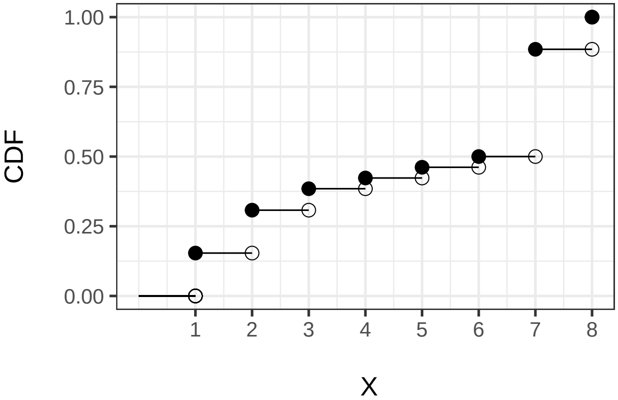
- right-continuous
- converges to 0 and 1 in the limits

NH Obama Ballot Position CDF Plot



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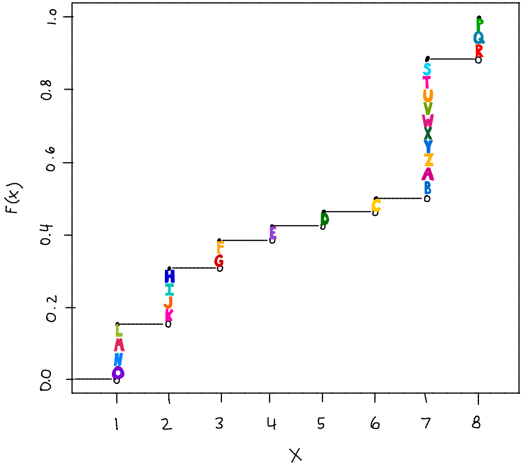

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- We will return to this in the last video of the week.

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Next time continuous random variables.

Where We've Been and Where We're Going...

- Last Week
  - welcome and outline of course
  - described uncertain outcomes with probability.
- This Week
  - define random variables
  - summarize random variables using expectation and variance
  - properties of joint and conditional distributions
  - famous distributions
- Next Week
  - estimating these features from data
  - estimating uncertainty
- Long Run
  - probability $\rightarrow$ inference $\rightarrow$ regression $\rightarrow$ causal inference

1. Definition of Random Variables

2. Continuous Distribution
   - Defining a Continuous Random Variable
   - Probability Density Functions and Cumulative Distribution Functions
   - Subtleties of the Continuous Setting

3. Expectation as a Measure of Central Tendency

4. Variance as a Measure of Dispersion

5. Joint and Conditional Distributions

6. Characterizing Conditional Distributions

7. Independence and Covariance

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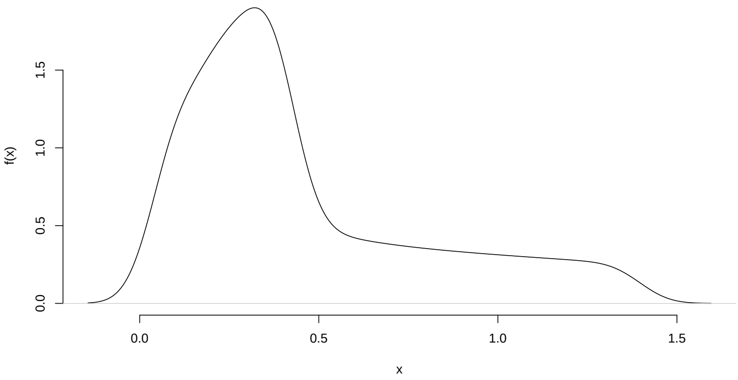
- This is often a useful approximation when variables take many values.
- A probability density function (PDF) and a cumulative distribution function (CDF) are two common ways to define the distribution for a continuous random variable.
- They are similar to the discrete case with a few subtle differences.

Calculus Review: Integration

Suppose we have some function $f(x)$



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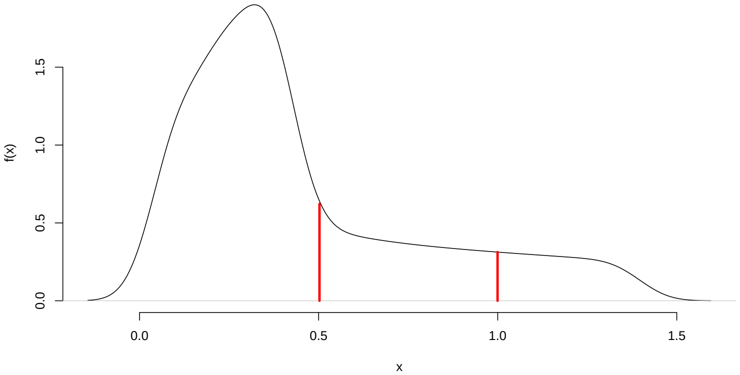

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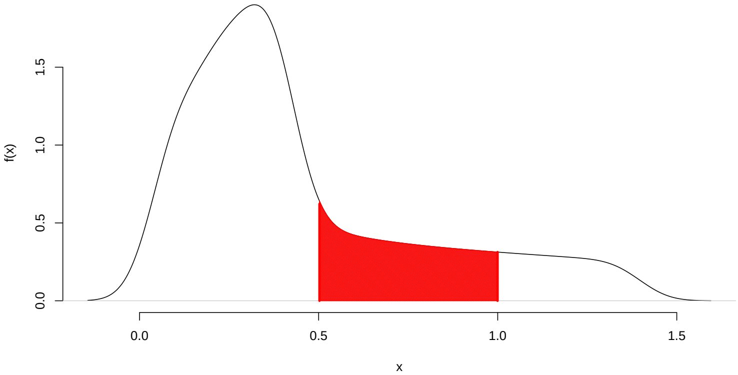

What is the area under $f(x)$ between $\frac{1}{2}$ and 1?

Area under curve $= \int_{1/2}^{1} f(x)dx = F(1) - F(1/2)$

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Definition (Continuous Distribution)

A random variable has a continuous distribution if its CDF is differentiable. We also allow there to be endpoints (or finitely many points) where the CDF is continuous but not differentiable, as long as the CDF is differentiable everywhere else. (Blizstein and Hwang Definition 5.1.1)

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- for any measurable set of real numbers B,

$$P(X \in B) = \int_B f_X(x)dx$$

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$$\begin{tikzcd} \text{pdf} \arrow[r, bend left, "\text{Integrate}"] & \text{cdf} \arrow[l, bend left, "\text{Differentiate}"] \end{tikzcd}$$

A Visual Example

Imagine you choose a number completely at random between 0 and 1 with all equally sized sets of values being equally likely.

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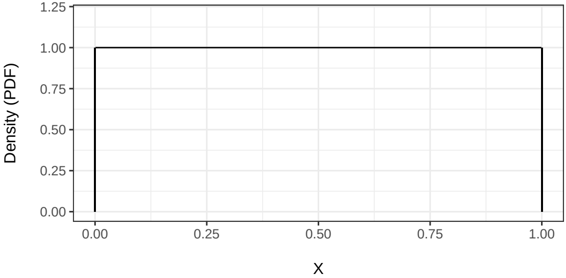
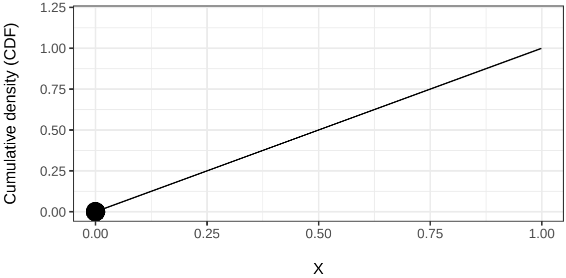
$$F_X(x) = x$$

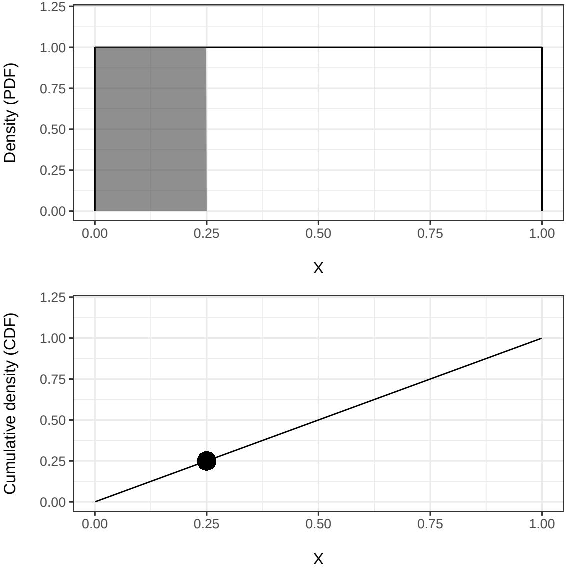
with support over $[0, 1]$.

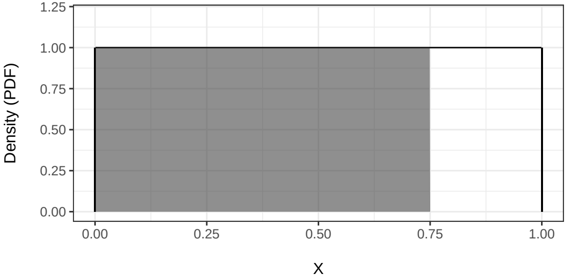


Density (PDF)
1.25
1.00
0.75
0.50
0.25
0.00
0.00
0.25
0.50
0.75
1.00
X



Cumulative density (CDF)
1.25
1.00
0.75
0.50
0.25
0.00
0.00
0.25
0.50
0.75
1.00
X


1.25
1.00
0.75
0.50
0.25
0.00
Density (PDF)
0.00
0.25
0.50
0.75
1.00
X
1.25
1.00
0.75
0.50
0.25
0.00
Cumulative density (CDF)
0.00
0.25
0.50
0.75
1.00
X



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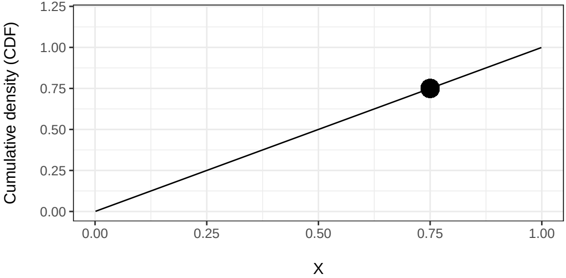

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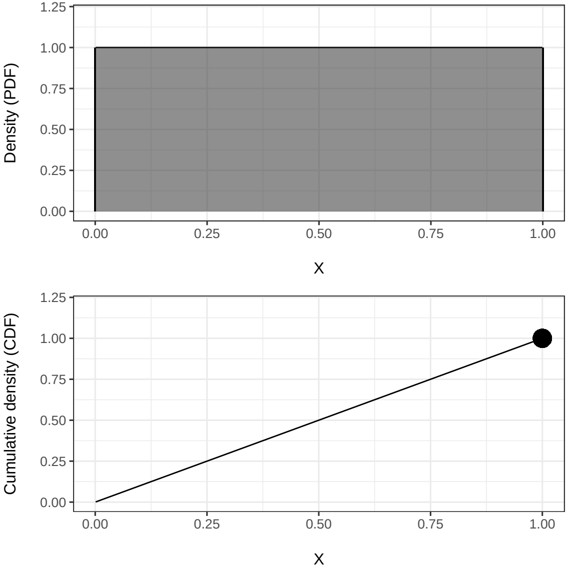
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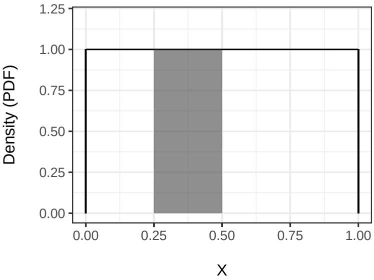

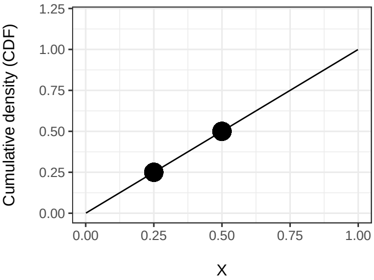

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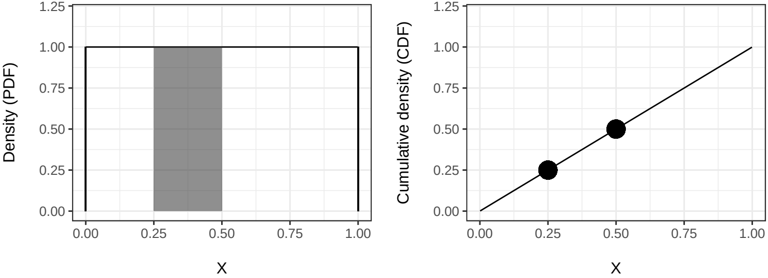

$$F_X(.5) - F_X(.25) = .25$$

The Core PMF/PDF Difference

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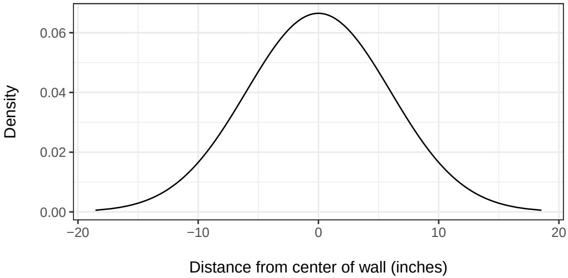
Let's explain!

A Numerical Example

Let's suppose we have someone throwing darts and we measure how far they are from the center of the wall in inches. In this case, perhaps the darts will be distributed with the following PDF.



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How would we calculate the probability that a dart lands within 6 inches of the center of the wall?

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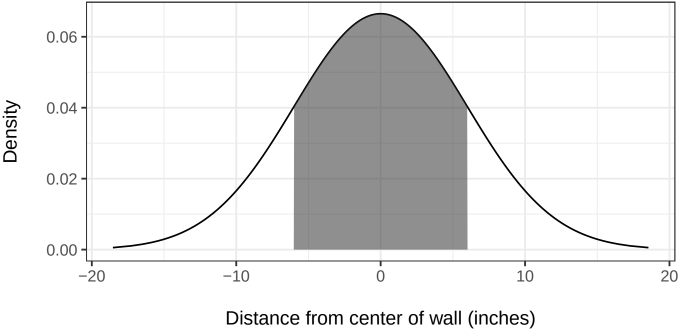

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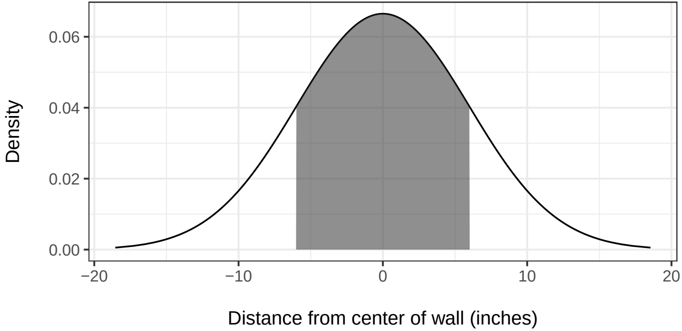

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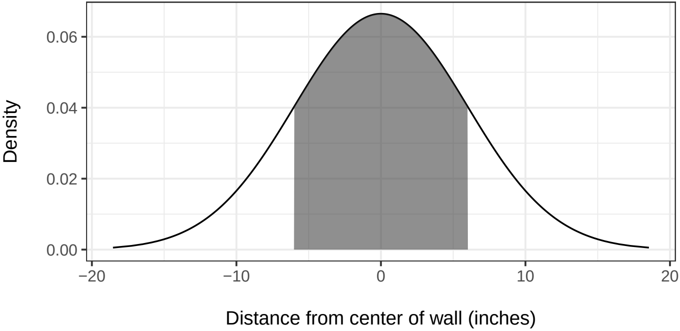

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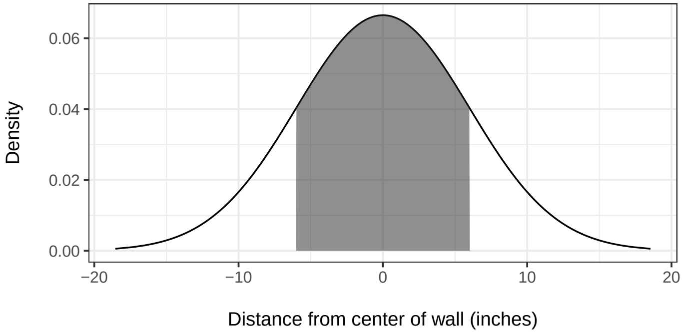
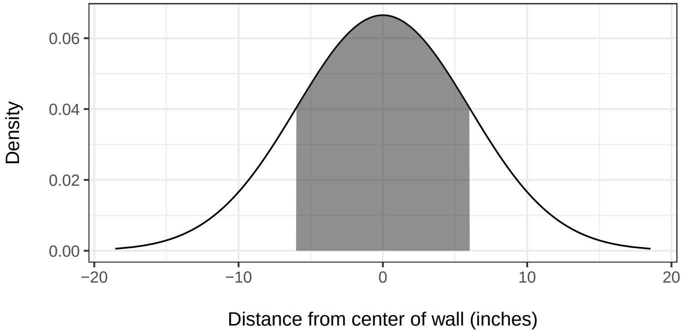


$$\begin{aligned} P(X \in (-6,6)) &= \int_{-6}^{6} f_X(x)dx \\ &= F_X(6) - F_X(-6) \end{aligned}$$

A Numerical Example

How would we calculate the probability that a dart lands within 6 inches of the center of the wall?



$$
\begin{aligned}
P(X \in (-6, 6)) &= \int_{-6}^{6} f_X(x)dx \\
&= F_X(6) - F_X(-6) \\
&= P(X < 6) - P(X < -6)
\end{aligned}
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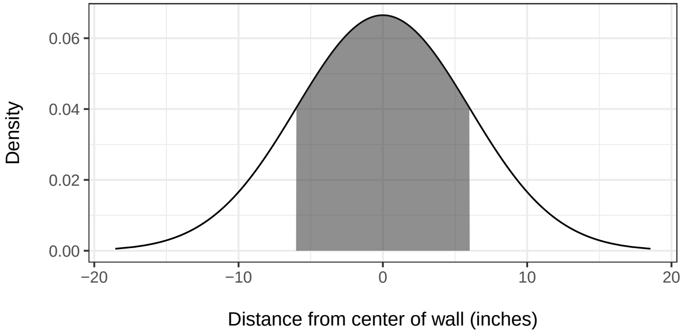

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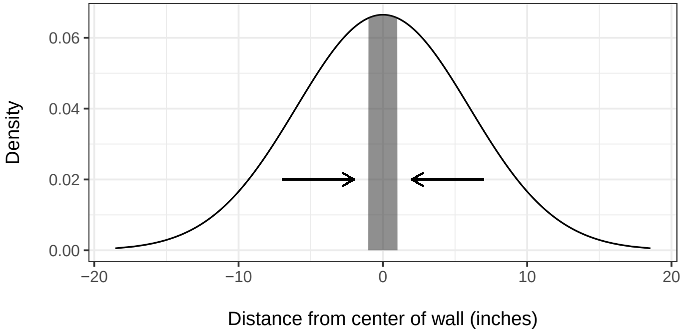
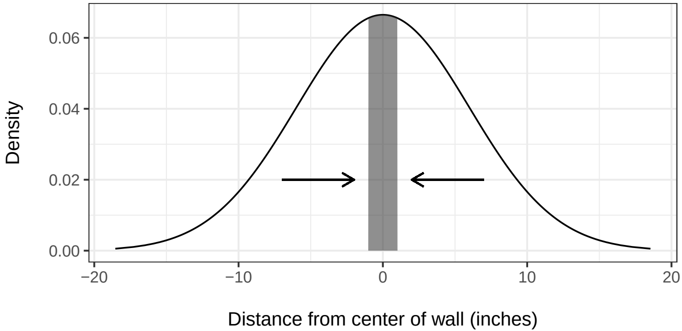
One inch?



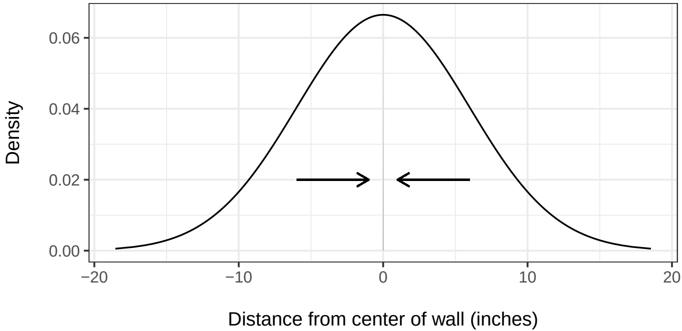
Density
0.06
0.04
0.02
0.00
−20
−10
0
10
20
Distance from center of wall (inches)

One inch?



$$P(X \in (-1, 1)) = 0.0664135$$

1/100th of an inch?



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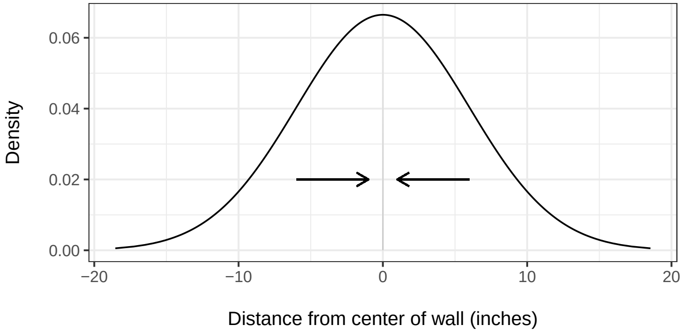
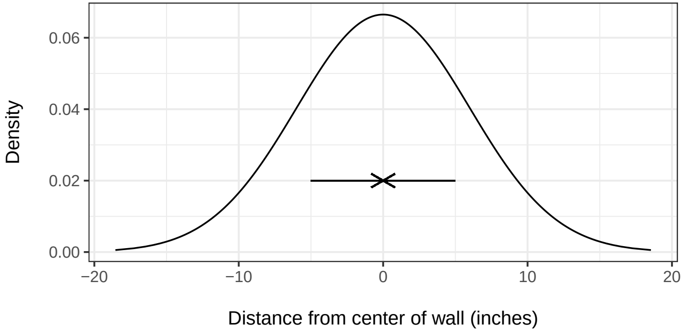


$$P(X \in (-.01, .01)) = 0.0006649037$$

A perfect bullseye?



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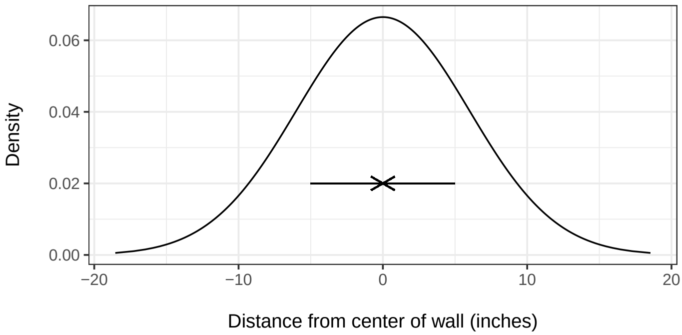

$$P(X = 0) = 0$$

The probability that a continuous variable takes on a discrete value is 0!

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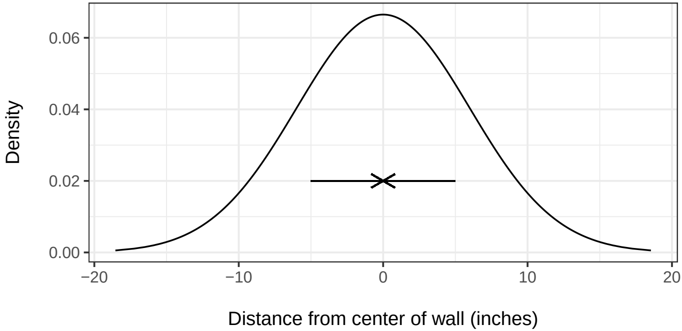

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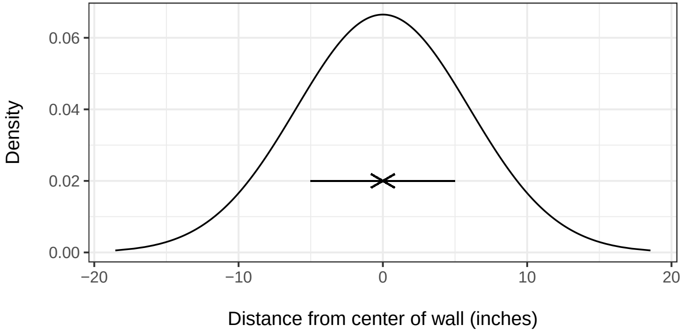

$$P(X = 0) = 0$$

The probability that a continuous variable takes on a discrete value is 0!
Why?
Because the width of the range we are calculating is zero, the area is zero.

The Practical Upshot

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- Reconciling the continuous/discrete divide is the purview of measure theory which is a layer deeper than we are going to go in this class.
- As with discrete random variables there are common families of distributions (last video of the week).

We Covered. . .

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Next time we will describe how to characterize a distribution.

Where We've Been and Where We're Going...

- Last Week
  - welcome and outline of course
  - described uncertain outcomes with probability.
- This Week
  - define random variables
  - summarize random variables using expectation and variance
  - properties of joint and conditional distributions
  - famous distributions
- Next Week
  - estimating these features from data
  - estimating uncertainty
- Long Run
  - probability $\rightarrow$ inference $\rightarrow$ regression $\rightarrow$ causal inference

Characterizing Distributions

Distributions have all kinds of wonky shapes. How do we characterize what they look like?

Expectation

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The expected value of a random variable X is denoted by $E[X]$ and is a measure of **central tendency** of X. Roughly speaking, an expected value is like a weighted average of all of the values weighted by probability of occurrence.

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What did we expect for Obama's NH position?

Candidates:

- Joe Biden
- Hillary Clinton
- Chris Dodd
- John Edwards
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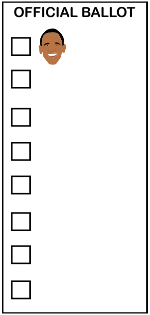
$4/26 \quad \times 1$

$+$



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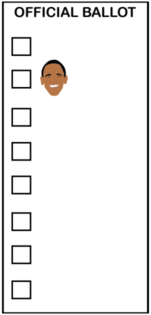

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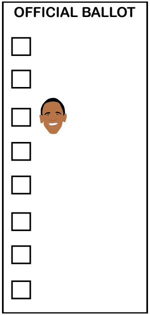
$$+$$



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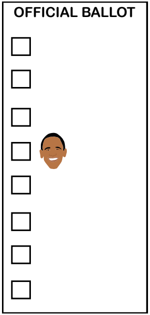

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$4/26 \quad \times 1$
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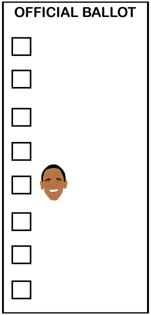
$2/26 \quad \times 3$
$1/26 \quad \times 4$
$1/26 \quad \times 5$

$+$ ____________



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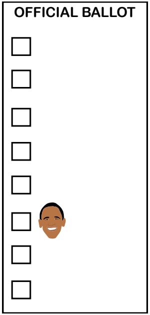

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10/26 & \times 7 \\
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\end{array}
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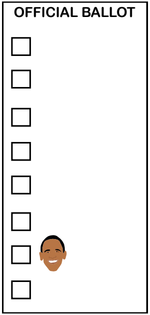

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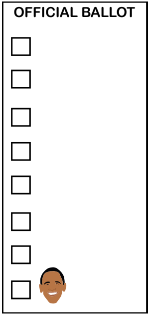

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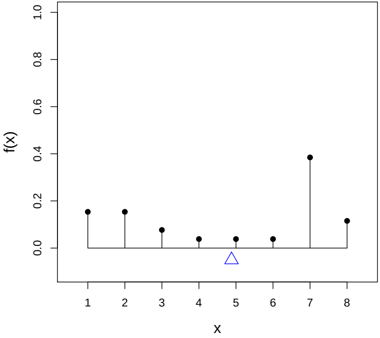
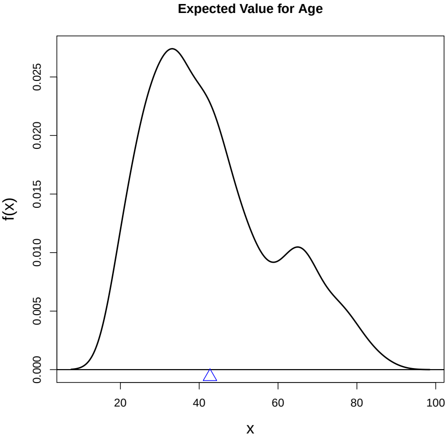
Interpreting Discrete Expected Value

The expected value for a discrete random variable is the balance point of the mass function.



Interpreting Continuous Expected Value

The expected value for a continuous random variable is the balance point of the density function.



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- It has some useful and convenient properties.

Population Mean as an Expected Value

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$$\bar{x} = \sum_{\text{all } x_i} x_i f_X(x_i), \text{ where } f_X(x_i) = \frac{1}{N}$$

Three properties of expectation:

- Additivity
- Homogenity
- LOTUS

Property 1 of Expected Value: Additivity

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Together properties 1 and 2 are linearity (and this is sometimes presented as Linearity of Expectations).

Property 3 of Expected Value: LOTUS

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Why the name LOTUS? "because this can be done very easily and mechanically, perhaps in a state of unconsciousness." (Blitzstein and Hwang, Sec 4.5)

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- $E[XY] = E[X]E[Y]$ only if X and Y are independent

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    3. large corporations polluting the environment.
  - second half, add a fourth item

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  - randomly split survey into two halves
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- We can use random variables!

Identifying the Percent Angry

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$$\begin{aligned} E[Y] &= E[X + A] \\ &= E[X] + E[A] \\ E[Y] - E[X] &= E[A] \end{aligned}$$

So if we know $E[Y]$ and $E[X]$ we can get the expected proportion angered by our item without knowing the individual status of anyone!

Racial Prejudice Example (Kuklinski et al, 1997)

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$X = \#$ of angering items on the baseline list for Southerners:

x	0	1	2	3
$f_X(x)$	?	?	?	?
$\widehat{f}_X(x)$	0.02	0.27	0.43	0.28
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$Y = \#$ of angering items on the treatment list for Southerners:

y	0	1	2	3	4
$f_Y(y)$	?	?	?	?	?
$\widehat{f}_Y(y)$	0.02	0.20	0.40	0.28	0.10
$\widehat{F}_Y(y)$	0.02	0.22	0.62	0.90	1.00

Racial Prejudice Example

$X = \#$ of angering items on the baseline list for Southerners:

x	0	1	2	3	Sum
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$$\widehat{E[A]} = 2.24 - 1.97 = 0.27$$

On List Experiments in Research

On List Experiments in Research

When to Worry about Sensitivity Bias: A Social Reference Theory and Evidence from 30 Years of List Experiments

GRAEME BLAIR *University of California, Los Angeles*
ALEXANDER COPPOCK *Yale University*
MARGARET MOOR *Yale University*

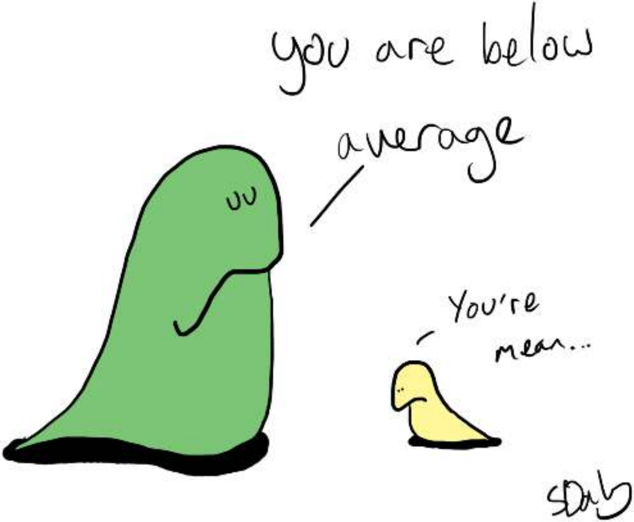
Eliciting honest answers to sensitive questions is frustrated if subjects withhold the truth for fear that others will judge or punish them. The resulting bias is commonly referred to as social desirability bias, a subset of what we label sensitivity bias. We make three contributions. First, we propose a social reference theory of sensitivity bias to structure expectations about survey responses on sensitive topics. Second, we explore the bias-variance trade-off inherent in the choice between direct and indirect measurement technologies. Third, to estimate the extent of sensitivity bias, we meta-analyze the set of published and unpublished list experiments (a.k.a., the item count technique) conducted to date and compare the results with direct questions. We find that sensitivity biases are typically smaller than 10 percentage points and in some domains are approximately zero.

Fun with

Fun with Averages

Fun with Averages

Central Tendency



The Story of Averages

Measurements

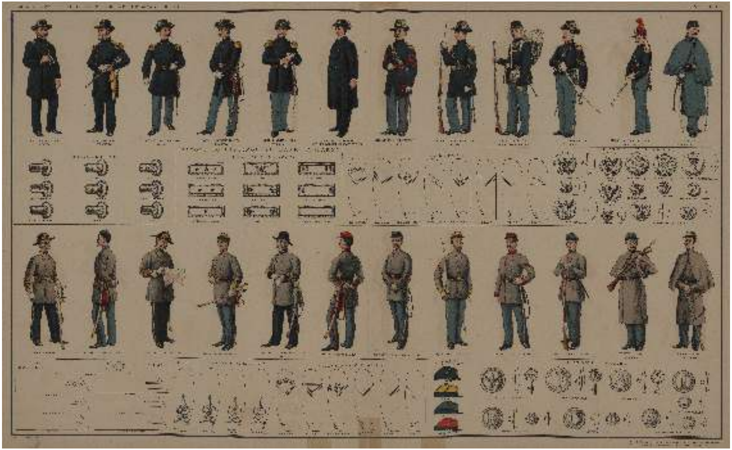
MESURES de la POITRINE.	NOMBRE d'hommes.	NOMBRE PROPORTIONNEL.	PROBABILITÉ d'après L'OBSERVATION.	RANG dans LA TABLE.	RANG d'après le CALCUL.	PROBABILITÉ d'après LA TABLE.	NOMBRE D'OBSERVATIONS calculé.
Pouces.							
33	3	5	0,5000			0,5000	7
34	18	31	0,4995	52	50	0,4993	29
35	81	141	0,4964	42,5	42,5	0,4964	110
36	185	322	0,4823	33,5	34,5	0,4854	323
37	420	732	0,4501	26,0	26,5	0,4531	732
38	749	1305	0,3769	18,0	18,5	0,3799	1333
39	1073	1867	0,2464	10,5	10,5	0,2466	1838
			0,0597	2,5	2,5	0,0628	
40	1079	1882	0,1285	5,5	5,5	0,1359	1987
41	934	1628	0,2913	13	13,5	0,3034	1675
42	658	1148	0,4061	21	21,5	0,4130	1096
43	370	645	0,4706	30	29,5	0,4690	560
44	92	160	0,4866	35	37,5	0,4911	221
45	50	87	0,4953	41	45,5	0,4980	69
46	21	38	0,4991	49,5	53,5	0,4996	16
47	4	7	0,4998	56	61,8	0,4999	3
48	1	2	0,5000			0,5000	1
	5738	1,0000					1,0000

Social Physics

Social Physics

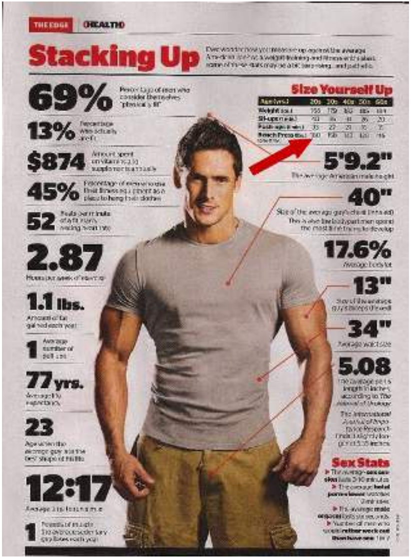
The determination of the average man is not merely a matter of speculative curiosity; it may be of the most important service to the science of man and the social system. It ought necessarily to precede every other inquiry into social physics, since it is, as it were, the basis. The average man, indeed, is in a nation what the centre of gravity is in a body; it is by having that central point in view that we arrive at the apprehension of all the phenomena of equilibrium and motion
- Quetelet

The Military Takes to the Idea



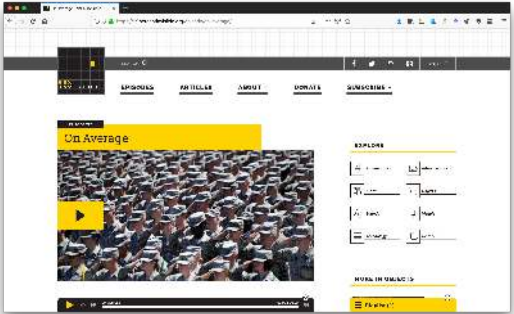
The Problem with Averages

The Average Man



The Face of the Average Man

On averages



https://99percentinvisible.org/episode/on-average/

We Covered. . .

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- Expectations (definitions, properties etc.)

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Next time: variance as a measure of a distribution's dispersion!

Where We've Been and Where We're Going...

- Last Week
  - welcome and outline of course
  - described uncertain outcomes with probability.
- This Week
  - define random variables
  - summarize random variables using expectation and variance
  - properties of joint and conditional distributions
  - famous distributions
- Next Week
  - estimating these features from data
  - estimating uncertainty
- Long Run
  - probability $\rightarrow$ inference $\rightarrow$ regression $\rightarrow$ causal inference

Variance: A Measure of Dispersion

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Expectation told us about the central tendency of a random variable, but what about dispersion?

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The expected value of a function $g()$ of the random variable X is denoted by $E[g(X)]$ and measures the central tendency of $g(X)$.

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Expectation told us about the central tendency of a random variable, but what about dispersion?
The expected value of a function $g()$ of the random variable X is denoted by $E[g(X)]$ and measures the central tendency of $g(X)$.

The variance is a special case of this, and the variance of a random variable X (a measure of its dispersion) is given by

$$\begin{aligned} V[X] &= E[(X - E[X])^2] \\ &= E[X^2] - E[X]^2 \end{aligned}$$

It is the expectation of the squared distances from the mean.

For a discrete random variable X

$$V[X] = \sum_{\text{all } x} (x - E[X])^2 p_X(x)$$

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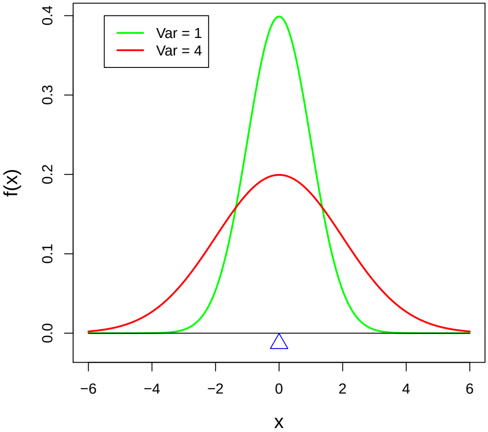
For a continuous random variable X

$$V[X] = \int_{-\infty}^{\infty} (x - E[X])^2 f_X(x) dx$$

Variance Measures the Spread of a Distribution



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- The Normal distribution—more later this week—is completely determined by its expected value (location) and variance (spread).
- The square root of the variance is the standard deviation.
- The variance and standard deviation have some useful properties.

Property 1 of Variance: Behavior with Constants

Suppose a and b are constants and X is a random variable. Then

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$$V[b] = 0$$
$$V[aX] = a^2 V[X]$$
$$V[aX + b] = a^2 V[X] + 0$$

Property 2 of Variance: Additivity for Independent Random Variables

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Variances of sums of independent RVs are sums of variances.

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Suppose we have k independent random variables $X_1, \ldots, X_k$. If $V[X_i]$ exists for all $i = 1, \ldots, k$, then

$$V\left[\sum_{i=1}^{k} X_i\right] = V[X_1] + \cdots + V[X_k]$$

NB: Technically independence is sufficient but not necessary.

What was the variance of Obama's NH position?

Candidates:

- Joe Biden
- Hillary Clinton
- Chris Dodd
- John Edwards
- Mike Gravel
- Dennis Kucinich
- Barack Obama
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$4/26 \quad \times (1 - 4.88)^2$

$+$

A,B,C,D,E,F,G,H,I,J,K,L,M,N,O,P,Q,R,S,T,U,V,W,X,Y,Z

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+ & \\
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Does variance matter for fairness?

One Step Deeper: Moments

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Suppose X is a random variable with pdf f_X. Define,

$$E[X^n] \;=\; \int_{-\infty}^{\infty} x^n f_X(x)dx$$

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- $V(X) =$ Second Moment $-$ First Moment^2
- We are assuming that the integral converges.
- Another way to characterize distributions is with their moment-generating function.

Expected Value as Mean Squared Error Minimizer

Now we can return to the question of why expectation? and offer one technical answer.

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Suppose we want to pick a single number (c) that summarizes a random variable X. What we mean by summarizes determines the best choice of c.

Expected Value as Mean Squared Error Minimizer

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Generally speaking we want a summary that is in the "center" of the data, i.e. that is as close as possible to all possible datapoints. Again though, the choice turns on what we mean by close.

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Let's prove the first result (see Blitzstein and Hwang 2014 Theorem 6.1.4 on pg 245 for this proof and the proof on mean absolute error).

Proof of Mean as Mean Squared Error Minimizer

Let X be a random variable and $E[X] = \mu$. We want to show that the value of c that minimizes the mean squared error $E\left[(X - c)^2\right]$ is the mean, μ (Blitzstein and Hwang Theorem 6.1.4).

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$$E\left[(X-c)^2\right] = V[X] + (\mu - c)^2 \tag{1}$$

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$$\begin{aligned} V[X] &= V[X-c] && \text{(Prop 1 of Variance)} \\ &= E\left[(X-c)^2\right] - (E[X-c])^2 && \text{(Defn of Variance)} \end{aligned}$$

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- Variance (definitions, properties etc.)

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Next time: Joint Distributions!

Where We've Been and Where We're Going...

- Last Week
  - welcome and outline of course
  - described uncertain outcomes with probability.
- This Week
  - define random variables
  - summarize random variables using expectation and variance
  - properties of joint and conditional distributions
  - famous distributions
- Next Week
  - estimating these features from data
  - estimating uncertainty
- Long Run
  - probability $\rightarrow$ inference $\rightarrow$ regression $\rightarrow$ causal inference

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- The conditional distribution describes one random variable given knowledge of another.
- We will start with a visual preview, then step back to go through the math more concretely.

Understanding Joint Distributions Mathematically

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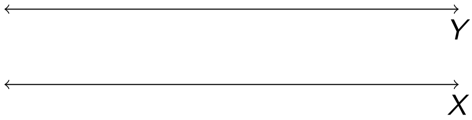

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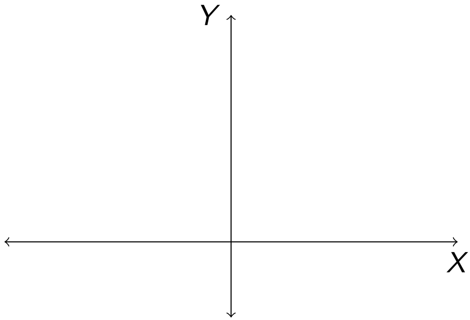

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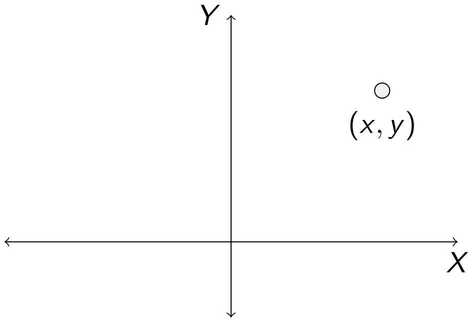
- The pair form a two-dimensional space, or $\mathbb{R} \times \mathbb{R}$
- One realization of the random variable is a point in that space



Example: Racial Prejudice

- Recall the list experiment about racial prejudice. Suppose we define $X = 0$ (Non-southern), 1 (Southern) and $Y =$ "number of angering items" for a randomly selected respondent receiving the treatment list.

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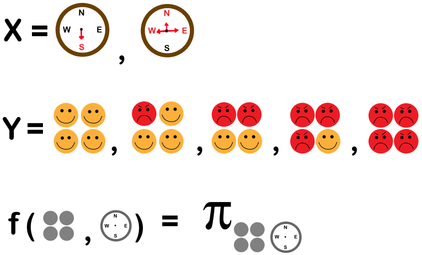

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$f_{X,Y}(x,y)$	x		
y	0	1	$f_Y(y)$
0	π_{00}	π_{01}	$\pi_{00}+\pi_{01}$
1	π_{10}	π_{11}	$\pi_{00}+\pi_{01}$
2	π_{20}	π_{21}	$\pi_{00}+\pi_{01}$
3	π_{30}	π_{31}	$\pi_{00}+\pi_{01}$
4	π_{40}	π_{41}	$\pi_{00}+\pi_{01}$
$f_X(x)$	$\sum_{y=0}^{4}\pi_{y0}$	$\sum_{y=0}^{4}\pi_{y1}$	

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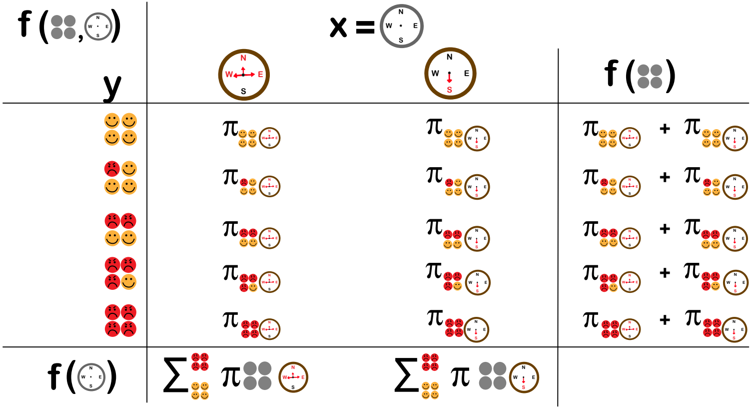

Discrete Conditional Distribution

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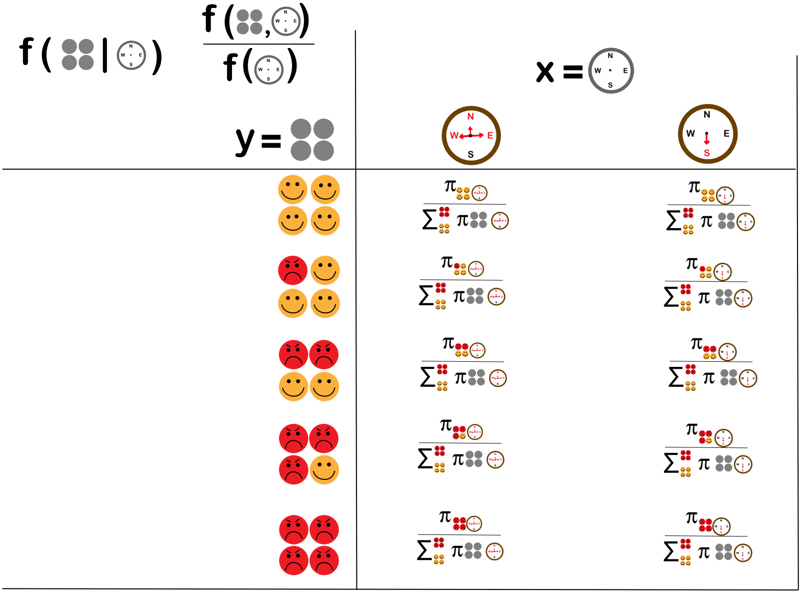

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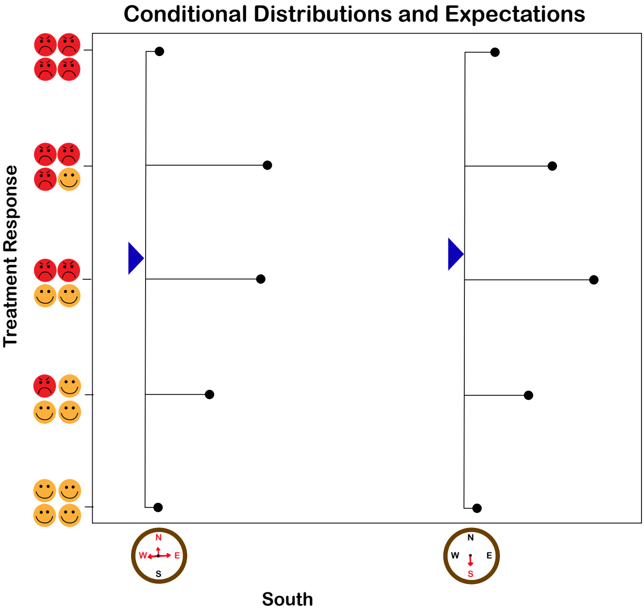

Example: Continuous Conditional Distribution

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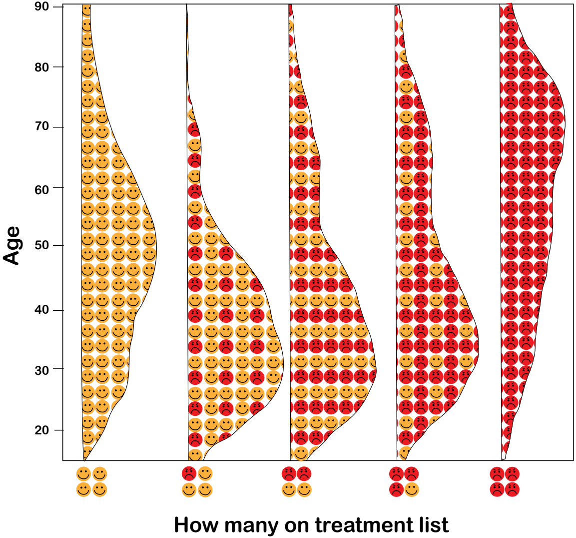
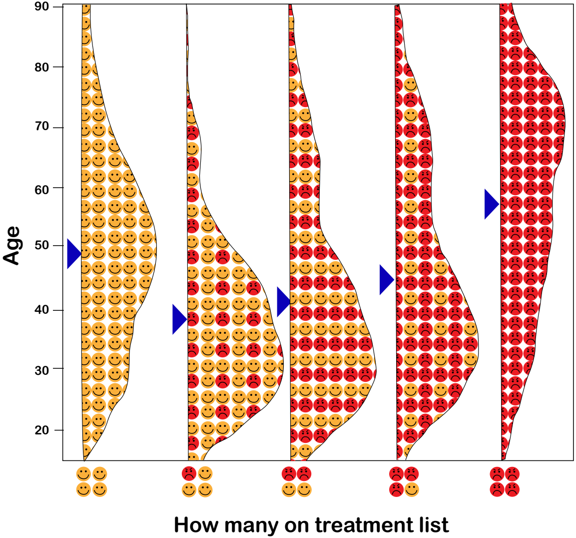


Conditional Expectation Function—next time!



Joint Probability Mass Function

Definition

For two discrete random variables X and Y the joint Probability Mass Function (PMF) $P_{X,Y}(x, y)$ gives the probability that $X = x$ and $Y = y$ for all x and y:

$$p_{X,Y}(x, y) \;=\; P(X = x \text{ and } Y = y)$$

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- $p_{X,Y}(x, y) \geq 0$ and $\sum_x \sum_y p_{X,Y}(x, y) = 1$.

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		X: Education			
		less HS	HS	College	BA
Y: Support	oppose	0.07	0.22	0.18	0.15
	neutral	0.02	0.06	0.05	0.05
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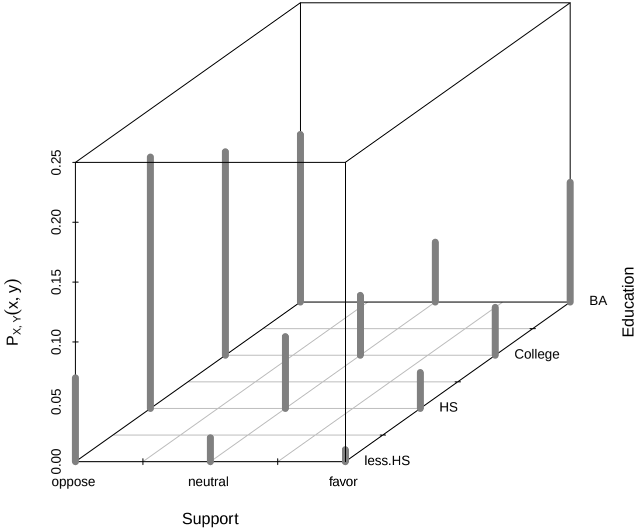
With discrete random variables this is very similar to thinking about a cross-tab, with frequencies/ probabilities in the cells instead of raw numbers.

Joint Probability Mass Function



From Joint to Marginal PMF

Given the joint PMF $p_{X,Y}(x, y)$ can we recover the marginal PMF $p_Y(y)$ (distribution over a single variable)?

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		X: Education				
		less HS	HS	College	BA	$p_Y(y)$
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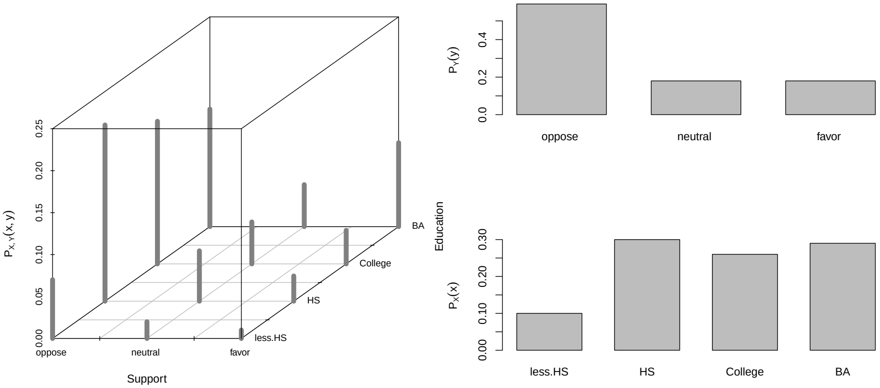
Y: Support	neutral	0.02	0.06	0.05	0.05	0.19
	favor	0.01	0.03	0.04	0.10	0.19

To obtain $p_Y(y)$ we marginalize the joint probability function $p_{X,Y}(x,y)$ over X:

$$p_Y(y) = \sum_x p_{X,Y}(x,y) = \sum_x P(X=x, Y=y)$$

Joint and Marginal Probability Mass Functions



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Define the conditional mass function $P(X = x|Y = y)$ as,

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Then it follows that:

$$p_{X,Y}(x, y) = p_{X|Y}(x|y)p_Y(y)$$

Marginalizing over y to get $p_X(x)$ is then,

$$p_X(x_j) = \sum_{i=1}^{N} p_{X|Y}(x_j|y_i)p_Y(y_i)$$

A Table

	$Y = 0$	$Y = 1$	
$X = 0$	$p(0,0)$	$p(0, 1)$	$p_X(0)$
$X = 1$	$p(1,0)$	$p(1,1)$	$p_X(1)$
	$p_Y\ (0)$	$p_Y\ (1)$	

A Table

	Y = 0	Y = 1	
X = 0	0.01	0.05	?
X = 1	0.25	0.69	?
	0.26	0.74	

$$
\begin{aligned}
p_X(0) &= P(X=0|Y=0)P(Y=0) + P(X=0|Y=1)P(Y=1) \\
&= \frac{0.01}{0.26} \times 0.26 + \frac{0.05}{0.74} \times 0.74 \\
&= 0.06
\end{aligned}
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$$\begin{aligned} p_X(1) &= P(X=1|Y=0)P(Y=0) + P(X=1|Y=1)P(Y=1) \\ &= \frac{0.25}{0.26} \times 0.26 + \frac{0.69}{0.74} \times 0.74 \\ &= 0.94 \end{aligned}$$

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Key relationships:

- $p_{X,Y}(x,y) = p_{Y|X}(y|x)p_X(x)$ (multiplicative rule)
- $p_{Y|X}(y|x) = p_{X|Y}(x|y)p_Y(y)/p_X(x)$ (Bayes' rule)

Conditional PMF

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The conditional PMF of Y given X, $p_{Y|X}(y|x)$, is the PMF of Y when X is known to be at a particular value $X = x$:

$$p_{Y|X}(y|x) = \frac{P(X = x \text{ and } Y = y)}{P(X = x)} = \frac{p_{X,Y}(x,y)}{p_X(x)}$$

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Conditional PMFs are just like ordinary PMFs, but refer to a universe where the "conditioning event" $(X = x)$ is known to have occurred.

Conditional distributions are key in statistical modeling because they inform us how the distribution of Y varies across different levels of X.

From Joint to Conditional: $p_{Y|X}(y|x) = \frac{p_{X,Y}(x,y)}{p_X(x)}$

Table: Joint PMF $p_{X,Y}(x,y)$ and Marginal PMFs $p_X(x), p_Y(y)$

		Education				
	$p_{X,Y}(x,y)$	less HS	HS	College	BA	$p_Y(y)$
Support	oppose	0.07	0.22	0.18	0.15	0.62
	neutral	0.02	0.06	0.05	0.05	0.19
	favor	0.01	0.03	0.04	0.11	0.19
	$p_X(x)$	0.11	0.32	0.27	0.31	1.00

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Table: Conditional PMF $p_{Y|X}(y|x)$

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	$p_{Y|X}(y|x)$	less HS	HS	College	BA	
Support	oppose	0.70	0.70	0.65	0.48	0.62
	neutral	0.20	0.20	0.19	0.17	0.19
	favor	0.10	0.10	0.15	0.34	0.19
		1.00	1.00	1.00	1.00	1.00

Joint and Conditional Probability Mass Functions

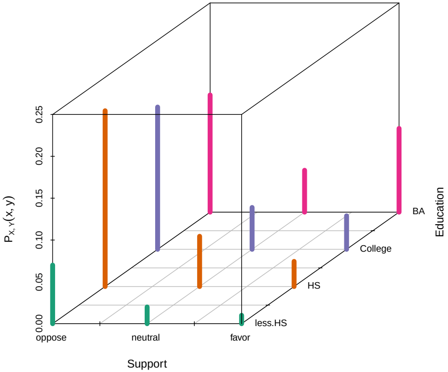

Figure: Joint

Joint and Conditional Probability Mass Functions

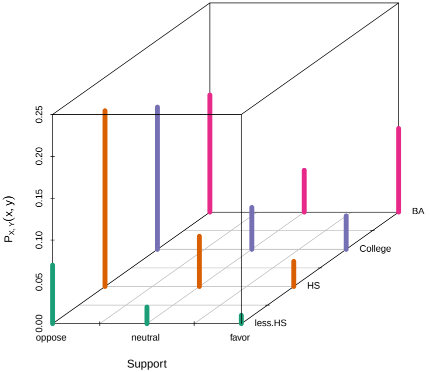

Figure: Joint

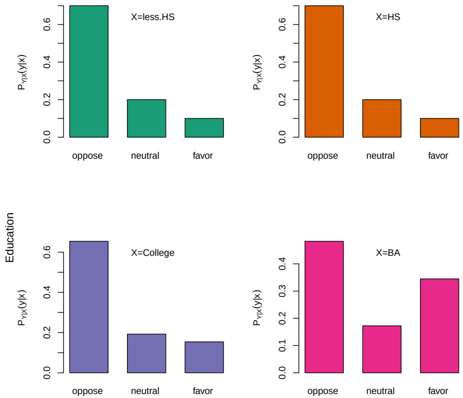

Figure: Conditional

Joint Probability Density Function

Definition

For two continuous random variables X and Y the joint PDF $f_{X,Y}(x, y)$ gives the density height where $X = x$ and $Y = y$ for all x and y.

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The multiplicative rule:

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where

- $f_{Y|X}(y|x)$: Conditional PDF of Y given $X = x$
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Restrictions:

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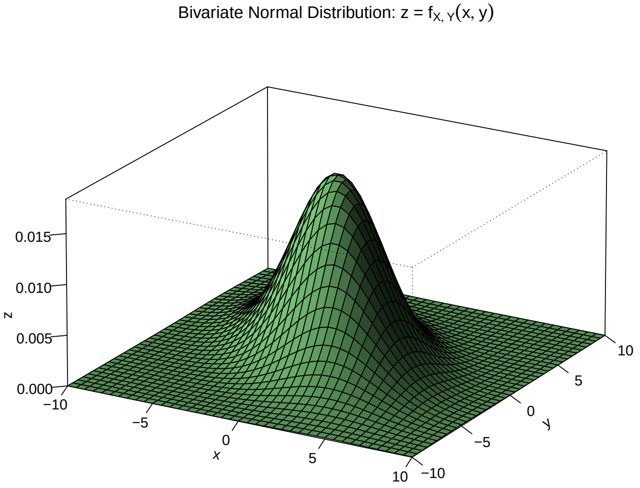
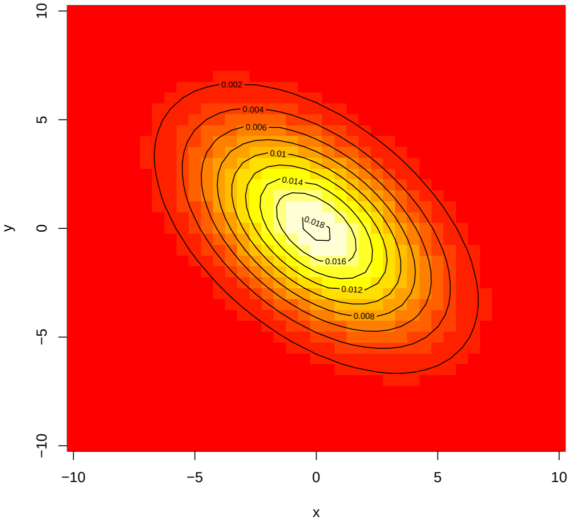
Restrictions:

- $\int_x \int_y f_{X,Y}(x,y)\, dy\, dx = 1$

3D Plot of a Joint Probability Density Function



Contour Plot of a Joint Probability Density Function



From Joint to Marginal PDF

How can we obtain $f_Y(y)$ from $f_{X,Y}(x,y)$?

From Joint to Marginal PDF

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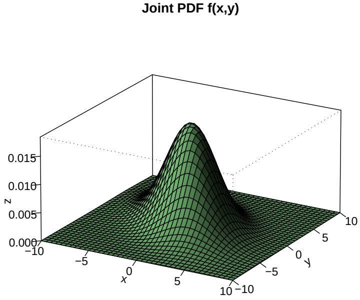
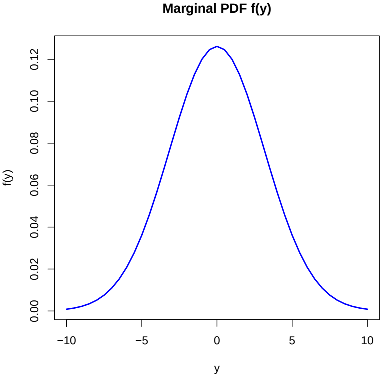
We marginalize the joint probability function $f_{X,Y}(x,y)$ over X:

$$f_Y(y) = \int_{-\infty}^{\infty} f_{X,Y}(x,y)dx$$





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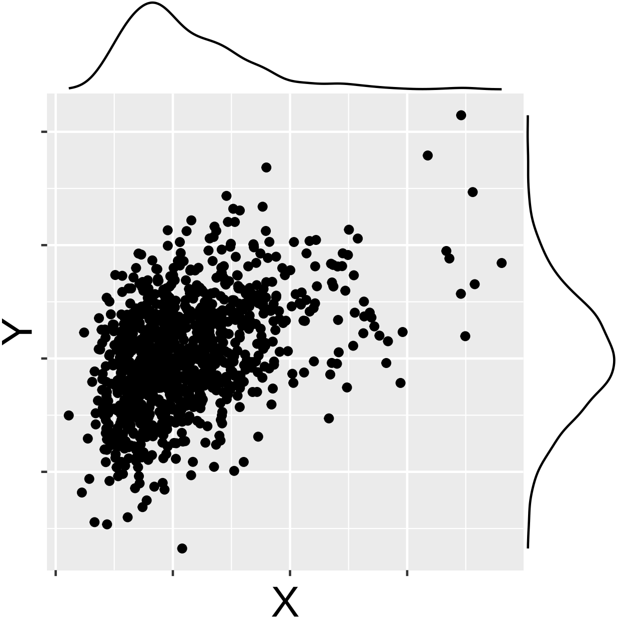

We Covered. . .

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- Joint distributions for discrete and continuous random variables.

We Covered...

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- Marginalization

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- Joint distributions for discrete and continuous random variables.
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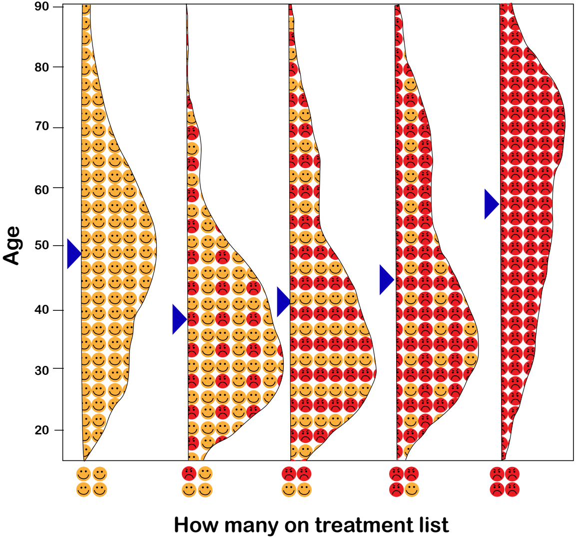
Next time: Characterizing Conditional Distributions!

Where We've Been and Where We're Going...

- Last Week
  - welcome and outline of course
  - described uncertain outcomes with probability.
- This Week
  - define random variables
  - summarize random variables using expectation and variance
  - properties of joint and conditional distributions
  - famous distributions
- Next Week
  - estimating these features from data
  - estimating uncertainty
- Long Run
  - probability $\rightarrow$ inference $\rightarrow$ regression $\rightarrow$ causal inference

Remember this?



Conditioning on X

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- Typically, we summarize the conditional distributions with a few parameters such as the conditional mean of $E[Y|X = x]$ and the conditional variance $V[Y|X = x]$

- Moreover, we are often interested in estimating $E[Y|X]$, i.e. the conditional expectation function that describes how the conditional mean of Y varies across all possible values of X.

Conditional Expectation

Definition (Conditional Expectation (Discrete))

Let Y and X be discrete random variables. The conditional expectation of Y given $X = x$ is defined as:

$$E[Y|X = x] = \sum_y y\, P(Y = y|X = x) = \sum_y y\, p_{Y|X}(y|x)$$

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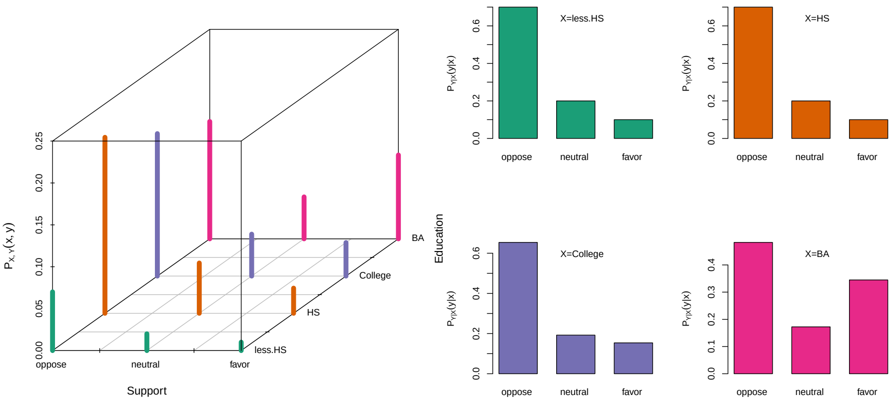
Definition (Conditional Expectation (Continuous))

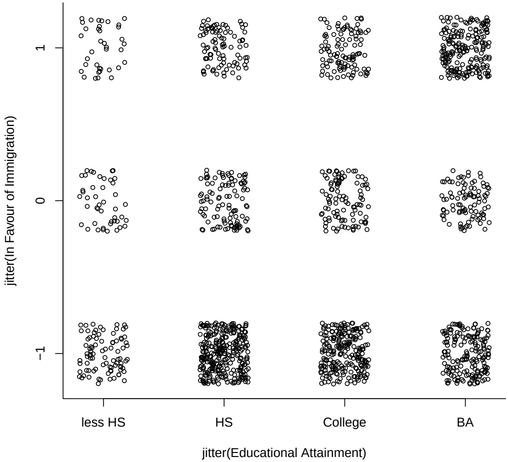
Let Y and X be continuous random variables. The conditional expectation of Y given $X = x$ is given by:

$$E[Y|X = x] = \int_{-\infty}^{\infty} y\, f_{Y|X}(y|x)dy$$

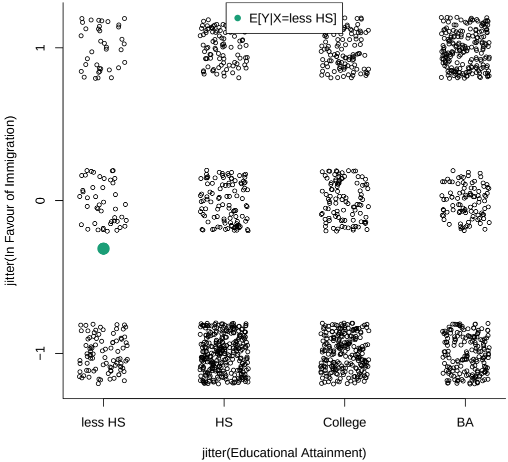
Joint and Conditional Probability Mass Functions



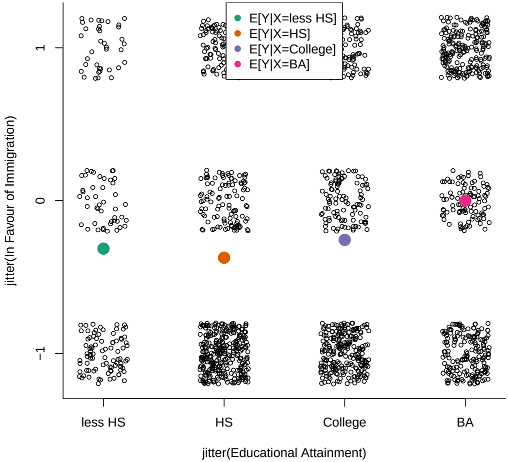
Conditional PMF $P_{Y|X}(y|x)$



Conditional Expectation $E[Y|X = 1]$



Conditional Expectation Function $E[Y|X]$



Law of Iterated Expectations

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Theorem (Law of Iterated Expectations/Adam's Law)

For two random variables X and Y,

$$E[Y] = E[E[Y|X]] = \begin{cases} \sum_{\text{all } x} E[Y|X=x] \cdot p_X(x) & (\textit{discrete } X) \\ \int_{-\infty}^{\infty} E[Y|X=x] \cdot f_X(x) dx & (\textit{continuous } X) \end{cases}$$

Note that the outer expectation is taken with respect to the distribution of X.

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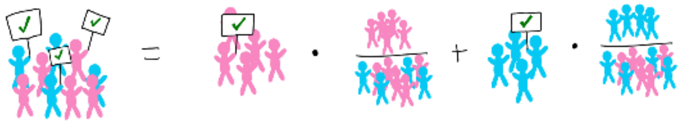
Note that the outer expectation is taken with respect to the distribution of X.

Example: Y (support) and $X \in \{1, 0\}$ (AfAm). Then, the LIE tells us:

$$\begin{aligned} \underbrace{E[Y]}_{\text{Average Support}} &= E[E[Y|X]] \\ &= \underbrace{E[Y|X=1]}_{\text{Average Support}|\text{AfAm}^c} \cdot \underbrace{p_X(1)}_{P(\text{AfAm}^c)} + \underbrace{E[Y|X=0]}_{\text{Average Support}|\text{AfAm}} \cdot \underbrace{p_X(0)}_{P(\text{AfAm})} \end{aligned}$$



Properties of Conditional Expectation

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   - This says that the conditional expectation is the function of X that minimizes the squared prediction error for Y across any possible function of X.
   - This is analogous to the result we saw a few videos ago about the mean.

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Remember, the conditional distribution of $Y|X$ is basically like any other probability distribution, so we are going to want to summarize the center *and* spread.

Conditional Variance

Definition

The conditional variance of Y given $X = x$ is defined as:

$$V[Y|X = x] = \begin{cases} \displaystyle\sum_{\text{all } y} (y - E[Y|X = x])^2 P_{Y|X}(y|x) & \text{(discrete } Y\text{)} \\ \displaystyle\int_{-\infty}^{\infty} (y - E[Y|X = x])^2 f_{Y|X}(y|x) dy & \text{(continuous } Y\text{)} \end{cases}$$

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A useful related result is the law of total variance (Eve's Law):

$$\underbrace{V[Y]}_{\text{Total variance}} \quad = \quad \underbrace{E[V[Y|X]]}_{\text{Average of Group Variances}} \quad + \quad \underbrace{V[E[Y|X]]}_{\text{Variance in Group Averages}}$$

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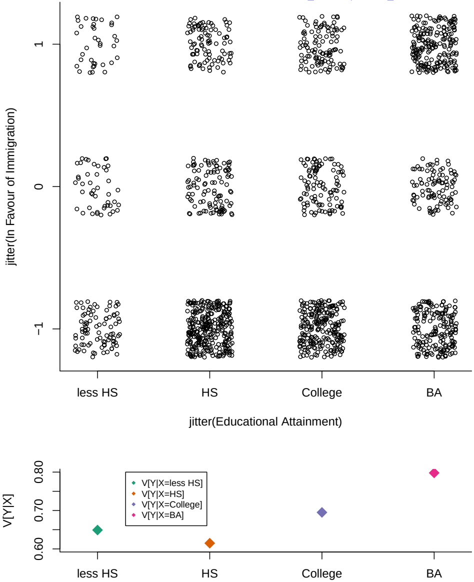
Example: Y (support) and $X \in \{1, 0\}$ (group). The LTV says that the total variance in support can be decomposed into two parts:

1. On average, how much support varies within groups (within variance)
2. How much average support varies between groups (between variance)

Conditional Variance Function $V[Y|X]$



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Let's look at this in pictures.
(If you want to know more: Blitzstein and Hwang pg 392-393)

Important Subtleties in Pictures

Sample space

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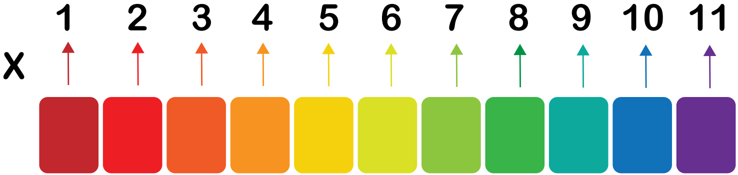
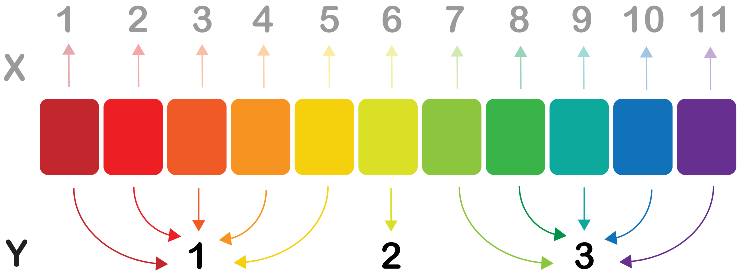


Random variable

Important Subtleties in Pictures



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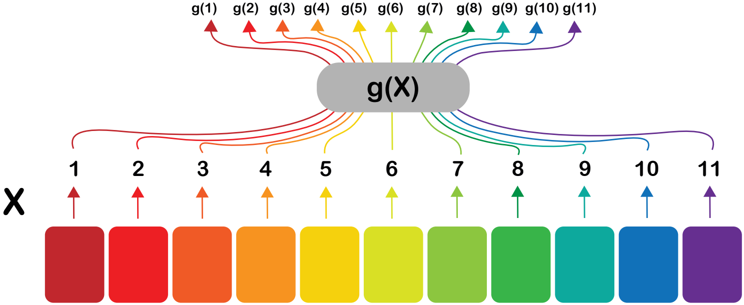
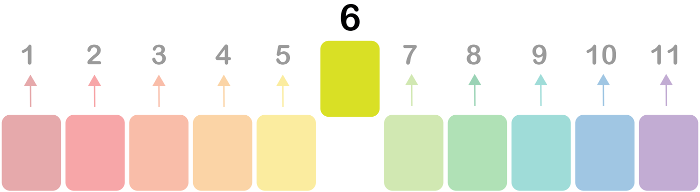


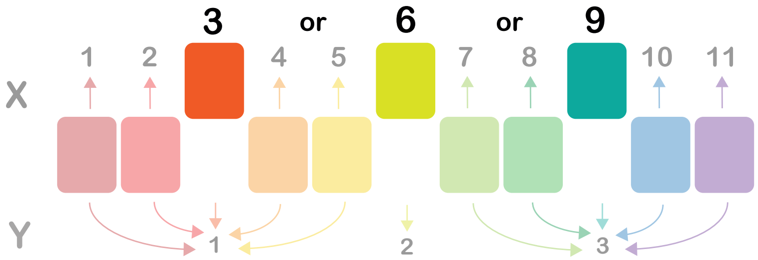
Function of a random variable is a random variable

Important Subtleties in Pictures



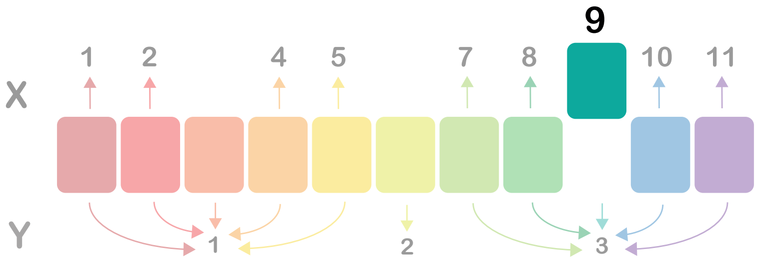
$E[X]$

Important Subtleties in Pictures



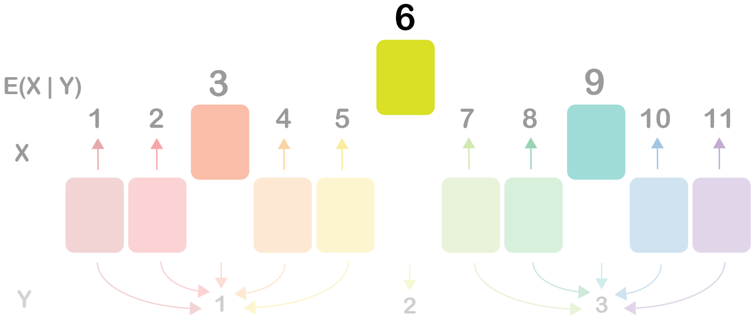
$$E[X|Y]$$

Important Subtleties in Pictures



$$E[X|Y=3]$$

Important Subtleties in Pictures



$$E[E[X|Y]] = E[X]$$

We Covered...

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Next time: Independence and Covariance!

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  - probability $\rightarrow$ inference $\rightarrow$ regression $\rightarrow$ causal inference

Independence

Definition (Independence of Random Variables)

Two random variables Y and X are independent if

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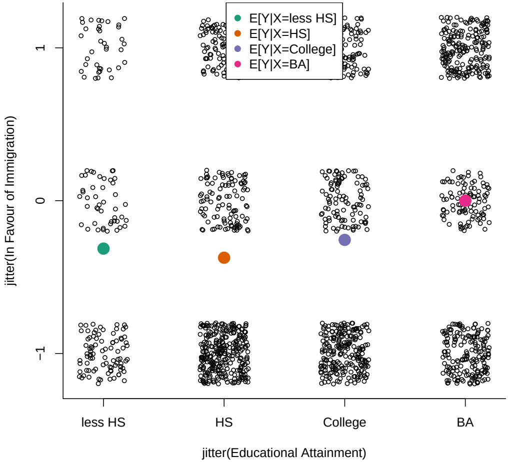

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We can prove the continuous case by following the same steps, with $\sum$ replaced by $\int$.

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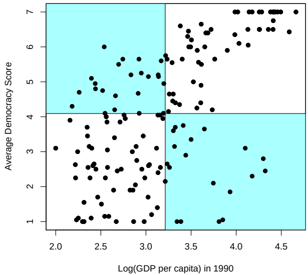
  - Points in upper right and lower left quadrants (relative to the means) add to the covariance.
  - Points in the upper left and lower right quadrants subtract from the covariance.



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Therefore, $X \perp\!\!\!\perp Y \implies Cov[X, Y] = 0$, but not vice versa.

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Proof: Plug in to the definition of variance and expand (try it yourself!)

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- Always satisfies: $-1 \leq Cor[X, Y] \leq 1$.

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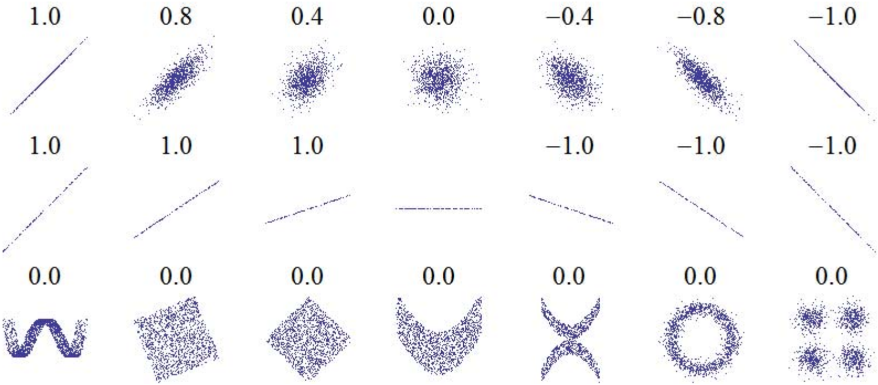

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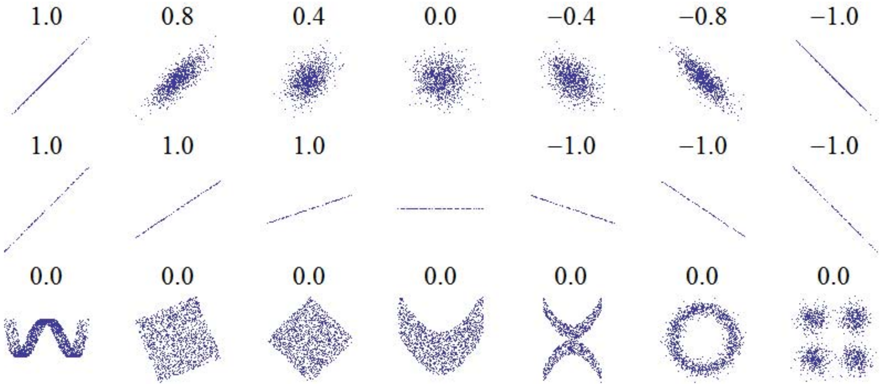

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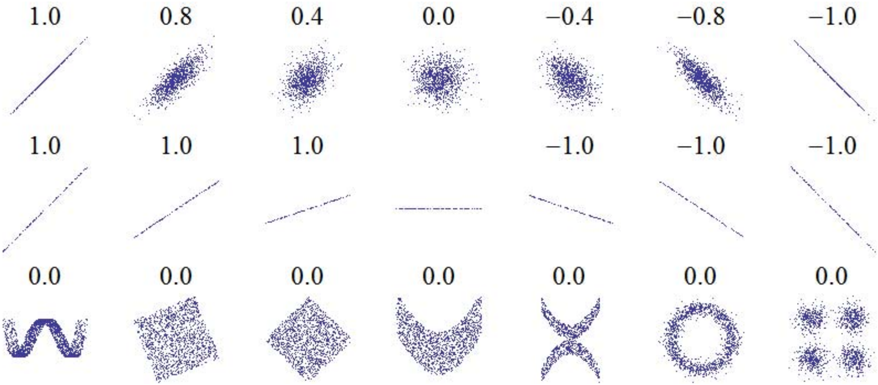

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$$f_{X,Y|Z}(x,y|z) \; = \; f_{Y|Z}(y|z) \cdot f_{X|Z}(x|z)$$

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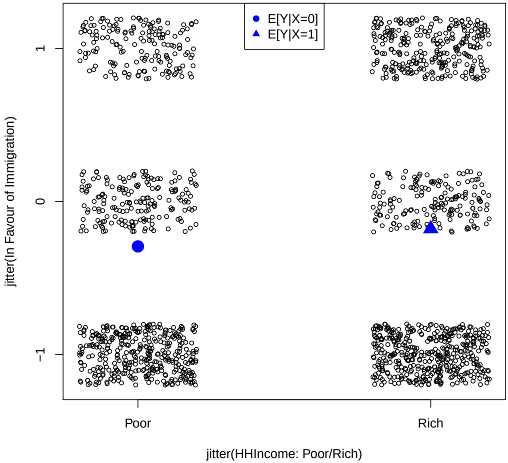

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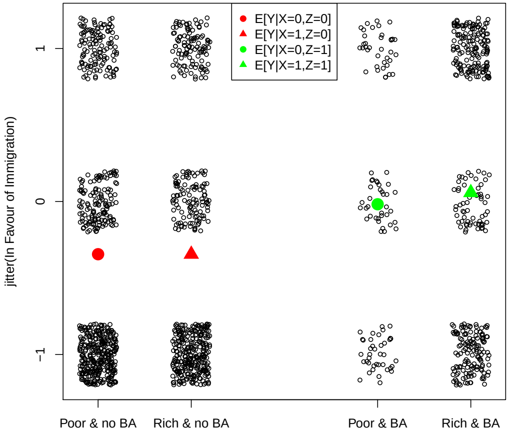

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Next time: Famous Distributions!

Where We've Been and Where We're Going...

- Last Week
  - welcome and outline of course
  - described uncertain outcomes with probability.
- This Week
  - define random variables
  - summarize random variables using expectation and variance
  - properties of joint and conditional distributions
  - famous distributions
- Next Week
  - estimating these features from data
  - estimating uncertainty
- Long Run
  - probability $\rightarrow$ inference $\rightarrow$ regression $\rightarrow$ causal inference

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- Examples: Bernoulli, Binomial, Gamma, Normal, Poisson, t-distribution

Bernoulli Random Variable

Definition

Suppose X is a random variable, with $X \in \{0, 1\}$ and $P(X = 1) = \pi$.
Then we will say that X is Bernoulli random variable,

$$P(X = x) \quad = \quad \pi^x (1 - \pi)^{1-x}$$

for $x \in \{0, 1\}$ and $P(X = x) = 0$ otherwise.
We will (equivalently) say that

$$X \quad \sim \quad \text{Bernoulli}(\pi)$$

$\sim$ means equality in distribution (not values!). Often $X \sim \text{Bernoulli}(\pi)$ would be read 'X is distributed Bernoulli with parameter π'

Bernoulli Random Variable Mean and Variance

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Suppose $X \sim \text{Bernoulli}(\pi)$

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\begin{aligned}
E[X] &= 1 \times P(X=1) + 0 \times P(X=0) \\
&= \pi + 0(1-\pi) = \pi \\
\text{var}(X) &= E[X^2] - E[X]^2 \\
E[X^2] &= 1^2 P(X=1) + 0^2 P(X=0) \\
&= \pi \\
\text{var}(X) &= \pi - \pi^2
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Importantly, we can also just look this up!

Normal/Gaussian Random Variables

Definition

Suppose X is a random variable with $X \in \mathbb{R}$ and density

$$f_X(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$$

Then X is a normally distributed random variable with parameters μ and σ^2.
Equivalently, we'll write

$$X \sim \text{Normal}(\mu, \sigma^2)$$

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Proposition

Scale/Location. If $Z \sim N(0, 1)$, then $X = aZ + b$ is,

$$X \sim Normal(b, a^2)$$

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$Y = 2Z + 6$

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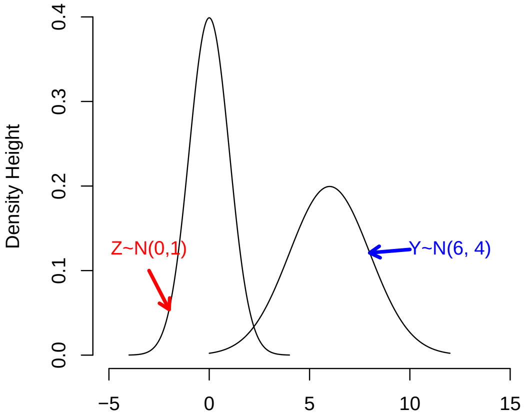
$Y = 2Z + 6$
$Y \sim \text{Normal}(6, 4)$



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Assume we know:

$$\begin{aligned} E[Z] &= 0 \\ Var(Z) &= 1 \end{aligned}$$

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Multivariate Normal

Definition

Suppose $\boldsymbol{X} = (X_1, X_2, \ldots, X_N)$ is a vector of random variables. If $\boldsymbol{X}$ has pdf

$$f_{X_1,X_2}(\boldsymbol{x}) \quad = \quad (2\pi)^{-N/2}\det\left(\boldsymbol{\Sigma}\right)^{-1/2}\exp\left(-\frac{1}{2}(\boldsymbol{x}-\boldsymbol{\mu})'\boldsymbol{\Sigma}(\boldsymbol{x}-\boldsymbol{\mu})\right)$$

Then we will say $\boldsymbol{X}$ has a Multivariate Normal Distribution,

$$\boldsymbol{X} \quad \sim \quad \text{Multivariate Normal}(\boldsymbol{\mu}, \boldsymbol{\Sigma})$$

Multivariate Normal Distribution

Consider the (bivariate) special case where $\boldsymbol{\mu} = (0, 0)$ and

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$$f(x_1, x_2) = (2\pi)^{-2/2} 1^{-1/2} \exp\left(-\frac{1}{2}\left((\boldsymbol{x} - \mathbf{0})' \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} (\boldsymbol{x} - \mathbf{0})\right)\right)$$

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$\rightsquigarrow$ product of univariate standard normally distributed random variables

Properties of the Multivariate Normal Distribution

Suppose $\boldsymbol{X} = (X_1, X_2, \ldots, X_N)$

$$\begin{aligned} E[\boldsymbol{X}] &= \boldsymbol{\mu} \\ \text{cov}(\boldsymbol{X}) &= \boldsymbol{\Sigma} \end{aligned}$$

So that,

$$\boldsymbol{\Sigma} = \begin{pmatrix} \text{var}(X_1) & \text{cov}(X_1, X_2) & \ldots & \text{cov}(X_1, X_N) \\ \text{cov}(X_2, X_1) & \text{var}(X_2) & \ldots & \text{cov}(X_2, X_N) \\ \vdots & \vdots & \ddots & \vdots \\ \text{cov}(X_N, X_1) & \text{cov}(X_N, X_2) & \ldots & \text{var}(X_N) \end{pmatrix}$$

One Step Deeper: Exponential Family

Nearly every distribution we will discuss is in the exponential family. An exponential family distribution has the density of the following form:

$$f_Y(y;\theta,\phi) = \exp\left\{\frac{y\theta - b(\theta)}{a(\phi)} + c(y,\phi)\right\}$$

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Many other examples, including: Normal, Bernoulli/binomial, Gamma, multinomial, exponential, negative binomial, beta, uniform, chi-squared, etc.

This slide and the following based on material from Teppei Yamamoto

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  $\Rightarrow \mathbb{E}(Y_i) = \frac{db(\theta_i)}{d\theta_i} = \exp(\theta_i) = \mu_i$ and $\mathbb{V}(Y_i) = \frac{d^2 b(\theta_i)}{d\theta_i^2} = \exp(\theta_i) = \mu_i$

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- We can characterize distributions in terms of their expectation (location) and variance (spread).
- Joint and conditional distributions capture the relationship between random variables.
- There is a common set of famous distributions such as the Normal distribution.

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Next week: inference!