Week 2: Random Variables

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These slides are heavily influenced by Adam Glynn, Justin Grimmer and Jens Hainmueller. Many illustrations by Shay O’Brien.
Where We’ve Been and Where We’re Going...

- Last Week
  - welcome and outline of course
  - described uncertain outcomes with probability.

This Week

- Monday:
  - summarize one random variable using expectation and variance
  - show how to condition on a variable

- Wednesday:
  - properties of joint distributions
  - conditional expectations
  - covariance, correlation, independence

Next Week

- estimating these features from data
- estimating uncertainty

Long Run

- probability
- → inference
- → regression
- → causal inference

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    - show how to *condition* on a variable
  - Wednesday:
    - *properties* of joint distributions
    - *conditional* expectations
    - *covariance*, *correlation*, *independence*

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Questions?
• Notation guide
- Notation guide
- Using the slides (links, what’s contained in a single deck etc.)
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- Using the slides (links, what’s contained in a single deck etc.)
- Any logistical hiccups?
Random Variables and Distributions
- What is a Random Variable?
- Discrete Distributions
- Continuous Distributions

Characteristics of Distributions
- Central Tendency
- Measures of Dispersion

Conditional Distributions

Fun with Averages

Fun with Sensitive Questions

Appendix: Why the Mean?

Joint Distributions
- Discrete Random Variable
- Continuous Random Variable

Conditional Expectation

Properties
- Independence
- Covariance and Correlation
- Conditional Independence

Famous Distributions

Fun With Spam
Example: Ballot Order

Evidence suggests that candidates gain a small advantage from ballot order. As a response, in 2008 New Hampshire chose a letter from the alphabet and then listed the candidates in alphabetical order starting with that letter.

We can use probability to assess the “fairness” of this process. 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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Example: Assessing Racial Prejudice

We often want to ask sensitive questions which a survey respondent is unlikely to honestly answer. A list experiment asks respondents how many items on a list they agree with, for example, what proportion of people would be upset by a black family moving in next door to them (Kuklinski et al. 1997).

Randomly split survey into two halves. First half ask how many of the following items upset you:
1. the federal government increasing the tax on gasoline
2. professional athletes getting million-dollar salaries
3. large corporations polluting the environment.

Second half, add a fourth item:
4. a black family moving in next door

Use the answers to infer the proportion upset by the fourth item.

To do this, we need to understand random variables.
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- To do this we need to understand **random variables**
What is a Random Variable?

Intuition: functions that map outcomes to numbers.
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Formal: $X$ is a function that maps the **sample space** to the **real numbers**.
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Imagine an experiment of two coin flips

$$
\Omega = \{\{\text{heads, heads}\}, \{\text{heads, tails}\}, \{\text{tails, heads}\}, \{\text{tails, tails}\}\}
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we could define a random variable $X(\omega)$ to be the function that returns the number of heads for each element of $\Omega$.

- $X(\{\text{heads, heads}\}) = 2$
- $X(\{\text{heads, tails}\}) = 1$
- $X(\{\text{tails, heads}\}) = 1$
- $X(\{\text{tails, tails}\}) = 0$
A Visual Example
A Visual Example
A Visual Example

X

1 2 3 4 5 6 7 8 9 10 11
A Brief Note on Notation

We almost always use capital roman letters for the “name” of the random variable such as $X$. We refer to a particular value with a lower case letter $x$. So we might write $P(X = x)$ to be the probability that the number of heads we observe is equal to $x$.

For more complicated random variables we often write out values as follows:

$$X = \begin{cases} 
1 & \text{if heads} \\
0 & \text{if tails}
\end{cases}$$

Sometimes the sample space is already numeric so it's more obvious (e.g. how long until the train arrives).
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- Sometimes the sample space is already numeric so it's more obvious (e.g. how long until the train arrives)
Quick FAQ

Why have random variables at all? It makes the math easier, even across very different sample spaces.

Why are they random variables? Realizations of a stochastic process (i.e. randomness in the outcome, not the mapping).

Is it really easier this way? It seems hard.

Yup. Seriously. Let's do an example!
Quick FAQ

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  *realizations of a stochastic process (i.e. randomness in the outcome, not the mapping)*

- Is it really easier this way? It seems hard.
  *yep. seriously. let’s do an example!*
NH Ballot Order Example

Candidates:

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

\[ X = \begin{cases} 1 \\ \end{cases} \]


\( X \) 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.
NH Ballot Order Example

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

\[ X = \begin{cases} 
1 \\
2 
\end{cases} \]

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NH Ballot Order Example

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

\[ X = \begin{cases} 1 \\ 2 \\ 3 \end{cases} \]


\(X\) 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.
NH Ballot Order Example

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

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


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NH Ballot Order Example

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

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

\[
\]

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

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


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Candidates:

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

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


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

\[
X = \begin{cases} 
1 \\
2 \\
3 \\
4 \\
5 \\
6 \\
7 \\
8 \\
\end{cases}
\]


\(X\) 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.
Discrete Distributions

For discrete distributions, the random variable $X$ takes on a finite, or a countably infinite number of values. A common shorthand is to think of discrete RVs taking on distinct values. A probability mass function (pmf) and a cumulative distribution function (cdf) are two common ways to define the probability distribution for a discrete RV. Probability mass functions provide a compact way to represent information about how likely various outcomes are.
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Where do Distributions Come From?

The probabilities associated with each realization of the r.v. come from the underlying experiment and sample space.
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Example: New Hampshire

Candidates:

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

\[
f(x) = \begin{cases} 
  4/26 & x = 1 \\
  & \text{(OFFICIAL BALLOT)} \\
\end{cases}
\]
Example: New Hampshire

Candidates:
- Joe Biden
- Hillary Clinton
- Chris Dodd
- John Edwards
- Mike Gravel
- Dennis Kucinich
- Barack Obama
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\[
f(x) = \begin{cases} 
4/26 & x = 1 \\
4/26 & x = 2 
\end{cases}
\]

Example: New Hampshire

Candidates:

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

\[ f(x) = \begin{cases} 
4/26 & x = 1 \\
4/26 & x = 2 \\
2/26 & x = 3 \\
\end{cases} \]

Example: New Hampshire

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- Joe Biden
- Hillary Clinton
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\[
f(x) = \begin{cases} 
4/26 & x = 1 \\
4/26 & x = 2 \\
2/26 & x = 3 \\
1/26 & x = 4 
\end{cases}
\]

Example: New Hampshire

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\[ f(x) = \begin{cases} 
4/26 & x = 1 \\
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2/26 & x = 3 \\
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1/26 & x = 5 
\end{cases} \]

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OFFICIAL BALLOT

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\[
\begin{align*}
f(x) = & \begin{cases} 
4/26 & x = 1 \\
4/26 & x = 2 \\
2/26 & x = 3 \\
1/26 & x = 4 \\
1/26 & x = 5 \\
1/26 & x = 6 \\
10/26 & x = 7 
\end{cases}
\end{align*}
\]

Example: New Hampshire

Candidates:

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

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

Discrete Probability Mass Functions

A probability mass function \( f(x) \) of a random variable \( X \) is a non-negative function that gives the probability that \( X = x \) and \( \sum_x f(x) = 1 \).
Discrete Probability Mass Functions

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NH Obama Ballot Position PMF Plot
NH Obama Ballot Position PMF Plot

![NH Obama Ballot Position PMF Plot](image-url)
Discrete Cumulative Distribution Function

A cumulative distribution function $F(x)$ of a random variable $X$ is a non-decreasing function that gives the probability that $X \leq x$. 
Discrete Cumulative Distribution Function

A cumulative distribution function $F(x)$ of a random variable $X$ is a non-decreasing function that gives the probability that $X \leq x$. 
NH Obama Ballot Position CDF Plot
NH Obama Ballot Position CDF Plot
Some Important Discrete Distributions

Let $X$ be a binary variable with $P(X = 1) = p$ and, thus, $P(X = 0) = 1 - p$, where $p \in [0, 1]$. Then we say that $X$ follows a Bernoulli distribution with the following pmf:

$$f_X(x) = px(1-p)^{1-x}$$

for $x \in \{0, 1\}$.

Probably the most famous distribution for a discrete r.v. is the discrete uniform distribution that puts equal probability on each value that $X$ can take:

$$f_X(x) = \begin{cases} 
\frac{1}{k} & \text{for } x = 1, \ldots, k \\
0 & \text{otherwise}
\end{cases}$$

We can summarize these distributions with one number (e.g. the probability of variables being 1).
Some Important Discrete Distributions

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Empirical Distributions

An empirical mass function $\hat{f}(x)$ of a variable $X$ is a non-negative function that gives the frequency of the value $x$ from data on $X$.

An empirical cumulative distribution function $\hat{F}(x)$ of a variable $X$ is a non-decreasing function that gives the frequency of values of $X$ less than $x$. 
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An empirical cumulative distribution function \( \hat{F}(x) \) of a variable \( X \) is a non-decreasing function that gives the frequency of values of \( X \) less than \( x \).
Example: Assessing Racial Prejudice

- We often want to ask sensitive questions which a survey respondent is unlikely to honestly answer.
- A list experiment asks respondents how many items on a list they agree with:
  - for example, what proportion of people would be upset by a black family moving in next door to them (Kuklinski et al 1997).
  - randomly split survey into two halves.
  - first half ask how many of the following items upset you:
    1. the federal government increasing the tax on gasoline
    2. professional athletes getting million-dollar salaries
    3. large corporations polluting the environment.
  - second half, add a fourth item:
    4. a black family moving in next door
    - use the answers to infer the proportion upset by the fourth item.
- To do this we need to understand random variables.
Racial Prejudice Example (Kuklinski et al, 1997)
Racial Prejudice Example (Kuklinski et al, 1997)

\[ X = \# \text{ of angering items on the baseline list for Southerners:} \]

<table>
<thead>
<tr>
<th>( x )</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>( f(x) )</td>
<td>?</td>
<td>?</td>
<td>?</td>
<td>?</td>
</tr>
<tr>
<td>( \hat{f}(x) )</td>
<td>0.02</td>
<td>0.27</td>
<td>0.43</td>
<td>0.28</td>
</tr>
<tr>
<td>( \hat{F}(x) )</td>
<td>0.02</td>
<td>0.29</td>
<td>0.72</td>
<td>1.00</td>
</tr>
</tbody>
</table>
**Racial Prejudice Example (Kuklinski et al, 1997)**

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<td>0.02</td>
<td>0.27</td>
<td>0.43</td>
<td>0.28</td>
</tr>
<tr>
<td>(\hat{F}(x))</td>
<td>0.02</td>
<td>0.29</td>
<td>0.72</td>
<td>1.00</td>
</tr>
</tbody>
</table>

\[
Y = \# \text{ of angering items on the treatment list for Southerners:}
\]

<table>
<thead>
<tr>
<th>(y)</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>(f(y))</td>
<td>?</td>
<td>?</td>
<td>?</td>
<td>?</td>
<td>?</td>
</tr>
<tr>
<td>(\hat{f}(y))</td>
<td>0.02</td>
<td>0.20</td>
<td>0.40</td>
<td>0.28</td>
<td>0.10</td>
</tr>
<tr>
<td>(\hat{F}(y))</td>
<td>0.02</td>
<td>0.22</td>
<td>0.62</td>
<td>0.90</td>
<td>1.00</td>
</tr>
</tbody>
</table>
Continuous Distributions

Continuous random variables take on an uncountably infinite number of values. This is often a useful approximation when a variable takes on many values. A probability density function (pdf) and a cumulative distribution function (cdf) are two common ways to define the distribution for a continuous RV.
Continuous Distributions

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Continuous random variables take on an uncountably infinite number of values.

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Continuous Distributions

- Continuous random variables take on an *uncountably infinite* number of values.
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- A probability density function (pdf) and a cumulative distribution function (cdf) are two common ways to define the distribution for a continuous RV.
Example: Age in the Racial Prejudice Example
Example: Age in the Racial Prejudice Example

Let $X$ be the age of a randomly selected individual from the Kuklinski et al. (1997) data set.
Example: Age in the Racial Prejudice Example

Let $X$ be the age of a randomly selected individual from the Kuklinski et al. (1997) data set. The probability distribution for this variable is well approximated by a probability density function.
Continuous Cumulative Distribution Functions

A cumulative distribution function \( F(x) \) of a random variable \( X \) is a non-decreasing function that gives the probability that \( X \leq x \). For a continuous RV, the cdf is continuous.

\[
F(x) = \int_{-\infty}^{x} f(z) \, dz
\]
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$$F(x) = \int_{-\infty}^{x} f(z)dz$$
From PDFs to CDFs
From PDFs to CDFs

\[ F(x) = P(X \leq x) = \int_{-\infty}^{x} f(z) \, dz \]

\[ 0.52 = P(X \leq 40) = \int_{-\infty}^{40} f(z) \, dz \]
From CDFs to PDFs

\[ f(x) = \frac{dF(x)}{dx} \]

CDF for Age

\[ F(x) \]

PDF for Age

\[ f(x) \]
From CDFs to PDFs

\[ f(x) = \frac{dF(x)}{dx} \]

\[ 0.015 = \frac{dF(50)}{dx} \]
Subtleties of Continuous Densities

Remember - the height of the curve is not the probability of $x$ occurring.
Subtleties of Continuous Densities

Remember— the height of the curve is not the probability of $x$ occurring. To get the probability that $X$ will fall in some region, you need the area under the curve.
Random Variables and Distributions

- What is a Random Variable?
- Discrete Distributions
- Continuous Distributions

Characteristics of Distributions

- Central Tendency
- Measures of Dispersion

Conditional Distributions

Fun with Averages

Fun with Sensitive Questions

Appendix: Why the Mean?

Joint Distributions

- Discrete Random Variable
- Continuous Random Variable

Conditional Expectation

Properties

- Independence
- Covariance and Correlation
- Conditional Independence

Famous Distributions

Fun With Spam
Random Variables and Distributions
- What is a Random Variable?
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Appendix: Why the Mean?

Joint Distributions
- Discrete Random Variable
- Continuous Random Variable

Conditional Expectation

Properties
- Independence
- Covariance and Correlation
- Conditional Independence

Famous Distributions

Fun With Spam
Expectation

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.

The expected value of a discrete random variable \( X \) is defined as

\[
E[X] = \sum_{all x} x \cdot f_X(x)
\]

The expected value of a continuous random variable \( X \) is defined as

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E[X] = \int_{-\infty}^{\infty} x \cdot f_X(x) \, dx
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What did we expect for Obama’s NH position?

Candidates:

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

$\frac{4}{26} \times 1$

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What did we expect for Obama’s NH position?

Candidates:

- Joe Biden  4/26 × 1
- Hillary Clinton  4/26 × 2
- Chris Dodd  2/26 × 3
- John Edwards
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- Barack Obama +
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Candidates:

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  \[4/26 \times 1\]
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- Chris Dodd
  \[2/26 \times 3\]
- John Edwards
  \[1/26 \times 4\]
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What did we expect for Obama’s NH position?

Candidates:

- Joe Biden 4/26 × 1
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- Dennis Kucinich: 10/26 \times 7
- Barack Obama: + 3/26 \times 8
- Bill Richardson: \text{Sum} = 4.88

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.
Why the Expected Value (Balance Point)?

It is the probabilistic equivalent of the sample average (mean).

It is a reasonable measure for the "center" of the data.

We have some intuition about balance points.

It has some useful and convenient properties.
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Population Mean as an Expected Value

Let $x_1, \ldots, x_N$ be our population. Then the population mean is the following:

$$ \bar{x} = \frac{1}{N} \sum_{i=1}^{N} x_i $$

This can be re-written in the following form:

$$ \bar{x} = \frac{1}{N} \sum_{i=1}^{N} \{ \frac{1}{N} x_i \} $$

Note how this resembles the definition of discrete expected value. If all values distinct (i.e. $x_i \neq x_j$ for all $i \neq j$),

$$ \bar{x} = \sum_{\text{all } x_i} x_i f(x_i), $$

where $f(x_i) = \frac{1}{N}$. 

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Stewart (Princeton)  Week 2: Random Variables  September 17/19, 2018  35 / 162
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Property 1 of Expected Value: Additivity

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

$$E[\sum_{i=1}^{k} X_i] = E[X_1] + \cdots + E[X_k]$$
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\[
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\]
Property 2 of Expected Value: Homogeneity

The expected value of a constant is the constant.
The expectation of a constant times a RV is the constant times the
expectation of the RV.
Suppose $a$ and $b$ are constants and $X$ is a random variable. Then
$E[b] = b$
$E[aX] = aE[X]$
$E[aX + b] = aE[X] + b$
Together properties 1 and 2 are linearity (and this is sometimes presented
as Linearity of Expectations).
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Law of the Unconscious Statistician: If $g(X)$ is a function of a discrete random variable, then

$$E[g(X)] = \sum_x x \cdot g(x) \cdot f_X(x),$$

essentially the expected value of the transformation of the random variable is just the weighted average of the transformed outcomes.

We will come back to this later. But it means that we can calculate the expected value of $g(X)$ without explicitly knowing the distribution of $g(X)$!
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Summary of Expected Value Properties

1) Additivity: expectation of sums are sums of expectations
   \[ E[X + Y] = E[X] + E[Y] \]

2) Homogeneity: expected value of a constant is the constant
   \[ E[aX + b] = aE[X] + b \]

3) LOTUS: Law of the Unconscious Statistician
   \[ E[g(X)] = \sum_x g(x) f_X(x) \]
   However, \( E[g(X)] \neq g(E[X]) \) unless \( g(\cdot) \) is a linear function

\[ E[XY] \neq E[X]E[Y] \] unless \( X \) and \( Y \) are independent
Summary of Expected Value Properties

The three properties:

1) Additivity: expectation of sums are sums of expectations

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3) LOTUS: Law of the Unconscious Statistician

\[ E[g(X)] = \sum_{x} g(x)f_X(x) \]
Summary of Expected Value Properties

The three properties:

1) Additivity: expectation of sums are sums of expectations

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However,

- \( E[g(X)] \neq g(E[X]) \) unless \( g(\cdot) \) is a linear function
- \( E[XY] \neq E[X]E[Y] \) unless \( X \) and \( Y \) are independent
Racial Prejudice Example

\[ X = \# \text{ of angering items on the baseline list for Southerners:} \]

<table>
<thead>
<tr>
<th>(x)</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>Sum</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\hat{f}(x))</td>
<td>0.02</td>
<td>0.27</td>
<td>0.43</td>
<td>0.28</td>
<td>1.00</td>
</tr>
<tr>
<td>(x \cdot \hat{f}(x))</td>
<td>0.00</td>
<td>0.27</td>
<td>0.86</td>
<td>0.84</td>
<td>1.97</td>
</tr>
</tbody>
</table>

\[ Y = \# \text{ of angering items on the treatment list for Southerners:} \]

<table>
<thead>
<tr>
<th>(y)</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>Sum</th>
</tr>
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<tbody>
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<td>0.20</td>
<td>0.40</td>
<td>0.28</td>
<td>0.10</td>
<td>1.00</td>
</tr>
<tr>
<td>(y \cdot \hat{f}(y))</td>
<td>0.00</td>
<td>0.20</td>
<td>0.80</td>
<td>0.84</td>
<td>0.40</td>
<td>2.24</td>
</tr>
</tbody>
</table>
Identifying the Percent Angry

Assume that \( Y = X + A \), where for a randomly sampled respondent,

- \( Y \) = the number of total angering items
- \( X \) = the number of angering items on baseline list
- \( A = 1 \) if angered by a black family moving in next door
- \( A = 0 \) if not angered by a black family moving in next door.

Exercises for Later:

Then we know that \( E[Y] - E[X] = E[A] \), but can you prove it?

Noting that \( A \) is a Bernoulli RV, how can we interpret \( E[A] \)? What properties and assumptions were necessary?
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The expected value of a function $g()$ of the random variable $X$, written $g(X)$, is denoted by $E[g(X)]$ and is a measure of 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 $V[X] = E[(X - E[X])^2]$ — it is the expectation of the squared distances from the mean.
Variance

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

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It is the expectation of the squared distances from the mean.
For a discrete random variable $X$

$$V[X] = \sum_{\text{all } x} (x - E[X])^2 f_X(x)$$
For a discrete random variable $X$

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

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

\[ f(x) \]

- \( \text{Var} = 1 \)
- \( \text{Var} = 4 \)

Stewart (Princeton)

Week 2: Random Variables

September 17/19, 2018 44 / 162
Why the Variance?

It is a reasonable measure for the "spread" of a distribution. The Normal distribution (bell shaped with thin tails) is completely determined by its expected value (location) and variance (spread). The square root of the variance is the standard deviation.
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- It is a reasonable measure for the “spread” of a distribution.
- The Normal distribution (bell shaped with thin tails) 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

\[
V[aX] = a^2 V[X] \]

\[
V[aX + b] = a^2 V[X] + 0
\]
Property 1 of Variance: Behavior with Constants

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

- The variance of a constant is zero.

$$\text{Var}(b) = 0$$

$$\text{Var}(aX) = a^2 \text{Var}(X)$$

$$\text{Var}(aX + b) = a^2 \text{Var}(X) + 0$$
Property 1 of Variance: Behavior with Constants

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

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- The variance of a constant times a RV is the constant squared times the variance of the RV.
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Suppose $a$ and $b$ are constants and $X$ is a random variable. Then

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- The variance of a constant times a RV is the constant squared times the variance of the RV.

\[
V[b] = 0
\]
\[
V[aX] = a^2 V[X]
\]
\[
V[aX + b] = a^2 V[X] + 0
\]
Property 2 of Variance: Additivity for Independent Random Variables

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

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

NB: Technically independence is sufficient but not necessary.
Property 2 of Variance: Additivity for Independent Random Variables

Variances of sums of independent RVs are sums of variances.
Property 2 of Variance: Additivity for Independent Random Variables

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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
- Bill Richardson

$\frac{4}{26} \times (1 - 4.88)^2$
What was the variance of Obama’s NH position?

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$$\frac{4}{26} \times (1 - 4.88)^2$$
$$\frac{4}{26} \times (2 - 4.88)^2$$

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  \[ \frac{4}{26} \times (1 - 4.88)^2 \]
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  \[ \frac{4}{26} \times (2 - 4.88)^2 \]
- Chris Dodd
  \[ \frac{2}{26} \times (3 - 4.88)^2 \]
- John Edwards
- Mike Gravel
- Dennis Kucinich
- Barack Obama
- Bill Richardson

\[ \frac{10}{26} \times (7 - 4.88)^2 \]

\[ + \]

What was the variance of Obama’s NH position?

Candidates:

- Joe Biden: \(\frac{4}{26} \times (1 - 4.88)^2\)
- Hillary Clinton: \(\frac{4}{26} \times (2 - 4.88)^2\)
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Candidates:

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- **Chris Dodd**
  
- **John Edwards**
  
- **Mike Gravel**
  
- **Dennis Kucinich**
  
- **Barack Obama**
  
- **Bill Richardson**

\[
\begin{align*}
\frac{4}{26} &\times (1 - 4.88)^2 \\
\frac{4}{26} &\times (2 - 4.88)^2 \\
\frac{2}{26} &\times (3 - 4.88)^2 \\
\frac{1}{26} &\times (4 - 4.88)^2 \\
\frac{1}{26} &\times (5 - 4.88)^2 \\
\frac{1}{26} &\times (6 - 4.88)^2 \\
\frac{10}{26} &\times (7 - 4.88)^2 \\
\end{align*}
\]

\[
\frac{10}{26} \times (7 - 4.88)^2 
\]

\[
\begin{align*}
\end{align*}
\]
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\[
\begin{align*}
4/26 \times (1 - 4.88)^2 \\
4/26 \times (2 - 4.88)^2 \\
2/26 \times (3 - 4.88)^2 \\
1/26 \times (4 - 4.88)^2 \\
1/26 \times (5 - 4.88)^2 \\
1/26 \times (6 - 4.88)^2 \\
10/26 \times (7 - 4.88)^2 \\
+ 3/26 \times (8 - 4.88)^2 \\
\end{align*}
\]

What was the variance of Obama’s NH position?

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- Hillary Clinton
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  \[ \frac{10}{26} \times (7 - 4.88)^2 \]
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- Bill Richardson

\[ \text{Variance} = 2.93 \]

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\[
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\frac{4}{26} \times (2 - 4.88)^2 \\
\frac{2}{26} \times (3 - 4.88)^2 \\
\frac{1}{26} \times (4 - 4.88)^2 \\
\frac{1}{26} \times (5 - 4.88)^2 \\
\frac{1}{26} \times (6 - 4.88)^2 \\
\frac{10}{26} \times (7 - 4.88)^2 \\
\frac{3}{26} \times (8 - 4.88)^2
\]

\[\frac{2}{26} \times (1 - 4.88)^2 + \frac{3}{26} \times (8 - 4.88)^2 = 2.93\]


Does variance matter for fairness?
Interpreting Continuous Standard Deviation

The standard deviation for a continuous random variable is a measure of the spread of the pdf.

![Standard Deviation for Age](chart.png)
Do we lose anything when we use the list experiment?

\[ Y = \# \text{ of angering items on the treatment list for Southerners:} \]

<table>
<thead>
<tr>
<th>( y )</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>Sum</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \hat{f}(y) )</td>
<td>0.03</td>
<td>0.20</td>
<td>0.40</td>
<td>0.28</td>
<td>0.10</td>
<td>1.00</td>
</tr>
<tr>
<td>( (y - 2.24)^2 \cdot \hat{f}(y) )</td>
<td>0.15</td>
<td>0.31</td>
<td>0.02</td>
<td>0.16</td>
<td>0.31</td>
<td>0.95</td>
</tr>
</tbody>
</table>

More on this next week when we talk about estimator properties!
Random Variables and Distributions
- What is a Random Variable?
- Discrete Distributions
- Continuous Distributions

Characteristics of Distributions
- Central Tendency
- Measures of Dispersion

Conditional Distributions

Fun with Averages

Fun with Sensitive Questions

Appendix: Why the Mean?

Joint Distributions
- Discrete Random Variable
- Continuous Random Variable

Conditional Expectation

Properties
- Independence
- Covariance and Correlation
- Conditional Independence

Famous Distributions

Fun With Spam
Joint and Conditional Distributions

We can describe more than one random variable with joint and conditional distributions.
Joint and Conditional Distributions

- We can describe more than one random variable with joint and conditional distributions.

- For example, suppose we define $X = 0$ (Non-southern), 1 (Southern) and $Y = \text{“number of angering items”}$ for a randomly selected respondent receiving the treatment list.
Joint and Conditional Distributions

- We can describe more than one random variable with joint and conditional distributions.
- For example, suppose we define $X = 0$ (Non-southern), 1 (Southern) and $Y = \text{"number of angering items"}$ for a randomly selected respondent receiving the treatment list.
- Furthermore, we define the probability that this respondent will have the values $X = x$ and $Y = y$ to be $f(y, x) = \pi_{yx}$.
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- Furthermore, we define the probability that this respondent will have the values $X = x$ and $Y = y$ to be $f(y, x) = \pi_{yx}$.

\[
\begin{align*}
X &= 0, 1, \\
Y &= \text{happy, sad, angry, sad, angry}, \\
\pi(x, y) &= \text{probability of } x \text{ and } y.
\end{align*}
\]
Example Conditional Distribution: Binary X, Discrete Y
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Although we cannot observe the responses for the entire population, we can imagine what they might look like as a joint distribution.
Example Conditional Distribution: Binary X, Discrete Y

Although we cannot observe the responses for the entire population, we can imagine what they might look like as a joint distribution.

<table>
<thead>
<tr>
<th></th>
<th>$f(y, x)$</th>
<th></th>
<th></th>
<th>$f(y)$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>0</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>y</td>
<td>$f(x)$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0</td>
<td>$\pi_{00}$</td>
<td>$\pi_{01}$</td>
<td>$\pi_{00} + \pi_{01}$</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>$\pi_{10}$</td>
<td>$\pi_{11}$</td>
<td>$\pi_{00} + \pi_{01}$</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>$\pi_{20}$</td>
<td>$\pi_{21}$</td>
<td>$\pi_{00} + \pi_{01}$</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>$\pi_{30}$</td>
<td>$\pi_{31}$</td>
<td>$\pi_{00} + \pi_{01}$</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>$\pi_{40}$</td>
<td>$\pi_{41}$</td>
<td>$\pi_{00} + \pi_{01}$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$\sum_{y=0}^{4} \pi_{y0}$</td>
<td>$\sum_{y=0}^{4} \pi_{y1}$</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Example Conditional Distribution: Binary $X$, Discrete $Y$

Although we cannot observe the responses for the entire population, we can imagine what they might look like as a joint distribution.
Discrete Conditional Distribution

Given the joint distribution, we can imagine what the conditional distribution and the conditional expectations would look like.
Discrete Conditional Distribution

Given the joint distribution, we can imagine what the conditional distribution and the conditional expectations would look like.

(More on conditional expectations on Wednesday)
Example: Conditional Distribution with “Continuous” Y

Suppose we define $X =$ "number of angering items" and $Y =$ "age" for a randomly selected respondent receiving the treatment list.

<table>
<thead>
<tr>
<th>Age</th>
<th>How many on treatment list</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td></td>
</tr>
<tr>
<td>30</td>
<td></td>
</tr>
<tr>
<td>40</td>
<td></td>
</tr>
<tr>
<td>50</td>
<td></td>
</tr>
<tr>
<td>60</td>
<td></td>
</tr>
<tr>
<td>70</td>
<td></td>
</tr>
<tr>
<td>80</td>
<td></td>
</tr>
<tr>
<td>90</td>
<td></td>
</tr>
</tbody>
</table>
Example: Conditional Distribution with “Continuous” $Y$

Suppose we define $X = “\text{number of angering items}”$ and $Y = “\text{age}”$ for a randomly selected respondent receiving the treatment list.
Example: Conditional Distribution with “Continuous” Y

Suppose we define $X = “number of angering items”$ and $Y = “age”$ for a randomly selected respondent receiving the treatment list.
Conditional Expectation Function (CEF)

The conditional expectations form a CEF:

$$E[Y | X] = h(x)$$

<table>
<thead>
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<th>Age</th>
<th>How many on treatment list</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td></td>
</tr>
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<td>30</td>
<td></td>
</tr>
<tr>
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<td></td>
</tr>
<tr>
<td>50</td>
<td></td>
</tr>
<tr>
<td>60</td>
<td></td>
</tr>
<tr>
<td>70</td>
<td></td>
</tr>
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<td>80</td>
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<td>90</td>
<td></td>
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</table>

Stewart (Princeton)

Week 2: Random Variables

September 17/19, 2018 56 / 162
Conditional Expectation Function (CEF)

The conditional expectations form a CEF: $E[Y|X = x] = h(x)$
Linear CEF Assumption

Often we will assume that the CEF is linear:

\[ E[Y|X] = \beta_0 + \beta_1 x \]
Linear CEF Assumption

Often we will assume that the CEF is linear: \( E[Y|X = x] = \beta_0 + \beta_1 x \)
Linear CEF Assumption

Often we will assume that the CEF is linear: 

$$E[Y|X = x] = \beta_0 + \beta_1 x$$
Conditional Variance and Standard Deviation
Conditional Variance and Standard Deviation

Similarly, we can assess the conditional standard deviation.
Linear CEF and Constant Variance Assumptions
Linear CEF and Constant Variance Assumptions

Often, we assume that variance is the same for all values of \( x \).
Because the CEF is defined merely in terms of the larger population and not in terms of a causal effect (e.g., the causal effect of "number of angering items" on Age), we will utilize a descriptive interpretation of $\beta_0$ and $\beta_1$.

For this example, $\beta_0$ is the expected age for an individual that is angered by zero items. $\beta_1$ is the expected difference in age between two individuals that have a one unit difference in the number of angering items.
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- For this example, $\beta_0$ is the expected age for an individual that is angered by zero items
- $\beta_1$ is the expected difference in age between two individuals that have a one unit difference in the number of angering items.
Random variables and probability distributions provide useful infrastructure for everything we will do this year. Expected value and variance are two useful characteristics of the probability distributions associated with random variables. These concepts can be extended by conditioning on other variables. Next class we will cover joint distributions and conditional expectations in more depth.
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Expected value and variance are two useful characteristics of the probability distributions associated with random variables.
Summary

- Random variables and probability distributions provide useful infrastructure for everything we will do this year.
- Expected value and variance are two useful characteristics of the probability distributions associated with random variables.
- These concepts can be extended by conditioning on other variables.
Random variables and probability distributions provide useful infrastructure for everything we will do this year.

Expected value and variance are two useful characteristics of the probability distributions associated with random variables.

These concepts can be extended by conditioning on other variables.

Next class we will cover joint distributions and conditional expectations in more depth.
Fun with
Fun with Averages
Fun with Averages

F(μn!)
WITH
you are below average
You're mean...
The Story of Averages
## Measurements

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<th>Mesures de la poitrine</th>
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<th>Probabilité d'après l'observation</th>
<th>Rang dans la table</th>
<th>Rang d'après le calcul</th>
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| 5758                   | 1,0000        |                    |                                    |                    |                         |                                | 1,0000                       |
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.

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- Quetelet
The Military Takes to the Idea
The Problem with Averages
Stacking Up

69%  Percentage of men who consider themselves physically fit
13%  Percentage of men who actually are

$874  Amount spent on vitamins and supplements annually
45%  Percentage of men who exercise regularly

52"  Waist circumference

2.87  Hours per week of exercise
1.1 lbs.  Average pounds gained each year
1  Average number of pull-ups
77 yrs.  Average life expectancy

23  Average age of the average guy in the best shape of his life

12:17  Average time to run a mile
1  Pounds of muscle the average secondary guy loses each year

Size Yourself Up

Age (yrs)  20s  30s  40s  50s  60s
Weight (lbs)  148  150  152  155  154
Height ("')  60-64  65-69  70-74  75-79  80
Pulse rate (per min)  22  25  28  31  34
Reach ("')  80  88  104  120  146

The Average American Male:

5'9.2"  Height
40"  Waist circumference

17.6%  Average body fat
13"  Size of the average guy's biceps (flexed)
34"  Average testicle size
5.08  Average penis size

Sex Stats:
- Average sex session: 3-4.5 minutes
- Average speed: 14-17 miles per hour
- Average fast-food time: 15 minutes
- Number of times you would rather work out
than have sex: 1,2,3
The Face of the Average Man

This is the World’s Most Typical Person
Fun with Sensitive Questions
Fun with Sensitive Questions

Graeme Blair
(slides that follow from Graeme)
Fun with Sensitive Questions

Cannot ask direct questions when there are incentives to conceal sensitive responses
Fun with Sensitive Questions

Cannot ask direct questions when there are incentives to conceal sensitive responses

1. Social pressure
Fun with Sensitive Questions

Cannot ask direct questions when there are incentives to conceal sensitive responses

1. Social pressure
2. Physical retaliation
Fun with Sensitive Questions

Cannot ask direct questions when there are incentives to conceal sensitive responses

1. Social pressure
2. Physical retaliation
3. Legal jeopardy
How to Address Incentives to Conceal

Develop trust with respondents, ask directly

Survey experimental methods

Endorsement experiment

Evaluation bias

List experiment

Aggregation

Randomized response

Random noise
How to Address Incentives to Conceal

Develop trust with respondents, ask directly
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Survey experimental methods

1. **Endorsement experiment**  Evaluation bias
2. **List experiment**  Aggregation
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3. **Randomized response**  Random noise
Bias in Direct Questions on Vote Buying

Estimated rate of vote buying from direct survey item
2.4%

Gonzalez-Ocantos et al. 2011, *AJPS*

Question text: "they gave you a gift or did you a favor"
Bias in Direct Questions on Vote Buying

Estimated rate of vote buying from direct survey item
2.4%

Estimate using list experiment
24.3%

Gonzalez-Ocantos et al. 2011, *AJPS*

Question text: "they gave you a gift or did you a favor"
Survey

- Survey of 2,448 civilians in the Niger Delta
Survey

- Survey of 2,448 civilians in the Niger Delta
- Randomly sampled 204 communities near oil interruption sites and camps of armed groups
Survey

- Survey of 2,448 civilians in the Niger Delta
- Random sample of 204 communities near and far from oil interruption sites and armed group camps
Survey

- Survey of 2,448 civilians in the Niger Delta
- Random sample of 204 communities near and far from oil interruption sites and armed group camps
- Interviewed 12 people per community
  Random walk pattern to select households; Kish grid within household

Funded by the International Growth Centre
"Did you share information with **militants** about their enemies in the community, state counterinsurgency forces, or oil facility activities?"
Problems with using list or endorsement experiments

Too sensitive for list experiment

Often difficult to define "control" condition in endorsement experiment for behaviors
Problems with using list or endorsement experiments

Too sensitive for list experiment

Often difficult to define "control" condition in endorsement experiment for behaviors

Alternative: **Randomized response technique**
Randomized response technique

**How?** Introducing random noise

- Roll the dice in private
- If you roll a 1, tell me “no”
- If you roll a 6, tell me “yes”
- Otherwise, answer: “Did you share information with armed groups”
Randomized response technique

**How?** Introducing random noise
- Roll the dice in private
Randomized response technique

**How?** Introducing random noise
- Roll the dice in private
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- Otherwise, answer: "Did you share information with armed groups"
Analysis of the randomized response technique

1. Used fair dice, and actually rolled it.
Analysis of the randomized response technique

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2. **Compliance.** Complied with ”forced” response.
Analysis of the randomized response technique

1. Used fair dice, and actually rolled it.
2. **Compliance.** Complied with "forced" response.
3. **No Liars.** When not forced, answered truthfully.

\[
\text{Proportion answered yes} = \frac{2}{3} \cdot \text{Proportion yes to sensitive item} + \frac{1}{6}
\]

\[
\text{Proportion yes to sensitive item} = \frac{3}{2} \cdot (\text{Proportion answered yes} - \frac{1}{6})
\]

Stewart (Princeton)
Analysis of the randomized response technique

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Proportion yes to sensitive item

\[
\frac{3}{2} \cdot (\text{Proportion answered yes} - \frac{1}{6})
\]
1. Civilians share information regularly with armed groups

![Graph showing percentage of respondents sharing information with armed groups.](image)
2. Civilians near oil interruptions dominate collaboration

![Graph showing the percentage of respondents with and without oil attacks in the community.](image)

- Oil Attack in Community
- No Oil Attack

Percentage of respondents
3. Civilians near armed group camps dominate collaboration

![Graph showing the estimated proportion of people who provide information to armed groups based on travel time from community to armed group camp. The graph indicates a decrease in the proportion as travel time increases.](image)
Software

- **rr package in R for randomized response**
  Blair with Yang-Yang Zhou and Kosuke Imai

- **list package in R for list experiments**
  Blair with Kosuke Imai

- **endorse package in R for endorsement experiments**
  Yuki Shiraito and Kosuke Imai
Random Variables and Distributions
- What is a Random Variable?
- Discrete Distributions
- Continuous Distributions

Characteristics of Distributions
- Central Tendency
- Measures of Dispersion

Conditional Distributions

Fun with Averages

Fun with Sensitive Questions

Appendix: Why the Mean?

Joint Distributions
- Discrete Random Variable
- Continuous Random Variable

Conditional Expectation

Properties
- Independence
- Covariance and Correlation
- Conditional Independence

Famous Distributions

Fun With Spam
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Fun With Spam
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 \(c\).

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.

Let’s say we want to minimize:

- **Mean Squared Error:** \(E(X - c)^2\)
  
  This leads to choosing the mean of \(X\): \(\mu\)

- **Mean Absolute Error:** \(E|X - c|\)
  
  This leads to choosing the median of \(X\): \(m\)

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 Square Error Minimizer

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

We will prove the following identity below:

$$E(X - c)^2 = \text{Var}(X) + (\mu - c)^2$$  \hspace{1cm} (1)

We are trying to choose $c$ to minimize this term. The choice cannot affect $\text{Var}(X)$. Setting $c = \mu$ sets $(\mu - c)^2 = 0$ and any other choice makes $(\mu - c)^2 > 0$. Therefore (assuming the identity holds), $c = \mu$ minimizes Eq 1.

Now to prove the identity:

$$\text{Var}(X) = \text{Var}(X - c) \quad \text{(Prop 1 of Variance)}$$

$$= E(X - c)^2 - (E[X - c])^2 \quad \text{(Defn of Variance)}$$

$$= E(X - c)^2 - (\mu - c)^2 \quad \text{(Linearity of Exp)}$$

$$\text{Var}(X) + (\mu - c)^2 = E(X - c)^2$$
References

- Kuklinski et al. 1997 “Racial prejudice and attitudes toward affirmative action” *American Journal of Political Science*
- Glynn 2013 “What can we learn with statistical truth serum? Design and analysis of the list experiment”
- All the Blair papers above.
Where We’ve Been and Where We’re Going...

- Last Week

- Welcome and outline of course
- Described uncertain outcomes with probability.

This Week

- Monday:
  - Summarize one random variable using expectation and variance
  - Show how to condition on a variable

- Wednesday:
  - Properties of joint distributions
  - Conditional expectations
  - Covariance, correlation, independence

Next Week

- Estimating these features from data
- Estimating uncertainty

Long Run

- Probability
  → Inference
  → Regression
  → Causal inference

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Questions?

Stewart (Princeton)

Week 2: Random Variables

September 17/19, 2018
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Famous Distributions

Fun With Spam
Joint Distributions

We've talked about joint probabilities of events—what was the probability of $A$ and $B$ occurring:

$$P(A \cap B)$$

We also talked about the conditional probability of $A$ given that $B$ occurred.

We also need to think about more than one r.v. at the same time.

▶ in regression we think about how the distribution of one variable changes under different values of another variable

▶ e.g. does running more negative ads decrease election turnout?

The joint distribution of two (or more) variables describes the pairs of observations that we are more or less likely to see.
Joint Distributions

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The joint distribution of two (or more) variables describes the pairs of observations that we are more or less likely to see.
Understanding Joint Distributions

Consider two r.v.s now, $X$ and $Y$, each on the real line, $\mathbb{R}$. The pair form a two-dimensional space, or $\mathbb{R} \times \mathbb{R}$. One realization of the r.v. is a point in that space $(x, y)$. 

Stewart (Princeton)  
Week 2: Random Variables  
September 17/19, 2018  
94 / 162
Understanding Joint Distributions

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Understanding Joint Distributions

- Consider two r.v.s now, $X$ and $Y$, each on the real line, $\mathbb{R}$.
- The pair form a two-dimensional space, or $\mathbb{R} \times \mathbb{R}$.
- One realization of the r.v. is a point in that space.

![Diagram](image)
Imagine we are throwing darts on a two-dimensional board: the joint distribution tells us where the darts are more likely to land. Distributions can be limited to a subset of the real line—e.g., two uniform random variables might be between 0 and 1. Discrete random variables typically only include integers. With two r.vs. there are now two dimensions to deal with. Often, we are interested in two random variables that are qualitatively different: $Y$ (response, outcome, dependent variable, etc.) = the random variable we want to explain, or predict. $X$ (predictor, explanatory/independent variable, covariate, etc.) = the random variable with which we want to explain $Y$. 
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- What is a Random Variable?
- Discrete Distributions
- Continuous Distributions

Characteristics of Distributions
- Central Tendency
- Measures of Dispersion

Conditional Distributions

Fun with Averages

Fun with Sensitive Questions

Appendix: Why the Mean?

Joint Distributions
- Discrete Random Variable
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Properties
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Joint Probability Mass Function

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

$$P_{X,Y}(x,y) = \Pr(X = x \text{ and } Y = y)$$

**Restrictions:**

$$P_{X,Y}(x,y) \geq 0 \text{ and } \sum_x \sum_y P_{X,Y}(x,y) = 1.$$
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Should the U.S. allow more immigrants to come and live here?

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With discrete r.v.s 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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To obtain $P_Y(y)$ we marginalize the joint probability function $P_{X,Y}(x,y)$ over $X$:

$$P_Y(y) = \sum_x P_{X,Y}(x,y) = \sum_x \Pr(X = x, Y = y)$$
Joint and Marginal Probability Mass Functions

\[
P_{X,Y}(x,y)
\]

\[
P_Y(y)
\]

\[
P_X(x)
\]
Why Does Marginalization Work?

Begin with discrete case. Consider jointly distributed discrete random variables, $X$ and $Y$. We’ll suppose they have joint pmf, $P(X = x, Y = y) = p(x, y)$.

Suppose that the distribution allocates its mass at $x_1, x_2, \ldots, x_M$ and $y_1, y_2, \ldots, y_N$.

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

$$P(X = x | Y = y) \equiv \frac{p(x, y)}{p(y)}$$

Then it follows that:

$$p(x, y) = p(x | y)p(y)$$

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

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<tr>
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\[
p_X(0) = p(0|y = 0)p(y = 0) + p(0|y = 1)p(y = 1)
\]
\[
= \frac{0.01}{0.26} \times 0.26 + \frac{0.05}{0.74} \times 0.74
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&= \frac{0.01}{0.26} \times 0.26 + \frac{0.05}{0.74} \times 0.74 \\
&= 0.06
\end{align*}
\]

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px(1) &= p(1|y = 0)p(y = 0) + p(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{align*}
\]
Conditional PMF

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 $X = x$:

$$P_{Y|X}(y|x) = \frac{P_{X,Y}(x,y)}{P_X(x)}$$

Key relationships:

- $P_{X,Y}(x,y) = P_{Y|X}(y|x)P_X(x)$ (multiplicative rule)
- $P_{Y|X}(y|x) = \frac{P_{X|Y}(x|y)P_Y(y)}{P_X(x)}$ (Bayes' rule)

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 $X$. 
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From Joint to Conditional: \( P_{Y|X}(y|x) = \frac{P_{X,Y}(x,y)}{P_X(x)} \)

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**Table:** Conditional PMF \( P_{Y|X}(y|x) \)

| Support | \( P_{Y|X}(y|x) \) | less HS | HS | College | BA |
|---------|------------------|--------|----|---------|----|
| oppose  | 0.70             | 0.70   | 0.65| 0.48    |    |
| neutral | 0.20             | 0.20   | 0.19| 0.17    |    |
| favor   | 0.10             | 0.10   | 0.15| 0.34    |    |
|         | 1.00             | 1.00   | 1.00| 1.00    |    |
Joint and Conditional Probability Mass Functions

Figure: Joint
Joint and Conditional Probability Mass Functions

Figure: Joint

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Fun With Spam
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 $y$. 

The **multiplicative rule**: 

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

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

$f_X(x)$: Marginal PDF of $X$ 

**Restrictions:** 

$$\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_{X,Y}(x,y) \, dy \, dx = 1$$
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 \( y \).

The multiplicative rule:

\[
f_{X,Y}(x,y) = f_{Y|X}(y|x)f_X(x)
\]

where

- \( f_{Y|X}(y|x) \): **Conditional** PDF of \( Y \) given \( X = x \)
- \( f_X(x) \): **Marginal** PDF of \( X \)

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where

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

**Restrictions:**

- $\int_x \int_y f_{X,Y}(x, y) \, dy \, dx = 1$
Bivariate Normal Distribution: $z = f_{X,Y}(x, y)$
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

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

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

$$f_Y(y) = \int_{-\infty}^{\infty} f_{X,Y}(x,y) \, dx$$
Random Variables and Distributions
- What is a Random Variable?
- Discrete Distributions
- Continuous Distributions

Characteristics of Distributions
- Central Tendency
- Measures of Dispersion

Conditional Distributions

Fun with Averages

Fun with Sensitive Questions

Appendix: Why the Mean?

Joint Distributions
- Discrete Random Variable
- Continuous Random Variable

Conditional Expectation

Properties
- Independence
- Covariance and Correlation
- Conditional Independence

Famous Distributions

Fun With Spam
Conditioning on $X$

Goal in statistical modeling is often to characterize the conditional distribution of the outcome variable $f(Y|X)(y|x)$ across different levels of $X = x$.

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 $X$ (we sometimes call this the population regression function).
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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:

$$E[Y|X = x] = \sum_{y} y \Pr(Y = y|X = x) = \sum_{y} y P_{Y|X}(y|x)$$
Conditional Expectation

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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

Theorem (Law of Iterated Expectations)

For two random variables $X$ and $Y$,

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

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

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

$$E[Y] = E[E[Y|X]] = E[Y|X = 1] \cdot P_X(1) + E[Y|X = 0] \cdot P_X(0)$$
Theorem (Law of Iterated Expectations)

For two random variables \( X \) and \( Y \),

\[
E[Y] = E[E[Y|X]] = \begin{cases} 
\sum_{x} E[Y|X = x] \cdot P_X(x) & \text{(discrete } X) \\
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\]

Average Support \cdot Average Support|Woman \cdot Pr(Woman) + Average Support|Man \cdot Pr(Man)
Properties of Conditional Expectation

1. Conditional expectations have some convenient properties. For any function $c(X)$, $E[c(X) | X] = c(X)$.

2. Basically, any function of $X$ is a constant with regard to the conditional expectation. If we know $X$, then we also know $X^2$, for instance.

If $E[Y^2] < \infty$ and $E[g(X)^2] < \infty$ for some function $g$, then

$$E[(Y - E[Y | X])^2 | X] \leq E[(Y - g(X))^2 | X]$$

The second property is quite important. It says that the conditional expectation is the function of $X$ that minimizes the squared prediction error for $Y$ across any possible function of $X$. 
Properties of Conditional Expectation

Conditional expectations have some convenient properties.
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1. \( E[c(X)|X] = c(X) \) for any function \( c(X) \).
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2. If $E[Y^2] < \infty$ and $E[g(X)^2] < \infty$ for some function $g$, then
   
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Properties of Conditional Expectation

Conditional expectations have some convenient properties

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The second property is quite important. It says that the conditional expectation is the function of \( X \) that minimizes the squared prediction error for \( Y \) across any possible function of \( X \).
Conditional Variance

Conditional expectation gives us information about the central tendency of a random variable given another random variable. We also want to know the conditional variance to understand our uncertainty about the conditional distribution. 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 gives us information about the central tendency of a random variable given another random variable.

We also want to know the conditional variance to understand our uncertainty about the conditional distribution.

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

**Definition**

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

$$V[Y|X = x] = \left\{ \begin{array}{ll}
\sum_{y \text{ all}} (y - E[Y|X = x])^2 P_{Y|X}(y|x) & \text{(discrete } Y) \\
\int_{-\infty}^{\infty} (y - E[Y|X = x])^2 f_{Y|X}(y|x)dy & \text{(continuous } Y) \end{array} \right.$$
Conditional Variance

Definition

The conditional variance of \( Y \) given \( X = x \) is defined as:

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V[Y|X = x] = \begin{cases} 
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\end{cases}
\]

A useful rule related to conditional variance is the law of total variance:

\[
V[Y] = E[V[Y|X]] + V[E[Y|X]]
\]

Total variance \quad Average of Group Variances \quad Variance in Group Averages
Conditional Variance

**Definition**

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

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A useful rule related to conditional variance is the *law of total variance*:

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

Total variance Average of Group Variances Variance in Group Averages

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

1. On average, how much support varies within gender groups (within variance)
2. How much average support varies between gender groups (between variance)
Conditional Variance Function $V[Y|X]$
Important Subtleties

It is important to distinguish between what is random/stochastic and what is constant. However, this can be tricky at first. If $X$ is a random variable, generally a function of $X(g(X))$ is also a random variable. $\mathbb{E}[X]$ is a constant though (we sometimes refer to $\mathbb{E}[\cdot]$ as an operator to make clear it doesn't behave the same as $g(\cdot)$). $\mathbb{E}[X|Y]$ is random though. Why? There is no longer anything stochastic in $\mathbb{E}[X]$. Take the discrete case: $\mathbb{E}[X] = \sum x p(X=x)$. Note that this is entirely in terms of realized values. By contrast $\mathbb{E}[X|Y]$ is a function into which one can plug a value of $Y = y$ and get the expectation of $X$ conditional on that value. Thus the randomness ‘comes from’ $Y$.

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

Sample space
Important Subtleties in Pictures

Sample space
Important Subtleties in Pictures

Random variable

Stewart (Princeton)
Important Subtleties in Pictures

Random variable
Important Subtleties in Pictures

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

\[ E[E[X|Y]] = E[X] \]
Random Variables and Distributions
- What is a Random Variable?
- Discrete Distributions
- Continuous Distributions

Characteristics of Distributions
- Central Tendency
- Measures of Dispersion

Conditional Distributions

Fun with Averages

Fun with Sensitive Questions

Appendix: Why the Mean?

Joint Distributions
- Discrete Random Variable
- Continuous Random Variable

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Properties
- Independence
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Famous Distributions

Fun With Spam
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Independence

Definition (Independence of Random Variables)

Two random variables $Y$ and $X$ are independent if

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

for all $x$ and $y$. We write this as $Y \independent X$. 
Independence

Definition (Independence of Random Variables)

Two random variables $Y$ and $X$ are independent if

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

for all $x$ and $y$. We write this as $Y \perp \!\!\!\!\!\!\! \perp X$.

Independence implies

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

and thus

$$E[Y|X = x] =$$
Definition (Independence of Random Variables)

Two random variables $Y$ and $X$ are independent if

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Is $Y \perp X$?

Diagram showing the relationship between $Y$ and $X$ with different educational attainment levels:
- $E[Y|X=less\ HS]$
- $E[Y|X=HS]$
- $E[Y|X=College]$
- $E[Y|X=BA]$

The diagram illustrates the conditional distributions of $Y$ given different levels of $X$.
Expected Values with Independent Random Variables

If random variables $X$ and $Y$ are independent, then

$$E[XY] = E[X]E[Y]$$
Expected Values with Independent Random Variables

If random variables $X$ and $Y$ are independent, then

$$E[XY] = E[X]E[Y]$$

Proof: For discrete $X$ and $Y$,

$$E[XY] =$$

We can prove the continuous case by following the same steps, with $\sum$ replaced by $\int$. 
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Proof: For discrete $X$ and $Y$,

$$E[XY] = \sum_{\text{all } x} \sum_{\text{all } y} xy P_{X,Y}(x,y)$$

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If random variables $X$ and $Y$ are independent, then

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Proof: For discrete $X$ and $Y$,

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$$= \sum_{all \, x} \sum_{all \, y} x \, y \, P_X(x)P_Y(y)$$
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If random variables $X$ and $Y$ are independent, then

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If random variables $X$ and $Y$ are independent, then

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

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

Covariance measures the linear association between two random variables. Points in the upper left and lower right quadrants (relative to the means) add to the covariance. Points in the upper right and lower left quadrants subtract from the covariance.

Definition

$$\text{Cov}(X, Y) = \frac{1}{n-1} \sum_{i=1}^{n} (X_i - \bar{X})(Y_i - \bar{Y})$$

where $\bar{X}$ and $\bar{Y}$ are the means of $X$ and $Y$, respectively.

Log(GDP per capita) in 1990

Goodness of Fit

Descriptive Statistics with Simple Linear Regression

Least Squares

Week 2: Random Variables

Stewart (Princeton)
## Covariance

### Definition

The **covariance** of $X$ and $Y$ is defined as:

$$\text{Cov}[X, Y] = E[(X - E[X])(Y - E[Y])]$$

$$= E[XY] - E[X]E[Y]$$
Covariance

Definition

The covariance of $X$ and $Y$ is defined as:

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- Covariance measures the linear association between two random variables.
## Covariance

### Definition

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$$\text{Cov}[X, Y] = E[(X - E[X])(Y - E[Y])]$$

$$= E[XY] - E[X]E[Y]$$

- Covariance measures the **linear association** between two random variables.
- If $\text{Cov}[X, Y] > 0$, observing an $X$ value greater than $E[X]$ makes it more likely to also observe a $Y$ value greater than $E[Y]$, and vice versa.
Covariance

Definition

The covariance of $X$ and $Y$ is defined as:

$$Cov[X, Y] = E[(X - E[X])(Y - E[Y])]$$

$$= E[XY] - E[X]E[Y]$$

- Covariance measures the linear association between two random variables.
- If $Cov[X, Y] > 0$, observing an $X$ value greater than $E[X]$ makes it more likely to also observe a $Y$ value greater than $E[Y]$, and vice versa.

- 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.
Covariance and Independence

Does $X \perp \perp Y$ imply $\text{Cov}[X, Y] = 0$?

**Proof:**

\[
\]

Therefore, $X \perp \perp Y \Rightarrow \text{Cov}[X, Y] = 0$, but not vice versa.
Covariance and Independence

Does $X \perp \perp Y$ imply $\text{Cov}[X, Y] = 0$? Yes!

Proof:


Does $\text{Cov}[X, Y] = 0$ imply $X \perp \perp Y$?

No!

Counterexample: Suppose $X \in \{-1, 0, 1\}$ with $P(X)(x) = 1/3$ and $Y = X^2$.

Is $X \perp \perp Y$?

No, because $P(Y|X)(y|x) \neq P(Y)(y)$. (Learning about $X$ gives meaningful information about $Y$.)

What is $\text{Cov}[X, Y]$?

\[
\]

Therefore, $X \perp \perp Y \Rightarrow \text{Cov}[X, Y] = 0$, but not vice versa.
Covariance and Independence

Does $X \perp \perp Y$ imply $\text{Cov}[X, Y] = 0$? Yes!

Proof:

\[
\]

\[
= 0
\]

Therefore, $X \perp \perp Y \Rightarrow \text{Cov}[X, Y] = 0$, but not vice versa.
Covariance and Independence

Does $X \perp \perp Y$ imply $\text{Cov}[X, Y] = 0$? Yes!

Proof:

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= E[X]E[Y] - E[X]E[Y] \quad \text{(independence)}
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No, because $\text{P}(Y|X = x) \neq \text{P}(Y)$.

(learning about $X$ gives meaningful information about $Y$.)
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Counterexample: Suppose $X \in \{-1, 0, 1\}$ with $P_X(x) = 1/3$ and $Y = X^2$. Is $X \perp \perp Y$?
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Important Identities for Variances and Covariances

For random variables \( X \) and \( Y \) and constants \( a \), \( b \), and \( c \),

\[
V[aX + bY + c] = a^2V[X] + b^2V[Y] + 2ab \text{Cov}[X, Y]
\]

Important special cases:

\[
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Furthermore, if \( X \) and \( Y \) are independent,

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V[X \pm Y] = V[X] + V[Y]
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Proof: Plug in to the definition of variance and expand (try it yourself!)
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Correlation

Correlation \( \text{between} \ X \text{and} \ Y \) depends not only on the strength of (linear) association between \( X \) and \( Y \), but also the scale of \( X \) and \( Y \).

Can we have a pure measure of association that is scale-independent?

**Definition (Correlation)**

The correlation between two random variables \( X \) and \( Y \) is defined as

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\text{Cor} \{X, Y\} = \frac{\text{Cov}\{X, Y\}}{\sqrt{\text{V}\{X\} \cdot \text{V}\{Y\}}}
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\( \text{Cor}\{X, Y\} \) is a standardized measure of linear association between \( X \) and \( Y \).

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$$\text{Cor} [X, Y] = \pm 1 \text{ iff } Y = aX + b \text{ where } a \neq 0.$$
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Conditional Independence

Definition (Conditional Independence of Random Variables)

Random variables $Y$ and $X$ are conditionally independent given $Z$ iff

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

for all $x$, $y$, and $z$. This is often written as $Y \perp \perp X | Z$.

Can also be written as $f_{Y|X,Z}(y|x,z) = f_{Y|Z}(y|z)$.

Interpretation: Once we know $Z$, $X$ contains no meaningful information about likely values of $Y$.

$Y \perp \perp X | Z$ implies $E[Y|X = x, Z = z] = E[Y|Z = z]$. 

Stewart (Princeton)
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Is $Y \perp X$?

Example: $X = \text{wealth}$, $Y = \text{support for immigration}$, $Z = \text{education}$. 
Is $Y \perp X | Z$?

Example: $X =$ wealth, $Y =$ support for immigration, $Z =$ education.
Random Variables and Distributions
- What is a Random Variable?
- Discrete Distributions
- Continuous Distributions

Characteristics of Distributions
- Central Tendency
- Measures of Dispersion

Conditional Distributions

Fun with Averages

Fun with Sensitive Questions

Appendix: Why the Mean?

Joint Distributions
- Discrete Random Variable
- Continuous Random Variable

Conditional Expectation

Properties
- Independence
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Famous Distributions

Fun With Spam
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Famous Distributions

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Distributions

We like random variables because they take complex real world phenomena and represent them with a common mathematical infrastructure. We can work with arbitrary pmf/pdfs but we will often work with particular families of distributions.

- Members of the same family have similar forms determined by parameters.
- The parameters determine the shape of the distribution.

When we can work with an existing set of distributions, it makes calculations simpler. Examples: Bernoulli, Binomial, Gamma, Normal, Poisson, $t$-distribution.
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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,

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

for $x \in \{0, 1\}$ and $p(X = x) = 0$ otherwise.

We will (equivalently) say that

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

$\sim$ means equality in distribution (not values!). Often $X \sim \text{Bernoulli}(\pi)$ would be read ‘$X$ is distributed Bernoulli with parameter $\pi$’
Bernoulli Random Variable Mean and Variance

Suppose $X \sim \text{Bernoulli}(\pi)$
Bernoulli Random Variable Mean and Variance

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

$$E[X] = 1 \times P(X = 1) + 0 \times P(X = 0)$$
$$= \pi + 0(1 - \pi) = \pi$$

$$E[X] = \pi$$
Bernoulli Random Variable Mean and Variance

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

$$E[X] = 1 \times P(X = 1) + 0 \times P(X = 0)$$
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$$\text{var}(X) = E[X^2] - E[X]^2$$

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$E[X] = \pi$

$\text{var}(X) = \pi(1 - \pi)$

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

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

Then $X$ is a normally distributed random variable with parameters $\mu$ and $\sigma^2$.

Equivalently, we’ll write

$$X \sim \text{Normal}(\mu, \sigma^2)$$
Expected Value/Variance of Normal Distribution

$Z$ is a standard normal distribution if

$Z \sim \text{Normal}(0, 1)$

We'll call the cumulative distribution function of $Z$, $F_Z(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{x} \exp(-z^2/2) \, dz$

Proposition Scale/Location. If $Z \sim \text{N}(0, 1)$, then $X = aZ + b$ is, $X \sim \text{Normal}(b, a^2)$
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*Scale/Location.* If $Z \sim \text{N}(0, 1)$, then $X = aZ + b$ is,

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Intuition

Suppose $Z \sim \text{Normal}(0, 1)$. 

![Normal distribution graph](image)
Intuition

Suppose $Z \sim \text{Normal}(0, 1)$.

$Y = 2Z + 6$
Intuition

Suppose $Z \sim \text{Normal}(0, 1)$.

$Y = 2Z + 6$

$Y \sim \text{Normal}(6, 4)$
Proof: $Z \sim N(0, 1)$ and $Y = aZ + b$, then $Y \sim N(b, a^2)$

To prove
Proof: $Z \sim N(0, 1)$ and $Y = aZ + b$, then $Y \sim N(b, a^2)$

To prove we need to show that density for $Y$ is a normal distribution.
Proof: $Z \sim N(0, 1)$ and $Y = aZ + b$, then $Y \sim N(b, a^2)$

To prove we need to show that density for $Y$ is a normal distribution. That is, we’ll show $F_Y(x)$ is Normal cdf.
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F_Y(x) = P(Y \leq x) \\
= P(aZ + b \leq x) \\
= P(Z \leq \frac{x - b}{a})
\]
Proof: $Z \sim N(0, 1)$ and $Y = aZ + b$, then $Y \sim N(b, a^2)$

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\[
F_Y(x) = P(Y \leq x) = P(aZ + b \leq x) = P(Z \leq \left[ \frac{x - b}{a} \right]) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\frac{x - b}{a}} \exp\left(-\frac{z^2}{2}\right)dz
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So, we can work with $F_Z\left(\frac{x-b}{a}\right)$. 
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So, we can work with $F_Z(\frac{x-b}{a})$.

$$\frac{\partial F_Y(x)}{\partial x} = \frac{\partial F_Z(\frac{x-b}{a})}{\partial x}$$
Proof: \( Z \sim N(0, 1) \) and \( Y = aZ + b \), then \( Y \sim N(b, a^2) \)

So, we can work with \( F_Z\left(\frac{x-b}{a}\right) \).

\[
\frac{\partial F_Y(x)}{\partial x} = \frac{\partial F_Z\left(\frac{x-b}{a}\right)}{\partial x} = f_Z\left(\frac{x-b}{a}\right) \frac{1}{a}
\]

By the chain rule
Proof: $Z \sim N(0, 1)$ and $Y = aZ + b$, then $Y \sim N(b, a^2)$

So, we can work with $F_Z\left(\frac{x-b}{a}\right)$.

\[
\frac{\partial F_Y(x)}{\partial x} = \frac{\partial F_Z\left(\frac{x-b}{a}\right)}{\partial x}
\]
\[
= f_Z\left(\frac{x-b}{a}\right) \frac{1}{a} \quad \text{By the chain rule}
\]
\[
= \frac{1}{\sqrt{2\pi a}} \exp\left[-\frac{(x-b)^2}{2a^2}\right] \quad \text{By definition of } f_Z(x) \text{ or FTC}
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Proof: $Z \sim N(0, 1)$ and $Y = aZ + b$, then $Y \sim N(b, a^2)$

So, we can work with $F_Z\left(\frac{x-b}{a}\right)$.

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$$= f_Z\left(\frac{x-b}{a}\right) \frac{1}{a} \text{ By the chain rule}$$

$$= \frac{1}{\sqrt{2\pi a}} \exp\left[-\left(\frac{x-b}{a}\right)^2\right] \text{ By definition of } f_Z(x) \text{ or FTC}$$

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\[
\frac{\partial F_Y(x)}{\partial x} = \frac{\partial F_Z\left(\frac{x-b}{a}\right)}{\partial x} \\
= f_Z\left(\frac{x-b}{a}\right) \cdot \frac{1}{a} \quad \text{By the chain rule} \\
= \frac{1}{\sqrt{2\pi a}} \exp\left[- \frac{\left(\frac{x-b}{a}\right)^2}{2}\right] \quad \text{By definition of } f_Z(x) \text{ or FTC} \\
= \frac{1}{\sqrt{2\pi a}} \exp\left[- \frac{(x-b)^2}{2a^2}\right] \\
= \text{Normal}(b, a^2)
Expectation and Variance

Assume we know:

\[ E[Z] = 0 \]
\[ \text{Var}(Z) = 1 \]
Expectation and Variance

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\[ \text{Var}(Y) = \text{Var}(\sigma Z + \mu) \]
Expectation and Variance

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This implies that, for \( Y \sim \text{Normal}(\mu, \sigma^2) \)

\[
E[Y] = E[\sigma Z + \mu] \\
= \sigma E[Z] + \mu \\
= \mu \\
Var(Y) = Var(\sigma Z + \mu) \\
= \sigma^2 Var(Z) + Var(\mu)
\]
Expectation and Variance

Assume we know:

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\[ = \sigma E[Z] + \mu \]
\[ = \mu \]
\[ \text{Var}(Y) = \text{Var}(\sigma Z + \mu) \]
\[ = \sigma^2 \text{Var}(Z) + \text{Var}(\mu) \]
\[ = \sigma^2 + 0 \]
Expectation and Variance

Assume we know:

\[ E[Z] = 0 \]
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This implies that, for \( Y \sim \text{Normal}(\mu, \sigma^2) \)

\[ E[Y] = E[\sigma Z + \mu] \]
\[ = \sigma E[Z] + \mu \]
\[ = \mu \]

\[ \text{Var}(Y) = \text{Var}(\sigma Z + \mu) \]
\[ = \sigma^2 \text{Var}(Z) + \text{Var}(\mu) \]
\[ = \sigma^2 + 0 \]
\[ = \sigma^2 \]
Multivariate Normal

Definition

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

\[
f(x) = (2\pi)^{-N/2} \det(\Sigma)^{-1/2} \exp \left( -\frac{1}{2} (x - \mu)' \Sigma (x - \mu) \right)
\]

Then we will say \( X \) has a \textbf{Multivariate Normal Distribution},

\[
X \sim \text{Multivariate Normal}(\mu, \Sigma)
\]
Multivariate Normal Distribution

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

$$
\Sigma = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}
$$
Multivariate Normal Distribution

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

$$\Sigma = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$$

Then

$$f(x_1, x_2) = (2\pi)^{-2/2}1^{-1/2} \exp \left( -\frac{1}{2} \left( (x - 0)' \left( \begin{array}{cc} 1 & 0 \\ 0 & 1 \end{array} \right) (x - 0) \right) \right) \Rightarrow \text{product of univariate standard normally distributed random variables}$$
Multivariate Normal Distribution

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

$$\Sigma = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$$

Then

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

$$= \frac{1}{2\pi} \exp \left( -\frac{1}{2}(x_1^2 + x_2^2) \right)$$
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\]

\[
= \frac{1}{\sqrt{2\pi}} \exp \left( -\frac{x_1^2}{2} \right) \frac{1}{\sqrt{2\pi}} \exp \left( -\frac{x_2^2}{2} \right)
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Multivariate Normal Distribution

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\end{pmatrix}
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$$

$\sim$ product of univariate standard normally distributed random variables
Properties of the Multivariate Normal Distribution

Suppose \( X = (X_1, X_2, \ldots, X_N) \)

\[
E[X] = \mu \\
\text{cov}(X) = \Sigma
\]

So that,

\[
\Sigma = \\
\begin{pmatrix}
\text{var}(X_1) & \text{cov}(X_1, X_2) & \ldots & \text{cov}(X_1, X_N) \\
\text{cov}(X_2, X_1) & \text{var}(X_2) & \ldots & \text{cov}(X_2, X_N) \\
\vdots & \vdots & \ddots & \vdots \\
\text{cov}(X_N, X_1) & \text{cov}(X_N, X_2) & \ldots & \text{var}(X_N)
\end{pmatrix}
\]
Nearly every distribution we will discuss is in the exponential family. An exponential family distribution has the density of the following form:

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

**Example:** Poisson(\(\mu\)):

\[ \text{Pr}(Y_i = y | \mu) = \exp \left\{ y\log \mu - \exp(\log \mu) - \log y! \right\} \]

\[ \Rightarrow \theta = \log \mu, \quad \phi = 1, \quad a(\phi) = \phi, \quad b(\theta) = \exp(\theta), \quad c(y, \phi) = -\log y! \]

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

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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
Mean is a function of $\theta$ and given by

$$E(Y) \equiv \mu = b'(\theta)$$
One Step Deeper: Properties of the Exponential Family

- Mean is a function of $\theta$ and given by

$$\mathbb{E}(Y) \equiv \mu = b'(\theta)$$

- Variance is a function of $\theta$ and $\phi$ and given by

$$\mathbb{V}(Y) \equiv V = b''(\theta)a(\phi)$$
One Step Deeper: Properties of the Exponential Family

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- Common forms of $a(\phi)$: 1 (Poisson, Bernoulli), $\phi$ (normal, Gamma), and $\phi/\omega_i$ (binomial)
One Step Deeper: Properties of the Exponential Family

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  \[
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  \]
Summary

Random variables and probability distributions provide useful models of the world. 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.
Random variables and probability distributions provide useful models of the world.
Summary

- Random variables and probability distributions provide useful models of the world.
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Stewart (Princeton)
Random variables and probability distributions provide useful models of the world.

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Random variables and probability distributions provide useful **models** of the world.

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**Joint** and **conditional** distributions capture the relationship between random variables.

There is a common set of famous distributions such as the **Normal** distribution.
Where We’ve Been and Where We’re Going . . .

This week:

- **Monday:**
  - summarize one random variable using expectation and variance
  - show how to condition on a variable

- **Wednesday:**
  - properties of joint distributions
  - conditional expectations
  - covariance, correlation, independence

Next week:

- estimating these features from data
- estimating uncertainty

New reading:

- Aronow and Miller Chapter 3.1-3.2.6, 3.4.1
- Optional: Fox Chapter 3: Examining Data
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Random Variables and Distributions
- What is a Random Variable?
- Discrete Distributions
- Continuous Distributions

Characteristics of Distributions
- Central Tendency
- Measures of Dispersion

Conditional Distributions

Fun with Averages

Fun with Sensitive Questions

Appendix: Why the Mean?

Joint Distributions
- Discrete Random Variable
- Continuous Random Variable

Conditional Expectation

Properties
- Independence
- Covariance and Correlation
- Conditional Independence

Famous Distributions

Fun With Spam
Fun With: Building a Spam Filter

Suppose we have an email $i$, ($i = 1, \ldots, N$) which we represent as a count of $J$ words
Fun With: Building a Spam Filter

Suppose we have an email $i$, ($i = 1, \ldots, N$) which we represent as a count of $J$ words

$$x_i = (x_{1i}, x_{2i}, \ldots, x_{Ji})$$
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Set of $K$ categories. Category $k$ ($k = 1, \ldots, K$)

$$\{ C_1, C_2, \ldots, C_K \}$$
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\]

Set of \( K \) categories. Category \( k \) \((k = 1, \ldots, K)\)

\[
\{ C_1, C_2, \ldots, C_K \}
\]

Subset of labeled documents \( Y = (Y_1, Y_2, \ldots, Y_N) \) where \( Y_i \in \{ C_1, C_2, \ldots, C_K \} \)
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**Goal:** classify every document into one category.
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Goal: classify every document into one category.

- Learn a function that maps from space of (possible) documents to categories
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**Goal**: classify every document into one category.

- Learn a function that maps from space of (possible) documents to categories
- Use documents with known categories to estimate function
Fun With: Building a Spam Filter

Suppose we have an email $i$, $(i = 1, \ldots, N)$ which we represent as a count of $J$ words

$$ x_i = (x_{1i}, x_{2i}, \ldots, x_{Ji}) $$

Set of $K$ categories. Category $k$ ($k = 1, \ldots, K$)

$$ \{ C_1, C_2, \ldots, C_K \} $$

Subset of labeled documents $Y = (Y_1, Y_2, \ldots, Y_N)$ where $Y_i \in \{ C_1, C_2, \ldots, C_K \}$.

**Goal**: classify every document into one category.

- Learn a function that maps from space of (possible) documents to categories
- Use documents with known categories to estimate function
- Then apply model to new data, classify those observations
Example: Building a Spam Filter

Goal: For each document $x_i$, we want to infer most likely category.
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We’re going to use Bayes’ rule to estimate $p(C_k | x_i)$. 

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p(C_k | x_i) = \frac{p(C_k, x_i)}{p(x_i)}
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Example: Building a Spam Filter

Goal: For each document $\mathbf{x}_i$, we want to infer most likely category

$$C_{\text{Max}} = \arg \max_k p(C_k | \mathbf{x}_i)$$

We’re going to use Bayes’ rule to estimate $p(C_k | \mathbf{x}_i)$.

$$p(C_k | \mathbf{x}_i) = \frac{p(C_k, \mathbf{x}_i)}{p(\mathbf{x}_i)}$$

$$= \frac{p(C_k)p(\mathbf{x}_i | C_k)}{p(\mathbf{x}_i)}$$
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\[ C_{\text{Max}} = \arg \max_k p(C_k|x_i) \]

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Baseline Proportion

\[
= \frac{\underbrace{p(C_k)}_{\text{Words Given Category}}}{{p(x_i|C_k)}} \cdot \frac{\underbrace{p(x_i)}_{\text{Baseline Proportion}}}{p(x_i)}
\]
Example: Building a Spam Filter

Two probabilities to estimate:

\[ p(C_k) = \frac{\text{No. Documents in } k}{\text{No. Documents (from our labeled set)}} \]

\[ p(x_i|C_k) \text{ complicated without heroic assumptions} \]

- Even if \( x_{ij} \) is binary. Then \( 2^J \) possible \( x_i \) documents
- Simplify: assume each word is independent given class

\[ p(x_i|C_k) = \prod_{j=1}^{J} p(x_{ij}|C_k) \]

This is called a Naive Bayes classifier.
Example: Building a Spam Filter

\[ C_{\text{Max}} = \arg \max_k \frac{p(C_k)p(x_i|C_k)}{p(x_i)} \]
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\begin{align*}
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This is called a Naïve Bayes classifier.
Estimating the Naïve Bayes Classifier

Two components to estimate:

\[ p(C_k) = \frac{\text{No. Documents in } k}{\text{No. Documents}} \]

\[ p(x_i|C_k) = \prod_{j=1}^{J} p(x_{ij}|C_k) \]

\[ p(x_{im} = z|C_k) = \frac{\text{No( Docs } x_{ij} = z \text{ and } C = C_k)}{\text{No(C = C_k)}} \]

Algorithm steps:
1) Learn \( \hat{p}(C) \) and \( \hat{p}(x_i|C_k) \) on labeled data
2) Use this to identify most likely \( C_k \) for each document \( i \) in unlabeled data

Simple intuition about Naïve Bayes:
Learn what documents in class \( j \) look like
Find class \( k \) that document \( i \) is most similar to
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Example: Building a Spam Filter

Scoring the algorithm is easy.

\[ p(C_k | x_i) \propto p(C_k) \prod_{j=1}^J p(x_i, j | C_k) x_{ij} \]

which is simply the probability of the class multiplied by the product of the probabilities for the words that are observed in the test document.
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Example: Building a Spam Filter

Learn the most probable class using Bayes Rule and a powerful but "naive" independence assumption. Despite that the model is "wrong" it classifies spam quite well. Shares the basic structure of many models, is a building block for more complex models.

This was a complicated example, it is okay if you didn't follow all of it. More on estimators next week!
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