THE UNIVERSITY OF TEXAS AT AUSTIN
Department of Statistics and Data Sciences
College of Natural Sciences

SDS 321: Introduction to Probability and Statistics

Lecture 15: Continuous random variables

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Roadmap

- Discrete vs continuous random variables
- Probability mass function vs Probability density function
  - Properties of the pdf
- Cumulative distribution function
  - Properties of the cdf
  - Relating the cdf to the pdf
  - Examples.
- Expectation, variance and properties
  - Example with uniform.
- Continuous random variables
  - The uniform distribution
  - The exponential distribution
  - The normal distribution

Mean of a uniform random variable

Let X be a uniform random variable over $[a, b]$. What is its expected value?

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

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- So, $$E[X] = \int_{-\infty}^{a} x \times 0 dx + \int_{a}^{b} \frac{x}{b-a} dx + \int_{b}^{\infty} x \times 0 dx$$ $$= \int_{a}^{b} \frac{x}{b-a} dx$$ $$= \left[\frac{x^2}{2(b-a)} \right]_a^b$$

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$$= \int_{a}^{b} \frac{x}{b-a} dx$$

$$= \left[\frac{x^2}{2(b-a)} \right]_a^b$$

$$= \frac{1}{2(b-a)}(b^2 - a^2) = \frac{(a+b)(b-a)}{2(b-a)} = \frac{a+b}{2}$$

Variance of a continuous random variable

- We can use the first and second moment to calculate the variance of X,

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

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

- We can also use our results for expectations and variances of linear functions:

$$\text{var}(aX + b) = a^2 \text{var}(X)$$

Variance of a uniform random variable

To calculate the variance, we need to calculate the second moment:

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Variance of a uniform random variable

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$$

So, the variance is

$$
\text{var}(X) = E[X^2] - E[X]^2 = \frac{a^2 + ab + b^2}{3} - \frac{(a+b)^2}{4} = \frac{(b-a)^2}{12}
$$

The uniform distribution

- $f_X(x) = \begin{cases} \frac{1}{b-a} & x \in [a, b] \\ 0 & otherwise \end{cases}$ $\qquad F_X(x) = \begin{cases} 0 & x < a \\ \frac{x-a}{b-a} & x \in [a, b] \\ 1 & otherwise \end{cases}$
- $E[X] = \frac{a+b}{2}$
- $\text{var}(X) = \frac{(b-a)^2}{12}$

The exponential distribution

- How to model the amount of time until something happens, such as
  - the next email arrives
  - an accident happens
  - a light bulb burns out
  - Notation: $X \sim Exp(\lambda)$

The exponential distribution

- An exponential r.v. has pdf and cdf:

$$f_X(x) = \begin{cases} \lambda e^{-\lambda x} & x \geq 0 \\ 0 & otherwise \end{cases} \qquad F_X(x) = \int_0^x \lambda e^{-\lambda y} dy = \int_0^{\lambda x} e^{-v} dv = 1 - e^{-\lambda x}$$

- $$E[X] = \int_0^\infty x \lambda e^{-\lambda x} dx = \frac{1}{\lambda} \int_0^\infty (\lambda x) e^{-\lambda x} d(\lambda x) = \frac{1}{\lambda} \int_0^\infty u e^{-u} du = \frac{1}{\lambda}$$

- $\mathrm{var}(X) = E[X^2] - E[X]^2 = \int_0^\infty x^2 \lambda e^{-\lambda x} dx - \frac{1}{\lambda^2} = \frac{1}{\lambda^2} \int_0^\infty u^2 e^{-u} du - \frac{1}{\lambda^2} = \frac{1}{\lambda^2}$

The exponential distribution

- Integration by parts anyone?

$$\int f(x)g'(x)dx = f(x)g(x) - \int f'(x)g(x)dx$$

$$\int xe^{-x}dx = x(-e^{-x}) + \int e^{-x}dx = -xe^{-x} - e^{-x}$$

$$\int_0^\infty xe^{-x}dx = -xe^{-x}\Big|_0^\infty - e^{-x}\Big|_0^\infty = 1$$

$$\int x^2e^{-x}dx = x^2(-e^{-x}) + 2\int xe^{-x}dx$$

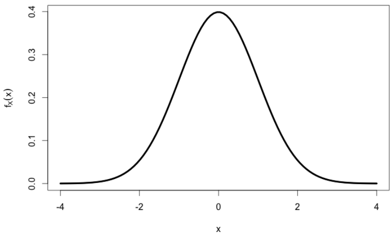
$$\int_0^\infty x^2e^{-x}dx = -x^2e^{-x}\Big|_0^\infty + 2\int_0^\infty xe^{-x}dx = 2$$

The normal distribution

- A normal, or Gaussian, random variable is a continuous random variable with PDF

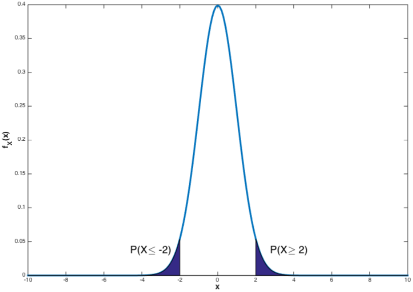
$$f_X(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-(x-\mu)^2/2\sigma^2}$$

where μ and σ are scalars, and $\sigma > 0$.
- We write $X \sim N(\mu, \sigma^2)$.
- The mean of X is μ, and the variance is σ^2 (how could we show this?)



The normal distribution

- The normal distribution is the classic "bell-shaped curve".
- It is a good approximation for a wide range of real-life phenomena.
  - Stock returns.
  - Molecular velocities.
  - Locations of projectiles aimed at a target.



- Further, it has a number of nice properties that make it easy to work with. Like symmetry. In the above picture, $P(X \geq 2) = P(X \leq -2)$.

Linear transformations of normal distributions

- Let $X \sim N(\mu, \sigma^2)$
- Let $Y = aX + b$
- What are the mean and variance of Y?

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Linear transformations of normal distributions

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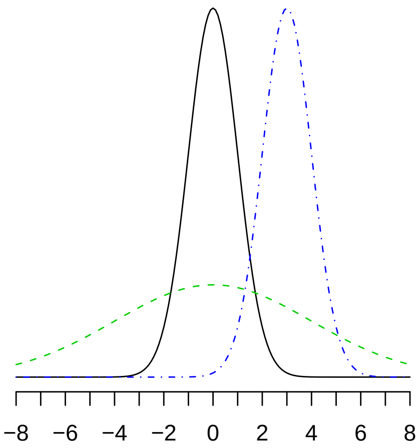
- Let $Y = aX + b$
- What are the mean and variance of Y?
- $E[Y] = a\mu + b$
- $\text{var}[Y] = a^2\sigma^2$.

- In fact, if $Y = aX + b$, then Y is *also* a normal random variable, with mean $a\mu + b$ and variance $a^2\sigma^2$:

$$Y \sim N(a\mu + b, a^2\sigma^2)$$

The normal distribution

- Example: Below are the pdfs of $X_1 \sim N(0,1)$, $X_2 \sim N(3,1)$, and $X_3 \sim N(0,16)$.
- Which pdf goes with which X?



The standard normal

- It is often helpful to map our normal distribution with mean μ and variance σ^2 onto a normal distribution with mean 0 and variance 1.
- This is known as the **standard normal**
- If we know probabilities associated with the standard normal, we can use these to calculate probabilities associated with normal random variables with arbitary mean and variance.
- If $X \sim N(\mu, \sigma^2)$, then $Z = \frac{x - \mu}{\sigma} \sim N(0, 1)$.
- (Note, we often use the letter Z for standard normal random variables)

The standard normal

- I tell you that, if $X \sim N(0, 1)$, then $P(X < -1) = 0.159$.
- If $Y \sim N(1, 1)$, what is $P(Y < 0)$?
- Well we need to use the table of the **Standard Normal**.
- How do I transform Y such that it has the standard normal distribution?
- We know that a linear function of a normal random variable is also normally distributed!

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- Well $Z = Y - 1$ has mean zero and variance 1.
- So $P(Y < 0) = P(Z < -1) = 0.159$.

The standard normal

- If $Y \sim N(0, 4)$, what value of y satisfies $P(Y < y) = 0.159$?
- The variance of Y is 4 times that of a standard normal random variable.
- Transform into a $N(0, 1)$ random variable!

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- Use $Z = Y/2$...Now $Z \sim N(0, 1)$.

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- Use $Z = Y/2$...Now $Z \sim N(0, 1)$.
- So, if $P(Y < y) = P(2Z < y) = P(Z < y/2)$.
- We want y such that $P(Z < y/2) = 0.159$. But we know that $P(Z < -1) = 0.159$, so?

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- So, if $P(Y < y) = P(2Z < y) = P(Z < y/2)$.
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- So $y/2 = -1$ and as a result $y = -2$...!

The standard normal

- The CDF of the standard normal is denoted Φ:

$$\Phi(z) = P(Z \leq z) = P(Z < z) = \frac{1}{\sqrt{(2\pi)}} \int_{-\infty}^{z} e^{-t^2/2} dt$$

- We cannot calculate this analytically.
- The **standard normal table** lets us look up values of $\Phi(y)$ for $y \geq 0$

	.00	.01	.02	0.03	0.04	$\cdots$
0.0	0.5000	0.5040	0.5080	0.5120	0.5160	$\cdots$
0.1	0.5398	0.5438	0.5478	0.5517	0.5557	$\cdots$
0.2	0.5793	**0.5832**	0.5871	0.5910	0.5948	$\cdots$
0.3	0.6179	0.6217	0.6255	0.6293	0.6331	$\cdots$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	

$$P(Z < 0.21) = 0.5832$$

CDF of a normal random variable

If $X \sim N(3, 4)$, what is $P(X < 0)$?

- First we need to **standardize**:

$$Z = \frac{X - \mu}{\sigma} = \frac{X - 3}{2}$$

- So, a value of $x = 0$ corresponds to a value of $z = -1.5$
- Now, we can translate our question into the standard normal:

$$P(X < 0) = P(Z < -1.5) = P(Z \leq -1.5)$$

- Problem... our table only gives $\Phi(z) = P(Z \leq z)$ for $z \geq 0$.

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- Our table only gives us "less than" values.
- But, $P(Z \geq 1.5) = 1 - P(Z < 1.5) = 1 - P(Z \leq 1.5) = 1 - \Phi(1.5)$.

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- Our table only gives us "less than" values.
- But, $P(Z \geq 1.5) = 1 - P(Z < 1.5) = 1 - P(Z \leq 1.5) = 1 - \Phi(1.5)$.
- And we're done!
  $P(X < 0) = 1 - \Phi(1.5) =$ (look at the table...)$1 - 0.9332 = 0.0668$

Recap

- With continuous random variables, any specific value of $X = x$ has zero probability.
- So, writing a function for $P(X = x)$ – like we did with discrete random variables – is pretty pointless.
- Instead, we work with **PDFs** $f_X(x)$ – functions that we can integrate over to get the probabilities we need.

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

- We can think of the PDF $f_X(x)$ as the "probability mass per unit area" near x.
- We are often interested in the probability of $X \leq x$ for some x – we call this the cumulative distribution function $F_X(x) = P(X \leq x)$.
- Once we know $f_X(x)$, we can calculate expectations and variances of X.

Multiple continuous random variables

- Let X and Y be two continuous random variables.
- Each one takes on values on the real line, i.e. $X \in \mathbb{R}$ and $Y \in \mathbb{R}$.
- Together, each possible pair of values describe a point in the real plane, i.e. $(X, Y) \in \mathbb{R}^2$.
- We say X and Y are **jointly continous** if the probability of them jointly taking on values in some subset B of the plane can be described as

$$P((X, Y) \in B) = \iint_{(x,y) \in B} f_{X,Y}(x, y) dx\, dy$$

  using some continuous function $f_{X,Y}$, for all $B \in \mathbb{R}^2$ – i.e. all subsets of the 2-D plane.
- Notation means "integrate over all values of x and y s.t. $(x, y) \in B$

Joint PDF

- We call $f_{X,Y}$ the **joint pdf** of X and Y.
- It allows us to calculate the probability of any set of combinations of X and Y
  - e.g. the probability that a person weighs over 200lb and is under 6'
  - e.g. the probability that a person's height in inches is more than twice their weight in pounds.
  - So, this could describe the first scenario above, $P(200 \leq X \leq \infty, -\infty \leq Y \leq 6)$
  - In this case B is a rectangle
- What is $\int_{x=-\infty}^{\infty} \int_{y=-\infty}^{\infty} f_{X,Y}(x, y) dx\, dy$?

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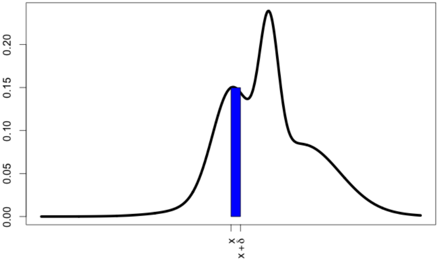
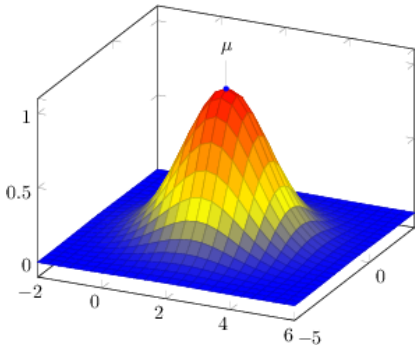
Joint PDF: Intuition

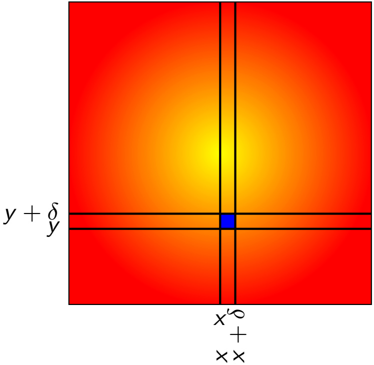
- Remember we could think of $f_X(x)$ as the "probability mass per unit length" near to x?



- Because $f_X(x) = \dfrac{P(x \leq X \leq x + \delta)}{\delta}$

Joint PDF: Intuition





- We can think of the joint PDF $f_{X,Y}(x, y)$ as the "probability mass per unit area" for a small area near X.
- Again, remember, $f_{X,Y}(x, y)$ **is not a probability!**

Multiple random variables to a single random variable

- We can get from the **joint PMF** of X and Y to the **marginal PMF** of X by summing over (marginalizing over) Y:

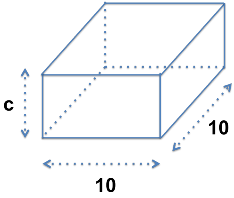
$$p_X(x) = \sum_y p_{X,Y}(x, y)$$

- We can get from the **joint PDF** of X and Y to the **marginal PDF** of X by integrating over (marginalizing over) Y:

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

Example: Bivariate uniform random variable

- Anita (X) and Benjamin (Y) both pick a number between 0 and 10, according to a continuous uniform distribution. What is $f_{X,Y}(x,y)$?



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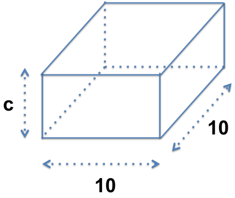


- Let's see... we know all pairs (x,y) are equally likely, so we know $f_{X,Y} = c$. It must satisfy $\int_{x=0}^{10}\int_{y=0}^{10} f_{X,Y}(x,y)\,dx\,dy = 1$.
- So, $c \underbrace{\int_{x=0}^{10}\int_{y=0}^{10} dx\,dy}_{100} = 1\ldots$
- So $c = f_{X,Y}(x,y) = 0.01$ for all $0 \le x, y \le 10$.

Example: marginal probability

- $f_{X,Y}(x,y) = \begin{cases} 0.01 & \text{If } x, y \in [0, 10] \\ 0 & \text{otherwise} \end{cases}$
- What is $f_X(x)$?

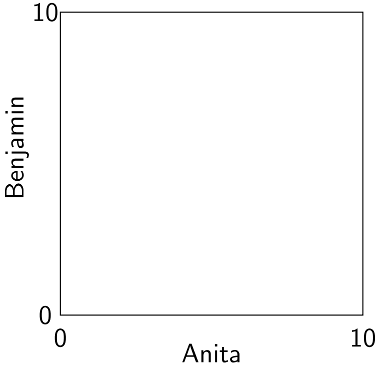
- In general, we will have $f_X(x) = \int_{-\infty}^{\infty} f_{X,Y}(x,y)dy$
- We have **marginalized out** one of our random variables... just like we did when looking at PMFs.
- We call $f_X(x)$ the **marginal PDF** of X

Example: marginal probability

- $f_{X,Y}(x,y) = \begin{cases} 0.01 & \text{If } x, y \in [0,10] \\ 0 & \text{otherwise} \end{cases}$
- What is $f_X(x)$?
- $f_X(x) = \begin{cases} \int_{y=0}^{10} 0.01 dy = 0.1 & \text{If } x \in [0,10] \\ 0 & \text{otherwise} \end{cases}$
- Not surprisingly $X \sim \mathit{Uniform}([0,10])$ and $Y \sim \mathit{Uniform}([0,10])$.
- In general, we will have $f_X(x) = \int_{-\infty}^{\infty} f_{X,Y}(x,y)dy$
- We have **marginalized out** one of our random variables... just like we did when looking at PMFs.
- We call $f_X(x)$ the **marginal PDF** of X

Example: marginalization

- What is the probability that Anita picks a number greater than 7?



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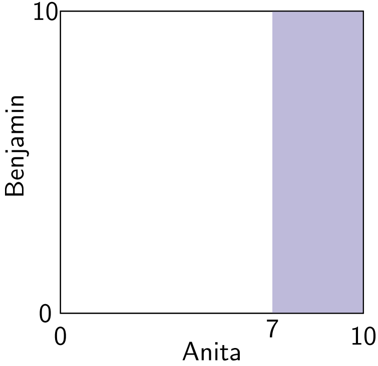
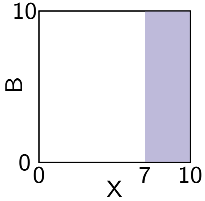


- That's going to correspond to the shaded region... $P(X > 7) = 0.01(3 \times 10) = 0.3$.
- Or, using calculus: $\int_{x=7}^{10} \int_{y=0}^{10} f_{X,Y}(x, y) dx\, dy$

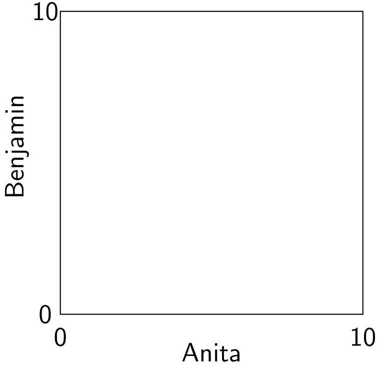
Marginalization



- $P(X > 7) = \int_{x=7}^{10} \int_{y=0}^{10} f_{X,Y}(x, y) dx\, dy$
- But, this doesn't depend on Benjamin at all! It is the same as $P(X > 7) = \int_{x>7} f_X(x) dx$.

Example: Uniform random variable

- What is the probability that they both pick numbers less than 4?



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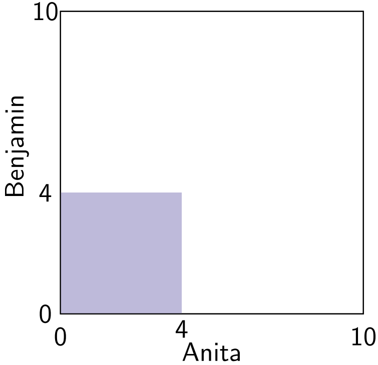
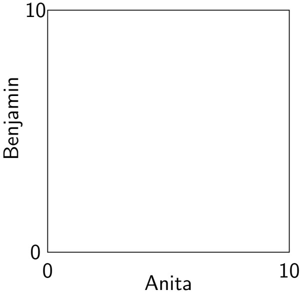


- It will be $0.01 \int_0^4 \int_0^4 dx\, dy = 0.01 \times 16 = 0.16$
  – i.e. $0.01 \times$ the shaded area.
  – Or $16/100$!

Example: Uniform random variable

- What is the probability that Benjamin picks a number at least twice that of Anita?



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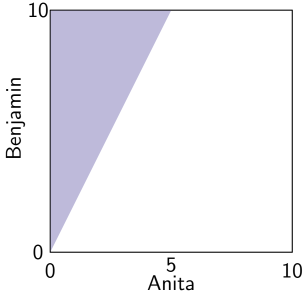

- That's going to correspond to the shaded region...
  $P(Y \geq 2X) = 0.01(0.5 \times 5 \times 10) = 0.25.$

- Or, using calculus: $\int_{x=0}^{10} \int_{y=2x}^{10} f_{X,Y}(x,y) dx\, dy = \int_{x=0}^{10} \int_{y=2x}^{10} c \times 1_{0 \leq x \leq 10, 0 \leq y \leq 10} dx\, dy$

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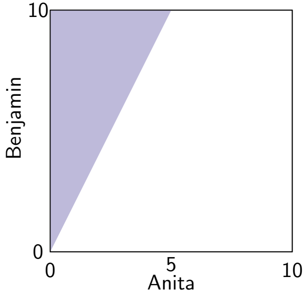

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- $\int_{x=0}^{10} \int_{y=2x}^{10} c \times 1_{0 \leq 2x \leq 10} dx\, dy = c \int_{0}^{5} dx = c \int_{x=0}^{5} (10 - 2x) dx$
  $= c(10 \times 5 - (5^2 - 0)) = 0.01 \times 25 = 0.25$

Conditional PDFs

- For *discrete* random variables, we looked at marginal PMFs $p_X(X)$, conditional PMFs $p_{X|Y}(x|y)$, and joint PMFs $p_{X,Y}(x,y)$.
- These corresponded to the probability of an event, $P(A)$, the conditional probability of an event given some other event, $P(A|B)$, and probability of the intersection of two events, $P(A \cap B)$.
- We've looked at marginal PDFs, $f_X(x)$ and joint PDFs, $f_{X,Y}(x,y)$.
- These don't directly give us probabilities of events, but we can use them to calculate such probabilities by integration.
- We can also look at conditional PDFs! These allow us to calculate the probability of events given extra information.

Conditional PDFs

- Recall, the PDF of a continuous random variable X is the non-negative function $f_X(x)$ that satisfies

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

for any subset B of the real line.
- Let A be some event with $P(A) > 0$
- The **conditional PDF** of X, given A, is the non-negative function $f_{X|A}$ that satisfies

$$P(X \in B|X \in A) = \int_B f_{X|A}(x)dx$$

for any subset B of the real line.
- If B is the entire line, then we have

$$\int_{-\infty}^{\infty} f_{X|A}(x)dx = 1$$

- So, $f_{X|A}(x)$ is a valid PDF.

Conditional PDFs

- The event we are conditioning on can also correspond to a range of values of our continuous random variable.
- **Definition-**

$$f_{X|\{X \in A\}}(x) = \begin{cases} \dfrac{f_X(x)}{P(X \in A)} & \text{if } X \in A \\ 0 & \text{otherwise.} \end{cases}$$

- In this case, we can write the conditional probability as

$$\begin{aligned} P(X \in B|X \in A) &= \int_B f_{X|A}(x)dx = \int_B \frac{f_X(x)1(x \in A)}{P(X \in A)}dx \\ &= \frac{\int_{A \cap B} f_X(x)dx}{P(X \in A)} = \frac{P(\{X \in A\} \cap \{X \in B\})}{P(X \in A)} \\ &= P(X \in B|X \in A) \end{aligned}$$

- This is a valid PDF–non-negative and integrates to one. Check?

Conditioning: memoryless property of the exponential

- $X \sim Exp(\lambda)$
- $P(X \geq s + t | X \geq s) = ?$

Conditioning: memoryless property of the exponential

- $X \sim Exp(\lambda)$
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- Remember the exponential? $F_X(x) = 1 - e^{-\lambda x}$.
- $$\begin{aligned} P(X > s + t | X > s) &= \frac{P(X > s + t, X > s)}{P(X > s)} \\ &= \frac{P(X > s + t)}{P(X > s)} = \frac{e^{-\lambda(s+t)}}{e^{-\lambda s}} \\ &= e^{-\lambda t} = P(X > t) \end{aligned}$$

Conditioning: memoryless property of the exponential

- $X \sim Exp(\lambda)$
- $\begin{cases} f_{X|X>s}(x) = \dfrac{\lambda e^{-\lambda x}}{P(X>s)} = \lambda e^{\lambda(x-s)} & \text{If } x > s \\ = 0 & \text{Otherwise} \end{cases}$
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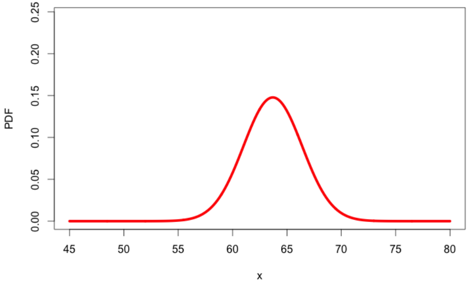
- $P(X > s+t | X > s) =?$
- Remember the exponential? $F_X(x) = 1 - e^{-\lambda x}$.
- $$\begin{aligned} P(X > s+t|X > s) &= \int_{s+t}^{\infty} f_{X|X>s}(x)dx = \lambda \int_{s+t}^{\infty} e^{-\lambda(x-s)} dx \\ &= \lambda \int_{t}^{\infty} e^{-\lambda u} du = e^{-\lambda t} \end{aligned}$$

Conditional PDFs: Example

- The height X of a randomly picked american woman can be modeled by $X \sim N(63.7, 2.7^2)$
- Whats the conditional PDF given that the randomly picked woman is at least 63 inches tall?
- The PDF of heights (X) is shown in red.



Conditional PDFs: Example

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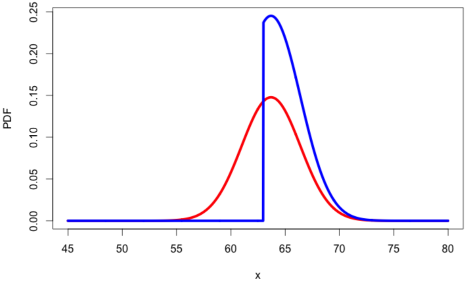
- Whats the conditional PDF given that the randomly picked woman is at least 63 inches tall?
- The PDF of heights (X) is shown in red.
- The conditional PDF given $X > 63$, shown in blue, is the same shape for $X > 63$... but scaled up to integrate to one.



Recap

- Last time, we introduced the idea of continuous random variables and PDFs.
- A PDF is a function we can integrate over to get $P(X \in B) = \int_B f_X(x)dx$.
- We extended this to look at **joint PDFs** and **conditional PDFs**.
- We can borrow results from conditional probability and probabilities of intersections!
- But we need to be careful to remember, a PDF is **not** a probability...
- Next time, we will continue looking at continuous probability distributions.