

SDS 321: Introduction to Probability and Statistics

Lecture 15: Continuous random variables

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Roadmap

- ▶ Continuous random variables
- ▶ PDF, CDF, Expectation, Variance
- ▶ Common distributions
 - ▶ The Uniform
 - ▶ The exponential
 - ▶ The normal distribution
 - ▶ Operations which preserve normality
 - ▶ Standardization
- ▶ Multiple random variables: joint distributions
 - ▶ Joint pdf
 - ▶ Joint pdf to a single pdf: Marginalization
 - ▶ Conditional pdf

Multiple random variables

We can also have multiple *continuous* random variables associated with the same experiment/sample space.

- ▶ For example, our experiment might be selecting a randomly selected person.
- ▶ The sample space would be the set of all possible characteristics of this person.
- ▶ We can summarize these characteristics into continuous random variables, e.g.
 - ▶ The person's height
 - ▶ The person's weight
 - ▶ The person's age
- ▶ Again, multiple random variables stemming from the same sample space!
- ▶ These random variables will often depend on each other: Knowing a person is taller than 6'5" tells us something about their expected weight.

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 continuous** 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

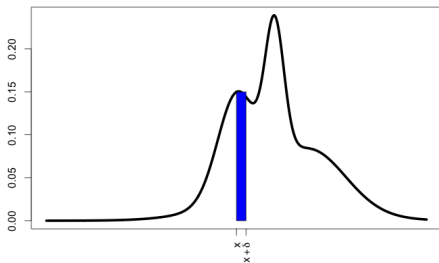
- ▶ We call $f_{X,Y}$ the **joint pdf** of X and Y .
- ▶ It allows us to calculate the probability of any set of combinations of X and Y
 - ▶ e.g. the probability that a person weighs over 200lb and is under 6'
 - ▶ e.g. the probability that a person's height in inches is more than twice their weight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

Joint PDF

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 $P(200 \leq X \leq \infty, -\infty \leq Y \leq 6)$
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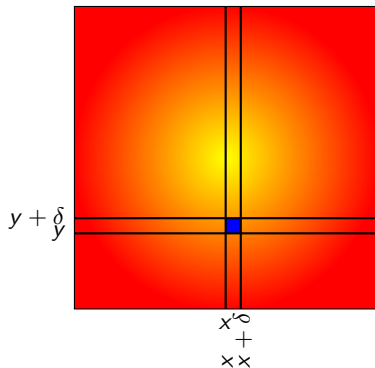
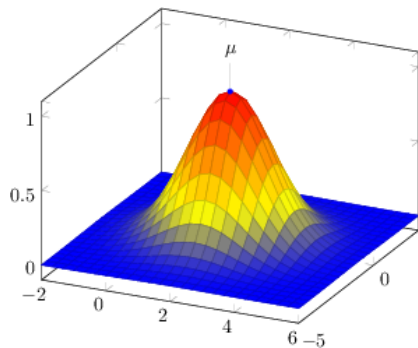
Joint PDF: Intuition

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



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

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 :

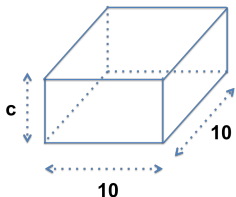
$$p_X(x) = \sum_y p_{X,Y}(x,y)$$

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

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

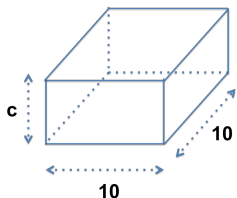
Example: Bivariate uniform random variable

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



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 $f_{X,Y}(x,y)$?



- ▶ 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, $c \underbrace{\int_{x=0}^{10} \int_{y=0}^{10} dx dy}_{100} = 1 \dots$
- ▶ So $c = f_{X,Y}(x,y) = 0.01$ for all $0 \leq x, y \leq 10$.

Example: marginal PDF

$$\blacktriangleright f_{X,Y}(x,y) = \begin{cases} 0.01 & \text{if } x,y \in [0, 10] \\ 0 & \text{otherwise} \end{cases}$$

\blacktriangleright What is $f_X(x)$?

\blacktriangleright In general, we will have $f_X(x) = \int_{-\infty}^{\infty} f_{X,Y}(x,y)dy$

\blacktriangleright We have **marginalized out** one of our random variables... just like we did when looking at PMFs.

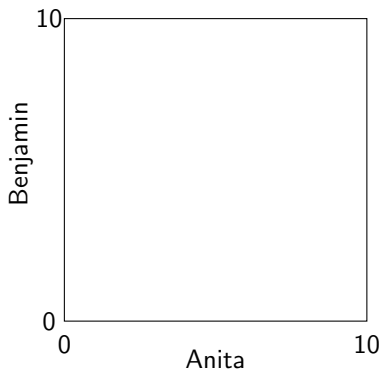
\blacktriangleright We call $f_X(x)$ the **marginal PDF** of X

Example: marginal PDF

- ▶ $f_{X,Y}(x,y) = \begin{cases} 0.01 & \text{if } x,y \in [0,10] \\ 0 & \text{otherwise} \end{cases}$
- ▶ 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 $X \sim \text{Uniform}([0,10])$ and $Y \sim \text{Uniform}([0,10])$.
- ▶ 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

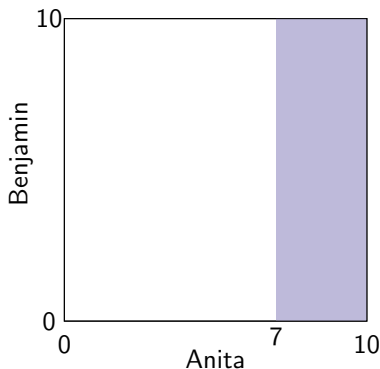
Example: marginalization

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



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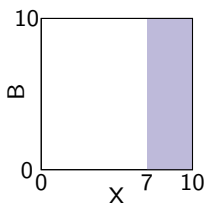


- ▶ That's going to correspond to the shaded region...

$$P(X > 7) = 0.01(3 \times 10) = 0.3.$$

- ▶ Or, using calculus: $\int_{x=7}^{10} \int_{y=0}^{10} f_{X,Y}(x,y) dx dy$

Marginalization



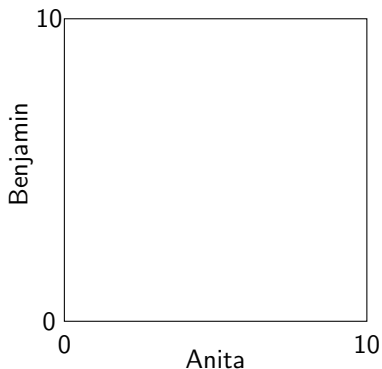
▶
$$P(X > 7) = \int_{x=7}^{10} \int_{y=0}^{10} f_{X,Y}(x,y) dx dy$$

▶ But, this doesn't depend on Benjamin at all! It is the same as

$$P(X > 7) = \int_{x>7} f_X(x) dx.$$

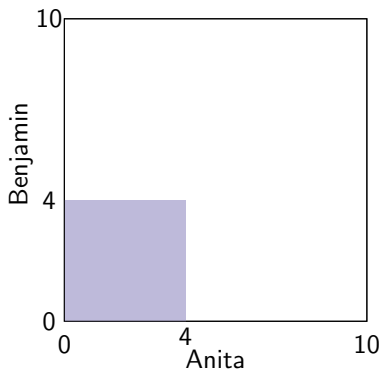
Example: Uniform random variable

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



Example: Uniform random variable

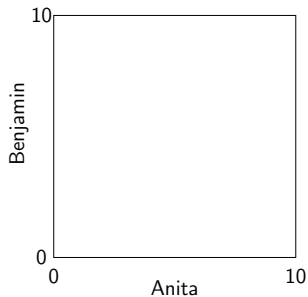
- ▶ What is the probability that they both pick numbers less than 4?



- ▶ 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 $16/100!$

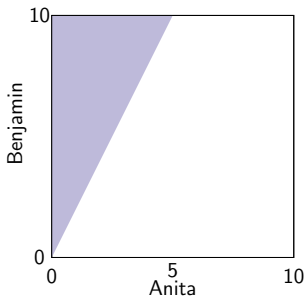
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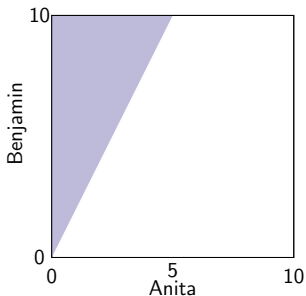
- ▶ That's going to correspond to the shaded region...

$$P(Y \geq 2X) = 0.01(0.5 \times 5 \times 10) = 0.25.$$

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

Example: Uniform random variable

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$$\begin{aligned} \int_{x=0}^{10} \int_{y=2x}^{10} c \times 1_{0 \leq 2x \leq 10} dx dy &= c \int_0^5 dx = c \int_{x=0}^5 (10 - 2x) dx \\ &= c(10 \times 5 - (5^2 - 0)) = 0.01 \times 25 = 0.25 \end{aligned}$$

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-**

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

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

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

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

Conditioning: memoryless property of the exponential

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

Conditioning: memoryless property of the exponential

▶ $X \sim \text{Exp}(\lambda)$

▶ $P(X \geq s + t | X \geq s) = ?$

▶ Remember the exponential? $F_X(x) = 1 - e^{-\lambda x}$.

$$P(X > s + t | X > s) = \frac{P(X > s + t, X > s)}{P(X > s)}$$

▶
$$= \frac{P(X > s + t)}{P(X > s)} = \frac{e^{-\lambda(s+t)}}{e^{-\lambda s}}$$
$$= e^{-\lambda t} = P(X > t)$$

Conditioning: memoryless property of the exponential

▶ $X \sim \text{Exp}(\lambda)$

▶
$$\begin{cases} f_{X|X>s}(x) = \frac{\lambda e^{-\lambda x}}{P(X > s)} = \lambda e^{\lambda(x-s)} & \text{If } x > s \\ = 0 & \text{Otherwise} \end{cases}$$

▶ $P(X > s + t | X > s) = ?$

Conditioning: memoryless property of the exponential

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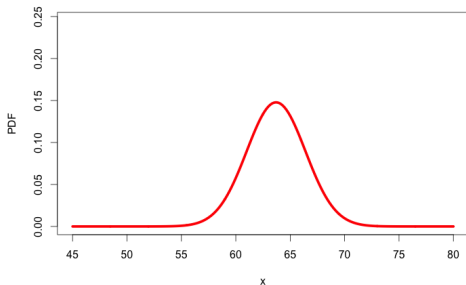
▶ $P(X > s + t | X > s) = ?$

▶ Remember the exponential? $F_X(x) = 1 - e^{-\lambda x}$.

▶
$$\begin{aligned} P(X > s + t | X > s) &= \int_{s+t}^{\infty} f_{X|X>s}(x) dx = \lambda \int_{s+t}^{\infty} e^{-\lambda(x-s)} dx \\ &= \lambda \int_t^{\infty} e^{-\lambda u} du = e^{-\lambda t} \end{aligned}$$

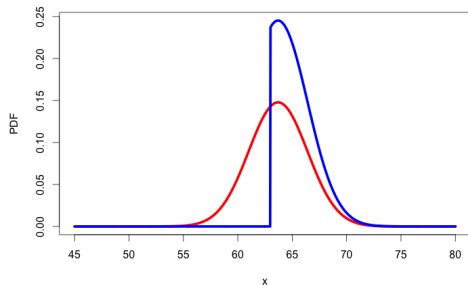
Conditional PDFs: Example

- ▶ 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.