Chapter 7 Continuous Random Variables

Continuous Random Variable

<u>Defn</u>: A **continuous random variable (r.v.)** has a continuous range of values that it can take on. This might be an interval or set of intervals. Thus a continuous r.v. can take on an **uncountable** set of possible values.

Examples:

- □ Time of an event
- Response time of a job
- □ Speed of a device
- Location of a satellite
- Distance between people's eyeballs

Probability for Continuous Random Variable

The probability that a continuous r.v. is equal to any particular value is defined to be 0.

Probability for a continuous r.v. is defined via a density function.

<u>Defn 7.2</u>: The **probability density function (p.d.f.)** of a continuous r.v. X is a non-negative function $f_X(\cdot)$, where

$$P\{a \le X \le b\} = \int_{a}^{b} f_X(x) dx \quad \text{and} \quad \int_{-\infty}^{\infty} f_X(x) dx = 1$$

Probability for Continuous Random Variable



 $f(x)dx \approx \mathbf{P}\{x \le X \le x + dx\}$



Density as a rate

Density functions are not necessarily related to probability.

<u>Example</u>: Filling a bathtub at rate $f_X(t) = t^2$ gallons/sec, where $t \ge 0$



Example: Computing probability from p.d.f.

Weight of two-year-olds ranges between 15 and 35 pounds with p.d.f. $f_W(x)$:

$$f_W(x) = \begin{cases} \frac{3}{40} - \frac{3}{4000} (x - 25)^2 & \text{if } 15 \le x \le 35 \\ 0 & \text{otherwise} \end{cases}$$



Q: What is the fraction of two-year-olds that weigh > 30 pounds?

A:

$$\int_{30}^{\infty} f_W(x) dx = \int_{30}^{35} \frac{3}{40} - \frac{3}{4000} (x - 25)^2 dx \approx 16\%$$



Cumulative distribution function

<u>Defn</u>: The **cumulative distribution function (c.d.f.)** of a continuous r.v. X is given by:

$$F_X(a) = \mathbf{P}\{-\infty < X \le a\} = \int_{-\infty}^a f_X(x) dx$$

The **tail** of *X* is given by:

$$\overline{F}_X(a) = 1 - F_X(a) = \mathbf{P}\{X > a\}$$

Q: How do we get $f_X(x)$ from $F_X(x)$?

F.T.C.
A:
$$f_X(x) = \frac{d}{dx} \int_{-\infty}^x f_X(t) dt = \frac{d}{dx} F_X(x)$$

(See Section 1.3 of your book)

Uniform distribution

<u>Defn</u>: **Uniform**(a, b), often written U(a, b), models the fact that any interval of length δ between a and b is equally likely. Specifically, if $X \sim U(a, b)$, then

$$f_X(x) = -\begin{cases} \frac{1}{b-a} & \text{if } a \le x \le b\\ 0 & \text{otherwise} \end{cases}$$

Q: If $X \sim U(a, b)$, what is $F_X(x)$?

A:
$$F_X(x) = \int_a^x \frac{1}{b-a} dt = \frac{x-a}{b-a}$$

Graphical depiction of Uniform distribution



Area of shaded pink region on left = Height of blue line on right

Exponential distribution

<u>Defn</u>: $Exp(\lambda)$ denotes the Exponential distribution with rate λ .

$$f_X(x) = - \begin{cases} \lambda e^{-\lambda x} & \text{if } x \ge 0\\ 0 & \text{if } x < 0 \end{cases}$$



$$F_X(x) = \int_{-\infty}^x f_X(t)dt = \begin{cases} 1 - e^{-\lambda x} & \text{if } x \ge 0\\ 0 & \text{if } x < 0 \end{cases}$$

$$\overline{F}_X(x) = e^{-\lambda x}, \qquad x \ge 0$$

[&]quot;Introduction to Probability for Computing", Harchol-Balter '24

Memorylessness

<u>Defn</u>: Random variable *X* has the **memoryless property** if

$$\boldsymbol{P}\{X > t + s \mid X > s\} = \boldsymbol{P}\{X > t\} \qquad \forall s, t \ge 0$$

X = Time to win lottery.

Suppose I haven't won the lottery by time s. Then the probability that I'll need > t more time to win is independent of s.

Equivalently: X has the **memoryless property** if

$$[X \mid X > s] =^d s + X \qquad \forall s \ge 0$$

That is, the r.v.s [X | X > s] and s + X have the same distribution.



Memorylessness

<u>Defn</u>: Random variable X has the **memoryless property** if

$$\boldsymbol{P}\{X > t + s \mid X > s\} = \boldsymbol{P}\{X > t\} \qquad \forall s, t \ge 0$$

Q: Prove that if
$$X \sim Exp(\lambda)$$
, then X has the memoryless property.

A: First recall that:
$$\overline{F}_X(x) = e^{-\lambda x}, \quad x \ge 0$$

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



Memorylessness

<u>Defn</u>: Random variable X has the **memoryless property** if

$$\boldsymbol{P}\{X > t + s \mid X > s\} = \boldsymbol{P}\{X > t\} \qquad \forall s, t \ge 0$$

Q: What other distribution has the memoryless property?

A: The Geometric distribution

Q: Does $X \sim Uniform(a, b)$ also have the memoryless property?

A: No. If $X \sim Uniform(a, b)$ and we're given that $X > b - \epsilon$, then we know that X will end soon.



Memorylessness Example

Mortality rate normally increases with age. But not for the naked mole-rat! Its remaining lifetime is independent of its age.



Q: Let $X \sim Exp(1)$ denote the lifetime of the naked mole-rat in years. If a naked mole-rate is 4 years old, what is the probability of surviving at least one more year?

A:

$$P{X > 4 + 1 | X > 4} = \frac{P{X > 5}}{P{X > 4}} = \frac{e^{-5}}{e^{-4}} = e^{-1} = P{X > 1}$$

Post Office Example

A post office has 2 clerks. When customer A walks in, customer B is being served by one clerk, and customer C is being served by the other. All service times $\sim Exp(\lambda)$.



Q: What is **P**{**A** is last to leave}?

A: $\frac{1}{2}$ One of B or C will leave first. At that point, the remaining customer's lifetime restarts. A will then compete with that remaining customer.

Expectation, Variance, and Higher Moments

<u>Defn</u>: For a continuous r.v. X with p.d.f. $f_X(\cdot)$, we have:

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

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

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

Uniform distribution: Mean and Variance

Q: Derive mean and variance of $X \sim U(a, b)$.

$$X \sim Uniform(a, b)$$

$$f_X(x) = \begin{cases} \frac{1}{b-a} & \text{if } a \le x \le b \\ 0 & \text{otherwise} \end{cases}$$

A:

$$E[X] = \int_{a}^{b} \frac{1}{b-a} \cdot t \, dt = \frac{1}{b-a} \cdot \frac{b^{2}-a^{2}}{2} = \frac{a+b}{2}$$

$$E[X^{2}] = \int_{a}^{b} \frac{1}{b-a} \cdot t^{2} dt = \frac{1}{b-a} \cdot \frac{b^{3}-a^{3}}{3} = \frac{b^{2}+ab+a^{2}}{3}$$

$$Var(X) = E[X^{2}] - E[X]^{2} = \frac{(b-a)^{2}}{12}$$

Exponential distribution: Mean and Variance

Q: Derive mean and variance of $X \sim Exp(\lambda)$.

A:

$$E[X] = \int_{-\infty}^{\infty} \lambda e^{-\lambda t} t \, dt = \frac{1}{\lambda}$$

$$E[X^2] = \int_{-\infty}^{\infty} \lambda e^{-\lambda t} \cdot t^2 dt = \frac{2}{\lambda^2}$$

$$Var(X) = E[X^2] - E[X]^2 = \frac{1}{\lambda^2}$$

$$X \sim Exp(\lambda)$$

$$f_X(x) = -\begin{cases} \lambda e^{-\lambda x} & \text{if } x \ge 0\\ 0 & \text{if } x < 0 \end{cases}$$



[&]quot;Introduction to Probability for Computing", Harchol-Balter '24

Example: Time to get from NYC to Boston

Distance from NYC to Boston is 180 miles. Motorized bikes have speeds $\sim U(30,60)$. You buy a random motorized bike.

T = Your time to get from NYC to Boston.



Goal: Derive E[T].

Idea 1: Avg. speed is 45 mph. Thus $E[T] = \frac{180}{45} = 4$ hours.

Idea 2:
$$E[T]$$
 is the average of $\frac{180}{30} = 6$ and $\frac{180}{60} = 3$. So $E[T] = 4.5$ hours.

Q: Which is correct, Idea 1 or Idea 2?

A: Neither!

Example: Time to get from NYC to Boston

New York City

180 miles

Distance from NYC to Boston is 180 miles. Motorized bikes have speeds $\sim U(30,60)$. You buy a random motorized bike.

T = Your time to get from NYC to Boston.

Q: What is E[T]?



Boston

Law of Total Probability for Continuous

Recall the **Law of Total Probability** for event *A* and **discrete** r.v. *X* :

$$P\{A\} = \sum_{x} P\{A \cap (X = x)\} = \sum_{x} P\{A \mid X = x\} \cdot p_X(x)$$

The same Law of Total Probability holds for event A and continuous r.v. X :

$$\mathbf{P}\{A\} = \int_{\mathcal{X}} f_X(x \cap A) dx = \int_{\mathcal{X}} \mathbf{P}\{A \mid X = x\} \cdot f_X(x) dx$$

Here $f_X(x \cap A)$ denotes the density of the intersection of the event A with X = x.

Law of Total Probability for Continuous

$$\boldsymbol{P}\{A\} = \int_{\mathcal{X}} f_X(x \cap A) dx = \int_{\mathcal{X}} \boldsymbol{P}\{A \mid X = x\} \cdot f_X(x) dx$$

Here $f_X(x \cap A)$ denotes the density of the intersection of the event A with X = x.

<u>Example</u>: Let *A* be the event X > 50.

$$f_X(x \cap A) = -\begin{cases} f_X(x) & \text{if } x > 50\\ 0 & \text{otherwise} \end{cases}$$

$$P\{X > 50\} = P\{A\} = \int_{-\infty}^{\infty} f_X(x \cap A) dx = \int_{50}^{\infty} f_X(x) dx$$

Likewise,

$$P\{X > 50\} = \int_{-\infty}^{\infty} P\{X > 50 \mid X = x\} \cdot f_X(x) dx = \int_{50}^{\infty} 1 \cdot f_X(x) dx$$

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Conditioning on a Zero-Probability Event

$$\boldsymbol{P}\{A\} = \int_{\mathcal{X}} f_X(x \cap A) dx = \int_{\mathcal{X}} \boldsymbol{P}\{A \mid X = x\} \cdot f_X(x) dx$$

Here $f_X(x \cap A)$ denotes the density of the intersection of the event A with X = x.

Q: In $P{A | X = x}$, we're conditioning on a zeroprobability event. So we have a zero in the denominator. How is this okay?

$$f_X(x \cap A) = -\begin{cases} f_X(x) & \text{if } x \in A \\ 0 & \text{otherwise} \end{cases}$$

A:

$$P{A \mid X = x} = \frac{f_X(x \cap A)}{f_X(x)}$$

The ratio is between densities, not probabilities, and the densities are not zero!

Conditioning on a Zero-Probability Event

Example: We have a coin with unknown bias. Specifically, the coin has probability P of heads where $P \sim Uniform(0,1)$.

Q: What is **P**{Next 10 flips are all heads}?

A:
$$P\{10 \ heads\} = \int_0^1 P\{10 \ heads \mid P = p\} \cdot f_P(p) dp$$
$$= \int_0^1 P\{10 \ heads \mid P = p\} \cdot 1 dp$$
$$= \int_0^1 p^{10} \cdot 1 dp$$
$$= \frac{1}{11}$$



Conditional p.d.f. and Bayes' Law

<u>Defn</u>: For a continuous r.v. *X* and an event *A*, the **conditional p.d.f. of r.v.** *X* **given** *A* is:

$$f_{X|A}(x) = \frac{f_X(x \cap A)}{P\{A\}} = \frac{P\{A \mid X = x\} \cdot f_X(x)}{P\{A\}}$$

Comments:

- 1. Conditional p.d.f $f_{X|A}(x)$ has value 0 outside of A.
- 2. The conditional p.d.f. is still a proper p.d.f. in that

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

Conditional p.d.f. and Bayes' Law

<u>Defn</u>: For a continuous r.v. X and an event A, the **conditional p.d.f. of r.v.** X given A is:

$$f_{X|A}(x) = \frac{f_X(x \cap A)}{P\{A\}} = \frac{P\{A \mid X = x\} \cdot f_X(x)}{P\{A\}}$$



Example:

X has p.d.f. $f_X(x)$ defined on 0 < x < 100. A is the event X > 50.

 $f_{X|A}(x)$ is a scaled-up version of $f_X(x)$, allowing it to integrate to 1.

$$f_{X|X>50}(x) = \frac{f_X(x \cap X > 50)}{P\{X > 50\}} = -\begin{cases} \frac{f_X(x)}{P\{X > 50\}} & \text{if } x > 50\\ 0 & \text{otherwise} \end{cases}$$

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Conditional expectation

<u>Defn</u>:

For a discrete r.v. X and an event A, where $P\{A\} > 0$, the conditional expectation of X given A is:

$$E[X|A] = \sum_{x} x \cdot p_{X|A}(x)$$

For a continuous r.v. X and an event A, where $P\{A\} > 0$, the conditional expectation of X given A is:

$$\boldsymbol{E}[X|A] = \int_{\mathcal{X}} \boldsymbol{x} \cdot f_{X|A}(\boldsymbol{x}) d\boldsymbol{x}$$

Example: Pittsburgh Supercomputing Center (PSC)

At the PSC, jobs are grouped into different bins based on their size. Suppose job sizes are Exponentially distributed with *mean* 1000 CPU-hours. Suppose all jobs of size < 500 CPU-hours are sent to bin 1.

- a. What is **P**{Job is sent to bin 1}?
- b. What is P{Job size < 200 | job is in bin 1}?
- c. What is $f_{X|A}(x)$, where X is the job size and A is the event that the job is in bin 1?
- d. What is *E*[Job size | job is in bin 1]?



Example: Pittsburgh Supercomputing Center (PSC)

At the PSC, jobs are grouped into bins based on their size. Suppose job sizes are Exponentially distributed with *mean* 1000 CPU-hours. Suppose all jobs of size < 500 CPU-hours are sent to bin 1.

a. What is **P**{Job is sent to bin 1}?

$$X \sim Exp\left(\frac{1}{1000}\right)$$

$$f_X(x) = -\begin{cases} \frac{1}{1000}e^{-\frac{1}{1000}x} & \text{if } x \ge 0\\ 0 & \text{if } x < 0 \end{cases}$$

$$\overline{F}_X(x) = \mathbf{P}\{X > x\} = e^{-\frac{1}{1000}x}$$

$$P$$
{Job is sent to bin 1} = $F_X(500) = 1 - e^{-\frac{500}{1000}} = 1 - e^{-\frac{1}{2}} \approx 0.39$

Example: Pittsburgh Supercomputing Center (PSC)

At the PSC, jobs are grouped into bins based on their size. Suppose job sizes are Exponentially distributed with *mean* 1000 CPU-hours. Suppose all jobs of size < 500 CPU-hours are sent to bin 1.

b. What is P{Job size < 200 | job is in bin 1}?

$$X \sim Exp\left(\frac{1}{1000}\right)$$

$$f_X(x) = -\begin{bmatrix} \frac{1}{1000}e^{-\frac{1}{1000}x} & \text{if } x \ge 0\\ 0 & \text{if } x < 0 \end{bmatrix}$$

$$\overline{F}_X(x) = \mathbf{P}\{X > x\} = e^{-\frac{1}{1000}x}$$

$$P$$
{Job size < 200 | job is in bin 1} = $\frac{P\{X < 200 \cap bin 1\}}{P\{bin 1\}} = \frac{F_X(200)}{F_X(500)} \approx 0.46$

Example: Pittsburgh Supercomputing Center (PSC)

At the PSC, jobs are grouped into bins based on their size. Suppose job sizes are Exponentially distributed with *mean* 1000 CPU-hours. Suppose all jobs of size < 500 CPU-hours are sent to bin 1.

c. What is $f_{X|A}(x)$, where X is the job size and A is the event that the job is in bin 1?

$$X \sim Exp\left(\frac{1}{1000}\right)$$

$$f_X(x) = -\begin{cases} \frac{1}{1000}e^{-\frac{1}{1000}x} & \text{if } x \ge 0\\ 0 & \text{if } x < 0 \end{cases}$$

$$\overline{F}_X(x) = \mathbf{P}\{X > x\} = e^{-\frac{1}{1000}x}$$

$$f_{X|A}(x) = \frac{f_X(x \cap A)}{P\{A\}} = \frac{f_X(x \cap A)}{F_X(500)} = -\begin{cases} \frac{f_X(x)}{F_X(500)} = \frac{1}{1 - e^{-\frac{1}{2}}} \cdot \frac{1}{1000} e^{-\frac{1}{1000}x} & \text{if } x < 500\\ 0 & \text{otherwise} \end{cases}$$

Example: Pittsburgh Supercomputing Center (PSC)

At the PSC, jobs are grouped into bins based on their size. Suppose job sizes are Exponentially distributed with *mean* 1000 CPU-hours. Suppose all jobs of size < 500 CPU-hours are sent to bin 1.

d. What is *E*[Job size | job is in bin 1]?

$$X \sim Exp\left(\frac{1}{1000}\right)$$

$$f_X(x) = -\begin{cases} \frac{1}{1000}e^{-\frac{1}{1000}x} & \text{if } x \ge 0\\ 0 & \text{if } x < 0 \end{cases}$$

$$\overline{F}_Y(x) = P\{X > x\} = e^{-\frac{1}{1000}x}$$

$$\boldsymbol{E}[\text{Job size } | \text{ job is in bin } 1] = \int_{-\infty}^{\infty} x f_{X|A}(x) dx = \int_{0}^{500} x \cdot \frac{1}{1 - e^{-\frac{1}{2}}} \cdot \frac{1}{1000} e^{-\frac{1}{1000}x} dx \approx 229$$

Example: Pittsburgh Supercomputing Center (PSC)

At the PSC, jobs are grouped into bins based on their size. Suppose job sizes are Exponentially distributed with *mean* 1000 CPU-hours. Suppose all jobs of size < 500 CPU-hours are sent to bin 1.

d. What is *E*[Job size | job is in bin 1]?

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E[Job size | job is in bin 1] \approx 229
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Why is the expected job
size for bin 1
< 250?
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Example: Pittsburgh Supercomputing Center (PSC)

At the PSC, jobs are grouped into bins based on their size. Suppose job sizes are Exponentially distributed with *mean* 1000 CPU-hours. Suppose all jobs of size < 500 CPU-hours are sent to bin 1.

d. What is **E**[Job size | job is in bin 1]?

```
E[Job size | job is in bin 1] \approx 229
```

How would the above answer change if $X \sim Uniform(0,2000)?$



Learning the bias of a coin, or a human





shaky ...

Example:

We're trying to estimate the likelihood that a human will click on an ad. We model the human as coin with unknown bias $P \sim Uniform(0,1)$. The coin has resulted in 10 heads out of the first 10 flips (call this event A).



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Learning a person's bias

Example:

We're trying to estimate the likelihood that a human will click on an ad. We model the human as coin with unknown bias $P \sim Uniform(0,1)$. The coin has resulted in 10 heads out of the first 10 flips (call this event A).

Q: What is $E[P \mid A]$?

A:

$$E[P \mid A] = \int_{0}^{1} f_{P|A}(p) \cdot p \, dp$$

$$f_{P|A}(p) = \frac{P\{A \mid P=p\} \cdot f_{P}(p)}{P\{A\}} = \frac{p^{10} \cdot 1}{P\{A\}}$$
So $f_{P|A}(p) = 11p^{10}$

$$P\{A\} = \int_{0}^{1} P\{A \mid P=p\} \cdot f_{P}(p) dp = \int_{0}^{1} p^{10} \cdot 1 dp = \frac{1}{11}$$



Learning a person's bias

Example:

We're trying to estimate the likelihood that a human will click on an ad. We model the human as coin with unknown bias $P \sim Uniform(0,1)$. The coin has resulted in 10 heads out of the first 10 flips (call this event A).



Q: What is *E*[*P* | *A*]?

A:
$$E[P \mid A] = \int_{0}^{1} f_{P|A}(p) \cdot p \, dp = \int_{0}^{1} 11p^{10} \cdot p dp = \underbrace{11}_{12}$$

Not 1 but close. The answer depends
on the initial assumption
that $P \sim Uniform(0,1)$, which is
referred to as **the prior** (see Chpt 17)
So $f_{P|A}(p) = 11p^{10}$