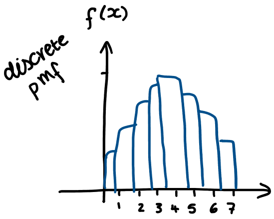
Set 13 and 14 - Continuous Random Variables

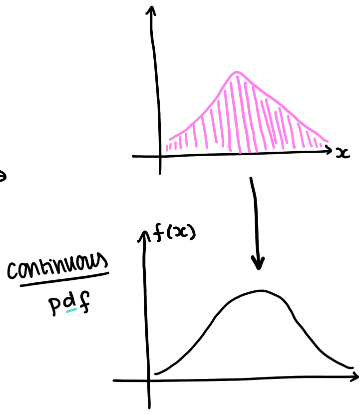
February 13, 2023 1:44 PM

Stat 260 Lecture Notes
Sets 13 and 14 - Continuous Random Variables

Recall: A continuous random variable X has an infinite number of possible values and it's impossible to list them all.

For a discrete random variable we could draw a picture of the pmf $f(x)$ - it looks like a histogram. Imagine making the bars of this histogram thinner and thinner. The top edges of the bars smooth out to a curve - a function. For a continuous random variable X the probability density function (pdf) $f(x)$ is this function.

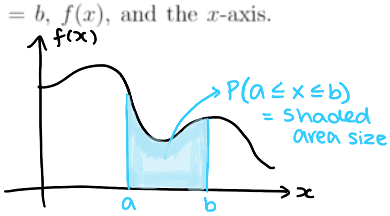




pmf = discrete
pdf = continuous

Rules for the pdf of a continuous random variable X:

- $f(x) \geq 0$ for all x values. (discrete version: probabilities ≥ 0) always above the x-axis
- The area bounded by the graph of $f(x)$ and the x-axis is 1. That is $\int_{-\infty}^{\infty} f(x)\,dx = 1$. (discrete: pmf probabilities sum to 1)
- $P(a \leq X \leq b)$ = area between $x = a$, $x = b$, $f(x)$, and the x-axis. That is, $P(a \leq X \leq b) = \int_a^b f(x)\,dx$.



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Rule: If X is a continuous random variable then for a constant c, $P(X = c) = 0$.

infinitely many

so many choices that getting a specific one is unlikely

This can be derived from $P(X = c) = P(c \leq X \leq c) = \int_c^c f(x)\,dx = 0$.

Since for a constant c we have that $P(X = c) = 0$, we therefore have that $P(a \leq X \leq b) = P(a < X \leq b) = P(a \leq X < b) = P(a < X < b)$.

can drop equality b/c chance of being equat to a or b is 0

Careful! This only applies to continuous random variables. We cannot use this rule if we are working with the binomial distribution or the Poisson distribution (as they are both discrete distributions).

Since $P(X = c) = 0$ for a continuous random variable, when we have a continuous random variable we usually deal with problems like $P(a \leq X \leq b)$ or $P(X \leq a)$ or $P(X \geq a)$.

The cumulative distribution function (cdf) $F(x)$ for a continuous random variable is defined by

$$F(x) = P(X \leq x) = \int_{-\infty}^{x} f(y)\,dy$$

dummy variable

where $f(x)$ is the pdf of the random variable X.

random variable is defined by

$$F(x) = P(X \le x) = \int_{-\infty}^{x} f(y)\,dy$$

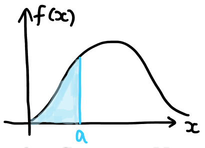
dummy variable

where $f(x)$ is the pdf of the random variable X.

Say $x = a$. Then $F(a)$ is the area under the pdf curve $f(x)$ to the left of the value $x = a$.

$F(a) = P(X \le a) = \text{shaded area} = \int_{-\infty}^{a} f(x)\,dx$

cdf



Rule: Suppose X is a continuous random variable with pdf $f(x)$ and cdf $F(x)$. Then at every x where the derivative $F'(x)$ exists, we have that $f(x) = F'(x)$.

pdf is derivative of cdf
cdf is integral of pmf

Even with using calculus, finding areas under the pdf $f(x)$ curve to solve things like $P(X \le a)$ can be difficult (some integrals may require advanced

techniques such as numerical approximation). In situations like this we often use cdf tables (our stat tables) to look up values for the cdf $F(x) = P(X \le x)$. If we have knowledge of the exact function $F(x)$ for our cdf, we could also evaluate this function at specific x values to calculate probabilities. (For example, if we wanted to find $P(X \le 2)$ we could evaluate the function $F(x)$ at $x = 2$, so we could find $F(2)$.)

Note: For a discrete random variable X,

where w is next smallest value below a. → often this is just a-1

$P(a \le X \le b) = P(X \le b) - P(X < a) = P(X \le b) - P(X \le w)$

not including a

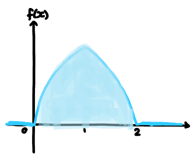
but for a continuous random variable X we have

$P(a \le X \le b) = P(X \le b) - P(X < a)$

$= P(X \le b) - P(X \le a)$ → include a

Example 1: Say X is a continuous random variable with pdf

$$f(x) = \begin{cases} c(4x - 2x^2) & 0 \le x \le 2 \\ 0 & \text{otherwise} \end{cases}.$$



What is the value of c?

We know $1 = \int_{-\infty}^{\infty} f(x)\,dx = \cancel{\int_{-\infty}^{0} 0\,dx} + \int_{0}^{2} c(4x - 2x^2)\,dx + \cancel{\int_{2}^{\infty} 0\,dx}$

$= \int_{0}^{2} c(4x-2x^2)\,dx = \left[c\left(\frac{4x^2}{2} - \frac{2x^3}{3}\right)\right]\Big|_0^2$

$= c\left(\frac{4(2^2)}{2} - \frac{2(2^3)}{3}\right) - 0$

$= \frac{8c}{3}$

So $1 = \frac{8c}{3}$

$\Rightarrow c = \frac{3}{8}.$

Find $P(X > 1)$.

$$P(X>1) = P(X \geq 1) = \int_1^{\infty} f(x)\,dx = \int_1^2 \frac{3}{8}(4x - 2x^2)\,dx$$

$$= \left[\frac{3}{8}\left(\frac{4x^2}{2} - \frac{2x^3}{3}\right)\right]_1^2$$

$$= \frac{3}{8}\left(\frac{4(2)^2}{2} - \frac{2(2)^3}{3}\right) - \frac{3}{8}\left(\frac{4(1)^2}{2} - \frac{2(1)^3}{3}\right) = \frac{1}{2}$$

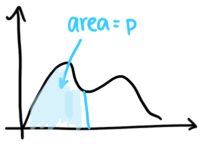
don't have to know how to graph functions

Percentiles: Let p be a value between 0 and 1. The $(100p)^{th}$ **percentile** of the distribution of a continuous random variable X, denoted by $\eta(p)$ is defined by

→ scales decimal

$$p = F(\eta(p)) = \int_{-\infty}^{\eta(p)} f(y)\,dy$$

In other words, $\eta(p)$ is the x value where $F(x) = p$, or rather where $P(X \leq x) = p$.



100pth percentile say it is x_0

Solve for x_0

Example 2: Suppose the pdf of a continuous random variable X is

$$f(x) = \begin{cases} \frac{3}{2}(1-x^2) & 0 \leq x \leq 1 \\ 0 & \text{otherwise} \end{cases}.$$

We can find $F(x)$:

This means that the $(100p)^{th}$ percentile $x = \eta(p)$ satisfies:

For the 50^{th} percentile (that is, when $p = 0.50$) we need to solve:

The **median** $\widetilde{\mu}$ is the 50^{th} percentile. (So using the notation, that is that $\eta(0.50) = \widetilde{\mu}$.) So half the area under $f(x)$ is to the left of $x = \widetilde{\mu}$ and half of the area is to the right.

Expected Value and Variance:

For a discrete random variable X: $\mu_X = E(X) = \sum x \cdot f(x) = \sum x \cdot P(X = x)$

For a continuous random variable X: $\mu_X = E(X) = \int_{-\infty}^{\infty} x \cdot f(x)\, dx$.

(Recall: Geometrically, $E(X)$ is the x value that would "balance" the graph of $f(x)$.)

Example 3: Say the pdf of a continuous random variable X is

$$f(x) = \begin{cases} \frac{3}{2}(1 - x^2) & 0 \leq x \leq 1 \\ 0 & \text{otherwise} \end{cases}.$$

Find $E(X)$.

For a discrete random variable X: $E(g(X)) = \sum g(x) \cdot f(x) = \sum g(x) \cdot P(X = x)$

For a continuous random variable X: $E(g(X)) = \int_{-\infty}^{\infty} g(x) \cdot f(x)\, dx$.

Just like before, $E(aX + b) = aE(X) + b$.

For a discrete random variable X: $\sigma_X^2 = V(X) = E((X-\mu)^2)$

For a continuous random variable X: $\sigma_X^2 = V(X) = E((X-\mu)^2) = \int_{-\infty}^{\infty}(x-\mu)^2 \cdot f(x)\,dx$.

The shortcut formula still holds: $V(X) = E(X^2) - [E(X)]^2 = \int_{-\infty}^{\infty} x^2 \cdot f(x)\,dx - \left(\int_{-\infty}^{\infty} x \cdot f(x)\,dx\right)^2$.

The evaluations of $\int_{-\infty}^{\infty} x^2 \cdot f(x)\,dx$ and $\int_{-\infty}^{\infty} x \cdot f(x)\,dx$ are why Math 101 is a corequisite for this course - note that integration by parts may be a useful technique here.

The standard deviation is still $\sigma_X = \sqrt{V(X)}$.

The Uniform Distribution:

X is a **uniform random variable** if it has pdf $f(x) = c$ where c is a constant.

More specifically, this means that $f(x) = \dfrac{1}{B-A}$ where the possible X values are in the interval $[A, B]$.

For a uniform random variable X, we have that $P(a \leq X \leq b) = \dfrac{b-a}{B-A}$.

Example 5: Suppose a person is just as likely to arrive at the bus stop any time between 7am and 7:30am. What is the probability that they arrive between 7:05am and 7:15am?

Example 6: Let X have a uniform distribution on the interval $[A, B]$. What is the cdf of X? That is, find $F(x)$.