PLSC 502 – Autumn 2016 Random Variables

September 22, 2016

Continuous and Discrete Variables

Discrete Variables

- $X \in S = \{s_0, s_1, ...\}$
- $Pr(s) \ge 0$ for each $s \in S$
- $\sum \Pr(s) = 1$

Continuous Variables

- $X \in S \in \mathfrak{R}$
- $\exists f(x)$ such that for any closed interval [a, b] $Pr(a < x \le b) = \int_{b}^{a} f(x) dx$.
- Requires:
 - $f(x) \ge 0$ for all x
 - $\int_{-\infty}^{\infty} f(x) dx = 1$

Probability Density Function

The PDF is the function f(x) that maps the possible values of X to some associated probability of their occurrence.

Discrete X:

$$f(x) = \Pr(X = x) \forall x$$

Continuous X:

$$\Pr(a < X \le b) = \int_a^b f(x) \, dx$$

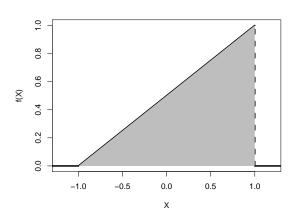
Again: Requires:

- $f(x) \ge 0$ for all x
- $\int_{-\infty}^{\infty} f(x) dx = 1$

An Example

Consider:

$$f(X) = \begin{cases} \frac{X+1}{2} & \text{for } -1 \leq y < 1, \\ 0 & \text{otherwise.} \end{cases}$$



- 1. Is $f(x) \ge 0 \forall x$? Yes.
- 2. Is $Pr(-\infty \le x \le \infty) \equiv Pr(-1 \le x \le 1) = \int_{-1}^{1} f(x) dx = 1$?

$$Pr(-1 \le Y \le 1) = \int_{-1}^{1} \frac{1}{2}(x+1)dx$$

$$= \frac{1}{2} \left(\frac{X^{2}}{2} + x\right) \Big|_{-1}^{1}$$

$$= \frac{1}{2} \left(\frac{1^{2}}{2} + 1\right) - \frac{1}{2} \left(\frac{-1^{2}}{2} - 1\right)$$

$$= 0.75 - (-0.25)$$

$$= 1.$$

Cumulative Distribution Function (CDF)

The CDF is the probability that X will take on a value less than or equal to than some value x in its range.

Discrete X:

$$Pr(X \le x) \equiv F(x) = \sum_{X \le x} Pr(X = x)$$

= $1 - \sum_{X \ge x} Pr(X = x)$

CDF (continued)

Continuous X:

$$\Pr(X \le x) \equiv F(x) = \int_{-\infty}^{x} f(t) dt$$

Properties:

- $0 \le F(x) \le 1$.
- Nondecreasing in X.
- $\Pr(x < k) = 1 F(k)$.
- $Pr(a < x \le b) = F(b) F(a)$.
- $F(-\infty)=0$.
- $F(\infty) = 1$.

Example, Again

For

$$f(x) = \begin{cases} \frac{1}{2}(x+1) & \text{for } -1 \leq y < 1, \\ 0 & \text{otherwise.} \end{cases}$$

we already know that $\int_{-1}^{1} f(x) dx = 1$.

$$F(x) = \int_{-1}^{1} f(t)dt$$

$$= \int_{-1}^{1} \frac{1}{2}(t+1)dt$$

$$= \frac{1}{2} \left(\frac{t^{2}}{2} + t\right) \Big|_{-1}^{1}$$

$$= \frac{1}{2} \left(\frac{1}{2}t^{2} + t\right) + c.$$

Expected Value

For X with PDF f(x) and CDF $F(x) = \int_{-\infty}^{x} f(t) dt$, the expected value of X (E(X) or μ) is the probability-weighted mean of the potential values of that variable.

Discrete X:

$$\mathsf{E}(X) = \sum_{x} [x \times f(x)]$$

E.g., number of heads in two coin flips:

0 Heads	Prob. = .25	$Prob \times Value = .25 \times 0$	=	0
1 Head	Prob. = .50	$Prob{\times}Value = .50{\times}1$	=	.50
2 Heads	Prob. = .25	$Prob{\times}Value = .25{\times}2$	=	.50
		\sum	=	1.0

Expected Value (continued)

Continuous *X*:

$$E(X) = \int [x \times f(x)] dx$$

Properties:

- E(c) = c
- E(x + y + z) = E(x) + E(y) + E(z)
- If g(x) is some function of x, then

$$E[g(x)] = \sum [g(x) \times Prob(X = x)] \forall x \text{ (discrete case)}$$
$$= \int g(x)f(x) dx \text{ (continuous case)}$$

- This includes a constant function:E(cx) = cE(x).
- Implies that for g(x) = a + bx, E(a + bx) = a + bE(x).

Example Again

For

$$f(x) = \begin{cases} \frac{1}{2}(x+1) & \text{for } -1 \le y < 1, \\ 0 & \text{otherwise.} \end{cases}$$

What is E(X)?

$$E[f(X)] = \int_{-1}^{1} x \left(\frac{x+1}{2}\right) dx$$

$$= \int_{-1}^{1} \frac{1}{2} (x^{2} + x) dx$$

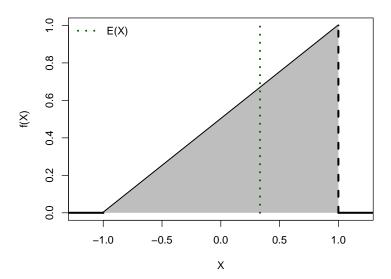
$$= \frac{1}{2} \int_{-1}^{1} x^{2} dx + \frac{1}{2} \int_{-1}^{1} x dx$$

$$= \frac{1}{2} \left(\frac{x^{3}}{3} + c_{1}\right) \Big|_{-1}^{1} + \frac{1}{2} \left(\frac{x^{2}}{2} + c_{2}\right) \Big|_{-1}^{1}$$

$$= \frac{1}{2} \left(\frac{x^{3}}{3} + \frac{x^{2}}{2} + c_{3}\right) \Big|_{-1}^{1}$$

$$= \frac{1}{2} \left[\left(\frac{1^{3}}{3} + \frac{1^{2}}{2} + c_{3}\right) - \left(\frac{-1^{3}}{3} + \frac{-1^{2}}{2} + c_{3}\right) \right]$$

$$= \frac{1}{3}$$



Variance

Generally:

$$Var(X) = E[(x - \mu)^2]$$

Discrete X:

$$\mathsf{Var}(X) = \sum (x - \mu)^2 f(x)$$

Continuous X:

$$Var(X) = \int (x - \mu)^2 f(x) \, dx$$

Variance (continued)

$$E[(x - \mu)^{2}] \equiv \sigma^{2} = E[x^{2} - 2x\mu + \mu^{2}]$$

$$= E(x^{2}) - 2\mu E(x) + E(\mu^{2})$$

$$= E(x^{2}) - 2\mu^{2} + \mu^{2}$$

$$= E(x^{2}) - \mu^{2}$$

$$\equiv \left(\int x^{2} f(x) dx - \mu^{2}\right)$$

- We often write the variance as σ^2 , and the positive square root of it (the standard deviation) as σ .
- This also implies that the expectation of the square of a variable X is $E(x^2) = \sigma^2 + \mu^2$.

Variance Properties

- Var(X) > 0, except
- Var(c) = 0
- $Var(a + bX) = b^2 Var(X)$
- Var(X + Y) = Var(X) + Var(Y) + 2Cov(X, Y)

Example Again

What is the variance of $f(X) = \frac{1}{2}(x+1)$ for the range -1 < x < 1?

Recall that $\mu = 1/3$:

$$\begin{split} \mathsf{E}[(x-\mu)^2] &\equiv \sigma^2 &= \int_{-1}^1 X^2 f(x) \, dx - \mu^2 \\ &= \int_{-1}^1 \frac{1}{2} x^2 (x+1) \, dx - \left(\frac{1}{3}\right)^2 \\ &= \frac{1}{2} \left(\frac{x^4}{4} + c_1\right) \Big|_{-1}^1 + \frac{1}{2} \left(\frac{x^3}{3} + c_2\right) \Big|_{-1}^1 - \frac{1}{9} \\ &= \frac{1}{2} \left(\frac{X^4}{4} + \frac{X^3}{3} + c_3\right) \Big|_{-1}^1 - \frac{1}{9} \\ &= \frac{1}{2} \left[\left(\frac{1^4}{4} + \frac{1^3}{3} + c_3\right) - \left(\frac{-1^4}{4} + \frac{-1^3}{3} + c_3\right) \right] - \frac{1}{9} \\ &= \frac{19}{72} \left(\approx 0.2639 \right). \end{split}$$

Moments, redux

The kth moment of X is:

$$M_k = \mathsf{E}(X^k)$$

The kth moment exists if:

$$E(|X|^k) < \infty$$

$$= \int_{-\infty}^{\infty} |x|^k f(x) dx < \infty \text{ (for continuous } X\text{)}$$

"Central" moments:

$$\mu_k = \mathsf{E}[(X - \mu)^k]$$

Moment-Generating Functions

For $t \in \mathfrak{R}$,

$$\psi(t) = \mathsf{E}[\mathsf{exp}(tX)]$$

For continuous X:

$$\psi(t) = \int_{-\infty}^{\infty} \exp(tx)f(x)dx$$

$$= \int_{-\infty}^{\infty} \left(1 + tx + \frac{t^2x^2}{2!} + \dots\right)f(x)dx$$

$$= 1 + tE(X) + \frac{t^2E(X^2)}{2} + \dots$$

$$= 1 + tM_1 + \frac{t^2M_2}{2} + \dots$$

Note that:

$$\psi(0) = \mathsf{E}[\mathsf{exp}(0)]$$
$$= 1$$

MGFs Can Be Useful

First:

$$\psi(t) = \int_{-\infty}^{\infty} \exp(tx) \, dF(x).$$

Second:

$$\frac{\partial^{k} \psi(t)}{\partial^{k} t} \Big|_{t=0} = \frac{\partial^{k} \mathbb{E}[\exp(tX)]}{\partial^{k} t} \Big|_{t=0}$$

$$= \mathbb{E}\left[\frac{\partial^{k} \exp(tX)}{\partial^{k} t} \Big|_{t=0}\right]$$

$$= \mathbb{E}\{[X^{k} \exp(tX)]|_{t=0}\}$$

$$= \mathbb{E}(X^{k})$$