

# PLSC 502 – Fall 2022

## Probability and Random Variables

September 22, 2022

Some concepts:

- **X**: *A random variable*
- **Outcome**: A possible event / result of a process
- **Realization**: One observation of the process ( $x$ )
- **Sample Space ( $S$ )**: The set of all possible outcomes

# What is a “Random Variable”?

Formally:

$$X : S \rightarrow M$$

where  $M$  is a *measurable space*. Often:

$$X : S \rightarrow \mathbb{R}$$

where  $\mathbb{R}$  are the real numbers.

More informally, a random variable is a formalization of an event or process in which the result is subject to unmeasured (and unaccounted-for) variation.

# Sample Spaces

For a *discrete* variable  $X$ :

$$X \in S = \{x_1, x_2, \dots, x_J\}$$

For a *continuous*  $X$ :

$$X \in S = [\ell, \tau].$$

E.g., for points in the English Premier League (match week six, that we discussed last class):

$$X \in S = \{0, 1, 2, \dots, 17, 18\}$$

and a realization of that random variable is:

$$X_{\text{Spurs}} = 14.$$

# Probability (*Frequentist*)

Probability = *Long-run relative frequency*.

$$\Pr(\text{Event}) = \frac{\text{The number of times the event of interest can or could occur}}{\text{The number of times any event can or could occur}}.$$

More formally:

$$\Pr(X = x) = \lim_{N \rightarrow \infty} \left( \frac{\sum_N I\{X_i = x\}}{N} \right)$$

where  $I\{\cdot\}$  is an *indicator function* for  $X_i = x$ .

# Probability: Characteristics

- Probabilities necessarily **range between zero and one**:

$$\Pr(X = x) \in [0, 1].$$

- The **sum of probabilities for all outcomes always equals one**:

$$\sum_{j=1}^J \Pr(X = x_j) \equiv \Pr(S) = 1.0$$

# The Multiplication Rule

The probability of obtaining a *combination* of independent, mutually exclusive outcomes is equal to the *product* of their separate probabilities.

Formally:

$$\Pr(X = x_j \cap X = x_\ell) = \Pr(X = x_j) \times \Pr(X = x_\ell), \quad j \neq \ell$$

# The Addition Rule

The probability of obtaining *any one* (or more) of several independent, mutually exclusive outcomes is equal to the *sum* of the probabilities for those events.

Formally:

$$\Pr(X = x_j \cup X = x_\ell) = \Pr(X = x_j) + \Pr(X = x_\ell), \quad j \neq \ell$$



## Addition Rule (continued)

If events are not mutually exclusive:

$$\Pr(X = x_j \cup X = x_\ell) = \Pr(X = x_j) + \Pr(X = x_\ell) - \Pr(X = x_j \cap X = x_\ell)$$

So, for example,  $\Pr(\text{Diamond or face-card})$ :

$$\begin{aligned}\Pr(Z) &= \Pr(\text{Diamond}) + \Pr(\text{Face-Card}) \\ &\quad - \Pr(\text{Diamond-Suited Face Card}) \\ &= \frac{1}{4} + \frac{12}{52} - \frac{3}{52} \\ &= 0.25 + 0.23 - 0.06 \\ &= \mathbf{0.42}\end{aligned}$$

Consider  $\Pr(X = x_j, X = x_\ell) = \Pr(X = x_j \cap X = x_\ell)$  (“joint PDF”)...

If  $x_j$  and  $x_\ell$  are *independent*:

- $\Pr(X = x_j, X = x_\ell) = \Pr(X = x_j) \times \Pr(X = x_\ell)$ .
- That is, *the joint PDF is equal to the product of the marginal PDFs*.
- We write  $X_j \perp X_\ell$ .

# Conditional Probability

If  $x_j$  and  $x_\ell$  are *not independent*...

Conditional probabilities:

- I.e.,  $\Pr(X = x_j | X = x_\ell)$  and/or  $\Pr(X = x_\ell | X = x_j)$
- Say “The probability of  $x_j$  given  $x_\ell$ ,” etc.

Implies:

$$\Pr(X = x_j | X = x_\ell) = \frac{\Pr(X = x_j, X = x_\ell)}{\Pr(X = x_\ell)}, \text{ and}$$

$$\Pr(X = x_\ell | X = x_j) = \frac{\Pr(X = x_j, X = x_\ell)}{\Pr(X = x_j)}$$

# Independence, Defined

If two variables are *independent*, then:

$$\begin{aligned}\Pr(X = x_j | X = x_\ell) &= \frac{\Pr(X = x_j, X = x_\ell)}{\Pr(X = x_\ell)} \\ &= \frac{\Pr(X = x_j) \times \Pr(X = x_\ell)}{\Pr(X = x_\ell)} \\ &= \Pr(X = x_j)\end{aligned}$$

Holds for any number of realizations; e.g. for  $x_j$ ,  $x_\ell$ , and  $x_k$ :

$$\begin{aligned}\Pr(X = x_j, X = x_\ell, X = x_k) &= \Pr(X = x_j | X = x_\ell, X = x_k) \\ &\quad \times \Pr(X = x_\ell | X = x_k) \\ &\quad \times \Pr(X = x_k)\end{aligned}$$

# Bayes' Rule

Because  $\Pr(X = x_j, X = x_\ell) = \Pr(X = x_\ell, X = x_j)$ , we can write:

$$\Pr(X = x_j|X = x_\ell) \times \Pr(X = x_\ell) = \Pr(X = x_\ell|X = x_j) \times \Pr(X = x_j)$$

and so:

$$\Pr(X = x_j|X = x_\ell) = \frac{\Pr(X = x_\ell|X = x_j) \times \Pr(X = x_j)}{\Pr(X = x_\ell)}.$$

# More Bayes' Rule

Generally:

$$\Pr(A|B) = \frac{\Pr(B|A) \times \Pr(A)}{\Pr(B)}$$

Informally:

$$\text{Posterior} = \frac{\text{Likelihood} \times \text{Prior}}{\text{Marginal}}$$

# Probability: Frequentist and Bayesian

“Frequentist”: Probability is the long-run relative frequency of an event.

- Sometimes: “physical” probability (a la a physical system) or “objective”
- E.g., Laplace, Neyman, Pearson, Fisher

“Bayesian”: Probability is the best subjective belief about the state of an event.

- Sometimes: “epistemic” (or “subjective”) probability
- E.g., Savage, de Finetti, Jeffreys, Wald

# Probability and Odds

$$\begin{aligned}\text{Odds}(X = x_j) &= \frac{\Pr(X = x_j)}{\Pr(X \neq x_j)} \\ &= \frac{\Pr(X = x_j)}{1 - \Pr(X = x_j)}\end{aligned}$$

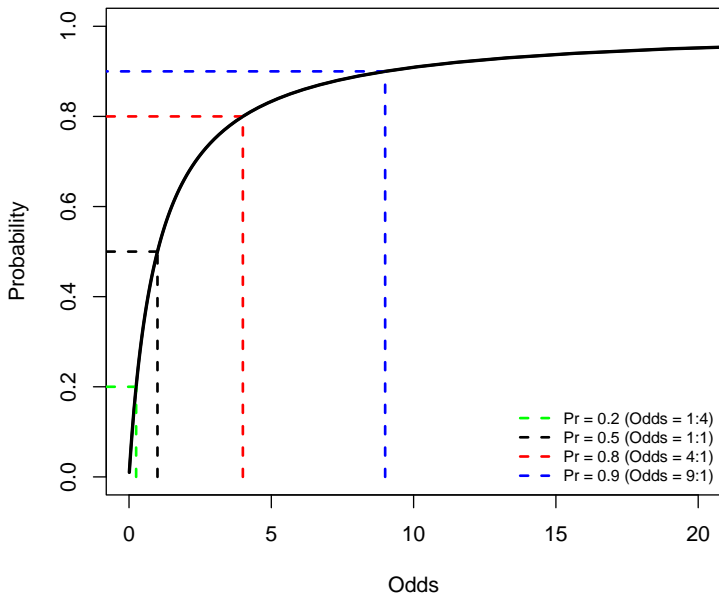
Often written as  $\Pr(X = x_j) : [1 - \Pr(X = x_j)]$ .

E.g., “The odds of  $x_j$  are 4:1 (in favor)”:

- $\Pr(X = x_j) = \frac{4}{4+1} = 0.8$
- $\Pr(X \neq x_j) = \frac{1}{4+1} = 0.2$



# Probability and Odds



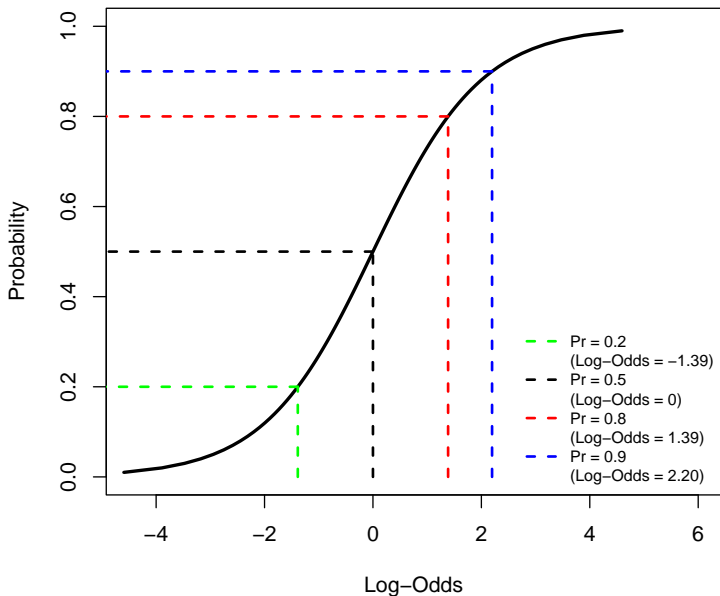
Log-odds:

$$\begin{aligned}\ln[\text{Odds}(X = x_j)] &= \ln \left[ \frac{\Pr(X = x_j)}{\Pr(X \neq x_j)} \right] \\ &= \ln \left[ \frac{\Pr(X = x_j)}{1 - \Pr(X = x_j)} \right]\end{aligned}$$

Note that:

- Odds  $\in [0, \infty)$ , but
- Log-odds  $\in (-\infty, \infty)$ .

# Log-Odds and Probability



For  $N$  realizations of  $X$ :

$$\begin{aligned}X_1 &= x_1 \\X_2 &= x_2 \\X_3 &= x_3 \\\vdots &\quad \vdots \\X_N &= x_N\end{aligned}$$

Likelihood:

$$L(X) = \Pr(X_1 = x_1, X_2 = x_2, \dots, X_N = x_N)$$

## Likelihood (continued)

If  $X_j \perp X_k \forall j, k$  then

$$\begin{aligned} L(X) &= \Pr(X_1 = x_1) \times \Pr(X_2 = x_2) \times \dots \times \Pr(X_N = x_N) \\ &= \prod_{i=1}^N \Pr(X_i = x_i). \end{aligned}$$

Log-Likelihood:

$$\begin{aligned} \ln L(X) &= \ln \left[ \prod_{i=1}^N \Pr(X_i = x_i) \right] \\ &= \sum_{i=1}^N \ln[\Pr(X_i = x_i)] \end{aligned}$$

# Random Variables

# Continuous and Discrete Variables

## Discrete Variables

- $X \in S = \{s_0, s_1, \dots\}$
- $\Pr(s) \geq 0$  for each  $s \in S$
- $\sum_{s \in S} \Pr(s) = 1$

## Continuous Variables

- $X \in S \in \mathfrak{R}$
- $\exists f(x)$  such that for any closed interval  $[a, b]$   
 $\Pr(a < x \leq b) = \int_a^b f(x) dx.$
- Requires:
  - $f(x) \geq 0$  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  $X$ :

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

Continuous  $X$ :

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

Again: Requires:

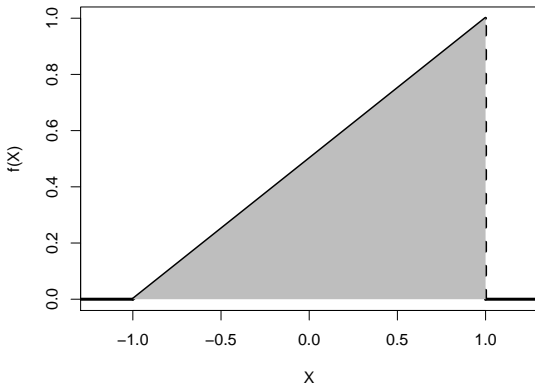
- $f(x) \geq 0$  for all  $x$
- $\int_{-\infty}^{\infty} f(x) dx = 1$



# An Example

Consider:

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



# Is It A PDF?

1. Is  $f(X) \geq 0 \forall x$ ? – Yes.

2. Is

$$\begin{aligned}\Pr(-\infty \leq x \leq \infty) &\equiv \Pr(-1 \leq x \leq 1) \\ &= \int_{-1}^1 f(x)dx = 1?\end{aligned}$$

Let's see:

$$\begin{aligned}\Pr(-1 \leq x \leq 1) &= \int_{-1}^1 \frac{1}{2}(x+1)dx \\ &= \frac{1}{2} \left( \frac{x^2}{2} + x \right) \Big|_{-1}^1 \\ &= \frac{1}{2} \left( \frac{1^2}{2} + 1 \right) - \frac{1}{2} \left( \frac{-1^2}{2} - 1 \right) \\ &= 0.75 - (-0.25) \\ &= 1\end{aligned}$$

# 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  $X$ :

$$\begin{aligned}\Pr(X \leq x) \equiv F(x) &= \sum_{X \leq x} \Pr(X = x) \\ &= 1 - \sum_{X > x} \Pr(X = x)\end{aligned}$$

## Continuous $X$ :

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

## Properties:

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

## Example, Again

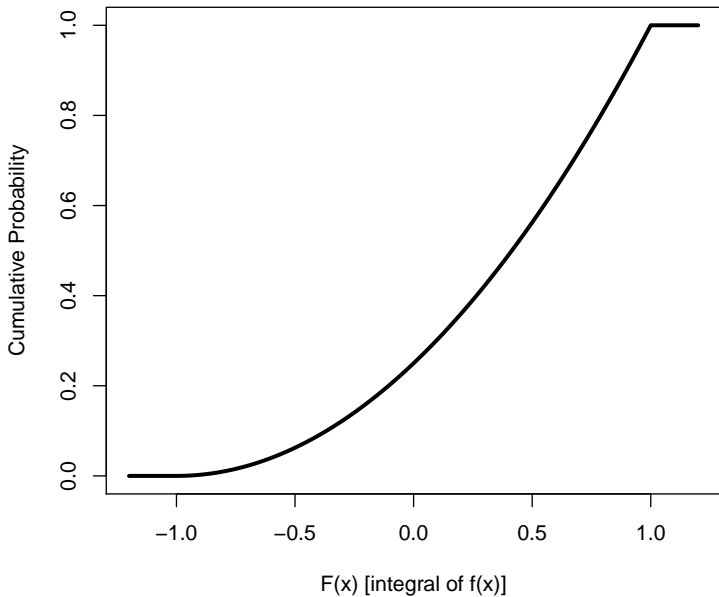
For:

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

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

$$\begin{aligned} F(x) &= \int_{-1}^1 f(t)dt \\ &= \int_{-1}^1 \frac{1}{2}(t+1)dt \\ &= \frac{1}{2} \left( \frac{t^2}{2} + t \right) \Big|_{-1}^1 \\ &= \frac{1}{2} \left( \frac{t^2}{2} + t \right) + c. \end{aligned}$$

# Example CDF, Illustrated



# Expected Value

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

Discrete  $X$ :

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

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
			$\Sigma$	= 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

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

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



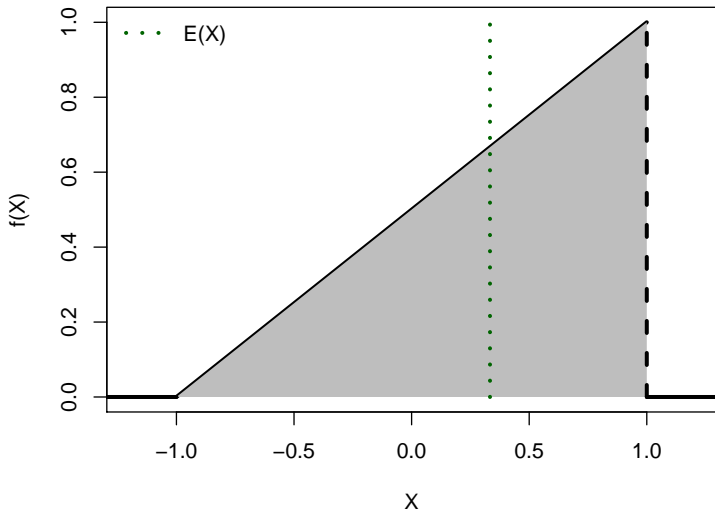
## Example Again

For random variable  $X$  with

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

What is  $E(X)$ ?

$$\begin{aligned} E(X) &= \int_{-1}^1 x \left( \frac{x+1}{2} \right) dx \\ &= \int_{-1}^1 \frac{1}{2}(x^2 + x) dx \\ &= \frac{1}{2} \int_{-1}^1 x^2 dx + \frac{1}{2} \int_{-1}^1 x dx \\ &= \frac{1}{2} \left( \frac{x^3}{3} + c_1 \right) \Big|_{-1}^1 + \frac{1}{2} \left( \frac{x^2}{2} + c_2 \right) \Big|_{-1}^1 \\ &= \frac{1}{2} \left( \frac{x^3}{3} + \frac{x^2}{2} + c_3 \right) \Big|_{-1}^1 \\ &= \frac{1}{2} \left[ \left( \frac{1^3}{3} + \frac{1^2}{2} + c_3 \right) - \left( \frac{-1^3}{3} + \frac{-1^2}{2} + c_3 \right) \right] \\ &= \frac{1}{3} \end{aligned}$$



Generally:

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

Discrete  $X$ :

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

Continuous  $X$ :

$$\text{Var}(X) = \int (x - \mu)^2 f(x) dx$$

## Variance (continued)

$$\begin{aligned} E[(x - \mu)^2] \equiv \sigma^2 &= E[x^2 - 2x\mu + \mu^2] \\ &= E(x^2) - 2\mu E(x) + E(\mu^2) \\ &= E(x^2) - 2\mu^2 + \mu^2 \\ &= E(x^2) - \mu^2 \\ &\equiv \left( \int x^2 f(x) dx - \mu^2 \right) \end{aligned}$$

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

# Variance Properties

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

## Example Again

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

Recall that  $\mu = 1/3$ , so:

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

The  $k$ th moment of  $X$  is:

$$M_k = E(X^k)$$

The  $k$ th moment exists if:

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

“Central” moments:

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

# Moment-Generating Functions

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

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

For continuous  $X$ :

$$\begin{aligned}\psi(t) &= \int_{-\infty}^{\infty} \exp(tx) f(x) dx \\ &= \int_{-\infty}^{\infty} \left( 1 + tx + \frac{t^2 x^2}{2!} + \dots \right) f(x) dx \\ &= 1 + tE(X) + \frac{t^2 E(X^2)}{2} + \dots \\ &= 1 + tM_1 + \frac{t^2 M_2}{2} + \dots\end{aligned}$$

Note that:

$$\begin{aligned}\psi(0) &= E[\exp(0)] \\ &= 1\end{aligned}$$



# MGFs Can Be Useful

First:

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

Second:

$$\begin{aligned} \left. \frac{\partial^k \psi(t)}{\partial^k t} \right|_{t=0} &= \left. \frac{\partial^k E[\exp(tX)]}{\partial^k t} \right|_{t=0} \\ &= E \left[ \left. \frac{\partial^k \exp(tX)}{\partial^k t} \right|_{t=0} \right] \\ &= E\{[X^k \exp(tX)]|_{t=0}\} \\ &= E(X^k) \end{aligned}$$

Next time: Probability  
Distributions