
Conditional Probability

$$P(\text{die} \mid \text{hand})$$

conditional probability and the chain rule

General defn: $P(E | F) = \frac{P(EF)}{P(F)}$ where $P(F) > 0$

Implies: $P(EF) = P(E|F) P(F)$ (“the chain rule”)

General definition of Chain Rule:

$$P(E_1 E_2 \cdots E_n) = P(E_1)P(E_2 | E_1)P(E_3 | E_1, E_2) \cdots P(E_n | E_1, E_2, \dots, E_{n-1})$$

law of total probability

$$\begin{aligned} P(E) &= P(EF) + P(EF^c) \\ &= P(E|F) P(F) + P(E|F^c) P(F^c) \\ &= P(E|F) P(F) + P(E|F^c) (1-P(F)) \end{aligned}$$

weighted average,
conditioned on event
F happening or not.

More generally, if F_1, F_2, \dots, F_n partition S (mutually exclusive, $\bigcup_i F_i = S, P(F_i) > 0$), then

$$P(E) = \sum_i P(E|F_i) P(F_i)$$

weighted average,
conditioned on events
 F_i happening or not.

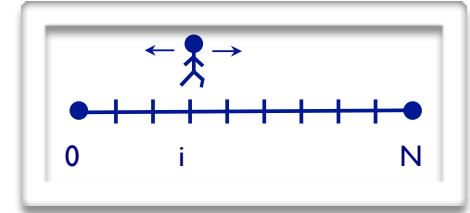
(Analogous to reasoning by cases; both are very handy.)

Gambler's ruin

BT pg. 63

A gambler makes a series of independent bets. In each bet, he wins \$1 with probability $\frac{1}{2}$ and loses \$1 with probability $\frac{1}{2}$. He starts with \$k.

What is the probability he makes \$N before he goes broke?



aka "Drunkard's Walk"

nice example of the utility of conditioning: future decomposed into two crisp cases instead of being a blurred superposition thereof

$$p_i = P(E_i) = P(E_i | H)P(H) + P(E_i | T)P(T)$$

$$p_i = \frac{1}{2}(p_{i+1} + p_{i-1})$$

$$2p_i = p_{i+1} + p_{i-1}$$

$$p_{i+1} - p_i = p_i - p_{i-1}$$

$$p_2 - p_1 = p_1 - p_0 = p_1, \text{ since } p_0 = 0$$

So: $p_2 = 2p_1$

...

$$p_i = ip_1$$

$$p_N = Np_1 = 1$$

$$p_i = i/N$$

Most common form:

$$P(F | E) = \frac{P(E | F)P(F)}{P(E)}$$

Expanded form (using law of total probability):

$$P(F | E) = \frac{P(E | F)P(F)}{P(E | F)P(F) + P(E | F^c)P(F^c)}$$

Why it's important:

Reverse conditioning

$P(\text{model} | \text{data}) \sim P(\text{data} | \text{model})$

Combine new evidence (E) with prior belief (P(F))

Posterior vs prior

	HIV+	HIV-
Test +	0.98 = $P(E F)$	0.01 = $P(E F^c)$
Test -	0.02 = $P(E^c F)$	0.99 = $P(E^c F^c)$

0.5% of population has HIV

Let E = you test positive for HIV

Let F = you actually have HIV

What is $P(F|E)$?

$$\begin{aligned}
 P(F | E) &= \frac{P(E | F)P(F)}{P(E | F)P(F) + P(E | F^c)P(F^c)} \\
 &= \frac{(0.98)(0.005)}{(0.98)(0.005) + (0.01)(1 - 0.005)} \\
 &\approx 0.330
 \end{aligned}$$

↖ $P(E) \approx 1.5\%$

Note difference between conditional and joint probability: $P(F|E) = 33\%$; $P(FE) = 0.49\%$

why testing is still good

	HIV+	HIV-
Test +	0.98 = $P(E F)$	0.01 = $P(E F^c)$
Test -	0.02 = $P(E^c F)$	0.99 = $P(E^c F^c)$

Let E^c = you test **negative** for HIV

Let F = you actually have HIV

What is $P(F|E^c)$?

$$\begin{aligned} P(F | E^c) &= \frac{P(E^c | F)P(F)}{P(E^c | F)P(F) + P(E^c | F^c)P(F^c)} \\ &= \frac{(0.02)(0.005)}{(0.02)(0.005) + (0.99)(1 - 0.005)} \\ &\approx 0.0001 \end{aligned}$$