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Review: Basic Axioms and Joint Probability

1. For any event a , $0 \leq P(a) \leq 1$.
2. $P(True) = 1$ and $P(False) = 0$.
3. $P(a \vee b) = P(a) + P(b) - P(a \wedge b)$.

- ▶ For random variables, $\{X_1, X_2, \dots, X_n\}$, the **joint distribution** gives the probability of each possible combination of outcomes

	StudentXGrade = A	StudentXGrade = B
StudentYGrade = A	0.72	0.08
StudentYGrade = B	0.18	0.02

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Review: Marginal Probability

	StudentXGrade = A	StudentXGrade = B
StudentYGrade = A	0.72	0.08
StudentYGrade = B	0.18	0.02

- ▶ Given the joint distribution we can get the probability of any outcome by **marginalizing**: summing all values where the outcome we want is true

- ▶ For example, probability student X gets an A:

$$P(\text{StudentXGrade} = A) = (0.72 + 0.18) = 0.9$$

- ▶ Probability that *either* X or Y gets an A:

$$\begin{aligned} P(\text{StudentXGrade} = A \vee \text{StudentYGrade} = A) \\ = (0.72 + 0.18 + 0.08) = 0.98 \end{aligned}$$

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Marginalizing and Conditioning

- ▶ For any variable X , the probability of one outcome, x , can be found by **marginalizing** over all the possible event combinations for the other variables that we have:

$$\begin{aligned} P(X = x) &= \sum_{\mathbf{y} \in \mathbf{Y}} P(X = x, \mathbf{y}) \\ &= \sum_{y_1 \in Y_1} \sum_{y_2 \in Y_2} \dots \sum_{y_n \in Y_n} P(X = x, Y_1 = y_1, Y_2 = y_2, \dots, Y_n = y_n) \end{aligned}$$

Note: comma notation here means AND (\wedge)

- ▶ By product rule, this is equivalent to **conditioning** on \mathbf{Y} :

$$\begin{aligned} P(X = x) &= \sum_{\mathbf{y} \in \mathbf{Y}} P(X = x | \mathbf{y}) P(\mathbf{y}) \\ &= \sum_{y_1 \in Y_1} \sum_{y_2 \in Y_2} \dots \sum_{y_n \in Y_n} P(X = x | Y_1 = y_1, \dots, Y_n = y_n) P(Y_1 = y_1, \dots, Y_n = y_n) \end{aligned}$$

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Additional Ideas: Chain Rule

- ▶ We already have the **product rule**:

$$P(a \wedge b) = P(a | b)P(b)$$

- ▶ Remember that b here can be *any* proposition, including a combination of different events
- ▶ Thus, using commas to mean AND (\wedge), we can apply the product rule over and over, giving us the **chain rule**:

$$\begin{aligned}P(a, b, c, d) &= P(a | b, c, d)P(b, c, d) \\&= P(a | b, c, d)P(b | c, d)P(c, d) \\&= P(a | b, c, d)P(b | c, d)P(c | d)P(d)\end{aligned}$$

▶

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Additional Ideas: Conditionalized Product Rule

- ▶ We can prove a form of product rule for cases where we have conjunction of two things (a, b) and some *further evidence*, e
- ▶ By the basic definition of **conditional probability**:

$$P(a, b | e) = \frac{P(a, b, e)}{P(e)}$$

- ▶ Which gives us, by the **chain rule**, a **conditionalized product rule**:

$$\begin{aligned}P(a, b | e) &= \frac{P(a | b, e) P(b, e)}{P(e)} \\&= P(a | b, e) \frac{P(b, e)}{P(e)} \\&= P(a | b, e) P(b | e)\end{aligned}$$

▶

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A Question to Ponder

- ▶ HIV is rare (1 million people of 300 million in US, or 0.33% have it), but it does occur
 - ▶ Suppose an HIV test is **98% accurate**, namely:
 - ▶ If you have HIV, says **YES** with probability 0.98
- $$P(PosTest | HaveHIV) = 0.98$$
- ▶ If you do not, says **NO** with probability 0.98
- $$P(\neg PosTest | \neg HaveHIV) = 0.98$$
- $$P(PosTest | \neg HaveHIV) = 0.02$$
- ▶ Now, suppose that you *do* test positive: what is the probability that you actually have HIV?

$$P(HaveHIV | PosTest) = ?$$

▶

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The Test-Positivity Question

- ▶ If HIV test is 98% accurate, and 0.33% of people have it, what is the chance that you have it, if you test positive?
- ▶ We want to calculate the chance:

$$P(HaveHIV | PosTest) = ?$$

- ▶ But this is *not the same* as:

$$P(PosTest | HaveHIV) = 0.98$$

- ▶ Believing that these are the same leads to some of the worst errors seemingly rational human beings can make!

▶

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Bayes' Rule



- ▶ Derived by Rev. Thomas Bayes (1702–1761), and published after his death
- ▶ Allows us to take *known* conditional and prior probabilities and calculate *new* conditionals
- ▶ Central to reasoning from evidence and diagnosis in AI systems

Statement of the Rule

- ▶ We can derive Bayes' Rule from dual forms of product rule:

$$P(a \wedge b) = P(a | b) P(b)$$

$$P(a \wedge b) = P(b | a) P(a)$$

- ▶ Which means, since the left-hand sides are equal:

$$P(b | a) P(a) = P(a | b) P(b)$$

$$P(b | a) = \frac{P(a | b) P(b)}{P(a)}$$

- ▶ If we know how likely *a* is given *b*, and how likely *a* and *b* are by themselves, we can now calculate how likely *b* is given *a*

An Example of Using the Rule

- ▶ My cell-phone screen is broken, and I no longer know if it's on silent mode or not at any time (unless it rings)
 - ▶ I press buttons randomly to change the mode
 - ▶ With 5 possible modes, what is the probability that it is now on silent (assuming uniformity)?
- ▶ Now, my wife is supposed to call at 3:00 PM; by 4:00, no call has yet arrived...
 - ▶ How does this affect the probability?

An Exact Calculation

- ▶ I know that if the phone is on silent, I will *certainly* get no call (probability 1.0)
- ▶ I estimate a 1% chance that if the phone were *not* on silent, my wife still wouldn't call when she said she would

$$\begin{aligned} P(Off | NoCall) &= \frac{P(NoCall | Off)P(Off)}{P(NoCall)} \\ &= \frac{P(NoCall | Off)P(Off)}{(P(NoCall | Off)P(Off)) + (P(NoCall | \neg Off)P(\neg Off))} \\ &= \frac{1.0 \times 0.2}{(1.0 \times 0.2) + (0.01 \times 0.8)} = \frac{0.2}{0.2008} \approx 0.996 \end{aligned}$$

- ▶ There is a *much higher* probability that my phone is *actually* on silent, conditional on the new evidence I have experienced

Generalizing the Rule

- ▶ Bayes' Rule can also be used in situations where we have more complex evidence
- ▶ The probability of some outcome a , given *both* that another outcome b has occurred, *and* that we have some other evidence e , is given by:

$$P(a | b, e) = \frac{P(b | a, e)P(a | e)}{P(b | e)}$$

▶

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The HIV Question, Revisited

- ▶ If HIV test is 98% accurate, and 0.33% of people have it, what is the chance that you have it, if you test positive?
- ▶ We want to calculate the chance:

$$P(\text{HaveHIV} | \text{PosTest}) = ?$$

- ▶ But this is *not the same* as:

$$P(\text{PosTest} | \text{HaveHIV}) = 0.98$$

- ▶ Believing that these are the same leads to some of the worst errors seemingly rational human beings can make!

▶

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Chances of Testing Positive

- ▶ Given these numbers, we can **condition** on infection-status to calculate the likelihood of a positive HIV test, given 98% accuracy and a 0.33% infection rate:

$$\begin{aligned} P(\text{PosTest}) &= (P(\text{PosTest} | \text{HaveHIV}) \times P(\text{HaveHIV})) + \\ &\quad (P(\text{PosTest} | \neg \text{HaveHIV}) \times P(\neg \text{HaveHIV})) \\ &= (0.98 \times 0.0033) + (0.02 \times 0.9967) \\ &= (0.003234 + 0.019934) = 0.023168 \end{aligned}$$

- ▶ Test is positive 2.3% of the time, including both correct diagnoses (**true positives**) and incorrect ones (**false positives**)

▶

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Using Bayes' Theorem

$$\begin{aligned} P(\text{HaveHIV} | \text{PosTest}) &= \frac{P(\text{PosTest} | \text{HaveHIV})P(\text{HaveHIV})}{P(\text{PosTest})} \\ &= \frac{0.98 \times 0.0033}{(0.98 \times 0.0033) + (0.02 \times 0.9967)} \\ &= \frac{0.003234}{0.003234 + 0.019934} = \frac{0.003234}{0.023168} \approx 0.1396 \end{aligned}$$

- ▶ The chance of actually having HIV is only about 14%!

▶

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Probability & Guilt

- ▶ In 1999, British mother Sally Clark was convicted of murder, after her two infant sons both died of what was originally thought to be Sudden Infant Death Syndrome (SIDS)
- ▶ Her conviction relied upon the expert testimony of famous pediatrician Sir Roy Meadow, who argued:
 1. The chance a random child dies of SIDS is about 1 in 3000
 2. Amongst non-smoking, older parents (like Clark), with at least one wage, this rises to about 1 in 8500
 3. The chance of both of Clark's sons dying of SIDS is therefore about $(1/8500 \times 1/8500)$, or 1 in 73 million
 4. The chance that Sally Clark is innocent is thus 1 in 73 million
- ▶ *What should we, the jury, make of this argument?*

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A Problem of Numbers

- ▶ When we roll two dice, the chance of them both coming up 5 is $(1/6 \times 1/6) = 1/36$
 - ▶ Since dice are **independent** of one another, the roll of one does not affect the other, so we simply **multiply** probabilities
 - ▶ We will look at this in more depth in upcoming lectures
- ▶ If *one* infant in a family dies of SIDS, is the chance of a *second* dying exactly the same? Lower? Higher?
 - ▶ Calculations in UK show that chances of a randomly selected *pair* of infants dying of SIDS actually 1 in 100,000 (0.0001)
 - ▶ If about 500,000 families in UK have two infants in any given year, how many times would this happen?

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A Problem of Reasoning

- ▶ Even if we accept the 1 in 100,000 value (instead of Meadow's 1 in 73 million), is *that* the probability that Clark is actually innocent?
- ▶ **No.** This is the **Prosecutor's Fallacy**: the claim that the chance of innocence equals the chance of a rare event
 - ▶ Rare events *do happen* (e.g., lotteries)
 - ▶ We then have to calculate the **conditional probability** of guilt, *given* that a tragic event did in fact happen

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The Real Chance of Innocence

- ▶ Let M = "The children were murdered"
- ▶ Let D = "The children died"
- ▶ We want $P(M|D)$, which is, by **Bayes' Rule**:

$$P(M|D) = \frac{P(D|M)P(M)}{P(D)}$$

- ▶ We can get the denominator, $P(D)$, by **normalizing**:

$$P(M|D) = \frac{P(D|M)P(M)}{P(D|M)P(M) + P(D|\neg M)P(\neg M)}$$

- ▶ Now, since $P(D|M) = 1$, and $P(\neg M) = 1 - P(M)$, we have:

$$P(M|D) = \frac{P(M)}{P(M) + P(D|\neg M)(1 - P(M))}$$

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The Real Chance of Innocence

- ▶ Now, unless we think that the probability of a pair of children being murdered is *very high*, the probability of the mother's innocence is high, too
- ▶ An estimate of the number of pairs of children who die of all causes other than murder in the UK in a year is 1 in 20,000: $P(D | \neg M) = 0.00005$
- ▶ Based on this, even if we concede an *extreme over-estimate* to the prosecution, the probability of murder in this case is still low
- ▶ Suppose that murder happens with frequency 1/10 of all other causes combined, so that 1 in 200,000 pairs of infants will be murdered in the UK in a year (i.e., $P(M) = 0.000005$); this gives us:

$$\begin{aligned} P(M | D) &= \frac{P(M)}{P(M) + P(D | \neg M)(1 - P(M))} \\ &= \frac{0.000005}{0.000005 + 0.00005 \times 0.999995} \\ &\approx 0.091 \end{aligned}$$



The Real Chance of Innocence

- ▶ Given the real probability of murder $P(M | D) = 0.091$, the probability of innocence is:

$$P(\neg M | D) = 1 - P(M | D) = 0.909$$

- ▶ Thus, even given *very generous* assumptions in the favor of the prosecution, Sally Clark would have been innocent over 90% of the time
 - ▶ Due to fallacious reasoning at her trial, she spent over 3 years in jail for a crime she almost certainly did not commit!

