


# Conditional Probability

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$P(\text{die roll} \mid \text{coin flip})$

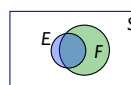
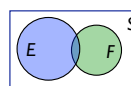


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## conditional probability

**Conditional probability** of E given F: probability that E occurs given that F has occurred.

**"Conditioning on F"**  
 Written as  $P(E|F)$   
 Means "P(E, given F observed)"  
 Sample space S reduced to those elements consistent with F (i.e.  $S \cap F$ )  
 Event space E reduced to those elements consistent with F (i.e.  $E \cap F$ )  
 With equally likely outcomes,

$$P(E | F) = \frac{\# \text{ of outcomes in } E \text{ consistent with } F}{\# \text{ of outcomes in } S \text{ consistent with } F} = \frac{|EF|}{|SF|} = \frac{|EF|}{|F|}$$


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

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## coin flipping

Suppose you flip two coins & all outcomes are equally likely.  
 What is the probability that both flips land on heads if...

- The first flip lands on heads?  
 Let  $B = \{HH\}$  and  $F = \{HH, HT\}$   
 $P(B|F) = P(BF)/P(F) = P(\{HH\})/P(\{HH, HT\})$   
 $= (1/4)/(2/4) = 1/2$
- At least one of the two flips lands on heads?  
 Let  $A = \{HH, HT, TH\}$ ,  $BA = \{HH\}$   
 $P(B|A) = |BA|/|A| = 1/3$
- At least one of the two flips lands on tails?  
 Let  $G = \{TH, HT, TT\}$   
 $P(B|G) = P(BG)/P(G) = P(\emptyset)/P(G) = 0/P(G) = 0$



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## Examples

2 random cards are selected from a deck of cards:

- What is the probability that both cards are aces given that one of the cards is the ace of spades?
- What is the probability that both cards are aces given that at least one of the cards is an ace?

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## conditional probability: the chain rule

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

Holds even when outcomes are *not* equally likely.

**What if  $P(F) = 0$ ?**  
 $P(E|F)$  undefined: (you can't observe the impossible)

For equally likely outcomes:

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

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## Conditional Probability

Satisfies usual axioms of probability

**Example:**  
 $\Pr(E | F) = 1 - \Pr(E^c | F)$

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**Conditional Probabilities yield a probability space**

Suppose that  $(S, Pr(\cdot))$  is a probability space.

Then  $(S, Pr(\cdot|F))$  is a probability space for  $F \subset S$  with  $Pr(F) > 0$

$$0 \leq Pr(w|F) \leq 1$$

$$\sum_{w \in S} Pr(w|S) = 1$$

$E_1, E_2, \dots, E_n$  disjoint implies

$$Pr(\cup_{i=1}^n E_i|F) = \sum_{i=1}^n Pr(E_i|F)$$

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**Chain rule application**

Draw 2 balls at random without replacement from an urn with 8 red balls and 4 white ones. What is the probability that both balls are red?

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**Chain rule example**

Alice and Bob play a game as follows: A die is thrown, and each time it is thrown, regardless of the history, it is equally likely to show any of the six numbers.

If it shows 5, Alice wins.

If it shows 1, 2 or 6, Bob wins.

Otherwise, they play a second round and so on.

What is P(Alice wins on n<sup>th</sup> round)?

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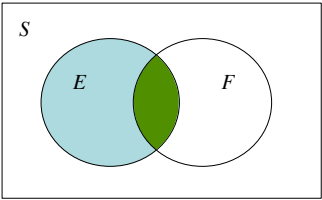
**Keys**

I have n keys, one of which opens a locked door. Trying keys at random without replacement, what is the chance of opening the door on the k<sup>th</sup> try?

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**law of total probability**

E and F are events in the sample space S

$$E = EF \cup EF^c$$


$$EF \cap EF^c = \emptyset$$

$$\Rightarrow P(E) = P(EF) + P(EF^c)$$

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**conditional probability: 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:

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

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**law of total probability**

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

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.)

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**total probability**

Sally has 1 elective left to take: either Phys or Chem. She will get A with probability 3/4 in Phys, with prob 3/5 in Chem. She flips a coin to decide which to take.

What is the probability that she gets an A?

$$\begin{aligned}
 P(A) &= P(A|Phys)P(Phys) + P(A|Chem)P(Chem) \\
 &= (3/4)(1/2) + (3/5)(1/2) \\
 &= 27/40
 \end{aligned}$$

Note that conditional probability was a means to an end in this example, not the goal itself. One reason conditional probability is important is that this is a common scenario.

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**gamblers ruin**  
BT pg. 63

2 Gamblers: Alice & Bob.  
A has  $i$  dollars; B has  $(N-i)$   
Flip a coin. Heads – A wins \$1; Tails – B wins \$1  
Repeat until A or B has all  $N$  dollars  
What is  $P(A \text{ wins})$ ?

Let  $E_i$  = event that A wins starting with \$ $i$   
Approach: Condition on  $i^{\text{th}}$  flip

How does  $p_i$  vary with  $i$ ?  $p_i = \frac{P(E_i)}{P(E_i)} = P(E_i | H)P(H) + P(E_i | T)P(T)$

$$\begin{aligned}
 p_i &= \frac{1}{2}(p_{i+1} + p_{i-1}) \\
 2p_i &= p_{i+1} + p_{i-1} \\
 p_{i+1} - p_i &= p_i - p_{i-1} \\
 p_2 - p_1 &= p_1 - p_0 = p_1, \text{ since } p_0 = 0
 \end{aligned}$$

So:  $p_2 = 2p_1$   
...  
 $p_i = ip_1$   
 $p_N = Np_1 = 1$   
 $p_i = i/N$

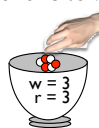
nice example of the utility of conditioning: future decomposed into two crisp cases instead of being a blurred superposition thereof

aka "Drunkard's Walk"


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**Bayes Theorem**

6 red or 3 red/3 white balls in an urn




Probability of drawing 3 red balls, given 3 in urn?



Rev. Thomas Bayes c. 1701-1761

Probability of only 3 red balls in urn, given that I drew three?



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**Bayes Theorem**

**Most common form:**

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

**Expanded form (using law of total probability):**

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

**Proof:**

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

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**Bayes Theorem**

**Most common form:**

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**Expanded form (using law of total probability):**


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**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

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### Bayes Theorem

An urn contains 6 balls, either 3 red + 3 white or all 6 red.  
 You draw 3; all are red.  
 Did urn have only 3 red?  
 Can't tell



Suppose it was 3 + 3 with probability  $p=3/4$ .  
 Did urn have only 3 red?  
 M = urn has 3 red + 3 white  
 D = I drew 3 red

*prior = 3/4 ; posterior = 3/23*


$$P(M | D) = P(D | M)P(M) / [P(D | M)P(M) + P(D | M^c)P(M^c)]$$

$$P(D | M) = (3 \text{ choose } 3) / (6 \text{ choose } 3) = 1/20$$

$$P(M | D) = (1/20)(3/4) / [(1/20)(3/4) + (1)(1/4)] = 3/23$$

### simple spam detection

Say that 60% of email is spam  
 90% of spam has a forged header  
 20% of non-spam has a forged header  
 Let  $F$  = message contains a forged header  
 Let  $J$  = message is spam  
 What is  $P(J|F)$  ?



Solution:

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


$$= \frac{(0.9)(0.6)}{(0.9)(0.6) + (0.2)(0.4)}$$

$$\approx 0.871$$

*prior = 60% posterior = 87%*

### simple spam detection

Say that 60% of email is spam  
 10% of spam has the word "Viagra"  
 1% of non-spam has the word "Viagra"  
 Let  $V$  = message contains the word "Viagra"  
 Let  $J$  = message is spam  
 What is  $P(J|V)$  ?



Solution:

$$P(J | V) = \frac{P(V | J)P(J)}{P(V | J)P(J) + P(V | J^c)P(J^c)}$$

$$= \frac{(0.1)(0.6)}{(0.1)(0.6) + (0.01)(1 - 0.6)}$$

$$\approx 0.9375$$

*prior = 60% posterior = 94%*

### DNA paternity testing

Child is born with (A,a) gene pair (event  $B_{Aa}$ )  
 Mother has (A,A) gene pair  
 Two possible fathers:  $M_1 = (a,a)$ ,  $M_2 = (a,A)$   
 $P(M_1) = p$ ,  $P(M_2) = 1-p$   
 What is  $P(M_1 | B_{Aa})$  ?

Solution:

$$P(M_1 | B_{Aa}) = \frac{P(B_{Aa} | M_1)P(M_1)}{P(B_{Aa} | M_1)P(M_1) + P(B_{Aa} | M_2)P(M_2)}$$

$$= \frac{1 \cdot p}{1 \cdot p + 0.5(1 - p)} = \frac{2p}{1 + p} \geq \frac{2p}{1 + 1} = p$$

*E.g., 1/2 → 2/3*

I.e., the given data about child raises probability that  $M_1$  is father

### HIV testing

Suppose an HIV test is 98% effective in detecting HIV, i.e., its "false negative" rate = 2%. Suppose furthermore, the test's "false positive" rate = 1%.  
 0.5% of population has HIV  
 Let  $E$  = you test positive for HIV  
 Let  $F$  = you actually have HIV  
 What is  $P(F|E)$  ?

Solution:

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

$$= \frac{(0.98)(0.005)}{(0.98)(0.005) + (0.01)(1 - 0.005)}$$

$$\approx 0.330$$

*P(E) ≈ 1.5%*

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

### 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  $P(F|E^c)$  ?

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

$$= \frac{(0.02)(0.005)}{(0.02)(0.005) + (0.99)(1 - 0.005)}$$

$$\approx 0.0001$$

## summary

**Conditional probability**

$P(E|F)$ : Conditional probability that E occurs given that F has occurred.

Reduce event/sample space to points consistent w/  $F$  ( $E \cap F; S \cap F$ )

$$P(E | F) = \frac{P(EF)}{P(F)} \quad (P(F) > 0)$$

$$P(E | F) = \frac{|EF|}{|F|}, \text{ if equiprobable outcomes.}$$

$$P(EF) = P(E|F) P(F) \quad (\text{"the chain rule"})$$

" $P(- | F)$ " is a probability law, i.e., satisfies the 3 axioms

$$P(E) = P(E|F) P(F) + P(E|F^c) (1-P(F)) \quad (\text{"the law of total probability"})$$

**Bayes theorem**

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