

Notes 2: Conditioning

$$\mathbb{P}(B \cap A) = \mathbb{P}(B|A)\mathbb{P}(A),$$

Conditional probability

$\mathbb{P}(B|A)$  = conditional probability that  $B$  is true given that  $A$  is true

This is computed using the formula

$$\mathbb{P}(B|A) = \frac{\mathbb{P}(B \cap A)}{\mathbb{P}(A)}, \quad \mathbb{P}(A) \neq 0$$

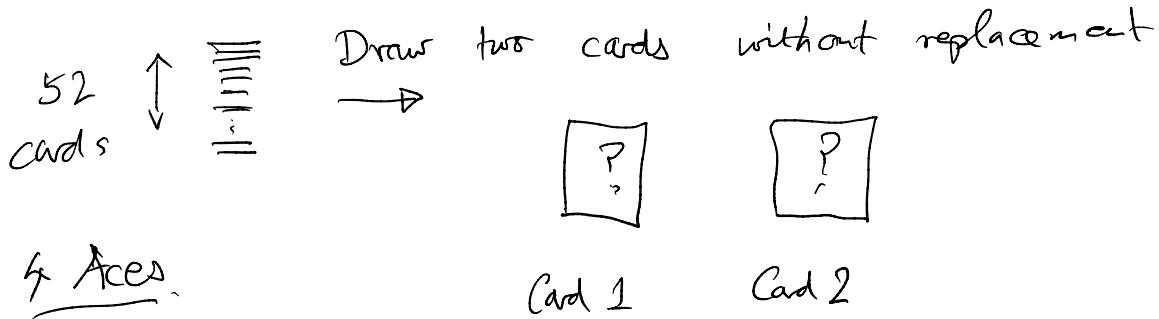
It is important to note that  $\mathbb{P}(B|A)$  is defined only if  $\mathbb{P}(A) \neq 0$ .

**Example 1** The probability of drawing an Ace from a standard deck of cards is

$$\mathbb{P}(\text{Ace}) = \frac{4}{52} = \frac{1}{13}$$

Draw two cards in sequence, and let  $A_1, A_2$  be the events that the first, second cards are Aces respectively, then it is easy to see that

$$\mathbb{P}(A_1) = \frac{4}{52}, \quad \mathbb{P}(A_2|A_1) = \frac{3}{51}, \quad \mathbb{P}(A_2|A_1^c) = \frac{4}{51}$$



$$A_1 = \{ \text{Card 1 is Ace} \}$$

$$A_2 = \{ \text{Card 2 is Ace} \}$$

$$\mathbb{P}(A_1) = \frac{4}{52} = \frac{1}{13}.$$

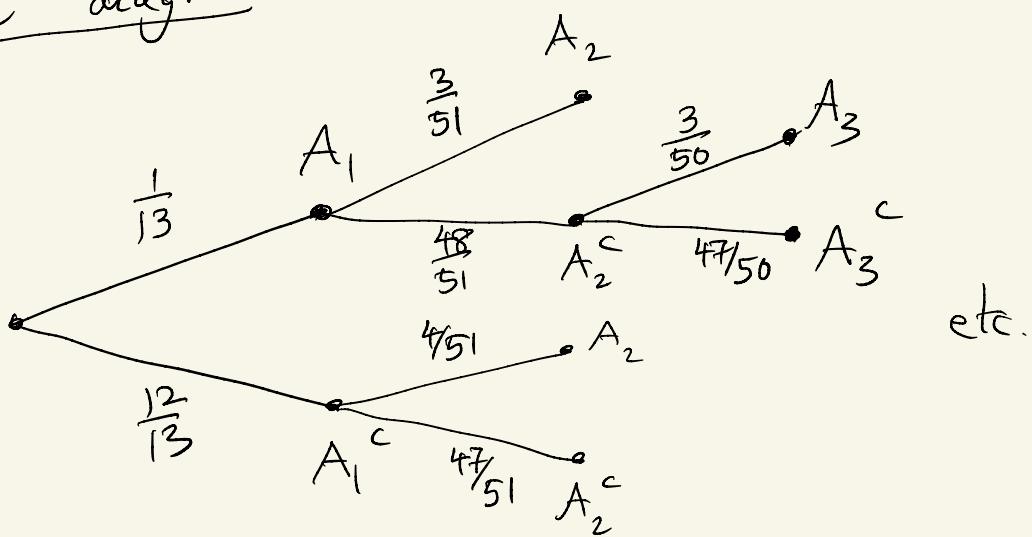
$\mathbb{P}(A_2|A_1) =$  conditional prob. That second card is Ace given that first card is Ace.

$$= \frac{3}{51}$$

$\mathbb{P}(A_2 | A_1^c) = \text{cond. prob } A_2 \text{ given that } A_1 \text{ is false}$

$$= \frac{4}{51}$$

Tree diagram.



$$\mathbb{P}(A_1) = \frac{1}{13}$$

$$\mathbb{P}(A_2^c | A_1) = \frac{48}{51}$$

$$P(A_3 | A_2^c \cap A_1) = P(A_3 | A_2^c, A_1)$$

$$= \frac{3}{50}$$

↗ joint probability

$$P(A_1 \cap A_2) = P(A_1 \text{ and } A_2)$$

$$= \underbrace{P(A_2 | A_1)}_{\downarrow} P(A_1)$$

- This is the definition of conditional prob.

- product of probs. along the branches of the tree.

$$= \frac{3}{51} \cdot \frac{1}{13}$$

$$P(A_1^c \cap A_2) = \text{joint prob.}$$

$$= P(A_2 | A_1^c) P(A_1^c)$$

$$= \frac{4}{51} \cdot \frac{12}{13}$$

Total probability formula.

$$\begin{aligned} P(A_2) &= P(A_2 \cap A_1) \\ &\quad + P(A_2 \cap A_1^c) \end{aligned}$$

$$\begin{aligned} P(A_2) &= P(A_2 | A_1) P(A_1) \\ &\quad + P(A_2 | A_1^c) P(A_1^c) \end{aligned}$$

Total probability formula

$$\begin{aligned} \Rightarrow P(A_2) &= \frac{3}{51} \cdot \frac{1}{13} + \frac{4}{51} \cdot \frac{12}{13} \\ &= \frac{1}{13} \end{aligned}$$

$$\text{So } P(A_2) = P(A_1) = \frac{1}{13}$$

similarly  $P(A_k) = \frac{1}{13}$  for any  
 $k = 1, 2, 3, \dots, 52$ .

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Total probability.

$$P(A_2) = P(A_2|A) P(A_1) + P(A_2|A_1^c) P(A_1^c)$$

Note:  $A_1 \cup A_1^c = S$  (sample space = all outcomes)

$$A_1 \cap A_1^c = \emptyset \quad (\text{null event} = \text{empty set})$$

events  $A_1, A_1^c$  are exhaustive

events  $A_1, A_1^c$  are mutually exclusive

Generalize:

events  $B_1, B_2, \dots, B_n$  are

• exhaustive  $B_1 \cup B_2 \cup \dots \cup B_n = S$ .

• mutually exclusive = disjoint

$$B_i \cap B_j = \emptyset \quad \text{any } i, j$$

Total prob. formula;  
for any event A

$$\begin{aligned} P(A) &= P(A|B_1) P(B_1) + P(A|B_2) P(B_2) \\ &\quad + \dots + P(A|B_n) P(B_n). \end{aligned}$$

Total prob. formula

Note: Such events arise naturally from a discrete random variable  $X$ :

$$\text{Ran } X = \{x_1, x_2, \dots, x_n\}.$$

Let  $B_i = \{X = x_i\}$

Then the events  $\{B_1, B_2, \dots, B_n\}$  are 'exhaustive' and 'mutually exclusive'.

In the above example it is perhaps not immediately obvious how to compute  $\mathbb{P}(A_2)$ . We can use the formula for total probability, which in this case says that

$$\begin{aligned}\mathbb{P}(A_2) &= \mathbb{P}(A_2 \text{ and } A_1) + \mathbb{P}(A_2 \text{ and } A_1^c) \\ &= \mathbb{P}(A_2|A_1)\mathbb{P}(A_1) + \mathbb{P}(A_2|A_1^c)\mathbb{P}(A_1^c) \\ &= \frac{3}{51} \frac{4}{52} + \frac{4}{51} \frac{48}{52} \\ &= \frac{4}{52}\end{aligned}$$

The general formula for total probability is this: suppose that there is a collection of events  $A_1, A_2, \dots, A_n$  which are mutually disjoint, so  $A_i \cap A_j = \emptyset$  for all  $i \neq j$ , and also exhaustive, meaning they include every outcome in the sample space  $S$ , so that  $A_1 \cup A_2 \cup \dots \cup A_n = S$ . Then for any event  $B$ ,

$$\begin{aligned}\mathbb{P}(B) &= \mathbb{P}(B \cap A_1) + \mathbb{P}(B \cap A_2) + \dots + \mathbb{P}(B \cap A_n) \\ &= \mathbb{P}(B|A_1)\mathbb{P}(A_1) + \mathbb{P}(B|A_2)\mathbb{P}(A_2) + \dots + \mathbb{P}(B|A_n)\mathbb{P}(A_n)\end{aligned}$$

$A = \{\text{applicant is non-smoker}\}$

$B = \{\text{applicant says they are non-smoker}\}$

$P(A|B) = P(\text{app is non-smoker given say are non-smoker})$ .

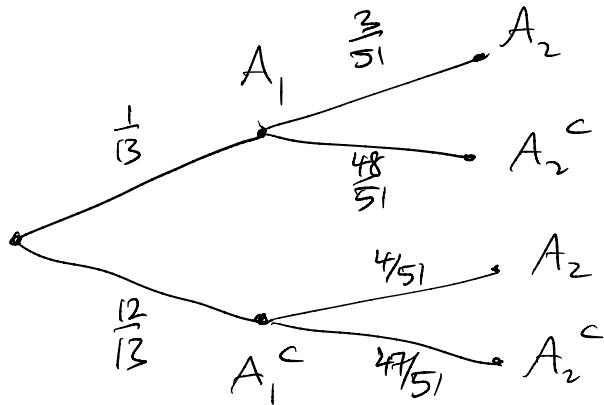
**Example 2** Bayes Rule is a useful application of conditional probability. The formula is

$$P(B|A) = \frac{P(A|B)P(B)}{P(A|B)P(B) + P(A|B^c)P(B^c)}$$

Suppose an insurance application contains the question "Is the applicant a smoker?". Assume that 30% of the population smokes, and that 40% of smokers will lie about it. Assuming no non-smokers will lie, what percentage of applicants who say they are non-smokers actually are non-smokers?

Situation: know  $P(A|B)$  and  $P(A|B^c)$   
but want  $P(B|A)$  and  $P(B|A^c)$ .

Ex: Draw 2 cards.



Find  $P(A_1 | A_2)$ .

Use definition to start:

$$P(A_1 | A_2) = \frac{P(A_1 \cap A_2)}{P(A_2)}$$

$$\bullet = \frac{\left(\frac{3}{51}\right)\left(\frac{1}{13}\right)}{\left(\frac{1}{13}\right)} = \frac{3}{51}$$

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graph LR
    Start(( )) --> A2_1[A2]
    Start --> A2_1^c[A2^c]
    A2_1^c -.-> A2_1
  
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## Bayes Rule

$$P(B|A) = \frac{P(B \cap A)}{P(A)} \quad (\text{definition})$$

$$= \frac{P(A \cap B)}{P(A)} \quad (\text{trivial})$$

$$= \frac{P(A|B) P(B)}{P(A)} \quad (\text{define})$$

$$P(B|A) = \frac{P(A|B) P(B)}{P(A|B) P(B) + P(A|B^c) P(B^c)}$$

(total prob)

Example (non-smoker question)

First step: name the events

Second step: identify question  $P(A|B)$ .

$A = \{ \text{app. is non-smoker} \}$

$B = \{ \text{ys says they are non-smoke} \}$ .

Third step: apply Bayes Rule

$$P(A|B) = \frac{P(B|A) P(A)}{P(B|A) P(A) + P(B|A^c) P(A^c)}$$

$$P(B|A) = 1. \quad (\text{non-smokers don't lie!})$$

$$P(B|A^c) = 0.4 \quad (40\% \text{ of smokers lie})$$

$$P(A) = 0.7 \quad (30\% \text{ of pop. smokers})$$

$$P(A^c) = 0.3$$

$$\Rightarrow P(A|B) = \frac{(1)(0.7)}{(1)(0.7) + (0.4)(0.3)} = 0.85$$

If the events  $A, B$  are independent then the formula  $\mathbb{P}(A \cap B) = \mathbb{P}(A) \mathbb{P}(B)$  implies that both of the following are true:

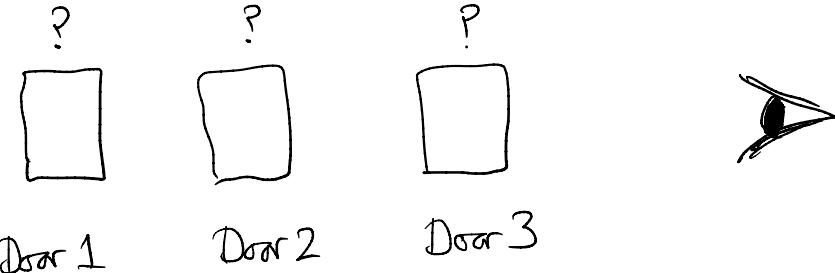
$$\mathbb{P}(A|B) = \mathbb{P}(A) \quad \text{and} \quad \mathbb{P}(B|A) = \mathbb{P}(B)$$

$$\mathbb{P}(A \cap B) = \mathbb{P}(A) \mathbb{P}(B)$$

$$\Rightarrow \mathbb{P}(A|B) = \frac{\mathbb{P}(A \cap B)}{\mathbb{P}(B)} = \mathbb{P}(A)$$

*↑                          ↗  
  doesnt case if B is true or not.*

The famous *Monty Hall* gameshow problem. There are 3 doors, and a prize is hidden behind one door. The contestant chooses a door. The host then opens *one of the other doors* to show that it does not conceal a prize. The contestant may now change her choice to the third remaining door. Should she switch her choice?



$T$  = door concealing the prize

$G$  = door first guessed by contestant.

$S$  = {contestant wins after switching}.

Total probability:

$$P(S) = P(S | G=T) P(G=T)$$

$$+ P(S | G \neq T) P(G \neq T)$$

$$= 0 \cdot \left(\frac{1}{3}\right)$$

$$+ 1 \cdot \left(\frac{2}{3}\right)$$

$$P(S) = \frac{2}{3}$$

$D = \{ \text{catastrophic wins without switching} \}.$

$$\begin{aligned} P(D) &= P(D | G=T) \cdot P(G=T) \\ &\quad + P(D | G \neq T) \cdot P(G \neq T) \\ &= (1) \left(\frac{1}{3}\right) + 0 \cdot \left(\frac{2}{3}\right) \\ P(D) &= \frac{1}{3}. \end{aligned}$$

### Conditional expectation

If  $X$  and  $Y$  are discrete r.v.'s then we can compute conditional probabilities as above:

$$\mathbb{P}(X = x | Y = y) = \frac{\mathbb{P}(X = x, Y = y)}{\mathbb{P}(Y = y)}$$

There is also the formula for total probability

$$\mathbb{P}(X = x) = \sum_y \mathbb{P}(X = x | Y = y) \mathbb{P}(Y = y)$$

where the sum runs over all possible values of  $Y$ . Conditioning is a very useful method for solving problems in probability, because it is often much easier to compute conditional probabilities and then sum over the result to find the 'unconditioned' probability.

→ Total prob.

$$\begin{aligned}
 \mathbb{P}(X = x) &= \mathbb{P}(X = x | Y = y_1) \mathbb{P}(Y = y_1) \\
 &\quad + \mathbb{P}(X = x | Y = y_2) \mathbb{P}(Y = y_2) \\
 &\quad + \dots + \mathbb{P}(X = x | Y = y_n) \mathbb{P}(Y = y_n) \\
 \text{where } \text{Ran}(Y) &= \{y_1, y_2, \dots, y_n\}.
 \end{aligned}$$

Note: if  $X$  and  $Y$  are independent then

$$\mathbb{P}(X = x | Y = y_i) = \mathbb{P}(X = x).$$

**Example 3** [Best prize:]  $n$  distinct prizes arrive in sequence, all have different values, and one is the best. You must pick a prize or else move on to the next one (no going back to earlier ones). Your knowledge consists of the values of the previous prizes. You want to use a strategy that will maximize the probability of selecting the best prize. The prizes are randomly arranged in sequence.

[Strategy:] reject the first  $k$  prizes, then select the first one which is better than all of these previous ones. Let  $X$  be the position of the best prize. Use

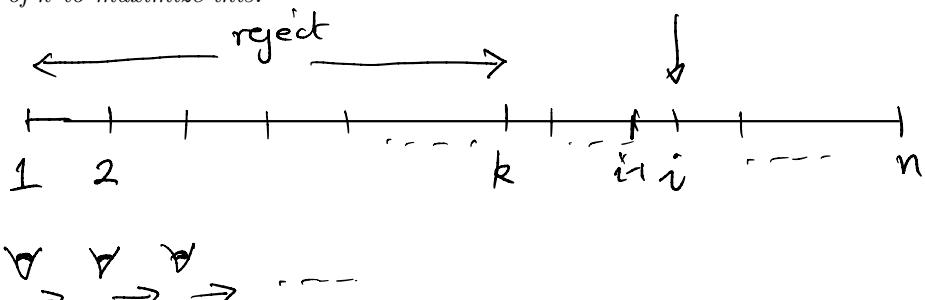
$$P_k(\text{best}) = \sum_{i=1}^n P_k(\text{best}|X=i) P(X=i)$$

to deduce

$$P_k(\text{best}) \simeq \frac{k}{n} \log \frac{n}{k}$$

$X = \text{best prize}$

Find value of  $k$  to maximize this.



$P_k(\text{best}) = P(\text{choose best prize using this strategy}).$

$X = \text{position of best prize.}$

$$P_k(\text{win} | X=i) = \begin{cases} 0 & \text{if } i \leq k \\ P(\text{best among } \{1, 2, \dots, i-1\} \text{ located in } \{1, \dots, k\}) & k+1 \leq i \leq n \end{cases}$$

$$= \begin{cases} 0 & \text{if } i \leq k \\ \frac{k}{i-1} & k+1 \leq i \leq n \end{cases}$$

$$P(X=i) = \frac{1}{n}$$

$$\begin{aligned}
 \Rightarrow P_k(\text{win}) &= \sum_{i=1}^n P_k(\text{win} | X=i) P(X=i) \\
 &= \sum_{i=k+1}^n \frac{k}{i-1} \cdot \frac{1}{n} \\
 &= \frac{k}{n} \sum_{i=k+1}^n \frac{1}{i-1} \\
 &= \frac{k}{n} \left\{ \frac{1}{k} + \frac{1}{k+1} + \frac{1}{k+2} + \dots + \frac{1}{n-1} \right\}.
 \end{aligned}$$

Scenario where  $k, n$  are large:

$$\begin{aligned}
 \sum_{i=k+1}^n \frac{1}{i-1} &= \int_{k+1}^n \frac{1}{x-1} dx \\
 &= \ln\left(\frac{n-1}{k}\right).
 \end{aligned}$$

let  $x = \frac{k}{n}$ , and  $\ln\left(\frac{n-1}{k}\right) \approx \ln\left(\frac{1}{x}\right)$ .

$$P_k(\text{win}) = x \ln\left(\frac{1}{x}\right)$$

$$x = \frac{k}{n} \Rightarrow 0 \leq x \leq 1.$$

What value of  $x$  maximizes this?

$$f(x) = x \ln\left(\frac{1}{x}\right) = -x \ln x,$$

$$f' = -\ln x - x \cdot \left(\frac{1}{x}\right) = \ln x - 1$$

$$\text{Max. } f' = 0 \Rightarrow x = \frac{1}{e}.$$

$$x = \frac{k}{n} \Rightarrow$$

$$k \approx \frac{1}{e} n = \frac{1}{3} n$$



Best strategy is:

- reject the first  $\frac{1}{e}$  of prizes
- pick the first one that

is better than anything  
previous.

We define the conditional expectation of  $X$  conditioned on the value  $Y = y$  as

$$\mathbb{E}[X|Y = y] = \sum_x x \mathbb{P}(X = x|Y = y)$$

This number is defined for each possible value of  $Y$ . Putting these all together we get the r.v.  $\mathbb{E}[X|Y]$  as a function of  $Y$ . You should think of  $\mathbb{E}[X|Y]$  as a random variable which is determined by the random variable  $Y$ , like  $Y^2$  or  $e^{tY}$ : if you know the value of  $Y$ , then you know the value of  $\mathbb{E}[X|Y]$ . There is a very useful relation between the conditional expectation  $\mathbb{E}[X|Y]$  and the ‘unconditioned’ expectation  $\mathbb{E}[X]$ .

### Theorem 1

$$\mathbb{E}[\mathbb{E}[X|Y]] = \mathbb{E}[X]$$

Note that on the left side we are first averaging over  $X$ , with  $Y$  fixed, and then we average over  $Y$ . On the right side we do it all in just one step.

$$\mathbb{E}[\mathbb{E}[X|Y]] = \mathbb{E}[X]$$

The diagram illustrates the double expectation formula. It shows two nested expectation operators. The inner operator is  $\mathbb{E}[X|Y]$ , with an arrow pointing to it labeled 'average over  $X$  with  $Y$  fixed'. The outer operator is  $\mathbb{E}[\mathbb{E}[X|Y]]$ , with an arrow pointing to it labeled 'average over  $Y$ '. An equals sign connects the two expressions.