

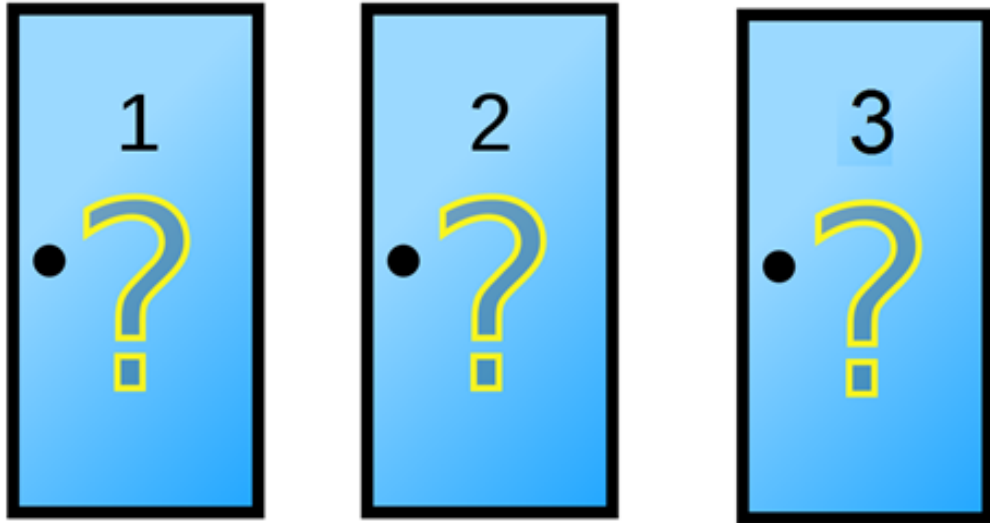
# 1179: Probability

## Lecture 4 — Conditional Probability

Ping-Chun Hsieh (謝秉均)

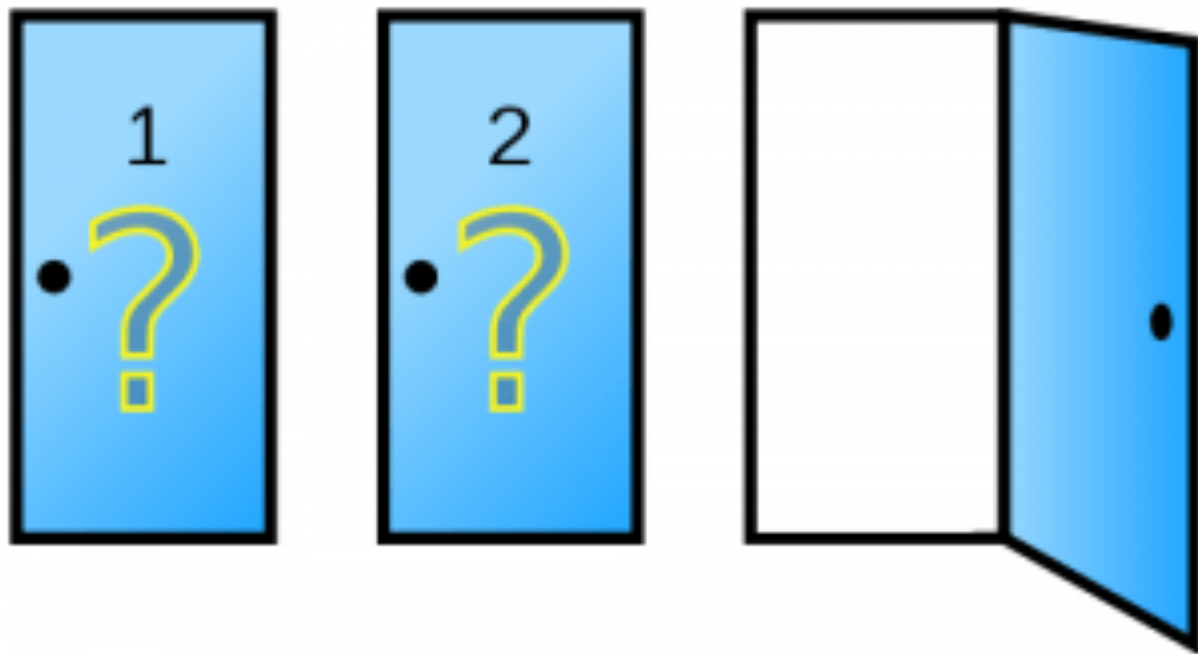
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# Monty Hall Problem



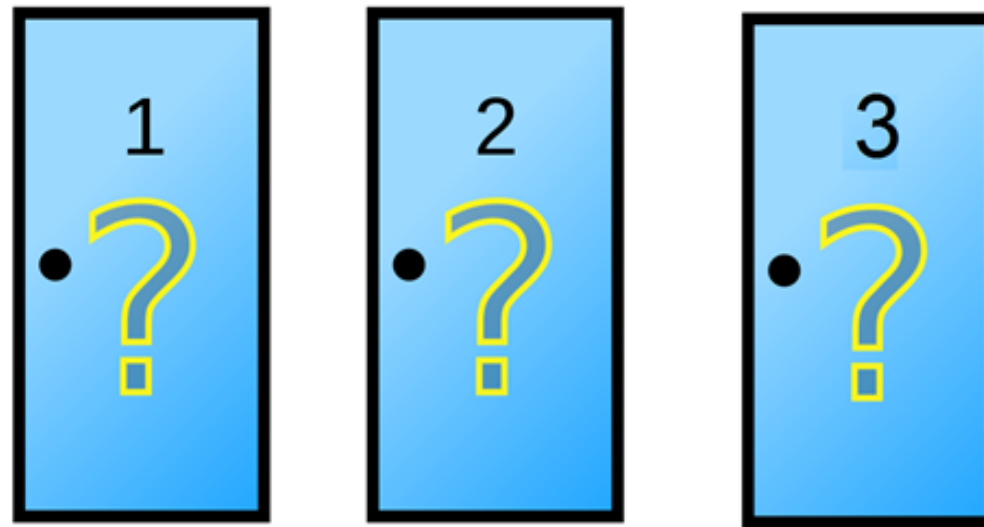
- ▶ Suppose Bill is given 3 options
- ▶ 2 of them are empty, and the remaining one has the prize

- ▶ Then, Bill picks a door (say Door #1).
- ▶ Next, the moderator opens an empty door.



- ▶ Bill is then asked by the moderator: “Do you want to switch or stay?”

# Monty Hall Problem (Cont.)



- ▶ What is random (from Bill's perspective)?
- ▶ Sample space?  $\Omega = \{1, 2, 3\}$
- ▶ What's the probability of winning the prize if Bill stays?  $\frac{1}{3}$
- ▶ What's the probability of winning the prize if Bill switches?  $\frac{2}{3}$

# Quick Review

if  $E_n$  is either an increasing or a decreasing event  
↑

► What is “continuity of probability”?  $\lim_{n \rightarrow \infty} P(E_n) = P(\lim_{n \rightarrow \infty} E_n)$

► What is conditional probability?  $P(A|B) = \frac{P(A \cap B)}{P(B)}$   
↓

called  $P A$  given  $B$

# This Lecture

## 1. Conditional Probability and 3 Useful Tools

- Reading material: Chapter 3.1~3.4

# Conditional Probability Defines a New Probability Assignment

## Theorem (Reduction of Sample Space):

Let  $\Omega$  be the sample space and let  $B$  be an event with  $P(B) > 0$ . Then, we have:

1.  $P(A | B) \geq 0$ , for any event  $A$   $P(A|B) = \frac{P(A \cap B)}{P(B)} \geq 0$  by axiom 1  $\neq$

2.  $P(\Omega | B) = 1$   $P(\Omega|B) = \frac{P(\Omega \cap B)}{P(B)} = \frac{P(B)}{P(B)} = 1$   $\neq$

3.  $A_1, A_2, \dots$  is an infinite sequence of mutually exclusive events, then

$$P\left(\bigcup_{i=1}^{\infty} A_i | B\right) = \sum_{i=1}^{\infty} P(A_i | B)$$

► Conditional universe!

$$P\left(\bigcup_{i=1}^{\infty} A_i | B\right) = \frac{P\left(\left(\bigcup_{i=1}^{\infty} A_i\right) \cap B\right)}{P(B)} = \frac{P\left(\bigcup_{i=1}^{\infty} (A_i \cap B)\right)}{P(B)} \stackrel{\text{By axiom 3}}{=} \frac{\sum_{i=1}^{\infty} P(A_i \cap B)}{P(B)} = \sum_{i=1}^{\infty} P(A_i | B) \neq$$

# Tool #1: Multiplication Rule

Assuming that all of the conditioning events have positive probability, we have:

$$P\left(\bigcap_{i=1}^n A_i\right) = P(A_1)P(A_2 | A_1) \cdots P(A_n | A_1 \cap A_2 \cap \cdots A_{n-1})$$

- ▶ How to intuitively interpret this?
- ▶ How to prove this? *mathematical induction*
  1.  $n=2$  :  $P(A_1 \cap A_2) = P(A_1) \cdot P(A_2 | A_1)$  (by the definition of conditional property)
  2. Assume that  $n=k$ ,  $P\left(\bigcap_{i=1}^k A_i\right) = P(A_1) \cdot P(A_2 | A_1) \cdots P(A_k | A_1 \cap A_2 \cap \cdots A_{k-1})$  is true  
then if  $n=k+1$  :  $P\left(\bigcap_{i=1}^{k+1} A_i\right) = P\left(\left(\bigcap_{i=1}^k A_i\right) \cap A_{k+1}\right) = P\left(\bigcap_{i=1}^k A_i\right) \cdot P(A_{k+1} | A_1 \cap A_2 \cap \cdots A_k)$   
by mathematical induction #

# Example: Find the Defective Fuses

- **Example:** Suppose that 7 good and 2 defective fuses are mixed up. To find the defective ones, we test them one by one.  $P(\text{we find both defective fuses in exactly 3 tests}) = ?$

$$\begin{cases} GDD \\ DGD \end{cases}$$

$$\begin{aligned} P(GDD) &= P(\text{1st is G}) \cdot P(\text{2nd is D} \mid \text{1st is G}) \cdot P(\text{3rd is D} \mid GD) \\ &= \frac{7}{9} \times \frac{2}{8} \times \frac{1}{7} = \frac{1}{36} \end{aligned}$$

$$\begin{aligned} P(DGD) &= P(\text{1st is D}) \cdot P(\text{2nd is G} \mid \text{1st is D}) \cdot P(\text{3rd is D} \mid DG) \\ &= \frac{2}{9} \cdot \frac{7}{8} \cdot \frac{1}{7} = \frac{1}{36} \end{aligned}$$

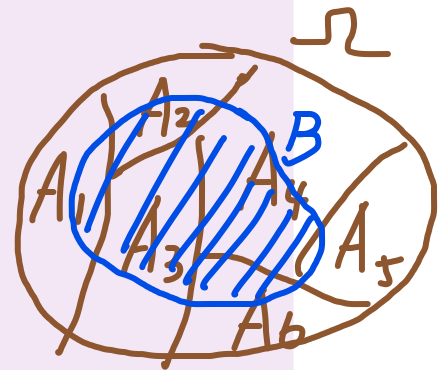
$$\frac{1}{36} + \frac{1}{36} = \frac{1}{18} \quad \#$$



# Tool #2: Total Probability Theorem

**Theorem:** Let  $A_1, A_2, \dots, A_n$  be mutually exclusive events that form a partition of  $\Omega$ , and  $P(A_i) > 0$ , for all  $i$ . Then, for any event  $B$ , we have

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

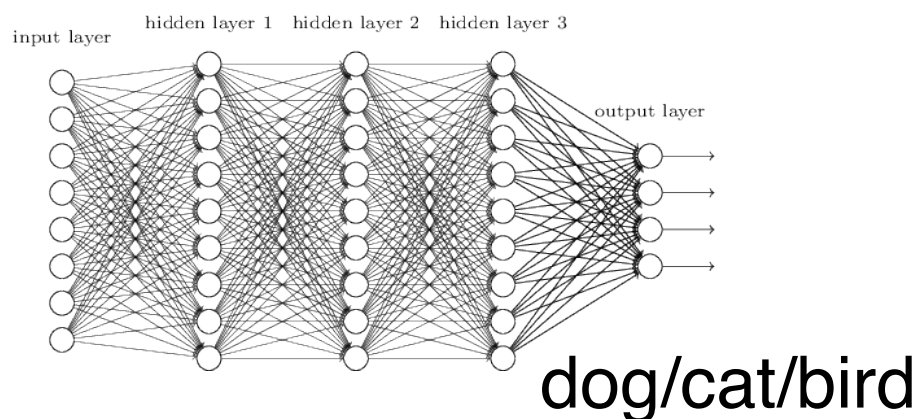


- Idea: Divide and conquer

# Example: Image Classifier

- ▶ **Example:** Suppose we have a well-trained image classifier
  - ▶ Each input image is either a dog/cat/bird with  $P(\text{dog}) = P(\text{cat}) = 2 \cdot P(\text{bird})$   $\longrightarrow$
  - ▶ The probability that a dog is misclassified is 0.1
  - ▶ The probability that a cat is misclassified is 0.05
  - ▶ The probability that a bird is misclassified is 0.15
  - ▶  $P(\text{an image is correctly classified}) = ?$

$$\begin{cases} P(\text{dog}) = \frac{2}{5} \\ P(\text{cat}) = \frac{2}{5} \\ P(\text{bird}) = \frac{1}{5} \end{cases}$$



$$\begin{aligned} & \frac{2}{5} \times 0.9 + \frac{2}{5} \times 0.95 + \frac{1}{5} \times 0.85 \\ &= 0.36 + 0.38 + 0.17 \\ &= 0.91 \# \end{aligned}$$

# Example: Gambler's Ruin

- ▶ **Example:** Two gamblers A and B keep tossing a fair coin
  - ▶ If “head” occurs, A pays \$1 to B; otherwise, B pays \$1 to A
  - ▶ Initially, A has 2 dollars, and B has 3 dollars
  - ▶ The game ends when either A or B has zero dollar
  - ▶ What is the probability that A wins the game?

# Tool #3: Bayes' Rule

**Theorem:** Let  $A_1, A_2, \dots, A_n$  be mutually exclusive events that form a partition of  $\Omega$ , and  $P(A_i) > 0$ , for all  $i$ . Then, for any event  $B$ , we have

$$P(A_i | B) = \frac{P(A_i)P(B | A_i)}{P(B)} = \frac{P(A_i)P(B | A_i)}{P(A_1)P(B | A_1) + \dots + P(A_n)P(B | A_n)}$$

- Why is Bayes' rule useful?  Inference

# Bayesian Inference: Crush and Dates

$$P(A_i | B) = \frac{P(A_i)P(B | A_i)}{P(B)} = \frac{P(A_i)P(B | A_i)}{P(A_1)P(B | A_1) + \cdots + P(A_n)P(B | A_n)}$$

- ▶ **Example:** Bill has a crush on Amy, and Bill wants to ask Amy out to see whether Amy likes him or not.
  - ▶  $A_1 = \{\text{Amy likes Bill}\}$ ,  $A_2 = \{\text{Amy does not like Bill}\}$
  - ▶  $B = \{\text{Amy looks happy during the date}\}$
  - ▶  $P(B | A_1) = 0.9$ , and  $P(B | A_2) = 0.3$
  - ▶ What are  $P(A_1 | B)$  and  $P(A_1 | B^c)$ ?

# Example: Answer an Exam Question

- ▶ **Example:** Bill answers a question with 4 choices (A, B, C, D)
  - ▶ Bill either knows the correct answer or makes a random guess
  - ▶  $P(\text{Bill knows the correct answer}) = 2/3$
  - ▶  $P(\text{Bill does not make a random guess} \mid \text{answer is correct}) = ?$

# 1-Minute Summary

## 1. Conditional Probability

- Multiplication rule / Total probability theorem / Bayes' rule
- Bayesian inference