

# Probability

# Uncertainty in the World

- An person can often be uncertain about the state of the world/domain since there is often ambiguity and uncertainty
- Plausible/**probabilistic inference**
  - I've got this evidence; what's the chance that this conclusion is true?
    - I've got a sore neck; how likely am I to have meningitis?
    - A mammogram test is positive; what's the probability that the patient has breast cancer?

# Uncertainty

- Say we have a rule:  
*if toothache then problem is cavity*
- But not all patients have toothaches due to cavities, so we could set up rules like:  
*if toothache and  $\neg$ gum-disease and  $\neg$ filling and ...  
then problem = cavity*
- This gets complicated; better method:  
*if toothache then problem is cavity with 0.8 probability*  
or  $P(\text{cavity} \mid \text{toothache}) = 0.8$   
*the probability of cavity is 0.8 given toothache is observed*

# Example of Uncertainty

- Assume a camera and vision system is used to estimate the curvature of the road ahead
- There's uncertainty about which way it curves
  - limited pixel resolution, noise in image
  - algorithm for “road detection” is not perfect
- This uncertainty can be represented with a simple probability model:

$$P(\text{road curves to left} \mid E) = 0.6$$

$$P(\text{road goes straight} \mid E) = 0.3$$

$$P(\text{road curves to right} \mid E) = 0.1$$

- where the probability of an event is a **measure of observer's belief** in the event given the evidence E

# Uncertainty in the World and our Models

- True uncertainty: rules *are probabilistic in nature*
  - quantum mechanics
  - rolling dice, flipping a coin
- Laziness: too hard to determine exception-less rules
  - takes too much work to determine *all* of the relevant factors
  - too hard to use the enormous rules that result
- Theoretical ignorance: don't know all the rules
  - problem domain has no complete, consistent theory (e.g., medical diagnosis)
- Practical ignorance: do know all the rules BUT
  - haven't collected all relevant information for a particular case

# Logics

Logics are characterized by what they commit to as "primitives"

Logic	What Exists in World	Knowledge States
Propositional	facts	true/false/unknown
First-Order	facts, objects, relations	true/false/unknown
Temporal	facts, objects, relations, times	true/false/unknown
Probability Theory	facts	degree of belief 0..1
Fuzzy	degree of truth	degree of belief 0..1

# Probability Theory

- **Probability theory** serves as a formal means for
  - Representing and reasoning with uncertain knowledge
  - Modeling **degrees of belief** in a proposition (event, conclusion, diagnosis, etc.)
- *Probability is the “language” of uncertainty*
  - A key modeling method in modern AI

# Source of Probabilities

- Frequentists
  - probabilities come from experiments
  - if 10 of 100 people tested have a cavity,  $P(\text{cavity}) = 0.1$
  - probability means the fraction that would be observed in the limit of infinitely many samples
- Objectivists
  - probabilities are real aspects of the world
  - objects have a propensity to behave in certain ways
  - coin has propensity to come up heads with probability 0.5
- Subjectivists
  - probabilities characterize an agent's belief
  - have no external physical significance



# Sample Space/Outcome Space

- $S$  is a outcome space: collection of all possible outcome
- Let,  $A$  be a part of the collection of outcomes in  $S$ ; that is,  $A \subset S$ . Then  $A$  is called an event.
- Events can be binary, multi-valued, or continuous

# Outcome and Event

- Outcome and event are not synonymous.
- **Outcome** is the result of a random experiment. Example: rolling a die has **six** possible outcomes.
- **Event** is a set of outcomes to which a probability is assigned. Example: One possible event is "rolling a number less than 3".

# Mutually Exclusive Event

- **Mutually exclusive** events are events that **cannot occur together (simultaneously)**.
- $A_1, A_2, \dots, A_k$  are mutually exclusive events means that  $A_i \cap A_j = \emptyset, i \neq j$ ; that is,  $A_1, A_2, \dots, A_k$  are disjoint sets.
- **Example:**
  - A = queen of diamonds; B = queen of clubs
  - Events A and B are mutually exclusive if only one card is selected

# Mutually Exhaustive Event

- $A_1, A_2, \dots, A_k$  are mutually exhaustive events means that  $A_i \cup A_j \cup \dots \cup A_k = S$

## Example:

Consider the experiment of throwing a die.

Sample space  $S = \{1, 2, 3, 4, 5, 6\}$

Assume that A, B and C are the events associated with this experiment.

Define: A be the event of getting a number greater than 3

B be the event of getting a number greater than 2 but less than 5

C be the event of getting a number less than 3

We can write these events as:

$$A = \{4, 5, 6\}$$

$$B = \{3, 4\}$$

$$\text{and } C = \{1, 2\}$$

We observe that

$$A \cup B \cup C = \{4, 5, 6\} \cup \{3, 4\} \cup \{1, 2\} = \{1, 2, 3, 4, 5, 6\} = S$$

# The Axioms of Probability

1.  $0 \leq P(A) \leq 1$
2.  $P(\text{true}) = 1, P(\text{false}) = 0$
3. For any two disjoint events  $A$  and  $B$ , we have
$$P(A \cup B) = P(A) + P(B)$$
4. For any infinite sequence of mutually disjoint events  $A_1, A_2, A_3, \dots$ , we have
$$\begin{aligned} P(A_1 \cup A_2 \cup A_3 \cup \dots) \\ = P(A_1) + P(A_2) + P(A_3) + \dots \end{aligned}$$

# Empirical Probability

- Refers to a probability that is based on historical data.

$$P(A) = \frac{\text{\# of times event } A \text{ occurs}}{\text{total \# of observed occurrences}}$$

# Empirical Probability

Find the probability of selecting a male taking statistics from the population described in the following table:

	Taking Stats	Not Taking Stats	Total
Male	84	145	229
Female	76	134	210
Total	160	279	439

$$\text{Probability of Male Taking Stats} = \frac{\text{number of males taking stats}}{\text{total number of people}} = \frac{84}{439} = 0.191$$

# Equiprobable Probability Space

- All outcomes equally likely (fair coin, fair die...)
- Laplace's definition of probability (only in finite equiprobable space)

$$P(A) = \frac{|A|}{|S|}$$



# Theoretical Probability

- Theoretical probability is finding the probability of events that come from an equiprobable sample space.

$$P(A) = \frac{\text{\textit{\# of outcomes in } A}}{\text{\textit{number of outcomes in } S}} = \frac{|A|}{|S|}$$

# Theoretical Probability

Find the probability of selecting a face card (Jack, Queen, or King) from a standard deck of 52 cards.

$$P(\textit{Face Card}) = \frac{|A|}{|S|} = \frac{12}{52} = \frac{3}{13}$$

# Simple vs Joint Probability

- **Simple (Marginal) Probability** refers to the probability of a simple event.
  - Example:  $P(\text{King})$
- **Joint Probability** refers to the probability of an occurrence of two or more events.
  - Example:  $P(\text{King and Spade})$

# Simple vs Joint Probability

## Computing Joint and Marginal Probabilities:

- The probability of a **joint** event, A and B:

$$P(A \text{ and } B) = \frac{\text{number of outcomes satisfying A and B}}{\text{total number of elementary outcomes}}$$

- Computing a **marginal (or simple)** probability:

$$P(A) = P(A \text{ and } B_1) + P(A \text{ and } B_2) + \cdots + P(A \text{ and } B_k)$$

Where  $B_1, B_2, \dots, B_k$  are  $k$  mutually exclusive and collectively exhaustive events

# Example of Joint Probability

	Ace	Not Ace	Total
Black	2	24	26
Red	2	24	26
Total	4	48	52

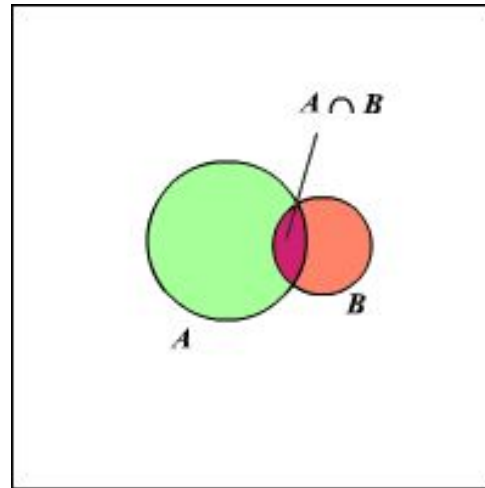
$$P(\text{Red and Ace}) = \frac{\text{number of cards that are red and ace}}{\text{total number of cards}} = \frac{2}{52}$$

# Example of Marginal Probability

	Ace	Not Ace	Total
Black	2	24	26
Red	2	24	26
Total	4	48	52

$$P(\text{Ace}) = P(\text{Ace and Red}) + P(\text{Ace and Black}) = \frac{2}{52} + \frac{2}{52} = \frac{4}{52}$$

# Laws of Probability: Additive Rule



- If A and B are two events in a probability experiment, then the probability that either one of the events will occur is

$$P(A \text{ or } B) = P(A) + P(B) - P(A \text{ and } B)$$

Or

$$P(A \cup B) = P(A) + P(B) - P(A \cap B)$$

# Laws of Probability: Additive Rule (Example)

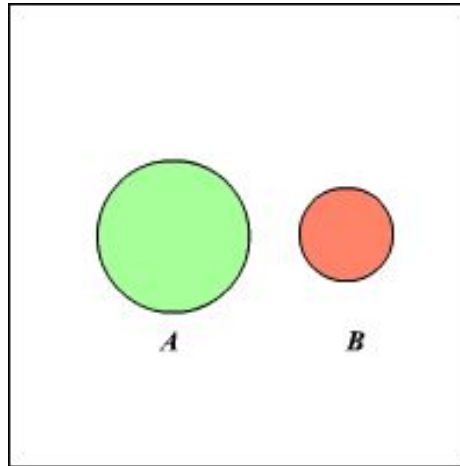
- Example: If I roll a number cube and flip a coin, What is the probability I will get a tails **or** a 3?

**Answer:**

$$P(\text{tails or a 3}) = \frac{1}{2} + \frac{1}{6} = \frac{8}{12} = \frac{2}{3}$$



# Laws of Probability: Additive Rule



- If A and B are two mutually exclusive events then  $P(A \cap B) = 0$ .

$$P(A \text{ or } B) = P(A) + P(B)$$

Or

$$P(A \cup B) = P(A) + P(B)$$

# Laws of Probability: Additive Rule (Example)

If you take out a single card from a regular pack of cards, what is probability that the card is either an ace or spade?

## Answer

Let  $X$  be the event of picking an ace and  $Y$  be the event of picking a spade.

$$P(X) = \frac{4}{52}$$

$$P(Y) = \frac{13}{52}$$

The two events are not mutually exclusive, as there is one favorable outcome in which the card can be both an ace and spade.

$$P(X \cap Y) = \frac{1}{52}$$

$$P(X \cup Y) = P(X) + P(Y) - P(X \cap Y) = \frac{4}{52} + \frac{13}{52} - \frac{1}{52} = \frac{4}{13}$$

# Complement Rule

- For any event  $A$ , we have

$$P(A^c) = 1 - P(A)$$

# Complement Rule

- Suppose that we flip eight fair coins. What is the probability that we have at least one head showing?

**Answer:**

The complement of the event “we flip at least one head” is the event “there are no heads.”

$$\begin{aligned} P(\text{At least one head}) &= 1 - P(\text{No head}) \\ &= 1 - \frac{1}{256} = 0.99609375 \end{aligned}$$

# Complement Rule

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# Random Variable

- A variable,  $X$ , whose domain is a sample space, and whose value is (somewhat) uncertain
- Examples:
  - $X$  = coin flip outcome
  - $X$  = first word in tomorrow's NYT newspaper
  - $X$  = tomorrow's high temperature

# Random Variable

- **Random Variables (RV):**

- are capitalized (usually) e.g., *Sky*, *Weather*, *Temperature*
- refer to attributes of the world whose "status" is *unknown*
- have one and only one value at a time
- have a **domain** of **values** that are possible states of the world:

- **Boolean:** domain =  $\langle \text{true}, \text{false} \rangle$

*Cavity = true* (often abbreviated as *cavity*)      *Cavity = false*  
(often abbreviated as  $\leftarrow \text{cavity}$ )

- **Discrete:** domain is countable (includes Boolean)  
values are ***mutually exclusive and exhaustive***

e.g. *Sky* domain =  $\langle \text{clear}, \text{partly\_cloudy}, \text{overcast} \rangle$

*Sky = clear* abbreviated as *clear*

*Sky  $\neq$  clear* also abbreviated as  $\neg \text{clear}$

- **Continuous:** domain is real numbers

# Conditional Probability

- **Conditional probabilities**
  - formalizes the process of accumulating evidence and updating probabilities based on new evidence
  - specifies the belief in a proposition (event, conclusion, diagnosis, etc.) that is *conditioned on* a proposition (evidence, feature, symptom, etc.) being true
- $P(a \mid e)$ : **conditional probability** of  $A=a$  given  $E=e$  evidence is *all that is known true*
  - $P(a \mid e) = P(a \wedge e) / P(e) = P(a, e) / P(e)$
  - conditional probability can viewed as the joint probability  $P(a, e)$  normalized by the prior probability,  $P(e)$



# Conditional Probability

Conditional probabilities behave exactly like standard probabilities; for example:

$$0 \leq P(a \mid e) \leq 1$$

conditional probabilities are between 0 and 1 inclusive

$$P(a_1 \mid e) + P(a_2 \mid e) + \dots + P(a_k \mid e) = 1$$

conditional probabilities sum to 1 where  $a_1, \dots, a_k$  are all values in the domain of random variable  $A$

$$P(\neg a \mid e) = 1 - P(a \mid e)$$

negation for conditional probabilities

# Conditional Probability

*$P(\text{conjunction of events} \mid e)$*

$P(a \wedge b \wedge c \mid e)$  or as  $P(a, b, c \mid e)$

is the agent's belief in the sentence  $a \wedge b \wedge c$   
conditioned on  $e$  being true

*$P(a \mid \text{conjunction of evidence})$*

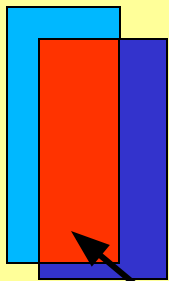
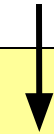
$P(a \mid e \wedge f \wedge g)$  or as  $P(a \mid e, f, g)$

is the agent's belief in the sentence  $a$   
conditioned on  $e \wedge f \wedge g$  being true

# Conditional Probability

The **conditional** probability  $P(A=a \mid B=b)$  is the fraction of time  $A=a$ , **within the region where**  $B=b$

$P(A=a)$ , e.g.  $P(1^{\text{st}} \text{ word on a random page} = \text{"San"}) = 0.001$



$P(B=b)$ , e.g.  $P(2^{\text{nd}} \text{ word} = \text{"Francisco"}) = 0.0008$



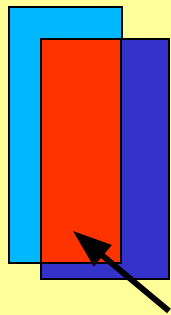
**$P(A=a \mid B=b)$** , e.g.  $P(1^{\text{st}} = \text{"San"} \mid 2^{\text{nd}} = \text{"Francisco"}) = ?$   
(possibly: San, Don, Pablo ...)



# Conditional Probability

- $P(\text{san} \mid \text{francisco})$   
 $= \#(1^{\text{st}}=\text{s and } 2^{\text{nd}}=\text{f}) / \#(2^{\text{nd}}=\text{f})$   
 $= P(\text{san} \wedge \text{francisco}) / P(\text{francisco})$   
 $= 0.0007 / 0.0008$   
 $= 0.875$

$$\begin{aligned} P(s) &= 0.001 \\ P(f) &= 0.0008 \\ P(s, f) &= 0.0007 \end{aligned}$$



$P(B=b)$ , e.g.  $P(2^{\text{nd}} \text{ word} = \text{"Francisco"}) = 0.0008$

$P(A=a \mid B=b)$ , e.g.  $P(1^{\text{st}}=\text{"San"} \mid 2^{\text{nd}}=\text{"Francisco"}) = \mathbf{0.875}$   
(possibly: San, Don, Pablo  
...)

Although “San” is rare and “Francisco” is rare,

given “Francisco” then “San” is quite likely!

# Conditional Probability

- In general, the conditional probability is

$$P(A = a \mid B) = \frac{P(A = a, B)}{P(B)} = \frac{P(A = a, B)}{\sum_{\text{all } a_i} P(A = a_i, B)}$$

- We can have everything *conditioned* on some other event(s),  $C$ , to get a conditionalized version of conditional probability:

$$P(A \mid B, C) = \frac{P(A, B \mid C)}{P(B \mid C)}$$

‘|’ has low precedence.  
This should read:  $P(A \mid (B, C))$

# The Chain Rule

- From the definition of conditional probability we have

$$P(A, B) = P(B) * P(A | B) = P(A | B) * P(B)$$

- It also works the other way around:

$$P(A, B) = P(A) * P(B | A) = P(B | A) P(A)$$

- It works with more than 2 events too:

$$\begin{aligned} P(A_1, A_2, \dots, A_n) = \\ P(A_1) * P(A_2 | A_1) * P(A_3 | A_1, A_2) * \dots \\ * P(A_n | A_1, A_2, \dots, A_{n-1}) \end{aligned}$$

Called  
“**Product  
Rule**”

Called “**Chain Rule**”

# Probabilistic Reasoning

How do we use probabilities in AI?

- You wake up with a headache
- Do you have the flu?
- $H$  = headache,  $F$  = flu



**Logical** Inference: if  $H$  then  $F$

(but the world is usually not this simple)

**Statistical** Inference: compute the probability of a query/diagnosis/decision given (i.e., conditioned on) evidence/symptom/observation, i.e.,  $P(F \mid H)$

# Example

Statistical Inference: Compute the probability of a diagnosis,  $F$ , given symptom,  $H$ , where  $H$  = “has a headache” and  $F$  = “has flu”

That is, compute  $P(F | H)$

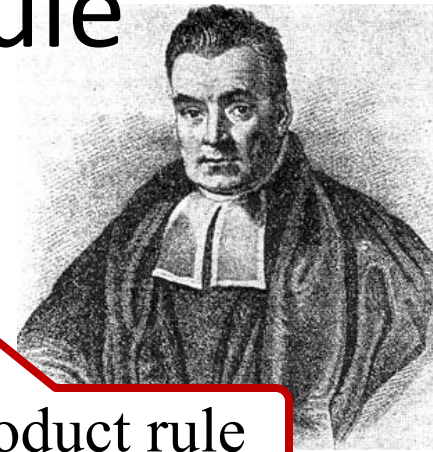
You know that

- $P(H) = 0.1$  “one in ten people has a headache”
- $P(F) = 0.01$  “one in 100 people has flu”
- $P(H | F) = 0.9$  “90% of people who have flu have a headache”



# Inference with Bayes's Rule

Thomas Bayes, “Essay Towards Solving a Problem in the Doctrine of Chances,” 1764



$$P(F | H) = \frac{P(F, H)}{P(H)} = \frac{P(H | F)P(F)}{P(H)}$$

Def of cond. prob.

Product rule

- $P(H) = 0.1$  “one in ten people has a headache”
- $P(F) = 0.01$  “one in 100 people has flu”
- $P(H | F) = 0.9$  “90% of people who have flu have a headache”
- $P(F | H) = 0.9 * 0.01 / 0.1 = 0.09$
- So, there's a 9% chance you have flu – much less than 90%
- But it's higher than  $P(F) = 1\%$ , since you have a headache

# Bayes's Rule

- Bayes's Rule is the basis for probabilistic reasoning given a prior model of the world,  $P(Q)$ , and a new piece of evidence,  $E$ , Bayes's rule says how this piece of evidence decreases our ignorance about the world
- Initially, know  $P(Q)$  (“prior”)
- Update after knowing  $E$  (“posterior”):

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

# Inference with Bayes's Rule

$$P(A | B) = P(B | A)P(A) / P(B) \quad \text{Bayes's rule}$$

- Why do we make things this complicated?
  - Often  $P(B|A)$ ,  $P(A)$ ,  $P(B)$  are easier to get
  - Some names:
    - **Prior**  $P(A)$ : probability of  $A$  *before* any evidence
    - **Likelihood**  $P(B|A)$ : assuming  $A$ , how likely is the evidence
    - **Posterior**  $P(A|B)$ : probability of  $A$  after knowing evidence  $B$
    - **(Deductive) Inference**: deriving an unknown probability from known ones
- If we have the full joint probability table, we can simply compute  $P(A | B) = P(A, B) / P(B)$

# Bayes's Rule in Practice



# Summary of Important Rules

- **Conditional Probability:**  $P(A | B) = P(A, B) / P(B)$
- **Product rule:**  $P(A, B) = P(A | B)P(B)$
- **Chain rule:**  $P(A, B, C, D) = P(A | B, C, D)P(B | C, D)P(C | D)P(D)$
- **Conditionalized version of Chain rule:**

$$P(A, B | C) = P(A | B, C)P(B | C)$$

- **Bayes's rule:**  $P(A | B) = P(B | A)P(A) / P(B)$
- **Conditionalized version of Bayes's rule:**

$$P(A | B, C) = P(B | A, C)P(A | C) / P(B | C)$$

- **Addition / Conditioning rule:**  $P(A) = P(A, B) + P(A, \neg B)$

$$P(A) = P(A | B)P(B) + P(A | \neg B)P(\neg B)$$

# Common Mistake

- $P(A) = 0.3$  so  $P(\neg A) = 1 - P(A) = 0.7$
- $P(A|B) = 0.4$  so  $P(\neg A|B) = 1 - P(A|B) = 0.6$   
because  $P(A|B) + P(\neg A|B) = 1$

***but***  $P(A|\neg B) \neq 0.6$  (in general)

because  $P(A|B) + P(A|\neg B) \neq 1$  in general

# Quiz

- A doctor performs a test that has 99% reliability, i.e., 99% of people who are sick test positive, and 99% of people who are healthy test negative. The doctor estimates that 1% of the population is sick.
- Question: A patient tests positive. What is the chance that the patient is sick?
- 0-25%, 25-75%, 75-95%, or 95-100%?

# Quiz

- A doctor performs a test that has 99% reliability, i.e., 99% of people who are sick test positive, and 99% of people who are healthy test negative. The doctor estimates that 1% of the population is sick.
- Question: A patient tests positive. What is the chance that the patient is sick?
- 0-25%, 25-75%, 75-95%, or 95-100%?
- Common answer: 99%; Correct answer: 50%



Given:

$$P(TP \mid S) = 0.99$$

$$P(\neg TP \mid \neg S) = 0.99$$

$$P(S) = 0.01$$

$TP$  = “tests positive”

$S$  = “is sick”

Query:

$$P(S \mid TP) = ?$$

$$P(TP \mid S) = 0.99$$

$$P(\neg TP \mid \neg S) = 0.99$$

$$P(S) = 0.01$$

$$P(S \mid TP) =$$

$$P(TP \mid S) P(S) / P(TP)$$

$$= (0.99)(0.01) / P(TP) = 0.0099/P(TP)$$

$$P(\neg S \mid TP) = P(TP \mid \neg S) P(\neg S) / P(TP)$$

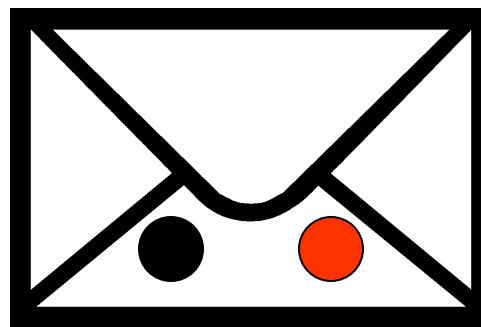
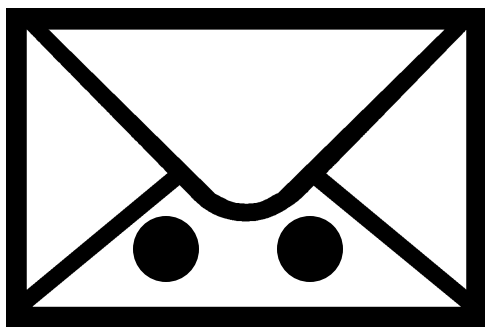
$$= (1 - 0.99)(1 - 0.01) / P(TP) = 0.0099/P(TP)$$

$$0.0099/P(TP) + 0.0099/P(TP) = 1, \text{ so } P(TP) = 0.0198$$

$$\text{So, } P(S \mid TP) = 0.0099 / 0.0198 = 0.5$$

# Inference with Bayes's Rule

- In a bag there are two envelopes
  - one has a red ball (worth \$100) and a black ball
  - one has two black balls. Black balls are worth nothing



- You randomly grab an envelope, and randomly take out one ball – it's **black**
- At this point you're given the option to switch envelopes. **Should you switch or not?**

Similar to the “Monty Hall Problem”