

# CS 540 Introduction to Artificial Intelligence **Probability**

University of Wisconsin-Madison Fall 2023

## Probability: What is it good for?

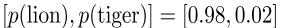
Language to express uncertainty





### In AI/ML Context

#### Quantify predictions







[p(lion), p(tiger)] = [0.01, 0.99]



[p(lion), p(tiger)] = [0.43, 0.57]

<sup>\*</sup> If we know for sure the photo must contain either a lion or a tiger

#### Model Data Generation

Model complex distributions



**StyleGAN2** (Kerras et al '20)

#### Win At Poker

Wisconsin Ph.D. student Ye Yuan 5<sup>th</sup> in WSOP

Not unusual: probability began as study of gambling techniques

#### Cardano

Liber de ludo aleae Book on Games of Chance 1564!





pokernews.com

#### Outline

Basics: definitions, axioms, RVs, joint distributions

Independence, conditional probability, chain rule

Bayes' Rule and Inference



#### **Basics: Outcomes & Events**

Outcomes: possible results of an experiment

$$\Omega = \underbrace{\{1, 2, 3, 4, 5, 6\}}_{\text{outcomes}}$$

• Events: subsets of outcomes we're interested in

$$\underbrace{\emptyset, \{1\}, \{2\}, \dots, \{1, 2\}, \dots, \Omega}_{\text{events}}$$

• Always include  $\emptyset, \Omega$ 



### **Basics: Probability Distribution**

- We have outcomes and events.
- Assign **probabilities**: for each event  $E, P(E) \in [0,1]$

#### Back to our example:

$$\underbrace{\emptyset, \{1\}, \{2\}, \dots, \{1, 2\}, \dots, \Omega}_{\text{events}}$$

$$P(\{1, 3, 5\}) = 0.2, P(\{2, 4, 6\}) = 0.8$$



#### Basics: Axioms

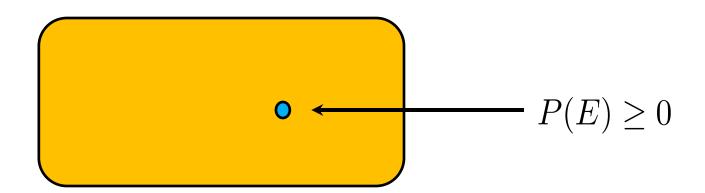
- Rules for probability:
  - For all events  $E, P(E) \ge 0$
  - Always,  $P(\emptyset) = 0, P(\Omega) = 1$
  - For disjoint events,  $P(E_1 \cup E_2) = P(E_1) + P(E_2)$

• Easy to derive other laws. Ex: non-disjoint events

$$P(E_1 \cup E_2) = P(E_1) + P(E_2) - P(E_1 \cap E_2)$$

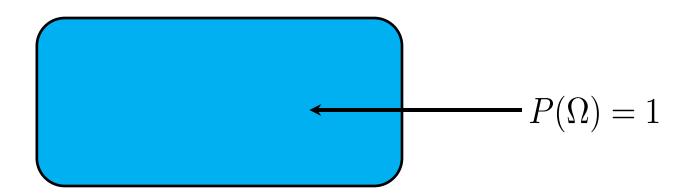
### Visualizing the Axioms: I

• Axiom 1: for all events  $E, P(E) \ge 0$ 



#### Visualizing the Axioms: II

• Axiom 2:  $P(\emptyset) = 0, P(\Omega) = 1$ 

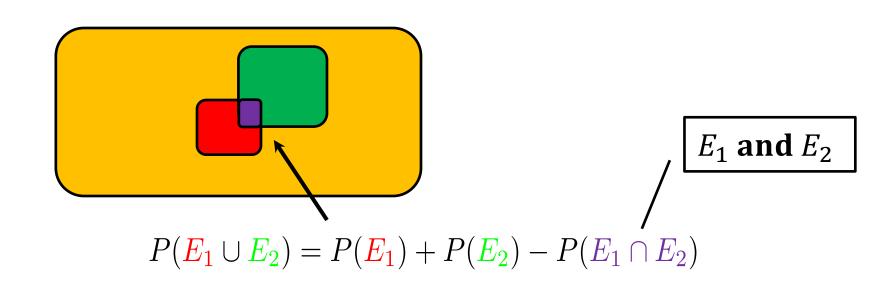


#### Visualizing the Axioms: III

• Axiom 3: disjoint  $P(E_1 \cup E_2) = P(E_1) + P(E_2)$   $E_1 \text{ or } E_2$   $P(E_1 \cup E_2) = P(E_1) + P(E_2)$ 

#### Visualizing the Axioms

Also, other laws:



- Q 1.1: We toss a biased coin. If P(heads) = 0.7, thenP(tails) = ?
- A. 0.4
- B. 0.3
- C. 0.6
- D. 0.5

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- Q 1.2: There are exactly 3 candidates for a presidential election. We know X has a 30% chance of winning, B has a 35% chance. What's the probability that C wins?
- A. 0.35
- B. 0.23
- C. 0.333
- D. 0.8

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- **Q 1.3**: What's the probability of selecting a black card or a number 6 from a standard deck of 52 cards?
- A. 26/52
- B. 4/52
- C. 30/52
- D. 28/52

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#### Basics: Random Variables

- Intuitively: a number X that's random
- Mathematically: map random outcomes to real values

$$X:\Omega\to\mathbb{R}$$

- Why?
  - Previously, everything is a set.
  - Real values are easier to work with



#### Basics: CDF & PDF

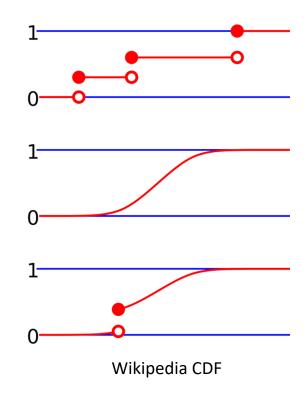
Can still work with probabilities:

$$P(X=3)$$

• Cumulative Distribution Func. (CDF)

$$F_X(x) := P(X \le x)$$

• Density / mass function  $p_X(x)$ 



## Basics: Expectation & Variance

Another advantage of RVs are ``summaries''

- Expectation:  $E[X] = \sum_a a \times P(x=a)$ 
  - The "average"

- Variance:  $Var[X] = E[(X E[X])^2]$ 
  - A measure of "spread"

#### Basics: Joint Distributions

- Move from one variable to several
- Joint distribution: P(X = a, Y = b)
  - Why? Work with multiple types of uncertainty that correlate with each other





## Basics: Marginal Probability

• Given a joint distribution P(X = a, Y = b)

— Get the distribution in just one variable:

$$P(X = a) = \sum_{b} P(X = a, Y = b)$$

This is the "marginal" distribution.

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	Packing 80/20						
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- 11	Coffee				-	4	6
12	Breakfast -						6.
		10					
	Breakfast -	4				1	0
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	See 4				"		
June 1	Sees -	-		,		/	
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## Jerry's super blurry camera

- One pixel, 1-bit color sensor (green=trees, white=snow)
- Model T: comes with 1-bit temperature sensor (hot, cold)

## Basics: Marginal Probability

$$P(X = a) = \sum_{b} P(X = a, Y = b)$$

	green	white
hot	150/365	45/365
cold	50/365	120/365

$$[P(\text{hot}), P(\text{cold})] = [\frac{195}{365}, \frac{170}{365}]$$

## **Probability Tables**

Write our distributions as tables

- # of entries? 4.
  - If we have n variables with k values, we get  $k^n$  entries
  - Big! For a 1080p screen, 12 bit color, size of table:  $10^{7490589}$
  - No way of writing down all terms

## Independence

• Independence between RVs:

$$P(X,Y) = P(X)P(Y)$$

- Why useful? Go from  $k^n$  entries in a table to  $\sim kn$
- Expresses joint as product of marginals

requires domain knowledge

## **Conditional Probability**

• For when we know something (i.e. Y=b),

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

	green	white
hot	150/365	45/365
cold	50/365	120/365

$$P(cold|white) = \frac{P(cold, white)}{P(white)} = \frac{120}{45 + 120} = 0.73$$

### Conditional independence

require domain knowledge

$$P(X,Y|Z) = P(X|Z)P(Y|Z)$$

#### Chain Rule

Apply repeatedly,

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

- Note: still big!
  - If some conditional independence, can factor!
  - Leads to probabilistic graphical models



**Q 2.1:** Given joint distribution table:

	Sunny	Cloudy	Rainy
hot	150/365	40/365	5/365
cold	50/365	60/365	60/365

What is the probability the temperature is hot given the weather is cloudy?

- A. 40/365
- B. 2/5
- C. 3/5
- D. 195/365

**Q 2.1:** Back to our joint distribution table:

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**Q 2.2:** Of a company's employees, 30% are women and 6% are married women. Suppose an employee is selected at random. If the employee selected is a woman, what is the probability that she is married?

- A. 0.3
- B. 0.06
- C. 0.24
- D. 0.2

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### Reasoning With Conditional Distributions

- Evaluating probabilities:
  - Wake up with a sore throat.
  - Do I have the flu?



- Too strong.
- Inference: compute probability given evidence P(F|S)
  - Can be much more complex!



# Using Bayes' Rule

- Want: P(F|S)
- Bayes' Rule:  $P(F|S) = \frac{P(F,S)}{P(S)} = \frac{P(S|F)P(F)}{P(S)}$
- Parts:
  - P(S) = 0.1 Sore throat rate
  - P(F) = 0.01 Flu rate
  - -P(S|F) = 0.9 Sore throat rate among flu sufferers

**So**: P(F|S) = 0.09

# Using Bayes' Rule

- Interpretation P(F|S) = 0.09
  - Much higher chance of flu than normal rate (0.01).
  - Very different from P(S|F) = 0.9
    - 90% of folks with flu have a sore throat
    - But, only 9% of folks with a sore throat have flu

Idea: update probabilities from

evidence





Fancy name for what we just did. Terminology:

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

- *H* is the hypothesis
- E is the evidence



Terminology:

$$P(H|E) = \frac{P(E|H)P(H)}{P(E)} \longleftarrow \text{Prior}$$

Prior: estimate of the probability without evidence

• Terminology:

Likelihood 
$$P(H|E) = \frac{P(E|H)P(H)}{P(E)}$$

Likelihood: probability of evidence given a hypothesis

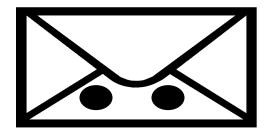
Terminology:

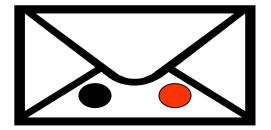
$$P(H|E) = \frac{P(E|H)P(H)}{P(E)}$$
Posterior

• Posterior: probability of hypothesis given evidence.

#### Two Envelopes Problem

- We have two envelopes:
  - $-E_1$  has two black balls,  $E_2$  has one black, one red
  - The red one is worth \$100. Others, zero
  - Open an envelope, see one ball. Then, can switch (or not).
  - You see a black ball. Switch?





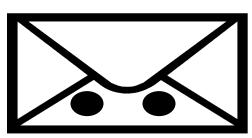
#### Two Envelopes Solution

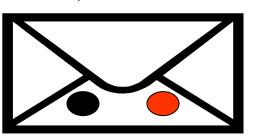
• Let's solve it.  $P(E_1|\text{Black ball}) = \frac{P(\text{Black ball}|E_1)P(E_1)}{P(\text{Black ball})}$ 

• Now plug in:  $P(E_1|\text{Black ball}) = \frac{1 \times \frac{1}{2}}{P(\text{Black ball})}$ 

$$P(E_2|\text{Black ball}) = \frac{\frac{1}{2} \times \frac{1}{2}}{P(\text{Black ball})}$$

So switch!





#### Naïve Bayes

Conditional Probability & Bayes:

$$P(H|E_1, E_2, \dots, E_n) = \frac{P(E_1, \dots, E_n|H)P(H)}{P(E_1, E_2, \dots, E_n)}$$

 If we further make the conditional independence assumption (a.k.a. Naïve Bayes)

$$P(H|E_1, E_2, \dots, E_n) = \frac{P(E_1|H)P(E_2|H) \cdots P(E_n|H)P(H)}{P(E_1, E_2, \dots, E_n)}$$

### Naïve Bayes

Expression

$$P(H|E_1, E_2, \dots, E_n) = \frac{P(E_1|H)P(E_2|H)\cdots, P(E_n|H)P(H)}{P(E_1, E_2, \dots, E_n)}$$

- H: some class we'd like to infer from evidence
  - We know prior P(H)
  - Estimate  $P(E_i|H)$  from data! ("training")
  - Very similar to envelopes problem.

**Q 3.1:** 50% of emails are spam. Software has been applied to filter spam. A certain brand of software claims that it can detect 99% of spam emails, and the probability for a false positive (a non-spam email detected as spam) is 5%. Now if an email is detected as spam, then what is the probability that it is in fact a nonspam email?

- A. 5/104
- B. 95/100
- C. 1/100
- D. 1/2

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- A. 1/8
- B. 2/8
- C. 3/8
- D. 5/8

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# Readings

- Vast literature on intro probability and statistics.
- Local classes: Math/Stat 431

#### Suggested reading:

Probability and Statistics: The Science of Uncertainty,

Michael J. Evans and Jeff S. Rosenthal

http://www.utstat.toronto.edu/mikevans/jeffrosenthal/book.pdf

(Chapters 1-3, excluding "advanced" sections)