CS 540 Introduction to Artificial Intelligence
Probability

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Probability: What is it good for?

- Language to express **uncertainty**

In AI/ML Context

- Quantify predictions

$[p(\text{lion}), p(\text{tiger})] = [0.98, 0.02]$

$[p(\text{lion}), p(\text{tiger})] = [0.01, 0.99]$

$[p(\text{lion}), p(\text{tiger})] = [0.43, 0.57]$

Model Data Generation

- Model complex distributions

StyleGAN2 (Kerras et al ’20)

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**
- **Events:** subsets of outcomes we're interested in

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

$$\mathcal{F} = \underbrace{\{\emptyset, \{1\}, \{2\}, \ldots, \{1,2\}, \ldots, \Omega\}}_{\text{events}}$$

Basics: Outcomes & Events

- Event space can be smaller:

$$\mathcal{F} = \underbrace{\{\emptyset, \{1,3,5\}, \{2,4,6\}, \Omega\}}_{\text{events}}$$

- Two components always in it!

$$\emptyset, \Omega$$

Basics: Probability Distribution

- We have outcomes and events.
- Now assign probabilities $\text{For } E \in \mathcal{F},\ P(E) \in [0,1]$

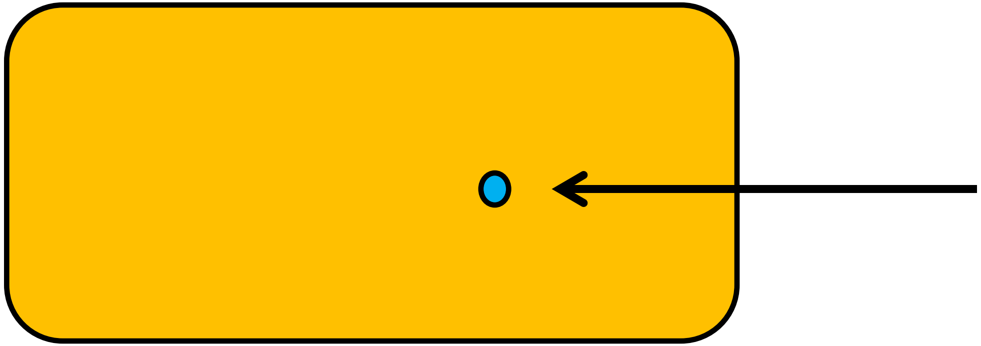
Back to our example:

$$\mathcal{F} = \underbrace{\{\emptyset, \{1,3,5\}, \{2,4,6\}, \Omega\}}_{\text{events}}$$

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

Probability Axioms

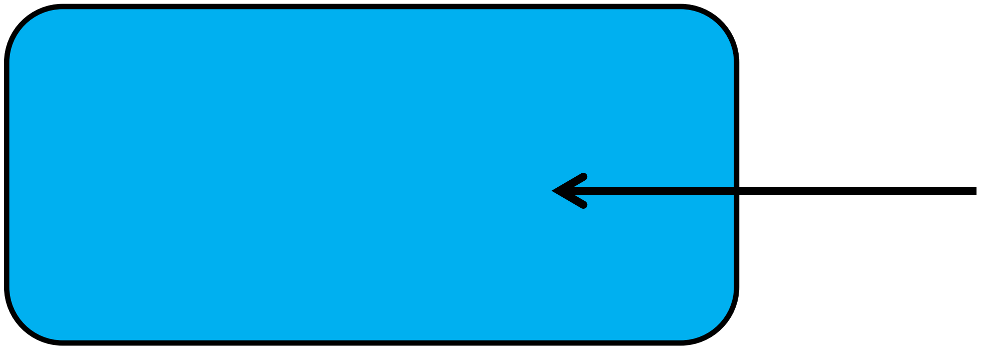
- Axiom 1: for all event $E \in \mathcal{F}, P(E) \geq 0$



$P(E) \geq 0$

Probability Axioms

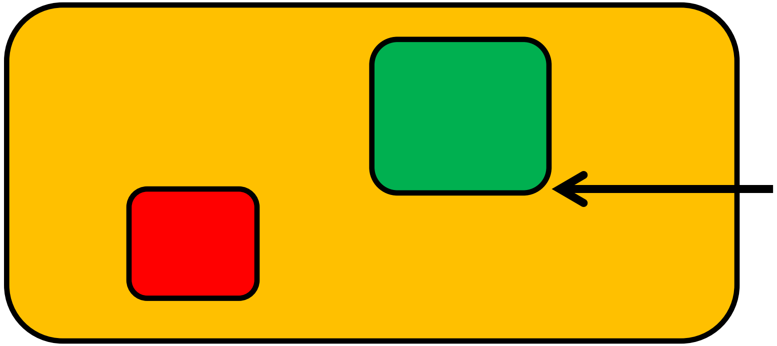
- Axiom 2: Always, $P(\emptyset) = 0, P(\Omega) = 1$



$P(\Omega) = 1$

Probability Axioms

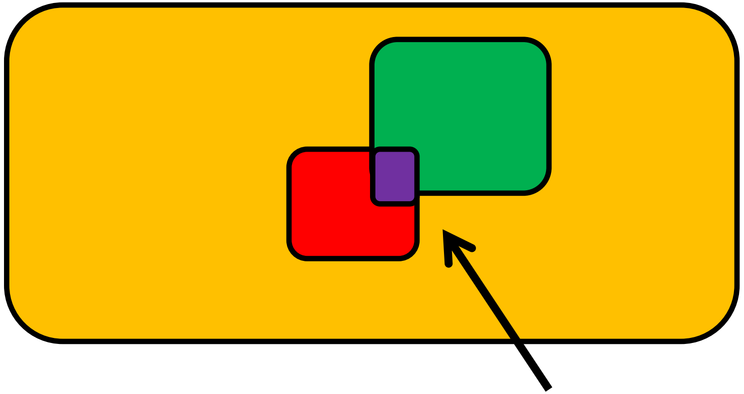
- Axiom 3: for disjoint events, $P(E_1 \cup E_2) = P(E_1) + P(E_2)$



$$P({\color{red}E_1} \cup {\color{green}E_2}) = P({\color{red}E_1}) + P({\color{green}E_2})$$

Other Probability Laws

- Ex: non-disjoint events



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

Break & Quiz

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

Break & Quiz

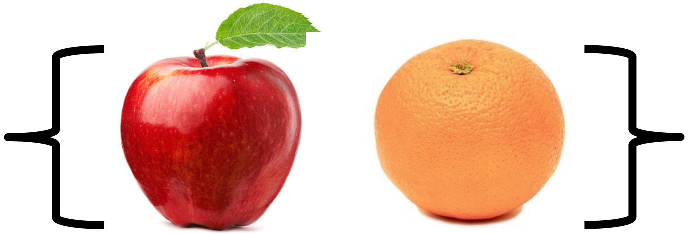
- **Q 1.2**: There are exactly 3 candidates, A, B and C, for a presidential election. We know A has a 30% chance of winning, B has a 35% chance. What’s the probability that C wins?
- A. 0.35
- B. 0.23
- C. 0.333
- D. 0.8

Break & Quiz

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

Basics: **Random Variables**

- Really, functions
- Map outcomes to real values $X : \Omega \to \mathbb{R}$



- Why?
  - Sets are hard to work with
  - Real values are more convenient

Basics: **CDF & PDF**

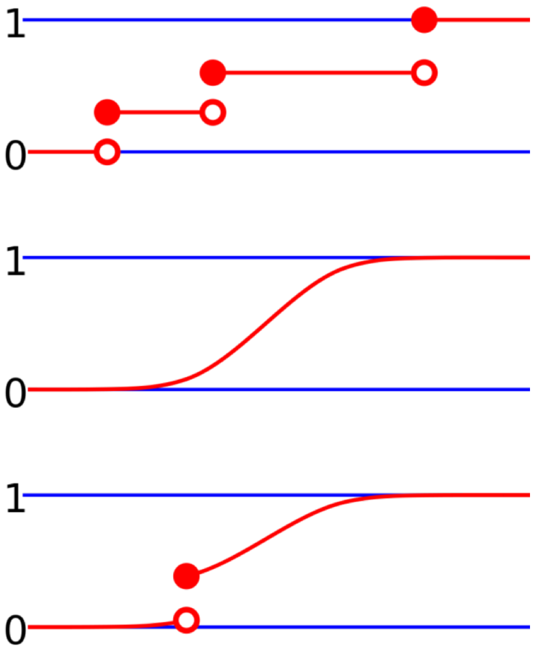
- Can still work with probabilities:

$$P(X = 3) := P(\{\omega : X(\omega) = 3\})$$

- Cumulative Distribution Func. (CDF)

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

- Density / mass function $p_X(x)$



Wiki CDF

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"
- Higher moments

Basics: **Joint Distributions**

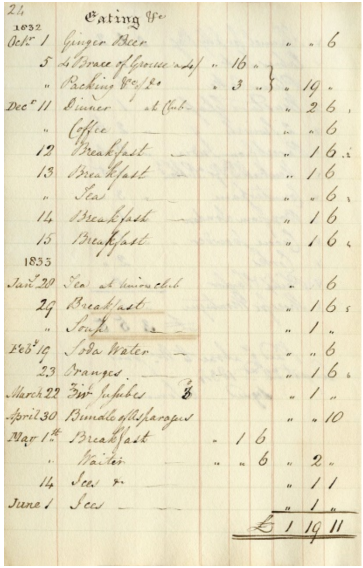
- Move from one variable to several
- Joint distribution: $P(X = a, Y = b)$
  - Allow us to work with **multiple** types of uncertainty

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 called the **marginal** distribution.



Basics: **Marginal** Probability

$$P(X=a)=\sum_b P(X=a,Y=b)$$

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

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

Probability Tables

- Write our distributions as tables

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

- # of entries? 6.
  - 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 $\sim kn$
- Reduces joint distribution into **product** of marginal distributions

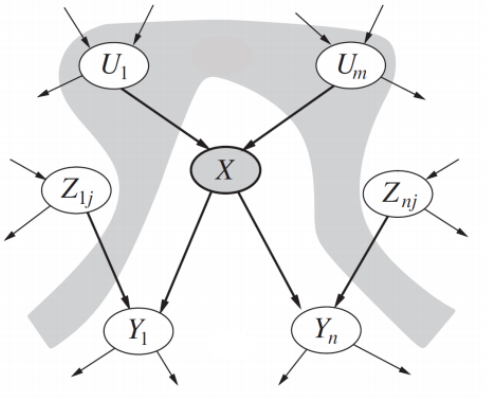
Conditional Probability

- For when we know something,

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

- Leads to **conditional independence**

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



Credit: **Devin Soni**

Chain Rule

- Apply repeatedly,

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

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

Break & Quiz

Q 2.1: Back to our 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

Break & Quiz

Q 2.2: Of a company's employees, 30% have CS degrees and 6% have CS Ph.D. degrees. Suppose an employee is selected at random. If the employee selected has a CS degree, what is the probability that the employee has a Ph.D. degree?

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

Reasoning With Conditional Distributions

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

- One approach: $S \rightarrow F$
  - Too strong.
- **Inference**: compute probability given evidence $P(F|S)$
  - Can be much more complex!

Using **Bayes' Rule**

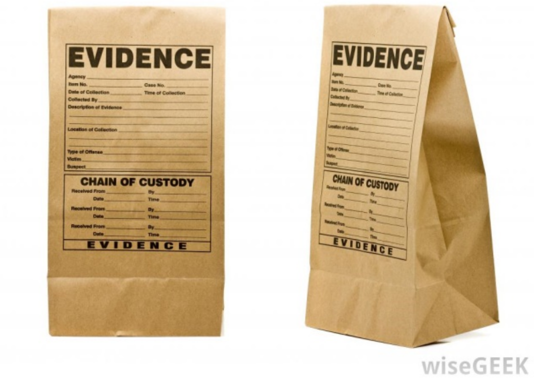
- Want: $P(F|S)$
- **Bayes' Rule:** $P(F|S) = \frac{P(F,S)}{P(S)} = \frac{P(S|F)P(F)}{P(S)}$
- Parts:
  - $P(S) = 0.1$ Sore throat rate
  - $P(F) = 0.01$ Flu rate
  - $P(S|F) = 0.9$ Sore throat rate among flu sufferers

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**



Bayesian **Inference**

- 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

Bayesian **Inference**

- Terminology:

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

- Prior: estimate of the probability **without** evidence

Bayesian Inference

- Terminology:

Likelihood

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

- Likelihood: probability of evidence **given a hypothesis**.

Bayesian Inference

- Terminology:

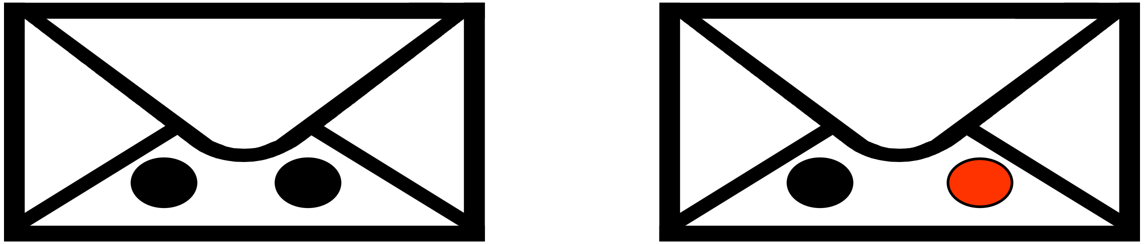
$$P(H|E) = \frac{P(E|H)P(H)}{P(E)}$$

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.

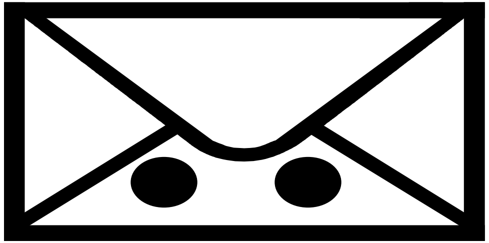
$$P(E_1|\text{Black ball}) = \frac{P(\text{Black ball}|E_1)P(E_1)}{P(\text{Black ball})}$$

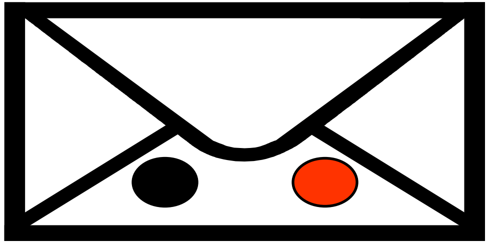
- Now plug in:

$$P(E_1|\text{Black ball}) = \frac{1 \times \frac{1}{2}}{P(\text{Black ball})}$$

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

So switch!





Break & Quiz

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 non-spam email?

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

Break & Quiz

Q 3.2: A fair coin is tossed three times. Find the probability of getting 2 heads and a tail

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