Lecture 16: Continuing Probability.

Wrap up: Probability Formalism.

Events, Conditional Probability, Independence, Bayes’ Rule
Probability Space: Formalism

Simplest physical model of a uniform probability space:

A bag of identical balls, except for their color (or a label). If the bag is well shaken, every ball is equally likely to be picked.

\[ \Omega = \{ \text{white, red, yellow, grey, purple, blue, maroon, green} \} \]

\[ Pr[\text{blue}] = \frac{1}{8}. \]
Probability Space: Formalism

Simplest physical model of a non-uniform probability space:

\[ \Omega = \{\text{Red, Green, Yellow, Blue}\} \]

\[ Pr[\text{Red}] = \frac{3}{10}, \quad Pr[\text{Green}] = \frac{4}{10}, \quad \text{etc.} \]

Note: Probabilities are restricted to rational numbers: \( \frac{N_k}{N} \).
Probability Space: Formalism

Physical model of a general non-uniform probability space:

The roulette wheel stops in sector $\omega$ with probability $p_\omega$.

$$\Omega = \{1, 2, 3, \ldots, N\}, \Pr[\omega] = p_\omega.$$
An important remark

- The random experiment selects **one and only one** outcome in $\Omega$.

- For instance, when we flip a fair coin **twice**
  
  - $\Omega = \{HH, TH, HT, TT\}$
  - The experiment selects **one** of the elements of $\Omega$.

- In this case, it's wrong to think that $\Omega = \{H, T\}$ and that the experiment selects two outcomes.

- Why? Because this would not describe how the two coin flips are related to each other.

- For instance, say we glue the coins side-by-side so that they face up the same way. Then one gets $HH$ or $TT$ with probability 50% each. This is not captured by ‘picking two outcomes.’
Lecture 15: Summary

**Modeling Uncertainty: Probability Space**

1. Random Experiment
2. Probability Space: $\Omega; Pr[\omega] \in [0, 1]; \sum_\omega Pr[\omega] = 1$.
3. Uniform Probability Space: $Pr[\omega] = 1/|\Omega|$ for all $\omega \in \Omega$. 
CS70: On to Calculation.

Events, Conditional Probability, Independence, Bayes’ Rule

1. Probability Basics Review
2. Events
3. Conditional Probability
4. Independence of Events
5. Bayes’ Rule
Probability Basics Review

Setup:

- Random Experiment.
  Flip a fair coin twice.

- Probability Space.
  
  - **Sample Space:** Set of outcomes, $\Omega$.
    $\Omega = \{HH, HT, TH, TT\}$
    (Note: Not $\Omega = \{H, T\}$ with two picks!)

  - **Probability:** $Pr[\omega]$ for all $\omega \in \Omega$.
    $Pr[HH] = \cdots = Pr[TT] = 1/4$

    1. $0 \leq Pr[\omega] \leq 1$.
    2. $\sum_{\omega \in \Omega} Pr[\omega] = 1$. 
Set notation review

Figure: Two events

Figure: Union (or)

Figure: Difference (A, not B)

Figure: Complement (not)

Figure: Intersection (and)

Figure: Symmetric difference (only one)
Probability of exactly one ‘heads’ in two coin flips?

Idea: Sum the probabilities of all the different outcomes that have exactly one ‘heads’: $HT, TH$.

This leads to a definition!

**Definition:**

- An event, $E$, is a subset of outcomes: $E \subset \Omega$.
- The probability of $E$ is defined as $Pr[E] = \sum_{\omega \in E} Pr[\omega]$. 

Event: Example

\[ \Omega = \{ \text{Red, Green, Yellow, Blue} \} \]

\[ Pr[\text{Red}] = \frac{3}{10}, \quad Pr[\text{Green}] = \frac{4}{10}, \quad \text{etc.} \]

\[ E = \{ \text{Red, Green} \} \Rightarrow Pr[E] = \frac{3 + 4}{10} = \frac{3}{10} + \frac{4}{10} = Pr[\text{Red}] + Pr[\text{Green}]. \]
Probability of exactly one heads in two coin flips?

Sample Space, $\Omega = \{HH, HT, TH, TT\}$.

Uniform probability space: $Pr[HH] = Pr[HT] = Pr[TH] = Pr[TT] = \frac{1}{4}$.

Event, $E$, “exactly one heads”: $\{TH, HT\}$.

$$Pr[E] = \sum_{\omega \in E} Pr[\omega] = \frac{|E|}{|\Omega|} = \frac{2}{4} = \frac{1}{2}.$$
Example: 20 coin tosses.

20 coin tosses

Sample space: $\Omega = \text{set of 20 fair coin tosses.}$
$\Omega = \{T, H\}^{20} \equiv \{0, 1\}^{20}; \ |\Omega| = 2^{20}.$

▶ What is more likely?

▶ $\omega_1 := (1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1),$ or
▶ $\omega_2 := (1, 0, 1, 1, 0, 0, 0, 1, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0, 0)?$

Answer: Both are equally likely: $Pr[\omega_1] = Pr[\omega_2] = \frac{1}{|\Omega|}.$

▶ What is more likely?

$(E_1)$ Twenty Hs out of twenty, or
$(E_2)$ Ten Hs out of twenty?

Answer: Ten Hs out of twenty.

Why? There are many sequences of 20 tosses with ten Hs; only one with twenty Hs. $\Rightarrow Pr[E_1] = \frac{1}{|\Omega|} \ll Pr[E_2] = \frac{|E_2|}{|\Omega|}.$

$|E_2| = \binom{20}{10} = 184,756.$
Probability of $n$ heads in 100 coin tosses.

$\Omega = \{H, T\}^{100}; \ |\Omega| = 2^{100}.$

Event $E_n = ‘n$ heads’; $|E_n| = \binom{100}{n}$

$p_n := Pr[E_n] = \frac{|E_n|}{|\Omega|} = \frac{\binom{100}{n}}{2^{100}}$

Observe:

- Concentration around mean: Law of Large Numbers;
- Bell-shape: Central Limit Theorem.
Roll a red and a blue die.

$$Pr[\text{Sum to 7}] = \frac{6}{36} \quad Pr[\text{Sum to 10}] = \frac{3}{36}$$
Exactly 50 heads in 100 coin tosses.

Sample space: $\Omega = \text{set of 100 coin tosses} = \{H, T\}^{100}$. 

$|\Omega| = 2 \times 2 \times \cdots \times 2 = 2^{100}$.

Uniform probability space: $Pr[\omega] = \frac{1}{2^{100}}$.

Event $E =$ “100 coin tosses with exactly 50 heads”

$|E|$?

Choose 50 positions out of 100 to be heads. 

$|E| = \binom{100}{50}$.

$$Pr[E] = \frac{\binom{100}{50}}{2^{100}}.$$
Calculation.
Stirling formula (for large $n$):

$$n! \approx \sqrt{2\pi n} \left(\frac{n}{e}\right)^n.$$ 

$$\binom{2n}{n} \approx \frac{\sqrt{4\pi n} (2n/e)^{2n}}{[\sqrt{2\pi n} (n/e)^n]^2} \approx \frac{4^n}{\sqrt{\pi n}}.$$ 

$$Pr[E] = \frac{|E|}{|\Omega|} = \frac{|E|}{2^{2n}} = \frac{1}{\sqrt{\pi n}} = \frac{1}{\sqrt{50\pi}} \approx .08.$$
Exactly 50 heads in 100 coin tosses.

\[ Pr[n \text{Hs out of } 2n] = \frac{\binom{2n}{n}}{2^{2n}} \]
Theorem

(a) If events $A$ and $B$ are disjoint, i.e., $A \cap B = \emptyset$, then

$$Pr[A \cup B] = Pr[A] + Pr[B].$$

(b) If events $A_1, \ldots, A_n$ are pairwise disjoint, i.e., $A_k \cap A_m = \emptyset$, $\forall k \neq m$, then

$$Pr[A_1 \cup \cdots \cup A_n] = Pr[A_1] + \cdots + Pr[A_n].$$

Proof:

Obvious.
Consequences of Additivity

Theorem

(a) $Pr[A \cup B] = Pr[A] + Pr[B] - Pr[A \cap B]$;

(inclusion-exclusion property)

(b) $Pr[A_1 \cup \cdots \cup A_n] \leq Pr[A_1] + \cdots + Pr[A_n]$;

(union bound)

(c) If $A_1, \ldots, A_N$ are a partition of $\Omega$, i.e., pairwise disjoint and $\bigcup_{m=1}^{N} A_m = \Omega$, then

$Pr[B] = Pr[B \cap A_1] + \cdots + Pr[B \cap A_N]$.

(law of total probability)

Proof:

(b) is obvious.

Proofs for (a) and (c)? Next...
Inclusion/Exclusion

\[ Pr[A \cup B] = Pr[A] + Pr[B] - Pr[A \cap B] \]

Another view. Any \( \omega \in A \cup B \) is in \( A \cap B \), \( A \cup B \), or \( \overline{A} \cap B \). So, add it up.
Total probability

Assume that $\Omega$ is the union of the disjoint sets $A_1, \ldots, A_N$.

Then,

$$Pr[B] = Pr[A_1 \cap B] + \cdots + Pr[A_N \cap B].$$

Indeed, $B$ is the union of the disjoint sets $A_n \cap B$ for $n = 1, \ldots, N$.

In “math”: $\omega \in B$ is in exactly one of $A_i \cap B$.

Adding up probability of them, get $Pr[\omega]$ in sum.

..Did I say...

Add it up.
Roll a Red and a Blue Die.

- $E_1 = \text{Red die shows 6}$
- $E_2 = \text{Blue die shows 6}$
- $E_1 \cup E_2 = \text{At least one die shows 6}$

$$|E_1 \cup E_2| = |E_1| + |E_2| - |E_1 \cap E_2|$$

$$Pr[E_1] = \frac{6}{36}, \quad Pr[E_2] = \frac{6}{36}, \quad Pr[E_1 \cup E_2] = \frac{11}{36}.$$
Conditional probability: example.

Two coin flips. First flip is heads. Probability of two heads? \( \Omega = \{HH, HT, TH, TT\} \); Uniform probability space. Event \( A = \) first flip is heads: \( A = \{HH, HT\} \).

\[ \Omega : \text{uniform} \]

New sample space: \( A \); uniform still.

Event \( B = \) two heads.

The probability of two heads if the first flip is heads. **The probability of \( B \) given \( A \) is 1/2.**
A similar example.

Two coin flips. At least one of the flips is heads. → Probability of two heads?

\[ \Omega = \{ HH, HT, TH, TT \} ; \text{uniform.} \]
Event \( A = \) at least one flip is heads. \( A = \{ HH, HT, TH \} \).

New sample space: \( A \); uniform still.

Event \( B = \) two heads.

The probability of two heads if at least one flip is heads. **The probability of \( B \) given \( A \) is 1/3.**
Conditional Probability: A non-uniform example

Physical experiment

\[ \Omega = \{ \text{Red, Green, Yellow, Blue} \} \]

\[ Pr[\text{Red} | \text{Red or Green}] = \frac{3}{7} = \frac{Pr[\text{Red} \cap (\text{Red or Green})]}{Pr[\text{Red or Green}]} \]
Another non-uniform example

Consider $\Omega = \{1, 2, \ldots, N\}$ with $Pr[n] = p_n$.
Let $A = \{3, 4\}$, $B = \{1, 2, 3\}$.

$$Pr[A|B] = \frac{p_3}{p_1 + p_2 + p_3} = \frac{Pr[A \cap B]}{Pr[B]}.$$
Yet another non-uniform example

Consider \( \Omega = \{1, 2, \ldots, N\} \) with \( Pr[n] = p_n \).

Let \( A = \{2, 3, 4\}, B = \{1, 2, 3\} \).

\[
Pr[A|B] = \frac{p_2 + p_3}{p_1 + p_2 + p_3} = \frac{Pr[A \cap B]}{Pr[B]}.
\]
Definition: The **conditional probability** of $B$ given $A$ is

$$Pr[B|A] = \frac{Pr[A \cap B]}{Pr[A]}$$

In $A!$

In $B$?

Must be in $A \cap B$.

$$Pr[B|A] = \frac{Pr[A \cap B]}{Pr[A]}.$$
More fun with conditional probability.

Toss a red and a blue die, sum is 4, What is probability that red is 1?

\[ \Pr[B|A] = \frac{|B \cap A|}{|A|} = \frac{1}{3}; \text{ versus } \Pr[B] = \frac{1}{6}. \]

\( B \) is more likely given \( A \).
Yet more fun with conditional probability.

Toss a red and a blue die, sum is 7, what is probability that red is 1?

$$Pr[B|A] = \frac{|B \cap A|}{|A|} = \frac{1}{6}; \text{ versus } Pr[B] = \frac{1}{6}.$$ 

Observing $A$ does not change your mind about the likelihood of $B$. 
Suppose I toss 3 balls into 3 bins. 
A = “1st bin empty”; B = “2nd bin empty.” What is \( Pr[A|B] \)?

\[
\Omega = \{1, 2, 3\}^3
\]

\[
\omega = (\text{bin of red ball, bin of blue ball, bin of green ball})
\]

\[
Pr[B] = Pr[\{(a, b, c) \mid a, b, c \in \{1, 3\}\}] = Pr[\{1, 3\}^3] = \frac{8}{27}
\]

\[
Pr[A \cap B] = Pr[(3, 3, 3)] = \frac{1}{27}
\]

\[
Pr[A|B] = \frac{Pr[A \cap B]}{Pr[B]} = \frac{(1/27)}{(8/27)} = 1/8; \text{ vs. } Pr[A] = \frac{8}{27}.
\]

A is less likely given \( B \): If second bin is empty the first is more likely to have balls in it.
Gambler’s fallacy.

Flip a fair coin 51 times.  
$A =$ “first 50 flips are heads”  
$B =$ “the 51st is heads”  
$Pr[B|A]$ ?

$A = \{HH \cdots HT, HH \cdots HH\}$  
$B \cap A = \{HH \cdots HH\}$

Uniform probability space.

$Pr[B|A] = \frac{|B \cap A|}{|A|} = \frac{1}{2}$.

Same as $Pr[B]$.

The likelihood of 51st heads does not depend on the previous flips.
Recall the definition:

\[ Pr[B|A] = \frac{Pr[A \cap B]}{Pr[A]} . \]

Hence,

\[ Pr[A \cap B] = Pr[A] Pr[B|A] . \]

Consequently,

\[
\begin{align*}
Pr[A \cap B \cap C] &= Pr[(A \cap B) \cap C] \\
&= Pr[A \cap B] Pr[C|A \cap B] \\
&= Pr[A] Pr[B|A] Pr[C|A \cap B].
\end{align*}
\]
**Theorem** Product Rule

Let $A_1, A_2, \ldots, A_n$ be events. Then

$$Pr[A_1 \cap \cdots \cap A_n] = Pr[A_1]Pr[A_2|A_1] \cdots Pr[A_n|A_1 \cap \cdots \cap A_{n-1}].$$

**Proof:** By induction.

Assume the result is true for $n$. (It holds for $n = 2$.) Then,

$$Pr[A_1 \cap \cdots \cap A_n \cap A_{n+1}]$$

$$= Pr[A_1 \cap \cdots \cap A_n]Pr[A_{n+1}|A_1 \cap \cdots \cap A_n]$$

$$= Pr[A_1]Pr[A_2|A_1] \cdots Pr[A_n|A_1 \cap \cdots \cap A_{n-1}]Pr[A_{n+1}|A_1 \cap \cdots \cap A_n],$$

so that the result holds for $n + 1$. □
An example.
Random experiment: Pick a person at random.
Event $A$: the person has lung cancer.
Event $B$: the person is a heavy smoker.

Fact:

$$Pr[A|B] = 1.17 \times Pr[A].$$

Conclusion:

- Smoking increases the probability of lung cancer by 17%.
- Smoking causes lung cancer.
Correlation


A second look.

Note that

$$Pr[A|B] = 1.17 \times Pr[A] \iff \frac{Pr[A \cap B]}{Pr[B]} = 1.17 \times Pr[A]$$

$$\iff Pr[A \cap B] = 1.17 \times Pr[A]Pr[B]$$

$$\iff Pr[B|A] = 1.17 \times Pr[B].$$

Conclusion:

- Lung cancer increases the probability of smoking by 17%.
- Lung cancer causes smoking. Really?
Causality vs. Correlation

Events $A$ and $B$ are **positively correlated** if

$$Pr[A \cap B] > Pr[A]Pr[B].$$

(E.g., smoking and lung cancer.)

$A$ and $B$ being positively correlated does not mean that $A$ causes $B$ or that $B$ causes $A$.

Other examples:

- Tesla owners are more likely to be rich. That does not mean that poor people should buy a Tesla to get rich.

- People who go to the opera are more likely to have a good career. That does not mean that going to the opera will improve your career.

- Rabbits eat more carrots and do not wear glasses. Are carrots good for eyesight?
Proving Causality

Proving causality is generally difficult. One has to eliminate external causes of correlation and be able to test the cause/effect relationship (e.g., randomized clinical trials).

Some difficulties:

- $A$ and $B$ may be positively correlated because they have a common cause. (E.g., being a rabbit.)

- If $B$ precedes $A$, then $B$ is more likely to be the cause. (E.g., smoking.) However, they could have a common cause that induces $B$ before $A$. (E.g., smart, CS70, Tesla.)

More about such questions later. For fun, check “N. Taleb: Fooled by randomness.”
Total probability

Assume that $\Omega$ is the union of the disjoint sets $A_1, \ldots, A_N$.

Then,

$$Pr[B] = Pr[A_1 \cap B] + \cdots + Pr[A_N \cap B].$$

Indeed, $B$ is the union of the disjoint sets $A_n \cap B$ for $n = 1, \ldots, N$. Thus,

Total probability

Assume that $\Omega$ is the union of the disjoint sets $A_1, \ldots, A_N$.

Is your coin loaded?

Your coin is fair w.p. 1/2 or such that $Pr[H] = 0.6$, otherwise.

You flip your coin and it yields heads.

What is the probability that it is fair?

**Analysis:**

$A = \text{‘coin is fair’}, B = \text{‘outcome is heads’}$

We want to calculate $P[A|B]$.

We know $P[B|A] = 1/2$, $P[B|\bar{A}] = 0.6$, $Pr[A] = 1/2 = Pr[\bar{A}]$

Now,

$$Pr[B] = Pr[A \cap B] + Pr[\bar{A} \cap B] = Pr[A]Pr[B|A] + Pr[\bar{A}]Pr[B|\bar{A}]$$

$$= (1/2)(1/2) + (1/2)0.6 = 0.55.$$  

Thus,

$$Pr[A|B] = \frac{Pr[A]Pr[B|A]}{Pr[B]} = \frac{(1/2)(1/2)}{(1/2)(1/2) + (1/2)0.6} \approx 0.45.$$
Is your coin loaded?

Imagine 100 situations, among which $m := 100\frac{1}{2}\frac{1}{2}$ are such that $A$ and $B$ occur and $n := 100\frac{1}{2}0.6$ are such that $\bar{A}$ and $B$ occur.

Thus, among the $m + n$ situations where $B$ occurred, there are $m$ where $A$ occurred.

Hence,

$$Pr[A|B] = \frac{m}{m+n} = \frac{(1/2)(1/2)}{(1/2)(1/2) + (1/2)0.6}.$$
Independence

**Definition:** Two events $A$ and $B$ are **independent** if

$$Pr[A \cap B] = Pr[A]Pr[B].$$

Examples:

- When rolling two dice, $A =$ sum is 7 and $B =$ red die is 1 are independent;
- When rolling two dice, $A =$ sum is 3 and $B =$ red die is 1 are **not** independent;
- When flipping coins, $A =$ coin 1 yields heads and $B =$ coin 2 yields tails are independent;
- When throwing 3 balls into 3 bins, $A =$ bin 1 is empty and $B =$ bin 2 is empty are **not** independent;
**Fact:** Two events $A$ and $B$ are independent if and only if

$$Pr[A|B] = Pr[A].$$

Indeed: $Pr[A|B] = \frac{Pr[A \cap B]}{Pr[B]}$, so that

$$Pr[A|B] = Pr[A] \iff \frac{Pr[A \cap B]}{Pr[B]} = Pr[A] \iff Pr[A \cap B] = Pr[A]Pr[B].$$
Bayes Rule

Another picture: We imagine that there are \( N \) possible causes \( A_1, \ldots, A_N \).

Imagine 100 situations, among which \( 100p_nq_n \) are such that \( A_n \) and \( B \) occur, for \( n = 1, \ldots, N \).

Thus, among the \( 100 \sum m p_m q_m \) situations where \( B \) occurred, there are \( 100p_nq_n \) where \( A_n \) occurred.

Hence,

\[
Pr[A_n|B] = \frac{p_nq_n}{\sum m p_m q_m}.
\]
Why do you have a fever?

Using Bayes’ rule, we find

- \[ Pr[\text{Flu}|\text{High Fever}] = \frac{0.15 \times 0.80}{0.15 \times 0.80 + 10^{-8} \times 1 + 0.85 \times 0.1} \approx 0.58 \]

- \[ Pr[\text{Ebola}|\text{High Fever}] = \frac{10^{-8} \times 1}{0.15 \times 0.80 + 10^{-8} \times 1 + 0.85 \times 0.1} \approx 5 \times 10^{-8} \]

- \[ Pr[\text{Other}|\text{High Fever}] = \frac{0.85 \times 0.1}{0.15 \times 0.80 + 10^{-8} \times 1 + 0.85 \times 0.1} \approx 0.42 \]

These are the posterior probabilities. One says that ‘Flu’ is the Most Likely a Posteriori (MAP) cause of the high fever.
Bayes’ Rule is the canonical example of how information changes our opinions.
Thomas Bayes

Portrait used of Bayes in a 1936 book, but it is doubtful whether the portrait is actually of him. No earlier portrait or claimed portrait survives.

- **Born**: c. 1701, London, England
- **Died**: 7 April 1761 (aged 59), Tunbridge Wells, Kent, England
- **Residence**: Tunbridge Wells, Kent, England
- **Nationality**: English
- **Known for**: Bayes' theorem

A Bayesian picture of Thomas Bayes.

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**Fig. 3. Joshua Bayes (1671–1746).**
Testing for disease.

Let’s watch TV!!
Random Experiment: Pick a random male.
Outcomes: \((\text{test}, \text{disease})\)
\(A\) - prostate cancer.
\(B\) - positive PSA test.

- \(Pr[A] = 0.0016\), (.16 % of the male population is affected.)
- \(Pr[B|A] = 0.80\) (80% chance of positive test with disease.)
- \(Pr[B|\overline{A}] = 0.10\) (10% chance of positive test without disease.)


Positive PSA test \((B)\). Do I have disease?

\(Pr[A|B]???\)
Using Bayes’ rule, we find

\[ P[A|B] = \frac{0.0016 \times 0.80}{0.0016 \times 0.80 + 0.9984 \times 0.10} = 0.013. \]

A 1.3% chance of prostate cancer with a positive PSA test.

Surgery anyone?

Impotence...

Incontinence..

Death.
Summary

Events, Conditional Probability, Independence, Bayes’ Rule

Key Ideas:

- **Conditional Probability:**
  \[
  Pr[A|B] = \frac{Pr[A \cap B]}{Pr[B]}
  \]

- **Independence:**
  \[
  Pr[A \cap B] = Pr[A]Pr[B].
  \]

- **Bayes’ Rule:**
  \[
  Pr[A_n|B] = \frac{Pr[A_n]Pr[B|A_n]}{\sum_m Pr[A_m]Pr[B|A_m]}.
  \]

  \[
  Pr[A_n|B] = \text{posterior probability}; Pr[A_n] = \text{prior probability}.
  \]

- **All these are possible:**
  \[
  \]