

9-16 Bayes

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9-16 Bayes

9-16: Bayes CSCI 3022 Fall 19

“Counting” Example 3: What is the probability of being dealt all 4 kings in poker (five cards)?

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Opening Example Sol'n

What is the probability of being dealt all 4 kings in poker (five cards)?

Deck: $\{4 \times K, 48 \times N\}$

$$P(\{\{NKKKK\}, \{KNKKK\}, \dots\} \in \mathcal{S} \text{ "ways"})$$

$$\begin{aligned} P(\{NKKKK\}) &= P(\#5 = K \mid \#1-4 = \{NKKKK\}) \cdot P(\#1-4 = \{NKKKK\}) \\ &= \frac{1}{48} \cdot P(\{NKKKK\}) \\ &= \frac{1}{48} \cdot \frac{48}{52} \cdot \frac{47}{51} \cdot \frac{46}{50} \cdot \frac{45}{49} \end{aligned}$$

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multiply this by 5

$$P(\#2 = K \mid \#1 = K)$$

$$\frac{4}{52} \cdot \frac{3}{51} \cdot \frac{2}{50} \cdot \frac{1}{49} \cdot \frac{48}{48}$$

Opening Example Sol'n

What is the probability of being dealt all 4 kings in poker (five cards)?

The 52 card deck has 48 "N" non-Kings and 4 "Ki" Kings. We are interested in 5 possible outcomes: that we are dealt NKiKiKiKi, KiNKiKiKi, KiKiNKiKi, KiKiKiNKi, or KiKiKiKiN. It turns out that these each have the same probability:

$$\begin{aligned} P(\{NKiKiKiKi\}) &= P(\#5 = N \mid KiKiKiKiKi) \cdot P(KiKiKiKiKi) \\ &= \frac{48}{52} \cdot P(KiKiKiKiKi) \end{aligned}$$

$$\begin{aligned}
P(\{NKiKiKiKi\}) &= P(\#5 = N | KiKiKiKiKi) \cdot P(KiKiKiKiKi) \\
&= \frac{48}{48} \cdot P(KiKiKiKiKi) \\
&= \frac{48}{48} \cdot P(\#4 = K | KiKiKiKi) \cdot P(KiKiKiKi) \dots \\
&= \frac{48}{48} \cdot \frac{1}{49} \cdot P(KiKiKiKi) \dots \\
&\dots \\
&= \frac{48}{48} \cdot \frac{1}{49} \cdot \frac{2}{50} \cdot \frac{3}{51} \cdot \frac{4}{52}
\end{aligned}$$

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Announcements and Reminders

- ▶ Homework 2 posted
- ▶ No notebook days this week :(→ ☺
- ▶ Last time in lecture: conditional probability

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Last Time...

A few big takeaways from our second lecture on probability.

- ▶ *Conditional Probability*: $P(A|B) = \frac{P(A \cap B)}{P(B)}$ ✓
- ▶ *Multiplication Rule*: $P(A \cap B) = P(A|B)P(B)$ ✓
- ▶ The following are equivalent:
 1. Two events A and B are said to be *independent*.
 2. $P(A|B) = P(A)$
 3. $P(B|A) = P(B)$
 4. $P(A \cap B) = P(A)P(B)$
- ▶ *Law of Total Probability*: Given disjoint E_1, E_2, \dots, E_k such that $E_1 \cup E_2 \cup \dots \cup E_k = \Omega$, for any A :
$$P(A) = P(A|\underline{E_1})P(E_1) + P(A|\underline{E_2})P(E_2) + \dots + P(A|\underline{E_k})P(E_k)$$

Recall: Independence.

Example: In a school of 1200 students, 250 are seniors, 150 students take math, and 40 students are seniors and are also taking math. One student is selected at random. Let S represent the a senior is chosen, and M represent that a student taking math is chosen.

If the randomly chosen student is a senior, then what is the probability that they are taking math?

$$\text{find } P(M|S) = \frac{P(S \cap M)}{P(S)} = \frac{40/1200}{250/1200} = \frac{4}{25} = .16.$$

Are these events independent?

$$\text{IS } P(M|S) = P(M)? = \frac{150}{1200} \neq \frac{4}{25} \quad \underline{\text{NOT}}$$

$$P(S) = \frac{250}{1200}$$

$$P(M) = \frac{150}{1200}$$

$$P(S \cap M) = \frac{40}{1200}$$

Recall: Independence.

Example: In a school of 1200 students, 250 are seniors, 150 students take math, and 40 students are seniors and are also taking math. One student is selected at random. Let S represent the a senior is chosen, and M represent that a student taking math is chosen.

If the randomly chosen student is a senior, then what is the probability that they are taking math?

$$P(S) = 250/1200; P(M) = 150/1200; P(M \cap S) = 40/1200/$$

$$\text{So, } P(M|S) = P(M \cap S)/P(S) = 40/250 = 4/25.$$

Are these events independent?

Does $P(M|S) = P(M)$? *No.*

Bayes' Theorem

The formula for $P(M|S)$ on the prior example is an example of Bayes' Theorem.

B is the data, A is the outcome studied.

$$P(A|B) = \frac{P(A \cap B)}{P(B)} = \frac{P(B|A)P(A)}{P(B)}$$

The proof follows directly from the multiplication rule, that

$$P(A|B)P(B) = P(A \cap B) = P(B|A) \cdot P(A)$$

Bayes' theorem is most important mathematical way to describe *how much new information matters*.

$P(A)$ is called the *prior* information about A , and $P(A|B)$ is the *posterior* (post-data!) information about A .

Bayes' Theorem

Example 1:

An individual has 3 different email accounts. Most of the messages, in fact 70%, come into account #1, whereas 20% come into account #2 and the remaining 10% into account #3. Of the messages into account #1, only 1% are spam, whereas the corresponding percentages for accounts #2 and #3 are 2% and 5%, respectively. What is the probability that a randomly selected message is spam?

$$\begin{aligned}
 P(S) &= P(S \cap 1) + P(S \cap 2) + P(S \cap 3) \\
 &= P(S|1) \cdot P(1) + \quad \quad \quad + \quad \quad \quad \\
 &= .01 \cdot .7 + .02 \cdot .2 + .05 \cdot .1 \\
 &= .016 \text{ or } 1.6\%
 \end{aligned}$$

$$\begin{aligned}
 A &= \{1, 2, 3\} & P(1) &= .7 & P(2) &= .2 \\
 S &= \{S\} & P(3) &= .1 \\
 P(S|1) &= .01 & P(S|2) &= .02 \\
 & & P(S|3) &= .05
 \end{aligned}$$

← Law of total Probability

Bayes' Theorem

Example 1:

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We know:

$$P(1) = .7; P(2) = .2; P(3) = .1; P(S|1) = .01; P(S|2) = .02; P(S|3) = .05;$$

and by LTP

$$P(S) = P(S|1)P(1) + P(S|2)P(2) + P(S|3)P(3)$$

$$P(S) = .007 + .004 + .005 = .018$$

Bayes' Theorem

Example 2:

An individual has 3 different email accounts. Most of the messages, in fact 70%, come into account #1, whereas 20% come into account #2 and the remaining 10% into account #3. Of the messages into account #1, only 1% are spam, whereas the corresponding percentages for accounts #2 and #3 are 2% and 5%, respectively. Say she selects a message at random and it is spam. What is the probability that the message came from account #1?

$$\begin{aligned}
 P(I | S) &= \frac{P(I \cap S)}{P(S)} \rightarrow \text{Law total probability} \\
 &= \frac{P(S|I) \cdot P(I)}{P(S|I) \cdot P(I) + P(S|2) \cdot P(2) + P(S|3) \cdot P(3)} \\
 &= \frac{.01 \cdot .7}{.016} = \frac{.007}{.016} = 7/16
 \end{aligned}$$

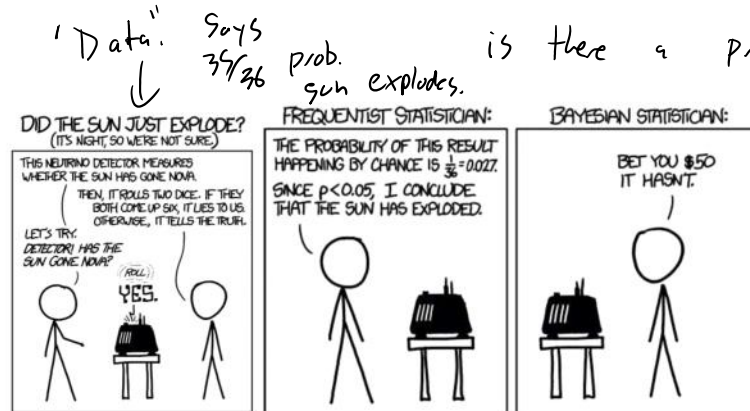
Bayes' Theorem

Example 2:

An individual has 3 different email accounts. Most of the messages, in fact 70%, come into account #1, whereas 20% come into account #2 and the remaining 10% into account #3. Of the messages into account #1, only 1% are spam, whereas the corresponding percentages for accounts #2 and #3 are 2% and 5%, respectively. Say she selects a message at random and it is spam. What is the probability that the message came from account #1?

Now we use Bayes'!

$$P(1|S) = \frac{P(S|1)P(1)}{P(S)}$$
$$P(1|S) = \frac{.007}{.018} = \frac{7}{18}$$



Definition: *Random Variable*

A *random variable* is a (measurable) function that maps elements or events in the sample space Ω to the real numbers a_1, a_2, \dots (or, more generally, to a measurable space. . . whatever that is!)

Example: Consider rolling two dice. The *Sample Space* is the full list of outcomes $\{\omega_1, \omega_2\}$.

But what if we only care about summing the two dice? We could skip the sample space and just count the *random variable*:

$X :=$ the sum of the two dice.

			1	2	3	4	5	6	Dice
			1	2	3	4	5	6	
			2	3	4	5	6	7	
			3	4	5	6	7	8	
			4	5	6	7	8	9	
			5	6	7	8	9	10	
			6	7	8	9	10	11	
			7	8	9	10	11	12	
			8	9	10	11	12		
			9	10	11	12			
			10	11	12				
			11	12					
			12						

$$X = \{2, 3, \dots, 12\}$$

Probability Distributions

Definition: Probability Density Function

A *Probability density function* (pdf) is a function f that describes the probability distribution of a random variable X .

If X is discrete, the pdf provides answers to questions like $P(X=x) = f(x)$. It is also called a probability mass function (pmf).

So for 2 fair dice..
 $f(2) = P(X=2)$
 $= 1/36$

$f(3) = P(X=3)$
 $= 2/36$

If X is continuous, then $P(X=x) = 0$ for all x . Why?! In this case, the distribution function is called a probability density function. In the continuous case, the pdf provides answers to questions like:

"The probability X is between two values".

Probability Distributions

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If X is continuous, then $P(X = x) = 0$ for all x . Why?! In this case, the distribution function is called a probability density function. In the continuous case, the pdf provides answers to questions like:
"What is the probability that X takes on a value between a and b ?"

Properties of pdfs

For $f(x)$ to be a legitimate pdf, it must satisfy the following two conditions:

$$f(x) = P(X=x) \geq 0$$

non-negative

2. (For discrete distributions:) unity

$$\sum_{x \in \Omega} f(x) = \sum_{x \in \Omega} P(X=x) = 1.$$

f is called a *probability mass function* because it describes how all of the possible outcomes in Ω have some probability or "mass" associated with them.

Properties of pdfs

For $f(x)$ to be a legitimate pdf, it must satisfy the following two conditions:

1.

$$f(x) = P(X = x) \geq 0 \quad \forall x \text{ (with events in } \Omega)$$

2. (For discrete distributions:)

$$\sum_{x \in \Omega} f(x) = \sum_{x \in \Omega} P(X = x) = 1$$

f is called a *probability mass function* because it describes how all of the possible outcomes in Ω have some probability or “mass” associated with them.

Making a pdf

Recall; last time our opening **example**: Suppose we flip a coin with a p chance per flip of landing on heads. Define X = the number of tails flips before we see a heads. What is $P(X = 0)$? $P(X = 1)$? $P(X = i)$? Verify that $P(X) = 1$ over all of Ω .

- State space: $\Omega = \{ \{H\}, \{TH\}, \{TTH\}, \{TTTH\}, \dots \}$
- Associated r.v. possible values or *support*: $X = \{0, 1, 2, \dots\}$
- pdf $P(X = x)$ = probability of x tails before a heads:

$$P(\{TTTH\}) = P(T) \cdot P(T) \cdot P(T) \cdot P(H) = (1-p)(1-p)(1-p)(p)$$

$$P(X=i) = (1-p)^i \cdot p$$

$$f(x) = P(X=x) = (1-p)^x \cdot p$$

Making a pdf

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- ▶ State space: $\{H, TH, TTH, TTTH, \dots\}$
- ▶ Associated r.v. possible values or *support*: $\{0, 1, 2, 3, \dots\}$
- ▶ pdf $P(X = x)$ = probability of x tails before a heads:

$$P(X = x) = P(\{T \dots TH\}) = P(\{T\})^x P(\{H\}) = (1 - p)^x \cdot p$$

So we report $f(x) = (1 - p)^x \cdot p$

Discrete pdfs

Example:

A lab has 6 computers. Let X denote the number of these computers that are in use during lunch hour, so

$$\Omega = \{0, 1, 2, \dots, 6\}.$$

Suppose that the probability distribution of X is as given in the following table:

x	0	1	2	3	4	5	6
$P(X = x)$.05	.1	.15	.25	.2	.15	.1

Discrete pdfs

Example, cont'd:

x	0	1	2	3	4	5	6
$P(X = x)$.05	.1	.15	.25	.2	.15	.1

From here, we can find almost anything we might want to know about X .

1. Probability that at most 2 computers are in use

$$P(X \leq 2) = P(X=0) + P(X=1) + P(X=2) = .05 + .1 + .15 = .25$$

2. Probability that at least half of the computers are in use

$$P(X \geq 3) = P(X=3) + P(X=4) + P(X=5) + P(X=6)$$

$$= 1 - P(X \leq 2) = 1 - .25 = .75$$

3. Probability that there are 3 or 4 computers free

$$1 - P(3 \text{ or } 4 \text{ are not free}) = 1 - (P(X=3) + P(X=4)) = 1 - .45 = .55$$

Discrete pdfs

Example, cont'd:

x	0	1	2	3	4	5	6
$P(X = x)$.05	.1	.15	.25	.2	.15	.1

From here, we can find almost anything we might want to know about X .

1. Probability that at most 2 computers are in use

$$P(X = 0) + P(X = 1) + P(X = 2) = .3$$

2. Probability that at least half of the computers are in use

$$P(X \geq 3) = 1 - P(X < 3) = 1 - (P(X = 0) + P(X = 1) + P(X = 2)) = 1 - .3 = .7$$

3. Probability that there are 3 or 4 computers free

$$P(X \geq 3) = 1 - P(X \leq 2) = 1 - (P(X = 0) + P(X = 1) + P(X = 2)) = 1 - (.05 + .1 + .15) = .55$$

Cumulative Distribution Functions

Definition: Cumulative Density Function

For a discrete r.v. X with pdf $f(x) = P(X = x)$, the *cumulative density function*, denoted $F(x)$, is defined for every real number x to be the probability that the observed value of X will be at most x .

Mathematically:

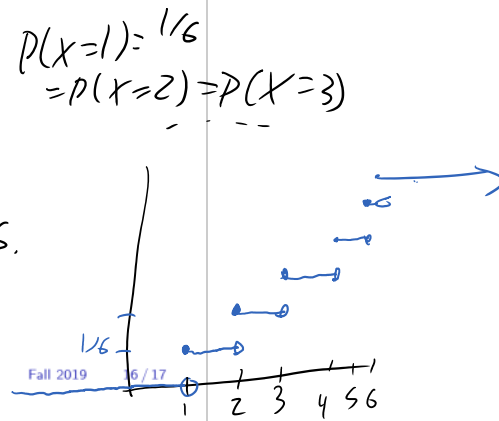
$$F(x) = P(X \leq x)$$

Example: If I roll a single fair die, what is the cdf?

1. $F(0) = P(X \leq 0) = 0$
2. $F(1) = P(X \leq 1) = 1/6 = P(X=1)$
3. $F(2) = P(X \leq 2) = P(X=1) + P(X=2) = 2/6$
4. $F(6) = P(X \leq 6) = 1$

$$= \underbrace{P(X \leq 7)}_{= P(X \leq 7)} = P(X \leq 42.4)$$

Bayes



Cumulative Distribution Functions

Definition: *Cumulative Density Function*

For a discrete r.v. X with pdf $f(x) = P(X = x)$, the *cumulative density function*, denoted $F(x)$, is defined for every real number x to be the probability that the observed value of X will be at most x .
Mathematically:

$$F(x) = P(X \leq x)$$

Example: If I roll a single fair die, what is the cdf?

1. $F(0) = 0$
2. $F(1) = 1/6$
3. $F(2) = 2/6$
4. $F(6) = 1$: with probability 1, our roll will be ≤ 6 .

