

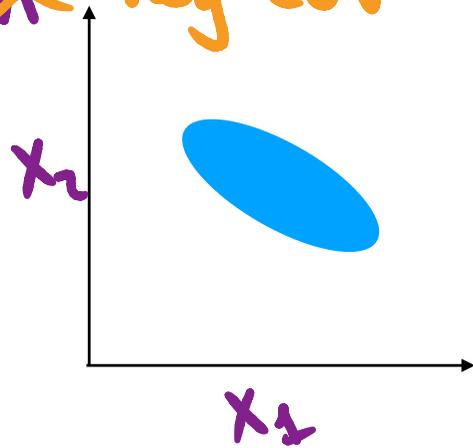


# conditional probabilities, Bayes' rule

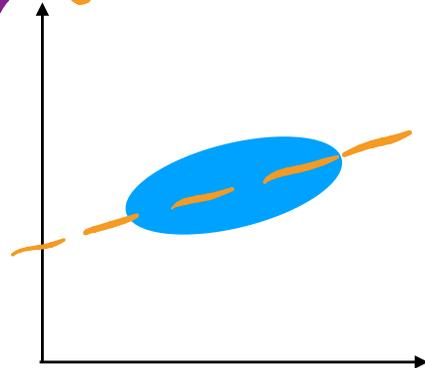
▷ slope is POS

You are told that  $cov(x_1, x_2) = 10$ . What do you know about  $x_1$  and  $x_2$ ? Which of the following might be underlying distributions of the data?

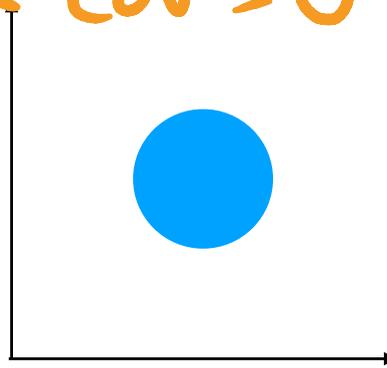
~~A~~ neg cov



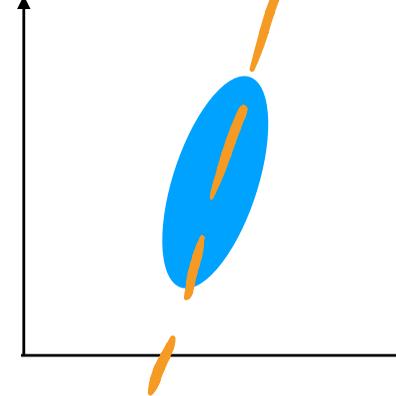
B ✓



~~C~~ cov = 0



D ✓



# Conditional Probabilities

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- A **conditional probability** is a calculation of probabilities for **dependent** random variables.
- It translates to "if variable  $Y$  has value  $y_j$ , then what is the probability that variable  $X$  has value  $x_i$ ?"

• dependent. r.v. tables

# ICA Question 1: Conditional Probabilities

What is  $P(X = 3)$ ?

$$0.06 + 0.25 + 0.16 = 0.47$$

What is  $P(X = 3)$  if we already know that the value of  $Y$  is 7?

$$\frac{0.25}{0.1 + 0.15 + 0.25} = 0.5$$

$$P(X=2 | Y=7) = \frac{0.15}{0.5} = 0.3$$

$X = \text{how I feel}$

	1	2	3
6	0.15	0.09	0.06
7	0.1	0.15	0.25
8	0.02	0.02	0.16

$Y$

$\rightarrow$  # of hours I slept

# Conditional Probability

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- The calculation that we actually just did was:

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

$$\frac{P(X=3, Y=7)}{P(Y=7)}$$

- We can use this to evaluate many things!

- What is the probability that school will close tomorrow based on if it's snowing today?
- What is the probability that the next word in a phrase will be "turtle" given that the previous word was "a"?

# Conditional Probability

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- What is the probability that school will close tomorrow based on if it's snowing today?
  - What counts do we need for this?

$$P(\text{snow})$$
$$\sim \cancel{P(\text{school closed})}$$
$$P(\text{school closed} + \text{snow})$$

$$P(A|B) = \frac{P(A, B)}{P(B)}$$
$$P(\text{school closed} | \text{snow})$$
$$\Downarrow$$
$$\frac{P(\text{school closed} + \text{snow})}{P(\text{snow})}$$

$$P(\text{snow}) = \frac{\text{count}(\text{snow})}{\text{count}(\text{days})}$$

$$P(\text{school closed} + \text{snow}) = \frac{\text{count}(\text{sch. closed} + \text{snow})}{\text{count}(\text{days})}$$

$$P(A|B) = \frac{\frac{\text{count}(\text{sch. closed} + \text{snow})}{\text{count}(\text{days})}}{\text{count}(\text{days})}$$

$$\frac{\text{count}(\text{snow})}{\text{count}(\text{days})}$$

# Conditional Probability

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- What is the probability that the next word in a phrase will be "turtle" given that the previous word was "a"?
- What counts do we need for this?

$$\frac{P(\text{a turtle})}{P(\text{a})}$$

- count of "a turtle"
- count of "a         "

$$P(\text{turtle} | \text{a})$$

$$P(W_1 = \text{turtle} | W_0 = \text{a})$$

# ICA Question 2: Phrase Probabilities

Given the following data, calculate the probability that I will be late to school for each mode of transport.

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

Number of days: 50

Days that Felix was late: 20

Biked: 25

Rode the T: 20

Walked: 5

Late + bike: 5

Late + T: 13

Late + walk: 2

$$P(\text{late} | \text{Bike}) = 0.2 = \frac{5}{\cancel{50}}$$

$$P(\text{late} | T) = 0.65 = \frac{25}{\cancel{50}}$$

$$P(\text{late} | \text{walk}) = 0.4$$

# Conditional Probability

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- Okay, but what if  $A$  and  $B$  are independent?
- What is the probability that I rolled a die and got a 6 given that I flipped a coin and got a tails?

- We can do the same calculation, but if  $P(A | B) = P(A) = \frac{P(A, B)}{P(B)}$ , then

$A$  and  $B$  are statistically independent

- $P(A = 6 | B = \text{heads})$

$$\frac{P(A = 6, B = \text{heads})}{P(B = \text{heads})} = \frac{\frac{1}{6} \cdot \frac{1}{2}}{\frac{1}{2}} = \frac{1}{6}$$

# ICA Question 3: $P(A|B) = P(B|A)$ ?

Given the following data, make an argument that  $P(A|B) = P(B|A)$  is or is not true. Let A be spam email and B be emails with "FREE".

$$P(\text{spam} | \text{FREE}) = \frac{10}{11}$$

$$P(\text{FREE} | \text{spam}) = \frac{10}{14}$$

$$P(A|B) \neq P(B|A)$$

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

	"FREE"	not "FREE"	
spam email	10	+ 4	14
not spam	1	15	
	11		

# ICA Question 4: $P(A|B) = \underline{\hspace{2cm}}$ ?

Given the following data, make an argument that  $P(A|B) = P(B|A)$  is or is not true.

$P(\text{FREE})$

Calculate  $P(A|B) * P(B)$

$$\frac{10}{11} * \frac{11}{30}$$

$P(\text{spam})$

Calculate  $P(B|A) * P(A)$

$$\frac{10}{14} * \frac{14}{30}$$

Do they have a relationship?

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

	"FREE"	not "FREE"	
spam email	10	4	14
not spam	1	15	
	11		

# Bayes' rule

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- Bayes' rule denotes the relationship between  $P(A | B)$  and  $P(B | A)$

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

- ... but, why might this be useful?

↳ what is prob. I have covid given test was negative?

↳ Naive Bayes classifier (ML)

↳ all over in NLP

# ICA Question 5: Bayes rule denominator

We want to know the probability that an email is not *actually* spam given that our detection software claims that it *is* spam.

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

What should the calculation be here? (Just in terms of variables)

$$P(\text{not spam} | \text{software says spam}) = \frac{(P(\text{says spam} | \text{not spam}) * P(\text{not spam}))}{P(\text{says spam})}$$

... and specifically for the denominator?

$$P(\text{says spam}) = P(\text{says spam} | \text{spam})P(\text{spam}) + P(\text{says spam} | \text{not spam})P(\text{not spam})$$

# Bayes' rule

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- Bayes' rule denotes the relationship between  $P(A | B)$  and  $P(B | A)$

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

- When calculating  $P(B)$  for the denominator, it's often useful to calculate this as the sum of  $\sum_i P(B | A_i)P(A_i)$

↑  
all values  $A$  can take

# ICA Question 5: Bayes rule denominator (cont'd)

We want to know the probability that an email is not *actually* spam given that our detection software claims that it *is* spam.

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

$P(\text{not spam} | \text{says spam})$

→ do not have  $P(\text{says spam})$

We have observed that  $P(\text{not spam}) = 16/30$  and  $P(\text{spam}) = 14/30$ . Our software has a false positive rate of 20%. It also claims that it will flag 99.5% of all spam email as spam.

$P(\text{says spam} | \text{not spam})$

$P(\text{says spam} | \text{spam})$

$$.2 * \frac{16}{30} = 0.1067$$

$$\left( .2 * \frac{16}{30} \right) + \left( .995 * \frac{14}{30} \right)$$

# Naïve Bayes classifiers

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- Bayes' rule denotes the relationship between  $P(A | B)$  and  $P(B | A)$

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

- Say that we want to know the probability that an email is spam given that it contains the word "FREE".
- Instead of calculating  $P(\text{spam} | \text{FREE})$ , we'll calculate

1)  $\frac{P(\text{FREE} | \text{spam})P(\text{spam})}{P(\text{FREE})} \rightarrow P(\text{doc})$

2)  $\frac{P(\text{FREE} | \text{not spam})P(\text{not spam})}{P(\text{FREE})} \rightarrow P(\text{doc})$

is #1 or #2 bigger?

# ICA Question 6: Mini Naïve Bayes

yes, so this email  
is spam

$$\frac{10}{14} * \frac{14}{30} > \frac{1}{16} * \frac{16}{30}$$

Calculate all of the following:

$$P(\text{FREE} \mid \text{spam}) = \frac{10}{14}$$

$$P(\text{FREE} \mid \text{not spam}) = \frac{1}{16}$$

$$P(\text{spam}) = \frac{14}{30}$$

$$P(\text{not spam}) = \frac{16}{30}$$

Now, make an argument for whether

$$P(\text{FREE} \mid \text{spam})P(\text{spam}) / P(\text{document})$$

or

$$P(\text{FREE} \mid \text{not spam})P(\text{not spam}) / P(\text{document})$$

is bigger

	"FREE"	not "FREE"	
spam email	10	4	
not spam	1	15	

# Naïve Bayes classifiers

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- Naïve Bayes classifiers are a little more complicated than this because we like to be able to have more than one feature
- This is where "naïve" comes in...

- Gist is: calculate  $\frac{P(\text{class} | \text{features})P(\text{class})}{P(\text{features})}$  for each candidate class, then use the class with the **biggest** value as the overall label

# Naïve Bayes classifiers

---

- Naïve Bayes classifiers are a little more complicated than this because we like to be able to have more than one feature
- This is where "naïve" comes in...

- Gist is: calculate  $\frac{P(\text{class} | \text{features})P(\text{class})}{P(\text{features})}$  for each candidate class, then use the class with the **biggest** value as the overall label

- Neat!

# Conditional Probability & natural language: wait, what?

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- Say that I have the following sentences, what is  $P(\text{turtle} \mid \text{_____})$  dependent on?
- "a"
- "I like my friend the"
- "I found a"

# Admin

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- **All** sections of 2810 will be dropping your lowest 4 ICAs.  
↳ is in canvas now
- Test 3 -> it's graded! Statistics look good at the moment. (Scores are higher than the first 2 tests)
  - We're working on double checking for consistency right now
  - Expect these grades before I see you next :)

# Admin

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- TRACE is available now!
- Please do fill these out. (in spite of survey fatigue)
  - I read them!
  - I use them to update and improve courses for the future.
- Specific feedback is helpful!
  - Something you liked? What was it?
  - Something that you'd like to see different? What was it?

# Schedule

if you have HW 8 qs, I'm happy to answer them now (or mini-projects)

Turn in **ICA 21** on Canvas (make sure that this is submitted by 2pm!) - passcode is "dragon"

**HW 8:** due on Sunday @ 11:59pm

**Test 4:** May 4th, 1 - 3pm, Snell Engineering 108

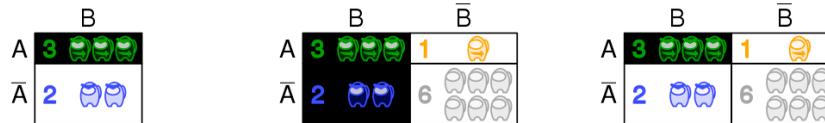
Mon	Tue	Wed	Thu	Fri	Sat	Sun
<b>April 11th</b> Lecture 21 - conditional probabilities, bayes	<b>Felix OH Calendly</b>	<b>Felix OH Calendly</b>	<b>Felix OH Calendly</b> Lecture 22 - conditional independence, bayes nets			<b>HW 8 due @ 11:59pm</b>
<b>April 18th</b> <b>No lecture - Patriot's Day</b> <i>(and no videos)</i>	<b>Felix OH Calendly</b>	<b>Felix OH Calendly</b>	<b>Felix OH Calendly</b> Lecture 23 - Regression: $R^2$ & F			
<b>April 25th</b> Lecture 24 - presentations, wrap-up <b>Mini-project due @ 11:45am</b>		<b>HW 9 due @ 11:59pm</b>				

# More recommended resources on these topics

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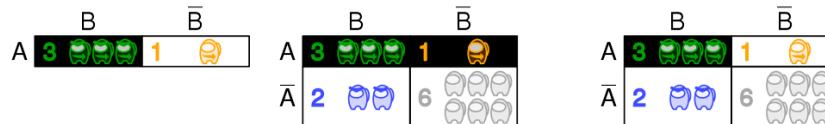
- Bayes theorem w/ Among Us characters: [https://en.wikipedia.org/wiki/Conditional\\_probability#/media/File:Bayes\\_theorem\\_assassin.svg](https://en.wikipedia.org/wiki/Conditional_probability#/media/File:Bayes_theorem_assassin.svg)
- (copied onto next slide)
- YouTube: 3Blue1Brown, Bayes theorem, the geometry of changing beliefs

Number of occurrences	Being suspicious B	Not being suspicious $\bar{B}$	sum
An assassin A	3 	1 	4
Not an assassin $\bar{A}$	2 	6 	8
sum	5	7	12



$$P(A, \text{ given } B) \cdot P(B) = P(A|B) \cdot P(B)$$

$$\frac{3}{3+2} \cdot \frac{3+2}{3+1+2+6} = \frac{3}{3+1+2+6}$$



$$P(B, \text{ given } A) \cdot P(A) = P(B|A) \cdot P(A)$$

$$\frac{3}{3+1} \cdot \frac{3+1}{3+1+2+6} = \frac{3}{3+1+2+6}$$

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

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