

# Finishing Up

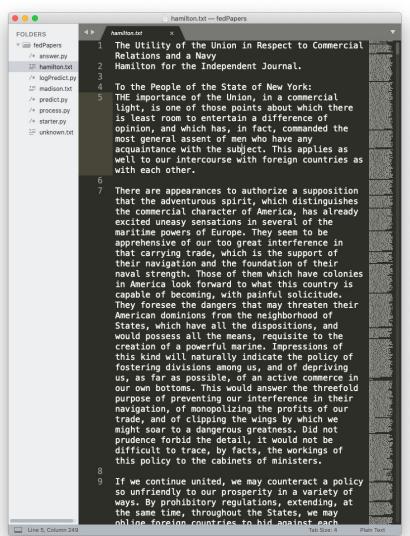


# Who wrote Federalist Paper 53?

#### madison.txt



#### hamilton.txt



#### unknown.txt

FOLDERS

▼ m fedPapers

/\* answer.py

/\* logPredict.py

= madison tyt

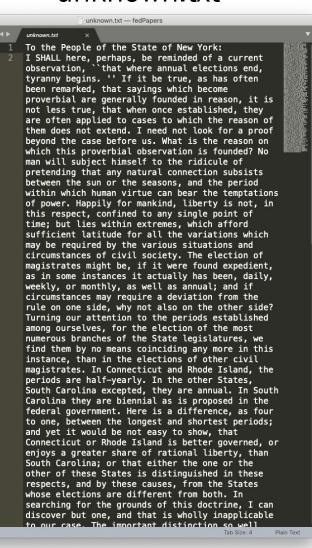
/\* predict.pv

/\* process.pv

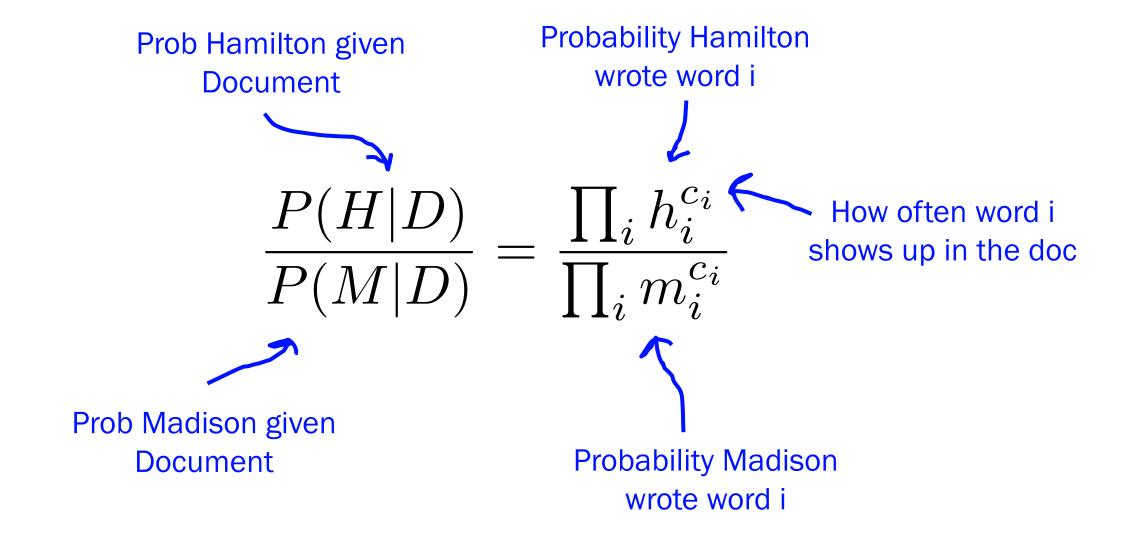
/\* starter.py

Line 2, Column 519

unknown.txt



#### What we want to calculate



## Use logs when probabilities become too small!

$$\log \frac{P(H|D)}{P(M|D)} = \log \frac{\prod_i h_i^{c_i}}{\prod_i m_i^{c_i}}$$
 
$$= \sum_i \log h_i^{c_i} - \sum_i \log m_i^{c_i}$$
 Hamilton Term -12925 
$$= \sum_i c_i \cdot \log h_i - \sum_i c_i \log m_i$$
 
$$= -1344$$
 
$$P(H|D)$$

# Madison wrote it!

# Where are we in CS109?

#### **Overview of Topics**



Counting Theory



Core Probability



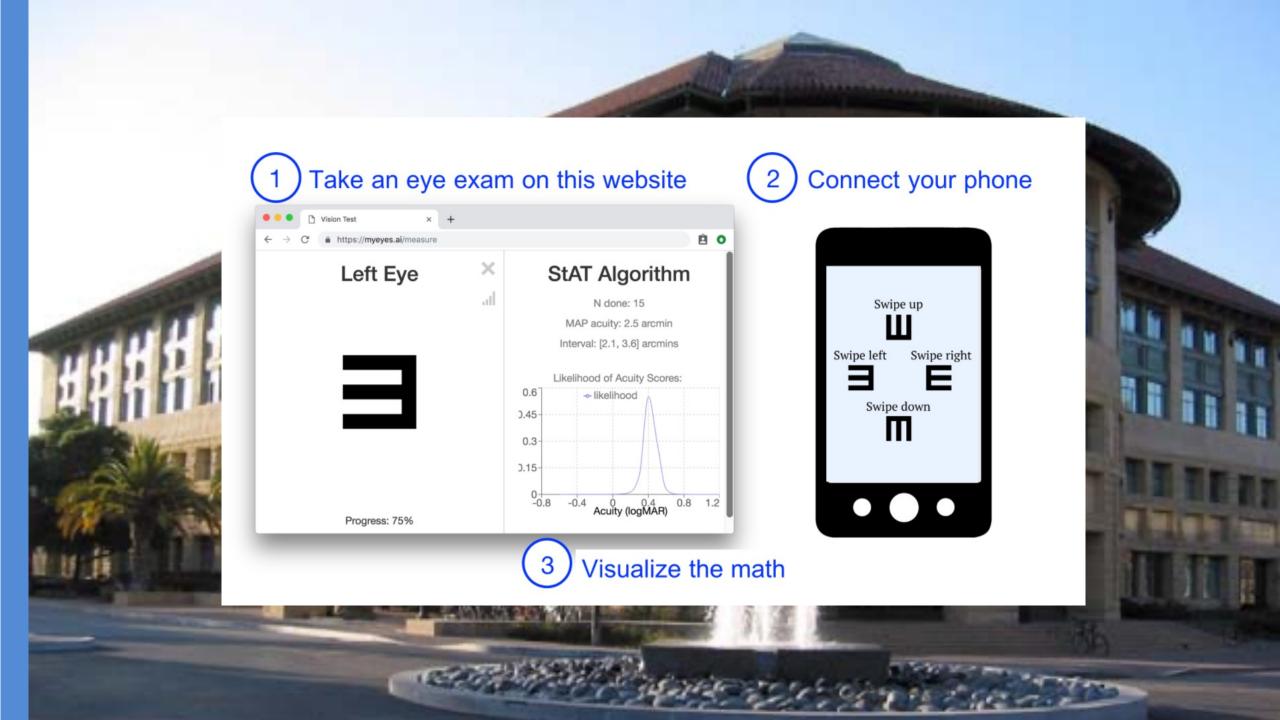
Random Variables



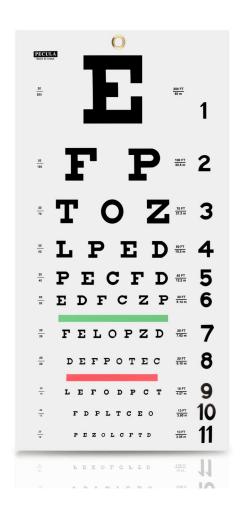


Theory

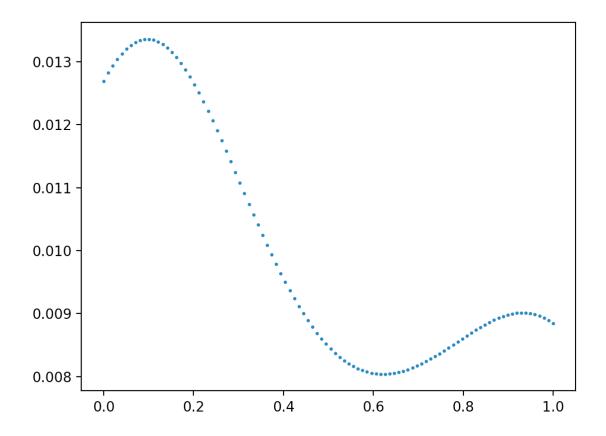
Machine Learning



# Belief in Vision Given User Responses



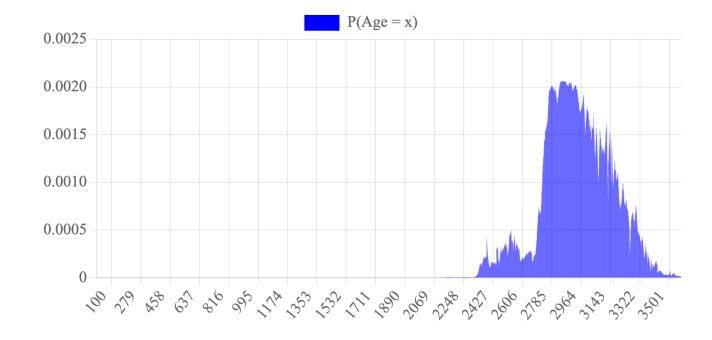
#### P(Ability to See | Observed Responses)



# Belief in Age Given Observed C14



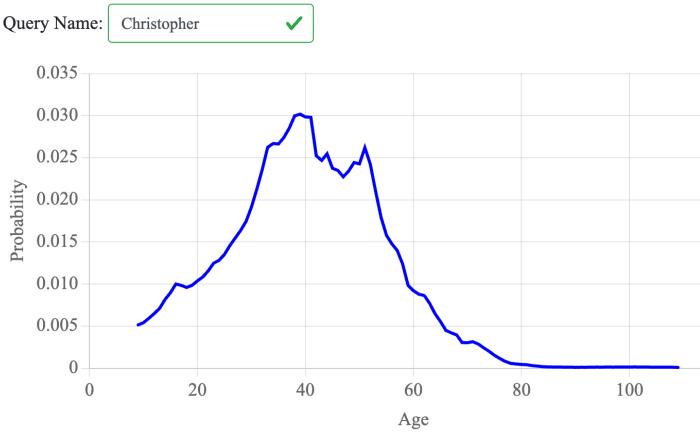
#### P(Age | Observed C14)



# Belief in Age Given Name



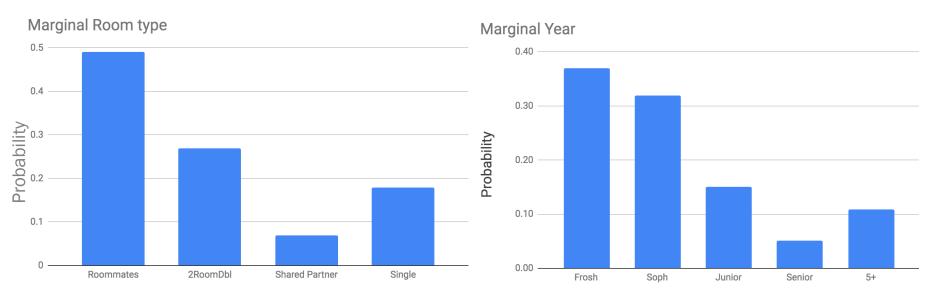
#### P(Age | Name)



# Review

# **Joint Probability Table**

	Roommates	2RoomDbl	Shared Partner	Single	
Frosh	0.30	0.07	0.00	0.00	0.37
Soph	0.12	0.18	0.00	0.03	0.32
Junior	0.04	0.01	0.00	0.10	0.15
Senior	0.01	0.02	0.02	0.01	0.05
5+	0.02	0.00	0.05	0.04	0.11
	0.49	0.27	0.07	0.18	1.00



#### Last Week

#### **Joint Distribution** noun

The probability of a simultaneous assignment to *all* the random variables in a probabilistic model.

### Eg:

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

$$f(X = x, Y = y)$$

$$P(X = x, Y = y, \dots, Z = z)$$

#### Notation: These are all the same

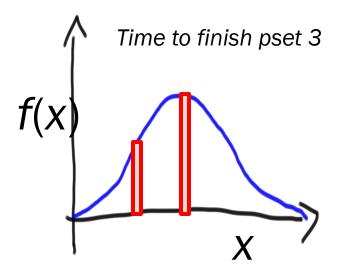
$$P(X = x, Y = y)$$

$$P_{X,Y}(x,y)$$

$$P(x,y)$$

## Relative Probability of Continuous Variables

$$X = \text{time to finish pset 3}$$
  
  $X \sim N(\mu = 10, \sigma^2 = 2)$ 



How much more likely are you to complete in 10 hours than in 5?

$$\frac{P(X=10)}{P(X=5)} = \frac{\varepsilon f(X=10)}{\varepsilon f(X=5)}$$

$$= \frac{f(X=10)}{f(X=5)}$$

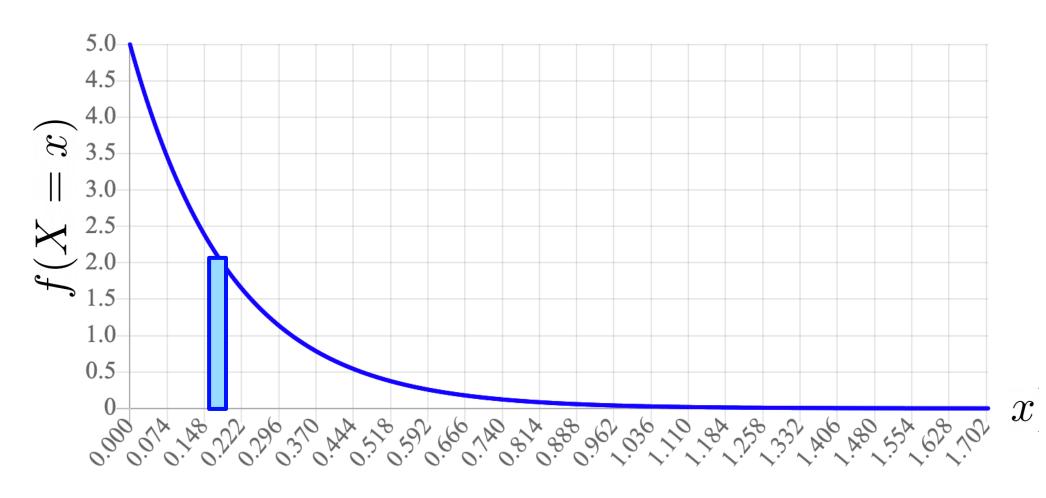
$$= \frac{\frac{1}{\sqrt{2\sigma^2\pi}}e^{-\frac{(10-\mu)^2}{2\sigma^2}}}{\frac{1}{\sqrt{2\sigma^2\pi}}e^{-\frac{(5-\mu)^2}{2\sigma^2}}}$$

$$= \frac{\frac{1}{\sqrt{4\pi}}e^{-\frac{(10-10)^2}{4}}}{\frac{1}{\sqrt{4\pi}}e^{-\frac{(5-10)^2}{4}}}$$

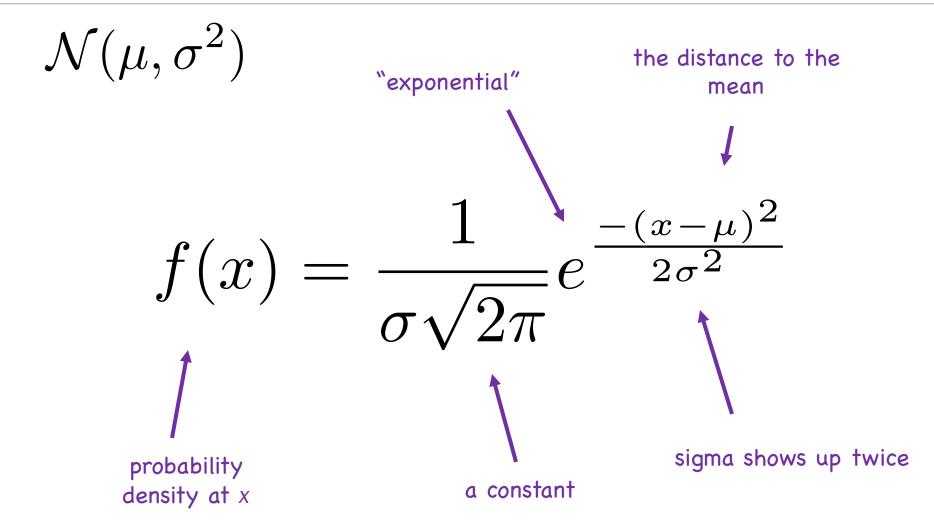
$$= \frac{e^0}{e^{-\frac{25}{4}}} = 518$$

# Epsilon: Useful perspective

$$P(X=x) = f(X=x) \cdot \epsilon_x$$



### Normal Probability Density Function





Get Ready...

# **Learning Goals**

- 1. Update a Random Variable Belief given evidence
- 2. Apply Bayes Theorem with Discrete and Continuous variables



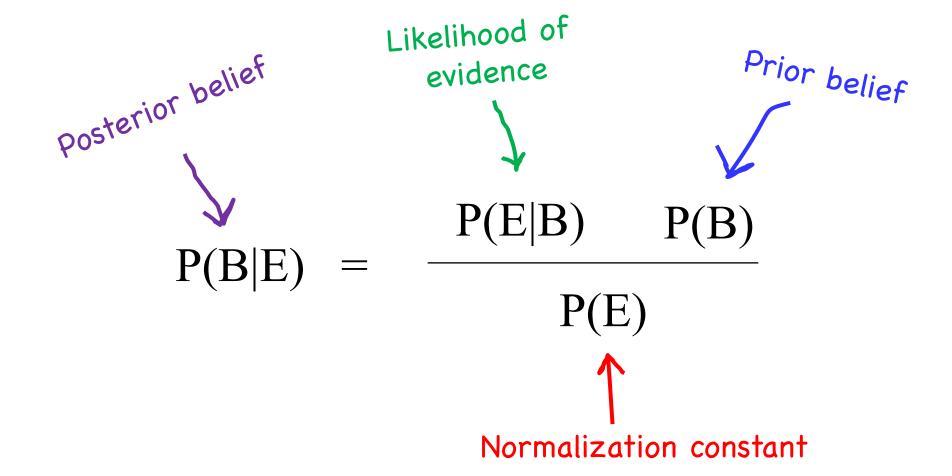
# Today: Inference

#### **Inference** noun

Updating one's belief about a random variable (or multiple) based on conditional knowledge regarding another random variable (or multiple) in a probabilistic model.

TLDR: conditional probability with random variables.

# Bayes Theorem



## Bayes with Discrete Random Variables

Let M be a discrete random variable

Let N be a discrete random variable

$$P(M = 2|N = 3) = \frac{P(N = 3|M = 2)P(M = 2)}{P(N = 3)}$$

$$P(M = m|N = n) = \frac{P(N = n|M = m)P(M = m)}{P(N = n)}$$

Shorthand notation

$$P(m|n) = \frac{P(n|m)P(m)}{P(n)}$$

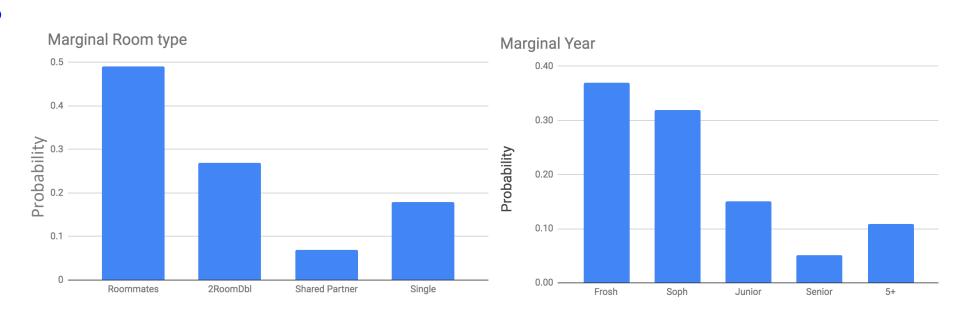
More generally

### What is the probability distribution of rooms | student is a senior?

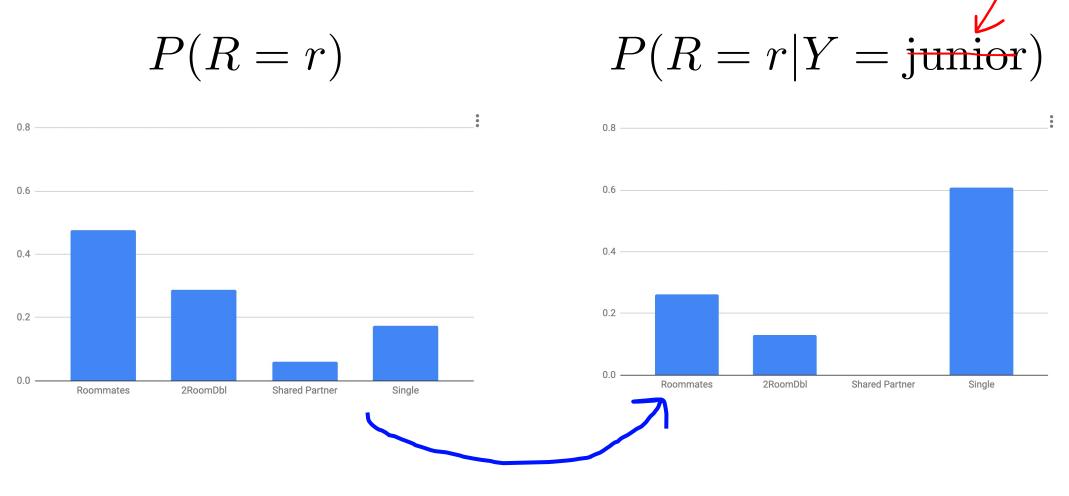
Joint >

	Roommates	2RoomDbl	Shared Partner	Single	
Frosh	0.30	0.07	0.00	0.00	0.37
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	0.49	0.27	0.07	0.18	1.00

Marginals



### What is the probability distribution of rooms | student is a senior?



Inference

### Inference is hard for two reasons:

- 1. Mix continuous and Discrete
- 2. Result can be a PMF or PDF

### Inference is hard for two reasons:

- 1. Mix continuous and Discrete
  - 2. Result can be a PMF

# All the Bayes Belong to Us

#### M,N are discrete. X, Y are continuous

$$P(m|n) = \frac{P(n|m)P(m)}{P(n)}$$

$$f(x|n) = \frac{P(n|x)f(x)}{P(n)}$$

$$P(n|x) = \frac{f(x|n)P(n)}{f(x)}$$

$$f(x|y) = \frac{f(y|x)f(x)}{f(y)}$$



#### I Heard That



Let X be the change in gaze (measured in degrees) over 3 seconds after a sound is played

Value of	PMF of X given	PMF of X given	
$\boldsymbol{X}$	Baby can hear the sound	Baby can not hear the sound	
0 to 5	0.08	0.40	
5 to 10	0.15	0.30	
10 to 15	0.35	0.12	
15 to 20	0.20	0.08	
20 to 25	0.12	0.05	
Above 25	0.10	0.05	

P(can hear the sound) = 
$$\frac{3}{4}$$

You observe X = 0 What is the probability the baby **can** hear the sound?

### Question: Have I Been Given the Joint?



Let X be the change in gaze (measured in degrees) over 3 seconds after a sound is played

Value of	PMF of X given	PMF of X given
$\boldsymbol{X}$	Baby can hear the sound	Baby can not hear the sound
0 to 5	0.08	0.40
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20 to 25	0.12	0.05
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#### I Heard That

Value of <i>X</i>	PMF of X given Baby can hear the sound	PMF of X given Baby can <b>not</b> hear the sound
0 to 5	0.08	0.40
5 to 10	0.15	0.30
10 to 15	0.35	0.12
15 to 20	0.20	0.08
20 to 25	0.12	0.05
Above 25	0.10	0.05

P(can hear the sound) = 
$$\frac{3}{4}$$

You observe X = 0. What is the probability the baby **can** hear the sound? Y = 1 means the child can hear the sound

$$P(Y = 1|X = 0) = \frac{P(X = 0|Y = 1) P(Y = 1)}{P(X = 0|Y = 1)P(Y = 1) + P(X = 0|Y = 0)P(Y = 0)}$$

$$P(Y = 1|X = 0) = \frac{0.08 * 0.75}{0.08 * 0.75 + 0.40 * 0.25} = \frac{3}{8}$$

#### I Heard That with Continuous

#### **Normal Assumption:**

For babies who can hear sounds, we approximate their gaze movement after the sound is played as:  $N(\mu = 15, \sigma^2 = 25)$ 

For babies who can **not** hear sounds, we approximate gaze movement as  $N(\mu = 8, \sigma^2 = 25)$ .

For a new baby we observe a 14 degree movement after the sound is played. What is your belief that a baby can hear, under The Normal Assumption?

# Equivalently

**Normal Assumption**: For babies who can hear sounds, we approximate their gaze movement after the sound is played as:  $N(\mu = 15, \sigma^2 = 25)$ .

For babies who can **not** hear sounds, we approximate gaze movement as  $N(\mu = 8, \sigma^2 = 25).$ 

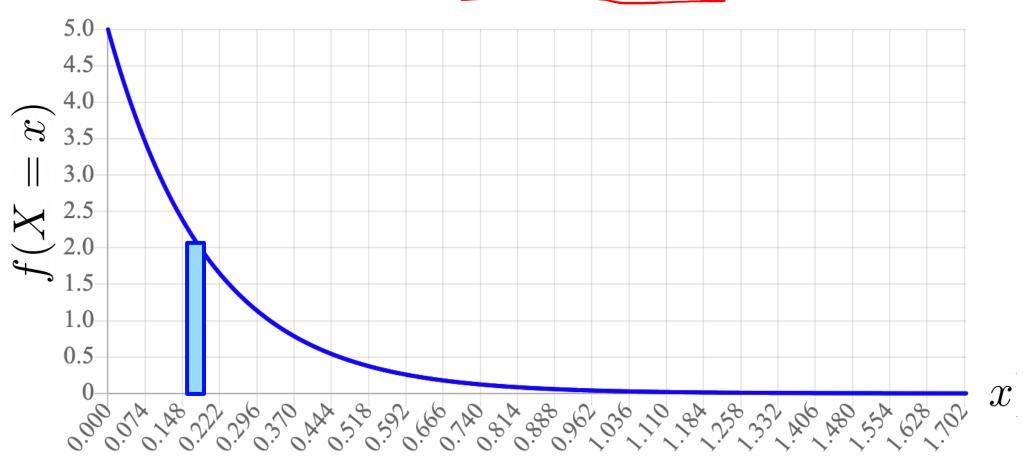
For a new baby we observe a 14 degree movement after the sound is played. What is your belief that a baby can hear, under The Normal Assumption?

```
def sample ():
   # bernoulli sample
   can_hear = rand_bern(0.75)
   if can_hear == 0:
       # gaussian sample
       return rand_gauss (mu = 15 , std = 5)
   else:
       # gaussian sample
       return rand_gauss (mu = 8, std = 5)
```

The function sample returned the value 14. What is the probability that can\_hear was 1? Aside: Models with continuous RVs

# Epsilon: Useful perspective

$$P(X=x) = f(X=x) \cdot \epsilon_x$$



# Mixing Discrete and Continuous

Let X be a continuous random variable

Let N be a discrete random variable

$$P(N = n | X = x) = \frac{P(X = x | N = n)P(N = n)}{P(X = x)}$$

$$P(N = n | X = x) = \frac{f(X = x | N = n) \cdot \epsilon \cdot P(N = n)}{f(X = x) \cdot \epsilon}$$

$$P(N = n | X = x) = \frac{f(X = x | N = n) \cdot P(N = n)}{f(X = x)}$$

# Mixing Discrete and Continuous

Let X be a continuous random variable

Let N be a discrete random variable

$$P(\underline{X=x}|N=n) = \frac{P(N=n|X=x)P(X=x)}{P(N=n)}$$
 Change notation 
$$P(x|n) = \frac{P(n|x)P(x)}{P(n)}$$

$$f(x|n) \cdot \epsilon_x = \frac{P(n|x)f(x) \cdot \epsilon_x}{P(n)}$$

$$f(x|n) = \frac{P(n|x)f(x)}{P(n)}$$
Chris Piech, CS109, 2022

# All the Bayes Belong to Us

#### M,N are discrete. X, Y are continuous

$$P(m|n) = \frac{P(n|m)P(m)}{P(n)}$$

$$f(x|n) = \frac{P(n|x)f(x)}{P(n)}$$

$$P(n|x) = \frac{f(x|n)P(n)}{f(x)}$$

$$f(x|y) = \frac{f(y|x)f(x)}{f(y)}$$

# LOTP? Chain Rule? You can play too!

#### N is discrete. X is continuous

#### Chain Rule

$$f(N = n, X = x) = f(X = x | N = n)P(N = n)$$

Law of total probability

$$f(X = x) = \sum_{n} f(X = x | N = n)P(N = n)$$

# End Aside

#### How can We Solve This Problem?

**Normal Assumption**: For babies who can hear sounds, we approximate their gaze movement after the sound is played as:  $N(\mu = 15, \sigma^2 = 25)$ .

For babies who can **not** hear sounds, we approximate gaze movement as  $N(\mu = 8, \sigma^2 = 25).$ 

For a new baby we observe a 14 degree movement after the sound is played. What is your belief that a baby can hear, under The Normal Assumption?

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```

The function sample returned the value 14. What is the probability that can\_hear was 1?

#### Inference with Continuous

Q: At birth, girl elephant weights are distributed as a Gaussian with mean = 160kg, std = 7kg. At birth, boy elephant weights are distributed as a Gaussian with mean = 165kg, std = 3kg. All you know about a newborn elephant is that it is 163kg. What is the probability that

it is a girl?



#### Inference with Continuous



Q: At birth, girl elephant weights are distributed as a Gaussian with mean = 160kg, std = 7kg. At birth, boy elephant weights are distributed as a Gaussian with mean = 165kg, std = 3kg. All you know about a newborn elephant is that it is 163kg. What is the probability that it is a girl?

#### Model:

Let  $\underline{G}$  be an indicator that the elephant is a girl. G is Bern(p = 0.5) Let X be the distribution of weight of the elephant.

$$X \mid G = 1 \text{ is } N(\mu = 160, \sigma^{2} = 7^{2})$$

$$X \mid G = 0 \text{ is } N(\mu = 165, \sigma^{2} = 3^{2})$$

#### Inference with Continuous



Q: What is 
$$P(G = 1 | X = 163)$$

Let G be an indicator that the elephant is a girl. G is Bern(p = 0.5)

Let X be the distribution of weight of the elephant.

$$X \mid G = 1 \text{ is } N(\mu = 160, \sigma^{2} = 7^{2})$$

$$X \mid G = 0 \text{ is } N(\mu = 165, \sigma^{2} = 3^{2})$$

# Pedagogical Pause

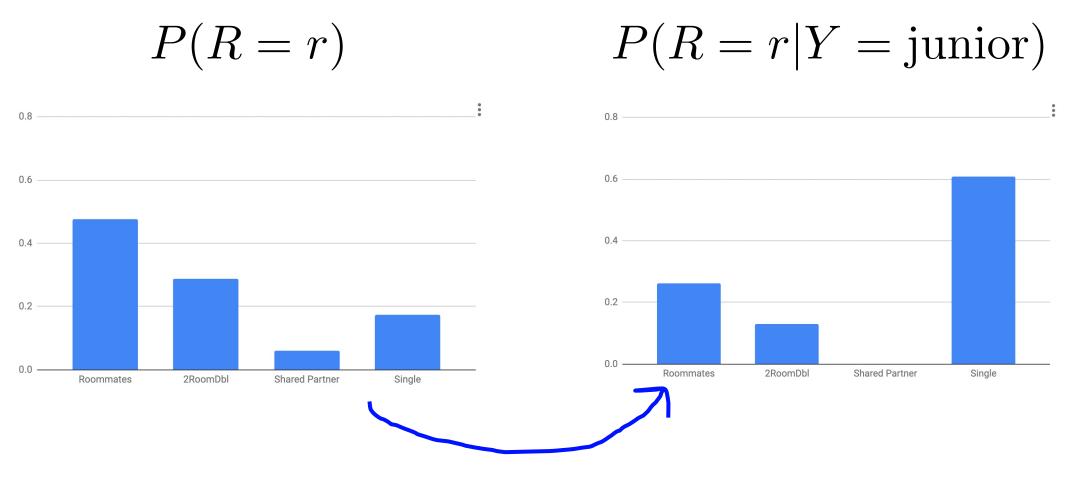
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### What is the probability distribution of rooms | student is a senior?



Inference

#### Goal: Inference



Change your belief distribution (Joint, PMF, or PDF) of random variables, based on observations

\*Note in the earlier examples, we were updating Bernoulli Random Variables

# Lets Play Number of Function!

#### Number or Function?

$$P(X=2|Y=5)$$

# Number

#### Number or Function?

$$P(X = x | Y = 2)$$

# Random Variable

(also a function or 1D table)

#### Number or Function?

$$P(X = x | Y = y)$$

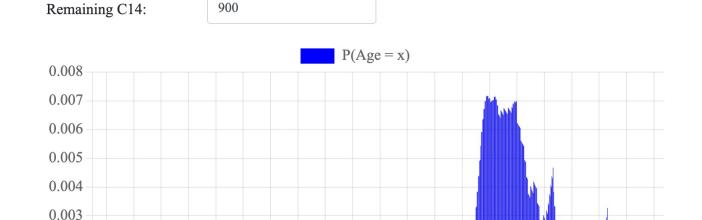
# 2D Function (or 2D table)

## Popularized in 2009: Bayesian Carbon Dating

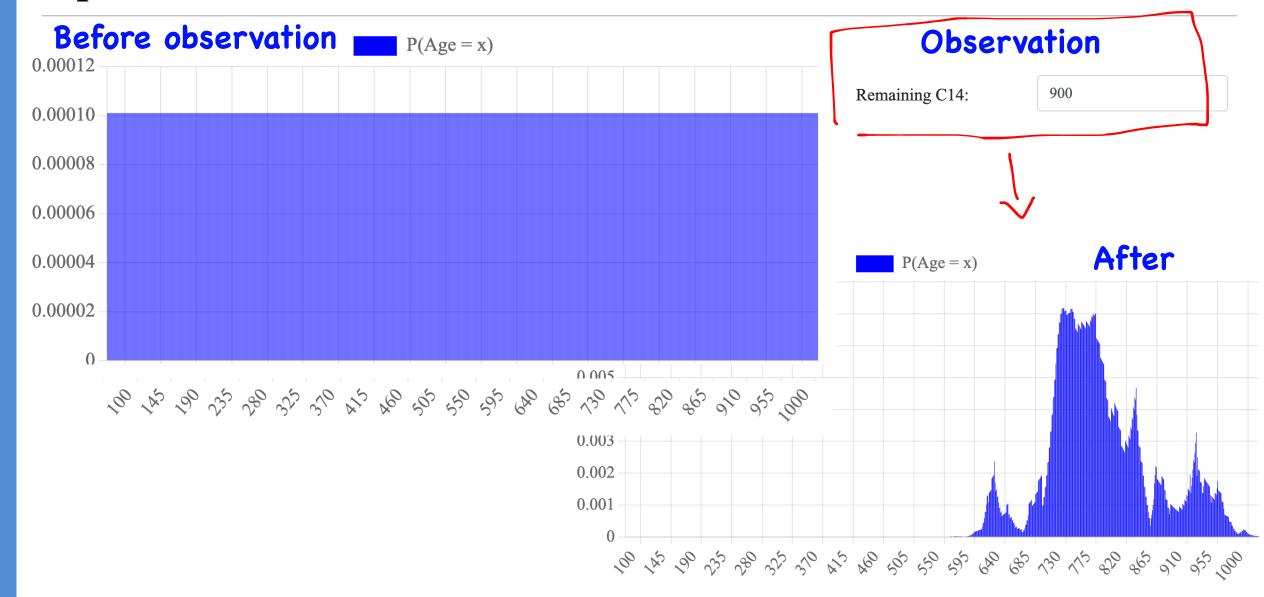
We are able to know the age of ancient artefacts using a process called carbon dating. This process involves a lot of uncertainty! You observe a measurement of 90% of natural C14 molecules in a sample. What is your belief distribution over the age of the sample? This task requires probabilistic models because we have to think about two random variables together: the age A of the sample, and M the remaining C14 molecules.

#### Carbon Dating Demo

Imagine you have just taken a sample from your artifact. For the sample size you took, a living organism would have had 1000 molecules of C14. Use this demo to explore the relationship between how much C14 is left and your belief ditribution for how old your artifact is.



# Update Belief PMF



# Bayesian Carbon Dating: Inference Overview

Let A be how many years old the sample is (A = 100 means the sample is 100 years old)Let M be the observed amount of C14 left in the sample

$$P(A = i | M = 900) = \frac{P(M = 900 | A = i)P(A = i)}{P(M = 900)}$$

$$= P(M = 900 | A = i) \cdot \frac{P(A = i)}{P(M = 900)}$$

$$= P(M = 900 | A = i) \cdot P(A = i) \cdot K$$

# Understanding Through Code

```
P(A = i|M = 900) = P(M = 900|A = i) \cdot P(A = i) \cdot K
def update_belief(m = 900):
   11 11 11
   Returns a dictionary A, where A[i] contains the
   corresponding probability, P(A = i | M = 900).
   m is the number of C14 molecules remaining and i
   is age in years. i is in the range 100 to 10000
   111111
   A = \{\}
   n years = 9901
   for i in range(100, 10000+1):
      prior = 1 / n_years # P(A = i)
      likelihood = calc_likelihood(m, i) # P(M=m | A=i)
      A[i] = prior * likelihood
   # implicitly computes the normalization constant
   normalize(A)
   etuin A
```

# Carbon Dating Specific Math

$$P(M = 900|A = 1)$$

There were originally 1000 C14 molecules. Each molecule remains independently with equal probability p<sub>i</sub> What is the probability that 900 remain?

$$M \sim \text{Bin}(n = 1000, p = p_i)$$

$$P(M = 900|A = i) = {1000 \choose 900} (p_i)^{900} \cdot (1 - p_i)^{100}$$

#### Each molecules' time to live is exponential with $\lambda = 1/8267$

Let T be the time to decay for any one molecule

$$T \sim \text{Exp}(\lambda = 1/8267)$$
  $p_i = P(T > i) = 1 - P(T < i) = e^{-\frac{i}{8267}}$ 

l University

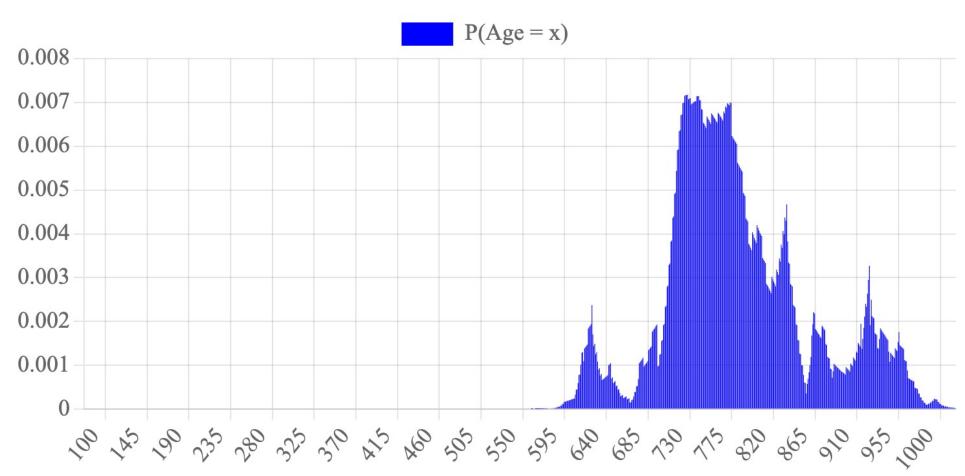
$$P(M = 900|A = i)$$

```
def calc_likelihood(m = 900, age):
   Computes P(M = m \mid A = age), the probability of
   having m molecules left given the sample is age
   years old. Uses the exponential decay of C14
   n_{original} = 1000
   p_remain = math.exp(-age/C14_MEAN_LIFE)
   return stats.binom.pmf(m, n_original, p_remain)
```

P(M = 900 | A = i)C14 Delta per 1000 Samples 100 def calc\_likelihood(m = 900, Computes  $P(M = m \mid A = age)$ having m molecules left given years old. Uses the expone n\_original = 1000 + delta\_start(age) p\_remain = math\_exp(-age/C14\_MEAN\_LIFE) return stats.binom.pmf(m, n\_original, p\_remain)

Remaining C14:

900

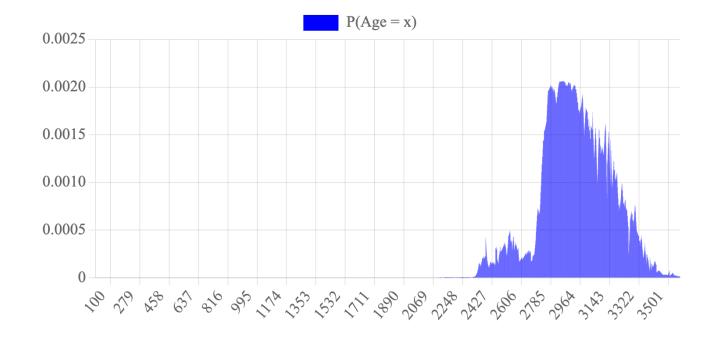


# Come Back for More!

# Belief in Age Given Observed C14



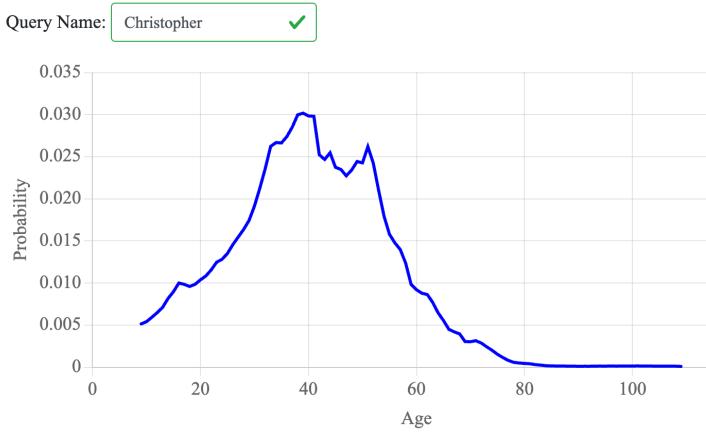
#### P(Age | Observed C14)



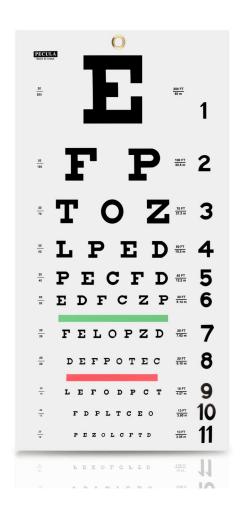
# Belief in Age Given Name



#### P(Age | Name)



# Belief in Vision Given User Responses



#### P(Ability to See | Observed Responses)

