



# Beta: The Random Variable for Probabilities

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Philosophical Ponderings:

You ask about the probability of rain tomorrow.

**Person A:** My leg itches when it rains and its kind of itchy.... Uh,  $p = .80$

**Person B:** I have done complex calculations and have seen 10,451 days like tomorrow...  $p = 0.80$

What is the difference between the two estimates?

*“Those who are able to  
represent what they do not  
know make better decisions”  
- CS109*

Today we are going to learn  
something unintuitive, beautiful and  
useful



Review



Conditioning with a  
continuous random  
variable is odd at first. But  
then it gets fun.

Its like snorkeling...

# Continuous Conditional Distributions

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Let  $X$  be continuous random variable

Let  $E$  be an event:

$$\begin{aligned} P(E|X = x) &= \frac{P(X = x, E)}{P(X = x)} \\ &= \frac{P(X = x|E)P(E)}{P(X = x)} \\ &= \frac{f_X(x|E)P(E)\epsilon_x}{f_X(x)\epsilon_x} \\ &= \frac{f_X(x|E)P(E)}{f_X(x)} \end{aligned}$$

# Continuous Conditional Distributions

---

Let  $X$  be a measure of time to answer a question

Let  $E$  be the event that the user is a human:

$$\begin{aligned} P(E|X = x) &= \frac{P(X = x, E)}{P(X = x)} \\ &= \frac{P(X = x|E)P(E)}{P(X = x)} \\ &= \frac{f_X(x|E)P(E)\epsilon_x}{f_X(x)\epsilon_x} \\ &= \frac{f_X(x|E)P(E)}{f_X(x)} \end{aligned}$$

# Biometric Keystrokes

---

Let  $X$  be a measure of time to answer a question

Let  $E$  be the event that the user is a human

What if you don't know normalization term?:

$$P(E|X = x) = \frac{f_X(x|E)P(E)}{f_X(x)}$$

Normal pdf

Prior

???

$$\frac{P(E|X = x)}{P(E^C|X = x)}$$

End Review



# Let's play a game!

---

Roll a dice three times. If I roll a six twice (or more) I win \$1 million.  
Otherwise you win \$1 million. What should we charge to play?



$$P(W) = \left(\frac{5}{6}\right)^2 \approx 0.69$$

# What if you don't know a probability?

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# What if you don't know a probability?

---







Pirate Supply Store, San Francisco



We are going to think of  
probabilities as random  
variables!!!



# Flip a coin with unknown probability

---

Flip a coin ( $n + m$ ) times, comes up with  $n$  heads

- We don't know probability  $X$  that coin comes up heads

Frequentist (never prior)

$$X = \lim_{n+m \rightarrow \infty} \frac{n}{n+m}$$
$$\approx \frac{n}{n+m}$$

$X$  is (often) a single value

Bayesian (prior is great)

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

$X$  is a random variable. Leads to a belief distribution which captures confidence



What is your belief that you  
successfully roll a 6 on my die?

# Flip a coin with unknown probability!

Flip a coin  $(n + m)$  times, comes up with  $n$  heads

- We don't know probability  $X$  that coin comes up heads
- Our belief before flipping coins is that:  $X \sim \text{Uni}(0, 1)$
- Let  $N$  = number of heads
- Given  $X = x$ , coin flips independent:  $(N \mid X) \sim \text{Bin}(n + m, x)$

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

Bayesian  
"posterior"  
probability distribution

Bayesian "prior"  
probability distribution

# Flip a coin with unknown probability!

Flip a coin  $(n + m)$  times, comes up with  $n$  heads

- We don't know probability  $X$  that coin comes up heads
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- Let  $N$  = number of heads
- Given  $X = x$ , coin flips independent:  $(N | X) \sim \text{Bin}(n + m, x)$

$$f_{X|N}(x|n) = \frac{P(N = n | X = x) f_X(x)}{P(N = n)} \quad 1$$

Binomial

$$= \frac{\binom{n+m}{n} x^n (1-x)^m}{P(N = n)}$$

$$= \frac{\binom{n+m}{n}}{P(N = n)} x^n (1-x)^m$$

$$= \frac{1}{c} \cdot x^n (1-x)^m \quad \text{where } c = \int_0^1 x^n (1-x)^m dx$$

Move terms around

# Flip a coin with unknown probability!



If you start with a  $X \sim \text{Uni}(0, 1)$  prior over probability, and observe:

$n$  “successes” and  
 $m$  “failures”...

Your new belief about the probability is:

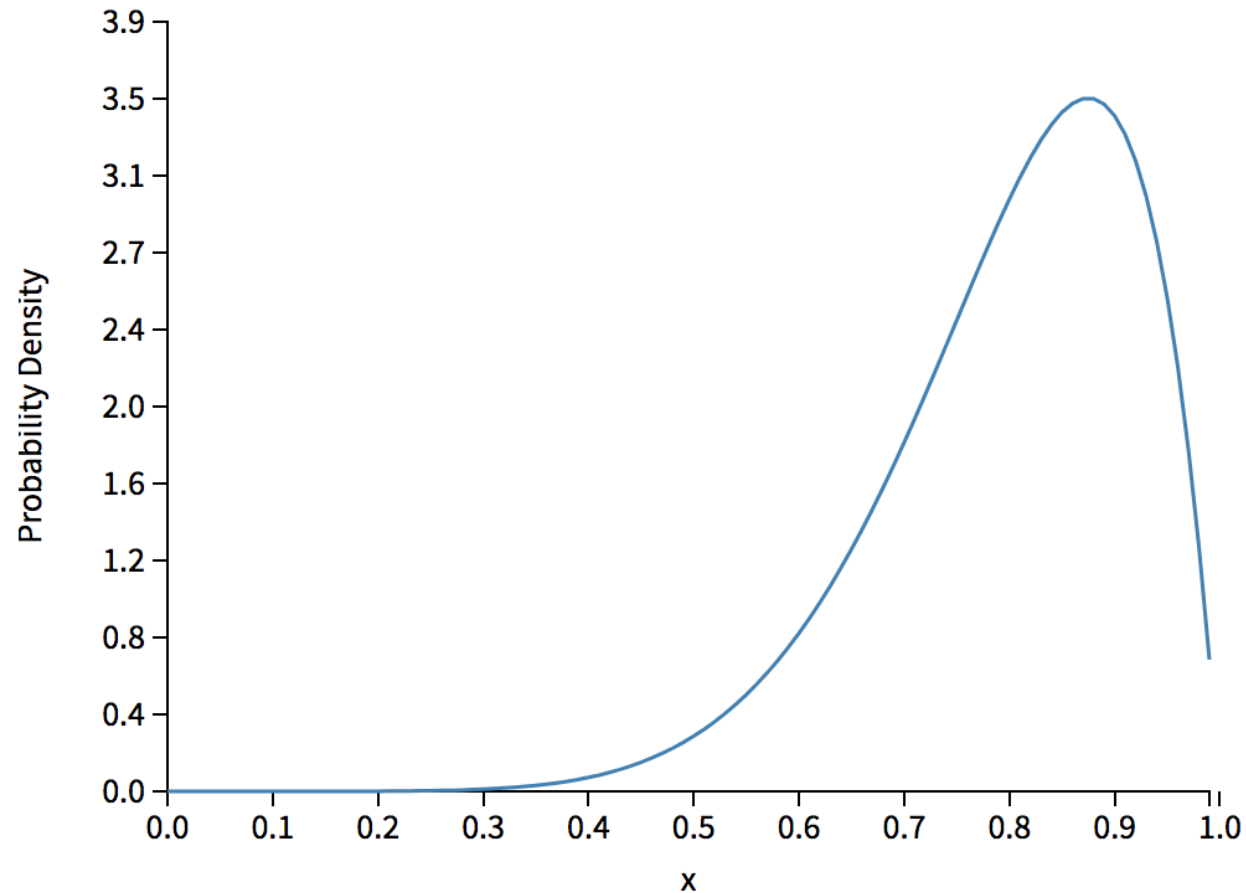
$$f_X(x) = \frac{1}{c} \cdot x^n (1 - x)^m$$

where  $c = \int_0^1 x^n (1 - x)^m$

# Belief after 7 success and 1 fail

$$f_X(x) = \frac{1}{c} \cdot x^n (1-x)^m$$

$n=7$   $m=1$



# Equivalently!



If you start with a  $X \sim \text{Uni}(0, 1)$  prior over probability, and observe:

let  $a = \text{num "successes"} + 1$

let  $b = \text{num "failures"} + 1$

Your new belief about the probability is:

$$f_X(x) = \frac{1}{c} \cdot x^{a-1} (1-x)^{b-1}$$

where  $c = \int_0^1 x^{a-1} (1-x)^{b-1}$



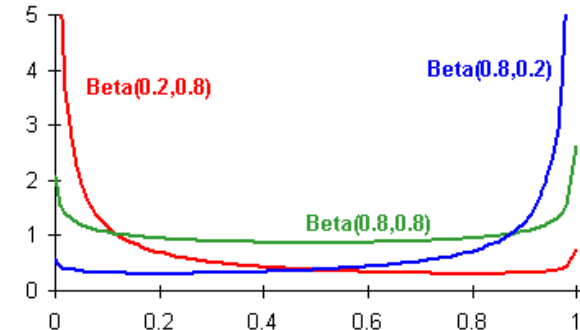
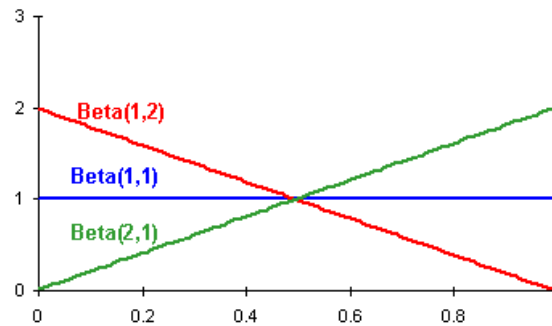
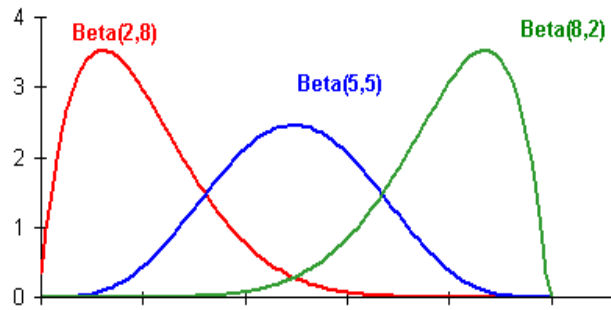
# Beta Random Variable

X is a **Beta Random Variable**:  $X \sim \text{Beta}(a, b)$

- Probability Density Function (PDF): (where  $a, b > 0$ )

$$f(x) = \begin{cases} \frac{1}{B(a,b)} x^{a-1} (1-x)^{b-1} & 0 < x < 1 \\ 0 & \text{otherwise} \end{cases}$$

$$B(a,b) = \int_0^1 x^{a-1} (1-x)^{b-1} dx$$

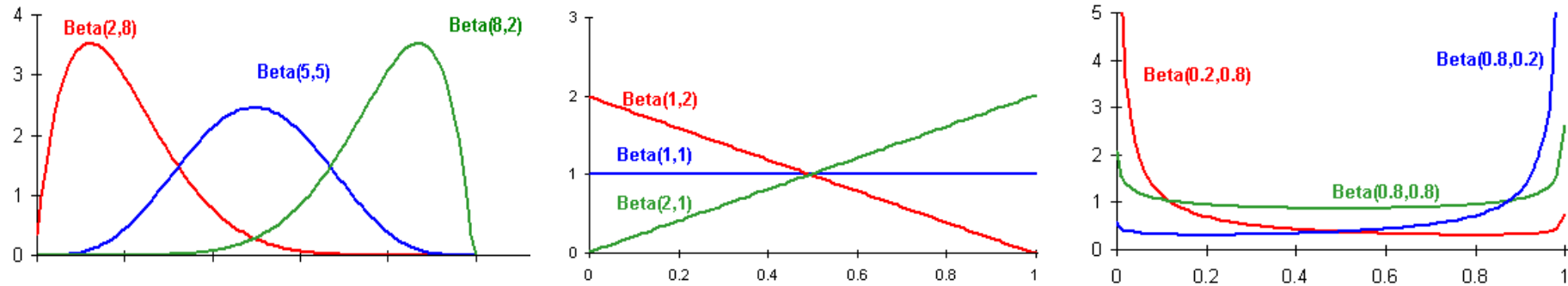


- Symmetric when  $a = b$

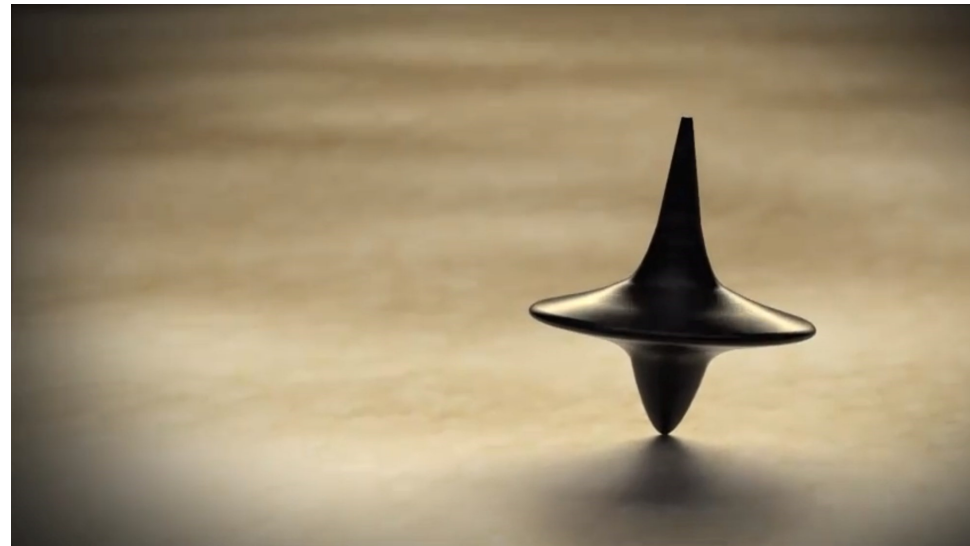
$$E[X] = \frac{a}{a+b}$$

$$\text{Var}(X) = \frac{ab}{(a+b)^2(a+b+1)}$$

# Beta is the Random Variable for Probabilities



Used to represent a distributed belief of a probability



Philosophical Ponderings:

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What is the difference between the two estimates?



Beta is a distribution for probabilities. Its range is values between 0 and 1



Beta Parameters *can*  
come from experiments:

$$a = \text{"successes"} + 1$$

$$b = \text{"failures"} + 1$$

# Back to Flipping Coins!

---

Flip a coin  $(n + m)$  times, comes up with  $n$  heads

- We don't know probability  $X$  that coin comes up heads
- Our belief before flipping coins is that:  $X \sim \text{Uni}(0, 1)$
- Let  $N$  = number of heads
- Given  $X = x$ , coin flips independent:  $(N \mid X) \sim \text{Bin}(n + m, x)$

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

$$= \frac{\binom{n+m}{n} x^n (1-x)^m}{P(N = n)}$$

$$= \frac{\binom{n+m}{n}}{P(N = n)} x^n (1-x)^m$$

$$= \frac{1}{c} \cdot x^n (1-x)^m \quad \text{where } c = \int_0^1 x^n (1-x)^m dx$$



# A beta understanding

---

$X \mid (N = n, M = m) \sim \text{Beta}(a = n + 1, b = m + 1)$

- Prior  $X \sim \text{Uni}(0, 1)$

- Check this out, boss:

$N$  successes

- $\text{Beta}(a = 1, b = 1) = ?$

$M$  failures

$$\begin{aligned} f(x) &= \frac{1}{B(a,b)} x^{a-1} (1-x)^{b-1} = \frac{1}{B(a,b)} x^0 (1-x)^0 \\ &= \frac{1}{\int_0^1 1 dx} 1 = 1 \quad \text{where } 0 < x < 1 \end{aligned}$$

- $\text{Beta}(a = 1, b = 1) = \text{Uni}(0, 1)$

- So, prior  $X \sim \text{Beta}(a = 1, b = 1)$

# If the Prior was Beta?

---

X is our random variable for probability

If our **prior belief** about X was beta

$$f(X = x) = \frac{1}{B(a, b)} x^{a-1} (1 - x)^{b-1}$$

What is our **posterior belief** about X after observing  $n$  heads  
(and  $m$  tails)?

$$f(X = x | N = n) = ???$$

# If the Prior was Beta?

---

$$\begin{aligned} f(X = x|N = n) &= \frac{P(N = n|X = x)f(X = x)}{P(N = n)} \\ &= \frac{\binom{n+m}{n} x^n (1-x)^m f(X = x)}{P(N = n)} \\ &= \frac{\binom{n+m}{n} x^n (1-x)^m \frac{1}{B(a,b)} x^{a-1} (1-x)^{b-1}}{P(N = n)} \\ &= K_1 \cdot \binom{n+m}{n} x^n (1-x)^m \frac{1}{B(a,b)} x^{a-1} (1-x)^{b-1} \\ &= K_3 \cdot x^n (1-x)^m x^{a-1} (1-x)^{b-1} \\ &= K_3 \cdot x^{n+a-1} (1-x)^{m+b-1} \end{aligned}$$

$$X|N \sim \text{Beta}(n + a, m + b)$$

# A beta understanding

---

- If “Prior” distribution of  $X$  (before seeing flips) is Beta
- Then “Posterior” distribution of  $X$  (after flips) is Beta

Beta is a **conjugate** distribution for Beta

- Prior and posterior parametric forms are the same!
- Practically, conjugate means easy update:
  - Add number of “heads” and “tails” seen to Beta parameters

# A beta understanding

---

Can set  $X \sim \text{Beta}(a, b)$  as prior to reflect how biased you think coin is apriori

- This is a subjective probability (aka Bayesian)!
- Prior probability for  $X$  based on seeing  $(a + b - 2)$  “imaginary” trials, where
  - $(a - 1)$  of them were heads.
  - $(b - 1)$  of them were tails.
- $\text{Beta}(1, 1) = \text{Uni}(0, 1) \rightarrow$  we haven’t seen any “imaginary trials”, so apriori know nothing about coin

Update to get posterior probability

- $X \mid (n \text{ heads and } m \text{ tails}) \sim \text{Beta}(a + n, b + m)$



# Enchanted Die

Let  $X$  be the probability of rolling a “6” on Chris’ die.

**Prior:** Imagine 5 die rolls where only showed up as a “6”

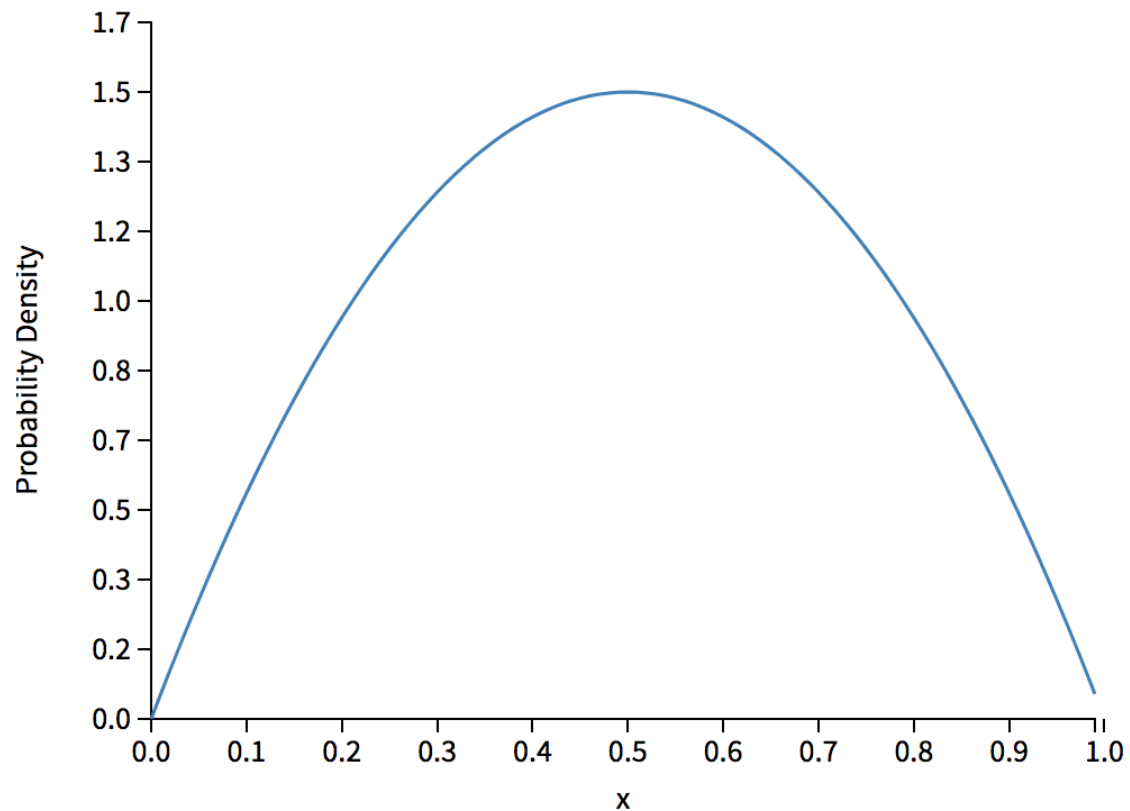
**Observation:** Roll it a few times...

What is the updated probability density function of  $X$  after our observations?



# Check out the Demo!

## Beta PDF



## Parameters

**a:**

**b:**

beta pdf

Damn

# A beta example

---

Before being tested, a medicine is believed to “work” about 80% of the time. The medicine is tried on 20 patients. It “works” for 14 and “doesn’t work” for 6. What is your new belief that the drug works?

---

Frequentist:

$$p \approx \frac{14}{20} = 0.7$$

# A beta example

---

Before being tested, a medicine is believed to “work” about 80% of the time. The medicine is tried on 20 patients. It “works” for 14 and “doesn’t work” for 6. What is your new belief that the drug works?

---

Bayesian:  $X \sim \text{Beta}$

Prior:

$$X \sim \text{Beta}(a = 81, b = 21)$$

Interpretation:

80 successes / 100 trials

$$X \sim \text{Beta}(a = 9, b = 3)$$

8 successes / 10 trials

$$X \sim \text{Beta}(a = 5, b = 2)$$

4 successes / 5 trials

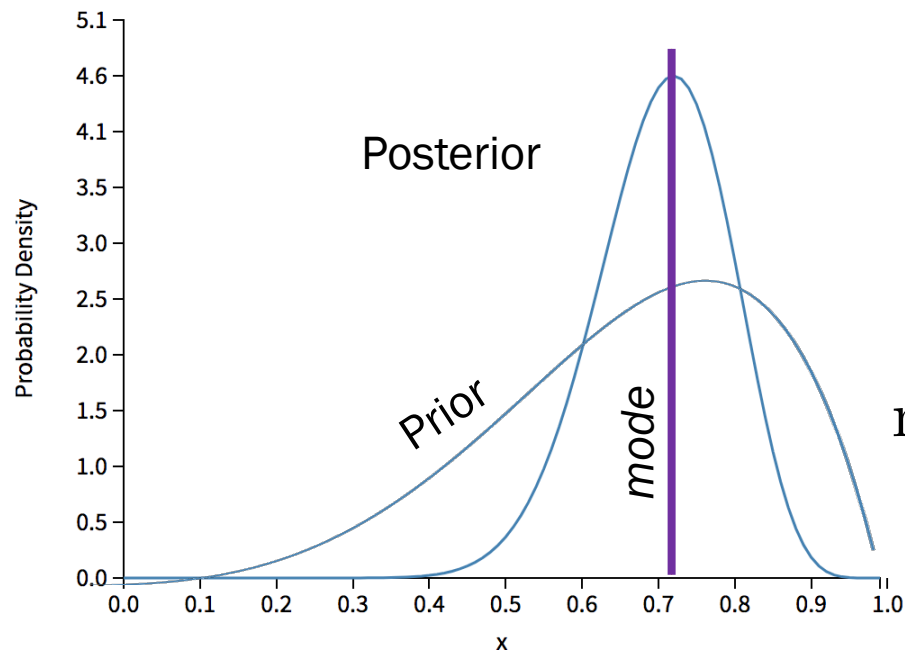
# A beta example

Before being tested, a medicine is believed to “work” about 80% of the time. The medicine is tried on 20 patients. It “works” for 14 and “doesn’t work” for 6. What is your new belief that the drug works?

Bayesian:  $X \sim \text{Beta}$

Prior:  $X \sim \text{Beta}(a = 5, b = 2)$

Posterior:  $X \sim \text{Beta}(a = 5 + 14, b = 2 + 6)$   
 $\sim \text{Beta}(a = 19, b = 8)$



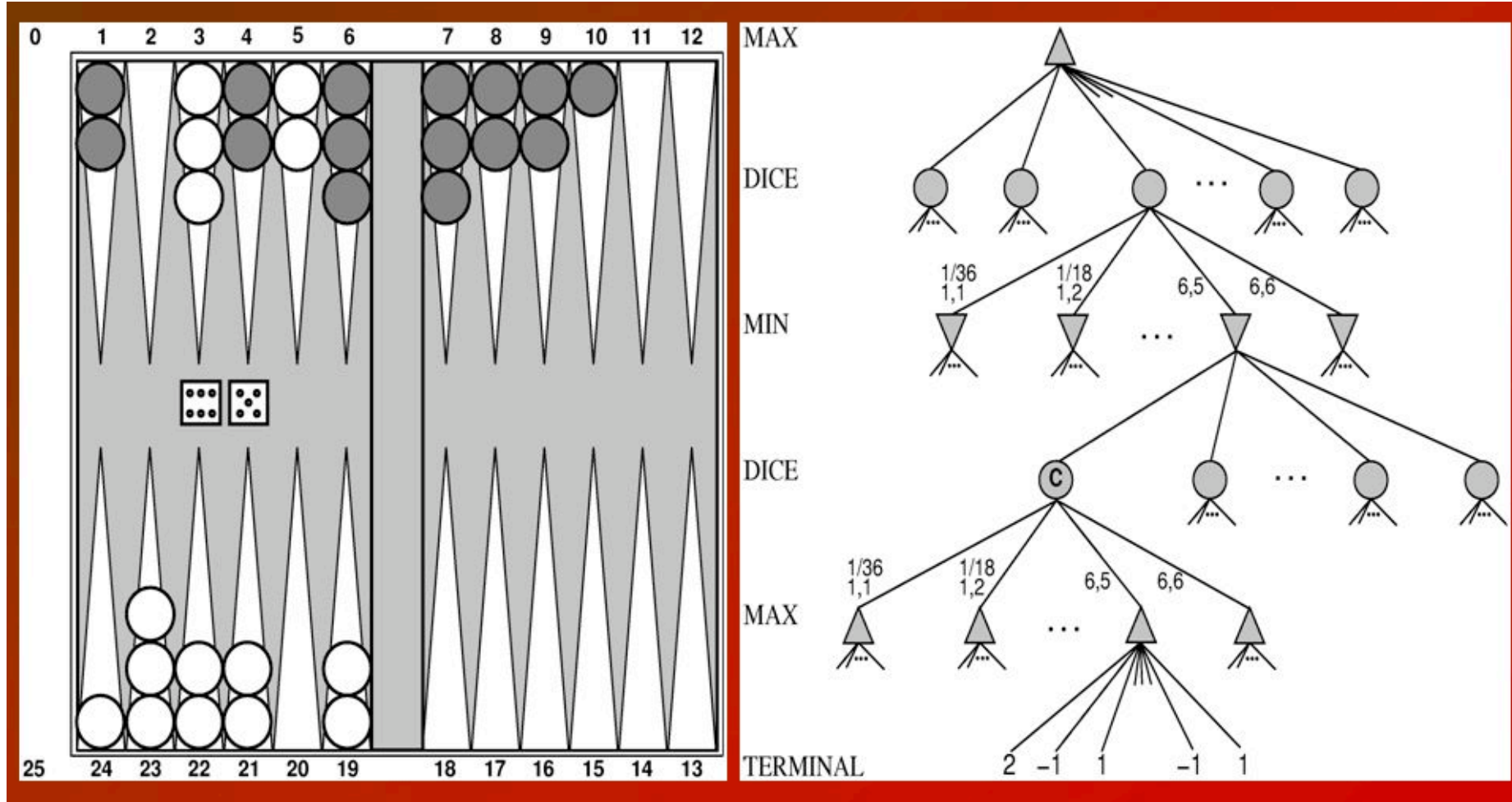
$$E[X] = \frac{a}{a + b} = \frac{19}{19 + 8} \approx 0.70$$

$$\begin{aligned} \text{mode}(X) &= \frac{a - 1}{a + b - 2} \\ &= \frac{19}{18 + 7} \approx 0.72 \end{aligned}$$

Next level?

Alpha GO mixed deep learning and  
core reasoning under uncertainty

# Multi Armed Bandit





# Multi Armed Bandit

Drug A



Drug B



Which one do you give to a patient?

# Lets Play!

Drug A



Drug B



Which one do you give to a patient?

# Lets Play!

```
sim.py x
1 import pickle
2 import random
3
4 def main():
5     X1, X2 = pickle.load(open('probs.pkl', 'rb'))
6
7     print("Welcome to the drug simulator. There are two drugs")
8
9     while True:
10        choice = getChoice()
11        prob = X1 if choice == "a" else X2
12        success = bernoulli(prob)
13        if success:
14            print('Success. Patient lives!')
15        else:
16            print('Failure. Patient dies!')
17        print('')
18
```

# Optimal Decision Making

You try drug B, 5 times. It is successful 2 times.

If you had a uniform prior, what is your posterior belief about the likelihood of success?

---

2 successes

3 failures

$$X \sim \text{Beta}(a = 3, b = 4)$$

# Optimal Decision Making

You try drug B, 5 times. It is successful 2 times.  
 $X$  is the probability of success.

$$X \sim \text{Beta}(a = 3, b = 4)$$

---

What is expectation of  $X$ ?

$$E[X] = \frac{a}{a + b} = \frac{3}{3 + 4} \approx 0.43$$

# Optimal Decision Making

You try drug B, 5 times. It is successful 2 times.  
 $X$  is the probability of success.

$$X \sim \text{Beta}(a = 3, b = 4)$$

---

What is the probability that  $X > 0.6$

$$P(X > 0.6) = 1 - P(X < 0.6) = 1 - F_X(0.6)$$

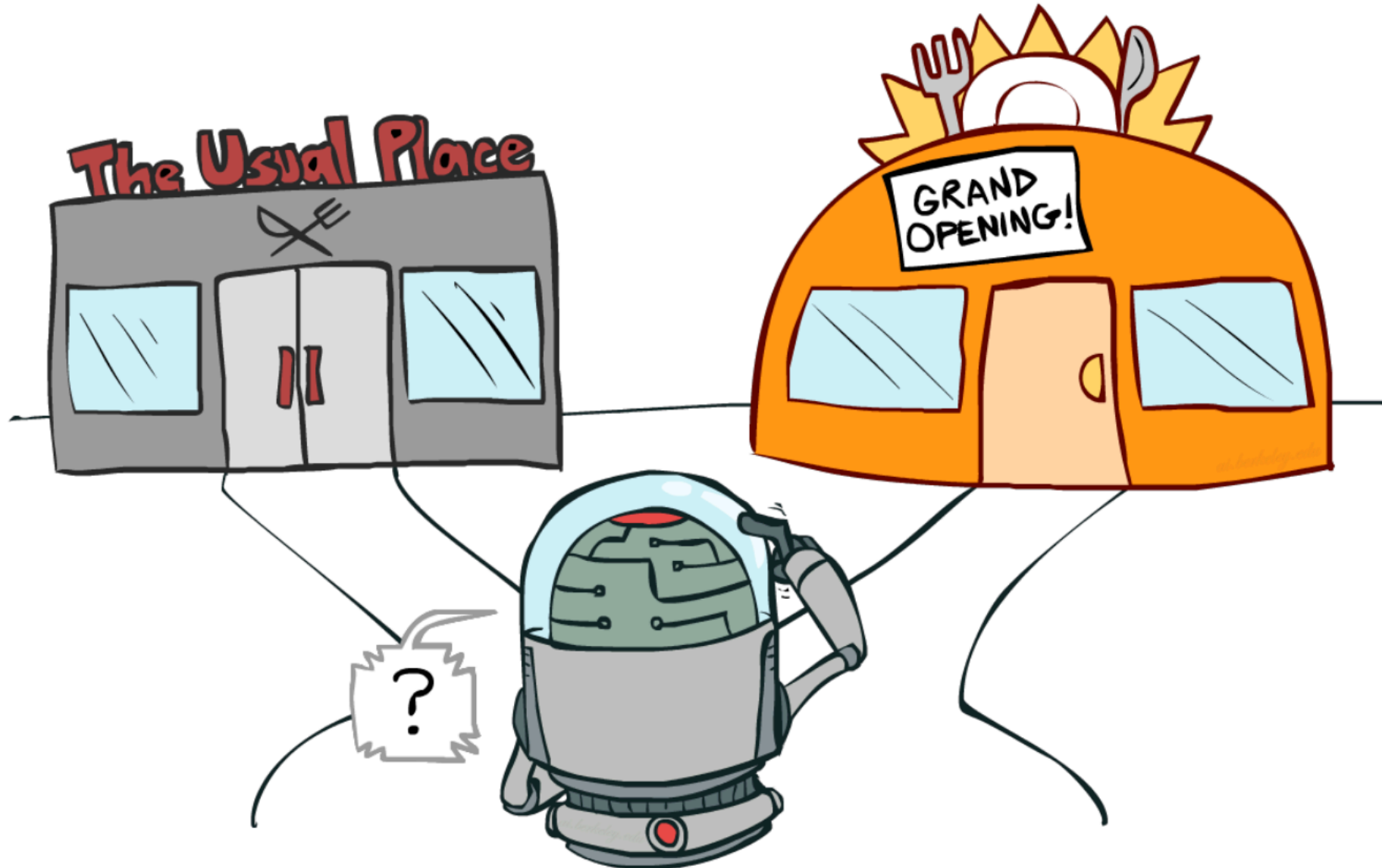
Wait what? Chris are you holding out on me?

```
stats.beta.cdf(x, a, b)
```

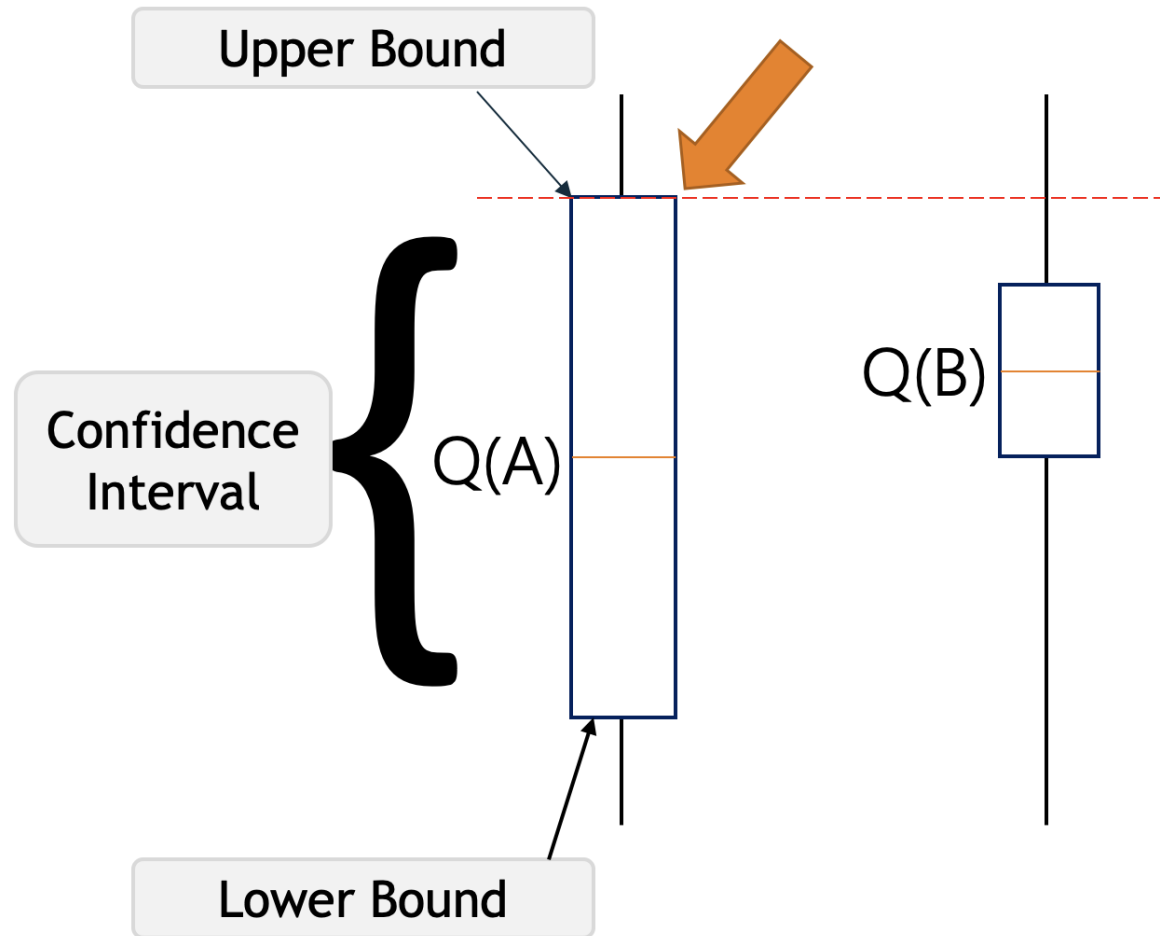
$$P(X > 0.6) = 1 - F_X(0.6) = 0.1792$$

# Explore something new? Or go for what looks good now?

---

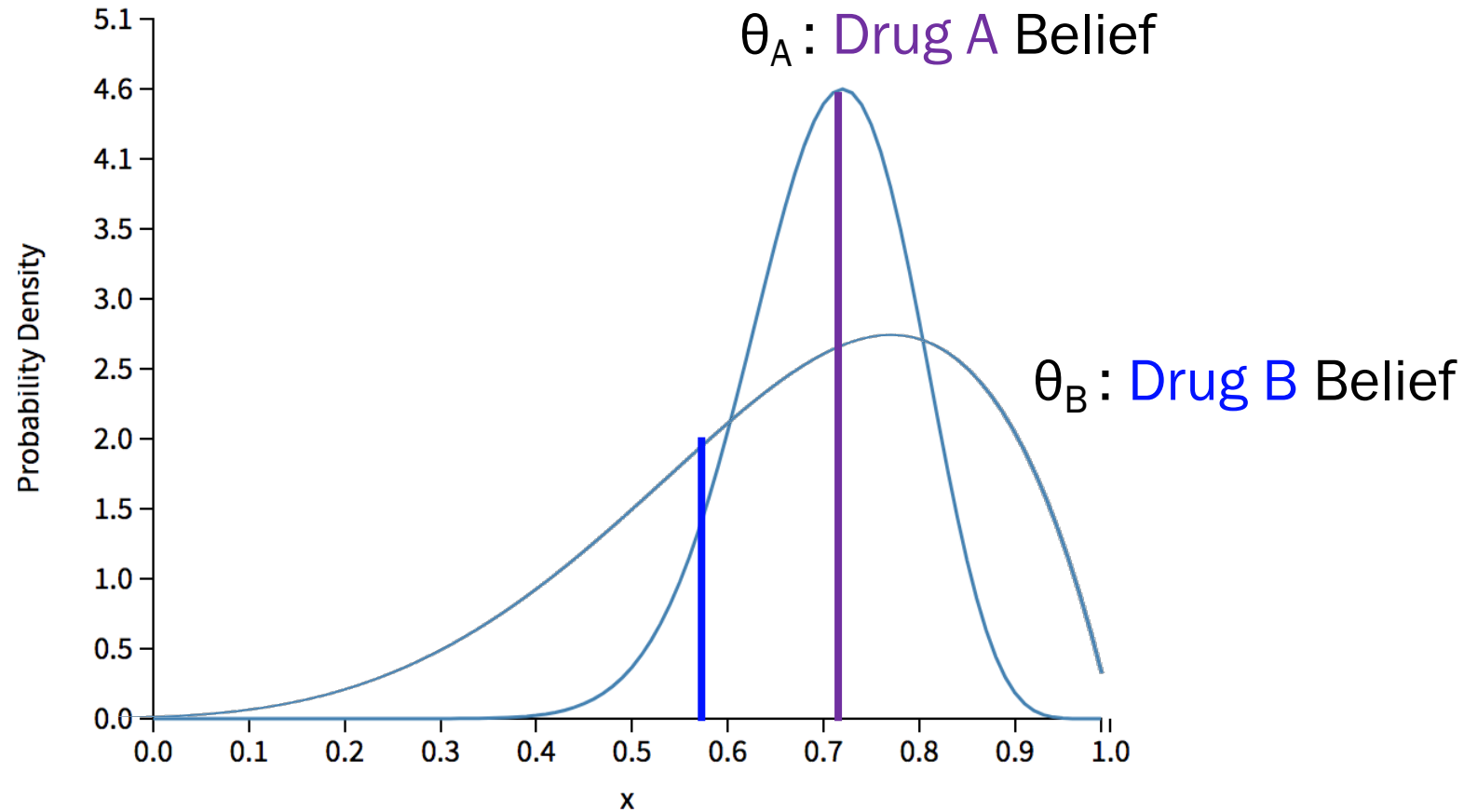


# One option: Upper Confidence Bound





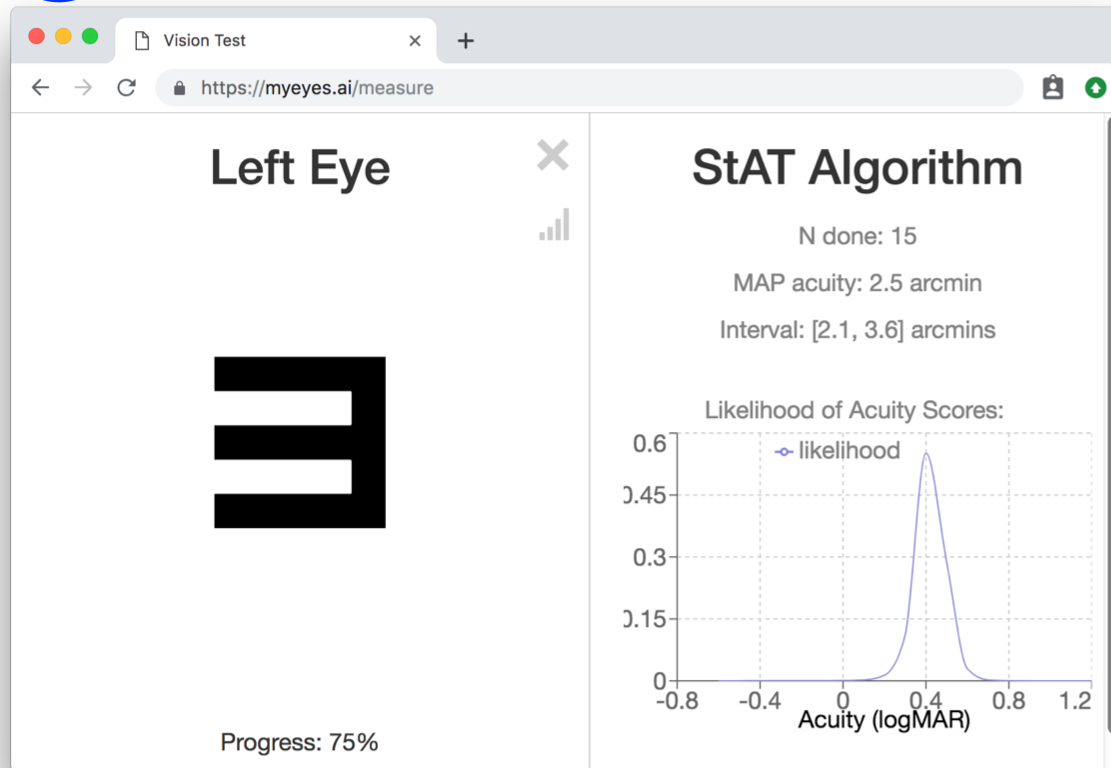
# Amazing option: Thompson Sampling



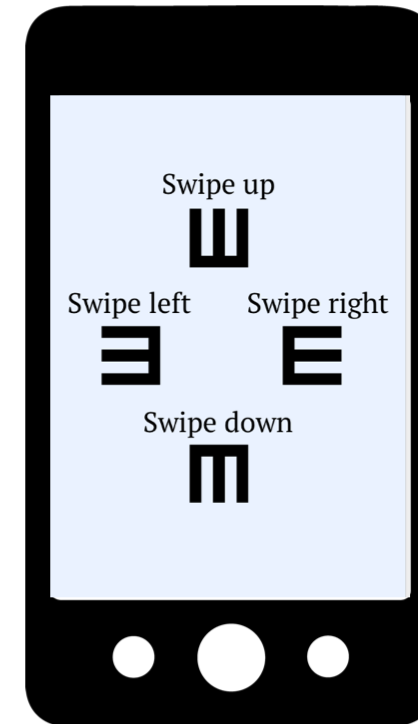
Probability that you chose drug A? Make  $\Pr(\theta_a > \theta_b)$

# Stanford Acuity Test

1 Take an eye exam on this website



2 Connect your phone

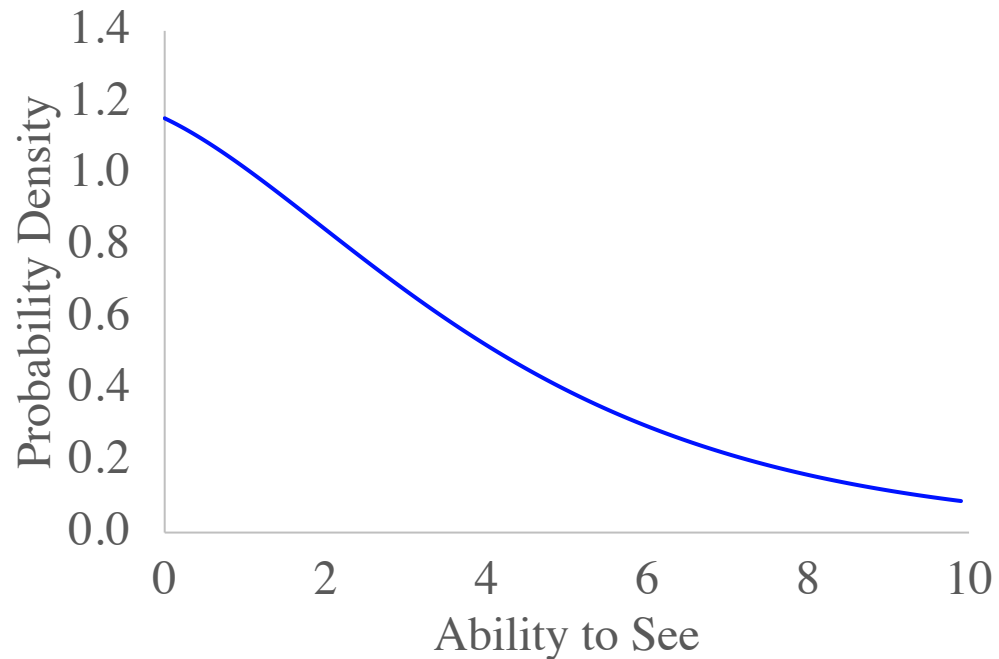


3 Visualize the math

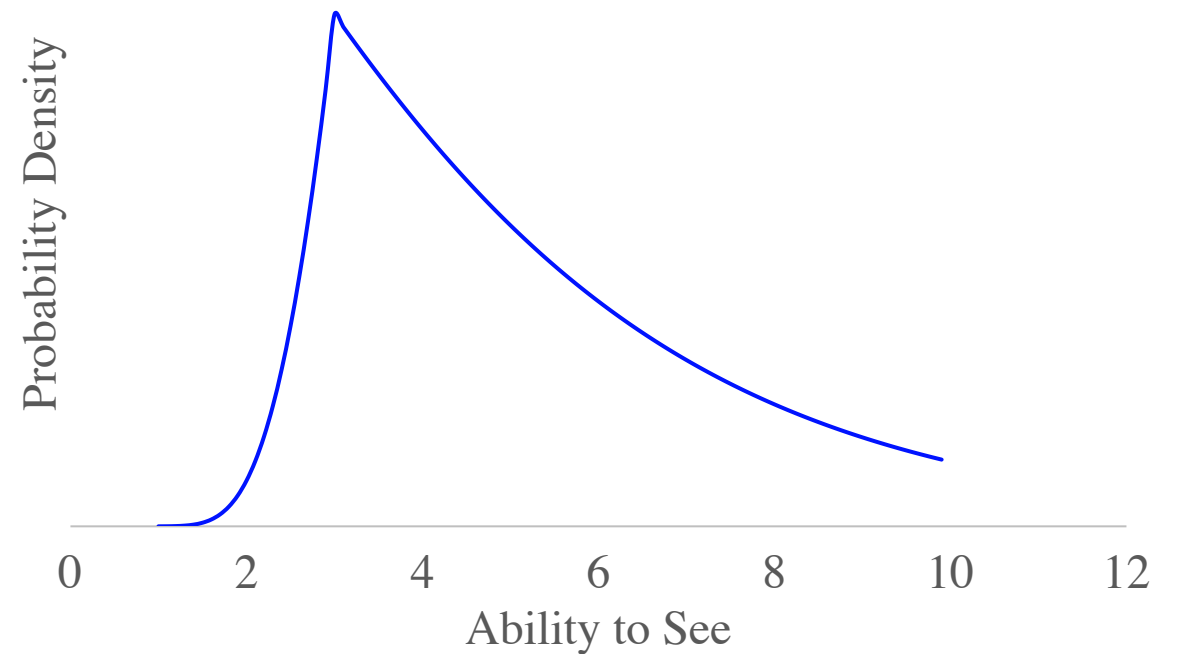
# An Updated Belief

A user is shown a letter at **font size 3** and gets it **wrong**.  
What is your new belief that their **visual ability is 3**?

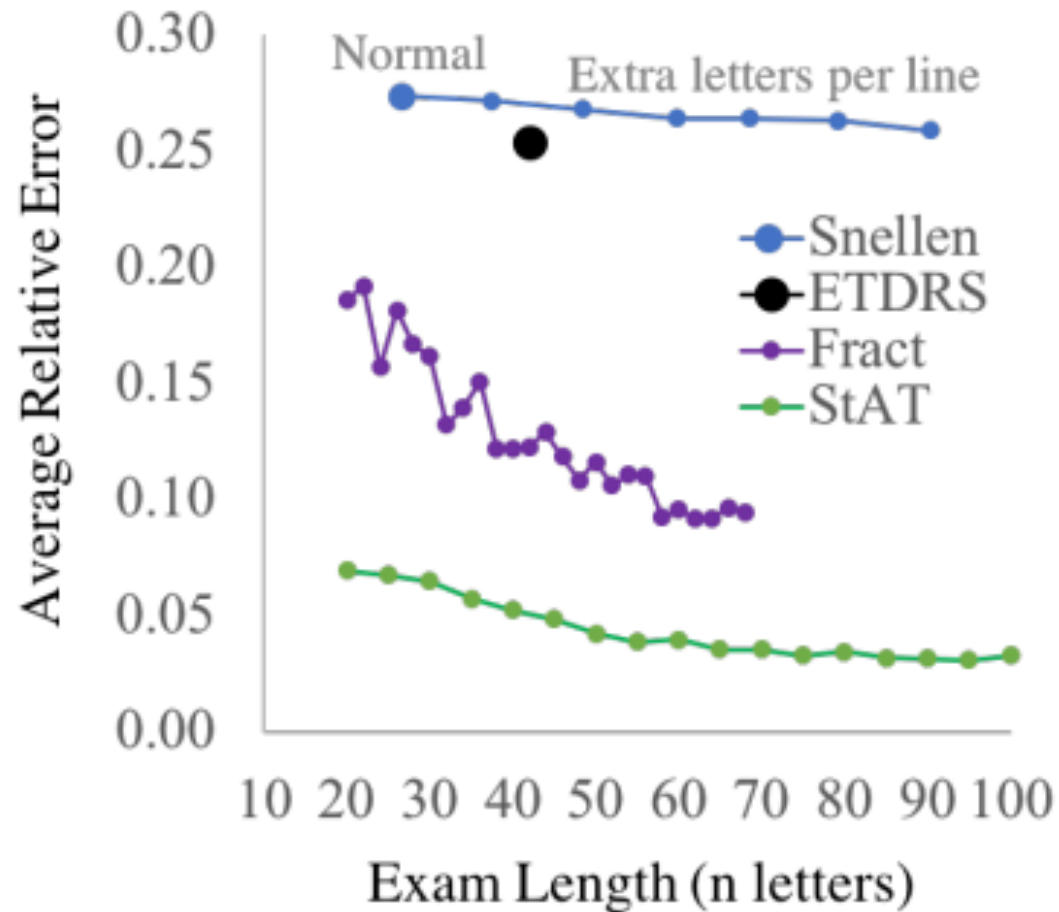
Prior



Posterior



# Thompson Sampling belongs to a family called Optimistic



Actual model also included  
+ a probability of "slip"  
+ **an intelligent algorithm for choosing the next letter size**

Beta:  
The probability density  
for probabilities



Beta is a distribution for  
probabilities

# Beta Distribution



If you start with a  $X \sim \text{Uni}(0, 1)$  prior over probability, and observe:

let  $a = \text{num "successes"} + 1$

let  $b = \text{num "failures"} + 1$

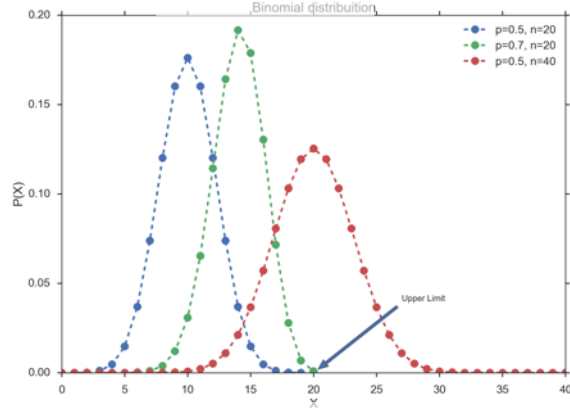
Your new belief about the probability is:

$$f_X(x) = \frac{1}{c} \cdot x^{a-1} (1-x)^{b-1}$$

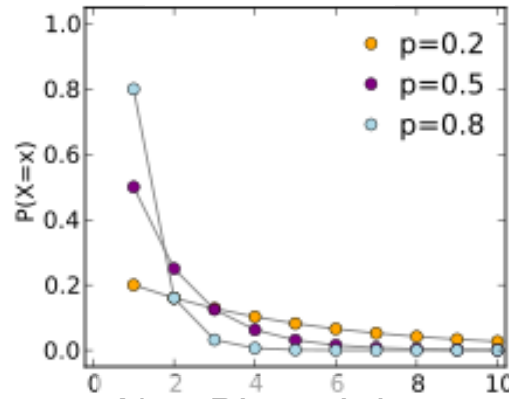
where  $c = \int_0^1 x^{a-1} (1-x)^{b-1}$

# Distributions

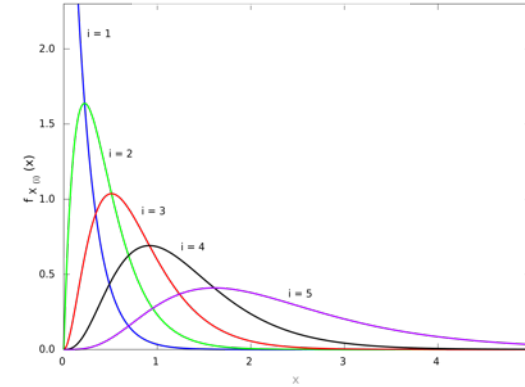
Binomial



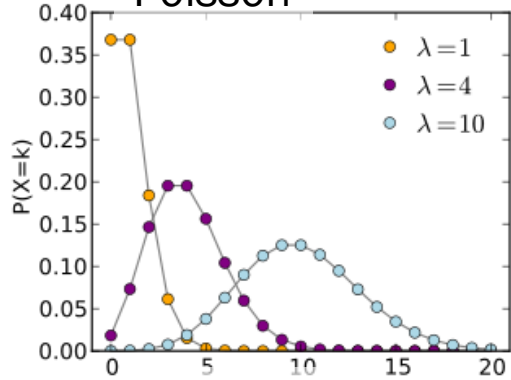
Geometric



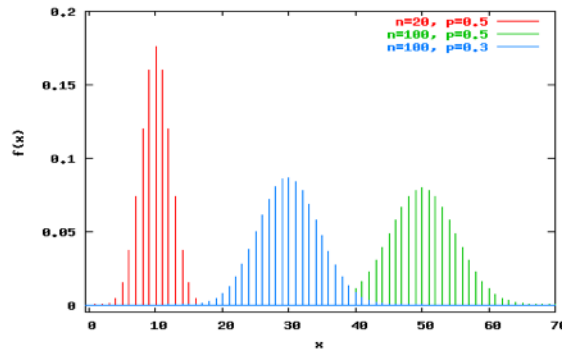
Exponential



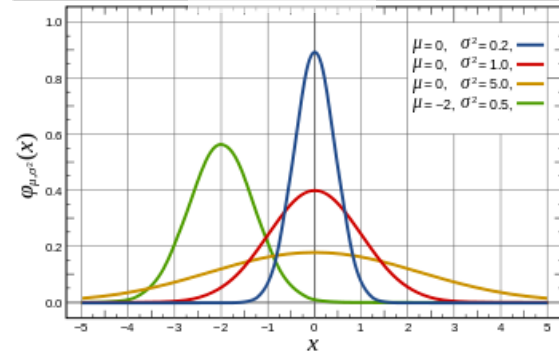
Poisson



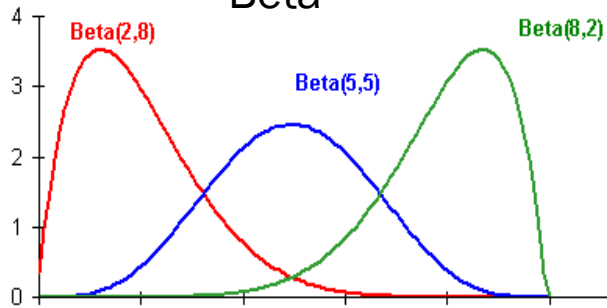
Neg Binomial



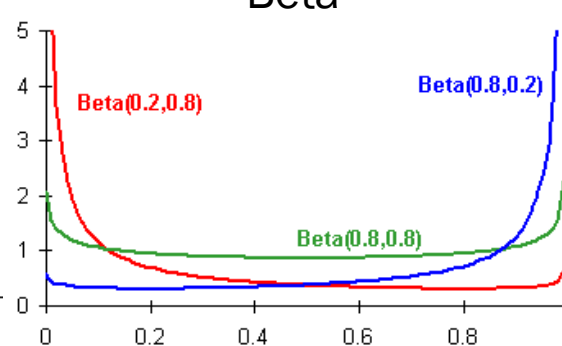
Normal



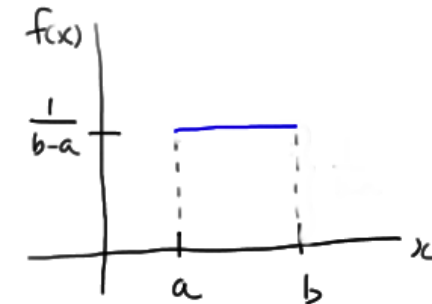
Beta



Beta



Uniform





Grades must be bounded

Normal: No

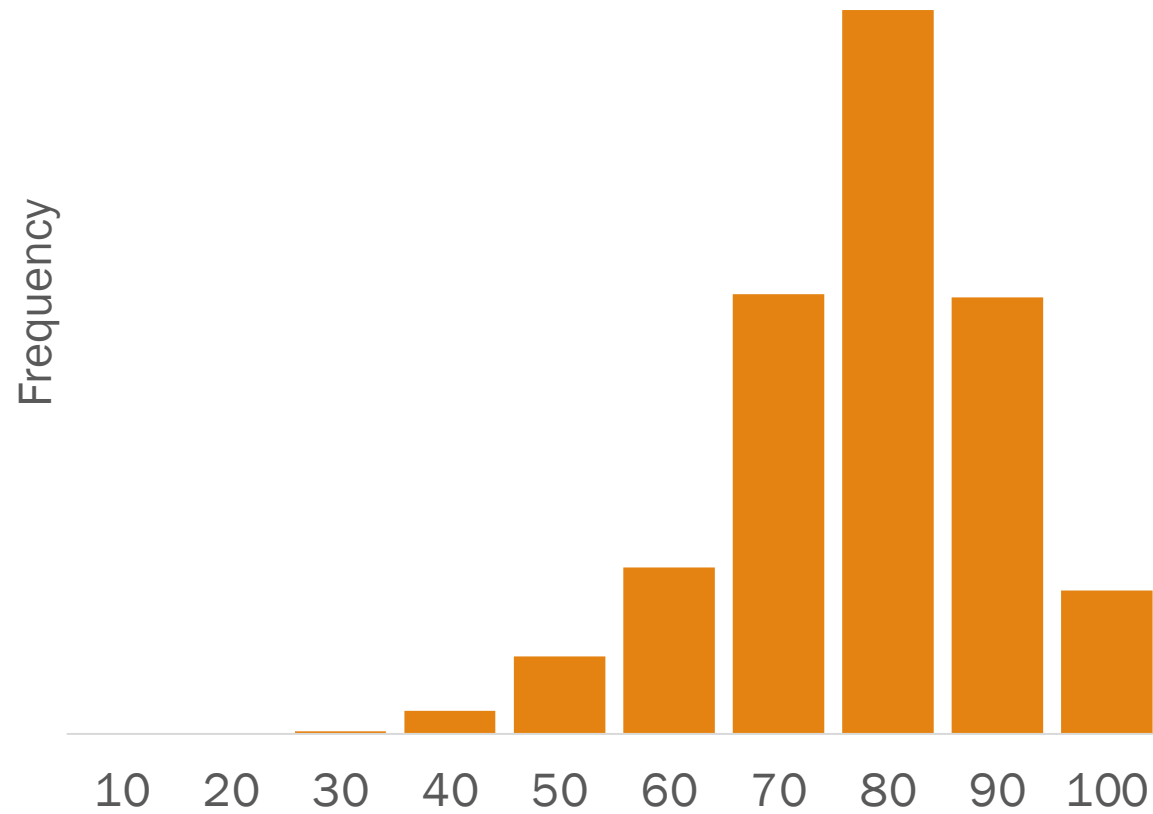
Poisson: No

Exponential: No

Beta: Looks Good!

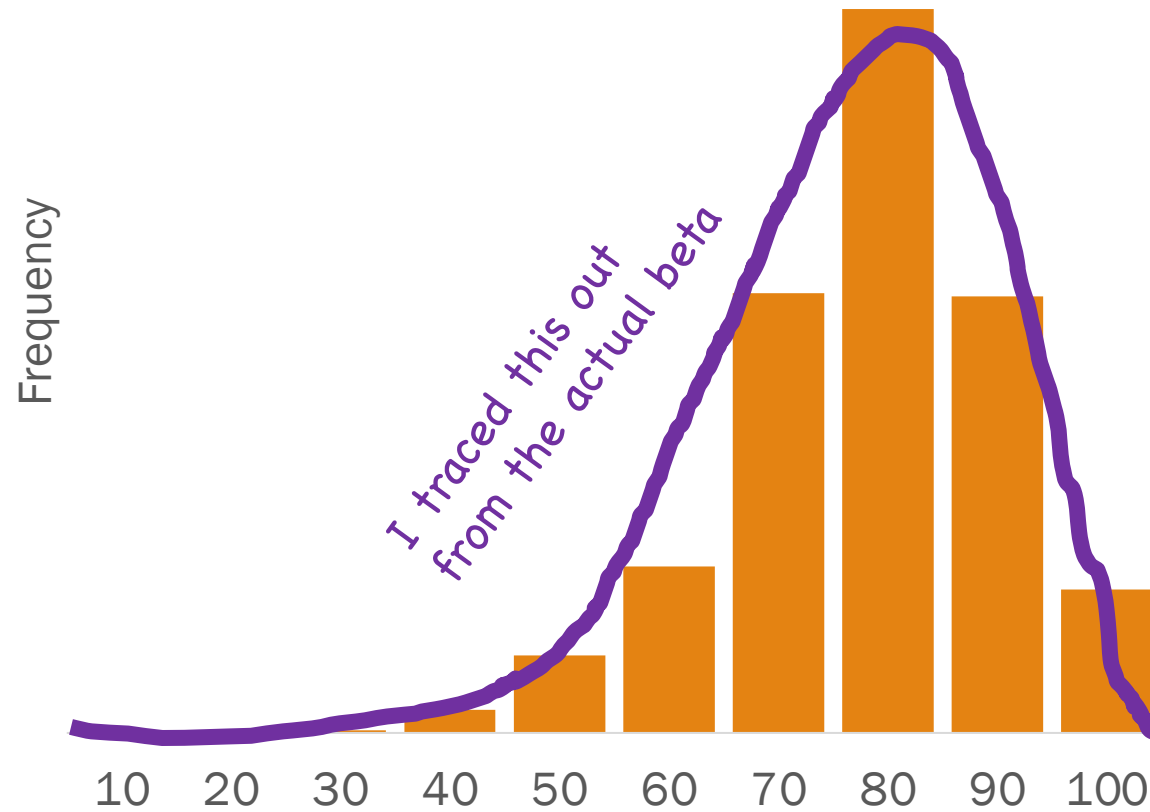
# Assignment Grades Demo

Assignment id = '1613'



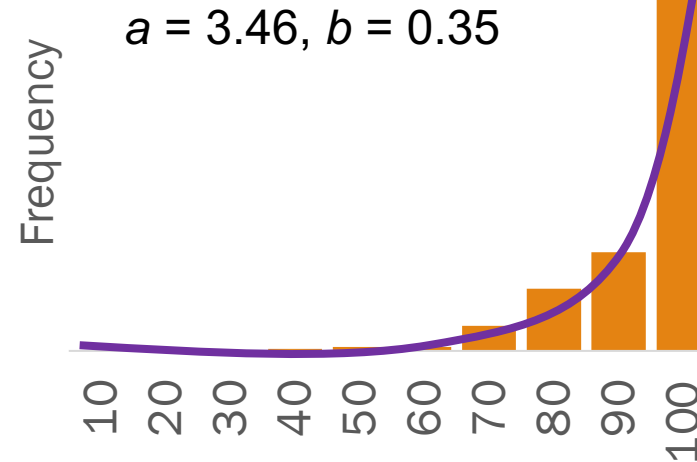
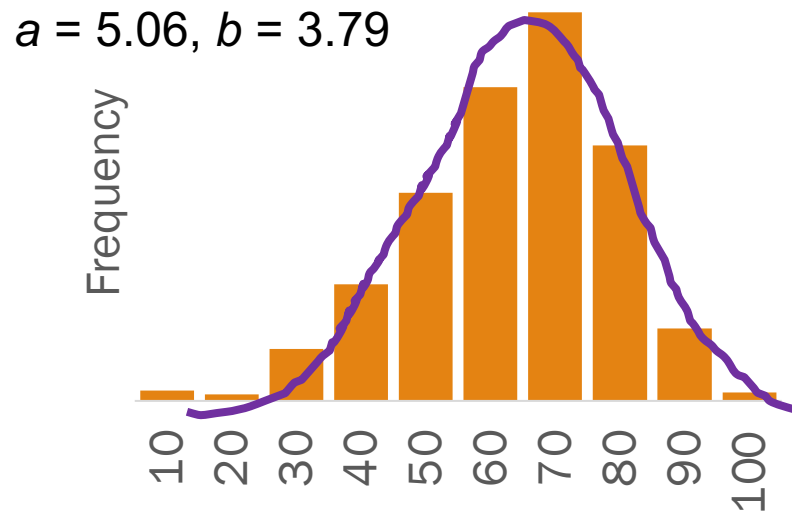
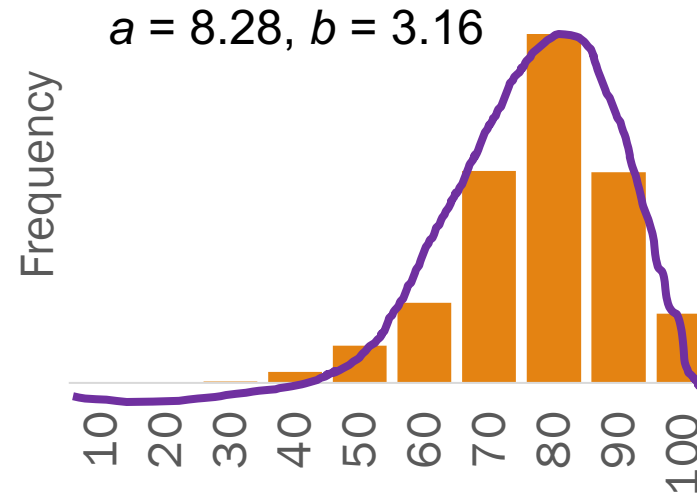
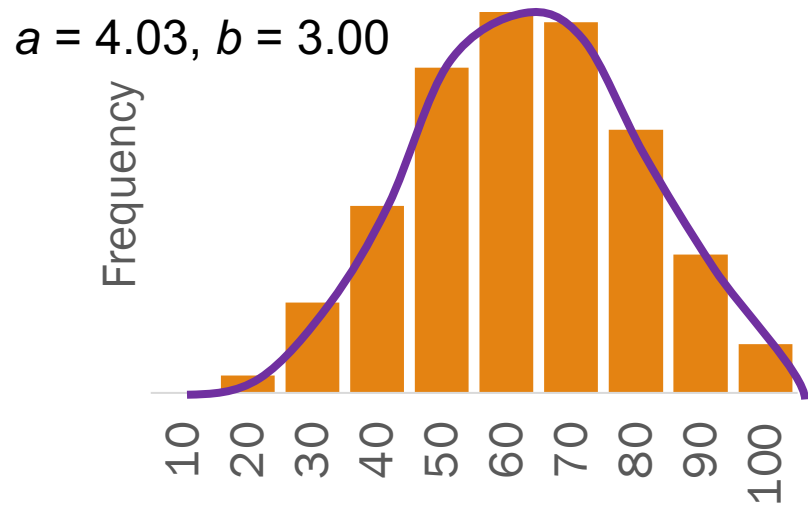
# Assignment Grades Demo

Assignment id = '1613'



$$X \sim \text{Beta}(a = 8.28, b = 3.16)$$

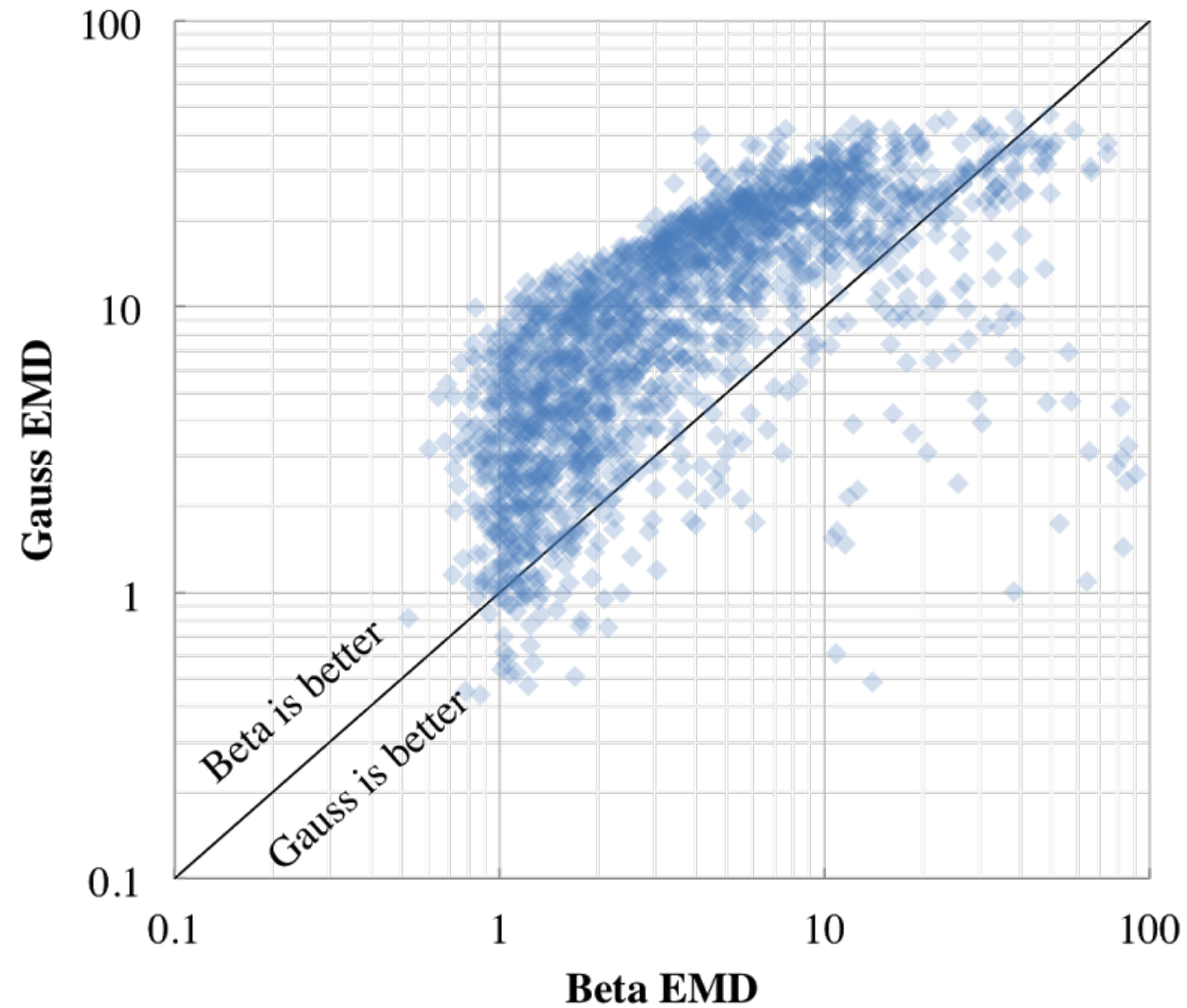
# Assignment Grades



We have 2055 assignment distributions from grade scope

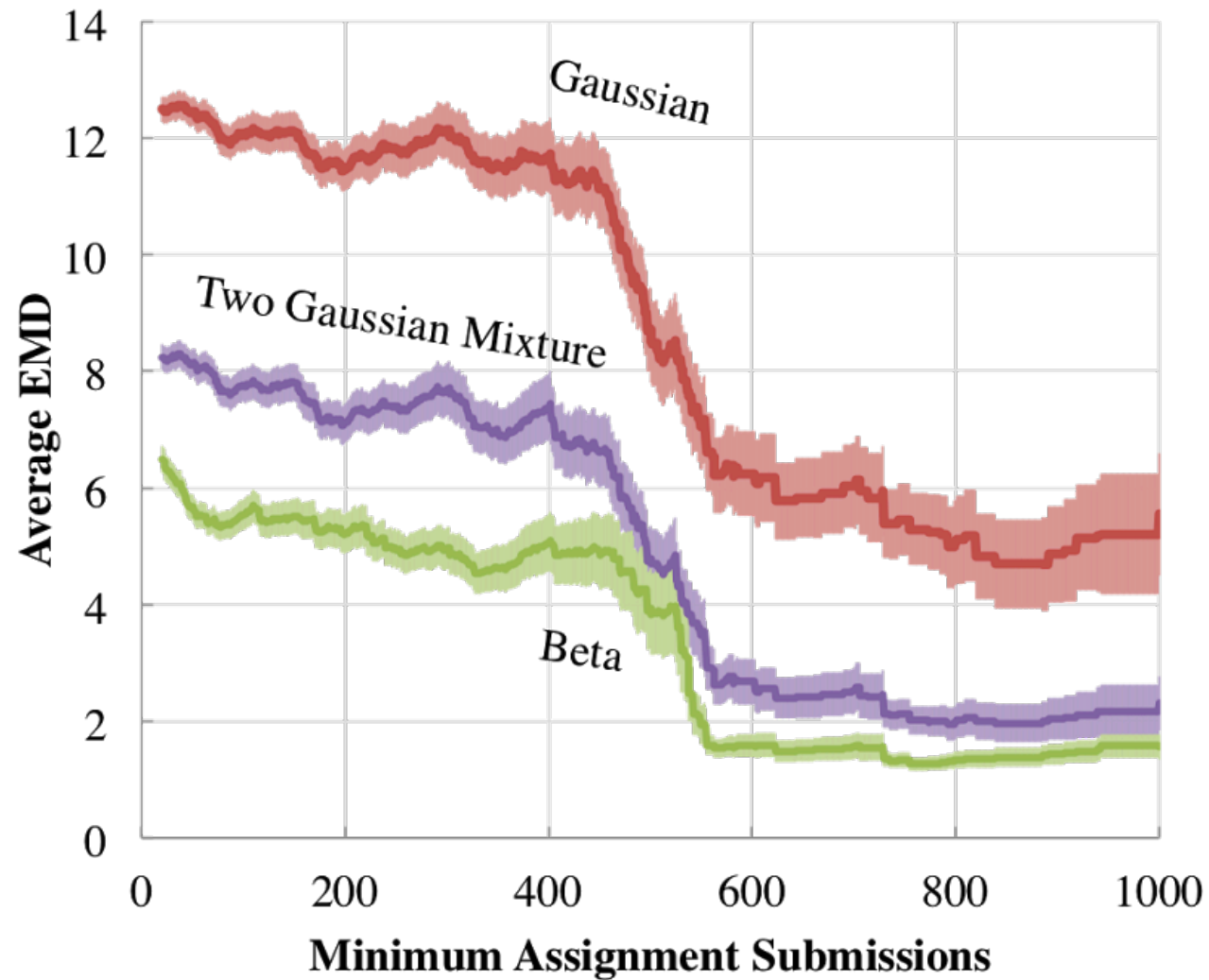


# Beta is a Better Fit



Unpublished results. Based on Gradescope data

# Beta is a Better Fit For All Class Sizes



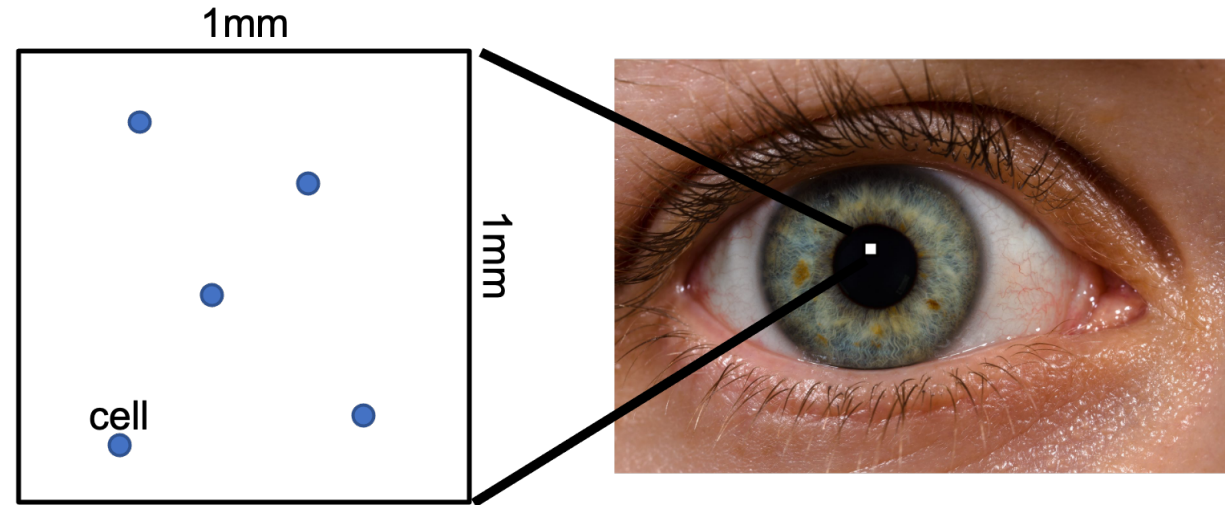
Unpublished results. Based on Gradescope data



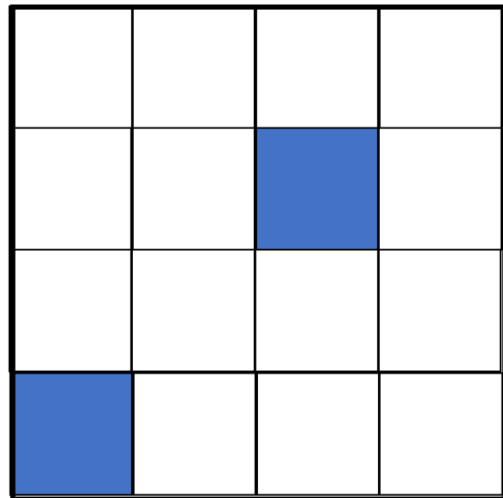
Any parameter for a “parameterized” random variable can be thought of as a random variable.

Eg:  $X \sim N(\mu, \sigma^2)$

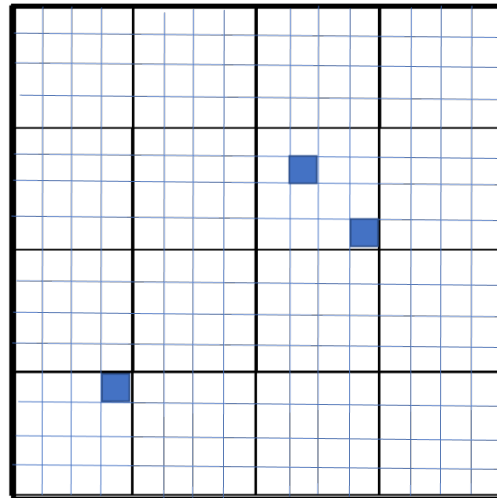
# Better Measure for Eye Disease: Counting Cells in Space



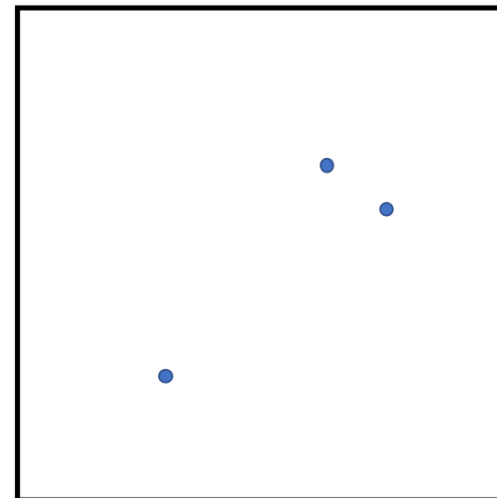
$$X \sim \text{Bin}(n = 16, p = \lambda/16)$$



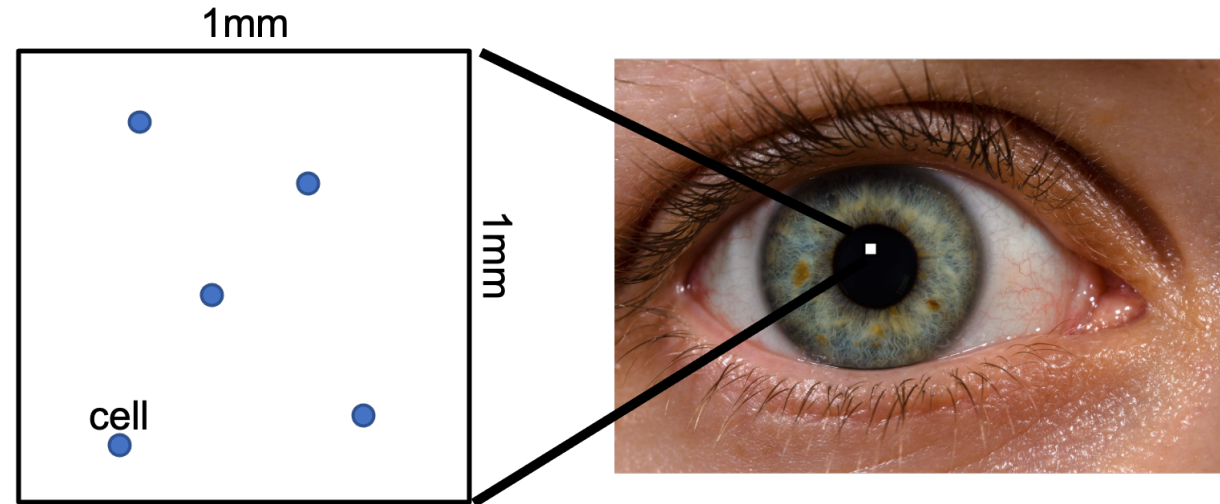
$$X \sim \text{Bin}(n = 256, p = \lambda/256)$$



$$X \sim \lim_{n \rightarrow \infty} \text{Bin}(n, p = \lambda/n)$$



# Better Measure for Eye Disease: Counting Cells in Space



On the exam: True lambda is 5, what is the probability of observing 4 cells?

Next level: You observe 4 cells, what is the distribution of belief over the true average?

Wow level: One day you observe 4 cells, two days later you observe 5. What is your belief that the patient actually got worse?

# Random Variables for Parameters

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Parameter	Chosen Distribution
Bernoulli $p$	Beta
Poisson $\lambda$	Gamma
Normal $\mu$	Normal
Normal $\sigma^2$	Gamma
Beta $\alpha$	Gone too far...