LEC 15

CSE 123

Machine Learning

Questions during Class?
Raise hand or send here

sli.do #cse123

BEFORE WE START

Talk to your neighbors:

What is your favorite beverage?

Respond on sli.do!

Instructor: Miya Natsuhara

TAs:

Arohan	Shiven	Yuntong	Anya
Sreshta	Vrinda	Amiya	Anisha
Rushil	Gavin	Sahana	Trien
Sean B	Shreya	Anirudh	Neal
Chloe	Jonah	Rohan	Evan
Jenny	Renee	Crystal	Rena
Nate	Chris	Eeshani	
Saachi	Ishita	Prakshi	
Hawa	Kuhu	Aidan	
Maggie	Kavya	Cora	
Sean E	Misha	Nhan	

Music: CSE 123 26sp Lecture Tunes

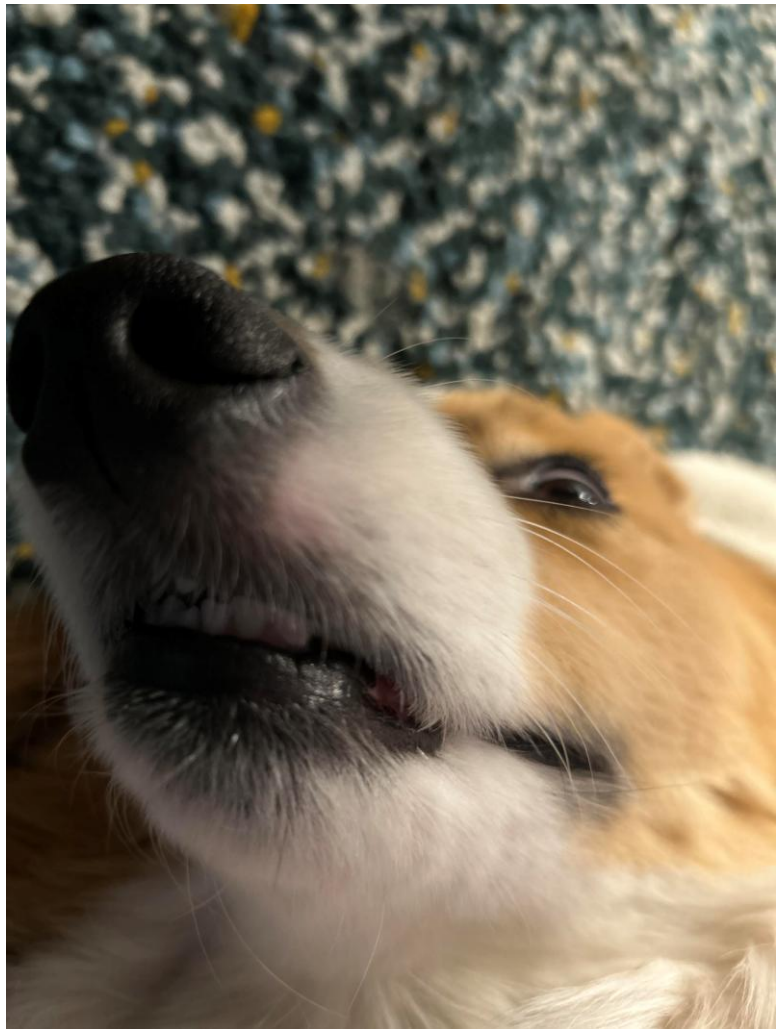
Announcements

- *Programming Assignment* 3 out, due next Friday! (May 29)
- Resubmission 5 closes tonight
  - Eligible assignments: P1, C2
- Monday (May 25) is a university holiday, so campus is closed
  - No Miya office hours
  - IPL is closed
  - Ed message board will still be available, but may have slower response times
- Quiz 2 next Tuesday (May 26)
- Check your section participation in Gradescope!
  - If something looks incorrect, reach out to your section TA

Feedback & Closing the Loop: The Good

- Quiz sections, the IPL, and your TAs!
- Project-based assignments
- Lectures, interactive activities, and live coding
- Resubmissions
- PCMs

Feedback & Closing the Loop: Suggestions



Suggestions that we're already working on:

- PCM walkthrough videos
- Adjustments to the course calendar (resub period, assignment spacing)
- Resources for quizzes

Other suggestions…

- Both faster and slower pacing?

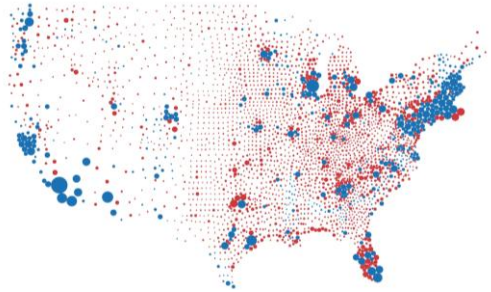
Feedback & Closing the Loop: Reminders

- Minimum grade guarantees
  - Minimum Grade Guarantee Calculator
- General Grading rubrics on the course website
- Building of knowledge + skill
  - PCM: introduction
  - Lecture: reinforcement + initial guided practice
  - Section: practice with minimal guidance
  - Assessments: learn by applying!

Applications of ML

Estimation

- *Opinion Polls*
  - How does a population feel about an issue?



Prediction

- *Content Recommendation*
  - Can we predict how much someone will like a movie based on past ratings?
- *Object Recognition*
  - Identify {Car, Road, Plane, Bird, Person} within an image?

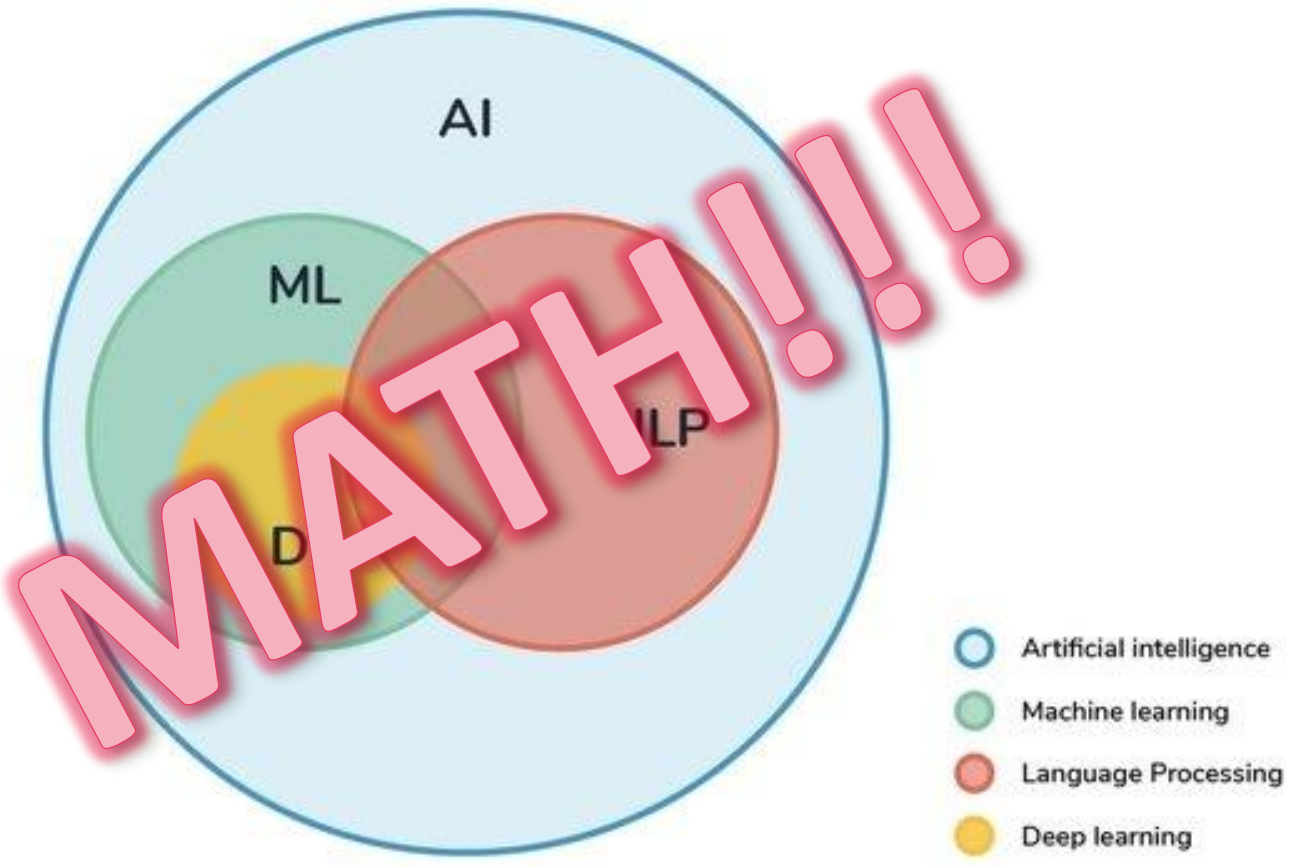
Generation

- *Text Generation*
  - *Can computers generate text written like a human?*

- *Image Generation*
  - *Can computers generate images from a prompt*

What is Machine Learning (ML)? Related fields

- Subset of Computer Science concerned with “learning” data trends
  - (Today’s lecture will not be tested on quizzes/exams.)



What is Machine Learning (ML)? Math premise

- Subset of Computer Science concerned with "learning" data trends
- Simple example: maximum likelihood estimation (MLE)

$$D = (HHTHT)$$

Is this coin biased or not?

What's the best guess for "how biased" it is?

$$\theta = coin\ bias, n = flips\ seen, k = heads\ seen$$

$$P(D|\theta) = \theta^k(1-\theta)^{n-k}$$

Goal: find $\hat{\theta}_{MLE}$, value that maximizes probability of what we saw

Maximum Likelihood Estimation: Step 1

$$P(D|\theta) = \theta^k(1-\theta)^{n-k}$$

$$\hat{\theta}_{MLE} = \text{argmax}_\theta \, P(D|\theta)$$

$$\frac{\partial}{\partial\theta}\left(\theta^k(1-\theta)^{n-k}\right) = 0$$

$$k\theta^{k-1}(1-\theta)^{n-k} - (n-k)\theta^k(1-\theta)^{n-k-1} = 0$$

Maximum Likelihood Estimation: Step 2

$$k\theta^{k-1}(1-\theta)^{n-k} = (n-k)\theta^{k}(1-\theta)^{n-k-1}$$

$$k(1-\theta) = (n-k)\theta$$

$$k = n\theta$$

$$\hat{\theta}_{MLE} = {}^{k}/_{n}$$

Takeaway: There are formal, mathematical ways to verify intuition!
+ We can perform this process with more complicated distributions!

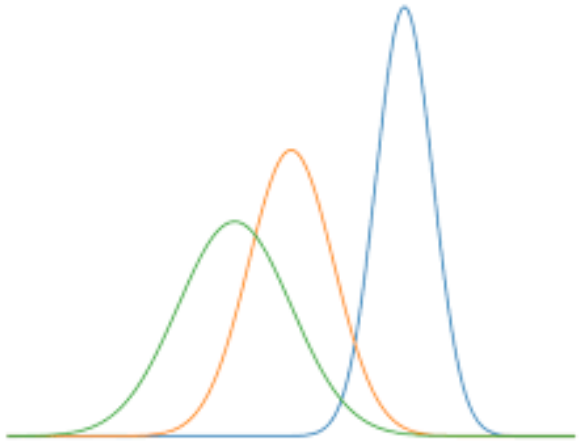
What is Machine Learning (ML)? Math conclusions

- Subset of Computer Science concerned with "learning" data trends
- Simple example: maximum likelihood estimation (MLE)
  - As $n \to \infty$, we know that $\hat{\theta}_{MLE} \to \theta^*$ (true distribution)
  - With enough data points, we can estimate any statistical distribution!
  - Central limit theorem: sample mean is normally distributed on true mean…

$$P(x \mid \mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2\sigma^2}}$$

What is Machine Learning (ML)? Making predictions

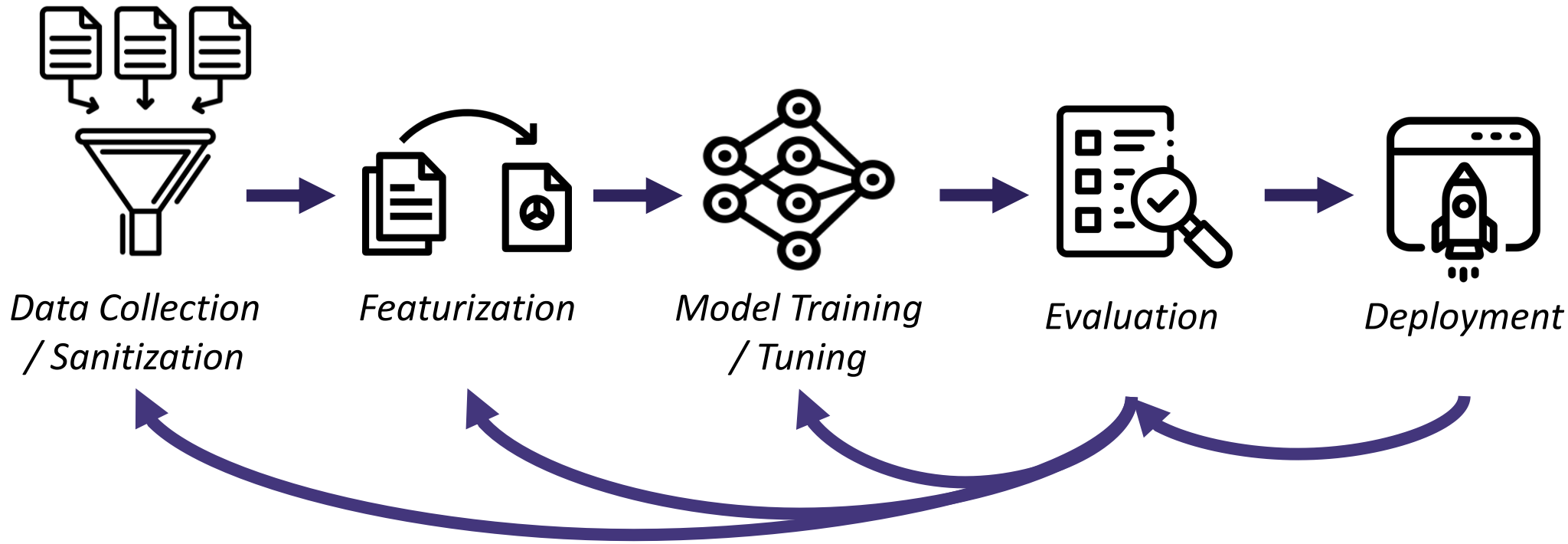
- Subset of Computer Science concerned with "learning" data trends
- Simple example: maximum likelihood estimation (MLE)
  - As $n \to \infty$, we know that $\hat{\theta}_{MLE} \to \theta^*$ (true distribution)
  - With enough data points, we can estimate any statistical distribution!
  - Central limit theorem: sample mean is normally distributed on true mean…



Given enough previous examples, we can estimate the underlying distribution and make predictions about… anything!

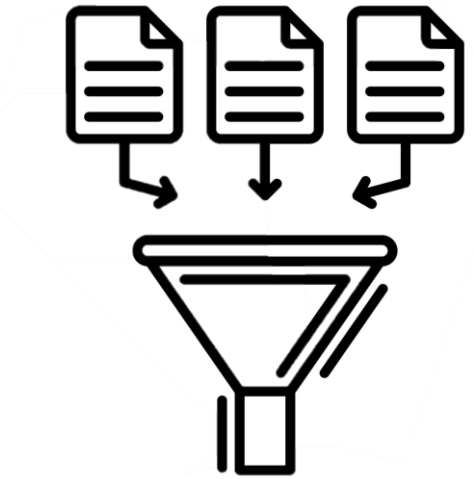
ML Pipeline

- Generally, building an ML model involves the following steps:



- Notice that you can step backwards!
  - ML in particular is an applied science, it's all an experiment!

1. Data Collection



- We *need* example data to understand a distribution
  - Lots and lots of it too ($n \to \infty$)
- Where does this data come from?
  - Language: Reddit, Twitter, Facebook, Wikipedia, Blogs, etc.
  - Images: Google, Twitter, Websites
  - Code: Github
  - Really, anywhere publicly (or not) accessible on the Internet
- Who determines what data is used? ¯_(ツ)_/¯
  - Often companies buy preprocessed data from others
  - Let's say that you accidentally post your phone number on your twitter
    - A model could scrape that info, memorize it, and regurgitate it when prompted
- **Data carries PII / bias that we need to account for**

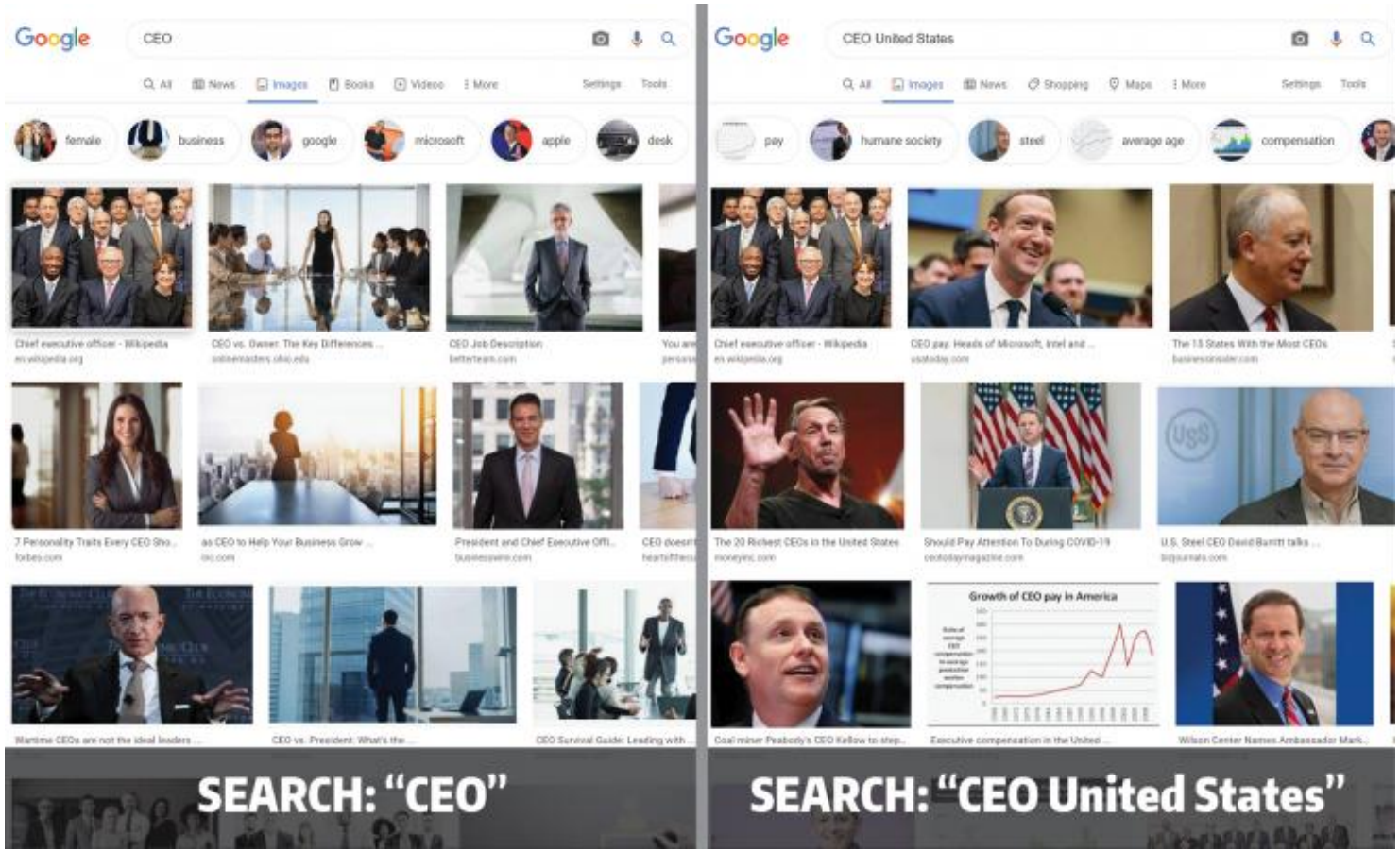
Data Bias: CEO in 2015

- Image results for searching the term “CEO” on Google (2015)
  - Notice anything about the results?

https://www.washington.edu/news/2015/04/09/whos-a-ceo-google-image-results-can-shift-gender-biases/

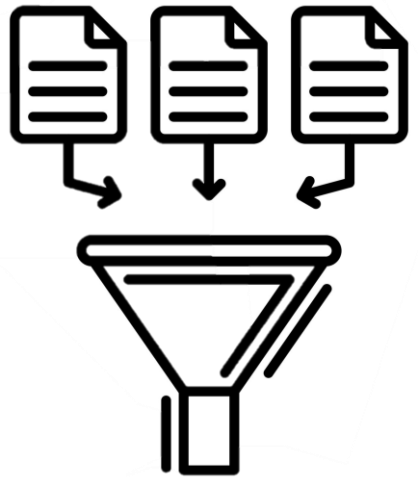
Data Bias: CEO and CEO United States in 2022

- Fix: Image results for searching “CEO” and “CEO United States” (2022)



https://www.washington.edu/news/2022/02/16/googles-ceo-image-search-gender-bias-hasnt-really-been-fixed

Data Sanitization



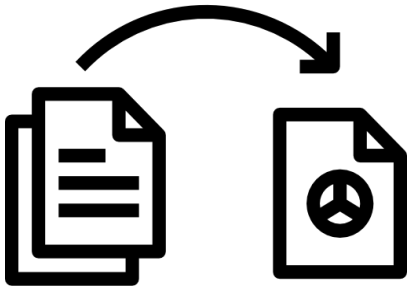
- **Data carries PII / bias that we need to account for**
- We don't want our model to memorize a phone number
  - Let's just remove all phone numbers from our inputs!
  - Is this an effective solution?

- Sanitization can be ethically gray – does it disproportionately affect subpopulations?
  - Correlated features

Our models are only as strong as the data they're built upon.

Garbage in, garbage out.

2. Featurization



- Now that we have all our data, we need to convert it into something a computer can understand (numbers)
  - How can we convert text / images into numbers?

- Determine what aspects of the data interest you (features)

- Words can be “vectorized”
  - Converted into n-dimensional vectors $n \in \{50, 200, 500, \dots\}$
  - Determined from the word2vec algorithm
- Images are already numbers… (2d array of RGB values)

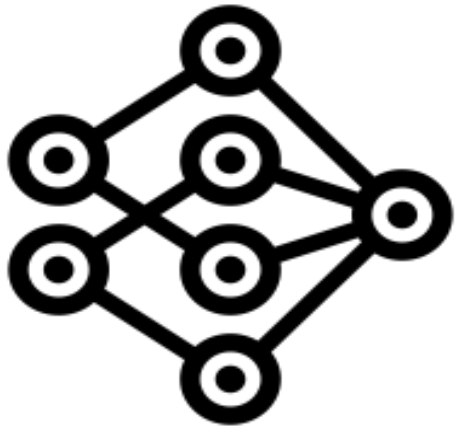
Word Embeddings

- We call these word vectors “embeddings” and they’re pretty interesting to mess around with

- Can perform mathematical operations on them
  - Find the nearest vectors to any given word (synonyms)
  - Compute comparisons (dog is to puppy as cat is to ___)
    - Take the difference between puppy and dog (age vector) and add it to cat
    - Find the nearest vectors to the result and you’ll likely see “kitten”

- These operations can further reveal bias
  - man is to doctor as woman is to _____
  - **Any model trained from biased data points will estimate a biased distribution**

3. Model Training



- Pick some way of using data to estimate
- Lots of different flavors of this
  - Regression (linear, logistic)
  - Neural Networks (CNNs, RNNs, Transformer, etc.)
  - Nearest neighbors
  - **Decision trees**
- Provide additional computation (memory / GPUs / time) until desired result is achieved

It's all one big experiment – try options until something sticks.

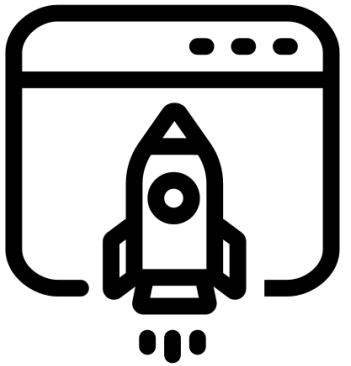
This should feel somewhat concerning…

4. Evaluation

- Does your model actually work?
- Typically we split our initial dataset into 3 different subsets:
  - Train (provided to the model during training)
  - Validation (used after a model has trained to compare to previous iterations)
  - Test (used once a model has been chosen to see how it performs)
- Determine whether or not your model is over / underfitting

- Most ML applications go no further than this step
  - No attempt to determine *why* a particular model is working well

5. Deployment



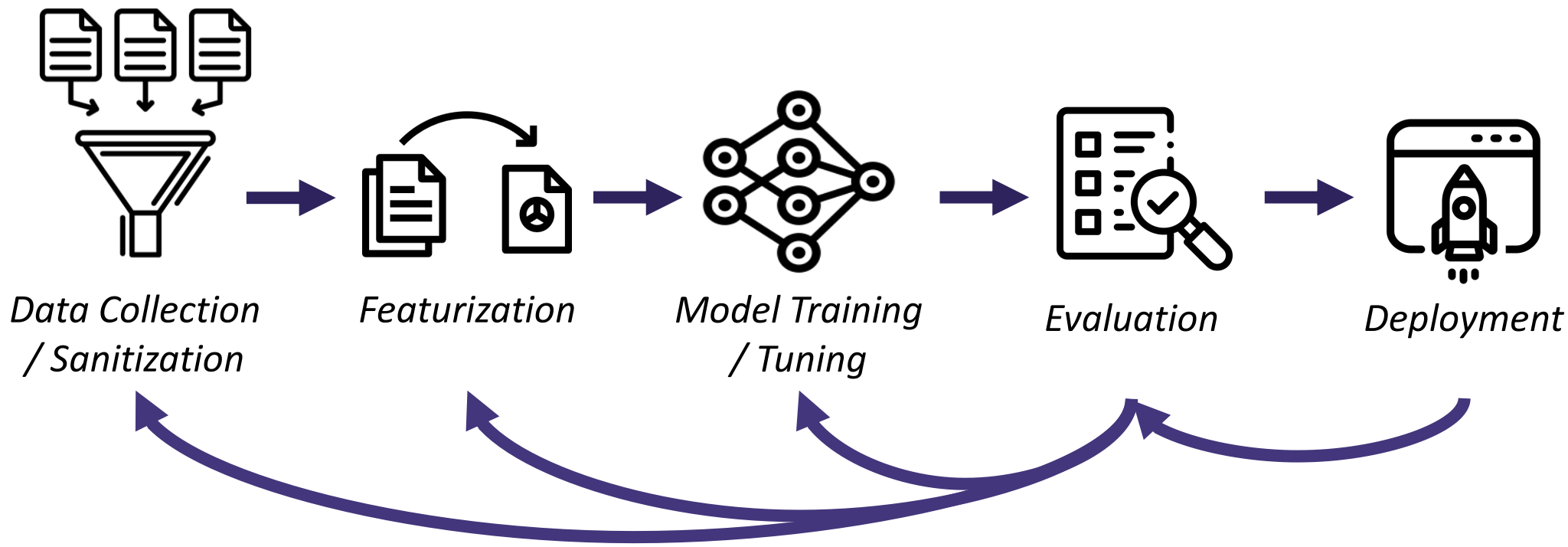
- Put your model out into the real world and see what happens
  - Does it perform the job as expected? Should further work be put into development?

- At this point, often the next iteration of refinement takes place
  - GPT 2.0 -> 3.0 -> 3.5 -> 4.0
  - Options include:
    - Collect more data, use more compute, discover better tuning, discover better model

- Often, not much effort is put into understanding negative impacts
  - Case in point: ChatGPT and the education system

ML Pipeline: Iteration and Refinement

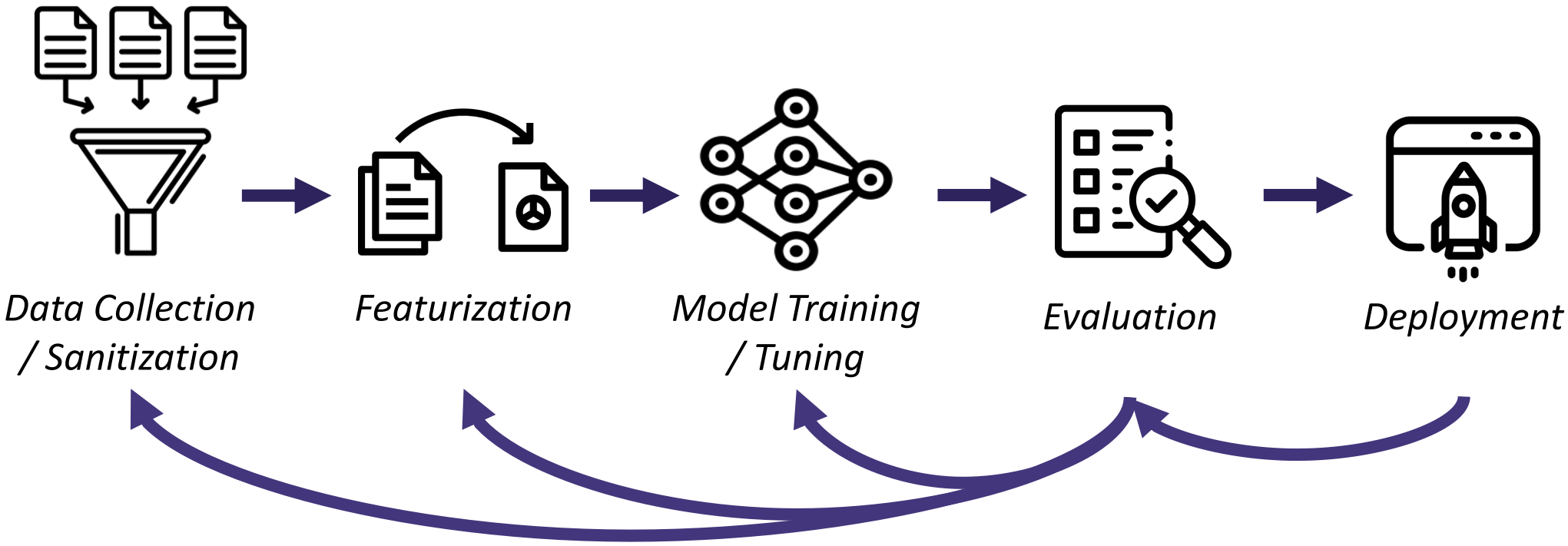
- That's it – in essence, that's how every ML model is created



Does this knowledge change your perspective on ML / AI?

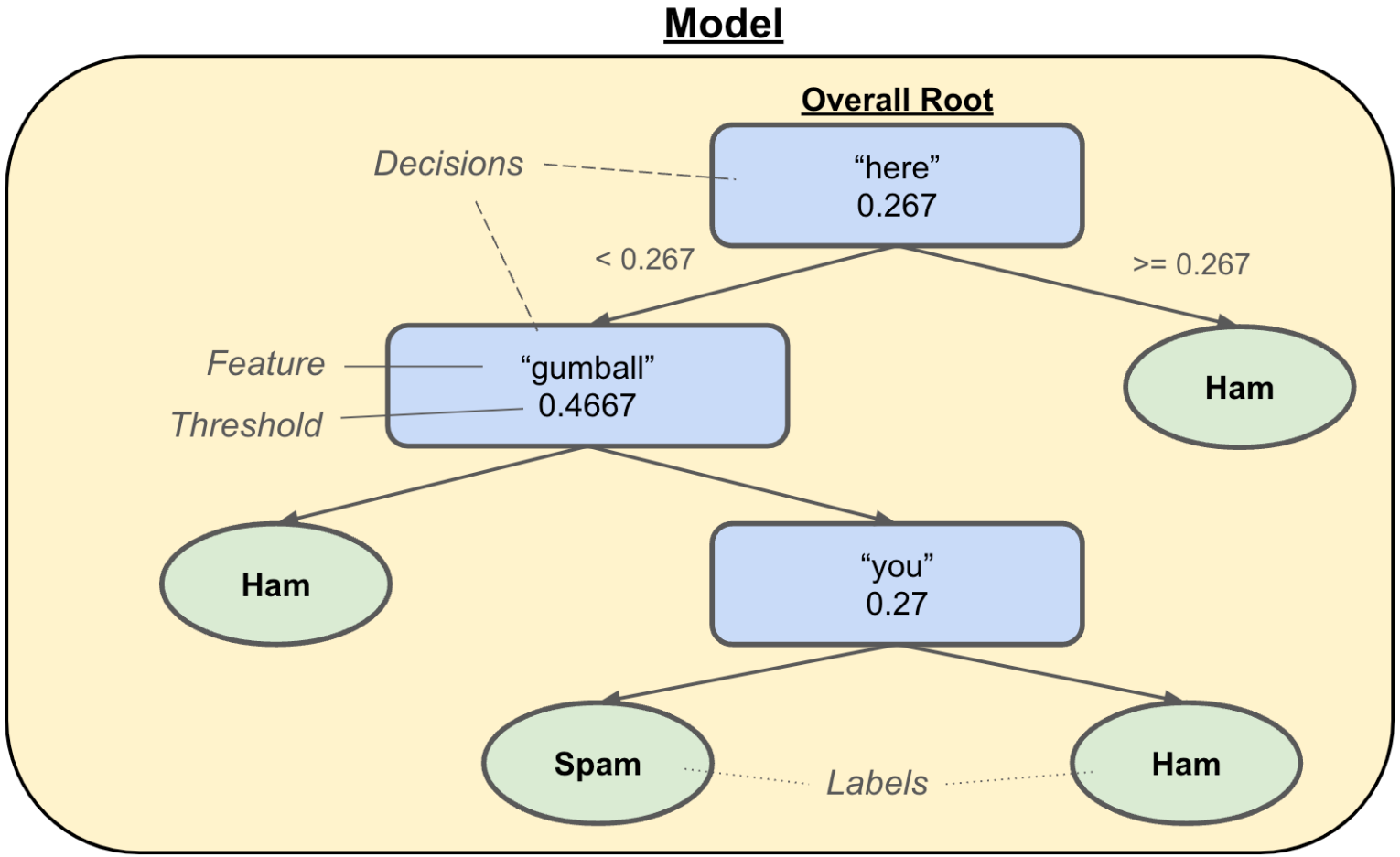
Cornbear's Classifier

- Programming assignment will involve part 3 of this pipeline
  - You'll implement a *decision tree* capable of classifying text



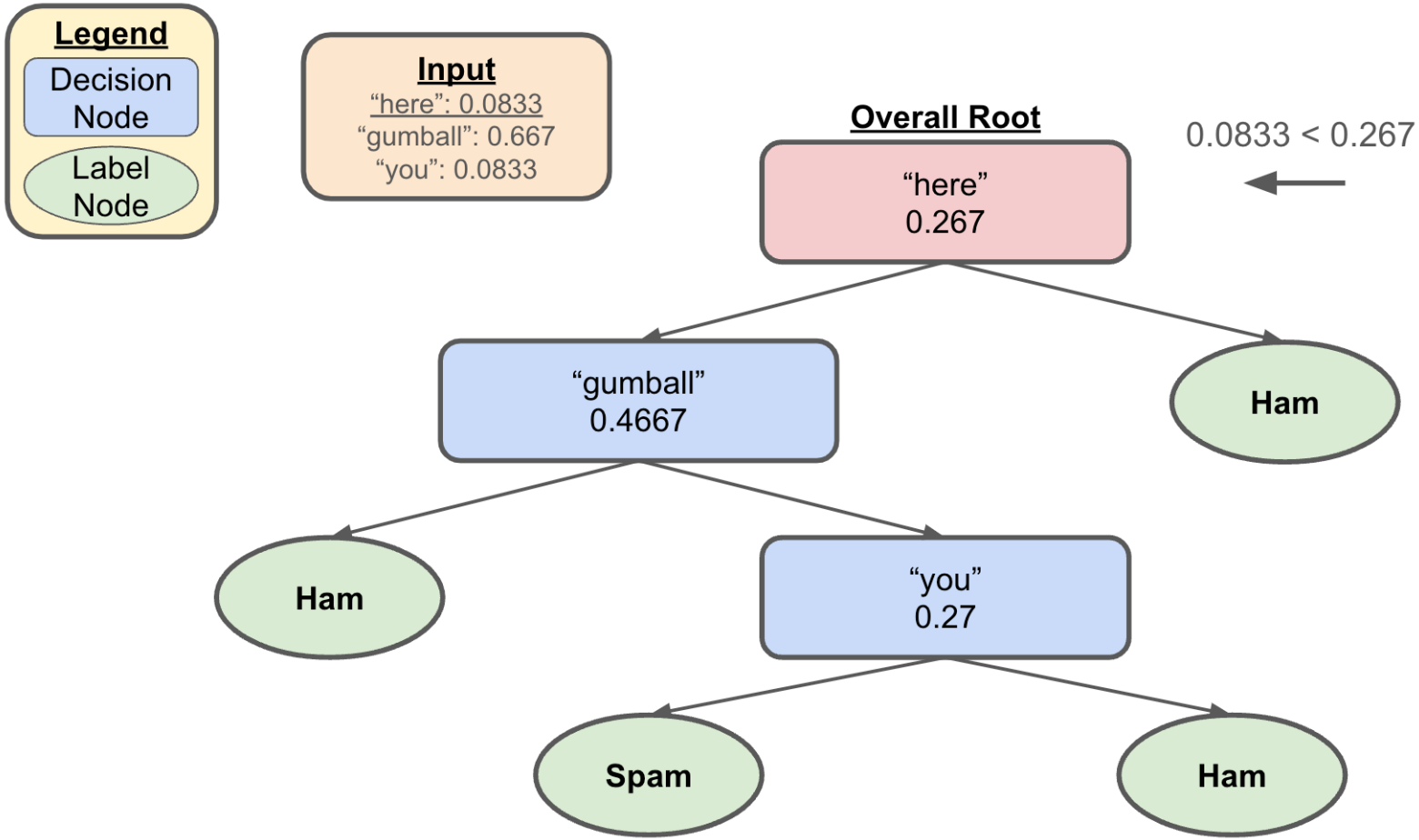
Decision Trees

- Tree structure where each intermediary node contains a feature / threshold pair (decision) and leaf nodes are labels



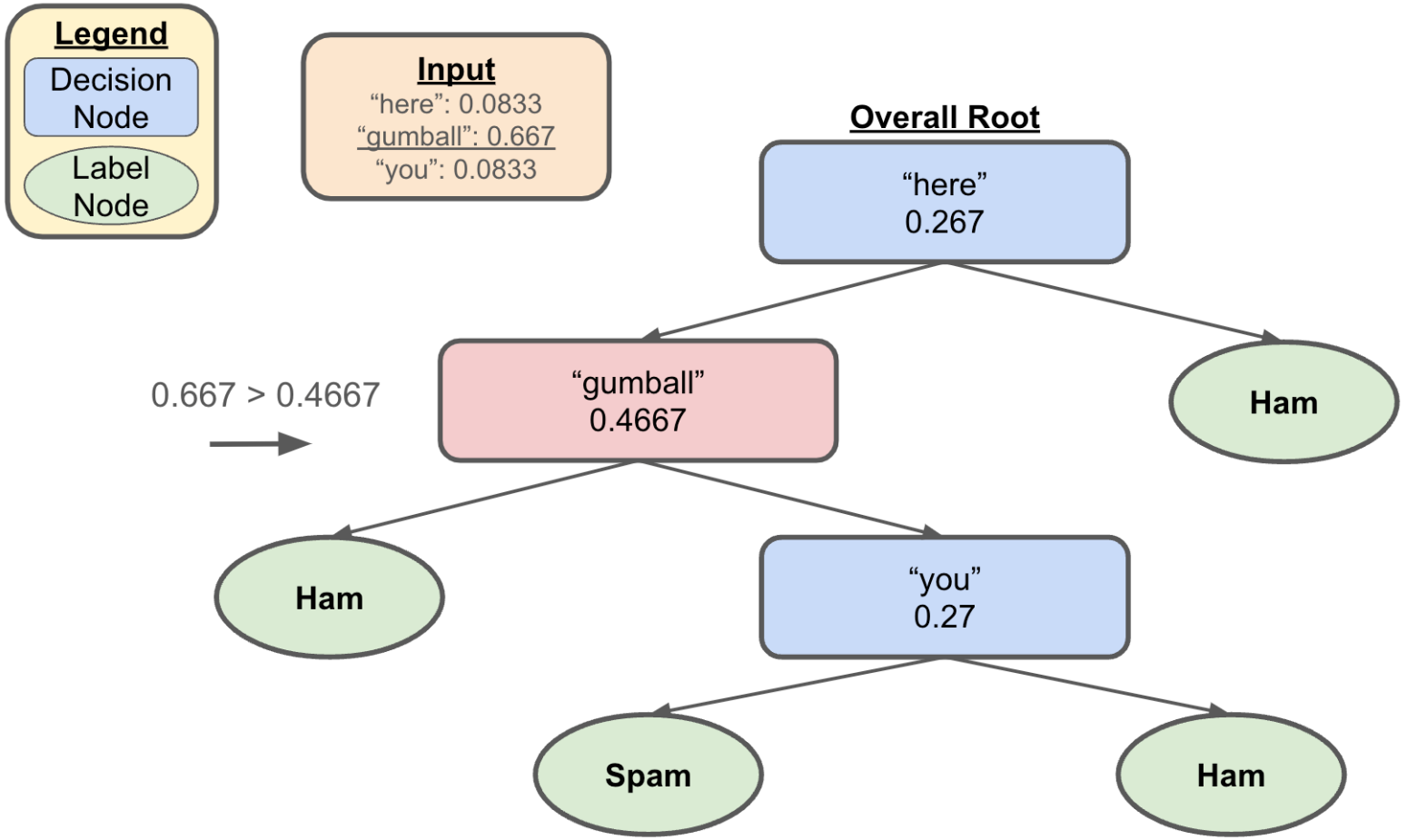
Decision Trees Example: Step 1

- Let's say we wanted to classify the following
  - `here gumball gumball gumball gumball you silly gumball gumball gumball gumball doggo`



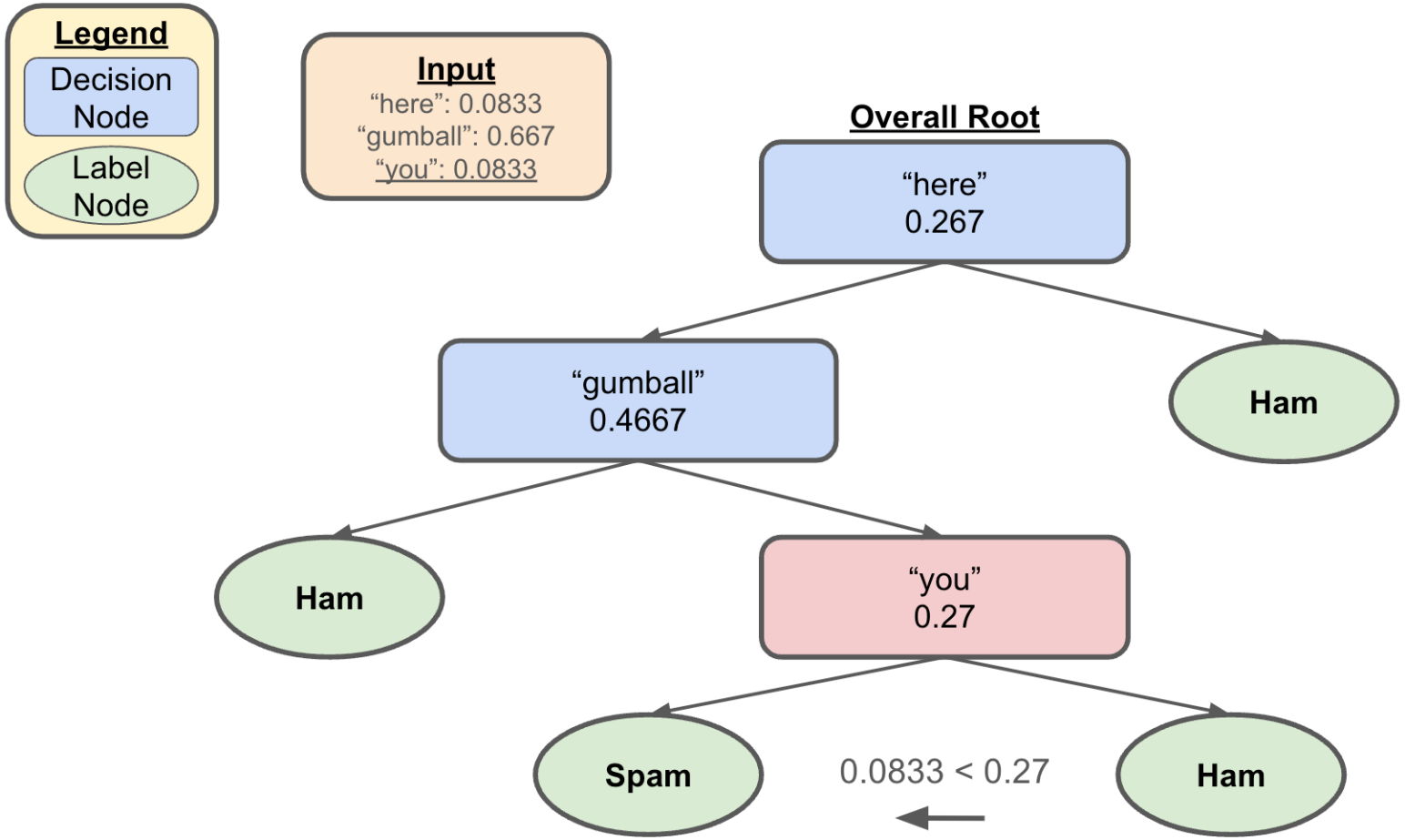
Decision Trees Example: Step 2

- Let's say we wanted to classify the following
  - `here gumball gumball gumball gumball you silly gumball gumball gumball gumball doggo`



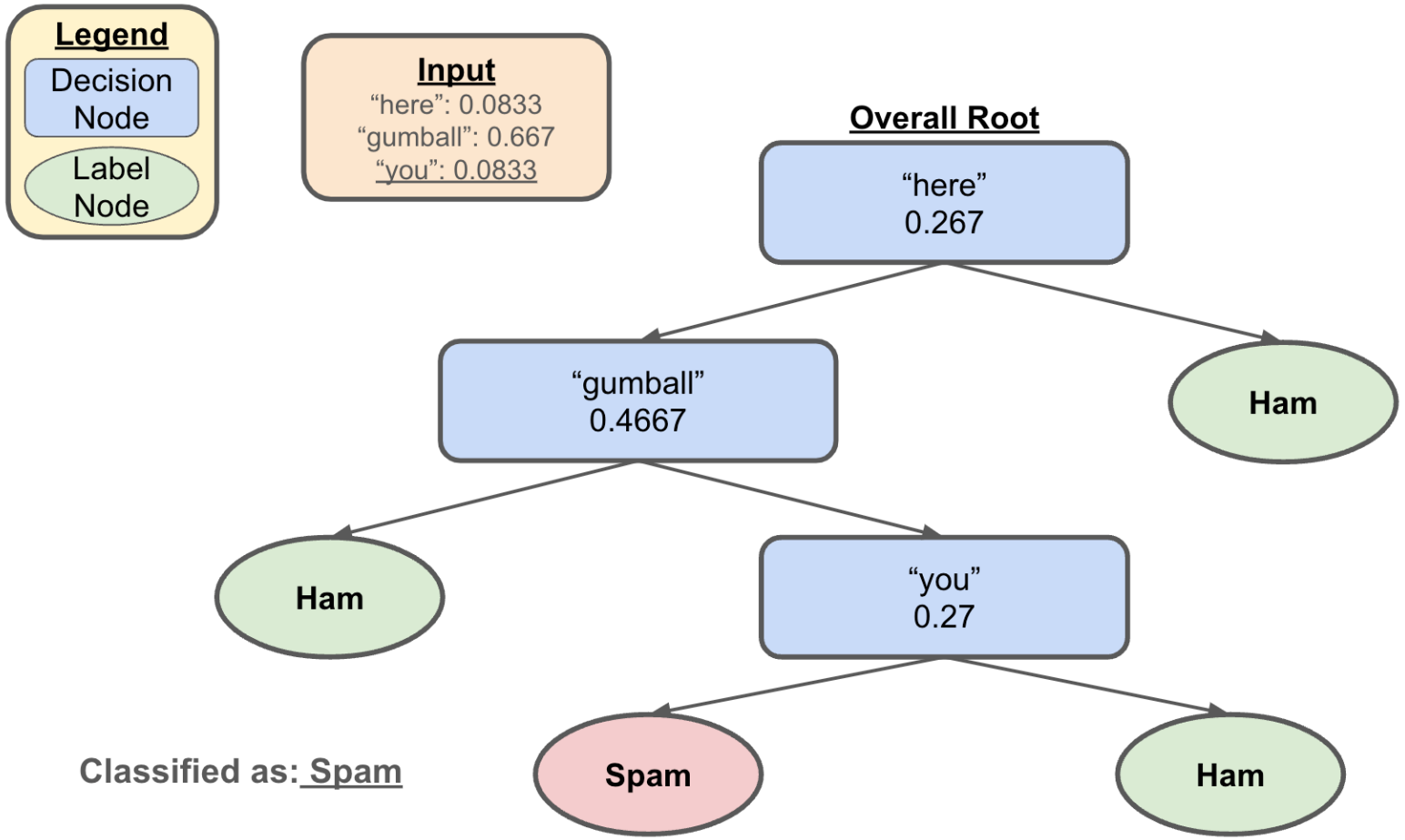
Decision Trees Example: Step 3

- Let's say we wanted to classify the following
  - `here gumball gumball gumball gumball you silly gumball gumball gumball gumball doggo`



Decision Trees Example: Step 4

- Let's say we wanted to classify the following
  - `here gumball gumball gumball gumball you silly gumball gumball gumball gumball doggo`



Questions to Consider

- Are ML models capable of “learning”?
  - i.e. is it possible to “learn” just by observing / memorizing?
  - Does ChatGPT actually “understand” language?
- If all output from ML models is based on previous examples, who gets credit / takes responsibility for generation?
  - Think AI art and your C2 / P2 reflection responses
- What harm could come from deploying ML models we don’t fully understand?
- If society itself is biased, how much should we worry about the bias present in data / ML models?
  - To what extent should concern about bias hinder further advancements?