LEC 15

CSE 123

Machine Learning

Questions during Class?

Raise hand or send here

sli.do #cse123A

BEFORE WE START

Talk to your neighbors:

What is your favorite spot on the Ave?

Instructors: Nathan Brunelle

TAs:

Arohan	Ashar	Neha	Rohini	Rushil
Ido	Zachary	Sebastian	Joshua	Sean
Hayden	Caleb	Justin	Heon	Rashad
Srihari	Benoit	Derek	Chris	Bhaumik
Kuhu	Kavya	Cynthia	Shreya	Ashley
Ziao	Kieran	Marcus	Crystal	Eeshani
Prakshi	Packard	Cora	Dixon	Nichole
Niyati	Trien	Lawrence	Evan	Cady

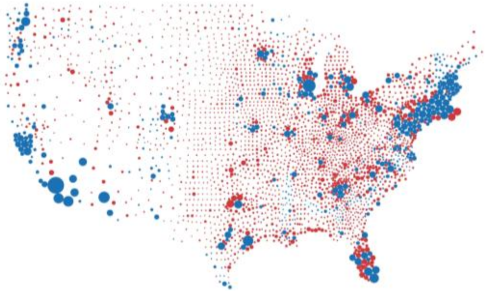
Announcements

- *Programming Assignment* 3 out, due next Friday! (5/30)
- Resubmission 5 closes tonight
- Quiz 2 next Tuesday (5/27)
- Memorial Day is 5/26
  - IPL closed

Applications of ML

Estimation

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



Prediction

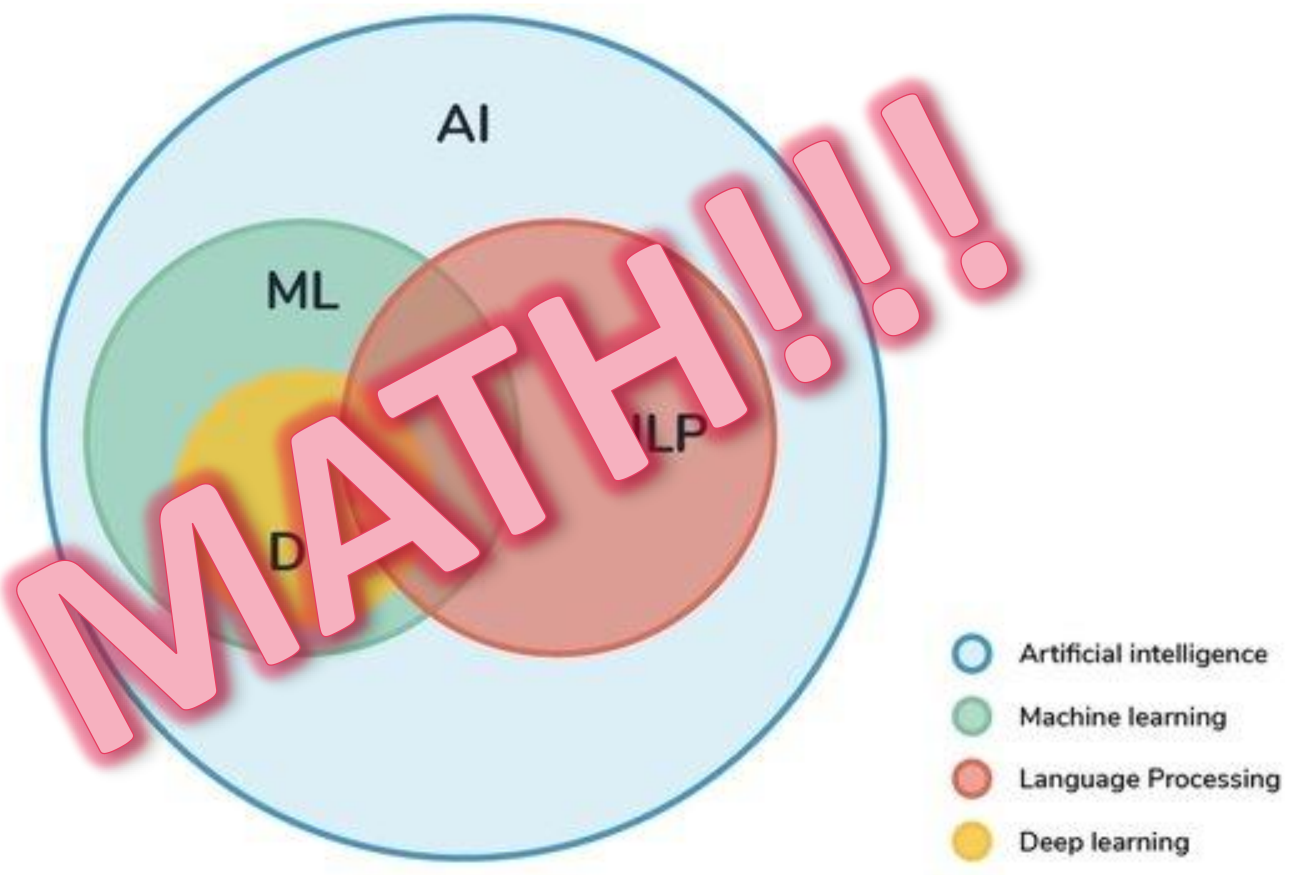
- *Content Recommendation*
  - Can we predict how much someone will like a movie based on past ratings?
- *Object Recognition*
  - Identify {Car, Road, Plane, Bird, Person} within an image?

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)?

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



What is Machine Learning (ML)?

- 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

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

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

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

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

Maximum Likelihood Estimation

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

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

$$k = n\theta$$

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

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

What is Machine Learning (ML)?

- 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…

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

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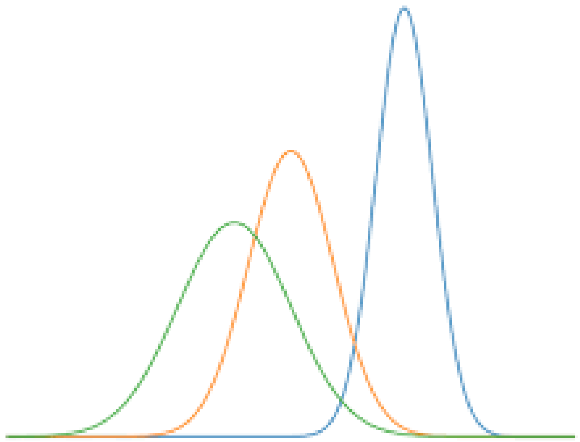
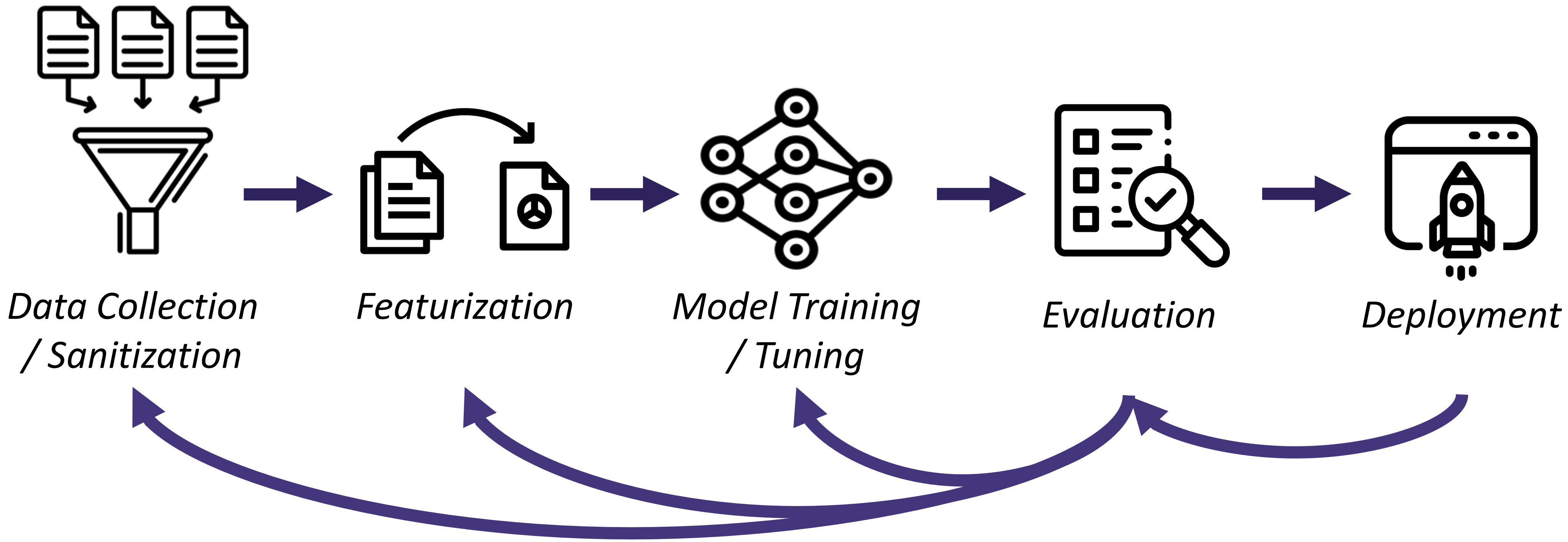


Given enough previous examples, we can estimate the underlying distribution and make predictions about… anything!

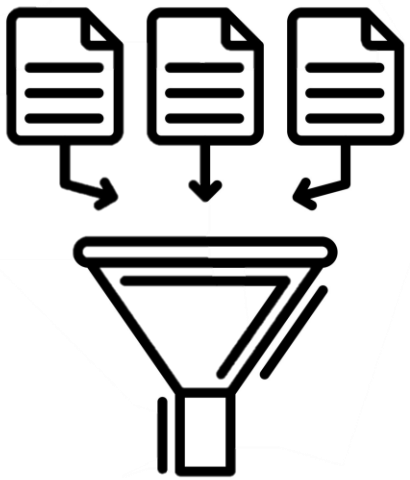
ML Pipeline

- 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**

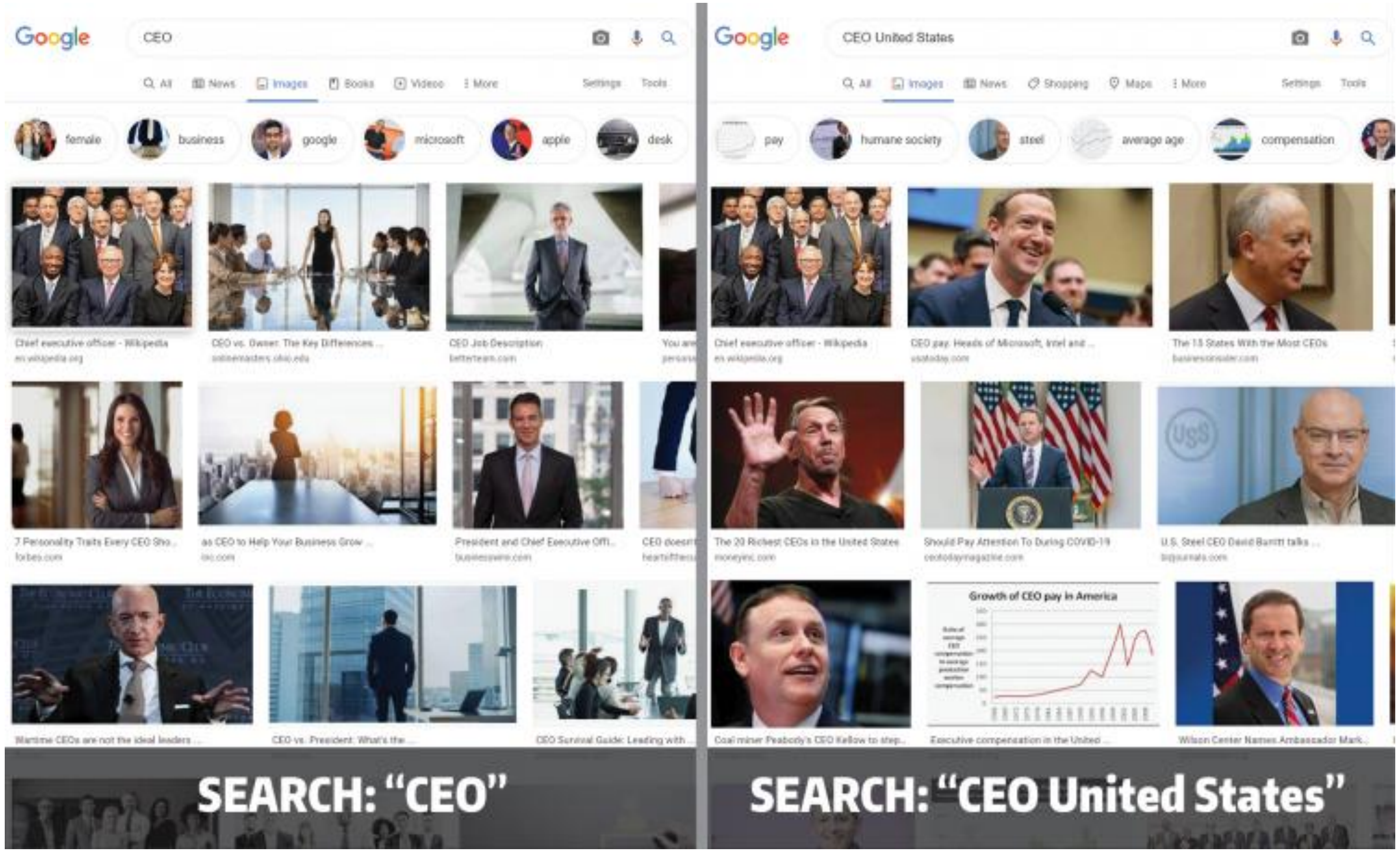
Data Bias

- 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/

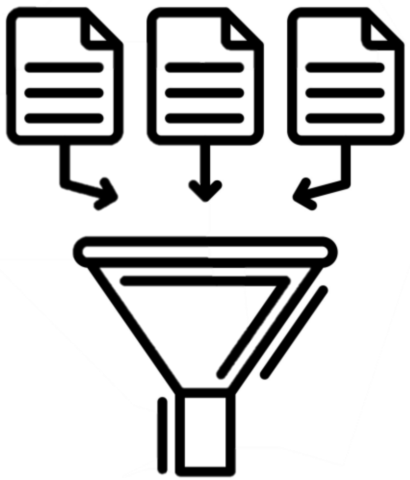
Data Bias

- 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



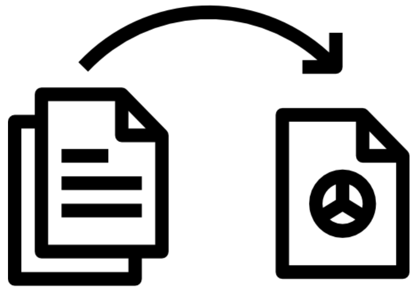
- **Data carries PII / bias that we need to account for**
- We don’t want our model to memorize a phone number
  - Let’s just remove all phone numbers from our inputs!
  - Is this an effective solution?

- 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)

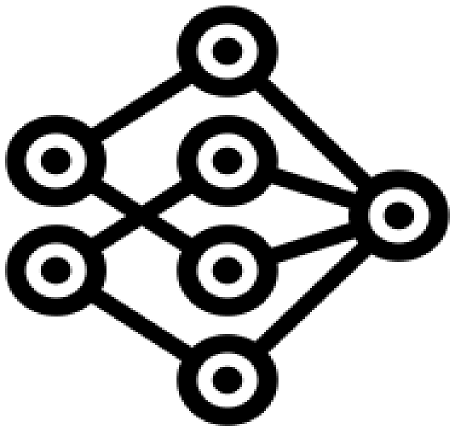
Word Embeddings

- 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

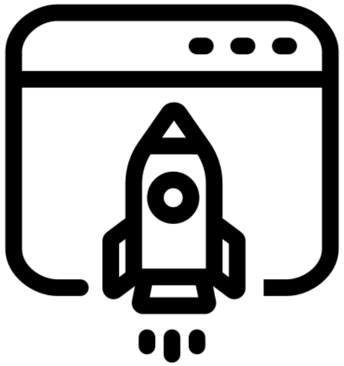
It's all one big experiment – try options until something sticks.

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



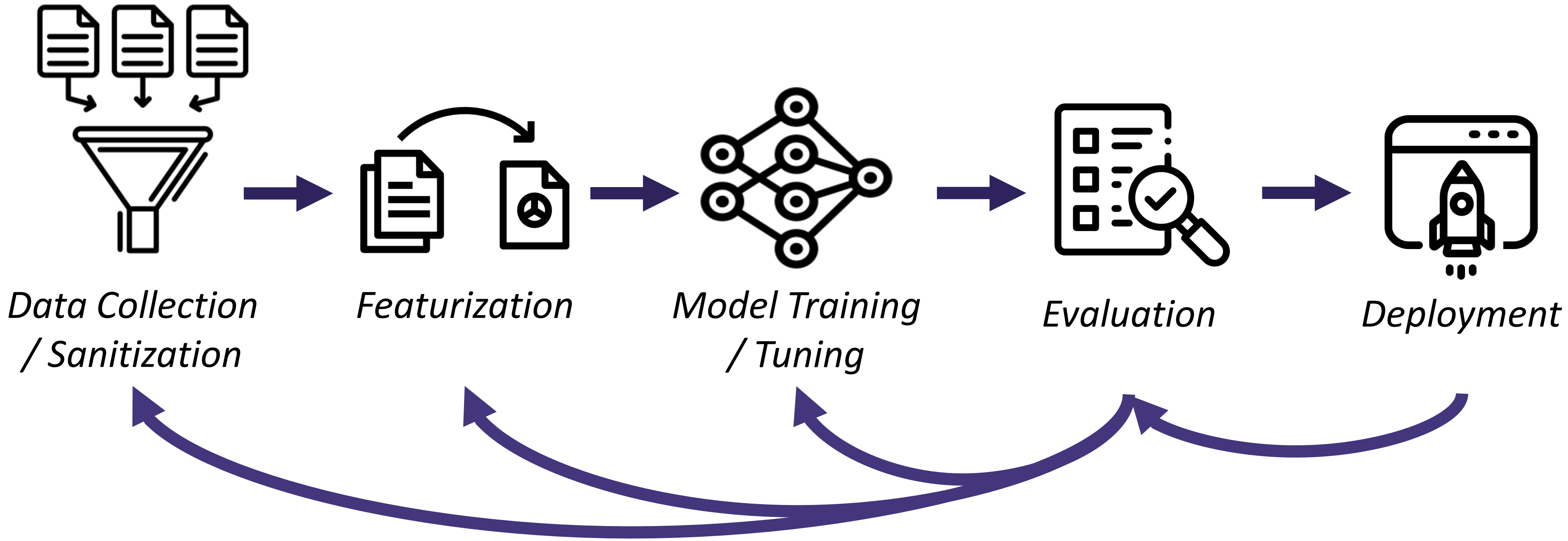
- Put your model out into the real world and see what happens
  - Does it perform the job as expected? Should further work be put into development?

- 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

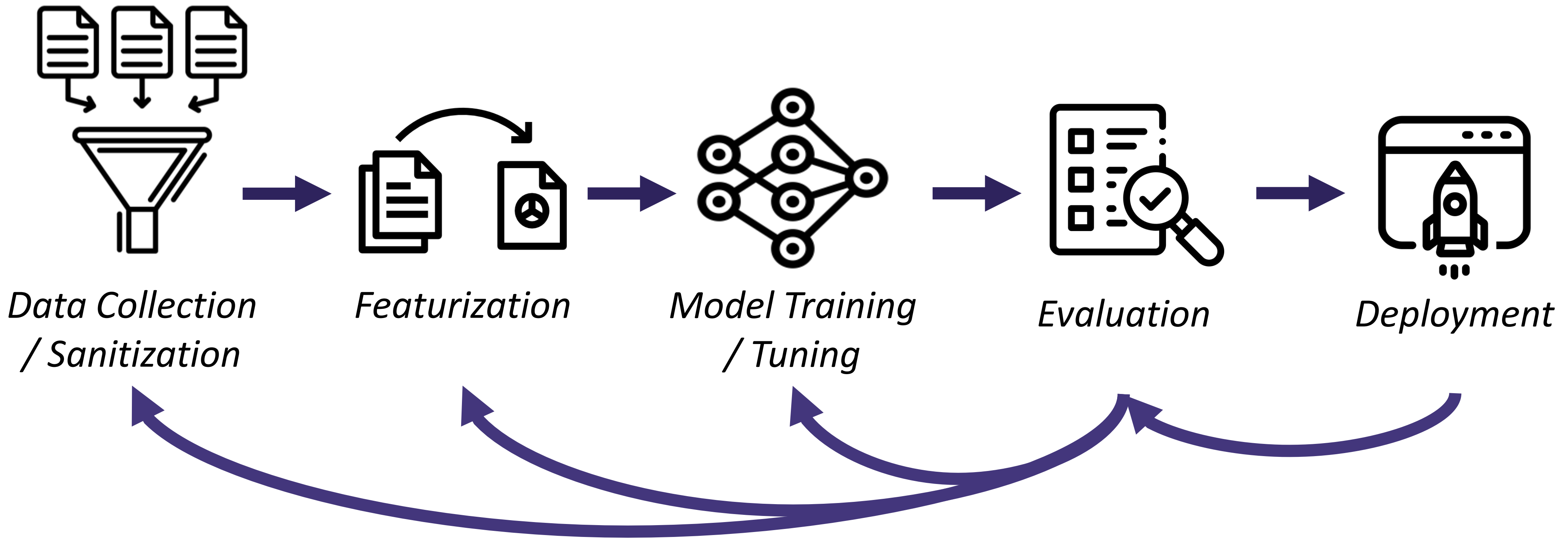
- That's it – in essence, that's how every ML model is created



Does this knowledge change your perspective on ML / AI?

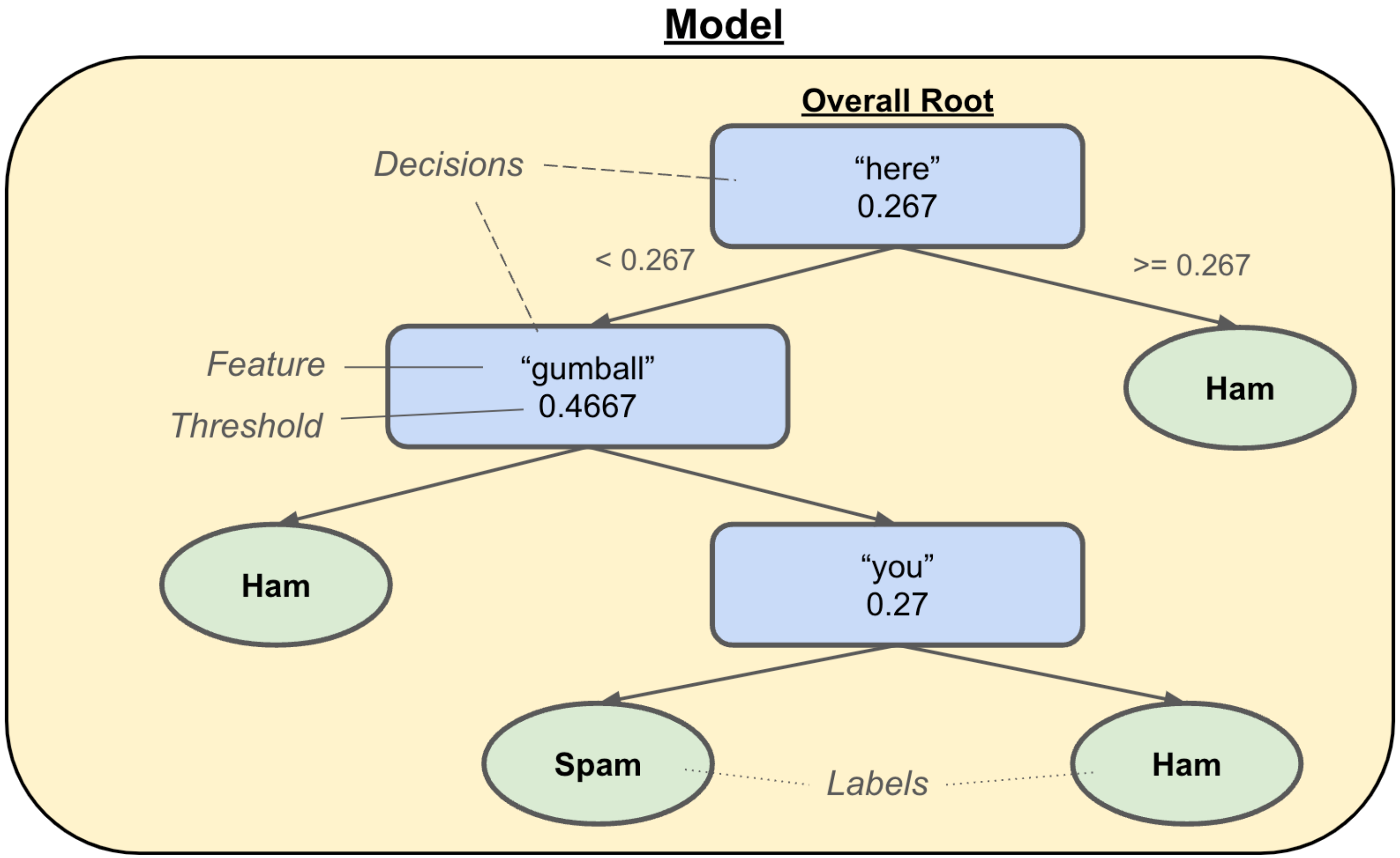
SpamClassifier

- Programming assignment will involve part 3 of this pipeline
  - You'll implement a *decision tree* capable of detecting spam emails (or other text classification)



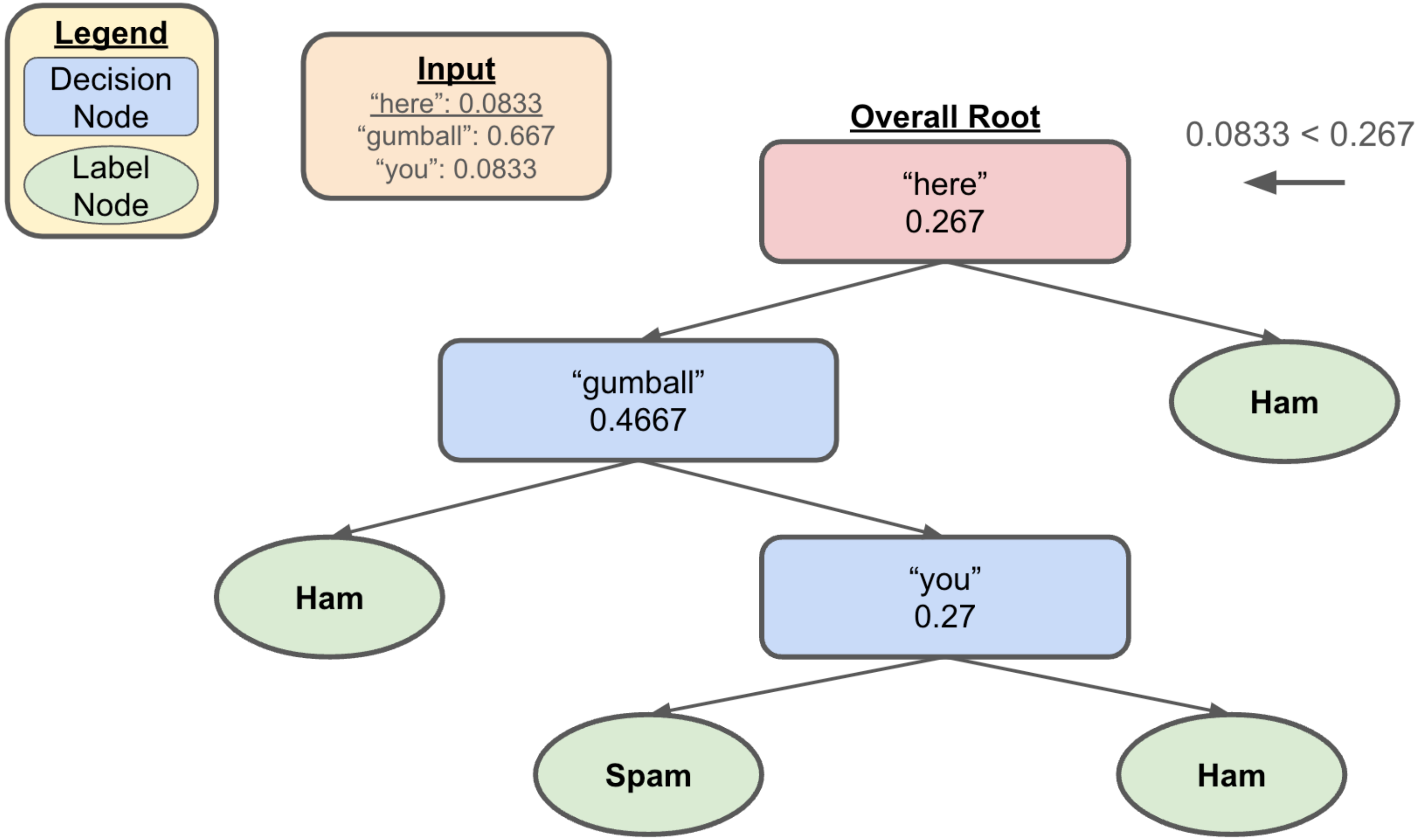
Decision Trees

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



Decision Trees

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



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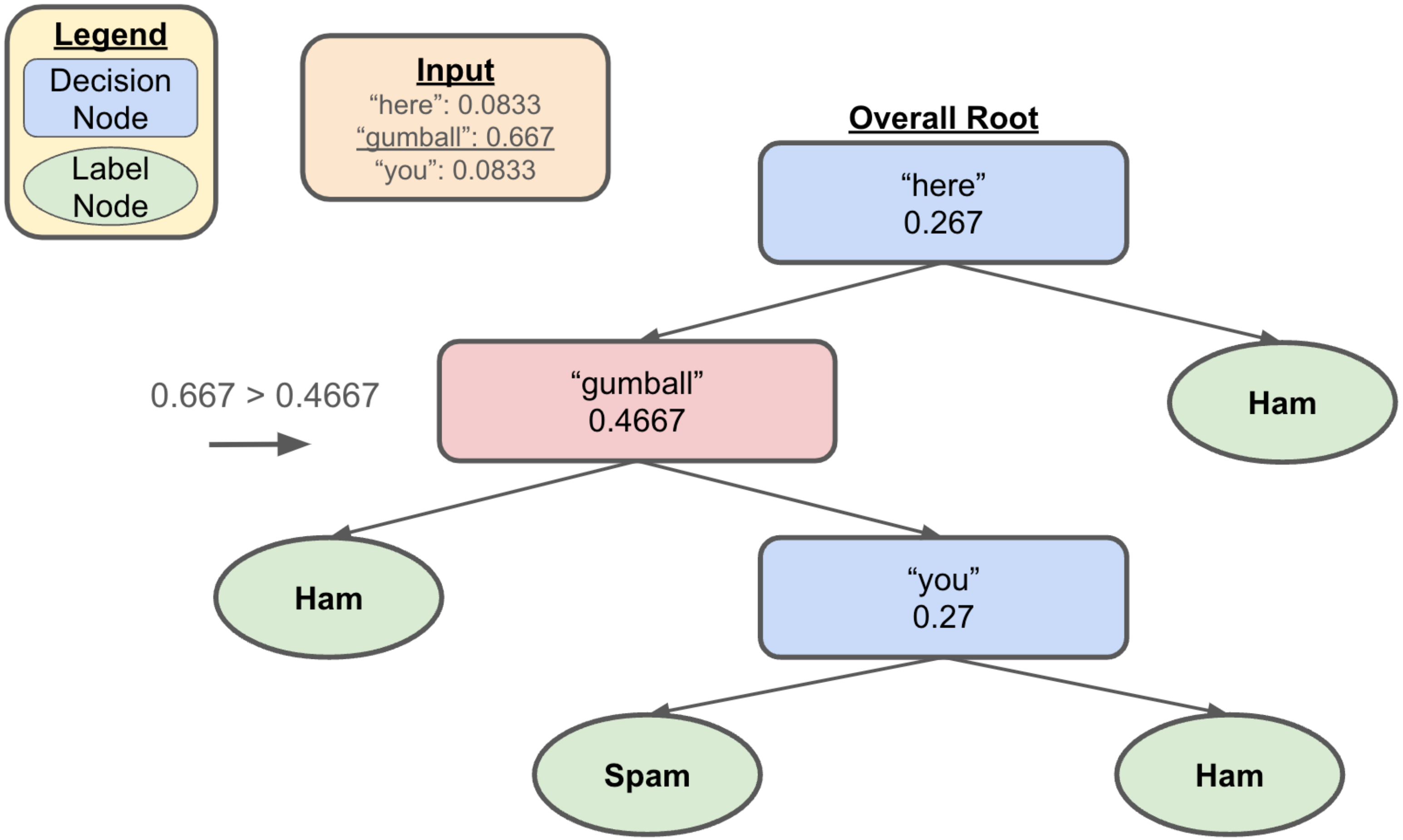

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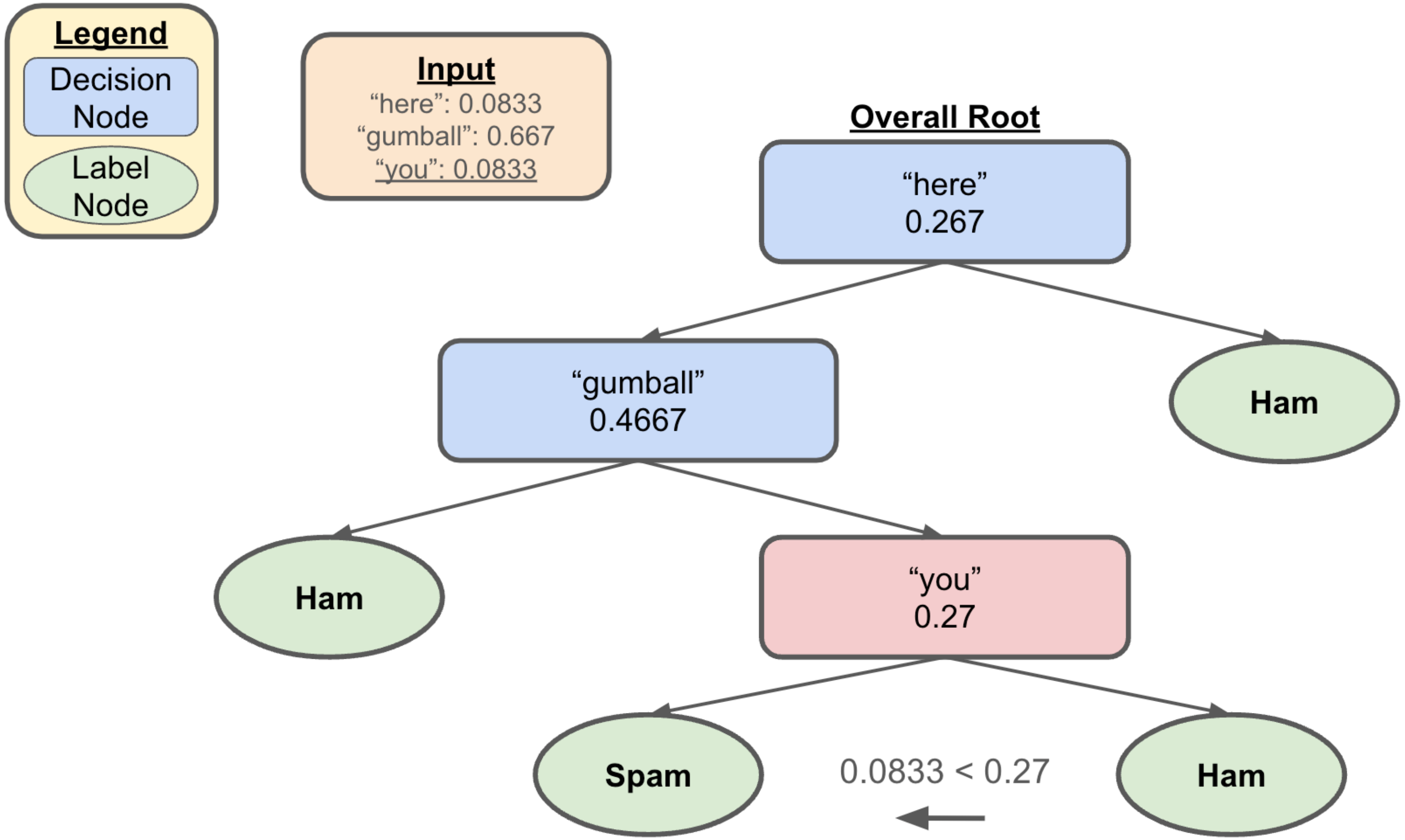

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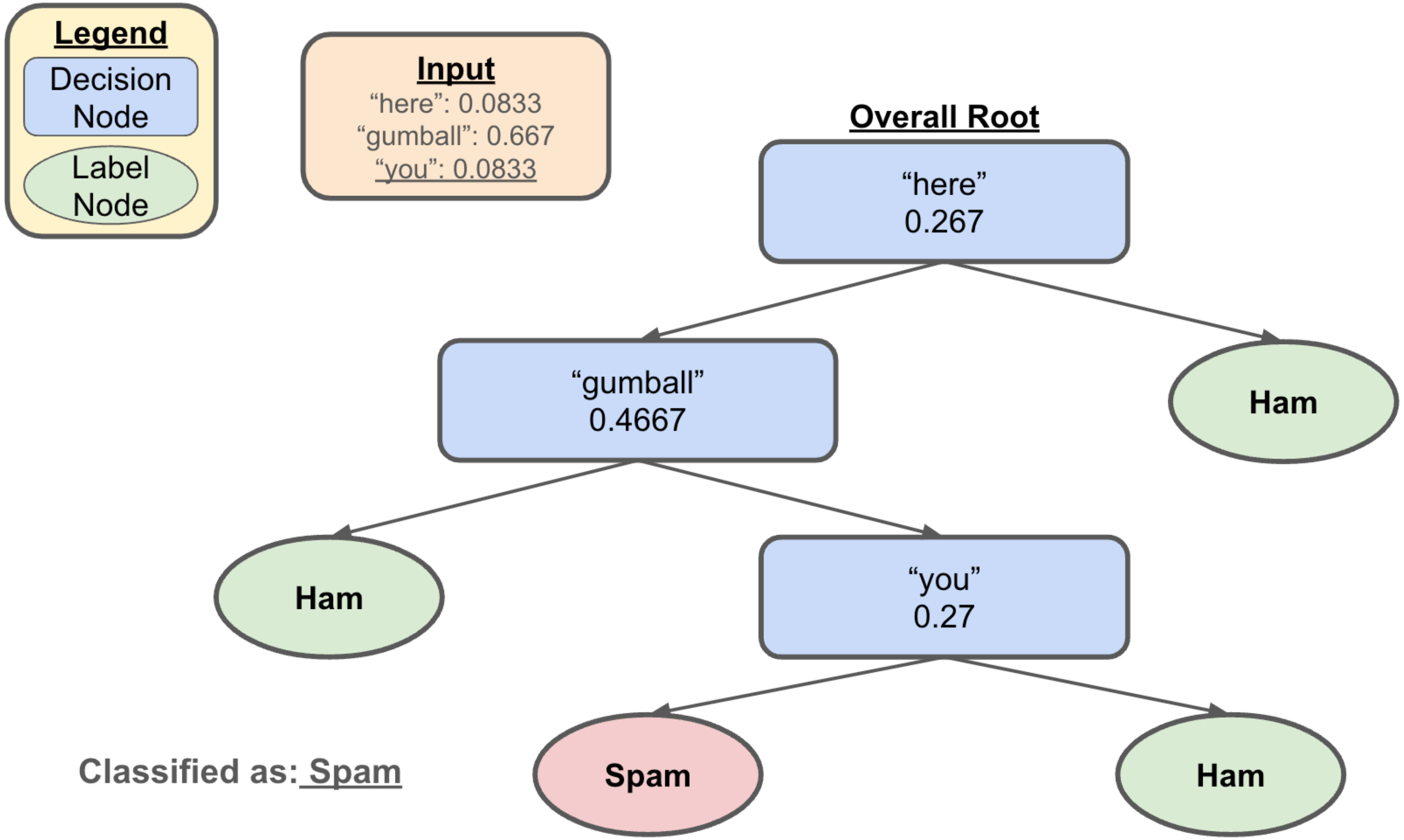

Questions to Consider

- 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?