CS 106A, Lecture 26
Life After CS 106A, Part 2

Plan for today

- Intro to machine learning
- Supervised Learning
- Applications of machine learning
- Implications of machine learning
- Educational Technology

Learning Goals

- Understand the basics of how machine learning works, its advantages, and its pitfalls
- Understand that CS is just a tool – now that you have begun to wield it, what will you use it for?

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Intro to Machine Learning

Machine Learning (ML) and Artificial Intelligence (AI) are increasingly prevalent in our lives.

It’s important to be able to think critically about these technologies, especially if you’re developing them!

Intro to Machine Learning

megapope

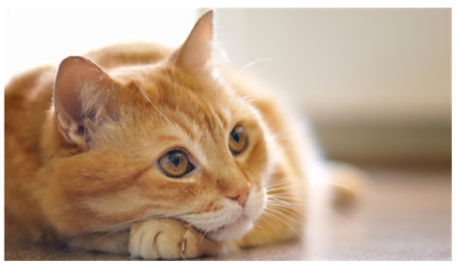
self driving cars aren't even hard to make lol
just program it not to hit stuff

ronpaulhdwallpapers

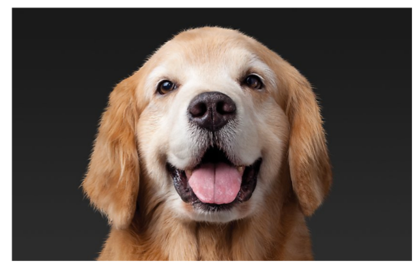
```
if(goingToHitStuff) {
dont();
}
```

Ex: Animal Classification

- We have a picture and we want to know if it’s a cat or not.



`true`



`false`

`true`

`false`

Ex: Animal Classification

Here's one way you might code this…

```
private void isCat(GImage animal) {
	int[][] pixels = animal.getPixelArray();
	if (containsTwoEyes(pixels)){
		if (hasWhiskers(pixels)){
			if (hasPointyEars(pixels)){
				return true;
			}
		}
	}
	return false;
}
```

Some tricky cases

Pros/Cons

- Pros
  - Matches our human intuition about what a cat is
  - Easy to understand the code
- Cons
  - Requires us to explicitly enumerate every feature that's important, and know how important it is
  - Need to write code to detect eyes, and whiskers, and the pointiness of ears
  - Will never improve… cannot learn from its mistakes

What is Machine Learning?

- "The field of study that gives computers the ability to learn without being explicitly programmed" - Arthur Samuel, 1959
- How can a computer do this?

Data.

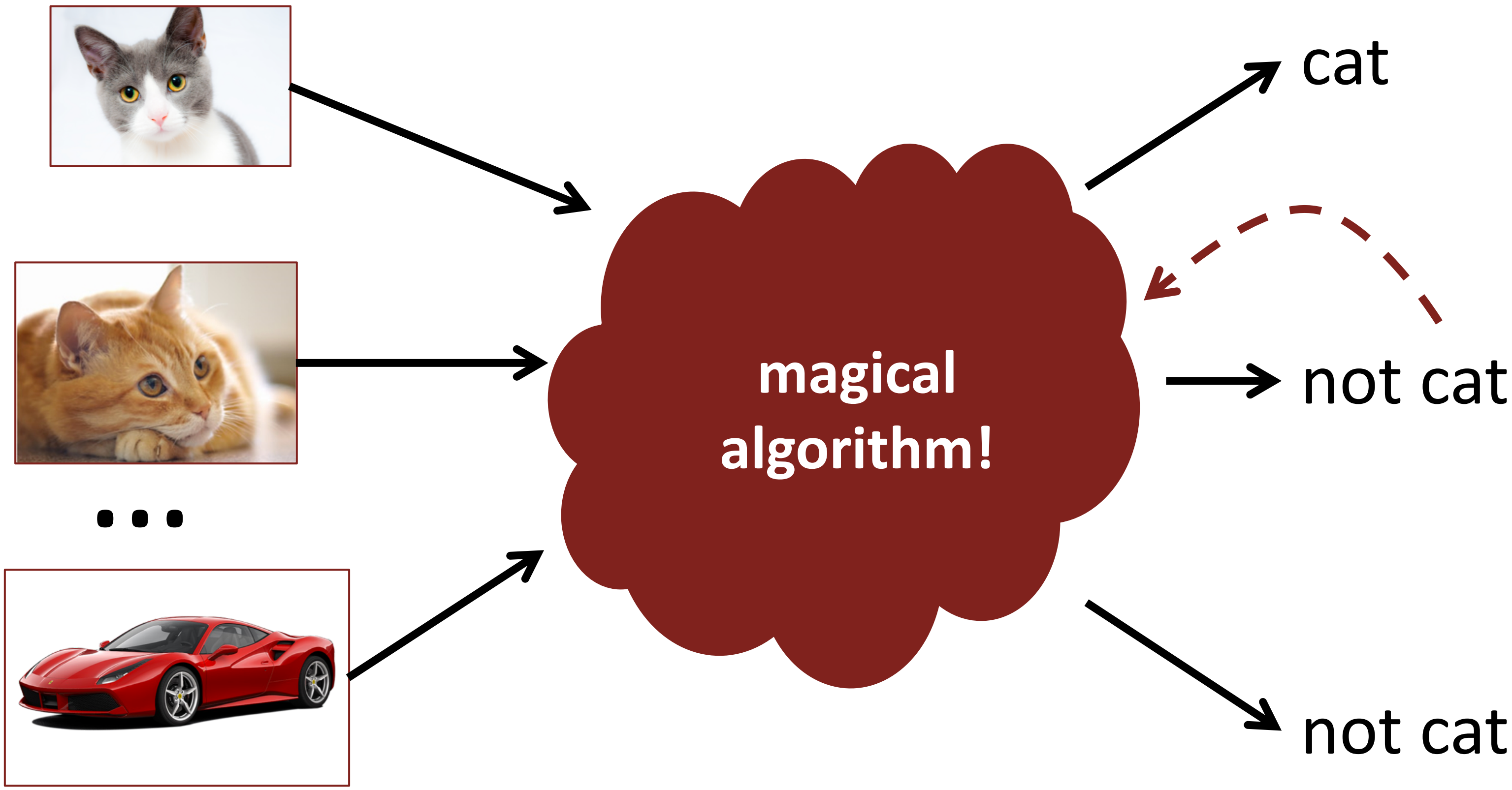
Train/Test Data

The algorithm gets **training data** that it can use to make predictions.

We use **test data** to evaluate how well it performs.

Animal Classification: Take 2

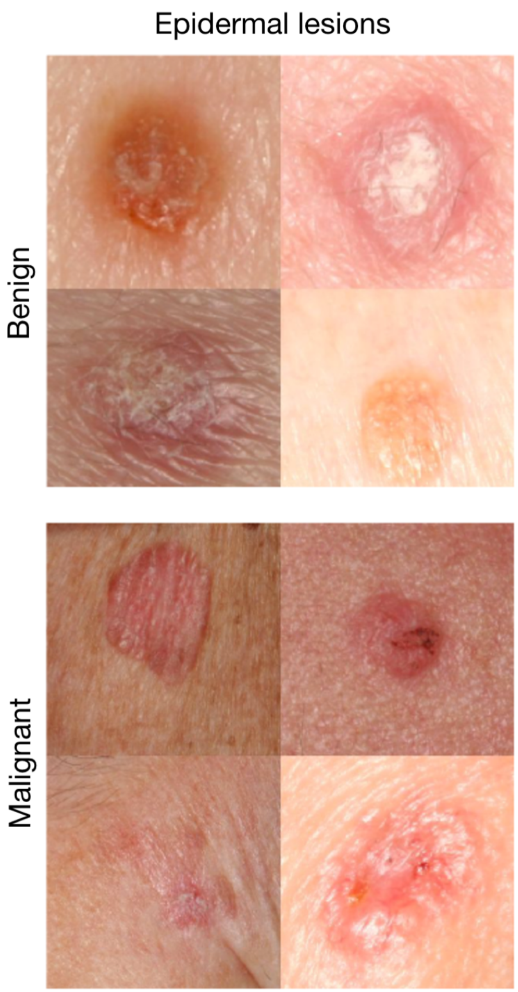
- Here's a sketch of how we can approach this problem through machine learning:
- Input to the algorithm: MANY cats and MANY not-cats



Pros/Cons

- Pros
  - Don’t have to explicitly tell the algorithm what’s important to distinguish between cats and not-cats
  - Not specific to the cat problem: we could show it images of **anything** and **train** it to learn the difference
  - Gets better the more data we give it
- Cons
  - Sometimes hard to know why the algorithm makes the predictions it does
  - Requires us to specify an **update** mechanism: how is the algorithm supposed to improve itself?
  - Might require a lot of data to perform well

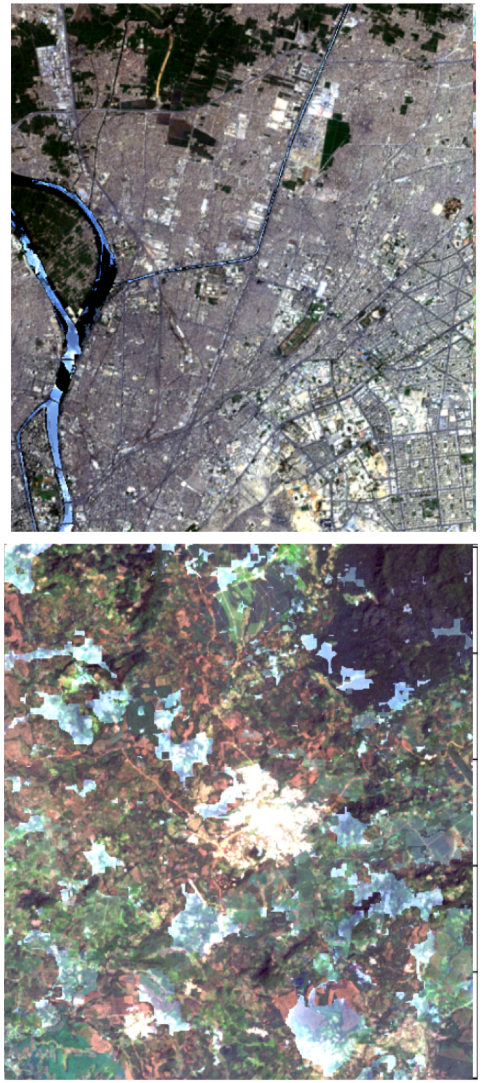
Where is this useful?



Esteva et al., Nature 2017.

- Skin cancer classification
  - Is a given lesion **benign** or **malignant**?
- A machine learning algorithm has been shown to perform **as well** as dermatologists.

Where is this useful?



piped water

no piped water

Oshri et al., 2018.

- Predicting infrastructure development from satellite images
  - previously required intense field surveys with large data gaps

- There are other tasks where machine learning algorithms perform **better** than skilled humans.

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Supervised Learning

- **Supervised learning** is when you know the "ground truth" correct answers
  - ex: classifying cats, skin lesions

- **Unsupervised learning** is when you don't – this is a much harder problem!
  - ex: text extraction, discovering new drugs

Ex: Digit Classification

- Task:
  - Given a picture of a **handwritten digit** from 0-9, predict which integer it is

 → 3

 → $\boxed{4}$ **“label”**

 → 2

 → 9

k-Nearest Neighbors

live demo!

k-Nearest Neighbors

- Idea: when given a **test** input, look through all the **training** examples to find the **"closest"** one.
- Under the assumption that "close" inputs share the same label, return the label of that closest training example.

k-Nearest Neighbors

- Idea: when given a **test** input, look through all the **training** examples to find the **k** **“closest”** inputs.
- Under the assumption that “close” inputs share the same label, return the **most common** label of the **k closest inputs**.

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What else can ML do?

- Supervised Learning
  - Classification, like the cat or skin cancer or digits examples
  - **Regression**

Regression Example

- **House price prediction**

Training Data

Square Footage	# Bedrooms	# Bathrooms	House Price
1,000	2	1	150,000
1,256	1	1	175,000
5,897	5	2	2,000,000
4,300	3	2	1,300,000
2,400	3	3	750,000
2,600	2	1	690,000
3,000	4	2	1,000,000

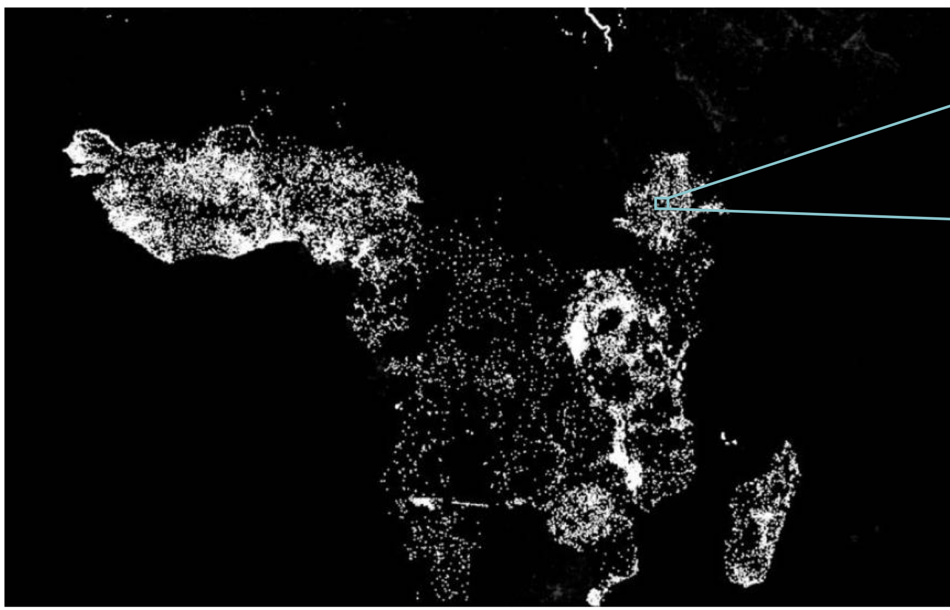
Test Time

"My house has 1,800 square feet, 2 bedrooms, and 2 bathrooms. How much should I expect it to sell for?"

Regression Example

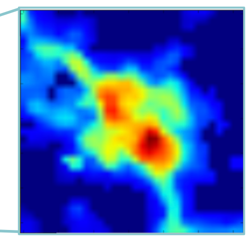
- **Poverty from nightlights**

<u>Training Data</u>



Xie et al., 2016.

<u>Test Time</u>



Average household income?

What else can ML do?

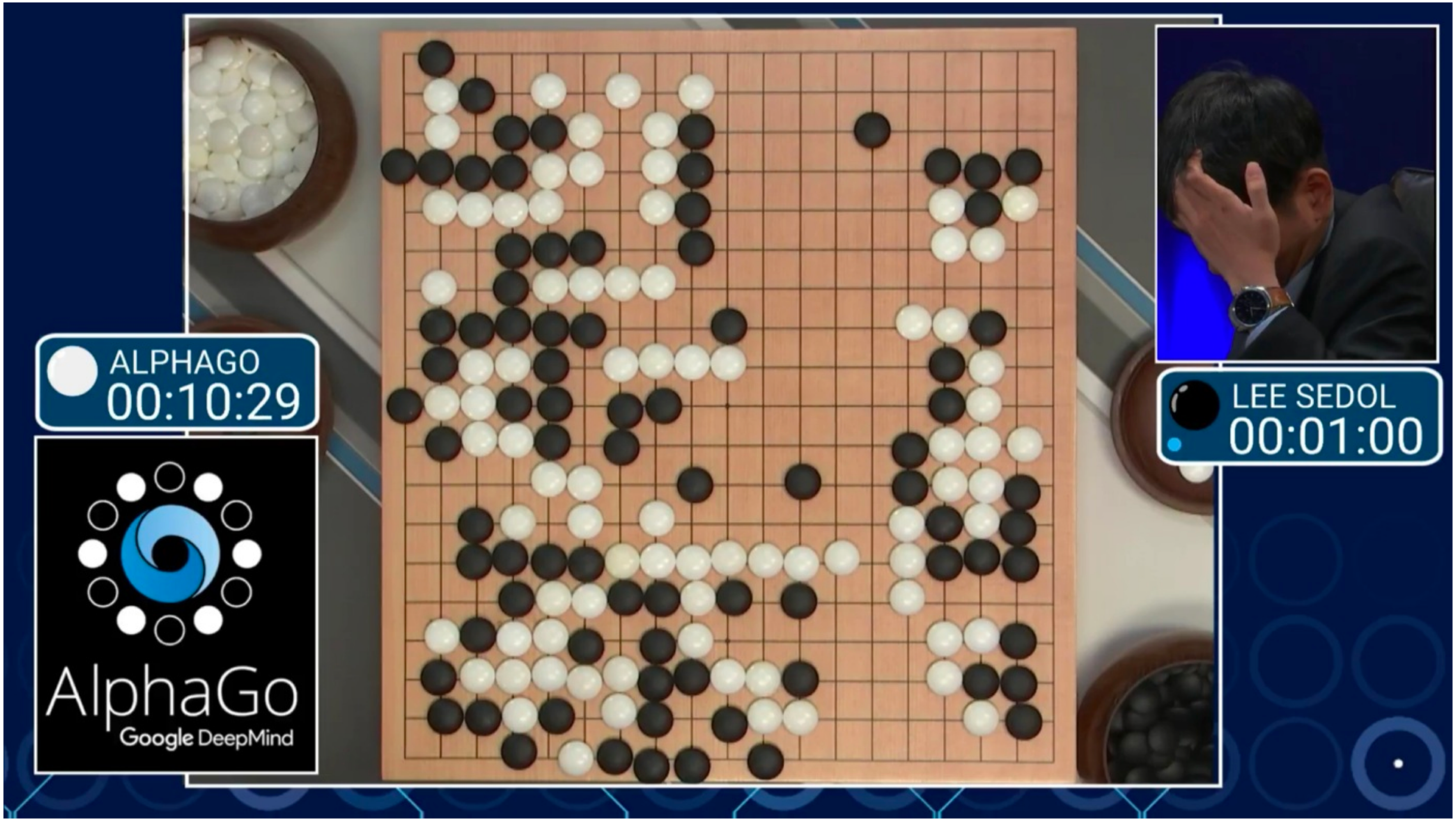
- Supervised Learning
  - Classification
  - Regression
- **Unsupervised Learning**
  - Finding **structure** in unlabeled data

Netflix Prize Example

What else can ML do?

- Supervised Learning
  - Classification
  - Regression
- Unsupervised Learning
- **Reinforcement Learning**

AlphaGo



What remains really hard?

- Human-like dialog
- Common-sense reasoning about the world
- **Strong** generalization
- Interpretability of decisions
- … and much else ☺

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Algorithmic bias

Man is to Computer Programmer as Woman is to Homemaker? Debiasing Word Embeddings

Tolga Bolukbasi, Kai-Wei Chang, James Zou, Venkatesh Saligrama, Adam Kalai

(Submitted on 21 Jul 2016)

Twitter taught Microsoft's AI chatbot to be a racist asshole in less than a day

The New York Times

Opinion

OP-ED CONTRIBUTOR

When an Algorithm Helps Send You to Prison

Algorithmic bias

- ML is powerful because it can learn from data, without explicit instruction
- … but because of that, is subject to the same flaws found in data

Artificial Intelligence

"With artificial intelligence we are summoning the demon" – Elon Musk

Recap

- ML is powerful because it can learn from data, without explicit instruction
- … but because of that, is subject to the same flaws found in data
- … and must be used safely, with thoughtful human input

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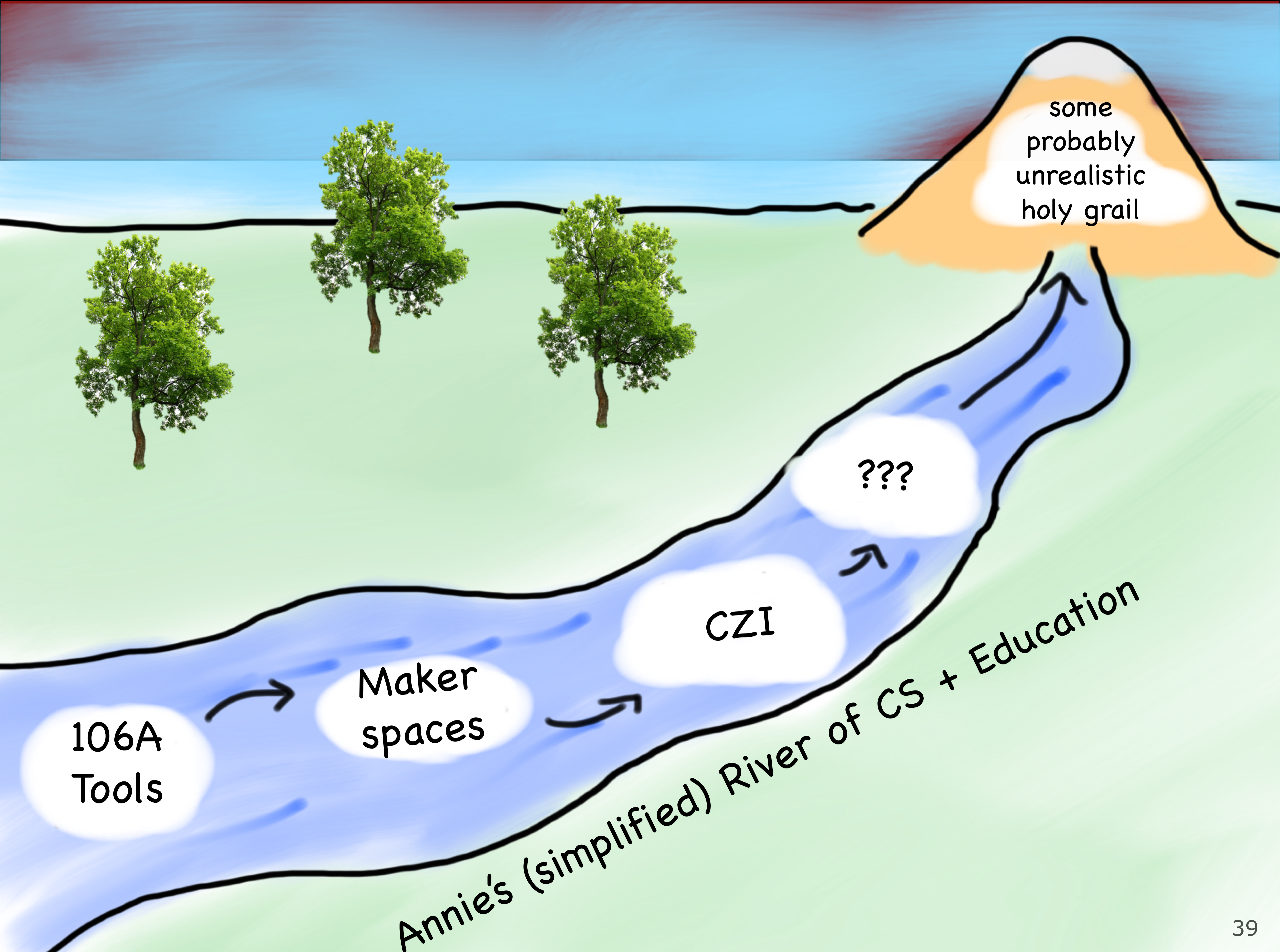
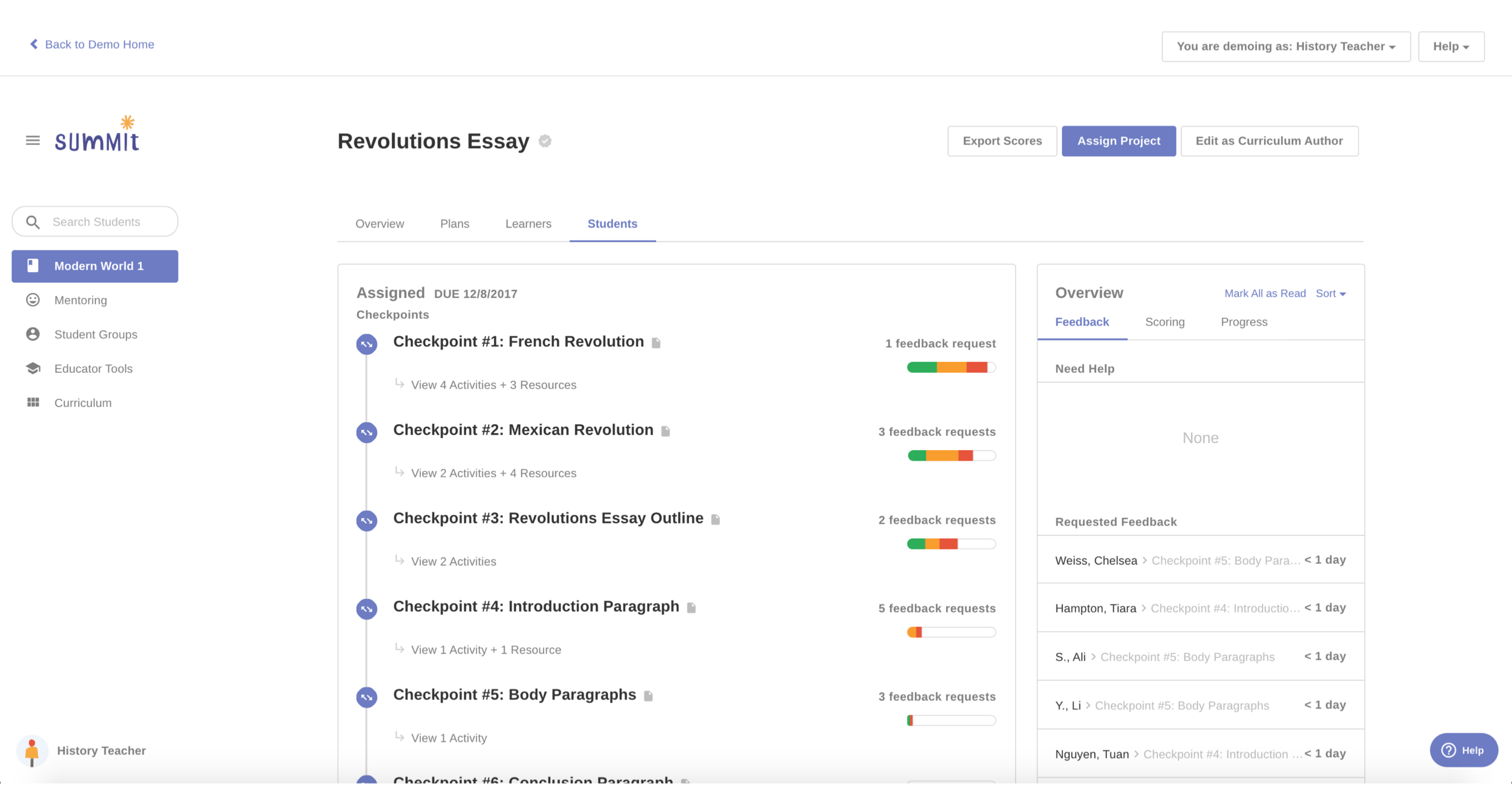
Educational Technology (EdTech)

- MOOCs (massive open online courses)
- tools to learn CS
- Chromebooks / iPads in classrooms
- online / AI tutoring
- autograding
- circuits / Arduinos / Raspberry Pi
- …and so much more


some probably unrealistic holy grail
???
CZI
Maker spaces
106A Tools
Annie's (simplified) River of CS + Education

Personalized Learning



Recap

- like much of tech + social good, the answers are unclear
- best solution may not involve tech at all!
- important to stay close to the problem and stay empathetic :-)

Recap

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Next time: final review 😱