DeepRob

Winter 2023
Deep Learning for Robot Perception
University of Michigan and University of Minnesota

4Progress
GO BLUE

4Progress

Sui, Zhou, Zeng, Jenkins 2017

**Our goal:
Perception and manipulation of objects in clutter…**

Sui, Zhou, Zeng, Jenkins 2017

Our goal:
Perception and manipulation of objects in clutter…

… through deep learning with neural networks (mostly) …

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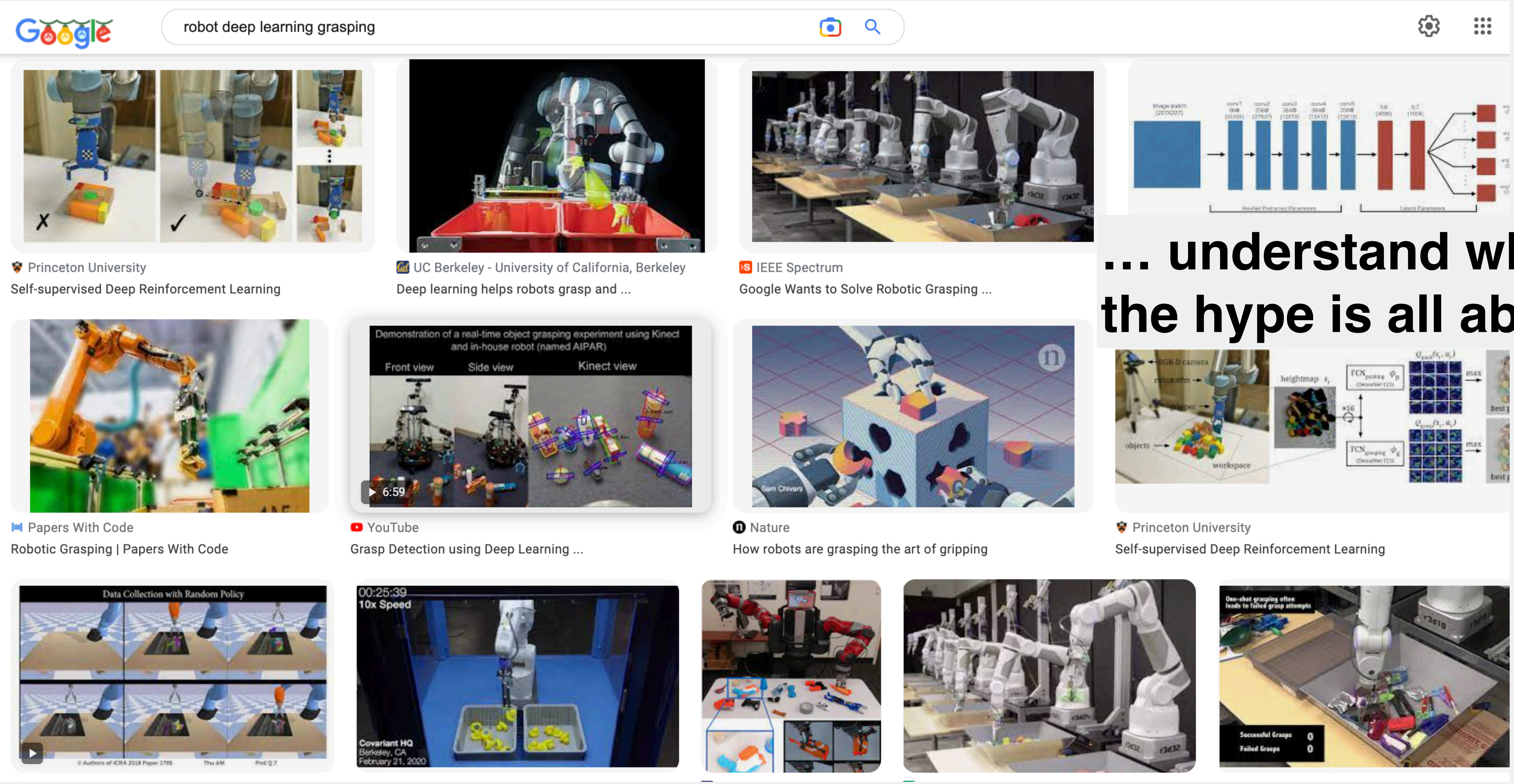


robot deep learning grasping

Princeton University
Self-supervised Deep Reinforcement Learning

UC Berkeley - University of California, Berkeley
Deep learning helps robots grasp and ...

IEEE Spectrum
Google Wants to Solve Robotic Grasping ...

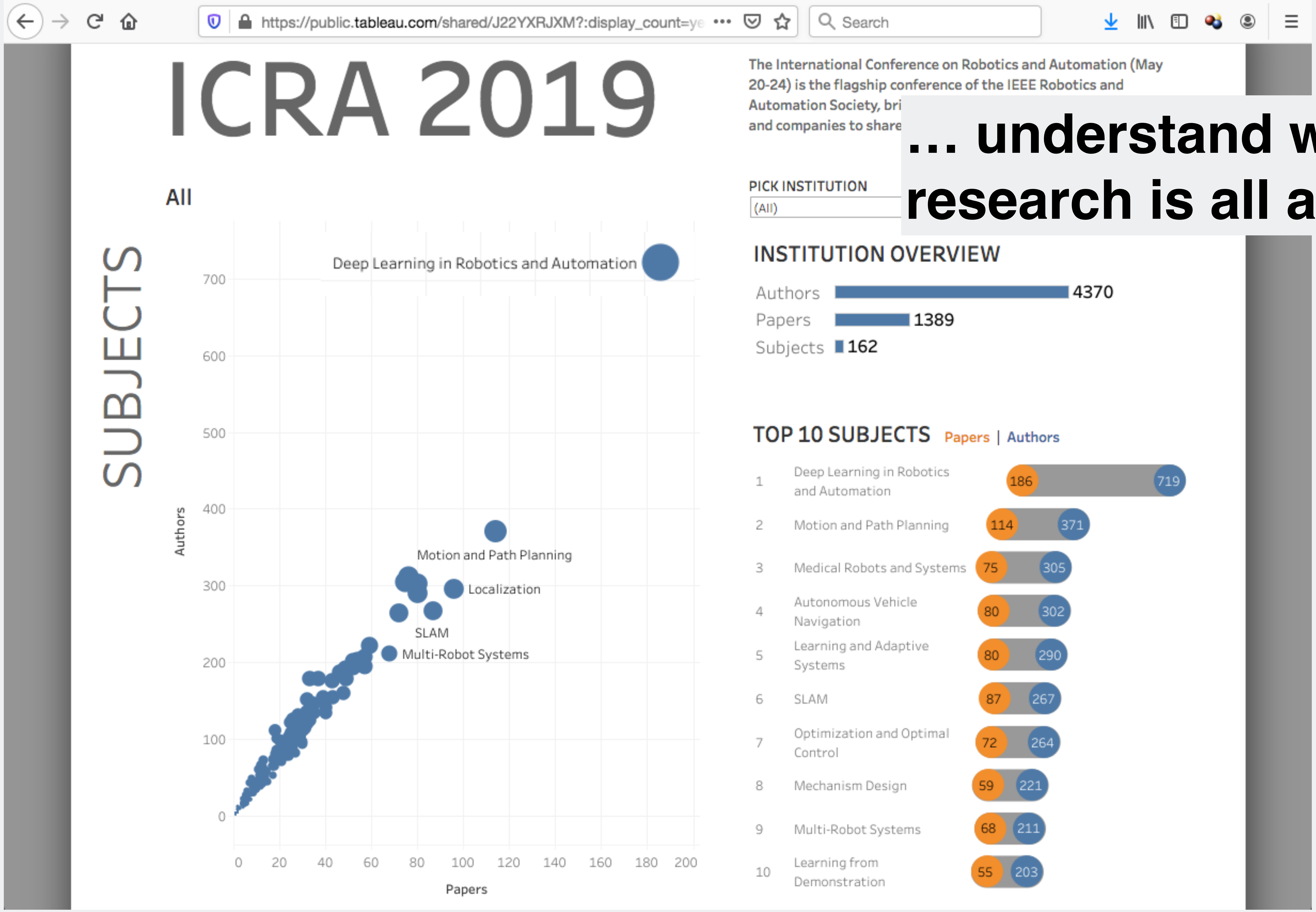
Papers With Code
Robotic Grasping | Papers With Code

YouTube
Grasp Detection using Deep Learning ...

Nature
How robots are grasping the art of gripping

Princeton University
Self-supervised Deep Reinforcement Learning

... understand what the hype is all about ...



https://public.tableau.com/shared/J22YXRJXM?:display_count=ye
Search

ICRA 2019

The International Conference on Robotics and Automation (May
20-24) is the flagship conference of the IEEE Robotics and
Automation Society, bri
and companies to share

PICK INSTITUTION
(All)

All

SUBJECTS

INSTITUTION OVERVIEW

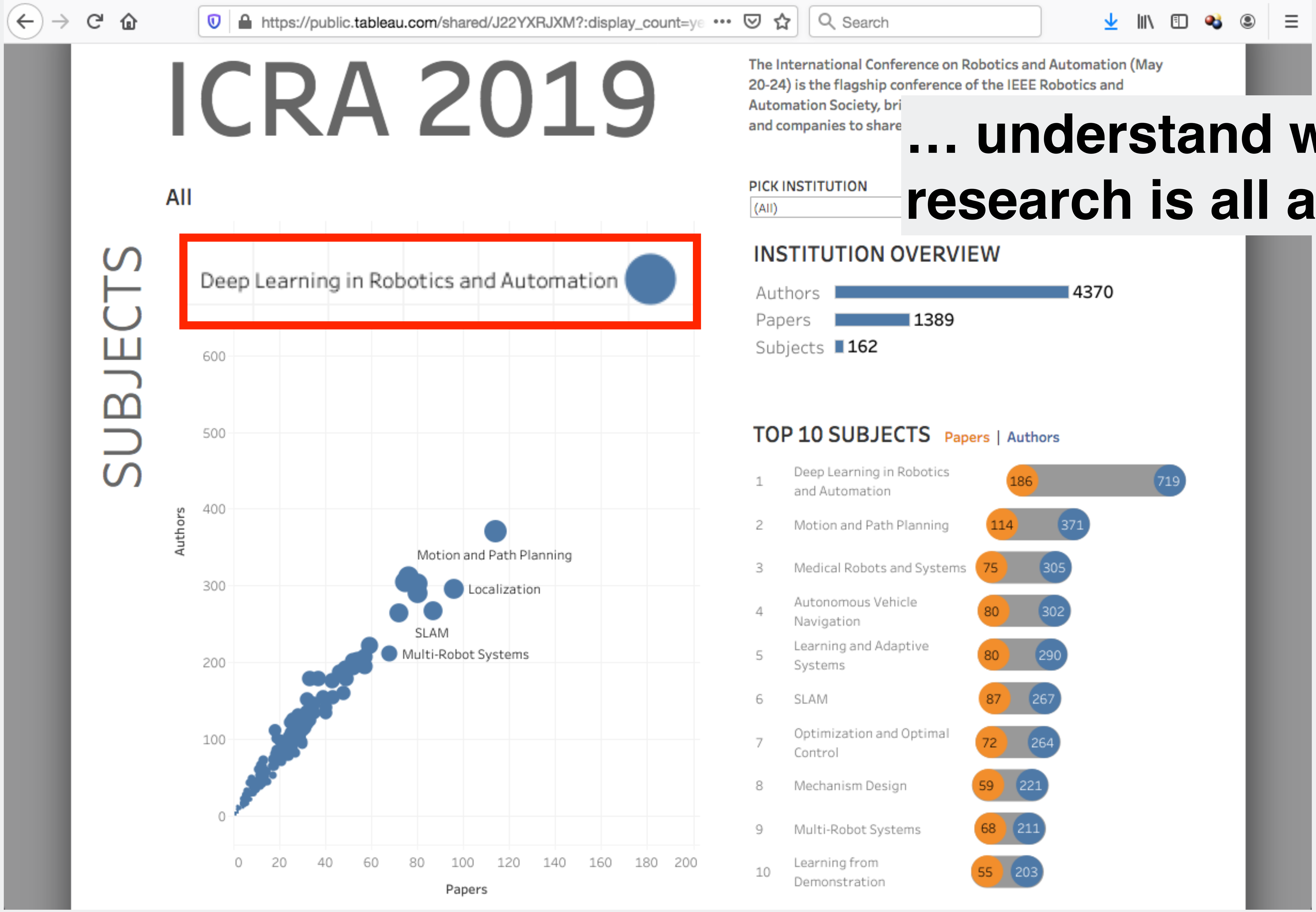
Authors	4370
Papers	1389
Subjects	162

TOP 10 SUBJECTS Papers | Authors

		Papers	Authors
1	Deep Learning in Robotics and Automation	186	719
2	Motion and Path Planning	114	371
3	Medical Robots and Systems	75	305
4	Autonomous Vehicle Navigation	80	302
5	Learning and Adaptive Systems	80	290
6	SLAM	87	267
7	Optimization and Optimal Control	72	264
8	Mechanism Design	59	221
9	Multi-Robot Systems	68	211
10	Learning from Demonstration	55	203

… understand what the research is all about …

]



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… understand what the research is all about …

… and generate new ideas for robotics research (hopefully)

LIT
[Zhou, Chen, Jenkins *IEEE RA-L 2020*]

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LIT

[Zhou, Chen, Jenkins *IEEE RA-L 2020*]

Welcome to DeepRob!

DR

Welcome to DeepRob!

Anthony Opipari

Prof. Chad Jenkins

Prof. Karthik Desingh

UNIVERSITY OF
MICHIGAN

THE
LABORATORY FOR
PROGRESS

UNIVERSITY
OF MINNESOTA

DeepRob Course Staff

Anthony Opipari

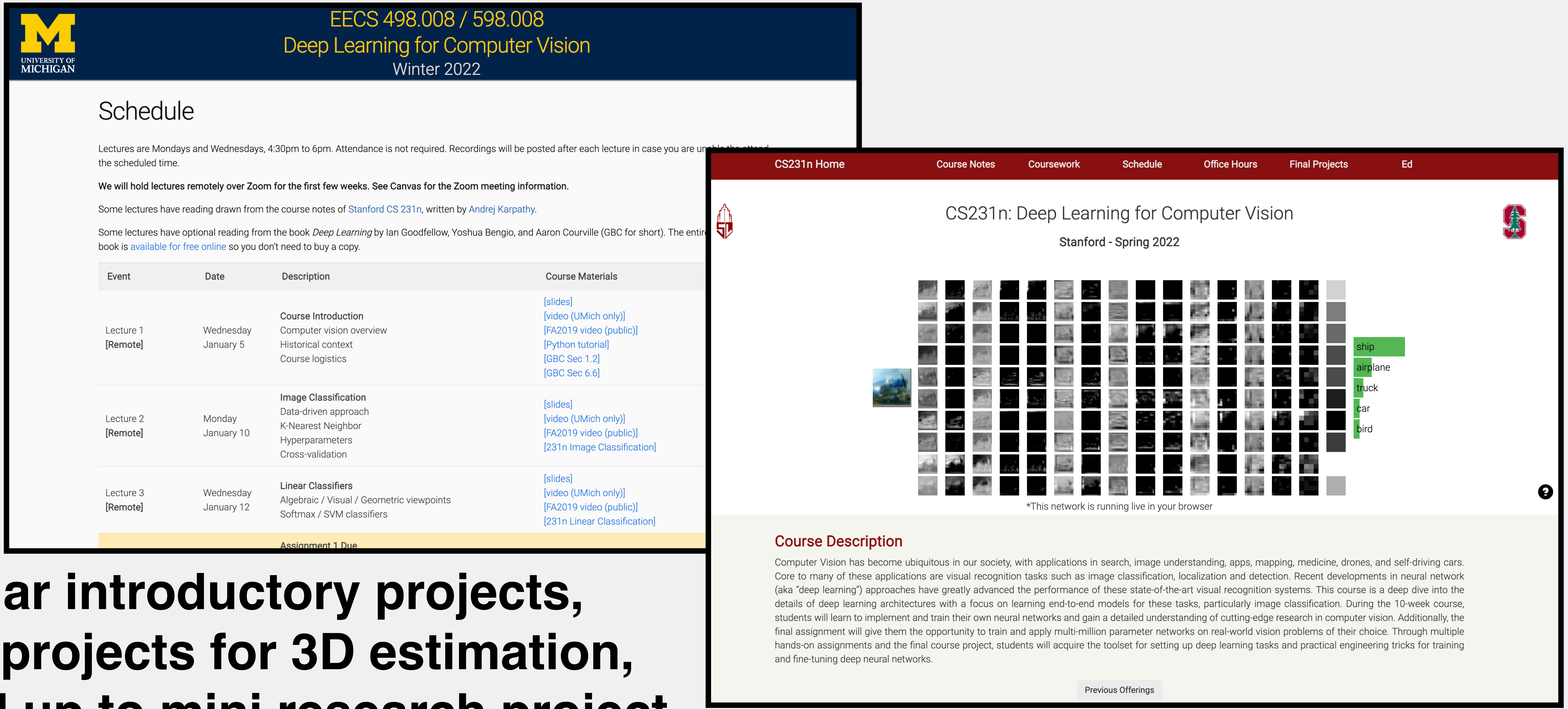
Prof. Chad Jenkins

Prof. Karthik Desingh

Huijie Zhang
Research Associate

Jiyue Zhu
Instructional Aide

DeepRob is a fork (and a star) of Deep Learning for Computer Vision



EECS 498.008 / 598.008
Deep Learning for Computer Vision
Winter 2022

Schedule

Lectures are Mondays and Wednesdays, 4:30pm to 6pm. Attendance is not required. Recordings will be posted after each lecture in case you are un
the scheduled time.

We will hold lectures remotely over Zoom for the first few weeks. See Canvas for the Zoom meeting information.

Some lectures have reading drawn from the course notes of Stanford CS 231n, written by Andrej Karpathy.

Some lectures have optional reading from the book *Deep Learning* by Ian Goodfellow, Yoshua Bengio, and Aaron Courville (GBC for short). The entir
book is available for free online so you don't need to buy a copy.

Event	Date	Description	Course Materials
Lecture 1 [Remote]	Wednesday January 5	**Course Introduction** Computer vision overview Historical context Course logistics	[slides] [video (UMich only)] [FA2019 video (public)] [Python tutorial] [GBC Sec 1.2] [GBC Sec 6.6]
Lecture 2 [Remote]	Monday January 10	**Image Classification** Data-driven approach K-Nearest Neighbor Hyperparameters Cross-validation	[slides] [video (UMich only)] [FA2019 video (public)] [231n Image Classification]
Lecture 3 [Remote]	Wednesday January 12	**Linear Classifiers** Algebraic / Visual / Geometric viewpoints Softmax / SVM classifiers	[slides] [video (UMich only)] [FA2019 video (public)] [231n Linear Classification]
		Assignment 1 Due	

CS231n: Deep Learning for Computer Vision

Stanford - Spring 2022

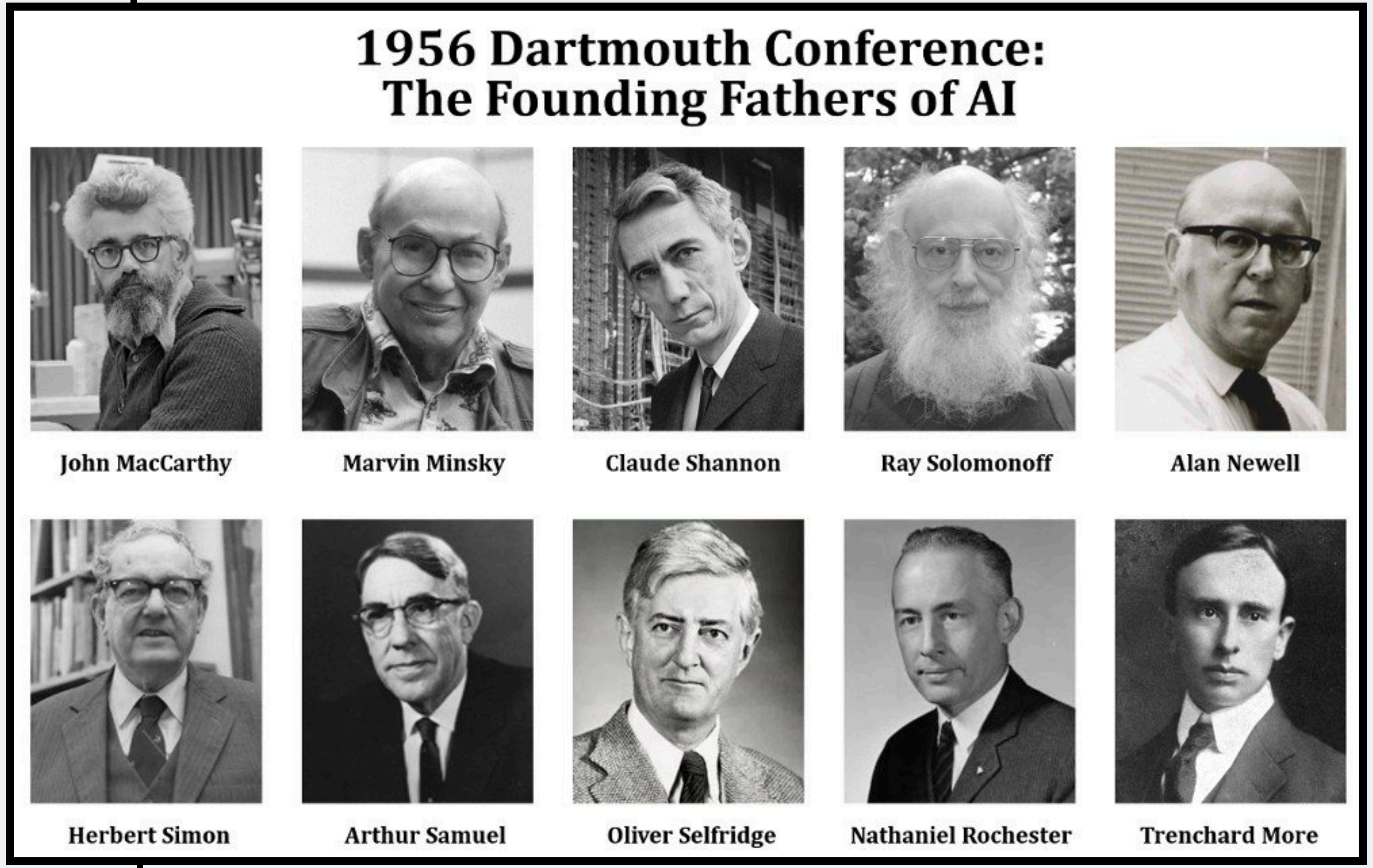
*This network is running live in your browser

Course Description

Computer Vision has become ubiquitous in our society, with applications in search, image understanding, apps, mapping, medicine, drones, and self-driving cars. Core to many of these applications are visual recognition tasks such as image classification, localization and detection. Recent developments in neural network (aka "deep learning") approaches have greatly advanced the performance of these state-of-the-art visual recognition systems. This course is a deep dive into the details of deep learning architectures with a focus on learning end-to-end models for these tasks, particularly image classification. During the 10-week course, students will learn to implement and train their own neural networks and gain a detailed understanding of cutting-edge research in computer vision. Additionally, the final assignment will give them the opportunity to train and apply multi-million parameter networks on real-world vision problems of their choice. Through multiple hands-on assignments and the final course project, students will acquire the toolset for setting up deep learning tasks and practical engineering tricks for training and fine-tuning deep neural networks.

Similar introductory projects,
New projects for 3D estimation,
Build up to mini research project

A brief history of AI



1956 Dartmouth Conference:
The Founding Fathers of AI

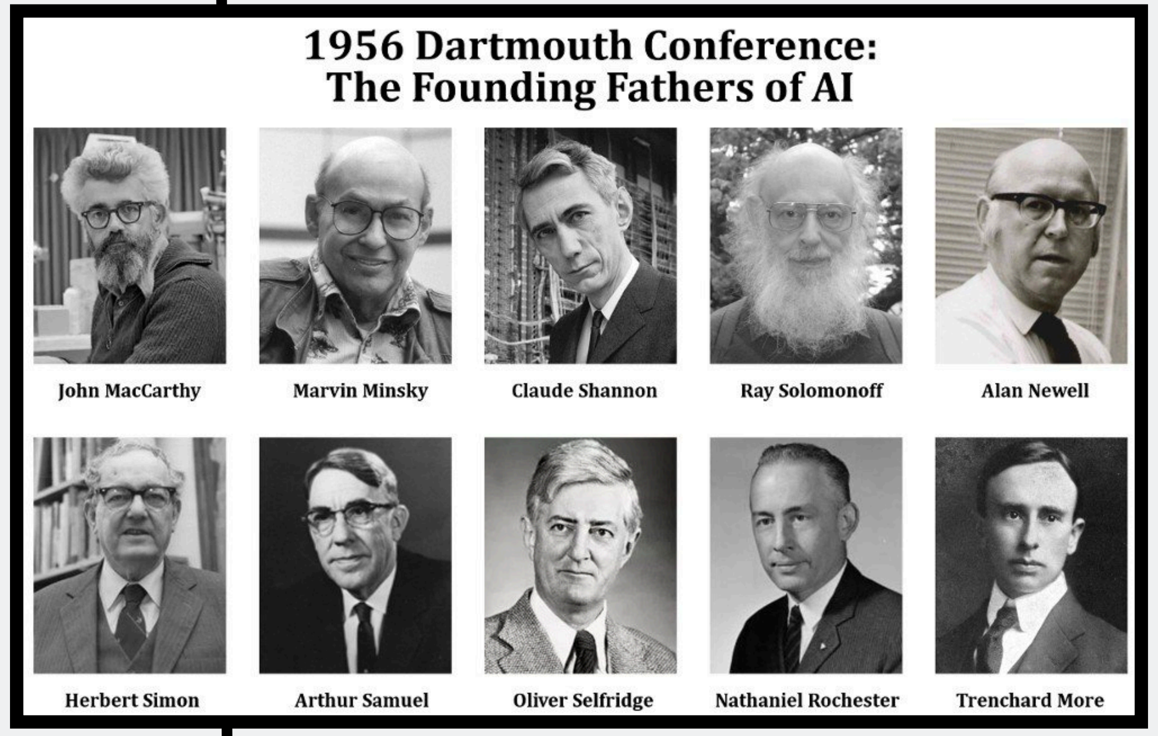
John MacCarthy
Marvin Minsky
Claude Shannon
Ray Solomonoff
Alan Newell

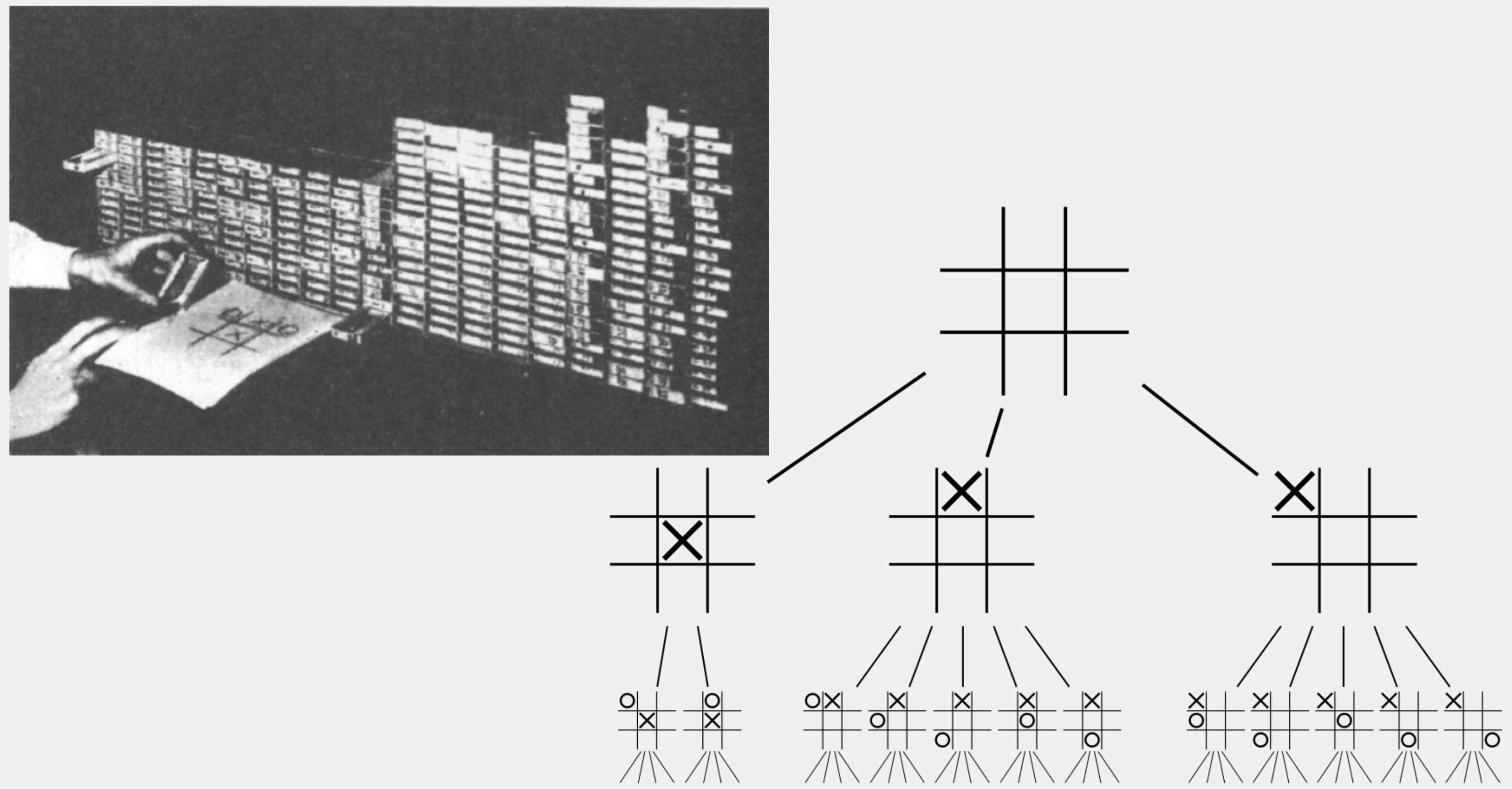
Herbert Simon
Arthur Samuel
Oliver Selfridge
Nathaniel Rochester
Trenchard More

1956 1960 1970 1980 1990 2000 2010 **Time**

First wave AI: Model-based

"Think through the entire problem"





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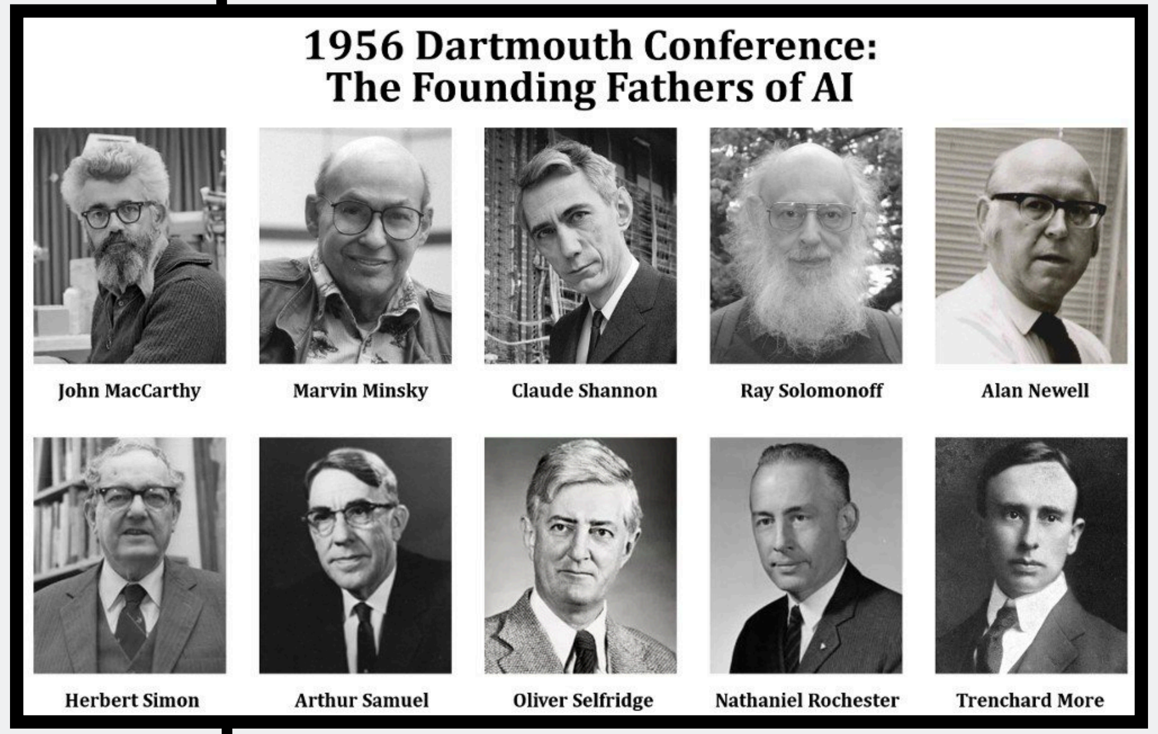

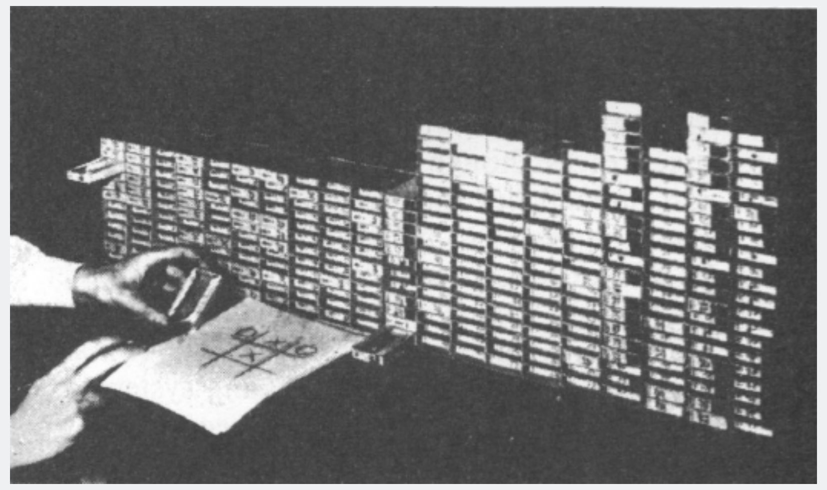

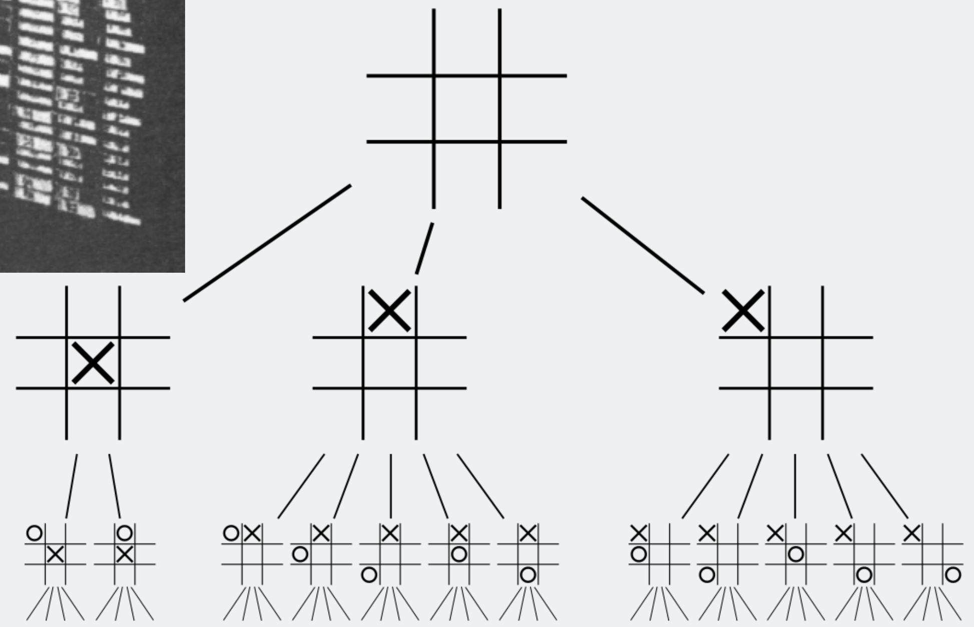

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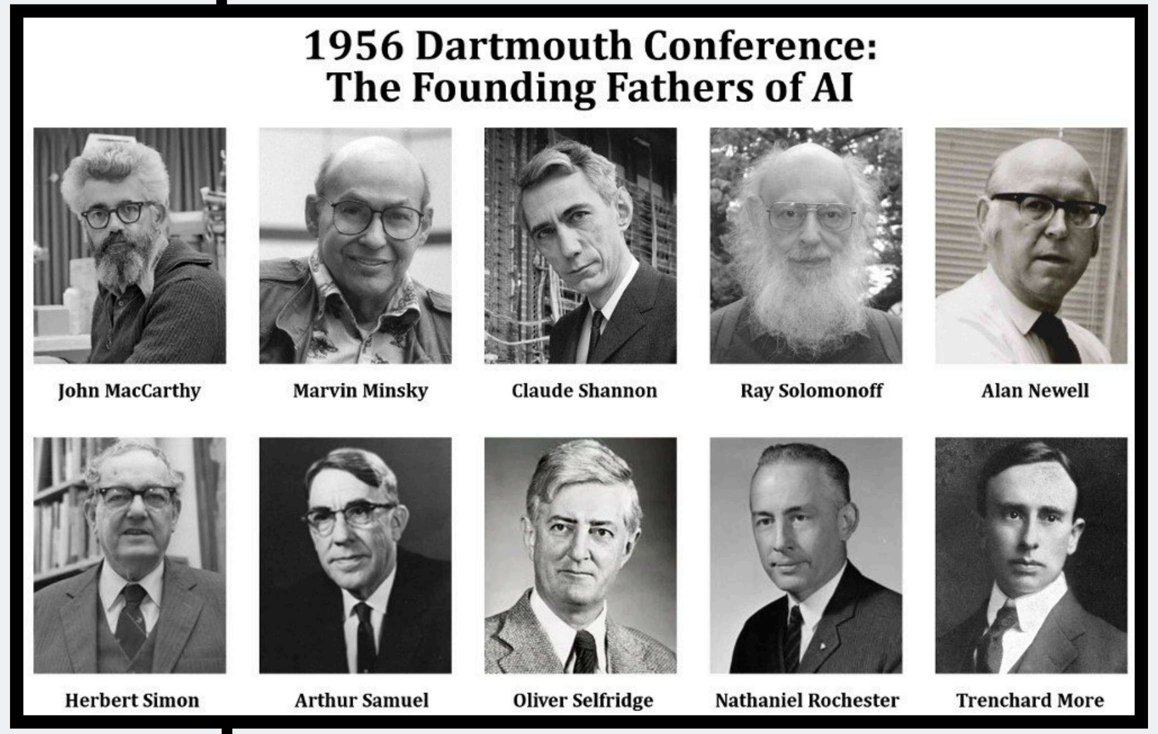

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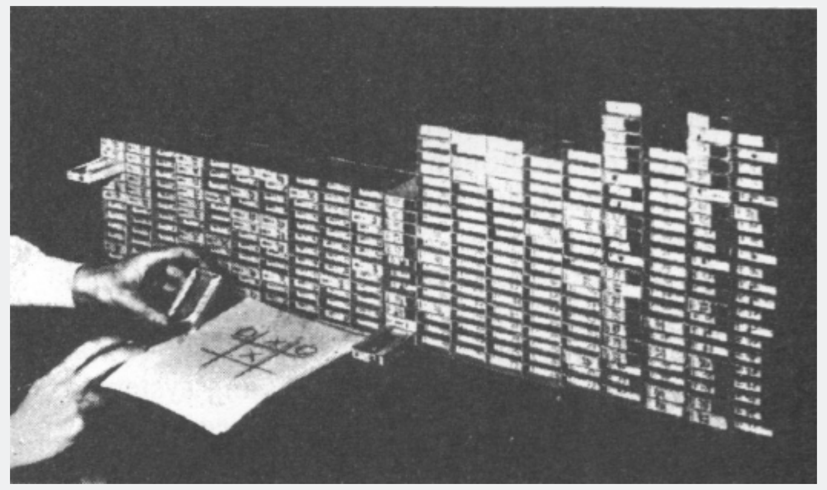
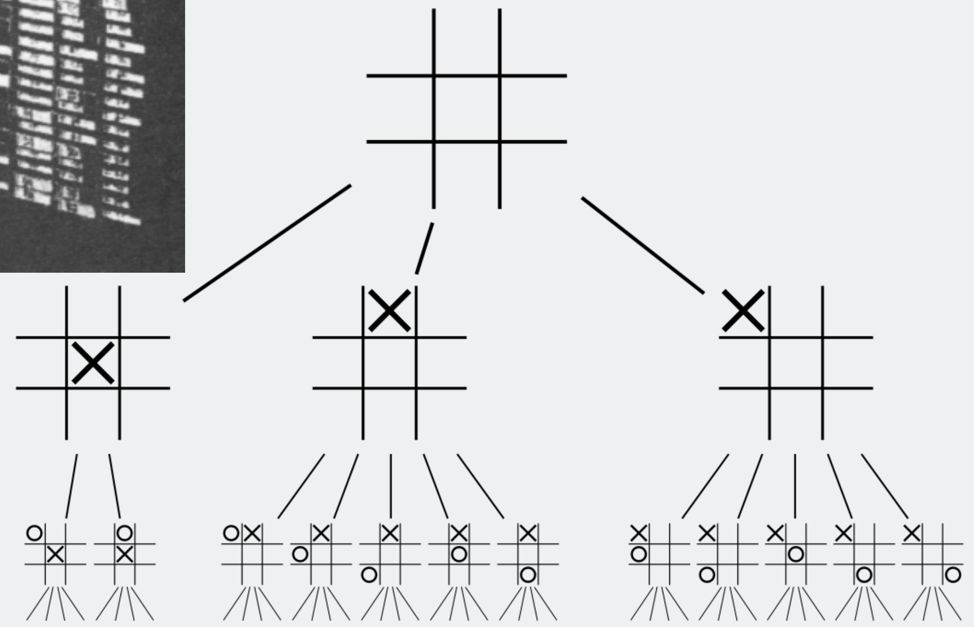
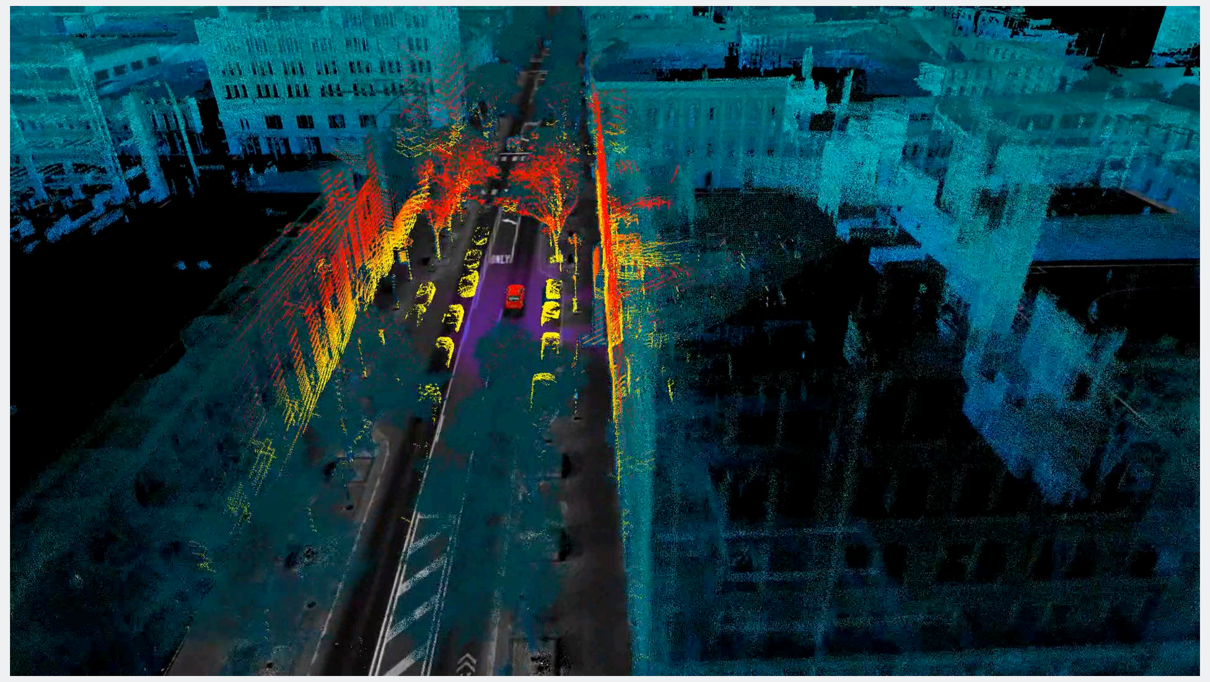


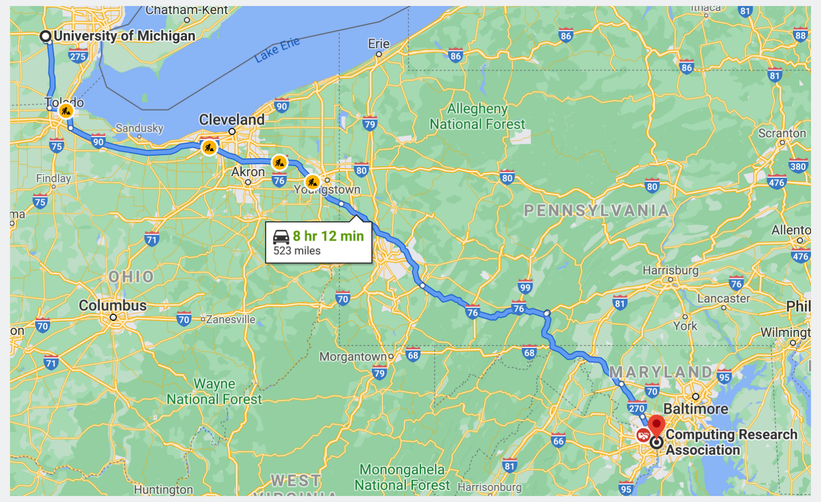


City-scale 3D mapping



Self-driving cars

Online route navigation



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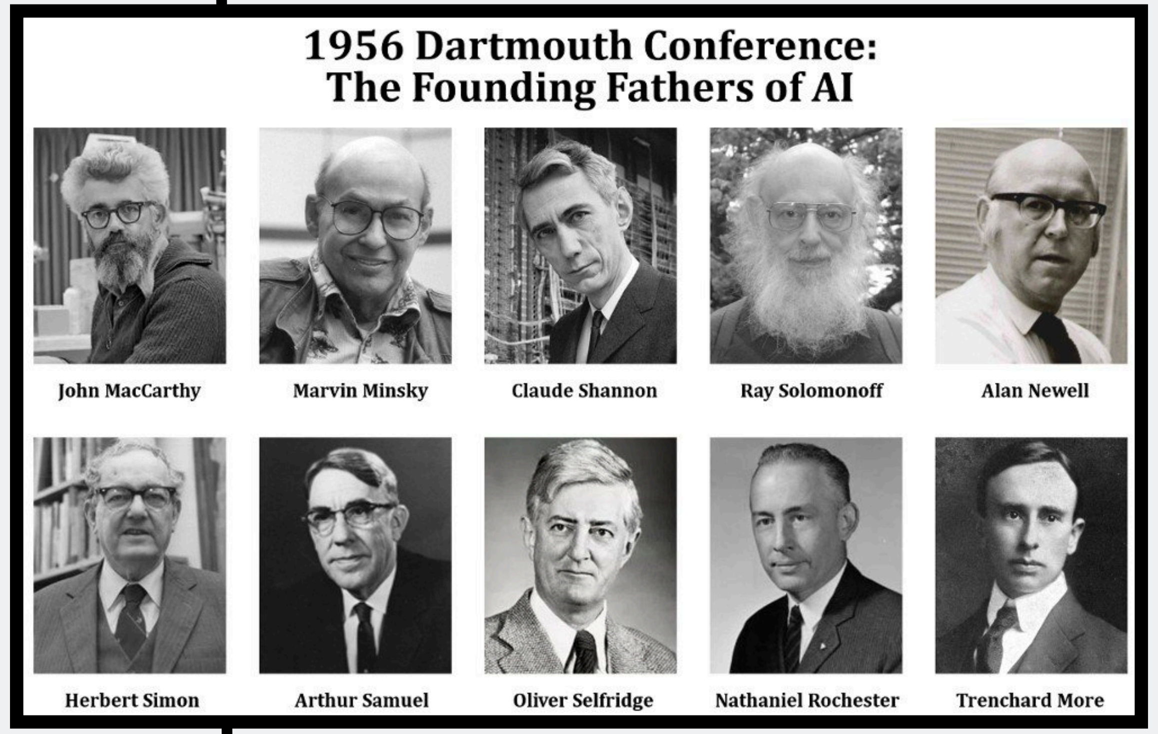

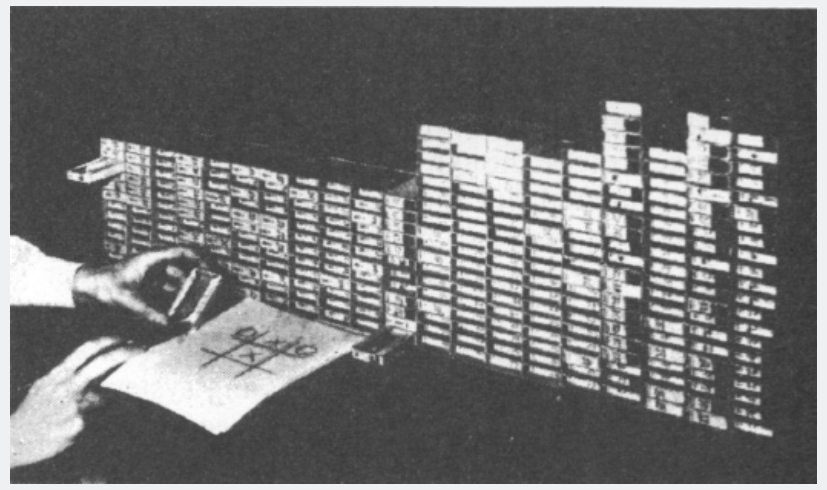

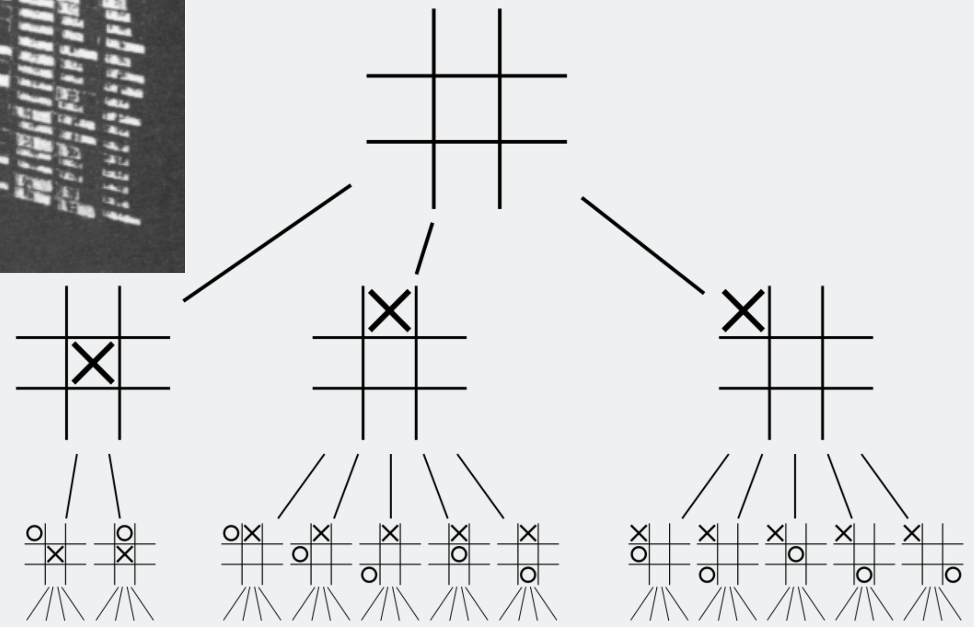

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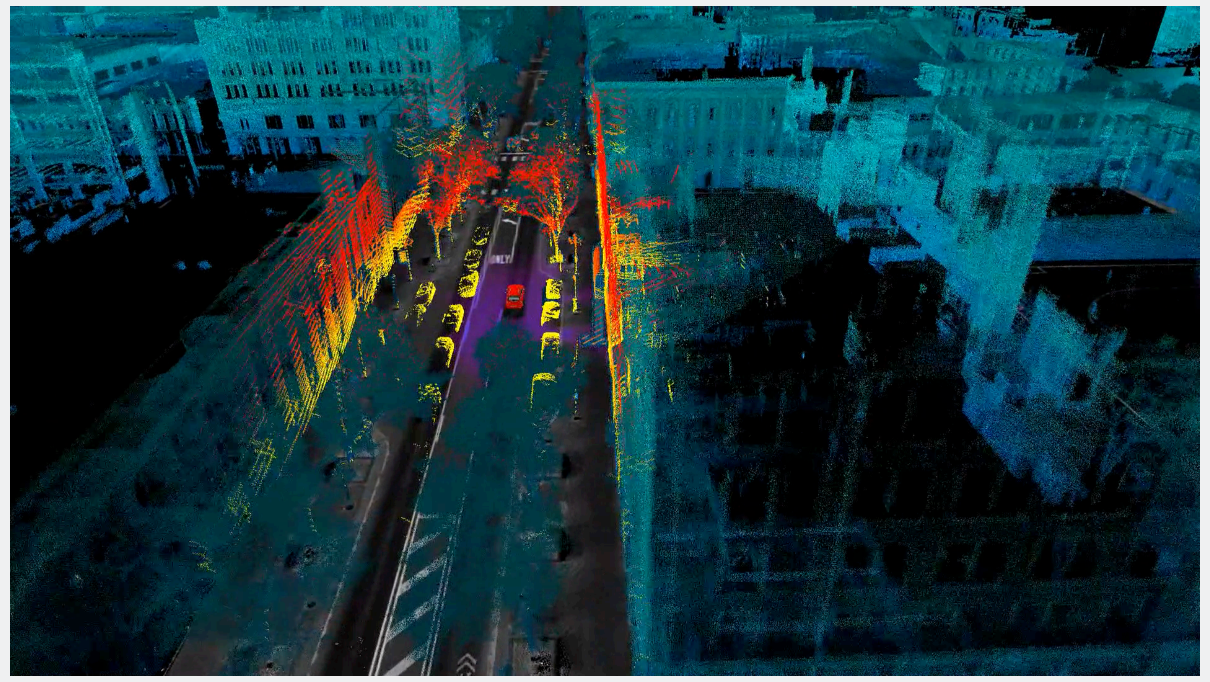

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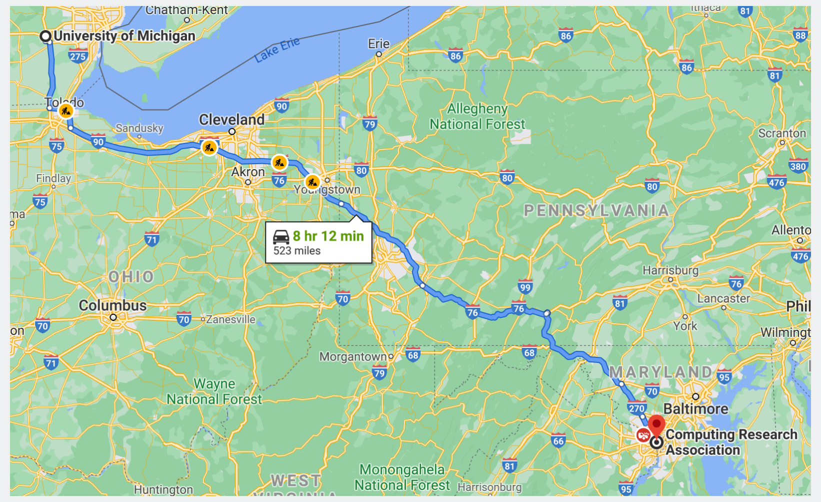

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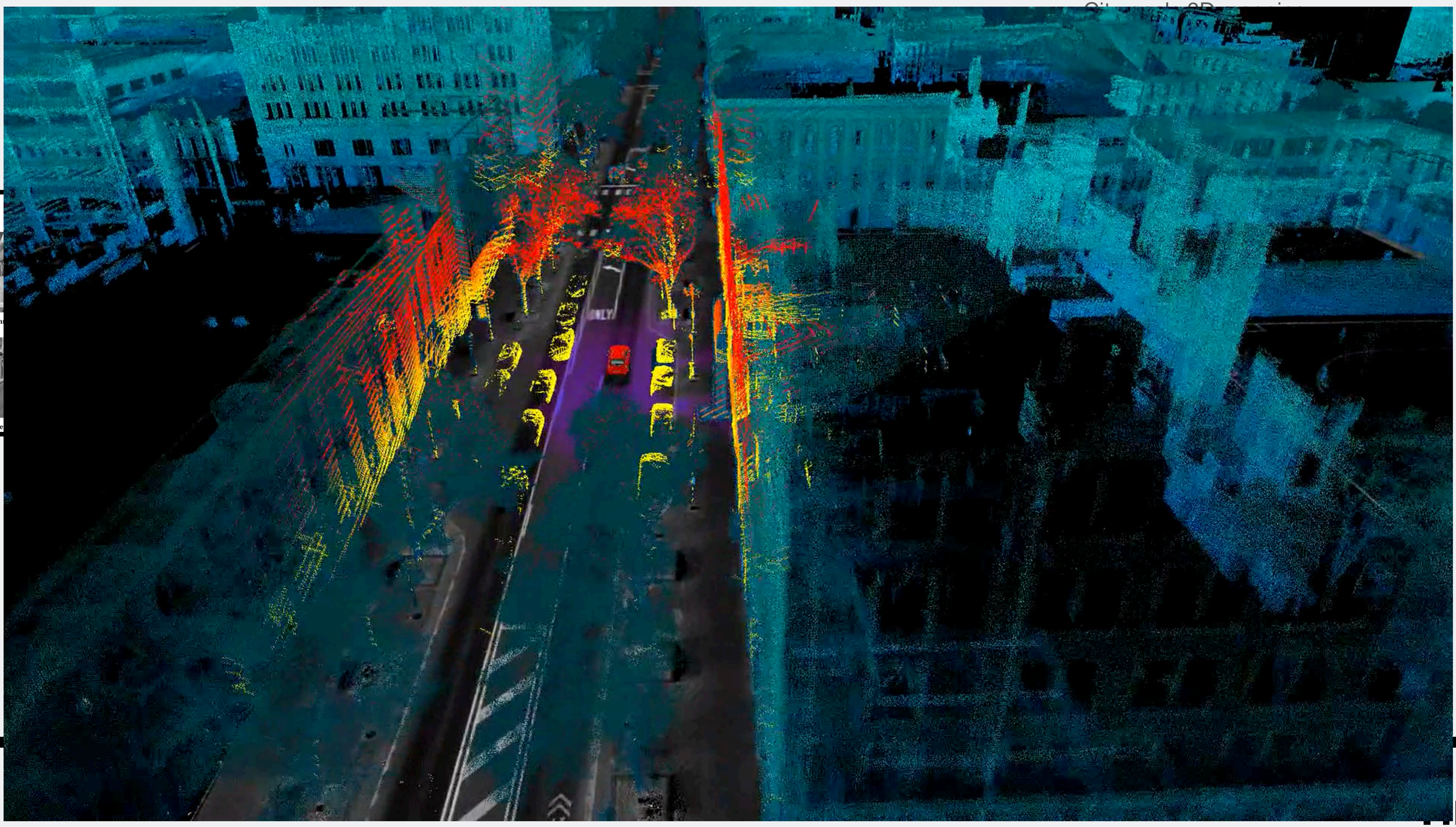
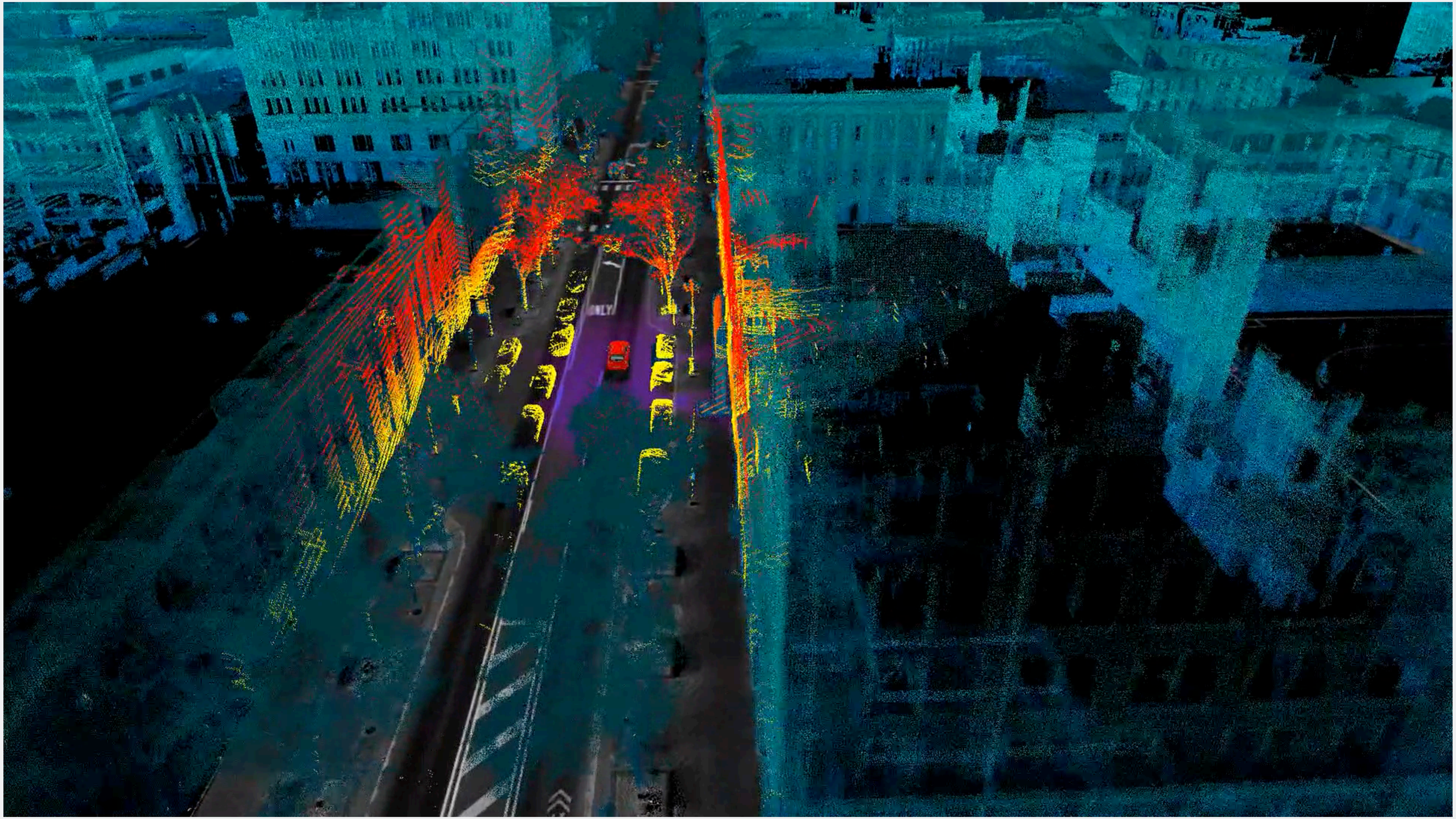


me

Let’s watch this video closely



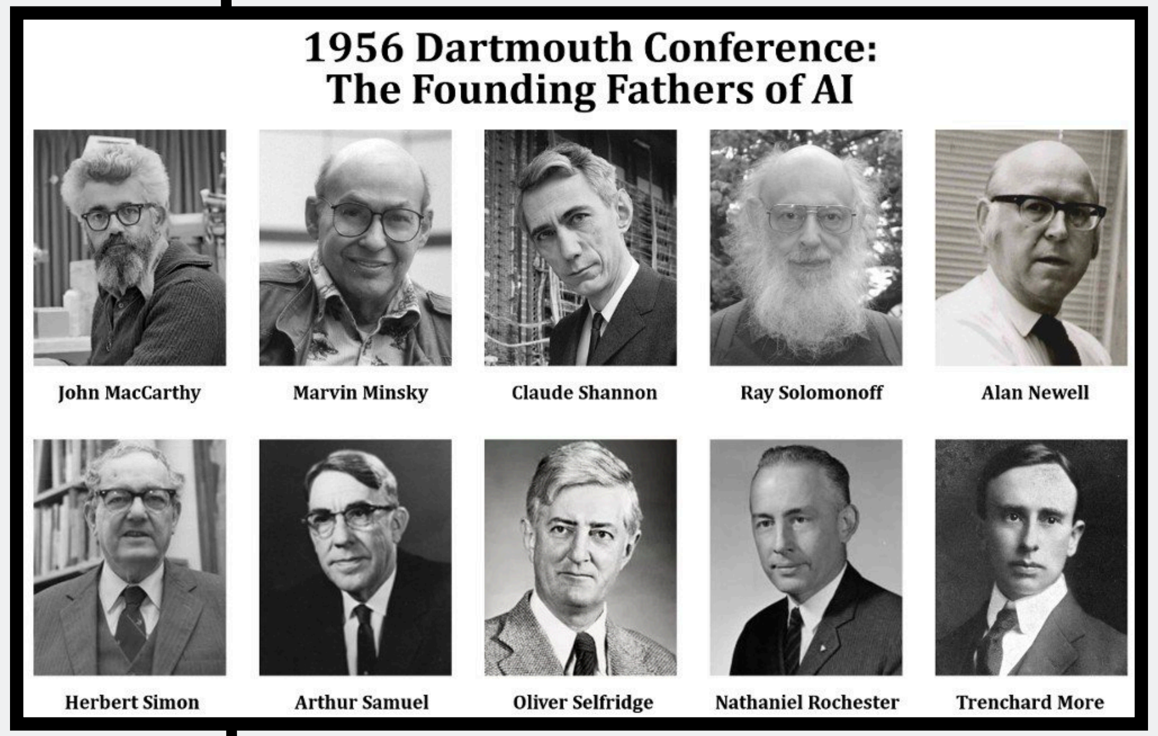
Let’s watch this video closely

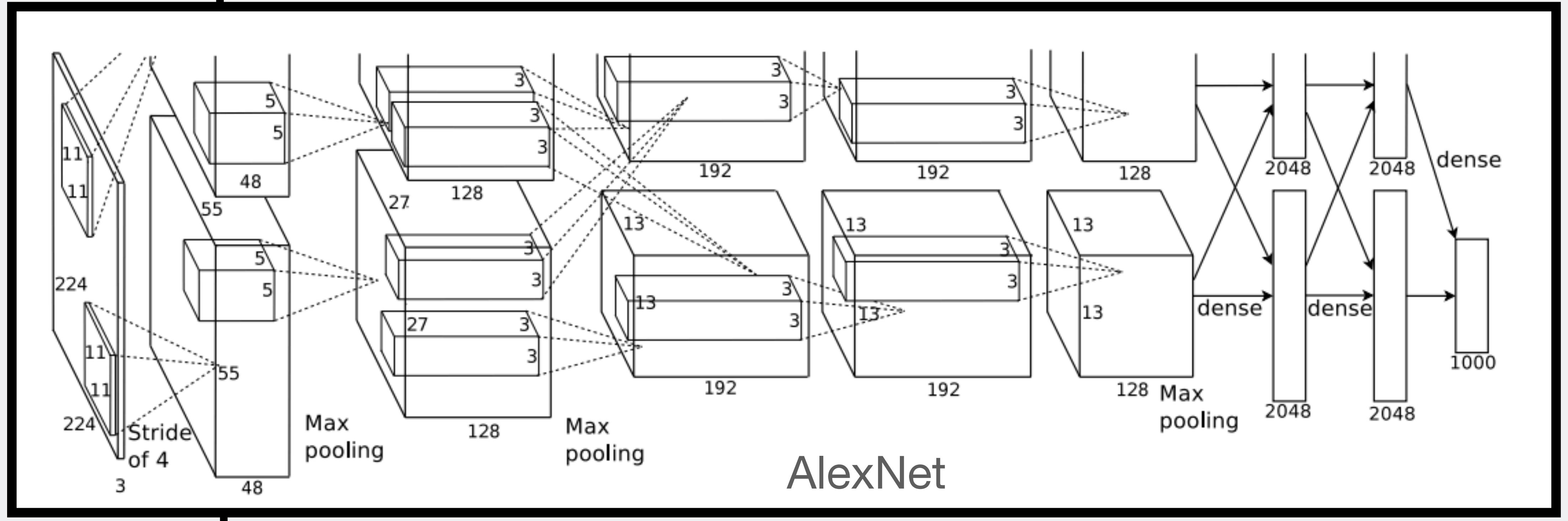
First wave AI: Model-based

“Think through the entire problem”

Second wave AI: Data-driven

“Learn from lots of data”





AlexNet

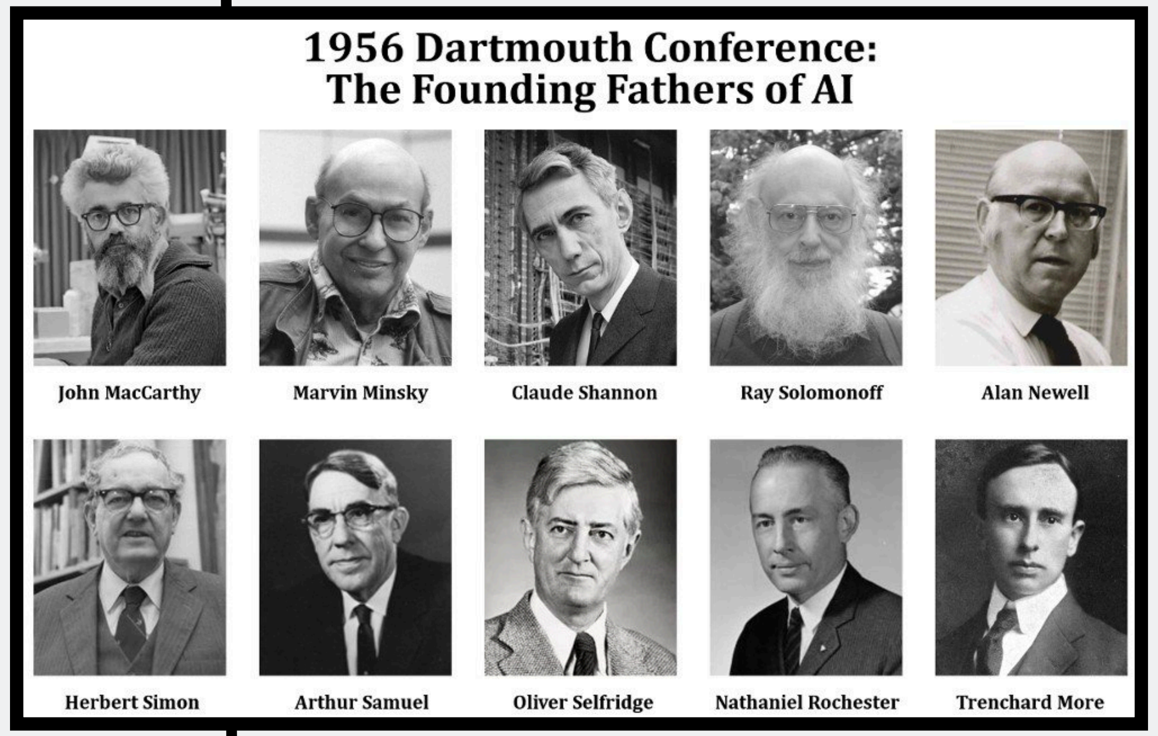
1956

2011

Time

First wave AI: Model-based

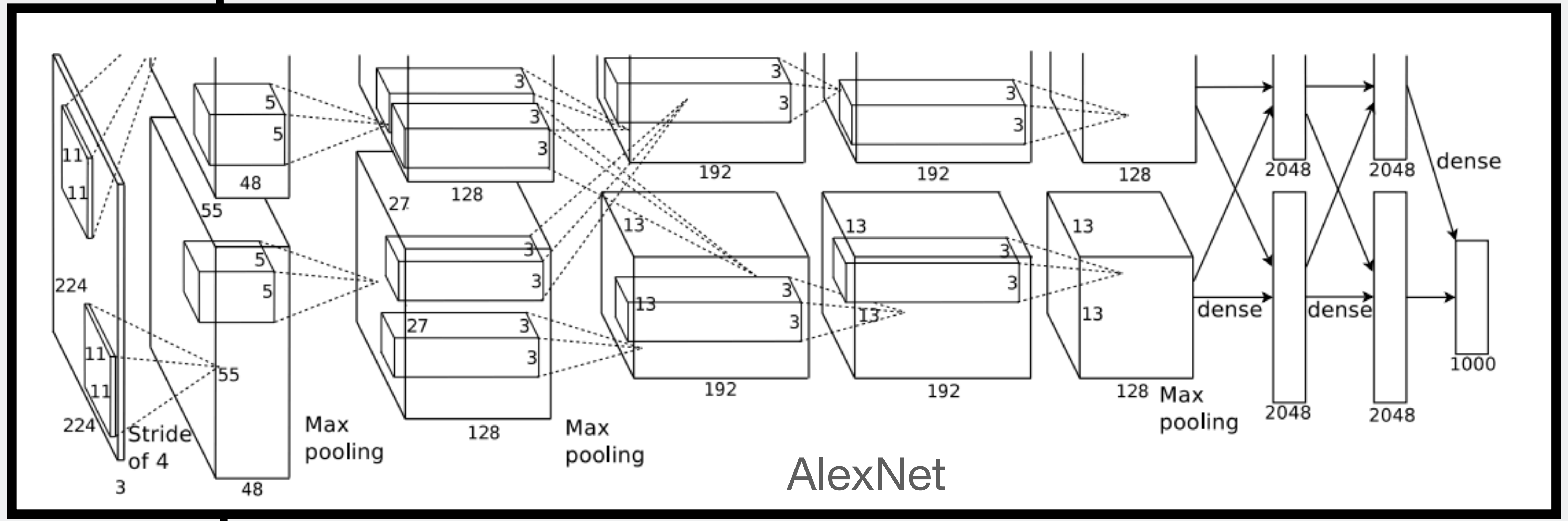
“Think through the entire problem”



Second wave AI: Data-driven

“Learn from lots of data”

Rise of “deep learning"



1956

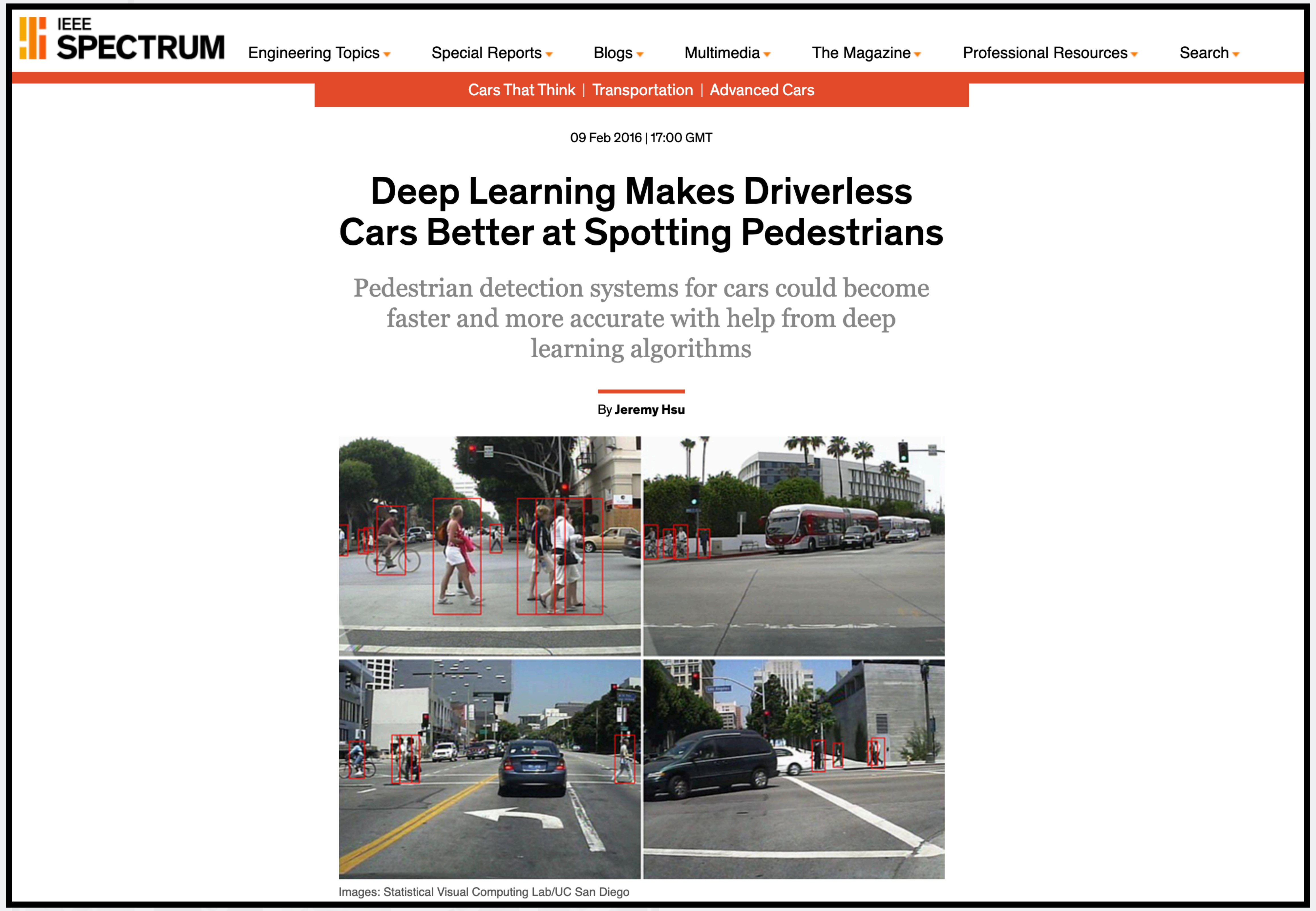
2011

Time

First wave AI: Model-based

Second wave AI: Data-driven

“Learn from lots of data”



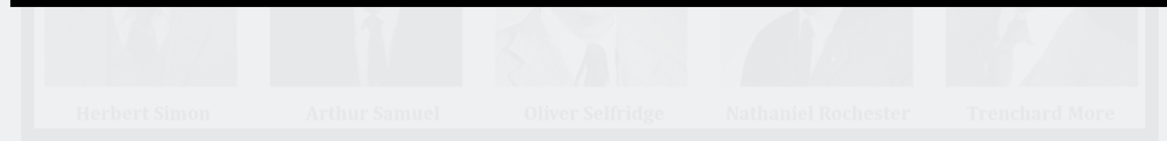
09 Feb 2016 | 17:00 GMT

Deep Learning Makes Driverless Cars Better at Spotting Pedestrians

Pedestrian detection systems for cars could become faster and more accurate with help from deep learning algorithms

By **Jeremy Hsu**

Images: Statistical Visual Computing Lab/UC San Diego



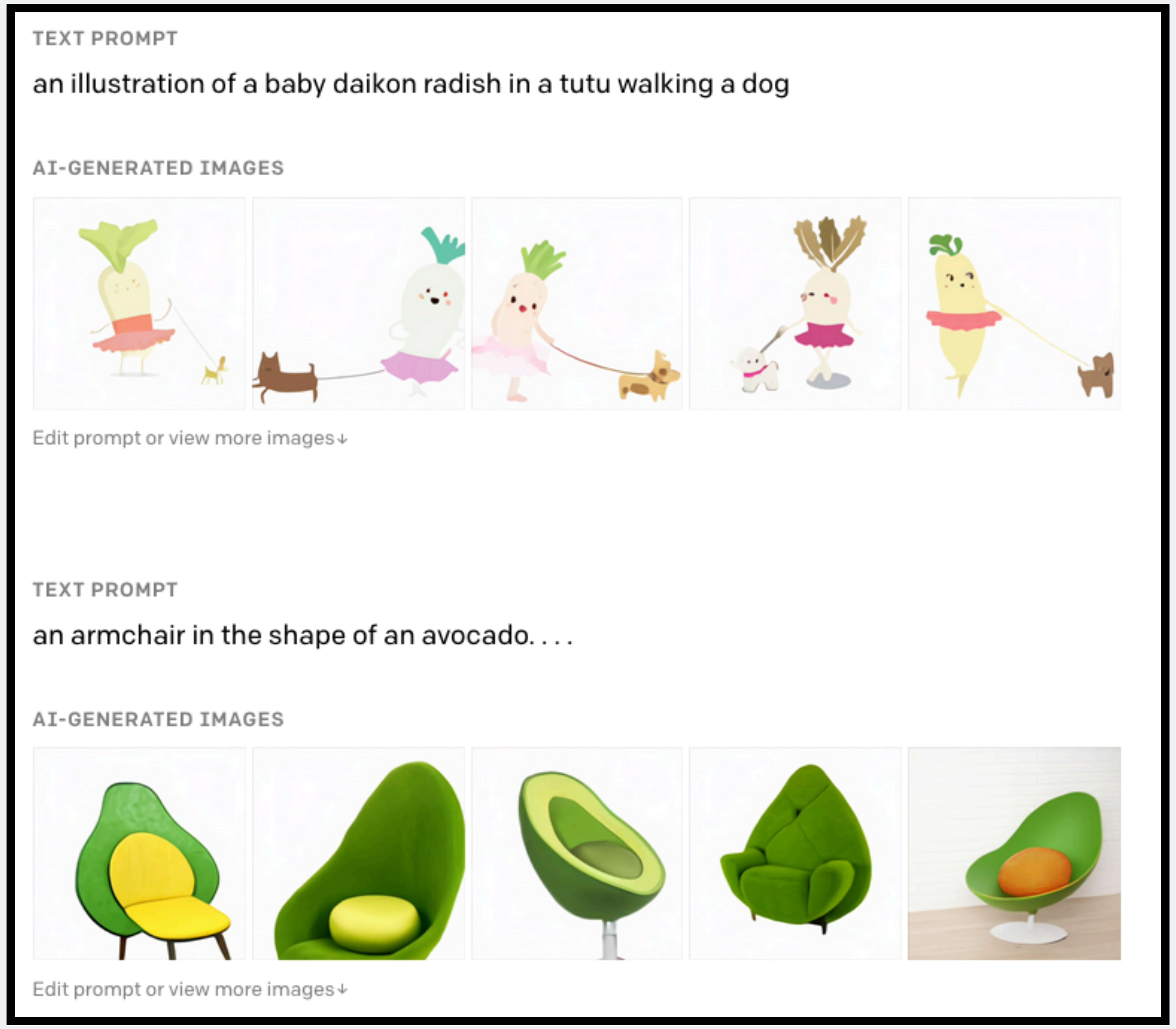
“deep learning"

1956

2011

Time

Second wave AI: Data-driven



TEXT PROMPT

an illustration of a baby daikon radish in a tutu walking a dog

AI-GENERATED IMAGES

Edit prompt or view more images↓

TEXT PROMPT

an armchair in the shape of an avocado. . . .

AI-GENERATED IMAGES

Edit prompt or view more images↓

DALL-E (OpenAI)

“Learn from lots of data”

“deep learning"

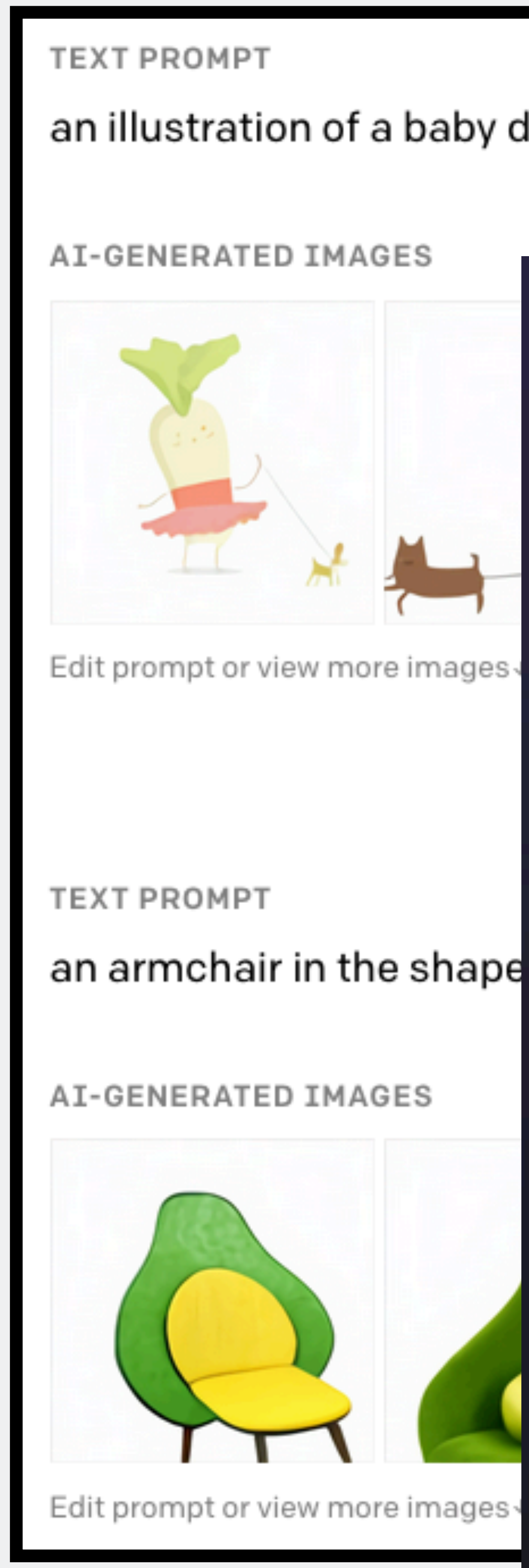
2011

Time

Second wave AI: Data-driven

“Learn from lots of data”

“deep learning"



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an armchair in the shape

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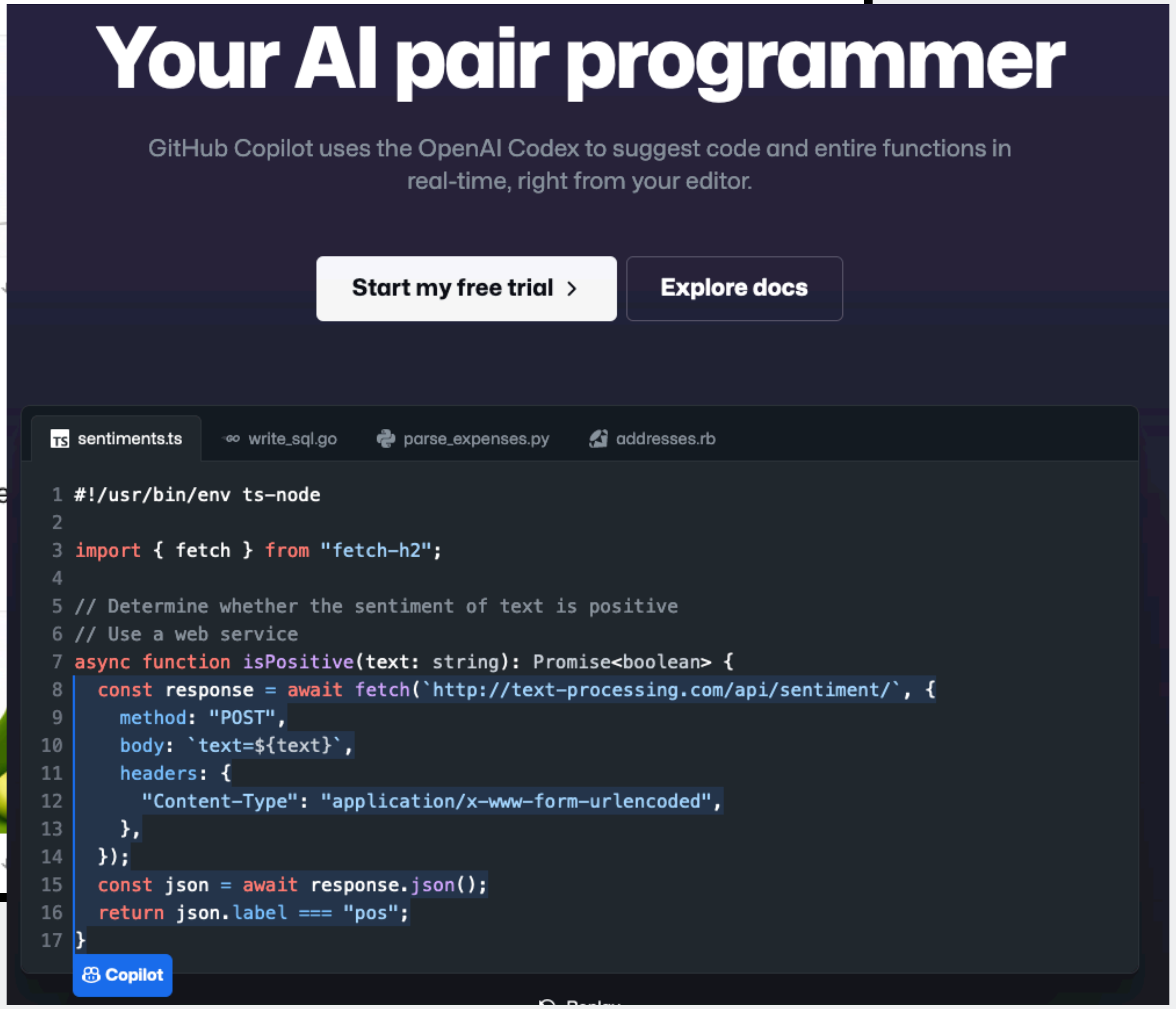


Your AI pair programmer

GitHub Copilot uses the OpenAI Codex to suggest code and entire functions in real-time, right from your editor.

```
#!/usr/bin/env ts-node

import { fetch } from "fetch-h2";

// Determine whether the sentiment of text is positive
// Use a web service
async function isPositive(text: string): Promise<boolean> {
  const response = await fetch(`http://text-processing.com/api/sentiment/`, {
    method: "POST",
    body: `text=${text}`,
    headers: {
      "Content-Type": "application/x-www-form-urlencoded",
    },
  });
  const json = await response.json();
  return json.label === "pos";
}
```

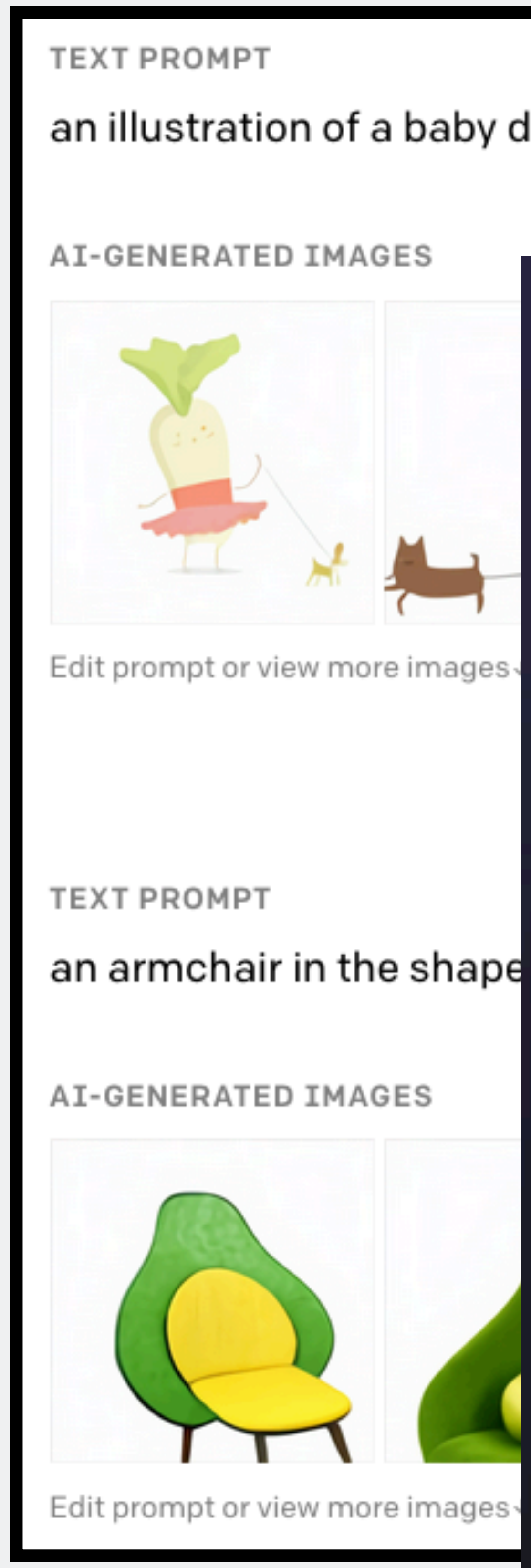
Copilot (OpenAI)

2011

Time

Second wave AI: Data-driven

“Learn from lots of data”



TEXT PROMPT

an illustration of a baby daikon radish in a tutu walking a dog

AI-GENERATED IMAGES

Edit prompt or view more images

TEXT PROMPT

an armchair in the shape

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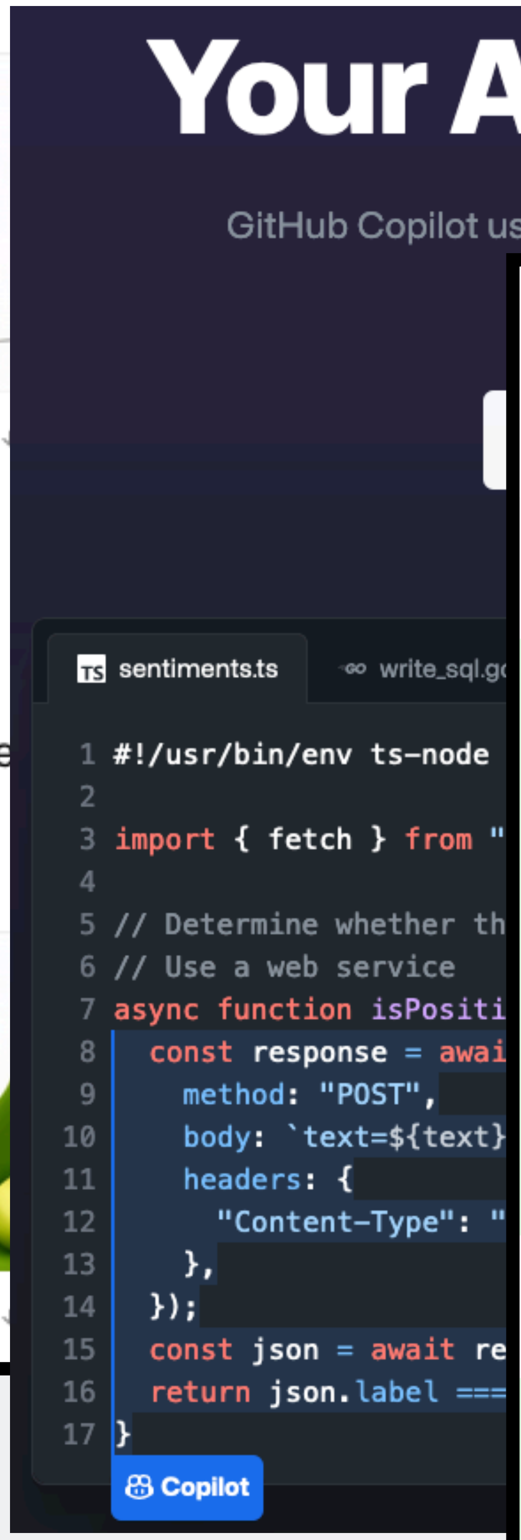

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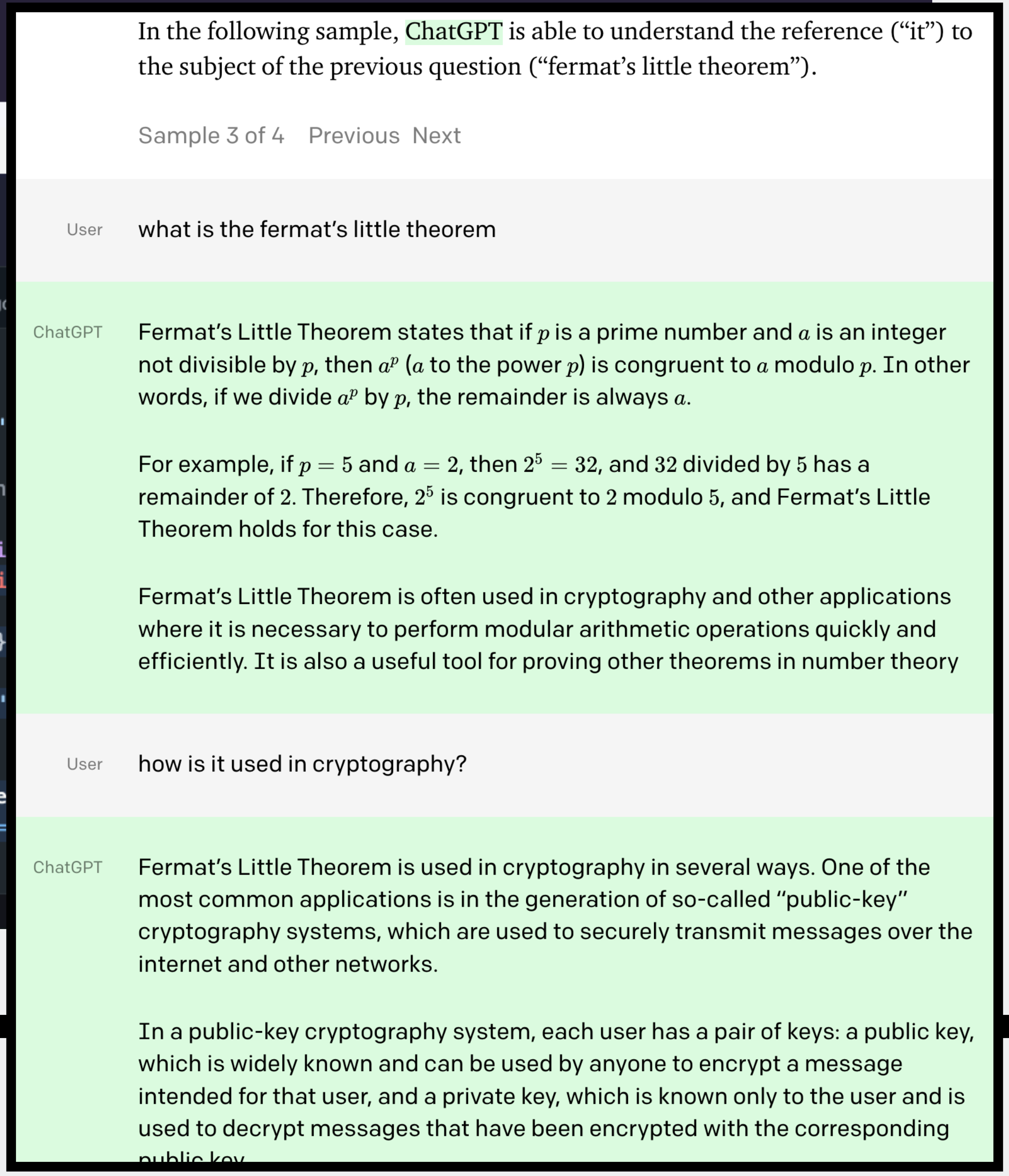
```
#!/usr/bin/env ts-node

import { fetch } from "

// Determine whether th
// Use a web service
async function isPositi
  const response = awai
    method: "POST",
    body: `text=${text}
    headers: {
      "Content-Type": "
    },
  });
  const json = await re
  return json.label ===
}
```

Copilot (OpenAI)



In the following sample, ChatGPT is able to understand the reference (“it”) to the subject of the previous question (“fermat’s little theorem”).

User what is the fermat’s little theorem

ChatGPT Fermat’s Little Theorem states that if p is a prime number and a is an integer not divisible by p, then a^p (a to the power p) is congruent to a modulo p. In other words, if we divide a^p by p, the remainder is always a.

For example, if $p = 5$ and $a = 2$, then $2^5 = 32$, and 32 divided by 5 has a remainder of 2. Therefore, 2^5 is congruent to 2 modulo 5, and Fermat’s Little Theorem holds for this case.

Fermat’s Little Theorem is often used in cryptography and other applications where it is necessary to perform modular arithmetic operations quickly and efficiently. It is also a useful tool for proving other theorems in number theory

User how is it used in cryptography?

ChatGPT Fermat’s Little Theorem is used in cryptography in several ways. One of the most common applications is in the generation of so-called “public-key” cryptography systems, which are used to securely transmit messages over the internet and other networks.

In a public-key cryptography system, each user has a pair of keys: a public key, which is widely known and can be used by anyone to encrypt a message intended for that user, and a private key, which is known only to the user and is used to decrypt messages that have been encrypted with the corresponding public key.

ChatGPT (OpenAI)

“deep learning"

2011

Time

The AI of today needed decades of investment and research

Vol. VI, No. 2, Summer 1958

research trends

CORNELL AERONAUTICAL LABORATORY, INC., BUFFALO 21, NEW YORK

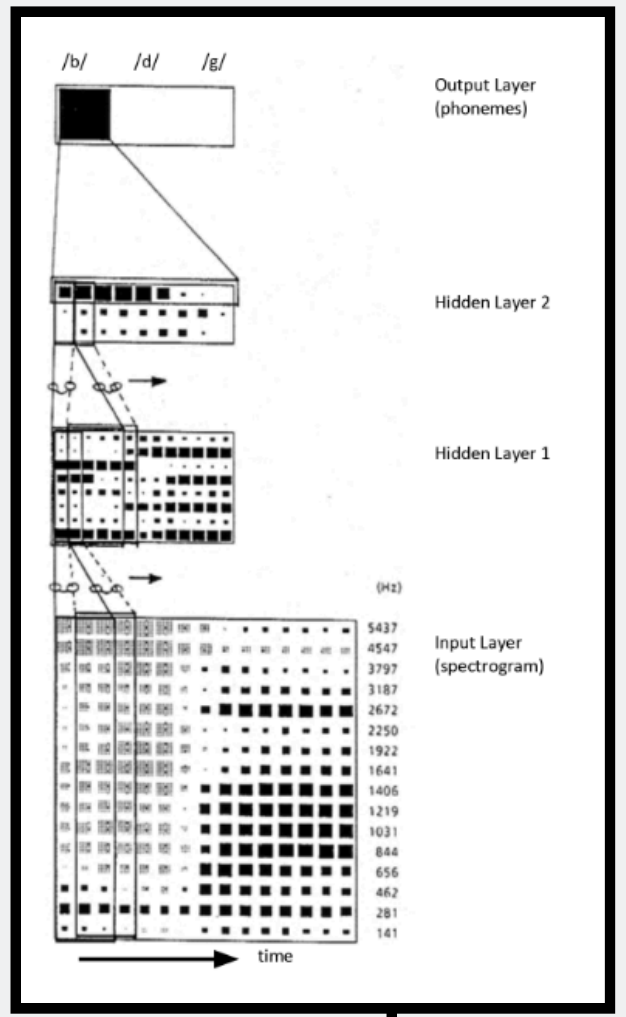
The Design of an Intelligent AUTOMATON

by FRANK ROSENBLATT

Introducing the perceptron — A machine which senses, recognizes, remembers, and responds like the human mind.

Rosenblatt's Perceptron

Speech recognition by neural networks



Waibel et al.

1956

1958

1989

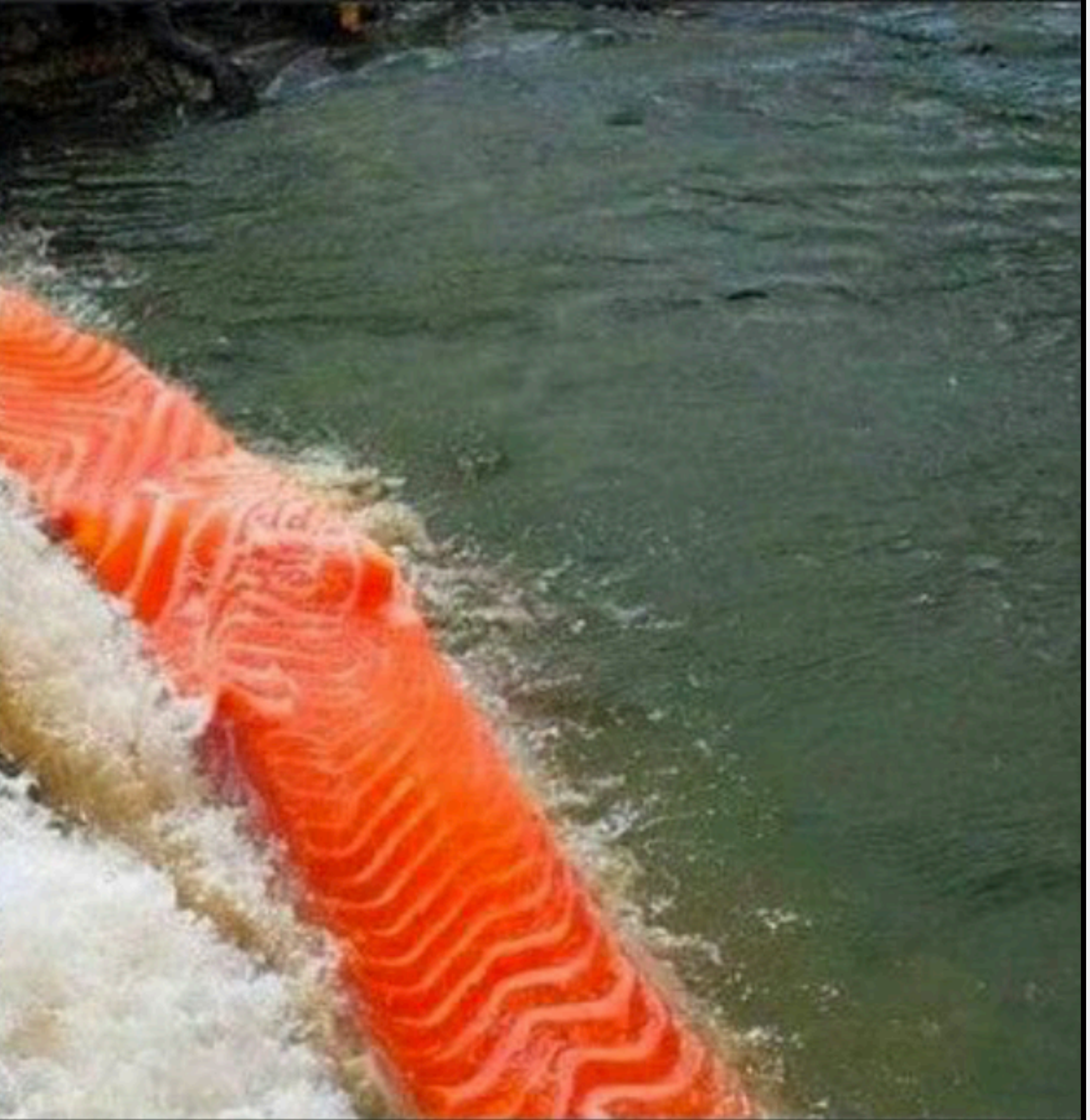
2011

Time

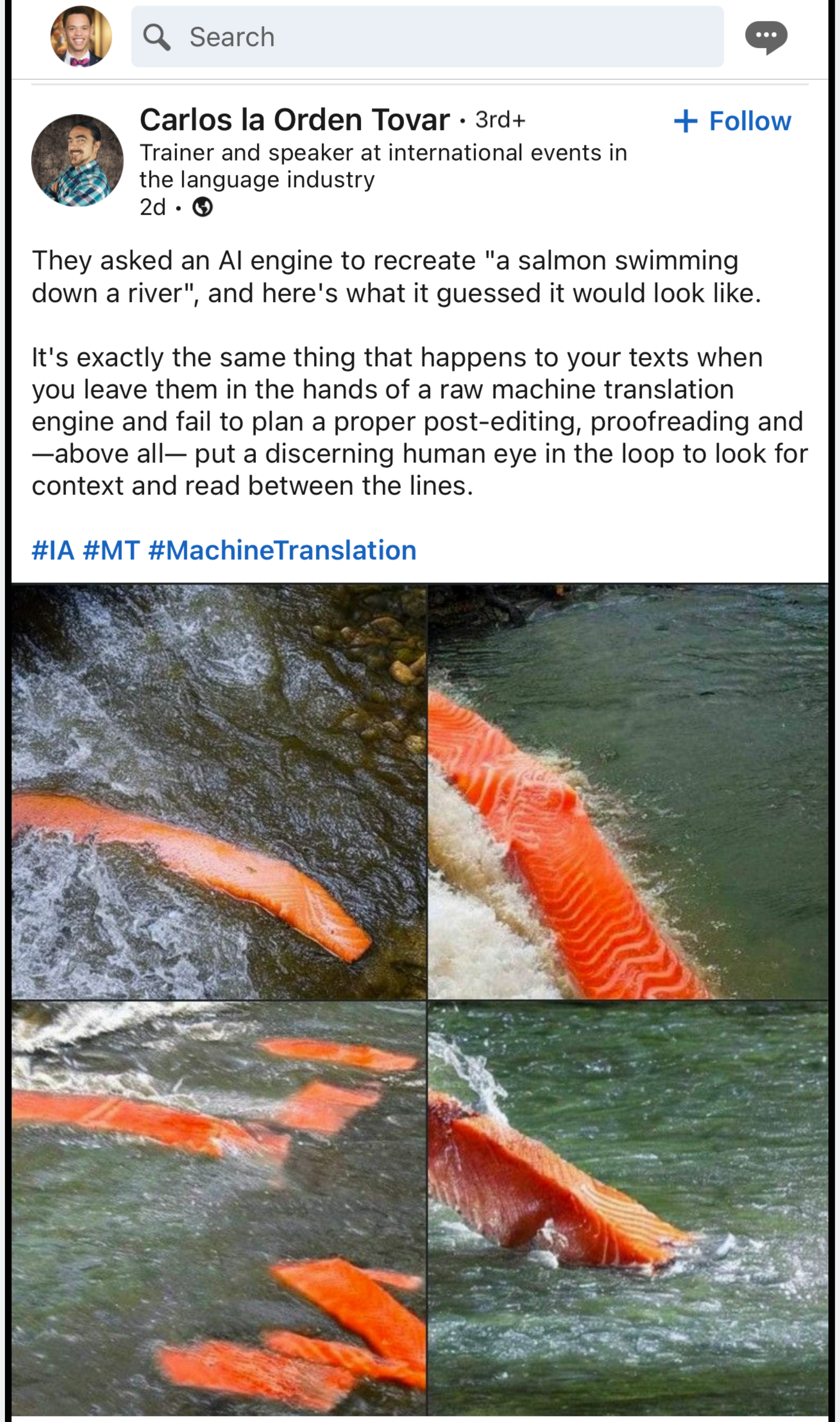
Second wave AI: Data-driven

"Learn from lots of data"

"deep learning"



What is this?



Carlos la Orden Tovar · 3rd+
Trainer and speaker at international events in the language industry
2d ·

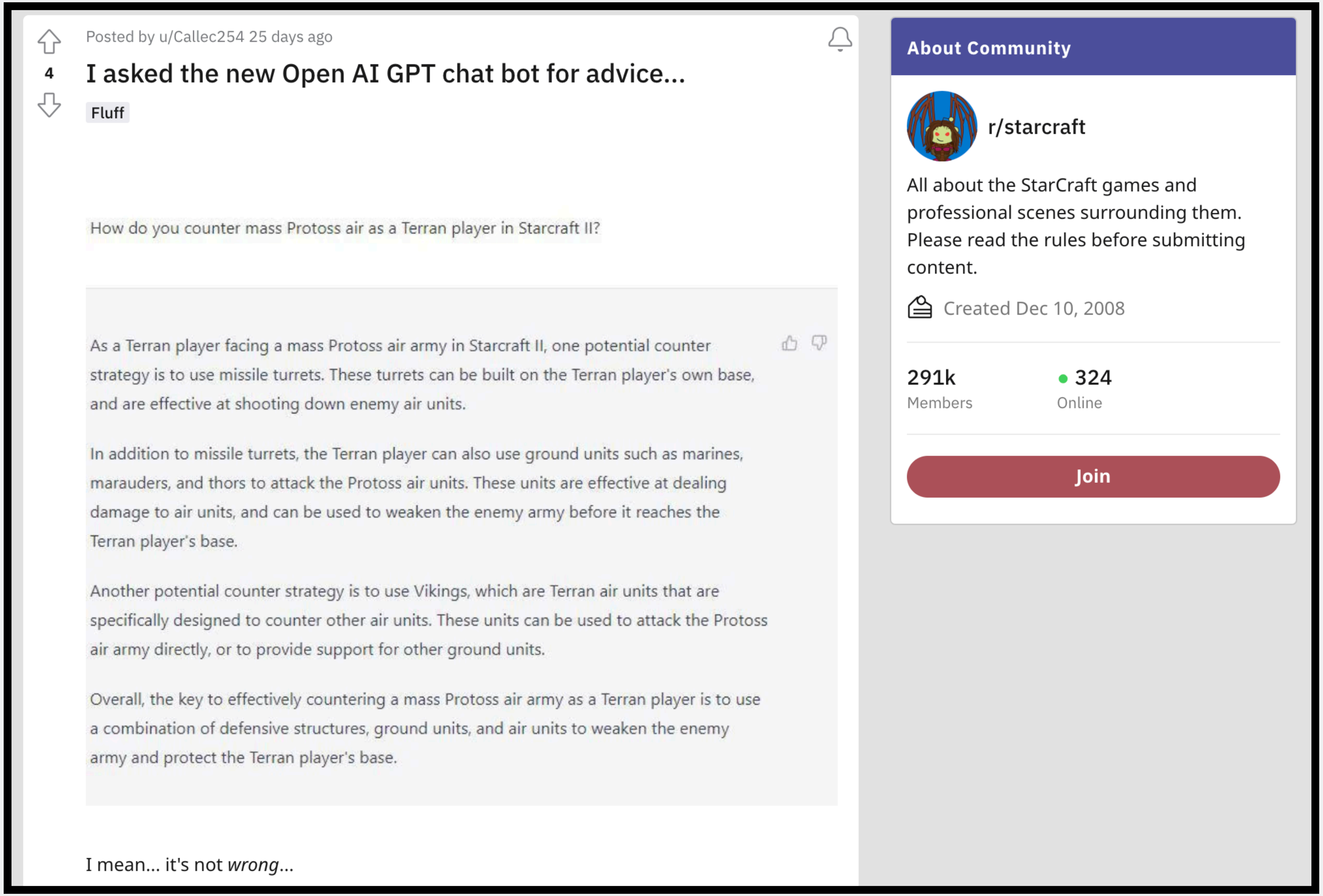
They asked an AI engine to recreate "a salmon swimming down a river", and here's what it guessed it would look like.

It's exactly the same thing that happens to your texts when you leave them in the hands of a raw machine translation engine and fail to plan a proper post-editing, proofreading and —above all— put a discerning human eye in the loop to look for context and read between the lines.

#IA #MT #MachineTranslation

Be mindful about how you use AI

"a salmon swimming down a river"



Posted by u/Callec254 25 days ago

4

I asked the new Open AI GPT chat bot for advice...

Fluff

How do you counter mass Protoss air as a Terran player in Starcraft II?

As a Terran player facing a mass Protoss air army in Starcraft II, one potential counter strategy is to use missile turrets. These turrets can be built on the Terran player's own base, and are effective at shooting down enemy air units.

In addition to missile turrets, the Terran player can also use ground units such as marines, marauders, and thors to attack the Protoss air units. These units are effective at dealing damage to air units, and can be used to weaken the enemy army before it reaches the Terran player's base.

Another potential counter strategy is to use Vikings, which are Terran air units that are specifically designed to counter other air units. These units can be used to attack the Protoss air army directly, or to provide support for other ground units.

Overall, the key to effectively countering a mass Protoss air army as a Terran player is to use a combination of defensive structures, ground units, and air units to weaken the enemy army and protect the Terran player's base.

I mean... it's not *wrong*...

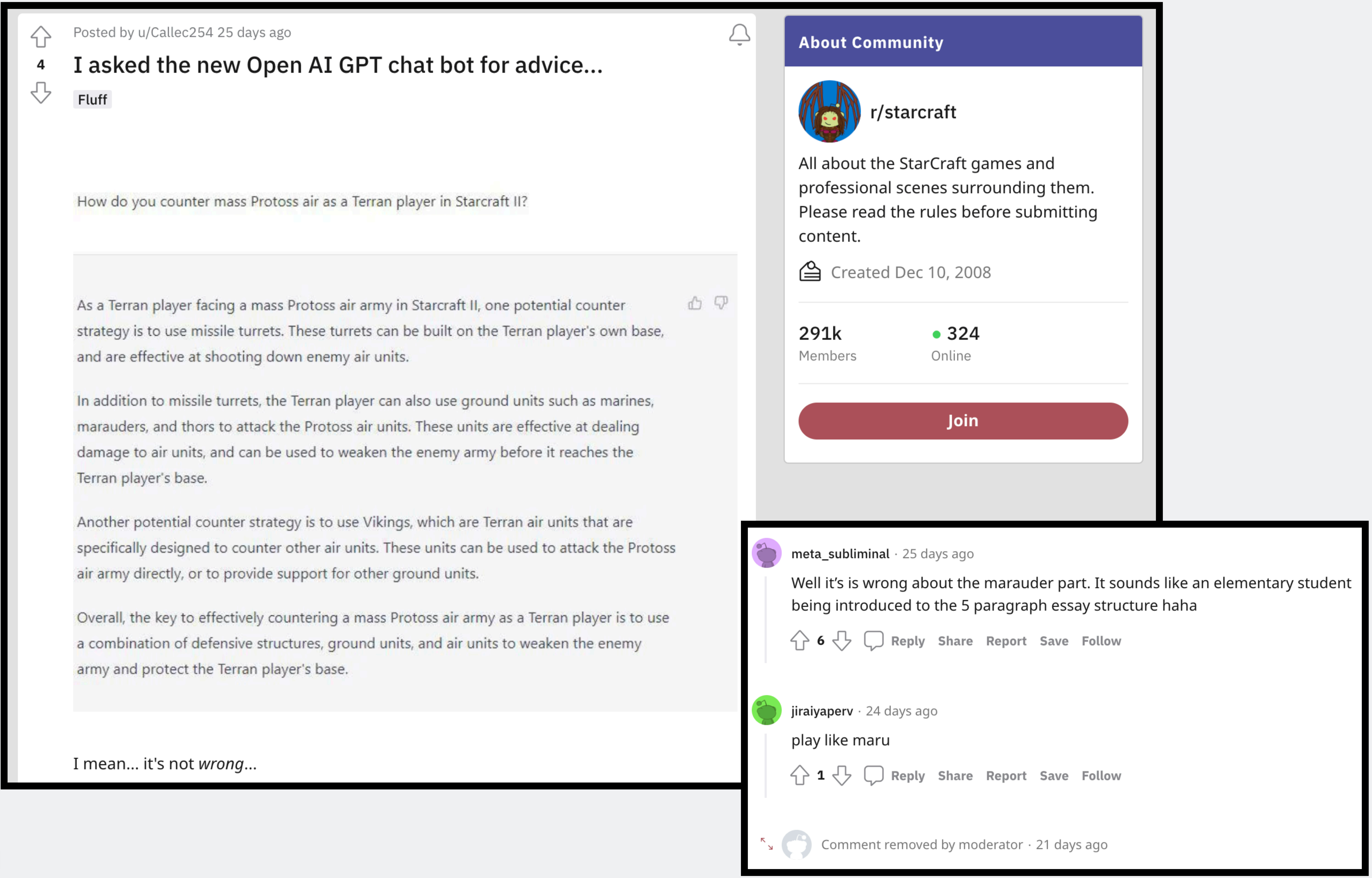
About Community

r/starcraft

All about the StarCraft games and professional scenes surrounding them. Please read the rules before submitting content.

Created Dec 10, 2008

291k	324
Members	Online



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How do you counter mass Protoss air as a Terran player in Starcraft II?

As a Terran player facing a mass Protoss air army in Starcraft II, one potential counter strategy is to use missile turrets. These turrets can be built on the Terran player's own base, and are effective at shooting down enemy air units.

In addition to missile turrets, the Terran player can also use ground units such as marines, marauders, and thors to attack the Protoss air units. These units are effective at dealing damage to air units, and can be used to weaken the enemy army before it reaches the Terran player's base.

Another potential counter strategy is to use Vikings, which are Terran air units that are specifically designed to counter other air units. These units can be used to attack the Protoss air army directly, or to provide support for other ground units.

Overall, the key to effectively countering a mass Protoss air army as a Terran player is to use a combination of defensive structures, ground units, and air units to weaken the enemy army and protect the Terran player's base.

I mean... it's not *wrong*...

About Community

r/starcraft

All about the StarCraft games and professional scenes surrounding them. Please read the rules before submitting content.

Created Dec 10, 2008

291k Members

● 324 Online

Join

meta_subliminal · 25 days ago

Well it's is wrong about the marauder part. It sounds like an elementary student being introduced to the 5 paragraph essay structure haha

6 Reply Share Report Save Follow

jiraiyaperv · 24 days ago

play like maru

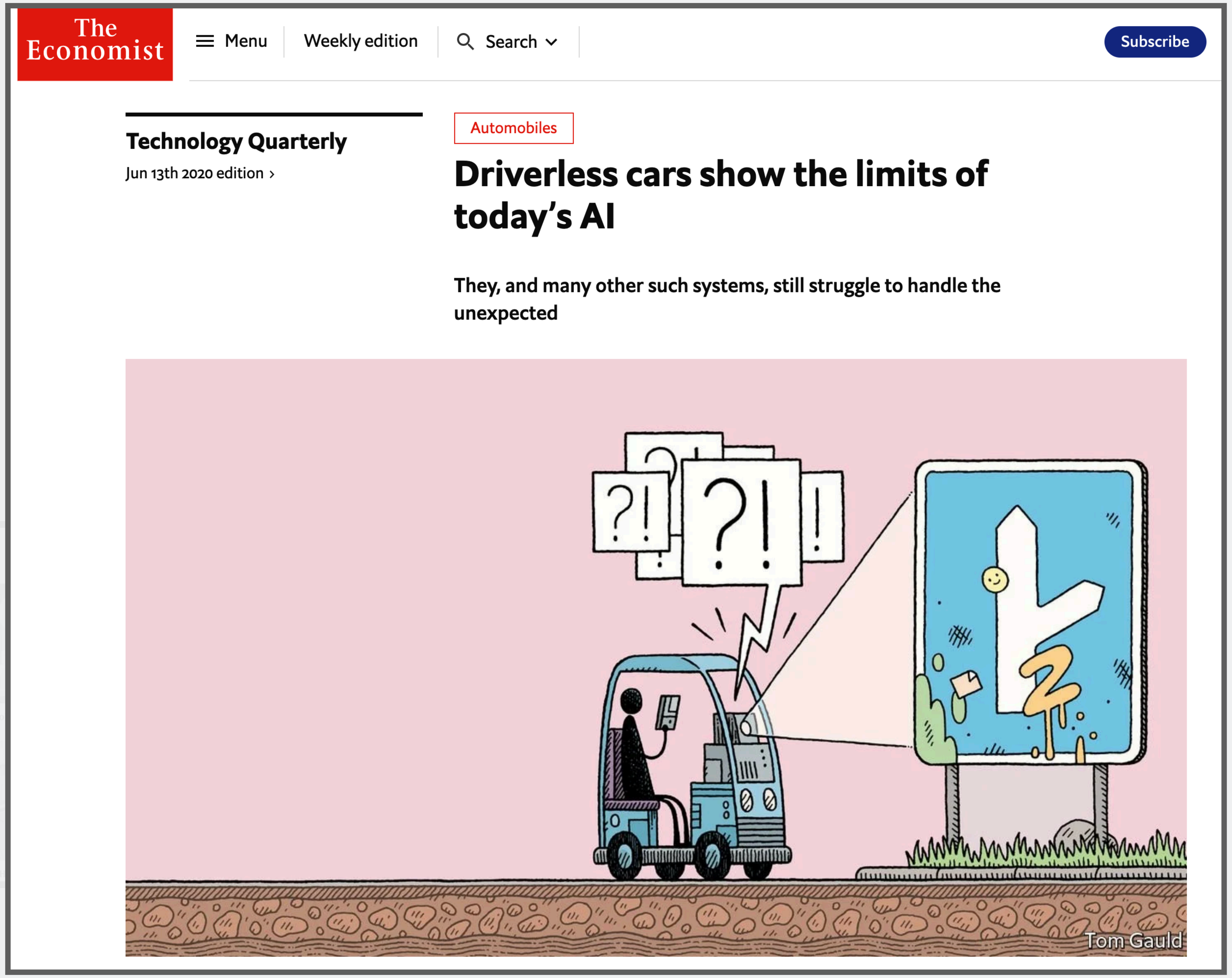
1 Reply Share Report Save Follow

Comment removed by moderator · 21 days ago

First wave AI: Model-based

Second wave AI: Data-driven

“Learn from lots of data”

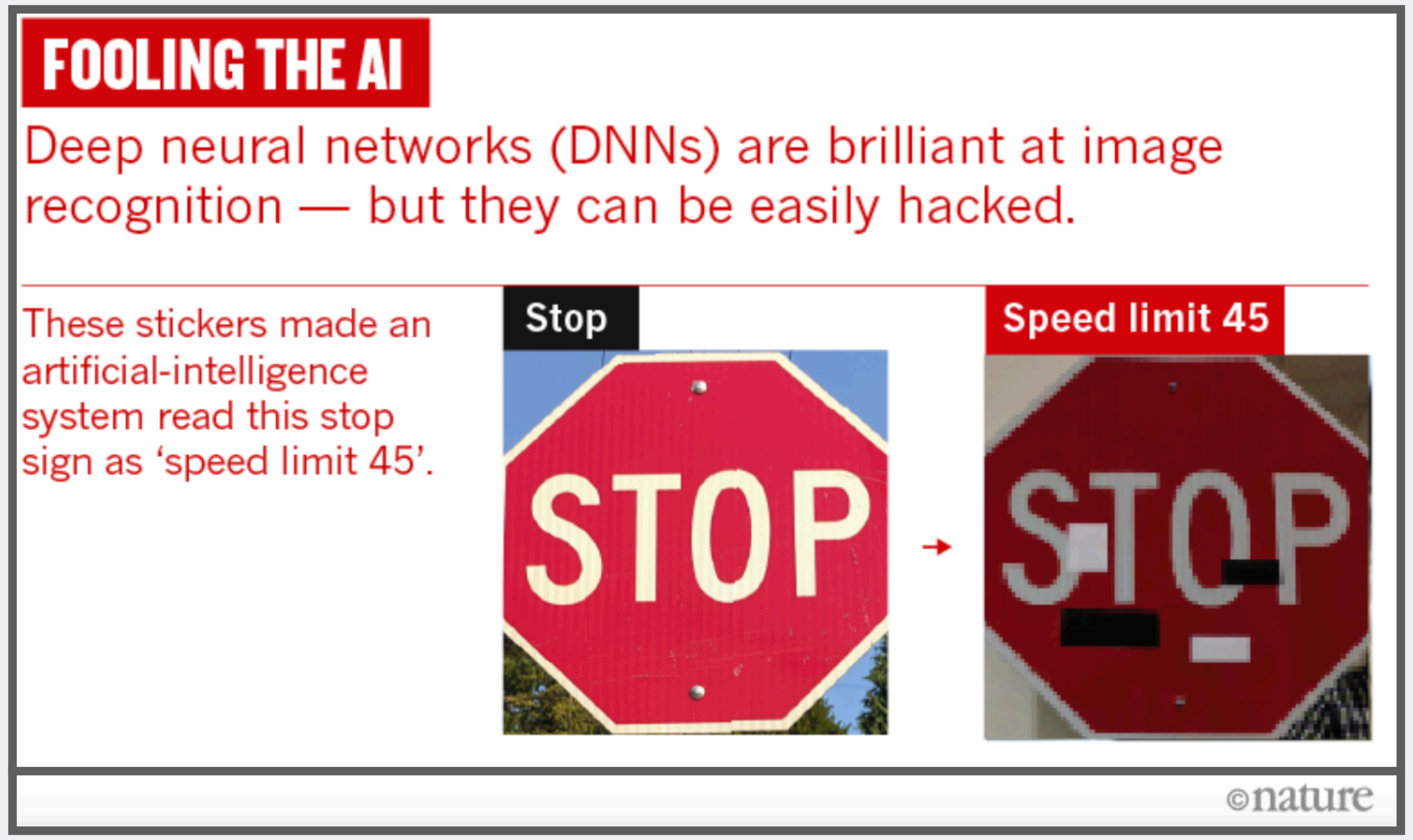


Technology Quarterly
Jun 13th 2020 edition ›

Automobiles

Driverless cars show the limits of today’s AI

They, and many other such systems, still struggle to handle the unexpected



FOOLING THE AI

Deep neural networks (DNNs) are brilliant at image recognition — but they can be easily hacked.

These stickers made an artificial-intelligence system read this stop sign as ‘speed limit 45’.

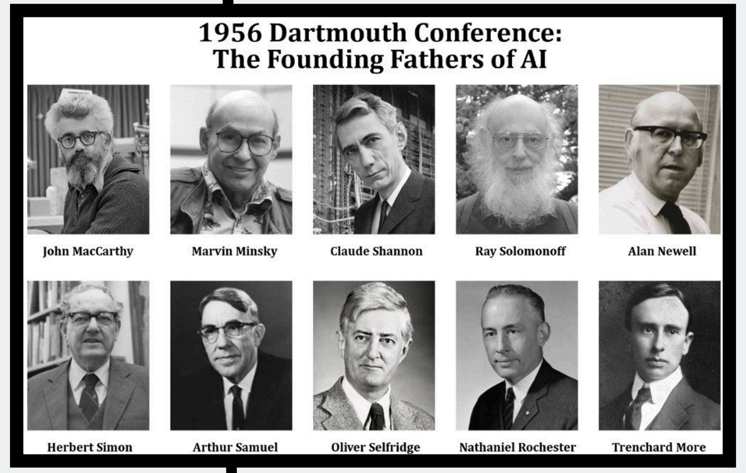
1956

2011

Time

First wave AI: Model-based

“Think through the entire problem”


1956 Dartmouth Conference:
The Founding Fathers of AI

1956

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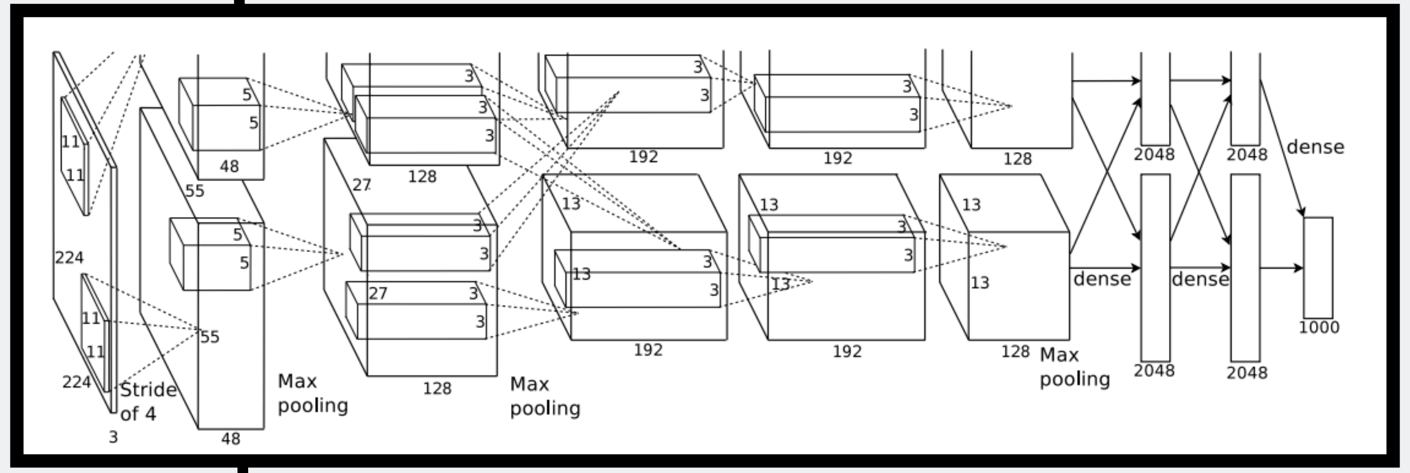
“Learn from lots of data”



2011

Third wave AI: Explainable

“Combine first and second wave
AI to generate explanations”

??

20??

Time

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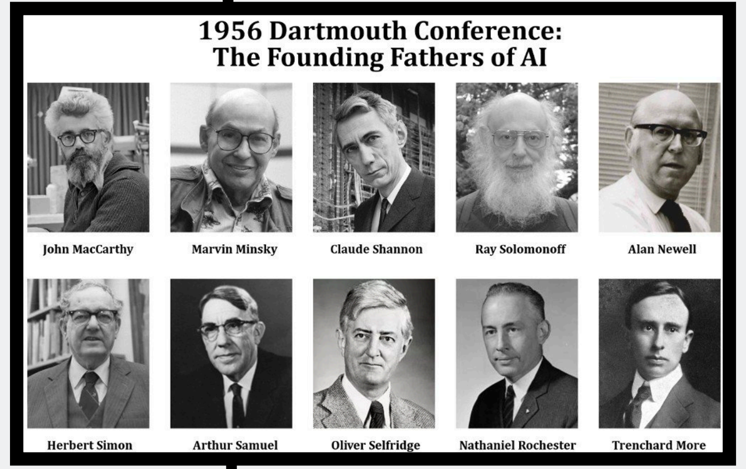

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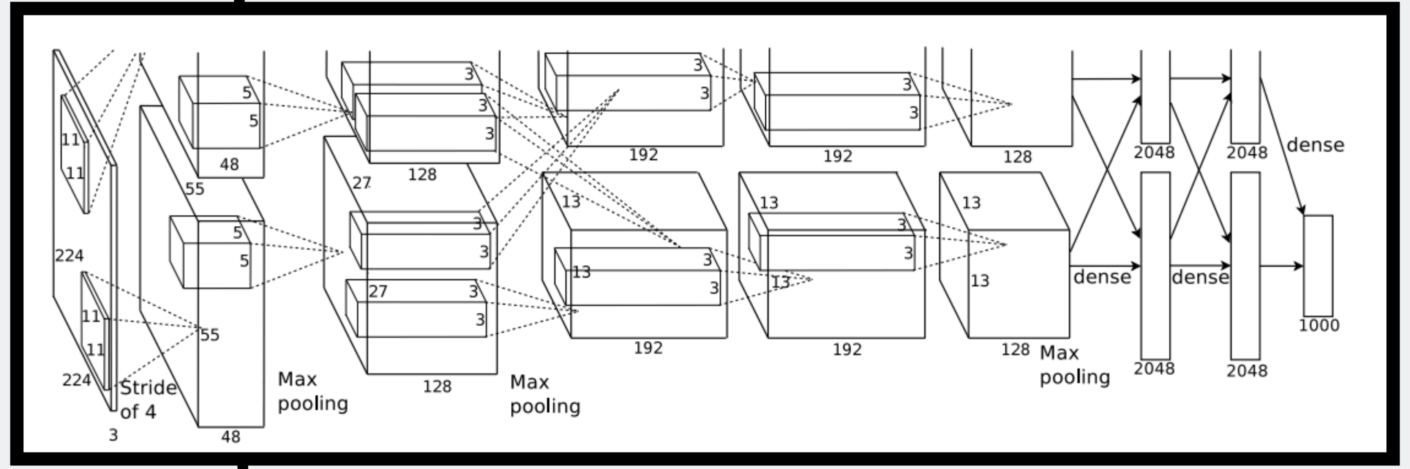

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A 20-Year Community Roadmap for
Artificial Intelligence Research in the US

CCC
Computing Community Consortium
Catalyst

AAAI

20??

Time

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“Think through the entire problem”

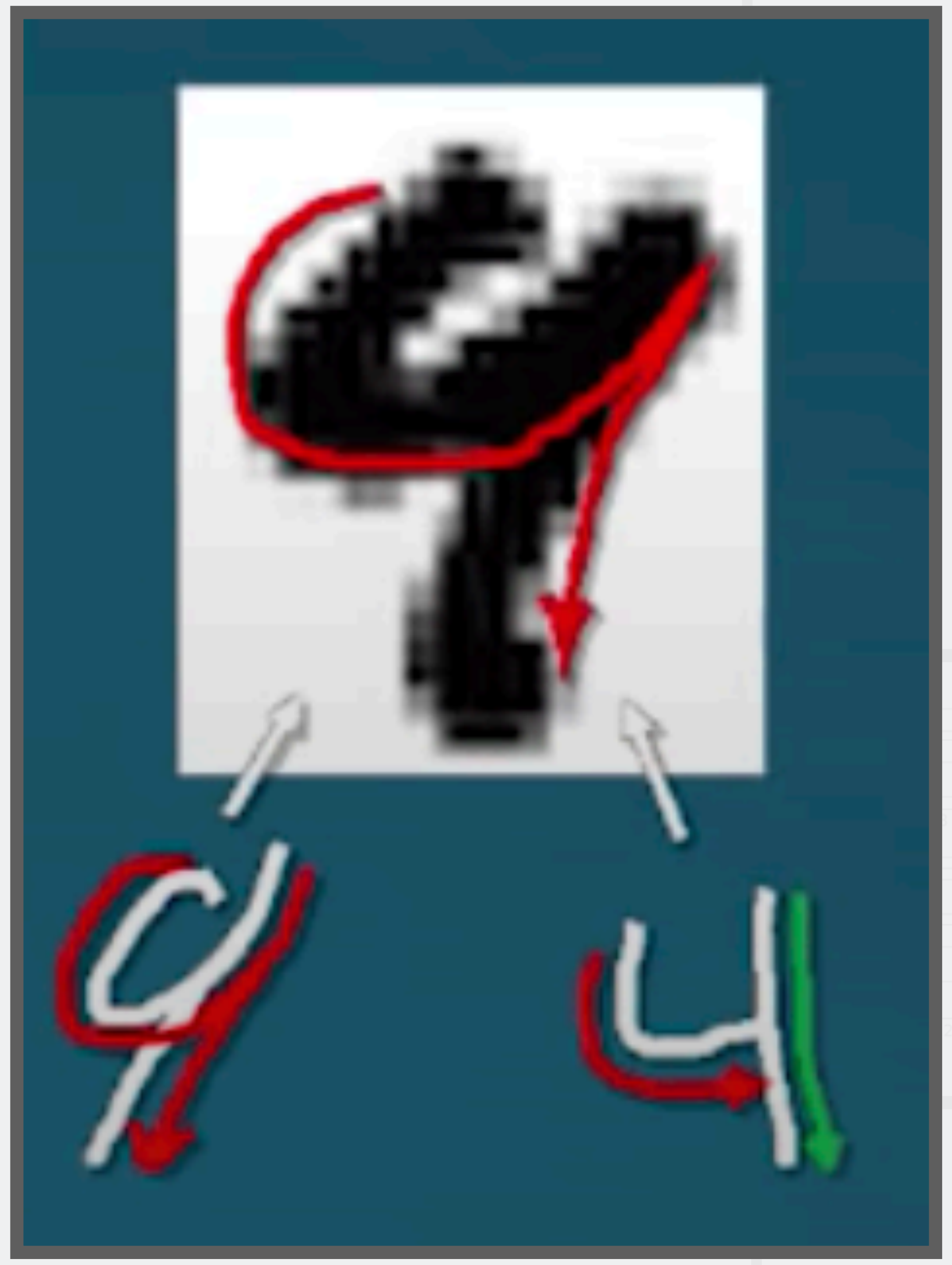
Second wave AI: Data-driven

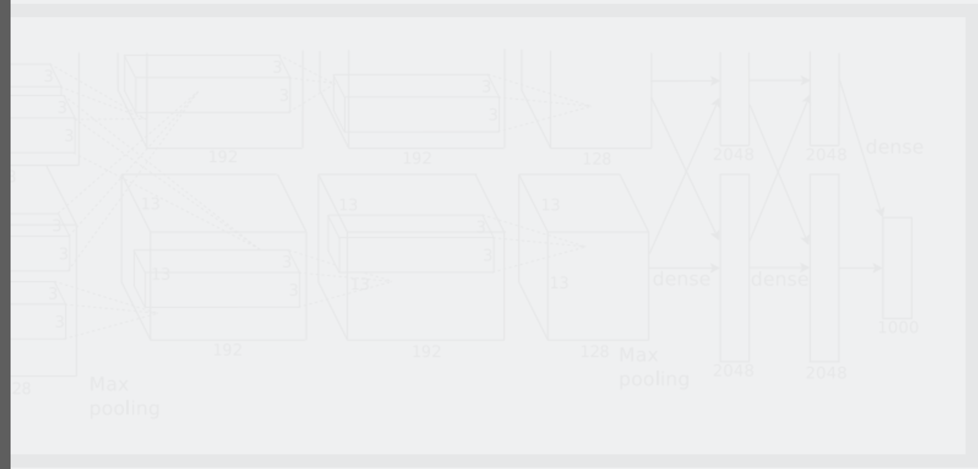
“Learn from lots of data”

Third wave AI: Explainable

“Combine first and second wave AI to generate explanations”

Is this handwritten character a ‘9’ or a ‘4’?





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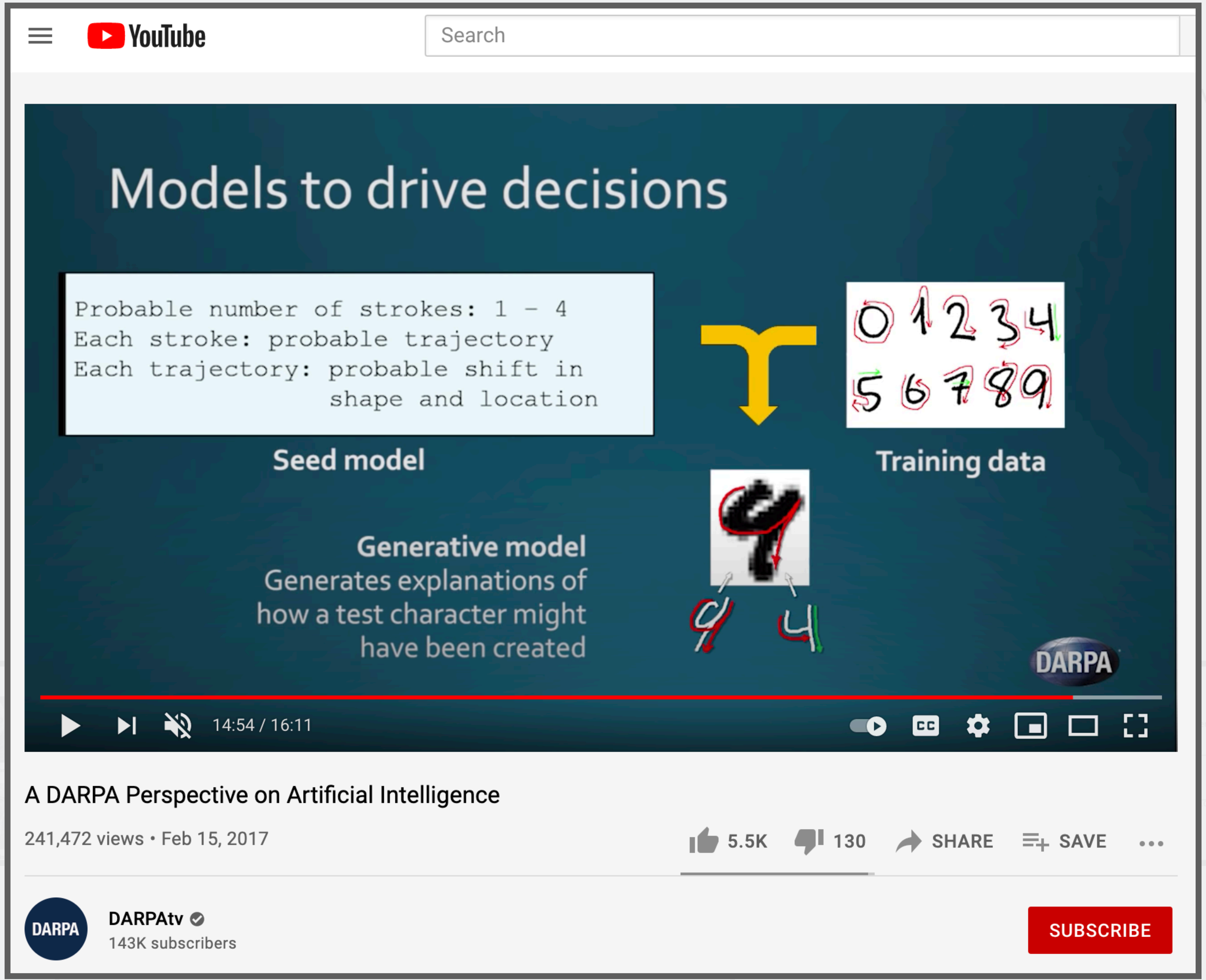

Models to drive decisions

```
Probable number of strokes: 1 – 4
Each stroke: probable trajectory
Each trajectory: probable shift in
                 shape and location
```

Seed model

Training data

Generative model
Generates explanations of how a test character might have been created

A DARPA Perspective on Artificial Intelligence

241,472 views • Feb 15, 2017

DARPAtv
143K subscribers

Third wave AI: Explainable

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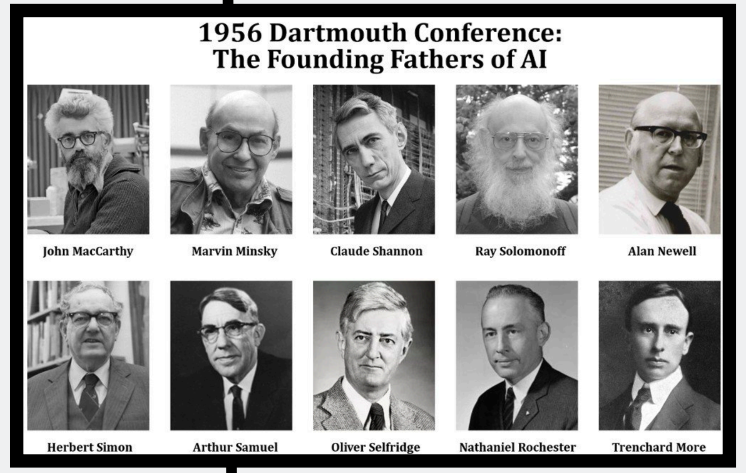

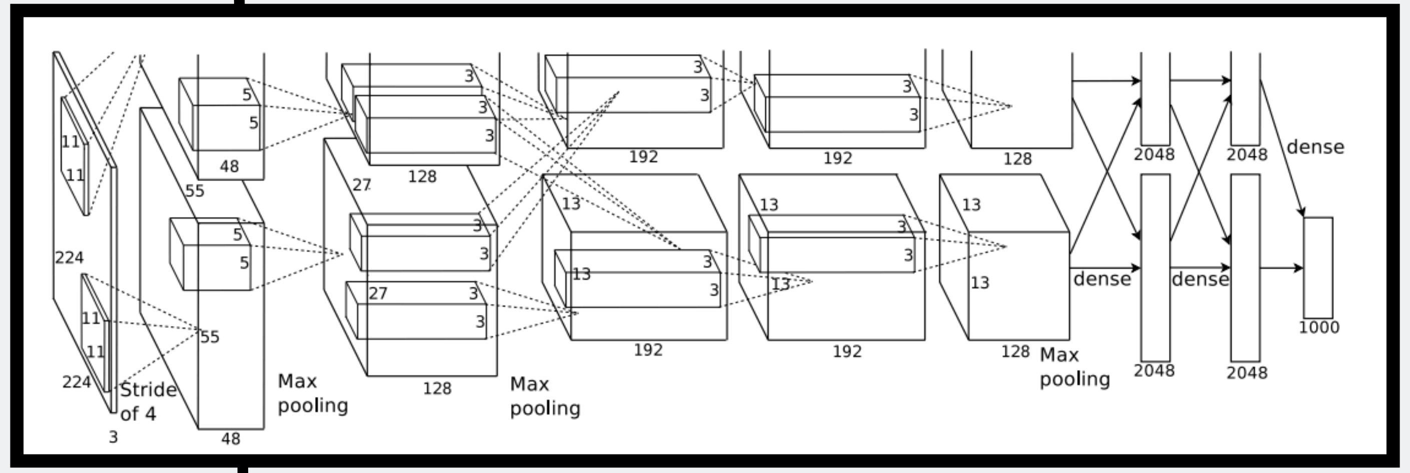

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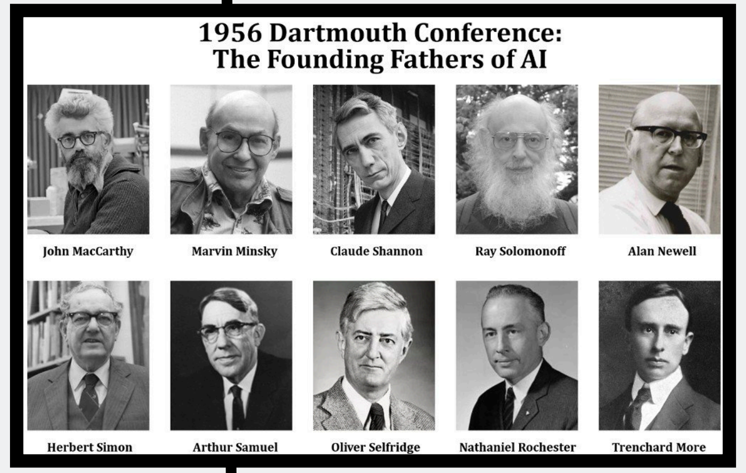

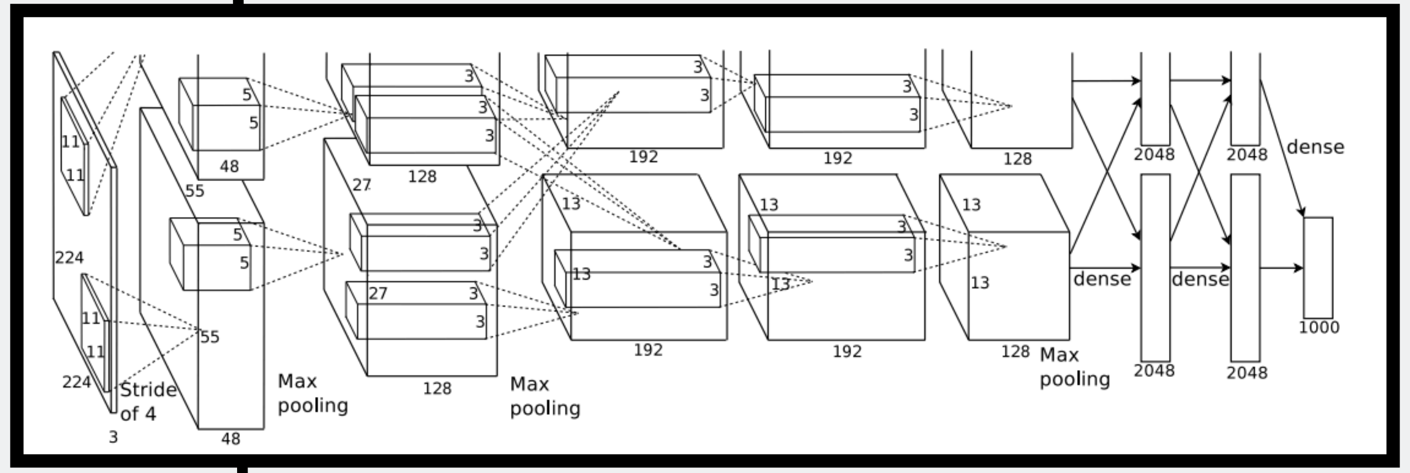

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DeepRob is a step into modern robot learning

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“Think through the entire problem”

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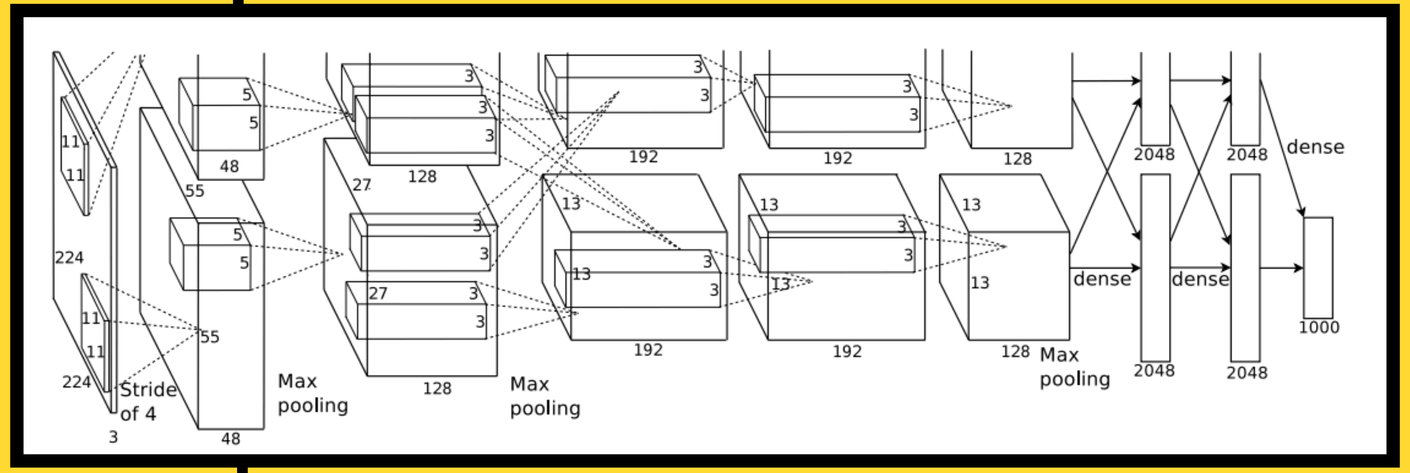

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Computing Community Consortium
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AAAI

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Time

Other Robotics and AI courses

DeepRob is a step into modern robot learning

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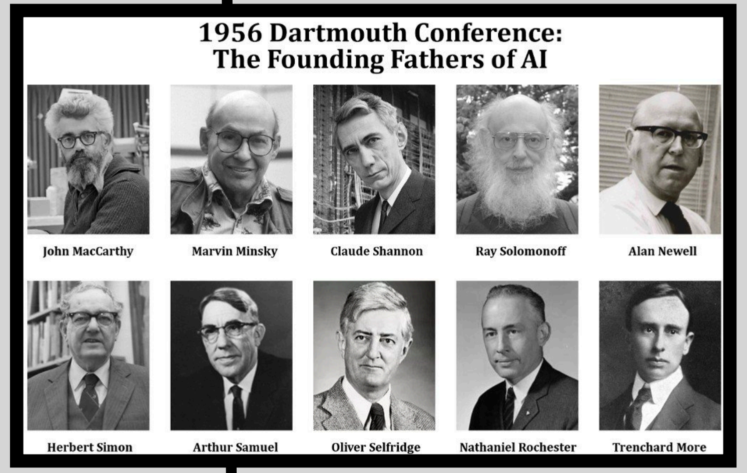
“Think through the entire problem”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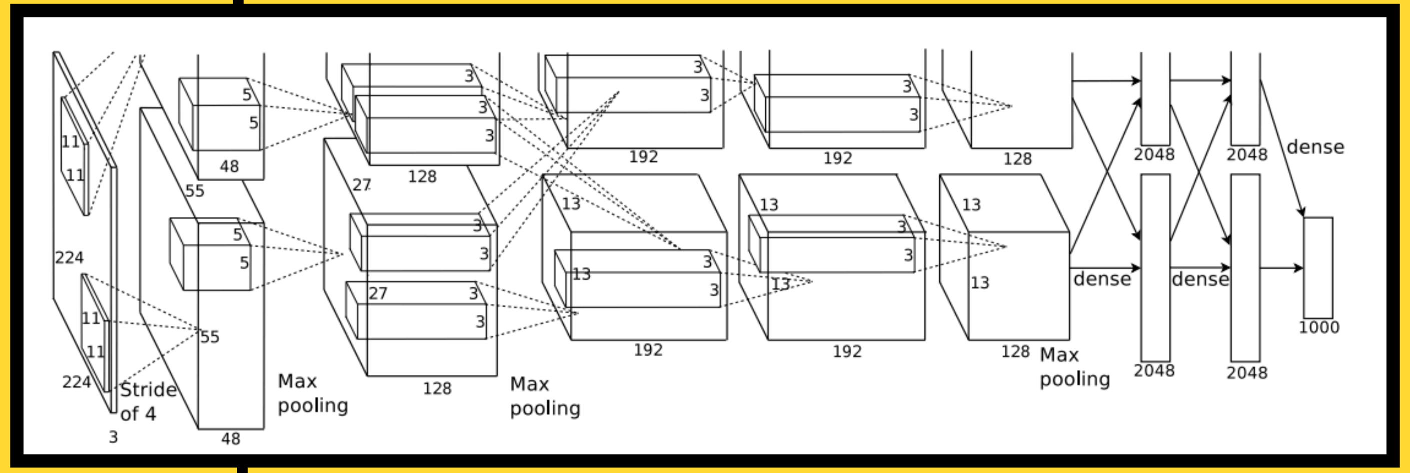

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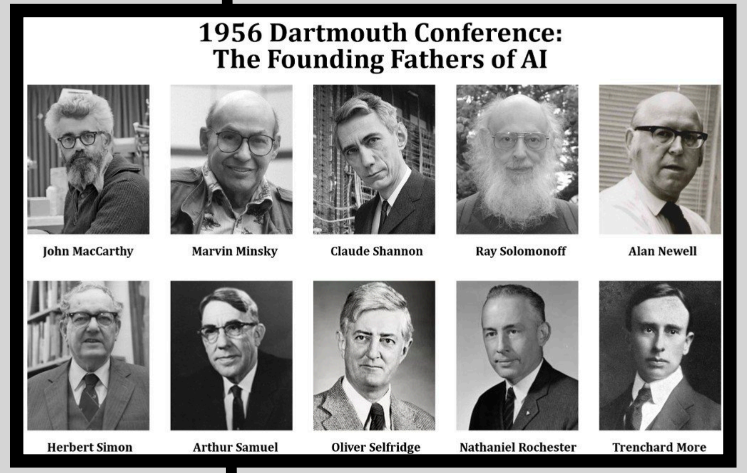

1956

DeepRob is a step into modern robot learning

Second wave AI: Data-driven

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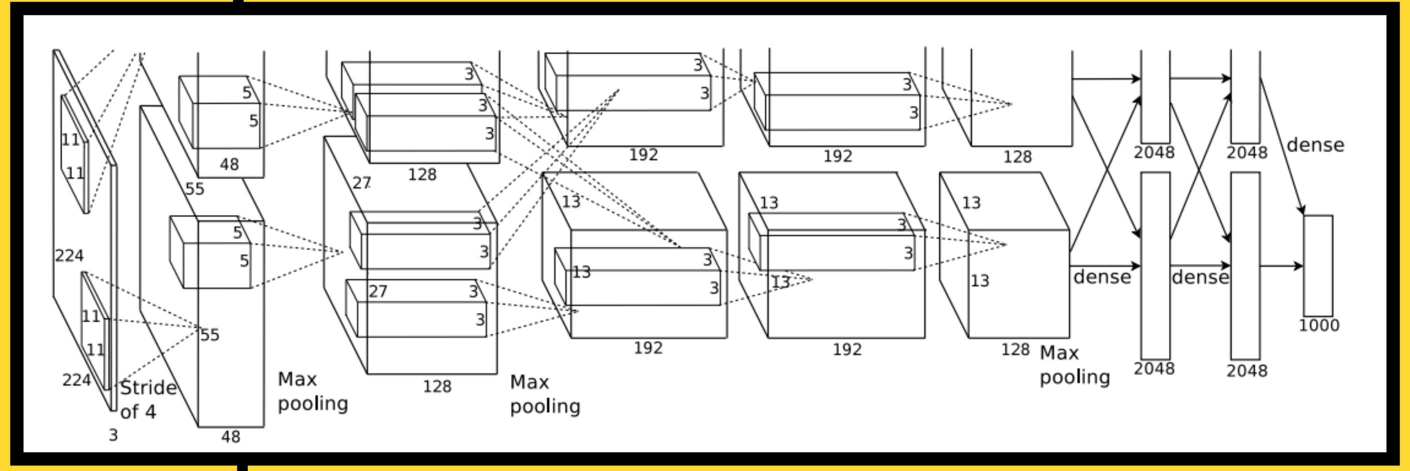


2011

Research for future AI

Third wave AI: Explainable

“Combine first and second wave AI to generate explanations”

??

A 20-Year Community Roadmap for Artificial Intelligence Research in the US

CCC Computing Community Consortium Catalyst

AAAI

20??

Time

DeepRob Course Staff

Anthony Opipari

Prof. Chad Jenkins

Prof. Karthik Desingh

Huijie Zhang

Research Associate

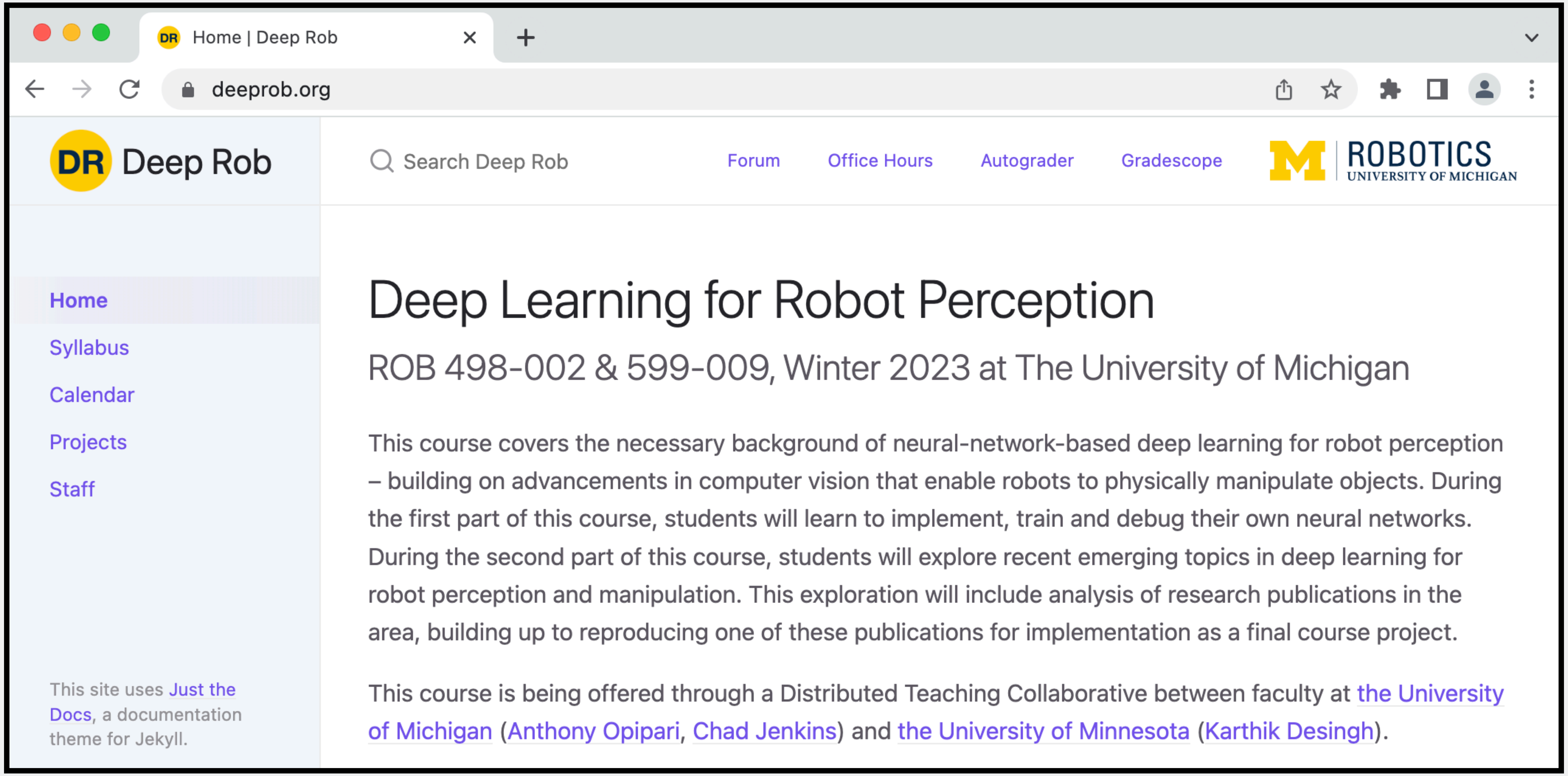
Jiyue Zhu

Instructional Aide

Course Resources

- Course Website: https://deeprob.org
    - Syllabus, calendar, project files, slides, links, etc.
- Ed Stem: https://edstem.org/us/courses/31008/discussion/
    - Forum for communication and question answering
    - Optional to join and shared across course offerings
- Autograder: https://autograder.io/web/course/199
    - Project submission and grading

Course Website—DeepRob.org



Deep Learning for Robot Perception

ROB 498-002 & 599-009, Winter 2023 at The University of Michigan

This course covers the necessary background of neural-network-based deep learning for robot perception – building on advancements in computer vision that enable robots to physically manipulate objects. During the first part of this course, students will learn to implement, train and debug their own neural networks. During the second part of this course, students will explore recent emerging topics in deep learning for robot perception and manipulation. This exploration will include analysis of research publications in the area, building up to reproducing one of these publications for implementation as a final course project.

This course is being offered through a Distributed Teaching Collaborative between faculty at the University of Michigan (Anthony Opipari, Chad Jenkins) and the University of Minnesota (Karthik Desingh).

This site uses Just the Docs, a documentation theme for Jekyll.

Meeting Logistics

- In-person Lectures
  - Tue/Th 3:00-4:30 PM EST
  - Zoom (Meeting ID: 936 5222 5304)
  - Recordings available on course website (deeprob.org)
- Discussion Section
  - Fri 4:30-5:30 PM EST
  - Zoom (Meeting ID: 936 5222 5304)
  - Tutorials and paper discussions

- Office Hours

Anthony

Wed, 1:30-3:00pm, **3320 FMCRB**
Fri, 9:00-10:30am, **3320 FMCRB**

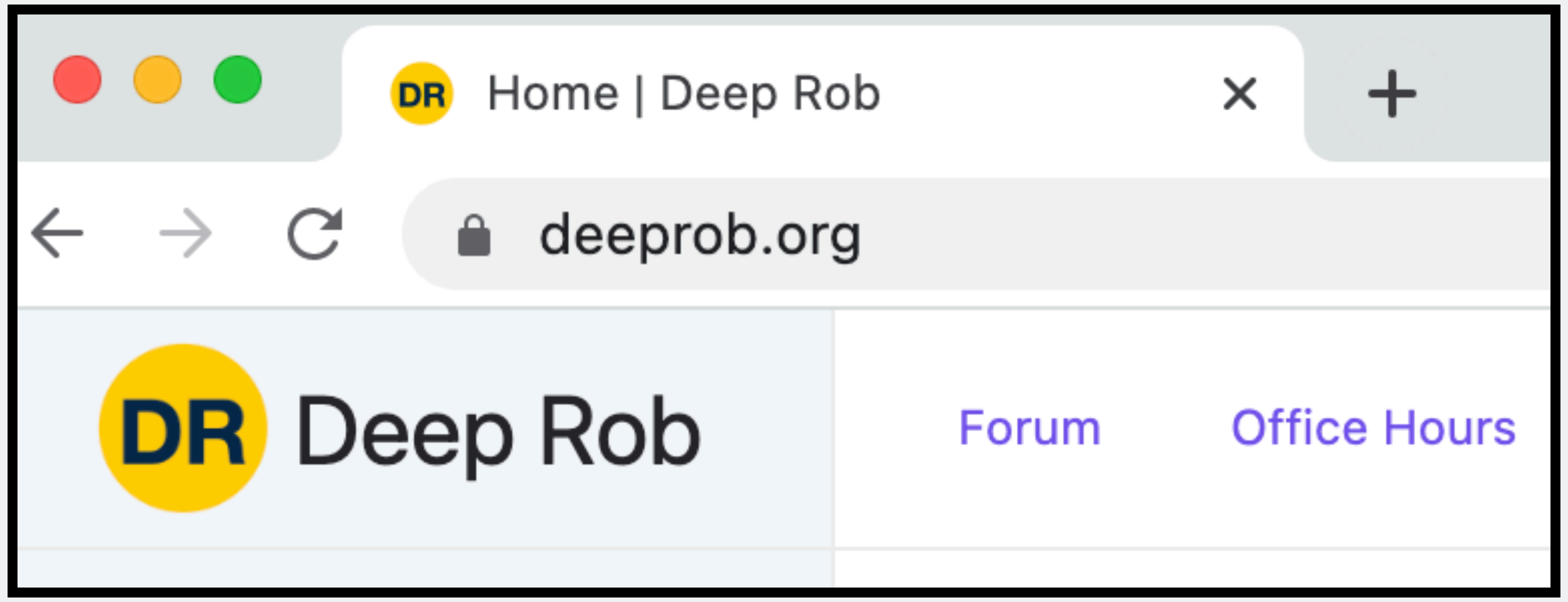
Huijie

Mon, 2:00-3:00pm, **2320 FMCRB**
Tue, 2:00-3:00pm, **2320 FMCRB**

Jiyue

Th, 1:00-3:00pm, **2320 FMCRB**

Office Hours Queue

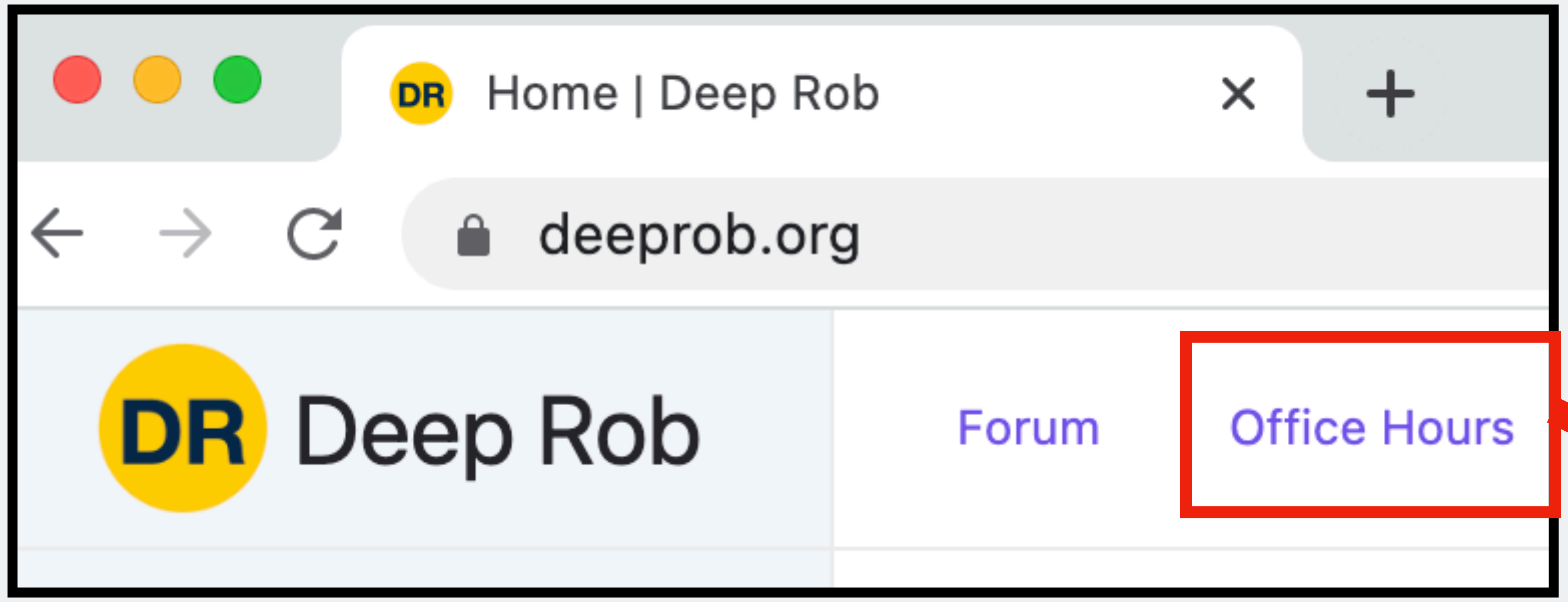


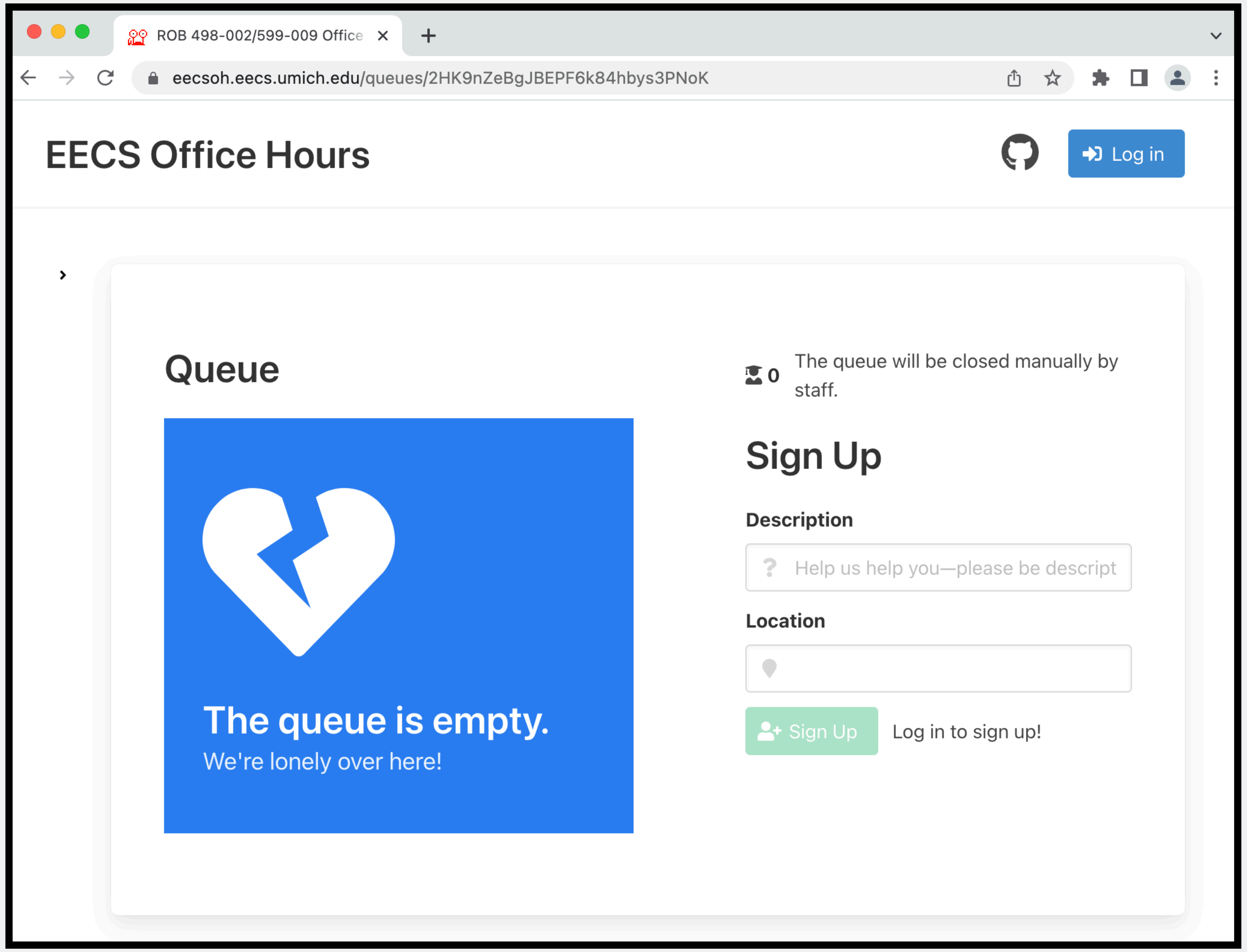
Home | Deep Rob

deeprob.org

Online queue management tool to ensure efficient use of the resource

Office Hours Queue




ROB 498-002/599-009 Office
eecsoh.eecs.umich.edu/queues/2HK9nZeBgJBEPF6k84hbys3PNoK
EECS Office Hours
Log in
Queue
0
Sign Up
Description
Help us help you—please be descript
Location
Sign Up

The queue will be closed manually by staff.

The queue is empty.

We're lonely over here!

Log in to sign up!

Online queue management tool to ensure efficient use of the resource

Course Structure

- Objective: Give you the computational skills to understand and reproduce emerging applications of deep learning for robot perception

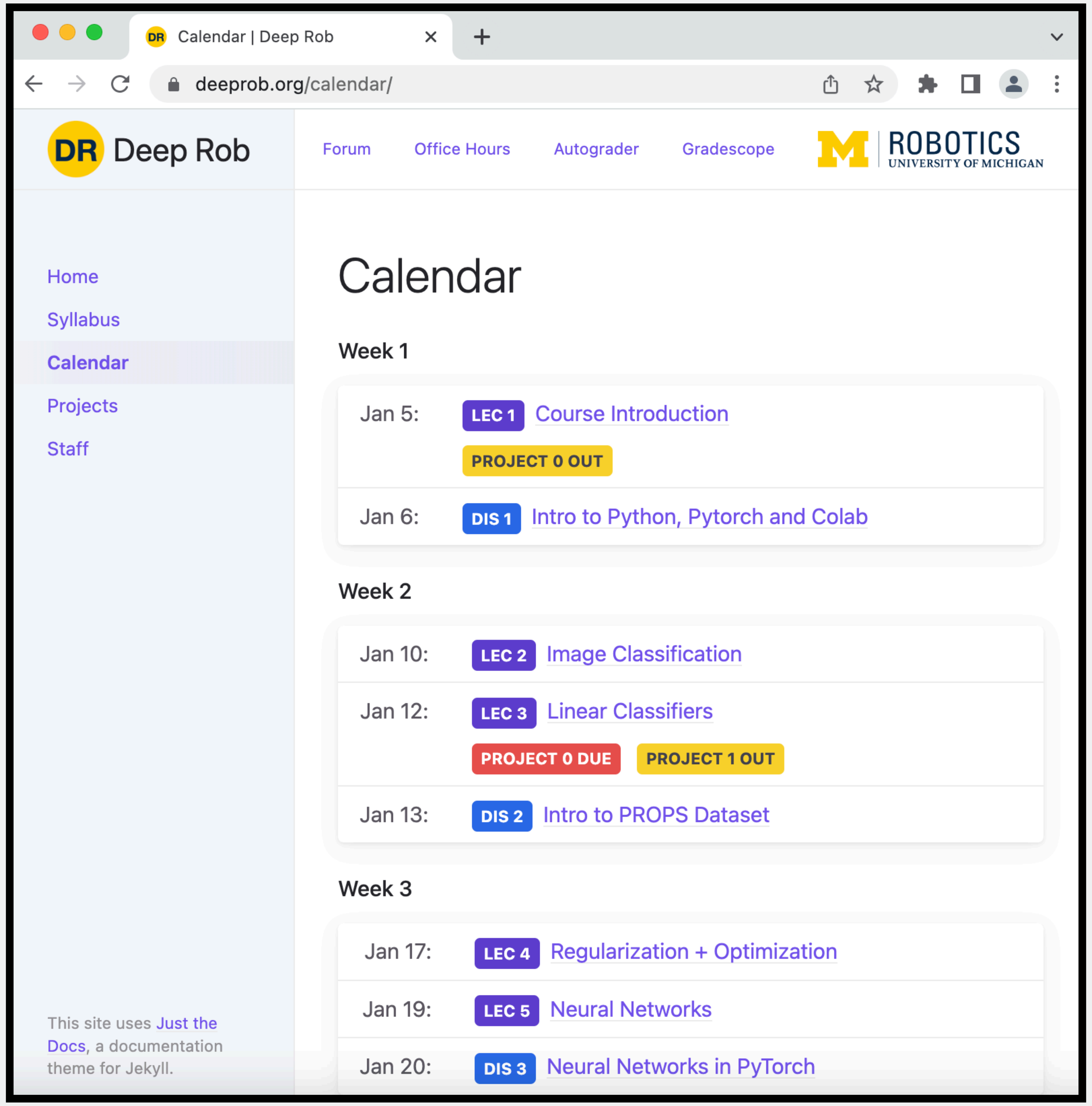
- Project focused class
  - 6 total projects: building in complexity from basic linear layers to state-of-the-art research topics

Course Structure

- First half: Fundamentals
  - How to implement, train and debug neural networks
  - Classifiers, fully-connected networks, convolutional networks
  - Weeks 1-6 and Projects 0-2

- Second half: Emerging topics
  - Seminar style coverage of active research areas in robotics
  - 3D perception, pose estimation, tracking, NeRFs, transformers
  - Weeks 7-14 and Projects 3 onward

Schedule—DeepRob.org/calendar



Calendar

Week 1

Jan 5: LEC 1 Course Introduction
PROJECT 0 OUT

Jan 6: DIS 1 Intro to Python, Pytorch and Colab

Week 2

Jan 10: LEC 2 Image Classification

Jan 12: LEC 3 Linear Classifiers
PROJECT 0 DUE PROJECT 1 OUT

Jan 13: DIS 2 Intro to PROPS Dataset

Week 3

Jan 17: LEC 4 Regularization + Optimization

Jan 19: LEC 5 Neural Networks

Jan 20: DIS 3 Neural Networks in PyTorch

This site uses Just the Docs, a documentation theme for Jekyll.

- Lecture slides
- Discussion resources
- Suggested readings
- Project schedule

Project Topics

Project Topics

- Project 0
  - Introduction to Python and PyTorch
- Project 1
  - Classification using K-Nearest Neighbors and Linear Models
- Project 2
  - Classification using Fully-Connected and Convolutional Neural Networks

Project Topics

- Project 0
  - Introduction to Python and PyTorch
- Project 1
  - Classification using K-Nearest Neighbors and Linear Models
- Project 2
  - Classification using Fully-Connected and Convolutional Neural Networks
- Project 3
  - Detection using convolutional neural networks
- Project 4
  - State estimation with deep networks
- Final Project
  - Published paper presentation, reproduction, extension and report

Final Project

- Published paper presentation, reproduction, extension and report
- Work as collaborative teams up to 3 people
- Deliverables:
  - Paper presentation during lecture
  - Result reproduction as code
  - Network extension as code
  - Project report as <= 2-page paper

Project Grading

- Projects 0-4 graded with autograder.io
  - 2 total late days available
  - 25% daily penalty after deadline and late days

- Final project graded manually by course staff

Overall Grading Policy

- Projects 0-4: 12% each
- Final Project: 24%
  - Presentation: 6%
  - Reproduction: 6%
  - Extension: 6%
  - Written report: 6%
- 16 Pre-Lecture Quizzes: 1% each

Collaboration Policy

- All work submitted must be your own
  - All code submitted must comply with College of Engineering Honor Code

- No code can be communicated, including verbally
  - Explicit use of external sources must be clearly cited

- Free flow of discussion and ideas is encouraged

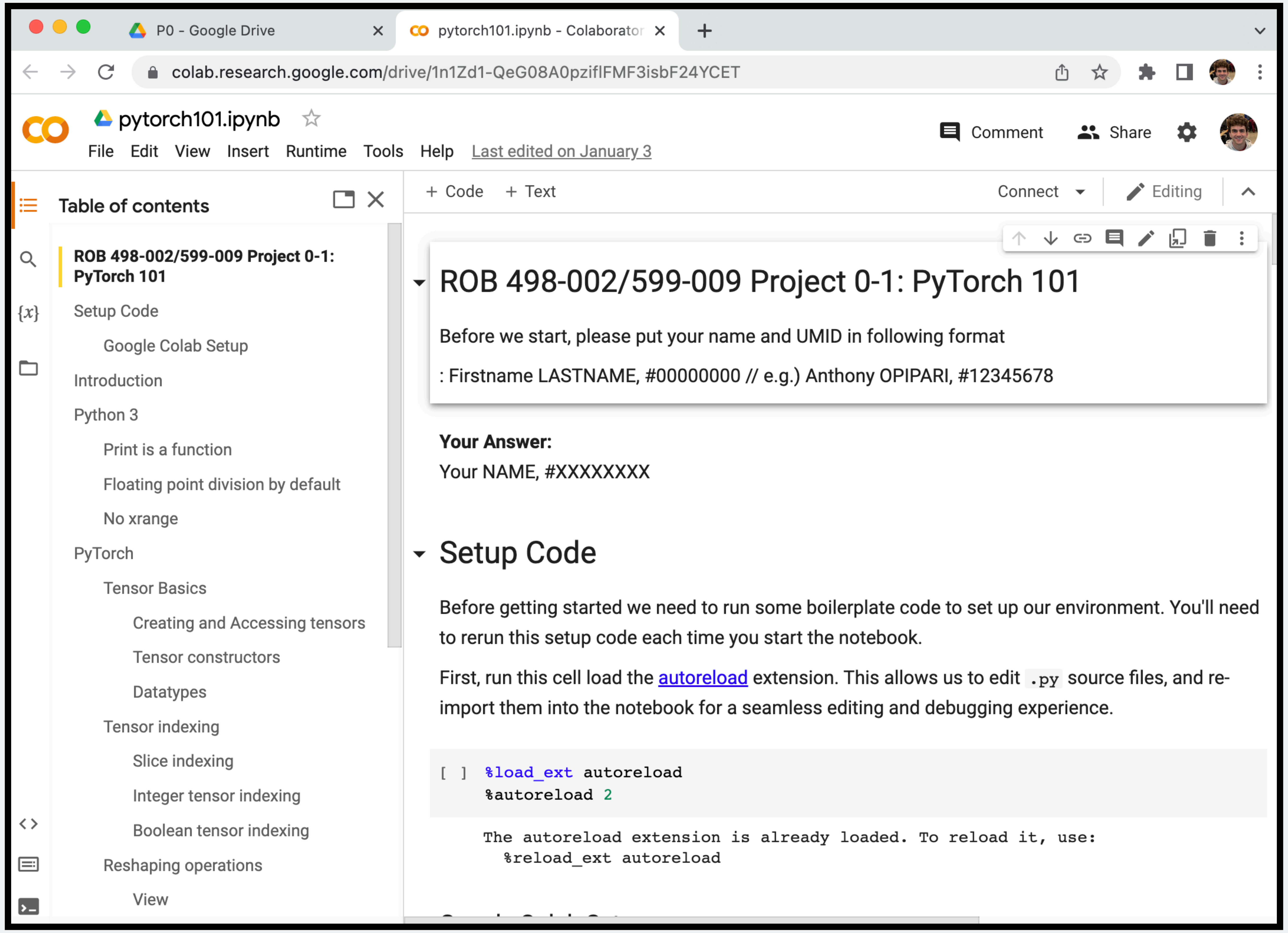
Discussion Forum

- Ed Stem available for course discussion and questions
  - Forum is shared across UMich and UMinn students
  - Participation and use is not required
  - Opt-in using this Google form
  - **Discussion of quizzes and verbatim code must be private**

Project 0

- Instructions and code available on the website
- Released today: deeprob.org/projects/project0/
- Intro at this week's discussion
- **Due next Thursday, January 12th 11:59 PM EST**

Project 0



ROB 498-002/599-009 Project 0-1: PyTorch 101

Before we start, please put your name and UMID in following format

: Firstname LASTNAME, #00000000 // e.g.) Anthony OPIPARI, #12345678

Your Answer:
Your NAME, #XXXXXXXX

Setup Code

Before getting started we need to run some boilerplate code to set up our environment. You'll need to rerun this setup code each time you start the notebook.

First, run this cell load the autoreload extension. This allows us to edit `.py` source files, and re-import them into the notebook for a seamless editing and debugging experience.

```
[ ] %load_ext autoreload
    %autoreload 2
```

```
The autoreload extension is already loaded. To reload it, use:
  %reload_ext autoreload
```

Next Week: Classification

Image Classification and Linear Classifiers

DeepRob

Winter 2023
Deep Learning for Robot Perception
University of Michigan and University of Minnesota