Neural Networks: Foundations to Generative AI

Course Logistics and Introduction

Today's Agenda

1. COURSE LOGISTICS

- Website, schedule, grading and evaluation criteria.
- Course textbook, lecture format, etc.

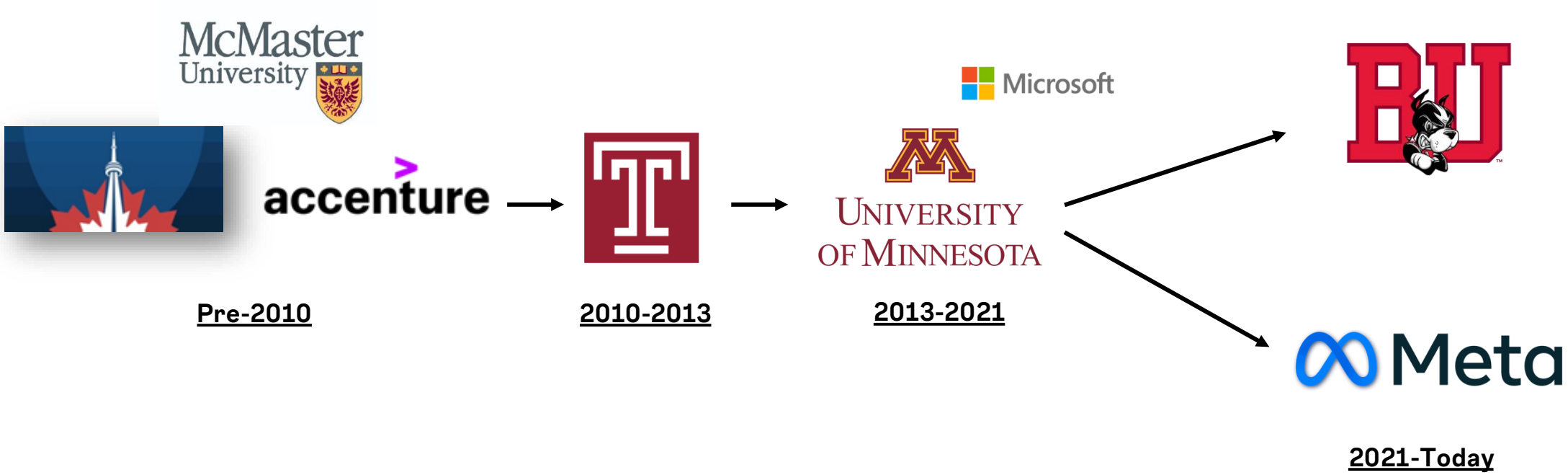
2. INTERESTING USE CASES

- Frivolous, academic, and practically useful.
- A recent failure, and societal concerns.

3. QUICK INTRODUCTION

- What is a neural network?
- How does it work?

My Background



My Research

Take Caution in Using LLMs as Human Surrogates: Scylla Ex Machina*

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This Version: Jan 23th, 2025†

Abstract

Recent studies suggest large language models (LLMs) can exhibit human-like reasoning, aligning with human behavior in economic experiments, surveys, and political discourse. This has led many to propose that LLMs can be used as surrogates or simulations for humans in social science research. However, LLMs differ fundamentally from humans, relying on probabilistic patterns, absent the embodied experiences or survival objectives that shape human cognition. We assess the reasoning depth of LLMs using the 11-20 money request game. Nearly all advanced approaches fail to replicate human behavior distributions across many models. Causes of failure are diverse and unpredictable, relating to input language, roles, and safeguarding. These results advise caution when using LLMs to study human behavior or as surrogates or simulations.

'She has twelve misshapen feet, and six necks of the most prodigious length; and at the end of each neck she has a frightful head with three rows of teeth in each'
— Homer, *Odyssey* (Describing Scylla)

Introduction

Recent studies report that Large Language Models (LLMs) can exhibit human-like cognitive abilities. These studies demonstrate that LLMs show behaviors that align closely with those of human subjects in seminal experiments from behavioral economics, and responses comparable to those of humans in

†Previous Version: Aug 28 , Oct 24, and Nov 13th 2024
*We thank seminar participants at the BU, Wharton (Sep 2024), USC, UC Irvine, and Meta. All errors are the author's own.

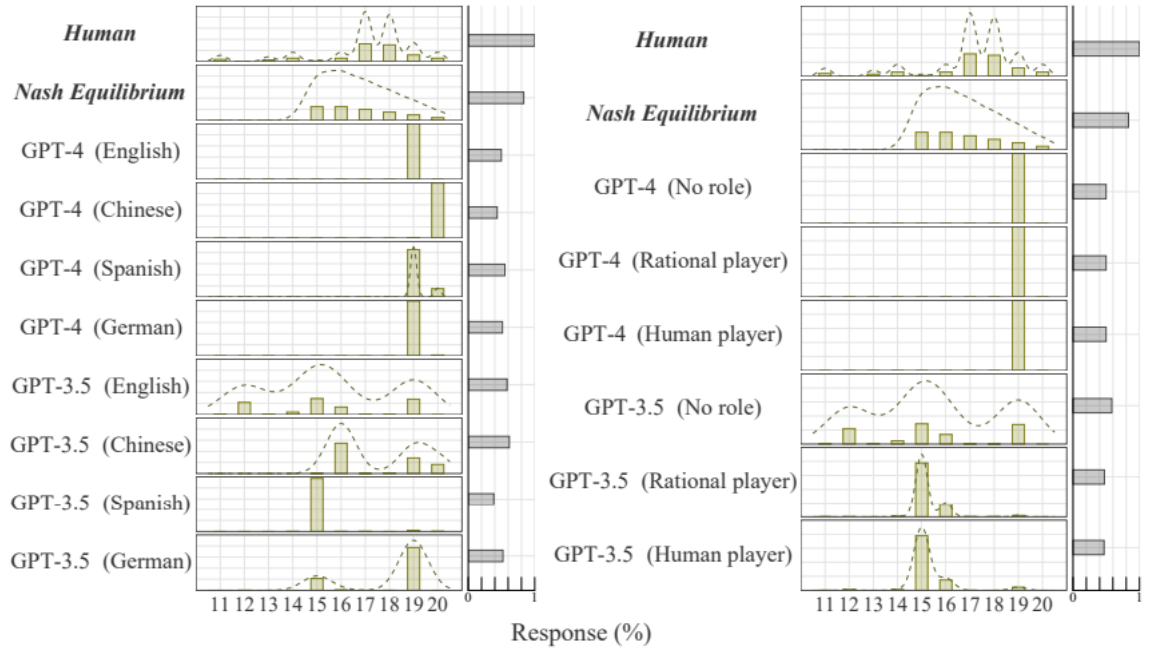
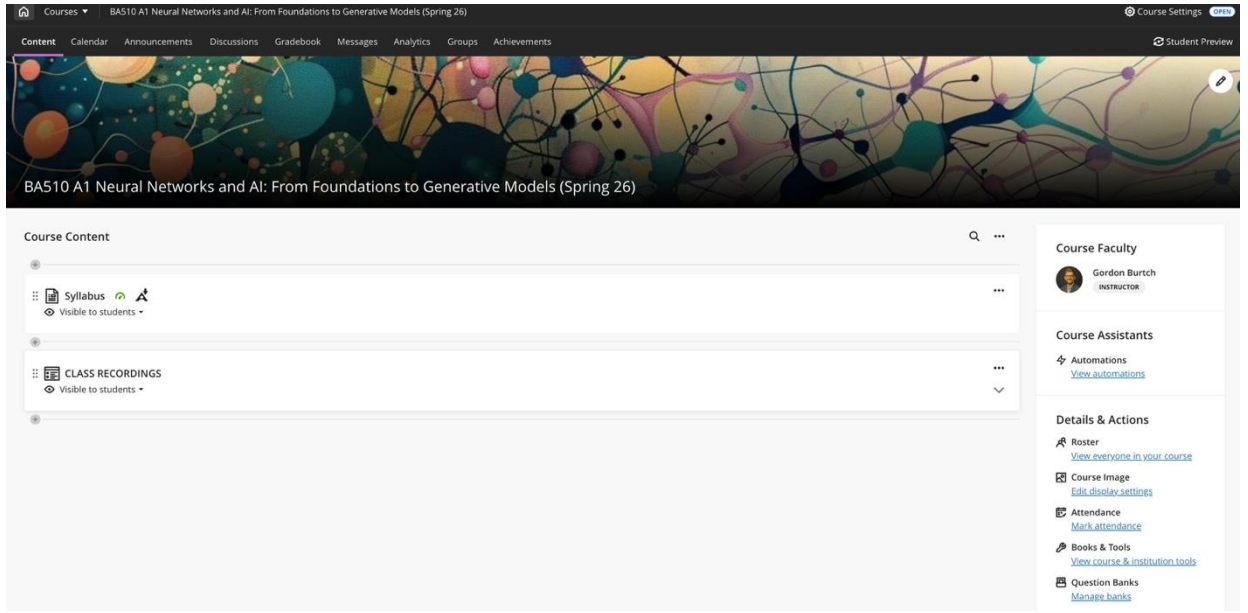


Figure 2: **Prompt Brittleness: Roles and Languages.** The bar chart on the right shows the similarity between the distribution of different subjects and human subjects, measured by Jensen-Shannon divergence scores. Density plots are omitted for subjects with over 98% of the data concentrated in a single choice to avoid potential misinterpretation.

Course Materials

COURSE WEBSITE

- The course website is on Blackboard – please let me know if you cannot see the site!
- You will submit all assignments and receive relevant course announcements via that site.
- I will post lecture materials and in-class exercises / examples via the GitHub Repository linked on Blackboard.



GOOGLE COLAB

- All homework and exercises in this course are to be implemented in Python. You should work in Google Colab because I cannot provide technical support if you run into issues with your local instance. For your project and individual assignment, you'll need to submit the .ipynb files that you produce in Colab.

Grading and Evaluation

GRADE BREAKDOWN	
(1) Participation	20%
(2) Individual Assignments (x1)	15%
(3) Case Write-up (x1)	15%
(4) Quizzes (x5)	25%
(5) Final Project	25%
TOTAL:	100%

PARTICIPATION / ATTENDANCE

- Regular attendance and participation will be worth 20% of your final grade.

INDIVIDUAL ASSIGNMENTS

- One individual assignment worth 15% of your final grade
- Due by 11:59pm on the date indicated in the course schedule –
  submit your Jupyter (Colab) Notebook file via Blackboard (submit the actual file with code, *not* a link to your notebook).
- Late submissions will result in grade deductions, per the syllabus.

CASE WRITE-UP

- We will discuss two HBS cases in class, and your submitted individual responses to case questions will be worth 15% of your final grade.

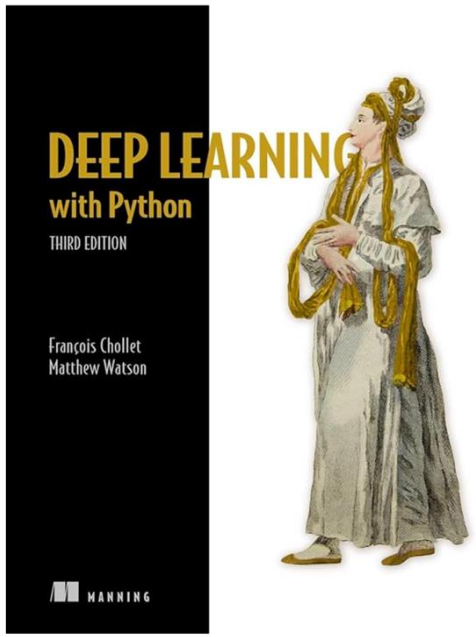
QUIZZES

- We will have 5 in-class, timed, paper and pencil, closed book / closed note quizzes. collectively worth 25% of your final grade.

FINAL PROJECT

- The final project (worth 25% of your final grade) is a hands-on implementation driven by you.
- You will work in pairs or individually to implement a neural network-based predictive model that addresses a practical problem of interest to you! You need to identify and motivate the prediction problem (explain why it's meaningful, who it would be of value to), and then implement your model.
- Deliverables include a project proposal, a mandatory mid-point check-in meeting with me to ensure you are on track, submission of final code and slides, and a final presentation during the last week of class.

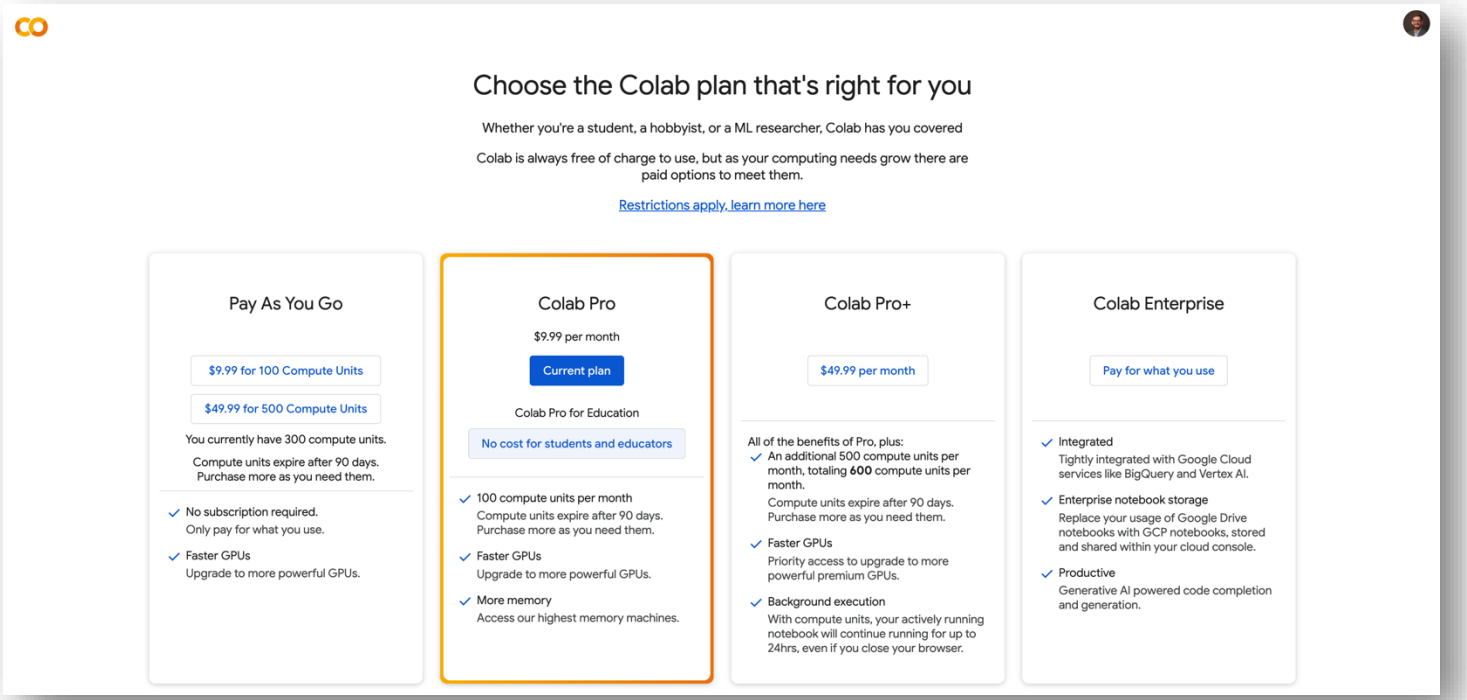
Course Textbook



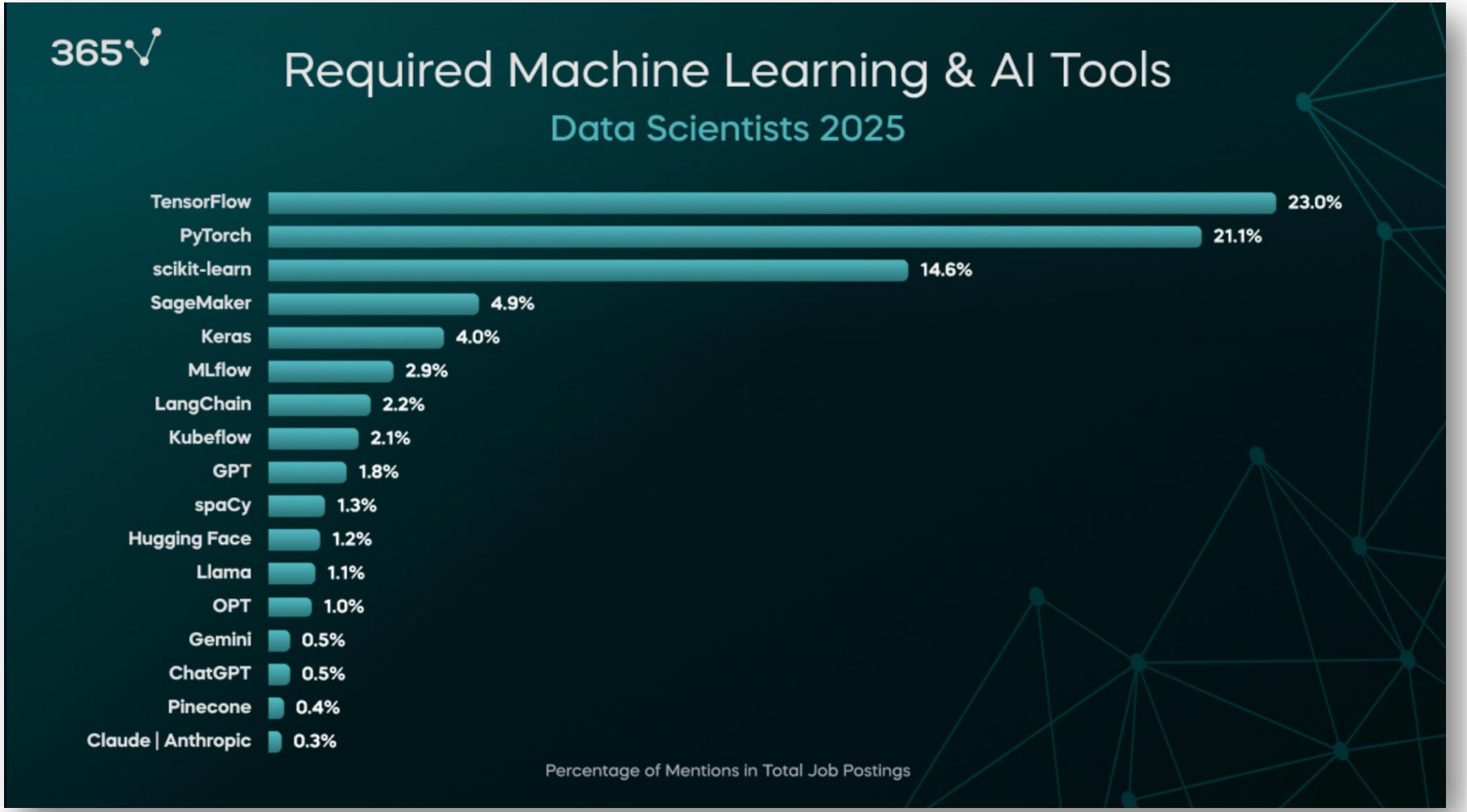
Chollet, François. (2025). *Deep Learning with Python (3rd Edition)*. Manning Publications Co. **ISBN-13: 978-1633436589.**
https://deeplearningwithpython.io

Required Software

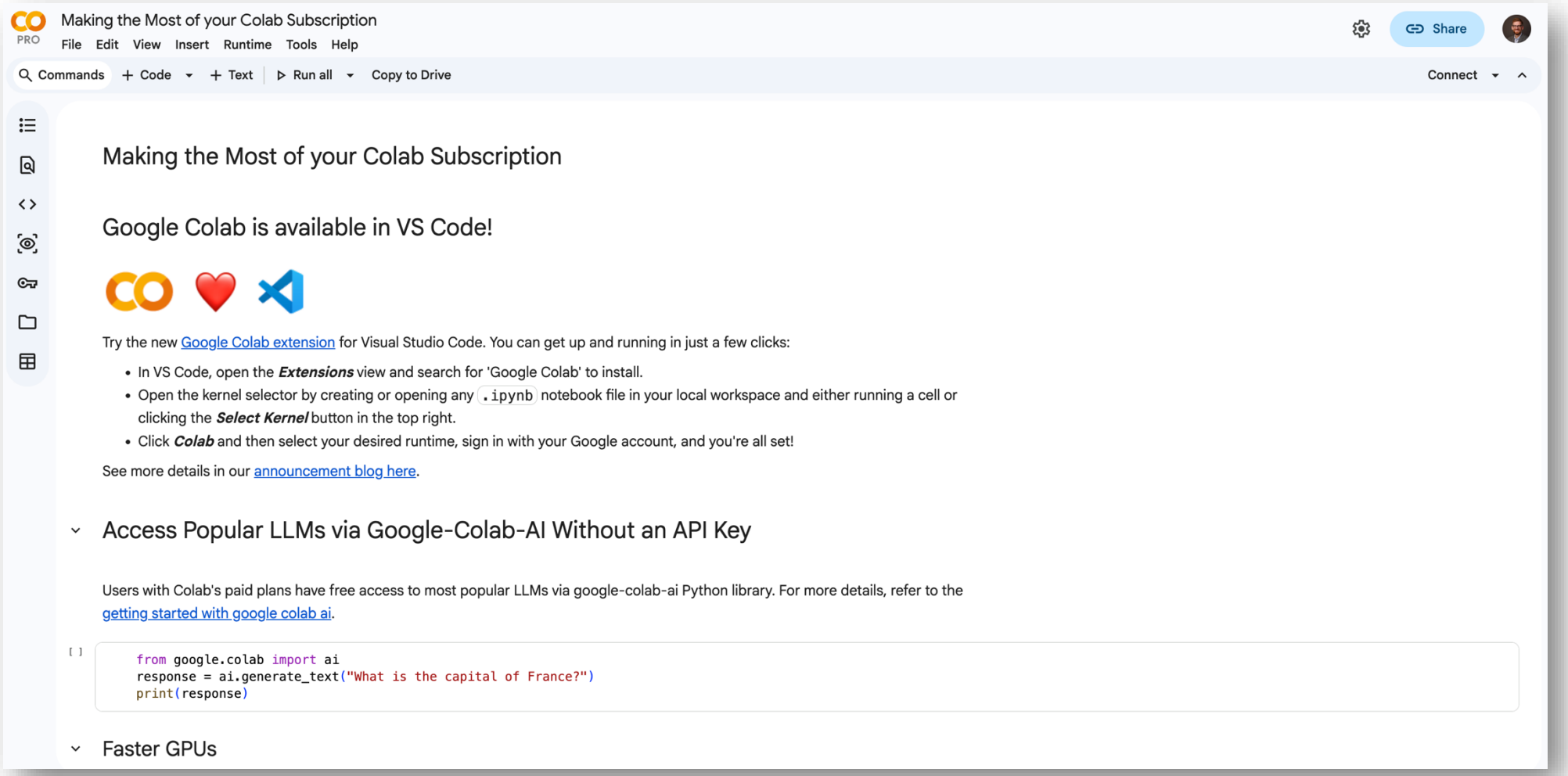
- You can access Google Colab at https://colab.research.google.com. You will want to use your BU Google account credentials!



Why Keras?



Google Colab



Course Timeline

AGENDA

- We will start with the basic math concepts.
- We will then get into neural networks for simple prediction problems with structured data (e.g., a spreadsheet).
- Then, we will explore prediction tasks where inputs are unstructured data (e.g., images, audio, and/or text).
- Finally, we will learn about generative neural networks and agentic models.

NOTE TIMING OF DELIVERABLES

- First quiz will take place on 2/10.
- Individual homework assignment will be due 2/27.
- I will announce sign-ups for the first project proposal check-in meeting that will take place on 3/3.

(Subject to Revision Depending on Progress)

Week	Dates	Topic	Assignments	Readings
1	Jan 20 & 22	**Course Intro**	--	Chapter 1
2	Jan 27 & 29	**Review of Concepts**	--	Chapters 5 and 6
3	Feb 3 & 5	**Multilayer Perceptron (MLP)**	--	Chapter 2
4	Feb 10 & 12	**First NN & Model Tuning**	Quiz 1 & Ind. Assignment Posted	Chapter 4
5	Feb 17 & 19	**Intro to Image Models**	--	Chapter 8
6	Feb 24 & 26	**Image Models (cont.)**	Quiz 2 & Ind. Assignment Due (Friday 11:59pm)	Chapters 9 and 10
7	Mar 3 & 5	***Project Check-ins*** **& Transfer Learning**	Proposal Due (Friday 11:59pm)	Chapters 11 and 12 (Optional)
SPRING RECESS				
8	Mar 17 & 19	**Intro to Text Models**	Quiz 3	Chapter 14
9	Mar 24 & 26	**Text Embeddings, Attention &** ***Project Work***	--	Chapter 15
10	Mar 31 & Apr 2	**Generative Text Models**	Quiz 4	Chapter 16
11	Apr 7 & 9	**Generative Image Models &** ***Project Work / Q&A***	--	Chapter 17
12	Apr 14 & 16	**Agentic AI, Other Concepts & JPMC Case**	Quiz 5	JPMC Case
13	Apr 21 & 23	**AI Wars Case &** ***Project Work / Q&A***	Case Responses Due (Friday at 11:59pm)	AI Wars Case
14	Apr 28 & 30	**Project Presentations**	Project Deliverables Due (Friday at 11:59pm)	

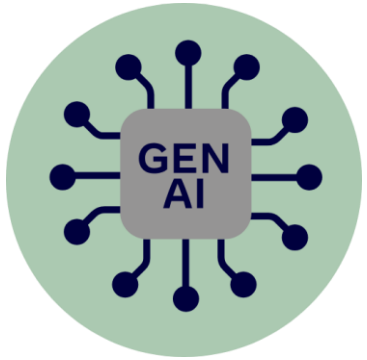
Course Format

LECTURES

- We will meet twice weekly for ~75 mins each session. The Tuesday session will typically focus on lecture / concepts / explanation.

HANDS-ON EXAMPLES

- During the second session each week, we will walk through hands-on examples and demonstrations in Colab notebooks. I will provide these Colab Notebooks and data-sets (typically via GitHub).
- You are encouraged to ask questions as we progress! Make it interactive!
- Note that the quizzes, the individual assignment, and the exam will be based on the in-class material. I will not test you on things that were not discussed in class.



Policy

YOU CAN USE IT TO HELP YOU LEARN AND PERFORM BASIC TASKS

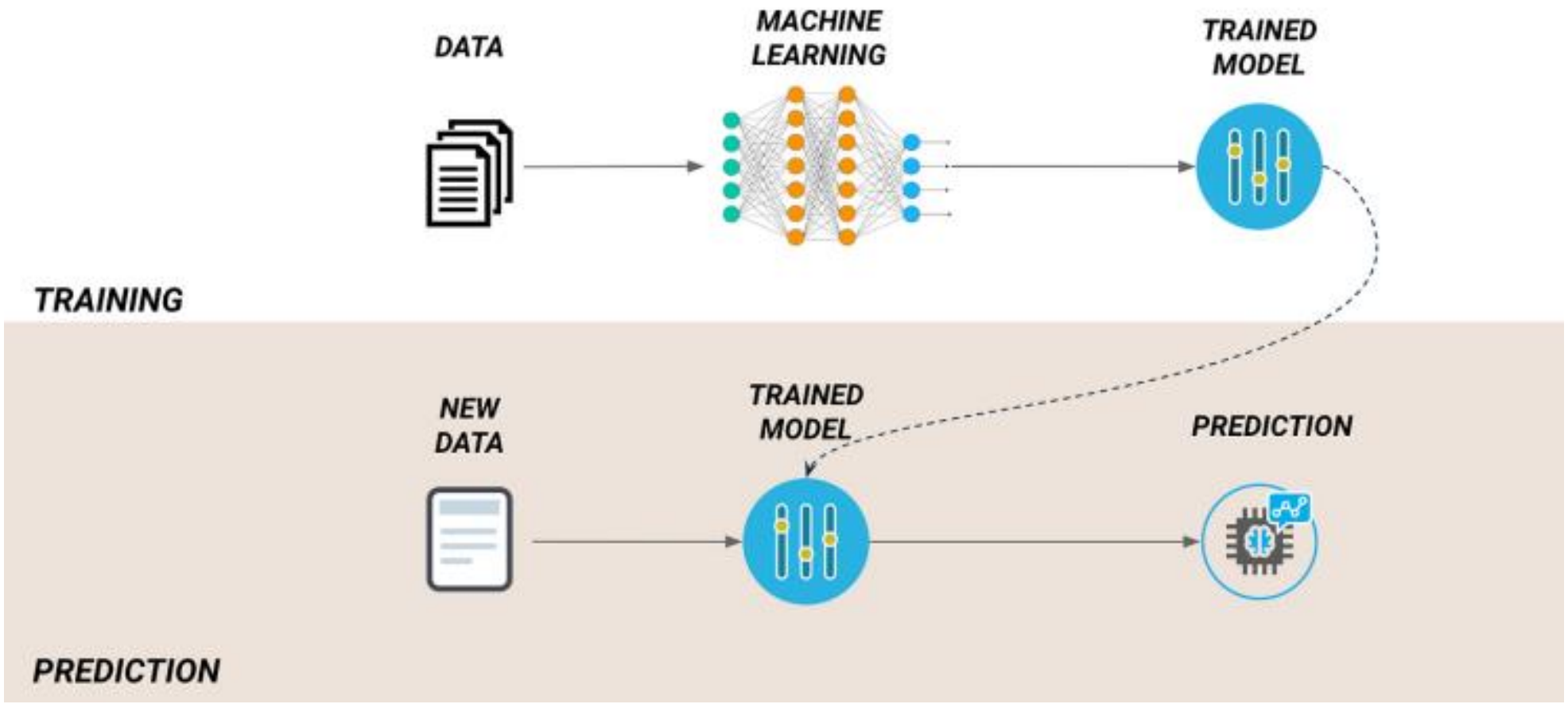
I expect you to use these tools, but the way you use them matters. Some valid use cases include i) implementing data munging tasks that you already understand based on past coursework, e.g., pre-processing text, or ii) automatic generation of code comments or documentation.

YOU SHOULD NOT GENERATE SOLUTIONS FROM SCRATCH

If you use these tools as a shortcut to avoid understanding the course material, you will not do well in the class. If I see you using functions and libraries that were not taught in the course (e.g., PyTorch), you may be asked to explain your code to me, verbally. If you are unable to explain what the code is doing, points will be deducted from your deliverable grade.

Questions?

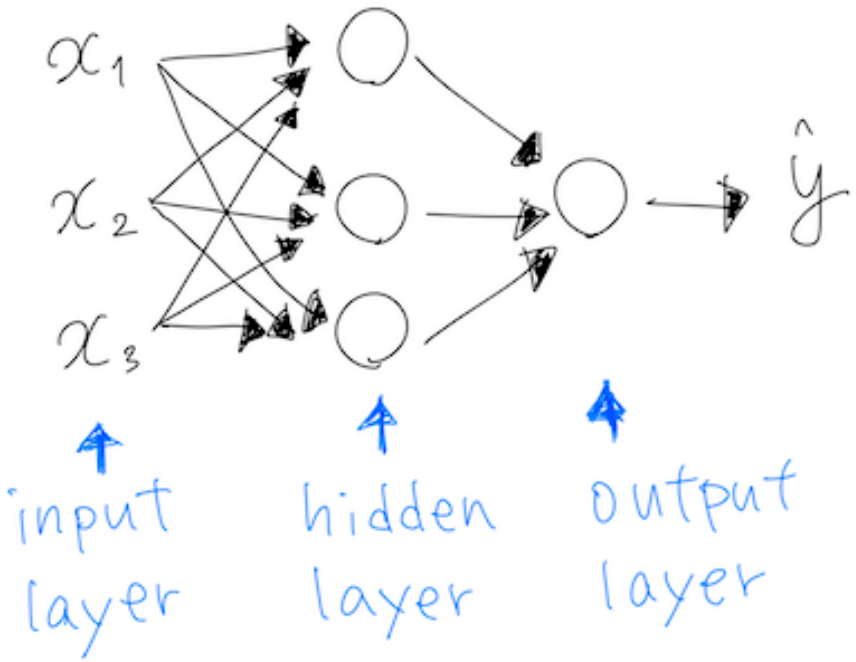
Supervised Learning



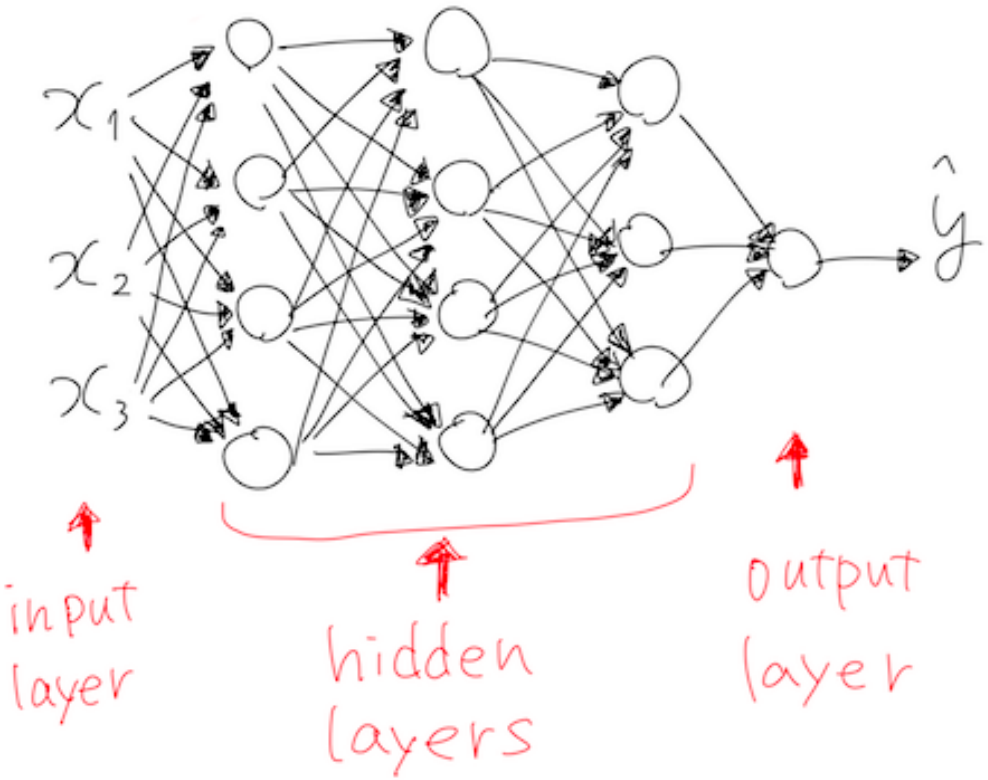
So, What is 'Deep' (vs. Shallow) Learning?

https://chat.openai.com/chat

Shallow Neural Network



Deep Neural Network



Where Deep Learning Started

Communicated by Dana Ballard

Backpropagation Applied to Handwritten Zip Code Recognition

Y. LeCun
B. Boser
J. S. Denker
D. Henderson
R. E. Howard
W. Hubbard
L. D. Jackel
AT&T Bell Laboratories Holmdel, NJ 07733 USA

The ability of learning networks to generalize can be greatly enhanced by providing constraints from the task domain. This paper demonstrates how such constraints can be integrated into a backpropagation network through the architecture of the network. This approach has been successfully applied to the recognition of handwritten zip code digits provided by the U.S. Postal Service. A single network learns the entire recognition operation, going from the normalized image of the character to the final classification.

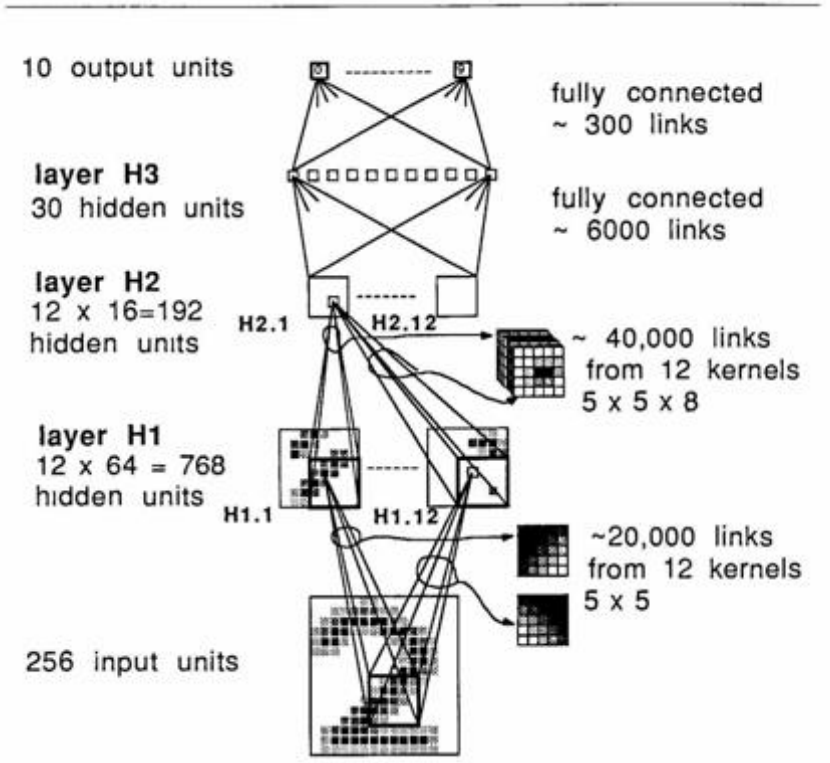
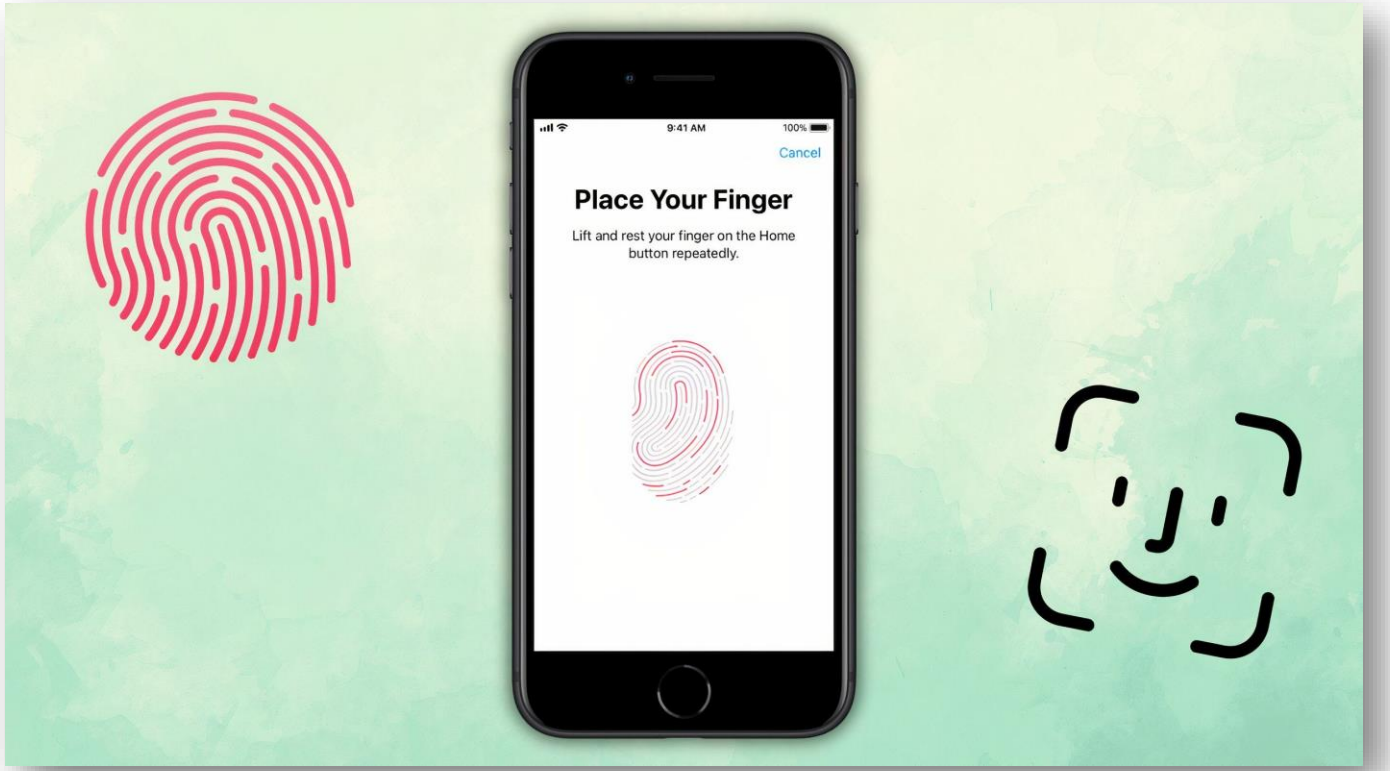
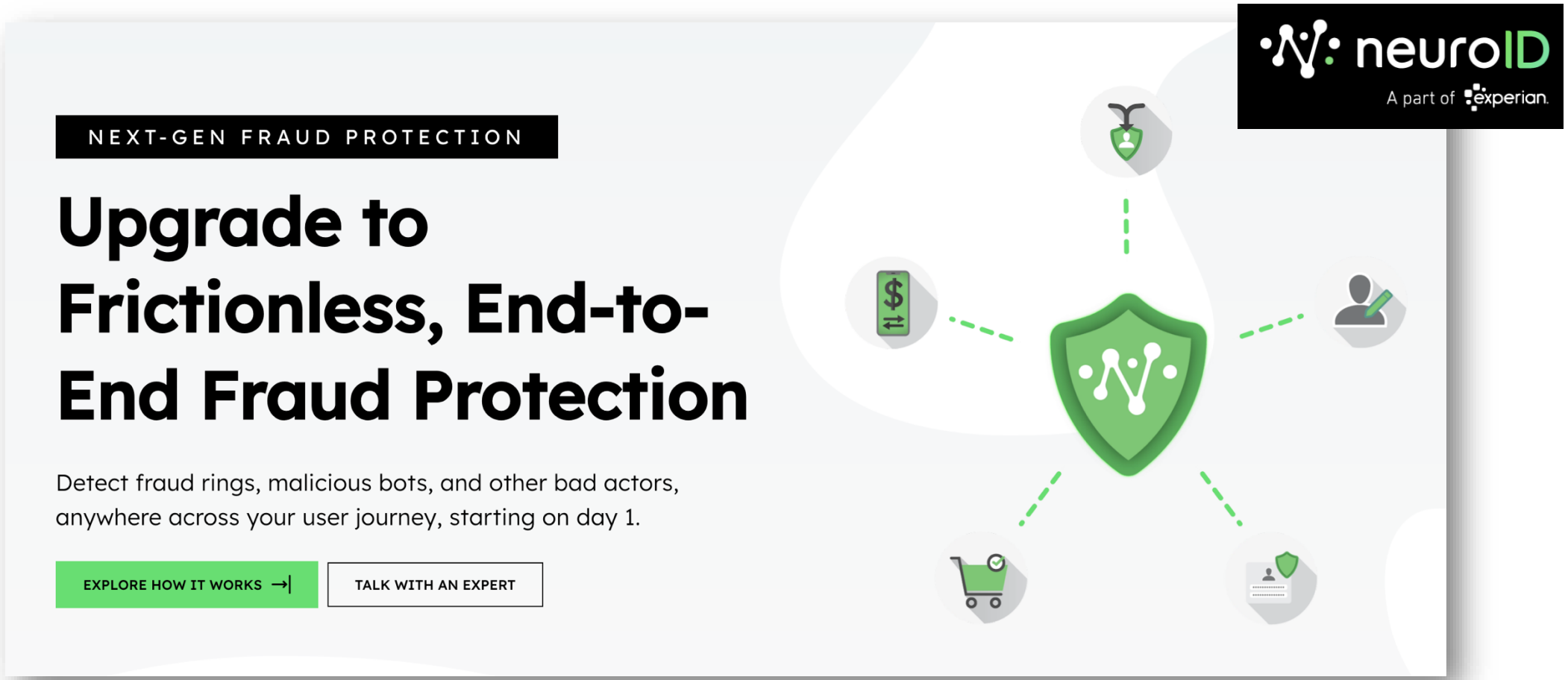


Figure 3 Log mean squared error (MSE) (top) and raw error rate (bottom) versus number of training passes

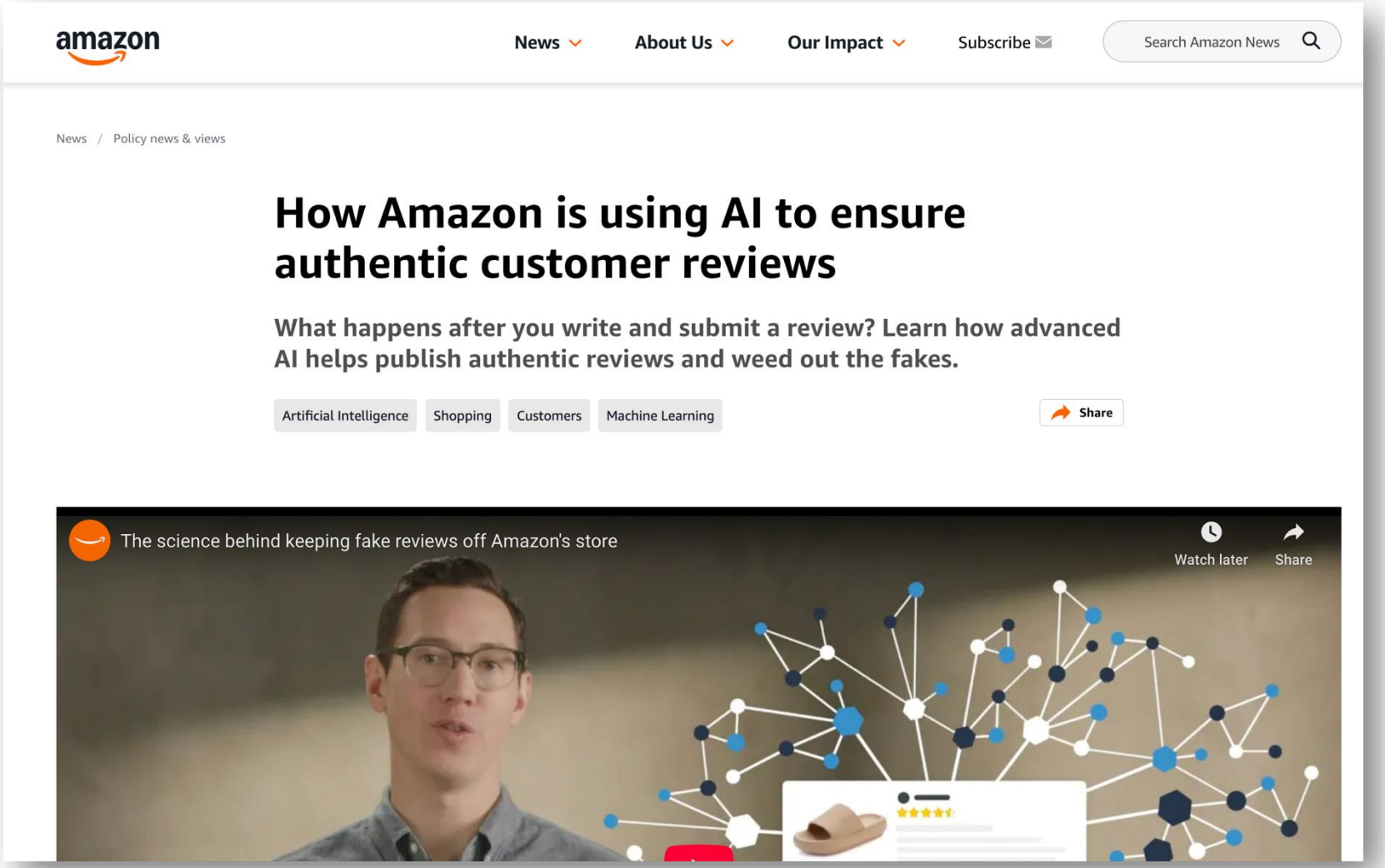
Modern Examples: Identity Verification



Modern Examples: Fraud Detection

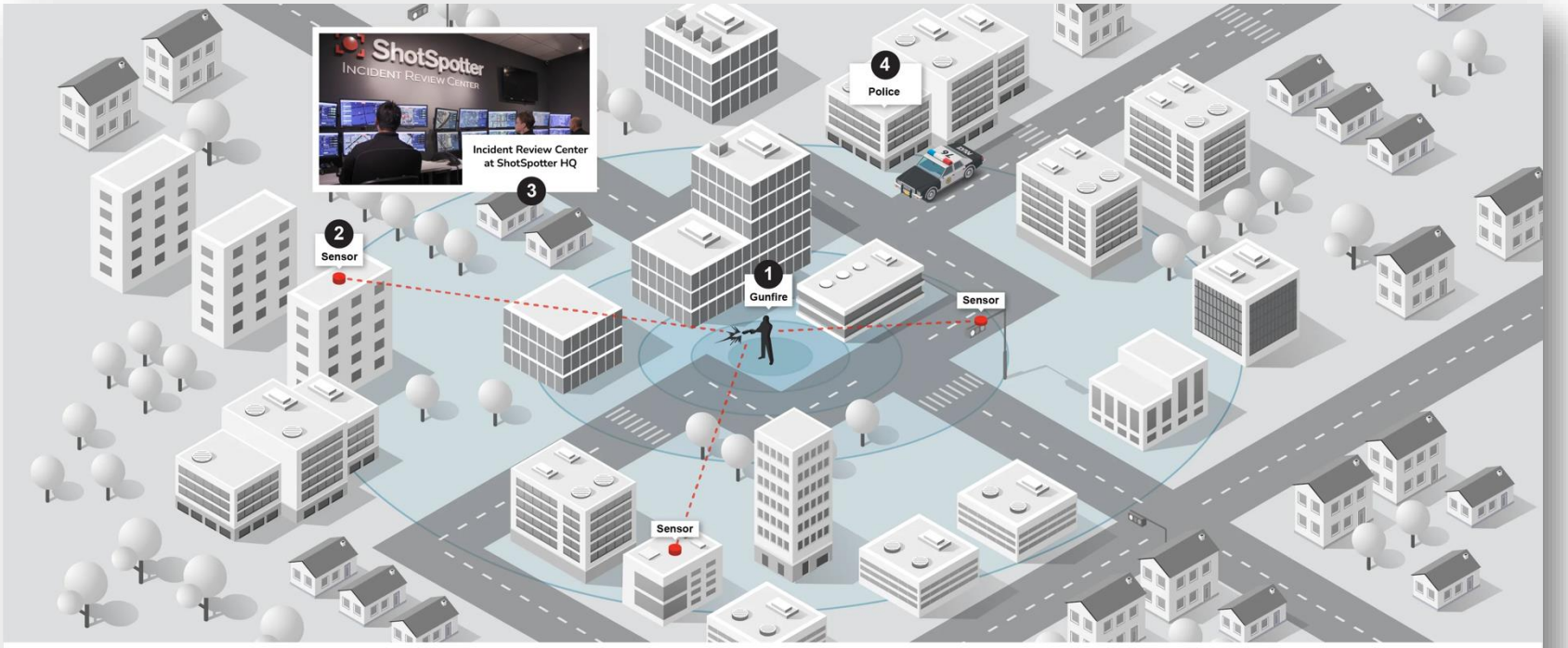


Modern Examples: Fake Review Detection



Modern Examples: Gunfire Detection

SoundThinking



Modern Examples: Part Failure Prediction

FLUKE® Reliability

Industries Products Resources Events Careers

Contact Us

COMPANIES

Azima DLI

Maximize uptime and demonstrate the ROI of your reliability program with vibration monitoring, advanced AI analysis, and enterprise reporting.

Contact Us

Modern Examples: Audio Transcription

Epic | EpicShare | Epic Research | Cosmos | MyChart | OPEN | UserWeb | SHOWROOM

Epic | Software | About Us | Newsroom

AI for Clinicians

Learn how clinicians in the Epic community use AI to more quickly learn about their patients, complete documentation, and wrap up visits.

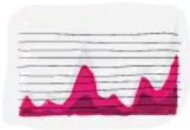
Before the Visit – Catching Up on Patients

Note Summarization

To help clinicians efficiently prep for outpatient visits, AI reviews recent notes and external data, and provides concise summaries of relevant details with references to the notes where specific details were discussed.

Inpatient Summarization

To help clinicians prepare for their patients, AI sifts through recent patient data and highlights important updates, providing concise summaries of each patient's status.

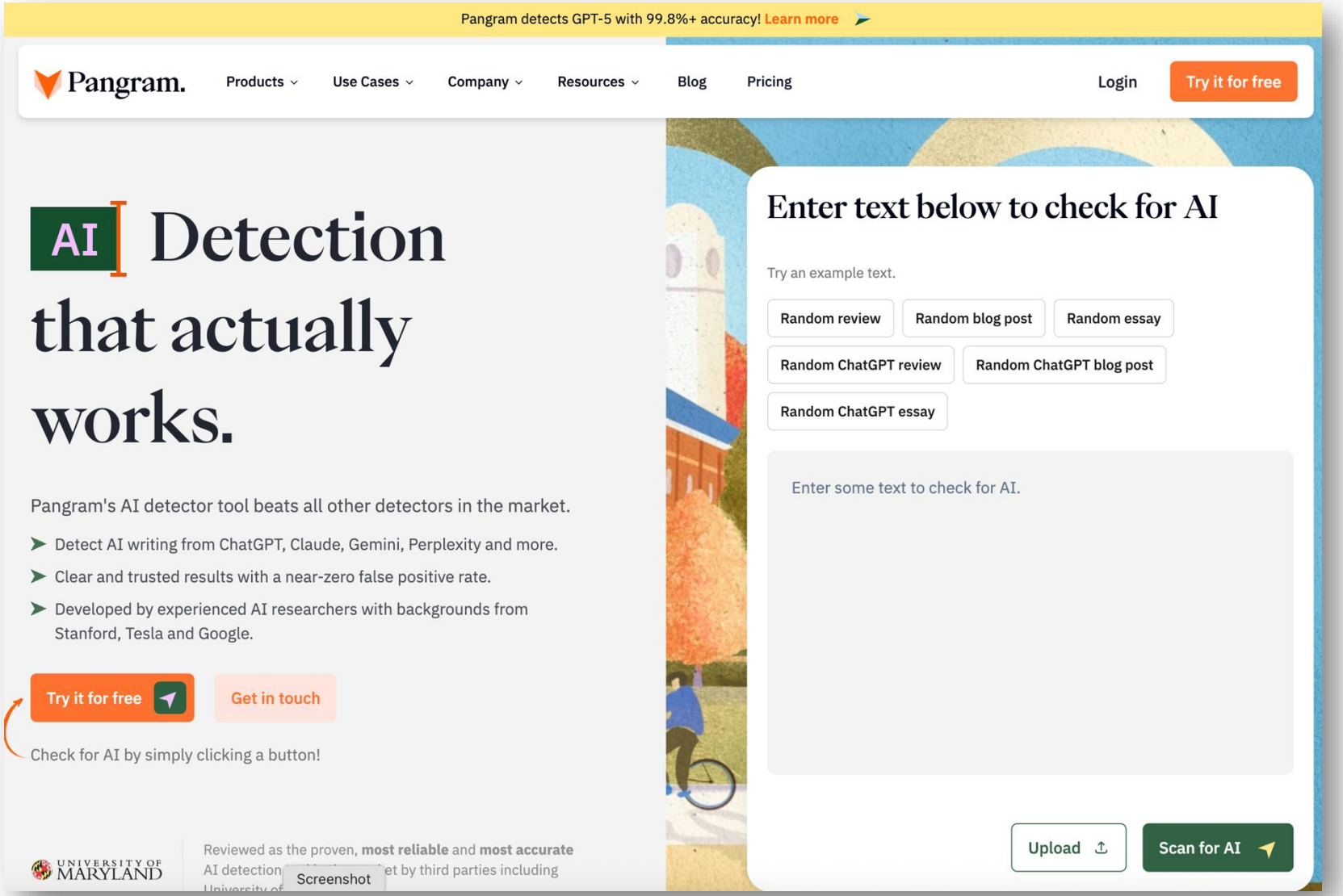


End of Shift Notes

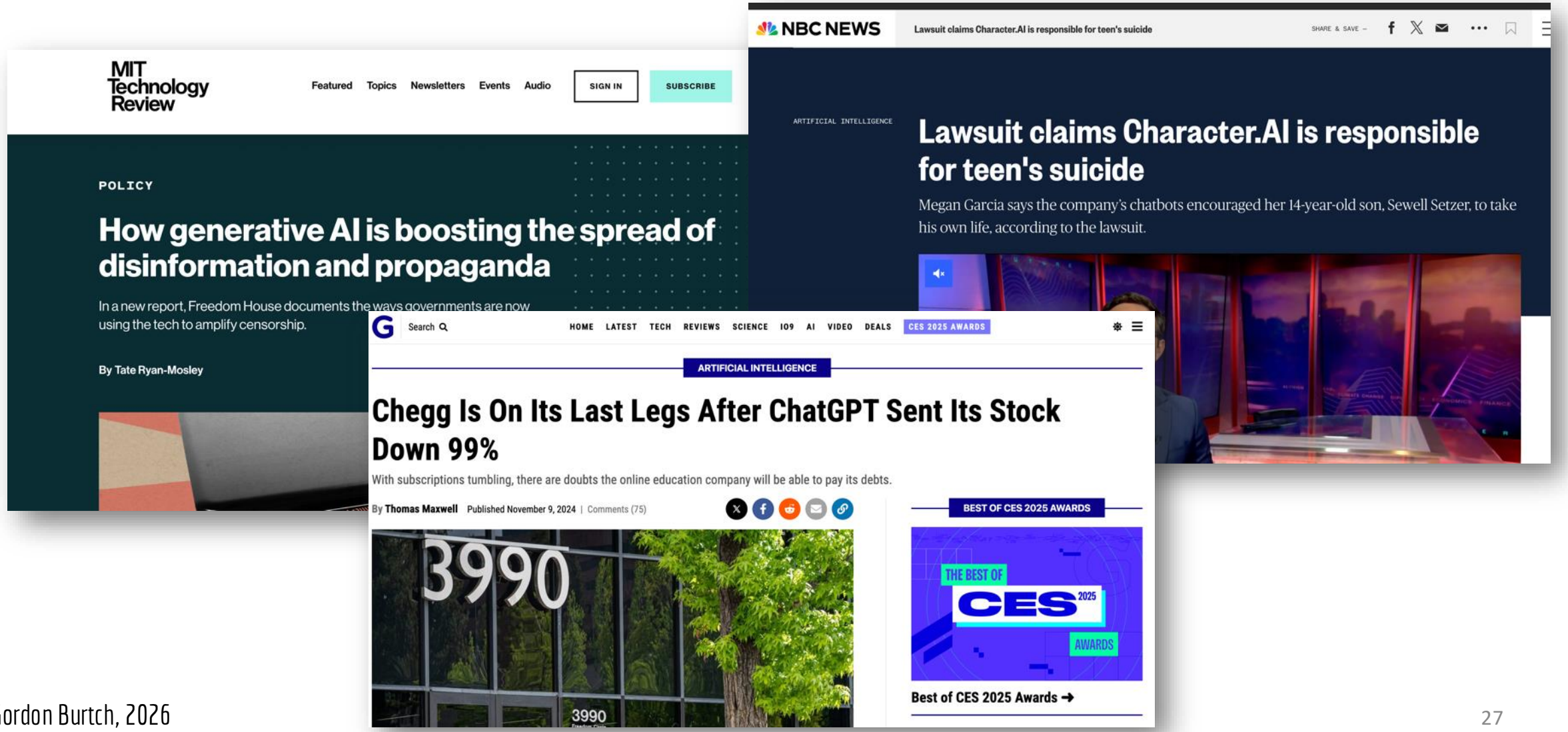
Nurses can get a head start on documentation by having AI draft end-of-shift notes using shift data already available in the patient's chart—including progress on patient goals. Concise, detailed summaries help the next shift get up to speed.

Audio Translation

Modern Examples: AI Text Detector



These Technologies Bring New Problems



Business Process / Model Still Matters

Bloomberg Opinion

Money Stuff

Sorry, Zillow's Computer Can't Buy Your House Right Now

Also CEO pay, the Boredom Markets Hypothesis and Big Short guys being big short.

By Matt Levine +Sign Up
October 18, 2021, 1:18 PM EDT

Matt Levine is a Bloomberg Opinion columnist covering finance. He was an editor of Dealbreaker, an investment banker at Goldman Sachs, a mergers and acquisitions lawyer at Wachtell, Lipton, Rosen & Katz, and a clerk for the U.S. Court of Appeals for the 3rd Circuit.

Zillow

Deciding how much you should pay for a share of large-cap publicly traded stock is not an *entirely* solved problem, but it's pretty close. If someone comes to you and says "hey I have 100 shares of Microsoft Corp. stock for sale, how much will you pay me for it," a pretty decent answer would be to look at the last price at which Microsoft traded – like a millisecond ago – and subtract, you know, one cent from that price. That will get you a price that is likely to be competitive (the seller might actually sell to you), likely to be profitable (you might be able to sell it for more than you paid), and

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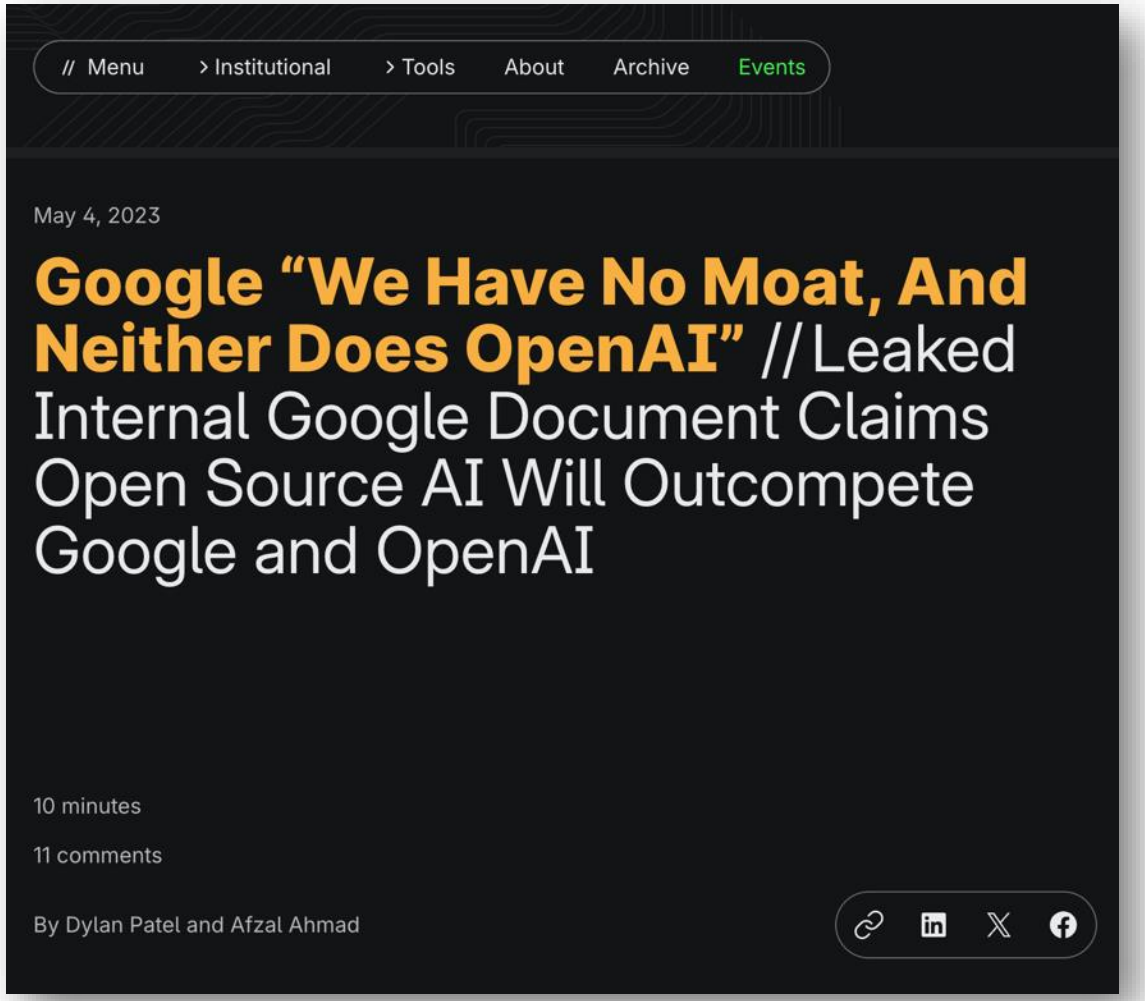


// Menu > Institutional > Tools About Archive Events

May 4, 2023

Google "We Have No Moat, And Neither Does OpenAI" // Leaked Internal Google Document Claims Open Source AI Will Outcompete Google and OpenAI

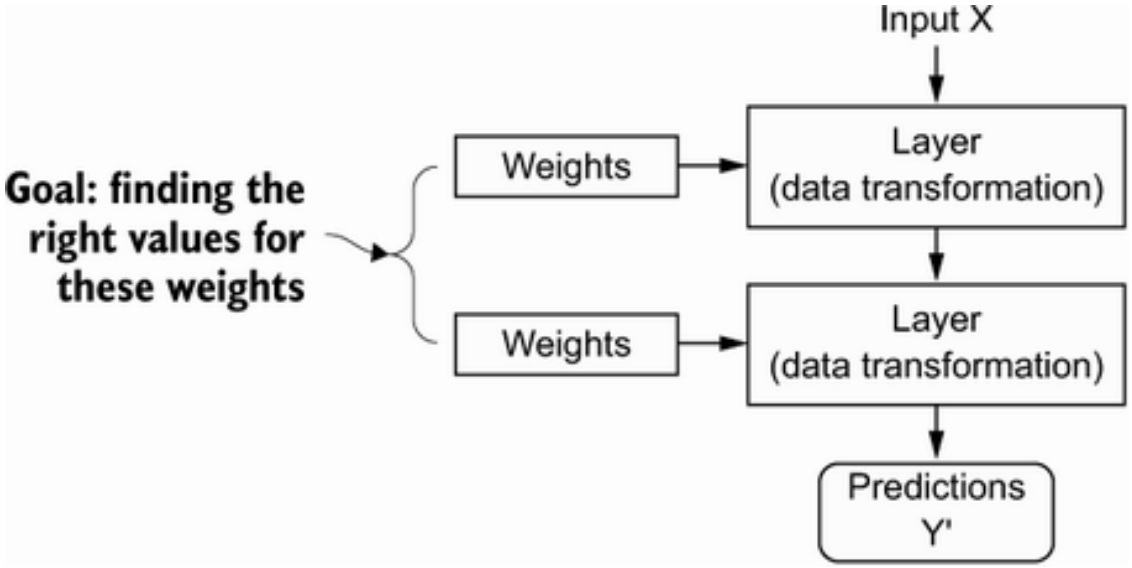
10 minutes

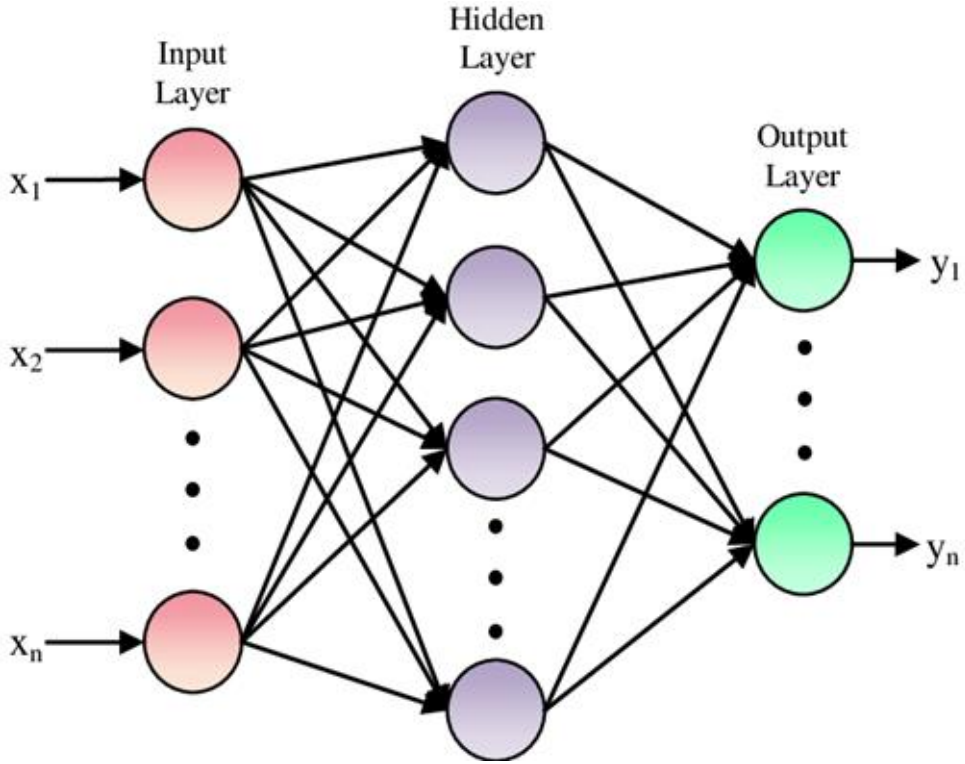
11 comments

By Dylan Patel and Afzal Ahmad

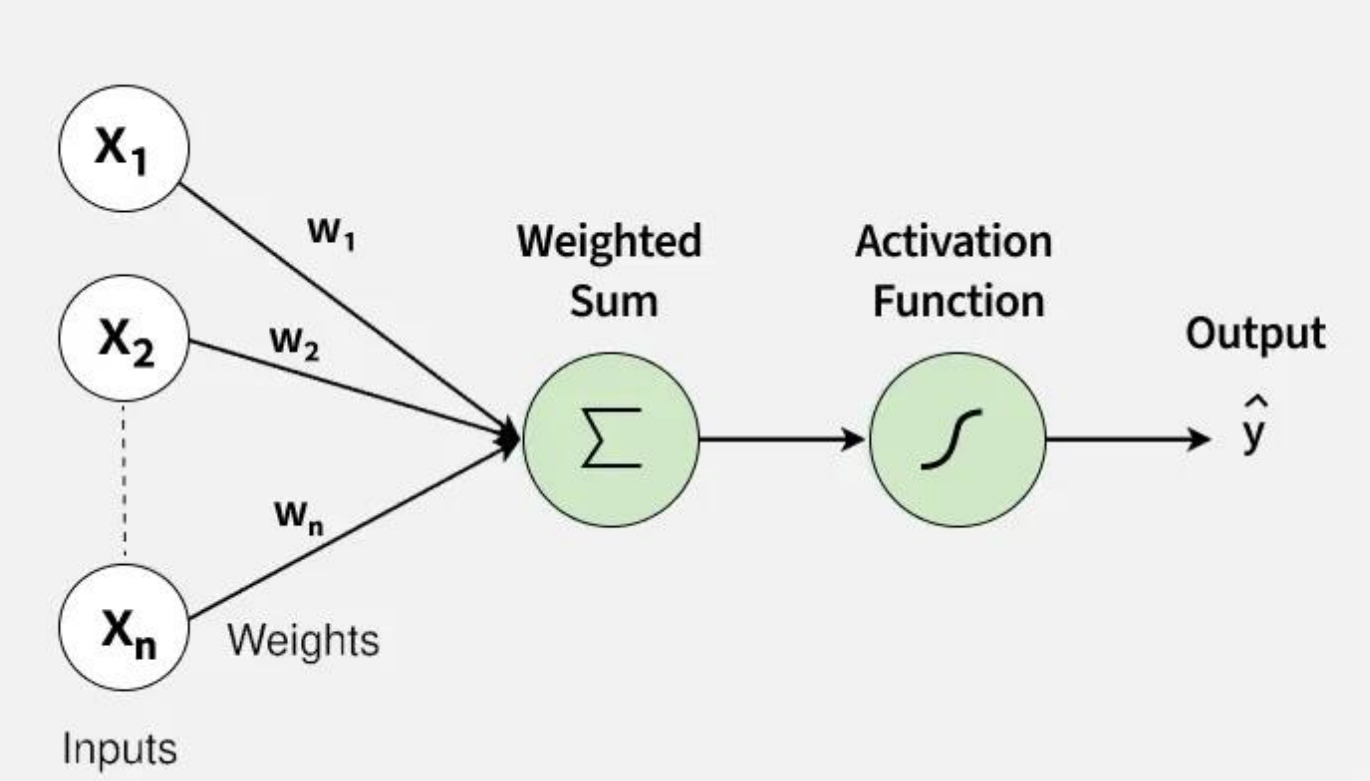
How It Works, Conceptually

Model Parameters

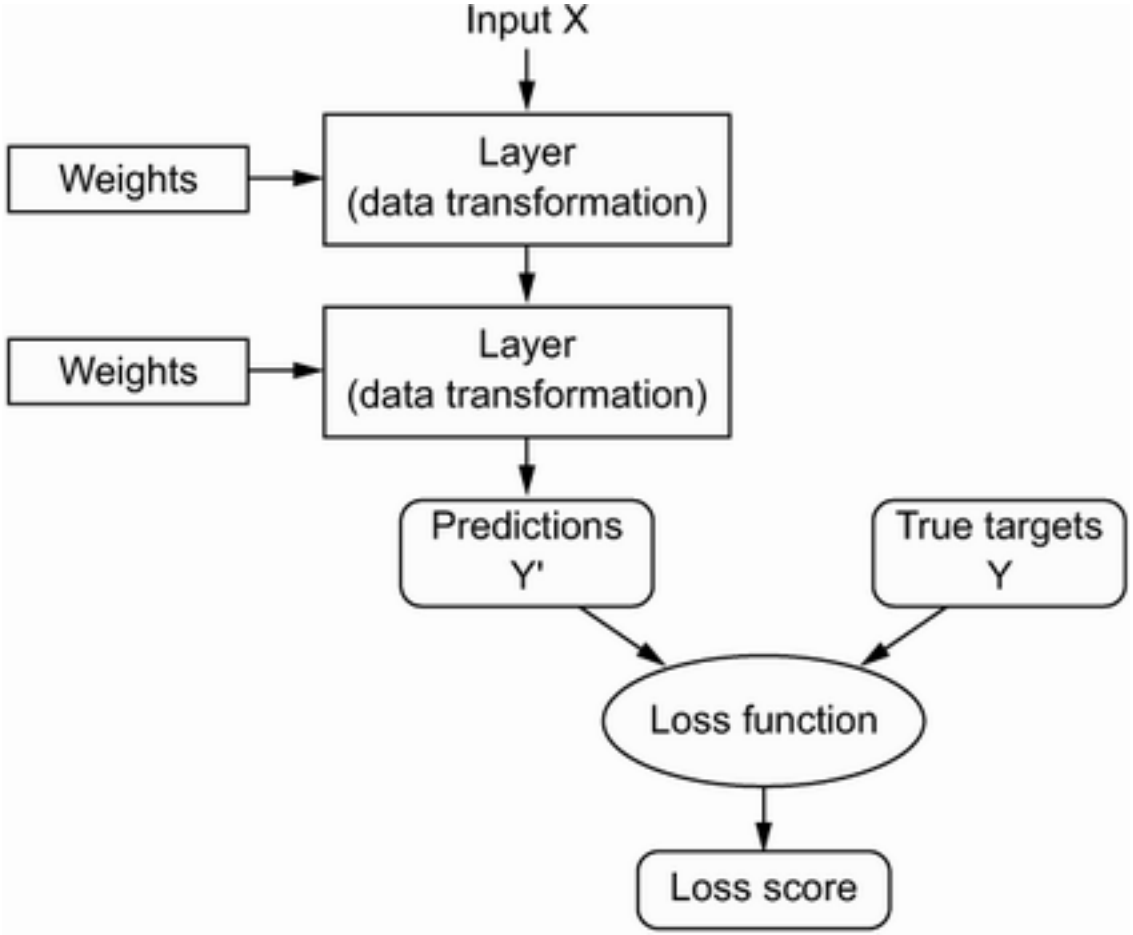




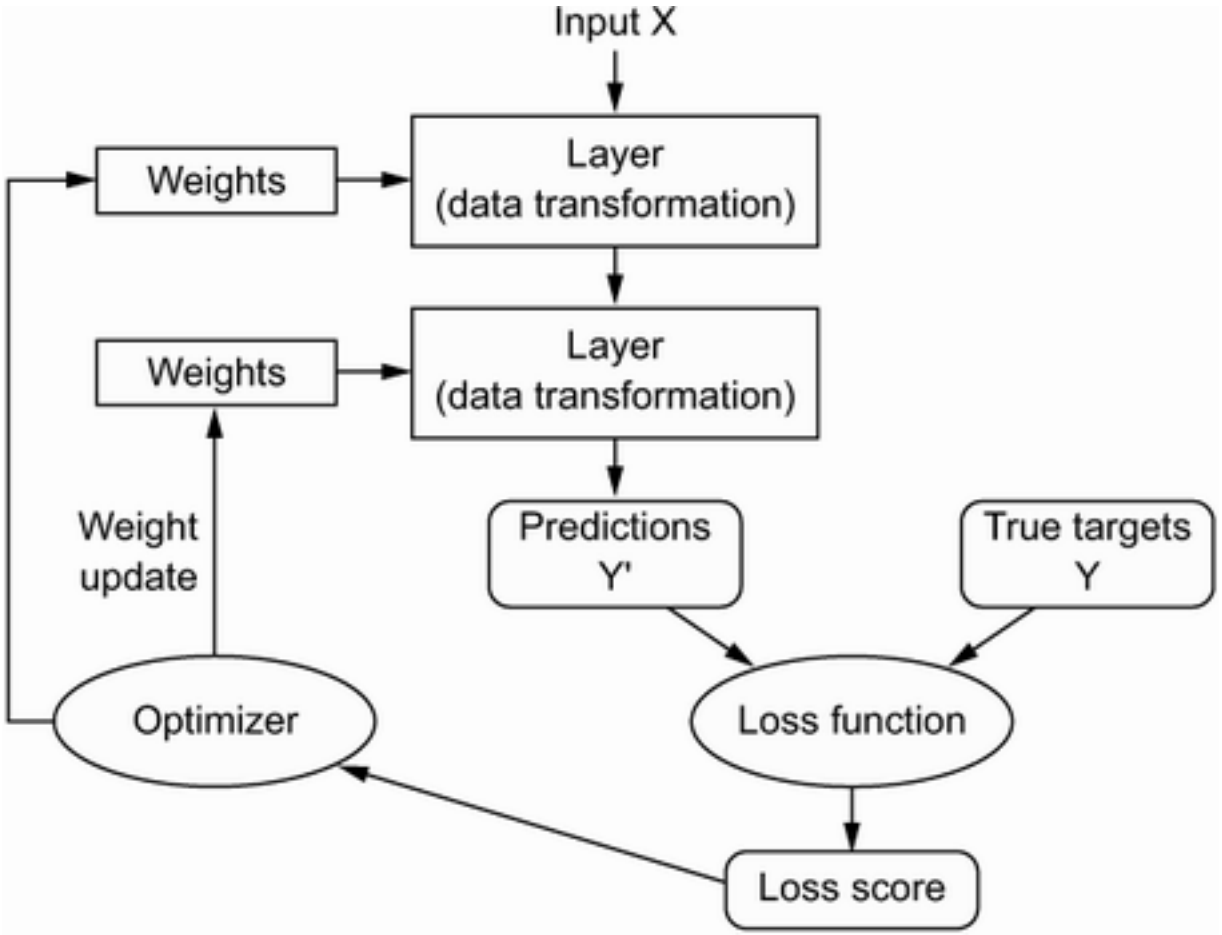
Model Parameters



Loss Function (Error)



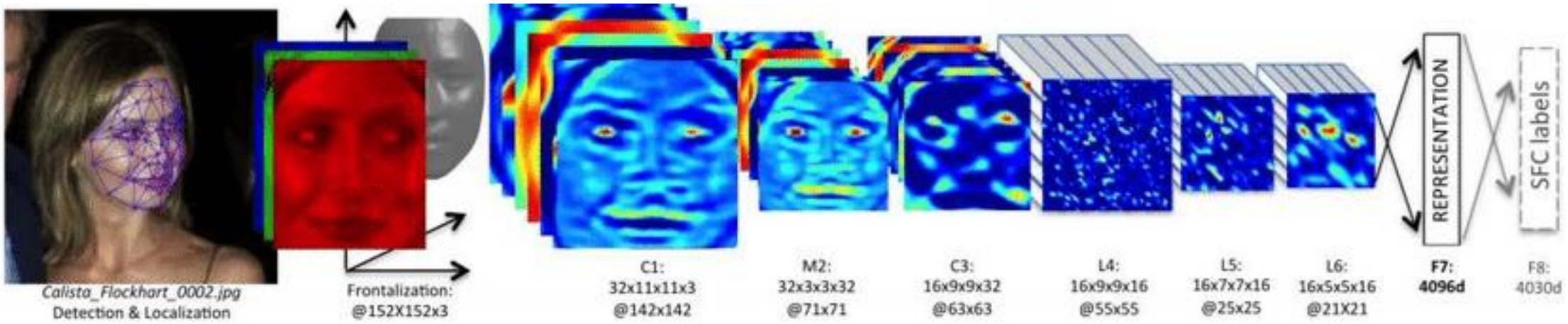
Optimization



When to Learn Deeply (vs. Not)

COMPLEX RELATIONSHIPS

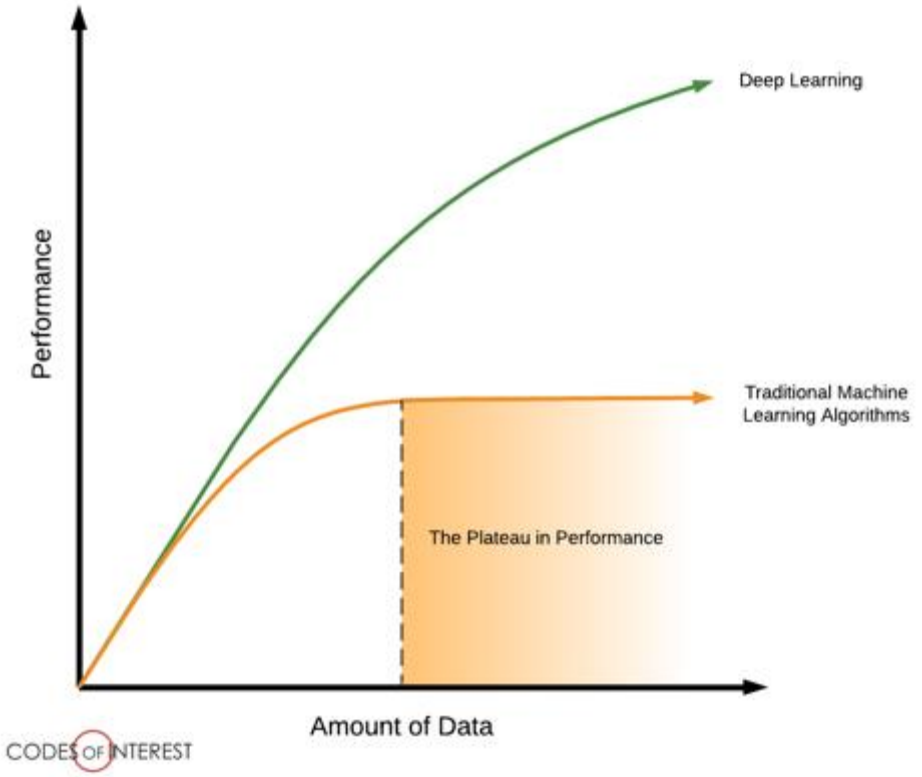
- Complex, non-linear, interactive relationships and mappings; common use cases involve unstructured (high dimensional) data. Deep learning techniques remove the need for feature engineering, a daunting task.



When to Learn Deeply (vs. Not)

LOTS OF DATA ON HAND

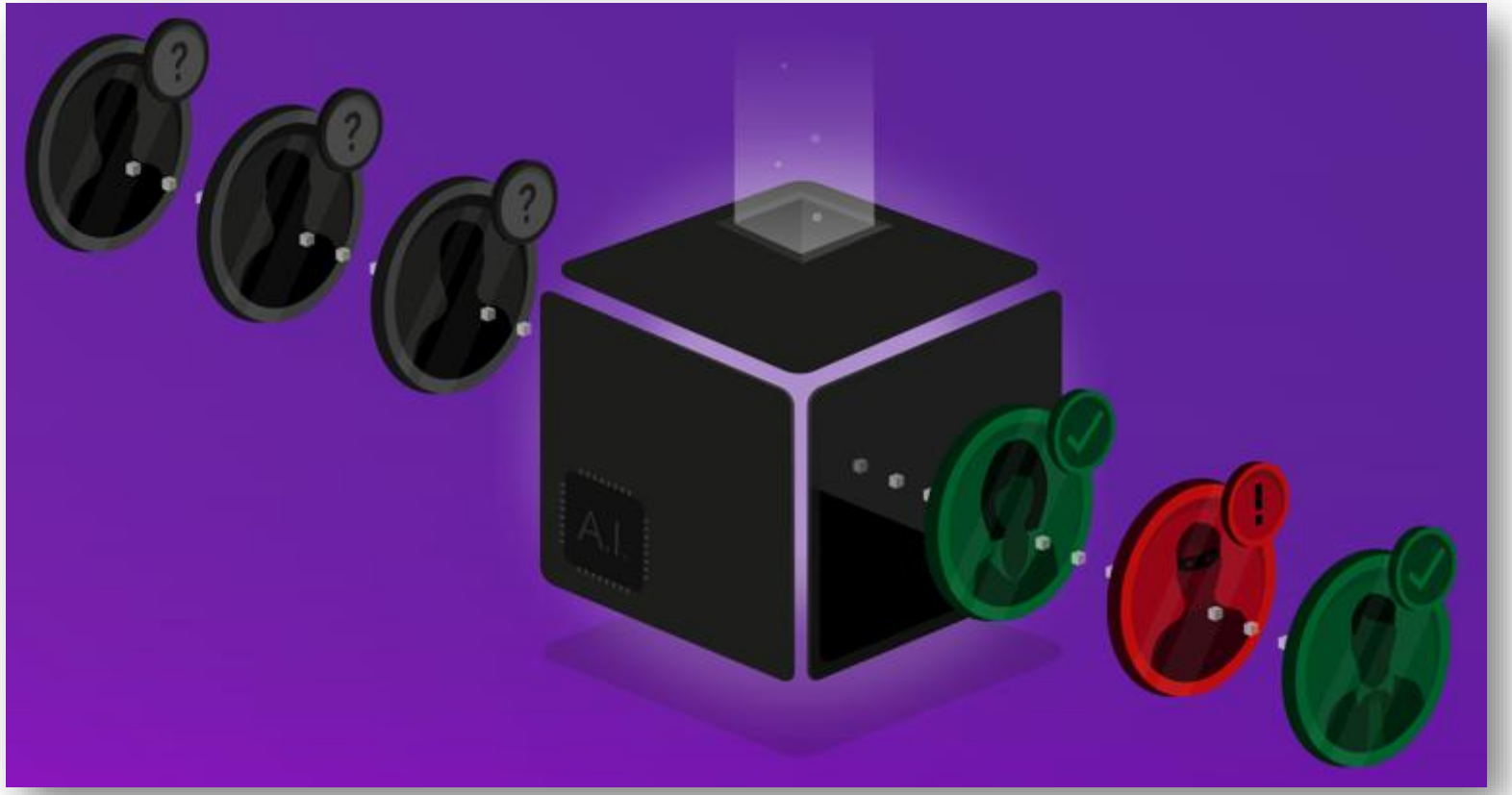
- To be able to learn those complex mappings, typically requires many, many, many training examples.



When to Learn Deeply (vs. Not)

LITTLE NEED FOR UNDERSTANDING

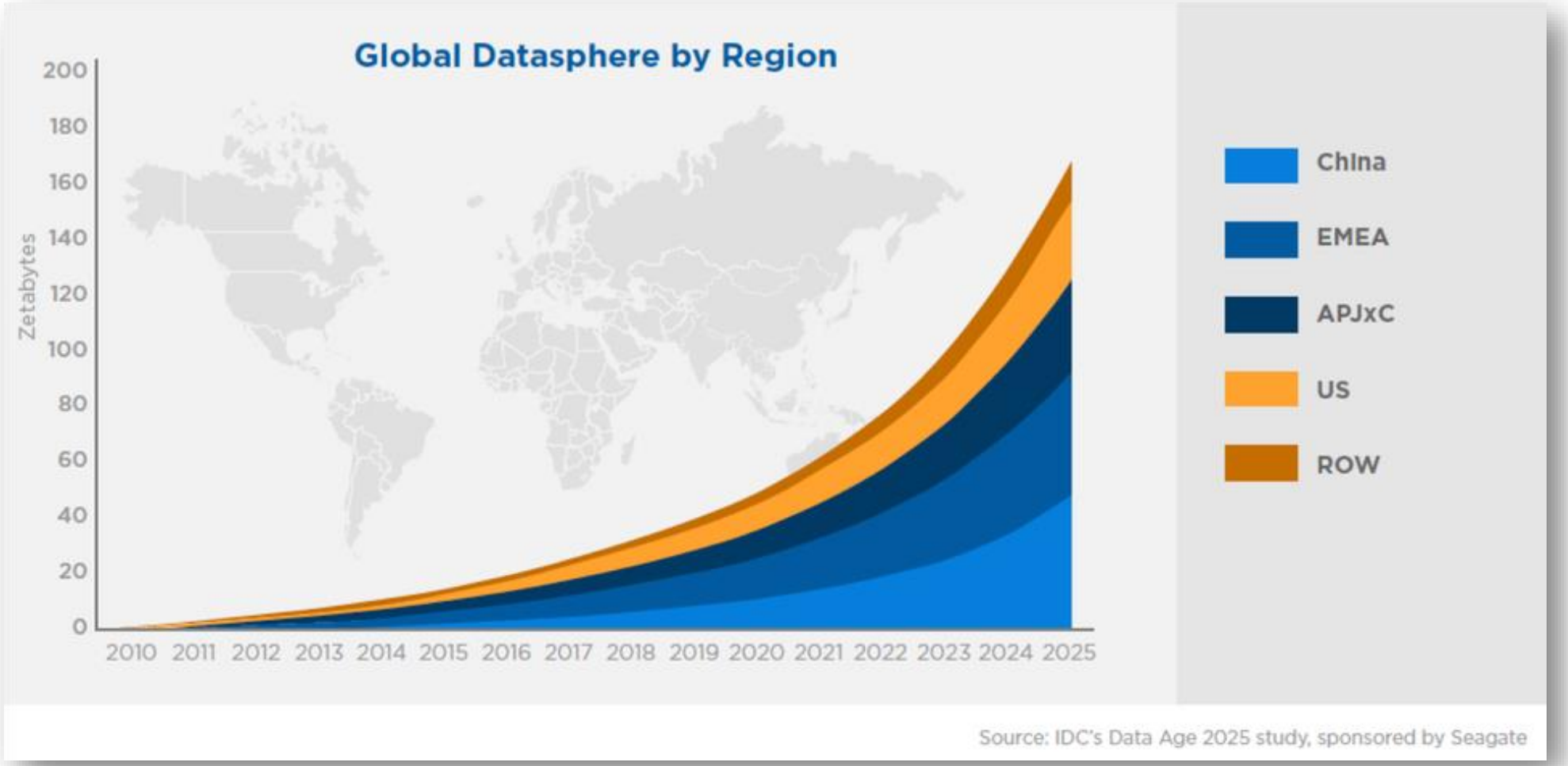
- Although there have been advancements in explainable and interpretable AI, deep nets are notoriously “black box” algorithms.



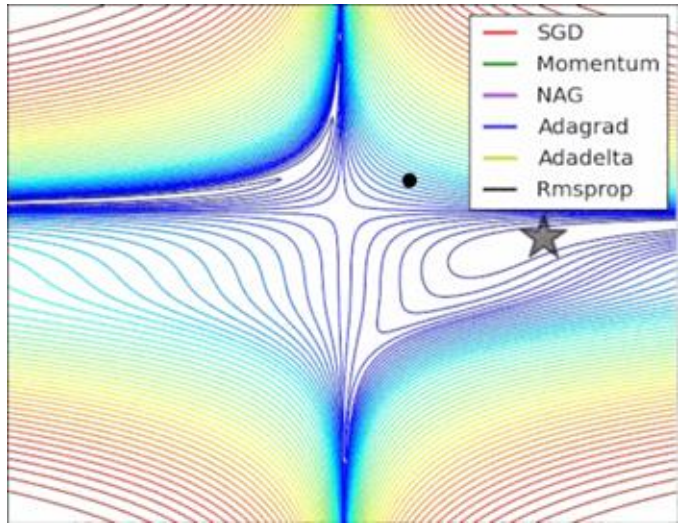
Why Did Deep Learning Take Off?

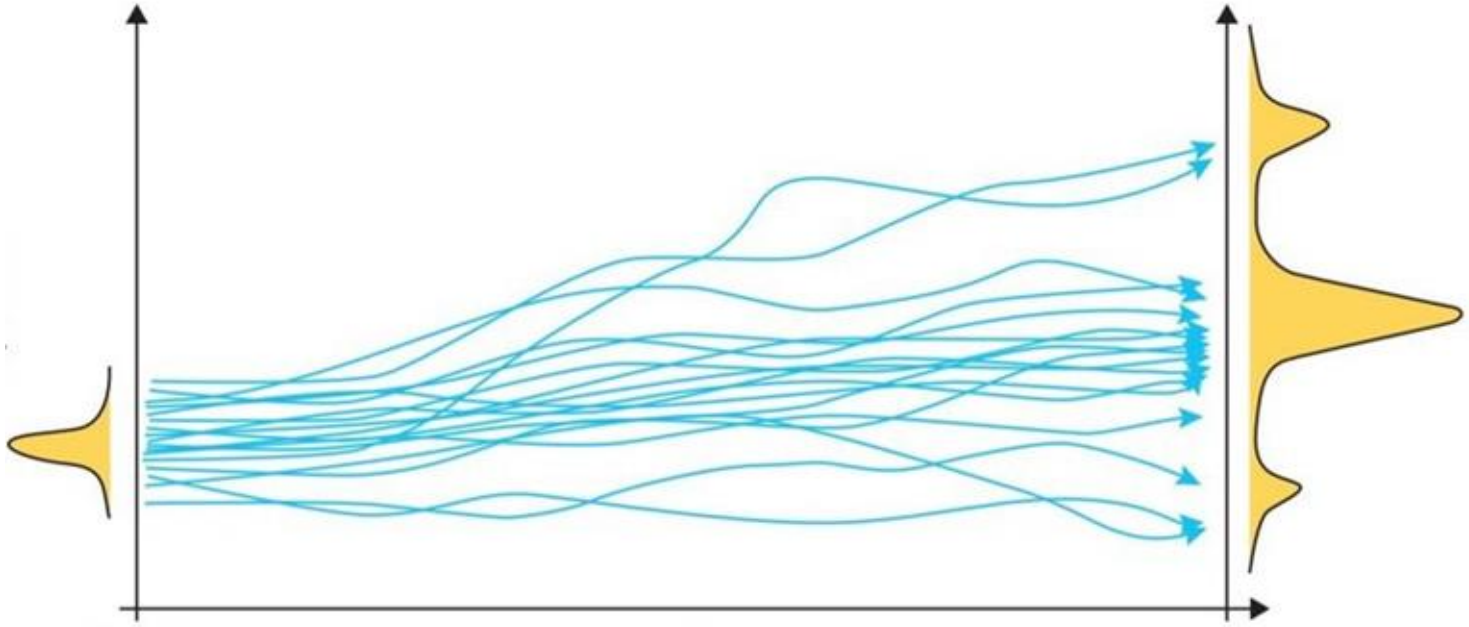
Video Games

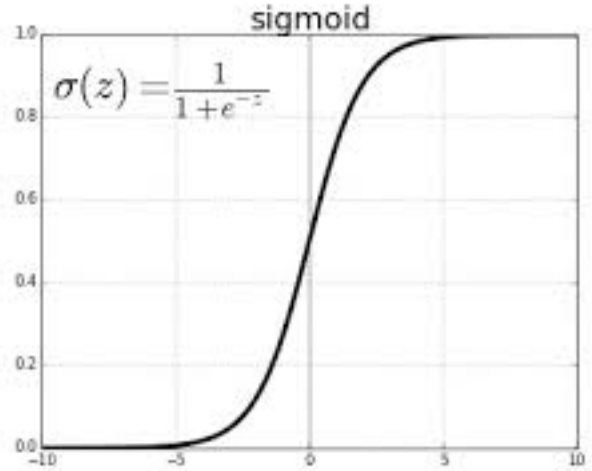
Data



Algorithmic Improvements







Questions?