Intro to Neural Nets

Course Logistics and Introduction

About Me

MSI at the ARF

NSF

FFG Forschung wirkt.

Adobe

3M

Microsoft

accenture

Today’s Agenda

1. COURSE LOGISTICS

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

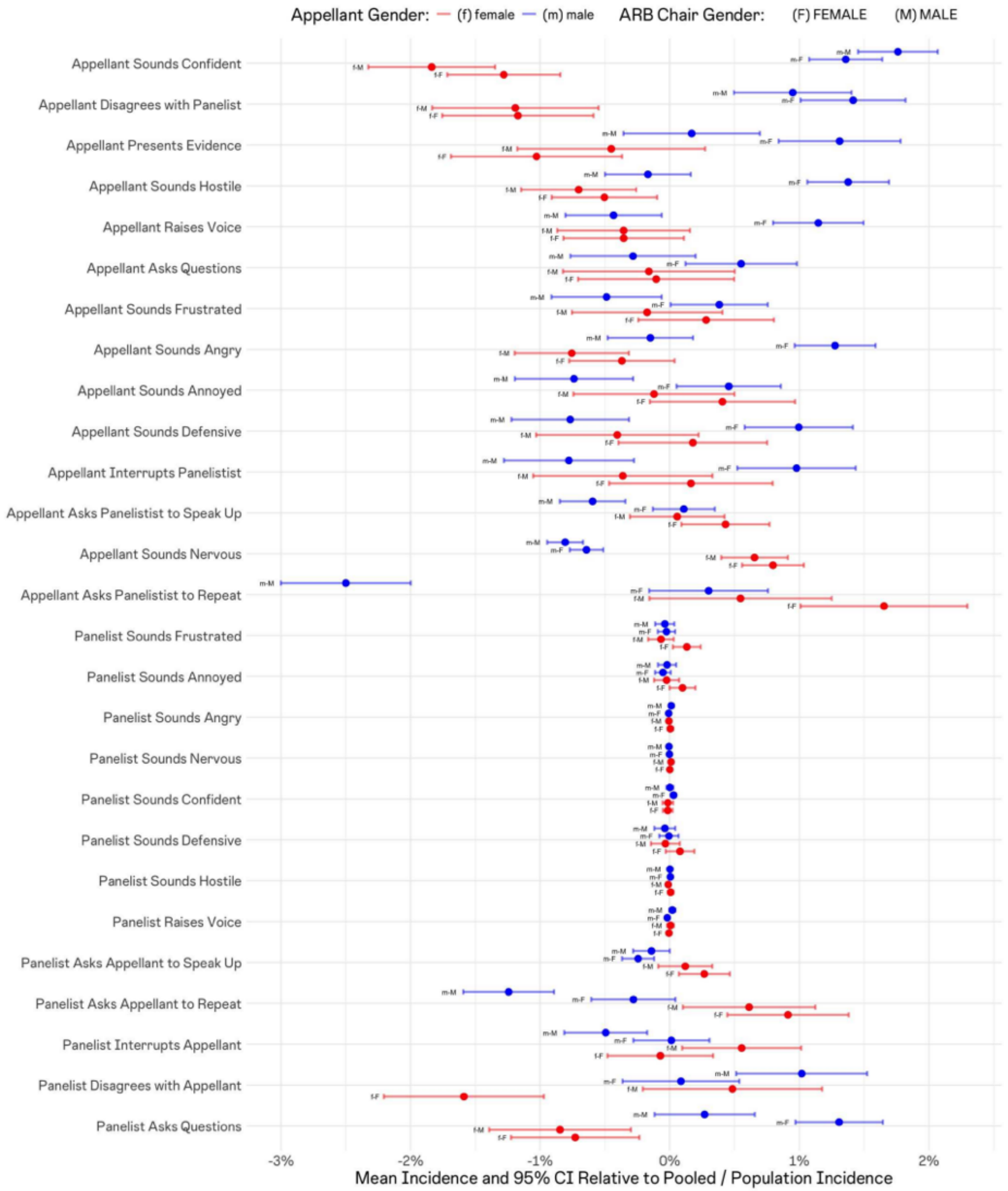
2. INTERESTING USE CASES

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

3. QUICK INTRODUCTION

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

Some Research



arXiv:2412.12610v2 [econ.GN] 4 Feb 2025

Gender Bias and Property Taxes

By Gordon Burtch[†] & Alejandro Zentner[‡]

Gender bias distorts the economic behavior and outcomes of women and households. We investigate gender biases in property taxes. We analyze records of more than 100,000 property tax appeal hearings and more than 2.7 years of associated audio recordings, considering how panelist and appellant genders associate with hearing outcomes. We first observe that female appellants fare systematically worse than male appellants in their hearings. Second, we show that, whereas male appellants' hearing outcomes do not vary meaningfully with the gender composition of the panel they face, those of female appellants' do, such that female appellants obtain systematically lesser (greater) reductions to their home values when facing female (male) panelists. Employing a multi-modal large language model (M-LLM), we next construct measures of participant behavior and tone from hearing audio recordings. We observe markedly different behaviors between male and female appellants and, in the case of male appellants, we find that these differences also depend on the gender of the panelists they face (e.g., male appellants appear to behave systematically more aggressively towards female panelists). In contrast, the behavior of female appellants remains relatively constant, regardless of their panel's gender. Finally, we show that female appellants continue to fare worse in front of female panels, even when we condition upon the appellant's in-hearing behavior and tone. Our results are thus consistent with the idea that gender biases are driven, at least in part, by unvoiced perceptions among ARB panelists. Our study documents the presence of gender biases in property appraisal appeal hearings and highlights the potential value of generative AI for analyzing large-scale, unstructured administrative data.

Keywords: Property Tax, Public Finance, Gender Bias, Generative AI, Gender Concordance, Multimodal Large Language Models

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* We would like to thank Emma Wiles, Jetson Leder-Luis, Dokyun Lee, Bin Gu, Patricia Cortés, and Zoe Cullen for helpful comments and suggestions, as well as seminar participants at Southern Methodist University, George Washington University, U Mass-Amherst, and Boston University. Joanna Jia, Heetal Binwani, and Tiffany Zhang provided superb research assistance.

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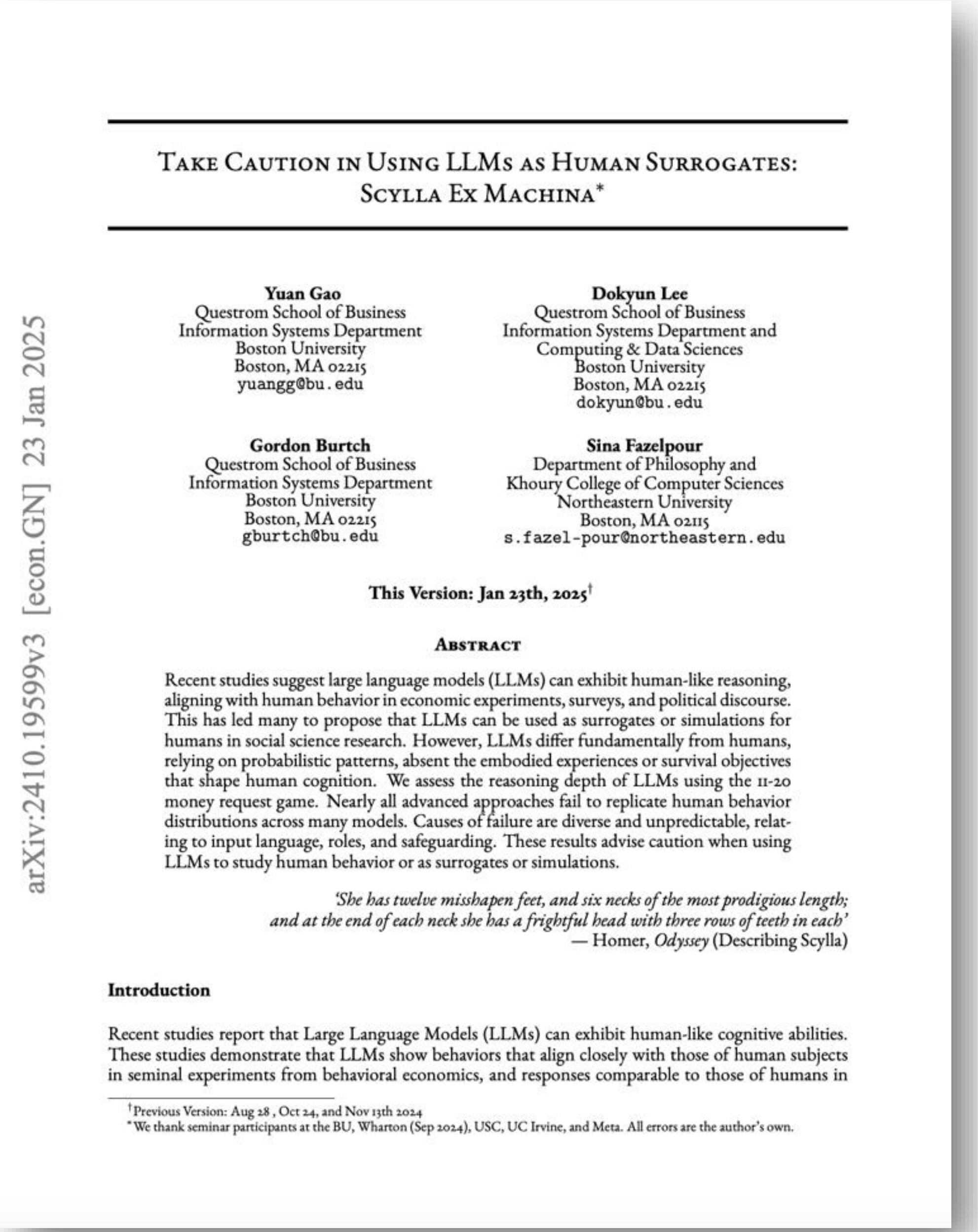
Some Research



arXiv:2410.19599v3 [econ.GN] 23 Jan 2025

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.

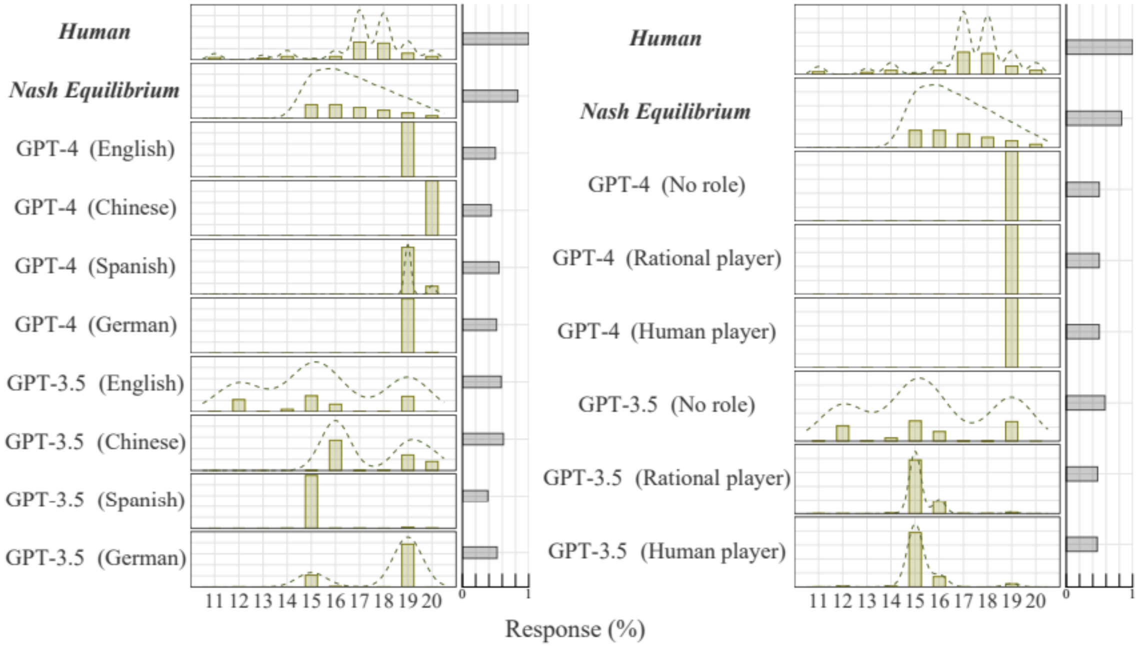


Figure 2: **Prompt Brittleness: Roles and Languages.** The bar chart on the right shows the similarity between the distribution of different subjects and human subjects, measured by Jensen-Shannon divergence scores. Density plots are omitted for subjects with over 98% of the data concentrated in a single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

Grading & Evaluation

25%

Pre-Module

1. Complete all the pre-module reading materials (see Reading Materials Section above)
2. Complete the pre-module quiz, which is based on the required pre-module readings (Chapters 1 and 2 of the text).
3. Make sure you are comfortable with the material from the Data Mining in R class (concepts such as Training/Test Sets, Logistic Regression, model error). I will provide no more than a quick review of these pre-requisite materials during class.
4. Create a google account and make sure you can access Google Colab. I recommend that you purchase a Google Colab Pro subscription. You can do this via the settings menu in Google Colab (click the gear icon, then choose Colab Pro).

40%

35%

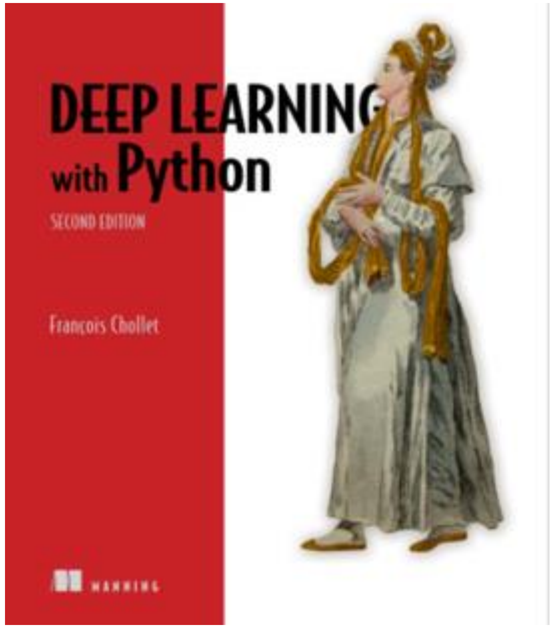
Post Module Exercise

First, read the post-module reading materials (see **Reading Materials** Section). Then, complete the following two post-module assignment items:

(1) The first part of the assignment is to be done ***independently***. Discussion is allowed, but each student needs to submit his/her own individual write-up. Please submit a single edited .ipynb file (with your name and ID in the file name). (40% of final grade).

(2) The second part is an open-ended (group) project; you can do it either independently or collaborate with up to two other students (maximum of three students in each group). Please submit a separate single WORD/PDF file with all group members' names and IDs. (35% of final grade)

Course Textbook



Chollet, François. (2021). *Deep Learning with Python (2nd Edition).* Manning Publications Co. **ISBN-13: 978-1617296864.**
https://www.manning.com/books/deep-learning-with-python-second-edition

Required Software

SOFTWARE CONFIGURATION

- You can access Google Colab at https://colab.research.google.com. You should have setup a colab account already.

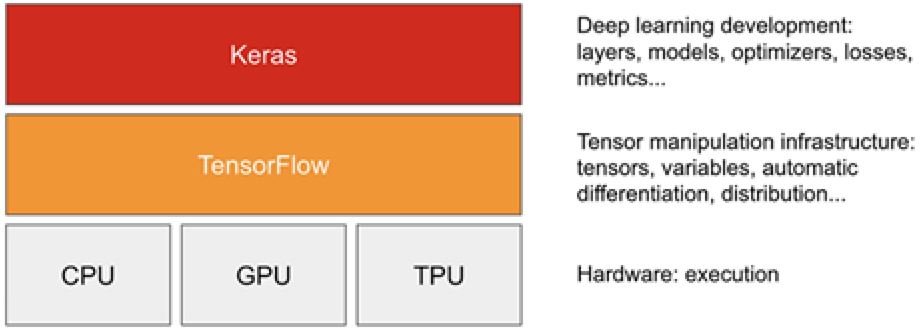
Keras and Tensorflow

1. Tensorflow

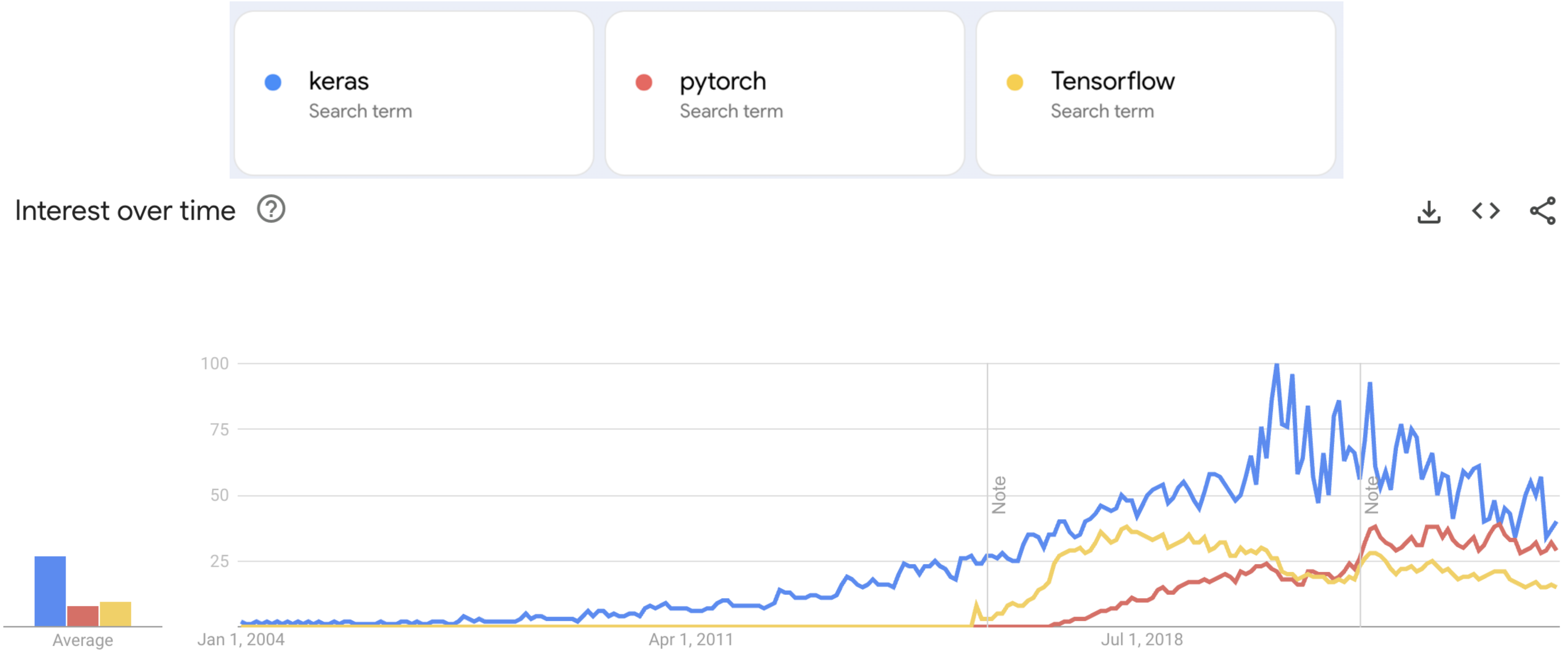
- A Python platform for working with tensors, implementing automatic differentiation, providing access to repositories of (well-known) pre-trained models.

2. Keras

- A higher-level API that wraps common usage patterns with Tensorflow functions, pre-defined loss functions, optimization algorithms, etc.
- Keras simplifies data scientists' interaction with Tensorflow.

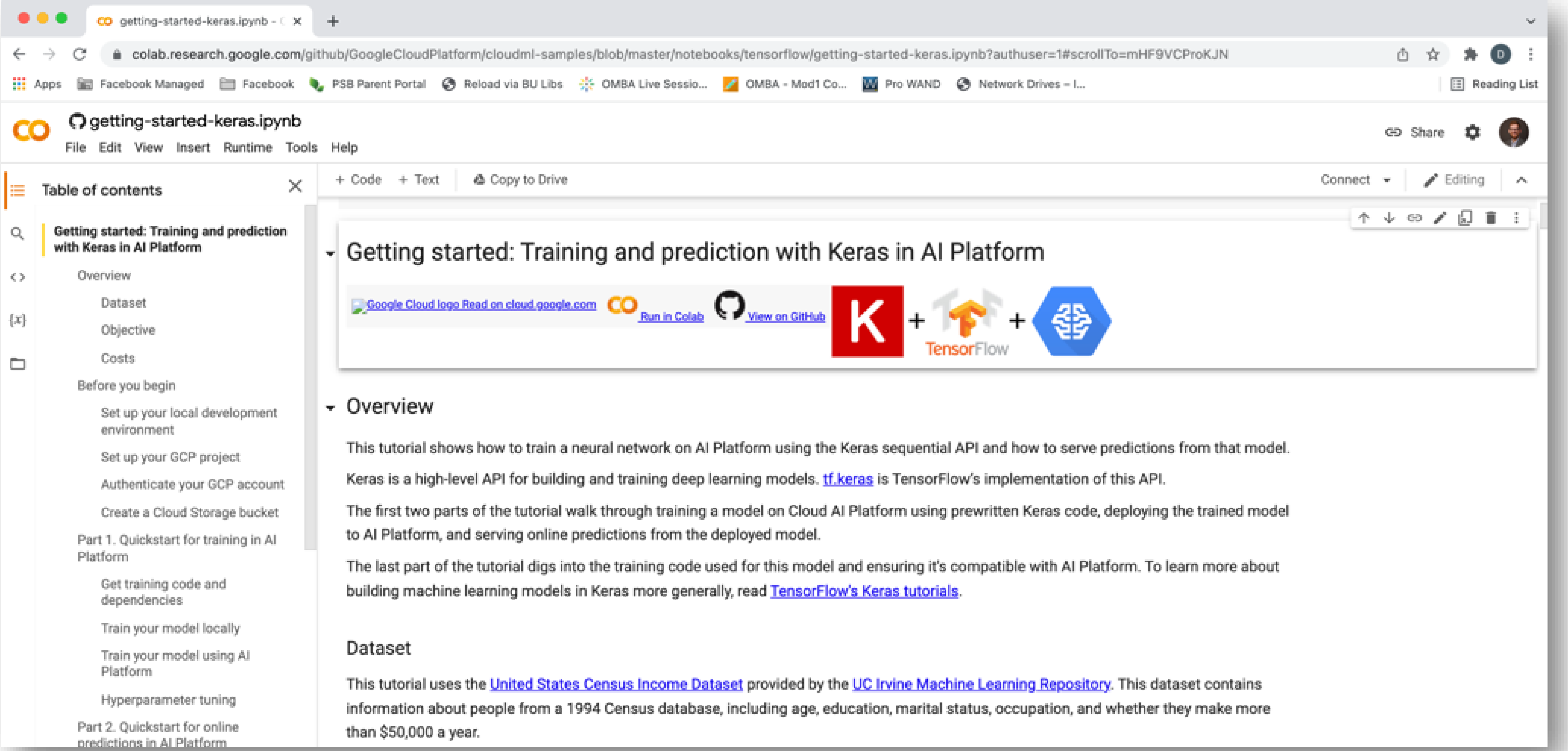


Why Keras?



keras
Search term
pytorch
Search term
Tensorflow
Search term
Interest over time
100
75
50
25
Note
Note
Average
Jan 1, 2004
Apr 1, 2011
Jul 1, 2018

Google Colab



Course Format

LECTURES

- We will meet twice weekly for ~2.5 hours each session. I will incorporate a 20-minute break in the middle of each session. The first half of each session will focus on lecture / concepts / explanation.

HANDS-ON EXAMPLES

- The second half of each session will be focused on walking through hands-on examples and demonstrations in Python notebooks. I will provide Jupyter Notebooks and data-sets (typically via GitHub), which we will walk through together.
- You are encouraged to ask questions as we progress.
- Note that the quizzes, individual assignment, and exam will be based on the in-class material. I will not test you on things that were not discussed in class.

Support

USE IT TO HELP YOU LEARN AND PERFORM BASIC TASKS

I expect you to use these tools. However, the way you use them matters. Some valid use cases include …

- Implementing data munging tasks that you might already understand based on past coursework, e.g., pre-processing text.
- Automatic generation of code comments or documentation.

NOT TO GENERATE SOLUTIONS FROM SCRATCH

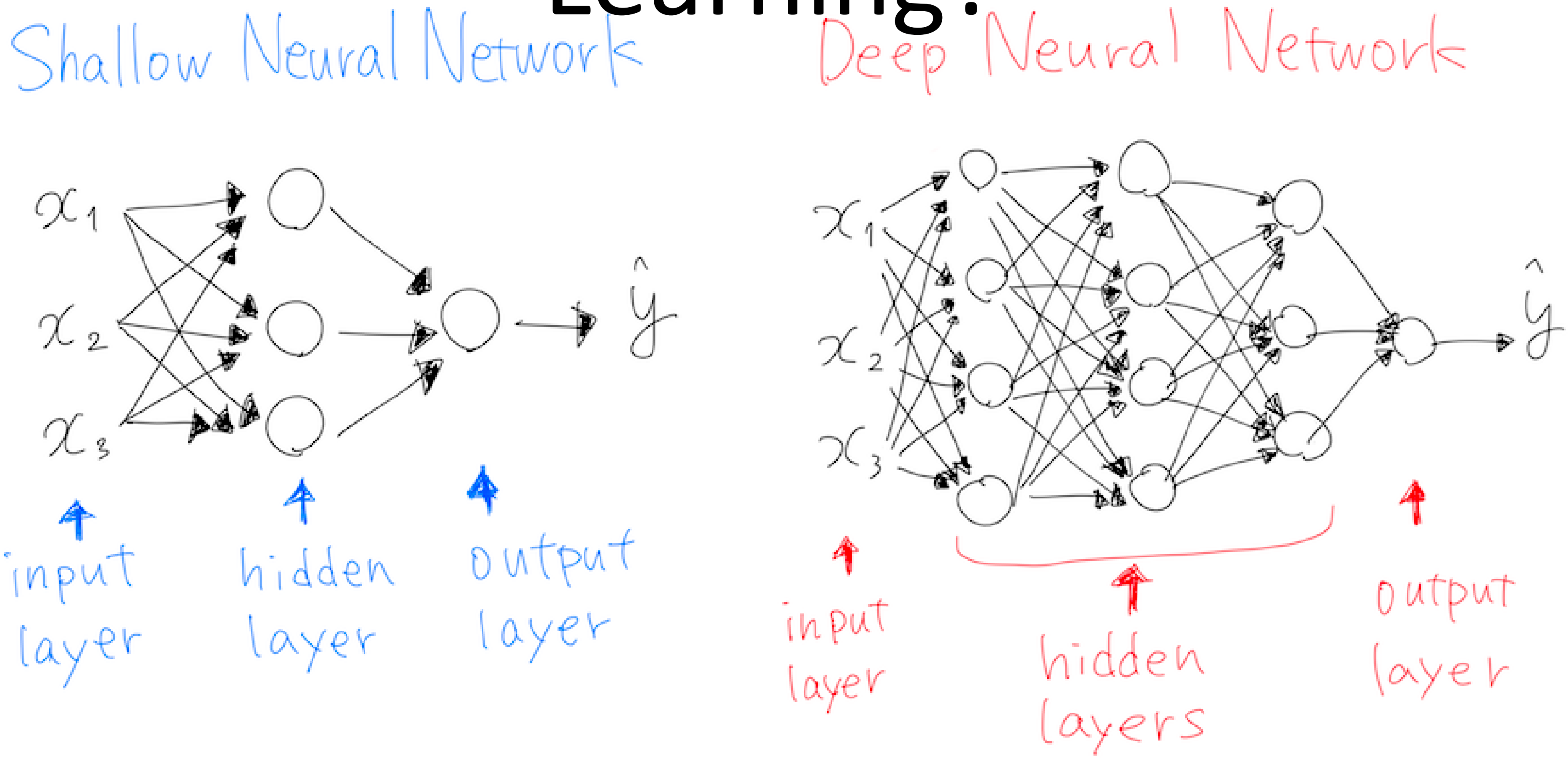
If you use these tools as a shortcut to avoid understanding the course material, you will not do well in this class. If we encounter functions and practices that were not taught in the course (e.g., PyTorch code), you will be asked to explain your code to us orally. If you are unable to explain what the code is doing, points *will* be deducted from your grade.

Any Questions?

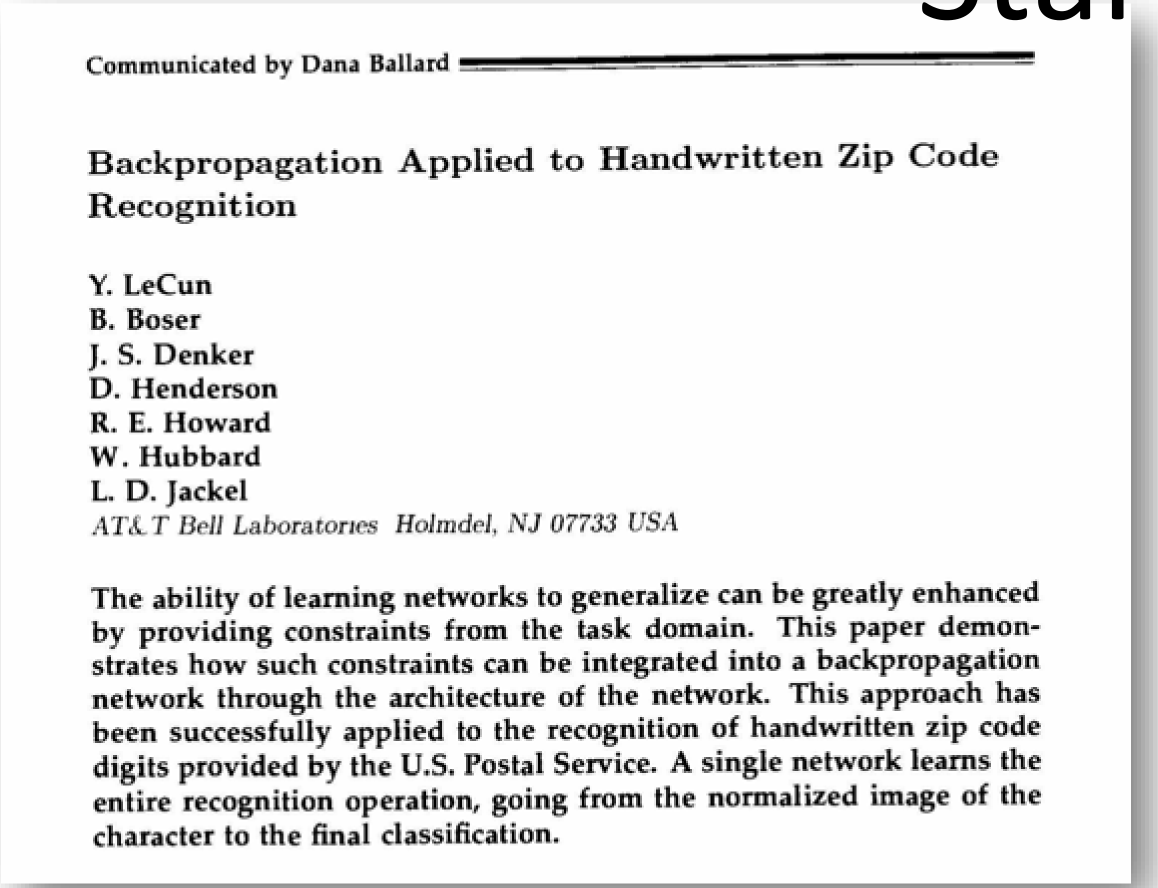
What is ‘Deep’ (vs. Shallow) Learning?

https://chat.openai.com/chat

What is ‘Deep’ Learning?



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.

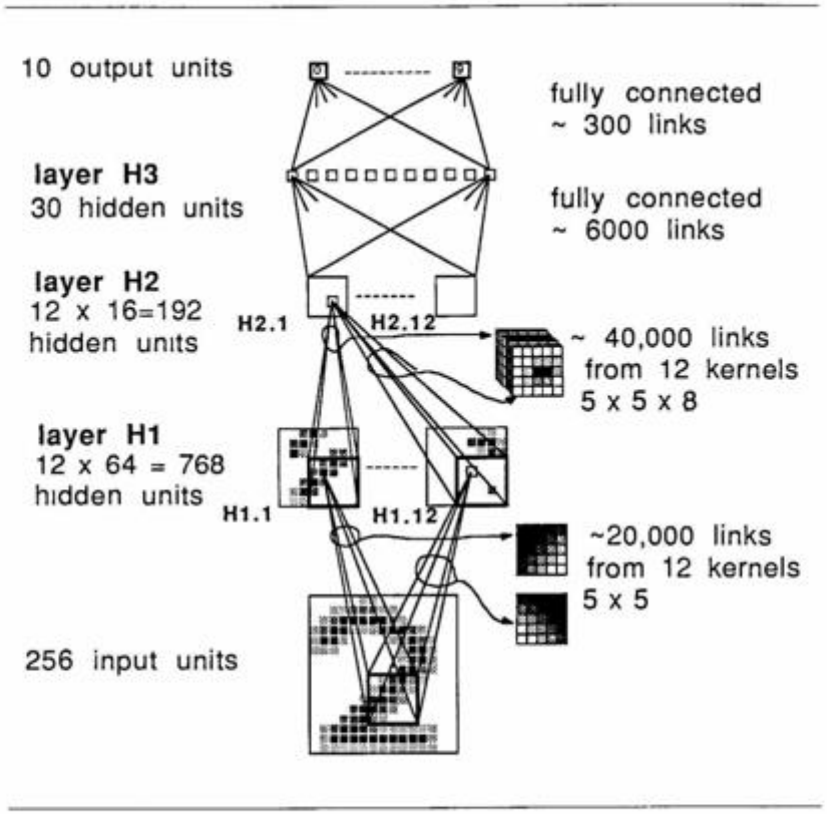
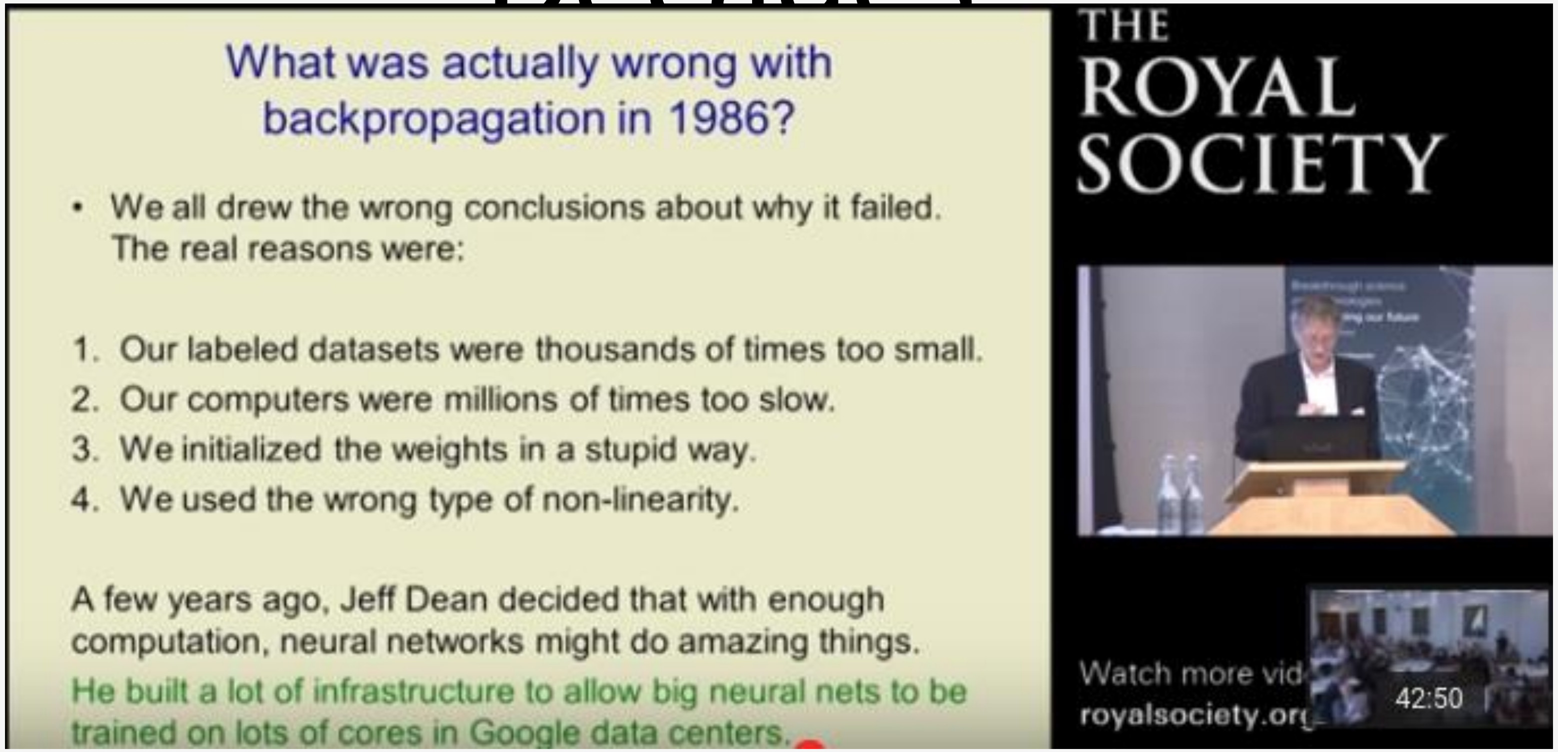


Figure 3 Log mean squared error (MSE) (top) and raw error rate (bottom) versus number of training passes

Then It Shuffled Along for Decades



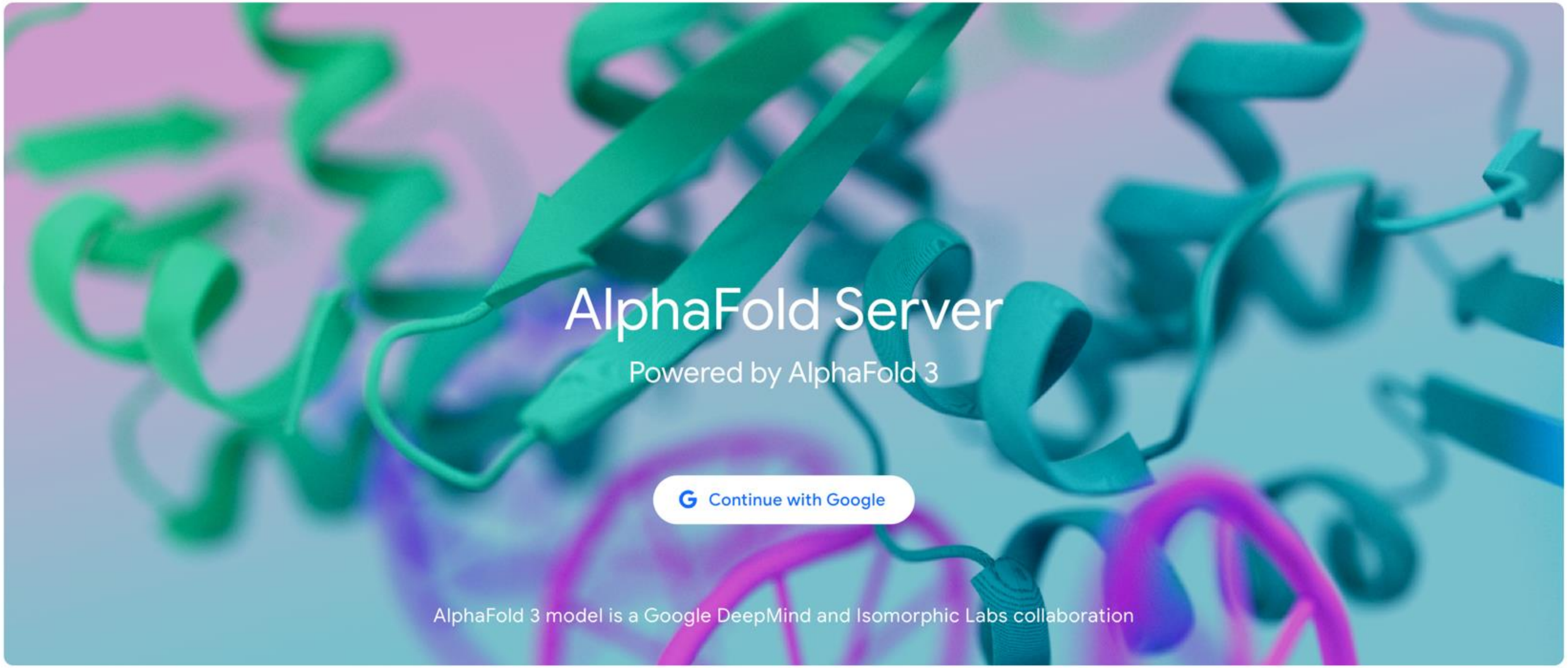
Now…

THE SHIFT

An A.I.-Generated Picture Won an Art Prize. Artists Aren't Happy.

"I won, and I didn't break any rules," the artwork's creator says.

Share full article 1.5K



How does AlphaFold Server work?

AlphaFold Server is a web-service that can generate highly accurate biomolecular structure predictions containing proteins, DNA, RNA, ligands, ions, and also model chemical modifications for proteins and nucleic acids in one platform. It's powered by the newest AlphaFold 3 model.

GitHub Copilot

Learn more >

Technical Preview

Your AI pair programmer

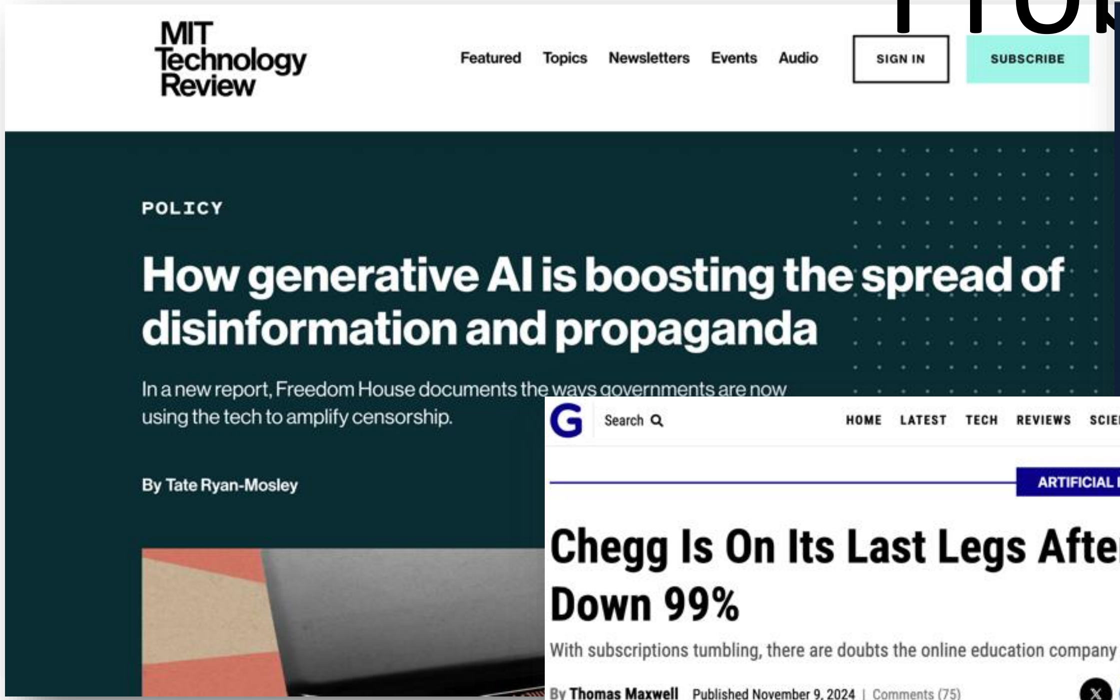
With GitHub Copilot, get suggestions for whole lines or entire functions right inside your editor.

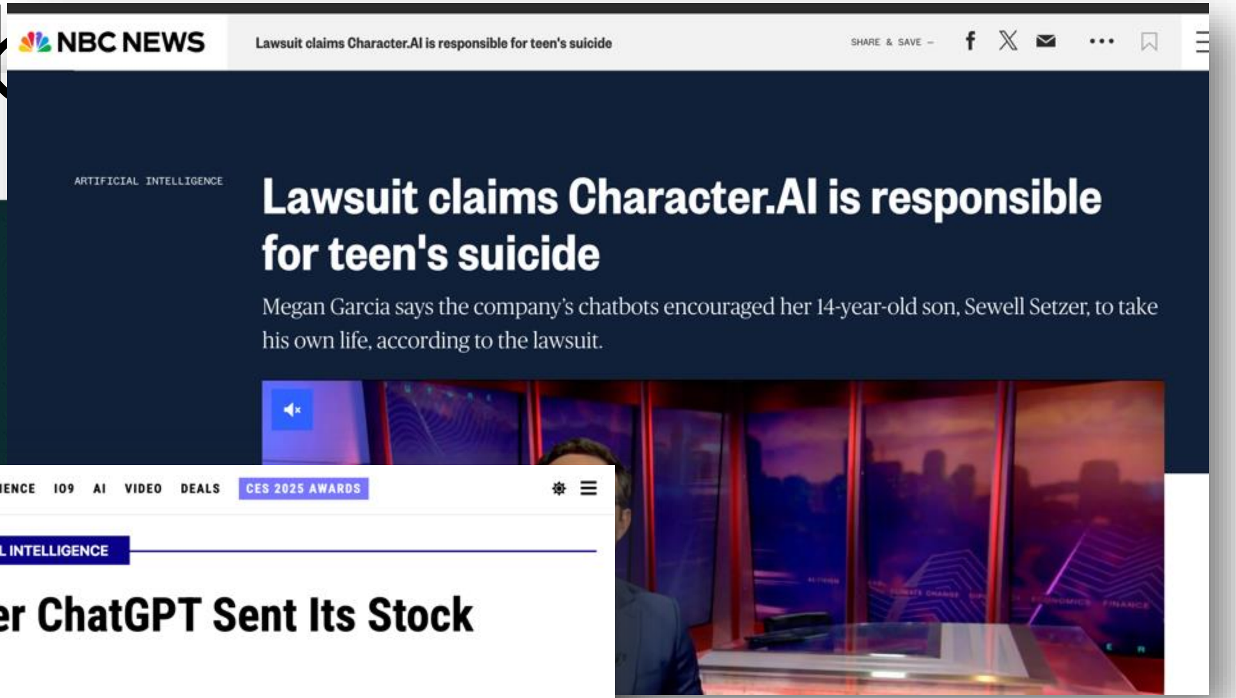
Sign up >

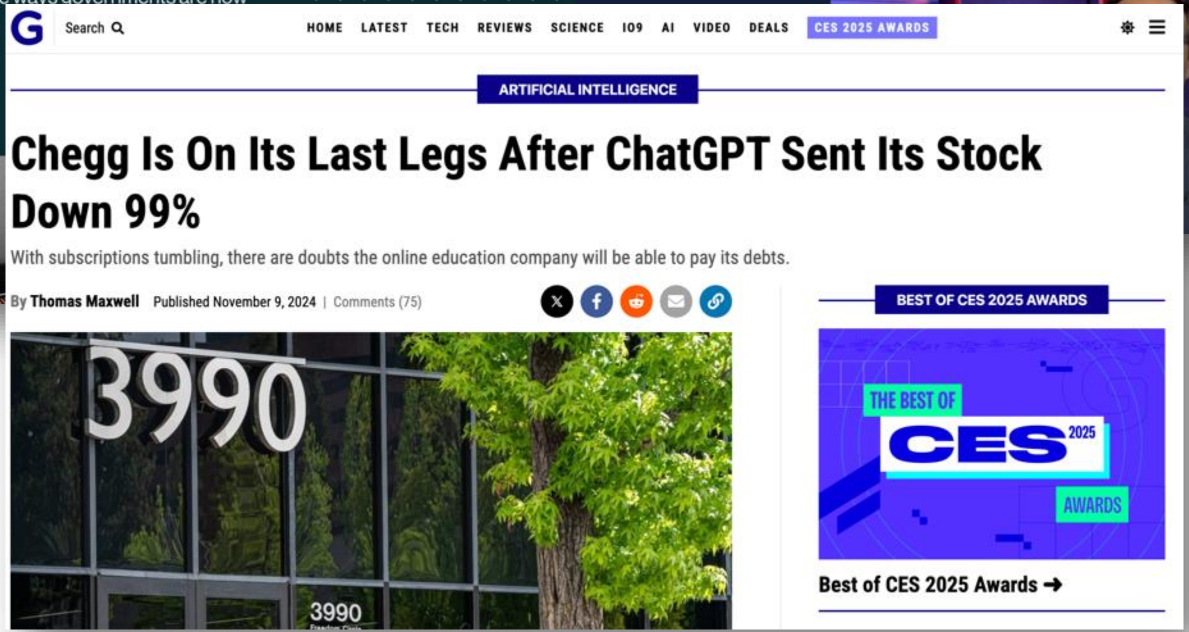
sentiment.ts | write_sql.go | parse_expenses.py | addresses.rb

```
#!/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: {
```

These Technologies Bring New Prob







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

// 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

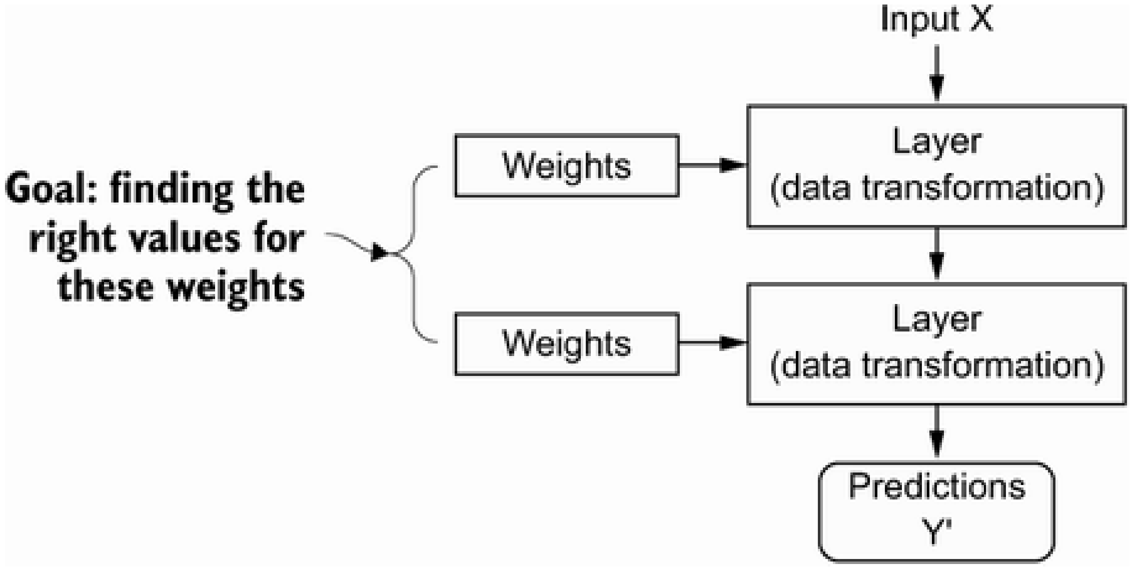
10 minutes

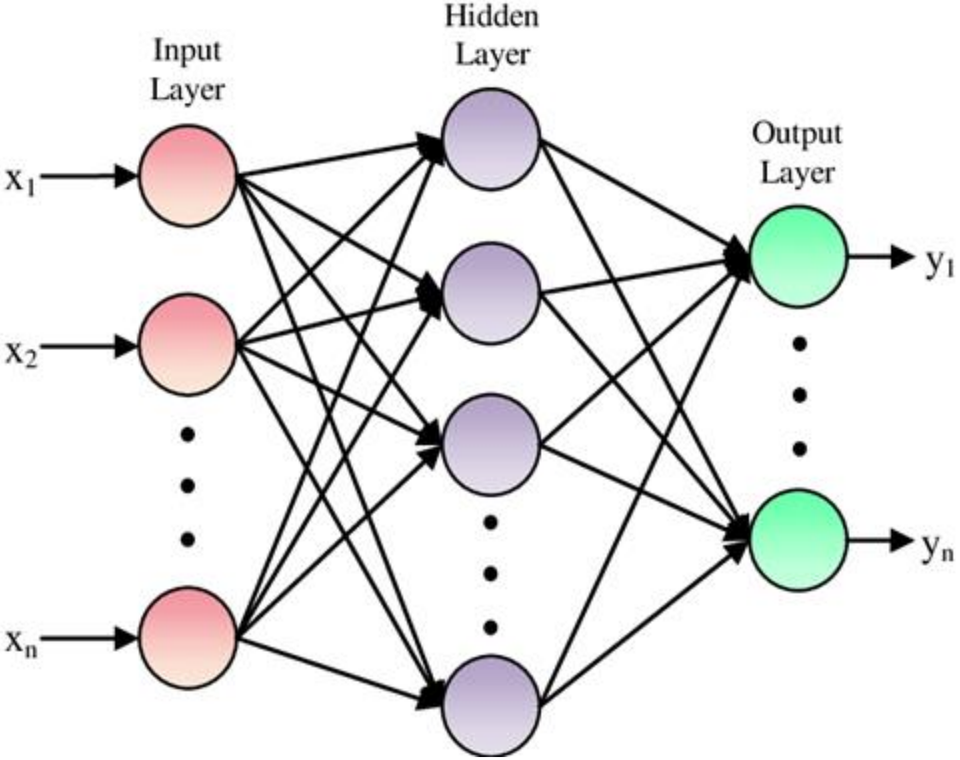
11 comments

By Dylan Patel and Afzal Ahmad

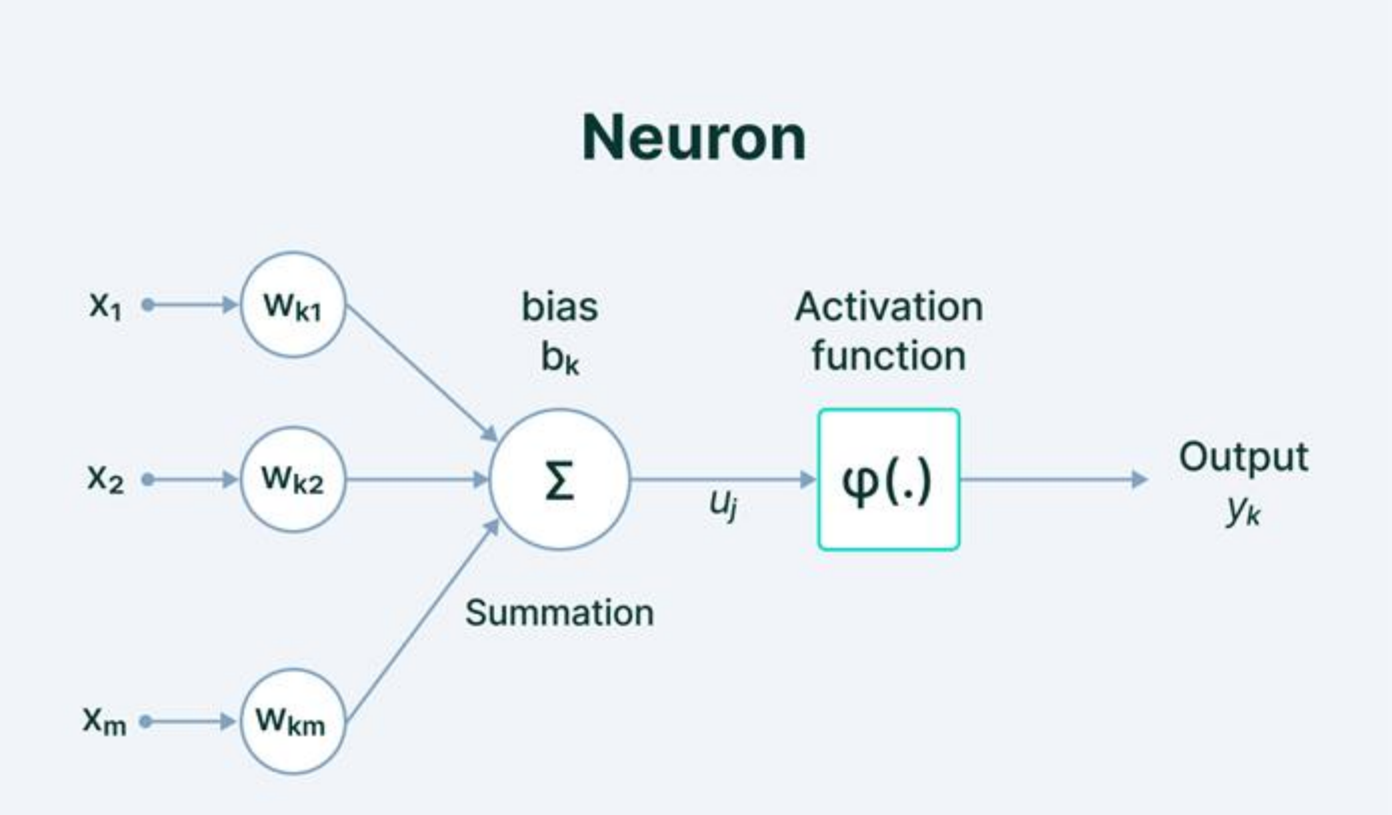
How It Works, Conceptually

Model Parameters

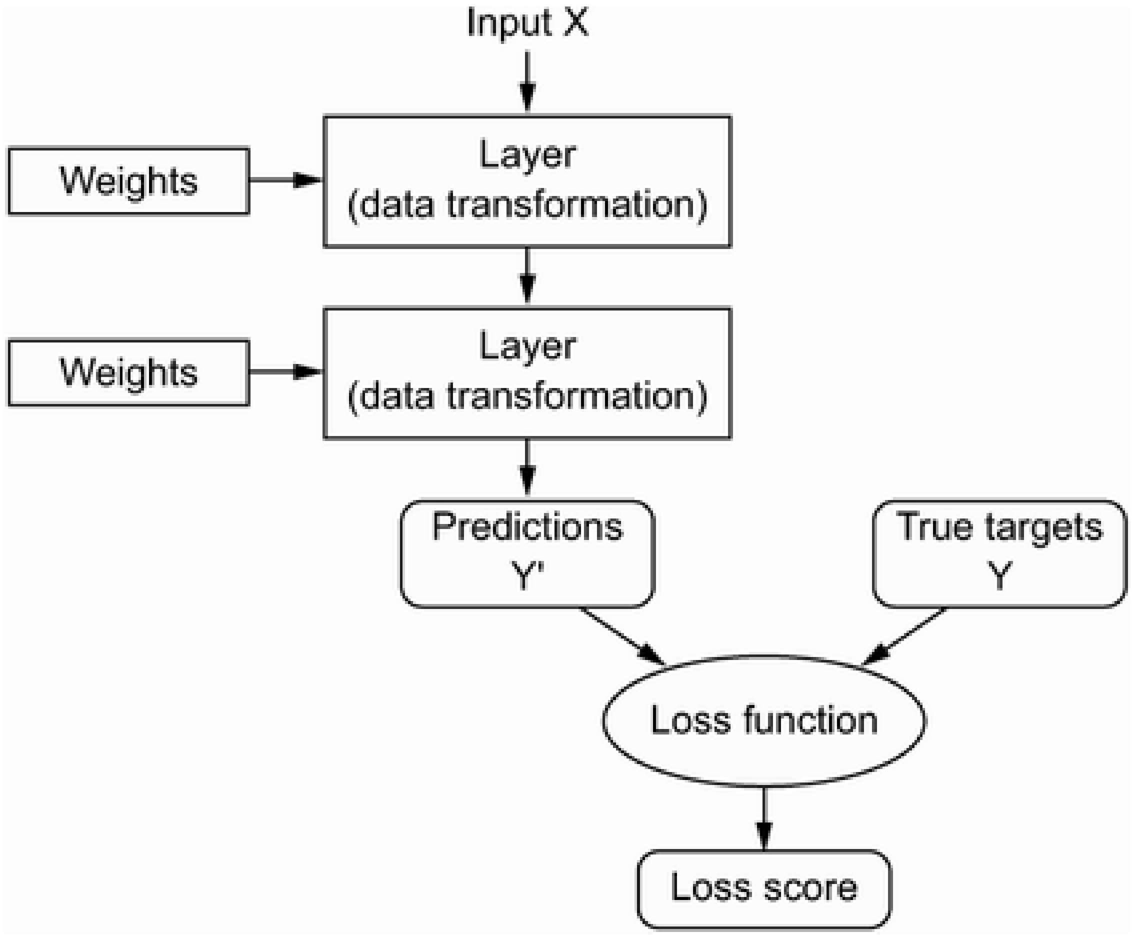




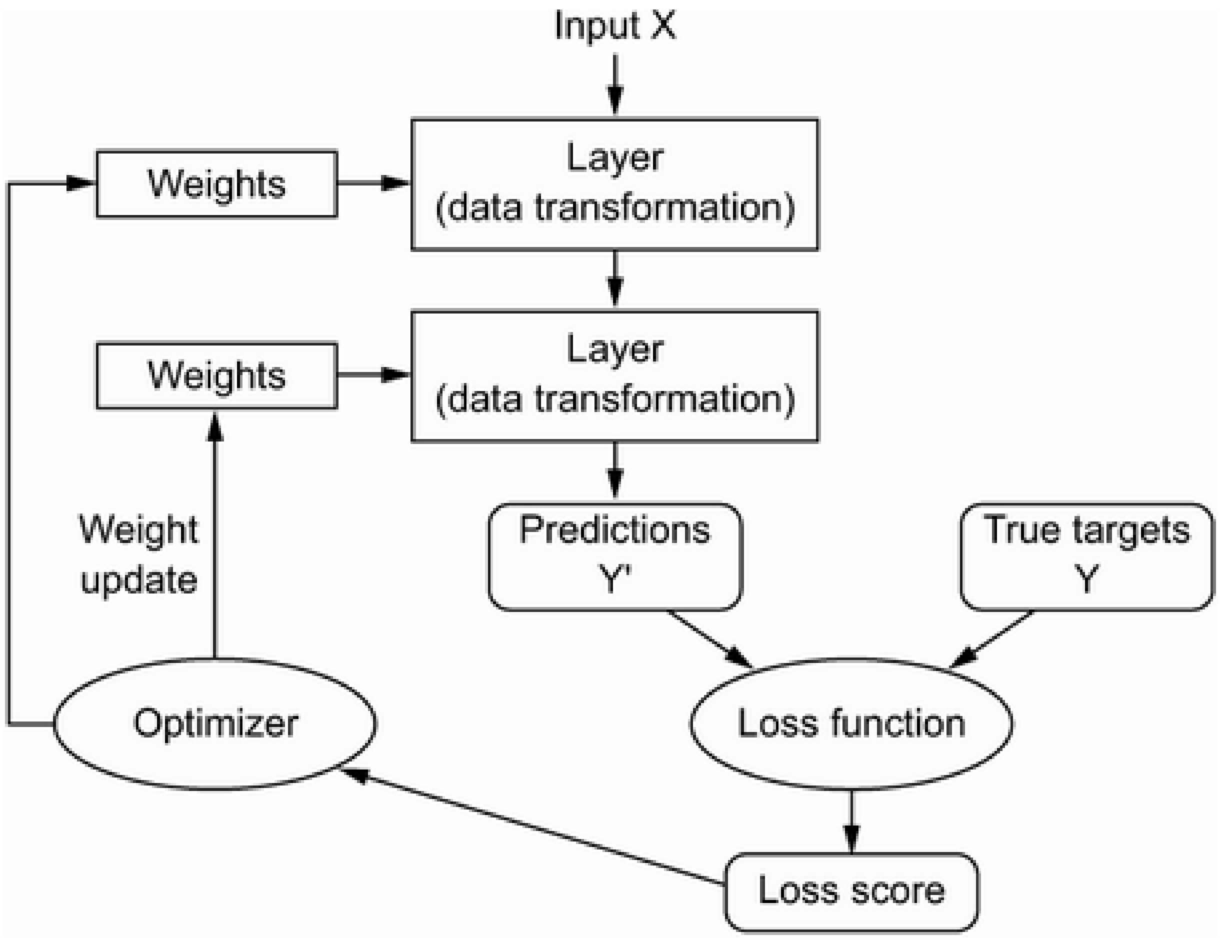
Model Parameters



Loss Function (Error)



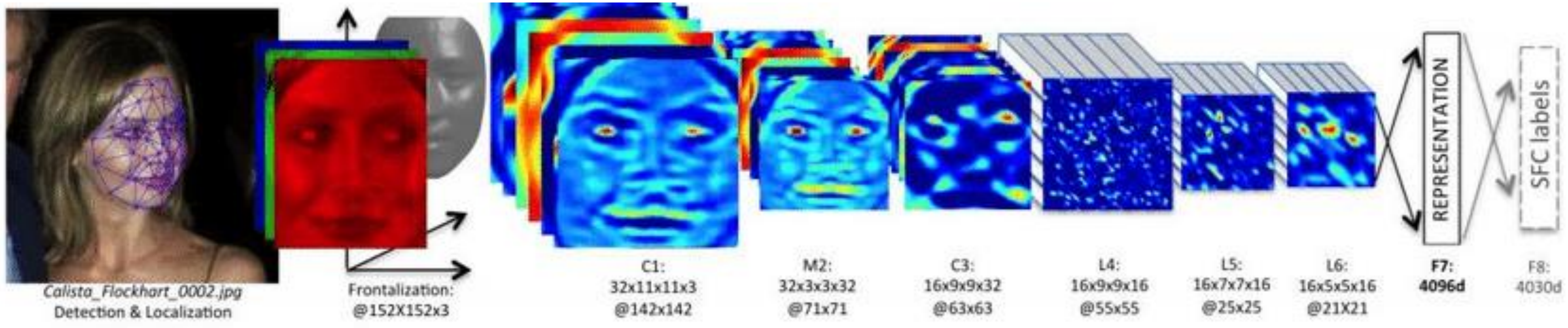
Optimization



When to Learn Deeply (vs. Not)

COMPLEX RELATIONSHIPS

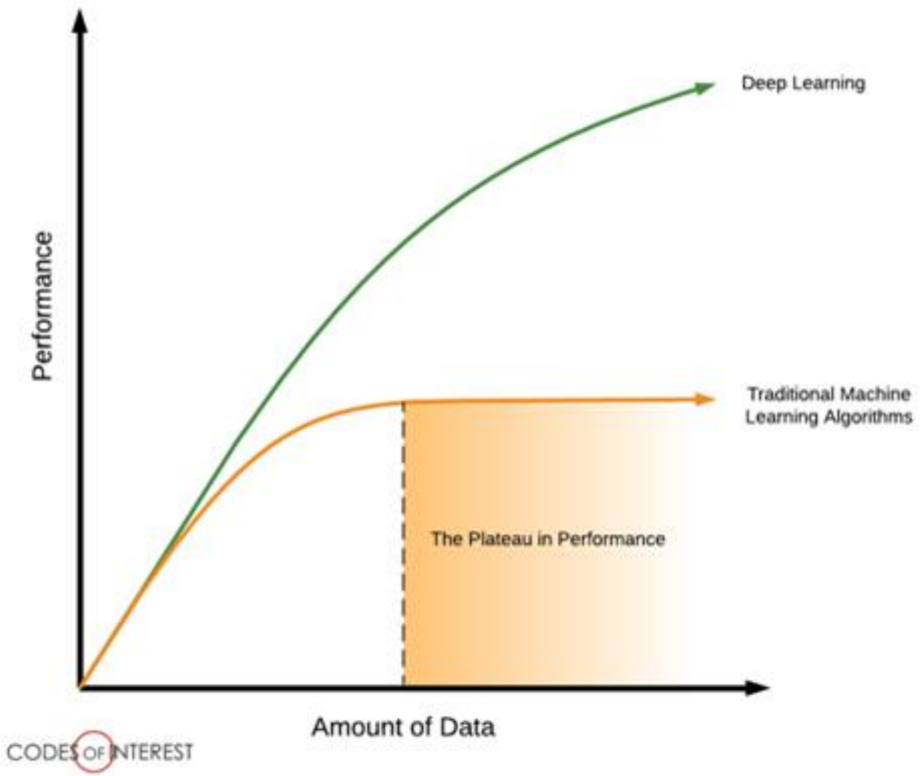
- Complex, non-linear, interactive relationships and mappings; common use cases involve unstructured (high dimensional) data. Deep learning techniques remove the need for feature engineering, a daunting task.



When to Learn Deeply (vs. Not)

LOTS OF DATA ON HAND

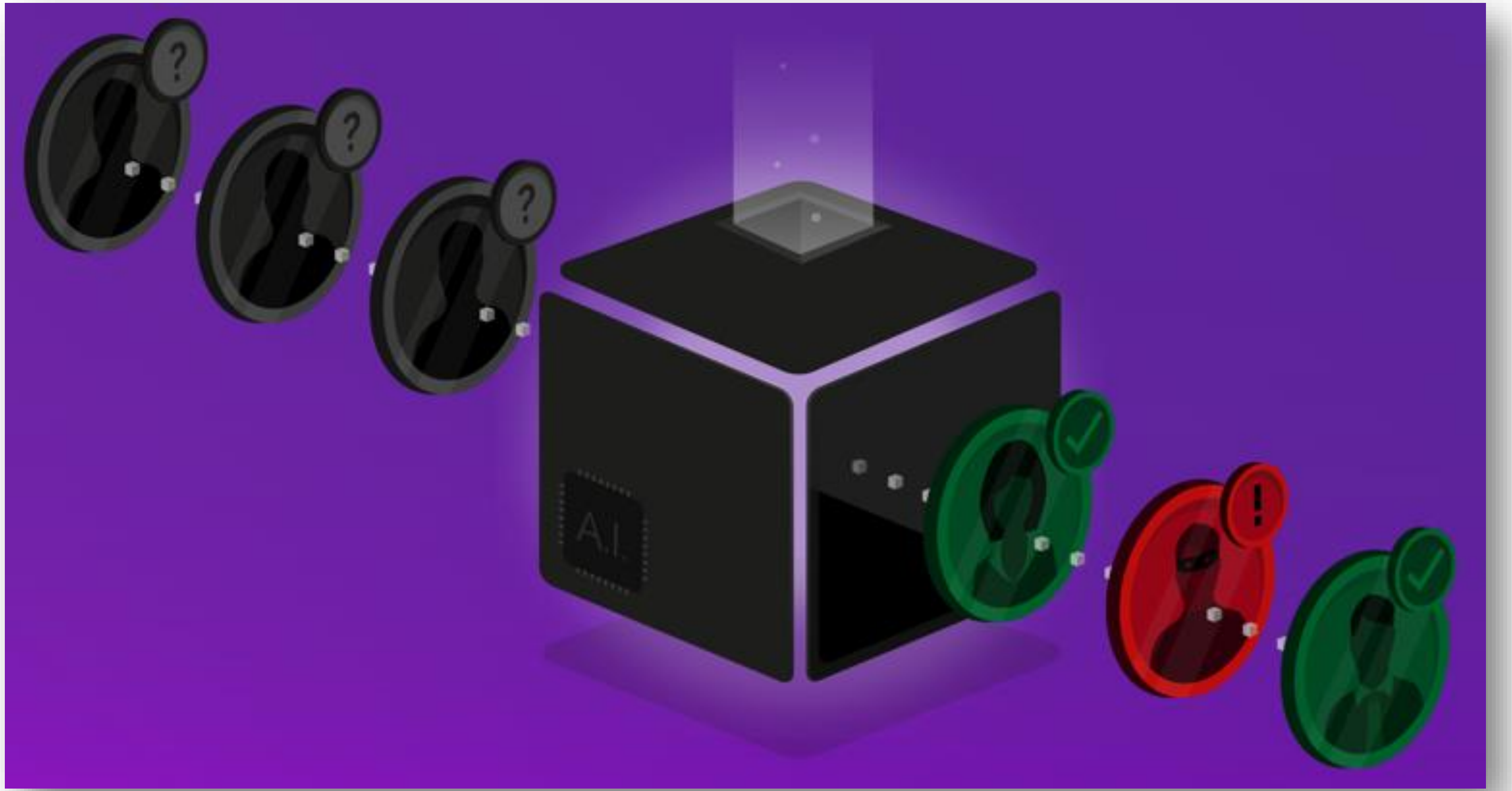
- To be able to learn those complex mappings, typically requires many, many, many training examples.



When to Learn Deeply (vs. Not)

LITTLE NEED FOR UNDERSTANDING

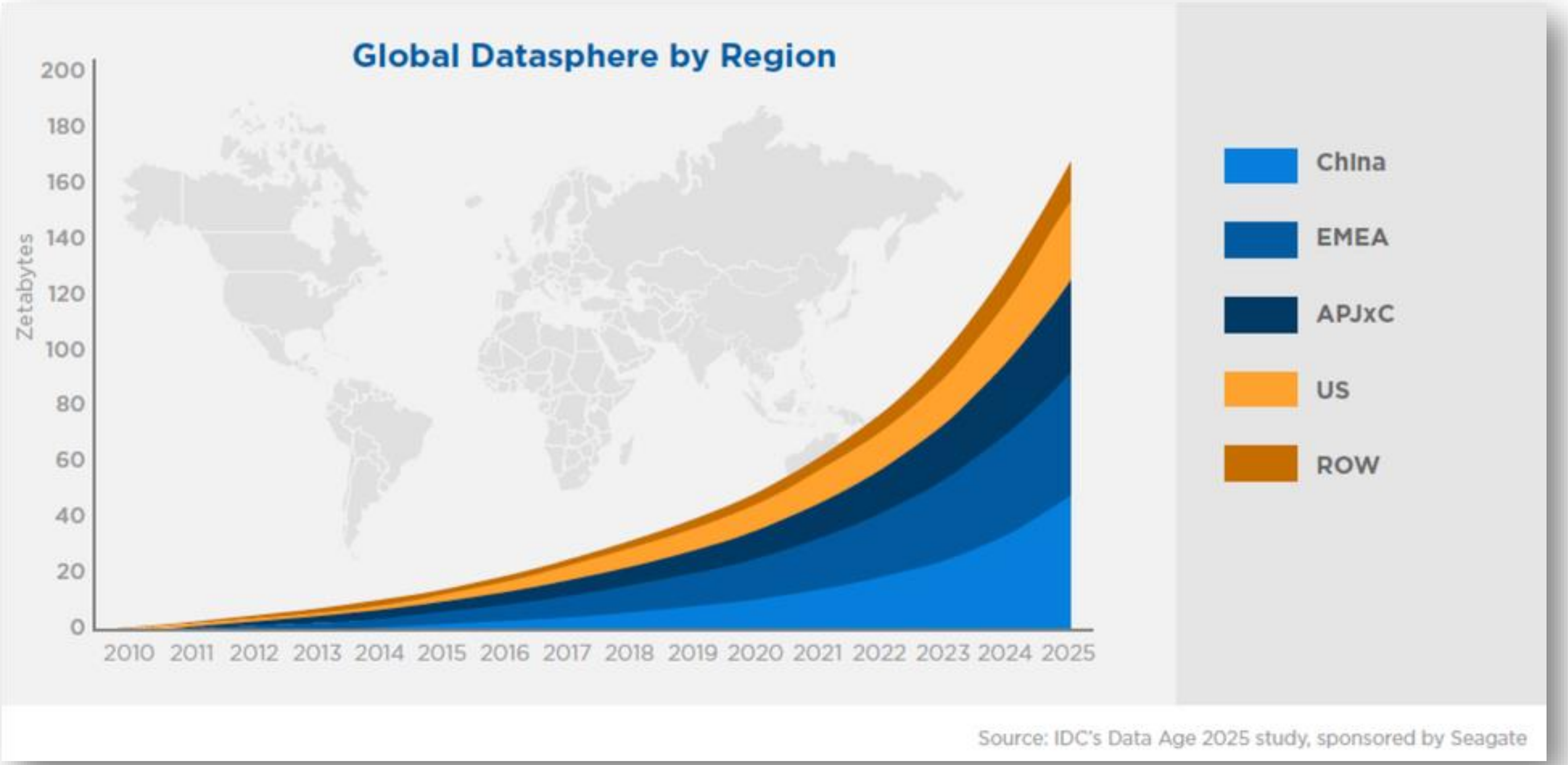
- Although there have been advancements in explainable and interpretable AI, deep nets are notoriously “black box” algorithms.



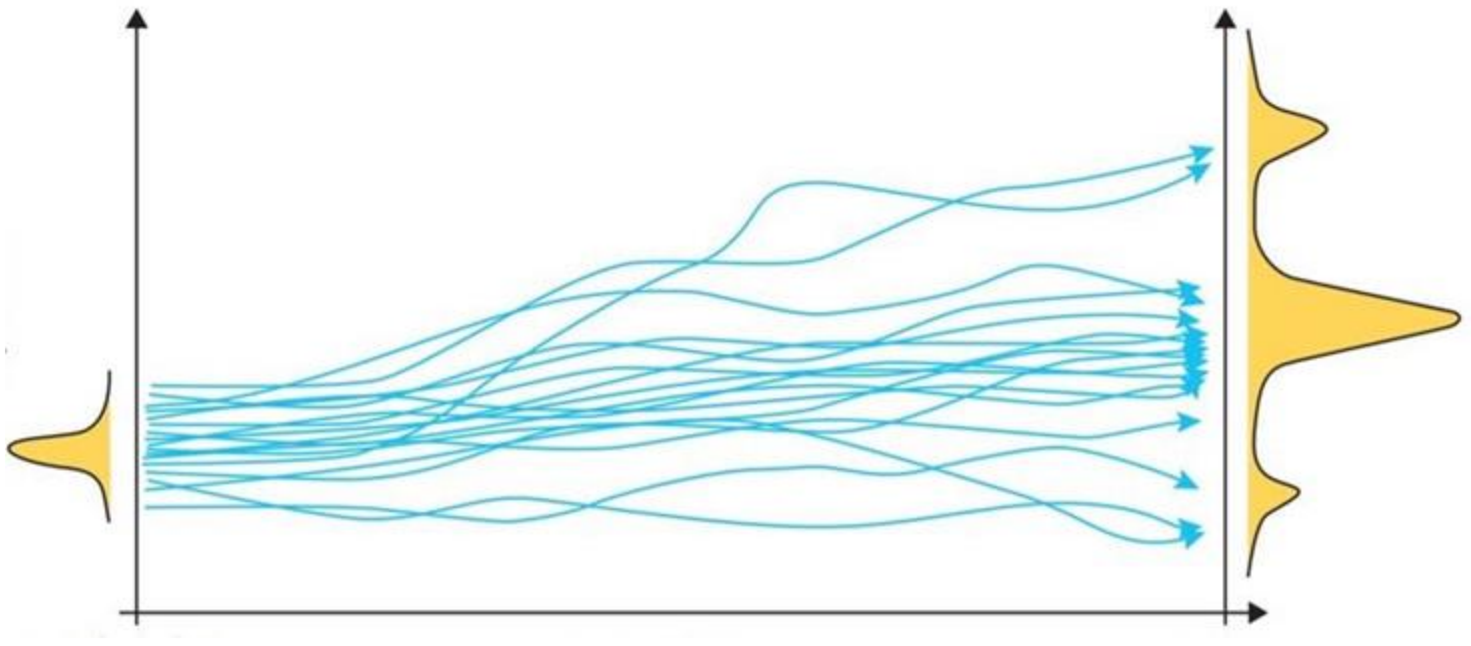
Why Did Deep Learning Take Off?

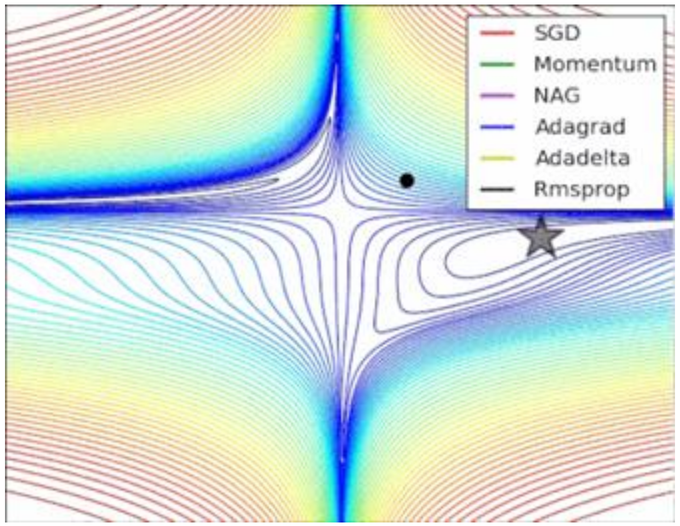
Video Games

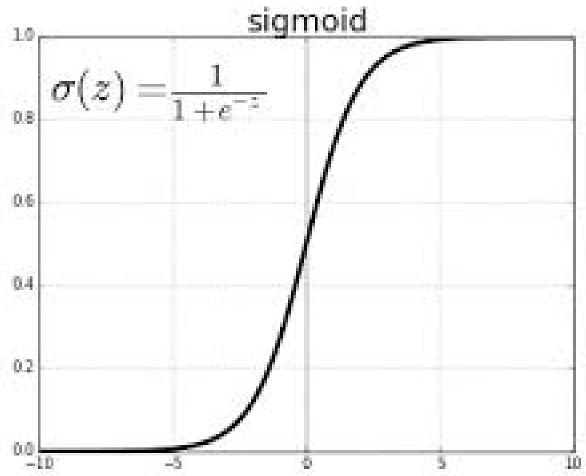
Data


Global Datasphere by Region
Zetabytes
200
180
160
140
120
100
80
60
40
20
0
2010 2011 2012 2013 2014 2015 2016 2017 2018 2019 2020 2021 2022 2023 2024 2025
China
EMEA
APJxC
US
ROW
Source: IDC's Data Age 2025 study, sponsored by Seagate

Algorithmic Improvements







Questions?