

# How Deep Learning Works

# Learning representations

- Learning representations from data
  - It is about the difference between deep learning and other ML approaches.
  - What ML algorithms do: to do ML, we need three things;
    - Input data points
    - Examples of the expected output
    - A way to measure whether the algorithm is doing a good job → adjusting the measurement is what we call learning.
  - The central problem of ML: how to meaningfully transform data → how to learn useful *representations* of the input data

# Learning representations

- What is a representation?
  - It is a different way to look at data – to represent or encode data.
    - E.g., a color image → RGB format or HSV format
  - We can solve some tasks very easily with a good representation.
    - E.g., “select all red pixels” → very easy in the RGB format
  - ML models are all about finding appropriate representations for their input data!
    - Searching for useful representations of some input data, within a predefined space of possibilities, using guidance from a feedback signal.

# Learning representations

- What is a representation?
  - Example
    - We want to develop an algorithm that can take  $(x,y)$  of a point and output whether that point is likely to be black or to be white.
    - Inputs?  $(x,y)$
    - The expected outputs? 1 or 0 Black or White
    - How to measure the performance? accuracy

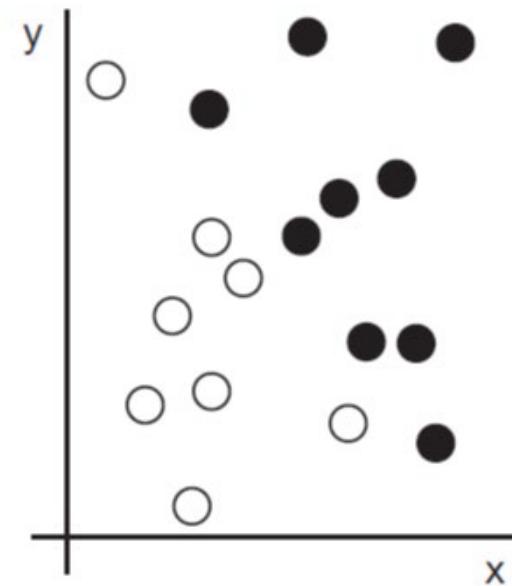
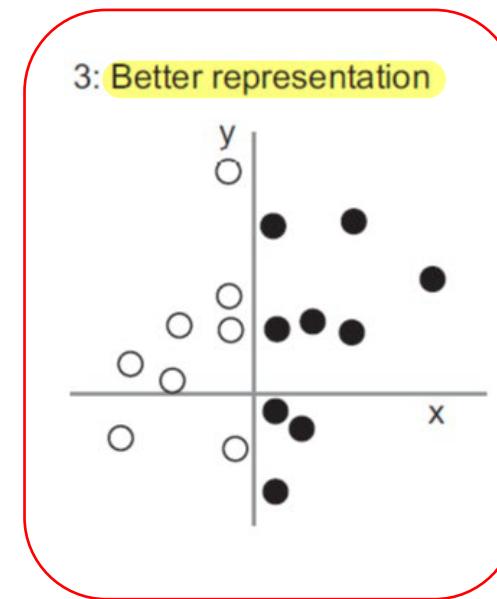
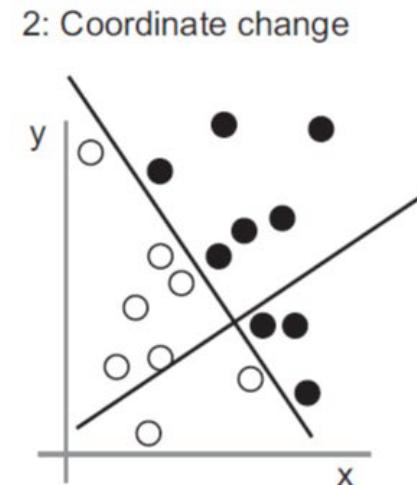
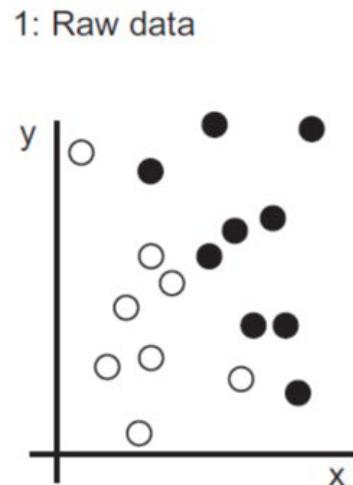


Figure 1.3  
Some sample data

# Learning representations

- What is a representation?
  - Example



If  $x>0$ , then a point is black  
If  $x<0$ , then a point is white

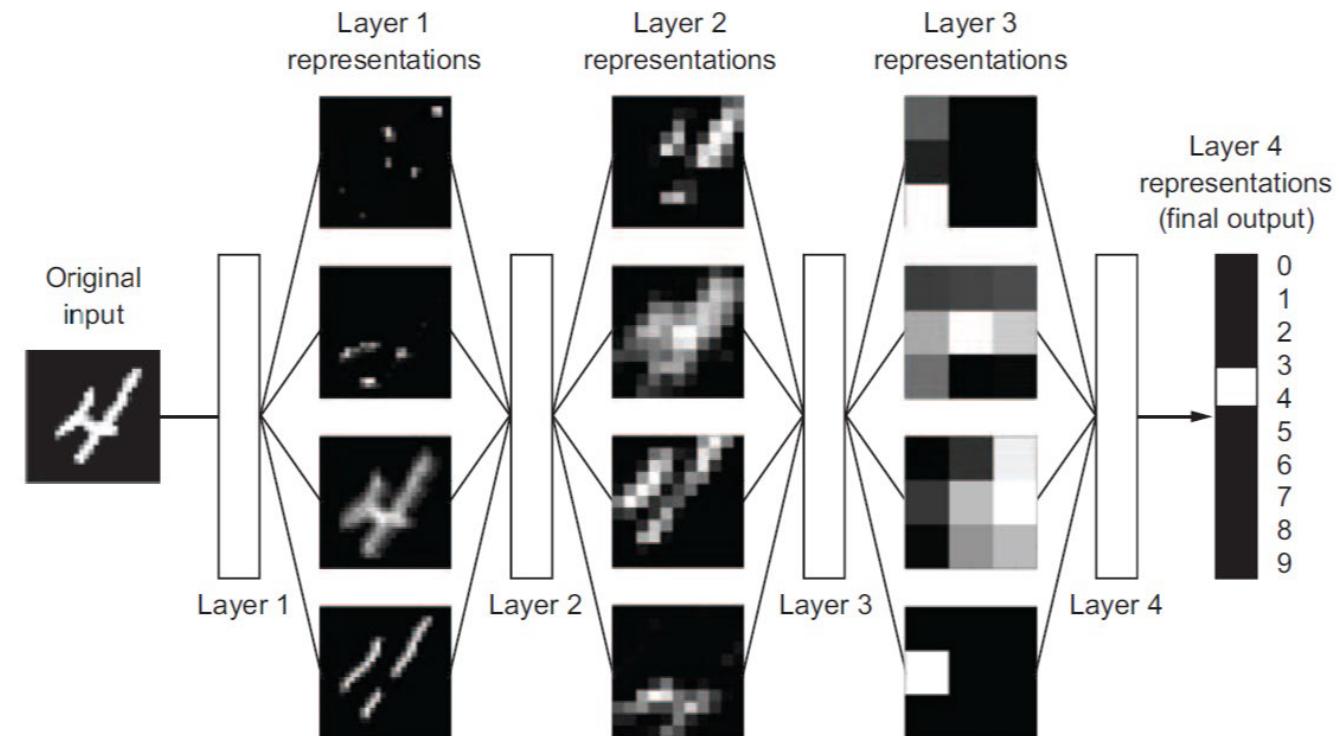
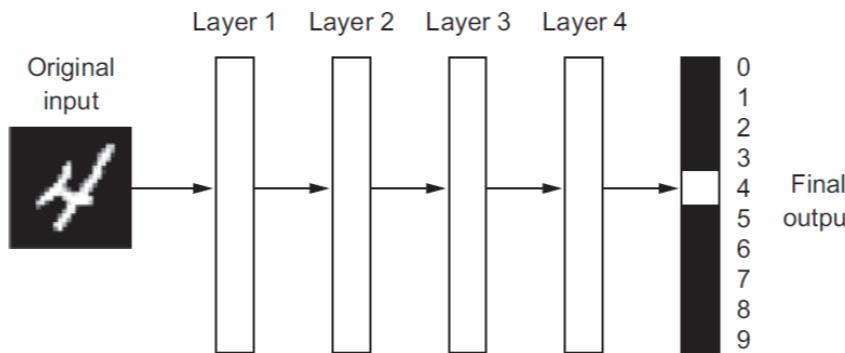
Figure 1.4 Coordinate change

# The “deep” in “deep learning”

- Deep learning
  - A new take on learning representations from data by learning successive layers.
  - “deep” stands for this idea of successive layers of representations.
  - Modern deep learning often involves tens of even hundreds of successive layers of representations – all learned automatically from training data.
  - In DL, these layered representations are learned via neural networks model.
  - Deep learning models are not models of the brain.

# The “deep” in “deep learning”

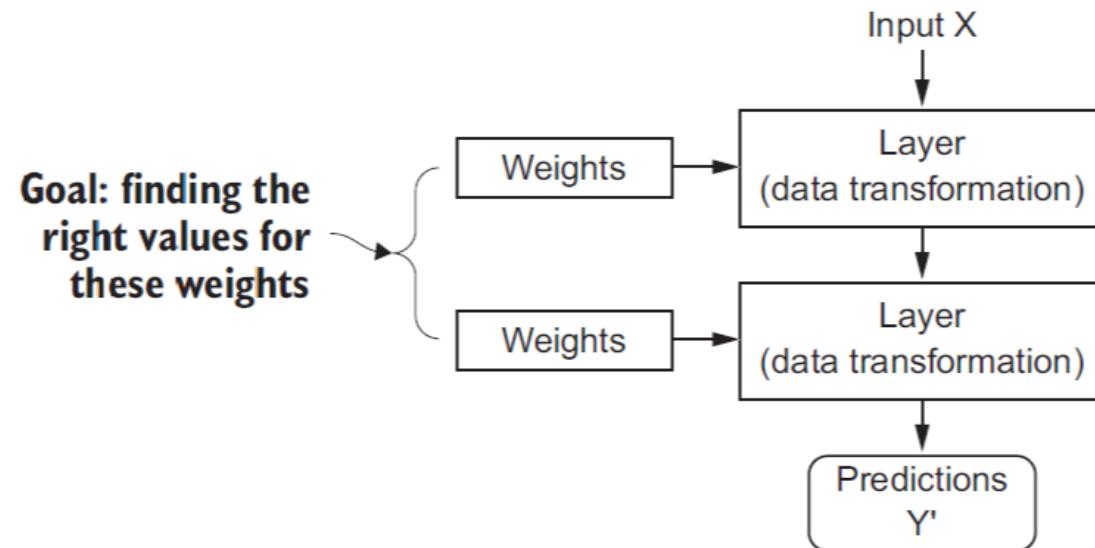
- Learned representations by a deep learning model



a multistage *information-distillation* process

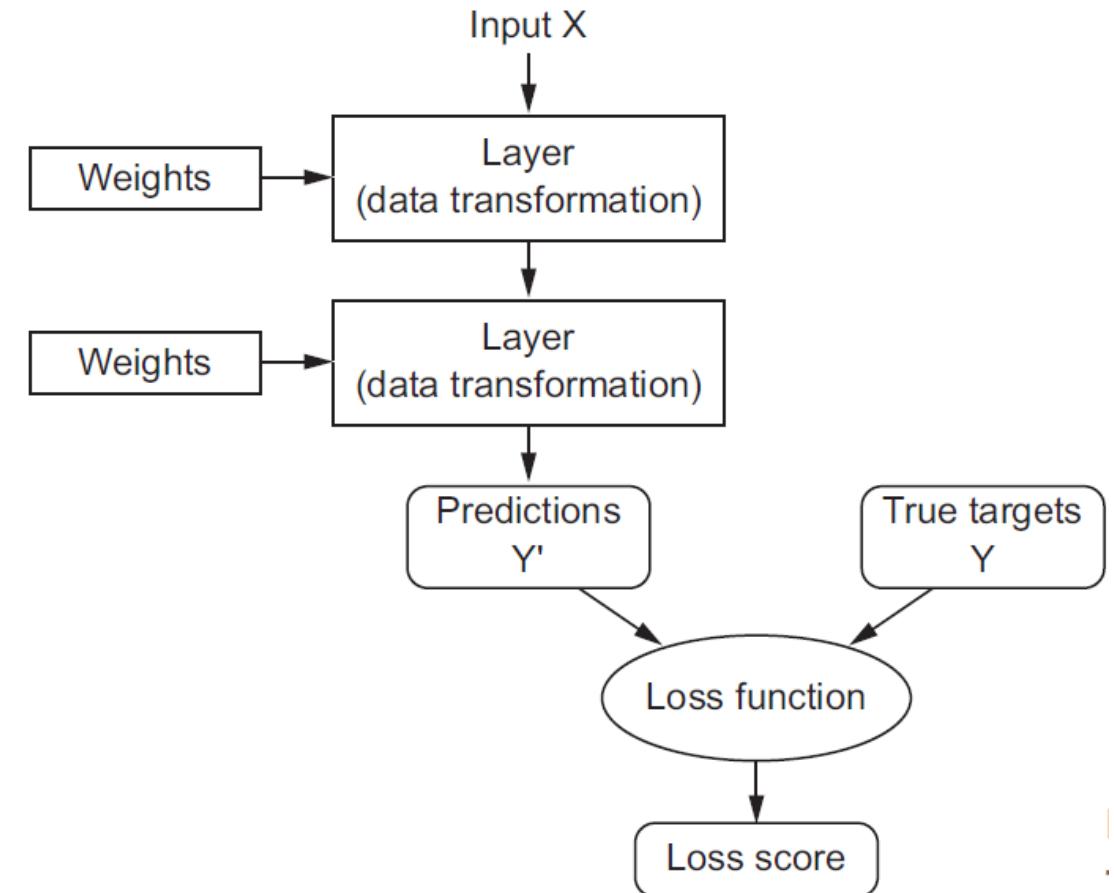
# How deep learning works

- What a layer does to its input data is stored in the layer's **weights**.
- In other words, the transformation (by a layer) is **parameterized by its weights**.
- Again, learning means **finding a set of weight values of all layers** in a network.



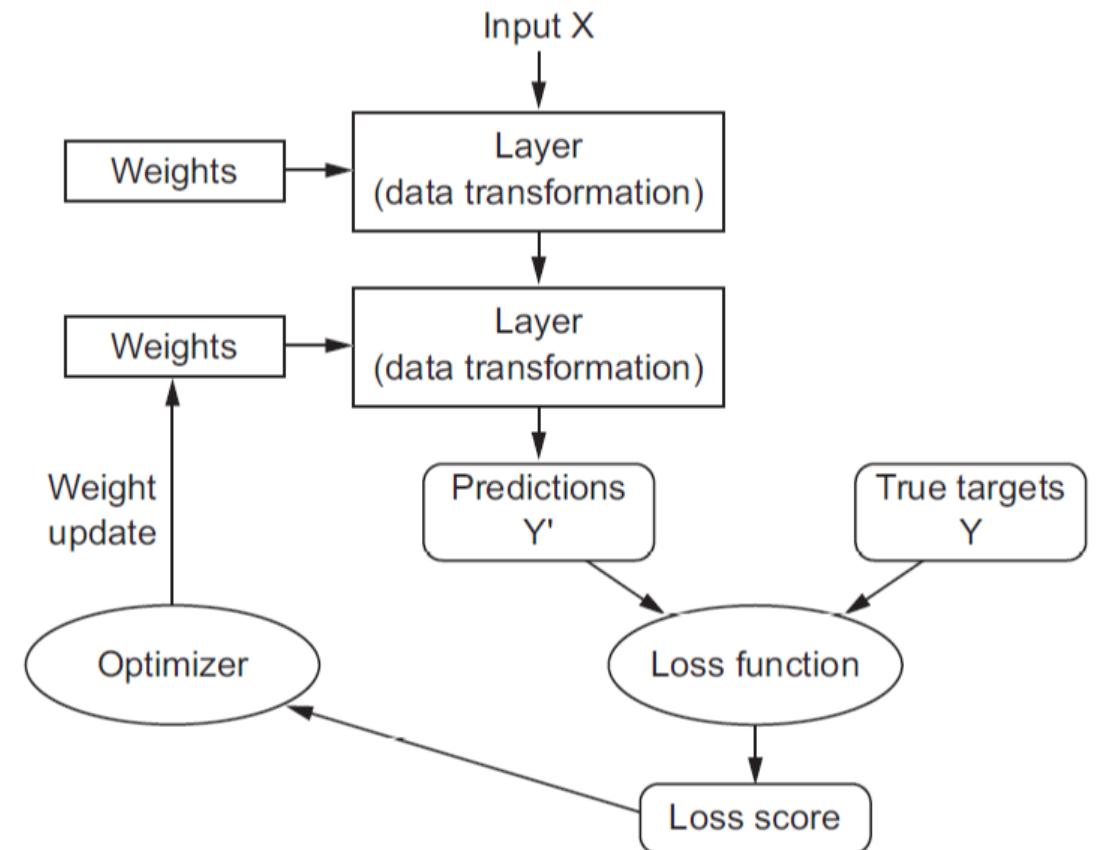
# How deep learning works

- To control something, we need to observe it!
- To control the output of a neural network, we need to measure how far this output is from what we expected. → the *loss function* of the network (also called the objective function)
- Loss(output, target) → how well the network performs our task



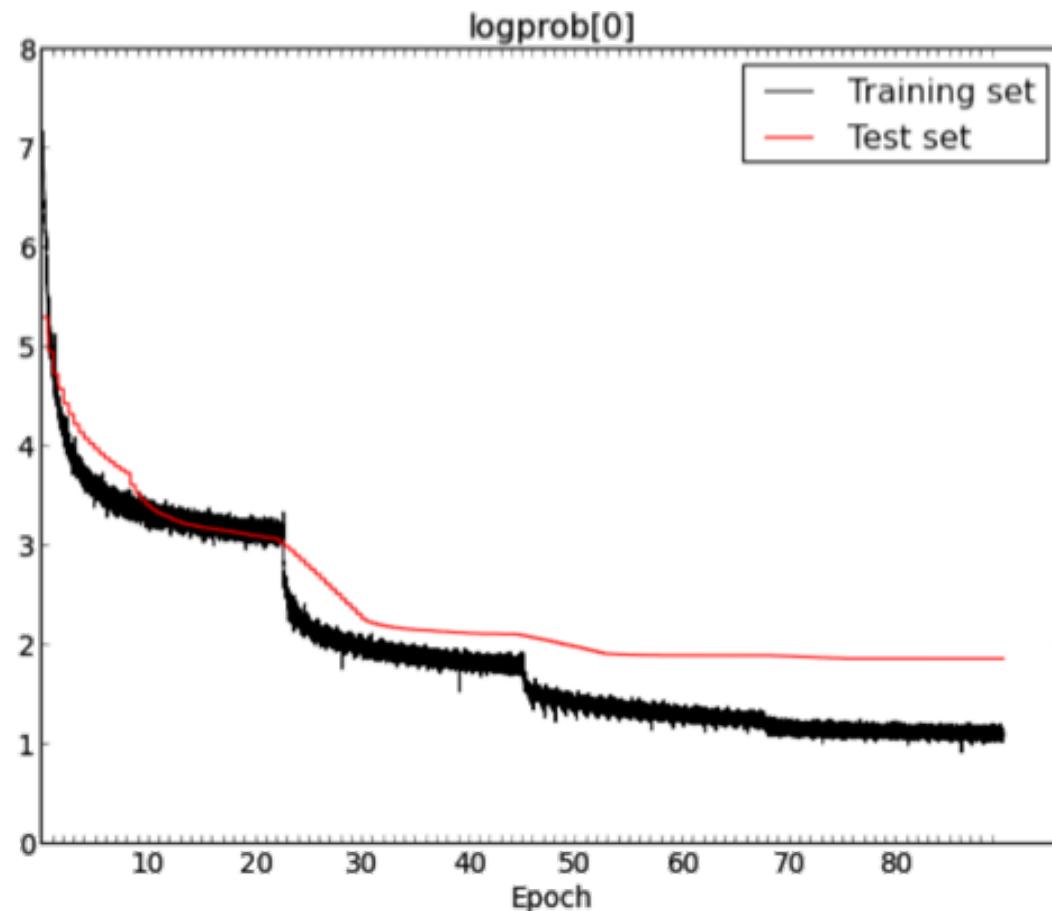
# How deep learning works

- Deep learning adjusts the weight values a little, in a direction that will lower the loss score for the current example. → **Optimizer's job**
- Specifically, the optimizer is based on the **backpropagation algorithm**.



# How deep learning works

- Loss curves



# How deep learning works

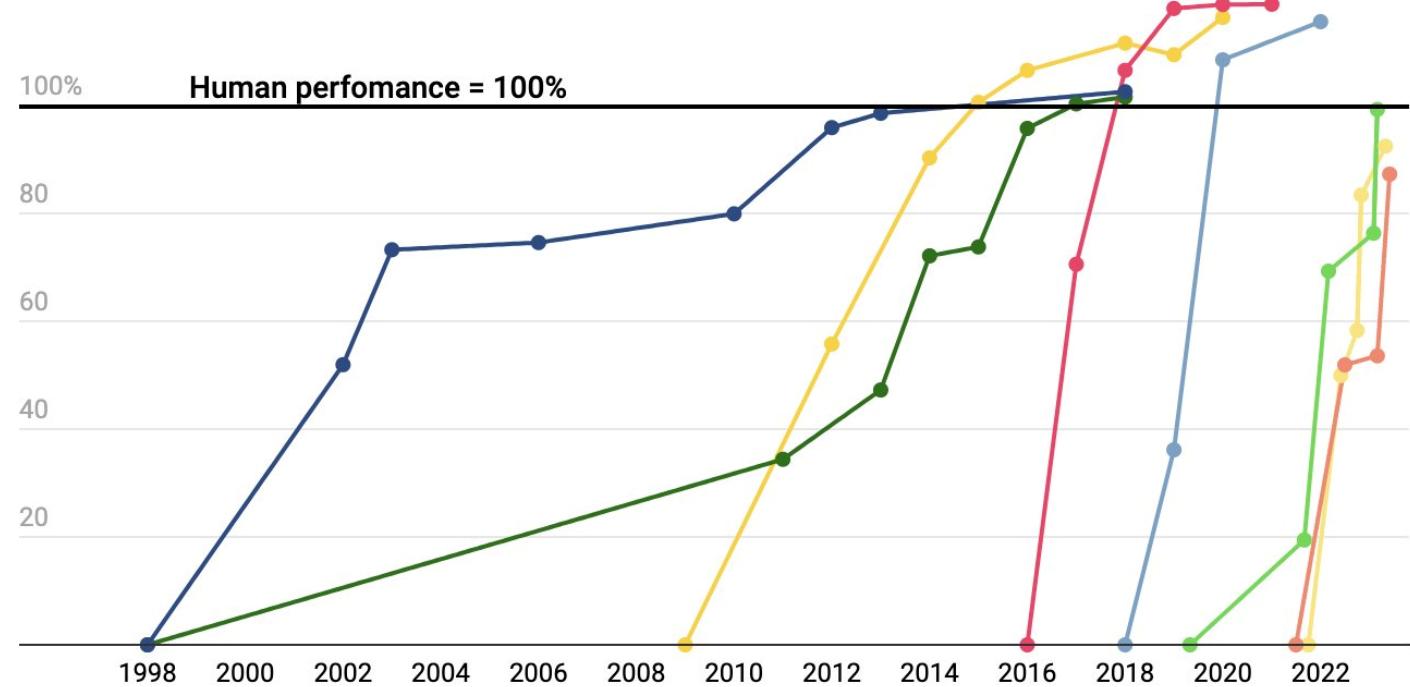
- Learning process
  - 1) Initially, the weights of the network are assigned random values.
  - 2) With every example the network processes, the weights are adjusted a little in the correct direction. → The loss scores decreases
  - 3) Repeat a sufficient number of times, then we can get weight values that minimize the loss function.
  - 4) This network with a minimal will produce the outputs which are close to the targets. → Trained network

# What DL has achieved

**AI has surpassed humans at a number of tasks and the rate at which humans are being surpassed at new tasks is increasing**

State-of-the-art AI performance on benchmarks, relative to human performance

- Handwriting recognition ● Speech recognition ● Image recognition ● Reading comprehension
- Language understanding ● Common sense completion ● Grade school math ● Code generation



For each benchmark, the maximally performing baseline reported in the benchmark paper is taken as the "starting point", which is set at 0%. Human performance number is set at 100%. Handwriting recognition = MNIST, Language understanding = GLUE, Image recognition = ImageNet, Reading comprehension = SQuAD 1.1, Reading comprehension = SQuAD 2.0, Speech recognition = Switchboard, Grade school math = GSK8k, Common sense completion = HellaSwag, Code generation = HumanEval.

Chart: Will Henshall for TIME • Source: [ContextualAI](#)

TIME

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