Deep Learning

Lecture 1: Introduction

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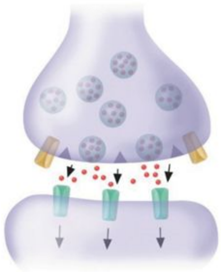
Lecture overview   a framework for your deep learning armamentarium

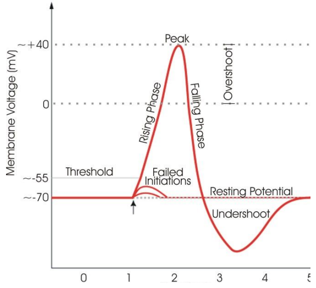
❶ Introduction
- definitions
- examples

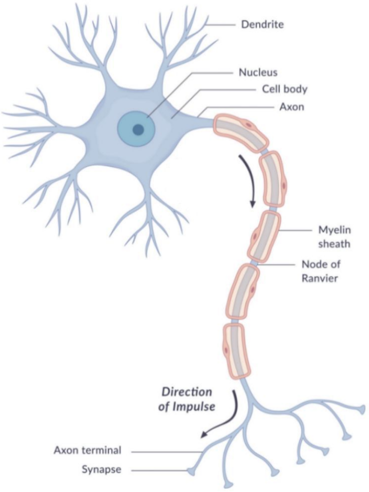
❷ Learning in Nature
- what is learning?
- how does the brain work?
- synaptic plasticity
- Hebbian theory

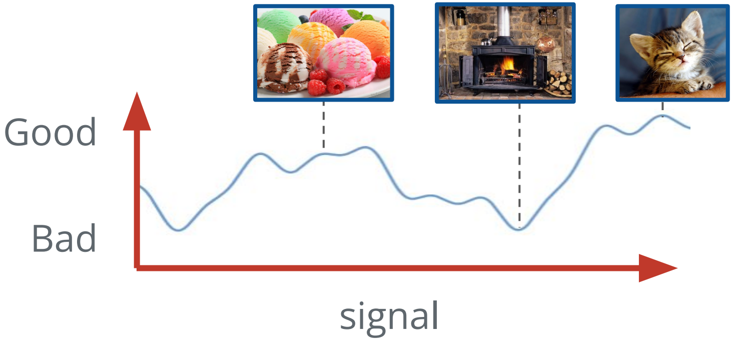
❸ A Brief History

❹ Key Concepts
- where it fits in to ML/RL
- three spaces







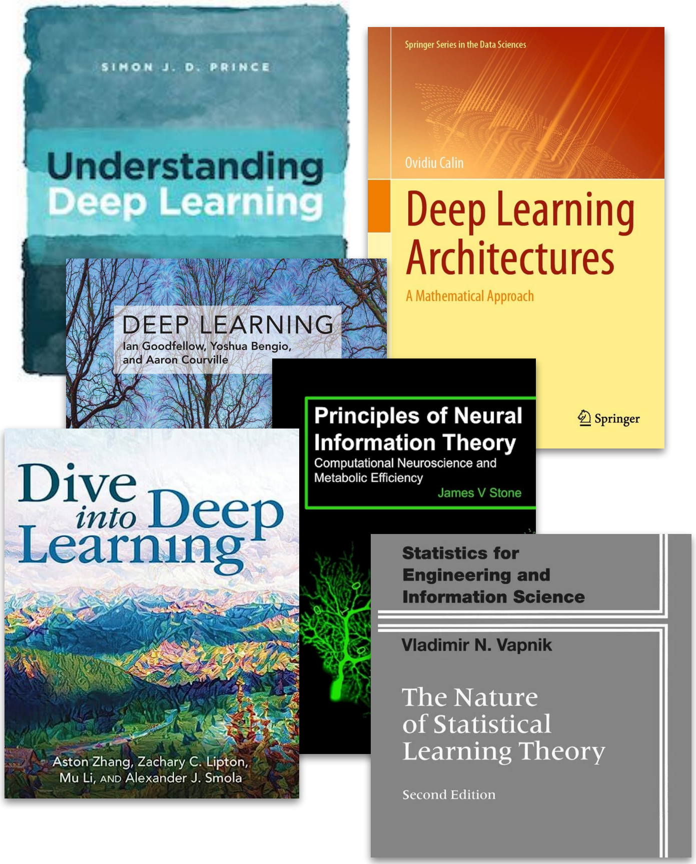


Module aims learning outcomes

The aims of the course are:

1. To be able to solve complex ill-defined problems that require deep layers of learning
2. To understand natural learning, and how it connects to the theory
3. To ask the right scientific questions given a new task, and use modern deep learning libraries to effectively design, train & test

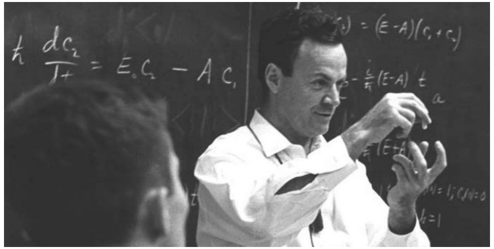
PyTorch colab



Definition: Learning

"We define learning as the transformative process of taking in information that—when internalized and mixed with what we have experienced—changes what we know and builds on what we do. It's based on input, process, and reflection. It is what changes us."

Tony Bingham and Marcia Conner



Introduction deep learning definition

Definition: Deep Learning

"Deep learning allows computational models that are composed of multiple processing layers to learn representations of data with multiple levels of abstraction. These methods have dramatically improved the state-of-the-art in speech recognition, visual object recognition, object detection and many other domains such as drug discovery and genomics. Deep learning discovers intricate structure in large data sets by using the backpropagation algorithm."

Yann LeCun, Yoshua Bengio & Geoffrey Hinton
Deep Learning, 2015, Nature - **Read Online**

On the Number of Linear Regions of Deep Neural Networks (Montúfar et al.)
The Power of Depth for Feedforward Neural Networks (Eldan et al.)

Introduction examples

Examples: Images and Vision

Non-photorealistic interpolation:

- Photos - video
- Paintings - video
- DeepFakes - video

End-to-end self-driving:

- Wayve - video

Examples: Multimodality

Examples from text:

- GPT-4 and **multimodality**
- **Input**: The internet
- **Output:** Any multimodal task

Examples with audio:

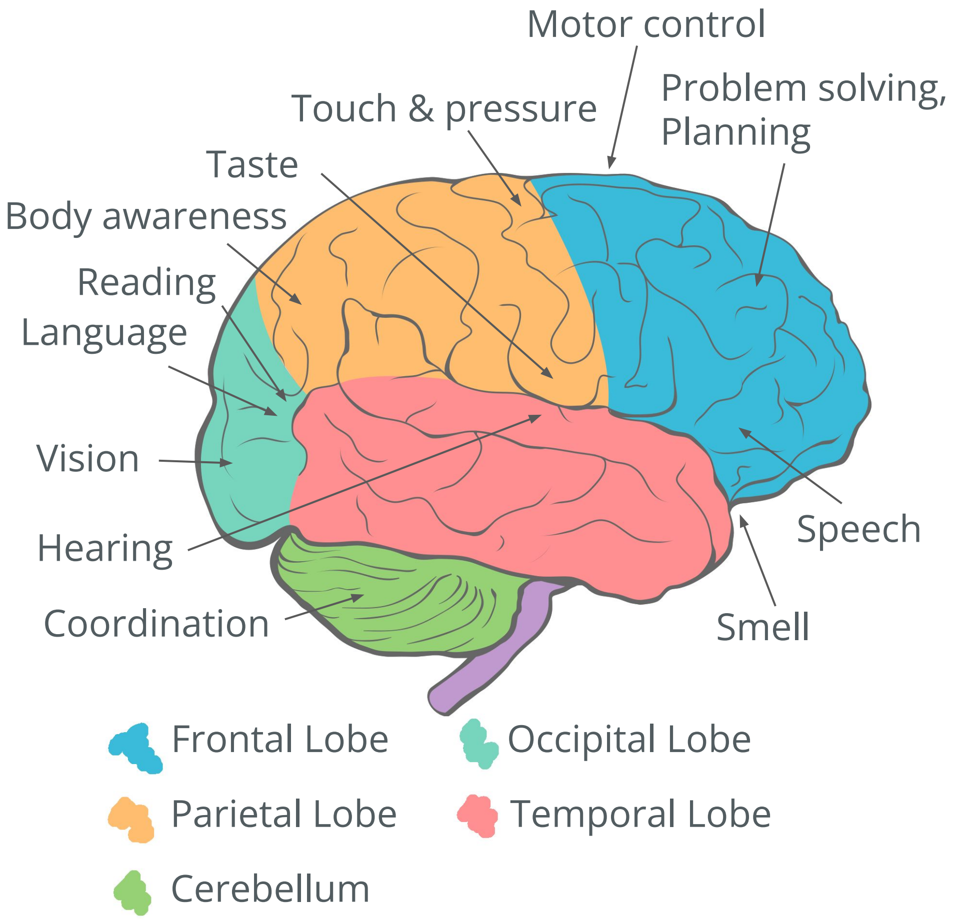
- OpenAI Jukebox - video
- **Input**: Artist, Genre, Lyrics
- **Output**: New music

Learning in nature how does the brain work?

Architecture of the brain

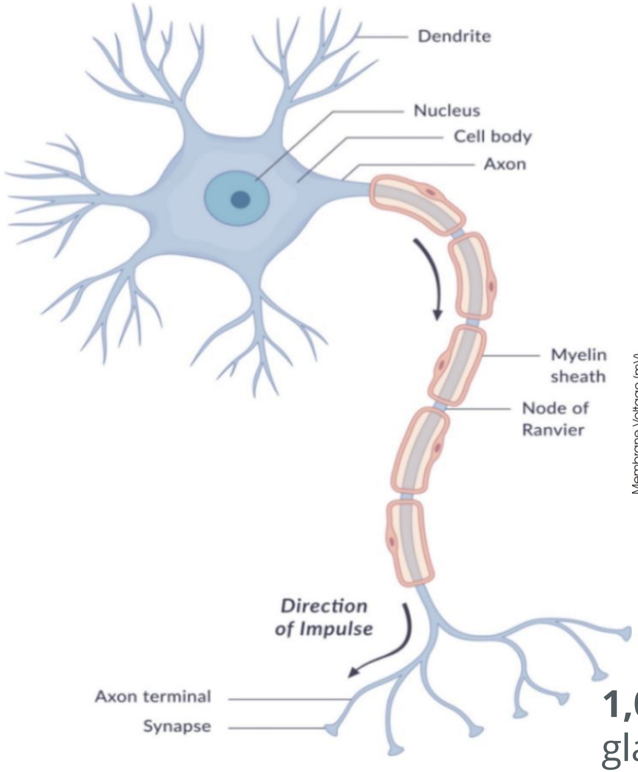
Right side/left side (hemispheres)

- Frontal lobe
    - executive functions, memory and planning
- Parietal lobe
    - sensation and spatial awareness
- Temporal lobe (banana shape)
    - hearing and language
- Occipital lobe at back
    - Vision from front along optic nerves

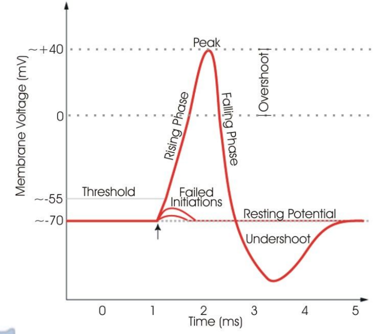


Learning in nature how does the brain work?

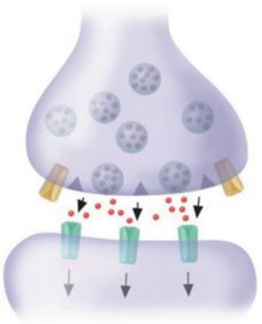
1,000’s of inputs (other neurons, sensory neurons e.g. taste buds from a salt or sugar molecule...)



- Neurons send out branches called **dendrites**, and a large output called an **axon**
- The axon is coated in myelin that helps it conduct electrical impulses
- The places where the nerve cells make their connections with each other is called a **synapse**



Synapse:



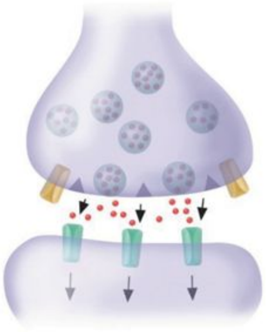
- “Synapse” (from the greek meaning “to clasp together”)
- **Signals** get **summed up**, and travel to the hillock (Axon neck)
  - If large enough, triggers an action potential travels down axon

1,000’s of output targets (e.g. other neurons, muscle cells, gland cells, blood vessels to release hormones...)

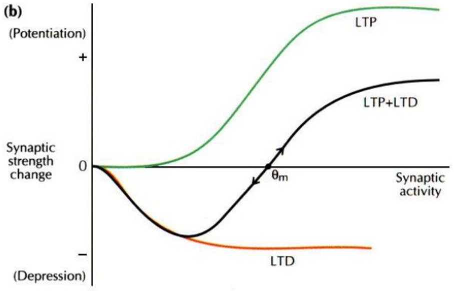
Figure by wetcake (left) and Andrej Kral (right)

Learning in nature synaptic plasticity

Presynaptic neuron



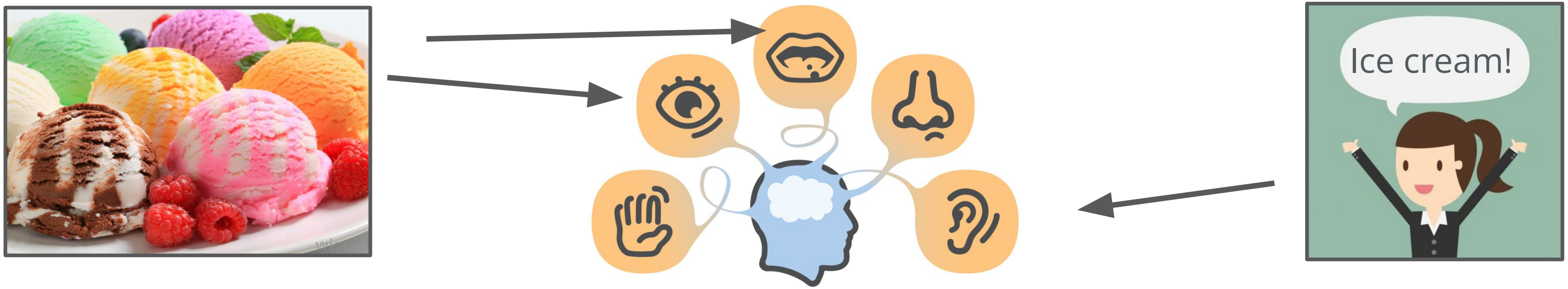
Postsynaptic neuron



- What's <u>very cool</u> is that with frequent repeated stimulation, the same level of presynaptic stimulation converts into **greater** postsynaptic potential
  - In other words, as a neuron gets a lot of practice sending signals to a specific target neuron, it gets better at sending those signals (the synapse strength increases)
    - Increased strength that lasts for a long time (from minutes to many months) is called **Long Term Potentiation** (weakening is **Long Term Depression**)
  - As synapses are strengthened and retain strength, we're able to more easily recall previous experiences

Figure from: "Synaptic Plasticity: A molecular mechanism for metaplasticity", Journal of Current Biology.

Learning in nature Hebbian theory



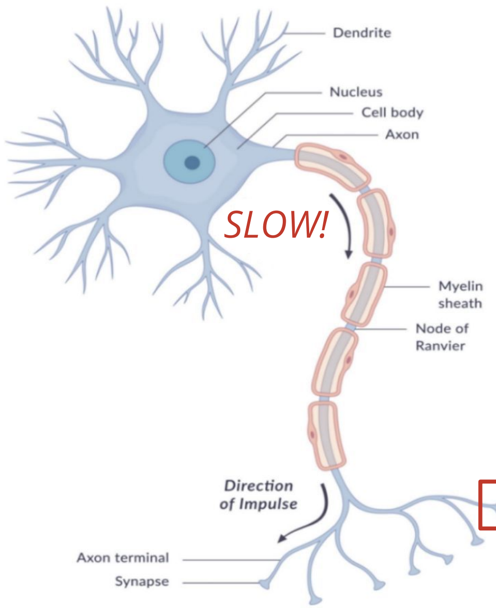
- Hebbian theory
  - If two neurons fire at the same time, the connections between them are strengthened, and thus are more likely to fire again together in the future
  - If two neurons fire in an uncoordinated manner, their connections are weakened, and they're more likely to act independently in the future

- Updated Hebbian hypothesis based on recent findings
  - If the presynaptic neuron fires within a window of 20ms before the postsynaptic neuron, the synapse will be strengthened
  - However if within a window of 20ms after, the synapse will be weakened

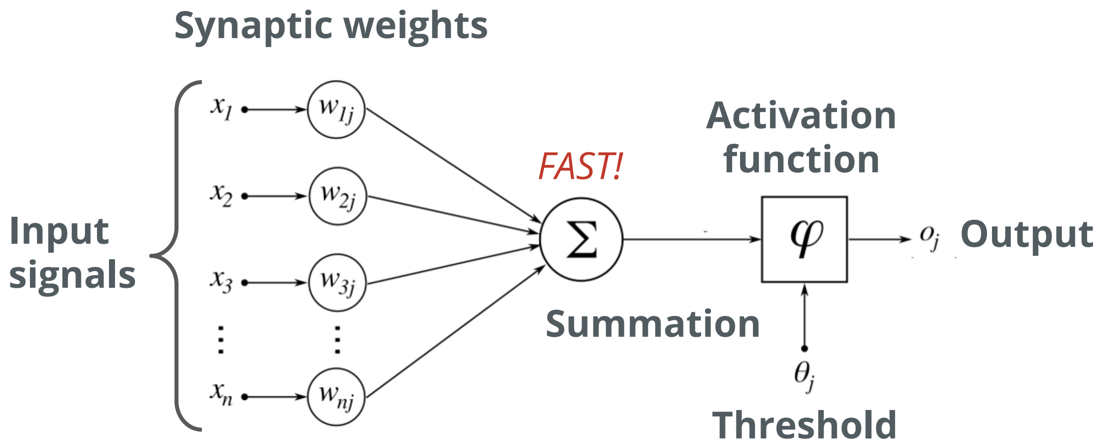
A brief history artificial neurons

Pitts and McCulloch, 1943

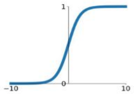
The Artificial Neuron



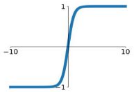
Quantum effects?
(article link)



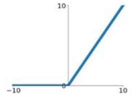
Sigmoid
$\sigma(x) = \frac{1}{1+e^{-x}}$



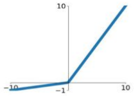
tanh
$\tanh(x)$



ReLU
$\max(0, x)$

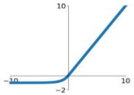


Leaky ReLU
$\max(0.1x, x)$

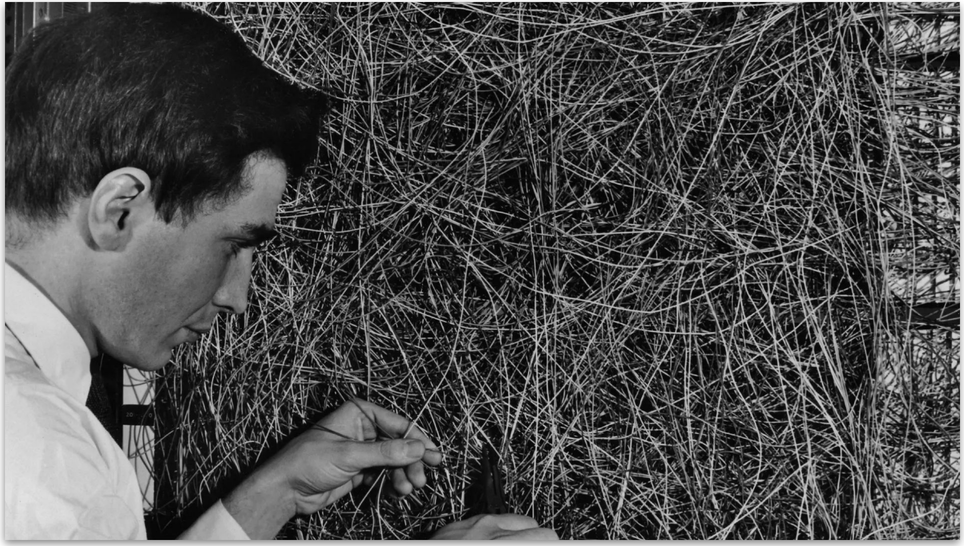


Maxout
$\max(w_1^T x + b_1, w_2^T x + b_2)$

ELU
$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$



A brief history the perceptron machine



Frank Rosenblatt, 1957

The perceptron machine was difficult to tune

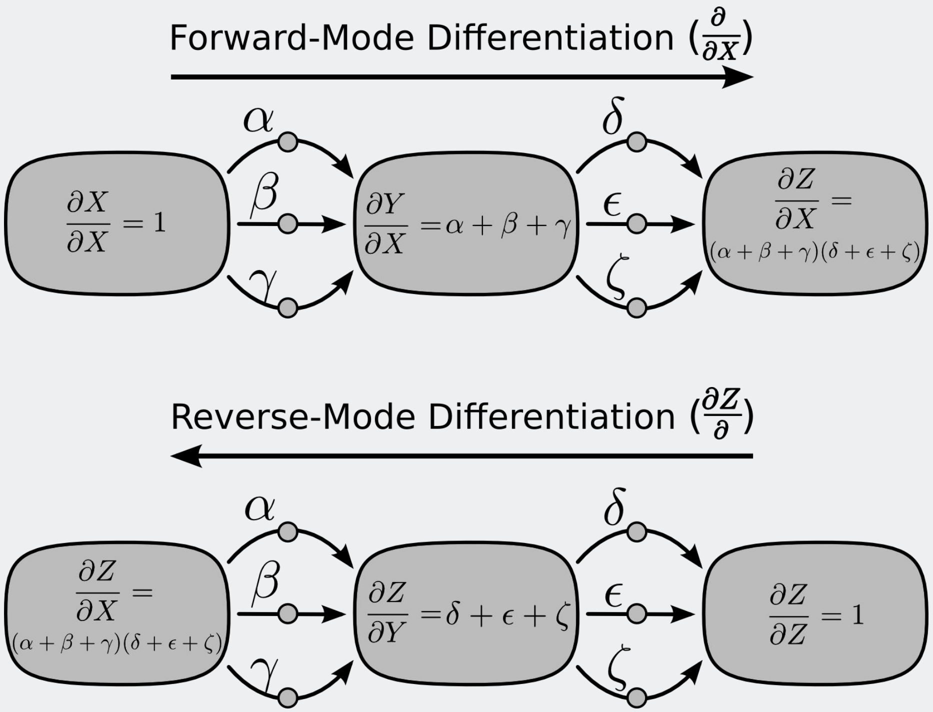
A brief history backpropagation

Backpropagation, 1970

The backpropagation algorithm (also called the reverse mode of automatic differentiation) was independently discovered by different researchers

Seppo Linnainmaa, 1970
Werbos, 1974 (with neural networks)

Reverse-mode differentiation



A brief history recurrent neural networks and the second AI winter

Rumelhart and Hinton, 1986

Learning representations by back-propagating errors

Nature, 1986. David E. Rumelhart, Geoffrey E. Hinton & Ronald J. Williams

- Backpropagation
- Multiple hidden layers
- Recurrent networks

The second AI winter 1987–1993

A brief history convolutional neural networks

History of CNNs

Convolutional neural networks were first introduced by Kunihiko Fukushima in 1980

- **1989** - Yann Lecun et al., trained a CNN with "Backpropagation Applied to Handwritten Zip Code Recognition"
- **1998** - Yann Lecun et al., released LeNet5 "Gradient-based learning applied to document recognition"

Example: LeNet5

```
class LeNet(nn.Module):
   def __init__(self):
      super(LeNet, self).__init__()
      self.conv1 = nn.Conv2d(1, 6, 5, padding=2)
      self.conv2 = nn.Conv2d(6, 16, 5)
      self.fc1   = nn.Linear(16*5*5, 120)
      self.fc2   = nn.Linear(120, 84)
      self.fc3   = nn.Linear(84, 10)

   def forward(self, x):
      x = F.max_pool2d(F.relu(self.conv1(x)), (2, 2))
      x = F.max_pool2d(F.relu(self.conv2(x)), (2, 2))
      x = flatten(x)
      x = F.relu(self.fc1(x))
      x = F.relu(self.fc2(x))
      x = self.fc3(x)
      return x
```

A brief history
the current AI spring - GPUs and large benchmarks

The 2010 AI spring

History of NNs on GPUs

- **2004** - first GPU implementation of a neural network
- **2006** - first GPU implementation of a CNN (just 4 times faster)
- **2012** - AlexNet - won state-of-the-art by significant margin with 60 million parameters
- **2015** - ImageNet state-of-the-art by a residual network with over 100 layers

A brief history
cloud computing - GANs, transformers, and beyond

Cloud Computing - GANs & GPT-4

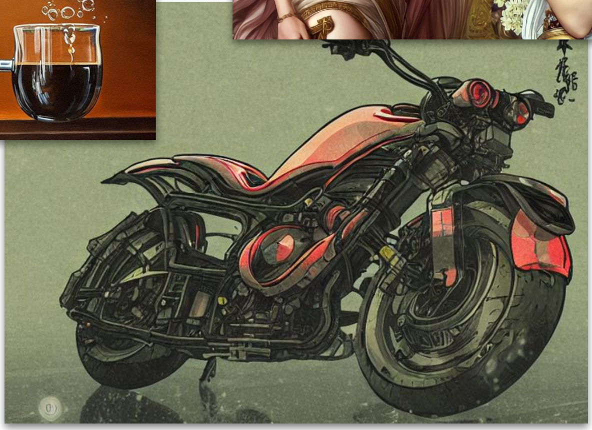
Fake faces generated by StyleGAN2

Unsupervised Generative Models

Progressively larger models are being trained on GPU cloud services

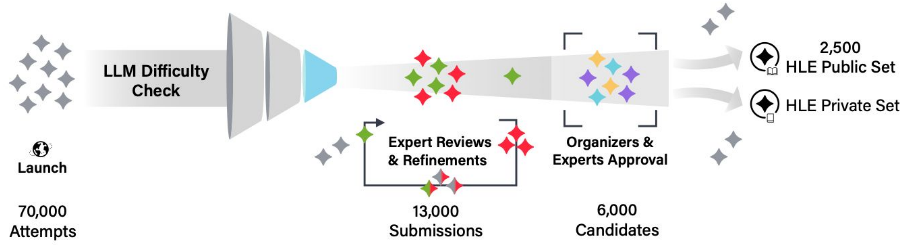
- **2014** - Ian Goodfellow releases “Generative Adversarial Nets”
- **2017** - GoogleBrain releases “Attention is all you need”
- **2019** - OpenAI GPT-2 “Language Models are Unsupervised Multitask Learners”
- **2020** OpenAI GPT-3 “Language Models are Few-Shot Learners”

2023 GPT-4 multimodality, stable diffusion, plugins…



"Cyberpunk style image of a motorcycle reflection in rain, ukiyo-e, unreal engine, trending on artstation"

2025+ …to context engineering, agents, tool use, pay-to-win



…building in progress…

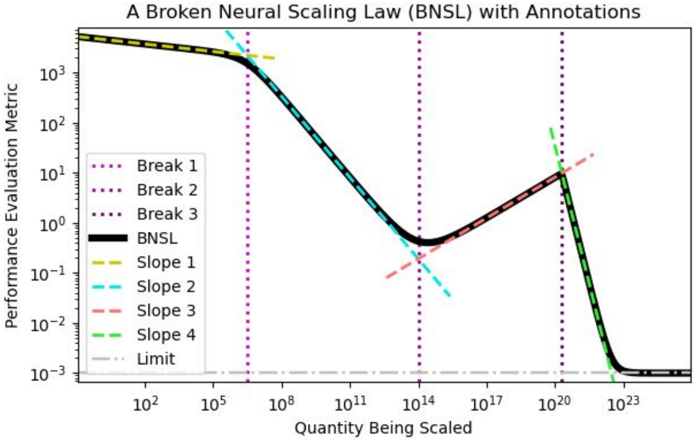
GPT-5 Grok

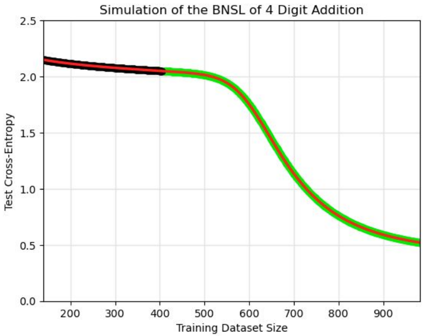
deepseek Claude

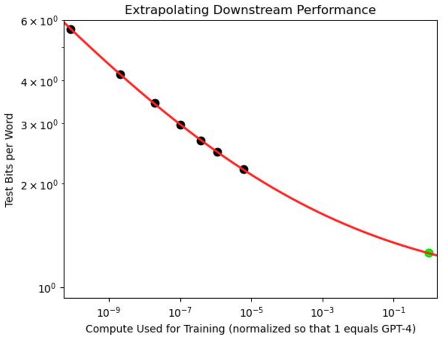
CURSOR MCP

https://scale.com/leaderboard/humanitys_last_exam

Scaling laws engineering success is because it is predictable







Neural scaling laws

Can make excellent predictions of future generalisation performance with more £.

- **2017** - Hestness et al., “Deep learning scaling is predictable, empirically” (when first started teaching DL at Durham!)
- **2023** - “Broken Neural Scaling Laws” captures double descent etc
- **2024+** “Scaling LLM Test-Time Compute Optimally can be More Effective than Scaling Model Parameters”

The reasoning debate where are you?

Several of these people's views have changed over the past 5 years...

Solving tasks ≠ reasoning

LLMs don't understand the world

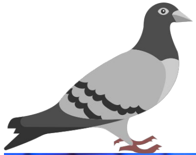
Predicting the future is intelligence

We're not so different

"Stochastic parrots... do not understand" + long-term value optimisation Superintelligence

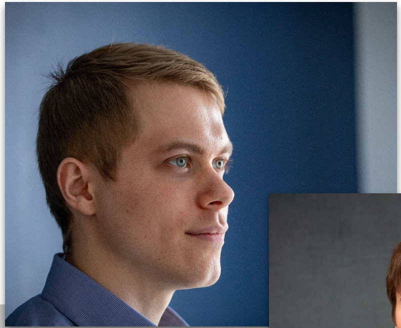
The safety & alignment debate where are you?

Address immediate real harms



Stop exaggerating

Policy and strategy, an OFF switch &...



Safety and regulation

We need better AI reward design

We're screwed

Existential risk

Key concepts overlap with other areas of machine learning

Machine Learning

Deep Learning
multiple layers
gradients
mostly IID

Shallow Learning
often hand-engineered

Supervised Learning
learning one task

Unsupervised Learning

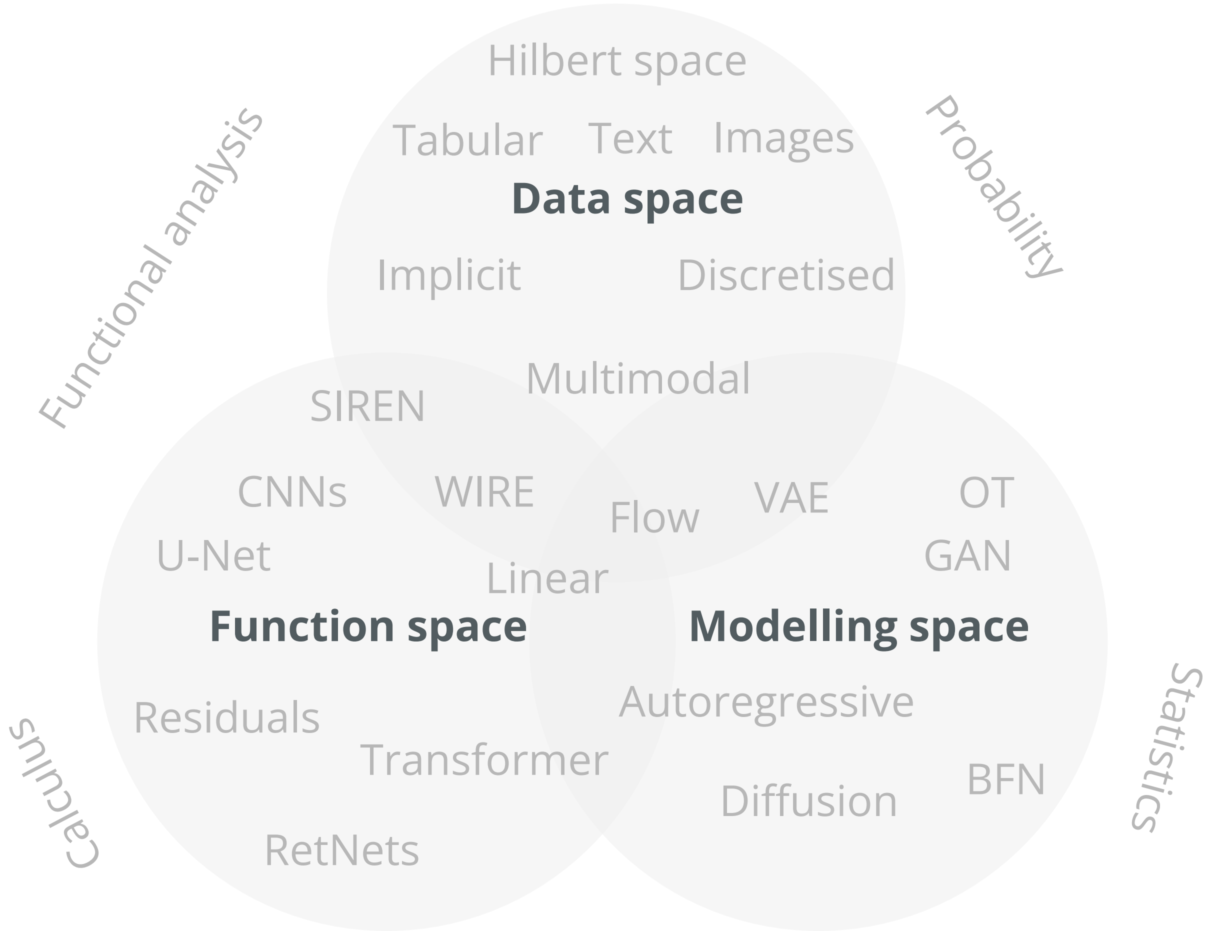
Reinforcement Learning
bad gradients
dynamic not IID
optimising future reward

Generative Models
learning the data distribution

Discriminative Models
classifying data
regression

Meta Learning
learning the task distribution

Key concepts deep learning contributions from three spaces



Take away points

Summary

In summary, deep learning:

- has overlap with many areas
- achieves state-of-the-art in ill-defined tasks and scales with...
  - very high-dimensional datasets
  - huge datasets
  - parallelizable hardware
- fields of maths: probability, calculus, statistics, functional analysis...
- is rapidly growing and evolving