Deep Learning

Lecture 1: Introduction

Chris G. Willcocks
Durham University

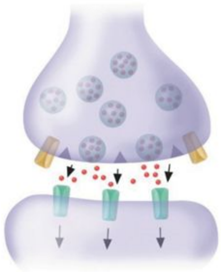
Lecture Overview

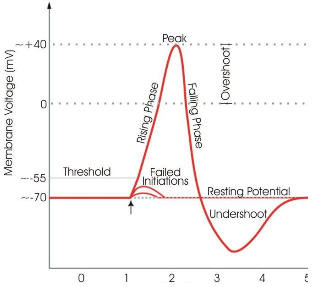
❶ Introduction
- definitions
- examples

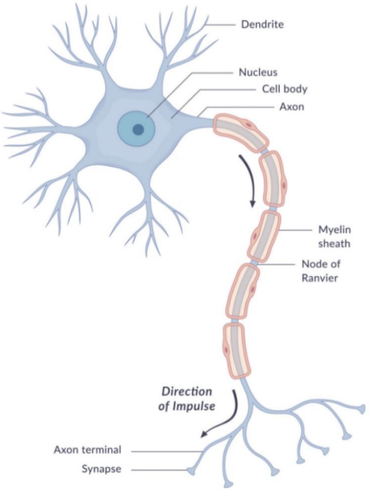
❷ Learning in Nature
- what is learning?
- how does the brain work?
- synaptic plasticity
- Hebbian theory

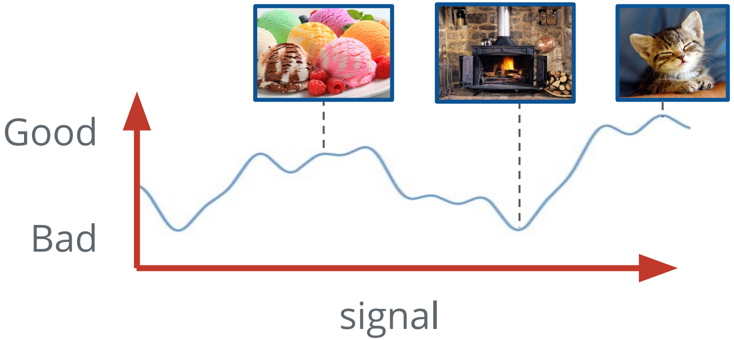
❸ A Brief History

❹ Key Concepts
- recap T, P and E
- how DL differs to ML







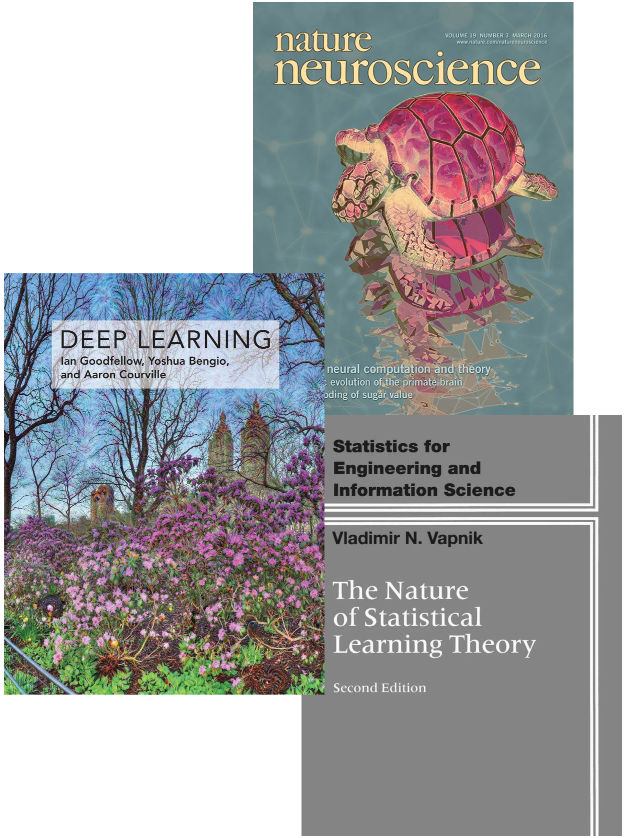


Submodule Aims learning outcomes

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 learning in nature, and the relevant theory in statistics and geometry
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: 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**

Introduction examples

Examples: Images and Vision

Non-photorealistic interpolation:

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

End-to-end self-driving:

- Wayve - video

Examples: Text and Audio

Examples from text:

- GPT-3 - video
- **Input**: The internet
- **Output:** Any language task

Examples with audio:

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

Learning in Nature what is learning?

Environment

Experiences	**Actions**	**Changed Actions**
Delicious	Put in mouth	Eat it again!
Cold	Get closer	Don’t touch.
Warm	Touch	
Burning		

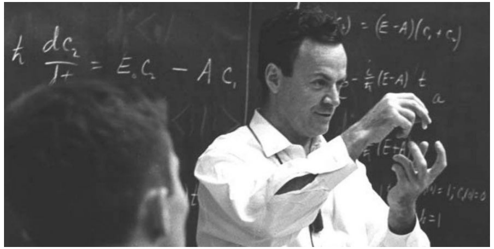
Time

Learning in Nature definition of learning

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

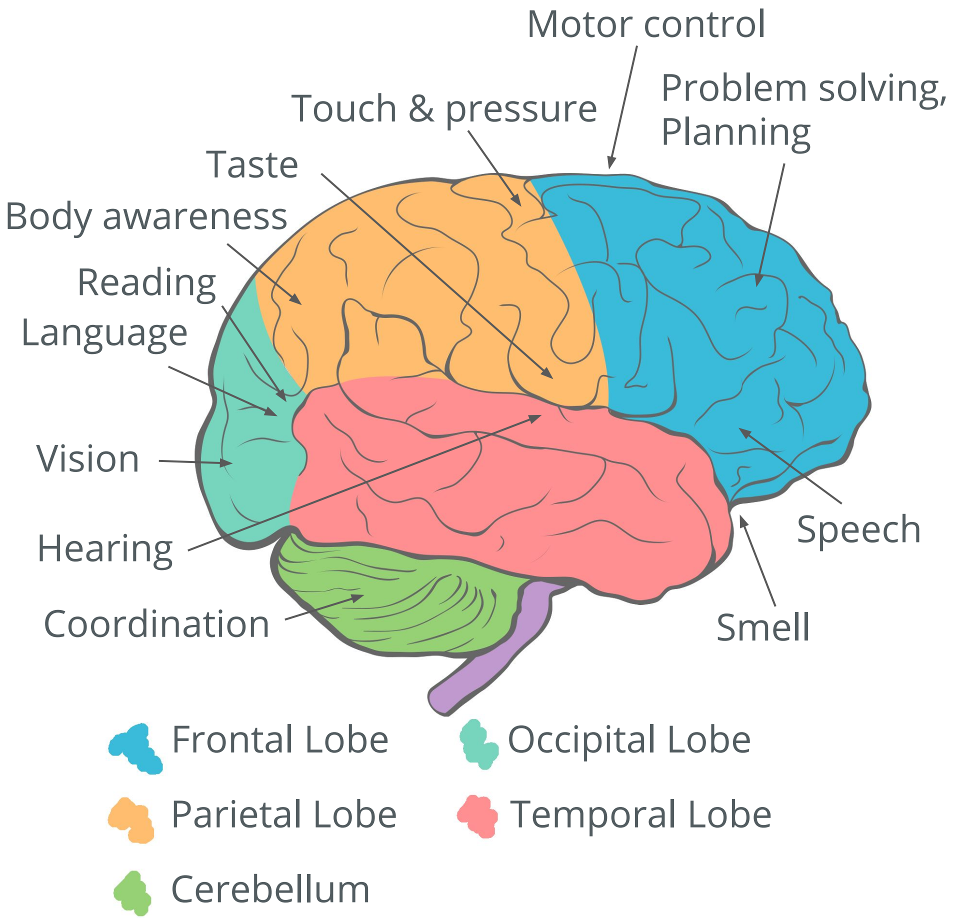


Learning in Nature how does the brain work?

Architecture of the brain

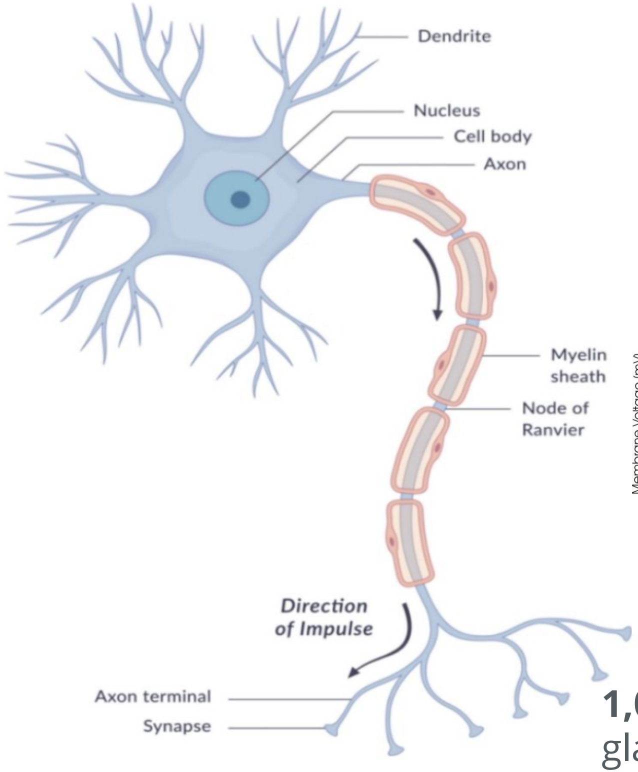
Right side/left side (hemispheres)

- 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

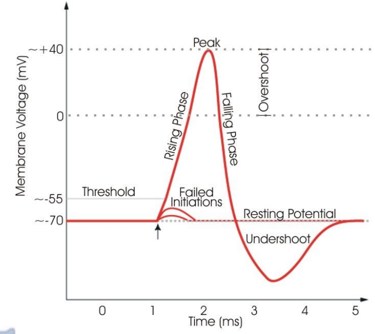


Learning in Nature how does the brain work?

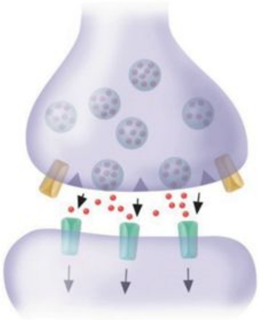
1,000's of inputs (other neurons, sensory neurons e.g. taste buds from a salt or sugar molecule...)



- 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:



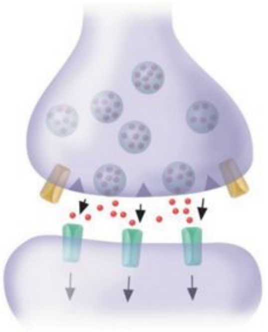
- "Synapse" (from the greek meaning "to clasp together")
- **Signals** get **summed up**, and travel to the hillock (Axon neck)
  - If large enough, triggers an action potential travels down axon

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

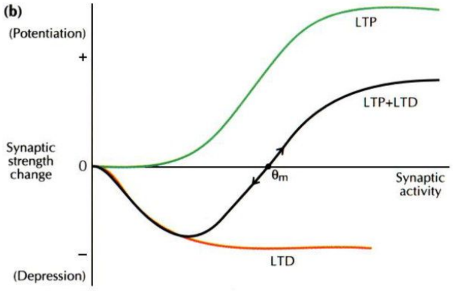
Figure by wetcake (left) and Andrej Kral (right)

Learning in Nature synaptic plasticity

Presynaptic neuron



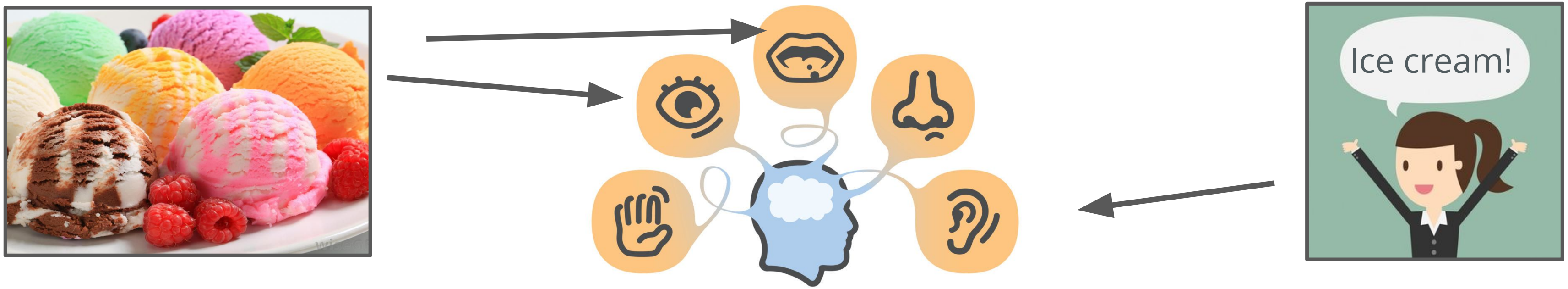
Postsynaptic neuron



- 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

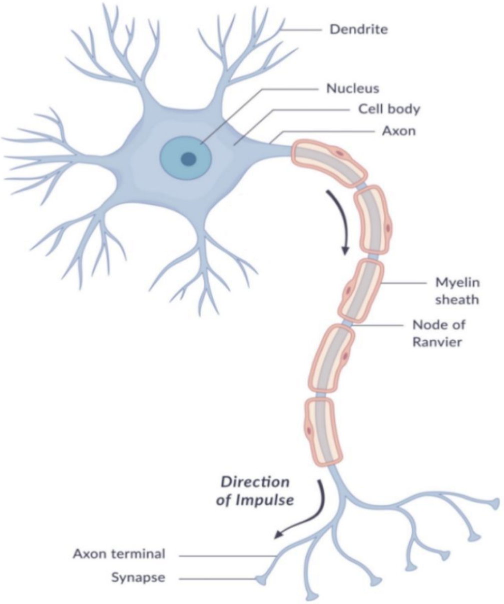


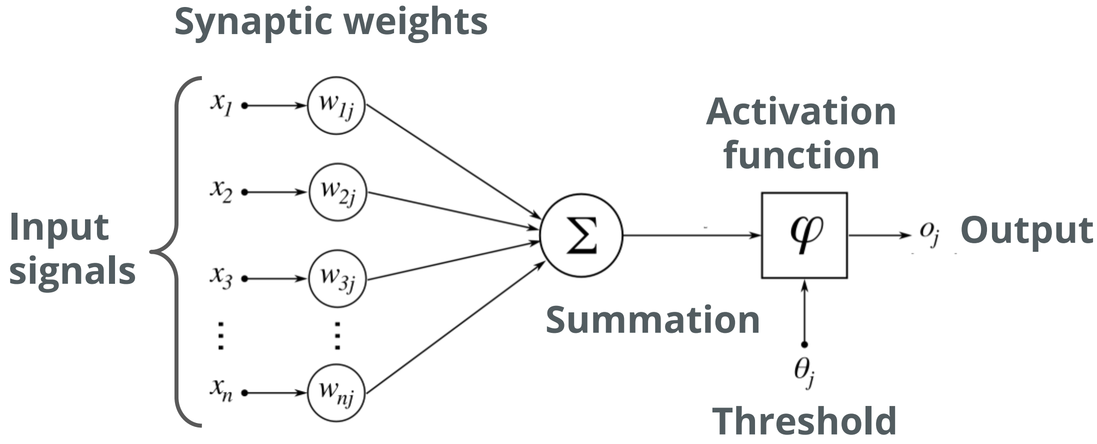
- Hebbian theory
    - If two neurons fire at the same time, the connections between them are strengthened, and thus are more likely to fire again together in the future
    - If two neurons fire in an uncoordinated manner, their connections are weakened and their more likely to act independently in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

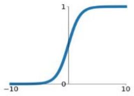
Pitts and McCulloch, 1943

The Artificial Neuron

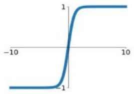




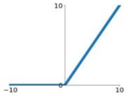
Sigmoid
$\sigma(x) = \frac{1}{1+e^{-x}}$



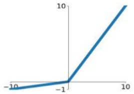
tanh
$\tanh(x)$



ReLU
$\max(0, x)$

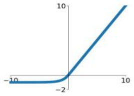


Leaky ReLU
$\max(0.1x, x)$



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

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



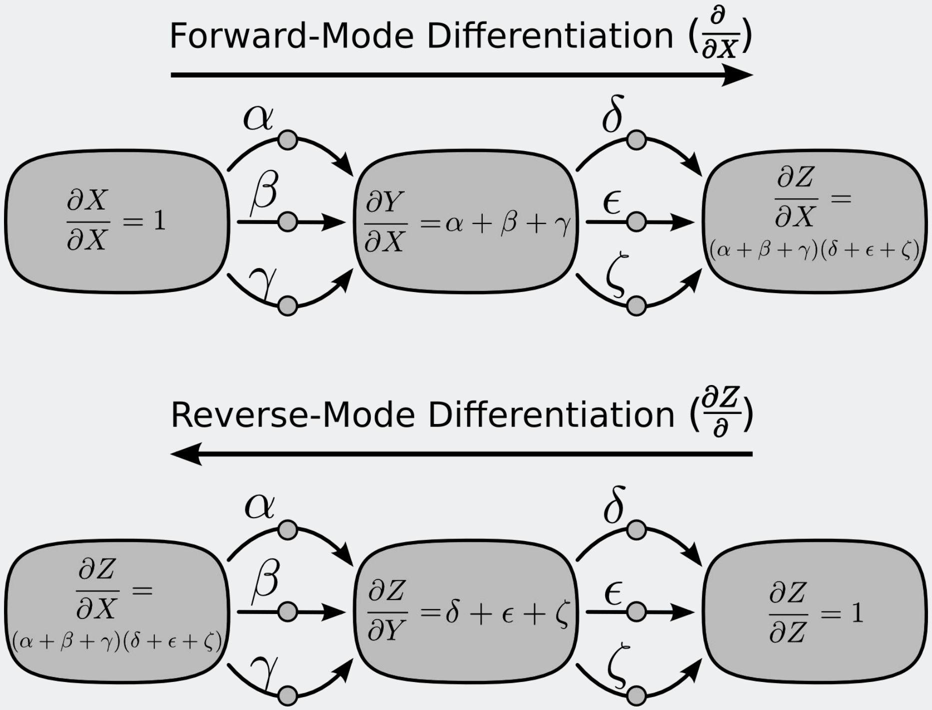
A Brief History backpropagation

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 current 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-3

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”

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 components required in deep learning

Shared components with ML

Deep learning shares the main components in machine learning

- experiencing $\boldsymbol{E}$ the data distribution p_{data}
- specifying the task $\boldsymbol{T}$
- optimising a specified performance measure $\boldsymbol{P}$

NEW priority

Deep learning puts additional emphasis on the following

- tensors and backpropagation
- modeling joint distributions
- statistical manifolds
- designing architectures
- regularising high-capacity networks
- GPU computing
- learning a distribution of tasks
- a deeper theory of generalisation

Take Away Points

Summary

Im summary, deep learning:

- has overlap with many areas of AI
- achieves state-of-the-art in many ill-defined tasks
    - high-dimensional datasets
    - huge datasets (the internet)
    - very parallelizable
- has a lot to do with statistics
- has a bit to do with geometry
- is rapidly growing and evolving