# Tools Seminar

## Week 8 - Deep Learning

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Apr 5, 2020

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# Introduction

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- 2011, IBM Watson defeated two champions at quiz show Jeopardy
- 2012, Jeff Dean and Andrew Ng used unsupervised learning to train neural network which learned to recognize cats

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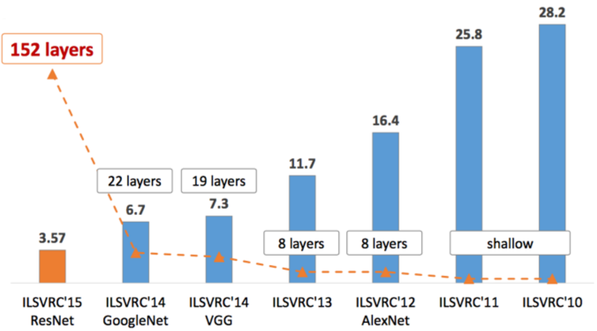
- 2018, Google BERT model achieved the state-of-the-art performance in 11 NLP tasks

# ImageNet & Deep Neural Network

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) [Feifei Li, Stanford]

- Labeled dataset → supervised learning
- 14+ million images, 20,000 categories




This is why it's called "**deep**" learning

# 2018 Turing Award

2018 Turing Award: Geoffrey Hinton, Yoshua Bengio, Yann LeCun

> *"for conceptual and engineering breakthroughs that have made deep neural networks a critical component of computing"*

- Geoffrey Hinton: Backpropagation, Boltzmann Machines, Improvements to Convolutional Neural Network (CNN)
- Yoshua Bengio: Probabilistic models of sequences, High-dimensional word embeddings and attention, Generative adversarial networks (GAN)
- Yann LeCun: CNN, backprop, Broadening the vision of neural networks (LeNet5)

# Impetus of Deep Learning

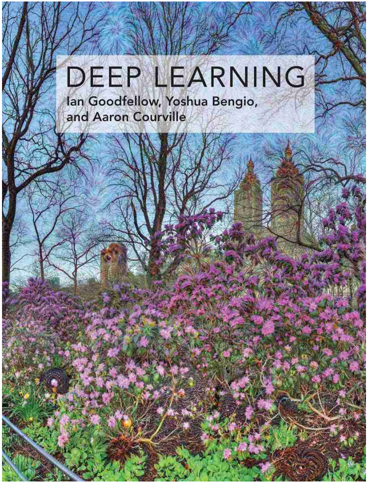
Looking back, we may know what leads to the boom of DL in 2010s

- Large amount of labeled **data**: ImageNet (2010)
- Improvement of **algorithms**: deep networks, dropout (2012)
- Invention of deep learning **systems**: TensorFlow (2015), PyTorch (2016)
- Improvement of **hardware**: GPU $\rightarrow$ GPGPU (general-purpose GPU)

All of them are indispensable and make up the whole DL stack

# Introductory Books and Courses

- Feifei Li, Stanford cs231n: Convolutional Neural Networks for Visual Recognition (highly recommended!)
- Chris Manning, Stanford cs224n: Natural Language Processing with Deep Learning
- Ian Goodfellow, Deep Learning, Chinese version



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# Deep Learning

# Linear Regression

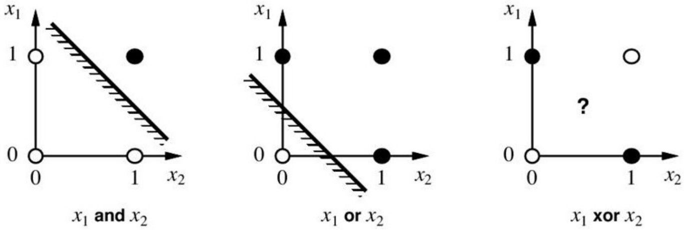
Recall the linear regression problem

$$y = \mathbf{w}^{\mathrm{T}}\mathbf{x} + b = \begin{bmatrix}\mathbf{x}^{\mathrm{T}} & b\end{bmatrix}\begin{bmatrix}\mathbf{x} \\ 1\end{bmatrix} = \boldsymbol{\theta}^{\mathrm{T}}\mathbf{x}$$

To minimize loss function (MSE)

$$\min_{\boldsymbol{\theta}} L(\boldsymbol{\theta}) = \frac{1}{m}\sum_{i=1}^{m}(y_i - \mathbf{w}^{\mathrm{T}}\mathbf{x}_i - b)^2$$

But linear function can only deal with linearly separable problems



# Powerful Models

Can we build a model that is powerful enough to represent all the functions?

- $f(\text{image}) = \text{location}$
- $f(\text{question}) = \text{answer}$
- $f(\text{speech}) = \text{text}$
- $\cdots$

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Actually, in ML area, we have built decision tree, SVM, etc., but they usually need feature engineering and are <u>not flexible</u>

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**But how?**

# Representation Learning

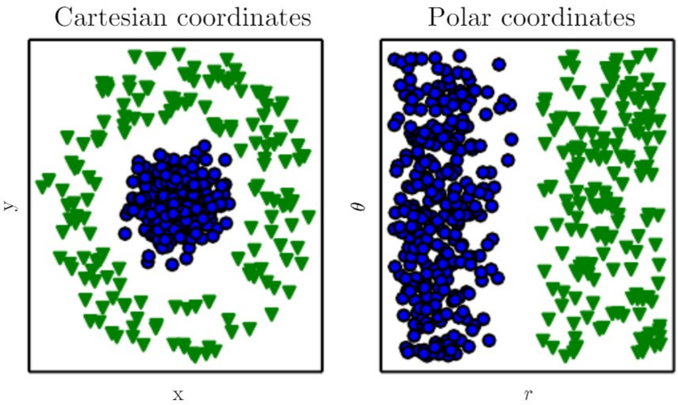


Fig source: *Deep Learning* book

**Representation matters!**

# Representation Learning

Different feature representation affects final performance

# Representation Learning

Different feature representation affects final performance

Then, let machine learn the feature itself!

$$\text{features} \rightarrow \text{mapping from features} \rightarrow \text{output}$$

e.g.

- Encoder-decoder
- Word embeddings, graph embeddings

# But...

We may have lots of features...
e.g. figure out what the object is in the photo

- size
- color
- material
- illumination
- view angle
- ...

Representation learning captures several features, but cannot capture all of them

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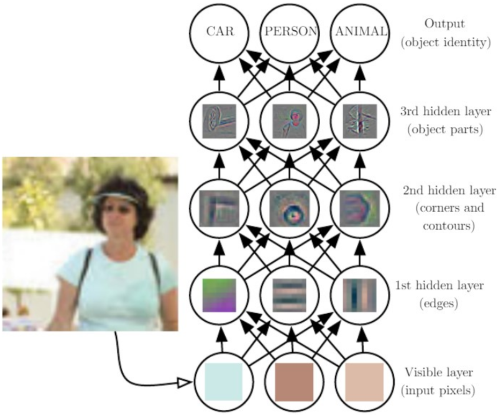
**So complex!**

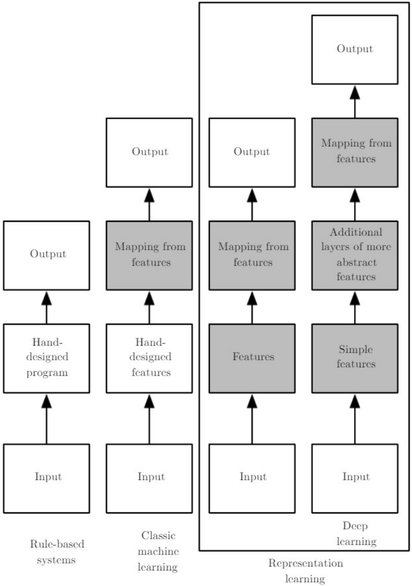
# Decouple to simple features!

Learn from simple/shallow features and gradually to complex/deep features




**Key: Get deeper!**

Fig source: *Deep Learning* book

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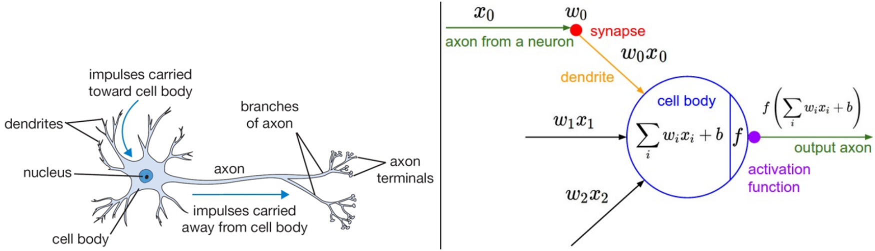
# Neuron Model

We can refer to our brain and see how we learn




A cartoon drawing of a biological neuron (left) and its mathematical model (right).

Fig source: http://cs231n.github.io/neural-networks-1/

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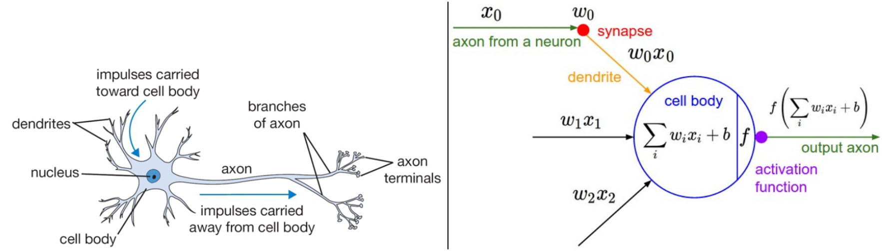


A cartoon drawing of a biological neuron (left) and its mathematical model (right).

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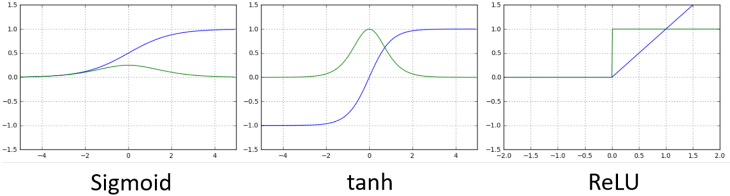
A neuron is just a linear model with **activation function**!

# Activation Function

Add non-linear part to the model, enabling it to approximate much more **complex** functions (key of NN!)




- Sigmoid: $g(z) = 1/(1 + \mathrm{e}^{-z})$ (S curve)
- Tanh: $g(z) = \tanh(z)$
- ReLU (Rectified Linear Unit): $g(z) = \max(0, z)$, can avoid gradient vanishing

# From one to more

Only one neuron can do limited things, what about more?

- More neurons in width:

  > *A feed-forward network with a single hidden layer containing a finite number of neurons can approximate continuous functions on compact subsets of* $\mathbb{R}^n$*.*
  >
  > — *The Universal Approximation Theorem*

  The question is that the theorem does not tell us how many neurons we need

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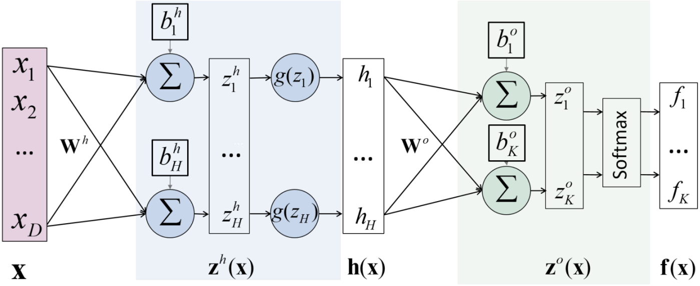
- More neurons in depth: We have multi-layer perceptron (MLP) — the basic model of nowadays deep learning!

# Multi-Layer Perceptron (MLP) / Fully-connected NN



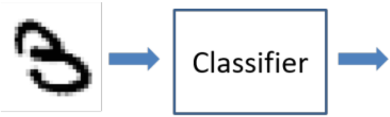

- Input layer: $\mathbf{x}$
- Hidden layer: $h(\mathbf{x}) = g(\mathbf{z}^h(\mathbf{x})) = g(W^h\mathbf{x} + \mathbf{b}^h)$
- Output layer: $f(\mathbf{x}) = \sigma(\mathbf{z}^o(\mathbf{x})) = \sigma(W^o h(\mathbf{x}) + b^o)$

* Softmax function: change output to probability ($K$-dimensional)

$$\sigma(\mathbf{z})_j = \frac{\mathrm{e}^{z_j}}{\sum_{k=1}^{K} \mathrm{e}^{z_k}}$$

# Classifier Training

- Find optimal parameters $\boldsymbol{\theta}^*$ of a classifier $\mathbf{y} = f(\mathbf{x}; \boldsymbol{\theta})$
- Rule: given input $\mathbf{x}$, classifier output $f(\mathbf{x}; \boldsymbol{\theta})$ should be as close to the ideal output as possible




| Probability | Ideal output | Class |
|---|---|---|
| 0.005 | 0 | 0 |
| 0.002 | 0 | 1 |
| 0.001 | 0 | 2 |
| 0.93 | 1 | 3 |
| 0.001 | 0 | 4 |
| 0.005 | 0 | 5 |
| 0.003 | 0 | 6 |
| 0.001 | 0 | 7 |
| 0.05 | 0 | 8 |
| 0.002 | 0 | 9 |

# Classifier Training

Use MSE or other loss function

$$\min_{\boldsymbol{\theta}} \frac{1}{N} \sum_{i=1}^{N} \|f(\mathbf{x}_i; \boldsymbol{\theta}) - y_i\|_2^2$$

Use gradient descent to optimize parameters

$$\boldsymbol{\theta}^{(k+1)} = \boldsymbol{\theta}^{(k)} - \alpha \nabla_{\boldsymbol{\theta}} L(\boldsymbol{\theta})$$

About how to optimize the above function on NN (backpropagation), please read http://cs231n.github.io/optimization-1/

# Training

Let's see how NN trains:

Tensorflow Playground

# Different Kinds of NN

- CNN (convolutional NN): CV
    - Pooling / subsampling
    - Dropout
    - Residual block
- RNN (recurrent NN): NLP
    - LSTM
    - GRU
- GAN (generative adversarial network): Image generation

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# Frameworks

# Deep Learning Frameworks

Framework: A large package consisting of lots of deep learning primatives/operators, and users can easily call them by API

- Google: Tensorflow (commonly used in industry)
  - Static computation graph
  - Jeff Dean
- Facebook: PyTorch (commonly used in academics)
  - Dynamic computation graph
  - Yangqing Jia, Caffe
- Amazon: MXNet
  - Tianqi Chen

[Domestic] PaddlePaddle (Baidu), Mindspore (Huawei), MegEngine (Face++), Jittor (Tsinghua)

* We focus on **PyTorch** in this seminar

# PyTorch

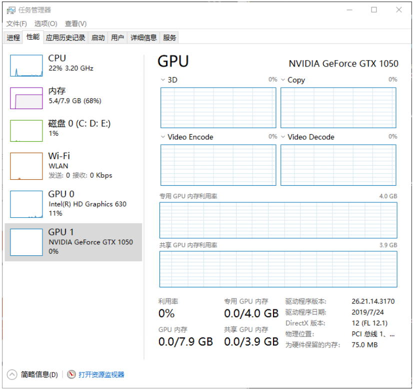
PyTorch: A Python-based deep learning framework

- A replacement for NumPy to use the power of GPUs
- A deep learning research platform that provides maximum flexibility and speed

Since it is highly embedded in Python, PyTorch is very Pythonic and easy-to-use

# Pytorch Installation

Firstly check if your computer has discrete graphics card (GPU)




Install Nvidia driver: https://zhuanlan.zhihu.com/p/54350088

- CUDA 10.1
- cuDNN 7: Installation guide

# Pytorch Installation

Select your configuration on this website and run the installation command

- Windows: Need to install Anaconda first
- WSL does not support GPU! Do NOT install Pytorch on WSL!
- Mac does not support GPU too (if you do not have external interface)!

e.g. For Windows with no GPUs

```
pip install torch==1.4.0+cpu torchvision==0.5.0+cpu -f https://
    download.pytorch.org/whl/torch_stable.html
```

Check if GPU works correctly by

```python
import torch
print(torch.cuda.is_available())
```

# Tutorials

PyTorch has very detailed documentations, make the best of them!

- Tutorials: https://pytorch.org/tutorials/
- Chinese tutorials: https://pytorch.apachecn.org/
- Documentation / API: https://pytorch.org/docs/stable/index.html
- Deep Learning with PyTorch: A 60 Minute Blitz
  - Chinese version
  - You can download the `.ipynb` file or directly run on Colab

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# Summary

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- Introduction
- Deep Learning Framework: PyTorch
  - Once you get into troubles concerning PyTorch, you can search the Docs of PyTorch for details. Alternatively you can try to find if there are similar problems on *PyTorch Discuss*.
- Get through cs231n!