(An Almost) No Math Introduction to Deep Learning

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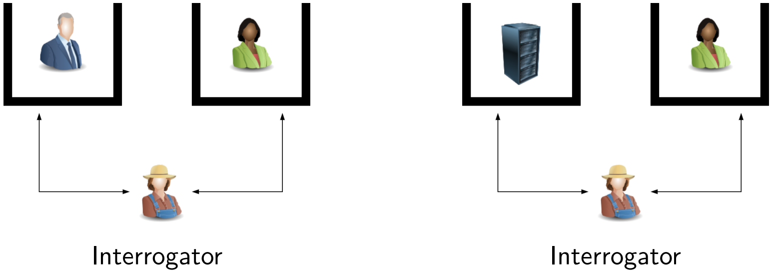
Summary

Imitation game



Artificial intelligence

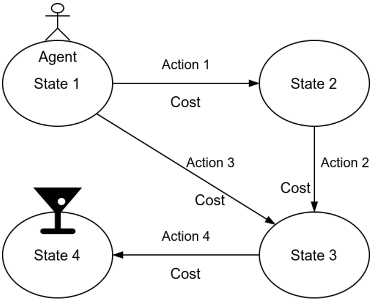
- Logic machines (50s)
- Knowledge based expert systems (80s)
- Language translation (60s) , 2000s, 2014 and later.
- Machine learning
  - Neural networks including deep learning (started in 1943)
  - Support vector machines
  - Baysian learning
- Graphs
- Genetic algorithms and genetic programs.

Expert systems

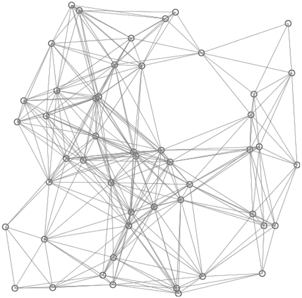
- Database of formally described ”facts” or ”knowledge”.
- A reasoning engine for answering questions or solving problems.

Not to be confused with a true natural language processing and question-answering system.

Search


Agent
State 1
Action 1
Cost
State 2
Action 3
Cost
Action 2
Cost
State 4
Action 4
Cost
State 3

?



?

Neural Networks

1943: Warren McCulloch and Walter Pits connected neurons, computation, logic and learning.

1950: Minsky and Dean Edmonds build first neural network computer. 3000 vacuum tubes, surplus auto-pilot parts from B-24 bomber. 40 Neurons.

1969: Minsky and Papert publishobama-funny perceptron - simple linear networks could not learn basic functions.

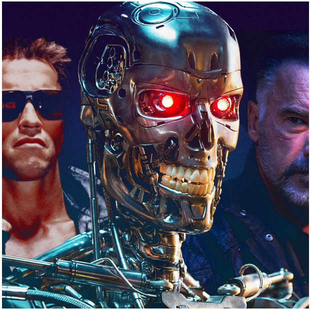
1980s: David Rumelhart, Jeff Hinton and Ronald Williams applied back propagation (again) for training multi-layer neural networks. Rumelhart's work also created the foundations for Recurrent Neural Networks.

1990s: LSTM networks by Hochreiter and Schmidhuber 1997. CNN for handwritten digit recognition - Yann LeCun.

2000s: LSTMs show promise in speech recognition

2012: Deep learning

Different views



Agent

General

Tool

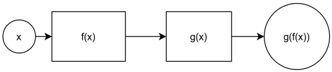
Narrow

Composition of functions

$$f(x) = ax + b \tag{1}$$

$$g(x) = \frac{1}{e^{-x} + 1} \tag{2}$$

$$g(f(x)) = \frac{1}{e^{-(ax+b)} + 1} \tag{3}$$



Composite

Derivatives

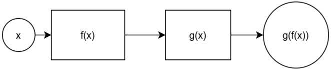
$$f(x) = ax + b \tag{4}$$

$$\frac{df(x)}{dx} = a \tag{5}$$

$$\sigma(z) = \frac{1}{e^{-z} + 1} \tag{6}$$

$$\frac{d\sigma(z)}{dz} = \sigma(z)(1 - \sigma(z)) \tag{7}$$

$$\frac{d\sigma(f(x))}{dx} = ? \tag{8}$$



Composite

Derivatives

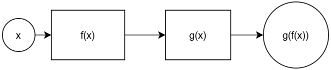
$$z = ax + b \tag{9}$$

$$\frac{dz}{dx} = a \tag{10}$$

$$\sigma(z) = \frac{1}{e^{-z} + 1} \tag{11}$$

$$\frac{d\sigma}{dz} = \sigma(z)(1 - \sigma(z)) \tag{12}$$

$$\frac{d\sigma}{dx} = \frac{d\sigma}{dz}\frac{dz}{dx} \tag{13}$$



Composite

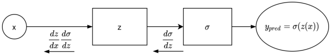
$$z = ax + b \tag{14}$$

$$\frac{dz}{dx} = a \tag{15}$$

$$\sigma(z) = \frac{1}{e^{-z} + 1} \tag{16}$$

$$\frac{d\sigma}{dz} = \sigma(z)(1 - \sigma(z)) \tag{17}$$

$$\frac{d\sigma}{dx} = \frac{d\sigma}{dz}\frac{dz}{dx} = \frac{dz}{dx}\frac{d\sigma}{dz} \tag{18}$$



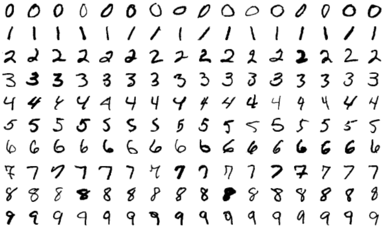
Back propagation of gradients

Datasets

- Modified National Institute of Standards and Technology - MNIST (60k/10k)
- Canadian Institute For Advanced Research - CIFAR-10 (50k/10k) and CIFAR-100 (2 level, 500/100)
- Pascal Visual Object Classes (VOC) - 22k images, 20 classes
- ...
- ImageNet

ImageNet Large Scale Visual Recognition Challenge

MNIST Dataset (60k, 10k)



ImageNet (14M+, 22k)

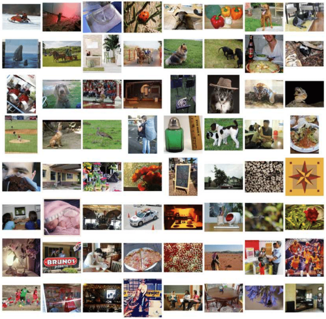
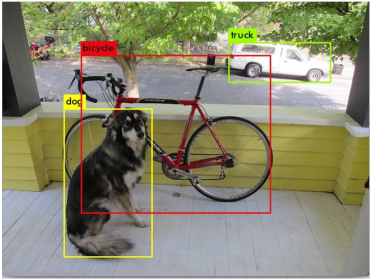
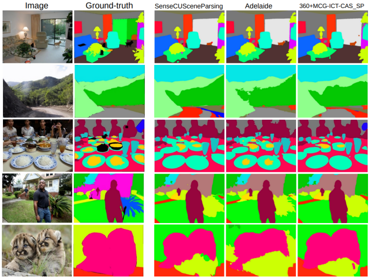


Image processing



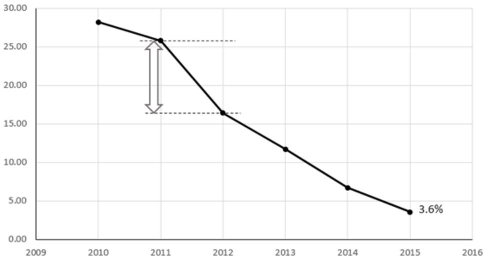
Localization



Segmentation

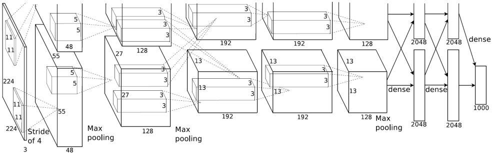
ImageNet Large Scale Visual Recognition Challenge

- Publicly available dataset - ImageNet (14M+, 22k categories)
- Annual competition
  - Image classification
  - Object detection and localization
- Increasing depth
  - 8 layer AlexNet
  - 19 layer GoogLeNet
  - 152 layer ResNet



Top 5 classification error rate

AlexNet 2012



Alex Krizhevsky, Sutskever, Ilya and Hinton, Geoffrey E., "ImageNet Classification with Deep Convolutional Neural Networks", 2012

AlexNet:] 61m parameters, 8 layers

GoogLeNet: 6.7m parameter, 22 layers

ResNet: ResNet-50, ResNet-101, ResNet-152

Question: Are deeper networks always better?

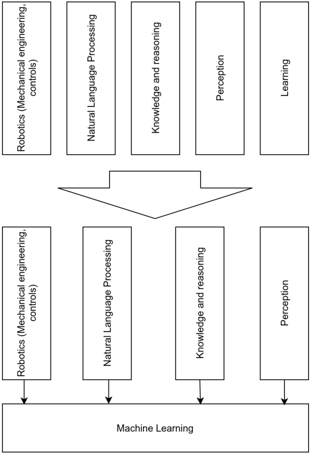
Not hotdog

https://www.youtube.com/watch?v=vIci3C4JkL0

Why do you think this picture is funny?

Credit: *http://karpathy.github.io/2012/10/22/state-of-computer-vision/*

Late 2000s - machine learning dominates



- Image classification, localization and segmentation
- Neural machine translation, question answering, summary.
- Game playing, helicopter flying (stunts)
- Planning, self driving cars
- Text, audio and video processing, generation
- ...

Machine learning I

Models

- Build a model of the world
- Infer/predict using the model.

Machine learning

- Supervised learning
- Unsupervised learning
- Reinforcement learning

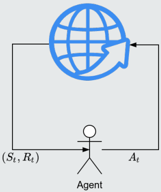
Machine learning II

Unsupervised learning

- Training a model to find patterns in a dataset, typically an unlabeled dataset.
- Learning how to extract *interesting* features.
- Learning data distribution for generating data.

Reinforcement learning

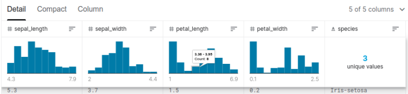
A family of algorithms that learn an optimal policy, whose goal is to maximize return when interacting with an environment.



Supervised learning I

Detail Compact Column

# sepal_length	# sepal_width	# petal_length	# petal_width	species
5.7	2.9	4.2	1.3	Iris-versicolor
6.2	2.9	4.3	1.3	Iris-versicolor
5.1	2.5	3	1.1	Iris-versicolor
5.7	2.8	4.1	1.3	Iris-versicolor
6.3	3.3	6	2.5	Iris-virginica
5.8	2.7	5.1	1.9	Iris-virginica
7.1	3	5.9	2.1	Iris-virginica
6.3	2.9	5.6	1.8	Iris-virginica
6.5	3	5.8	2.2	Iris-virginica

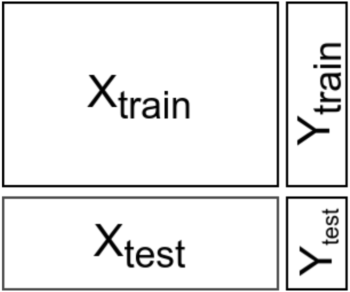


# sepal_length	# sepal_width	# petal_length	# petal_width	species
5.3	3.7	1.5	0.2	Iris-setosa
5	3.3	1.4	0.2	Iris-setosa
7	3.2	4.7	1.4	Iris-versicolor
6.4	3.2	4.5	1.5	Iris-versicolor
6.9	3.1	4.9	1.5	Iris-versicolor

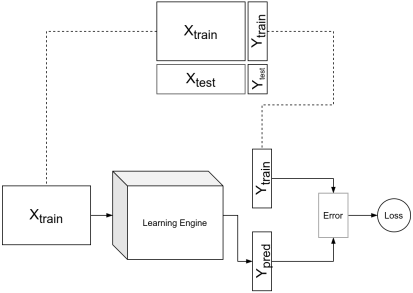
Supervised learning II

Source: *https://www.kaggle.com/arshid/iris-flower-dataset?select=IRIS.csv*

150 rows, 5 attributes (columns), 4 numerical and 1 categorical.

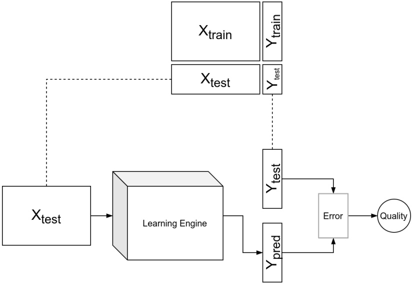


Data

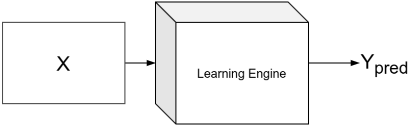


Training

Supervised learning III



Testing



Predicting

Fitting a function to data

Description (supervised learning)

Given a set of data $(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)$, can we find a function $y = f(x)$ that "fits" this data?

Questions

- What is this function $f(x)$?
- What does "fit" mean?
- How do we know this works?
- What kinds of problems can we solve?

More about $f(x)$

Class of functions

Starting with a function $f(x;\theta_1,\theta_2,\ldots,\theta_n)$ where x is the input to the function and θs are its parameters, we need to find the set of θs that best "fits" the give data $(x_1,y_1),(x_2,y_2),\ldots,(x_n,y_n)$

Class of linear functions

Consider $f(x)=ax+b$. If we can say, with some confidence, that our data is linearly related, we need to find $\theta_1=a$, $\theta_2=b$ that *fits* the given data. We can also write it as $f(x;a,b)=ax+b$. Preferred,

$$f(x;\theta_1,\theta_2)=\theta_1 x+\theta_2 \tag{19}$$

Fit

Mean squared Euclidean distance as one possible measure of fit

Let L_i be the squared Euclidean distance between the predicted value, $\hat{y}_i = f(x_i)$ and the actual, y_i. Then,

$$L_i = z_i^2 \tag{20}$$

$$z_i = y_i - f(x_i) \tag{21}$$

$$= y_i - \theta_1 x_i - \theta_2 \tag{22}$$

Minimizing L_i with respect to the parameters θ_1 and θ_2,

$$\frac{\partial L_i}{\partial \theta_1} = \frac{\partial z_i^2}{\partial z_i} \frac{\partial z_i}{\partial \theta_1} \tag{23}$$

$$\frac{\partial L_i}{\partial \theta_2} = \frac{\partial z_i^2}{\partial z_i} \frac{\partial z_i}{\partial \theta_2} \tag{24}$$

For n data points, mean loss is

$$L = \frac{1}{n}\sum_{i=1}^{i=n} L_i = \frac{1}{n}\sum_{i=1}^{i=n}(y_i - \theta_1 x_i - \theta_2)^2$$

In practice

- Choose a small (64 or 128) random subset of training data.
- Compute predicted values, then loss.
- Compute gradients of loss W.R.T. parameters then update parameters.

An **epoch** refers to a single iteration over all training data.

Two different spaces

- Space spanned by x and y. Optimization tries to find the surface (model) in this space that best fits the data.
- Space spanned by θs. We minimize the loss function in this space.

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