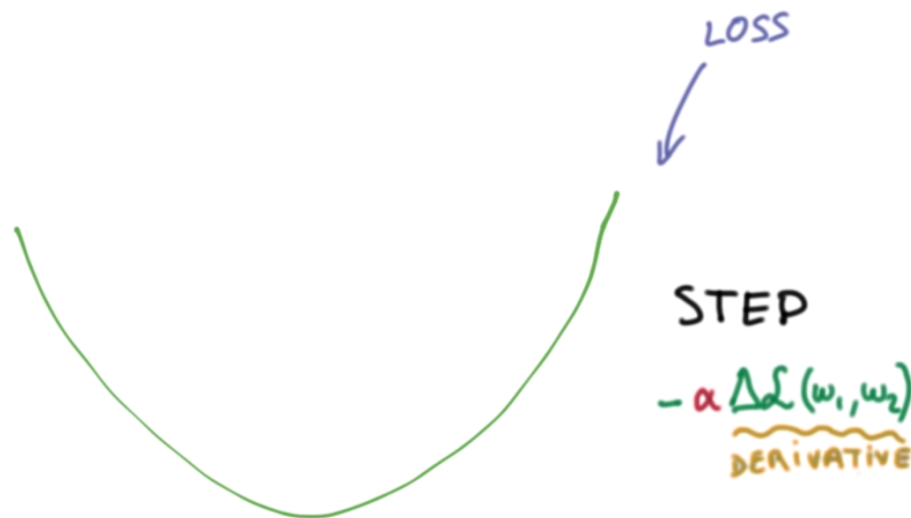


Lecture7

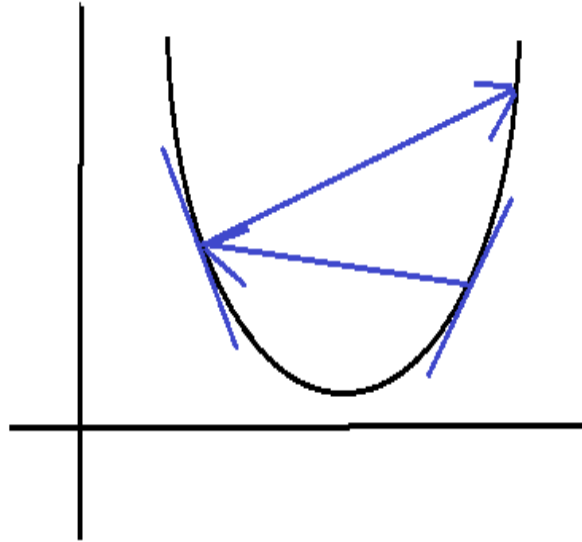
- Learning Rate
- Preprocessing
- Overfitting (Regularization)
- Training/Testing Data Set

Learning Rate

Gradient descent

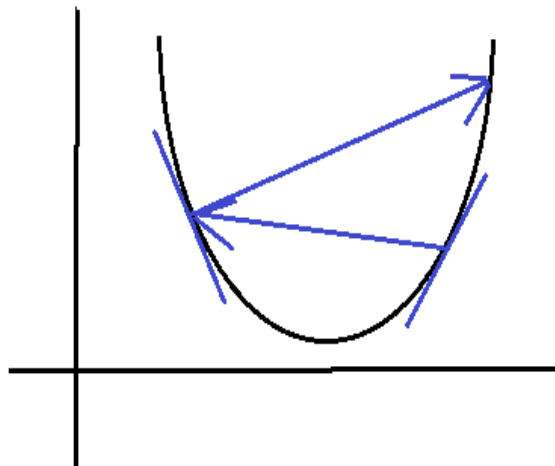


Learning Rate

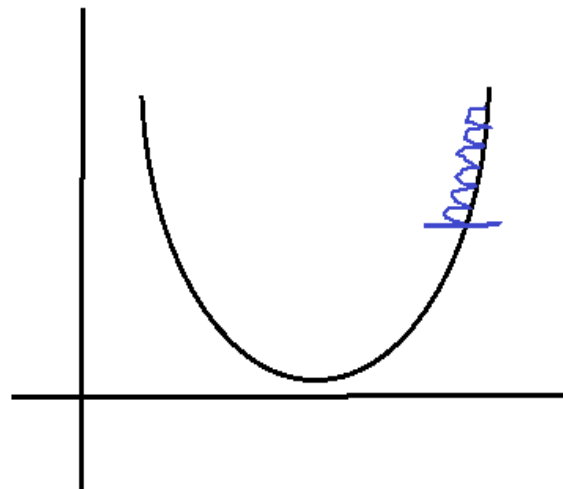


Learning Rate

Lr 너무 클 때

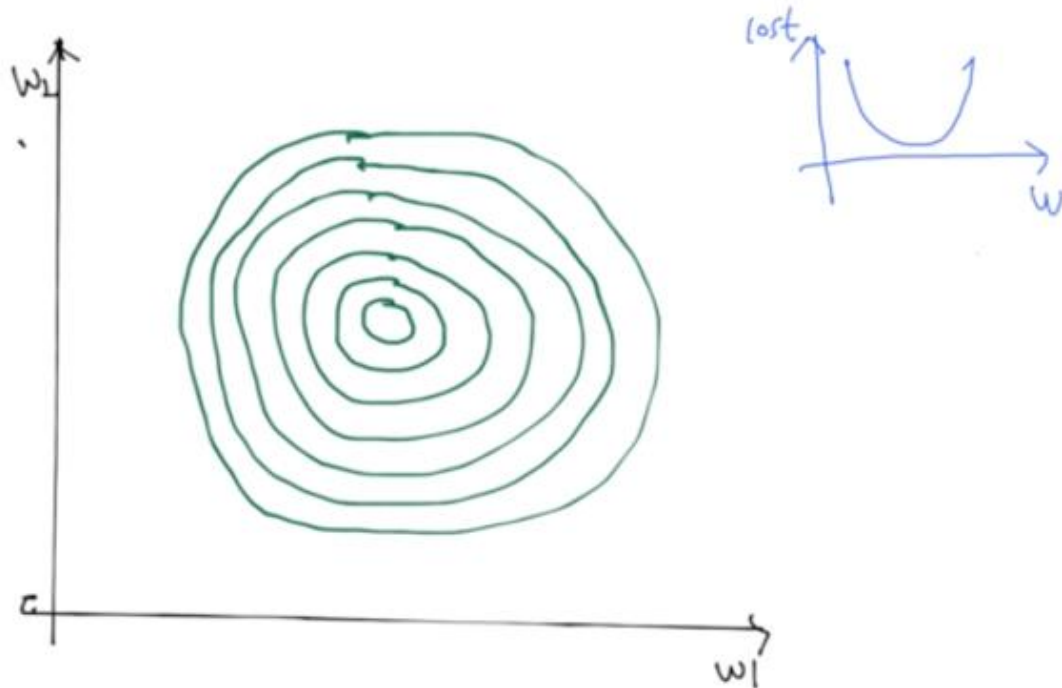


Lr 너무 작을 때



Preprocessing

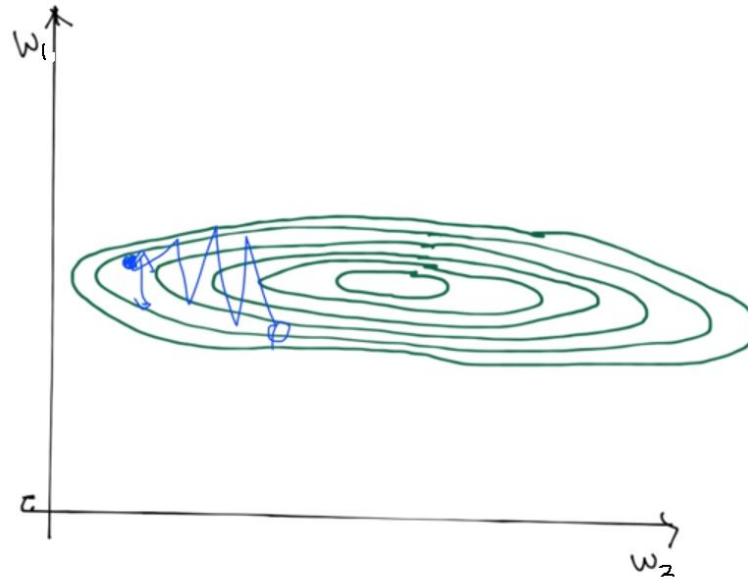
Data (X) preprocessing for gradient descent



Preprocessing

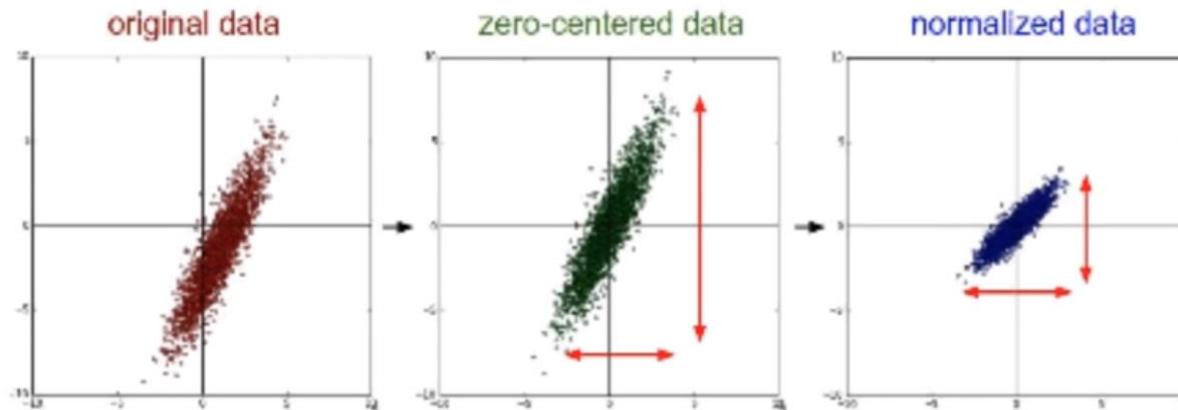
Data (X) preprocessing for gradient descent

x1	x2	y
1	9000	A
2	-5000	A
4	-2000	B
6	8000	B
9	9000	C



Preprocessing

Data (X) preprocessing for gradient descent



Preprocessing

2. 정규화(normalization)

정규화는 데이터의 범위를 0과 1로 변환하여 데이터 분포를 조정하는 방법이다.
(해당 값 - 최소값) / (최대값 - 최소값) 을 해주면 된다.

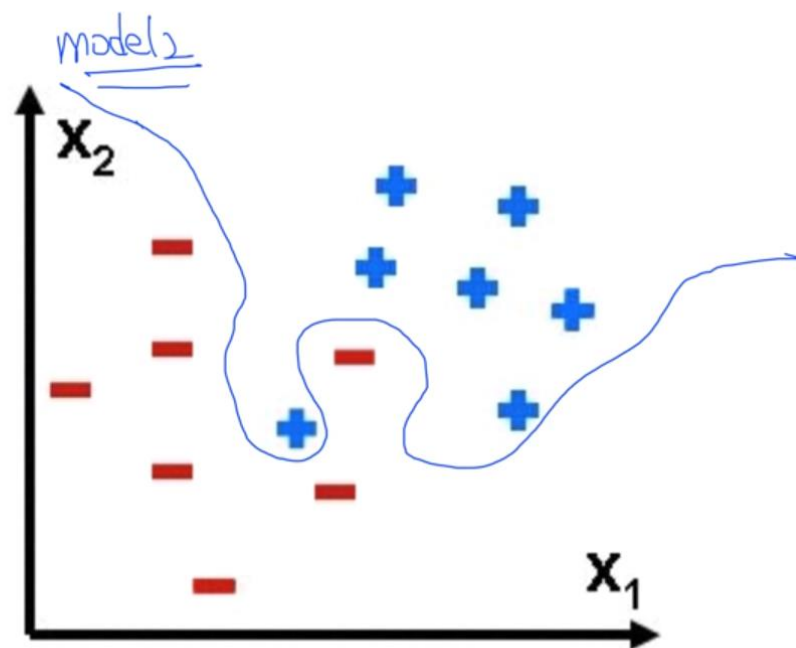
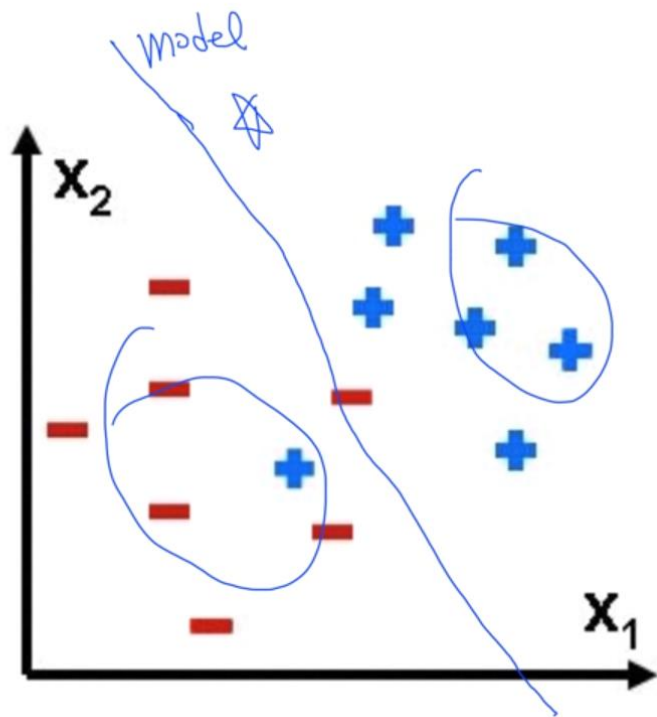
$$x_{new} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

1. 표준화(standardization)

각 observation이 평균을 기준으로 어느 정도 떨어져 있는지를 나타낼때 사용된다. 값의 스케일이 다른 두 개의 변수가 있을 때, 이 변수들의 스케일 차이를 제거해 주는 효과가 있다. 제로 평균 으로 부터 각 값들의 분산을 나타낸다. 각 요소의 값에서 평균을 빼 다음 표준편차로 나누어 준다.

$$x_{new} = \frac{x - \mu}{\sigma}$$

Overfitting



Overfitting

- Solutions

More training data

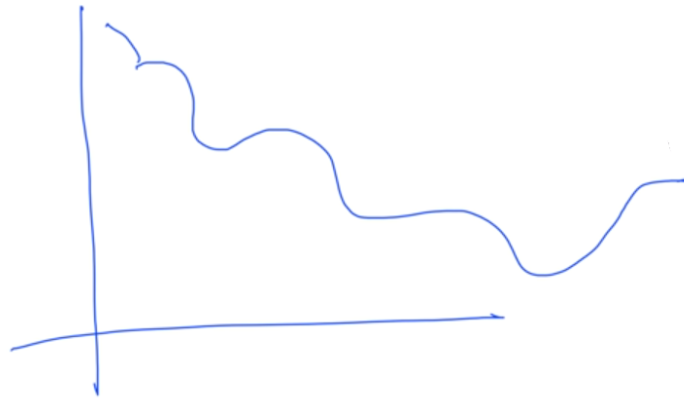
Reduce the number of features

Regularization

Overfitting

Regularization

- Let's not have too big numbers in the weight



Overfitting

- Let's not have too big numbers in the weight

The diagram shows the loss function $\mathcal{L} = \frac{1}{N} \sum_i \mathcal{D}(s(w x_i + b), L_i) + \lambda \sum W^2$ with several handwritten annotations in blue ink. An arrow labeled "LOSS" points to the entire equation. An arrow labeled "TRAINING SET" points to the index i in the summation. An arrow points from "TRAINING SET" to the input x_i in the sigmoid function. Another arrow points from "TRAINING SET" to the target L_i . A third arrow points from the text "regularization strength" to the coefficient λ .

$$\mathcal{L} = \frac{1}{N} \sum_i \mathcal{D}(s(w x_i + b), L_i) + \lambda \sum W^2$$

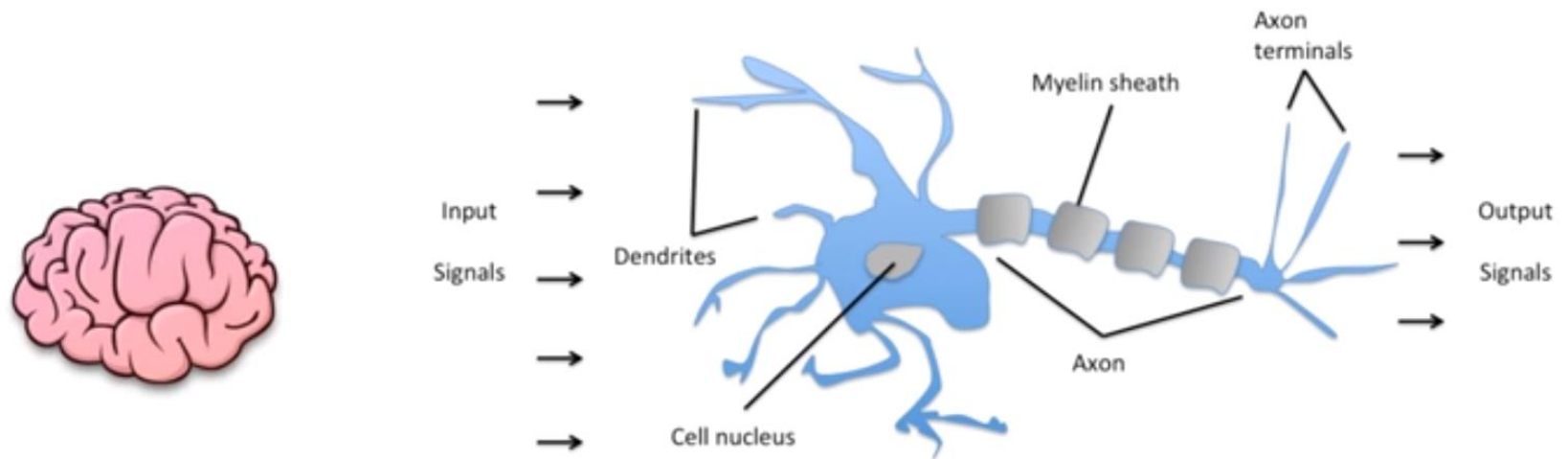
Annotations:

- LOSS (points to the equation)
- TRAINING SET (points to i and x_i)
- regularization strength (points to λ)

Lecture 8

- 딥러닝의 시작과 역사

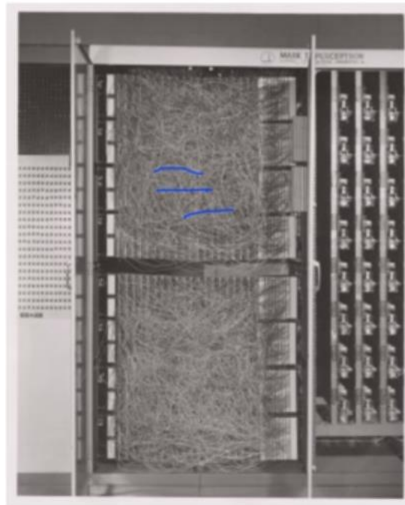
Ultimate dream: thinking machine



Schematic of a biological neuron.

<http://sebastianraschka.com/>

Hardware implementations



Frank Rosenblatt, ~1957: Perceptron

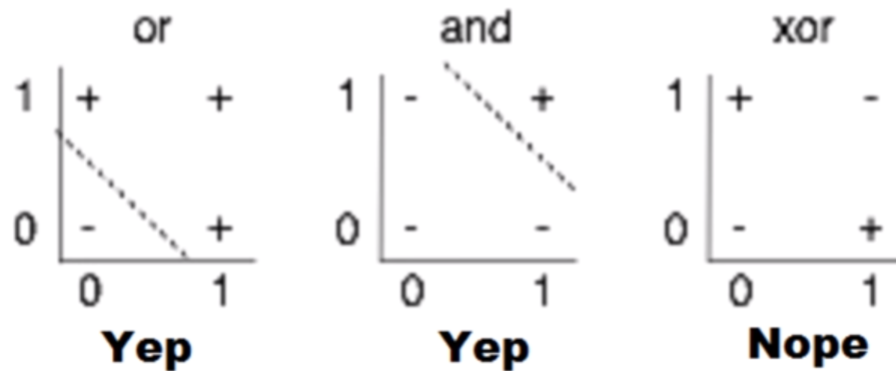


Widrow and Hoff, ~1960: Adaline/Madaline

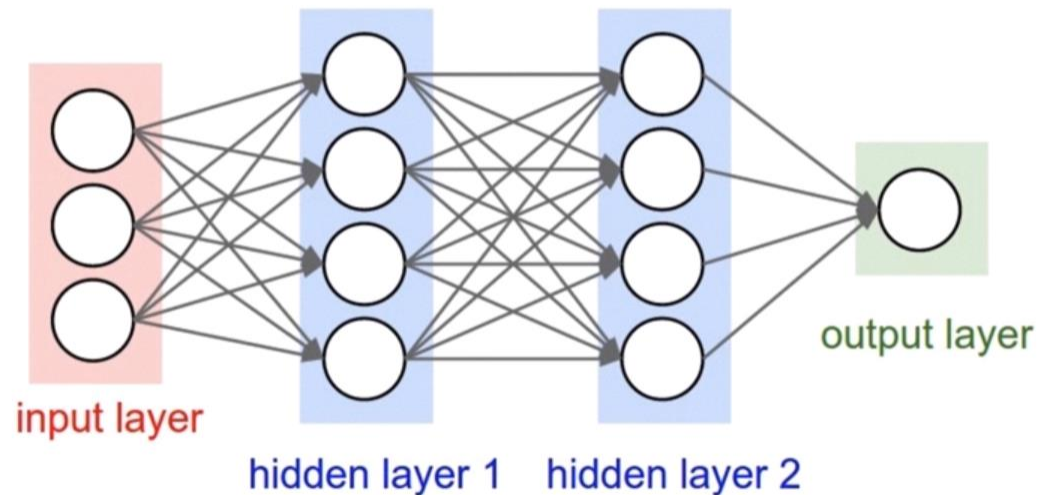
False Promises

“The Navy revealed the embryo of an electronic computer today that it expects will be able to walk, talk, see, write, reproduce itself and be conscious of its existence ... Dr. Frank Rosenblatt, a research psychologist at the Cornell Aeronautical Laboratory, Buffalo, said Perceptrons might be fired to the planets as mechanical space explorers” *The New York Times* July 08, 1958

(Simple) XOR problem: linearly separable?



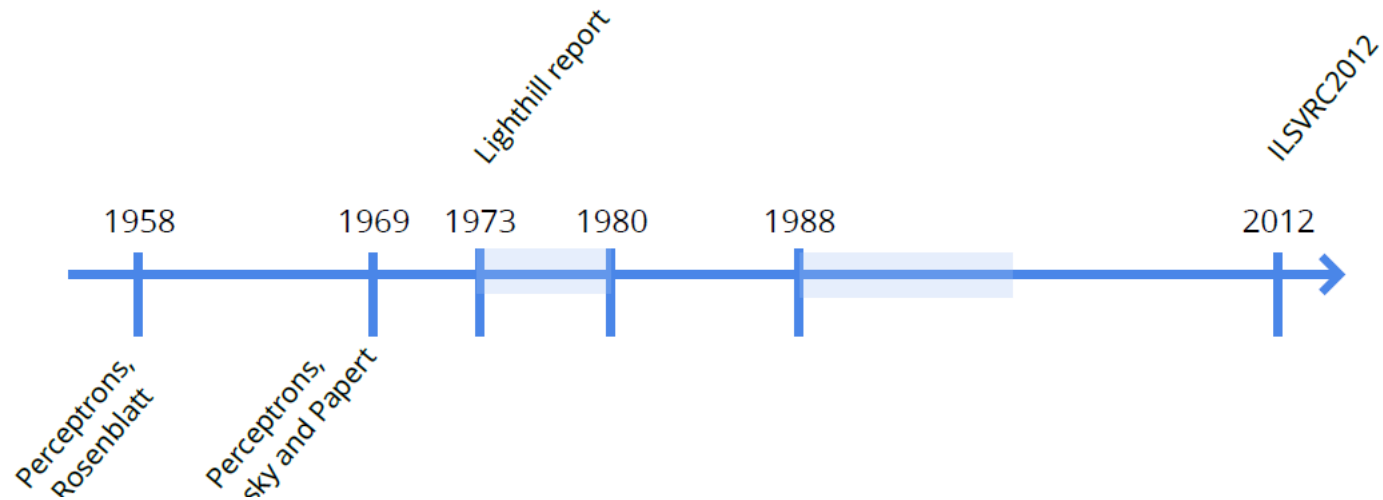
“No one on earth had found a viable way to train*”



***Marvin Minsky, 1969**

<http://cs231n.github.io/convolutional-networks/>

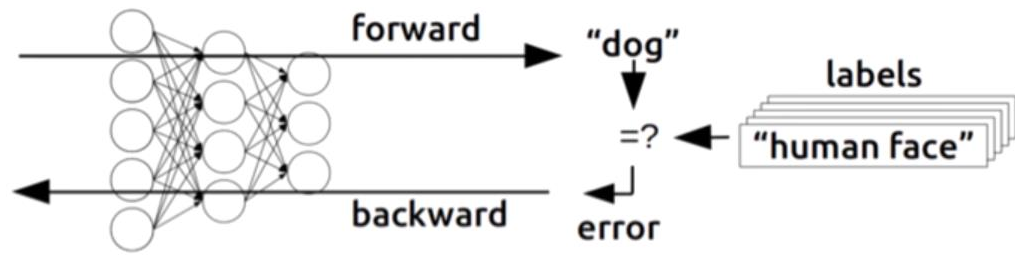
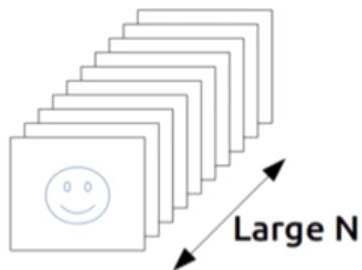
The AI Winter



Backpropagation

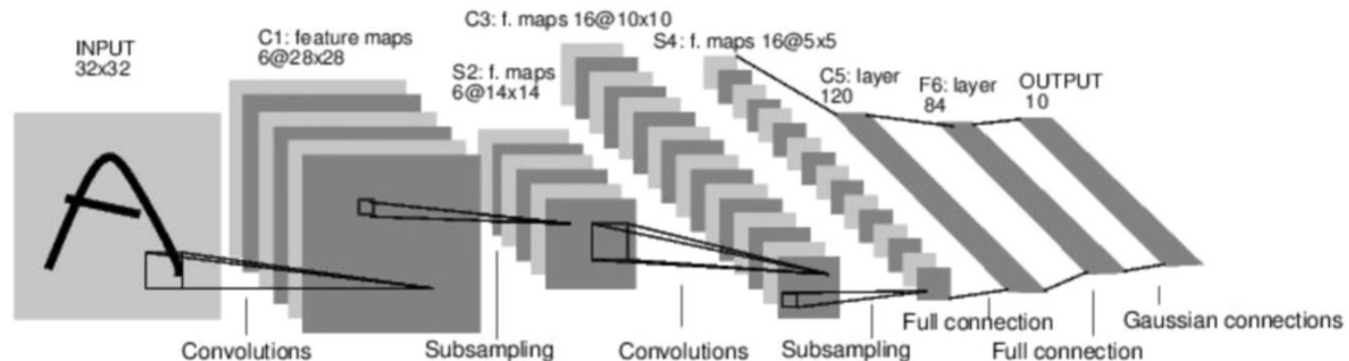
(1974, 1982 by Paul Werbos, 1986 by Hinton)

Training



<https://devblogs.nvidia.com/parallelforall/inference-next-step-gpu-accelerated-deep-learning/>

Convolutional Neural Networks

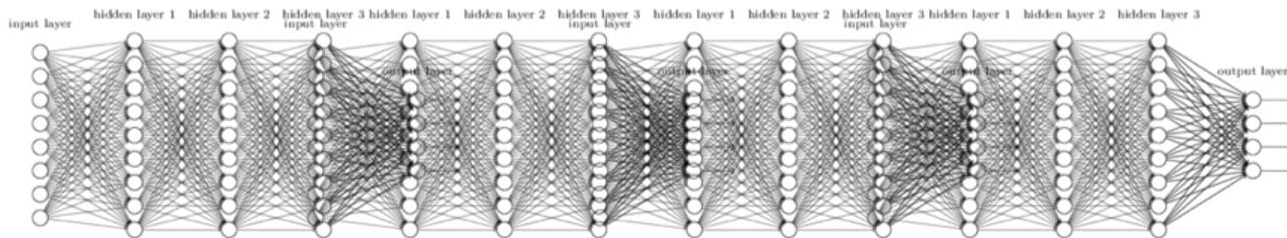


“At some point in the late 1990s, one of these systems was reading 10 to 20% of all the checks in the US.”

[LeNet-5, LeCun 1980]

A BIG problem

- Backpropagation just did not work well for normal neural nets with many layers
- Other rising machine learning algorithms: SVM, RandomForest, etc.
- **1995** “Comparison of Learning Algorithms For Handwritten Digit Recognition” by LeCun et al. found that this new approach worked better



<http://neuralnetworksanddeeplearning.com/chap6.html>

CIFAR

- Canadian Institute for Advanced Research (CIFAR)
- CIFAR encourages basic research without direct application, was what motivated **Hinton** to move to Canada in 1987, and funded his work afterward.



CIFAR

CANADIAN INSTITUTE
for ADVANCED RESEARCH

<http://www.andreykurenkov.com/writing/a-brief-history-of-neural-nets-and-deep-learning-part-4/>

Breakthrough

in 2006 and 2007 by Hinton and Bengio

- Neural networks with many layers really could be trained well, if the weights are initialized in a clever way rather than randomly.
- Deep machine learning methods are more efficient for difficult problems than shallow methods.
- Rebranding to Deep Nets, Deep Learning

<http://www.andreykurenkov.com/writing/a-brief-history-of-neural-nets-and-deep-learning-part-4/>

IMAGENET Large Scale Visual Recognition Challenge

Steel drum

The Image Classification Challenge:
1,000 object classes
1,431,167 images



Output:
Scale
T-shirt
Steel drum
Drumstick
Mud turtle



Output:
Scale
T-shirt
Giant panda
Drumstick
Mud turtle



Russakovsky et al. arXiv, 2014

ImageNet Classification (2010 – 2015)

