A Soft Introduction to Deep Learning

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What this course is about

At the end of these lectures

- You will NOT be able to train a gaming algorithm
- You will NOT be able to design a self-driving car
- You will NOT be able to solve PDEs using AI
- You will NOT be able to predict the stock-market

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- You will get the courage to experiment and explore

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- You will NOT be able to predict the stock-market
- You will see that Deep Learning is uncomplicated
- You will understand the fundamentals of training networks
- You will get the courage to experiment and explore
- You might get ideas to use Deep Learning solve your problems

Where have we seen AI in action

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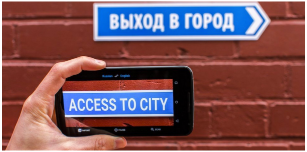

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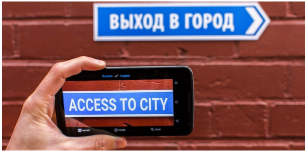

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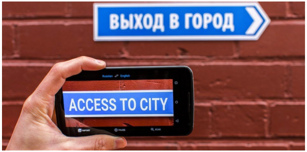

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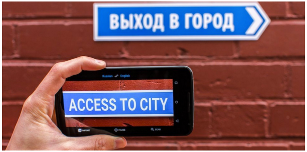

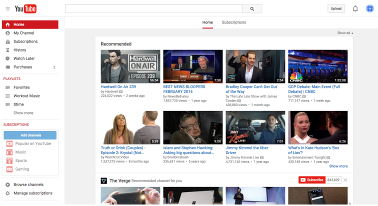

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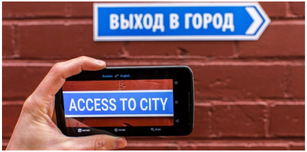

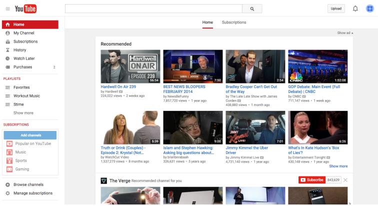

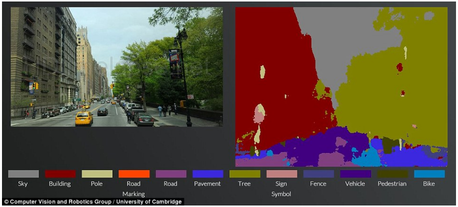

How did we get here?

The Thresholded Logic Unit

1940	1950	1960	1970	1980	1990	2000	2010
McCulloch and Pitts (1943)							

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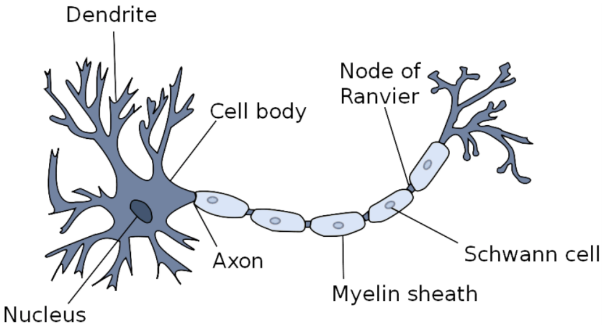

Biological neuron

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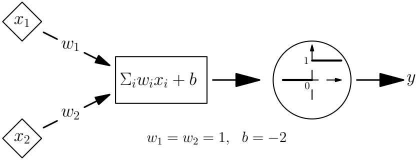

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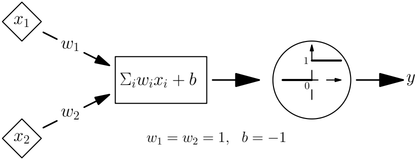

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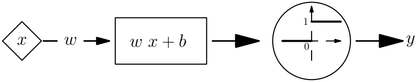

$w = -1, \quad b = 0$

NOT

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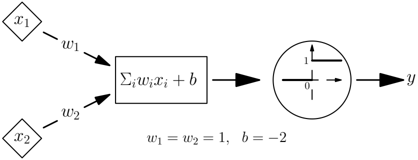
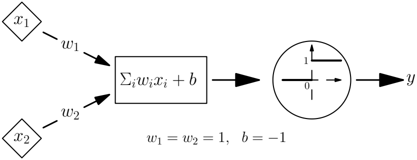


$w_1 = w_2 = 1, \quad b = -2$

AND



$w_1 = w_2 = 1, \quad b = -1$

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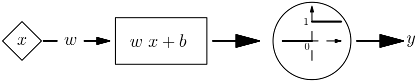


$w = -1, \quad b = 0$

NOT

Weights are adjustable but not learned!

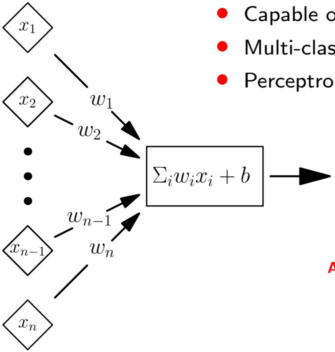
The Perceptron

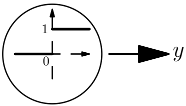
1940 1950 1960 1970 1980 1990 2000 2010

McCulloch and Pitts (1943)

Rosenblatt (1957)

- Weights are learnable
- Capable of classifying data into 2 classes
- Multi-class classification using One-vs-All
- Perceptron convergence theorem





Activation function

1940	1950	1960	1970	1980	1990	2000	2010

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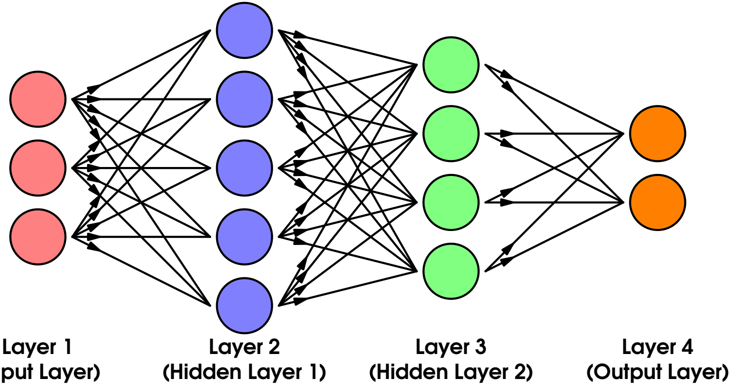
Multilayer perceptron (MLP)



The Perceptron: Criticism

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McCulloch and Pitts (1943)		Rosenblatt (1957)	Minsky and Papert (1969)				

Perceptron: An Introduction to Computational Geometry

- Detailed mathematical analysis of perceptrons
- Limitations of perceptrons – for e.g. XOR problem
- Claimed issues exist for other variants

INPUT		OUTPUT
X_1	X_2	
0	0	0
0	1	1
1	0	1
1	1	0

The Perceptron: Criticism

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"The perceptron has shown itself worthy of study despite (and even because of!) its severe limitations. It has many features to attract attention: its linearity; its intriguing learning theorem; its clear paradigmatic simplicity as a kind of parallel computation. There is no reason to suppose that any of these virtues carry over to the many-layered version. Nevertheless, we consider it to be an important research problem to elucidate (or reject) our intuitive judgement that the <u>extension to multilayer systems is sterile</u>."

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Revival with Backpropagation

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Backprop and theory (1986)

- *Learning representations by back-propagating errors* by Rumelhart, Hinton and Williams (1986)
- Other advancements by Bengio, Lecun and others ...
- Efficient evaluation of gradients
- Universal Function Approximation theorem for MLPs by Cybenko (1989)
- Theoretical investigation by Barron, Pinkus, Mhaskar ...

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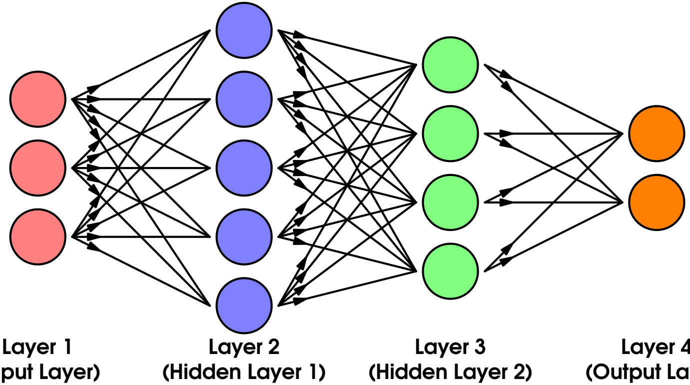

What is backpropogation?

Second freeze and resurgence

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2nd A.I. Winter (1993-2008)

Issues with back-propagation

- Not enough labelled data
- Learning time scales badly (exponentially) with multiple layers
- Deep networks can have several local minima

Second freeze and resurgence

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Resurgence (2006)

Issues with back-propagation

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Resurgence

- Hinton's idea of unsupervised pre-training and Deep Belief Nets – helps with semi-supervised training
- Availability of large data sets
- GPUs and other computational advancements
- Better training algorithms

Components of MLPs

- Depth Vs width
- Data sets
- Activation functions
- Loss/cost functions
- Initialization
- Stochasticity and mini-batches
- Overfitting and underfitting
- Optimizers and learning-rate
- Hyper-parameter tuning

Depth Vs Width

- Several partial results exist about the width and depth
- Need $O(N_{inp} + N_{out} + M)$ parameters to represent a dataset of size M
- There is a gap between theory and training
- Going "deeper and narrow" gives better results than staying "shallow but wider"
- Need to find optimal structure based on application

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Training, validation and testing

Three types of data sets:

- **Training data:** Used to optimize the weights and biases.

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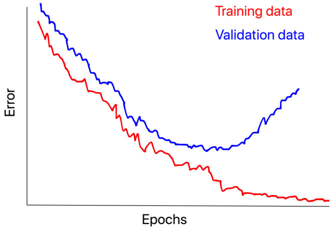

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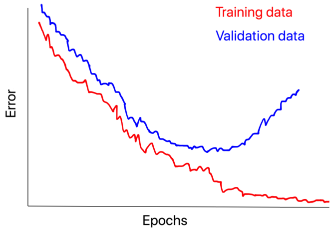

- **Test data:** Used to test final trained model – DO NOT TOUCH DURING TRAINING PHASE!

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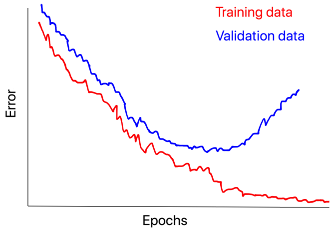

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Scaling and pre-processing the input data – important for generalization.

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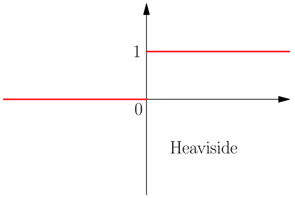
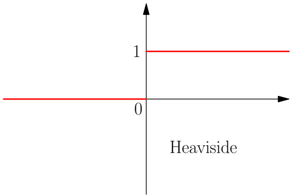
Activation functions

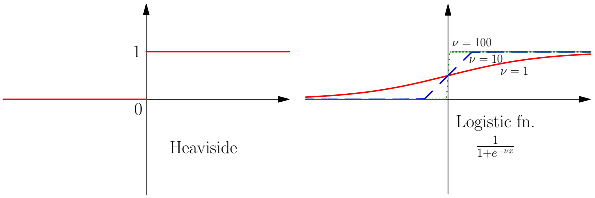


Activation functions



- McCullock-Pitts neuron
- Zero gradient – bad for backpropagation
- Not used anymore

Activation functions



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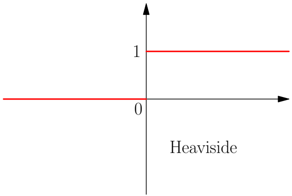

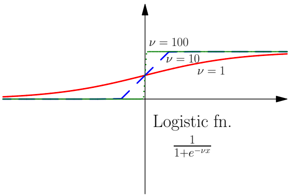

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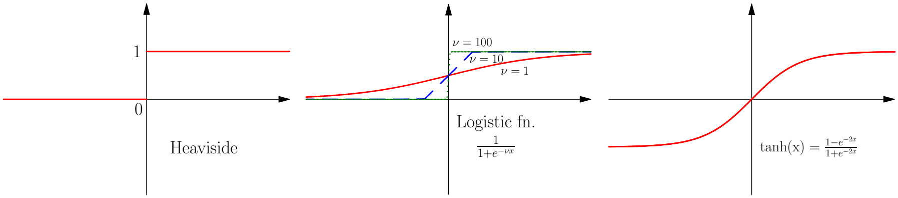
- Sigmoidal function – used in most proofs
- Good for binary classification
- Not symmetric

Activation functions



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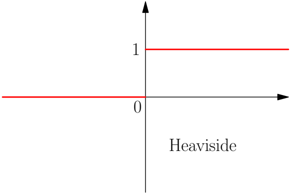

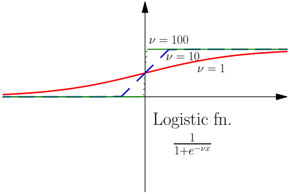

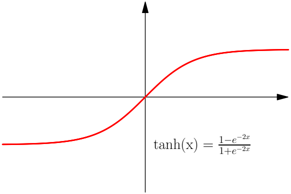

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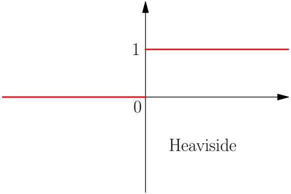
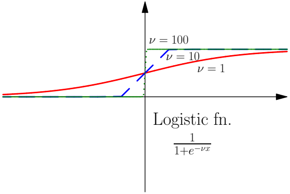
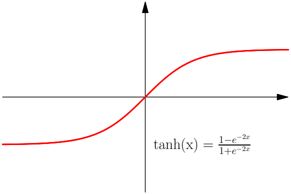
- Symmetric unlike Logisitic func.
- Smooth
- Vanishing gradients away from 0.



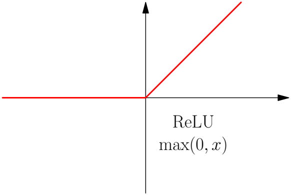
1
0
Heaviside



$\nu = 100$
$\nu = 10$
$\nu = 1$
Logistic fn.
$\frac{1}{1+e^{-\nu x}}$

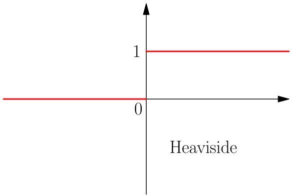


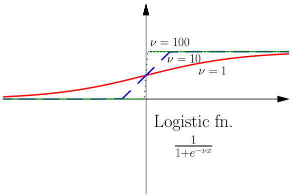
$\tanh(\mathrm{x}) = \frac{1-e^{-2x}}{1+e^{-2x}}$

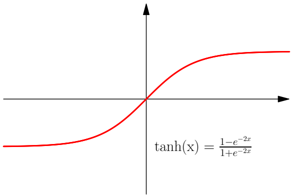


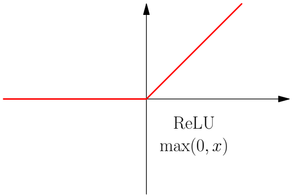
ReLU
$\max(0, x)$

Activation functions

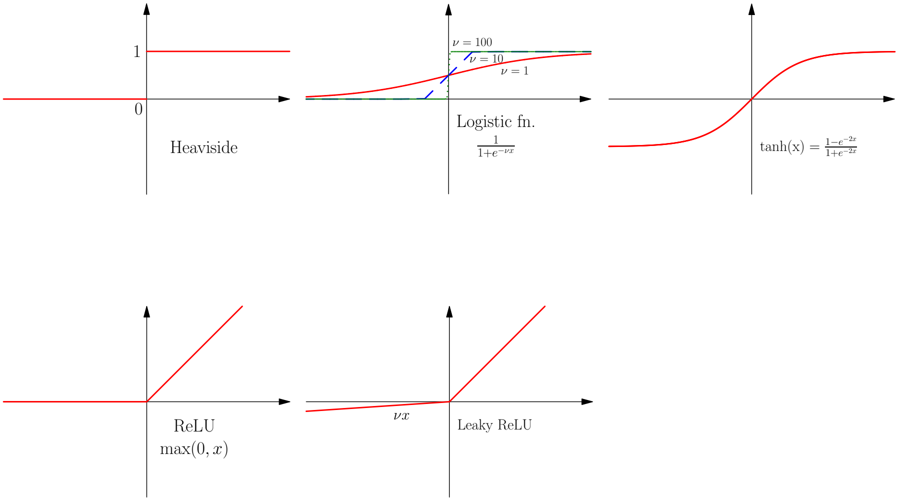




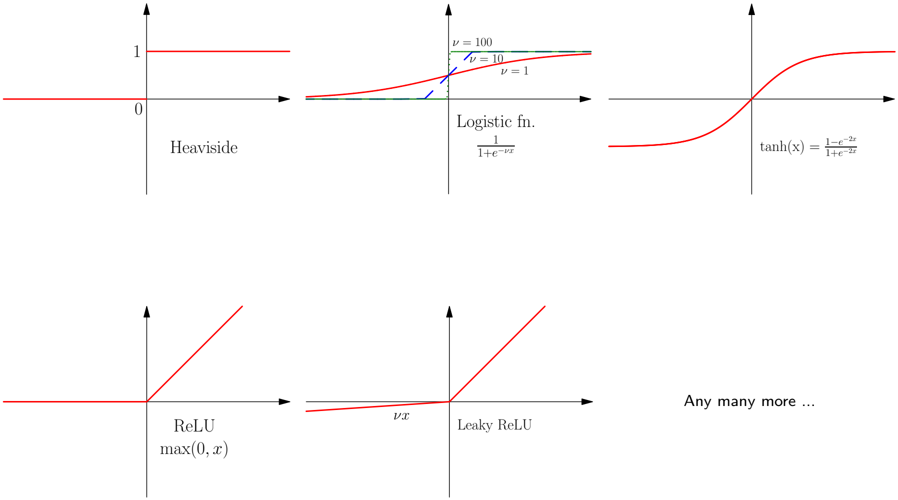




- Easy to compute
- Reduces vanishing gradient problem
- Scale invariant
- Issue of dying neurons


1
0
Heaviside
$\nu = 100$
$\nu = 10$
$\nu = 1$
Logistic fn.
$\frac{1}{1+e^{-\nu x}}$
$\tanh(x) = \frac{1-e^{-2x}}{1+e^{-2x}}$
ReLU
$\max(0, x)$
νx
Leaky ReLU

Activation functions



Any many more ...

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Loss/cost function

Regression problem

- Mean squared error
- Mean L1 error
- Mean absolute error
- ...

Loss/cost function

Regression problem

- Mean squared error
- Mean L1 error
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- ...

Classification problem

- Use softmax output function

$$\hat{Y}^{(k)} = \frac{e^{\hat{Y}^{(k)}}}{\sum_j e^{\hat{Y}^{(j)}}} \quad \in \quad [0,1] \quad \longrightarrow \quad \text{probabilities/classification}$$

- Cross-entropy loss function

$$C = -\sum_{i=1}^{\mathsf{M}} \sum_j Y_i^{(j)} \log\left(\hat{Y}_i^{(j)}\right)$$

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- Do not initialize w to be zero – leads to linear model
- Initialize randomly using normal distribution etc
- Exploding gradients – avoided using heuristic scaling depending on activation function – minimize variance of the weights
  - For ReLU

$$w^l = \text{nrand}(N_l \ , \ N_{l-1}).\sqrt{\frac{2}{N_{l-1}}}$$

  - For tanh (Xavier initialization)

$$w^l = \text{nrand}(N_l \ , \ N_{l-1}).\sqrt{\frac{1}{N_{l-1}}}$$

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Stochasticity and mini-batches

Training $\longrightarrow$ M samples

Randomly shuffle data $\longrightarrow$ introduces stochasticity – speeds-up convergence

Choose m samples at a time to take one optimization step

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Randomly shuffle data $\longrightarrow$ introduces stochasticity – speeds-up convergence

Choose m samples at a time to take one optimization step

$m = M \longrightarrow$ Batch optimization
$m = 1 \;\longrightarrow$ Stochastic optimization

Stochasticity and mini-batches

Training $\longrightarrow$ M samples

Randomly shuffle data $\longrightarrow$ introduces stochasticity – speeds-up convergence

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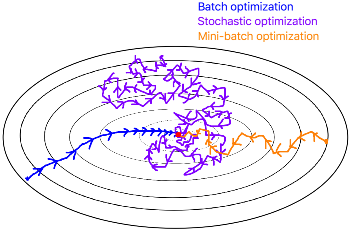

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We complete **1 epoch** when we have finished striding over the whole dataset – approx. M/m optimizations steps.

- Depth Vs width
- Data sets
- Activation functions
- Loss/cost functions
- Initialization
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- Overfitting and underfitting
- Optimizers and learning-rate
- Hyper-parameter tuning

Overfitting and underfitting

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Regularization

Improves generalization error

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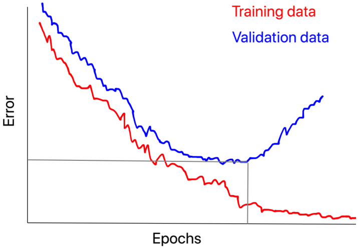
- Early stopping of training after M succesive increases in validation error



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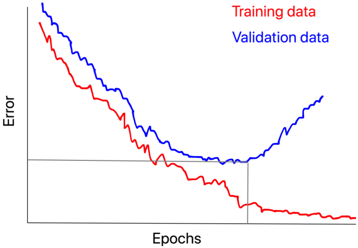

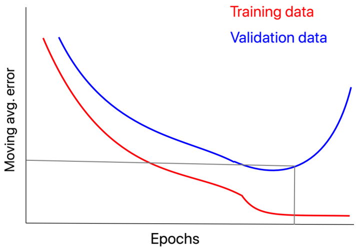

$$\overline{E_n} = \frac{1}{n}\sum_{i=1}^{n} E_i$$

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b not regularized as

- b easier to fit
- W model variable interactions
- regularizing b can cause severe underfitting

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- Dropout – randomly kill hidden neuron outputs while training (only)

Components of MLPs

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Optimizers and learning-rate

Several optimizers are available (a nice summary available here)

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Estimate the first and second moments of gradient g_t

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Learning-rate η needs to be chosen. Can be adapted if needed

$$\eta_t = \frac{\eta_0}{1+\gamma t}, \quad \text{or} \quad \eta_t = 0.9^t \eta_0, \quad \text{or} \quad \ldots$$

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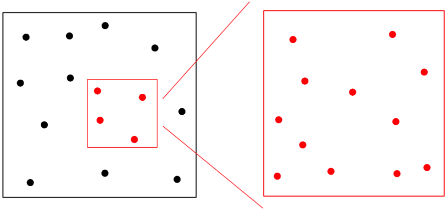
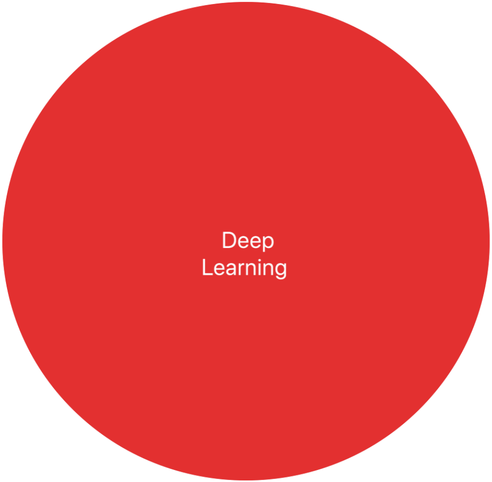
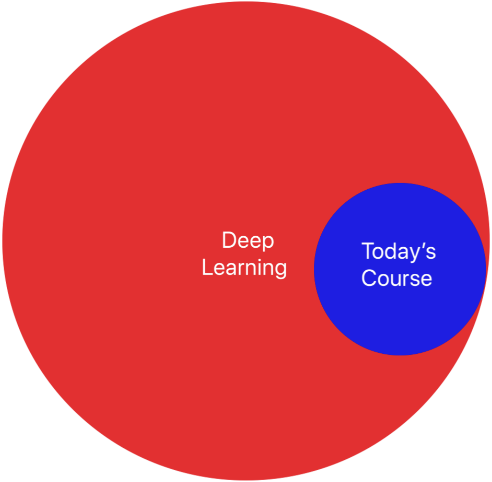
Several strategies proposed. For instance random coarse to fine search




Deep
Learning


Deep
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Today's
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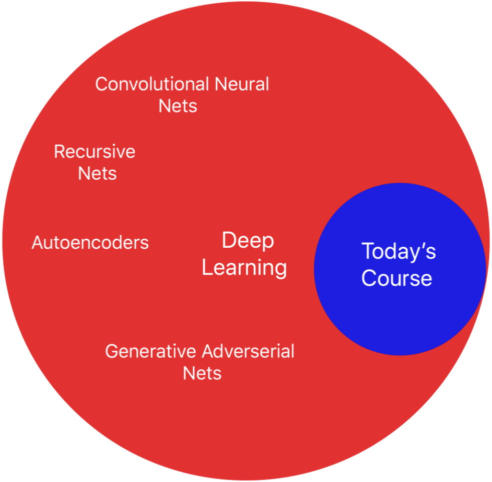
Convolutional Neural Nets
Recursive Nets
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Generative Adverserial Nets