ANCHORMEN
data activators

DEEP LEARNING

Raoul Grouls

14-DEC-20

INTRODUCTION DEEP LEARNING

- ***Deep*** refers to the many-layered computations
- At first **impossible** to feasibly train
- Around 2012, the ML community realized that with current resources this is no longer true
  - Computation power/GPU
  - Large datasets
  - Simple yet powerful cleverness

COMPUTER VISION

- Object and activity recognition

Large-scale Video Classification with Convolutional Neural Networks, CVPR 2014

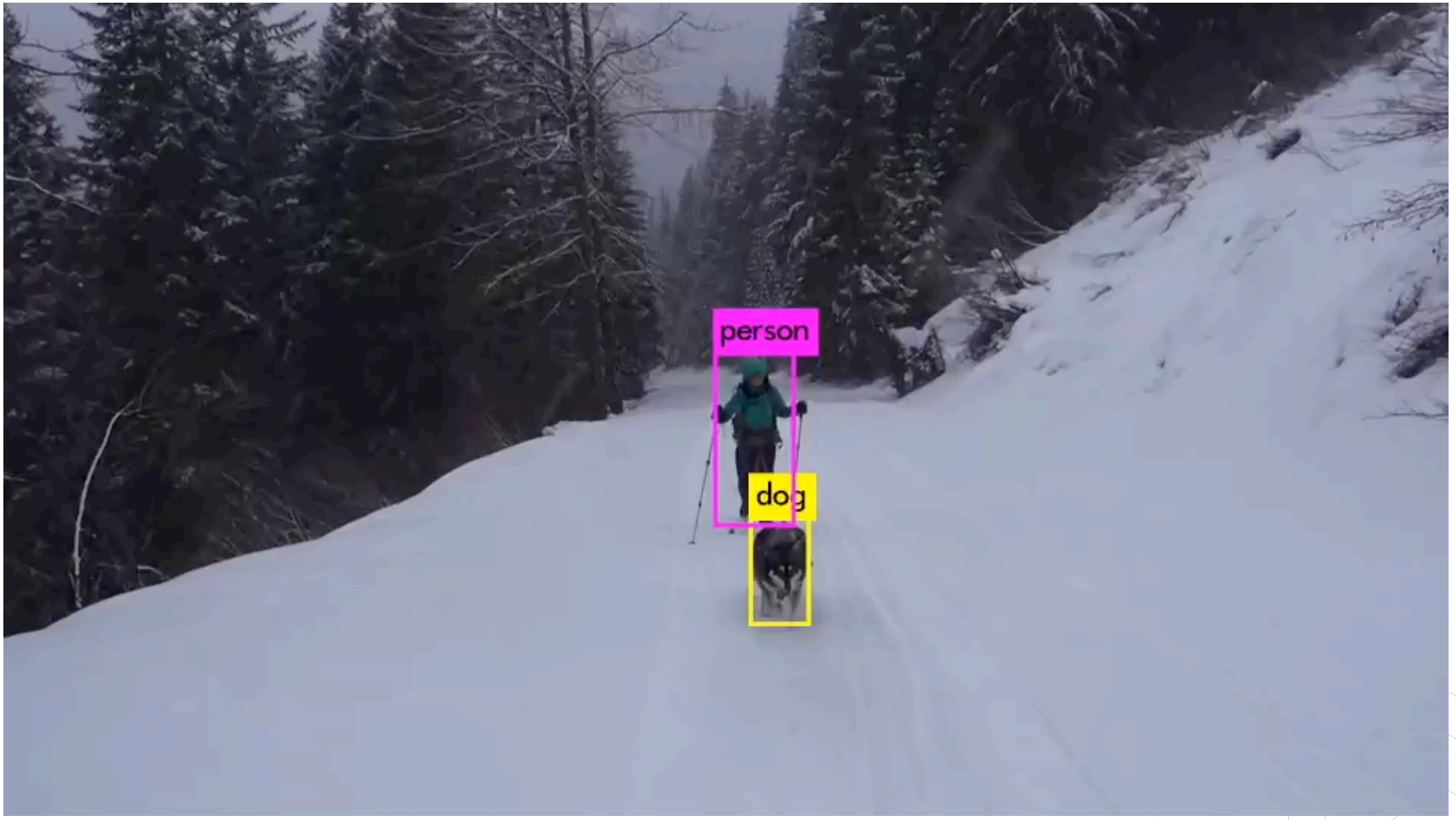
- Object segmentation

Microsoft Deep Learning Semantic Image Segmentation

- Image captioning

NeuralTalk and Walk, recognition, text description of the image while walking

YOLO ALGORITHM



ROBOTICS

- Self driving cars

- Drones & robots

Stanford Autonomous Helicopter - Airshow #1

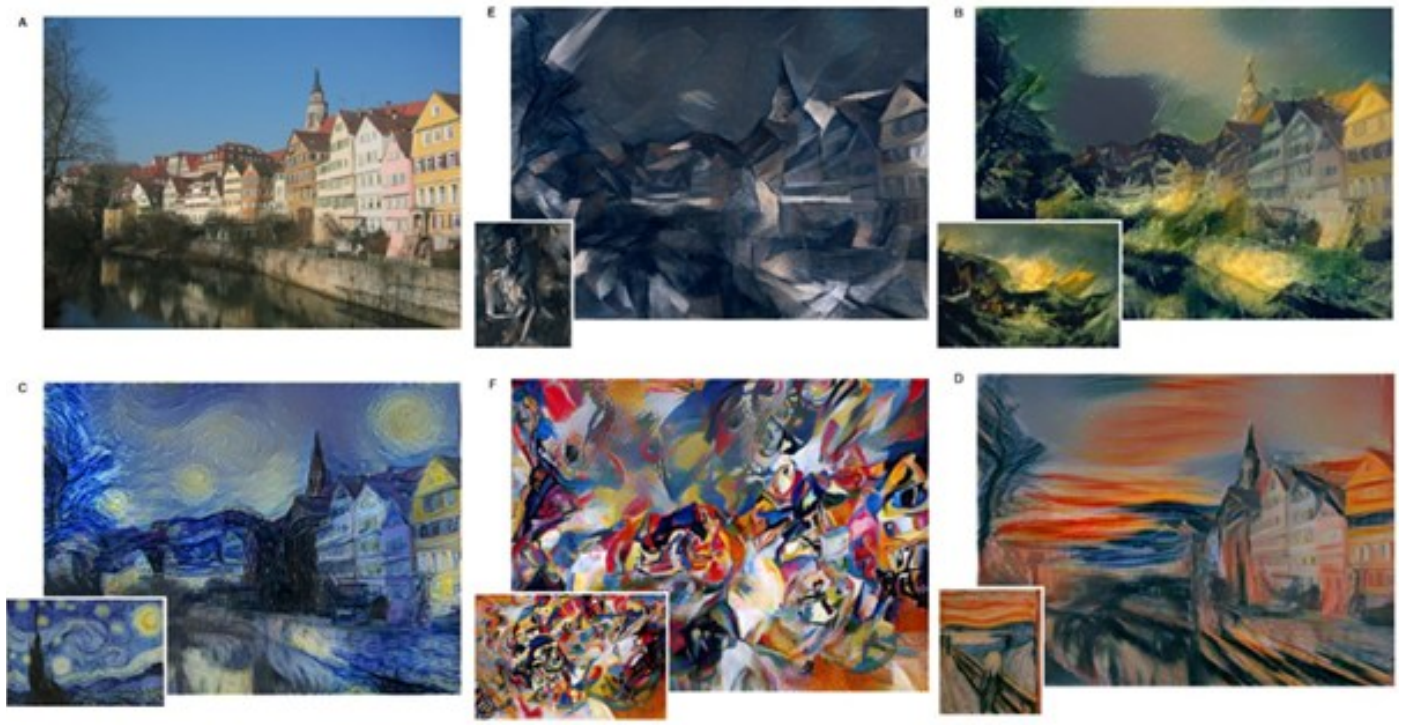
- Games (go, Atari, poker….)

NLP AND SEQUENCE PROCESSING

- Speech recognition
- Generating voices
- Machine translation or question answering

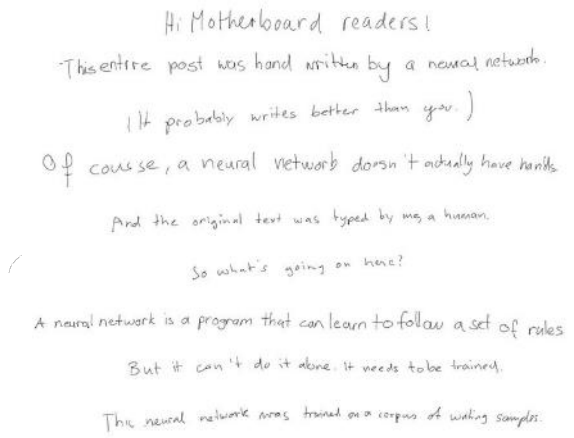
OTHER COOL PROJECTS

- Imitating famous painters



- Create music

- Create handwriting



THE ILSVC CHALLENGE

CNN based non-CNN based

2012 Teams	%error
Supervision (Toronto)	15.3
ISI (Tokyo)	26.1
VGG (Oxford)	26.9
XRCE/INRIA	27.0
UvA (Amsterdam)	29.6
INRIA/LEAR	33.4

2013 Teams	%error
Clarifai (NYU spinoff)	11.7
NUS (singapore)	12.9
Zeiler-Fergus (NYU)	13.5
A. Howard	13.5
OverFeat (NYU)	14.1
UvA (Amsterdam)	14.2
Adobe	15.2
VGG (Oxford)	15.2
VGG (Oxford)	23.0

2014 Teams	%error
GoogLeNet	6.6
VGG (Oxford)	7.3
MSRA	8.0
A. Howard	8.1
DeeperVision	9.5
NUS-BST	9.7
TTIC-ECP	10.2
XYZ	11.2
UvA	12.1

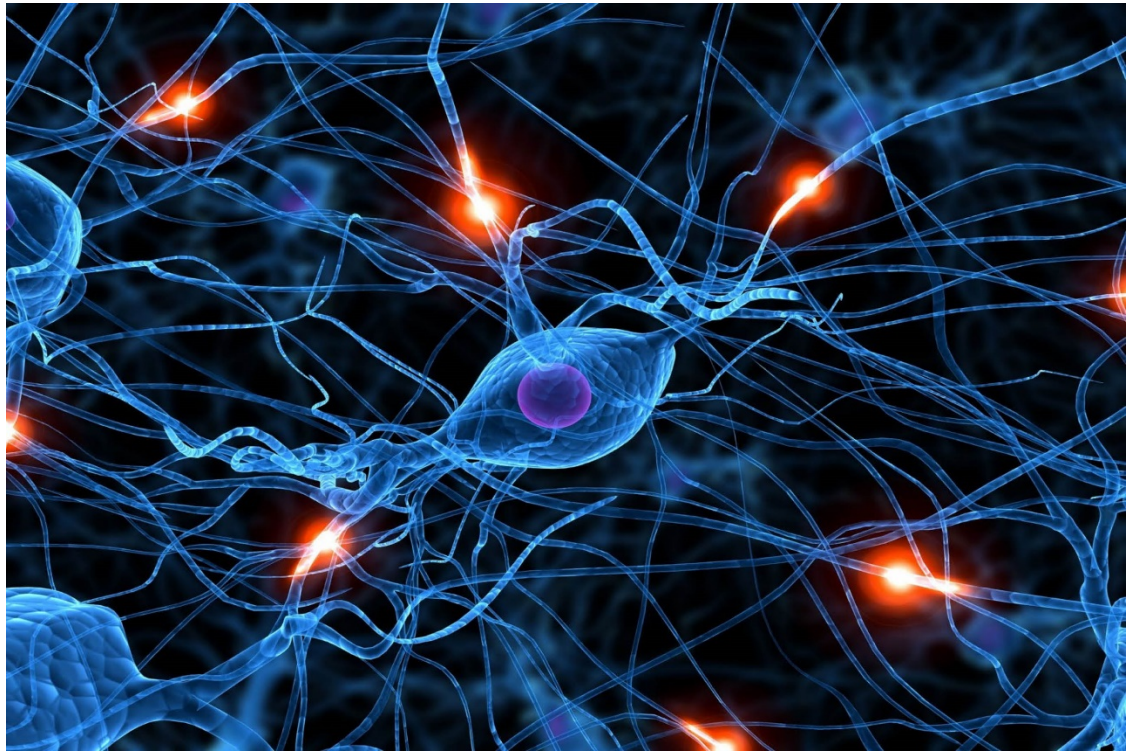
Figure taken from Y. LeCun's CVPR 2015 plenary talk

SO, WHY NOW?

1. Better hardware
2. Bigger data
3. Better regularization methods, such as dropout
4. Better optimization protocols, such as batch normalization

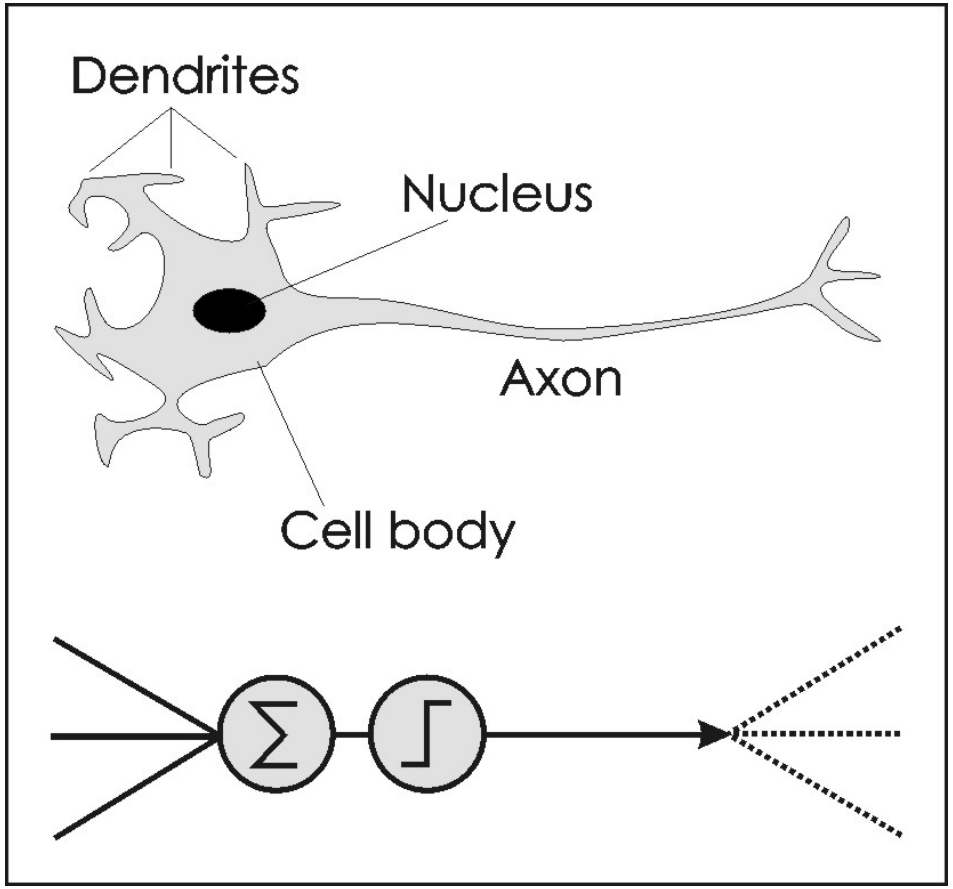
The brain

- The brain has neurons
- Connected by synapses
- 10^{11} neurons per brain
- 10^{4} connections per neuron

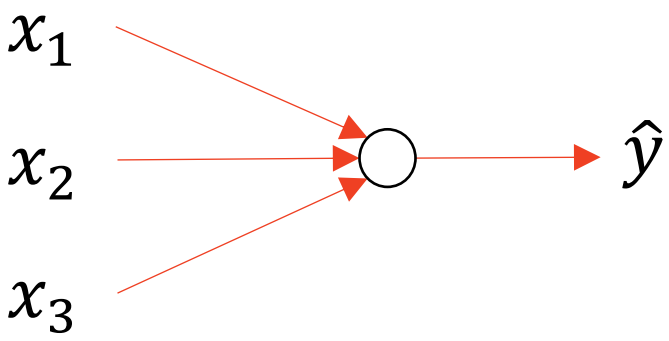


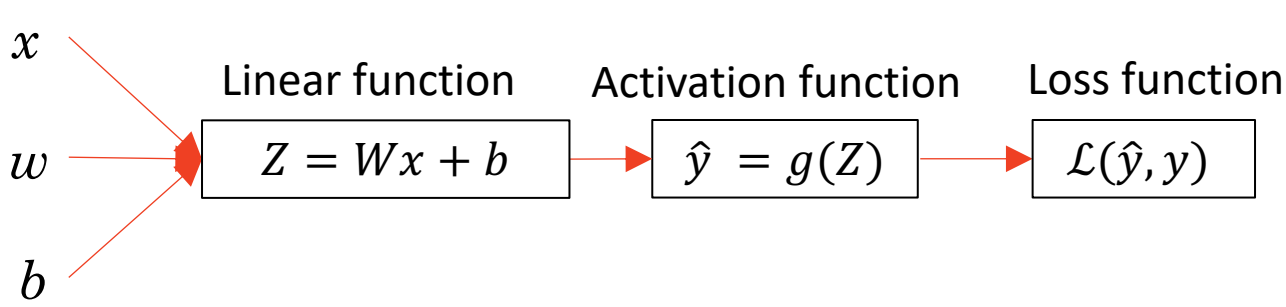
The brain

- Neuron can have many input and many output connections
- Electrical signal is fired which is a complex time series of spikes.
- Mathematical simplification
  - Only focus on neuron signaling
  - One output value instead of series of spikes



NEURAL NETWORK





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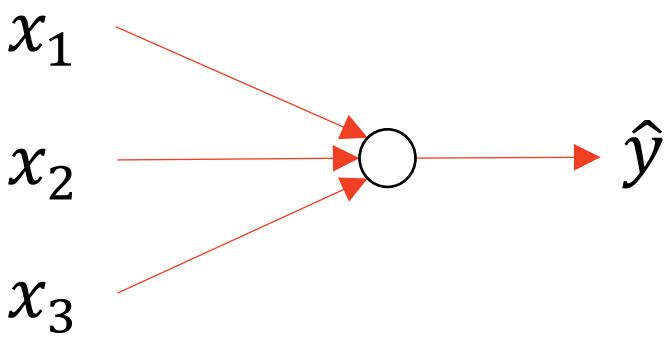

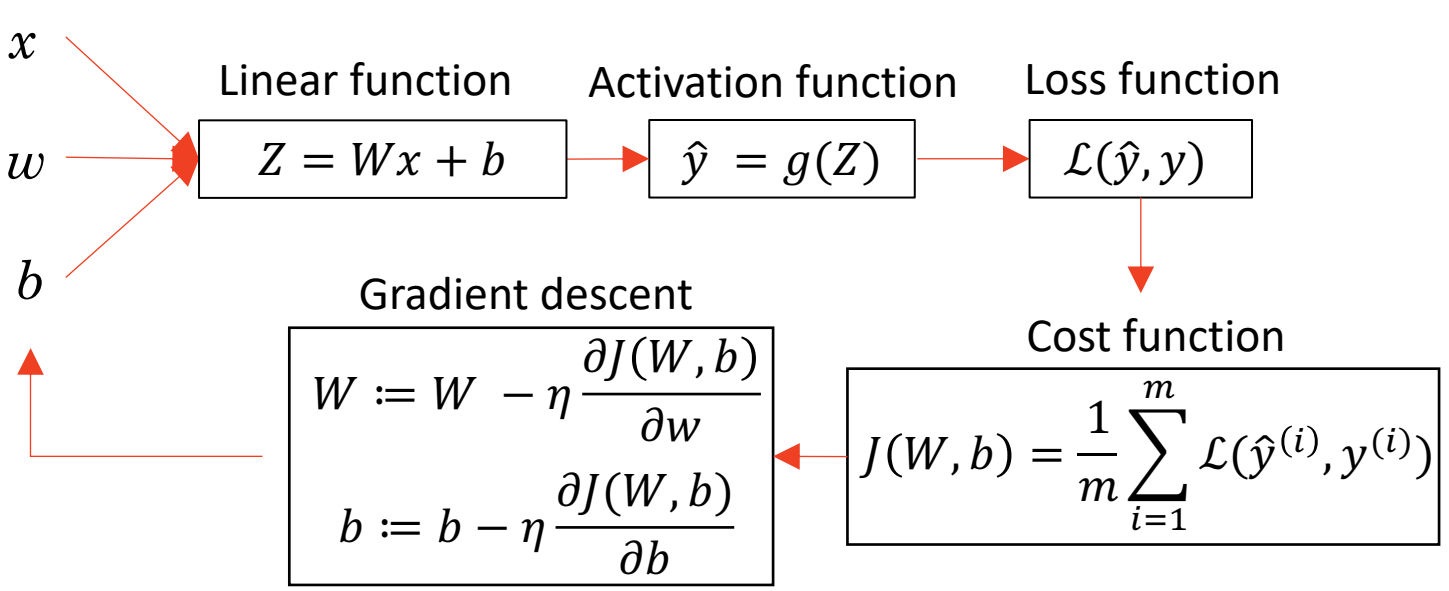

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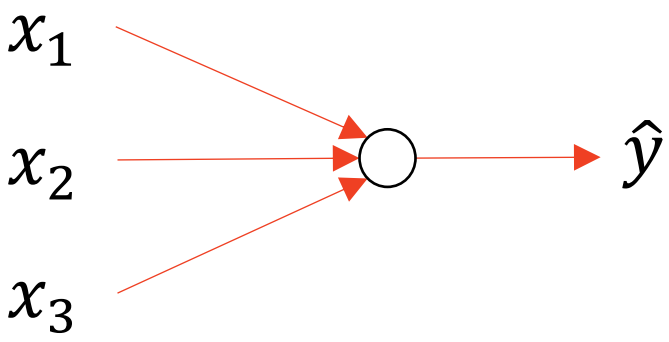
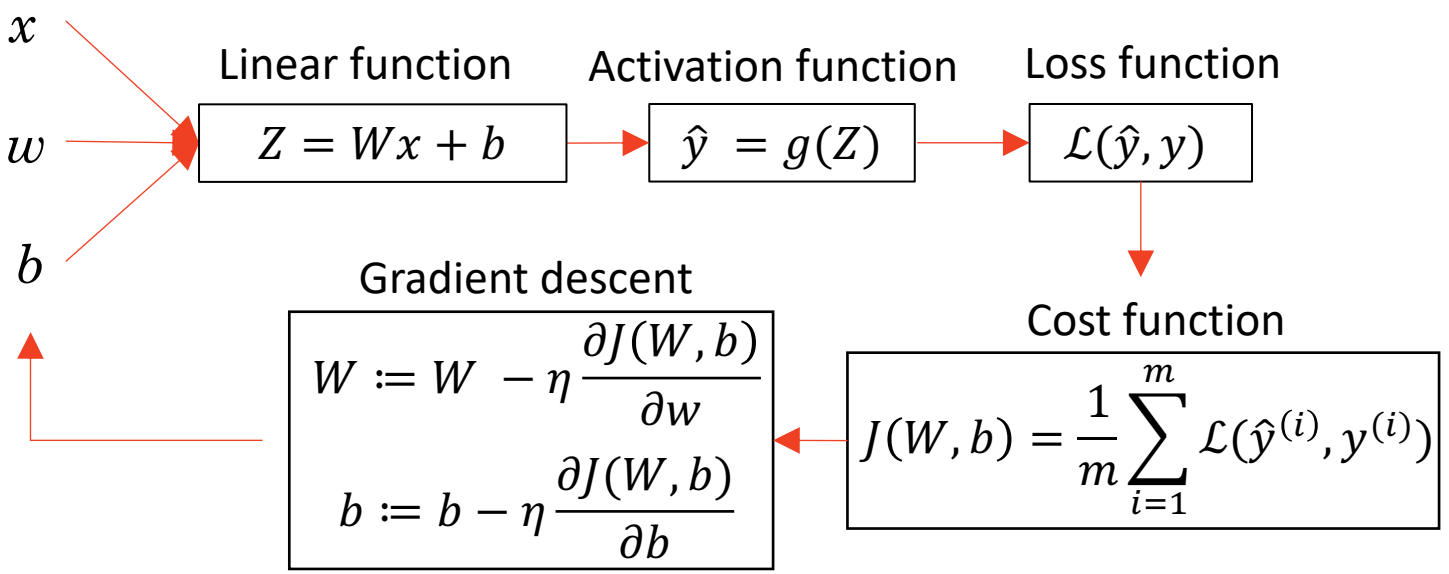




Activation functions:

Sigmoid:

$$g(z) = \frac{1}{1+e^{-z}}$$

ReLU:

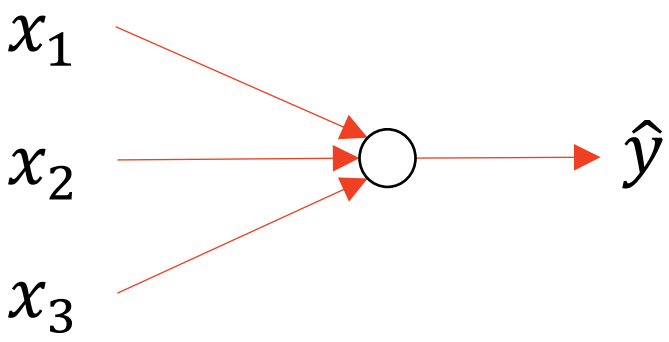
$$g(z) = \max(0, z)$$

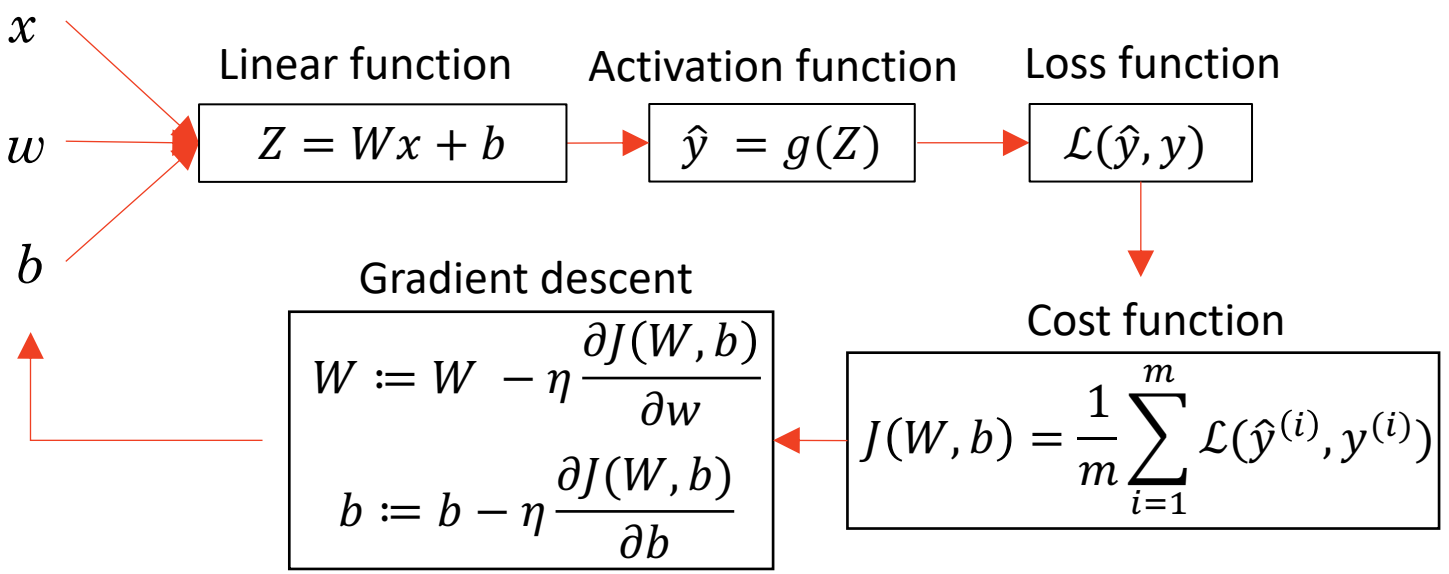
tanh:

$$g(z) = \frac{e^{z}-e^{-z}}{e^{z}+e^{-z}}$$

etc.

NEURAL NETWORK





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etc.

Loss functions:

Cross entropy loss:

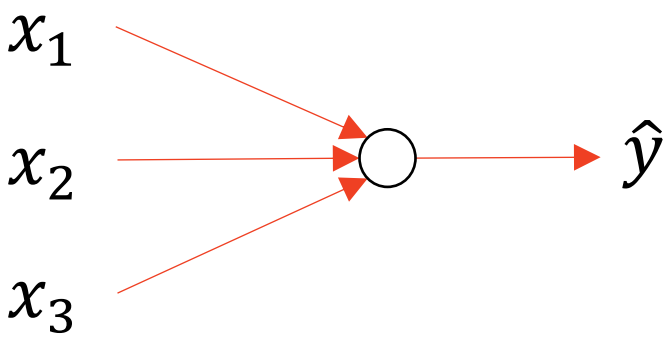
$$\mathcal{L}(\hat{y}, y) = -(y log(\hat{y}) + (1-y) log(1-\hat{y}))$$

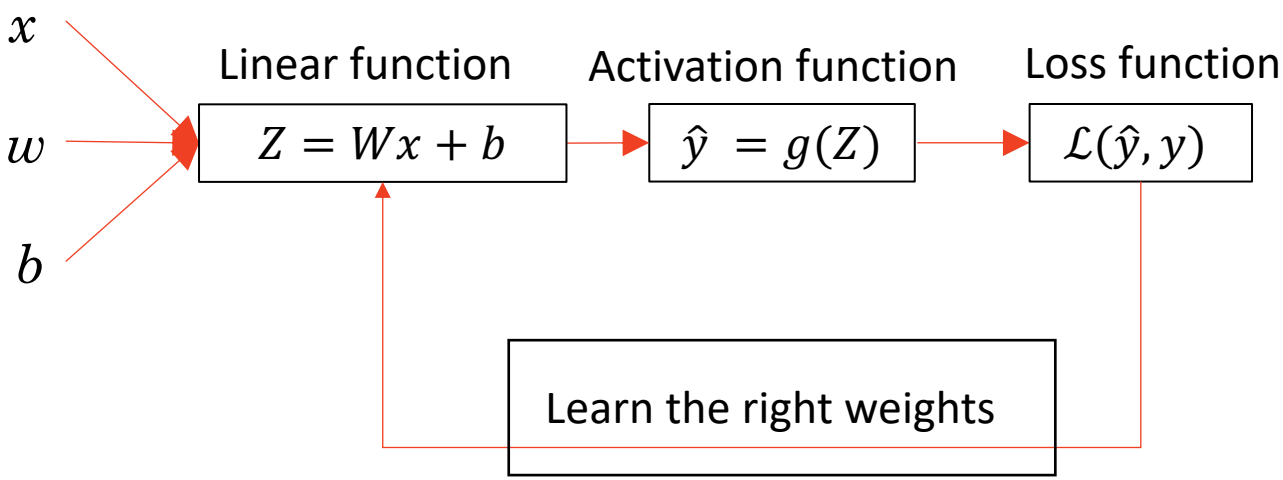
Squared loss:

$$\mathcal{L}(\hat{y}, y) = (\hat{y} - y)^2$$

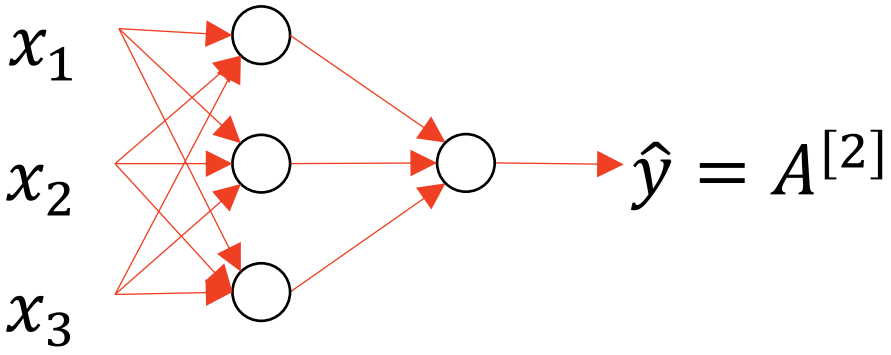
etc.

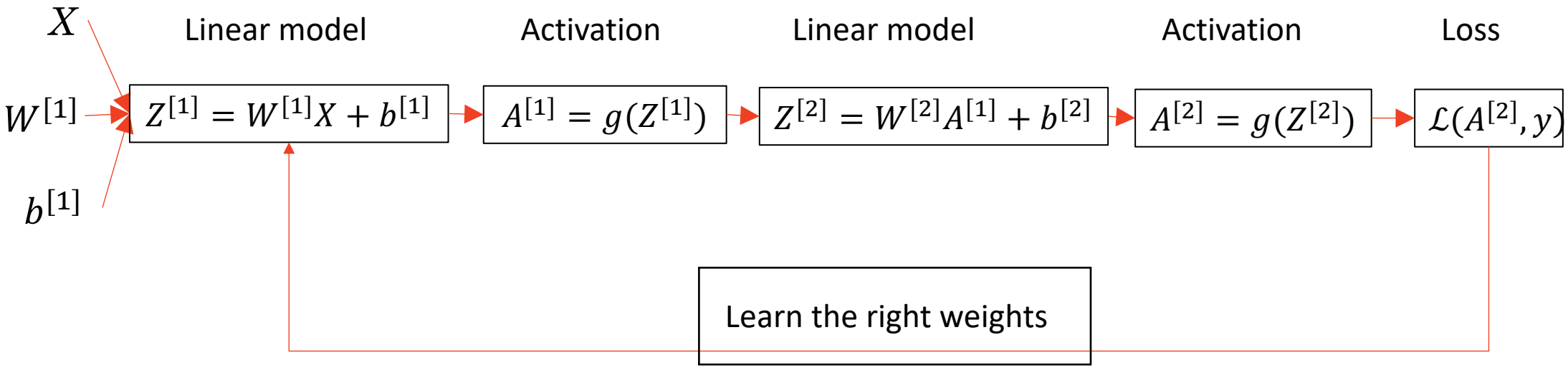
NEURAL NETWORK





NEURAL NETWORK





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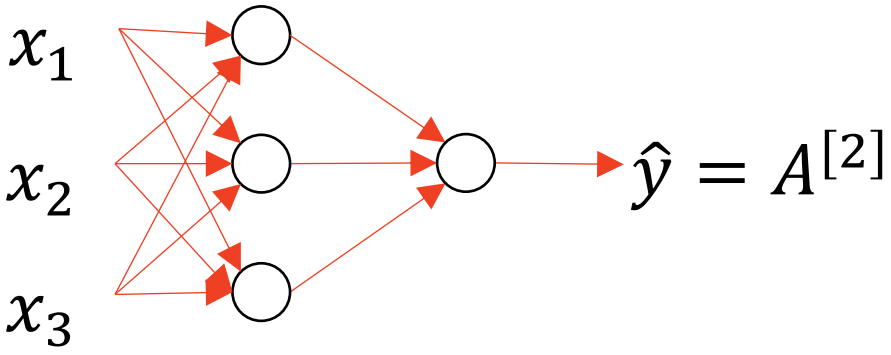


X

$W^{[1]}$

$b^{[1]}$

Linear model

$Z^{[1]} = W^{[1]}X + b^{[1]}$

Activation

$A^{[1]} = g(Z^{[1]})$

$W^{[2]}$

$b^{[2]}$

Linear model

$Z^{[2]} = W^{[2]}A^{[1]} + b^{[2]}$

Activation

$A^{[2]} = g(Z^{[2]})$

Loss

$\mathcal{L}(A^{[2]}, y)$

Cost function

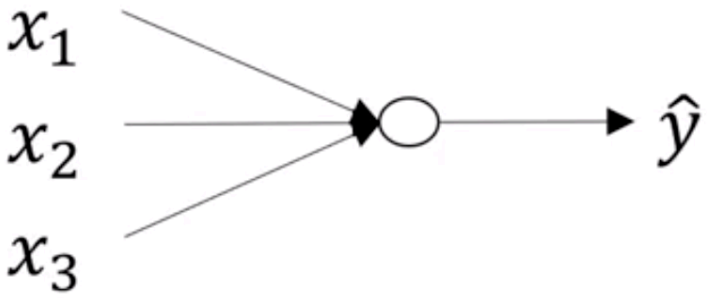
$$J(W^{[1]}, b^{[1]}, W^{[2]}, b^{[1]}) = \frac{1}{m}\sum_{i=1}^{m}\mathcal{L}(A^{[2]}, y)$$

Gradient descent

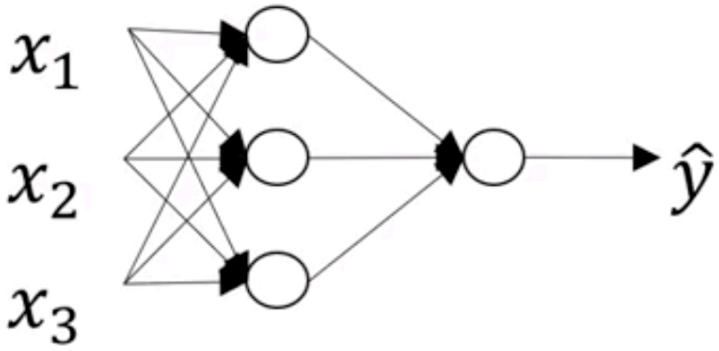
$$W^{[1]} := W^{[1]} - \eta\frac{\partial J}{\partial W^{[1]}} \qquad W^{[2]} := W^{[2]} - \eta\frac{\partial J}{\partial W^{[2]}}$$

$$b^{[1]} := b^{[1]} - \eta\frac{\partial J}{\partial b^{[1]}} \qquad b^{[2]} := b^{[2]} - \eta\frac{\partial J}{\partial b^{[2]}}$$

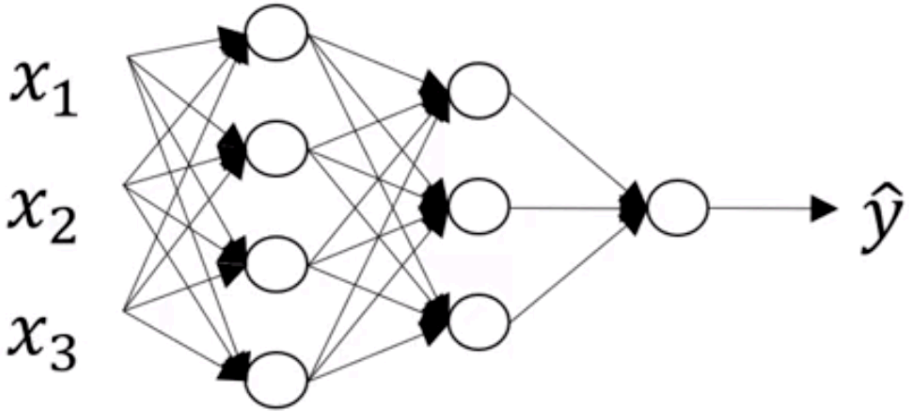
SHALLOW AND DEEP NEURAL NETWORK



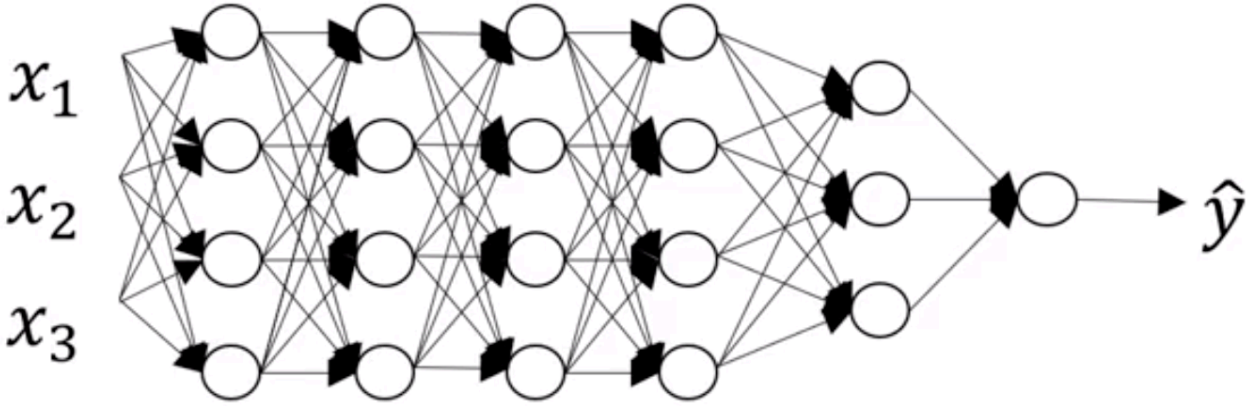
1-layer neural network



2-layer neural network



3-layer neural network



6-layer neural network

SO, WHY DEEP AND NOT SHALLOW?

- Although with two-layer (shallow) network, we can approximate all possible functions
  - Given the network layers are wide enough
- Deep architectures tend to be more efficient
- Also, deep and narrow architectures tend to generalize better than shallow and wide architectures

PARAMETERS VS HYPERPARAMETERS

- Parameters
  - $W^{[1]}, b^{[1]}, W^{[2]}, b^{[2]}, W^{[3]}, b^{[3]}, \ldots$
- Hyperparameters
  - Learning rate α
  - Number of iterations
  - Number of hidden layers
  - Number of units per hidden layer
  - Choice of activation function

ISSUES WITH TRAINING

OVERVIEW OF ISSUES

- Gradient descent
- Learning rate
- Lots of layers and inputs
  - Demands more data
  - Overfitting
  - Vanishing gradients

GRADIENT DESCENT IMPROVEMENTS

- A few slides back we had the following equations:

$$\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} - \eta \frac{\partial L}{\partial \boldsymbol{\theta}}$$

$$J(\theta) = \frac{1}{m} \sum_{i=1}^{m} \mathcal{L}(\hat{y}^{(i)}, y^{(i)})$$

- Most (all?) neural net libraries use more advanced ways of implementing gradient descent.
- One concept is mini-batch gradient descent

MINI-BATCH GRADIENT DESCENT

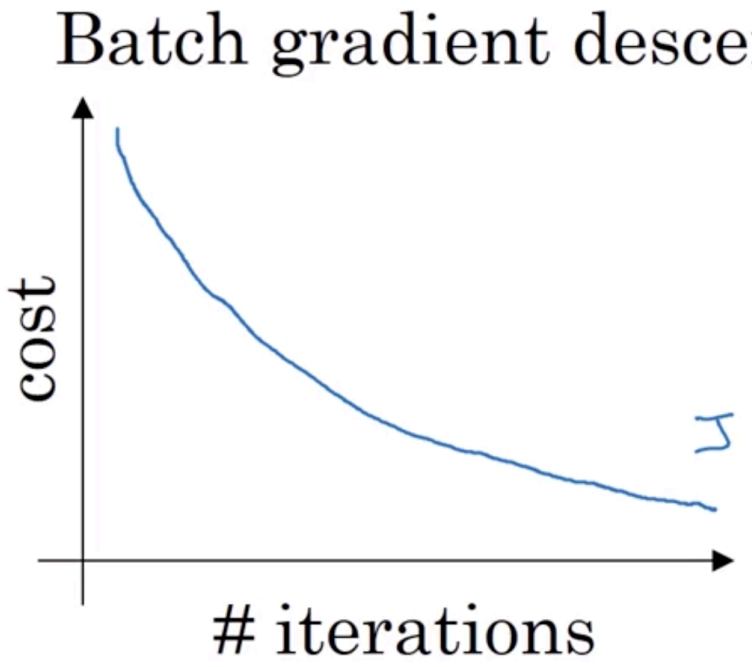
- Standard gradient descent computes error gradient over entire training set

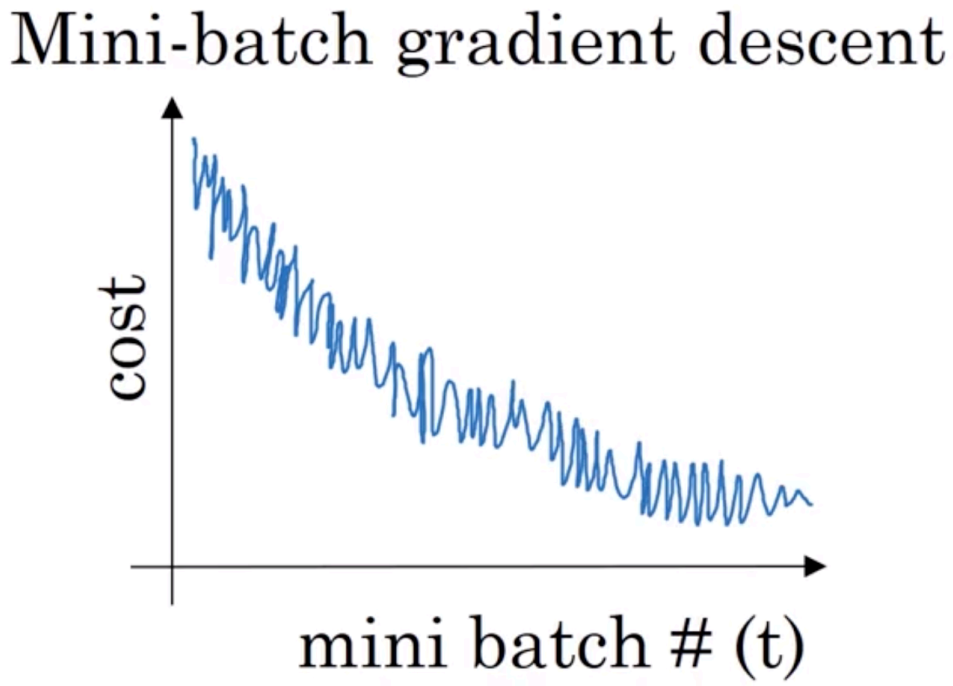
$$\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} - \eta \frac{\partial L}{\partial \boldsymbol{\theta}}$$

- This can be very slow for large datasets and impossible for datasets which don't fit into memory!
- Mini-batch gradient descent (SGD) applies gradient descent on x training example

MINI-BATCH GRADIENT DESCENT

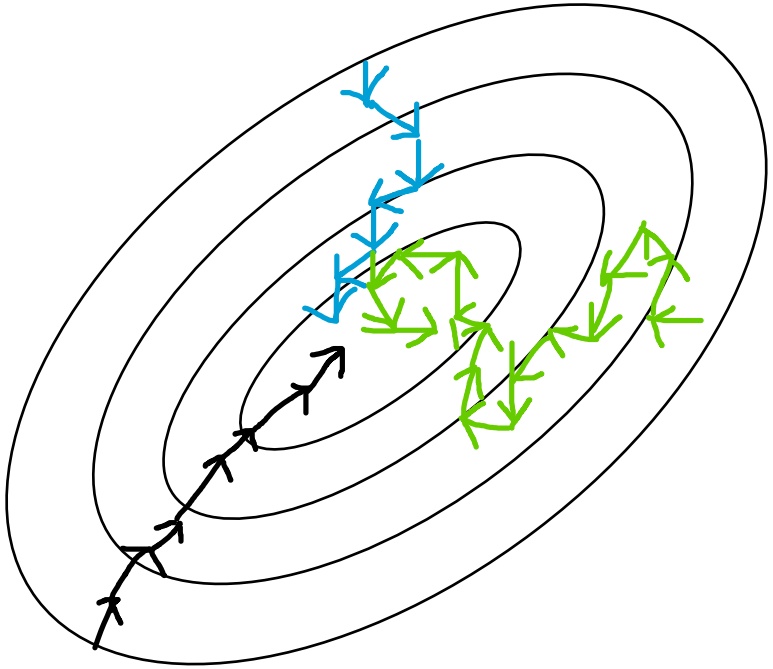
- Mini-batch is an improvement over gradient descent in terms of speed.
- Complicates the convergence process (see figure).





MINI-BATCH GRADIENT DESCENT

- Batch gradient descent
  - Too long per iteration to update parameters
  - Not able to process dataset that don’t fit into memory
- Stochastic gradient descent
  - Introduces much noise
  - Not able to perform vectorized calculations
- Mini-batch gradient descent
  - Able to use vectorization
  - Able to quickly update parameters



MINI-BATCH GRADIENT DESCENT

- Mini-batch gradient descent solves this unstable convergence process by computing the gradient over a subset of the training data

$$J(w,b) = \frac{1}{n}\sum_{i=1}^{n} \mathcal{L}(\hat{y}^{(i)}, y^{(i)})$$

$$\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} - \eta \frac{\partial L}{\partial \boldsymbol{\theta}}$$

- Here, if N is the number of mini-batch training samples, $n \ll N$.
- A common mini-batch sizes is 32.
- In literature, SGD usually refers to mini-batch gradient descent.

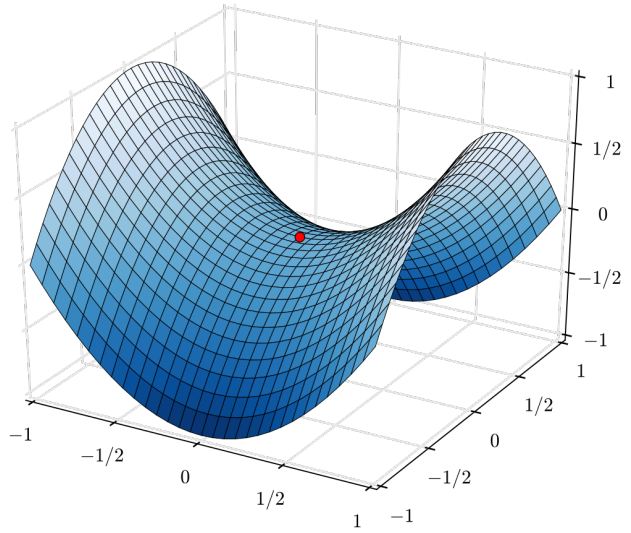
MOMENTUM

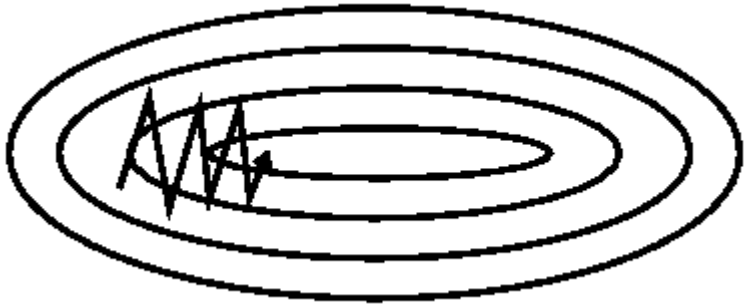
- SGD has trouble navigating ravines, i.e. areas where the surface curves much more steeply in one dimension than in another.
- Momentum is a method which helps SGD move in the right direction by adding a fraction of the previous update to the current update

$$v_{d\theta} = \beta_1 v_{d\theta} + (1 - \beta_1)\frac{\partial L}{\partial \theta}$$

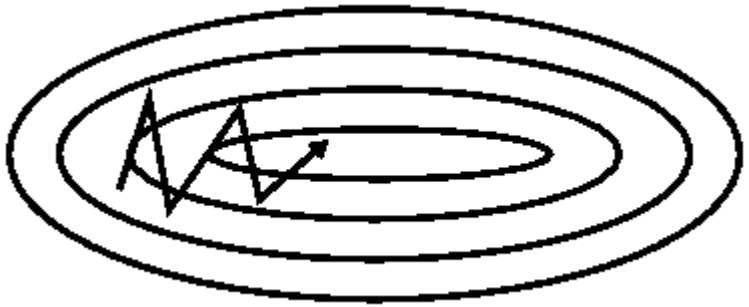
$$\theta = \theta - \eta v_{d\theta}$$

- β_1 is usually chosen to be around 0.9





SGD without momentum



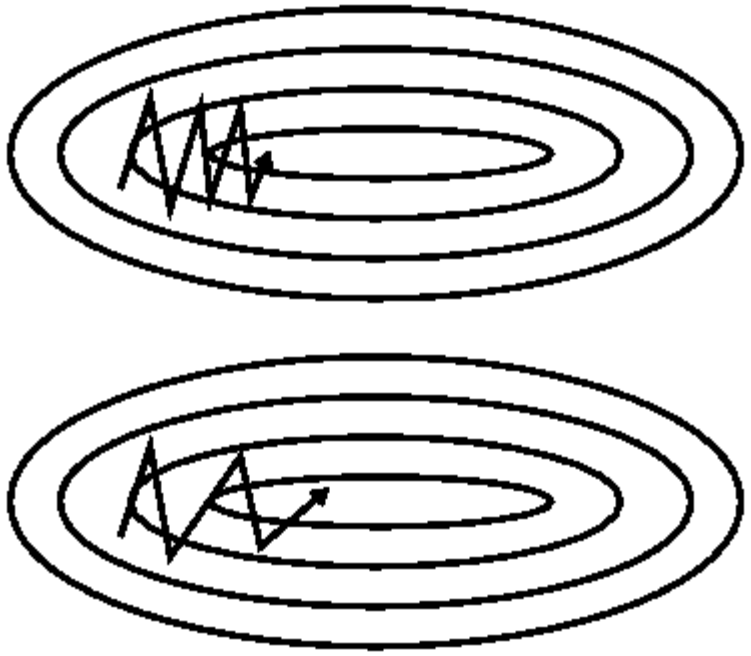
SGD with momentum

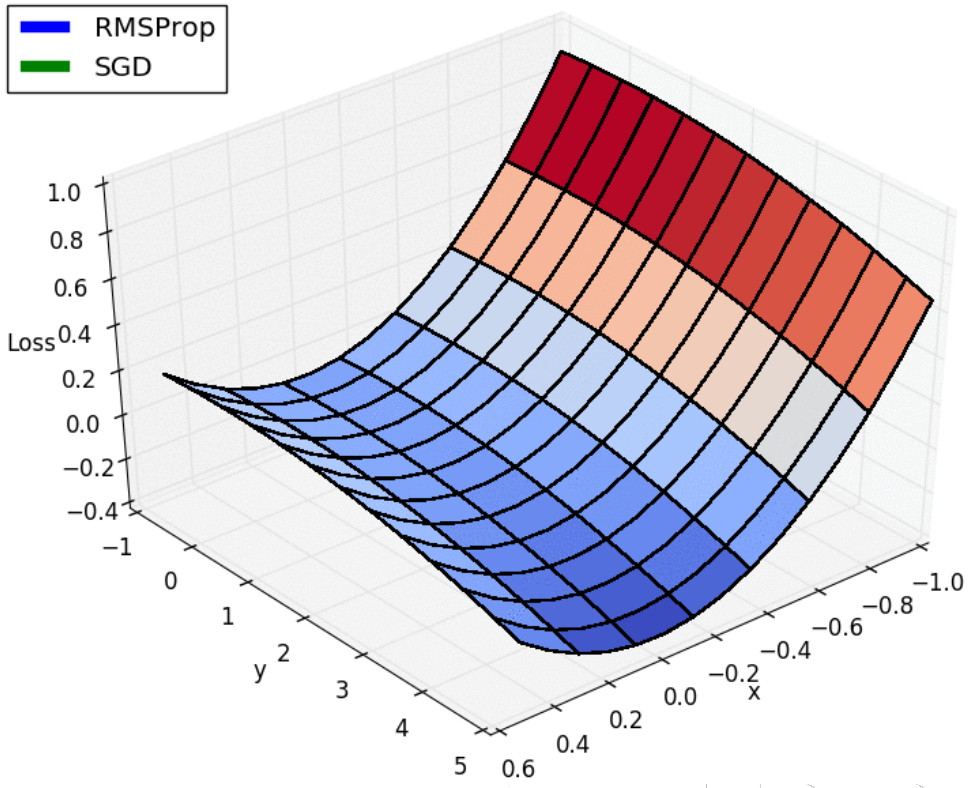
RMSPROP

- Moving in direction of steepest descent divided by root mean square (RMS) estimate

$$s_{d\theta} = \beta_1 s_{d\theta} + (1 - \beta_1)(\frac{\partial L}{\partial \theta})^2$$

$$\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} - \eta \frac{\frac{\partial L}{\partial \theta}}{\sqrt{s_{d\theta}} + eps}$$





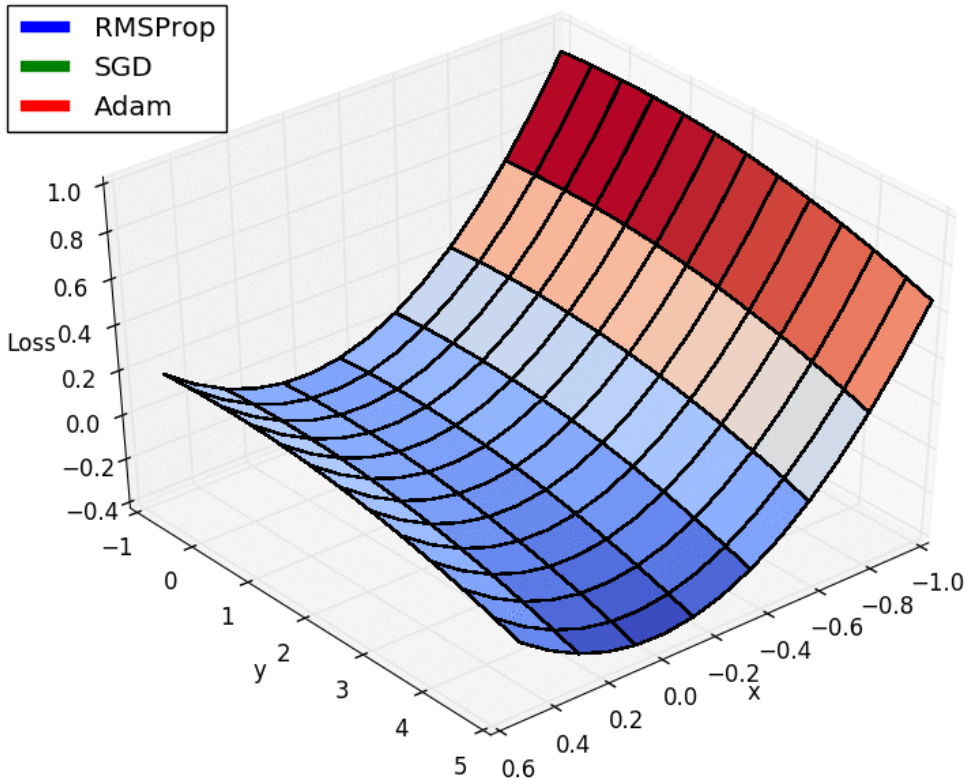
ADAM

- Moving in smoothed direction of steepest descent divided by root mean square estimate

$$v_\theta = \beta_1 v_\theta + (1-\beta_1)\frac{\partial L}{\partial \theta}$$

$$s_\theta = \beta_1 s_\theta + (1-\beta_1)(\frac{\partial L}{\partial \theta})^2$$

$$\theta \leftarrow \theta - \eta \frac{v_\theta}{\sqrt{s_\theta} + eps}$$

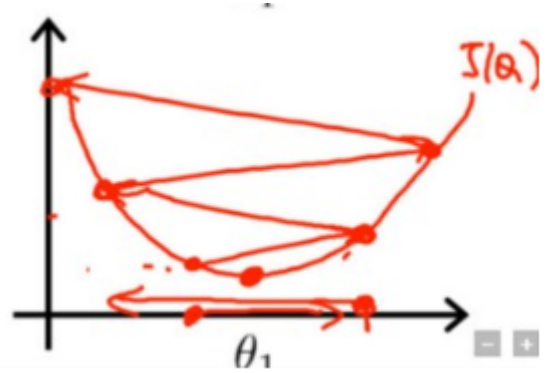


OVERVIEW OF ISSUES

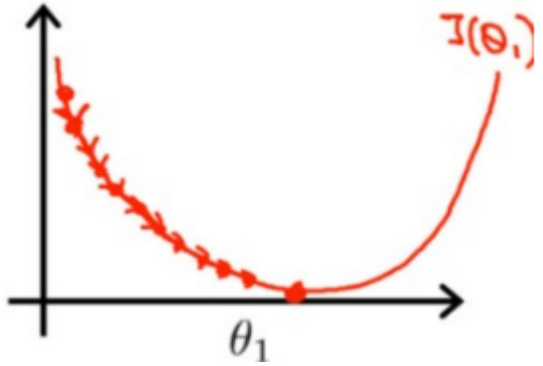
- Gradient descent
- Learning rate
- Lots of layers and inputs
  - Demands more data
  - Overfitting
  - Vanishing gradients

LEARNING RATE

- Determining the learning rate η is an important part of our training process.
- Choosing a η that is too large will cause our gradient descent method to overshoot.
- If η is too small, gradient descent converges very slowly.



η too large



η too small

LEARNING RATE DECAY

- $\eta = \frac{1}{1+decay\_rate * epoch\_num}\eta_0$

OVERVIEW OF ISSUES

- Gradient descent
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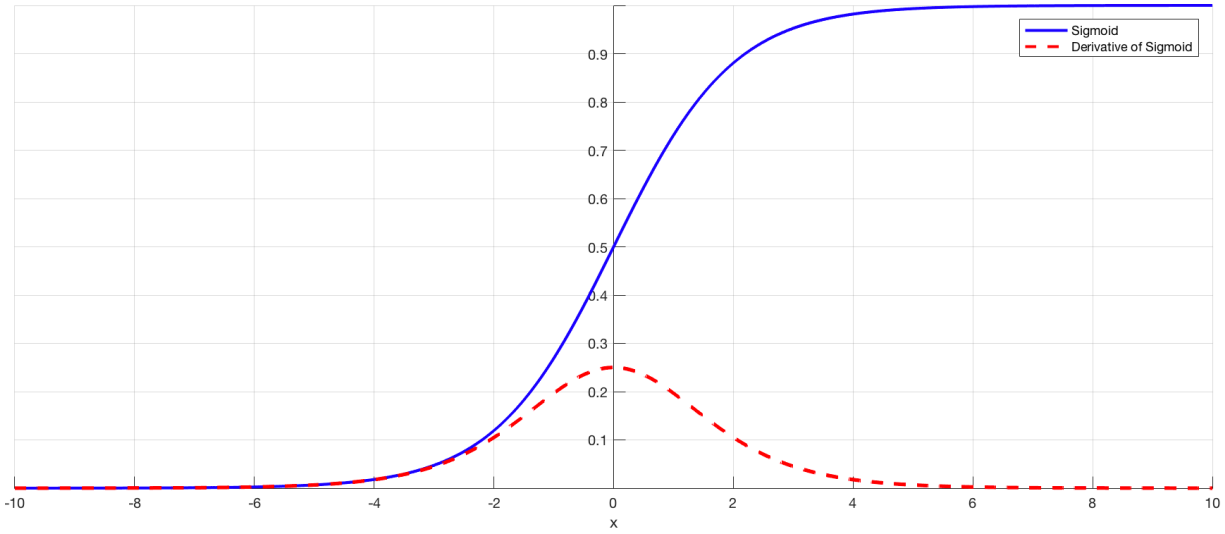
FIRST ISSUE: THE DEMAND OF DATA

OVERVIEW OF ISSUES

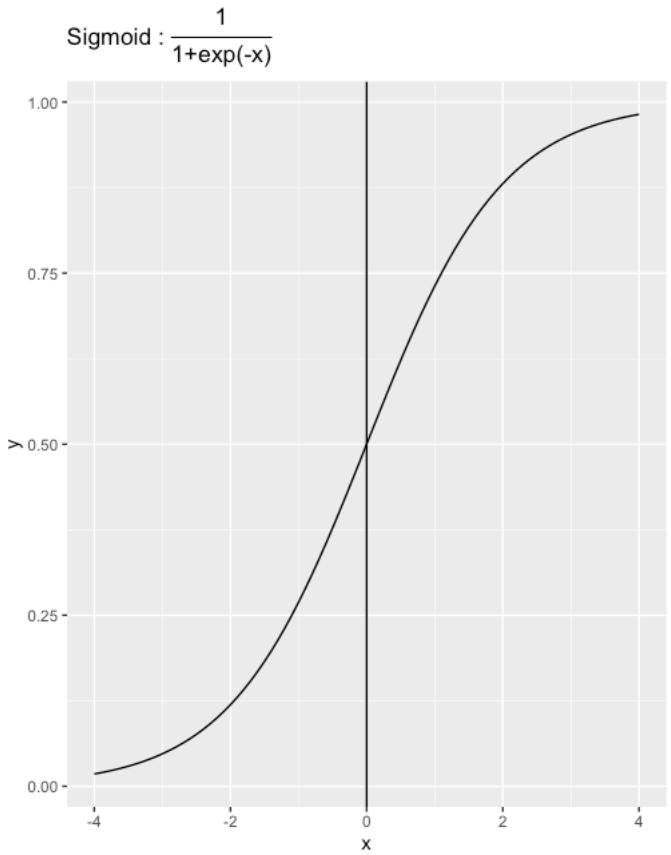
- Gradient descent
- Learning rate
- Lots of layers and inputs
  - Demands more data
  - Vanishing gradients
  - Overfitting

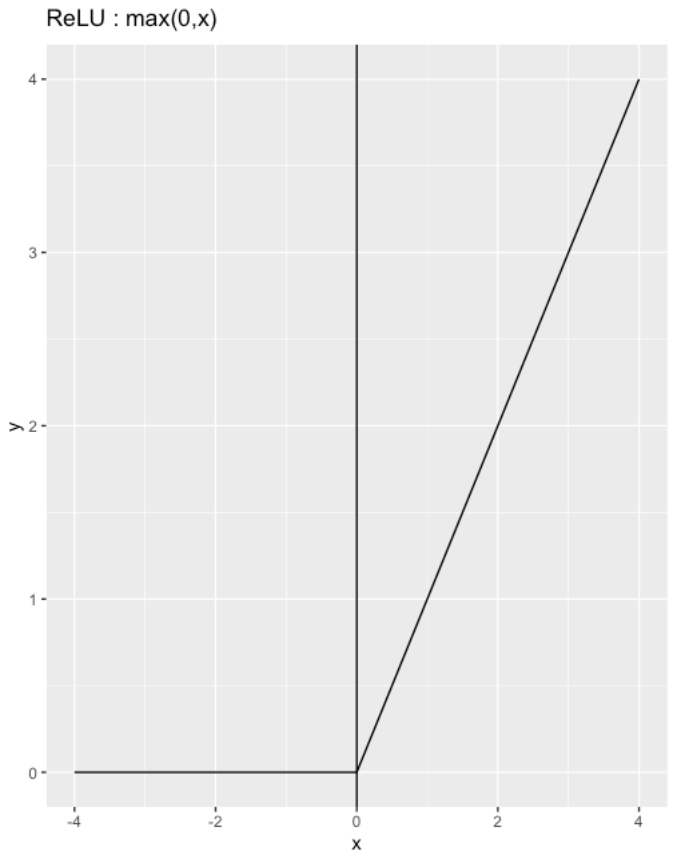
SECOND ISSUE: VANISHING GRADIENTS

- More layers are added to the neural network, the gradients of the loss function approaches zero, making the network hard to train.
- Solution
  - Activation function
    - RELU instead of sigmoid
  - Better initialization of the weights
    - **he_normal** -> stddev = sqrt(2 / N_in)
    - **glorot_normal (Xavier) ->** stddev = sqrt(2 / (N_in + N_out))
  - Residual networks

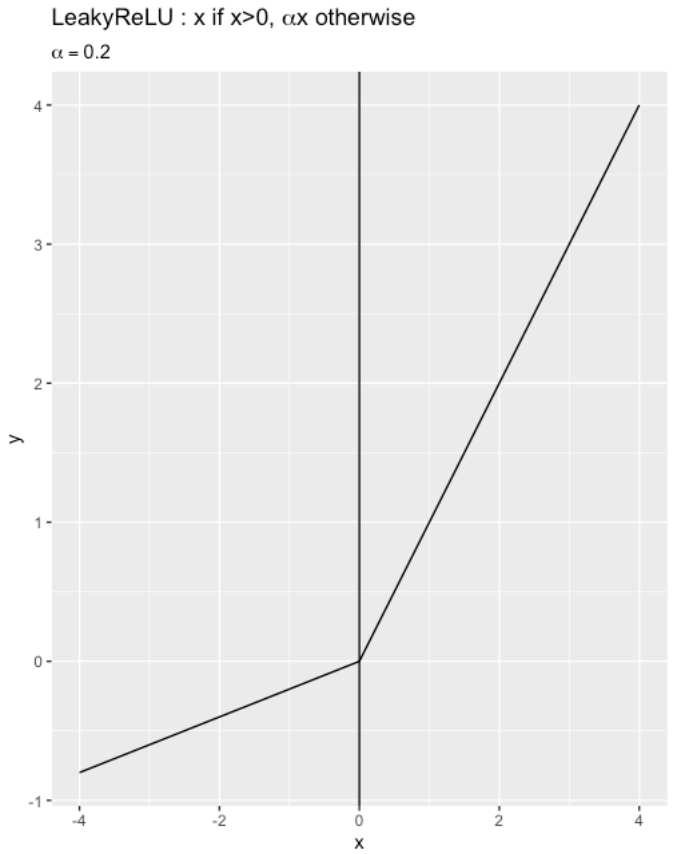


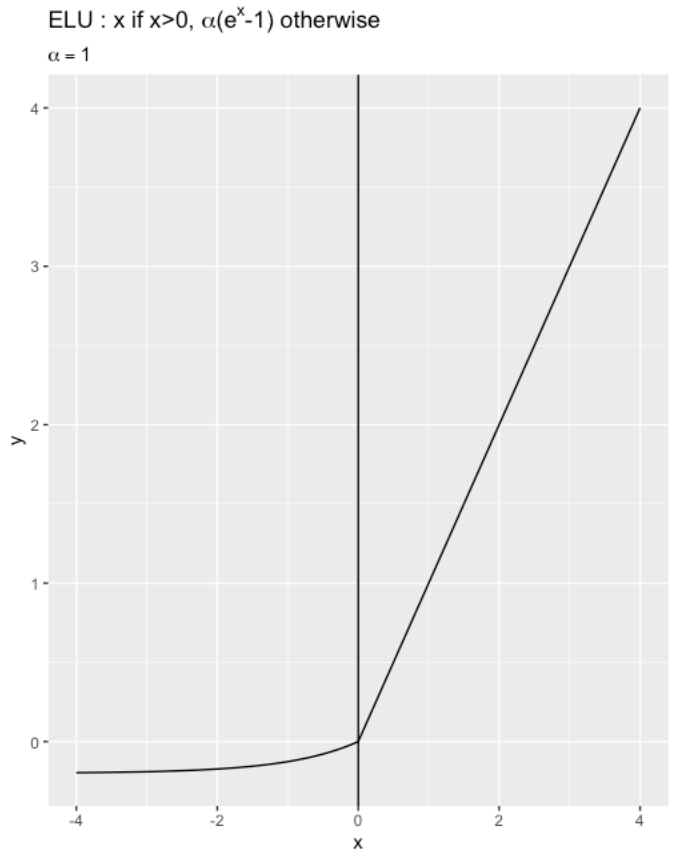
SECOND ISSUE: VANISHING GRADIENTS

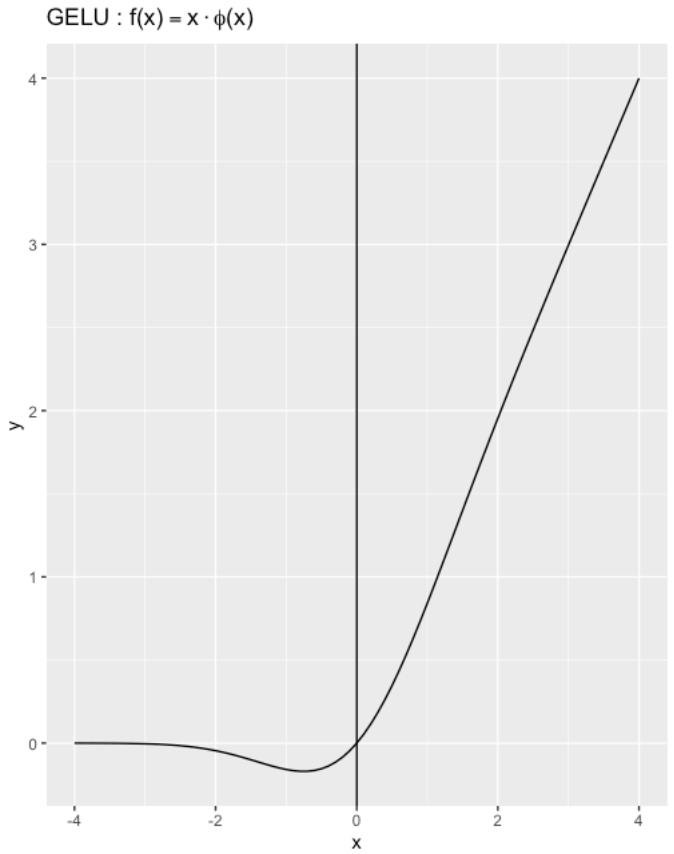




SECOND ISSUE: VANISHING GRADIENTS





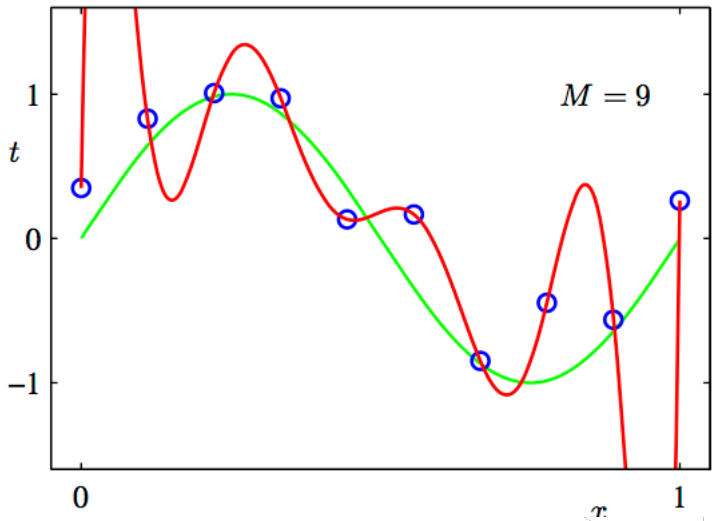


OVERVIEW OF ISSUES

- Gradient descent
- Learning rate
- Lots of layers and inputs
  - Demands more data
  - Vanishing gradients
  - Overfitting

THIRD ISSUE: OVERFITTING

- This happens due to the enormous amount of parameters
  - Yields high flexibility/nonlinearity
  - Potentially ‘remember’ outliers
  - Inability to generalize
- Countermeasures
  - Weight norm penalty
  - Early stopping
  - Dropout
  - …



WEIGHT PENALTIES

- A weight should only code for regular patterns
- Idea: force network to forget irregularities
- Accomplished by augmenting loss function
- Example
  - Classification → cross-entropy loss with L2 loss:

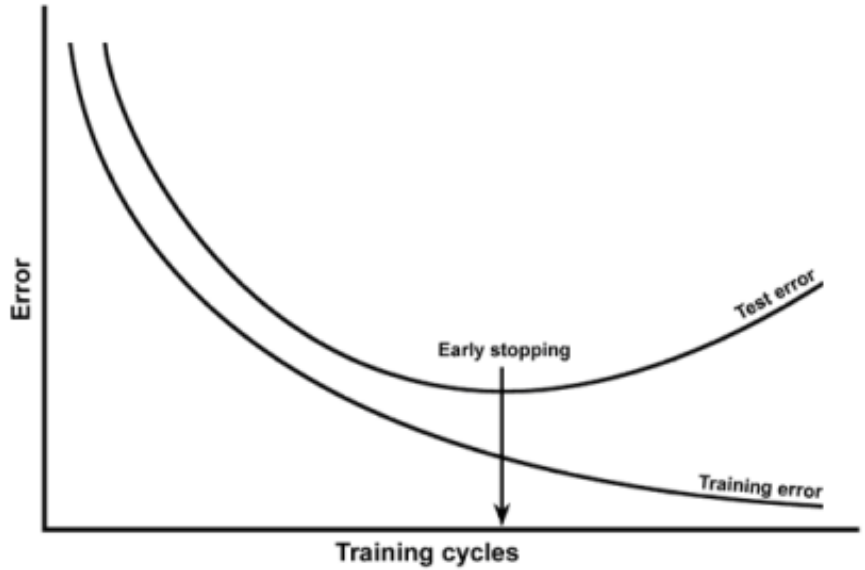
$$L = \sum_{i=1}^{K} y_i \log(\hat{y}_i) + \lambda ||\boldsymbol{w}||_2^2$$

  - Regression → sum of squared errors with L1 loss:
  -

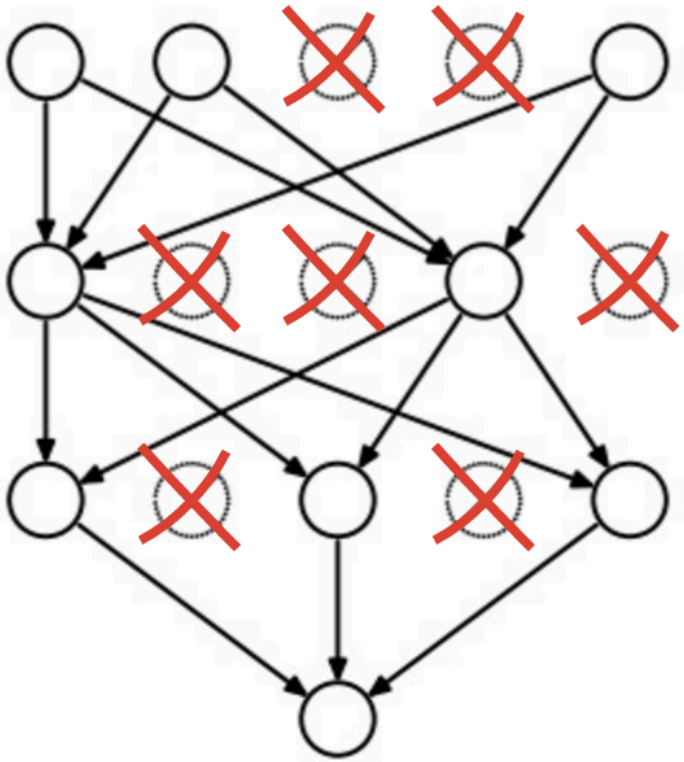
$$L = \sum_{i=1}^{K} (y_i - \hat{y}_i)^2 + \lambda ||\boldsymbol{w}||_1$$

EARLY STOPPING

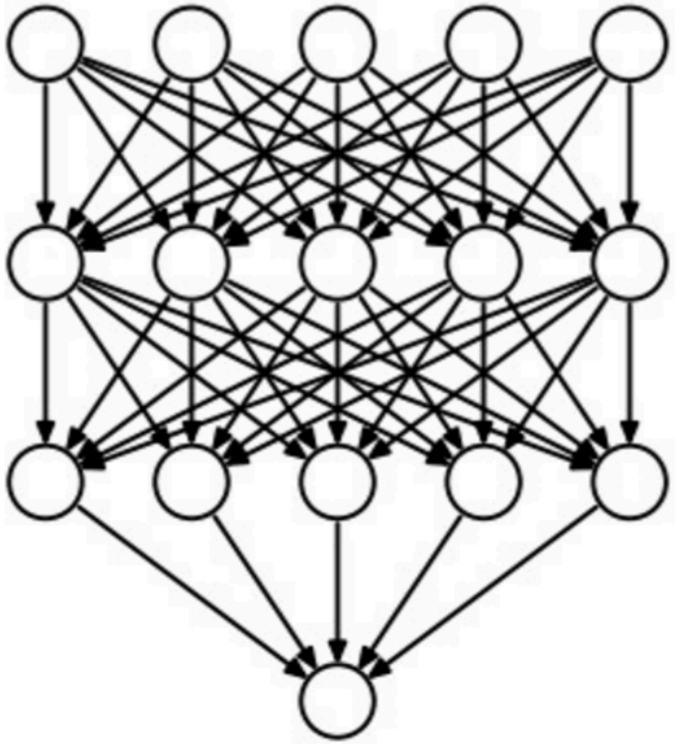
- When validation error starts increasing
- Protects against overfitting



DROPOUT



Training
pkeep = 0.50



Test
pkeep = 1.0

CONCLUSION

We have learned:

- What a (deep) neural network is
- Gradient descent and the different optimizers
- Learning rate decay
- Some problems of a deep neural network and how to solve them

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THANK YOU FOR YOUR ATTENTION

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