INTRODUCTION TO DEEP LEARNING

BOSCH

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Introduction to deep learning
Contents

BOSCH

LET'S START WITH SOME EXAMPLES

Introduction
Object detection

https://www.youtube.com/watch?v=VOC3huqHrss

Introduction
Image segmentation

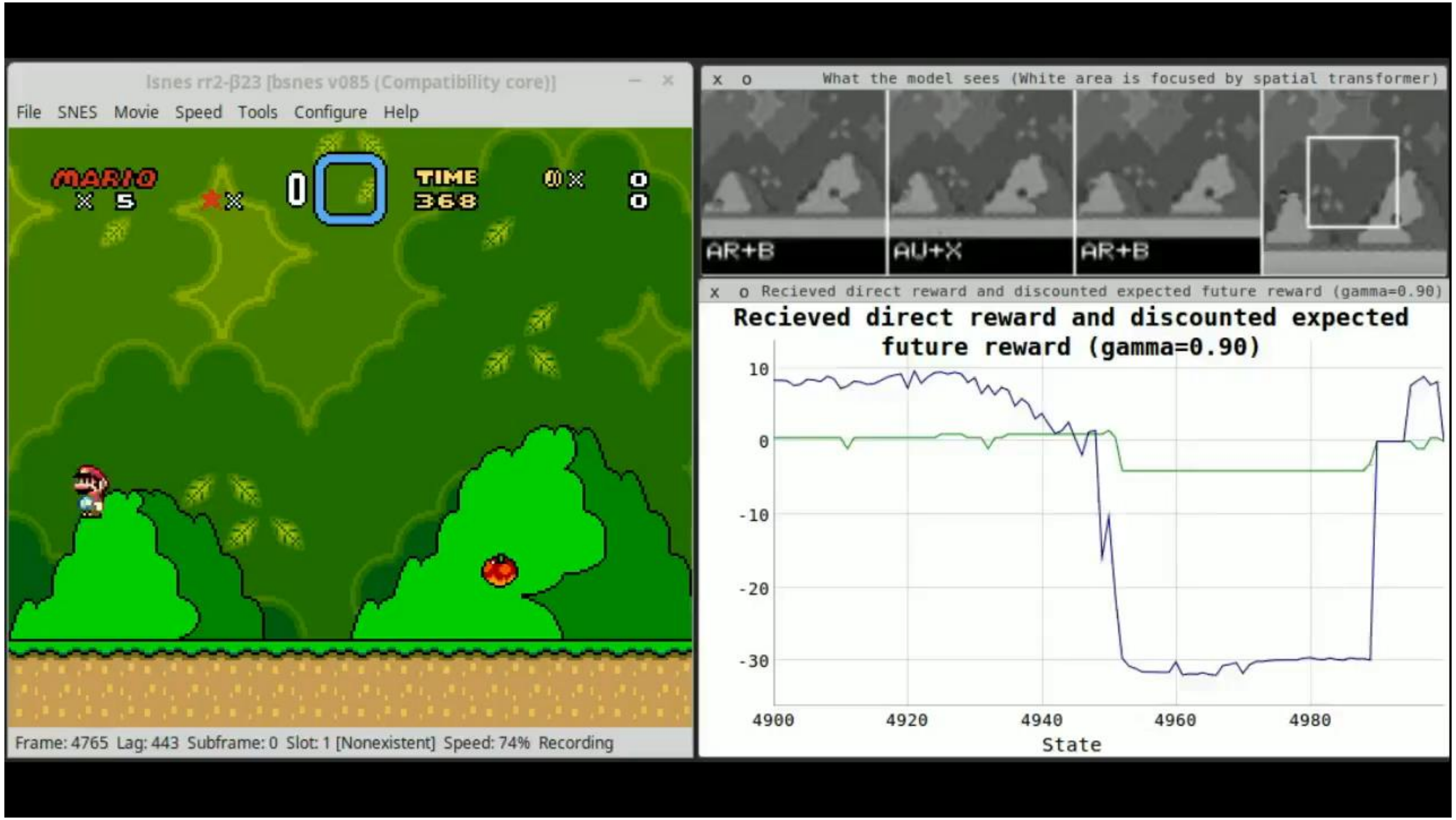
https://www.youtube.com/watch?v=1HJSMR6LW2g

Introduction
Image colorization

100 year old pictures...

https://www.youtube.com/watch?v=ys5nMO4Q0iY

Introduction
Mario

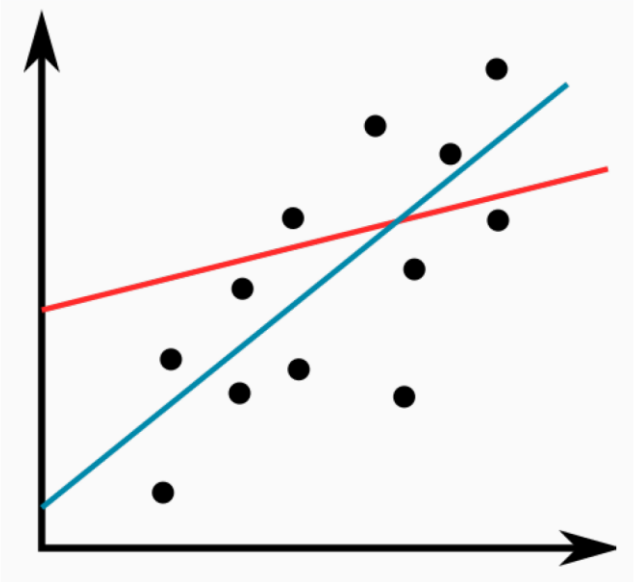


https://www.youtube.com/watch?v=L4KBBAwF_bE

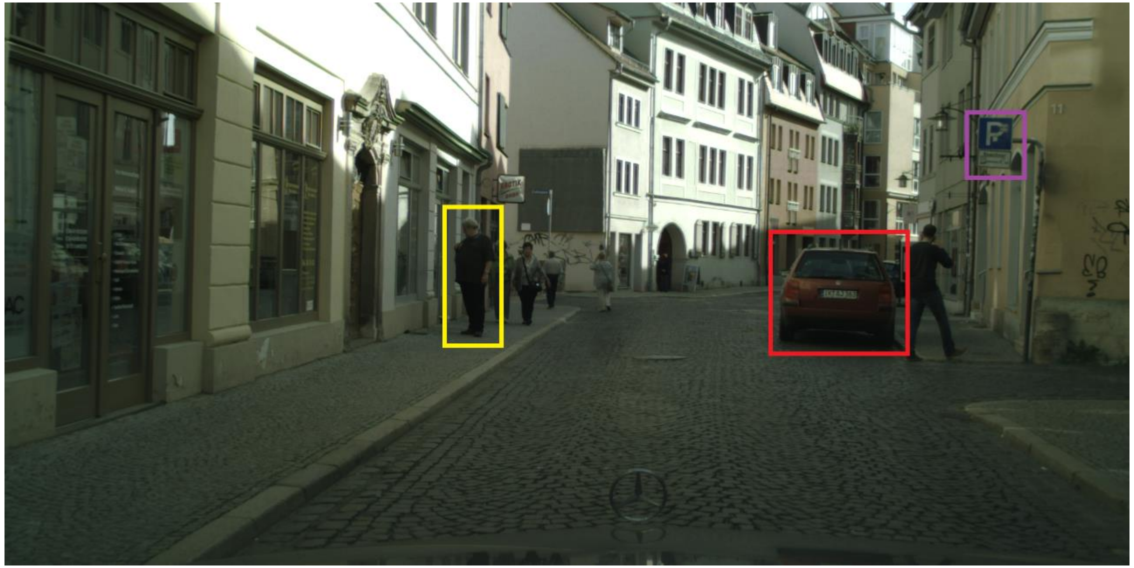
MACHINE LEARNING

Machine learning
What is machine learning?

To learn = algorithmically find the choice of parameters that best explain the data.



- Linear regression -



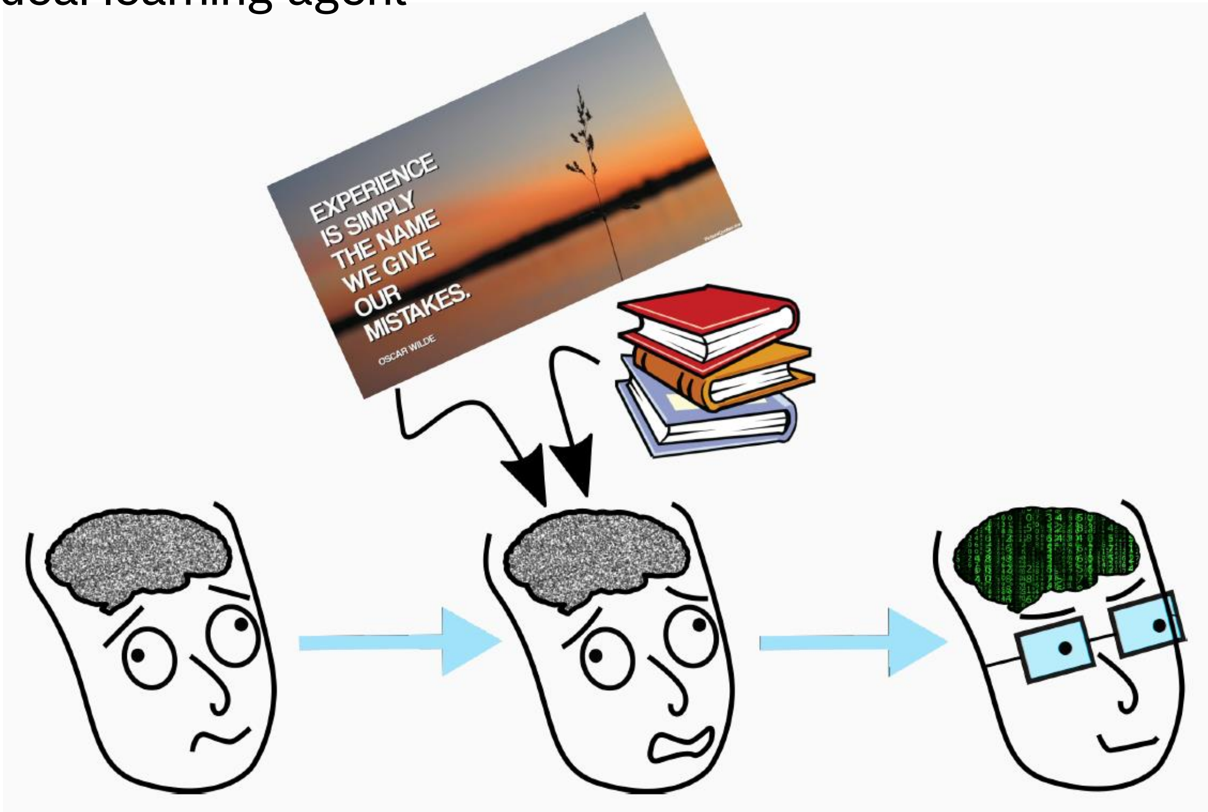
- Object detection -

Machine learning
Uses machine learning in industry

- Object detection
- Image segmentation
- Image classification
- Speech recognition
- Language understanding and translation
- Spam filters and fraud detection
- Automatic email labelling and sorting
- Personalized search results and recommendations
- Automatic image captioning
- Online advertising
- Medical diagnosis

Machine learning
Deep learning – what is it?

- A particular subset of ML algorithms a.k.a. “enhanced neural network”
- The closest to an ideal learning agent



NEURAL NETWORKS

Introduction to neural networks
Biological motivation and connections

- **Intuition** : as humans we use our brains to learn the characteristics of different objects and phenomena.
- **Brain neurons**: receive input signals from dendrites and produce output signals along axon.

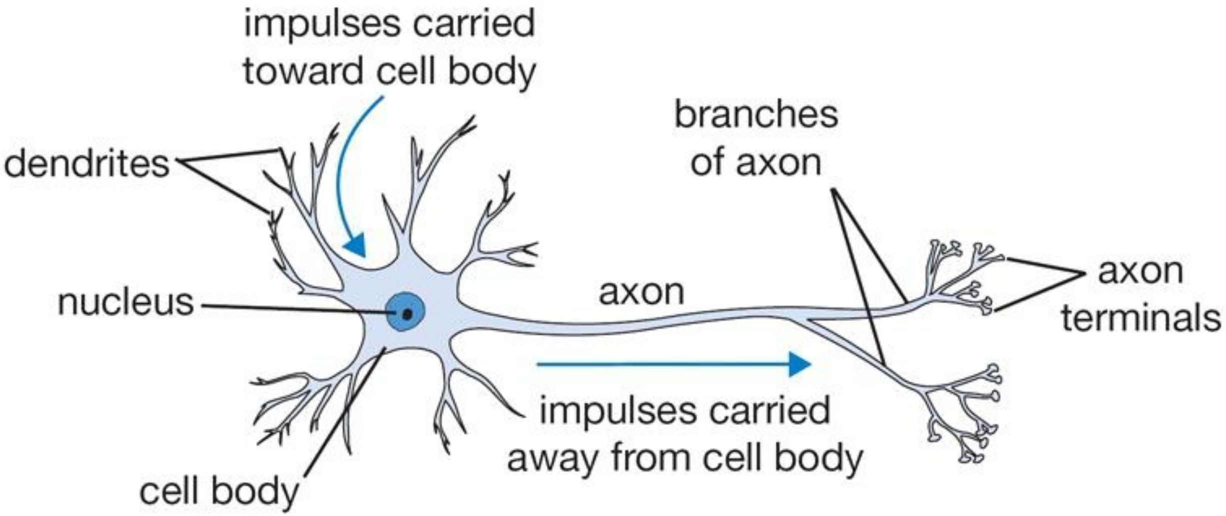
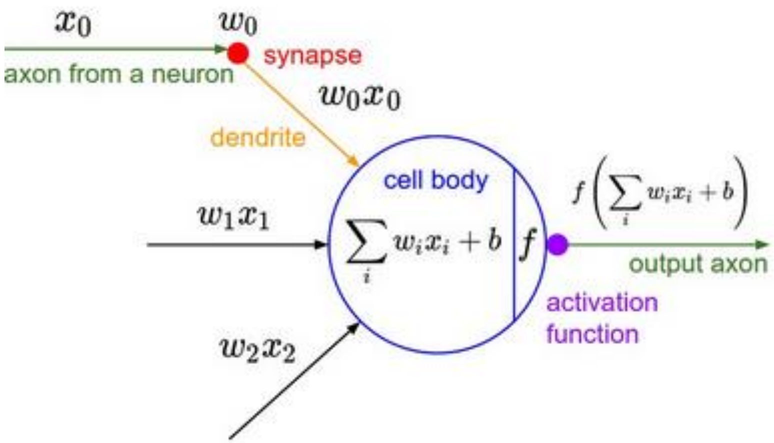


Image taken from http://cs231n.github.io/neural-networks-1

Introduction to neural networks
Biological motivation and connections

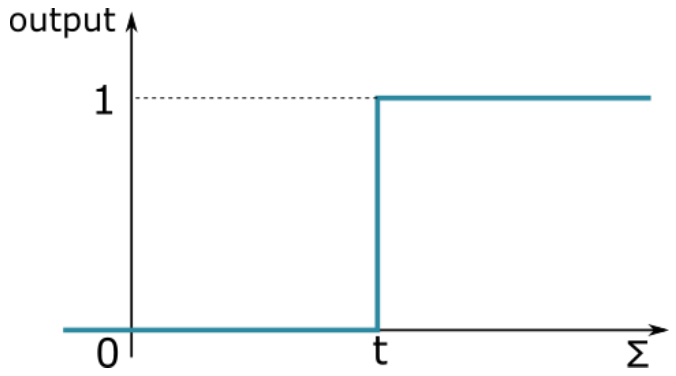
- **Computational model** : signals interact multiplicatively with dendrites of the next neuron (**linear combination of the input signals**).
- The **weights** (synaptic strengths) and **bias** (threshold) are learnable. They control the influence of one neuron over another.



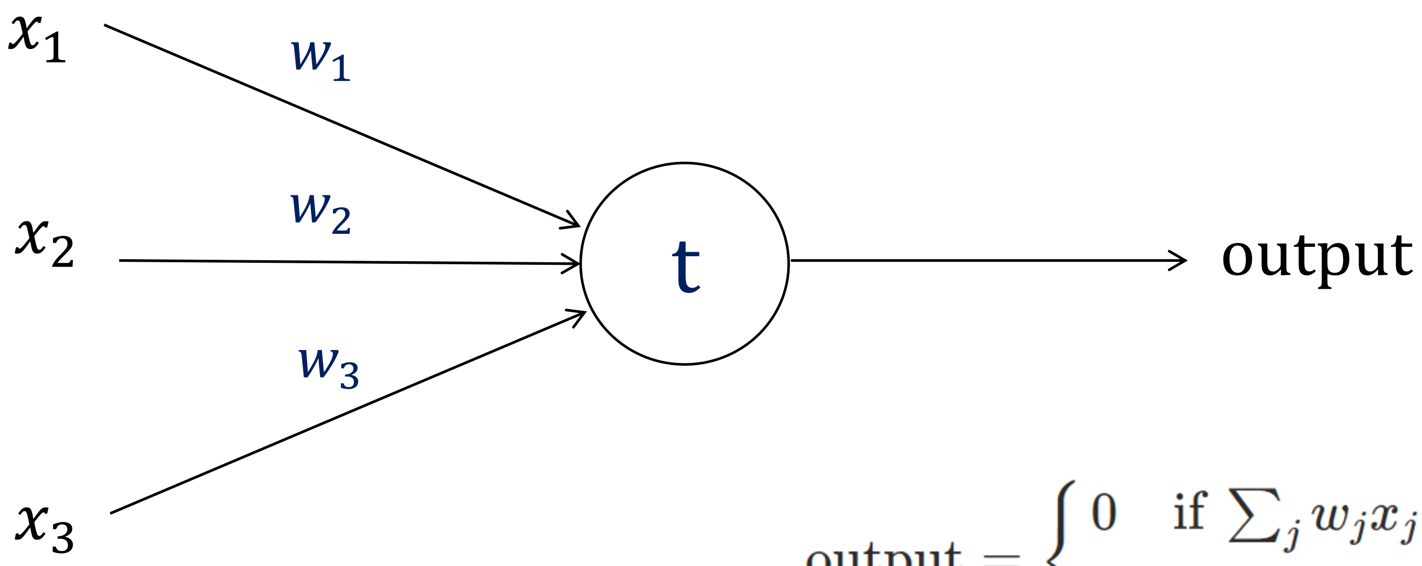
The **weights** w_i and **bias** b are parameters **learned** through **training**.

Image taken from http://cs231n.github.io/neural-networks-1

Introduction to neural network
Perceptron



- Element (neuron) that takes decisions based on evidences
- Takes several binary inputs and produces a single binary output



$x_1, x_2, x_3 \in \{0,1\}$

$$\text{output} = \begin{cases} 0 & \text{if } \sum_j w_j x_j \leq \text{ threshold} \\ 1 & \text{if } \sum_j w_j x_j > \text{ threshold} \end{cases}$$

Introduction to neural network
Perceptron: example

You are trying to decide whether to go to a concert or not.

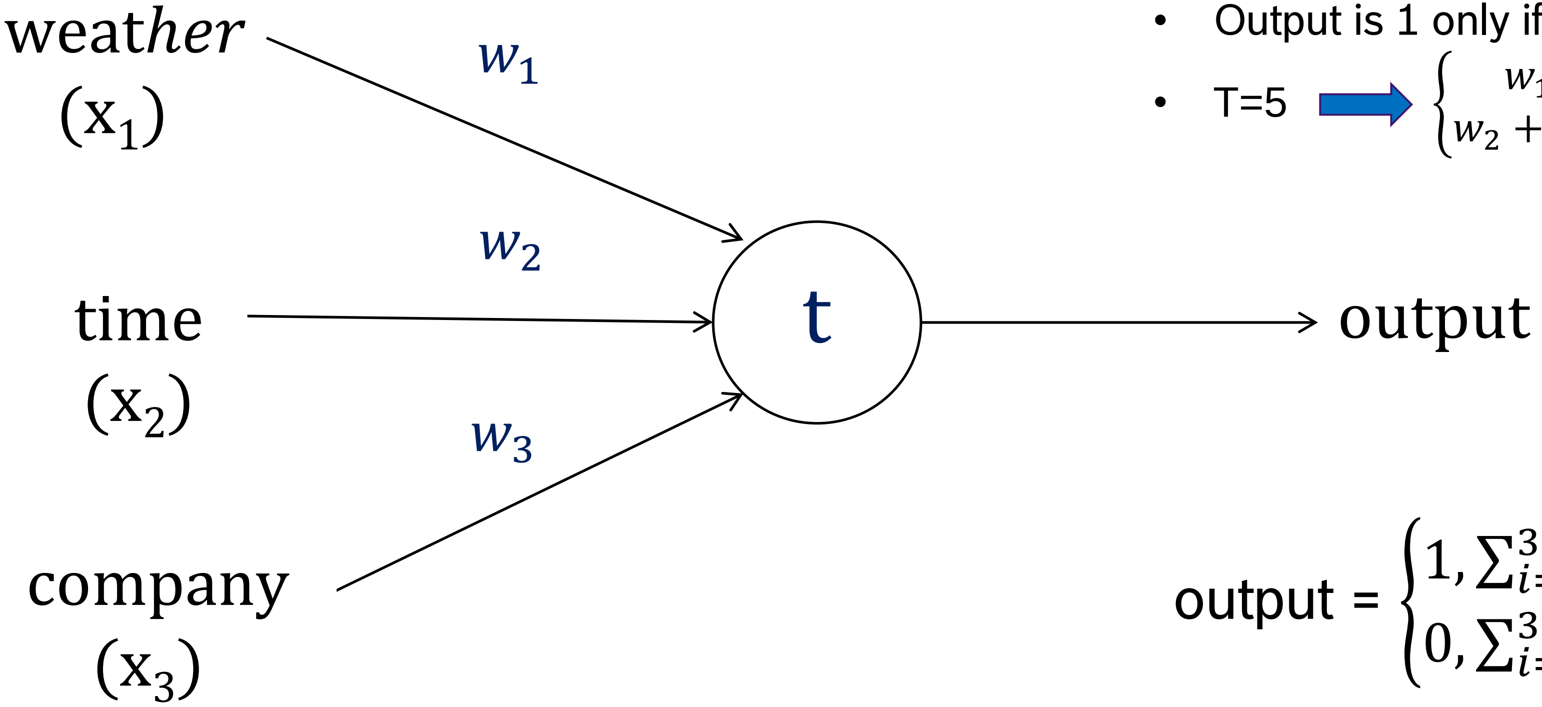
You might make your decision by weighing up three factors:

1. Is the weather good?
2. Do you have enough time to attend the concert?
3. Does your boyfriend or girlfriend want to accompany you?

Introduction to neural networks

Perceptron: example

I only go if the weather is good



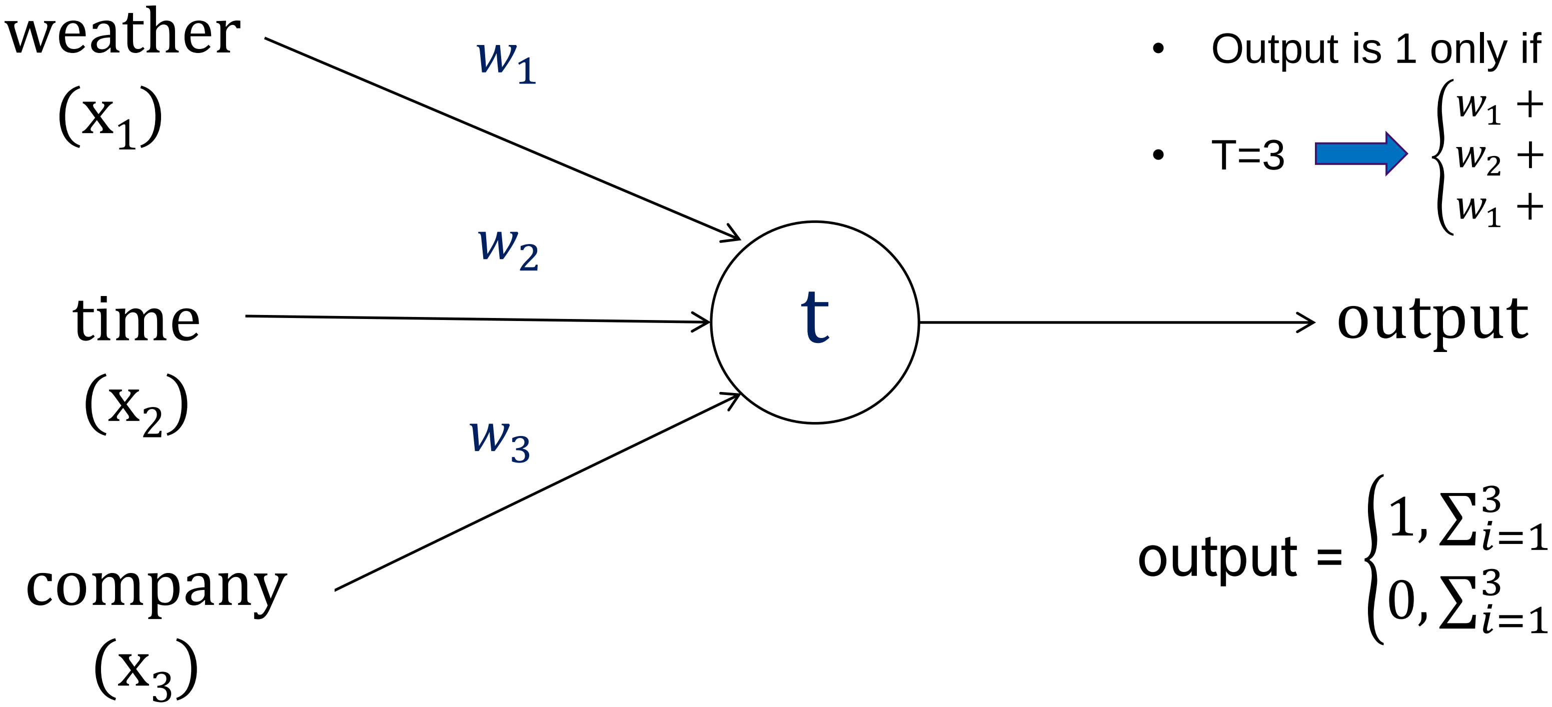
- Output is 1 only if weather's input is 1
- T=5 $\Rightarrow \begin{cases} w_1 > 5 \\ w_2 + w_3 \leq 5 \end{cases}$

$$\text{output} = \begin{cases} 1, \sum_{i=1}^{3} w_i * x_i > 5 \\ 0, \sum_{i=1}^{3} w_i * x_i \leq 5 \end{cases}$$

Introduction to neural networks

Perceptron: example

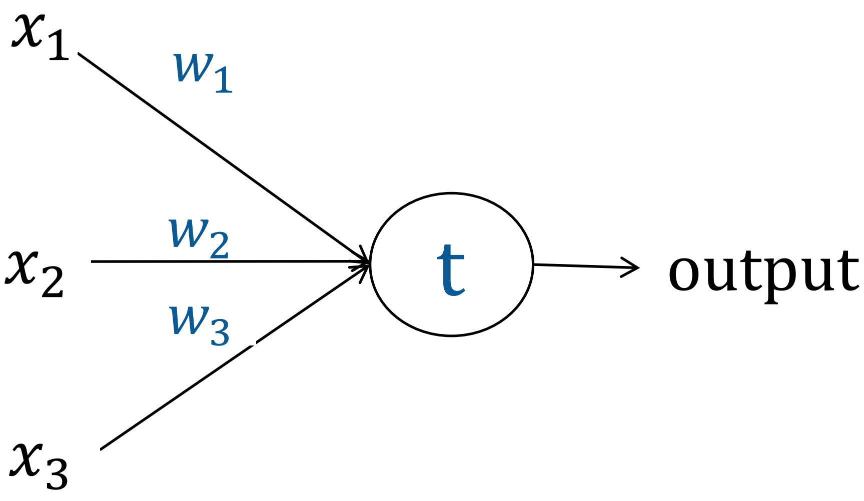
I go if the weather is good and I have enough time!



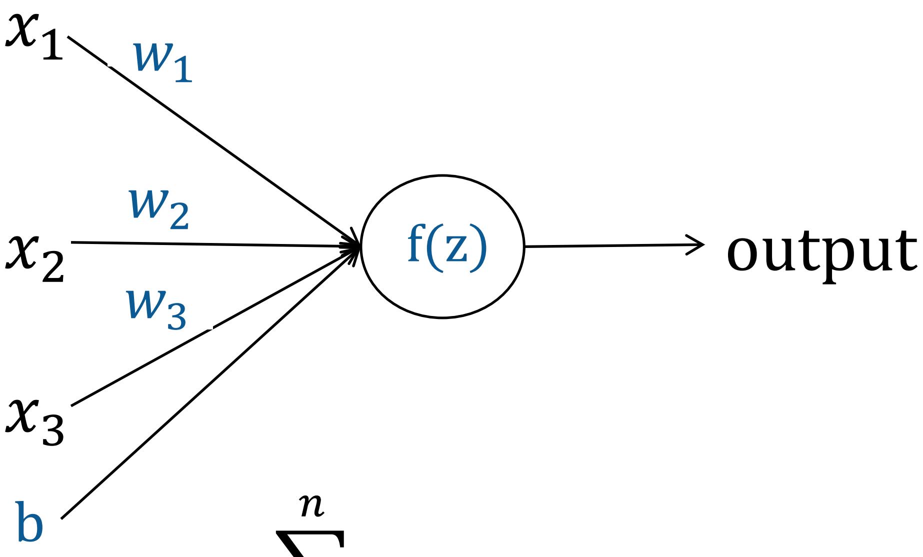
- Output is 1 only if weather’s input is 1
- T=3 ➡ $\begin{cases} w_1 + w_2 > 3 \\ w_2 + w_3 \leq 3 \\ w_1 + w_3 \leq 3 \end{cases}$

$$\text{output} = \begin{cases} 1, \sum_{i=1}^{3} w_i * x_i > 3 \\ 0, \sum_{i=1}^{3} w_i * x_i \leq 3 \end{cases}$$

Introduction to neural networks
Perceptron vs Artificial neuron



$$\text{output} = \begin{cases} 0 & \text{if } \sum_j w_j x_j \leq \text{ threshold} \\ 1 & \text{if } \sum_j w_j x_j > \text{ threshold} \end{cases}$$



$$z = \sum_{i=1}^{n} w_i * x_i + b$$

$$output = f(z)$$

activation function

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ACTIVATION FUNCTIONS AND ARCHITECTURES

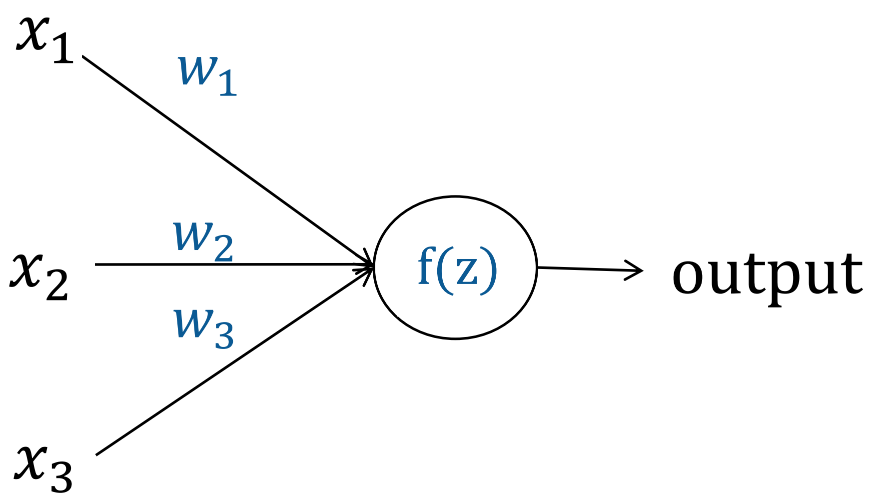
Architectures and activation functions
Activation functions

- Properties:
  - Nonlinear function: makes possible to solve more complex problems -> **artificial neural networks are universal function approximators** [Cybenko 1989, Hornik 1991]
  - Differentiable function: necessary for learning parameters

- The **activation function** is applied after computing the linear value **z** of the neuron

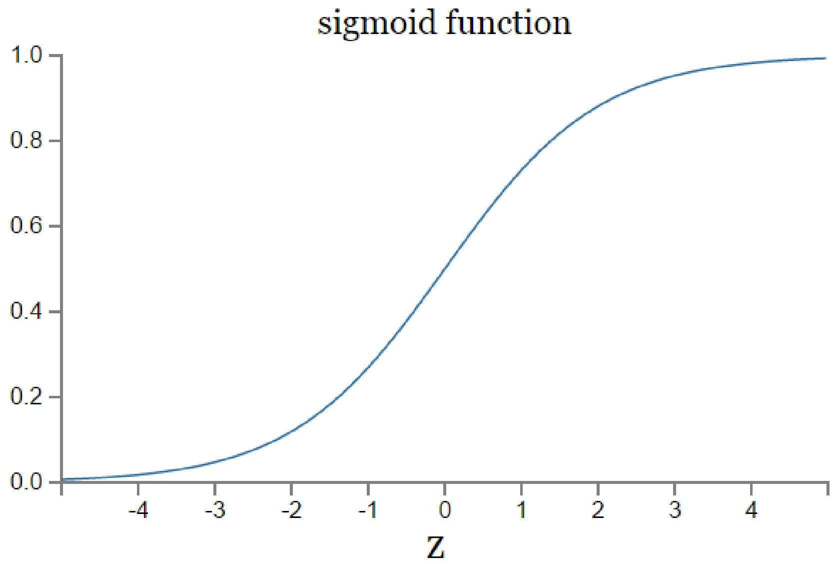
$$z = \sum_{i=1}^{n} w_i * x_i + b$$

$$output = f(z)$$



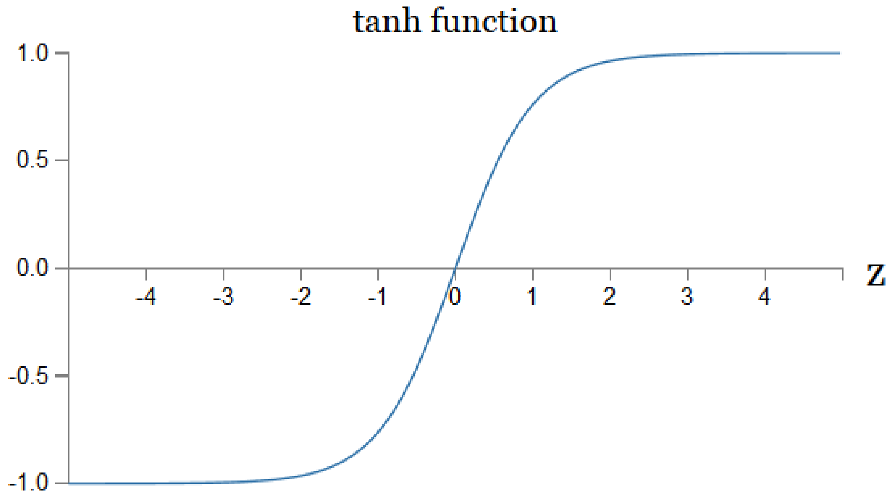
Architectures and activation functions
Activation functions

- **Sigmoid function**



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

- **Tanh function**

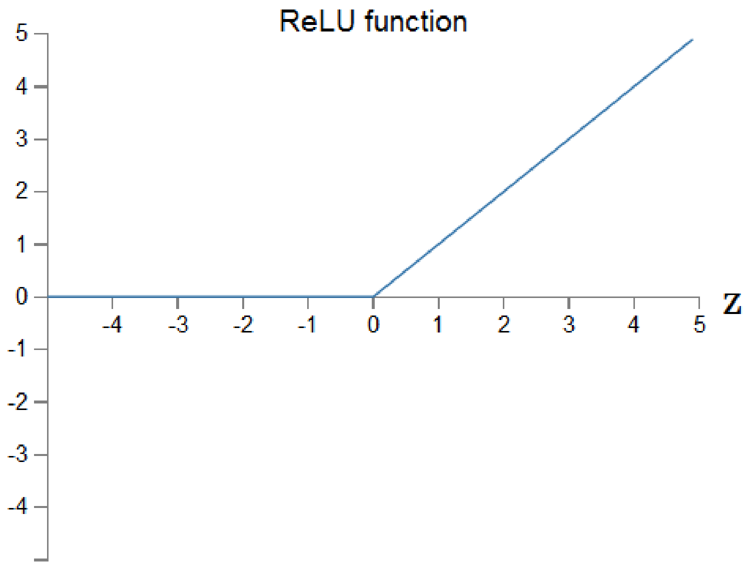


$$\tan(z) = \frac{e^{z}-e^{-z}}{e^{z}+e^{-z}}$$

Images taken from http://neuralnetworksanddeeplearning.com"”

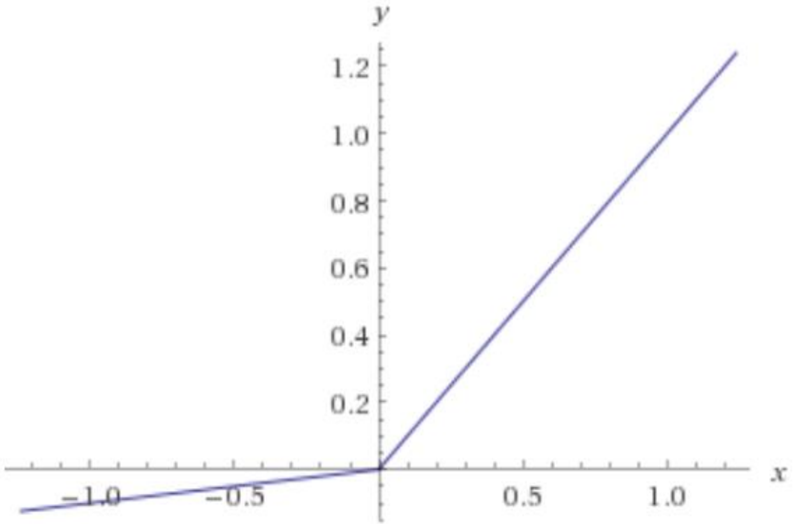
Architectures and activation functions
Activation functions

- ReLU function



$$\text{relu}(z) = \max(0, z)$$

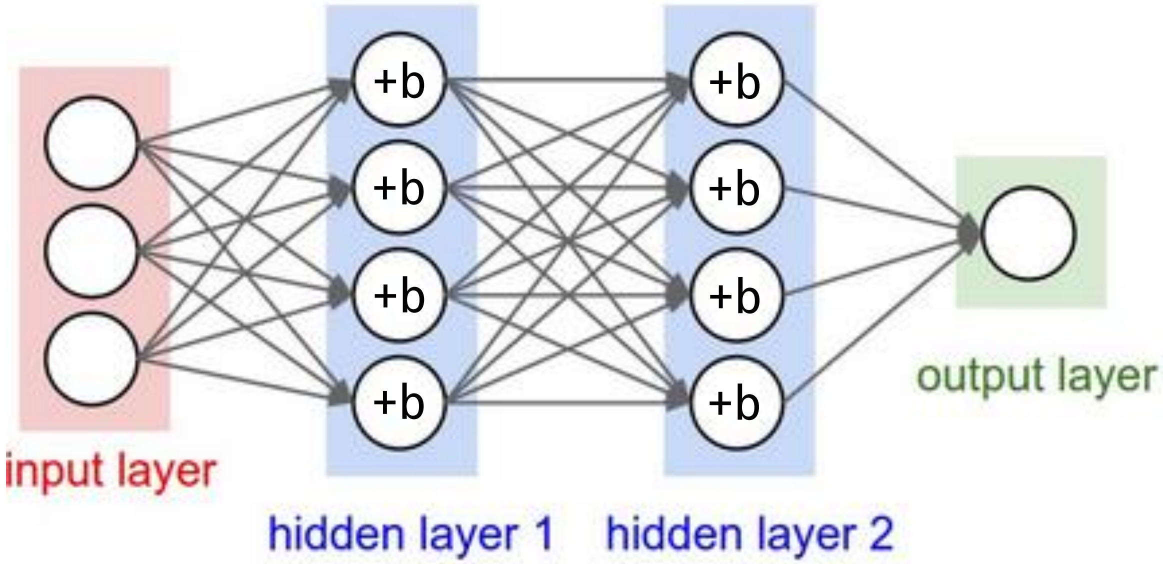
- Leaky ReLU function



$$\text{Lrelu}(z) = \max(0.01 * z, z)$$

Images taken from https://datascience.stackexchange.com/questions/5706/what-is-the-dying-relu-problem-in-neural-networks""

Architectures and activation functions
Architectures



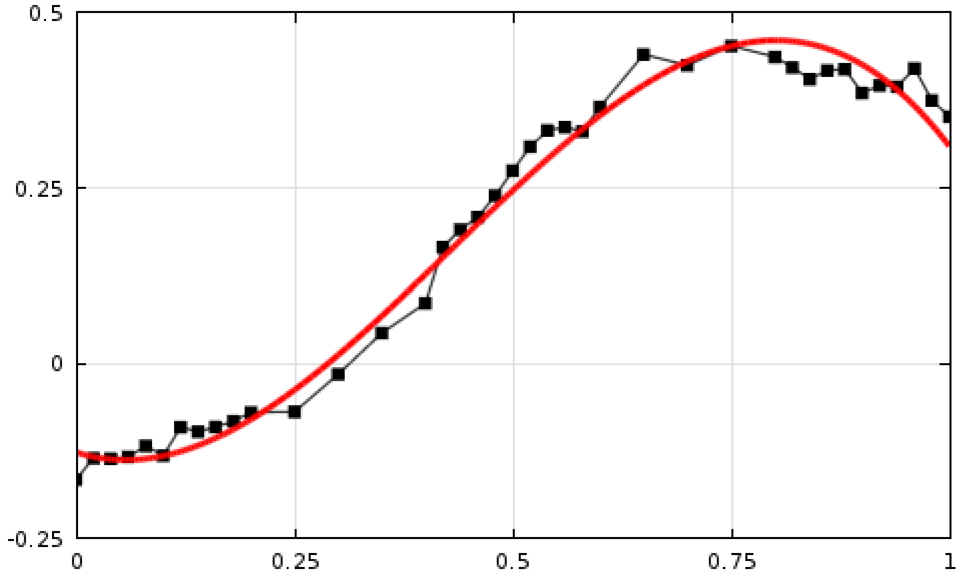
Images taken from http://cs231n.github.io/neural-networks-1””

APPLICATIONS

Neural networks

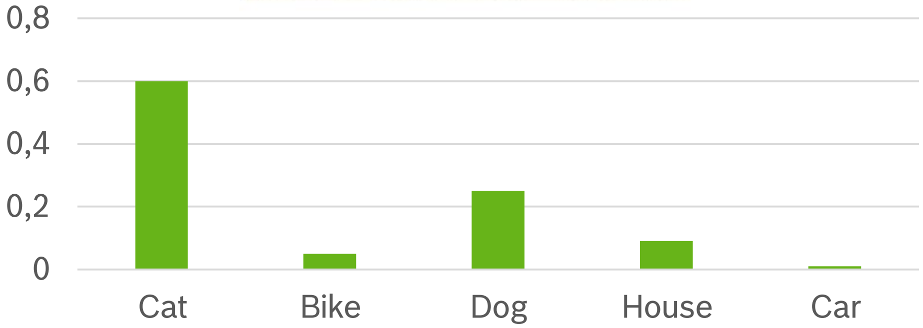
Regression vs Classification

- Fit some real-valued function
- $y_i = f(x_i, W), y_i \in \mathbb{R}$



https://cdn.comsol.com/wordpress/2015/03/Experimental-data-and-fitted-function.png

- Assign a label to an input vector
- $y_i = f(x_i, W),\ y_i \in \{cat, bike, dog, house, car\}$



Applications
Applications of shallow neural networks

Handwritten digit/character recognition

https://knowm.org/wp-content/uploads/Screen-Shot-2015-08-14-at-2.44.57-PM.png

Stock market (time series) prediction

http://milenia-finance.com/wp-content/uploads/635963392980931659203580943З_stock-market.jpg

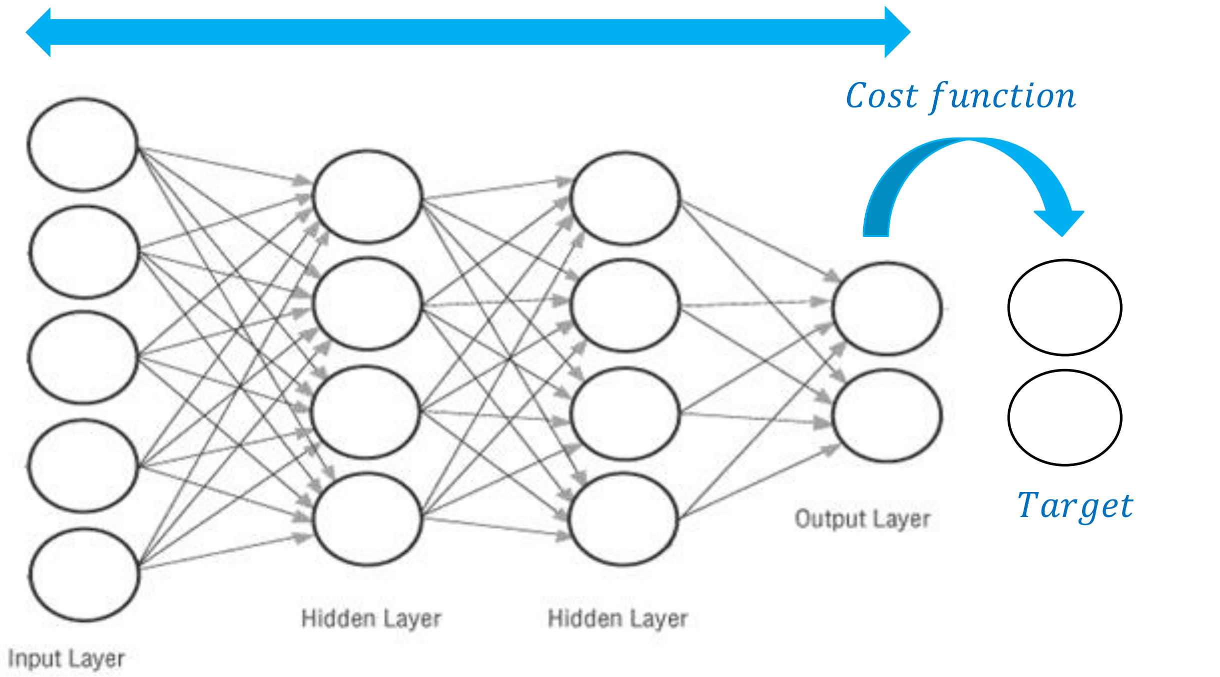
Image compression

https://ai2-s2-public.s3.amazonaws.com/figures/2016-11-08/1e50094bcaf81dac5ea44cea87fd84b25ceb9090/2-Figure3-1.png

TRAINING A NEURAL NETWORK
BACKPROPAGATION

Training a neural network - Backpropagation
General aspects

- Common method for training a neural network
- Goal: optimize the weights so that the neural network can learn how to correctly map arbitrary inputs to outputs (learn to generalize a problem)
- Steps:
  - ➢ Forward step
  - ➢ Compute the error
  - ➢ Backward step
  - ➢ Update parameters



*example valid for supervised learning

Image taken from “” https://mattmazur.com/2015/03/17/a-step-by-step-backpropagation-example””

Training a neural network - Backpropagation
Cost function

The Squared Error: $$C(w,b) = \frac{1}{2}\sum_{i=1}^{m}\|y(x_i) - \hat{y}(x_i,w,b)\|^2$$

- x_i: network input set
- $y(x_i)$: labeled output set (expected, true outputs)
- $\hat{y}(x_i,w,b)$: network outputs

- “How good" a neural network did w.r.t. it's given *m* training samples and the expected output
- The set of weights and biases have done a great job if $C(w,b) \approx 0$
- Our aim is to minimize it such that $\hat{y}(x_i,w,b)$ **becomes identical to** $y(x_i)$

How ?

Training a neural network - Backpropagation
Gradient descent

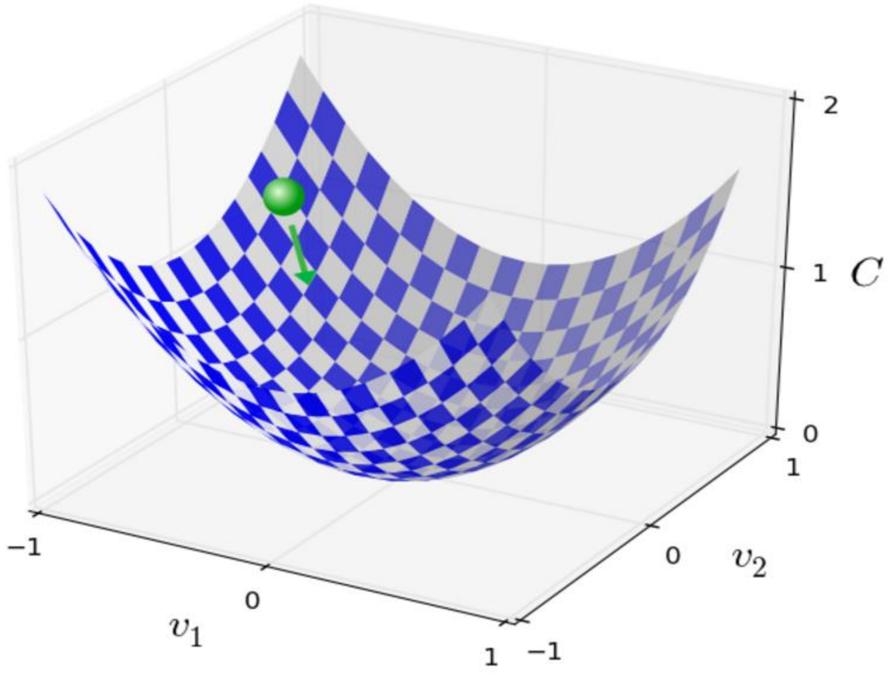
- Optimization algorithm used for finding the minimum of a cost function
- Cost function depends on weights and biases
- Gradient finds how much a weight or bias

causes the cost function's value

- Update weights and biases to minimize the cost

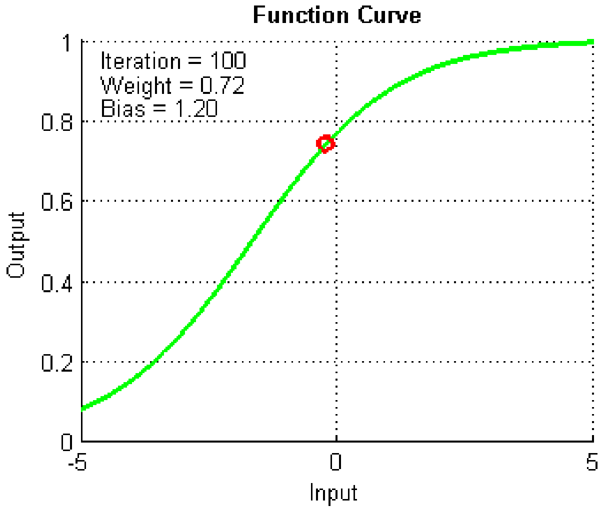
function

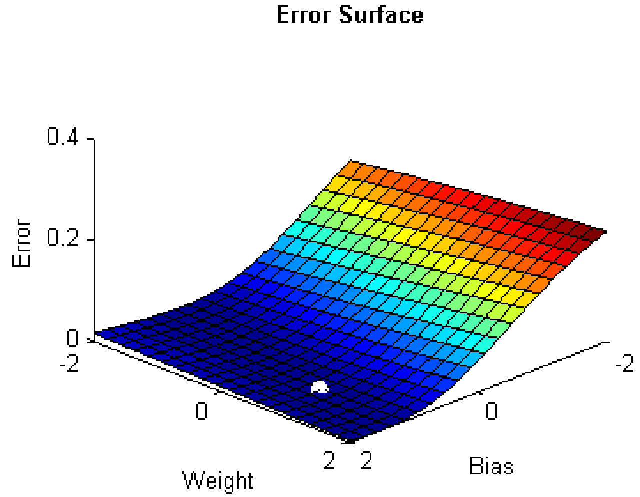
- **Learning rate:**
  - ➢ used for weights and bias updates
  - ➢ small, positive parameter
  - ➢ fixed or dynamic



Images taken from http://neuralnetworksanddeeplearning.com""

Training a neural network - Backpropagation
Gradient descent





Weight and bias update after a training sample:

learning rate

$$w_k \rightarrow w'_k = w_k - \eta \frac{\partial C}{\partial w_k}$$

$$b_l \rightarrow b'_l = b_l - \eta \frac{\partial C}{\partial b_l}$$

Images taken from http://neuralnetworksanddeeplearning.com""

DEEP LEARNING

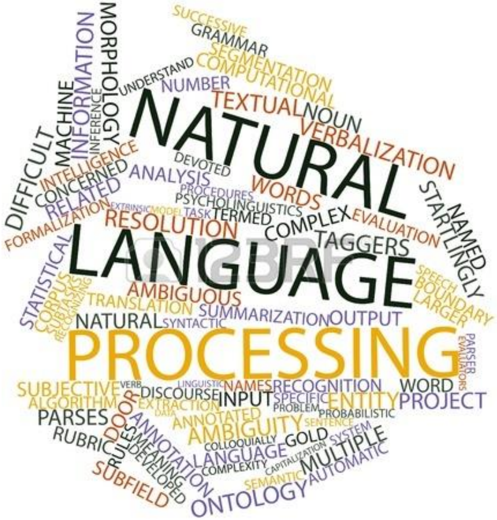
NAÏVE DEEP LEARNING

Naïve deep learning
Applications

- Exceptional effective at learning patterns
- Solves complex problems
- Applications:

Speech recognition

Computer vision



Natural language processing

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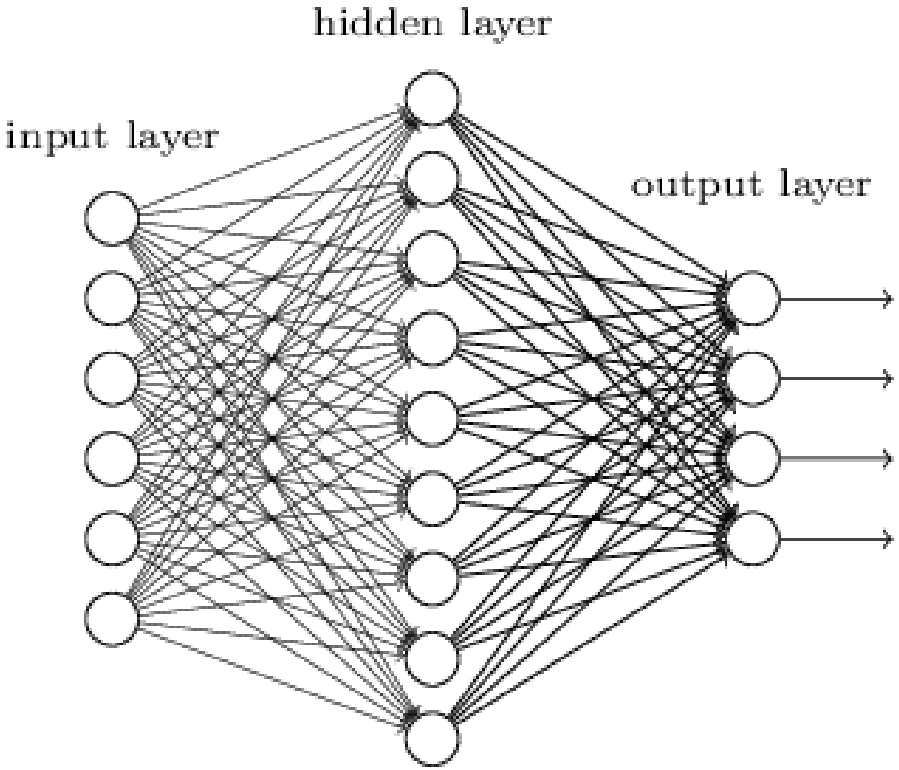
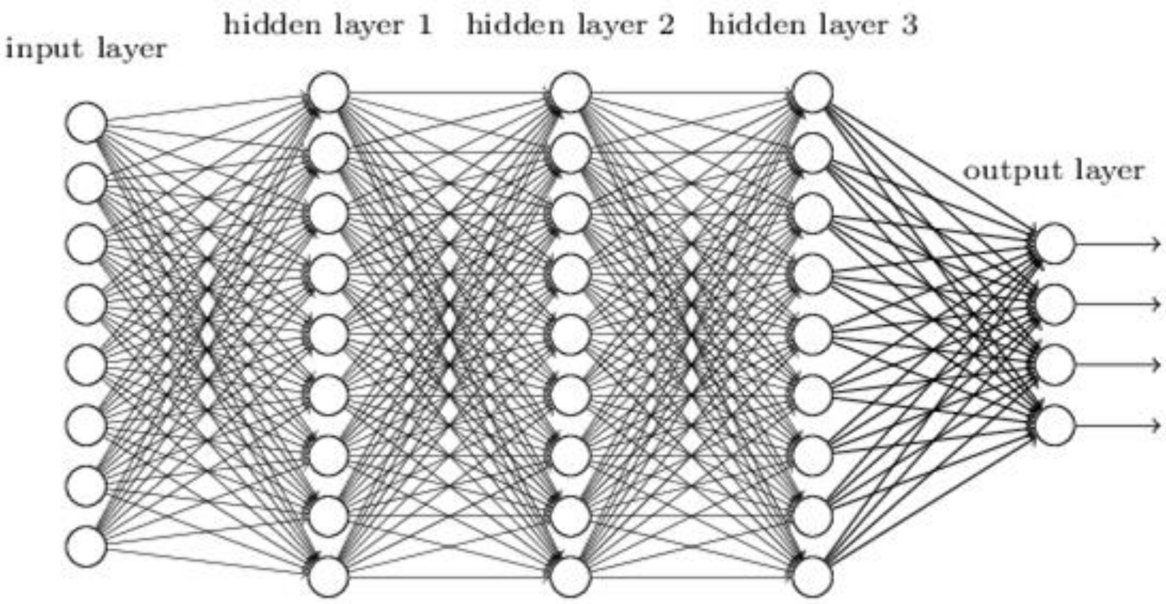
Naïve deep learning
From shallow to deep



Shallow Neural Network



Deep Neural Network

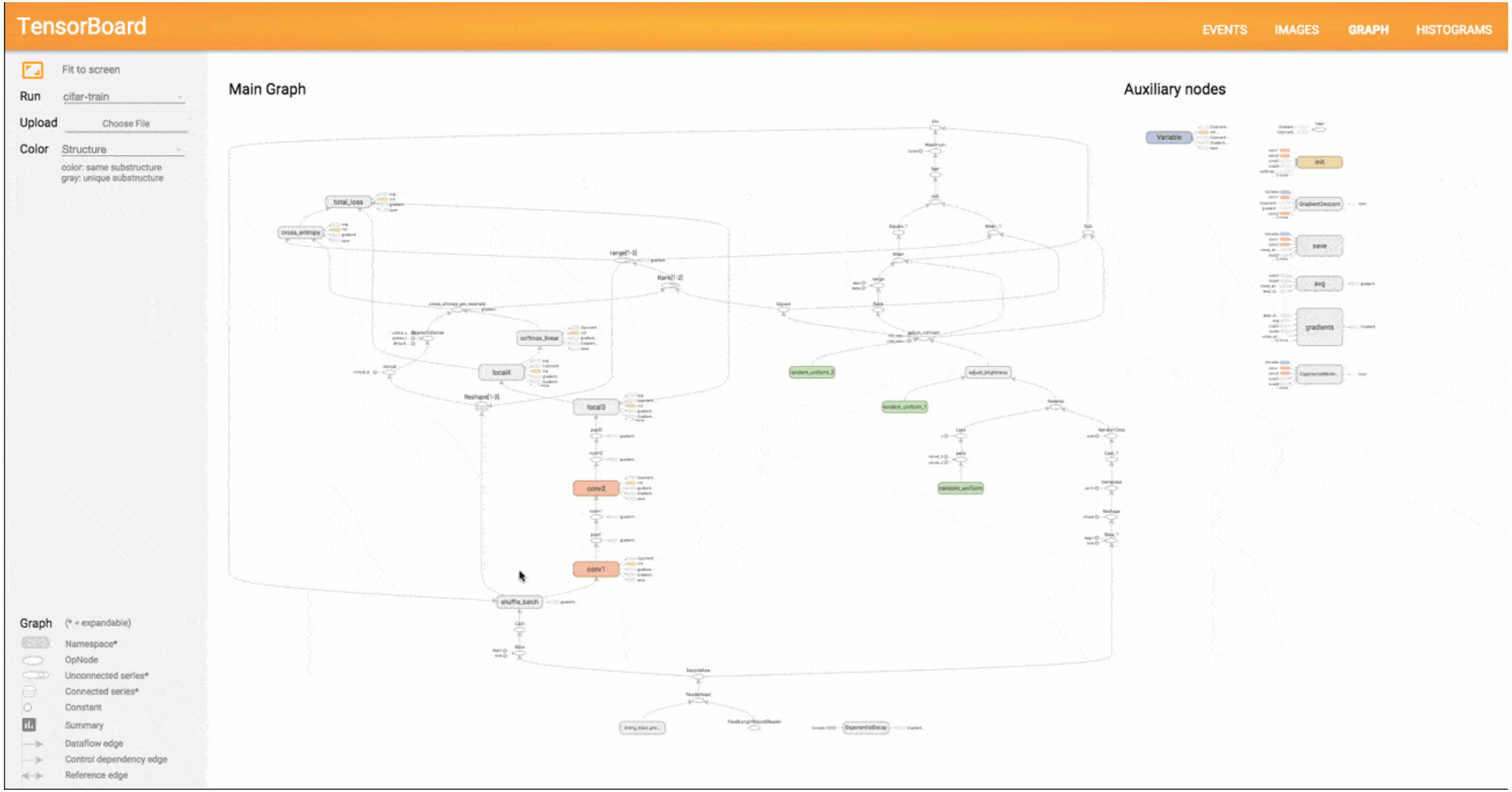
Source: http://neuralnetworksanddeeplearning.com

Naïve deep learning
Deep neural networks challenges

- Inputs are vectors => spatial relationships are not preserved (input scrambling)
- The number of parameters increases exponentially with the number of layers
- Huge number of parameters would quickly lead to overfitting
- Networks with many layers have an unstable gradient problem

DEEP LEARNING

Deep learning
Neural networks as computational graphs



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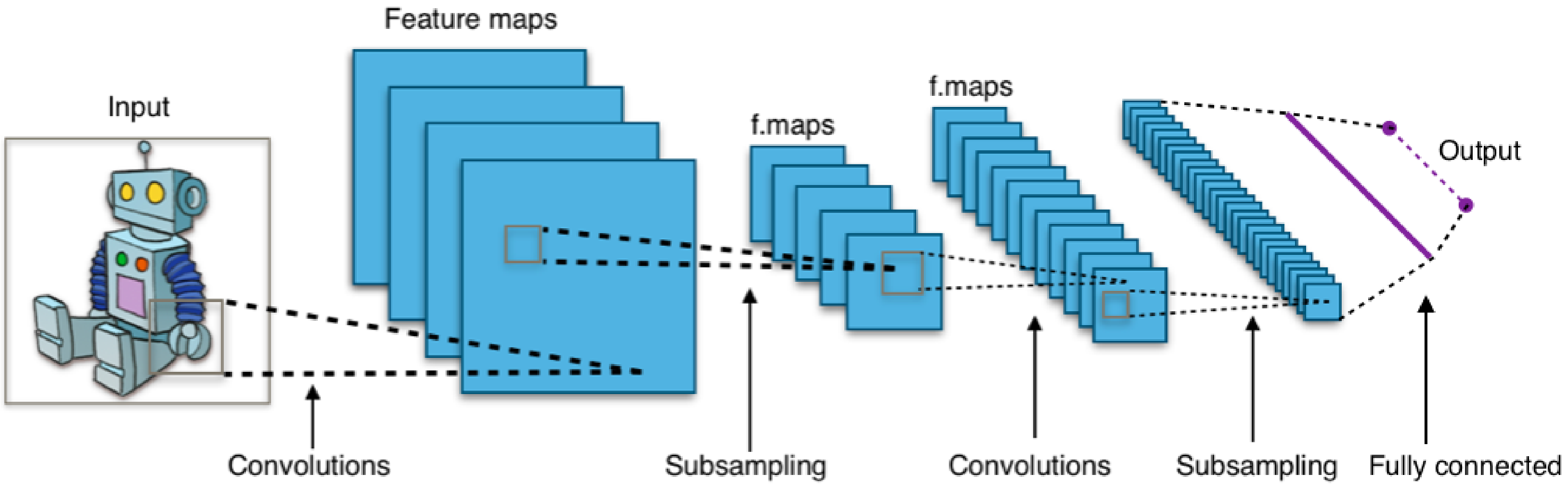
CONVOLUTIONAL NEURAL NETWORK

Convolutional Neural Network
Layers of Convolutional Neural Network

1. Input layer
2. Convolutional layer
3. Subsampling layer
4. Fully connected layer



Source: https://en.wikipedia.org/wiki/Convolutional_neural_network#/media/File:Typical_cnn.png

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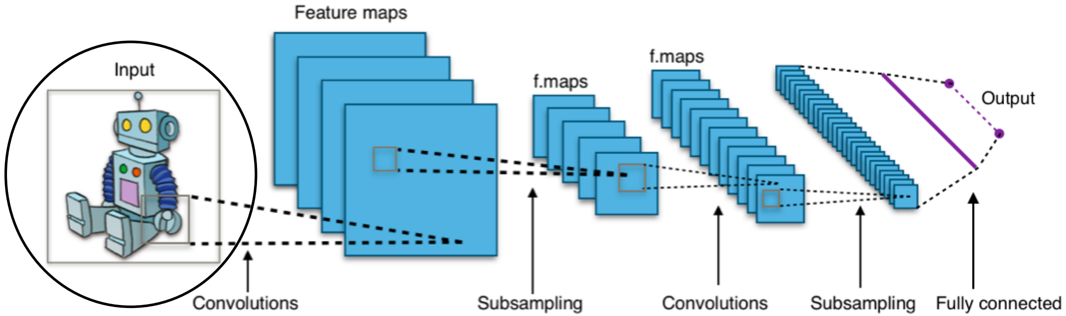
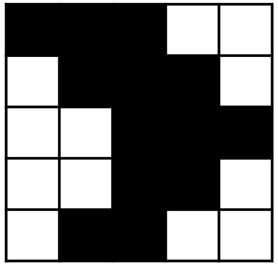
Convolutional Neural Network

Input layer: What is an image?



Binary image:

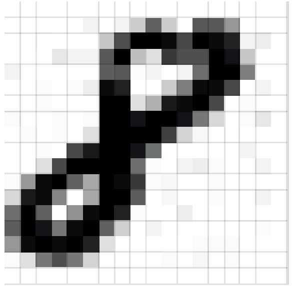
- A matrix of pixel values – each pixel is either 0 or 1



Binary

Grayscale image:

- A matrix of pixel values – each pixel is a natural number between 0 and 255
- Pixel value – intensity of light



Grayscale

RGB image:

- 3 matrices of pixel values – each pixel is a natural number between 0 and 255
- Pixel value – intensity of the color (red, green or blue)

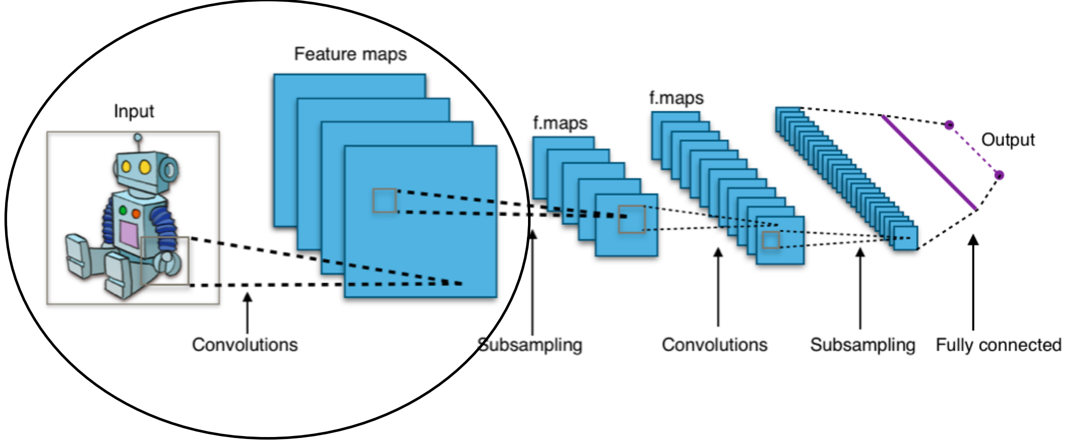
RGB image

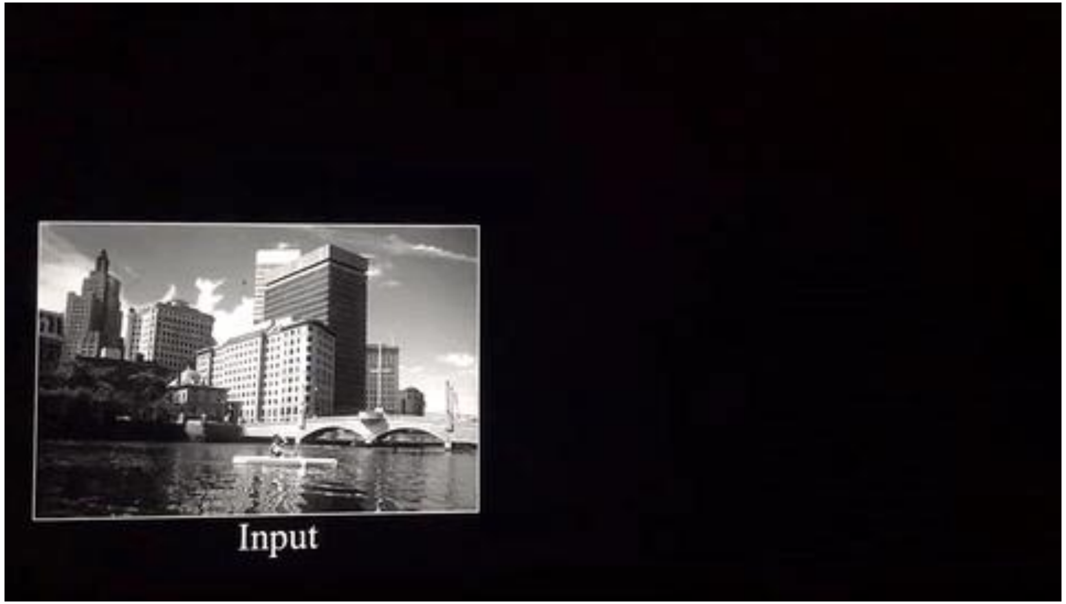
Source: https://medium.com/@ageitgey/machine-learning-is-fun-part-3-deep-learning-and-convolutional-neural-networks-f40359318721

Convolutional Neural Network
Convolutional layer

The purpose of convolution is to **extract features** from the input:

1. Gets a 3D matrix as an input
   e.g.: an RGB image with depth 3
2. “Convolves” multiple kernels on the input 3D matrix
3. Creates the output 3D matrix: the feature maps – also called activation maps





Source: http://cs.nyu.edu/~fergus/tutorials/deep_learning_cvpr12/

Convolutional Neural Network
Convolution on a single matrix

Input:

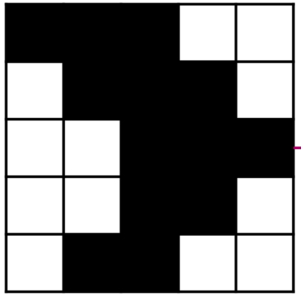
- W_1 x H_1 matrix (e.g. binary image)
- Kernel (filter): W_2 x H_2 matrix

Convolution operation:

- Slide the kernel over the W_1 x H_1 matrix
- At each position calculate element wise multiplication
- Calculate the sum of multiplications

Output:

- W_3 x H_3 matrix –> feature map (activation map)



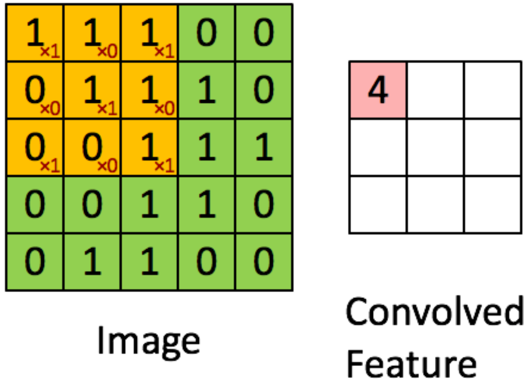
Input image

1	1	1	0	0
0	1	1	1	0
0	0	1	1	1
0	0	1	1	0
0	1	1	0	0

Input matrix

1	0	1
0	1	0
1	0	1

Kernel



Source: http://deeplearning.stanford.edu/wiki/index.php/Feature_extraction_using_convolution

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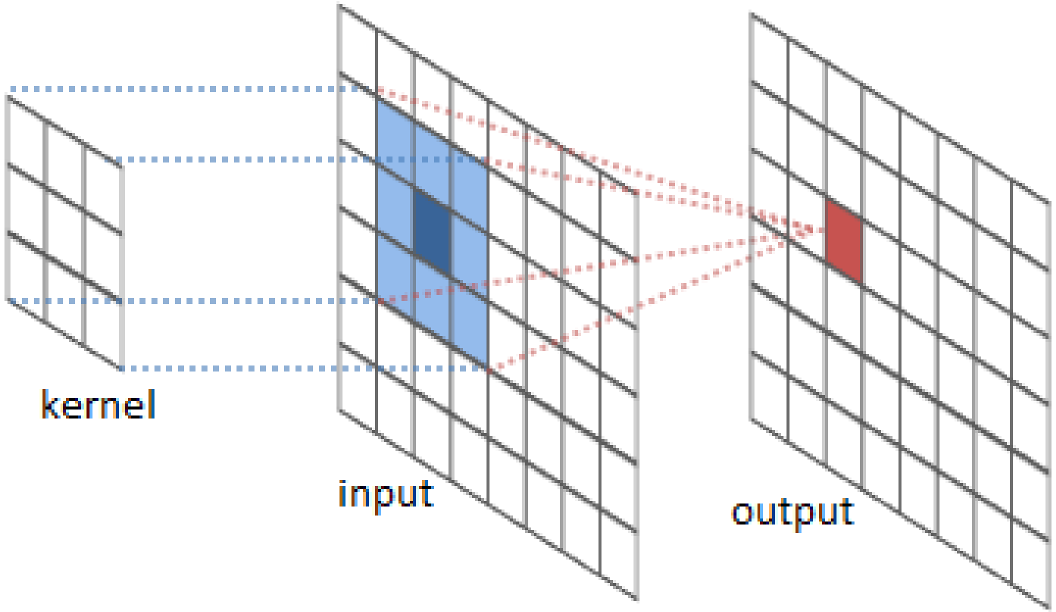
Convolutional Neural Network
Convolution on a single matrix

- Another view of the convolution operation



W_1 x H_1 matrix

W_2 x H_2 matrix

W_3 x H_3 matrix (feature map)

http://intellabs.github.io/RiverTrail/tutorial/

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Convolutional Neural Network
What is a kernel?

- **It is a learnable filter**
- The values (weights) of the kernel will be learned during the training process
- The trained filter will activate on the image (during the forward pass) when it sees some type of visual feature on the image (e.g.: edges)

- The **size of the kernel** is a **hypermarameter** of the convolutional layer
- Typical kernel sizes: 3x3, 5x5

-5	8	-1
-2	6	3
7	-1	4

Random kernel

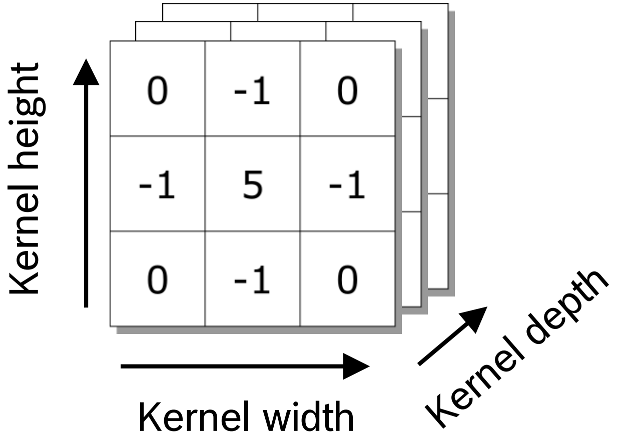
→

0	-1	0
-1	5	-1
0	-1	0

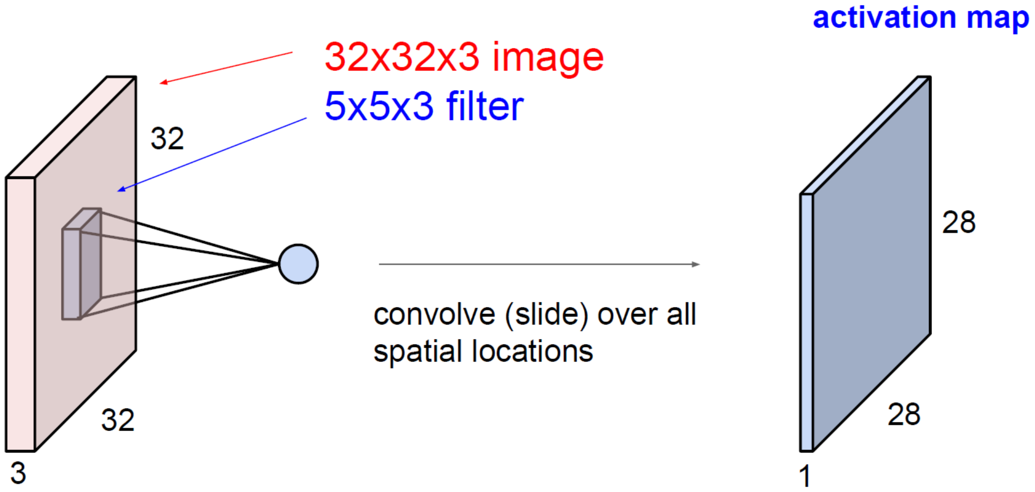
Trained kernel

Convolutional Neural Network
Convolution on a 3D matrix

- The input is an W_1 x H_1 x $\mathbf{D_1}$ 3D matrix
  - W_1 x H_1 is the width and height of the 3D matrix
  - $\mathbf{D_1}$ is the depth of the 3D matrix
  - E.g.: an RGB image (with 3 channels)
- To convolve a kernel on the 3D matrix, the depth of the kernel should be the same: W_2 x H_2 x $\mathbf{D_1}$



- The convolution operation is still the same:
  - Slide (convolve) the kernel across the width and height of the input 3D matrix
  - At each position calculate element wise multiplication
  - Calculate the sum of multiplications
  - (It produces 1 value at each position)
- The output of the convolution is an W_3 x H_3 x 1 feature map



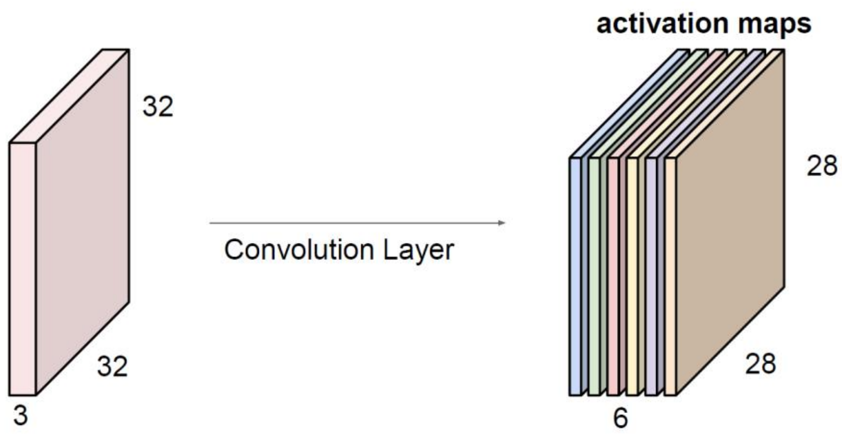
Source: https://leonardoaraujosantos.gitbooks.io/artificial-inteligence/content/convolutional_neural_networks.html

Convolutional Neural Network
Multiple kernels

- A convolution layer usually contains **multiple kernels**
- Each kernel produces a separate 2 dimensional feature map
- Stacking these feature maps, one can get the output volume of the convolution layer

- The number of kernels (the depth of the output volume) is defined by the **depth hyperparameter**

Convolution with 6 different kernels:



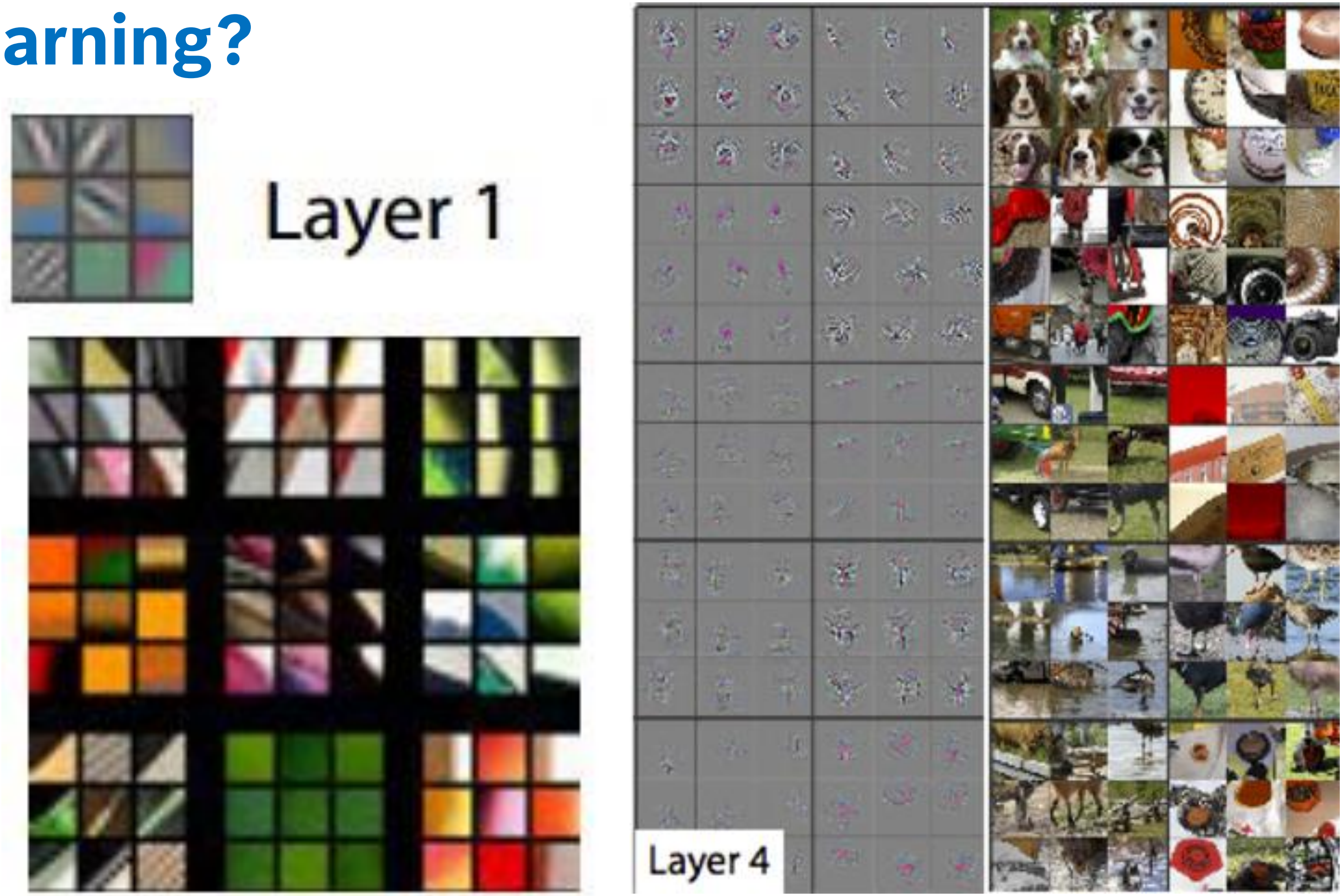
Input 3D matrix

Output - 3D matrix
6 different feature maps

Source: https://leonardoaraujosantos.gitbooks.io/artificial-inteligence/content/convolutional_neural_networks.html

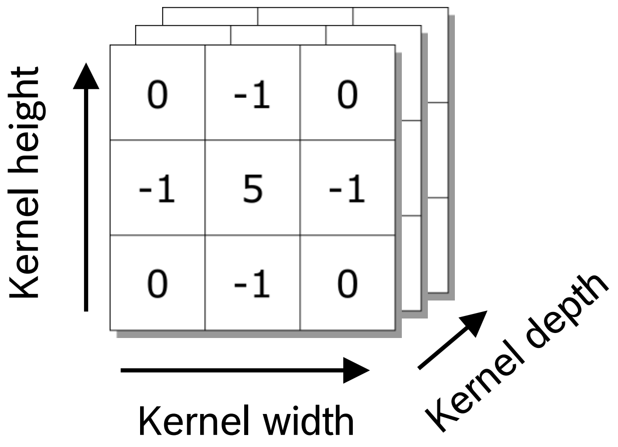
Convolutional Neural Network
What are the filters learning?

- ▶ 1st layer: edges
- ▶ 2nd layer: corners, local textures
- ▶ 3rd layer: simple shapes
- ▶ ...
- ▶ nth layer: complex shapes, objects



Source: Zeiler & Fergus, 2014

Convolutional Neural Network
Convolutional Layer - Summary

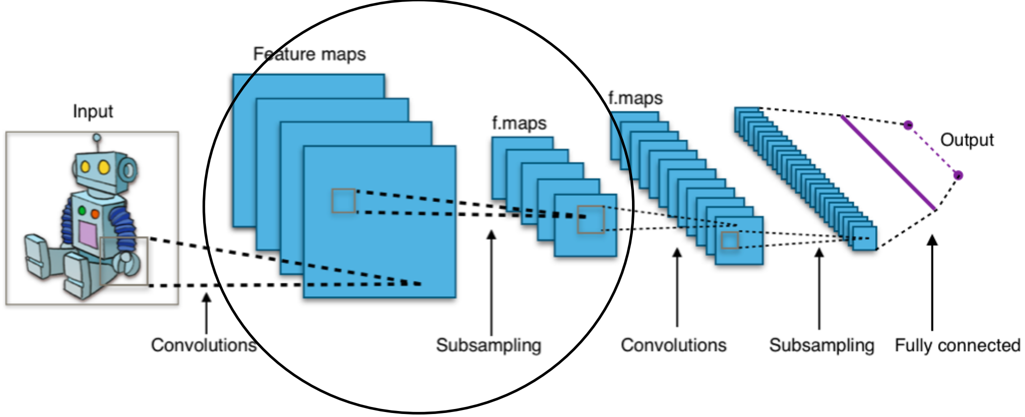


Convolution:

- Input: W_1 x H_1 x D_1 3D matrix
- Output: W_3 x H_3 x D_3 3D matrix

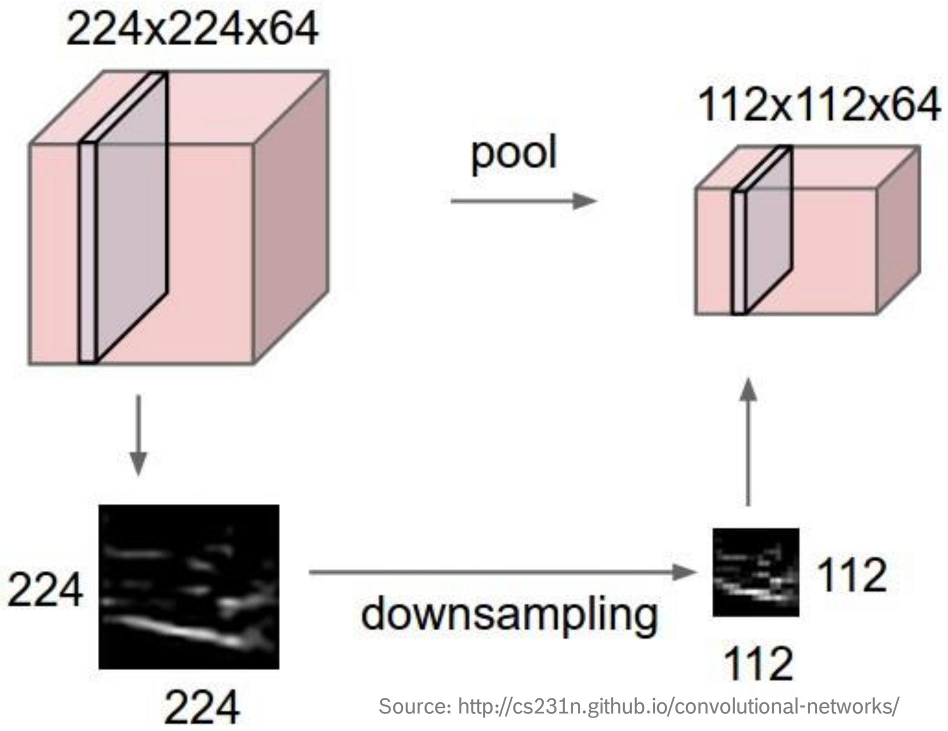
- Hyperparameters of the convolutional layer:
  - Size of the kernel: $\mathbf{W_2}$ **x** $\mathbf{H_2}$ (the depth of the kernel is equal with the input depth)
  - Number of kernels (depth of the output): $\mathbf{D_3}$
  - Stride: **S**
  - Padding: **P**

Convolutional Neural Network
Subsampling (Pooling) Layer



- Perform a downsampling operation along the spatial dimensions – width, height
- It reduces the spatial size of the representation

- It operates independently on every depth slice of the representation
- Most common subsampling operation: **max pooling**

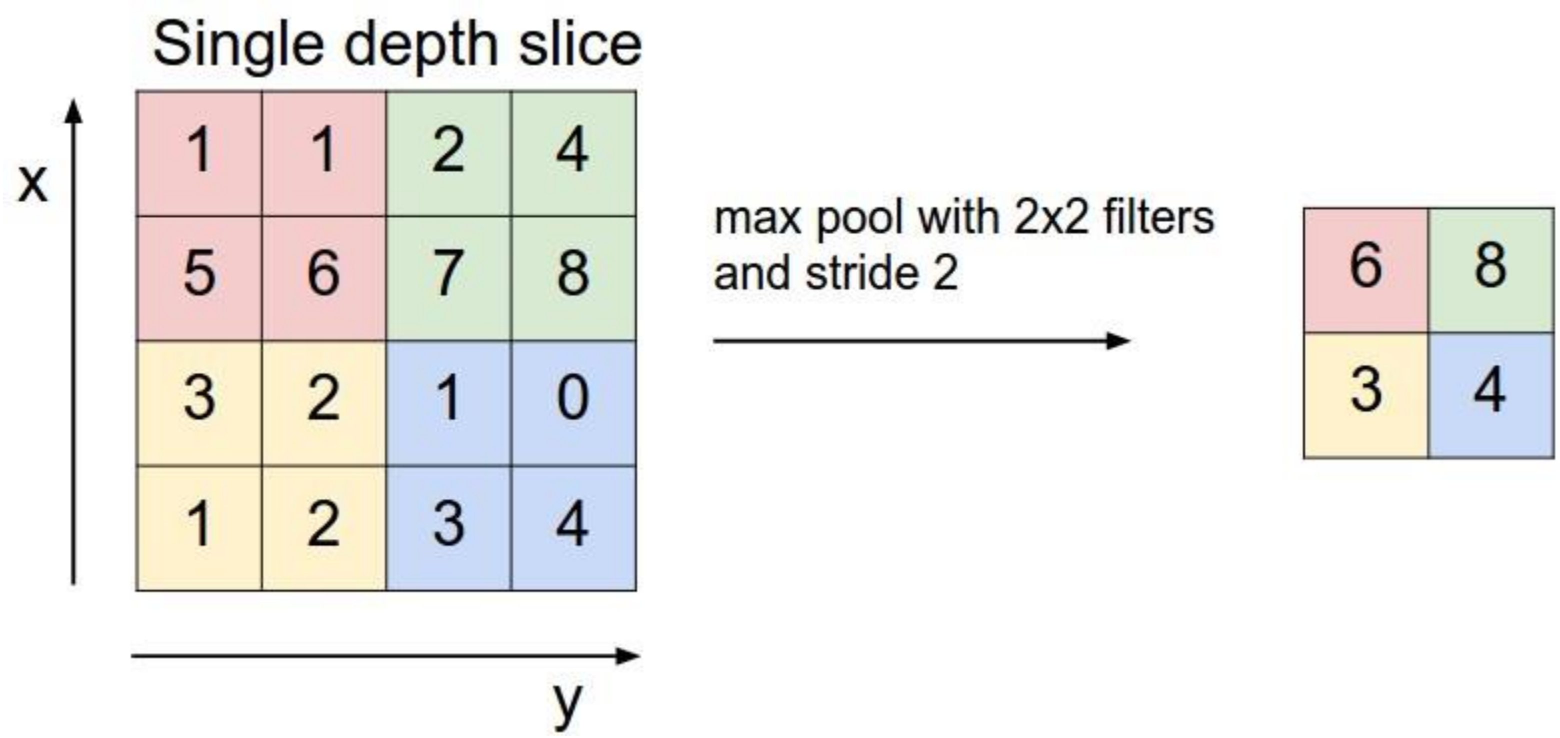


Source: http://cs231n.github.io/convolutional-networks/

Convolutional Neural Network
Example: max pooling

Hyperparameters:

- Size of stride
- Size of the filter



Source: http://cs231n.github.io/convolutional-networks/

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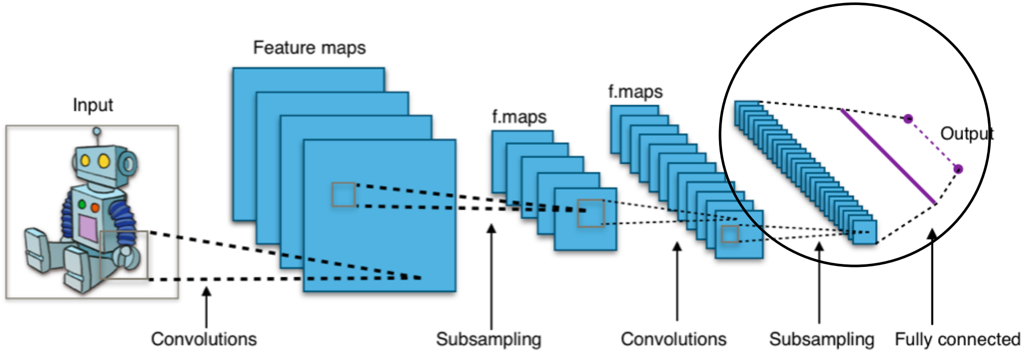
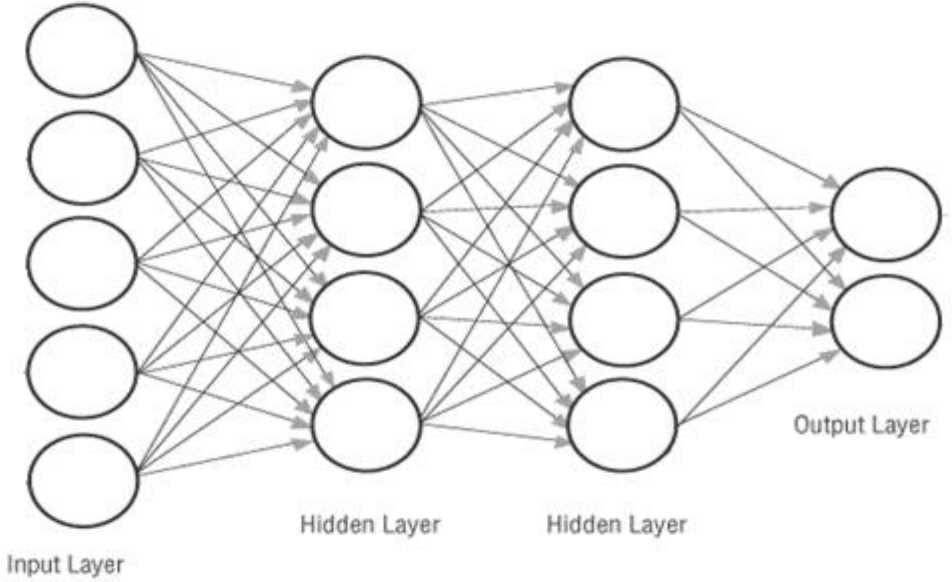
Convolutional Neural Network
Fully Connected Layer

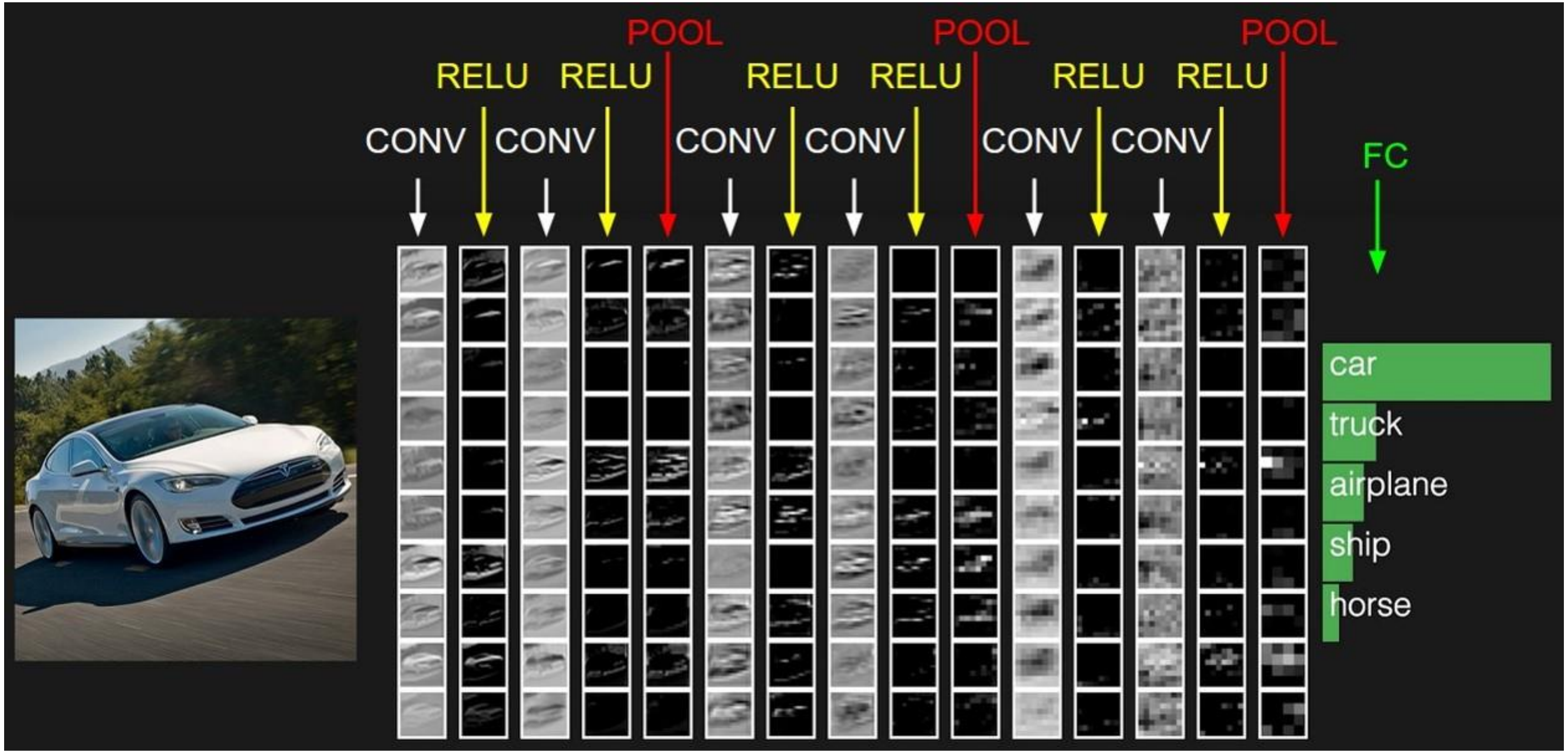
- It is a neural network (similar as in the previous course)
- The **input** of the layer are the features extracted by the convolution and subsampling layers
- The **output** of the layer is the output of the full CNN
(for example class probabilities)





Source: http://cs231n.github.io/convolutional-networks/

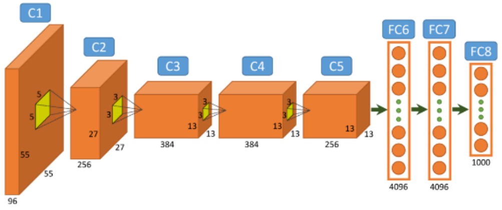
Convolutional Neural Network
Information flow in a CNN

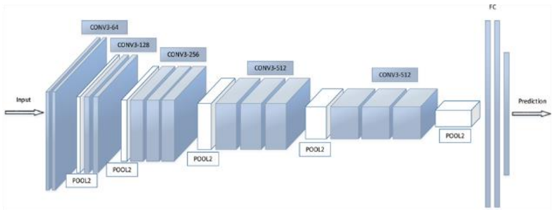


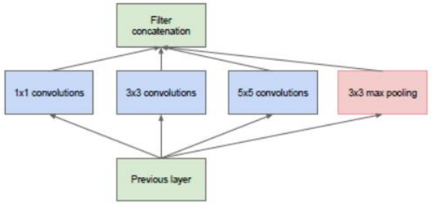
Source: http://cs231n.github.io/convolutional-networks/

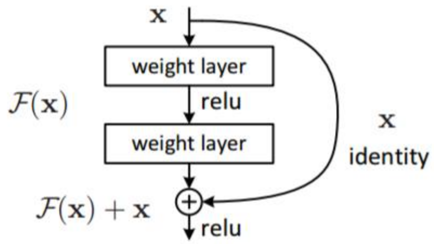
Convolutional Neural Network
History and state of the art

- **AlexNet**
  - Initial architecture that had good performance (2012)
  - 7 layers
- **VGGNet**
  - Better performance using deeper network with less parameters (2014)
  - 16 layers
- **GoogLeNet**
  - Better performance using processing done in parallel on same input (2014)
  - Over 100 layers
- **ResNet (Microsoft)**
  - Better performance using residual information (2015)
  - 152 layers





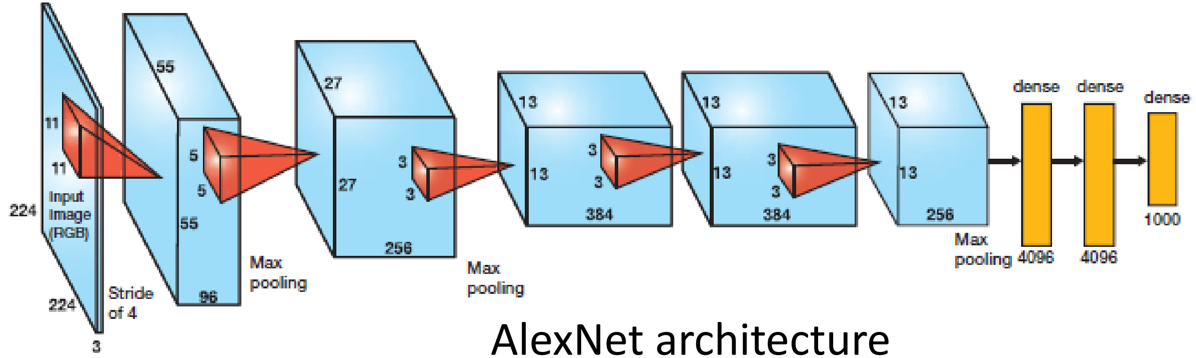




- Models can be trained to perform many different tasks, with few modifications

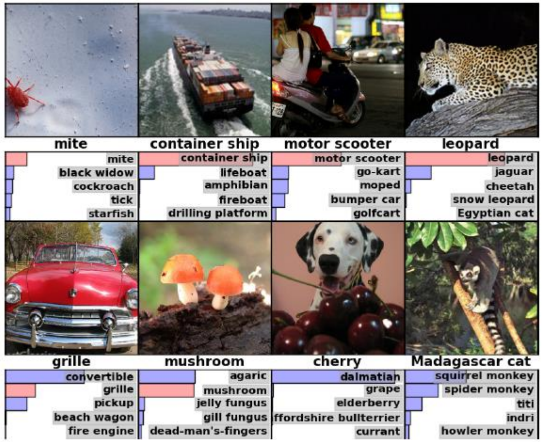
Sources: http://cv-tricks.com/cnn/understand-resnet-alexnet-vgg-inception/
https://www.saagie.com/blog/object-detection-part1
http://file.scirp.org/Html/4-7800353_65406.htm

Convolutional Neural Network
Case study: AlexNet



AlexNet architecture

Train images



Results on test images

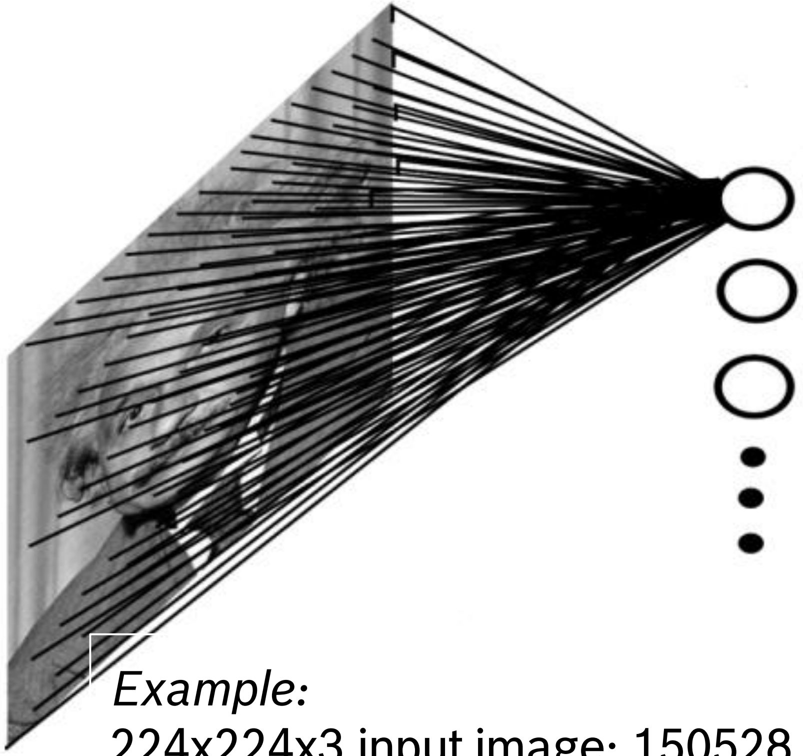
- ImageNet Large Scale Visual Recognition Challenge winner in 2012
- Task: images classification (each image is associated with a class)
- Dataset:
  - ImageNet 2012
  - Training set: 1.2 million images containing 1000 categories (classes)
  - Testing set: 200.000 images
- Training details:
  - 90 full training cycle on the training set
  - The **training took 6 days** on two GeForce 580

Sources: http://cv-tricks.com/cnn/understand-resnet-alexnet-vgg-inception/
https://papers.nips.cc/paper/4824-imagenet-classification-with-deep-convolutional-neural-networks.pdf

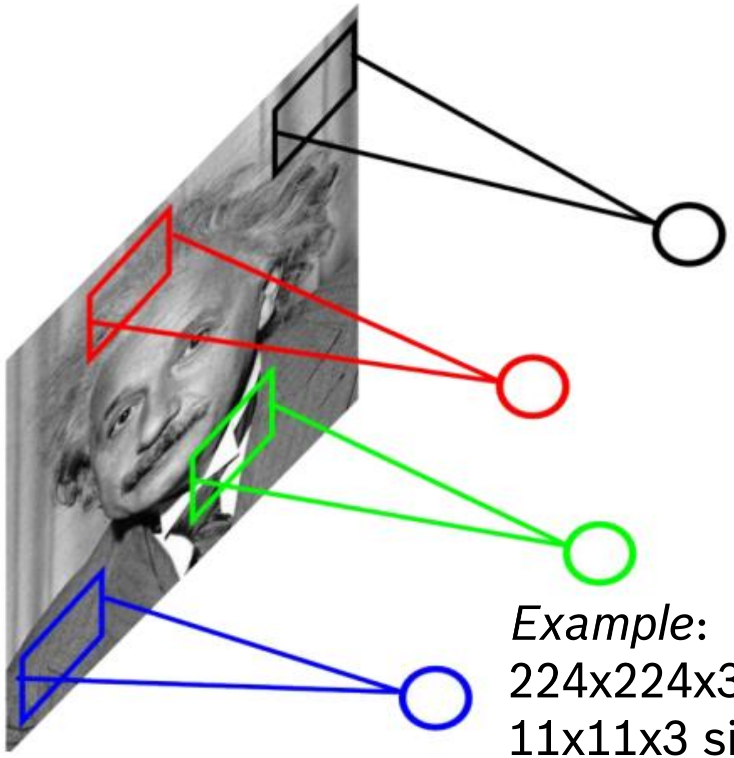
MOTIVATION OF CONVOLUTIONAL NEURAL NETWORK

BOSCH

Motivation of Convolutional Neural Network
Parameter sharing



Example:
224x224x3 input image: 150528 long input
=> 150528 weights per neuron
150528*3 (451584) parameters (for 3 neurons)

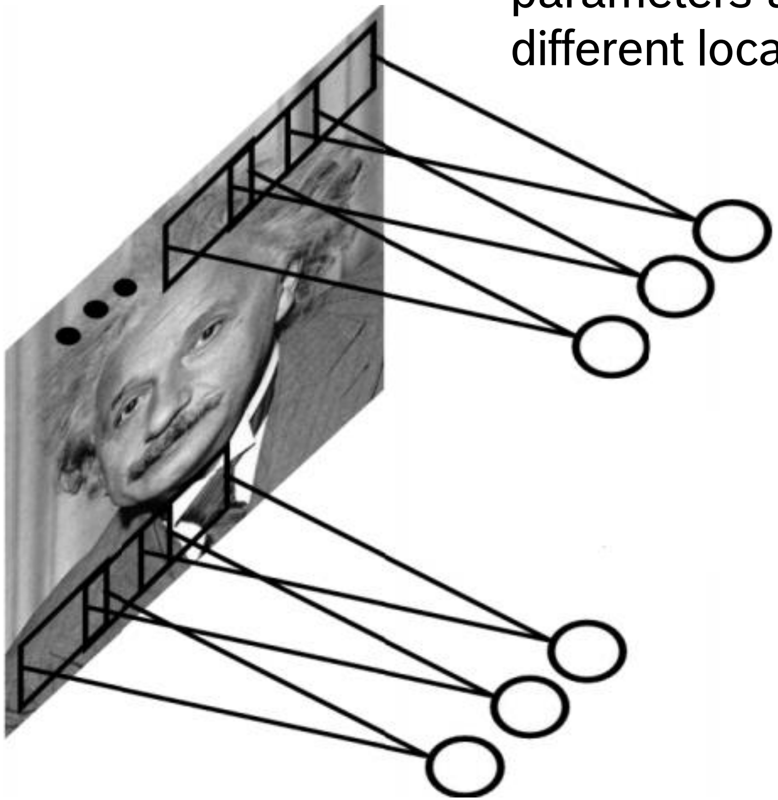


Example:
224x224x3 input image
11x11x3 size of a filter
3 filters
11*11*3*3 (1089) parameters (for 3 filters)

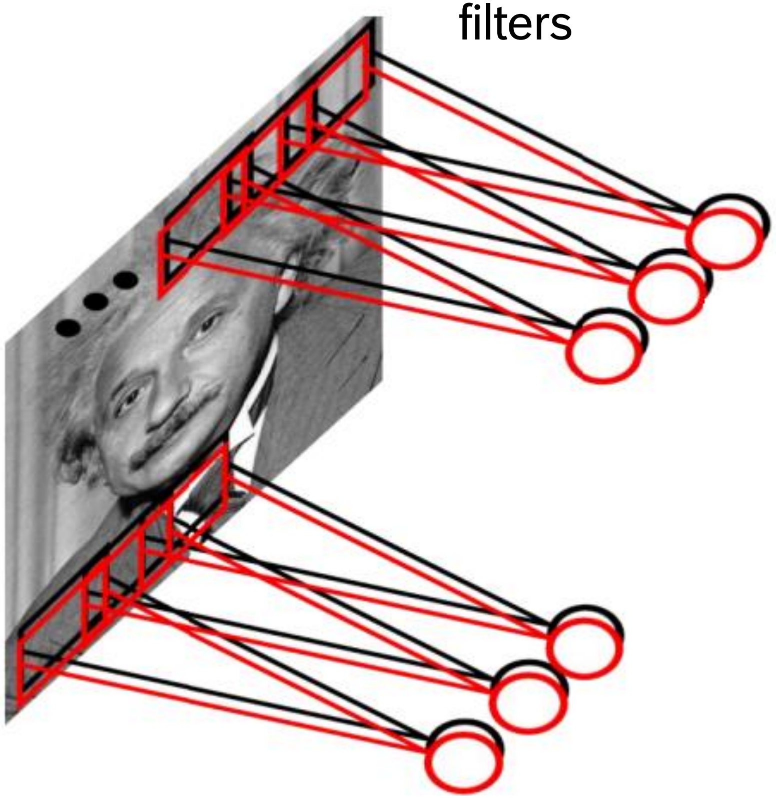
Source: https://noppa.oulu.fi/noppa/kurssi/521010j/luennot/521010J_convolutional_neural_network.pdf

Motivation of Convolutional Neural Network
Local connectivity and spatial invariance

Share the same parameters across different locations



Apply and learn multiple filters



Source: https://noppa.oulu.fi/noppa/kurssi/521010j/luennot/521010J_convolutional_neural_network.pdf

Motivation of Convolutional Neural Network
Benefits

- The same small set of weights (parameters) is applied on an entire image
- Better training. Better generalization
- Preserves spatial relationships in the receptive field
- Spatial invariance

Parameter sharing

Local connectivity

BOSCH

CONCLUSION

Conclusion
And some tips

Strengths of deep learning:

- It's a general framework
- Efficient graph structure
- Well performing given the right circumstances

You should consider deep learning if:

- you have access to quite large amounts of data
- the problem is reasonably complex, in a high dimensional space
- no hard constraints or hard logic (smooth, differentiable)

RESOURCES

Resources
Libraries and networks

- C++ fans for easy prototyping:
  - OpenCV – both Neural Networks and Adaboost
  - FANN – Fast Artificial Neural Network Library
  - OpenNN – Open Neural Network Library
  - Nnabla – Neural network libraries by Sony

- Python:
  - **Tensorflow**
  - Keras
  - Theano
  - **Caffe(also for C++)**
  - **Torch7**
  - **PyTorch**
  - **DeepLearning4J**
  - **MXNet**
  - Deepy
  - Lasagne
  - Nolearn
  - NeuPy

Resources

Learning resources

- Stanford CS231n course (Karpathy et. al.)
- Deep learning book (Goodfellow)
- various introductory YouTube videos
- For beginners: www.reddit.com/r/LearnMachineLearning
- After you grasp the concepts: www.reddit.com/r/MachineLearning

THANK YOU

QUESTIONS?