Introduction to Deep Learning

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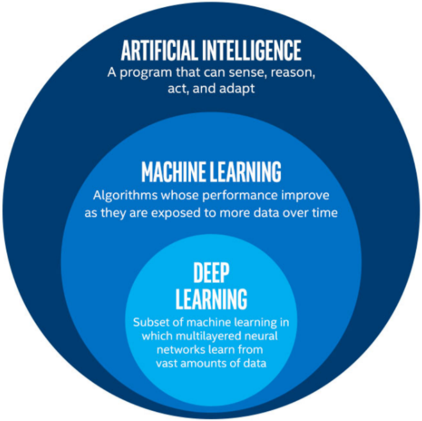
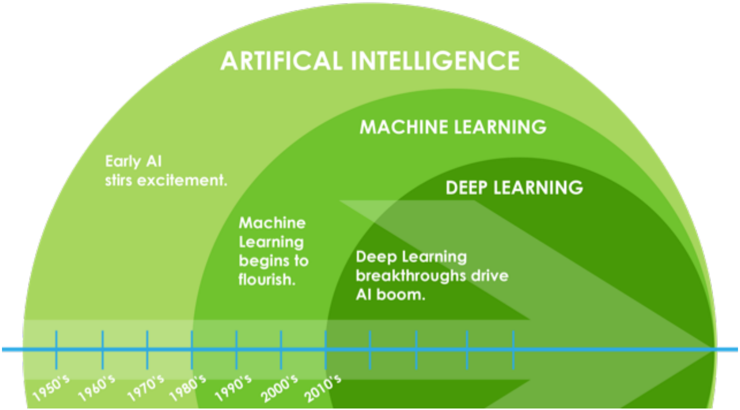
Artificial Intelligence, Machine Learning and Deep Learning



Source: Cousins of AI, https://towardsdatascience.com/cousins-of-artificial-intelligence-dda4edc27b55

A bit of history



Source: https://buzzrobot.com/difference-between-artificial-intelligence-machine-learning-and-deep-learning-ccfd779eca7b

Learning Algorithm

Definition of Learning Algorithm [Mitchell 1997][1]

A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E.

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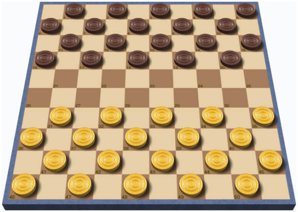
- the measure of performance P
- the source of experience E

Example: checkers game



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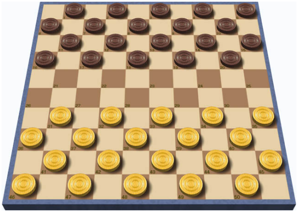

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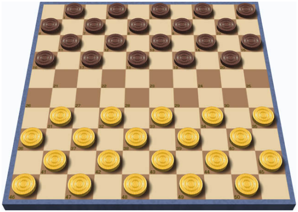

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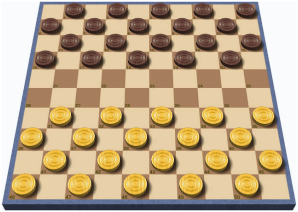

- **task class T:** playing checkers
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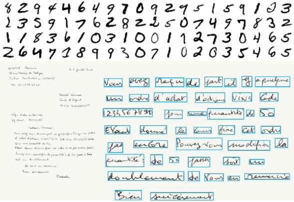
- **training experience E:** playing practice games against itself

Example: handwritten characters recognition



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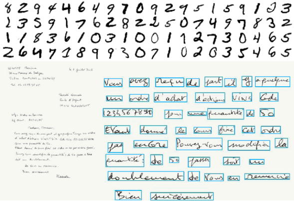

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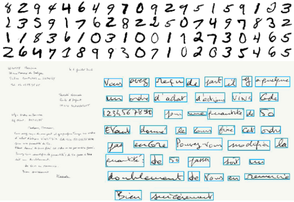

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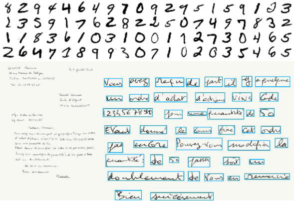

- **task class T:** recognizing and classifying handwritten characters within images
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Example: supervised learning

- **training experience E:** a number of traininig examples $E = \{z_1, z_2, z_3 \dots\}$
  each example is a (input,target) pair: $Z_i = (X_i, Y_i)$

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Examples:

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  - Y is a scalar real value
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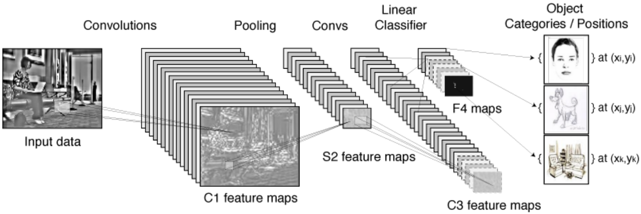
  - L is usually the euclidean norm
- classification
  - X is a real-valued scalar or vector (features)
  - Y is an integer (label) corresponding to a class index
  - f is able to provide the probability of X_i being in class Y_i
  - L is usually the negative log-likelihood

Deep Learning



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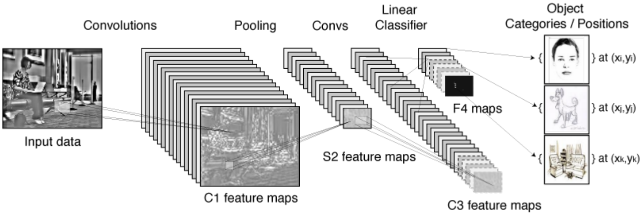
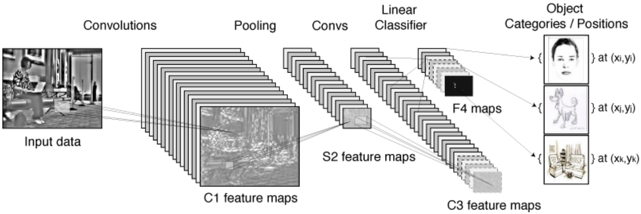
Deep Learning



- Application of an Artificial Neural Network to a data set to find a pattern

Deep Learning



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- Multiple hidden layers (to mimic human brain processes associated to vision/hearing)

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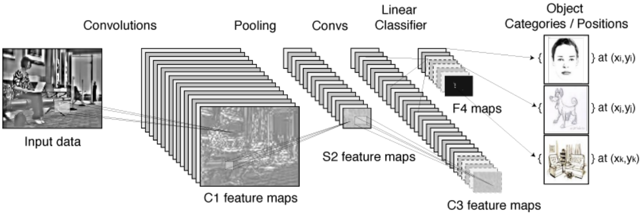

- Application of an Artificial Neural Network to a data set to find a pattern
- Multiple hidden layers (to mimic human brain processes associated to vision/hearing)
- Big data sets and relevant number of variables

Deep Learning

A recently published review[1] can help on summarizing main aspects of deep learning.

1. Models are composed of multiple processing layers:
   - multiple layers of abstraction to learn data representations.
2. Improved state-of-the-art in:
   - speech recognition, object recognition, object detection;
   - drug discovery, genomics.
3. Discovers complex patterns in large datasets:
   - backpropagation to change layer parameters;
   - representation in each layer is based on previous layer results;
4. Specialized networks for different data;
   - deep convolutional networks: image, video, speech;
   - recurrent networks: sequential data (text, speech).

[1] Yann LeCun, Yoshua Bengio, Geoffrey Hinton, **Deep Learning**, Nature 2015

Limits of conventional ML techniques

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- feature extraction is a necessary step for transforming raw data into an internal representation;
- considerable domain expertise is needed to pick a representation suitable to the task.

On the other side, they consider deep learning methods as representation-learning methods.

"Representation learning is a set of methods that allows a machine to be fed with raw data and to automatically discover the representation needed for detection or classification"

Neural networks as representation learning methods

Data flow:

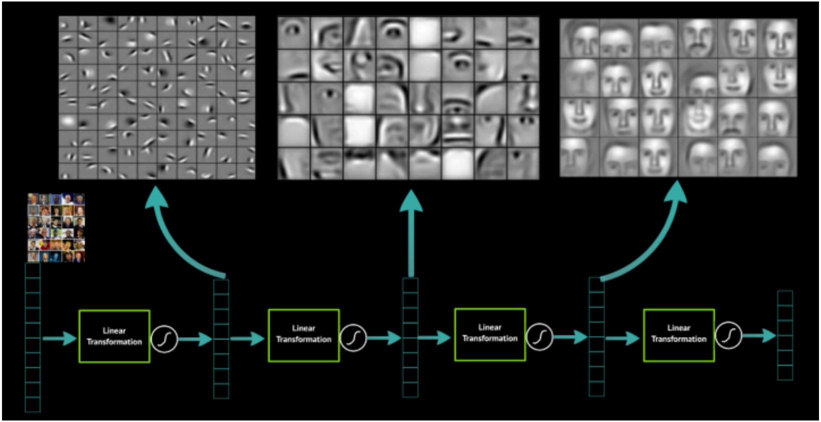
- input: raw data;
- output: detection/classification distribution probabilities;
- in the process: a layer is fed with data representation learned from previous layer.

Key aspects:

- no a-priori design of features;
- they are learned from data using a general purpose procedure.

Image Example

edges motifs familiar objects



Deep learning main results (I)

- Good at discovering intricate structures in high-dimensional data.
- Exhibits superior performances (compared to other ML techniques):
  - image and speech recognition;
  - prediction of the activity of potential drug molecules;
  - analysing particle accelerator data;
  - reconstructing brain circuits;
  - predicting the effects of mutations in non-coding DNA on gene expression and disease.
- Shows promising results in natural language processing (NLP):
  - topic classification, sentiment analysis, question answering and language translation.

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Deep learning main results (II)

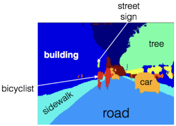
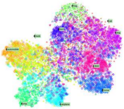
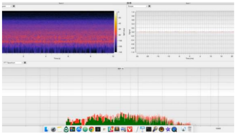


Image recognition

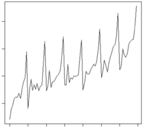


Natural language processing



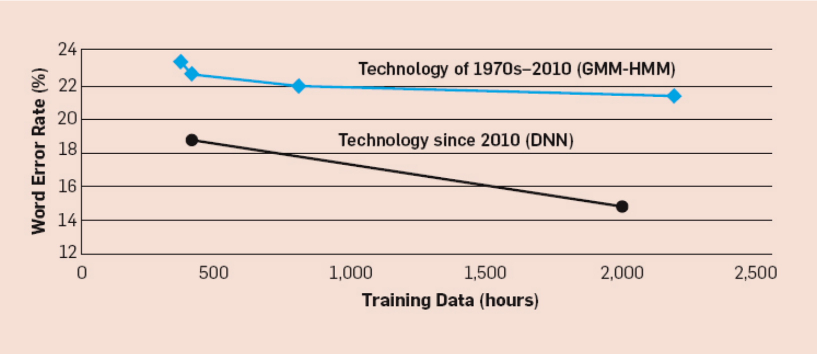
Speech recognition

Video activity detection



Tabular and time-series data applications

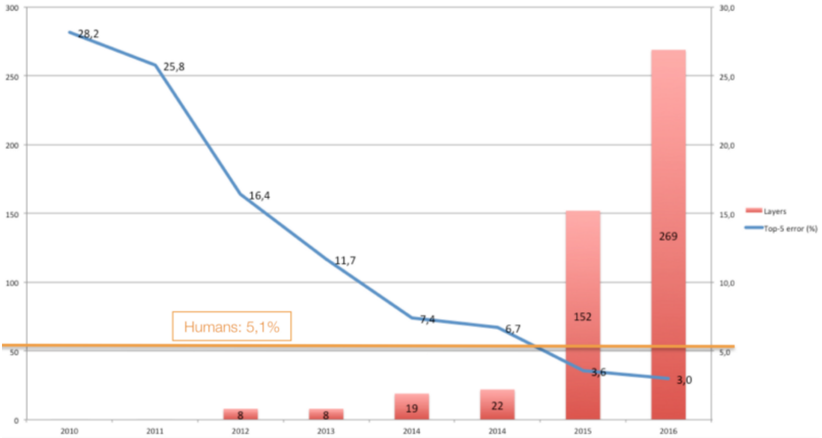
Accuracy on Speech Recognition



Source: Huang, Baker, Reddy, **A Historical Perspective of Speech Recognition**, Communications of the ACM, January 2014

GMM: Gaussian Mixture Models, **HMM:** Hidden Markov Models, **DNN:** Deep Neural Networks

How deep is deep learning?



Number of layers in ILSVRC (ImageNet Large Scale Visual Recognition Competion) winners, compared to accuracy.

How deep learning works?

In the following, we will see:

- the effect of adding a fully connected layer to an existing classifier;
- the effect of describing our data in a "wider" hyperspace.

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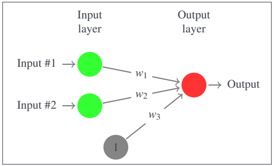
Idea from a blog post: Olah, **Neural Networks, Manifolds, and Topology**:
http://colah.github.io/posts/2014-03-NN-Manifolds-Topology/

2d example (I)

Define a simple network:



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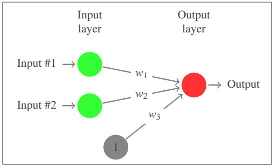

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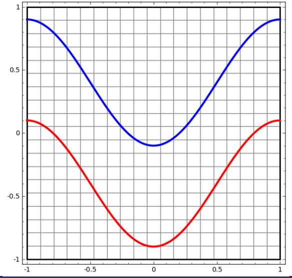
Labeled observations: $\forall i \; (x_i, y_i) \rightarrow l_i$



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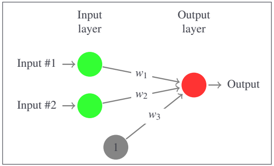

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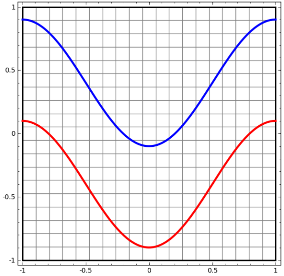
Labeled observations: $\forall i \ (x_i, y_i) \rightarrow l_i$ optimize: $w = \arg\min \sum_i (l_i - o_i)^2$



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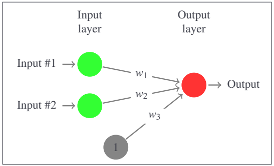

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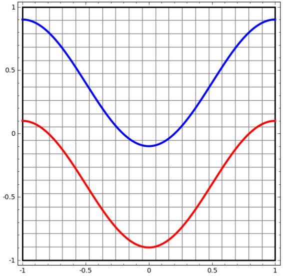

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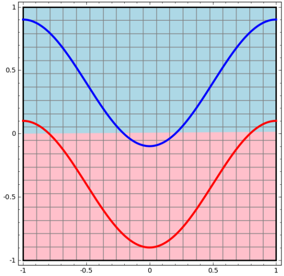

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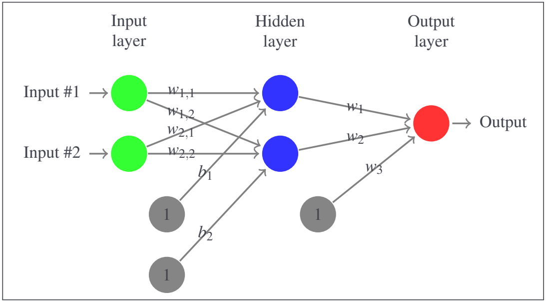

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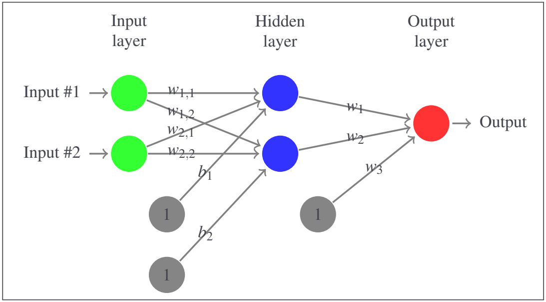

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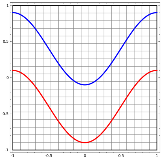
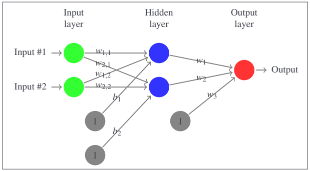
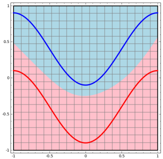
Hidden layer: evaluated features







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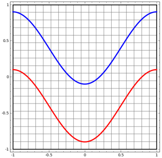
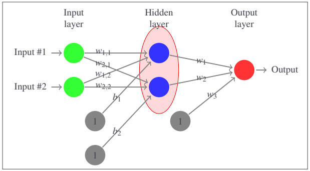
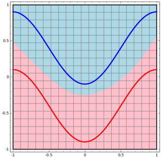
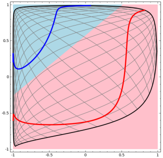
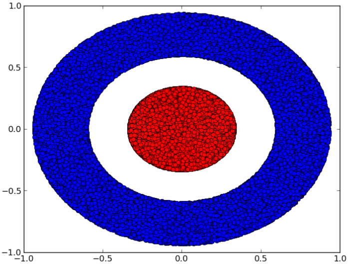








Increase the dimensionality



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- Even if it can get an 80% of classification accuracy

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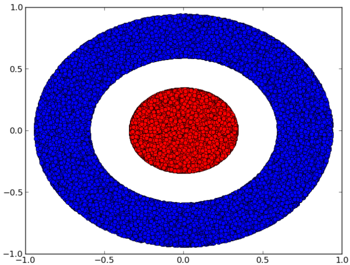

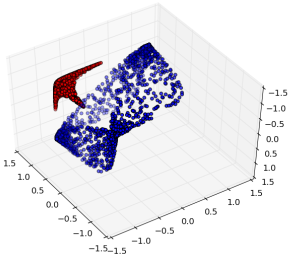

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Neural Network Internals: classification problem

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$$\hat{y} = f(\boldsymbol{x}; \boldsymbol{W})$$

prediction input NN parameters

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- a Stochastic Gradient Descent (SGD) algorithm step is:

$$\boldsymbol{W}^{(k+1)} = \boldsymbol{W}^{(k)} - \varepsilon_k \hat{\boldsymbol{g}}^{(k)} \qquad \text{where} \qquad \hat{\boldsymbol{g}}^{(k)} = \frac{1}{n}\nabla_{\boldsymbol{W}} \sum_{l \in \text{batch}} L(f(\boldsymbol{x}^{(l)}; \boldsymbol{W}^{(k)}), \boldsymbol{y}^{(l)}), \quad n = \#\text{batch}$$

Backpropagation

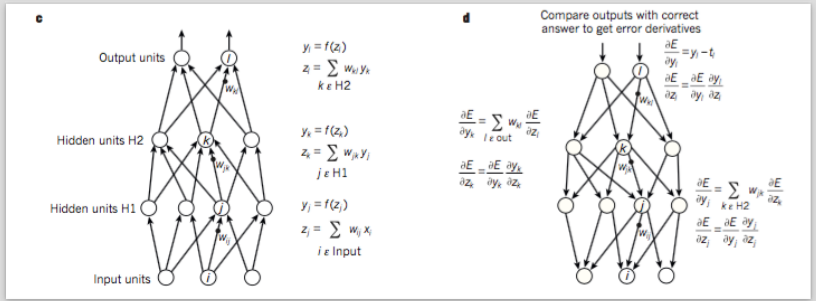


Image from Yann LeCun, Yoshua Bengio, Geoffrey Hinton, **Deep Learning**, Nature 2015.

See also:
https://google-developers.appspot.com/machine-learning/crash-course/backprop-scroll/

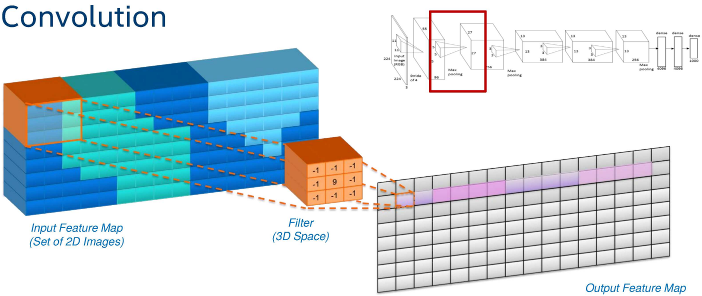
Introduction

Machine Learning Background

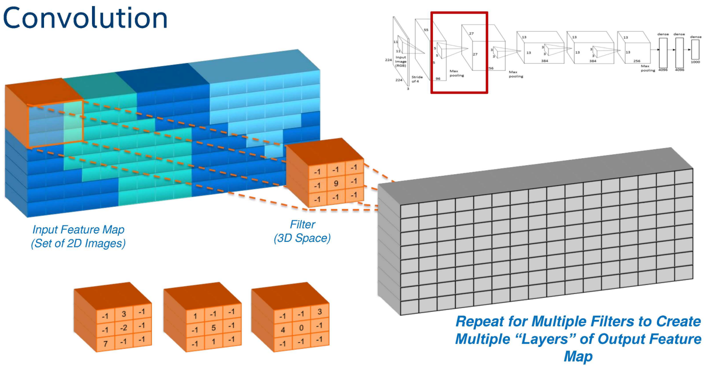
Deep Learning: a review

Convolutional Networks

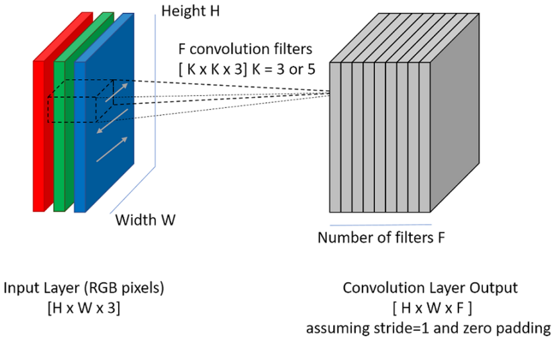
Convolutional layer (I)



Convolutional layer (I)

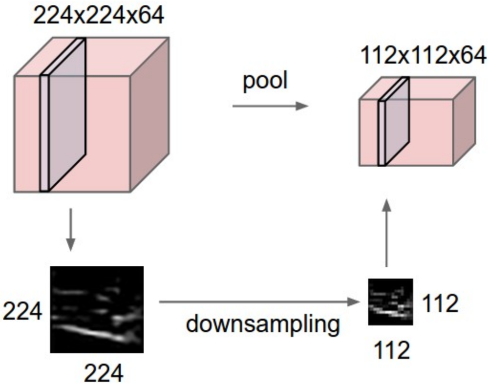


Convolutional layer (II)



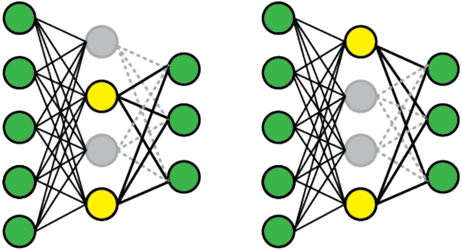
- Convolution Layer output: $H - \frac{K-1}{2}, W - \frac{K-1}{2}$ with *stride* $= 1$ and without padding
- For each filter we have $K \times K \times 3$ weights
- The filter convolves over all spatial locations, producing a scalar for each location
- An activation function is finally applied

Pooling layer



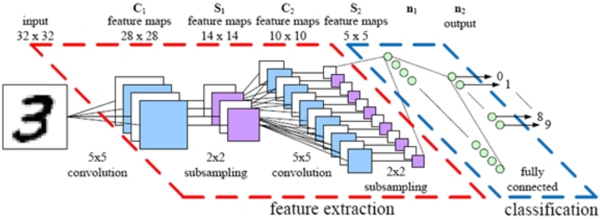
- makes the representations smaller and more manageable
- operates over each activation map independently
- Example: max pooling computes the maximum with $K \times K$ filter

Dropout layer



- In each forward pass, randomly set some neurons to zero.
- Probability of dropping is a hyperparameter; 0.5 is common

Convolutional network



- LeNet[2] . The first successful convolutional neural network
- Designed to identify hand-written digits in the MNIST dataset
- LeNet-5 takes a single-channel 2D input
- Performs 6 convolution (5×5) , then subsamples by max-pooling (2×2).
- The convolution-pooling layer sequence occurs again
- Finally 2 fully connected layer followed by a fully connected softmax layer is performed

[2] Yann Lecun and Léon Bottou and Yoshua Bengio and Patrick Haffner, **Gradient-based learning applied to document recognition**, 1998

Reference Convolutional Neural Networks

CNN used in image classification with reference results available:

- VGG 16 (Simonyan, Zisserman, 2014)
  - thirteen convolutional layers (kernel size: 3×3 output channels: $64, 128, 256, 512$)
  - five maxpool layers
  - three fully connected layers
  - Rectified Linear Unit ReLU as nonlinear activation function
- ResNet 50 and 152 (He, Zhang, Ren, Sun, 2015)
  - fifty and one hundred fifthy-two convolutional layers
    - various kernel sizes (7×7,3×3,1×1);
    - various output channels: 64, 128, 256, 512;
  - max-pool and fully-connected layers;
  - "residual" learning: output of convolutional layer is summed to input that generated it;
  - Rectified Linear Unit (ReLU) as nonlinear activation function
- Inception (Szegedy, Vanhoucke, Ioffe, Shlens, Wojna 2015)
  - six convolutional layers
  - ten Inception modules
  - Rectified Linear Unit ReLU as nonlinear activation function

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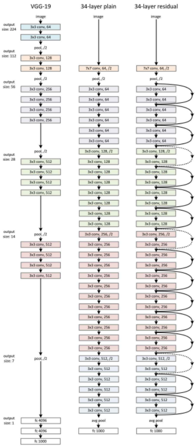
VGG

ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

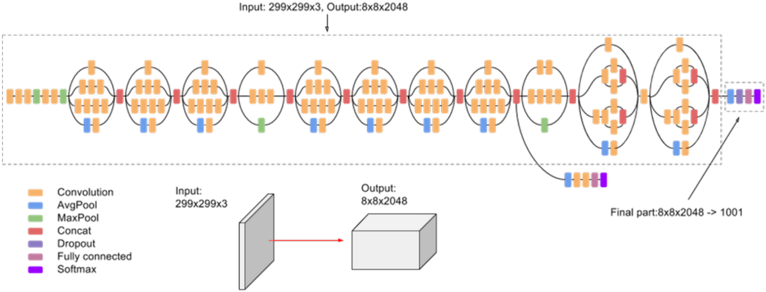
Source: Simonyan & Zisserman, Very Deep Convolutional Networks for Large-Scale Image Recognition, 2014

ResNet



Source: He, Zhang, Ren & Sun, Deep Residual Learning for Image Recognition, 2015

Inception



Source: Advanced Guide to Inception v3 on Cloud TPU

Szegedy, Vanhoucke, Ioffe, Shlens, & Wojna, Rethinking the Inception Architecture for Computer Vision, 2015

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Imagenet dataset

- 22000 classes 11M labeled image examples
- Reduced to 1000 classes and 1.4M images
- The smaller dataset has both fine and coarse-grained classes
- Synthetic version keeps size intact (224x224)

image-net.org

Training Imagenet results

Table 1 : Training time and top-1 1-crop validation accuracy with ImageNet/ResNet-50

	Batch Size	Processor	DL Library	Time	Accuracy
He et al. [7]	256	Tesla P100 x8	Caffe	29 hours	75.3%
Goyal et al. [1]	8K	Tesla P100 x256	Caffe2	1 hour	76.3%
Smith et al. [4]	8K→16K	full TPU Pod	TensorFlow	30 mins	76.1%
Akiba et al. [5]	32K	Tesla P100 x1024	Chainer	15 mins	74.9%
Jia et al. [6]	64K	Tesla P40 x2048	TensorFlow	6.6 mins	75.8%
This work	**34K→68K**	**Tesla V100 x2176**	**NNL**	**224 secs**	**75.03%**

Table 2 : GPU scaling efficiency with ImageNet/ResNet-50 training

	Processor	Interconnect	GPU scaling efficiency
Goyal et al. [1]	Tesla P100 x256	50Gbit Ethernet	~90%
Akiba et al. [5]	Tesla P100 x1024	Infiniband FDR	80%
Jia et al. [6]	Tesla P40 x2048	100Gbit Ethernet	87.9%
This work	**Tesla V100 x1088**	**Infiniband EDR x2**	**91.62%**

Mikami, Suganuma, U-chupala, Tanaka & Kageyama, ImageNet/ResNet-50 Training in 224 Seconds

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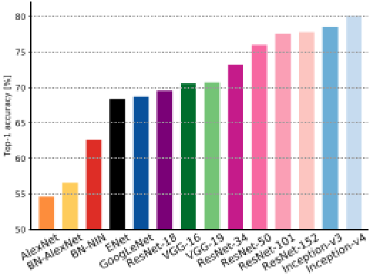
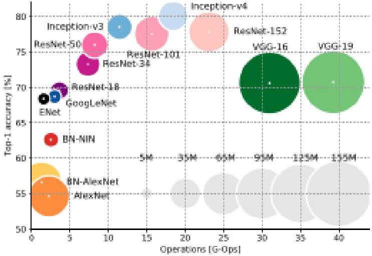
CNN comparison





- Inception-v4: Resnet + Inception
- VGG High memory and operations
- GoogLeNet very efficient
- Alexnet few operations but high memory and low accuracy
- Resnet moderate efficency and high accuracy

Canziani, Alfredo; Paszke, Adam; Culurciello, Eugenio; An Analysis of Deep Neural Network Models for Practical Applications, 2017

Links and credits

- Fei-Fei Li, Justin Johnson, Serena Yeung - CS231n
- https://developers.google.com/machine-learning/crash-course/
- https://eu.udacity.com/course/deep-learning–ud730
- https://www.kaggle.com/competitions
- Deep Learning, Ian Goodfellow; Yoshua Bengio; Aaron Courville. https://www.deeplearningbook.org/
- http://neuralnetworksanddeeplearning.com/
- Deep Learning with Python, François Chollet

- Credits to Riccardo Zanella for the first version of this course, and Stefano Tagliaventi.