Deep Learning and Neural Network

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Artificial Intelligence?

The fathers

- Lee Marvin Minsky and John McCarthy created the expression -Working at MIT in the fifties.
- Foundation at the Dartmouth conference on summer 1956.
- Minsky defined AI as "the science of making machines do things that would require intelligence if done by men."
- On the road to achieve the Turing machine.



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Copying human being?

- Learning is the main characteristic of Intelligence.
- In the 80's symbolic approach wins against connexionist approach.
- End of the first turn!



Back to the futur

ECCV 2012

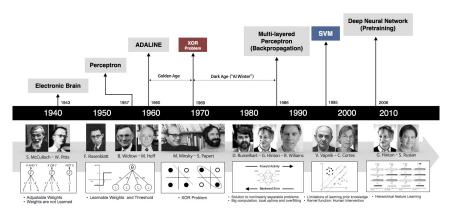
 Hinton, Krizhevsky and Sutskever propose the first model to classify ImageNet DB with a deep network - and outperform (g.t. 10%) all the results.

https://hal.archives-ouvertes.fr/hal-01925644/document

Neural Network revival

- Reuse the architecture proposed by Lecun more than 20 years before (listen the Collège de France talk of Y. Lecun to know more about the main principles).
- Intelligence is a connexionist system with layers composition of simple layers.

History



[beamandrew, 2017]



Deep Learning today

Why using Deep learning?

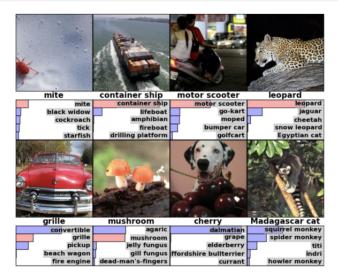
- Production of huge amount of Data by machines.
- Evolution of Data Mining domain/statistical methods.
- Extraction of features to classify data, to predict results ...
- Pretty all domains are concerned: machine log, images, medical/biological data ...

Requirements

- Data storage and computing ressources.
- Way to display and to perform the results.
- Graphical interfaces and statistics tests are mandatory.

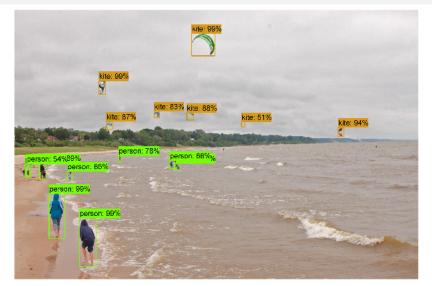


Deep Learning - Images classification



[Machine Learning Mastery, 2016]

Deep Learning - Object detection



Deep Learning - Machine translation



Traduction





Deep Learning - Speech recognition





Deep learning is a class of machine learning that:

- use a cascade of multiple layers for extracting and transforming the features.
- learn in supervised or unsupervised mode
- learn with different levels of presentation



[ZDNet, 2018]



[Silicon ANGLE, 2016]

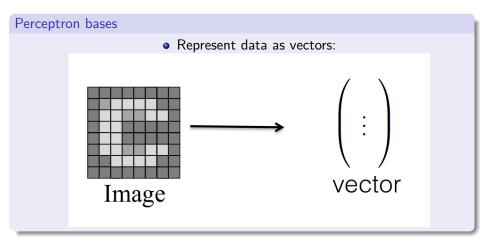


[Siecle Digital, 2016]



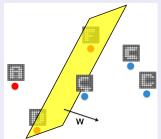
ROSS Intelligence, 2018

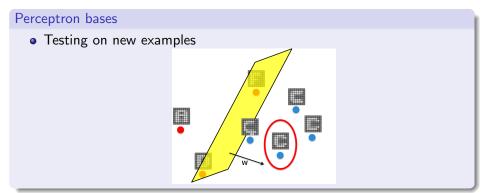
Perceptron bases • Collect data for training: includes positive and negative examples



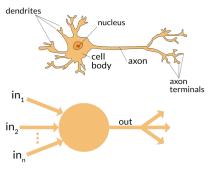
Perceptron bases

- Function: $f(x) = w^T x + b$
- Train the function on training data: find w and b so that
 - If sample x is positive, f(x) is positive
 - If sample x is negative, f(x) is negative

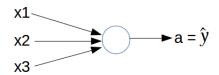


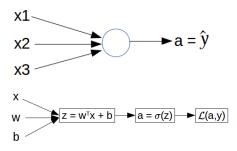


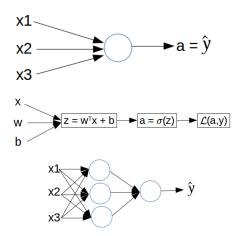
Biological Inspiration



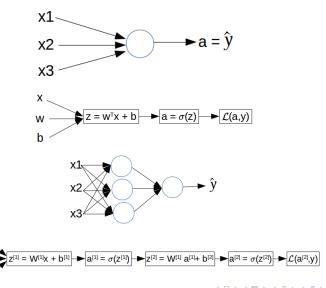
[appliedgo, 2016]







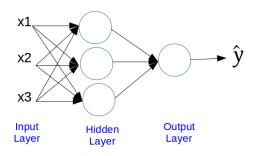




Х

 $b^{[1]}$

NN Representation

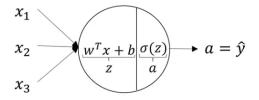


This is a:

- 2 layers neural network
- The hidden layers and output layer (sometime) will have the parameters (W,b)



NN Computing

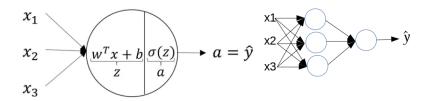


$$z = w^T x + b$$

$$a = \sigma(z)$$



NN Computing

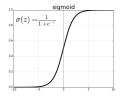


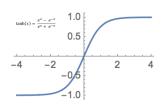
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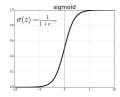


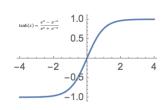
Activation functions





Activation functions





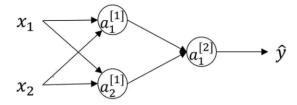




- For hidden units: use tanh, ReLU should be better than sigmoid
- For output layer $(0 \le \hat{y} \le 1)$, we can use sigdmoid.

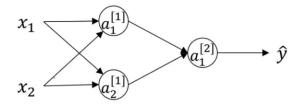
Parameters random initialization

If W = [0] then the computing of neural network is exactly the same function at every layer?



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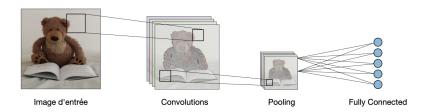
Solution: Randomly initialization the parameters

- W = np.random.randn((2,2)) * 0.01
- b = np.zero((2,1))



Introduction

- In CNN we identify :
 - Input data that has to be transform.
 - Convolutional layers
 - Pooling layer(s)
 - Fully connected layer.



Goal

- Extract features of the input volume.
- Need to set the size of each filter on the layers. Could be different for each layer.

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

1	0	1
0	1	0
1	0	1

Input

Filter / Kernel

Goal

- Extract features of the input volume.
- Need to set the size of each filter on the layers. Could be different for each layer.

1x1	1x0	1x1	0	0
0x0	1x1	1x0	1	0
0x1	0x0	1x1	1	1
0	0	1	1	0
0	1	1	0	0



Input x Filter

Feature Map

Goal

- Extract features of the input volume.
- Need to set the size of each filter on the layers. Could be different for each layer.

1	1x1	1x0	0x1	0
0	1x0	1x1	1x0	0
0	0x1	1x0	1x1	1
0	0	1	1	0
0	1	1	0	0



Input x Filter

Feature Map

Goal

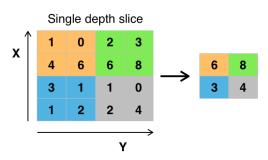
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1	1	1	0	0
0	1	1	1	0
0	0	1x1	1 x 0	1x1
0	0	1x0	1x1	0x0
0	1	1x1	0x0	0x1

4	3	4
2	4	3
2	3	4

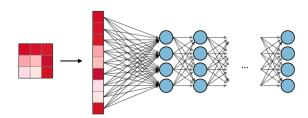
Pooling Layer

- Pooling layer reduces the spatial dimensions of the input.
- Allows to control **overfitting**.
- Several functions are available: max pooling, average pooling, L2-norm



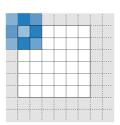
Fully Connected Layer

- Use as input a vector where each data is connected to a neurone.
- Main goal is to achieve the task classification, scores...



Parameters

- Stride: pixel number of the sliding window for convolution or pooling.
- Zero-padding : adding value to adjust image/matrix size.



Parameters

- Batch size: define the number of samples to work through before updating the internal model parameters.
- Learning rate: control how much to change the model in response to the estimated error each time the model weights are updated.
- Epochs number : define the number times that the learning algorithm will work through the entire training datase.

Convolutional Neural Network

Evaluation - Metric

- Loss value: evaluate how the madel is training produced from the loss function that estimates the loss of the model so that the weights can be updated to reduce the loss on the next evaluation.
- Accuracy: a metric to measure the algorithm performance at the end.
- Mean Average Precision: compute the average precision value for recall value over 0 to 1. Seee Precision/Recall.
- F1 Score: combine precision and recall relative to a specific positive class. It is a weighted average of the precision and recall, where an F1 score reaches its best value at 1 and worst at 0

Activation Functions -

Goals

- Modified in a non-linear way the representation of data.
- As multi-layers are activated, several modifications can occur.
- Don't confuse between activation function and loss function.

Way to work

• Each neurone of one layer will apply the activation function of this layer to the data, as each neurone has a different weight, this will have a different effect.



Activation Functions

ReLU Layer^a

- ^aRelu Module http://cs231n.github.io/convolutional-networks/
- Layer to correct data take into account the non-linearity of the process of classification.
- One example of Relu fonction f(x) = max(0, x)
- By consequences all values less than 0 are set as 0.

PyTorch coding

- Just define a layer : relu1=nn.ReLU(inplace=False)
- Add a module with this layer: model.add_module(''Relu1'', relu1)
- It is authorized to define and add module at the same time.
- Never use the ReLU function in the last layer. It is only for the intermediate layers.

Activation Functions

SoftMax

- Transform a vector of reals in a vector of probability.
- Use a score vector as inputs.
- Often used in the final layer of classifier model.

PyTorch coding

calling Softmax :

```
y=torch.softmax(x,dim=0)
// dim=-1 if your input is a vector.
```



Using a Deep Network

Data organisation

- Training and Validation data set are rebuild at each epoch.
- Don't miss to shuffle at each epoch.
- Usual parameters are 80% for training and 20% for validation.
- Test data has to be kept apart and never seen before the test step.

Re-using a model

- Saving the model to apply to test data or to fine-tune another CNN.
- Transfert learning or fine-tuning: re-use a training model to feed another one for another task and another data set.



CNN Architecture

- Creating in 2010 for the ILSVRC challenge, won in 2012 with an error-rate of 15.3%.
- Original paper: ImageNet Classification with Deep Convolutional Neural Networks by Alex Krizhevsky et al.
- Imagenet dataset: 22 000 classes and 15 millions of images.
- 8 Layers including Dropout layer. producing 60 millions of parameters.
- Replace tanh function by Rectified Linear Units (ReLU), fastest computing.
- Able to use multiple GPU.
- Special pooling with overlap.
- Data augmentation: 2048 times.

- Conv. layer 1: input 224X224X3 image tensor, 96(11X11) kernels, stride 4 and padding 2. Produced a 55X55X96 output tensor to pass to ReLu activation function - This layer contains 34,944 parameters to train.
- Max-Pooling layer 2: 55X55X96 tensor as input. Perform a zero-padding with a kernel 3X3 and a stride 2. Produce a 27X27X96 output tensor.
- Conv. Layer 3: convolution layer input 27X27X96, apply a convolutional operation 256 (5X5) kernels with a stride 1 and a padding 2. Produce 27X27X256 output tensor, passed to ReLu function. Contain 614,656 parameters to train.
- Max-Pooling layer 4: 27X27X256 input tensor, zero padded operation and 3X3 kernel with a stride 2. Produce a 13X13X256 output tensor to pass to ReLU function.

- Conv. Layer 5: receive a 13X13X256 input tensor. Conv operation uses 384(3X3) kernels with stride and padding 1. Produce 13X13X384 output tensor to feed the ReLU function. Contain 885,120 parameters.
- Conv. Layer 6: perform the same operation than layer 5 with same kernel. Contain 1.327.488 parameters.
- Conv. Layer 7: 13X13X384 input tensor, convolutional operation with a 256(3X3) kernels with stride and padding 1. Produce a 13X13X256 output tensor to feed the ReLU function. Contain 884,992 parameters.

- Max-Pooling layer 8: receive a 13X13X256 input tensor. Perform a zero-padding, apply a 3X3 window with a stride 2. Produce a 6X6X256 output tensor to pass to the ReLU function.
- Fully-Connected layer 9: accept the 6X6X256 input tensor. Perform a
 weighted sum operation including a bias term. Produce a 456X1
 output tensor to pass to the ReLU function. Contain 37,752,832
 parameters.
- Fully-connected layer 10: accept the 4096X1 inpmut tensor, perform the same operation than layer 9 and produce the same size output tensor.
- Fully-connected layer 11: accept the input tensor from the previous layer, perform the same operation and produce a 1000X1 output tensor, i.e. number of waited classes, to pass to the softmax activation function.

- For ImageNet experiment, the other parameters values are:
 - Batch size 128
 - Momentum 0.9
 - Learning rate 0.0005
 - Dropout has been added in the first two fully-connected layer.
- A graphic card with 2 GPU has been used.



CNN Architecture

VGG Family

- Creating in 2014 for the ILSVRC challenge.
- VGG16: 16 convolutional layers. 138 millions of parameters.
- 13 convolutional layers, Reduce the size filter to 3X3.
- 3 fully connected layers.
- Original paper: Very Deep Convolutional Networks for Large Scale Image Recognition by Karen Simonyan et al.

CNN Architecture

Full description at: https://neurohive.io/en/popular-networks/vgg16/ 224 x 224 x 3 224 x 224 x 64 112 x 112 x 128 56 x 56 x 256 7 x 7 x 512 28 x 28 x 512 1 x 1 x 4096 1 x 1 x 1000 convolution + ReLU max pooling fully nected+ReLU softmax

ResNet Architecture

Residual Block

- Adding the input of the previous layer to the output of a subsequent layer.
- Give a solution to the vanishing/exploded gradient.
- Skipping a connection does not add additional computational load.

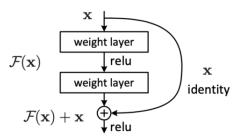


Figure 2. Residual learning: a building block.

Transfer Learning

Re-Use learning from large dataset

- Deep Learning needs large (huge) dataset.
- Data Augmentation could be a solution.
- Pre-training with a large dataset ImageNet.
- Re-use the weights beside to train from scratch.
- Fine tune and retrain the network.



GAN to Generate new data

Creating data

- A way to obtain new data from an initial one.
- Very popular for some applications as face recognition.
- Contains two submodels Generator to create new examples,
 Discriminator to classify/discriminate generated examples from real ones.

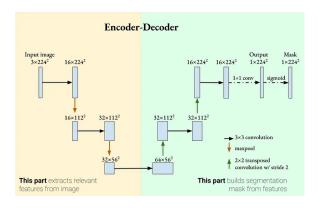
Encoder - Decoder

Sequence to Sequence model

- Encoder takes in an input sequence and produces a fixed-length vector representation of it, often referred to as a hidden or "latent representation"
- Decoder takes the latent representation and generates an output sequence based on it.
- Used in natural language processing, computer vision ...
- Could include CNN layers or LSTM ones.
- U-Net is the most famous.



Encoder - Decoder - U-Net



Transformer Network

A new network without convolution

- Use the mechanism attention, i.e. differentially weighing the significance of each part of the input data.
- Built using encoder/decoder architecture.
- Can be understood in terms of its 3 components :
 - An Encoder to encode an input sequence into state representation vectors.
 - An Attention mechanism to enable the Transformer model to focus on the right aspects of the sequential input stream.
 - An Decoder to decode the state representation vector to generate the target output sequence
- The most popular to work with language ... translation, generation (ChatGPT) or video analysis.

