Convolutional neural networks

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Contents

1. Introduction
2. Application of fully-connected networks to image classification
3. From fully-connected layers to convolutional layers
4. Building convolutional networks
5. Practical considerations
6. Visualization
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Contents

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7. Conclusion

A picture is worth a thousand words

Definition

- Classically, an image is a matrix of values belonging to $[0, \ldots, 255]$ (grey level images) or to $[0, \ldots, 255]^3$ (color images).
- More generally, an image is a q-dimensional array of values belonging to R^d.

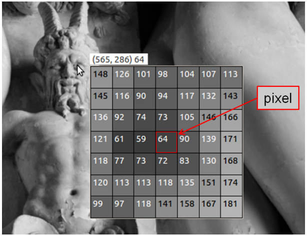


Figure: Grey level values around the left eye of the faun.

Designing computer vision systems that are able to extract semantic information from an image is a difficult task. How can we build systems that extract meaning from an image?

Extracting semantic information from an image

- Where is the phone? (localization task)
- How many mugs are there? (quantification task)
- Is there a window in the room?
- At what time of the day was the photograph taken?

MNIST database [Lecun et al., 1998]

- The Modified National Institute of Standards and Technology (MNIST) database contains $60\,000$ training images of hand-written digits, and $10,000$ test images.
- Image size: 28×28
- It has been used since 1998
- Human performance on a similar database (NIST) is reported to be around 1.5% error [Simard et al., 1993]
- Best methods, based on convolutional neural networks, give around 0.21% test error.

MNIST database

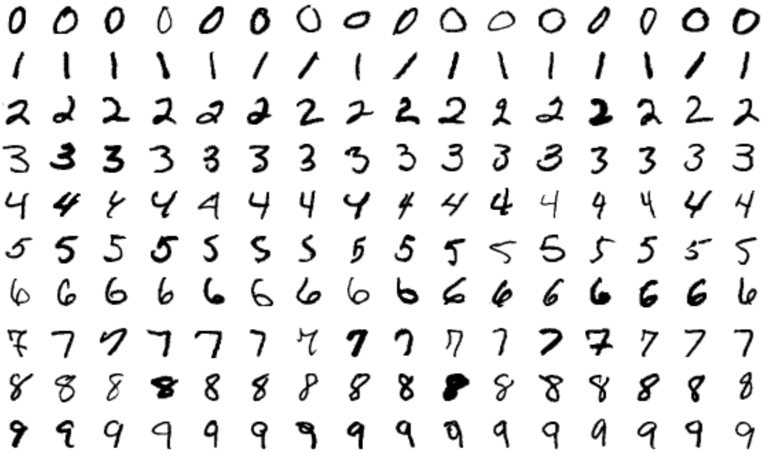


Figure: Images from MNIST assembled by Josef Stepan (licensed under CC BY-SA 4.0)

Pascal VOC project [Everingham et al., 2010, Everingham et al., 2014]

This project organized a challenge from 2005 to 2012, divided into several tasks, including an image classification task.

Pascal VOC image classification task (2012)

Train/val: $11\,540$ images where the presence of 20 categories of objects was annotated. The test dataset is unknown and tests are run online (still available).

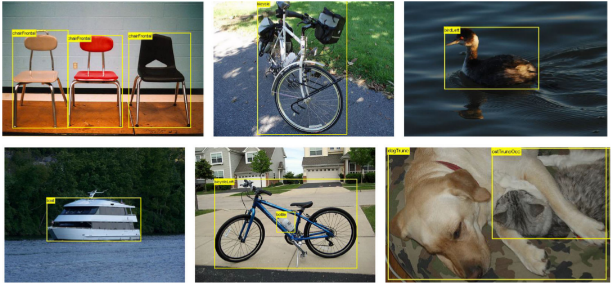


Figure: From [Everingham et al., 2014]

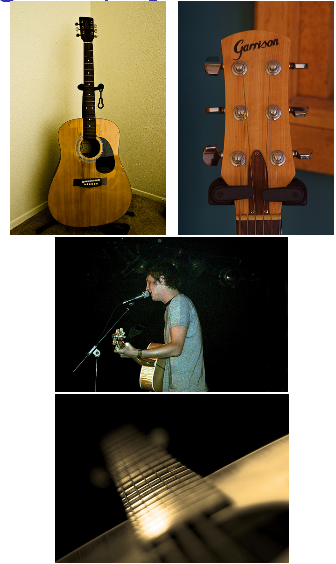
ImageNet project

Since 2010, ImageNet organizes and annual challenge: The ImageNet Large Scale Visual Recognition Challenge (ILSVRC), that constitutes a breakthrough in the design of image analysis challenges by its size.

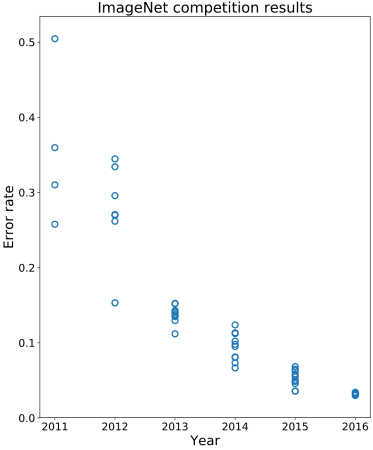
Image classification task (since 2012)

- Training: $1\,281\,167$; validation: $50\,000$; test: $100\,000$.
- $1\,000$ classes (90 dog breeds!).

ImageNet projet



Examples from the *acoustic guitar* class



Source: Wikipedia

Image processing approach

- Build a mathematical model for the objects you are interested in
- Implement this model using image processing operators

+ This approach works correctly when the objects are not too complex.

- If objects are difficult to model, machine learning methods can bring a solution.

Classical machine learning approach

- Compute features from the image
- Apply machine learning to those features

\+ Works well when you engineer the right features

\- An expert is required to define those features - and this can be a long process

\- Annotated data is required

Deep learning approach

Modern neural networks approach

- Directly take as input the image pixels
- The network is supposed to build its own features

+ Good (impressive!) results
- A large amount of annotated data is required

Some accomplishments

ImageNet Large Scale Visual Recognition Challenge (ILSVRC)

2012: *AlexNet* [Krizhevsky et al., 2012] won this challenge by a large margin

The database contains more that 1 million training images, belonging to 1000 different classes (including 120 dog breeds!).

Some accomplishments (cont.)

- 2011: first super-human performance, IJCNN 2011 traffic sign recognition contest [Cireșan et al., 2011]
- 2012: visual object detection (Mitosis detection in breast cancer histology [Cireșan et al., 2013])
- 2012: segmentation competition (neuronal membranes in electron microscopy images [Ciresan et al., 2012])
- 2016: AlphaGo beats Lee Sedol, one of the best go players, in a 5-game match

Deep learning image applications

- classification
- object localization
- semantic segmentation
- instance segmentation
- transformation (filtering, in-painting, editing, colorization...)
- quantification
- compression
- image caption generation
- 2D to 3D (stereo matching, 3D reconstruction, ...)
- motion estimation
- Style transfer
- Anomalous image detection
- Image generation

Convolutional neural networks in deep learning

- They are pivotal to many of the successes achieved by neural networks these recent years
- They are interesting for dealing with regular structured data, such as images (or board games!)

Acronyms

Two acronyms are used for convolutional neural networks in the literature: *CNN* and *ConvNet*.

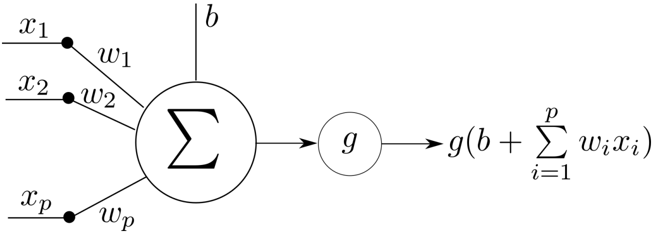
Essential milestones

- 1979: Neocognitron (CNN architecture) [Fukushima, 1979, Fukushima, 1980]
- 1989: Backpropagation applied to CNNs [LeCun et al., 1989]
- 2006, 2010: GPU implementation [Chellapilla et al., 2006, Cireșan et al., 2010]

Contents

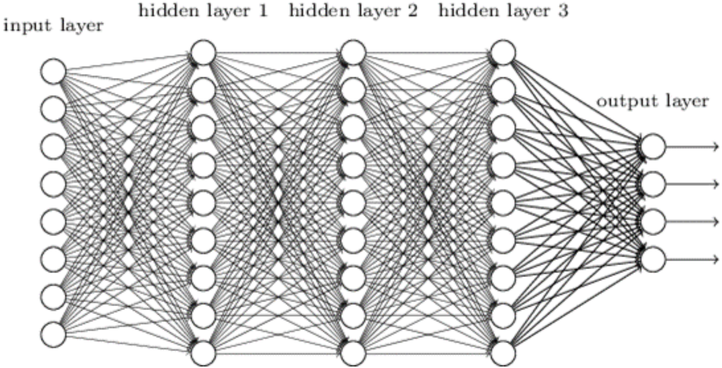
1. Introduction
2. Application of fully-connected networks to image classification
3. From fully-connected layers to convolutional layers
4. Building convolutional networks
5. Practical considerations
6. Visualization
7. Conclusion

Artificial neuron



- $b, w_1, \ldots, w_n$ are the neuron parameters, to be learnt
- g is the activation or transfer function

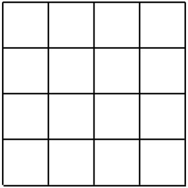
Neural network



(from http://www.jtoy.net)

Input image, input neurons

In the scalar case (single-valued images), each input pixel is considered as an input neuron.



Input image, input neurons

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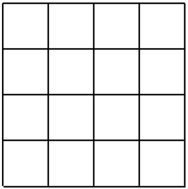


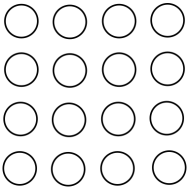


Image classification problem

Classification problem:

- Input: image $\mathbf{x}$
- Output: class $y \in \{label_1, label_2, \ldots, label_q\}$

Class coding

Often, classes are denoted by integers, but this is only a coding commodity. For instance, it would be meaningless to use a regression approach for this problem.

Class coding

If there are q possible classes, then a class will be coded as a vector $\mathbf{y}$ of length q. If its class is r then for $0 \leq i < q$:

$$\mathbf{y}[i] = \begin{cases} 1, & \text{if } i = r \\ 0, & \text{otherwise} \end{cases}$$

Example with 4 classes

- Label $0 \longmapsto [1, 0, 0, 0]$
- Label $1 \longmapsto [0, 1, 0, 0]$
- Label $2 \longmapsto [0, 0, 1, 0]$
- Label $3 \longmapsto [0, 0, 0, 1]$

Image classification with a neural network

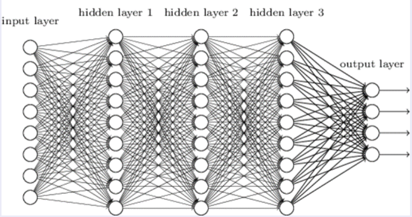
Input

Scalar image is transformed into a vector of length p.

Output

For q classes, the output will be a vector of length q.

Example: image of size 4×2, 4 possible classes



Activation of the last layer

Loss function for classification: cross-entropy

Conclusion on fully-connected networks for image classification

Fully connected layers:

- scale badly to large size images
- do not take into account the local structure of images

Today:

- Fully-connected networks are almost never used for image analysis.
- Fully-connected layers are only used in the middle (auto-encoders) or at the end (classification) of the pipeline.

Contents

1. Introduction
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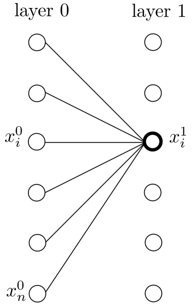
7. Conclusion

Towards convolutional layers

For illustration purposes, in the following slides images and filters will be displayed as rows of neurons - these can be seen as 1D arrays or as sections of 2D arrays.



Fully connected layer: $n(s+1)$ weights

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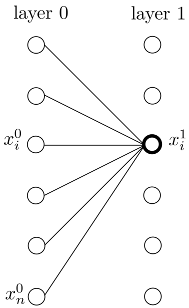
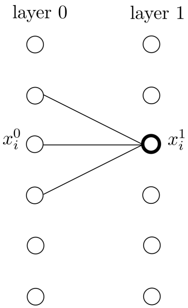


Fully connected layer: $n(s+1)$ weights



Locally conn. layer: $n(s+1)$ weights

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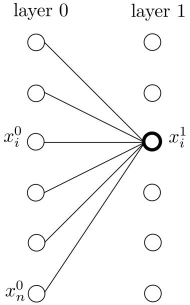
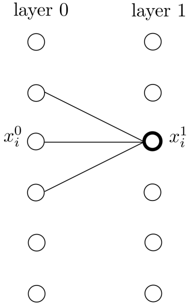
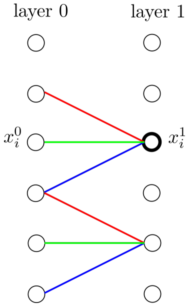


Fully connected layer: $n(s+1)$ weights



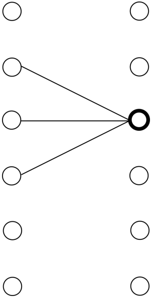
Locally conn. layer: $n(s+1)$ weights



Weight replication: $s+1$ weights

Stride

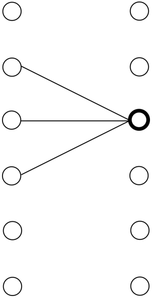
A convolutional layer can at the same time downsample the image by applying a sampling step, or *stride*.



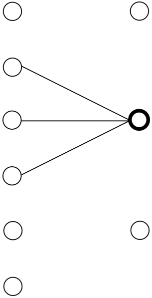
Stride 1

Stride

A convolutional layer can at the same time downsample the image by applying a sampling step, or *stride*.



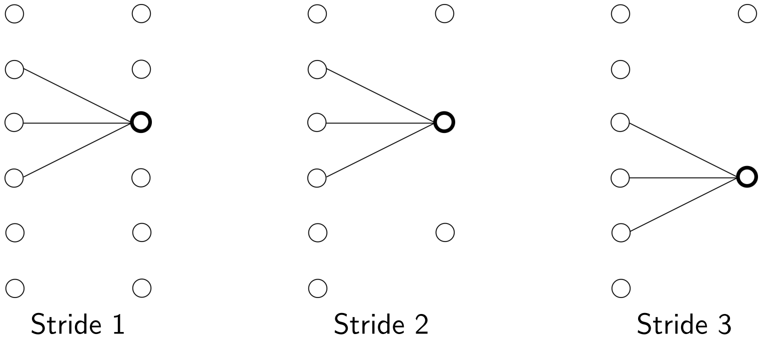
Stride 1



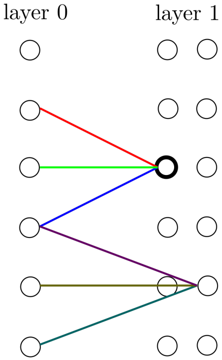
Stride 2

Stride

A convolutional layer can at the same time downsample the image by applying a sampling step, or *stride*.

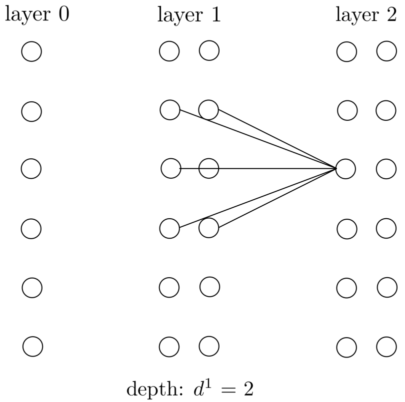


Several filters in the same convolutional layer

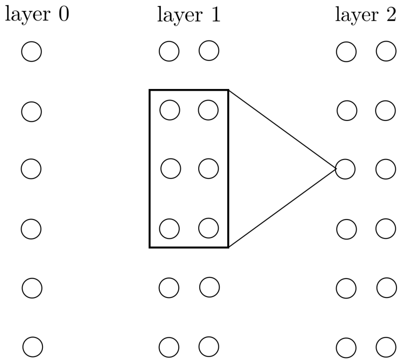


depth: $d^1 = 2$

Several filters in the same convolutional layer

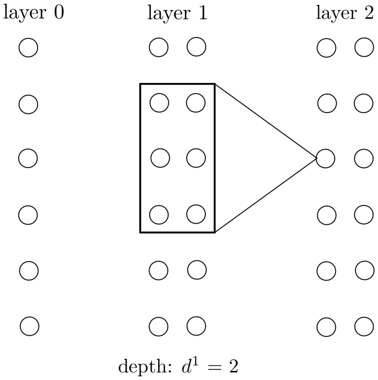


Several filters in the same convolutional layer



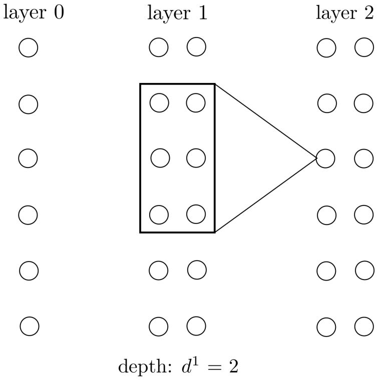
depth: $d^1 = 2$

Consequences on the parameter number



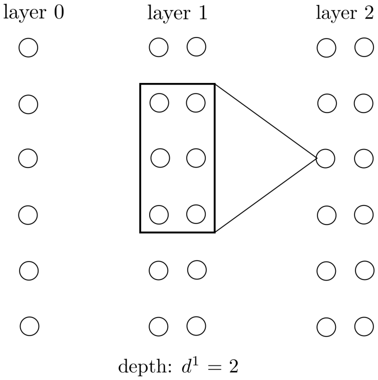
- How many parameters do we have in layer 1?

Consequences on the parameter number



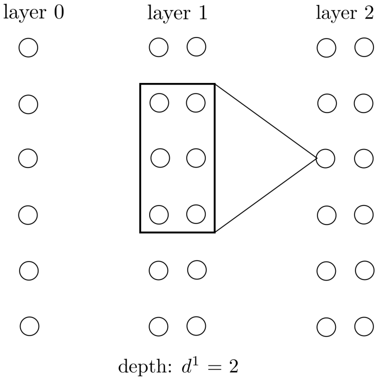
- How many parameters do we have in layer 1?
- $d^1 \times (s + 1)$

Consequences on the parameter number



- How many parameters do we have in layer 1?
- $d^1 \times (s+1)$
- In layer 2?

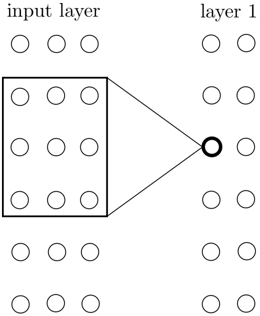
Consequences on the parameter number



- How many parameters do we have in layer 1?
- $d^1 \times (s + 1)$
- In layer 2?
- $d^2 \times (d^1 \times s + 1)$

Multi-valued images

An input image with p channels (for instance a colour image with 3 channels) can be represented by an input layer of depth 3



1D representations

2D representations

Some properties

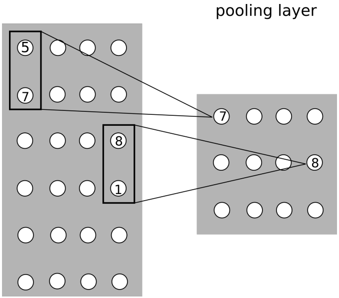
- Translation invariance
- Efficient implementation using matrix operations and Graphical Processing Units (GPUs)

Contents

1. Introduction
2. Application of fully-connected networks to image classification
3. From fully-connected layers to convolutional layers
4. Building convolutional networks
5. Practical considerations
6. Visualization
7. Conclusion

Max pooling

- Convolutional networks often contain subsampling steps. The most popular way of doing this today is by using *max pooling* layers.
- Note however a current trend that consists in using convolutional layers with a stride of 2
- Sampling is only applied along the spatial dimensions, not along the dimension of the filters.



Dimension reduction

Decomposed convolutions

Skip connections

Main components of a convolutional neural network

Many successful architectures, especially for image classification, follow the same pattern:

1. Several iterations of: One or several convolutional layers, with increasing depth, followed by max pooling
2. A few fully connected layers

VGGnet

- Proposed by K. Simonyan and A. Zisserman from the University of Oxford [Simonyan and Zisserman, 2014]
- Runner-up in the ImageNet Large Scale Visual Recognition Competition (ILSVRC) in 2014.
- Number of parameters (VGG16): 138 million.

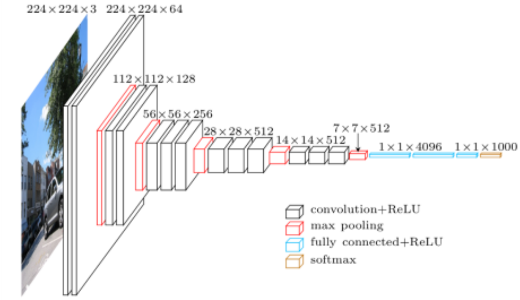


Figure: VGG16 (From https://www.cs.toronto.edu/ frossard/post/vgg16/)

GoogLeNet (a.k.a. Inception v1)

- Winner of the ImageNet Large Scale Visual Recognition Competition (ILSVRC) in 2014.
- Number of parameters: *only* 5 million.

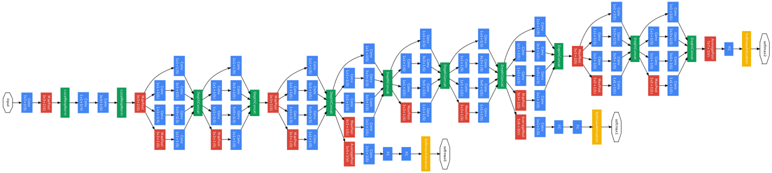


Figure: From [Szegedy et al., 2014]

ResNet won the following year...

Inception module

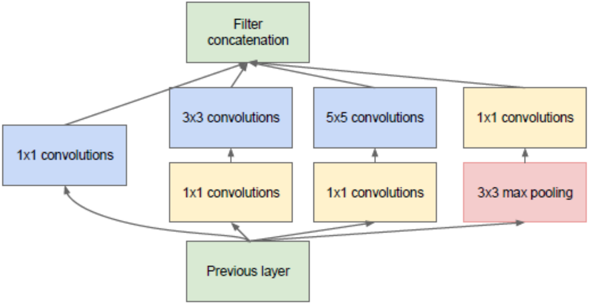


Figure: From [Szegedy et al., 2014]

ResNet

- Winner of the ImageNet Large Scale Visual Recognition Competition (ILSVRC) in 2015.
- The authors tested up to 1202 layers. They reported no training difficulties, but overfitting [He et al., 2015]

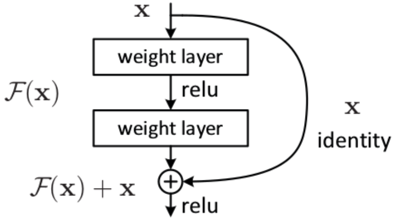


Figure: Residual learning block (from [He et al., 2015])

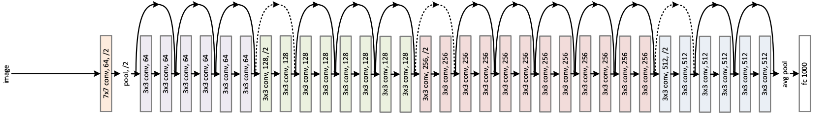


Figure: Residual network with 34 layers (from [He et al., 2015])

Current trends

- Small convolutions (3×3)
- Dimension reduction using 1×1 convolutions
- Increasing number of layers
- Skip connections

VGG, GoogLeNet and ResNet (and their variants) are still among the most used architectures for image classification and other related tasks.

Contents

1 Introduction

2 Application of fully-connected networks to image classification

3 From fully-connected layers to convolutional layers

4 Building convolutional networks

5 Practical considerations

6 Visualization

7 Conclusion

Designing a convolutional neural network

- Network architecture
- Hyper-parameter setting
- Optimization method and parameters

Learning, specially for complex networks, can be difficult. It is always time consuming.

Using an existing network

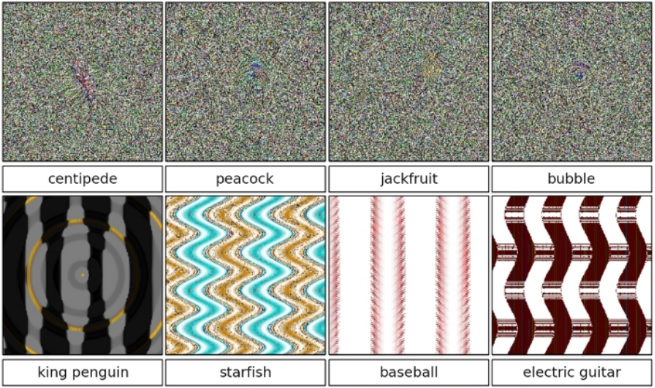
- Replicate network architecture and hyper-parameters
- Load weights

With standard libraries this is very simple. Prediction time is usually fast.

- One can also start with a standard model and adapt it to a new situation (we will talk about *domain adaptation* and *transfer learning* later).

ConvNets can be fooled

Deep learning can produce astonishing results [Nguyen et al., 2015]...



Main deep learning libraries

Deep learning is a very competitive domain, where code sharing is very common.

- Theano
- Tensorflow
- Torch, PyTorch
- Caffe
- Microsoft Cognitive Toolkit (previously known as CNTK)
- MatConvNet

Keras

Keras is a very easy to use interface to Tensorflow, Theano and CNTK.

Contents

1. Introduction
2. Application of fully-connected networks to image classification
3. From fully-connected layers to convolutional layers
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5. Practical considerations
6. Visualization
7. Conclusion

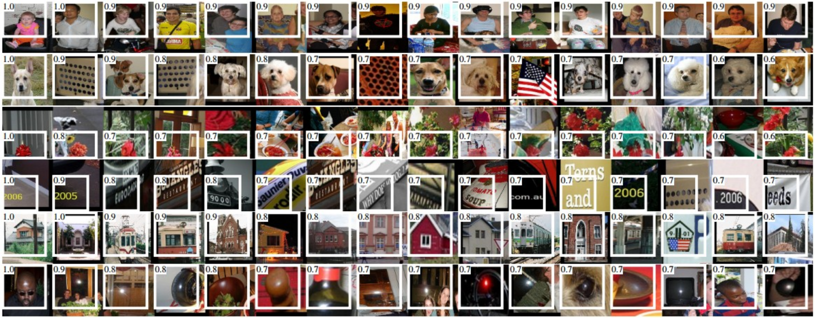
Visualizing at least what we don't understand

We do not fully understand today where the good performances of deep learning come from. But we can at least have a look at what is going on inside the networks.

- Neuron outputs (activations)
- Filter values
- "Important" pixels

Maximal neuron activation

Which images maximally activate a given neuron?
[Girshick et al., 2014]



Contents

1 Introduction

2 Application of fully-connected networks to image classification

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A revolution in image analysis

- Deep learning has brought an undeniable break-through in image analysis (as in other fields)
- A significant part of research efforts in image analysis today is base on deep learning
- Its applications are ubiquitous

Limitations

For a deep-learning solution to work, you need:

- Enough annotated data
- A lot of fiddling (different architectures; hyper-parameters; optimization)
- One (or, even better, several) powerful GPUs

Moreover, these models lack interpretability.

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