More on Convolutional Neural Networks

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Data science/machine learning journal club at WFAIS UJ

Outline

Convolutional Neural Networks (CNN)

Going deep

CNN example: MNIST

Image classification datasets

Recent CNN architectures

- Inception/Xception
- Residual networks
- Densely connected convolutional networks

Interlude — fooling deep CNN's

CNN for segmentation

- Fully Convolutional Networks — U-Net

Conclusions

What are neural networks?

- Each neuron with inputs x_k from previous layer has the output y_i given by

$$y_i = f(W_{ik} x_k + b_i)$$

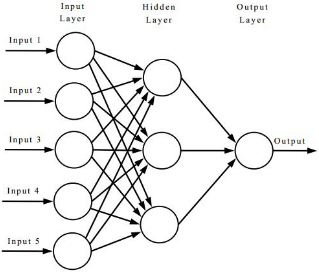
- The coefficients W_{ik} (*weights*) and b_i (*bias*) are determined during training
- $f(.)$ is a **nonlinear** 'activation function'

$$f(x) = \tanh x \longrightarrow \underbrace{f(x) = max(0, x)}_{ReLU}$$

- All neurons of a layer are connected to all neurons of the previous one
- This is good for general situations – but has lots of parameters (especially for deep networks)!
- Suboptimal for images

Neural networks

What are neural networks?



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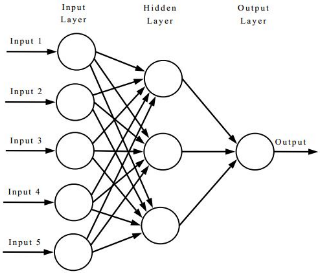

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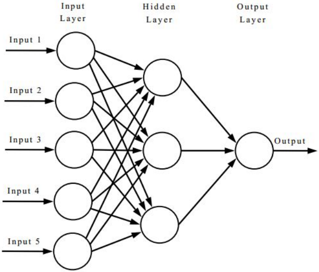

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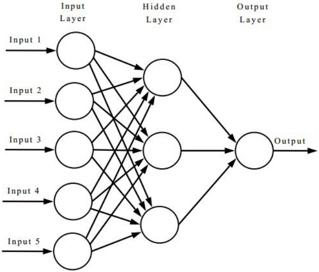

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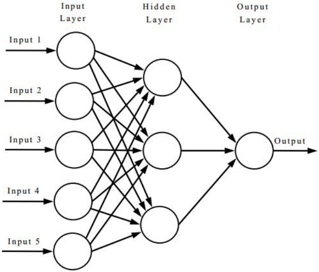

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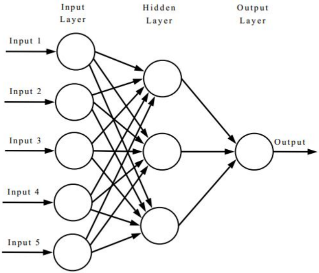

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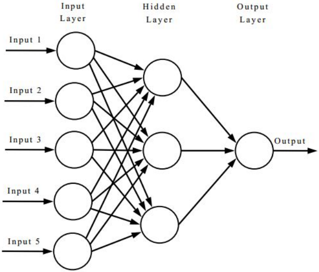

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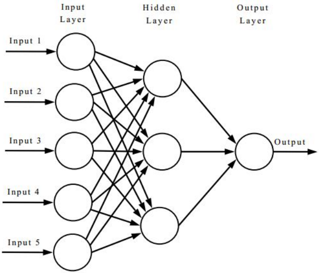

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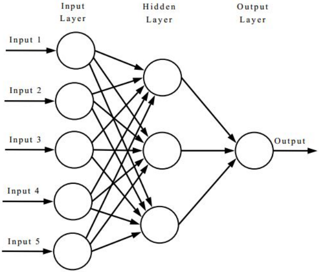

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Convolutional Neural Networks (CNN)

Main ideas:

1. Preserve the 2D structure of the input layer
2. Connect neurons in the next layer only to a block of say $3x3$ neurons in the previous layer
3. For all these connections take the same weights

from `http://deeplearning.stanford.edu/wiki/index.php/Feature_extraction_using_convolution`

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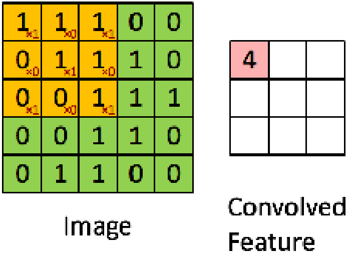

$1_{\times 1}$	$1_{\times 0}$	$1_{\times 1}$	0	0
$0_{\times 0}$	$1_{\times 1}$	$1_{\times 0}$	1	0
$0_{\times 1}$	$0_{\times 0}$	$1_{\times 1}$	1	1
0	0	1	1	0
0	1	1	0	0

Image

4		

Convolved Feature

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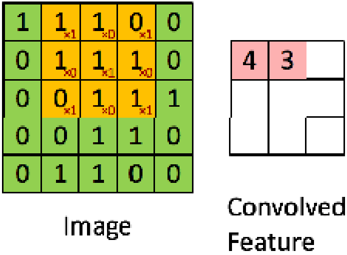

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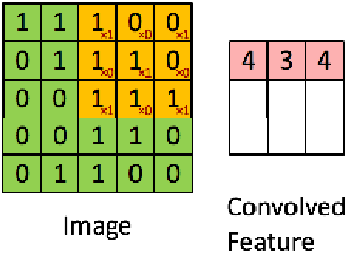

1	1	$1_{\times 1}$	$0_{\times 0}$	$0_{\times 1}$
0	1	$1_{\times 0}$	$1_{\times 1}$	$0_{\times 0}$
0	0	$1_{\times 1}$	$1_{\times 0}$	$1_{\times 1}$
0	0	1	1	0
0	1	1	0	0

4	3	4

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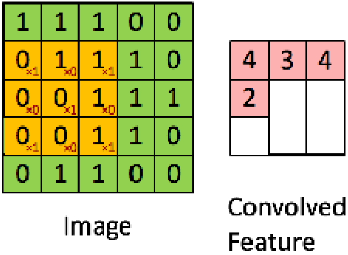

1	1	1	0	0
$0_{\times 1}$	$1_{\times 0}$	$1_{\times 1}$	1	0
$0_{\times 0}$	$0_{\times 1}$	$1_{\times 0}$	1	1
$0_{\times 1}$	$0_{\times 0}$	$1_{\times 1}$	1	0
0	1	1	0	0

4	3	4
2		

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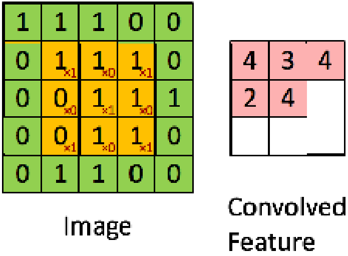

1	1	1	0	0
0	$1_{\times1}$	$1_{\times0}$	$1_{\times1}$	0
0	$0_{\times0}$	$1_{\times1}$	$1_{\times0}$	1
0	$0_{\times1}$	$1_{\times0}$	$1_{\times1}$	0
0	1	1	0	0

Image

4	3	4
2	4	

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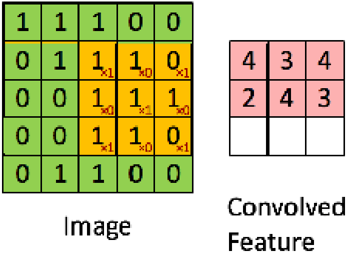

1	1	1	0	0
0	1	$1_{\times1}$	$1_{\times0}$	$0_{\times1}$
0	0	$1_{\times0}$	$1_{\times1}$	$1_{\times0}$
0	0	$1_{\times1}$	$1_{\times0}$	$0_{\times1}$
0	1	1	0	0

4	3	4
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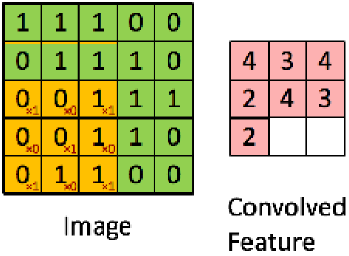

1	1	1	0	0
0	1	1	1	0
$0_{\times 1}$	$0_{\times 0}$	$1_{\times 1}$	1	1
$0_{\times 0}$	$0_{\times 1}$	$1_{\times 0}$	1	0
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4	3	4
2	4	3
2		

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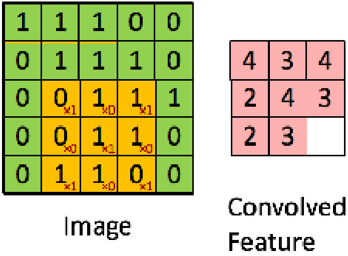

1	1	1	0	0
0	1	1	1	0
0	$0_{\times 1}$	$1_{\times 0}$	$1_{\times 1}$	1
0	$0_{\times 0}$	$1_{\times 1}$	$1_{\times 0}$	0
0	$1_{\times 1}$	$1_{\times 0}$	$0_{\times 1}$	0

4	3	4
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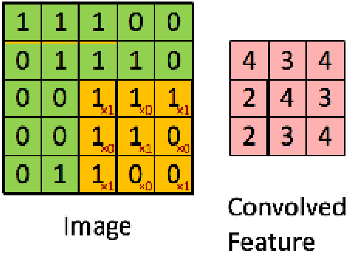

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0	1	1	1	0
0	0	$1_{\times 1}$	$1_{\times 0}$	$1_{\times 1}$
0	0	$1_{\times 0}$	$1_{\times 1}$	$0_{\times 0}$
0	1	$1_{\times 1}$	$0_{\times 0}$	$0_{\times 1}$

Image

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2	4	3
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Convolutional Neural Networks (CNN)

- Motivation from visual system:
  1. First layers detect simple features – like edges at various angles (convolution weights are also called filters)
  2. This information is composed into higher level features in deeper layers of the network
- We will have multiple filters at each hidden layer

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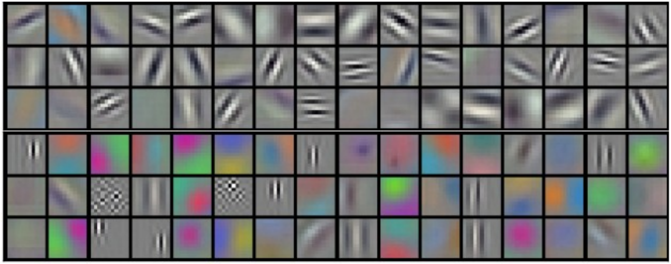

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Sample structure of a CNN:

Implement translational invariance

⟶ pooling layers

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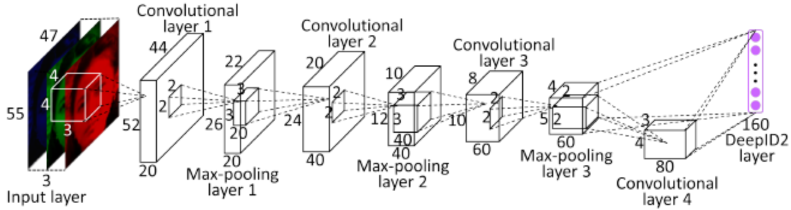

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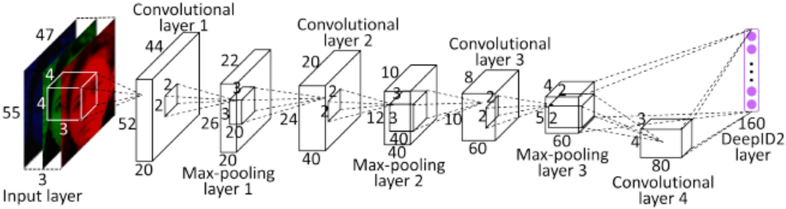

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⟶ **pooling layers**

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Max-pooling layer

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Less popular: Average-pooling

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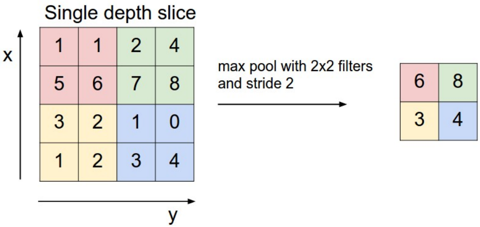

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5	6	7	8
3	2	1	0
1	2	3	4

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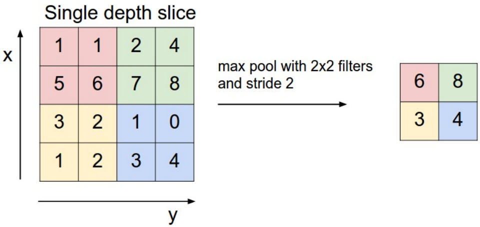

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In a machine learning model we can distinguish:

- **Parameters** – learned during training (e.g. weights of the connections between neurons)
- **Hyperparameters** – fixed *a-priori* – define the structure of the network:

  For a CNN:

  1. number and type of layers
  2. for each convolutional layer: filter size, number of channels/filters, stride (stride=2 in the figure below)
  3. Additional layers: dropout/batch normalization/flatten/fully connected..

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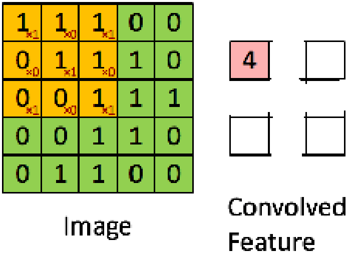

Convolutional Neural Networks (CNN)

In a machine learning model we can distinguish:

- **Parameters** – learned during training (e.g. weights of the connections between neurons)
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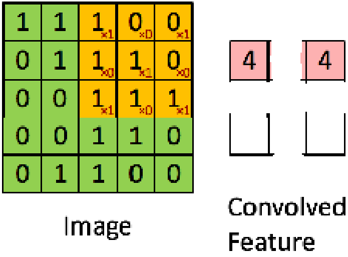

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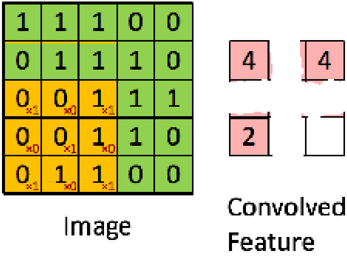

1	1	1	0	0
0	1	1	1	0
$0_{\times1}$	$0_{\times0}$	$1_{\times1}$	1	1
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4	4
2	

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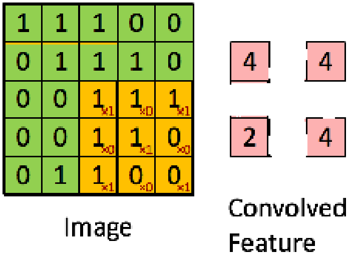

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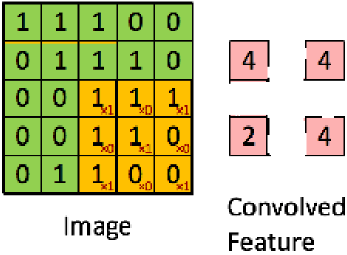
1 1 1 0 0
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Image
4 4
2 4
Convolved Feature

Going deep

Key advances allowing for training deep networks:

1. **ReLU activation:** (Rectified Linear Unit) i.e. nonlinearity for a neuron:

$$y_i = f(W_{ik} x_k + b_i) \qquad \underbrace{f(x) = max(0, x)}_{ReLU}$$

2. **Dropout:** during training we turn off say 50% randomly chosen neurons from the previous layer

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Example from the first journal club using keras:

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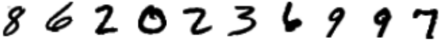

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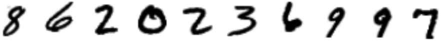

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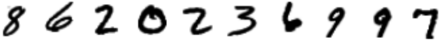

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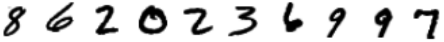

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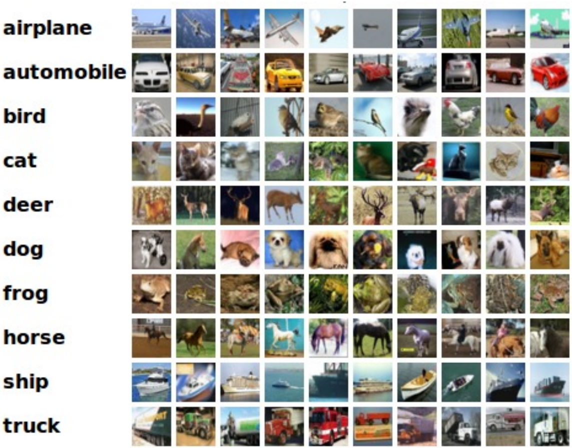

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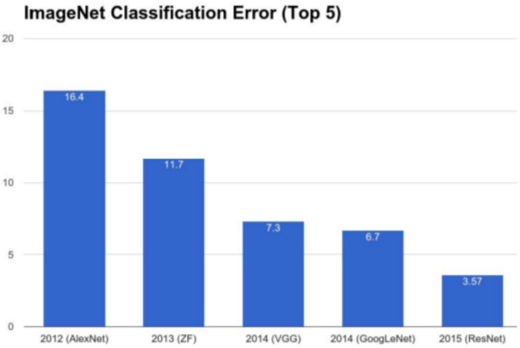

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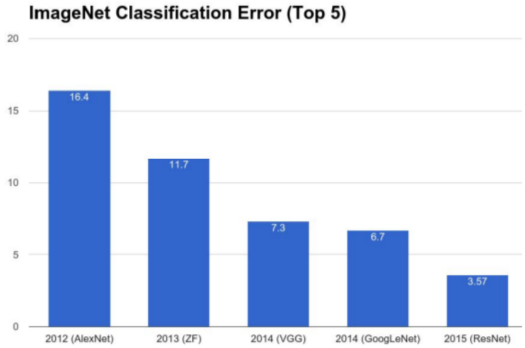

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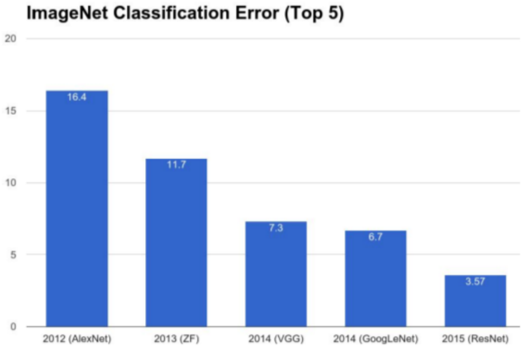

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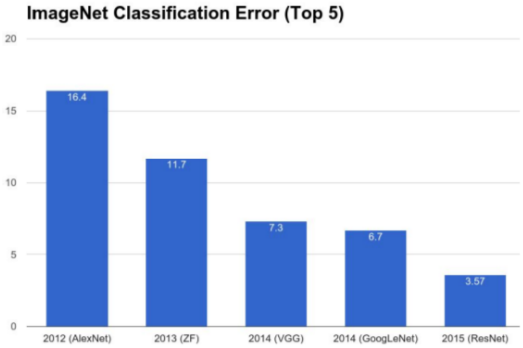

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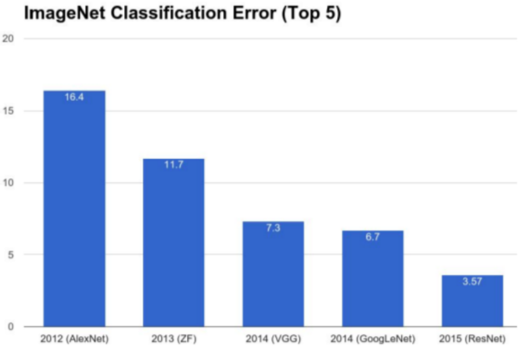

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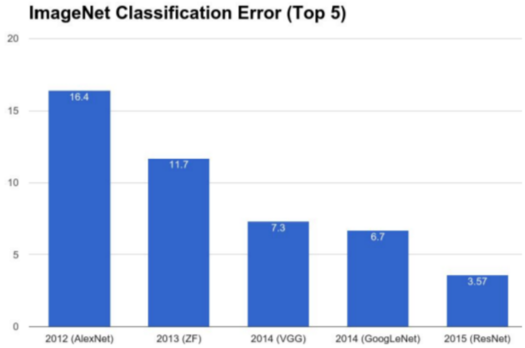

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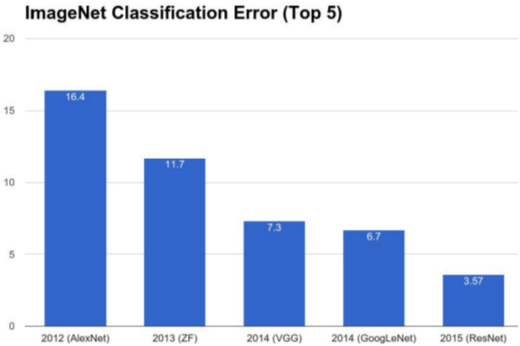

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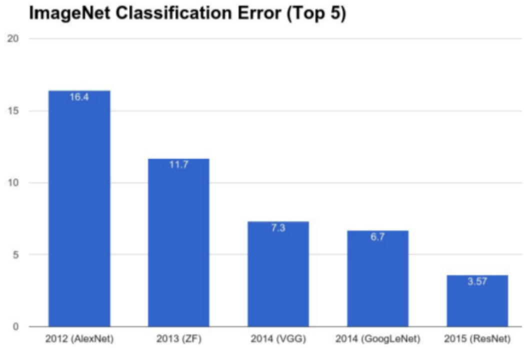

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Recent CNN architectures

GoogLeNet – Inception

Google

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Google

https://arxiv.org/abs/1409.4842

- Classical CNN's are a sequence of convolution and pooling layers
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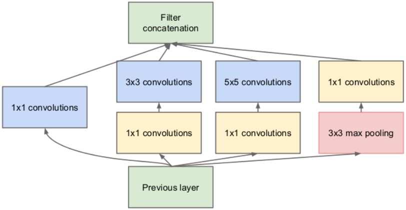

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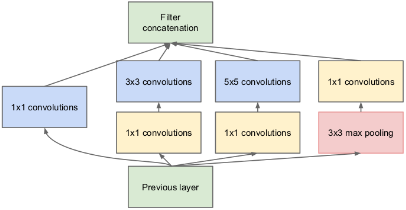

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F. Chollet https://arxiv.org/abs/1610.02357

- One can take factorization to an extreme...
- Factor all convolutions into a pointwise and spatial convolution
- This implemented in TensorFlow/Keras as first performing spatial convolution for each channel separately and then projecting pointwise by a 1×1 convolution
- Works better than Inception V3 with same number of parameters
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Residual networks Microsoft

https://arxiv.org/abs/1512.03385
https://arxiv.org/abs/1603.05027

- In what way are *very* deep networks difficult to train?
  Not due to overfitting! – have difficulty learning the training set

- But in principle one could find a trivial 56-layer network which is as good as a 20 layer one — just take a 20 layer one an add 36 layers which realize an identity mapping..
- **Conclusion:** in conventional CNN's it is difficult to make deep layers learn the identity mapping!

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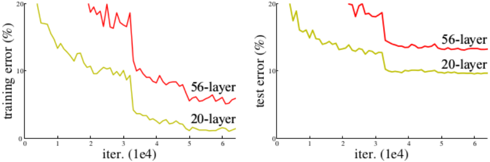

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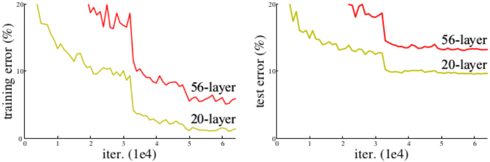

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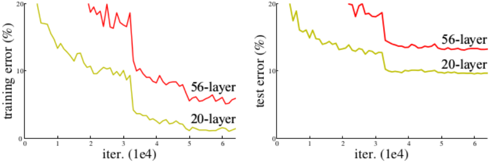

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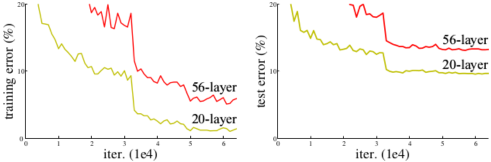

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Proposal: Learn deviations from identity rather than the full mapping...

- Stacking such residual units gives CNN's with many layers: 200 on ImageNet and even 1001 on CIFAR!
- Various variations of this idea have been tested in the second paper (this is the latest version)
- Residual networks have become the state-of-the-art
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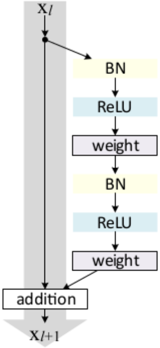

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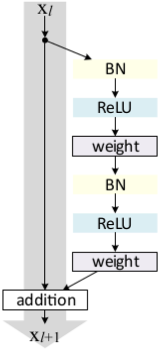

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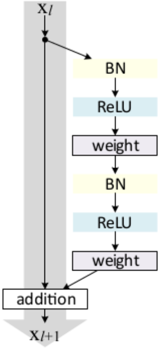

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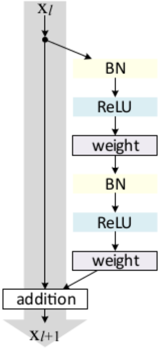

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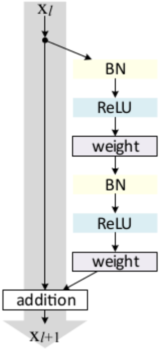

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Densely connected convolutional networks

Facebook+Cornell+Tsinghua U.

https://arxiv.org/abs/1608.06993

- Residual networks (and earlier more complicated *Highway networks* + other ideas: *stochastic depth*, *FractalNets*) provide multiple paths for data to flow through the networks
- Densely connected convolutional networks (DensNet) exploit this idea

- The outputs of the layers in each block are concatenated (and not summed)
- In the transition layers the authors reduce the number of features while in the convolution layers introduce 1×1 convolutions (bottleneck layers)

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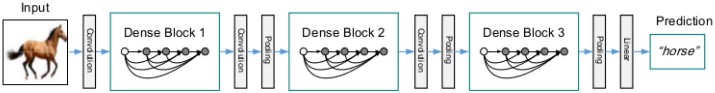

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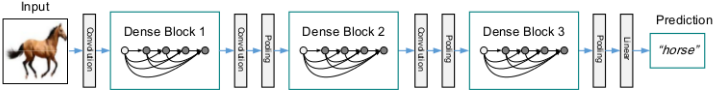

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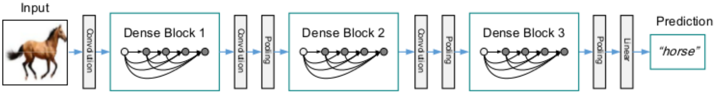

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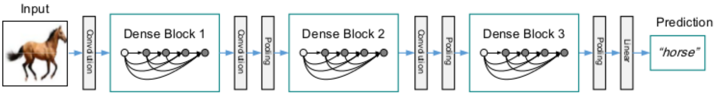

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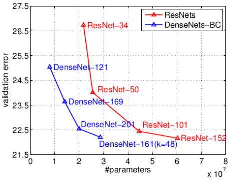


Top-1 error on ImageNet

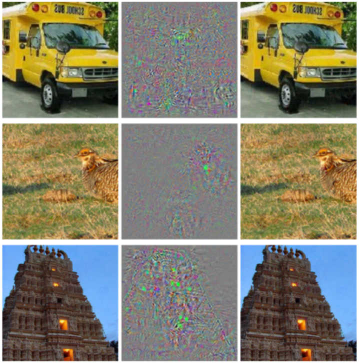
Interlude

Intriguing properties of neural networks

https://arxiv.org/abs/1312.6199

- On the left: images which correctly classified by AlexNet (deep CNN trained on ImageNet)
- Center: perturbations magnified $10\times$
- On the right: images classified by the same net as **ostrich!!!**

Intriguing properties of neural networks



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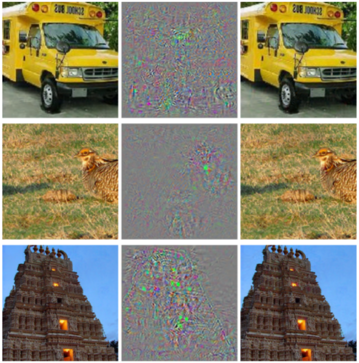

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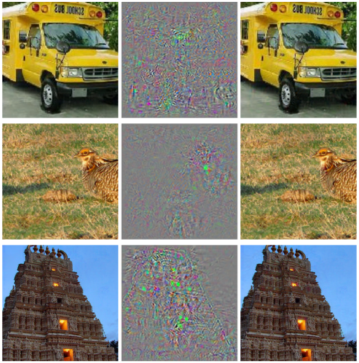

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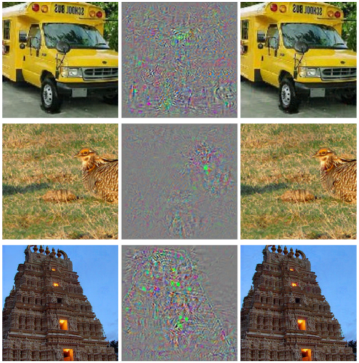

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Deep Neural Networks are Easily Fooled: High Confidence Predictions for Unrecognizable Images

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- These examples were constructed by a kind of evolutionary procedure...

Our results shed light on interesting differences between human vision and current DNNs, and raise questions about the generality of DNN computer vision.

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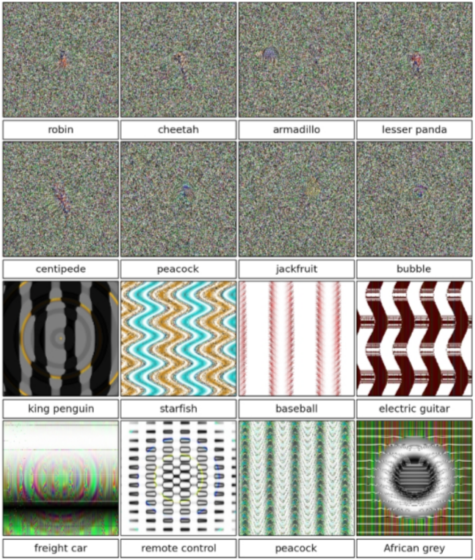

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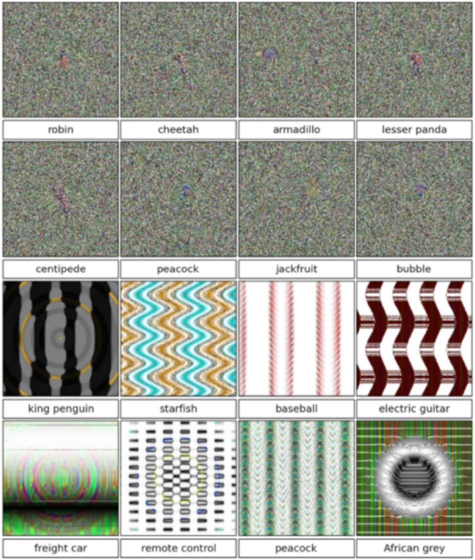

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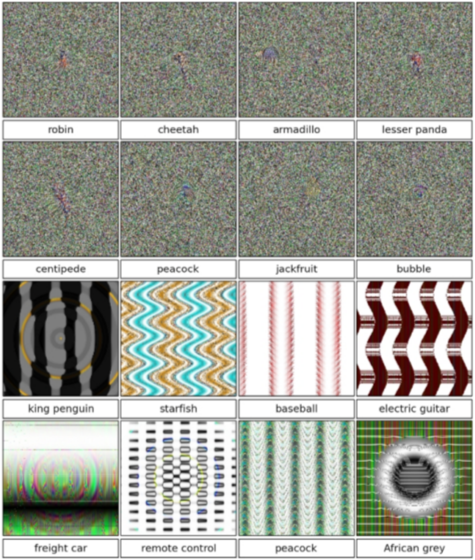

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Image segmentation

Image segmentation task:

Not only identify the class(es) of the objects in the image but locate them pixelwise

Very good set of lectures @Stanford '16 (slides and notes online!):
CS321n: Convolutional Neural Networks for Visual Recognition
http://cs231n.stanford.edu/syllabus.html

Image segmentation

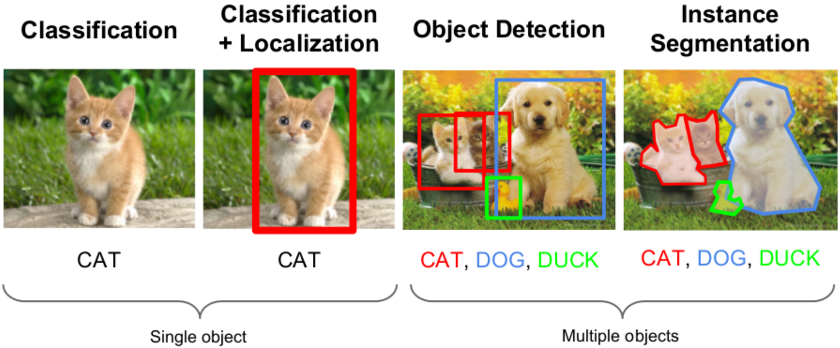

Image segmentation task:

Not only identify the class(es) of the objects in the image but locate them pixelwise

Very good set of lectures @Stanford '16 (slides and notes online!):
CS321n: Convolutional Neural Networks for Visual Recognition

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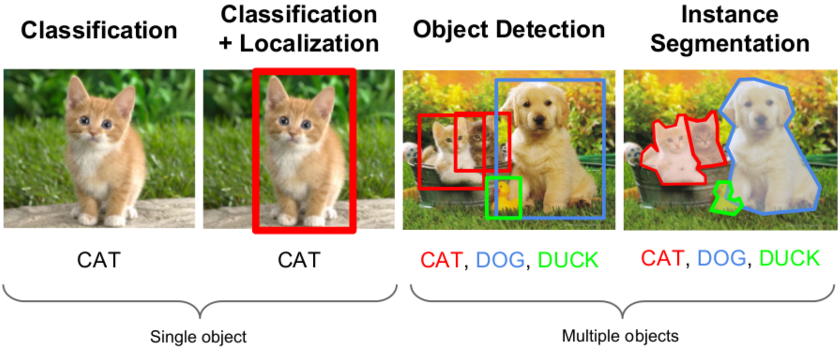

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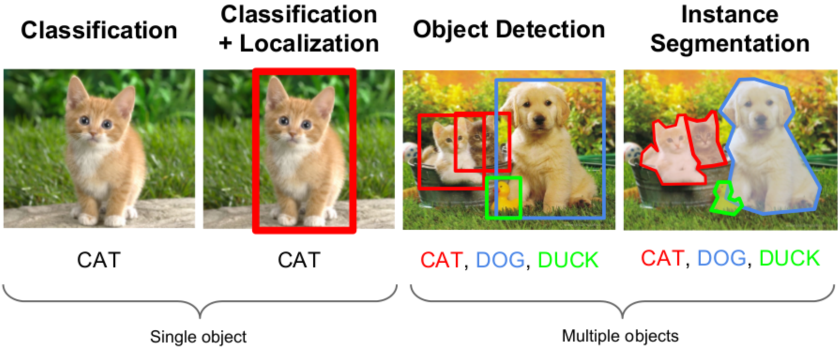

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Fully Convolutional Networks — U-Net

https://arxiv.org/abs/1505.04597

- Network used for biomedical image segmentation... (but generic segmentation architecture)
- Lots of papers, see e.g. https://arxiv.org/abs/1611.09326 Y. Bengio et.al. *Fully convolutional DenseNets for semantic segmentation*

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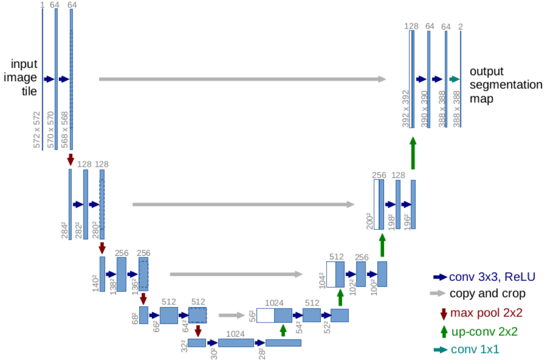

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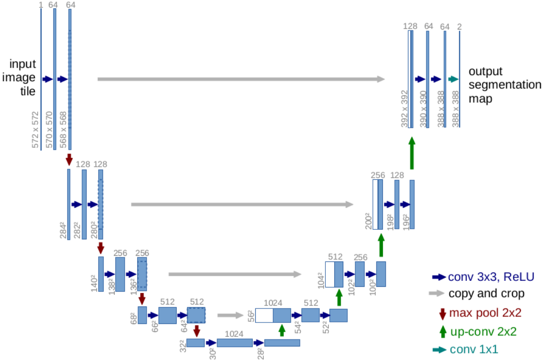

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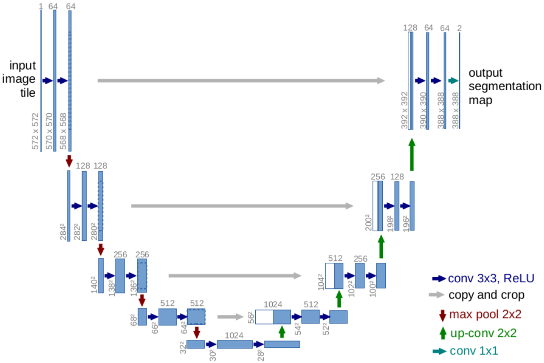

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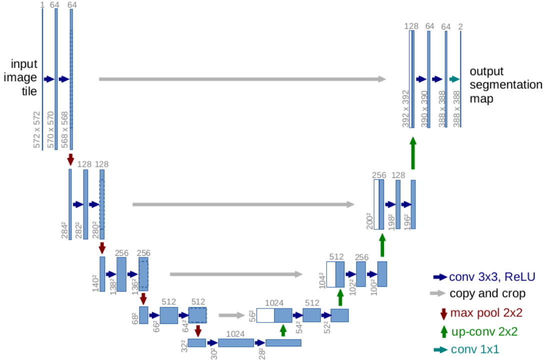

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- Convolutional networks are used primarily for images but can be also used for time-series data (1D convolutions) and video (3D convolution)
- Apart from classification, CNNs are also used e.g. for image segmentation
- GPU's are currently absolutely crucial for computation...
- Convolutional networks are still being developed and improved...
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