Machine Intelligence: Deep Learning
Week 5

Zurich University of Applied Sciences

CNNs part II

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Remark: Much of the material has been developed together with Elvis Murina and Oliver Dürr

Topics

- Recap

- What to do in case of limited data?
  - Data augmentation
  - Transfer learning: use pre-trained CNNs and fine tune only last couple of layers

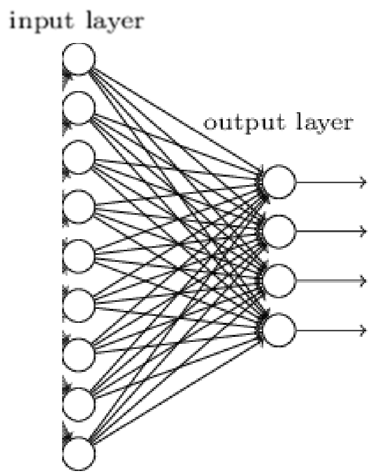
- Understand what a CNN has learned
  - Visualize the image patches that give rise for high activations of intermediate neurons
  - visualize image parts that are important for the assignment to a certain class

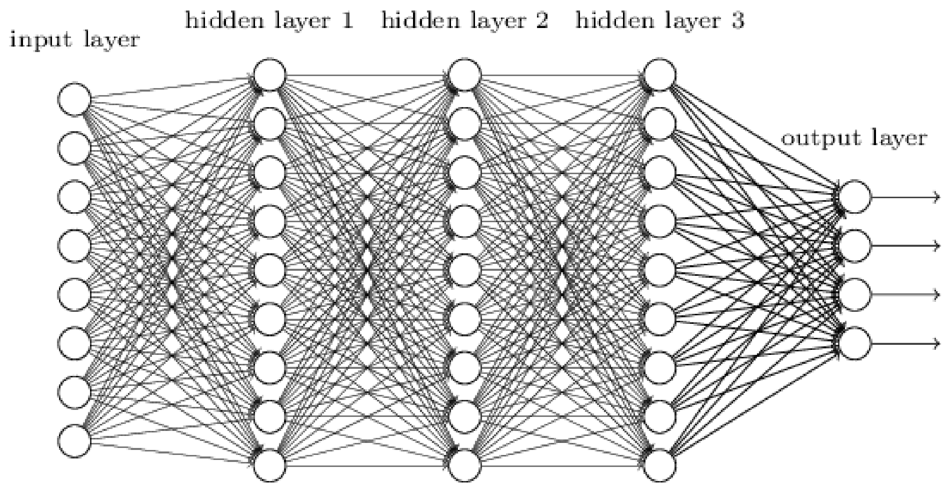
- Famous CNN architectures and tricks they make use of
  - LeNet, AlexNet, GoogleNet, VGG, Microsoft ResNet

- Causal and dilated 1D CNNs for time-ordered data

Discussed architectures NNs to CNNs

Fully connected Neural Networks (fcNN) without and with hidden layers:





Convolutional Neural Network:

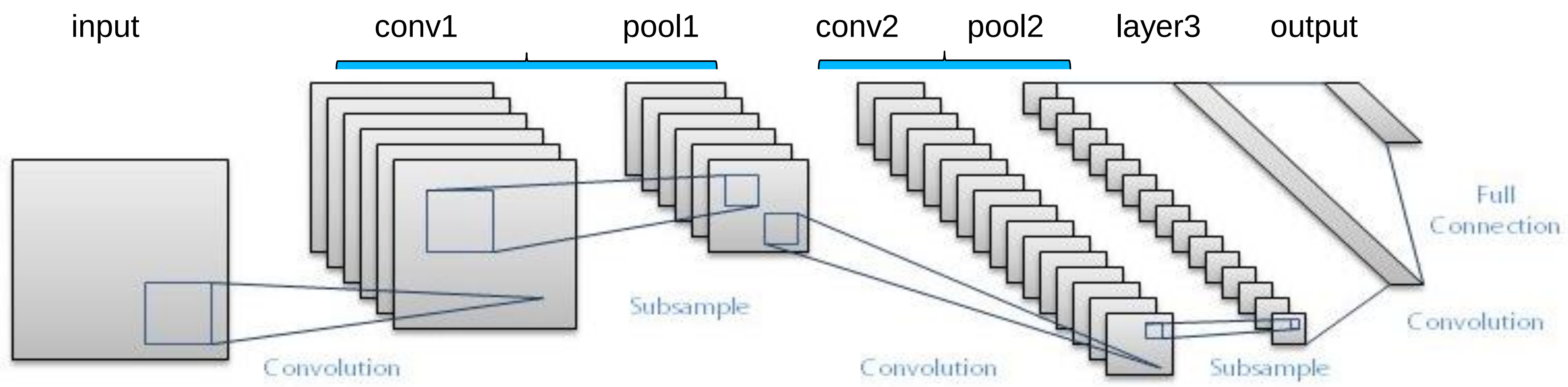
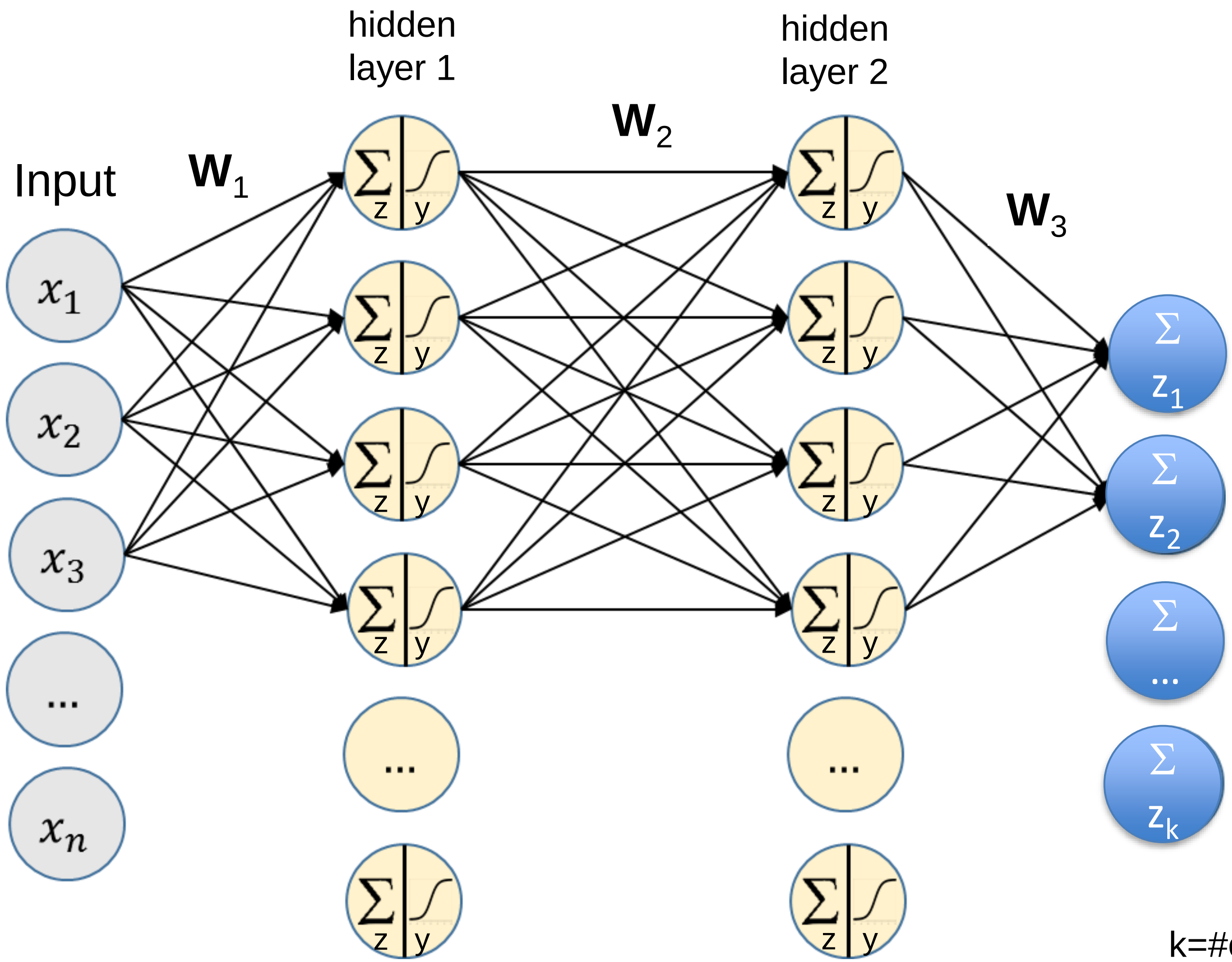


Image credits: http://neuralnetworksanddeeplearning.com/chap6.html, http://www.cemetech.net/projects/ee/scouter/thesis.pdf

A fully conneted neural networks with 2 hidden layers



$$\hat{p}_1 = \frac{e^{z_1}}{\sum_{j=1}^{k} e^{z_j}}$$

$$\hat{p}_2 = \frac{e^{z_2}}{\sum_{j=1}^{k} e^{z_j}}$$

$$\vdots$$

$$\hat{p}_k = \frac{e^{z_k}}{\sum_{j=1}^{k} e^{z_j}}$$

k=#classes

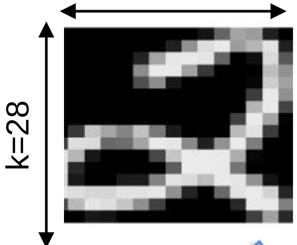
$$z = b + \sum_i (x_i \cdot w_i) \quad y = f(z)$$

Remark: weight values in the weight matrices that are learned during training.

What is going on in our 1 layer fully connected NN?

input
$\mathbf{x}^t$

k=28



Flatten to vector with k^2 elements

$$\begin{bmatrix} 24.0 \\ -5.1 \\ 12.2 \\ 89.9 \\ \vdots \\ 3.2 \end{bmatrix}$$

$$\mathbf{x}_{(1,k^2)} \cdot \mathbf{W}_{(k^2,2)} + \mathbf{b}_{(1,2)} = \mathbf{z}_{(1,2)}$$

Score or logit
$\mathbf{z}^t$

$$\begin{bmatrix} 2.3 \\ 0.1 \end{bmatrix}$$

$$\hat{\mathrm{p}}_k = \frac{e^{z_k}}{\sum_j e^{zj}}$$

Softmax or probability
$\mathbf{p}$=S($\mathbf{z}$)

$$\begin{bmatrix} 0.9 \\ 0.1 \end{bmatrix}$$

1-hot labels
$\mathbf{y}$

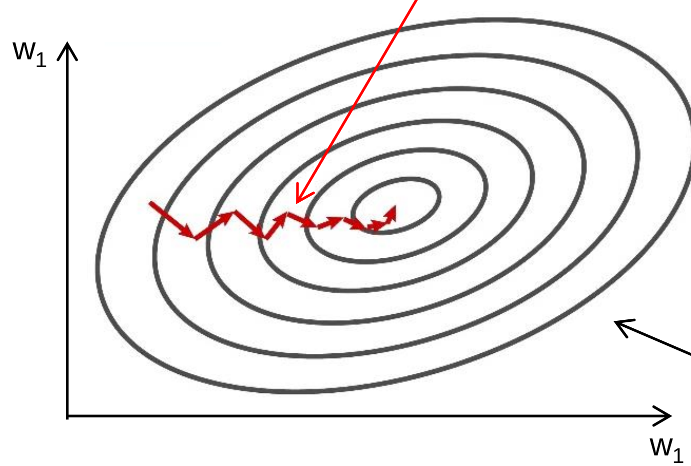
$$\begin{bmatrix} 1 \\ 0 \end{bmatrix} \begin{matrix} \text{“2”} \\ \text{“1”} \end{matrix}$$

$D(\mathbf{p}, \mathbf{y})$ cross-entropy

$$= -\sum_{k=1}^{2} y_k \cdot \log\left(p_k\right)$$

Take step in direction of descent gradient: $w_i^{(t)} = w_i^{(t-1)} - \varepsilon^{(t)} \left.\frac{\partial C(\mathbf{w})}{\partial w_i}\right|_{w_i = w_i^{(t-1)}}$

(the gradient is oriented orthogonal to contour lines)



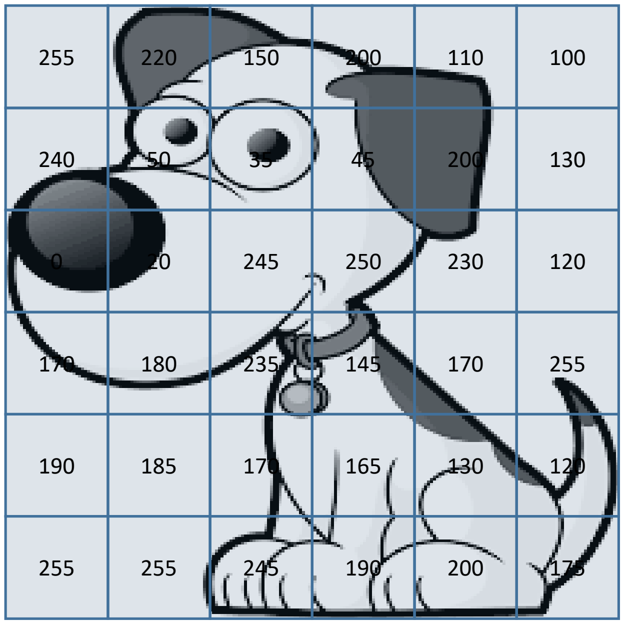
$\mathrm{C}\left(w_1, w_2\right)$

Cost C or Loss = cross-entropy averaged over all images in mini-batch

$$\mathrm{C} = \frac{1}{N} \sum_i D(\mathbf{p}_i, \mathbf{y}_i)$$

Convolutional neural networks

Input image 6x6x1



255	220	150	200	110	100
240	50	35	45	200	130
0	20	245	250	230	120
170	180	235	145	170	255
190	185	170	165	130	120
255	255	245	190	200	175

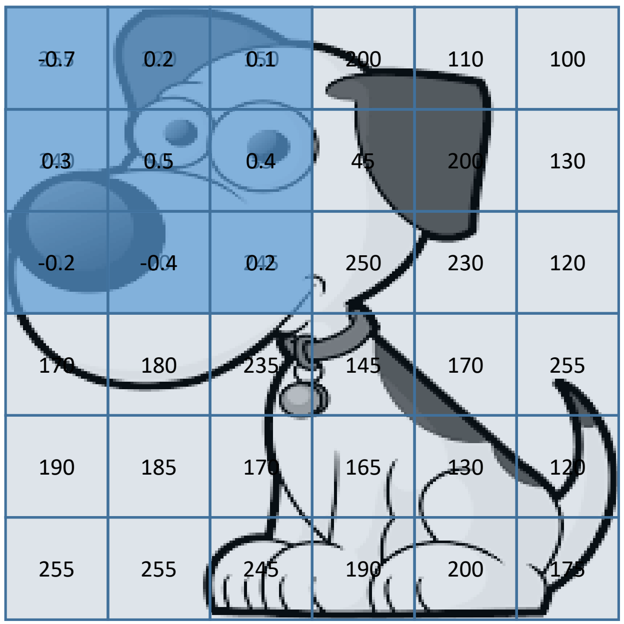
-0.7	0.2	0.1
0.3	0.5	0.4
-0.2	-0.4	0.2

3x3 filter

$$z_j = \sum_i \left(x_i \cdot w_{ij} \right)$$

Convolutional neural networks

Input image 6x6x1



Feature map
4x4x1

32.5

-0.7	0.2	0.1
0.3	0.5	0.4
-0.2	-0.4	0.2

3x3 filter

$$z_j = \sum_i \left(x_i \cdot w_{ij} \right)$$

Convolutional neural networks

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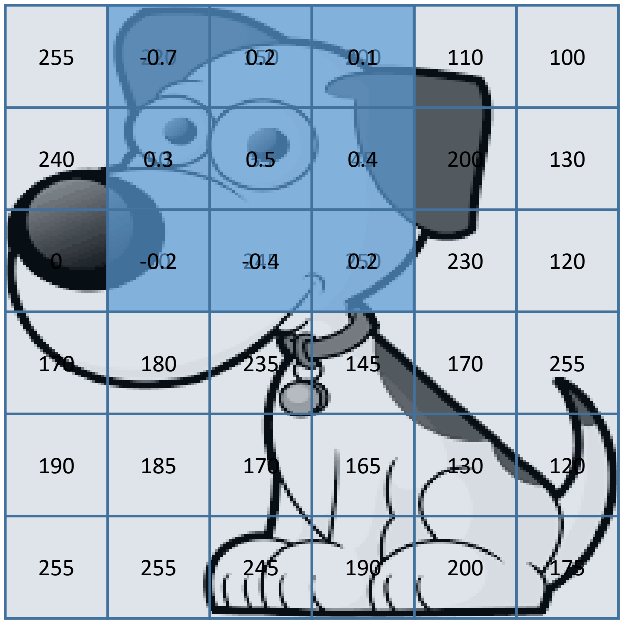

255	-0.7	0.2	0.1	110	100
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0	-0.2	-0.4	0.2	230	120
170	180	235	145	170	255
190	185	170	165	130	120
255	255	245	190	200	175

Feature map
4x4x1

32.5	-105.5

-0.7	0.2	0.1
0.3	0.5	0.4
-0.2	-0.4	0.2

3x3 filter

$$z_j = \sum_i \left(x_i \cdot w_{ij} \right)$$

Convolutional neural networks

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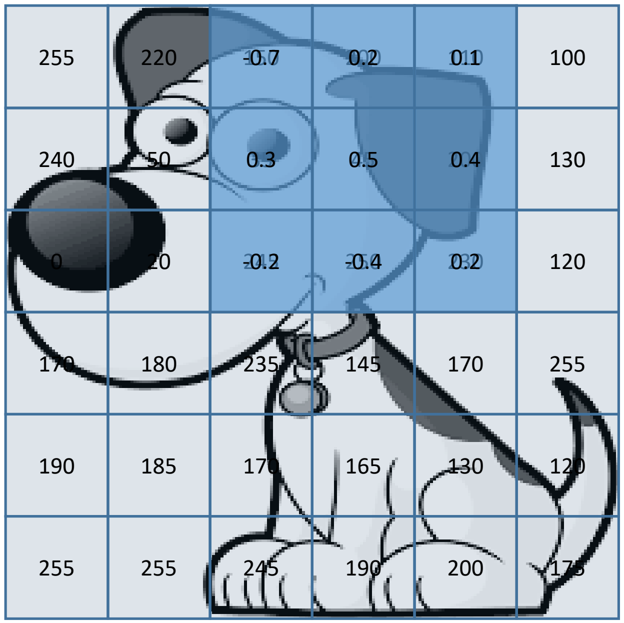

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0	20	-0.2	-0.4	0.2	120
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Feature map
4x4x1

32.5	-105.5	185.5

-0.7	0.2	0.1
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3x3 filter

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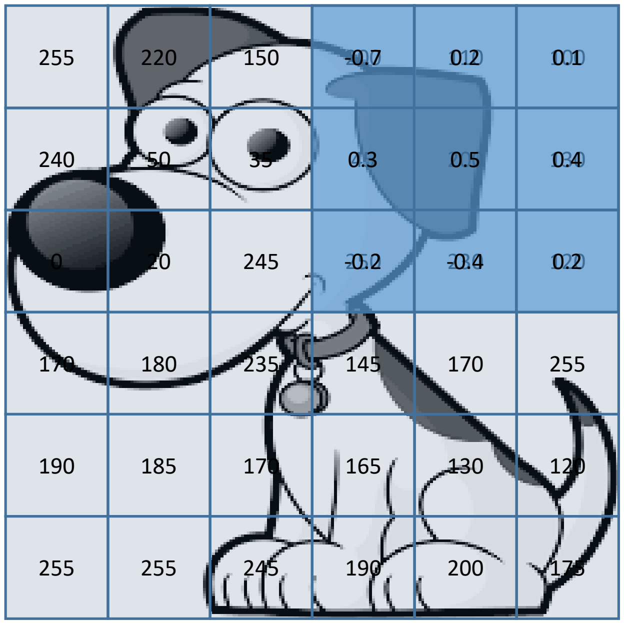

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0	20	245	-0.2	-0.4	0.2
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Feature map
4x4x1

32.5	-105.5	185.5	54

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Convolutional neural networks

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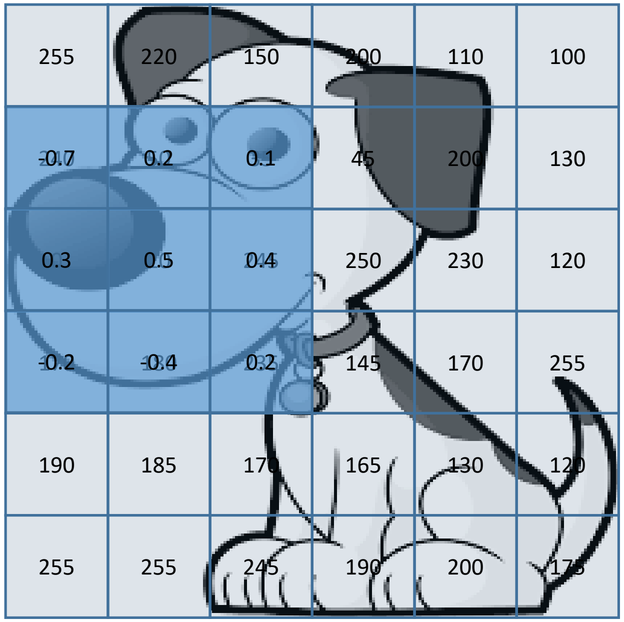

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0.3	0.5	0.4	250	230	120
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Feature map
4x4x1

32.5	-105.5	185.5	54
-105.5			

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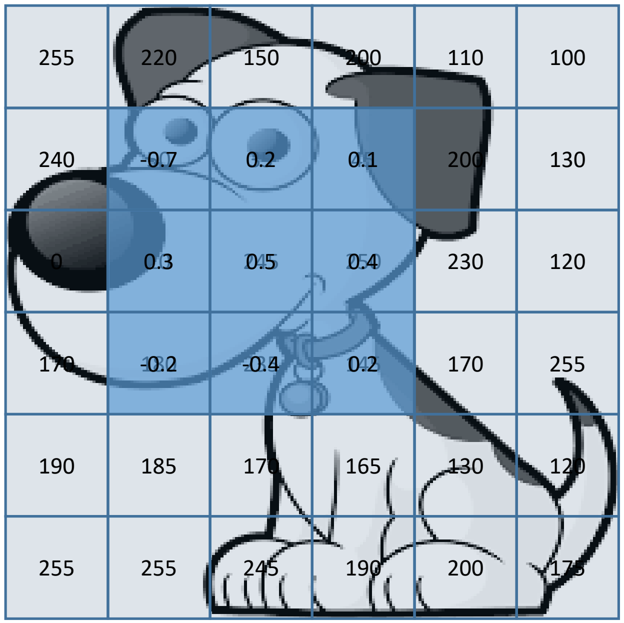

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170	-0.2	-0.4	0.2	170	255
190	185	170	165	130	120
255	255	245	190	200	175

Feature map 4x4x1

32.5	-105.5	185.5	54
-105.5	104		

-0.7	0.2	0.1
0.3	0.5	0.4
-0.2	-0.4	0.2

3x3 filter

$$z_j = \sum_i \left(x_i \cdot w_{ij} \right)$$

Convolutional neural networks

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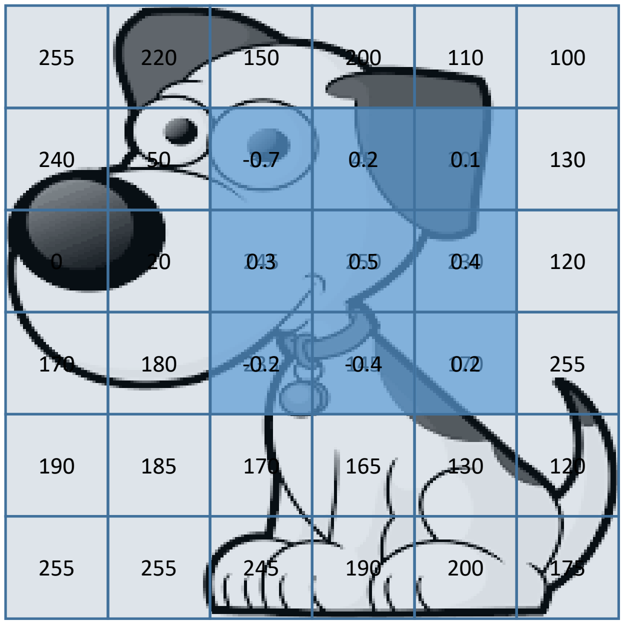

Feature map
4x4x1

32.5	-105.5	185.5	54
-105.5	104	217.5	

-0.7	0.2	0.1
0.3	0.5	0.4
-0.2	-0.4	0.2

3x3 filter

$$z_j = \sum_i \left(x_i \cdot w_{ij} \right)$$

Convolutional neural networks

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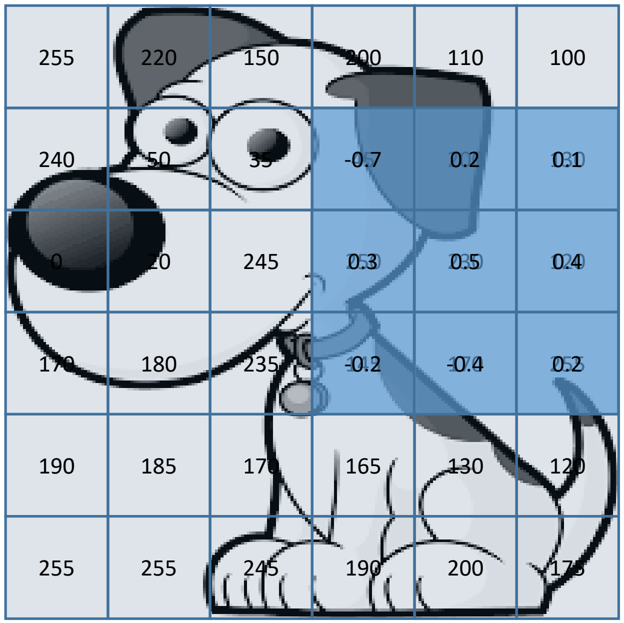

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0	20	245	0.3	0.5	0.4
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190	185	170	165	130	120
255	255	245	190	200	175

Feature map 4x4x1

32.5	-105.5	185.5	54
-105.5	104	217.5	31

-0.7	0.2	0.1
0.3	0.5	0.4
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3x3 filter

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Convolutional neural networks

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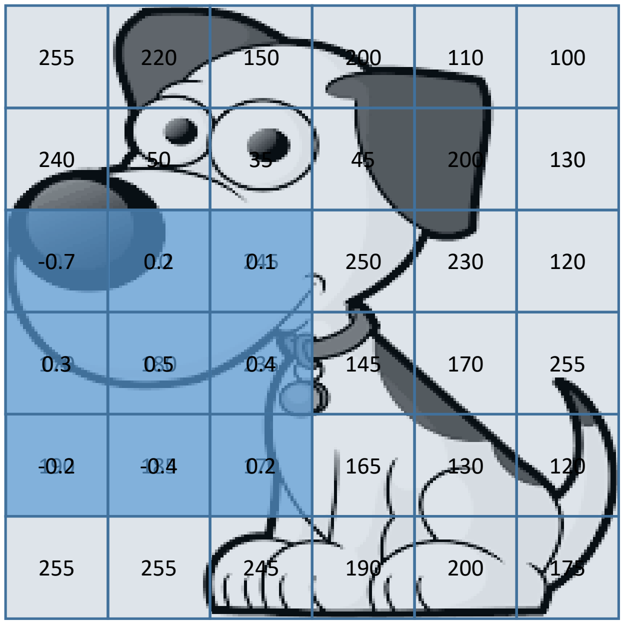

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0.3	0.5	0.4	145	170	255
-0.2	-0.4	0.2	165	130	120
255	255	245	190	200	175

Feature map
4x4x1

32.5	-105.5	185.5	54
-105.5	104	217.5	31
-44			

-0.7	0.2	0.1
0.3	0.5	0.4
-0.2	-0.4	0.2

3x3 filter

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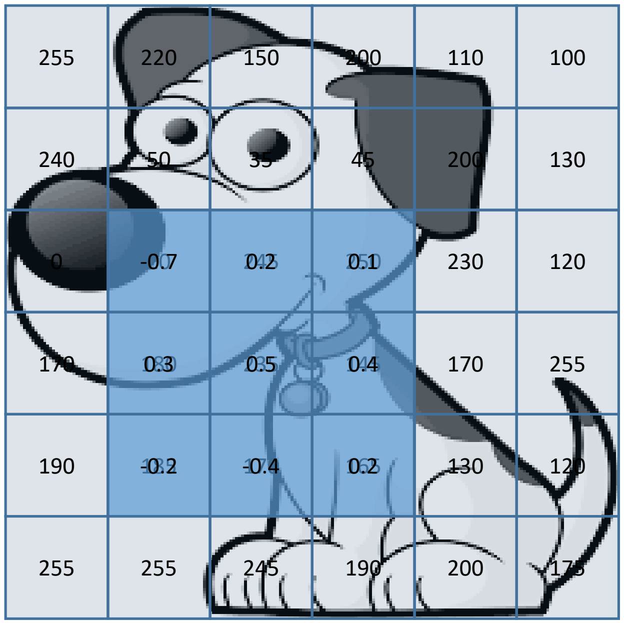
Convolutional neural networks

Input image 6x6x1



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190	-0.2	-0.4	0.2	130	120
255	255	245	190	200	175

Feature map 4x4x1

32.5	-105.5	185.5	54
-105.5	104	217.5	31
-44	224		

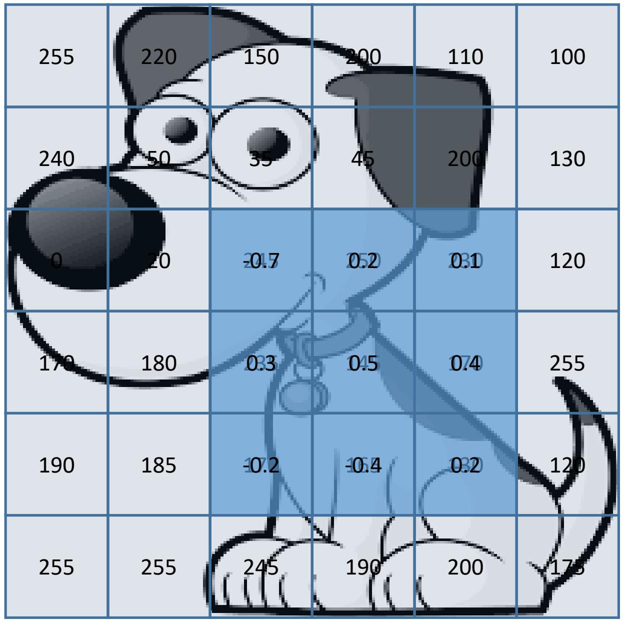
-0.7	0.2	0.1
0.3	0.5	0.4
-0.2	-0.4	0.2

3x3 filter

$$z_j = \sum_i \left(x_i \cdot w_{ij} \right)$$

Convolutional neural networks

Input image 6x6x1



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170	180	0.3	0.5	0.4	255
190	185	-0.2	-0.4	0.2	120
255	255	245	190	200	175

Feature map 4x4x1

32.5	-105.5	185.5	54
-105.5	104	217.5	31
-44	224	38.5	

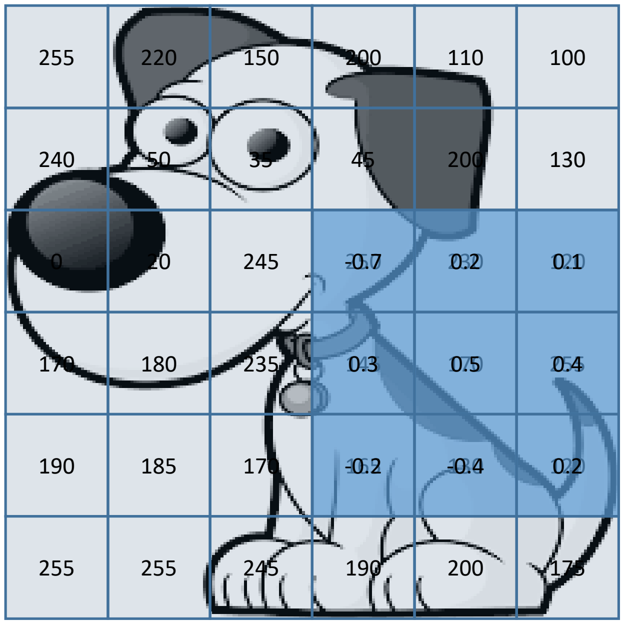
-0.7	0.2	0.1
0.3	0.5	0.4
-0.2	-0.4	0.2

3x3 filter

$$z_j = \sum_i \left(x_i \cdot w_{ij} \right)$$

Convolutional neural networks

Input image 6x6x1



Feature map
4x4x1

32.5	-105.5	185.5	54
-105.5	104	217.5	31
-44	224	38.5	-18

-0.7	0.2	0.1
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3x3 filter

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Convolutional neural networks

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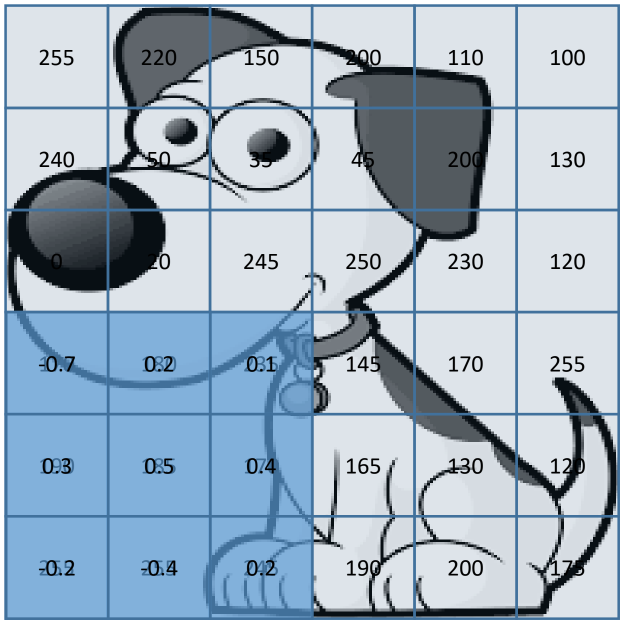

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0.3	0.5	0.4	165	130	120
-0.2	-0.4	0.2	190	200	175

Feature map
4x4x1

32.5	-105.5	185.5	54
-105.5	104	217.5	31
-44	224	38.5	-18
-60.5			

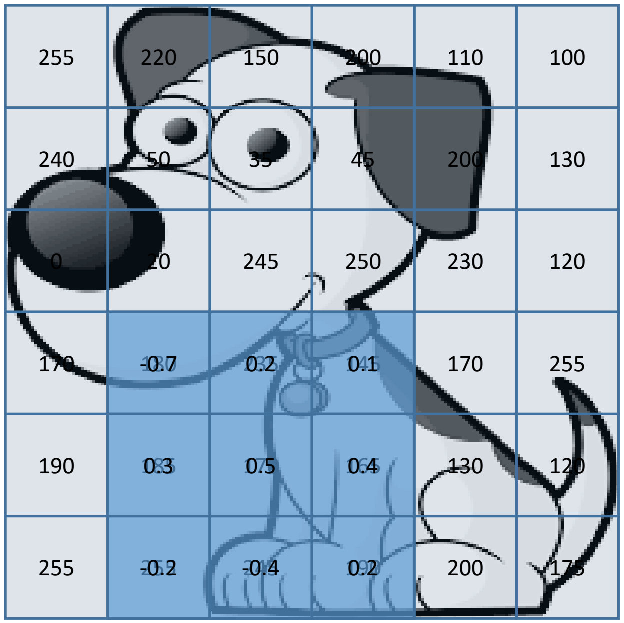
-0.7	0.2	0.1
0.3	0.5	0.4
-0.2	-0.4	0.2

3x3 filter

$$z_j = \sum_i \left(x_i \cdot w_{ij} \right)$$

Convolutional neural networks

Input image 6x6x1



Feature map
4x4x1

32.5	-105.5	185.5	54
-105.5	104	217.5	31
-44	224	38.5	-18
-60.5	213.5		

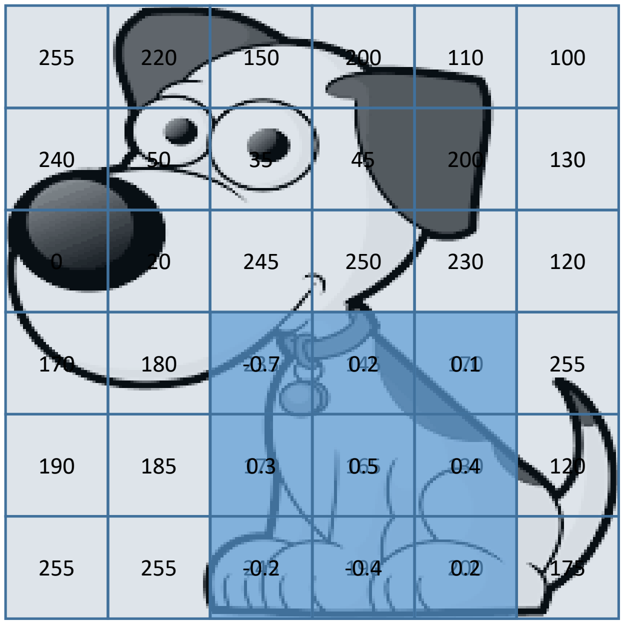
-0.7	0.2	0.1
0.3	0.5	0.4
-0.2	-0.4	0.2

3x3 filter

$$z_j = \sum_i \left(x_i \cdot w_{ij} \right)$$

Convolutional neural networks

Input image 6x6x1



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255	255	-0.2	-0.4	0.2	175

Feature map
4x4x1

32.5	-105.5	185.5	54
-105.5	104	217.5	31
-44	224	38.5	-18
-60.5	213.5	52.5	

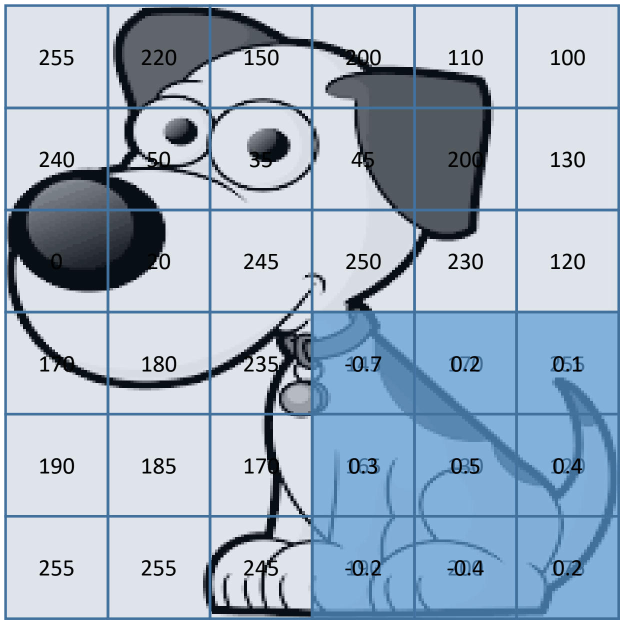
-0.7	0.2	0.1
0.3	0.5	0.4
-0.2	-0.4	0.2

3x3 filter

$$z_j = \sum_i \left(x_i \cdot w_{ij} \right)$$

Convolutional neural networks

Input image 6x6x1



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170	180	235	-0.7	0.2	0.1
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Feature map
4x4x1

32.5	-105.5	185.5	54
-105.5	104	217.5	31
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-0.7	0.2	0.1
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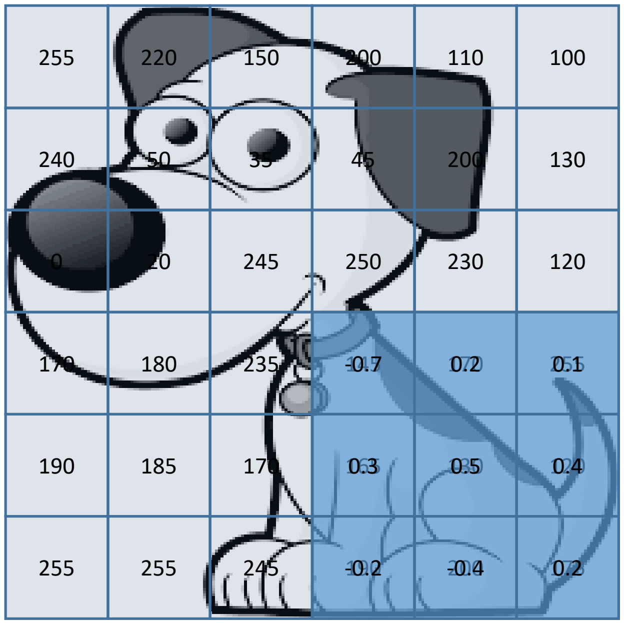
3x3 filter

Convolutional neural networks

Input image 6x6x1



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Feature map 4x4x1

32.5	-105.5	185.5	54
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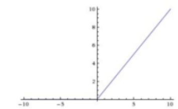


Relu

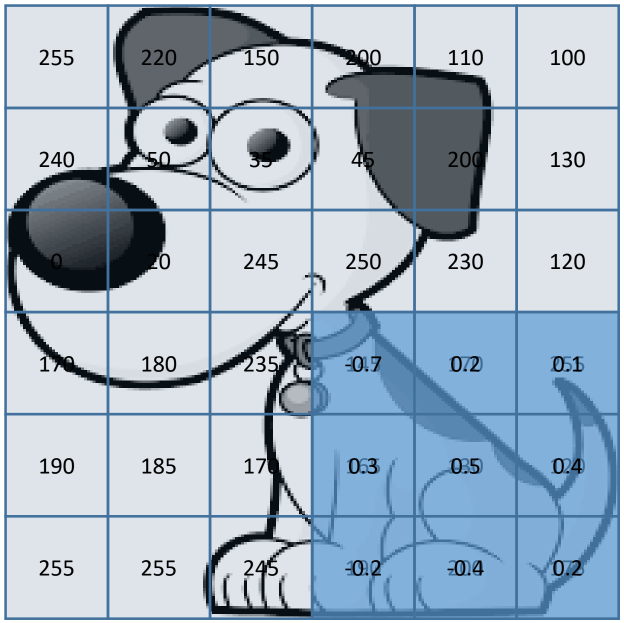
32.5	0	185.5	54
0	104	217.5	31
0	224	38.5	0
0	213.5	52.5	37.5

-0.7	0.2	0.1
0.3	0.5	0.4
-0.2	-0.4	0.2

3x3 filter

Convolutional neural networks

Input image 6x6x1



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Feature map 4x4x1

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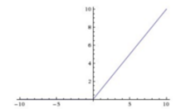


Relu

32.5	0	185.5	54
0	104	217.5	31
0	224	38.5	0
0	213.5	52.5	37.5

Maxpool (2x2x1)

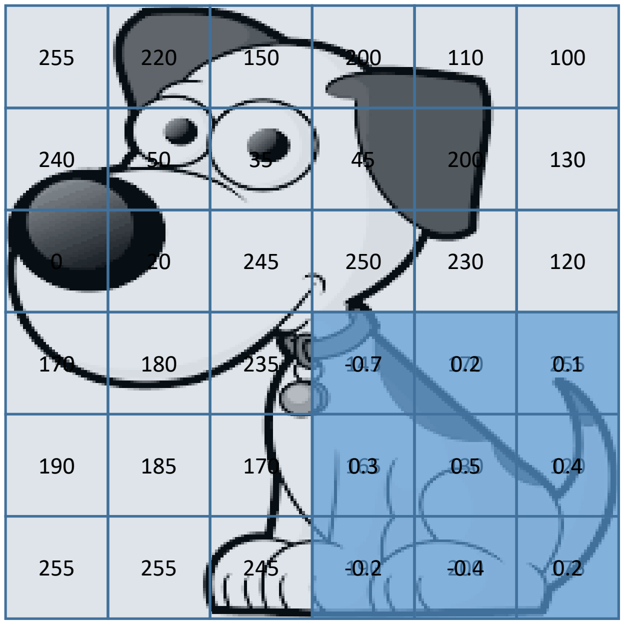
104

-0.7	0.2	0.1
0.3	0.5	0.4
-0.2	-0.4	0.2

3x3 filter

Convolutional neural networks

Input image 6x6x1



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Feature map 4x4x1

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-105.5	104	217.5	31
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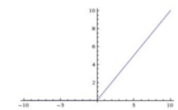


Relu

32.5	0	185.5	54
0	104	217.5	31
0	224	38.5	0
0	213.5	52.5	37.5

Maxpool (2x2x1)

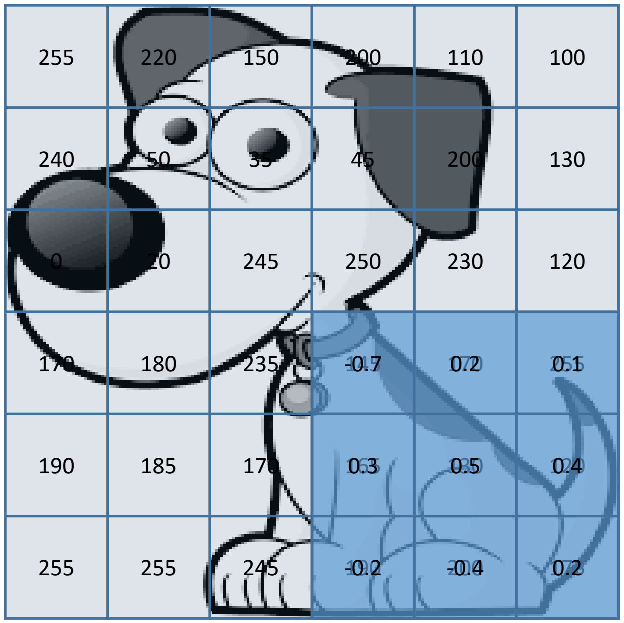
104	217.5

-0.7	0.2	0.1
0.3	0.5	0.4
-0.2	-0.4	0.2

3x3 filter

Convolutional neural networks

Input image 6x6x1



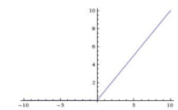
255	220	150	200	110	100
240	50	35	45	200	130
0	20	245	250	230	120
170	180	235	-0.7	0.2	0.1
190	185	170	0.3	0.5	0.4
255	255	245	-0.2	-0.4	0.2

-0.7	0.2	0.1
0.3	0.5	0.4
-0.2	-0.4	0.2

3x3 filter

Feature map 4x4x1

32.5	-105.5	185.5	54
-105.5	104	217.5	31
-44	224	38.5	-18
-60.5	213.5	52.5	37.5



Relu

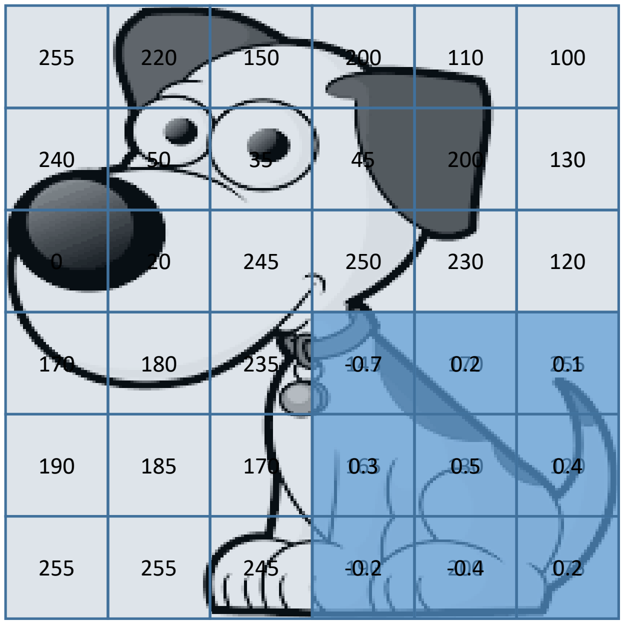
32.5	0	185.5	54
0	104	217.5	31
0	224	38.5	0
0	213.5	52.5	37.5

Maxpool (2x2x1)

104	217.5
224	

Convolutional neural networks

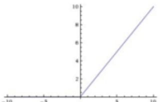
Input image 6x6x1



255	220	150	200	110	100
240	50	35	45	200	130
0	20	245	250	230	120
170	180	235	-0.7	0.2	0.1
190	185	170	0.3	0.5	0.4
255	255	245	-0.2	-0.4	0.2

Feature map 4x4x1

32.5	-105.5	185.5	54
-105.5	104	217.5	31
-44	224	38.5	-18
-60.5	213.5	52.5	37.5



Relu

32.5	0	185.5	54
0	104	217.5	31
0	224	38.5	0
0	213.5	52.5	37.5

Maxpool (2x2x1)

104	217.5
224	52.5

-0.7	0.2	0.1
0.3	0.5	0.4
-0.2	-0.4	0.2

3x3 filter

One kernel or filter searches for specific local feature

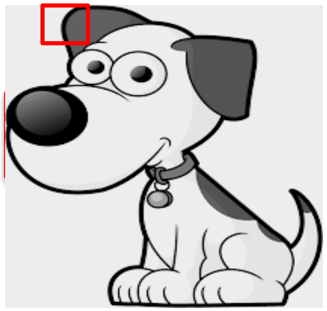


image patch

0	0	0	0	0	0	30
0	0	0	0	50	50	50
0	0	0	20	50	0	0
0	0	0	50	50	0	0
0	0	0	50	50	0	0
0	0	0	50	50	0	0
0	0	0	50	50	0	0

Pixel representation of the receptive field

*

filter/kernel: curve detector

0	0	0	0	0	30	0
0	0	0	0	30	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	0	0	0	0

Pixel representation of filter

=6600

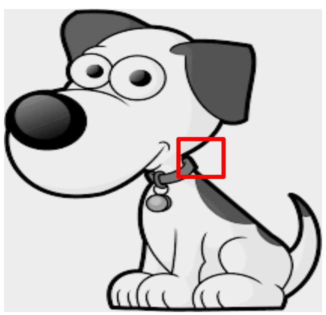


image patch

0	0	0	0	0	0	0
0	40	0	0	0	0	0
40	0	40	0	0	0	0
40	20	0	0	0	0	0
0	50	0	0	0	0	0
0	0	50	0	0	0	0
25	25	0	50	0	0	0

Pixel representation of receptive field

*

filter/kernel: curve detector

0	0	0	0	0	30	0
0	0	0	0	30	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	0	0	0	0

Pixel representation of filter

=0

We get a large resulting value if the filter resembles the pattern in the image patch on which the filter was applied.

credits: https://adeshpande3.github.io/adeshpande3.github.io/A-Beginner's-Guide-To-Understanding-Convolutional-Neural-Networks/

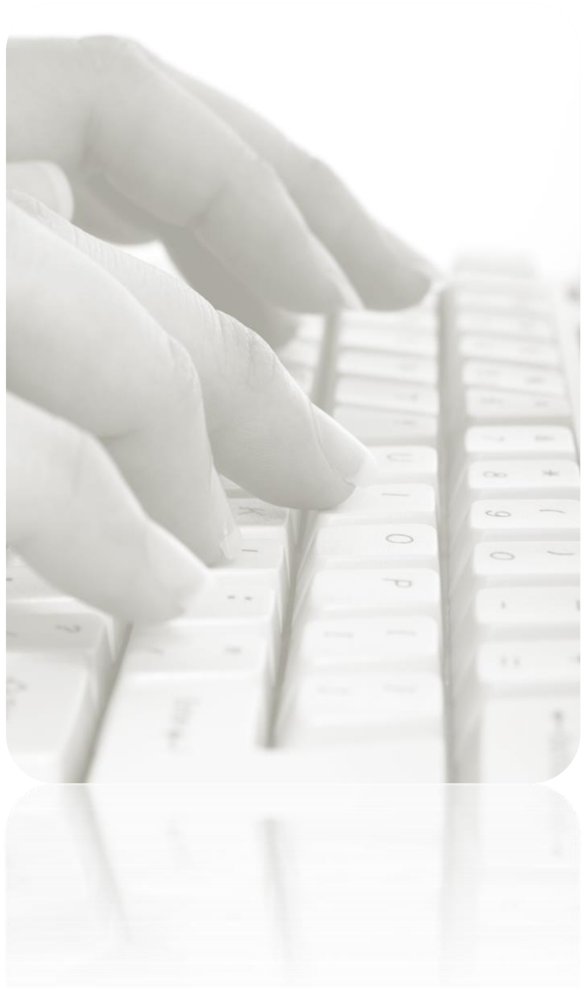
Exercise: Image based classification of celebrities

Task: Build and evaluate a fcNN and CNN for discrimination between 8 celebs.

For each of 8 celebrities you get 250 images in the training data set, 50 images in the validation data set and 50 images in test data set.

Example images:

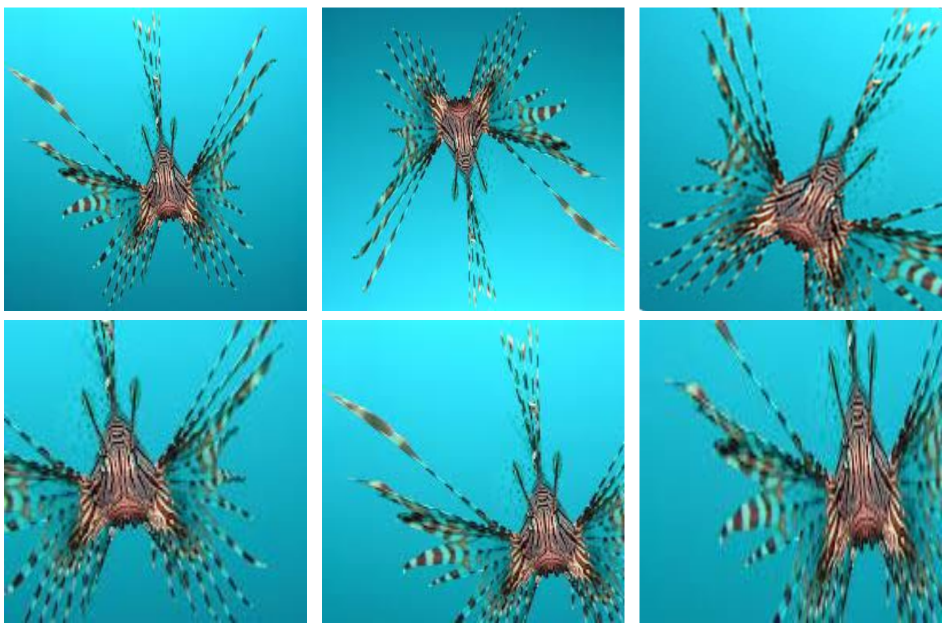
Label: Steve Jobs (entrepreneur)



What to do in case of limited data?

Fighting overfitting by Data augmentation ("always" done): "generate more data" on the flight during fitting the model

- Rotate image within an angle range
- Flip image: left/right, up, down
- resize
- Take patches from images
- ….



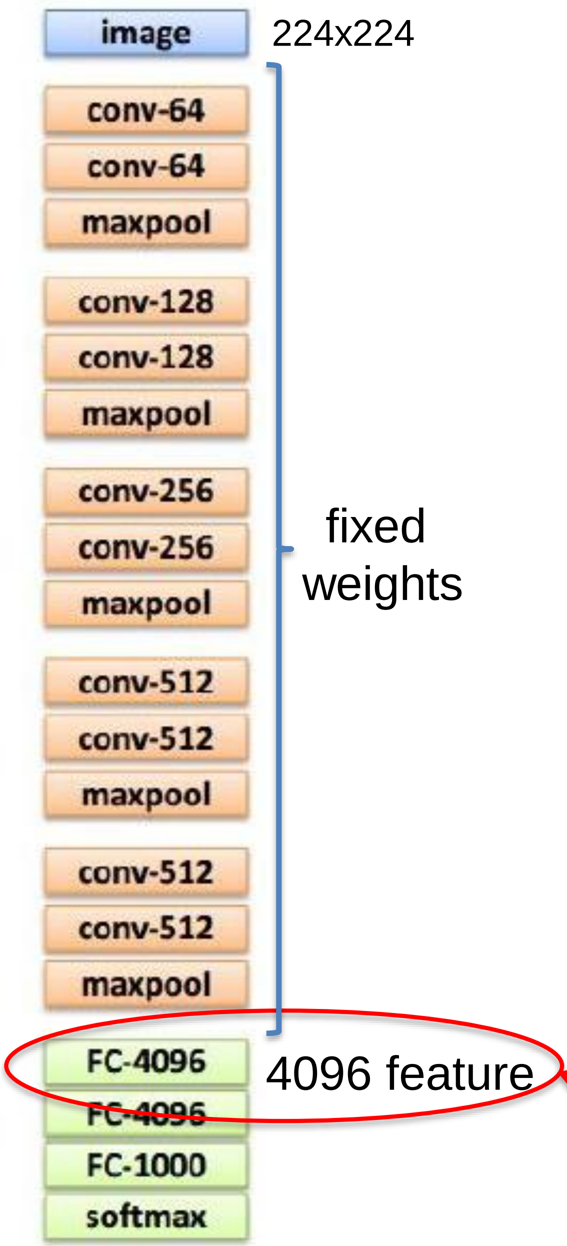
Data augmentation in Keras:

```
from keras.preprocessing.image import ImageDataGenerator

datagen = ImageDataGenerator(
    rotation_range=10,
    width_shift_range=0.1,
    height_shift_range=0.1,
    horizontal_flip=True,
    vertical_flip=True,
    #zoom_range=[0.1,0.1]
)
```

```
train_generator = datagen.flow(
          x = X_train_new,
          y = Y_train,
          batch_size = 128,
          shuffle = True)
```

```
history = model.fit_generator(
                    train_generator,
                    samples_per_epoch = X_train_new.shape[0],
                    epochs = 400,
                    validation_data = (X_valid_new, Y_valid),
                    verbose = 2,callbacks=[checkpointer]
)
```

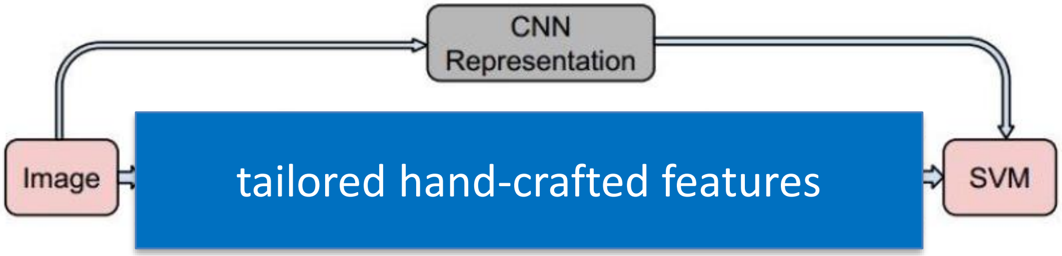
Use pre-trained CNNs for feature generation

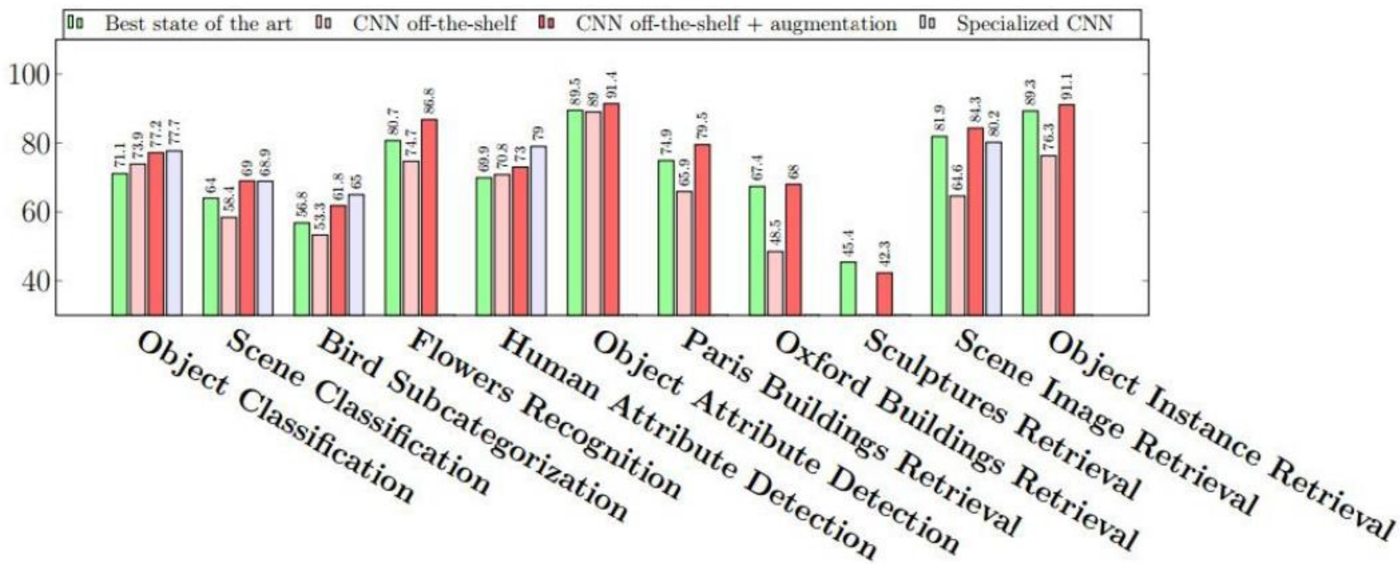


- Load a pre-trained CNN – e.g.g VGG16
- Resize image to required size (224x224 for VGG16)
- Rescaling of the pixel values to "VGG range"
- Do a forward pass and fetch 4096 features that are used as CNN representations, dump these features into a file on disk
- Use these CNN features as input to a simple classifier – e.g. fc NN, RF, SVM …
  (here it is easily possible to adapt to the new number of class labels)

Fetch this CNN feature vector for each image

Performance of off-the-shelf CNN features when compared to tailored hand-crafted features



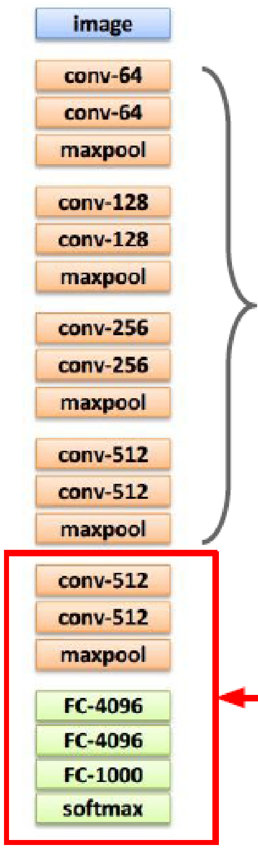


“Astonishingly, we report consistent superior results compared to the highly tuned state-of-the-art systems in all the visual classification tasks on various datasets.”

CNN Features off-the-shelf: an Astounding Baseline for Recognition [Razavian et al, 2014]

Transfer learning beyond using off-shelf CNN feature

e.g. medium data set (<1M images)



finetuning

more data = retrain more of the network (or all of it)

Freeze these (learning rate =0)

tip: use only ~1/10th of the original learning rate in finetuning top layer, and ~1/100th on intermediate layers

Train this

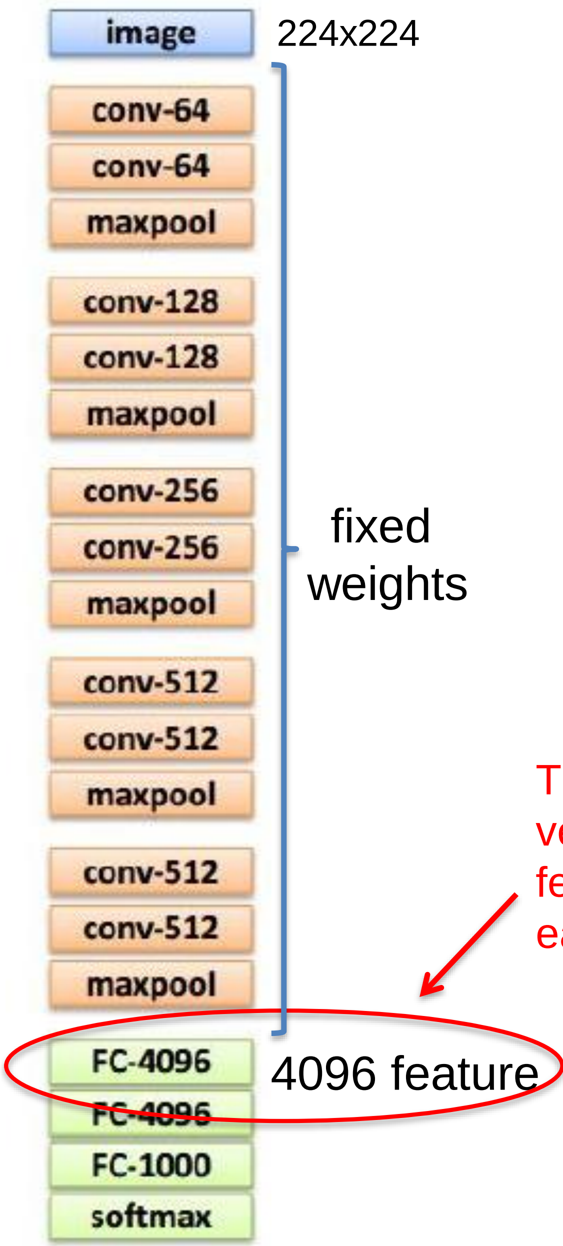
The strategy for fine-tuning depends on the size of the data set and the type of images:

	Similar task (to imageNet challenge)	**Very different task** (to imageNet challenge)
little data	Extract CNN representation of one top fc layer and use these features to train an external classifier	You are in trouble - try to extract CNN representations from different stages and use them as input to new classifier
lots of data	Fine-tune a few layers including few convolutional layers	Fine-tune a large number of layers

Hint: first retrain only fully connected layer, only then add convolutional layers for fine-tuning.

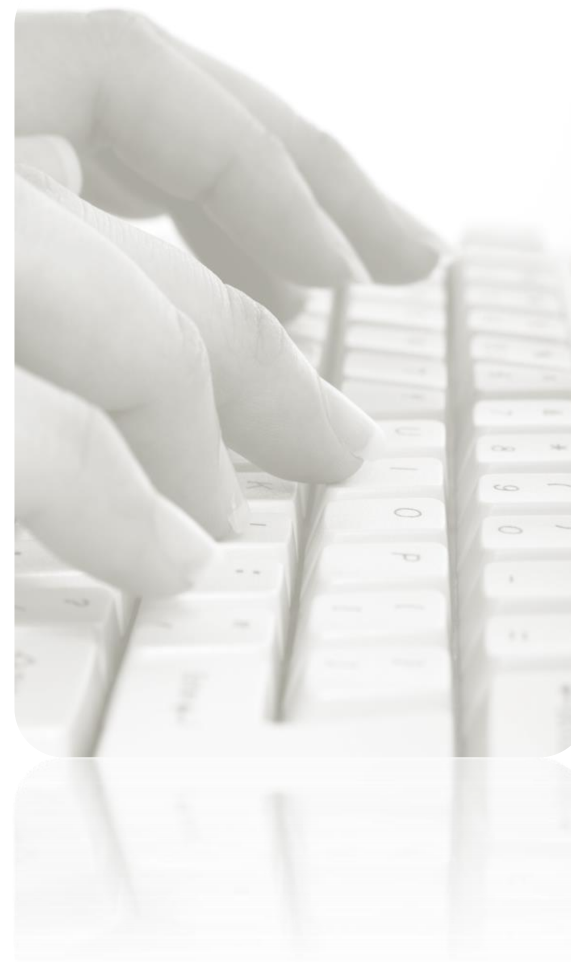
Slide credits (modified): cs231n

Exercise: Use CNN features for classification of 8 celebs



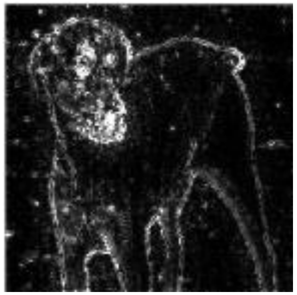
These CNN feature vectors have been fetched and stored for each image

Work through exercises 'transfer_learning'



What does the CNN look at?

Which pixels are important for the classification? *Saliency Maps*



Determine the strength of the pixels influence on the correct class score:

Forward image through trained CNN.
Start from softmax neuron of correct class and set its gradient to 1. Back-propagate the gradient through the CNN.

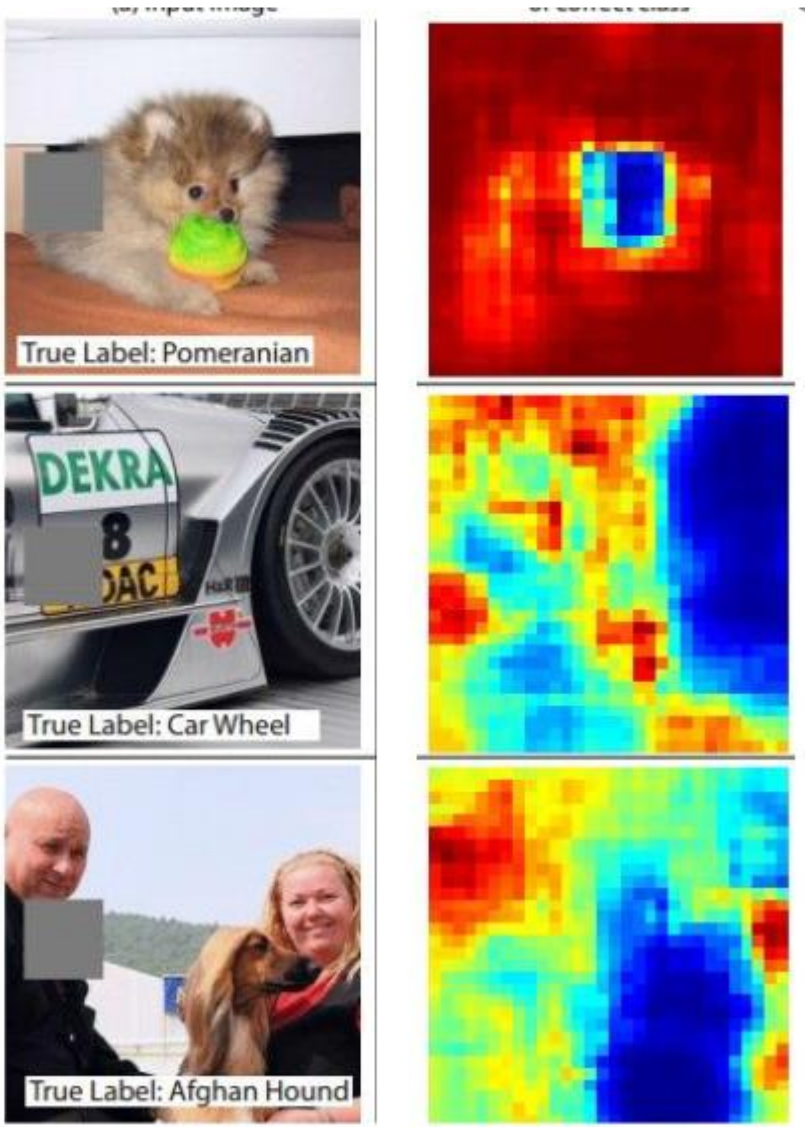
Visualize the gradient that arrives at the image as 2D heatmap (each pixel intensity corresponds to the absolute value of the gradients at this position maximized over the channels).

Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps, Karen Simonyan, Andrea Vedaldi, Andrew Zisserman, 2014

Example how to compute [saliency with keras]()

image credit: cs231n

Which pixels are important for the classification?
Occlusion experiments



Occlude part of the image with a mask
and check for each position of the mask how strongly the score for the correct class is changing.

Warning:
Usefulness depends on application…

Occlusion experiments [Zeiler & Fergus 2013]

image credit: cs231n

Which pixels are important for the classification?
LIME: Local Interpretable Model-agnostic Explanations

Idea:

1) perturb interpretable features of the instance – e.g. randomly delete super-pixels in an image and track as perturbation vector such as (0,1,1,0,…,1)=x.
2) Classify perturbed instance by your model, here a CNN, and track the achieved classification-score=y
3) Identify for which features/super-pixels the presence in the perturbed input version are important to get a high classification score (use RF or lasso for y~x)

(a) Husky classified as wolf (b) Explanation

-> presence of snow was used to distinguish wolf and husky

-> Explain the CNN classification by showing instance-specific important features
visualize important feature allows to judge the individual classification

(a) Original Image (b) Explaining *Electric guitar* (c) Explaining *Acoustic guitar* (d) Explaining *Labrador*

DOI: http://dx.doi.org/10.1145/2939672.2939778

Tf, python code: https://github.com/marcotcr/lime -> image tutorial

Modern CNN architectures

Review of ImageNet winning CNN architectures

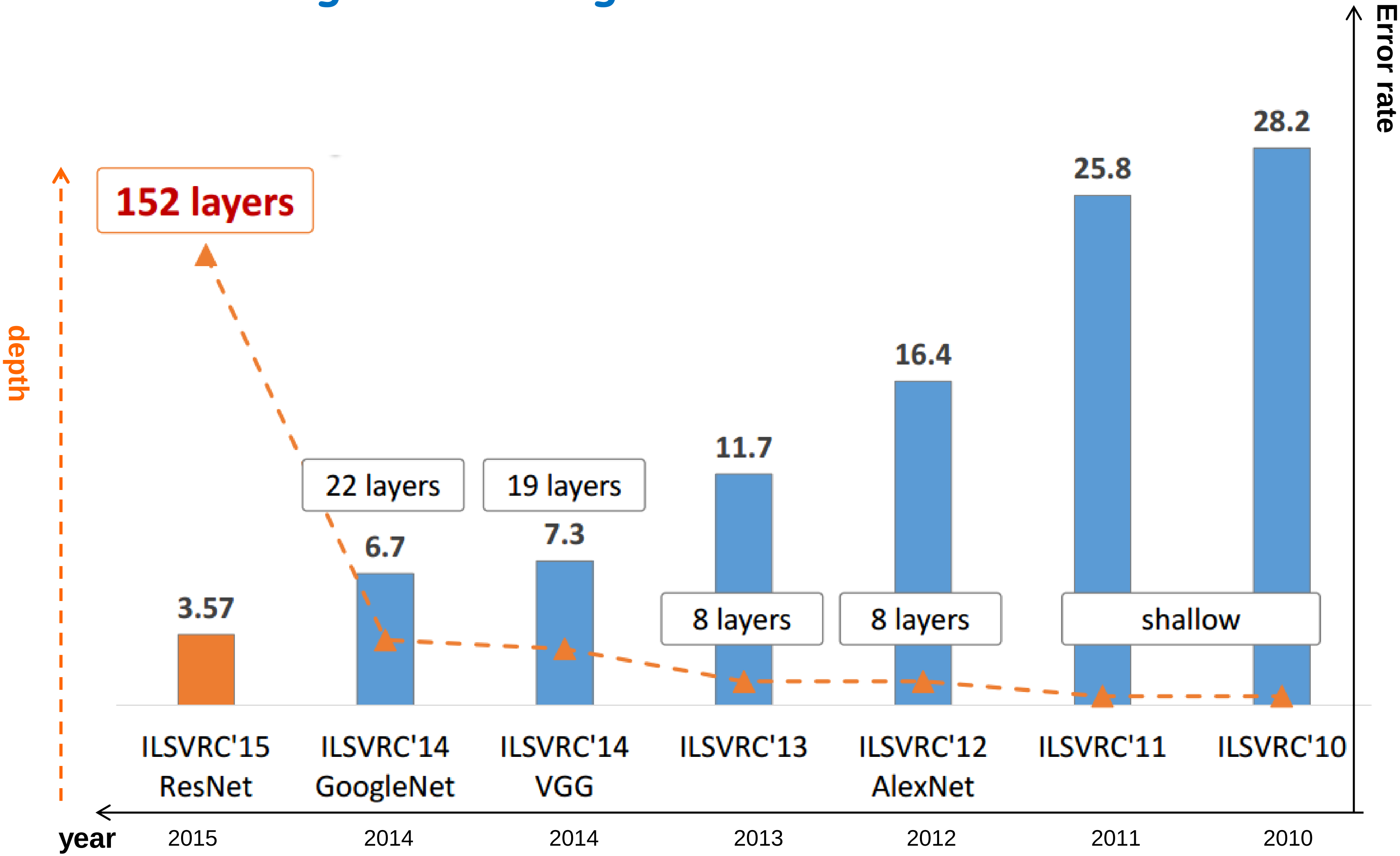


Image credits (modified): K.He, X.Zhang, S.Ren, J.Sun. “Deep Residual Learning for Image Recognition”. arXiv 2015

Going deeper is easy – or not?

The challenge is to design a network in which the gradient can reach all the layers of a network which might be dozens, or even hundreds of layers deep.

This was achieved by some recent improvements, such as ReLU and batch normalization, and by designing the architecture in a way which allows the gradient to reach deep layer, e.g. by additional skip connections.

LeNet-5 1998: first CNN for ZIP code recognition

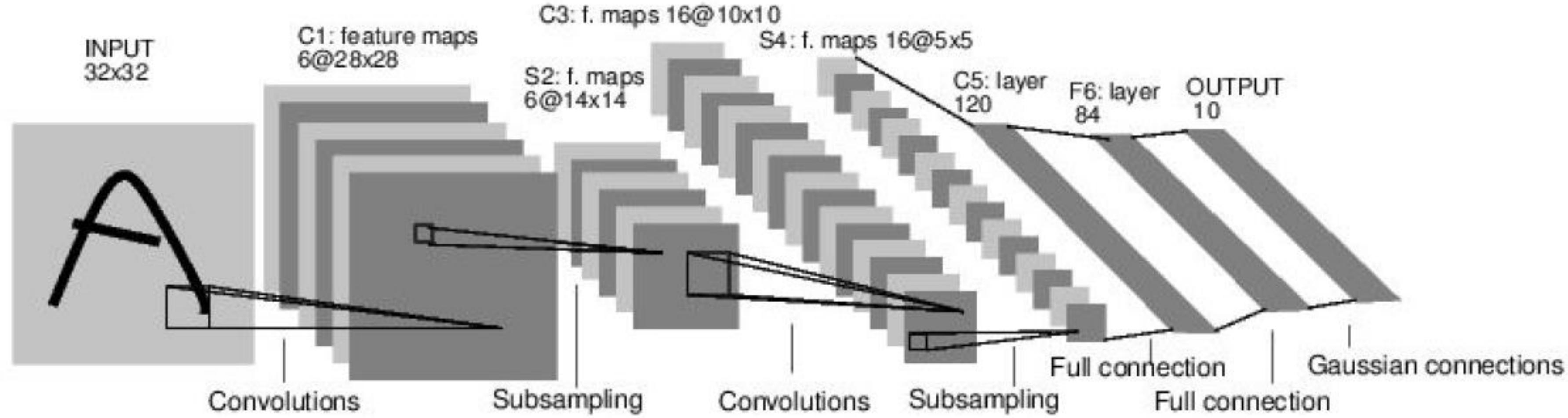
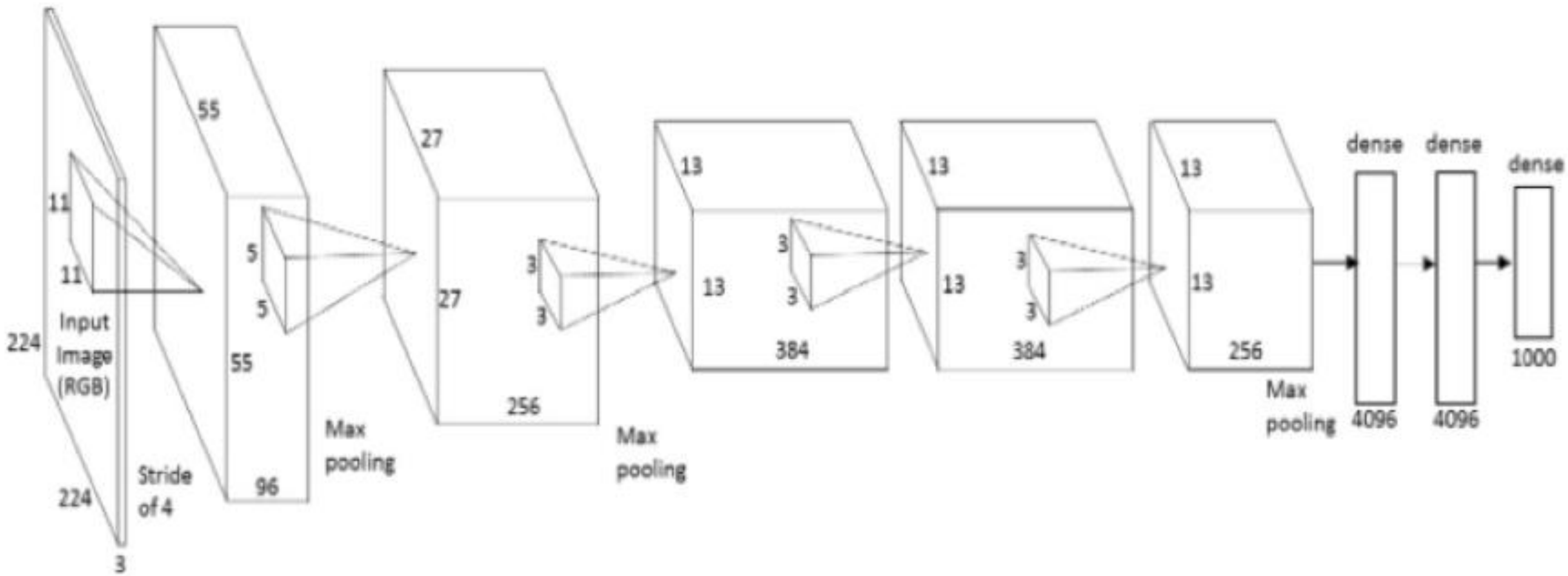


Image credits: http://yann.lecun.com/exdb/publis/pdf/lecun-98.pdf

Conv filters were 5x5, applied at stride 1
Subsampling (Pooling) layers were 2x2 applied at stride 2
i.e. architecture is [CONV-POOL-CONV-POOL-CONV-FC]

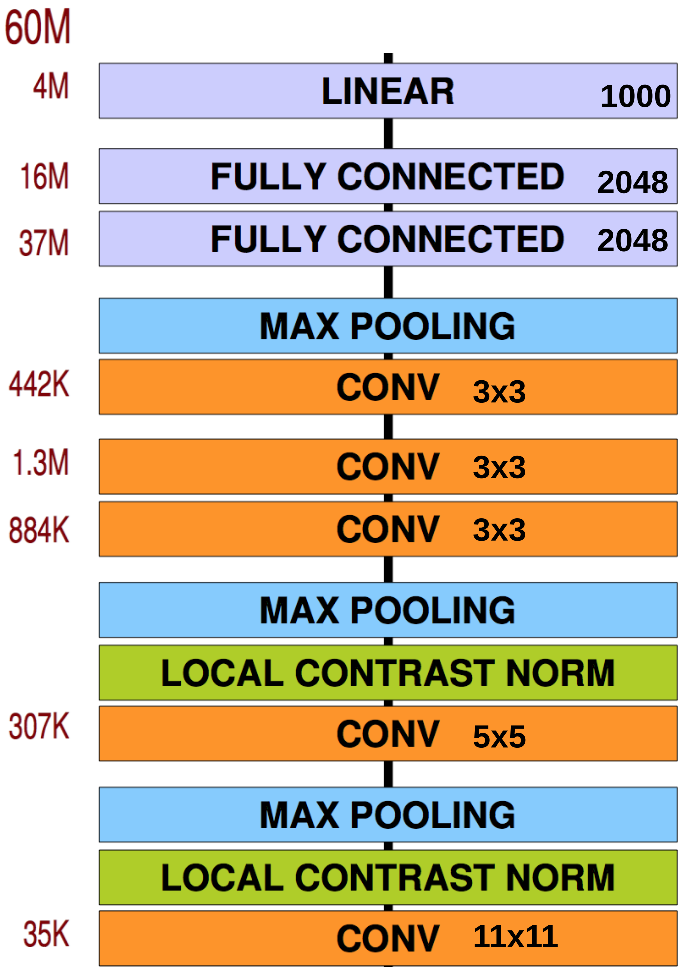
http://yann.lecun.com/exdb/lenet/index.html

"AlexNet", 2012 winner of the imageNet challenge



Architecture of AlexNet

"AlexNet", 2012 winner of the imageNet challenge



Seminal paper. 26.2% error → 16.5%

- Dropout
- ReLU instead of sigmoid
- Used data augmentation techniques

- 5 conv layer (filter: 11x11, 5x5, 3x3, 3x3, 3x3)

- Parallelisation on two GPUs
- Local Response Normalization (not used anymore)

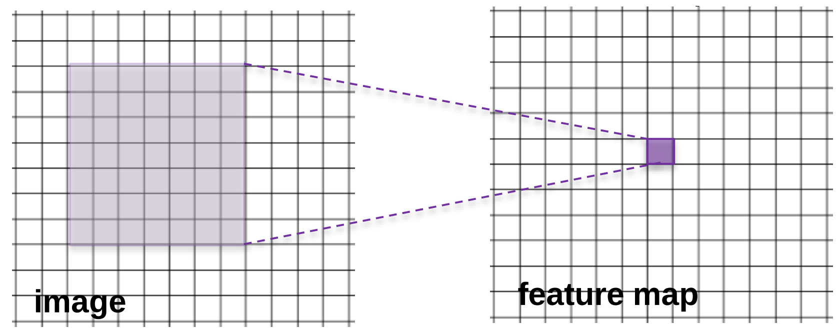
The trend in modern CNN architectures goes to small filters

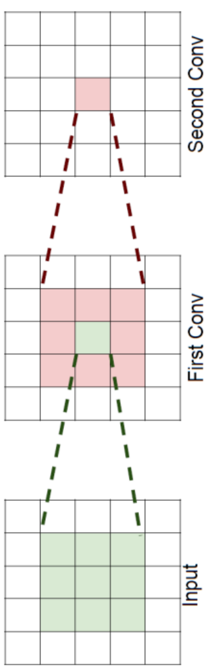
Why do modern architectures use very small filters?
Determine the receptive field in the following situation:

1) Suppose we have **one** 7x7 conv layers (stride 1)

49 weights

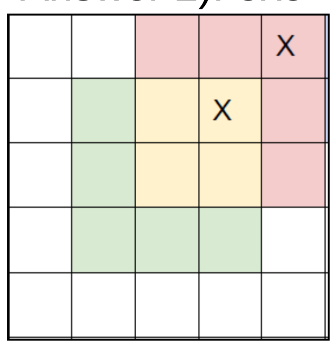
Answer1): 7x7





2) Suppose we stack **two** 3x3 conv layers (stride 1)

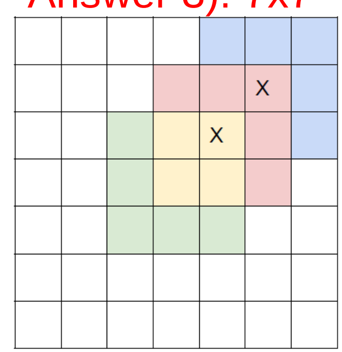
Answer 2): 5x5



3) Suppose we stack **three** 3x3 conv layers (stride 1)

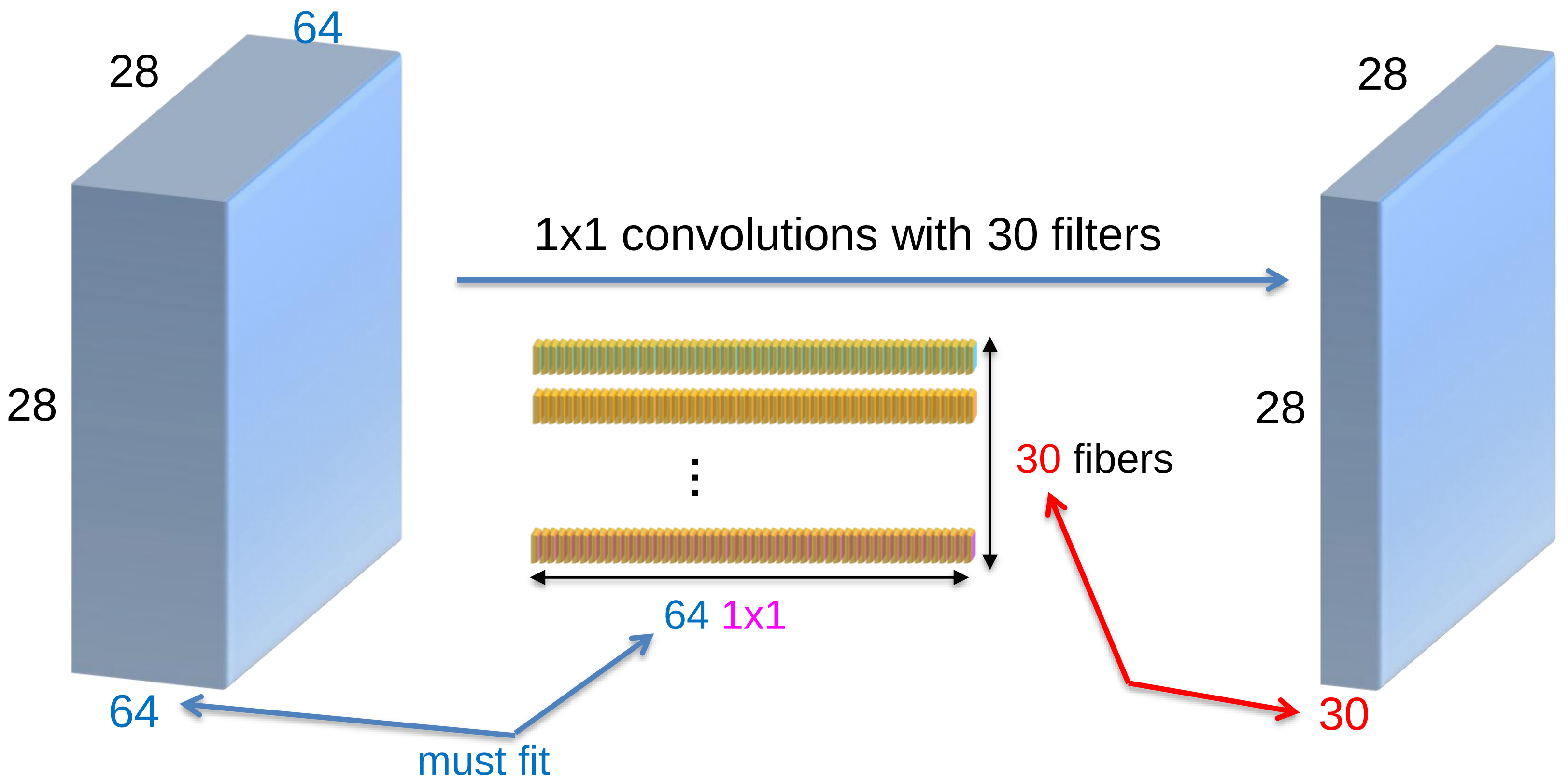
3*9=27 weights

Answer 3): 7x7



We need less weights for the same receptive field when stacking small filters!

Go to the extreme: What is about filter size 1?
1x1 convolutions act only in depth dimension

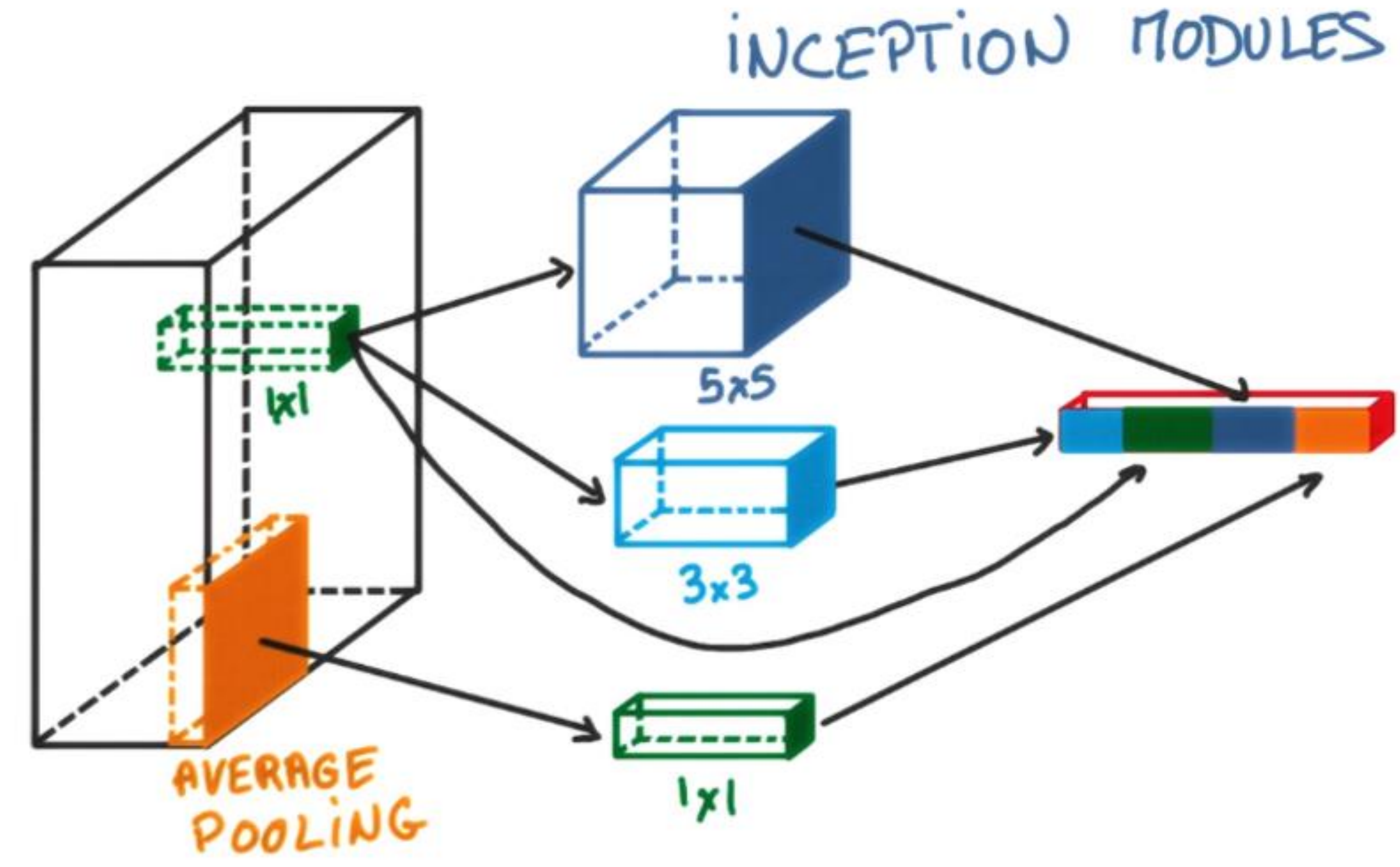


1x1 convolution act along a "fiber" in depth dimension across the channels.

→ efficient way to reduce/change the depth dimension

→ simultaneously introduce more non-linearity

The idea of inception modules



Between two layers just do several operations in parallel: pooling and 1x1 conv, and 3x3 and 5x5. “same”-conv and concatenate them together. Benefit: total number of parameters is small, yet performance better.

Slide (modified) credit: Google MOOC on tensorflow

How to concatenate tensors of different dimensions?

DepthConcat needs to make the tensor the same in all, but the depth dimension:

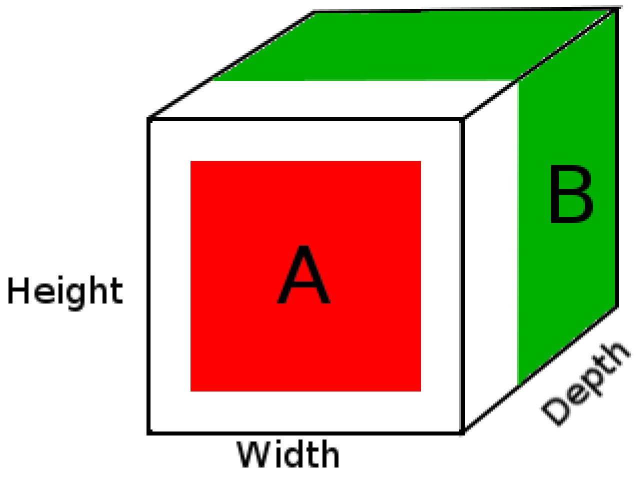
To deal with different output dimensions, the largest spatial dimension is select and zero-padding around the smaller dimensions is added.

Usually depth gets large!
Do 1x1 conv afterwards!

Pseudo code for an example:

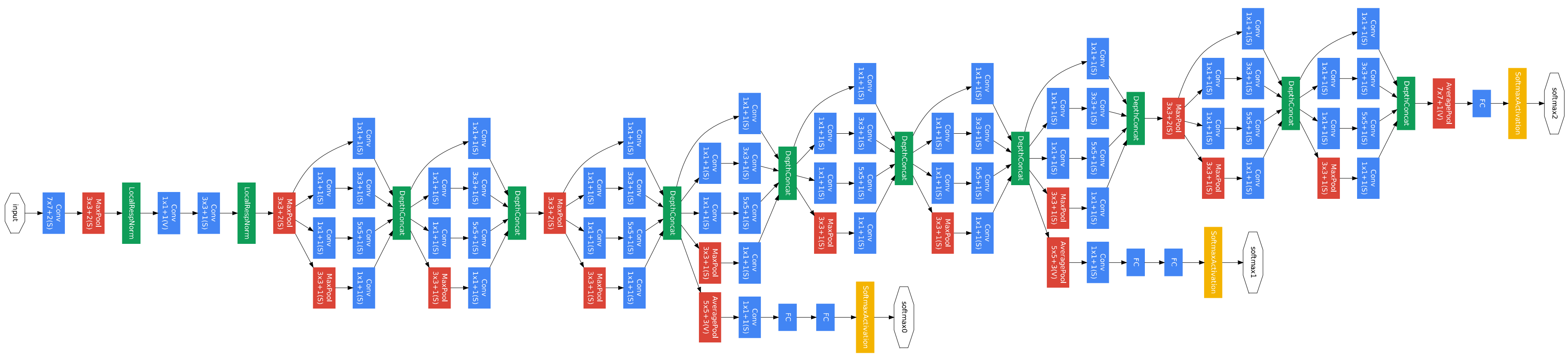
```
A = tensor of size (14, 14, 2)
B = tensor of size (16, 16, 3)
result = DepthConcat([A, B])
```

where result with have a
height of 16,
width of 16 and a
depth of 5 (2 + 3)

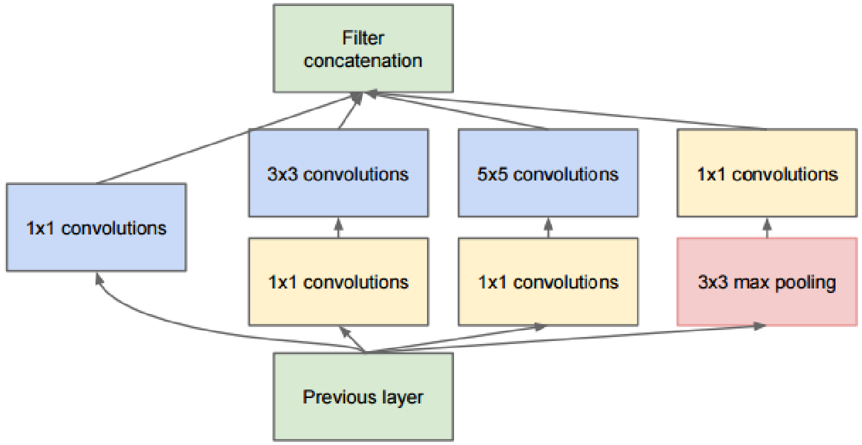


See: http://stats.stackexchange.com/questions/184823/how-does-the-depthconcat-operation-in-going-deeper-with-convolutions-work

Winning architecture (GoogLeNet, 2014)



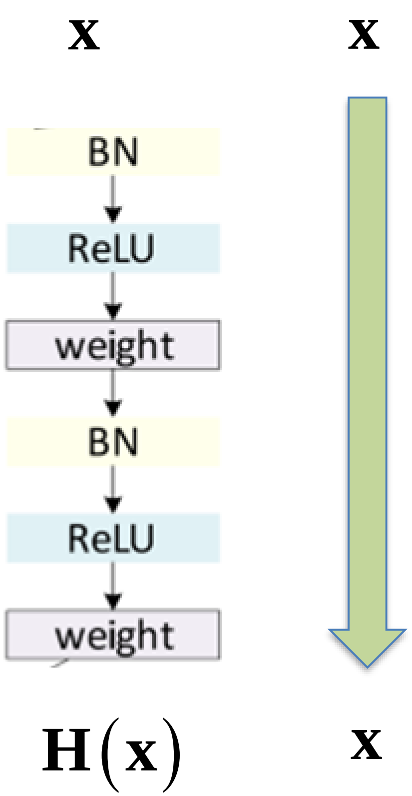
The inception module (convolutions and maxpooling)



Few parameters, hard to train.
Comments see [here]

[Going deeper with convolution http://arxiv.org/abs/1409.4842]

Highway Networks: providing a highway for the gradient



Idea: Use nonlinear transform T to determine how much of the output **y** is produced by H or the identity mapping. Technically we do that by:

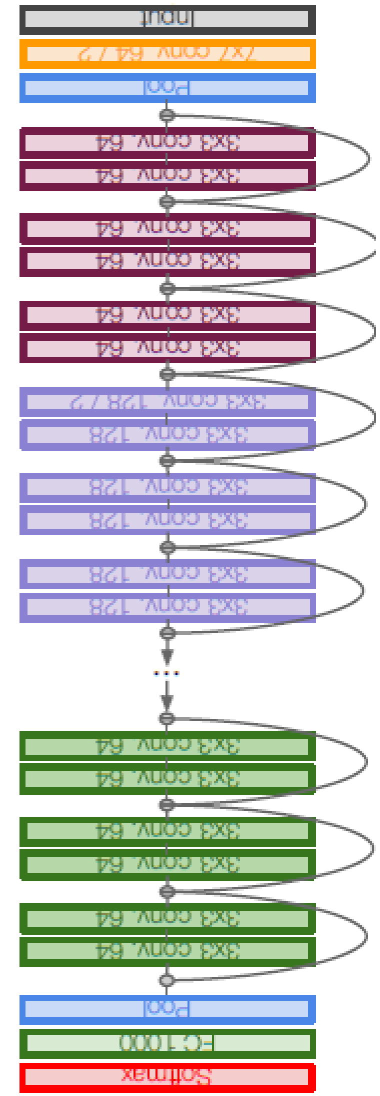
$$\mathbf{y} = H(\mathbf{x}, \mathbf{W_H}) \cdot T(\mathbf{x}, \mathbf{W_T}) + \mathbf{x} \cdot (1 - T(\mathbf{x}, \mathbf{W_T})).$$

Special case:

$$\mathbf{y} = \begin{cases} \mathbf{x}, & \text{if } T(\mathbf{x}, \mathbf{W_T}) = \mathbf{0} \\ H(\mathbf{x}, \mathbf{W_H}), & \text{if } T(\mathbf{x}, \mathbf{W_T}) = \mathbf{1} \end{cases}$$

This opens a highway for the gradient:

$$\frac{d\mathbf{y}}{d\mathbf{x}} = \begin{cases} \mathbf{I}, & \text{if } T(\mathbf{x}, \mathbf{W_T}) = \mathbf{0}, \\ H'(\mathbf{x}, \mathbf{W_H}), & \text{if } T(\mathbf{x}, \mathbf{W_T}) = \mathbf{1}. \end{cases}$$



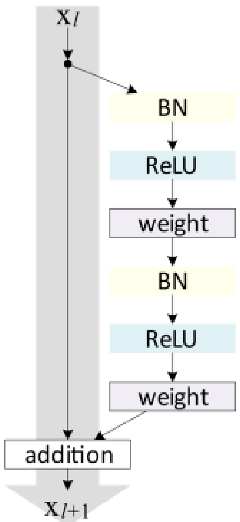
Srivastava, Greff, Schmidhuber 2014, “Highway Networks” https://arxiv.org/pdf/1505.00387.pdf

"ResNet" from Microsoft 2015 winner of imageNet

152 layers

ResNet basic design (VGG-style)

- add shortcut connections every two
- all 3x3 conv (almost)



$F(x_l)$

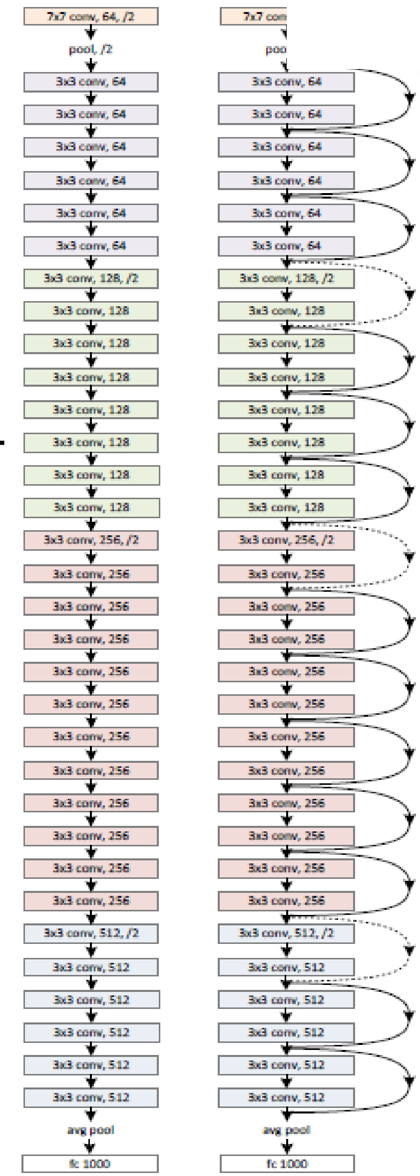
152 layers:
Why does this train at all?

This deep architecture could still be trained, since the gradients can skip layers which diminish the gradient!

$H(x_l)=x_{l+1} = x_l + F(x_l)$

F(x) is called "residual" since it only learns the "delta" which is needed to add to x to get H(x)

plain VGG



ResNet

credits: https://chatbotslife.com/resnets-highwaynets-and-densenets-oh-my-9bb15918ee32

“Oxford Net” or “VGG Net” 2014 2nd place

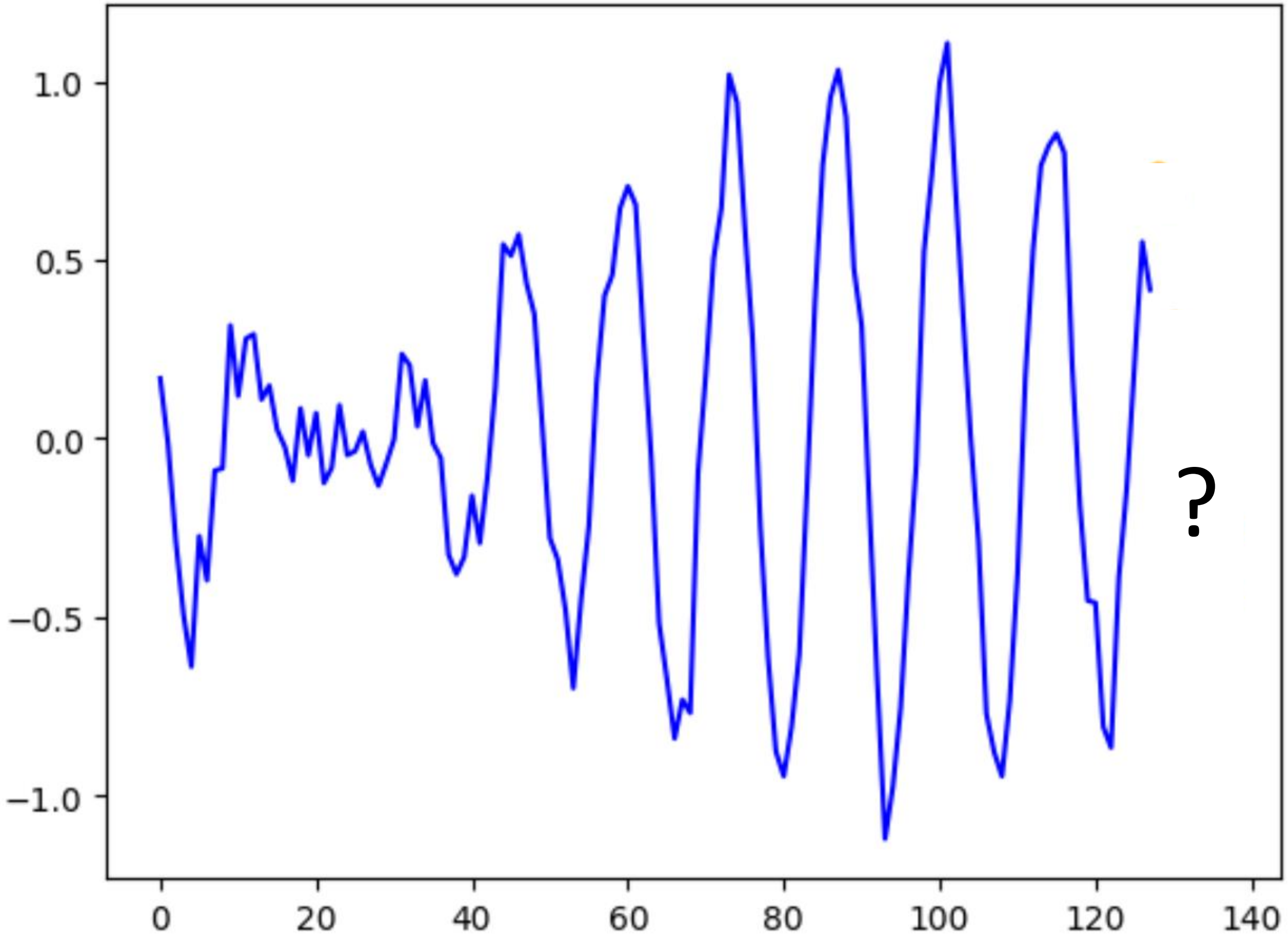
- 2nd place in the imageNet challenge
- More traditional, easier to train
- More weights than GoogLeNet
- Small pooling
- Stacked 3x3 convolutions before maxpooling

  -> large receptive field
- no strides (stride 1)
- ReLU after conv. and FC (batchnorm was not used)
- Pre-trainined model is available

http://arxiv.org/abs/1409.1556

1D CNNs for sequence data

How to make predictions based on a given time series?

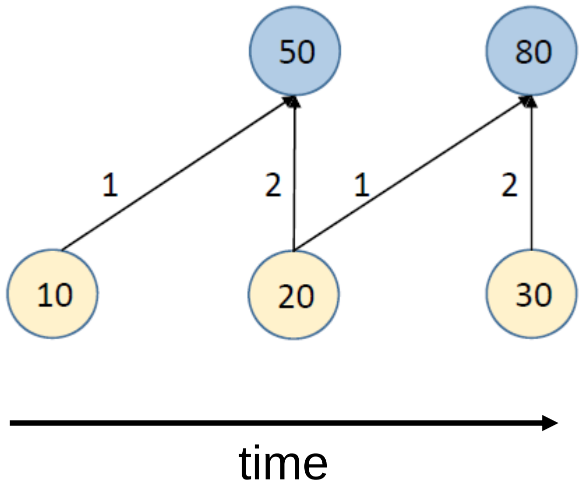


1D "causal" convolution for time-ordered data

Toy example:

Input X: 10,20,30

1D kernel of size 2: 1,2



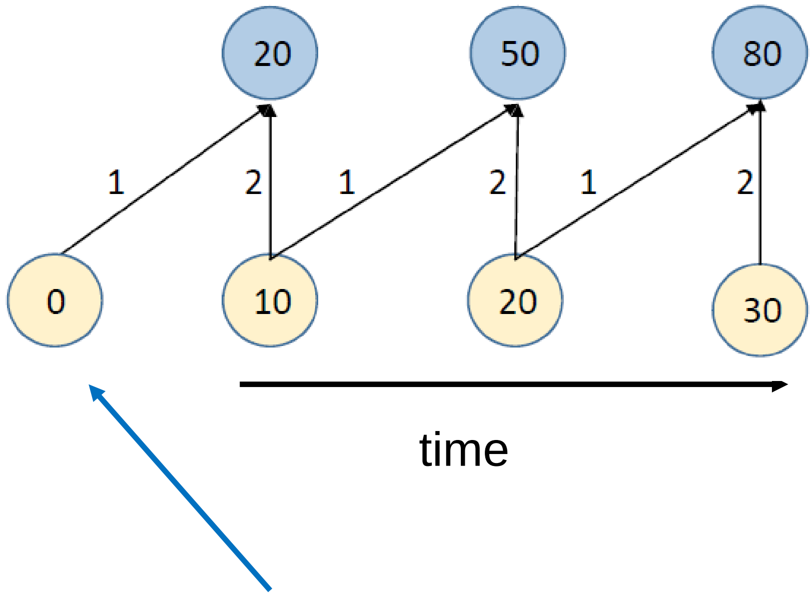
It's called "causal" networks, because the architecture ensured that only information from the past has an influence on the present and future.

Zero-padding in 1D "causal" CNNs

Toy example:

Input X: 10,20,30

1D kernel of size 2: 1,2

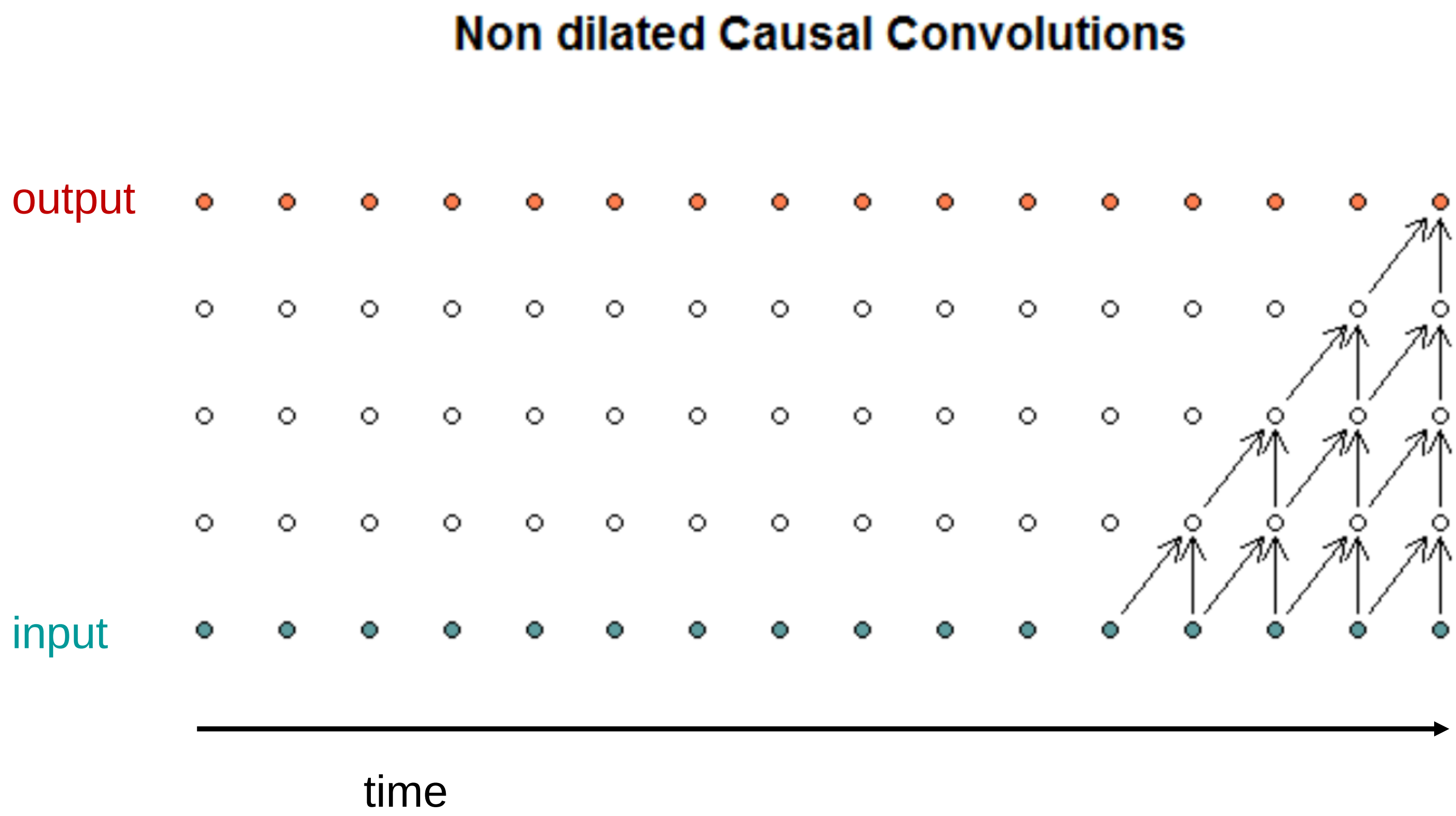


To make all layers the same size, a zero padding is added to the beginning of the input layers

1D “causal” convolution in Keras

```
model = Sequential()
model.add(Convolution1D(filters=1,
                        kernel_size=2,
                        padding='causal',
                        dilation_rate=1,
                        use_bias=False,
                        batch_input_shape=(None,3, 1)))
model.summary()
```

Stacking 1D "causal" convolutions without dilation



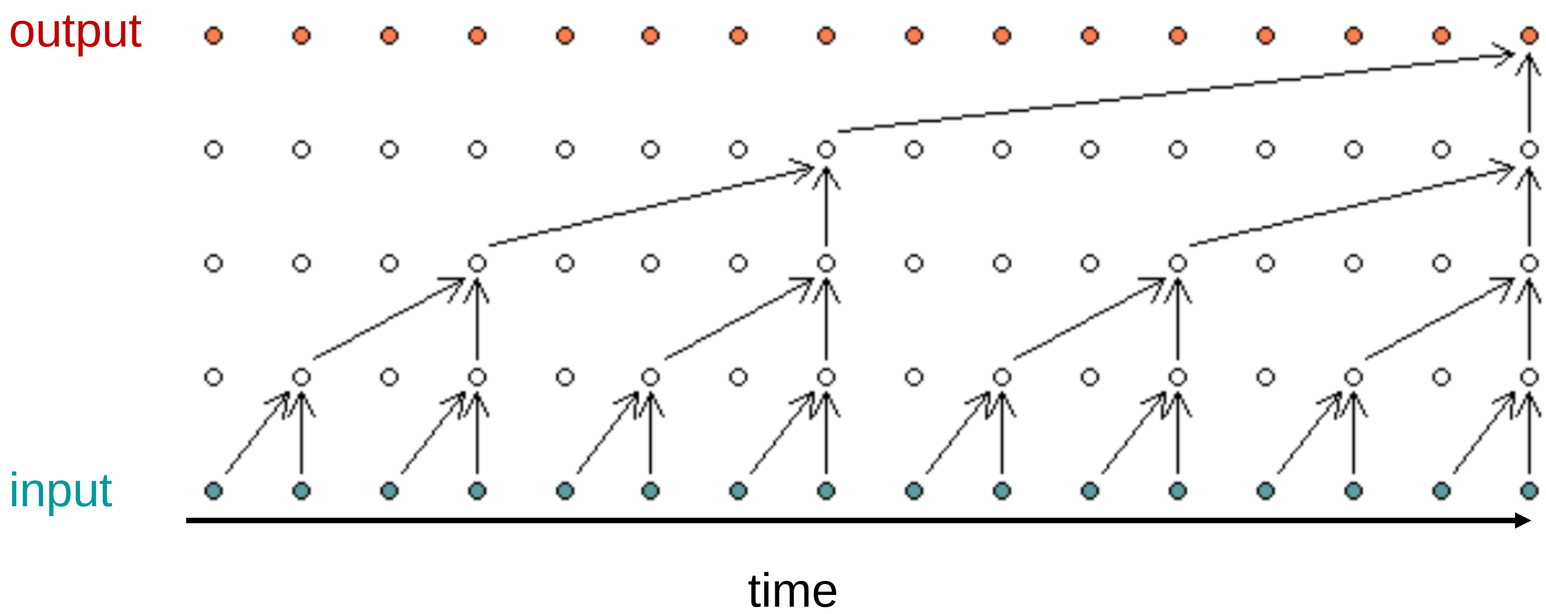
Stacking k causal 1D convolutions with kernel size 2 allows to look back k time-steps.

After 4 layers each neuron has a "memory" of 4 time-steps back in the past.

https://deepmind.com/blog/wavenet-generative-model-raw-audio/

Dilation allows to increase receptive field

To increase the memory of neurons in the output layer, you can use "dilated" convolutions:



After 4 layers each neuron has a "memory" of 15 time-steps back in the past.

https://deepmind.com/blog/wavenet-generative-model-raw-audio/

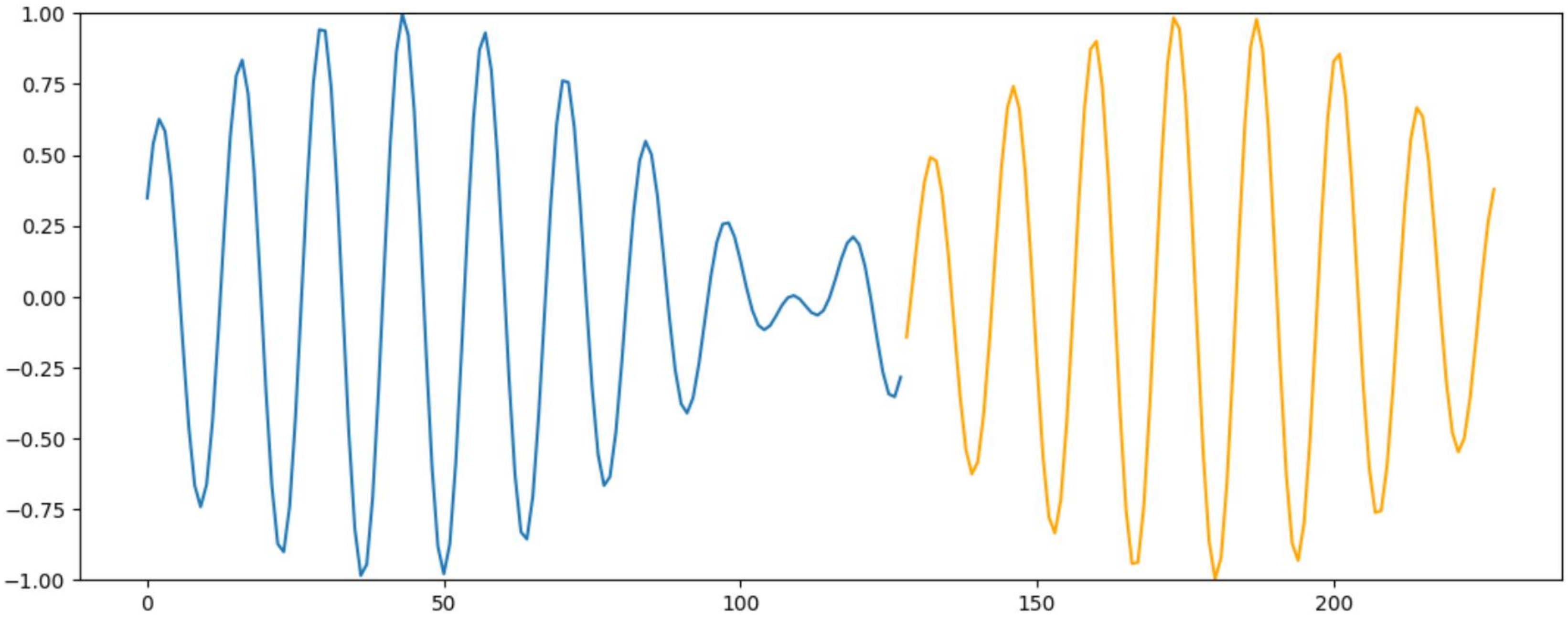
Dilated 1D causal convolution in Keras

To use time-dilated convolutions, simply use the argument rate dilation_rate=... in the Convolution1D layer.

```
X,Y = gen_data(noise=0)

modeldil = Sequential()
#<------ Just replaced this block
modeldil.add(Convolution1D(filters=32, kernel_size=ks, padding='causal', dilation_rate=1,
                           batch_input_shape=(None, None, 1)))
modeldil.add(Convolution1D(filters=32, kernel_size=ks, padding='causal', dilation_rate=2))
modeldil.add(Convolution1D(filters=32, kernel_size=ks, padding='causal', dilation_rate=4))
modeldil.add(Convolution1D(filters=32, kernel_size=ks, padding='causal', dilation_rate=8))
#<------ Just replaced this block

modeldil.add(Dense(1))
modeldil.add(Lambda(slice, arguments={'slice_length':look_ahead}))

modeldil.summary()

modeldil.compile(optimizer='adam',loss='mean_squared_error')

histdil = modeldil.fit(X[0:800], Y[0:800],
                    epochs=200,
                    batch_size=128,
                    validation_data=(X[800:1000],Y[800:1000]), verbose=0)
```

Dilated 1D causal CNNs help if long memory is needed

Dilated 1D CNNs can picked up the long-range time dependencies.



If you want to get a better understanding how 1D convolution work, you can go through the notebook at https://github.com/tensorchiefs/dl_book/blob/master/chapter_02/nb_ch02_04.ipynb.