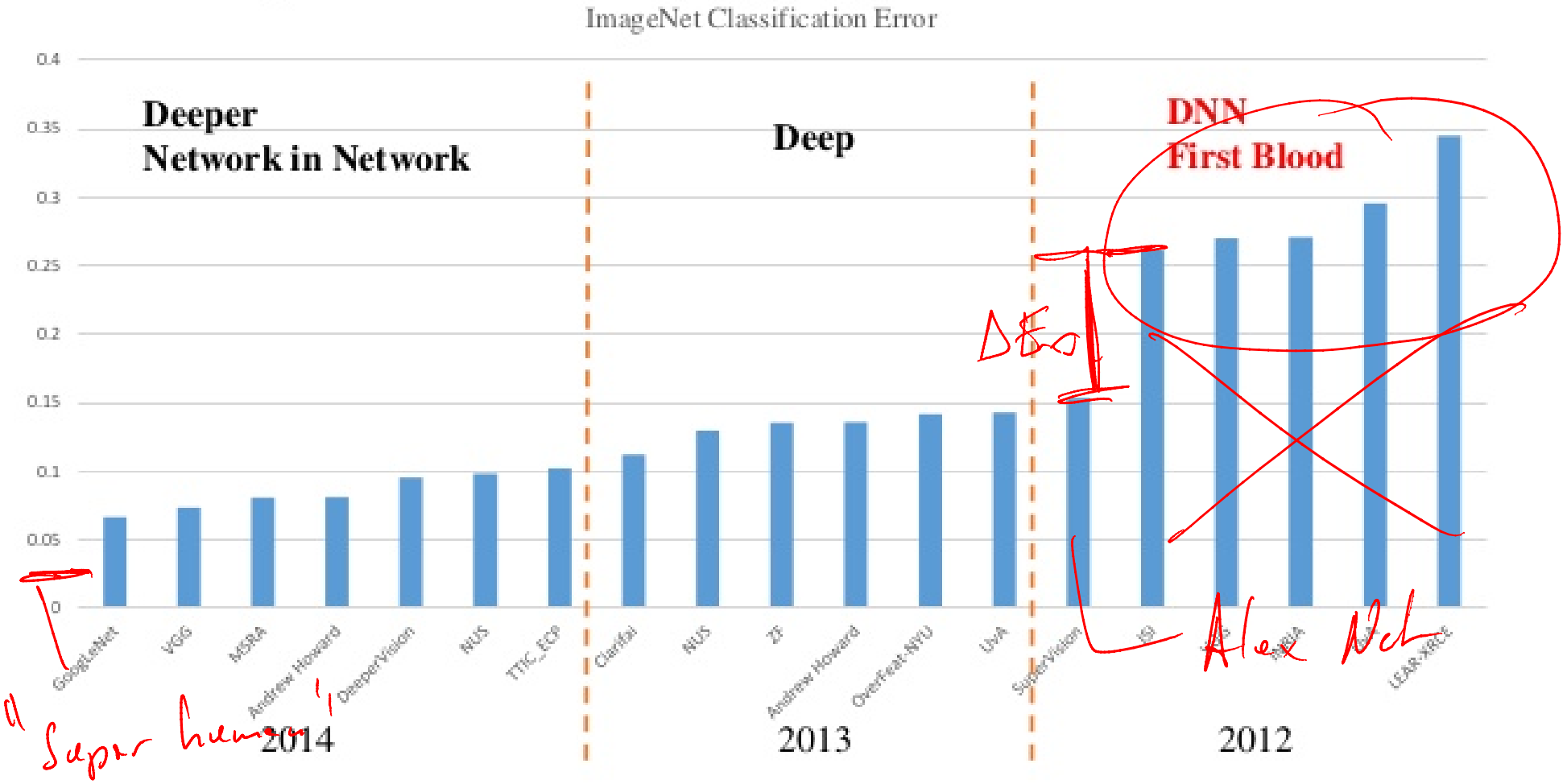
Neural Networks

Jan Chorowski

ImageNet Classification

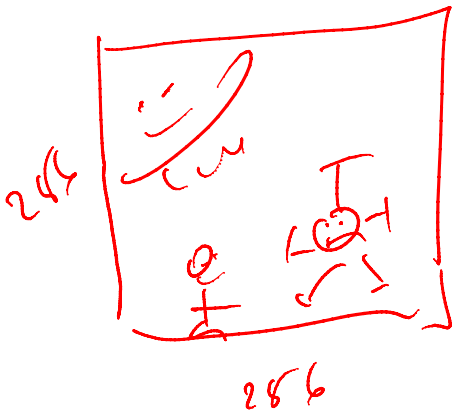
- **1000** categories and **1.2** million training images



Li Fei-Fei: ImageNet Large Scale Visual Recognition Challenge, 2014 http://image-net.org/


CONVNETS, CONVNETS
EVERYWHERE
memegen.com

Intuitions

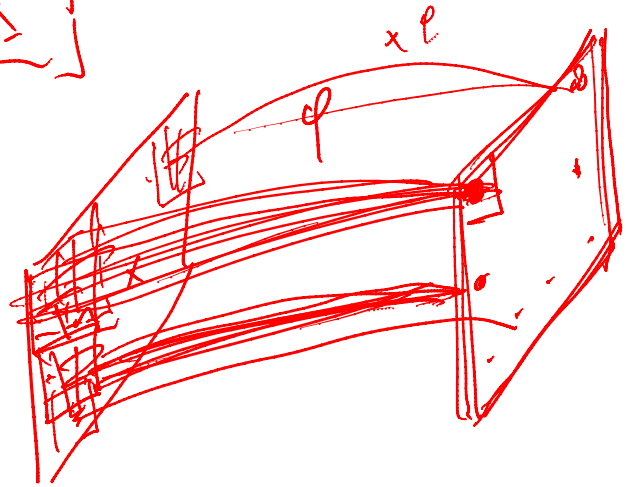


① Up to now: $W \times$ (256 × 256) $\in \mathbb{R}$

$W \in \mathbb{R}^{256 \times 256 \times 256 \times 256}$

$(2^8)^4 = 2^{32} = 4 \cdot 10^9$

4G Weight



② LOCAL CONNECTIVITY

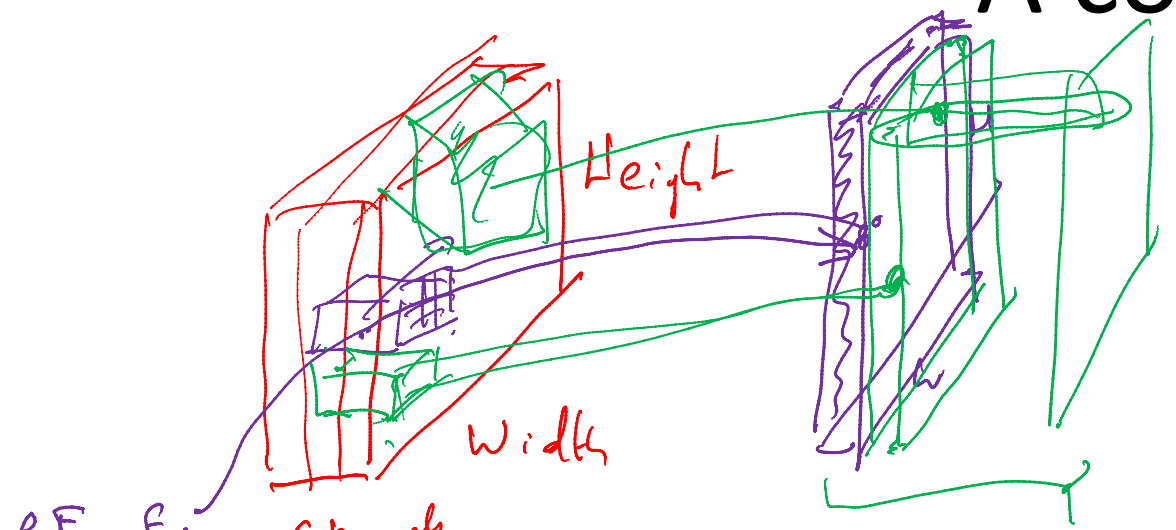
$256^2 \cdot 9 =$

$9 \cdot 2^{10} \cdot 2^6 = 6 \cdot 10^5 = 600$ k Weight

③ Weight Sharing + Local Connectivity

9 weight !?!

A conv layer



$I_x \in \mathbb{R}^{C \times W \times H}$

$C_o \times W \times H$

↑

number of output filters

How many weights?

C_o filters / signa proces

each having $C \times F_W \times F_H$

Total:

$$C_o \times C_{in} \times F_W \times F_H$$

How many multiplications?

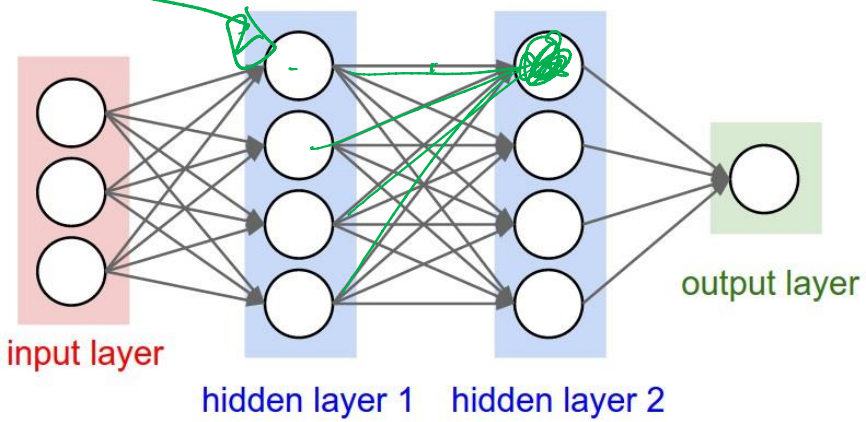
$W \times H \times C_o \times C_{in} \times F_W \times F_H$

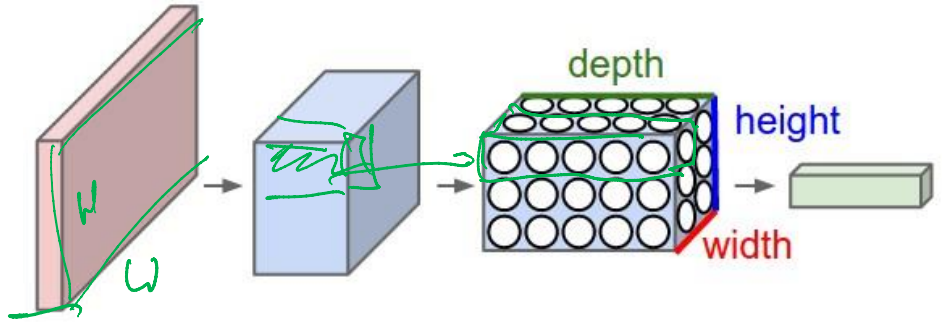
Sharing neurons - convolutions

Note: material from http://cs231n.github.io/convolutional-networks/

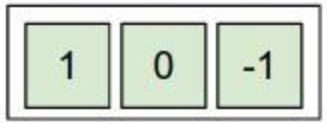
In a conv net we use a different connection pattern between layers:

- In a dense feed-forward layer used an all-to-all scheme
- In a conv-net we use local connectivity!

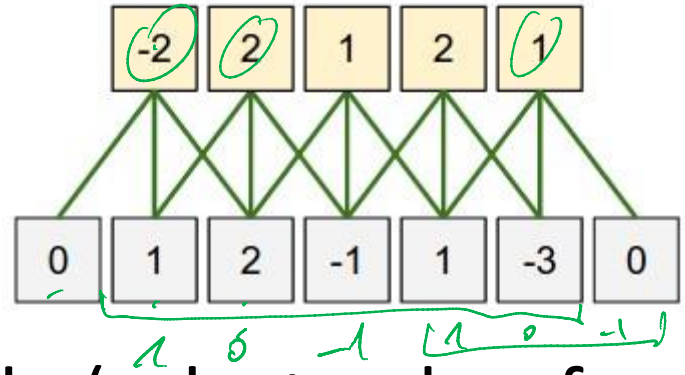




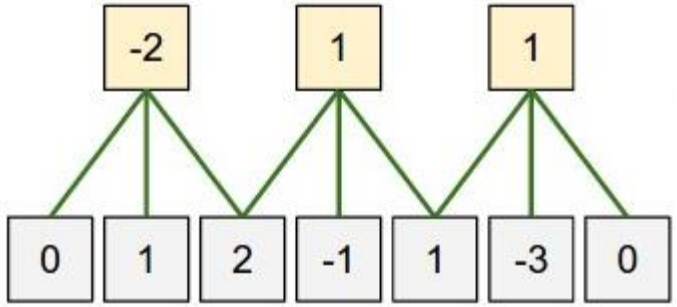
1D Convolution layer

- Small filter (neuron): 

- Swipe the filter over the sequence



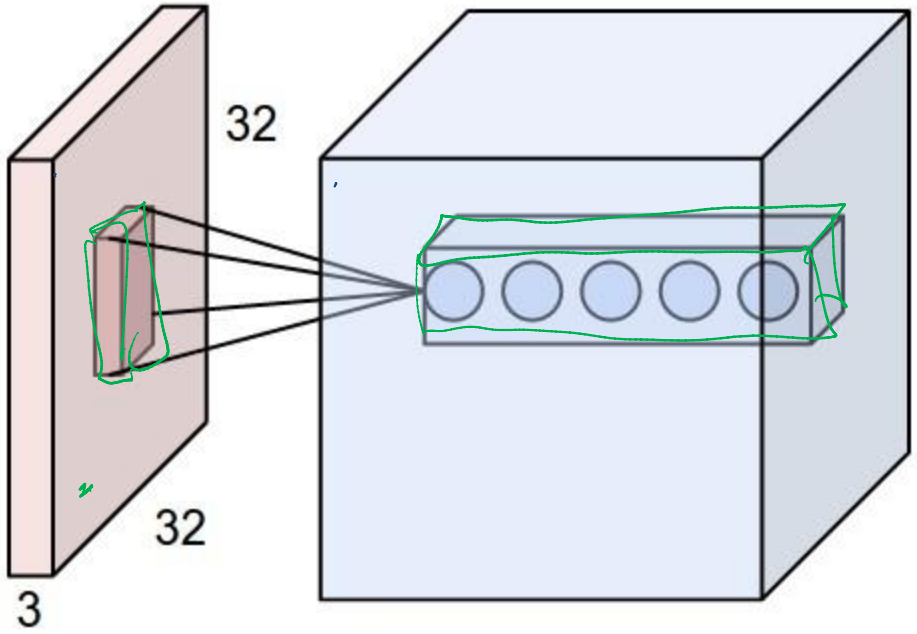
- Pool or stride (select only a few outputs)



Caveat: in math / signal processing we also flip the filter

2D conv layer

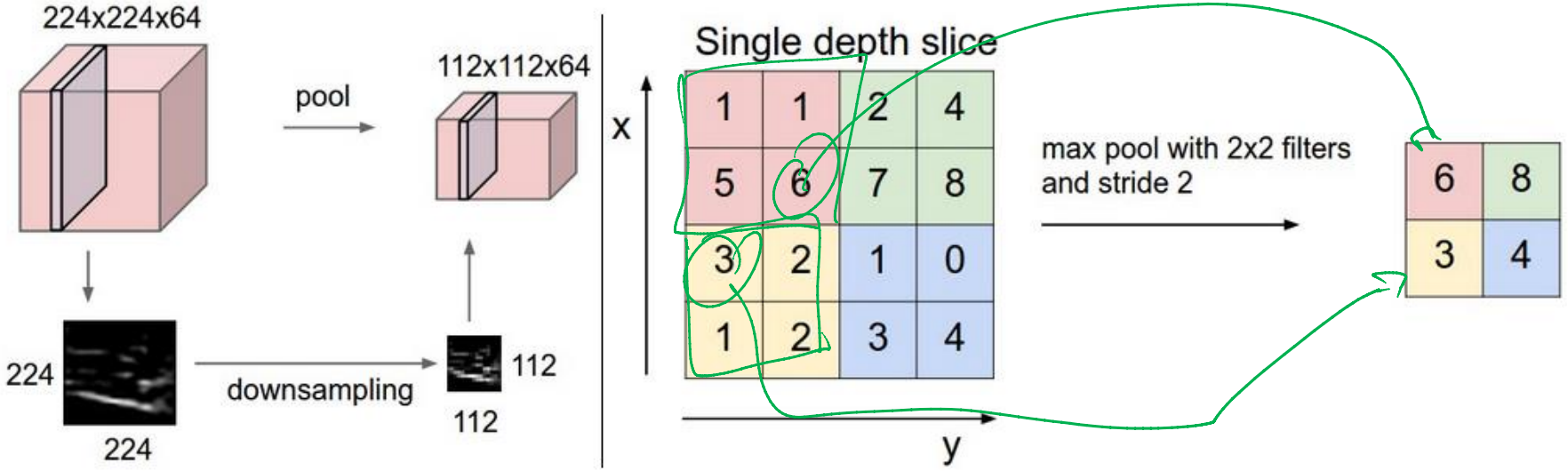
- http://cs231n.github.io/convolutional-networks/



Pooling

→ NO PARAMS !

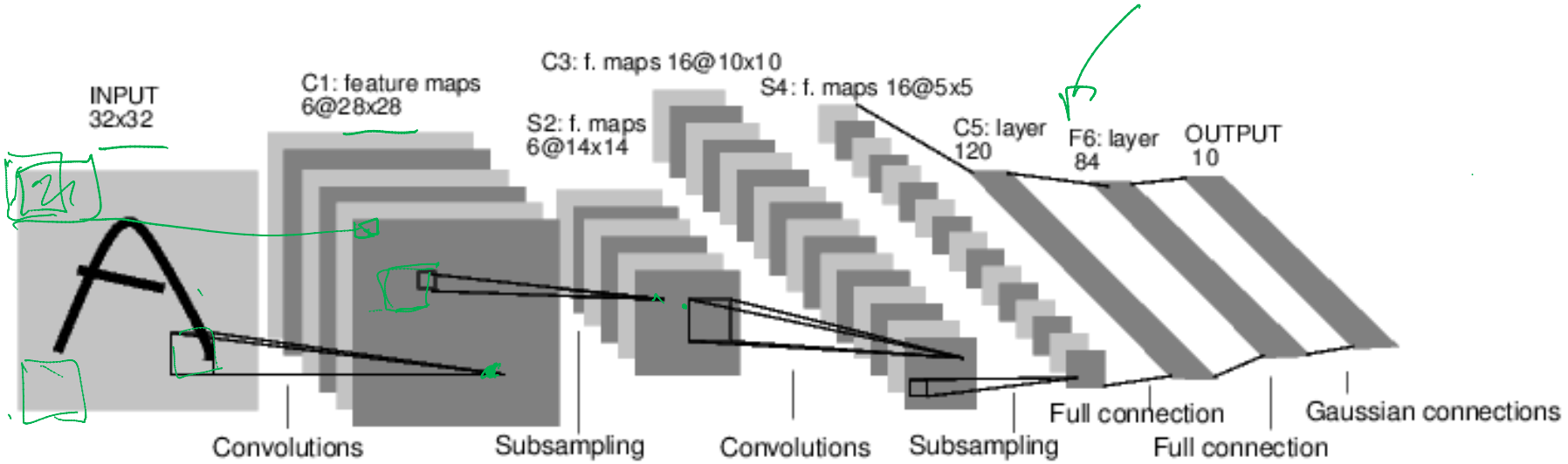
→ Reduces dimensions W & H



Pooling layer downsamples the volume spatially, independently in each depth slice of the input volume. **Left:** In this example, the input volume of size [224x224x64] is pooled with filter size 2, stride 2 into output volume of size [112x112x64]. Notice that the volume depth is preserved. **Right:** The most common downsampling operation is max, giving rise to **max pooling**, here shown with a stride of 2. That is, each max is taken over 4 numbers (little 2x2 square).

Full network - LeNet

Y. LeCun et al. „Gradient-Based Learning Applied to Document Recognition”
http://yann.lecun.com/exdb/publis/pdf/lecun-98.pdf



1x6x5x5 | 6x16x5x5 | 16x120x5x5 | 120 x 84

150 weights, 6 x 24 x 18 x 6 + 6

117k

2400

240k

48k

48k

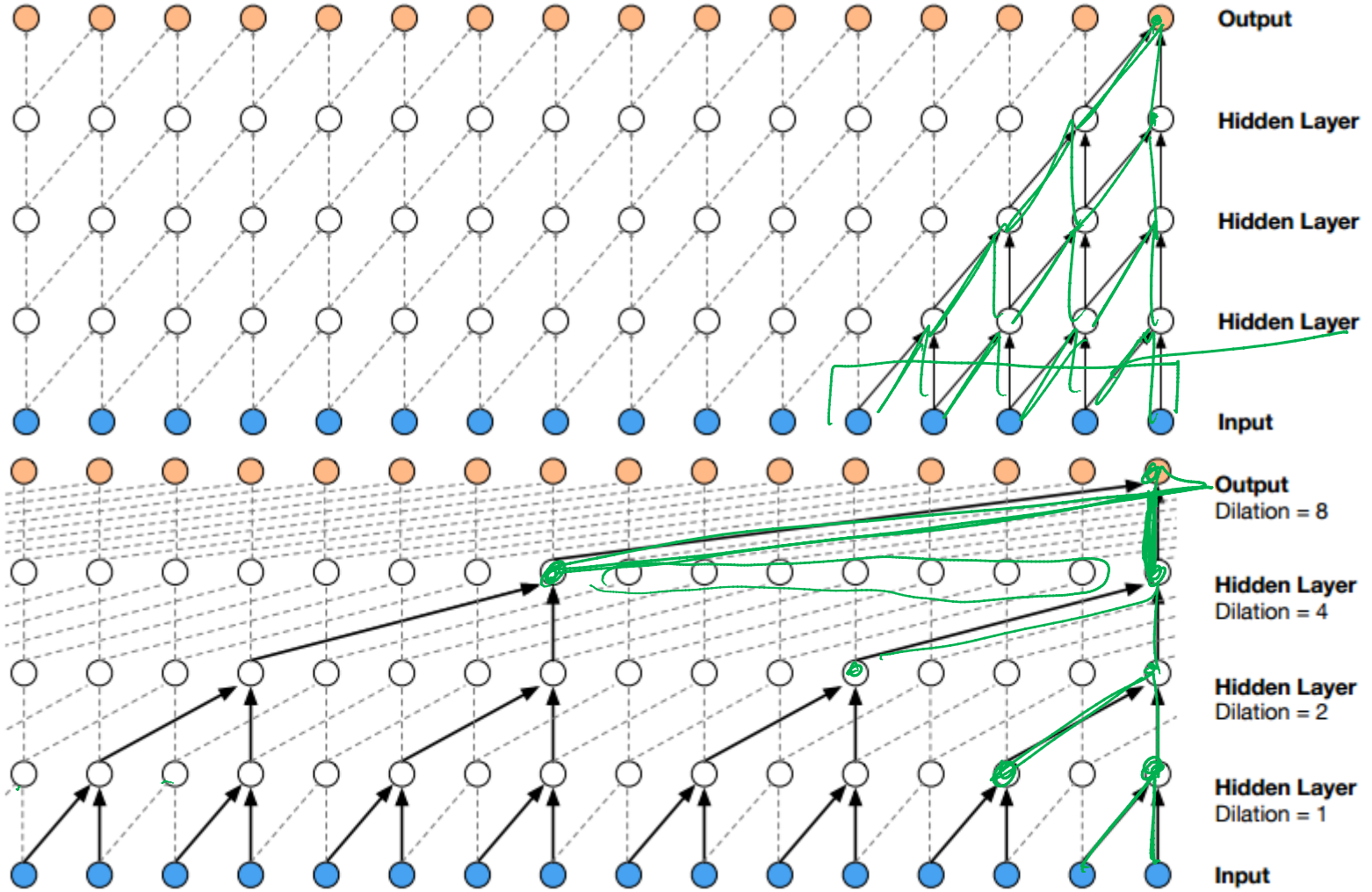
10k

10k

Compute heavy

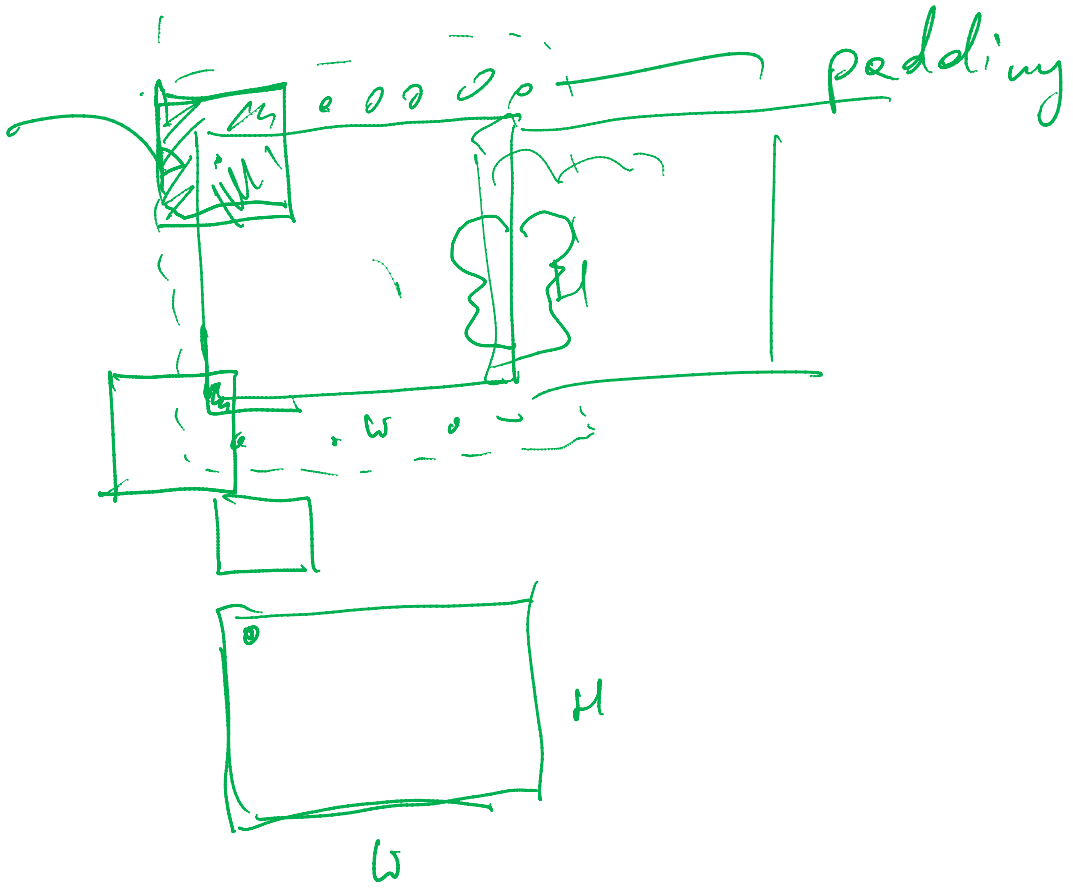
Param heavy

Dilated convolutions:
wide receptive field at high resolutions



Wavenet: https://arxiv.org/pdf/1609.03499.pdf
https://deepmind.com/blog/wavenet-generative-model-raw-audio/

Technicality: Edge padding



- SAME padding

- VALID conv.

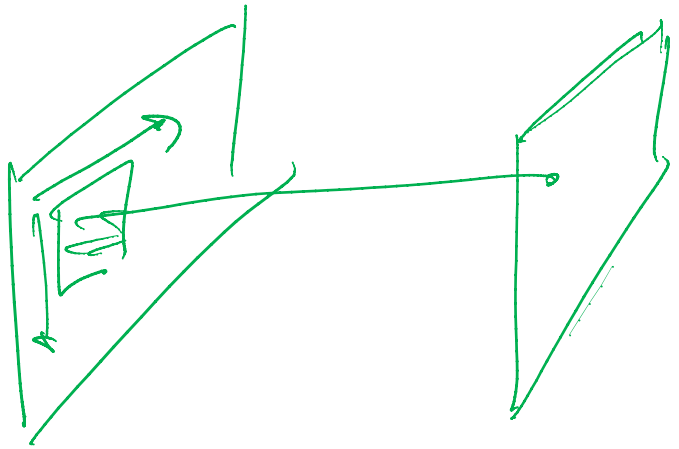
if input is $W \times H$ $F_W \times F_H$

$$W - F_W + 1 \times H - F_H + 1$$

- FULL

$$W + F_W - 1 \times H + F_H - 1$$

Technicality: bias

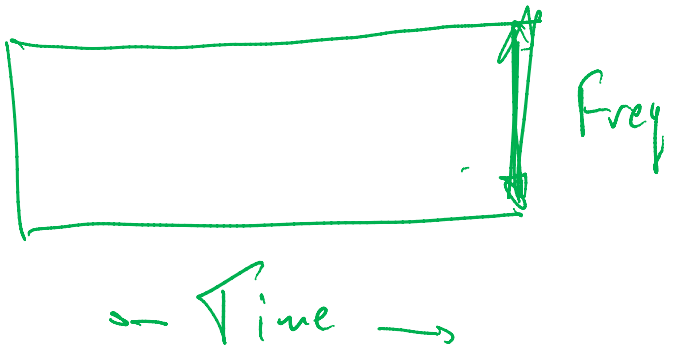


C x W x H

C x 1 x 1

bias : a number per filter

Ex



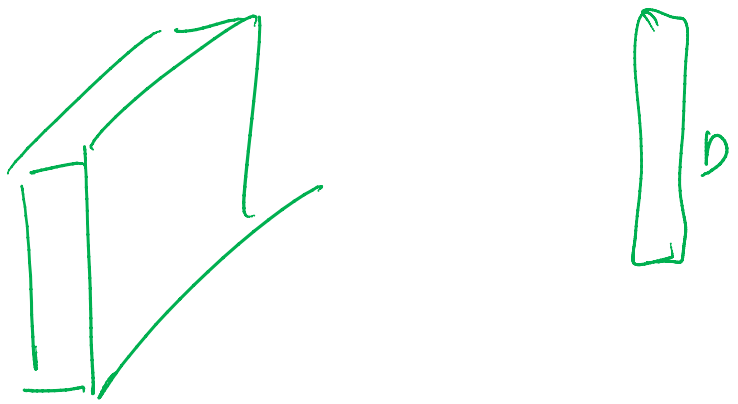
weights : the same all over

bias : 1 x # Freqs

Time Freq

Convs can mimick FC layers

Fully Connected or Dense



$C \times W \times H \rightarrow D \times 1 \times 1$

Filter size $D \times C \times W \times H$

VALID conv

$W - F_W + 1 = W - W + 1 = 1$

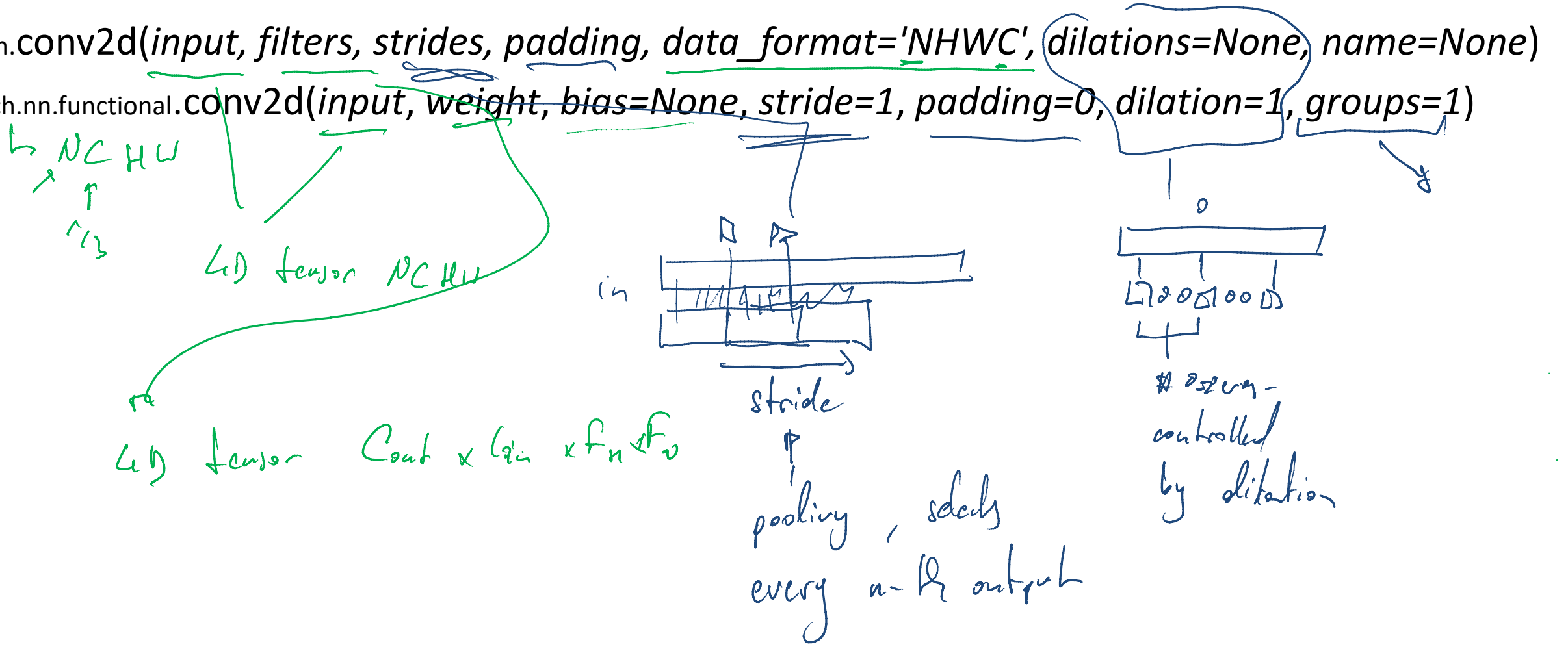
Input: $C \times W \times H$

Filters: $D \times C \times 1 \times 1$ → pixelwise FC network

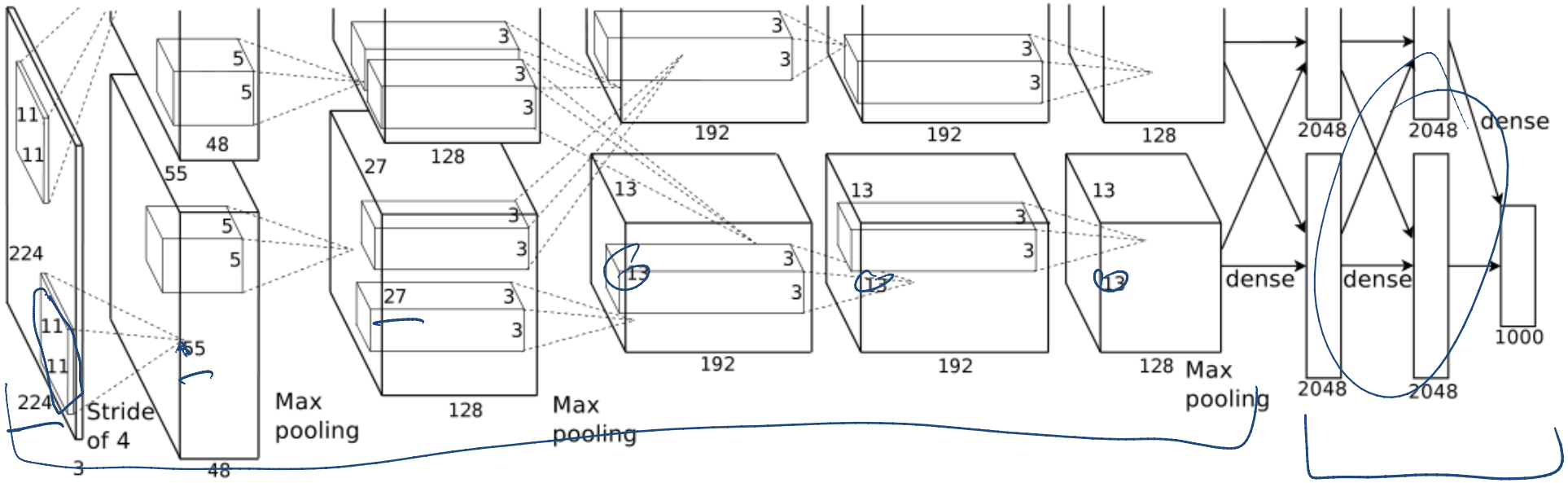
Conv Layers: All the Options

tf.nn.conv2d(*input, filters, strides, padding, data_format='NHWC', dilations=None, name=None*)

torch.nn.functional.conv2d(*input, weight, bias=None, stride=1, padding=0, dilation=1, groups=1*)



AlexNet (2012)



60M parameters

The last dense layers takes:

4096*4096 + 4096*1000≈20M params!

Separable Filters

- Someties a 2D conv == 2* 1D conv:

$$\frac{1}{3}\begin{bmatrix}1\\1\\1\end{bmatrix} * \frac{1}{3}\begin{bmatrix}1 & 1 & 1\end{bmatrix} = \frac{1}{9}\begin{bmatrix}1 & 1 & 1\\1 & 1 & 1\\1 & 1 & 1\end{bmatrix}$$

$$\mathbf{G_x} = \begin{bmatrix}1 & 0 & -1\\2 & 0 & -2\\1 & 0 & -1\end{bmatrix} * A = \begin{bmatrix}1\\2\\1\end{bmatrix} * \begin{bmatrix}+1 & 0 & -1\end{bmatrix} * A$$

- Inception and VGGnet use filter approximate sepration, with more nonlinearity

Conv (x_1 9×9 filter) =

Conv (Conv (x_1 3×1), 1×3)

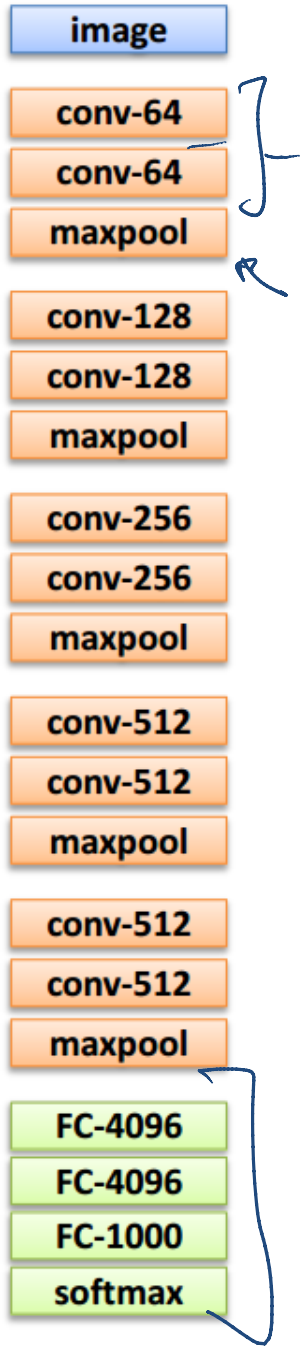
VGGNet: Network Design

Key design choices:

- 3x3 conv. kernels – very small
- conv. stride 1 – no loss of information

Other details:

- Rectification (ReLU) non-linearity
- 5 max-pool layers (x2 reduction)
- no normalisation
- 3 fully-connected (FC) layers

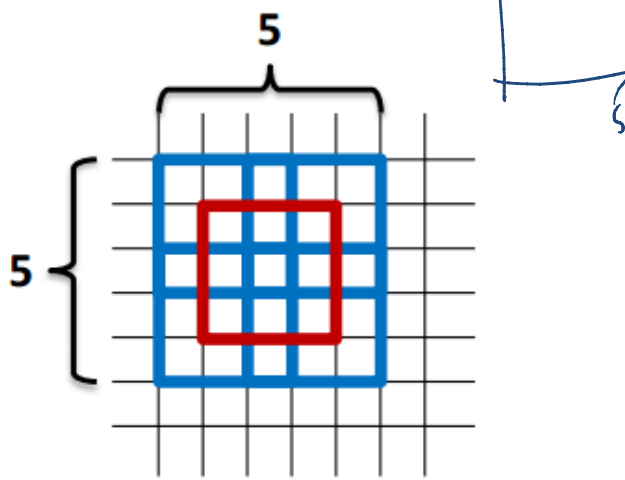


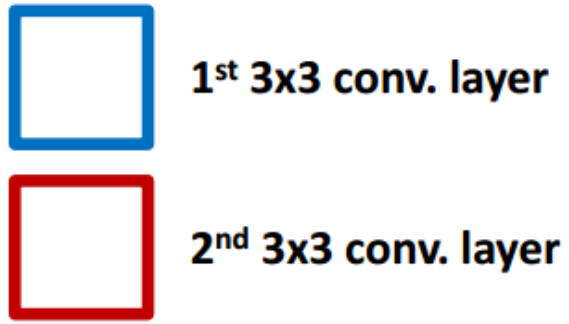
Slide from http://www.robots.ox.ac.uk/~karen/pdf/ILSVRC_2014.pdf

VGGNet: Discussion

Why 3x3 layers?

- Stacked conv. layers have a large receptive field
  - two 3x3 layers – 5x5 receptive field
  - three 3x3 layers – 7x7 receptive field
- More non-linearity
- Less parameters to learn
  - ~140M per net



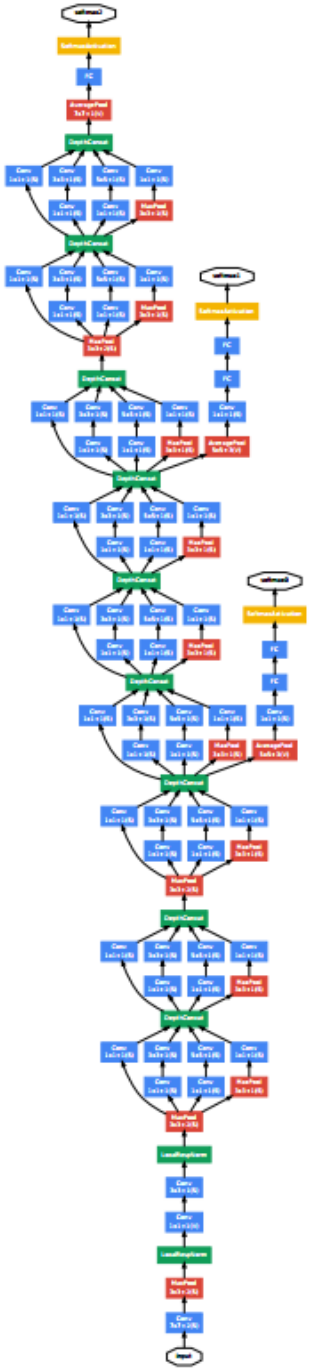


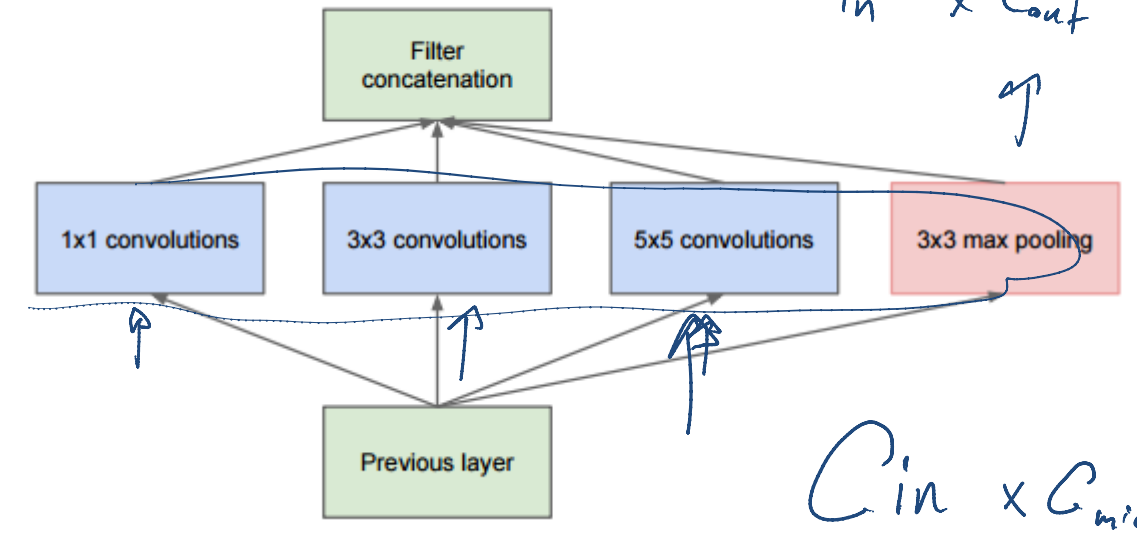
Slide from http://www.robots.ox.ac.uk/~karen/pdf/ILSVRC_2014.pdf

VGGNet (2014)

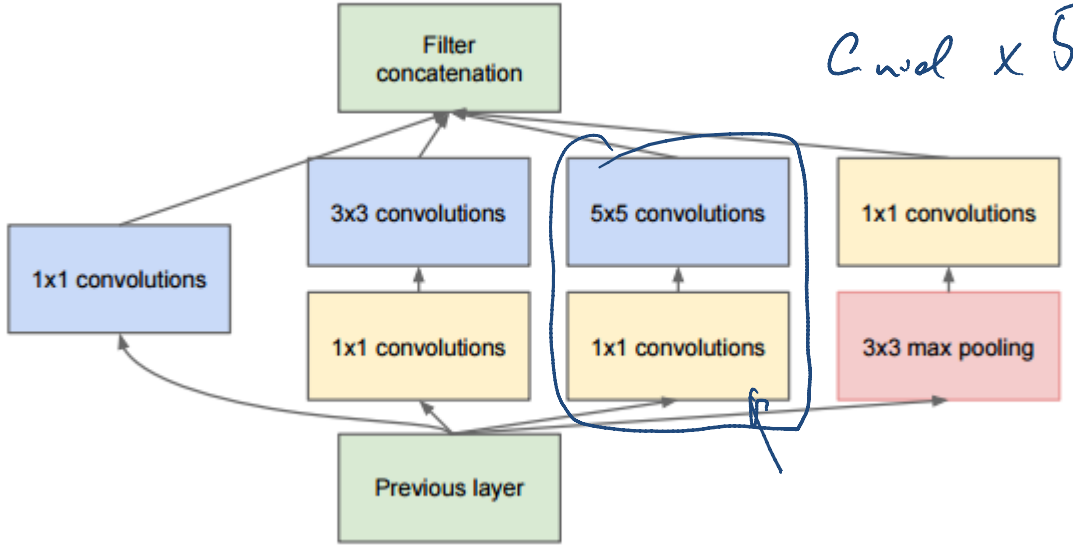
INPUT: [224x224x3] memory: 224*224*3=150K weights: 0
CONV3-64: [224x224x64] memory: 224*224*64=3.2M weights: (3*3*3)*64 = 1,728
CONV3-64: [224x224x64] memory: 224*224*64=3.2M weights: (3*3*64)*64 = 36,864
POOL2: [112x112x64] memory: 112*112*64=800K weights: 0
CONV3-128: [112x112x128] memory: 112*112*128=1.6M weights: (3*3*64)*128 = 73,728
CONV3-128: [112x112x128] memory: 112*112*128=1.6M weights: (3*3*128)*128 = 147,456
POOL2: [56x56x128] memory: 56*56*128=400K weights: 0
CONV3-256: [56x56x256] memory: 56*56*256=800K weights: (3*3*128)*256 = 294,912
CONV3-256: [56x56x256] memory: 56*56*256=800K weights: (3*3*256)*256 = 589,824
CONV3-256: [56x56x256] memory: 56*56*256=800K weights: (3*3*256)*256 = 589,824
POOL2: [28x28x256] memory: 28*28*256=200K weights: 0
CONV3-512: [28x28x512] memory: 28*28*512=400K weights: (3*3*256)*512 = 1,179,648
CONV3-512: [28x28x512] memory: 28*28*512=400K weights: (3*3*512)*512 = 2,359,296
CONV3-512: [28x28x512] memory: 28*28*512=400K weights: (3*3*512)*512 = 2,359,296
POOL2: [14x14x512] memory: 14*14*512=100K weights: 0
CONV3-512: [14x14x512] memory: 14*14*512=100K weights: (3*3*512)*512 = 2,359,296
CONV3-512: [14x14x512] memory: 14*14*512=100K weights: (3*3*512)*512 = 2,359,296
CONV3-512: [14x14x512] memory: 14*14*512=100K weights: (3*3*512)*512 = 2,359,296
POOL2: [7x7x512] memory: 7*7*512=25K weights: 0
FC: [1x1x4096] memory: 4096 weights: 7*7*512*4096 = 102,760,448
FC: [1x1x4096] memory: 4096 weights: 4096*4096 = 16,777,216
FC: [1x1x1000] memory: 1000 weights: 4096*1000 = 4,096,000
TOTAL memory: 24M * 4 bytes ~= 93MB / image (only forward! ~*2 for bwd) TOTAL params: 138M parameters

GoogLeNet (Inception) 2014





$C_{in} \times C_{out} \times F_W \times F_H$

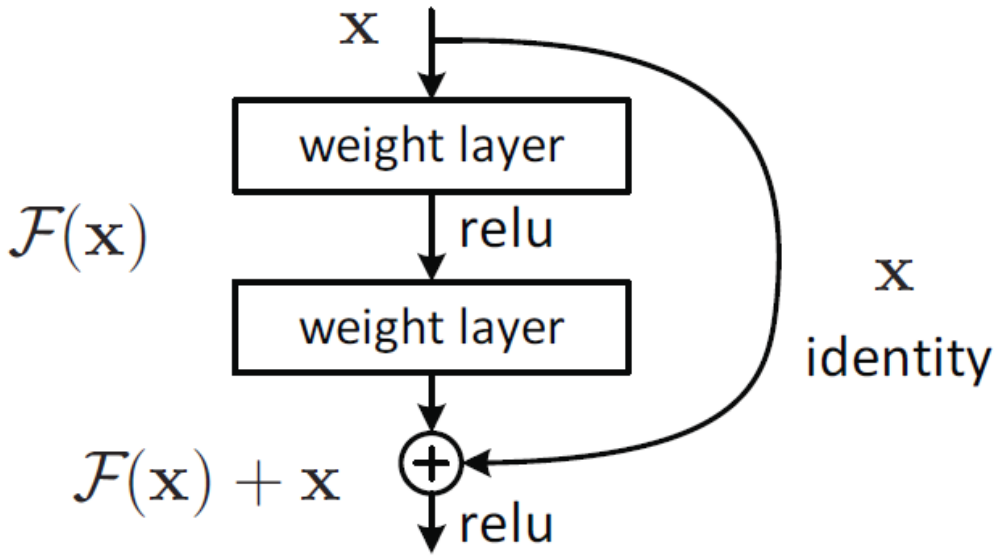


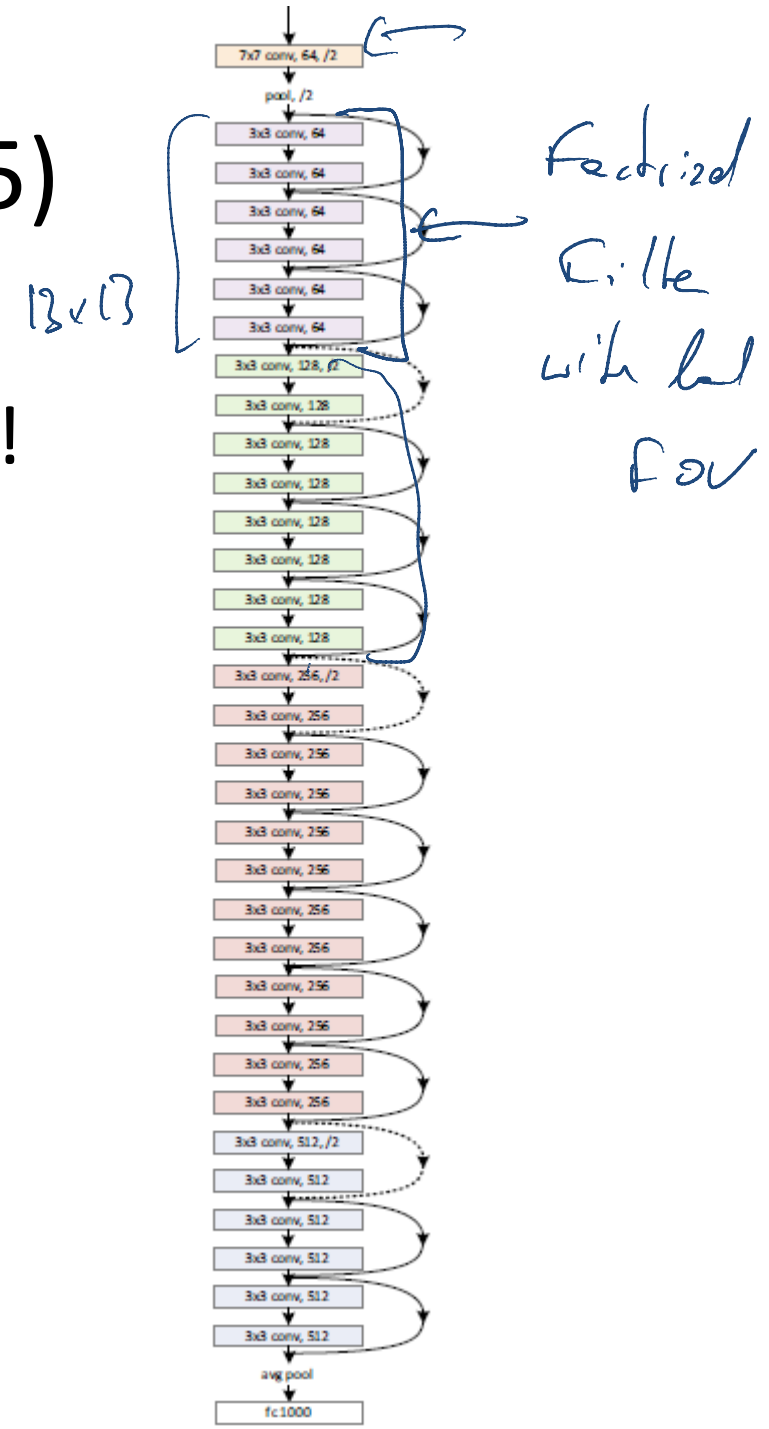
$C_{in} \times C_{mid} \times 1 \times 1$

$C_{mid} \times 5 \times 5 \times C_{out}$

ResNest (Residual Nets, 2015)

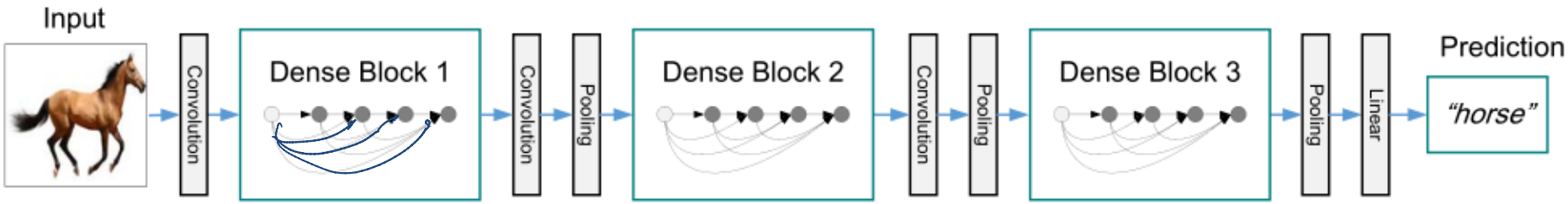
- Add bypases to ease gradient flow
- Networks with more than 150 layers!
- 3x3 convs with number of feature maps doubling after every pooling



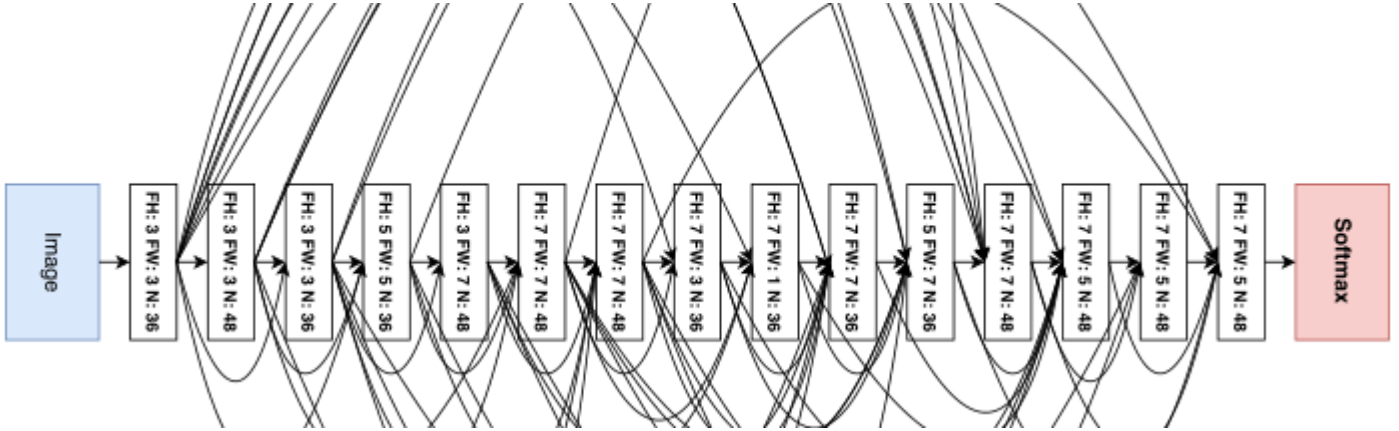


Quest for models

- DenseNets (https://arxiv.org/pdf/1608.06993)



- Automatic architecture search (https://arxiv.org/pdf/1611.01578)



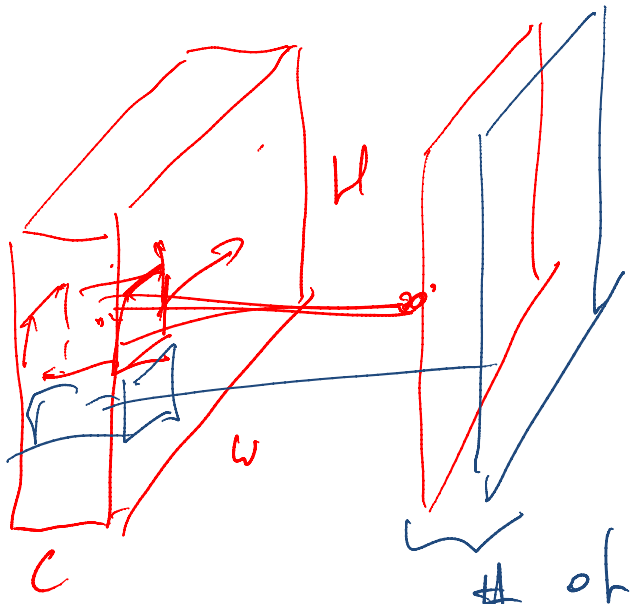
Which ConvNet to use?

- Take current best on Imagenet
- Many networks are available for download (google tensorflow model and caffe model zoo)

- For your use – take a pretrained net and retrain only the last layers!
- On ImageNet (1M images) data augmentation and regularization is as important as the network!

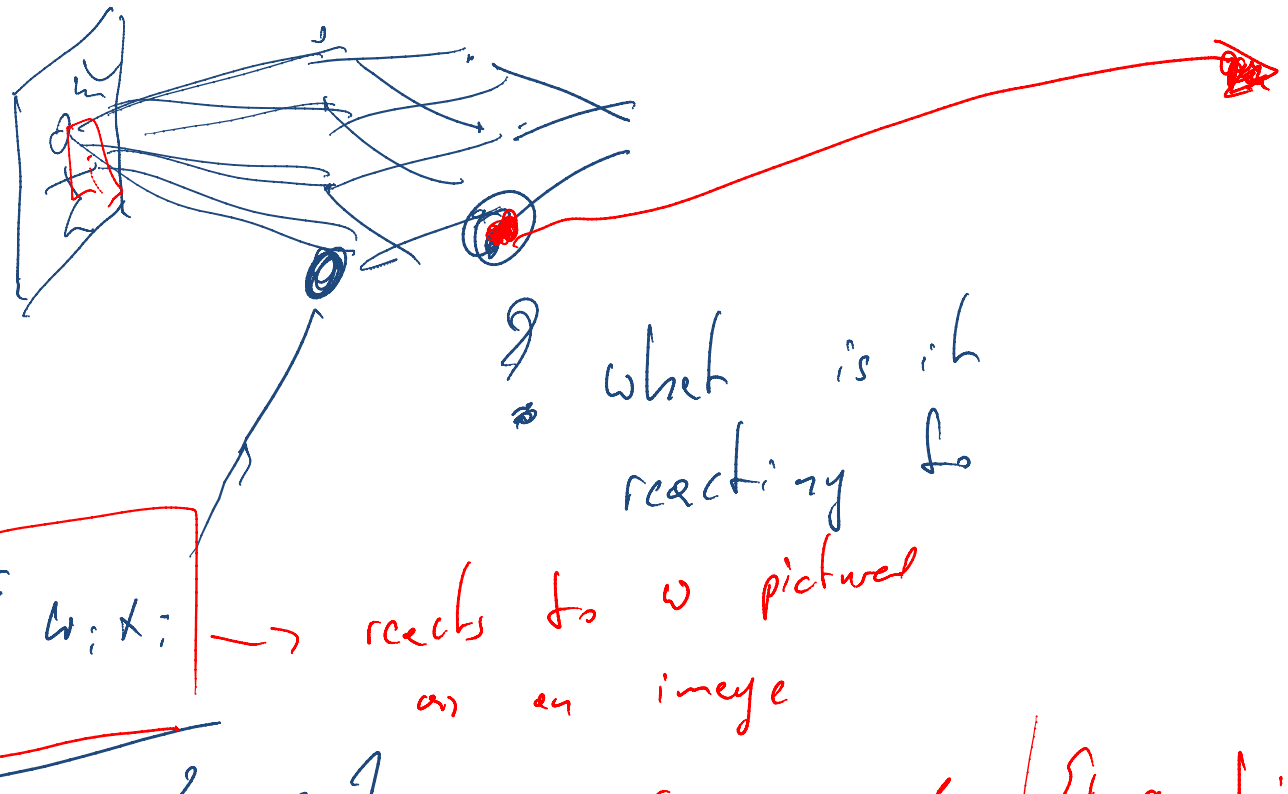
Conv recap

- Local connectivity → small, localized features make sense
- Weight sharing → same feature can be detected everywhere



# of feature maps = # number of output channels = # filters

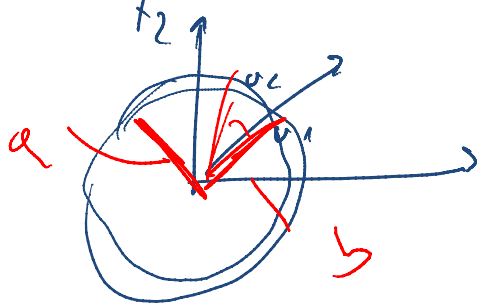
How to understand a model?



? what is it reacting to

$\sum_i w_i x_i$ → reacts to a pictured as an image

$\|x\|_2^2 \leq 1$



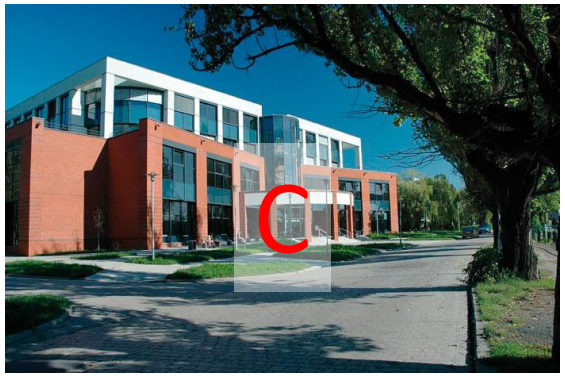
$\sum_i a_i w_i < \left(\sum_i a_i b_i\right)$

$\sum_i a_i w_i$

1 Build a linear approx to this unit $o(x+\Delta x) =$ $o(x) + \Delta x \frac{\partial o}{\partial x} + \epsilon$

2 Solve for an input that maximally excite this neuron

Sidenote Style Transfer



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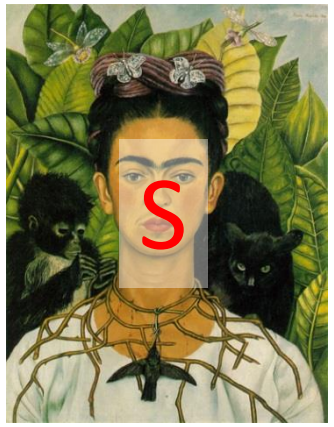


=

Find image (backpropagation toward pixels) minimizing:

$$\mathcal{L} = \mathcal{L}_c + \mathcal{L}_S =$$

$$= (F(C) - F(I))^2 + \left(G(S) - G(I)\right)^2$$

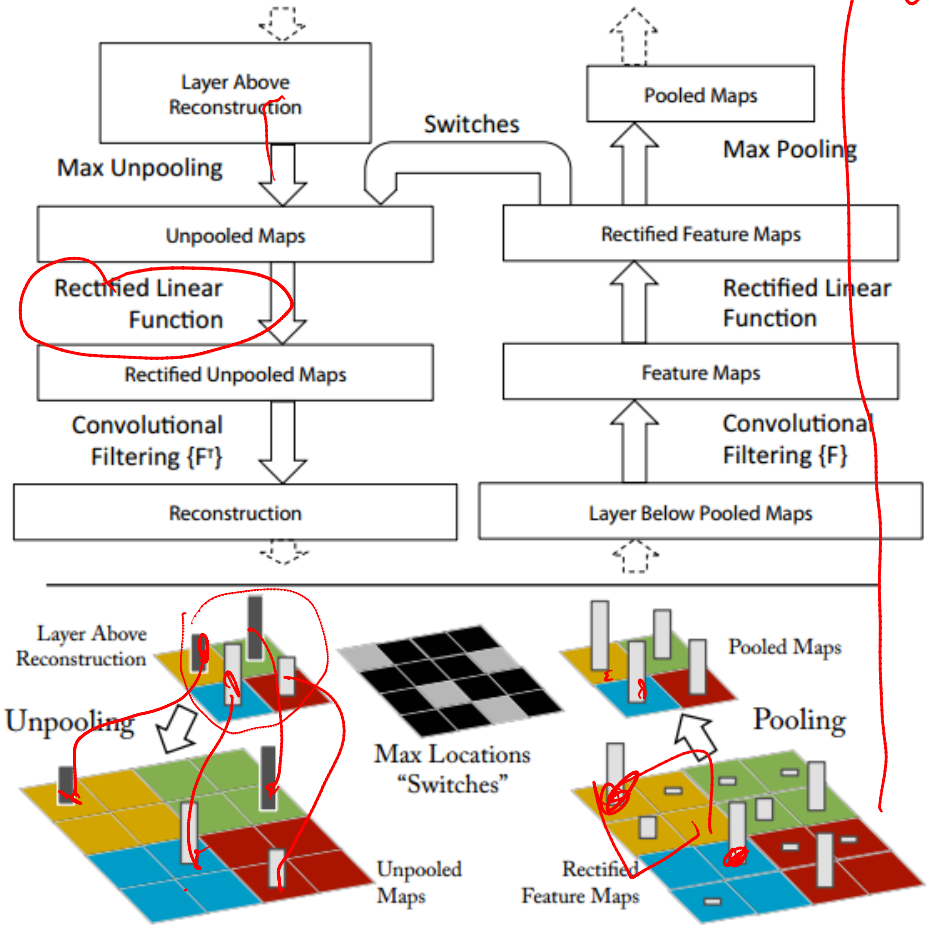
Where:

$F(x)$ features of a CNN layer on image x

$G(x)$ matrix of correlations between a layer's features over pixels of image x

Gatys et al., „A Neural Algorithm of Artistic Style", 2015

Visualizing CNN features



Main idea:

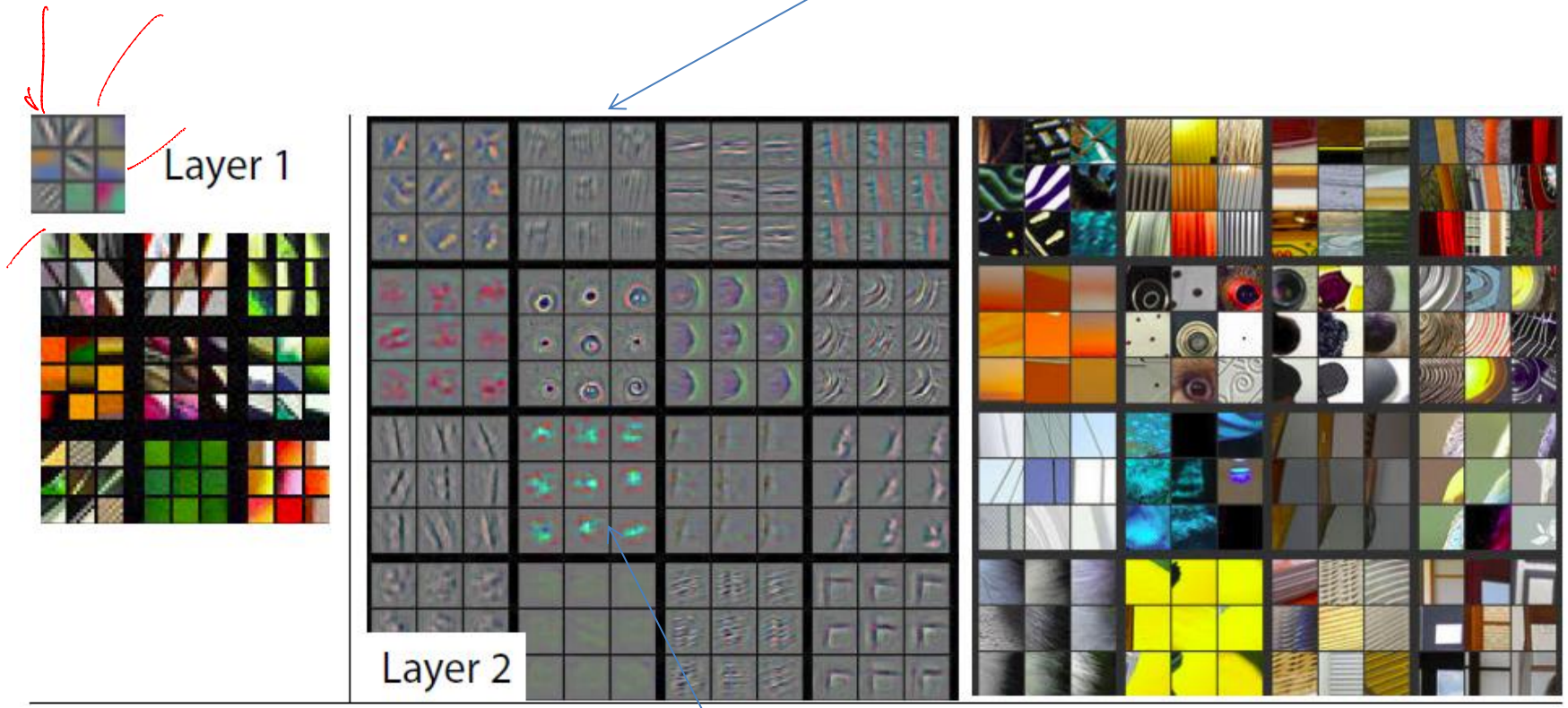
1. Do a forward propagation,
2. Save state of max-poolings,
3. „Deconvolve”: trace back the activations of chosen units to inputs

Note: similar to gradient computation, but applies ReLU during deconvolution (gradient would use the saved jacobian of relu)

M. Zieler, “Visualizing and Understanding Convolutional Networks”

Low-level features

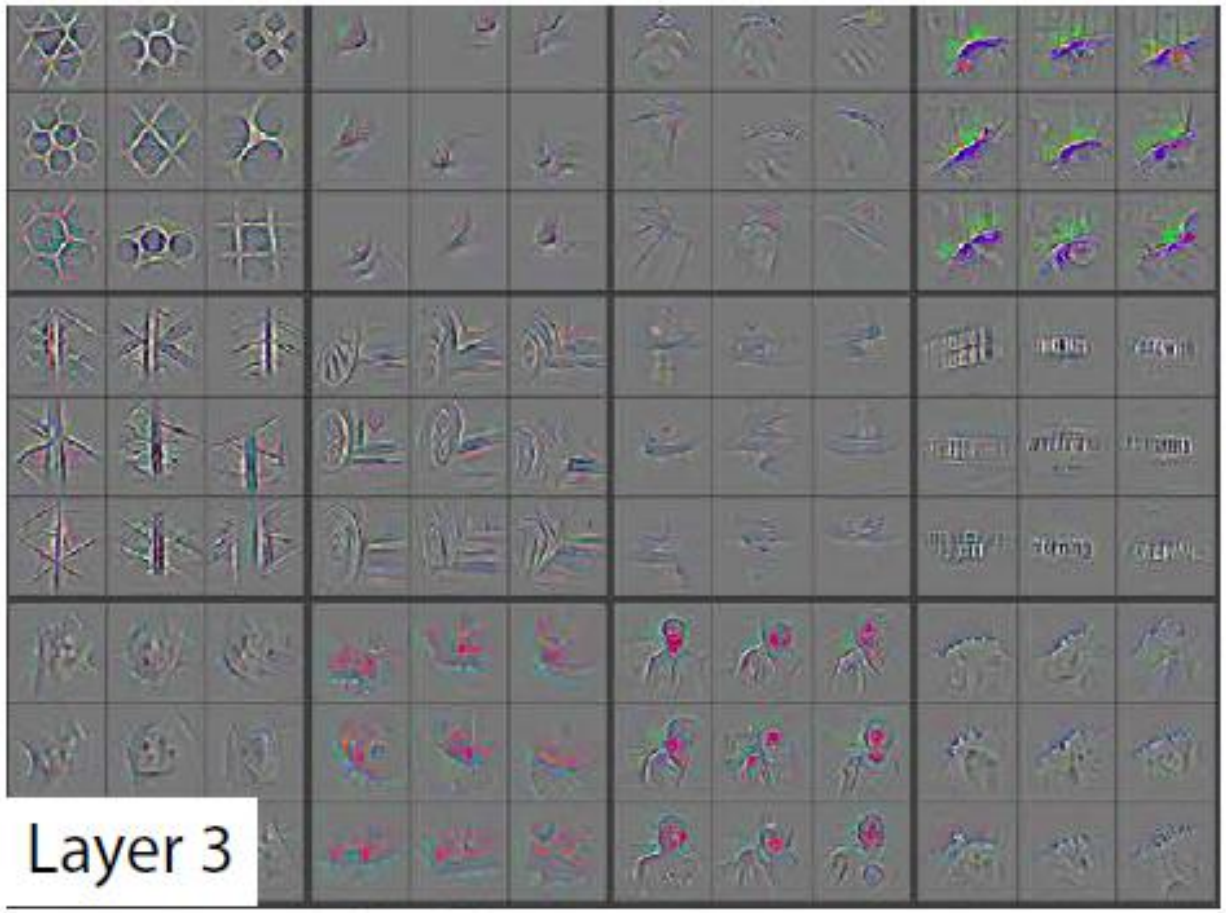
What the neuron (feature-detector looks for)



What images are selected by the neuron

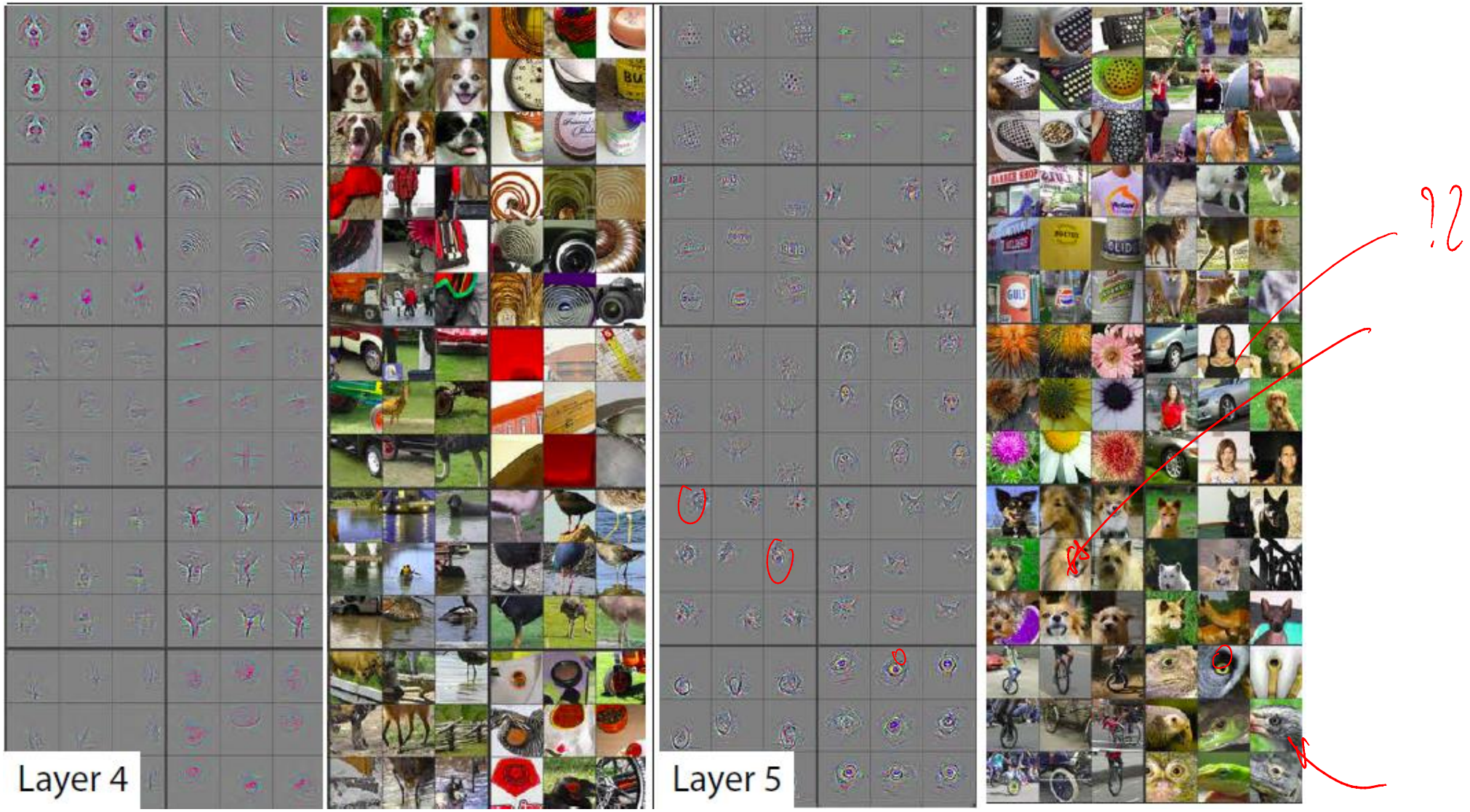
M. Zieler, “Visualizing and Understanding Convolutional Networks”

Mid-level features



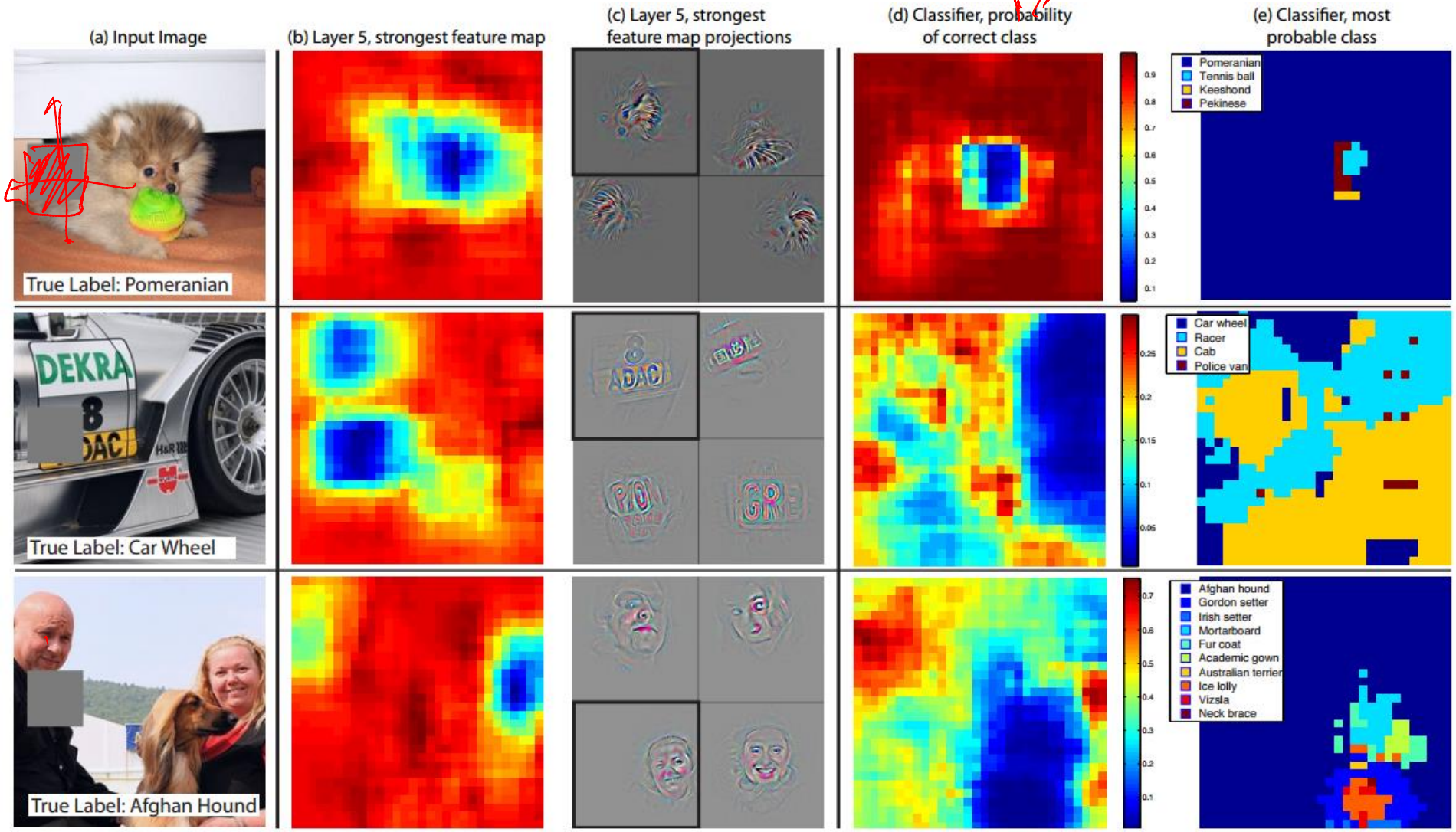
M. Zieler, “Visualizing and Understanding Convolutional Networks”

High-level features

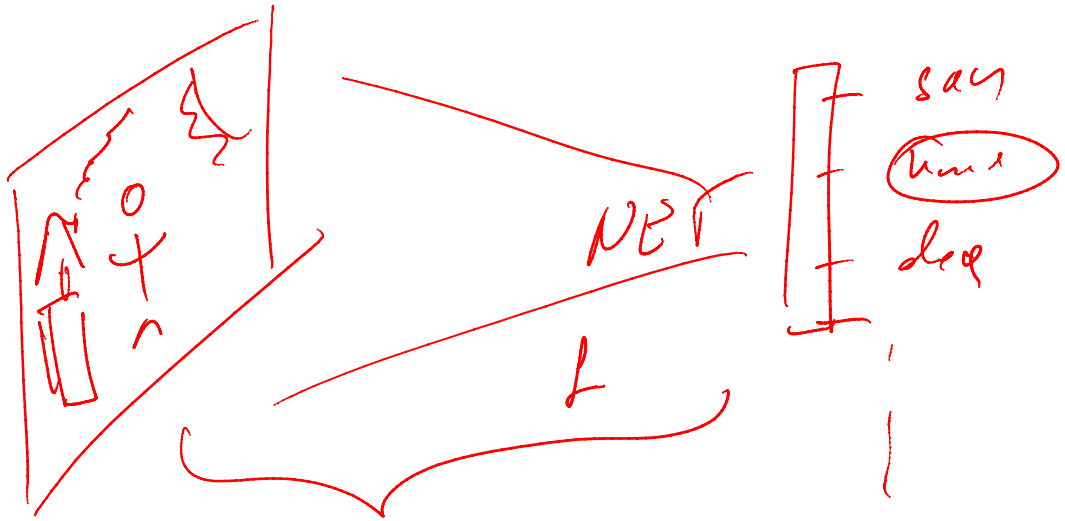


M. Zieler, “Visualizing and Understanding Convolutional Networks”

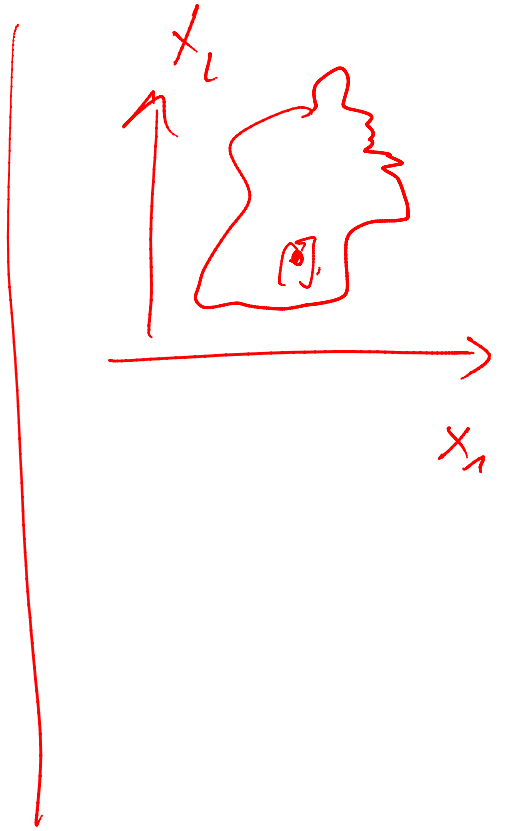
Where Convnets look?



Gradient saliency map

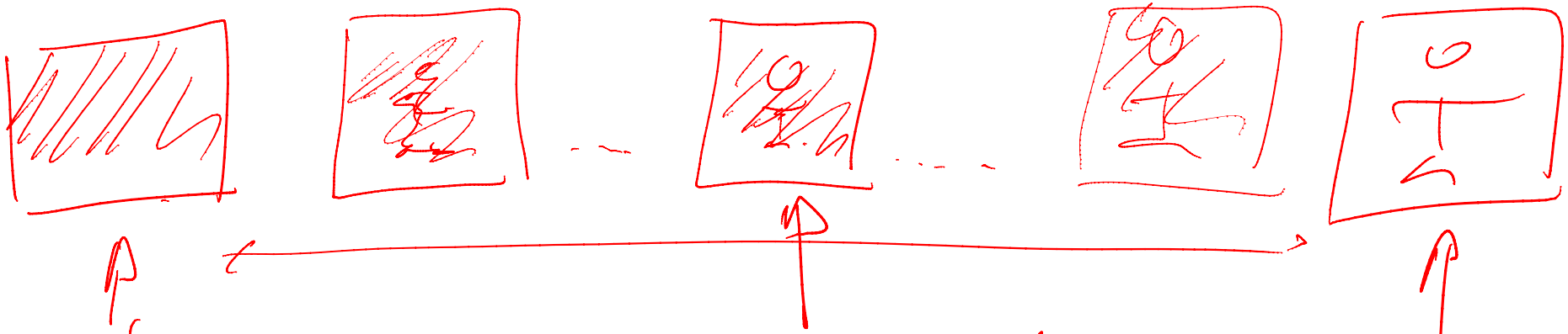


$$f(x + \Delta x) \simeq f(x) + \Delta x \frac{\partial f}{\partial x}$$



Saturation or stability → we hope flat $f(x + \Delta x) \simeq f(x)$

Saliency maps with integrated gradients



uniform gray

↑ uniform boi

img, $\frac{\partial f}{\partial x}$ should be small

subject barely visible

$\frac{\partial f}{\partial x}$ is large

End img pattern clearly seen

is stable and $\frac{\partial f}{\partial x}$ is tiny

Idea: integrate (add) gradients over linear interpolation from uniform grey to image

LIME: local surrogate models

Idea: build a surrogate (model of a model)

that explains locally the decision boundary → f on small neighb.

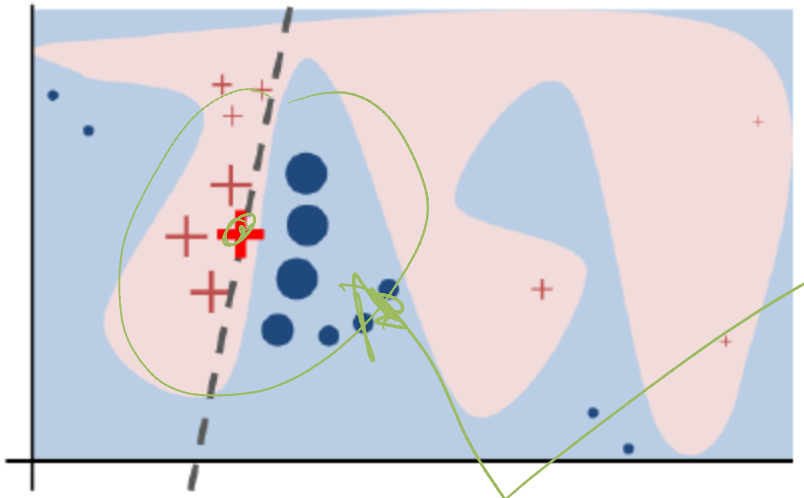
→ great

$p_1 \dots p_N$ Several sampled points close to x

Eval them with f on them

p_1	$f(p_1)$	used as train, train lin regression
p_2	$f(p_2)$	
p_3	$f(p_3)$	
⋮	⋮	

LIME details



focus on vicinity of x

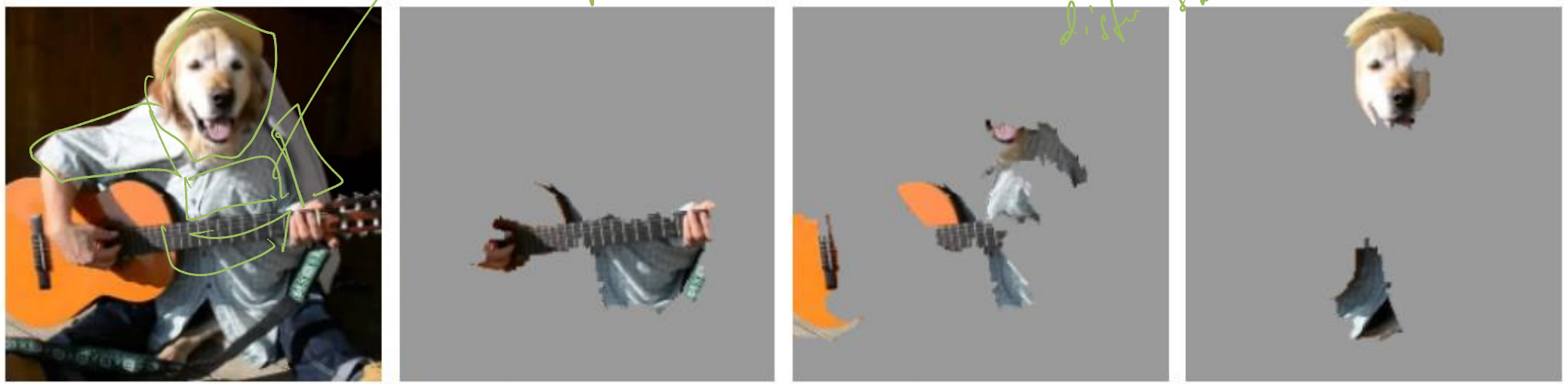
π_x – weights points closer to x higher

g is simple

$$\xi(x) = \underset{g \in G}{\operatorname{argmin}} \; \mathcal{L}(f, g, \pi_x) + \Omega(g)$$

surrogate classifier g

LIME on images



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

Figure 4: Explaining an image classification prediction made by Google's Inception neural network. The top 3 classes predicted are "Electric Guitar" ($p = 0.32$), "Acoustic guitar" ($p = 0.24$) and "Labrador" ($p = 0.21$)

Beware: some methods lie

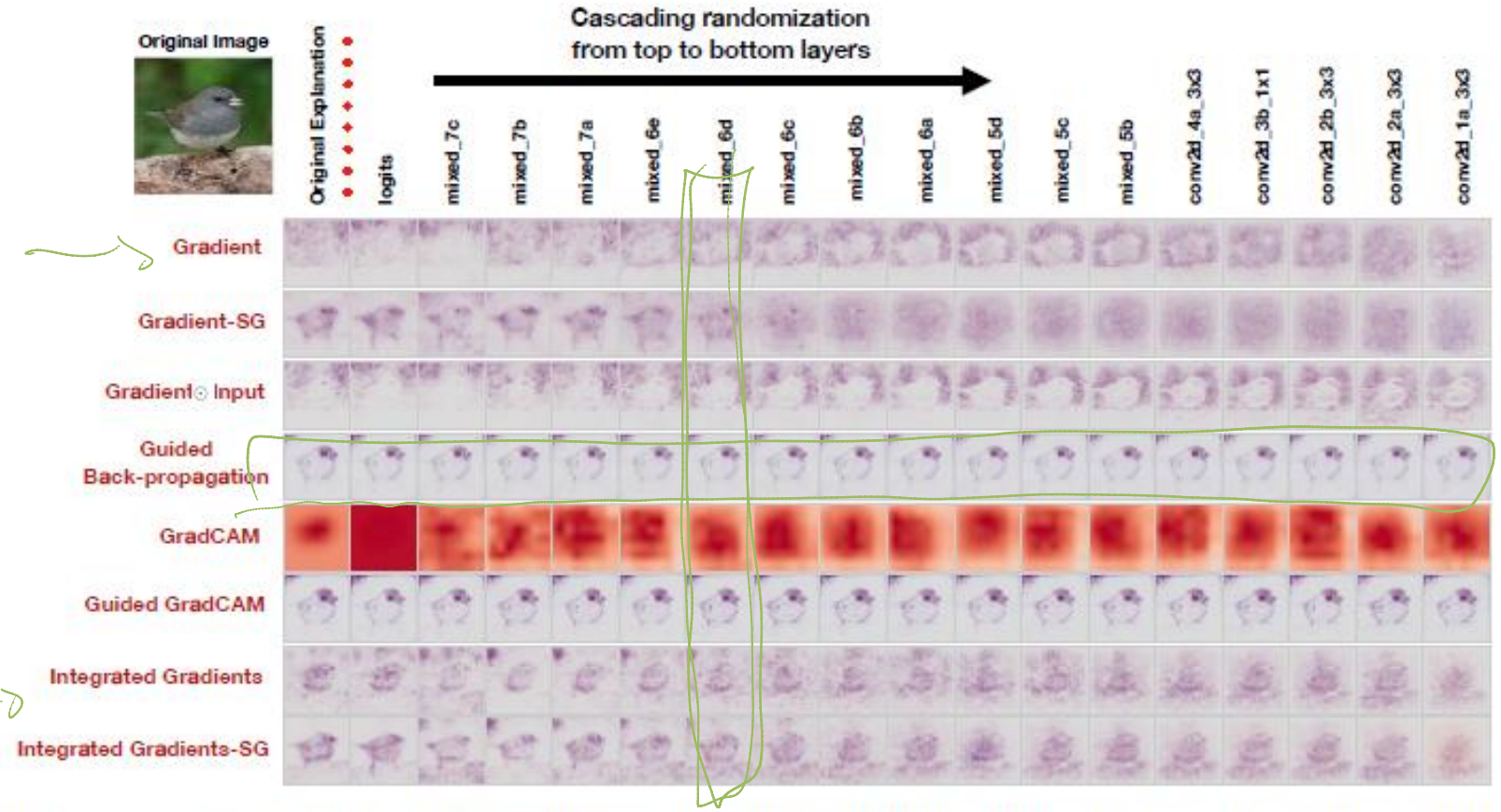


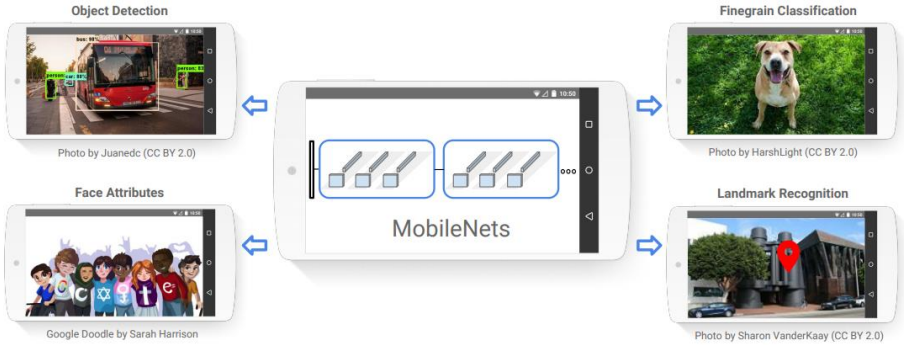
Figure 2: **Cascading randomization on Inception v3 (ImageNet).** Figure shows the original explanations (first column) for the Junco bird. Progression from left to right indicates complete randomization of network weights (and other trainable variables) up to that 'block' inclusive. We show images for 17 blocks of randomization. Coordinate (Gradient, mixed_7b) shows the gradient explanation for the network in which the top layers starting from Logits up to mixed_7b have been reinitialized. The last column corresponds to a network with completely reinitialized weights.

http://papers.nips.cc/paper/8160-sanity-checks-for-saliency-maps.pdf

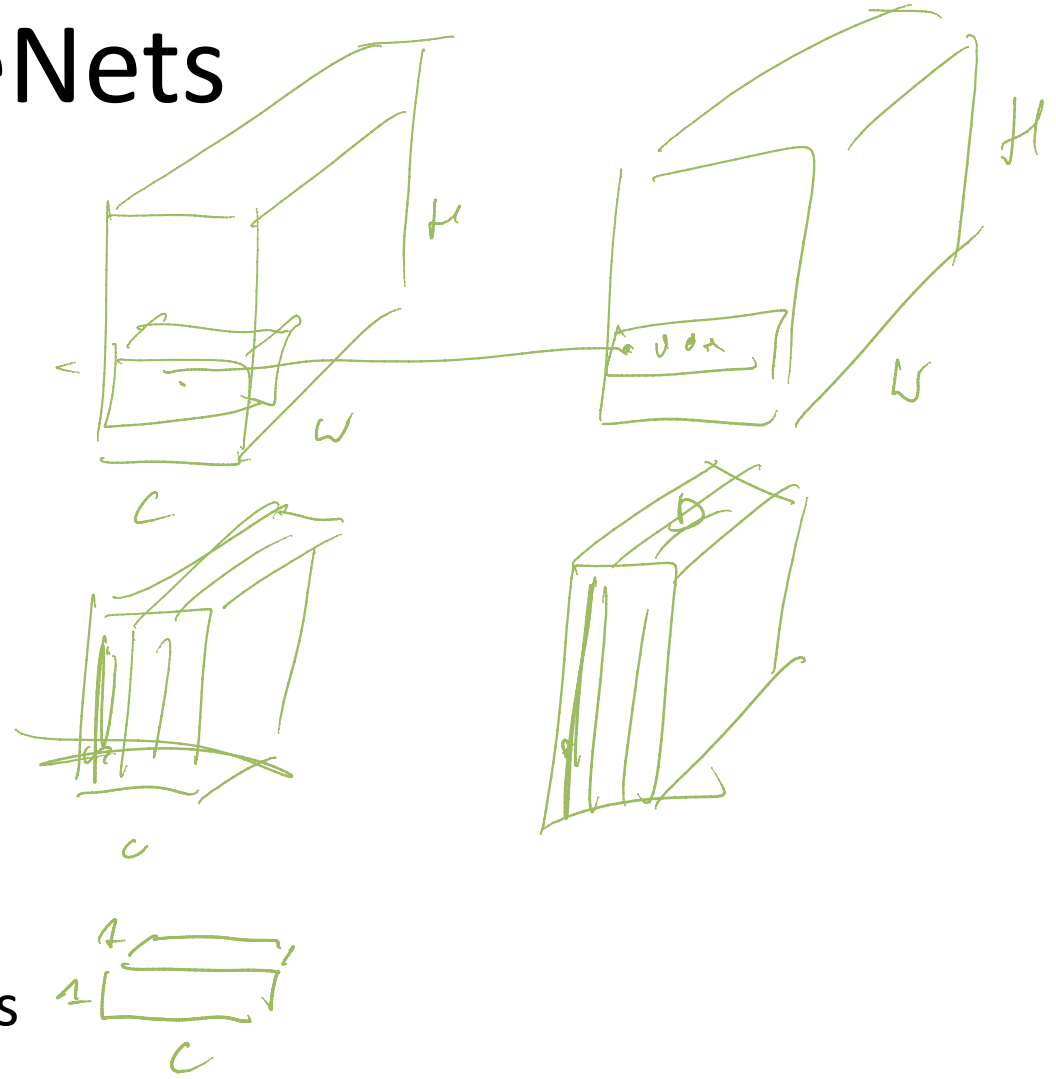
Model explanations, further reading

- Integrated gradients: https://arxiv.org/abs/1703.01365v2
- Important analysis of saliency maps http://papers.nips.cc/paper/8160-sanity-checks-for-saliency-maps.pdf
- LIME: https://arxiv.org/abs/1602.04938v3
- SHAP (similar to LIME, more stable and justified): http://papers.nips.cc/paper/7062-a-unified-approach-to-interpreting-model-predictions.pdf

SPECIALIZED CONVNETS



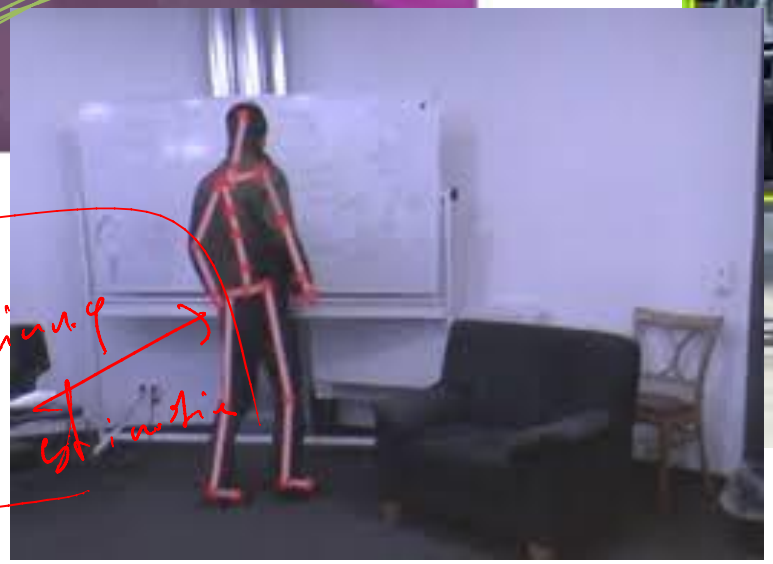
MobileNets

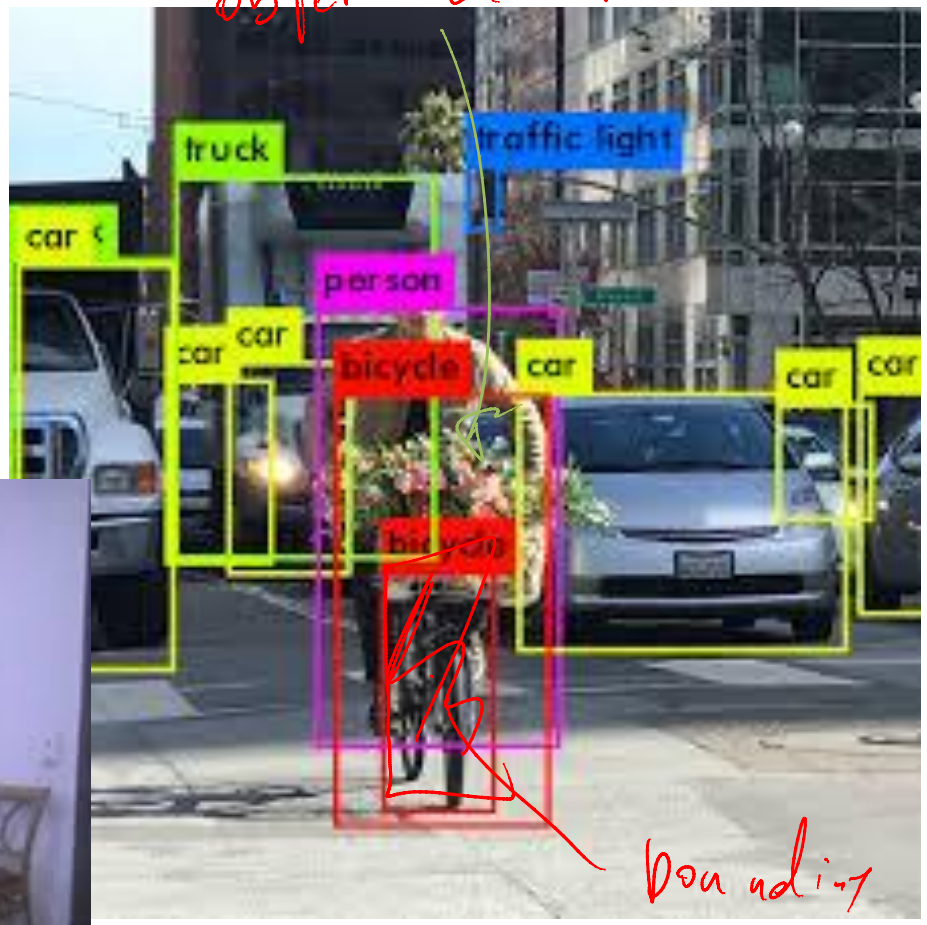


1. Std convolution
   Filter size: $D \times C \times W \times H$
   Matmuls per pixel: $D \times C \times W \times H$
2. Depthwise convolution
   (each filter sees only one input channel)
   Filter size: $C \times W \times H$ (nb: no D)
   Matmuls per pixel: $C \times W \times H$
3. MobileNet: Depthwise + 1x1 convs
   Why? Depthwise: fast, doesn't mix channels
   1x1: mixes channels, still small

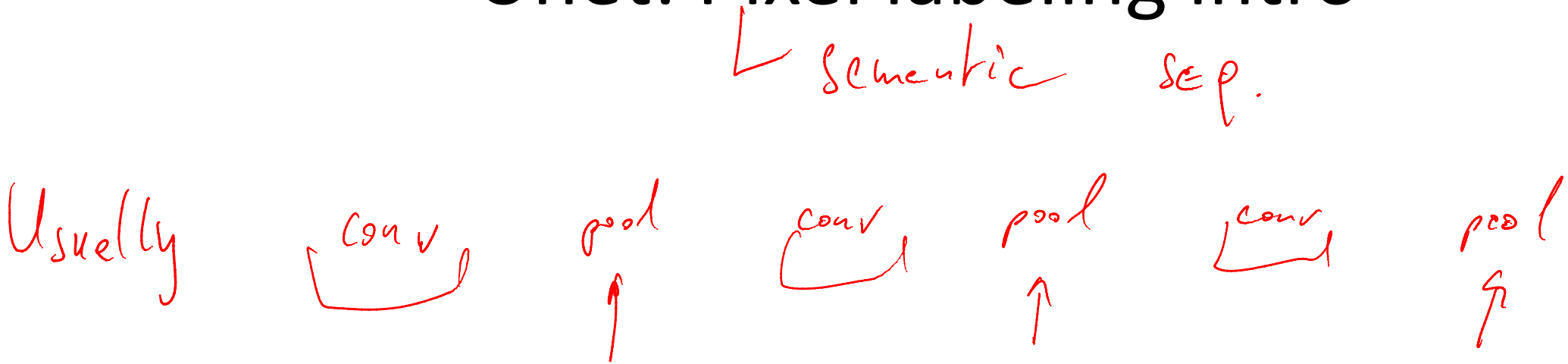
https://arxiv.org/pdf/1704.04861.pdf

More image processing tasks

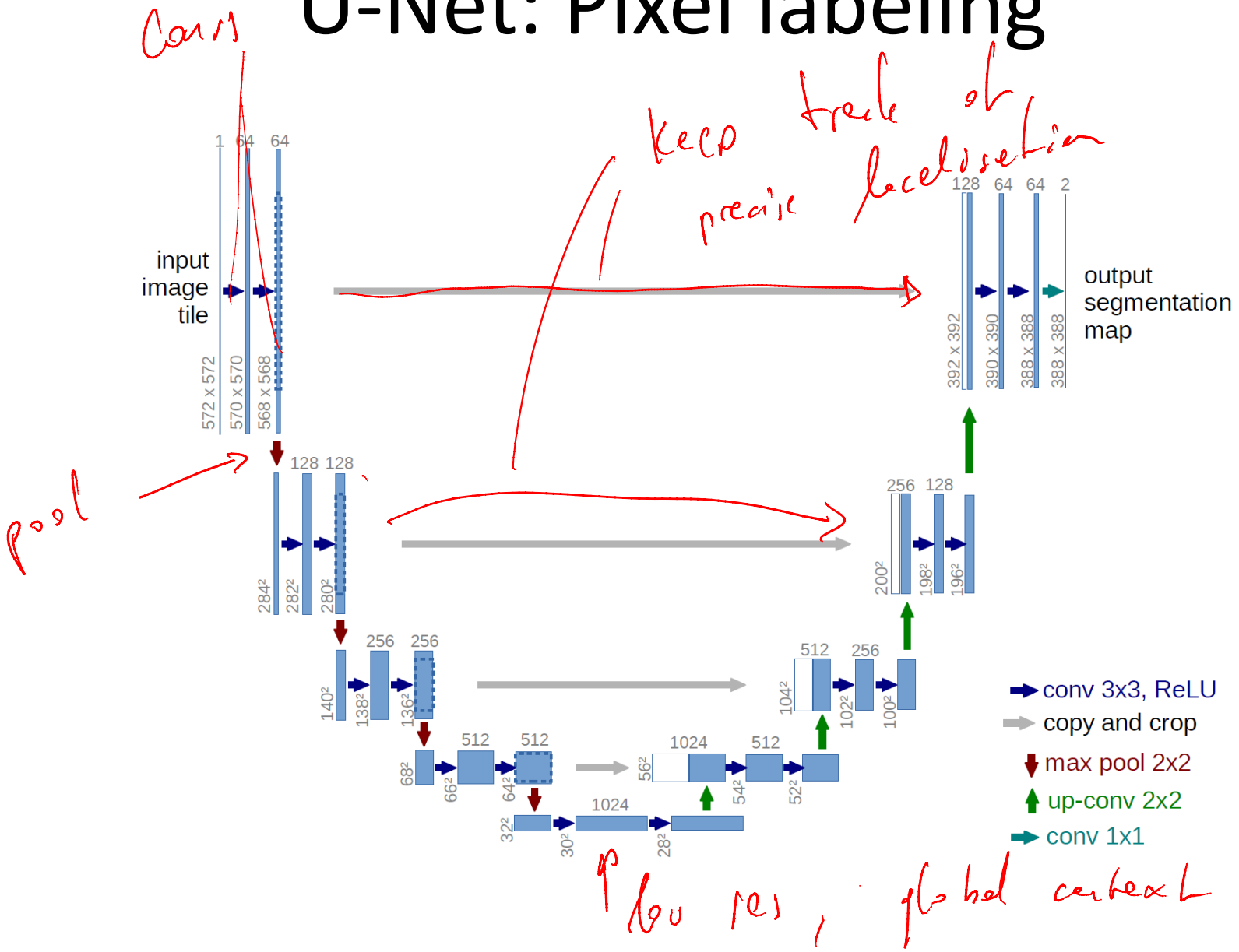




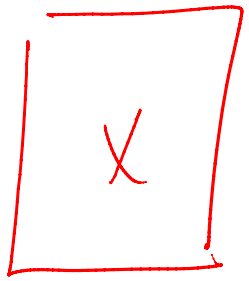
Unet: Pixel labeling intro



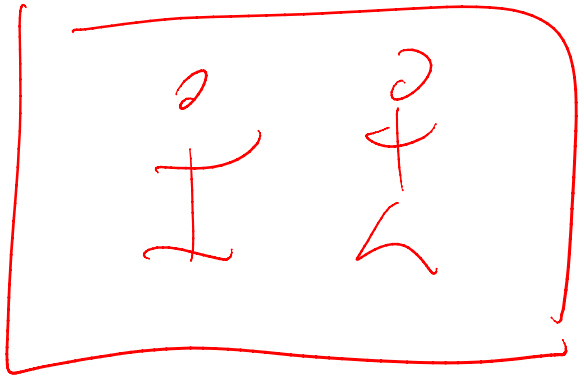
U-Net: Pixel labeling



From Classification to Detection



→ y → what's in the img



For a convnet the two can be equivalent,

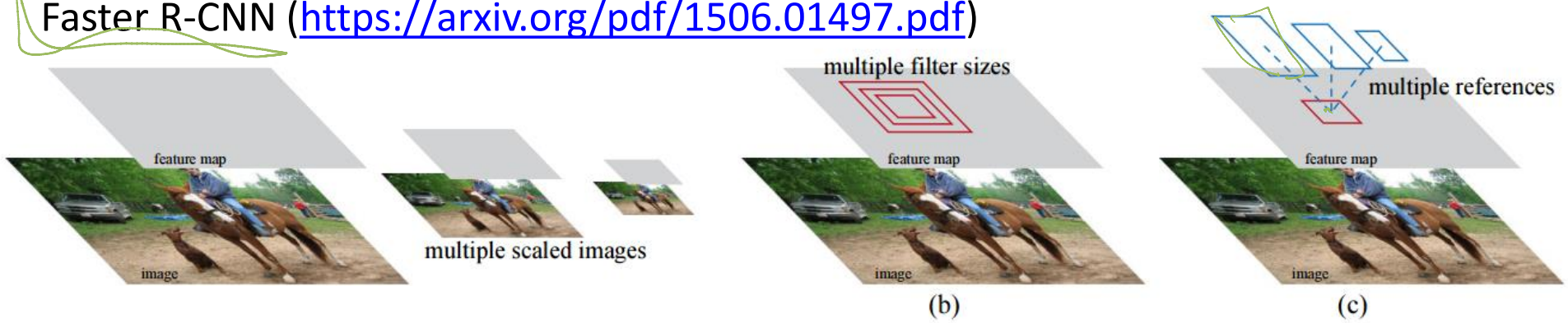
1 take crops at all locations run all through the convnet indep. => slow

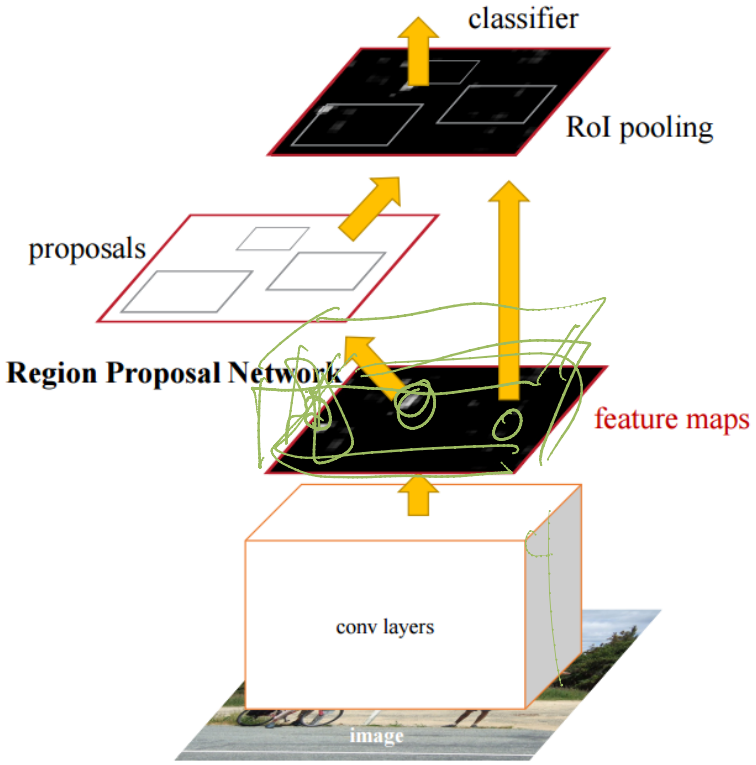
2. Run the convnet over large image.

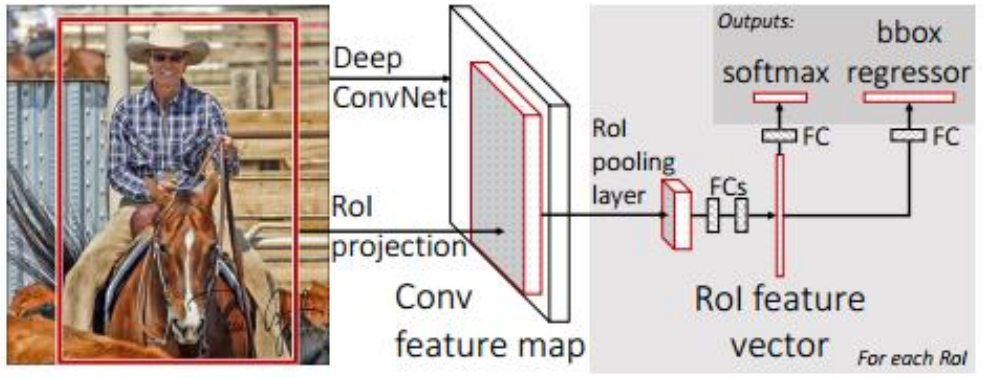
Object detection and segmentation

Fast R-CNN (https://arxiv.org/pdf/1504.08083.pdf)

Faster R-CNN (https://arxiv.org/pdf/1506.01497.pdf)







YOLO – fast object detection

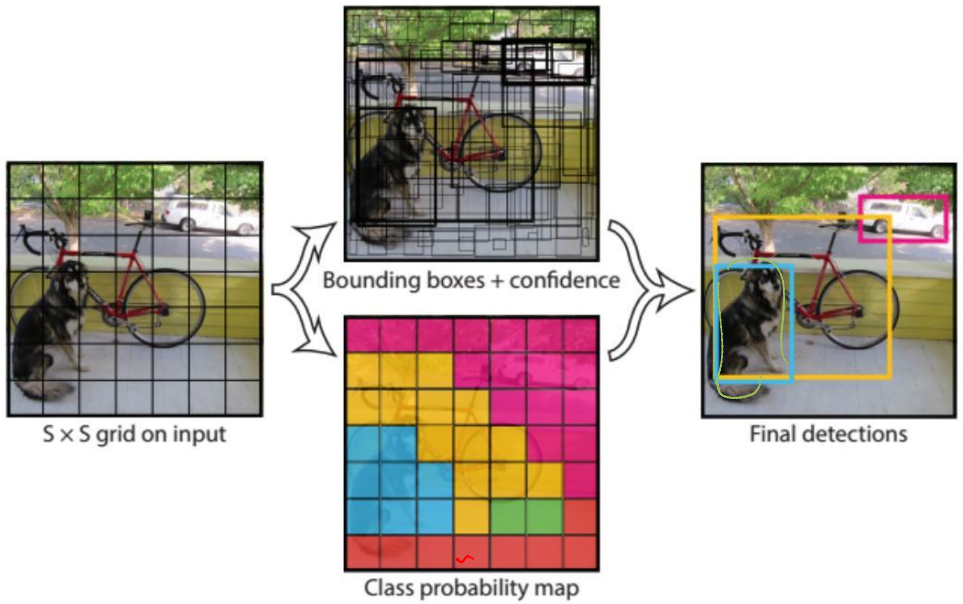


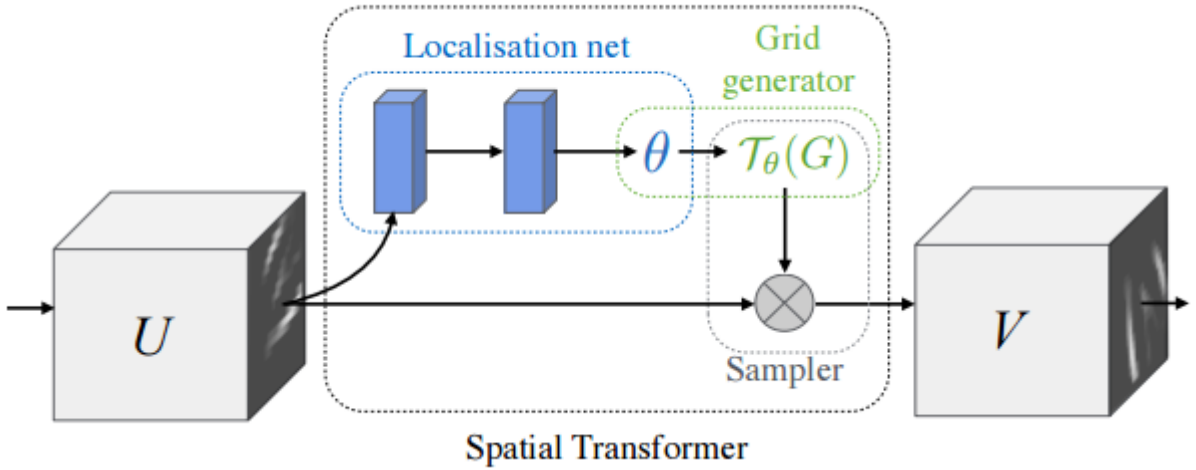
Figure 2: The Model. Our system models detection as a regression problem. It divides the image into an $S \times S$ grid and for each grid cell predicts B bounding boxes, confidence for those boxes, and C class probabilities. These predictions are encoded as an $S \times S \times (B * 5 + C)$ tensor.

- No region proposal and looping over ROIs!
- In a fully convolutional net predict for each pixel of a feature map:
  - Objectness – is something there
  - Bounding Box – how large it is

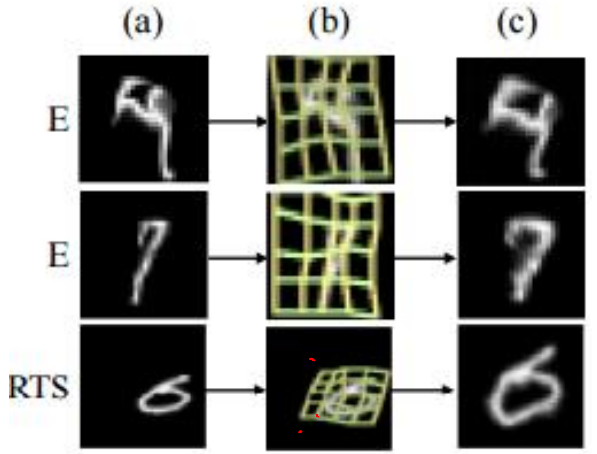
https://arxiv.org/pdf/1506.02640v5.pdf

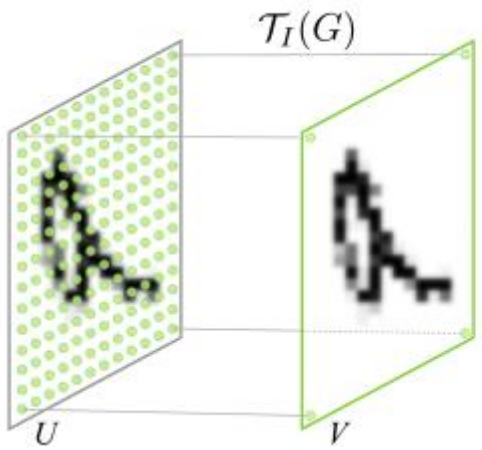
Spatial Transformer Networks

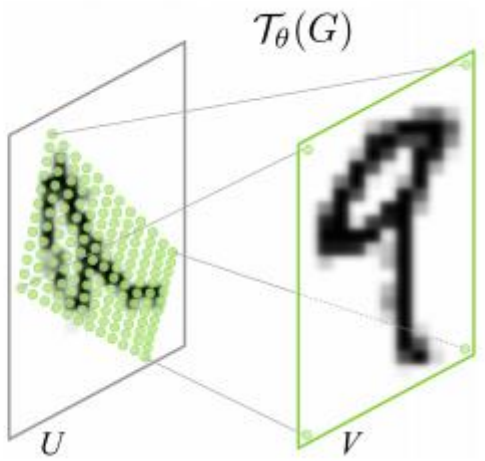
https://arxiv.org/pdf/1506.02025.pdf

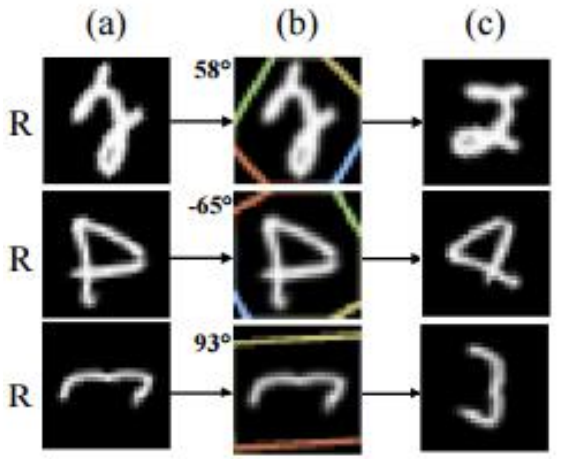


Spatial Transformer

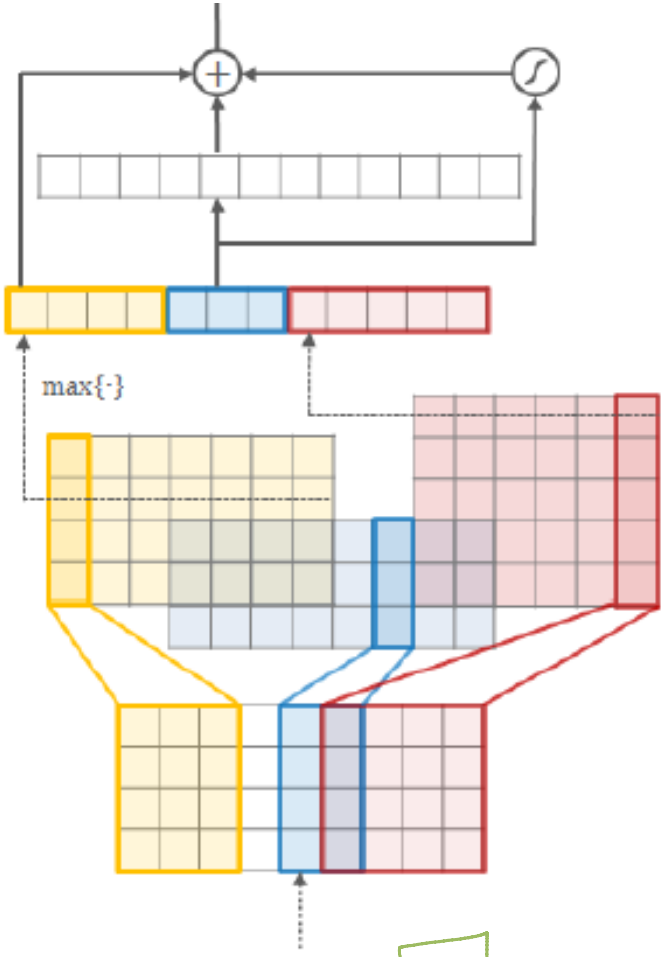








CNN beyond images
Or character-to-word embeding



Highway layers – very nonlinear transformation of data

Glue best word representations together

Convolutional filters of varying lengths. Can react to pre-, in-, and post-fixes of words

Character embedings concatenated into a matrix

Y. Kim, Y. Jernite, D. Sontag, and A. M. Rush, “Character-Aware Neural Language Models,” *arXiv:1508.06615 [cs, stat]*, Aug. 2015.

Additional references

- Goodfellow Chp. 9
- http://cs231n.github.io
- How transferable are features in deep neural networks? studies the transfer learning performance in detail, including some unintuitive findings about layer co-adaptations.
- CNN Features off-the-shelf: an Astounding Baseline for Recognition trains SVMs on features from ImageNet-pretrained ConvNet and reports several state of the art results.