UNIVERSITAT DE BARCELONA

DATASCIENCE@UB

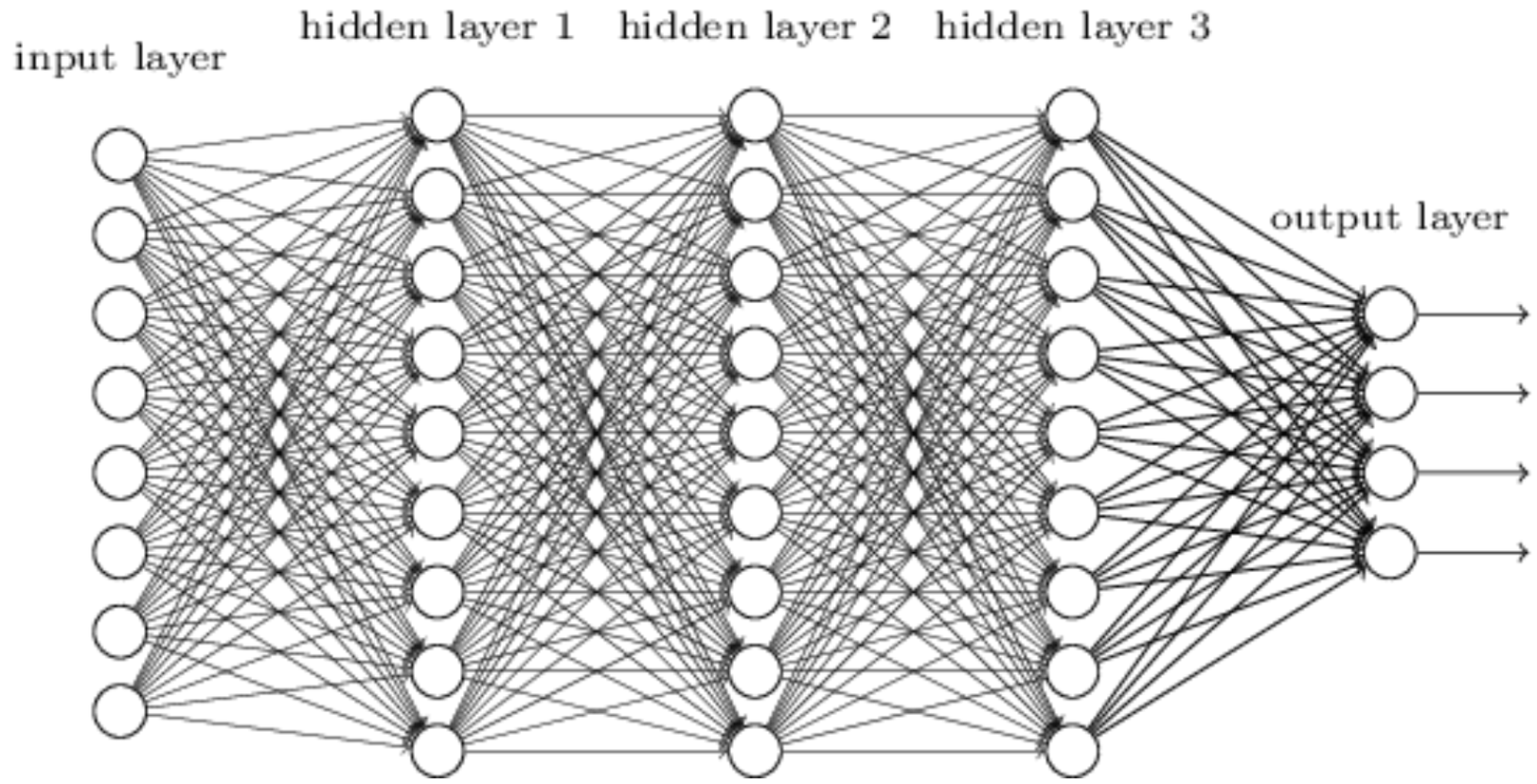
Deep Learning From Scratch

Convolutional Neural Networks

Santi Seguí

Neural Networks for Images

Multi Layer Perceptron



How many parameter?

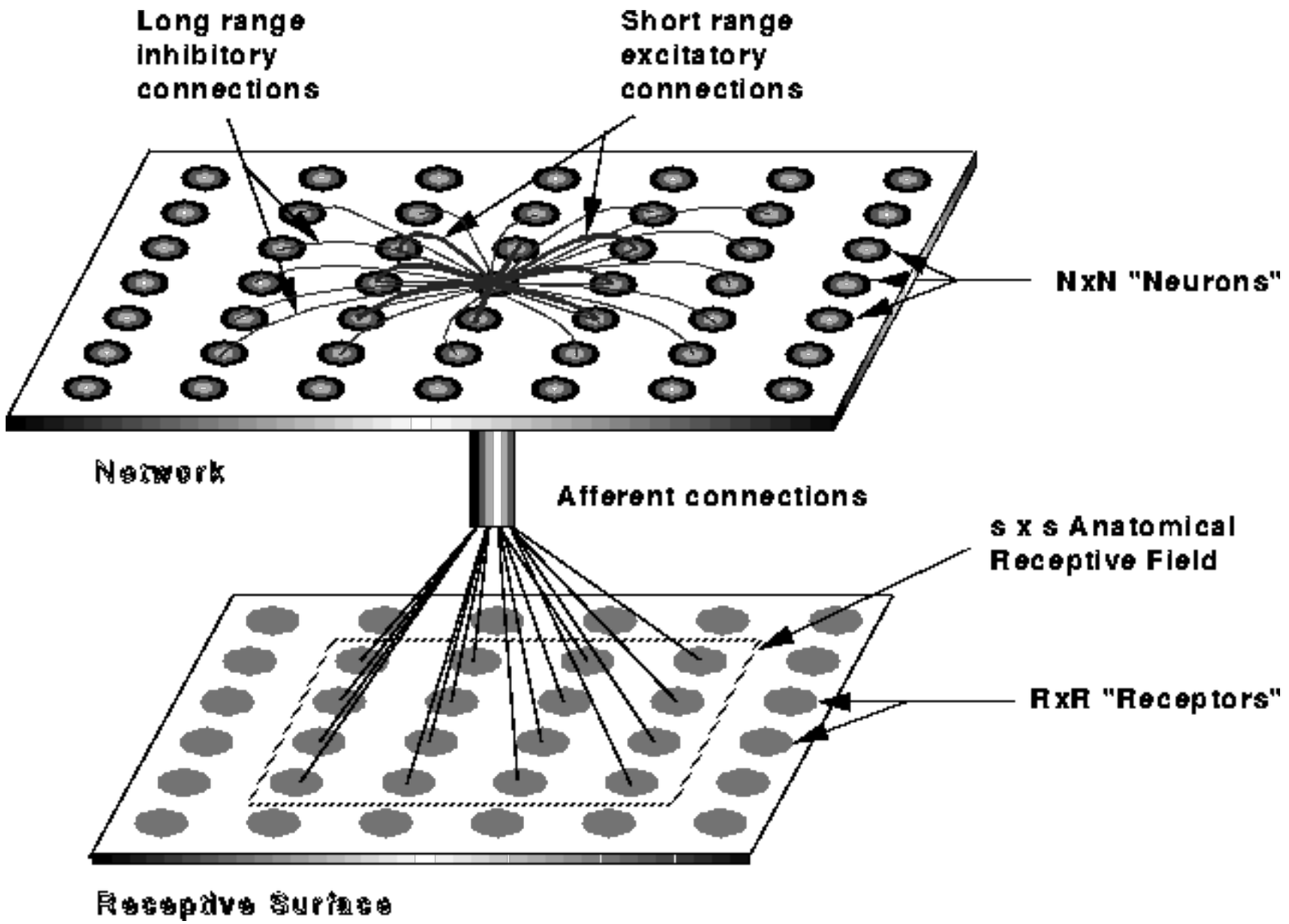
8 * 9 + 9 * 9 + 9 * 9 +9 *4 = 570

Neural Networks for Images

Neural Networks for Images

- An image is just a Matrix of N x M pixels.
- So, input is a standard vector of size N x M
  - Imagine an medium resolution color image of 256x256 pixels
  - If we think on a Multi Layer Perceptron with just one hidden layer of 256 neurons + an output layer of 1 neuron it will have more than **48 milion** parameters.
    - **Does it make sense? Can we do it better?**

Local Receptive Fields



But, in an image:

A dog can appear **anywhere** in the image!

Doesn’t matter where they appear,
they look similar anywhere!

Convolutional Neural Networks (CNNs)

- Three main ideas:

  1. **local receptive fields**,
  2. **shared weights**,
  3. **sub-sampling**

Convolutional Neural Networks (CNNs)

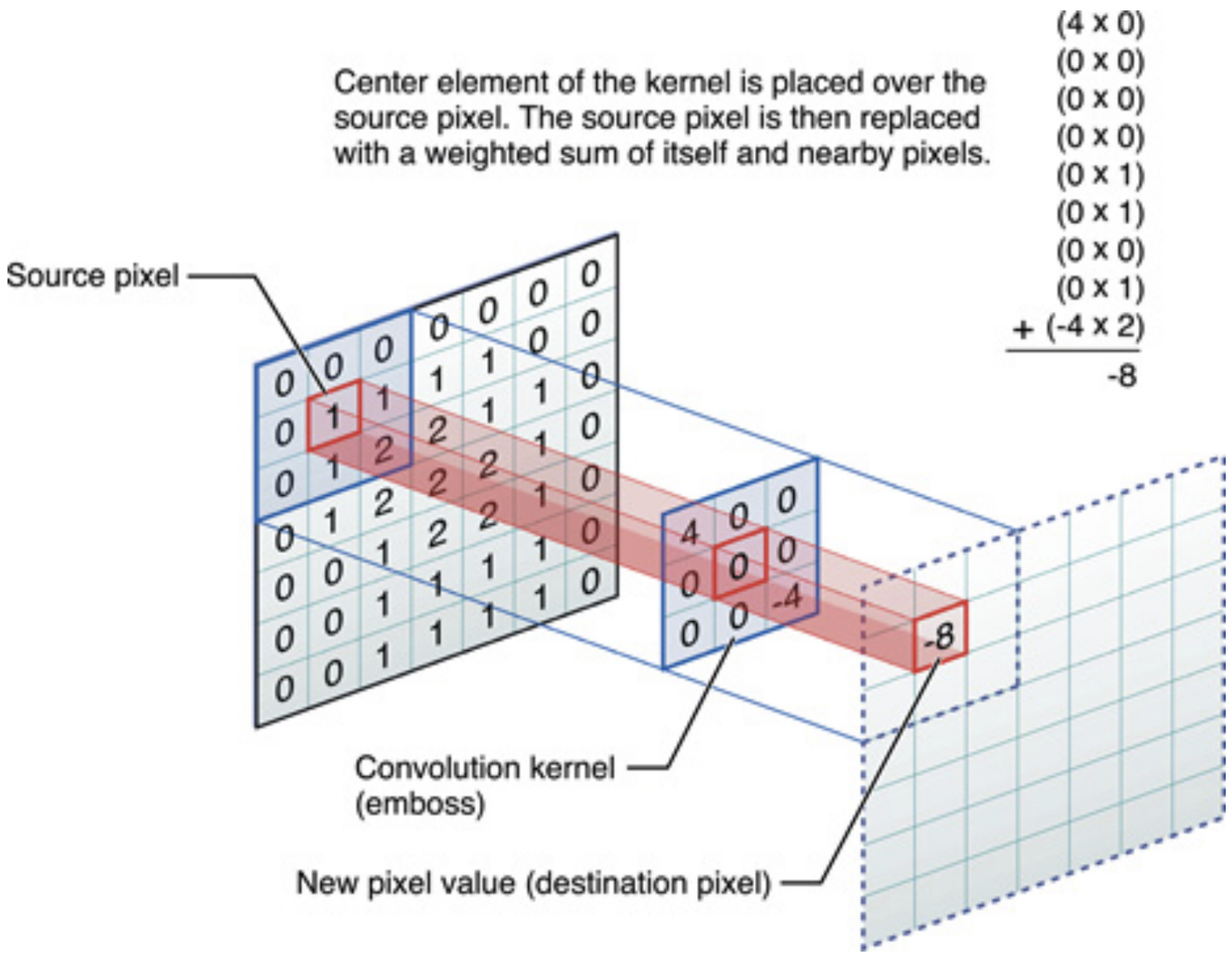
- **Repetitive** blocks of neurons that are **applied across space** (for images) or time (for audio signals etc).

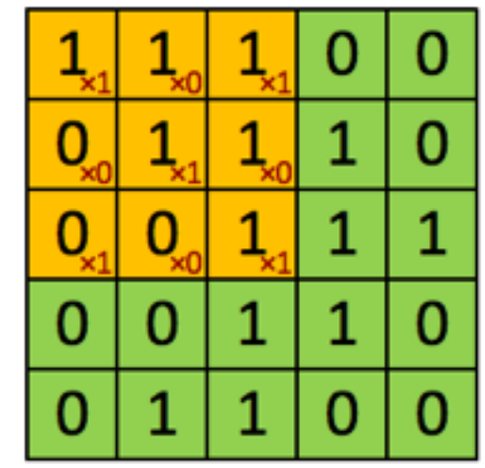
- For **images**, these blocks of neurons can be interpreted as **2D convolutional kernels**, repeatedly applied over each patch of the image.

- For **speech**, they can be seen as the 1**D convolutional kernels** applied across time-windows.

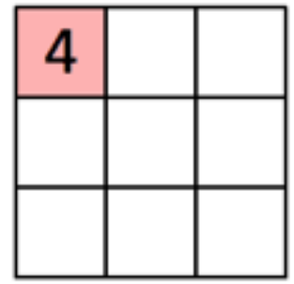
- At training time, the **weights** for these repeated blocks are '**shared**', i.e. the weight gradients learned over various image patches are averaged.

What is an image convolution?





Image

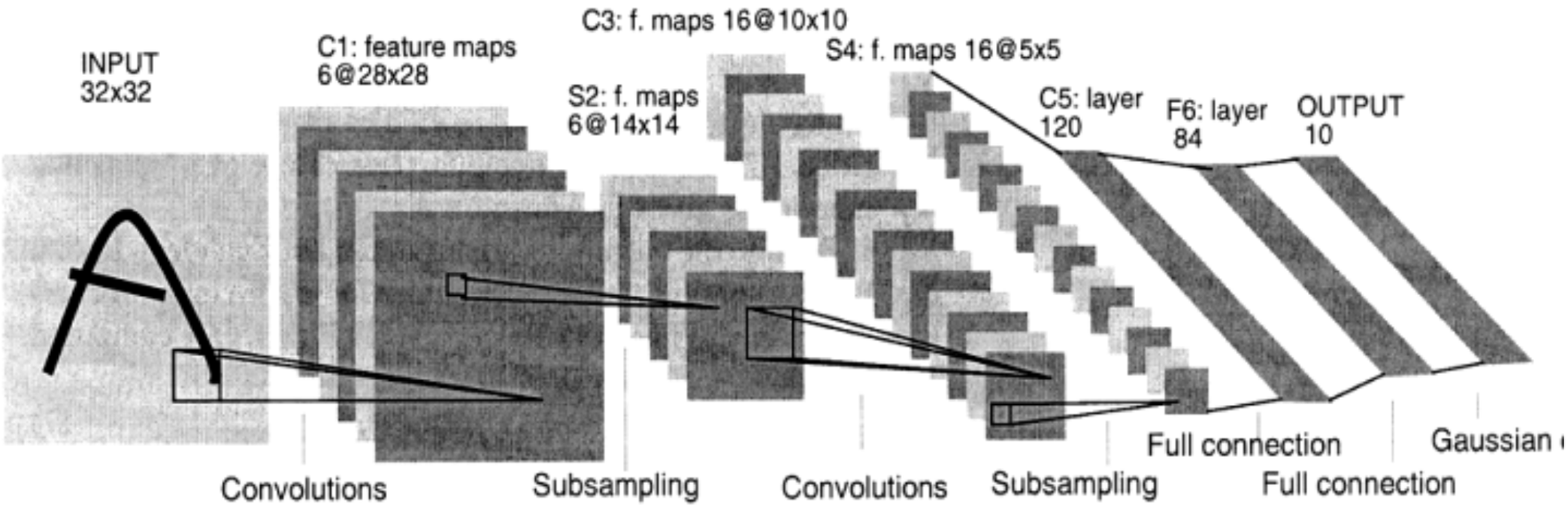


Convolved Feature

What is an image convolution?

Weighted moving sum

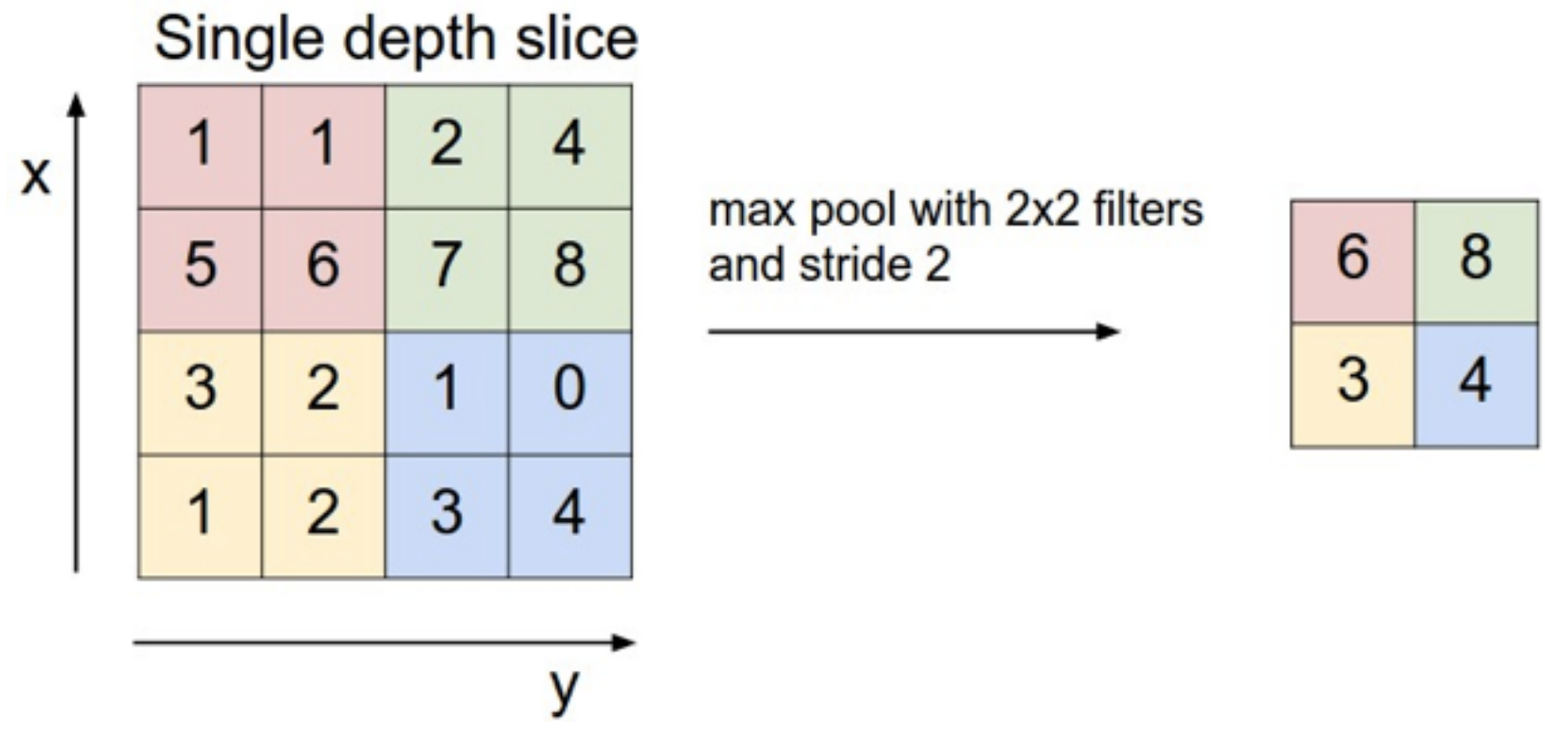
“Nothing New”



LeCun et al. 1992

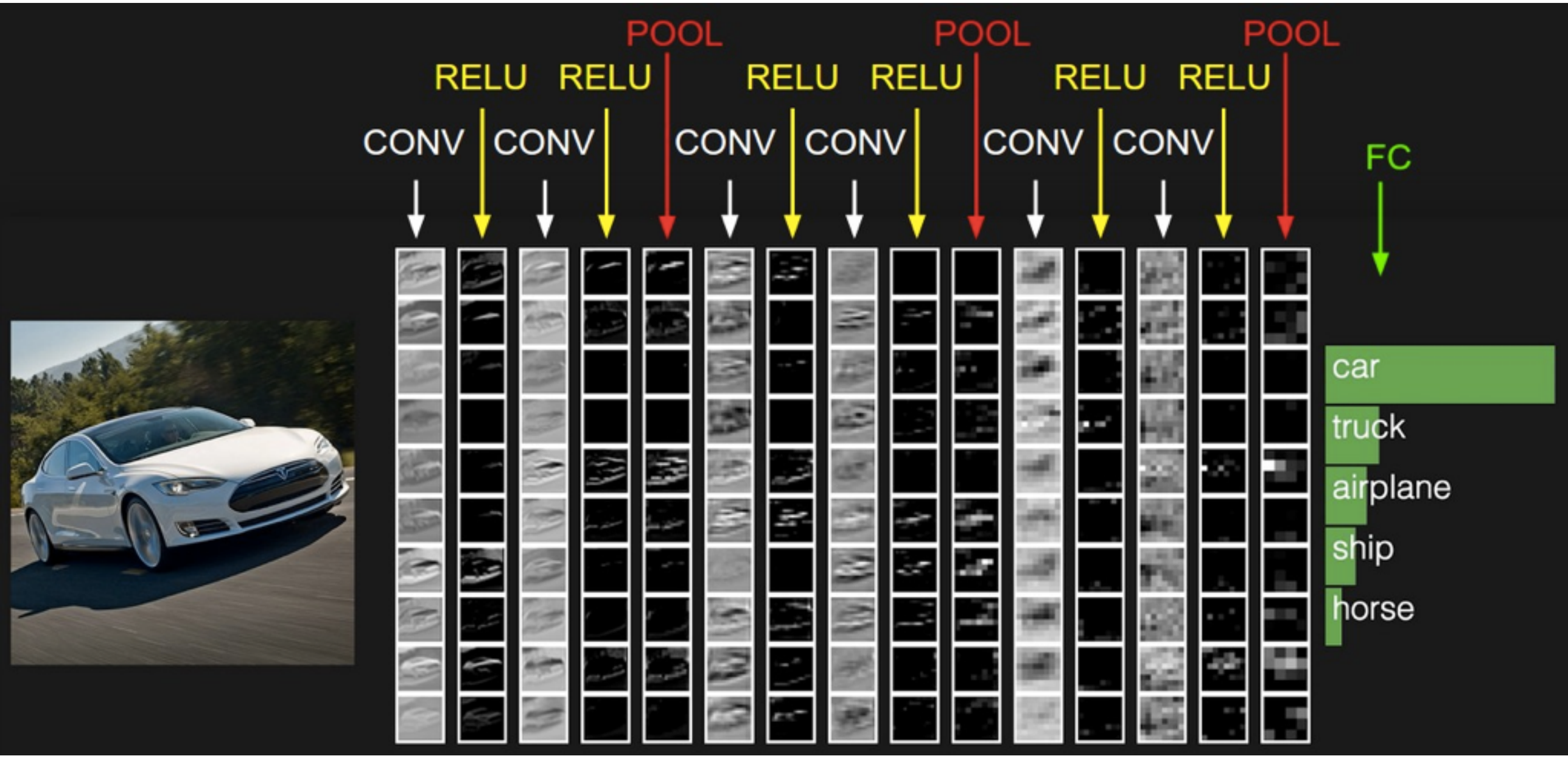
Max pooling

Pooling is a way of sub-sampling, i.e. reducing the dimension of the input (or at some hidden layer).
It is usually done after some of the convolutional layers



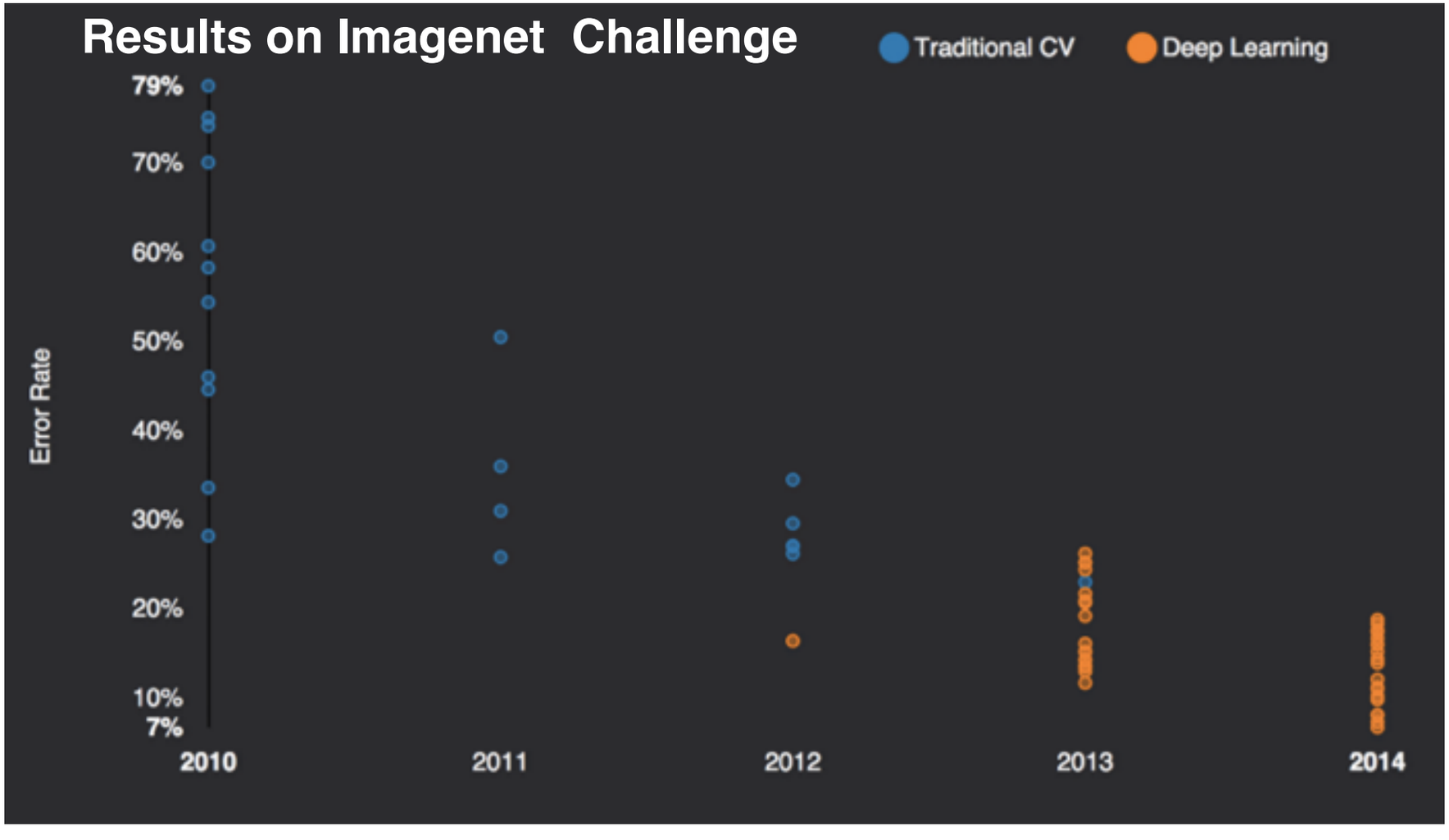
But it is also useful since it provides a form of translation **invariance**

Finally..


POOL
POOL
POOL
RELU
RELU
RELU
RELU
RELU
RELU
CONV
CONV
CONV
CONV
CONV
CONV
FC
car
truck
airplane
ship
horse

Convolutional Neural Networks (CNNs)

In computer Vision the breakthrough resulted in 2011 when Ciresan et.al introduced an algorithm to train these networks by using graphical cards (GPUs)



AlexNet

Similar framework to LeCun’98 but:

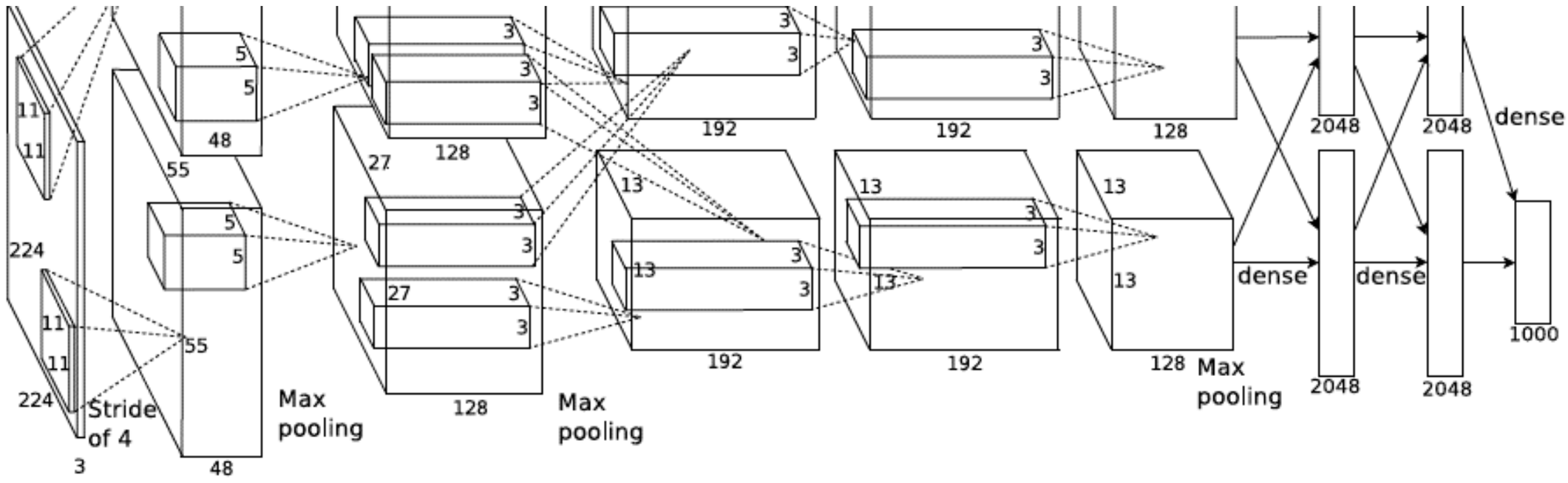
Bigger model:

7 hidden layers, 650.000 units, 60 million parameter

More Data:

10^6 vs 10^3 images

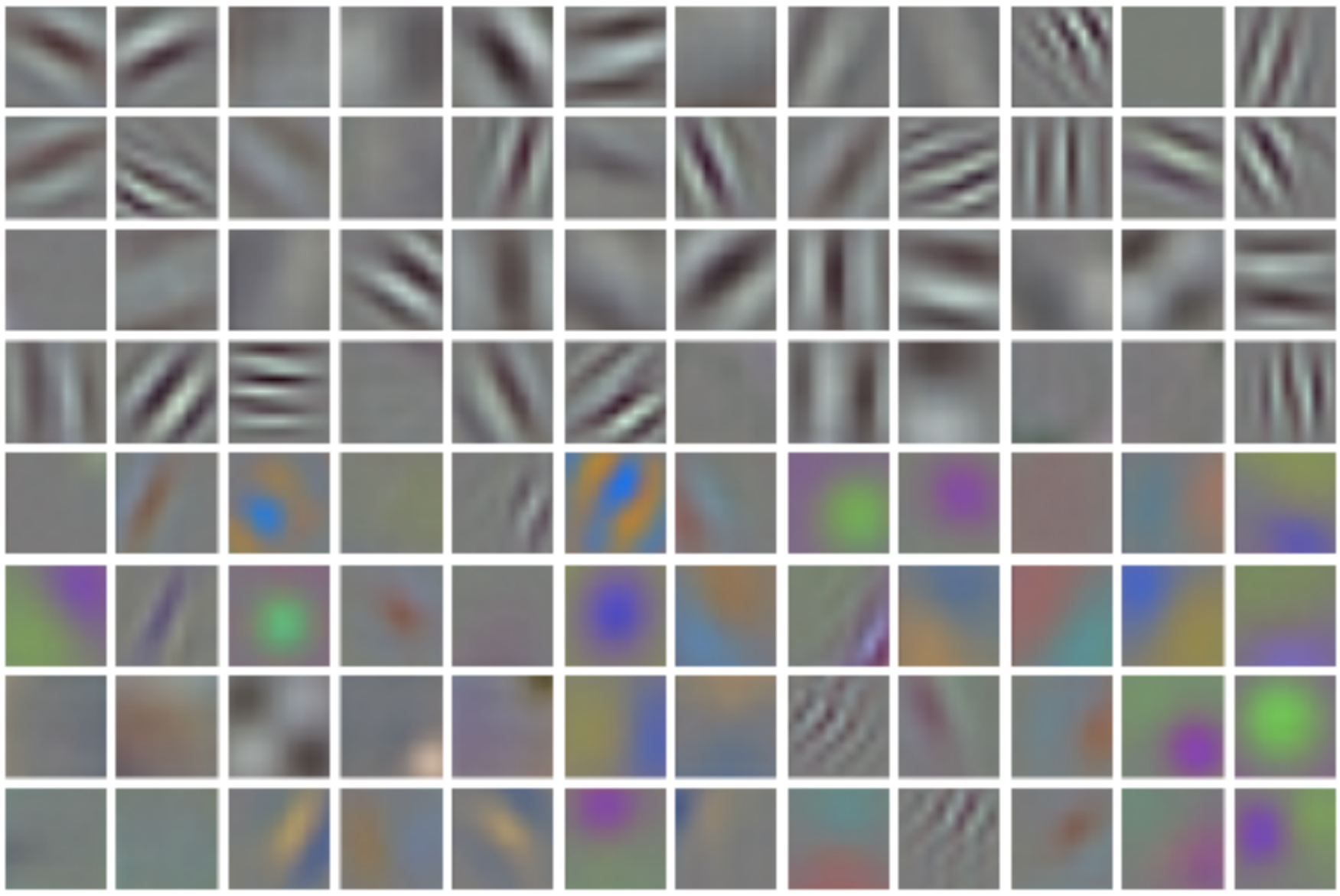
GPU implementation (50x speedup over CPU)



AlexNet

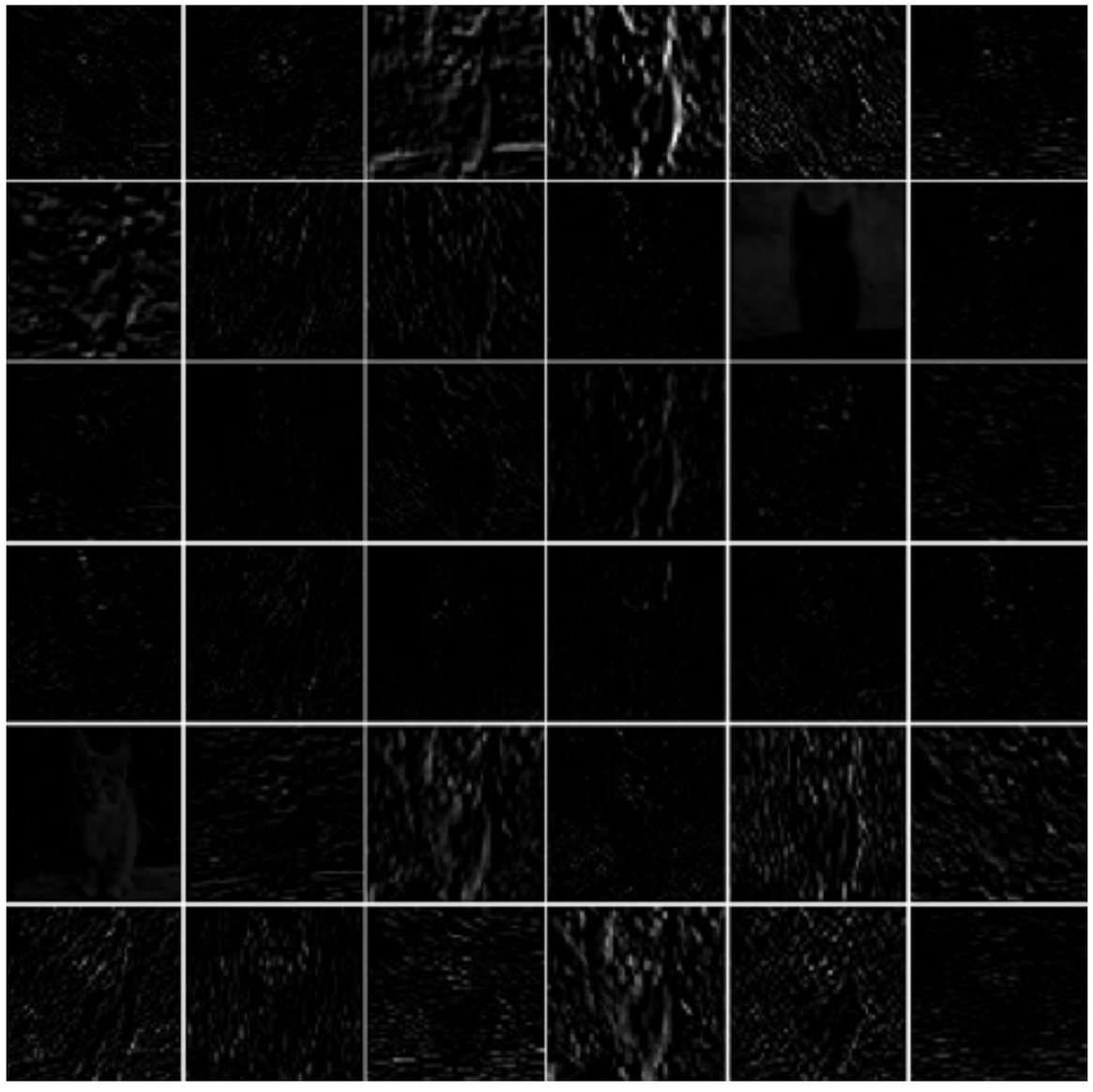
- 1st Layer: 96 conv filters. Size 11x11 (step 4)
    - Pooling + norm
- 2nd Layer: 256 conv filters. Size 5x5
    - Pooling + norm
- 3rd Layer: 384 conv filters. Size 3x3
- 4th Layer: 385 conv filters. Size 3x3
- 5th Layer: 256 conv filters. Size 3x3
    - Pooling
- 6th Layers: Fully Connect. 4096 Neurons
- 7th Layers: Fully Connect. 4096 Neurons
- Output Layer: Fully Connect. 1000 Neurons

Alexnet 1st Conv Filters

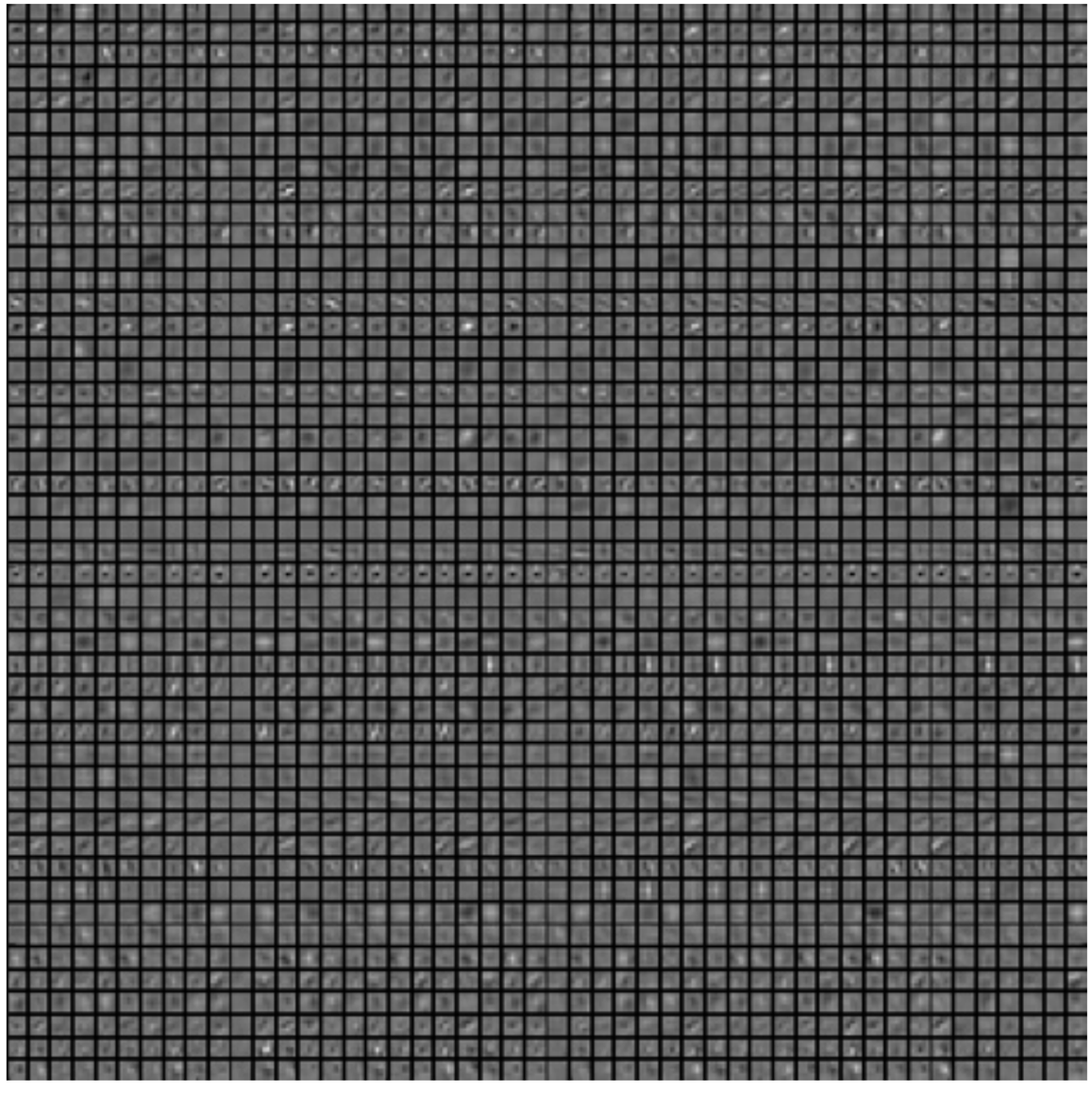


Alexnet

Feature Map Conv1

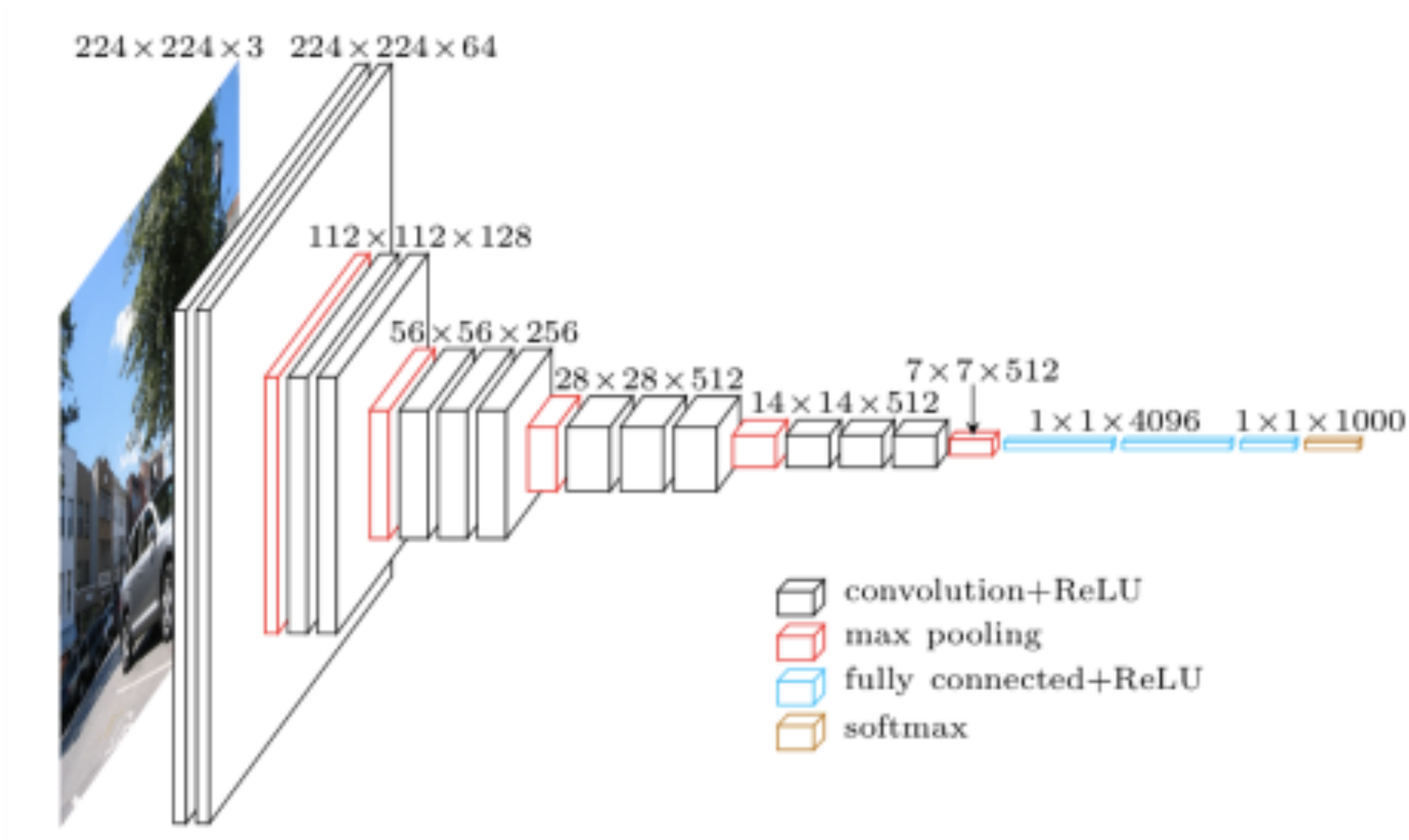


Conv2

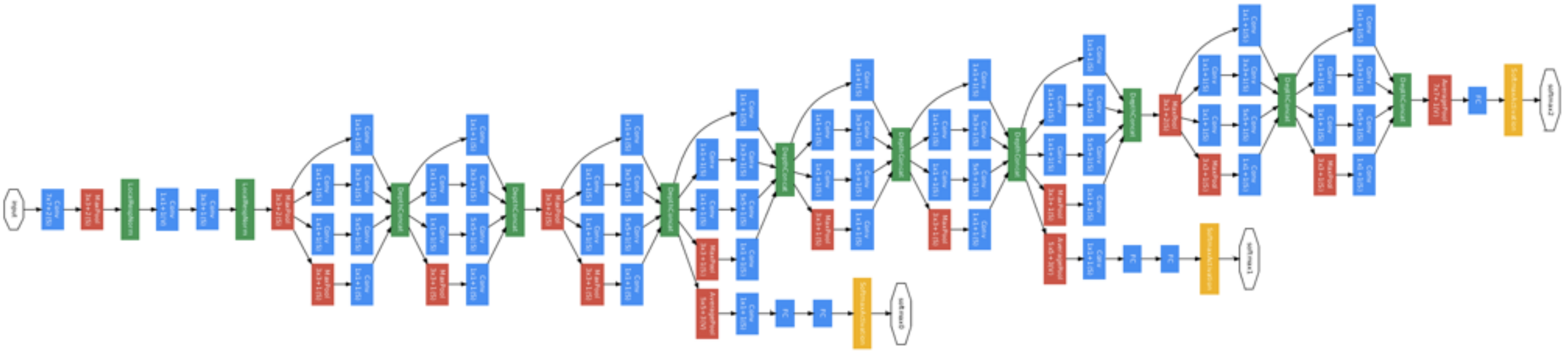



WE NEED TO GO
DEEPER
troll-fac

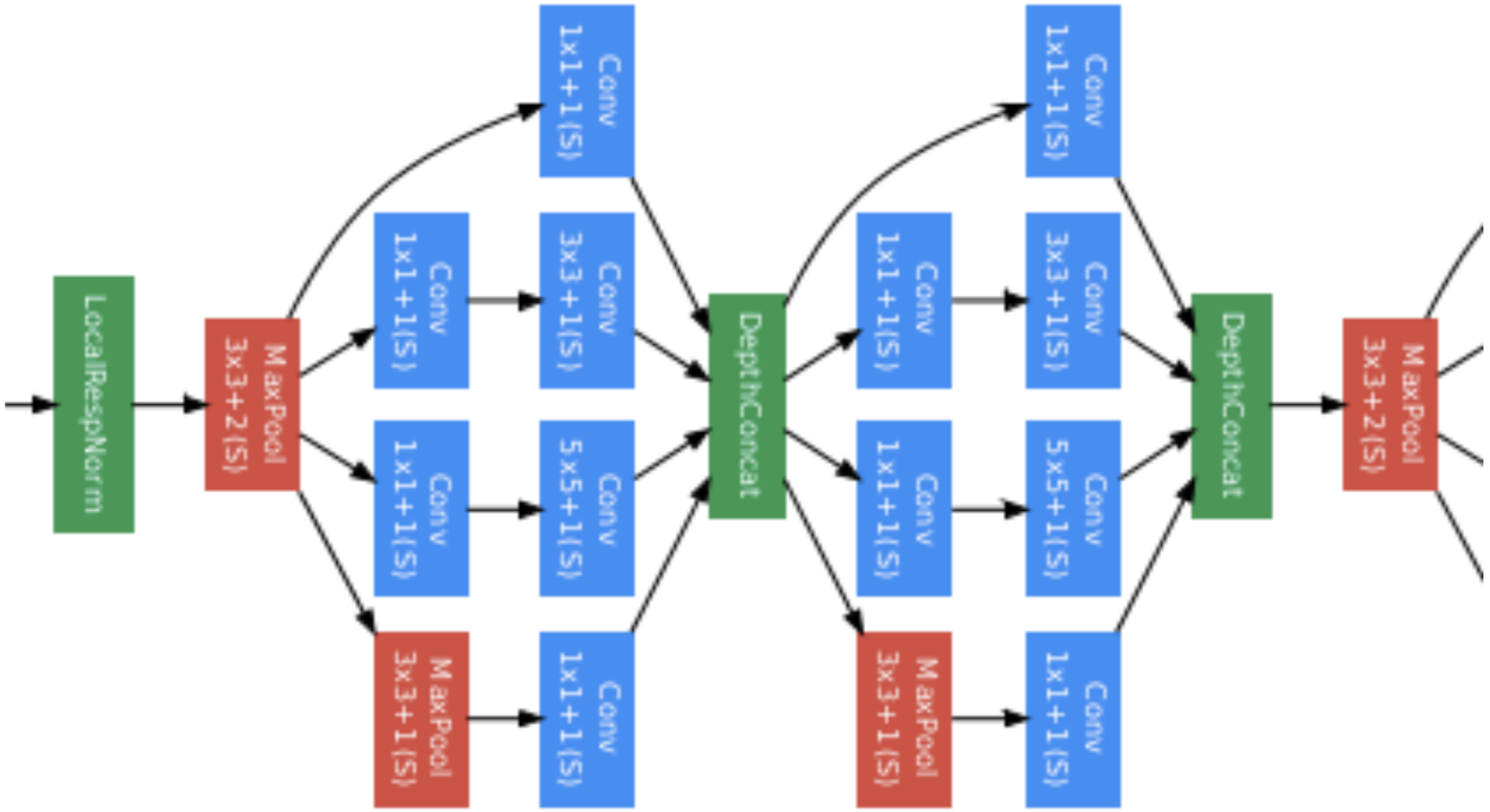
VGG Net


224 × 224 × 3
224 × 224 × 64
112 × 112 × 128
56 × 56 × 256
28 × 28 × 512
14 × 14 × 512
7 × 7 × 512
1 × 1 × 4096
1 × 1 × 1000
convolution+ReLU
max pooling
fully connected+ReLU
softmax

GoogleNet

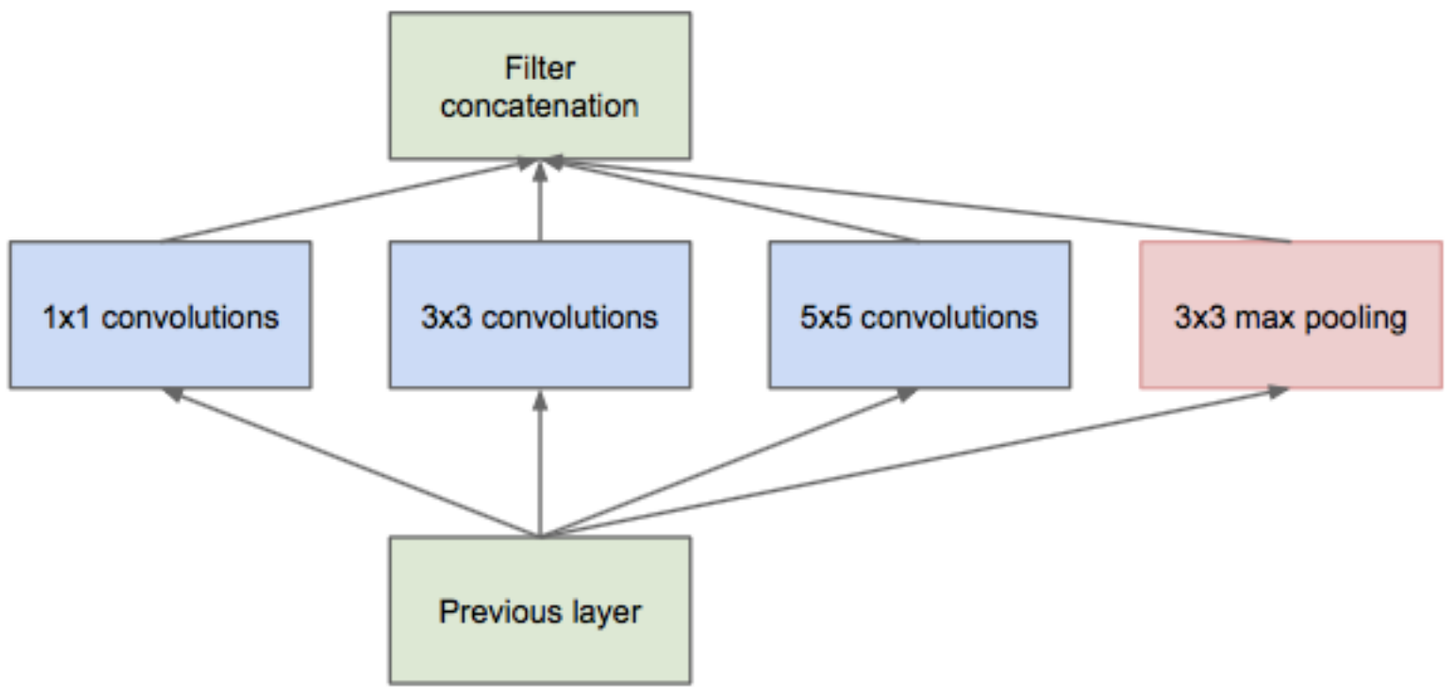

input
Conv 7x7+2(S)
MaxPool 3x3+2(S)
LocalRespNorm
Conv 1x1+1(V)
Conv 3x3+1(S)
LocalRespNorm
MaxPool 3x3+2(S)
Conv 1x1+1(S)
Conv 3x3+1(S)
Conv 5x5+1(S)
MaxPool 3x3+1(S)
Conv 1x1+1(S)
DepthConcat
Conv 1x1+1(S)
Conv 3x3+1(S)
Conv 5x5+1(S)
MaxPool 3x3+1(S)
Conv 1x1+1(S)
DepthConcat
MaxPool 3x3+2(S)
Conv 1x1+1(S)
Conv 3x3+1(S)
Conv 5x5+1(S)
MaxPool 3x3+1(S)
Conv 1x1+1(S)
DepthConcat
Conv 1x1+1(S)
Conv 3x3+1(S)
Conv 5x5+1(S)
MaxPool 3x3+1(S)
Conv 1x1+1(S)
DepthConcat
Conv 1x1+1(S)
Conv 3x3+1(S)
Conv 5x5+1(S)
MaxPool 3x3+1(S)
Conv 1x1+1(S)
DepthConcat
Conv 1x1+1(S)
Conv 3x3+1(S)
Conv 5x5+1(S)
MaxPool 3x3+1(S)
Conv 1x1+1(S)
DepthConcat
MaxPool 3x3+2(S)
Conv 1x1+1(S)
Conv 3x3+1(S)
Conv 5x5+1(S)
MaxPool 3x3+1(S)
Conv 1x1+1(S)
DepthConcat
AveragePool 5x5+3(V)
Conv 1x1+1(S)
FC
FC
SoftmaxActivation
softmax0
AveragePool 7x7+1(V)
FC
SoftmaxActivation
softmax1

GoogleNet


LocalRespNorm
MaxPool 3x3+2(S)
Conv 1x1+1(S)
Conv 1x1+1(S)
Conv 3x3+1(S)
Conv 1x1+1(S)
Conv 5x5+1(S)
MaxPool 3x3+1(S)
Conv 1x1+1(S)
DepthConcat
Conv 1x1+1(S)
Conv 1x1+1(S)
Conv 3x3+1(S)
Conv 1x1+1(S)
Conv 5x5+1(S)
MaxPool 3x3+1(S)
Conv 1x1+1(S)
DepthConcat
MaxPool 3x3+2(S)

Inception Module: Naive Version

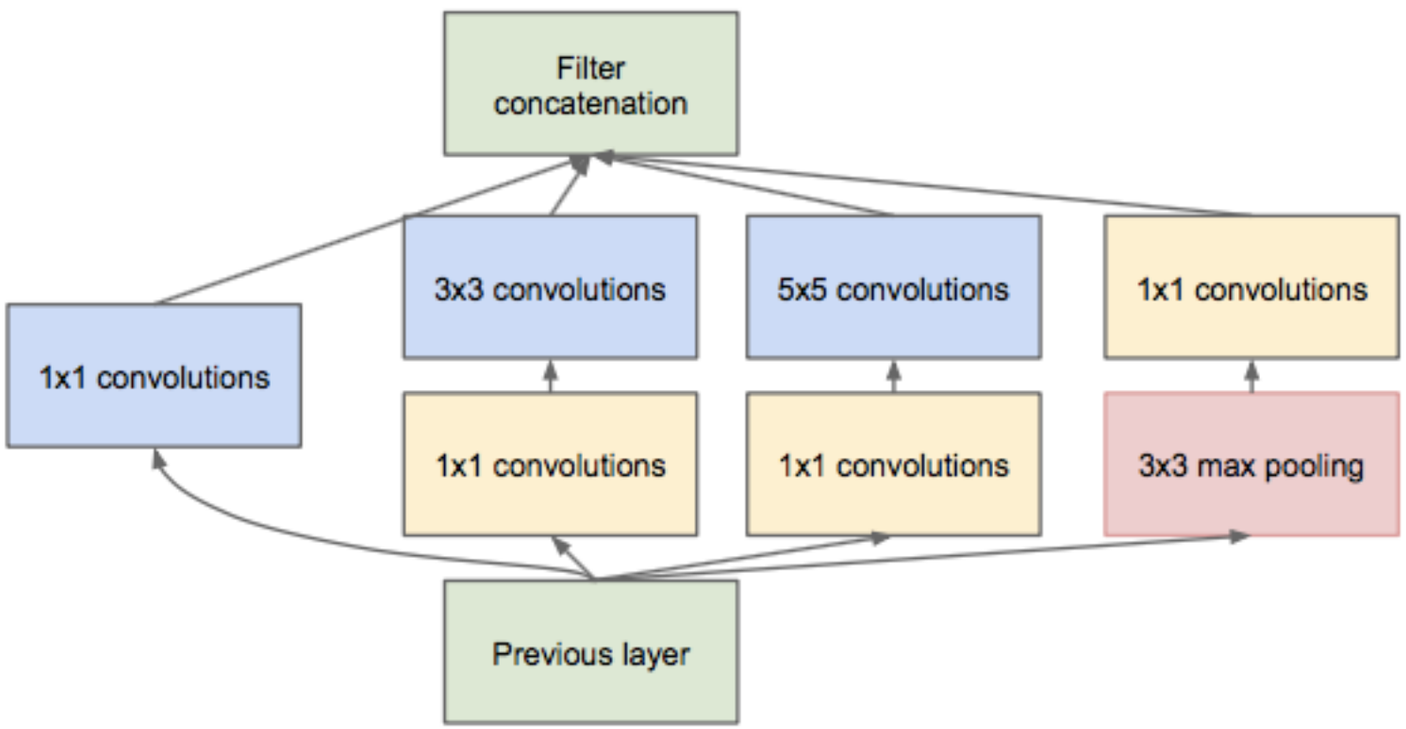
Convolutional filters with different sizes can cover different clusters of information.
By finding the optimal local construction and repeating it spatially, they approximate the optimal sparse structure with dense components.
For convenience of computation, they use 1 x 1, 3 x 3 and 5 x 5 filters + pooling.
Together these made up the naive Inception module.



Inception Module: Naive Version

Stacking these inception modules on top of each would lead to an exploding number of outputs

Solution: inspired by "Network in Network" add 1x1 convolutions for dimensionality reduction



GoogleNet

type	patch size/ stride	output size	depth	#1×1	#3×3 reduce	#3×3	#5×5 reduce	#5×5	pool proj	params	ops
convolution	7×7/2	112×112×64	1							2.7K	34M
max pool	3×3/2	56×56×64	0								
convolution	3×3/1	56×56×192	2		64	192				112K	360M
max pool	3×3/2	28×28×192	0								
inception (3a)		28×28×256	2	64	96	128	16	32	32	159K	128M
inception (3b)		28×28×480	2	128	128	192	32	96	64	380K	304M
max pool	3×3/2	14×14×480	0								
inception (4a)		14×14×512	2	192	96	208	16	48	64	364K	73M
inception (4b)		14×14×512	2	160	112	224	24	64	64	437K	88M
inception (4c)		14×14×512	2	128	128	256	24	64	64	463K	100M
inception (4d)		14×14×528	2	112	144	288	32	64	64	580K	119M
inception (4e)		14×14×832	2	256	160	320	32	128	128	840K	170M
max pool	3×3/2	7×7×832	0								
inception (5a)		7×7×832	2	256	160	320	32	128	128	1072K	54M
inception (5b)		7×7×1024	2	384	192	384	48	128	128	1388K	71M
avg pool	7×7/1	1×1×1024	0								
dropout (40%)		1×1×1024	0								
linear		1×1×1000	1							1000K	1M
softmax		1×1×1000	0								

ImageNet Challenge 2012-2014

Team	Year	Place	Error (top-5)	External data
SuperVision – Toronto (7 layers)	2012	-	16.4%	no
SuperVision	2012	1st	15.3%	ImageNet 22k
Clarifai – NYU (7 layers)	2013	-	11.7%	no
Clarifai	2013	1st	11.2%	ImageNet 22k
VGG – Oxford (16 layers)	2014	2nd	7.32%	no
GoogLeNet (19 layers)	2014	1st	6.67%	no
Human expert*			5.1%	

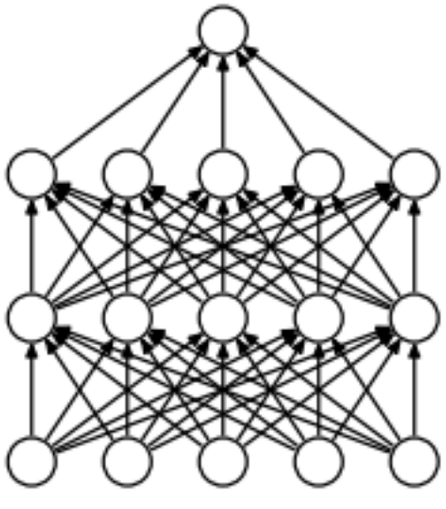
Training a CNN

- Backpropagation + stochastic gradient descent with momentum
- Dropout
- Data Augmetation
- Batch Normalization
- Initialization
  - Transfer Learning

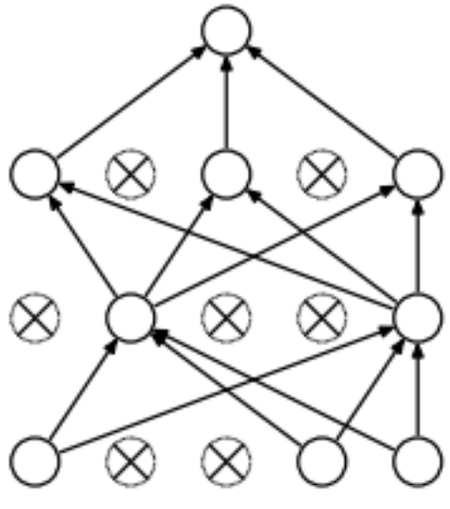
Dropout

Dropout: A Simple Way to Prevent Neural Networks from Overfitting

Journal of Machine Learning Research 15 (2014) 1929-1958



(a) Standard Neural Net



(b) After applying dropout.