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Convolutional Neural Network

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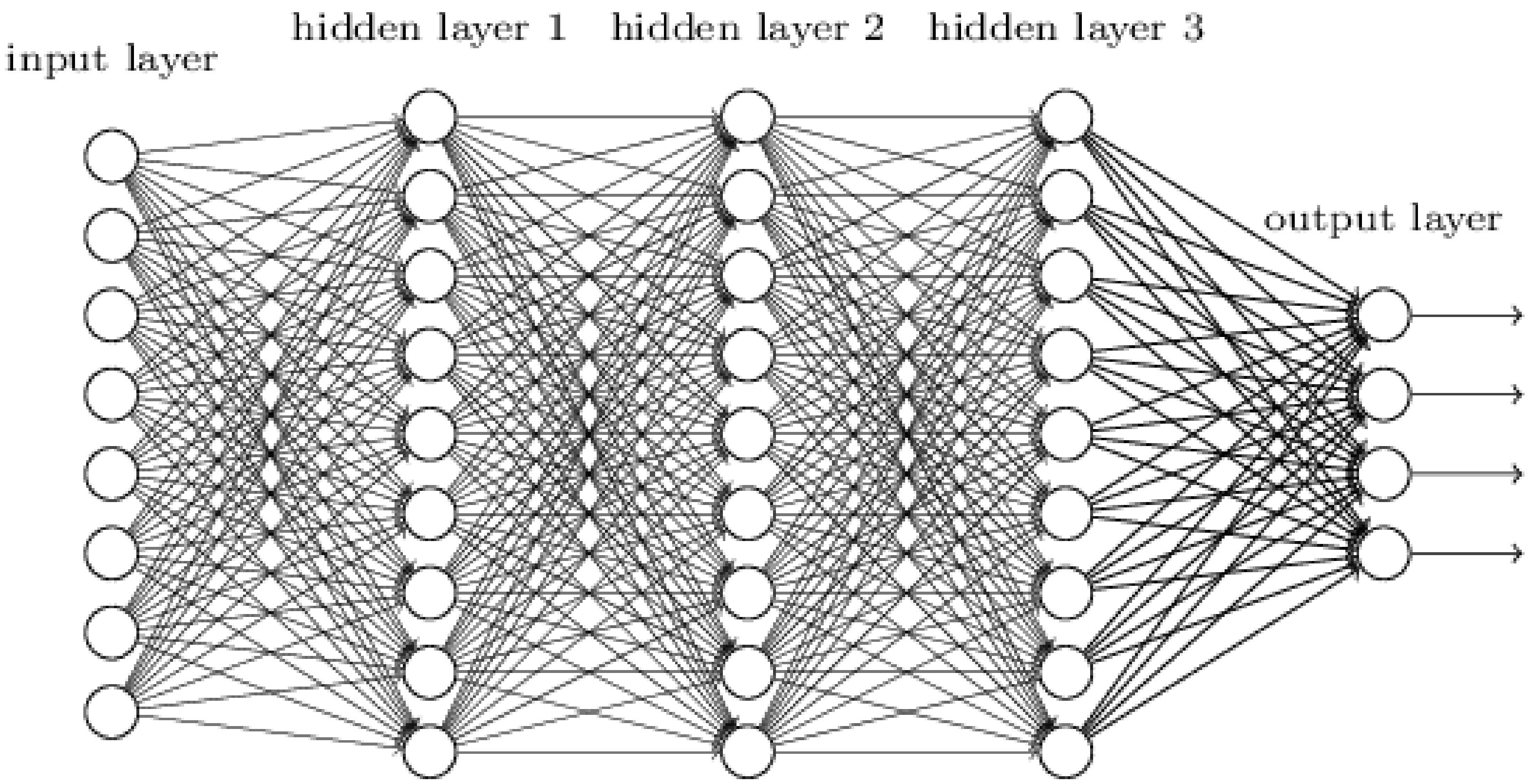
Smaller Network: CNN

- We know it is good to learn a small model.
- From this fully connected model, do we really need all the edges?
- Can some of these be shared?



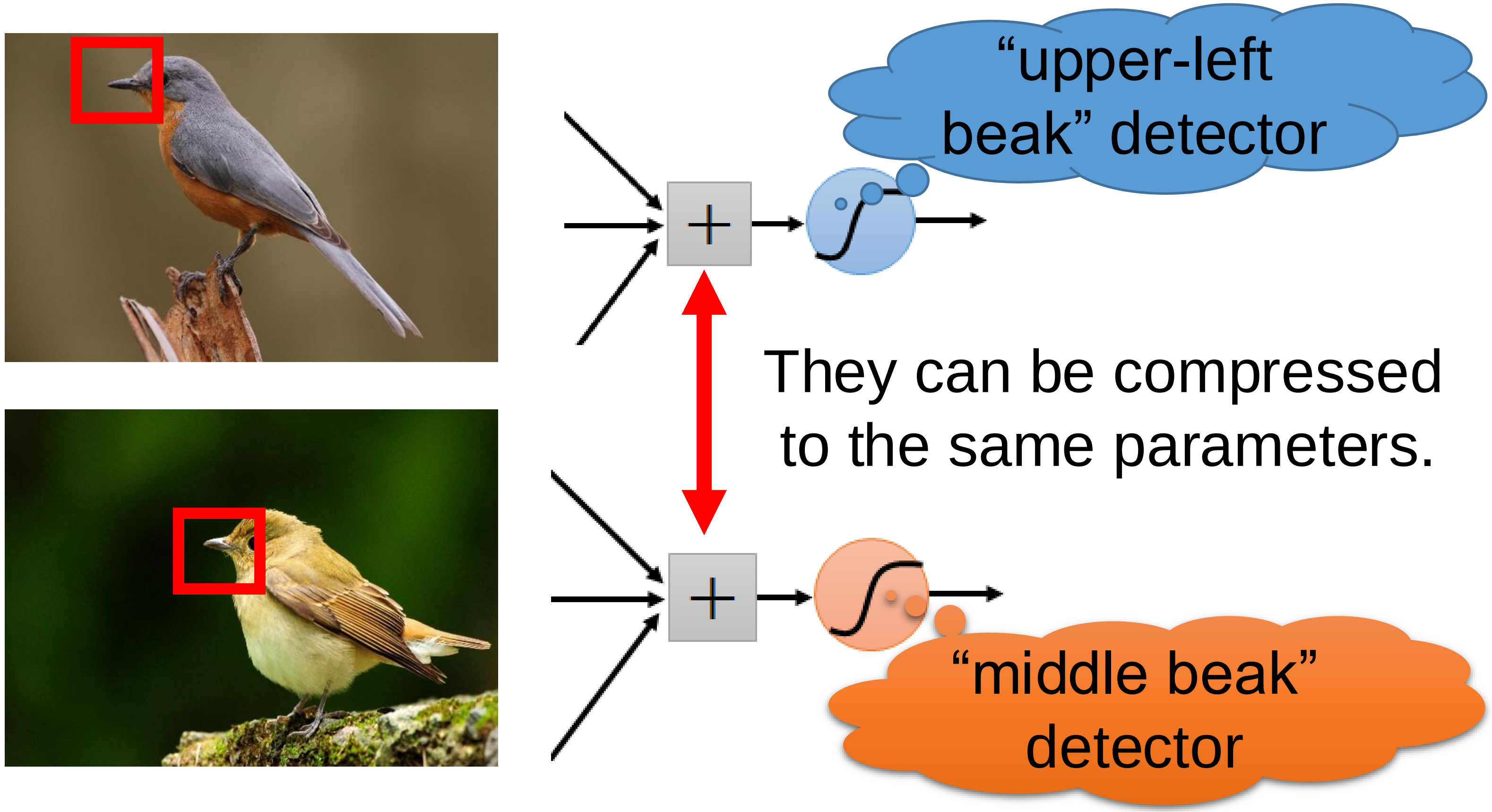
Consider learning an image:

- Some patterns are much smaller than the whole image

Can represent a small region with fewer parameters

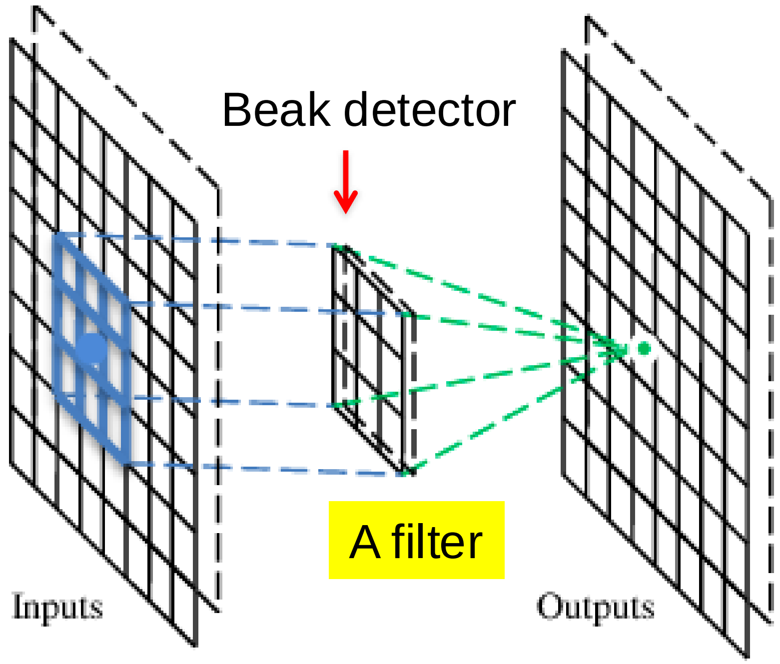
Consider learning an image:

Same pattern appears in different places:
They can be compressed!
What about training a lot of such "small" detectors
and each detector must "move around".



A convolutional layer

A CNN is a neural network with some convolutional layers (and some other layers). A convolutional layer has a number of filters that does convolutional operation.



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Convolution

These are the network parameters to be learned.

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

6 x 6 image

1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

-1	1	-1
-1	1	-1
-1	1	-1

Filter 2

⋮ ⋮

Each filter detects a small pattern (3 x 3).

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Convolution

1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

stride=1

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

Dot product

3 -1

6 x 6 image

Convolution

1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

If stride=2

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

6 x 6 image

3 -3

Convolution

1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

stride=1

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

6 x 6 image

3	-1	-3	-1
-3	1	0	-3
-3	-3	0	1
3	-2	-2	-1

Convolution

-1	1	-1
-1	1	-1
-1	1	-1

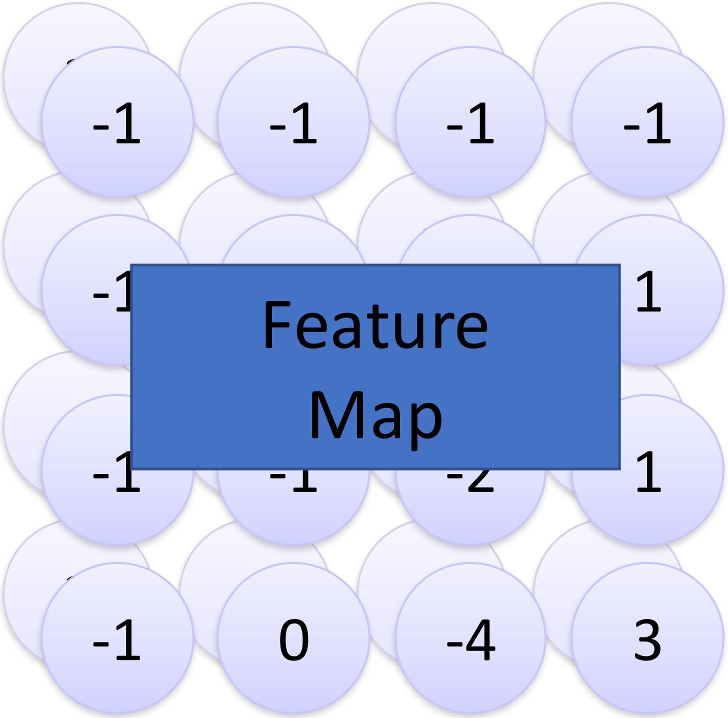
Filter 2

stride=1

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

6 x 6 image

Repeat this for each filter



Two 4 x 4 images
Forming 2 x 4 x 4 matrix

Color image: RGB 3 channels

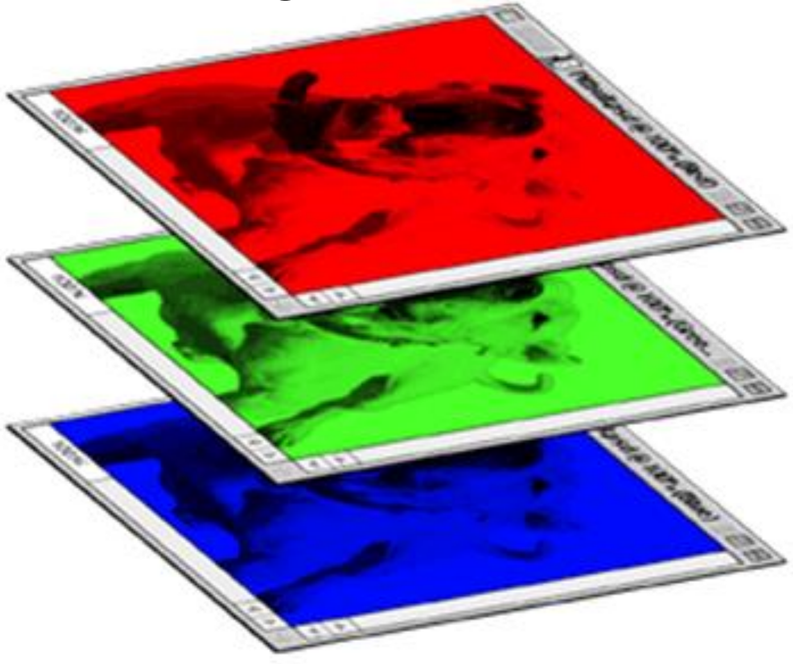
1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

-1	1	-1
-1	1	-1
-1	1	-1

Filter 2

Color image



1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

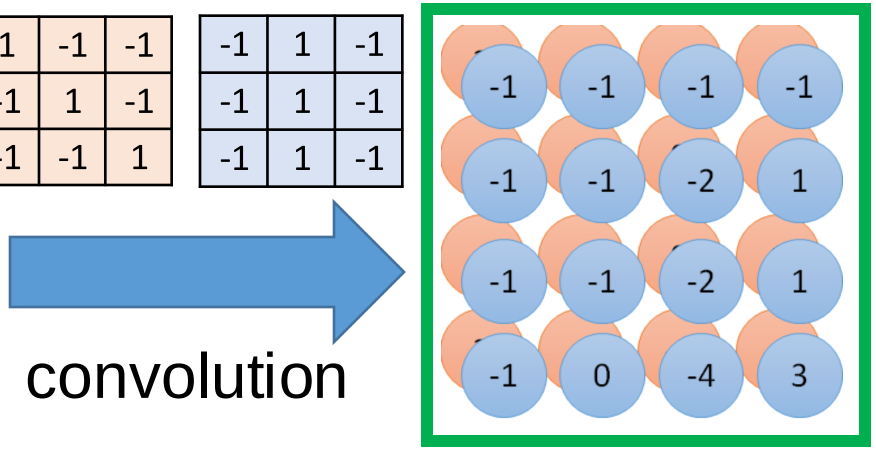
Convolution v.s. Fully Connected

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

image

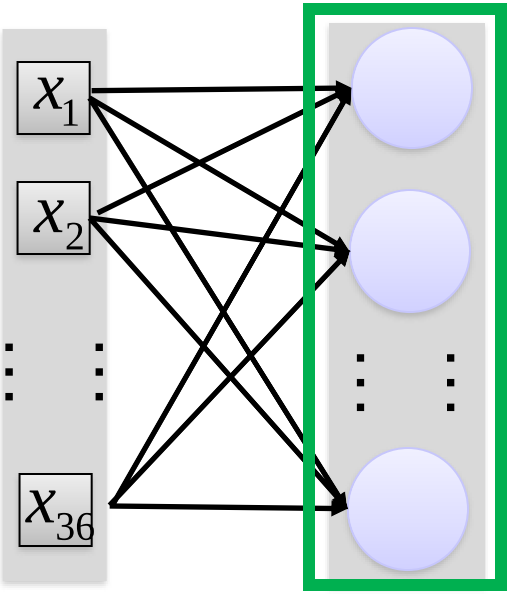
1	-1	-1
-1	1	-1
-1	-1	1

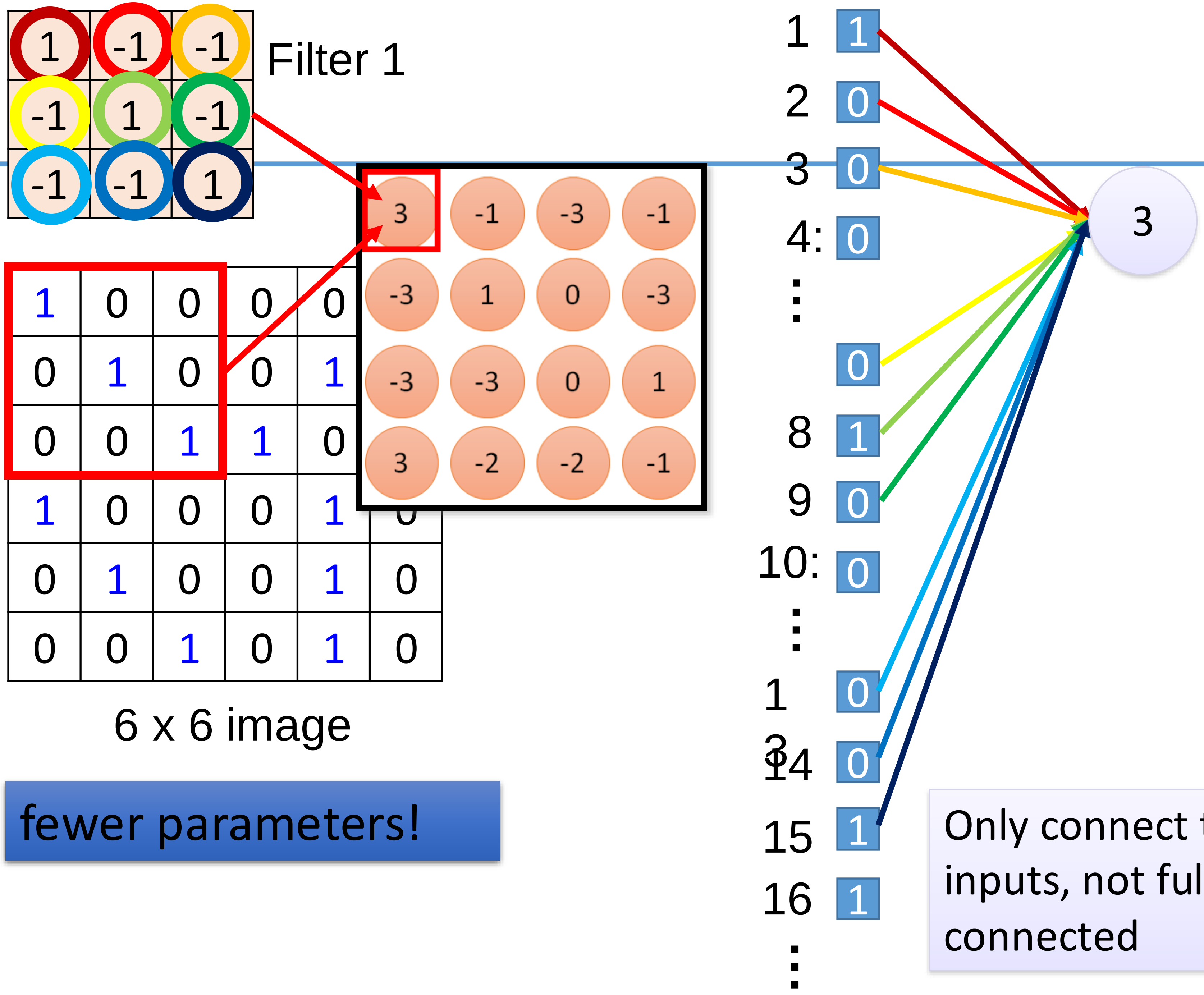
-1	1	-1
-1	1	-1
-1	1	-1



Fully-connected

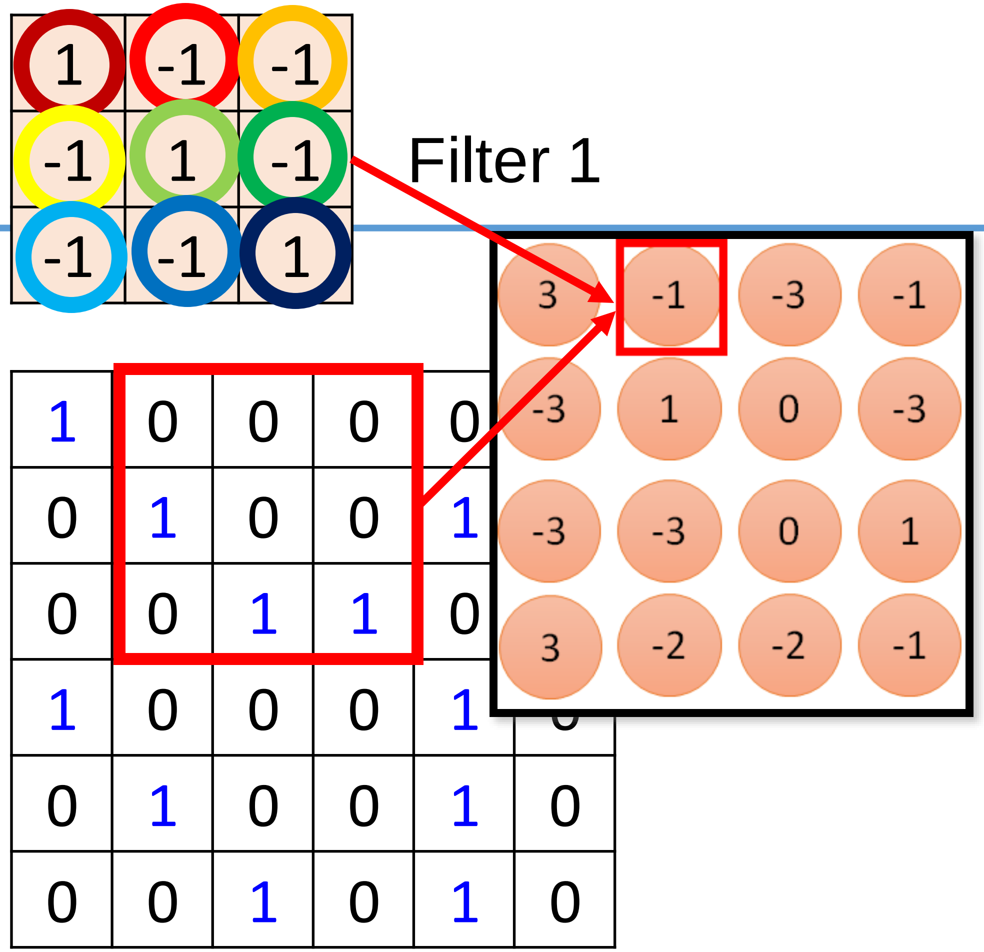
1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

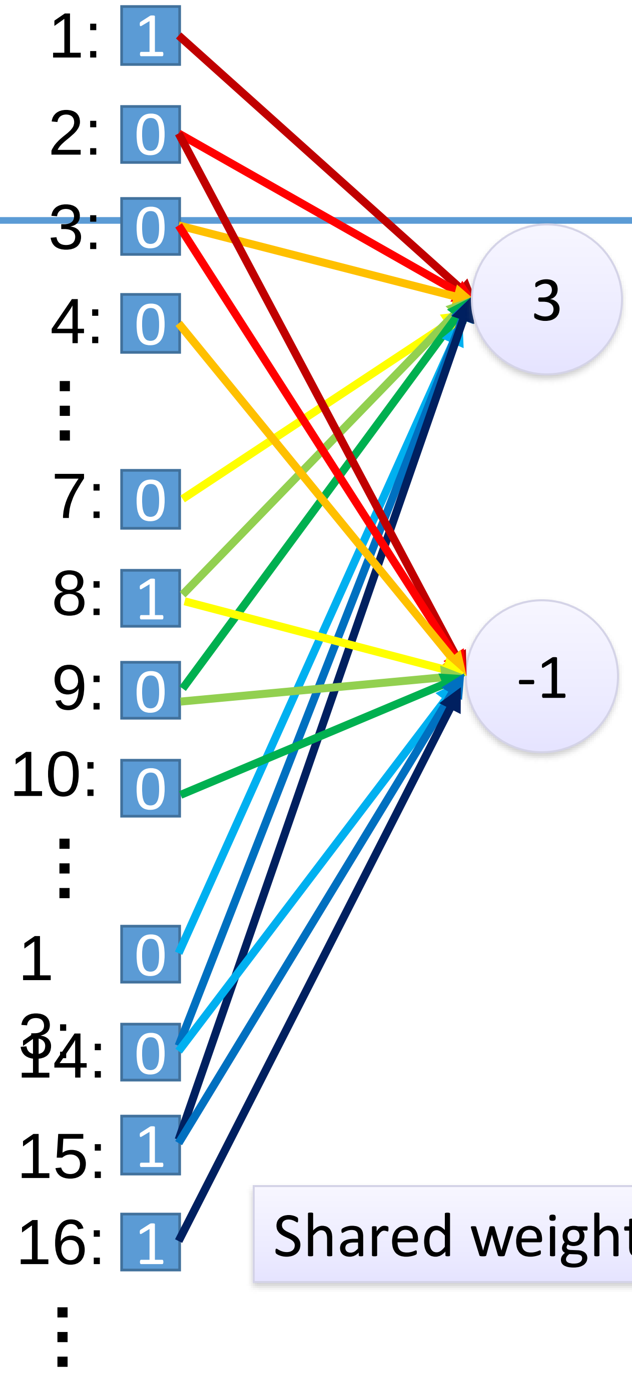




fewer parameters!

Only connect to 9 inputs, not fully connected



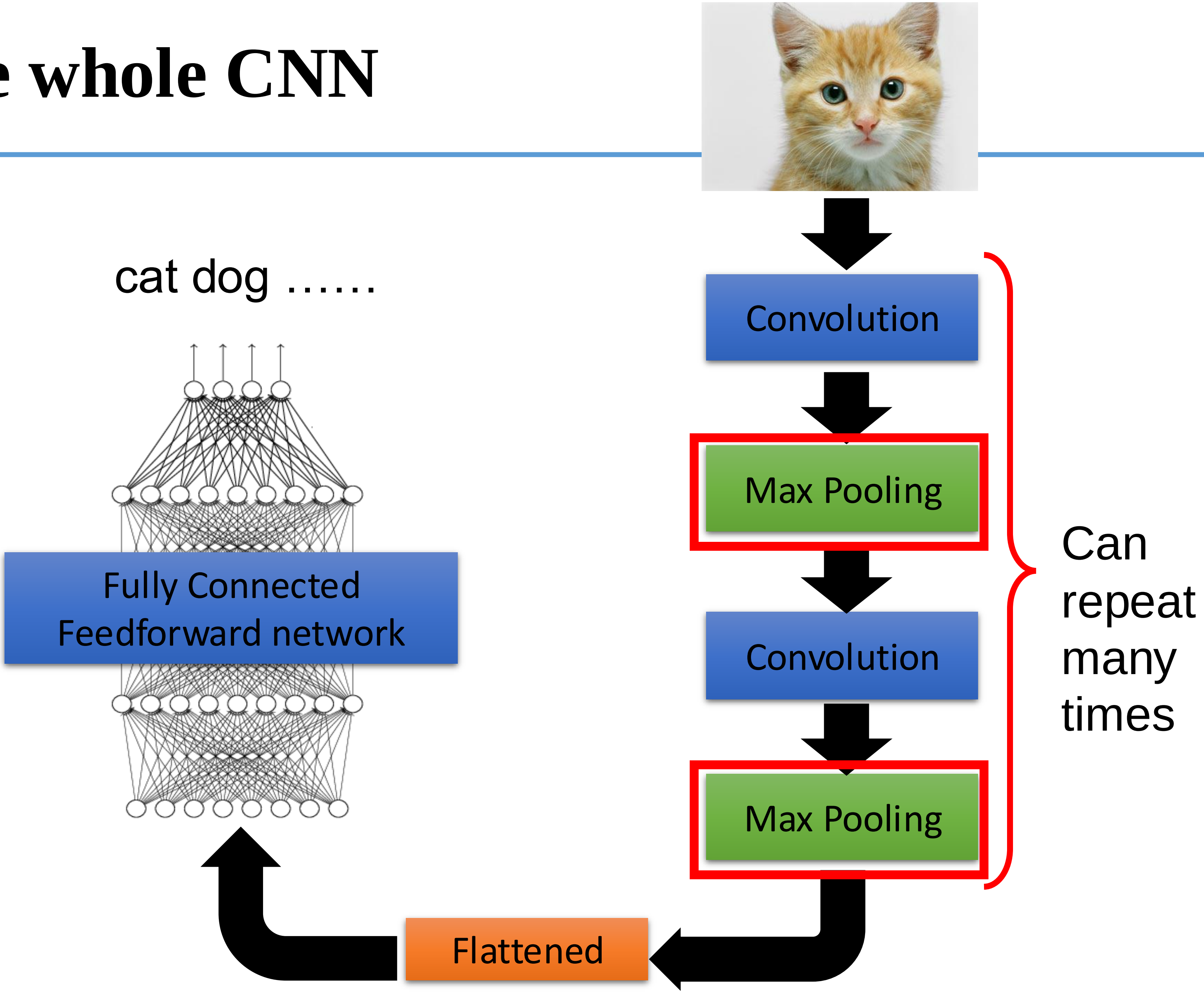


Fewer parameters

Even fewer parameters

Shared weights

The whole CNN



Max Pooling

1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

-1	1	-1
-1	1	-1
-1	1	-1

Filter 2

3	-1	-3	-1
-3	1	0	-3
-3	-3	0	1
3	-2	-2	-1

-1	-1	-1	-1
-1	-1	-2	1
-1	-1	-2	1
-1	0	-4	3

Why Pooling?

- Subsampling pixels will not change the object

bird

Subsampling

bird

We can subsample the pixels to make image smaller

fewer parameters to characterize the image

A CNN compresses a fully connected network in two ways:

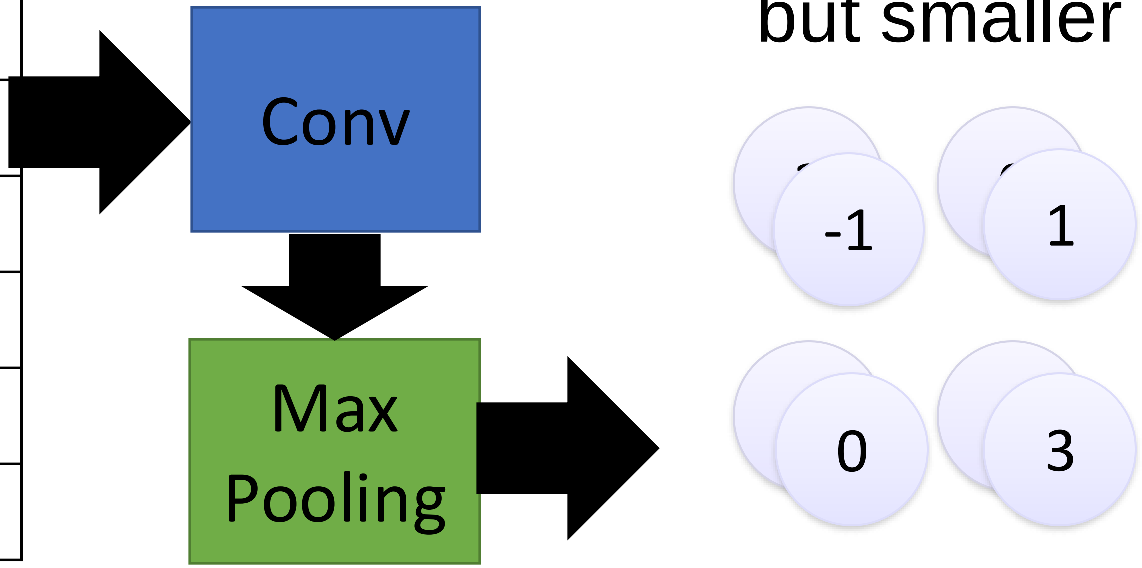
- Reducing number of connections
- Shared weights on the edges
- Max pooling further reduces the complexity

Max Pooling

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

6 x 6 image

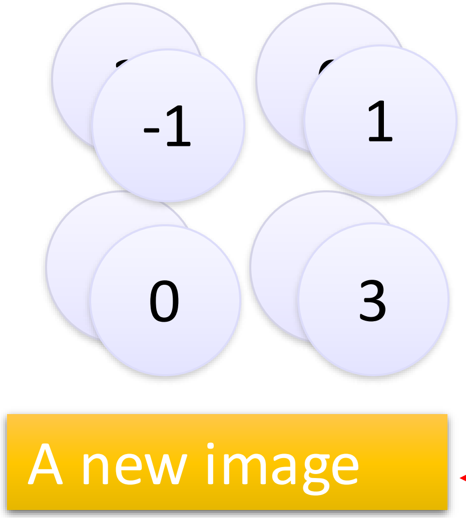
New image but smaller



2 x 2 image

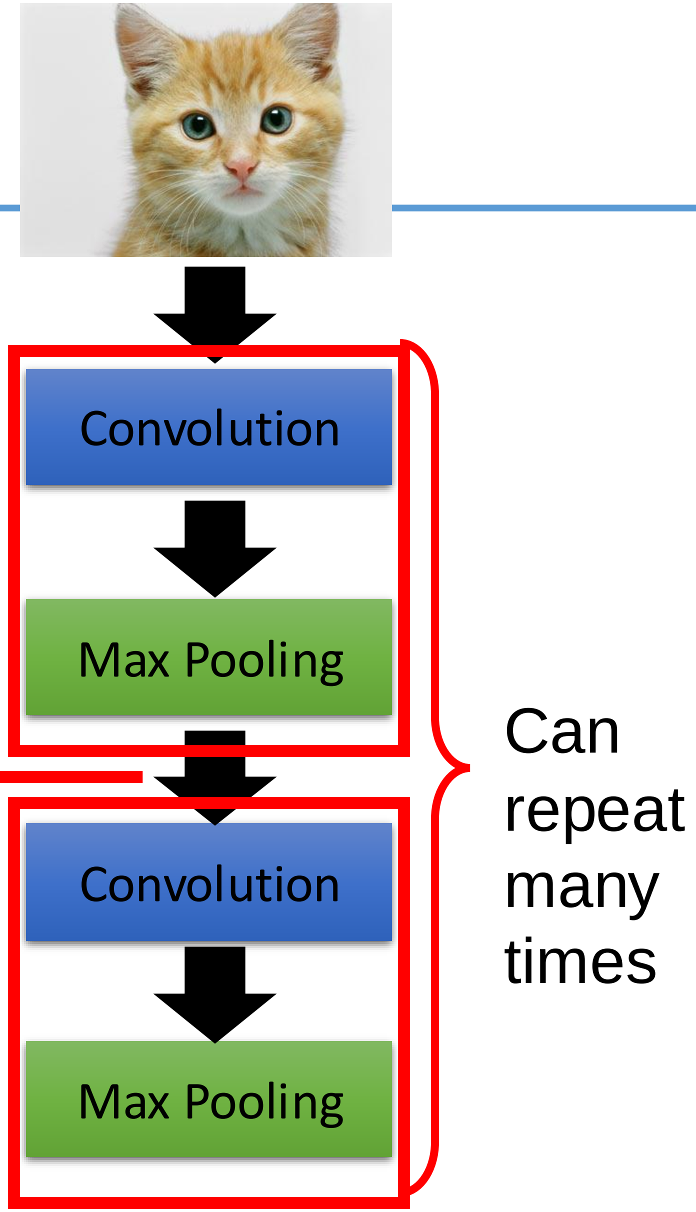
Each filter is a channel

The whole CNN

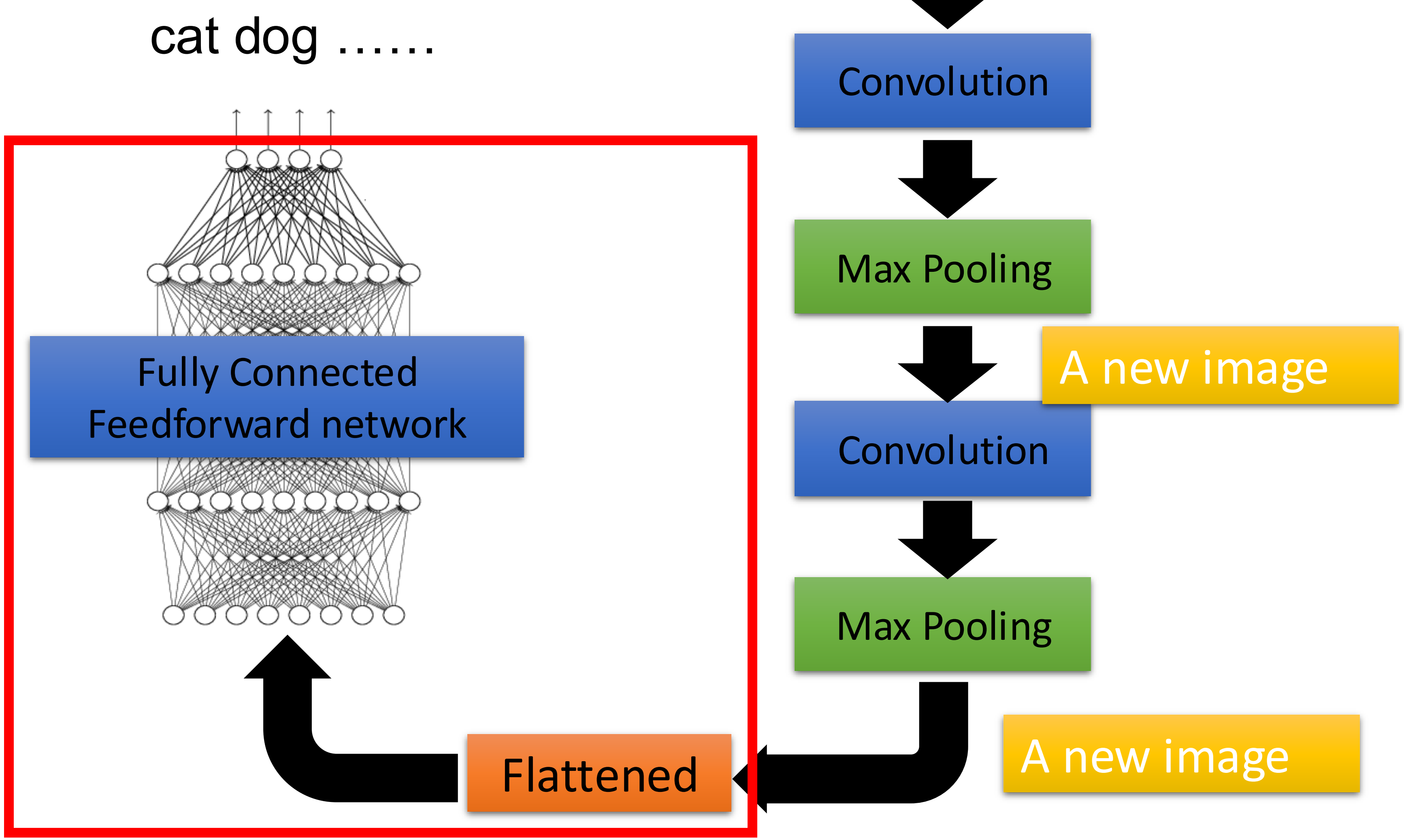


Smaller than the original image

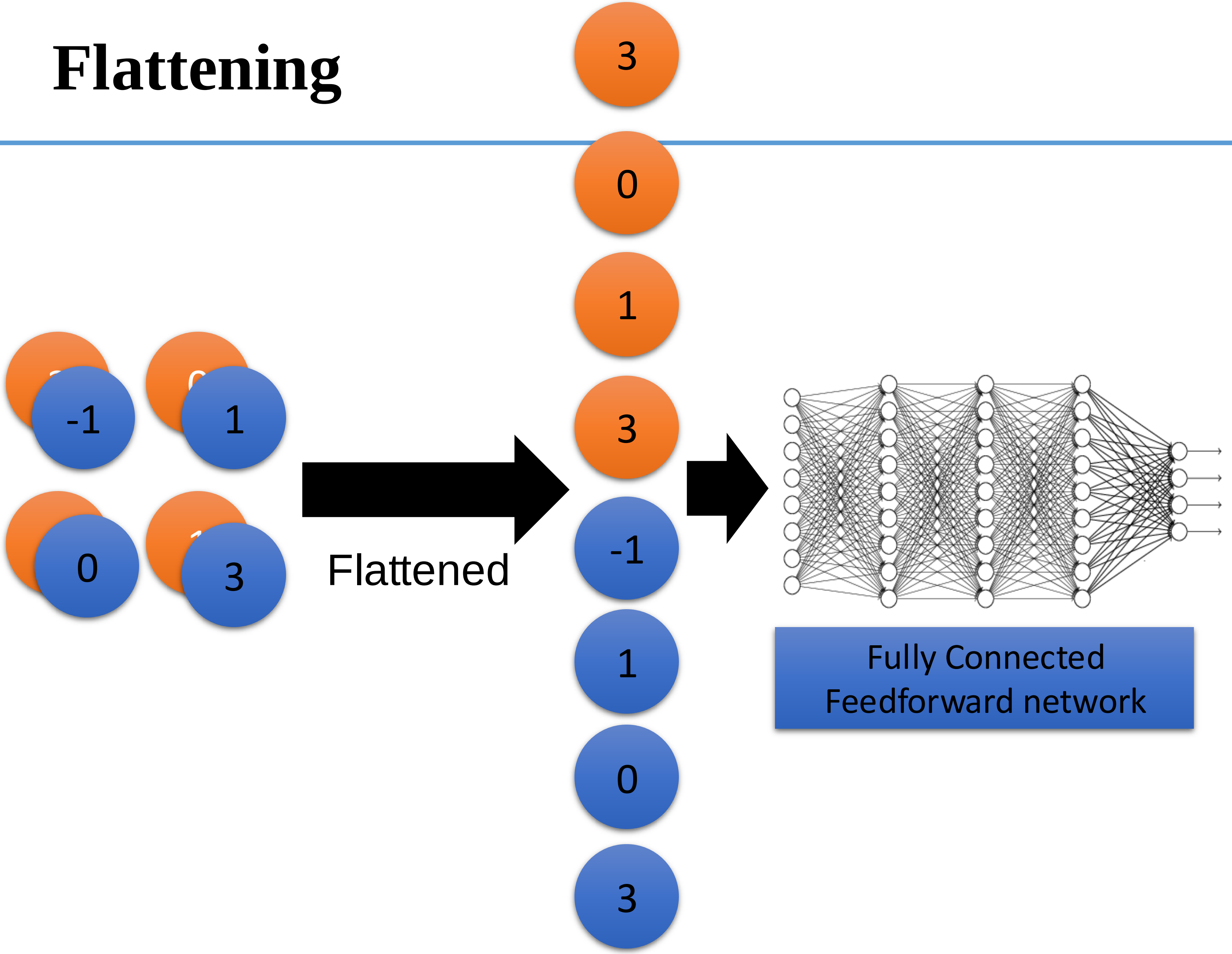
The number of channels is the number of filters



The whole CNN



Flattening


-1
1
0
3
Flattened
3
0
1
3
-1
1
0
3
Fully Connected
Feedforward network

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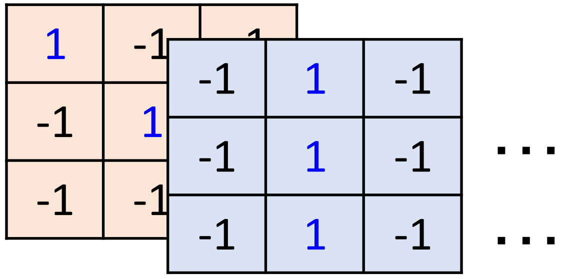
CNN in Keras

Only modified the ***network structure*** and ***input format (vector -> 3-D tensor)***

```
model2.add(Conv2D(25,3,
            input_shape=(28,28,1)))
```



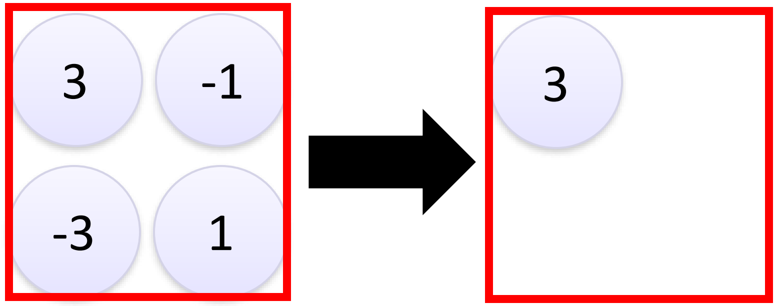
There are 25 3x3 filters.

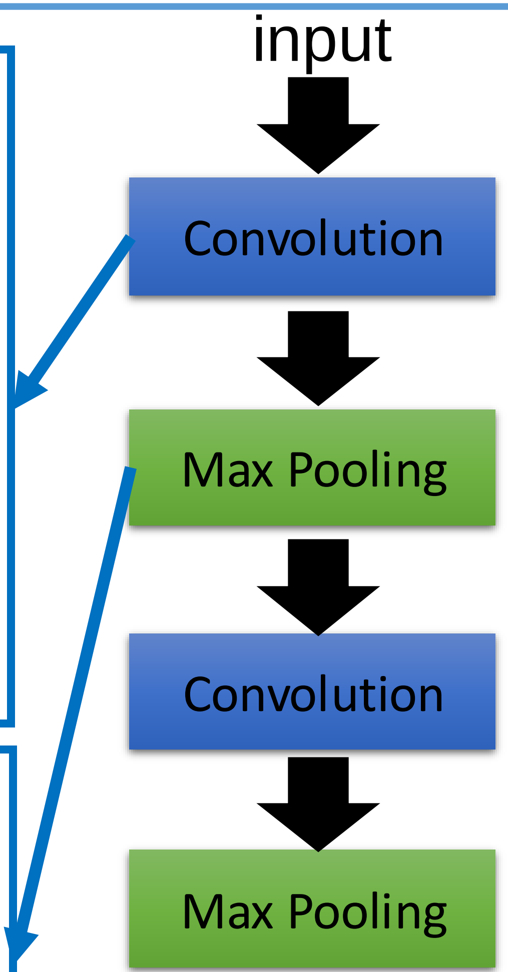
Input_shape = (28 , 28 , 1)

28 x 28 pixels

1: black/white, 3: RGB

```
model2.add(MaxPooling2D((2,2)))
```





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CNN in Keras

Only modified the ***network structure*** and ***input format (vector -> 3-D array)***

Input

1 x 28 x 28

Convolution

```
model2.add(Conv2D(25,3,
           input_shape=(28,28,1)))
```

How many parameters for each filter? 9

25 x 26 x 26

Max Pooling

```
model2.add(MaxPooling2D((2,2)))
```

25 x 13 x 13

Convolution

```
model2.add(Conv2D(50,3))
```

How many parameters for each filter? 225= 25x9

50 x 11 x 11

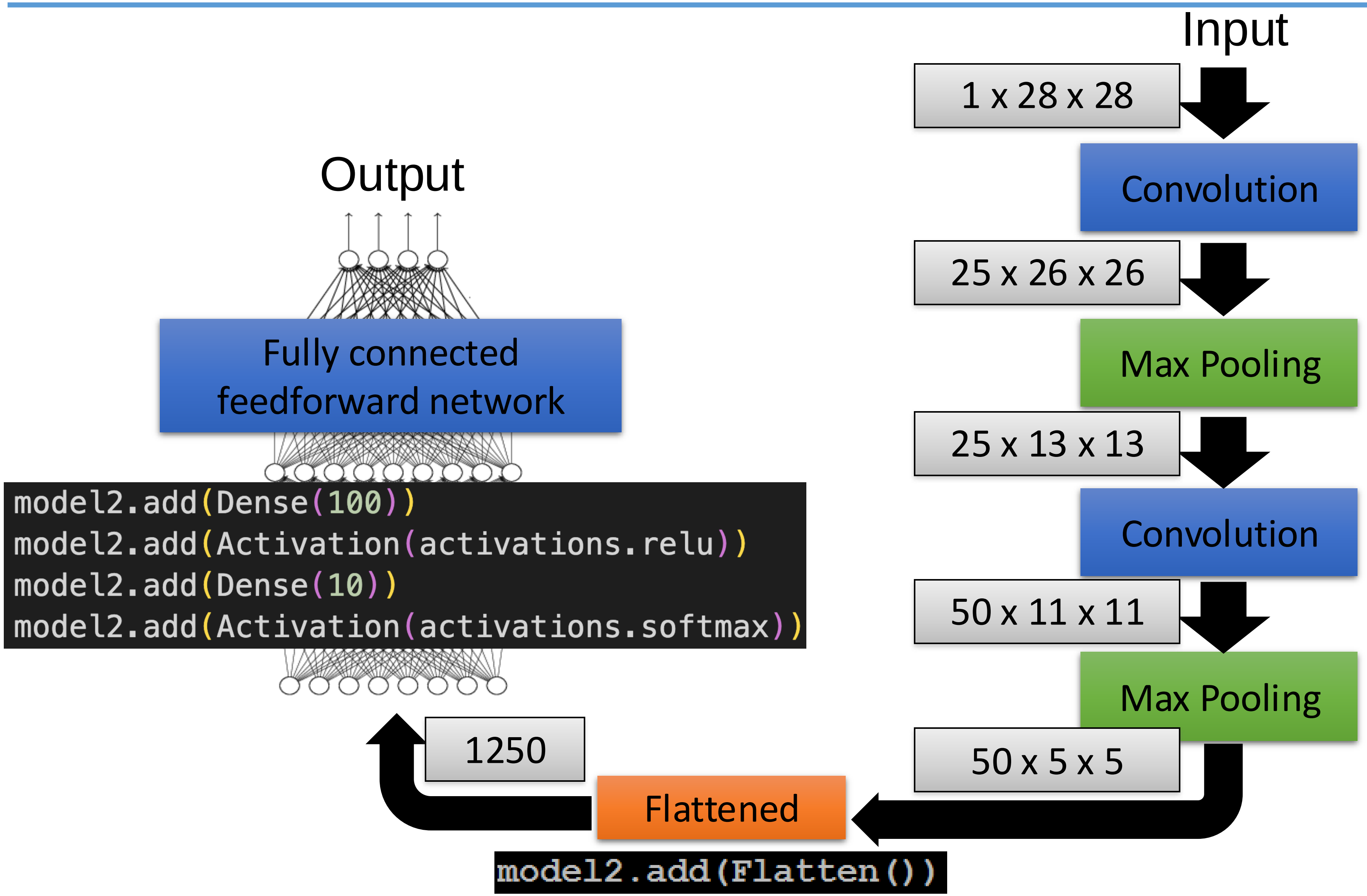
Max Pooling

```
model2.add(MaxPooling2D((2,2)))
```

50 x 5 x 5

CNN in Keras

Only modified the ***network structure*** and ***input format (vector -> 3-D array)***




```
model2.add(Dense(100))
model2.add(Activation(activations.relu))
model2.add(Dense(10))
model2.add(Activation(activations.softmax))
```

```
model2.add(Flatten())
```

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AlphaGo

19 x 19 matrix

Black: 1

white: -1

none: 0

Neural Network

Next move

(19 x 19 positions)

Fully-connected feedforward network can be used

But CNN performs much better

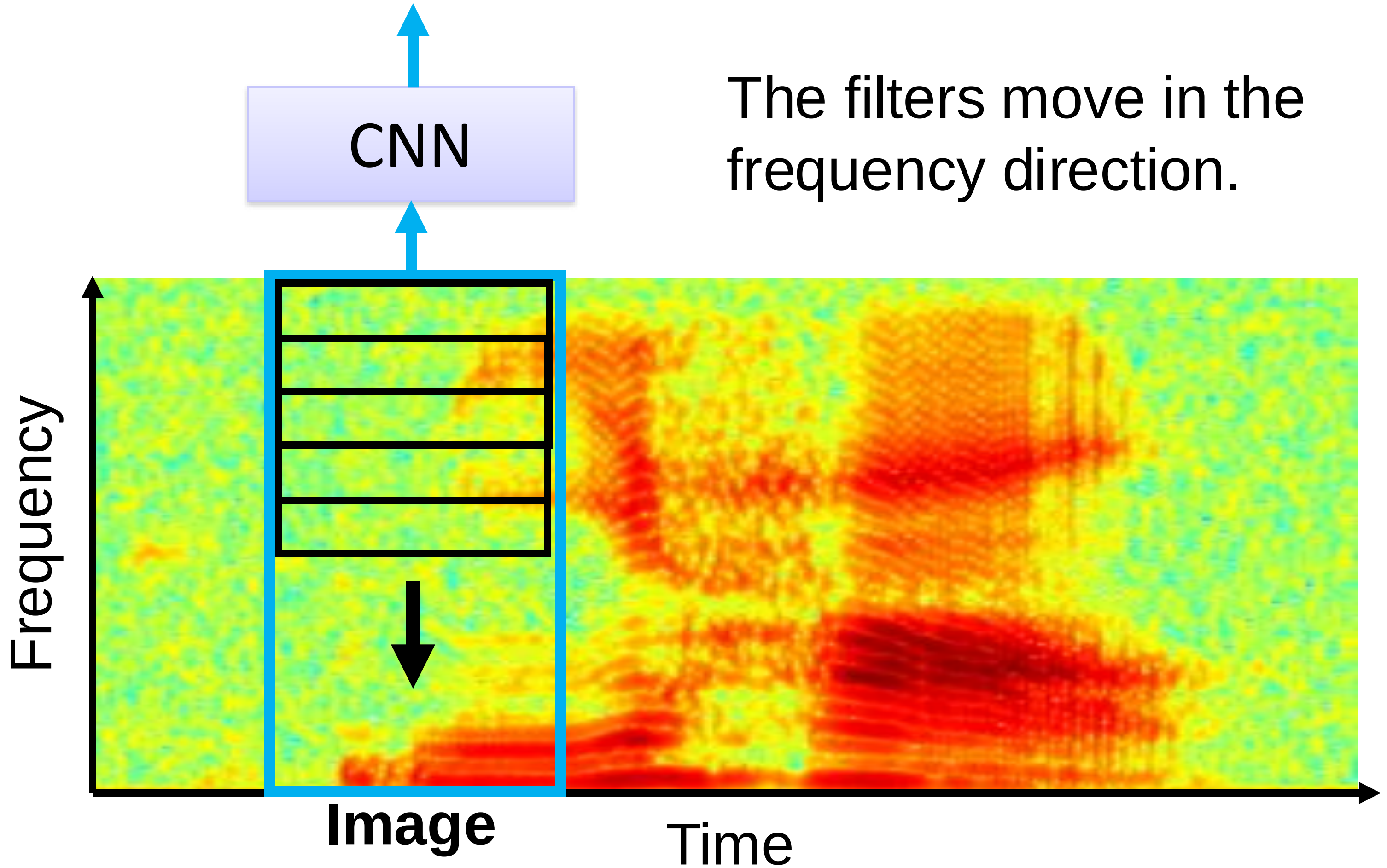
AlphaGo's policy network

The following is quotation from their Nature article:

Note: AlphaGo does not use Max Pooling.

Neural network architecture. The input to the policy network is a $19 \times 19 \times 48$ image stack consisting of 48 feature planes. The first hidden layer zero pads the input into a 23×23 image, then convolves k filters of kernel size 5×5 with stride 1 with the input image and applies a rectifier nonlinearity. Each of the subsequent hidden layers 2 to 12 zero pads the respective previous hidden layer into a 21×21 image, then convolves k filters of kernel size 3×3 with stride 1, again followed by a rectifier nonlinearity. The final layer convolves 1 filter of kernel size 1×1 with stride 1, with a different bias for each position, and applies a softmax function. The match version of AlphaGo used $k = 192$ filters; Fig. 2b and Extended Data Table 3 additionally show the results of training with $k = 128$, 256 and 384 filters.

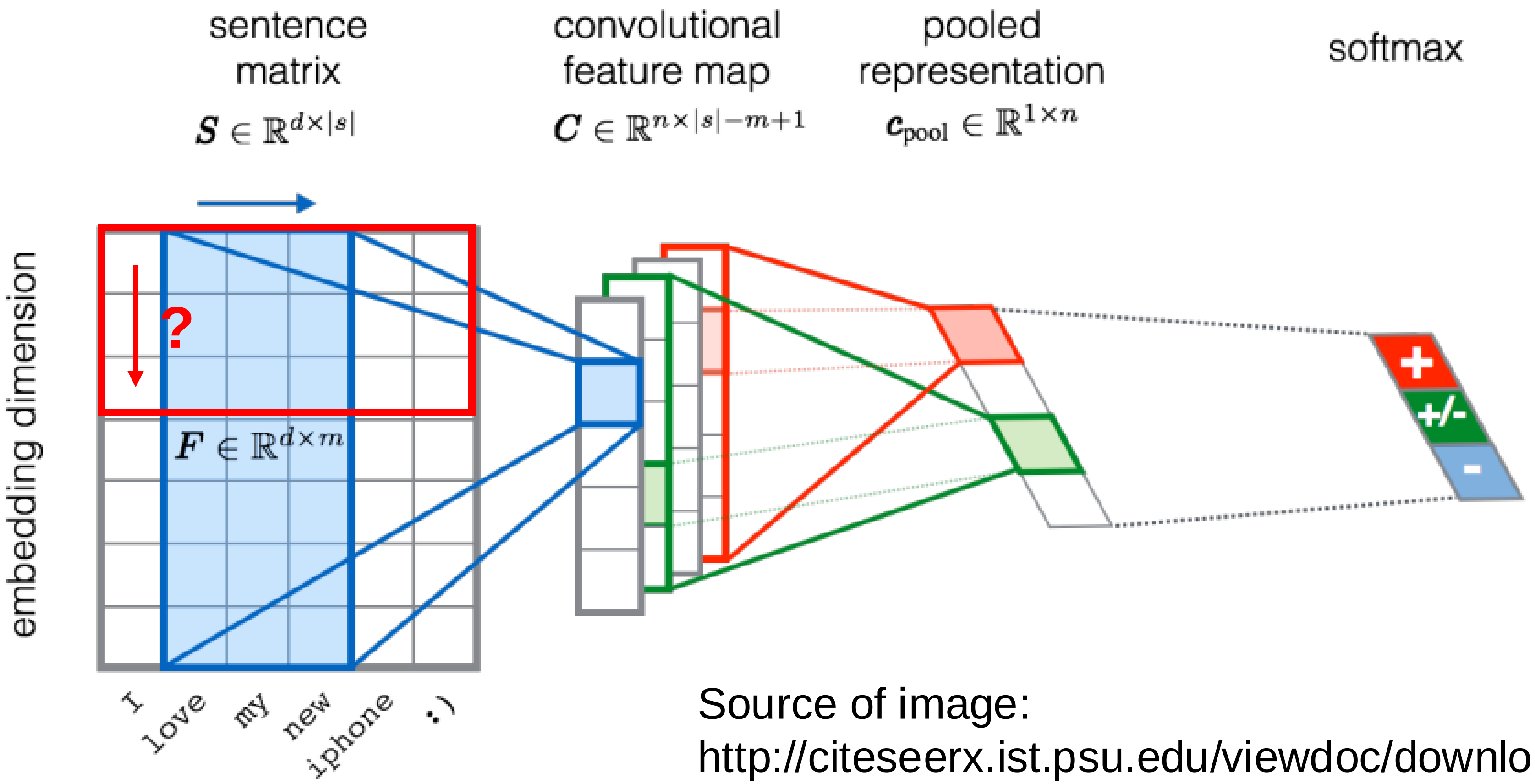
CNN in speech recognition



The filters move in the frequency direction.

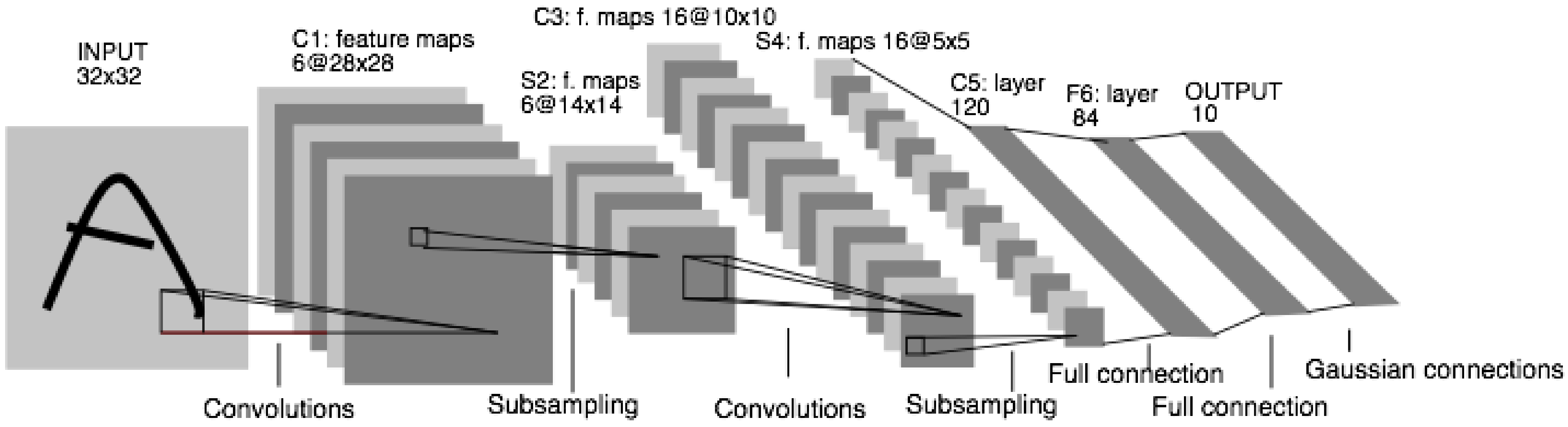
Spectrogram

CNN in text classification



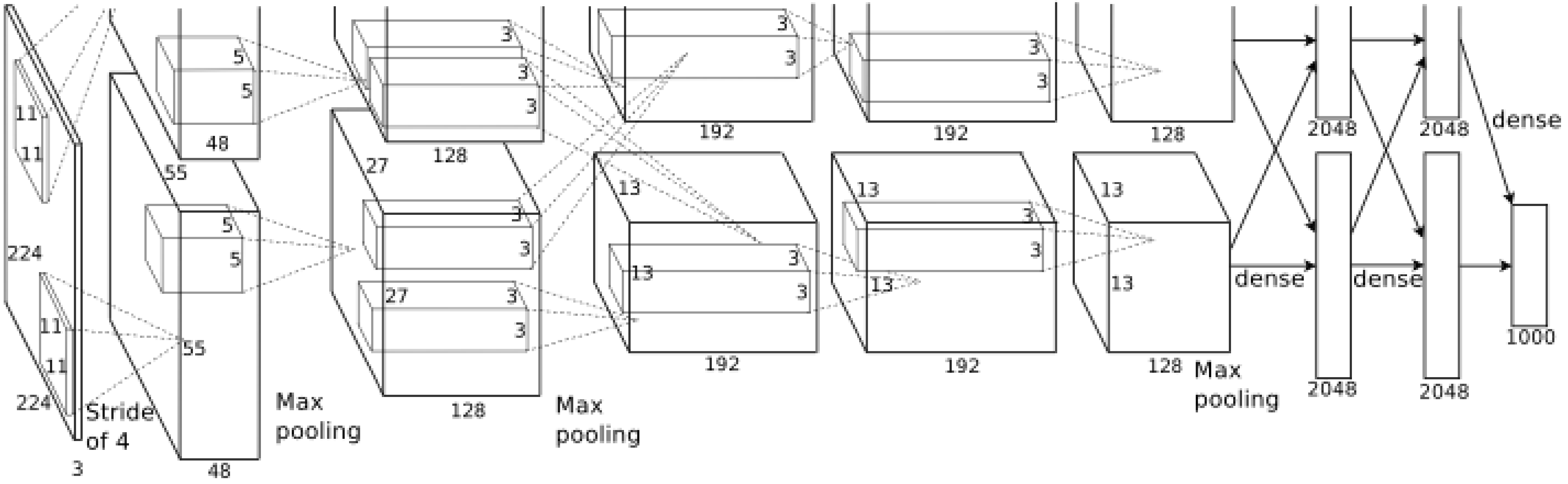
Source of image: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.703.6858&rep=rep1&type=pdf

Convolutional Neural Networks: 1998.
Input 32*32. CPU



LeNet: a layered model composed of convolution and subsampling operations followed by a holistic representation and ultimately a classifier for handwritten digits. [LeNet]

Convolutional Neural Networks: 2012. Input 224*224*3. GPU.

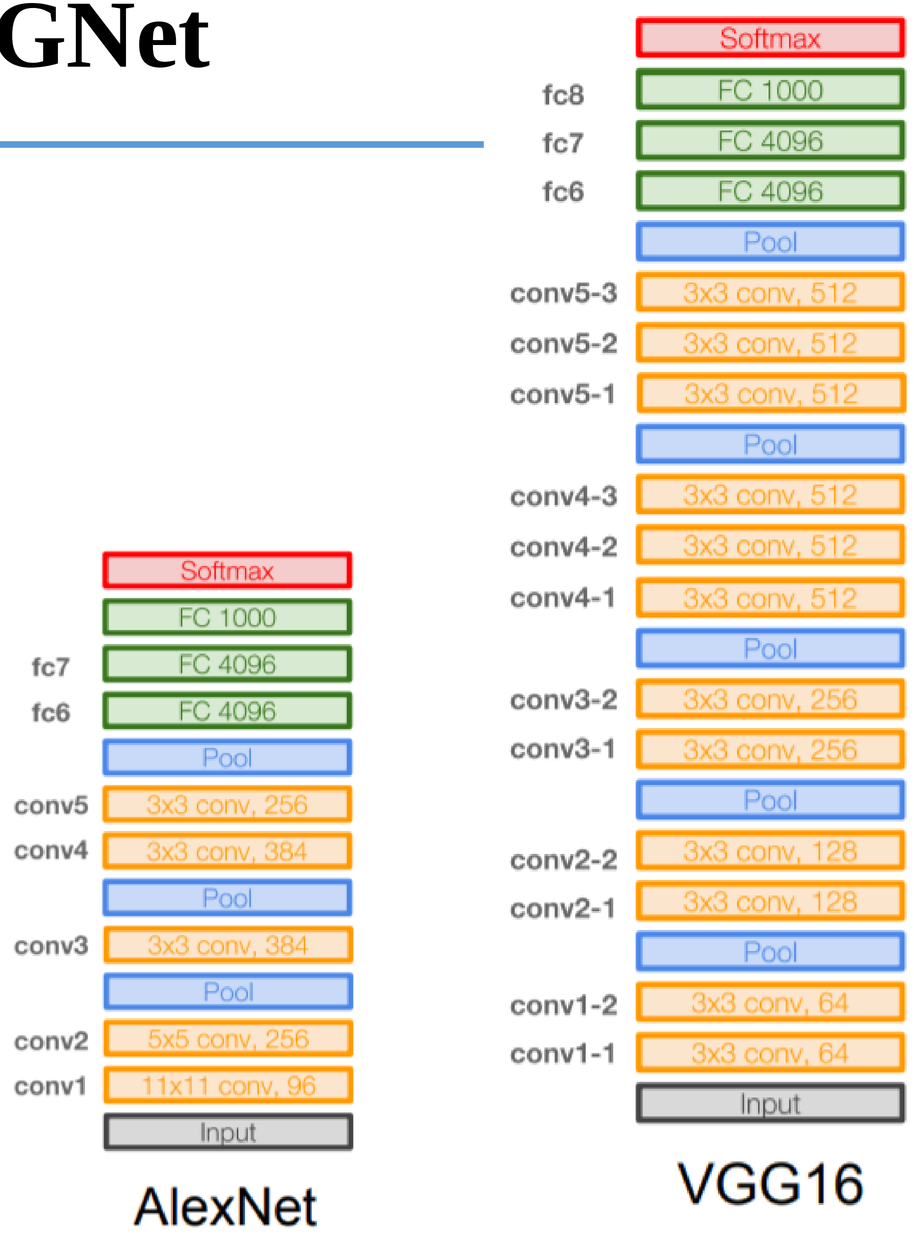


AlexNet: a layered model composed of convolution, subsampling, and further operations followed by a holistic representation and all-in-all a landmark classifier on ILSVRC12. [AlexNet]

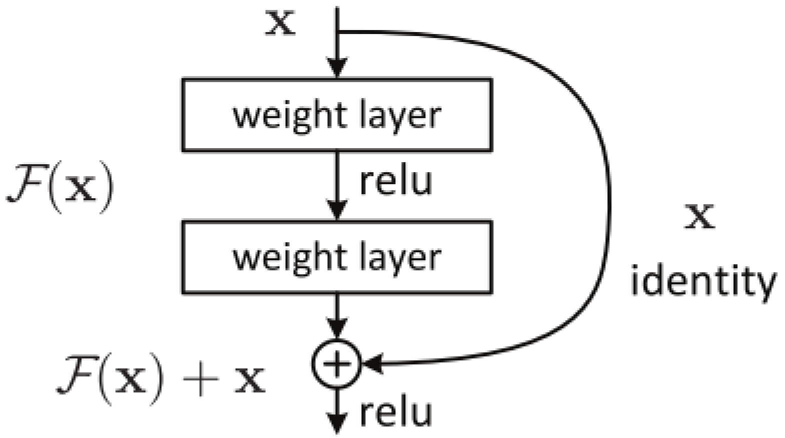
+ data
+ gpu
+ non-saturating nonlinearity
+ regularization

VGGNet

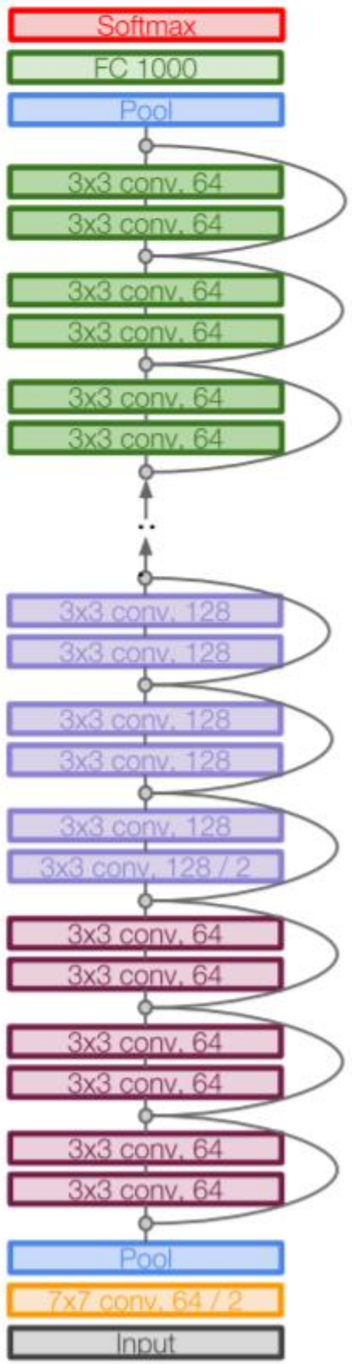
- 16 layers
- Only 3*3 convolutions
- 138 million parameters



ResNet

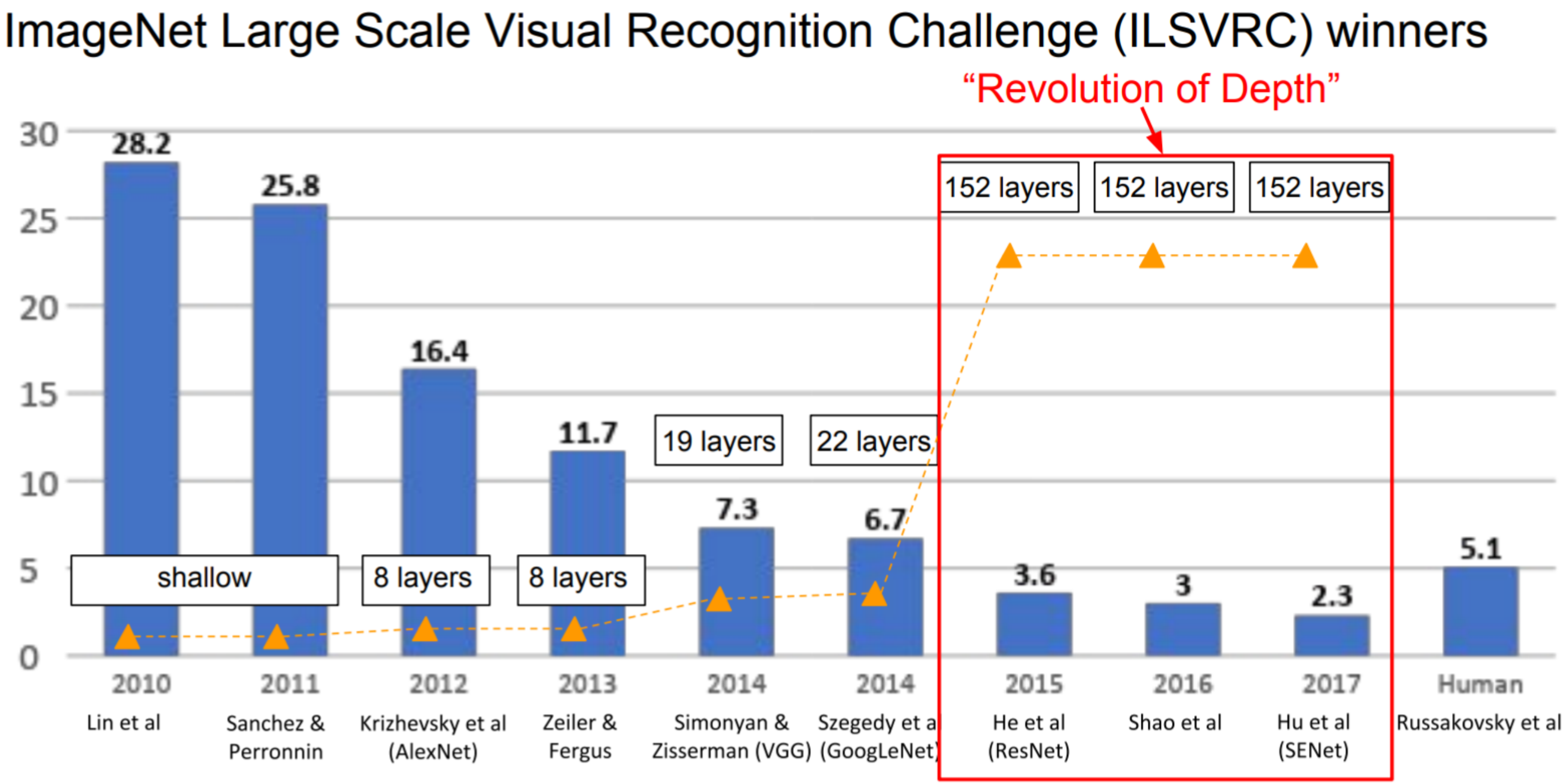


- 152 layers
- ResNet50



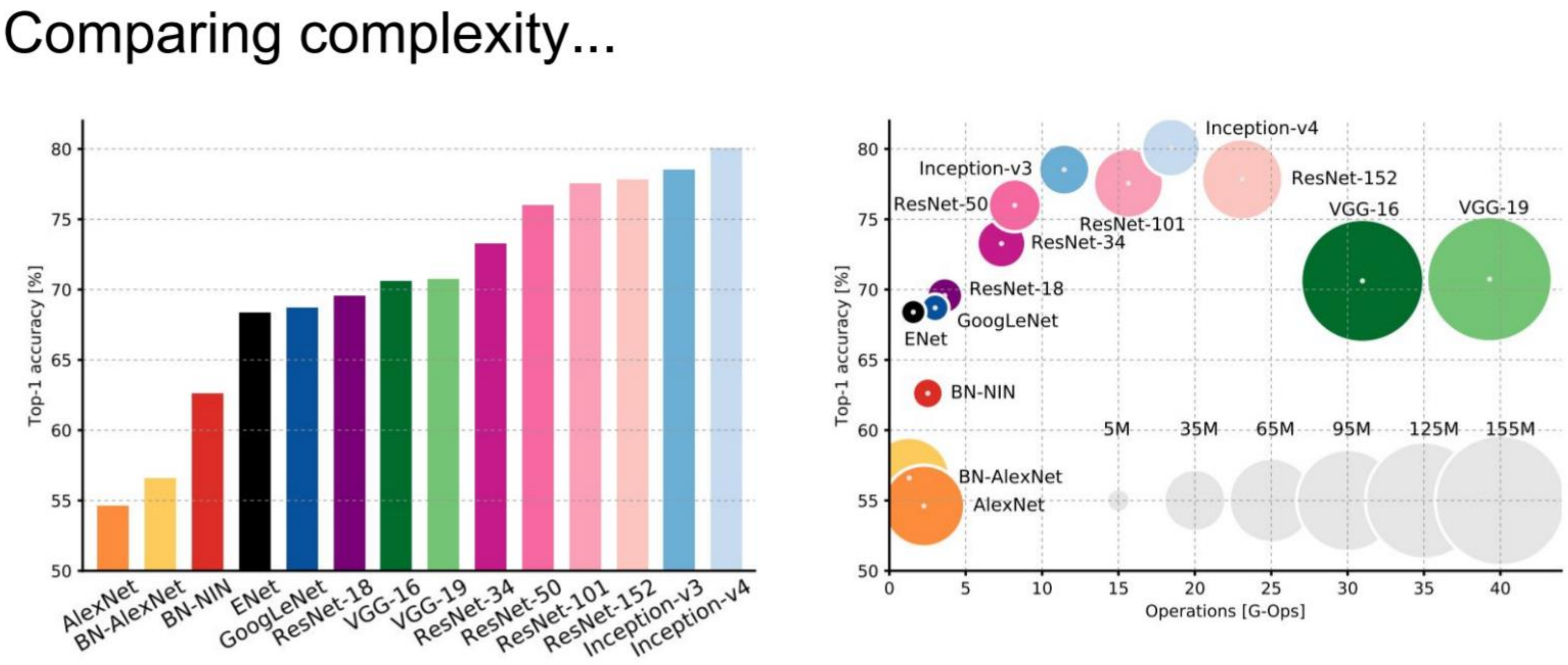
The popular CNN

- LeNet, 1998
- AlexNet, 2012
- VGGNet, 2014
- ResNet, 2015



Computational complexity

- The memory bottleneck
- GPU, a few GB



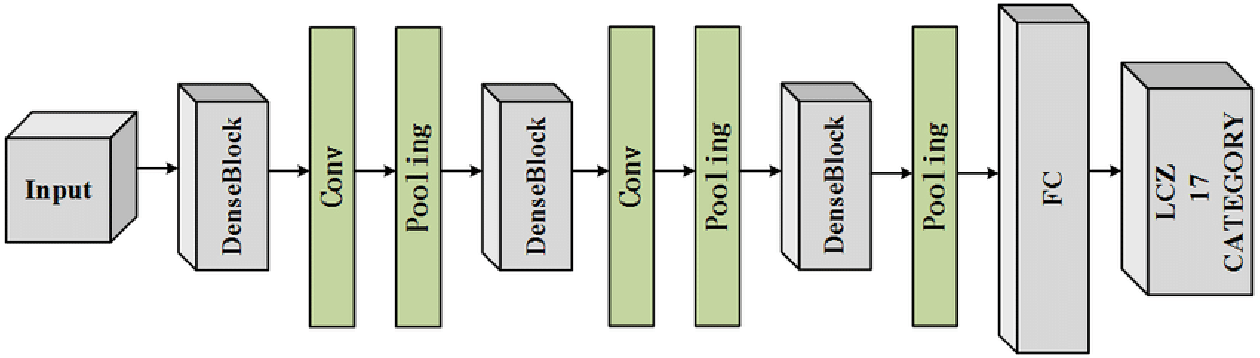
An Analysis of Deep Neural Network Models for Practical Applications, 2017.

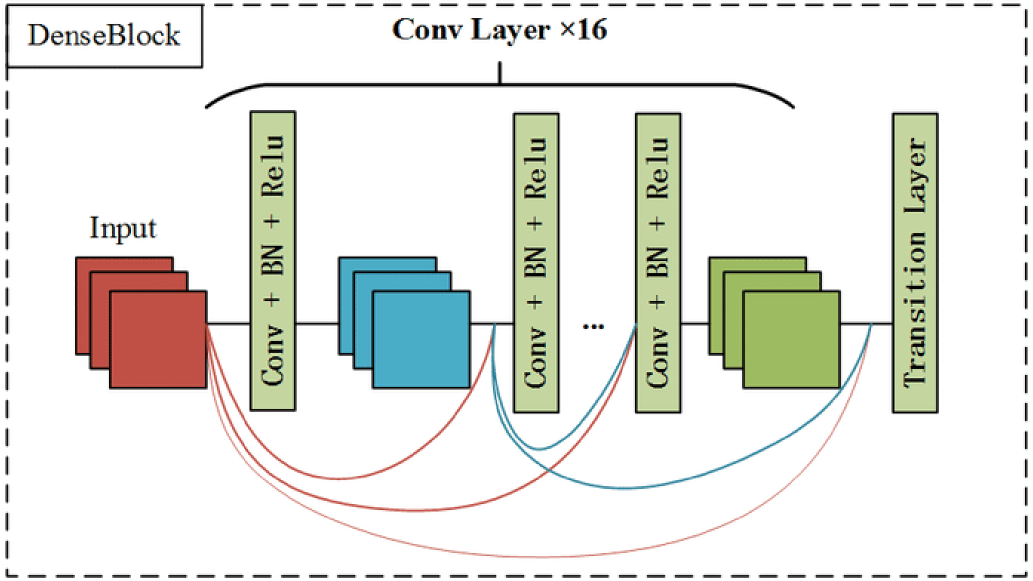
CNN applications

- Transfer learning
- Fine-tuning the CNN
  - Keep some early layers
    - Early layers contain more generic features, edges, color blobs
    - Common to many visual tasks
  - Fine-tune the later layers
    - More specific to the details of the class
- CNN as feature extractor
  - Remove the last fully connected layer
  - A kind of descriptor or CNN codes for the image
  - AlexNet gives a 4096 Dim descriptor

CNN classification/recognition nets

- CNN layers and fully-connected classification layers
- From ResNet to DenseNet
  - Densely connected
  - Feature concatenation





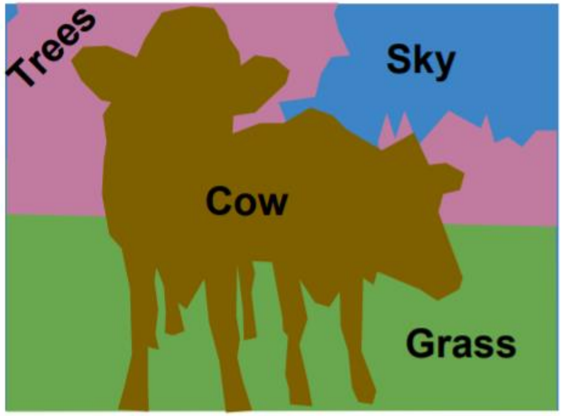
Fully convolutional nets: semantic segmentation

- Classification/recognition nets produce ‘non-spatial’ outputs
  - the last fully connected layer has the fixed dimension of classes, throws away spatial coordinates

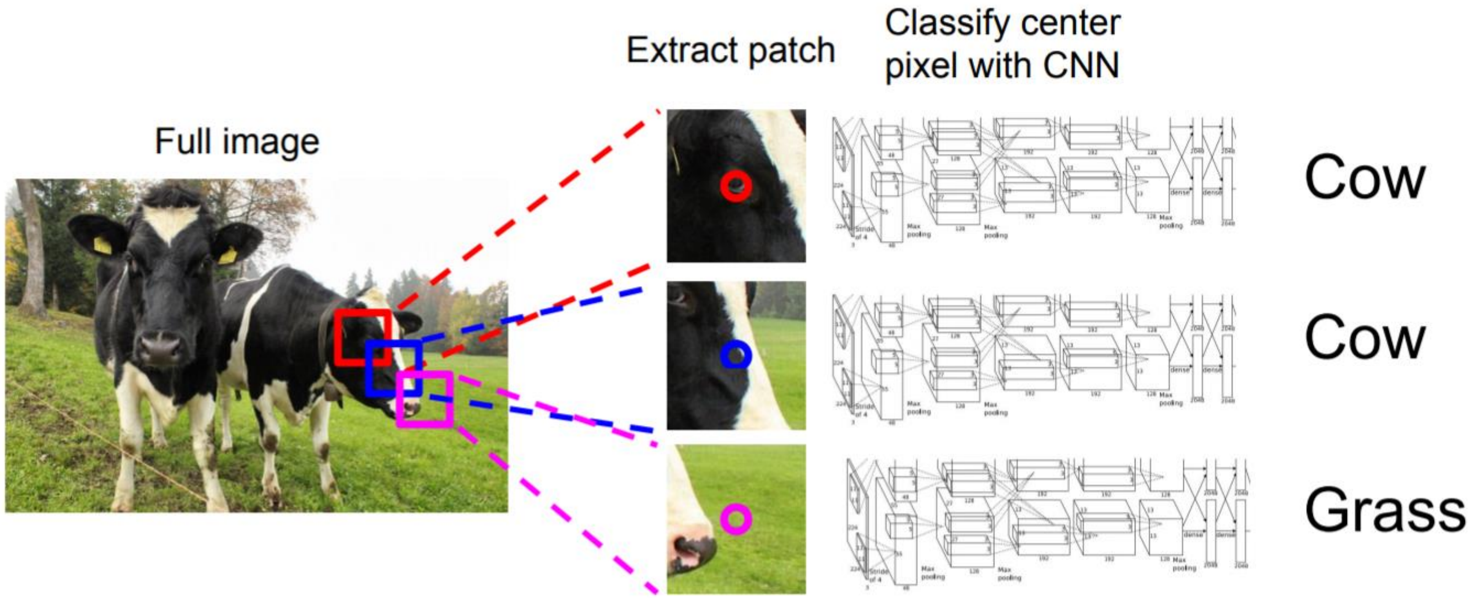
- Fully convolutional nets output maps as well

Semantic segmentation

This image is CC0 public domain



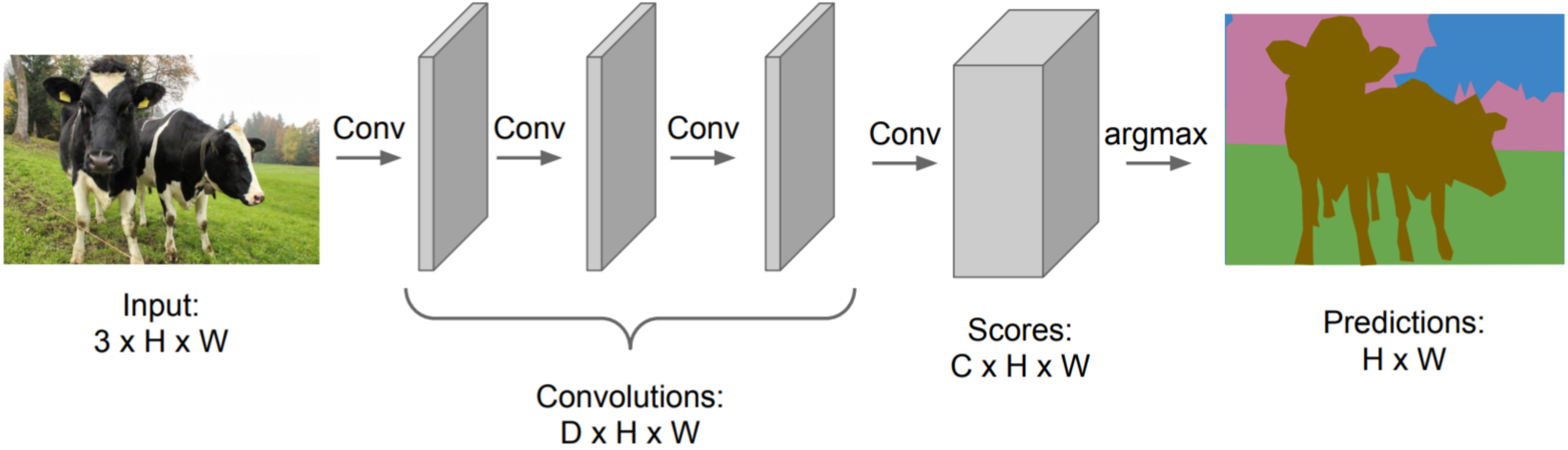
Using sliding windows for semantic segmentation



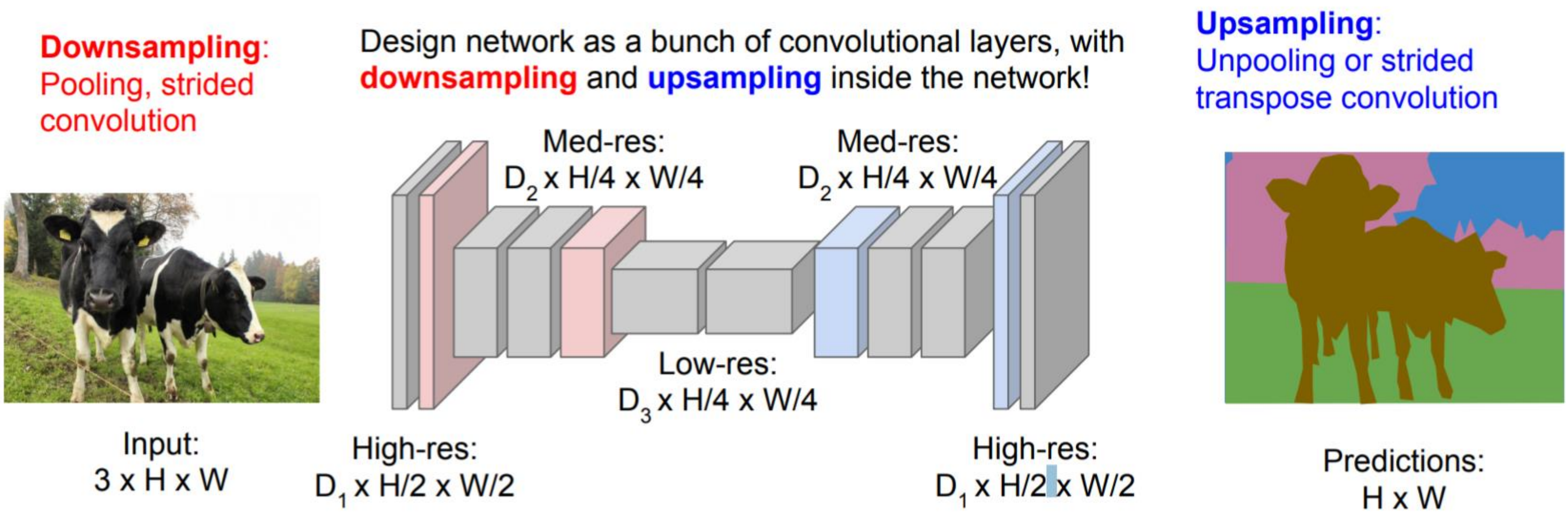
Farabet et al, “Learning Hierarchical Features for Scene Labeling,” TPAMI 2013
Pinheiro and Collobert, “Recurrent Convolutional Neural Networks for Scene Labeling”, ICML 2014

Fully convolutional

Design a network as a bunch of convolutional layers
to make predictions for pixels all at once!



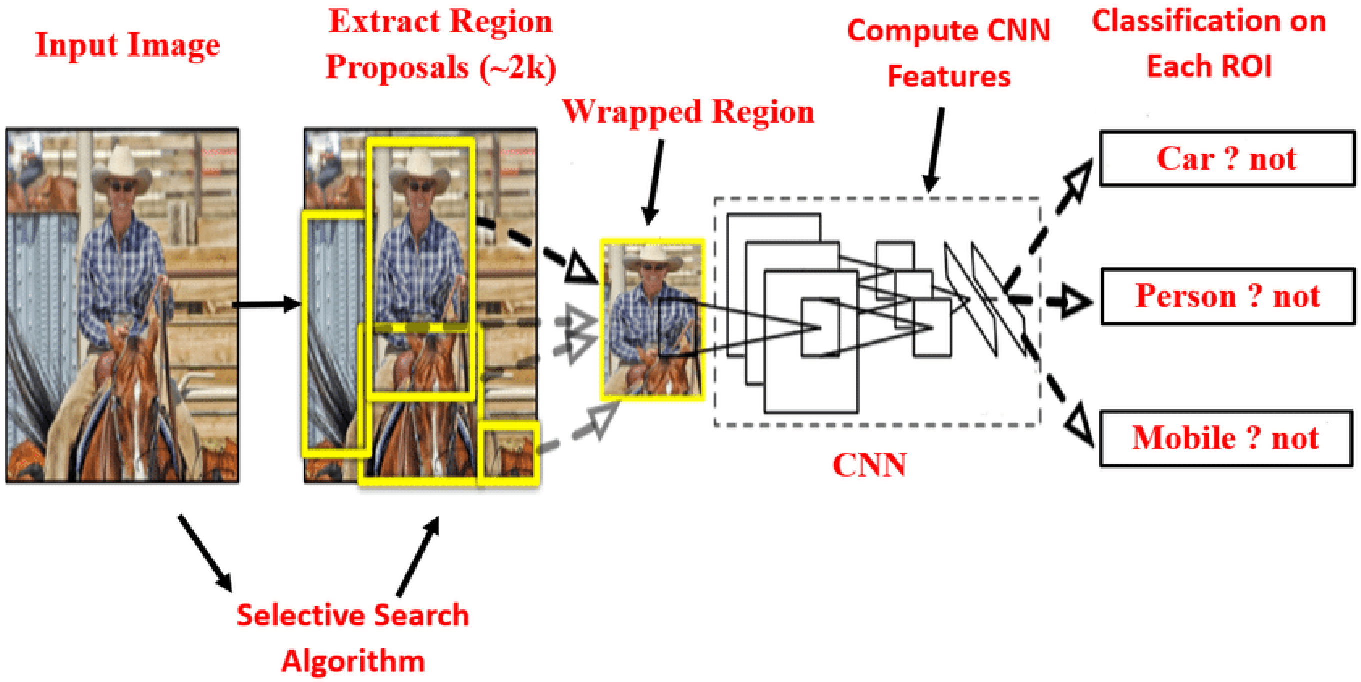
Fully convolutional



Long, Shelhamer, and Darrell, "Fully Convolutional Networks for Semantic Segmentation", CVPR 2015
Noh et al, "Learning Deconvolution Network for Semantic Segmentation", ICCV 2015

Detection and segmentation nets: The Mask Region-based CNN (R-CNN):

- Class-independent region (bounding box) proposals
  - From selective search to region proposal net with objectness
- Use CNN to class each region
- Regression on the bounding box or contour segmentation



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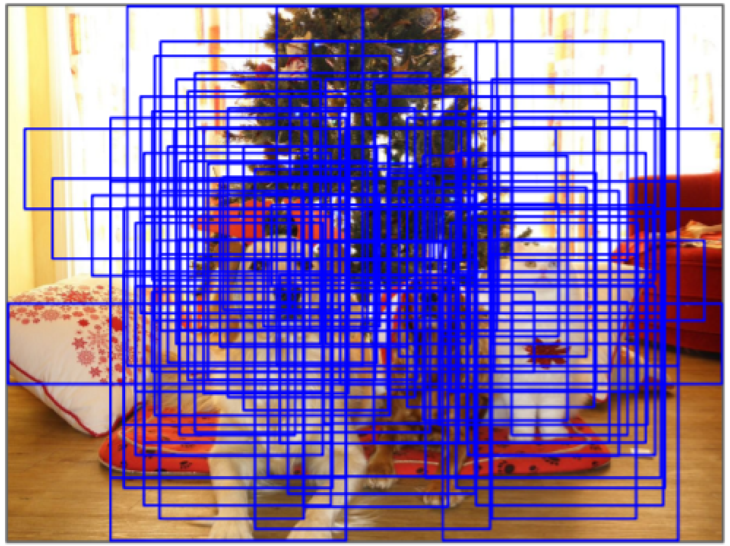
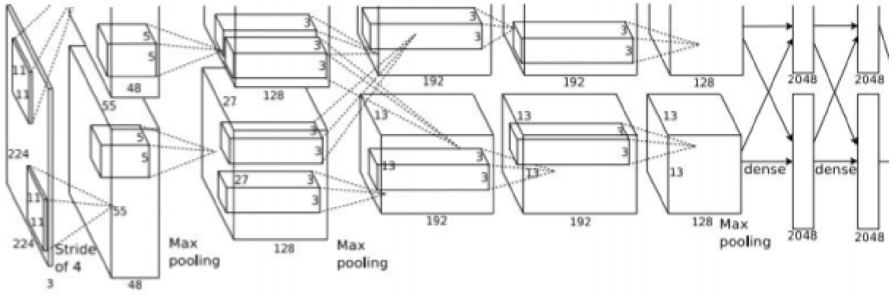
Using sliding windows for object detection as classification



Apply a CNN to many different crops of the image, CNN classifies each crop as object or background

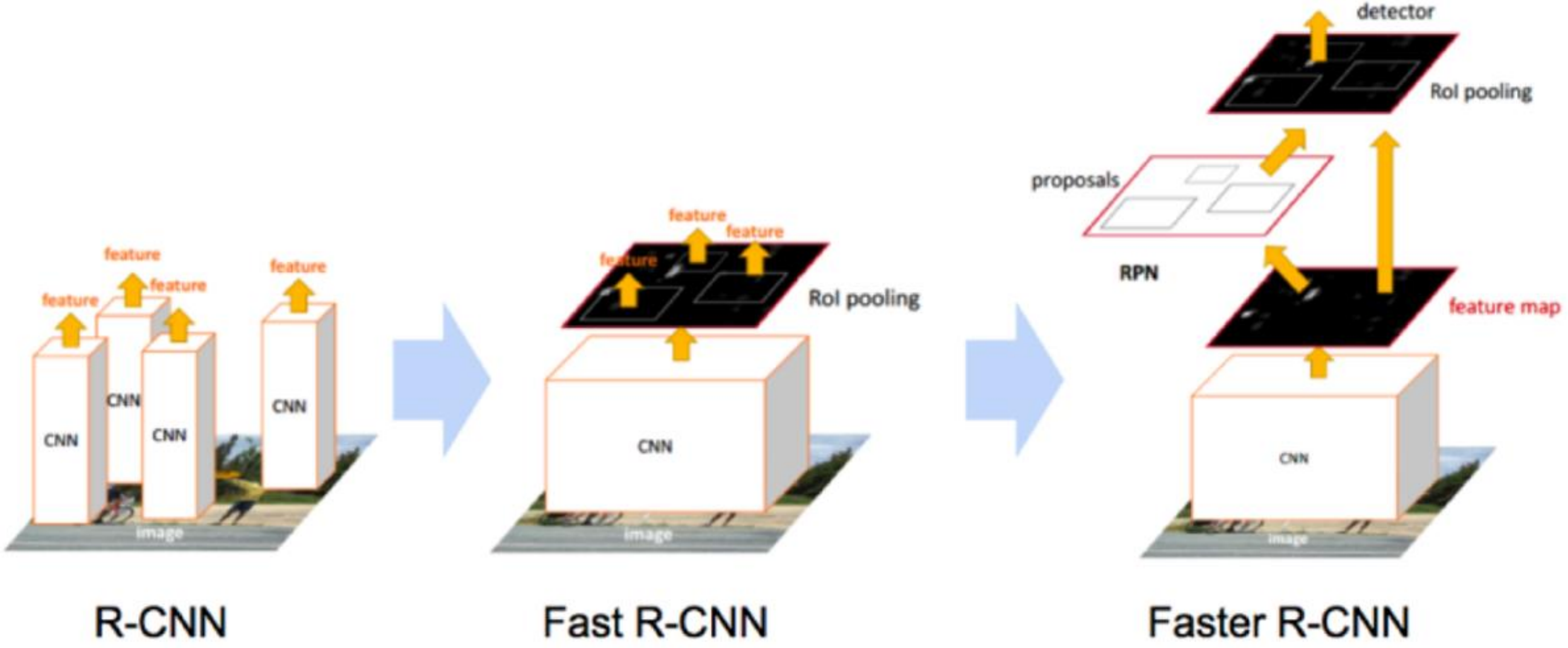


Dog? NO
Cat? YES
Background? NO

Problem: Need to apply CNN to huge number of locations, scales, and aspect ratios, very computationally expensive!

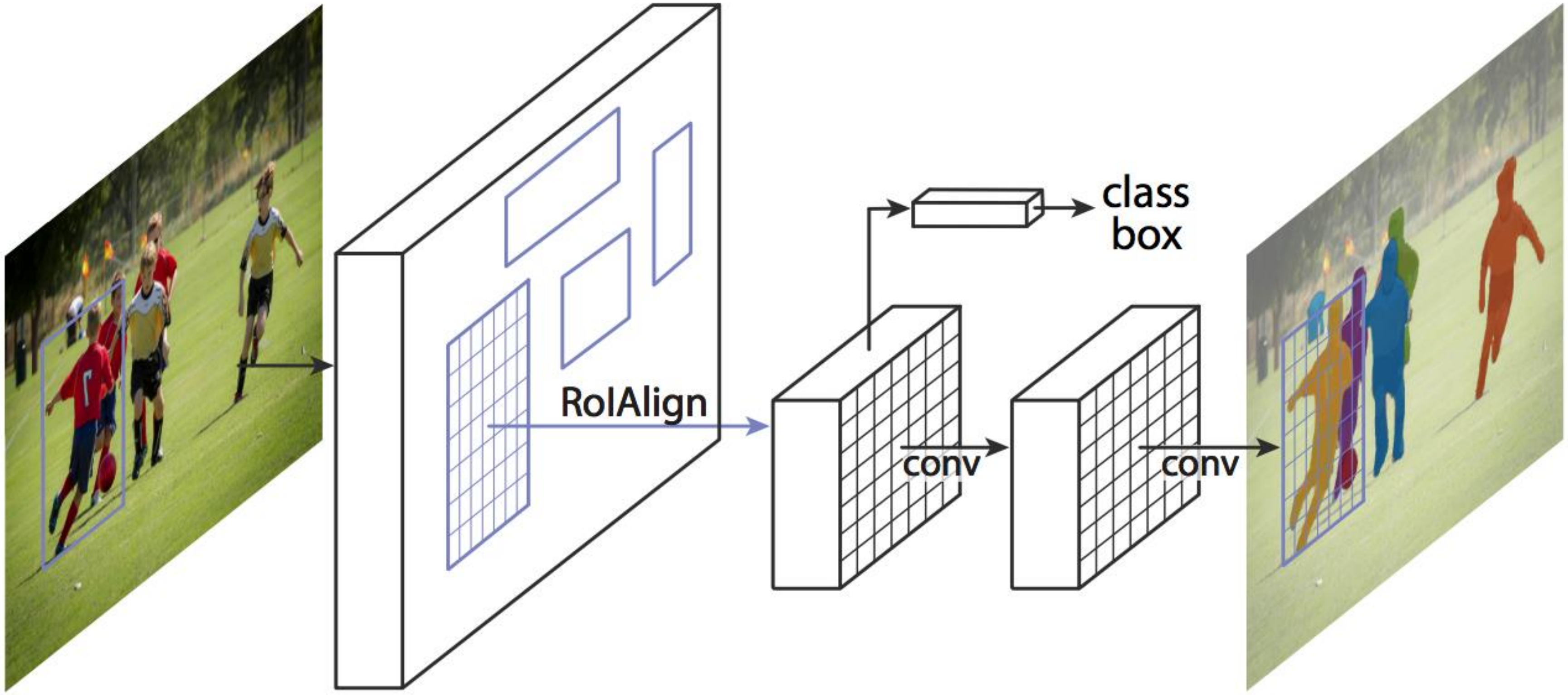
Detection and segmentation nets: The Mask Region-based CNN (R-CNN):

- Class-independent region (bounding box) proposals
  - From selective search to region proposal net with objectness
- Use CNN to class each region
- Regression on the bounding box or contour segmentation

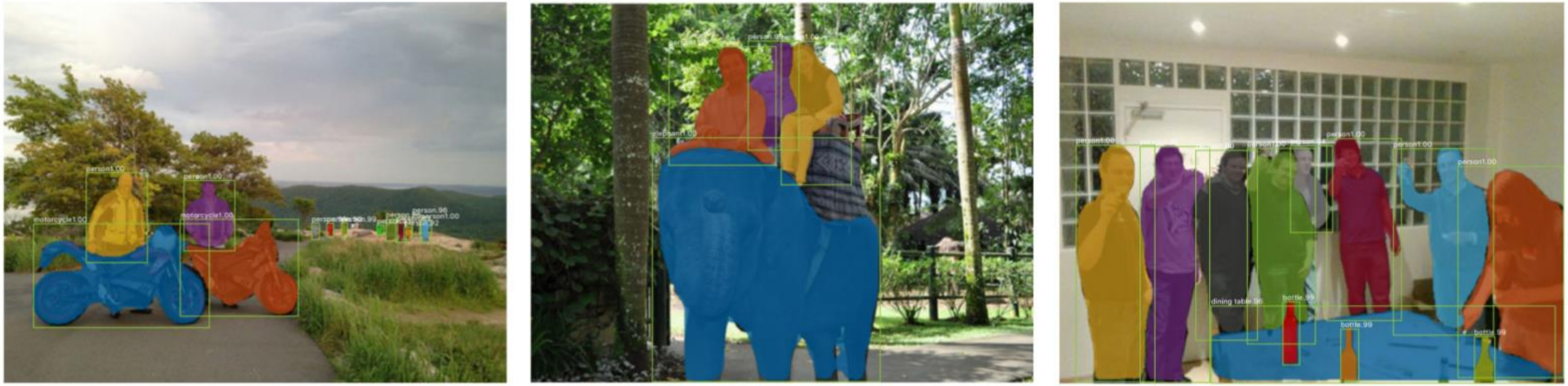


Detection and segmentation nets: The Mask Region-based CNN (R-CNN):

- Mask R-CNN: end-to-end
  - Use CNN to make proposals on object/non-object in parallel



Excellent results



He et al, “Mask R-CNN”, arXiv 2017

Bài tập 11

Trong dữ liệu ex7data.mat chưa dữ liệu lưu dưới dạng dict gồm:

X: 5000x400 là 5000 ảnh nhị phân chữ số viết tay có kích thước 20x20

y: 5000x1 là nhãn của các ảnh tương ứng

Các bạn làm các công việc sau:

- Reshape X về kích thước 5000x1x20x20 (pytorch) hoặc 5000x20x20x1 (keras)
- Chia dữ liệu thành 70% train, 30% test (train_test_split) đảm bảo tính ngẫu nhiên và đồng đều về nhãn.
- Chia dữ liệu train thành 90% train, 10% val (train_test_split) đảm bảo tính ngẫu nhiên và đồng đều về nhãn.
- Xây dựng một mạng CNN cho phù hợp với dữ liệu trên để đạt được hiệu suất tốt nhất
- Show đường cong loss trong quá trình học
- Show độ chính xác trên tập test