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MINISTERSTVO ŠKOLSTVÍ, MLÁDEŽE A TĚLOVÝCHOVY

Image Analysis II

AlexNet, ZFNet, VGGNet, GoogLeNet, ResNet, …

Radovan Fusek

VSB TECHNICAL UNIVERSITY OF OSTRAVA | FACULTY OF ELECTRICAL ENGINEERING AND COMPUTER SCIENCE | DEPARTMENT OF COMPUTER SCIENCE

CovNet Architectures

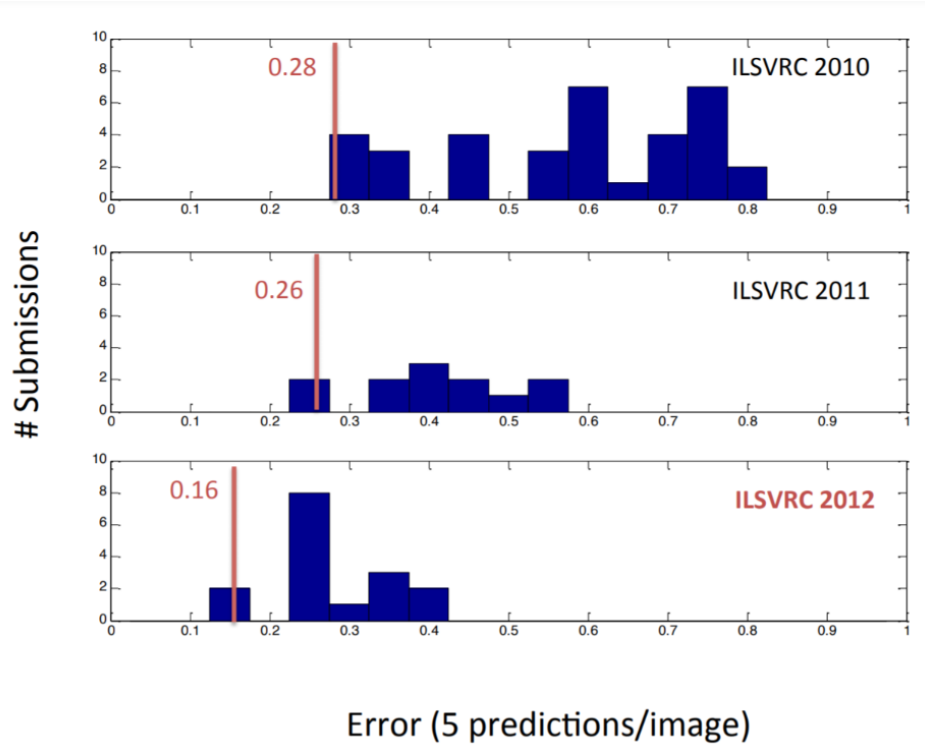
- LeNet (1990s)
- AlexNet (2012)
- ZF Net (2013)
- VGGNet (2014)
- GoogLeNet (2014)
- ResNets (2015)
- DenseNet (2017)

https://ujjwalkarn.me/2016/08/11/intuitive-explanation-convnets/

CovNet Architectures

2012

- **ImageNet Database and competition**
- **http://image-net.org/challenges/LSVRC/2012/**
- **http://www.image-net.org/**
- **http://image-net.org/challenges/LSVRC/2012/ilsvrc2012.pdf**



https://en.wikipedia.org/wiki/ImageNet

AlexNet - 2012

- similar architecture as LeNet but deeper (5 convolutional, 3 fully-connected)
- 1000 different classes (e.g. cats, dogs etc.)

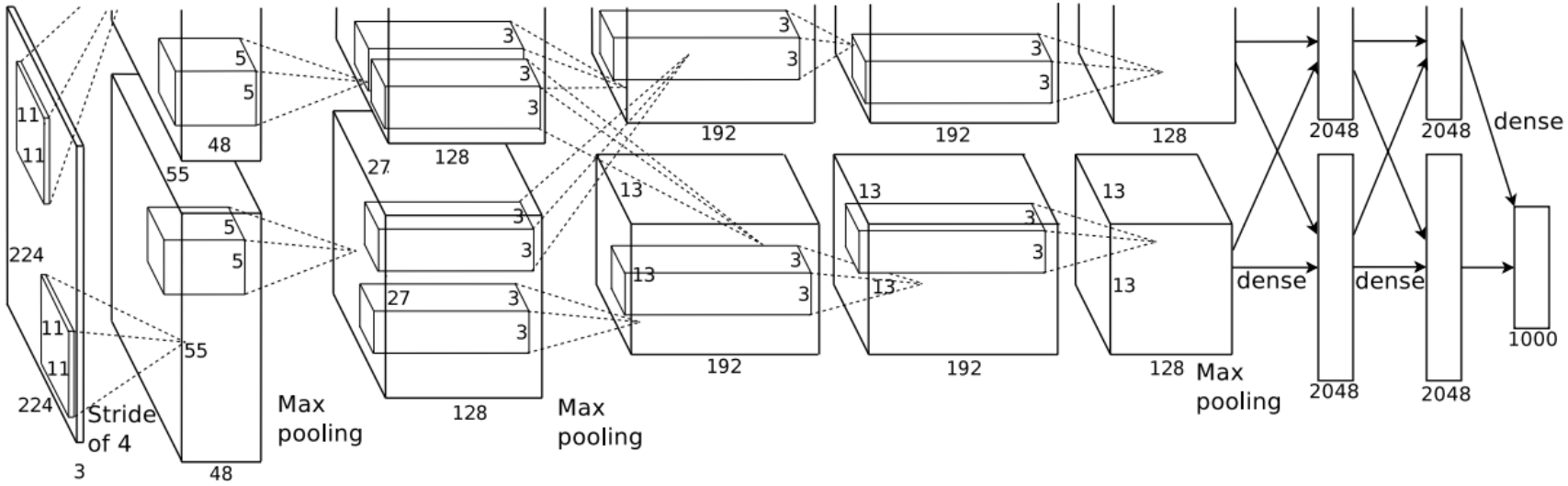
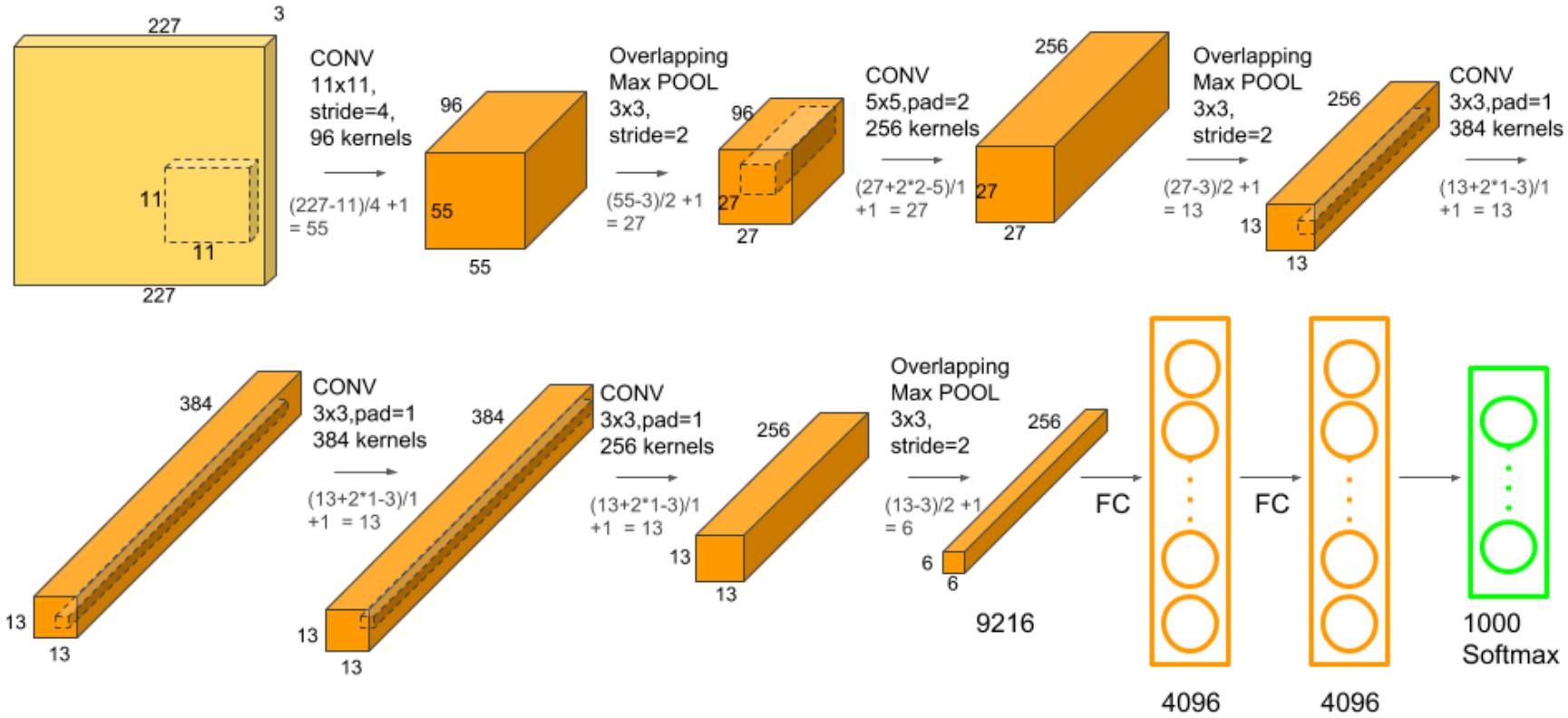


Figure 2: An illustration of the architecture of our CNN, explicitly showing the delineation of responsibilities between the two GPUs. One GPU runs the layer-parts at the top of the figure while the other runs the layer-parts at the bottom. The GPUs communicate only at certain layers. The network's input is 150,528-dimensional, and the number of neurons in the network's remaining layers is given by 253,440–186,624–64,896–64,896–43,264–4096–4096–1000.

Krizhevsky, Alex & Sutskever, Ilya & Hinton, Geoffrey. (2012). ImageNet Classification with Deep Convolutional Neural Networks. Neural Information Processing Systems. 25. 10.1145/3065386.

AlexNet - 2012

- 5-6 days to train on two GTX 580 GPUs (90 epochs)
- Image augmentation (flip, color changes, ..)
- Dropout



https://www.learnopencv.com/understanding-alexnet/
https://medium.com/@RaghavPrabhu/cnn-architectures-lenet-alexnet-vgg-googlenet-and-resnet-7c81c017b848

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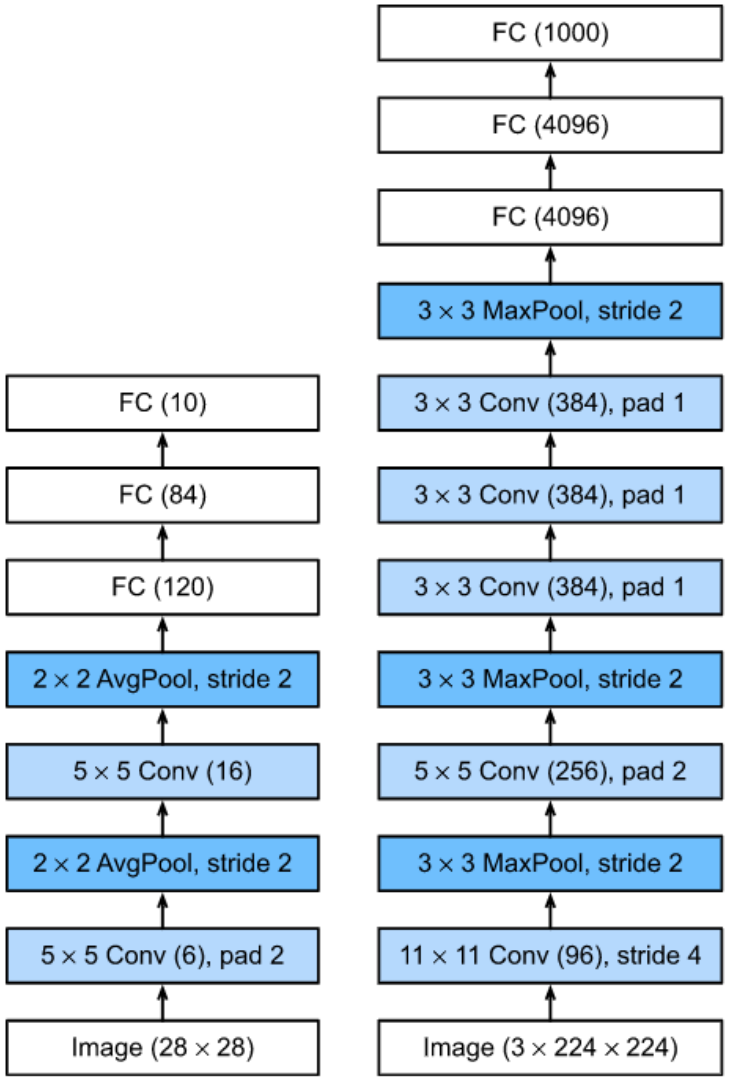
AlexNet – 2012



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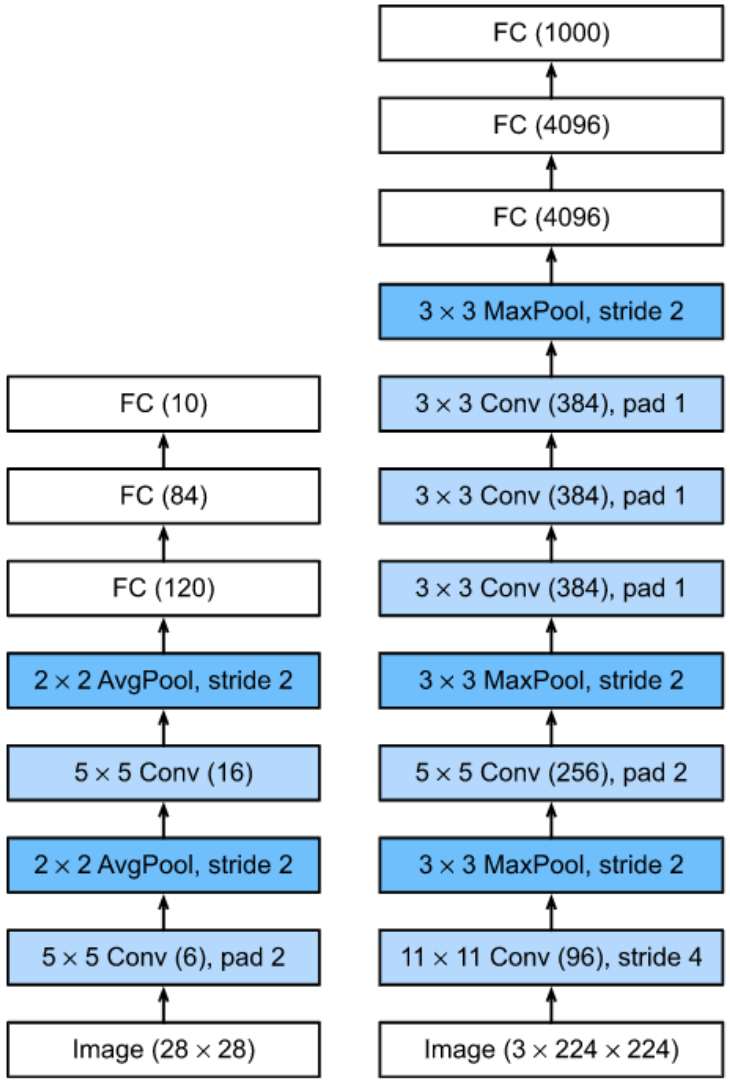
AlexNet – 2012 (Dlib/C++)

```
fc<10,
relu<fc<84,
relu<fc<120,
max_pool<2,2,2,2,relu<con<16,5,5,1,1,
max_pool<2,2,2,2,relu<con<6,5,5,1,1,
input<matrix<unsigned char>>
```



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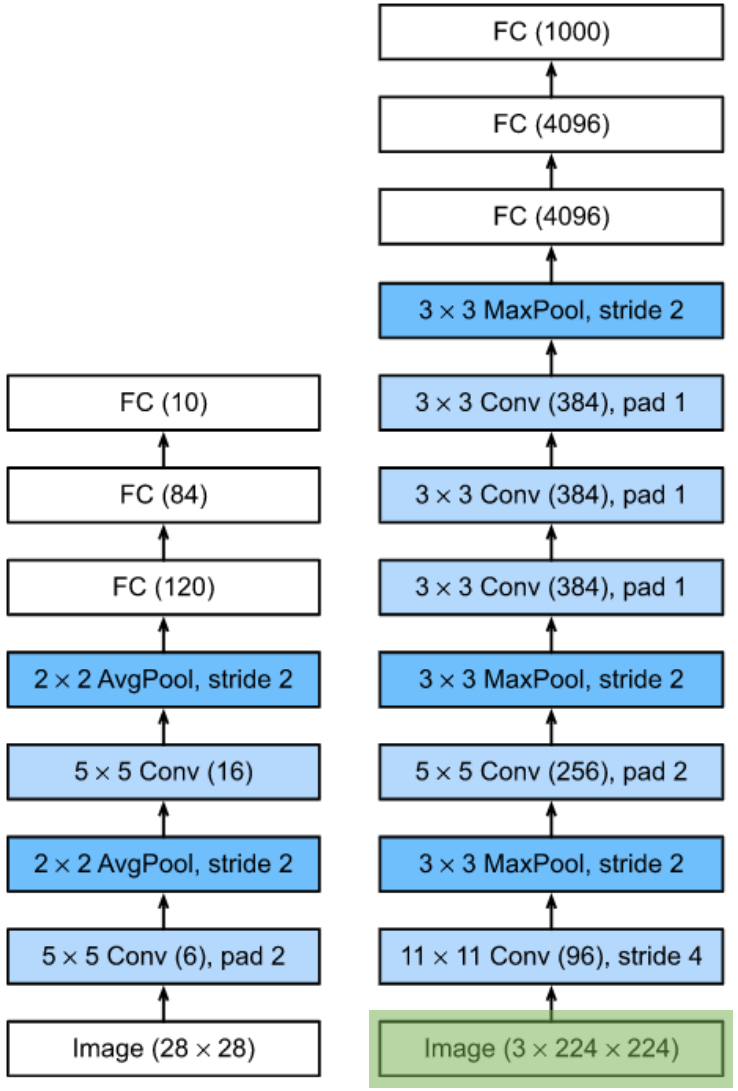


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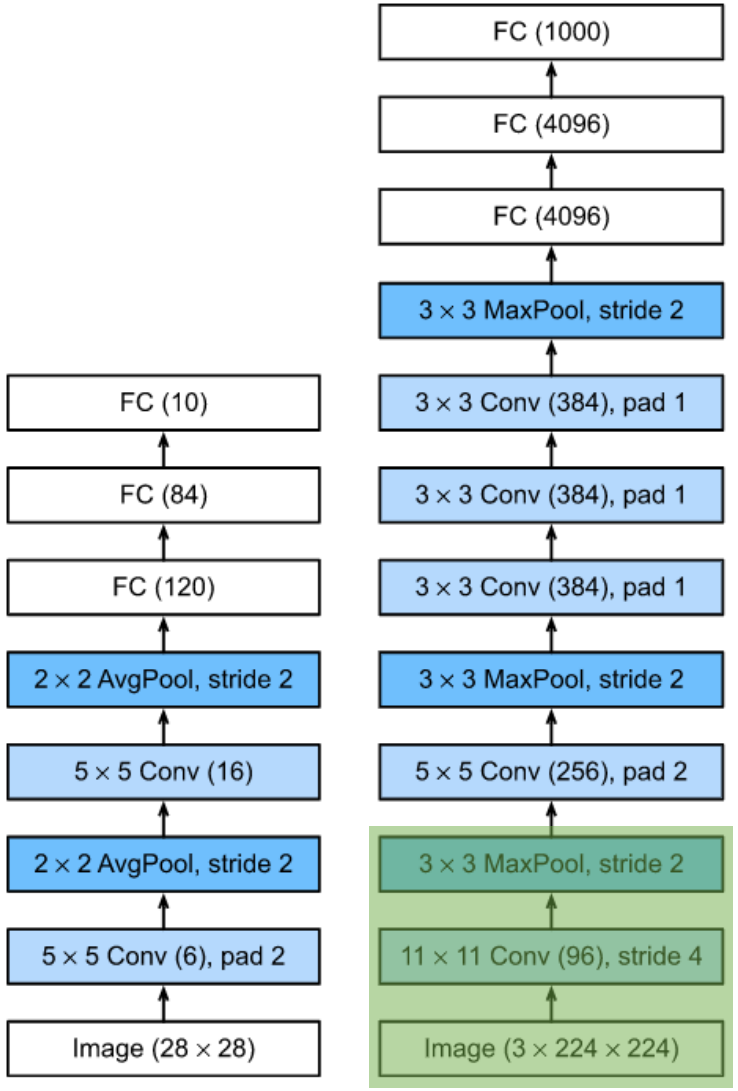


```
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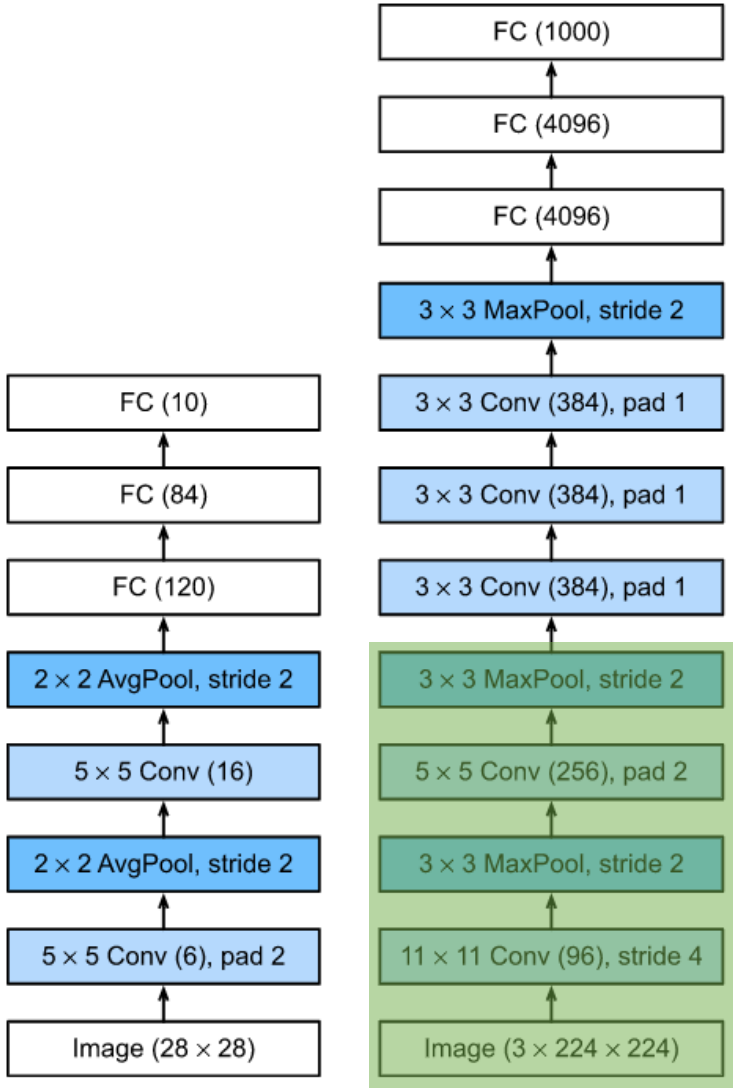


```
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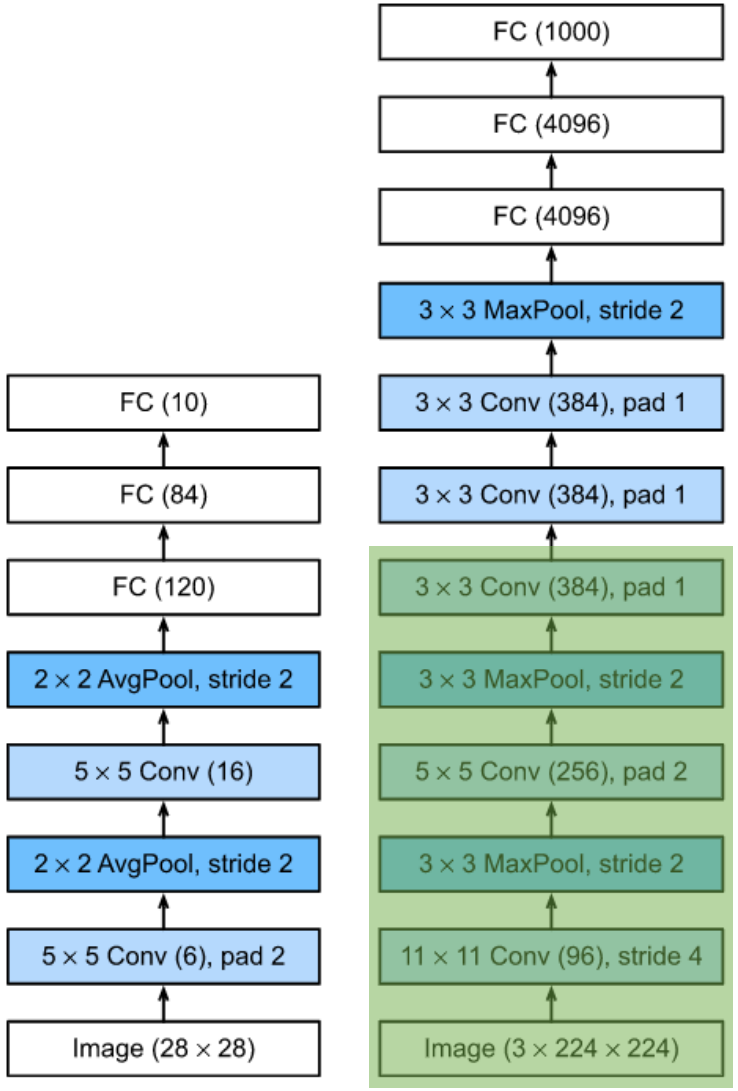


```
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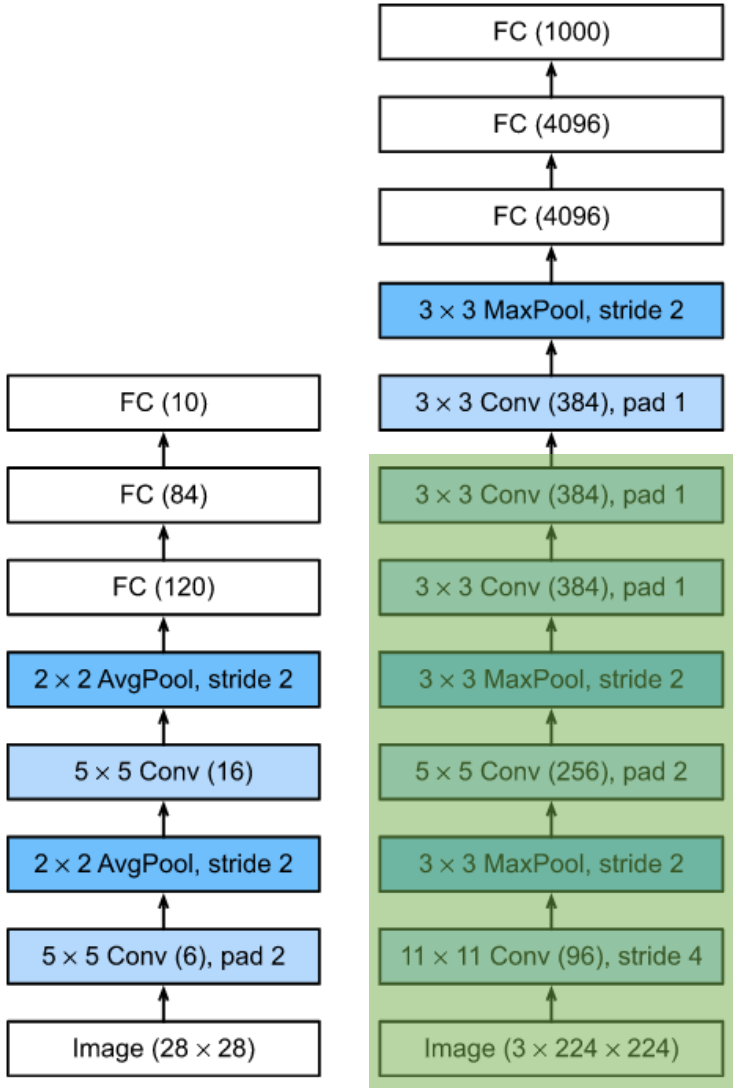


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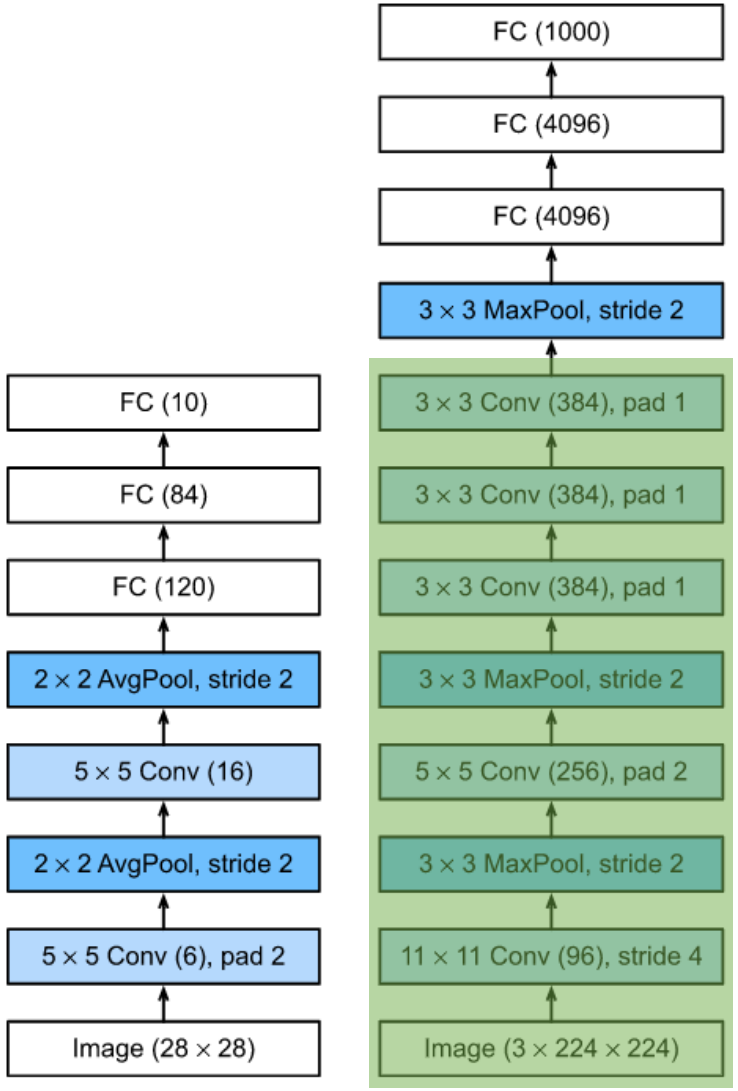


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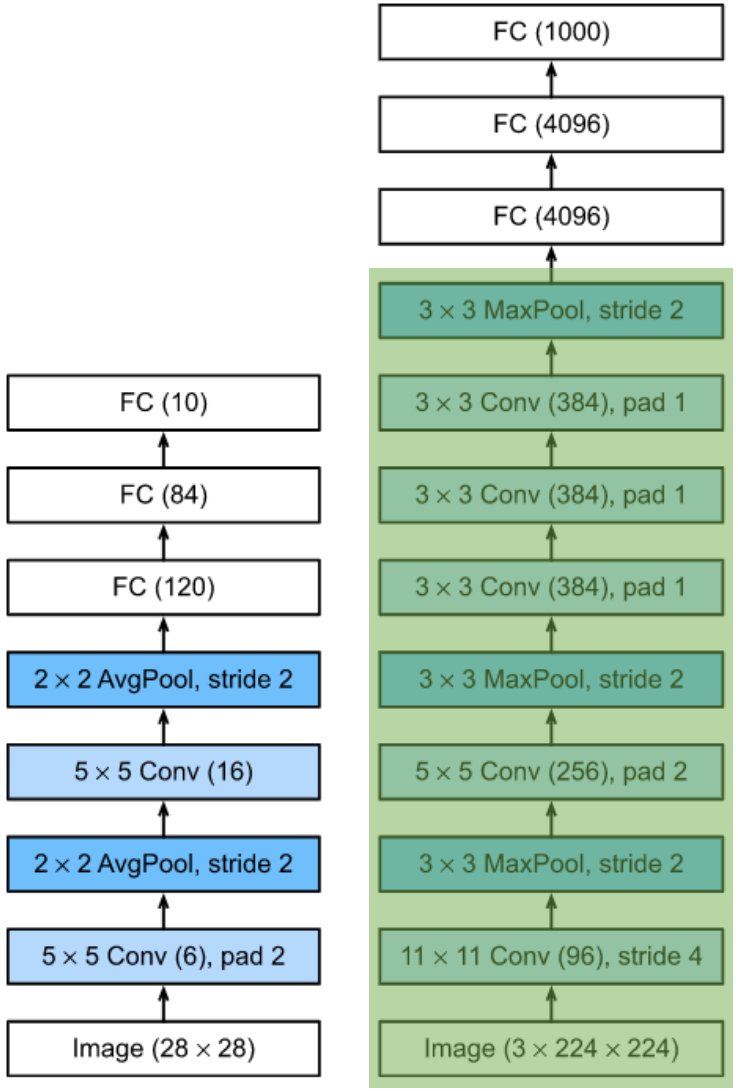


```
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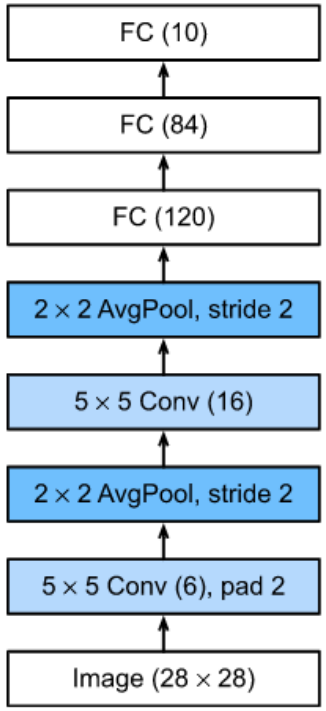

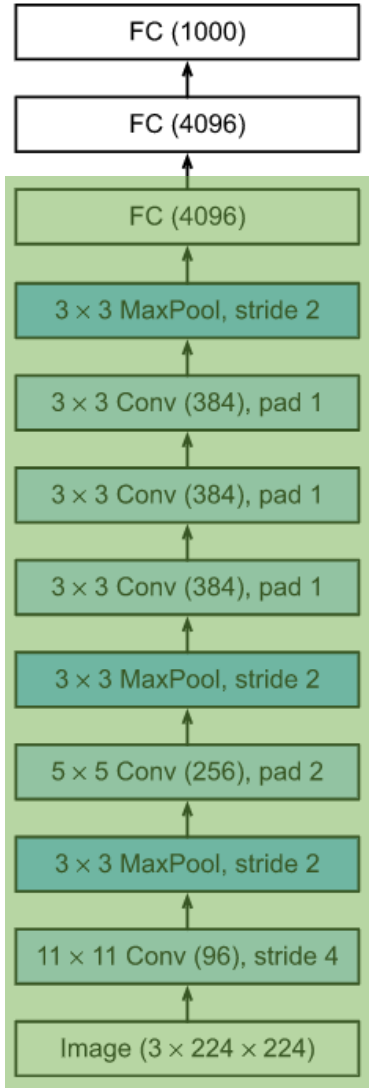


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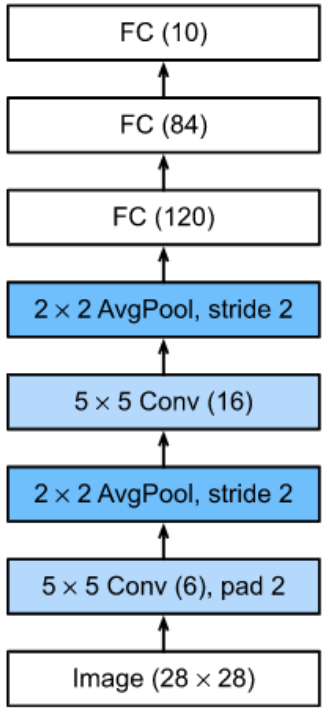

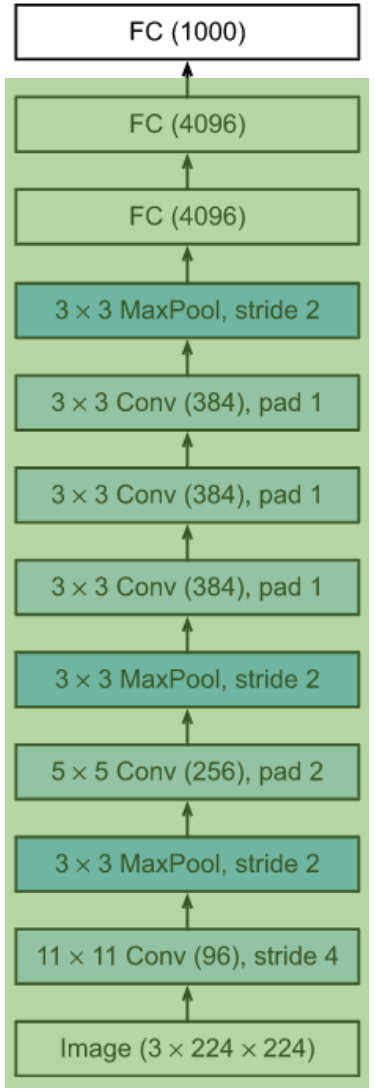


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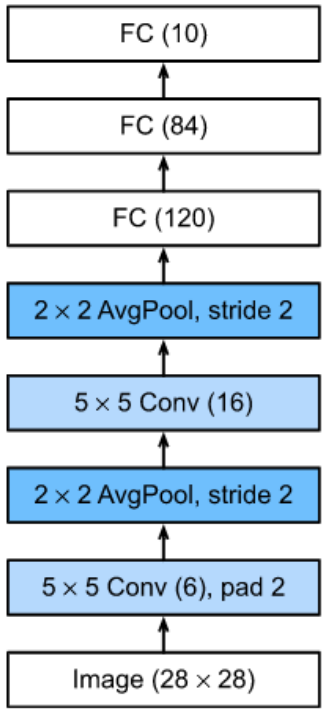

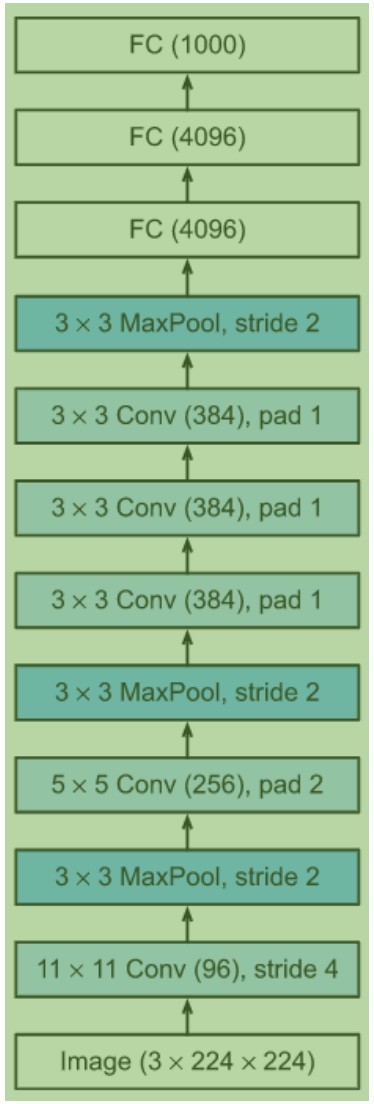


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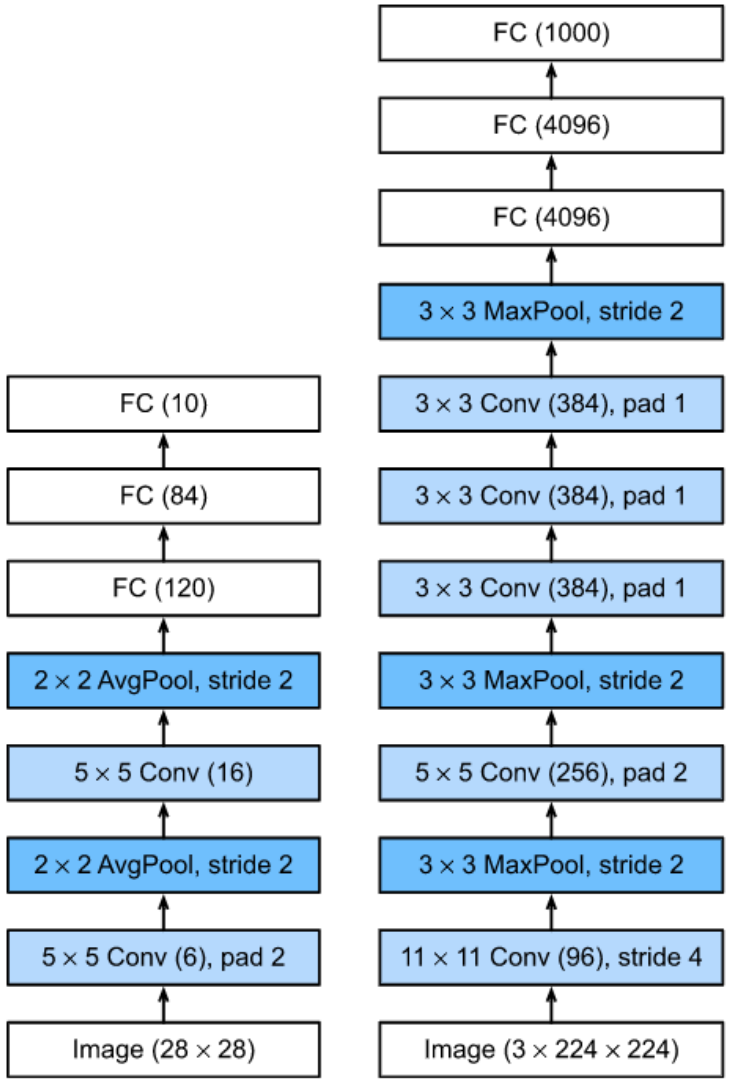


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relu<con<384,3,3,1,1,
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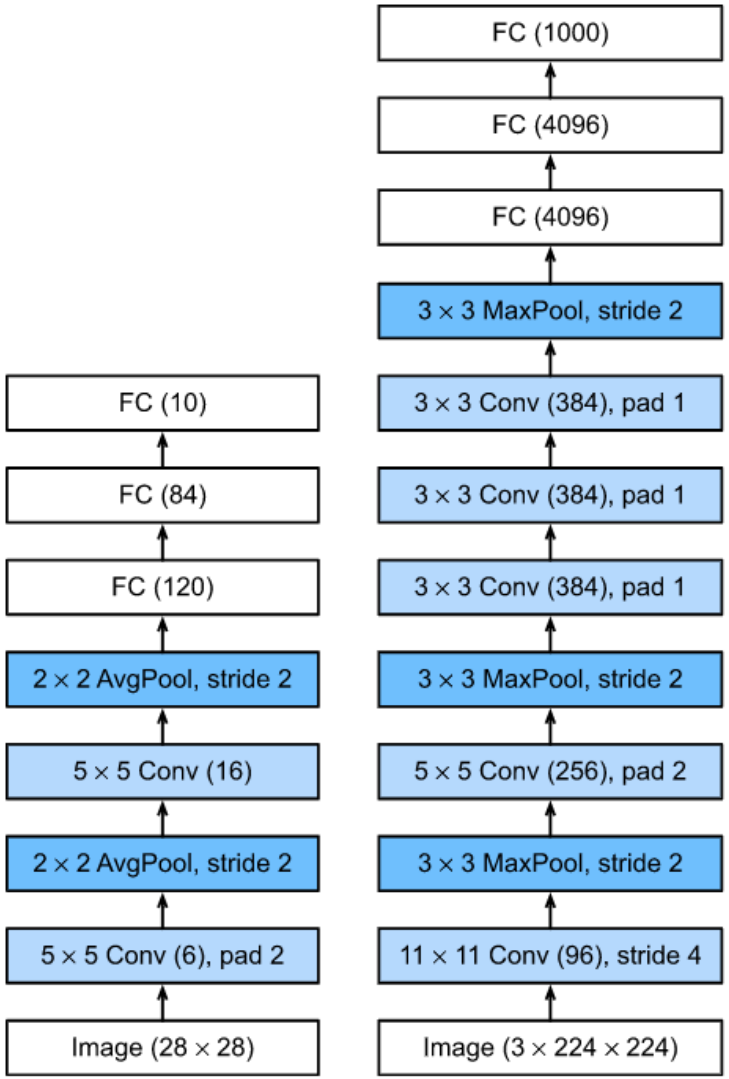
AlexNet – 2012 (PyTorch)



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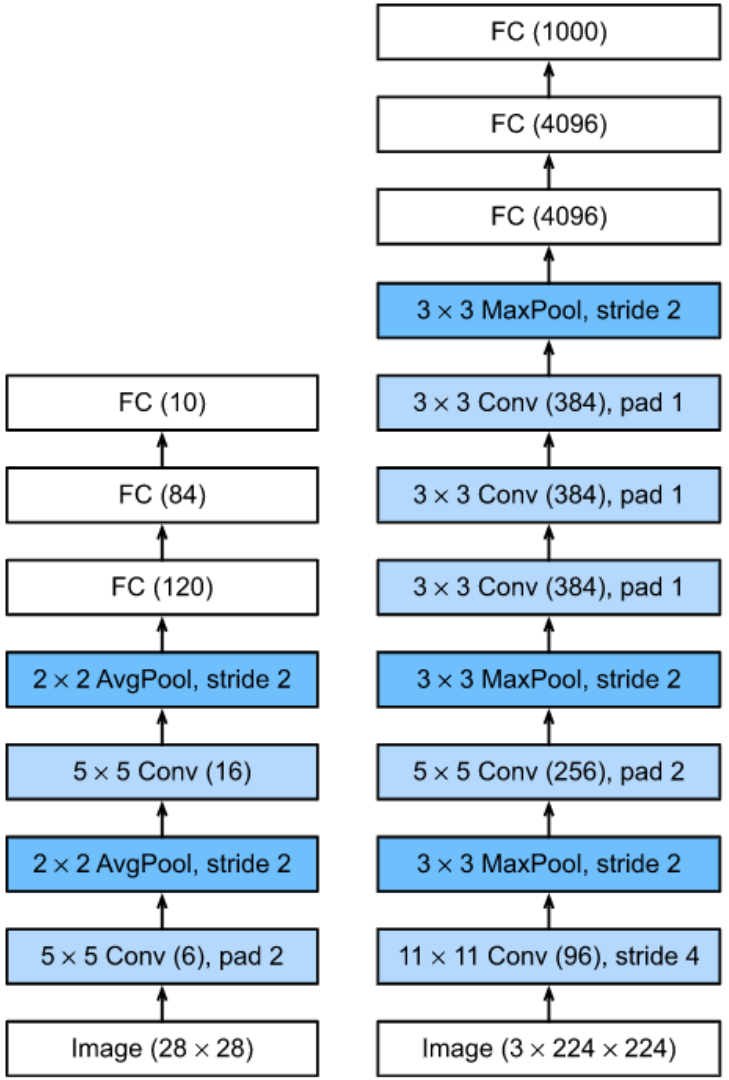
AlexNet – 2012 (PyTorch)

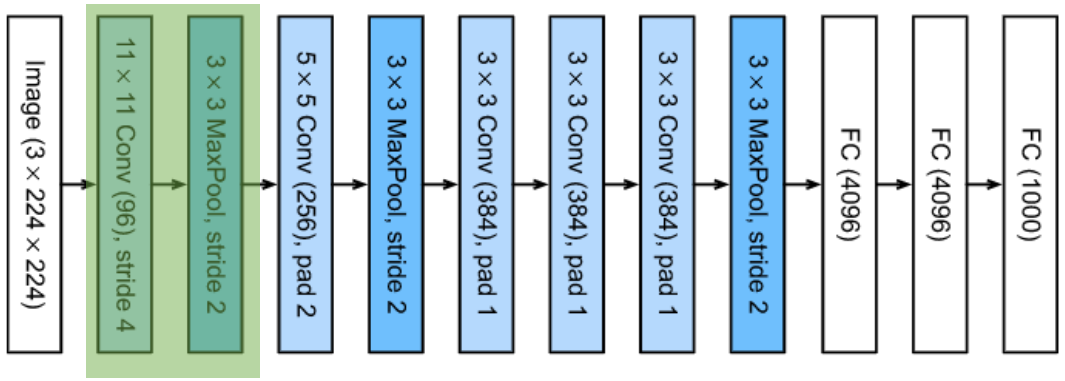
```
net = nn.Sequential(
    nn.Conv2d(3, 6, kernel_size=5, padding=0, stride=1),
    nn.ReLU(),
    nn.AvgPool2d(kernel_size=2, stride=2),
    nn.Conv2d(6, 16, kernel_size=5, padding=0, stride=1),
    nn.ReLU(),
    nn.AvgPool2d(kernel_size=2, stride=2),
    nn.Flatten(),
    nn.LazyLinear(120),
    nn.ReLU(),
    nn.LazyLinear(84),
    nn.ReLU(),
    nn.LazyLinear(2))
```



http://d2l.ai/chapter_convolutional-modern/alexnet.html

Krizhevsky, Alex & Sutskever, Ilya & Hinton, Geoffrey. (2012). ImageNet Classification with Deep Convolutional Neural Networks. Neural Information Processing Systems. 25. 10.1145/3065386.

AlexNet – 2012 (PyTorch)




```
net = nn.Sequential(
)
```

http://d2l.ai/chapter_convolutional-modern/alexnet.html

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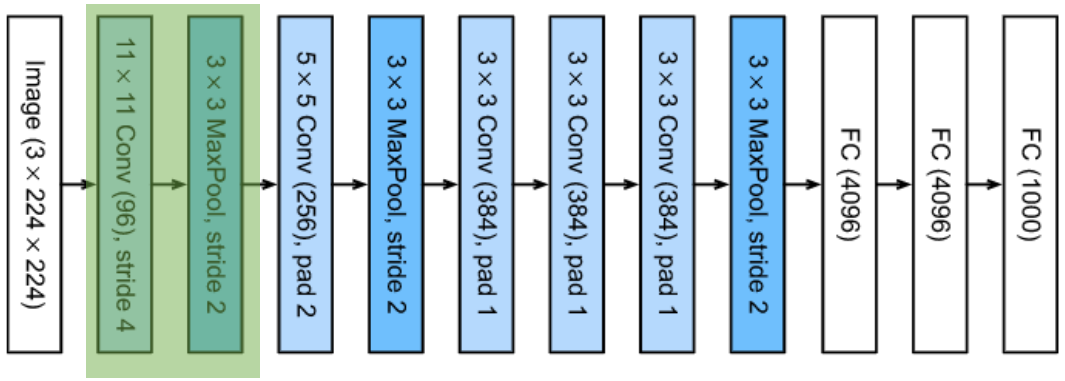


```
net = nn.Sequential(
    nn.Conv2d(3, 96, kernel_size=11, stride=4, padding=1),
    nn.ReLU(),
    nn.MaxPool2d(kernel_size=3, stride=2),
    )
```

http://d2l.ai/chapter_convolutional-modern/alexnet.html

Krizhevsky, Alex & Sutskever, Ilya & Hinton, Geoffrey. (2012). ImageNet Classification with Deep Convolutional Neural Networks. Neural Information Processing Systems. 25. 10.1145/3065386.

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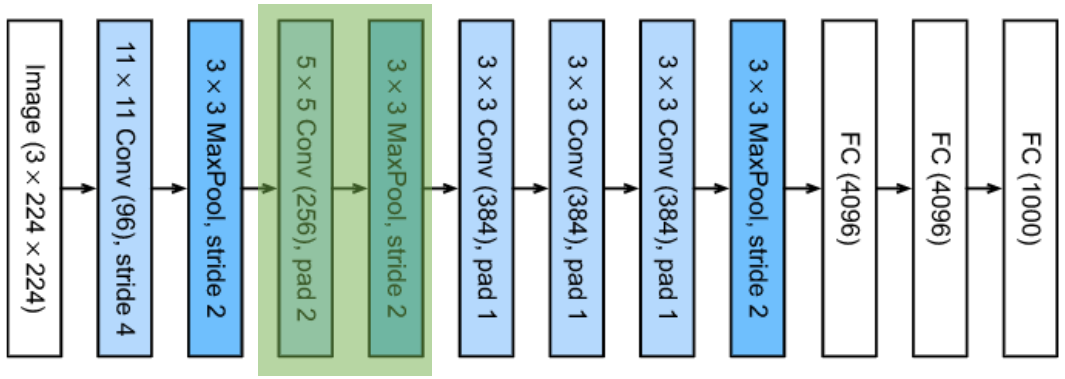
AlexNet – 2012 (PyTorch)




```
net = nn.Sequential(
    nn.Conv2d(3, 96, kernel_size=11, stride=4, padding=1),
    nn.ReLU(),
    nn.MaxPool2d(kernel_size=3, stride=2),
    nn.Conv2d(96, 256, kernel_size=5, padding=2),
    nn.ReLU(),
    nn.MaxPool2d(kernel_size=3, stride=2),
    )
```

http://d2l.ai/chapter_convolutional-modern/alexnet.html

Krizhevsky, Alex & Sutskever, Ilya & Hinton, Geoffrey. (2012). ImageNet Classification with Deep Convolutional Neural Networks. Neural Information Processing Systems. 25. 10.1145/3065386.

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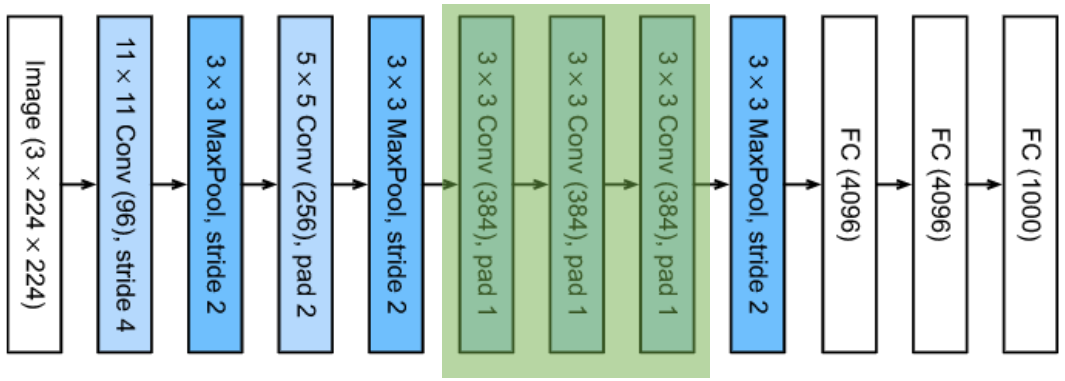
AlexNet – 2012 (PyTorch)




```
net = nn.Sequential(
    nn.Conv2d(3, 96, kernel_size=11, stride=4, padding=1),
    nn.ReLU(),
    nn.MaxPool2d(kernel_size=3, stride=2),
    nn.Conv2d(96, 256, kernel_size=5, padding=2),
    nn.ReLU(),
    nn.MaxPool2d(kernel_size=3, stride=2),
    nn.Conv2d(256, 384, kernel_size=3, padding=1),
    nn.ReLU(),
    nn.Conv2d(384, 384, kernel_size=3, padding=1),
    nn.ReLU(),
    nn.Conv2d(384, 256, kernel_size=3, padding=1),
    nn.ReLU(),
    )
```

http://d2l.ai/chapter_convolutional-modern/alexnet.html

Krizhevsky, Alex & Sutskever, Ilya & Hinton, Geoffrey. (2012). ImageNet Classification with Deep Convolutional Neural Networks. Neural Information Processing Systems. 25. 10.1145/3065386.

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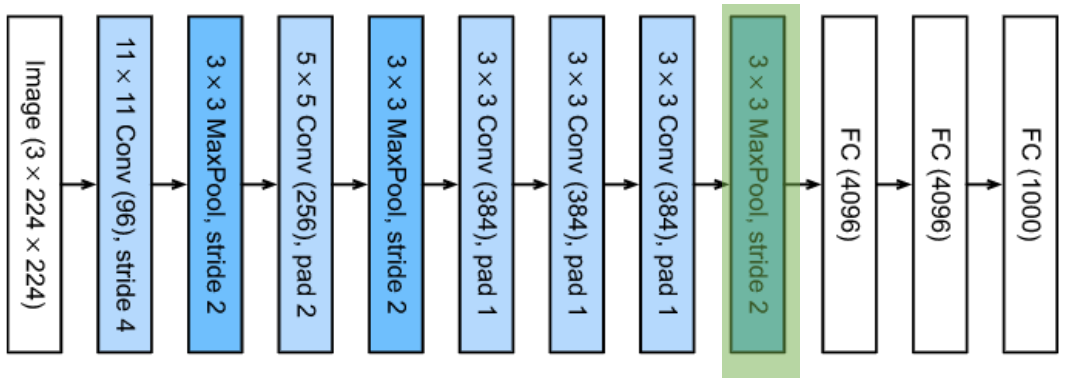
AlexNet – 2012 (PyTorch)




```
net = nn.Sequential(
    nn.Conv2d(3, 96, kernel_size=11, stride=4, padding=1),
    nn.ReLU(),
    nn.MaxPool2d(kernel_size=3, stride=2),
    nn.Conv2d(96, 256, kernel_size=5, padding=2),
    nn.ReLU(),
    nn.MaxPool2d(kernel_size=3, stride=2),
    nn.Conv2d(256, 384, kernel_size=3, padding=1),
    nn.ReLU(),
    nn.Conv2d(384, 384, kernel_size=3, padding=1),
    nn.ReLU(),
    nn.Conv2d(384, 256, kernel_size=3, padding=1),
    nn.ReLU(),
    nn.MaxPool2d(kernel_size=3, stride=2),
    nn.Flatten(),
    
    )
```

http://d2l.ai/chapter_convolutional-modern/alexnet.html

Krizhevsky, Alex & Sutskever, Ilya & Hinton, Geoffrey. (2012). ImageNet Classification with Deep Convolutional Neural Networks. Neural Information Processing Systems. 25. 10.1145/3065386.

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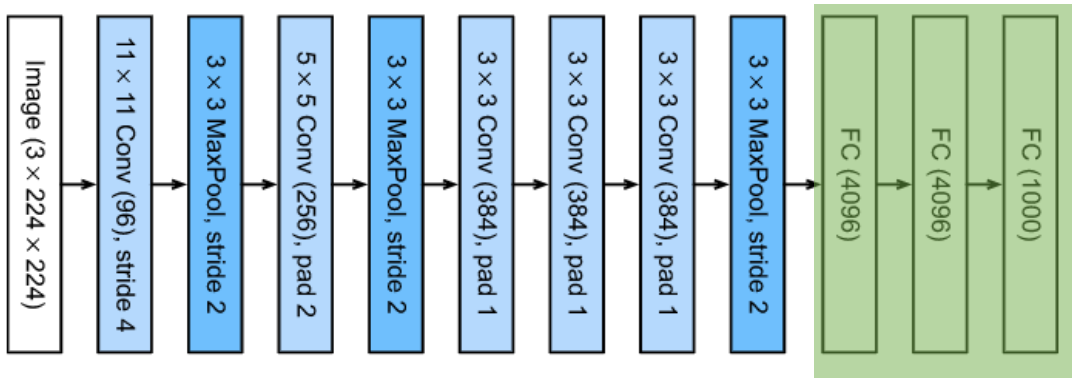
AlexNet – 2012 (PyTorch)




```
net = nn.Sequential(
    nn.Conv2d(3, 96, kernel_size=11, stride=4, padding=1),
    nn.ReLU(),
    nn.MaxPool2d(kernel_size=3, stride=2),
    nn.Conv2d(96, 256, kernel_size=5, padding=2),
    nn.ReLU(),
    nn.MaxPool2d(kernel_size=3, stride=2),
    nn.Conv2d(256, 384, kernel_size=3, padding=1),
    nn.ReLU(),
    nn.Conv2d(384, 384, kernel_size=3, padding=1),
    nn.ReLU(),
    nn.Conv2d(384, 256, kernel_size=3, padding=1),
    nn.ReLU(),
    nn.MaxPool2d(kernel_size=3, stride=2),
    nn.Flatten(),
    nn.Linear(6400, 4096),
    nn.ReLU(),
    nn.Dropout(p=0.5),
    nn.Linear(4096, 4096),
    nn.ReLU(),
    nn.Dropout(p=0.5),
    nn.Linear(4096, 2)
    )
```

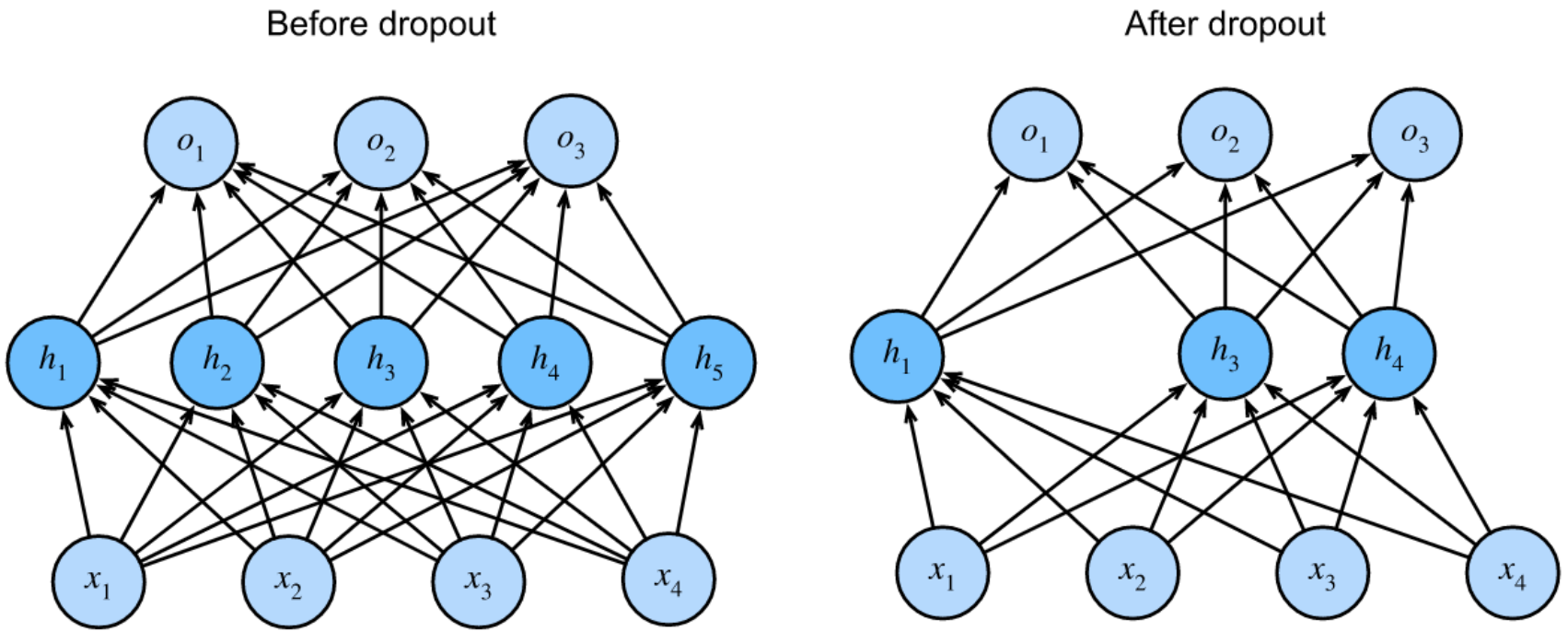
http://d2l.ai/chapter_convolutional-modern/alexnet.html

Krizhevsky, Alex & Sutskever, Ilya & Hinton, Geoffrey. (2012). ImageNet Classification with Deep Convolutional Neural Networks. Neural Information Processing Systems. 25. 10.1145/3065386.

AlexNet - 2012

DROPOUT

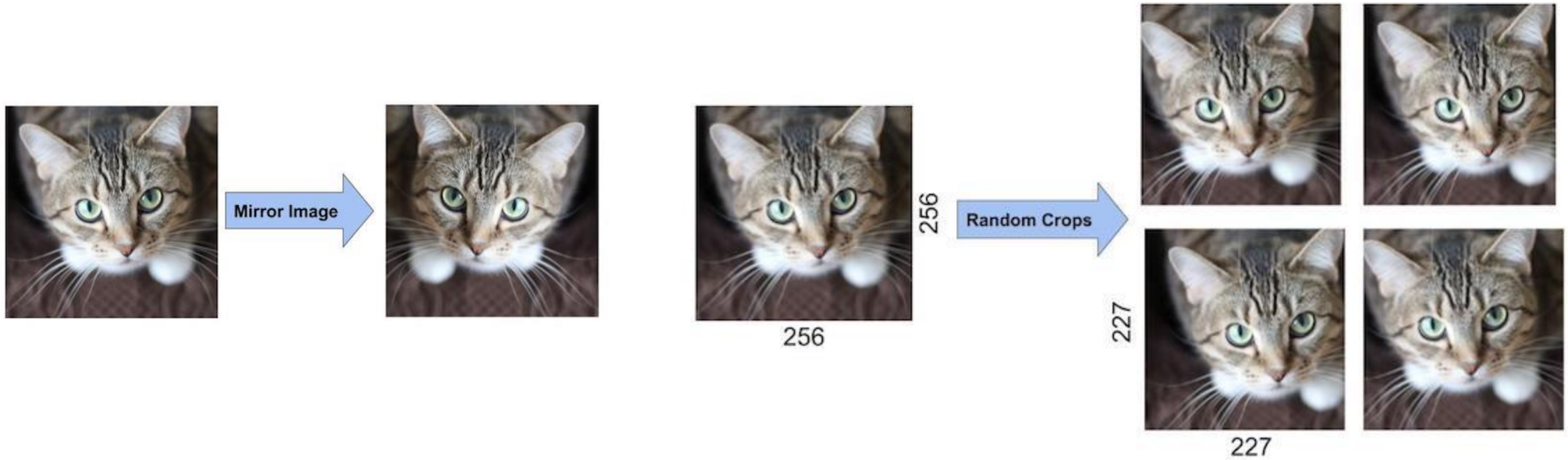
- in some situations, the model is larger than we need – the model can be modified manually or using dropout technique
- ***drop out*** some neurons during training to avoid overfitting
- randomly **dropping out neurons**
  - neuron is dropped from the network with a probability of 0.5



Geoffrey E. Hinton, Nitish Srivastava, Alex Krizhevsky, Ilya Sutskever, Ruslan Salakhutdinov: Improving neural networks by preventing co-adaptation of feature detectors. CoRR abs/1207.0580 (2012)
https://www.learnopencv.com/understanding-alexnet/
http://d2l.ai/chapter_multilayer-perceptrons/dropout.html#sec-dropout
Krizhevsky, Alex & Sutskever, Ilya & Hinton, Geoffrey. (2012). ImageNet Classification with Deep Convolutional Neural Networks. Neural Information Processing Systems. 25. 10.1145/3065386.

AlexNet - 2012

Data Augmentation



https://www.learnopencv.com/understanding-alexnet/
http://d2l.ai/chapter_multilayer-perceptrons/dropout.html#sec-dropout

Krizhevsky, Alex & Sutskever, Ilya & Hinton, Geoffrey. (2012). ImageNet Classification with Deep Convolutional Neural Networks. Neural Information Processing Systems. 25. 10.1145/3065386.

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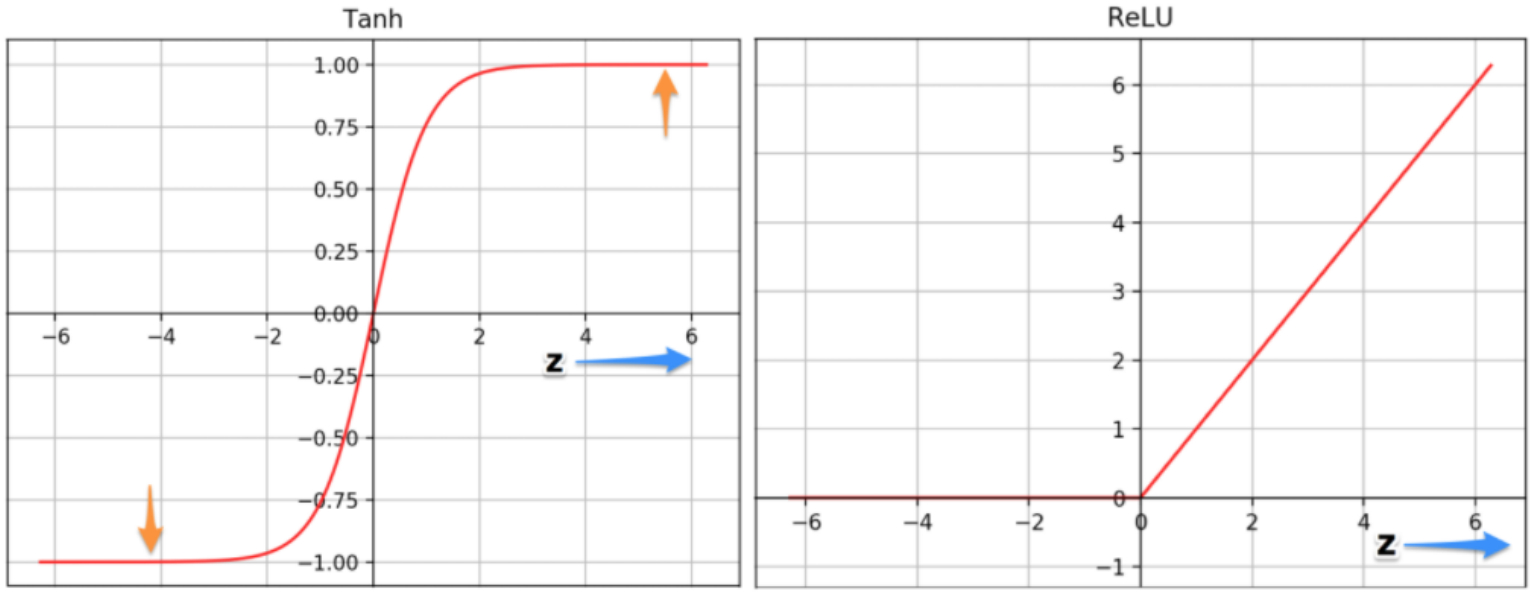
AlexNet - 2012

ReLU (Rectified Linear Unit)



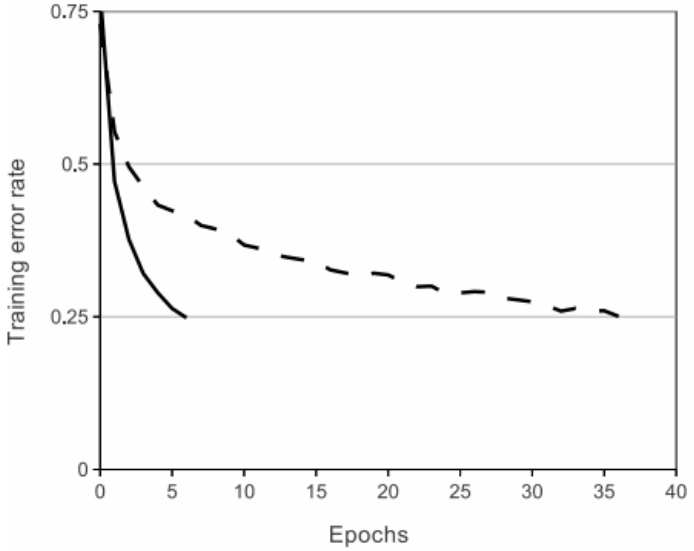


Figure 1: A four-layer convolutional neural network with ReLUs **(solid line)** reaches a 25% training error rate on CIFAR-10 six times faster than an equivalent network with tanh neurons **(dashed line)**. The learning rates for each network were chosen independently to make training as fast as possible. No regularization of any kind was employed. The magnitude of the effect demonstrated here varies with network architecture, but networks with ReLUs consistently learn several times faster than equivalents with saturating neurons.

https://www.learnopencv.com/understanding-alexnet/
http://d2l.ai/chapter_multilayer-perceptrons/dropout.html#sec-dropout

Krizhevsky, Alex & Sutskever, Ilya & Hinton, Geoffrey. (2012). ImageNet Classification with Deep Convolutional Neural Networks. Neural Information Processing Systems. 25. 10.1145/3065386.

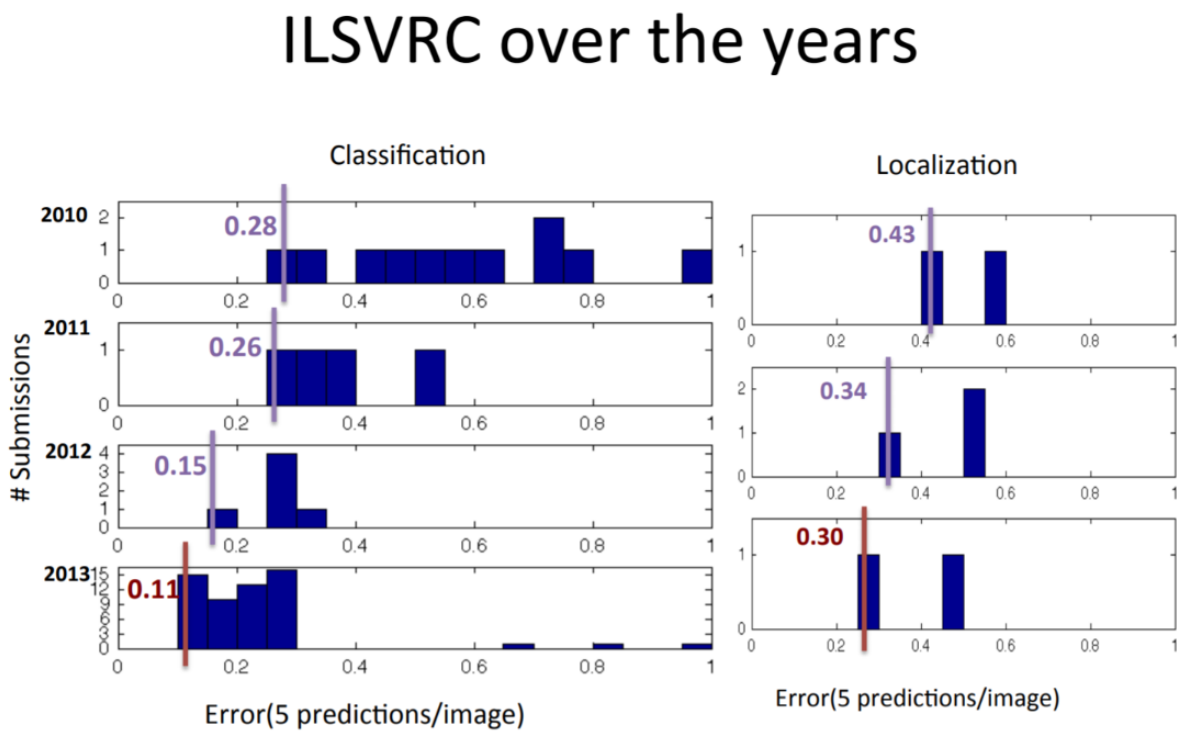
CovNet Architectures

- LeNet (1990s)
- AlexNet (2012)
- ZF Net (2013)
- VGGNet (2014)
- GoogLeNet (2014)
- ResNets (2015)
- DenseNet (2017)

ZFNet

2013

- http://image-net.org/challenges/LSVRC/2013/
- http://www.image-net.org/challenges/LSVRC/2013/slides/ILSVRC2013_12_7_13_clsloc.pdf



https://adeshpande3.github.io/The-9-Deep-Learning-Papers-You-Need-To-Know-About.html

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ZFNet

- Similar architecture to AlexNet
- 11x11 vs. 7x7 filters in the first layer
- Number of filters is increasing
- Visualization of features - Deconvolutional Network

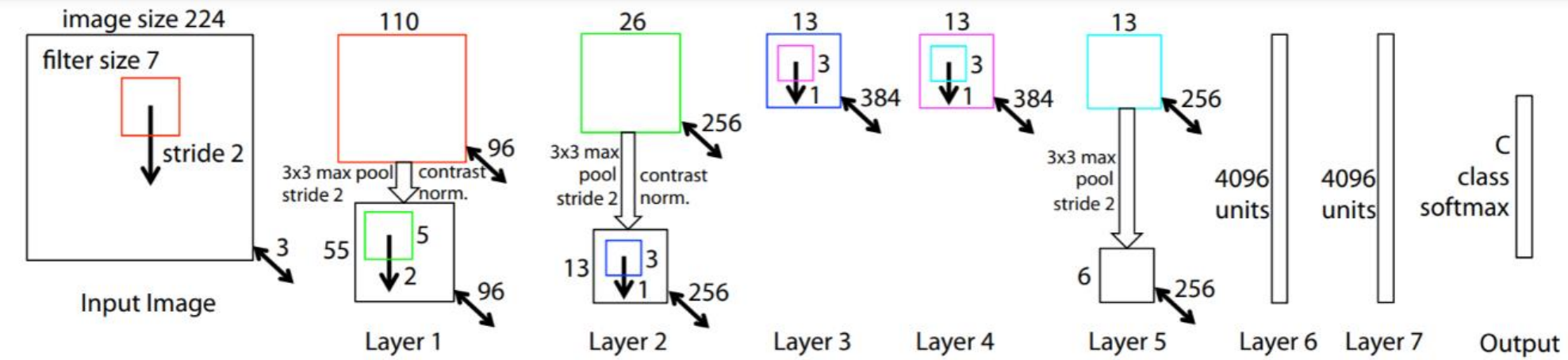

Figure 3. Architecture of our 8 layer convnet model. A 224 by 224 crop of an image (with 3 color planes) is presented as the input. This is convolved with 96 different 1st layer filters (red), each of size 7 by 7, using a stride of 2 in both x and y. The resulting feature maps are then: (i) passed through a rectified linear function (not shown), (ii) pooled (max within 3x3 regions, using stride 2) and (iii) contrast normalized across feature maps to give 96 different 55 by 55 element feature maps. Similar operations are repeated in layers 2,3,4,5. The last two layers are fully connected, taking features from the top convolutional layer as input in vector form ($6 \cdot 6 \cdot 256 = 9216$ dimensions). The final layer is a C-way softmax function, C being the number of classes. All filters and feature maps are square in shape.

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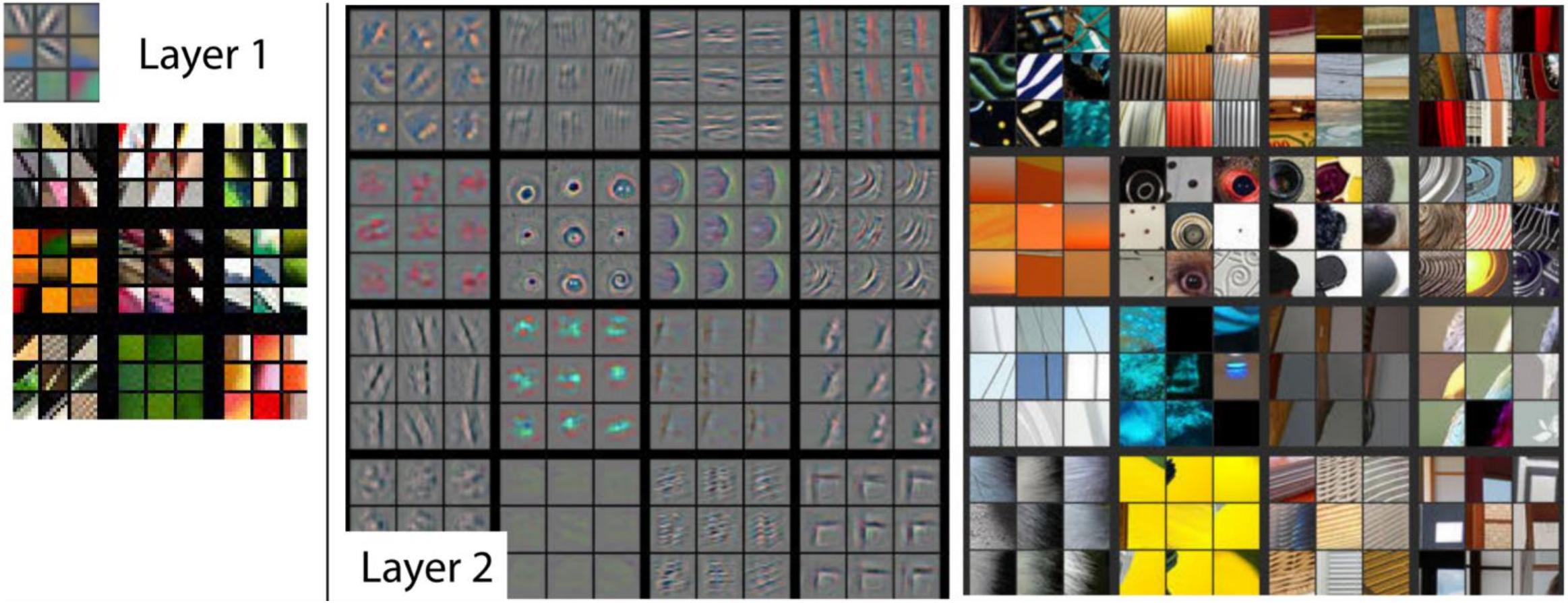
ZFNet

First Layers - low level feature detector (edge detector, circular features)



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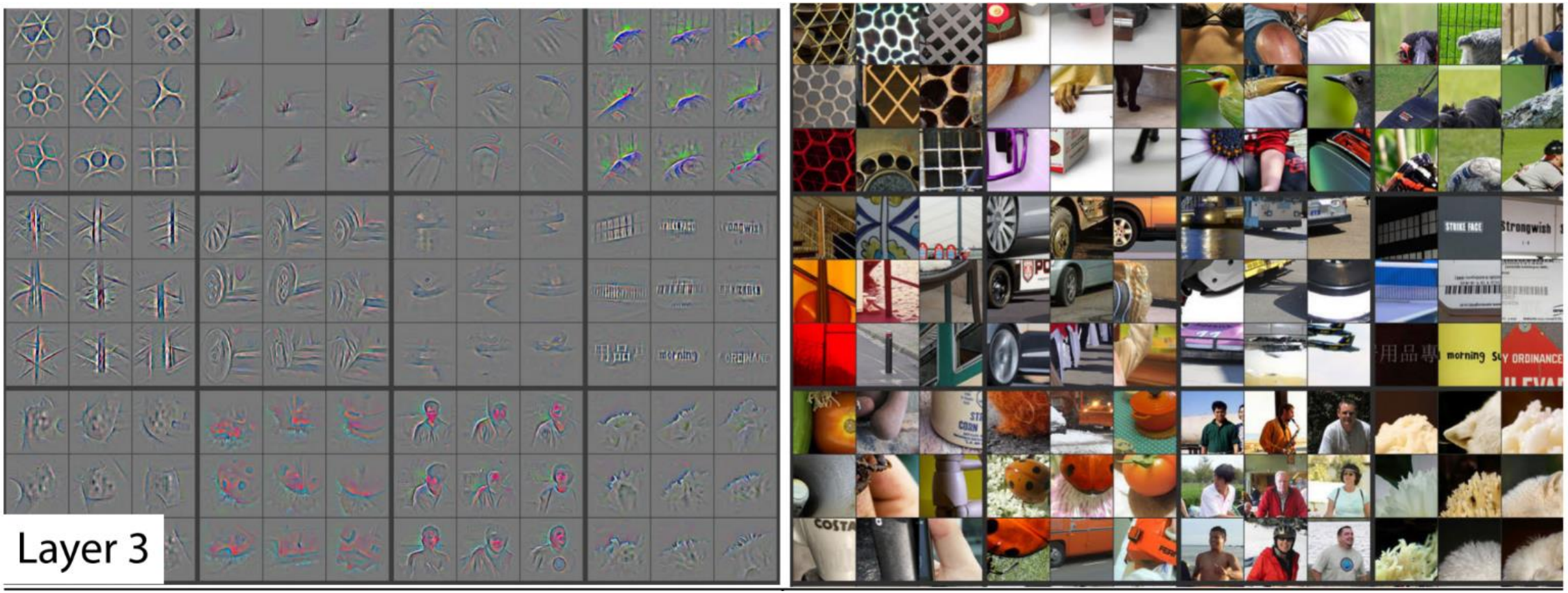
ZFNet

Deep Layers - higher level features such as dogs faces or flowers



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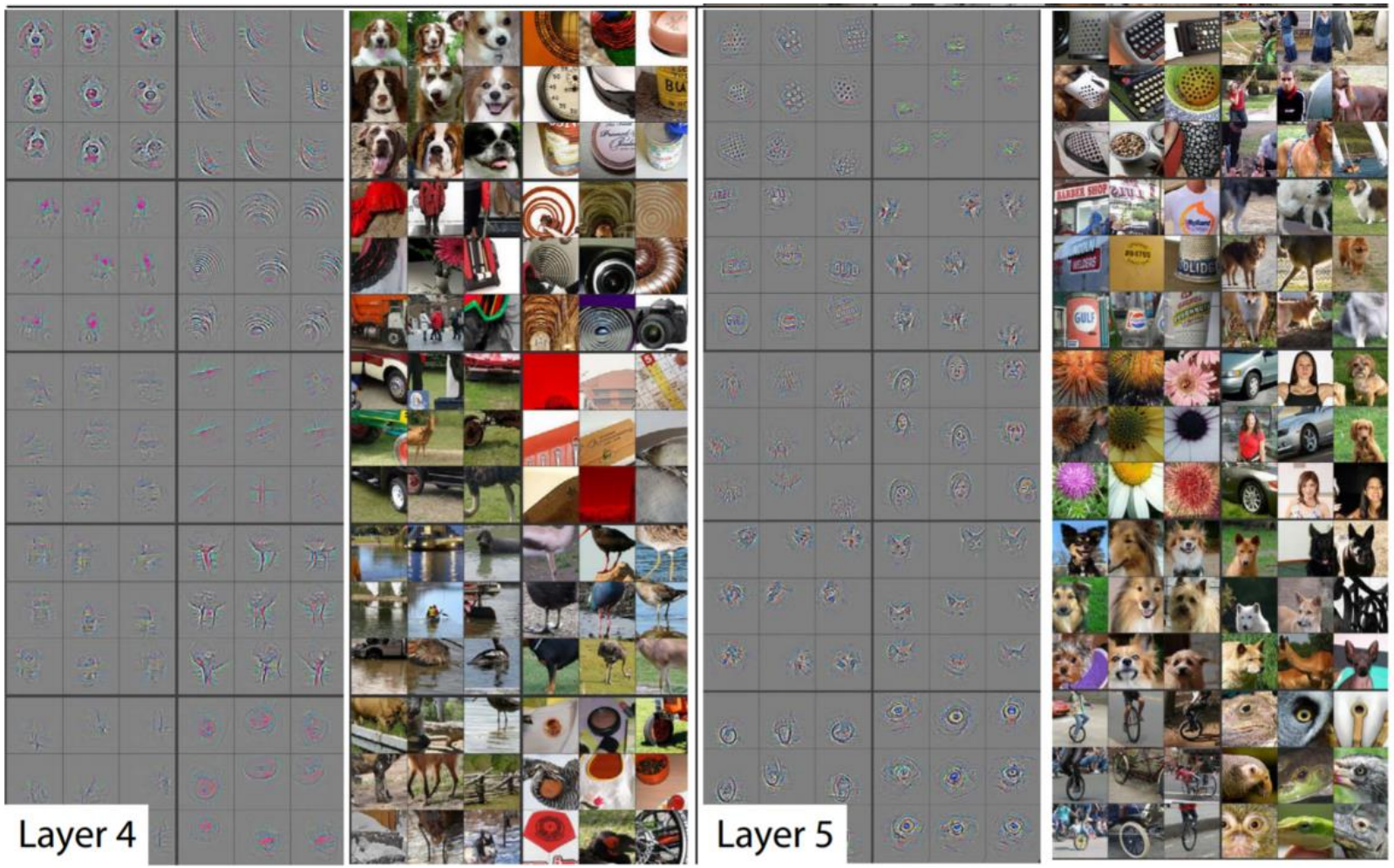

https://adeshpande3.github.io/The-9-Deep-Learning-Papers-You-Need-To-Know-About.html

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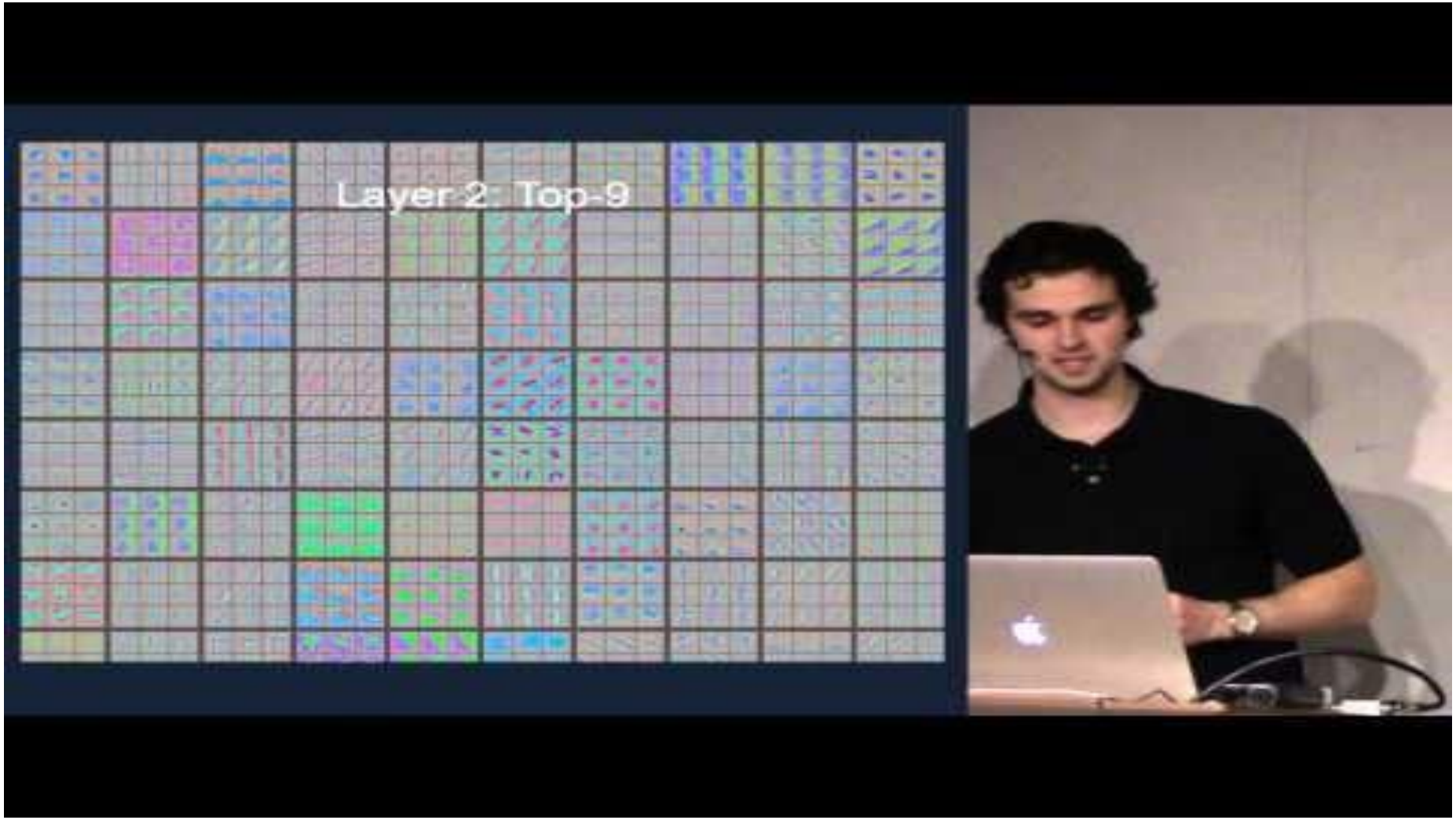
ZFNet

https://www.youtube.com/watch?reload=9&v=ghEmQSxT6tw



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CovNet Architectures

- LeNet (1990s)
- AlexNet (2012)
- ZF Net (2013)
- VGGNet (2014)
- GoogLeNet (2014)
- ResNets (2015)
- DenseNet (2017)

VGG - 2014

2014

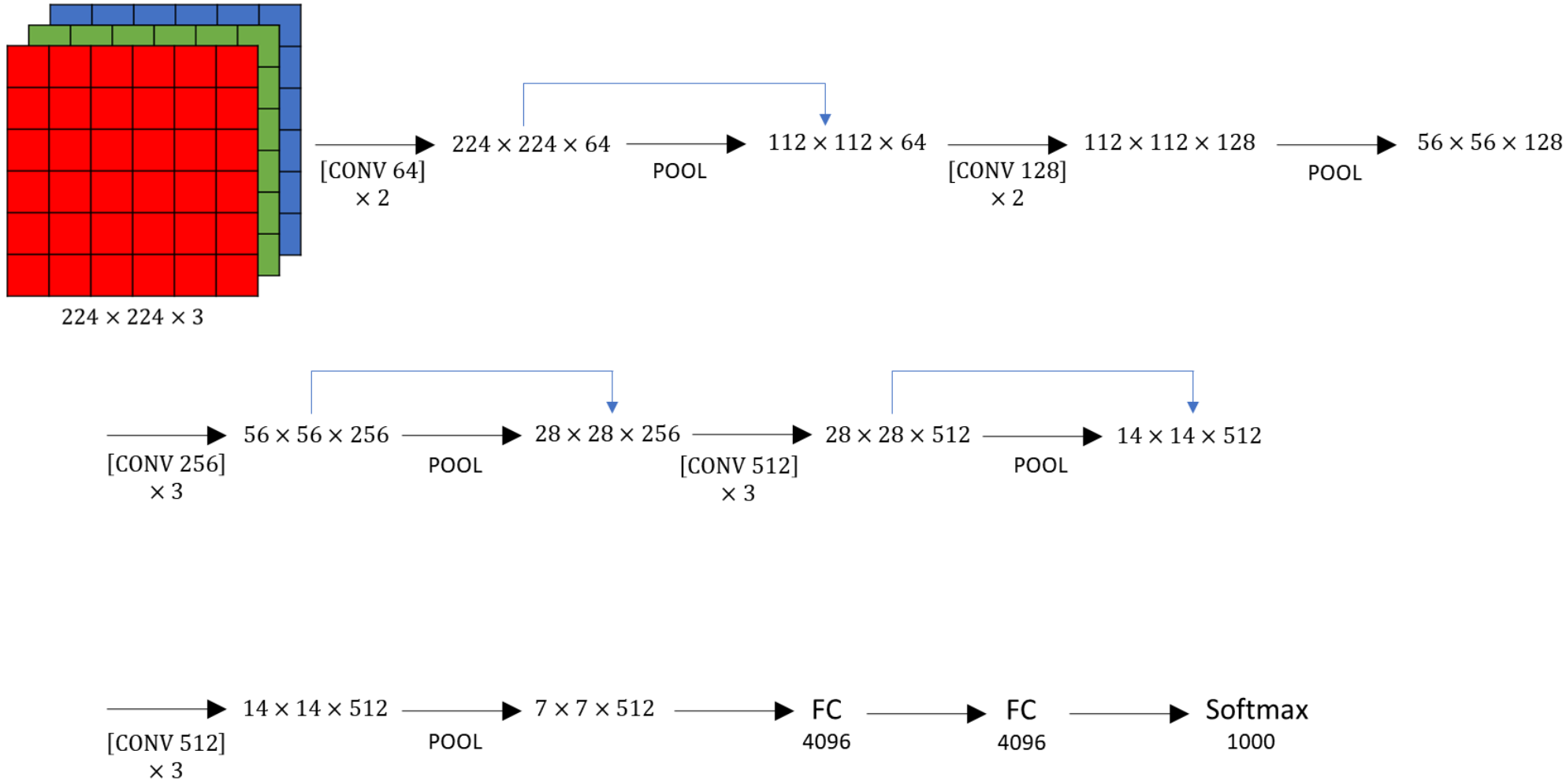
- ImageNet Challenge http://www.image-net.org/challenges/LSVRC/2014/
- http://www.image-net.org/challenges/LSVRC/2014/results
- **Idea:**
  - stack the convolutional layers with increasing filter sizes
  - 3 x 3 filter size stride of 1
  - MaxPooling 2 x 2 stride of 2
  - **VGG Block**
  - Dropout, MaxPooling, ReLu
  - On a system equipped with four NVIDIA Titan Black GPUs, training a single net took 2–3 weeks depending on the architecture

http://d2l.ai/chapter_convolutional-modern/vgg.html https://arxiv.org/pdf/1409.1556v6.pdf

Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*.

VGG - 2014

CONV = 3 x 3 filter, s=1, same MAX-POOL = 2 x 2, s=2



http://datahacker.rs/deep-learning-vgg-16-vs-vgg-19/

Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*.

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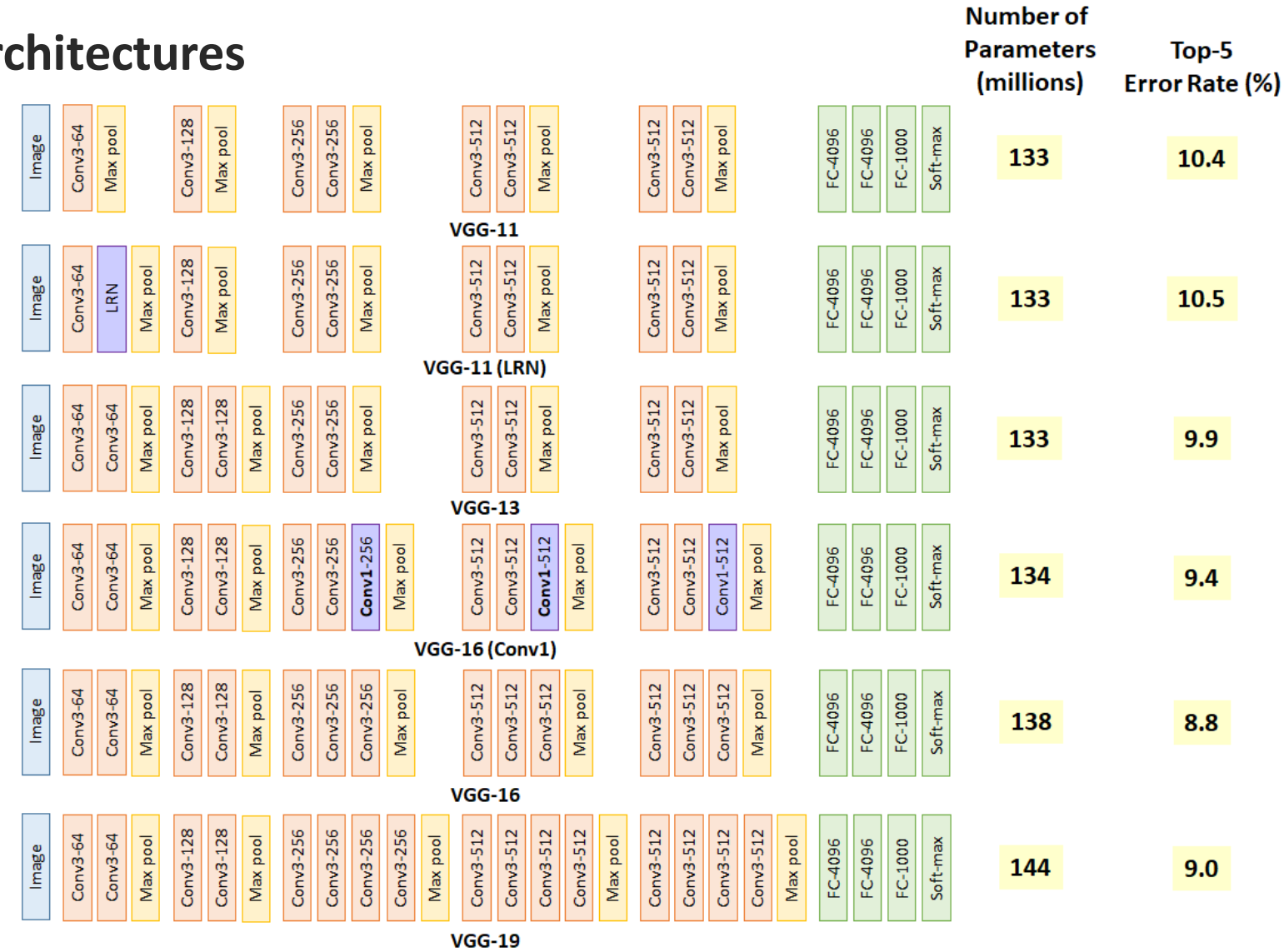
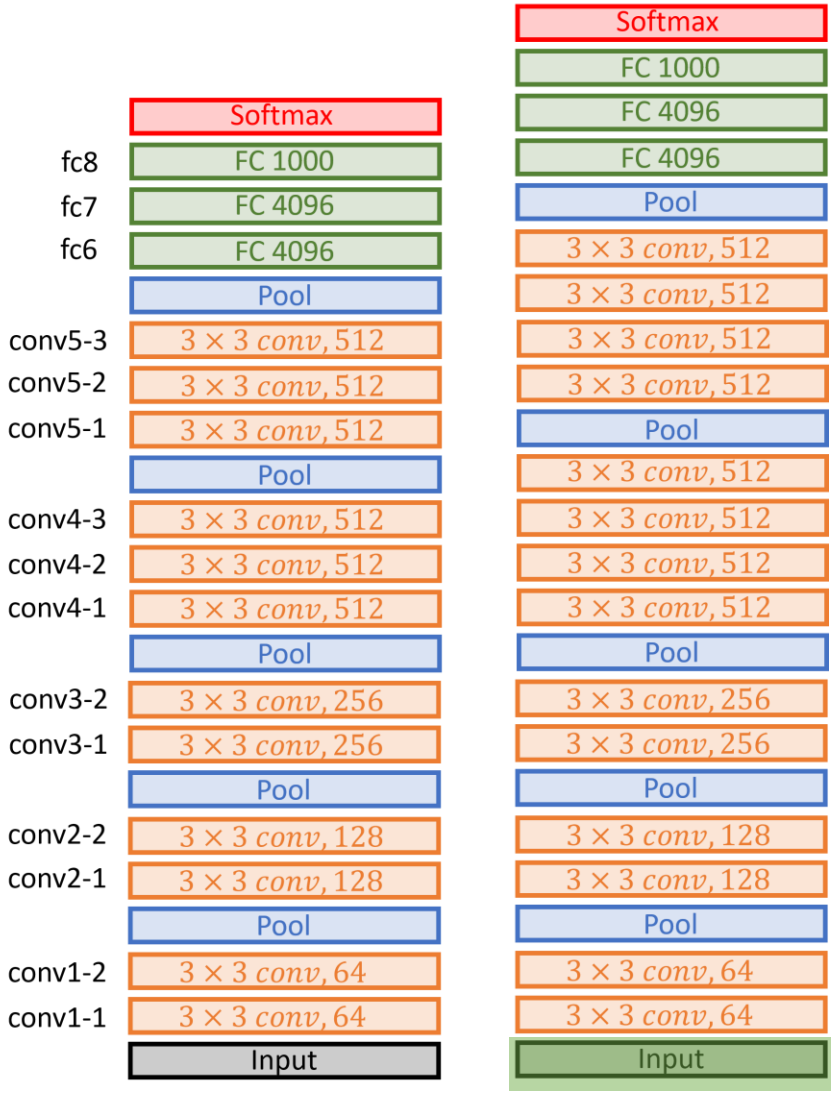
VGG - 2014

6 VGGNet Architectures



https://towardsdatascience.com/cnn-architectures-a-deep-dive-a99441d18049
http://d2l.ai/chapter_convolutional-modern/vgg.html
Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*.

VGG - 2014



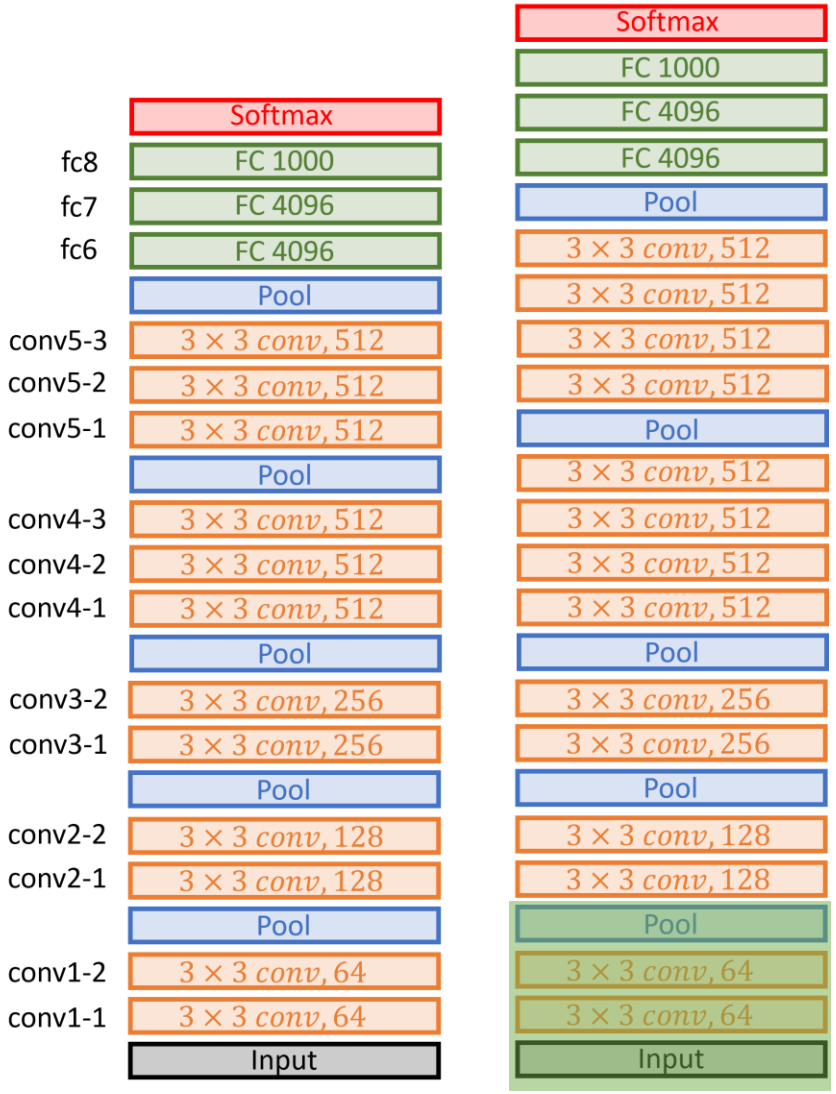

```
input<matrix<unsigned char>>
```

http://datahacker.rs/deep-learning-vgg-16-vs-vgg-19/

http://d2l.ai/chapter_convolutional-modern/vgg.html

Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*.

VGG - 2014




```
max_pool<2,2,2,2,
relu<con<64,3,3,1,1,
relu<con<64,3,3,1,1,
input<matrix<unsigned char>>
```

http://datahacker.rs/deep-learning-vgg-16-vs-vgg-19/

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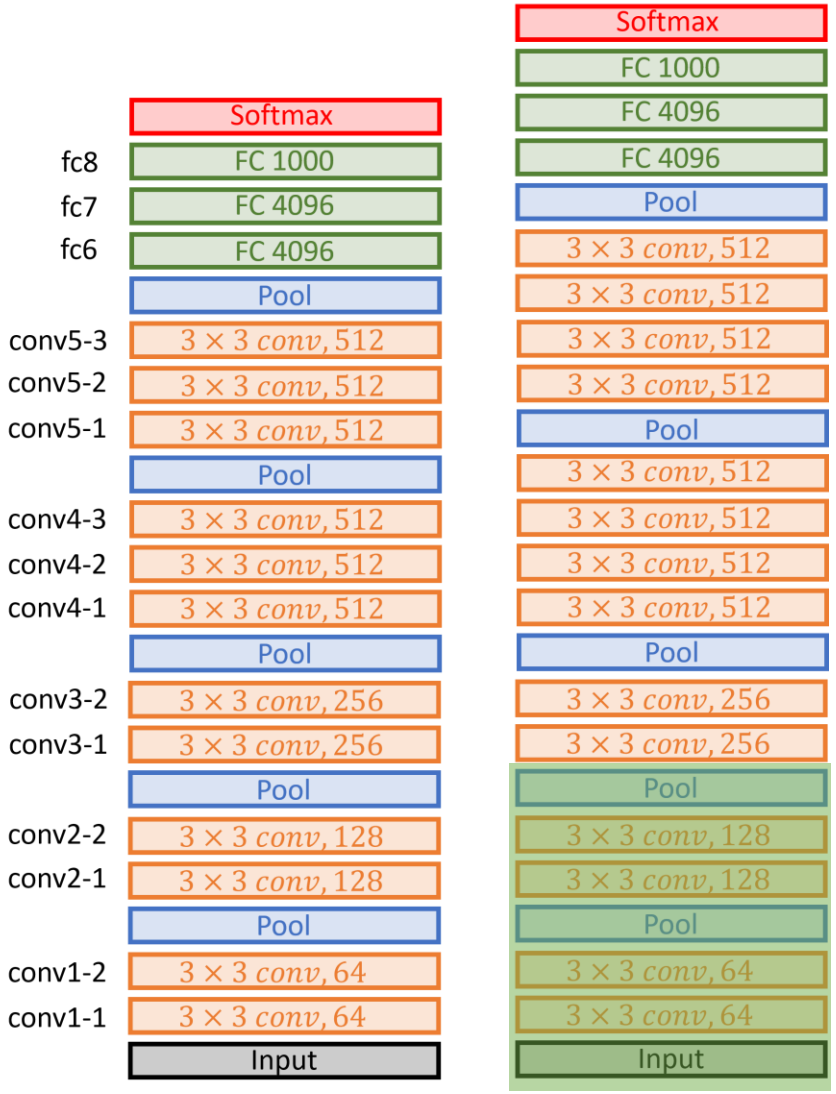
VGG - 2014




```
max_pool<2,2,2,2,
relu<con<128,3,3,1,1,
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relu<con<64,3,3,1,1,
input<matrix<unsigned char>>
```

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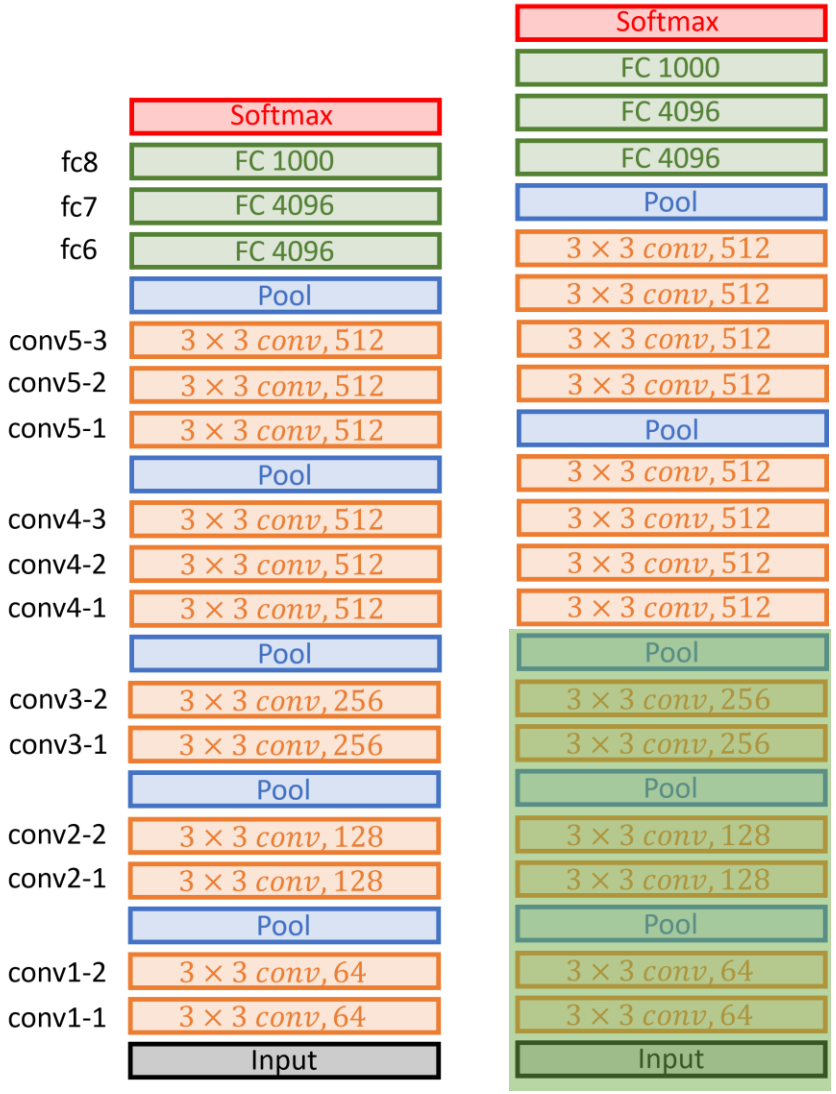
VGG - 2014




```
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input<matrix<unsigned char>>
```
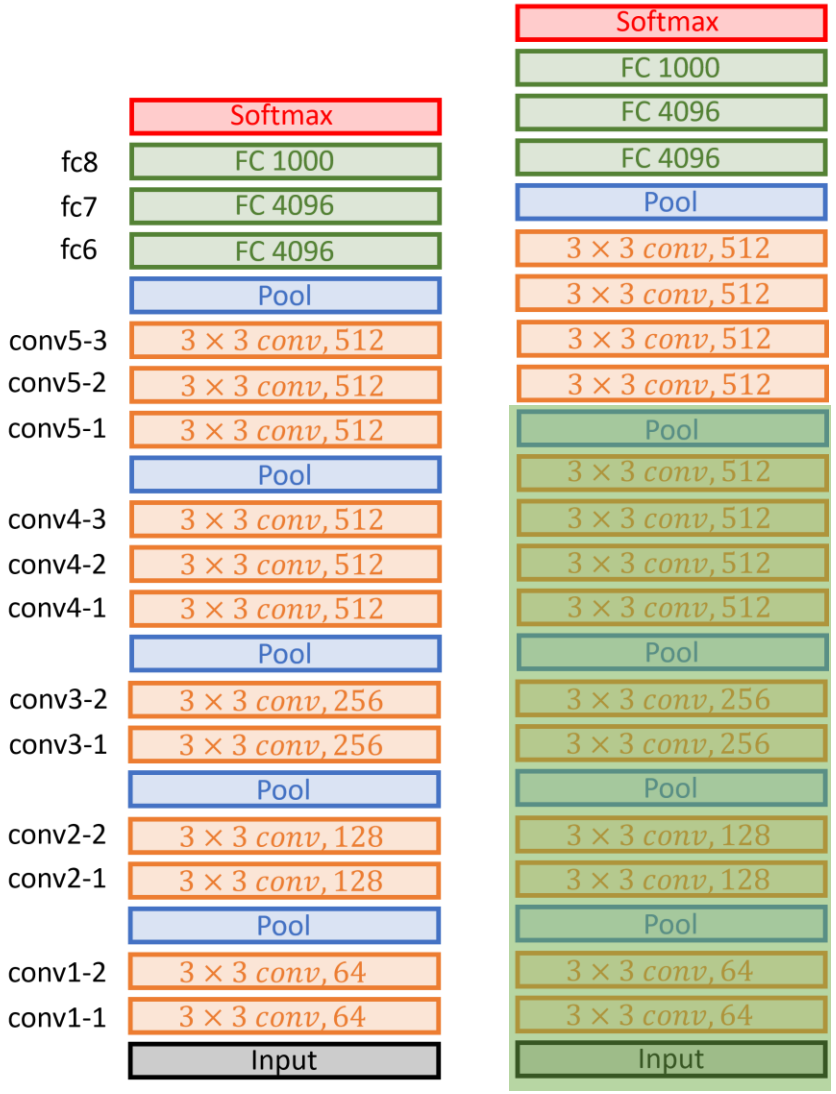

http://datahacker.rs/deep-learning-vgg-16-vs-vgg-19/

http://d2l.ai/chapter_convolutional-modern/vgg.html

Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*.

VGG - 2014




```
max_pool<2,2,2,2,
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max_pool<2,2,2,2,
relu<con<64,3,3,1,1,
relu<con<64,3,3,1,1,
input<matrix<unsigned char>>
```
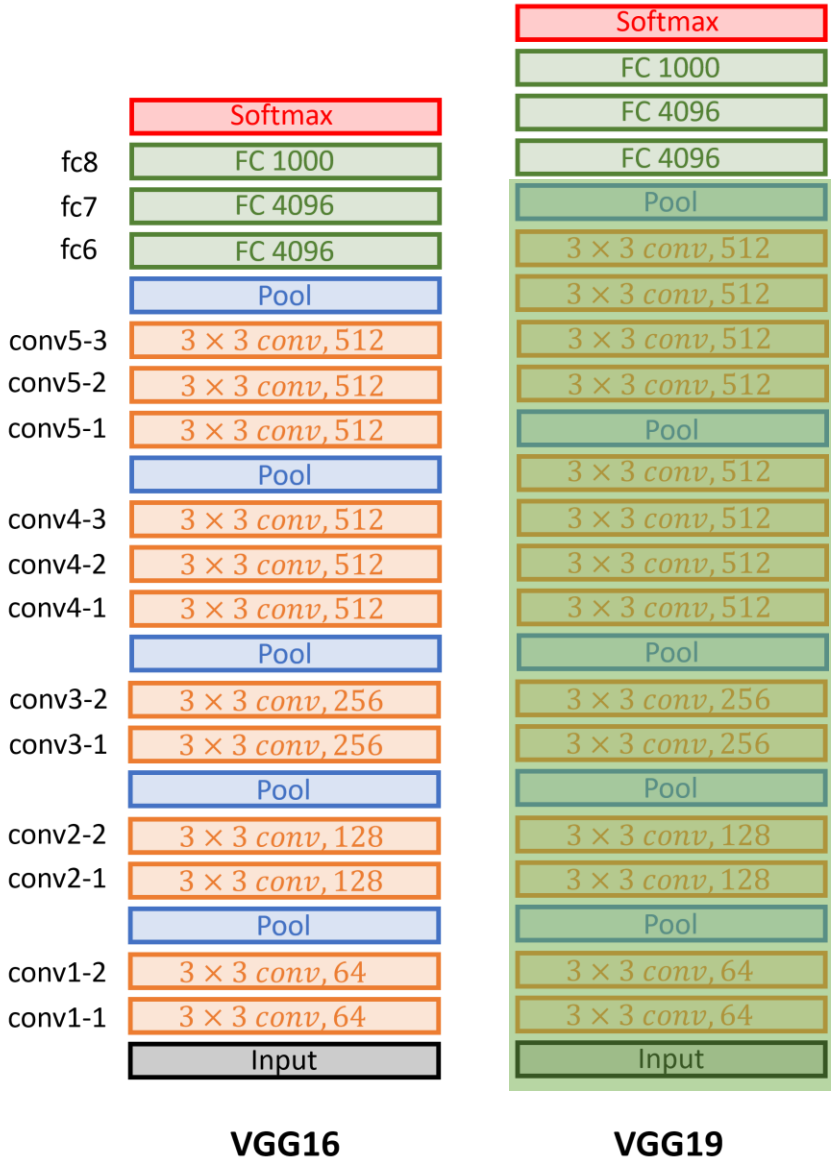

http://datahacker.rs/deep-learning-vgg-16-vs-vgg-19/

http://d2l.ai/chapter_convolutional-modern/vgg.html

Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*.

VGG - 2014




```
max_pool<2,2,2,2,
relu<con<512,3,3,1,1,
relu<con<512,3,3,1,1,
relu<con<512,3,3,1,1,
relu<con<512,3,3,1,1,
max_pool<2,2,2,2,
relu<con<512,3,3,1,1,
relu<con<512,3,3,1,1,
relu<con<512,3,3,1,1,
relu<con<512,3,3,1,1,
max_pool<2,2,2,2,
relu<con<256,3,3,1,1,
relu<con<256,3,3,1,1,
max_pool<2,2,2,2,
relu<con<128,3,3,1,1,
relu<con<128,3,3,1,1,
max_pool<2,2,2,2,
relu<con<64,3,3,1,1,
relu<con<64,3,3,1,1,
input<matrix<unsigned char>>
```

http://datahacker.rs/deep-learning-vgg-16-vs-vgg-19/

http://d2l.ai/chapter_convolutional-modern/vgg.html

Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*.

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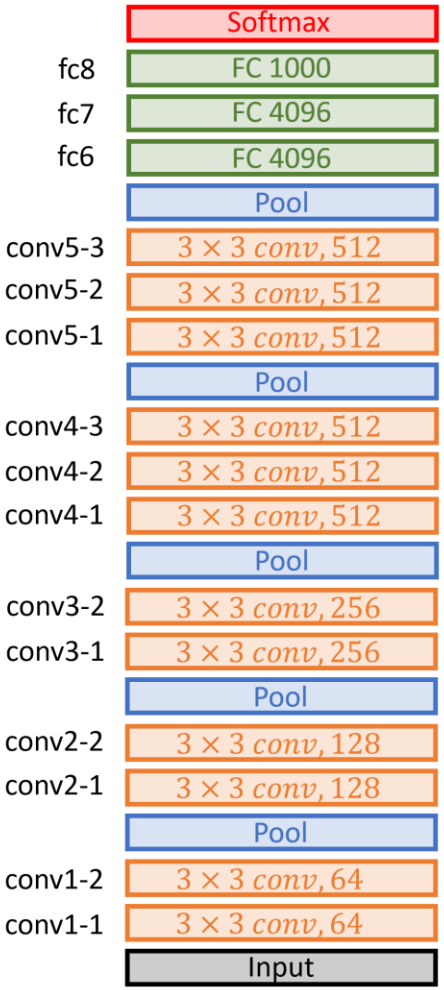
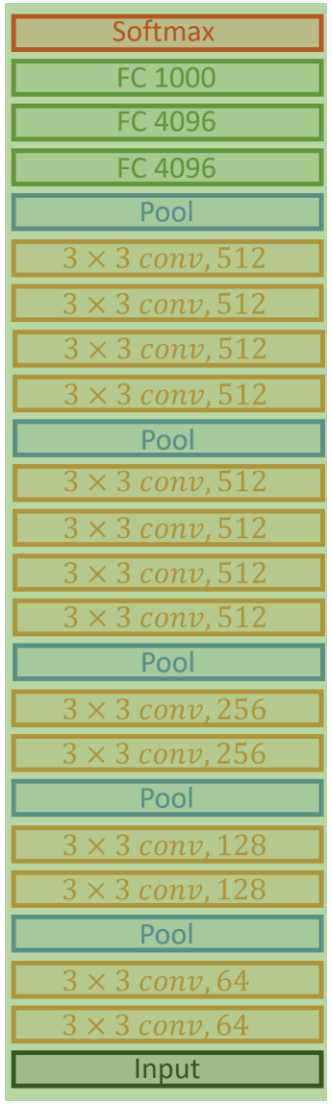
VGG - 2014



VGG16



VGG19

```
fc<1000,
dropout<relu<fc<4096,
dropout<relu<fc<4096,
max_pool<2,2,2,2,
relu<con<512,3,3,1,1,
relu<con<512,3,3,1,1,
relu<con<512,3,3,1,1,
relu<con<512,3,3,1,1,
max_pool<2,2,2,2,
relu<con<512,3,3,1,1,
relu<con<512,3,3,1,1,
relu<con<512,3,3,1,1,
relu<con<512,3,3,1,1,
max_pool<2,2,2,2,
relu<con<256,3,3,1,1,
relu<con<256,3,3,1,1,
max_pool<2,2,2,2,
relu<con<128,3,3,1,1,
relu<con<128,3,3,1,1,
max_pool<2,2,2,2,
relu<con<64,3,3,1,1,
relu<con<64,3,3,1,1,
input<matrix<unsigned char>>
```

http://datahacker.rs/deep-learning-vgg-16-vs-vgg-19/

http://d2l.ai/chapter_convolutional-modern/vgg.html

Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*.

VGG - 2014

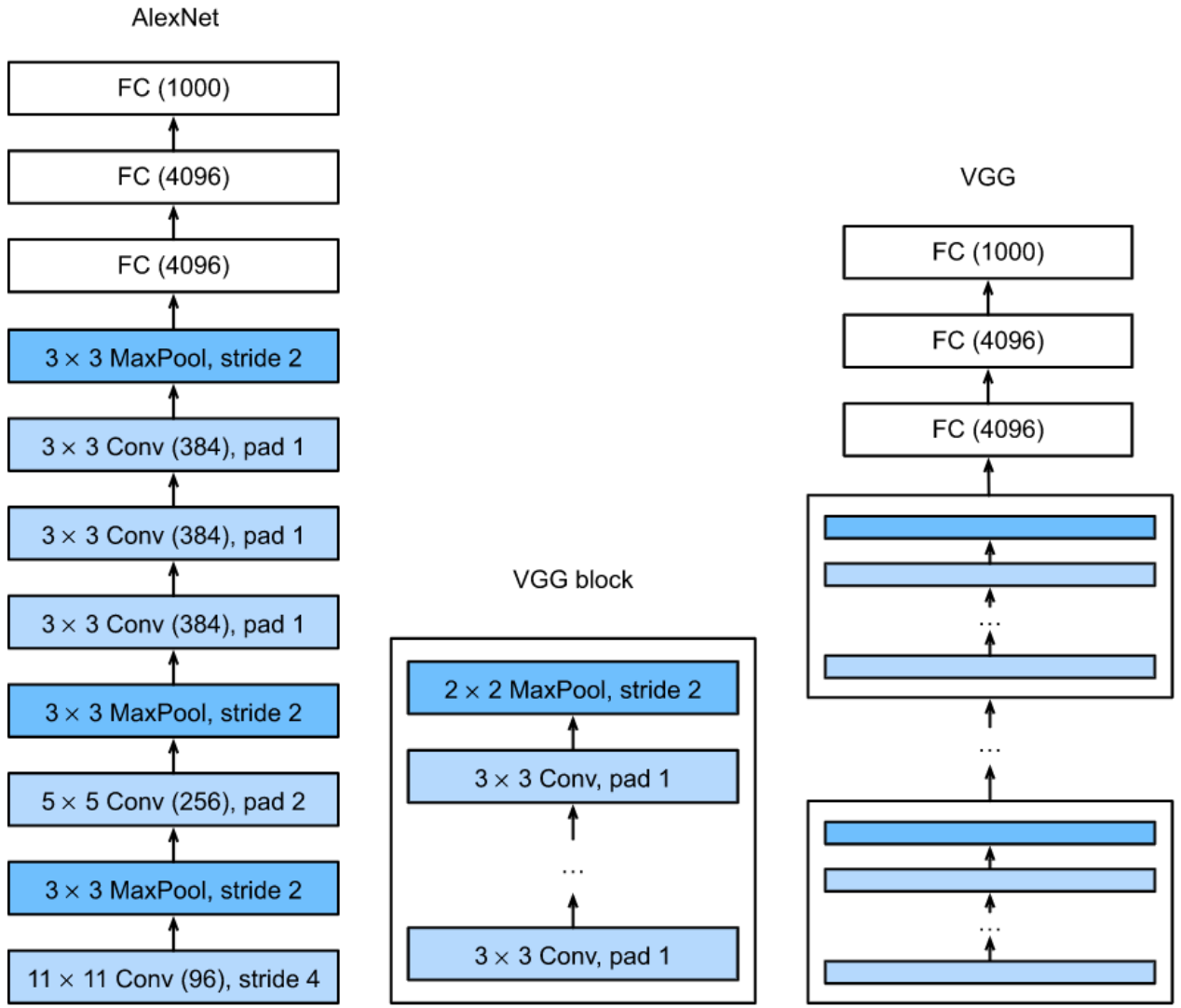
```
using net_type_vgg = loss_multiclass_log<
                                fc<2,
                                dropout<relu<fc<4096,
                                dropout<relu<fc<4096,
                                max_pool<2,2,2,2,
                                relu<con<128,3,3,1,1,
                                relu<con<128,3,3,1,1,
                                max_pool<2,2,2,2,
                                relu<con<64,3,3,1,1,
                                relu<con<64,3,3,1,1,
                                max_pool<2,2,2,2,
                                relu<con<32,3,3,1,1,
                                relu<con<32,3,3,1,1,
                                max_pool<2,2,2,2,
                                relu<con<16,3,3,1,1,
                                relu<con<16,3,3,1,1,
                                max_pool<2,2,2,2,
                                relu<con<8,3,3,1,1,
                                relu<con<8,3,3,1,1,
                                input<matrix<unsigned char>>
                                >>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>>;
```

http://datahacker.rs/deep-learning-vgg-16-vs-vgg-19/

http://d2l.ai/chapter_convolutional-modern/vgg.html

Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*.

VGG - 2014



http://datahacker.rs/deep-learning-vgg-16-vs-vgg-19/

http://d2l.ai/chapter_convolutional-modern/vgg.html

Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*.

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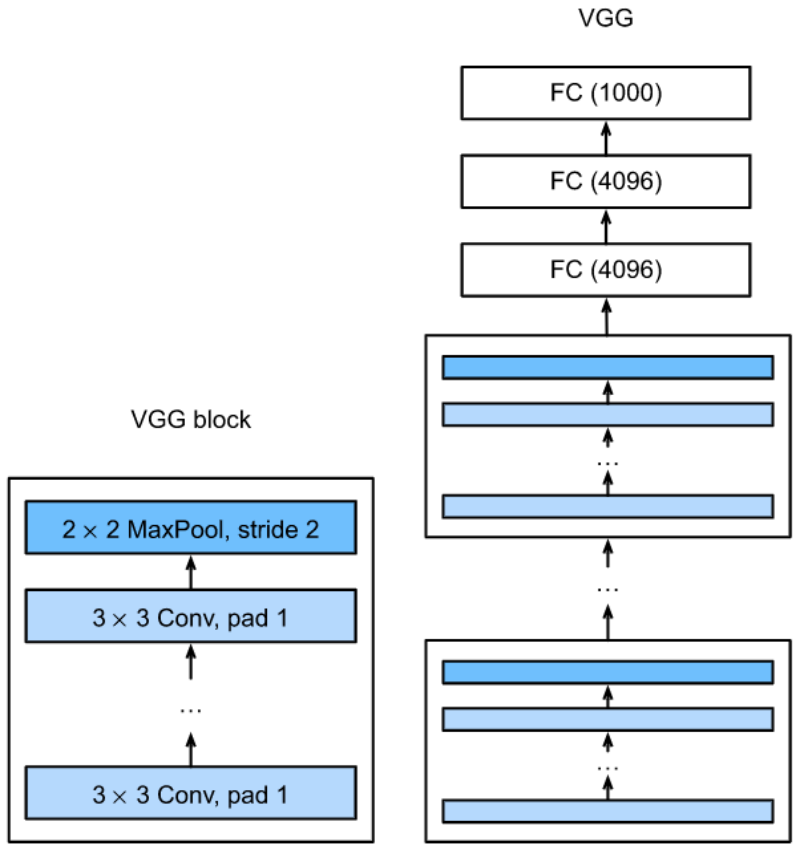
VGG - 2014

```
template <typename SUBNET> using block_1 = max_pool<2,2,2,2, relu<con<8,3,3,1,1, relu<con<8,3,3,1,1, SUBNET>>>>>;
template <typename SUBNET> using block_2 = max_pool<2,2,2,2, relu<con<16,3,3,1,1, relu<con<16,3,3,1,1, SUBNET>>>>>;
template <typename SUBNET> using block_3 = max_pool<2,2,2,2, relu<con<32,3,3,1,1, relu<con<32,3,3,1,1, SUBNET>>>>>;
template <typename SUBNET> using block_4 = max_pool<2,2,2,2, relu<con<64,3,3,1,1, relu<con<64,3,3,1,1, SUBNET>>>>>;
template <typename SUBNET> using block_5 = max_pool<2,2,2,2, relu<con<128,3,3,1,1, relu<con<128,3,3,1,1, SUBNET>>>>>;
```

```
using net_type_vgg_3 = loss_multiclass_log<
                        fc<2,
                        dropout<relu<fc<4096,
                        dropout<relu<fc<4096,
                        block_5<
                        block_4<
                        block_3<
                        block_2<
                        block_1<
                        input<matrix<unsigned char>>
                        >>>>>>>>>>>>>;
```



http://dlib.net/dnn_introduction2_ex.cpp.html

http://datahacker.rs/deep-learning-vgg-16-vs-vgg-19/

http://d2l.ai/chapter_convolutional-modern/vgg.html

Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*.

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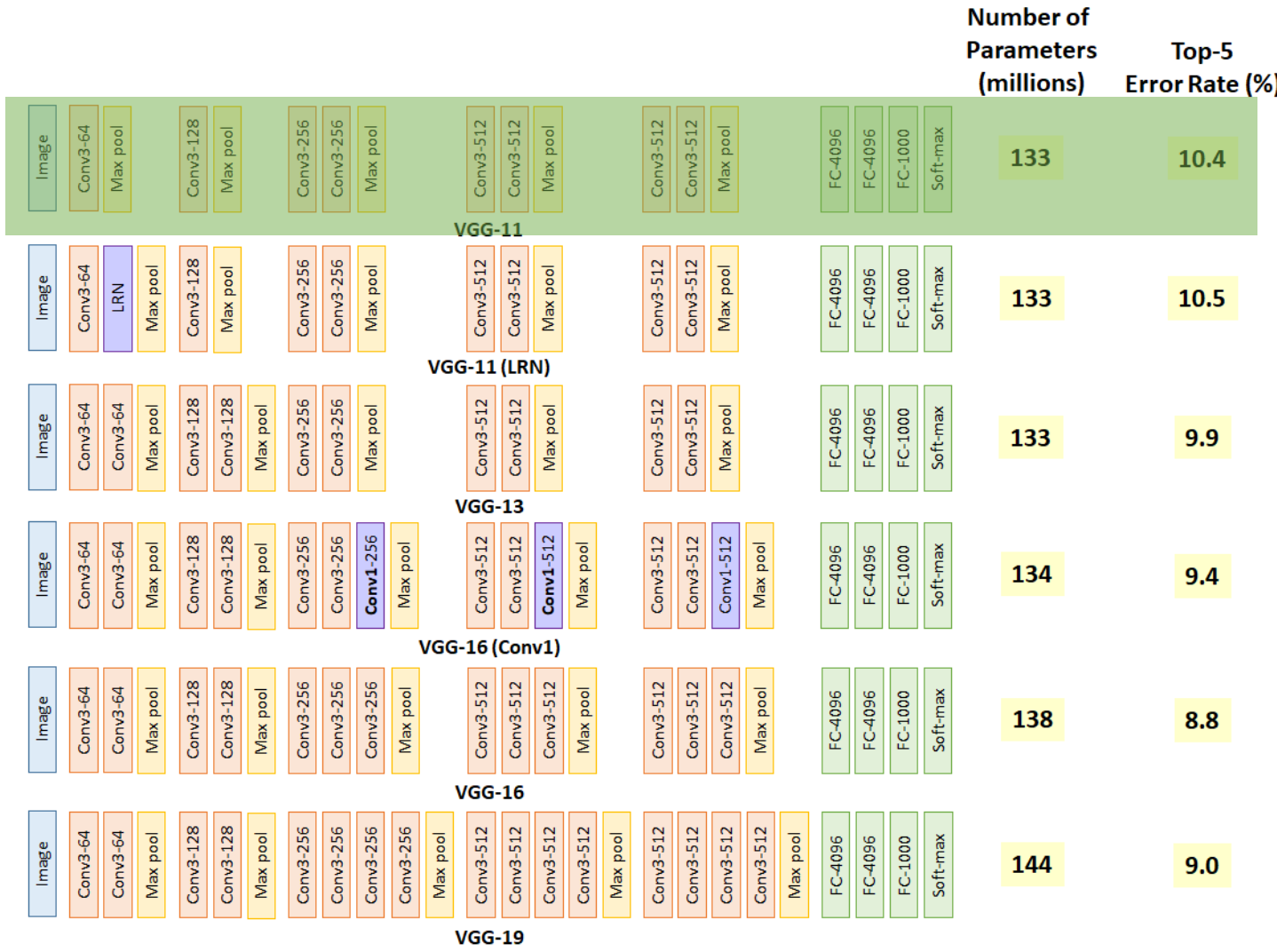
VGG – 2014 Pytorch

```
VGGNet = nn.Sequential(
    nn.Conv2d(3, 64, kernel_size=3, padding=1),
    nn.ReLU(),
    nn.MaxPool2d(kernel_size=2, stride=2),
    nn.Conv2d(64, 128, kernel_size=3, padding=1),
    nn.ReLU(),
    nn.MaxPool2d(kernel_size=2, stride=2),
    nn.Conv2d(128, 256, kernel_size=3, padding=1),
    nn.ReLU(),
    nn.Conv2d(256, 256, kernel_size=3, padding=1),
    nn.ReLU(),
    nn.MaxPool2d(kernel_size=2, stride=2),
    nn.Conv2d(256, 512, kernel_size=3, padding=1),
    nn.ReLU(),
    nn.Conv2d(512, 512, kernel_size=3, padding=1),
    nn.ReLU(),
    nn.MaxPool2d(kernel_size=2, stride=2),
    nn.Conv2d(512, 512, kernel_size=3, padding=1),
    nn.ReLU(),
    nn.Conv2d(512, 512, kernel_size=3, padding=1),
    nn.ReLU(),
    nn.MaxPool2d(kernel_size=2, stride=2),
    nn.Flatten(),
    nn.LazyLinear(4096),
    nn.ReLU(),
    nn.Dropout2d(0.5),
    nn.LazyLinear(4096),
    nn.ReLU(),
    nn.Dropout2d(0.5),
    nn.LazyLinear(2)
)
```



http://d2l.ai/chapter_convolutional-modern/vgg.html

Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*.

CovNet Architectures

- LeNet (1990s)
- AlexNet (2012)
- ZF Net (2013)
- VGGNet (2014)
- GoogLeNet (2014)
- ResNets (2015)
- DenseNet (2017)

GoogLeNet - 2014

2014

- ImageNet Challenge http://www.image-net.org/challenges/LSVRC/2014/
- http://www.image-net.org/challenges/LSVRC/2014/results
- **GoogLe**Net > Google/LeNet
- **1 x 1 convolution**
- Network In Network
- **Variously-sized kernels**
- **Inception Blocks**

Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., … Rabinovich, A. (2015). **Going deeper with convolutions**. *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 1–9).

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GoogLeNet - 2014

https://www.csfd.cz/film/254156-pocatek/prehled/

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GoogLeNet - 2014

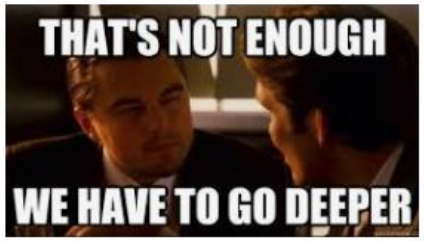
Google inception we need to go deeper

Vše | Obrázky | Videa | Nákupy | Zprávy | Více | Nastavení | Nástroje

gif | meme | leonardo dicaprio | di caprio | neural networks | leo dicaprio | deep | inception meme generator | deep learning | machine learning

We Need To Go Deeper | Know Your Meme
knowyourmeme.com

We Need To Go Deeper Inception GIFs | Tenor
tenor.com



That's not enough We have to go deeper - Incep...
quickmeme.com

Beta inception we need to go deeper ...
memegenerator.net


Create meme "We need to go deep...
meme-arsenal.com


Inception - We need to ...
9gag.com

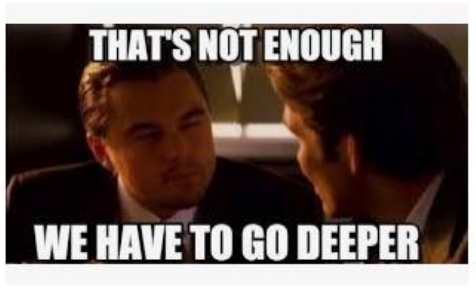
we need to go deeper - I...
memegenerator.net

we-need-to-go-deeper-yoga-leonardo-di...
pinterest.com

We Need To Go Deeper | ...
knowyourmeme.com

This conversation is ge...
quickmeme.com


Inception still slaps 10 ...
vox.com



A Simple Guide to the Versions of the Inception Netw...
towardsdatascience.com

go deeper - Imgflip
imgflip.com

We need to go deeper... | Inception | Know Y...
knowyourmeme.com

We need to go dee
theshiznit.co.uk

GoogLeNet - 2014

- **Deep Network > overfitting**
- **What kernel sizes is right?**
  - **3 x 3 (VGGNet)**
  - **5 x 5 (LeNet)**
  - **7 x 7 (ZFNet)**
  - **11 x 11 (AlexNet)**

http://datahacker.rs/building-inception-network/
http://d2l.ai/chapter_convolutional-modern/googlenet.html
https://towardsdatascience.com/a-simple-guide-to-the-versions-of-the-inception-network-7fc52b863202

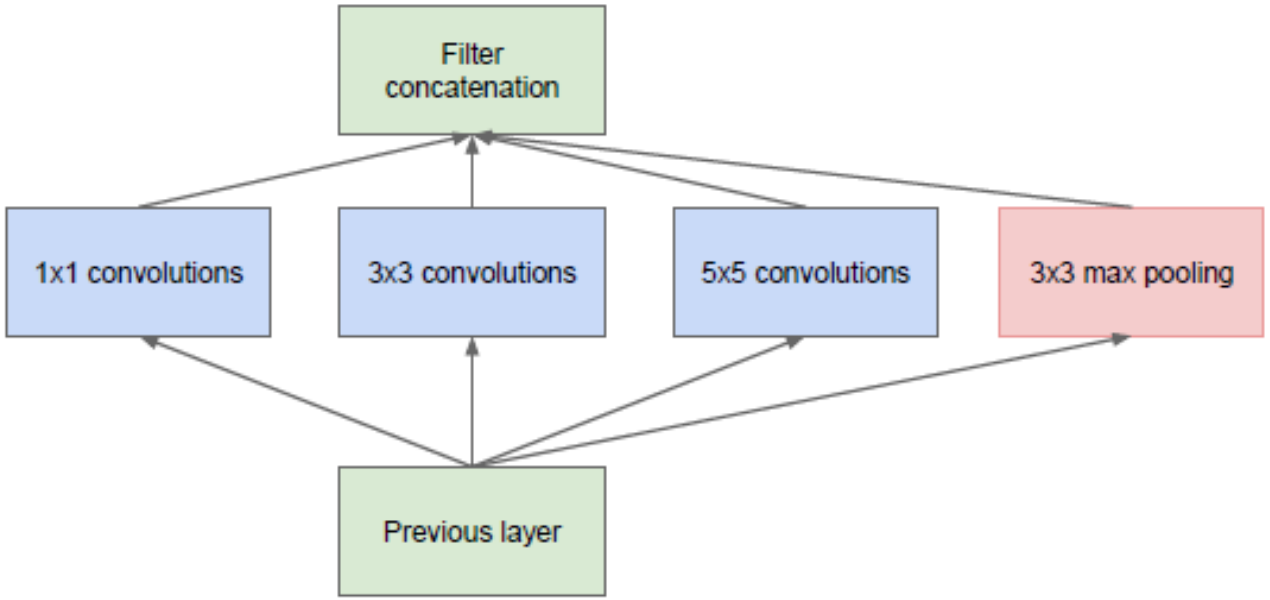
GoogLeNet - 2014

- **Multiple filter sizes** in on the same level
- **“Wider”** rather than “Deeper”

http://datahacker.rs/building-inception-network/
http://d2l.ai/chapter_convolutional-modern/googlenet.html
https://towardsdatascience.com/a-simple-guide-to-the-versions-of-the-inception-network-7fc52b863202

GoogLeNet - 2014

- **Multiple filter sizes** in on the same level
- **“Wider”** rather than “Deeper” - **3 different filters**

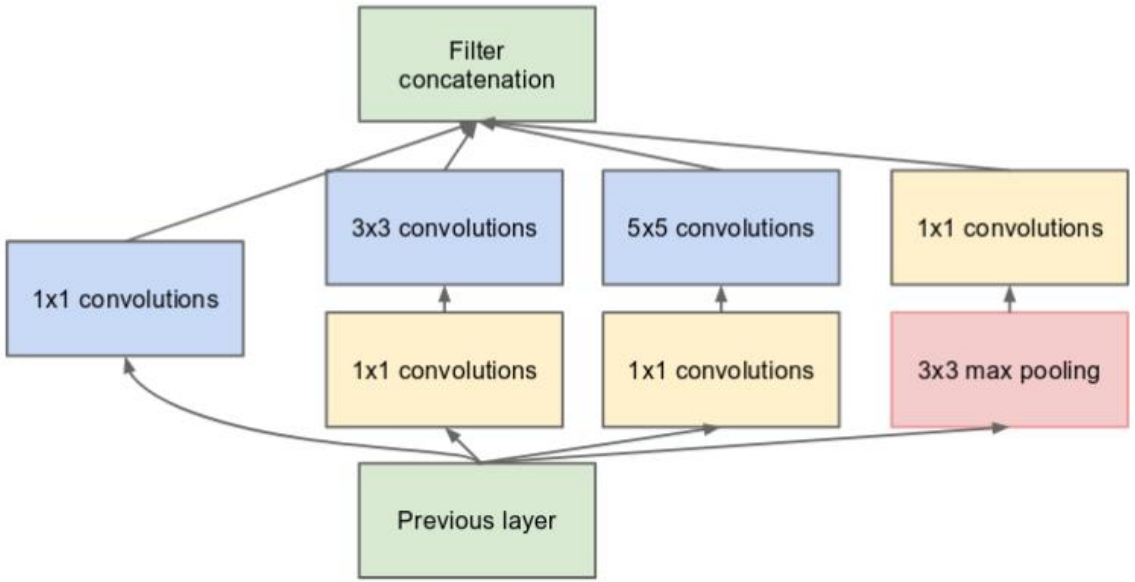


(a) Inception module, naïve version

http://datahacker.rs/building-inception-network/
http://d2l.ai/chapter_convolutional-modern/googlenet.html
https://towardsdatascience.com/a-simple-guide-to-the-versions-of-the-inception-network-7fc52b863202

GoogLeNet - 2014

- **1 x 1 filters for dimension reduction**
- **“Wider”** rather than “Deeper” - **3 different filters**

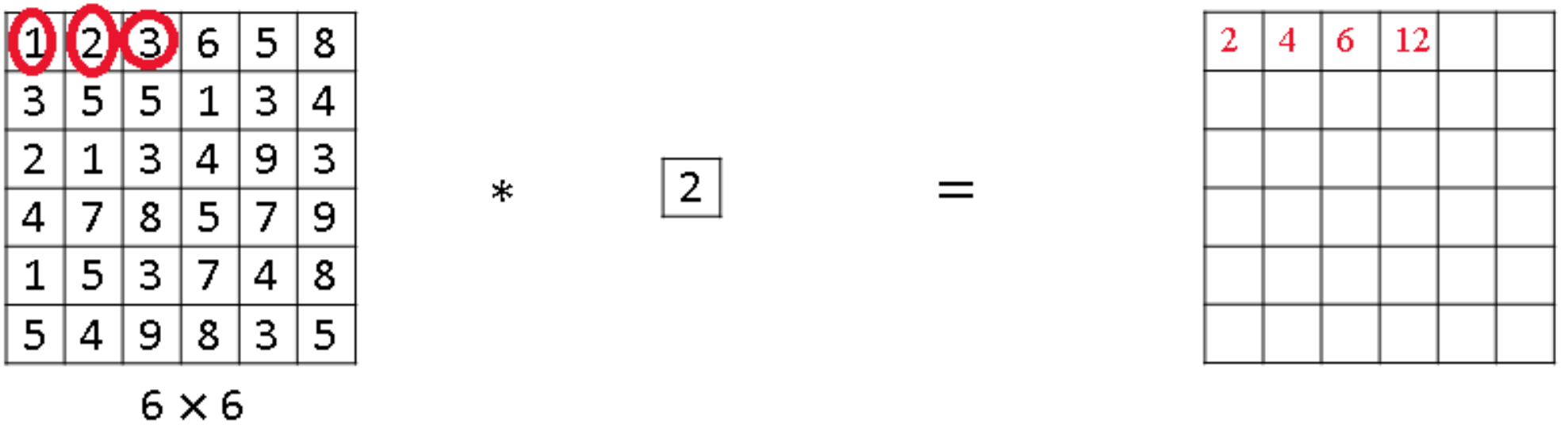


(b) Inception module with dimension reductions

http://datahacker.rs/building-inception-network/
http://d2l.ai/chapter_convolutional-modern/googlenet.html
https://towardsdatascience.com/a-simple-guide-to-the-versions-of-the-inception-network-7fc52b863202

GoogLeNet - 2014

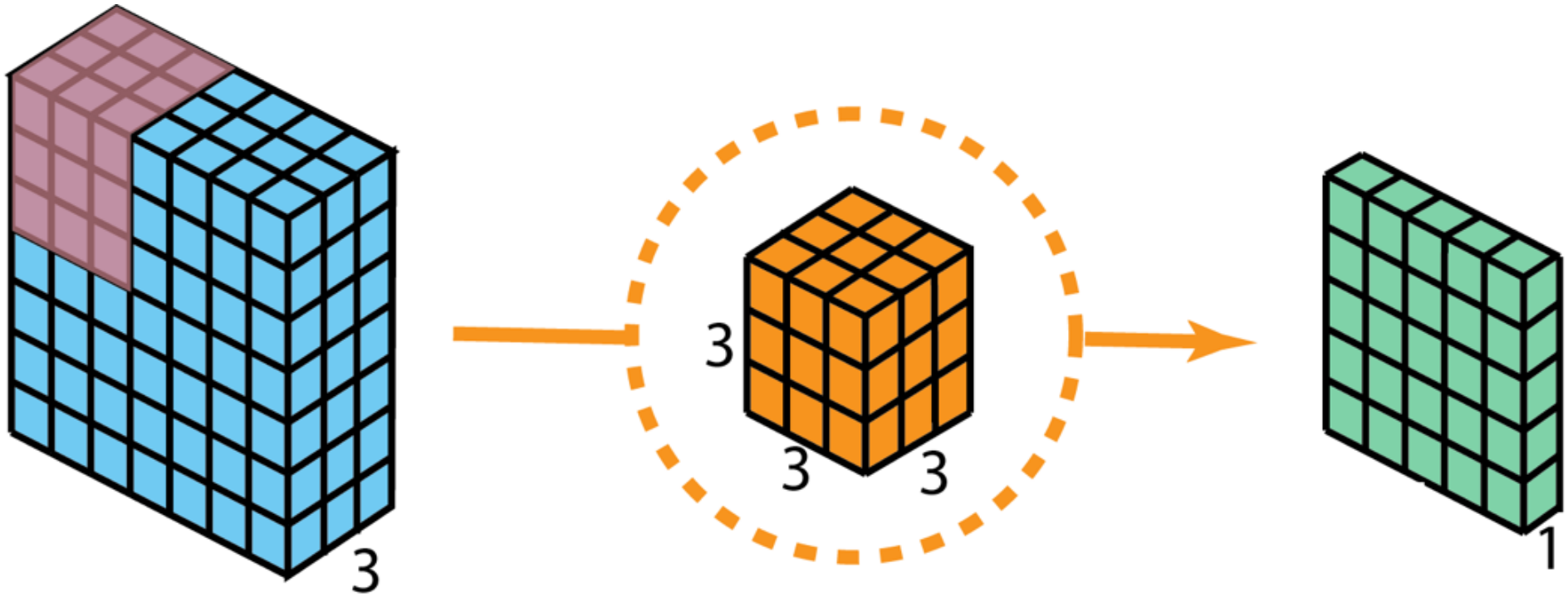
- **1 x 1 filters in 2D**



https://upscfever.com/upsc-fever/en/data/deeplearning4/15.html
http://datahacker.rs/building-inception-network/
http://d2l.ai/chapter_convolutional-modern/googlenet.html
https://towardsdatascience.com/a-simple-guide-to-the-versions-of-the-inception-network-7fc52b863202

GoogLeNet - 2014

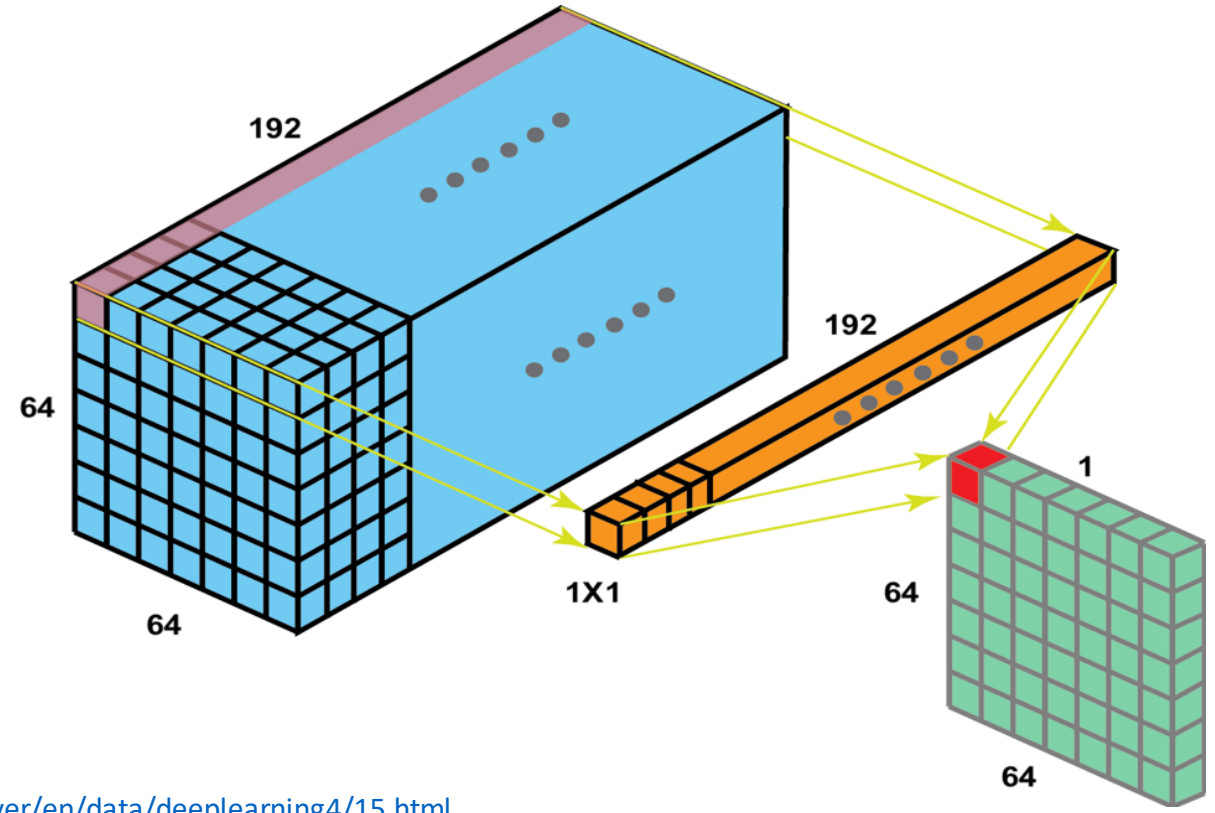
- **filter in 3D**



https://medium.com/analytics-vidhya/talented-mr-1x1-comprehensive-look-at-1x1-convolution-in-deep-learning-f6b355825578
http://datahacker.rs/building-inception-network/
http://d2l.ai/chapter_convolutional-modern/googlenet.html
https://towardsdatascience.com/a-simple-guide-to-the-versions-of-the-inception-network-7fc52b863202

GoogLeNet - 2014

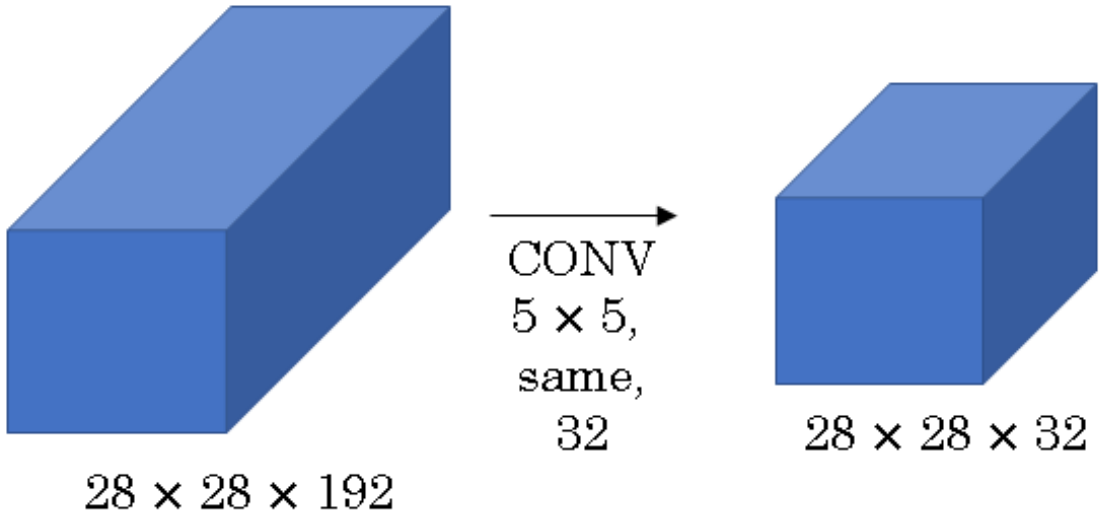
- **1 x 1 filters in** large number of channels - **192**



https://upscfever.com/upsc-fever/en/data/deeplearning4/15.html
https://medium.com/analytics-vidhya/talented-mr-1x1-comprehensive-look-at-1x1-convolution-in-deep-learning-f6b355825578
http://datahacker.rs/building-inception-network/
http://d2l.ai/chapter_convolutional-modern/googlenet.html
https://towardsdatascience.com/a-simple-guide-to-the-versions-of-the-inception-network-7fc52b863202

GoogLeNet - 2014

- convolve 28 X 28 X 192 input feature maps with 5 X 5 X 32 filters.
- **This will result in aprox. 120 *Million operations***



https://upscfever.com/upsc-fever/en/data/deeplearning4/15.html
https://medium.com/analytics-vidhya/talented-mr-1x1-comprehensive-look-at-1x1-convolution-in-deep-learning-f6b355825578
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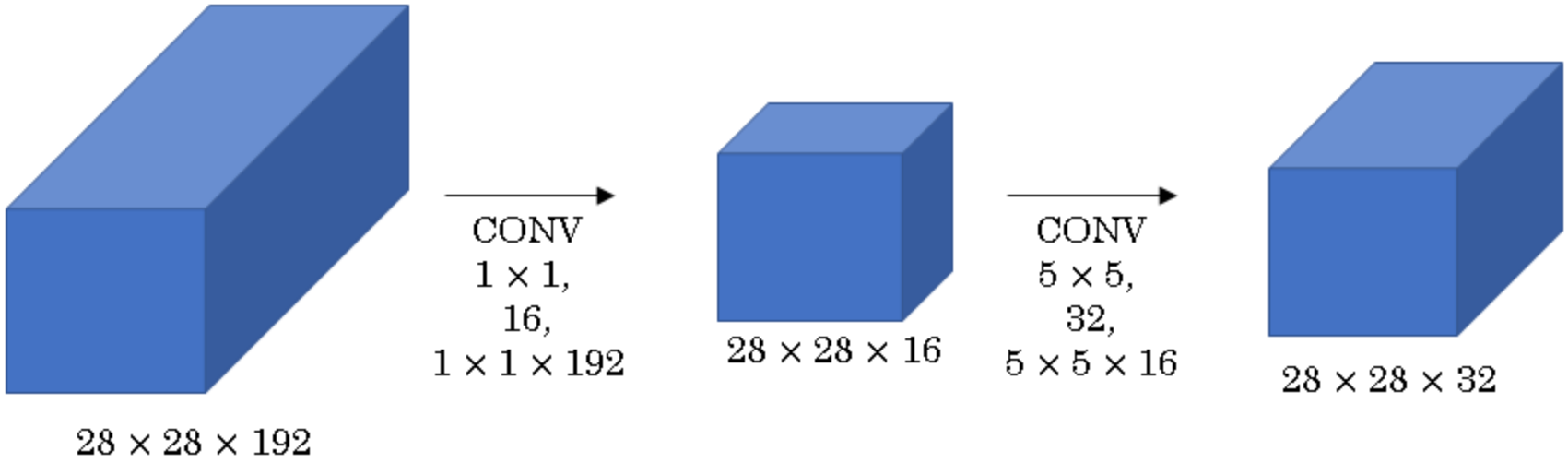
http://d2l.ai/chapter_convolutional-modern/googlenet.html
https://towardsdatascience.com/a-simple-guide-to-the-versions-of-the-inception-network-7fc52b863202

GoogLeNet - 2014

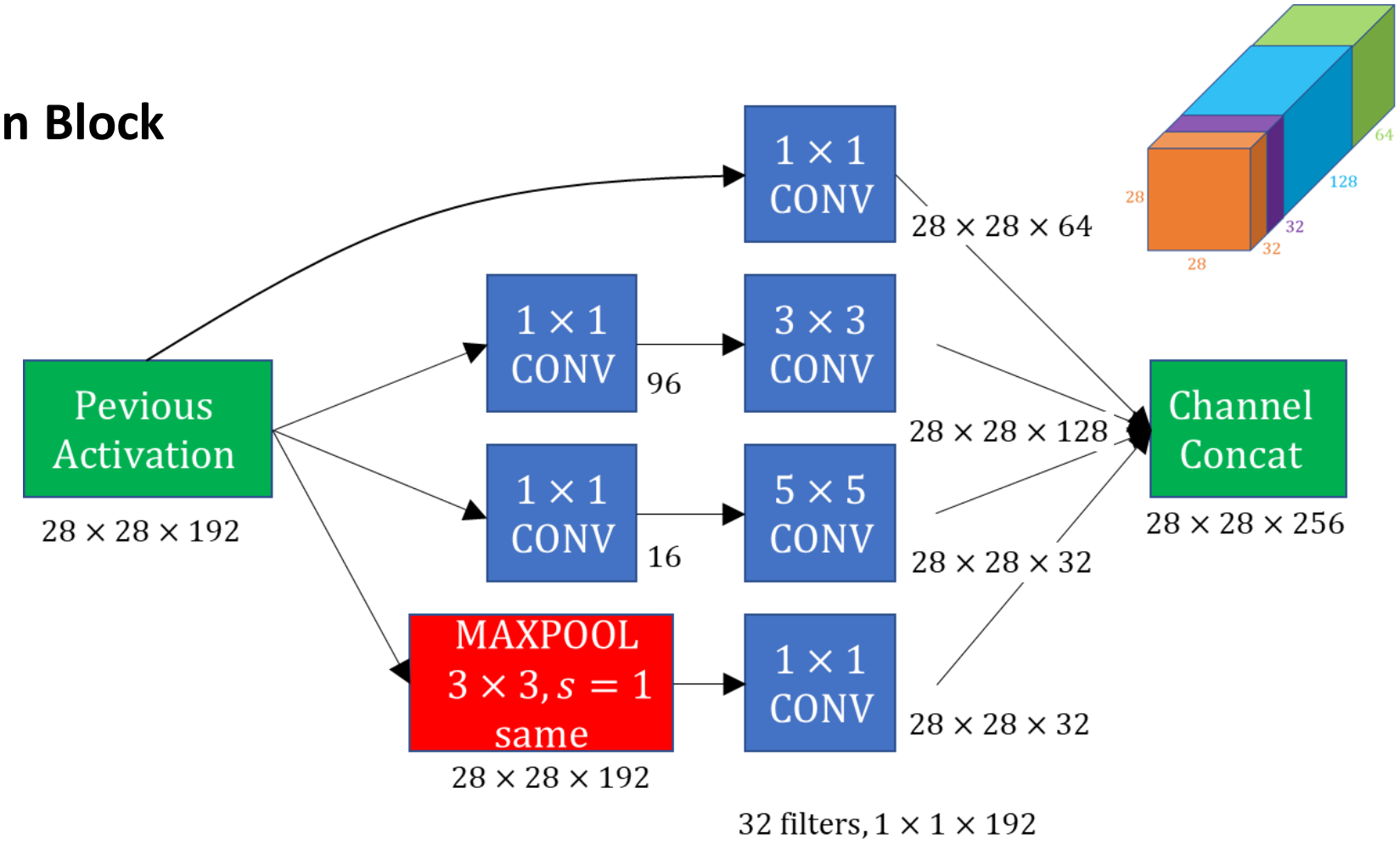
- Using 1 X 1 filters - **aprox. 12 *Million operations***
- **“Bottleneck layer”**



https://upscfever.com/upsc-fever/en/data/deeplearning4/15.html
https://medium.com/analytics-vidhya/talented-mr-1x1-comprehensive-look-at-1x1-convolution-in-deep-learning-f6b355825578
http://datahacker.rs/building-inception-network/
http://d2l.ai/chapter_convolutional-modern/googlenet.html
https://towardsdatascience.com/a-simple-guide-to-the-versions-of-the-inception-network-7fc52b863202

GoogLeNet - 2014

- **Inception Block**



https://upscfever.com/upsc-fever/en/data/deeplearning4/15.html
https://medium.com/analytics-vidhya/talented-mr-1x1-comprehensive-look-at-1x1-convolution-in-deep-learning-f6b355825578
http://datahacker.rs/building-inception-network/
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https://towardsdatascience.com/a-simple-guide-to-the-versions-of-the-inception-network-7fc52b863202

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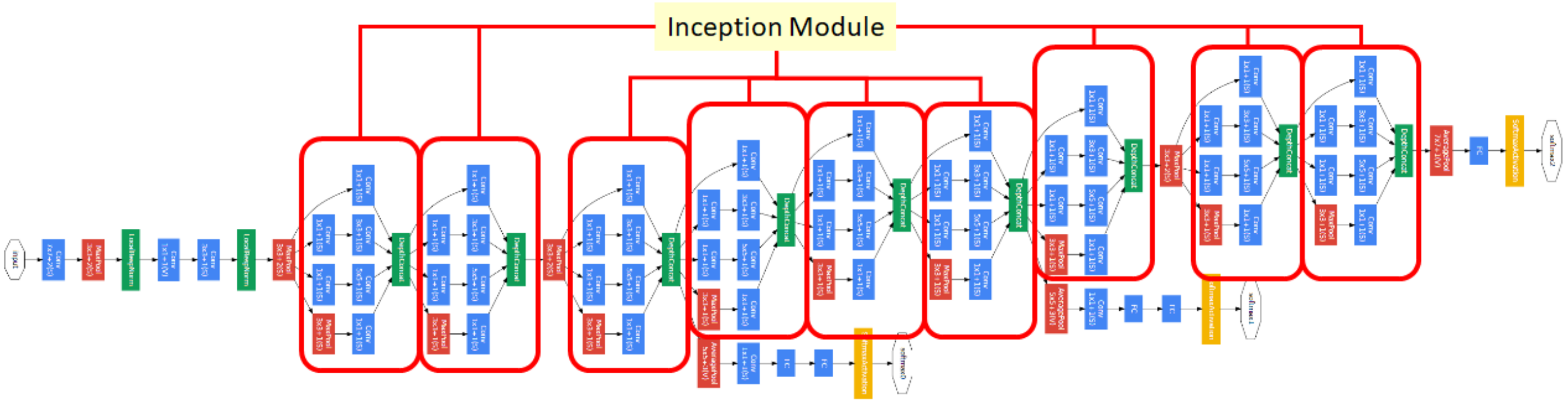
GoogLeNet - 2014



https://towardsdatascience.com/review-inception-v4-evolved-from-googlenet-merged-with-resnet-idea-image-classification-5e8c339d18bc
http://datahacker.rs/building-inception-network/
http://d2l.ai/chapter_convolutional-modern/googlenet.html
https://towardsdatascience.com/a-simple-guide-to-the-versions-of-the-inception-network-7fc52b863202

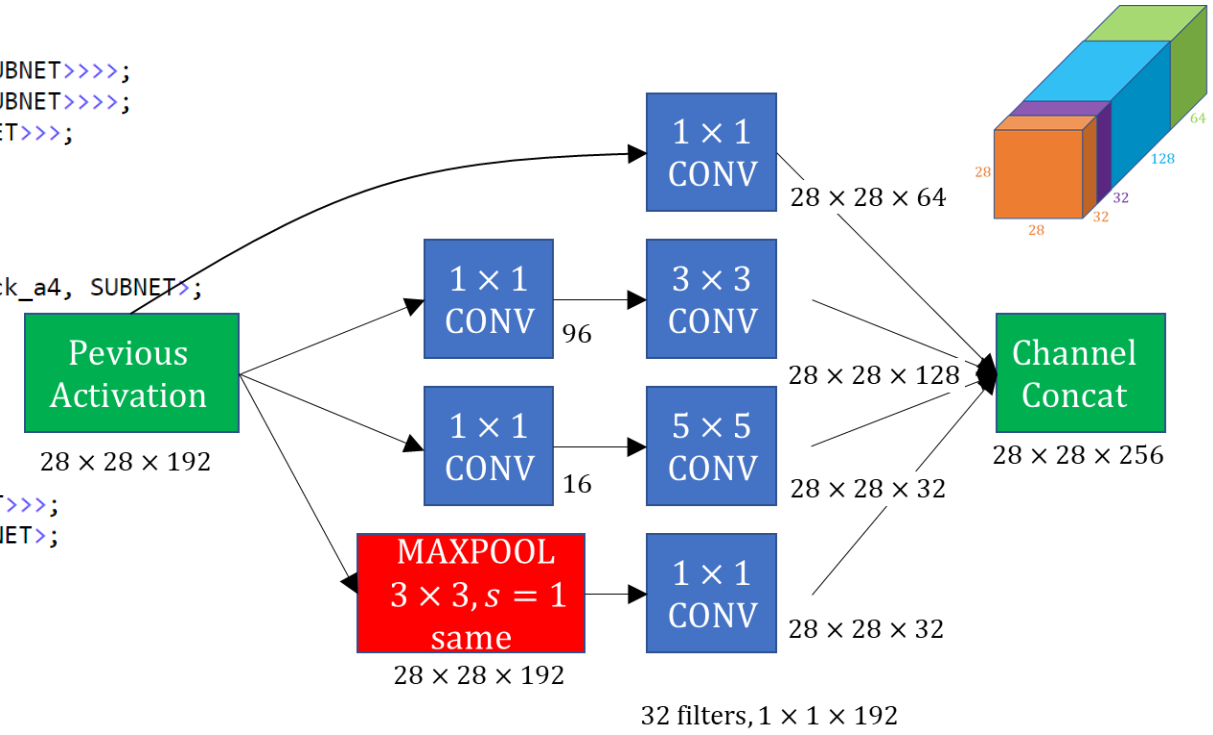
GoogLeNet – 2014 Dlib

```
// Inception layer has some different convolutions inside.  Here we define
// blocks as convolutions with different kernel size that we will use in
// inception layer block.
template <typename SUBNET> using block_a1 = relu<con<10,1,1,1,1,SUBNET>>;
template <typename SUBNET> using block_a2 = relu<con<10,3,3,1,1,relu<con<16,1,1,1,1,SUBNET>>>>;
template <typename SUBNET> using block_a3 = relu<con<10,5,5,1,1,relu<con<16,1,1,1,1,SUBNET>>>>;
template <typename SUBNET> using block_a4 = relu<con<10,1,1,1,1,max_pool<3,3,1,1,SUBNET>>>;

// Here is inception layer definition. It uses different blocks to process input
// and returns combined output.  Dlib includes a number of these inceptionN
// layer types which are themselves created using concat layers.
template <typename SUBNET> using incept_a = inception4<block_a1,block_a2,block_a3,block_a4, SUBNET>;

// Network can have inception layers of different structure.  It will work
// properly so long as all the sub-blocks inside a particular inception block
// output tensors with the same number of rows and columns.
template <typename SUBNET> using block_b1 = relu<con<4,1,1,1,1,SUBNET>>;
template <typename SUBNET> using block_b2 = relu<con<4,3,3,1,1,SUBNET>>;
template <typename SUBNET> using block_b3 = relu<con<4,1,1,1,1,max_pool<3,3,1,1,SUBNET>>>;
template <typename SUBNET> using incept_b = inception3<block_b1,block_b2,block_b3,SUBNET>;

// Now we can define a simple network for classifying MNIST digits.  We will
// train and test this network in the code below.
using net_type = loss_multiclass_log<
        fc<10,
        relu<fc<32,
        max_pool<2,2,2,2,incept_b<
        max_pool<2,2,2,2,incept_a<
        input<matrix<unsigned char>>
        >>>>>>>>>;
```



http://dlib.net/dnn_inception_ex.cpp.html
http://datahacker.rs/building-inception-network/
http://d2l.ai/chapter_convolutional-modern/googlenet.html
https://towardsdatascience.com/a-simple-guide-to-the-versions-of-the-inception-network-7fc52b863202

GoogLeNet – 2014 - Pytorch

nn.LazyConv2D(...)

```
class Inception(nn.Block):
    # `c1`--`c4` are the number of output channels for each path
    def __init__(self, c1, c2, c3, c4, **kwargs):
        super(Inception, self).__init__(**kwargs)

        # Path 1 is a single 1 x 1 convolutional layer
        self.p1_1 = nn.Conv2D(c1, kernel_size=1, activation='relu')
```

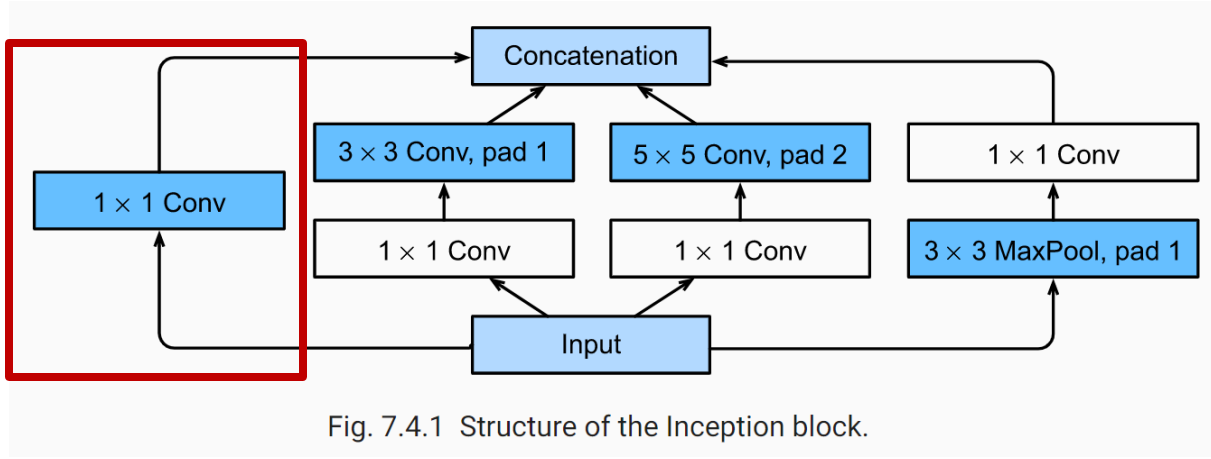


Fig. 7.4.1 Structure of the Inception block.

source: http://d2l.ai/chapter_convolutional-modern/googlenet.html

http://dlib.net/dnn_inception_ex.cpp.html
http://datahacker.rs/building-inception-network/
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https://towardsdatascience.com/a-simple-guide-to-the-versions-of-the-inception-network-7fc52b863202

GoogLeNet – 2014 - Pytorch

```
class Inception(nn.Block):
    # `c1`--`c4` are the number of output channels for each path
    def __init__(self, c1, c2, c3, c4, **kwargs):
        super(Inception, self).__init__(**kwargs)

        # Path 1 is a single 1 x 1 convolutional layer
        self.p1_1 = nn.Conv2D(c1, kernel_size=1, activation='relu')

        # Path 2 is a 1 x 1 convolutional layer followed by a 3 x 3
        # convolutional layer
        self.p2_1 = nn.Conv2D(c2[0], kernel_size=1, activation='relu')
        self.p2_2 = nn.Conv2D(c2[1], kernel_size=3, padding=1, activation='relu')
```

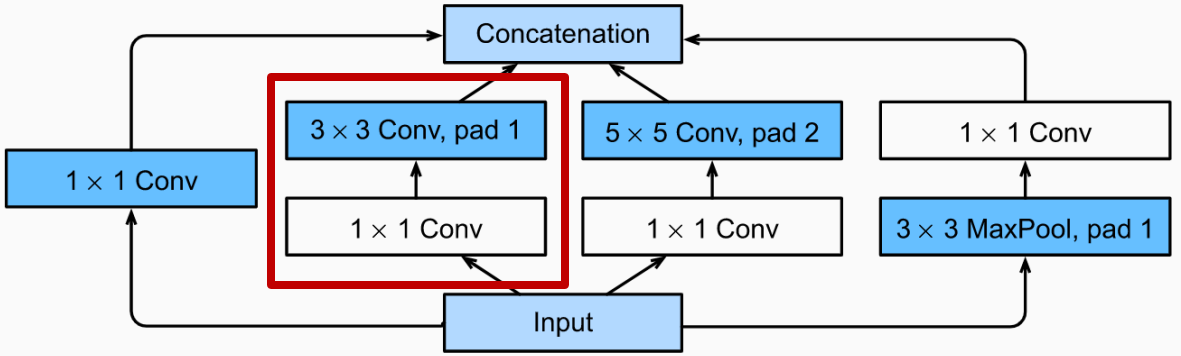

Fig. 7.4.1 Structure of the Inception block.

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http://dlib.net/dnn_inception_ex.cpp.html
http://datahacker.rs/building-inception-network/
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https://towardsdatascience.com/a-simple-guide-to-the-versions-of-the-inception-network-7fc52b863202

GoogLeNet – 2014 - Pytorch

```
class Inception(nn.Block):
    # `c1`--`c4` are the number of output channels for each path
    def __init__(self, c1, c2, c3, c4, **kwargs):
        super(Inception, self).__init__(**kwargs)

        # Path 1 is a single 1 x 1 convolutional layer
        self.p1_1 = nn.Conv2D(c1, kernel_size=1, activation='relu')

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        # convolutional layer
        self.p2_1 = nn.Conv2D(c2[0], kernel_size=1, activation='relu')
        self.p2_2 = nn.Conv2D(c2[1], kernel_size=3, padding=1, activation='relu')

        # Path 3 is a 1 x 1 convolutional layer followed by a 5 x 5
        # convolutional layer
        self.p3_1 = nn.Conv2D(c3[0], kernel_size=1, activation='relu')
        self.p3_2 = nn.Conv2D(c3[1], kernel_size=5, padding=2, activation='relu')
```

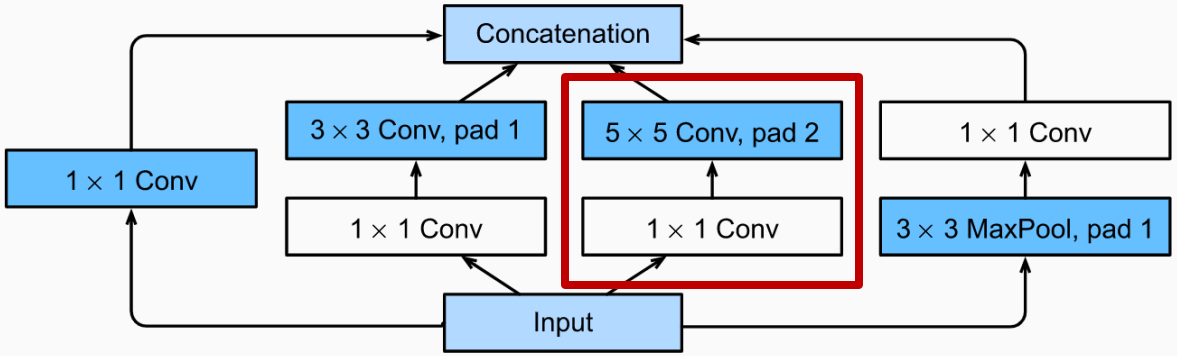

Fig. 7.4.1 Structure of the Inception block.

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http://dlib.net/dnn_inception_ex.cpp.html
http://datahacker.rs/building-inception-network/
http://d2l.ai/chapter_convolutional-modern/googlenet.html
https://towardsdatascience.com/a-simple-guide-to-the-versions-of-the-inception-network-7fc52b863202

GoogLeNet – 2014 - PyTorch

```
class Inception(nn.Block):
    # `c1`--`c4` are the number of output channels for each path
    def __init__(self, c1, c2, c3, c4, **kwargs):
        super(Inception, self).__init__(**kwargs)

        # Path 1 is a single 1 x 1 convolutional layer
        self.p1_1 = nn.Conv2D(c1, kernel_size=1, activation='relu')

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        # Path 3 is a 1 x 1 convolutional layer followed by a 5 x 5
        # convolutional layer
        self.p3_1 = nn.Conv2D(c3[0], kernel_size=1, activation='relu')
        self.p3_2 = nn.Conv2D(c3[1], kernel_size=5, padding=2, activation='relu')

        # Path 4 is a 3 x 3 maximum pooling layer followed by a 1 x 1
        # convolutional layer
        self.p4_1 = nn.MaxPool2D(pool_size=3, strides=1, padding=1)
        self.p4_2 = nn.Conv2D(c4, kernel_size=1, activation='relu')
```

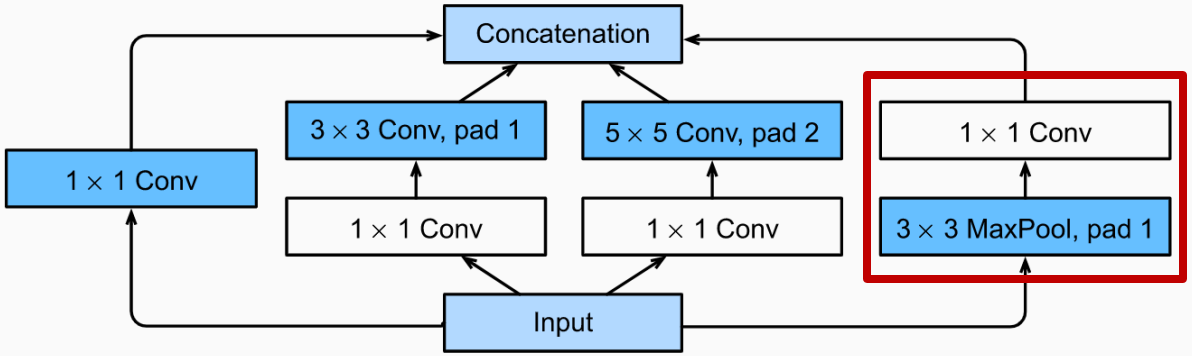

Fig. 7.4.1 Structure of the Inception block.

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https://towardsdatascience.com/a-simple-guide-to-the-versions-of-the-inception-network-7fc52b863202

GoogLeNet – 2014 - PyTorch

```
class Inception(nn.Block):
    # `c1`--`c4` are the number of output channels for each path
    def __init__(self, c1, c2, c3, c4, **kwargs):
        super(Inception, self).__init__(**kwargs)

        # Path 1 is a single 1 x 1 convolutional layer
        self.p1_1 = nn.Conv2D(c1, kernel_size=1, activation='relu')

        # Path 2 is a 1 x 1 convolutional layer followed by a 3 x 3
        # convolutional layer
        self.p2_1 = nn.Conv2D(c2[0], kernel_size=1, activation='relu')
        self.p2_2 = nn.Conv2D(c2[1], kernel_size=3, padding=1, activation='relu')

        # Path 3 is a 1 x 1 convolutional layer followed by a 5 x 5
        # convolutional layer
        self.p3_1 = nn.Conv2D(c3[0], kernel_size=1, activation='relu')
        self.p3_2 = nn.Conv2D(c3[1], kernel_size=5, padding=2, activation='relu')

        # Path 4 is a 3 x 3 maximum pooling layer followed by a 1 x 1
        # convolutional layer
        self.p4_1 = nn.MaxPool2D(pool_size=3, strides=1, padding=1)
        self.p4_2 = nn.Conv2D(c4, kernel_size=1, activation='relu')

    def forward(self, x):
        p1 = self.p1_1(x)
        p2 = self.p2_2(self.p2_1(x))
        p3 = self.p3_2(self.p3_1(x))
        p4 = self.p4_2(self.p4_1(x))
        # Concatenate the outputs on the channel dimension
        return np.concatenate((p1, p2, p3, p4), axis=1)
```

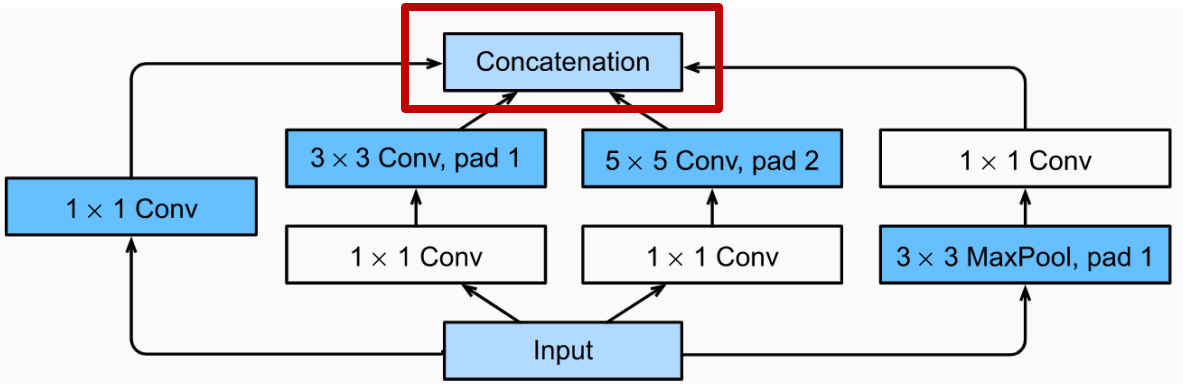

Fig. 7.4.1 Structure of the Inception block.

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http://dlib.net/dnn_inception_ex.cpp.html
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https://towardsdatascience.com/a-simple-guide-to-the-versions-of-the-inception-network-7fc52b863202

GoogLeNet – 2014 - PyTorch

```
class Inception(nn.Block):
    # `c1`--`c4` are the number of output channels for each path
    def __init__(self, c1, c2, c3, c4, **kwargs):
        super(Inception, self).__init__(**kwargs)

        # Path 1 is a single 1 x 1 convolutional layer
        self.p1_1 = nn.Conv2D(c1, kernel_size=1, activation='relu')

        # Path 2 is a 1 x 1 convolutional layer followed by a 3 x 3
        # convolutional layer
        self.p2_1 = nn.Conv2D(c2[0], kernel_size=1, activation='relu')
        self.p2_2 = nn.Conv2D(c2[1], kernel_size=3, padding=1, activation='relu')

        # Path 3 is a 1 x 1 convolutional layer followed by a 5 x 5
        # convolutional layer
        self.p3_1 = nn.Conv2D(c3[0], kernel_size=1, activation='relu')
        self.p3_2 = nn.Conv2D(c3[1], kernel_size=5, padding=2, activation='relu')

        # Path 4 is a 3 x 3 maximum pooling layer followed by a 1 x 1
        # convolutional layer
        self.p4_1 = nn.MaxPool2D(pool_size=3, strides=1, padding=1)
        self.p4_2 = nn.Conv2D(c4, kernel_size=1, activation='relu')

    def forward(self, x):
        p1 = self.p1_1(x)
        p2 = self.p2_2(self.p2_1(x))
        p3 = self.p3_2(self.p3_1(x))
        p4 = self.p4_2(self.p4_1(x))
        # Concatenate the outputs on the channel dimension
        return np.concatenate((p1, p2, p3, p4), axis=1)
```

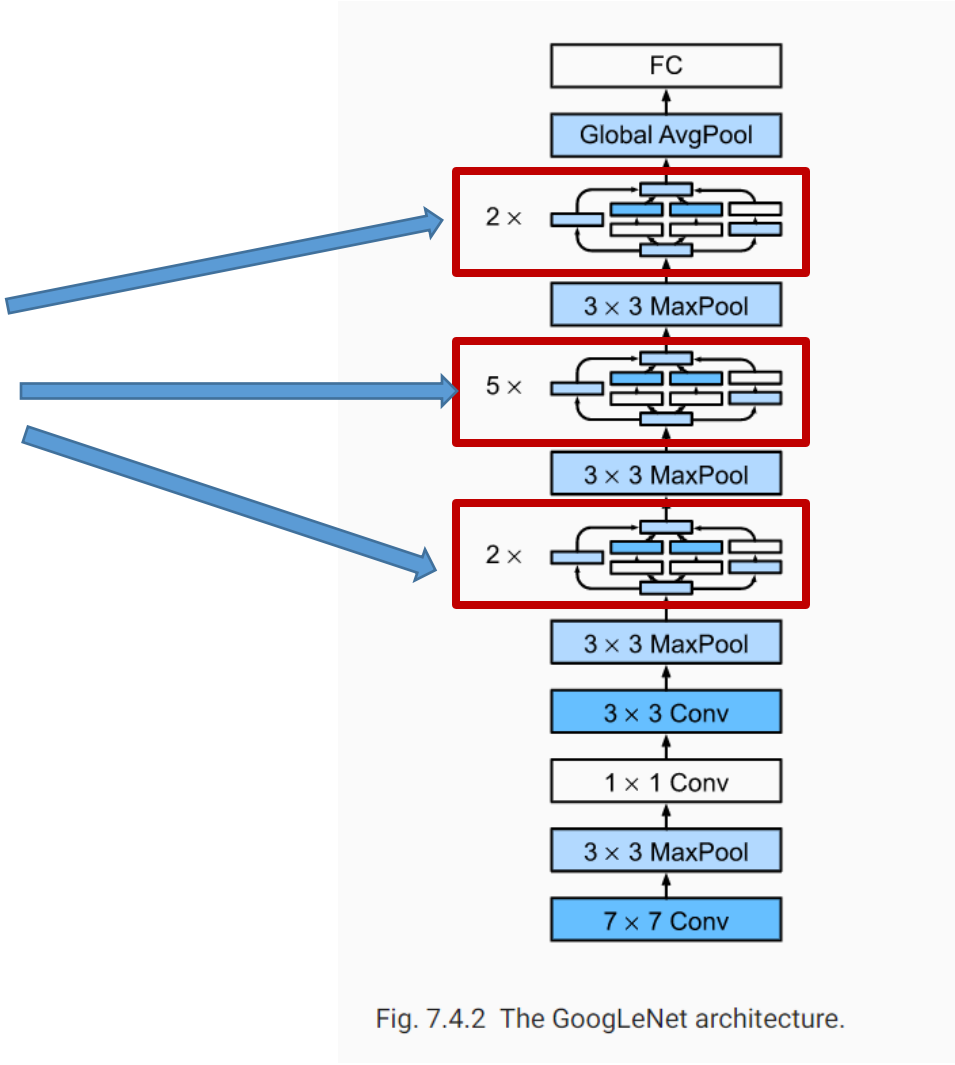

Fig. 7.4.2 The GoogLeNet architecture.

http://dlib.net/dnn_inception_ex.cpp.html
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http://d2l.ai/chapter_convolutional-modern/googlenet.html
https://towardsdatascience.com/a-simple-guide-to-the-versions-of-the-inception-network-7fc52b863202

source: http://d2l.ai/chapter_convolutional-modern/googlenet.html

GoogLeNet – 2014 - PyTorch

```
b1 = nn.Sequential(nn.Conv2d(3, 64, kernel_size=7, stride=2, padding=3),
                   nn.ReLU(), nn.MaxPool2d(kernel_size=3, stride=2, padding=1))

b2 = nn.Sequential(nn.Conv2d(64, 64, kernel_size=1), nn.ReLU(),
                   nn.Conv2d(64, 192, kernel_size=3, padding=1), nn.ReLU(),
                   nn.MaxPool2d(kernel_size=3, stride=2, padding=1))

b3 = nn.Sequential(Inception(192, 64, (96, 128), (16, 32), 32),
                   Inception(256, 128, (128, 192), (32, 96), 64),
                   nn.MaxPool2d(kernel_size=3, stride=2, padding=1))

b4 = nn.Sequential(Inception(480, 192, (96, 208), (16, 48), 64),
                   Inception(512, 160, (112, 224), (24, 64), 64),
                   Inception(512, 128, (128, 256), (24, 64), 64),
                   Inception(512, 112, (144, 288), (32, 64), 64),
                   Inception(528, 256, (160, 320), (32, 128), 128),
                   nn.MaxPool2d(kernel_size=3, stride=2, padding=1))

b5 = nn.Sequential(Inception(832, 256, (160, 320), (32, 128), 128),
                   Inception(832, 384, (192, 384), (48, 128), 128),
                   nn.AdaptiveAvgPool2d((1, 1)), nn.Flatten())

GoogLeNet = nn.Sequential(b1, b2, b3, b4, b5, nn.Linear(1024, 2))
```

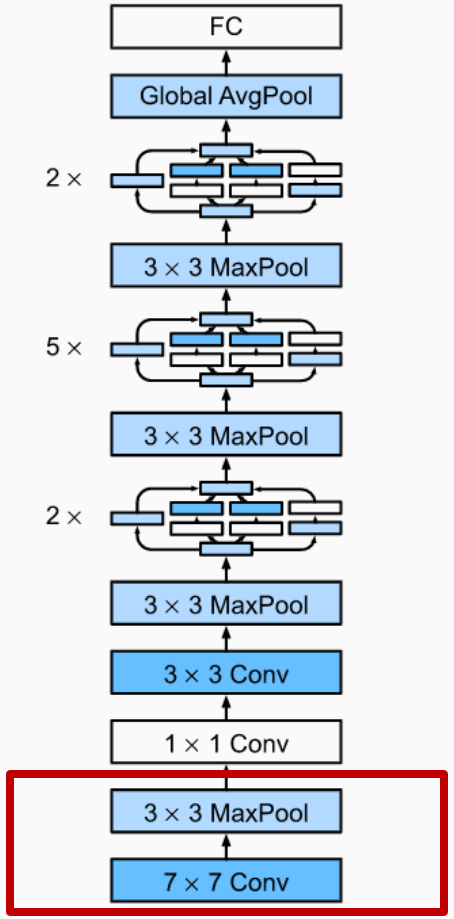

Fig. 7.4.2 The GoogLeNet architecture.

http://dlib.net/dnn_inception_ex.cpp.html
http://datahacker.rs/building-inception-network/
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https://towardsdatascience.com/a-simple-guide-to-the-versions-of-the-inception-network-7fc52b863202

source: http://d2l.ai/chapter_convolutional-modern/googlenet.html

GoogLeNet – 2014 - PyTorch

```
b1 = nn.Sequential(nn.Conv2d(3, 64, kernel_size=7, stride=2, padding=3),
                   nn.ReLU(), nn.MaxPool2d(kernel_size=3, stride=2, padding=1))

b2 = nn.Sequential(nn.Conv2d(64, 64, kernel_size=1), nn.ReLU(),
                   nn.Conv2d(64, 192, kernel_size=3, padding=1), nn.ReLU(),
                   nn.MaxPool2d(kernel_size=3, stride=2, padding=1))

b3 = nn.Sequential(Inception(192, 64, (96, 128), (16, 32), 32),
                   Inception(256, 128, (128, 192), (32, 96), 64),
                   nn.MaxPool2d(kernel_size=3, stride=2, padding=1))

b4 = nn.Sequential(Inception(480, 192, (96, 208), (16, 48), 64),
                   Inception(512, 160, (112, 224), (24, 64), 64),
                   Inception(512, 128, (128, 256), (24, 64), 64),
                   Inception(512, 112, (144, 288), (32, 64), 64),
                   Inception(528, 256, (160, 320), (32, 128), 128),
                   nn.MaxPool2d(kernel_size=3, stride=2, padding=1))

b5 = nn.Sequential(Inception(832, 256, (160, 320), (32, 128), 128),
                   Inception(832, 384, (192, 384), (48, 128), 128),
                   nn.AdaptiveAvgPool2d((1, 1)), nn.Flatten())

GoogLeNet = nn.Sequential(b1, b2, b3, b4, b5, nn.Linear(1024, 2))
```

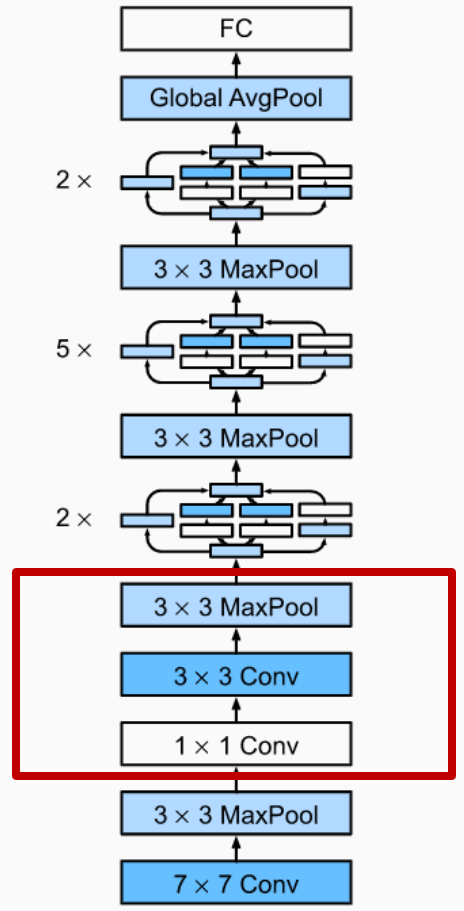

Fig. 7.4.2 The GoogLeNet architecture.

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http://datahacker.rs/building-inception-network/
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source: http://d2l.ai/chapter_convolutional-modern/googlenet.html

GoogLeNet – 2014 - PyTorch

```
b1 = nn.Sequential(nn.Conv2d(3, 64, kernel_size=7, stride=2, padding=3),
                   nn.ReLU(), nn.MaxPool2d(kernel_size=3, stride=2, padding=1))

b2 = nn.Sequential(nn.Conv2d(64, 64, kernel_size=1), nn.ReLU(),
                   nn.Conv2d(64, 192, kernel_size=3, padding=1), nn.ReLU(),
                   nn.MaxPool2d(kernel_size=3, stride=2, padding=1))

b3 = nn.Sequential(Inception(192, 64, (96, 128), (16, 32), 32),
                   Inception(256, 128, (128, 192), (32, 96), 64),
                   nn.MaxPool2d(kernel_size=3, stride=2, padding=1))

b4 = nn.Sequential(Inception(480, 192, (96, 208), (16, 48), 64),
                   Inception(512, 160, (112, 224), (24, 64), 64),
                   Inception(512, 128, (128, 256), (24, 64), 64),
                   Inception(512, 112, (144, 288), (32, 64), 64),
                   Inception(528, 256, (160, 320), (32, 128), 128),
                   nn.MaxPool2d(kernel_size=3, stride=2, padding=1))

b5 = nn.Sequential(Inception(832, 256, (160, 320), (32, 128), 128),
                   Inception(832, 384, (192, 384), (48, 128), 128),
                   nn.AdaptiveAvgPool2d((1, 1)), nn.Flatten())

GoogLeNet = nn.Sequential(b1, b2, b3, b4, b5, nn.Linear(1024, 2))
```

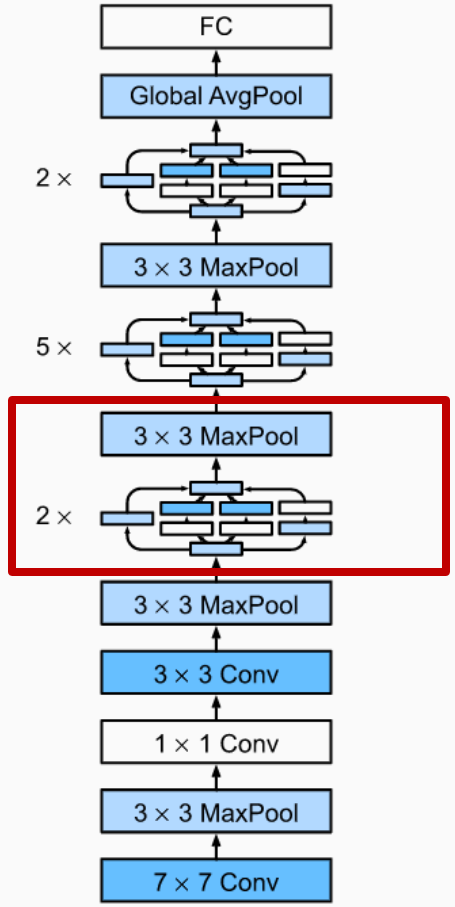

Fig. 7.4.2 The GoogLeNet architecture.

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Evropské strukturální a investiční fondy
Operační program Výzkum, vývoj a vzdělávání
MINISTERSTVO ŠKOLSTVÍ, MLÁDEŽE A TĚLOVÝCHOVY

GoogLeNet – 2014 - PyTorch

```
b1 = nn.Sequential(nn.Conv2d(3, 64, kernel_size=7, stride=2, padding=3),
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b2 = nn.Sequential(nn.Conv2d(64, 64, kernel_size=1), nn.ReLU(),
                   nn.Conv2d(64, 192, kernel_size=3, padding=1), nn.ReLU(),
                   nn.MaxPool2d(kernel_size=3, stride=2, padding=1))

b3 = nn.Sequential(Inception(192, 64, (96, 128), (16, 32), 32),
                   Inception(256, 128, (128, 192), (32, 96), 64),
                   nn.MaxPool2d(kernel_size=3, stride=2, padding=1))

b4 = nn.Sequential(Inception(480, 192, (96, 208), (16, 48), 64),
                   Inception(512, 160, (112, 224), (24, 64), 64),
                   Inception(512, 128, (128, 256), (24, 64), 64),
                   Inception(512, 112, (144, 288), (32, 64), 64),
                   Inception(528, 256, (160, 320), (32, 128), 128),
                   nn.MaxPool2d(kernel_size=3, stride=2, padding=1))

b5 = nn.Sequential(Inception(832, 256, (160, 320), (32, 128), 128),
                   Inception(832, 384, (192, 384), (48, 128), 128),
                   nn.AdaptiveAvgPool2d((1, 1)), nn.Flatten())

GoogLeNet = nn.Sequential(b1, b2, b3, b4, b5, nn.Linear(1024, 2))
```

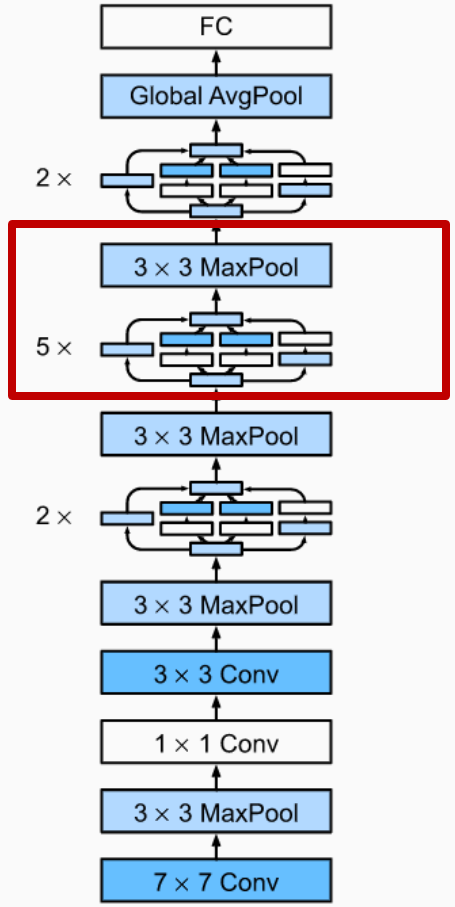

Fig. 7.4.2 The GoogLeNet architecture.

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source: http://d2l.ai/chapter_convolutional-modern/googlenet.html

GoogLeNet – 2014 - PyTorch

```
b1 = nn.Sequential(nn.Conv2d(3, 64, kernel_size=7, stride=2, padding=3),
                   nn.ReLU(), nn.MaxPool2d(kernel_size=3, stride=2, padding=1))

b2 = nn.Sequential(nn.Conv2d(64, 64, kernel_size=1), nn.ReLU(),
                   nn.Conv2d(64, 192, kernel_size=3, padding=1), nn.ReLU(),
                   nn.MaxPool2d(kernel_size=3, stride=2, padding=1))

b3 = nn.Sequential(Inception(192, 64, (96, 128), (16, 32), 32),
                   Inception(256, 128, (128, 192), (32, 96), 64),
                   nn.MaxPool2d(kernel_size=3, stride=2, padding=1))

b4 = nn.Sequential(Inception(480, 192, (96, 208), (16, 48), 64),
                   Inception(512, 160, (112, 224), (24, 64), 64),
                   Inception(512, 128, (128, 256), (24, 64), 64),
                   Inception(512, 112, (144, 288), (32, 64), 64),
                   Inception(528, 256, (160, 320), (32, 128), 128),
                   nn.MaxPool2d(kernel_size=3, stride=2, padding=1))

b5 = nn.Sequential(Inception(832, 256, (160, 320), (32, 128), 128),
                   Inception(832, 384, (192, 384), (48, 128), 128),
                   nn.AdaptiveAvgPool2d((1, 1)), nn.Flatten())

GoogLeNet = nn.Sequential(b1, b2, b3, b4, b5, nn.Linear(1024, 2))
```

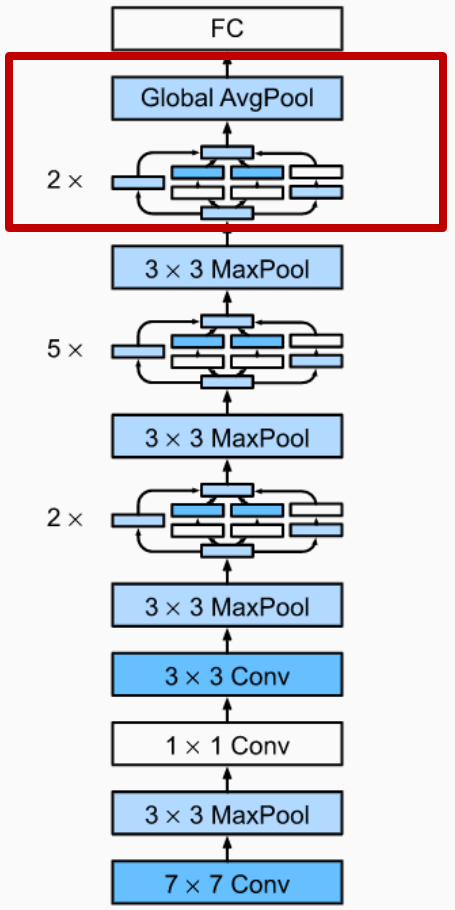

Fig. 7.4.2 The GoogLeNet architecture.

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GoogLeNet – 2014 - PyTorch

```
b1 = nn.Sequential(nn.Conv2d(3, 64, kernel_size=7, stride=2, padding=3),
                   nn.ReLU(), nn.MaxPool2d(kernel_size=3, stride=2, padding=1))

b2 = nn.Sequential(nn.Conv2d(64, 64, kernel_size=1), nn.ReLU(),
                   nn.Conv2d(64, 192, kernel_size=3, padding=1), nn.ReLU(),
                   nn.MaxPool2d(kernel_size=3, stride=2, padding=1))

b3 = nn.Sequential(Inception(192, 64, (96, 128), (16, 32), 32),
                   Inception(256, 128, (128, 192), (32, 96), 64),
                   nn.MaxPool2d(kernel_size=3, stride=2, padding=1))

b4 = nn.Sequential(Inception(480, 192, (96, 208), (16, 48), 64),
                   Inception(512, 160, (112, 224), (24, 64), 64),
                   Inception(512, 128, (128, 256), (24, 64), 64),
                   Inception(512, 112, (144, 288), (32, 64), 64),
                   Inception(528, 256, (160, 320), (32, 128), 128),
                   nn.MaxPool2d(kernel_size=3, stride=2, padding=1))

b5 = nn.Sequential(Inception(832, 256, (160, 320), (32, 128), 128),
                   Inception(832, 384, (192, 384), (48, 128), 128),
                   nn.AdaptiveAvgPool2d((1, 1)), nn.Flatten())

GoogLeNet = nn.Sequential(b1, b2, b3, b4, b5, nn.Linear(1024, 2))
```

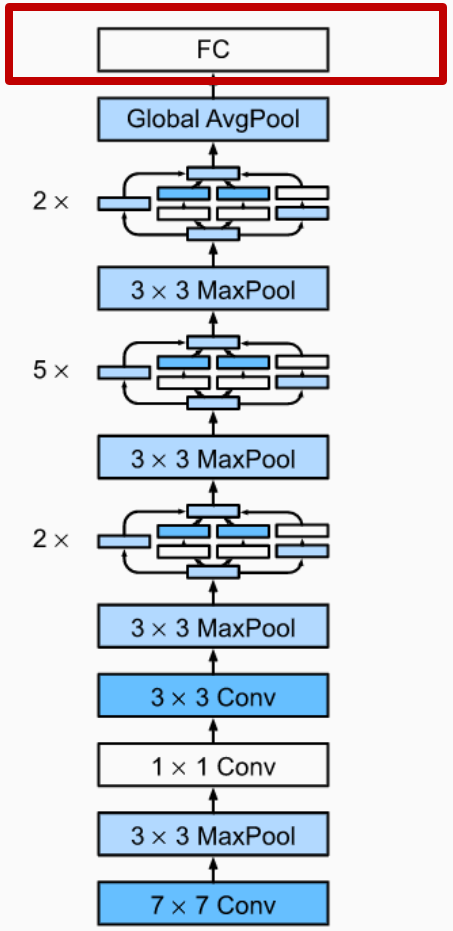


Fig. 7.4.2 The GoogLeNet architecture.

http://dlib.net/dnn_inception_ex.cpp.html
http://datahacker.rs/building-inception-network/
http://d2l.ai/chapter_convolutional-modern/googlenet.html
https://towardsdatascience.com/a-simple-guide-to-the-versions-of-the-inception-network-7fc52b863202

source: http://d2l.ai/chapter_convolutional-modern/googlenet.html

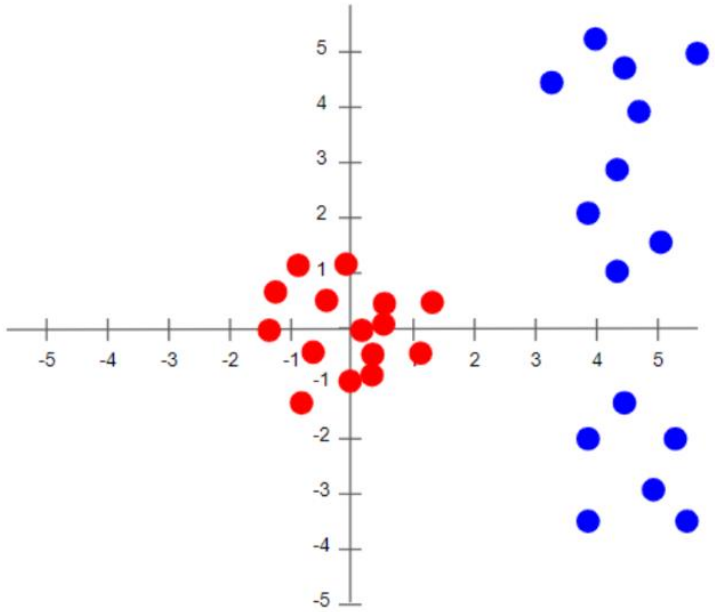
Batch normalization

- Additional layer that standardize the inputs to a network
- Helps to train very deep neural networks
- Accelerates training
- Can be used in many architectures of deep neural networks
- Solves the problem that the large feature can overshadow the small feature
- Uses mean and variance (průměr, rozptyl) of the current batch for a more stable distribution of values.
- https://pytorch.org/docs/stable/generated/torch.nn.BatchNorm2d.html

https://arxiv.org/pdf/1502.03167.pdf

http://d2l.ai/chapter_convolutional-modern/batch-norm.html

In the picture below, we can see the effect of normalizing data. The original values (in blue) are now centered around zero (in red). This ensures that all the feature values are now on the same scale.



source: https://towardsdatascience.com/batch-norm-explained-visually-how-it-works-and-why-neural-networks-need-it-b18919692739

CovNet Architectures

- LeNet (1990s)
- AlexNet (2012)
- ZF Net (2013)
- VGGNet (2014)
- GoogLeNet (2014)
- ResNets (2015)
- DenseNet (2017)

ResNets - 2015

2015

- ImageNet Challenge http://www.image-net.org/challenges/LSVRC/2015/
- http://www.image-net.org/challenges/LSVRC/2015/results
- http://image-net.org/challenges/talks/ILSVRC2015_12_17_15_clsloc.pdf
- **Deep networks are hard to train - Vanishing gradient issue**
- **Residual Blocks**
- **1 x 1 convolutions**

http://datahacker.rs/deep-learning-residual-networks/

He, Kaiming & Zhang, Xiangyu & Ren, Shaoqing & Sun, Jian. (2016). Deep Residual Learning for Image Recognition. 770-778. 10.1109/CVPR.2016.90.

ResNets - 2015

"Is learning better networks as easy as stacking more layers?"

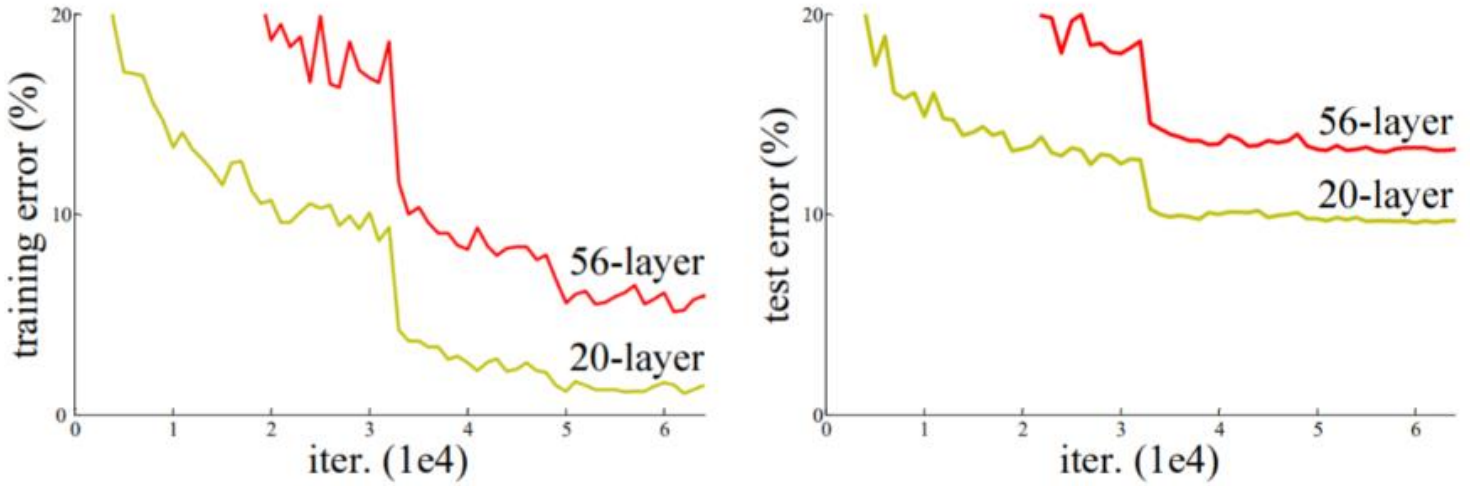


Figure 1. Training error (left) and test error (right) on CIFAR-10 with 20-layer and 56-layer "plain" networks. The deeper network has higher training error, and thus test error. Similar phenomena on ImageNet is presented in Fig. 4.

He, Kaiming & Zhang, Xiangyu & Ren, Shaoqing & Sun, Jian. (2016). Deep Residual Learning for Image Recognition. 770-778. 10.1109/CVPR.2016.90.

ResNets - 2015

- in the **classical** way: the output of layer 1 is pass to layer 2
- in **ResNet**: information can go much deeper into the neural network
  - information (gradient) from higher layer can directly pass to the lower layer
  - via **shortcut** or **skip connection** (identity connection, addition operator)
  - stacking a lot of residual blocks together, we can build much deeper neural networks

"shortcut connections"

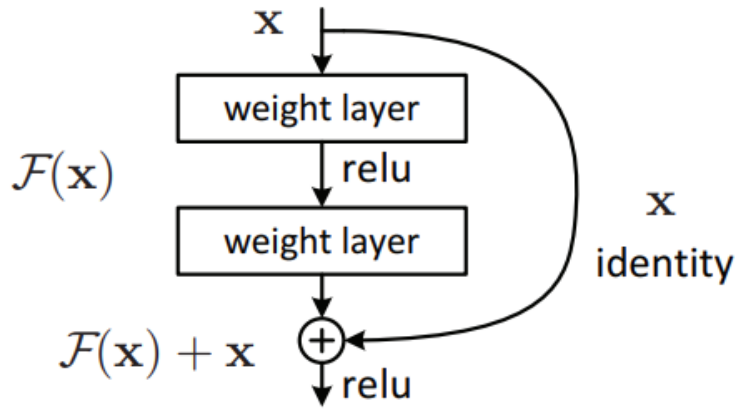


Figure 2. Residual learning: a building block.

He, Kaiming & Zhang, Xiangyu & Ren, Shaoqing & Sun, Jian. (2016). Deep Residual Learning for Image Recognition. 770-778. 10.1109/CVPR.2016.90.

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ResNets - 2015

“shortcut connections”

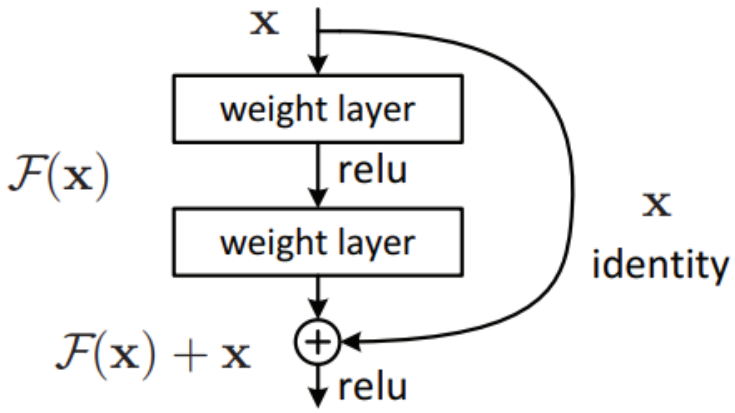

Figure 2. Residual learning: a building block.

“bottleneck”

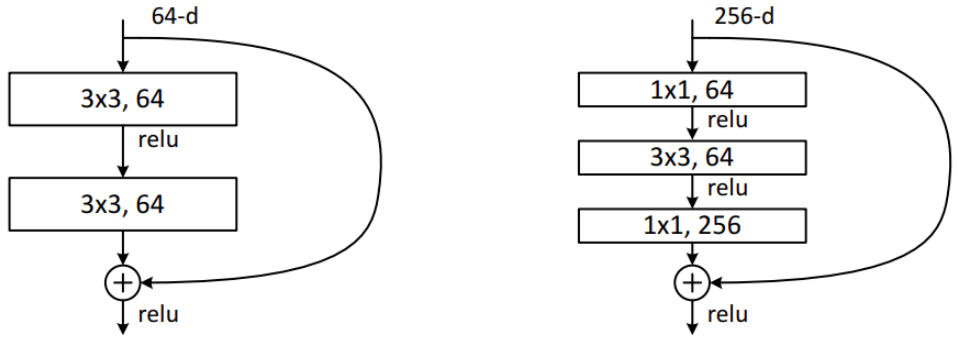

Figure 5. A deeper residual function $\mathcal{F}$ for ImageNet. Left: a building block (on 56×56 feature maps) as in Fig. 3 for ResNet-34. Right: a “bottleneck” building block for ResNet-50/101/152.

He, Kaiming & Zhang, Xiangyu & Ren, Shaoqing & Sun, Jian. (2016). Deep Residual Learning for Image Recognition. 770-778. 10.1109/CVPR.2016.90.

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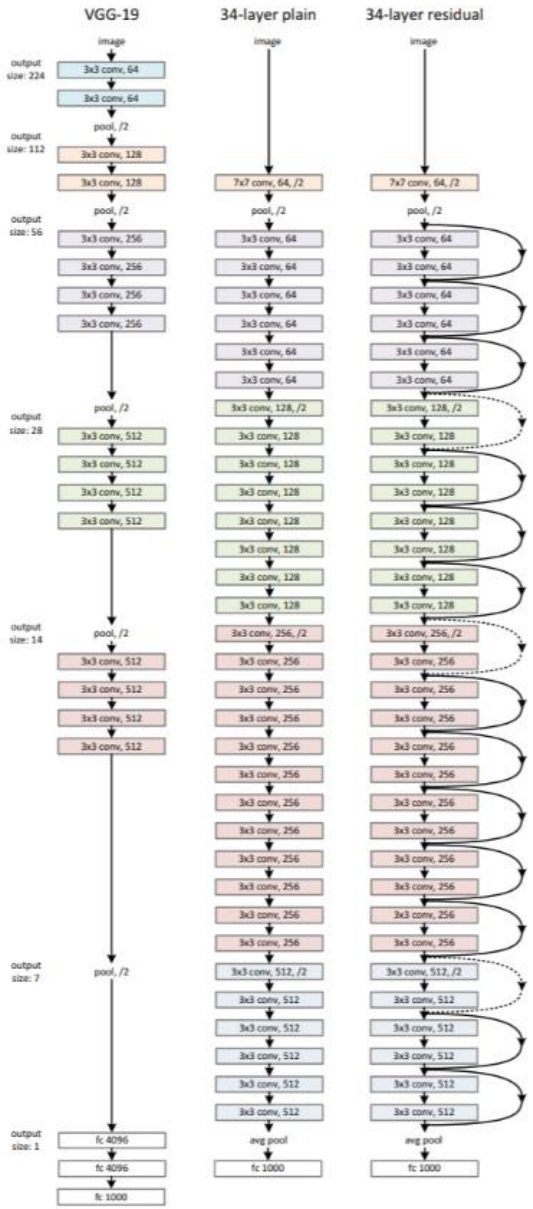
ResNets - 2015



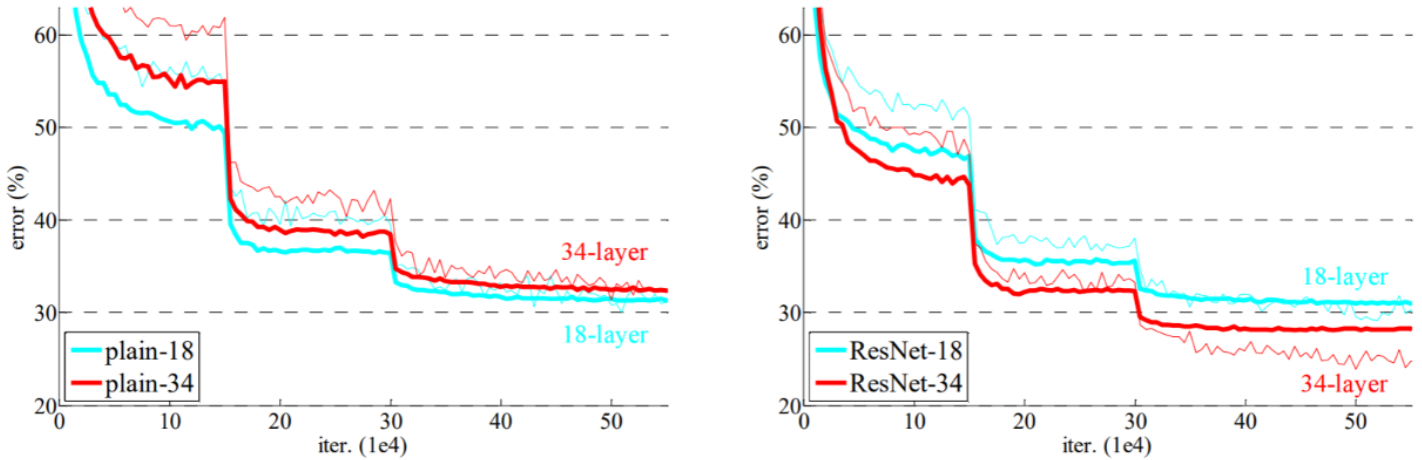


Figure 4. Training on **ImageNet**. Thin curves denote training error, and bold curves denote validation error of the center crops. Left: plain networks of 18 and 34 layers. Right: ResNets of 18 and 34 layers. In this plot, the residual networks have no extra parameter compared to their plain counterparts.

He, Kaiming & Zhang, Xiangyu & Ren, Shaoqing & Sun, Jian. (2016). Deep Residual Learning for Image Recognition. 770-778. 10.1109/CVPR.2016.90.

ResNets - 2015

Table 2. Classification error (%) on the CIFAR-10 test set using different activation functions.

case	Fig.	ResNet-110	ResNet-164
original Residual Unit [1]	Fig. 4(a)	6.61	5.93
BN after addition	Fig. 4(b)	8.17	6.50
ReLU before addition	Fig. 4(c)	7.84	6.14
ReLU-only pre-activation	Fig. 4(d)	6.71	5.91
full pre-activation	Fig. 4(e)	**6.37**	**5.46**

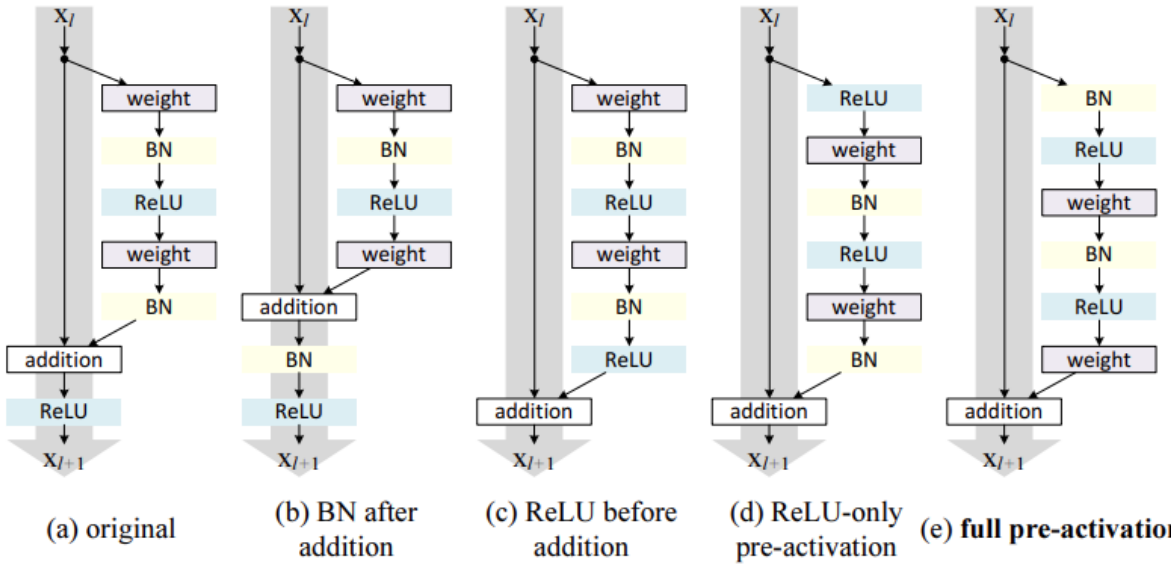


Figure 4. Various usages of activation in Table 2. All these units consist of the same components — only the orders are different.

He, Kaiming & Zhang, Xiangyu & Ren, Shaoqing & Sun, Jian. (2016). Identity Mappings in Deep Residual Networks. 9908. 630-645. 10.1007/978-3-319-46493-0_38.
He, Kaiming & Zhang, Xiangyu & Ren, Shaoqing & Sun, Jian. (2016). Deep Residual Learning for Image Recognition. 770-778. 10.1109/CVPR.2016.90.

- **Variations of ResNets:**
  - **Inception-ResNet V1**
  - **Inception-ResNet-v2**
  - **ResNeXt - 1st Runner Up of ILSVRC classification task**
    - http://image-net.org/challenges/LSVRC/2016/results

		224×224		320×320 / 299×299	
		top-1 err	top-5 err	top-1 err	top-5 err
Winner of ILSVRC 2015	ResNet-101 [14]	22.0	6.0	-	-
Pre-Activation ResNet	ResNet-200 [15]	21.7	5.8	20.1	4.8
1st Runner-Up of ILSVRC 2015	Inception-v3 [39]	-	-	21.2	5.6
Better Than Inception-v3	Inception-v4 [37]	-	-	20.0	5.0
Inception-v4 + ResNet	Inception-ResNet-v2 [37]	-	-	19.9	4.9
	ResNeXt-101 (**64** × **4d**)	20.4	5.3	**19.1**	**4.4**

https://towardsdatascience.com/review-inception-v4-evolved-from-googlenet-merged-with-resnet-idea-image-classification-5e8c339d18bc

https://towardsdatascience.com/review-resnext-1st-runner-up-of-ilsvrc-2016-image-classification-15d7f17b42ac

S. Xie, R. Girshick, P. Dollár, Z. Tu and K. He, "Aggregated Residual Transformations for Deep Neural Networks," *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Honolulu, HI, 2017, pp. 5987-5995, doi: 10.1109/CVPR.2017.634.

He, Kaiming & Zhang, Xiangyu & Ren, Shaoqing & Sun, Jian. (2016). Identity Mappings in Deep Residual Networks. 9908. 630-645. 10.1007/978-3-319-46493-0_38.

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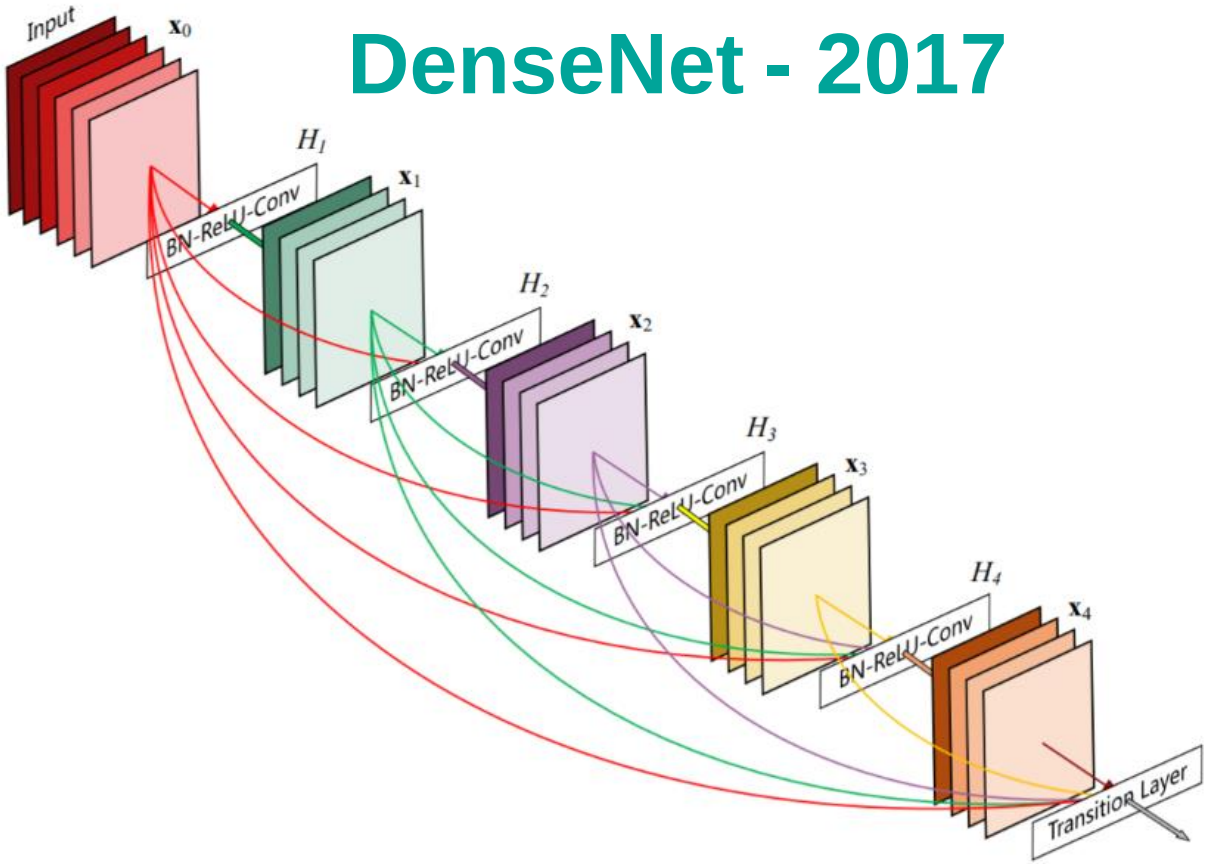
DenseNet - 2017

- connects all layers directly with each other
- handle vanishing gradients problem
- addition vs. concatenation (ResNet vs. DenseNet)
- dense blocks



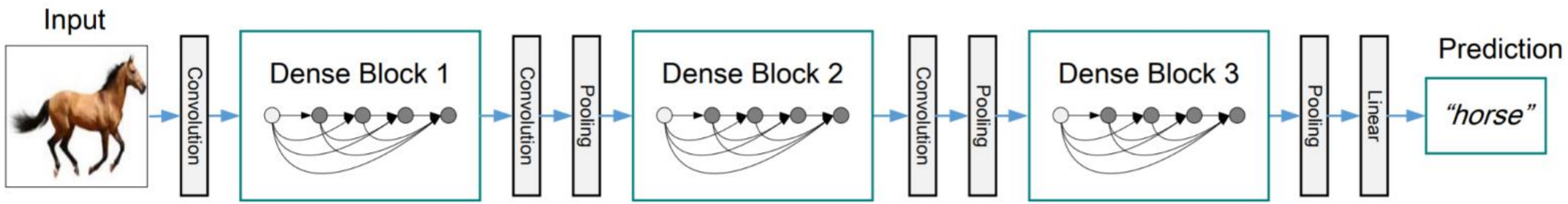


Figure 2: A deep DenseNet with three dense blocks. The layers between two adjacent blocks are referred to as transition layers and change feature-map sizes via convolution and pooling.

Huang, G., Liu, Z., Van Der Maaten, L., & Weinberger, K. Q. (2017). Densely connected convolutional networks. *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 4700–4708).

Transfer Learning - PyTorch

- reuse the parameters of the trained network
  - for example on large dataset (ImageNet)

- modified the network with the use of freezing the parameters or changing the output layer

- **Option 1 - Freeze all layers except the last fc layer that needs to be modified due to the class number:**

```
resnet18 = models.resnet18(pretrained = True)

#print info
for name, child in resnet18.named_children():
    print("name: ", name)

# turn off gradient computation
for param in resnet18.parameters():
    param.requires_grad = False

# change number of out classes
num_ftrs = resnet18.fc.in_features
print("resnet18.fc ", resnet18.fc)
resnet18.fc = nn.Linear(num_ftrs, 2)
resnet18 = resnet18.to(device)

#optimize params in fc layer only
optimizer = optim.SGD(resnet18.fc.parameters(), lr=0.001, momentum=0.9)
```

https://pytorch.org/tutorials/beginner/transfer_learning_tutorial.html
https://pytorch.org/tutorials/beginner/finetuning_torchvision_models_tutorial.html

Transfer Learning - PyTorch

- **Option 2 - Freeze and Unfreeze selected layers:**

```
resnet18 = models.resnet18(pretrained = True)

# freeze all layers in the body of the network
for param in resnet18.parameters():
    param.requires_grad = False

num_ftrs = resnet18.fc.in_features
# modified class number in fc layer
resnet18.fc = nn.Linear(num_ftrs, 2)

# unfreeze layer4 + fc
for name,param in resnet18.named_parameters():
    print("\t",name)
    if( ("fc" in name) or ("layer4" in name)):
        param.requires_grad = True

resnet18 = resnet18.to(device)
#optimize selected params
params_to_update = [param for param in resnet18.parameters() if param.requires_grad==True]
print(len(params_to_update))
optimizer = optim.SGD(params_to_update, lr=0.001, momentum=0.9)
```

https://pytorch.org/tutorials/beginner/transfer_learning_tutorial.html
https://pytorch.org/tutorials/beginner/finetuning_torchvision_models_tutorial.html

Transfer Learning - PyTorch

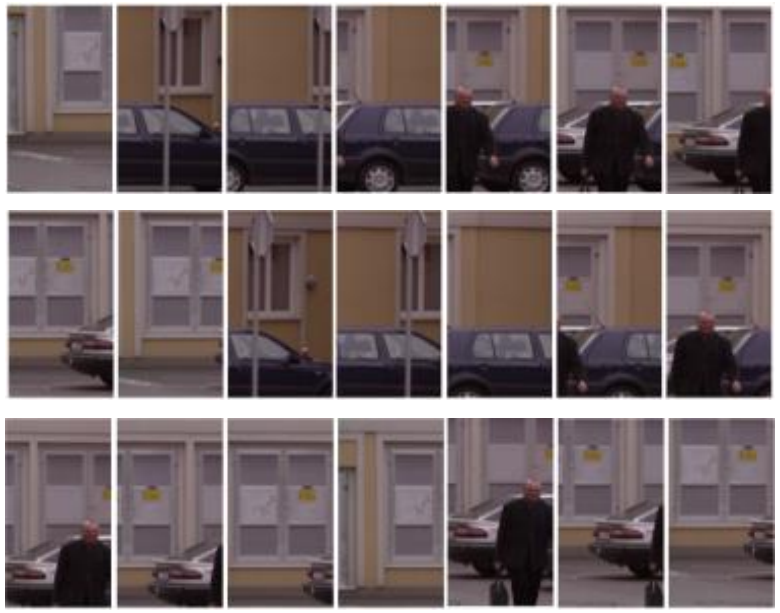
- **Option 3 – Add a new FC layer (similar to Option 1):**

```
# freeze all layers in the body of the network
for param in resnet18.parameters():
    param.requires_grad = False

num_ftrs = resnet18.fc.in_features
#define last layer with modified class number
myFC = nn.Sequential(
    nn.Linear(num_ftrs, 512),
    nn.ReLU(),
    nn.Dropout(0.5),
    nn.Linear(512, 256),
    nn.ReLU(),
    nn.Dropout(0.5),
    nn.Linear(256, 2)
)

resnet18.fc = myFC
resnet18 = resnet18.to(device)

#optimize params in fc layer only
optimizer = optim.SGD(resnet18.fc.parameters(), lr=0.001, momentum=0.9)
```

https://pytorch.org/tutorials/beginner/transfer_learning_tutorial.html
https://pytorch.org/tutorials/beginner/finetuning_torchvision_models_tutorial.html

Region-Based CNNs (R-CNNs)

- Classical way (how to localize/detect object) is based on sliding window technique



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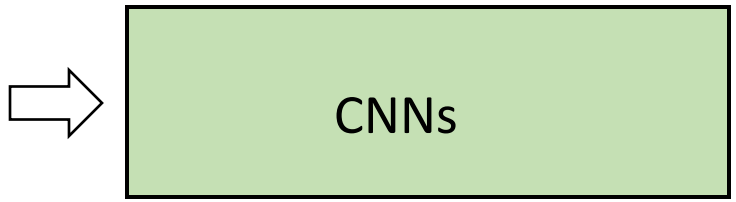
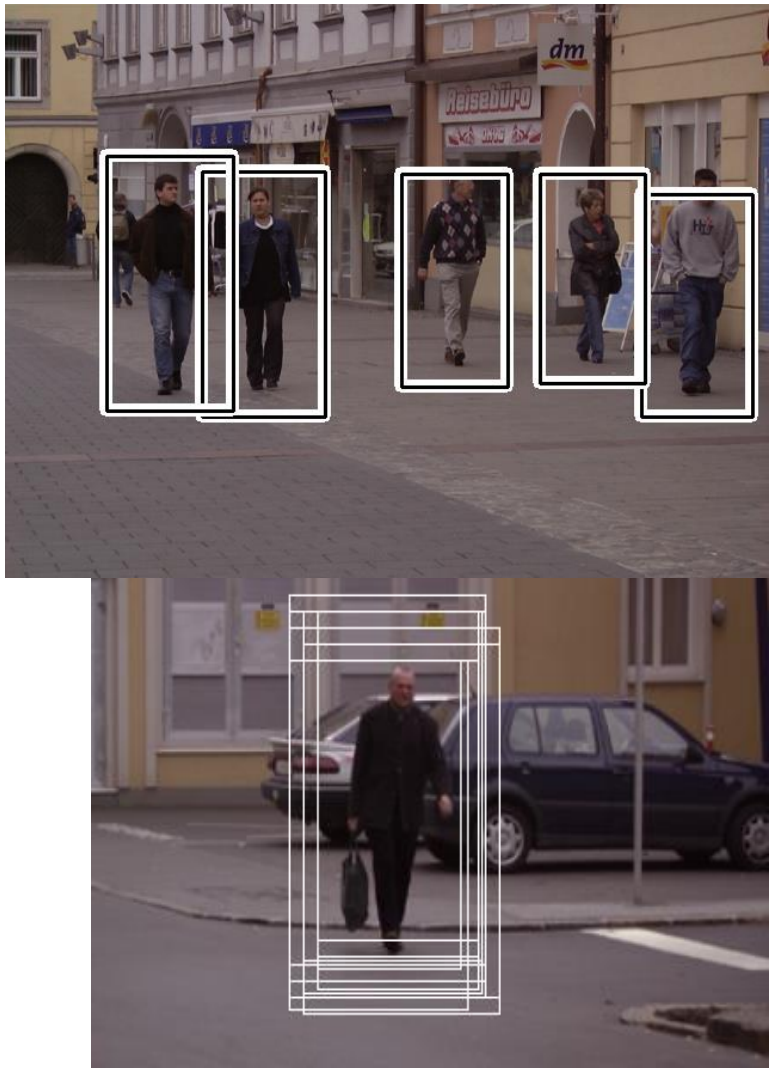
Region-Based CNNs (R-CNNs)

- Disadvantages of sliding window with the use off very deep CNNs for object detection
  - many different image regions
  - each region is used as an input for CNNs
    - computational cost – overlapping regions (stride parameters)
    - duplicated operations



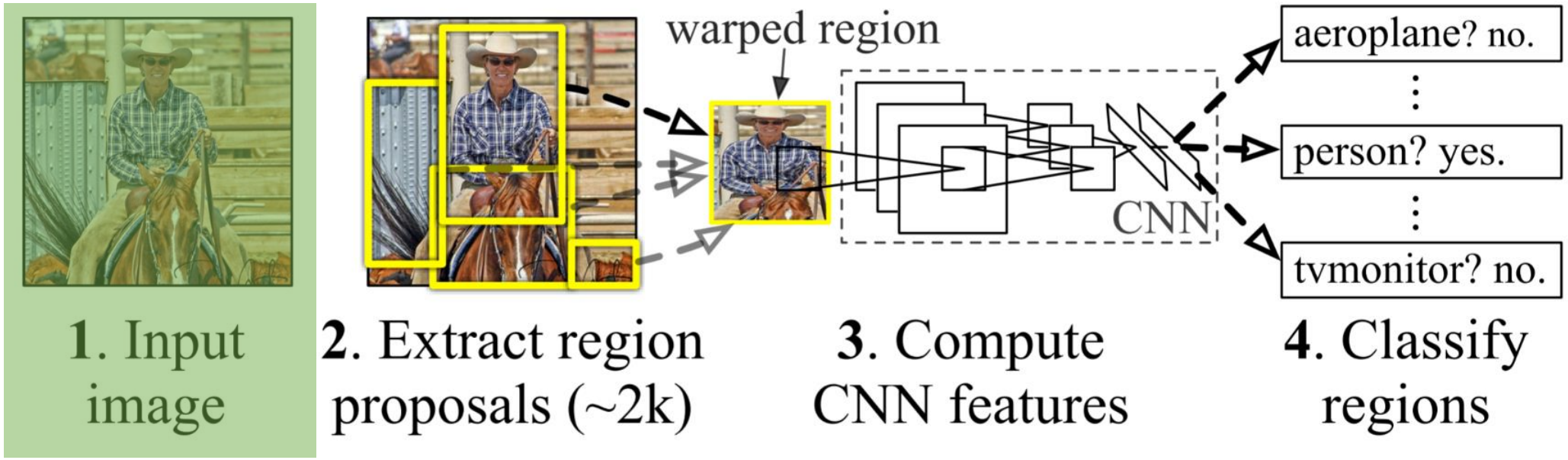


Region-Based CNNs (R-CNNs)

- **R-CNN**
  - Girshick, R., Donahue, J., Darrell, T., & Malik, J. (2014). Rich feature hierarchies for accurate object detection and semantic segmentation. *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 580–587).
- **Fast R-CNN**
  - Girshick, R. (2015). Fast r-cnn. *Proceedings of the IEEE international conference on computer vision* (pp. 1440–1448).
- **Faster R-CNN**
  - Ren, S., He, K., Girshick, R., & Sun, J. (2015). Faster r-cnn: towards real-time object detection with region proposal networks. *Advances in neural information processing systems* (pp. 91–99).
- **Mask R-CNN**
  - He, K., Gkioxari, G., Dollár, P., & Girshick, R. (2017). Mask r-cnn. *Proceedings of the IEEE international conference on computer vision* (pp. 2961–2969).

Region-Based CNNs (R-CNNs)

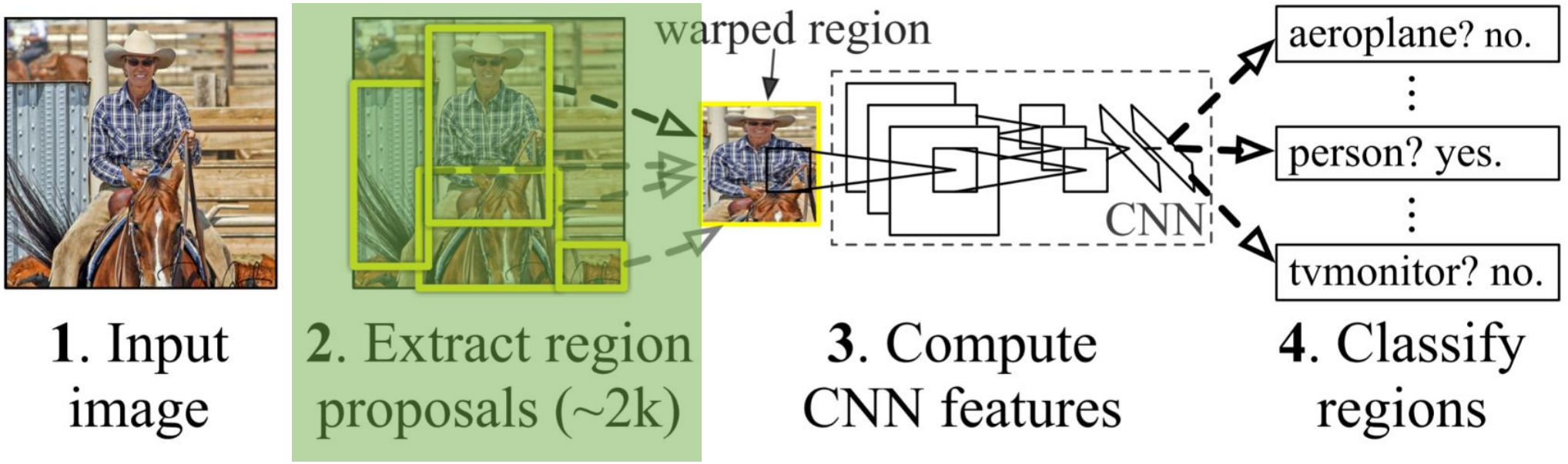
- **R-CNN - 2014**
- **(1) takes an input image**



Region-Based CNNs (R-CNNs)

- **R-CNN - 2014**

- (1) takes an input image
- **(2) extracts around 2000 bottom-up regions using selective search**
  - J. Uijlings, K. van de Sande, T. Gevers, and A. Smeulders. Selective search for object recognition. IJCV, 2013



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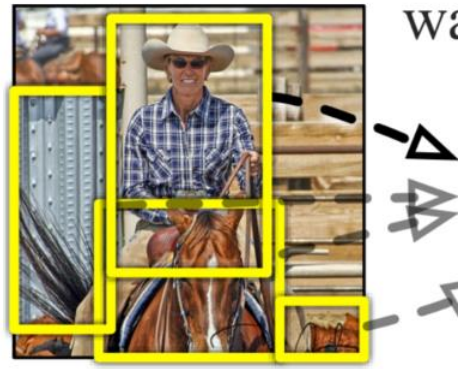
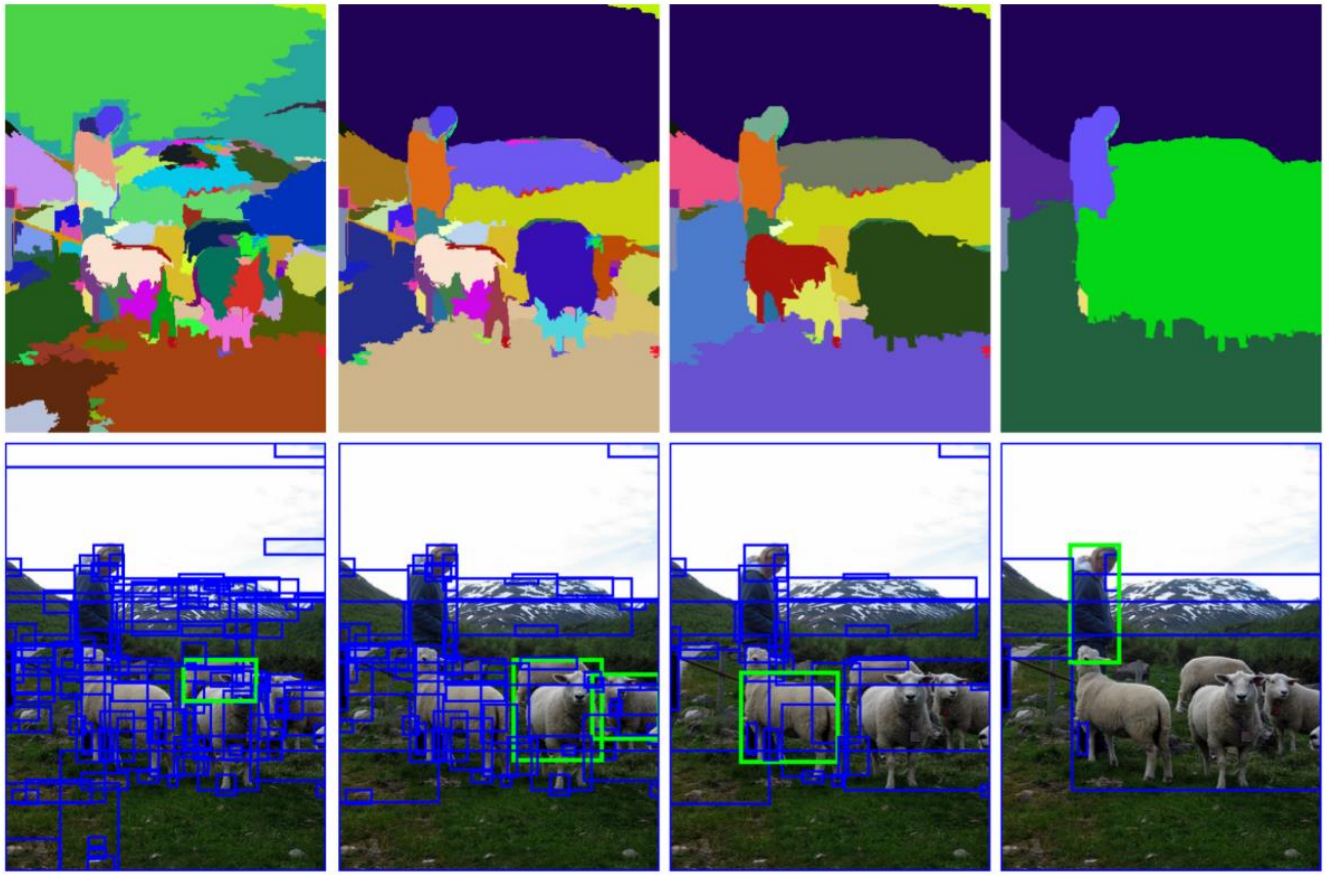


2. Extract region proposals (~2k)



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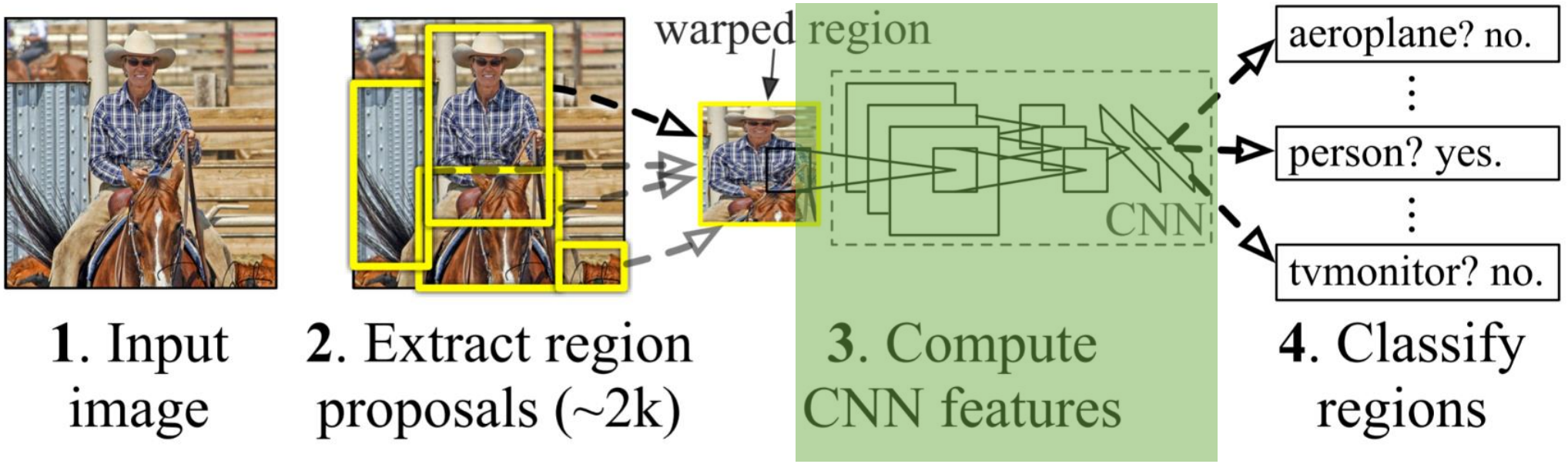
- **(3) computes features for each region using a large convolutional neural network (CNN)**
  - AlexNet is used to compute the features



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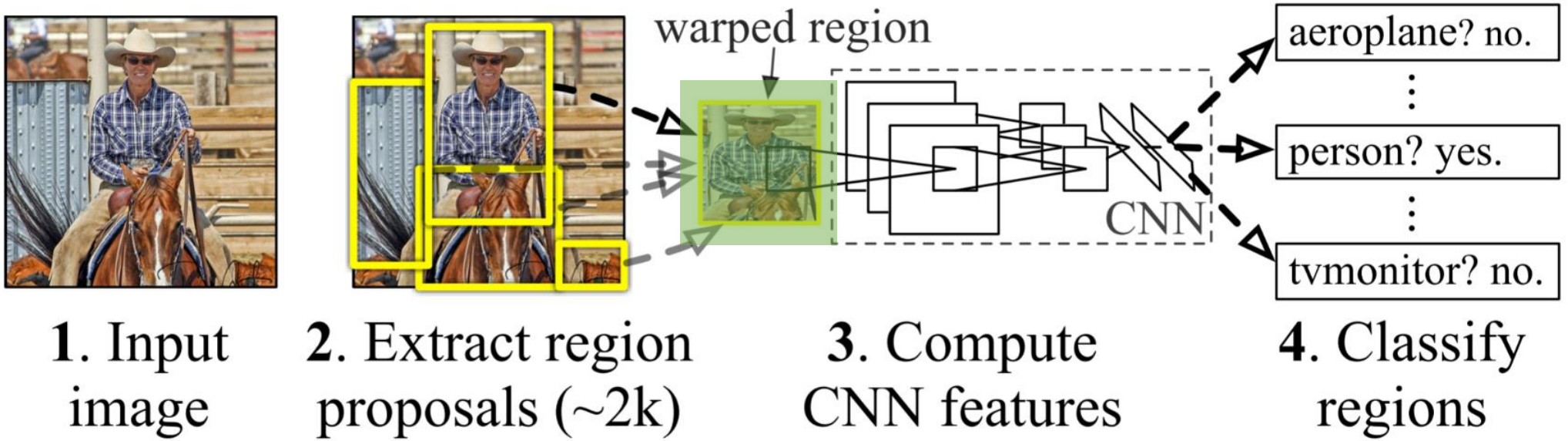
  - AlexNet is used to compute the features **(227×227 pixels)**



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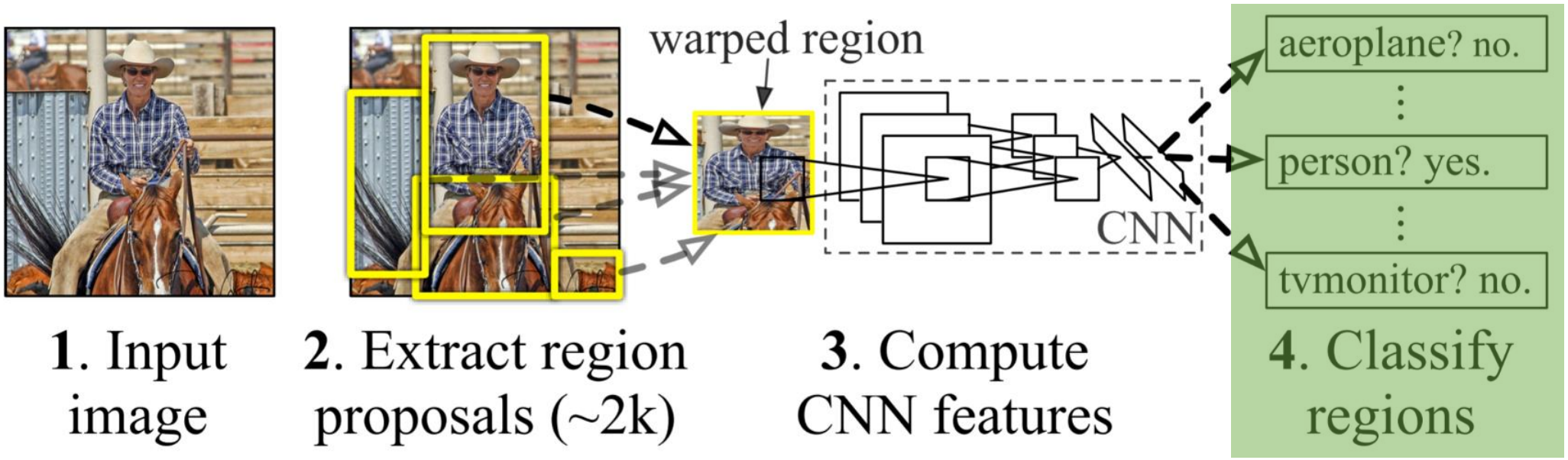
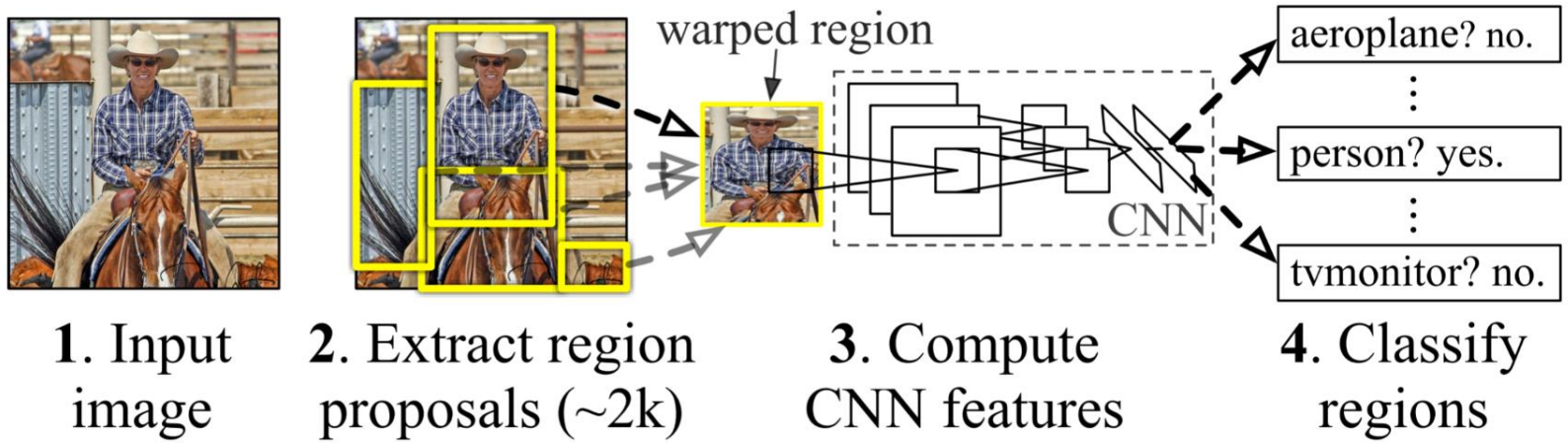
  - J. Uijlings, K. van de Sande, T. Gevers, and A. Smeulders. Selective search for object recognition. IJCV, 2013
- (3) computes features for each region using a large convolutional neural network (CNN)
  - AlexNet is used to compute the features (227×227 pixels)
- **(4) classifies each region using class-specific linear SVMs**



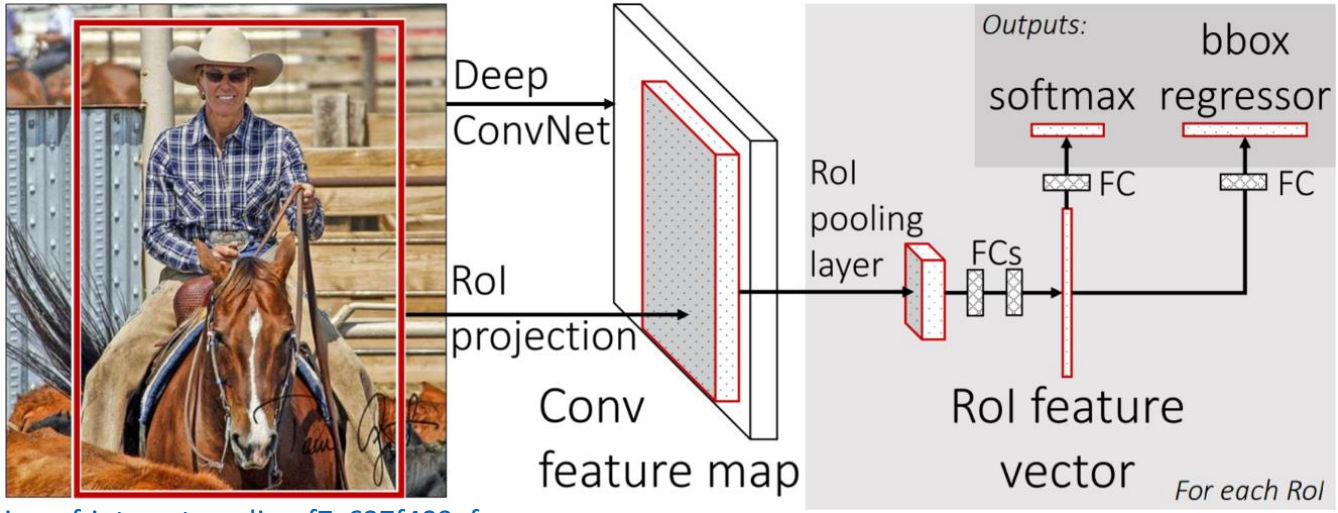
Region-Based CNNs (Fast R-CNNs)

- **R-CNN vs. Fast R-CNN – 2015**
- different shapes of regions > fully connected layers require fixed shape

R-CNN



Fast R-CNN

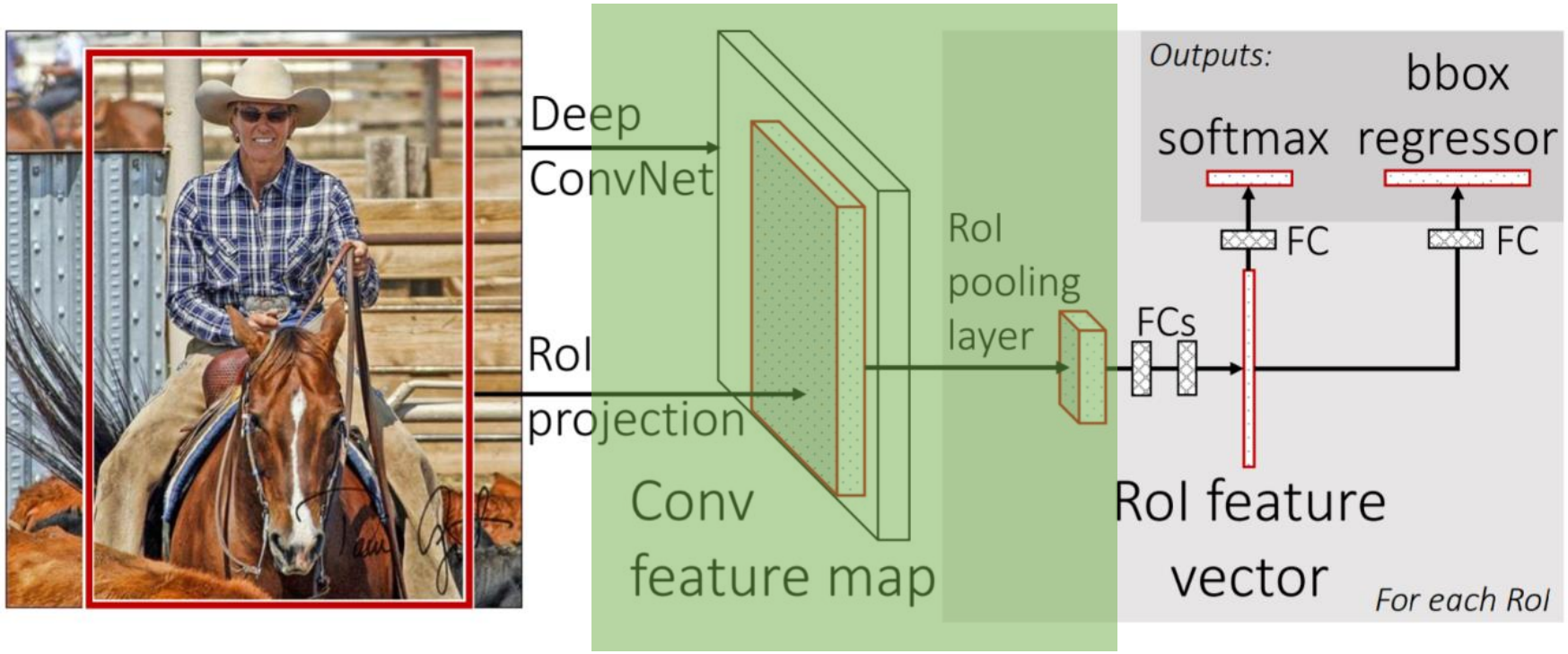


[1] https://towardsdatascience.com/region-of-interest-pooling-f7c637f409af
[2] https://towardsdatascience.com/understanding-region-of-interest-part-1-roi-pooling-e4f5dd65bb44

Region-Based CNNs (Fast R-CNNs)

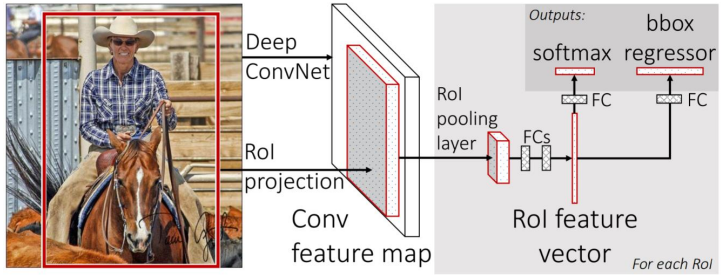
- **Fast R-CNN – 2015**
- different shapes of regions > fully connected layers require fixed shape

- **ROI Pooling (Region of interest pooling)** solves the problem
  - for every ROI (**proposal**) from the input, feature map which corresponds to that ROI is selected
  - transform this feature-map into a fixed dimension map



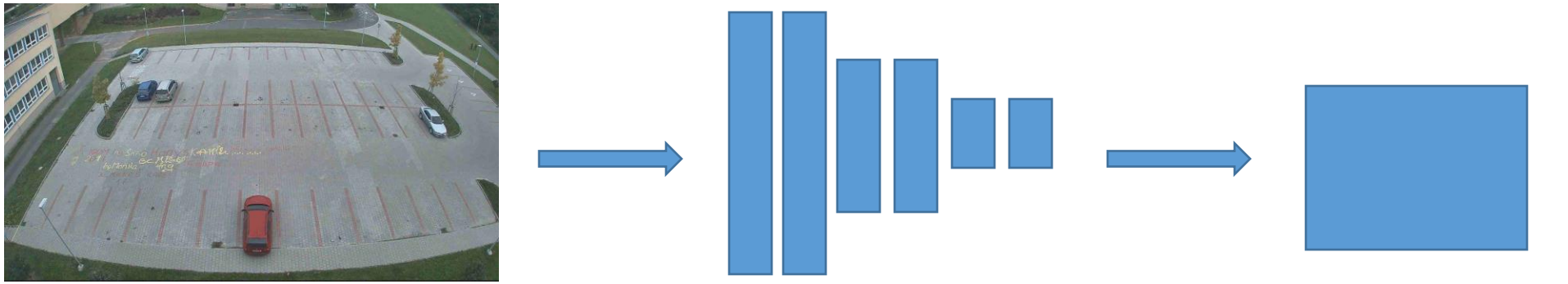
[1] https://towardsdatascience.com/region-of-interest-pooling-f7c637f409af
[2] https://towardsdatascience.com/understanding-region-of-interest-part-1-roi-pooling-e4f5dd65bb44

Region-Based CNNs (Fast R-CNNs)



- **Fast R-CNN – 2015**
- different shapes of regions > fully connected layers require fixed shape

- Example ([1, 2]):
  - input image size is **1056x640**
  - after several conv and pool operations the output feature map size is **reduced to 66x40**
  - **this feature map is used by ROI pooling layer**



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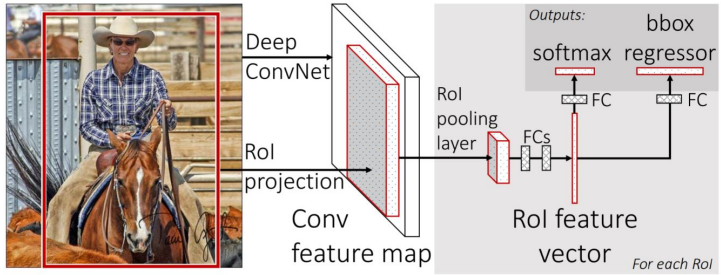
Region-Based CNNs (Fast R-CNNs)



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  - input image size is **1056x640**
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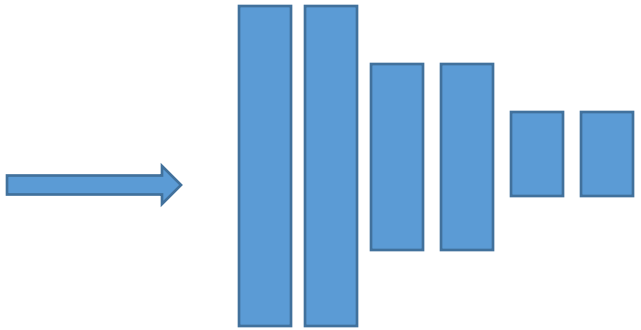
  - **this feature map is used by ROI pooling layer**
  - **Get RoIs from the feature map?**

1056x640



VGG-16

66x40 feature map

[1] https://towardsdatascience.com/region-of-interest-pooling-f7c637f409af
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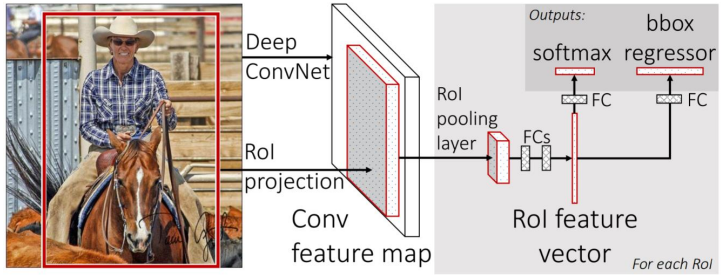
Region-Based CNNs (Fast R-CNNs)



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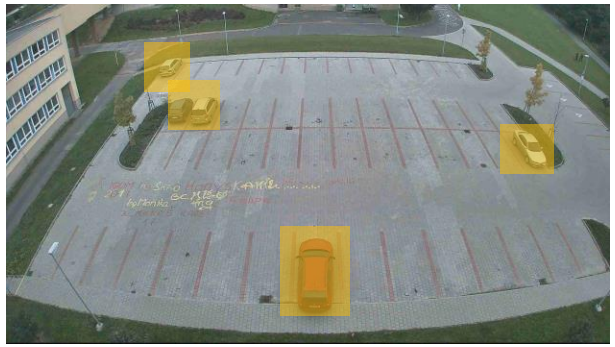
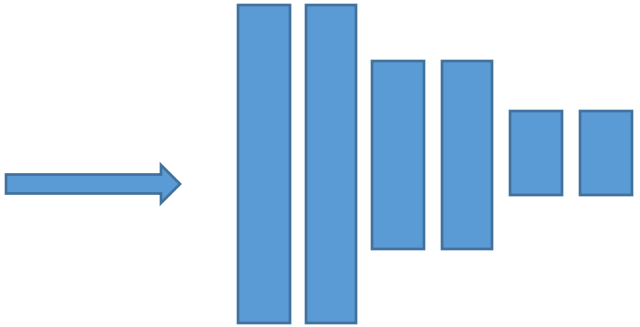
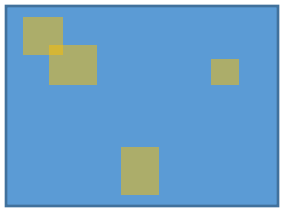
  - **Get RoIs from the feature map?**
  - The extracted regions of interest (**proposal**) are generated based on input image size, so we need to rescale these regions to feature map size. In this particular case by 16 (1056/66=16 or 640/40=16).



1056x640



VGG-16



66x40 feature map

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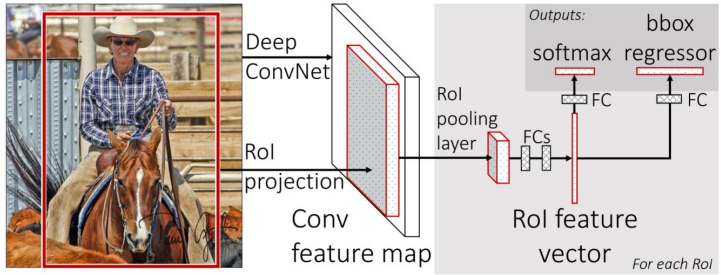
Region-Based CNNs (Fast R-CNNs)



- **Fast R-CNN – 2015**
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  - input image size is **1056x640**
  - after several conv and pool operations the output feature map size is **reduced to 66x40**
  - **this feature map is used by ROI pooling layer**
  - **Get RoIs from the feature map?**
  - The extracted regions of interest (**proposal**) are generated based on input image size, so we need to rescale these regions to feature map size. In this particular case by 16 (1056/66=16 or 640/40=16).
  - **For every proposal in the input proposals, we take the corresponding feature map section and divide that section into W*H. After that take the maximum element of each block and copy to the output. So as the output we obtain fixed dimension feature map irrespective of the various sizes of the input proposals.**

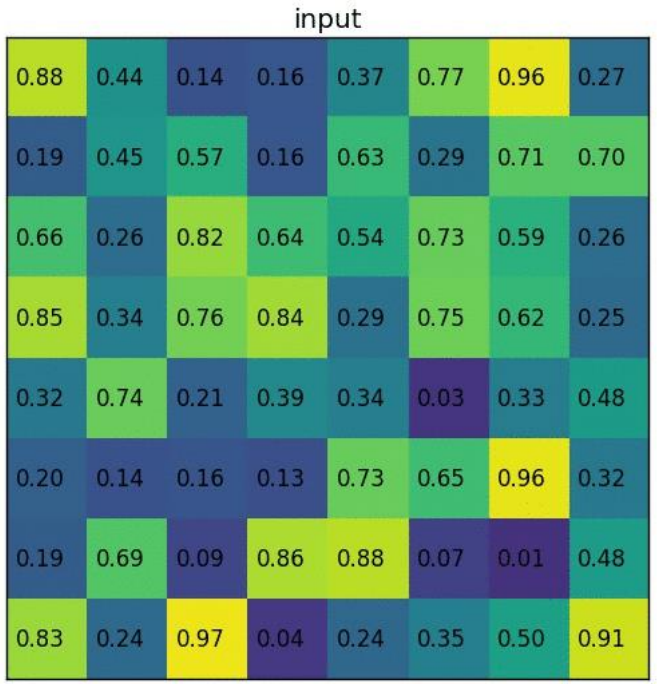
```
Scaled_Proposals = Proposals * spatial_scale
for every ROI in Scaled_Proposals:
    fmap_subset = feature_map[ROI] (Feature_map for that ROI)
    Divide fmap_subset into P_wxP_h blocks (ex: 6*6 blocks)
    Take the maximum element of each block and copy to output block
```

[1] https://towardsdatascience.com/region-of-interest-pooling-f7c637f409af
[2] https://towardsdatascience.com/understanding-region-of-interest-part-1-roi-pooling-e4f5dd65bb44

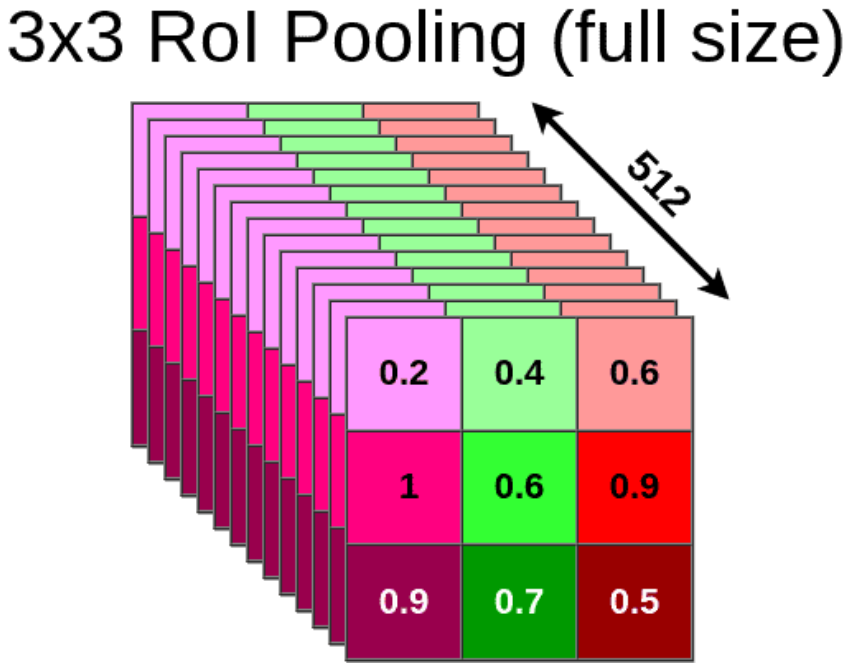
Region-Based CNNs (Fast R-CNNs)

- **Fast R-CNN – 2015**
- different shapes of regions > fully connected layers require fixed shape

- **ROI Pooling (Region of interest pooling)** solves the problem



source: https://miro.medium.com/max/840/1*5V5mycIRNu-mK-rPywL57w.gif



After the pooling process, (for example) the 3x3x512 matrixes can be used as input for FC layers for further processing. For each region we obtain fixed size of vector.

[1] https://towardsdatascience.com/region-of-interest-pooling-f7c637f409af
[2] https://towardsdatascience.com/understanding-region-of-interest-part-1-roi-pooling-e4f5dd65bb44

Region-Based CNNs (Faster R-CNNs)

- **Faster R-CNN – 2015**

- Selective search in R-CNN and Fast R-CNN is replaced by **Region Proposal Network**

- two modules:
  - 1. module is a deep fully convolutional network that proposes regions
  - 2. module is the Fast R-CNN detector that uses the proposed regions

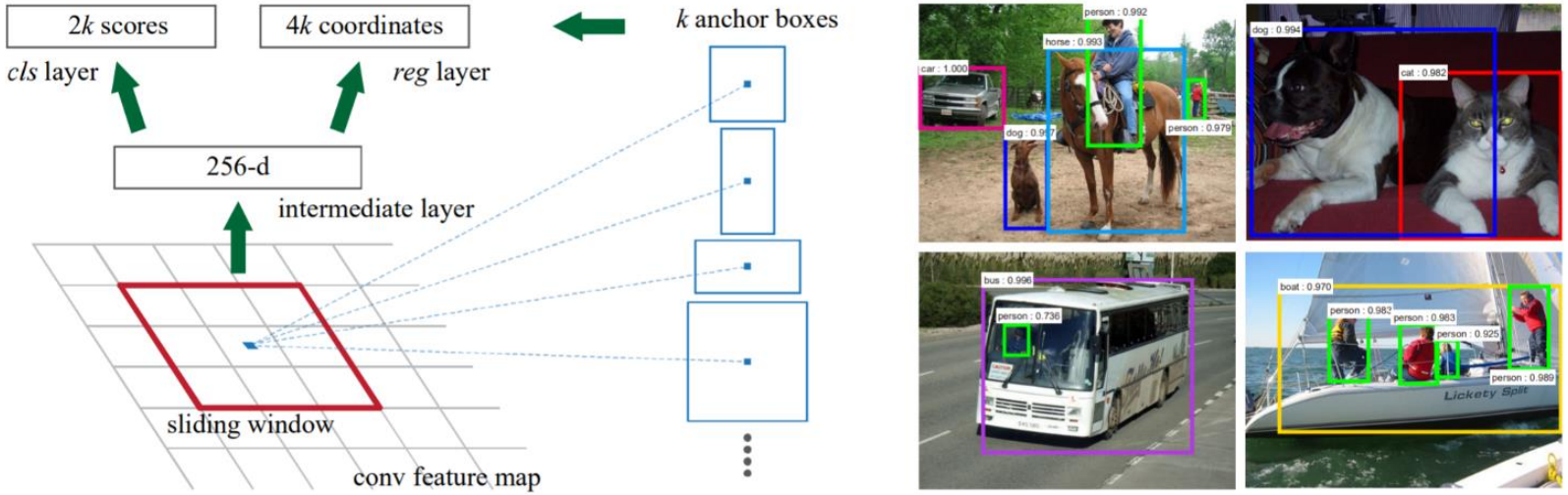
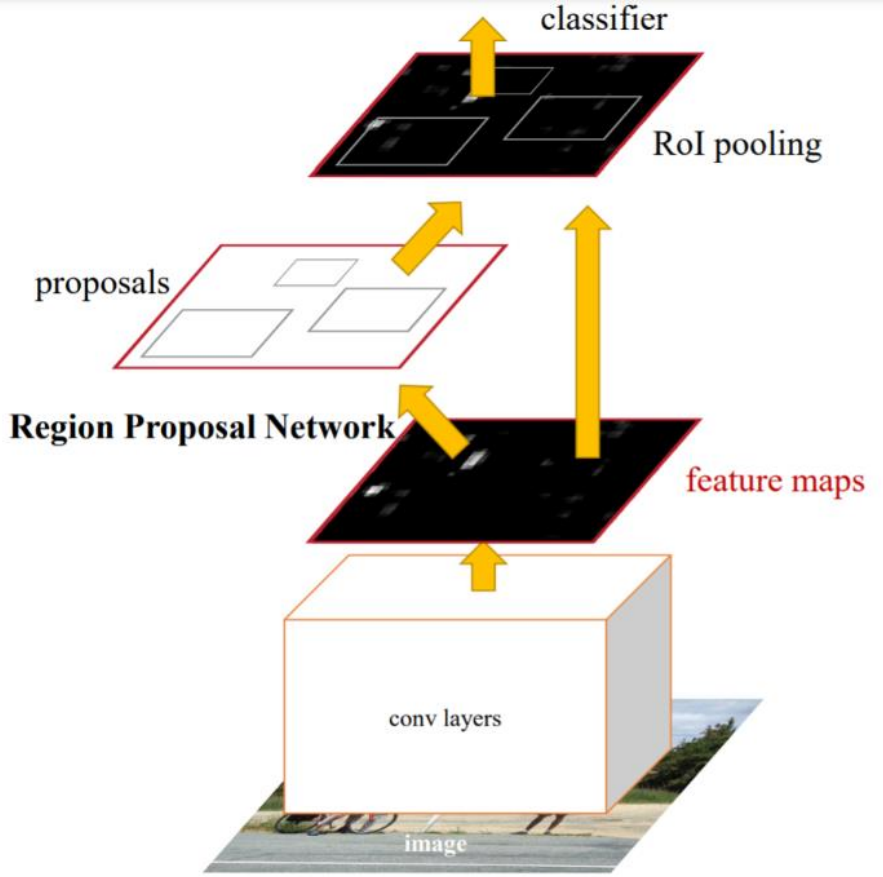


Figure 3: **Left**: Region Proposal Network (RPN). **Right**: Example detections using RPN proposals on PASCAL VOC 2007 test. Our method detects objects in a wide range of scales and aspect ratios.



https://arxiv.org/abs/1506.01497

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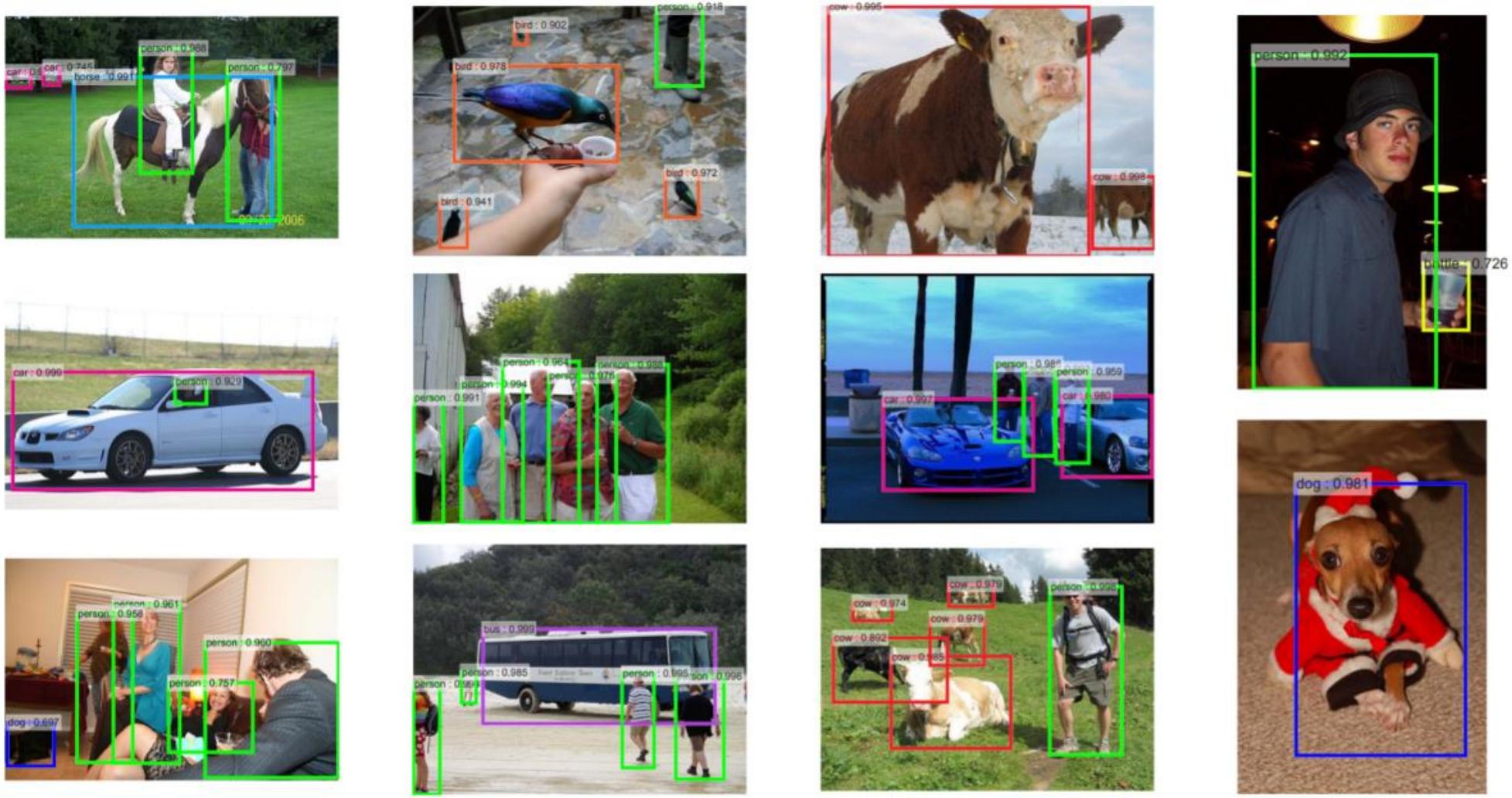
Region-Based CNNs (Faster R-CNNs)

- **Faster R-CNN – 2015**

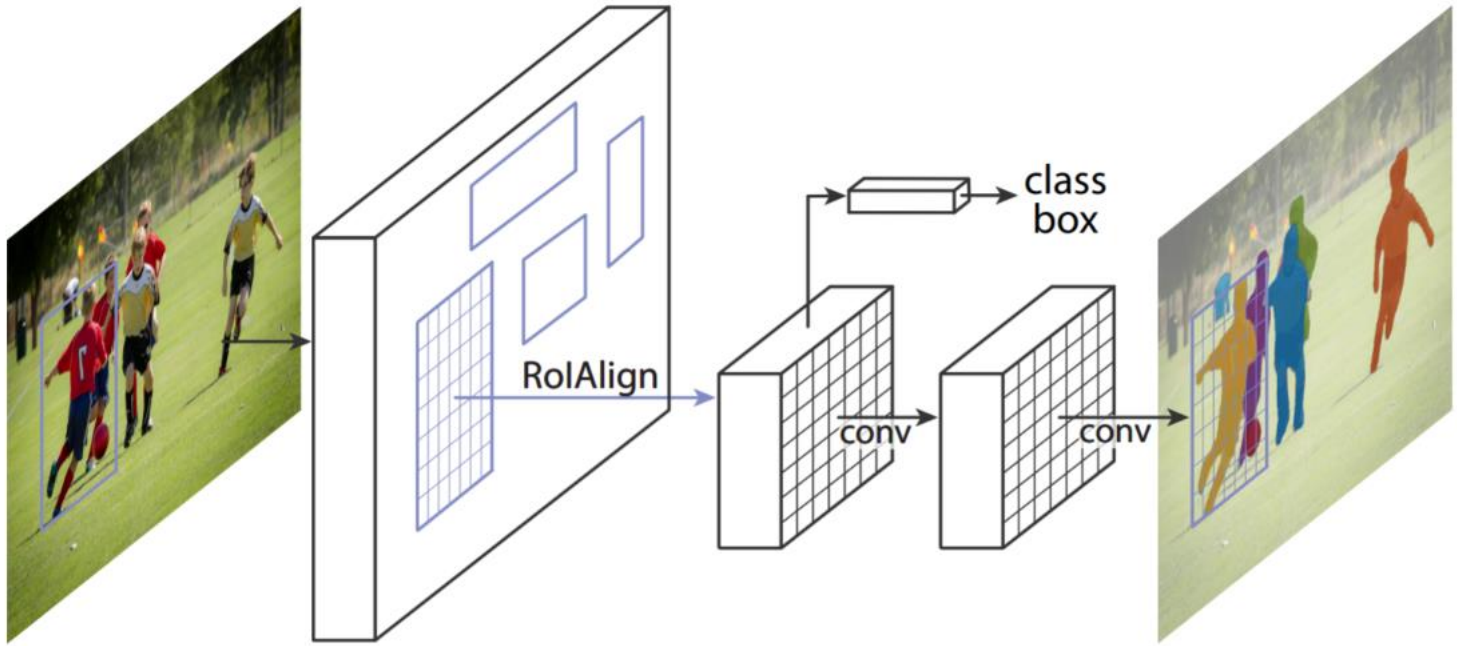


https://arxiv.org/abs/1506.01497

Region-Based CNNs (Mask R-CNNs)

- **Mask R-CNN – 2017**

- **Extends Faster R-CNN**
  - With the use of branch for predicting segmentation masks on each Region of Interest (RoI)



https://arxiv.org/abs/1506.01497
https://arxiv.org/abs/1703.06870

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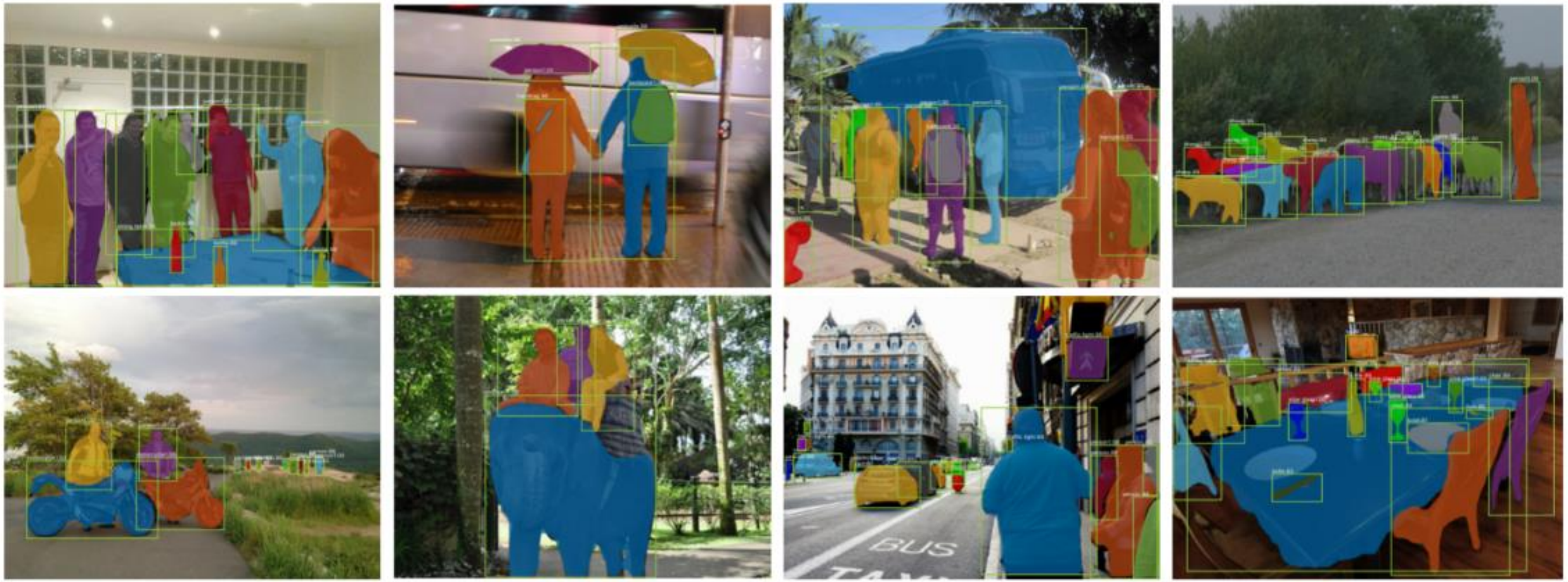
Region-Based CNNs (Mask R-CNNs)

- **Mask R-CNN – 2017**



https://arxiv.org/abs/1506.01497
https://arxiv.org/abs/1703.06870

Region-Based CNNs (Faster R-CNNs)

- **EXAMPLE Faster R-CNN – PyTorch**

https://pytorch.org/vision/main/generated/torchvision.models.detection.fasterrcnn_resnet50_fpn.html

```
def main():

    cv2.namedWindow("detection", 0)
    print("main")

    test_images = [img for img in glob.glob("test_images/*.jpg")]
    test_images.sort()

    model = torchvision.models.detection.fasterrcnn_resnet50_fpn(pretrained=True)
    device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
    model.eval().to(device)

    transformRCNN = transforms.Compose([
        transforms.ToTensor(),
    ])
```

https://arxiv.org/abs/1506.01497
https://arxiv.org/abs/1703.06870

Region-Based CNNs (Faster R-CNNs)

- **EXAMPLE Faster R-CNN – PyTorch**

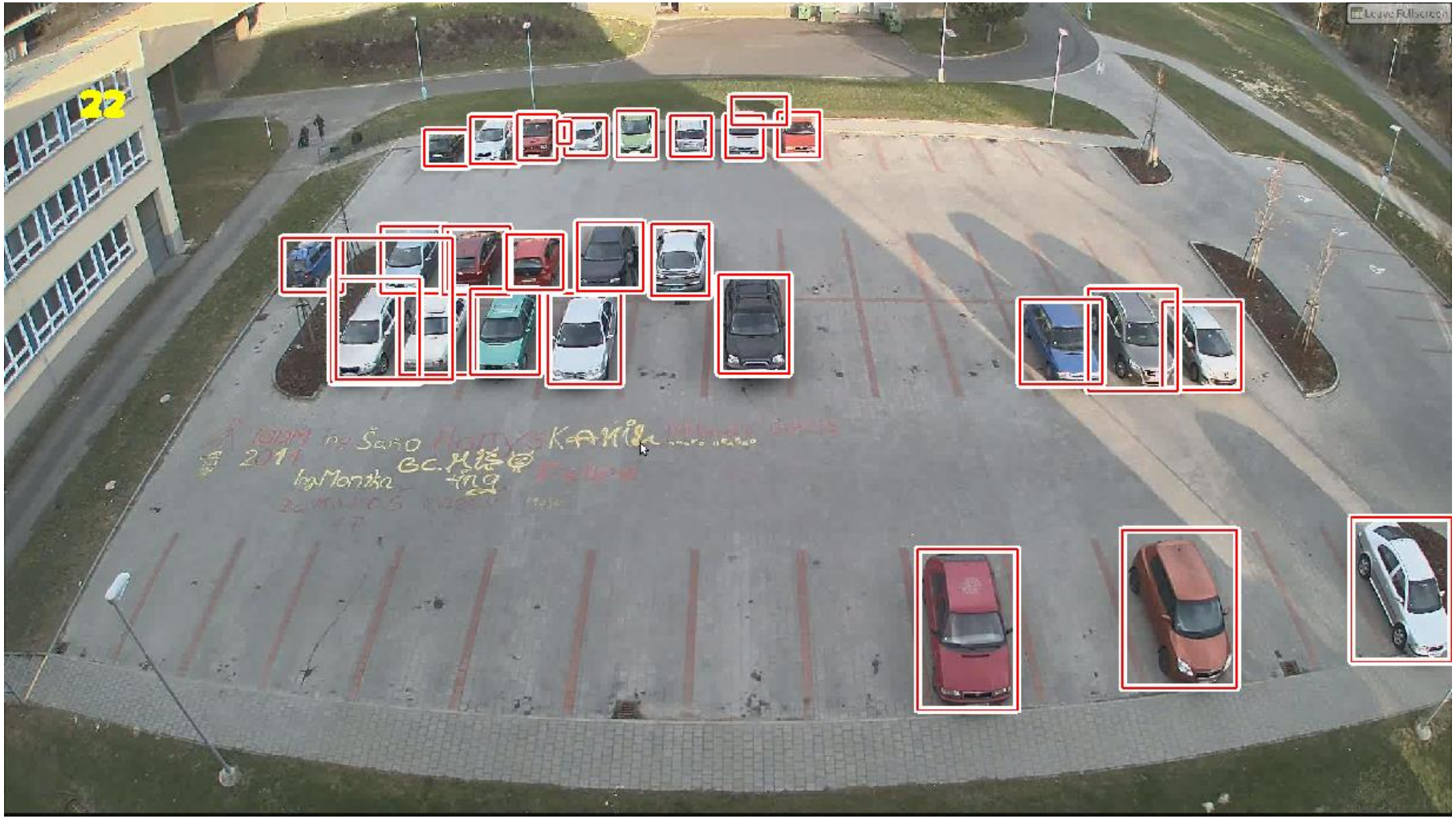
```
coco_names = [ '__background__', 'person', 'bicycle', 'car', 'motorcycle', 'airplane', 'bus', 'train', 'truck',
'boat', 'traffic light', 'fire hydrant', 'N/A', 'stop sign', 'parking meter', 'bench', 'bird', 'cat', 'dog', 'horse', 'sheep',
'cow', 'elephant', 'bear', 'zebra', 'giraffe', 'N/A', 'backpack', 'umbrella', 'N/A', 'N/A', 'handbag', 'tie', 'suitcase',
'frisbee', 'skis', 'snowboard', 'sports ball', 'kite', 'baseball bat', 'baseball glove', 'skateboard', 'surfboard',
'tennis racket', 'bottle', 'N/A', 'wine glass', 'cup', 'fork', 'knife', 'spoon', 'bowl', 'banana', 'apple', 'sandwich',
'orange', 'broccoli', 'carrot', 'hot dog', 'pizza', 'donut', 'cake', 'chair', 'couch', 'potted plant', 'bed', 'N/A', 'dining
table', 'N/A', 'N/A', 'toilet', 'N/A', 'tv', 'laptop', 'mouse', 'remote', 'keyboard', 'cell phone', 'microwave', 'oven',
'toaster', 'sink', 'refrigerator', 'N/A', 'book', 'clock', 'vase', 'scissors', 'teddy bear', 'hair drier', 'toothbrush' ]
```

```
for img in test_images:
    one_img = cv2.imread(img)
    one_img_paint = one_img.copy()

    one_img_rgb = cv2.cvtColor(one_img, cv2.COLOR_BGR2RGB)
    img_pil = Image.fromarray(one_img_rgb)
    imageRCNN = transformRCNN(img_pil).to(device)
    imageRCNN = imageRCNN.unsqueeze(0)
    outputsRCNN = model(imageRCNN)
    pred_classes = [coco_names[i] for i in outputsRCNN[0]['labels'].cpu().numpy()]
    pred_scores = outputsRCNN[0]['scores'].detach().cpu().numpy()
    pred_bboxes = outputsRCNN[0]['boxes'].detach().cpu().numpy()

    print(pred_scores)
    print(pred_classes)
```

https://arxiv.org/abs/1506.01497
https://arxiv.org/abs/1703.06870

Region-Based CNNs (Faster R-CNNs)

- **EXAMPLE Faster R-CNN – PyTorch**



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YOLO

- **YOLO - You Only Look Once**

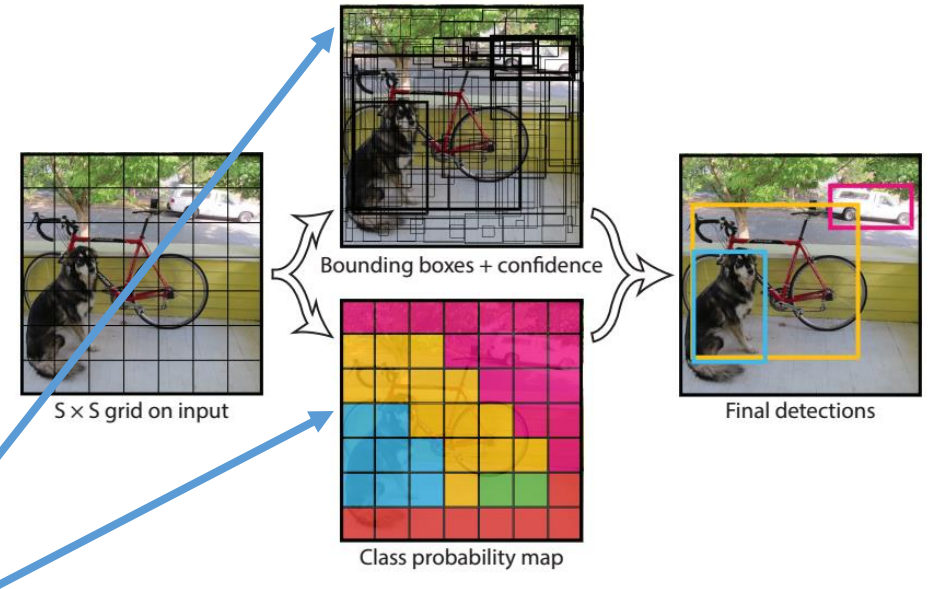


Figure 2: The Model. Our system models detection as a regression problem. It divides the image into an $S \times S$ grid and for each grid cell predicts B bounding boxes, confidence for those boxes, and C class probabilities. These predictions are encoded as an $S \times S \times (B * 5 + C)$ tensor.

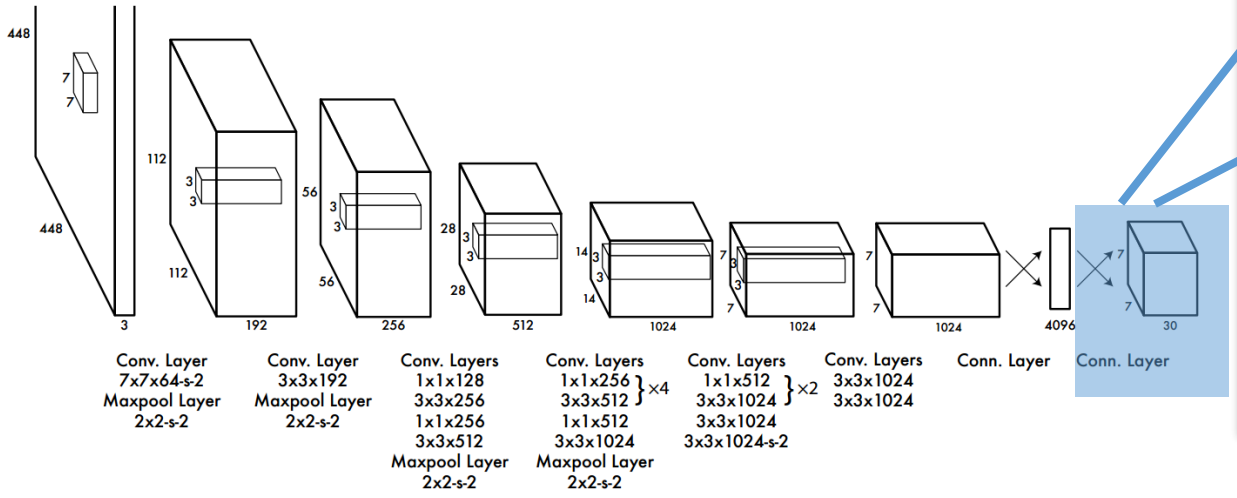


Figure 3: The Architecture. Our detection network has 24 convolutional layers followed by 2 fully connected layers. Alternating 1×1 convolutional layers reduce the features space from preceding layers. We pretrain the convolutional layers on the ImageNet classification task at half the resolution (224×224 input image) and then double the resolution for detection.

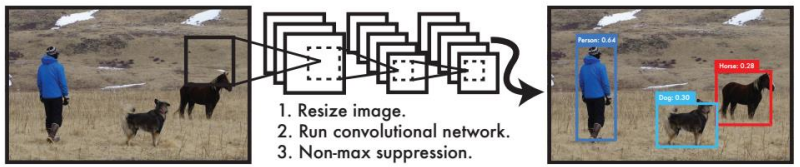


Figure 1: The YOLO Detection System. Processing images with YOLO is simple and straightforward. Our system (1) resizes the input image to 448×448, (2) runs a single convolutional network on the image, and (3) thresholds the resulting detections by the model's confidence.

https://arxiv.org/abs/1506.02640

YOLO vs. Fast R-CNN

- **YOLO - You Only Look Once**

Figure 4 shows the breakdown of each error type averaged across all 20 classes.

YOLO struggles to localize objects correctly. Localization errors account for more of YOLO's errors than all other sources combined. Fast R-CNN makes much fewer localization errors but far more background errors. 13.6% of it's top detections are false positives that don't contain any objects. Fast R-CNN is almost 3x more likely to predict background detections than YOLO.

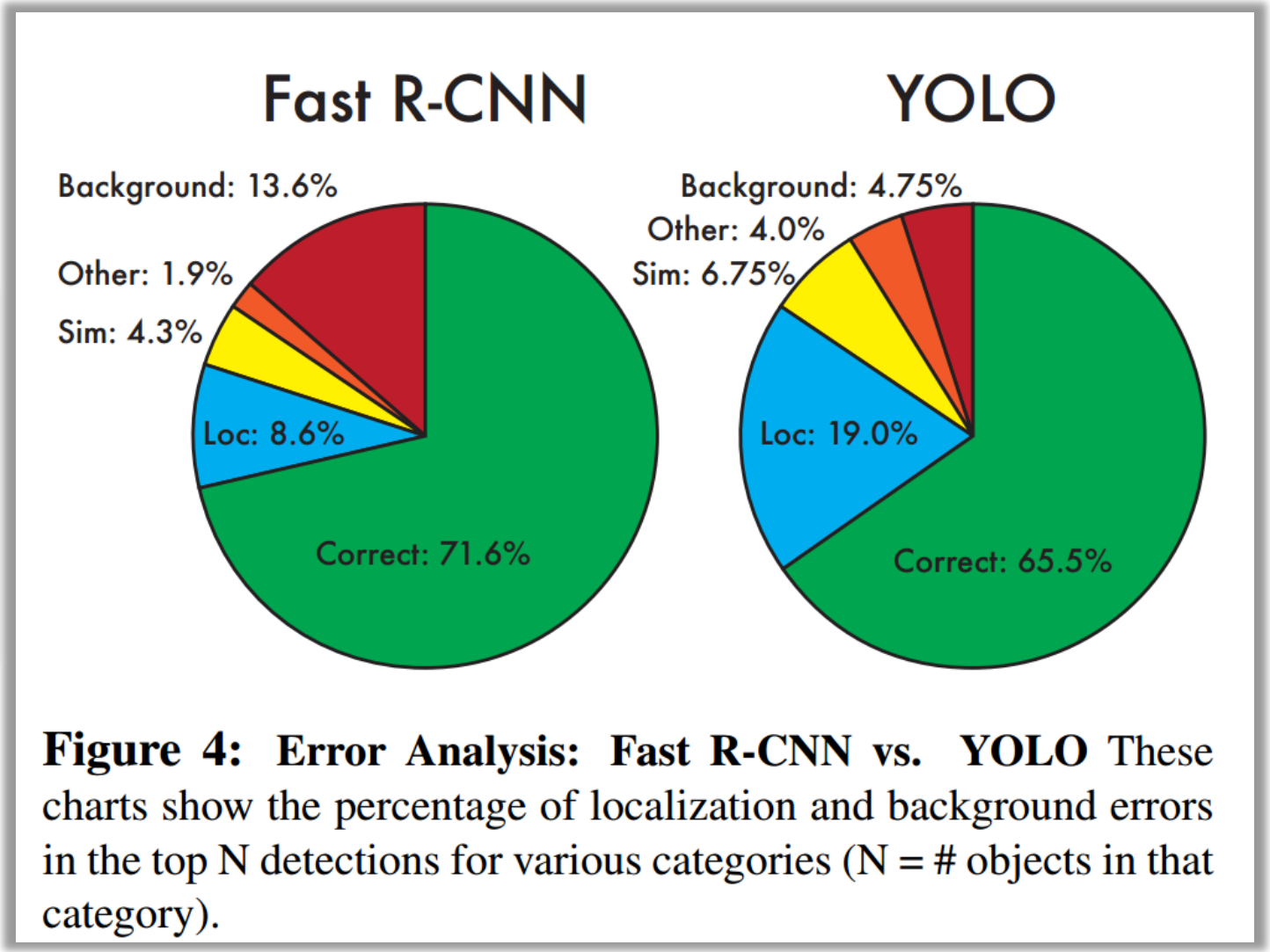


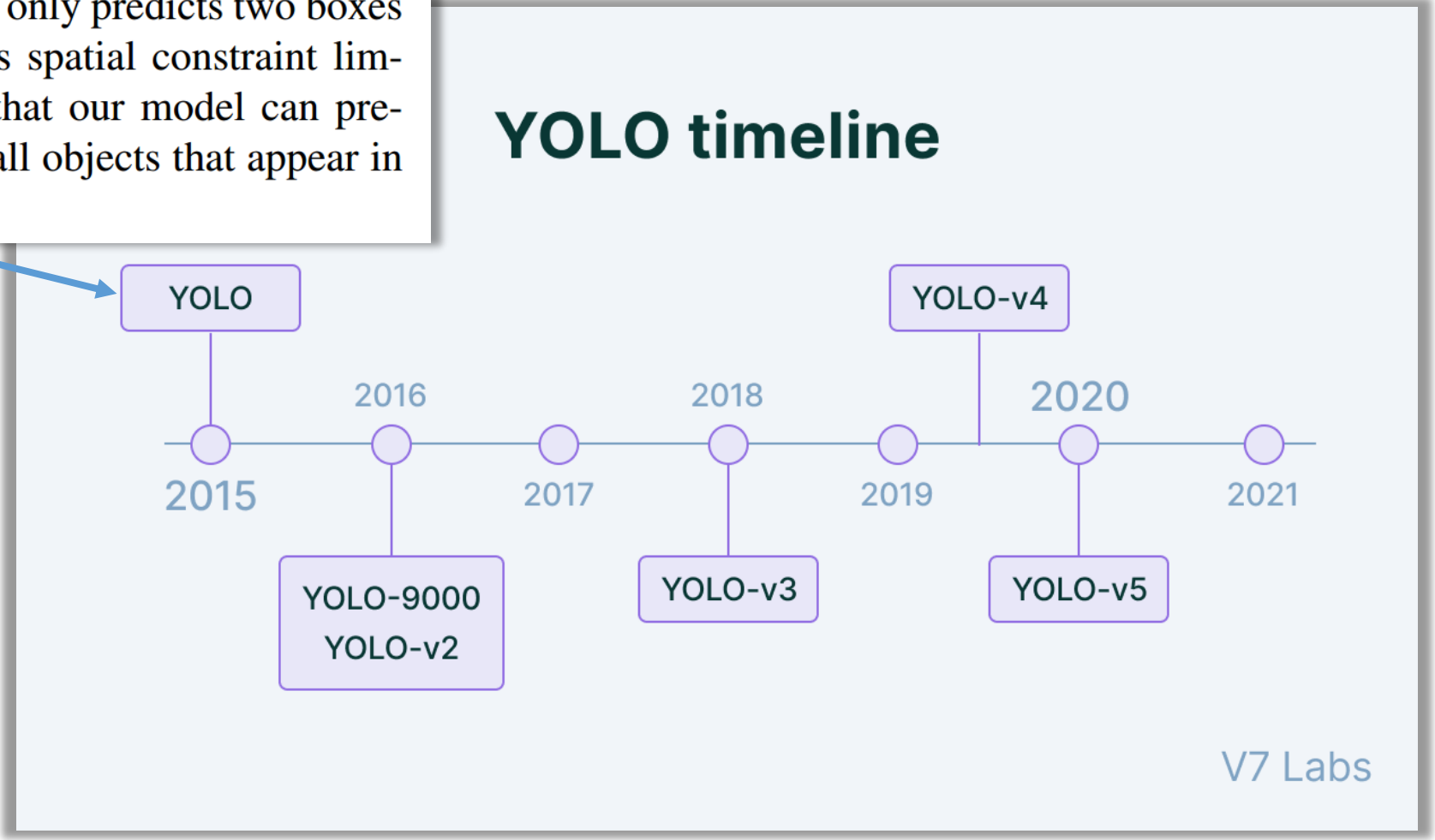
Figure 4: Error Analysis: Fast R-CNN vs. YOLO These charts show the percentage of localization and background errors in the top N detections for various categories (N = # objects in that category).

https://arxiv.org/abs/1506.02640

Versions of YOLO

2.4. Limitations of YOLO

YOLO imposes strong spatial constraints on bounding box predictions since each grid cell only predicts two boxes and can only have one class. This spatial constraint limits the number of nearby objects that our model can predict. Our model struggles with small objects that appear in groups, such as flocks of birds.



https://www.v7labs.com/blog/yolo-object-detection

https://arxiv.org/abs/1506.02640

Mobile Devices

MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications

Andrew G. Howard Menglong Zhu Bo Chen Dmitry Kalenichenko
Weijun Wang Tobias Weyand Marco Andreetto Hartwig Adam

Google Inc.

{howarda,menglong,bochen,dkalenichenko,weijunw,weyand,anm,hadam}@google.com

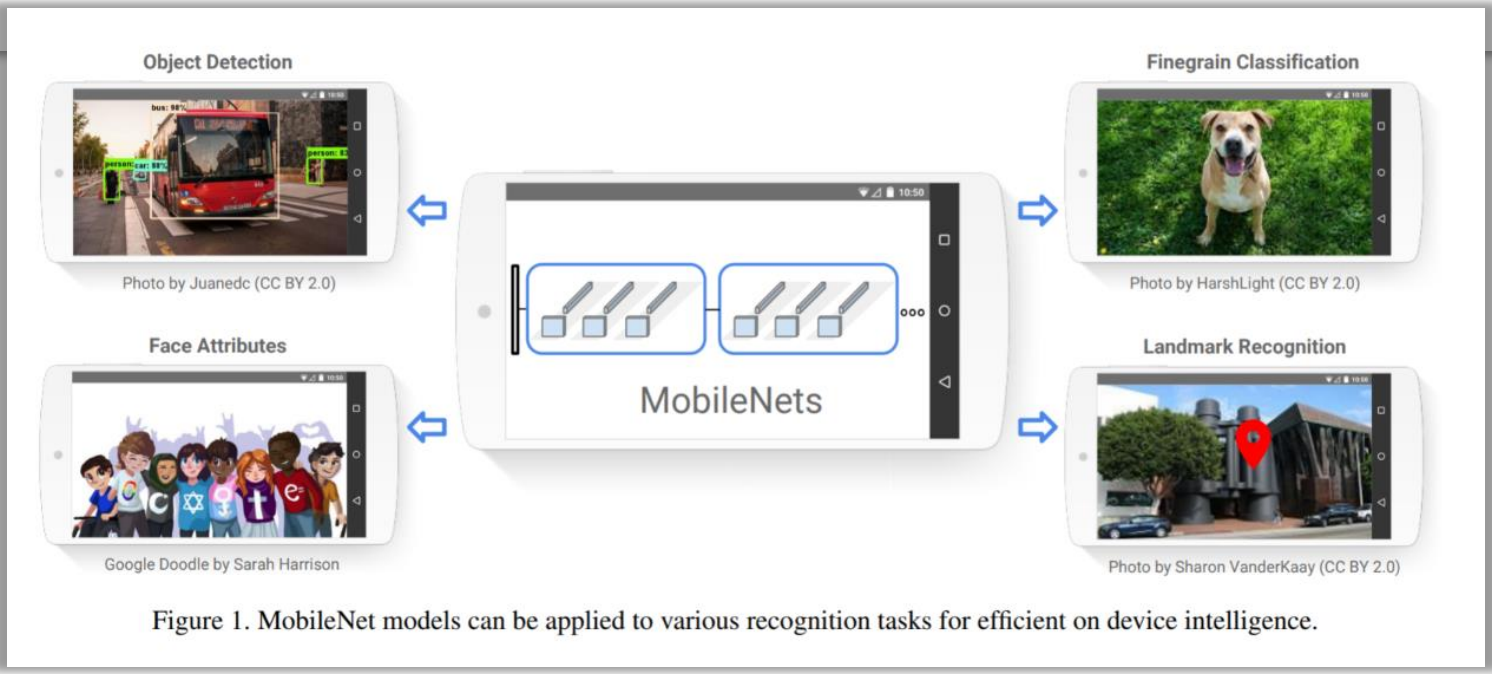


Figure 1. MobileNet models can be applied to various recognition tasks for efficient on device intelligence.

https://arxiv.org/abs/1704.04861

Mobile Devices

Standard convolutions have the computational cost of:

$$D_K \cdot D_K \cdot M \cdot N \cdot D_F \cdot D_F \quad (2)$$

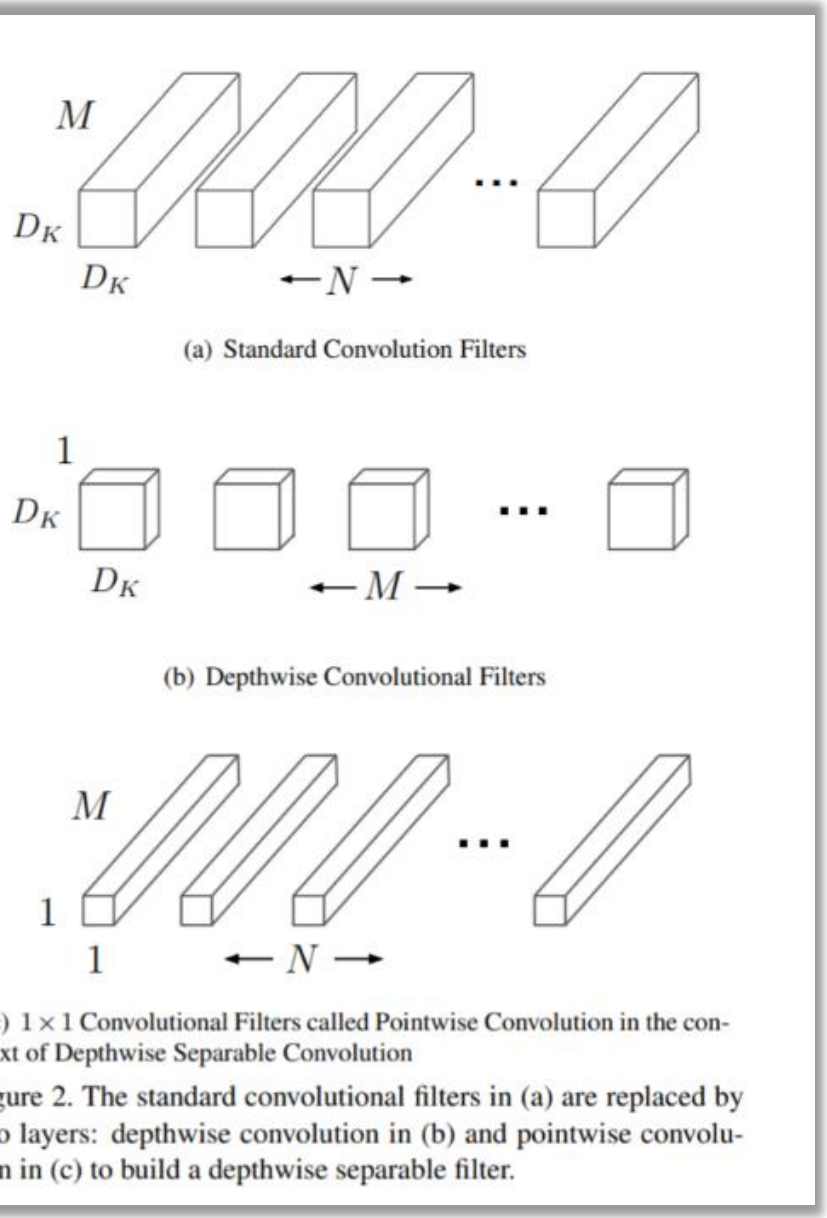
where the computational cost depends multiplicatively on the number of input channels M, the number of output channels N the kernel size $D_k \times D_k$ and the feature map size $D_F \times D_F$. MobileNet models address each of these terms and their interactions. First it uses depthwise separable convolutions to break the interaction between the number of output channels and the size of the kernel.

Depthwise separable convolutions cost:

$$D_K \cdot D_K \cdot M \cdot D_F \cdot D_F + M \cdot N \cdot D_F \cdot D_F \quad (5)$$

which is the sum of the depthwise and 1×1 pointwise convolutions.

MobileNet uses 3×3 depthwise separable convolutions which uses between 8 to 9 times less computation than standard convolutions at only a small reduction in accuracy as seen in Section 4.



(a) Standard Convolution Filters

(b) Depthwise Convolutional Filters

(c) 1×1 Convolutional Filters called Pointwise Convolution in the context of Depthwise Separable Convolution

Figure 2. The standard convolutional filters in (a) are replaced by two layers: depthwise convolution in (b) and pointwise convolution in (c) to build a depthwise separable filter.

https://arxiv.org/abs/1704.04861

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Mobile Devices

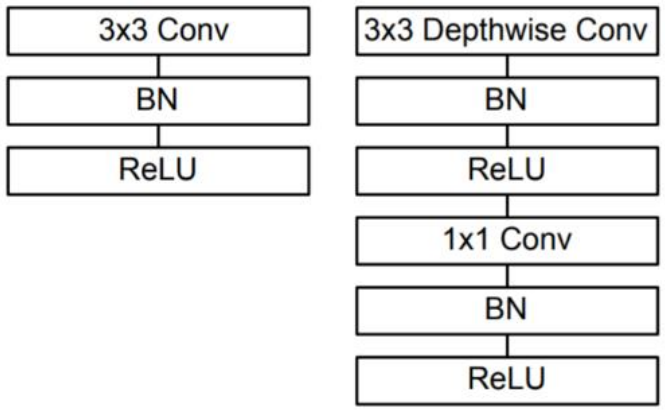

Figure 3. Left: Standard convolutional layer with batchnorm and ReLU. Right: Depthwise Separable convolutions with Depthwise and Pointwise layers followed by batchnorm and ReLU.

Table 1. MobileNet Body Architecture

Type / Stride	Filter Shape	Input Size
Conv / s2	$3 \times 3 \times 3 \times 32$	$224 \times 224 \times 3$
Conv dw / s1	$3 \times 3 \times 32$ dw	$112 \times 112 \times 32$
Conv / s1	$1 \times 1 \times 32 \times 64$	$112 \times 112 \times 32$
Conv dw / s2	$3 \times 3 \times 64$ dw	$112 \times 112 \times 64$
Conv / s1	$1 \times 1 \times 64 \times 128$	$56 \times 56 \times 64$
Conv dw / s1	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 128$	$56 \times 56 \times 128$
Conv dw / s2	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 256$	$28 \times 28 \times 128$
Conv dw / s1	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 256$	$28 \times 28 \times 256$
Conv dw / s2	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 512$	$14 \times 14 \times 256$
$5\times$ Conv dw / s1	$3 \times 3 \times 512$ dw	$14 \times 14 \times 512$
$5\times$ Conv / s1	$1 \times 1 \times 512 \times 512$	$14 \times 14 \times 512$
Conv dw / s2	$3 \times 3 \times 512$ dw	$14 \times 14 \times 512$
Conv / s1	$1 \times 1 \times 512 \times 1024$	$7 \times 7 \times 512$
Conv dw / s2	$3 \times 3 \times 1024$ dw	$7 \times 7 \times 1024$
Conv / s1	$1 \times 1 \times 1024 \times 1024$	$7 \times 7 \times 1024$
Avg Pool / s1	Pool 7×7	$7 \times 7 \times 1024$
FC / s1	1024×1000	$1 \times 1 \times 1024$
Softmax / s1	Classifier	$1 \times 1 \times 1000$

https://arxiv.org/abs/1704.04861

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Table 6. MobileNet Width Multiplier

Width Multiplier	ImageNet Accuracy	Million Mult-Adds	Million Parameters
1.0 MobileNet-224	70.6%	569	4.2
0.75 MobileNet-224	68.4%	325	2.6
0.5 MobileNet-224	63.7%	149	1.3
0.25 MobileNet-224	50.6%	41	0.5

Table 7. MobileNet Resolution

Resolution	ImageNet Accuracy	Million Mult-Adds	Million Parameters
1.0 MobileNet-224	70.6%	569	4.2
1.0 MobileNet-192	69.1%	418	4.2
1.0 MobileNet-160	67.2%	290	4.2
1.0 MobileNet-128	64.4%	186	4.2

Table 8. MobileNet Comparison to Popular Models

Model	ImageNet Accuracy	Million Mult-Adds	Million Parameters
1.0 MobileNet-224	70.6%	569	4.2
GoogleNet	69.8%	1550	6.8
VGG 16	71.5%	15300	138

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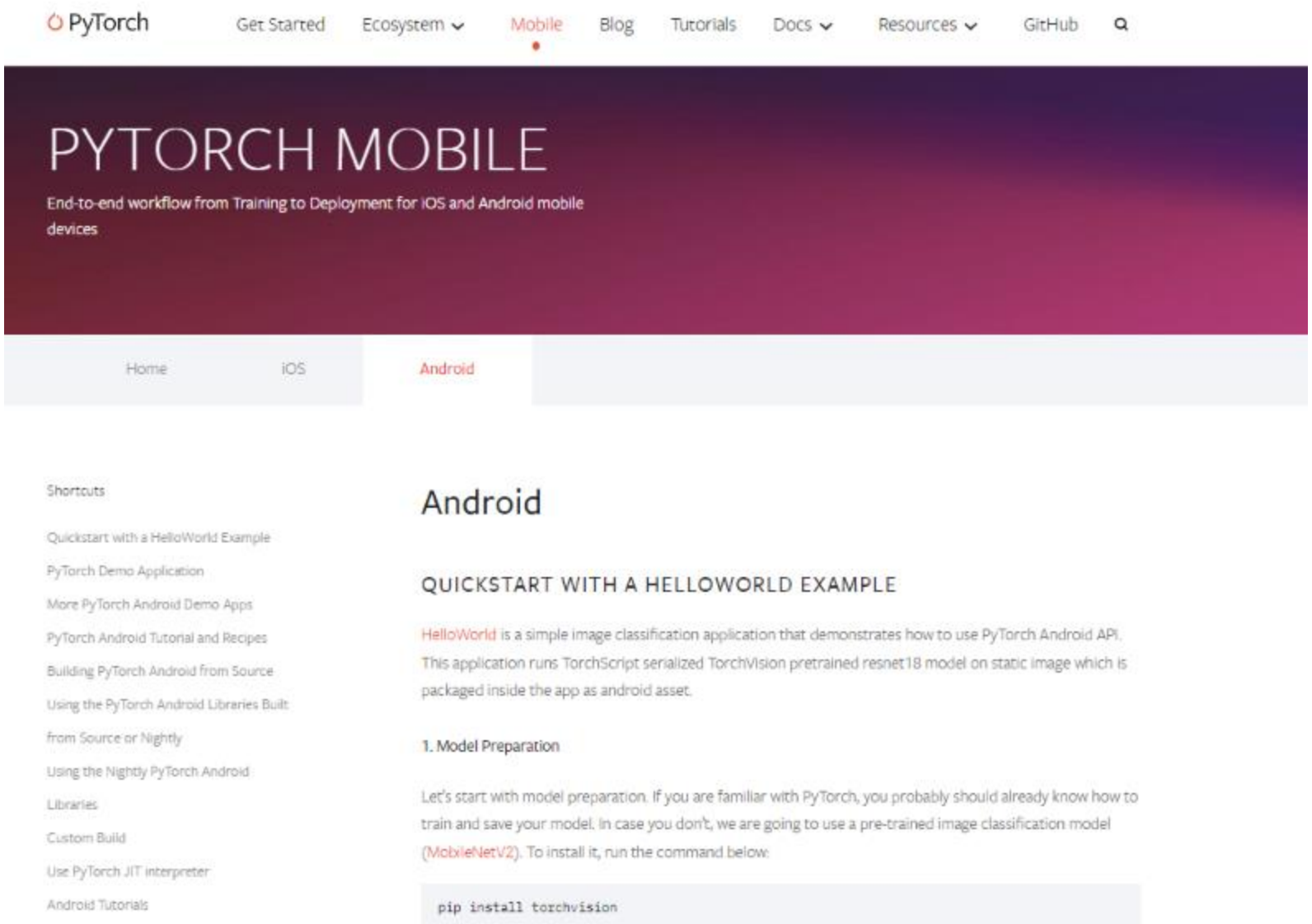

https://pytorch.org/mobile/android/

Mobile Devices

Quickstart

HelloWorld is a simple image classification application that demonstrates how to use PyTorch Android API. This application runs TorchScript serialized TorchVision pretrained MobileNet v3 model on static image which is packaged inside the app as android asset.

1. Model Preparation

Let's start with model preparation. If you are familiar with PyTorch, you probably should already know how to train and save your model. In case you don't, we are going to use a pre-trained image classification model(MobileNet v3), which is packaged in TorchVision. To install it, run the command below:

```
pip install torch torchvision
```

To serialize and optimize the model for Android, you can use the Python script in the root folder of HelloWorld app:

```
import torch
import torchvision
from torch.utils.mobile_optimizer import optimize_for_mobile

model = torchvision.models.mobilenet_v3_small(pretrained=True)
model.eval()
example = torch.rand(1, 3, 224, 224)
traced_script_module = torch.jit.trace(model, example)
optimized_traced_model = optimize_for_mobile(traced_script_module)
optimized_traced_model._save_for_lite_interpreter("app/src/main/assets/model.ptl")
```

If everything works well, we should have our scripted and optimized model - `model.pt` generated in the assets folder of android application. That will be packaged inside android application as `asset` and can be used on the device.

https://github.com/pytorch/android-demo-app/tree/master/HelloWorldApp

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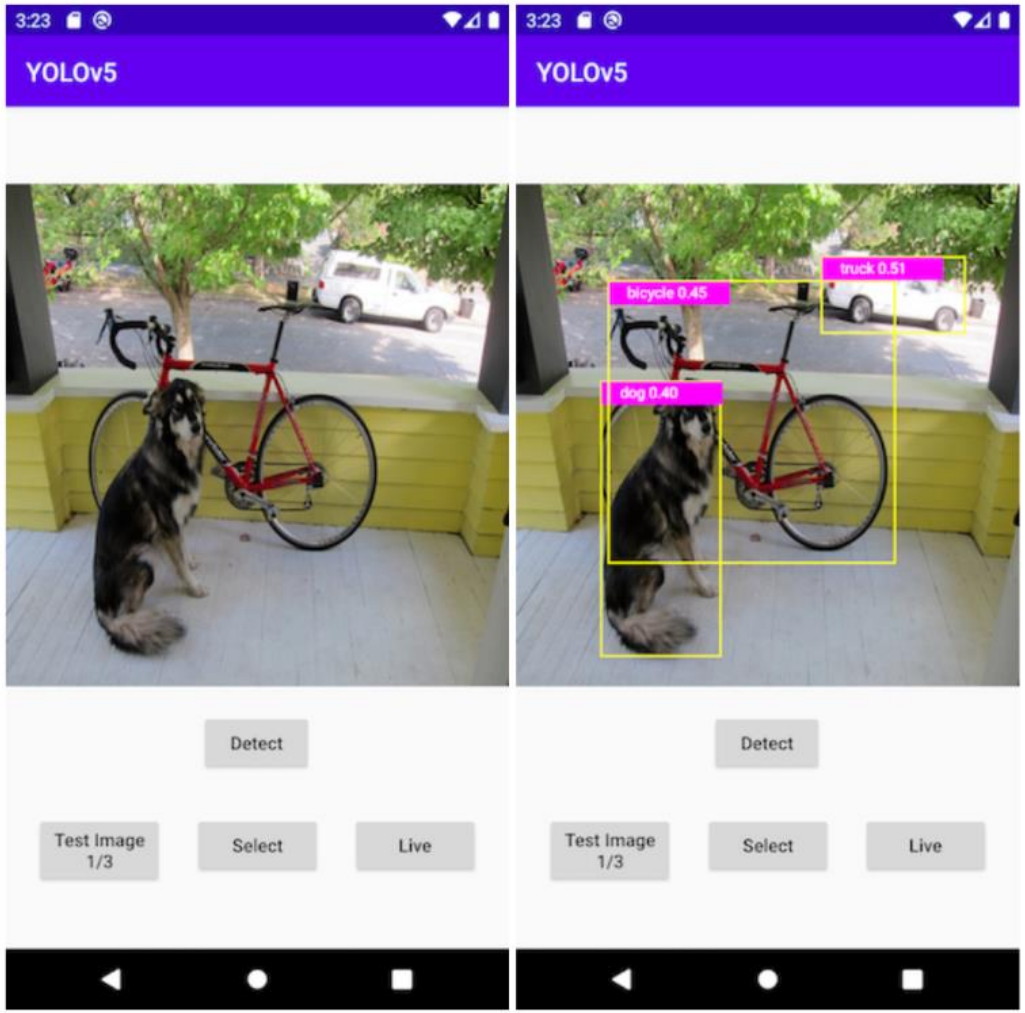
README.md

detection - see this video for a screencast of the app running.

Some example images and the detection results are as follows:



https://github.com/pytorch/android-demo-app/tree/master/ObjectDetection