Lecture 13

Introduction to Convolutional Neural Networks

Part 2

STAT 479: Deep Learning, Spring 2019

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http://stat.wisc.edu/~sraschka/teaching/stat479-ss2019/

A Simple CNN in PyTorch

```
class ConvNet(torch.nn.Module):

    def __init__(self, num_classes):
        super(ConvNet, self).__init__()

        # calculate same padding:
        # (w - k + 2*p)/s + 1 = o
        # => p = (s(o-1) - w + k)/2

        # 28x28x1 => 28x28x4
        self.conv_1 = torch.nn.Conv2d(in_channels=1,
                                      out_channels=4,
                                      kernel_size=(3, 3),
                                      stride=(1, 1),
                                      padding=1) # (1(28-1) - 28 + 3) / 2 = 1
        # 28x28x4 => 14x14x4
        self.pool_1 = torch.nn.MaxPool2d(kernel_size=(2, 2),
                                         stride=(2, 2),
                                         padding=0) # (2(14-1) - 28 + 2) = 0
        # 14x14x4 => 14x14x8
        self.conv_2 = torch.nn.Conv2d(in_channels=4,
                                      out_channels=8,
                                      kernel_size=(3, 3),
                                      stride=(1, 1),
                                      padding=1) # (1(14-1) - 14 + 3) / 2 = 1
        # 14x14x8 => 7x7x8
        self.pool_2 = torch.nn.MaxPool2d(kernel_size=(2, 2),
                                         stride=(2, 2),
                                         padding=0) # (2(7-1) - 14 + 2) = 0

        self.linear_1 = torch.nn.Linear(7*7*8, num_classes)
```

(forward method on the next slide)

A Simple CNN in PyTorch

```
    def forward(self, x):
        out = self.conv_1(x)
        out = F.relu(out)
        out = self.pool_1(out)

        out = self.conv_2(out)
        out = F.relu(out)
        out = self.pool_2(out)

        logits = self.linear_1(out.view(-1, 7*7*8))
        probas = F.softmax(logits, dim=1)
        return logits, probas


torch.manual_seed(random_seed)
model = ConvNet(num_classes=num_classes)
```

(model parameters on the previous slide)

Working example:
https://github.com/rasbt/stat479-deep-learning-ss19/blob/master/L13_intro-cnn/code/cnn-with-diff-init/default.ipynb

Padding

output size

output size

padding pixels per side

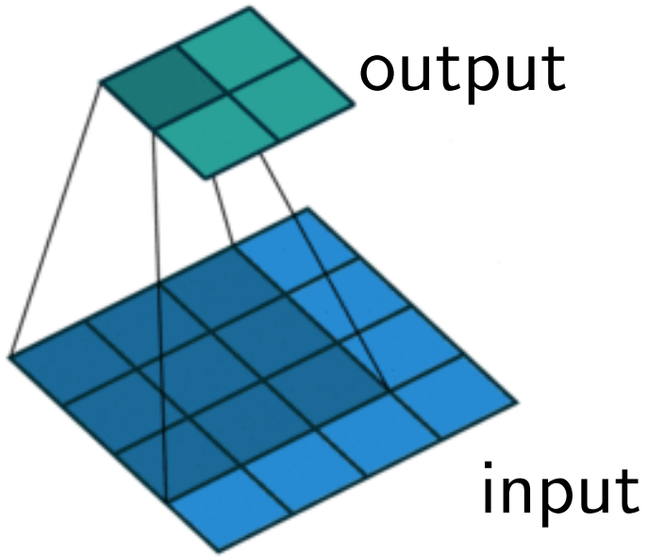
$$o = \left\lfloor \frac{i + 2p - k}{s} \right\rfloor + 1$$

"floor" function

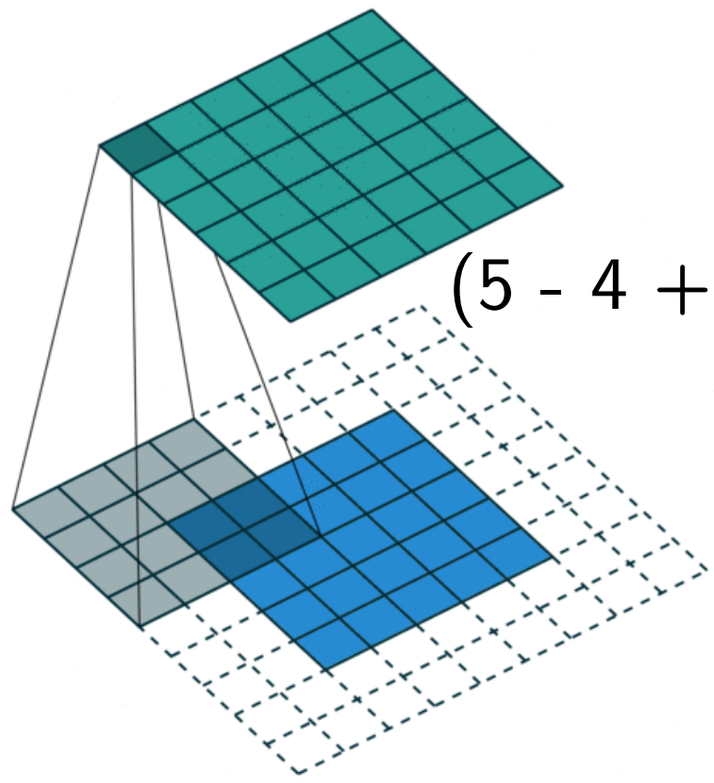
stride

kernel size

$(4 - 3 + 2*0)/1 + 1 = 2$

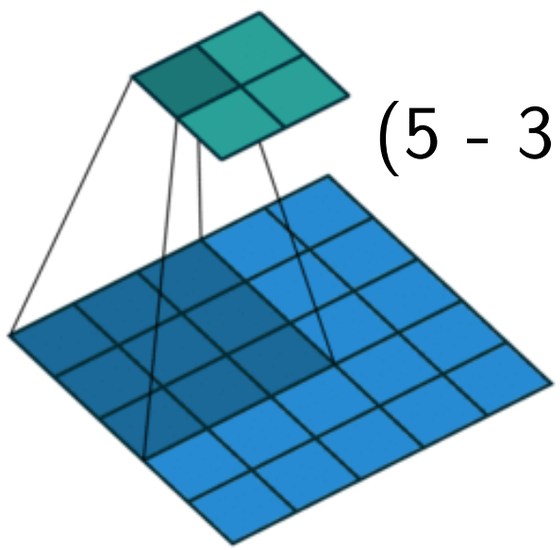


No padding, stride=1



$(5 - 4 + 2*2)/1 + 1 = 6$

padding=2, stride=1



$(5 - 3 + 2*0)/2 + 1 = 2$

No padding, stride=2

Highly recommended:

Dumoulin, Vincent, and Francesco Visin. "A guide to convolution arithmetic for deep learning." *arXiv preprint arXiv:1603.07285* (2016).

Padding Jargon

"valid" convolution: no padding (feature map may shrink)

"same" convolution: padding such that the output size
is equal to the input size

Common kernel size conventions:
3x3, 5x5, 7x7 (sometimes 1x1 in later layers to reduce channels)

Padding

$$o = \left\lfloor \frac{i + 2p - k}{s} \right\rfloor + 1$$

Assume you want to use a convolutional operation with stride 1 and maintain the input dimensions in the output feature map:

How much padding do you need for "same" convolution?

$$o = i + 2p - k + 1$$

$$\Leftrightarrow p = (o - i + k - 1)/2$$

$$\Leftrightarrow p = (k - 1)/2$$

Padding

$$o = i + 2p - k + 1$$

$$\Leftrightarrow p = (o - i + k - 1)/2$$

$$\Leftrightarrow p = (k - 1)/2$$

Probably explains why common kernel size conventions are 3x3, 5x5, 7x7 (sometimes 1x1 in later layers to reduce channels)

Spatial Dropout -- Dropout2D

- Problem with regular dropout and CNNs: Adjacent pixels are likely highly correlated (thus, may not help with reducing the "dependency" much as originally intended by dropout)

- Hence, it may be better to drop entire feature maps

Idea comes from

Tompson, Jonathan, Ross Goroshin, Arjun Jain, Yann LeCun, and Christoph Bregler. "Efficient object localization using convolutional networks." In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 648-656. 2015.

Spatial Dropout -- Dropout2D

- Dropout2d will drop full feature maps (channels)

```
import torch

m = torch.nn.Dropout2d(p=0.5)
input = torch.randn(1, 3, 5, 5)
output = m(input)
```

```
output
```

```
tensor([[[[-0.0000,  0.0000,  0.0000,  0.0000, -0.0000],
          [ 0.0000, -0.0000,  0.0000, -0.0000,  0.0000],
          [ 0.0000,  0.0000, -0.0000,  0.0000, -0.0000],
          [-0.0000,  0.0000,  0.0000, -0.0000, -0.0000]],

         [[-3.5274,  0.8163,  0.2440,  1.2410,  1.5022],
          [-1.2455,  6.3875, -2.6224,  0.0261,  1.7487],
          [ 1.6471,  0.7444, -2.1941, -2.0119, -1.5232],
          [ 0.3720, -1.5606,  0.7630,  0.9177, -0.1387],
          [-1.2817, -3.5804,  0.4367, -0.1384, -0.8148]],

         [[-0.0000, -0.0000, -0.0000, -0.0000,  0.0000],
          [ 0.0000, -0.0000, -0.0000, -0.0000,  0.0000],
          [ 0.0000, -0.0000,  0.0000, -0.0000, -0.0000],
          [-0.0000, -0.0000,  0.0000,  0.0000, -0.0000],
          [-0.0000,  0.0000,  0.0000,  0.0000,  0.0000]]]])
```

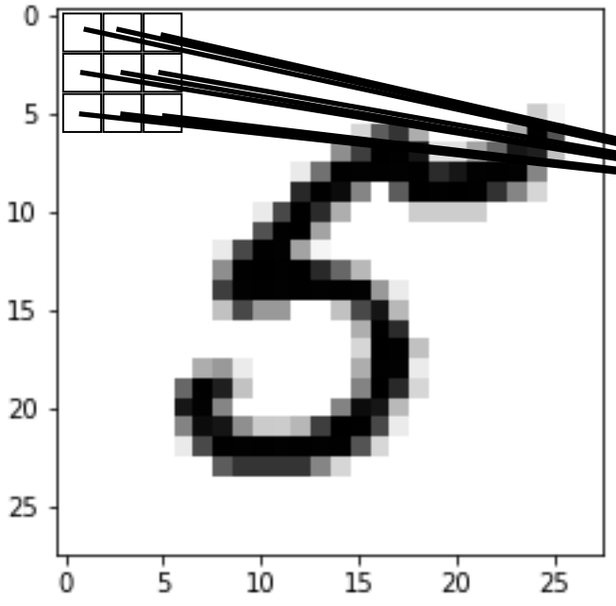
Cross-Correlation vs Convolution

Deep Learning Jargon: convolution in DL is actually cross-correlation

Cross-correlation is our sliding dot product over the image

$A \in \mathbb{R}^{3\times3}$

$Z \in \mathbb{R}^{3\times3}$



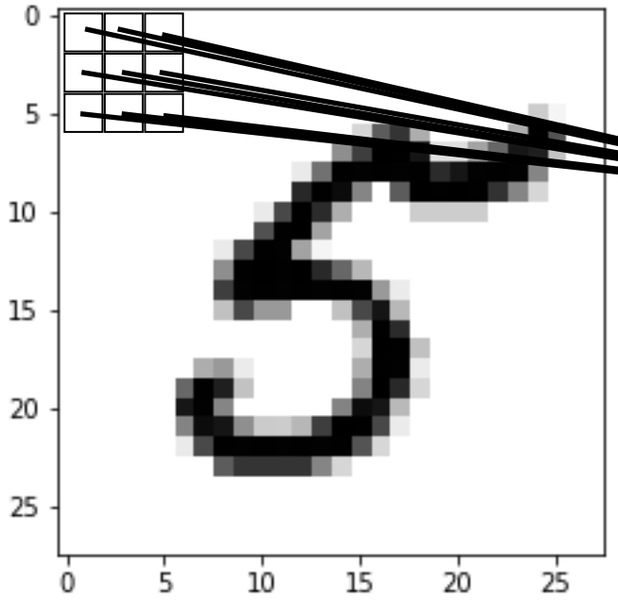
$Z[i, j]$

"feature map"

Cross-Correlation vs Convolution

$A \in \mathbb{R}^{3\times3}$

$Z \in \mathbb{R}^{3\times3}$



$Z[i, j]$

"feature map"

Cross-Correlation:

$$Z[i, j] = \sum_{u=-k}^{k} \sum_{v=-k}^{k} K[u, v]A[i + u, j + v]$$

$$Z[i, j] = K \otimes A$$

Cross-Correlation vs Convolution

Cross-Correlation:

$$Z[i,j] = \sum_{u=-k}^{k} \sum_{v=-k}^{k} K[u,v] A[i+u, j+v]$$

$$Z[i,j] = K \otimes A$$

Looping direction indicated in red

1) -1,-1	2) -1,0	3) -1,1
4) 0,-1	5) 0,0	6) 0,1
7) 1,-1	8) 1,0	9) 1,1

Cross-Correlation vs Convolution

Cross-Correlation: $Z[i,j] = \sum_{u=-k}^{k} \sum_{v=-k}^{k} K[u,v]A[i+u, j+v]$ $\qquad Z[i,j] = K \otimes A$

Convolution: $$Z[i,j] = \sum_{u=-k}^{k} \sum_{v=-k}^{k} K[u,v]A[i-u, j-v]$$

$$Z[i,j] = K * A$$

Basically, we are flipping the kernel (or the receptive field) horizontally and vertically

Looping direction indicated in red

9) -1,-1	8) -1,0	7) -1,1
6) 0,-1	5) 0,0	4) 0,1
3) 1,-1	2) 1,0	1) 1,1

Cross-Correlation vs Convolution

Deep Learning Jargon: convolution in DL is actually cross-correlation

"Real" convolution has the nice associative property:

$$(A * B) * C = A * (B * C)$$

In DL, we usually don't care about that (as opposed to many traditional computer vision and signal processing applications).

Also, cross-correlation is easier to implement.

Maybe the term "convolution" for cross-correlation became popular, because "Cross-Correlational Neural Network" sounds weird ;)

Computing Convolutions on the GPU

- There are many different approaches to compute (approximate) convolution operations

- DL libraries usually use NVIDIA's CUDA & CuDNN libraries, which implement many different convolution algorithms

- These algorithms are usually more efficient than the CPU variants (convolutions on the CPU e.g., in CPU usually take up much more memory due to the algorithm choice compared to using the GPU)

If you are interested, you can find more info in:

Lavin, Andrew, and Scott Gray. "Fast algorithms for convolutional neural networks." *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. 2016.
https://www.cv-foundation.org/openaccess/content_cvpr_2016/papers/Lavin_Fast_Algorithms_for_CVPR_2016_paper.pdf

Computing Convolutions on the GPU

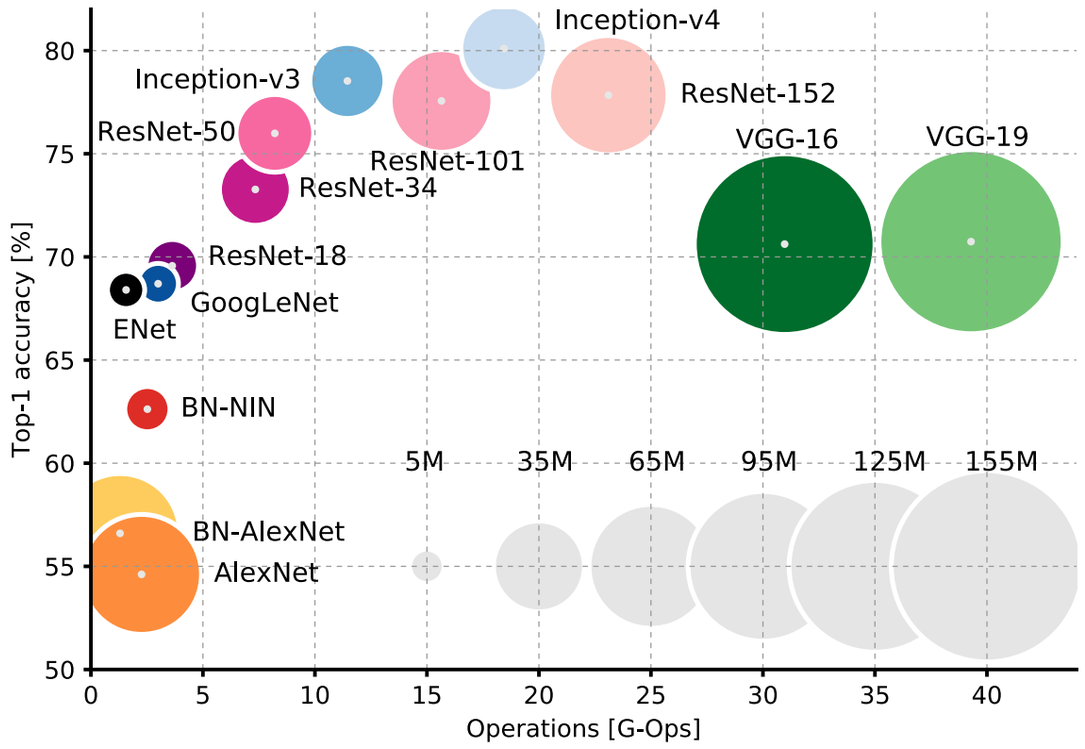
- CuDNN is more geared towards engineers & speed rather than scientists and is unfortunately not deterministic/reproducible by default
- I.e., it determines which convolution algorithm to choose during run-time automatically, based on predicted speeds given the data flow
- For reproducibility and consistent results, I recommend setting the deterministic flag (speed is about the same, often even a bit faster, sometimes a bit slower)

```
import torch
import torch.nn as nn
import torch.nn.functional as F

if torch.cuda.is_available():
    torch.backends.cudnn.deterministic = True
```

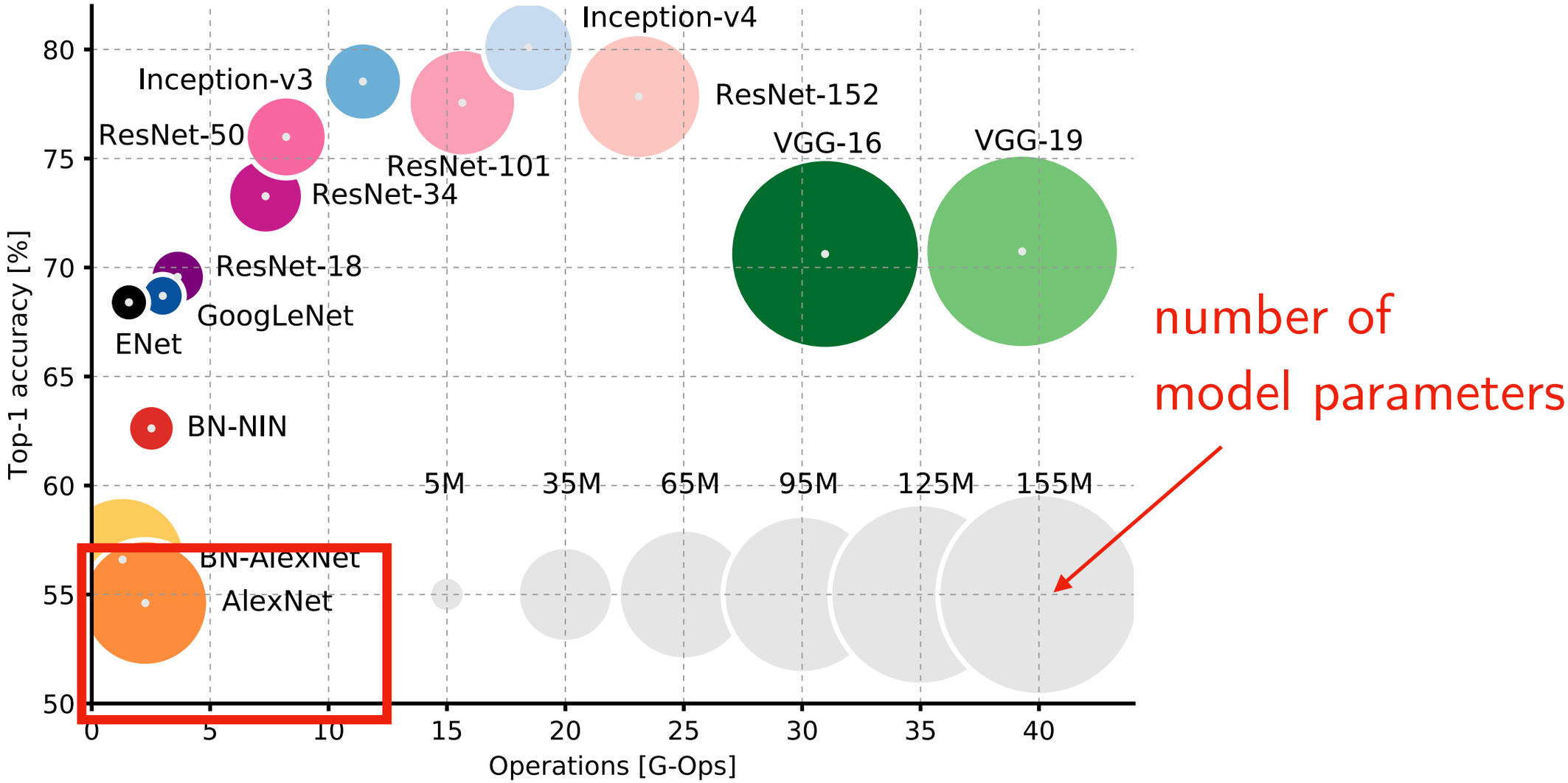
Common Architectures Revisited

We will discuss some additional common CNN architectures since the field evolved quite a bit since 2012 ...



Canziani, A., Paszke, A., & Culurciello, E. (2016). An analysis of deep neural network models for practical applications. *arXiv preprint arXiv:1605.07678*.

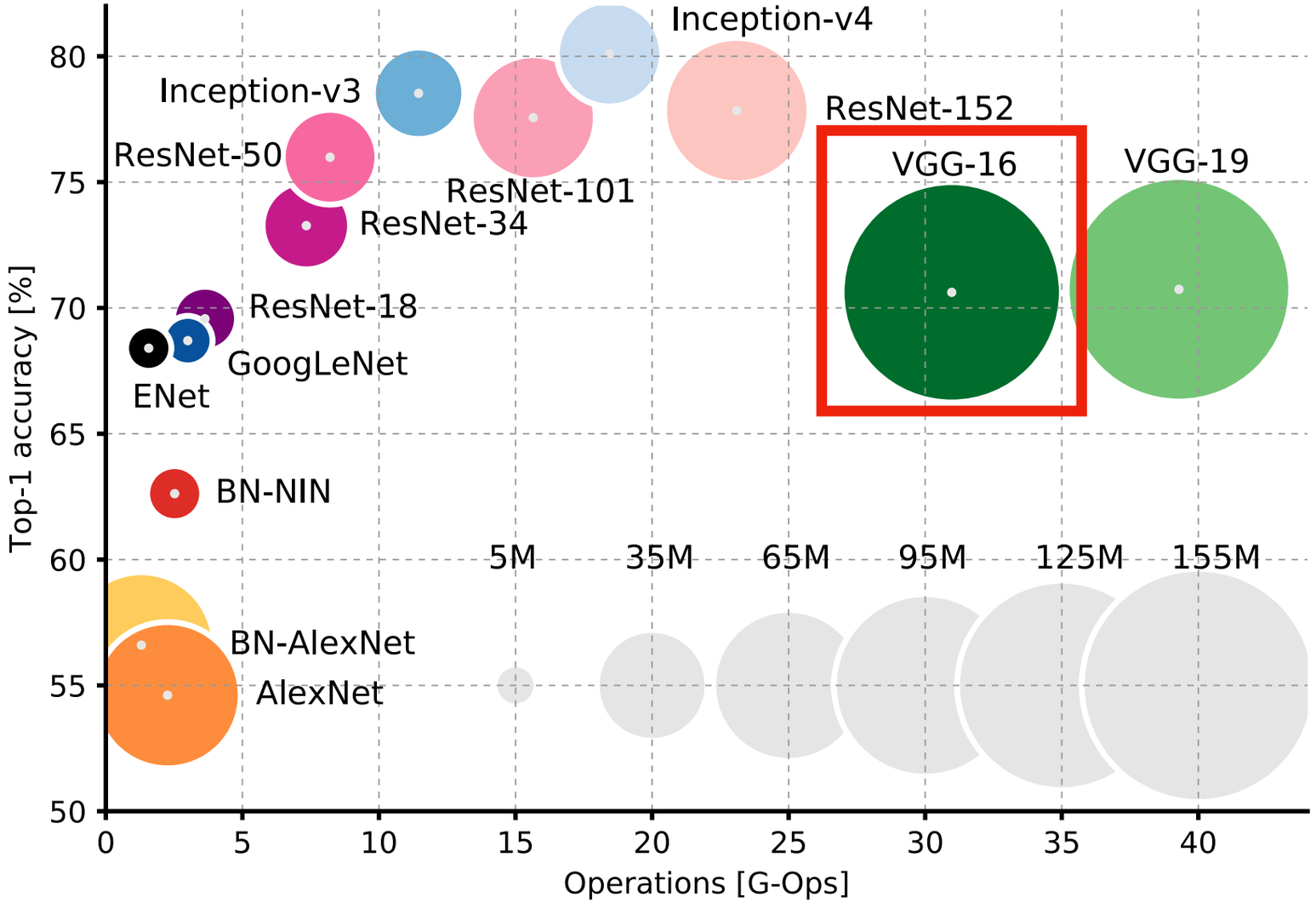
Common Architectures Revisited



You will work with this in HW4

Canziani, A., Paszke, A., & Culurciello, E. (2016). An analysis of deep neural network models for practical applications. *arXiv preprint arXiv:1605.07678*.

Common Architectures Revisited



Canziani, A., Paszke, A., & Culurciello, E. (2016). An analysis of deep neural network models for practical applications. *arXiv preprint arXiv:1605.07678*.

VGG-16

PyTorch implementation: https://github.com/rasbt/stat479-deep-learning-ss19/blob/master/L13_intro-cnn/code/vgg16.ipynb

ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

Advantages:

very simple architecture,
3x3 convs, stride=1,
"same" padding, 2x2 max pooling

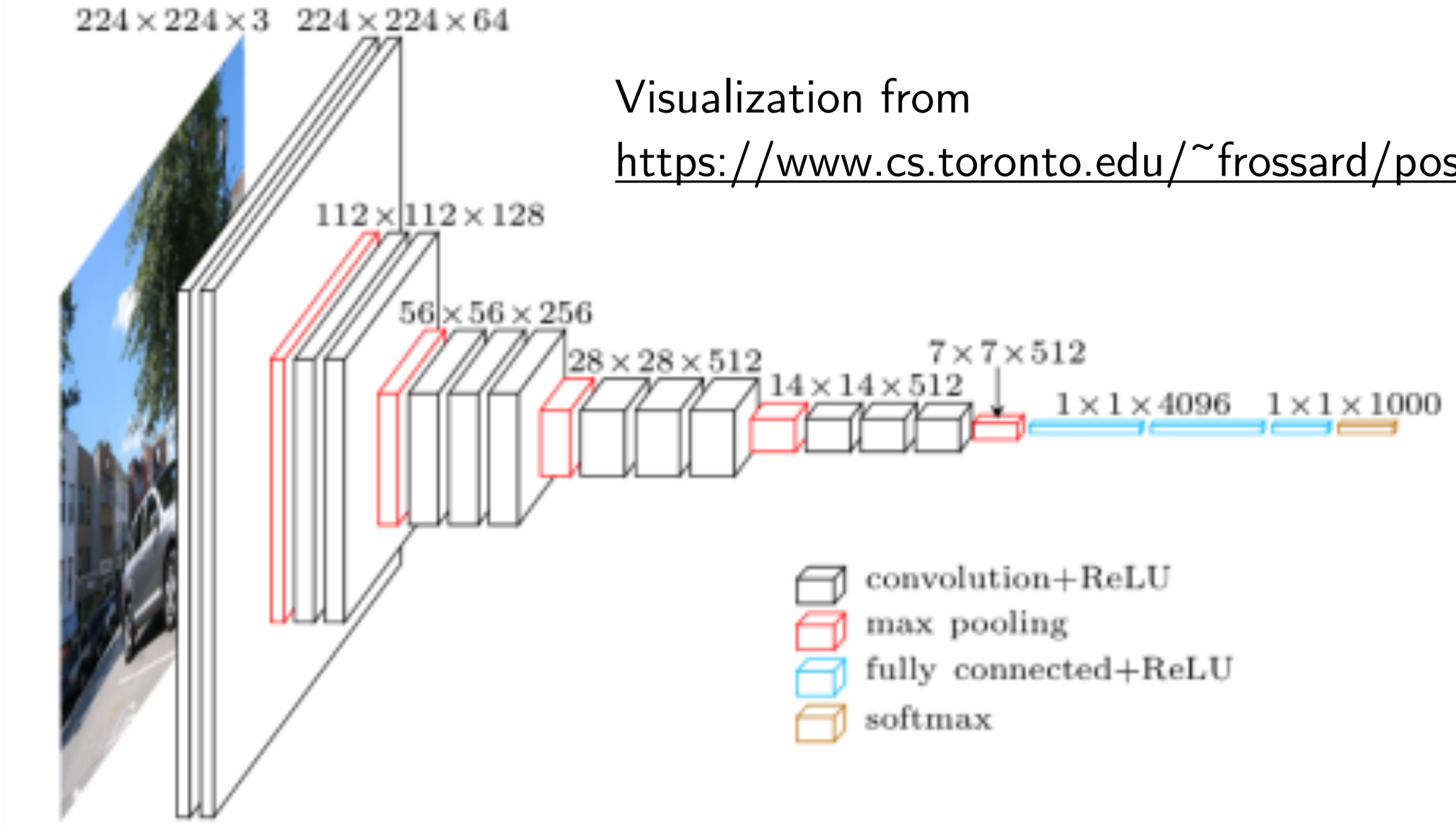
Disadvantage:

very large number of parameters and slow
(see previous slide)

Simonyan, Karen, and Andrew Zisserman. "Very deep convolutional networks for large-scale image recognition." *arXiv preprint arXiv:1409.1556* (2014).

VGG-16

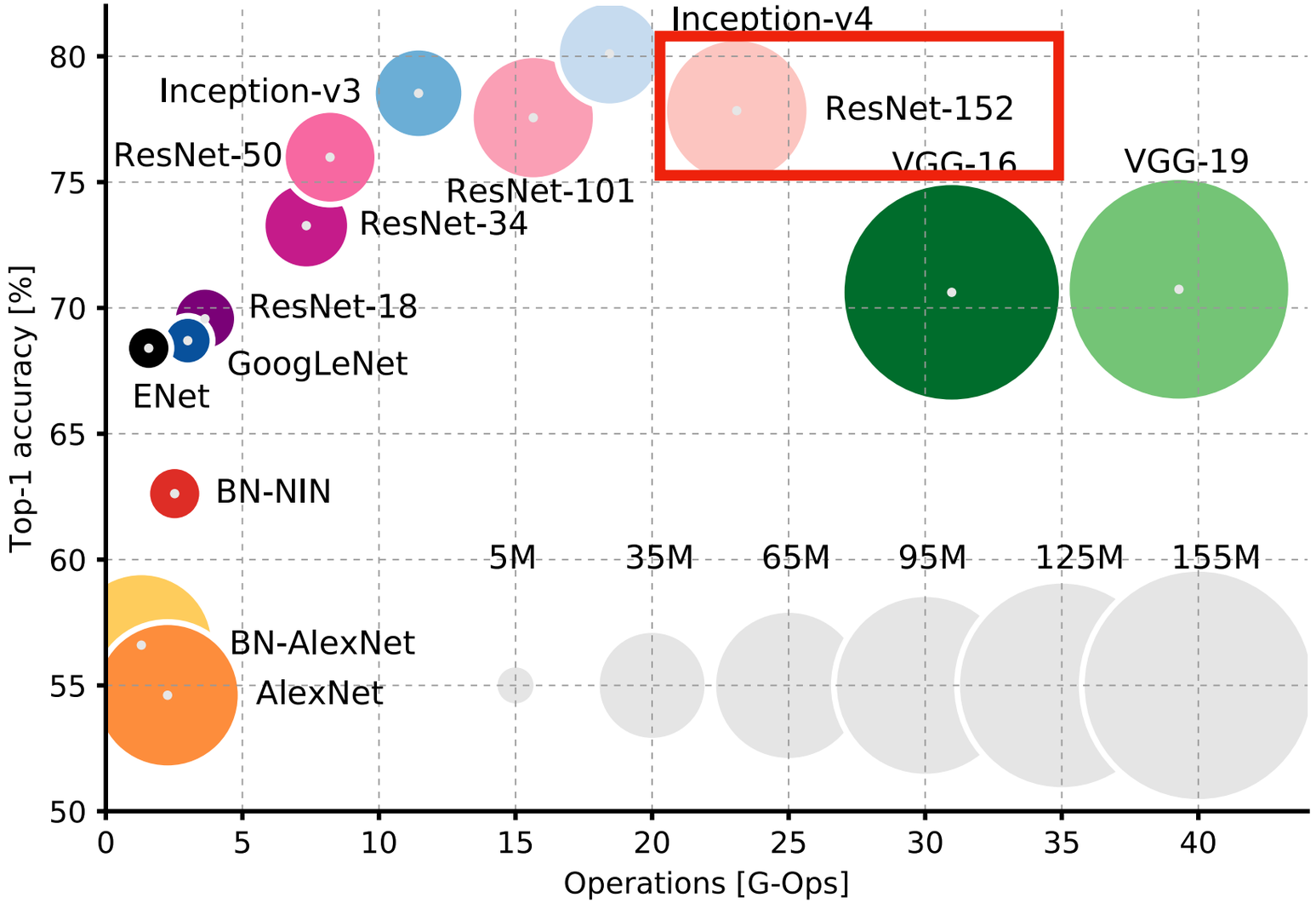
PyTorch implementation: https://github.com/rasbt/stat479-deep-learning-ss19/blob/master/L13_intro-cnn/code/vgg16.ipynb



Visualization from
https://www.cs.toronto.edu/~frossard/post/vgg16/

Simonyan, Karen, and Andrew Zisserman. "Very deep convolutional networks for large-scale image recognition." *arXiv preprint arXiv:1409.1556* (2014).

Common Architectures Revisited



Canziani, A., Paszke, A., & Culurciello, E. (2016). An analysis of deep neural network models for practical applications. *arXiv preprint arXiv:1605.07678*.

ResNets

He, Kaiming, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. "Deep residual learning for image recognition." In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 770-778. 2016.

With their simple trick of allowing skip connections (the possibility to learn identity functions and skip layers that are not useful), ResNets allow us to to implement very, very deep architectures

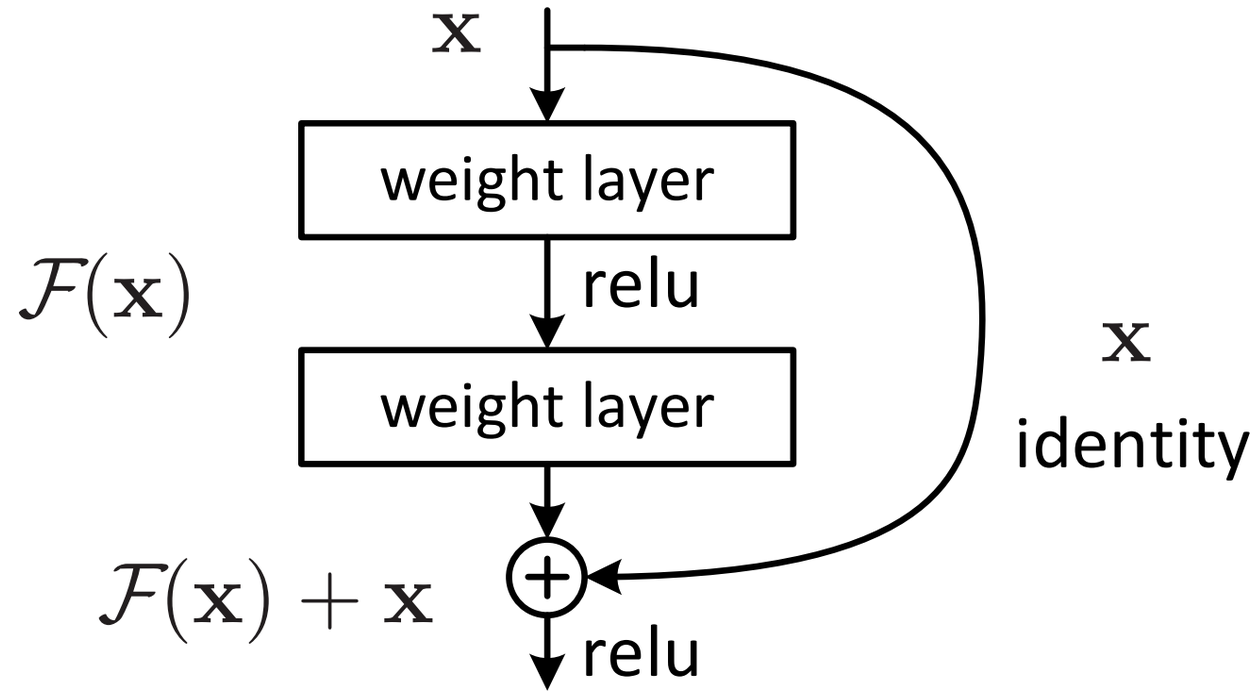
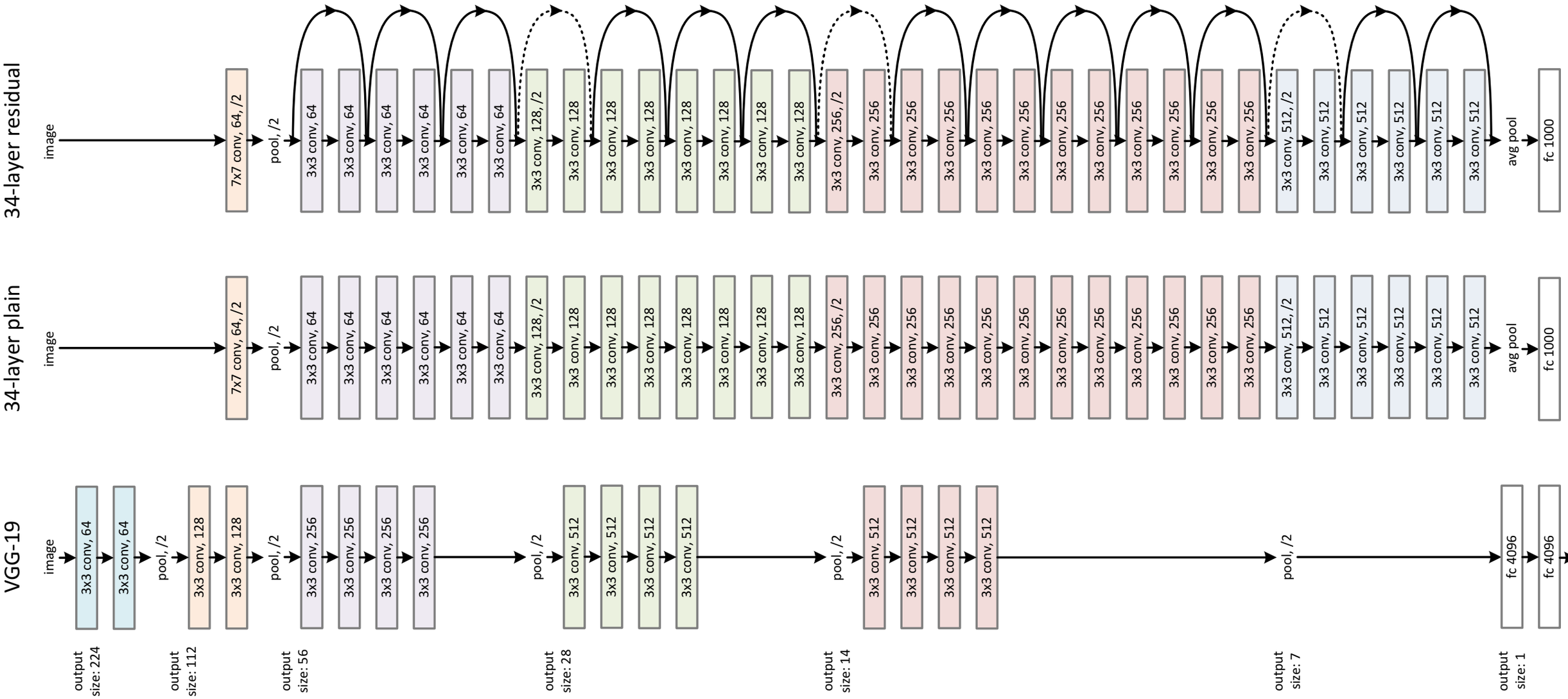


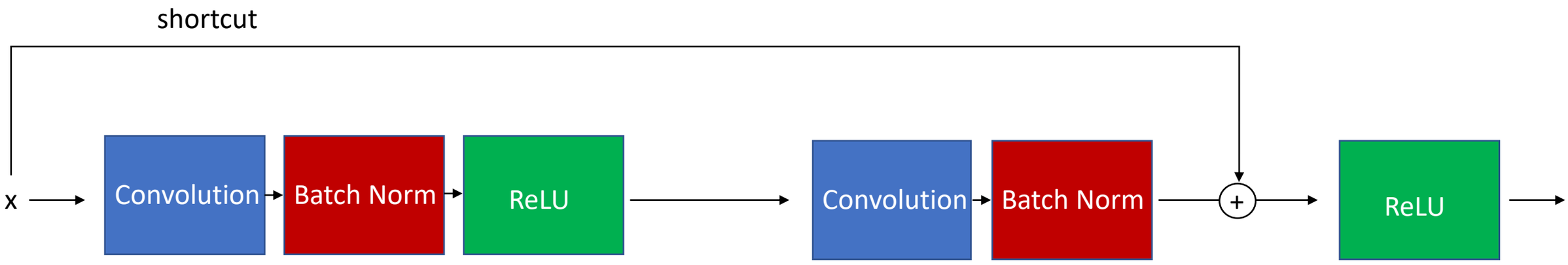
Figure 2. Residual learning: a building block.

ResNets

He, Kaiming, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. "Deep residual learning for image recognition." In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 770-778. 2016.

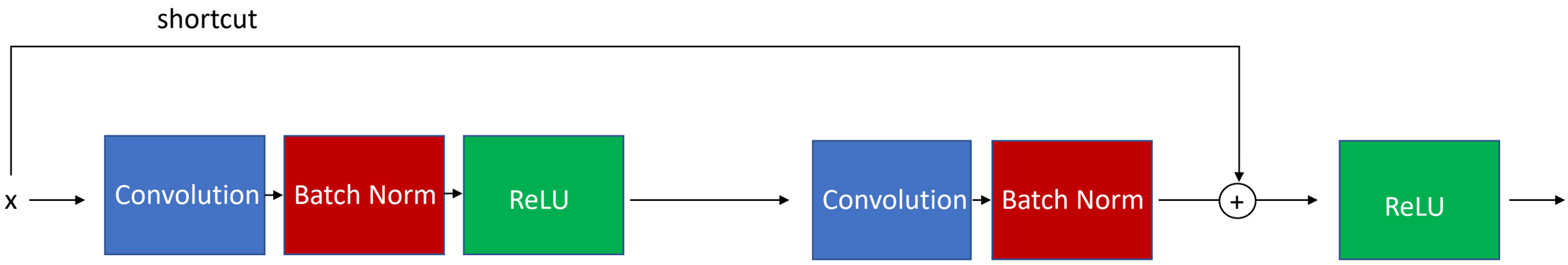


ResNets



In general: $a^{(l+2)} = \sigma\left(z^{(l+2)} + a^{(l)}\right)$

ResNets



$$a^{(l+2)} = \sigma\left(z^{(l+2)} + a^{(l)}\right)$$

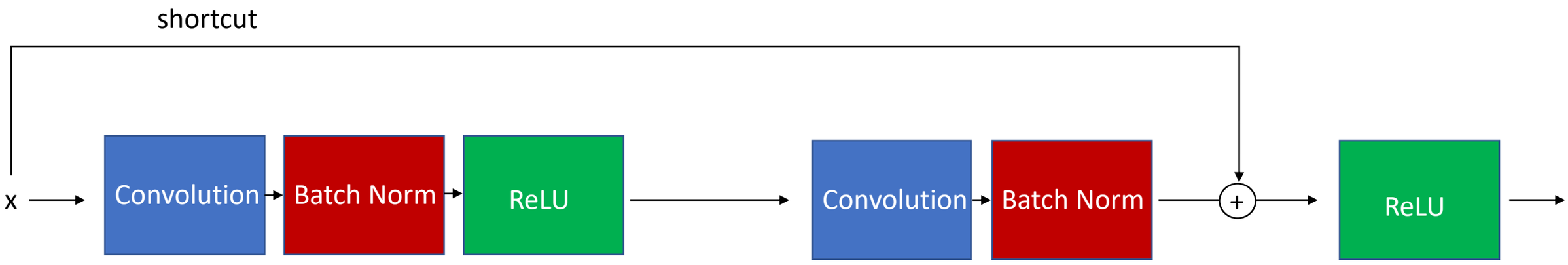
$$= \sigma\left(a^{(l+1)} W^{(l+2)} + b^{(l+2)} + a^{(l)}\right)$$

If all weights and the bias are zero, then

$$= \sigma\left(a^{(l)}\right) = a^{(l)}$$ (identity function)

due to ReLU

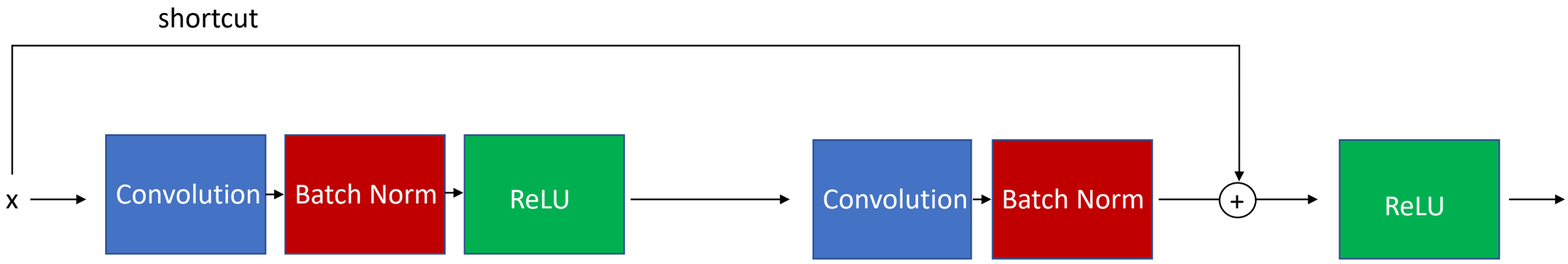
ResNets

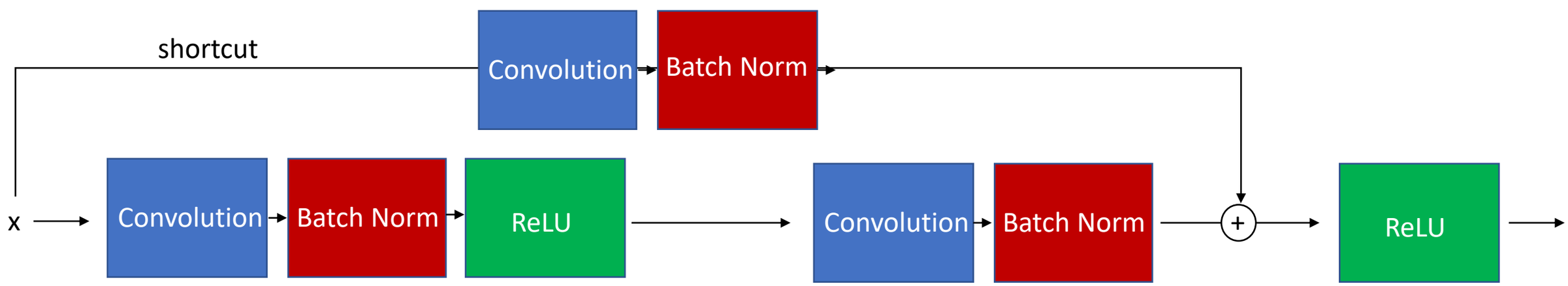


$$a^{(l+2)} = \sigma\big(z^{(l+2)} + a^{(l)}\big)$$

We assume these have the same dimension
(e.g., via "same" convolution)

ResNets





alternative residual blocks with skip connections such that the input passed via the shortcut is resized to dimensions of the main path's output

ResNet Block Implementation

PyTorch implementations of the previous slides:

https://github.com/rasbt/stat479-deep-learning-ss19/blob/master/L13_intro-cnn/code/resnet-blocks.ipynb

ResNet-34 and ResNet-152

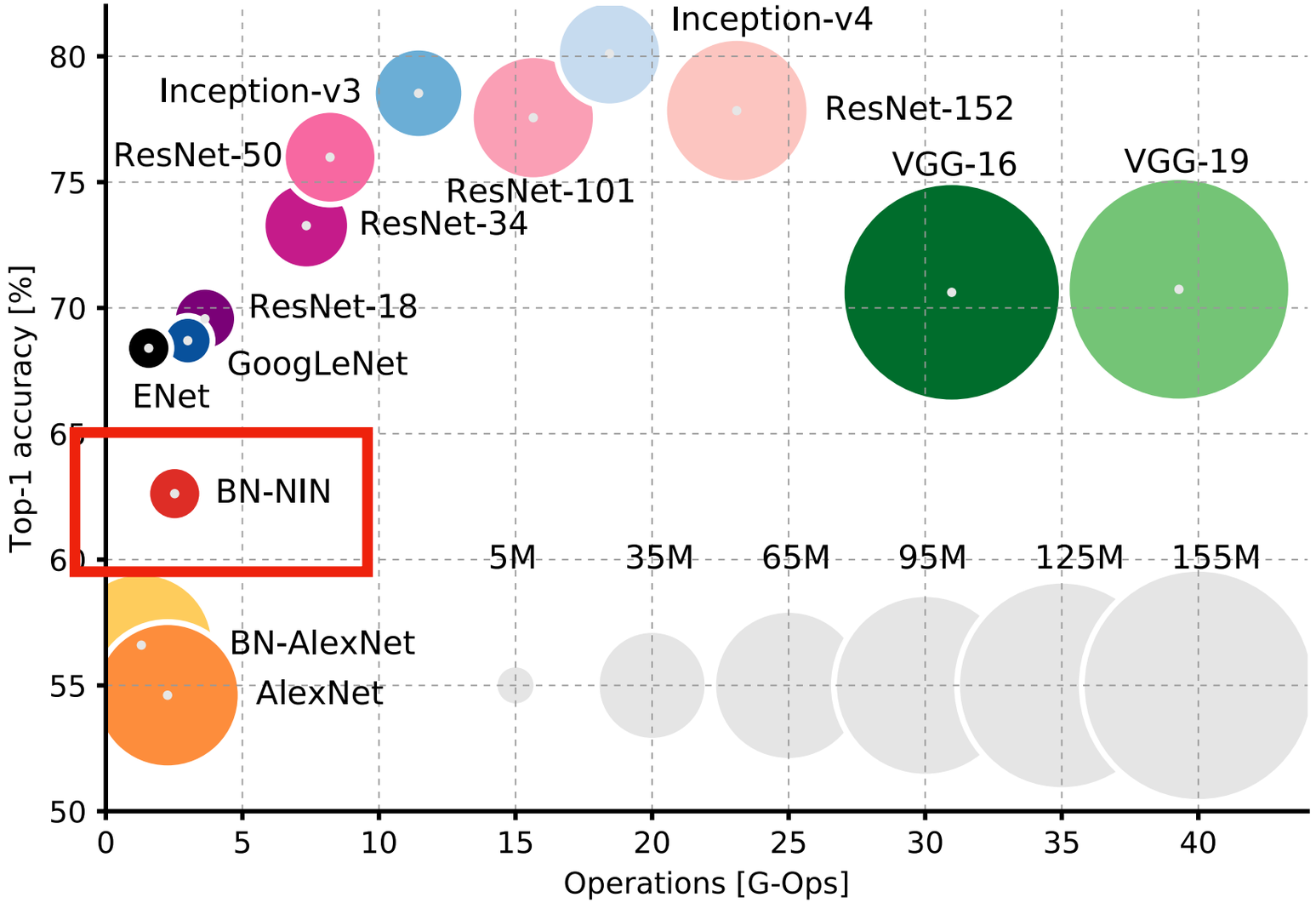
PyTorch implementations:

https://github.com/rasbt/stat479-deep-learning-ss19/blob/master/L13_intro-cnn/code/resnet-34.ipynb

https://github.com/rasbt/stat479-deep-learning-ss19/blob/master/L13_intro-cnn/code/resnet-152.ipynb

(Note that I had to implement them rather quickly yesterday; thus, I didn't tune hyperparameters, and the performance can be improved a lot, e.g., by using some of the image augmentation steps from your home work, among others)

Common Architectures Revisited



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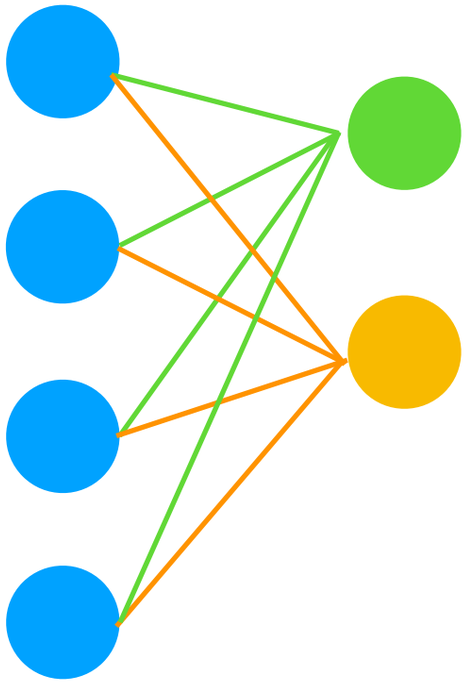
Side Note: It is Possible to Replace Fully Connected Layers by Convolutional Layers

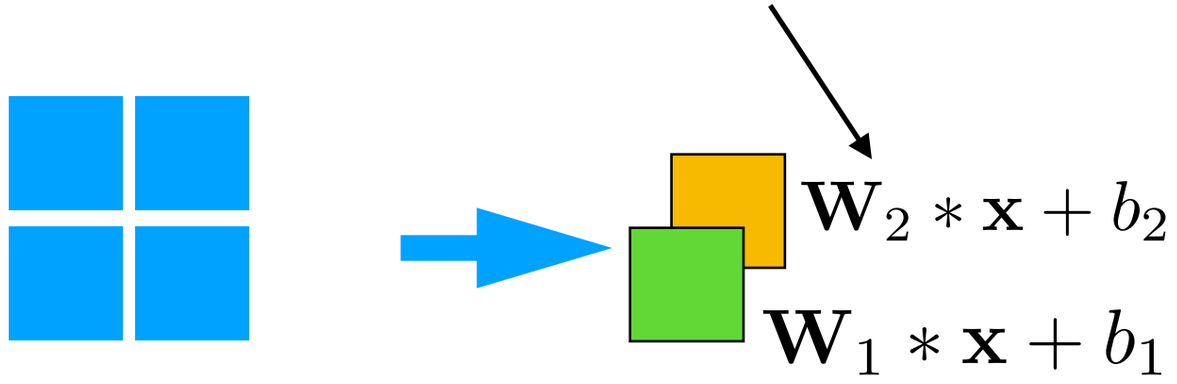


$$\mathbf{w}_1^T \mathbf{x} + b_1$$

$$\mathbf{w}_2^T \mathbf{x} + b_2$$

Fully connected layer

remember, these also involve dot products between the receptive fields and kernels



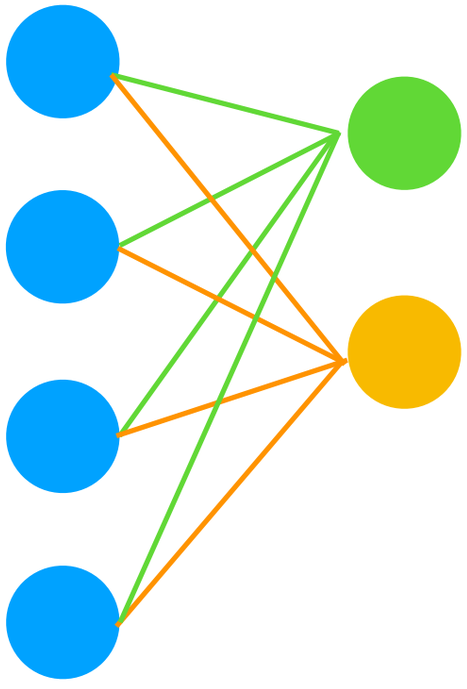
$$\mathbf{W}_2 * \mathbf{x} + b_2$$

$$\mathbf{W}_1 * \mathbf{x} + b_1$$

where $\mathbf{W}_1 = \begin{bmatrix} w_{1,1} & w_{1,2} \\ w_{1,3} & w_{1,4} \end{bmatrix}$

$$\mathbf{W}_2 = \begin{bmatrix} w_{2,1} & w_{2,2} \\ w_{2,3} & w_{2,4} \end{bmatrix}$$

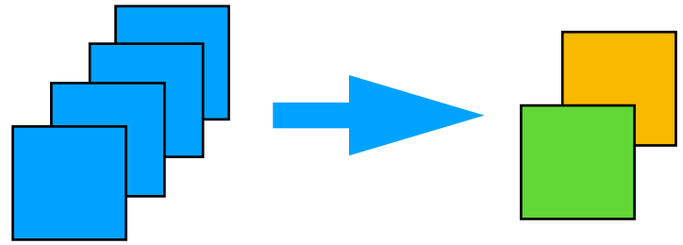
Side Note: It is Possible to Replace Fully Connected Layers by Convolutional Layers



$$\mathbf{w}_1^T \mathbf{x} + b_1$$

$$\mathbf{w}_2^T \mathbf{x} + b_2$$

Fully connected layer



Or, we can concatenate the inputs into 1x1 images with 4 channels and then use 2 kernels
(remember, each kernel then also has 4 channels)

Example: https://github.com/rasbt/stat479-deep-learning-ss19/blob/master/L13_intro-cnn/code/fc-to-conv.ipynb

Network in Network (NiN)

Lin, Min, Qiang Chen, and Shuicheng Yan. "Network in network." *arXiv preprint arXiv:1312.4400* (2013).

Key Ideas

1)

- A convolution kernel can be thought of as a generalized linear model (GLM)
- Using a "sophisticated" nonlinear function approximator (e.g., an MLP) may enhance the abstraction ability of the local model
- => Replace GLM by "micro network" (sliding an MLP over the feature map)

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Key Ideas

1)

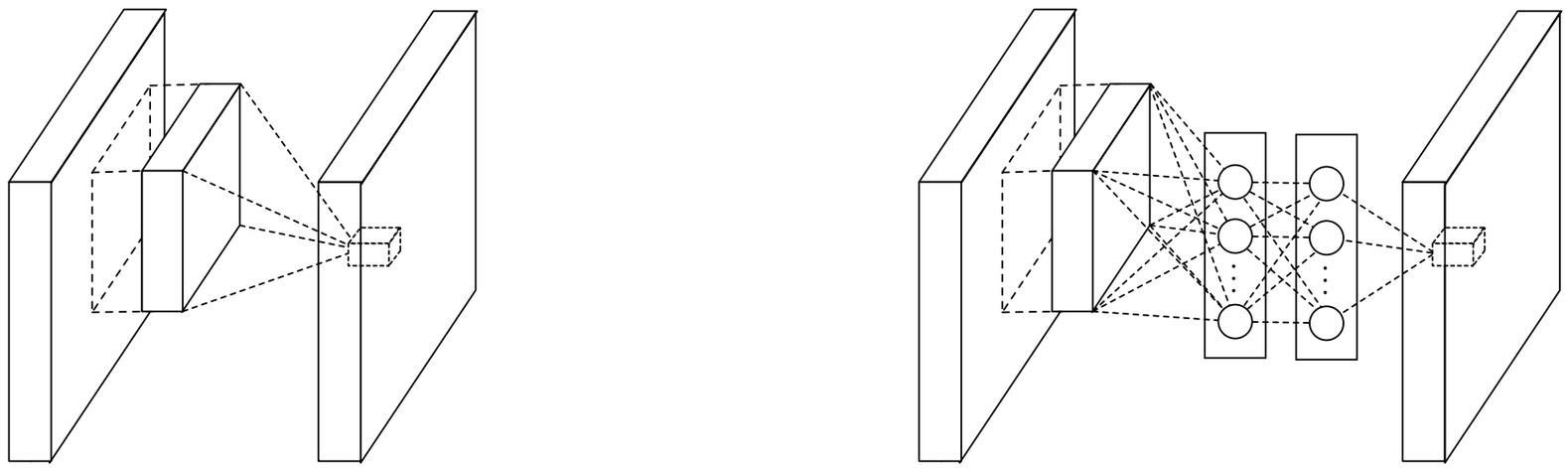
- A convolution kernel can be thought of as a generalized linear model (GLM)
- Using a "sophisticated" nonlinear function approximator (e.g., an MLP) may enhance the abstraction ability of the local model
- => Replace GLM by "micro network" (sliding an MLP over the feature map)

2)

- Replace the MLP "micro structure" via convolutions (explanation on the previous slides)
- Replace the fully connected layers in the last layers by *global average pooling*

Network in Network (NiN)

Lin, Min, Qiang Chen, and Shuicheng Yan. "Network in network." *arXiv preprint arXiv:1312.4400* (2013).



(a) Linear convolution layer (b) Mlpconv layer

Figure 1: Comparison of linear convolution layer and mlpconv layer. The linear convolution layer includes a linear filter while the mlpconv layer includes a micro network (we choose the multilayer perceptron in this paper). Both layers map the local receptive field to a confidence value of the latent concept.

- Using a "sophisticated" nonlinear function approximator (e.g., an MLP) may enhance the abstraction ability of the local model

Global Average Pooling in Last Layer

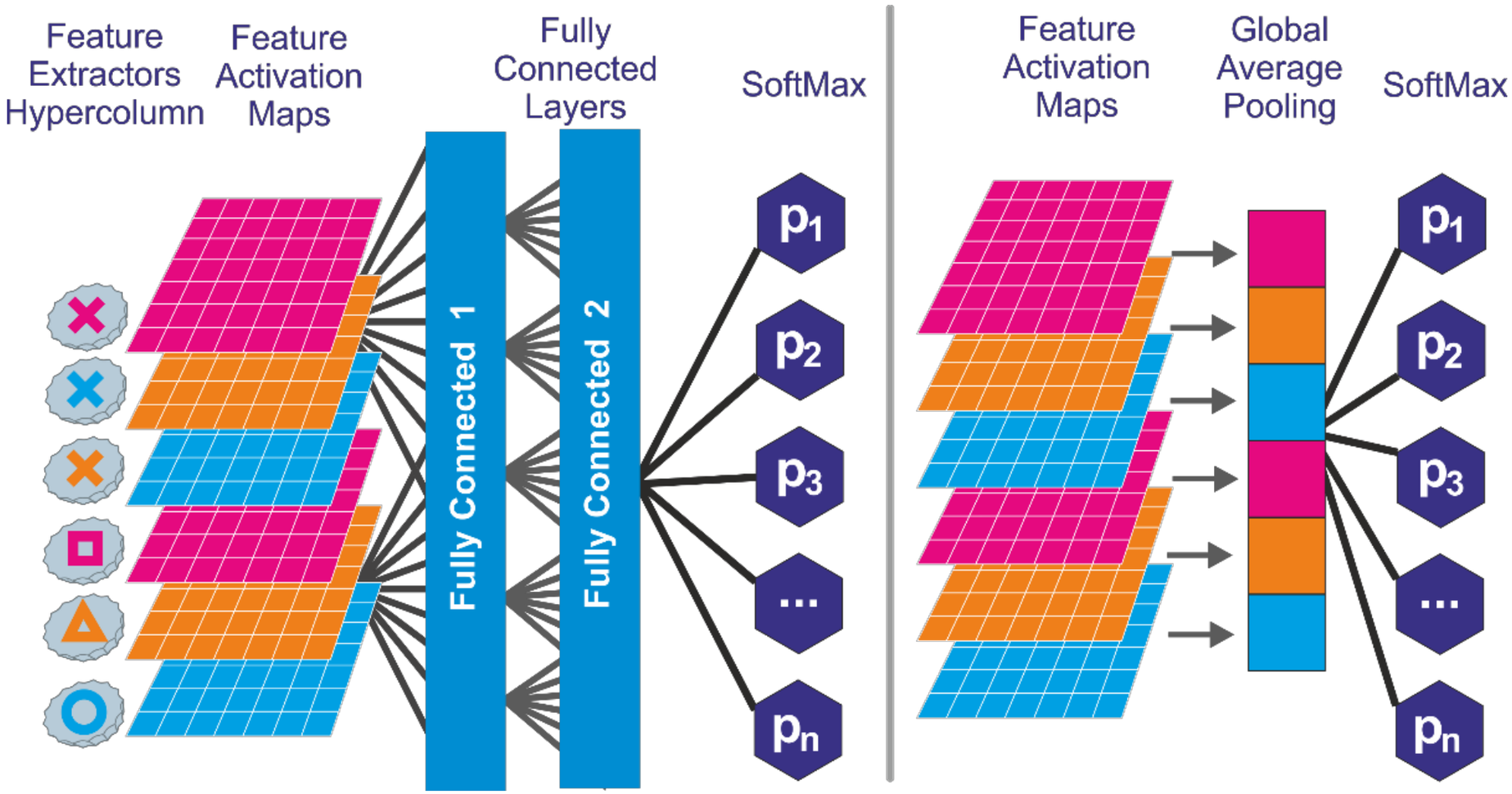


Figure 16: Global average pooling layer replacing the fully connected layers. The output layer implements a Softmax operation with $p_1, p_2, \ldots, p_n$ the predicted probabilities for each class.

Figure Source: Singh, Anshuman Vikram. "Content-based image retrieval using deep learning." (2015).

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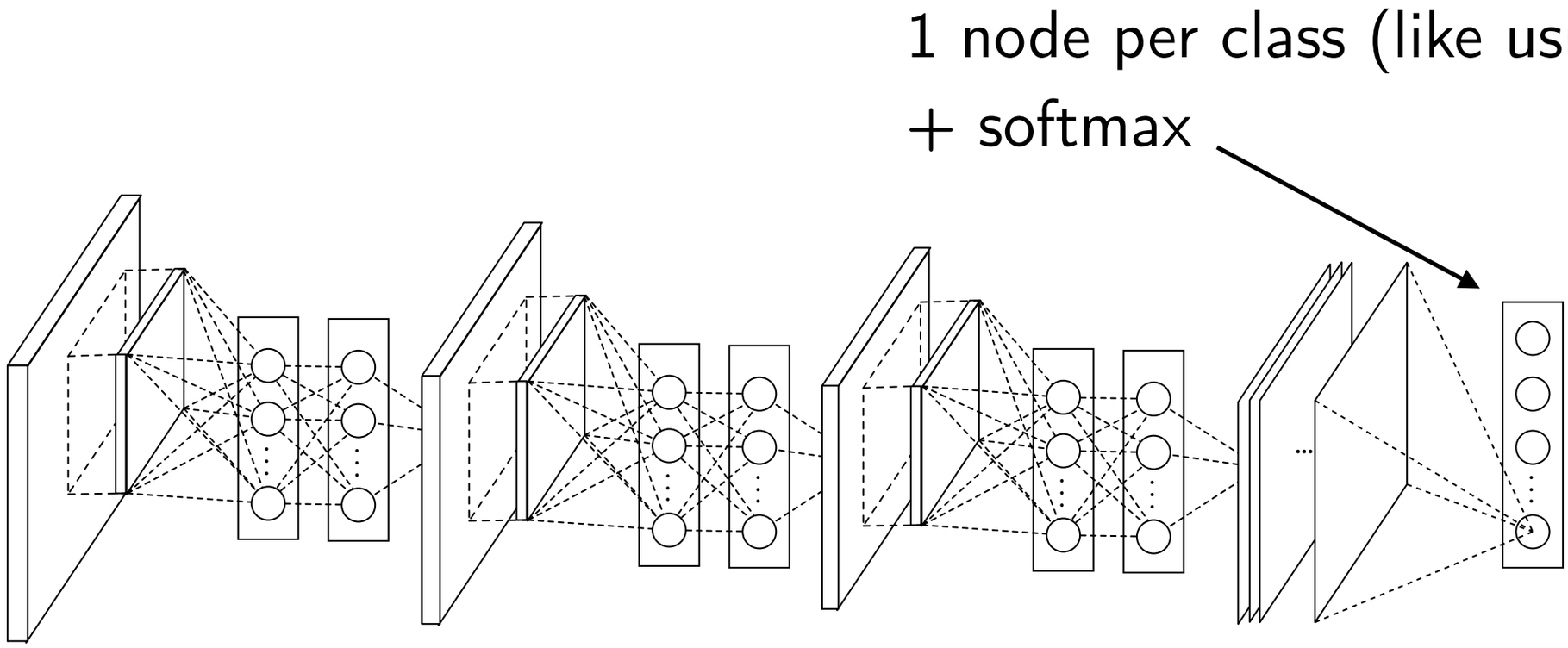

Figure 2: The overall structure of Network In Network. In this paper the NINs include the stacking of three mlpconv layers and one global average pooling layer.

- Replace the fully connected layers in the last layers by *global average pooling*

Network in Network (NiN)

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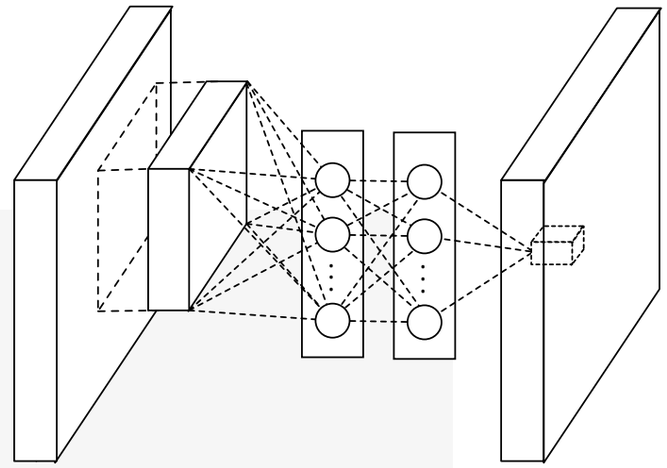
Example Implementation:

https://github.com/rasbt/stat479-deep-learning-ss19/blob/master/L13_intro-cnn/code/nin-cifar10.ipynb

- Replace the MLP "micro structure" via convolutions (explanation on the previous slides)



```
class NiN(nn.Module):
    def __init__(self, num_classes):
        super(NiN, self).__init__()
        self.num_classes = num_classes
        self.classifier = nn.Sequential(
                nn.Conv2d(3, 192, kernel_size=5, stride=1, padding=2),
                nn.ReLU(inplace=True),
                nn.Conv2d(192, 160, kernel_size=1, stride=1, padding=0),
                nn.ReLU(inplace=True),
                nn.Conv2d(160,  96, kernel_size=1, stride=1, padding=0),
                nn.ReLU(inplace=True),
                nn.MaxPool2d(kernel_size=3, stride=2, padding=1),
                nn.Dropout(0.5),

                nn.Conv2d(96, 192, kernel_size=5, stride=1, padding=2),
```

Network in Network (NiN)

Lin, Min, Qiang Chen, and Shuicheng Yan. "Network in network." *arXiv preprint arXiv:1312.4400* (2013).

Why it might work well in practice

Using the micro-networks allow us to extract more sophisticated features (non-linear functions); we may need fewer extractors and can avoid learning too simple or redundant abstractions

Fully-connected layers have a lot of parameters and may cause overfitting, replacing those by global average pooling might help with better generalization

(nice side-effect: we can make the network be somewhat agnostic to the input size)

Different but related idea: "All-Convolutional Network"

Springenberg, Jost Tobias, Alexey Dosovitskiy, Thomas Brox, and Martin Riedmiller. "Striving for simplicity: The all convolutional net." *arXiv preprint arXiv:1412.6806* (2014).

Key Idea: Replace Maxpooling by strided convolutions

(i.e., conv layers with stride=2)

$$s_{i,j,u}(f) = \left(\sum_{h=-\lfloor k/2 \rfloor}^{\lfloor k/2 \rfloor} \sum_{w=-\lfloor k/2 \rfloor}^{\lfloor k/2 \rfloor} |f_{g(h,w,i,j,u)}|^p \right)^{1/p},$$

definition of max-pooling with stride=2 to when $p \to \infty$

$$c_{i,j,o}(f) = \sigma \left(\sum_{h=-\lfloor k/2 \rfloor}^{\lfloor k/2 \rfloor} \sum_{w=-\lfloor k/2 \rfloor}^{\lfloor k/2 \rfloor} \sum_{u=1}^{N} \theta_{h,w,u,o} \cdot f_{g(h,w,i,j,u)} \right)$$

definition of a convolutional layer with stride=2

Different but related idea: "All-Convolutional Network"

Springenberg, Jost Tobias, Alexey Dosovitskiy, Thomas Brox, and Martin Riedmiller. "Striving for simplicity: The all convolutional net." *arXiv preprint arXiv:1412.6806* (2014).

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definition of a convolutional layer with stride=2

We can think of "strided convolutions" as learnable pooling

"All-Convolutional Network"

Springenberg, Jost Tobias, Alexey Dosovitskiy, Thomas Brox, and Martin Riedmiller. "Striving for simplicity: The all convolutional net." *arXiv preprint arXiv:1412.6806* (2014).

Experimental Ablation Study with 3 Base Models:

Table 1: The three base networks used for classification on CIFAR-10 and CIFAR-100.

Model		
A	B	C
Input 32×32 RGB image		
5×5 conv. 96 ReLU	5×5 conv. 96 ReLU 1×1 conv. 96 ReLU	3×3 conv. 96 ReLU 3×3 conv. 96 ReLU
3×3 max-pooling stride 2		
5×5 conv. 192 ReLU	5×5 conv. 192 ReLU 1×1 conv. 192 ReLU	3×3 conv. 192 ReLU 3×3 conv. 192 ReLU
3×3 max-pooling stride 2		
3×3 conv. 192 ReLU		
1×1 conv. 192 ReLU		
1×1 conv. 10 ReLU		
global averaging over 6×6 spatial dimensions		
10 or 100-way softmax		

"All-Convolutional Network"

Springenberg, Jost Tobias, Alexey Dosovitskiy, Thomas Brox, and Martin Riedmiller. "Striving for simplicity: The all convolutional net." *arXiv preprint arXiv:1412.6806* (2014).

Experimental Ablation Study with 3 Base Models: Shown are the modifications for Model C

Model		
Strided-CNN-C	ConvPool-CNN-C	All-CNN-C
Input 32×32 RGB image		
3×3 conv. 96 ReLU 3×3 conv. 96 ReLU with stride $r = 2$	3×3 conv. 96 ReLU 3×3 conv. 96 ReLU 3×3 conv. 96 ReLU	3×3 conv. 96 ReLU 3×3 conv. 96 ReLU
	3×3 max-pooling stride 2	3×3 conv. 96 ReLU with stride $r = 2$
3×3 conv. 192 ReLU 3×3 conv. 192 ReLU with stride $r = 2$	3×3 conv. 192 ReLU 3×3 conv. 192 ReLU 3×3 conv. 192 ReLU	3×3 conv. 192 ReLU 3×3 conv. 192 ReLU
	3×3 max-pooling stride 2	3×3 conv. 192 ReLU with stride $r = 2$

$\vdots$

"All-Convolutional Network"

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Experimental Ablation Study with 3 Base Models: Shown are the modifications for Model C

Remove pooliong & increase stride of the previous layer

Model		
Strided-CNN-C	ConvPool-CNN-C	All-CNN-C
Input 32×32 RGB image		
3×3 conv. 96 ReLU 3×3 conv. 96 ReLU with stride $r = 2$	3×3 conv. 96 ReLU 3×3 conv. 96 ReLU 3×3 conv. 96 ReLU	3×3 conv. 96 ReLU 3×3 conv. 96 ReLU
	3×3 max-pooling stride 2	3×3 conv. 96 ReLU with stride $r = 2$
3×3 conv. 192 ReLU 3×3 conv. 192 ReLU with stride $r = 2$	3×3 conv. 192 ReLU 3×3 conv. 192 ReLU 3×3 conv. 192 ReLU	3×3 conv. 192 ReLU 3×3 conv. 192 ReLU
	3×3 max-pooling stride 2	3×3 conv. 192 ReLU with stride $r = 2$

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Experimental Ablation Study with 3 Base Models: Shown are the modifications for Model C

Remove pooling & add a strided conv. layer

Model		
Strided-CNN-C	ConvPool-CNN-C	All-CNN-C
Input 32×32 RGB image		
3×3 conv. 96 ReLU 3×3 conv. 96 ReLU with stride $r = 2$	3×3 conv. 96 ReLU 3×3 conv. 96 ReLU 3×3 conv. 96 ReLU	3×3 conv. 96 ReLU 3×3 conv. 96 ReLU
	3×3 max-pooling stride 2	3×3 conv. 96 ReLU with stride $r = 2$
3×3 conv. 192 ReLU 3×3 conv. 192 ReLU with stride $r = 2$	3×3 conv. 192 ReLU 3×3 conv. 192 ReLU 3×3 conv. 192 ReLU	3×3 conv. 192 ReLU 3×3 conv. 192 ReLU
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	3×3 max-pooling stride 2	3×3 conv. 96 ReLU with stride $r = 2$
3×3 conv. 192 ReLU 3×3 conv. 192 ReLU with stride $r = 2$	3×3 conv. 192 ReLU 3×3 conv. 192 ReLU 3×3 conv. 192 ReLU	3×3 conv. 192 ReLU 3×3 conv. 192 ReLU
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Table 3: Comparison between the base and derived models on the CIFAR-10 dataset.

CIFAR-10 classification error

Model	Error (%)	# parameters
without data augmentation		
Model A	12.47%	≈ 0.9 M
Strided-CNN-A	13.46%	≈ 0.9 M
ConvPool-CNN-A	**10.21%**	≈ 1.28 M
ALL-CNN-A	10.30%	≈ 1.28 M
Model B	10.20%	≈ 1 M
Strided-CNN-B	10.98%	≈ 1 M
ConvPool-CNN-B	9.33%	≈ 1.35 M
ALL-CNN-B	**9.10%**	≈ 1.35 M
Model C	9.74%	≈ 1.3 M
Strided-CNN-C	10.19%	≈ 1.3 M
ConvPool-CNN-C	9.31%	≈ 1.4 M
ALL-CNN-C	**9.08%**	≈ 1.4 M

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Removing maxpooling and increasing the stride of the previous layer performs worse

"All-Convolutional Network"

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Replacing maxpooling with an convolutional layer (stride=2) improves the performance

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Replacing maxpooling with an convolutional layer (stride=2) improves the performance
(this may be unfair because of the additional parameters)

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Difference to "All-Convolutional Network"

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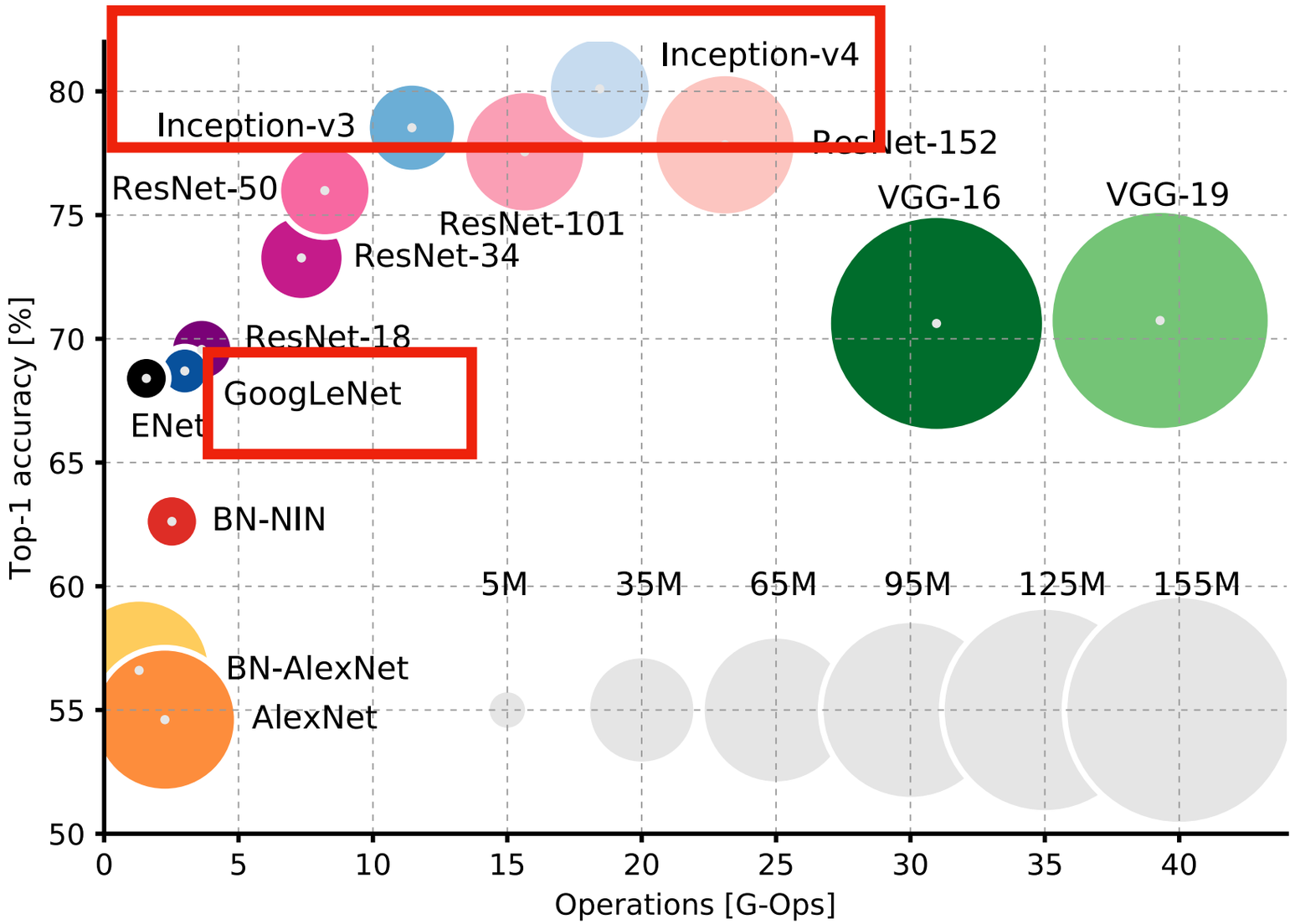
Code example https://github.com/rasbt/stat479-deep-learning-ss19/blob/master/L13_intro-cnn/code/convnet-allconv.ipynb

Common Architectures Revisited



Canziani, A., Paszke, A., & Culurciello, E. (2016). An analysis of deep neural network models for practical applications. *arXiv preprint arXiv:1605.07678*.

GoogLeNet / Inception v1

Szegedy, Christian, Wei Liu, Yangqing Jia, Pierre Sermanet, Scott Reed, Dragomir Anguelov, Dumitru Erhan, Vincent Vanhoucke, and Andrew Rabinovich. "Going deeper with convolutions." In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 1-9. 2015.

3 key ideas:

1. 1x1 in the middle of the network
2. global average pooling instead of fully connected layers
3. inception module

Note that the name inception doesn't have to make sense and is unrelated to the main concept; according to the authors, it comes from an internet meme that is in turn based on a movie called "Inception"

GoogLeNet / Inception v1

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Key Ideas/Features:

- 1x1 convolutions: An efficient way to reduce the number of channels (from NiN)
- Global Average Pooling at the last layer (from NiN)
- Use of auxiliary losses that are added to the total loss
- New: Inception module

GoogLeNet / Inception v1

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Full Architecture

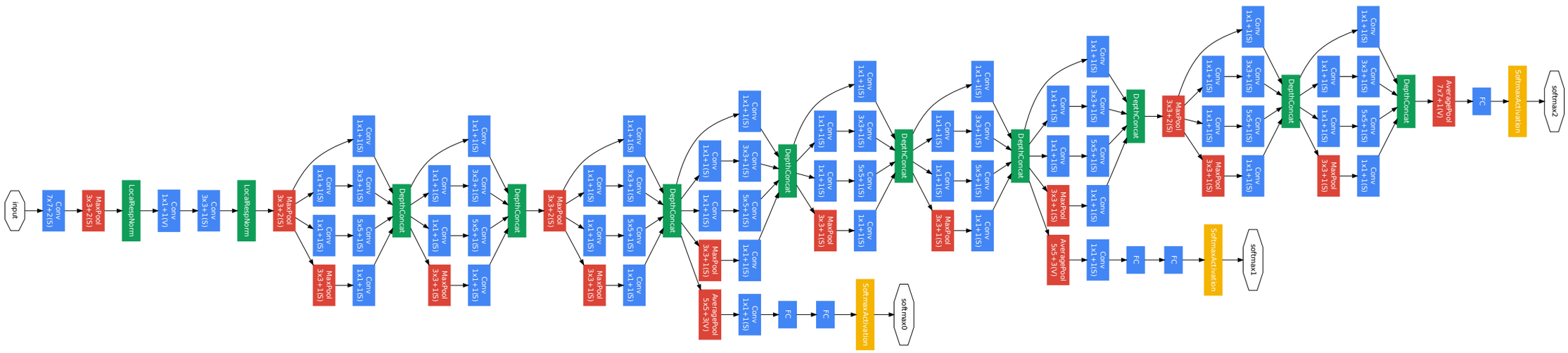

Figure 3: GoogLeNet network with all the bells and whistles.

GoogLeNet / Inception v1

Szegedy, Christian, Wei Liu, Yangqing Jia, Pierre Sermanet, Scott Reed, Dragomir Anguelov, Dumitru Erhan, Vincent Vanhoucke, and Andrew Rabinovich. "Going deeper with convolutions." In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 1-9. 2015.

Zoomed in

GoogLeNet / Inception v1

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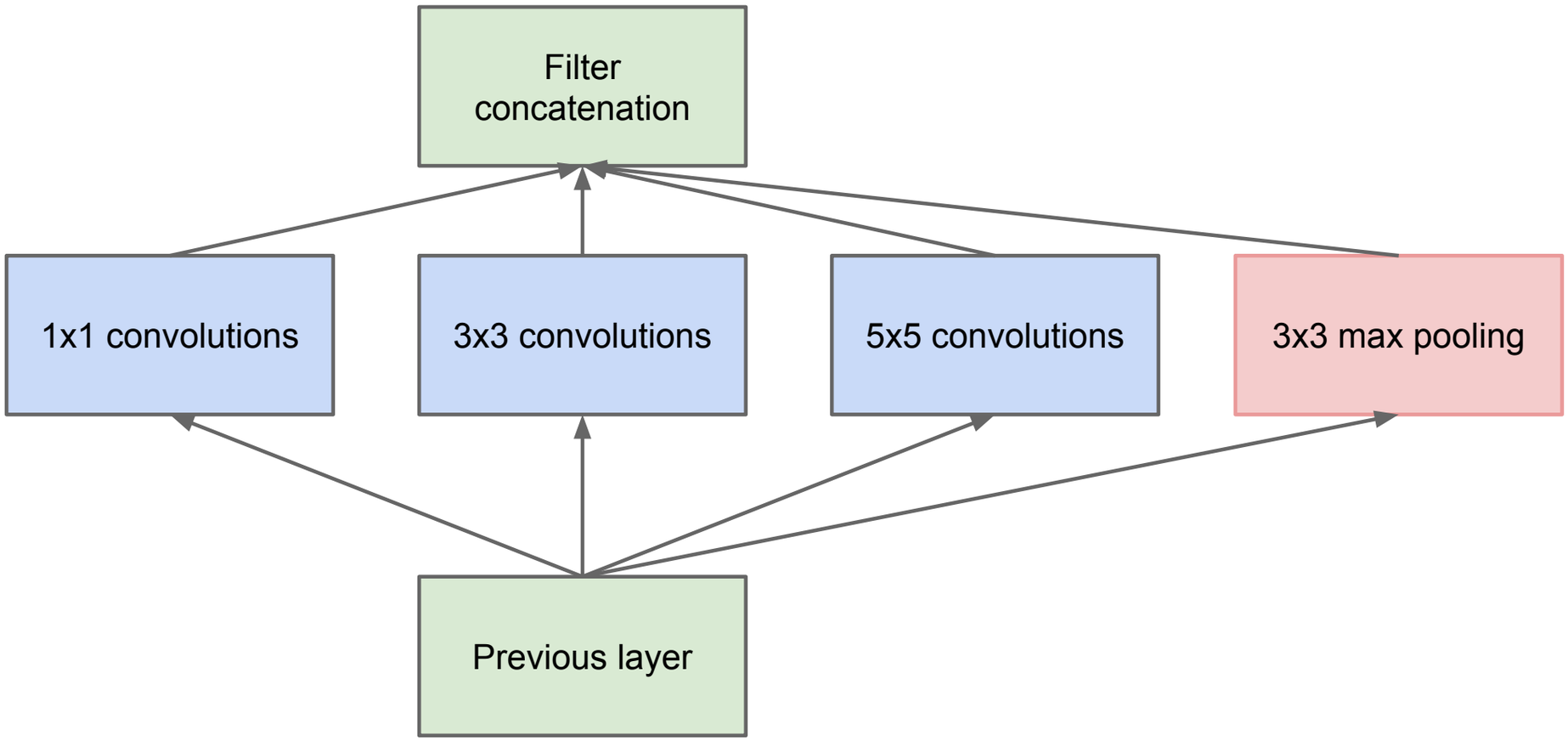

(a) Inception module, naïve version

GoogLeNet / Inception v1

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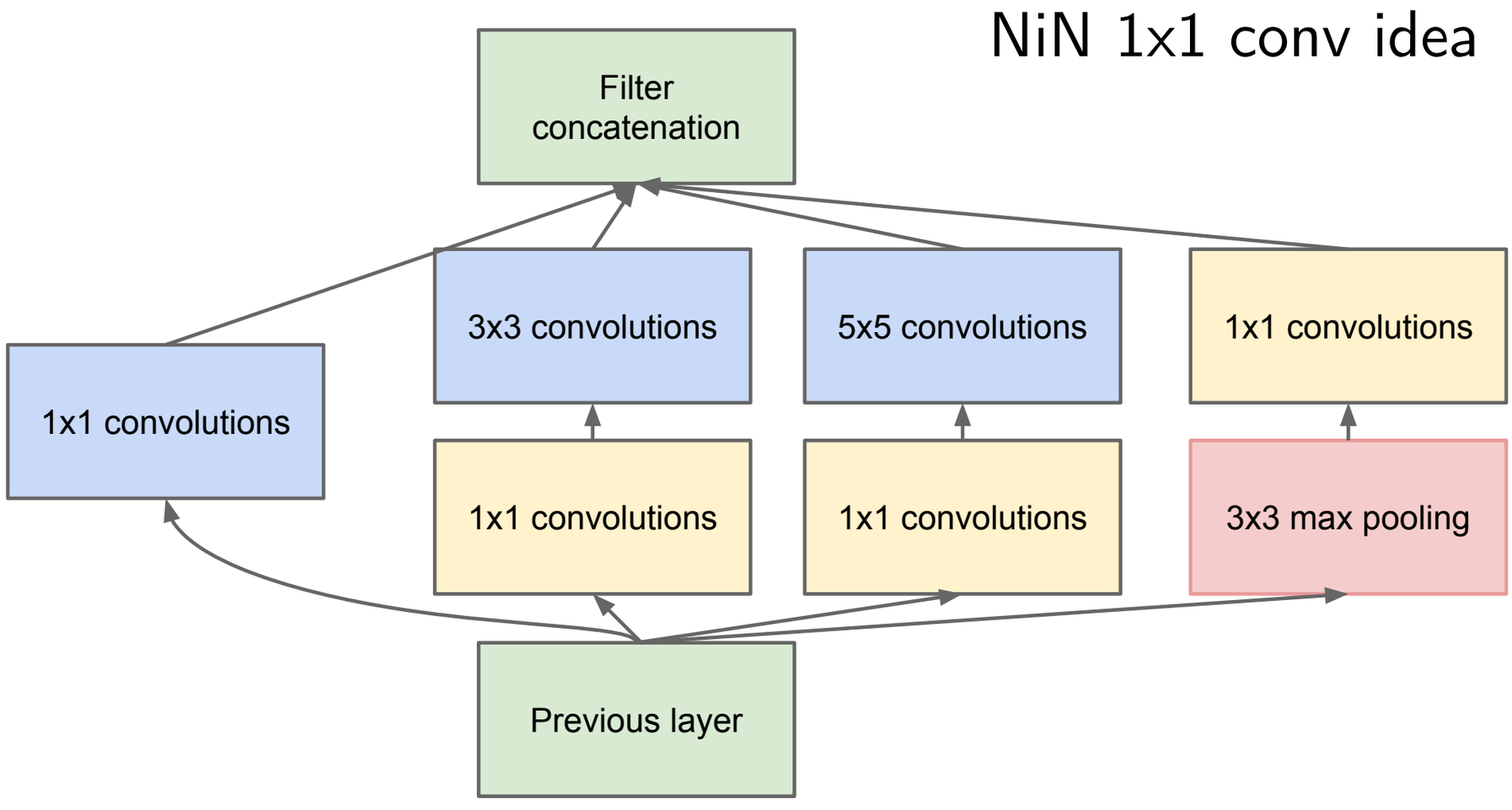

(b) Inception module with dimensionality reduction

GoogLeNet / Inception v1

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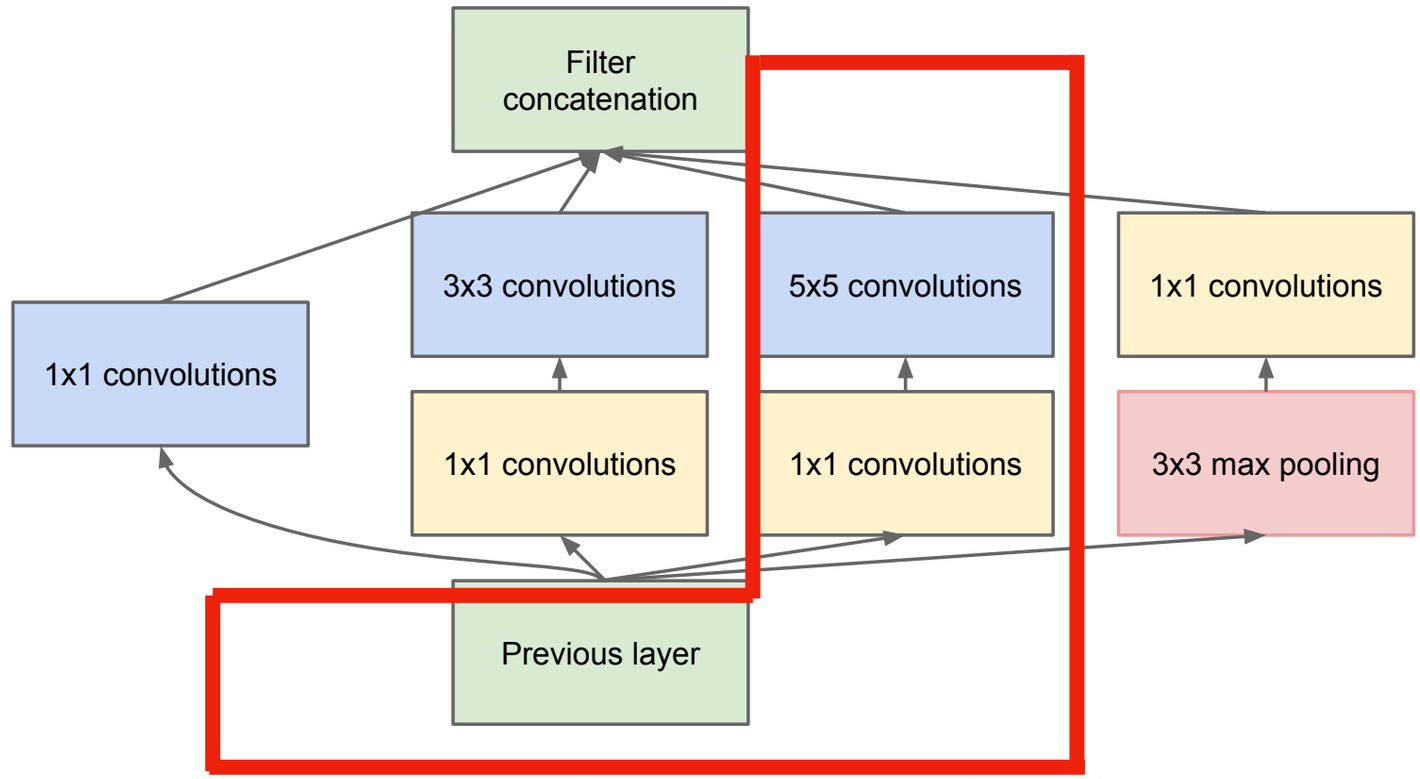
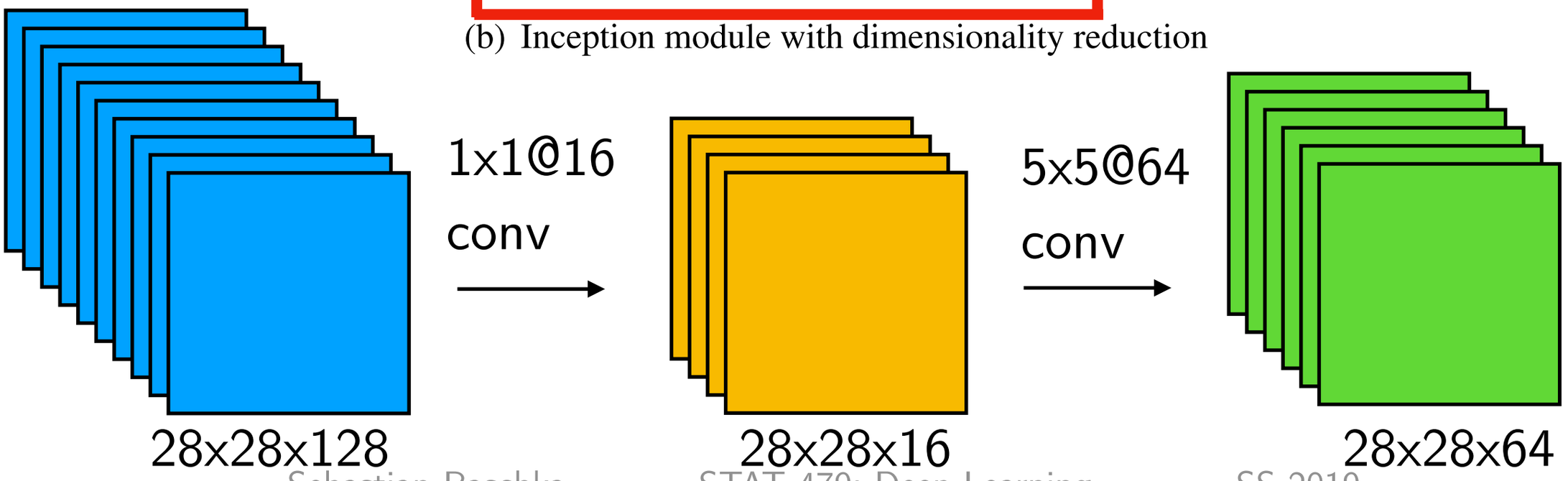


(b) Inception module with dimensionality reduction

Example:



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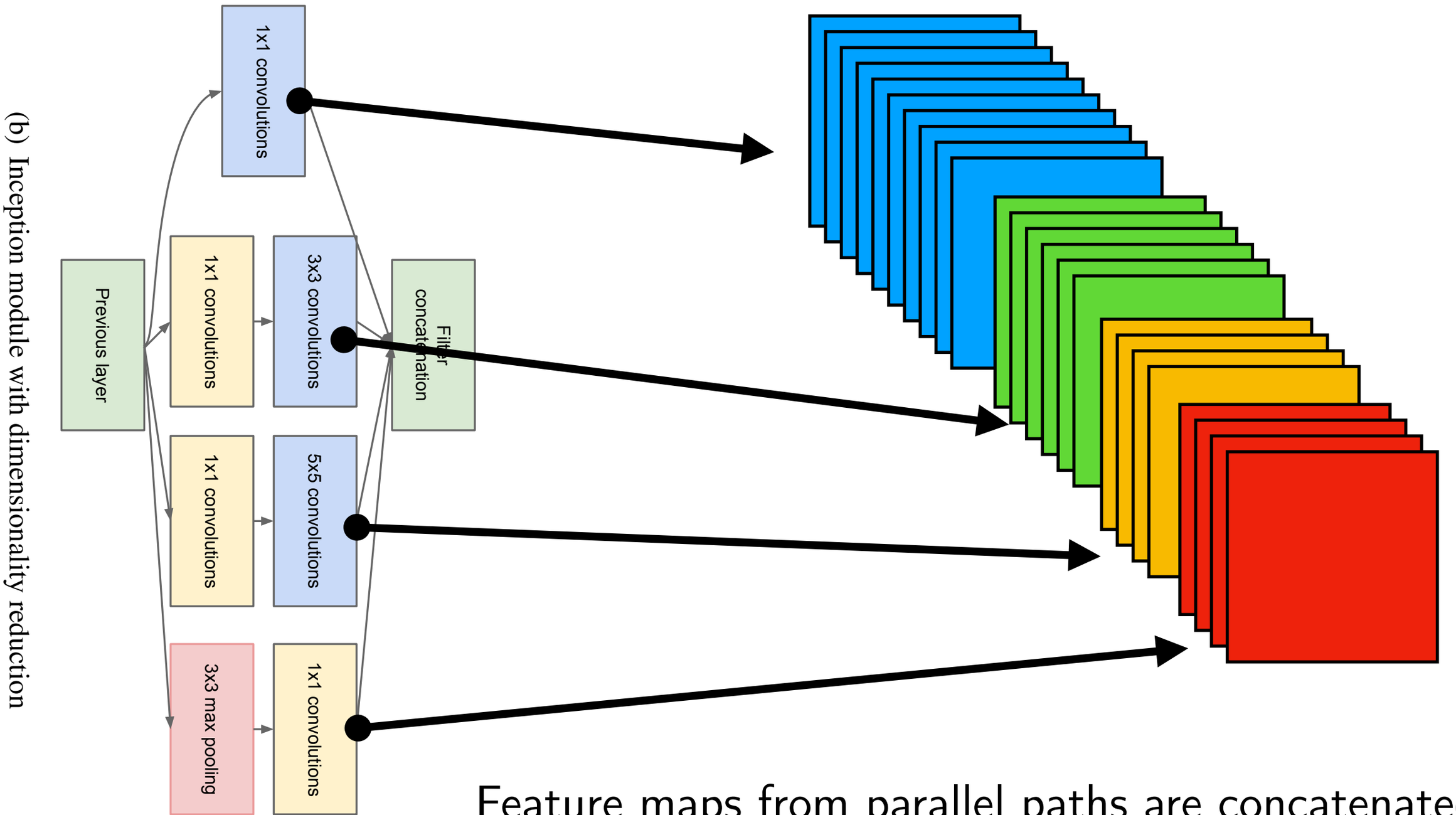

Feature maps from parallel paths are concatenated

To be continued ...