یادگیری عمیق

جلسه ۱۷

معماری‌های گوناگون شبکه‌های عصبی کانولوشنال

Various Architectures of Convolutional Neural Networks

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دانشگاه تهران

http://courses.fouladi.ir/deep

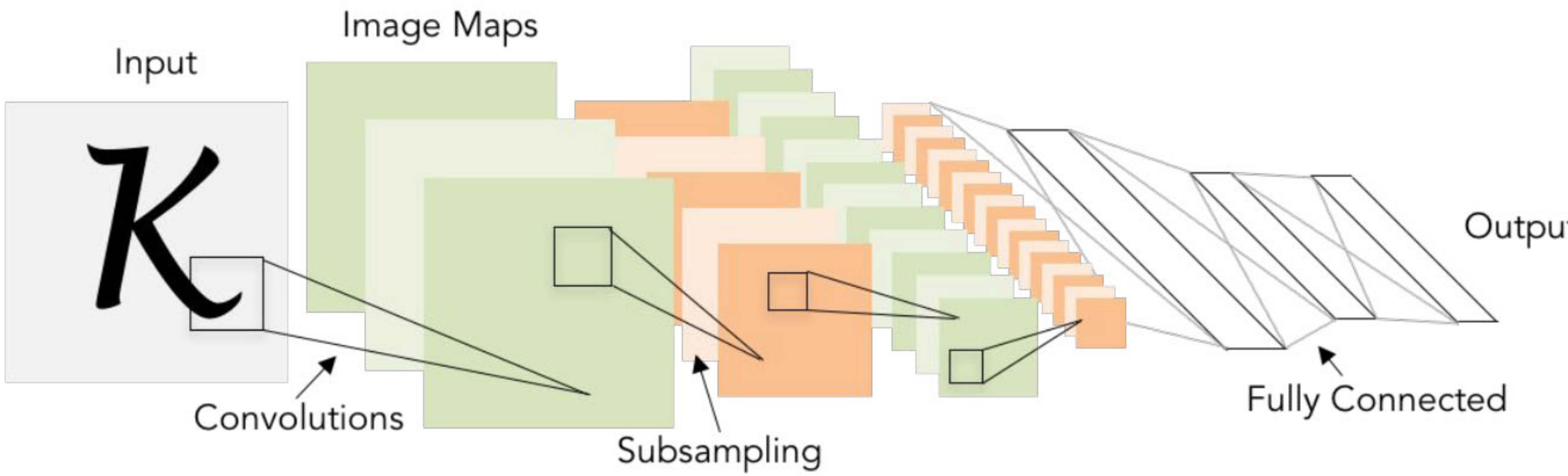
معماری‌های گوناگون
شبکه‌های عصبی کانوولوشنال

۱

معماری‌های پایه

LeNet-5

[LeCun et al., 1998]



Conv filters were 5x5, applied at stride 1
Subsampling (Pooling) layers were 2x2 applied at stride 2
i.e. architecture is [CONV-POOL-CONV-POOL-FC-FC]

Ref: http://cs231n.stanford.edu/

Gradient-Based Learning Applied to Document Recognition

Yann LeCun, Léon Bottou, Yoshua Bengio, and Patrick Haffner

Abstract—
Multilayer Neural Networks trained with the backpropagation algorithm constitute the best example of a successful Gradient-Based Learning technique. Given an appropriate network architecture, Gradient-Based Learning algorithms can be used to synthesize a complex decision surface that can classify high-dimensional patterns such as handwritten characters, with minimal preprocessing. This paper reviews various methods applied to handwritten character recognition and compares them on a standard handwritten digit recognition task. Convolutional Neural Networks, that are specifically designed to deal with the variability of 2D shapes, are shown to outperform all other techniques.

Real-life document recognition systems are composed of multiple modules including field extraction, segmentation, recognition, and language modeling. A new learning paradigm, called Graph Transformer Networks (GTN), allows such multi-module systems to be trained globally using Gradient-Based methods so as to minimize an overall performance measure.

Two systems for on-line handwriting recognition are described. Experiments demonstrate the advantage of global training, and the flexibility of Graph Transformer Networks.

A Graph Transformer Network for reading bank check is also described. It uses Convolutional Neural Network character recognizers combined with global training techniques to provides record accuracy on business and personal checks. It is deployed commercially and reads several million checks per day.

Keywords— **Neural Networks, OCR, Document Recognition, Machine Learning, Gradient-Based Learning, Convolutional Neural Networks, Graph Transformer Networks, Finite State Transducers.**

Nomenclature

- GT Graph transformer.
- GTN Graph transformer network.
- HMM Hidden Markov model.
- HOS Heuristic oversegmentation.
- K-NN K-nearest neighbor.
- NN Neural network.
- OCR Optical character recognition.
- PCA Principal component analysis.
- RBF Radial basis function.
- RS-SVM Reduced-set support vector method.
- SDNN Space displacement neural network.
- SVM Support vector method.
- TDNN Time delay neural network.
- V-SVM Virtual support vector method.

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I. Introduction

Over the last several years, machine learning techniques, particularly when applied to neural networks, have played an increasingly important role in the design of pattern recognition systems. In fact, it could be argued that the availability of learning techniques has been a crucial factor in the recent success of pattern recognition applications such as continuous speech recognition and handwriting recognition.

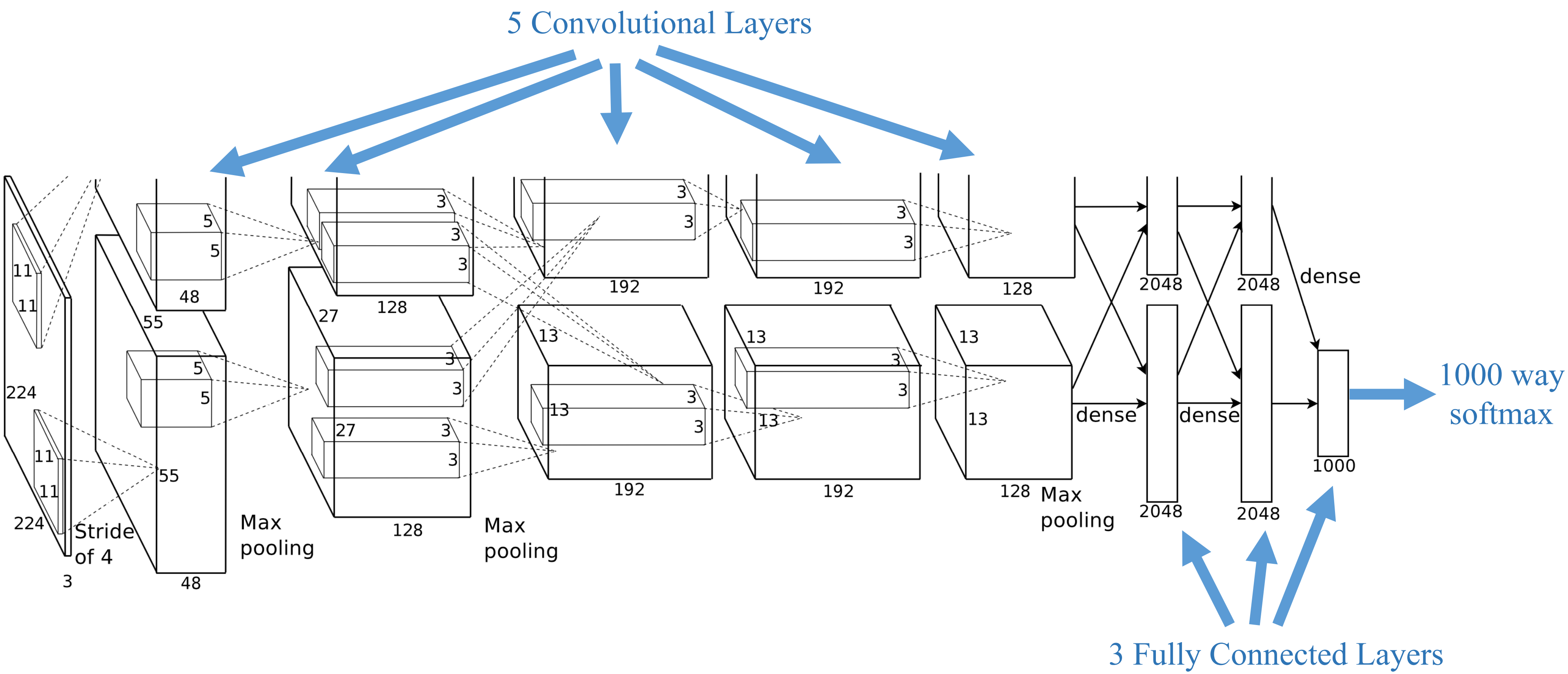
The main message of this paper is that better pattern recognition systems can be built by relying more on automatic learning, and less on hand-designed heuristics. This is made possible by recent progress in machine learning and computer technology. Using character recognition as a case study, we show that hand-crafted feature extraction can be advantageously replaced by carefully designed learning machines that operate directly on pixel images. Using document understanding as a case study, we show that the traditional way of building recognition systems by manually integrating individually designed modules can be replaced by a unified and well-principled design paradigm, called *Graph Transformer Networks*, that allows training all the modules to optimize a global performance criterion.

Since the early days of pattern recognition it has been known that the variability and richness of natural data, be it speech, glyphs, or other types of patterns, make it almost impossible to build an accurate recognition system entirely by hand. Consequently, most pattern recognition systems are built using a combination of automatic learning techniques and hand-crafted algorithms. The usual method of recognizing individual patterns consists in dividing the system into two main modules shown in figure 1. The first module, called the feature extractor, transforms the input patterns so that they can be represented by low-dimensional vectors or short strings of symbols that (a) can be easily matched or compared, and (b) are relatively invariant with respect to transformations and distortions of the input patterns that do not change their nature. The feature extractor contains most of the prior knowledge and is rather specific to the task. It is also the focus of most of the design effort, because it is often entirely hand-crafted. The classifier, on the other hand, is often general-purpose and trainable. One of the main problems with this approach is that the recognition accuracy is largely determined by the ability of the designer to come up with an appropriate set of features. This turns out to be a daunting task which, unfortunately, must be redone for each new problem. A large amount of the pattern recognition literature is devoted to describing and comparing the relative

AlexNet

معماری

AlexNet: Architecture



ImageNet Classification with Deep Convolutional Neural Networks

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Abstract

We trained a large, deep convolutional neural network to classify the 1.2 million high-resolution images in the ImageNet LSVRC-2010 contest into the 1000 different classes. On the test data, we achieved top-1 and top-5 error rates of 37.5% and 17.0% which is considerably better than the previous state-of-the-art. The neural network, which has 60 million parameters and 650,000 neurons, consists of five convolutional layers, some of which are followed by max-pooling layers, and three fully-connected layers with a final 1000-way softmax. To make training faster, we used non-saturating neurons and a very efficient GPU implementation of the convolution operation. To reduce overfitting in the fully-connected layers we employed a recently-developed regularization method called "dropout" that proved to be very effective. We also entered a variant of this model in the ILSVRC-2012 competition and achieved a winning top-5 test error rate of 15.3%, compared to 26.2% achieved by the second-best entry.

1 Introduction

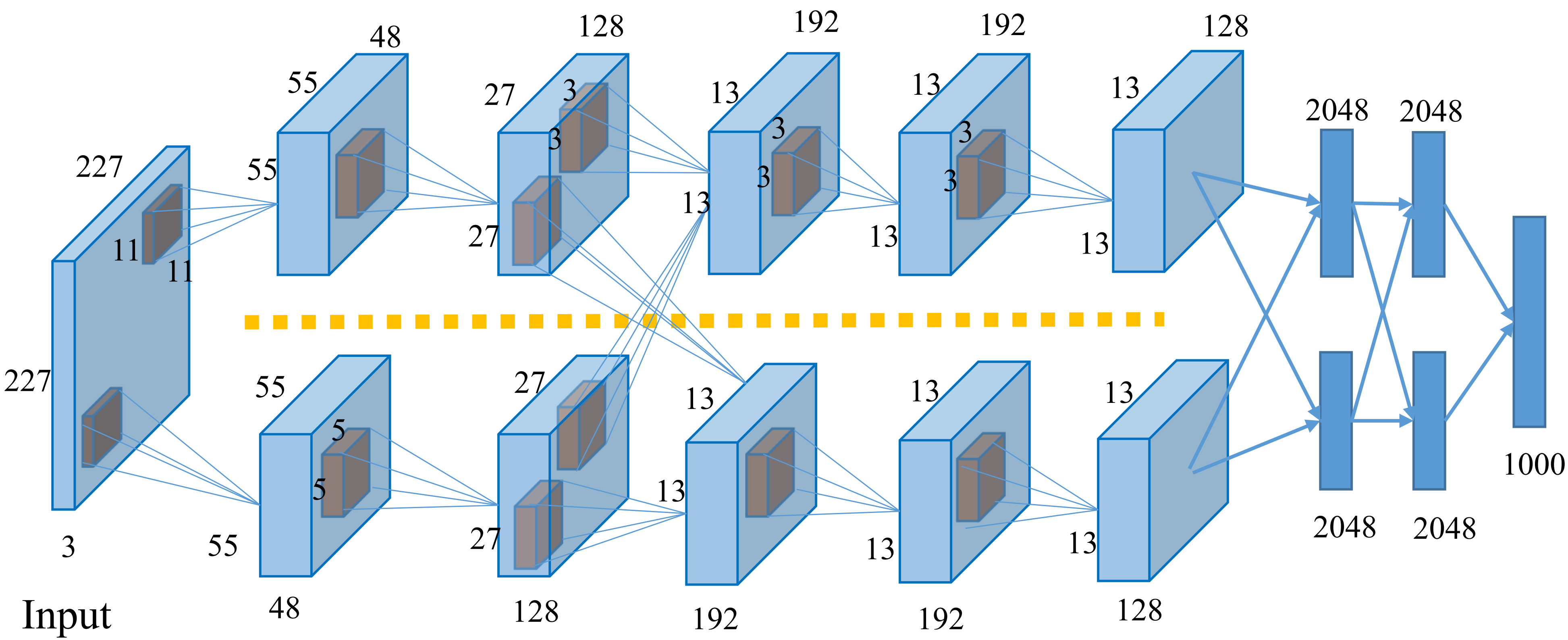
Current approaches to object recognition make essential use of machine learning methods. To improve their performance, we can collect larger datasets, learn more powerful models, and use better techniques for preventing overfitting. Until recently, datasets of labeled images were relatively small — on the order of tens of thousands of images (e.g., NORB [16], Caltech-101/256 [8, 9], and CIFAR-10/100 [12]). Simple recognition tasks can be solved quite well with datasets of this size, especially if they are augmented with label-preserving transformations. For example, the current-best error rate on the MNIST digit-recognition task (<0.3%) approaches human performance [4]. But objects in realistic settings exhibit considerable variability, so to learn to recognize them it is necessary to use much larger training sets. And indeed, the shortcomings of small image datasets have been widely recognized (e.g., Pinto et al. [21]), but it has only recently become possible to collect labeled datasets with millions of images. The new larger datasets include LabelMe [23], which consists of hundreds of thousands of fully-segmented images, and ImageNet [6], which consists of over 15 million labeled high-resolution images in over 22,000 categories.

To learn about thousands of objects from millions of images, we need a model with a large learning capacity. However, the immense complexity of the object recognition task means that this problem cannot be specified even by a dataset as large as ImageNet, so our model should also have lots of prior knowledge to compensate for all the data we don't have. Convolutional neural networks (CNNs) constitute one such class of models [16, 11, 13, 18, 15, 22, 26]. Their capacity can be controlled by varying their depth and breadth, and they also make strong and mostly correct assumptions about the nature of images (namely, stationarity of statistics and locality of pixel dependencies). Thus, compared to standard feedforward neural networks with similarly-sized layers, CNNs have much fewer connections and parameters and so they are easier to train, while their theoretically-best performance is likely to be only slightly worse.

AlexNet

معماری: برای طبقه‌بندی تصاویر ImageNet

ALEXNET: ARCHITECTURE

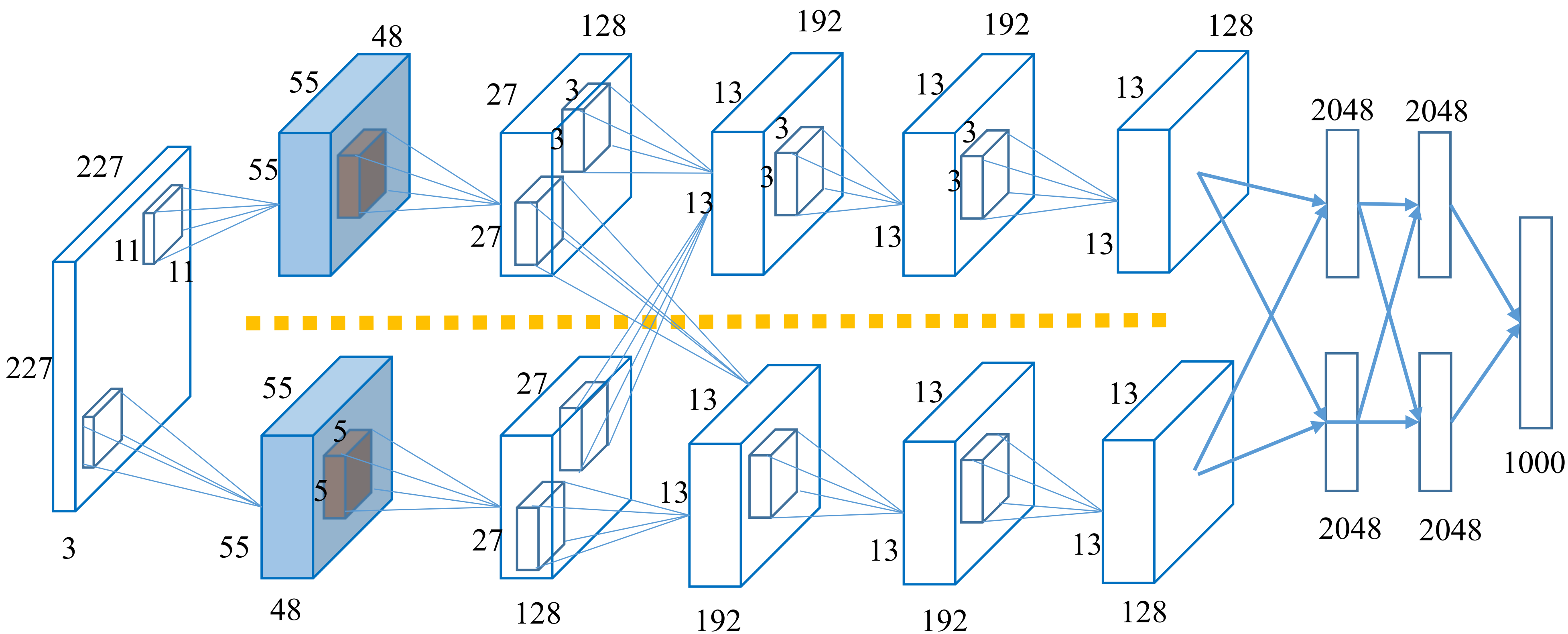


AlexNet

معماری: تعداد پارامترها

ALEXNET: ARCHITECTURE

- $55\times55\times96$ = 290,400 neurons, each having $11\times11\times3$ = 363 weights + 1 bias
- 290400×364 = 105,705,600 parameters in first layer alone if fully connected.



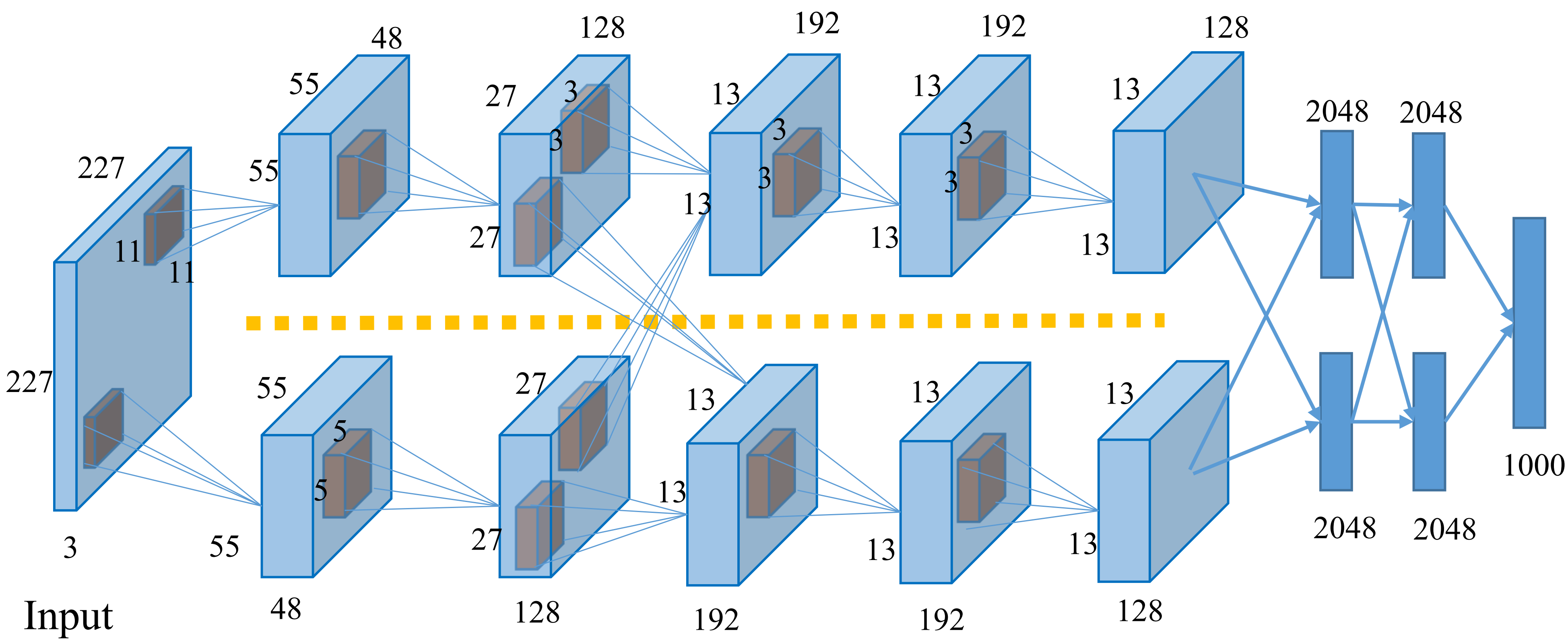
AlexNet

معماری: جزئیات لایه‌ها

ALEXNET: ARCHITECTURE

for layer details refer to:

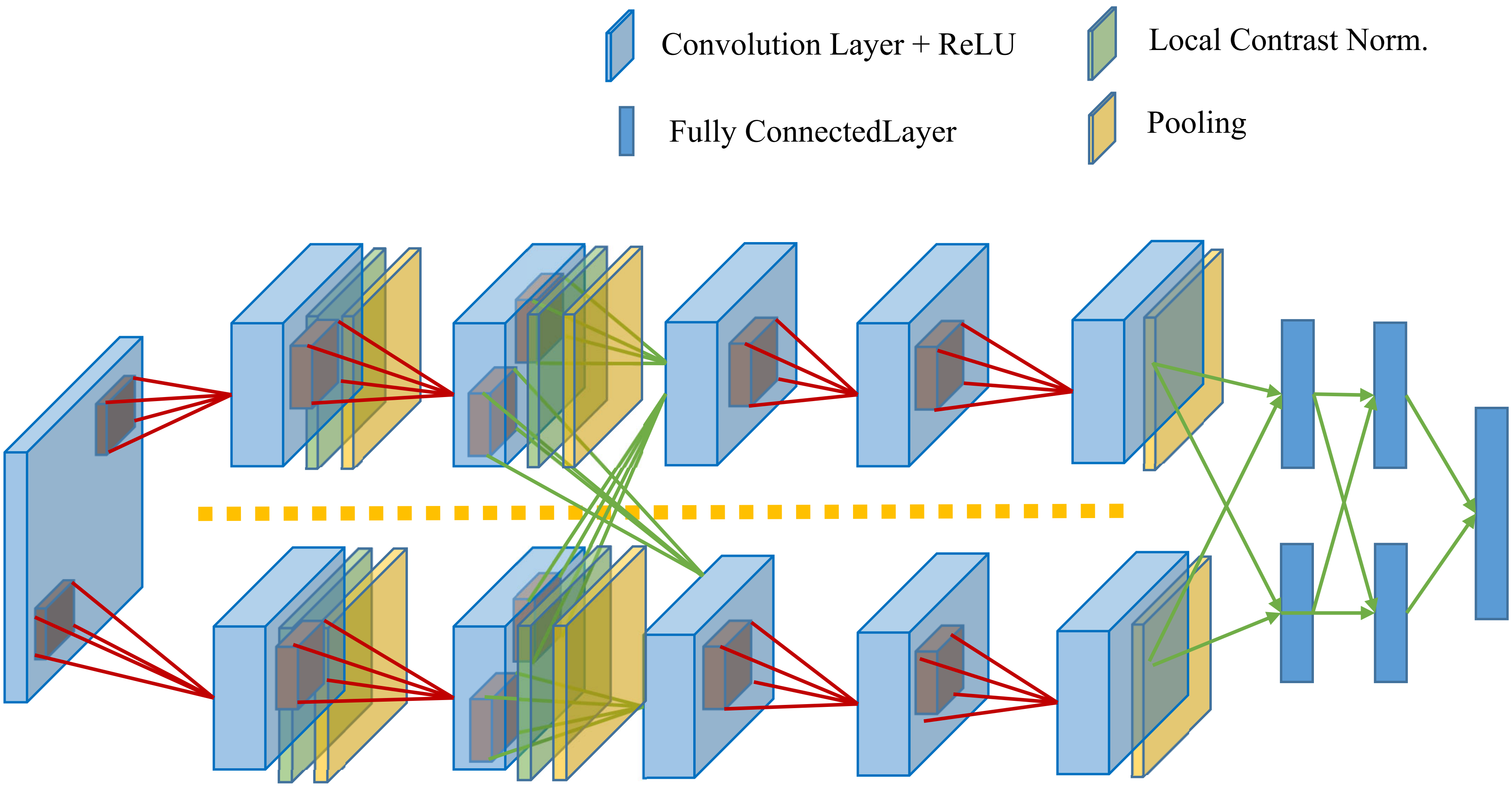
https://github.com/BVLC/caffe/blob/master/models/bvlc_alexnet/deploy.prototxt



AlexNet

معماری: نمایش لایه‌های جانبی

ALEXNET: ARCHITECTURE

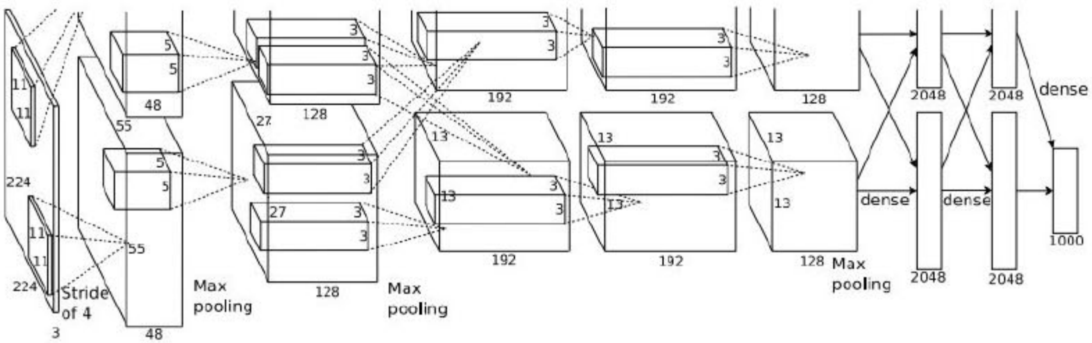


AlexNet

معماری

AlexNet

[Krizhevsky et al. 2012]

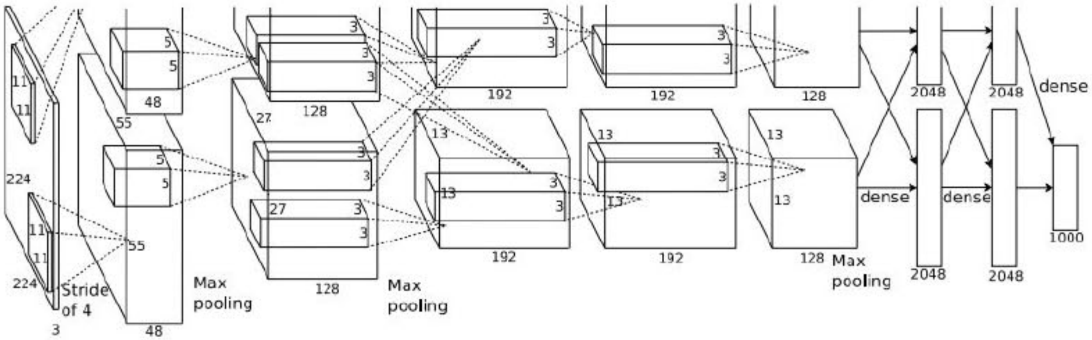


Architecture:
CONV1
MAX POOL1
NORM1
CONV2
MAX POOL2
NORM2
CONV3
CONV4
CONV5
Max POOL3
FC6
FC7
FC8

Ref: http://cs231n.stanford.edu/

AlexNet

[Krizhevsky et al. 2012]

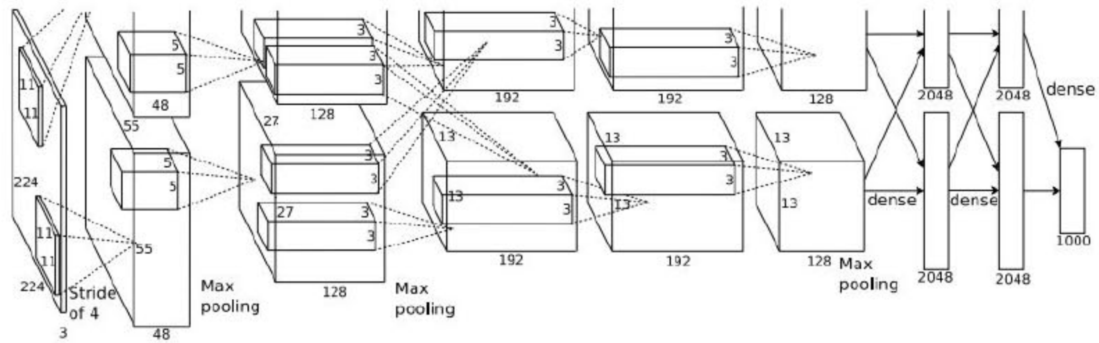


Input: 227x227x3 images

First layer (CONV1): 96 11x11 filters applied at stride 4
=>
Q: what is the output volume size? Hint: (227-11)/4+1 = 55

AlexNet

[Krizhevsky et al. 2012]



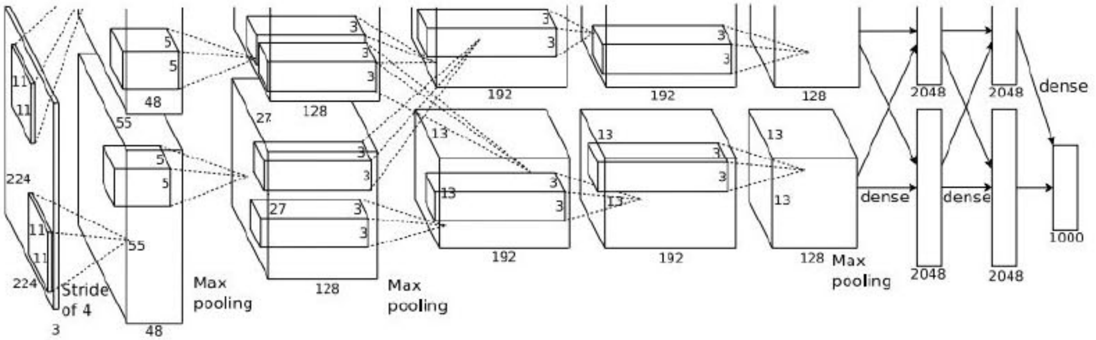
Input: 227x227x3 images

First layer (CONV1): 96 11x11 filters applied at stride 4
=>
Output volume **[55x55x96]**

Q: What is the total number of parameters in this layer?

AlexNet

[Krizhevsky et al. 2012]

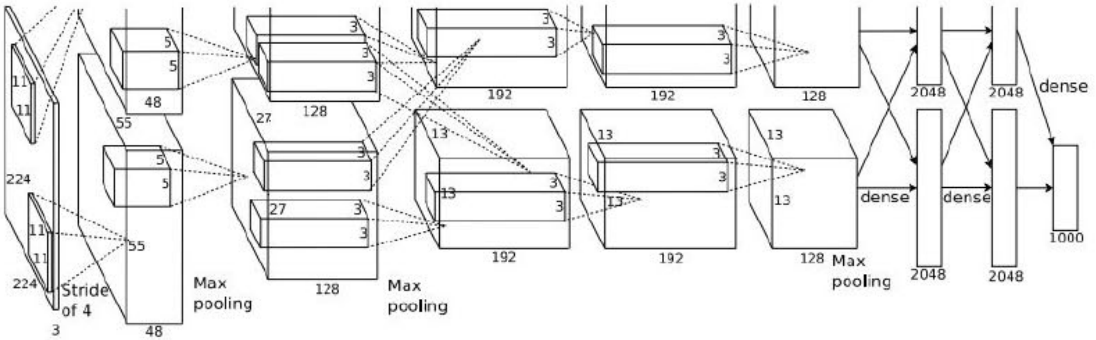


Input: 227x227x3 images

First layer (CONV1): 96 11x11 filters applied at stride 4
=>
Output volume **[55x55x96]**
Parameters: (11*11*3)*96 = **35K**

AlexNet

[Krizhevsky et al. 2012]



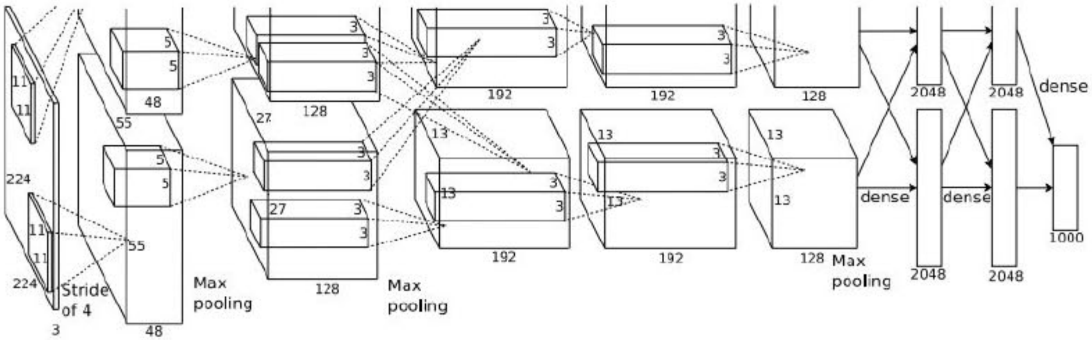
Input: 227x227x3 images
After CONV1: 55x55x96

Second layer (POOL1): 3x3 filters applied at stride 2

Q: what is the output volume size? Hint: (55-3)/2+1 = 27

AlexNet

[Krizhevsky et al. 2012]



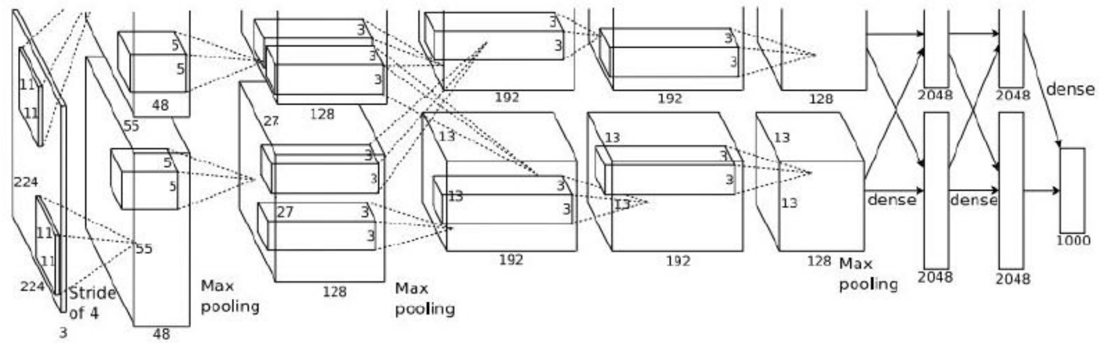
Input: 227x227x3 images
After CONV1: 55x55x96

Second layer (POOL1): 3x3 filters applied at stride 2
Output volume: 27x27x96

Q: what is the number of parameters in this layer?

AlexNet

[Krizhevsky et al. 2012]



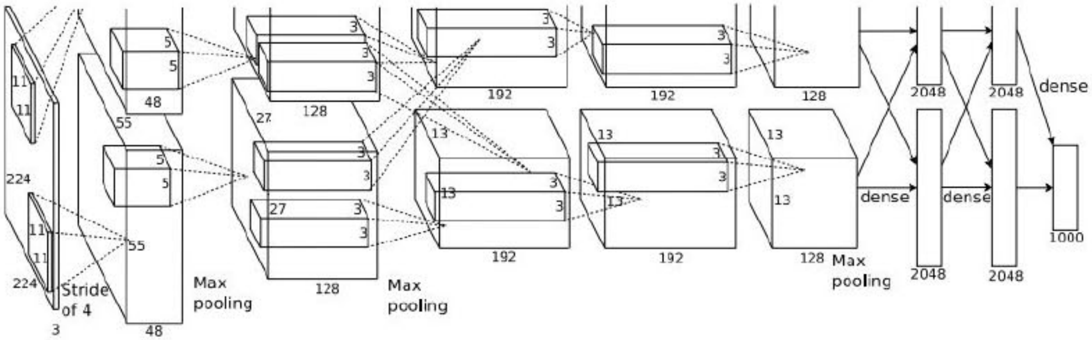
Input: 227x227x3 images
After CONV1: 55x55x96

Second layer (POOL1): 3x3 filters applied at stride 2
Output volume: 27x27x96
Parameters: 0!

AlexNet

AlexNet

[Krizhevsky et al. 2012]



Input: 227x227x3 images
After CONV1: 55x55x96
After POOL1: 27x27x96
...

AlexNet

[Krizhevsky et al. 2012]

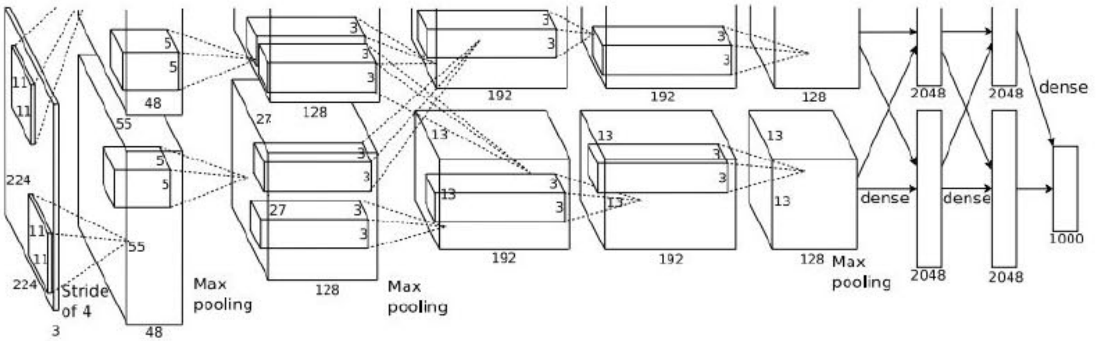


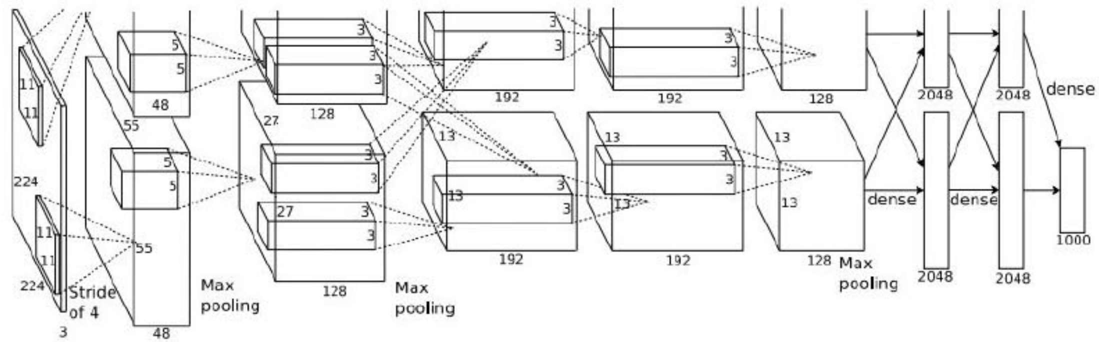
Figure copyright Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, 2012. Reproduced with permission.

Full (simplified) AlexNet architecture:
[227x227x3] INPUT
[55x55x96] CONV1: 96 11x11 filters at stride 4, pad 0
[27x27x96] MAX POOL1: 3x3 filters at stride 2
[27x27x96] NORM1: Normalization layer
[27x27x256] CONV2: 256 5x5 filters at stride 1, pad 2
[13x13x256] MAX POOL2: 3x3 filters at stride 2
[13x13x256] NORM2: Normalization layer
[13x13x384] CONV3: 384 3x3 filters at stride 1, pad 1
[13x13x384] CONV4: 384 3x3 filters at stride 1, pad 1
[13x13x256] CONV5: 256 3x3 filters at stride 1, pad 1
[6x6x256] MAX POOL3: 3x3 filters at stride 2
[4096] FC6: 4096 neurons
[4096] FC7: 4096 neurons
[1000] FC8: 1000 neurons (class scores)

Ref: http://cs231n.stanford.edu/

AlexNet

[Krizhevsky et al. 2012]



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[227x227x3] INPUT
[55x55x96] CONV1: 96 11x11 filters at stride 4, pad 0
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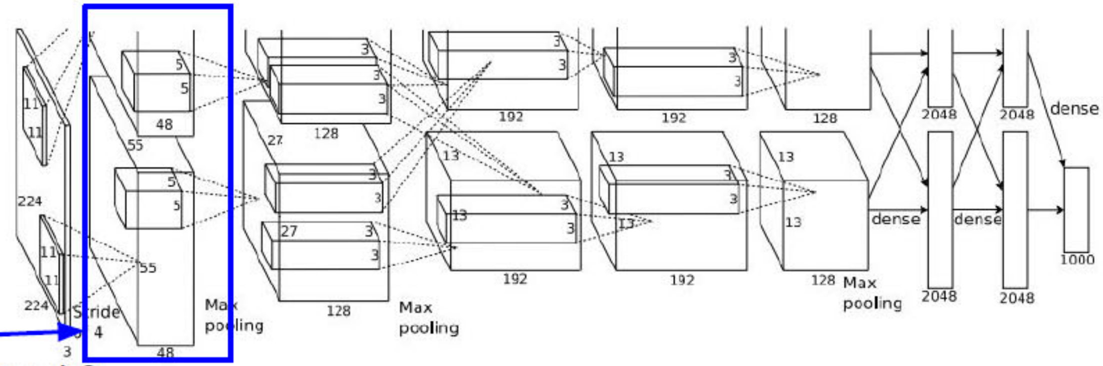
[27x27x96] NORM1: Normalization layer
[27x27x256] CONV2: 256 5x5 filters at stride 1, pad 2
[13x13x256] MAX POOL2: 3x3 filters at stride 2
[13x13x256] NORM2: Normalization layer
[13x13x384] CONV3: 384 3x3 filters at stride 1, pad 1
[13x13x384] CONV4: 384 3x3 filters at stride 1, pad 1
[13x13x256] CONV5: 256 3x3 filters at stride 1, pad 1
[6x6x256] MAX POOL3: 3x3 filters at stride 2
[4096] FC6: 4096 neurons
[4096] FC7: 4096 neurons
[1000] FC8: 1000 neurons (class scores)

Details/Retrospectives:
- first use of ReLU
- used Norm layers (not common anymore)
- heavy data augmentation
- dropout 0.5
- batch size 128
- SGD Momentum 0.9
- Learning rate 1e-2, reduced by 10 manually when val accuracy plateaus
- L2 weight decay 5e-4
- 7 CNN ensemble: 18.2% -> 15.4%

AlexNet

[Krizhevsky et al. 2012]



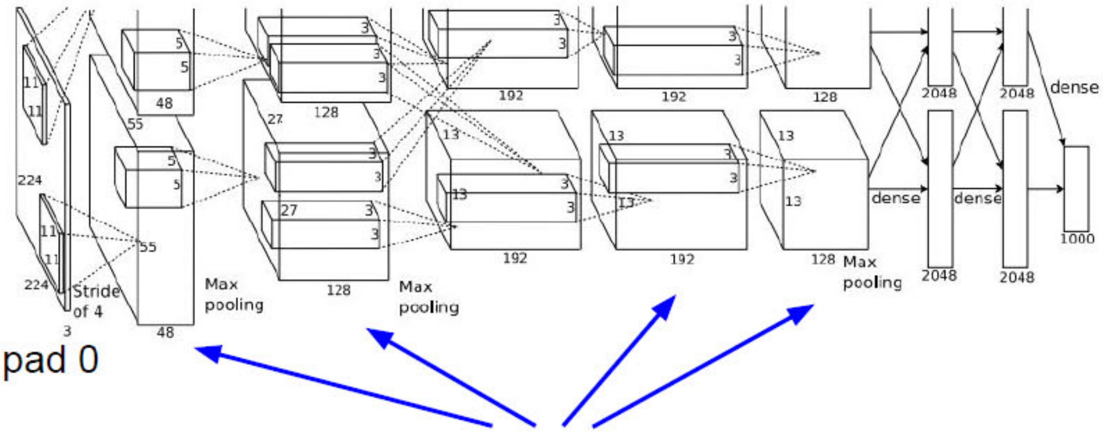
Full (simplified) AlexNet architecture:
[227x227x3] INPUT
[55x55x96] CONV1: 96 11x11 filters at stride 4, pad 0
[27x27x96] MAX POOL1: 3x3 filters at stride 2
[27x27x96] NORM1: Normalization layer
[27x27x256] CONV2: 256 5x5 filters at stride 1, pad 2
[13x13x256] MAX POOL2: 3x3 filters at stride 2
[13x13x256] NORM2: Normalization layer
[13x13x384] CONV3: 384 3x3 filters at stride 1, pad 1
[13x13x384] CONV4: 384 3x3 filters at stride 1, pad 1
[13x13x256] CONV5: 256 3x3 filters at stride 1, pad 1
[6x6x256] MAX POOL3: 3x3 filters at stride 2
[4096] FC6: 4096 neurons
[4096] FC7: 4096 neurons
[1000] FC8: 1000 neurons (class scores)

Historical note: Trained on GTX 580 GPU with only 3 GB of memory. Network spread across 2 GPUs, half the neurons (feature maps) on each GPU.

Ref: http://cs231n.stanford.edu/

AlexNet

[Krizhevsky et al. 2012]



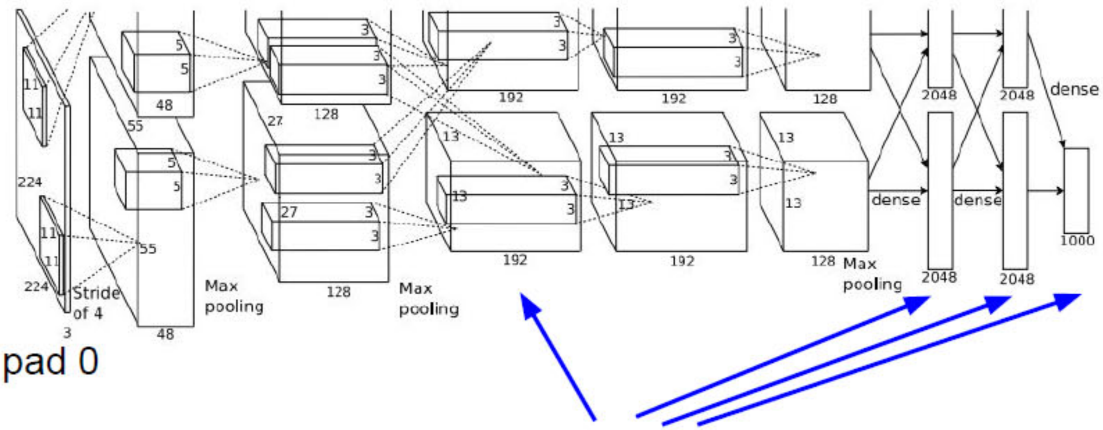
CONV1, CONV2, CONV4, CONV5:
Connections only with feature maps on same GPU

Full (simplified) AlexNet architecture:
[227x227x3] INPUT
[55x55x96] CONV1: 96 11x11 filters at stride 4, pad 0
[27x27x96] MAX POOL1: 3x3 filters at stride 2
[27x27x96] NORM1: Normalization layer
[27x27x256] CONV2: 256 5x5 filters at stride 1, pad 2
[13x13x256] MAX POOL2: 3x3 filters at stride 2
[13x13x256] NORM2: Normalization layer
[13x13x384] CONV3: 384 3x3 filters at stride 1, pad 1
[13x13x384] CONV4: 384 3x3 filters at stride 1, pad 1
[13x13x256] CONV5: 256 3x3 filters at stride 1, pad 1
[6x6x256] MAX POOL3: 3x3 filters at stride 2
[4096] FC6: 4096 neurons
[4096] FC7: 4096 neurons
[1000] FC8: 1000 neurons (class scores)

Ref: http://cs231n.stanford.edu/

AlexNet

[Krizhevsky et al. 2012]



Full (simplified) AlexNet architecture:
[227x227x3] INPUT
[55x55x96] CONV1: 96 11x11 filters at stride 4, pad 0
[27x27x96] MAX POOL1: 3x3 filters at stride 2
[27x27x96] NORM1: Normalization layer
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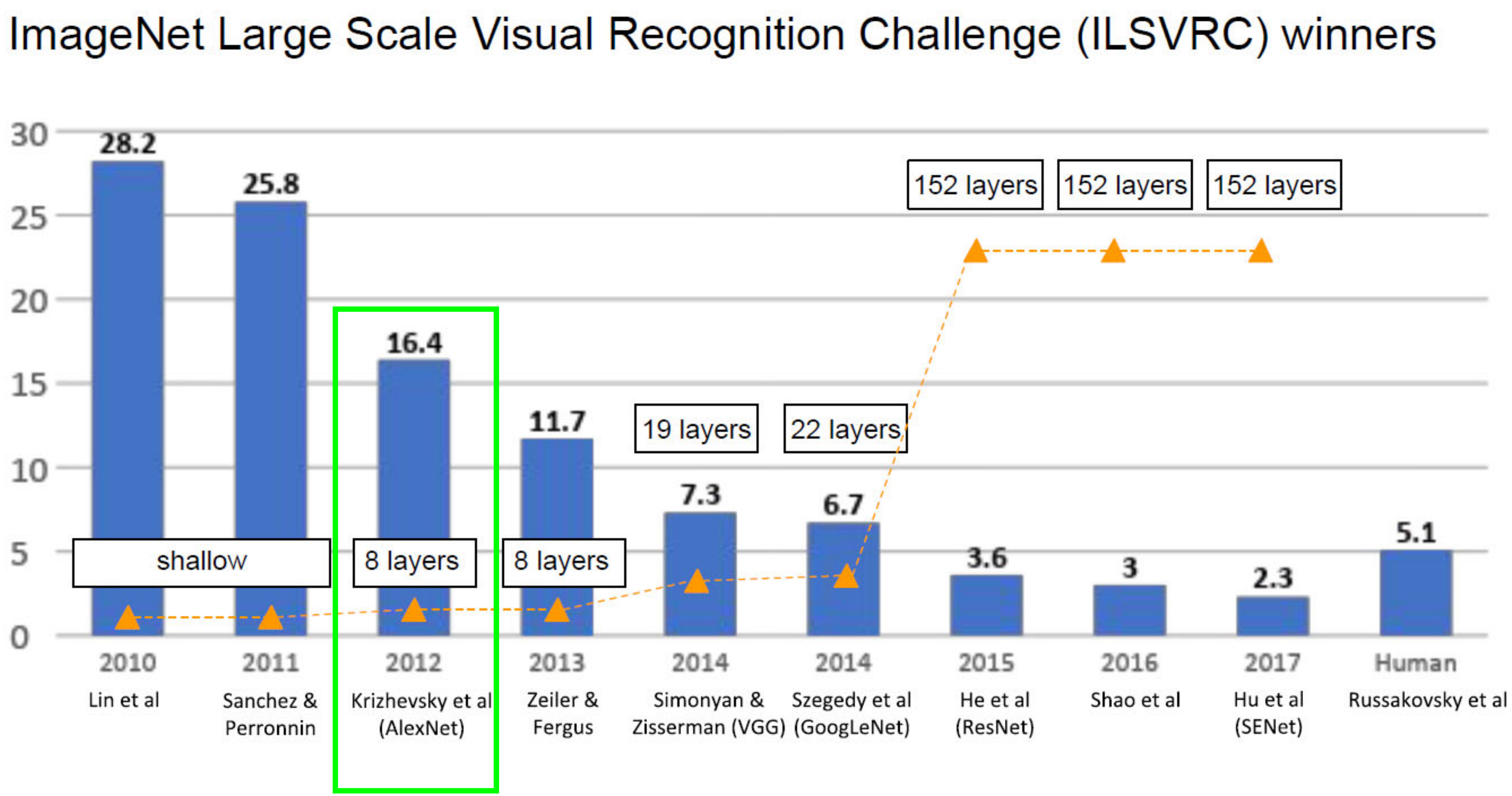
[13x13x256] MAX POOL2: 3x3 filters at stride 2
[13x13x256] NORM2: Normalization layer
[13x13x384] CONV3: 384 3x3 filters at stride 1, pad 1
[13x13x384] CONV4: 384 3x3 filters at stride 1, pad 1
[13x13x256] CONV5: 256 3x3 filters at stride 1, pad 1
[6x6x256] MAX POOL3: 3x3 filters at stride 2
[4096] FC6: 4096 neurons
[4096] FC7: 4096 neurons
[1000] FC8: 1000 neurons (class scores)

CONV3, FC6, FC7, FC8:
Connections with all feature maps in preceding layer, communication across GPUs

Ref: http://cs231n.stanford.edu/

AlexNet

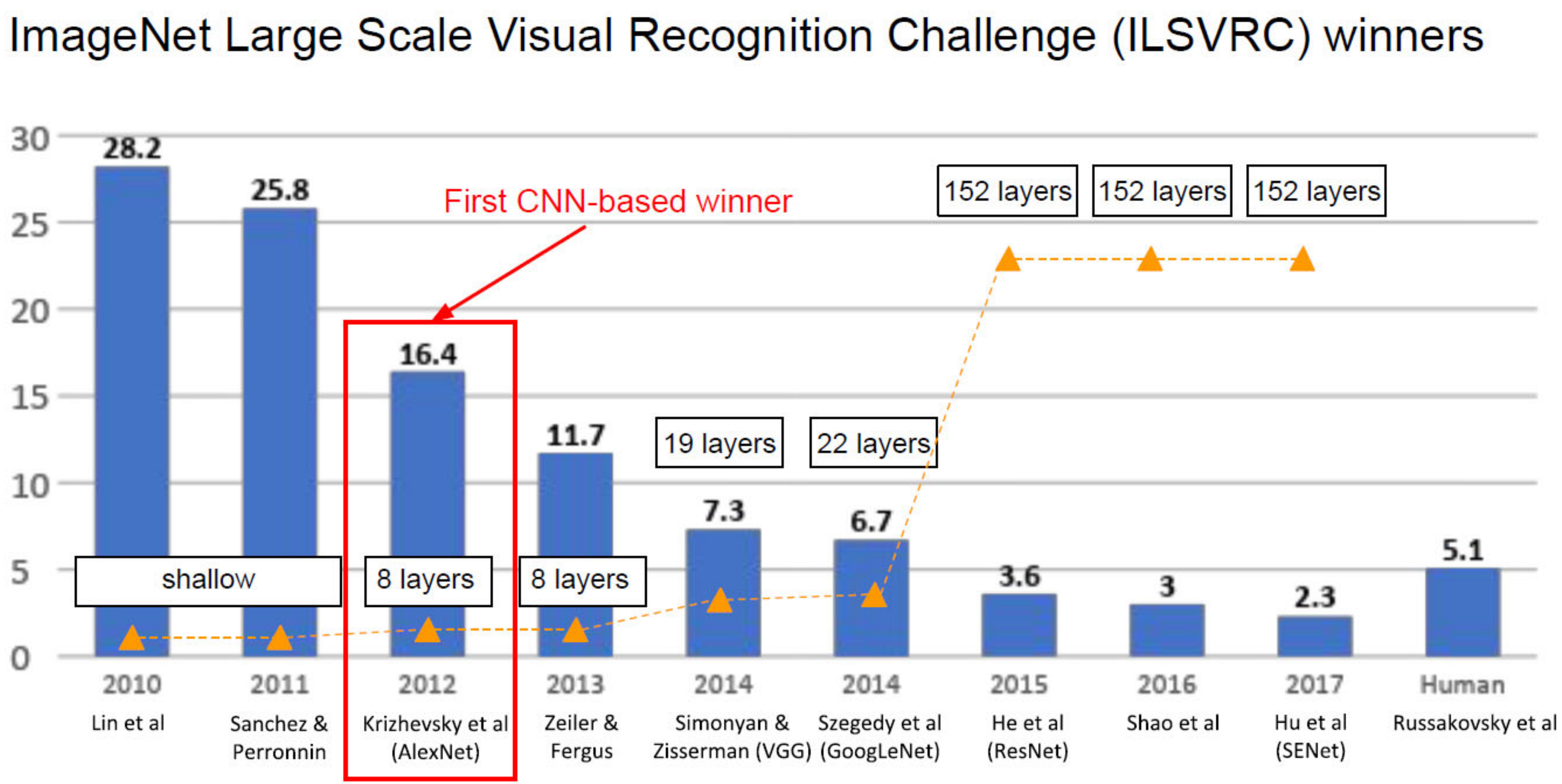
نتایج در چالش بازشناسی دیداری در مقیاس بالا ImageNet در مقایسه با سایر روش‌ها



Ref: http://cs231n.stanford.edu/

AlexNet

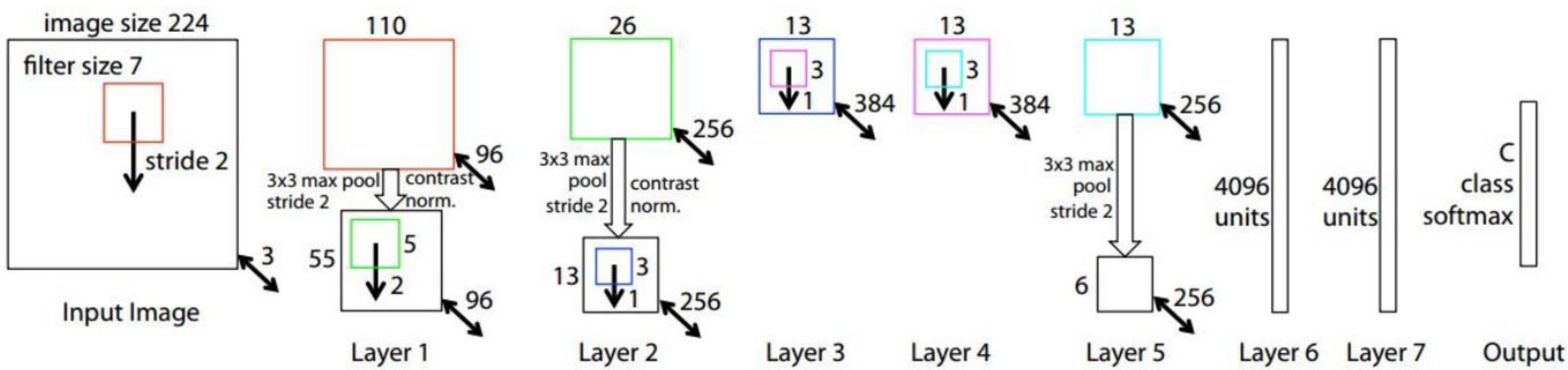
نتایج در چالش بازشناسی دیداری در مقیاس بالا ImageNet در مقایسه با سایر روش‌ها



Ref: http://cs231n.stanford.edu/

ZFNet

[Zeiler and Fergus, 2013]



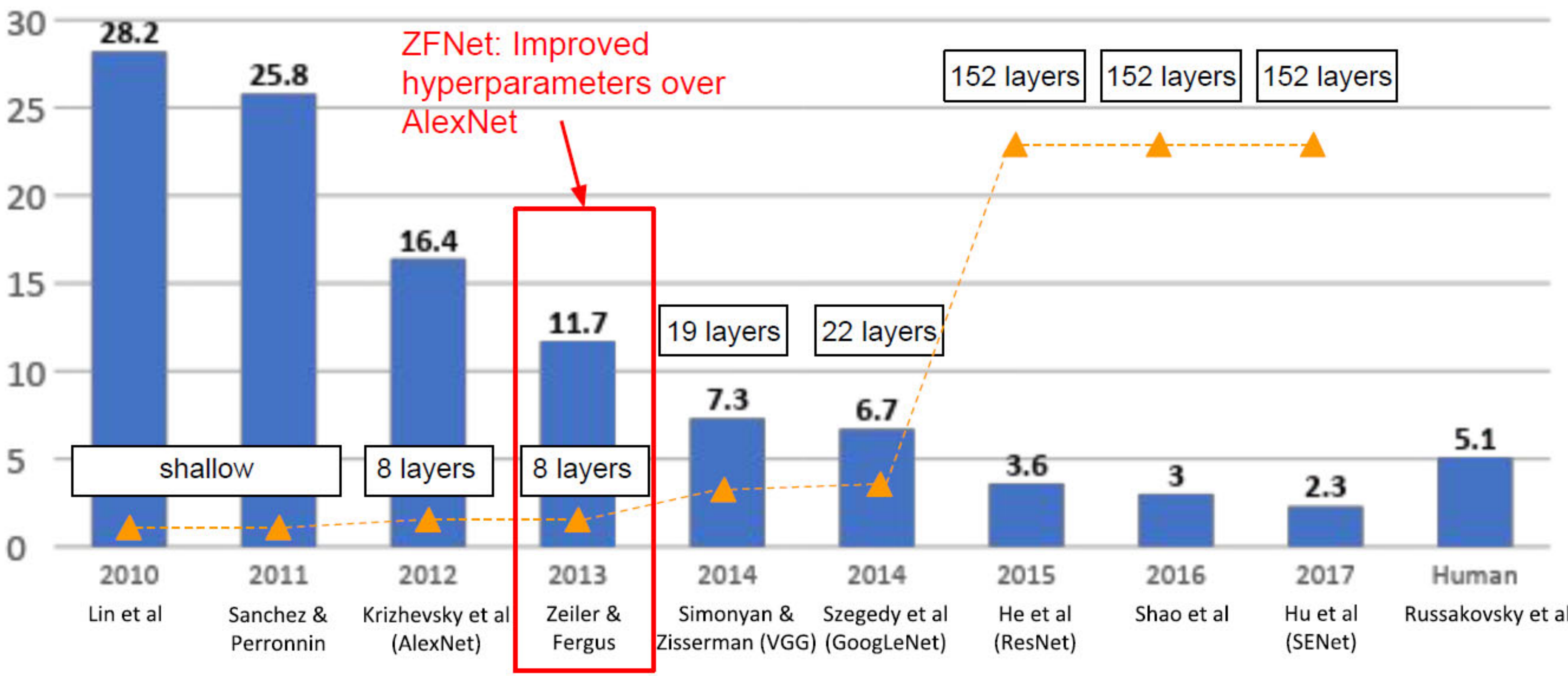
AlexNet but:
CONV1: change from (11x11 stride 4) to (7x7 stride 2)
CONV3,4,5: instead of 384, 384, 256 filters use 512, 1024, 512

ImageNet top 5 error: 16.4% -> 11.7%

ZFNet

نتایج در چالش بازشناسی دیداری در مقیاس بالا ImageNet در مقایسه با سایر روش‌ها

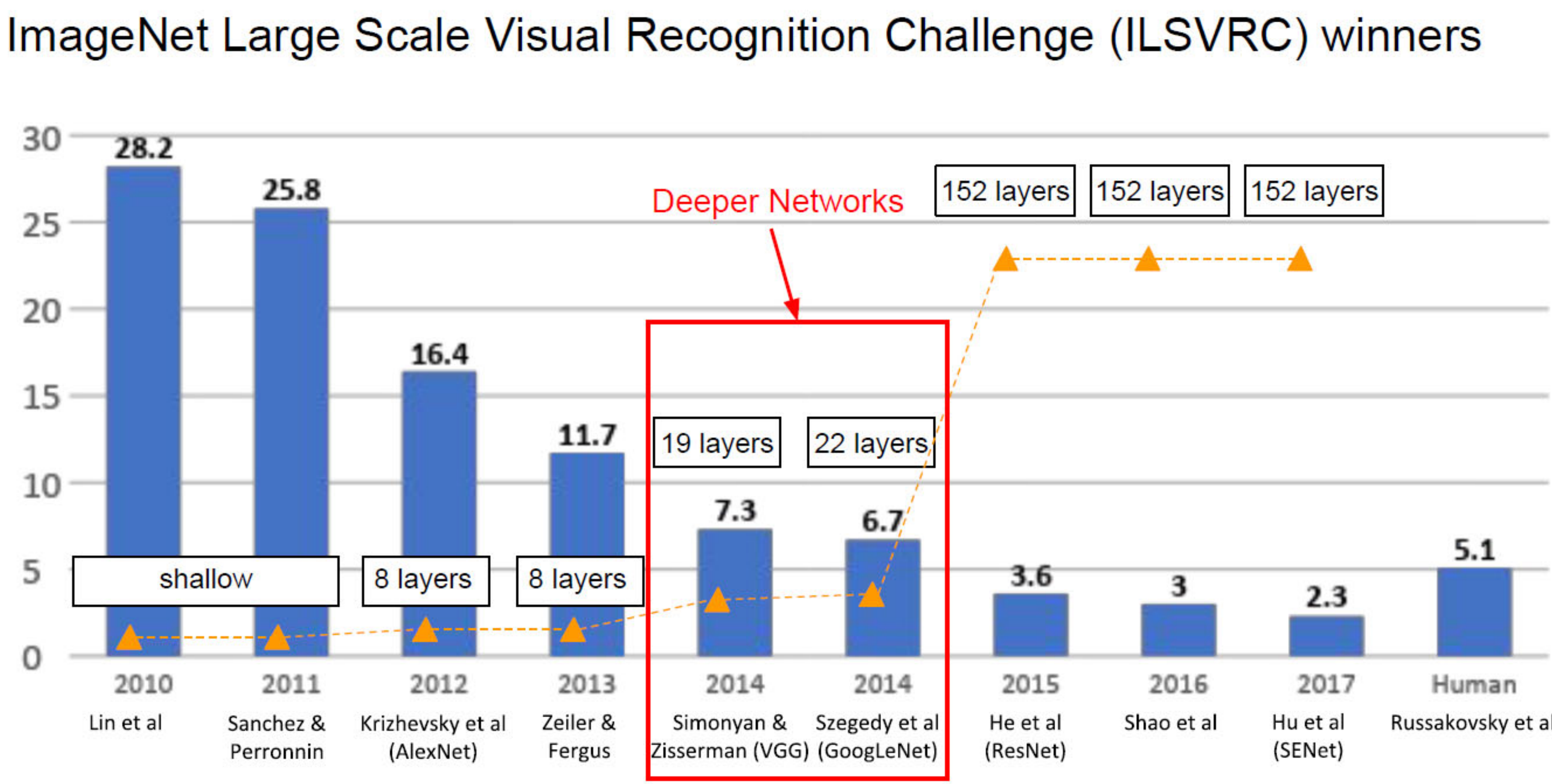
ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



Ref: http://cs231n.stanford.edu/

VGGNet - GoogLeNet

نتایج در چالش بازشناسی دیداری در مقیاس بالا ImageNet در مقایسه با سایر روش‌ها



Ref: http://cs231n.stanford.edu/

VGGNet

[Simonyan and Zisserman, 2014]

Small filters, Deeper networks

8 layers (AlexNet)
-> 16 - 19 layers (VGG16Net)

Only 3x3 CONV stride 1, pad 1
and 2x2 MAX POOL stride 2

11.7% top 5 error in ILSVRC'13 (ZFNet)
-> 7.3% top 5 error in ILSVRC'14

Ref: http://cs231n.stanford.edu/

VERY DEEP CONVOLUTIONAL NETWORKS FOR LARGE-SCALE IMAGE RECOGNITION

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Visual Geometry Group, Department of Engineering Science, University of Oxford
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ABSTRACT

In this work we investigate the effect of the convolutional network depth on its accuracy in the large-scale image recognition setting. Our main contribution is a thorough evaluation of networks of increasing depth using an architecture with very small (3×3) convolution filters, which shows that a significant improvement on the prior-art configurations can be achieved by pushing the depth to 16–19 weight layers. These findings were the basis of our ImageNet Challenge 2014 submission, where our team secured the first and the second places in the localisation and classification tracks respectively. We also show that our representations generalise well to other datasets, where they achieve state-of-the-art results. We have made our two best-performing ConvNet models publicly available to facilitate further research on the use of deep visual representations in computer vision.

1 INTRODUCTION

Convolutional networks (ConvNets) have recently enjoyed a great success in large-scale image and video recognition (Krizhevsky et al., 2012; Zeiler & Fergus, 2013; Sermanet et al., 2014; Simonyan & Zisserman, 2014) which has become possible due to the large public image repositories, such as ImageNet (Deng et al., 2009), and high-performance computing systems, such as GPUs or large-scale distributed clusters (Dean et al., 2012). In particular, an important role in the advance of deep visual recognition architectures has been played by the ImageNet Large-Scale Visual Recognition Challenge (ILSVRC) (Russakovsky et al., 2014), which has served as a testbed for a few generations of large-scale image classification systems, from high-dimensional shallow feature encodings (Perronnin et al., 2010) (the winner of ILSVRC-2011) to deep ConvNets (Krizhevsky et al., 2012) (the winner of ILSVRC-2012).

With ConvNets becoming more of a commodity in the computer vision field, a number of attempts have been made to improve the original architecture of Krizhevsky et al. (2012) in a bid to achieve better accuracy. For instance, the best-performing submissions to the ILSVRC-2013 (Zeiler & Fergus, 2013; Sermanet et al., 2014) utilised smaller receptive window size and smaller stride of the first convolutional layer. Another line of improvements dealt with training and testing the networks densely over the whole image and over multiple scales (Sermanet et al., 2014; Howard, 2014). In this paper, we address another important aspect of ConvNet architecture design – its depth. To this end, we fix other parameters of the architecture, and steadily increase the depth of the network by adding more convolutional layers, which is feasible due to the use of very small (3×3) convolution filters in all layers.

As a result, we come up with significantly more accurate ConvNet architectures, which not only achieve the state-of-the-art accuracy on ILSVRC classification and localisation tasks, but are also applicable to other image recognition datasets, where they achieve excellent performance even when used as a part of a relatively simple pipelines (e.g. deep features classified by a linear SVM without fine-tuning). We have released our two best-performing models[1] to facilitate further research.

The rest of the paper is organised as follows. In Sect. 2, we describe our ConvNet configurations. The details of the image classification training and evaluation are then presented in Sect. 3, and the

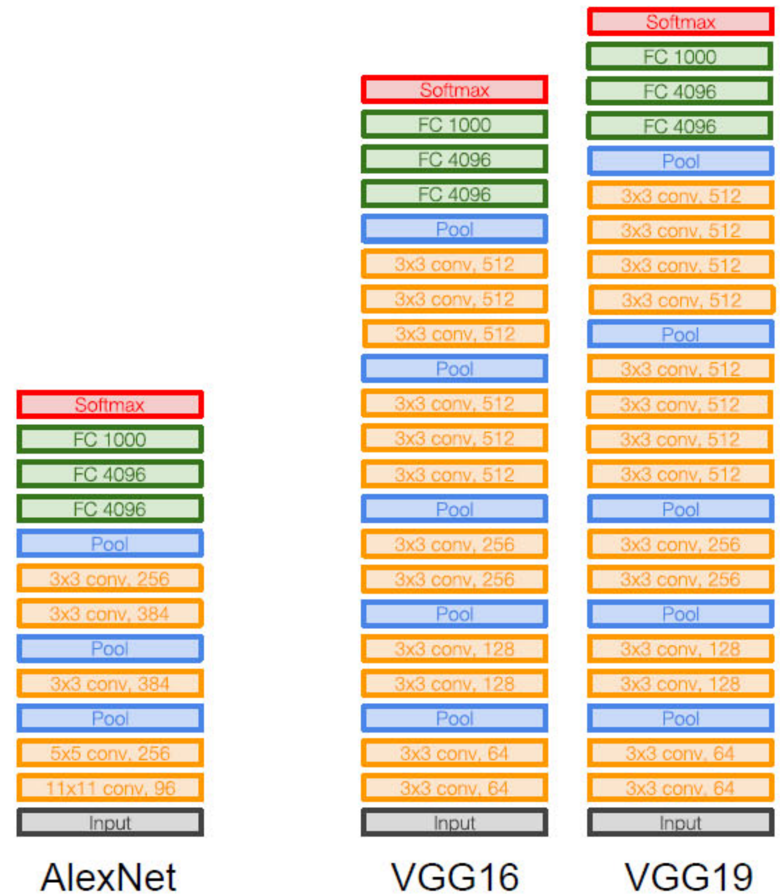
*current affiliation: Google DeepMind +current affiliation: University of Oxford and Google DeepMind
[1] http://www.robots.ox.ac.uk/~vgg/research/very_deep/

VGGNet

VGGNet

[Simonyan and Zisserman, 2014]

Q: Why use smaller filters? (3x3 conv)



Ref: http://cs231n.stanford.edu/

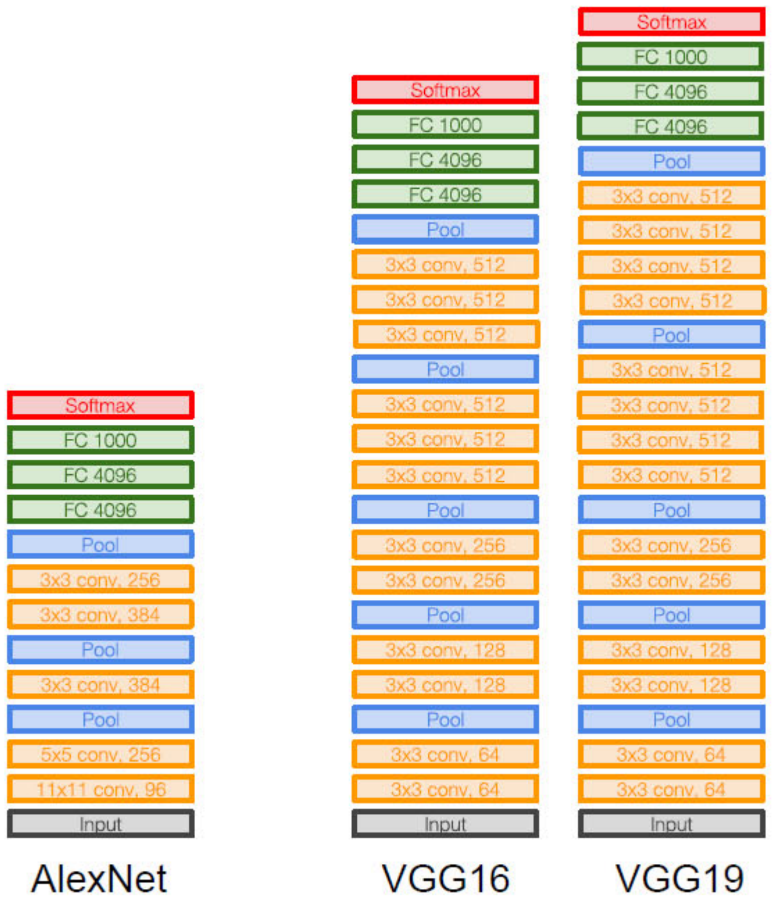
VGGNet

[Simonyan and Zisserman, 2014]

Q: Why use smaller filters? (3x3 conv)

Stack of three 3x3 conv (stride 1) layers has same **effective receptive field** as one 7x7 conv layer

Q: What is the effective receptive field of three 3x3 conv (stride 1) layers?



VGGNet

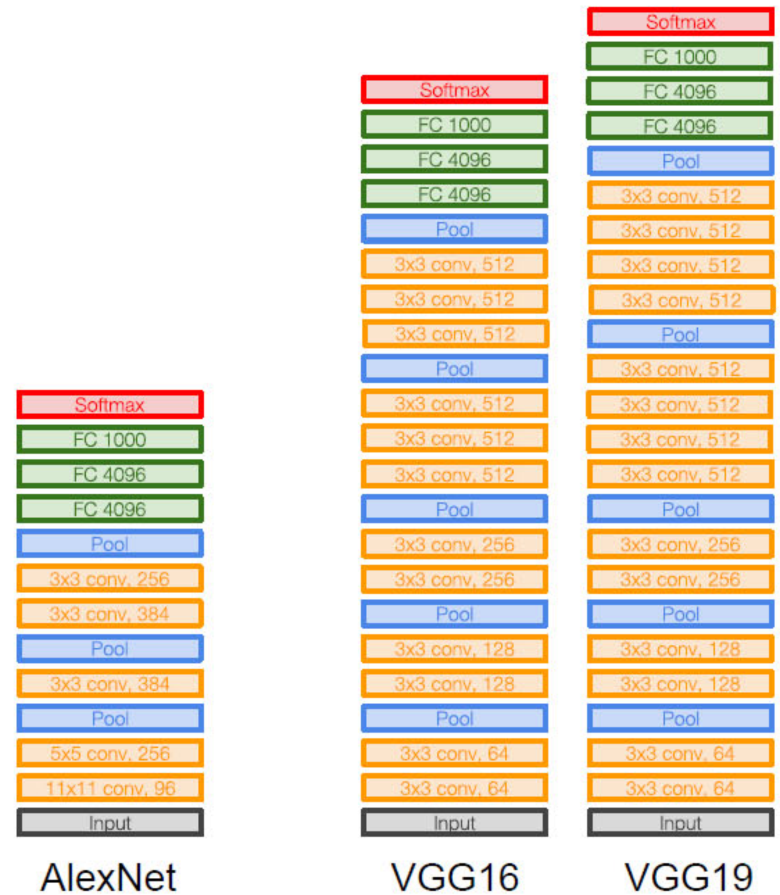
VGGNet

[Simonyan and Zisserman, 2014]

Q: Why use smaller filters? (3x3 conv)

Stack of three 3x3 conv (stride 1) layers has same **effective receptive field** as one 7x7 conv layer

[7x7]



Ref: http://cs231n.stanford.edu/

VGGNet

VGGNet

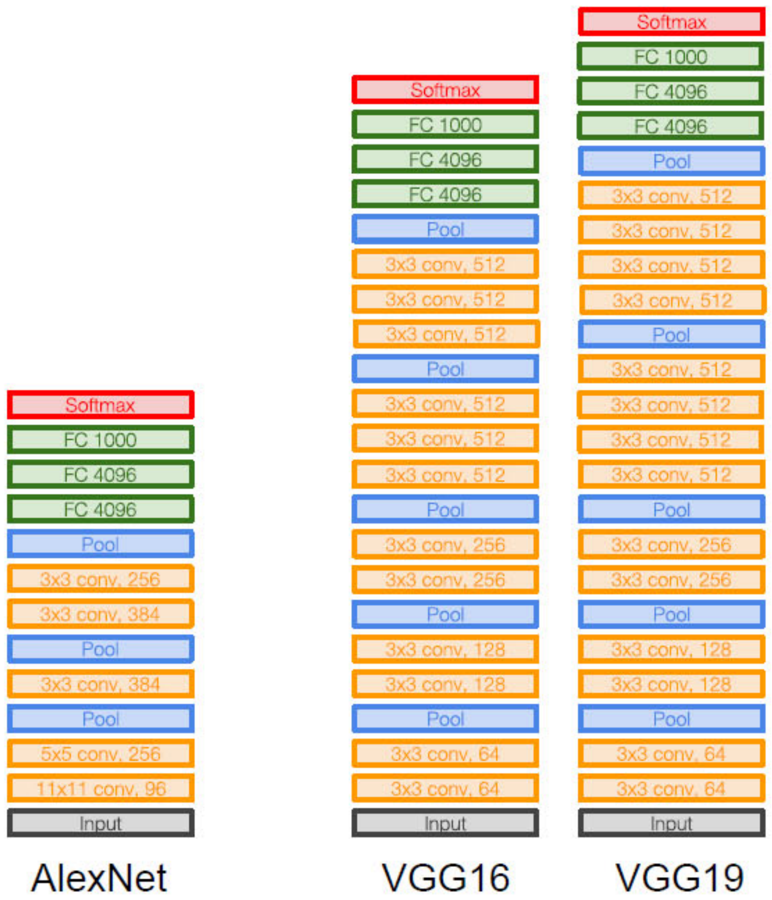
[Simonyan and Zisserman, 2014]

Q: Why use smaller filters? (3x3 conv)

Stack of three 3x3 conv (stride 1) layers has same **effective receptive field** as one 7x7 conv layer

But deeper, more non-linearities

And fewer parameters: $3 * (3^2C^2)$ vs. 7^2C^2 for C channels per layer



Ref: http://cs231n.stanford.edu/

VGGNet

جزئیات معماری

(not counting biases)

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

VGG16

Ref: http://cs231n.stanford.edu/

VGGNet

جزئیات معماری

(not counting biases)

INPUT: [224x224x3] memory: 224*224*3=150K params: 0
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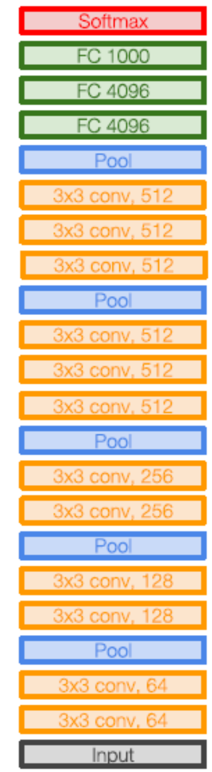
POOL2: [7x7x512] memory: 7*7*512=25K params: 0
FC: [1x1x4096] memory: 4096 params: 7*7*512*4096 = 102,760,448
FC: [1x1x4096] memory: 4096 params: 4096*4096 = 16,777,216
FC: [1x1x1000] memory: 1000 params: 4096*1000 = 4,096,000

TOTAL memory: 24M * 4 bytes ~= 96MB / image (for a forward pass)
TOTAL params: 138M parameters



VGG16

Ref: http://cs231n.stanford.edu/

VGGNet

جزئیات معماری

(not counting biases)

INPUT: [224x224x3] memory: 224*224*3=150K params: 0
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FC: [1x1x4096] memory: 4096 params: 4096*4096 = 16,777,216
FC: [1x1x1000] memory: 1000 params: 4096*1000 = 4,096,000

Note:

Most memory is in early CONV

Most params are in late FC

TOTAL memory: 24M * 4 bytes ~= 96MB / image (only forward! ~*2 for bwd)
TOTAL params: 138M parameters

Ref: http://cs231n.stanford.edu/

VGGNet

جزئیات معماری

(not counting biases)

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TOTAL memory: 24M * 4 bytes ~= 96MB / image (only forward! ~*2 for bwd)
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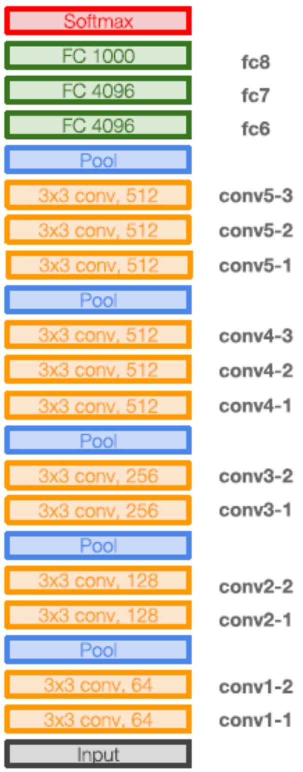


VGG16

Common names

Ref: http://cs231n.stanford.edu/

VGGNet

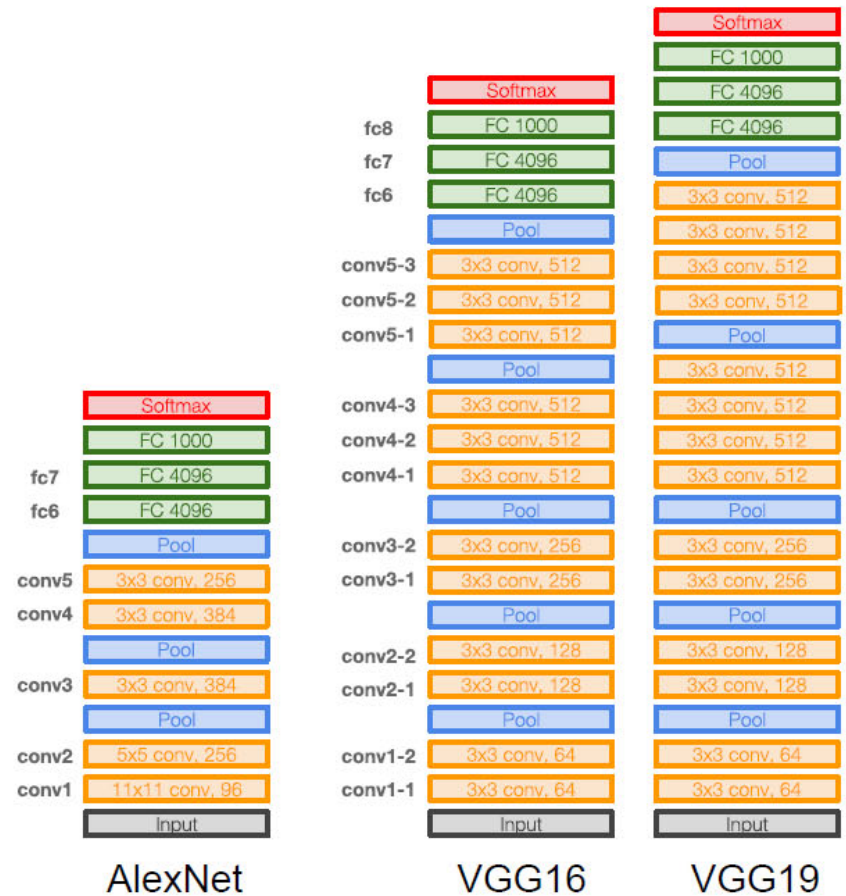
ملاحظات

VGGNet

[Simonyan and Zisserman, 2014]

Details:

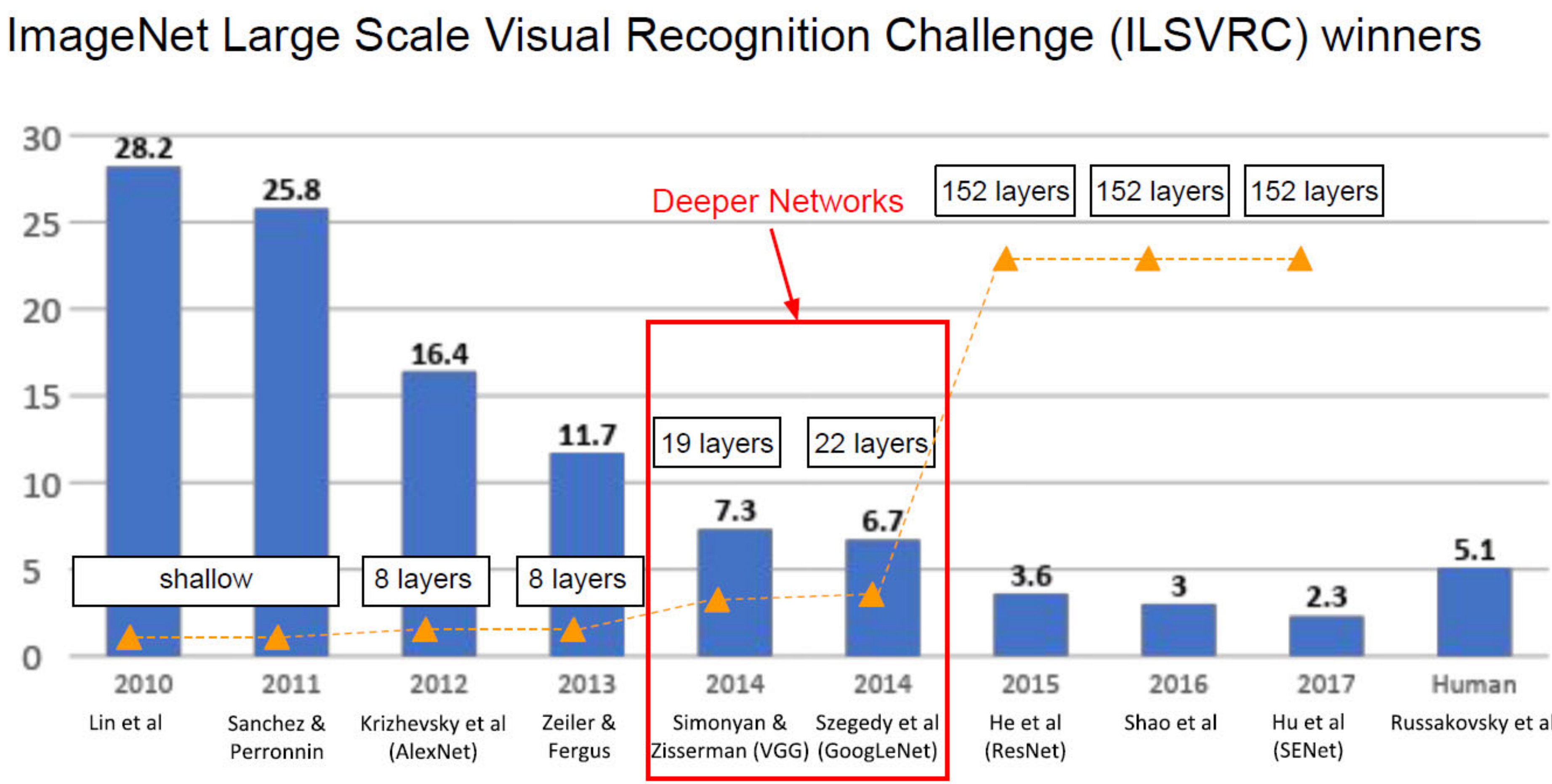
- ILSVRC’14 2nd in classification, 1st in localization
- Similar training procedure as Krizhevsky 2012
- No Local Response Normalisation (LRN)
- Use VGG16 or VGG19 (VGG19 only slightly better, more memory)
- Use ensembles for best results
- FC7 features generalize well to other tasks



Ref: http://cs231n.stanford.edu/

VGGNet - GoogLeNet

نتایج در چالش بازشناسی دیداری در مقیاس بالا ImageNet در مقایسه با سایر روش‌ها



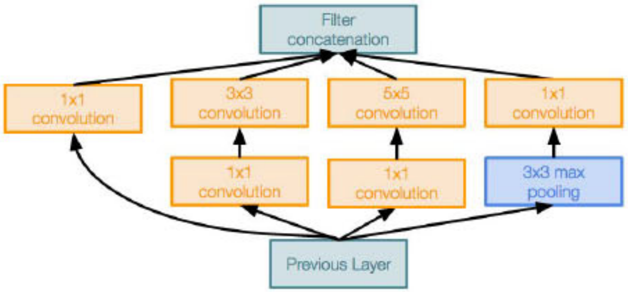
Ref: http://cs231n.stanford.edu/

GoogLeNet

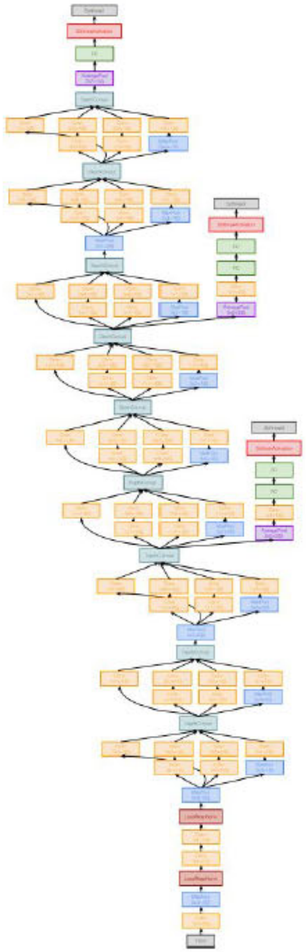
[Szegedy et al., 2014]

Deeper networks, with computational efficiency

- 22 layers
- Efficient "Inception" module
- No FC layers
- Only 5 million parameters!
  12x less than AlexNet
- ILSVRC'14 classification winner (6.7% top 5 error)



Inception module



Going deeper with convolutions

Christian Szegedy
Google Inc.

Wei Liu
University of North Carolina, Chapel Hill

Yangqing Jia
Google Inc.

Pierre Sermanet
Google Inc.

Scott Reed
University of Michigan

Dragomir Anguelov
Google Inc.

Dumitru Erhan
Google Inc.

Vincent Vanhoucke
Google Inc.

Andrew Rabinovich
Google Inc.

Abstract

We propose a deep convolutional neural network architecture codenamed Inception, which was responsible for setting the new state of the art for classification and detection in the ImageNet Large-Scale Visual Recognition Challenge 2014 (ILSVRC14). The main hallmark of this architecture is the improved utilization of the computing resources inside the network. This was achieved by a carefully crafted design that allows for increasing the depth and width of the network while keeping the computational budget constant. To optimize quality, the architectural decisions were based on the Hebbian principle and the intuition of multi-scale processing. One particular incarnation used in our submission for ILSVRC14 is called GoogLeNet, a 22 layers deep network, the quality of which is assessed in the context of classification and detection.

1 Introduction

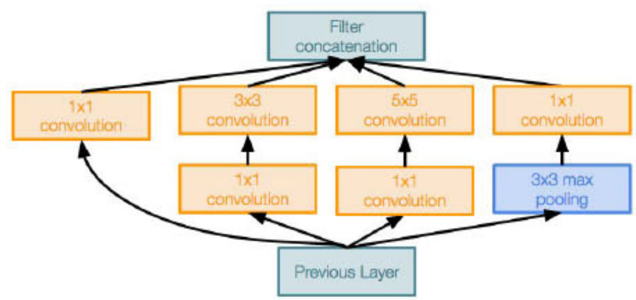
In the last three years, mainly due to the advances of deep learning, more concretely convolutional networks [10], the quality of image recognition and object detection has been progressing at a dramatic pace. One encouraging news is that most of this progress is not just the result of more powerful hardware, larger datasets and bigger models, but mainly a consequence of new ideas, algorithms and improved network architectures. No new data sources were used, for example, by the top entries in the ILSVRC 2014 competition besides the classification dataset of the same competition for detection purposes. Our GoogLeNet submission to ILSVRC 2014 actually uses $12\times$ fewer parameters than the winning architecture of Krizhevsky et al [9] from two years ago, while being significantly more accurate. The biggest gains in object-detection have not come from the utilization of deep networks alone or bigger models, but from the synergy of deep architectures and classical computer vision, like the R-CNN algorithm by Girshick et al [6].

Another notable factor is that with the ongoing traction of mobile and embedded computing, the efficiency of our algorithms – especially their power and memory use – gains importance. It is noteworthy that the considerations leading to the design of the deep architecture presented in this paper included this factor rather than having a sheer fixation on accuracy numbers. For most of the experiments, the models were designed to keep a computational budget of 1.5 billion multiply-adds at inference time, so that the they do not end up to be a purely academic curiosity, but could be put to real world use, even on large datasets, at a reasonable cost.

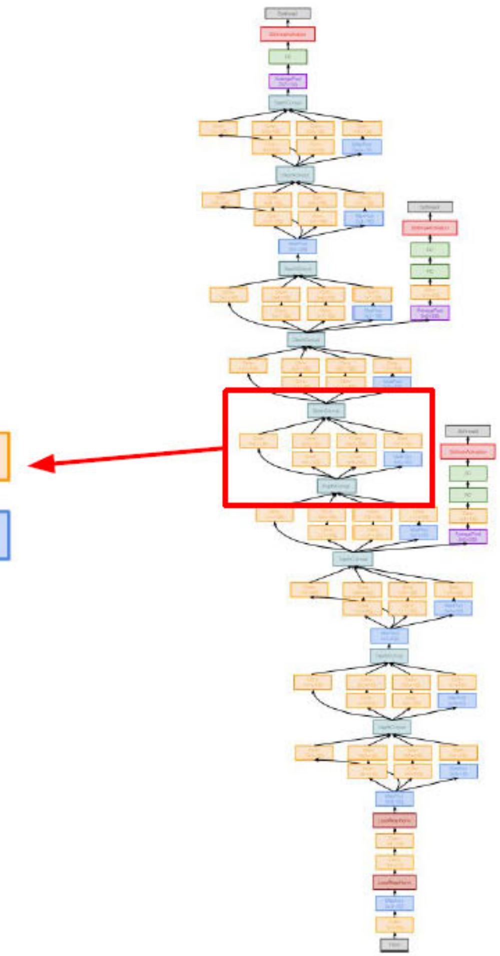
GoogLeNet

[Szegedy et al., 2014]

"Inception module": design a good local network topology (network within a network) and then stack these modules on top of each other



Inception module

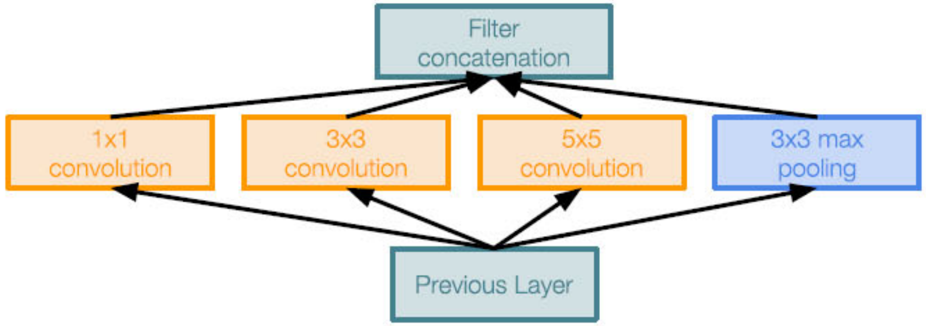


Ref: http://cs231n.stanford.edu/

ماژول آغازش خام

GoogLeNet

[Szegedy et al., 2014]



Naive Inception module

Apply parallel filter operations on the input from previous layer:
- Multiple receptive field sizes for convolution (1x1, 3x3, 5x5)
- Pooling operation (3x3)

Concatenate all filter outputs together depth-wise

Q: What is the problem with this?
[Hint: Computational complexity]

Ref: http://cs231n.stanford.edu/

GoogLeNet

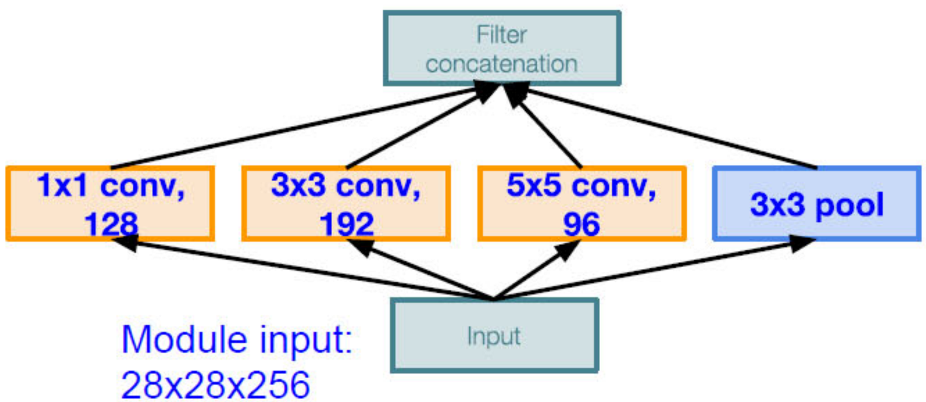
ماژول آغازش خام: مشکل پیچیدگی محاسباتی

GoogLeNet

[Szegedy et al., 2014]

Q: What is the problem with this?
[Hint: Computational complexity]

Example:



Naive Inception module

GoogLeNet

ماژول آغازش خام: مشکل پیچیدگی محاسباتی

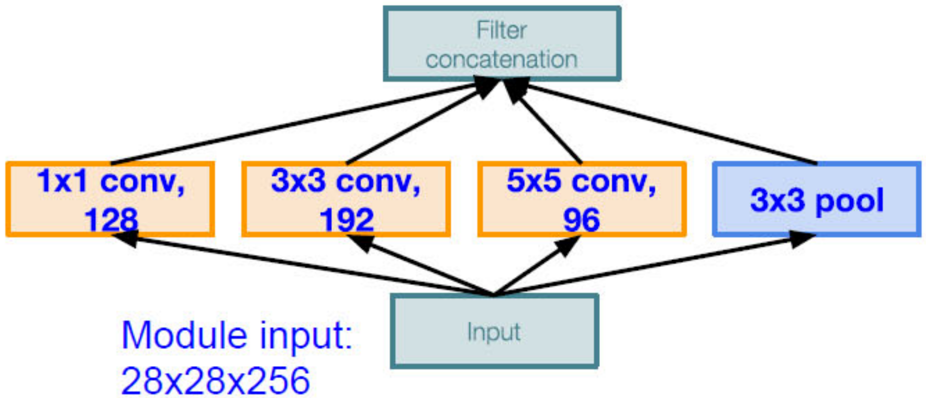
GoogLeNet

[Szegedy et al., 2014]

Q: What is the problem with this?
[Hint: Computational complexity]

Example:

Q1: What is the output size of the 1x1 conv, with 128 filters?



Naive Inception module

Ref: http://cs231n.stanford.edu/

GoogLeNet

ماژول آغازش خام: مشکل پیچیدگی محاسباتی

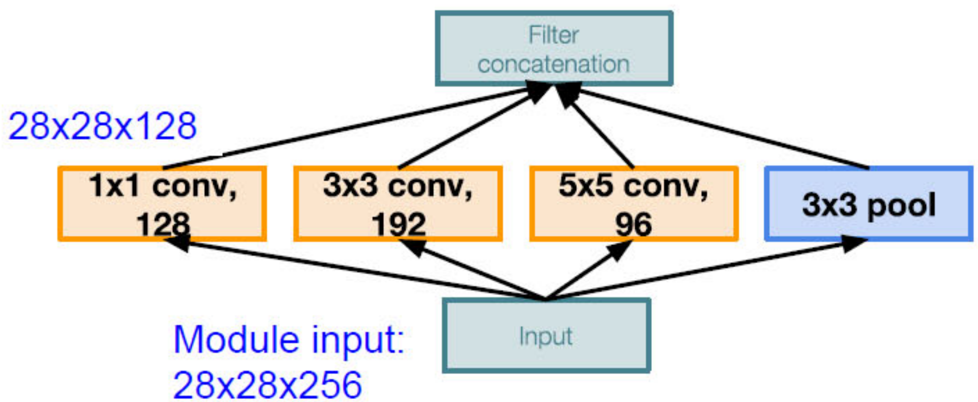
GoogLeNet

[Szegedy et al., 2014]

Q: What is the problem with this?
[Hint: Computational complexity]

Example:

Q2: What are the output sizes of all different filter operations?



Naive Inception module

Ref: http://cs231n.stanford.edu/

GoogLeNet

ماژول آغازش خام: مشکل پیچیدگی محاسباتی

GoogLeNet

[Szegedy et al., 2014]

Q: What is the problem with this?
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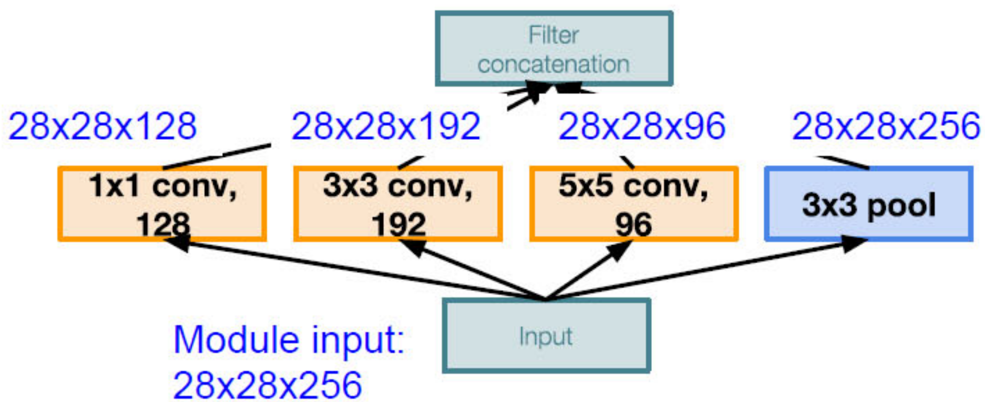
Example:

Q2: What are the output sizes of all different filter operations?



Naive Inception module

ماژول آغازش خام: مشکل پیچیدگی محاسباتی

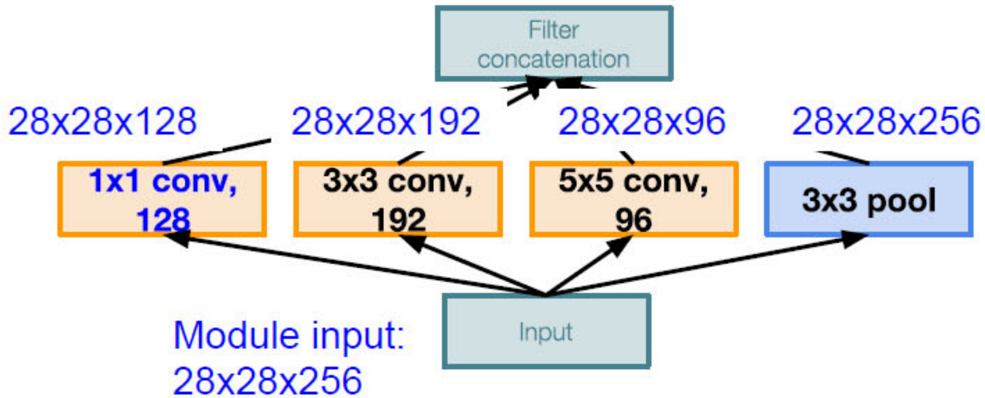
GoogLeNet

[Szegedy et al., 2014]

Q: What is the problem with this?
[Hint: Computational complexity]

Example:

Q3:What is output size after filter concatenation?



Naive Inception module

Ref: http://cs231n.stanford.edu/

GoogLeNet

ماژول آغازش خام: مشکل پیچیدگی محاسباتی

GoogLeNet

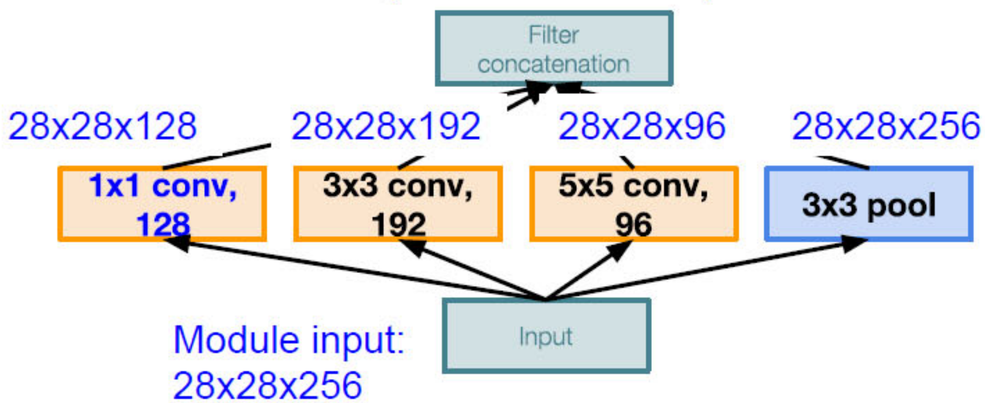
[Szegedy et al., 2014]

Q: What is the problem with this?
[Hint: Computational complexity]

Example:

Q3:What is output size after filter concatenation?

28x28x(128+192+96+256) = 28x28x672



Naive Inception module

Ref: http://cs231n.stanford.edu/

GoogLeNet

ماژول آغازش خام: مشکل پیچیدگی محاسباتی

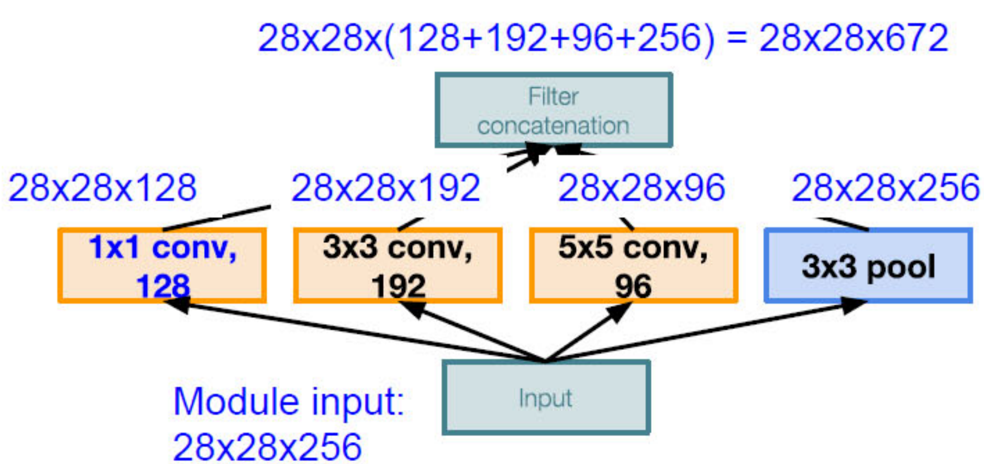
GoogLeNet

[Szegedy et al., 2014]

Q: What is the problem with this?
[Hint: Computational complexity]

Example:

Q3:What is output size after filter concatenation?



Naive Inception module

Conv Ops:

[1x1 conv, 128] 28x28x128x1x1x256
[3x3 conv, 192] 28x28x192x3x3x256
[5x5 conv, 96] 28x28x96x5x5x256
Total: 854M ops

Ref: http://cs231n.stanford.edu/

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[Szegedy et al., 2014]

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[Hint: Computational complexity]

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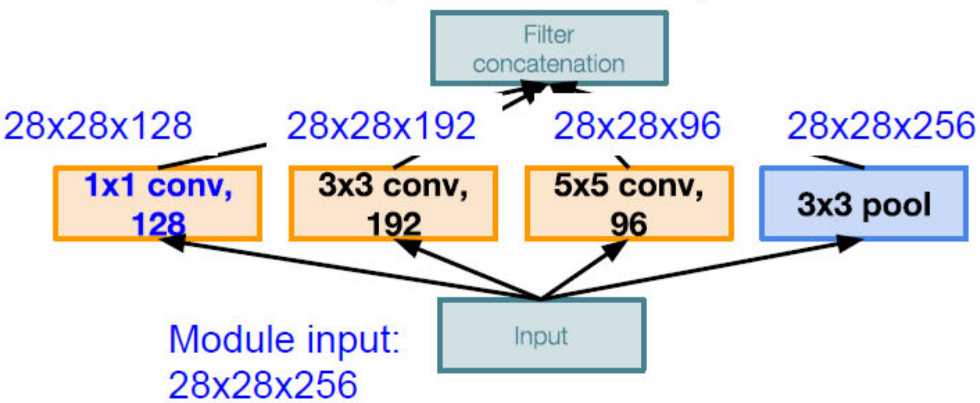
28x28x(128+192+96+256) = 28x28x672



Naive Inception module

Conv Ops:
[1x1 conv, 128] 28x28x128x1x1x256
[3x3 conv, 192] 28x28x192x3x3x256
[5x5 conv, 96] 28x28x96x5x5x256
Total: 854M ops

Very expensive compute

Pooling layer also preserves feature depth, which means total depth after concatenation can only grow at every layer!

Ref: http://cs231n.stanford.edu/

GoogLeNet

ماژول آغازش خام: مشکل پیچیدگی محاسباتی؛ راه‌حل: استفاده از لایه‌های «گلوگاهی» برای کاهش عمق نقشه‌ی ویژگی

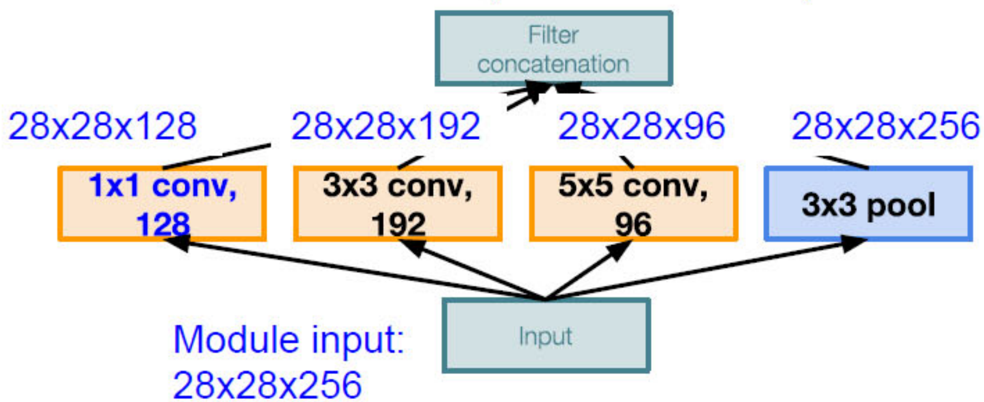
GoogLeNet

[Szegedy et al., 2014]

Example:

Q3:What is output size after filter concatenation?

28x28x(128+192+96+256) = **529k**



Naive Inception module

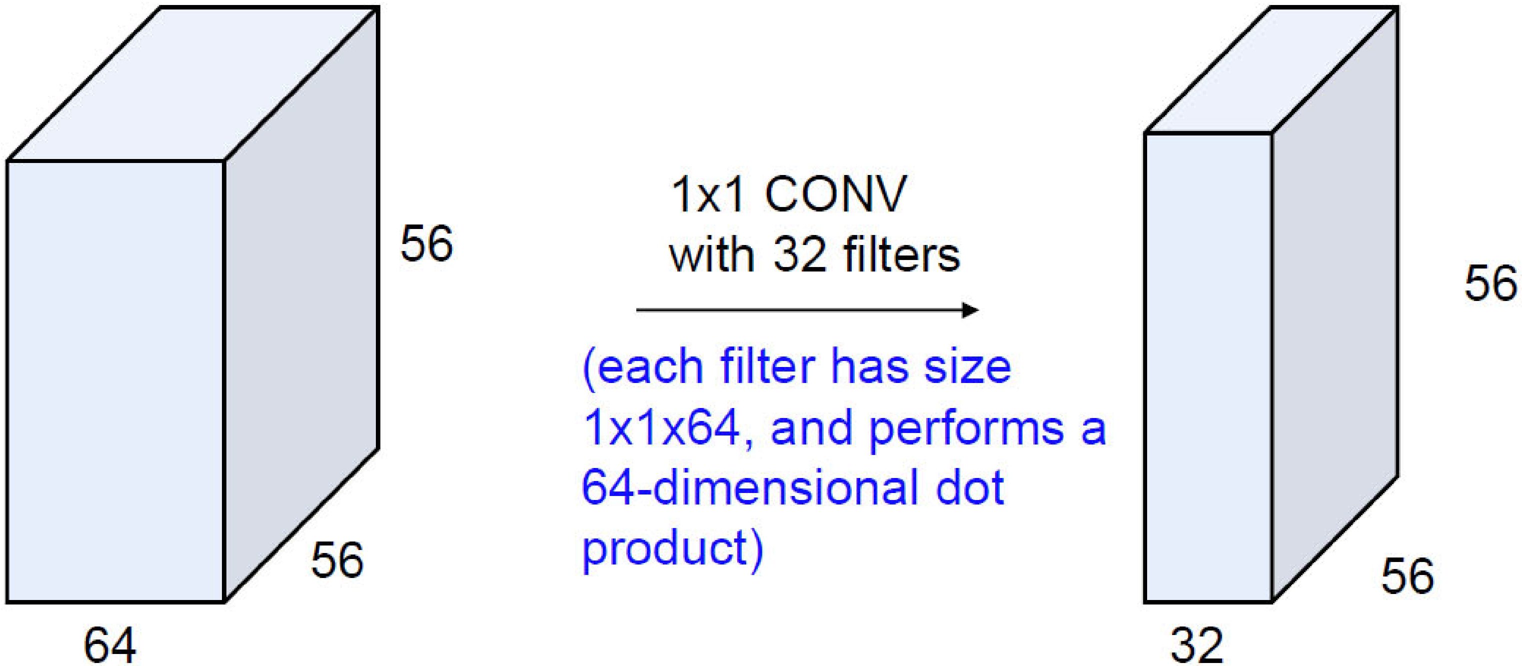
Q: What is the problem with this?
[Hint: Computational complexity]

Solution: "bottleneck" layers that use 1x1 convolutions to reduce feature depth

GoogLeNet

کانوولوشن ۱×۱

Review: 1x1 convolutions

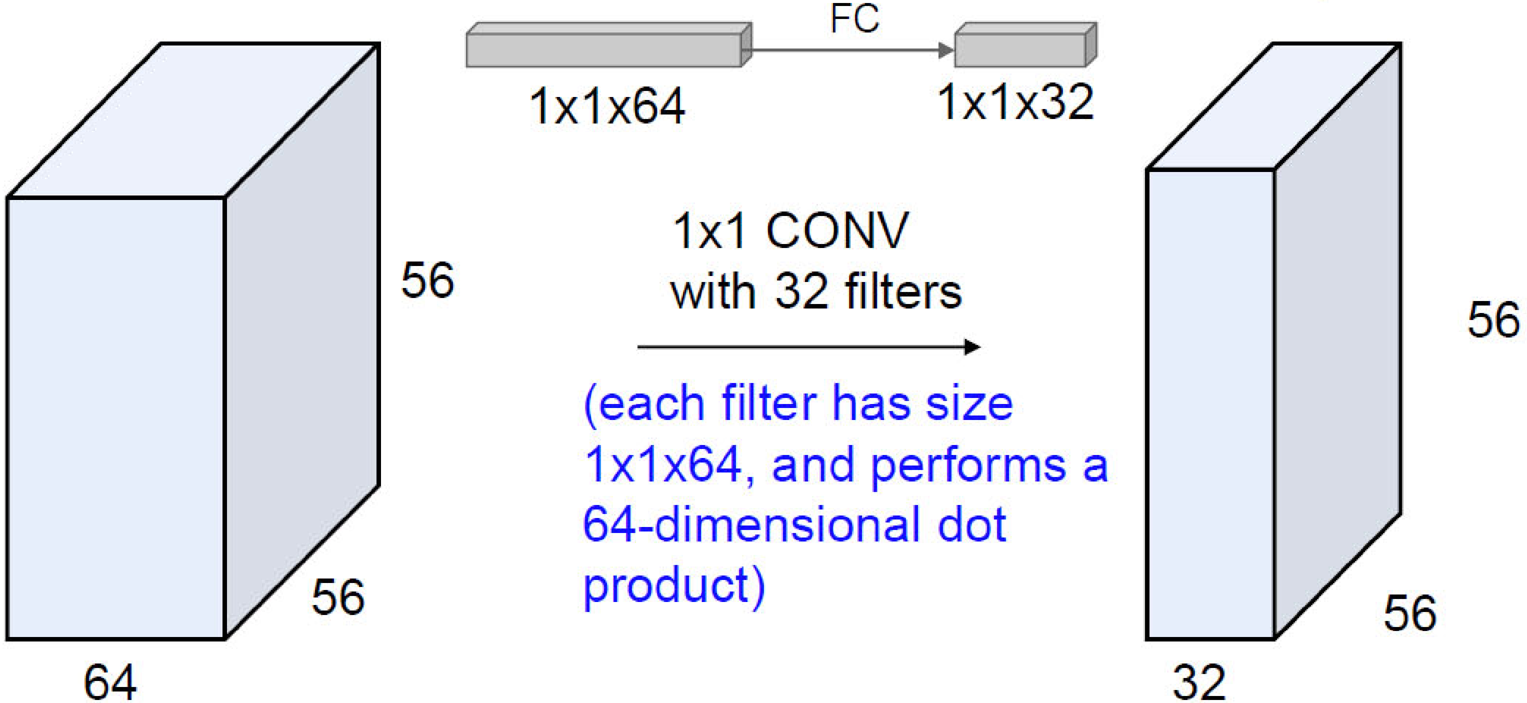


GoogLeNet

کانوولوشن ۱×۱

Review: 1x1 convolutions

Alternatively, interpret it as applying the same FC layer on each input pixel



GoogLeNet

کانوولوشن ۱×۱

Review: 1x1 convolutions

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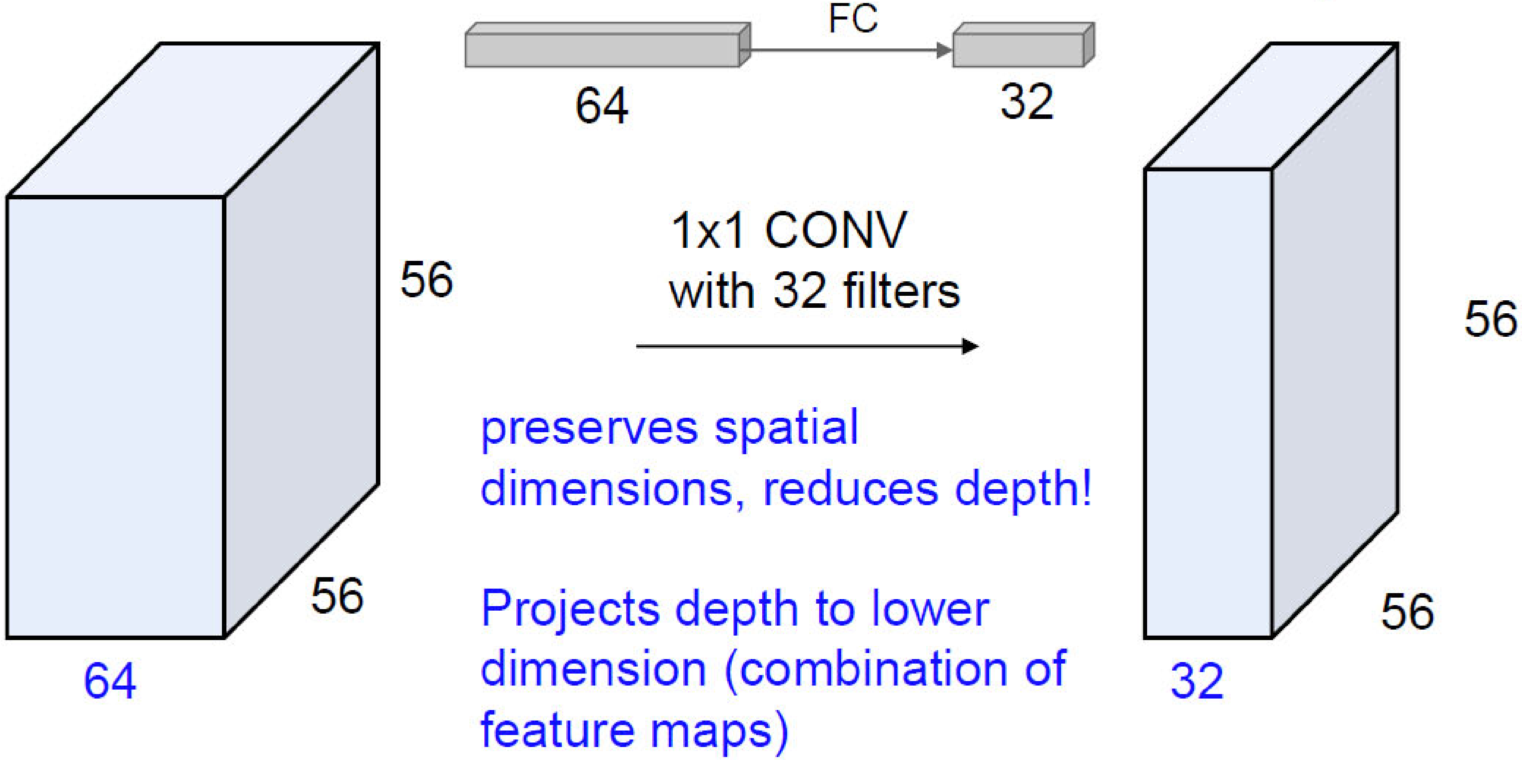


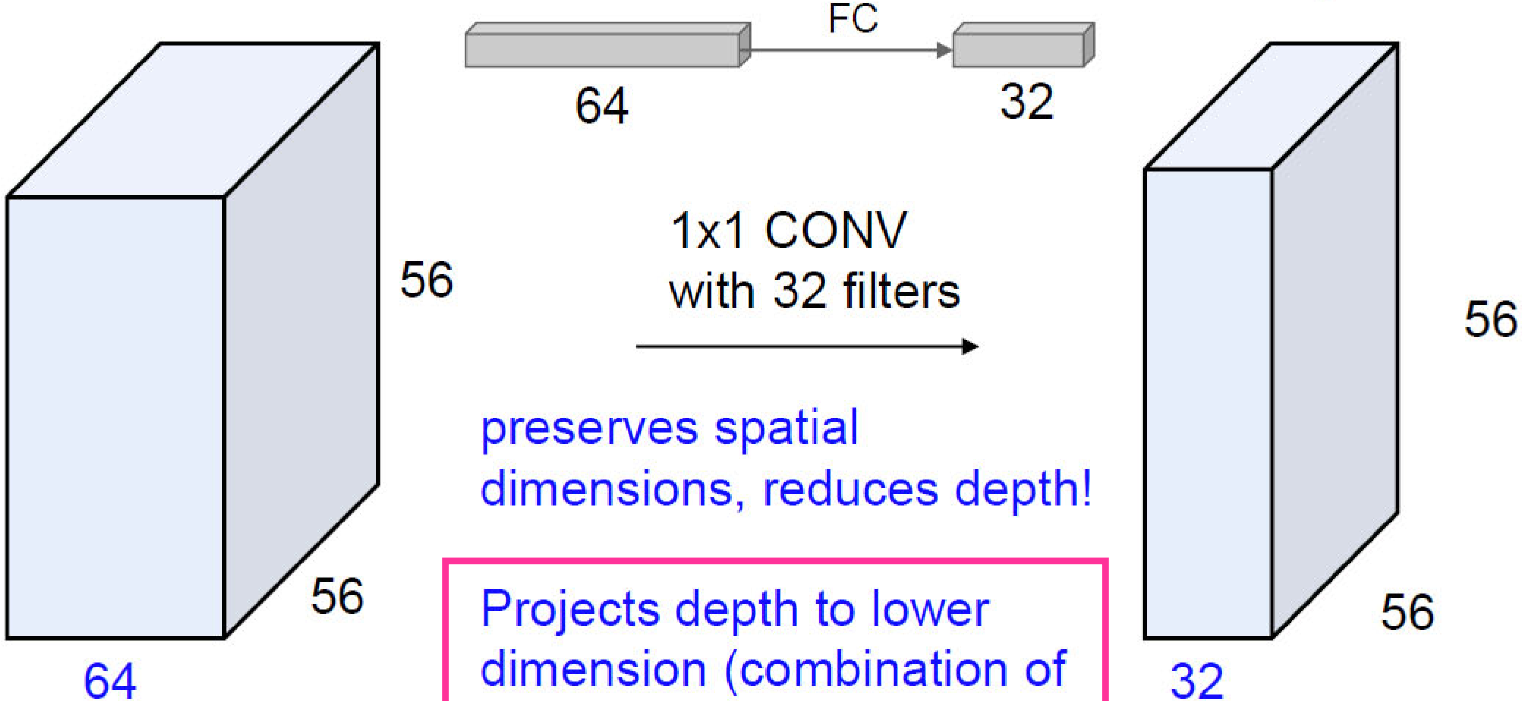
Ref: http://cs231n.stanford.edu/

GoogLeNet

کانوولوشن ۱×۱

Review: 1x1 convolutions

Alternatively, interpret it as applying the same FC layer on each input pixel



preserves spatial dimensions, reduces depth!

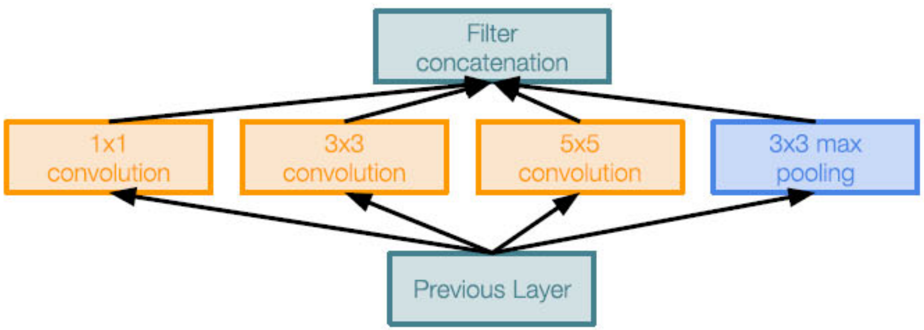
Projects depth to lower dimension (combination of feature maps)

GoogLeNet

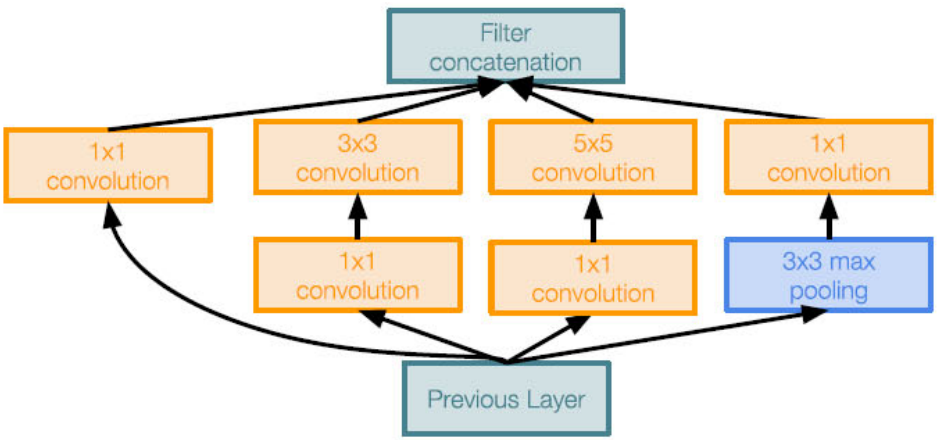
ماژول آغازش با کاهش بعد

GoogLeNet

[Szegedy et al., 2014]



Naive Inception module



Inception module with dimension reduction

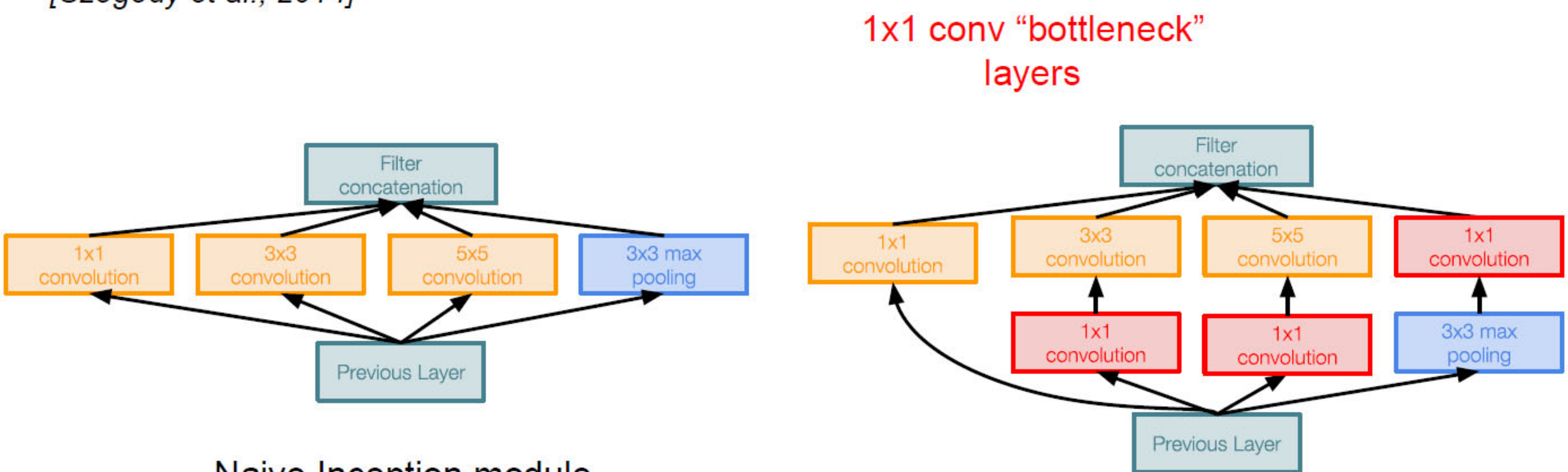
Ref: http://cs231n.stanford.edu/

GoogLeNet

ماژول آغازش با کاهش بعد: لایه‌های گلوگاهی کانوولوشن ۱×۱

GoogLeNet

[Szegedy et al., 2014]



Naive Inception module

Inception module with dimension reduction

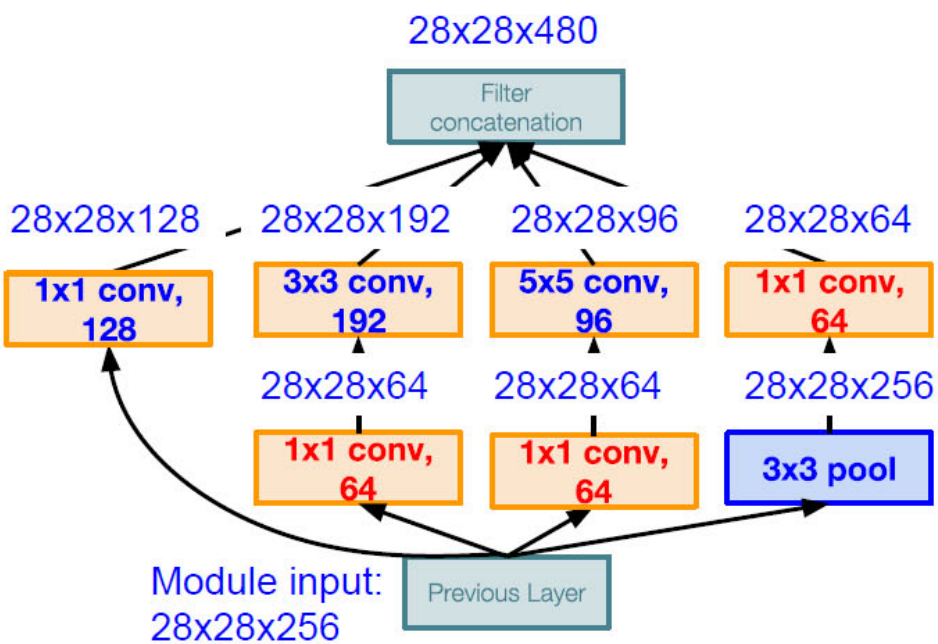
Ref: http://cs231n.stanford.edu/

GoogLeNet

ماژول آغازش با کاهش بعد: معماری

GoogLeNet

[Szegedy et al., 2014]



Inception module with dimension reduction

Using same parallel layers as naive example, and adding "1x1 conv, 64 filter" bottlenecks:

Conv Ops:

[1x1 conv, 64] 28x28x64x1x1x256
[1x1 conv, 64] 28x28x64x1x1x256
[1x1 conv, 128] 28x28x128x1x1x256
[3x3 conv, 192] 28x28x192x3x3x64
[5x5 conv, 96] 28x28x96x5x5x64
[1x1 conv, 64] 28x28x64x1x1x256
Total: 358M ops

Compared to 854M ops for naive version
Bottleneck can also reduce depth after pooling layer

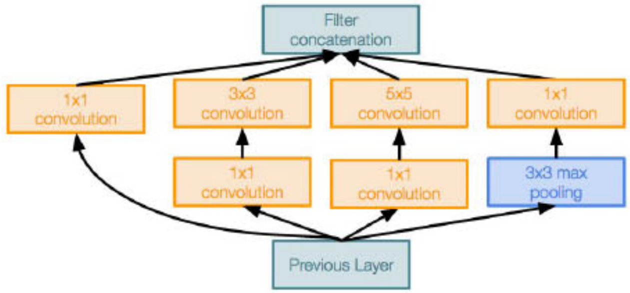
GoogLeNet

پشته‌سازی با ماژول‌های آغازش با کاهش بعد

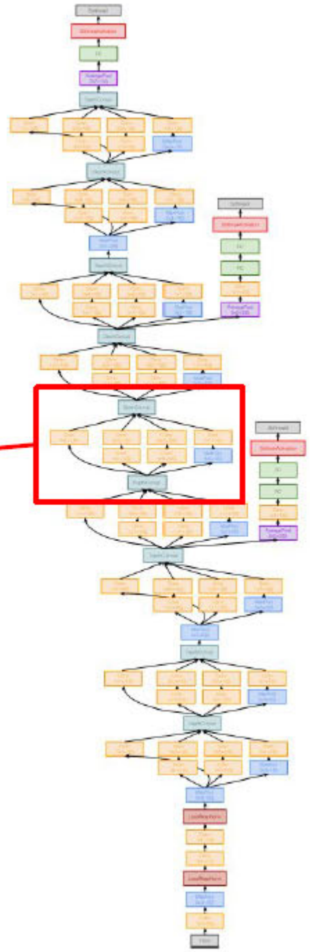
GoogLeNet

[Szegedy et al., 2014]

Stack Inception modules with dimension reduction on top of each other



Inception module



Ref: http://cs231n.stanford.edu/

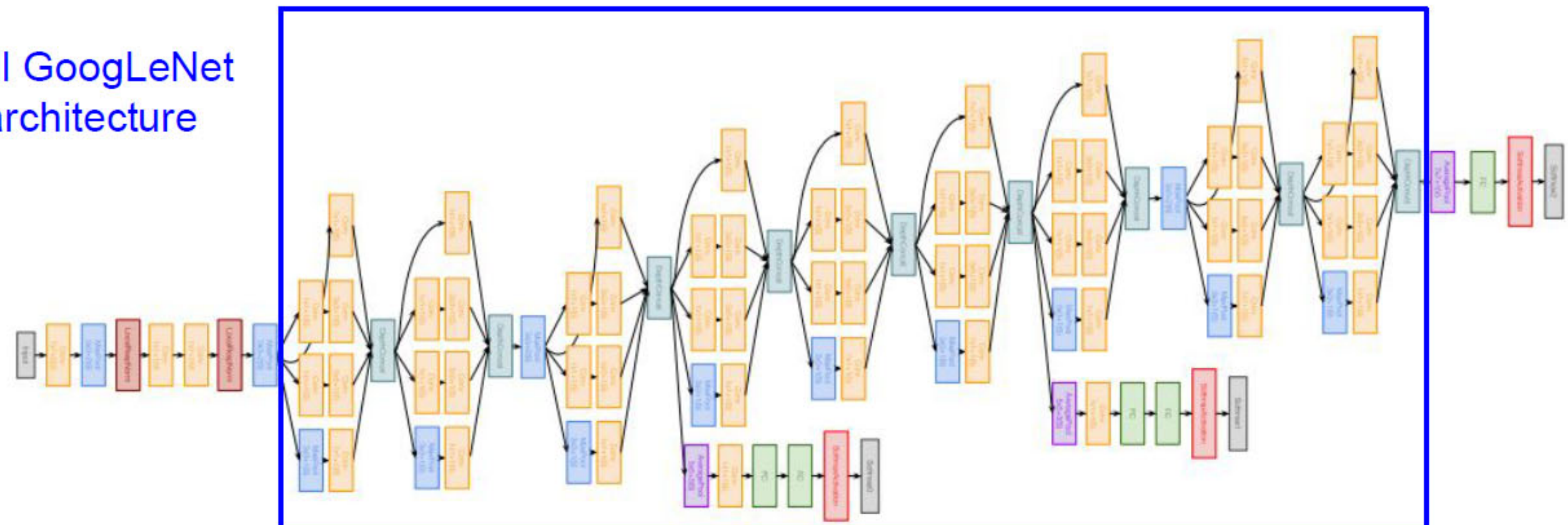
GoogLeNet

معماری کامل

GoogLeNet

[Szegedy et al., 2014]

Full GoogLeNet architecture



Stacked Inception Modules

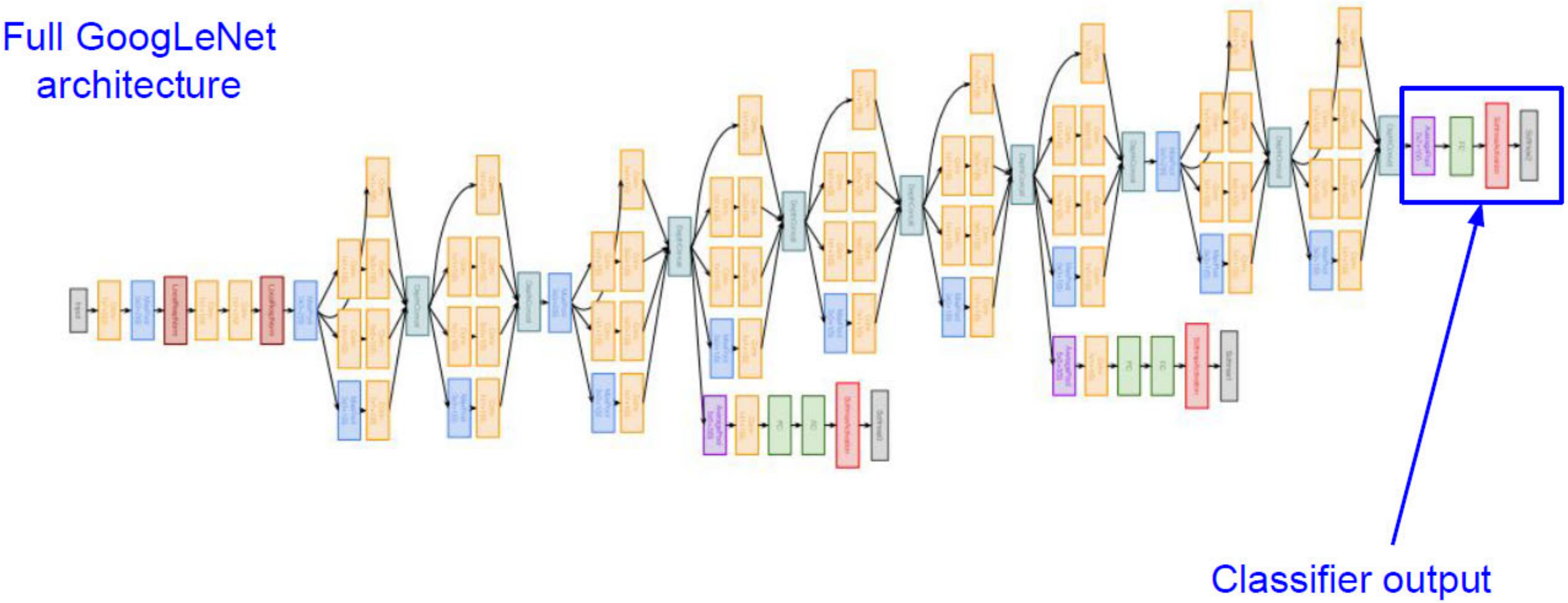
Ref: http://cs231n.stanford.edu/

GoogLeNet

معماری کامل: خروجی طبقه‌بندی کننده

GoogLeNet

[Szegedy et al., 2014]



Ref: http://cs231n.stanford.edu/

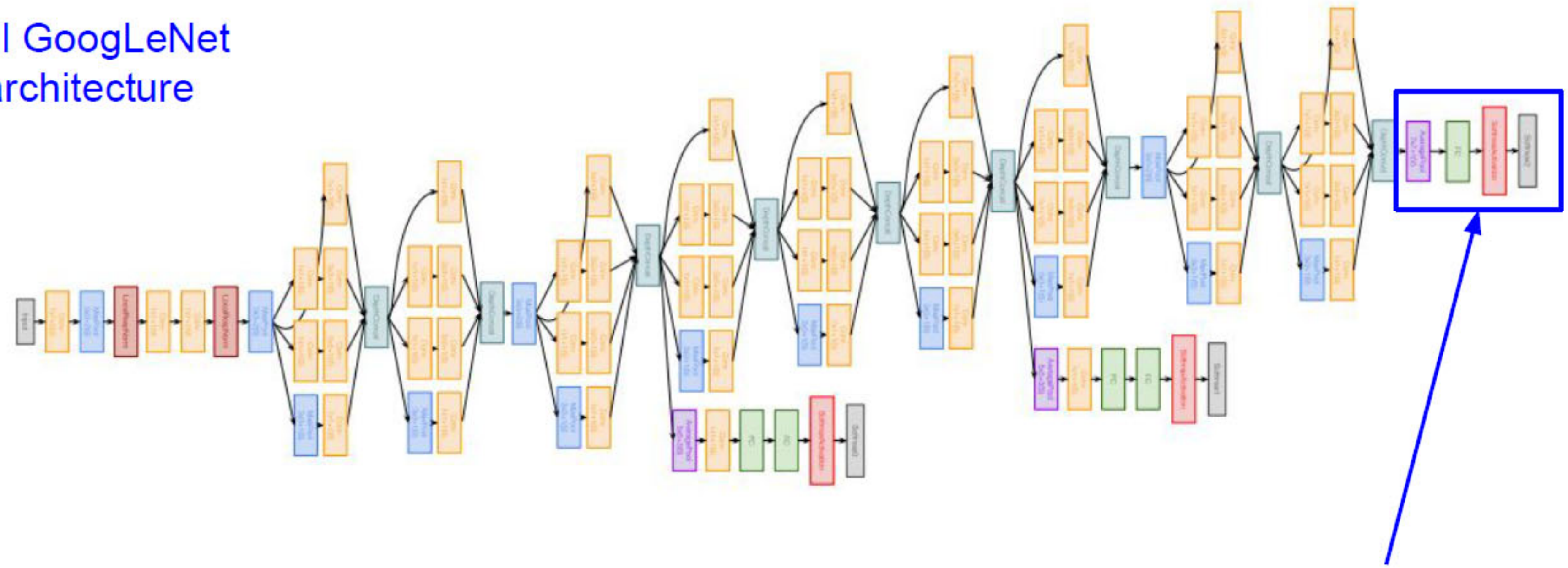
GoogLeNet

معماری کامل: خروجی طبقه‌بندی کننده (حذف لایه‌های تماماً متصل گران)

GoogLeNet

[Szegedy et al., 2014]

Full GoogLeNet architecture



Classifier output
(removed expensive FC layers!)

Ref: http://cs231n.stanford.edu/

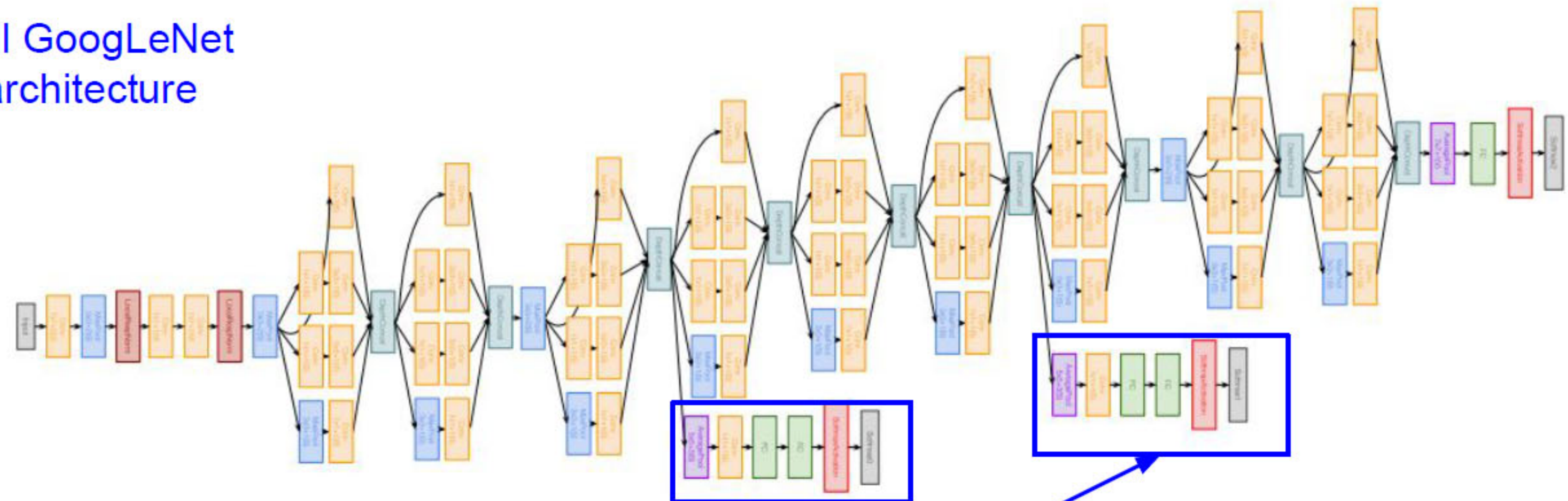
GoogLeNet

معماری کامل: خروجی‌های کمکی طبقه‌بندی کننده

GoogLeNet

[Szegedy et al., 2014]

Full GoogLeNet architecture



Auxiliary classification outputs to inject additional gradient at lower layers
(AvgPool-1x1Conv-FC-FC-Softmax)

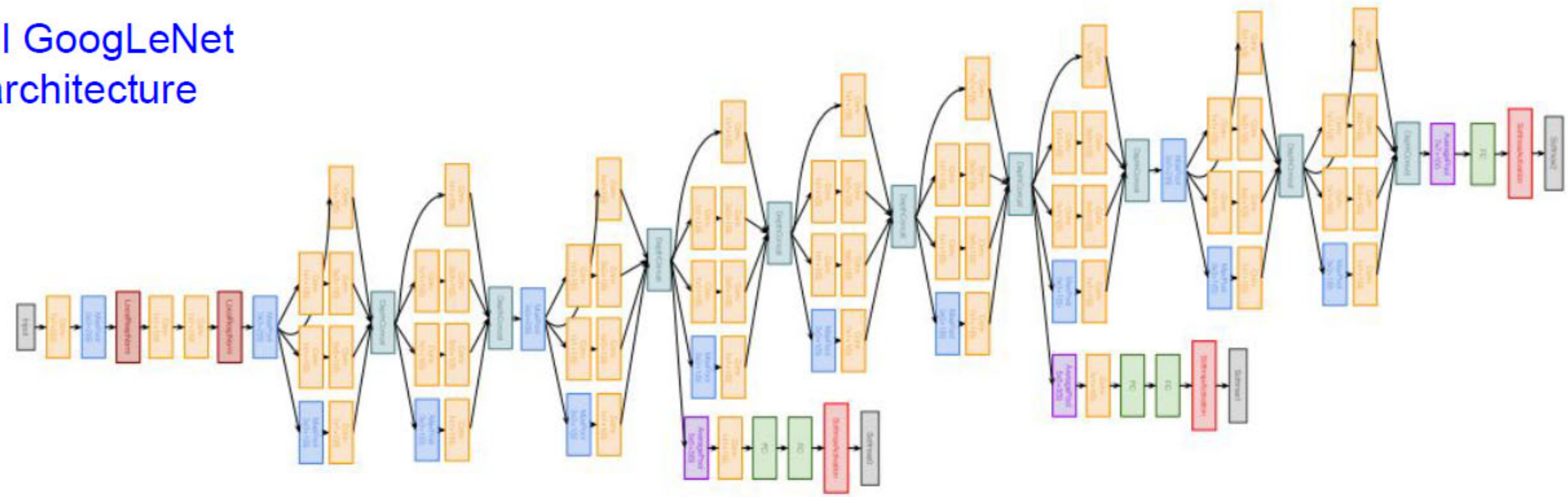
Ref: http://cs231n.stanford.edu/

معماری کامل

GoogLeNet

[Szegedy et al., 2014]

Full GoogLeNet architecture



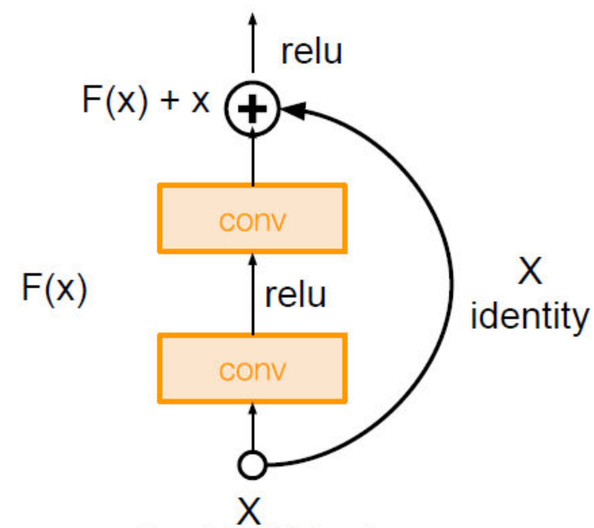
22 total layers with weights
(parallel layers count as 1 layer => 2 layers per Inception module. Don't count auxiliary output layers)

ResNet

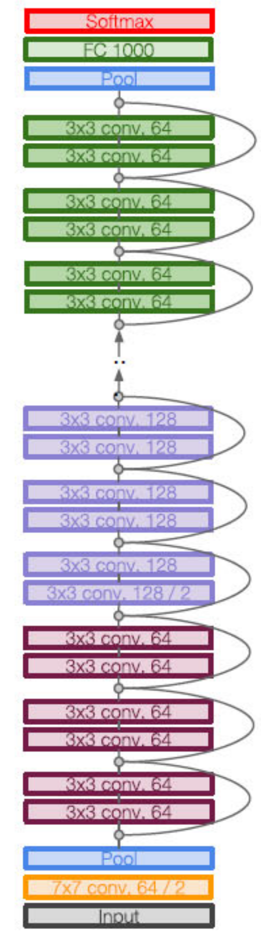
[He et al., 2015]

Very deep networks using residual connections

- 152-layer model for ImageNet
- ILSVRC'15 classification winner (3.57% top 5 error)
- Swept all classification and detection competitions in ILSVRC'15 and COCO'15!



Residual block



Ref: http://cs231n.stanford.edu/

ResNet

[He et al., 2015]

What happens when we continue stacking deeper layers on a “plain” convolutional neural network?

با ادامه دادن روی هم قرار دهی لایه‌های عمیق‌تر بر روی یک شبکه‌ی عصبی کانوولوشنال «ساده» چه اتفاقی می‌افتد؟

ResNet

[He et al., 2015]

What happens when we continue stacking deeper layers on a "plain" convolutional neural network?

Q: What's strange about these training and test curves?
[Hint: look at the order of the curves]

ResNet

[He et al., 2015]

What happens when we continue stacking deeper layers on a “plain” convolutional neural network?

56-layer model performs worse on both training and test error
-> The deeper model performs worse, but it’s not caused by overfitting!

مدل عمیق‌تر بدتر عمل کرده است، اما این به‌سبب بیش‌برازش نیست!

ResNet

[He et al., 2015]

Hypothesis: the problem is an *optimization* problem, deeper models are harder to optimize

فرضیه: مشکل، مسئله‌ی بهینه‌سازی است: بهینه‌سازی مدل‌های عمیق‌تر سخت‌تر است.

ResNet

[He et al., 2015]

Hypothesis: the problem is an *optimization* problem, deeper models are harder to optimize

The deeper model should be able to perform at least as well as the shallower model.

مدل عمیق‌تر باید بتواند حداقل به‌خوبی مدل کم‌عمق‌تر عمل کند.

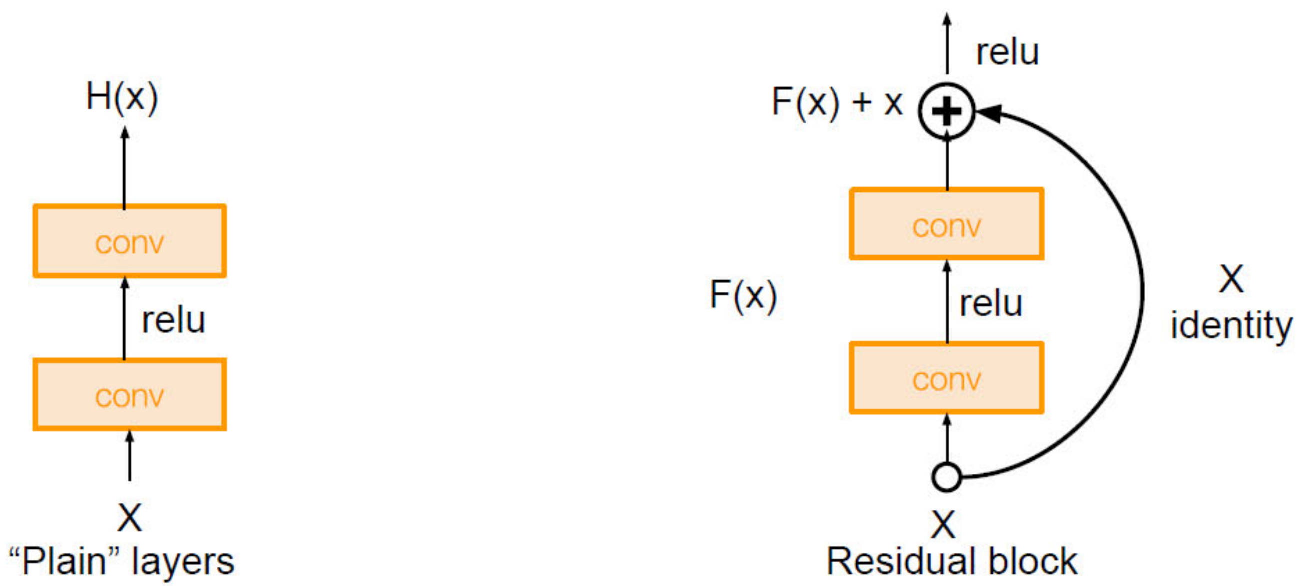
A solution by construction is copying the learned layers from the shallower model and setting additional layers to identity mapping.

یک راه‌حل از طریق ساختن: کپی کردن لایه‌های یادگیری شده از مدل کم‌عمق‌تر و قرار دادن لایه‌های بیشتر برای نگاشت همانی

ResNet

[He et al., 2015]

Solution: Use network layers to fit a residual mapping instead of directly trying to fit a desired underlying mapping



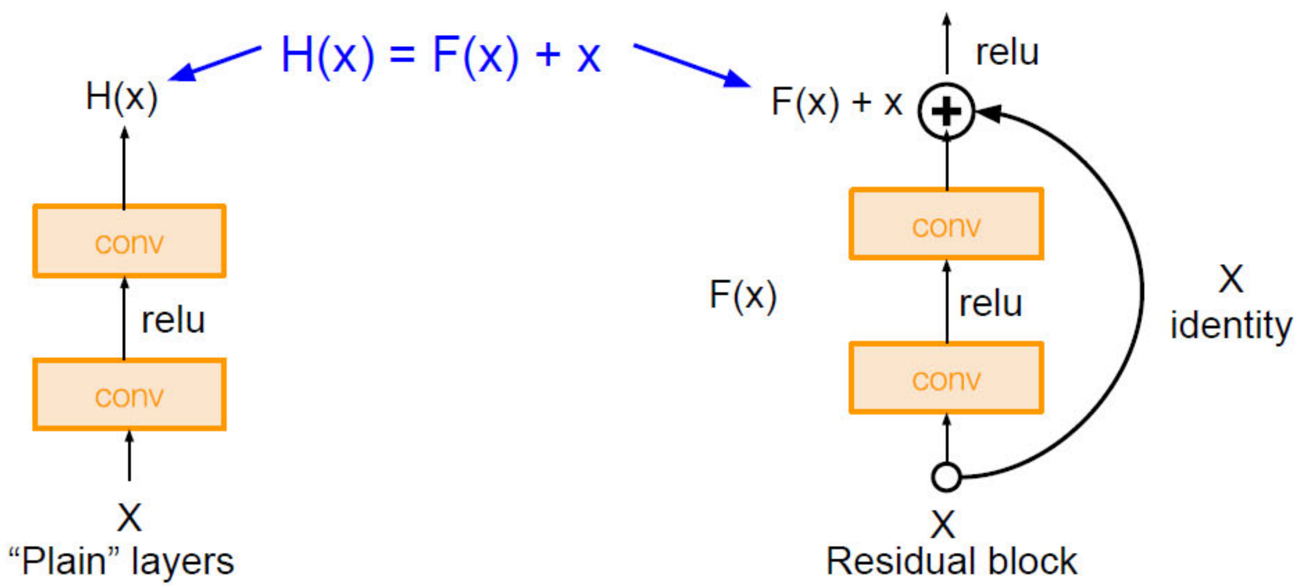
راه‌حل: استفاده از لایه‌های شبکه برای برازش یک نگاشت باقیمانده‌ای به‌جای تلاش مستقیم برای برازش نگاشت مورد نظر مطلوب

Ref: http://cs231n.stanford.edu/

ResNet

[He et al., 2015]

Solution: Use network layers to fit a residual mapping instead of directly trying to fit a desired underlying mapping



Use layers to fit residual F(x) = H(x) - x instead of H(x) directly

از لایه‌ها برای برازش باقیمانده $F(x) = H(x) - x$ به‌جای $H(x)$ به‌طور مستقیم استفاده می‌کنیم.

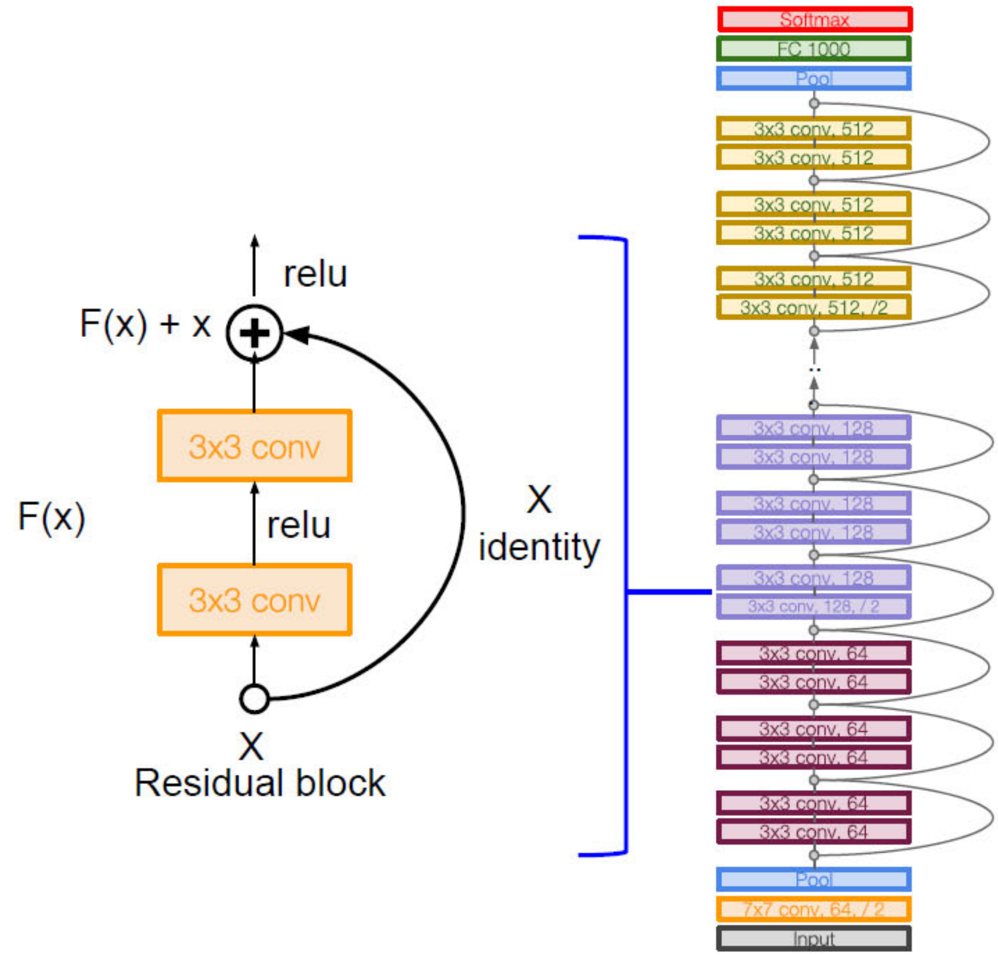
Ref: http://cs231n.stanford.edu/

جزئیات معماری

ResNet

[He et al., 2015]

Full ResNet architecture:
- Stack residual blocks
- Every residual block has two 3x3 conv layers

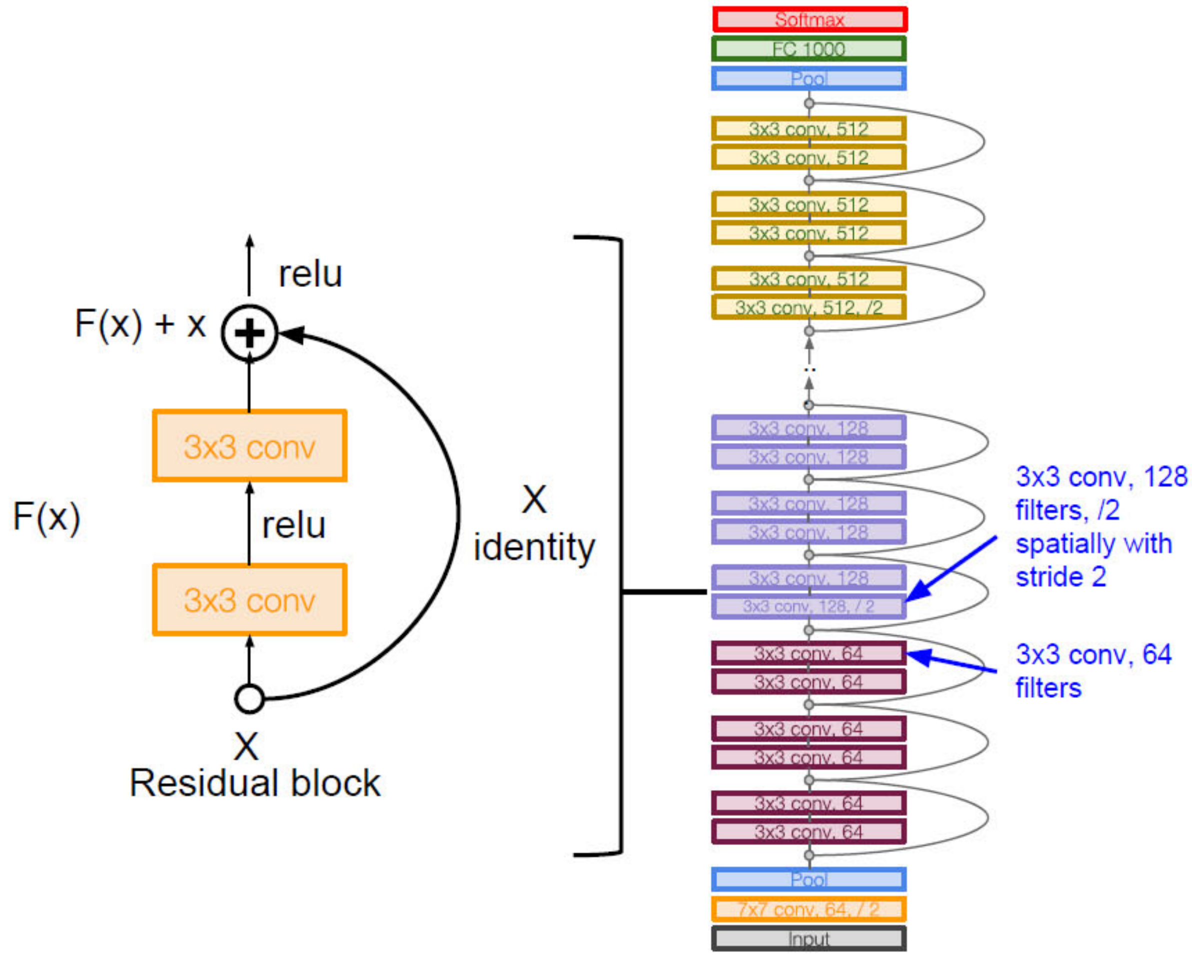


Ref: http://cs231n.stanford.edu/

ResNet

[He et al., 2015]

Full ResNet architecture:
- Stack residual blocks
- Every residual block has two 3x3 conv layers
- Periodically, double # of filters and downsample spatially using stride 2 (/2 in each dimension)



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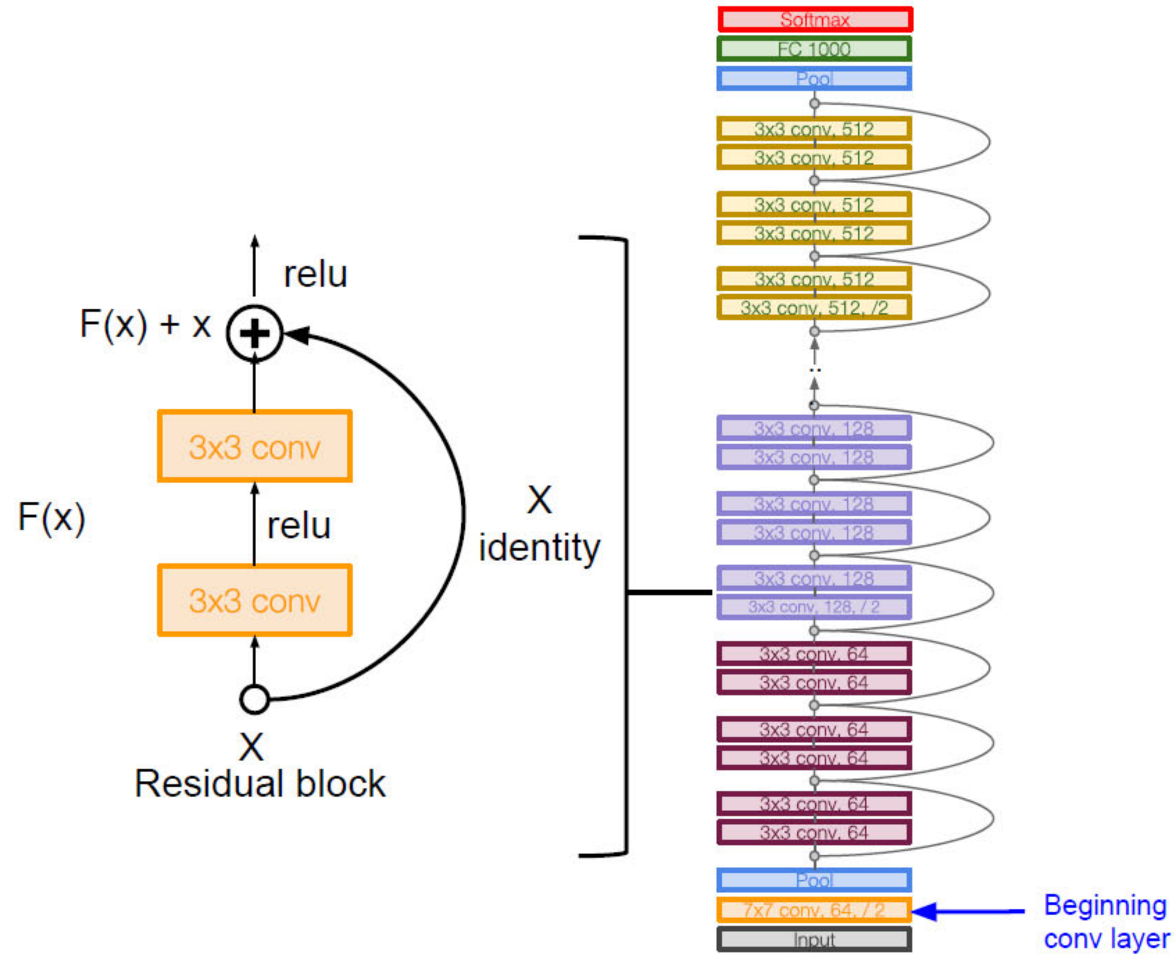
ResNet

جزئیات معماری

ResNet

[He et al., 2015]

Full ResNet architecture:
- Stack residual blocks
- Every residual block has two 3x3 conv layers
- Periodically, double # of filters and downsample spatially using stride 2 (/2 in each dimension)
- Additional conv layer at the beginning



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ResNet

جزئیات معماری

ResNet

[He et al., 2015]

Full ResNet architecture:
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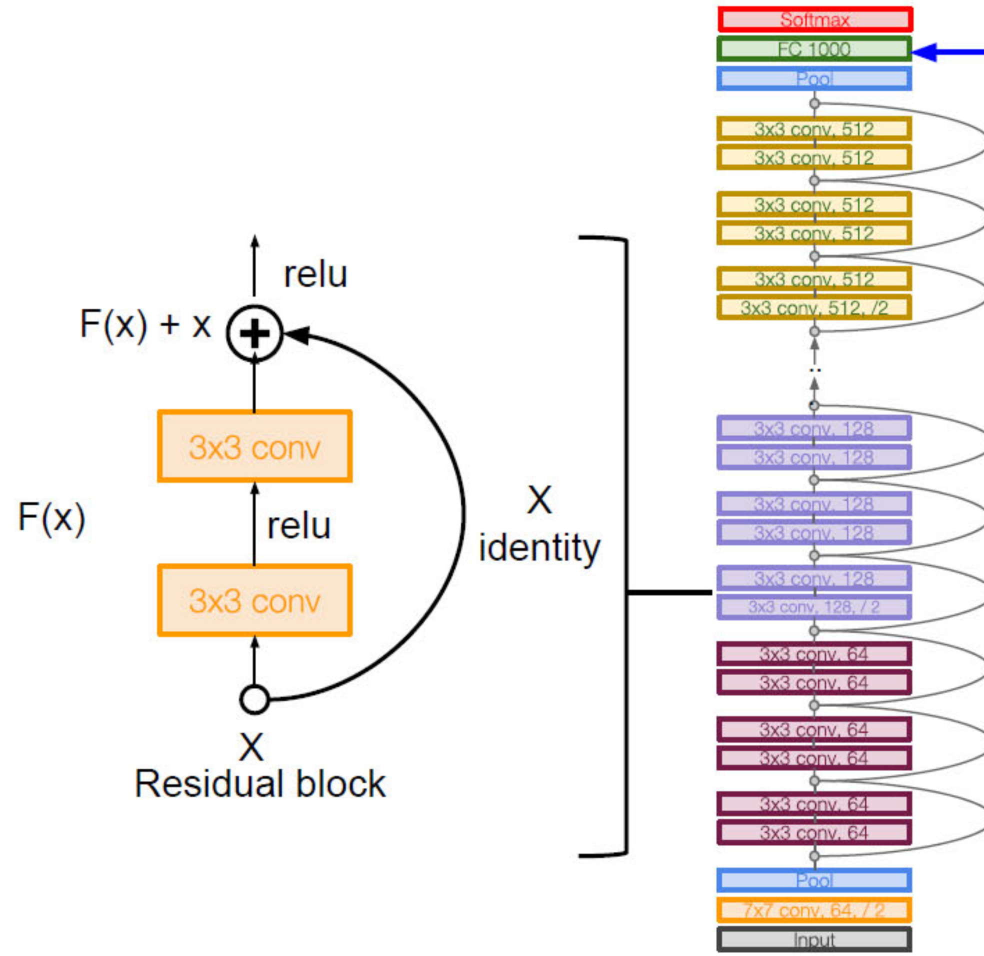
- Every residual block has two 3x3 conv layers
- Periodically, double # of filters and downsample spatially using stride 2 (/2 in each dimension)
- Additional conv layer at the beginning
- No FC layers at the end (only FC 1000 to output classes)



No FC layers besides FC 1000 to output classes

Global average pooling layer after last conv layer

Ref: http://cs231n.stanford.edu/

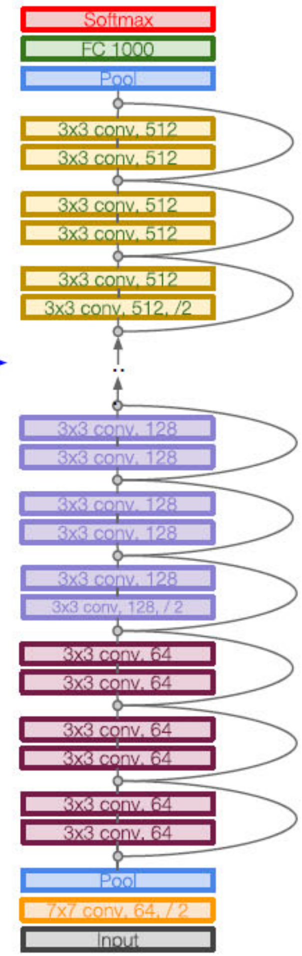
ResNet

جزئیات معماری

ResNet

[He et al., 2015]

Total depths of 34, 50, 101, or 152 layers for ImageNet



Ref: http://cs231n.stanford.edu/

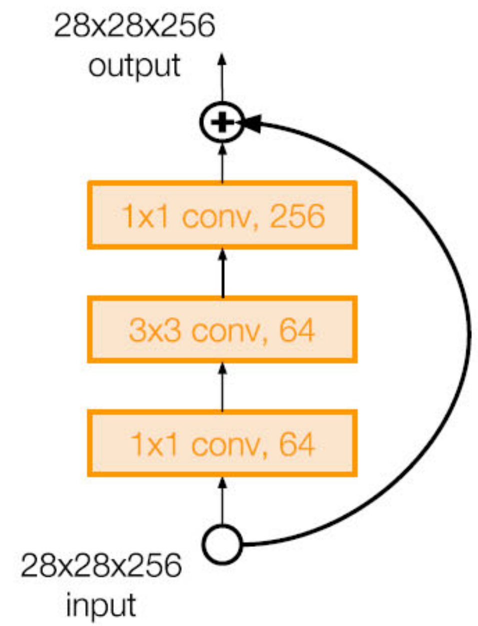
ResNet

جزئیات معماری

ResNet

[He et al., 2015]

For deeper networks (ResNet-50+), use “bottleneck” layer to improve efficiency (similar to GoogLeNet)



ResNet

[He et al., 2015]

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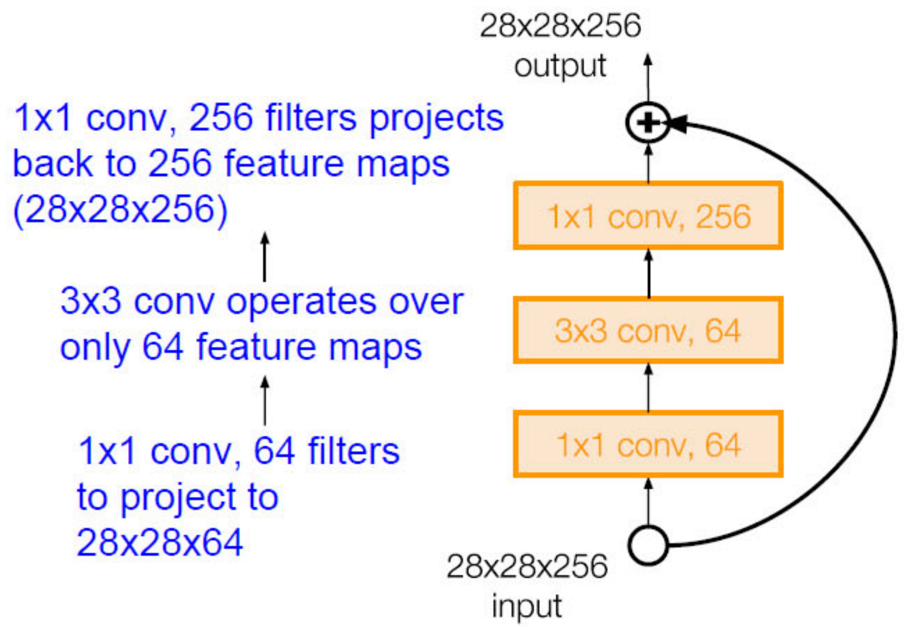

Ref: http://cs231n.stanford.edu/

ResNet

[He et al., 2015]

Training ResNet in practice:

- Batch Normalization after every CONV layer
- Xavier 2/ initialization from He et al.
- SGD + Momentum (0.9)
- Learning rate: 0.1, divided by 10 when validation error plateaus
- Mini-batch size 256
- Weight decay of 1e-5
- No dropout used

نتایج تجربی

ResNet

[He et al., 2015]

Experimental Results

- Able to train very deep networks without degrading (152 layers on ImageNet, 1202 on Cifar)
- Deeper networks now achieve lowing training error as expected
- Swept 1st place in all ILSVRC and COCO 2015 competitions

MSRA @ ILSVRC & COCO 2015 Competitions

- **1st places in all five main tracks**
  - ImageNet Classification: *"Ultra-deep"* (quote Yann) 152-layer nets
  - ImageNet Detection: 16% better than 2nd
  - ImageNet Localization: 27% better than 2nd
  - COCO Detection: 11% better than 2nd
  - COCO Segmentation: 12% better than 2nd

نتایج تجربی

ResNet

[He et al., 2015]

Experimental Results

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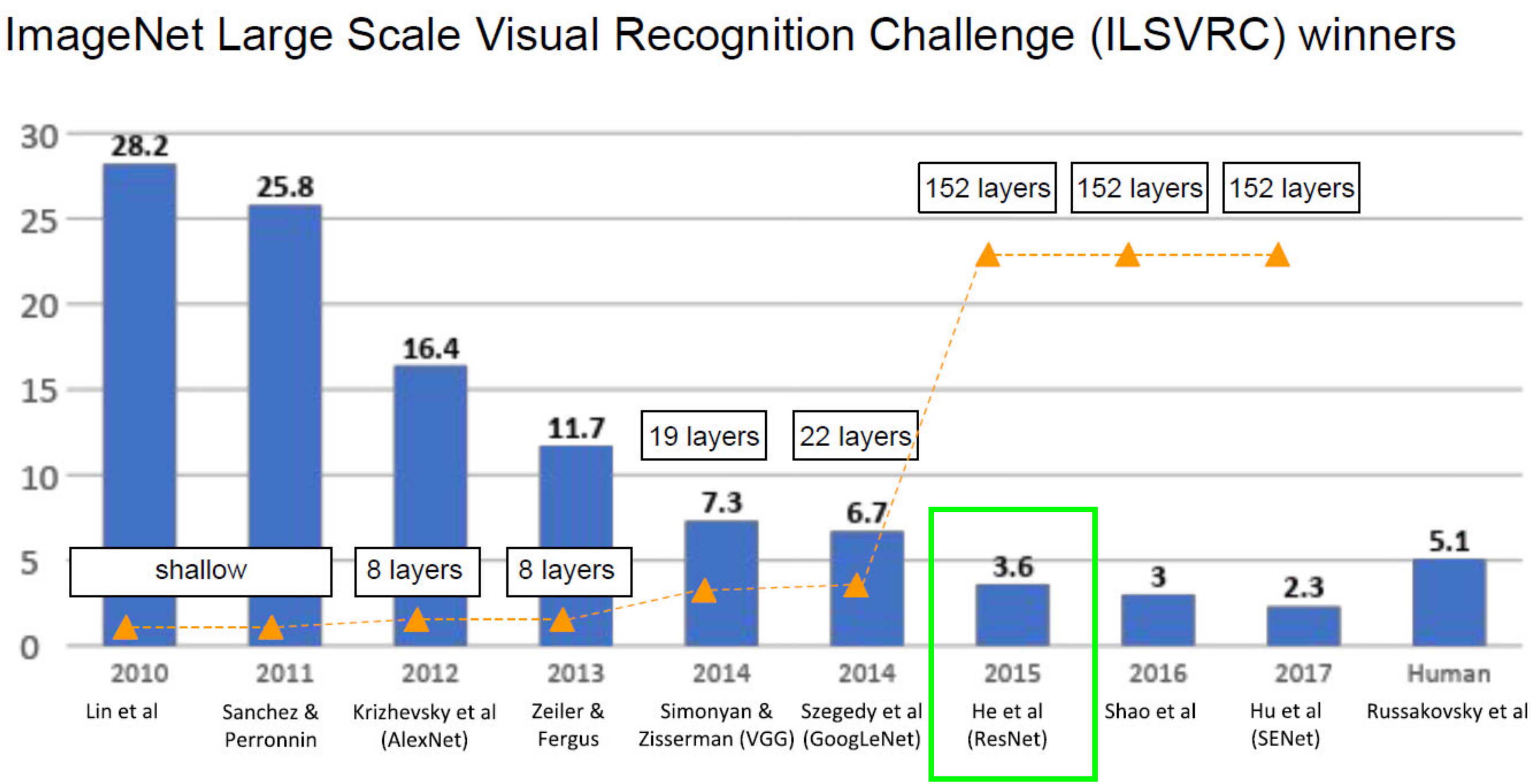
  - COCO Detection: 11% better than 2nd
  - COCO Segmentation: 12% better than 2nd

ILSVRC 2015 classification winner (3.6% top 5 error) -- better than "human performance"! (Russakovsky 2014)

ResNet

نتایج در چالش بازشناسی دیداری در مقیاس بالا ImageNet در مقایسه با سایر روش‌ها



Ref: http://cs231n.stanford.edu/

یادگیری عمیق

معماری‌های گوناگون
شبکه‌های عصبی کانوولوشنال

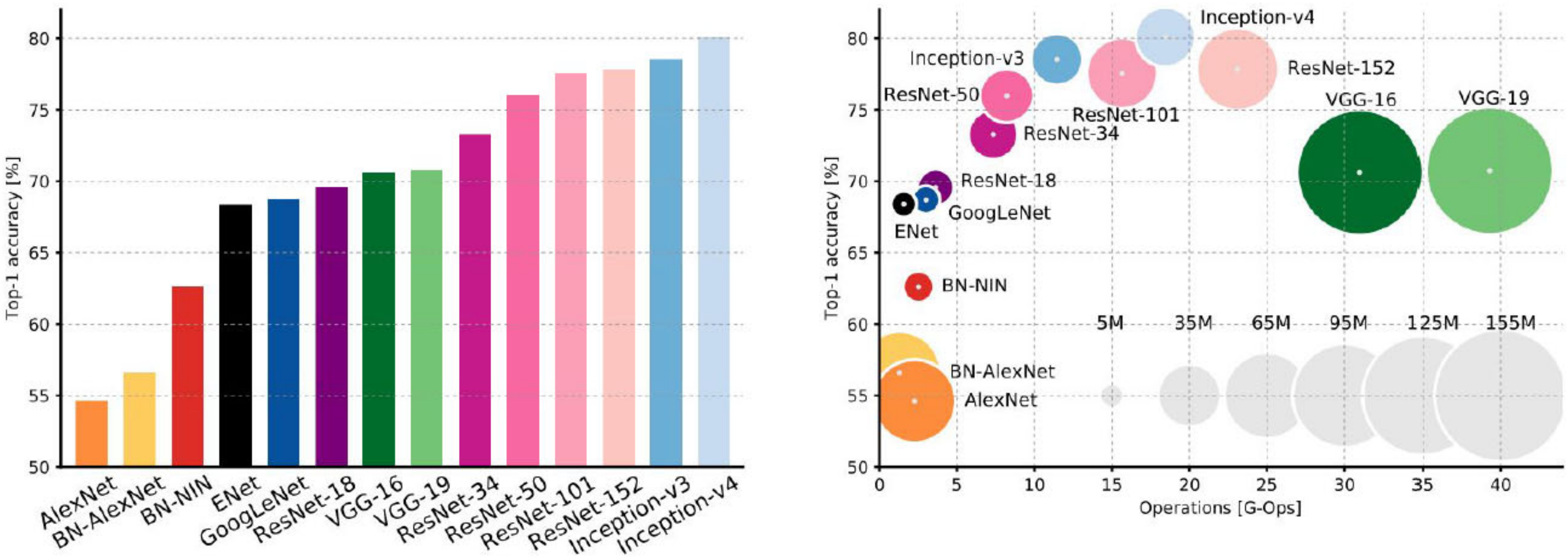
۲

مقایسه‌ی معماری‌ها

معماری‌های گوناگون شبکه‌های عصبی کانوولوشنال

مقایسه‌ی پیچیدگی

Comparing complexity...



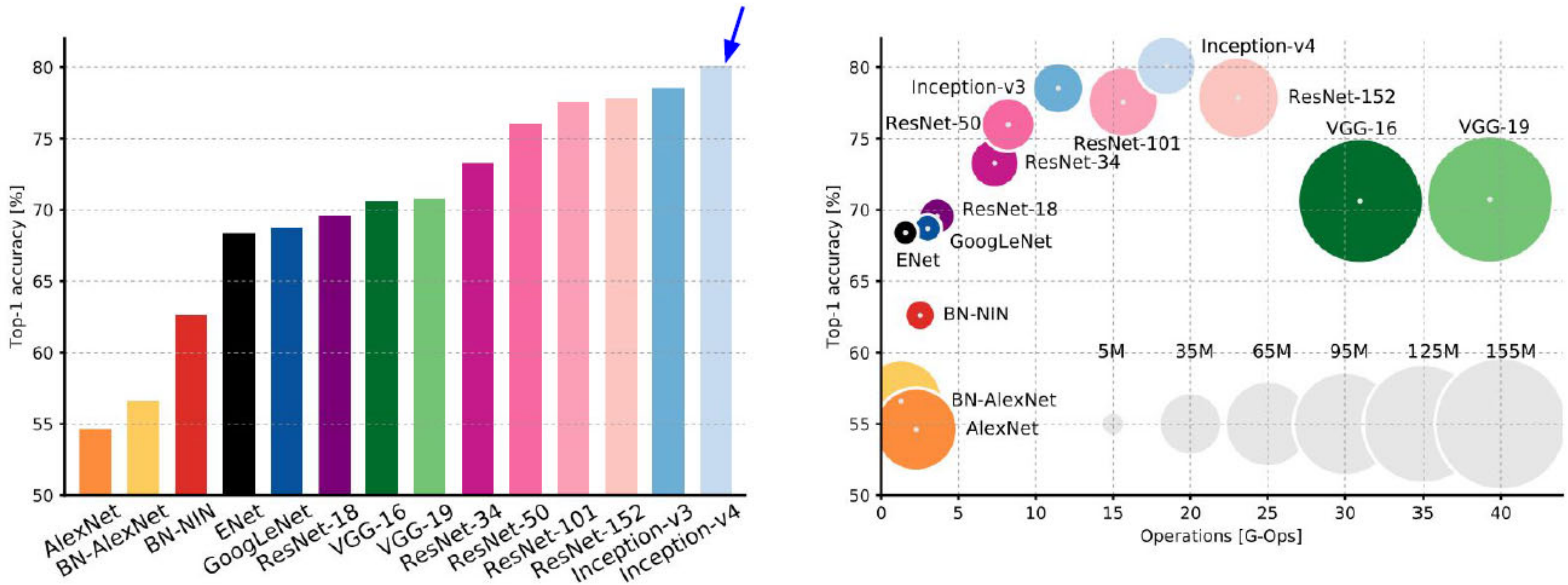
An Analysis of Deep Neural Network Models for Practical Applications, 2017.

معماری‌های گوناگون شبکه‌های عصبی کانوولوشنال

مقایسه‌ی پیچیدگی : Inception-v4

Comparing complexity...

Inception-v4: Resnet + Inception!



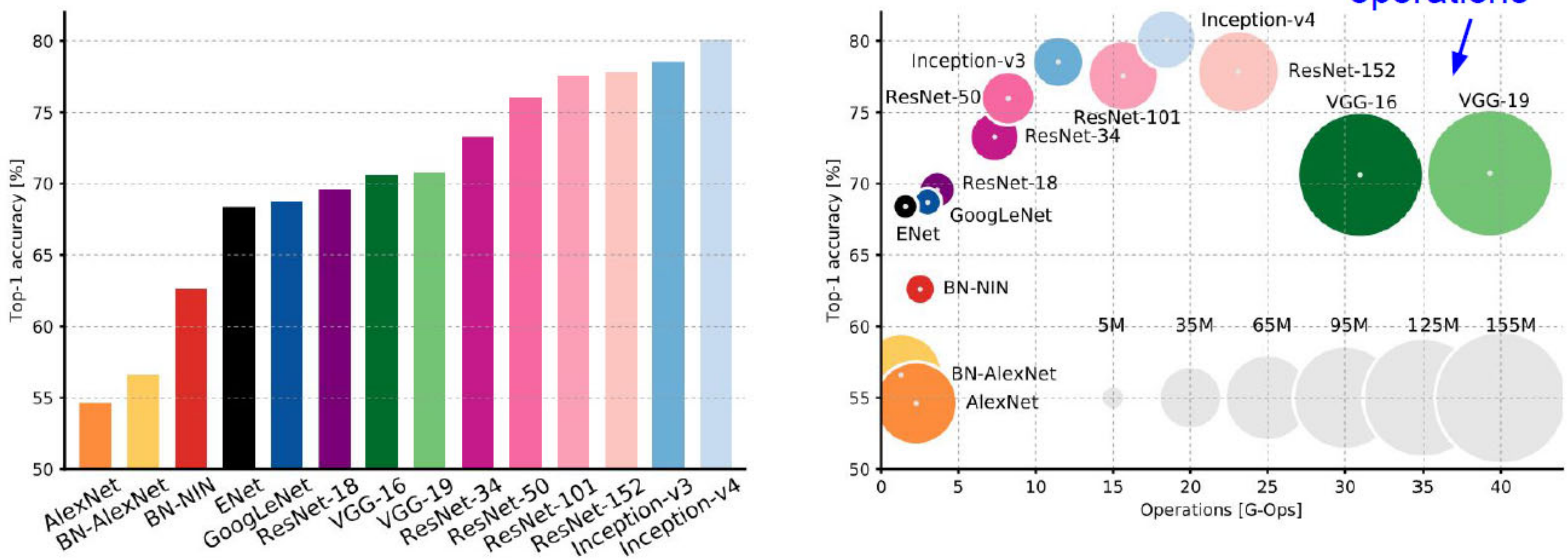
An Analysis of Deep Neural Network Models for Practical Applications, 2017.

معماری‌های گوناگون شبکه‌های عصبی کانوولوشنال

مقایسه‌ی پیچیدگی: VGG

Comparing complexity...

VGG: Highest memory, most operations



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

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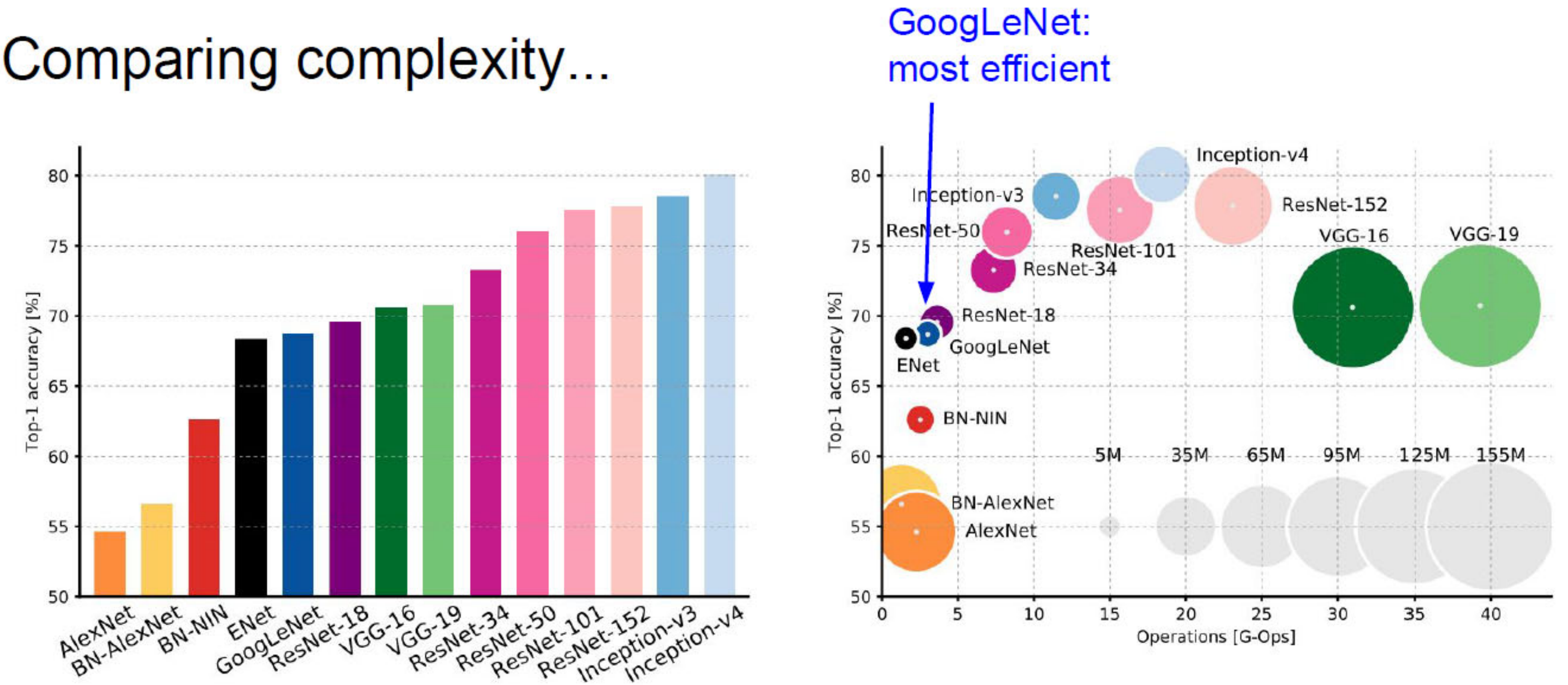
معماری‌های گوناگون شبکه‌های عصبی کانوولوشنال

مقایسه‌ی پیچیدگی : GoogLeNet

Comparing complexity...



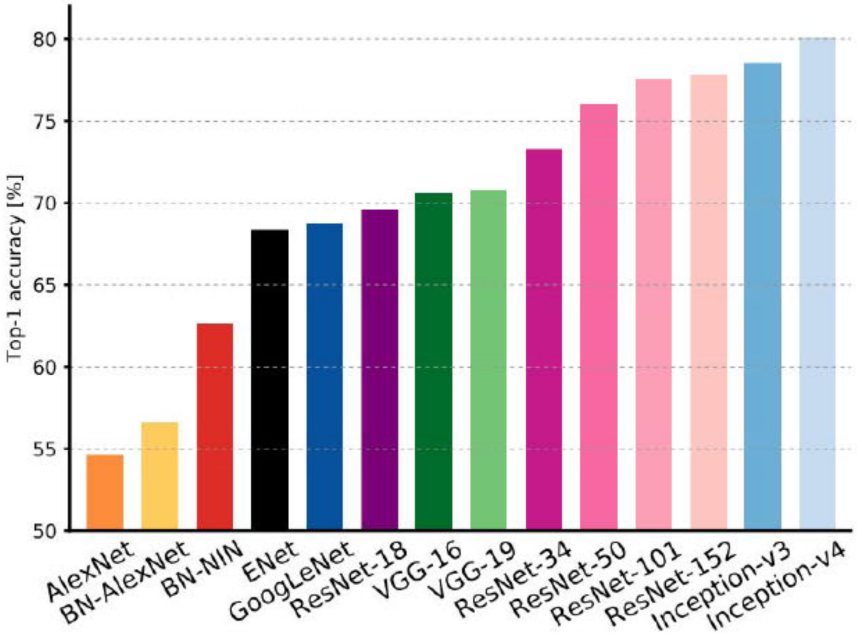
An Analysis of Deep Neural Network Models for Practical Applications, 2017.

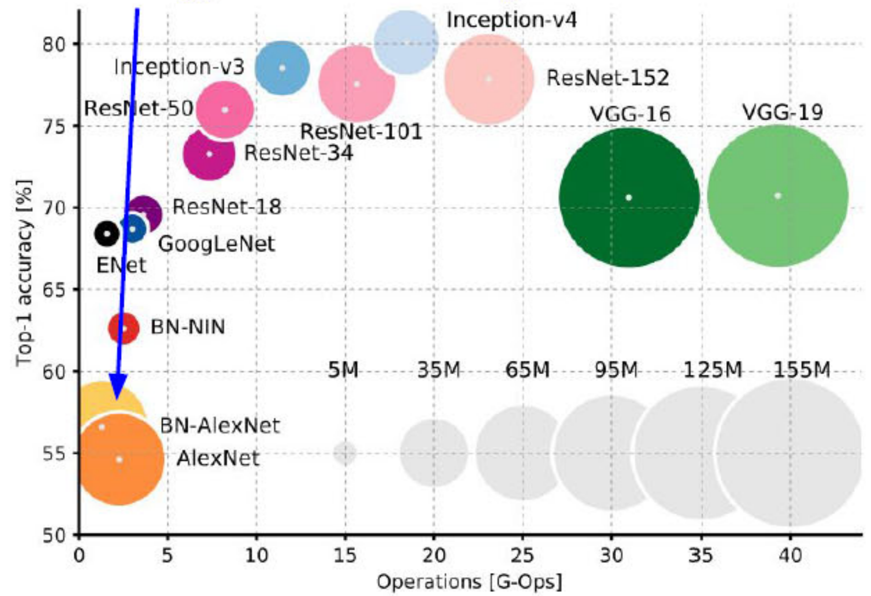
معماری‌های گوناگون شبکه‌های عصبی کانوولوشنال

مقایسه‌ی پیچیدگی: AlexNet

Comparing complexity...

AlexNet:
Smaller compute, still memory heavy, lower accuracy





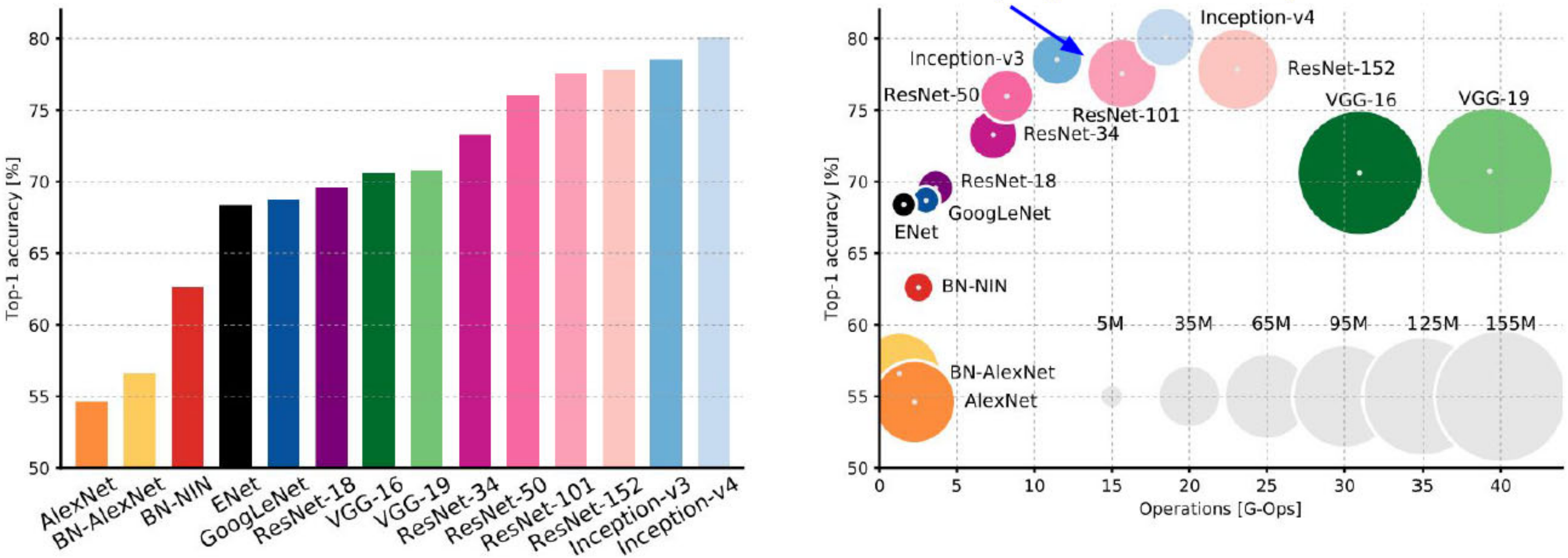
An Analysis of Deep Neural Network Models for Practical Applications, 2017.

معماری‌های گوناگون شبکه‌های عصبی کانوولوشنال

مقایسه‌ی پیچیدگی : ResNet

Comparing complexity...

ResNet:
Moderate efficiency depending on model, highest accuracy



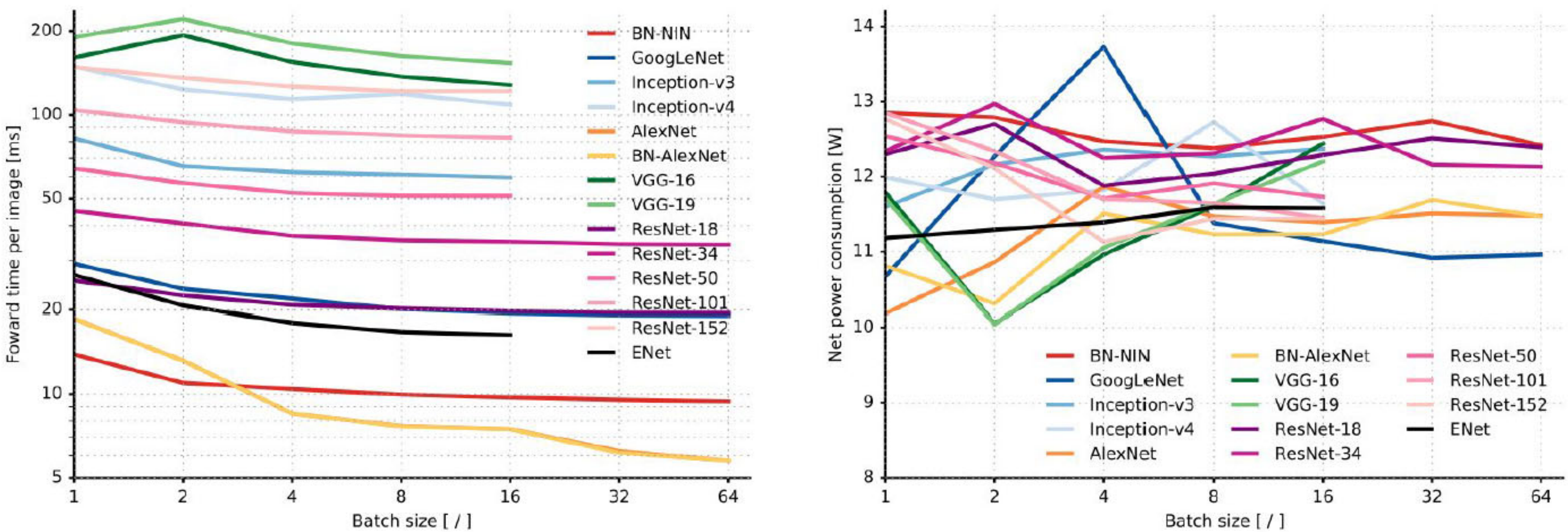
An Analysis of Deep Neural Network Models for Practical Applications, 2017.

Ref: http://cs231n.stanford.edu/

معماری‌های گوناگون شبکه‌های عصبی کانوولوشنال

مقایسه‌ی زمان اجرای گذر پیشرو و توان مصرفی

Forward pass time and power consumption



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

معماری‌های گوناگون
شبکه‌های عصبی کانوولوشنال

۲

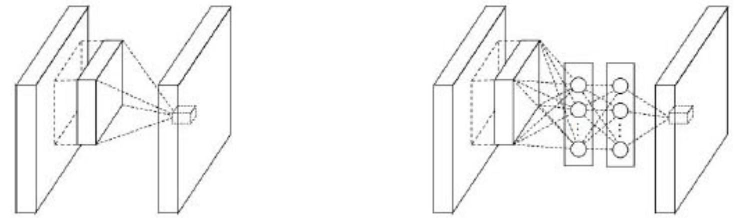
سایر معماری‌ها

شبکه در شبکه

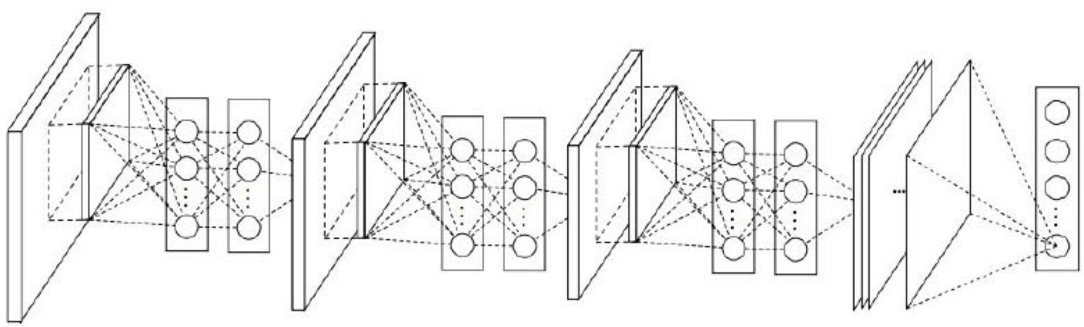
Network in Network (NiN)

[Lin et al. 2014]

- Mlpconv layer with "micronetwork" within each conv layer to compute more abstract features for local patches
- Micronetwork uses multilayer perceptron (FC, i.e. 1x1 conv layers)
- Precursor to GoogLeNet and ResNet "bottleneck" layers
- Philosophical inspiration for GoogLeNet



(a) Linear convolution layer (b) Mlpconv layer



ResNetهای در حال بهبود

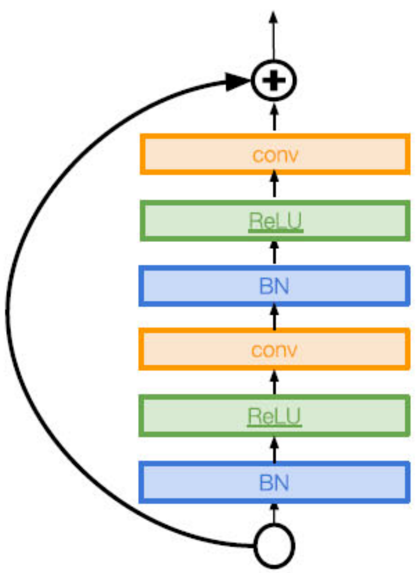
نگاشت‌های همانی در شبکه‌های باقیمانده‌ای عمیق

Improving ResNets...

Identity Mappings in Deep Residual Networks

[He et al. 2016]

- Improved ResNet block design from creators of ResNet
- Creates a more direct path for propagating information throughout network (moves activation to residual mapping pathway)
- Gives better performance



ResNetهای در حال بهبود

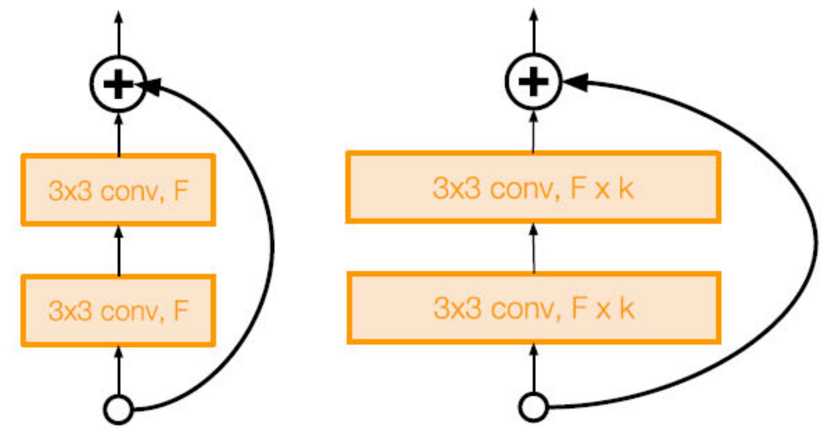
شبکه‌های باقیمانده‌ای عریض

Improving ResNets...

Wide Residual Networks

[Zagoruyko et al. 2016]

- Argues that residuals are the important factor, not depth
- User wider residual blocks (F x k filters instead of F filters in each layer)
- 50-layer wide ResNet outperforms 152-layer original ResNet
- Increasing width instead of depth more computationally efficient (parallelizable)



Basic residual block   Wide residual block

Ref: http://cs231n.stanford.edu/

ResNetهای در حال بهبود

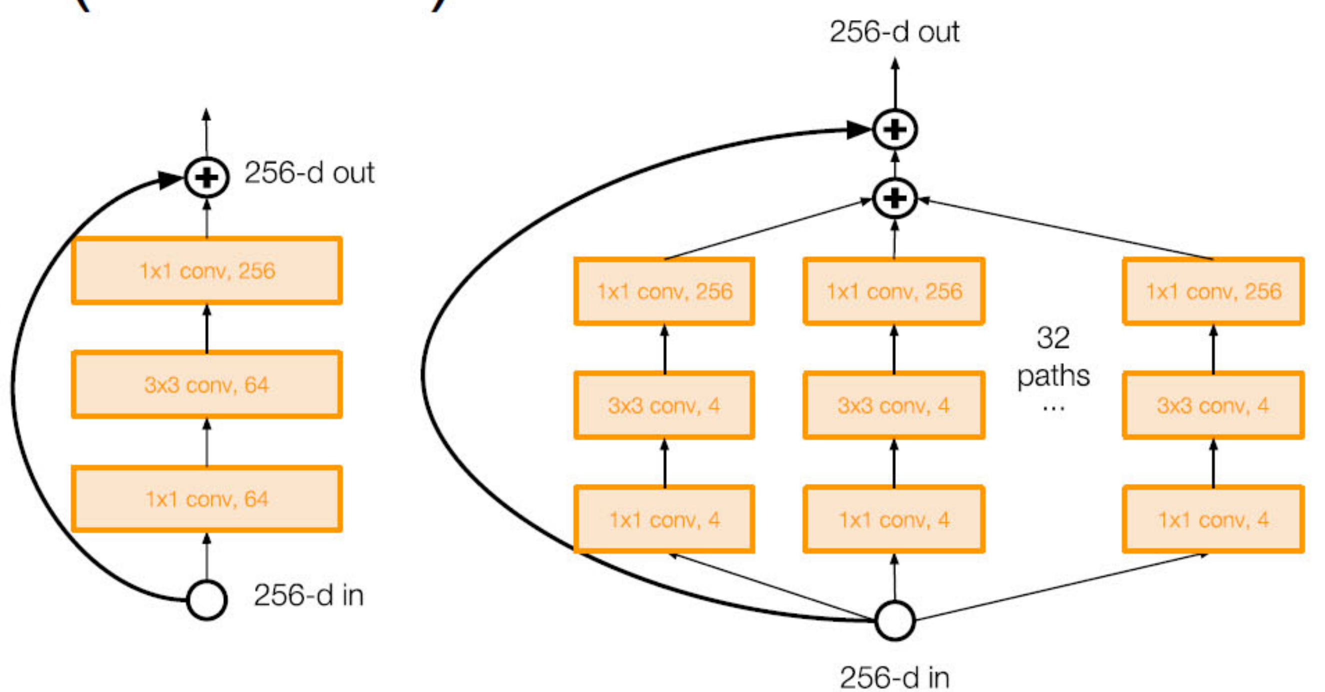
تبدیل‌های باقیمانده‌ای تجمیع‌شده برای شبکه‌های عصبی عمیق (ResNeXt)

Improving ResNets...

Aggregated Residual Transformations for Deep Neural Networks (ResNeXt)

[Xie et al. 2016]

- Also from creators of ResNet
- Increases width of residual block through multiple parallel pathways ("cardinality")
- Parallel pathways similar in spirit to Inception module



Ref: http://cs231n.stanford.edu/

ResNetهای در حال بهبود

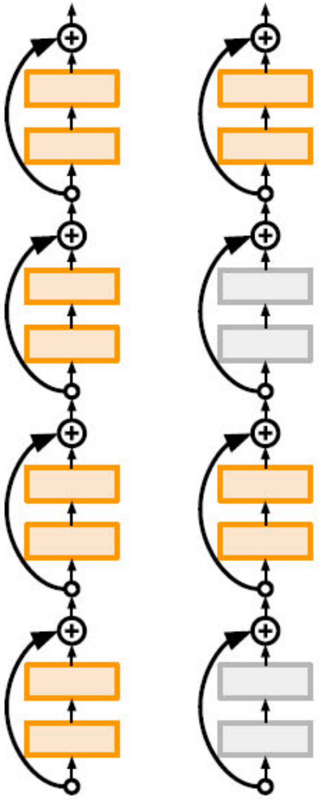
شبکه‌های عمیق‌تر با عمق اتفاقی

Improving ResNets...

Deep Networks with Stochastic Depth

[Huang et al. 2016]

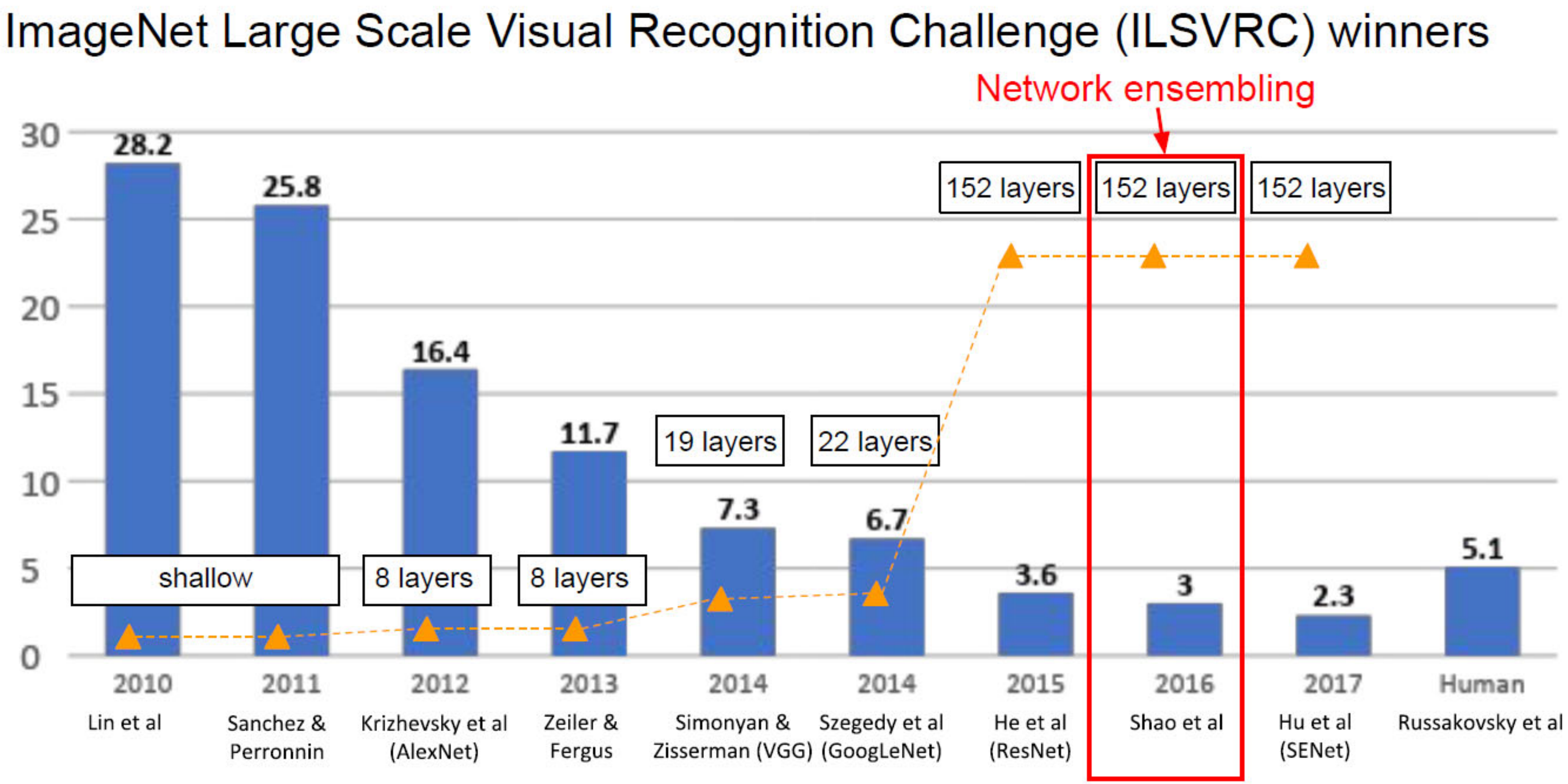
- Motivation: reduce vanishing gradients and training time through short networks during training
- Randomly drop a subset of layers during each training pass
- Bypass with identity function
- Use full deep network at test time



Ref: http://cs231n.stanford.edu/

ResNetهای در حال بهبود

نتایج در چالش بازشناسی دیداری در مقیاس بالا ImageNet در مقایسه با سایر روش‌ها



Ref: http://cs231n.stanford.edu/

ResNetهای در حال بهبود

تجربه‌های عملی خوب برای هم‌جوشی عمیق ویژگی‌ها (تکنیک یادگیری دسته‌جمعی)

Improving ResNets...

"Good Practices for Deep Feature Fusion"

[Shao et al. 2016]

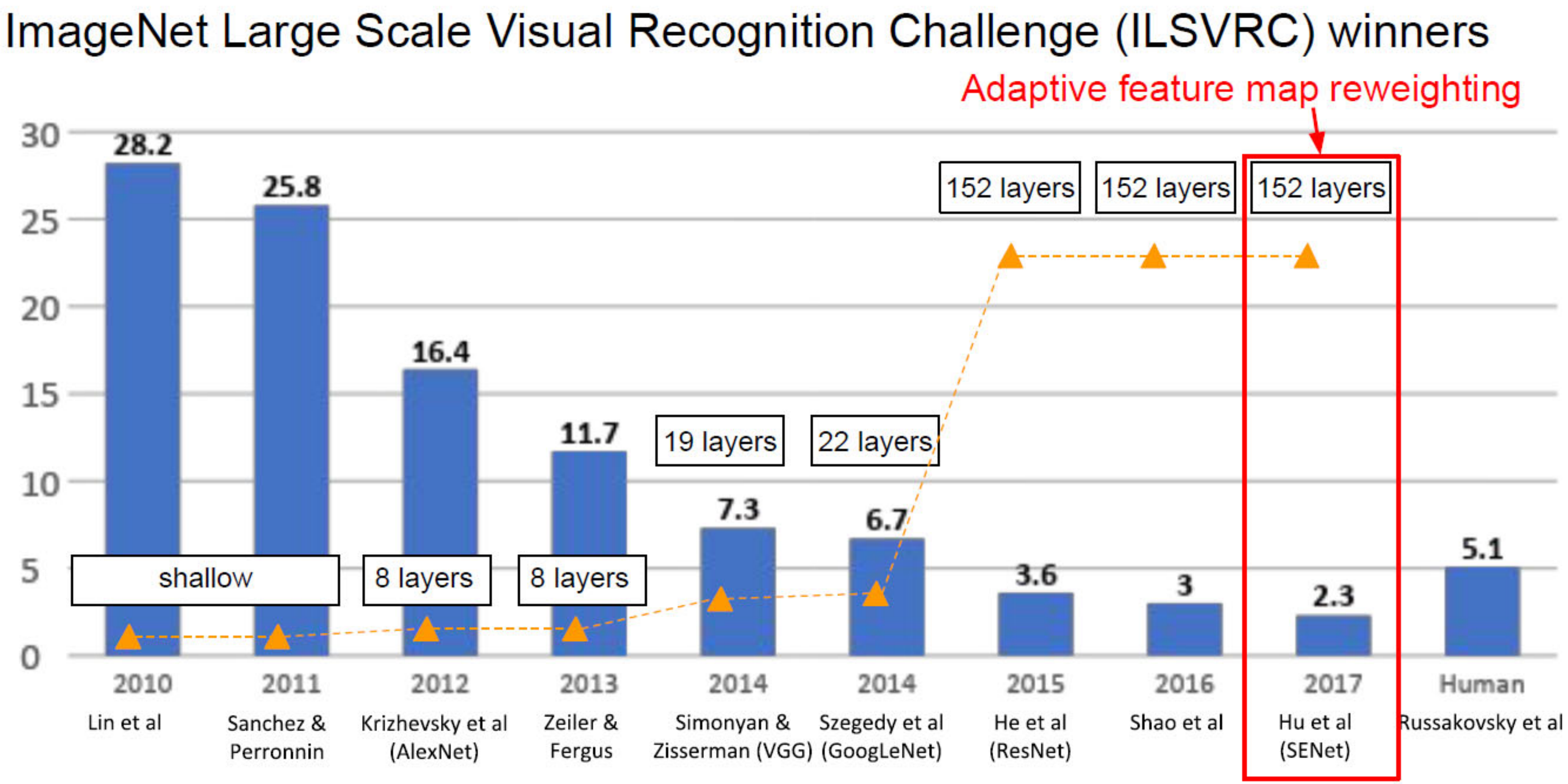
- Multi-scale ensembling of Inception, Inception-Resnet, Resnet, Wide Resnet models
- ILSVRC'16 classification winner

	Inception-v3	Inception-v4	Inception-Resnet-v2	Resnet-200	Wrn-68-3	Fusion (Val.)	Fusion (Test)
Err. (%)	4.20	4.01	3.52	4.26	4.65	2.92 (-0.6)	2.99

Ref: http://cs231n.stanford.edu/

ResNetهای در حال بهبود

نتایج در چالش بازشناسی دیداری در مقیاس بالا ImageNet در مقایسه با سایر روش‌ها



Ref: http://cs231n.stanford.edu/

ResNetهای در حال بهبود

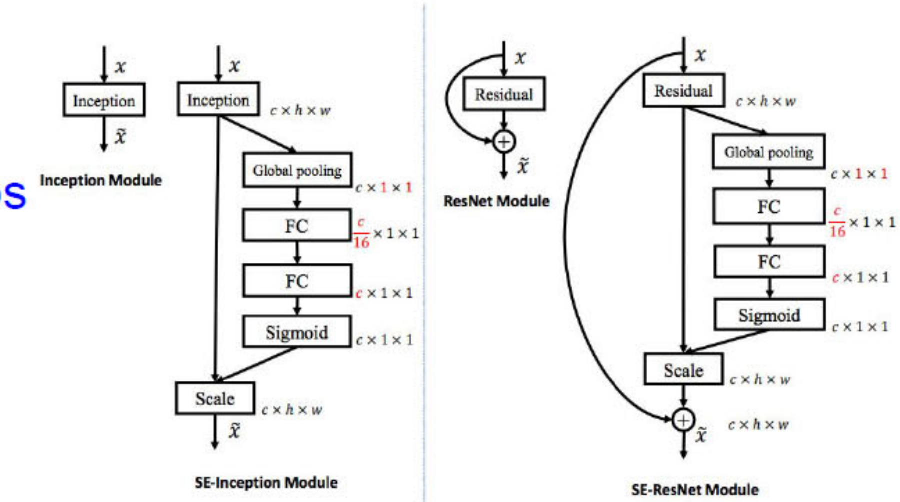
شبکه‌های Squeeze-and-Excitation (SENet)

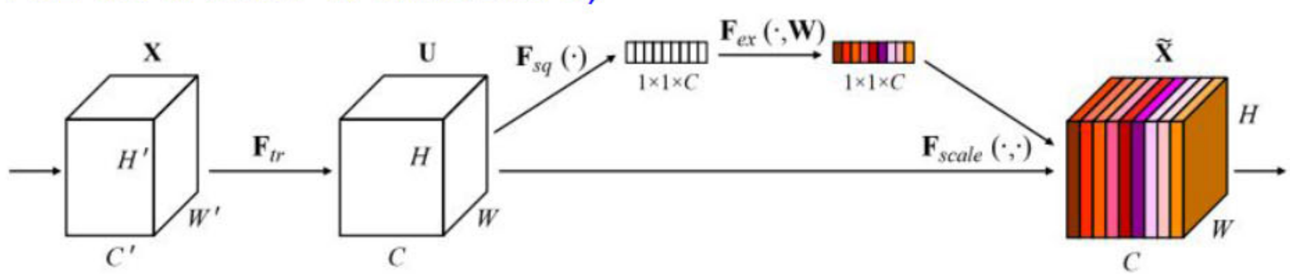
Improving ResNets...

Squeeze-and-Excitation Networks (SENet)

[Hu et al. 2017]

- Add a “feature recalibration” module that learns to adaptively reweight feature maps
- Global information (global avg. pooling layer) + 2 FC layers used to determine feature map weights
- ILSVRC’17 classification winner (using ResNeXt-152 as a base architecture)





فراتر از ResNetها

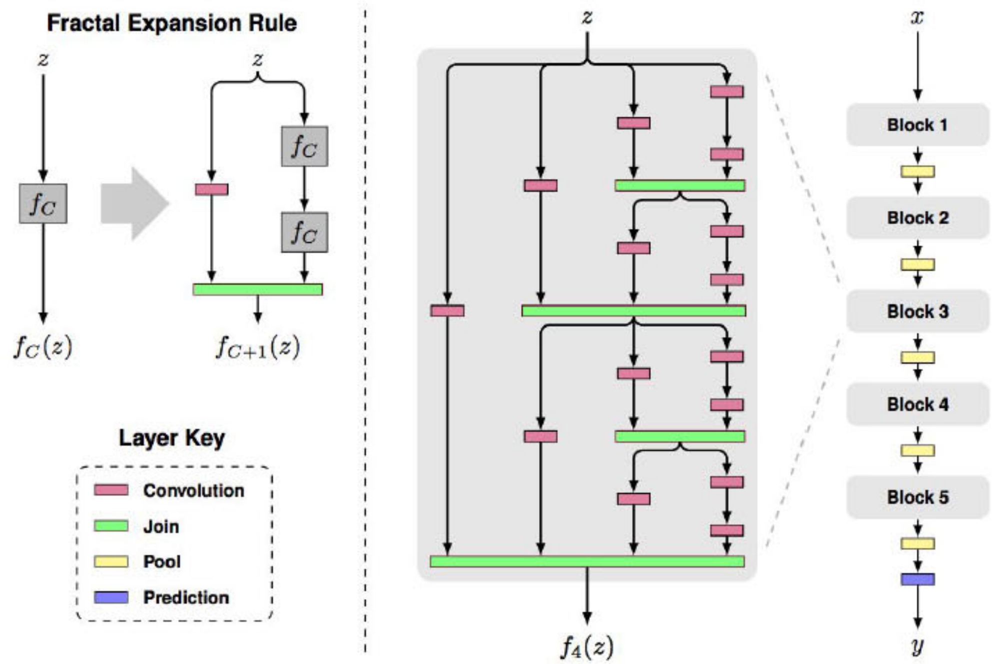
شبکه‌ی فراکتالی: شبکه‌های عصبی ماورای عمیق بدون استفاده از باقیمانده‌ای‌ها

Beyond ResNets...

FractalNet: Ultra-Deep Neural Networks without Residuals

[Larsson et al. 2017]

- Argues that key is transitioning effectively from shallow to deep and residual representations are not necessary
- Fractal architecture with both shallow and deep paths to output
- Trained with dropping out sub-paths
- Full network at test time



Figures copyright Larsson et al., 2017. Reproduced with permission.

فراتر از ResNetها

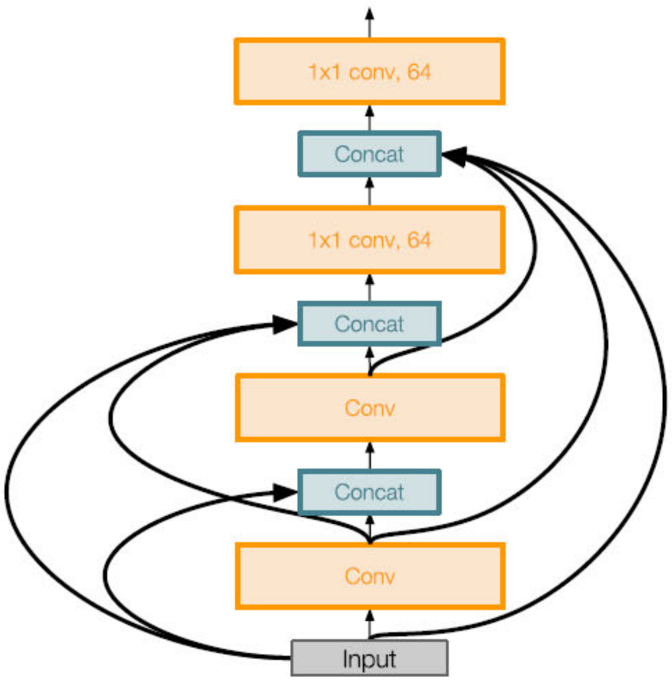
شبکه‌های کانوولوشنال متصل متراکم

Beyond ResNets...

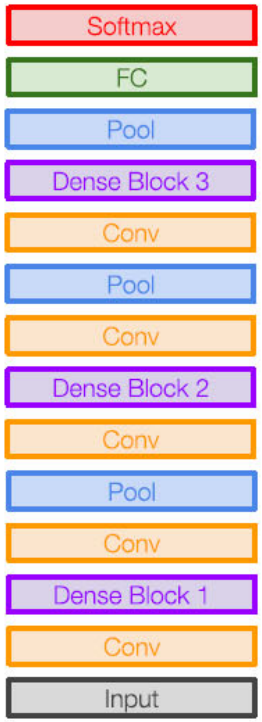
Densely Connected Convolutional Networks

[Huang et al. 2017]

- Dense blocks where each layer is connected to every other layer in feedforward fashion
- Alleviates vanishing gradient, strengthens feature propagation, encourages feature reuse



Dense Block



Ref: http://cs231n.stanford.edu/

Efficient networks...

SqueezeNet: AlexNet-level Accuracy With 50x Fewer Parameters and <0.5Mb Model Size

[Iandola et al. 2017]

- Fire modules consisting of a ‘squeeze’ layer with 1x1 filters feeding an ‘expand’ layer with 1x1 and 3x3 filters
- AlexNet level accuracy on ImageNet with 50x fewer parameters
- Can compress to 510x smaller than AlexNet (0.5Mb)

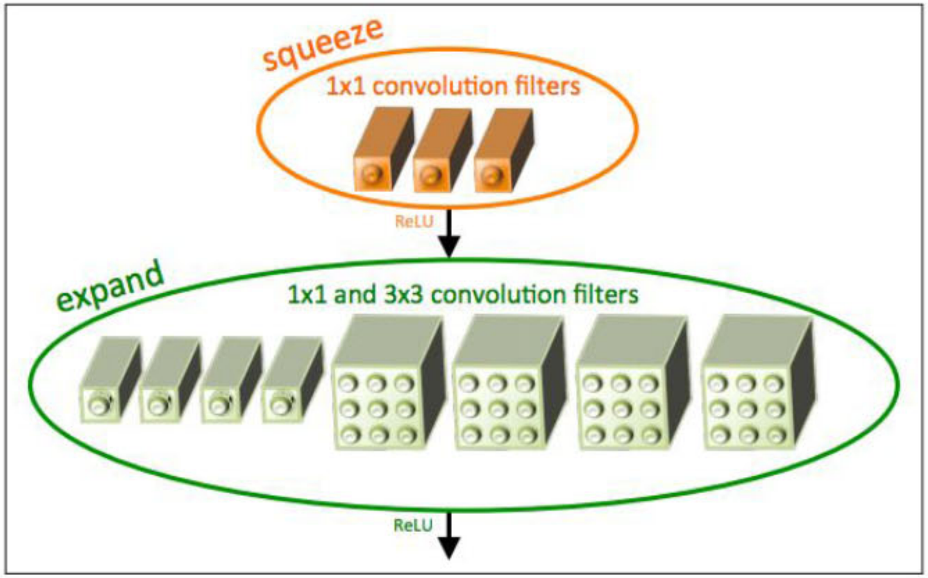


Figure copyright Iandola, Han, Moskewicz, Ashraf, Dally, Keutzer, 2017. Reproduced with permission.

فرا–یادگیری

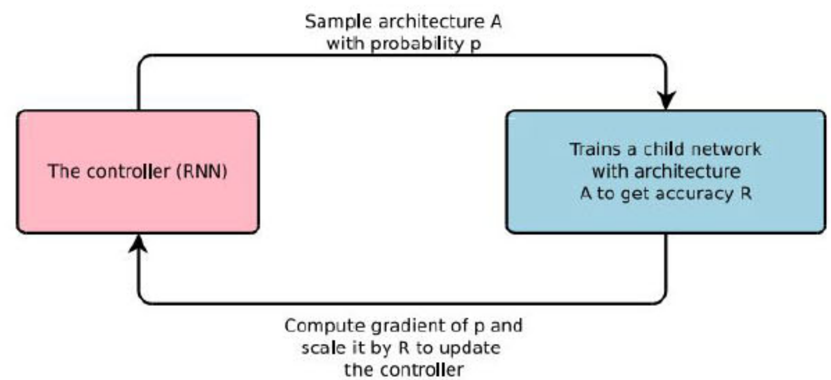
یادگرفتن یادگیری معماری‌های شبکه : جستجوی معماری عصبی با یادگیری تقویتی (NAS)

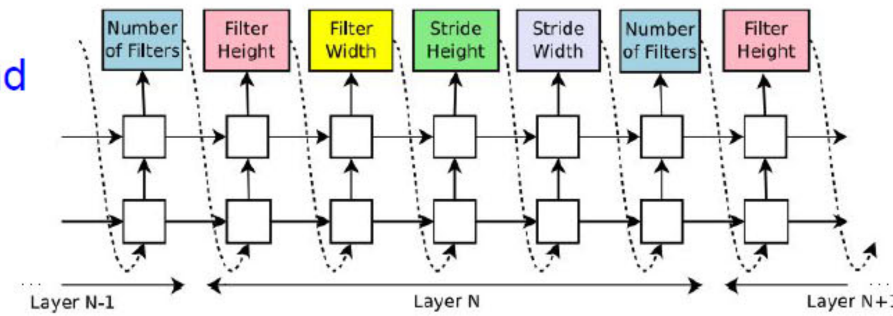
Meta-learning: Learning to learn network architectures...

Neural Architecture Search with Reinforcement Learning (NAS)

[Zoph et al. 2016]

- "Controller" network that learns to design a good network architecture (output a string corresponding to network design)
- Iterate:
  1) Sample an architecture from search space
  2) Train the architecture to get a "reward" R corresponding to accuracy
  3) Compute gradient of sample probability, and scale by R to perform controller parameter update (i.e. increase likelihood of good architecture being sampled, decrease likelihood of bad architecture)





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فرا–یادگیری

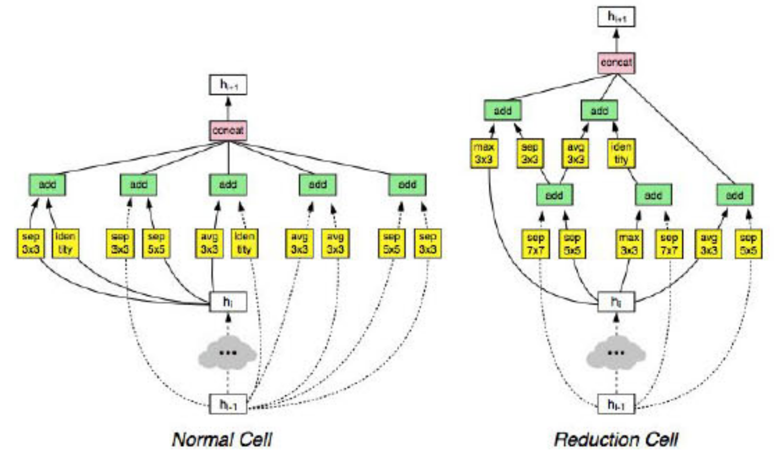
یادگرفتن یادگیری معماری‌های شبکه: یادگیری معماری‌های انتقال‌پذیر برای بازشناسی مقیاس‌پذیر تصاویر

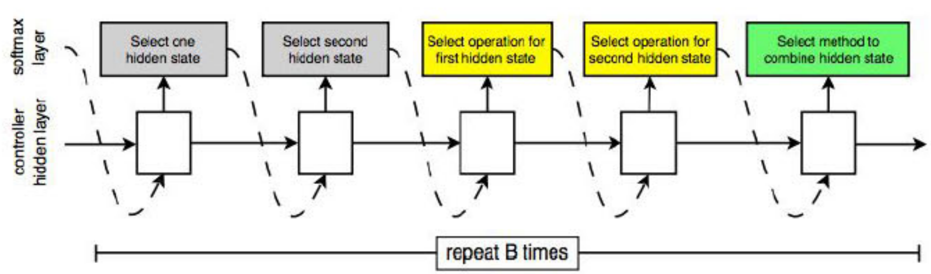
Meta-learning: Learning to learn network architectures...

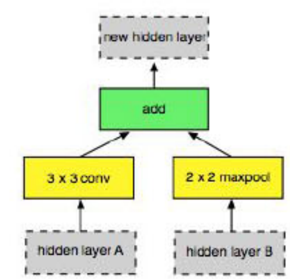
Learning Transferable Architectures for Scalable Image Recognition

[Zoph et al. 2017]

- Applying neural architecture search (NAS) to a large dataset like ImageNet is expensive
- Design a search space of building blocks ("cells") that can be flexibly stacked
- NASNet: Use NAS to find best cell structure on smaller CIFAR-10 dataset, then transfer architecture to ImageNet







Ref: http://cs231n.stanford.edu/

Summary: CNN Architectures

Case Studies

- AlexNet
- VGG
- GoogLeNet
- ResNet

Also....

- NiN (Network in Network)
- Wide ResNet
- ResNeXT
- Stochastic Depth
- Squeeze-and-Excitation Network
- DenseNet
- FractalNet
- SqueezeNet
- NASNet

Weights & Biases Documentation

Choose the product for which you need documentation.

W&B Weave

Use AI models in your app

Use W&B Weave to manage AI models in your code. Features include tracing, output evaluation, cost estimates, and a playground for comparing different large language models (LLMs) and settings.

- Introduction
- Quickstart
- YouTube Demo
- Try the Playground (Free sign up required)

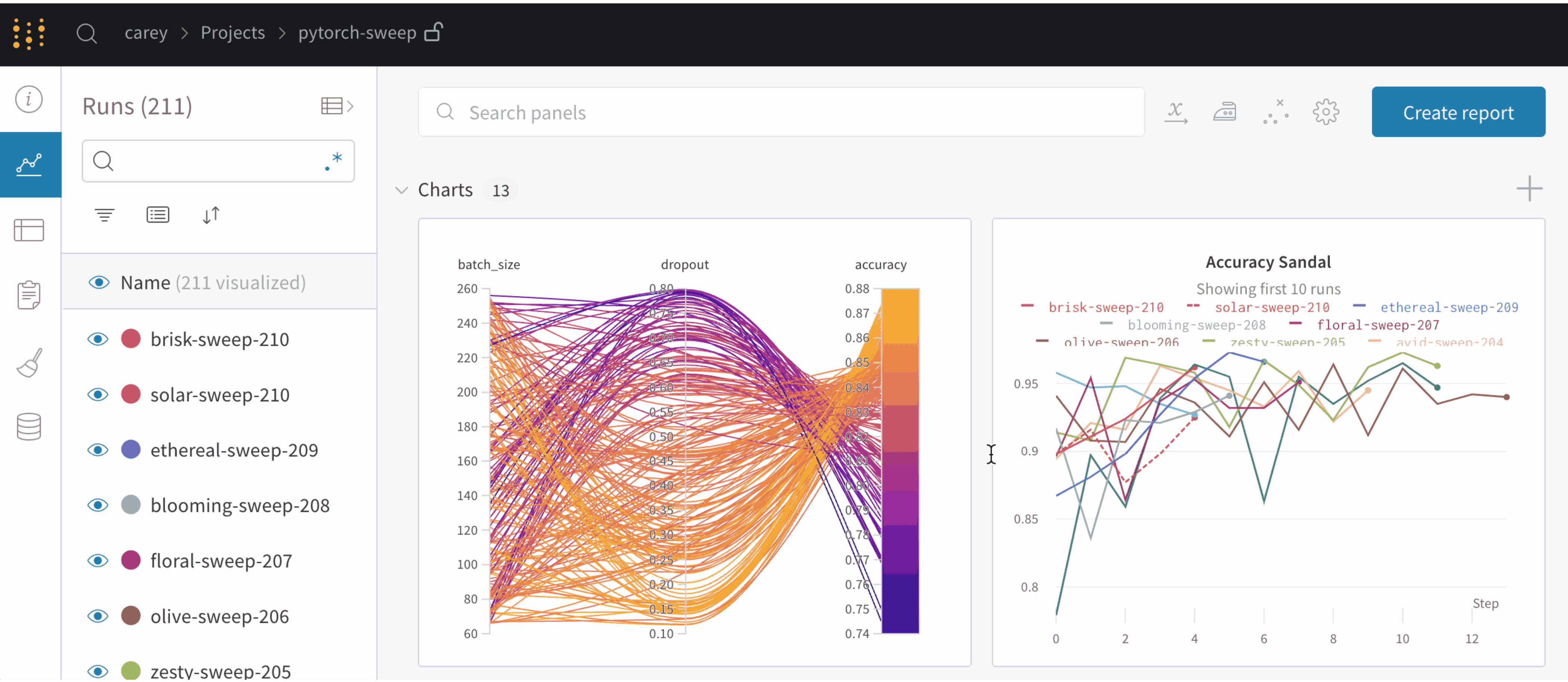
W&B Models

Develop AI models

Use W&B Models to manage AI model development. Features include training, fine-tuning, reporting, automating hyperparameter sweeps, and utilizing the model registry for versioning and reproducibility.

- Introduction
- Quickstart
- YouTube Tutorial
- Online Course

https://docs.wandb.ai/



https://docs.wandb.ai/guides/track/workspaces/

معماری‌های شبکه‌های عصبی کانوولوشنال

جمع‌بندی

- VGG, GoogLeNet, ResNet all in wide use, available in model zoos
- ResNet current best default, also consider SENet when available
- Trend towards **extremely deep** networks
- Significant research centers around **design of layer / skip connections** and **improving gradient flow**
- Efforts to investigate necessity of depth vs. width and residual connections
- Even more recent trend towards meta-learning

معماری‌های گوناگون
شبکه‌های عصبی کانوولوشنال

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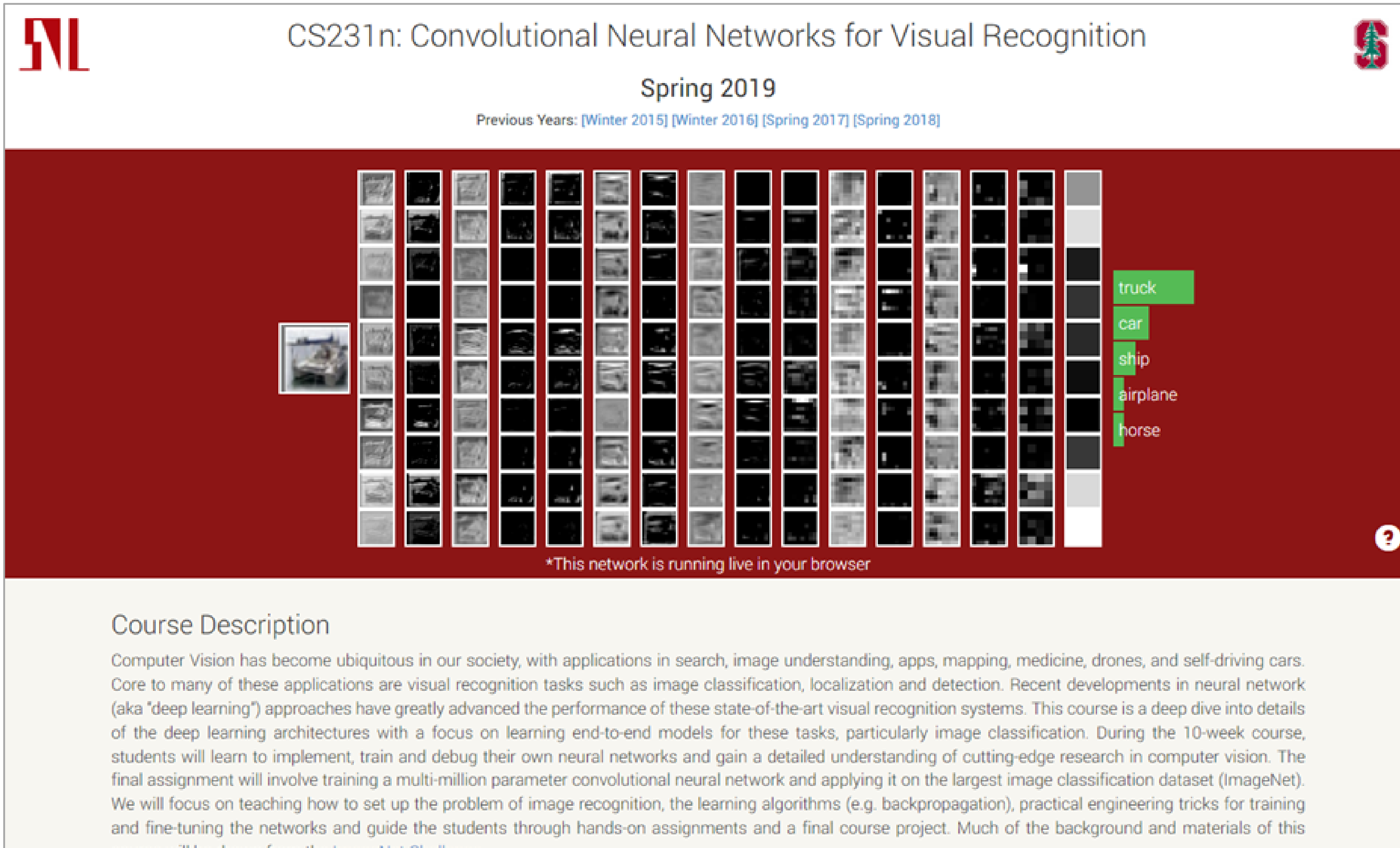
منابع

منبع اصلی



http://cs231n.stanford.edu

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