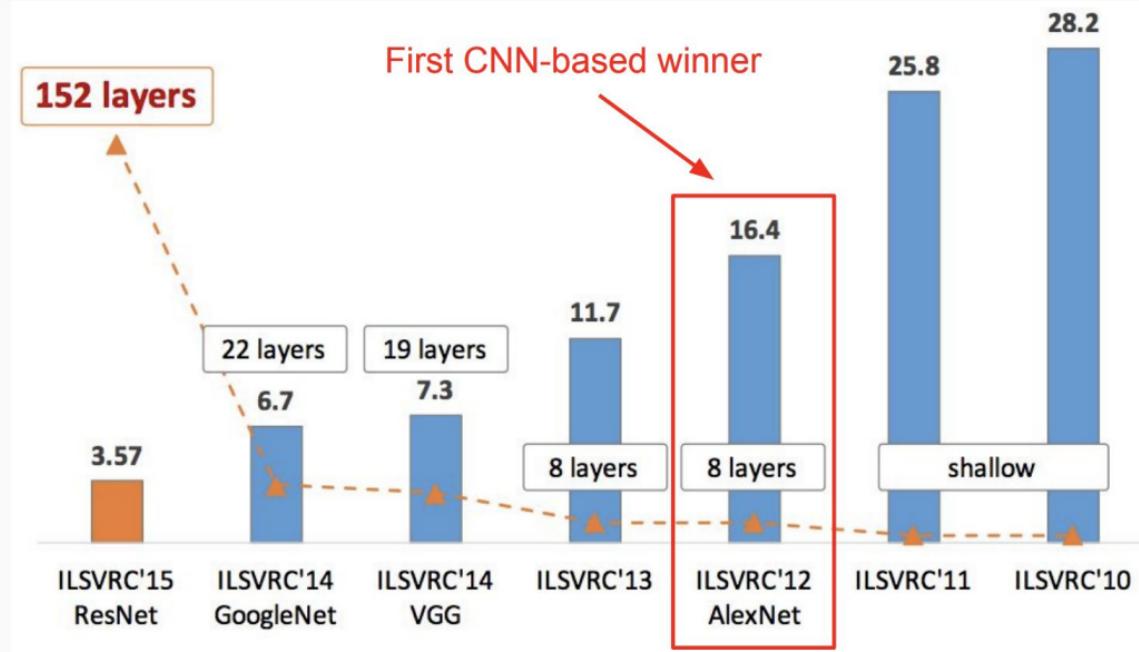

Popular CNN architectures and regularization methods

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Topics to cover today

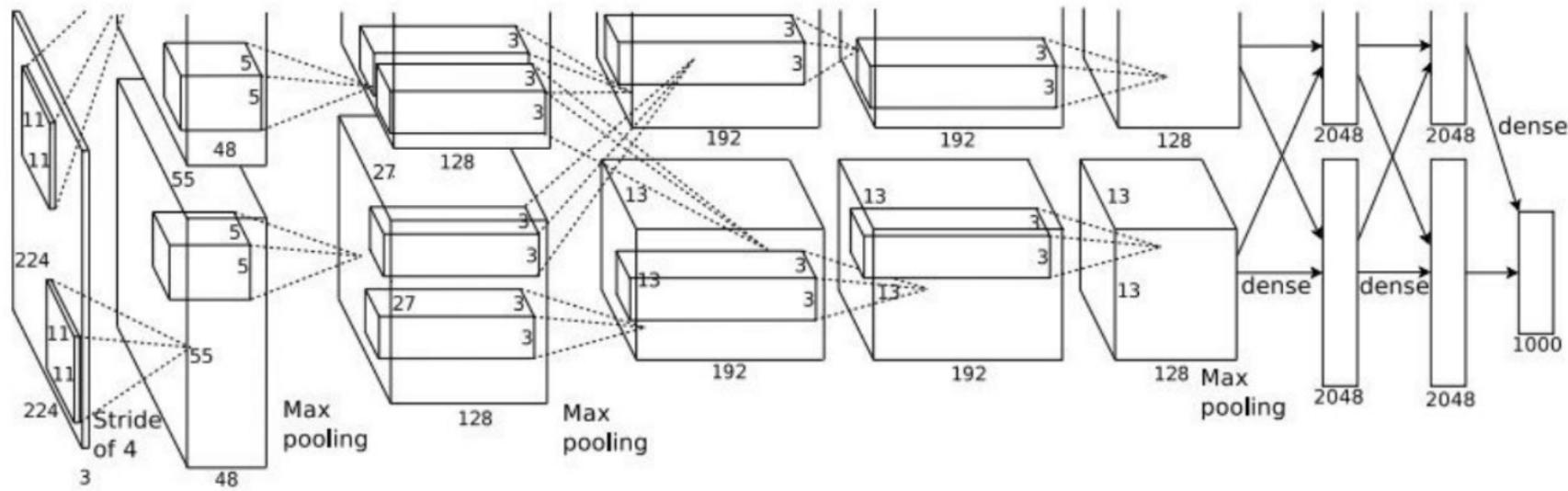
- Popular CNN architectures: AlexNet, ZFNet, VGGNet, GoogLeNet, ResNet
- Data augmentation
- Dropout

ImageNet challenge



AlexNet

Architecture overview



AlexNet

Architecture overview

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

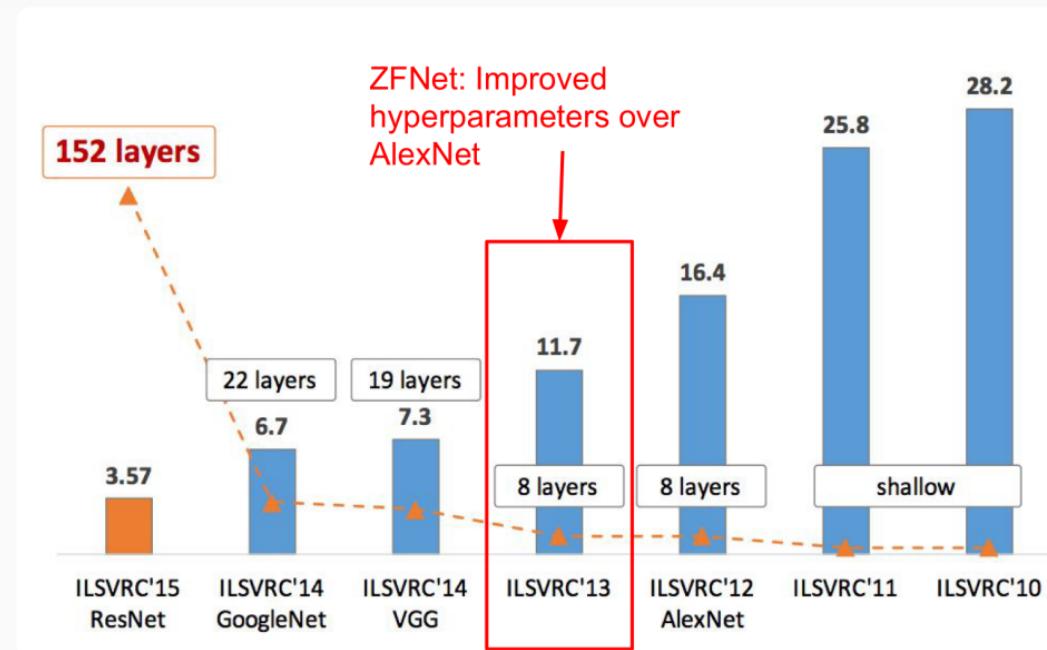
[6x6x256] MAX POOL3: 3x3 filters at stride 2

[4096] FC6: 4096 neurons

[4096] FC7: 4096 neurons

[1000] FC8: 1000 neurons (class scores)

ZFNet



ZFNet

Architecture overview

Similar to AlexNet except:

CONV1: change from (11x11 stride 4) to (7x7 stride 2)

CONV3,4,5: instead of 384, 384, 256 filters use 512, 1024, 512

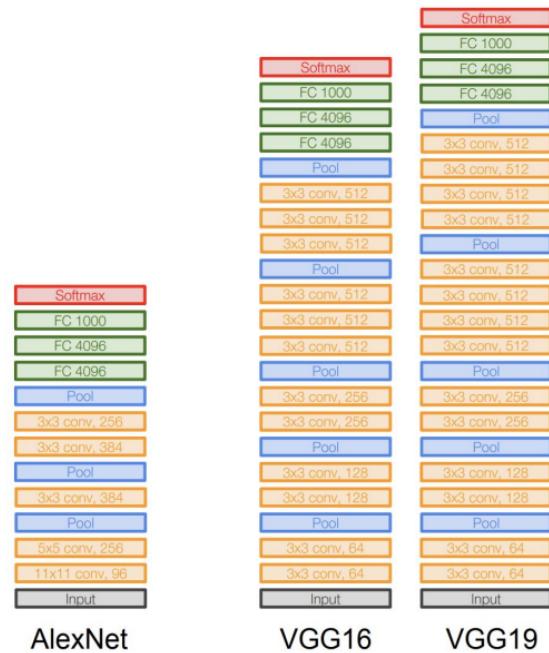
VGGNet

Architecture overview

- Small filters, Deeper networks
- Only 3x3 CONV stride 1, pad 1, 2x2 MAX POOL stride 2

Advantages of using smaller filters

- Stack of three 3x3 conv (stride 1) layers has same effective receptive field as one 7x7 conv layer.
- Deeper and more non-linearities.
- Fewer parameters



VGGNet

Architecture overview

INPUT: [224x224x3] memory: $224 \times 224 \times 3 = 150K$ params: 0 (not counting biases)

CONV3-64: [224x224x64] memory: $224 \times 224 \times 64 = 3.2M$ params: $(3 \times 3 \times 3) \times 64 = 1,728$

CONV3-64: [224x224x64] memory: $224 \times 224 \times 64 = 3.2M$ params: $(3 \times 3 \times 64) \times 64 = 36,864$

POOL2: [112x112x64] memory: $112 \times 112 \times 64 = 800K$ params: 0

CONV3-128: [112x112x128] memory: $112 \times 112 \times 128 = 1.6M$ params: $(3 \times 3 \times 64) \times 128 = 73,728$

CONV3-128: [112x112x128] memory: $112 \times 112 \times 128 = 1.6M$ params: $(3 \times 3 \times 128) \times 128 = 147,456$

POOL2: [56x56x128] memory: $56 \times 56 \times 128 = 400K$ params: 0

CONV3-256: [56x56x256] memory: $56 \times 56 \times 256 = 800K$ params: $(3 \times 3 \times 128) \times 256 = 294,912$

CONV3-256: [56x56x256] memory: $56 \times 56 \times 256 = 800K$ params: $(3 \times 3 \times 256) \times 256 = 589,824$

CONV3-256: [56x56x256] memory: $56 \times 56 \times 256 = 800K$ params: $(3 \times 3 \times 256) \times 256 = 589,824$

POOL2: [28x28x256] memory: $28 \times 28 \times 256 = 200K$ params: 0

CONV3-512: [28x28x512] memory: $28 \times 28 \times 512 = 400K$ params: $(3 \times 3 \times 256) \times 512 = 1,179,648$

CONV3-512: [28x28x512] memory: $28 \times 28 \times 512 = 400K$ params: $(3 \times 3 \times 512) \times 512 = 2,359,296$

CONV3-512: [28x28x512] memory: $28 \times 28 \times 512 = 400K$ params: $(3 \times 3 \times 512) \times 512 = 2,359,296$

POOL2: [14x14x512] memory: $14 \times 14 \times 512 = 100K$ params: 0

CONV3-512: [14x14x512] memory: $14 \times 14 \times 512 = 100K$ params: $(3 \times 3 \times 512) \times 512 = 2,359,296$

CONV3-512: [14x14x512] memory: $14 \times 14 \times 512 = 100K$ params: $(3 \times 3 \times 512) \times 512 = 2,359,296$

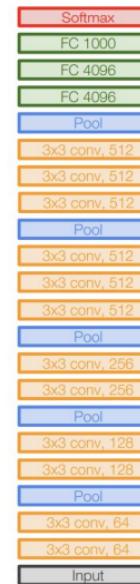
CONV3-512: [14x14x512] memory: $14 \times 14 \times 512 = 100K$ params: $(3 \times 3 \times 512) \times 512 = 2,359,296$

POOL2: [7x7x512] memory: $7 \times 7 \times 512 = 25K$ params: 0

FC: [1x1x4096] memory: 4096 params: $7 \times 7 \times 512 \times 4096 = 102,760,448$

FC: [1x1x4096] memory: 4096 params: $4096 \times 4096 = 16,777,216$

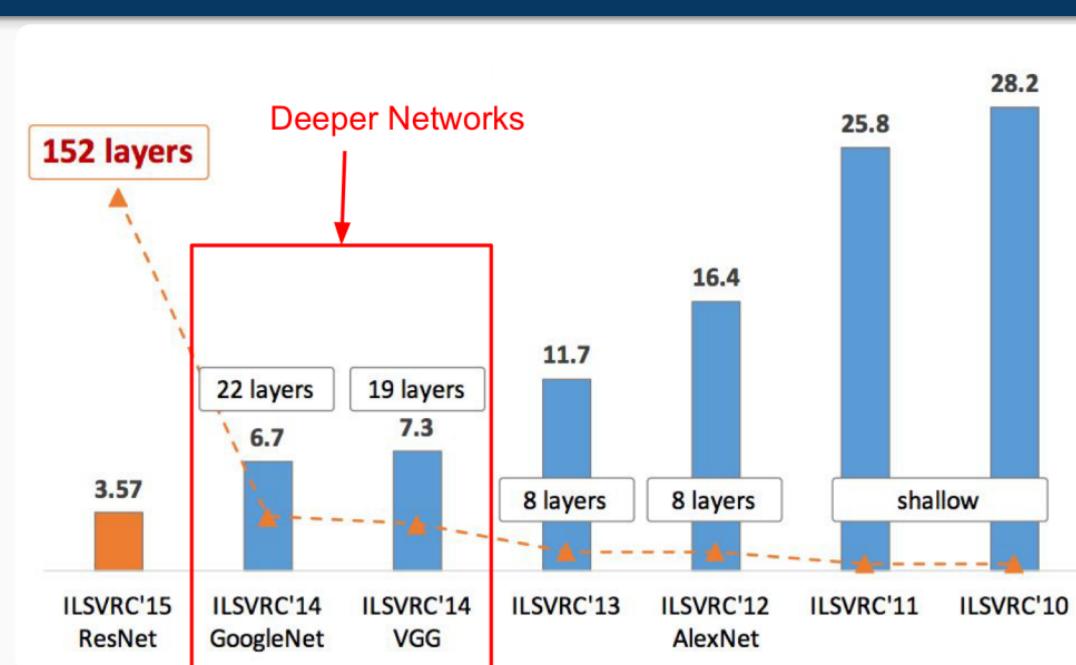
FC: [1x1x1000] memory: 1000 params: $4096 \times 1000 = 4,096,000$



Total parameters: 138M

VGG16

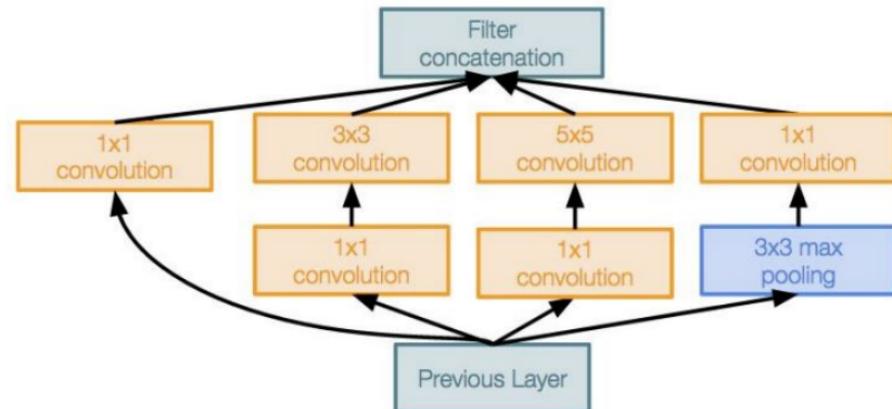
GoogLeNet



GoogLeNet

Architecture overview

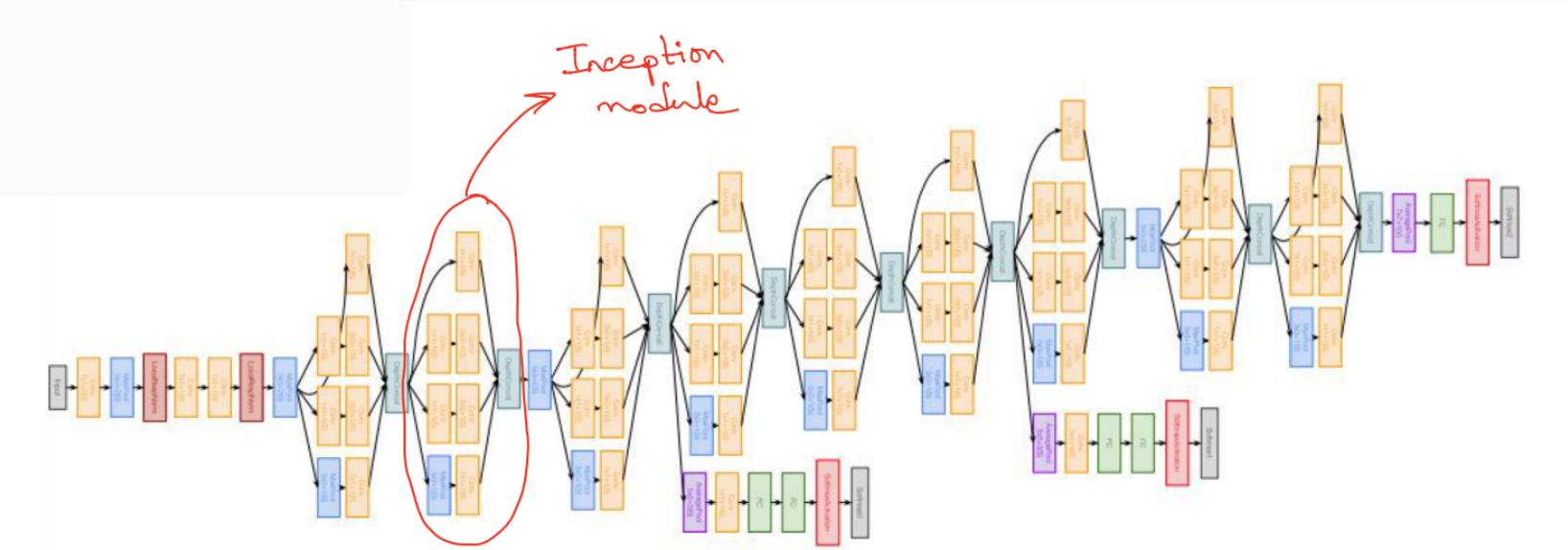
- 22 layers
- Efficient “Inception” module - No FC layers
- Only 5 million parameters! (12x less than AlexNet)



Inception module

GoogLeNet

Architecture overview

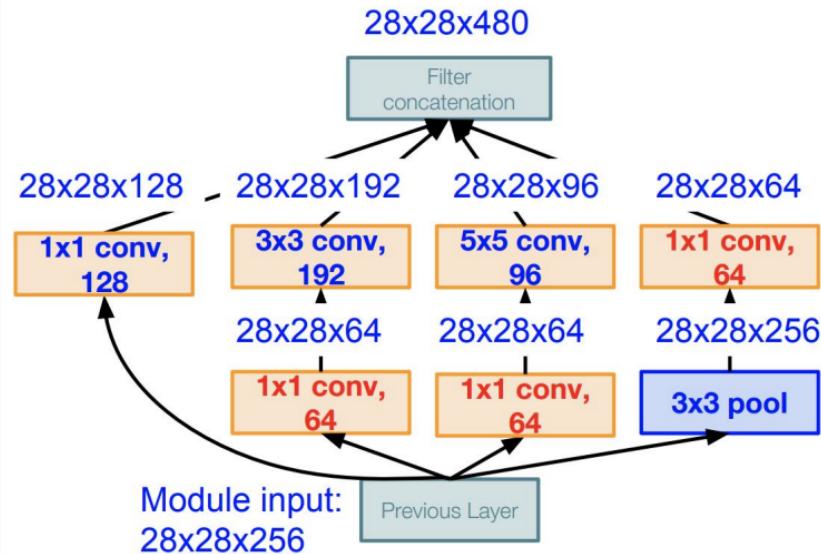


GoogLeNet

Inception module details

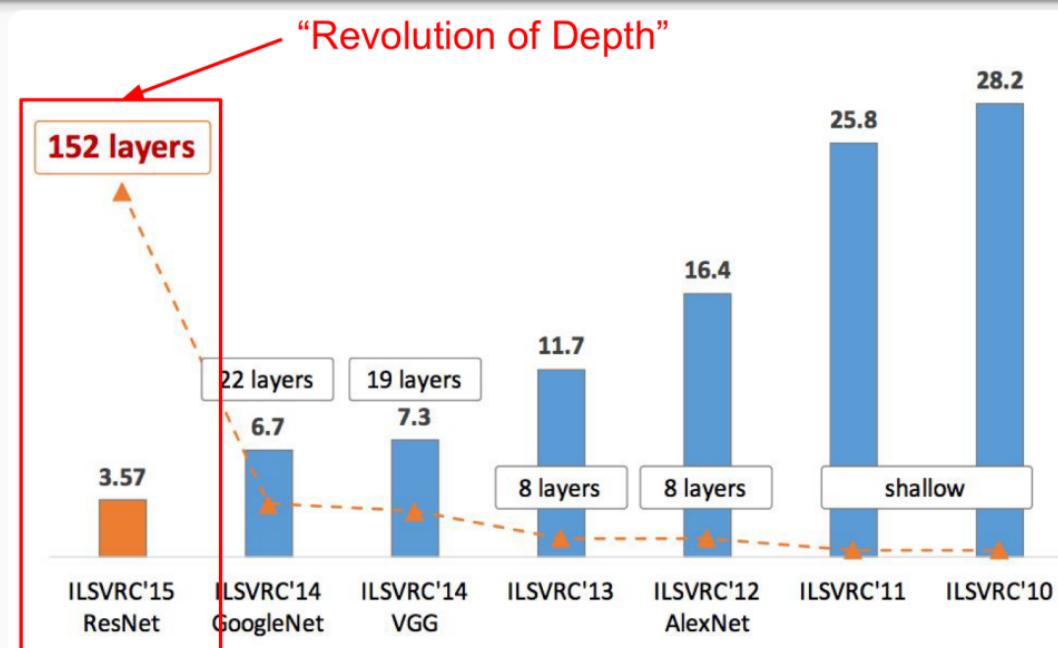
Key idea of Inception module:

Apply parallel filter operations on the input from previous layer



ResNet

Architecture overview

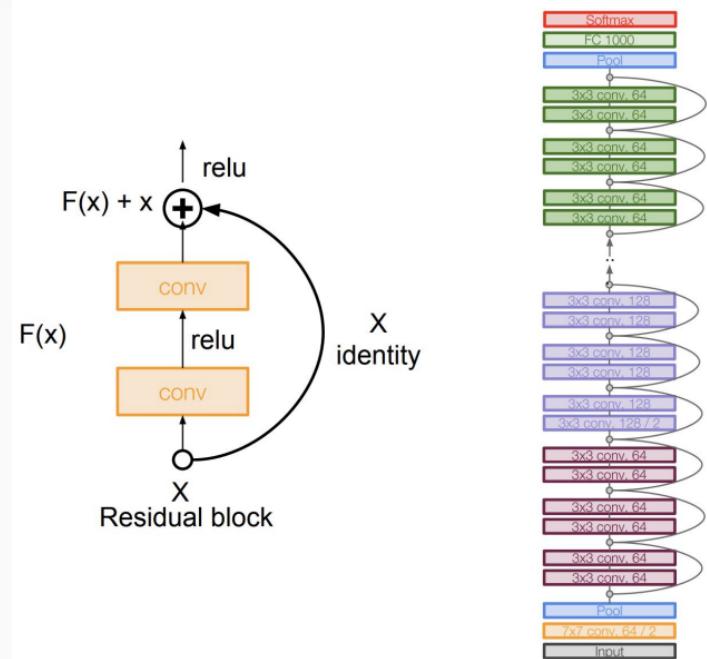


ResNet

Architecture overview

Very deep networks using **residual connections**

- 152-layer model for ImageNet
- 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
- No FC layers at the end (only FC 1000 to output classes)



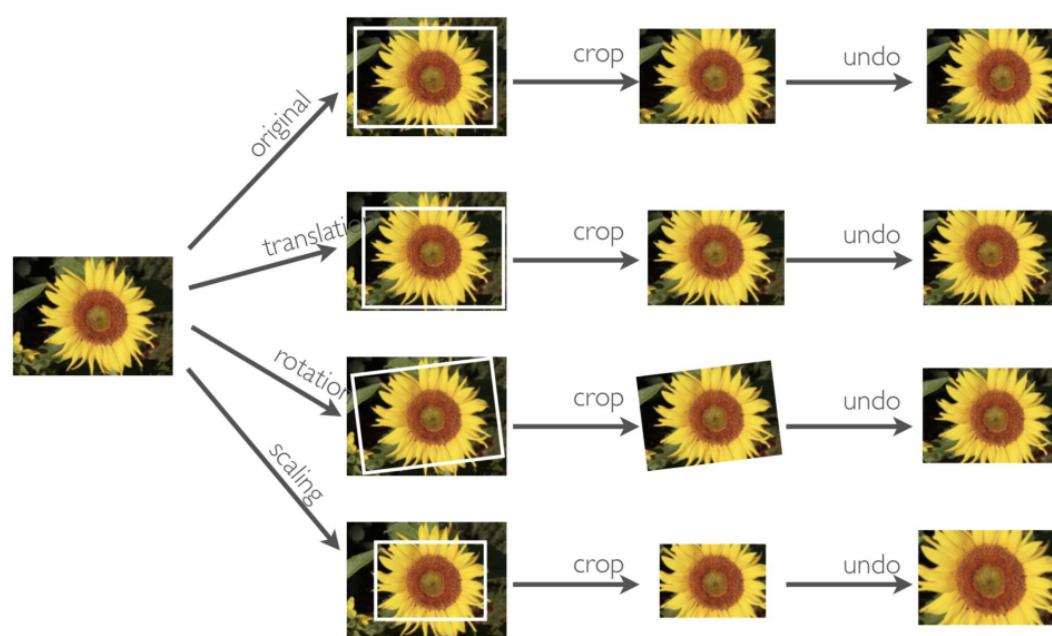
Regularization methods

When we see signs of overfitting, we can chose to take some of the following steps:

- Increase the training dataset size
 - Collect more training data
 - **Artificially generate more data points**
- Decrease the model capacity
 - By decreasing the number of parameters
 - **By employing explicit regularization methods -- L2, dropout**

Data augmentation

Generating additional training data



Dropout

Regularization by randomly dropping some neurons

Recipe:

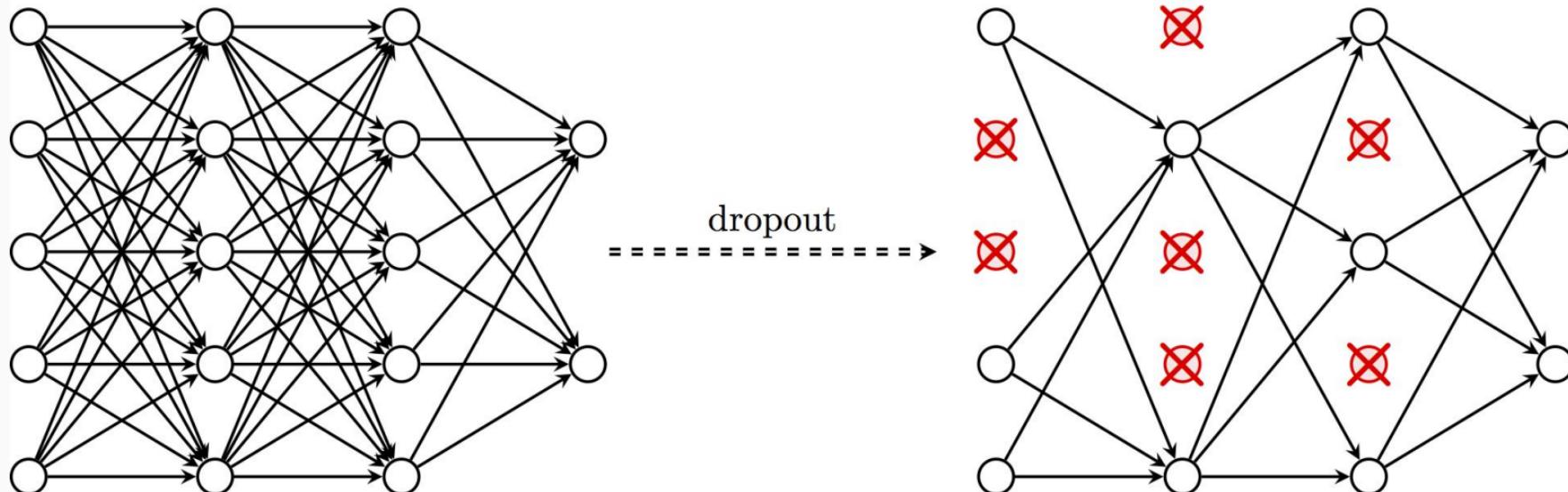
- Each time we present data example x , randomly delete each hidden node with a probability of p .
- At test time, **multiply each weight by p** .

Effect 1: Reduce overfitting by preventing co-adaptation

Effect 2: Ensemble of many models

Dropout

Regularization by randomly dropping some neurons



Dropout

Interpretations as ensemble of models

