
Deep Learning 과정

# CNN

Gunhee Kim

Computer Science and Engineering


서 울 대 학 교

SEOUL NATIONAL UNIVERSITY

# Outline

- Filters and Convolution
- Convolutional Neural network
- Training Tips
- Parameter Updates
- Case Studies

(Credits: Stanford CS231n Lecture Notes)

# Filters in Images

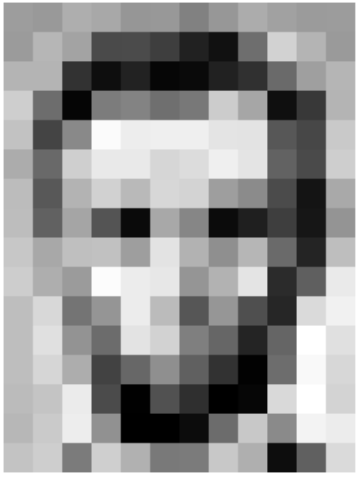
It is a basic tool for image processing

- Transform images, or extract meaningful information from digital images via algorithms using computers

Digital image as a function

$$f: \mathbb{R}^2 \longrightarrow \mathbb{R}$$

- $f(x, y)$ gives the intensity [0,255] at position $(x, y)$



| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 157 | 153 | 174 | 168 | 150 | 152 | 129 | 151 | 172 | 161 | 155 | 156 |
| 155 | 182 | 163 | 74 | 75 | 62 | 33 | 17 | 110 | 210 | 180 | 154 |
| 180 | 180 | 50 | 14 | 34 | 6 | 10 | 33 | 48 | 106 | 159 | 181 |
| 206 | 109 | 5 | 124 | 131 | 111 | 120 | 204 | 166 | 15 | 56 | 180 |
| 194 | 68 | 137 | 251 | 237 | 239 | 239 | 228 | 227 | 87 | 71 | 201 |
| 172 | 105 | 207 | 233 | 233 | 214 | 220 | 239 | 228 | 98 | 74 | 206 |
| 188 | 88 | 179 | 209 | 185 | 215 | 211 | 158 | 139 | 75 | 20 | 169 |
| 189 | 97 | 165 | 84 | 10 | 168 | 134 | 11 | 31 | 62 | 22 | 148 |
| 199 | 168 | 191 | 193 | 158 | 227 | 178 | 143 | 182 | 106 | 36 | 190 |
| 205 | 174 | 155 | 252 | 236 | 231 | 149 | 178 | 228 | 43 | 95 | 234 |
| 190 | 216 | 116 | 149 | 236 | 187 | 86 | 150 | 79 | 38 | 218 | 241 |
| 190 | 224 | 147 | 108 | 227 | 210 | 127 | 102 | 36 | 101 | 255 | 224 |
| 190 | 214 | 173 | 66 | 103 | 143 | 96 | 50 | 2 | 109 | 249 | 215 |
| 187 | 196 | 235 | 75 | 1 | 81 | 47 | 0 | 6 | 217 | 255 | 211 |
| 183 | 202 | 237 | 145 | 0 | 0 | 12 | 108 | 200 | 138 | 243 | 236 |
| 195 | 206 | 123 | 207 | 177 | 121 | 123 | 200 | 175 | 13 | 96 | 218 |


| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 157 | 153 | 174 | 168 | 150 | 152 | 129 | 151 | 172 | 161 | 155 | 156 |
| 155 | 182 | 163 | 74 | 75 | 62 | 33 | 17 | 110 | 210 | 180 | 154 |
| 180 | 180 | 50 | 14 | 34 | 6 | 10 | 33 | 48 | 106 | 159 | 181 |
| 206 | 109 | 5 | 124 | 131 | 111 | 120 | 204 | 166 | 15 | 56 | 180 |
| 194 | 68 | 137 | 251 | 237 | 239 | 239 | 228 | 227 | 87 | 71 | 201 |
| 172 | 105 | 207 | 233 | 233 | 214 | 220 | 239 | 228 | 98 | 74 | 206 |
| 188 | 88 | 179 | 209 | 185 | 215 | 211 | 158 | 139 | 75 | 20 | 169 |
| 189 | 97 | 165 | 84 | 10 | 168 | 134 | 11 | 31 | 62 | 22 | 148 |
| 199 | 168 | 191 | 193 | 158 | 227 | 178 | 143 | 182 | 106 | 36 | 190 |
| 205 | 174 | 155 | 252 | 236 | 231 | 149 | 178 | 228 | 43 | 95 | 234 |
| 190 | 216 | 116 | 149 | 236 | 187 | 86 | 150 | 79 | 38 | 218 | 241 |
| 190 | 224 | 147 | 108 | 227 | 210 | 127 | 102 | 36 | 101 | 255 | 224 |
| 190 | 214 | 173 | 66 | 103 | 143 | 96 | 50 | 2 | 109 | 249 | 215 |
| 187 | 196 | 235 | 75 | 1 | 81 | 47 | 0 | 6 | 217 | 255 | 211 |
| 183 | 202 | 237 | 145 | 0 | 0 | 12 | 108 | 200 | 138 | 243 | 236 |
| 195 | 206 | 123 | 207 | 177 | 121 | 123 | 200 | 175 | 13 | 96 | 218 |


cf. A color image is a function

$$f: \mathbb{R}^2 \longrightarrow \mathbb{R}^3$$

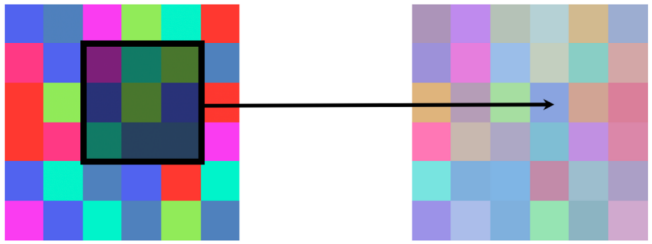
$$f(x, y) = \begin{bmatrix} r(x, y) \\ g(x, y) \\ b(x, y) \end{bmatrix}$$

# Filters in Images

Filters change the pixel value of images

- Apply a function to digital image
- Modify image properties and/or to extract valuable information
- ex. Noise reduction, blurring, sharpening, edge detection, ….

Neighborhood operation



Convolution!

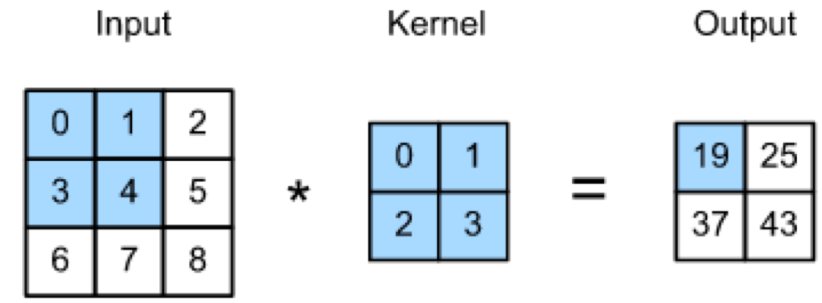
Image

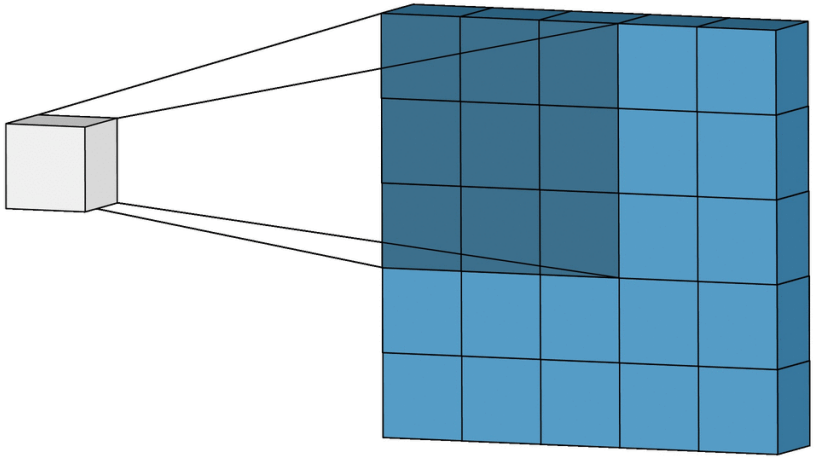
Edge detection

Blur

# Convolution

Multiply each kernel (filter) value by the corresponding pixel value

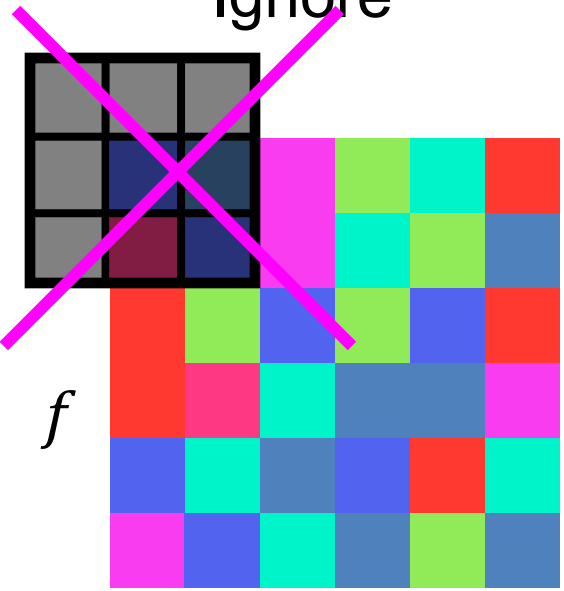


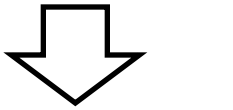
https://towardsdatascience.com/intuitively-understanding-convolutions-for-deep-learning-1f6f42faee1

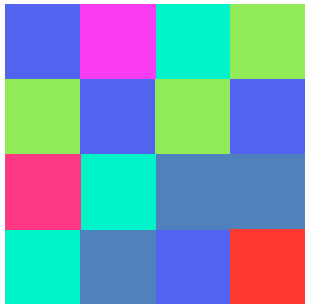
# Convolution – Border Problem

Ignore



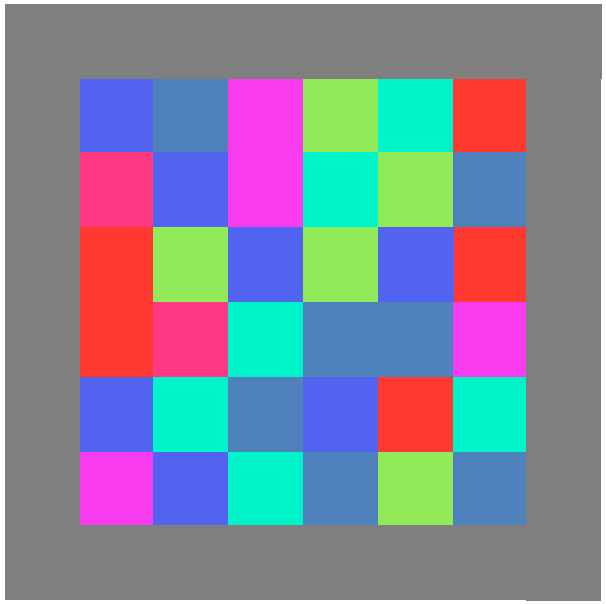
$f$





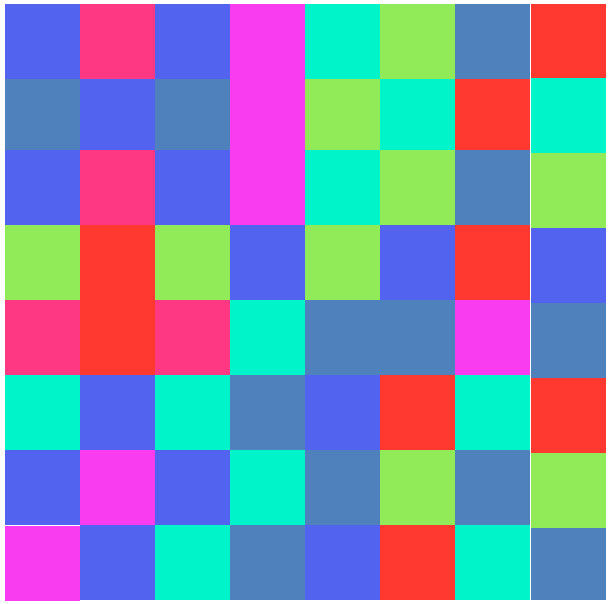
$g$

Pad with
constant values



EX) Pad with zeros

Pad with
reflection



# Convolution

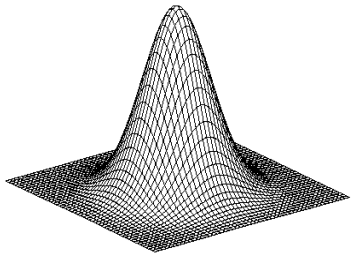
Image processing can be done by convolution with filters (kernels)

Image

| | | |
|---|---|---|
| -1 | 0 | 1 |
| -2 | 0 | 2 |
| -1 | 0 | 1 |

| | | |
|---|---|---|
| 1 | 2 | 1 |
| 0 | 0 | 0 |
| -1 | -2 | -1 |

Edge detection



1/273

| | | | | |
|---|---|---|---|---|
| 1 | 4 | 7 | 4 | 1 |
| 4 | 16 | 26 | 16 | 4 |
| 7 | 26 | 41 | 26 | 7 |
| 4 | 16 | 26 | 16 | 4 |
| 1 | 4 | 7 | 4 | 1 |

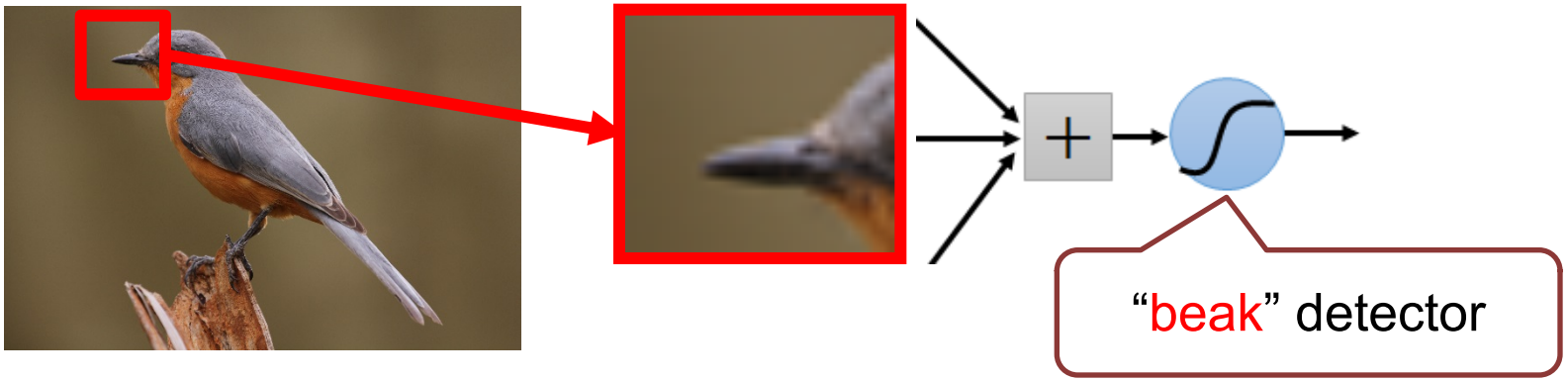
Blur

# Why Do CNNs Need Filters?

Some patterns for recognition are much smaller than the whole image

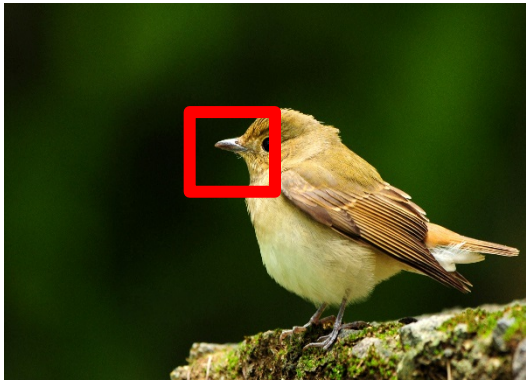
Also want to represent a small region with fewer parameters

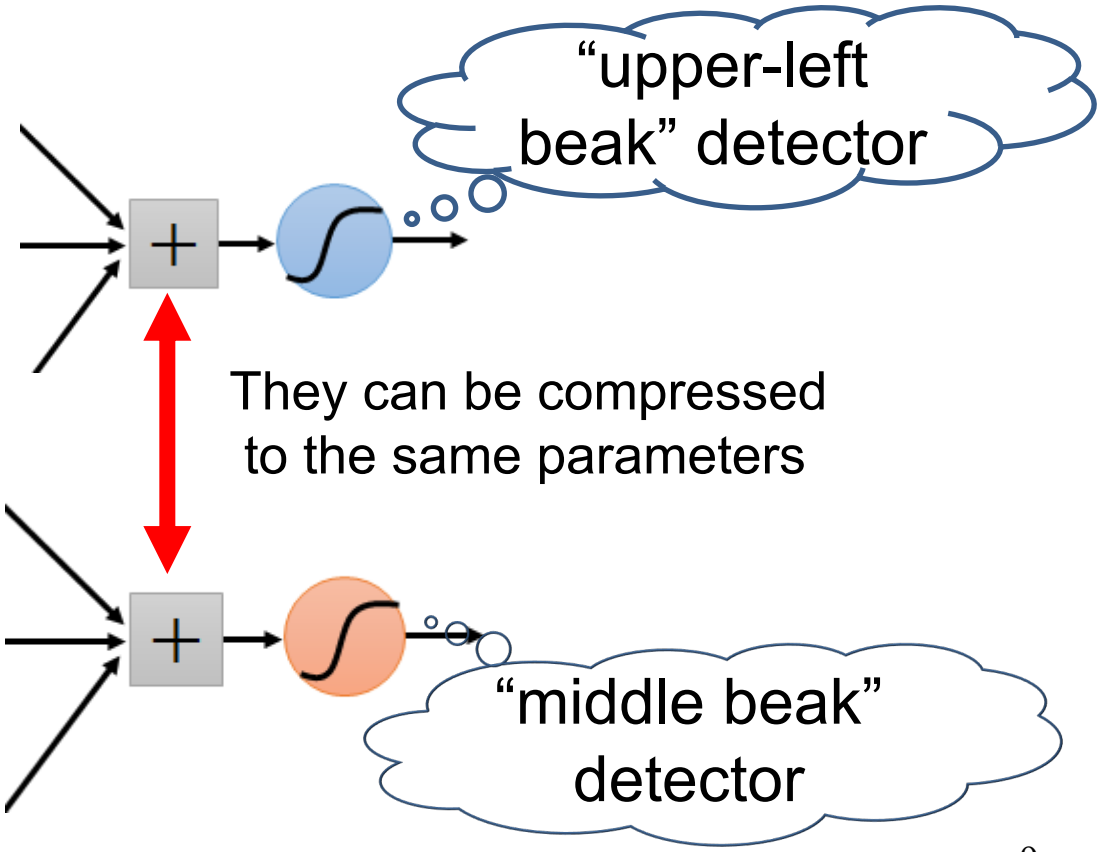
Beak detector is a filter in some upper layers of CNN!



# Why Do CNNs Need Filters?

What about training a lot of such **small** detectors and each detector must move around



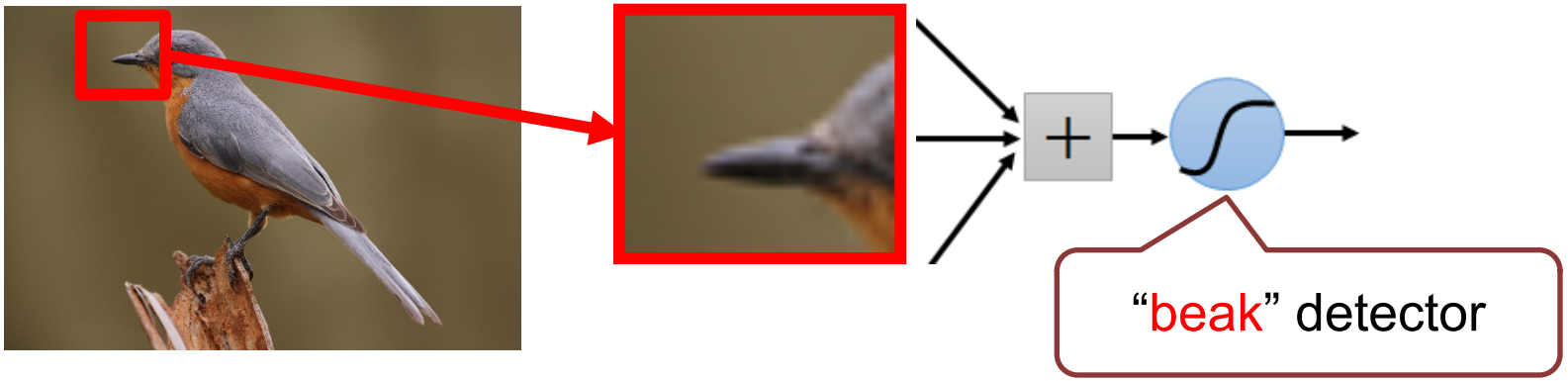


# Why Do CNN Need Filters?

However, we do not know which patterns are important to detect a bird beforehand

Let CNNs learn a set of filters!

- More correctly, a hierarchy of sets of filters



# Outline

- Convolutional Neural network
- Training Tips
- Parameter Updates
- Case Studies

(Credits: Stanford CS231n Lecture Notes)

# Convolutional Neural Network (ConvNet)

Some background knowledge

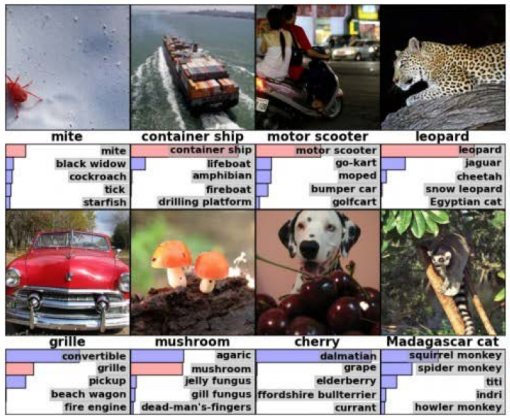
- Convolution of the image with filters
- Back propagation + gradient based optimization

A ConvNet consists of a number of convolutional + subsampling (i.e. pooling) + fully-connected layers

- In most cases, input is a 2D images and output is class labels

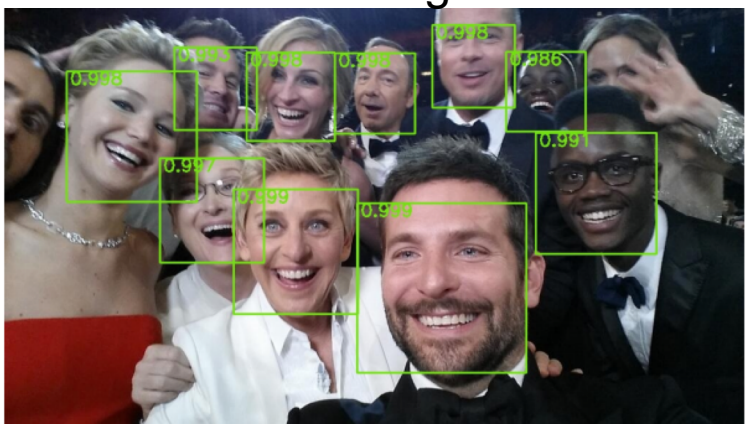
ConvNets are everywhere in computer vision

Classification



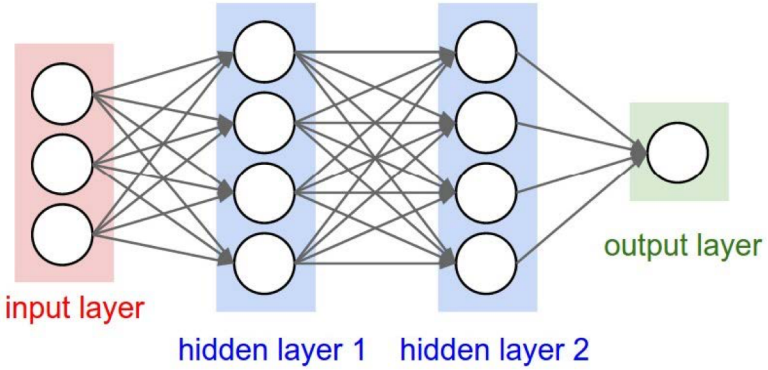

Retrieval

Face recognition

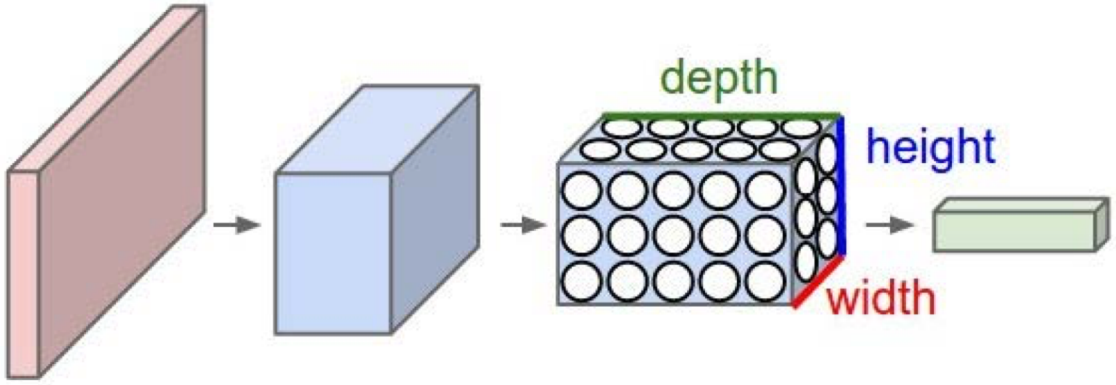


# ConvNet Representation

In previous multi-layer NN




Each layer of ConvNet is represented by 3D volume of neurons (width, height, depth)



# ConvNet Representation

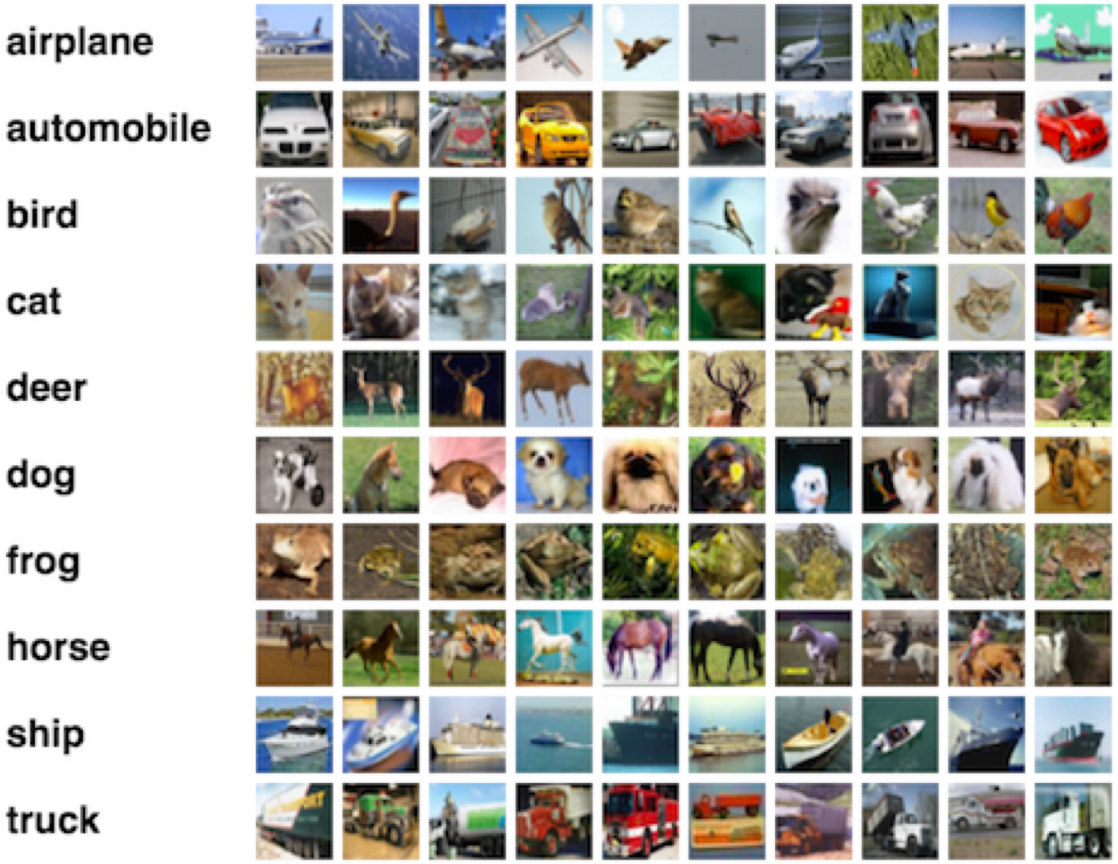
1. INPUT layer: Raw pixel values of the image
2. COV (Convolutional) layer: Output of neurons that are connected to local regions in the input
   - Computing a dot product between their weights and the region they are connected to in the input volume
3. Activation layer (RELU): Element-wise activation function
4. POOL layer: Downsampling (summation) operation
5. FC (Fully-connected) Layer: Computing class score

Parameters

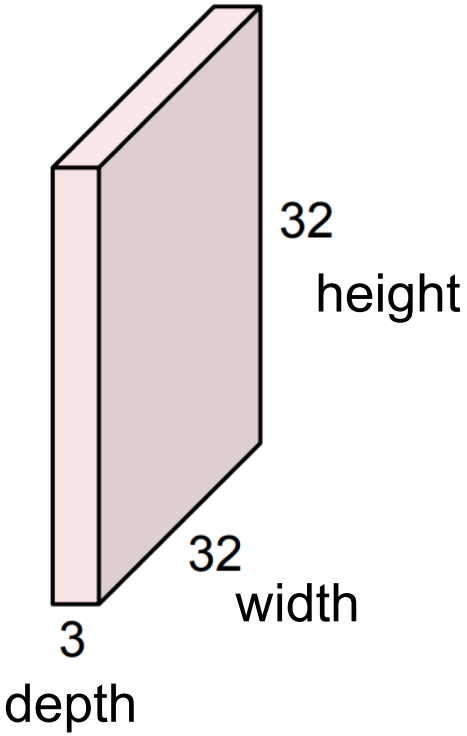
- CONV/FC have parameters (weights and bias of neurons)
- RELU/POOL have NO parameters

# Input Layer

Ex. CIFAR-10: Images of 10 classes with 32x32x3 (RGB)



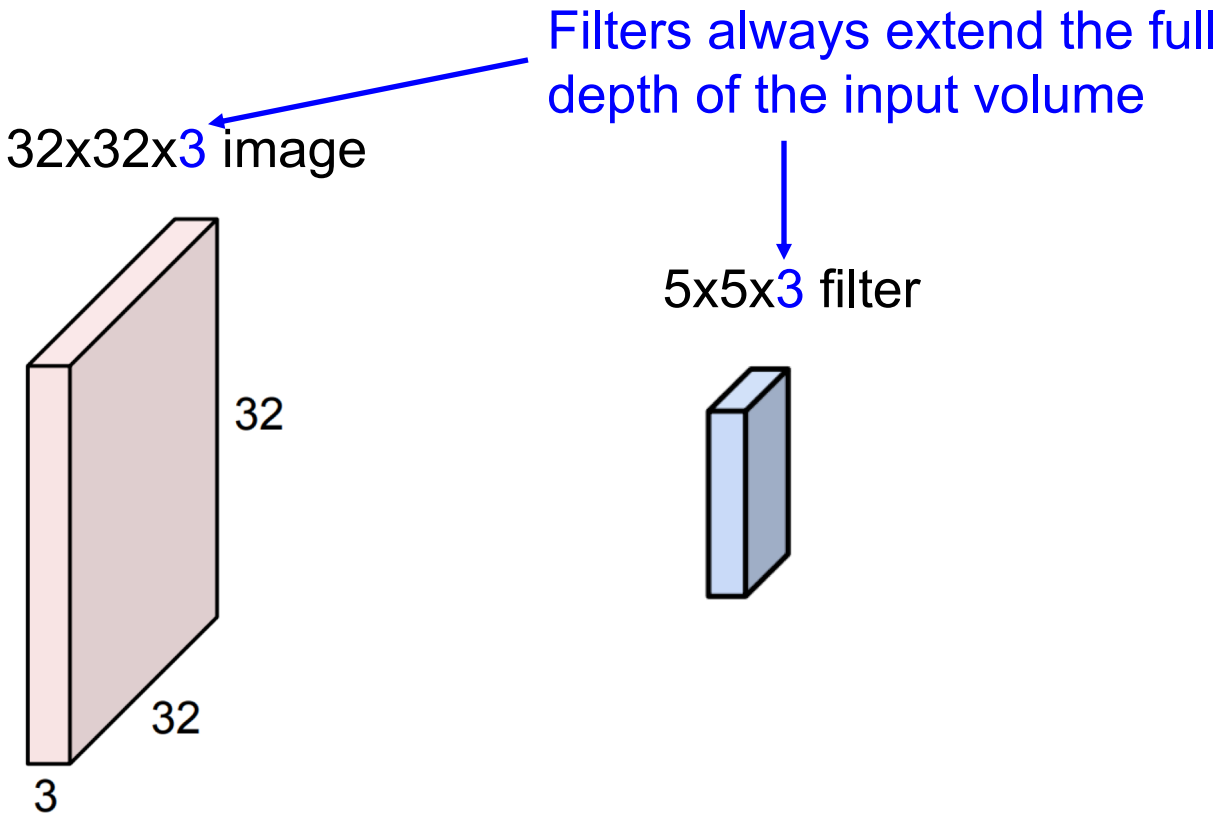

- Input layer (Raw pixels of an image)



# Convolutional Layer

Convolve the filter with the image

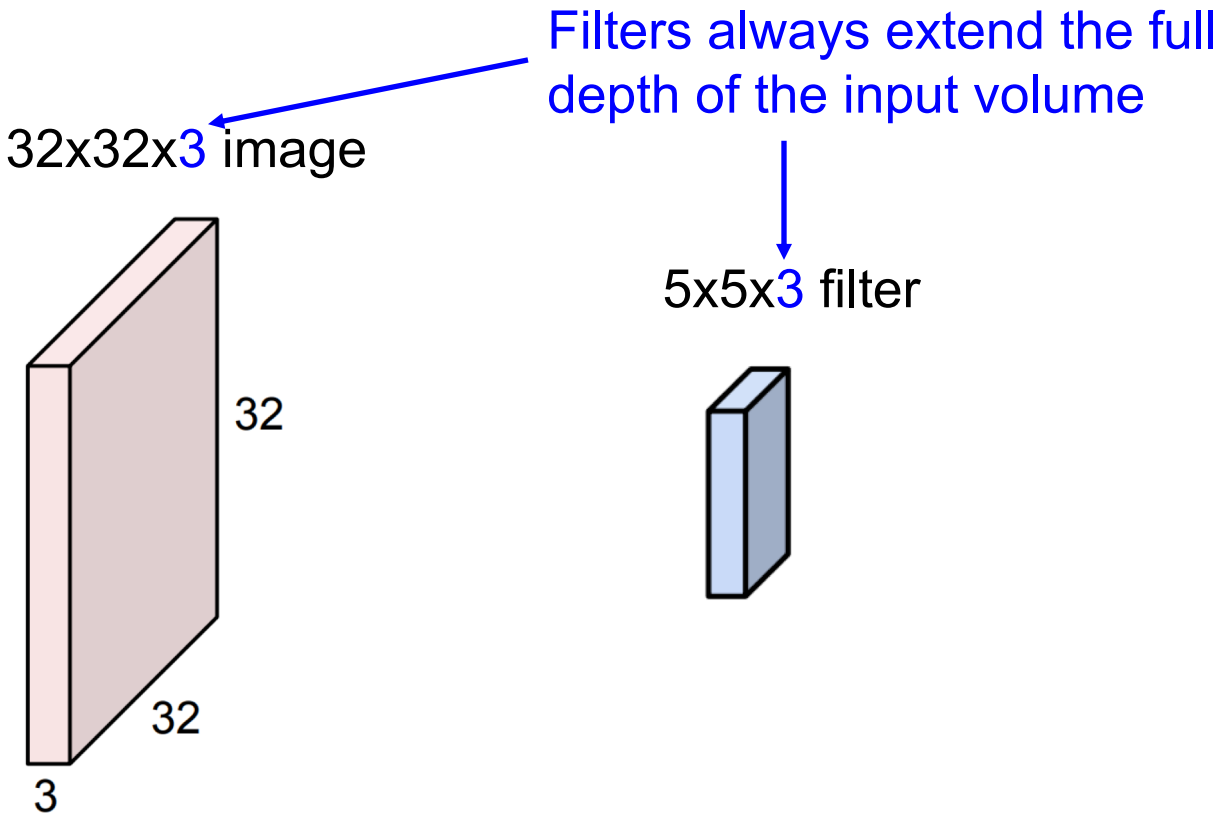
- Slide over the image spatially, computing dot products



# Convolutional Layer

Convolve the filter with the image

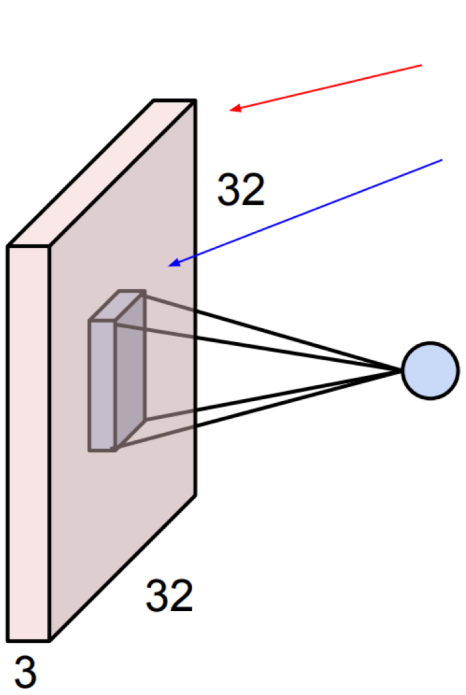
- Slide over the image spatially, computing dot products



# Convolutional Layer

Convolve the filter with the image

- Slide over the image spatially, computing dot products



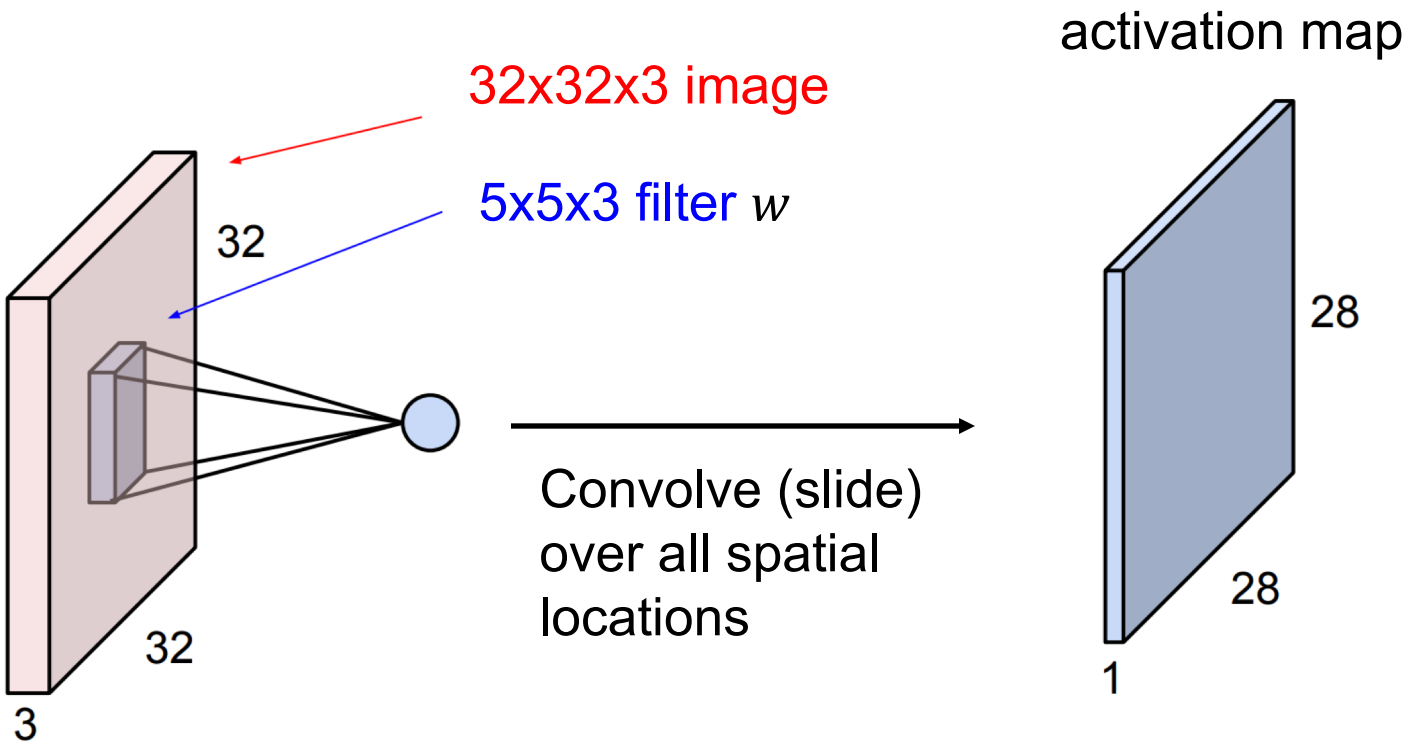

**1 number**:
the result of taking a dot product between the filter and a small 5x5x3 chunk of the image
(i.e. 5x5x3 = 75-dimensional dot product + bias)

$$w^T x + b$$

# Convolutional Layer

Convolve the filter with the image

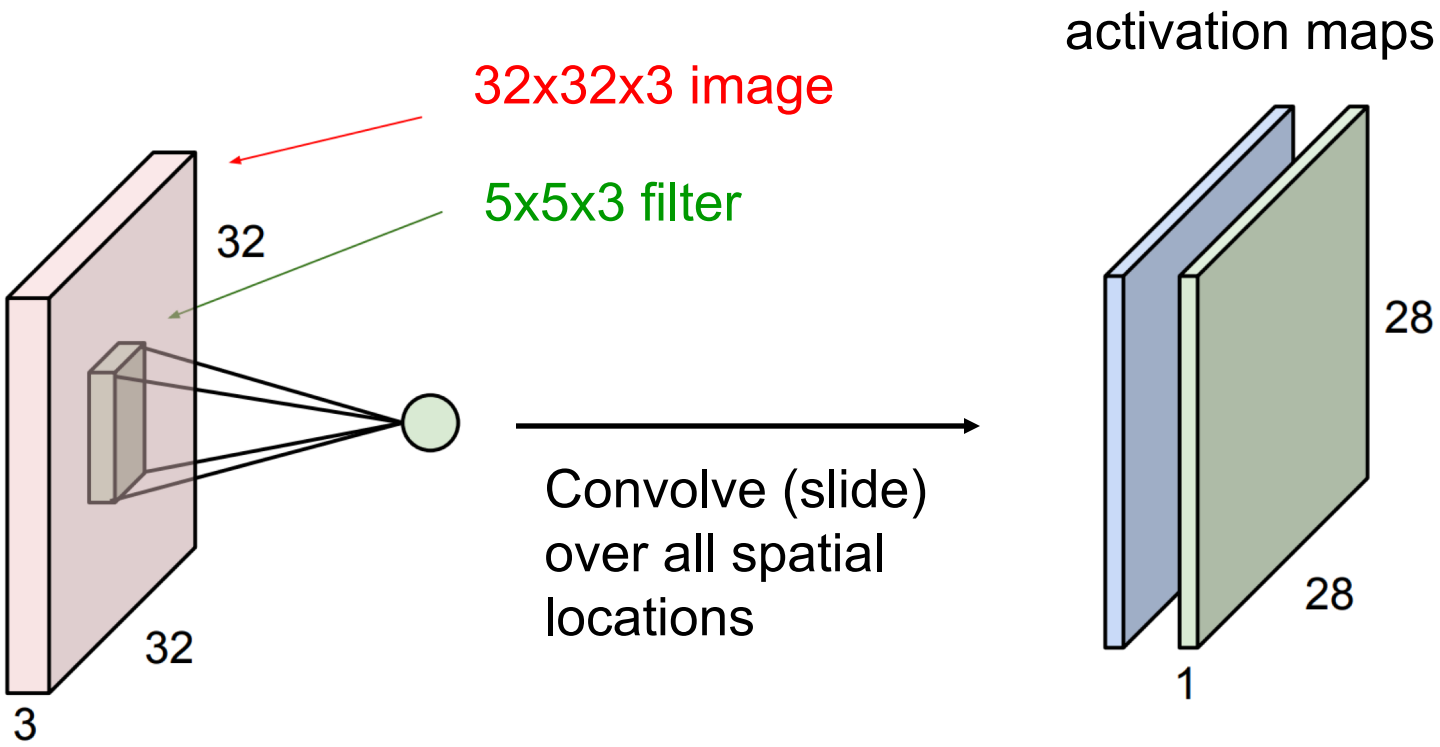
- Slide over the image spatially, computing dot products



# Convolutional Layer

Convolve the filter with the image

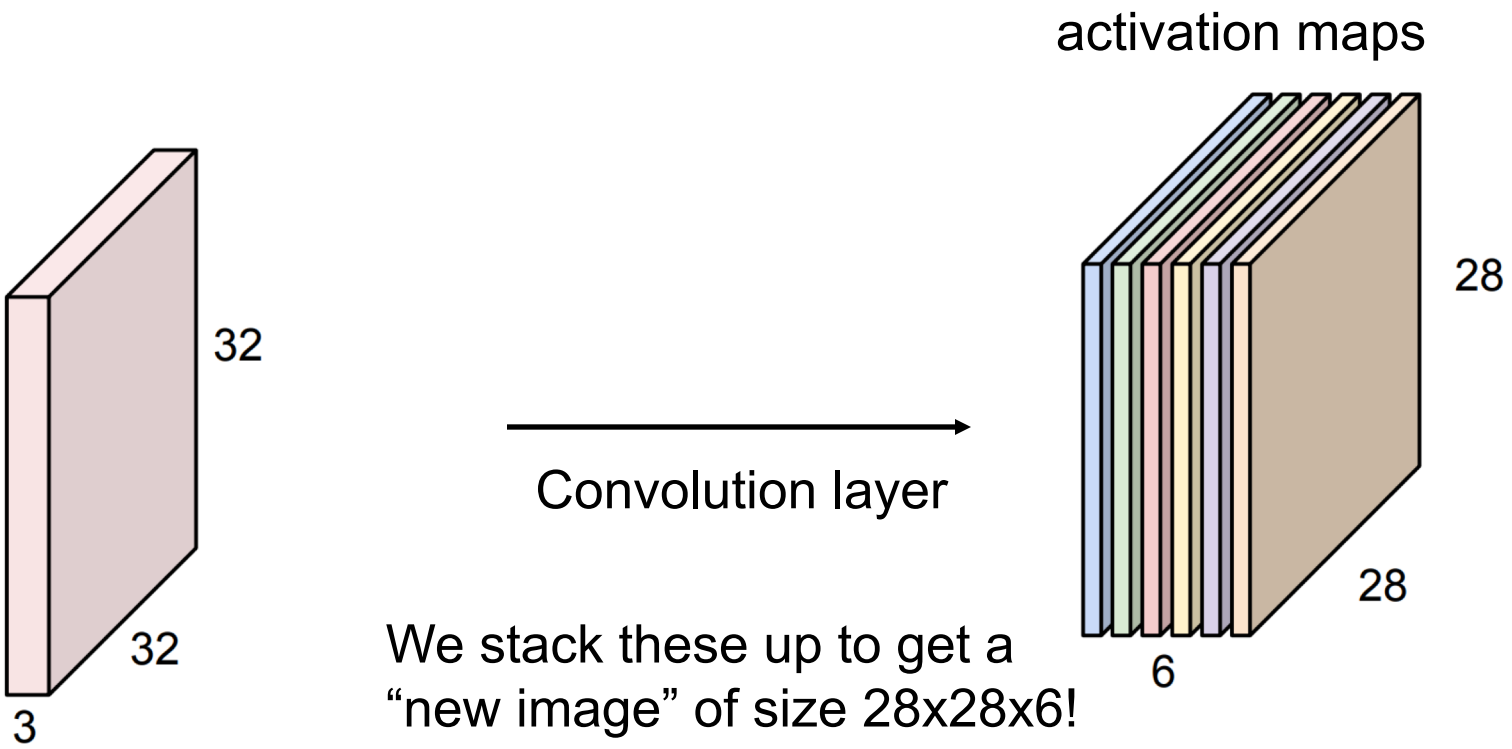
- Slide over the image spatially, computing dot products
- Consider a second, green filter



# Convolutional Layer

If we had 6 5x5 filters, we'll get 6 separate activation maps

- The 6 5x5 filters should be learned from data during training
- a.k.a. kernels, receptive fields

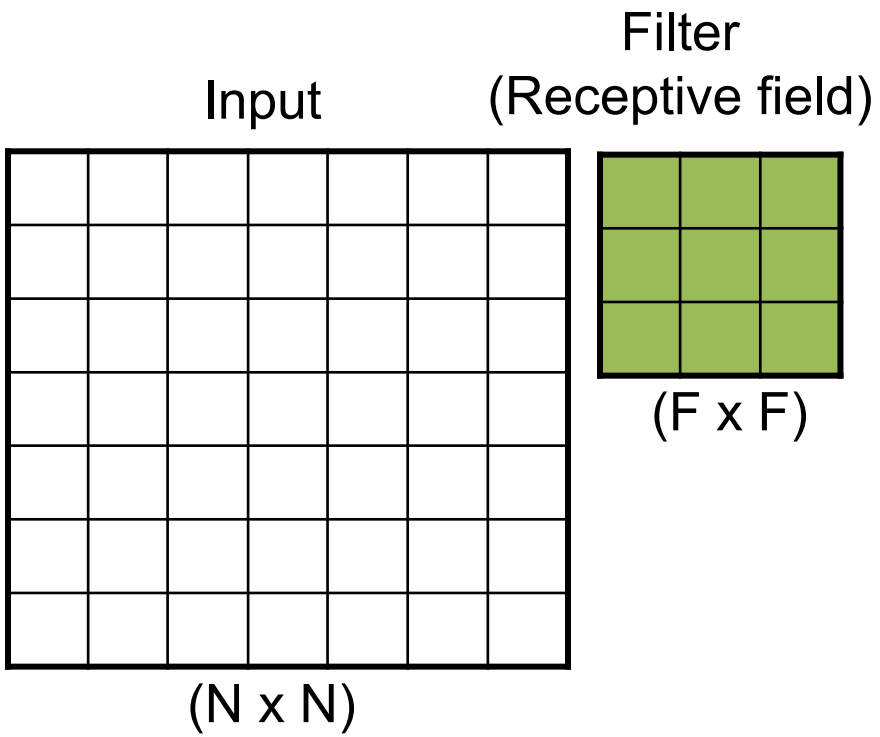


# Convolutional Layer

A closer look at spatial dimension

Stride: distance between consecutive filter application

An example




- 7x7 input (spatially) and 3x3 filter
- with stride 1?

  → 5x5 output
- with stride 2?

  → 3x3 output
- with stride 3?

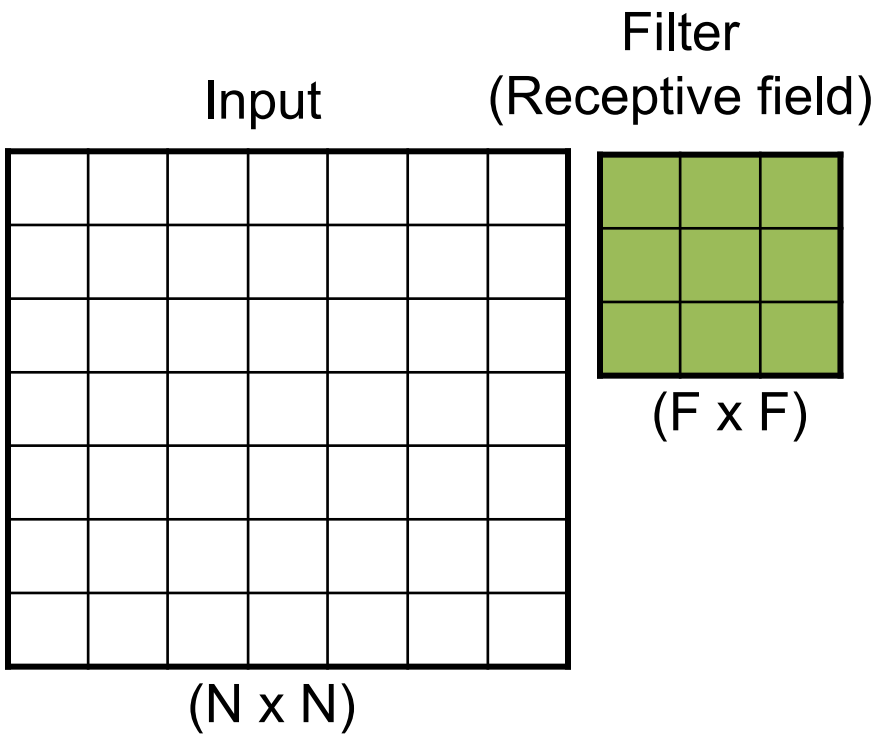
  → doesn't fit!
  cannot apply 3x3 filter on
  7x7 input with stride 3

# Convolutional Layer

A closer look at spatial dimension

Stride: distance between consecutive filter application

An example

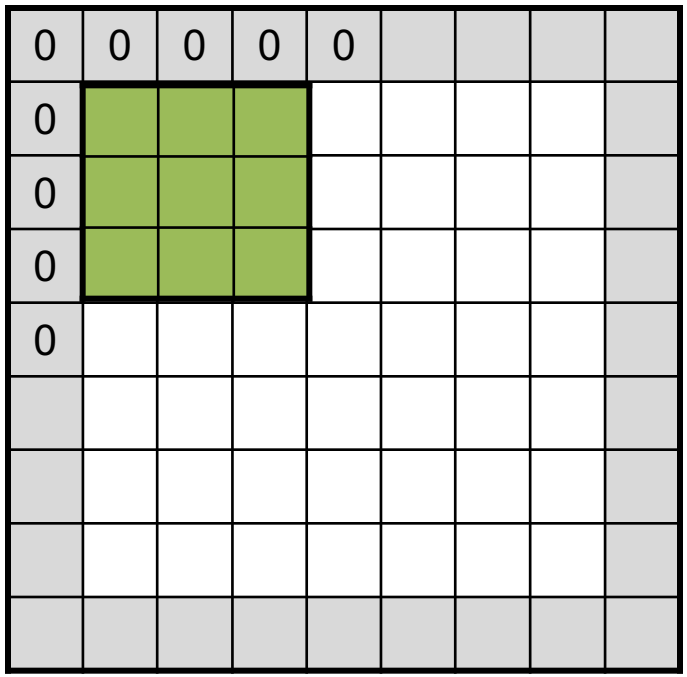



- 7x7 input (spatially) and 3x3 filter
- Output size: (N - F) / Stride+1
- e.g. Stride 1 → (7-3)/1+1=5
  Stride 2 → (7-3)/1+1=3
  Stride 3 → (7-3)/1+1=2.33?

# Convolutional Layer

In practice: common to zero pad the border

- Pad the input with zeros spatially on the border
- In general, common to see CONV layers with stride 1, filters of size FxF, and zero-padding with (F-1)/2 (will preserve size spatially)

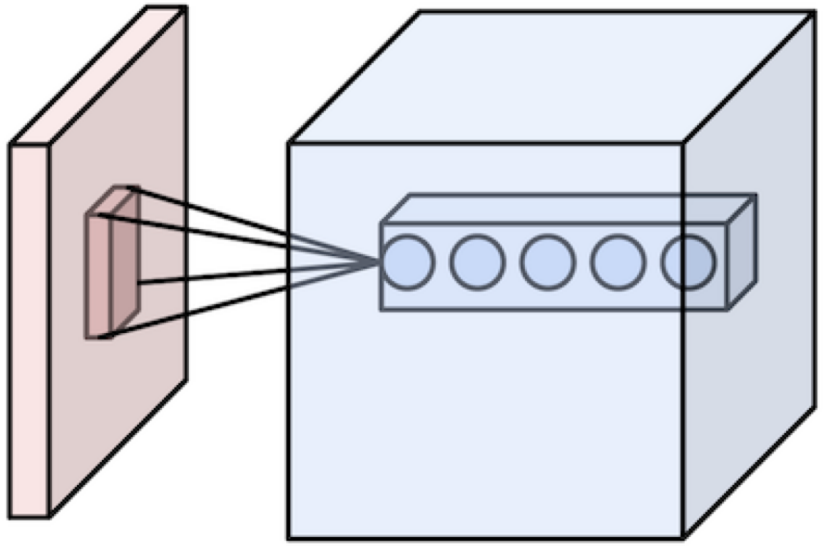



- Input 7x7, filter 3x3, stride 1, zero-pad 1. What is the output?
- 7x7 → Preserved size!
- e.g. F=3 → zero-pad with 1
  F=5 → zero-pad with 2
  F=7 → zero-pad with 3
- No headaches when sizing architecture

# Example of Convolutional Layer

Question

- Input volume: **32x32x3**
- Filters: **5x5**, stride **1**
- Number of filters: **5**



Answer

- Output size: (32 - 5)/1+1 = 28
- Output volume: 28x28x5
- How many weights for each of 28x28x5 filters? 5x5x3 = 75
- Total # of weights: 294,000 (= (28x28x5)x(5x5x3))

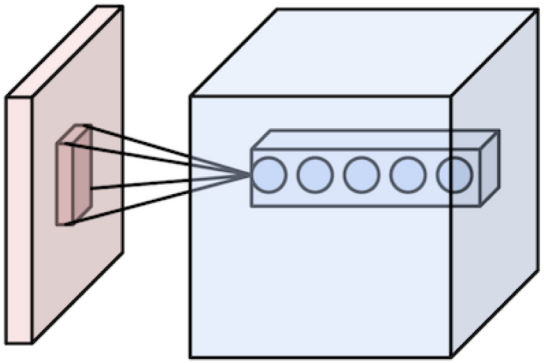
# Parameter Sharing

Input layer of [32x32x3] with 30 5x5 filters at stride of 1 and pad 1

- Output volume: [32x32x30]
- Each neuron has 5x5x3 (=75) weights (Too high!)
- Total number of weights: (32x32x30) x 75 ~ **2.3 millions**

Parameter sharing constraints the neurons in each depth slide to use the same weights

- Total number of weights: 30 x 75 = **2250**



30 Examples of trained weights of size [5x5x3]

Use the same filter across all spatial location!

# Activation Layer

An activation layer follows every CONV layer

- The most common activation function is ReLU (Rectified Linear Unit)

$$f(x) = \max(0, x)$$

- ReLU's purpose is to introduce non-linearity in our ConvNet
- Point-wise operation with no parameter

| | | | | | | |
|---|---|---|---|---|---|---|
| 0.77 | -0.11 | 0.11 | 0.33 | 0.55 | -0.11 | 0.33 |
| -0.11 | 1.0 | -0.11 | 0.33 | -0.11 | 0.11 | -0.11 |
| 0.11 | -0.11 | 1.0 | -0.33 | 0.11 | -0.11 | 0.55 |
| 0.33 | 0.33 | -0.33 | 0.55 | -0.33 | 0.33 | 0.33 |
| 0.55 | -0.11 | 0.11 | -0.33 | 1.00 | -0.11 | 0.11 |
| -0.11 | 0.11 | -0.11 | 0.33 | -0.11 | 1.00 | -0.11 |
| 0.33 | -0.11 | 0.55 | 0.33 | 0.11 | -0.11 | 0.77 |

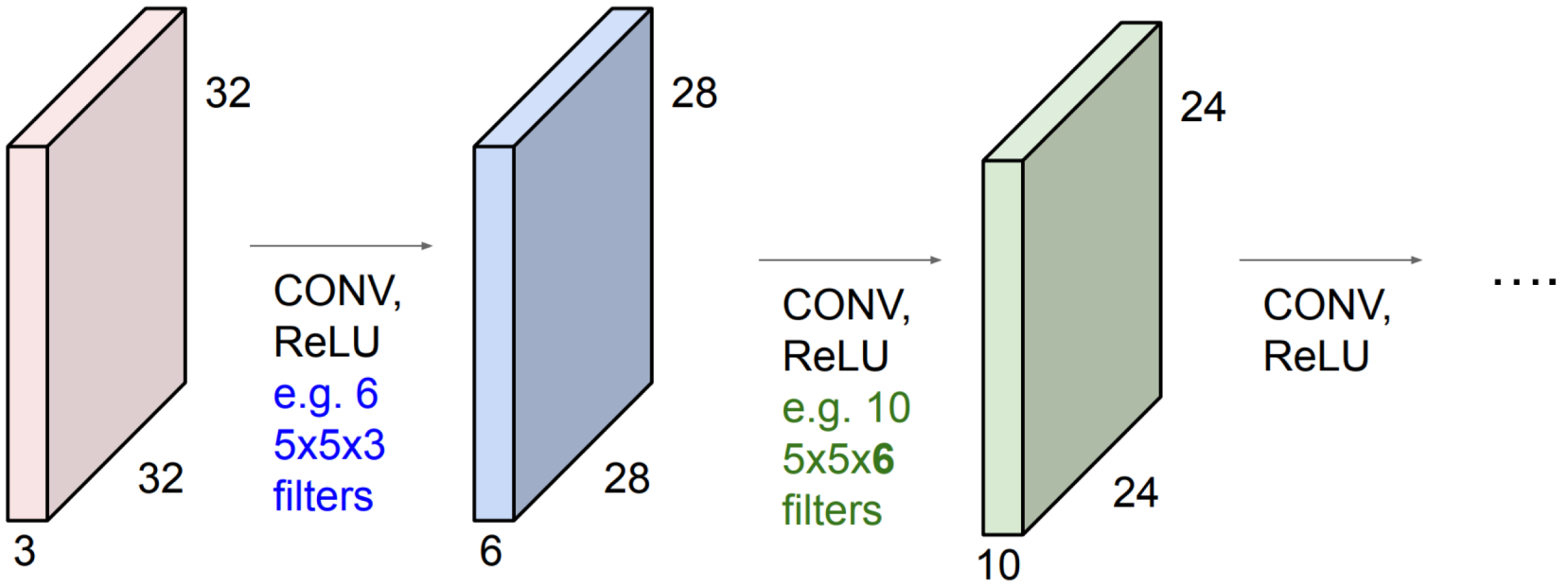
| | | | | | | |
|---|---|---|---|---|---|---|
| 0.77 | 0 | 0.11 | 0.33 | 0.55 | 0 | 0.33 |
| 0 | 1.00 | 0 | 0.33 | 0 | 0.11 | 0 |
| 0.11 | 0 | 1.00 | 0 | 0.11 | 0 | 0.55 |
| 0.33 | 0.33 | 0 | 0.55 | 0 | 0.33 | 0.33 |
| 0.55 | 0 | 0.11 | 0 | 1.00 | 0 | 0.11 |
| 0 | 0.11 | 0 | 0.33 | 0 | 1.00 | 0 |
| 0.33 | 0 | 0.55 | 0.33 | 0.11 | 0 | 1.77 |



https://medium.com/analytics-vidhya/convolutional-neural-networks-for-computer-vision-applications-4808a6d984c2

# ConvNet

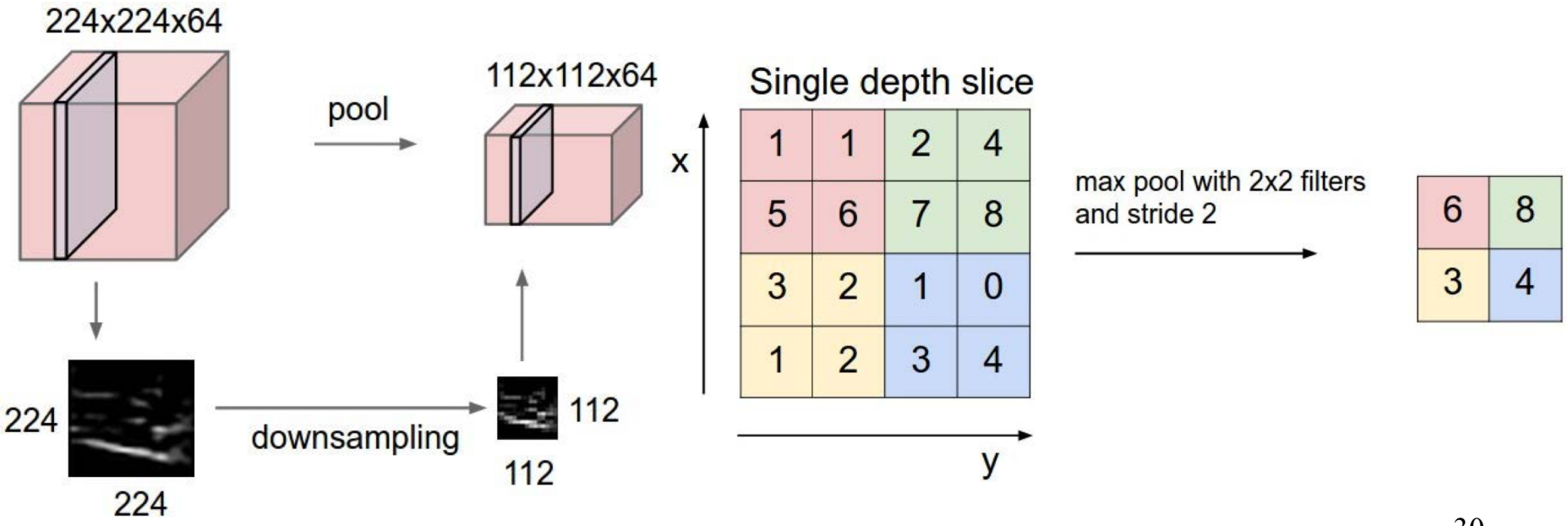
ConvNet is a sequence of Convolution Layers, interspersed with activation functions



# Pooling Layer

Make the representation smaller and more manageable without losing too much information

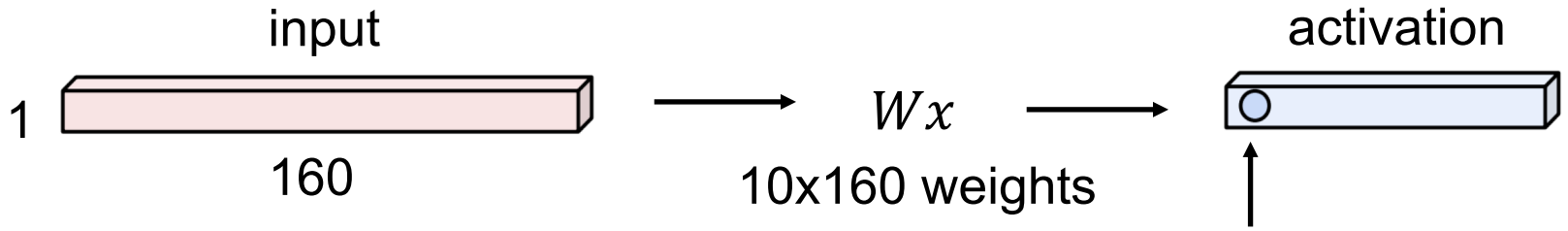
- Operates over each activation map independently:
- Computes MAX operation (most common)
- Average pooling or L2-norm pooling (less used)



# Fully Connected Layer

Takes the feature map (the output of Conv/POOL layers) as input and predicts the label to describe the image

- e.g. Given a 4x4x10 feature map as input, stretch to 160x1

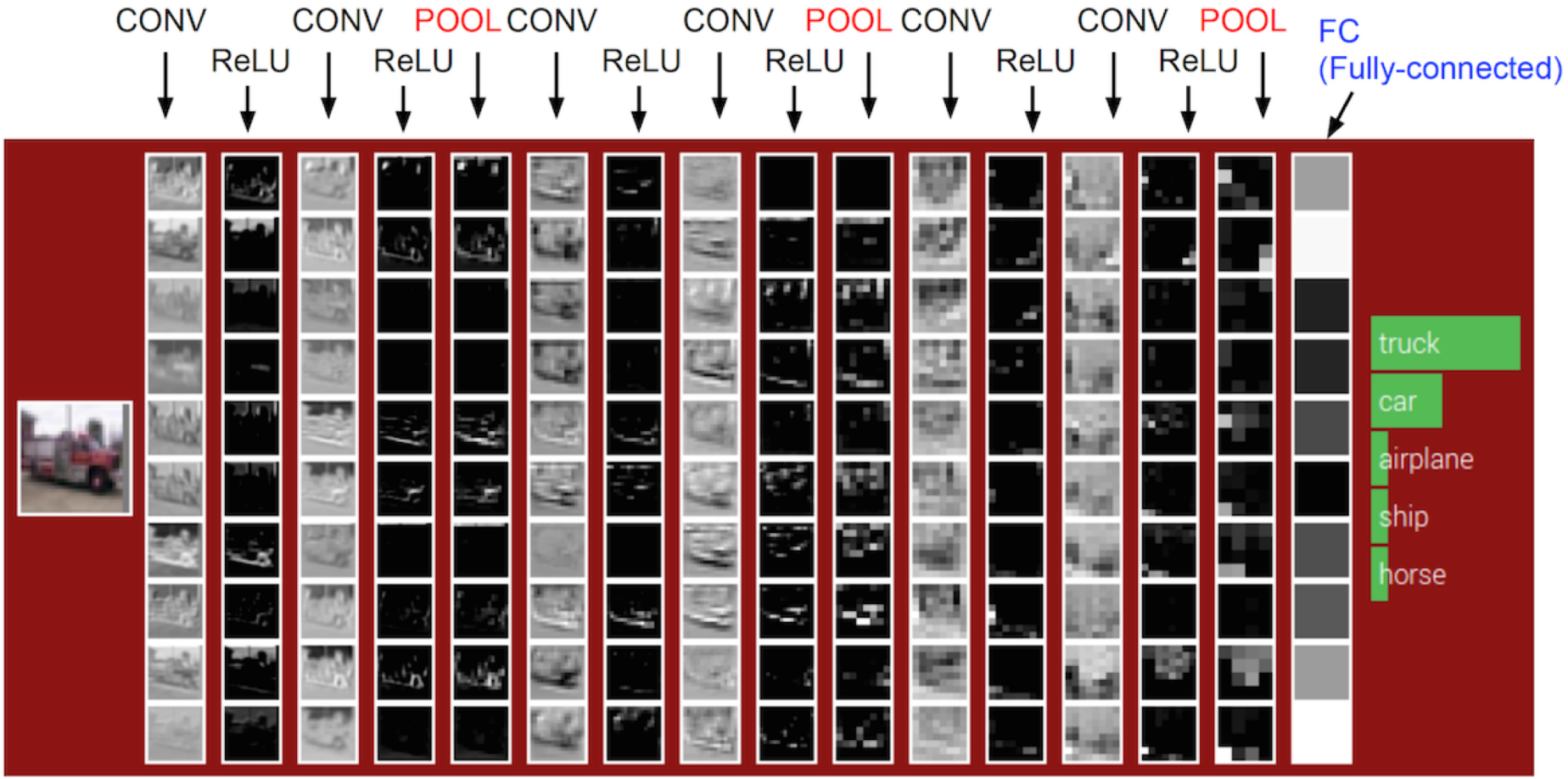



**1 number**:
the result of taking a dot product between a row of $W$ and the input (a 160-dimensional dot product)

# Layer Patterns

Most common form of ConvNet architecture

- Stacks a few CONV-RELU layers, follows them with POOL layers, repeats this pattern, finally adds FC layer



# CNNs In Practice

Prefer a stack of small receptive field CONV to one large CONV layer

- Ex) Three CONV layer consisting of 3x3 filters vs one CONV layer consisting 7x7 filters
- Which is better? The former is BETTER!

1. Filtering is a linear function over the input. Thus, three stacks of CONV layer contain non-linearity to make features more expressive

2. Fast computation!

Ex. If all volumes have depths of C,

7x7 CONV layer: $Cx(7x7xC) = 49C^2$

3 3x3 CONV layer: $3x(Cx(3x3xC)) = 27C^2$

# Rule of Thumbs for Sizing CNNs

Input layer: divisible by 2 many times

- 32 for CIFAR-10, 64 or 96 for STL-10, 224, 384, 512 for AlexNet

CONV layer: Use small filters (3x3 or at most 5x5) with zero-padding of P=1 at stride of S=1

- Smaller strides work better in practice
- Ex. Input volume of size $[W_i \times H_i \times D_i]$ using K number of FxF filters at stride of S
- Output volume: $[W_o \times H_o \times D_o]$
- $W_o = (W_i - F)/S + 1$, $H_o = (H_i - F)/S + 1$, $D_o = K$

POOL layer: Use pooling size of 2x2 with stride of S=2

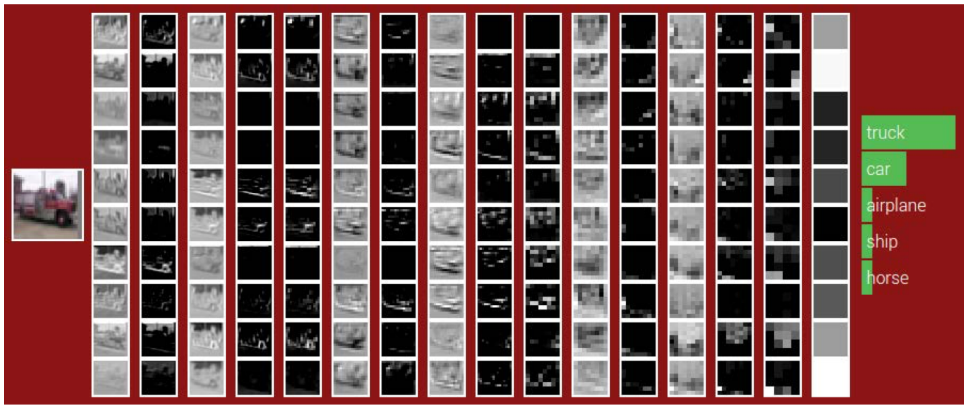
- 3/4 of the activations will be discarded

Go deep! Use small ones multiple times instead of big

# Sizing Example

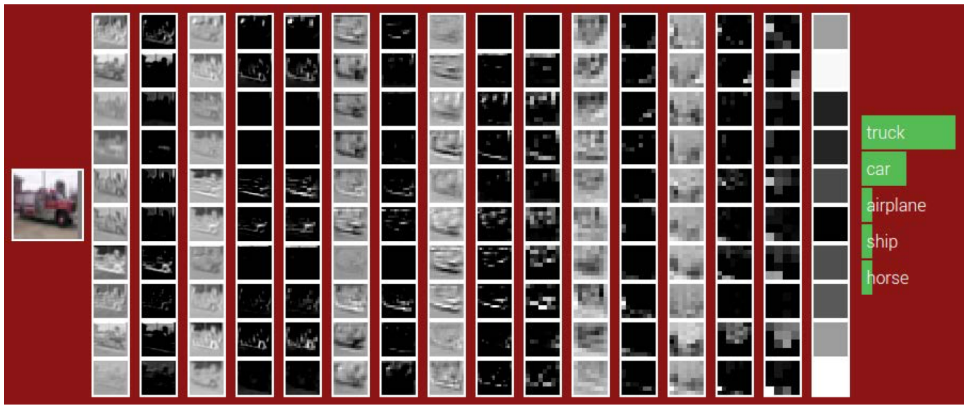
Input layer: [32x32x3]

1. CONV with 10 3x3 filters, stride 1, pad 1 → [32x32x10]
   - New parameters: (3*3*3)*10+10 = 280
2. RELU
3. CONV with 10 3x3 filters, stride 1, pad 1 → [32x32x10]
   - New parameters: (3*3*10)*10+10 = 910
4. RELU
5. POOL with 2x2 filters, stride 2 → [16x16x10]
   - New parameters: 0



# Sizing Example

6. CONV with 10 3x3 filters, stride 1, pad 1 → [16x16x10]
   - New parameters: (3*3*10)*10+10 = 910
7. RELU
8. CONV with 10 3x3 filters, stride 1, pad 1 → [16x16x10]
   - New parameters: (3*3*10)*10+10 = 910
9. RELU
10. POOL with 2x2 filters, stride 2 → [8x8x10]
    - New parameters: 0



# Sizing Example

11~15. Once again CONV-RELU-CONV-RELU-POOL → [4x4x10]

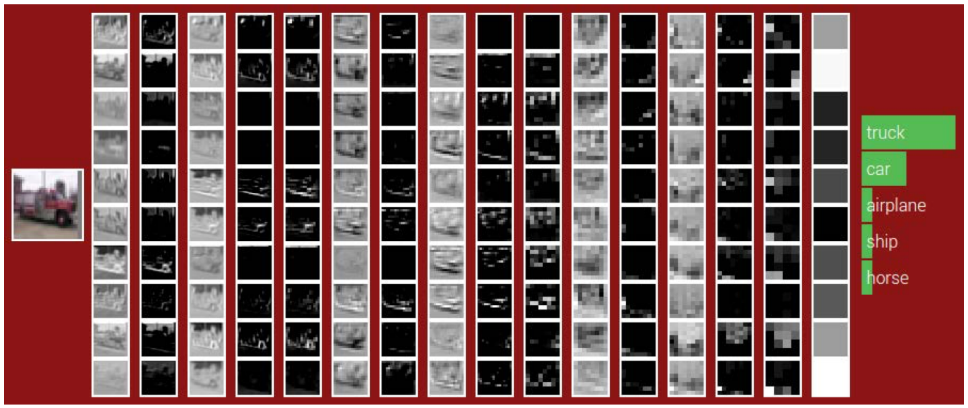
16. FC layer to 10 neurons (each of which for class score)

- New parameters: 10*4*4*10+10 = 1600

Done!

GPU memory constraints!

- Ex. 224x224x3 image with three 3x3 CONV layers with 64 filters each and padding 1 → [224x224x64] = 72MB
- Most GPUs have 3/4/6GB memory. Tesla K40 = 12GB!

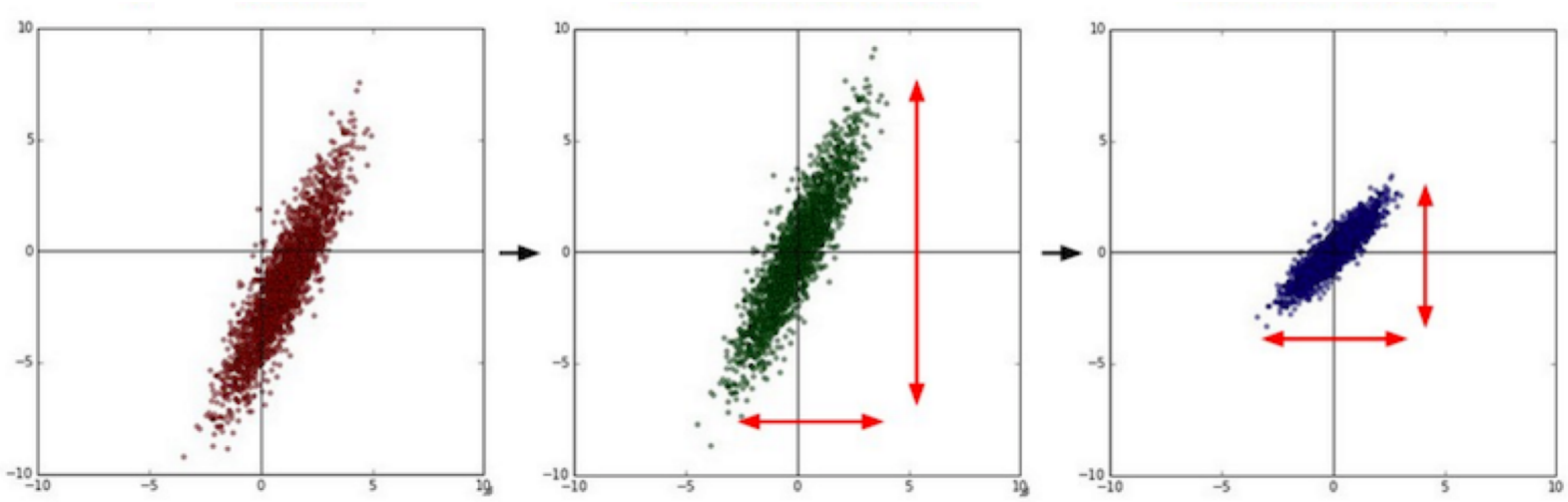


# Outline

- Convolutional Neural network
- Training Tips
- Parameter Updates
- Case Studies

(Credits: Stanford CS231n Lecture Notes)

# Data Preprocessing



original data zero-centered data normalized data

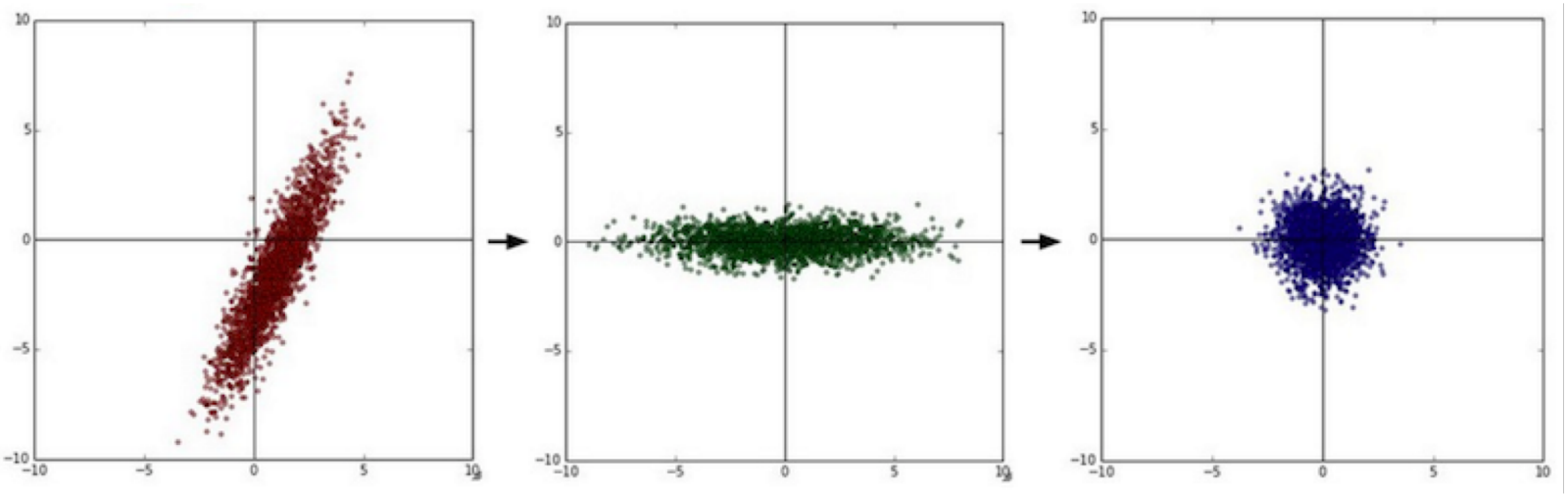
## Mean-subtraction

- Zero-centered by subtracting the mean in each dimension

## Normalization

- Each dimension is additionally scaled by its standard deviation
- The red lines indicate the extent of the data

# Data Preprocessing



original data de-correlated data whitened data

PCA decorrelates the data

- The covariance matrix is diagonal (rotated into the eigenbasis)

Each dimension is additionally scaled by eigenvalues

- Transform the data covariance matrix into the identity matrix

Don’t PCA/whiten the data with ConvNet

# Weight Initialization and Regularization

Do not set all the initial weights to zero

- May lead **exact** same parameter updates

One heuristic recommendation

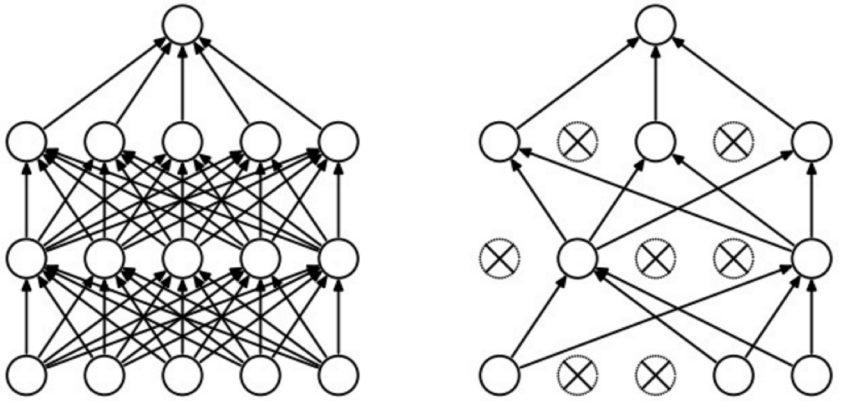
- uniform (0,1) / sqrt(n) where n is the number of input
- Can initialization all biases to zero (or small random numbers)

Droupout

- Training: Only update the parameters of the sampled nodes
- Test: No dropout applied

In practice

- Use dropout to all layers with 0.5 rate
- L2 norm can be used



# Loss Functions

An average over the data losses for individual examples

$$L = \sum_i L_i / N$$

Classification

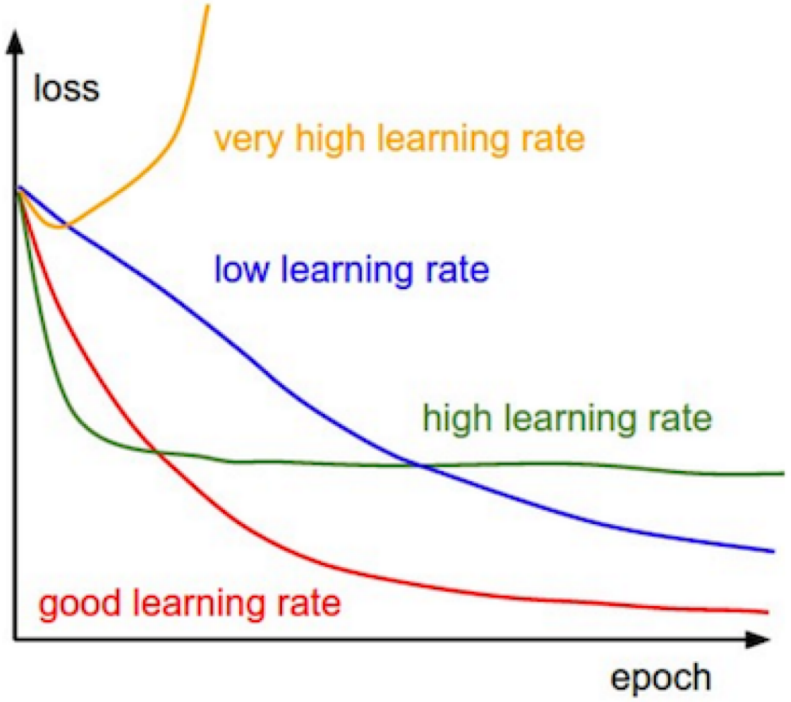
- Hinge loss $L_i = \sum_{j \neq y_i} \max(0, f_i - f_{y_i} + 1)$ ($f$: activation of output layer)
- Cross-entropy loss $L_i = -\log(\frac{\exp(f_{y_i})}{\sum_j \exp(f_j)})$
- Hierarchical loss when the set of labels is very large

Regression

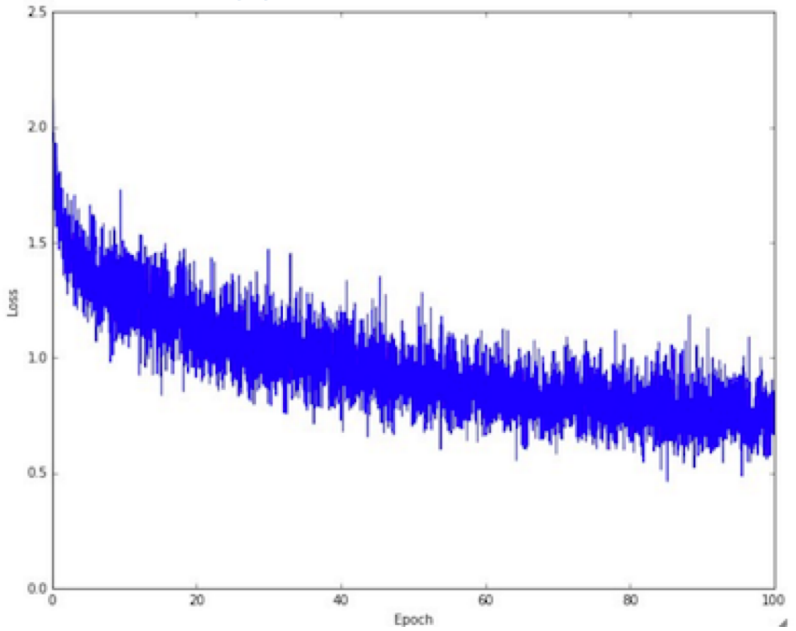
- L2 (L1) loss $L_i = \|f - y_i\|_2^2$ $(L_i = \|f - y_i\|_1)$
- The L2 loss is much harder to optimize than a more stable loss such as Softmax

# Monitoring Learning Process

1. Loss function



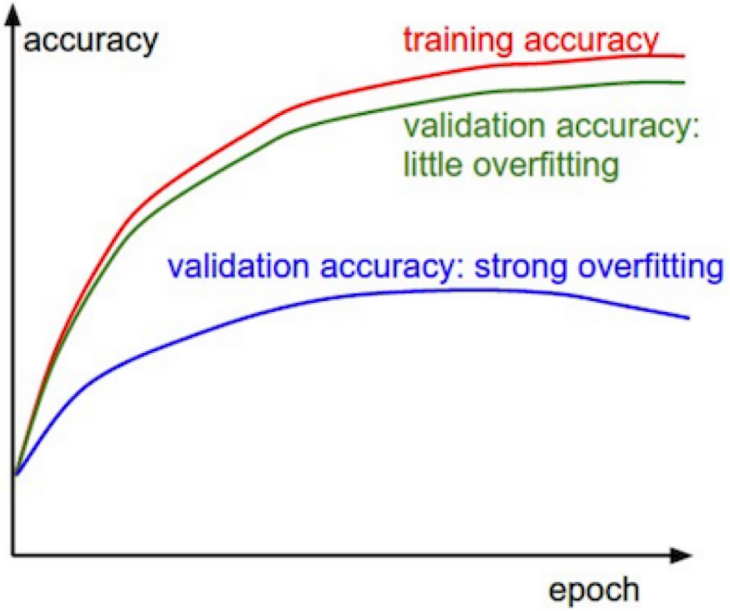

More wiggle with smaller batch size




- Low learning rate: slow convergence
- High learning rate: decay the loss faster, but they get stuck at worse values of loss

# Monitoring Learning Process

2. Train/Val accuracy

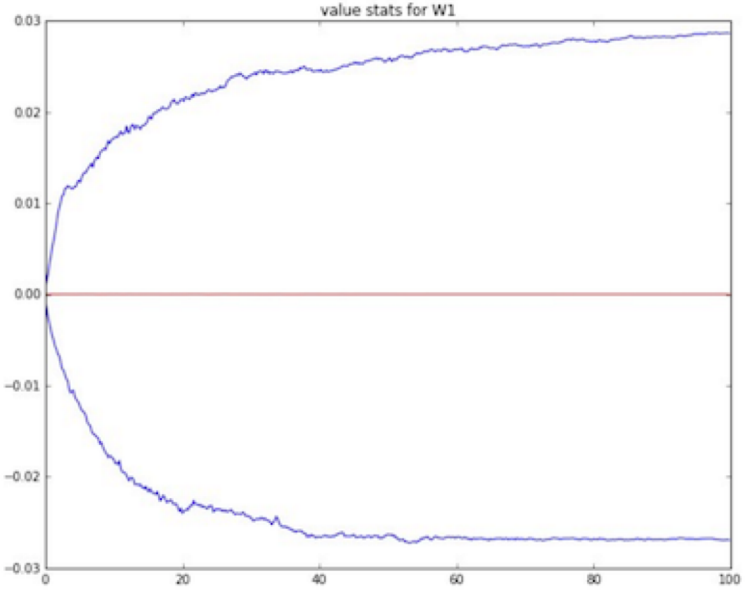



- The gap between the training and validation accuracy indicates the amount of overfitting
- When overfitting occurs, increase regularization (stronger L2 weight penalty, more dropout, etc.) or collect more data

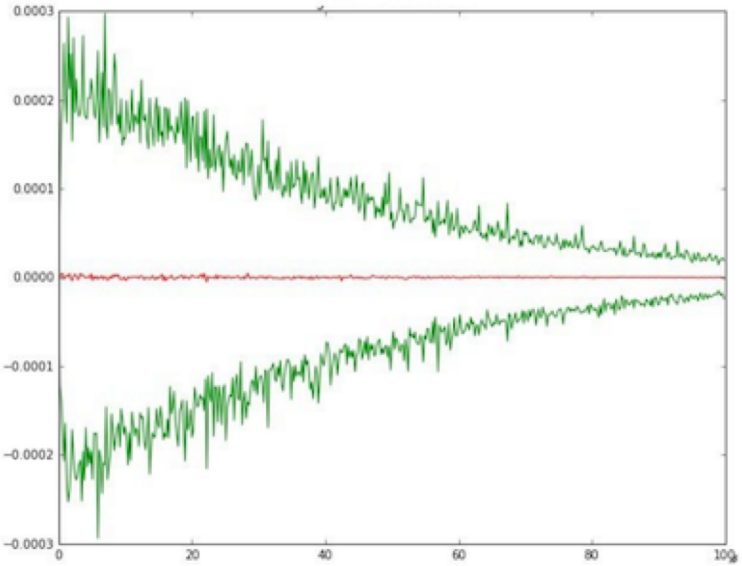
# Monitoring Learning Process

3. Ratio of updates / weights

Min and max across all weights




Min and max of weight updates




- A rough heuristic is that the ratio is around 1e-3
- If the ratio is lower than that, increase the learning rate
- Ex. 0.0002 / 0.02 ~ 1e-2: within a relatively healthy limit

# Monitoring Learning Process

## 4. Activation / Gradient distributions per layer

- Variance of the activations on each layer

Bad

```
Layer 0: Variance: 1.005315e+00
Layer 1: Variance: 3.123429e-04
Layer 2: Variance: 1.159213e-06
Layer 3: Variance: 5.467721e-10
Layer 4: Variance: 2.757210e-13
Layer 5: Variance: 3.316570e-16
Layer 6: Variance: 3.123025e-19
Layer 7: Variance: 6.199031e-22
Layer 8: Variance: 6.623673e-25
```

Good

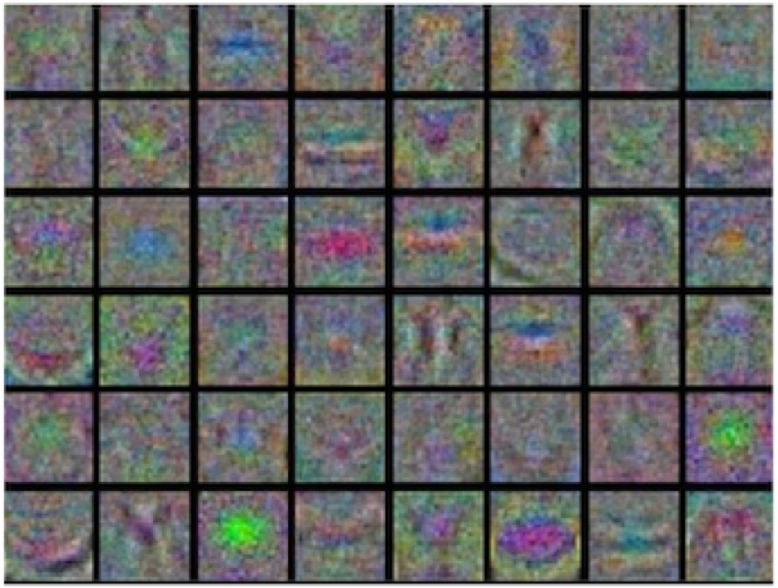
```
Layer 0: Variance: 1.002860e+00
Layer 1: Variance: 7.015103e-01
Layer 2: Variance: 6.048625e-01
Layer 3: Variance: 8.517882e-01
Layer 4: Variance: 6.362898e-01
Layer 5: Variance: 4.329555e-01
Layer 6: Variance: 3.539950e-01
Layer 7: Variance: 3.809120e-01
Layer 8: Variance: 2.497737e-01
```

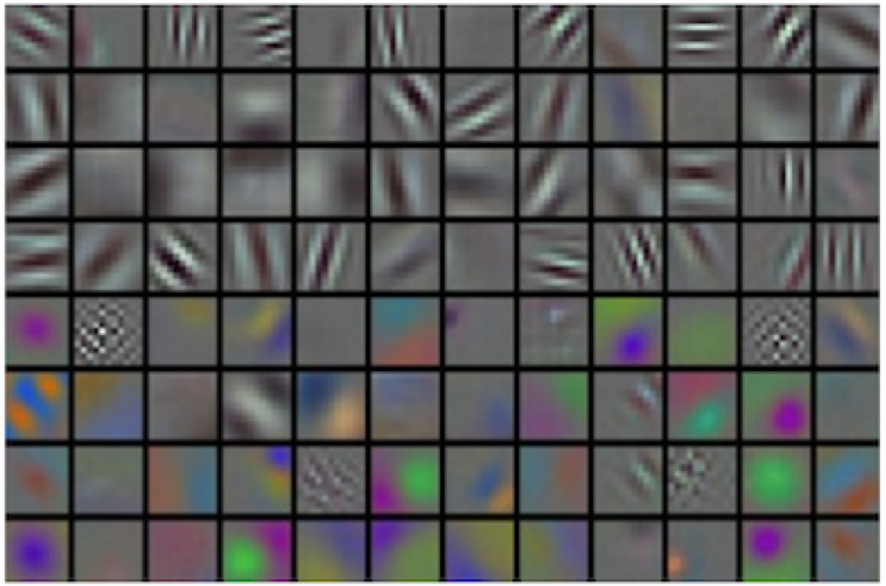
- (Left) Activations vanish extremely quickly in the higher layers
- (Right) Variance through the network is preserved

# Monitoring Learning Process

5. Visualization of each layer's feature map

- Two extreme cases of feature maps for the first layer





- (Left) Problematic! (e.g. Unconverged network, improperly set learning rate, very low weight regularization penalty)
- (Right) Good indication that the training is proceeding well

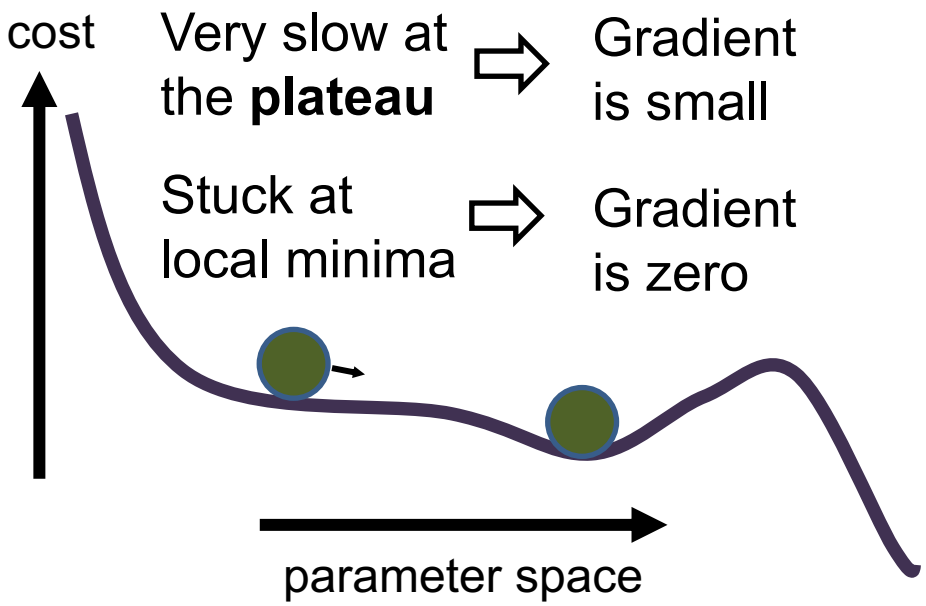
# Outline

- Convolutional Neural network
- Training Tips
- Parameter Updates
- Case Studies

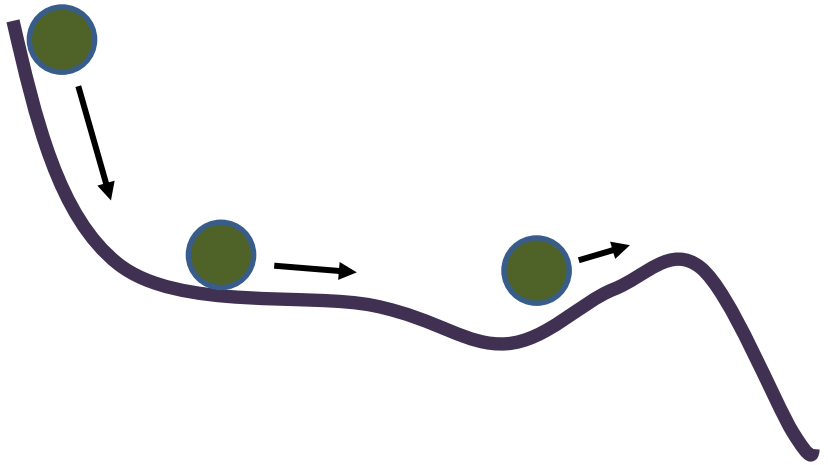
(Credits: Hung-yi Lee's More Tips for Training Neural Network)

# Gradient Descent with Momentum

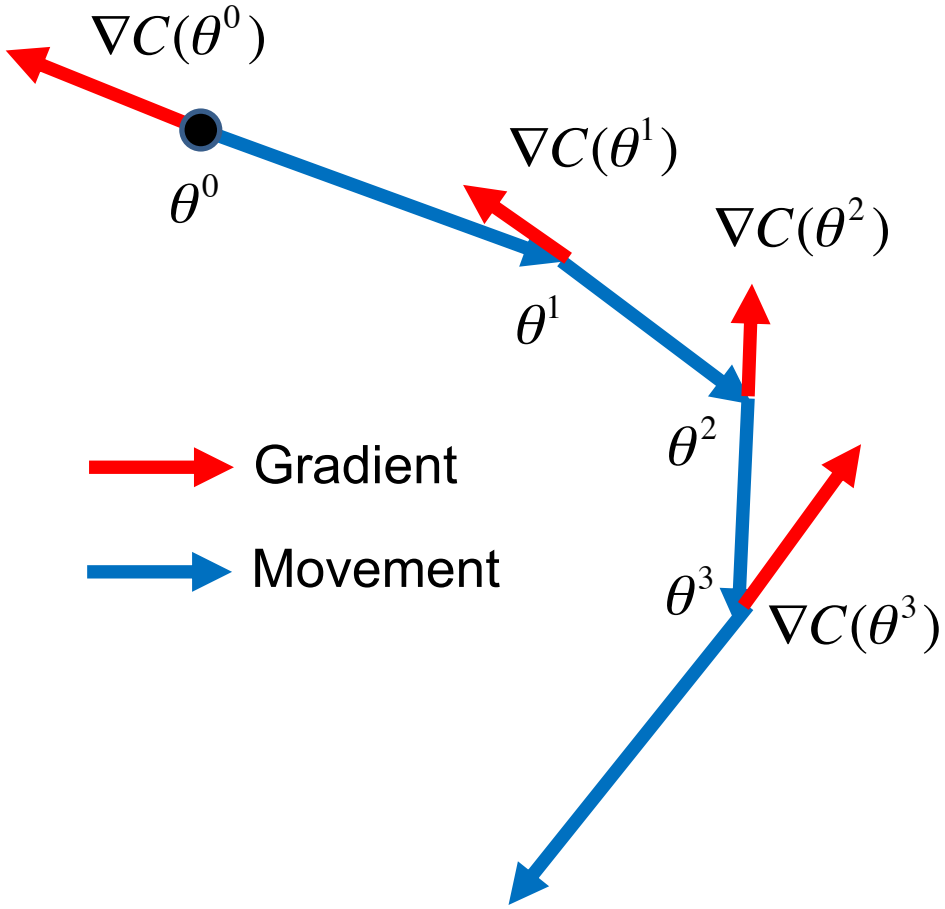
Without momentum




With momentum



# Original Gradient Descent




Start at position $\theta^0$

Compute gradient at $\theta^0$

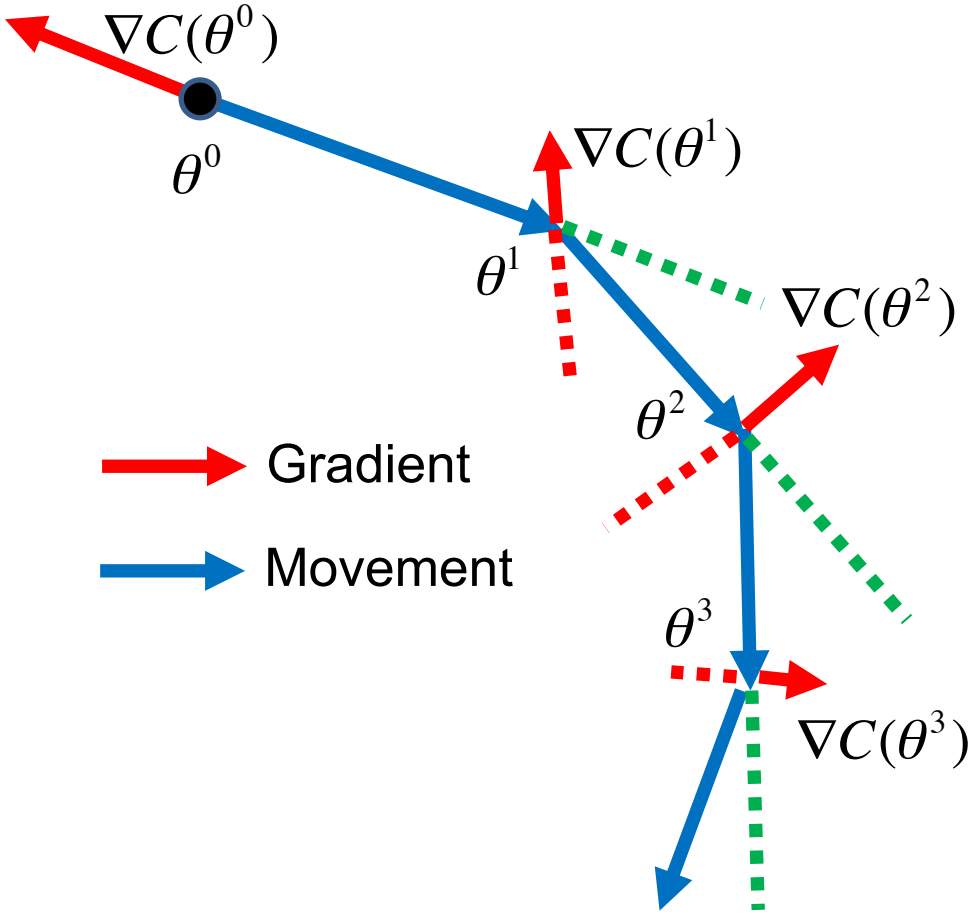
Move to $\theta^1 = \theta^0 - \eta\nabla C(\theta^0)$

Compute gradient at $\theta^1$

Move to $\theta^2 = \theta^1 - \eta\nabla C(\theta^1)$

⋮

# Gradient Descent with Momentum




Start at position $\theta^0$

Momentum $v^0 = 0$

Compute gradient at $\theta^0$

Momentum $v^1 = \lambda v^0 - \eta \nabla C(\theta^0)$

Move to $\theta^1 = \theta^0 + v^1$

Compute gradient at $\theta^1$

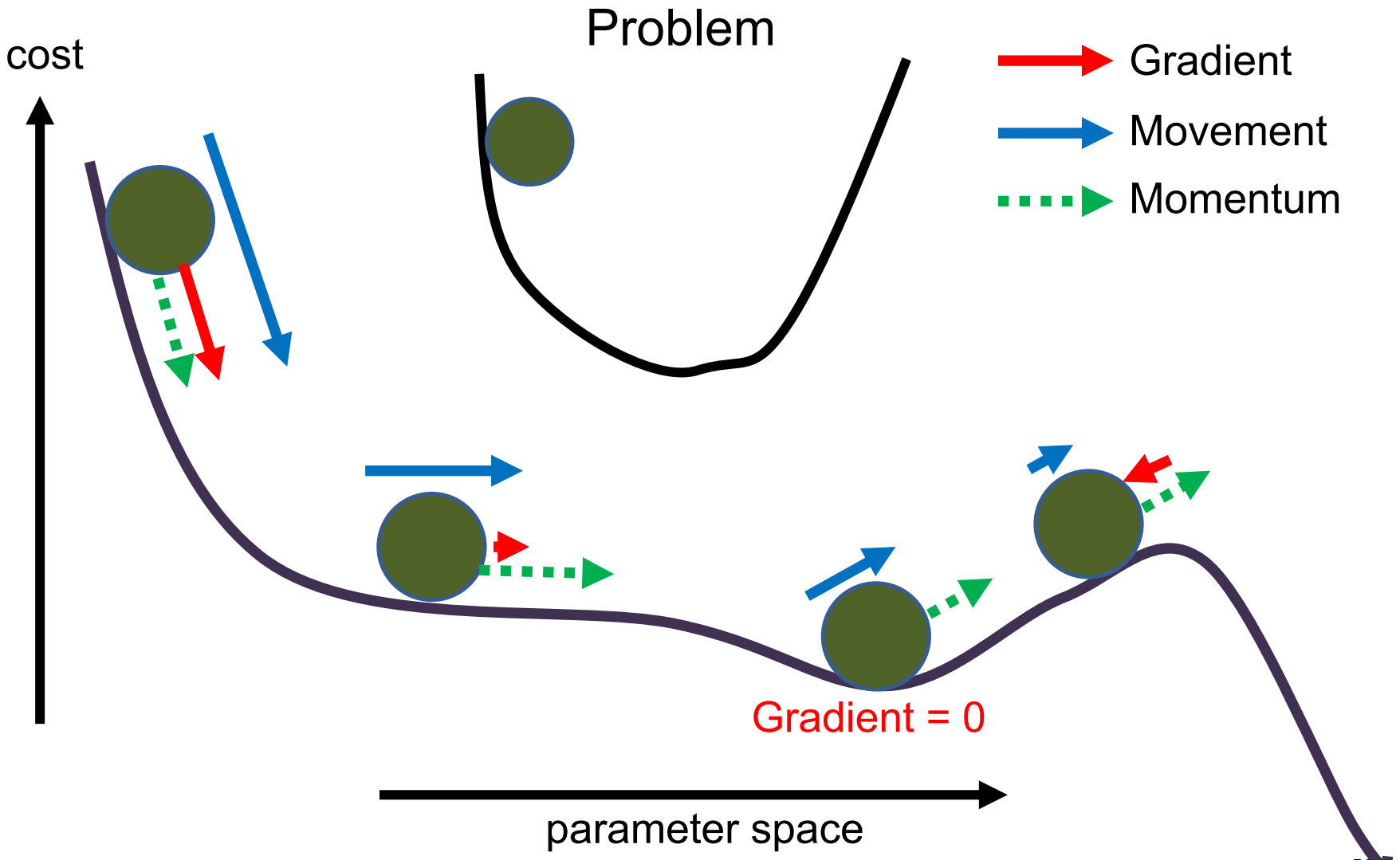
Momentum $v^2 = \lambda v^1 - \eta \nabla C(\theta^1)$

Move to $\theta^2 = \theta^1 + v^2$

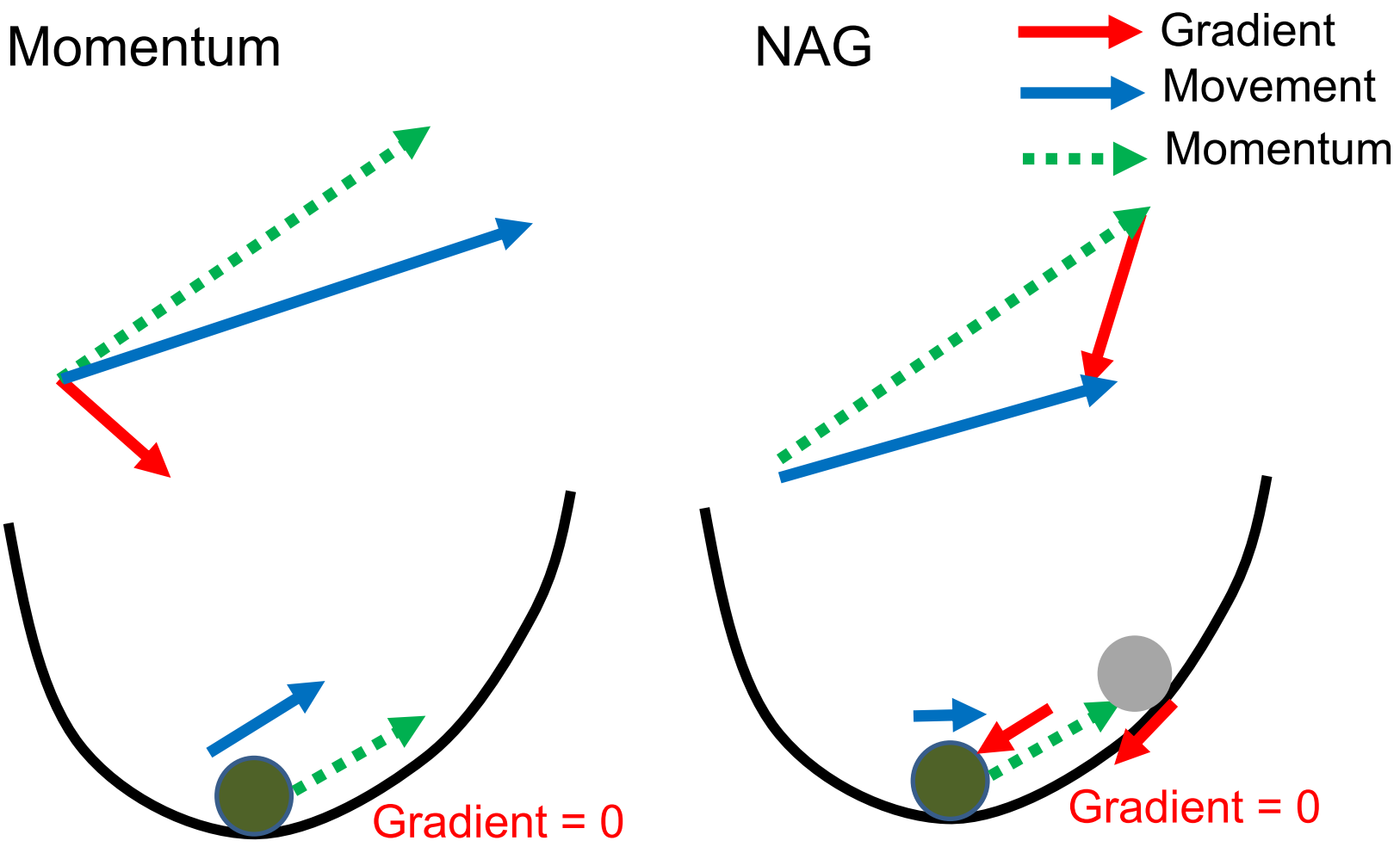
⋮

- $v^i$ is the weighted sum of all the previous gradient $(\nabla C(\theta^0), \nabla C(\theta^1), \cdots, \nabla C(\theta^{i-1})$

# Gradient Descent with Momentum

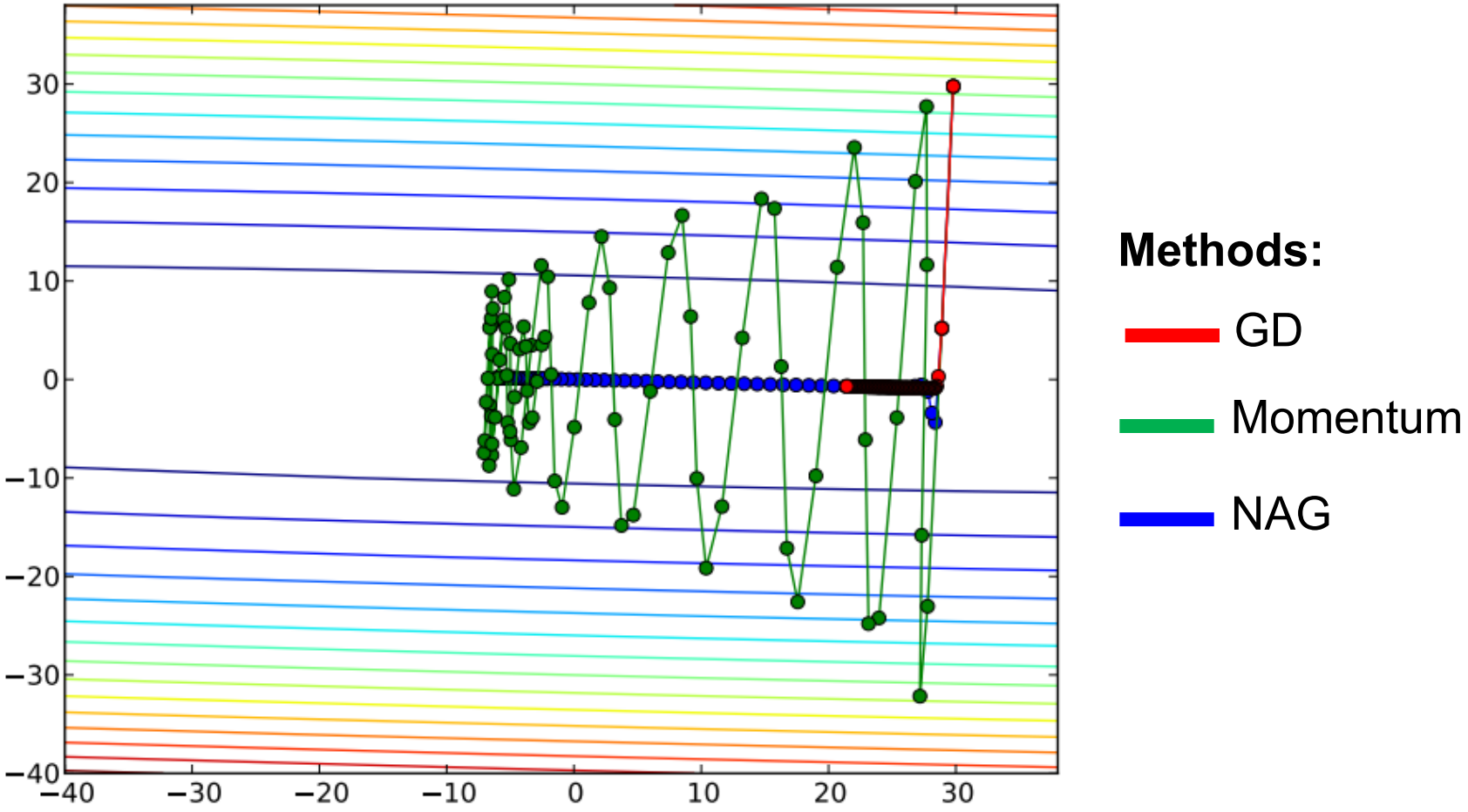


# Nesterov's Accelerated Gradient




- Do not compute the gradient at old state

# Gradient descent, Momentum, NAG



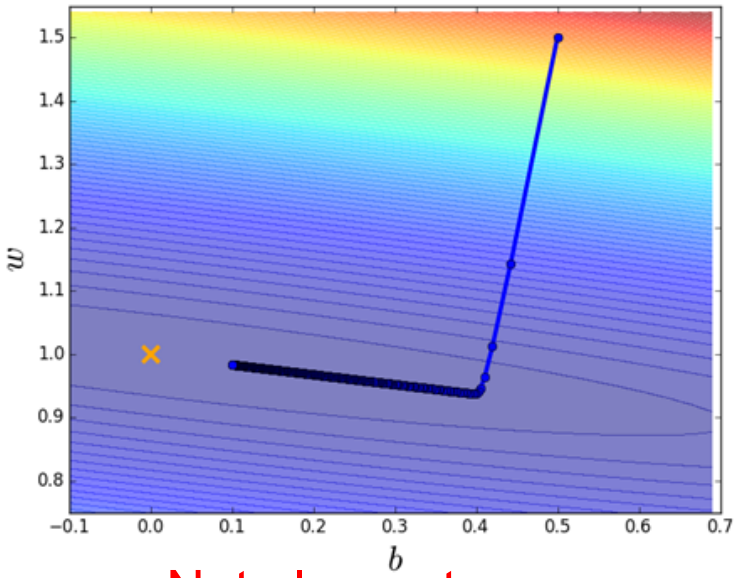

I.Sutskever et al. On the importance of initialization and momentum in deep learning. ICML 2013

# How to Set Learning Rates

One of the most difficult hyperparameters to set

Popular Idea: Reduce the learning rate by some factor every few epochs

- At the beginning, we are far from a minimum, so we use larger learning rate
- After several epochs, we are close to a minimum, so we reduce the learning rate
- 1/t decay: $\eta = \eta_0 / (1+kt)$ where t is the iteration number, and $\eta_0$, k are hyperparameters
- Exponential decay: $\eta = \eta_0 \exp(-kt)$



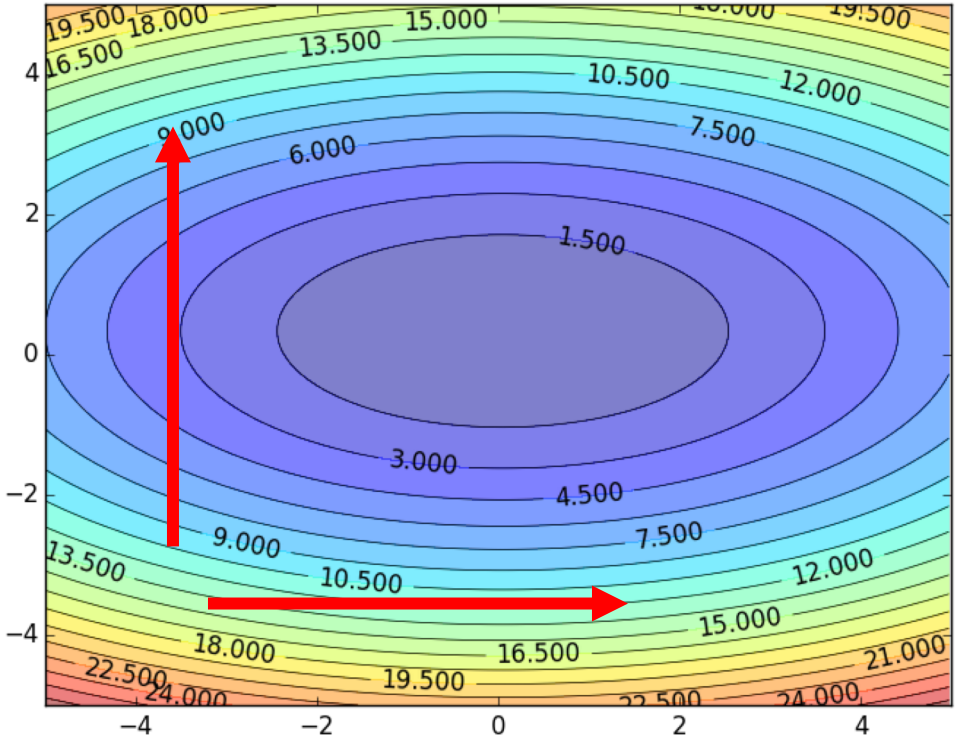

Not always true

# Adaptive Learning Rates

Each parameter should have different learning

- Automatically adapt the axis-aligned learning rates throughout the course of learning

Smaller learning rate




Larger learning rate

Larger gradient

Smaller learning rate

# Adagrad

Different adaptive learning rates for each weight

$$\Delta w_i(t) = \eta / (\sum_{k=1}^{t} \sqrt{(\partial E_k / \partial w_i)^2})$$

- Divide the learning rate elementwise by history of *average* gradient
- If w has small average gradient → large learning rate
  If w has large average gradient → small learning rate

Empirical behavior

- The accumulation of squared gradients from the beginning of training can cause a excessive decrease in the learning rate

J. Duchi et al. Adaptive Subgradient Methods for Online Learning and Stochastic Optimization. JMLR 2011.

# RMSprop

Suggested by G. Hinton in the Coursera course lecture 6

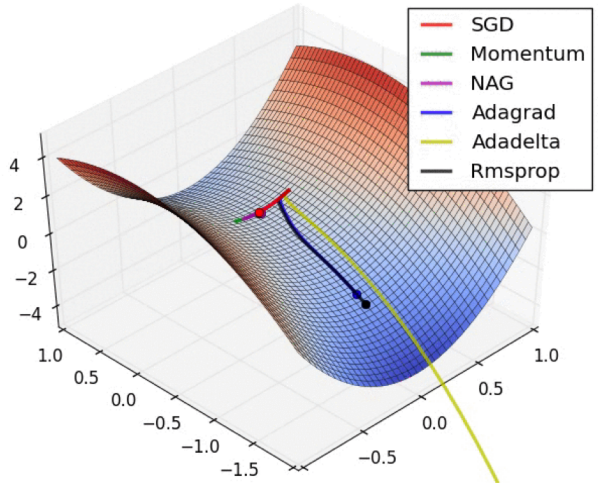
$$MS(w,t) = 0.9\,MS(w,t-1) + 0.1(\partial E / \partial w)^2$$

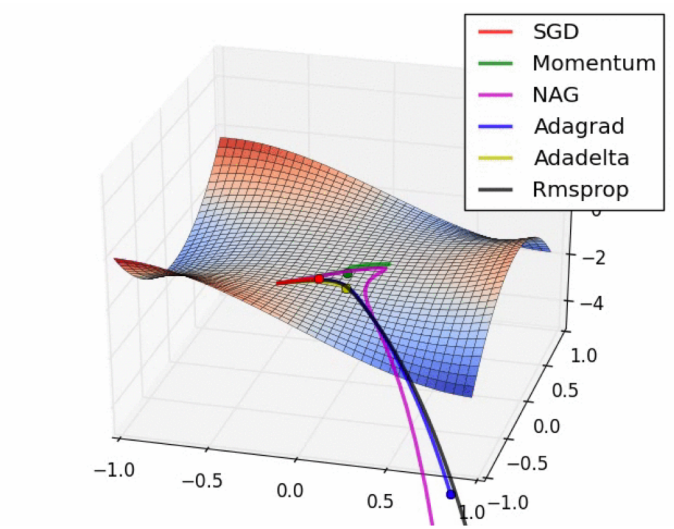
$$\Delta w(t) = \eta \times (\partial E / \partial w) / (\sqrt{MS(w,t)} + \mu)$$

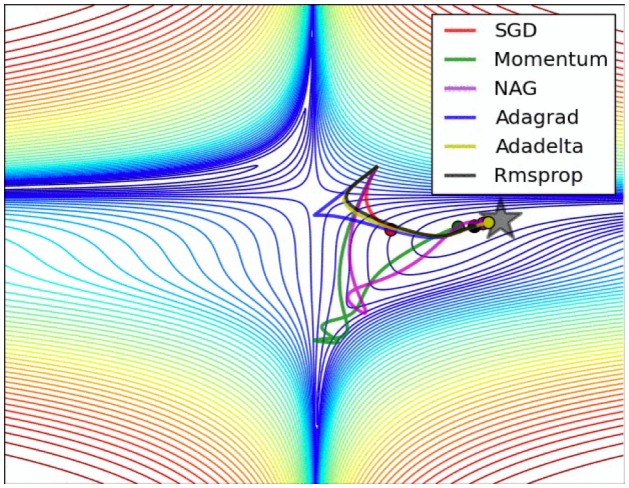
- Keeps running average of its recent gradient magnitudes
- Divide the next gradient by this average so that loosely gradient values are normalized
- Still modulates the learning rate of each weight

# Visualizing Optimization Algorithms

Check animated gifs at http://imgur.com/a/Hqolp



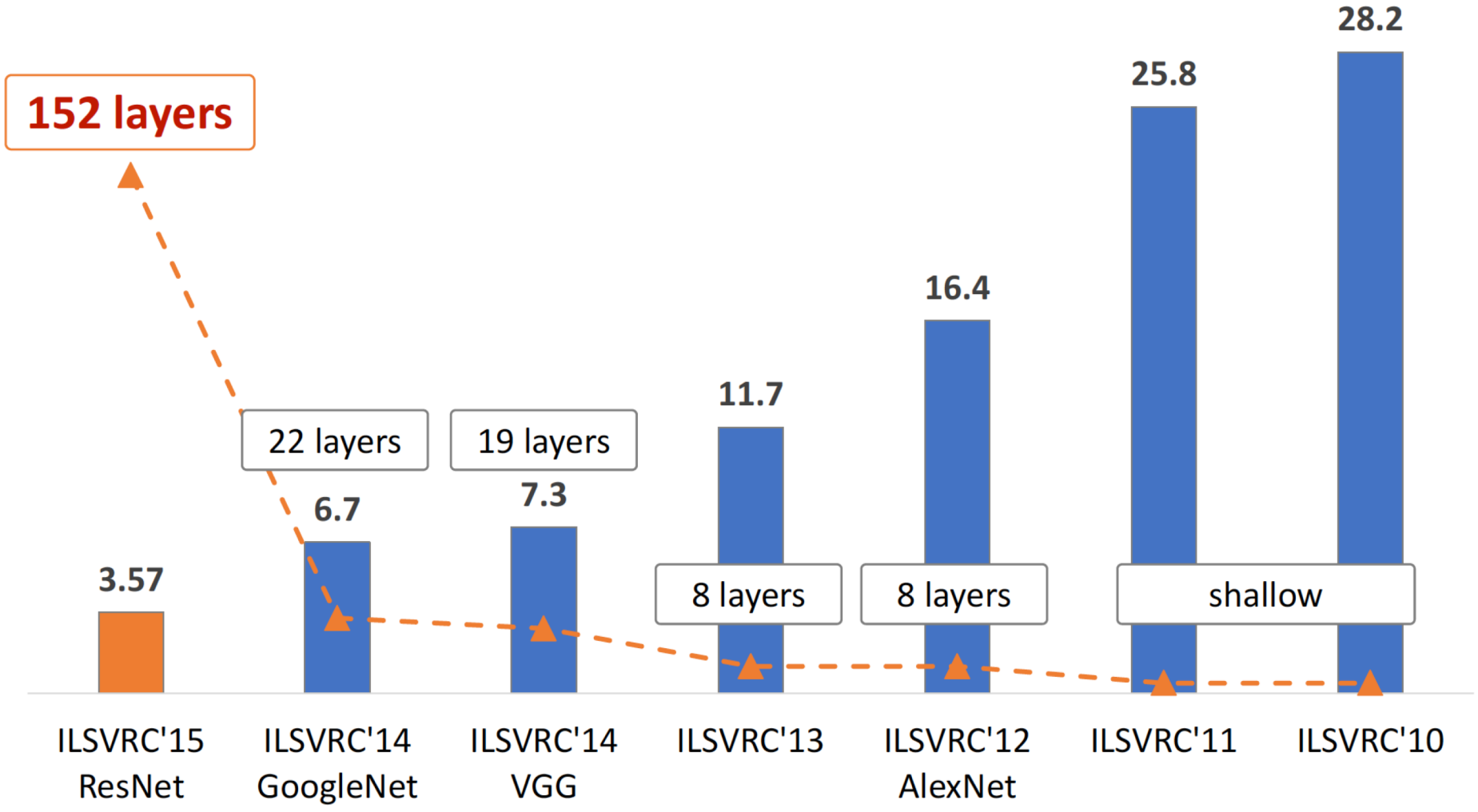
# Outline

- Convolutional Neural network
- Training Tips
- Case Studies

(Credits: Stanford CS231n Lecture Notes and Kaiming He's tutorial)

# Revolution of Depth

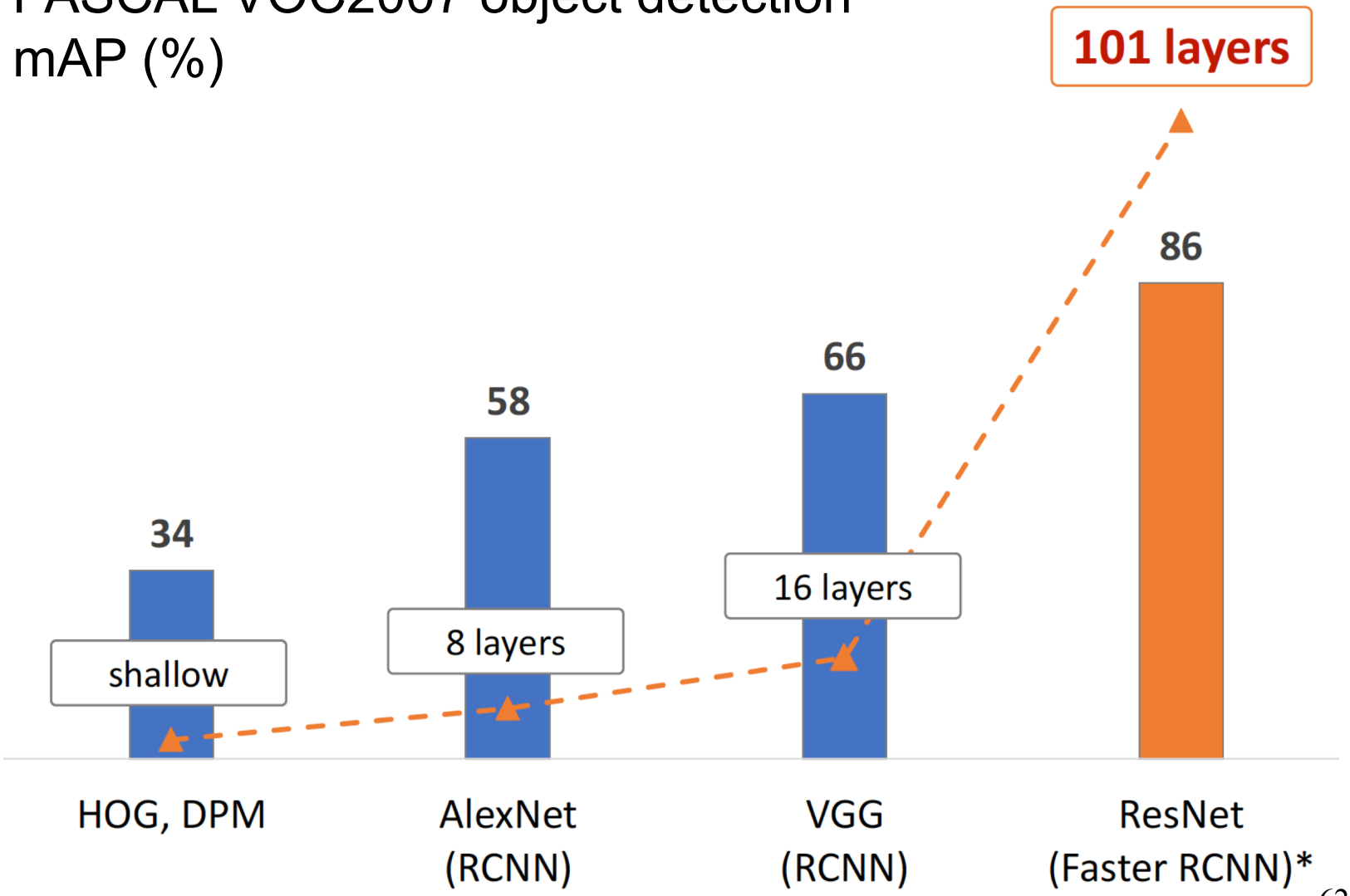
ImageNet classification top-5 error (%)




[Kaiming He]

# Revolution of Depth

PASCAL VOC2007 object detection mAP (%)



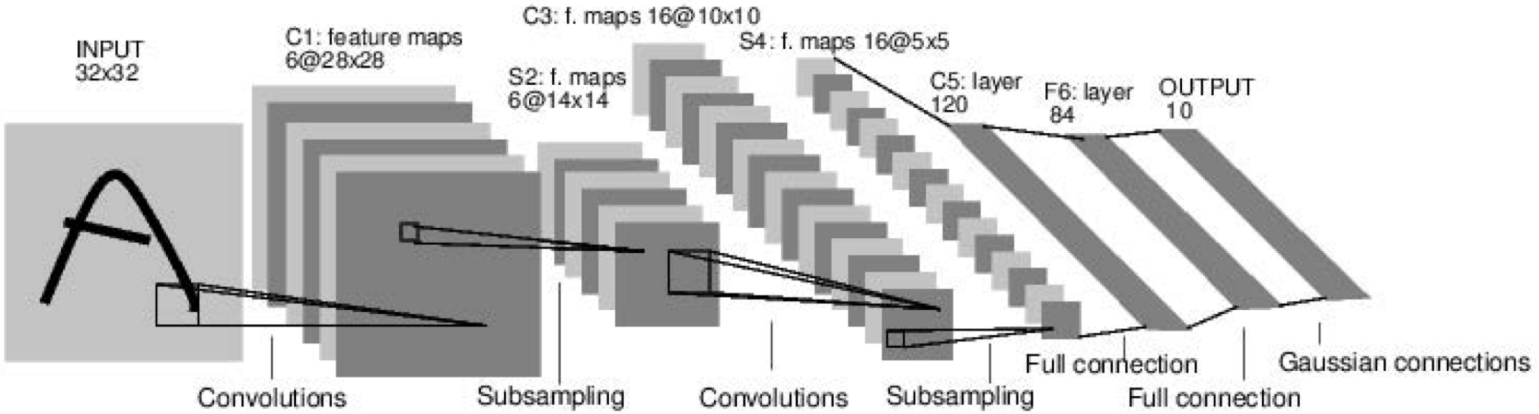

[Kaiming He]

# Case Study – LeNet

First successful CNN for recognition of hand-written digits

Propose basic components of modern ConvNets

- Convolution: locally-connected, spatially weight-sharing (5x5 at stride 1)
- Subsampling (pooling) (2x2 at stride 2)
- [CONV-POOL-CONV-POOL-FC-FC]
- Training by Backpropagation

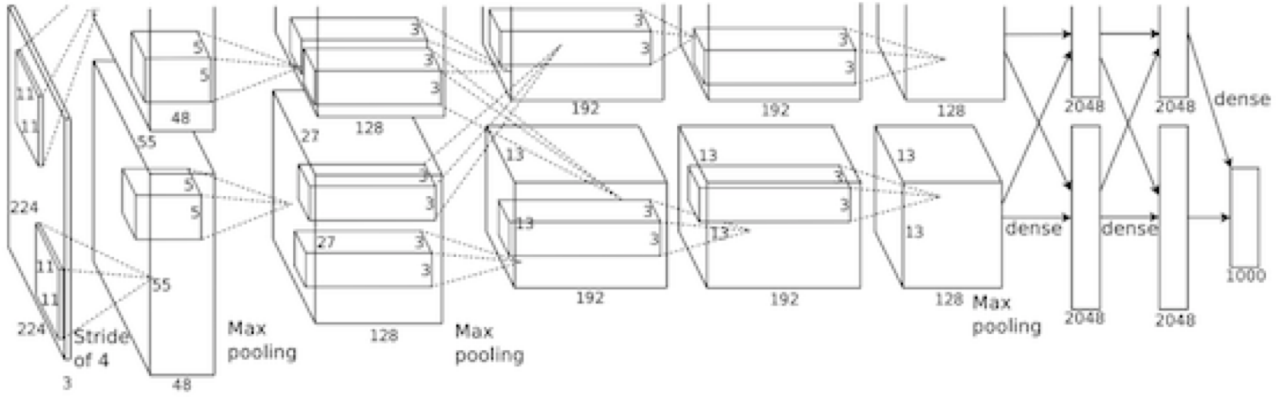



Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner. Gradient-based Learning Applied to Document Recognition. Proc IEEE 1998

# Case Study – AlexNet

The first work revolutionized CNN in computer Vision

- Similar to LeNet, but deeper, bigger, and featured layers of CONV, RELU, POOL
- In ImageNet ILSVRC challenge 2012, significantly outperform the runner-up (top 5 error of 16% < 26%)
- ReLU: accelerate training and better grad prop (vs. tanh)
- Dropout: In-network ensembling for reducing overfitting
- Heavy data augmentation: Label-preserving transformation




A. Krizhevsky, I. Sutskever and G. Hinton. *Imagenet Classification with Deep Convolutional Neural Networks*. NIPS 2012

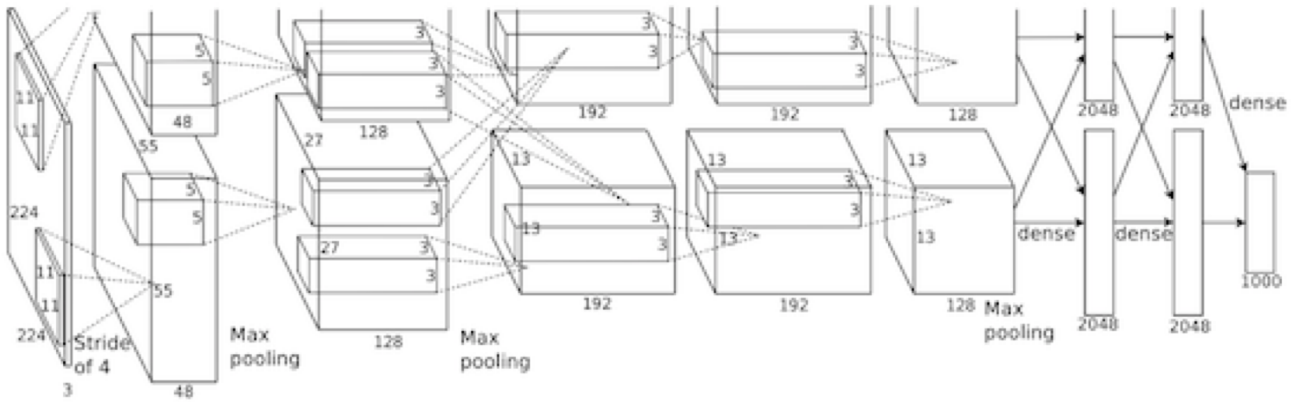
# Case Study – AlexNet

## Architecture details

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)

## Other details

- Used Norm layers (not common anymore)
- Dropout 0.5
- Batch size 128
- SGD Momentum 0.9
- Learning rate 1e-2, reduced by 10 manually when val acc. plateaus
- L2 weight decay 5e-4
- 7 CNN ensemble: 18.2% -> 15.4%

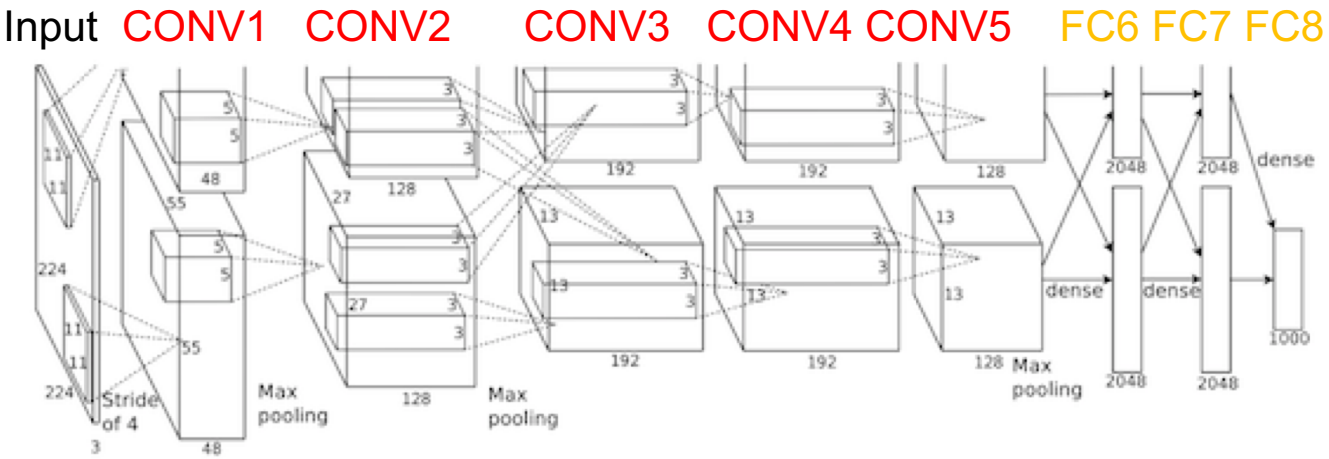



[cs231n]

# Case Study – AlexNet

## Implementation details

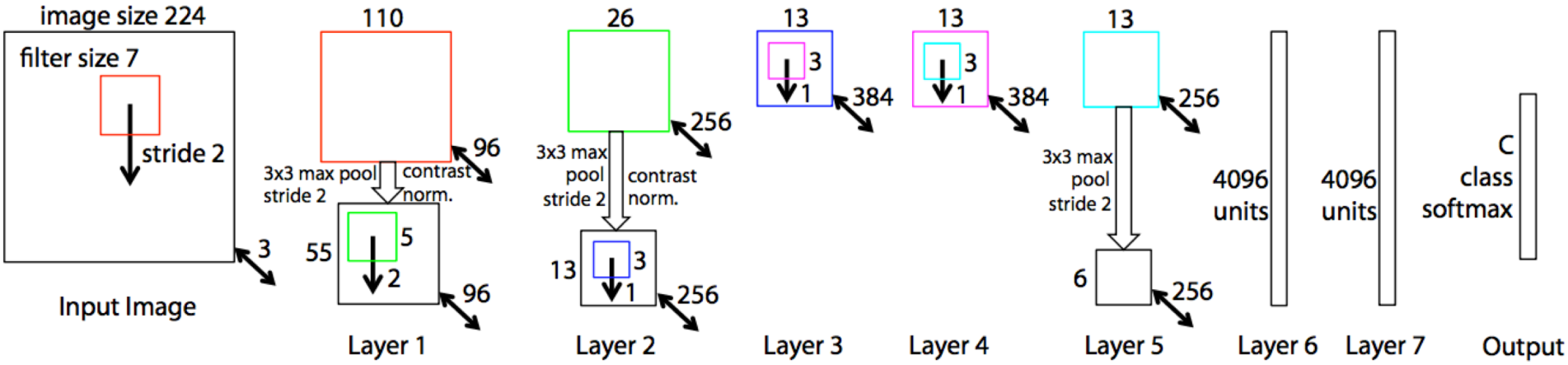
- Trained on GTX 580 GPU with only 3 GB of memory
- Network spread across 2 GPUs, half the neurons (feature maps) on each GPU
- CONV1/2/4/5: Connections only with feature maps on same GPU
- CONV3, FC6/7/8: Connections with all feature maps in preceding layer, communication across GPUs



# Case Study – ZFNet

## Engineered AlexNet

- The winner of ILSVRC 2013 (ImageNet Top-5: 16.4% → 11.7%)
- e.g. Compared to AlexNet,
  CONV1: (11x11 stride 4) to (7x7 stride 2)
  CONV3,4,5: (384, 384, 256) filters to (512, 1024, 512)
- Not popularly used these days

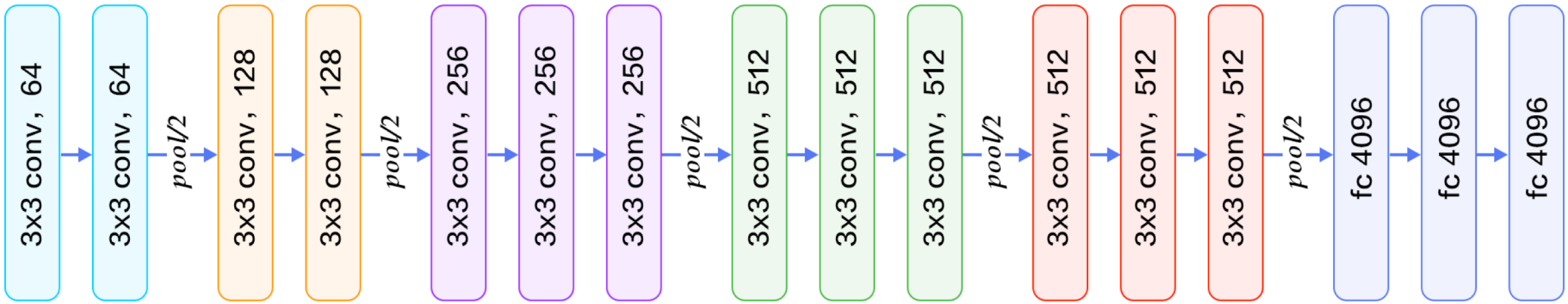



M. D. Zeiler and R. Fergus. *Visualizing and Understanding Convolutional Networks*. ECCV 2014

# Case Study – VGGNet

Deeper versions of AlexNet (8 layers)

- The runner-up of ILSVRC 2014 (ImageNet Top-5: 11.7% → 7.3%)
- Good performance but not so efficient
- Modularized design:
  - Stack the same module (3x3 Conv stride 1, pad 1)
  - Same computation per module (1/2 spatial size → 2x filters)
- Stage-wise training: VGG-11 → VGG-13 → VGG-16




K. Simonyan and A. Zisserman. *Very Deep Convolutional Networks for Large-Scale Image Recognition*. ICLR 2015

# Case Study – VGGNet

Most memory is in early CONV

| | | |
|---|---|---|
| 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 |
| CONV3-512: [28x28x512] | memory: 28*28*512=400K | params: (3*3*512)*512 = 2,359,296 |
| POOL2: [14x14x512] | memory: 14*14*512=100K | params: 0 |
| CONV3-512: [14x14x512] | memory: 14*14*512=100K | params: (3*3*512)*512 = 2,359,296 |
| CONV3-512: [14x14x512] | memory: 14*14*512=100K | params: (3*3*512)*512 = 2,359,296 |
| 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 |

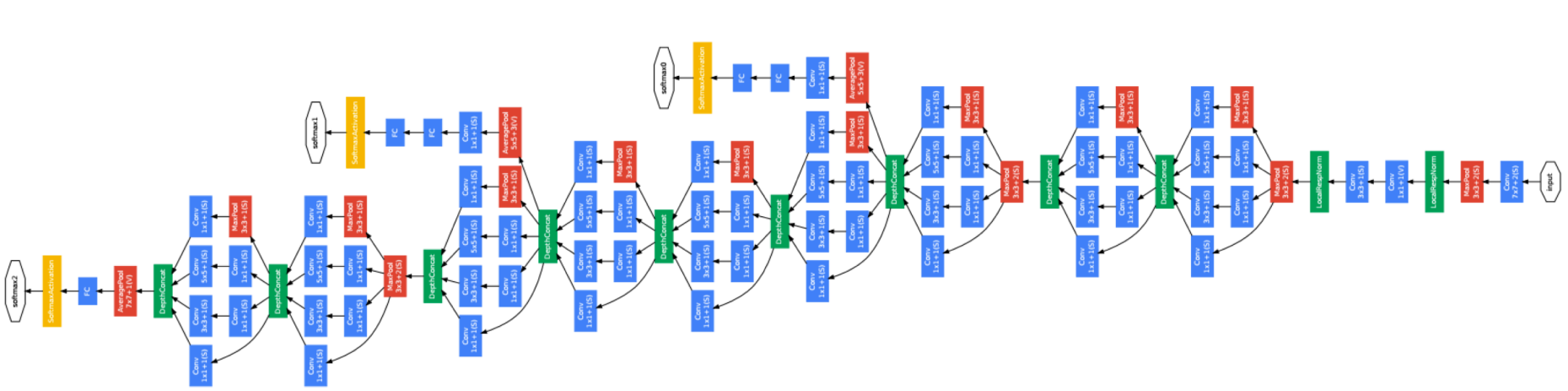
TOTAL memory: 24M * 4 bytes ~= 96MB/image
TOTAL params: 138M parameters

Most params are in late FC

# Case Study – GoogLeNet

Inception (network in network) structure

- The winner of ILSVRC 2014 (ImageNet Top-5: 7.3% → 6.7%)
- Much fewer parameters of 5M compared to 60M of AlexNet
- No FC layers and 22 layers in total (v1)
- Keep updating… to Inception-v4 (Inception-ResNet)

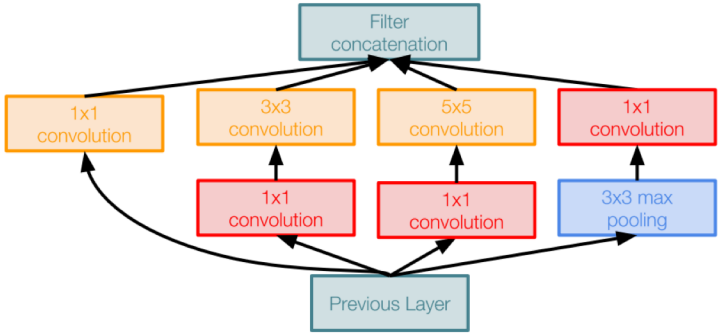


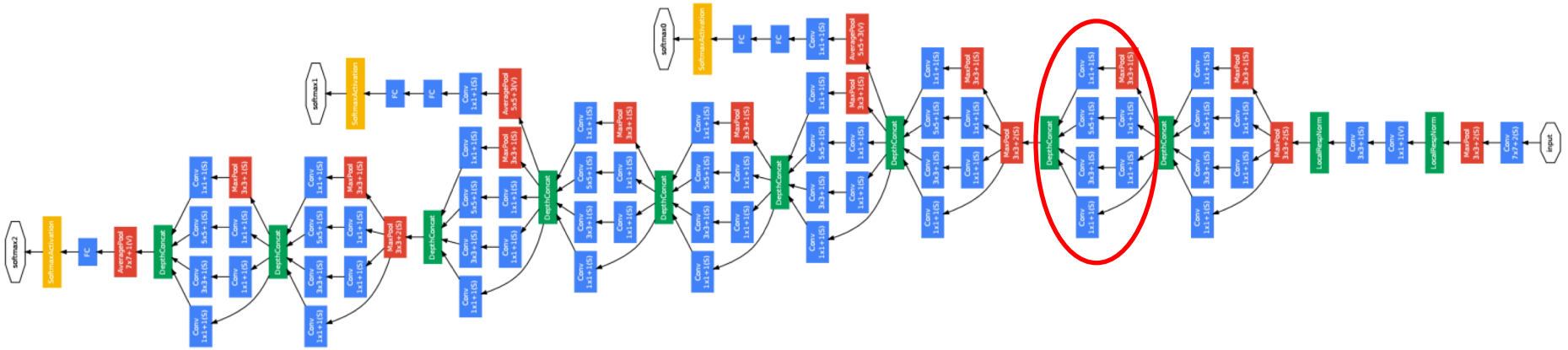
C. Szegedy et al. *Going Deeper with Convolutions*. CVPR 2015

# Case Study – GoogLeNet

## Inception module

- Design a good local network topology (network within a network) and then stack these modules on top of each other

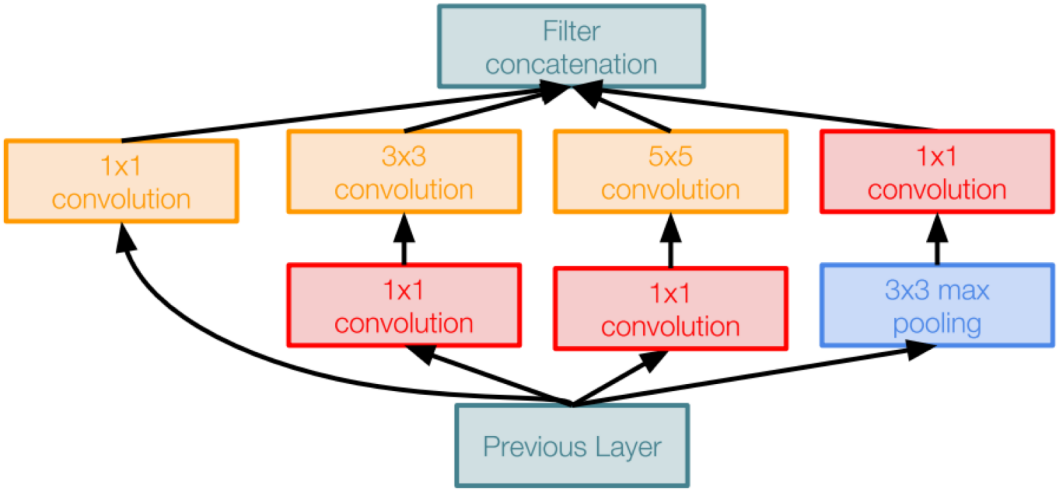


# Case Study – GoogLeNet

Key ideas of Inception module

- Multiple branches: e.g., 1x1, 3x3, 5x5, pool
- Shortcuts: stand-alone 1x1
- Bottleneck: reduce dim by 1x1 before expensive 3x3/5x5 conv
- Concatenate all filter outputs together depth-wise




cf) 1x1 CONV with 32 filters

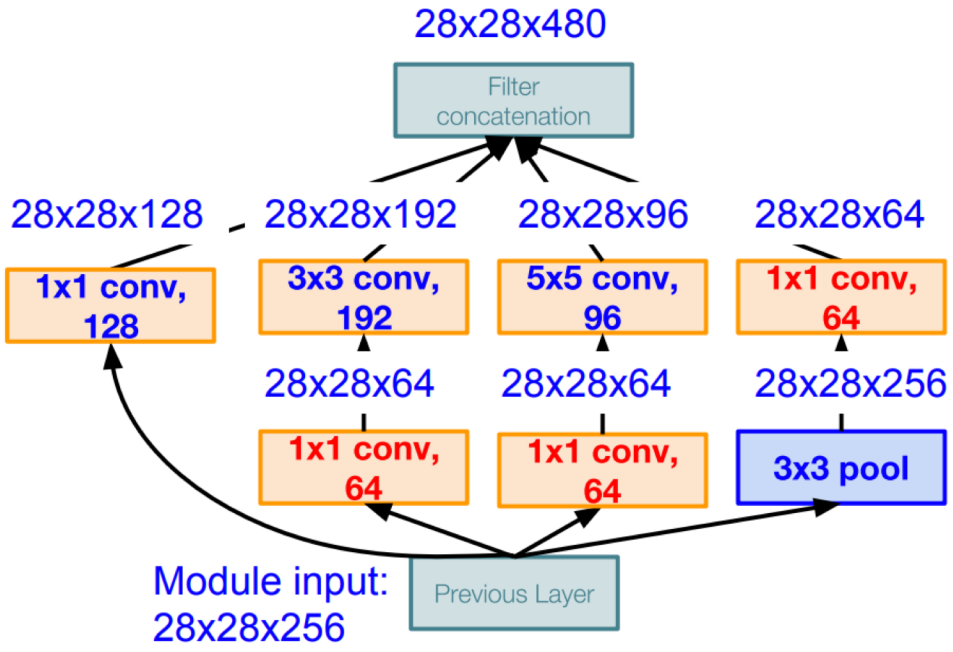

Each filter has size 1x1x64, and performs a 64-dim dot product

[Kaiming He, cs231n]

# Case Study – GoogLeNet

## Inception module with dimension reduction

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




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

[cs231n]

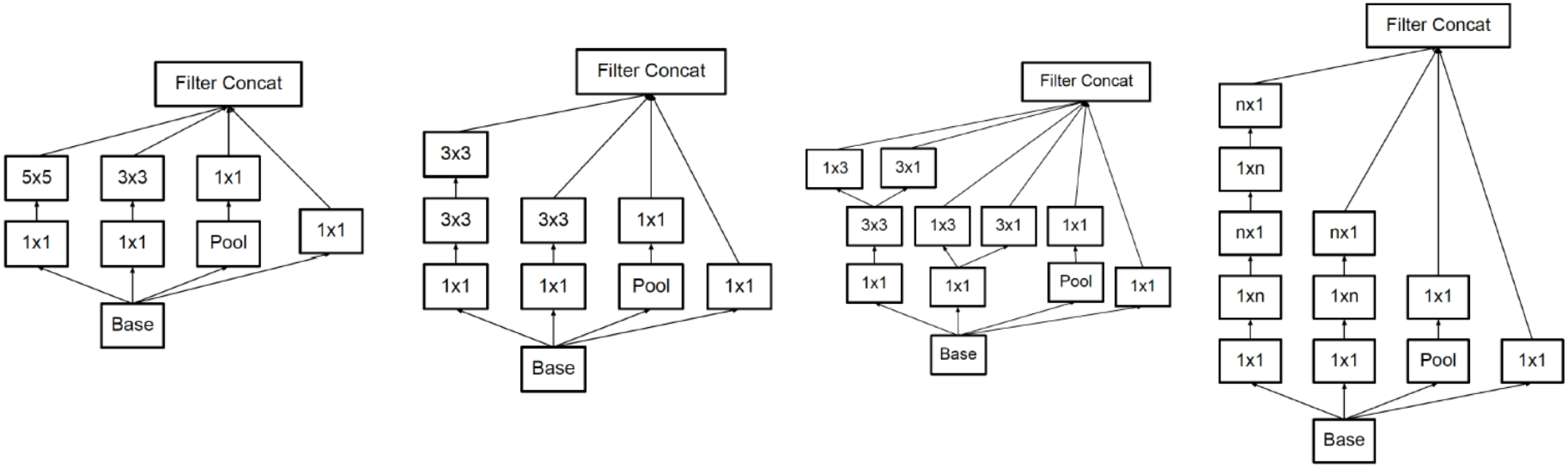
# Case Study – GoogLeNet / Inception v1-v3

More templates, but the same 3 properties are kept

- Multiple branches, shortcuts, bottleneck

Optimizing multi-branch CNNs largely benefits from BN

- Including all Inceptions and ResNets



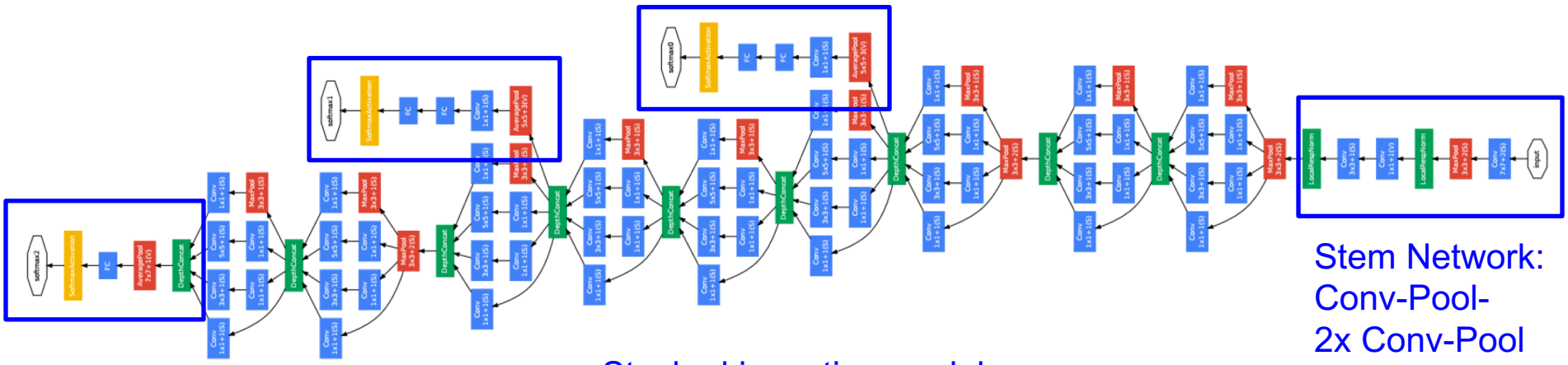

[Kaiming He]

# Case Study – GoogLeNet

## Full GoogLeNet architecture

- Stack Inception modules with dim reduction on top of each other
- 22 total layers with weights (parallel layers count as 1 → 2 layers per Inception module. Don't count auxiliary output layers)

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



Stem Network: Conv-Pool-2x Conv-Pool

Stacked inception modules

Classifier output (removed expensive FC layers!)

# ResNet – Degradation Problem

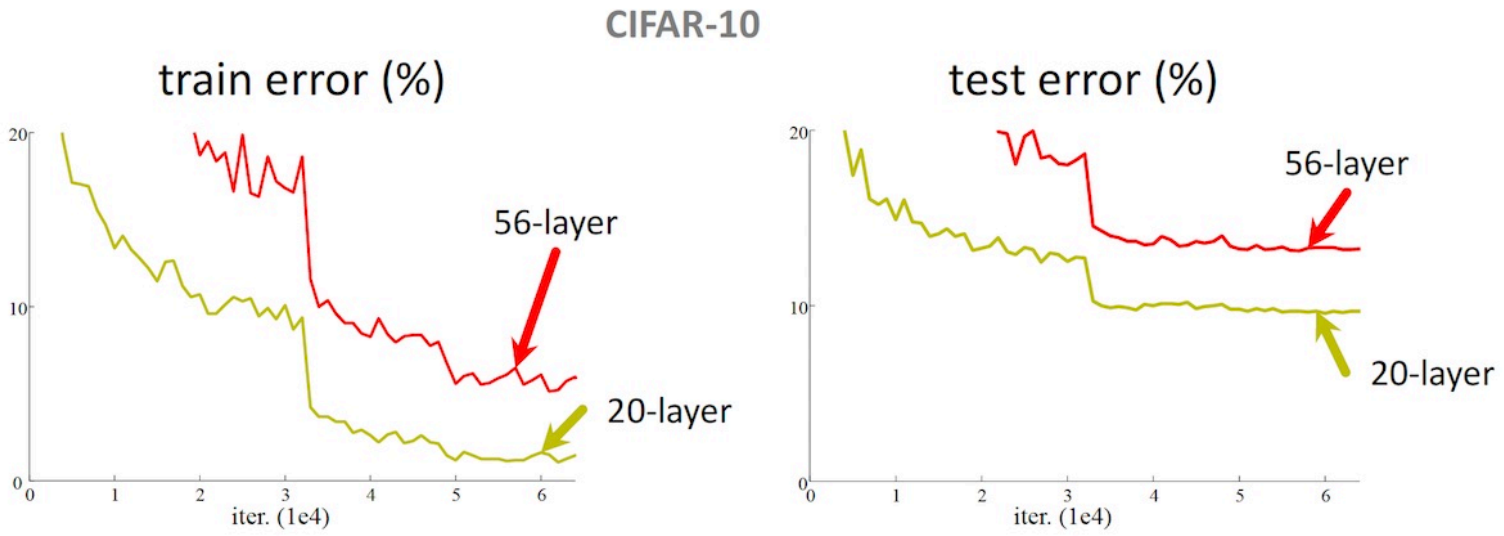
Learn better networks by simply stacking more layers?

*Plain nets*: stacking 3x3 conv layers…

- With the network depth increasing, accuracy gets saturated and then degraded rapidly

NOT caused by overfitting

- 56-layer net has higher *training* and *test* error than 20-layer net

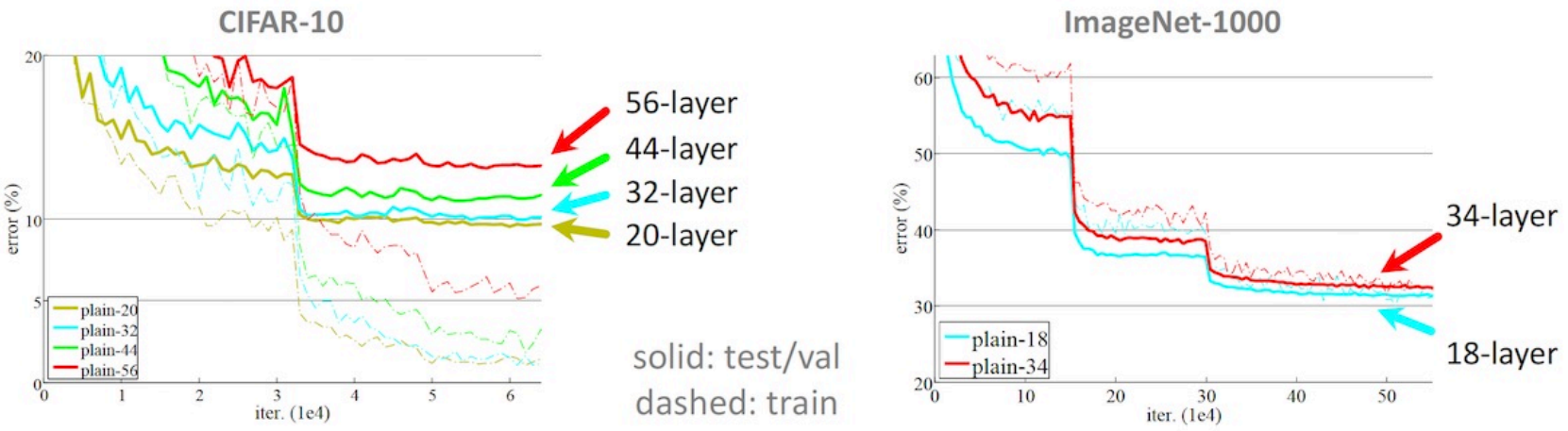



Kaiming He et al. *Deep Residual Learning for Image Recognition*. CVPR 2016

# ResNet – Degradation Problem

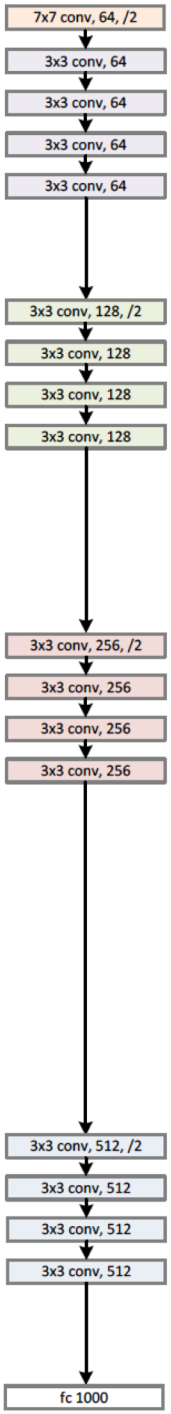
*Overly deep* plain nets have higher training error

A general phenomenon, observed in many datasets

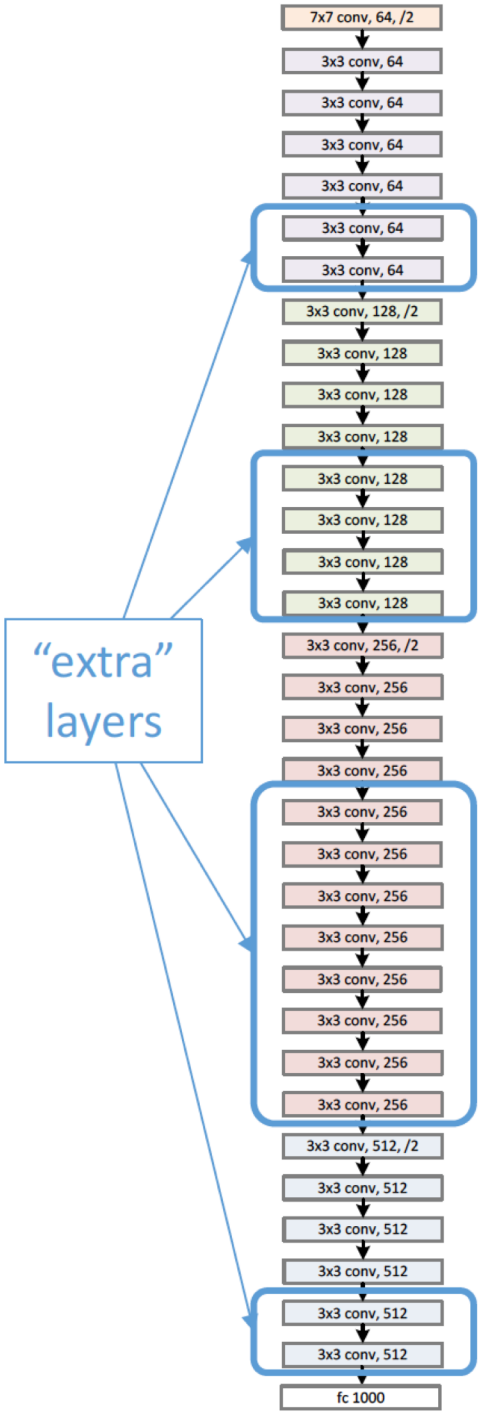



Kaiming He et al. *Deep Residual Learning for Image Recognition*. CVPR 2016

A shallower model (18 layers)




[Kaiming He]




"extra" layers

A deeper counterpart (34 layers)

A richer solution space

A deeper model should not have higher training error

A solution by construction

- Original layers: copied from a learned shallower model
- Extra layers: set as identity
- At least same training error

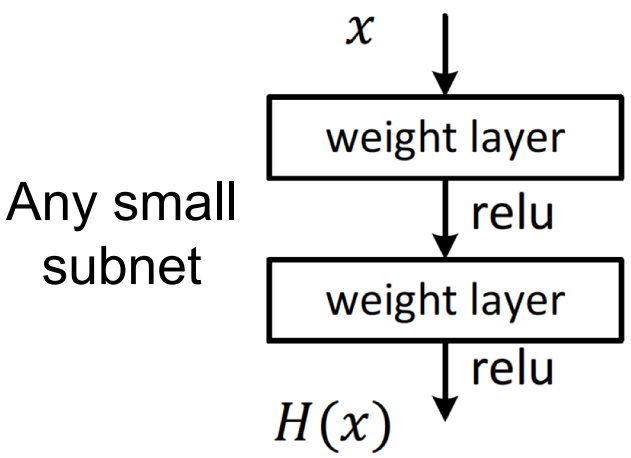
(Hypothesis) Optimization difficulties: solvers cannot find the solution when going deeper…

# Deep Residual Learning

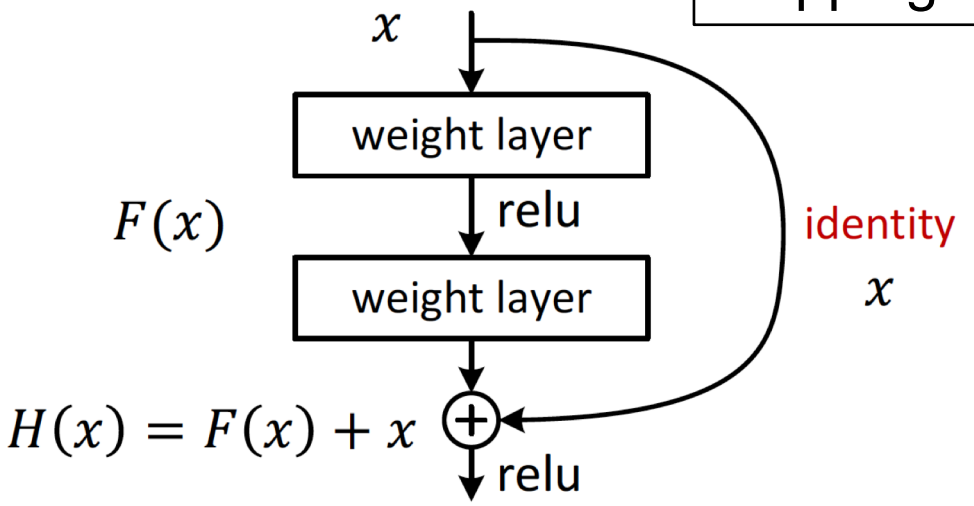
Feedforward neural networks with *shortcut connections* (i.e. identity mapping)

Let $H(x)$ is a desired mapping

Plain net




Residual net




Hope the small net fit $H(x)$

Hope the small net fit $F(x)$

Then $H(x) \cong F(x) + x$

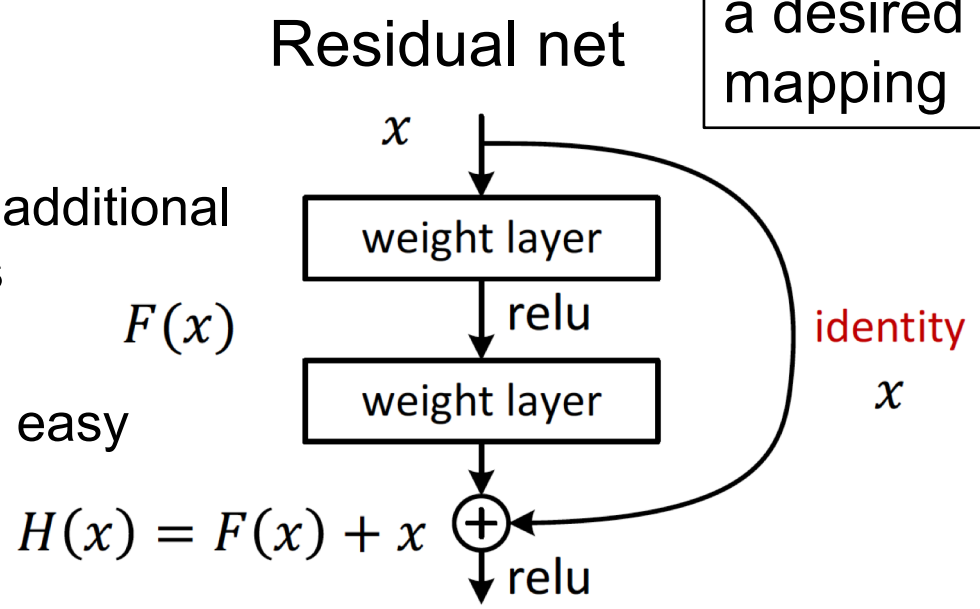
# Deep Residual Learning

Feedforward neural networks with *shortcut connections* (i.e. identity mapping)

Let $H(x)$ is a desired mapping

$F(x)$ is a residual mapping w.r.t. identity

- Focus on representing additional info from what previous layers already learned
- If identity were optimal, easy to set weights as 0 (cf. Identity mappings that plain models have difficulty in representing)




Hope the small net fit $F(x)$

Then $H(x) \cong F(x) + x$

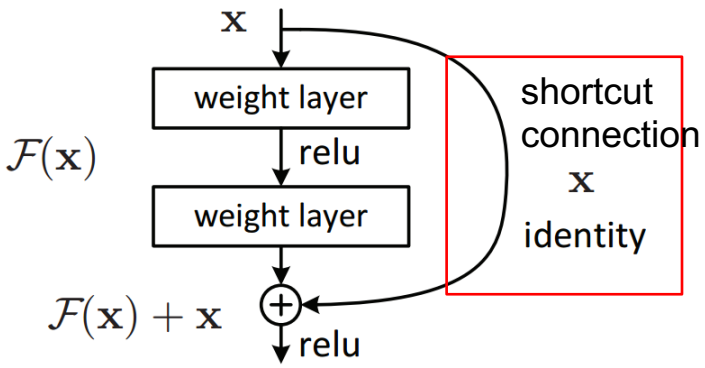
# Advantage of Residual Learning

Identity shortcut connections add neither extra parameter nor computational complexity

Easy end-to-end optimization by backpropagation

Accuracy gains from greatly increased depth

- 152-layer ResNet achieves 3.57% top-5 errors on ImageNet datasets with lower complexity than VGGNet

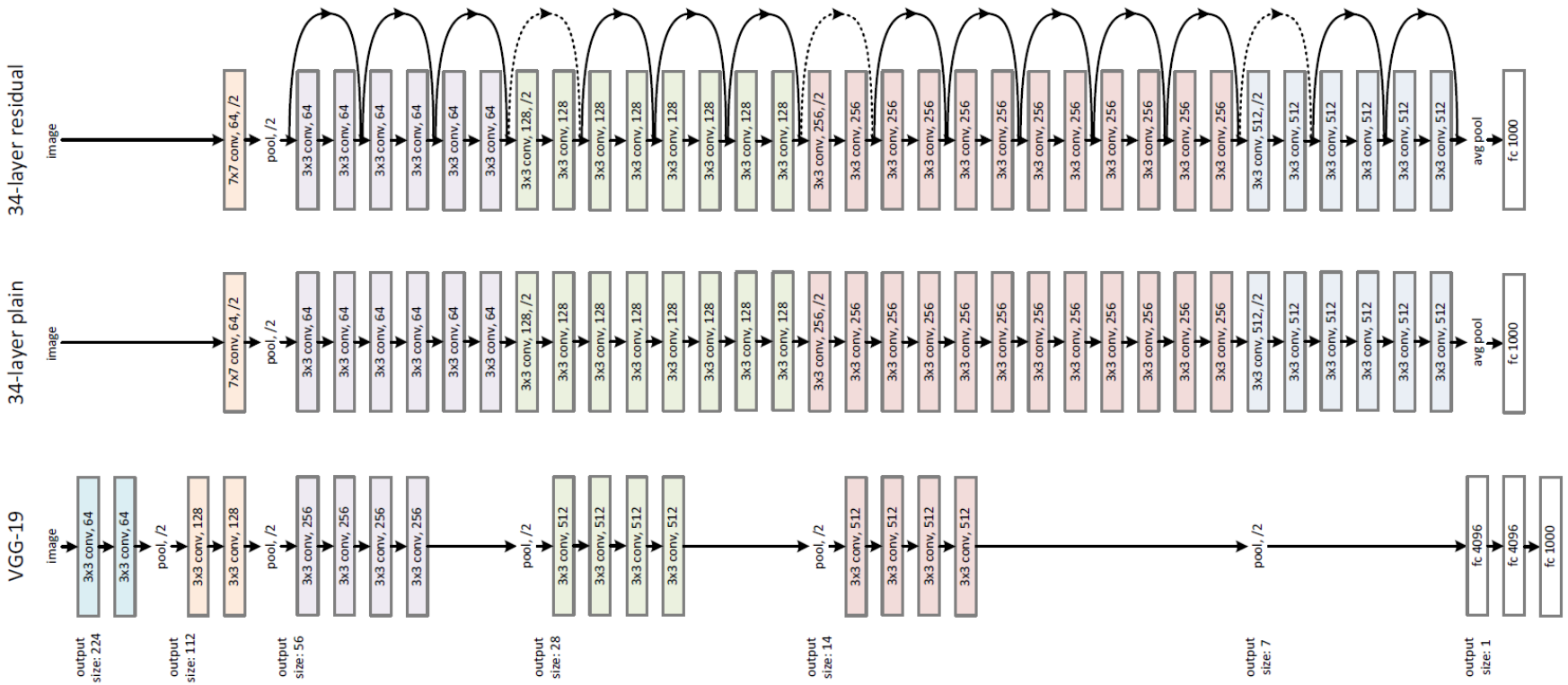



$\cong \mathcal{H}(x)$ (desired function)

# 34-Layer ResNet

Design principles – similar to VGG-19

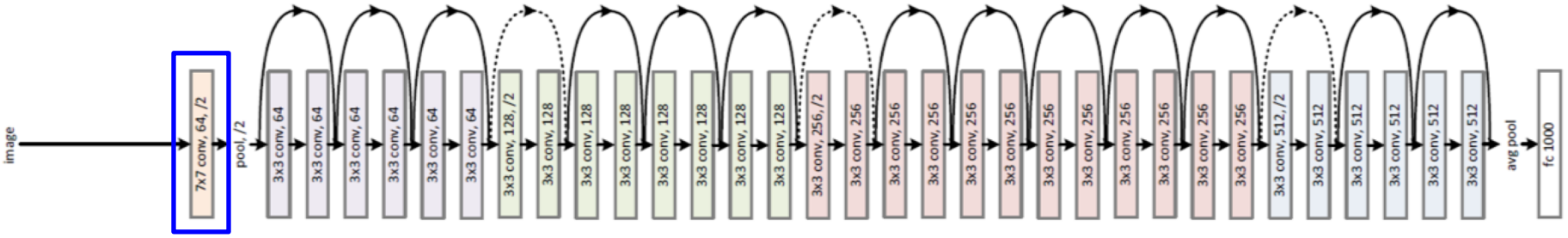
- Same feature map size, same # filters (channels)
- Whenever feature map size is halved, # filters is doubled to preserve the time complexity per layer



# 34-Layer ResNet

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)
- 34-layer ResNet has only 19% FLOPs of VGG-19: (i) 1/2 input size (224/14 -> 112/7), ii) No hidden FC layer
- Total depths of 34, 50, 101, or 152 layers for ImageNet




Additional conv layer at the beginning

No FC layers except fc1000 to output classes

# 34-Layer ResNet

Design principles – similar to VGG-19

- Same feature map size, same # filters (channels)
- Whenever feature map size is halved, # filters is doubled to preserve the time complexity per layer

For ResNet, use blocks for every 2 conv layers

- Use project shortcut when # filters increases

34-layer residual networks have only 19% FLOPs of VGG-19

- 1/2 input size (224~14 -> 112~7)
- Gradually increase # filters
- No hidden FC layer

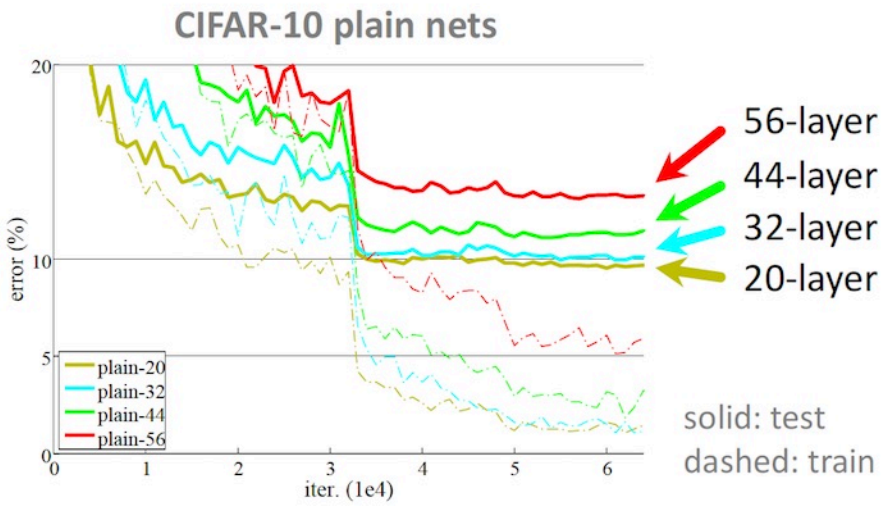
# 34-Layer ResNet

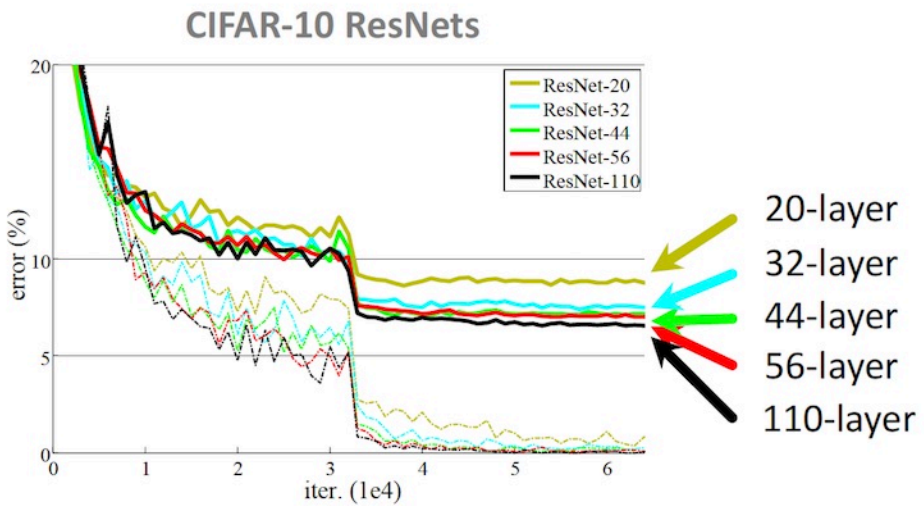
Comparing 18/34-layer residual/plain on ImageNet

- Plain-18/34: degradation problem
- ResNet-18/34: ResNet-34 better
- Plain/ResNet-18: ResNet-18 converges faster
- Deeper ResNets have lower training error, and also lower test error

Top-1 error on ImageNet validation

| | plain | ResNet |
|---|---|---|
| 18 layers | 27.94 | 27.88 |
| 34 layers | 28.54 | **25.03** |

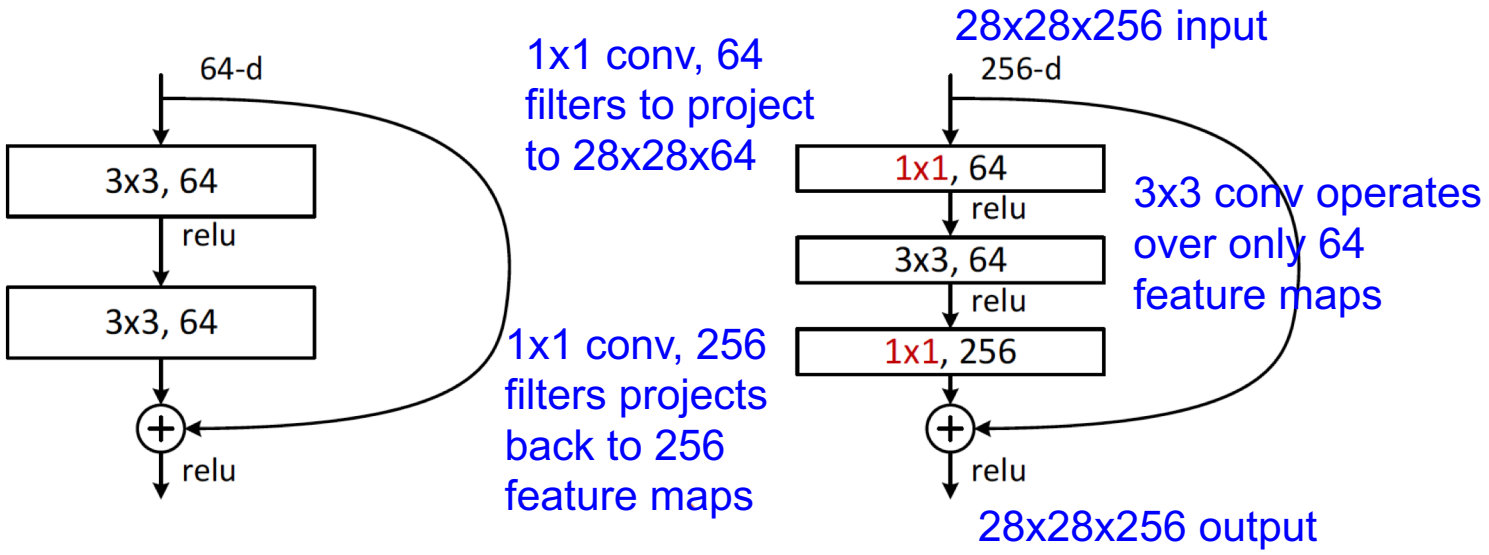


# A Practical Design of Deeper ResNet

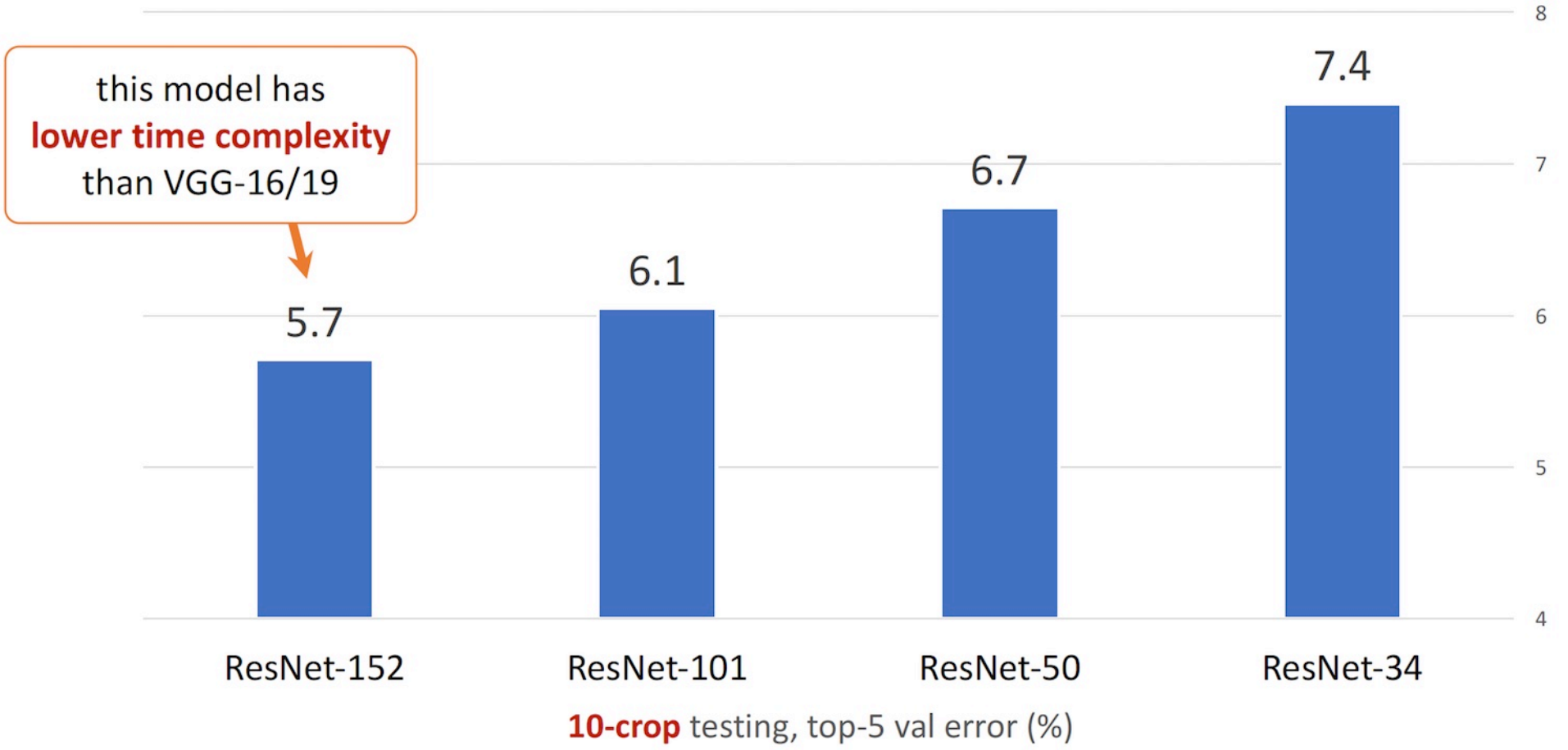
Deeper bottleneck architectures (ResNet-50+)

- Two 3x3 CONV layers → 1x1, 3x3, 1x1 layers
- Use bottleneck 1x1 layers – reducing and increasing dimensions
- Both designs have similar time complexity
- For 50/101/152-layers: 152-layer ResNet still has lower complexity than VGG-19 (15.3/19.6 BFLOPs)



# ImageNet Experiments

Deeper ResNet have lower errors



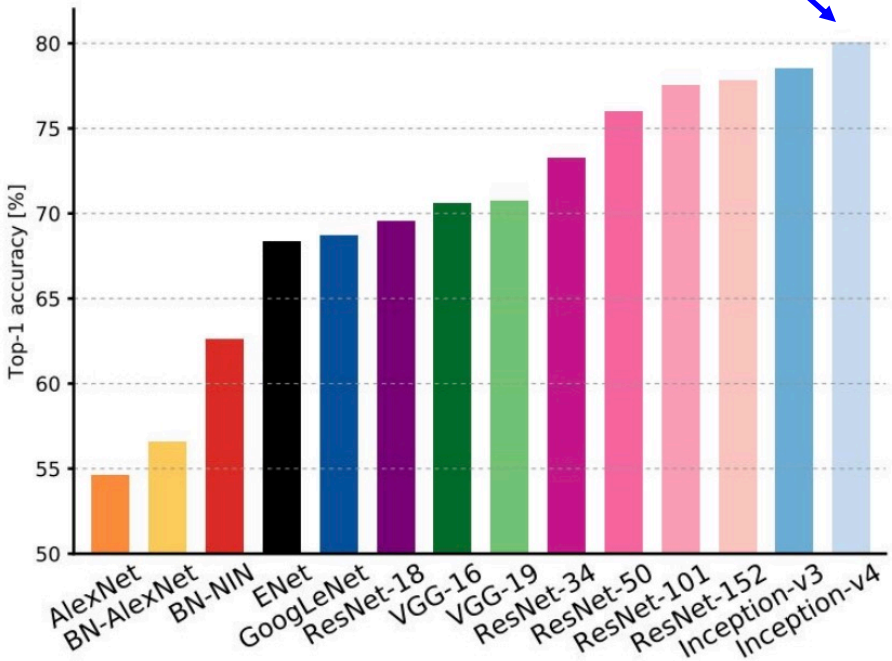
# ResNet Summary

Swept 1st place in all ILSVRC&COCO 2015 competitions

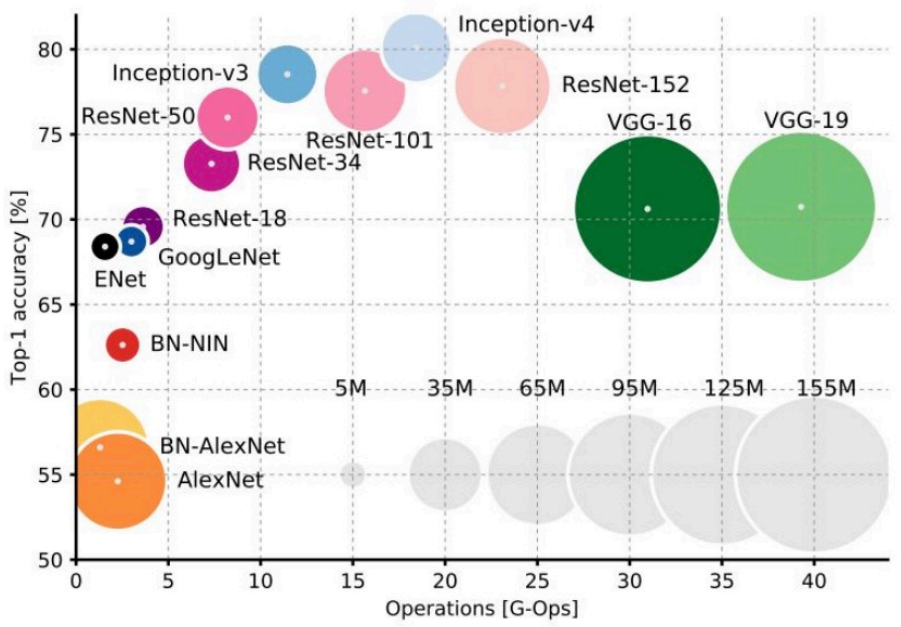
- ImageNet classification/detection/localization, COCO detection/ segmentation
- Able to train very deep networks without degrading (152 layers on ImageNet, 1202 on CIFAR)
- ImageNet Top-5: 6.7% → 3.5% better than human (5.1%)

# Comparing Complexity

Inception-v4: Resnet + Inception




- VGG: Highest memory, most operations
- GoogLeNet: most efficient
- AlexNet: Smaller compute, still memory heavy, lower accuracy




Alfredo Canziani, Adam Paszke, Eugenio Culurciello. *An Analysis of Deep Neural Network Models for Practical Applications.* arXiv 2017.