Lecture 6: Training CNNs and CNN Architectures

Course Logistics

- Assignment 1 is due **today** at 11:59PM!
- Project proposal will be announced **today** as well

Student Spotlight!

- **Ed Posts:**
  - Adem Rimpapa, Sky Wang, Ben Wengreen, Eyas Taifour, Anurabh Sharma
- **Discussions after lecture:**
  - Christina Duong, Michael Liu, Ali Ahmad
- **Participation in Section:**
  - Ozair Ismail

Lecture Overview – Two Broad Sets of Topics

How to build CNNs?

- **Layers in CNNs**
- **Activation Functions**
- **CNN Architectures**
- **Weight Initialization**

How to train CNNs?

- **Data Preprocessing**
- **Data augmentation**
- **Transfer Learning**
- **Hyperparameter Selection**

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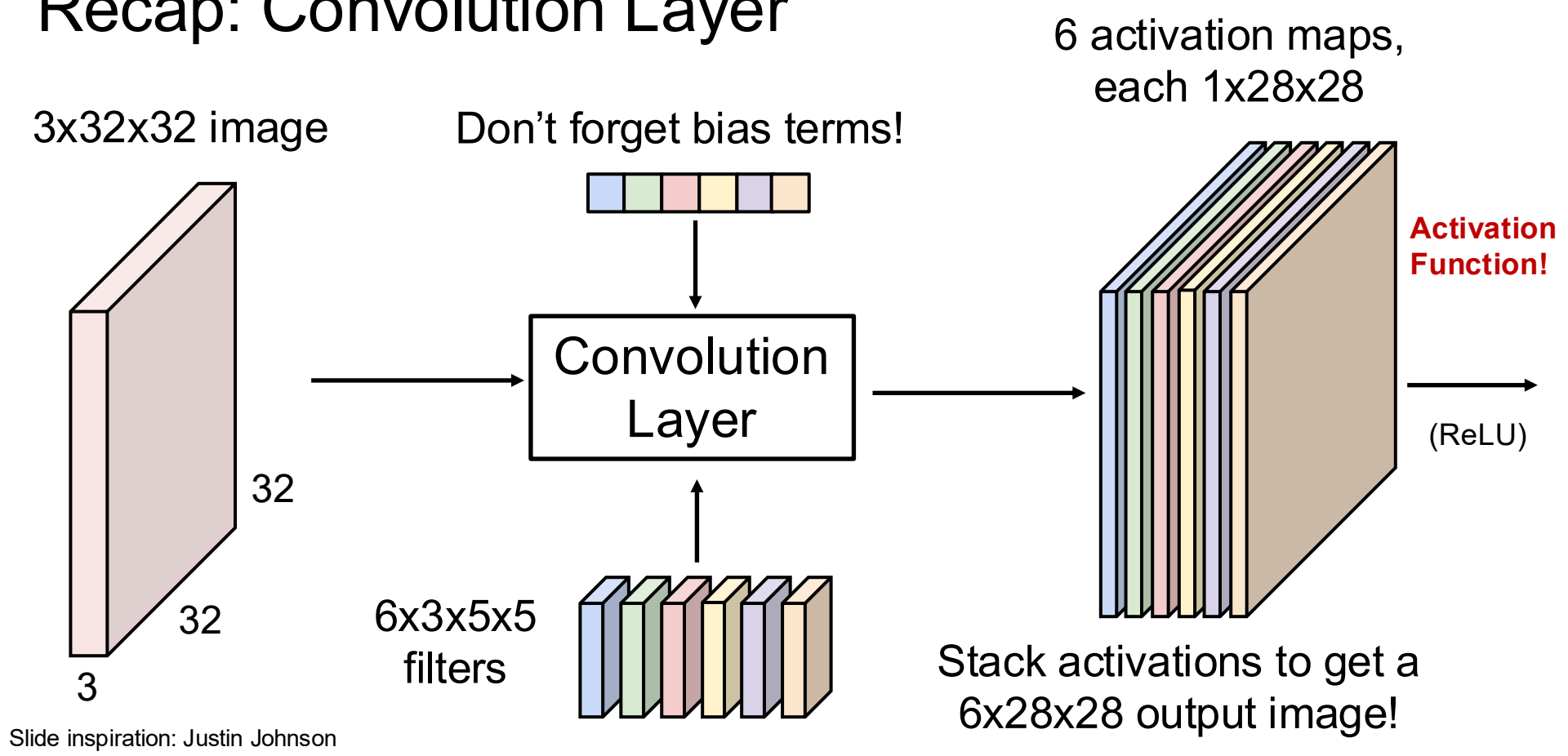
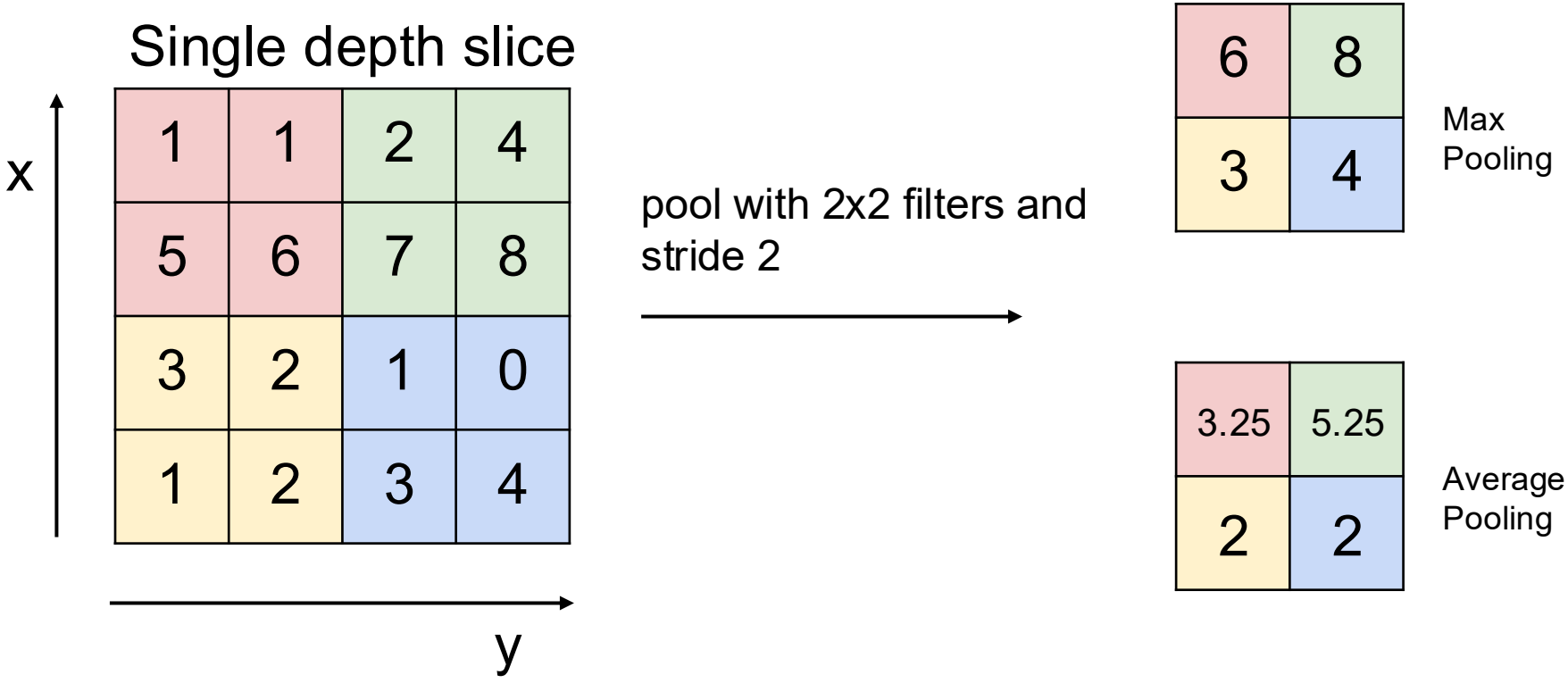
Recap: Convolution Layer



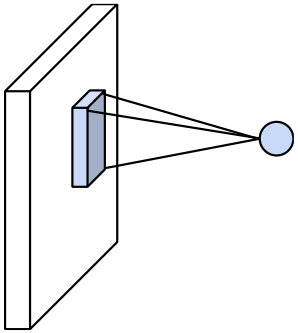
Slide inspiration: Justin Johnson

Recap: Pooling Layer

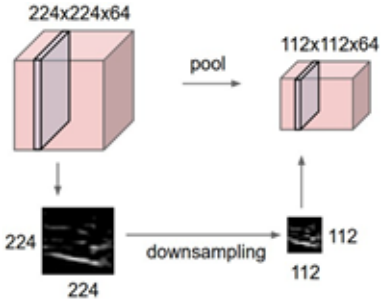


Components of CNNs

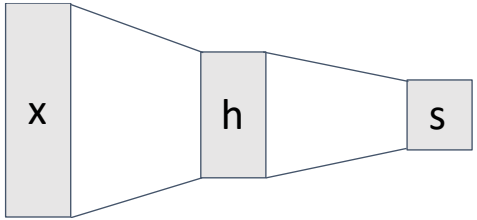
Convolution Layers



Pooling Layers



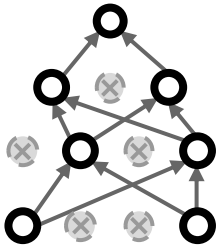
Fully-Connected Layers



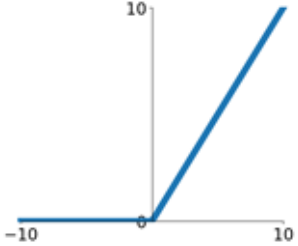
Normalization Layers

$$\hat{x}_{i,j} = \frac{x_{i,j} - \mu_j}{\sqrt{\sigma_j^2 + \varepsilon}}$$

Dropout (sometimes)



Activation Functions



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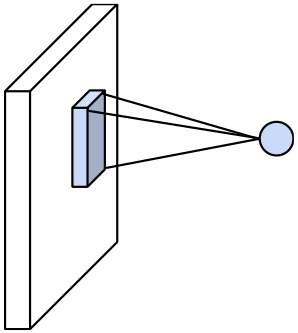

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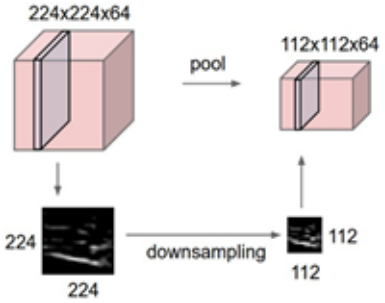

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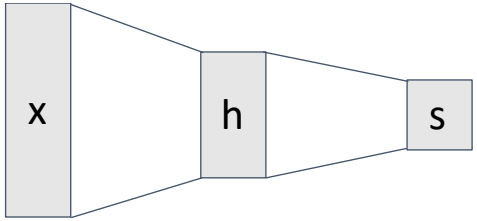

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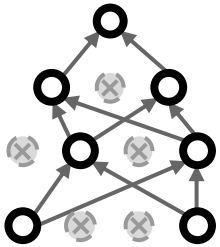

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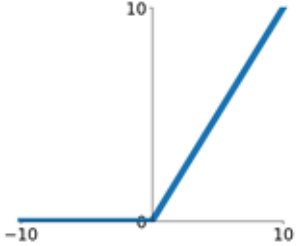

Example Normalization Layer: LayerNorm

High-level Idea: Learn parameters that let us scale / shift the input data

1. Normalize input data
2. Scale / shift using learned parameters

Ba, Kiros, and Hinton, “Layer Normalization”, arXiv 2016

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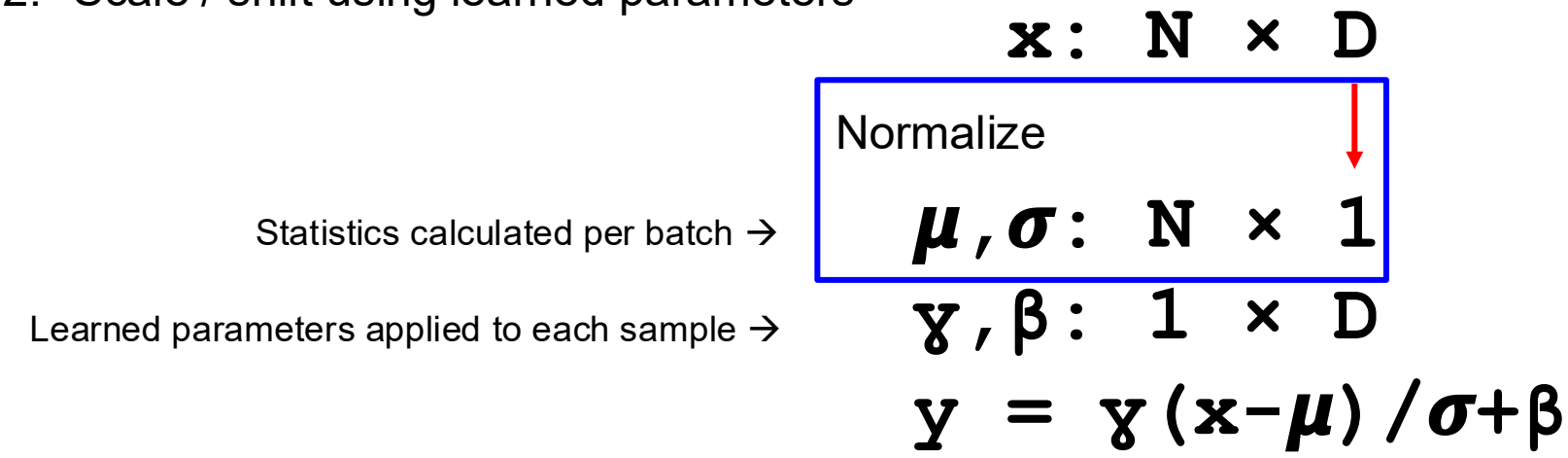

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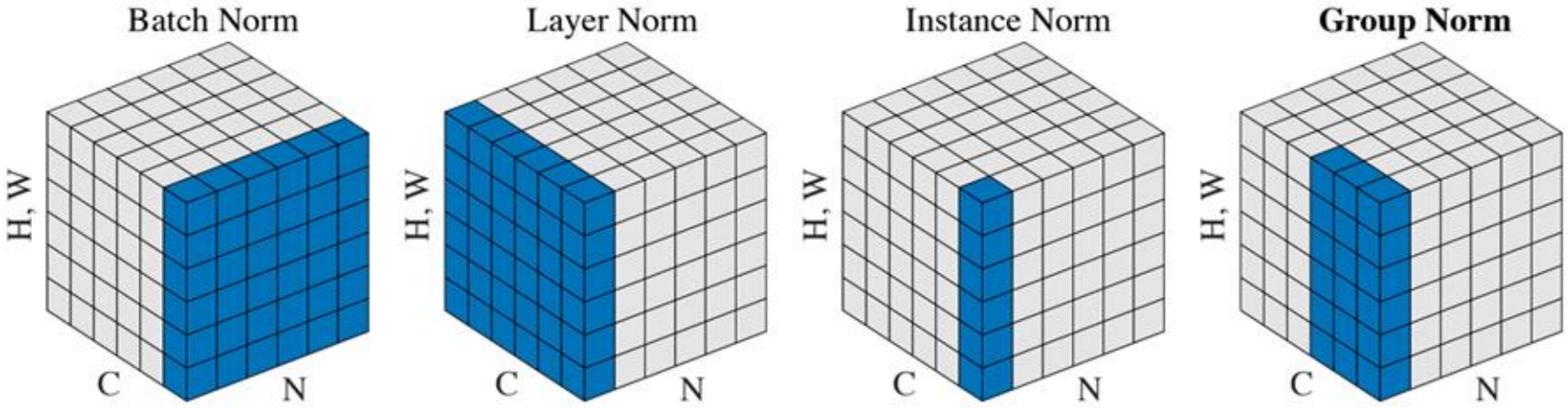
Other Normalization Layers

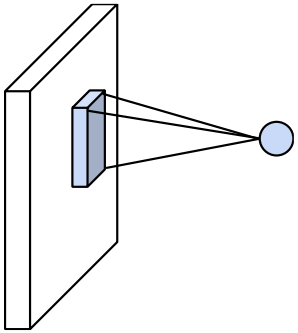


You will implement some of these in assignment 2!

Wu and He, “Group Normalization”, ECCV 2018

Components of CNNs

Convolution Layers



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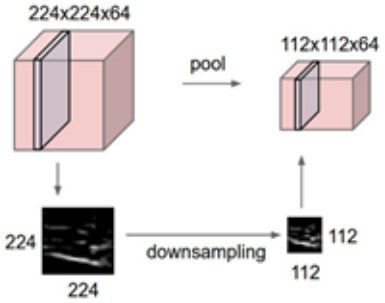

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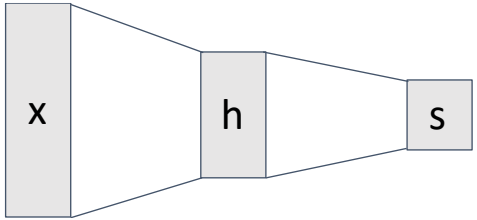

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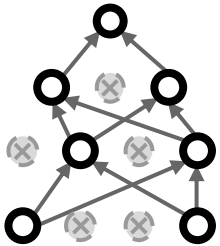

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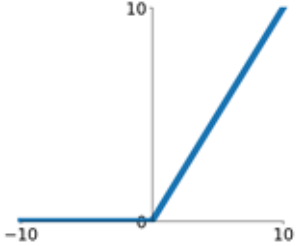

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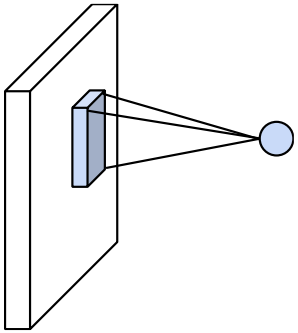

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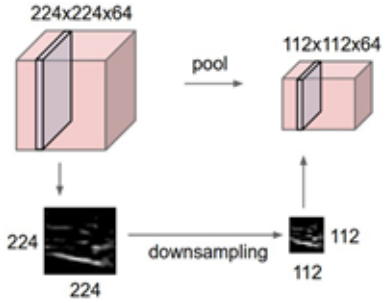

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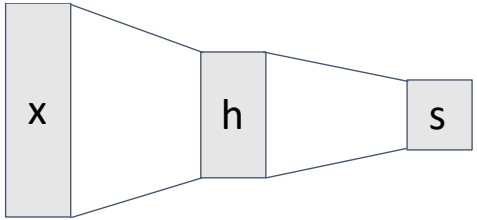

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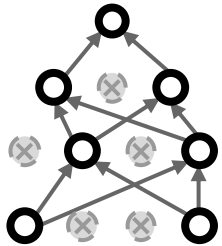

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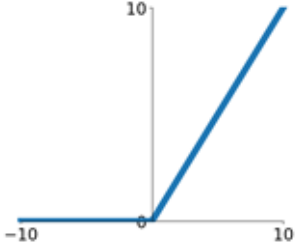
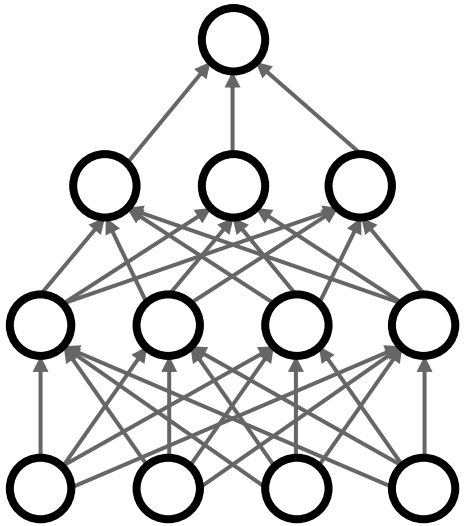
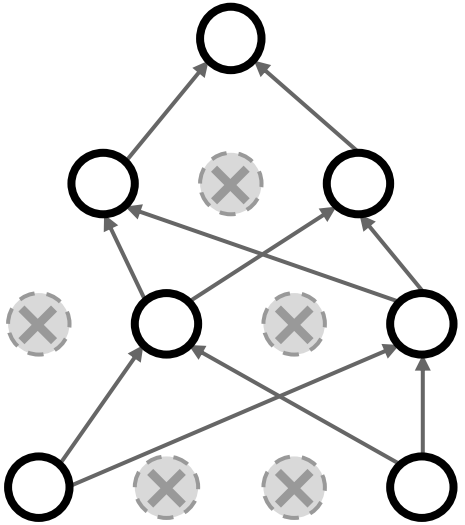


Regularization: Dropout

In each forward pass, randomly set some neurons to zero

Probability of dropping is a hyperparameter; 0.5 is common

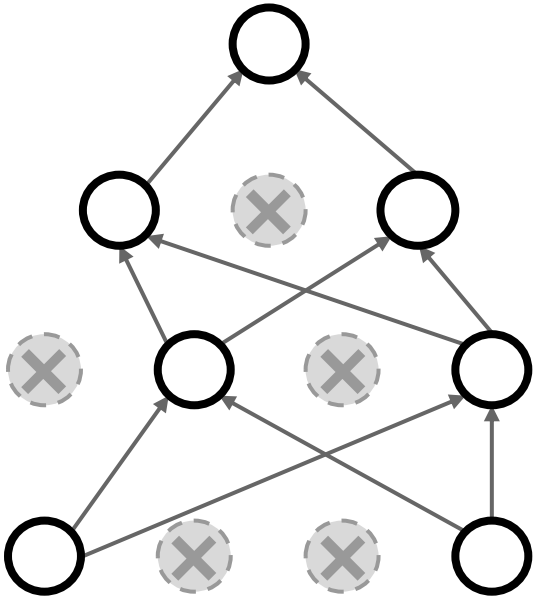




Srivastava et al, “Dropout: A simple way to prevent neural networks from overfitting”, JMLR 2014

Regularization: Dropout

How can this possibly be a good idea?



Forces the network to have a redundant representation;
Prevents co-adaptation of features

Regularization: Dropout

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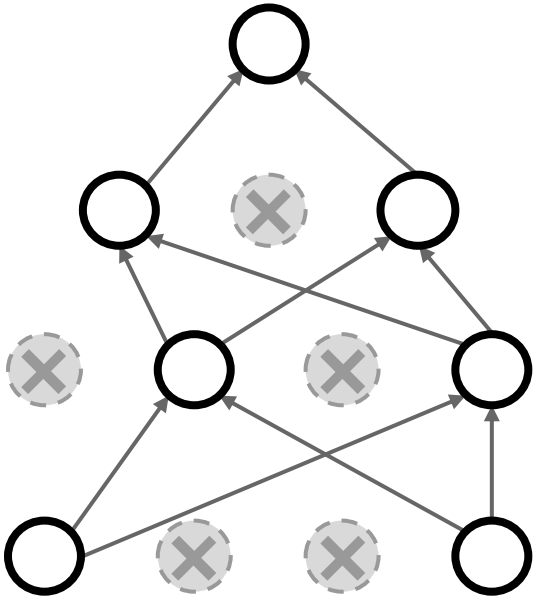

Another interpretation:

Dropout is training a large **ensemble** of models (that share parameters).

Each binary mask is one model

An FC layer with 4096 units has
$2^{4096} \sim 10^{1233}$ possible masks!
Only $\sim 10^{82}$ atoms in the universe...

Dropout: Test time

```
def predict(X):
  # ensembled forward pass
  H1 = np.maximum(0, np.dot(W1, X) + b1) * p # NOTE: scale the activations
  H2 = np.maximum(0, np.dot(W2, H1) + b2) * p # NOTE: scale the activations
  out = np.dot(W3, H2) + b3
```

At test time all neurons are active always
=> We must scale the activations so that for each neuron:
output at test time = expected output at training time

Dropout Summary

```
""" Vanilla Dropout: Not recommended implementation (see notes below) """

p = 0.5 # probability of keeping a unit active. higher = less dropout

def train_step(X):
  """ X contains the data """

  # forward pass for example 3-layer neural network
  H1 = np.maximum(0, np.dot(W1, X) + b1)
  U1 = np.random.rand(*H1.shape) < p # first dropout mask
  H1 *= U1 # drop!
  H2 = np.maximum(0, np.dot(W2, H1) + b2)
  U2 = np.random.rand(*H2.shape) < p # second dropout mask
  H2 *= U2 # drop!
  out = np.dot(W3, H2) + b3

  # backward pass: compute gradients... (not shown)
  # perform parameter update... (not shown)

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drop in train time

scale at test time

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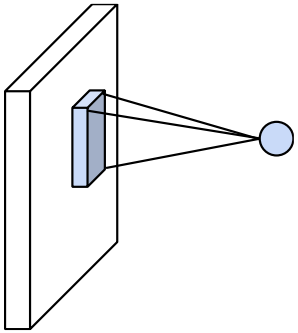

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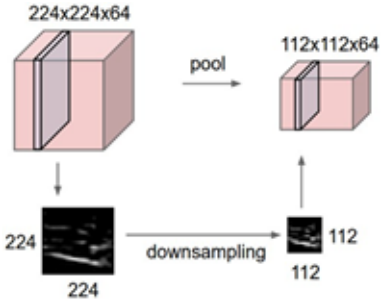

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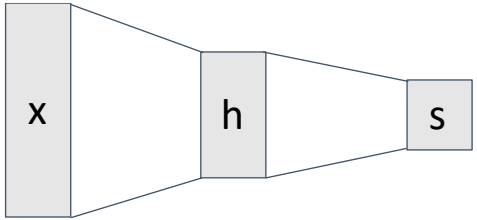

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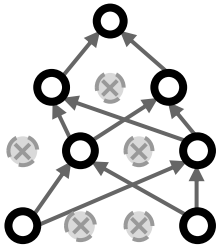
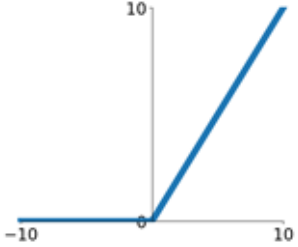


Activation Functions



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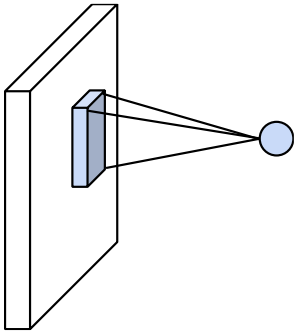

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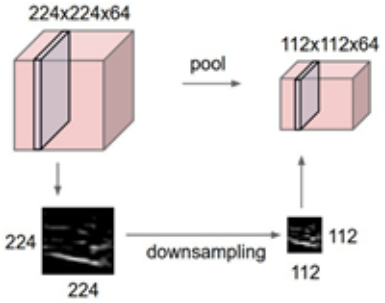

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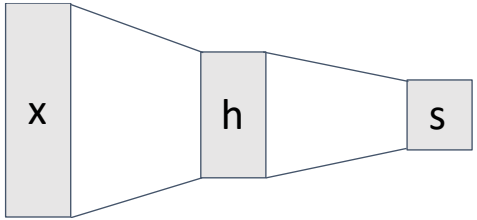
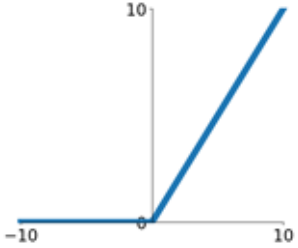


Normalization Layers

Dropout (sometimes)

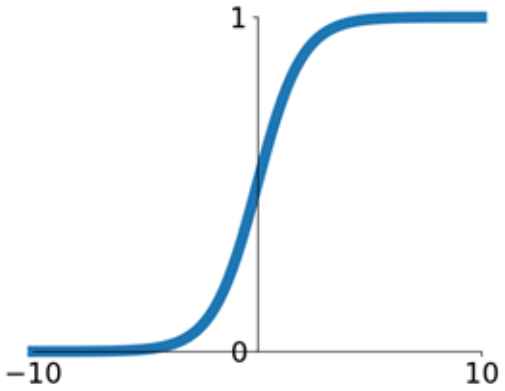
Goal: Introduce non-linearities to our model!

Activation Functions



Activation Functions

$$\sigma(x) = 1/(1+e^{-x})$$



Sigmoid

- Squashes numbers to range [0,1]
- Historically popular since they have nice interpretation as a saturating “firing rate” of a neuron

Key problem:

Many layers of sigmoids → smaller and smaller gradients.

Q: In which regions does sigmoid have a small gradient?

Activation Functions

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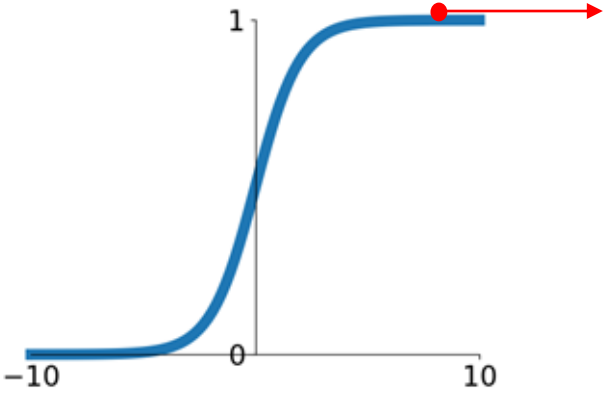


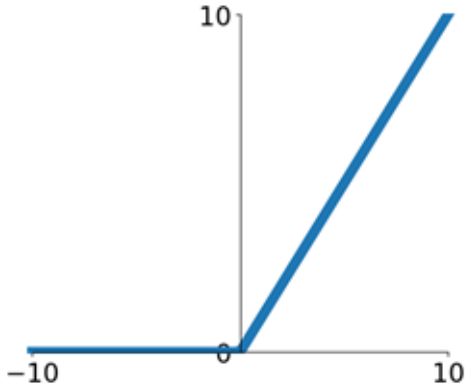
Sigmoid

- Squashes numbers to range [0,1]
- Historically popular since they have nice interpretation as a saturating “firing rate” of a neuron

Key problem:

Large positive or negative values can “kill” the gradients. Many layers of sigmoids → smaller and smaller gradients in practice

Activation Functions



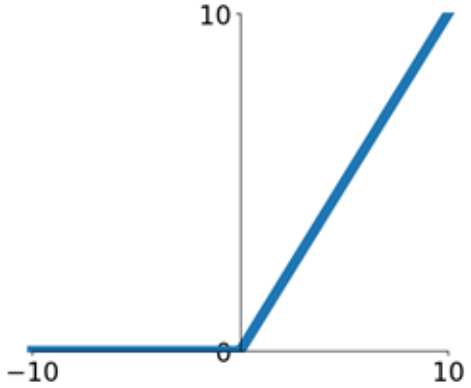
ReLU
(Rectified Linear Unit)

- Computes **f(x) = max(0,x)**

- Does not saturate (in +region)
- Very computationally efficient
- Converges much faster than sigmoid in practice (e.g. 6x)

[Krizhevsky et al., 2012]

Activation Functions



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- Computes **f(x) = max(0,x)**

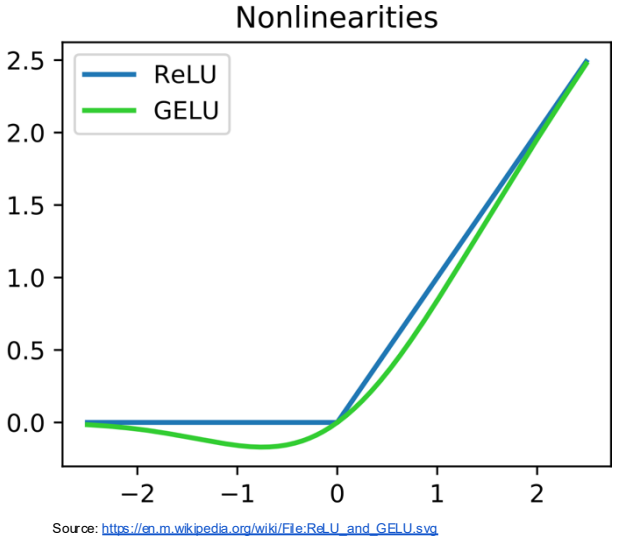
- Does not saturate (in +region)
- Very computationally efficient
- Converges much faster than sigmoid in practice (e.g. 6x)

- Not zero-centered output
- An annoyance:

Dead ReLUs when x < 0!

Activation Functions

[Hendrycks et al., 2016]



Source: https://en.m.wikipedia.org/wiki/File:ReLU_and_GELU.svg

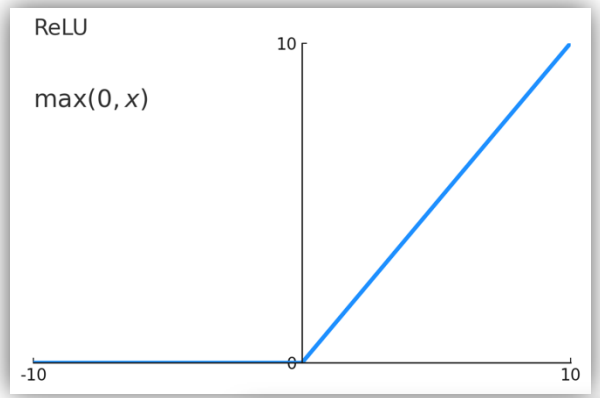
GELU
(Gaussian Error Linear Unit)

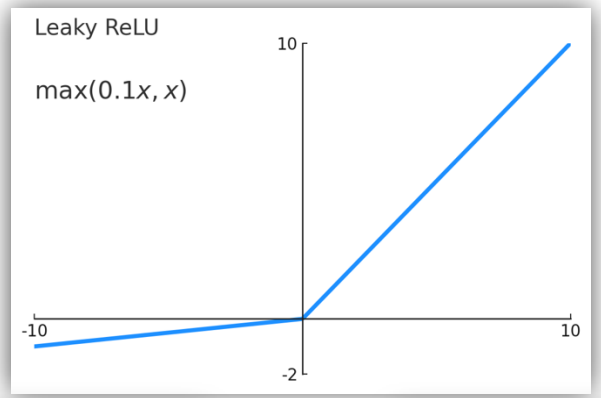
- Computes **f(x) = x*Φ(x)**

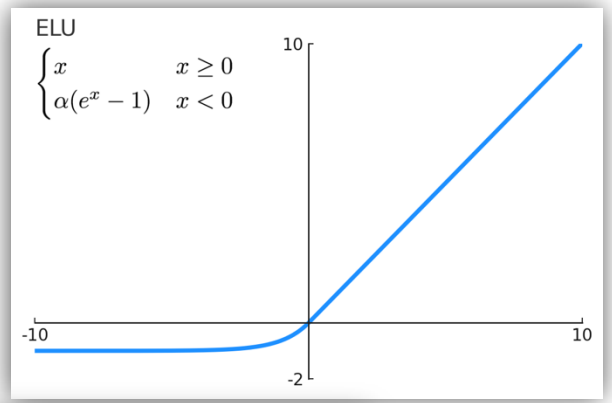
- Very nice behavior around 0
- Smoothness facilitates training in practice

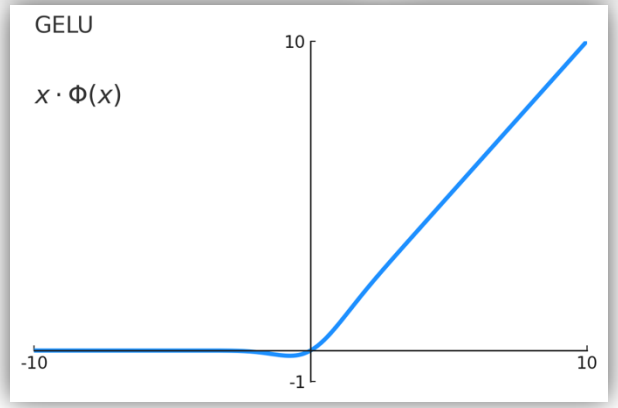
- Higher computational cost than ReLU
- Large negative values can still have gradient → 0

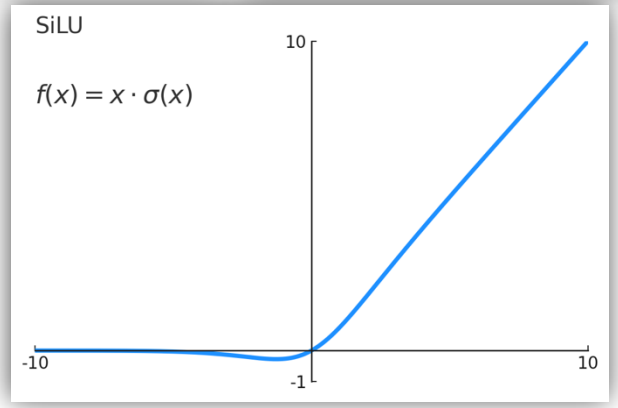
Activation Function Zoo





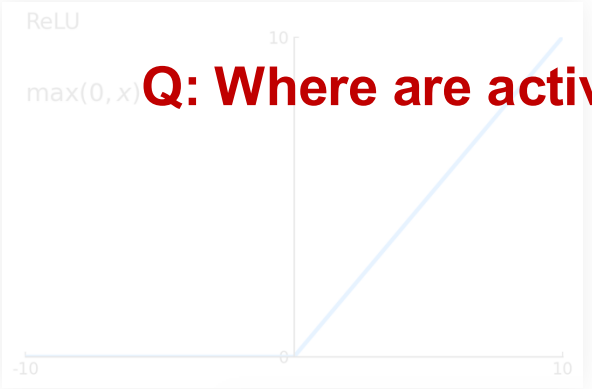


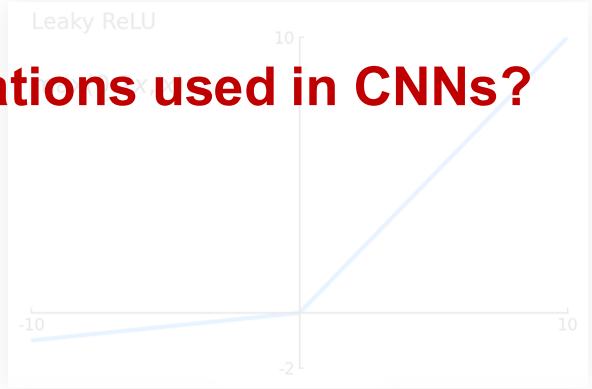


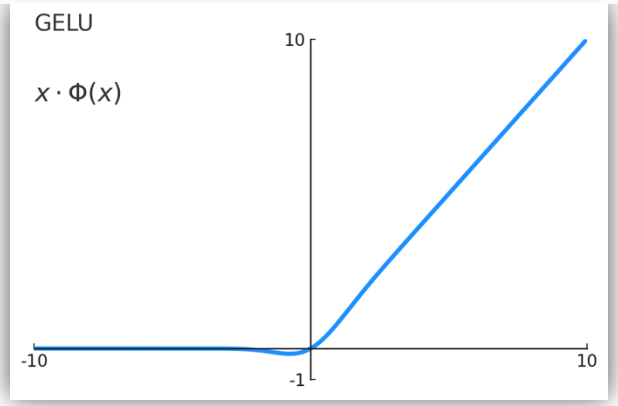


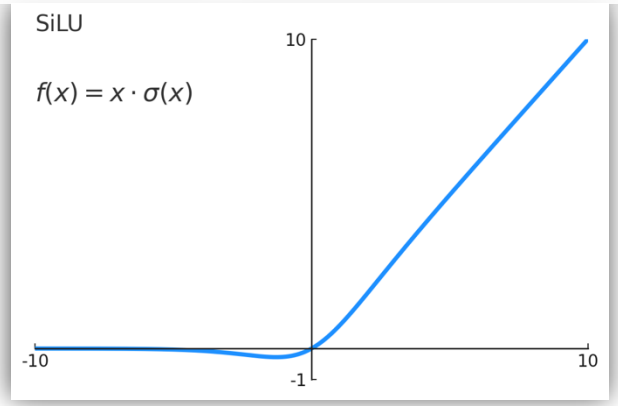
Activation Function Zoo

Q: Where are activations used in CNNs?





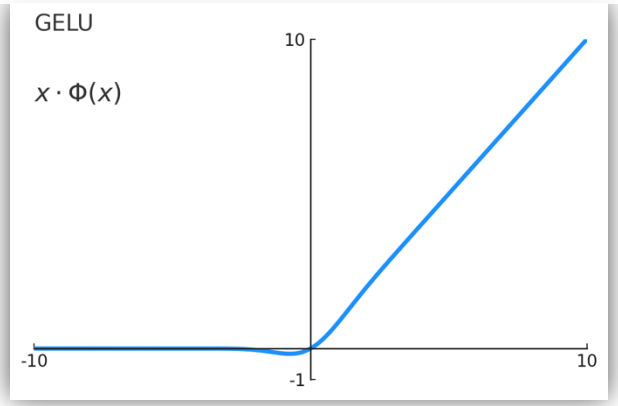


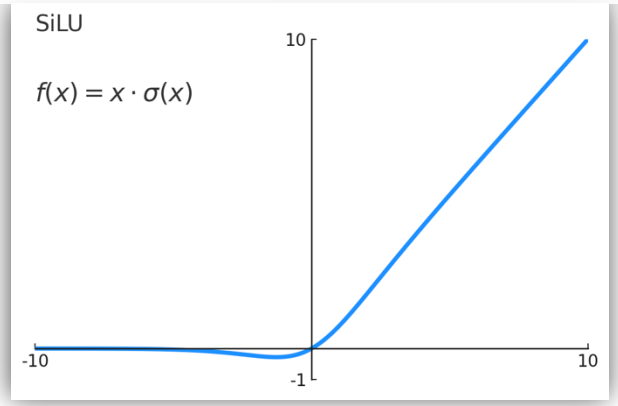


Activation Function Zoo

Q: Where are activations used in CNNs?

A: Generally placed after linear operators (feedforward/linear layer, convolutional layer, etc.)





Lecture Overview – Two Broad Sets of Topics

How to build CNNs?

- **Layers in CNNs**
- **Activation Functions**
- **CNN Architectures**
- **Weight Initialization**

How to train CNNs?

- **Data Preprocessing**
- **Data augmentation**
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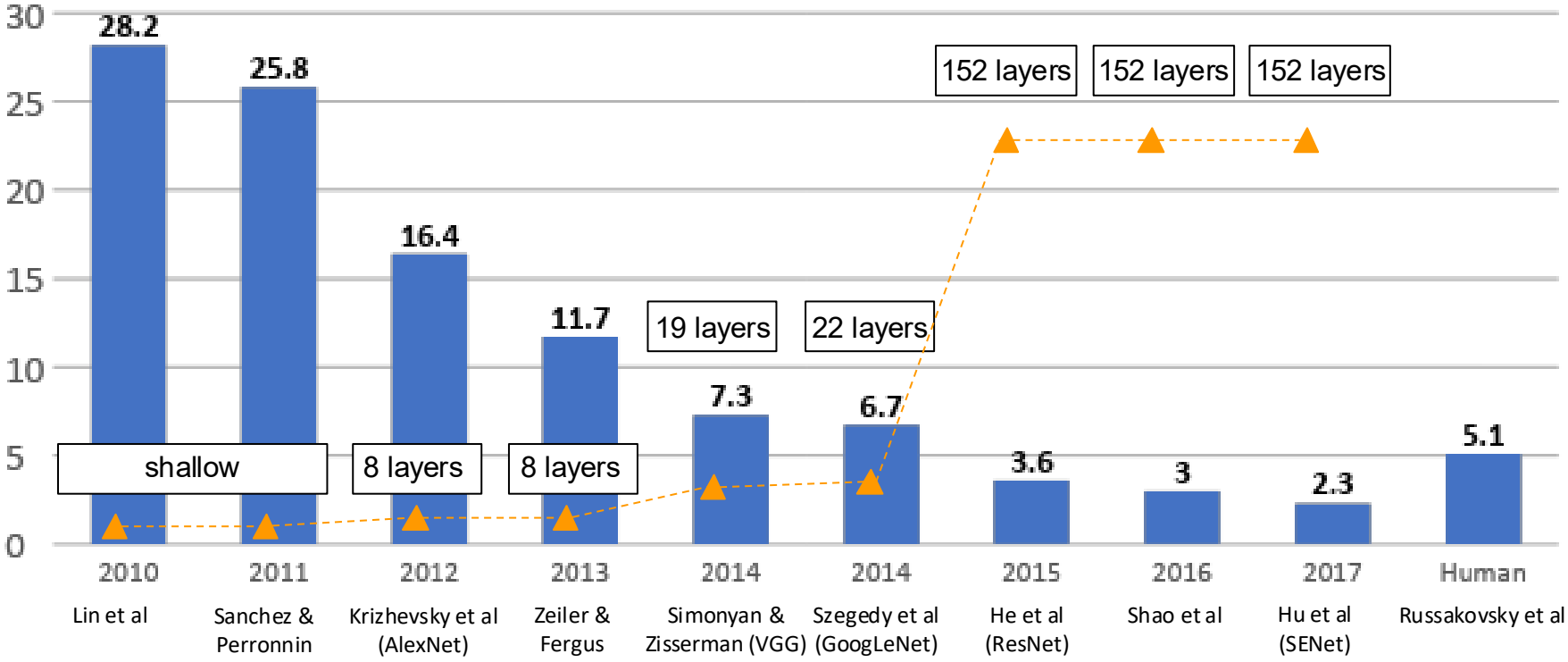
ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



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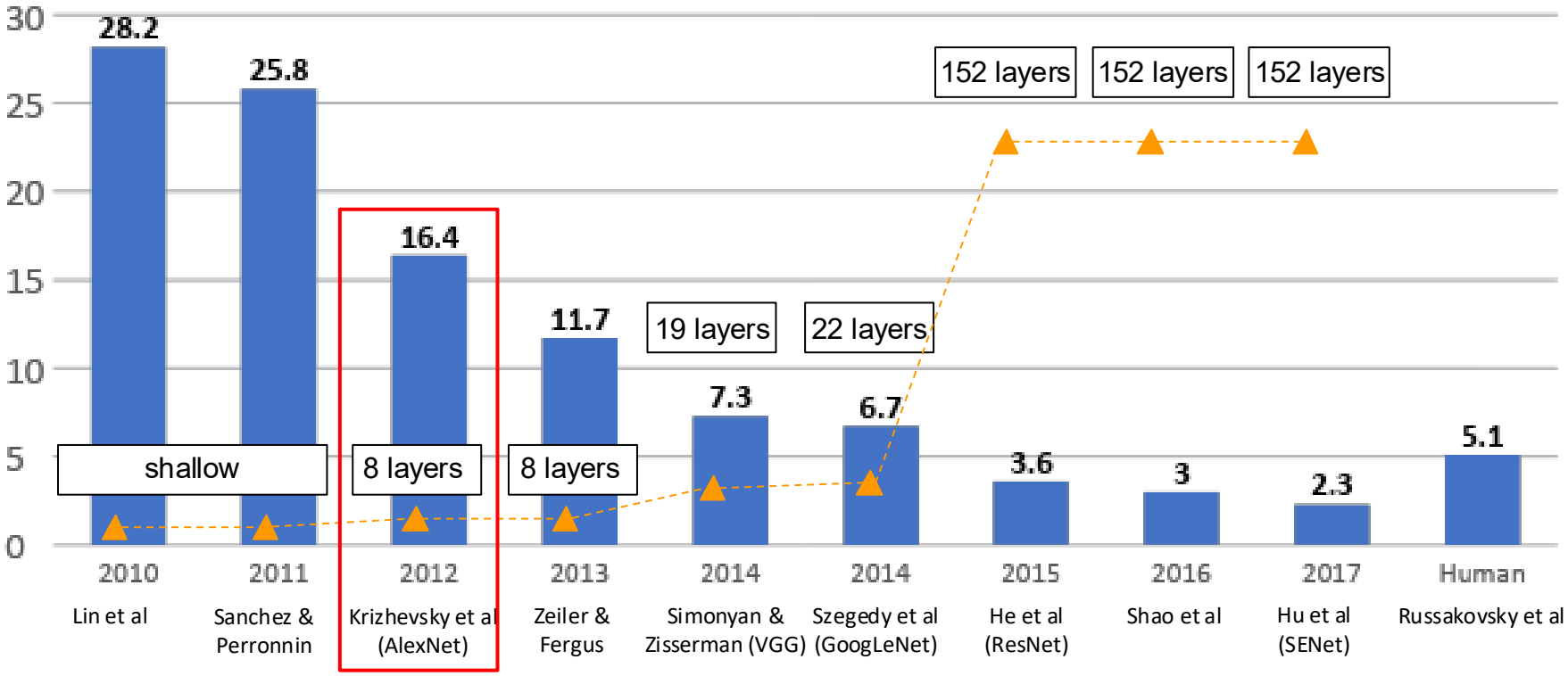

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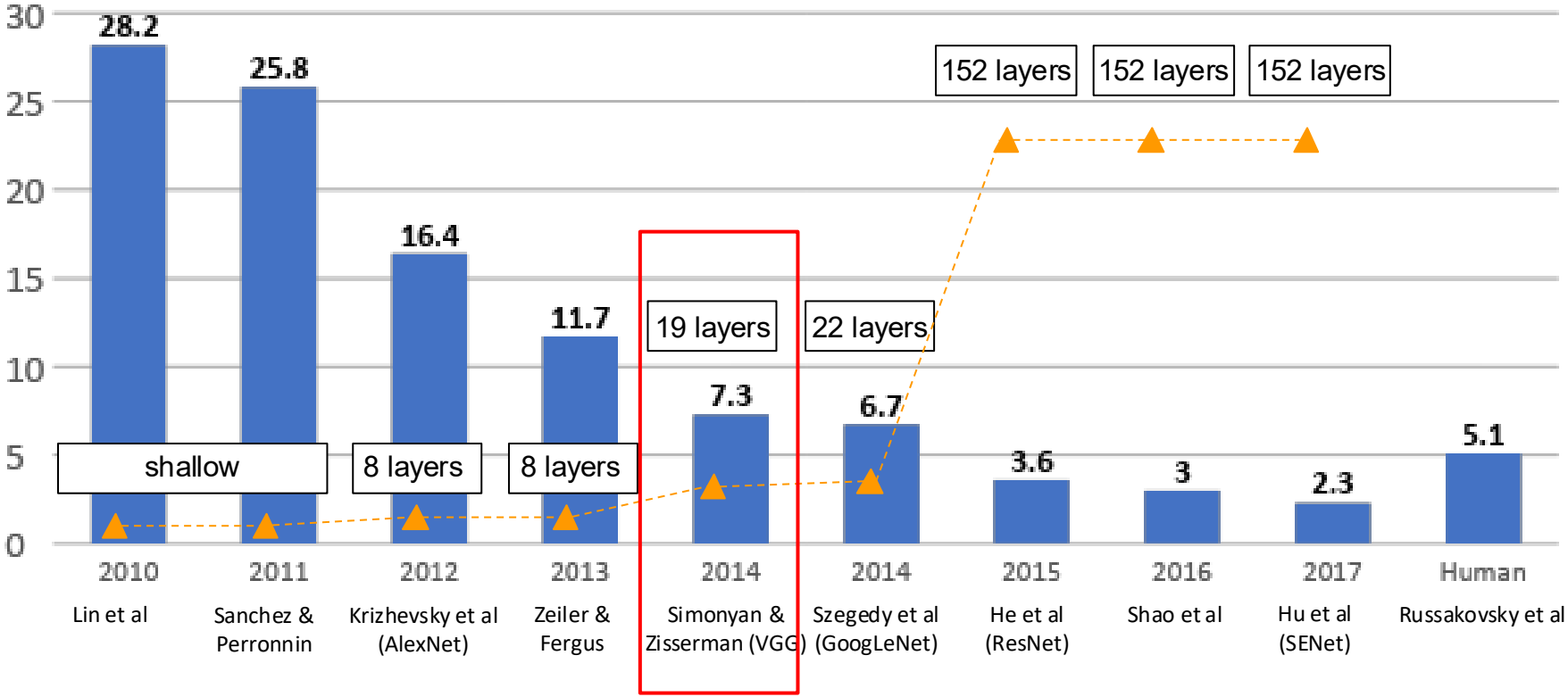


Case Study: VGGNet

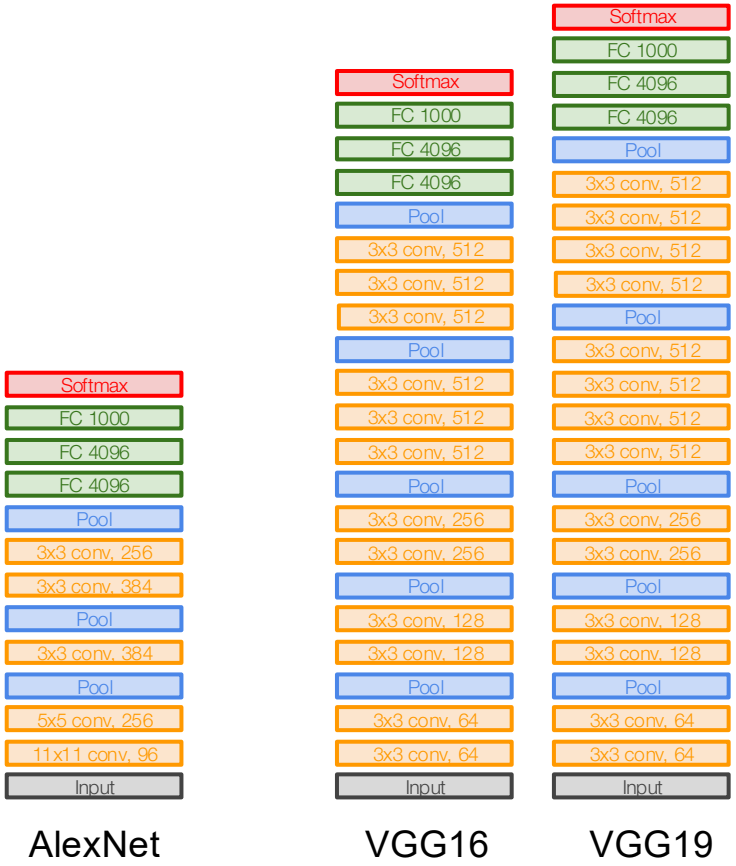
[Simonyan and Zisserman, 2014]

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



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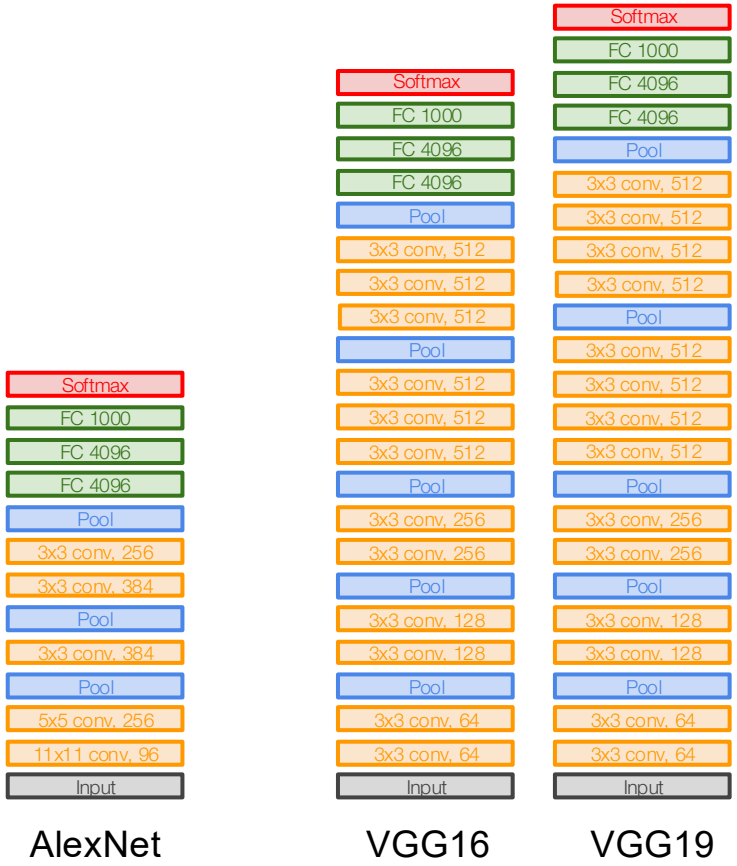

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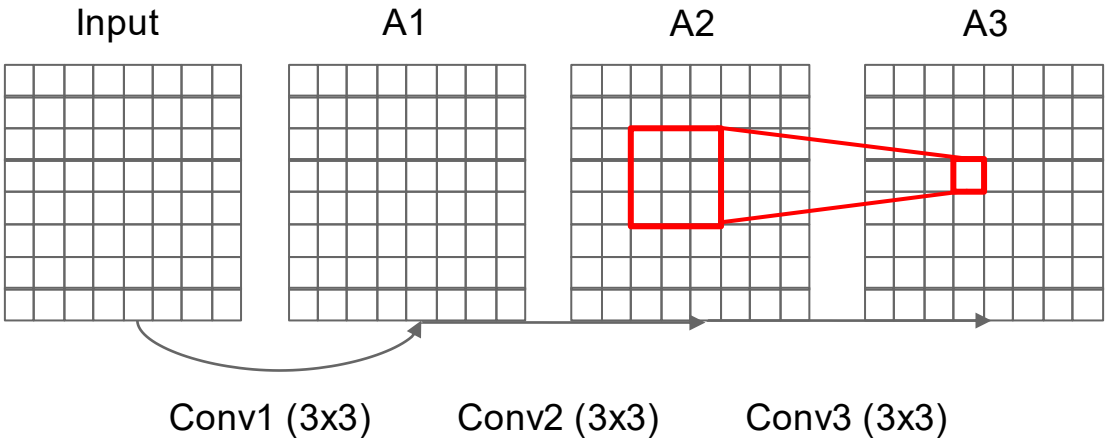
Q: What is the effective receptive field of three 3x3 conv (stride 1) layers?



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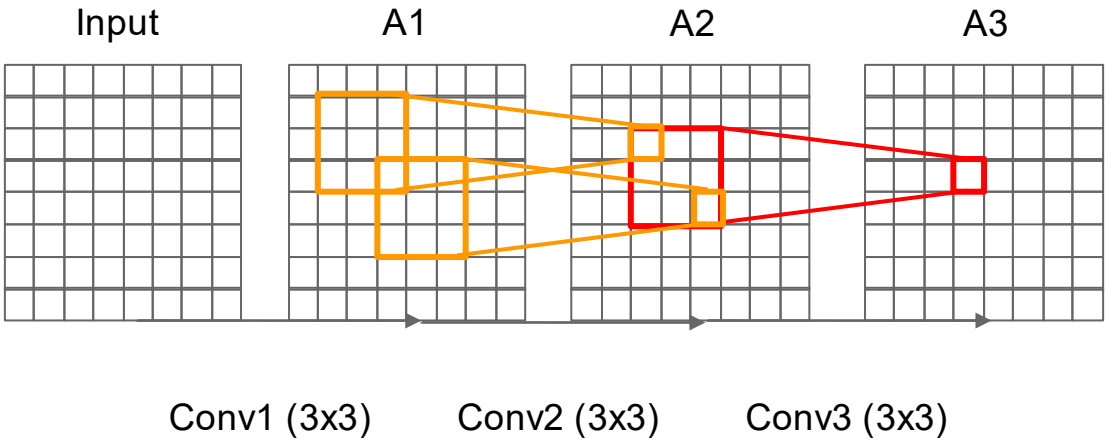

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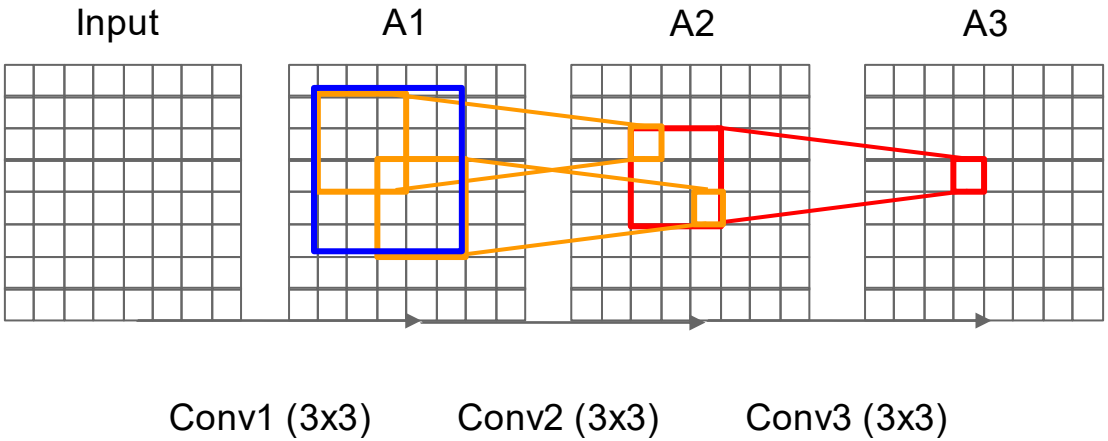

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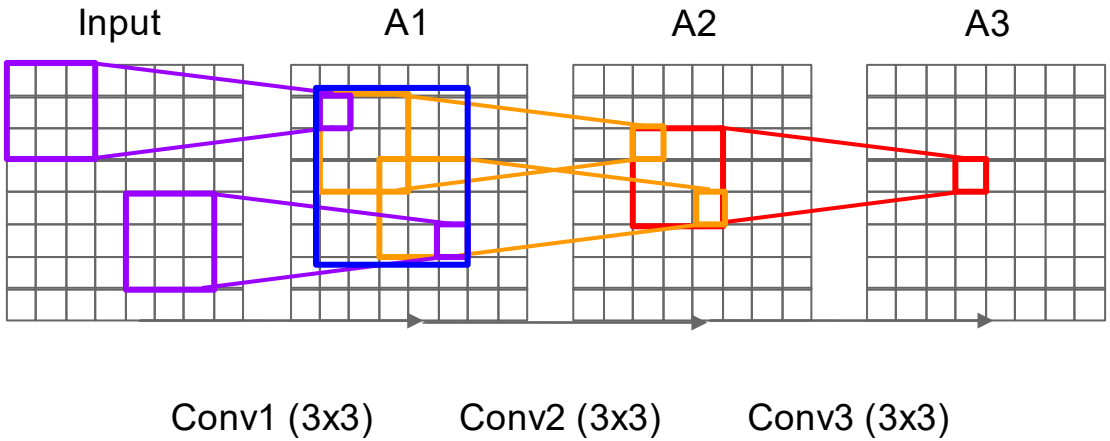

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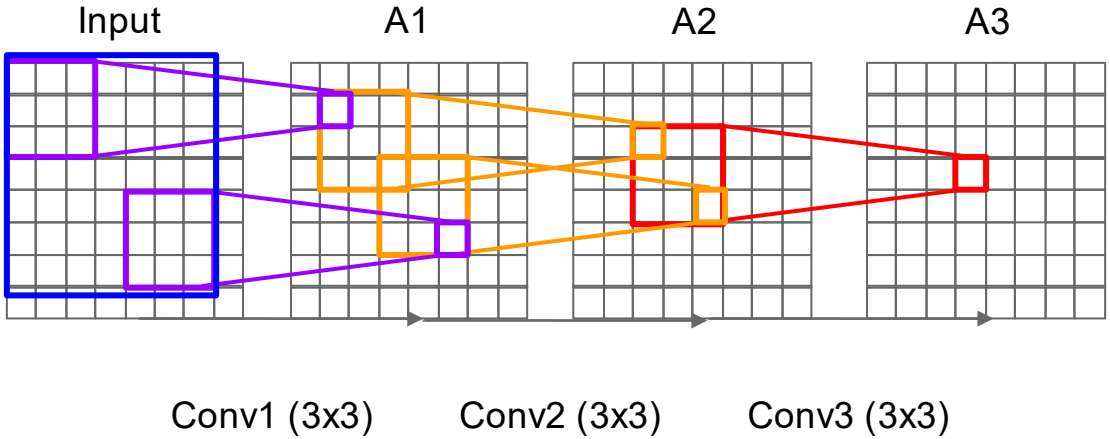

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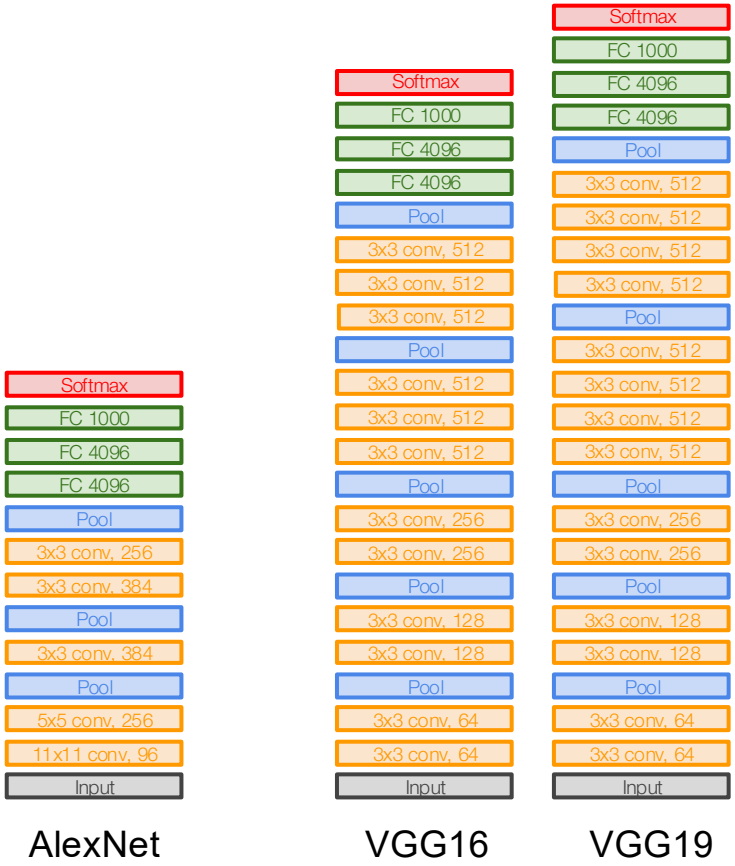
Stack of three 3x3 conv (stride 1) layers has same **effective receptive field** as one 7x7 conv layer

[7x7]



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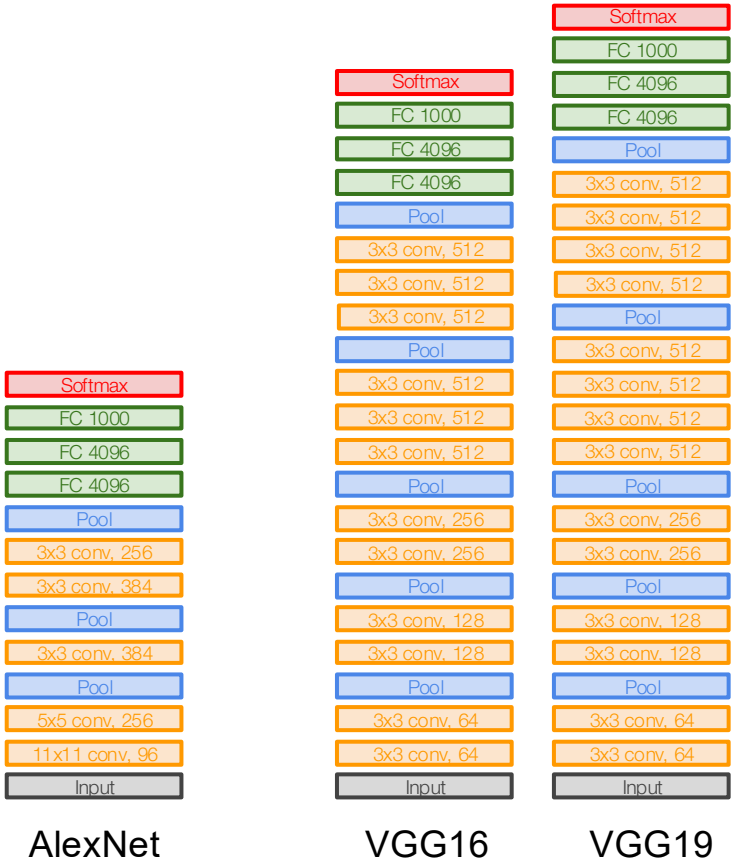
Stack of three 3x3 conv (stride 1) layers has same **effective receptive field** as one 7x7 conv layer

But deeper, more non-linearities

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



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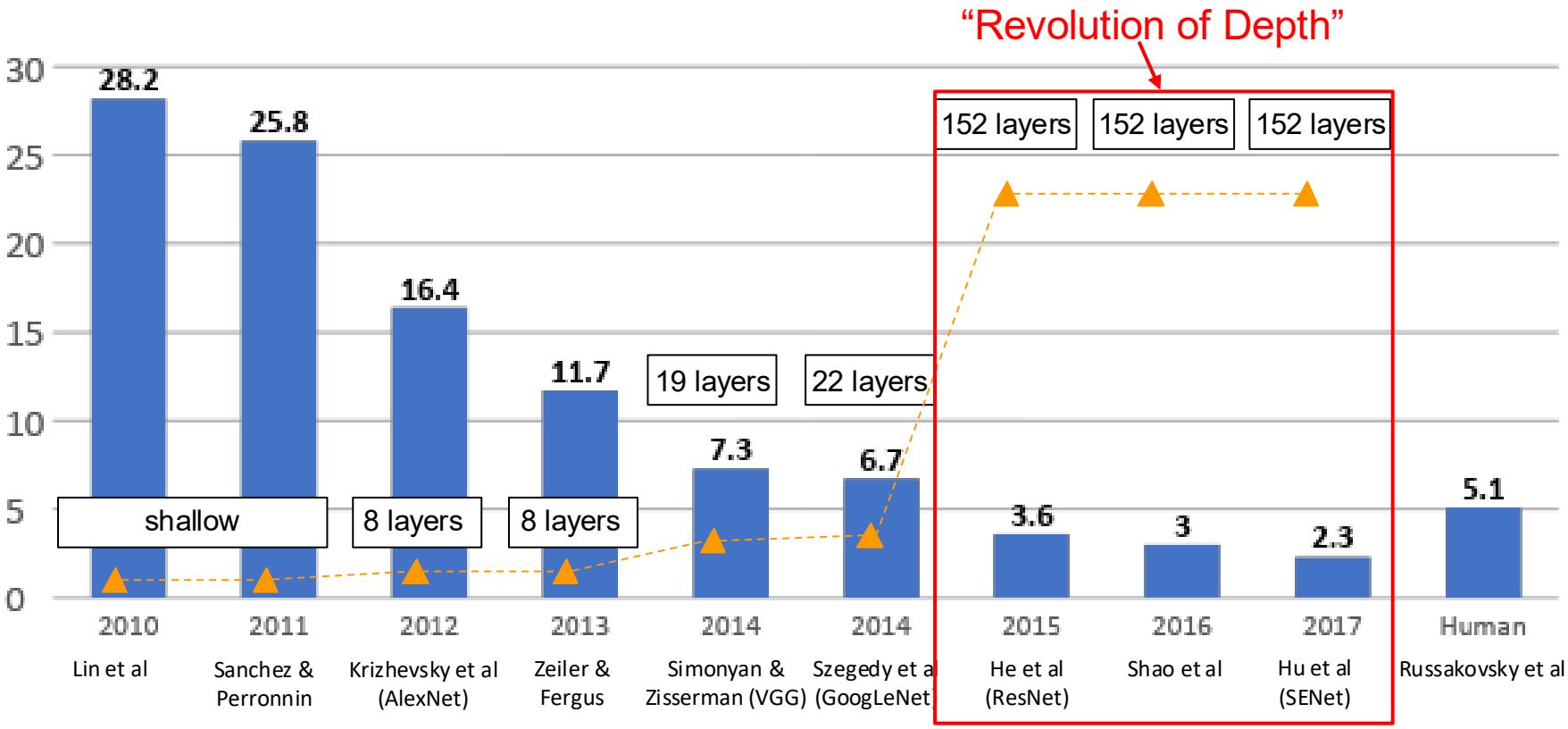

Case Study: ResNet

[He et al., 2015]

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

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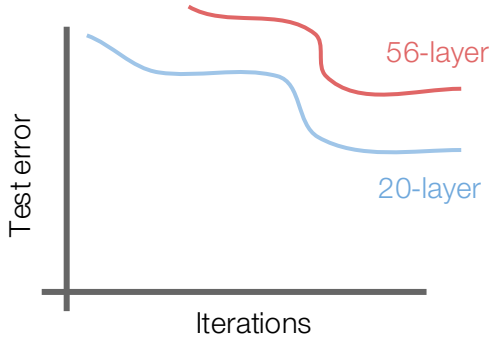

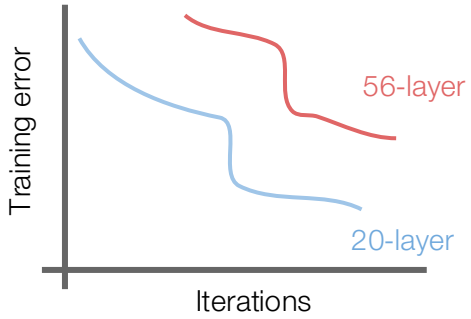

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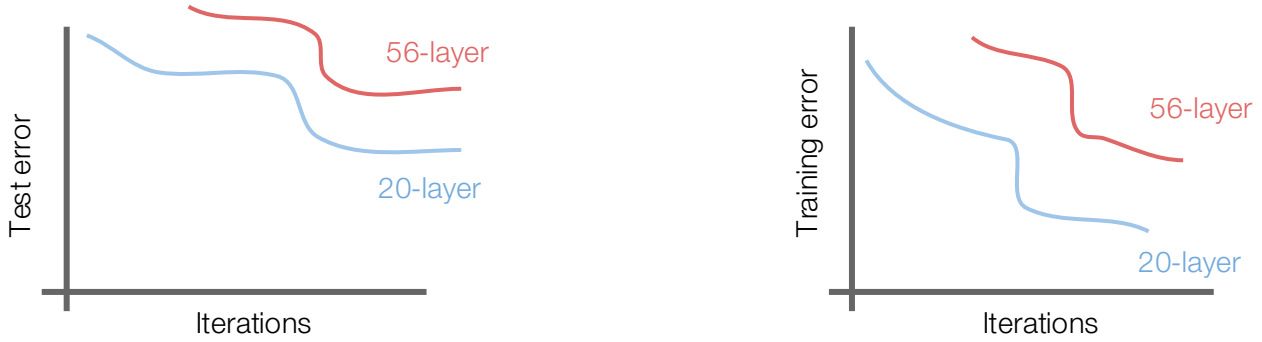

56-layer model performs worse on both test and training error
-> The deeper model performs worse, but it’s not caused by overfitting!

Case Study: ResNet

[He et al., 2015]

Fact: Deep models have more representation power (more parameters) than shallower models.

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

Case Study: ResNet

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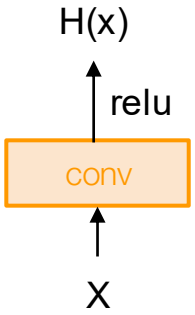
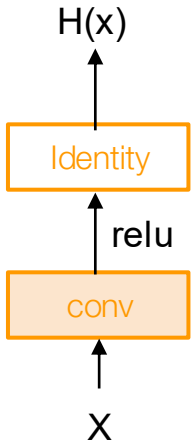
Fact: Deep models have more representation power (more parameters) than shallower models.

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

What should the deeper model learn to be at least as good as the shallower model?

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

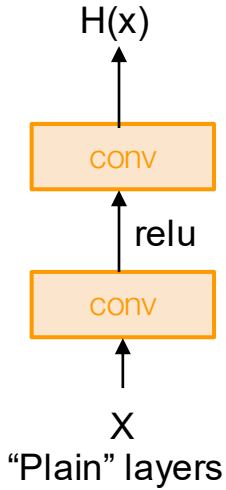




Case Study: ResNet

[He et al., 2015]

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



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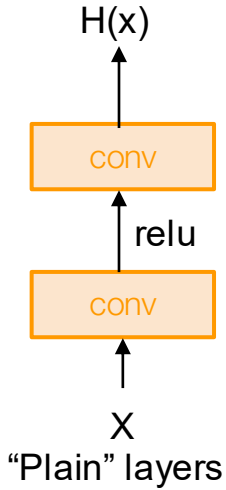
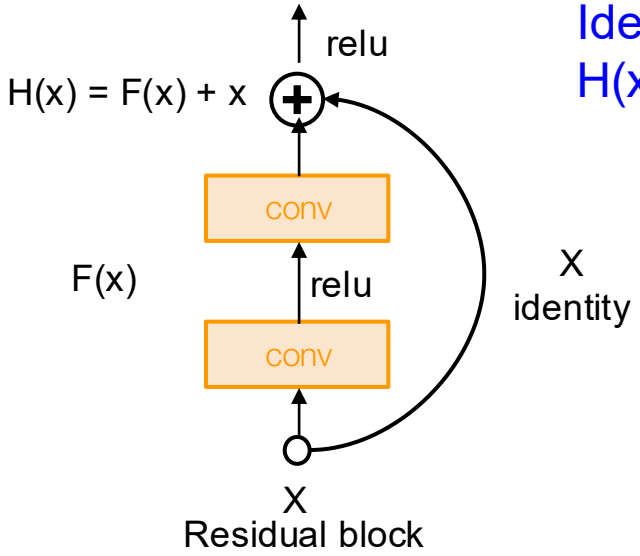


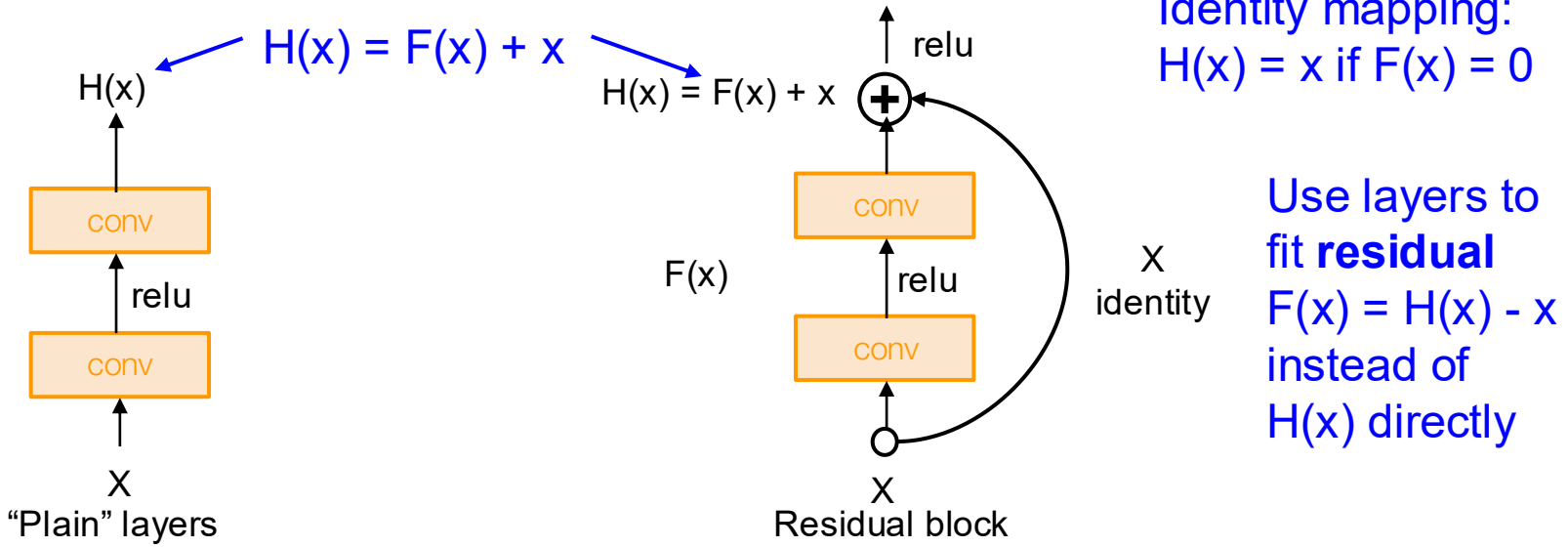


Identity mapping:
H(x) = x if F(x) = 0

Case Study: ResNet

[He et al., 2015]

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



Identity mapping:
H(x) = x if F(x) = 0

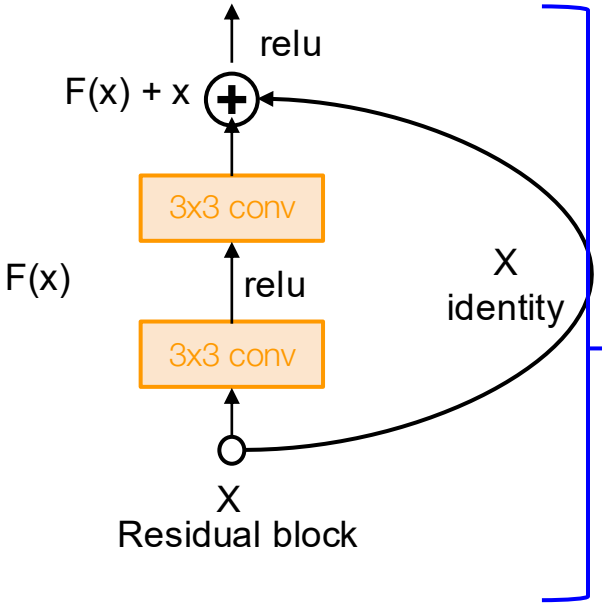
Use layers to fit **residual** F(x) = H(x) - x instead of H(x) directly

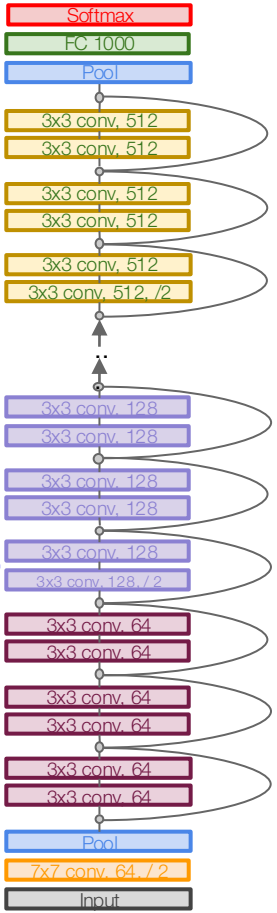
Case Study: ResNet

[He et al., 2015]

Full ResNet architecture:

- Stack residual blocks
- Every residual block has two 3x3 conv layers



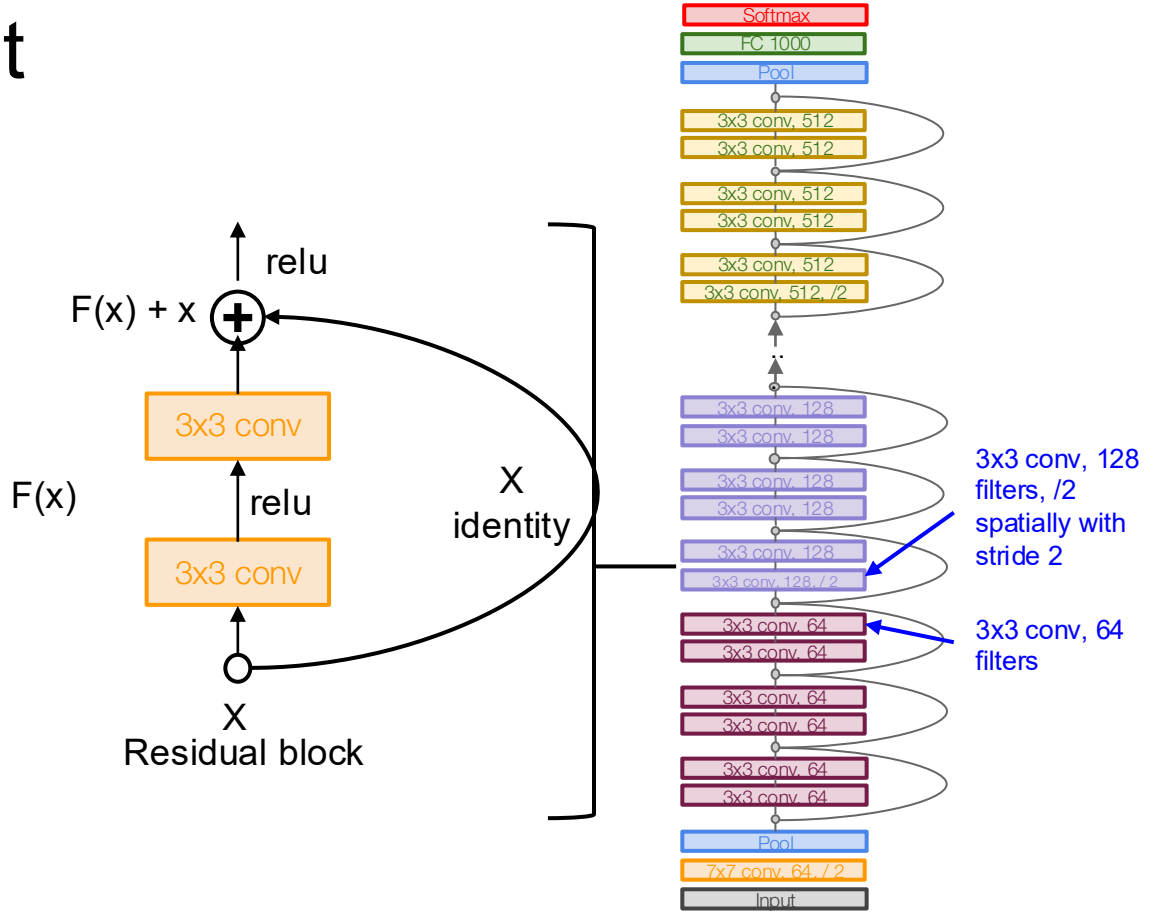


Case Study: ResNet

[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) Reduce the activation volume by half.



Case Study: ResNet

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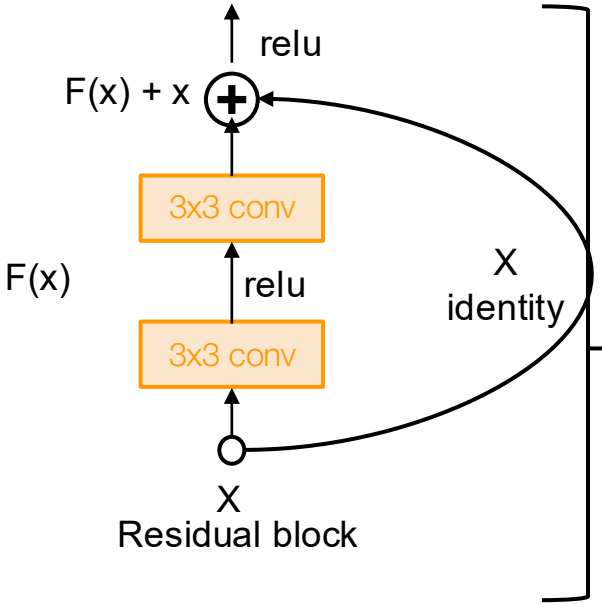
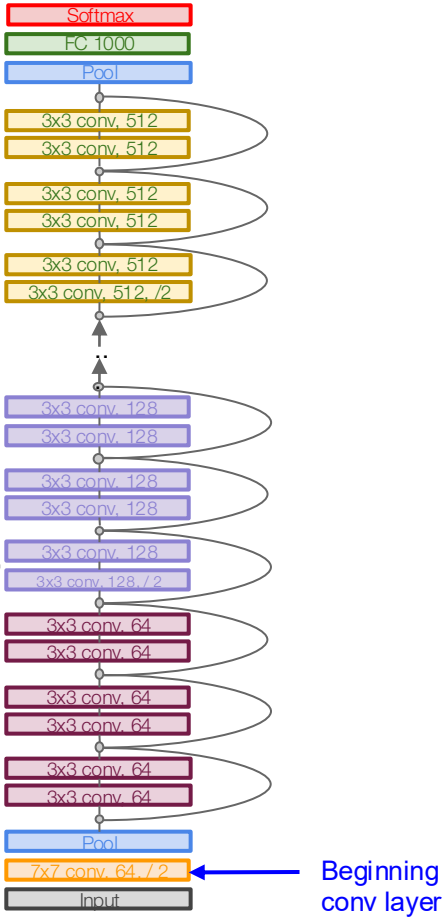
Full ResNet architecture:

- 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 (stem)

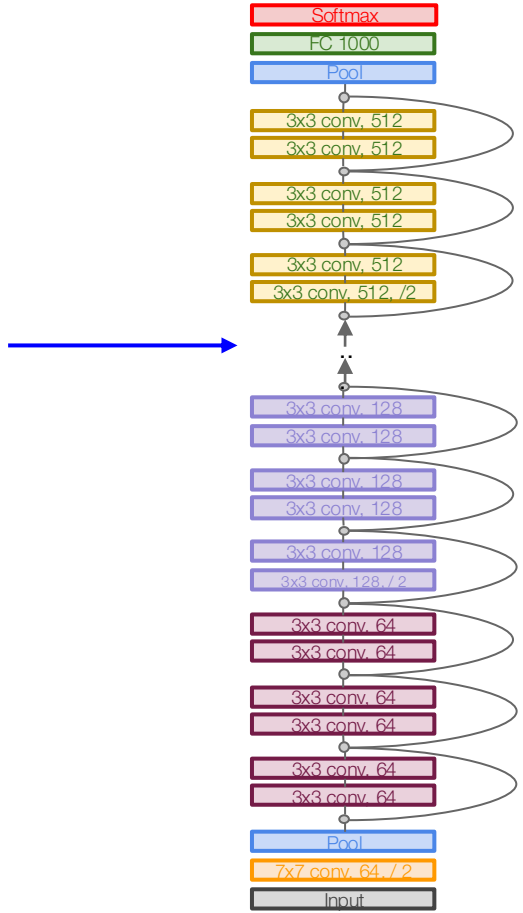




Case Study: ResNet

[He et al., 2015]

Total depths of 18, 34, 50, 101, or 152 layers for ImageNet

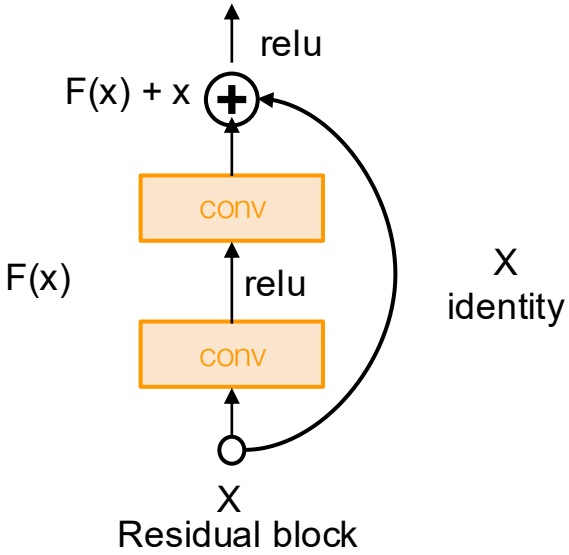


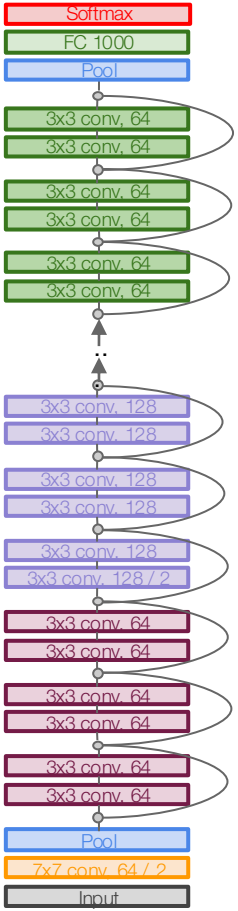
Case Study: ResNet

[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!





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How to initialize weights in neural network layers?

Weight Initialization Case: Values too small

```
dims = [4096] * 7
hs = []
x = np.random.randn(16, dims[0])
# Forward pass with ReLU activation
for Din, Dout in zip(dims[:-1], dims[1:]):
    W = 0.01 * np.random.randn(Din, Dout)  # Small weight init
    x = np.maximum(0, x.dot(W))  # ReLU activation
    hs.append(x)
```

Forward pass for a 6-layer net with hidden size 4096

Weight Initialization Case: Values too small

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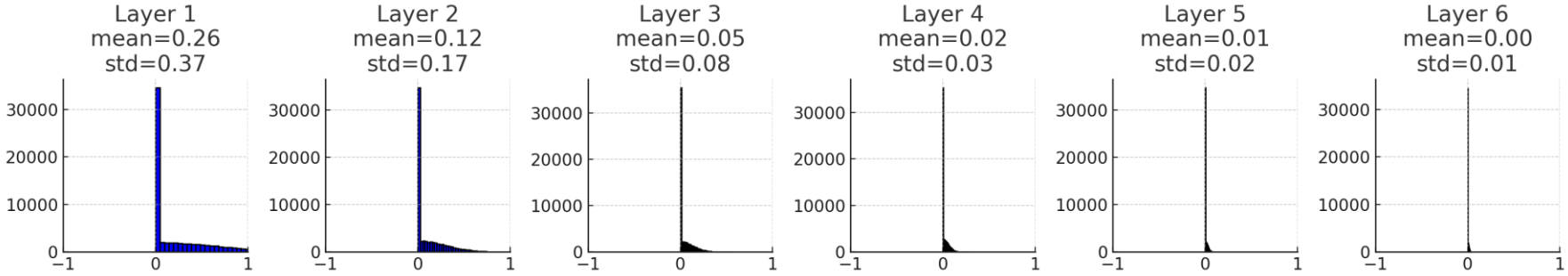
All activations tend to zero for deeper network layers



Weight Initialization Case: Values too large

```
dims = [4096] * 7
hs = []
x = np.random.randn(16, dims[0])
# Forward pass with ReLU activation
for Din, Dout in zip(dims[:-1], dims[1:]):
    W = 0.05 * np.random.randn(Din, Dout)  # Small weight init
    x = np.maximum(0, x.dot(W))  # ReLU activation
    hs.append(x)
```

Increase std of initial weights from 0.01 to 0.05

Weight Initialization Case: Values too large

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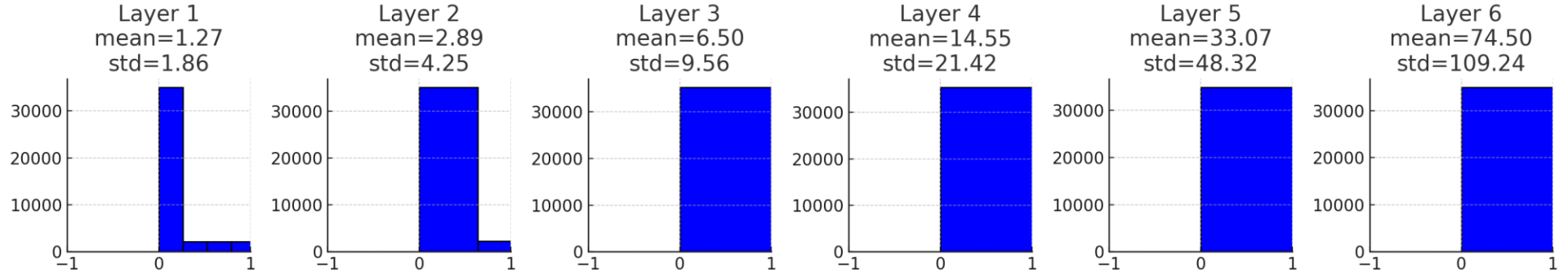
Activations blow up quickly

Increase std of initial weights from 0.01 to 0.05



How to fix this? Depends on the size of the layer

```
dims = [4096] * 7
hs = []
x = np.random.randn(16, dims[0])
for Din, Dout in zip(dims[:-1], dims[1:]):
    W = np.random.randn(Din, Dout) * np.sqrt(2/Din)
    x = np.maximum(0, x.dot(W))
    hs.append(x)
```

He et al, “Delving Deep into Rectifiers: Surpassing Human-Level Performance on ImageNet Classification”, ICCV 2015

One solution: Kaiming / MSRA Initialization

```
dims = [4096] * 7
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x = np.random.randn(16, dims[0])
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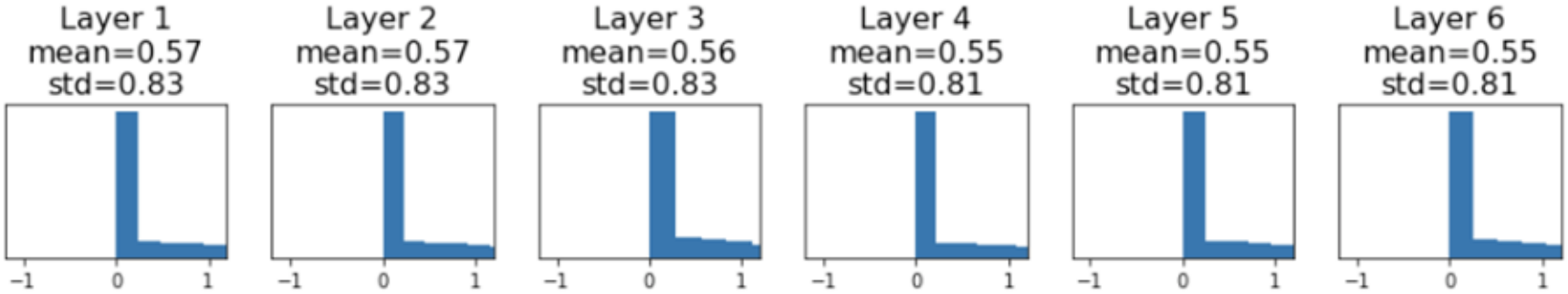
    x = np.maximum(0, x.dot(W))
    hs.append(x)
```

ReLU correction: std = sqrt(2 / Din)

"Just right": Activations are nicely scaled for all layers!



He et al, "Delving Deep into Rectifiers: Surpassing Human-Level Performance on ImageNet Classification", ICCV 2015

Lecture Overview – Two Broad Sets of Topics

How to build CNNs?

- Layers in CNNs
- Activation Functions
- CNN Architectures
- Weight Initialization

How to train CNNs?

- **Data Preprocessing**
- **Data augmentation**
- **Transfer Learning**
- **Hyperparameter Selection**

TLDR for Image Normalization: center and scale for each channel

- Subtract per-channel mean and
  Divide by per-channel std (almost all modern models)
  (stats along each channel = 3 numbers)
- Requires pre-computing means and std for each pixel channel (given your dataset)

```
norm_pixel[i,j,c] = (pixel[i,j,c] - np.mean(pixel[:,:,c])) / np.std(pixel[:,:,c])
```

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Regularization: A common pattern

Training: Add some kind of randomness

$$y = f_W(x, z)$$

Testing: Average out randomness (sometimes approximate)

$$y = f(x) = E_z\big[f(x, z)\big] = \int p(z) f(x, z) dz$$

Regularization: A common pattern

Training: Add some kind of randomness

$$y = f_W(x, z)$$

Testing: Average out randomness (sometimes approximate)

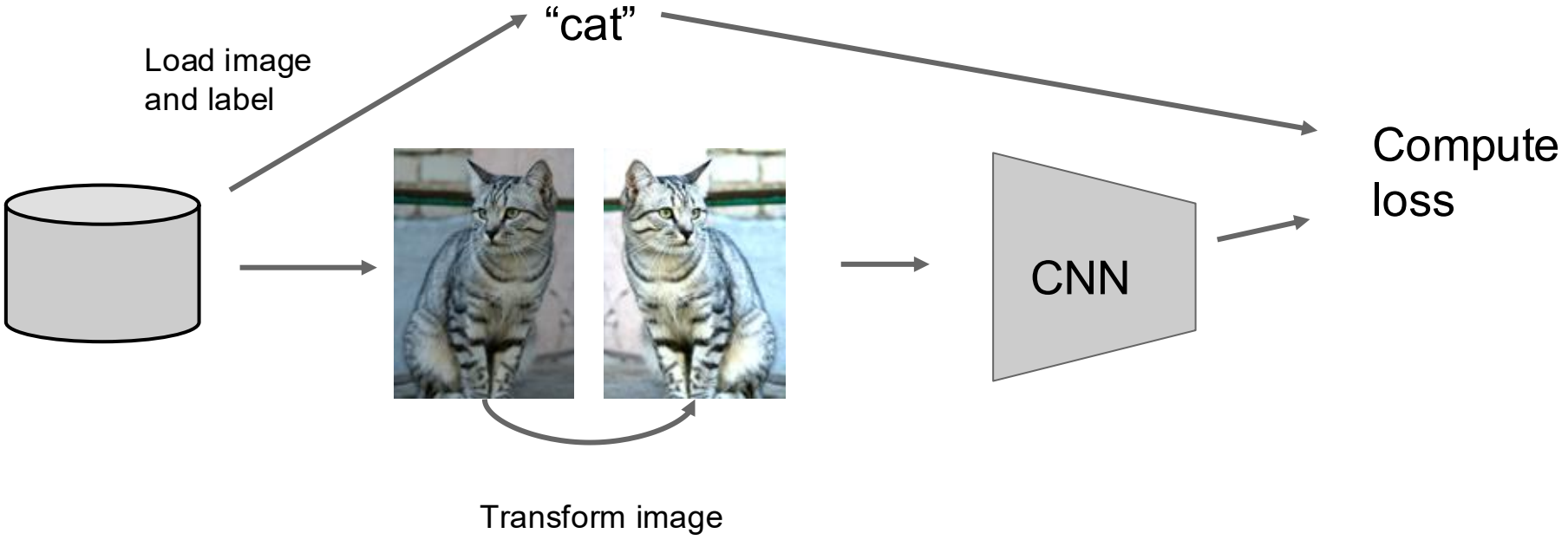
$$y = f(x) = E_z\big[f(x, z)\big] = \int p(z) f(x, z) dz$$

Example: Dropout

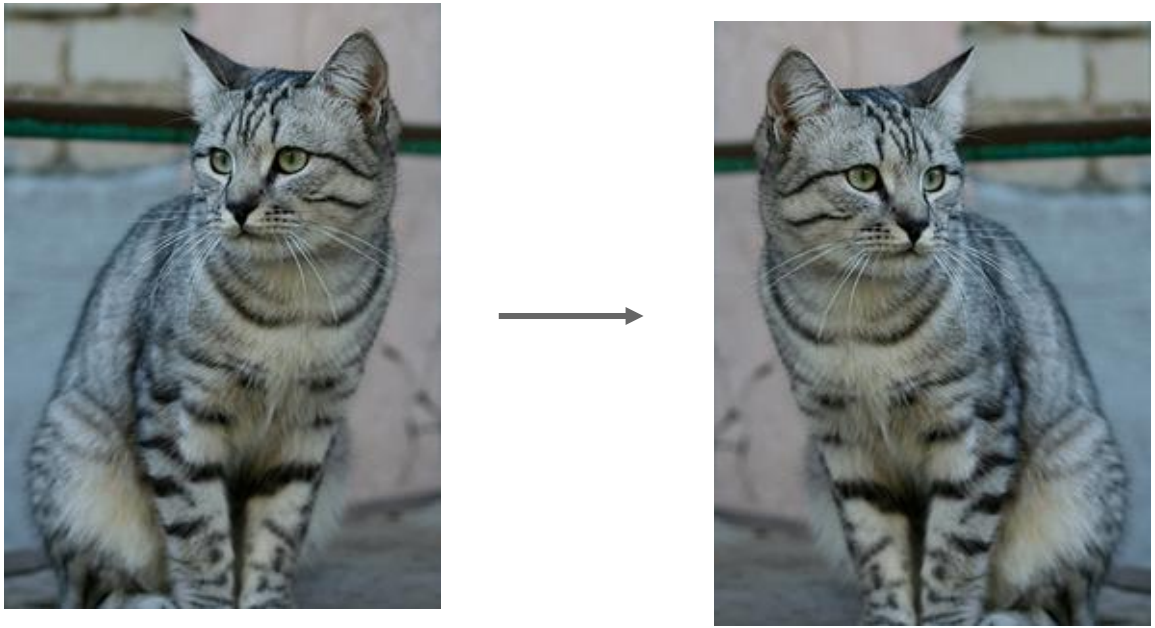
Training: Randomly drop activations

Testing: Use all activations and scale with p

Regularization: Data Augmentation

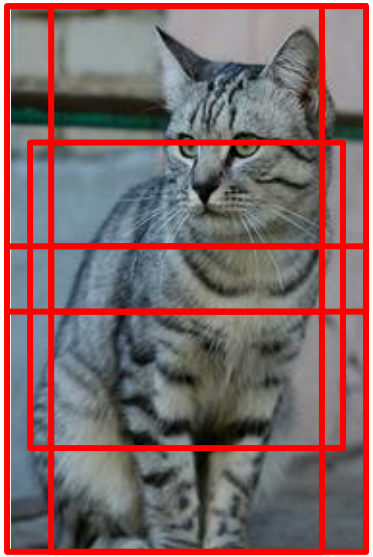


Data Augmentation
Horizontal Flips



Data Augmentation

Random crops and scales



Training: sample random crops / scales

ResNet:

1. Pick random L in range [256, 480]
2. Resize training image, short side = L
3. Sample random 224 x 224 patch

Test Time Augmentation: average a fixed set of crops

ResNet:

1. Resize image at 5 scales: {224, 256, 384, 480, 640}
2. For each size, use 10 224 x 224 crops: 4 corners + center, + flips

Data Augmentation
Color Jitter

Simple: Randomize
contrast and brightness

Regularization: Cutout

Training: Set random image regions to zero

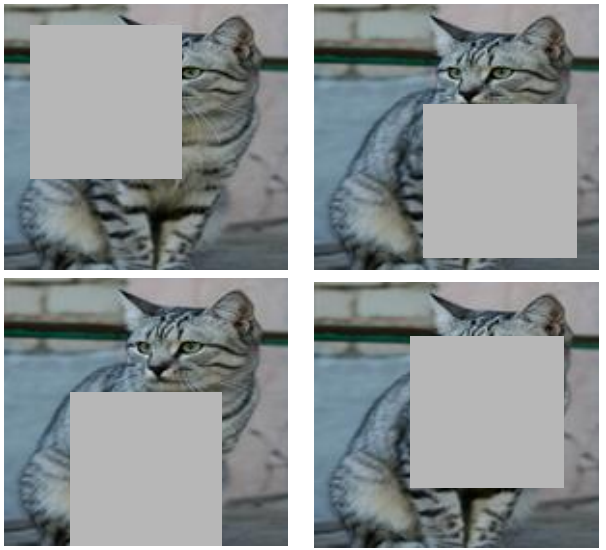
Testing: Use full image

Examples:

Dropout

Data Augmentation

Cutout / Random Crop



Works very well for small datasets like CIFAR, less common for large datasets like ImageNet

DeVries and Taylor, “Improved Regularization of Convolutional Neural Networks with Cutout”, arXiv 2017

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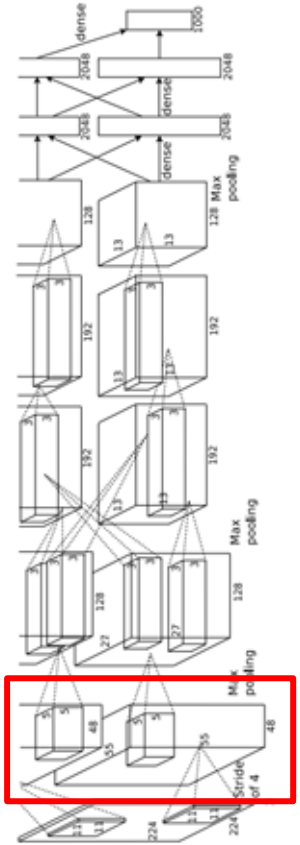
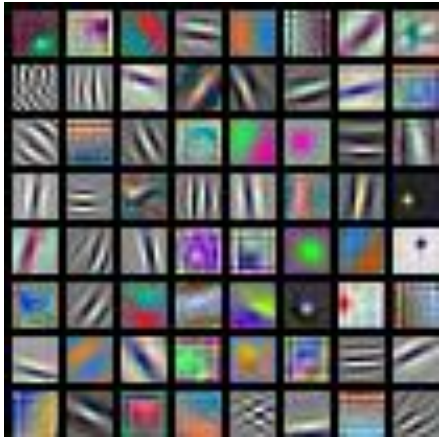
What if you don’t have a lot of data? Can you still train CNNs?

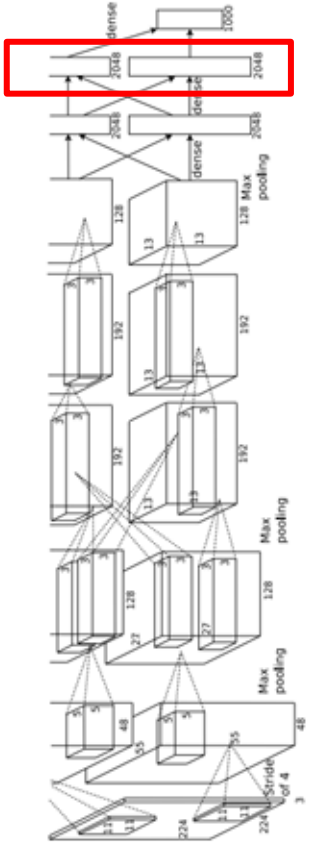
Transfer Learning with CNNs





AlexNet:
64 x 3 x 11 x 11

Transfer Learning with CNNs

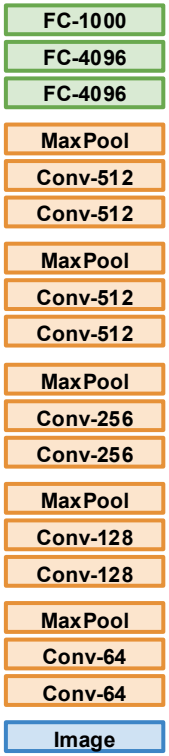


Test image L2 Nearest neighbors in feature space

Transfer Learning with CNNs

Donahue et al, “DeCAF: A Deep Convolutional Activation Feature for Generic Visual Recognition”, ICML 2014
Razavian et al, “CNN Features Off-the-Shelf: An Astounding Baseline for Recognition”, CVPR Workshops 2014

1. Train on Imagenet (or internet scale data)



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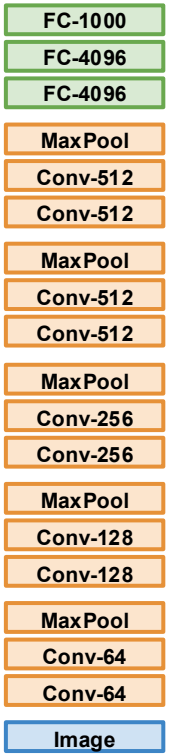
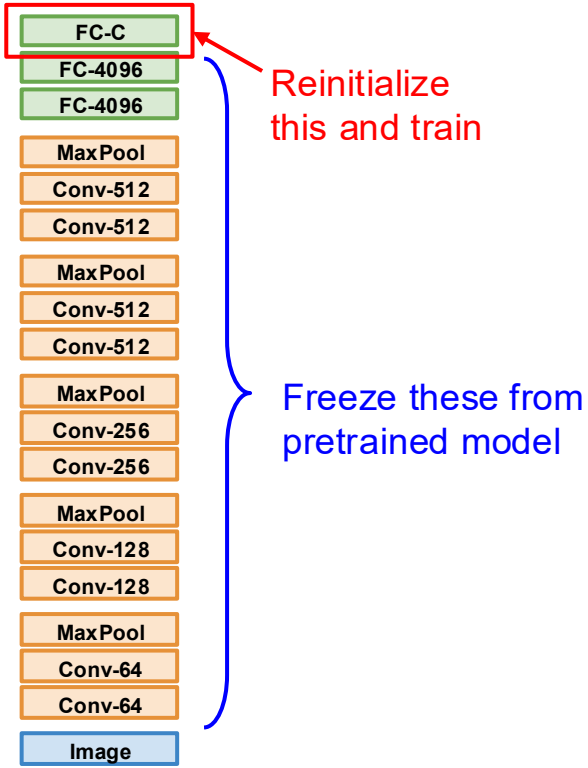


2. Small Dataset (C classes)



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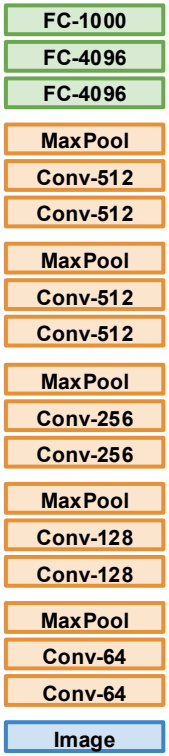

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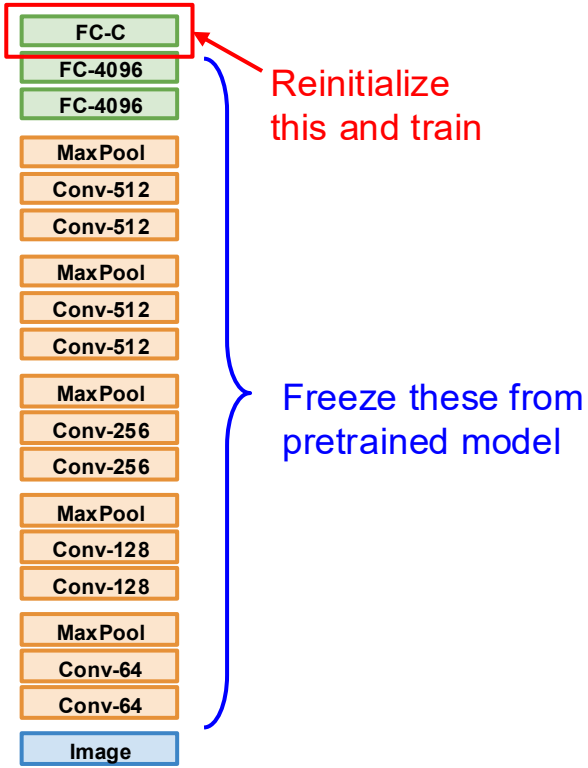
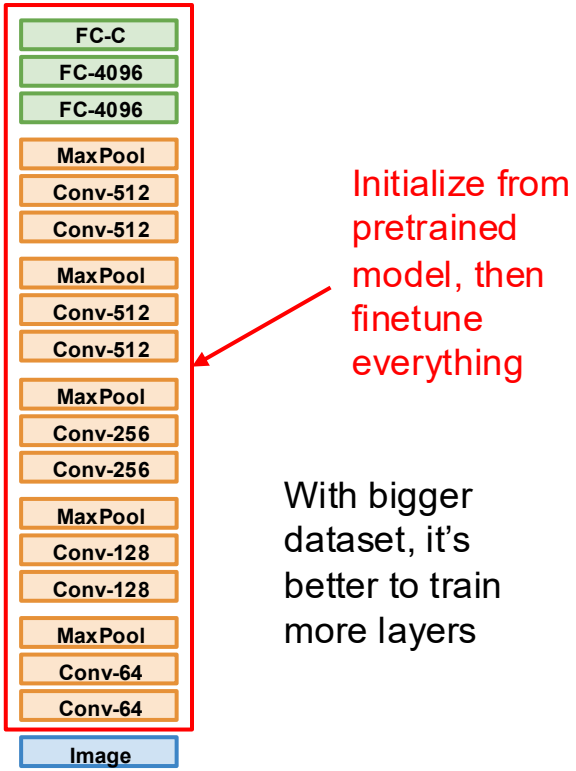
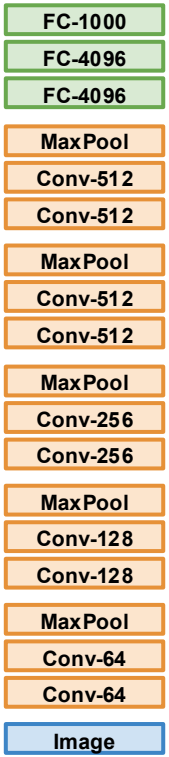


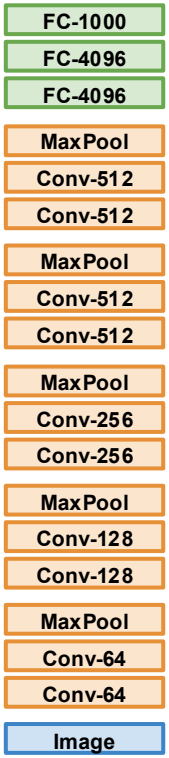
3. Bigger dataset



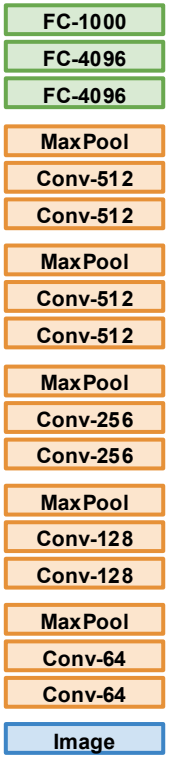
With bigger dataset, it's better to train more layers



	very similar dataset	very different dataset
very little data	?	?
quite a lot of data	?	?



	very similar dataset	**very different dataset**
very little data	Use Linear Classifier on final layer	?
quite a lot of data	Finetune all model layers	?



	very similar dataset	**very different dataset**
very little data	Use Linear Classifier on final layer	Try another pretrained model or collect more data ☹
quite a lot of data	Finetune all model layers	Either finetune all model layers or train from scratch!

Takeaway for your projects and beyond:

Have some dataset of interest but it has < ~1M images?

1. Find a very large dataset that has similar data, train a big model there
2. Transfer learn to your dataset

Deep learning frameworks provide a “Model Zoo” of pretrained models so you don’t need to train your own

PyTorch: https://github.com/pytorch/vision
Huggingface: https://github.com/huggingface/pytorch-image-models

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Choosing Hyperparameters

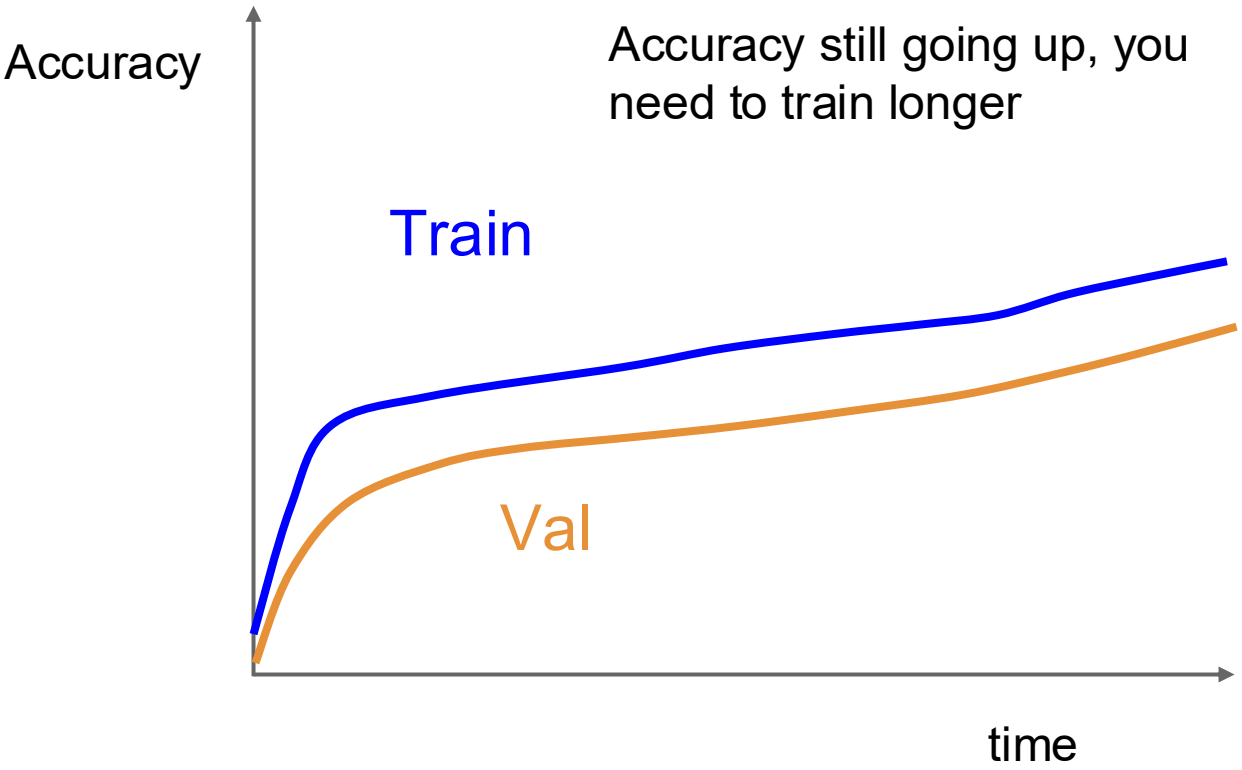
Step 1: Check initial loss
Step 2: Overfit a small sample
Step 3: Find LR that makes loss go down

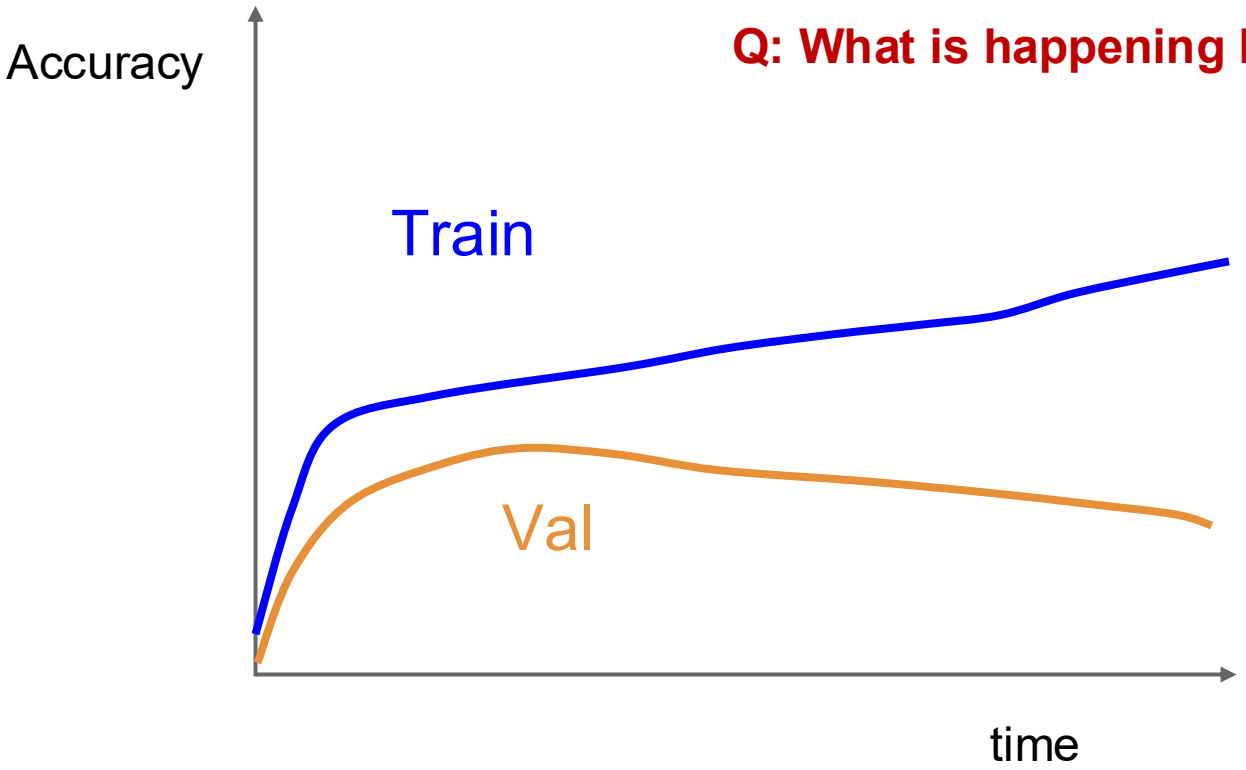
Use the architecture from the previous step, use all training data, turn on small weight decay, find a learning rate that makes the loss drop significantly within ~100 iterations

Good learning rates to try: 1e-1, 1e-2, 1e-3, 1e-4, 1e-5

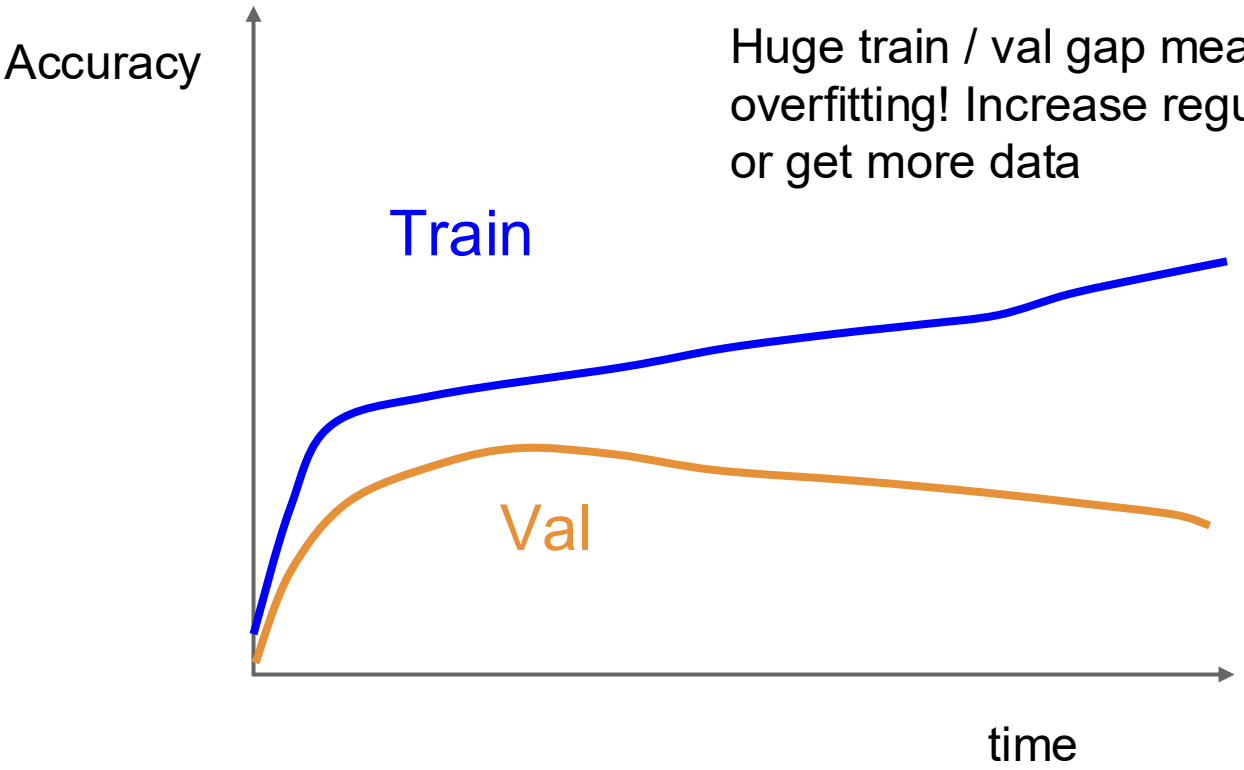
Choosing Hyperparameters

Step 1: Check initial loss
Step 2: Overfit a small sample
Step 3: Find LR that makes loss go down
Step 4: Coarse grid of hyperparams, train for ~1-5 epochs
Step 5: Refine grid, train longer
Step 6: Look at loss and accuracy curves (next slides)

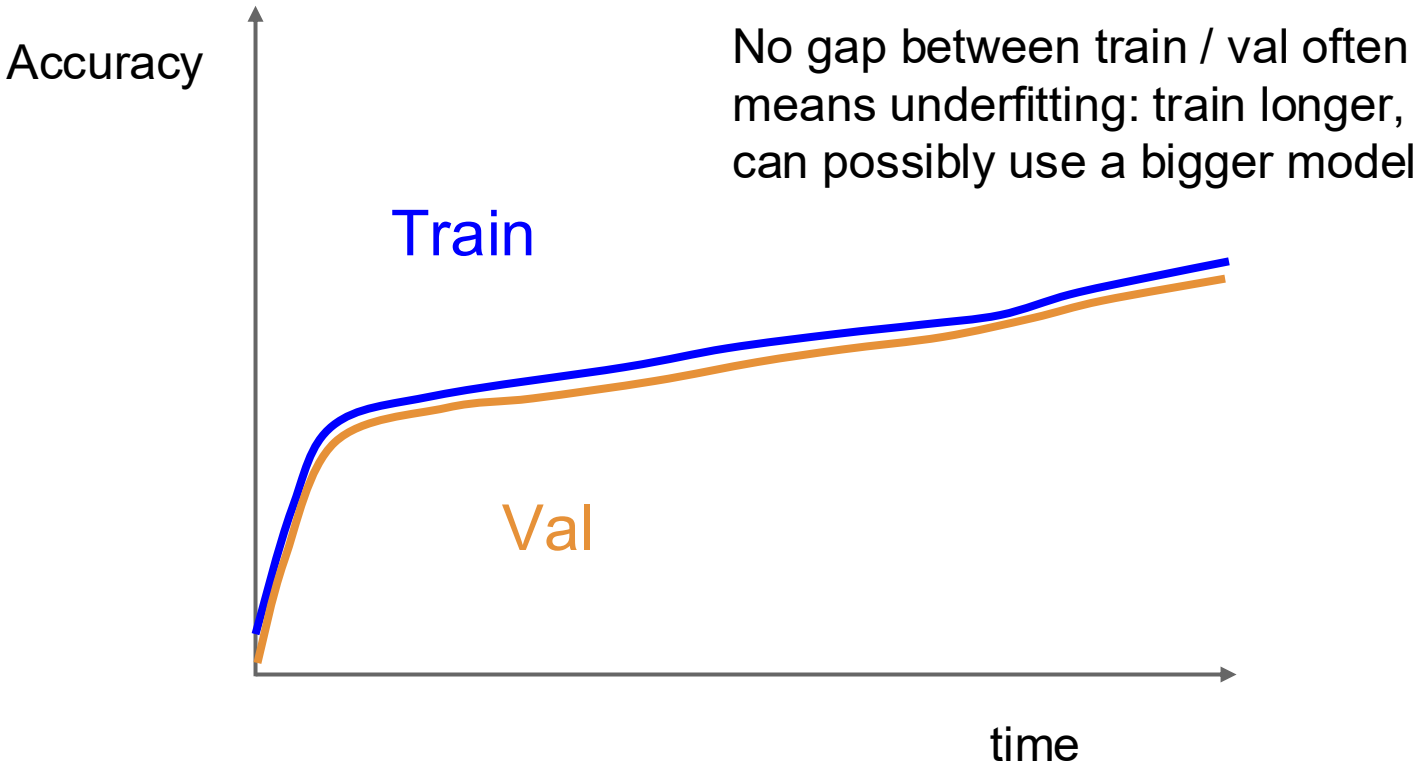

Accuracy
Accuracy still going up, you need to train longer
Train
Val
time



Q: What is happening here?



Huge train / val gap means overfitting! Increase regularization or get more data


Accuracy
No gap between train / val often means underfitting: train longer, can possibly use a bigger model
Train
Val
time

Choosing Hyperparameters

Step 1: Check initial loss
Step 2: Overfit a small sample
Step 3: Find LR that makes loss go down
Step 4: Coarse grid, train for ~1-5 epochs
Step 5: Refine grid, train longer
Step 6: Look at loss and accuracy curves
Step 7: GOTO step 5

Random Search vs. Grid Search

Random Search for Hyper-Parameter Optimization
Bergstra and Bengio, 2012

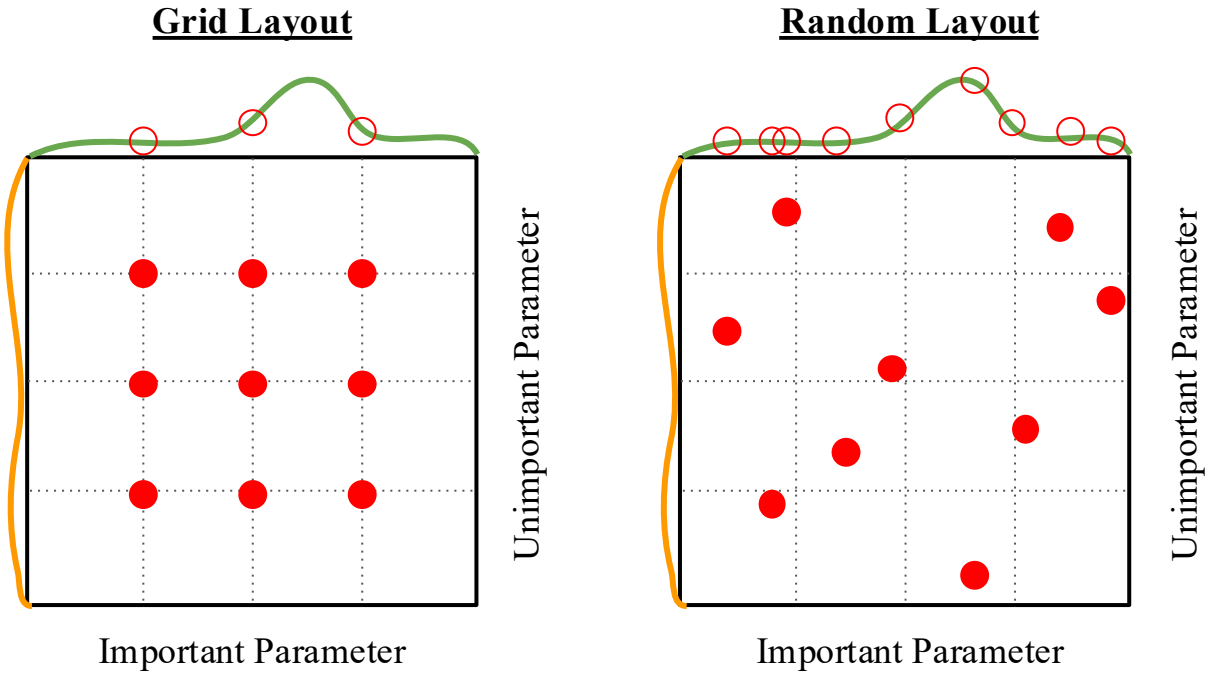


Illustration of Bergstra et al., 2012 by Shayne Longpre, copyright CS231n 2017

Summary

We reviewed 8 topics at a high level:

1. Layers in CNNs (Conv, FC, Norm, Dropout)
2. Activation Functions in NNs (ReLU, GELU, etc.)
3. CNN Architectures (VGG, ResNets)
4. Weight Initialization (Maintain Activation Distribution)

Summary

We reviewed 8 topics at a high level:

5. Data Preprocessing (subtract mean, divide std)
6. Data augmentation (cropping, jitter)
7. Transfer Learning (train on ImageNet first)
8. Hyperparameter (Checking Losses + Random Search)