DeepRob

Lecture 10
Training Neural Networks II
University of Michigan and University of Minnesota

Project 2—Updates

- Instructions available on the website
  - Here: https://rpm-lab.github.io/CSCI5980-Spr23-DeepRob/projects/project2/
- Implement two-layer neural network and generalize to FCN
- **Autograder is online!**
- **Due Tuesday, February 21st 11:59 PM CT**

Final Project Tasks

1. [Graded] Final Project Proposal document submission (2%)
2. [Graded] In-class topic-paper(s) presentation (4%)
3. In-class final project pitch
4. In-class final project checkpoint
5. [Graded] Reproduce published results (12%)
   - Algorithmic extension to obtain results with new idea, technique or dataset
6. [Graded] Video Presentation + Poster (4%)
7. [Graded] Final Report (2%)

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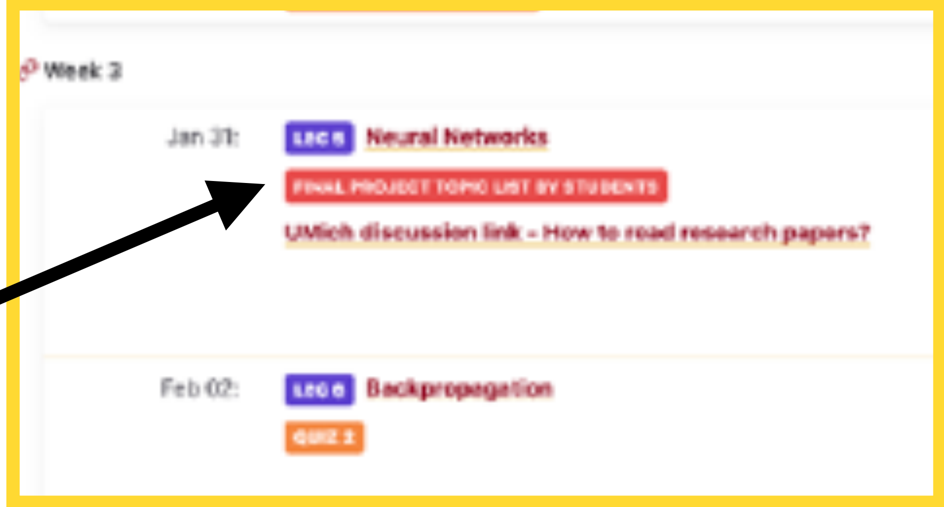
7. [Graded] Final Report (2%)

1. Form your team
2. Update your team info on the spreadsheet by Sunday 02/19
3. On Monday 02/20, I will release final teams and their schedule in-class topic-paper(s) presentation.
4. In-class topic-paper(s) presentation will start on 03/02



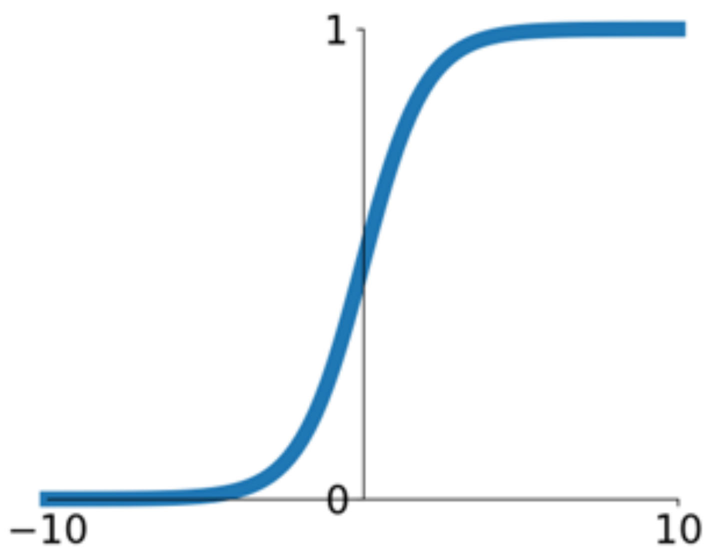
Recap

1. **One time setup:** Last time
   - Activation functions, data preprocessing, weight initialization, regularization
2. **Training dynamics:** Today
   - Learning rate schedules; large-batch training; hyperparameter optimization
3. **After training:**
   - Model ensembles, transfer learning

Last time: Activation Functions

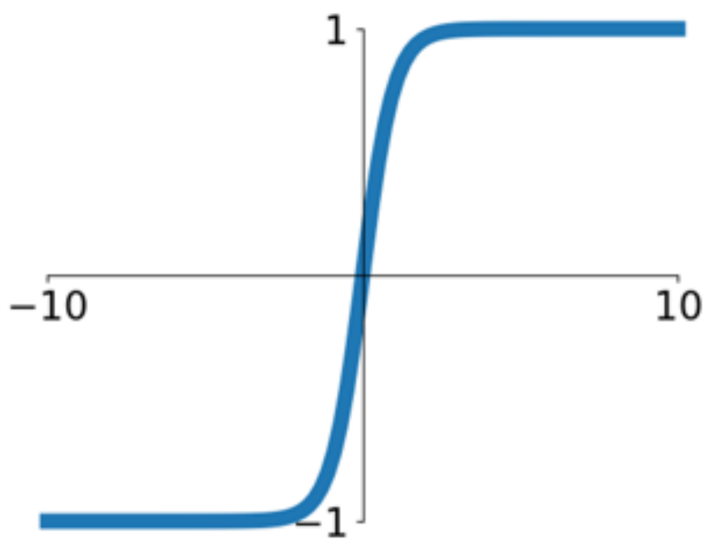
Sigmoid

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



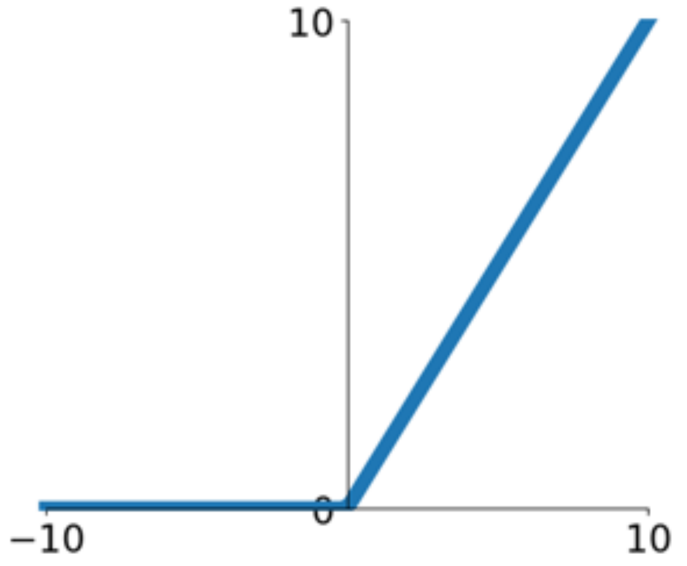
tanh

$$\tanh(x)$$



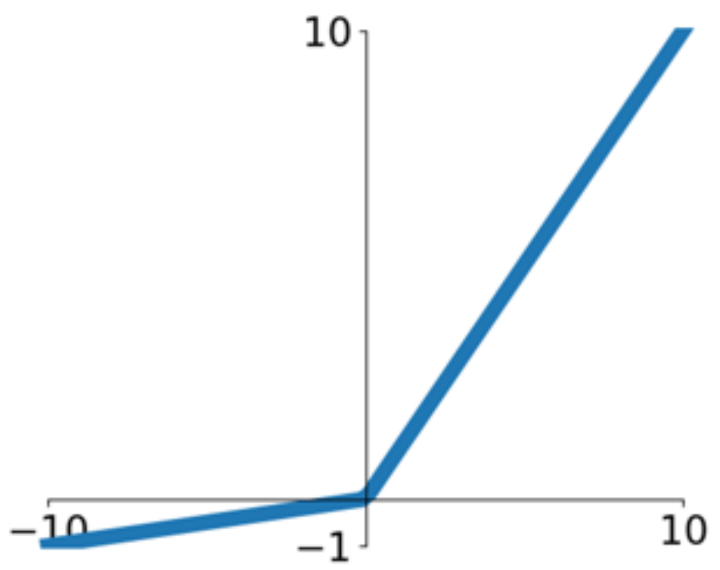
ReLU

$$\max(0,x)$$



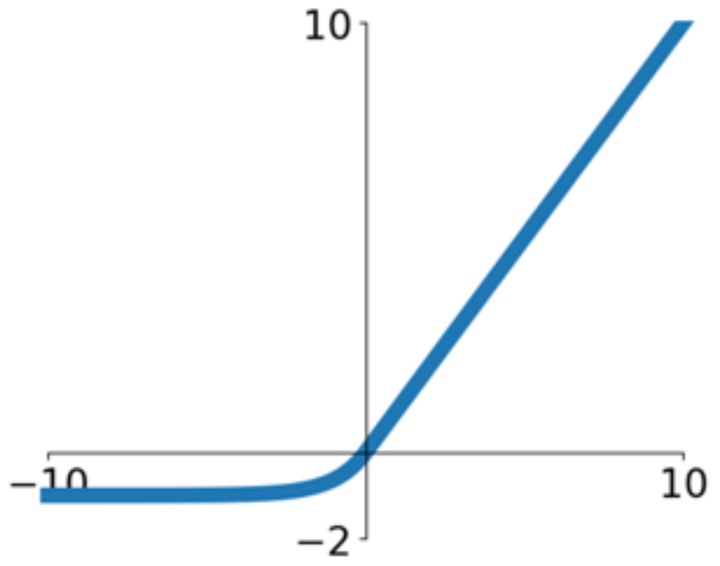
Leaky ReLU

$$\max(0.1x, x)$$



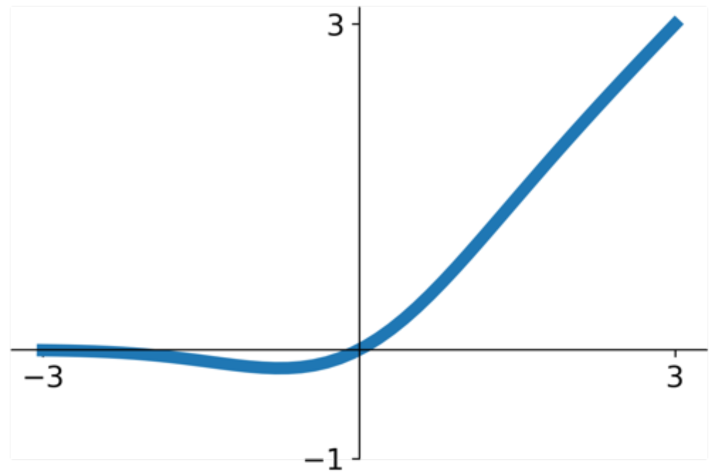
ELU

$$\begin{cases} x & x \geq 0 \\ \alpha(\exp^x - 1) & x < 0 \end{cases}$$

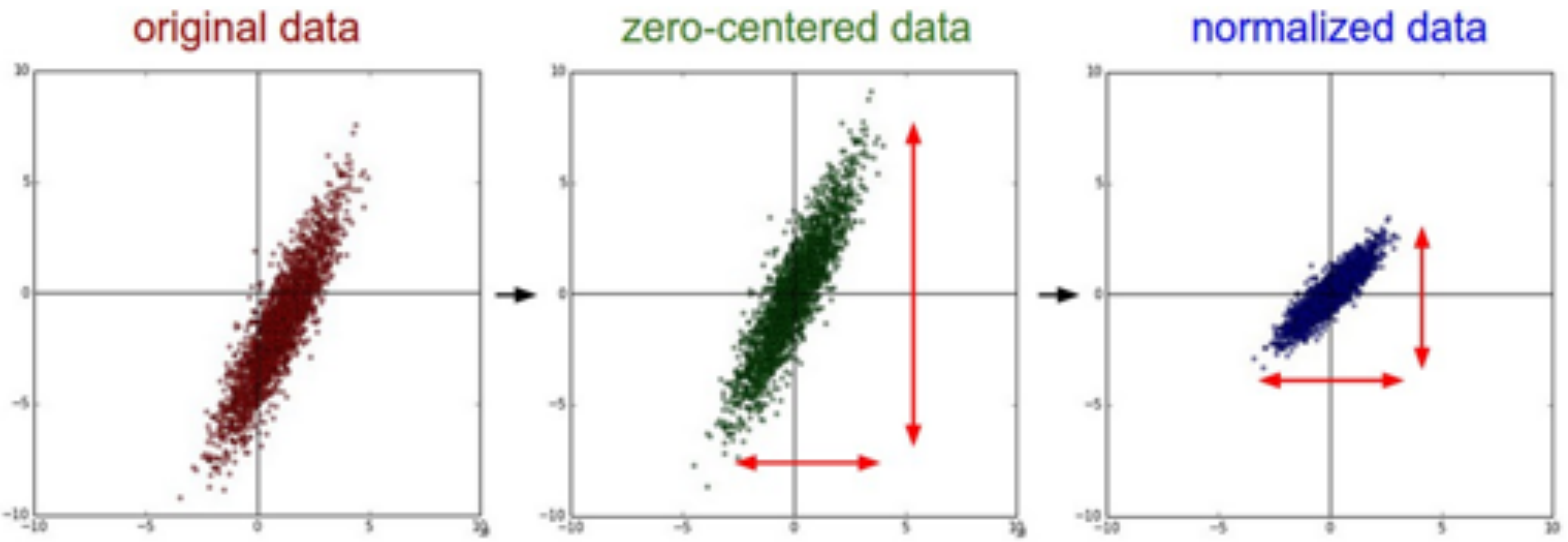


GELU

$$\approx x\alpha(1.702x)$$



Last time: Data Preprocessing

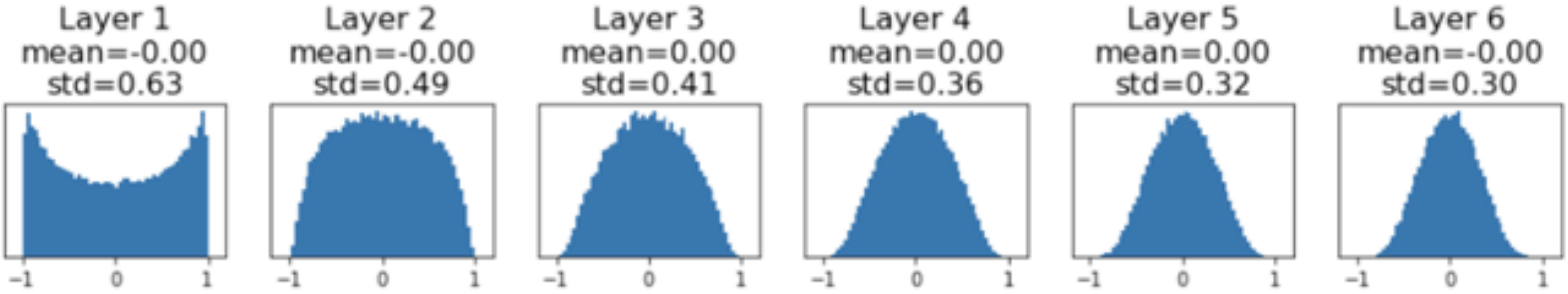


Last time: Weight initialization

```
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(Din)
    x = np.tanh(x.dot(W))
    hs.append(x)
```

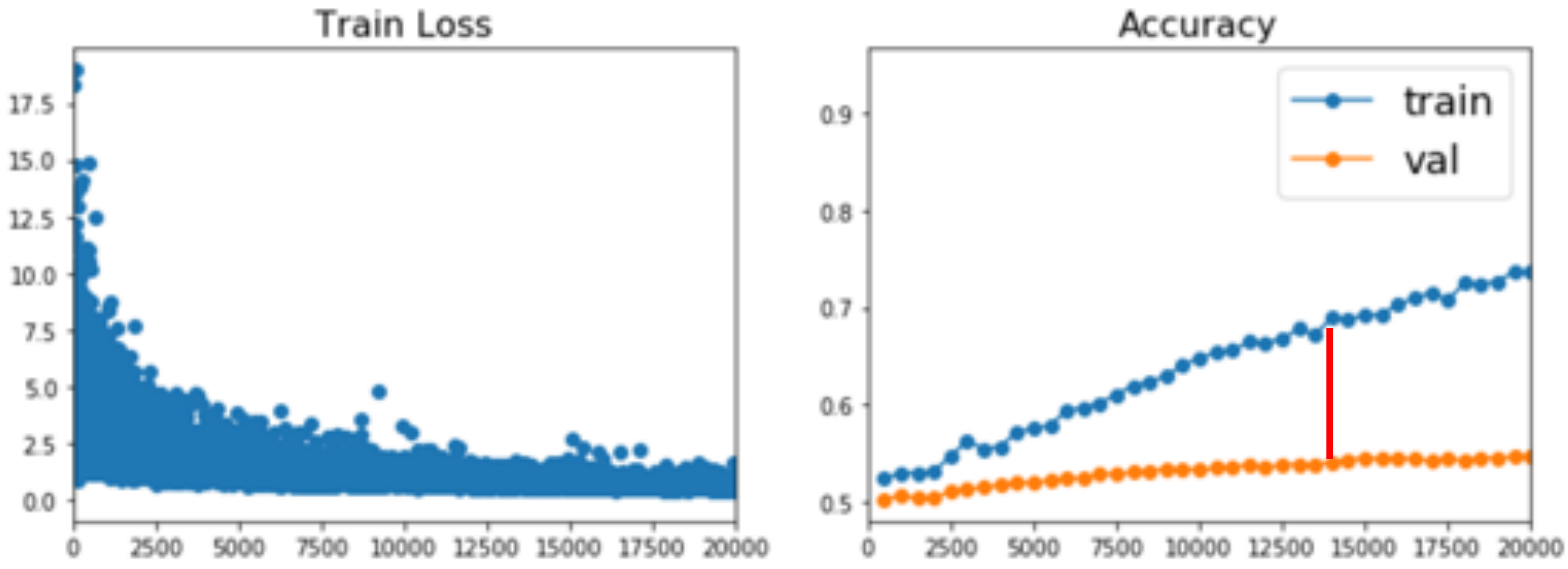
"Xavier" initialization:
std = 1/sqrt(Din)

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



Glorot and Bengio, "Understanding the difficulty of training deep feedforward neural networks", AISTAT 2010

Now your model is training … but it overfits!



Regularization

Regularization: Add term to the loss

$$L = \frac{1}{N}\sum_{i=1}^{N}\sum_{j\neq y_i}\max(0, f(x_i; W)_j - f(x_i; W)_{y_i} + 1) + \lambda R(W)$$

In common use:

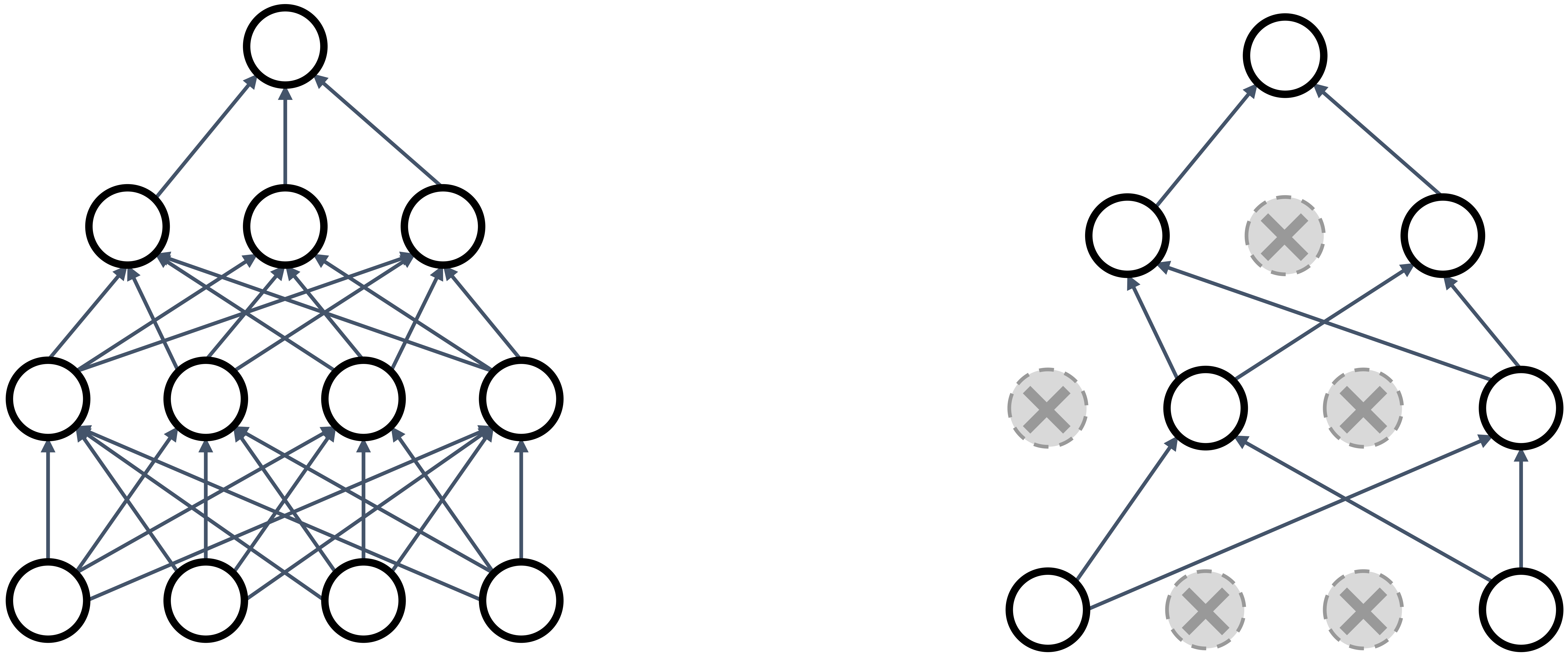
L2 regularization $R(W) = \sum_k \sum_l W_{k,l}^2$ (Weight decay)

L1 regularization $R(W) = \sum_k \sum_l |W_{k,l}|$

Elastic net (L1 + L2) $R(W) = \sum_k \sum_l \beta W_{k,l}^2 + |W_{k,l}|$

Regularization: Dropout

In each forward pass, randomly set some neurons to zero
Probability of dropping is a hyperparameter; 0.5 is common

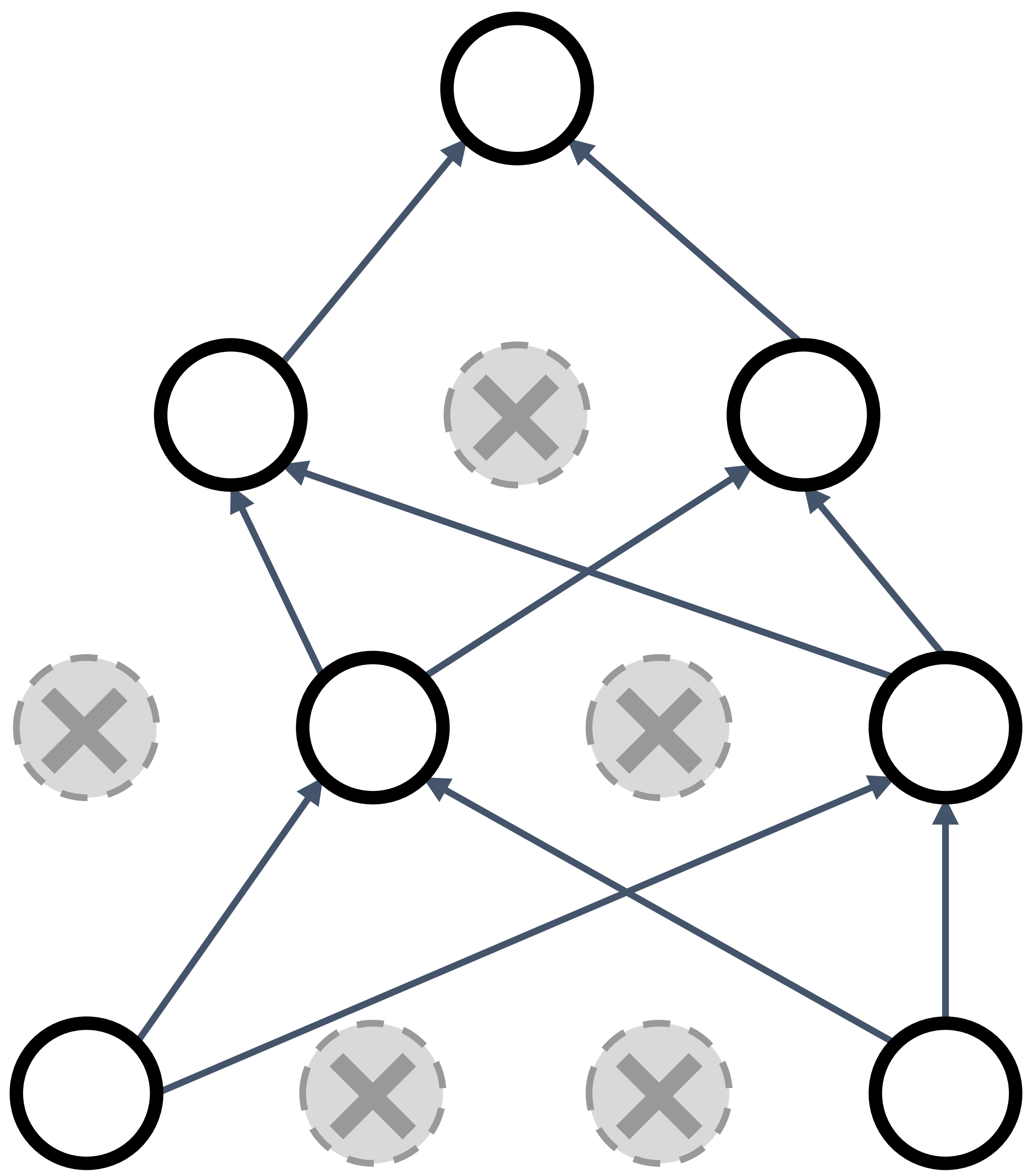


Srivastava et al, "Dropout: A simple way to prevent neural networks from overfitting", JMLR 2014

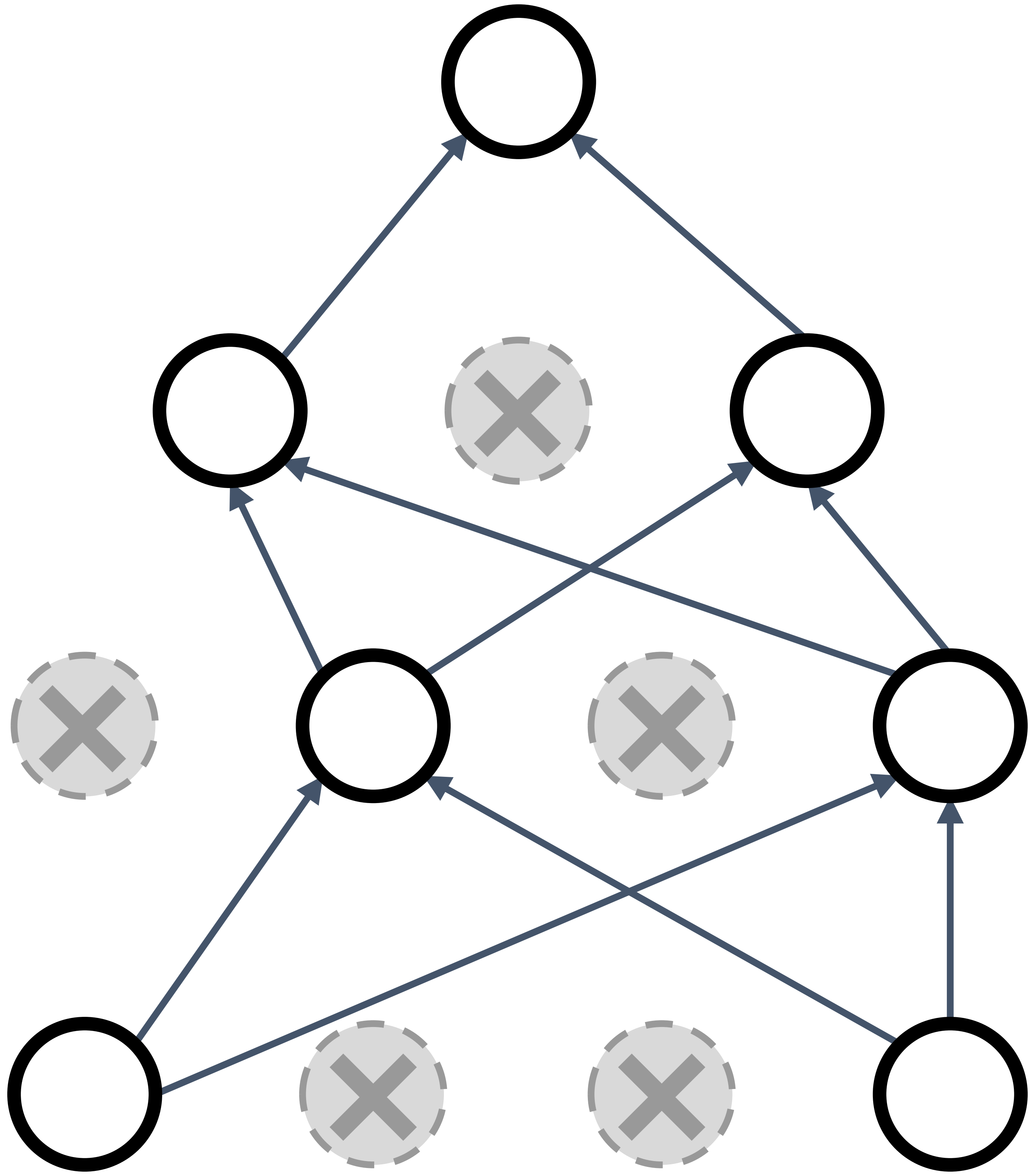
Regularization: Dropout

```
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)
```

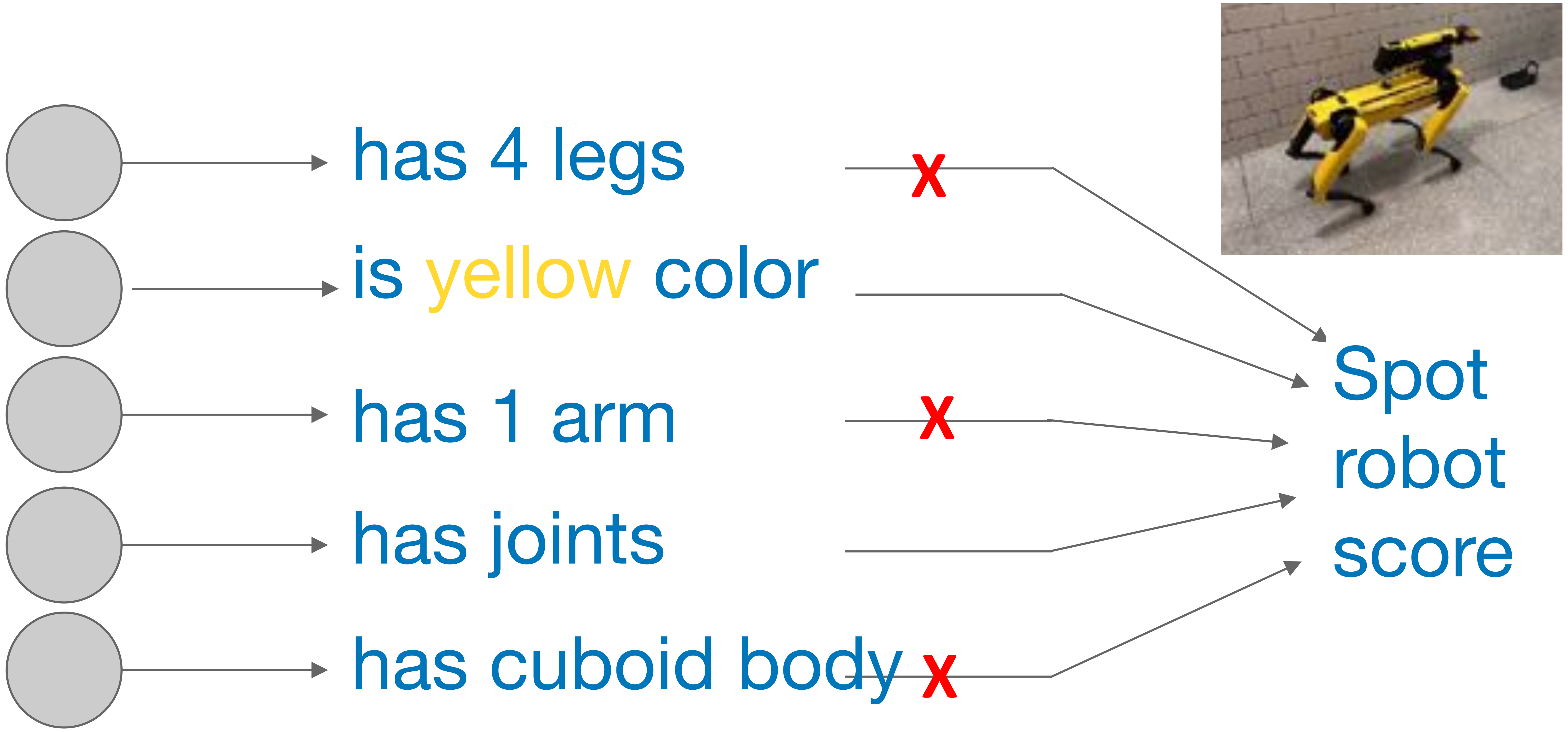
Example forward pass with a 3-layer network using dropout



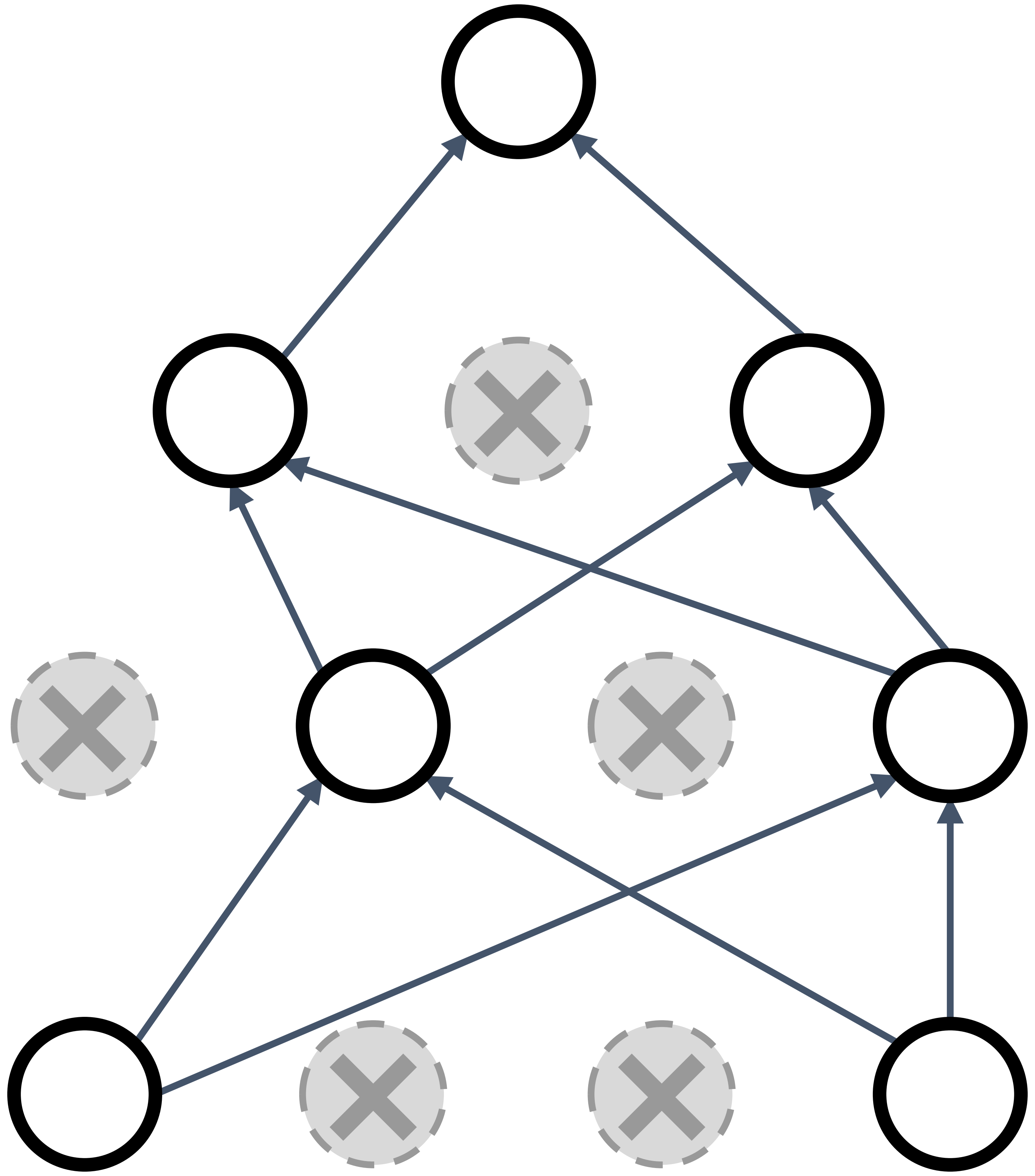
Regularization: Dropout



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



Regularization: Dropout



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

Dropout makes our output random!

$$\boxed{y} = f_W(\boxed{x}, \boxed{z})$$

Random mask

Output label

Input image

Want to "average out" the randomness at test-time

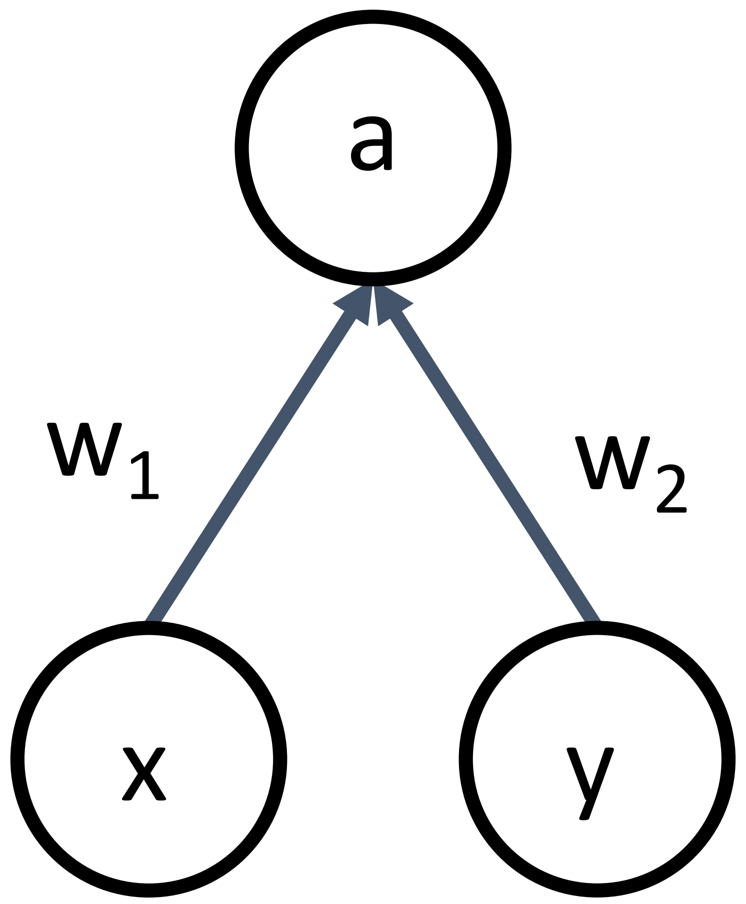
$$y = f(x, z) = \mathbb{E}_z[f(x, z)] = \int p(z) f(x, z) dz$$

But this integral seems hard…

Dropout: Test time

Want to approximate the integral

$$y = f(x, z) = \mathbb{E}_z[f(x, z)] = \int p(z) f(x, z) dz$$



Consider a single neuron:

At test time we have: $\mathbb{E}[a] = w_1 x + w_2 y$

Dropout: Test time

Want to approximate the integral

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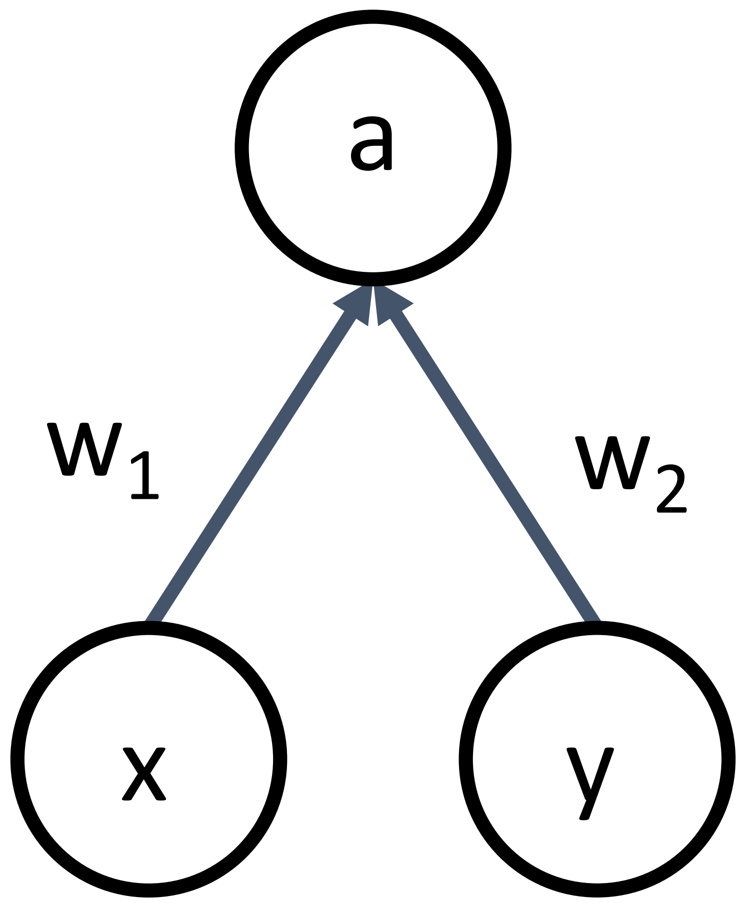


Consider a single neuron:

At test time we have: $\mathbb{E}[a] = w_1 x + w_2 y$

During training time we have:

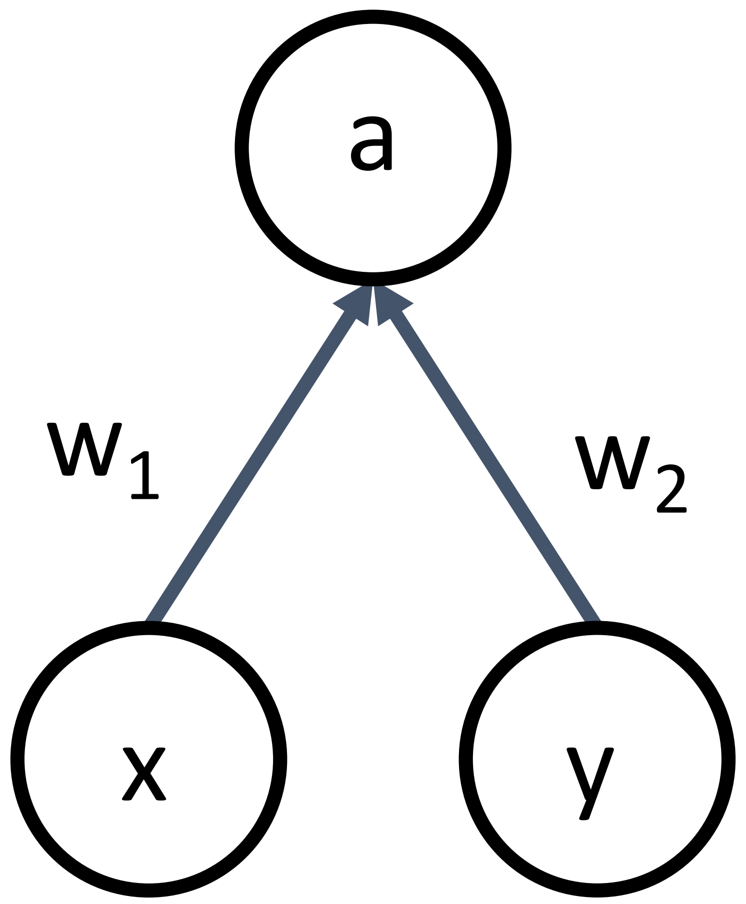
$$\mathbb{E}[a] = \frac{1}{4}(w_1 x + w_2 y) + \frac{1}{4}(w_1 x + 0y) + \frac{1}{4}(0x + 0y) + \frac{1}{4}(0x + w_2 y)$$

$$= \frac{1}{2}(w_1 x + w_2 y)$$

Dropout: Test time

Want to approximate the integral

$$y = f(x, z) = \mathbb{E}_z[f(x, z)] = \int p(z)f(x, z)dz$$



Consider a single neuron:

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During training time we have:

$$\mathbb{E}[a] = \frac{1}{4}(w_1x + w_2y) + \frac{1}{4}(w_1x + 0y) + \frac{1}{4}(0x + 0y) + \frac{1}{4}(0x + w_2y) = \frac{1}{2}(w_1x + w_2y)$$

At test time, drop nothing and ***multiply*** by dropout probability

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)

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
```

Drop in forward pass

Scale at test time

More common: "Inverted dropout"

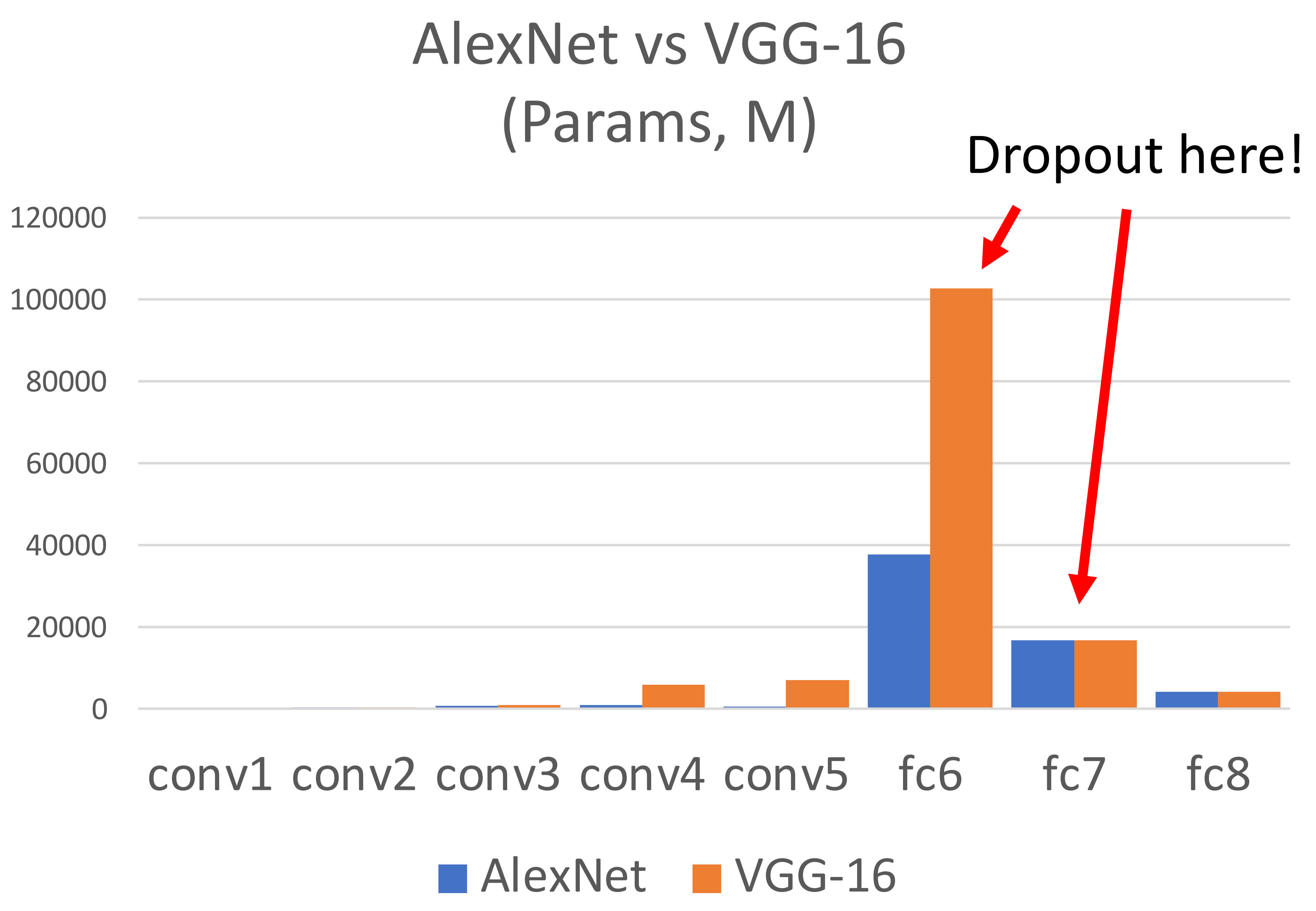
```python
p = 0.5 # probability of keeping a unit active. higher = less dropout

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

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

def predict(X):
  # ensembled forward pass
  H1 = np.maximum(0, np.dot(W1, X) + b1) # no scaling necessary
  H2 = np.maximum(0, np.dot(W2, H1) + b2)
  out = np.dot(W3, H2) + b3
```

Drop and scale during training

test time is unchanged!

Dropout architectures

Recall AlexNet, VGG have most of their parameters in **fully-connected layers**; usually Dropout is applied there



Later architectures (GoogLeNet, ResNet, etc) use global average pooling instead of fully-connected layers: they don't use dropout at all!

Regularization: A common pattern

Training: Add some kind of randomness

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

Testing: Average out randomness (sometimes approximate)

$$y = f(x, z) = \mathbb{E}_z[f(x, z)] = \int p(z) f(x, z) dz$$

Regularization: A common pattern

Training: Add some kind of randomness

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

For ResNet and later, often L2 and Batch Normalization are the only regularizers!

Testing: Average out randomness (sometimes approximate)

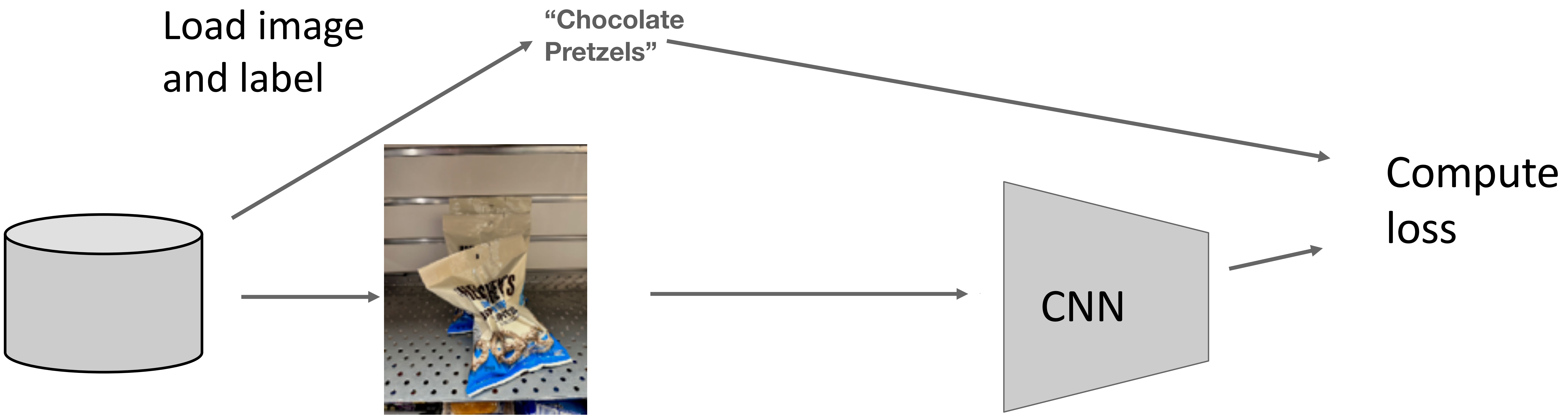
$$y = f(x, z) = \mathbb{E}_z[f(x, z)] = \int p(z)f(x, z)dz$$

Example: Batch Normalization

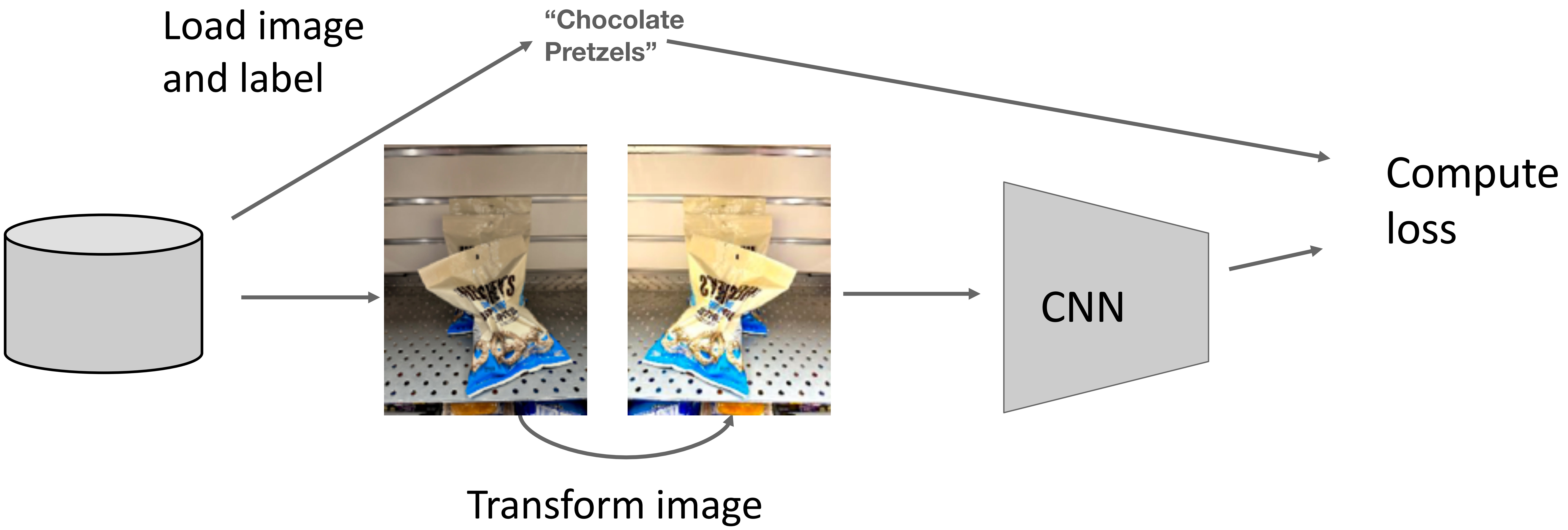
Training: Normalize using stats from random mini batches

Testing: Use fixed stats to normalize

Data Augmentation



Data Augmentation



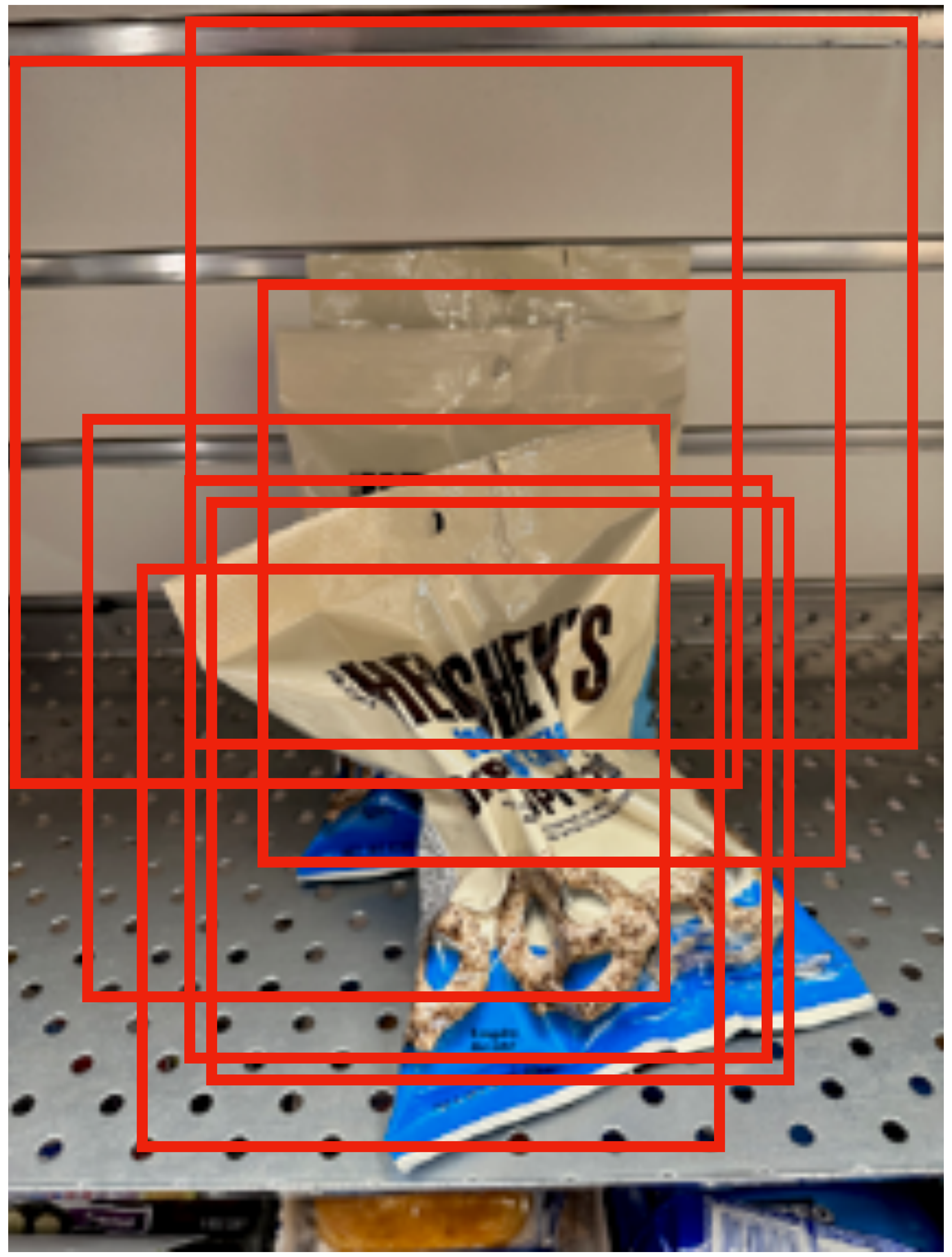
Data Augmentation: Horizontal Flips

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



Testing: 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

More complex:

1. Apply PCA to all [R, G, B] pixels in training set
2. Sample a "color offset" along principal component directions
3. Add offset to all pixels of a training image

(Used in AlexNet, ResNet, etc)

Data Augmentation: RandAugment

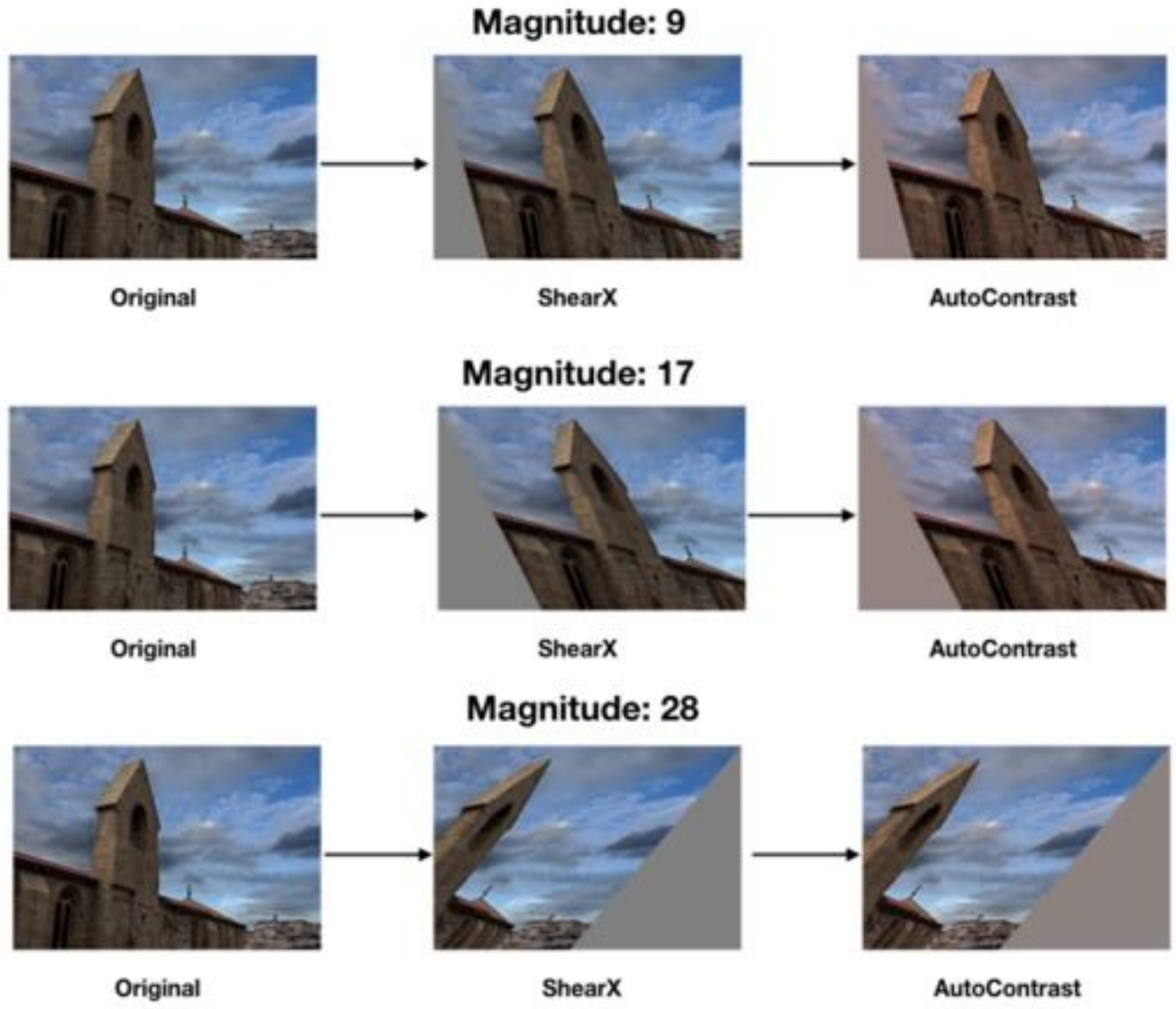
```
transforms = [
'Identity', 'AutoContrast', 'Equalize',
'Rotate', 'Solarize', 'Color', 'Posterize',
'Contrast', 'Brightness', 'Sharpness',
'ShearX', 'ShearY', 'TranslateX', 'TranslateY']

def randaugment(N, M):
"""Generate a set of distortions.

  Args:
    N: Number of augmentation transformations to
       apply sequentially.
    M: Magnitude for all the transformations.
"""

 sampled_ops = np.random.choice(transforms, N)
 return [(op, M) for op in sampled_ops]
```

Apply random combinations of transforms:

- **Geometric:** Rotate, translate, shear
- **Color:** Sharpen, contrast, brightness, solarize, posterize, color

Cubuk et al, "RandAugment: Practical augmented data augmentation with a reduced search space", NeurIPS 2020

Data Augmentation: RandAugment



Apply random combinations of transforms:

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Data Augmentation: Get creative for your problem!

Data augmentation encodes **invariances** in your model

Think for your problem: what changes to the image should **not** change the network output?

Maybe different for different tasks!

Regularization: A common pattern

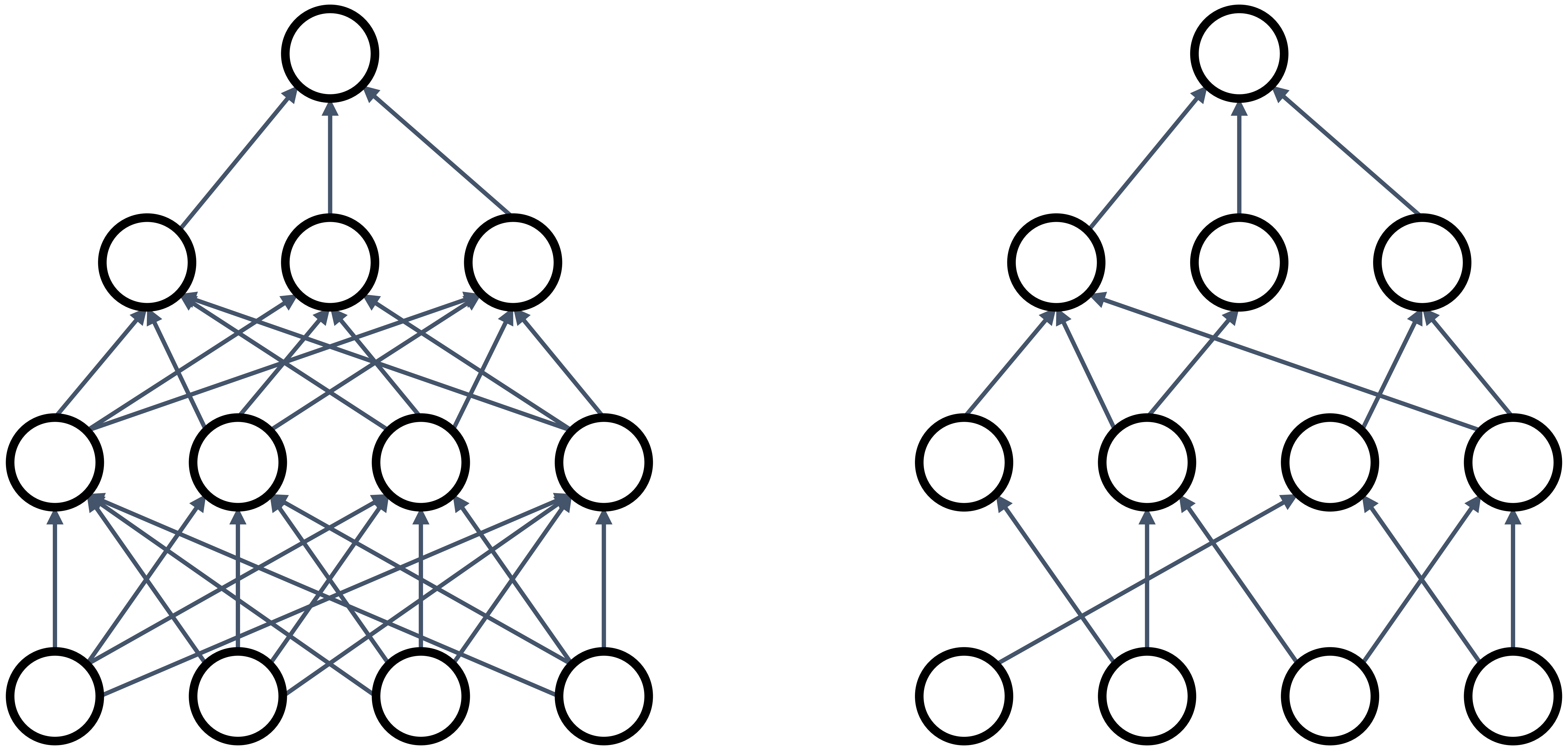
Training: Add some randomness
Testing: Marginalize over randomness

Examples:
Dropout
Batch Normalization
Data Augmentation

Regularization: DropConnect

Training: Drop random connections between neurons (set weight=0)
Testing: Use all the connections

Examples:
Dropout
Batch Normalization
Data Augmentation
DropConnect

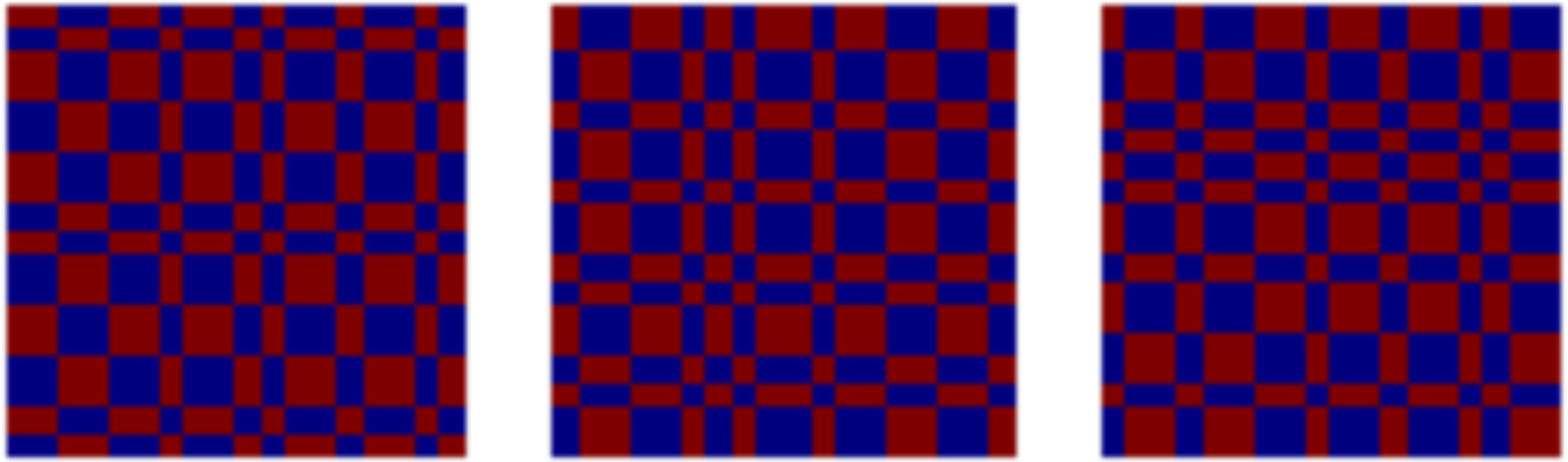


Wan et al, “Regularization of Neural Networks using DropConnect”, ICML 2013

Regularization: Fractional Pooling

Training: Use randomized pooling regions
Testing: Average predictions over different samples

Examples:
Dropout
Batch Normalization
Data Augmentation
DropConnect
Fractional Max Pooling



Graham, "Fractional Max Pooling", arXiv 2014

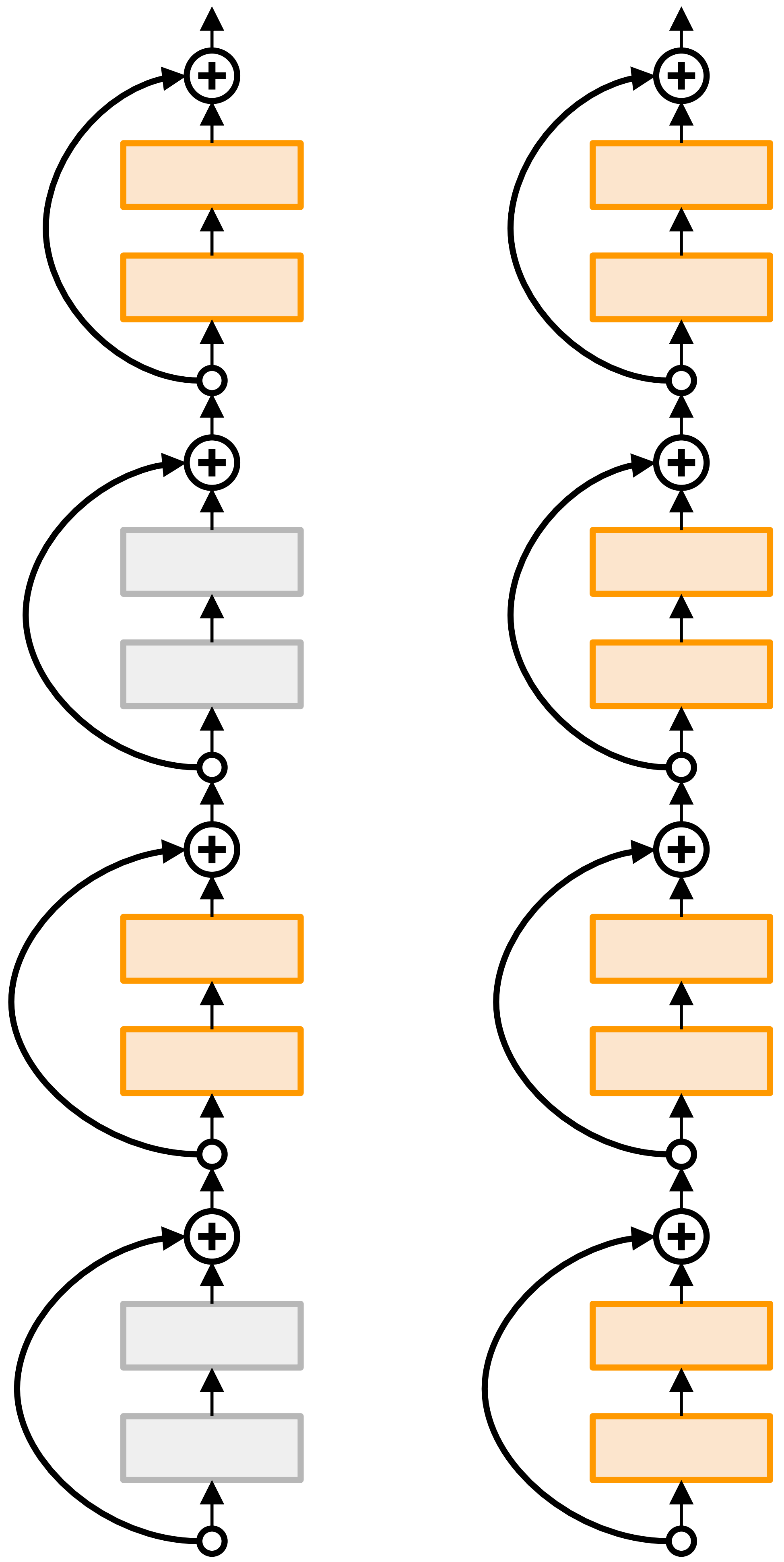
Regularization: Stochastic Depth

Training: Skip some residual blocks in ResNet
Testing: Use the whole network

Examples:
Dropout
Batch Normalization
Data Augmentation
DropConnect
Fractional Max Pooling
Stochastic Depth

Starting to become common in recent architectures:

- Pham et al, “Very Deep Self-Attention Networks for End-to-End Speech Recognition”, INTERSPEECH 2019
- Tan and Le, “EfficientNetV2: Smaller Models and Faster Training”, ICML 2021
- Fan et al, “Multiscale Vision Transformers”, ICCV 2021
- Bello et al, “Revisiting ResNets: Improved Training and Scaling Strategies”, NeurIPS 2021
- Steiner et al, “How to train your ViT? Data, Augmentation, and Regularization in Vision Transformers”, arXiv 2021

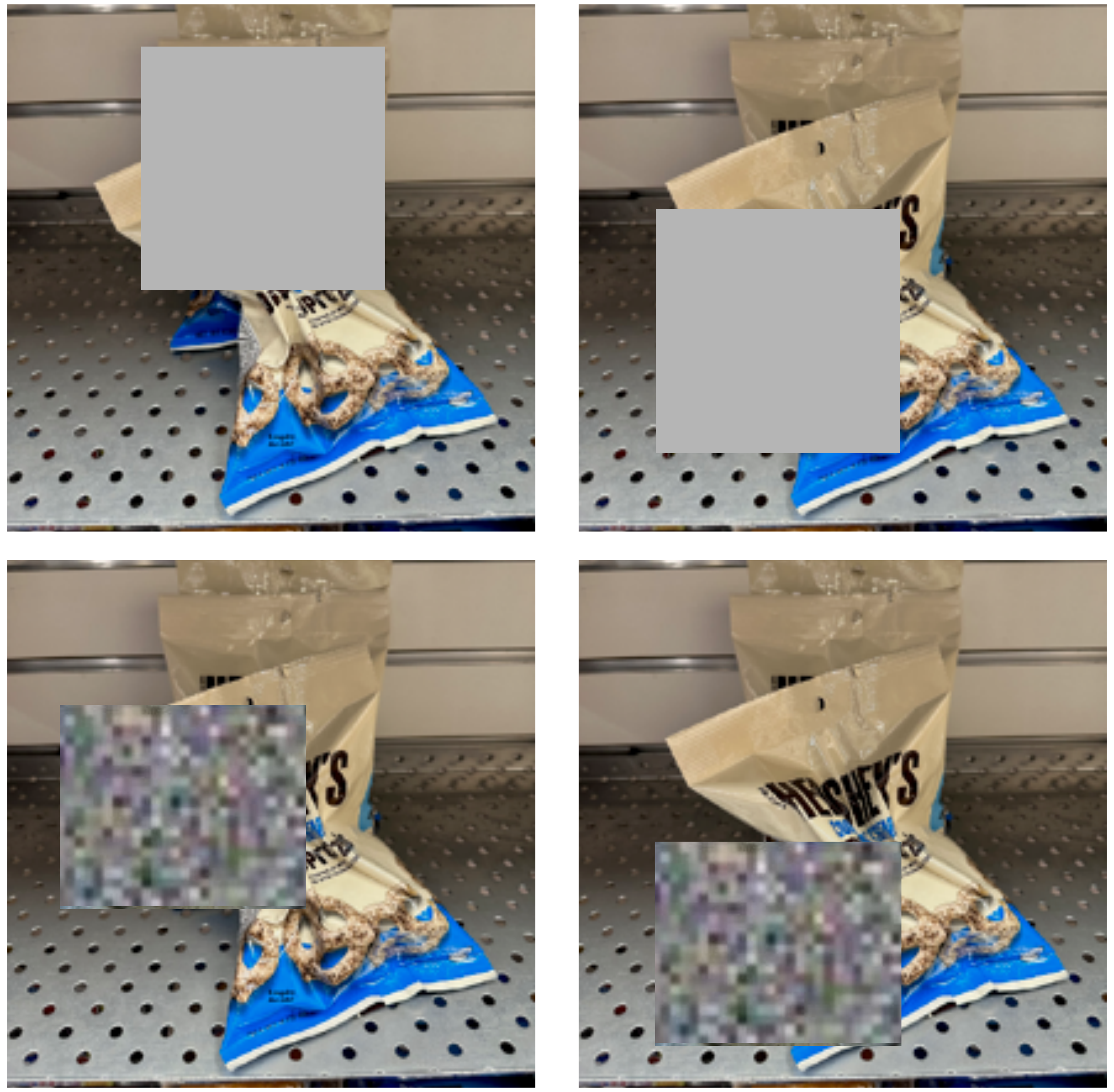


Huang et al, “Deep Networks with Stochastic Depth”, ECCV 2016

Regularization: CutOut

Training: Set random image regions to 0
Testing: Use the whole image

Examples:
Dropout
Batch Normalization
Data Augmentation
DropConnect
Fractional Max Pooling
Stochastic Depth
Cutout / Random Erasing



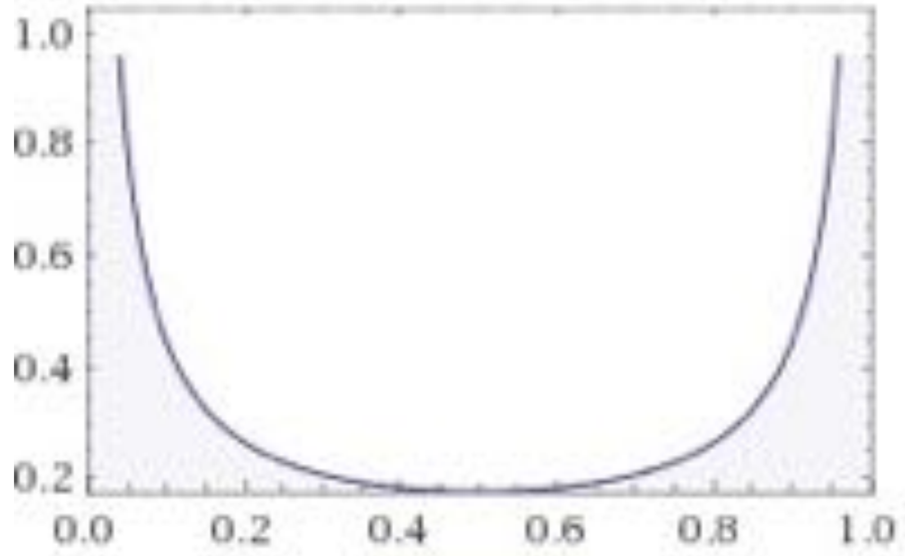
Replace random regions with mean value or random values

DeVries and Taylor, “Improved Regularization of Convolutional Neural Networks with Cutout”, arXiv 2017
Zhong et al, “Random Erasing Data Augmentation”, AAAI 2020

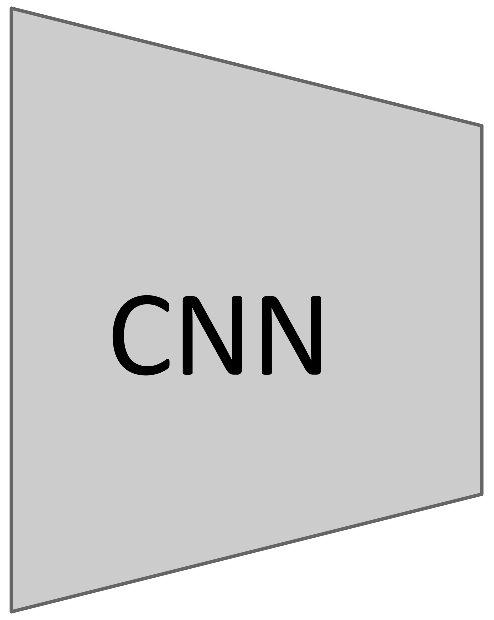
Regularization: Mixup

Training: Train on random blends of images
Testing: Use original images

Examples:
Dropout
Batch Normalization
Data Augmentation
DropConnect
Fractional Max Pooling
Stochastic Depth
Cutout / Random Erasing
Mixup



Sample blend probability from a beta distribution Beta(a, b) with a=b=0 so blend weights are close to 0/1



Target label:
Pretzels: 0.6
Robot: 0.4

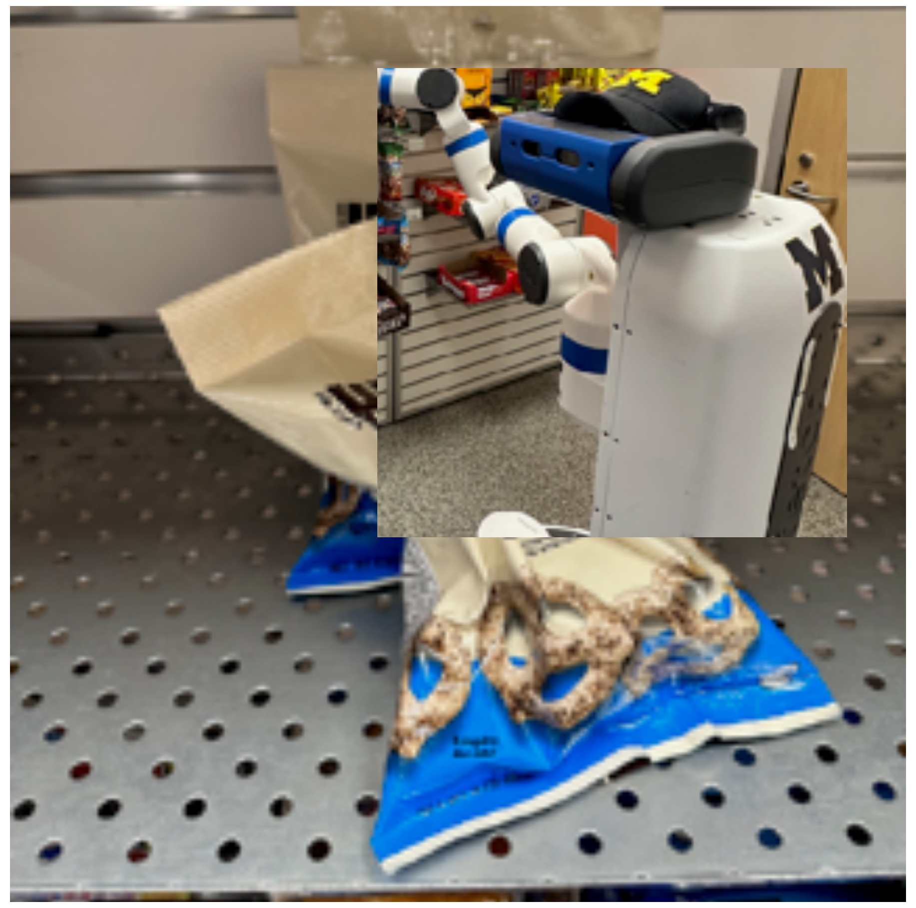
Randomly blend the pixels of pairs of training images, e.g. 60% pretzels, 40% robot

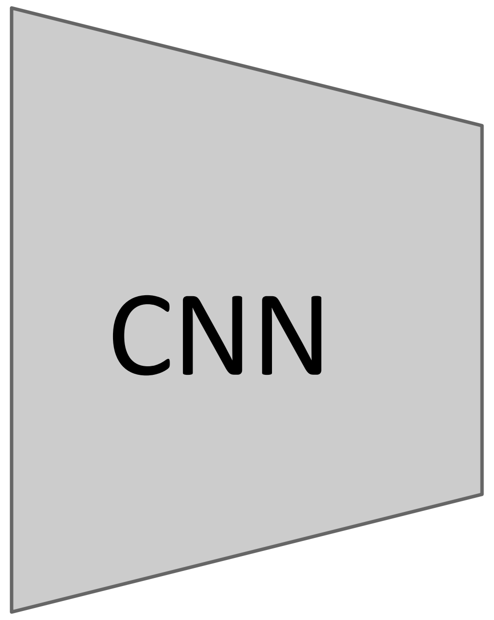
Zhang et al, "*mixup*: Beyond Empirical Risk Minimization", ICLR 2018

Regularization: CutMix

Training: Train on random blends of images
Testing: Use original images

Examples:
Dropout
Batch Normalization
Data Augmentation
DropConnect
Fractional Max Pooling
Stochastic Depth
Cutout / Random Erasing
Mixup / CutMix





Target label:
Pretzels: 0.6
Robot: 0.4

Replace random crops of one image with another, e.g. 60% of pixels from pretzels, 40% from robot

Yun et al, "CutMix: Regularization Strategies to Train Strong Classifiers with Localizable Features", ICCV 2019

Regularization: Label Smoothing

Training: Train on smooth labels
Testing: Use original images

Examples:
Dropout
Batch Normalization
Data Augmentation
DropConnect
Fractional Max Pooling
Stochastic Depth
Cutout / Random Erasing
Mixup / CutMix
Label Smoothing

Standard Training	**Label Smoothing**
Pretzels: 100%	Pretzels: 90%
Robot: 0%	Robot: 5%
Sugar: 0%	Sugar: 5%

Set target distribution to be $1 - \frac{K-1}{K}\epsilon$ on the correct category and ϵ / K on all other categories, with K categories and $\epsilon \in (0,1)$.

Loss is cross-entropy between predicted and target distribution.

Szegedy et al, "Rethinking the Inception Architecture for Computer Vision", CVPR 2015

Regularization: Summary

Training: Add some randomness
Testing: Marginalize over randomness

Examples:
Dropout
Batch Normalization
Data Augmentation
DropConnect
Fractional Max Pooling
Stochastic Depth
Cutout / Random Erasing
Mixup / CutMix
Label Smoothing

- Use DropOut for large fully-connected layers
- Data augmentation is always a good idea
- Use BatchNorm for CNNs (but not ViTs)
- Try Cutout, Mixup, CutMix, Stochastic Depth, Label Smoothing to squeeze out a bit of extra performance

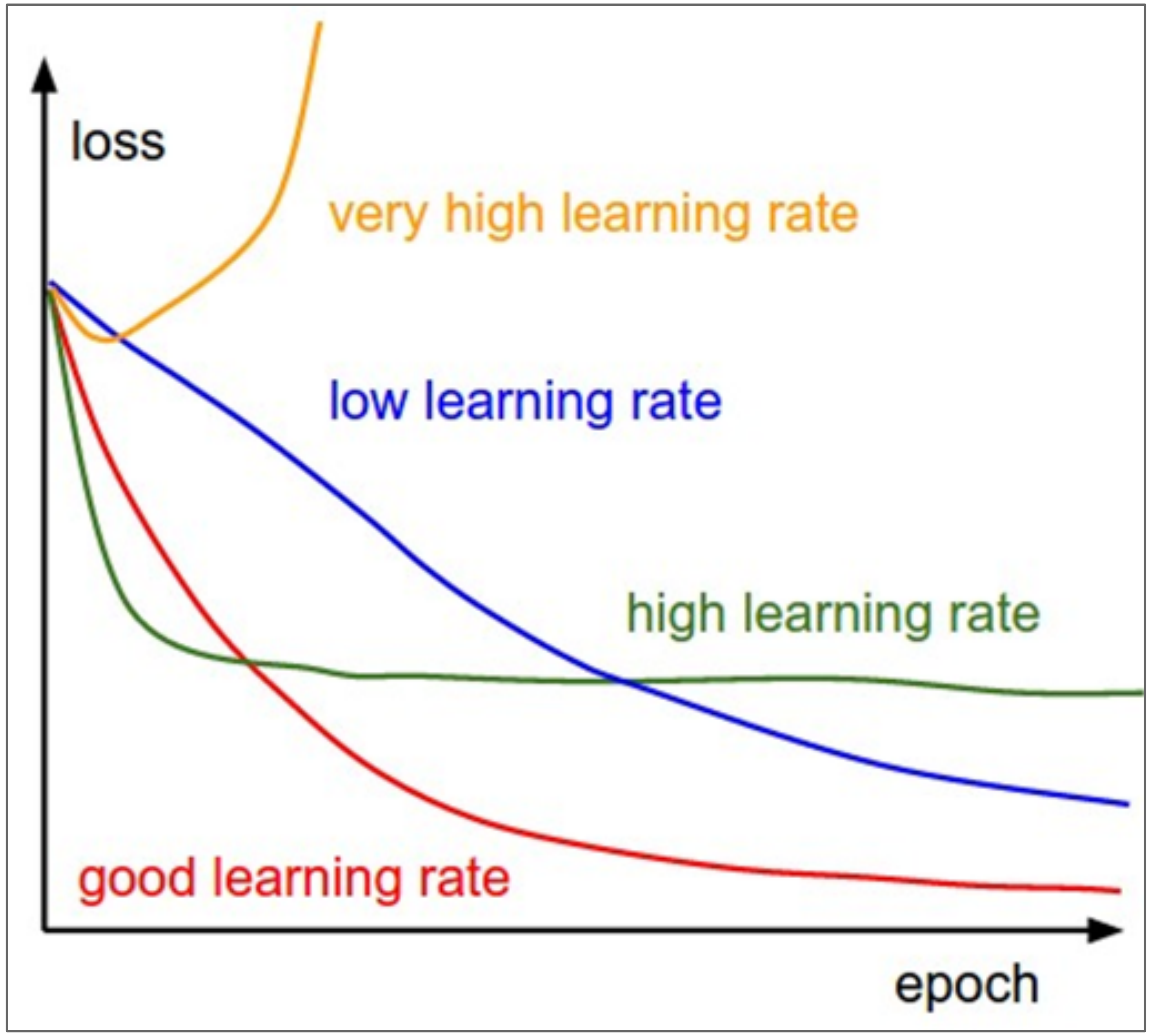
Recap

1. **One time setup:**
   - Activation functions, data preprocessing, weight initialization, regularization
2. **Training dynamics:**
   - Learning rate schedules; large-batch training; hyperparameter optimization
3. **After training:**
   - Model ensembles, transfer learning

Today

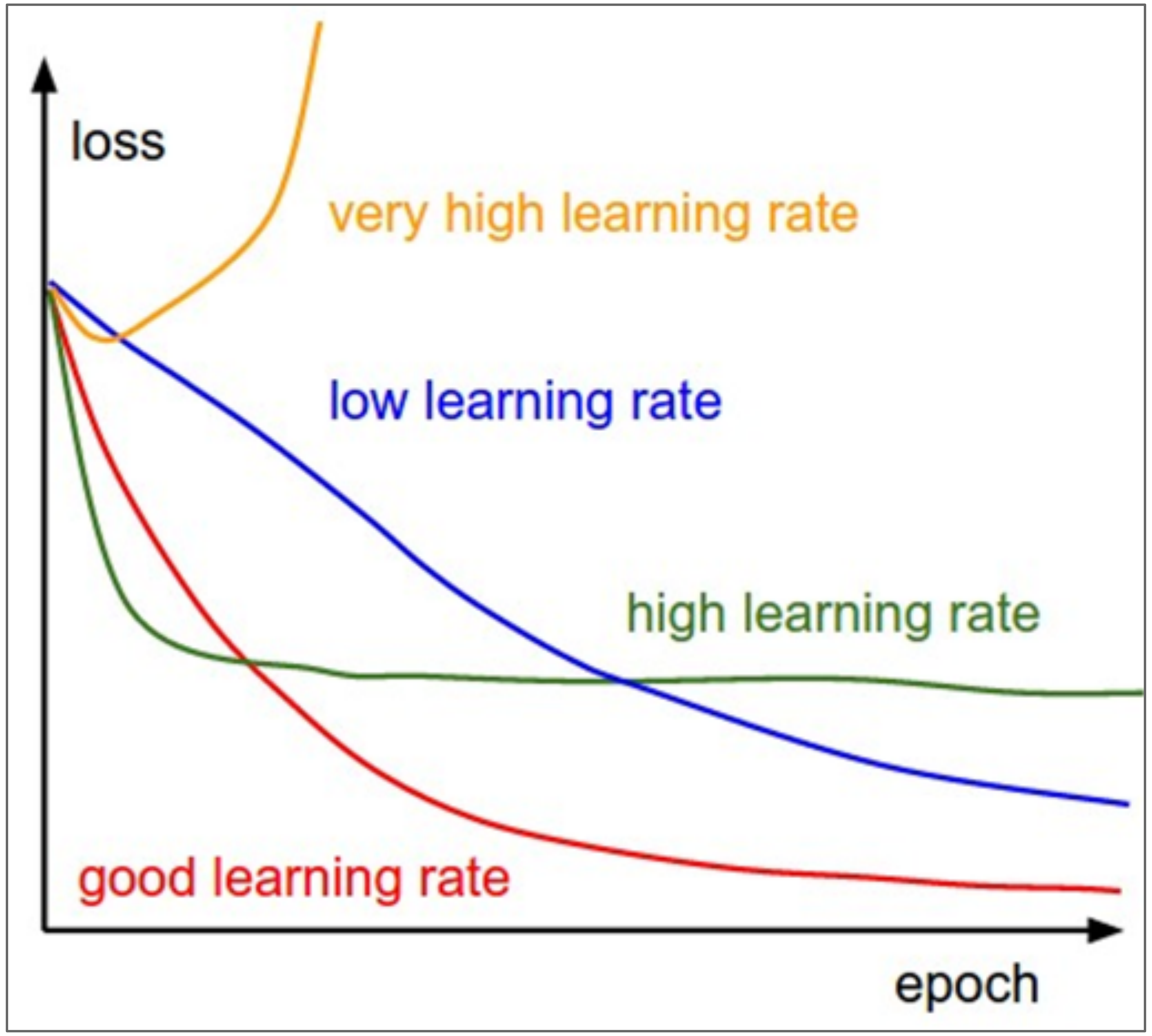
Learning Rate Schedules

SGD, SGD+Momentum, Adagrad, RMSProp, Adam all have **learning rate** as hyper parameter



Q: Which one of these learning rates is best to use?

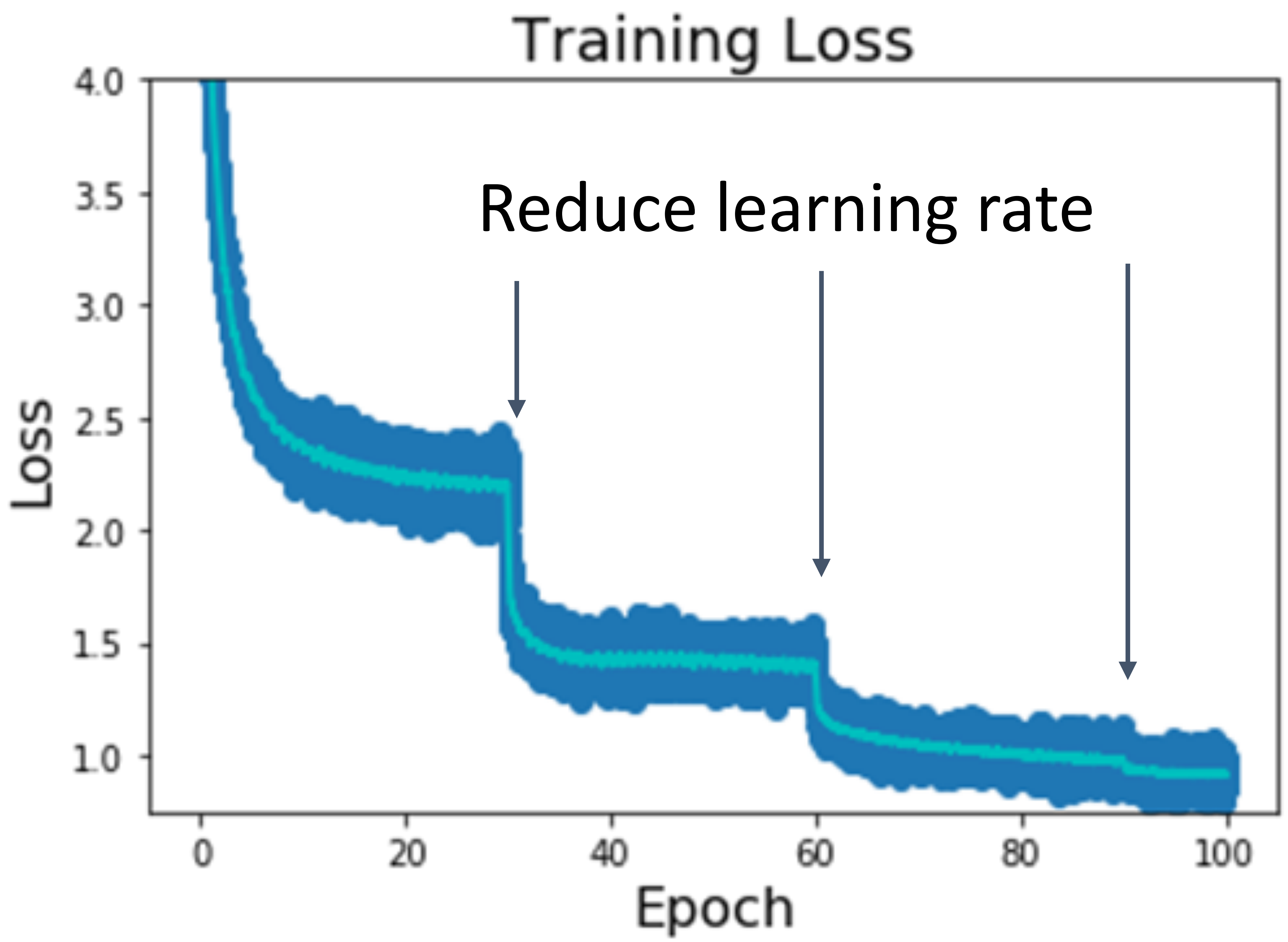
SGD, SGD+Momentum, Adagrad, RMSProp, Adam all have **learning rate** as hyper parameter



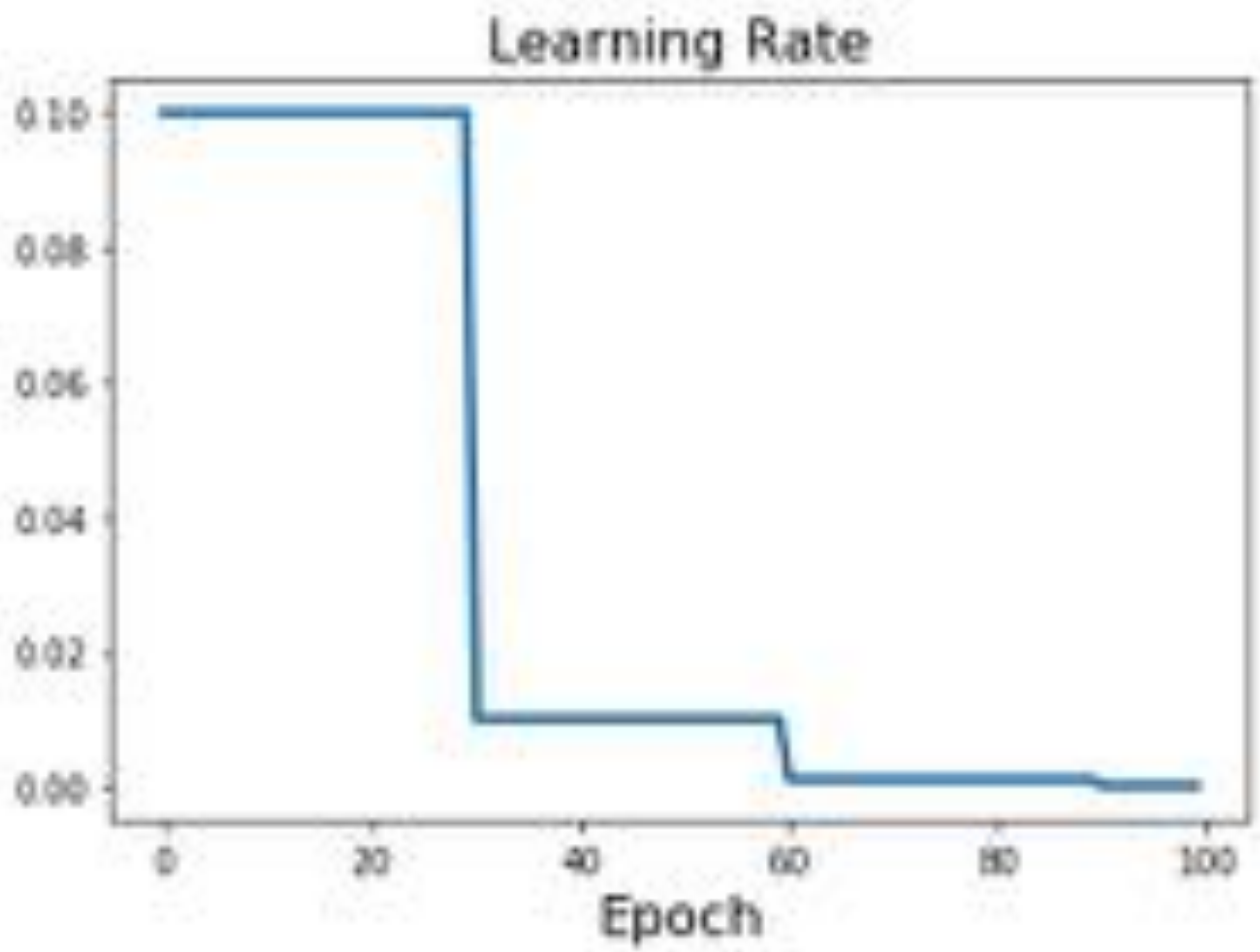
Q: Which one of these learning rates is best to use?

A: All of them! Start with large learning rate and decay over time.

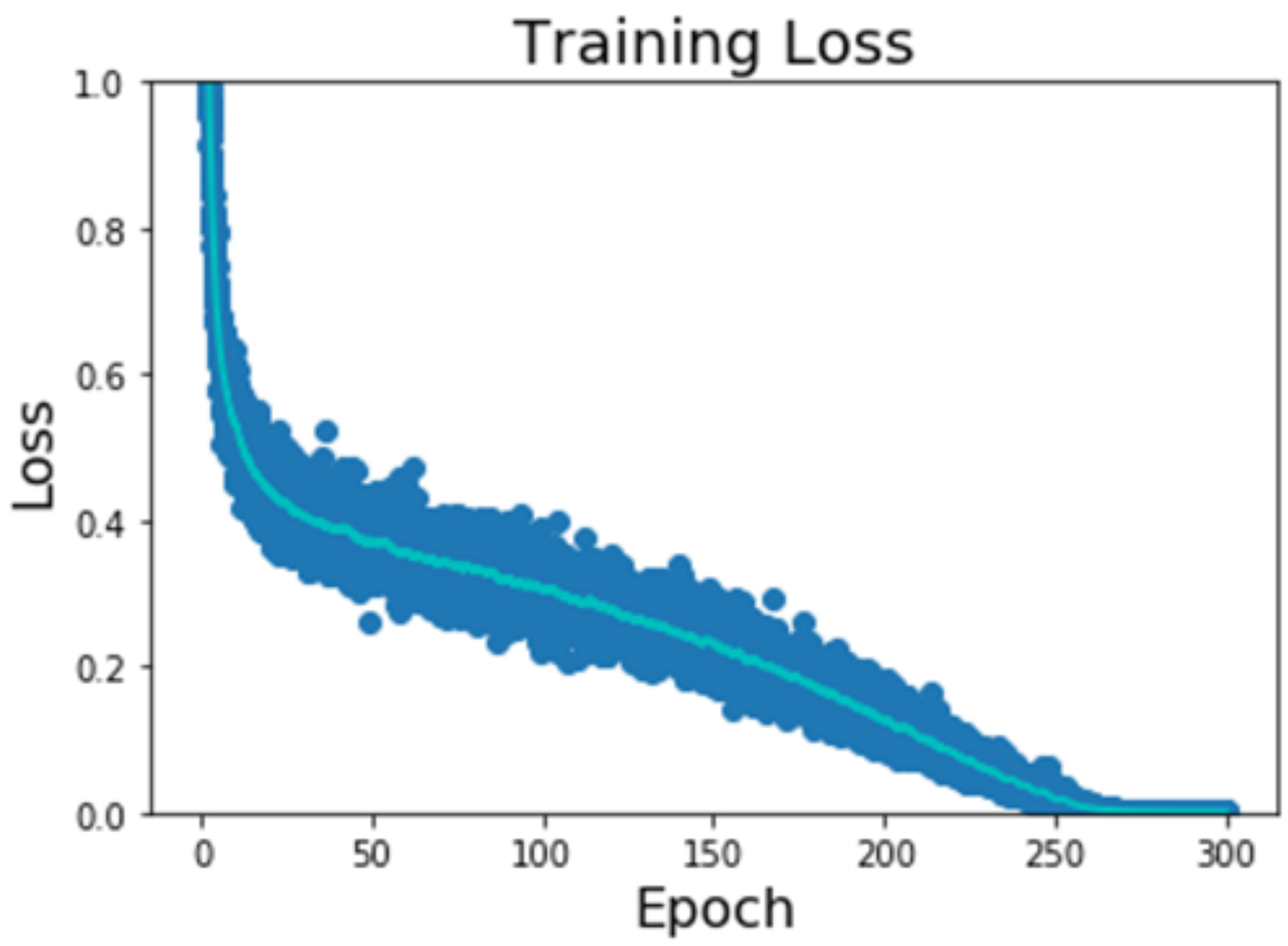
Learning Rate Decay: Step



Step: Reduce learning rate at a few fixed points. E.g. for ResNets, multiply LR by 0.1 after epochs 30, 60, and 90.

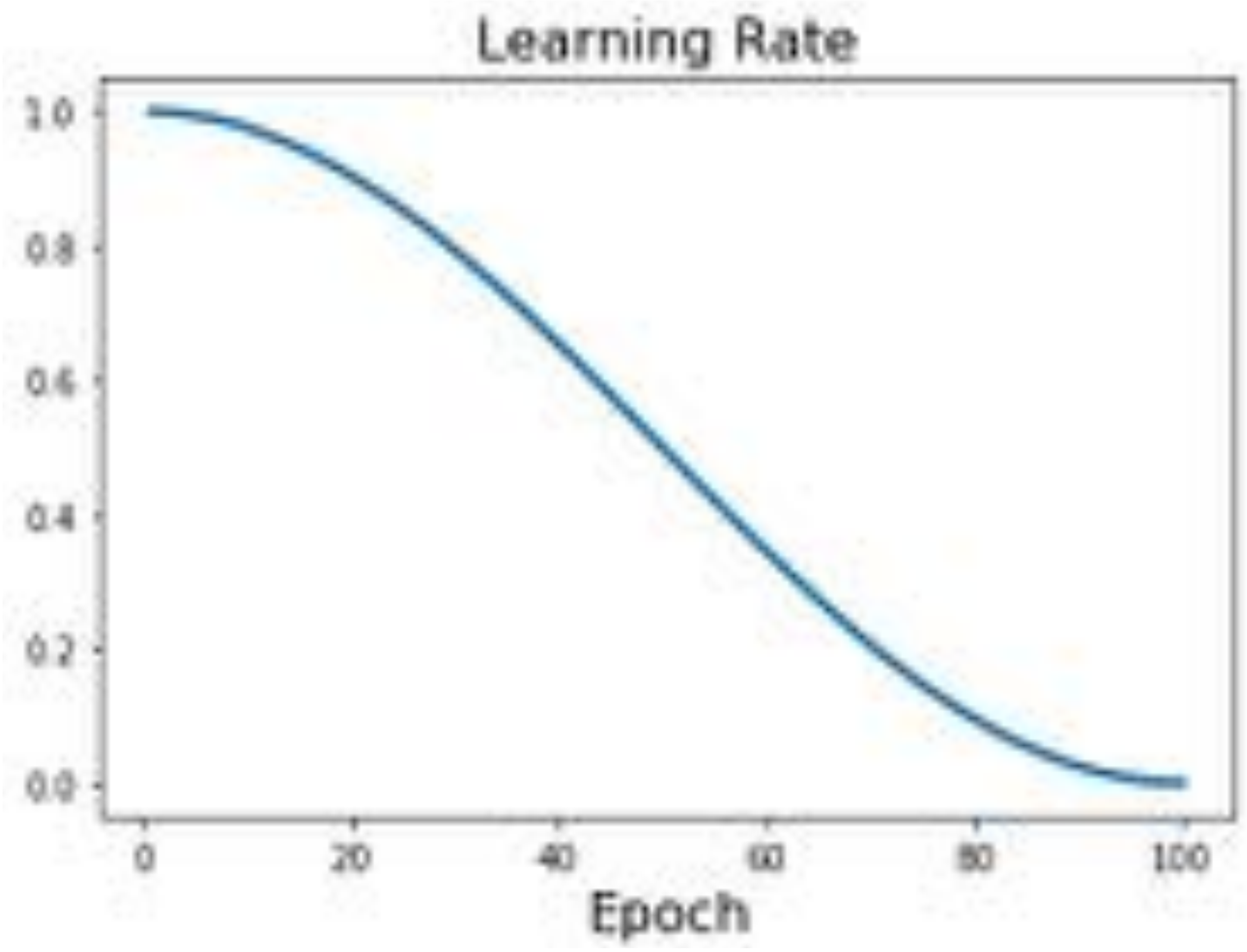


Learning Rate Decay: Cosine



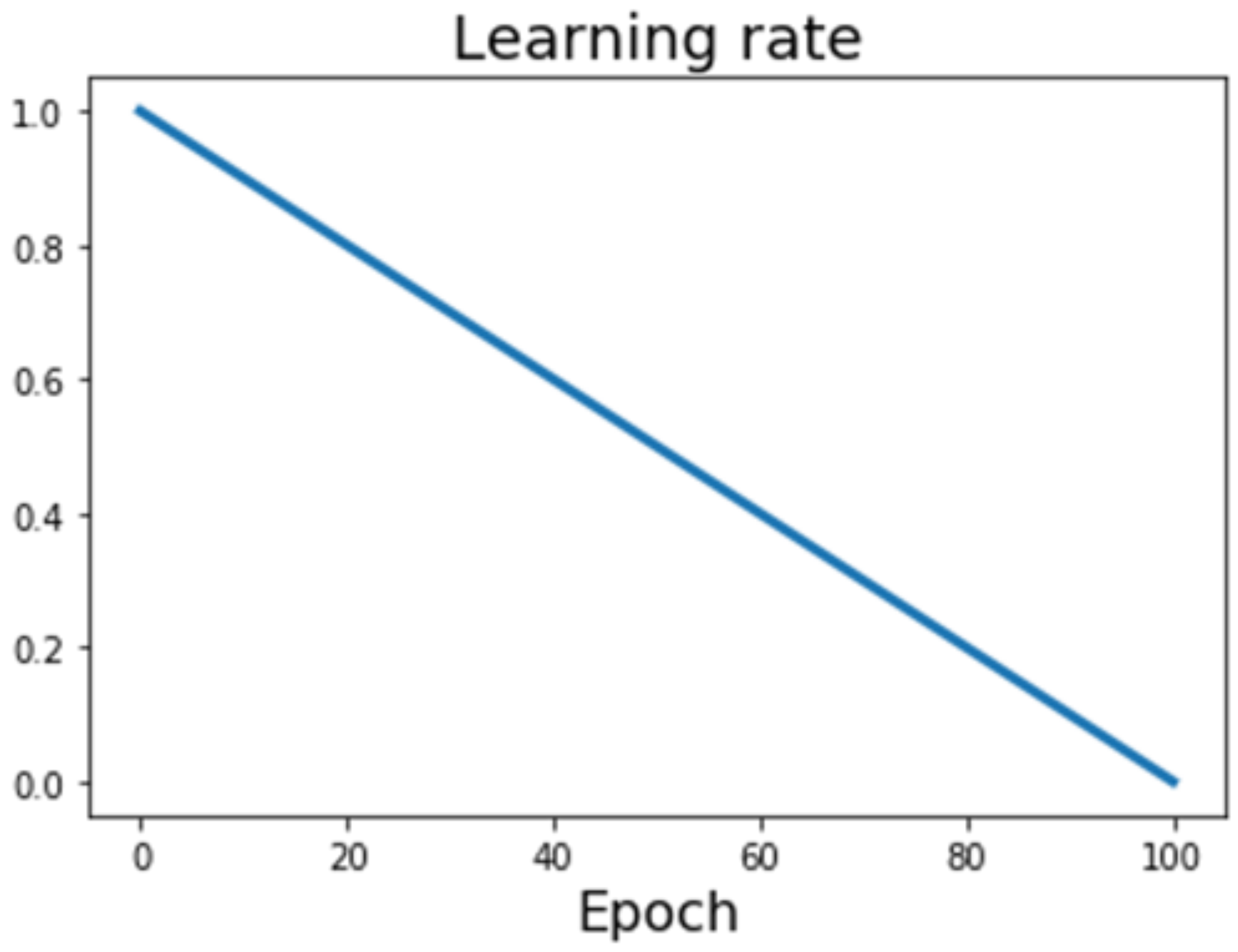
Step: Reduce learning rate at a few fixed points. E.g. for ResNets, multiply LR by 0.1 after epochs 30, 60, and 90.

Cosine: $\alpha_t = \frac{1}{2}\alpha_0(1 + \cos(\frac{t\pi}{T}))$



Loshchilov and Hutter, "SGDR: Stochastic Gradient Descent with Warm Restarts", ICLR 2017
Radford et al, "Improving Language Understanding by Generative Pre-Training", 2018
Feichtenhofer et al, "SlowFast Networks for Video Recognition", ICCV 2019
Radosavovic et al, "On Network Design Spaces for Visual Recognition", ICCV 2019
Child at al, "Generating Long Sequences with Sparse Transformers", arXiv 2019

Learning Rate Decay: Linear



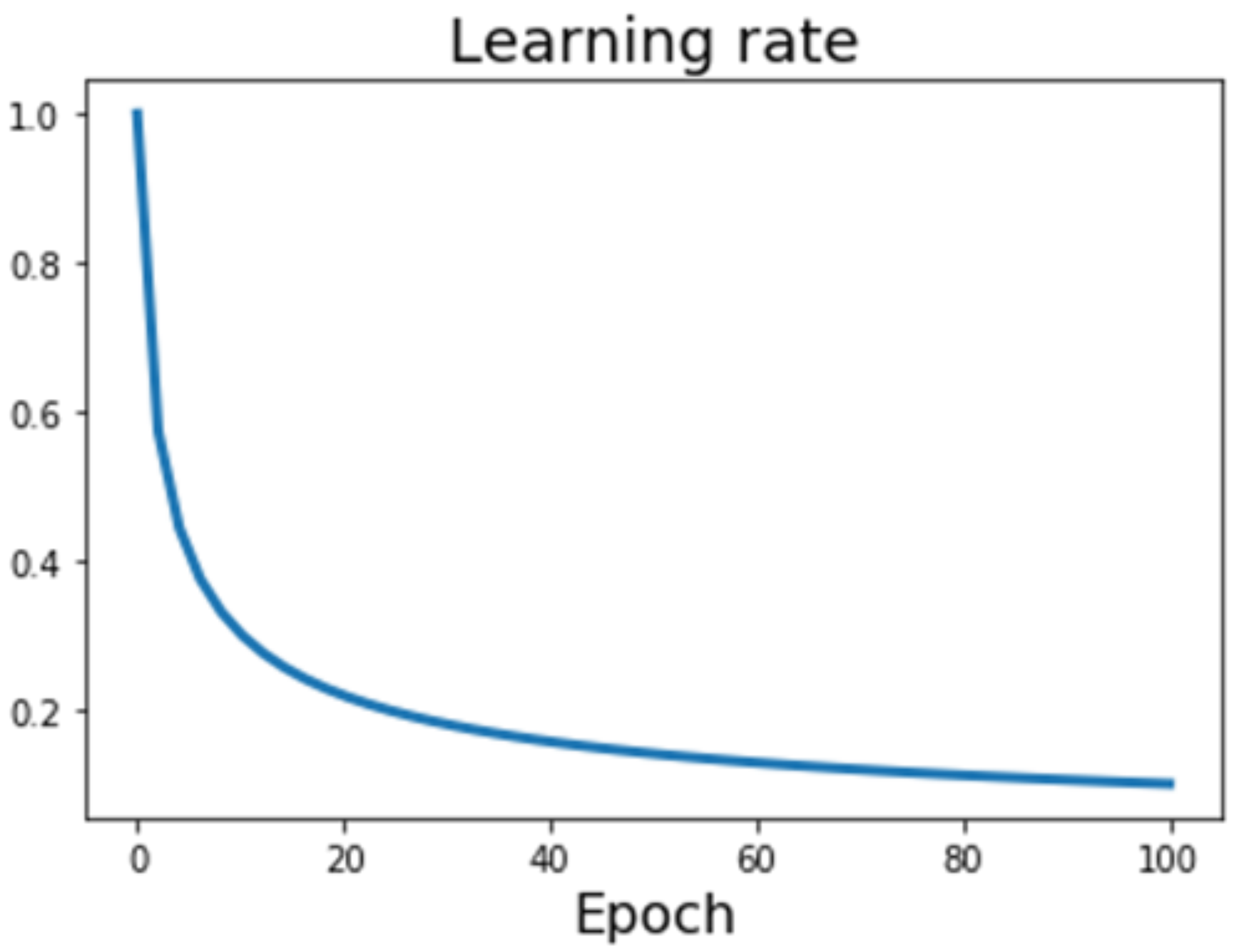
Step: Reduce learning rate at a few fixed points. E.g. for ResNets, multiply LR by 0.1 after epochs 30, 60, and 90.

Cosine: $\alpha_t = \frac{1}{2}\alpha_0(1 + \cos(\frac{t\pi}{T}))$

Linear: $\alpha_t = \alpha_0(1 - \frac{t}{T})$

Devlin et al, "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding", NAACL 2018
Liu et al, "RoBERTa: A Robustly Optimized BERT Pretraining Approach", 2019
Yang et al, "XLNet: Generalized Autoregressive Pretraining for Language Understanding", NeurIPS 2019

Learning Rate Decay: Inverse Sqrt



Step: Reduce learning rate at a few fixed points. E.g. for ResNets, multiply LR by 0.1 after epochs 30, 60, and 90.

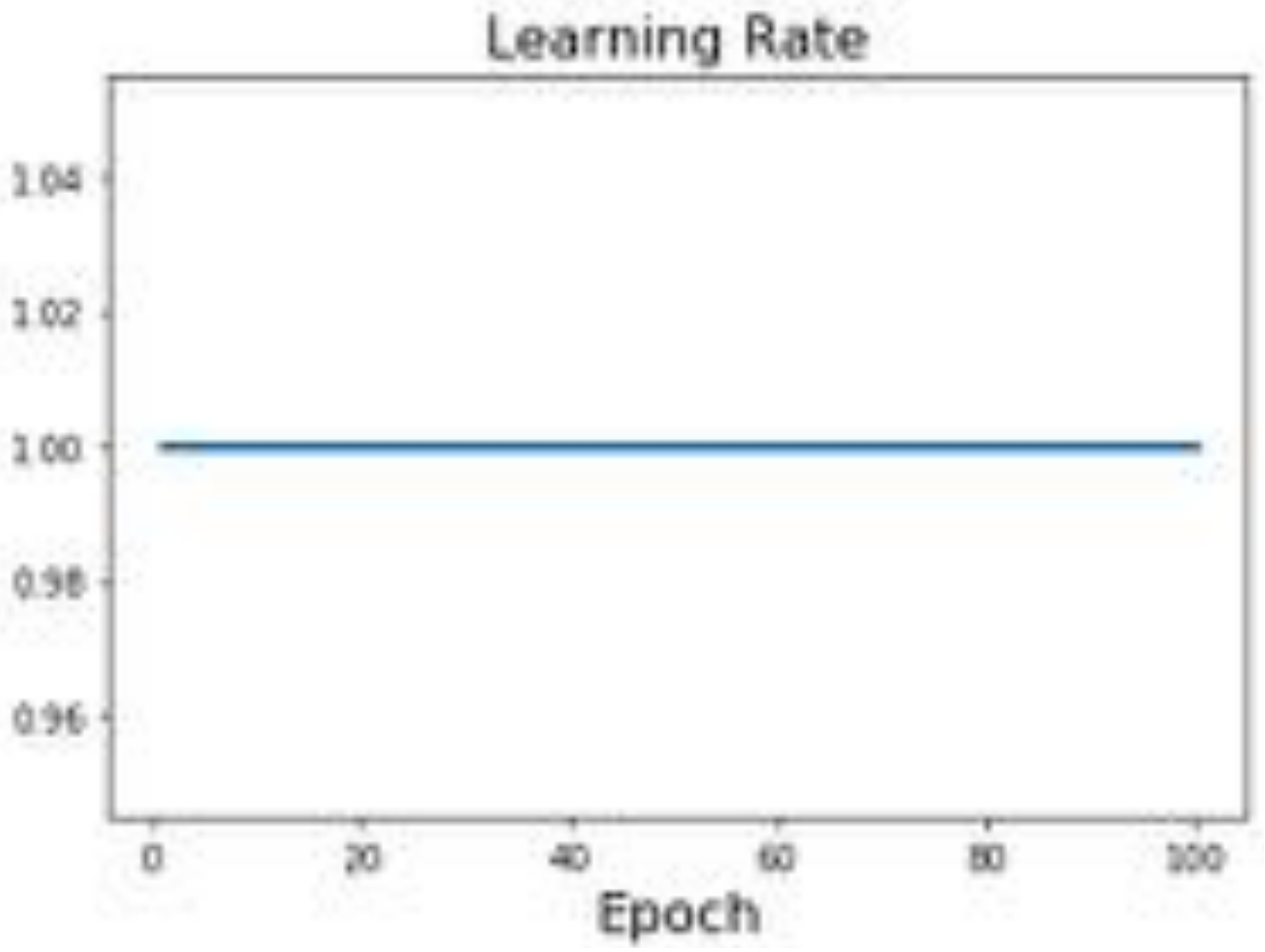
Cosine: $\alpha_t = \frac{1}{2}\alpha_0(1 + \cos(\frac{t\pi}{T}))$

Linear: $\alpha_t = \alpha_0(1 - \frac{t}{T})$

Inverse sqrt: $\alpha_t = \alpha_0/\sqrt{t}$

Vaswani et al, "Attention is all you need", NIPS 2017

Learning Rate Decay: Constant!



Step: Reduce learning rate at a few fixed points. E.g. for ResNets, multiply LR by 0.1 after epochs 30, 60, and 90.

Cosine: $\alpha_t = \frac{1}{2}\alpha_0(1 + \cos(\frac{t\pi}{T}))$

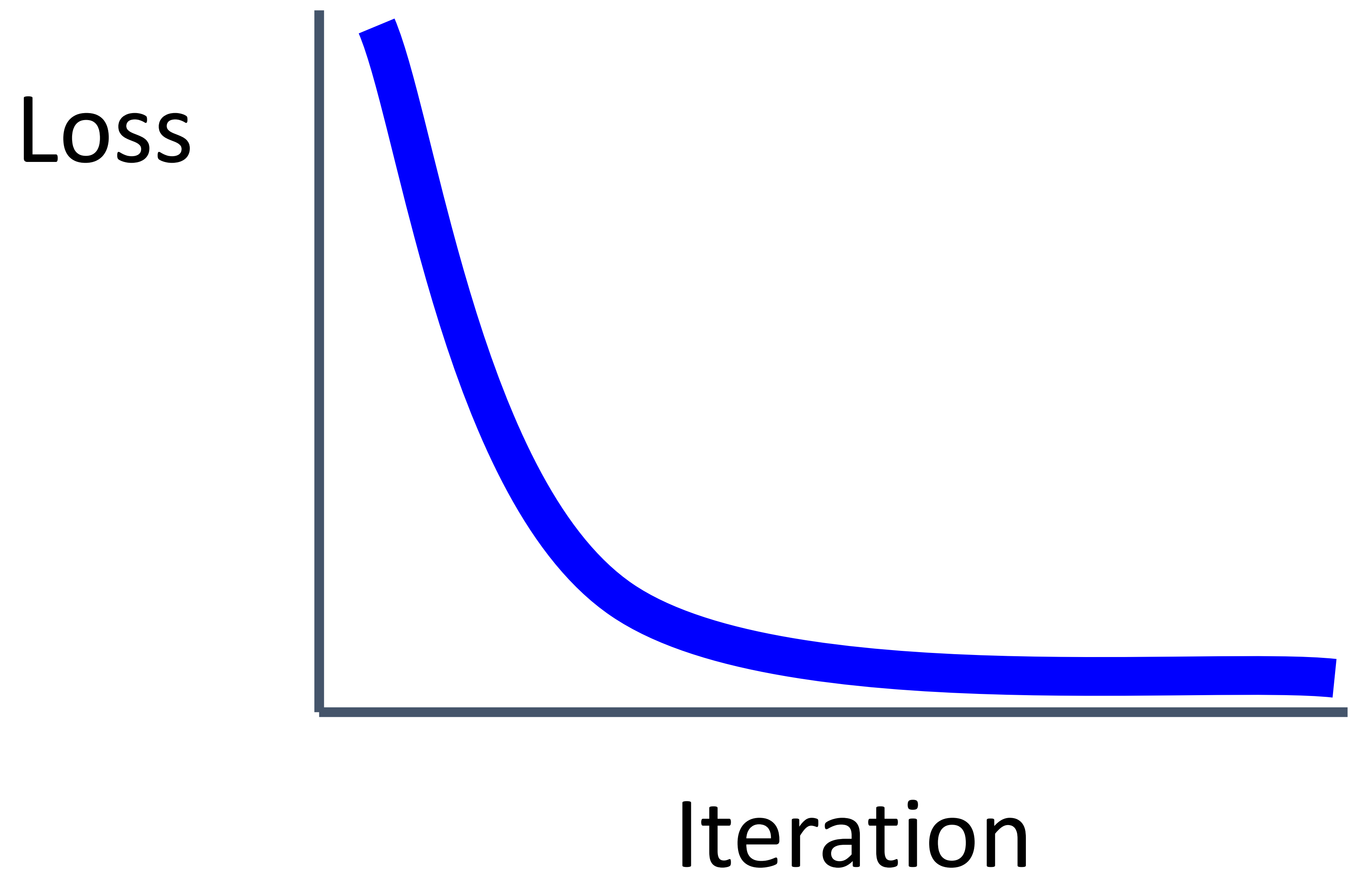
Linear: $\alpha_t = \alpha_0(1 - \frac{t}{T})$

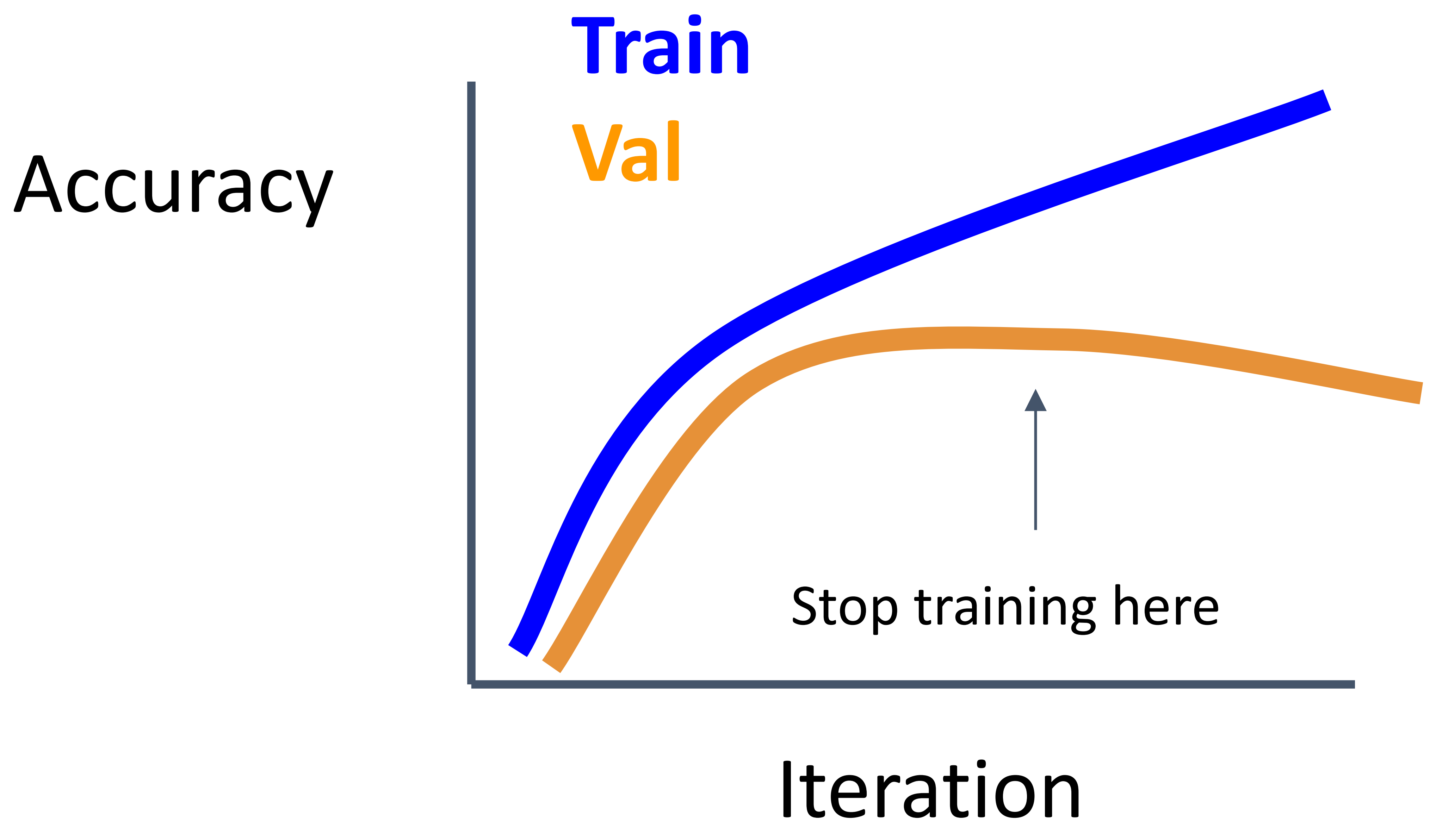
Inverse sqrt: $\alpha_t = \alpha_0 / \sqrt{t}$

Constant: $\alpha_t = \alpha_0$

Brock et al, "Large Scale GAN Training for High Fidelity Natural Image Synthesis", ICLR 2019
Donahue and Simonyan, "Large Scale Adversarial Representation Learning", NeurIPS 2019

How long to train? Early Stopping





Stop training the model when accuracy on the validation set decreases Or train for a long time, but always keep track of the model snapshot that worked best on val. **Always a good idea to do this!**

Choosing Hyperparameters

Choosing Hyperparameters: Grid Search

Choose several values for each hyper parameter
(Often space choices log-linearly)

Example:
Weight decay: [1×10^{-4}, 1×10^{-3}, 1×10^{-2}, 1×10^{-1}]
Learning rate: [1×10^{-4}, 1×10^{-3}, 1×10^{-2}, 1×10^{-1}]

Evaluate all possible choices on this **hyperparameter grid**

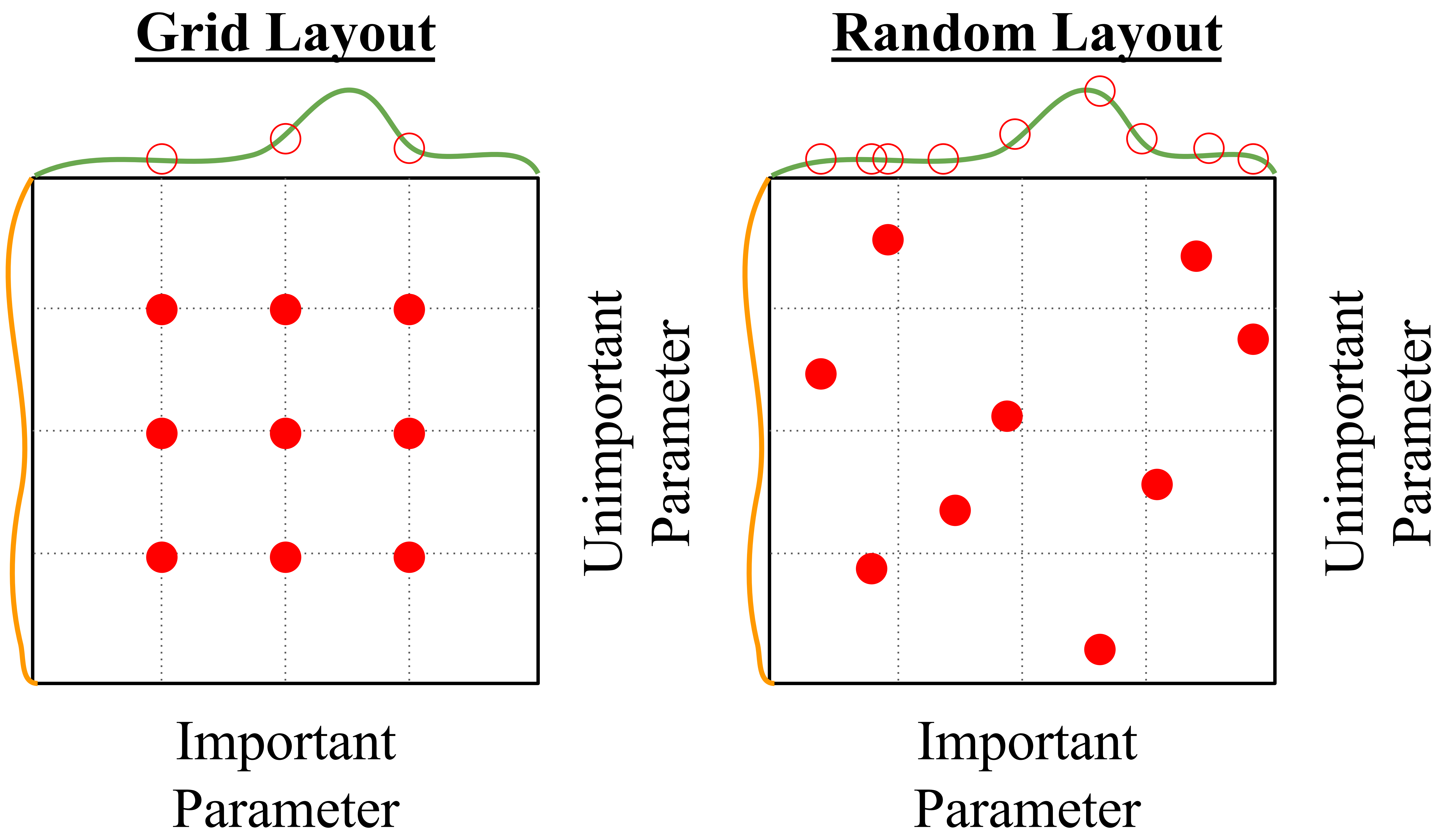
Choosing Hyperparameters: Random Search

Choose several values for each hyper parameter
(Often space choices log-linearly)

Example:
Weight decay: log-uniform on $[1\text{x}10^{-4}, 1\text{x}10^{-1}]$
Learning rate: log-uniform on $[1\text{x}10^{-4}, 1\text{x}10^{-1}]$

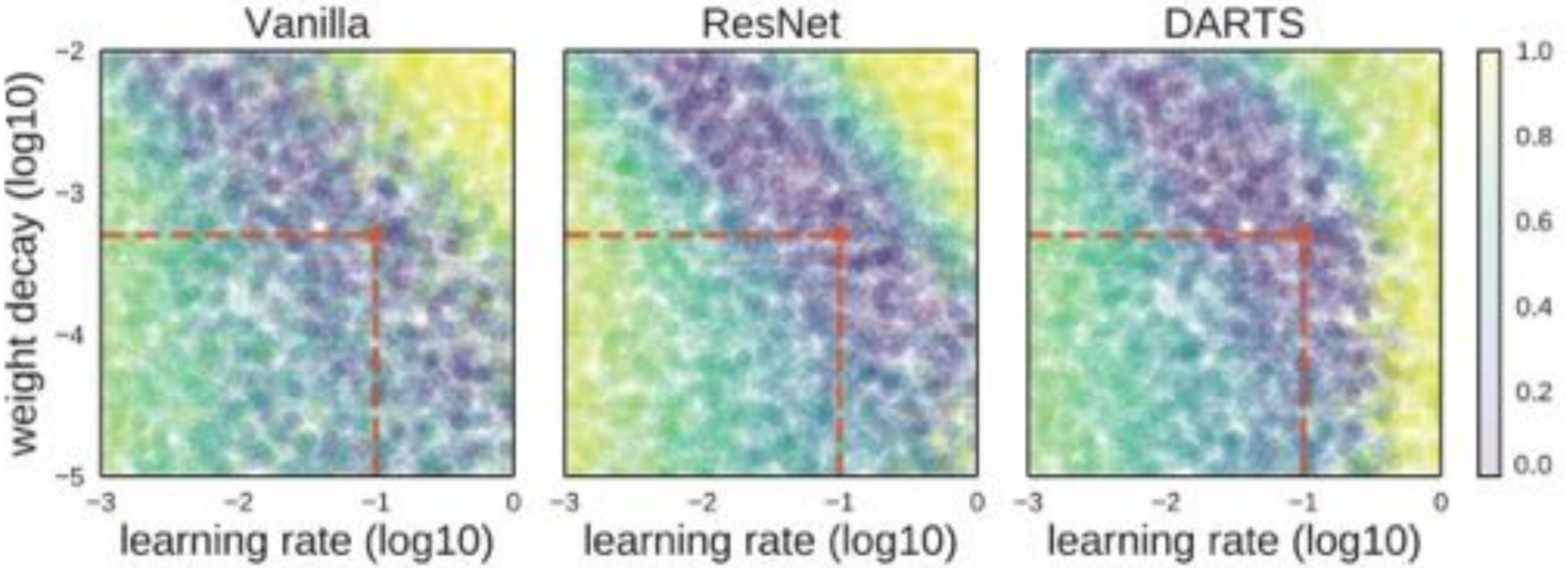
Run many different trials

Hyperparameters: Random vs Grid Search



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

Choosing Hyperparameters: Random Search



Radosavovic et al, "On Network Design Spaces for Visual Recognition", ICCV 2019

Choosing Hyperparameters

(without tons of GPUs)

Choosing Hyperparameters

Step 1: Check initial loss

Turn off weight decay, sanity check loss at initialization
e.g. log(C) for softmax with C classes

Choosing Hyperparameters

Step 1: Check initial loss

Step 2: Overfit a small sample

Try to train to 100% training accuracy on a small sample of training data (~5-10 mini batches); fiddle with architecture, learning rate, weight initialization. Turn off regularization.

Loss not going down? LR too low, bad initialization
Loss explodes to Inf or NaN? LR too high, bad initialization

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

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

Choose a few values of learning rate and weight decay around what worked from Step 3, train a few models for ~1-5 epochs

Good learning rates to try: 1e-4, 1e-5, 0

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

Pick best models from Step 4, train them for longer (~10-20 epochs) without learning rate decay

Choosing Hyperparameters

Step 1: Check initial loss

Step 2: Overfit a small sample

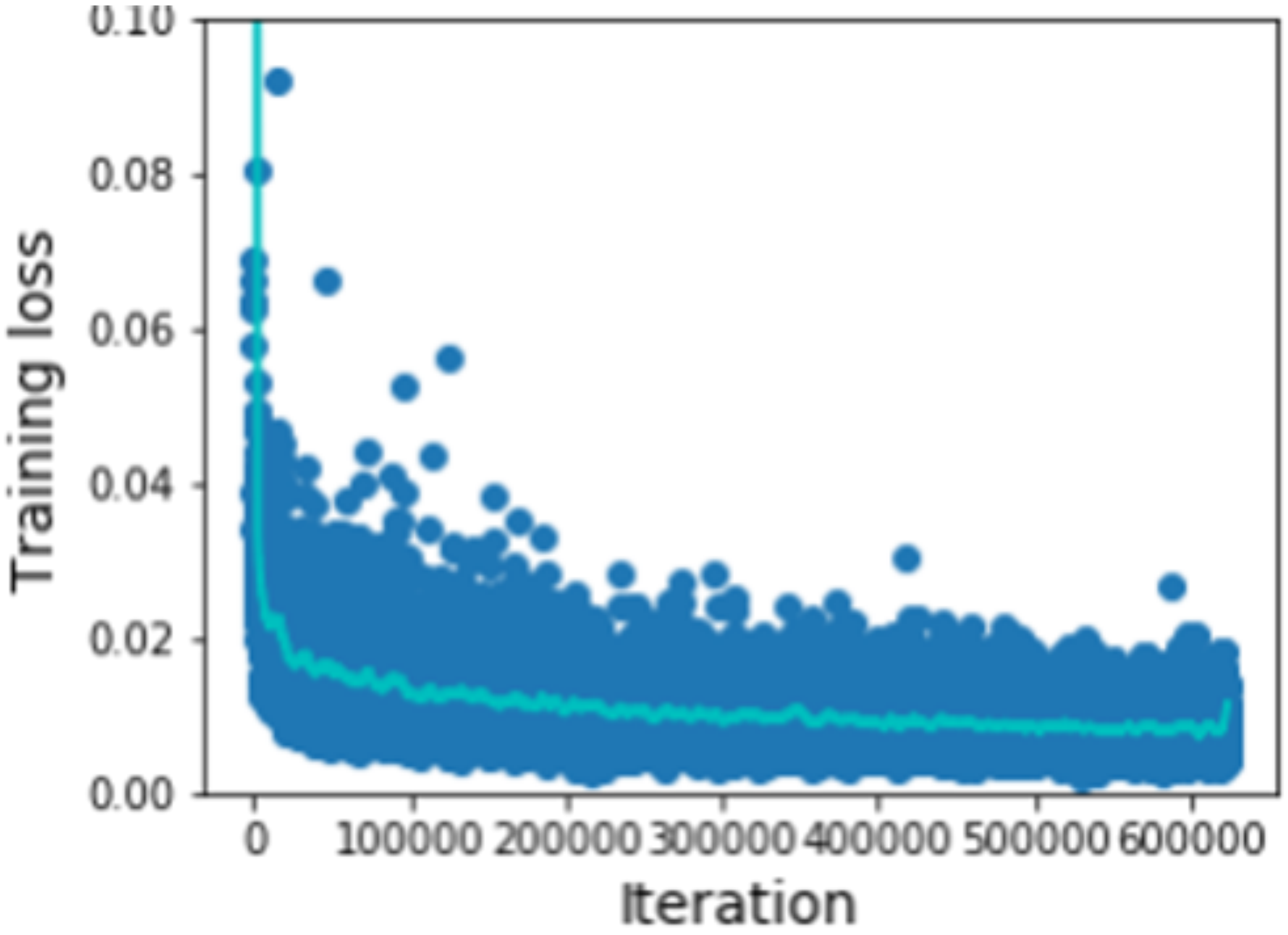
Step 3: Find LR that makes loss go down

Step 4: Coarse grid, train for ~1-5 epochs

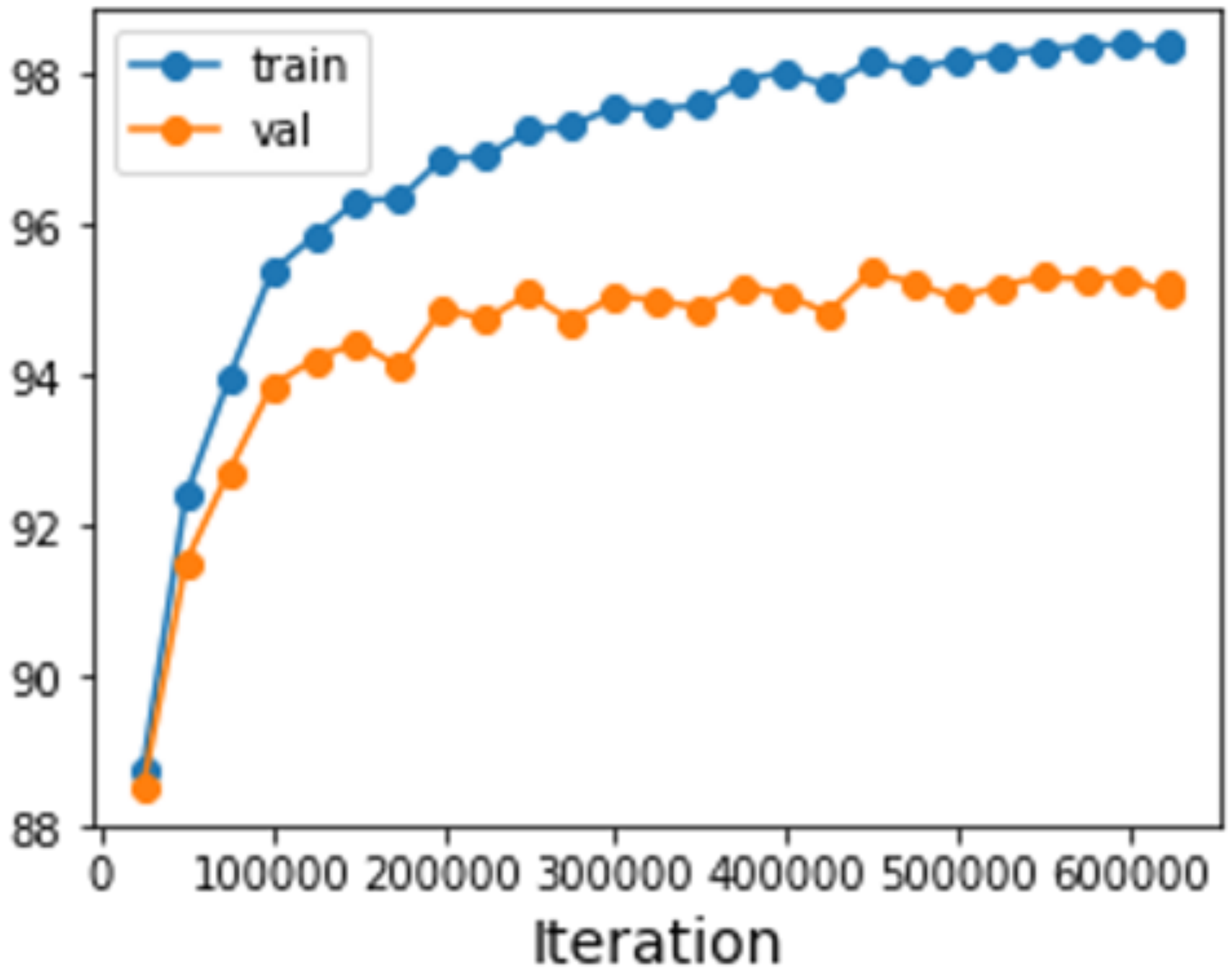
Step 5: Refine grid, train longer

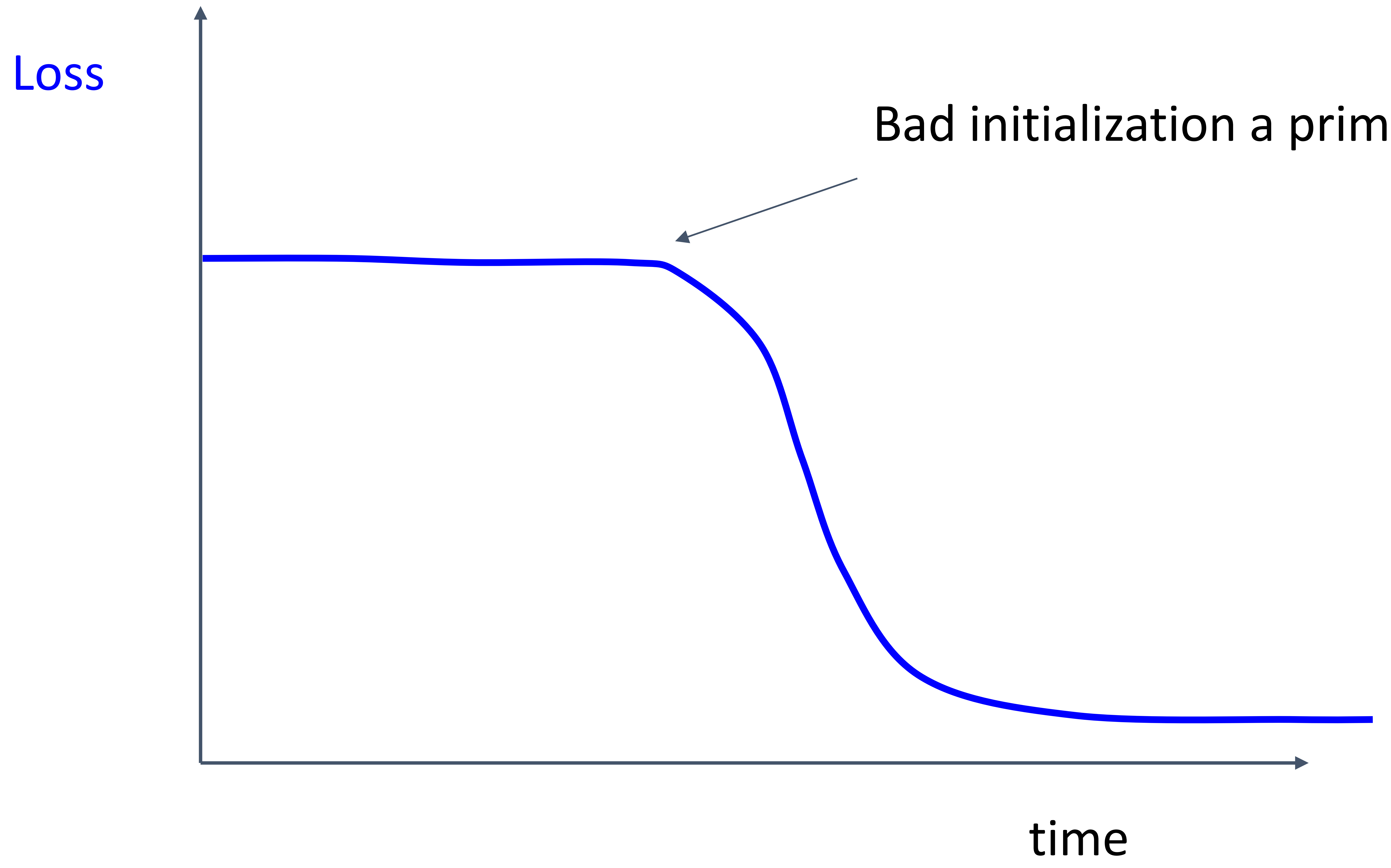
Step 6: Look at learning curves

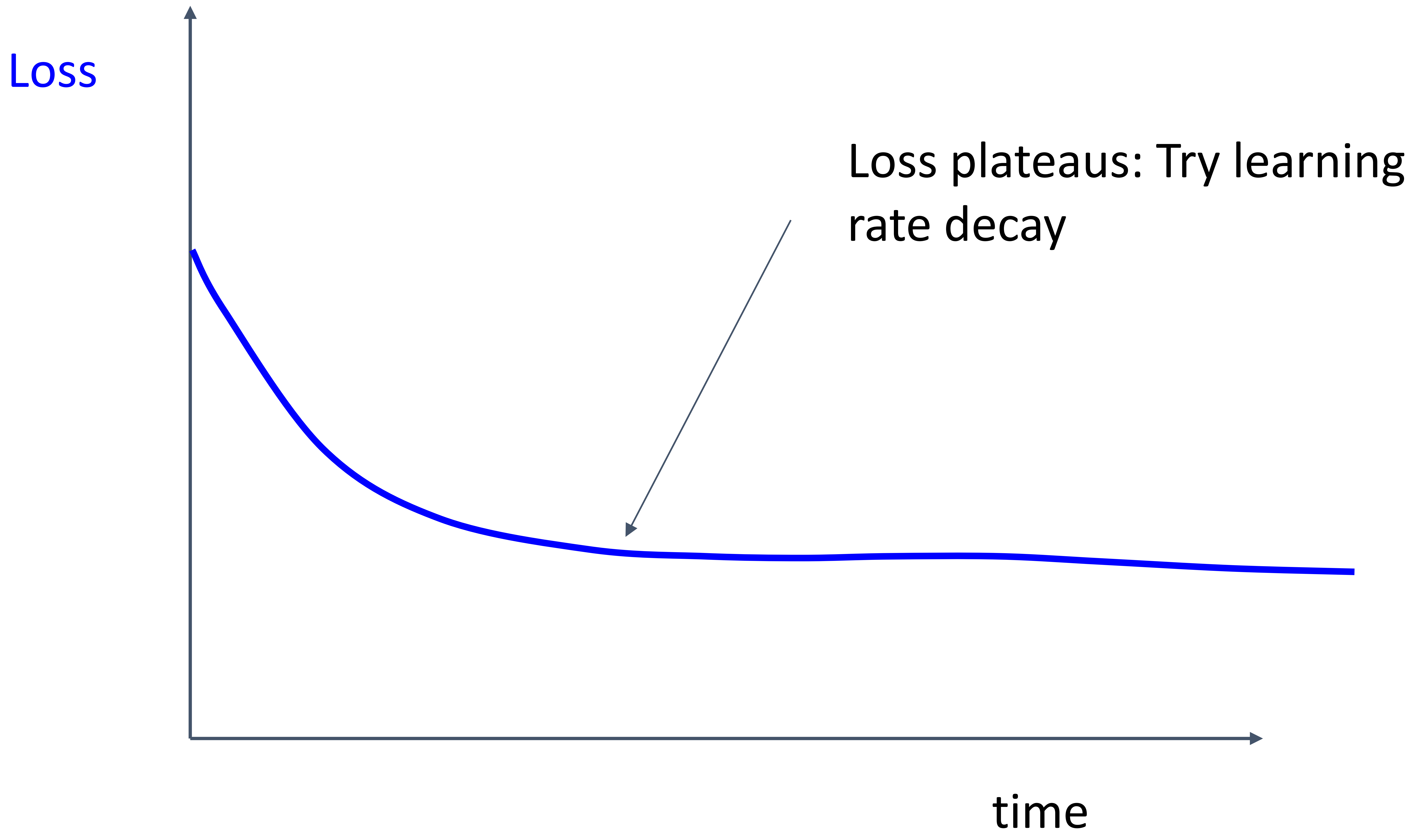
Look at Learning Curves!

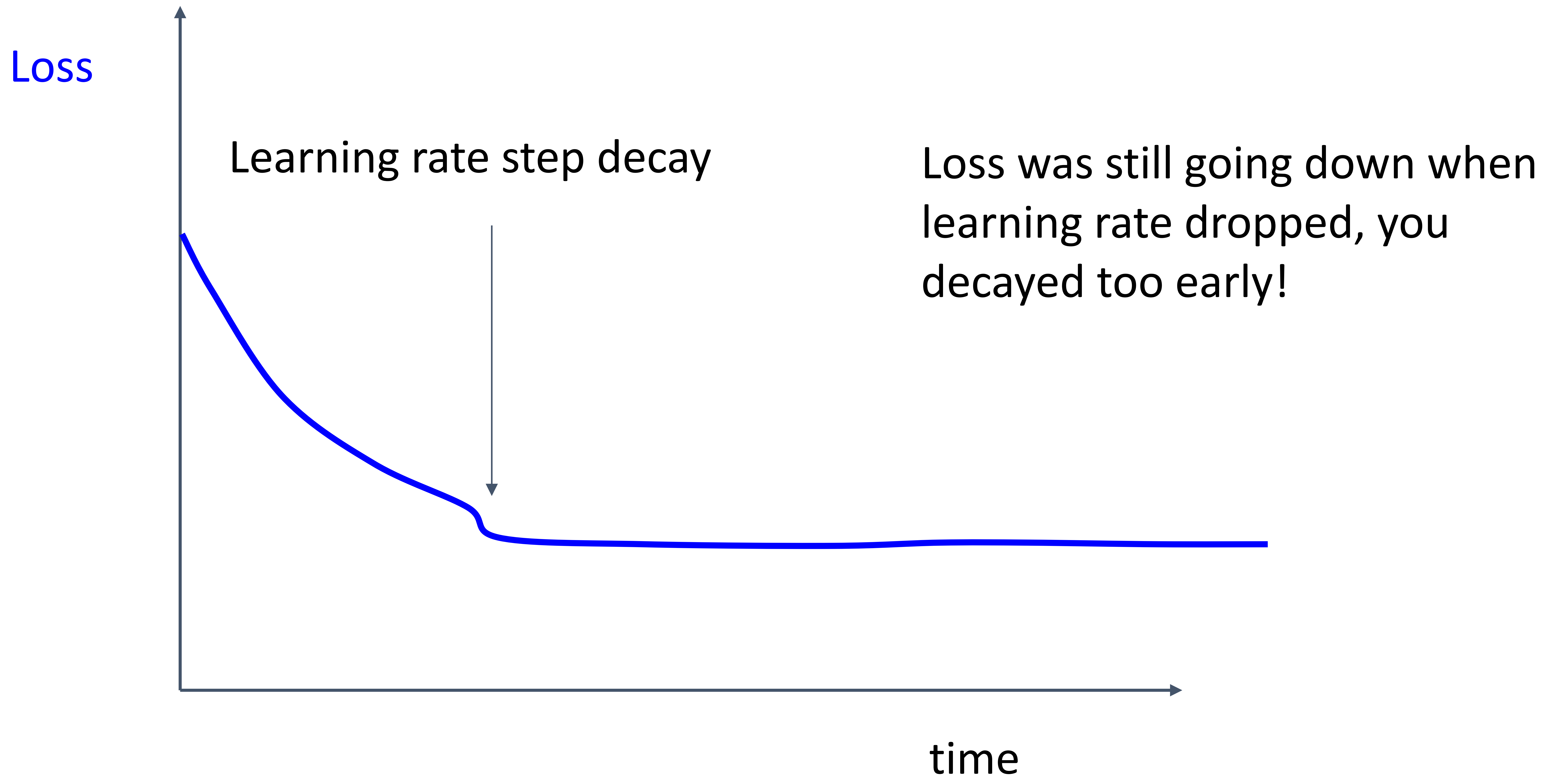


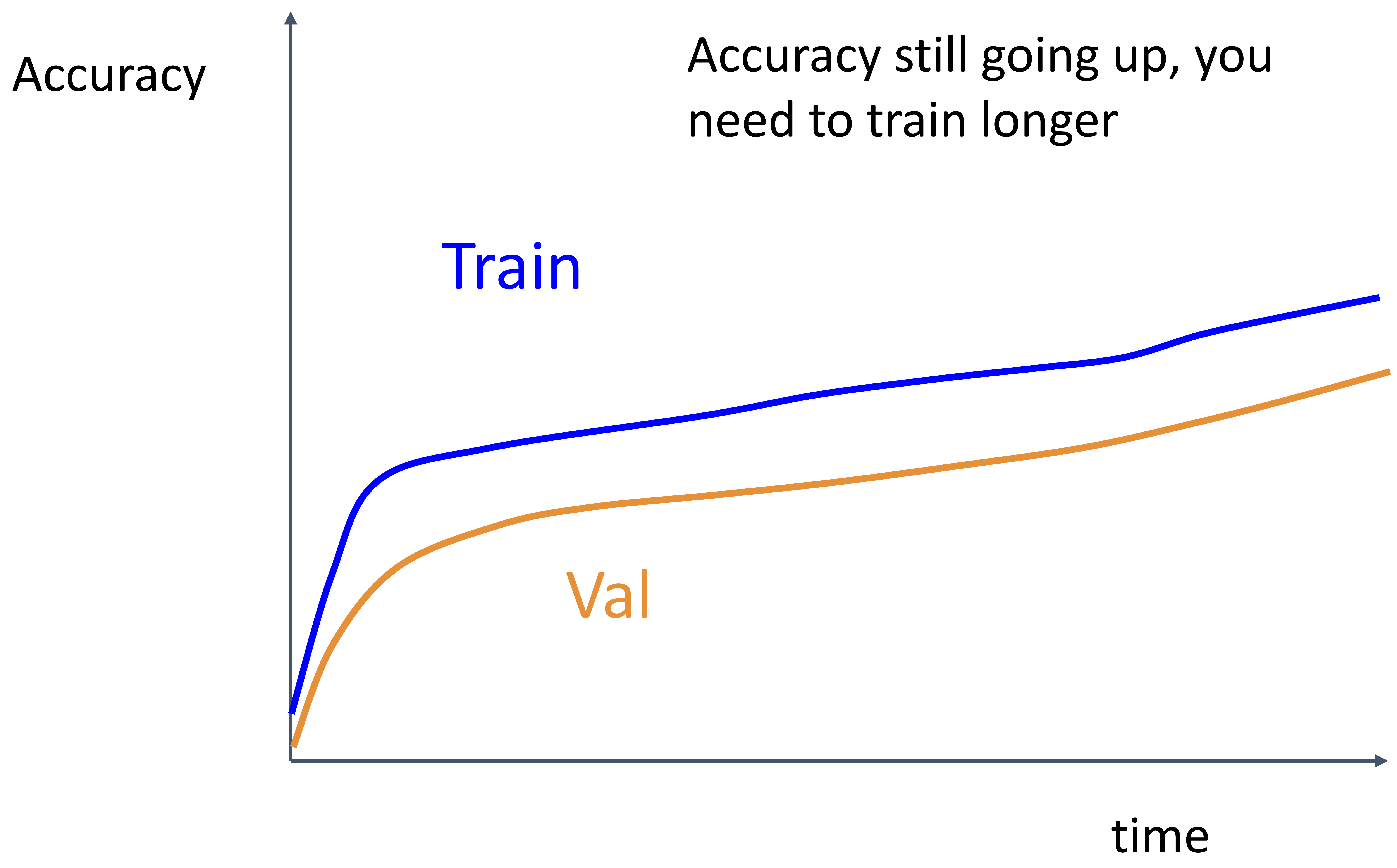
Losses may be noisy, use a scatter plot and also plot moving average to see trends better

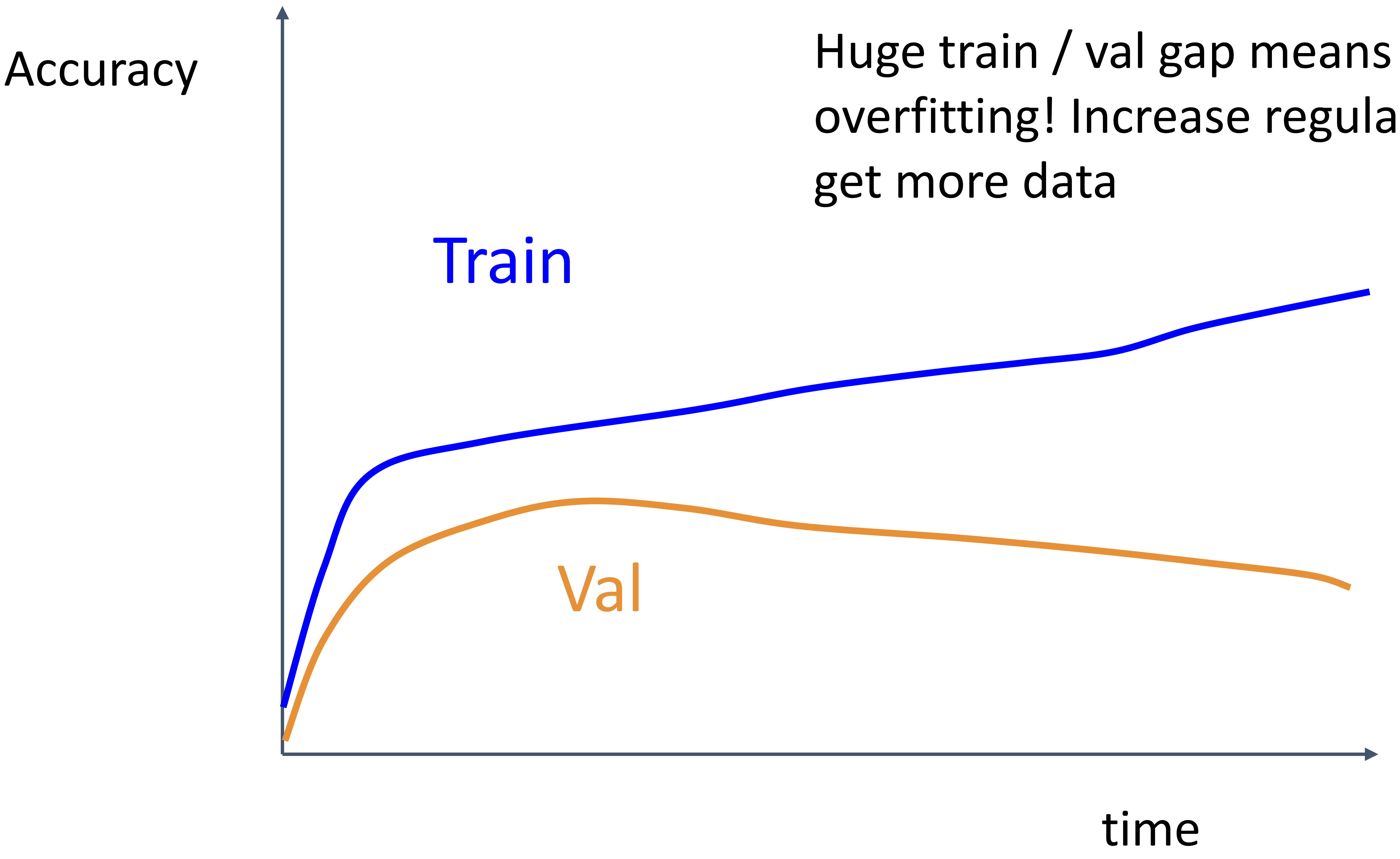



Loss
Bad initialization a prime suspect
time

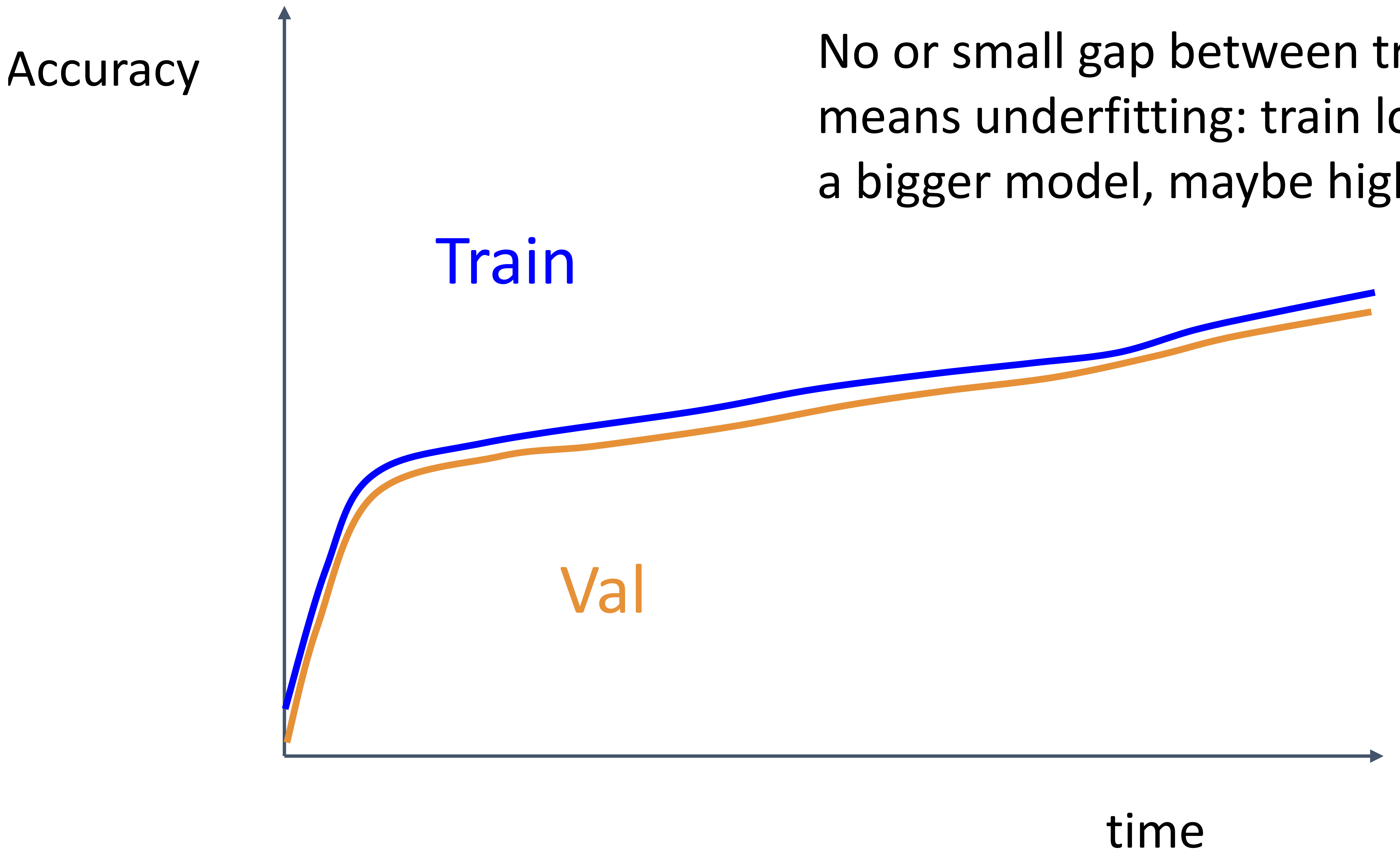

Loss
Loss plateaus: Try learning rate decay
time


Loss
Learning rate step decay
Loss was still going down when learning rate dropped, you decayed too early!
time


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



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



No or small gap between train / val means underfitting: train longer, use a bigger model, maybe higher LR

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

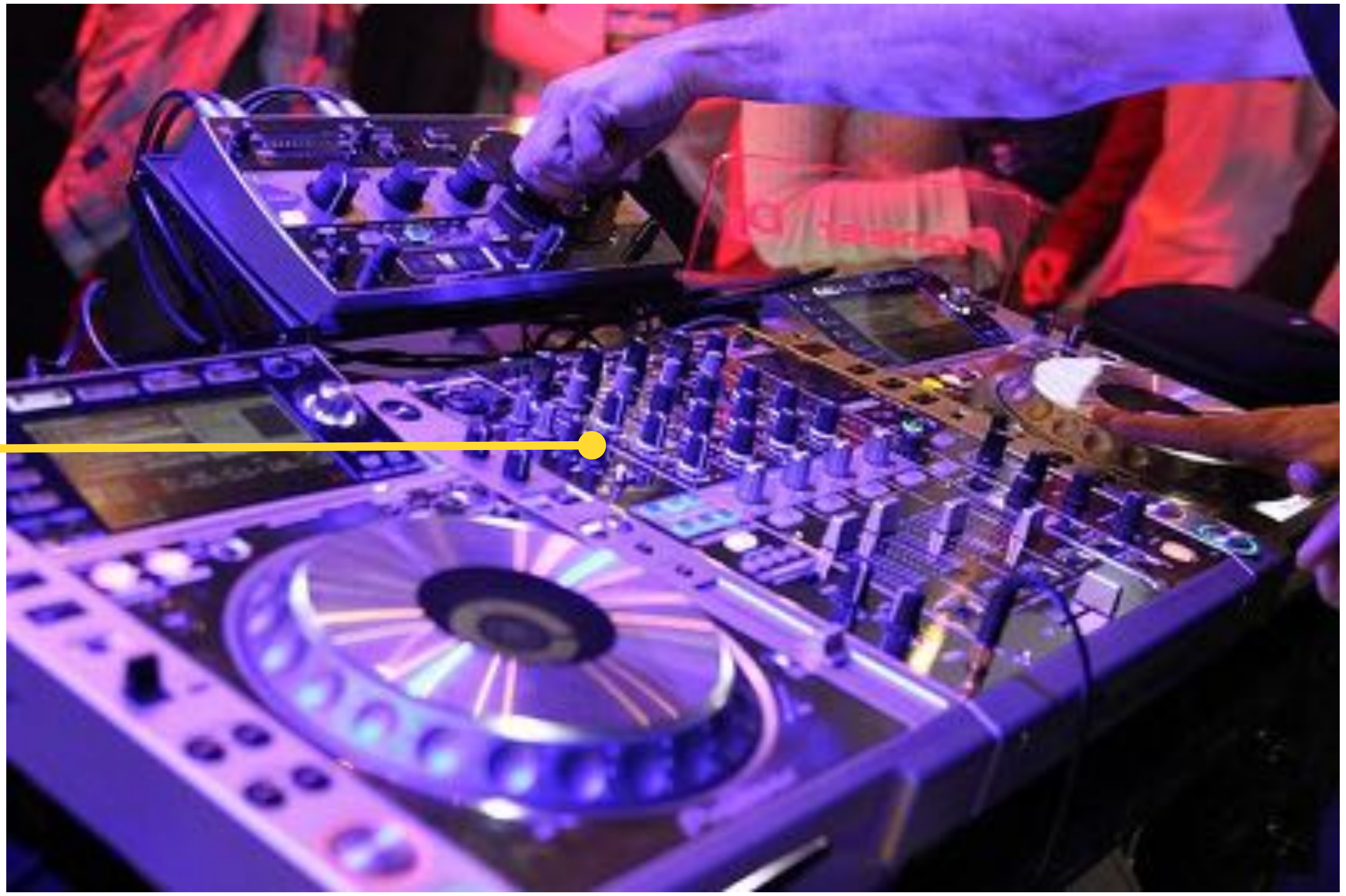
Step 6: Look at ~~learning curves~~ loss curves

Step 7: GOTO step 5

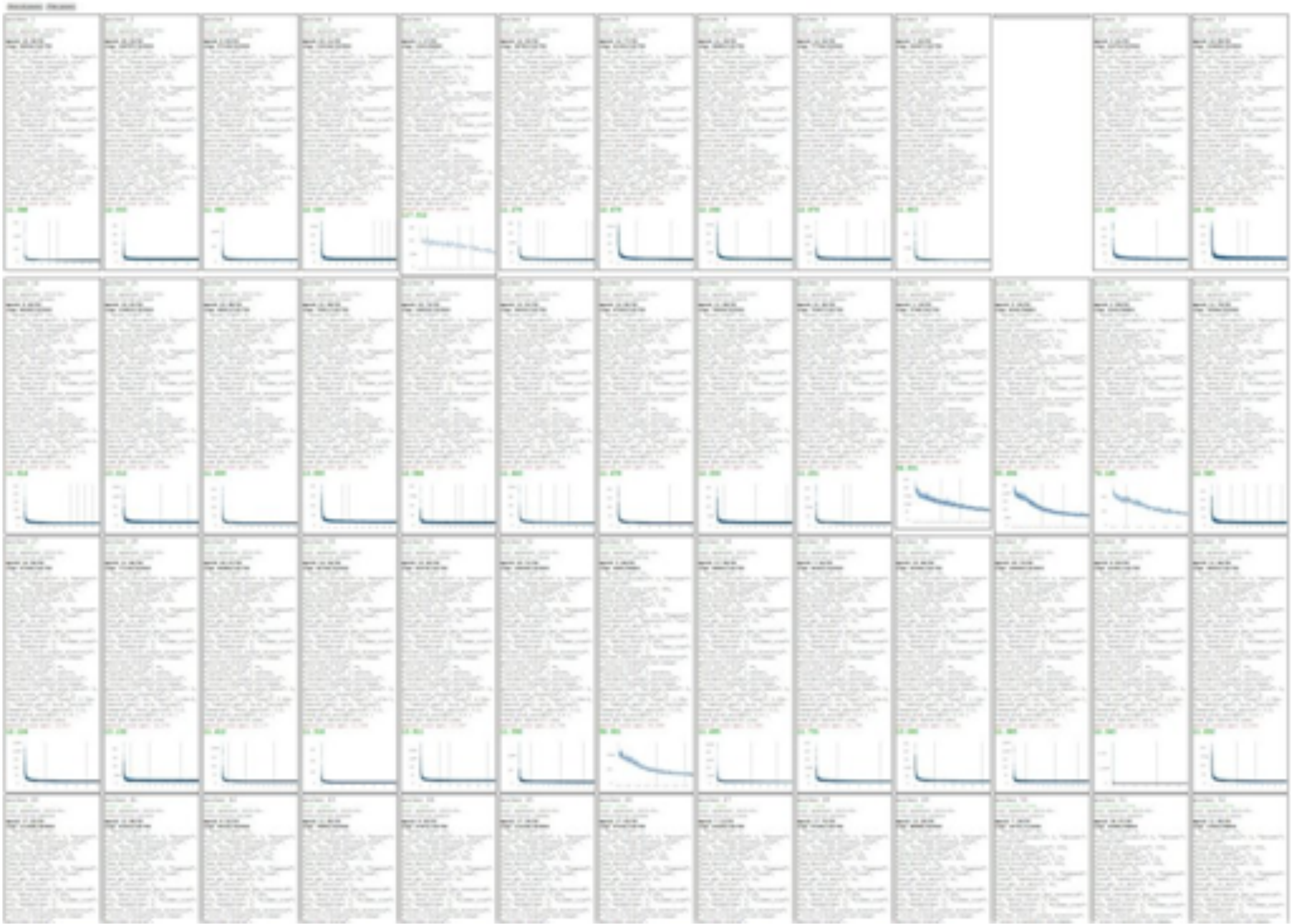
Hyperparameters to play with:

- Network architecture
- Learning rate, its decay schedule, update type
- Regularization (L2/ Dropout strength)

Neural networks practitioner
Music = loss function



Cross-validation “command center”



Track ratio of weight update / weight magnitude

```
# assume parameter vector W and its gradient vector dW
param_scale = np.linalg.norm(W.ravel())
update = -learning_rate*dW # simple SGD update
update_scale = np.linalg.norm(update.ravel())
W += update # the actual update
print update_scale / param_scale # want ~1e-3
```

Ratio between the updates and values: ~0.0002 / 0.02 = 0.01 (about okay)
want this to be somewhere around 0.001 or so

Overview

1. **One time setup:**
   - Activation functions, data preprocessing, weight initialization, regularization
2. **Training dynamics:**
   - Learning rate schedules; hyperparameter optimization
3. **After training:**
   - Model ensembles, transfer learning, large-batch training

Model Ensembles

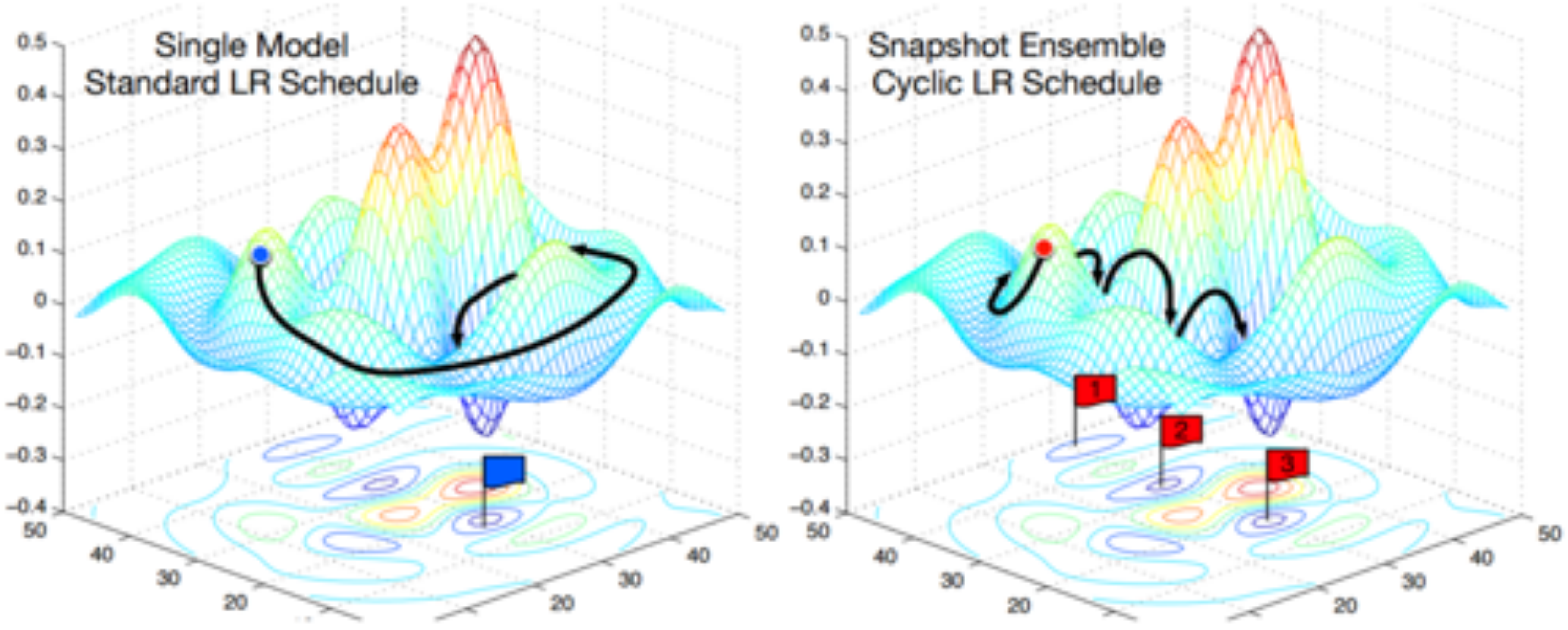
1. **Train multiple independent models**
2. **At test time average their results:**

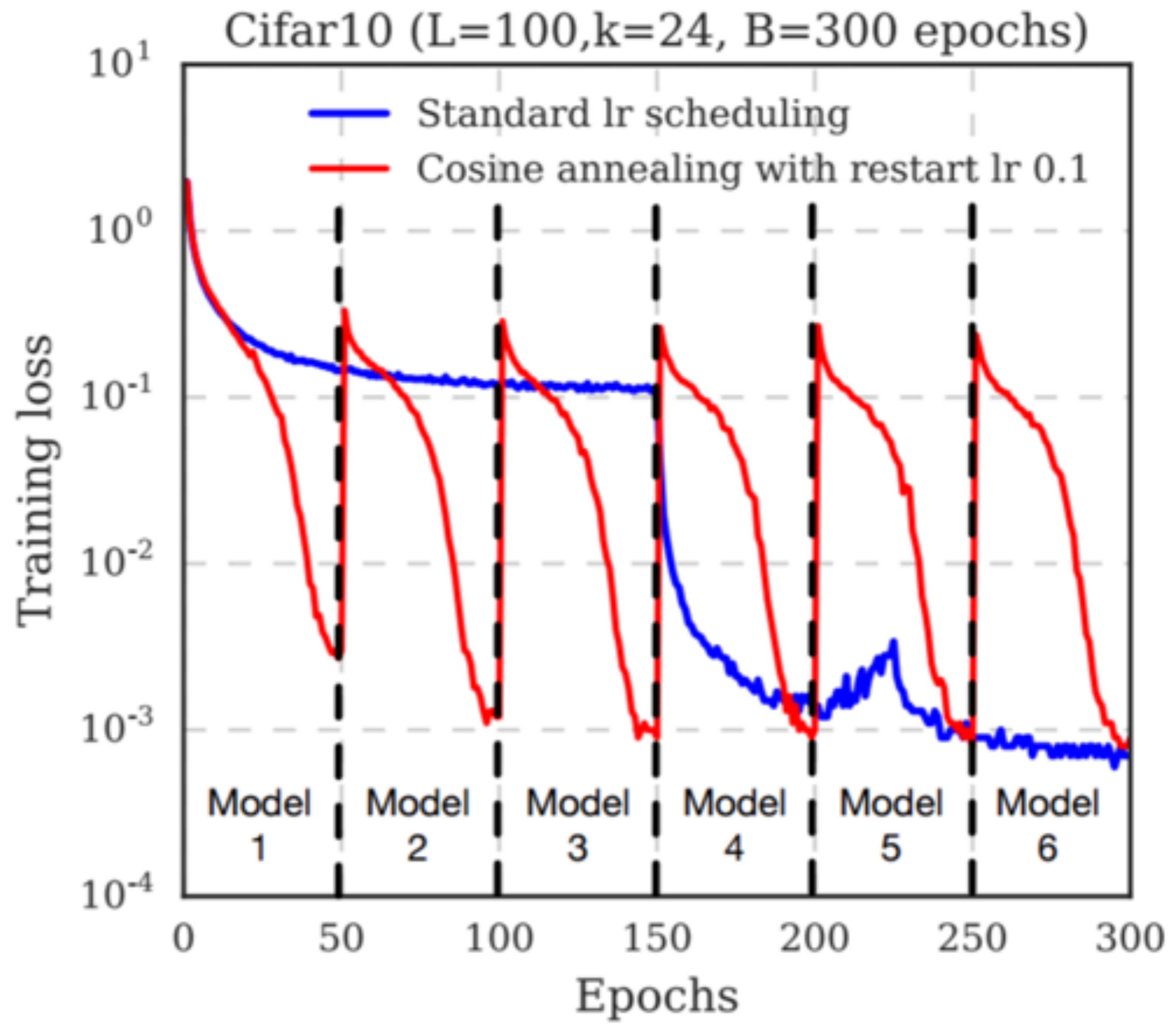
   (Take average of predicted probability distributions, then choose argmax)

Enjoy 2% extra performance

Model Ensembles: Tips and Tricks

Instead of training independent models, use multiple snapshots of a single model during training!





Loshchilov and Hutter, "SGDR: Stochastic gradient descent with restarts", arXiv 2016
Huang et al, "Snapshot ensembles: train 1, get M for free", ICLR 2017
Figures copyright Yixuan Li and Geoff Pleiss, 2017. Reproduced with permission.

Cyclic learning rate schedules can make this work even better!

Model Ensembles: Tips and Tricks

Instead of using actual parameter vector, keep a moving average of the parameter vector and use that at test time (Polyak averaging)

```
while True:
  data_batch = dataset.sample_data_batch()
  loss = network.forward(data_batch)
  dx = network.backward()
  x += - learning_rate * dx
  x_test = 0.995*x_test + 0.005*x # use for test set
```

Polyak and Juditsky, "Acceleration of stochastic approximation by averaging", SIAM Journal on Control and Optimization, 1992.
Karras et al, "Progressive Growing of GANs for Improved Quality, Stability, and Variation", ICLR 2018
Brock et al, "Large Scale GAN Training for High Fidelity Natural Image Synthesis", ICLR 201

Transfer Learning

"You need a lot of data if you want to train / use CNNs"

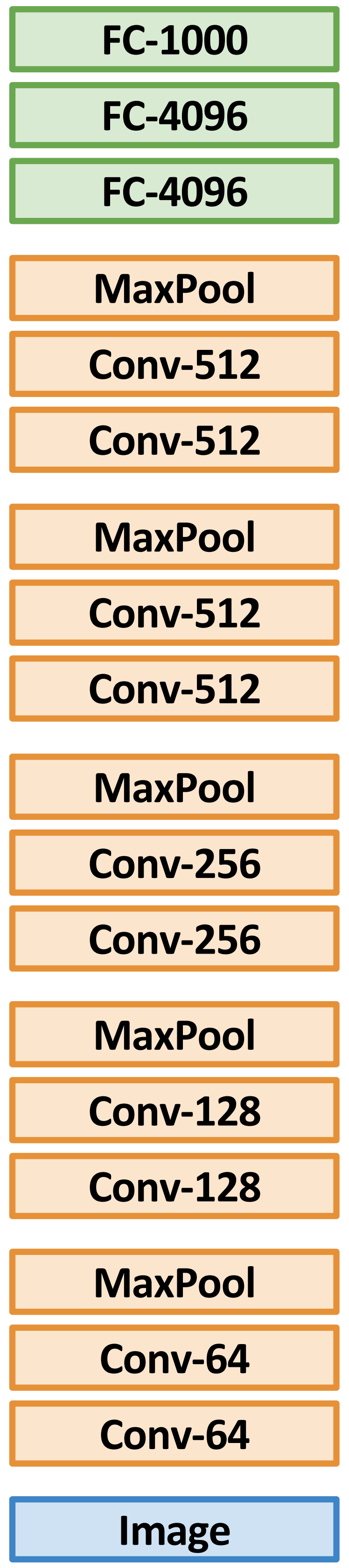
Transfer Learning

"You need a lot of data if you want to train / use CNNs"

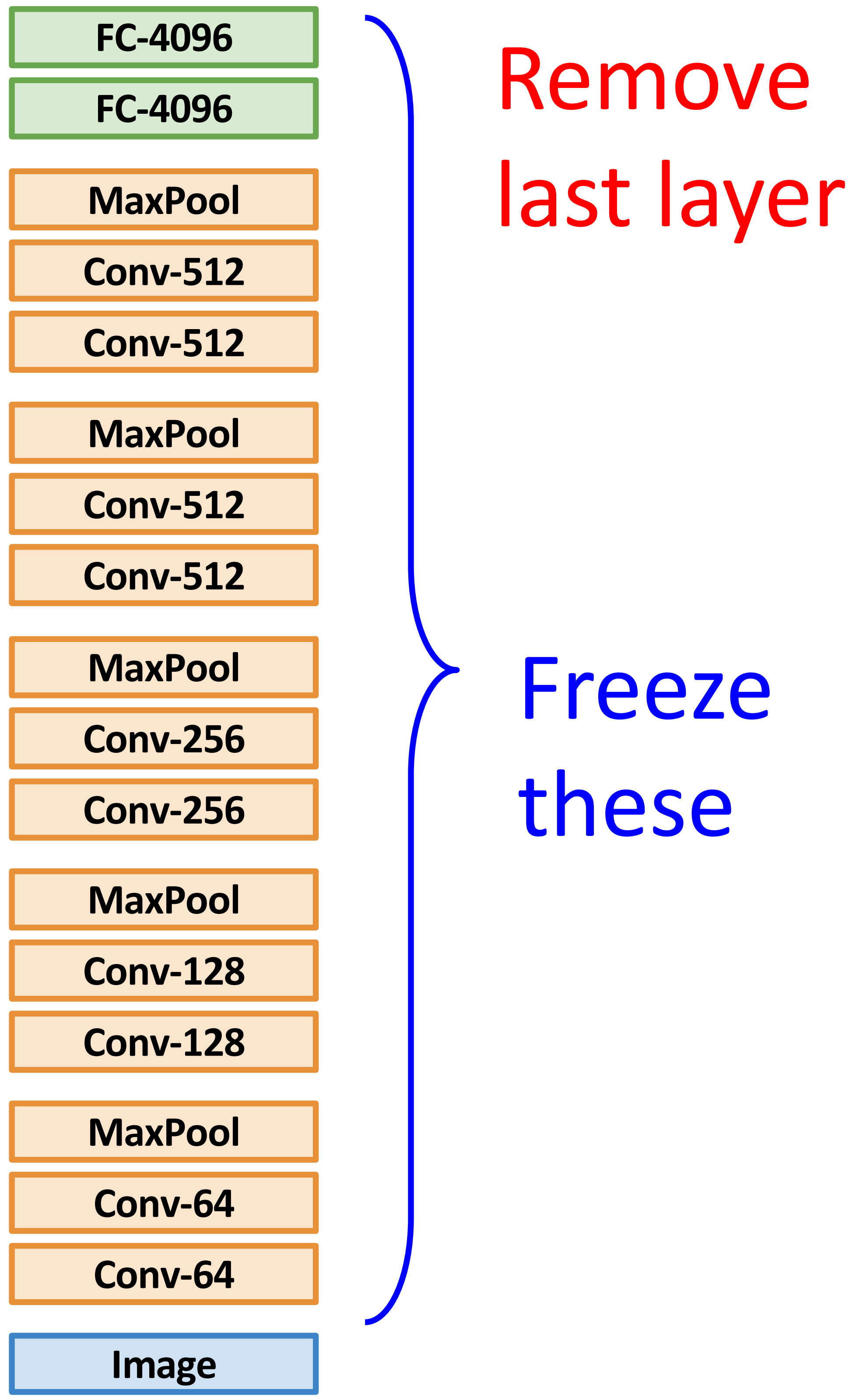
BUSTED

Transfer Learning with CNNs

1. Train on ImageNet



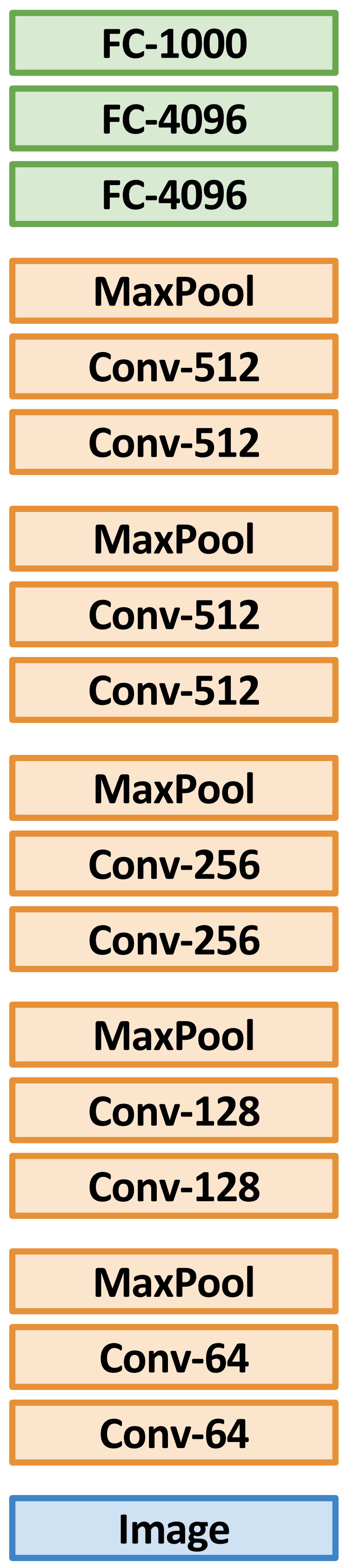
2. Use CNN as a feature extractor



Donahue et al, "DeCAF: A Deep Convolutional Activation Feature for Generic Visual Recognition", ICML 2014

Transfer Learning with CNNs

1. Train on ImageNet



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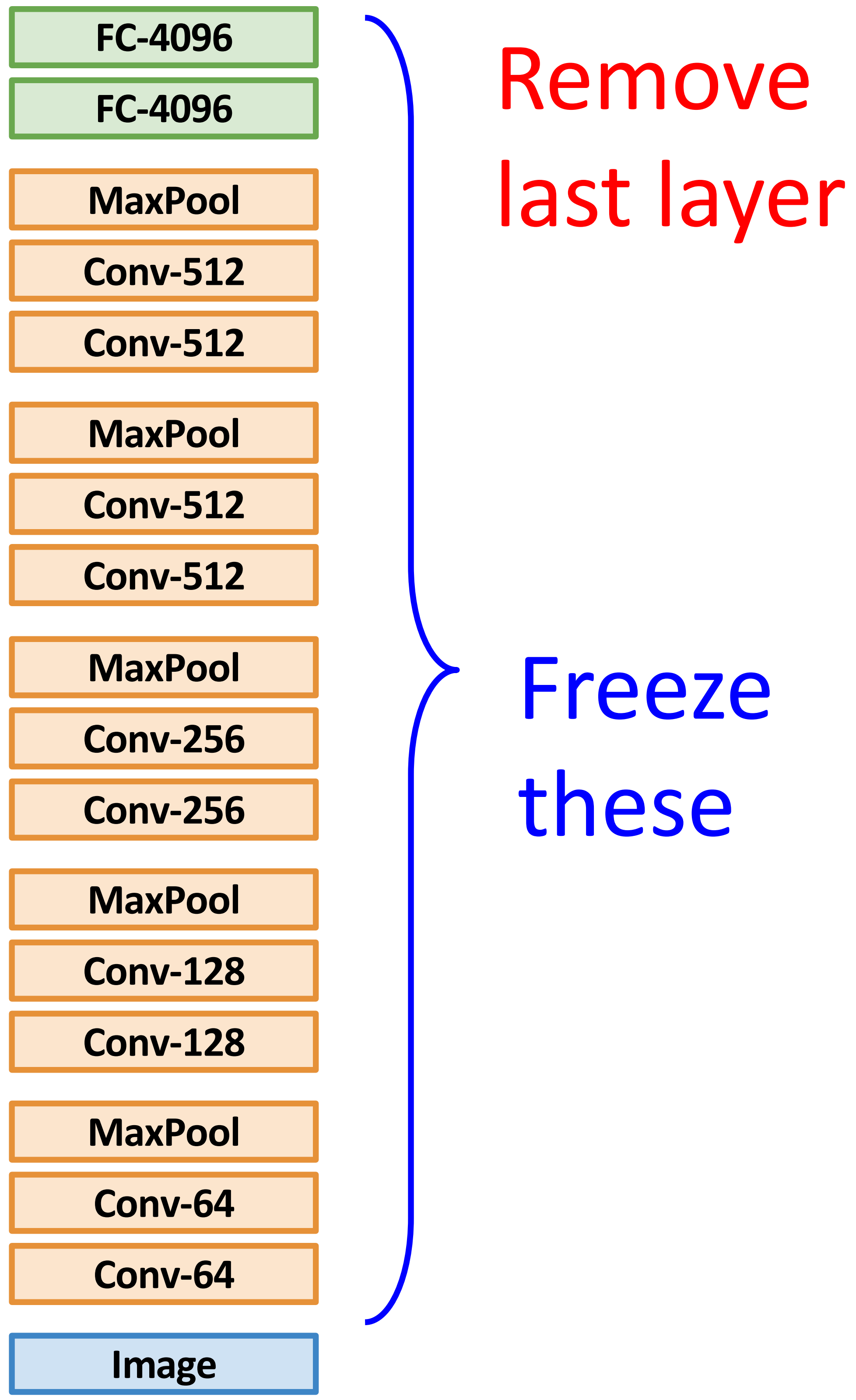
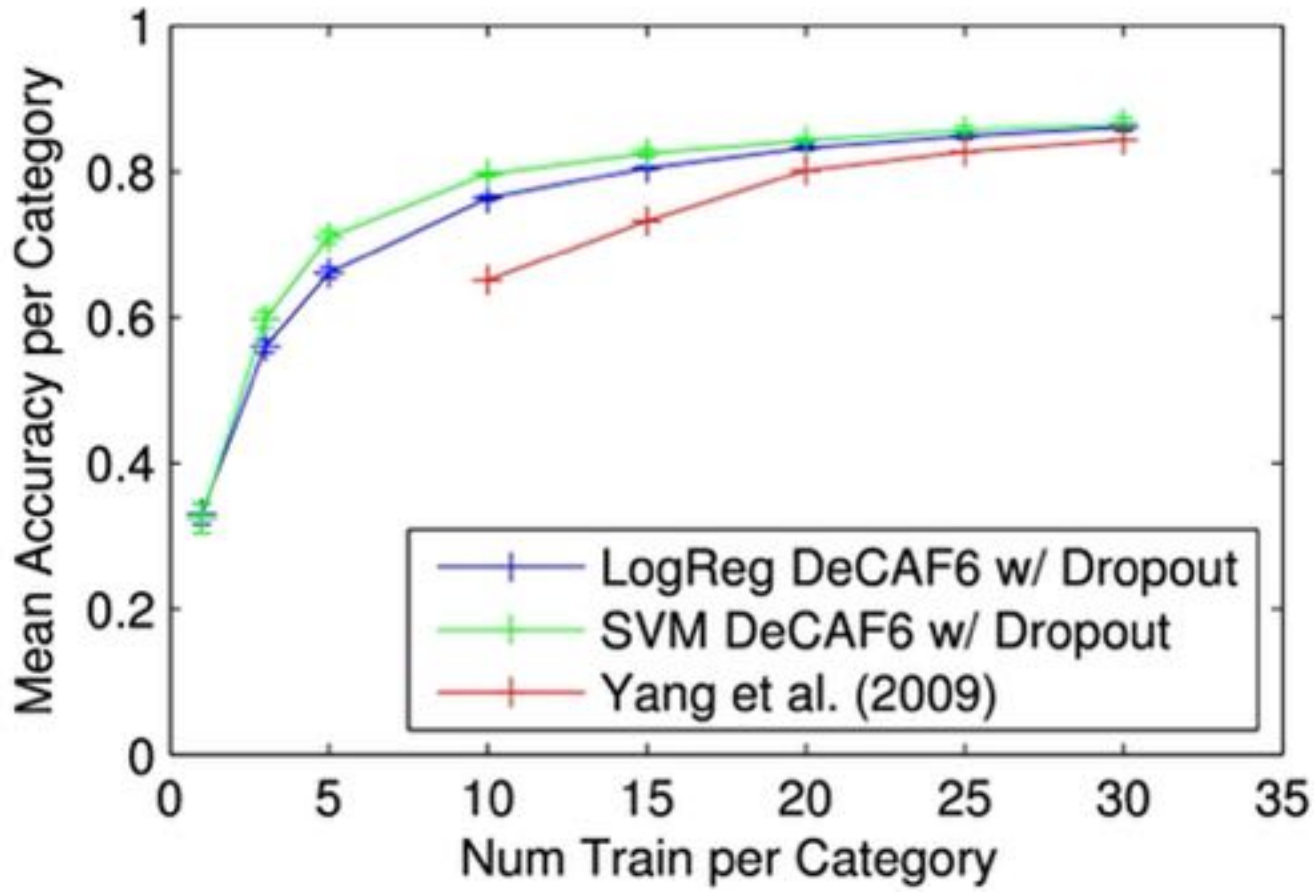


Classification on Caltech-101



Donahue et al, “DeCAF: A Deep Convolutional Activation Feature for Generic Visual Recognition”, ICML 2014

Transfer Learning with CNNs

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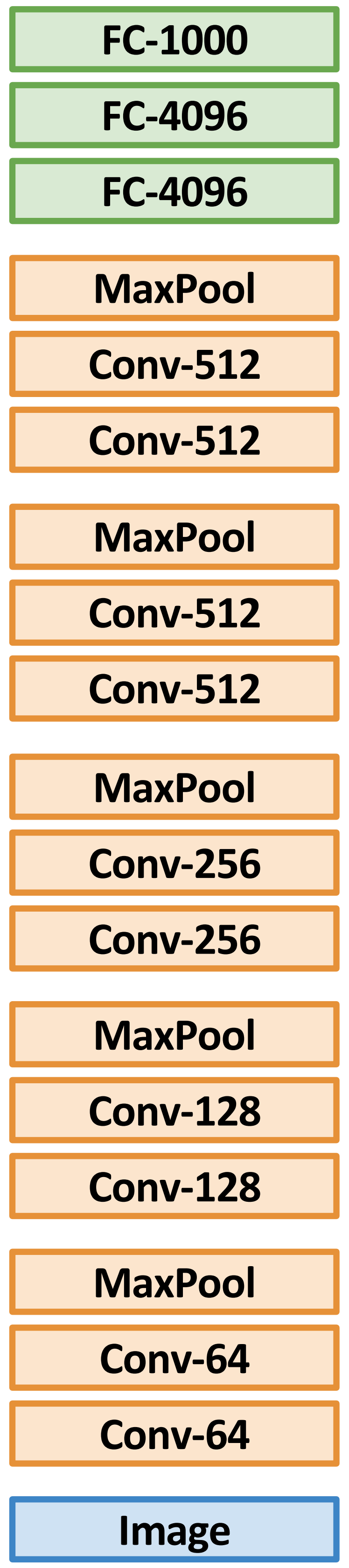
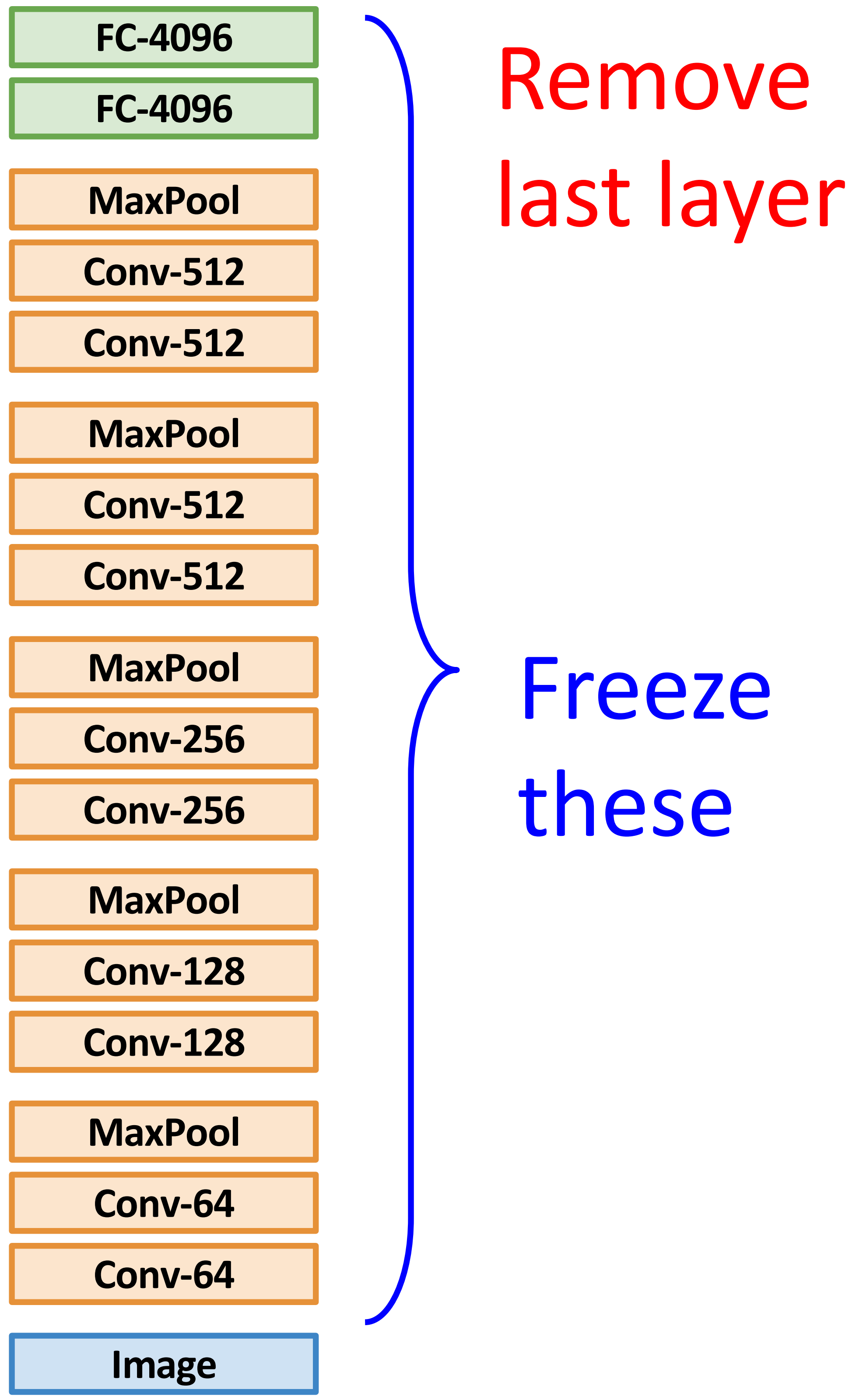
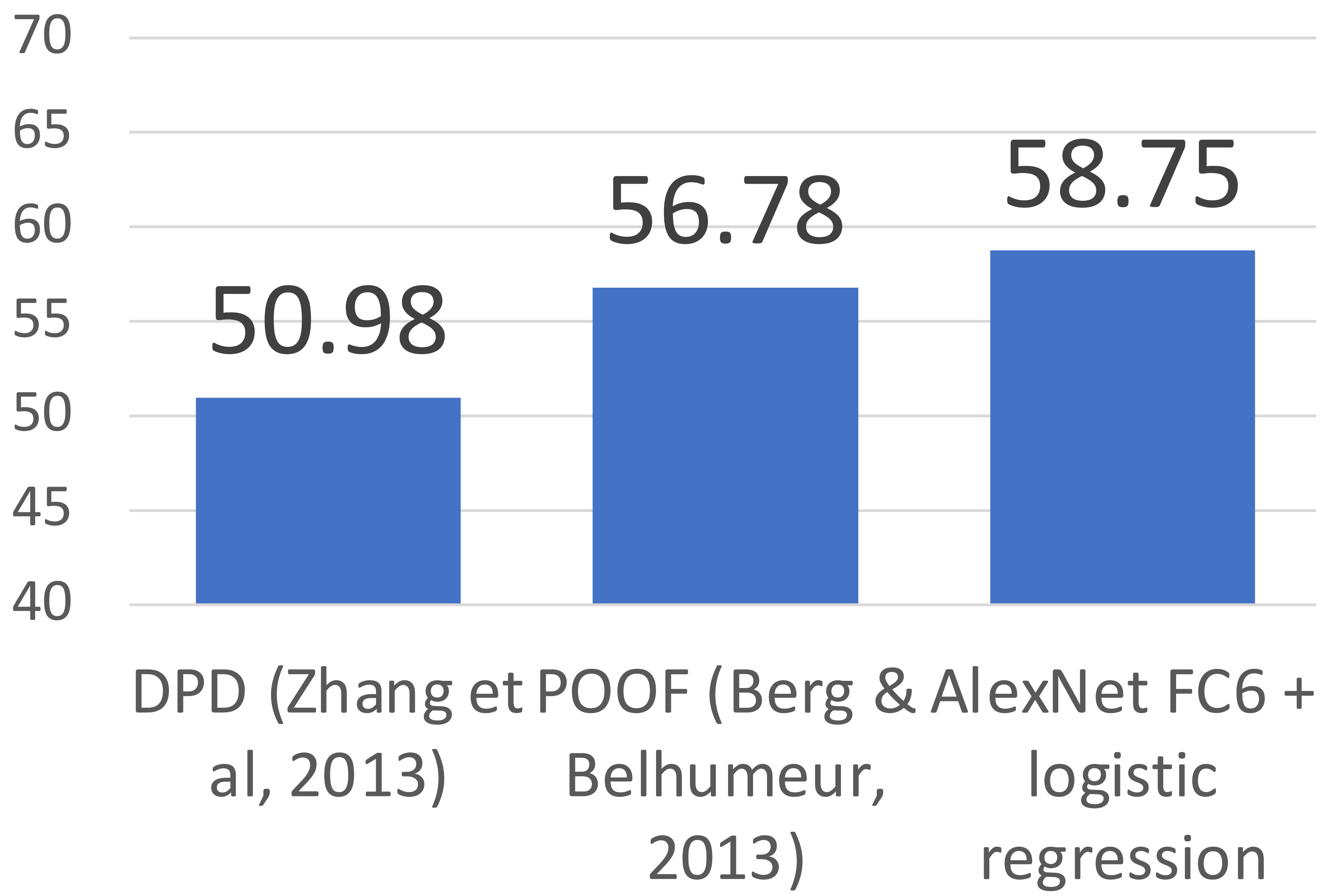


2. Use CNN as a feature extractor



Bird Classification on Caltech-UCSD



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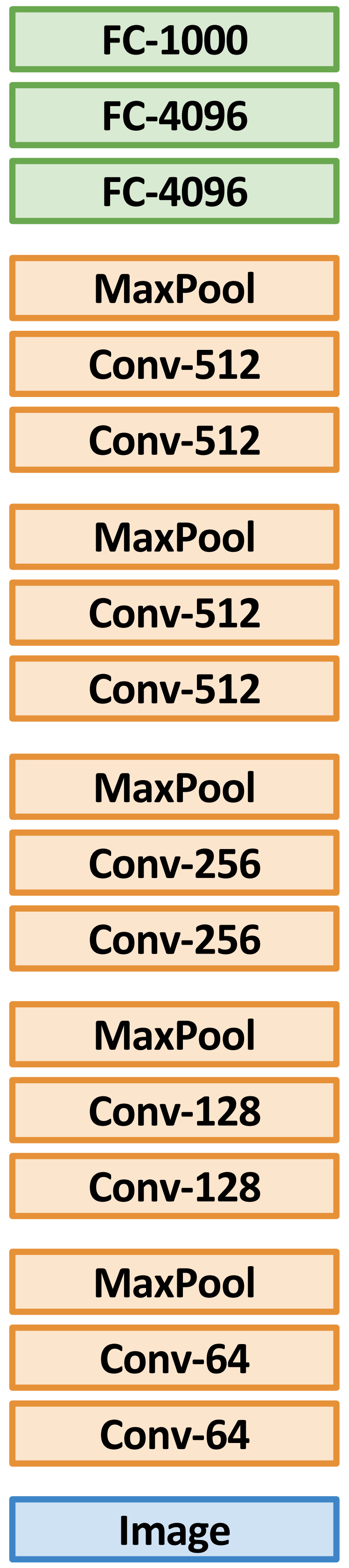
Transfer Learning with CNNs

1. Train on ImageNet



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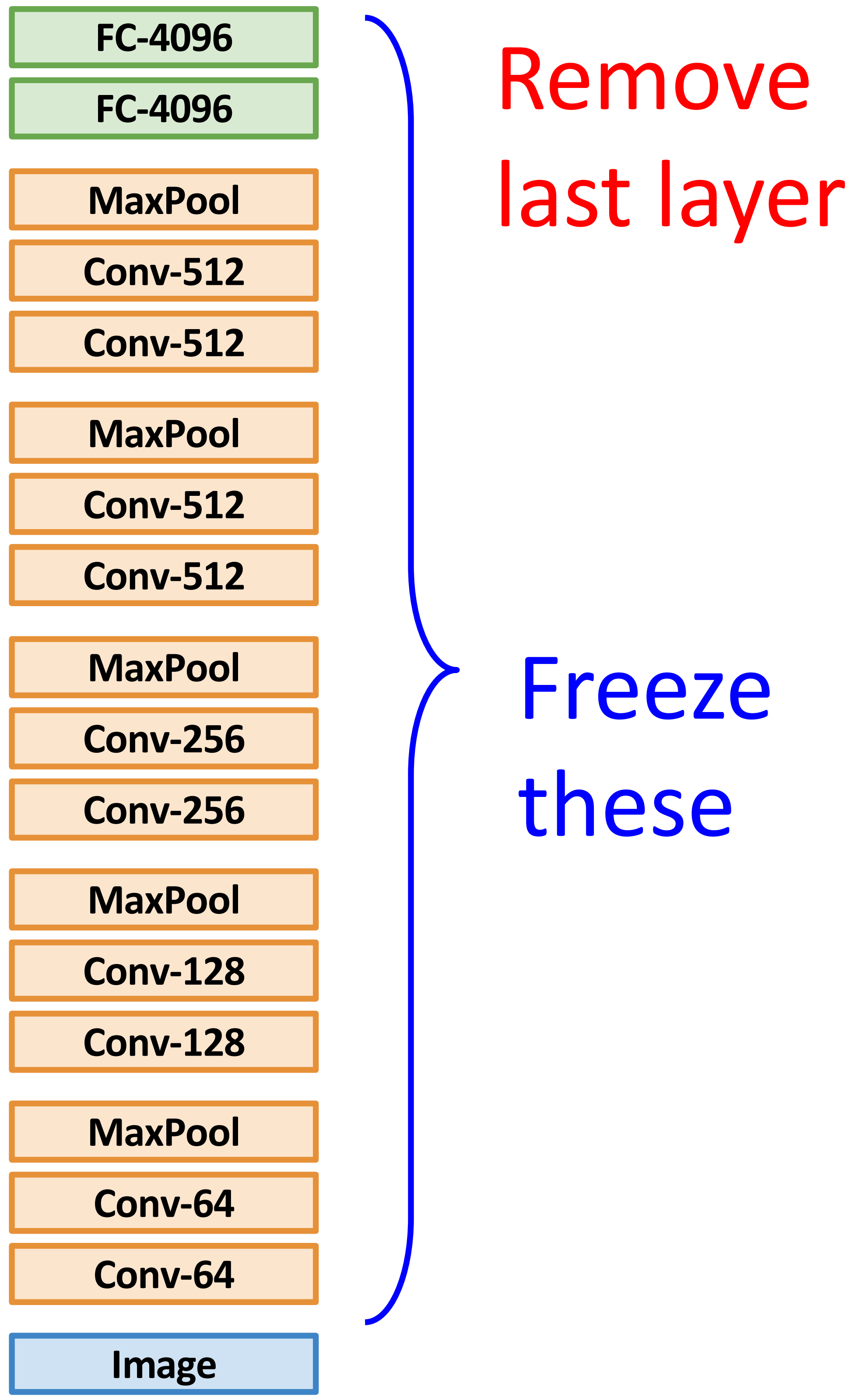

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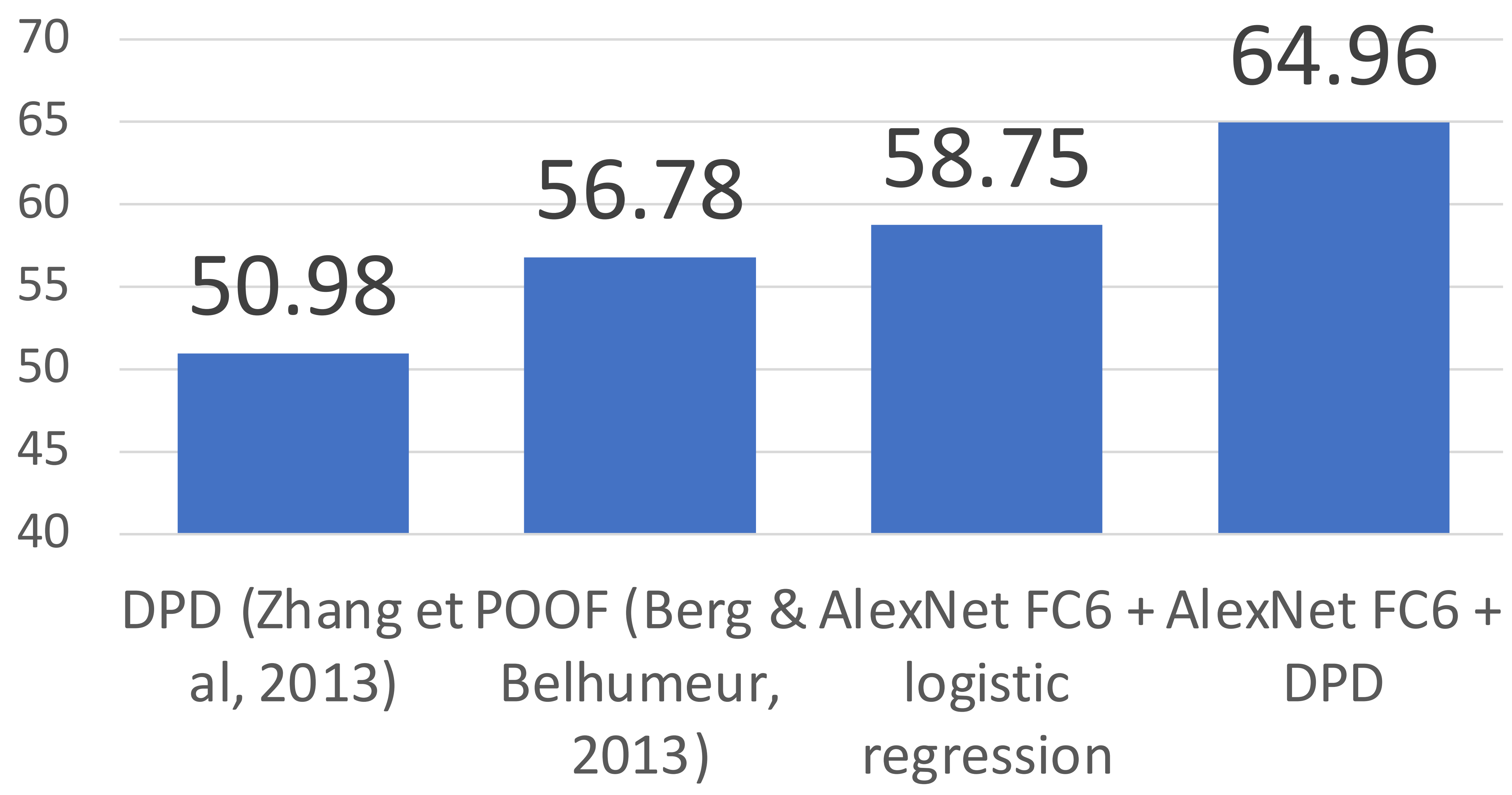
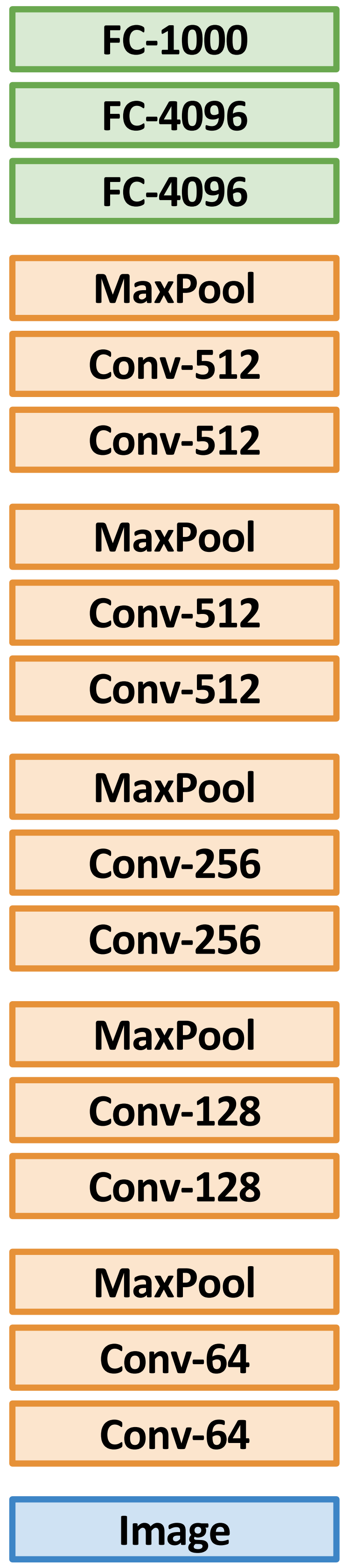


Donahue et al, “DeCAF: A Deep Convolutional Activation Feature for Generic Visual Recognition”, ICML 2014

Transfer Learning with CNNs

1. Train on ImageNet



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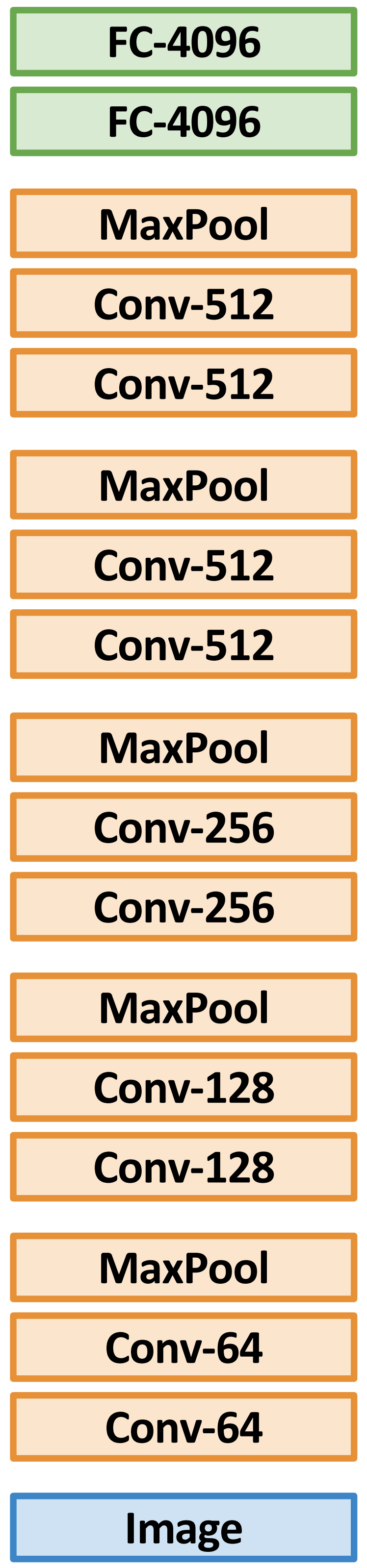
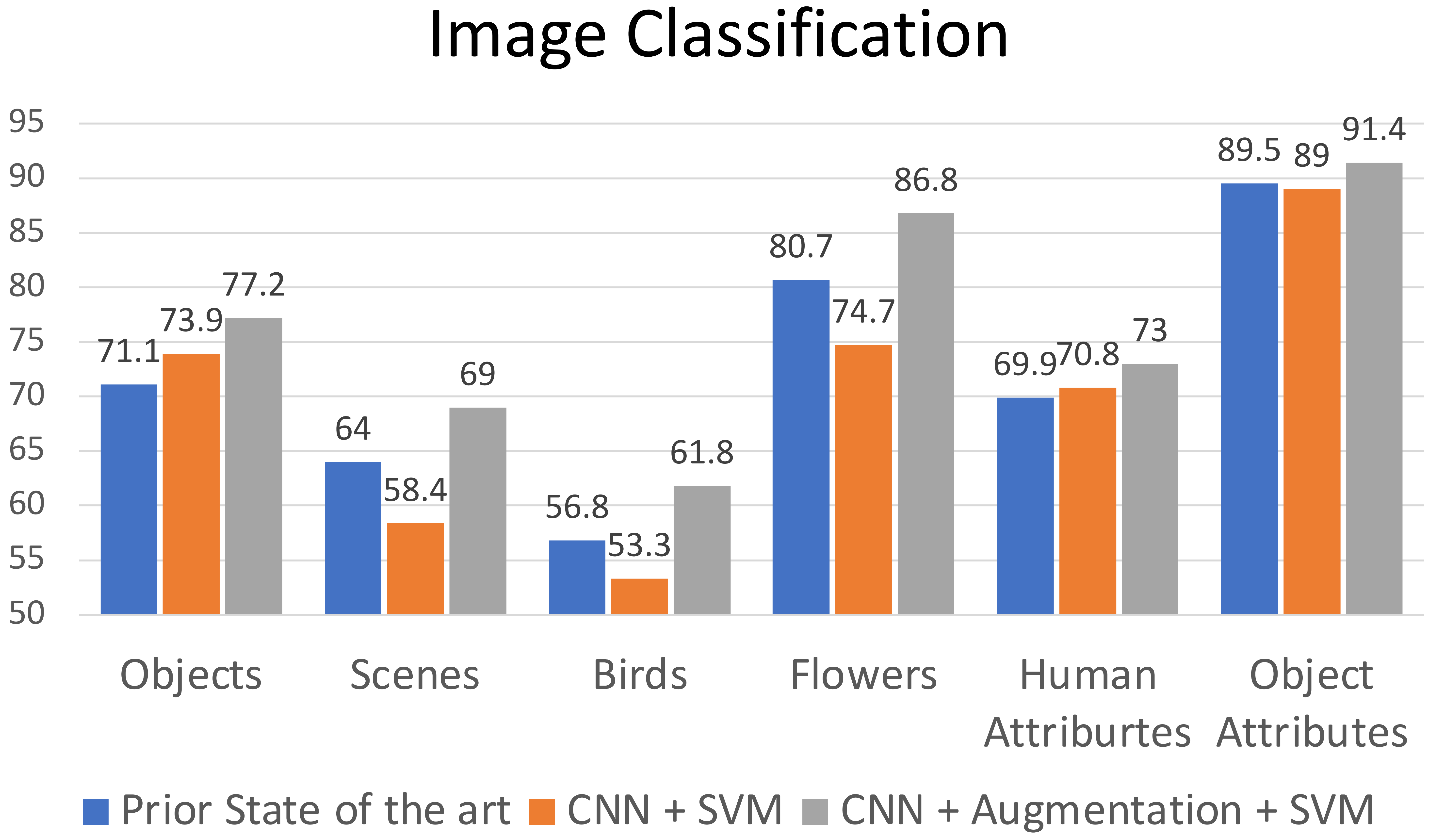
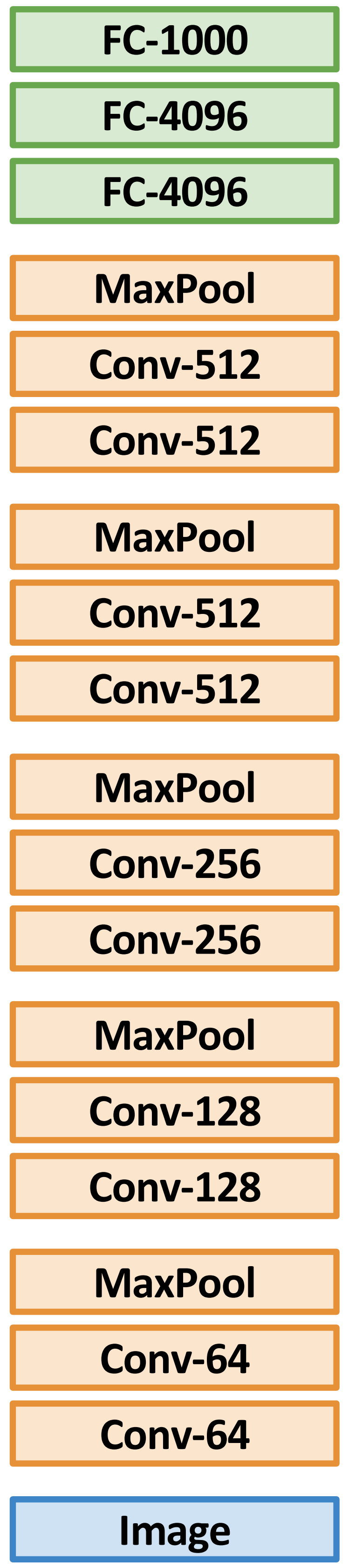




Transfer Learning with CNNs

1. Train on ImageNet



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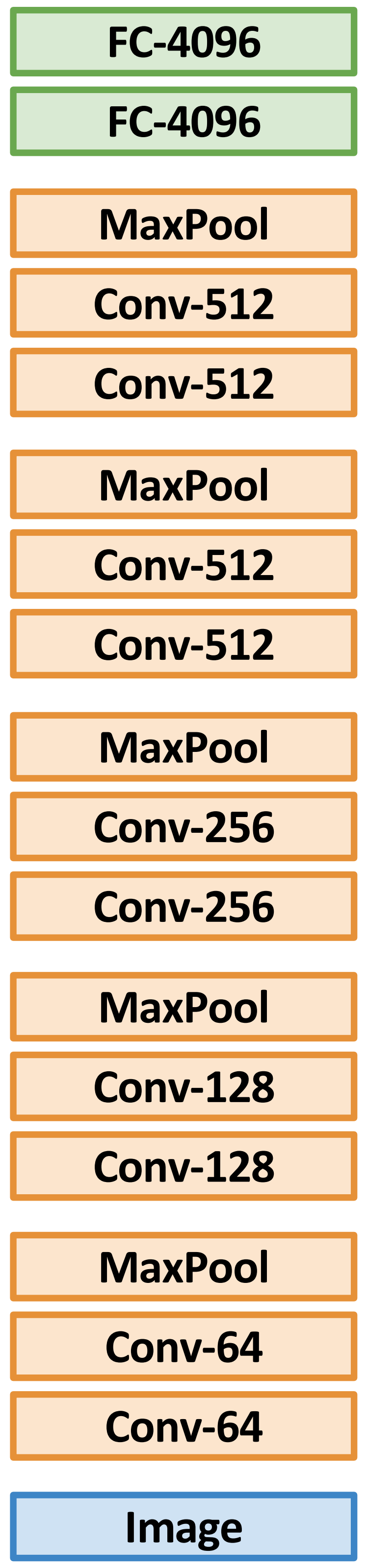
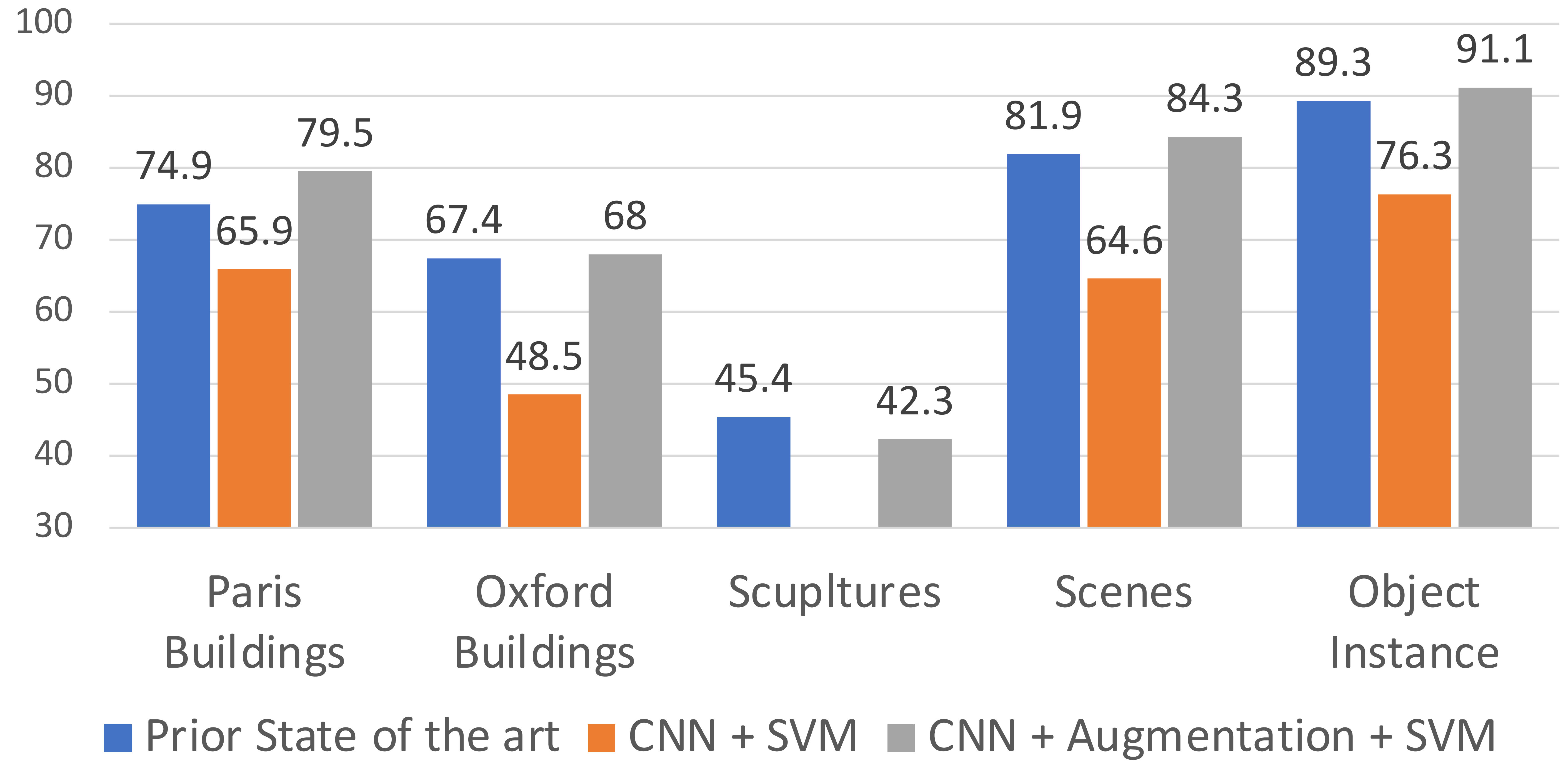


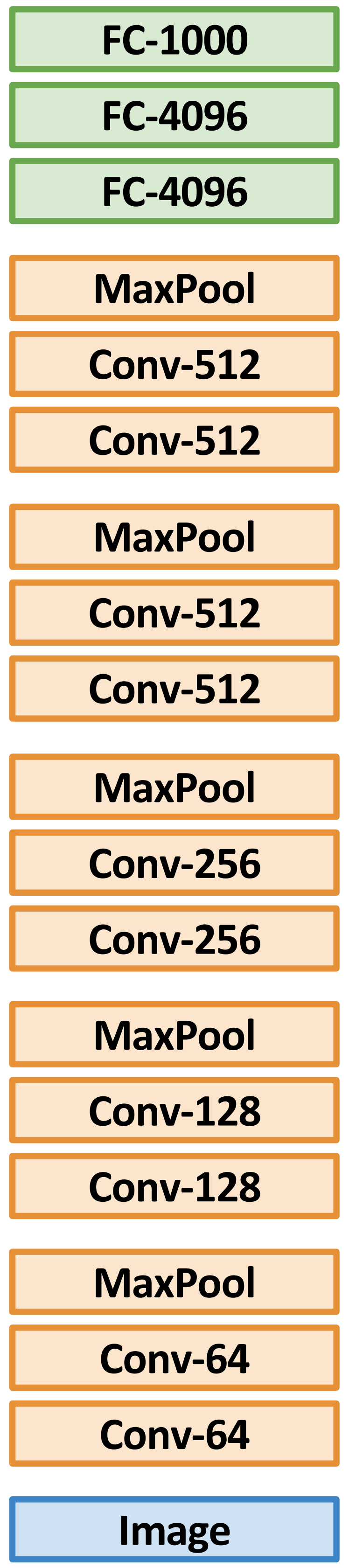
Image Retrieval: Nearest-Neighbor



Razavian et al, “CNN Features Off-the-Shelf: An Astounding Baseline for Recognition”, CVPR Workshops 2014

Transfer Learning with CNNs

1. Train on ImageNet



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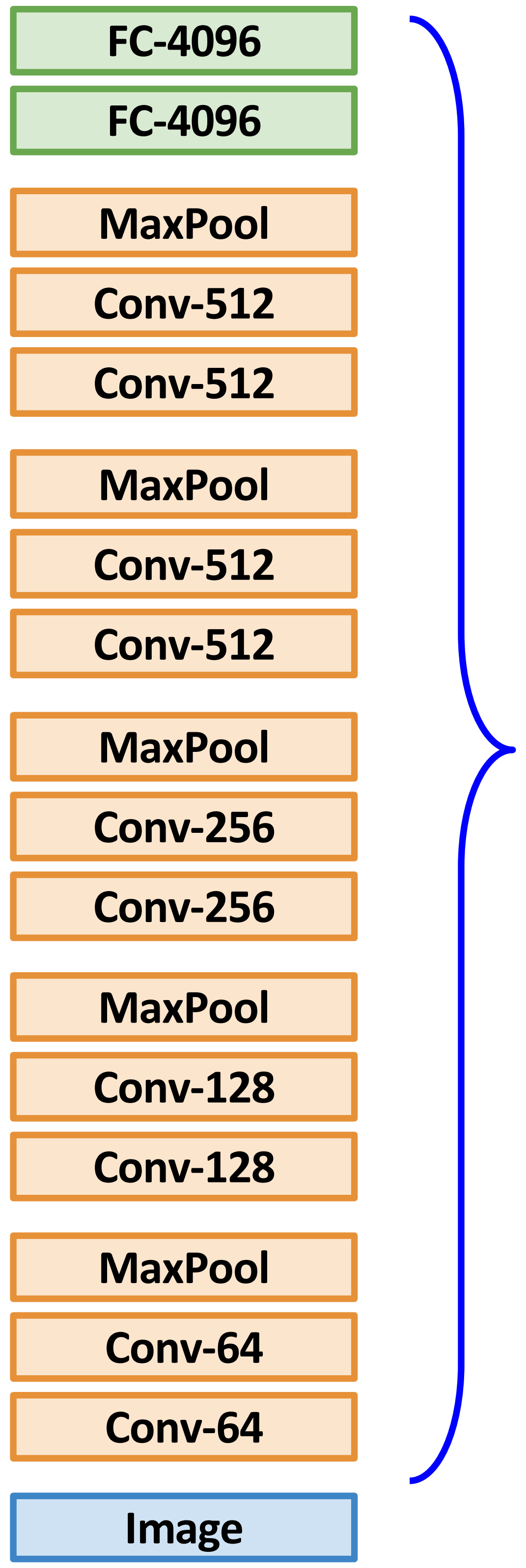
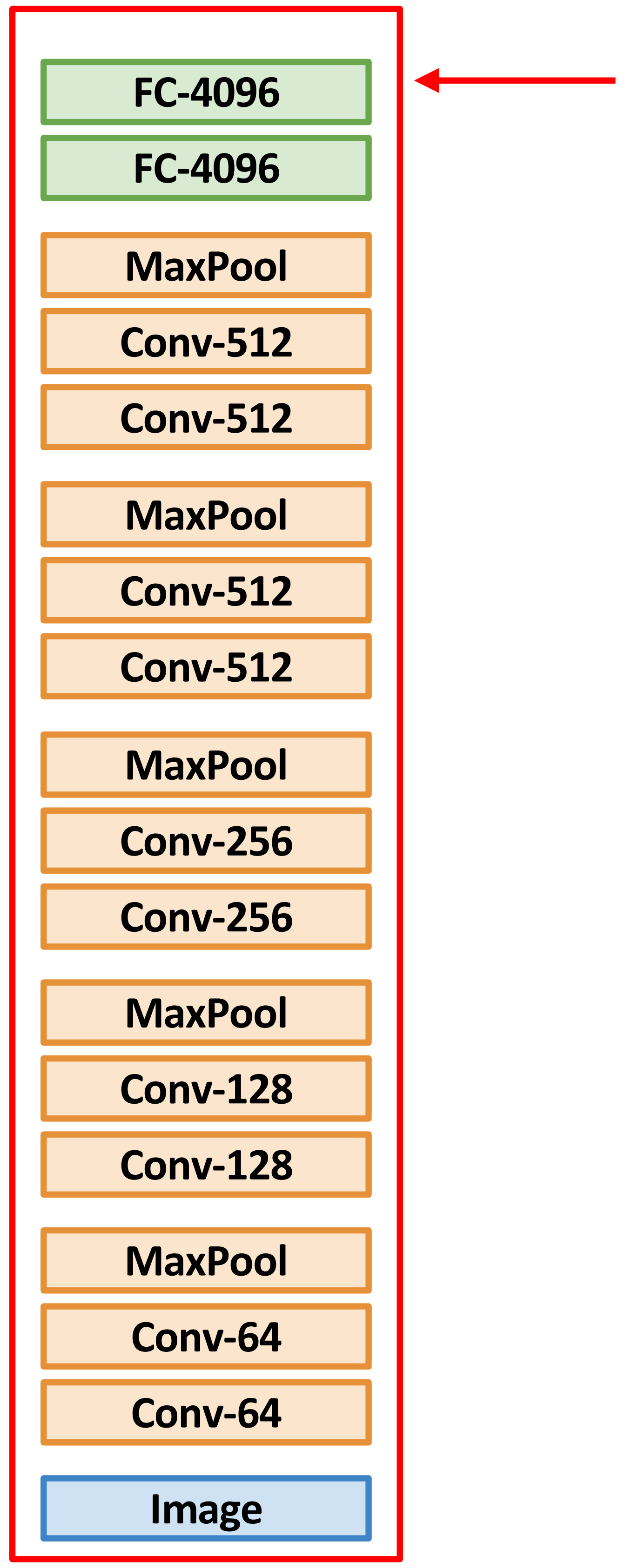


Remove last layer

Freeze these

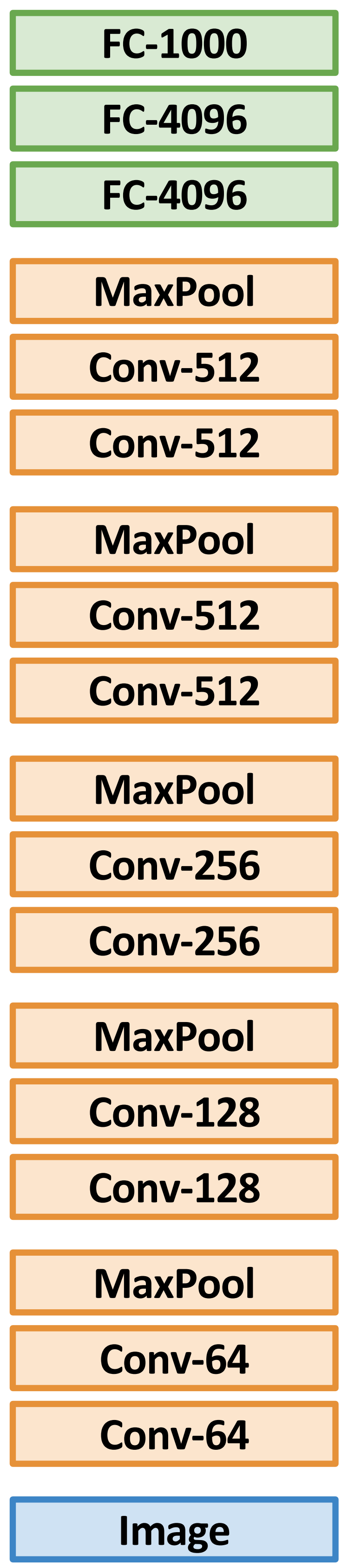
3. Bigger dataset: **Fine-Tuning**



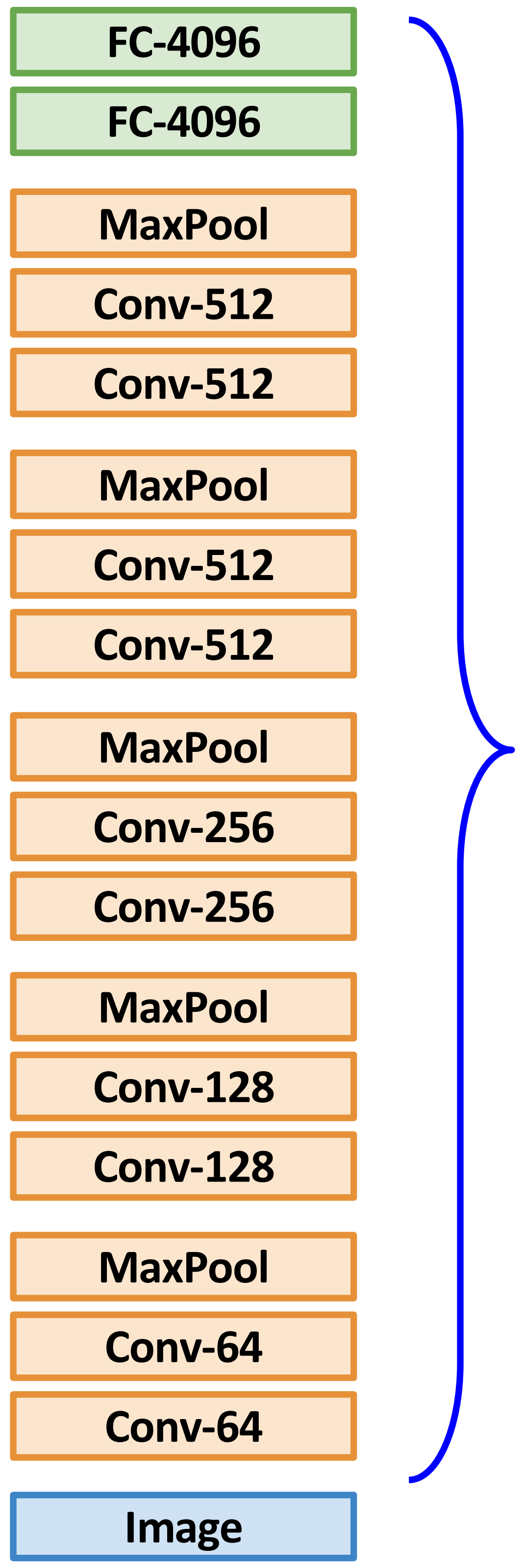
Continue training CNN for new task!

Transfer Learning with CNNs

1. Train on ImageNet



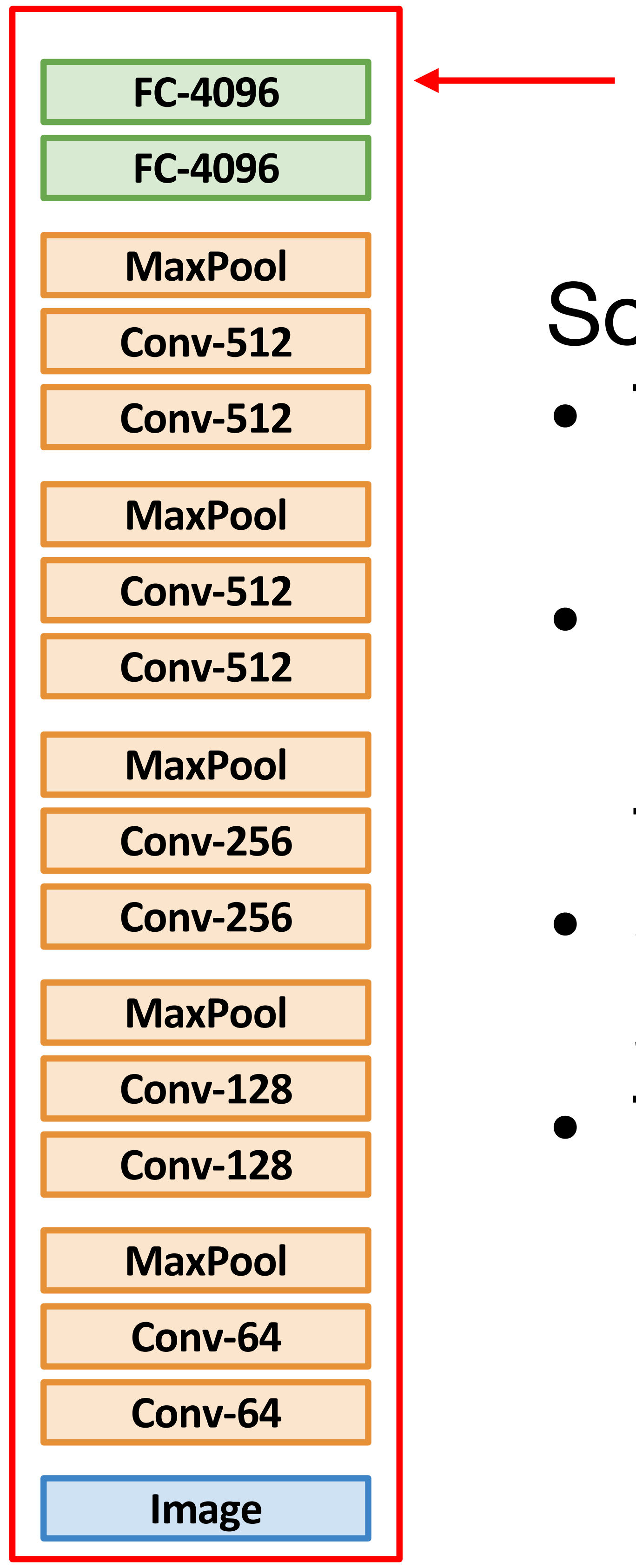
2. Use CNN as a feature extractor



Remove last layer

Freeze these

3. Bigger dataset: **Fine-Tuning**

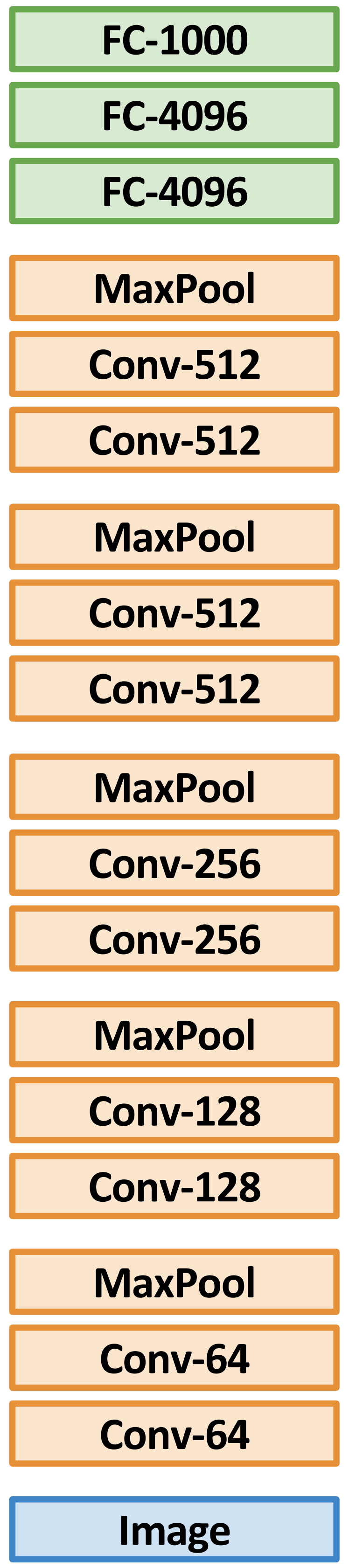


Continue training CNN for new task!

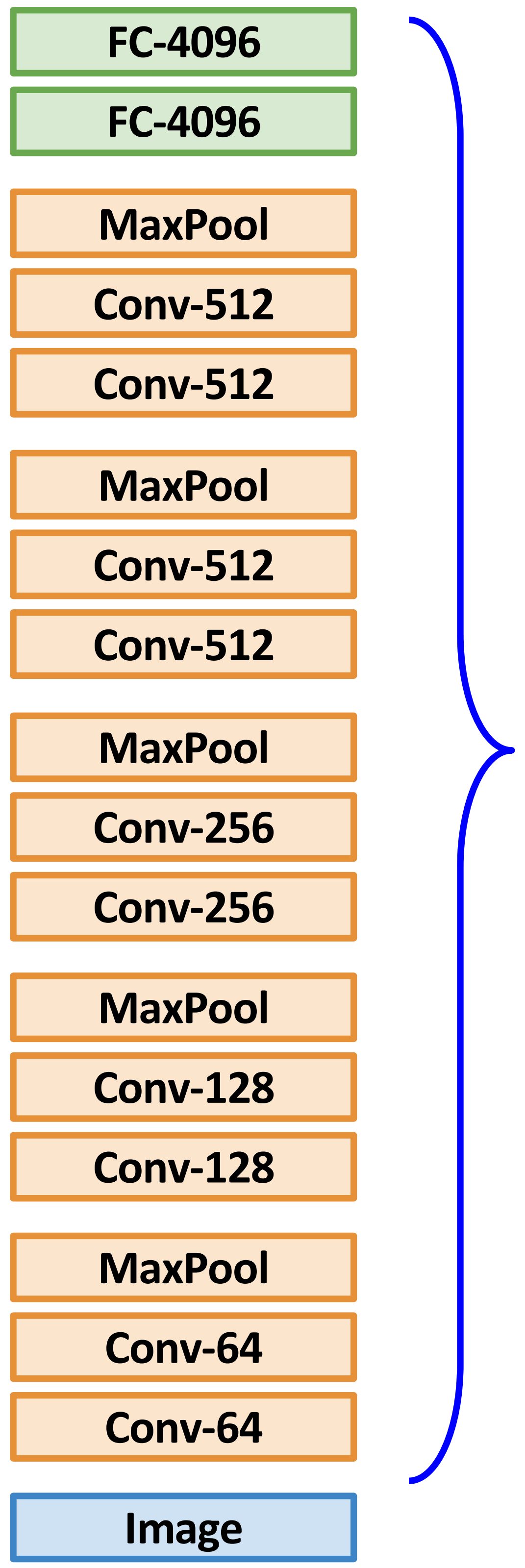
Some tricks:
- Train with feature extraction first before fine-tuning
- Lower the learning rate: use ~1/10 of LR used in original training
- Sometimes freeze lower layers to save computation
- Train with BatchNorm in “test” mode

Transfer Learning with CNNs

1. Train on ImageNet



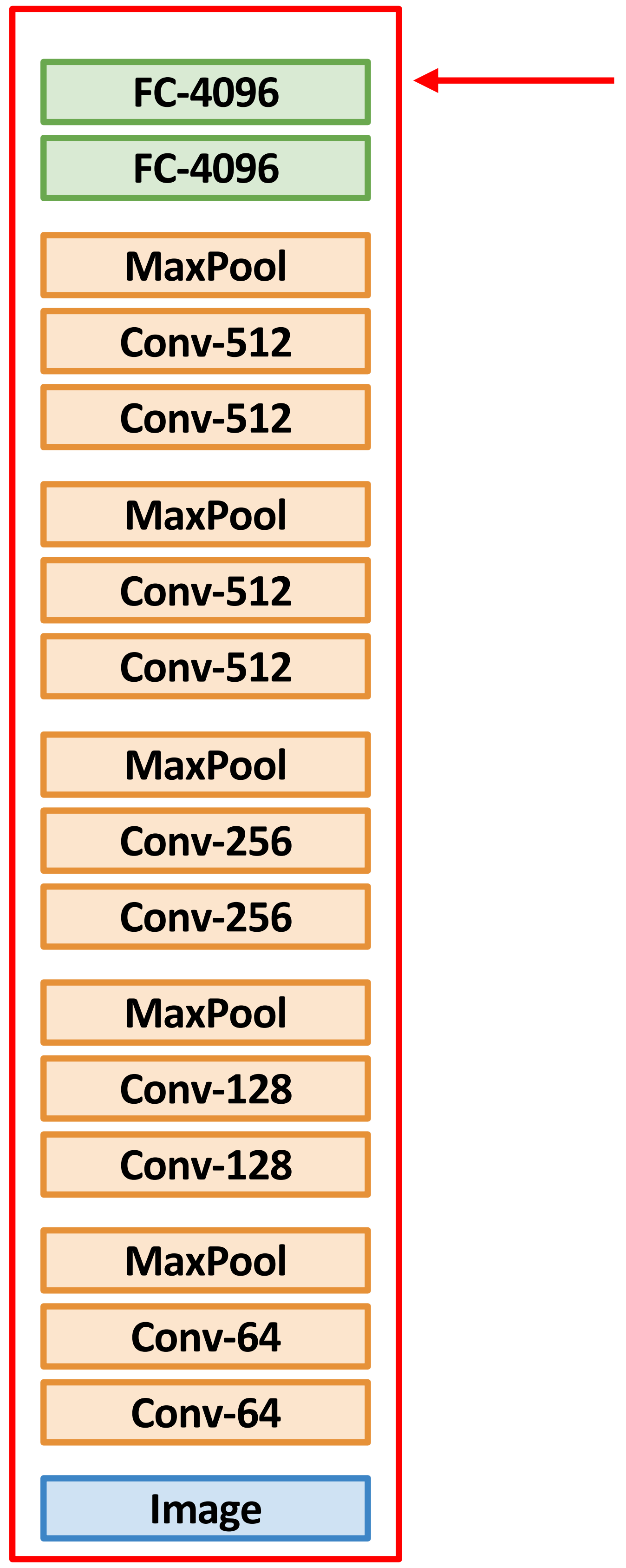
2. Use CNN as a feature extractor



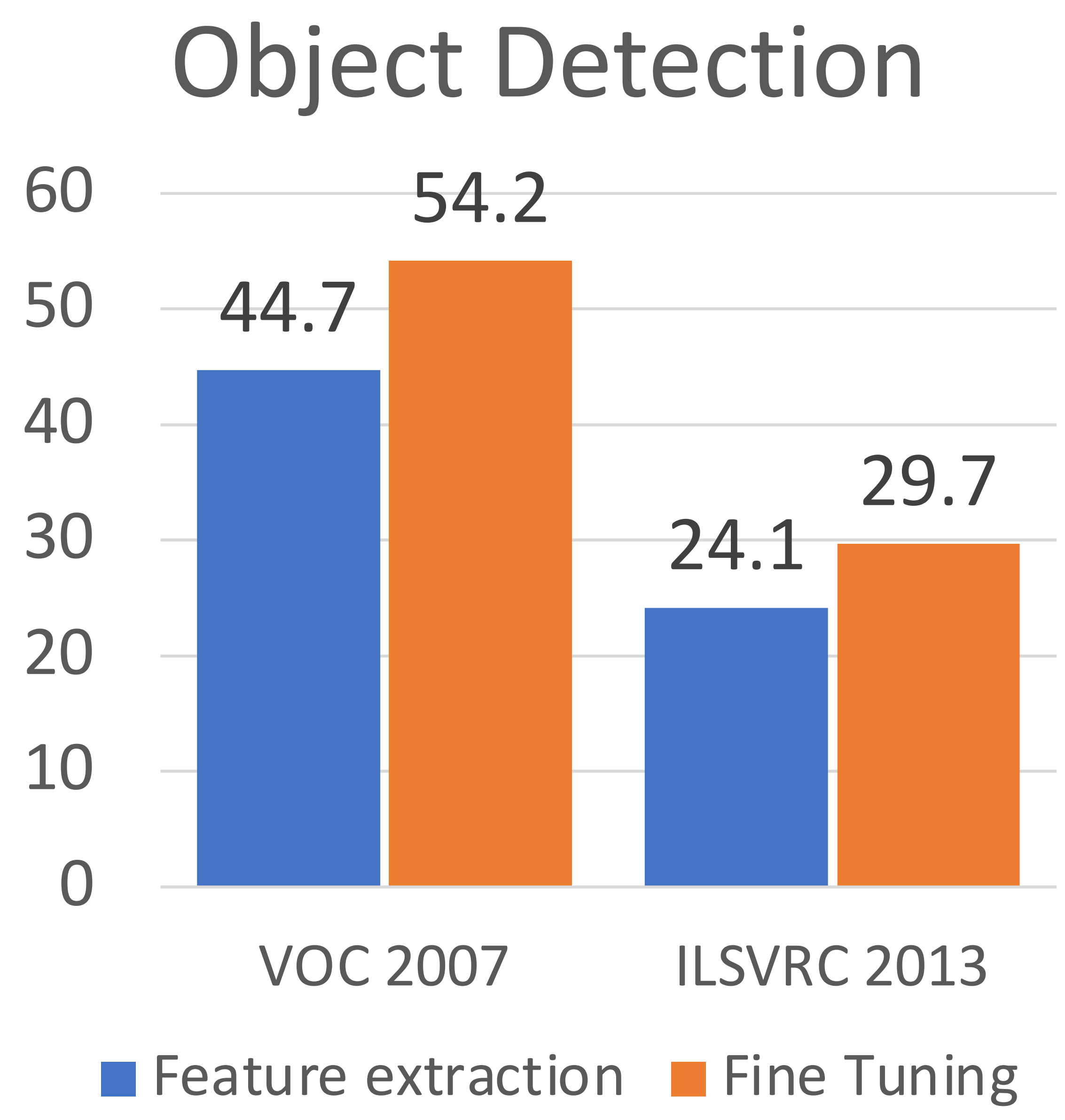
Remove last layer

Freeze these

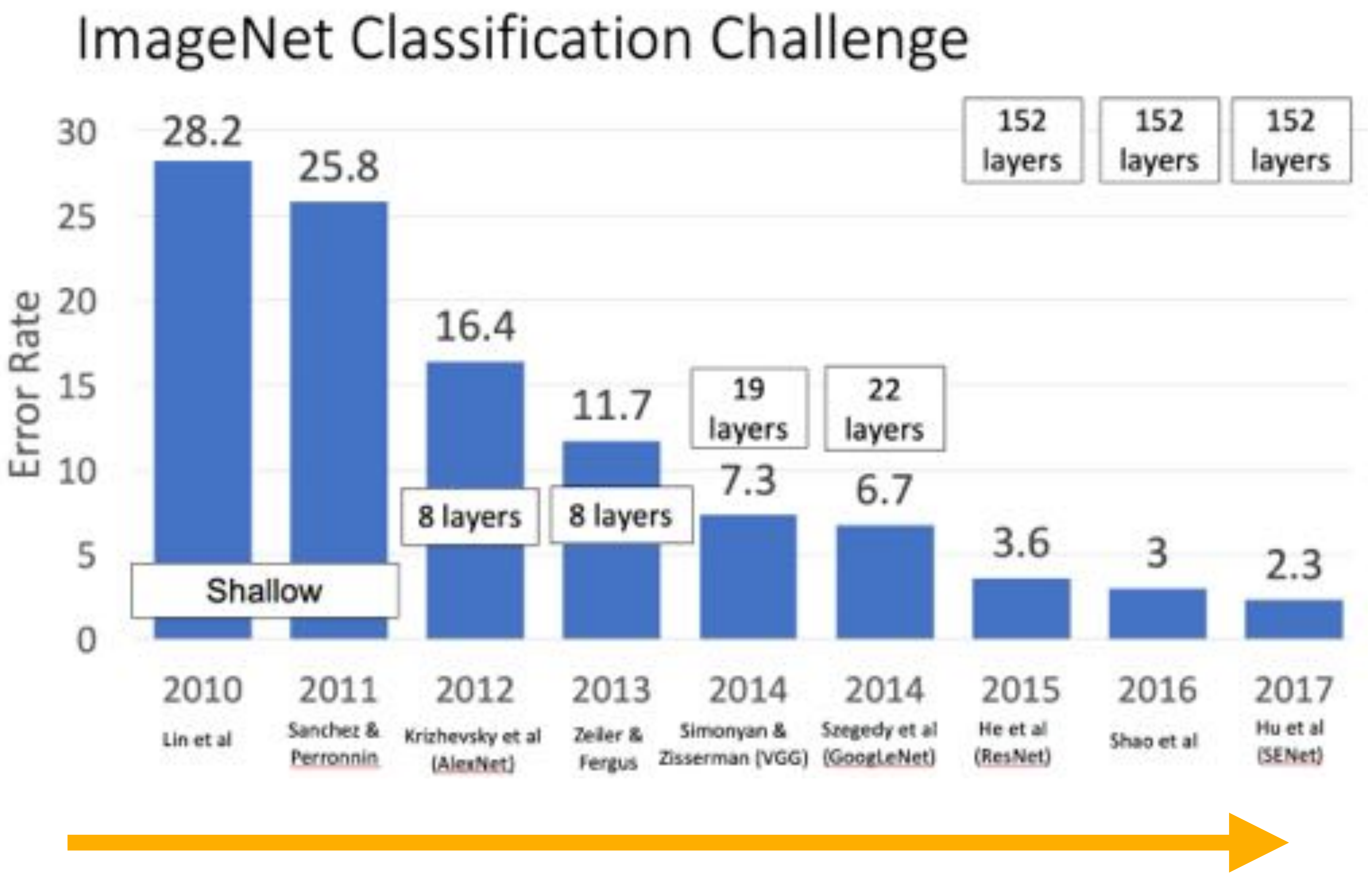
3. Bigger dataset: **Fine-Tuning**



Continue training CNN for new task!

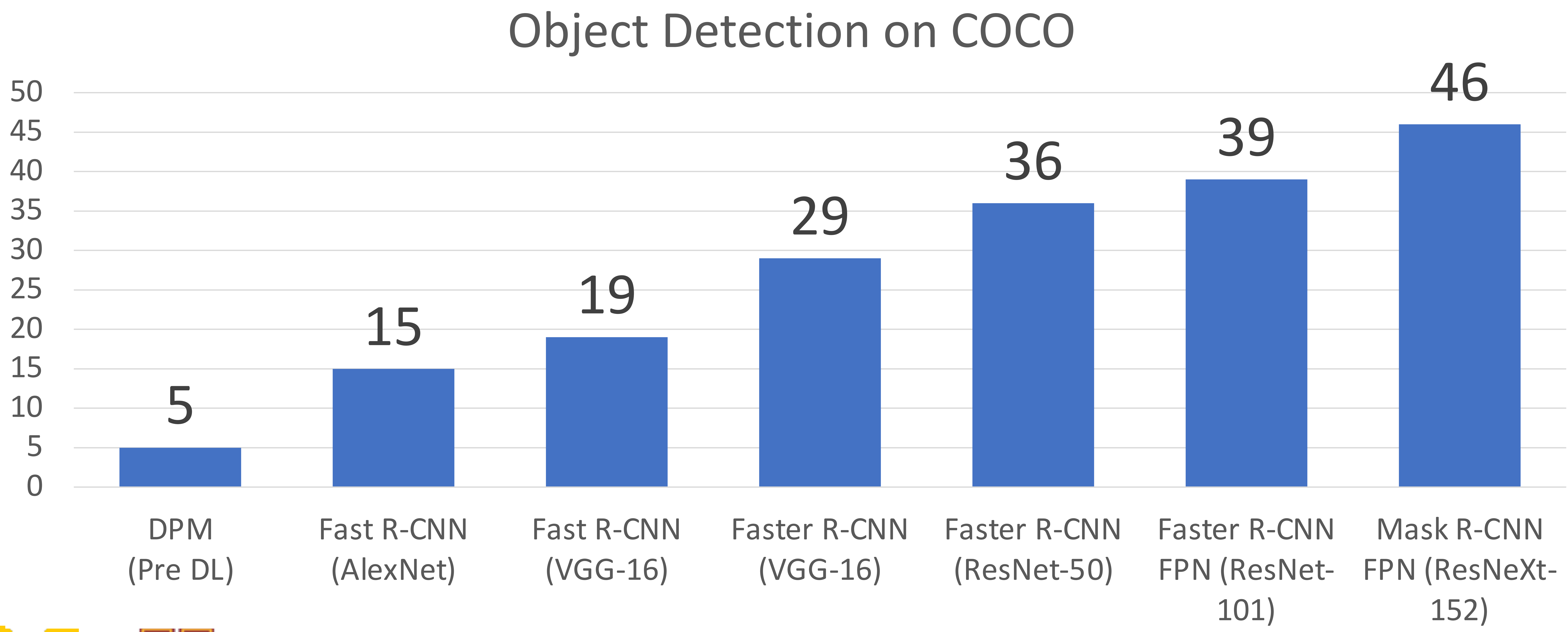


Transfer Learning with CNNs: Architecture Matters!



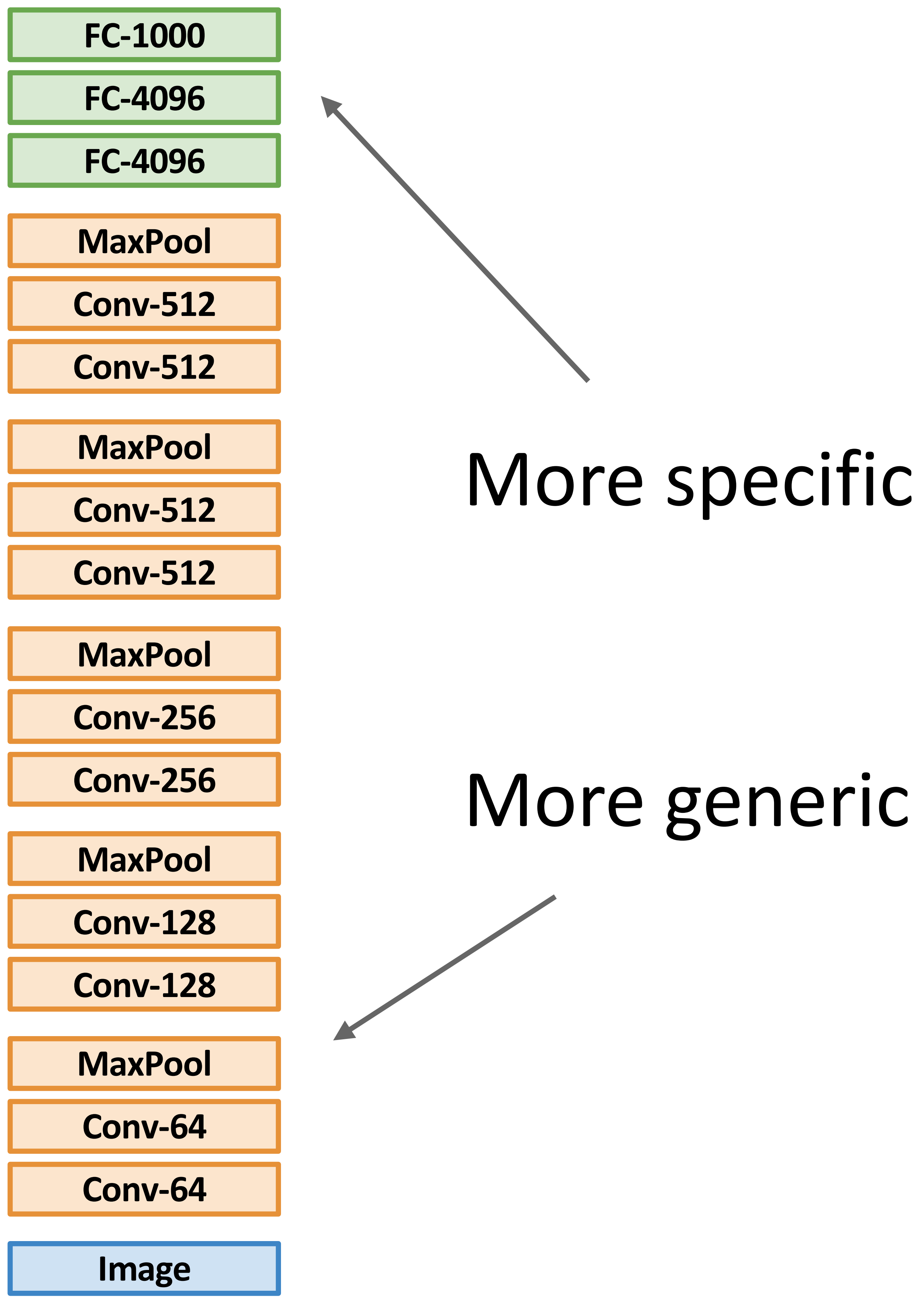
Improvements in CNN architectures lead to improvements in many downstream tasks thanks to transfer learning!

Transfer Learning with CNNs: Architecture Matters!



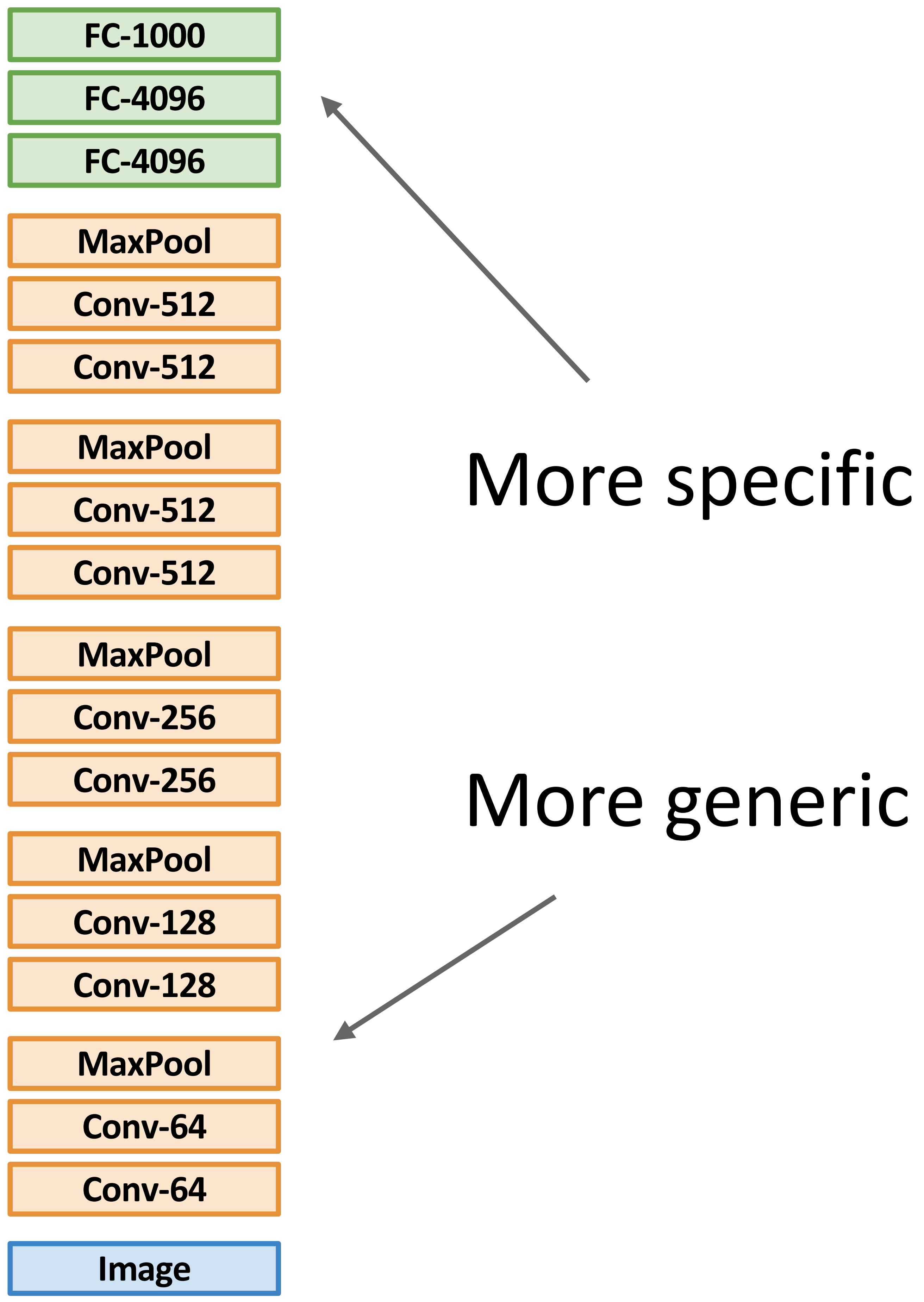
Ross Girshick, "The Generalized R-CNN Framework for Object Detection", ICCV 2017 Tutorial on Instance-Level Visual Recognition

Transfer Learning with CNNs



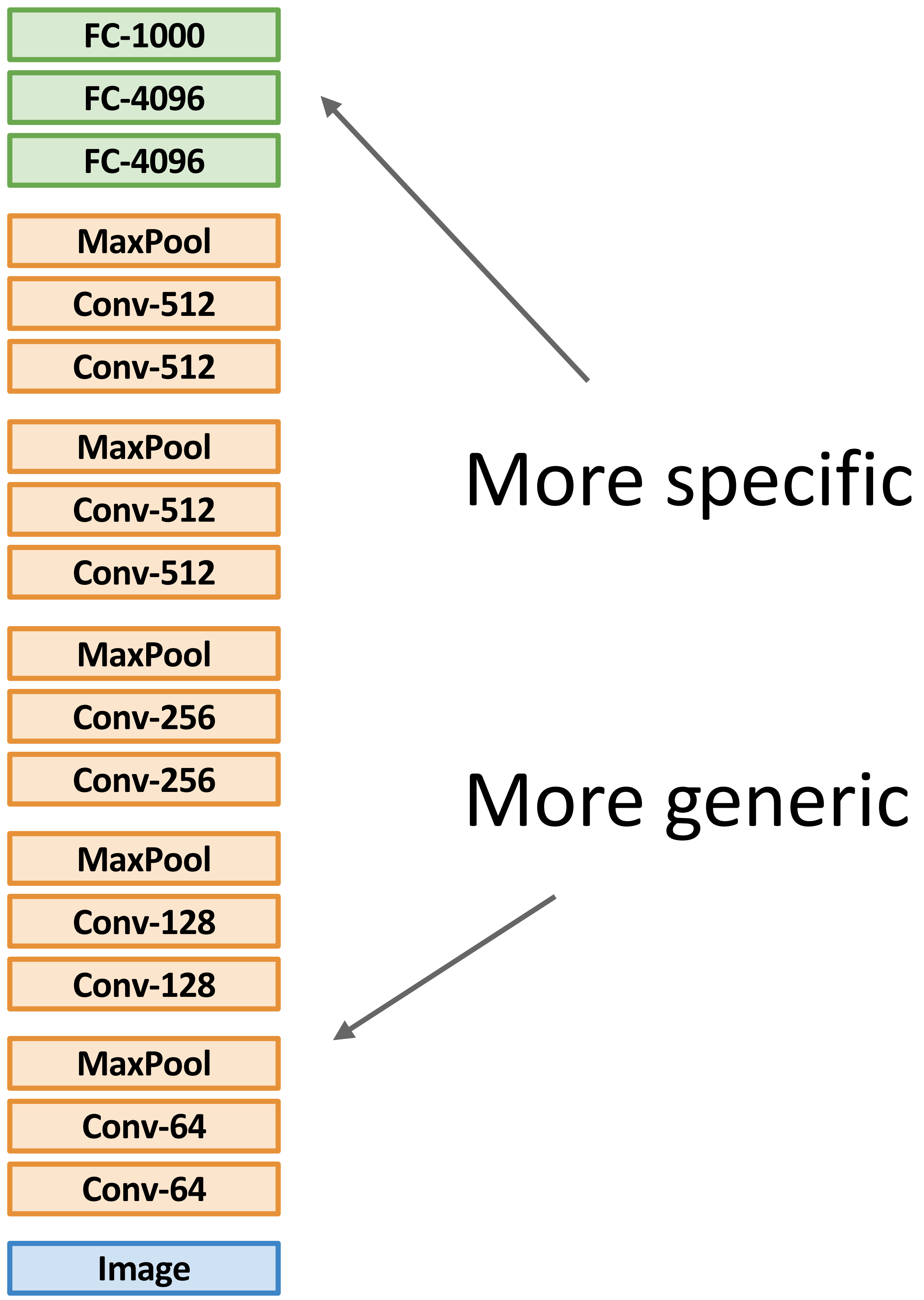
	Dataset similar to ImageNet	Dataset very different from ImageNet
Very little data (10s to 100s)	?	?
Quite a lot of data (100s to 1000s)	?	?

Transfer Learning with CNNs



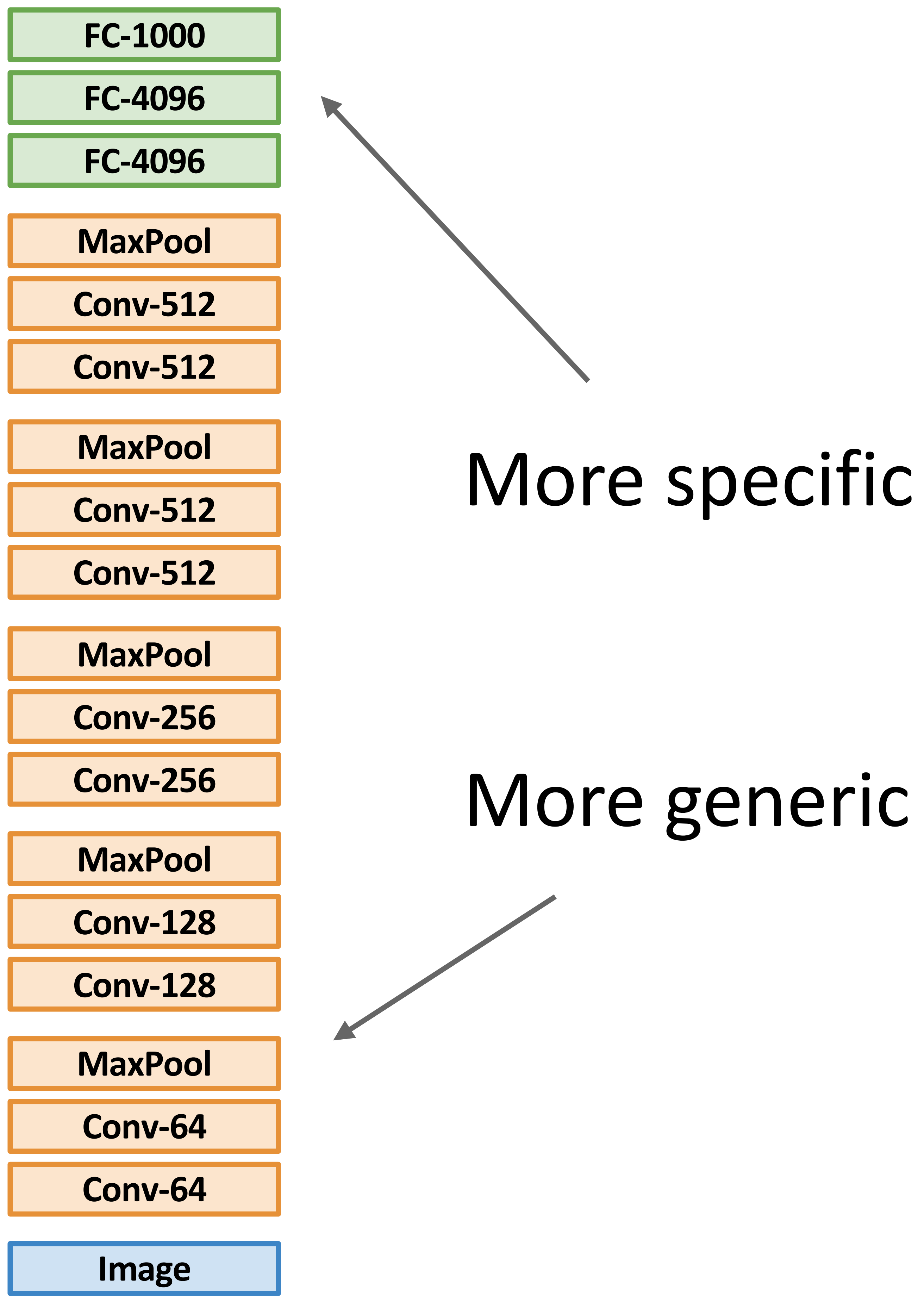
	Dataset similar to ImageNet	Dataset very different from ImageNet
Very little data (10s to 100s)	Use Linear Classifier on top layer	?
Quite a lot of data (100s to 1000s)	Finetune a few layers	?

Transfer Learning with CNNs



	Dataset similar to ImageNet	Dataset very different from ImageNet
Very little data (10s to 100s)	Use Linear Classifier on top layer	?
Quite a lot of data (100s to 1000s)	Finetune a few layers	Finetune a larger number of layers

Transfer Learning with CNNs

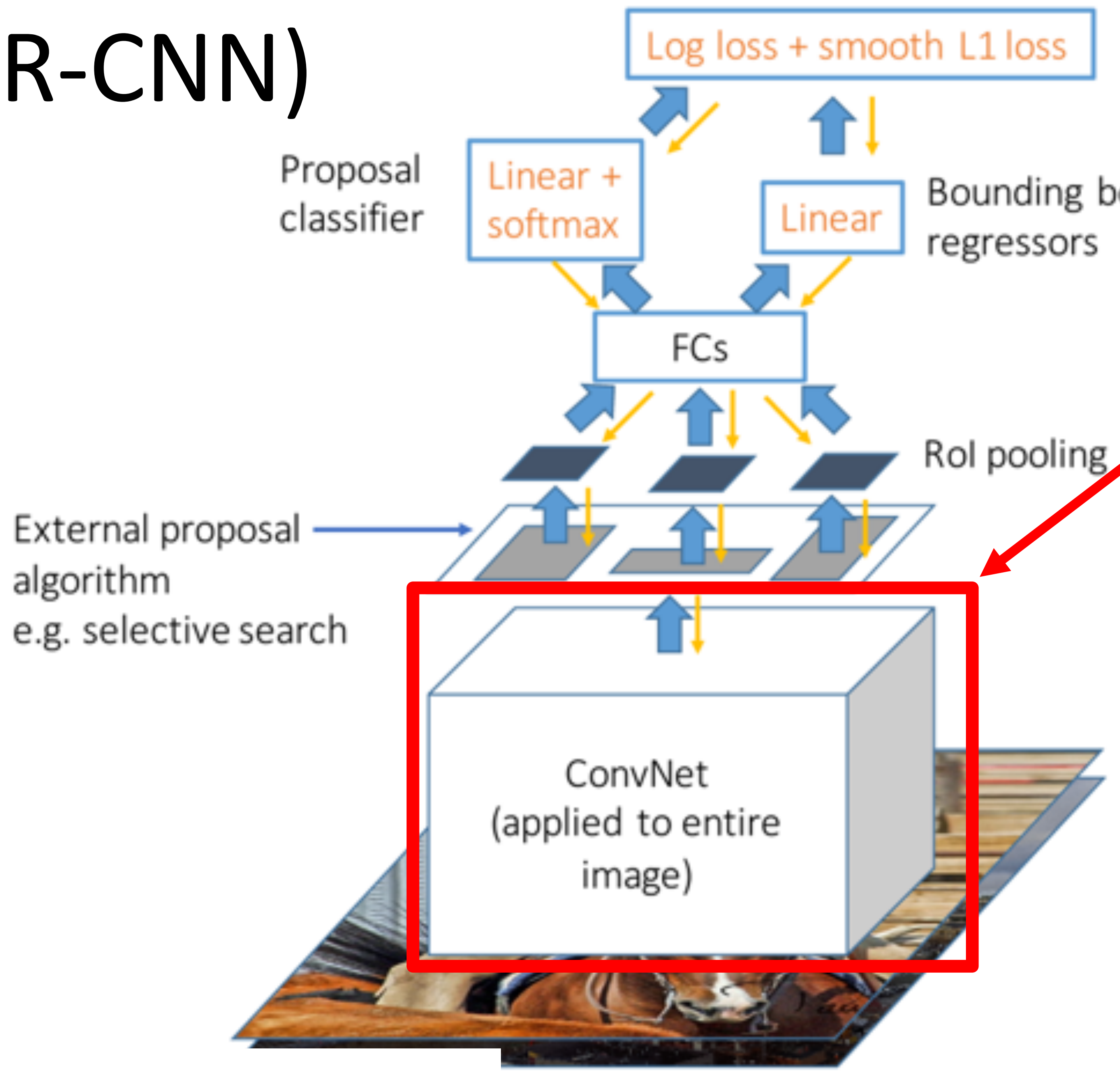


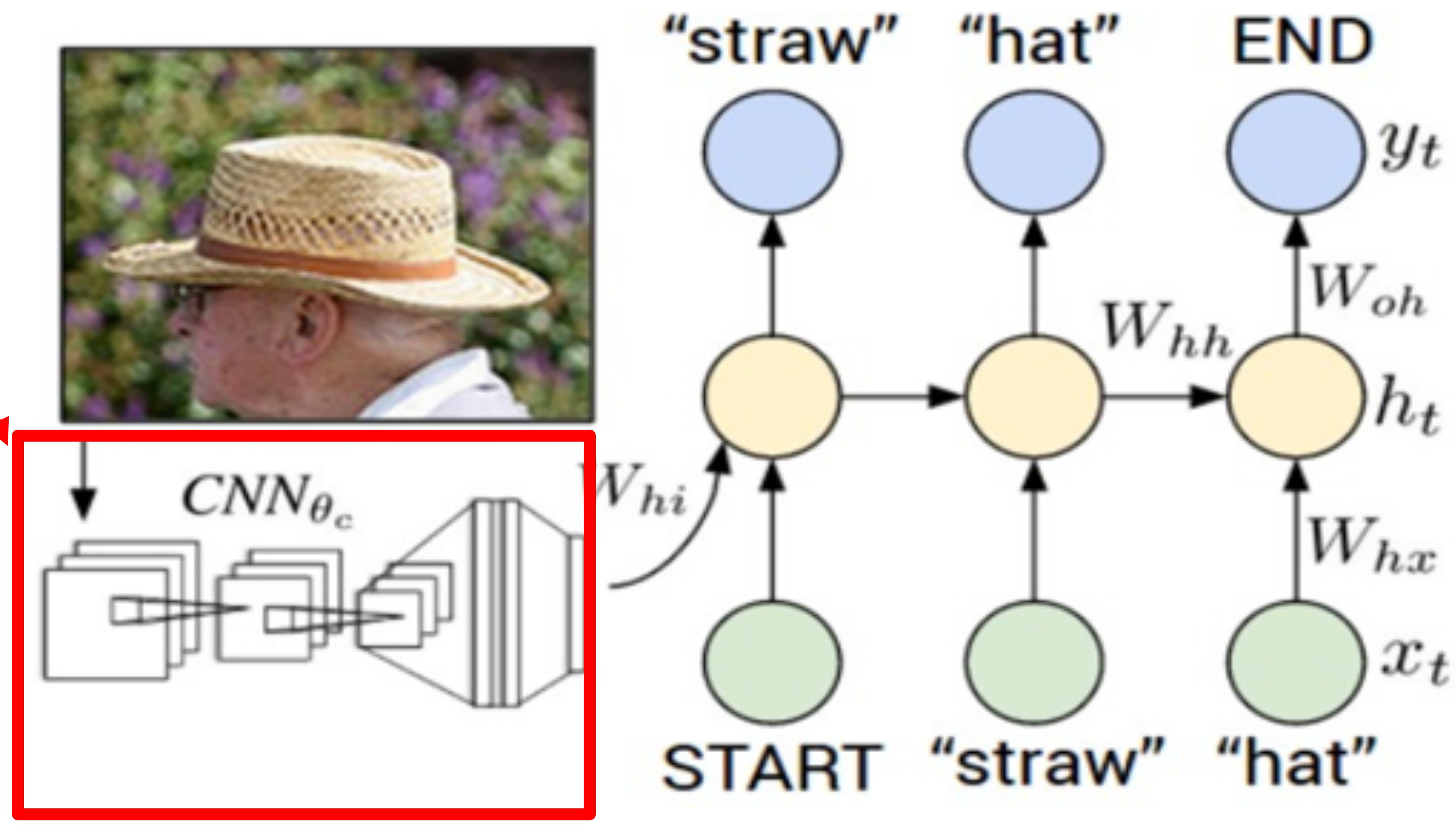
	Dataset similar to ImageNet	Dataset very different from ImageNet
Very little data (10s to 100s)	Use Linear Classifier on top layer	You're in trouble… Try linear classifier from different stages
Quite a lot of data (100s to 1000s)	Finetune a few layers	Finetune a larger number of layers

Transfer Learning is pervasive!
Its the norm, not the exception

Object
Detection
(Fast R-CNN)

CNN pretrained
on ImageNet





Girshick, "Fast R-CNN", ICCV 2015
Figure copyright Ross Girshick, 2015. Reproduced with permission.

Karpathy and Fei-Fei, "Deep Visual-Semantic Alignments for Generating Image Descriptions", CVPR 2015

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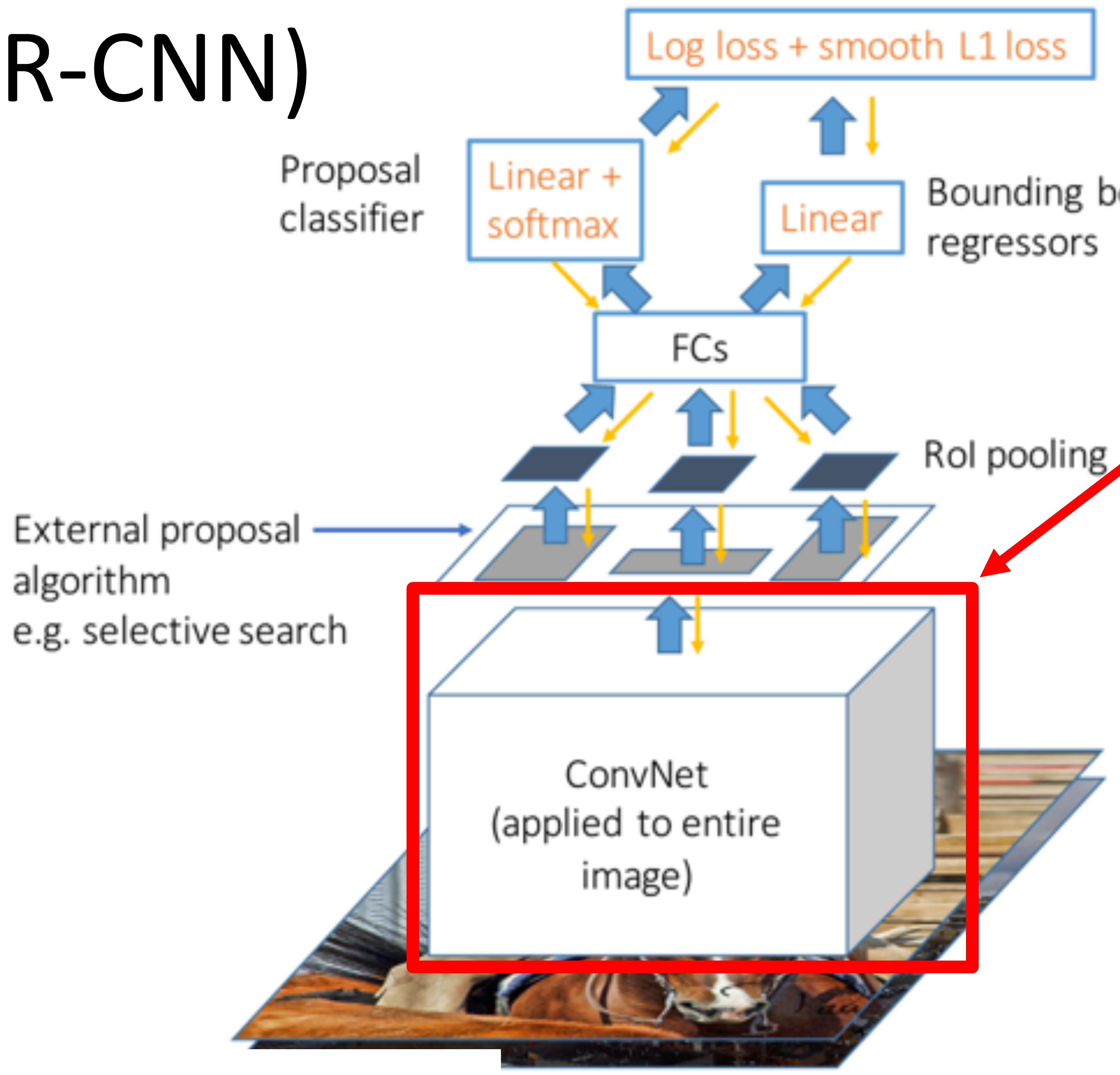
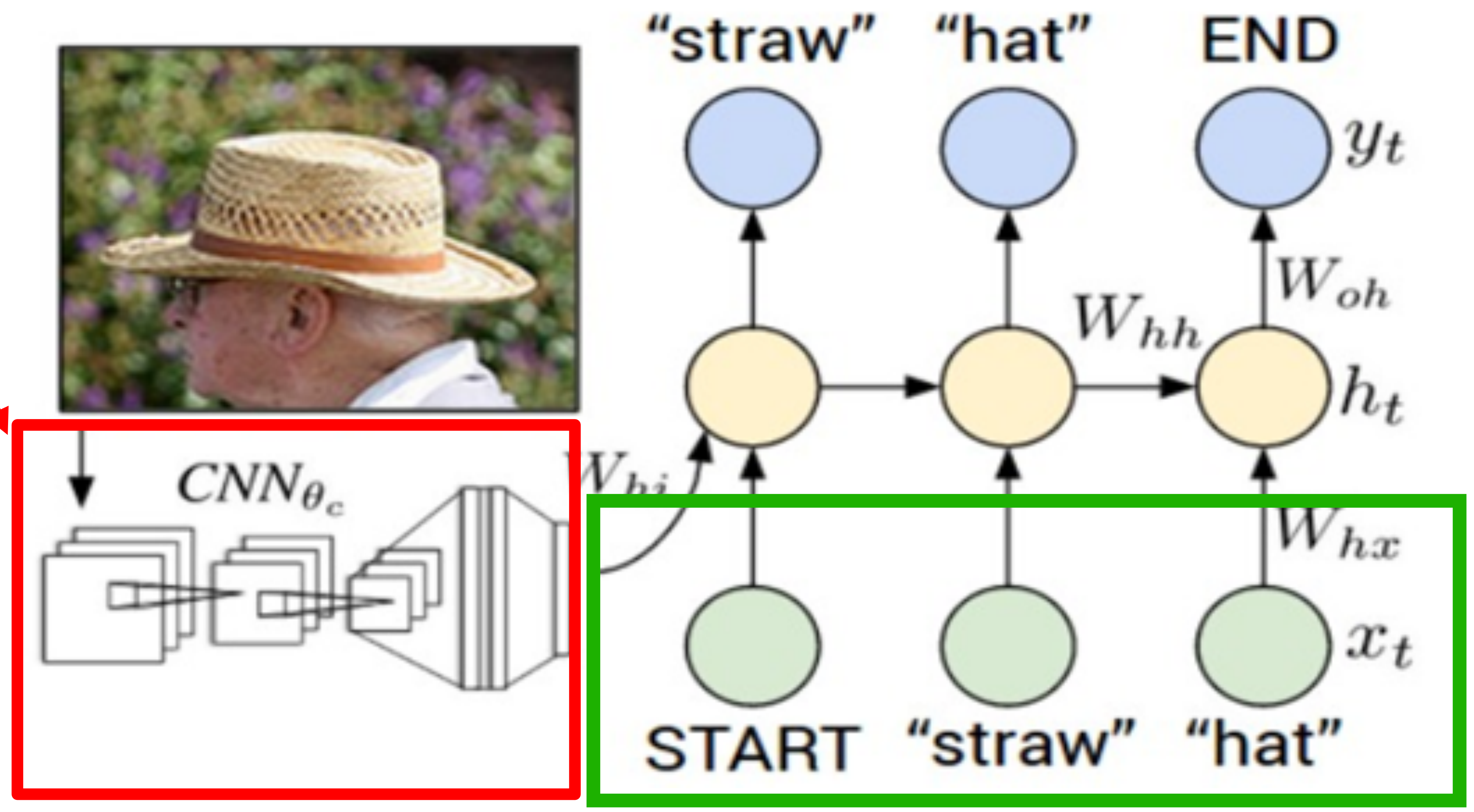
Its the norm, not the exception

Object Detection (Fast R-CNN)



CNN pretrained on ImageNet



Word vectors pretrained with word2vec

Girshick, "Fast R-CNN", ICCV 2015
Figure copyright Ross Girshick, 2015. Reproduced with permission.

Karpathy and Fei-Fei, "Deep Visual-Semantic Alignments for Generating Image Descriptions", CVPR 2015

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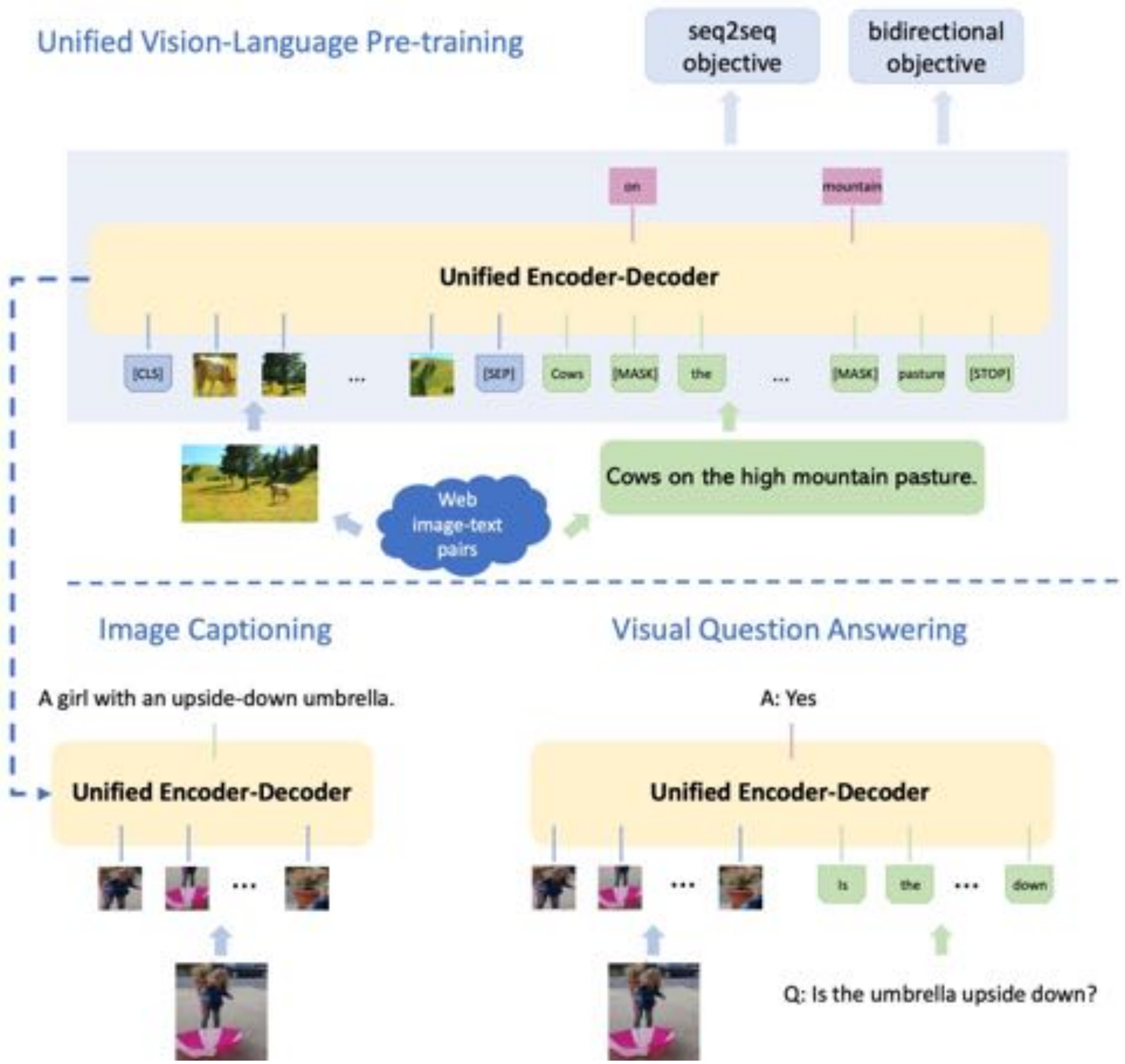
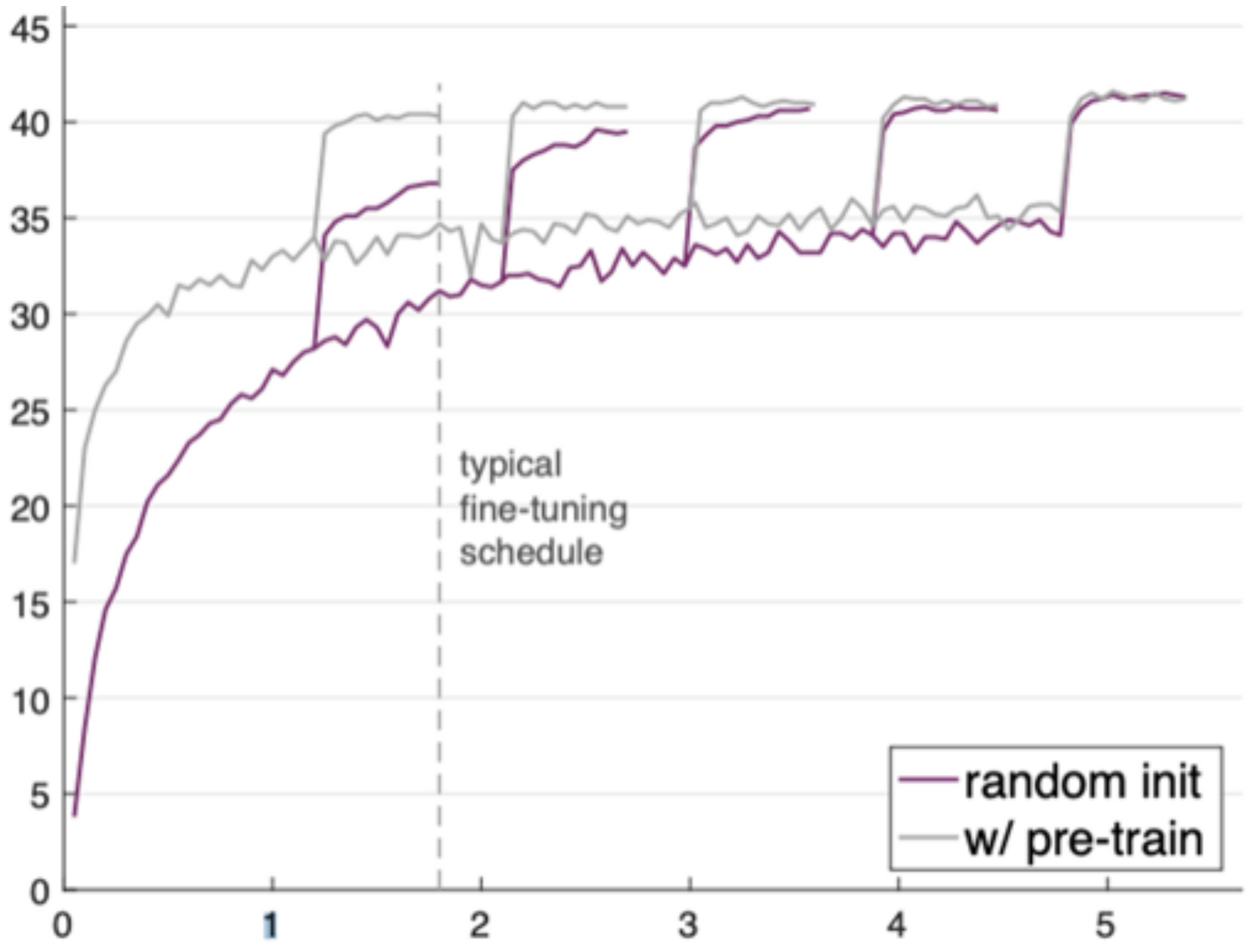


1. Train CNN on ImageNet
2. Fine-Tune (1) for object detection on Visual Genome
3. Train BERT language model on lots of text
4. Combine (2) and (3), train for joint image / language modeling
5. Fine-tune (5) for image captioning, visual question answering, etc.

Zhou et al, "Unified Vision-Language Pre-Training for Image Captioning and VQA", arXiv 2019

Transfer Learning is pervasive!
Some very recent results have questioned it

COCO object detection

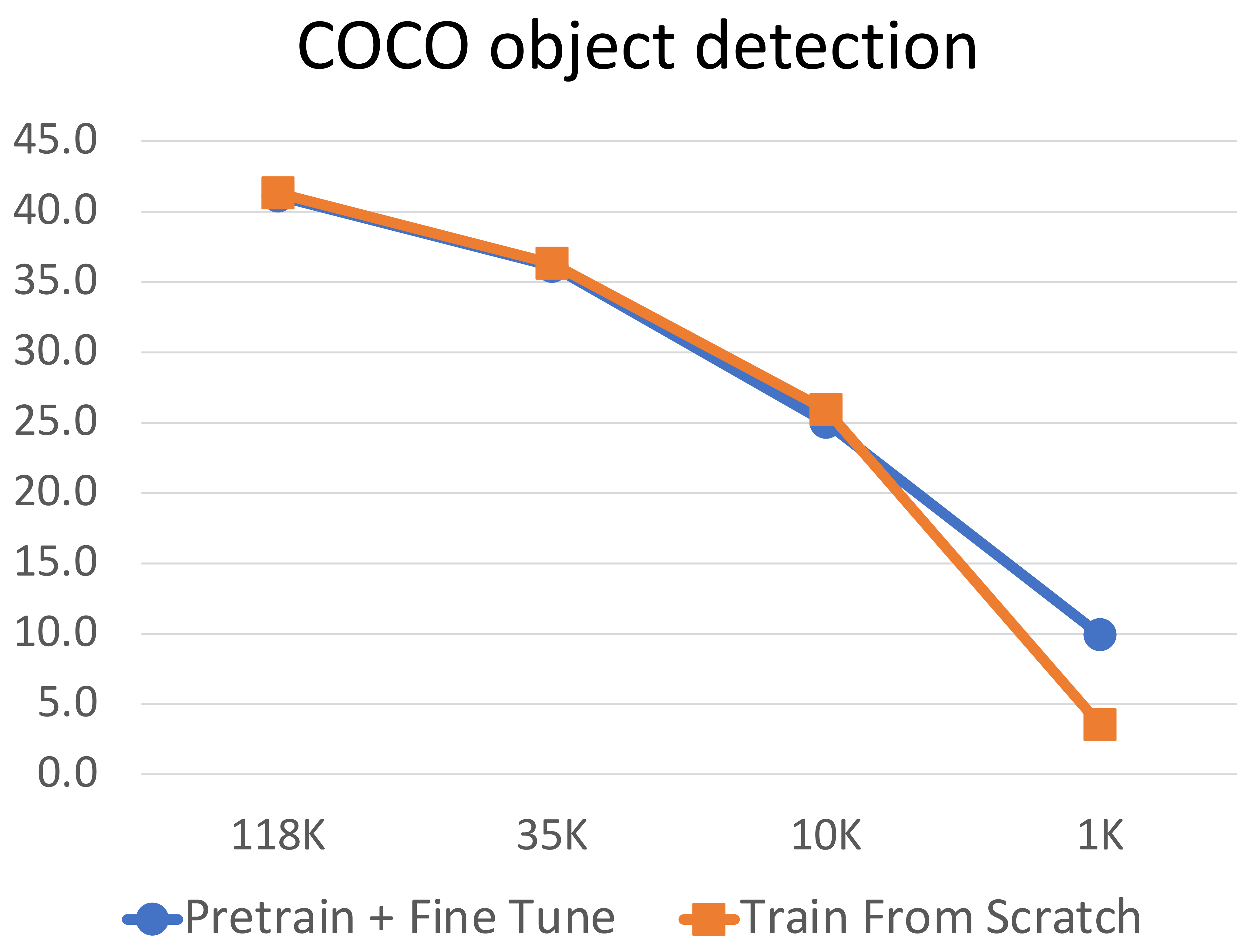


Training from scratch can work as well as pertaining on ImageNet!

… if you train for 3x as long

He et al, "Rethinking ImageNet Pre-Training", ICCV 2019

Transfer Learning is pervasive!
Some very recent results have questioned it



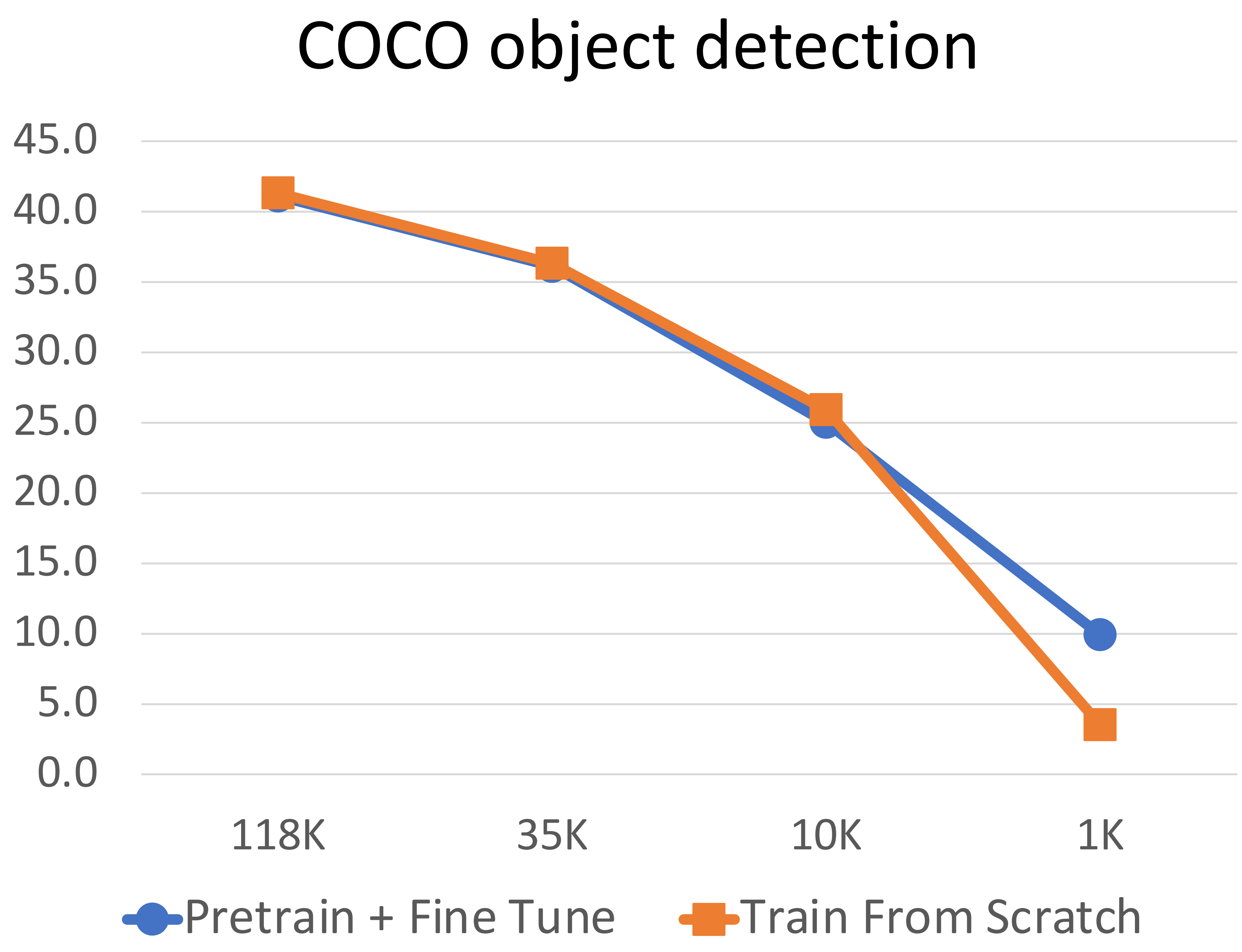
Pretraining + Finetuning beats training from scratch when dataset size is very small

Collecting more data is more effective than pretraining

He et al, "Rethinking ImageNet Pre-Training", ICCV 2019

Transfer Learning is pervasive!

Some very recent results have questioned it



My current view on transfer learning:

- Pretrain + finetune makes your training faster, so practically very useful
- Training from scratch works well once you have enough data
- Lots of work left to be done

He et al, "Rethinking ImageNet Pre-Training", ICCV 2019

Summary

1. **One time setup:** Last time
   - Activation functions, data preprocessing, weight initialization, regularization
2. **Training dynamics:** Today
   - Learning rate schedules; hyperparameter optimization
3. **After training:**
   - Model ensembles, transfer learning

Next Time: Deep Learning Software

DeepRob

Lecture 10
Training Neural Networks II
University of Michigan and University of Minnesota