Lecture 10:
Training Neural Networks
(Part 2)

Reminder: A3

Due Friday, February 11

Midterm

- Wednesday, February 23
- Will be remote as a Canvas quiz (most likely)
- Exam is 90 minutes
- You can take it any time in a 24-hour window
- We will have 3-4 "on-call" periods during the 24-hour window where GSIs will answer questions within ~15 minutes
- Open note
- True / False, multiple choice, short answer
- For short answer questions requiring math, either write LaTeX or upload an image with handwritten math

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

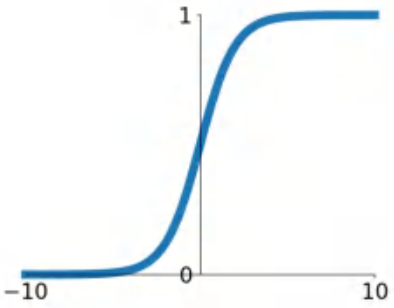
Last Time

Today

Last Time: Activation Functions

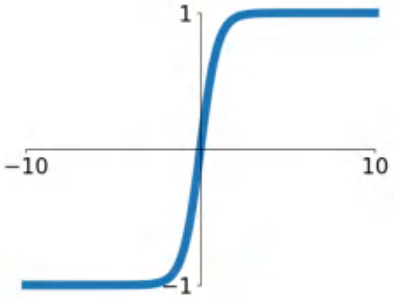
Sigmoid

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



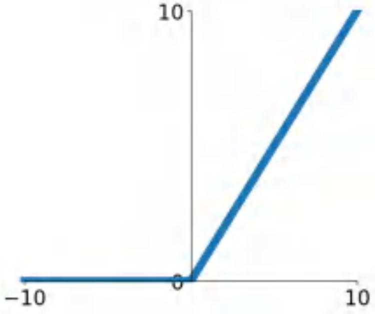
tanh

$\tanh(x)$



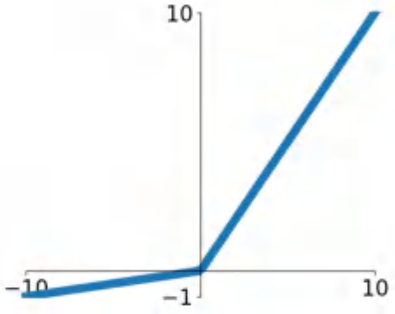
ReLU

$\max(0, x)$



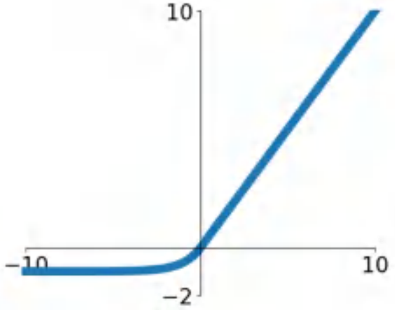
Leaky ReLU

$\max(0.1x, x)$



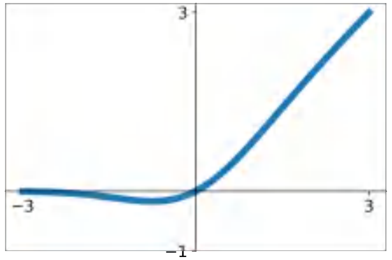
ELU

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

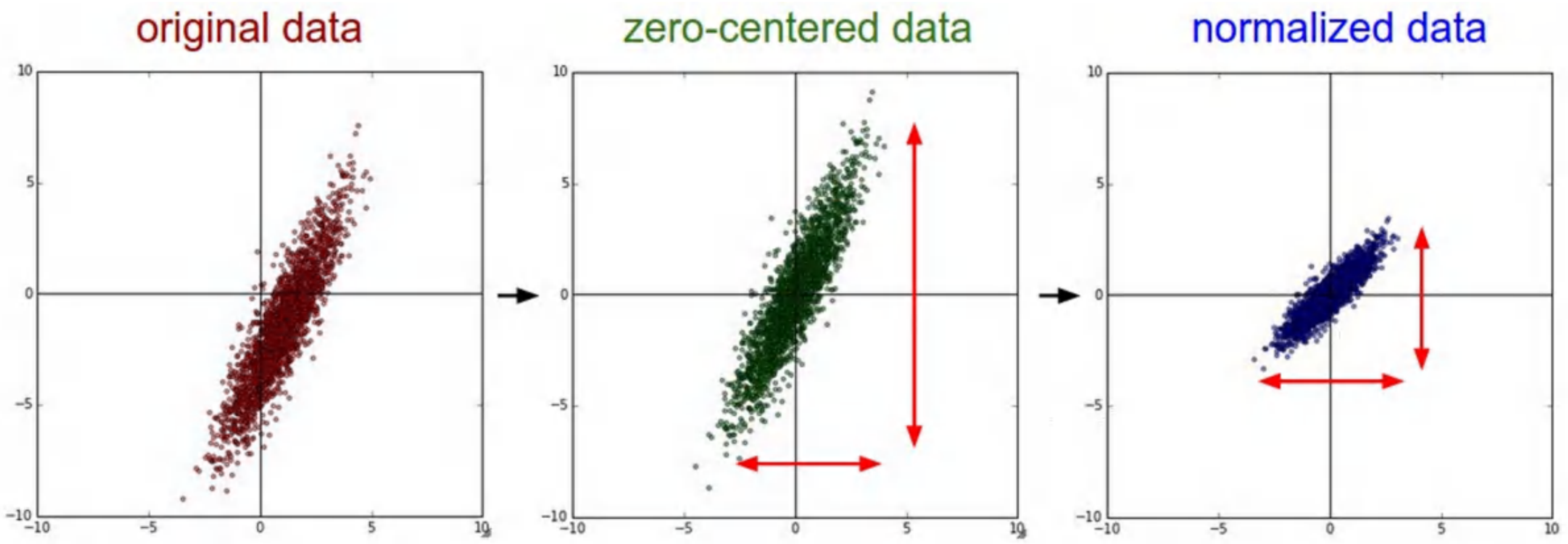


GELU

$\approx x\sigma(1.702x)$



Last Time: Data Preprocessing

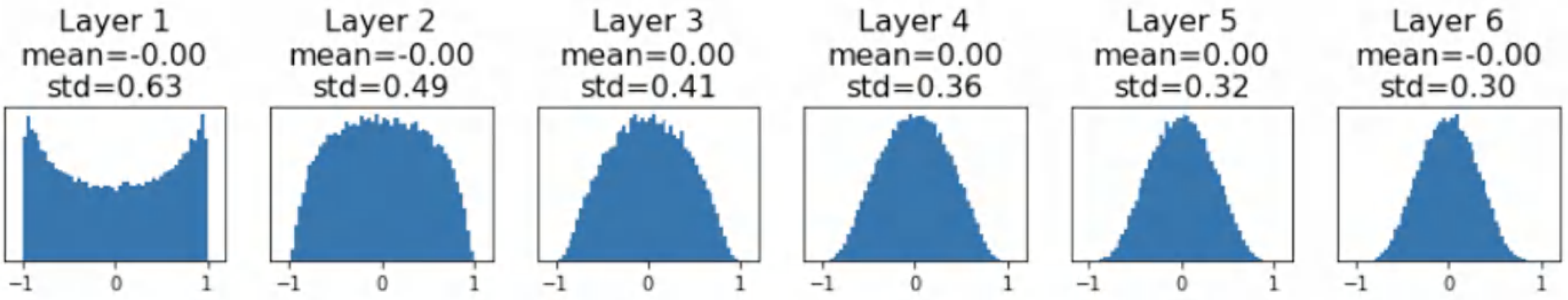


Last Time: Weight Initialization

```
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)

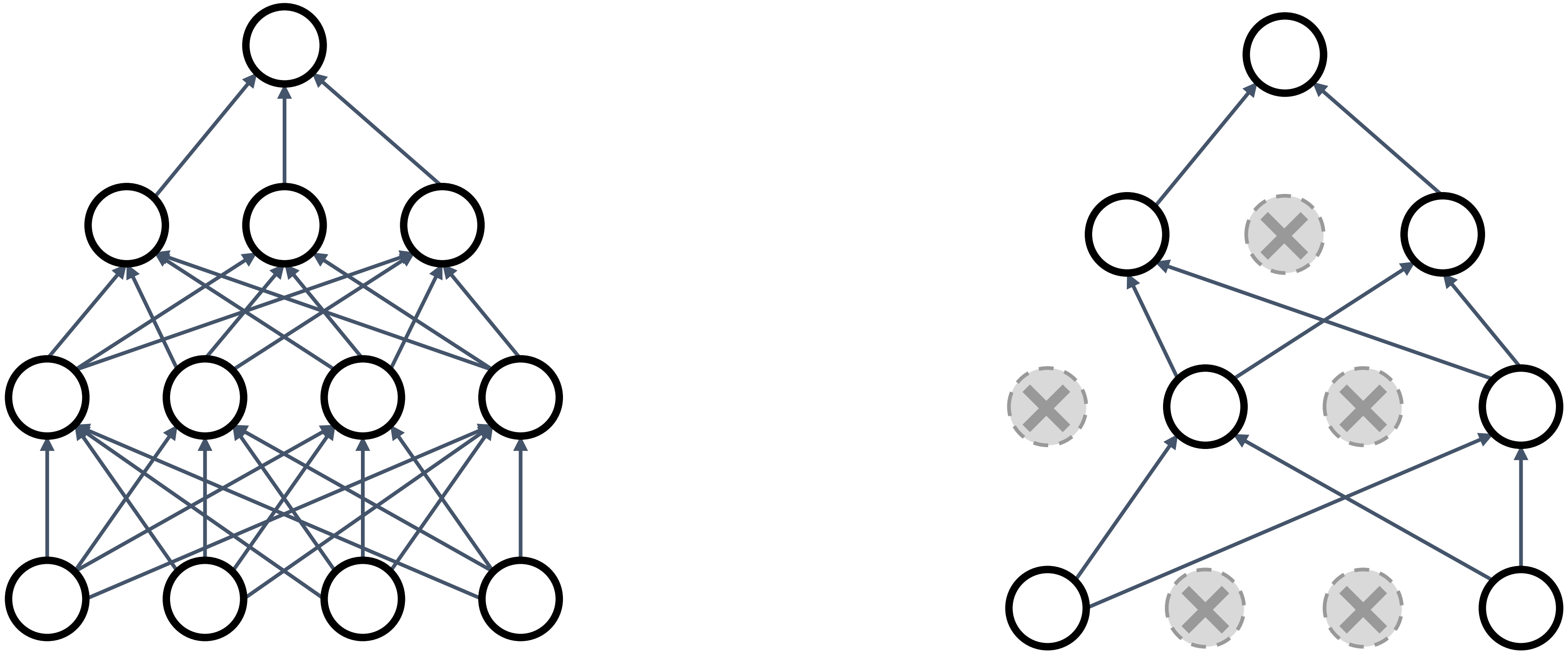
"Just right": Activations are nicely scaled for all layers!



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

Last Time: Dropout Regularization

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: A common pattern

Training: Add some kind of randomness

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

Testing: Average out randomness (sometimes approximate)

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

Regularization: A common pattern

Training: Add some kind of randomness

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

Testing: Average out randomness (sometimes approximate)

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

Example: Batch Normalization

Training: Normalize using stats from random minibatches

Testing: Use fixed stats to normalize

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)

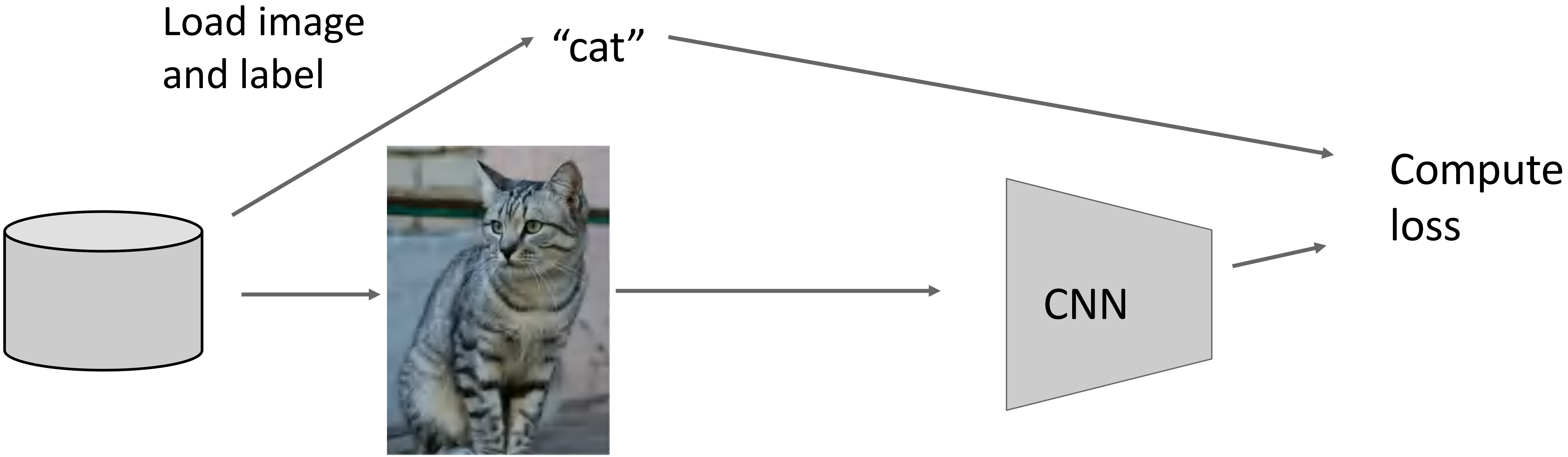
$$y = f(x) = E_z[f(x, z)] = \int p(z) f(x, z) dz$$

Example: Batch Normalization

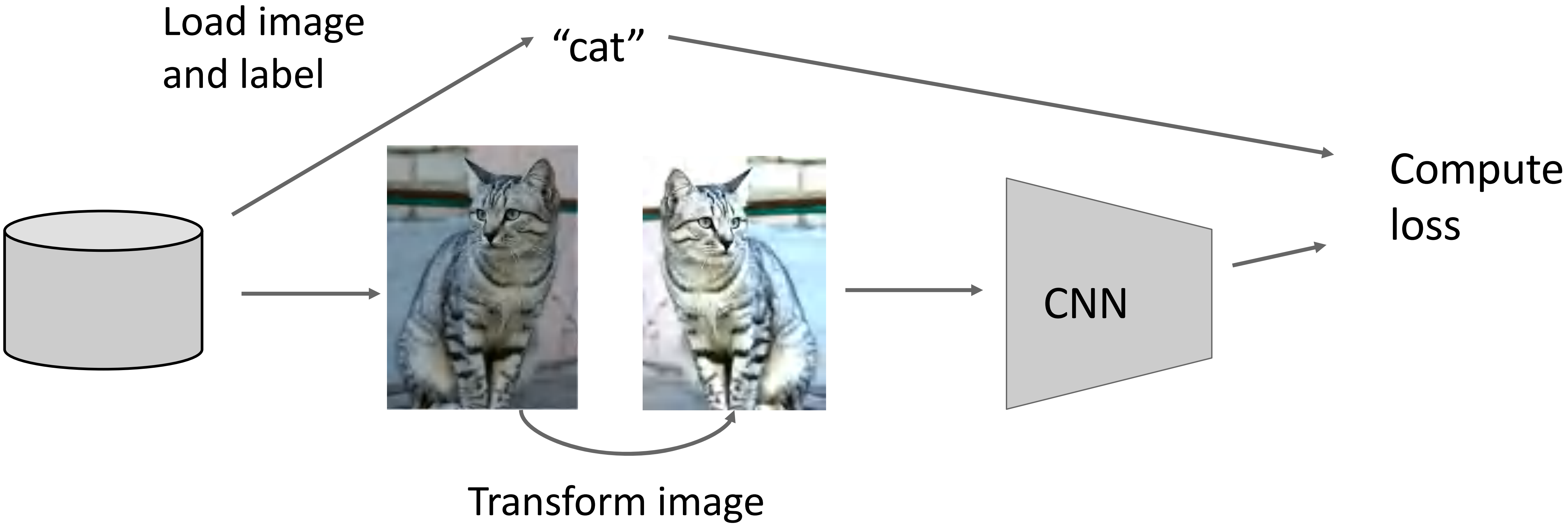
Training: Normalize using stats from random minibatches

Testing: Use fixed stats to normalize

Data Augmentation



Data Augmentation

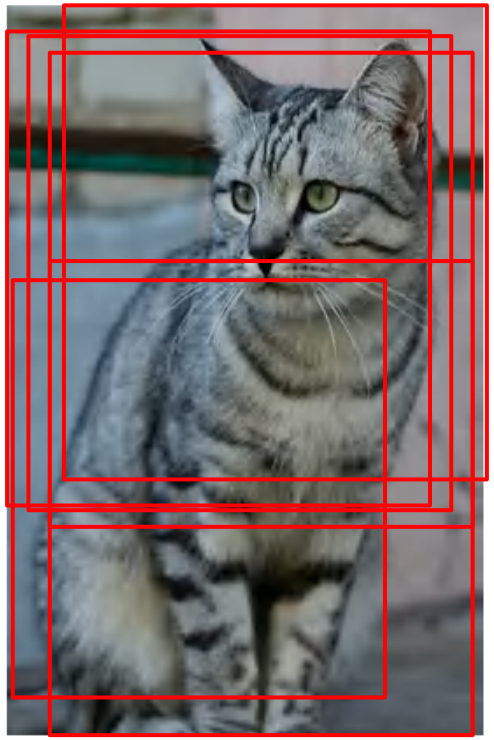


Data Augmentation: Horizontal Flips

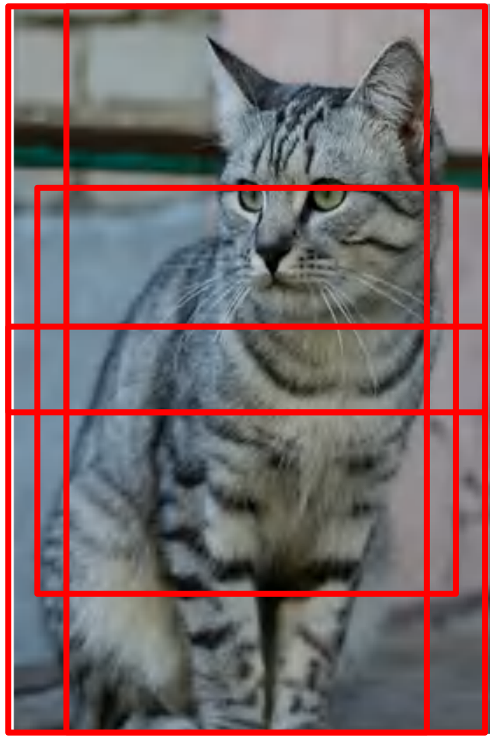
Data Augmentation: Random Crops and Scales

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



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

Apply random combinations of transforms:
- **Geometric**: Rotate, translate, shear
- **Color**: Sharpen, contrast, brightness, solarize, posterize, color

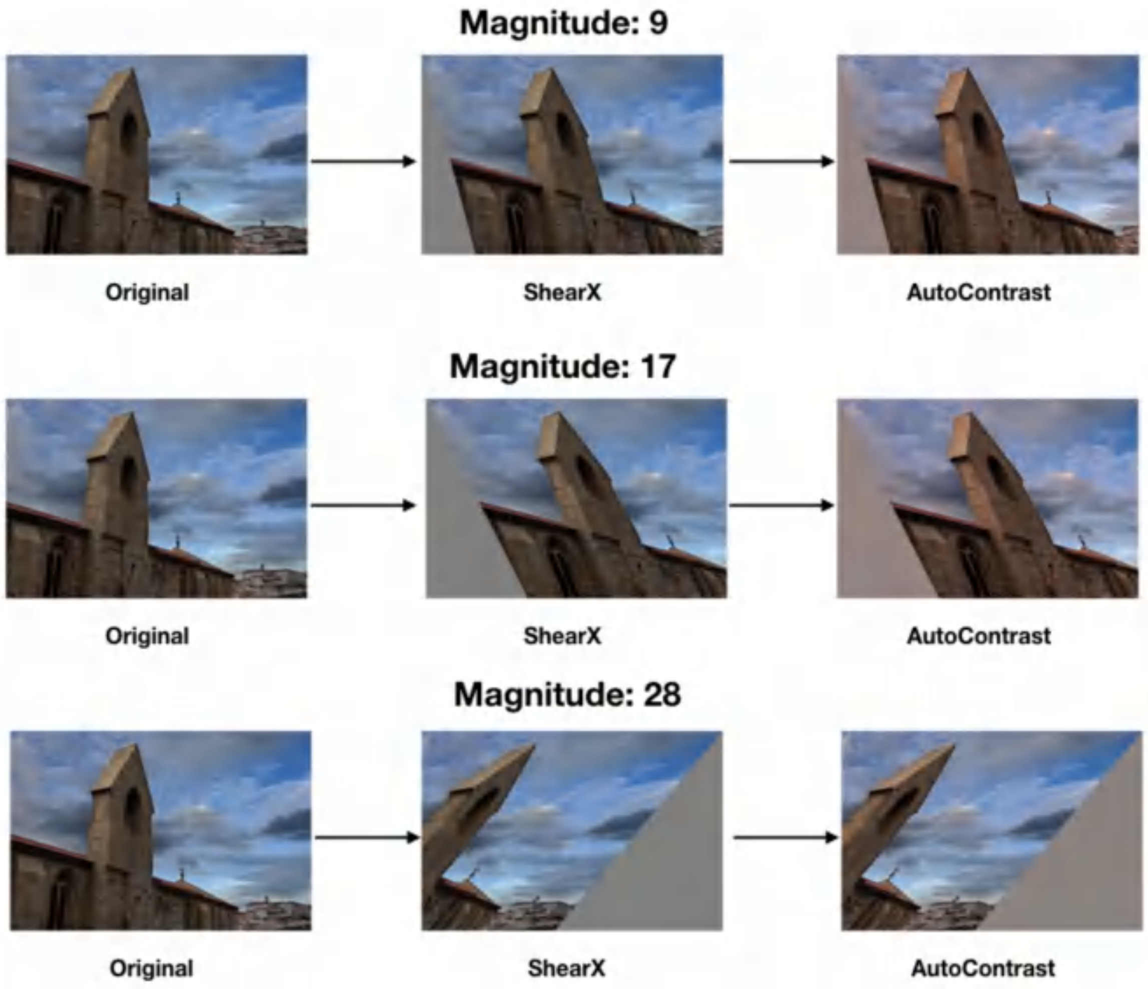
```
transforms = [
'Identity', 'AutoContrast', 'Equalize',
'Rotate', 'Solarize', 'Color', 'Posterize',
'Contrast', 'Brightness', 'Sharpness',
'ShearX', 'ShearY', 'TranslateX', 'TranslateY']

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]
```

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

Data Augmentation: RandAugment

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: 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?

May be different for different tasks!

Regularization: A common pattern

Training: Add some randomness

Testing: Marginalize over randomness

Examples:

Dropout

Batch Normalization

Data Augmentation

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

Regularization: DropConnect

Training: Drop random connections between neurons (set weight=0)

Testing: Use all the connections

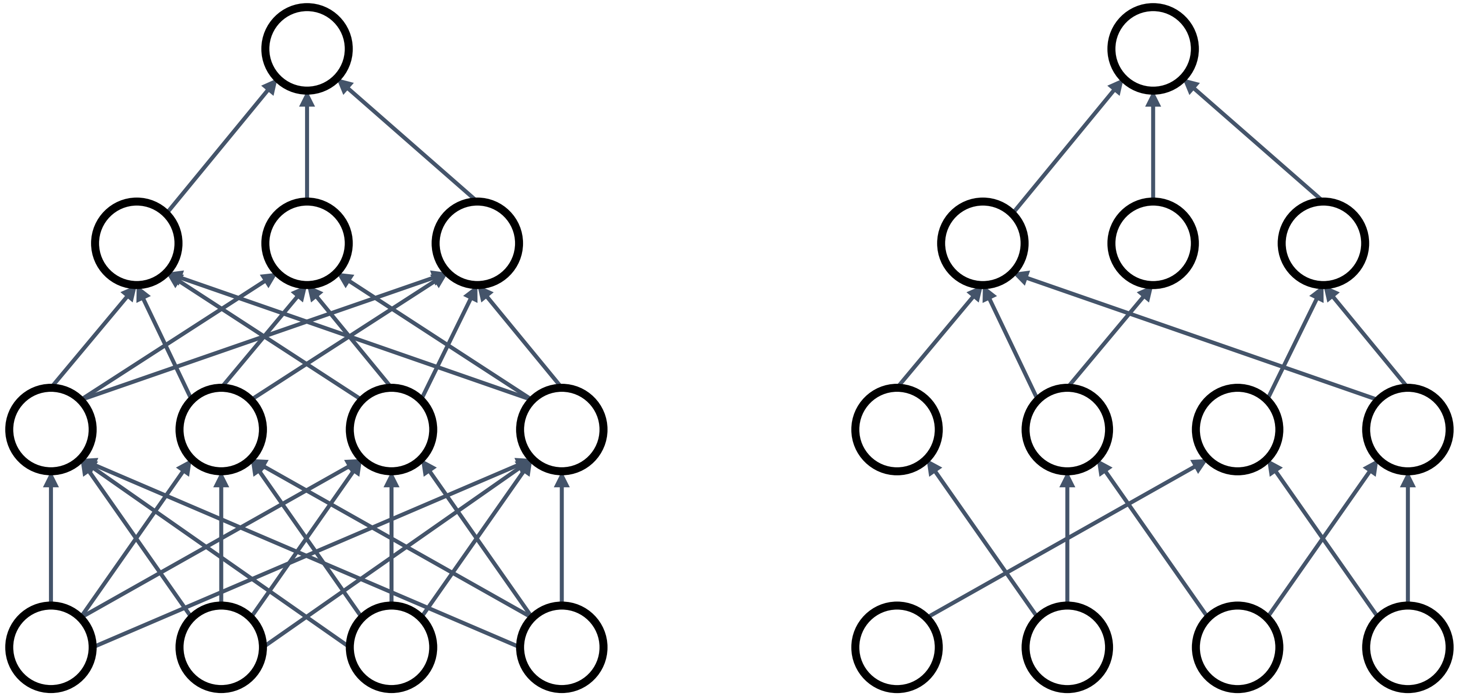
Examples:

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:

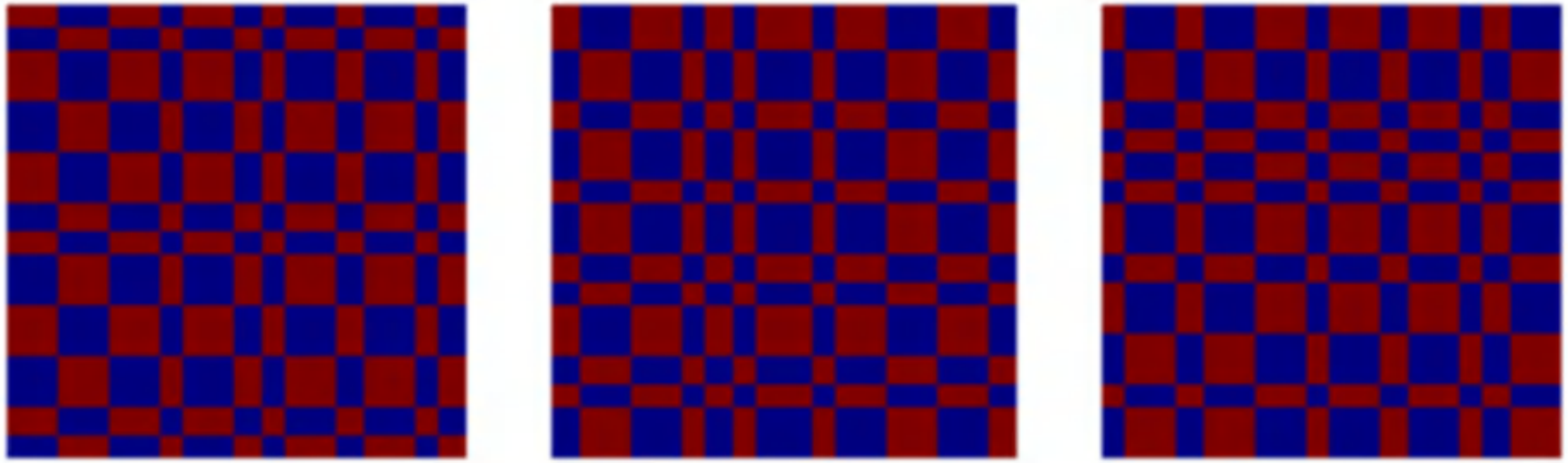
Dropout

Batch Normalization

Data Augmentation

DropConnect

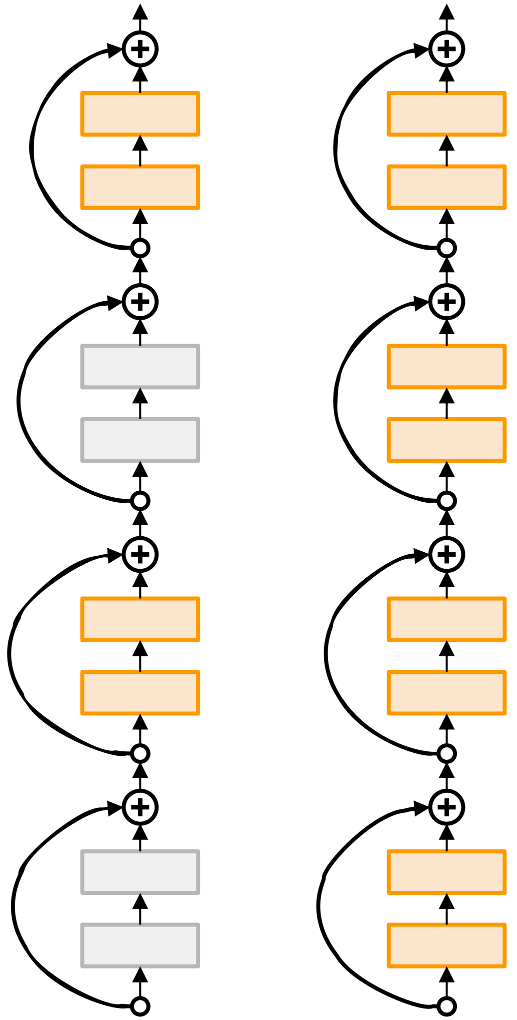
Fractional Max Pooling



Graham, "Fractional Max Pooling", arXiv 2014

Regularization: Stochastic Depth

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



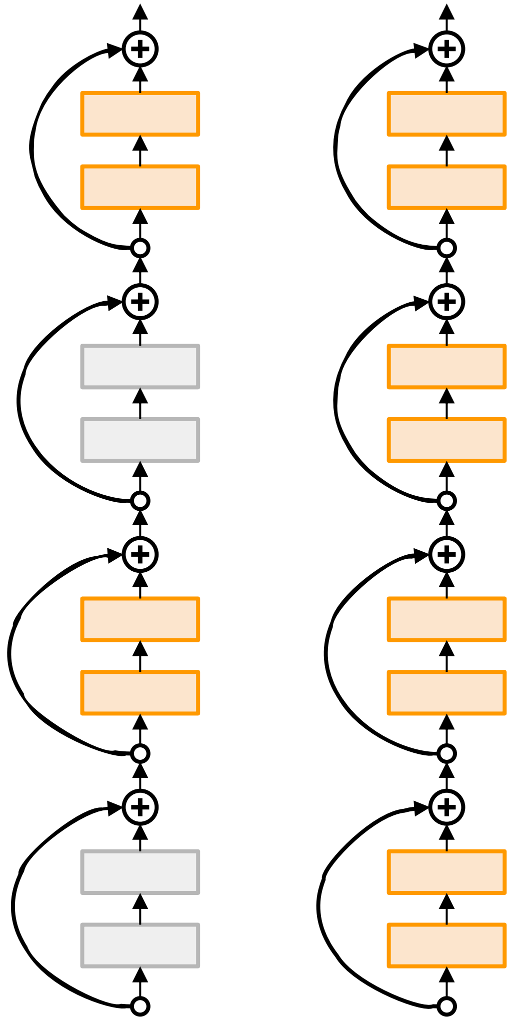
Examples:

Dropout
Batch Normalization
Data Augmentation
DropConnect
Fractional Max Pooling
Stochastic Depth

Huang et al, "Deep Networks with Stochastic Depth", ECCV 2016

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!

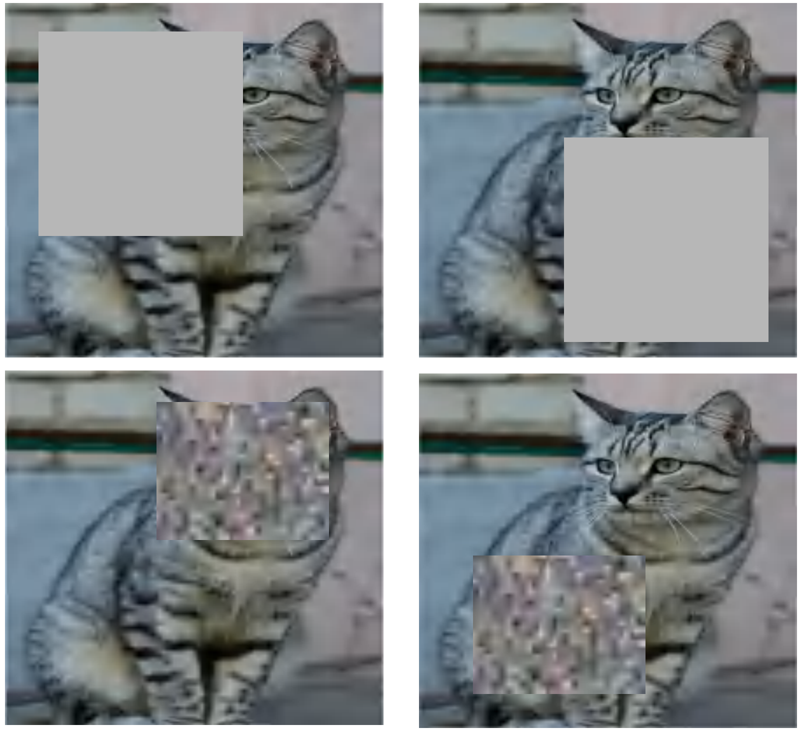
- Pham et al, “Very Deep Self-Attention Networks for End-to-End Speech Recognition”, INTERSPEECH 2019
- Tan and Le, “EfficientNetV2: Smaller Models and Faster Training”, ICML 2021
- Fan et al, “Multiscale Vision Transformers”, ICCV 2021
- Bello et al, “Revisiting ResNets: Improved Training and Scaling 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 images 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

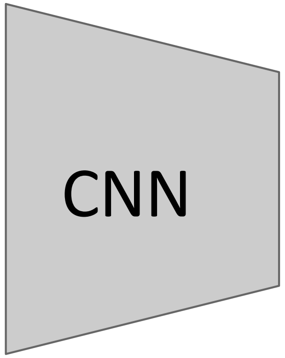
Regularization: Mixup

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



Target label:
cat: 0.4
dog: 0.6

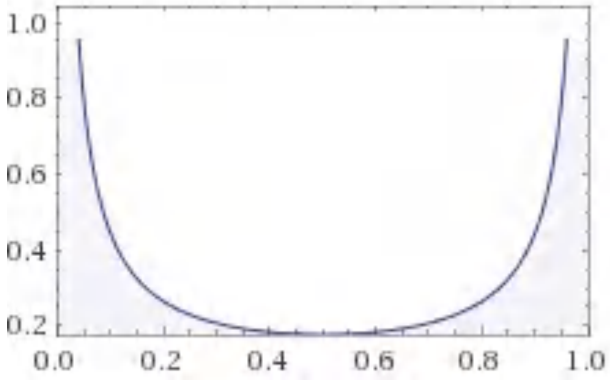
Randomly blend the pixels of pairs of training images, e.g. 40% cat, 60% dog

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

Regularization: Mixup

Training: Train on random blends of images

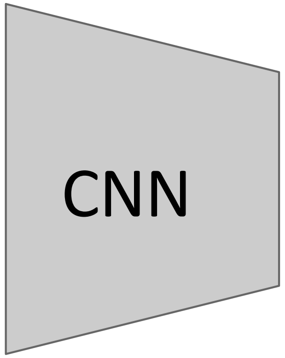
Testing: Use original images



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

Examples:

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



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

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

Regularization: CutMix

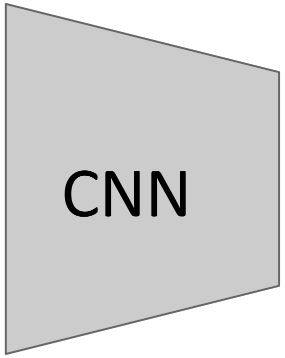
Training: Train on random blends of images

Testing: Use original images

Examples:

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

Replace random crops of one image with another: e.g. 60% of pixels from cat, 40% from dog



Target label:
cat: 0.6
dog: 0.4

Regularization: Label Smoothing

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

Training: Change target distribution

Testing: Take argmax over predictions

Examples:

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

Target Distribution

Standard Training	Label Smoothing
Cat: 100%	Cat: 90%
Dog: 0%	Dog: 5%
Fish: 0%	Fish: 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.

Regularization: Summary

Training: Add 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 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

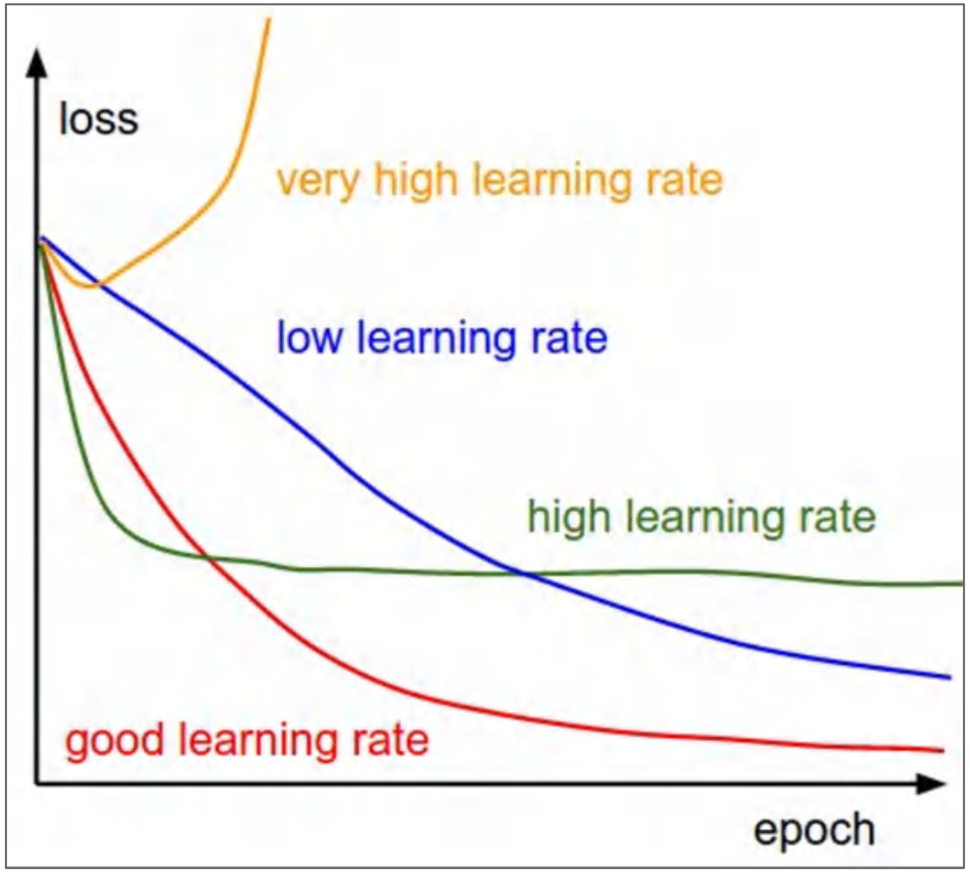
Overview

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

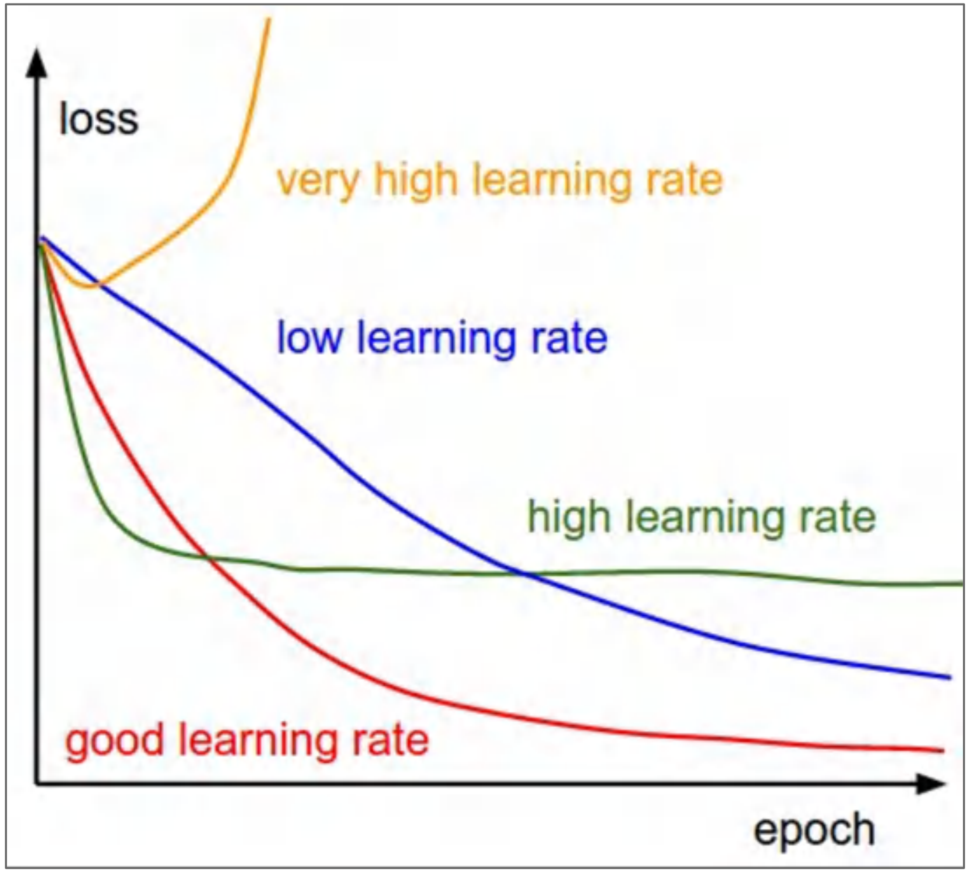
Today

Learning Rate Schedules

SGD, SGD+Momentum, Adagrad, RMSProp, Adam all have **learning rate** as a hyperparameter.

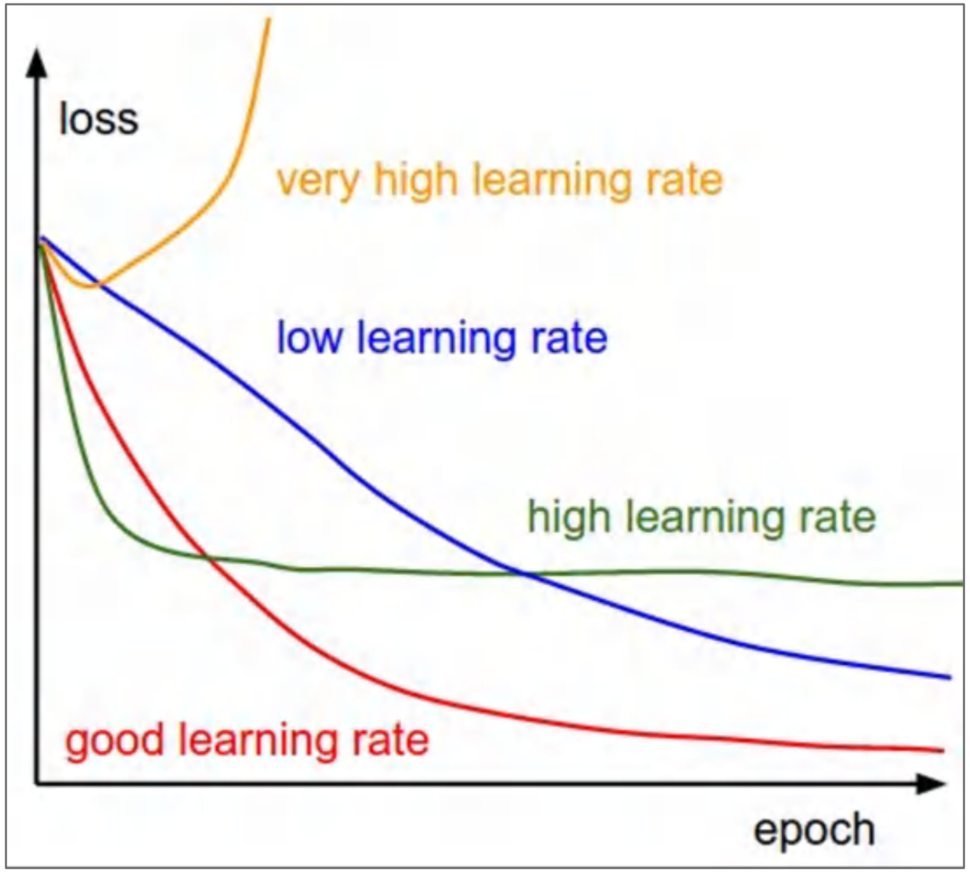


SGD, SGD+Momentum, Adagrad, RMSProp, Adam
all have **learning rate** as a hyperparameter.



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

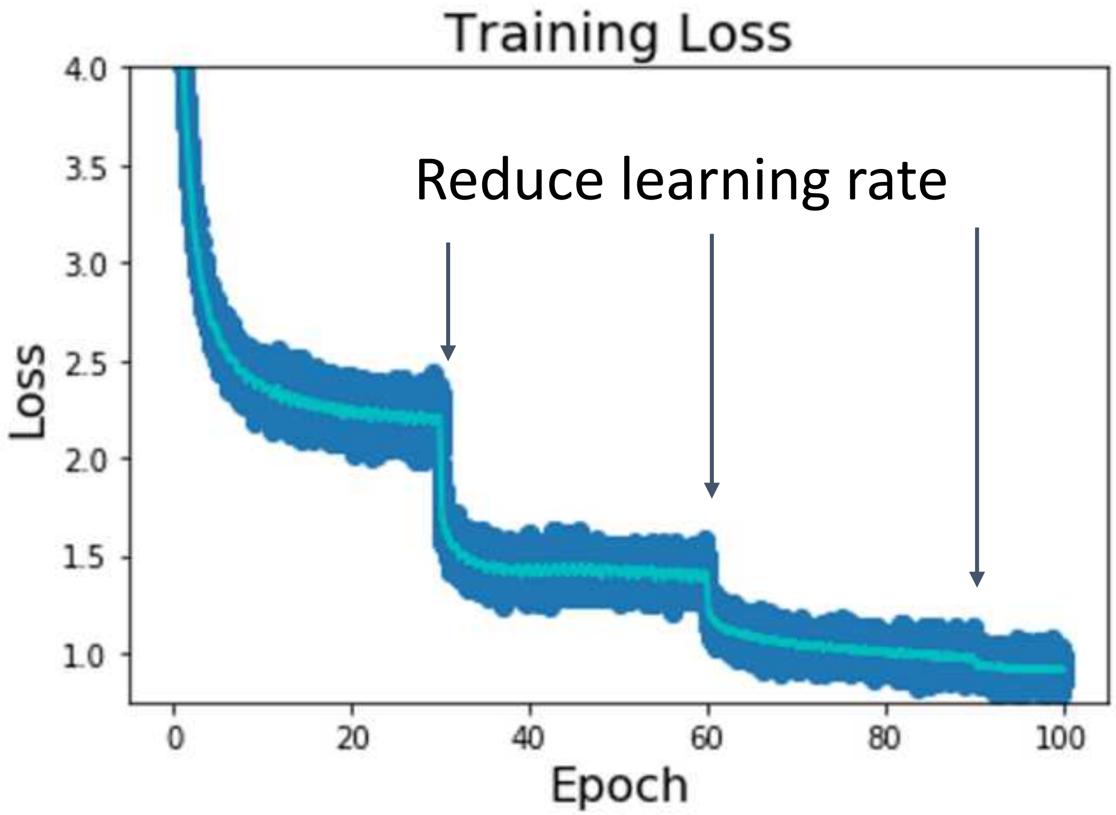
SGD, SGD+Momentum, Adagrad, RMSProp, Adam
all have **learning rate** as a hyperparameter.



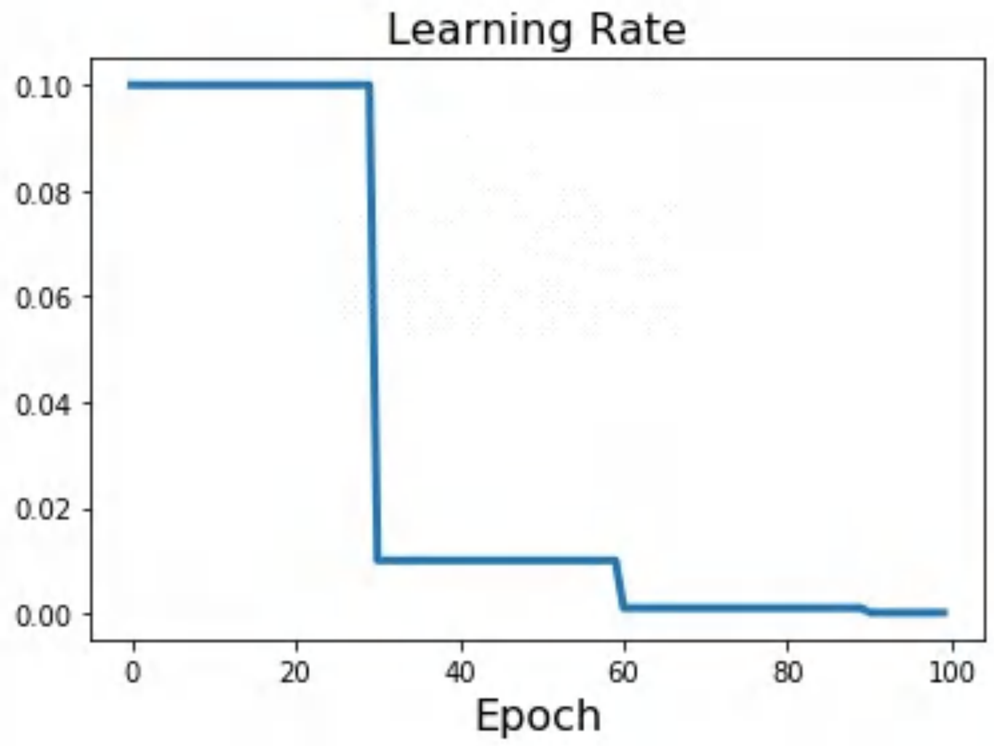
Q: Which one of these learning rates is best to use?

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

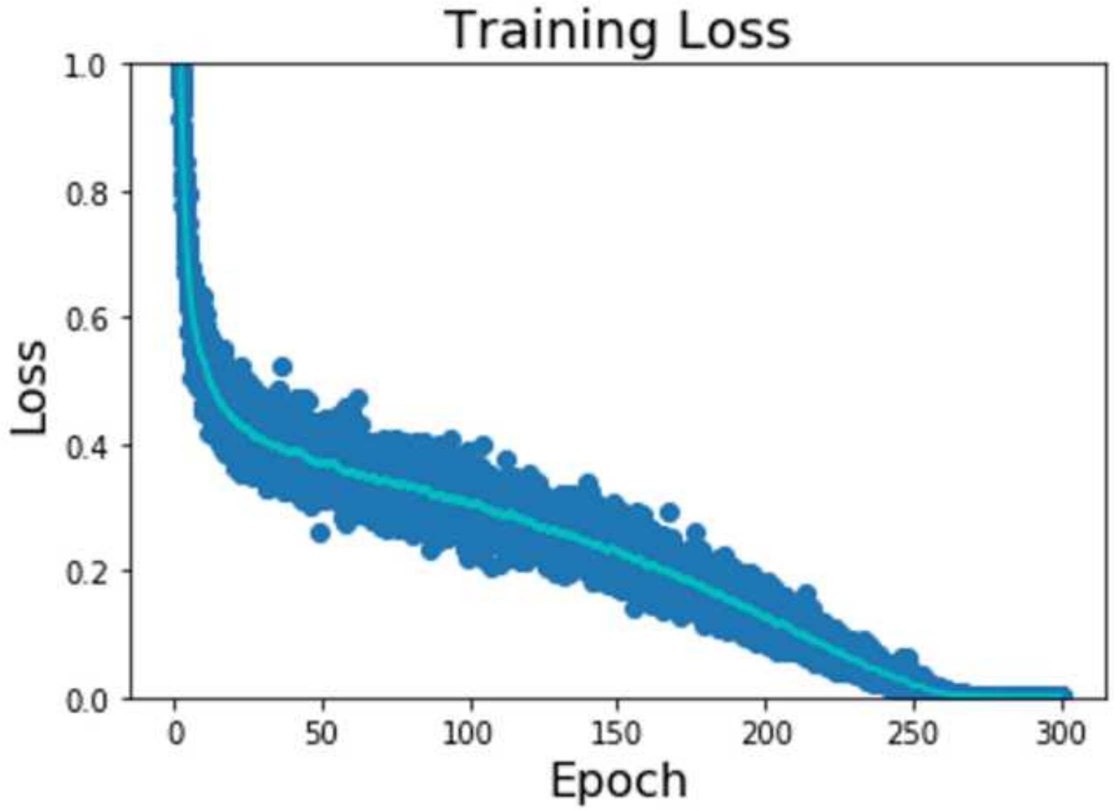
Learning Rate Decay: Step



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

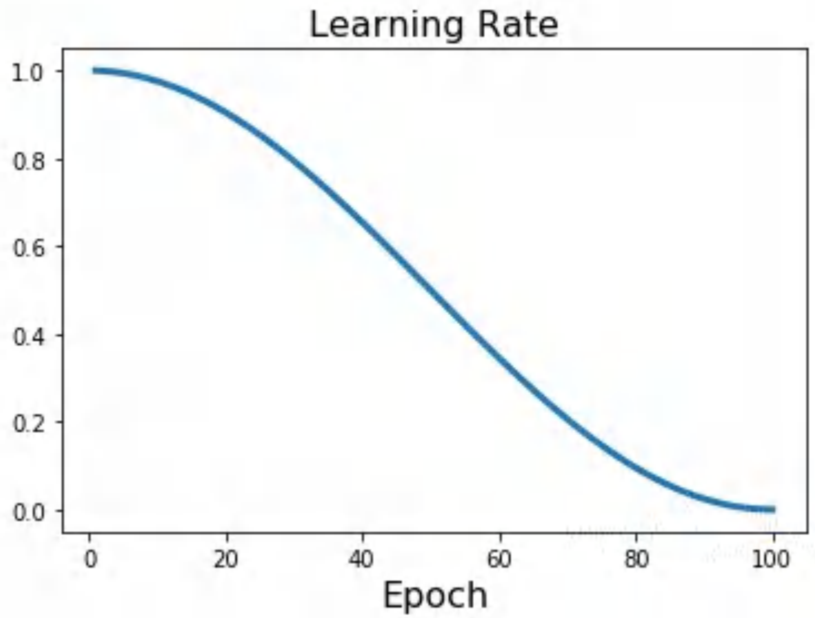


Learning Rate Decay: Cosine



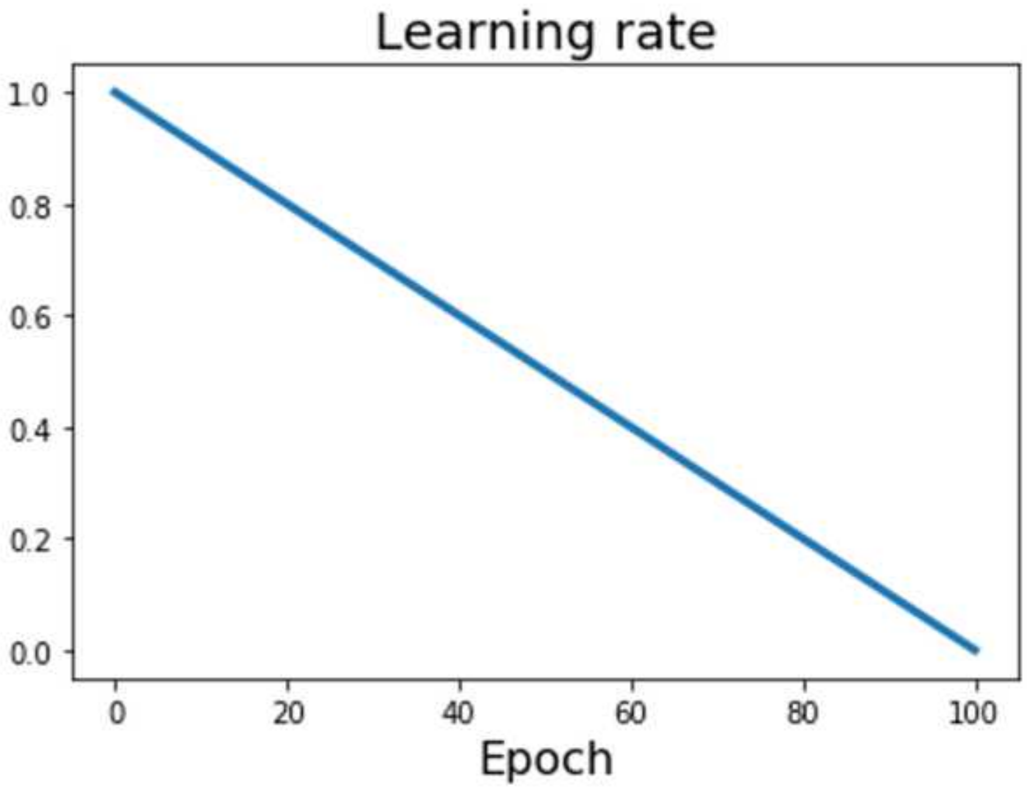
Step: Reduce learning rate at a few fixed points. E.g. for ResNets, multiply LR by 0.1 after epochs 30, 60, and 90.

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



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



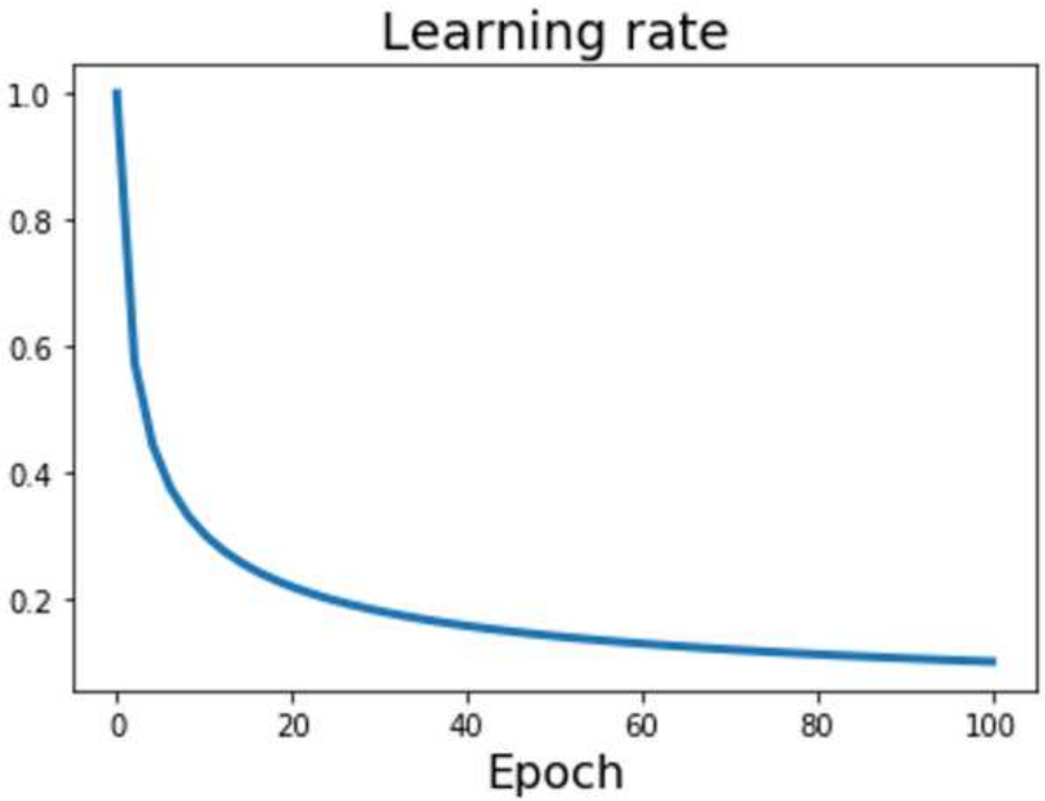
Step: Reduce learning rate at a few fixed points. E.g. for ResNets, multiply LR by 0.1 after epochs 30, 60, and 90.

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

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

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



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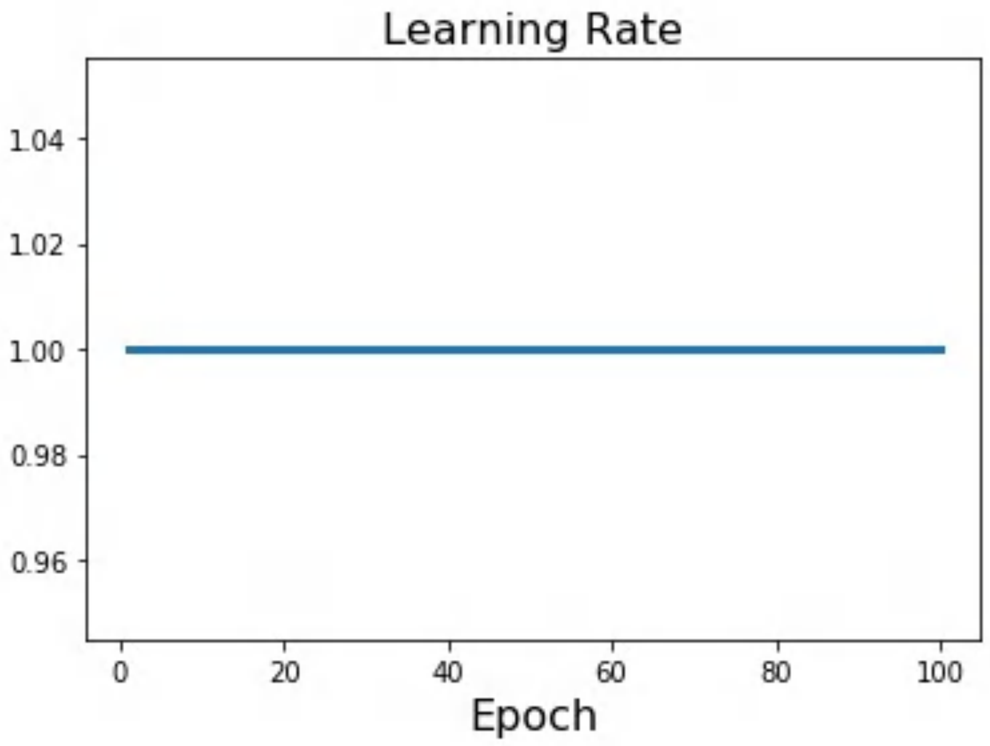
Cosine: $$\alpha_t = \frac{1}{2}\alpha_0\left(1 + \cos\left(\frac{t\pi}{T}\right)\right)$$

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

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

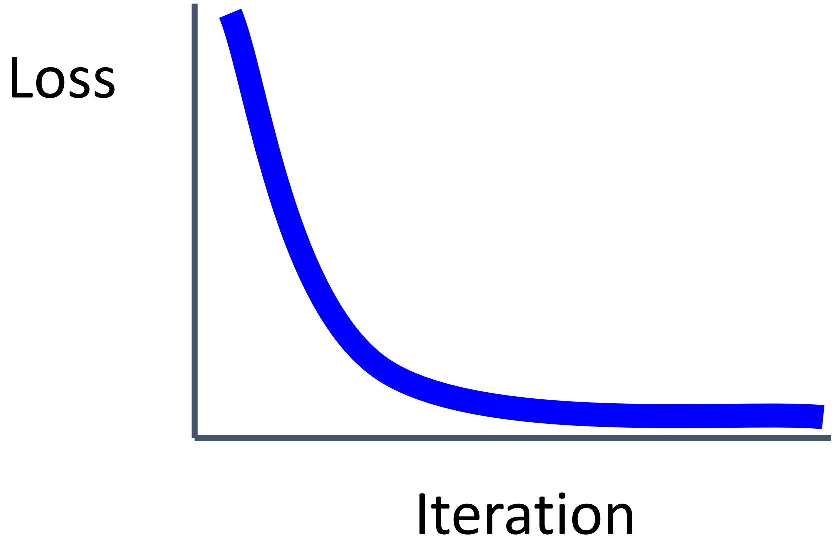
Linear: $\alpha_t = \alpha_0\left(1 - \frac{t}{T}\right)$

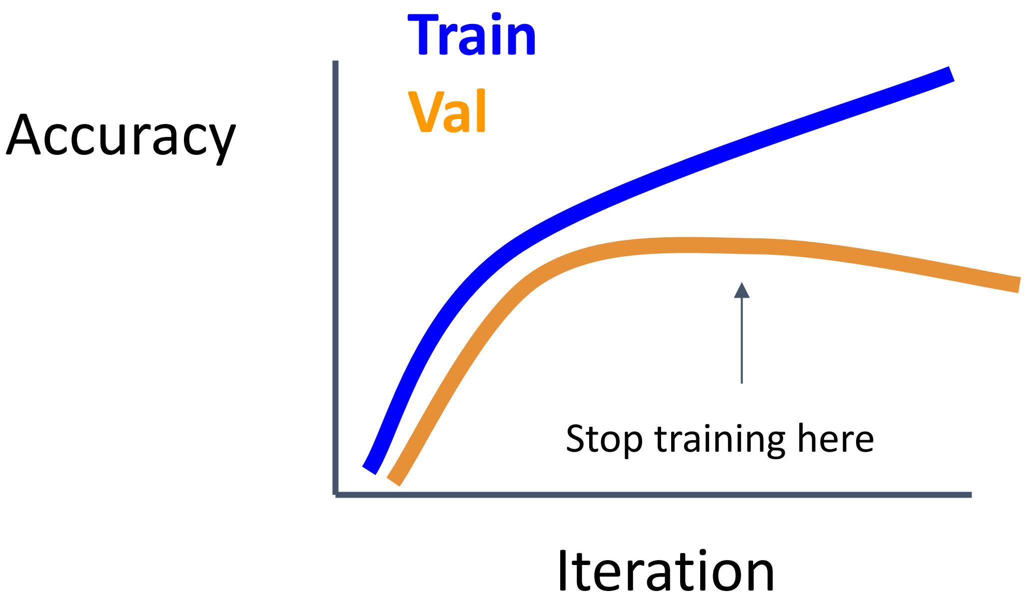
Inverse sqrt: $\alpha_t = \alpha_0/\sqrt{t}$

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 hyperparameter
(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**

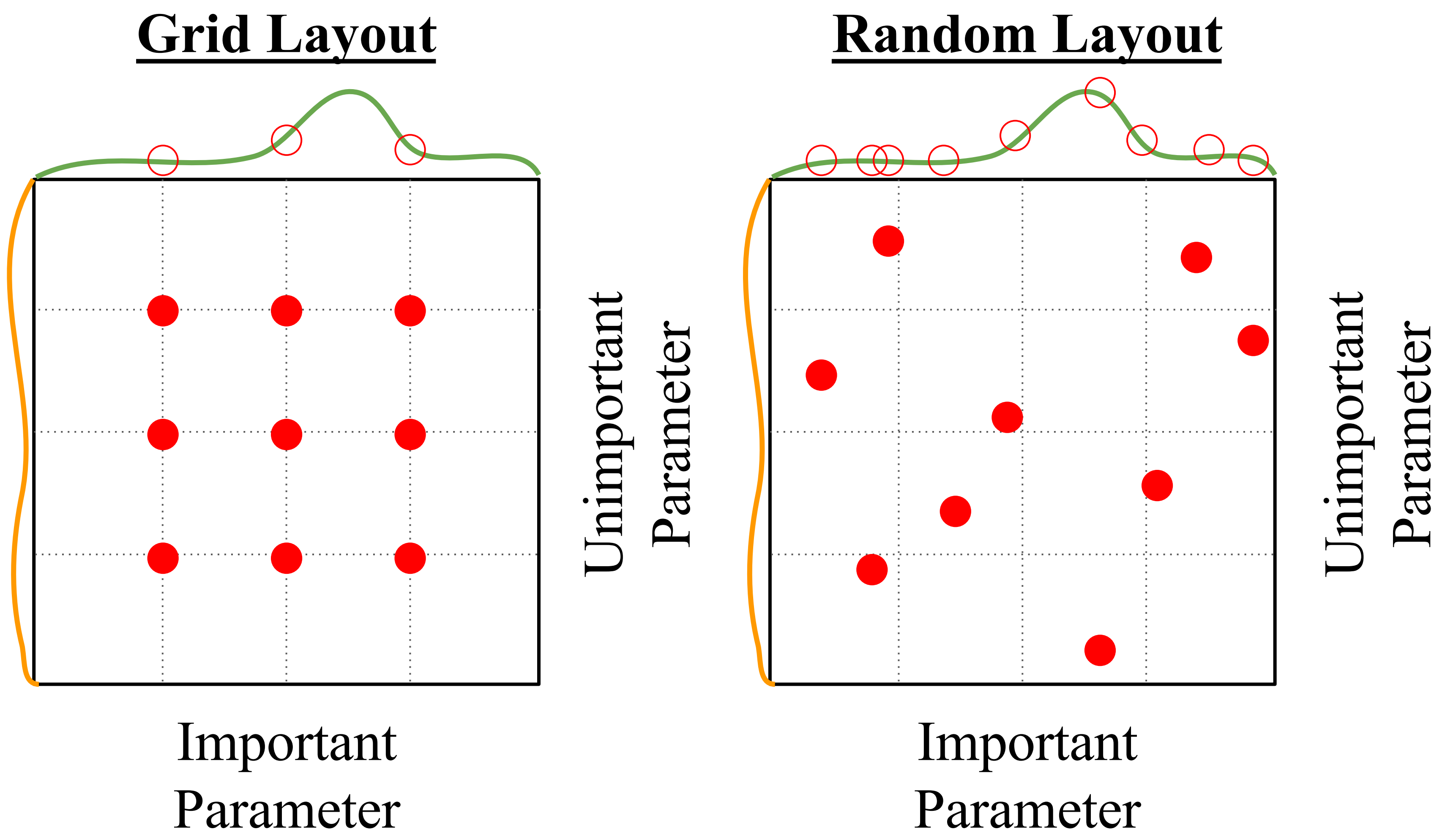
Choosing Hyperparameters: Random Search

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

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

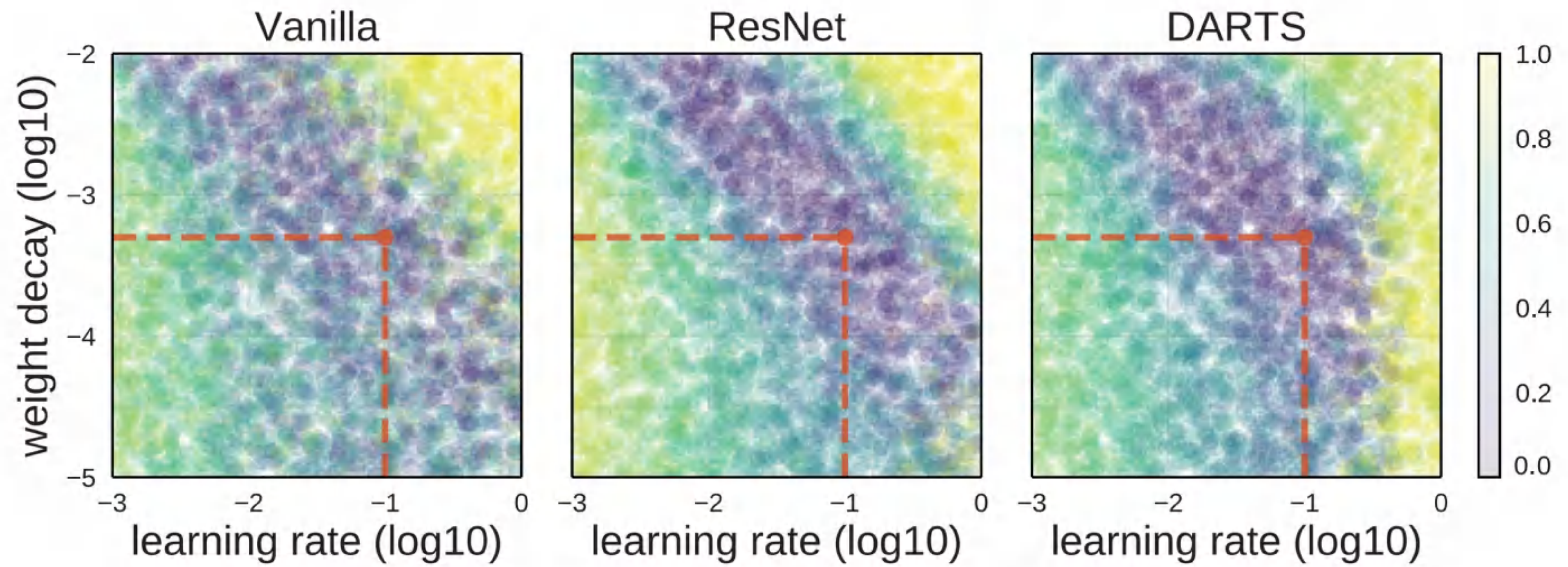
Run many different trials

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 minibatches); 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 weight decay to try: 1e-4, 1e-5, 0

Choosing Hyperparameters

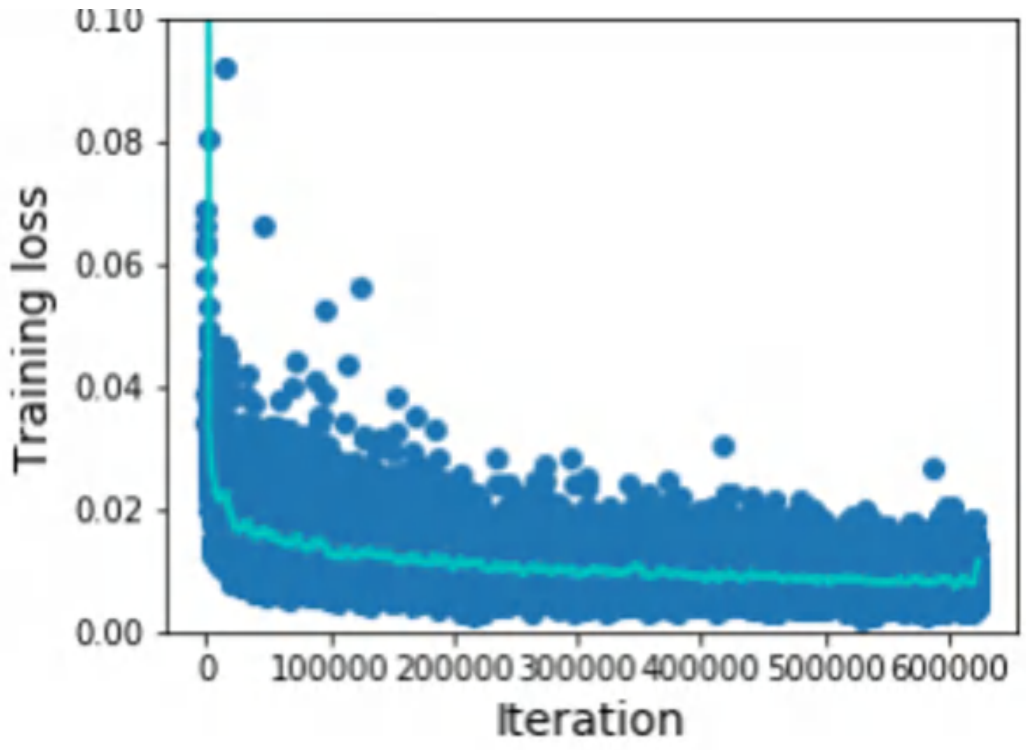
Step 1: Check initial loss
Step 2: Overfit a small sample
Step 3: Find LR that makes loss go down
Step 4: Coarse grid, train for ~1-5 epochs
Step 5: Refine grid, train longer

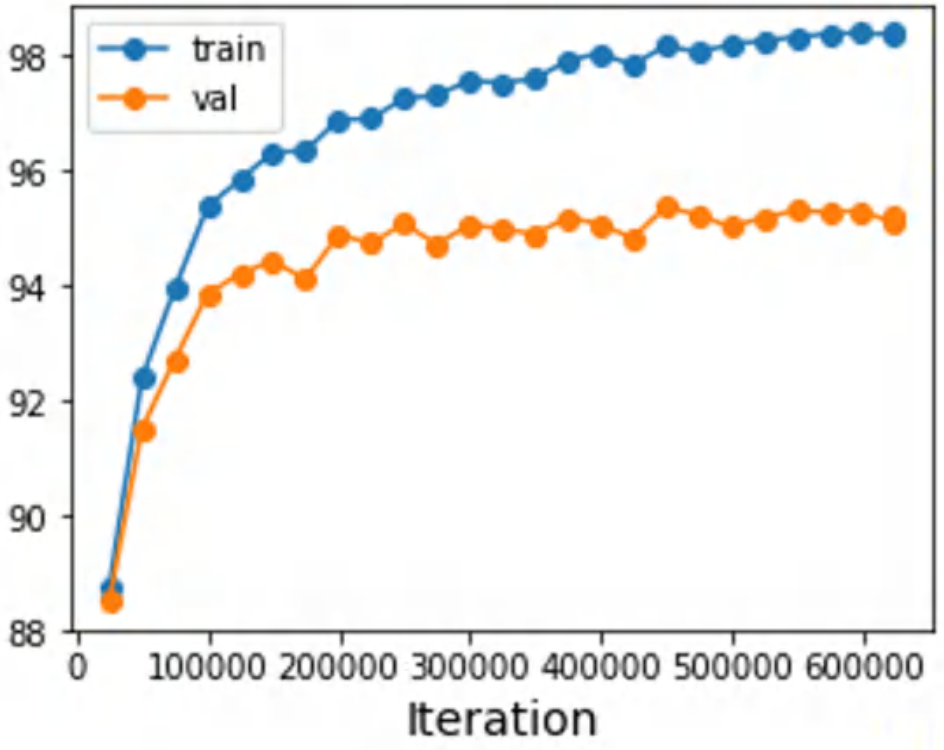
Pick best models from Step 4, train them for longer (~10-20 epochs) without learning rate decay

Choosing Hyperparameters

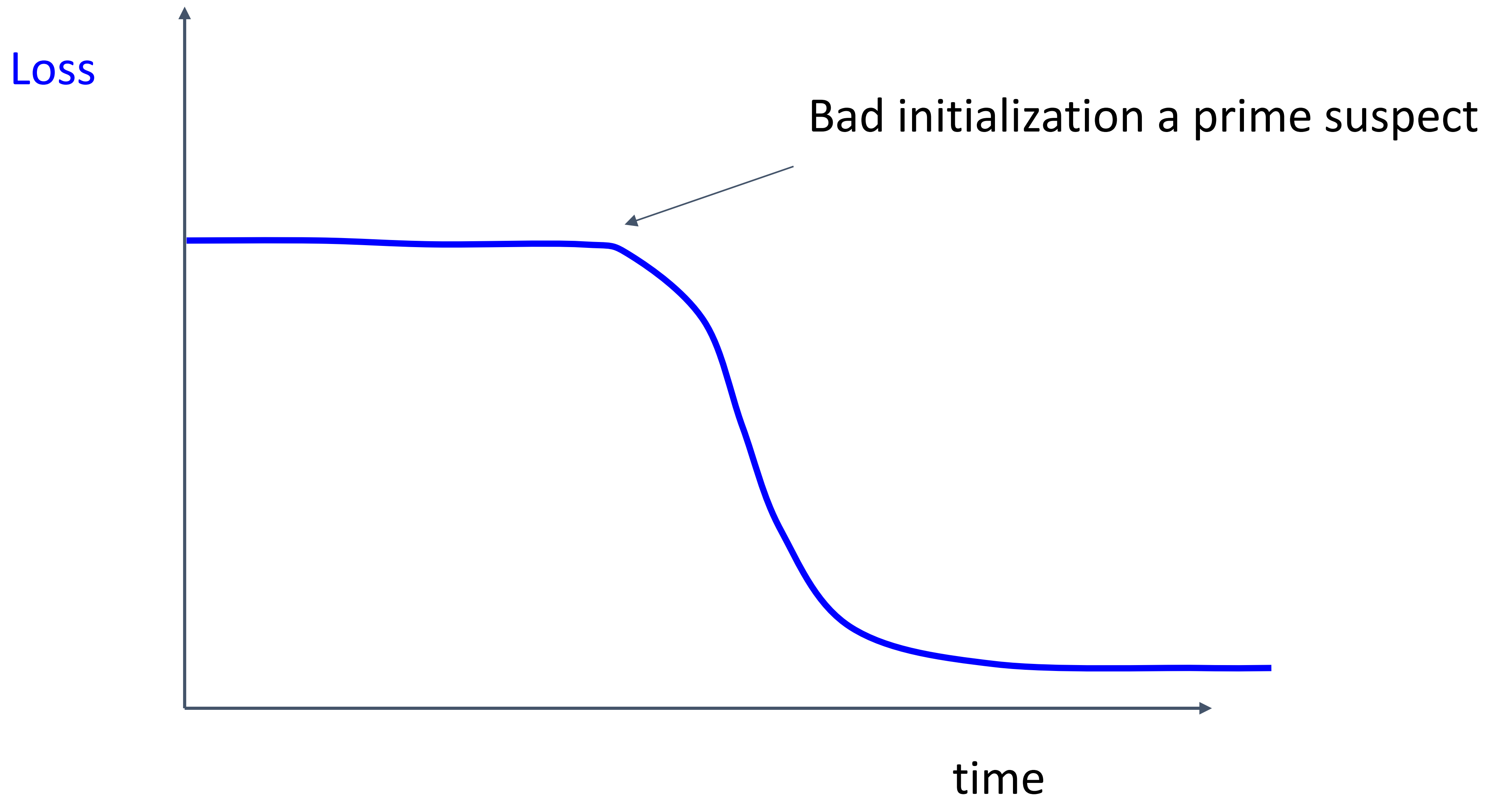
Step 1: Check initial loss
Step 2: Overfit a small sample
Step 3: Find LR that makes loss go down
Step 4: Coarse grid, train for ~1-5 epochs
Step 5: Refine grid, train longer
Step 6: Look at learning curves

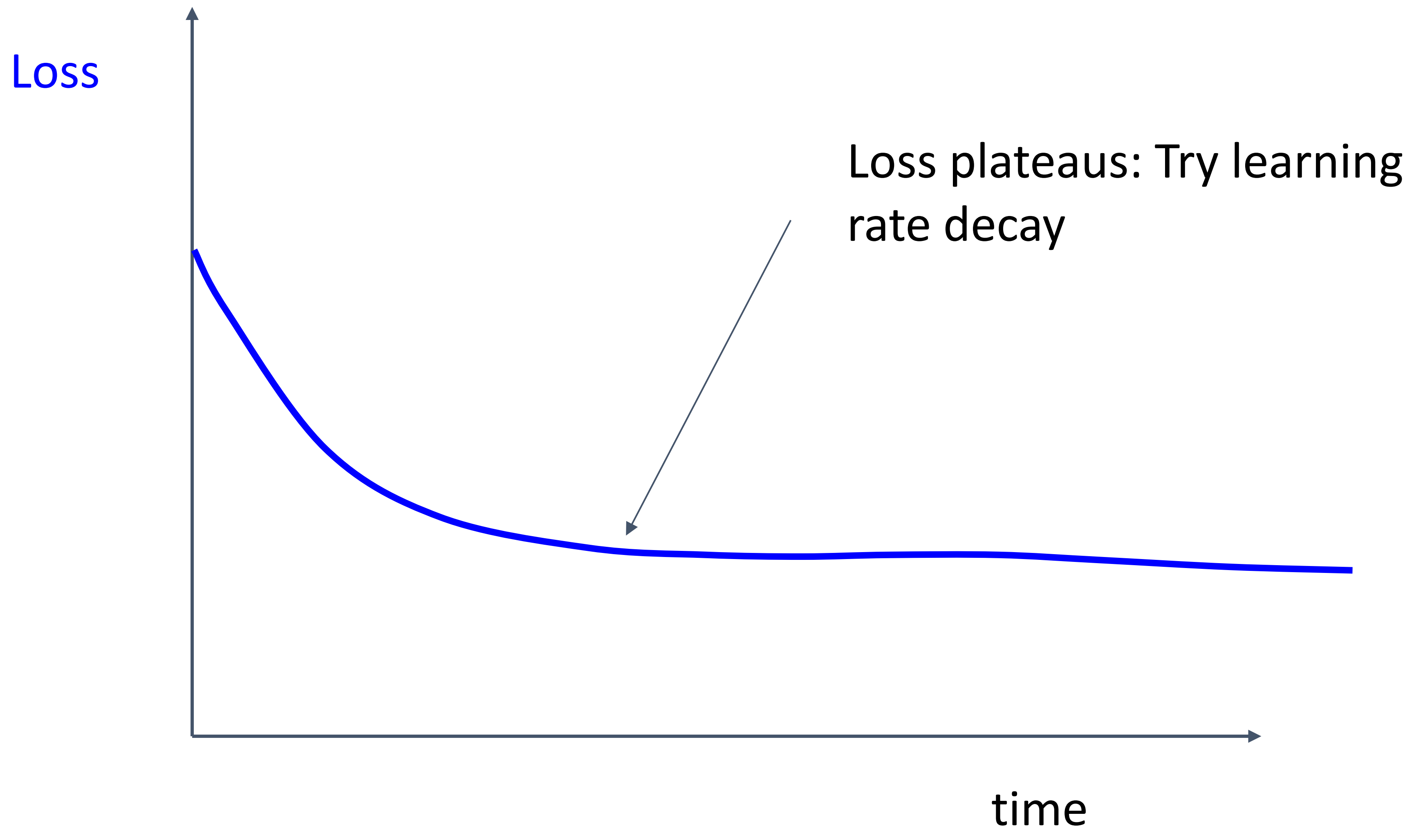
Look at Learning Curves!

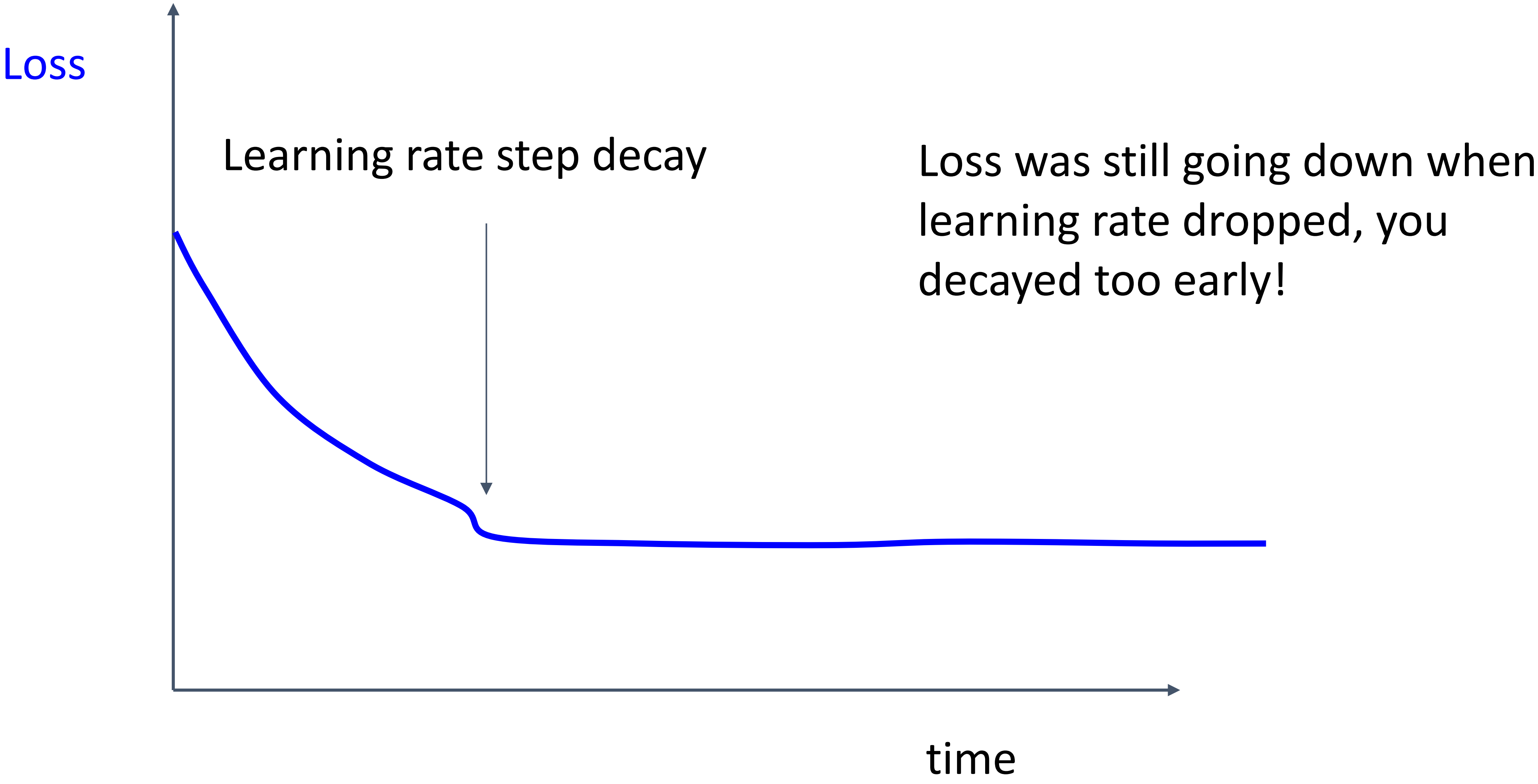




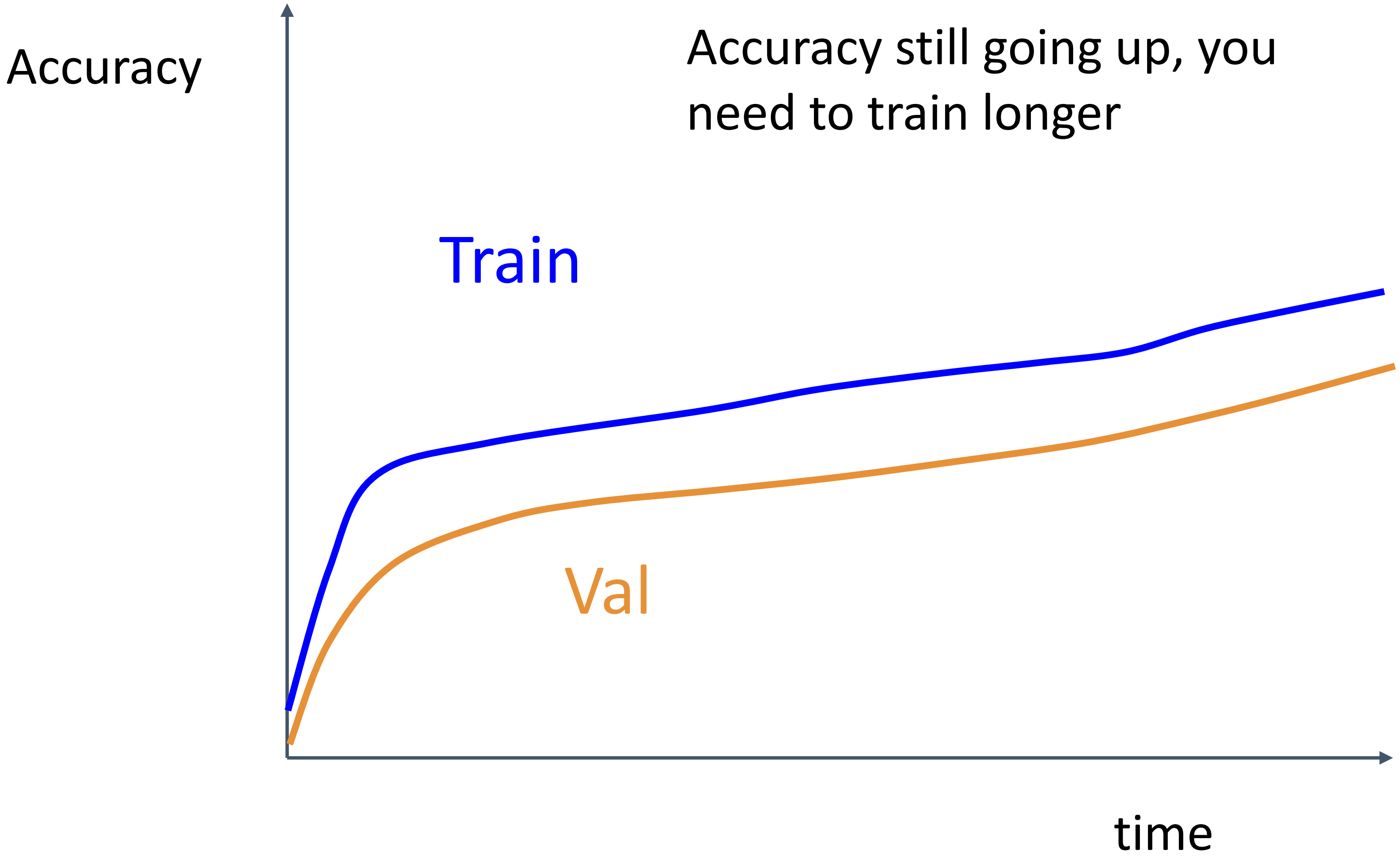
Losses may be noisy, use a scatter plot and also plot moving average to see trends better


Loss
Bad initialization a prime suspect
time

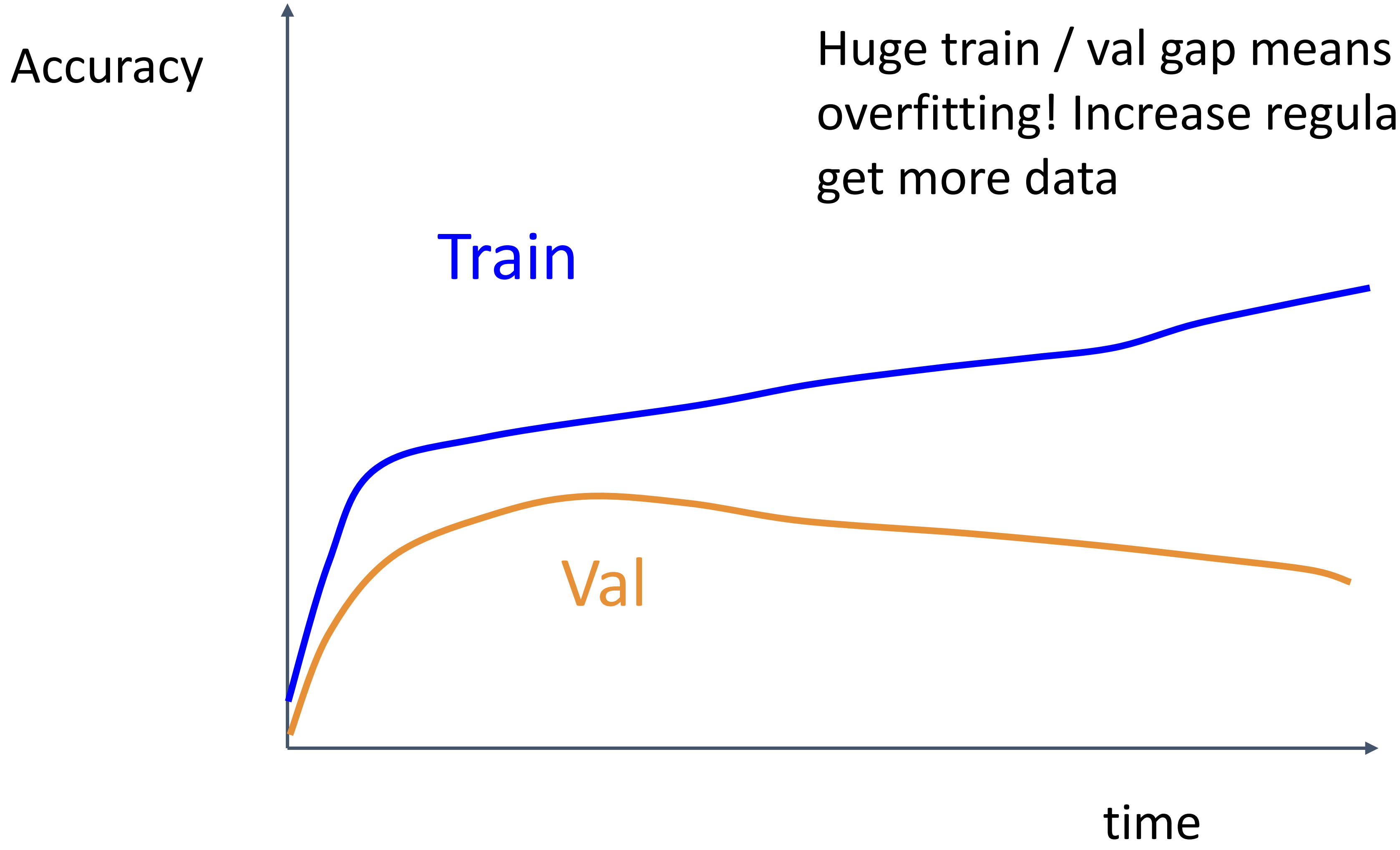

Loss
Loss plateaus: Try learning rate decay
time

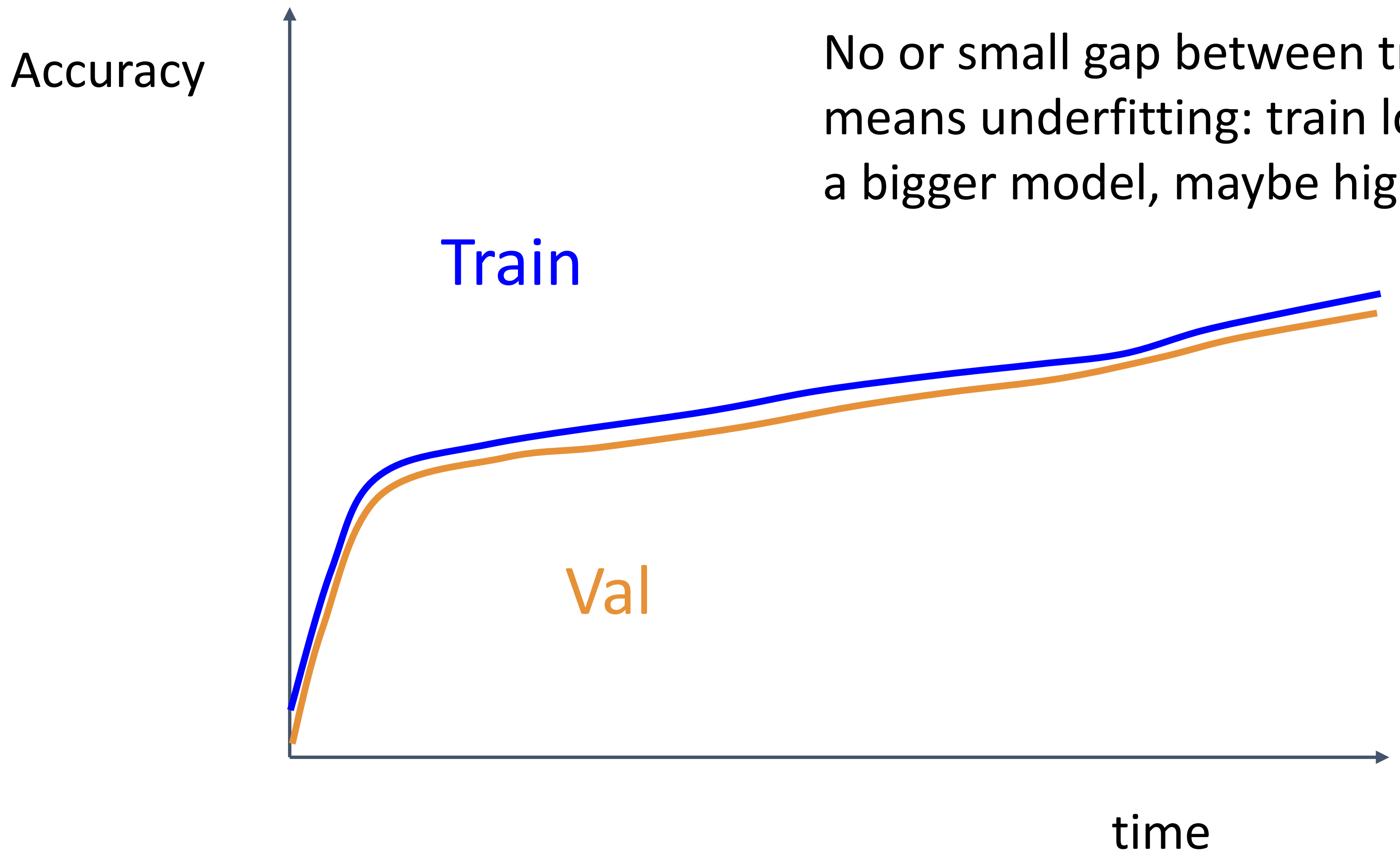

Loss
Learning rate step decay
Loss was still going down when learning rate dropped, you decayed too early!
time

Accuracy still going up, you need to train longer



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

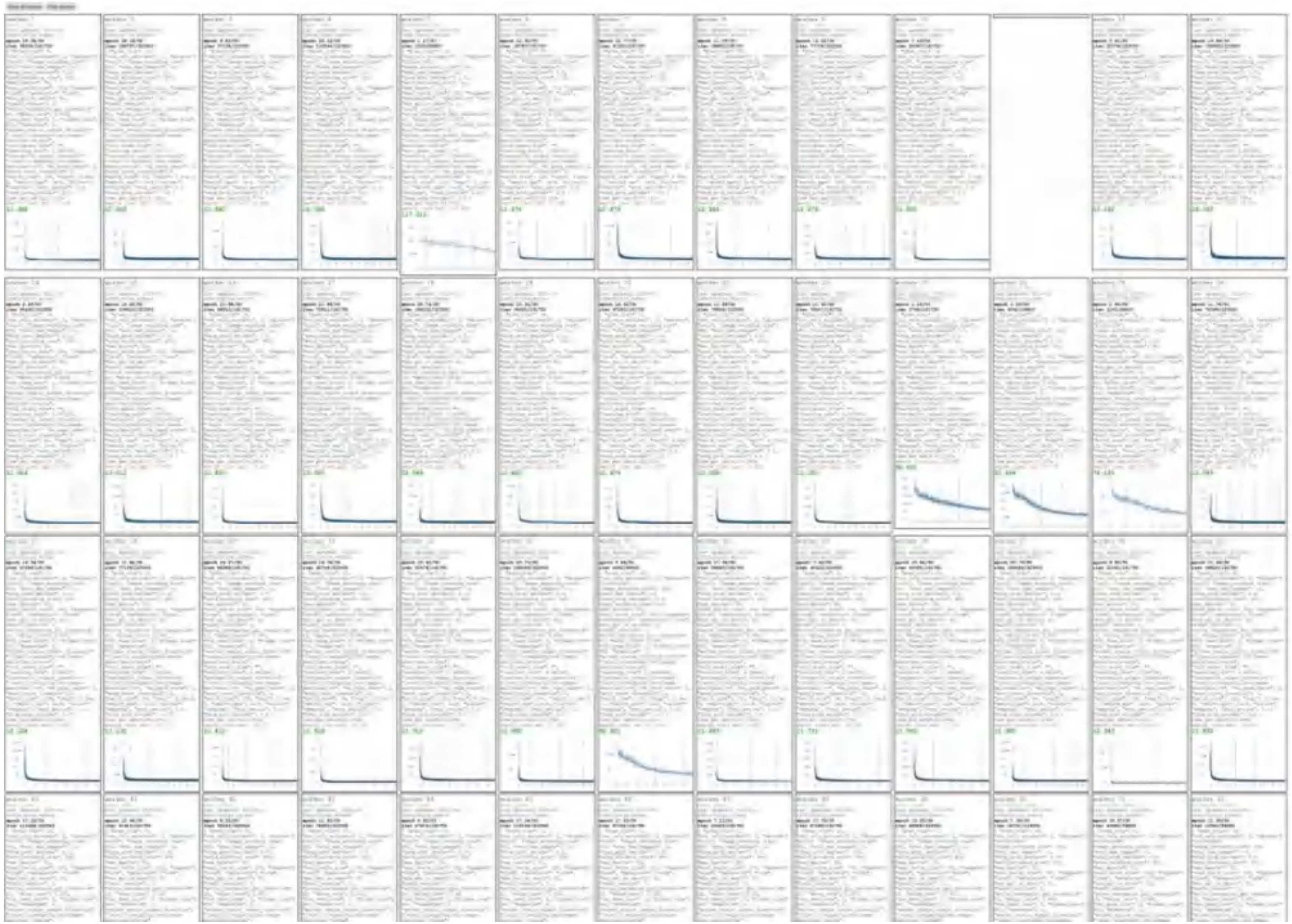
Step 1: Check initial loss
Step 2: Overfit a small sample
Step 3: Find LR that makes loss go down
Step 4: Coarse grid, train for ~1-5 epochs
Step 5: Refine grid, train longer
Step 6: Look at loss curves
Step 7: GOTO step 5

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

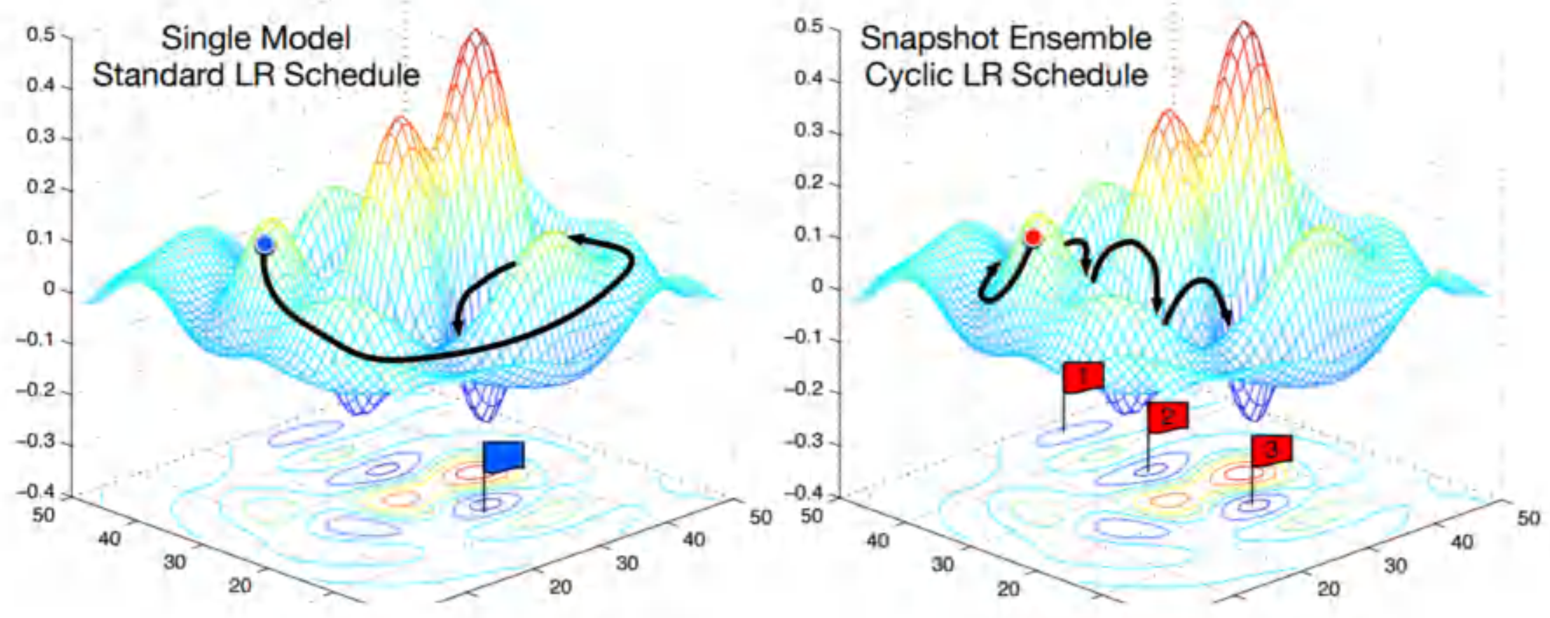
1. Train multiple independent models
2. At test time average their results

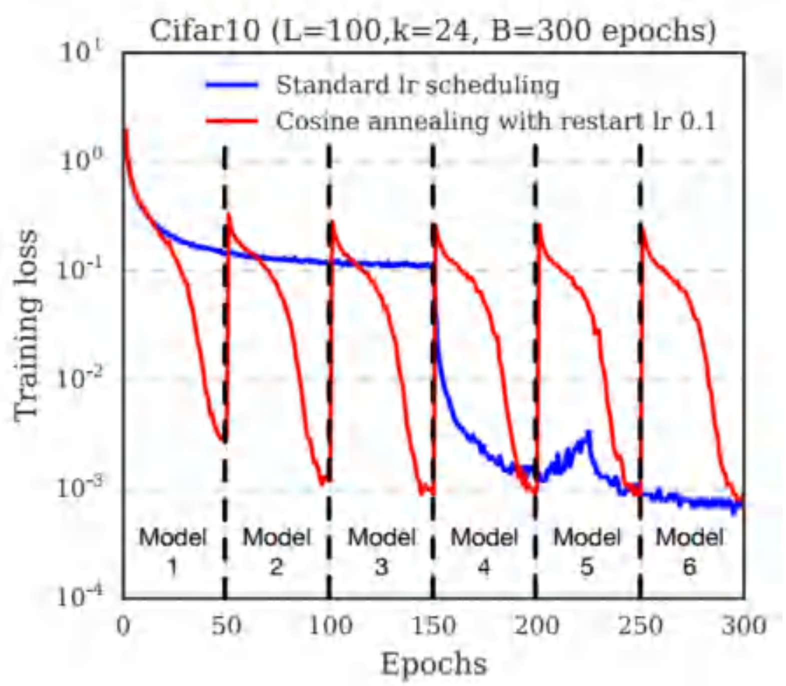
   (Take average of predicted probability distributions, then choose argmax)

Enjoy 2% extra performance

Model Ensembles: Tips and Tricks

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





Cyclic learning rate schedules can make this work even better!

Loshchilov and Hutter, "SGDR: Stochastic gradient descent with restarts", arXiv 2016
Huang et al, "Snapshot ensembles: train 1, get M for free", ICLR 2017

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 2019

Transfer Learning

Transfer Learning

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

Transfer Learning

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

BUSTED

Transfer Learning with CNNs

1. Train on ImageNet

FC-1000
FC-4096
FC-4096

MaxPool
Conv-512
Conv-512

MaxPool
Conv-512
Conv-512

MaxPool
Conv-256
Conv-256

MaxPool
Conv-128
Conv-128

MaxPool
Conv-64
Conv-64

Image

2. Use CNN as a feature extractor

FC-4096
FC-4096

MaxPool
Conv-512
Conv-512

MaxPool
Conv-512
Conv-512

MaxPool
Conv-256
Conv-256

MaxPool
Conv-128
Conv-128

MaxPool
Conv-64
Conv-64

Image

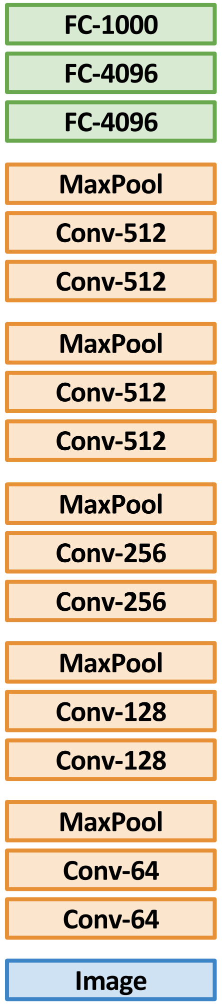
Remove last layer

Freeze these

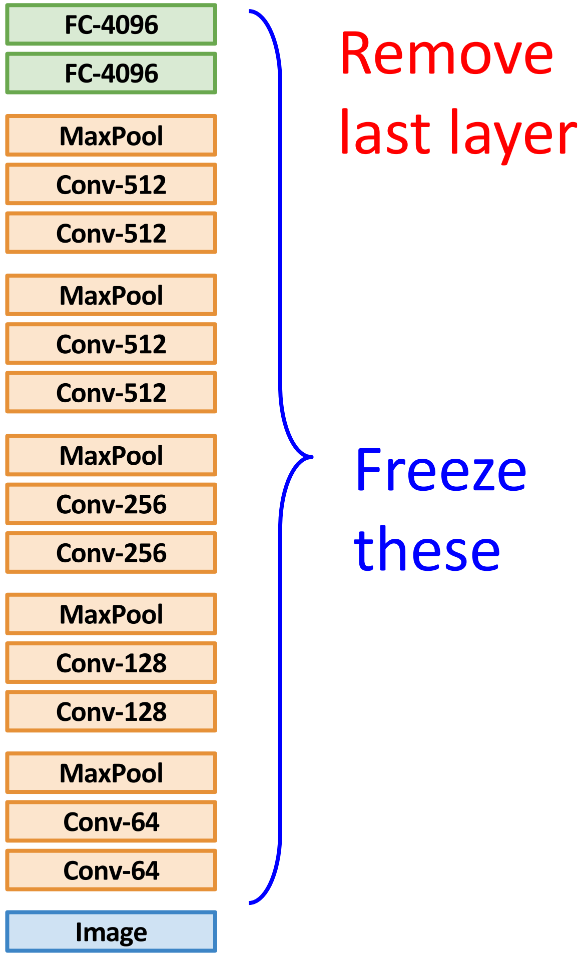
Donahue et al, "DeCAF: A Deep Convolutional Activation Feature for Generic Visual Recognition", ICML 2014

Transfer Learning with CNNs

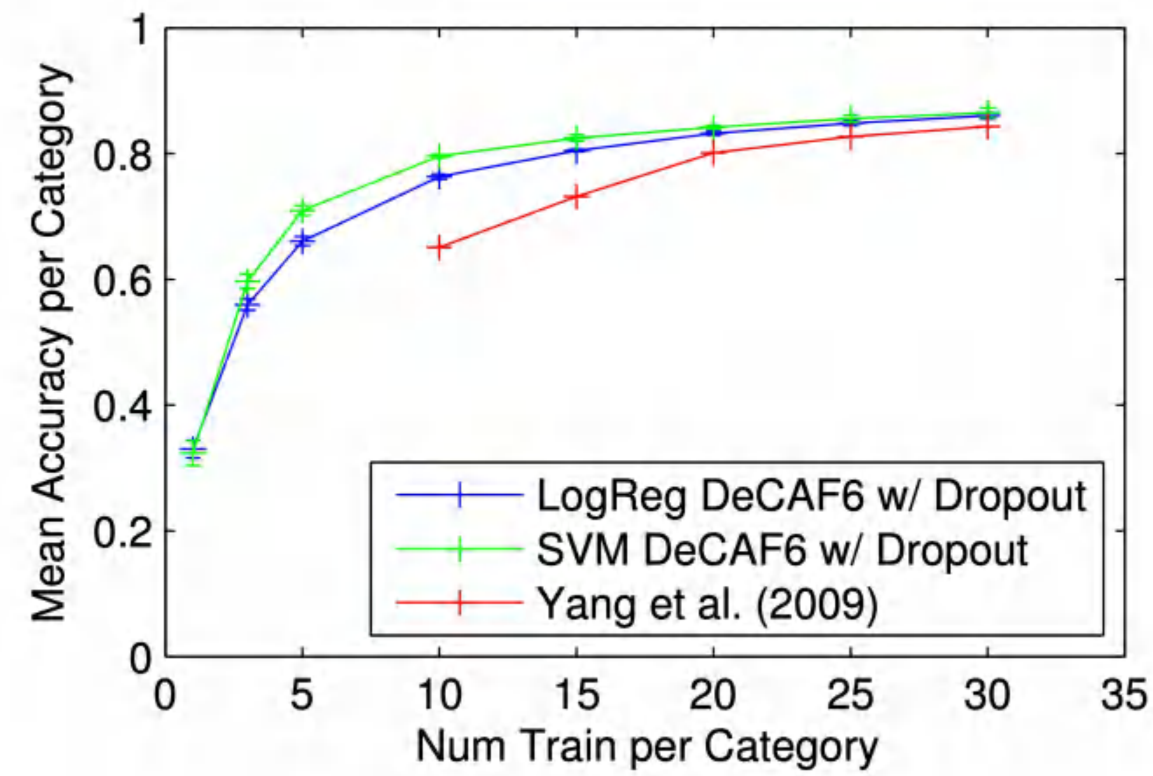
1. Train on ImageNet



2. Use CNN as a feature extractor



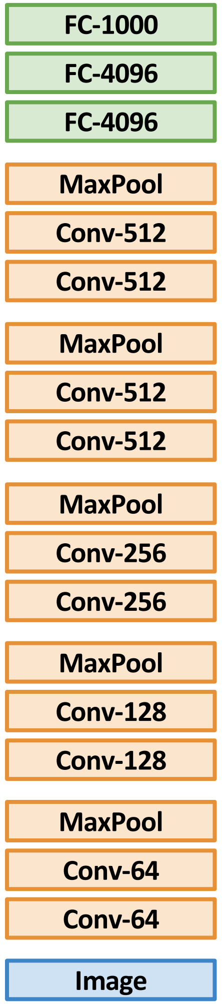
Classification on Caltech-101



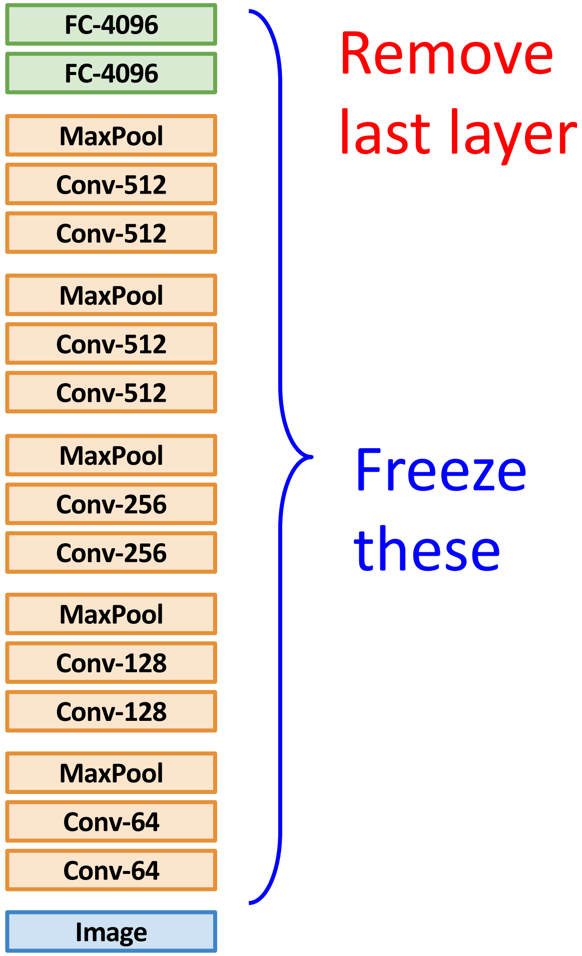
Donahue et al, “DeCAF: A Deep Convolutional Activation Feature for Generic Visual Recognition”, ICML 2014

Transfer Learning with CNNs

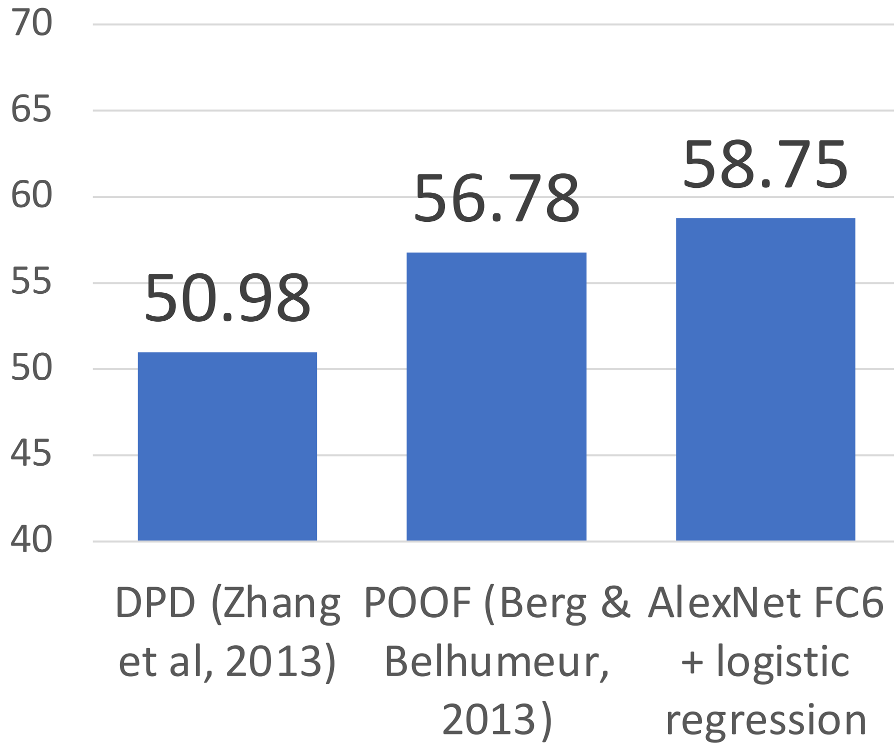
1. Train on ImageNet



2. Use CNN as a feature extractor



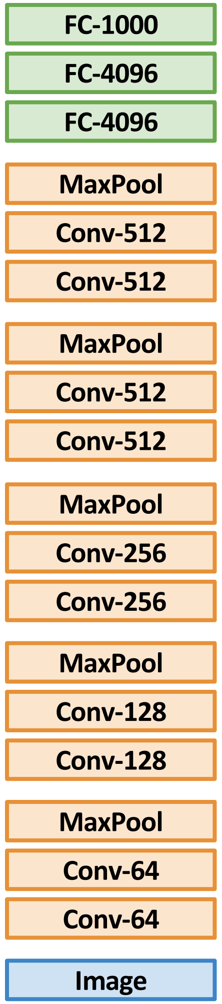
Bird Classification on Caltech-UCSD



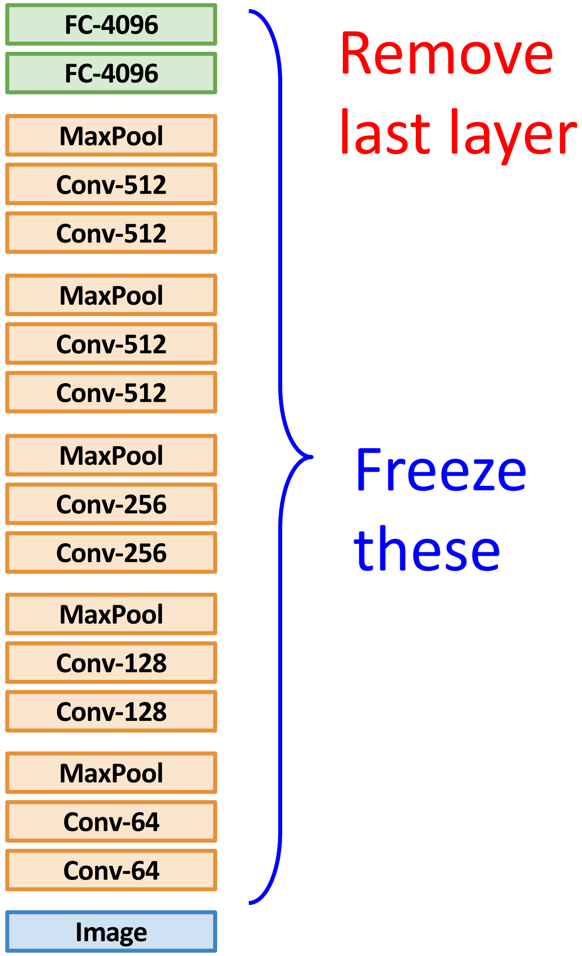
Donahue et al, “DeCAF: A Deep Convolutional Activation Feature for Generic Visual Recognition”, ICML 2014

Transfer Learning with CNNs

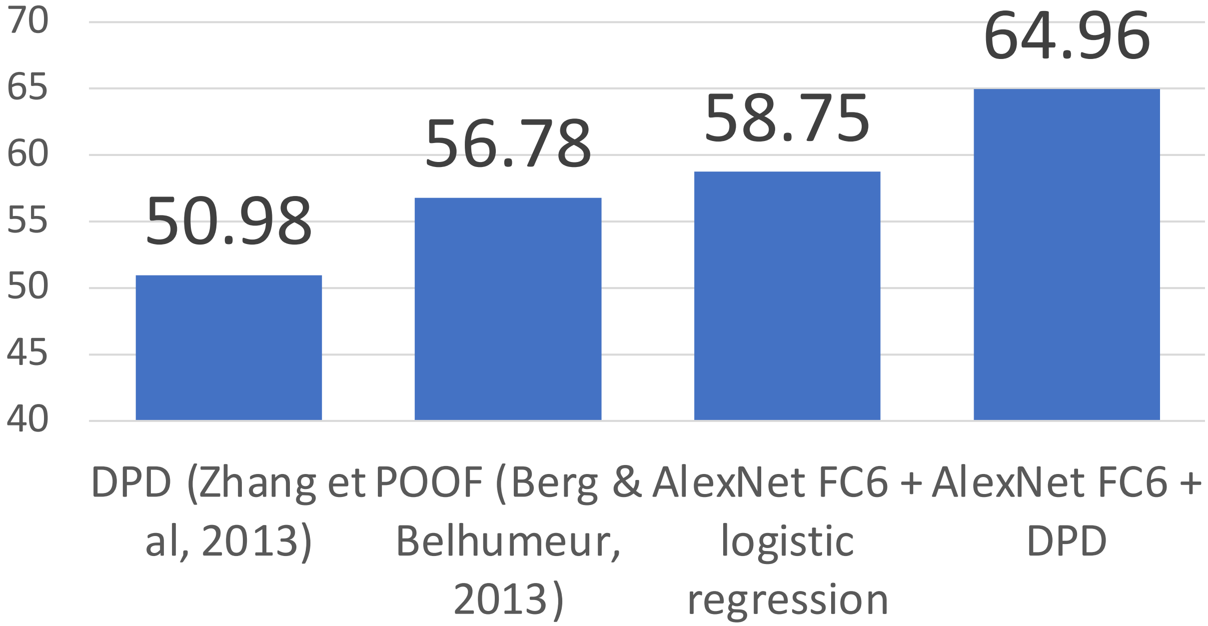
1. Train on ImageNet



2. Use CNN as a feature extractor



Bird Classification on Caltech-UCSD



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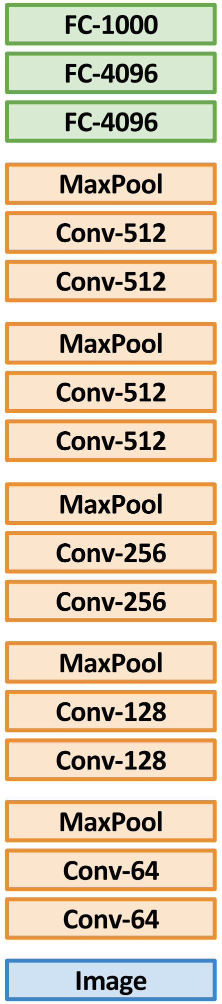
Transfer Learning with CNNs

1. Train on ImageNet



2. Use CNN as a feature extractor

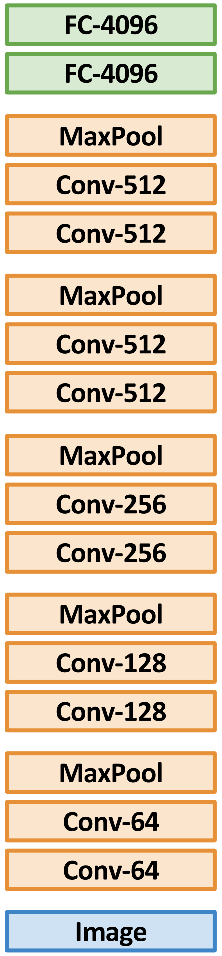
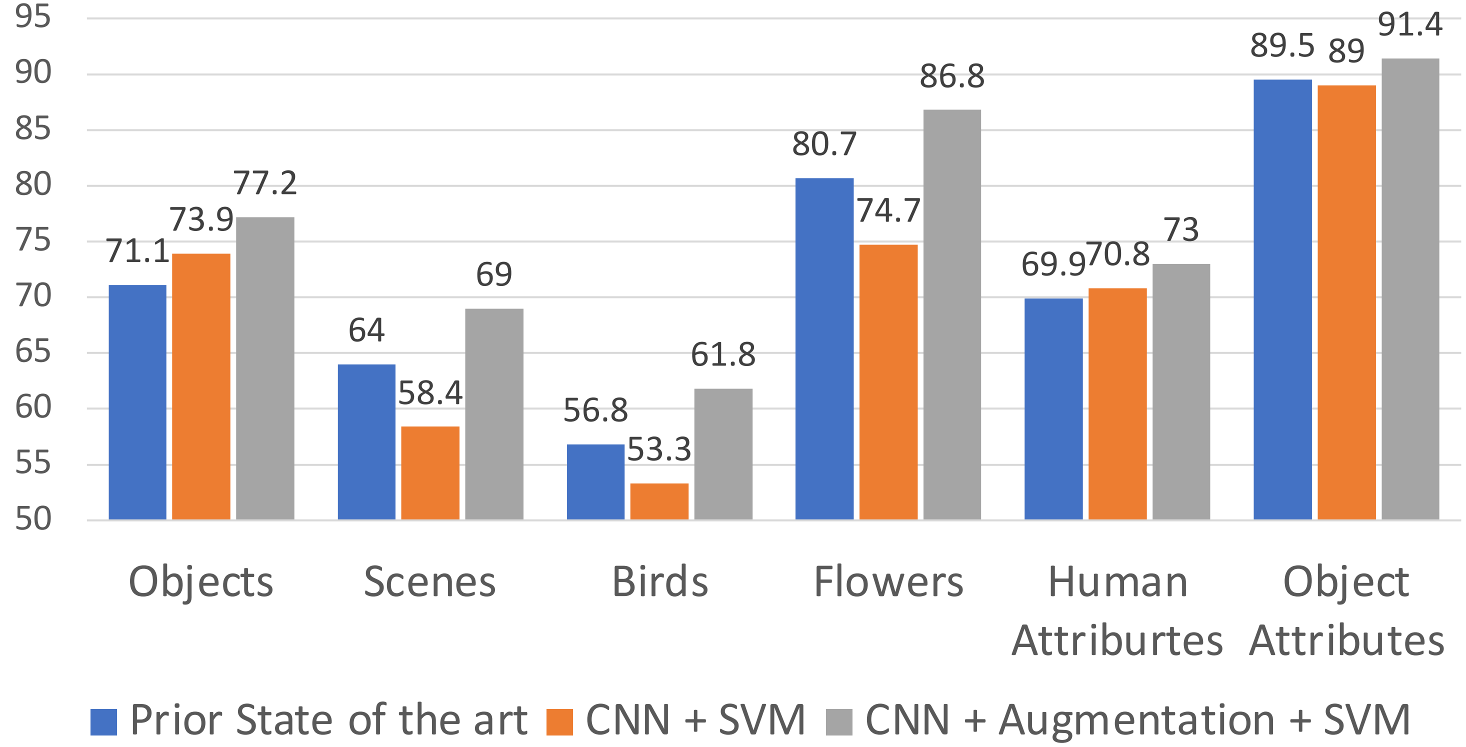


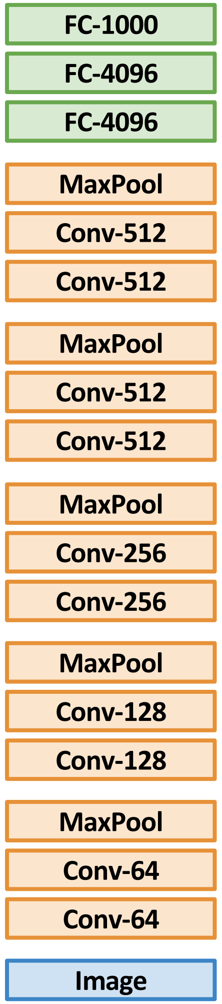
Image Classification



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

Transfer Learning with CNNs

1. Train on ImageNet



2. Use CNN as a feature extractor

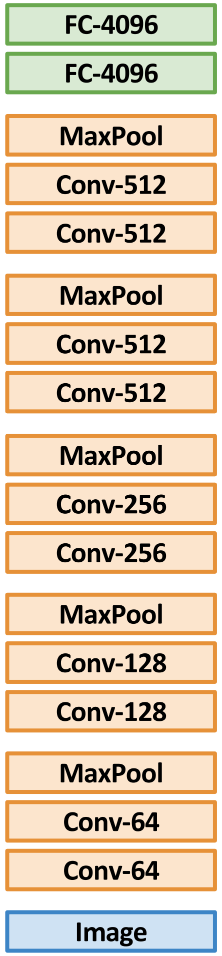
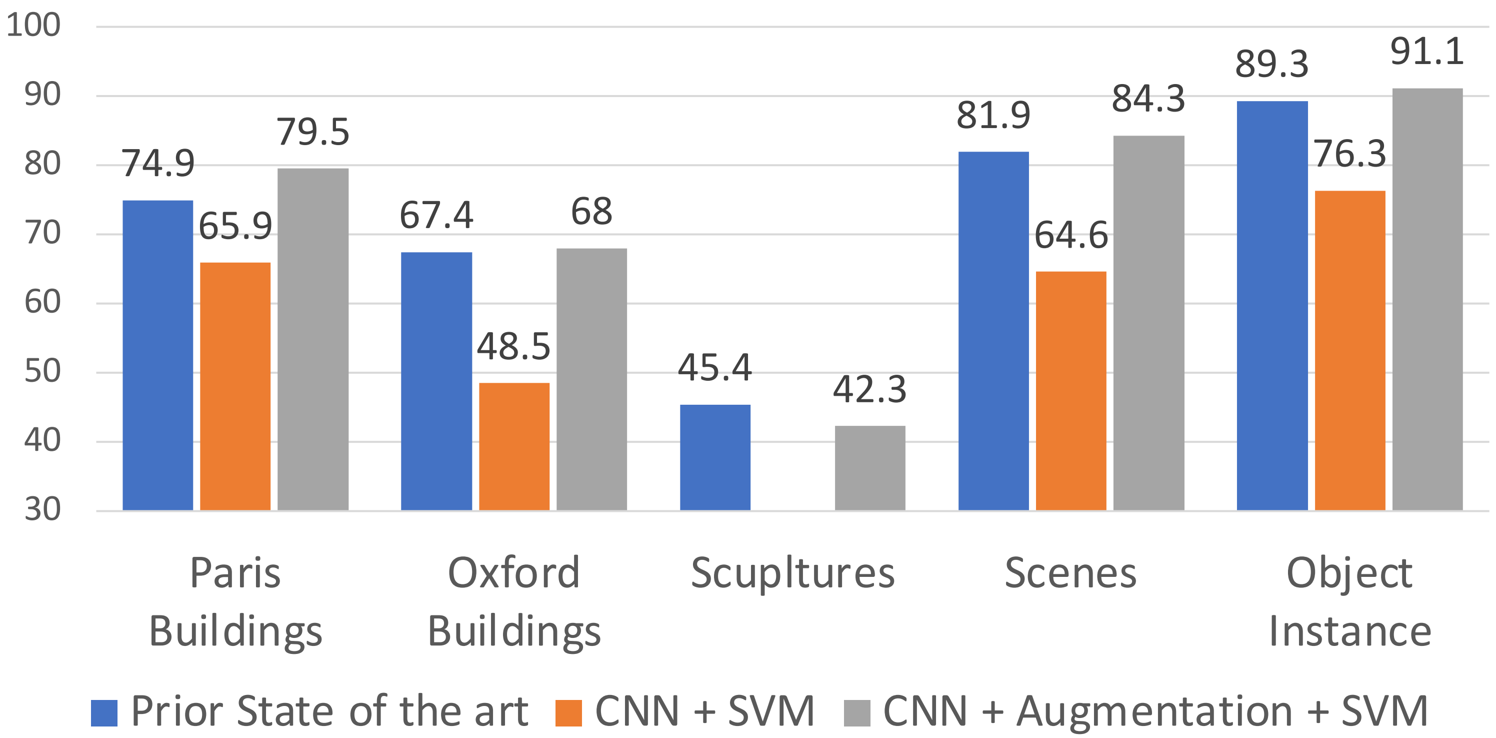


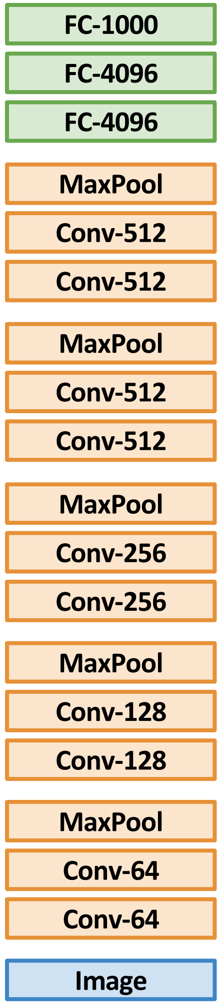
Image Retrieval: Nearest-Neighbor



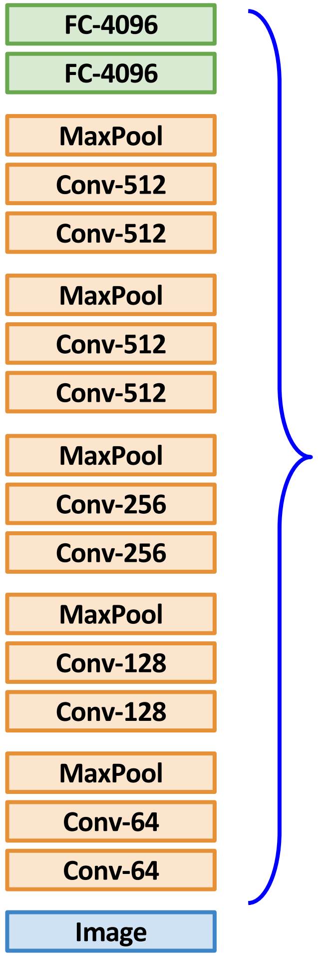
Razavian et al, “CNN Features Off-the-Shelf: An Astounding Baseline for Recognition”, CVPR Workshops 2014

Transfer Learning with CNNs

1. Train on Imagenet



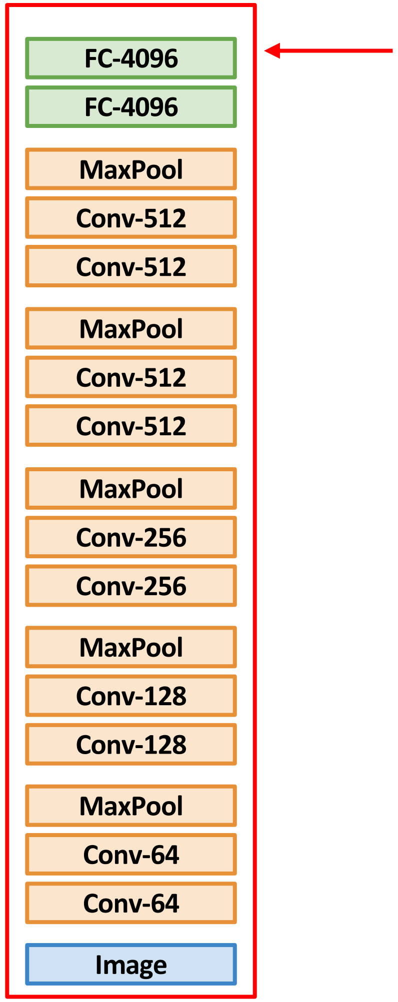
2. Use CNN as a feature extractor



Remove last layer

Freeze these

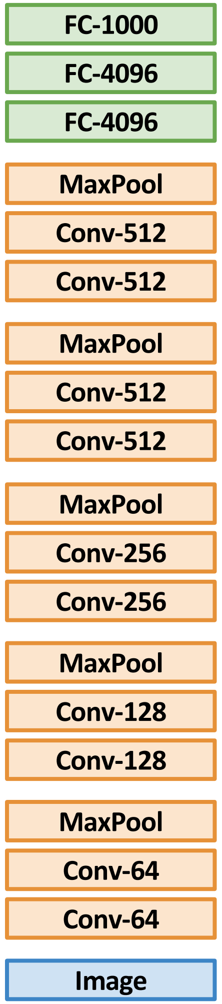
3. Bigger dataset: **Fine-Tuning**



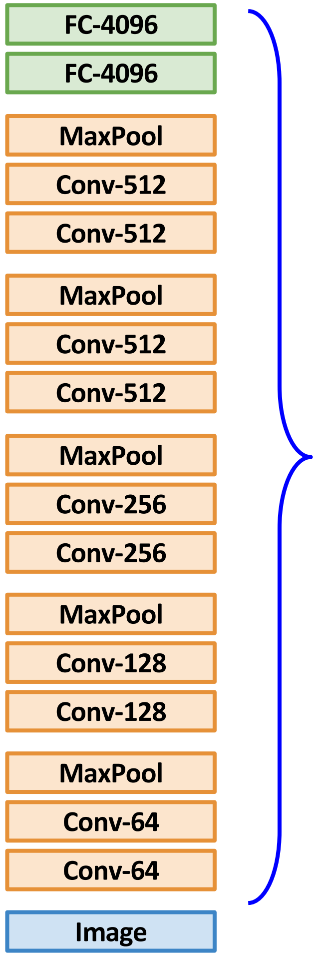
Continue training CNN for new task!

Transfer Learning with CNNs

1. Train on Imagenet



2. Use CNN as a feature extractor



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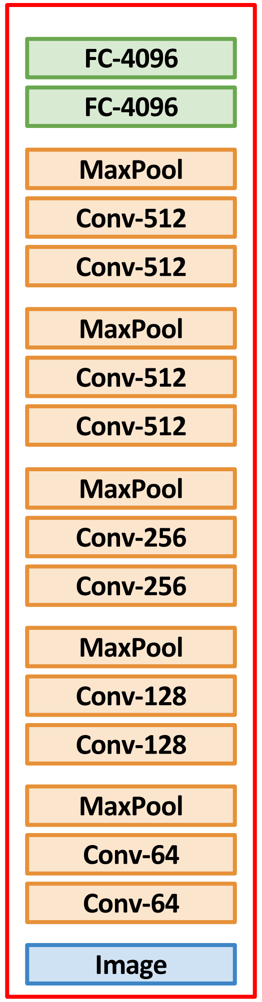
3. Bigger dataset: **Fine-Tuning**



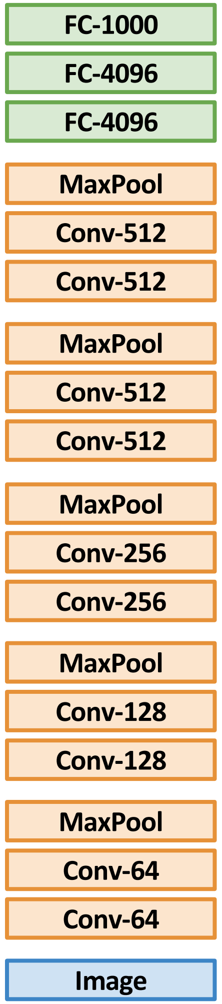
Continue training CNN for new task!

Some tricks:

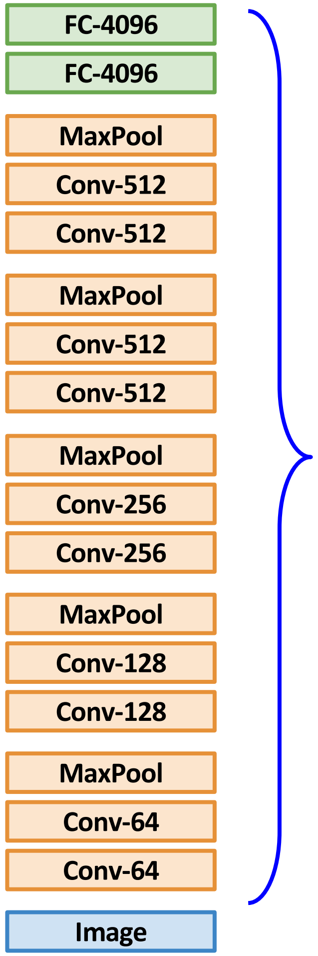
- Train with feature extraction first before fine-tuning
- Lower the learning rate: use ~1/10 of LR used in original training
- Sometimes freeze lower layers to save computation
- Train with BatchNorm in “test” mode

Transfer Learning with CNNs

1. Train on Imagenet



2. Use CNN as a feature extractor



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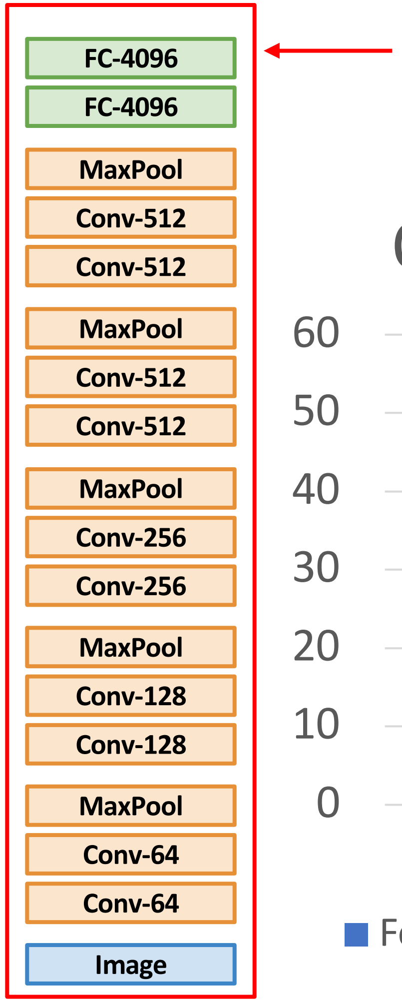
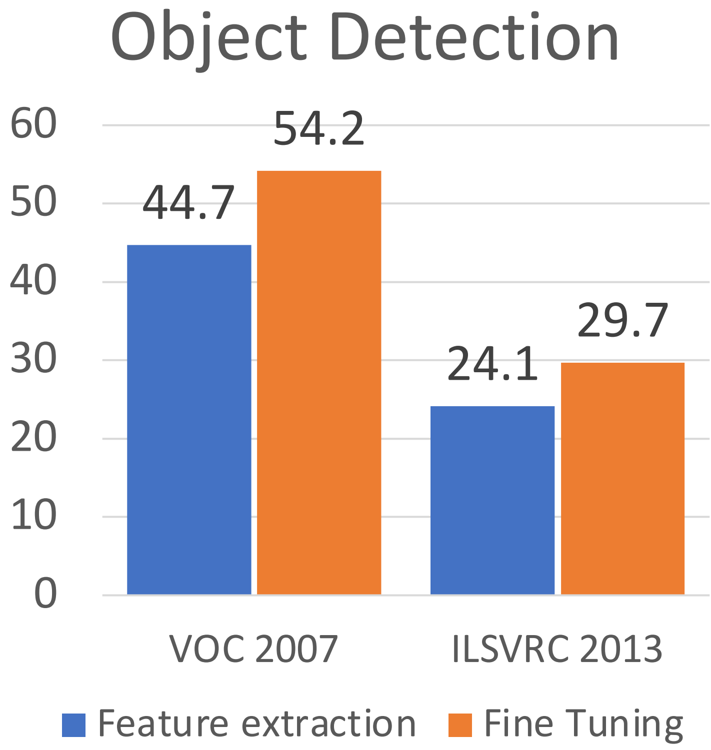
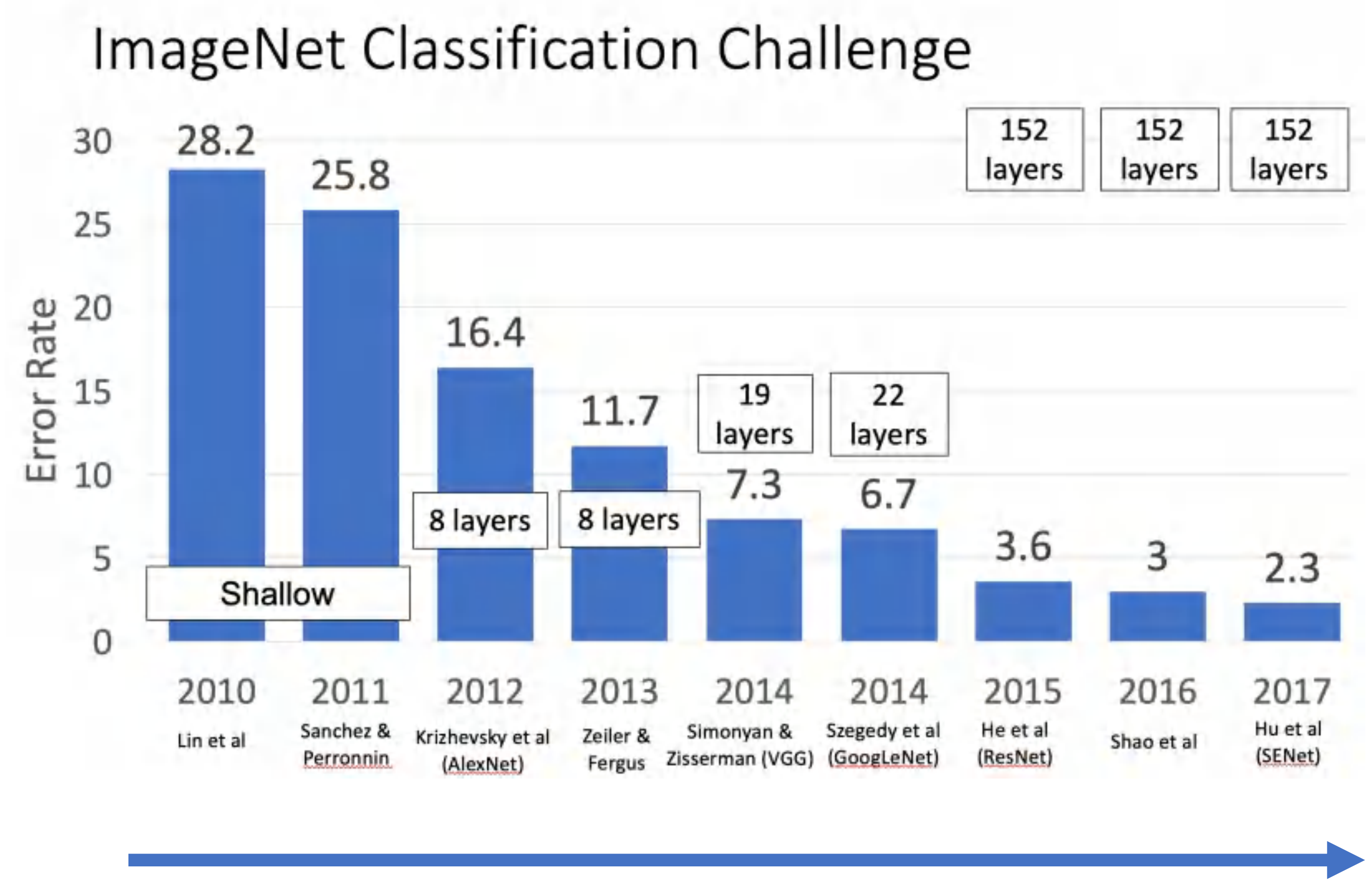


Continue training CNN for new task!

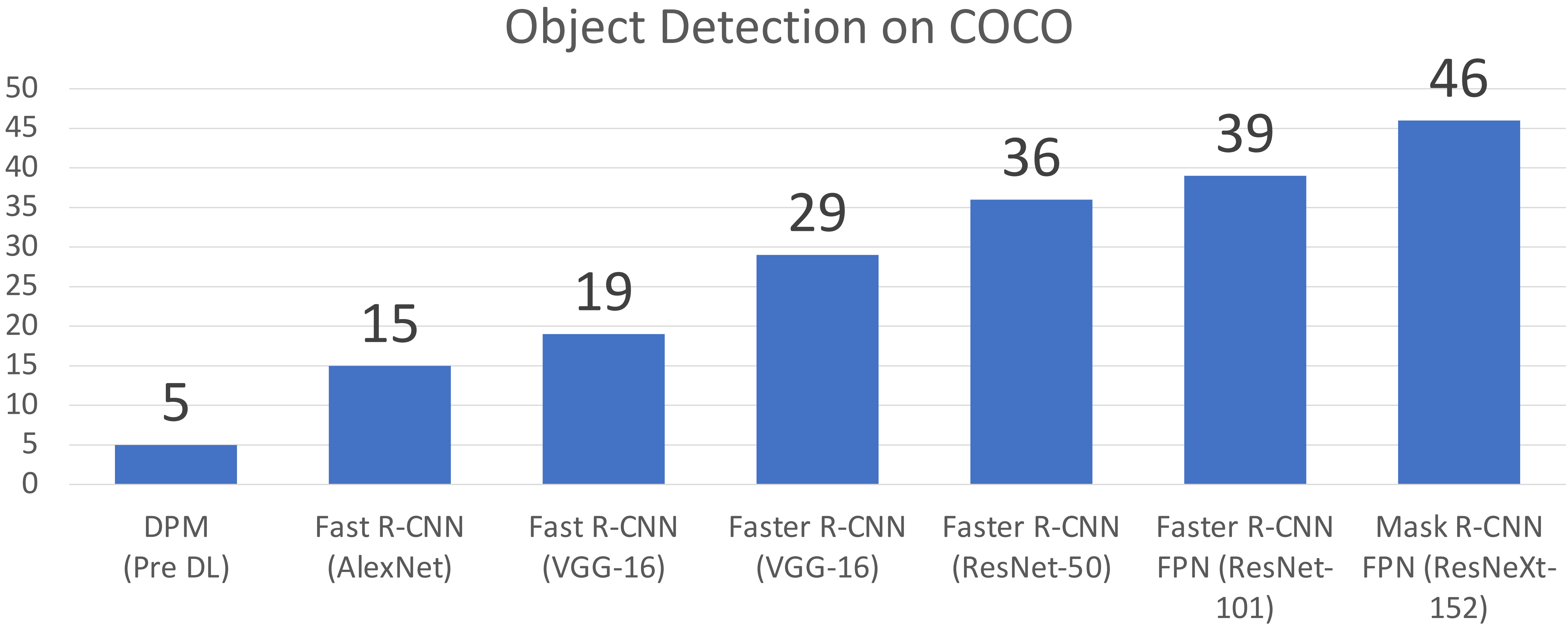


Transfer Learning with CNNs: Architecture Matters!



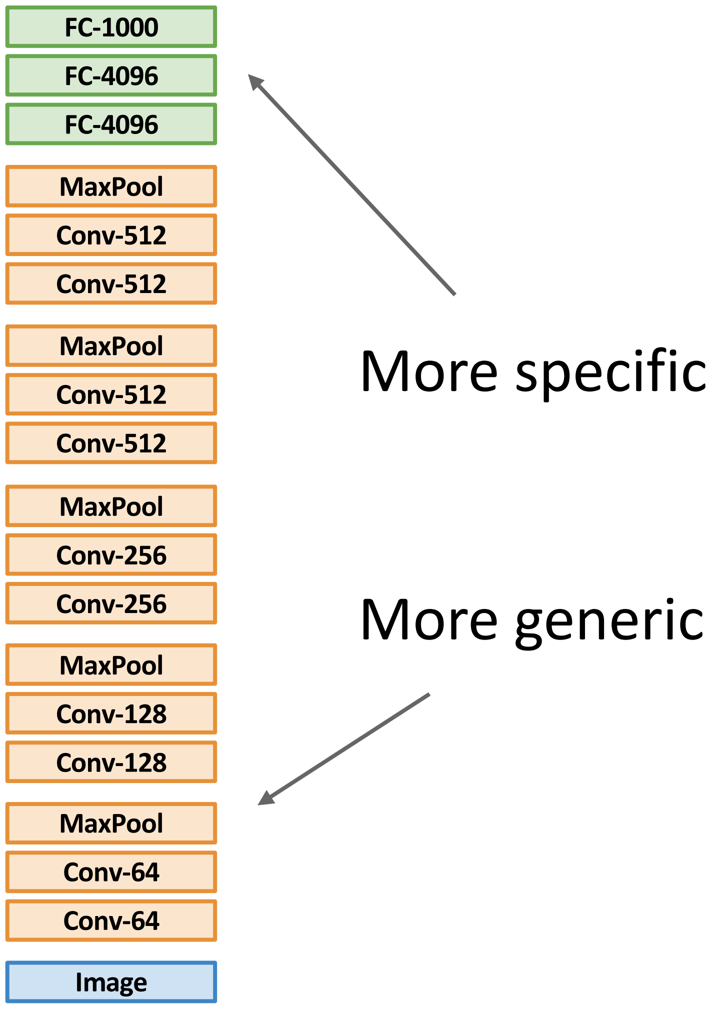
Improvements in CNN architectures lead to improvements in many downstream tasks thanks to transfer learning!

Transfer Learning with CNNs: Architecture Matters!



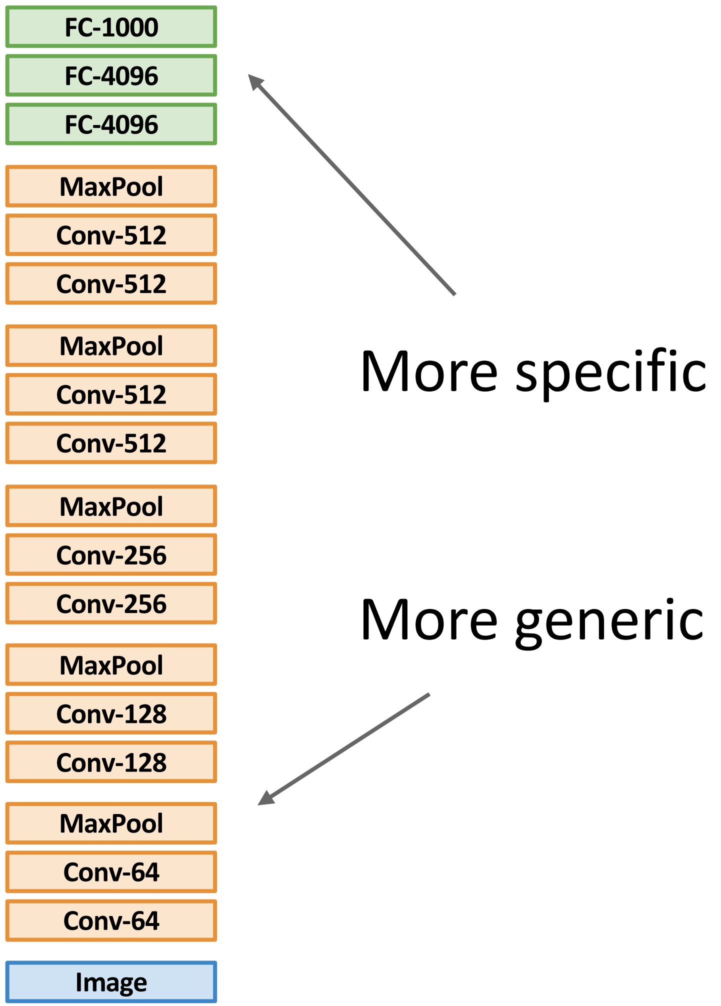
Ross Girshick, "The Generalized R-CNN Framework for Object Detection", ICCV 2017 Tutorial on Instance-Level Visual Recognition

Transfer Learning with CNNs



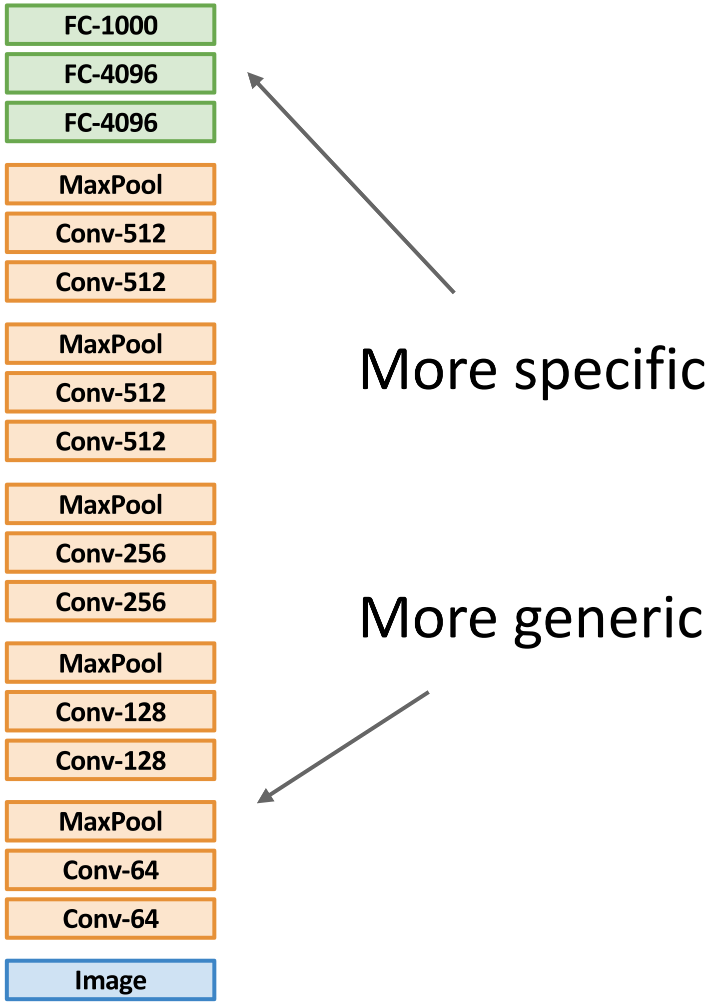
	Dataset similar to ImageNet	**Dataset very different from ImageNet**
very little data (10s to 100s)	?	?
quite a lot of data (100s to 1000s)	?	?

Transfer Learning with CNNs



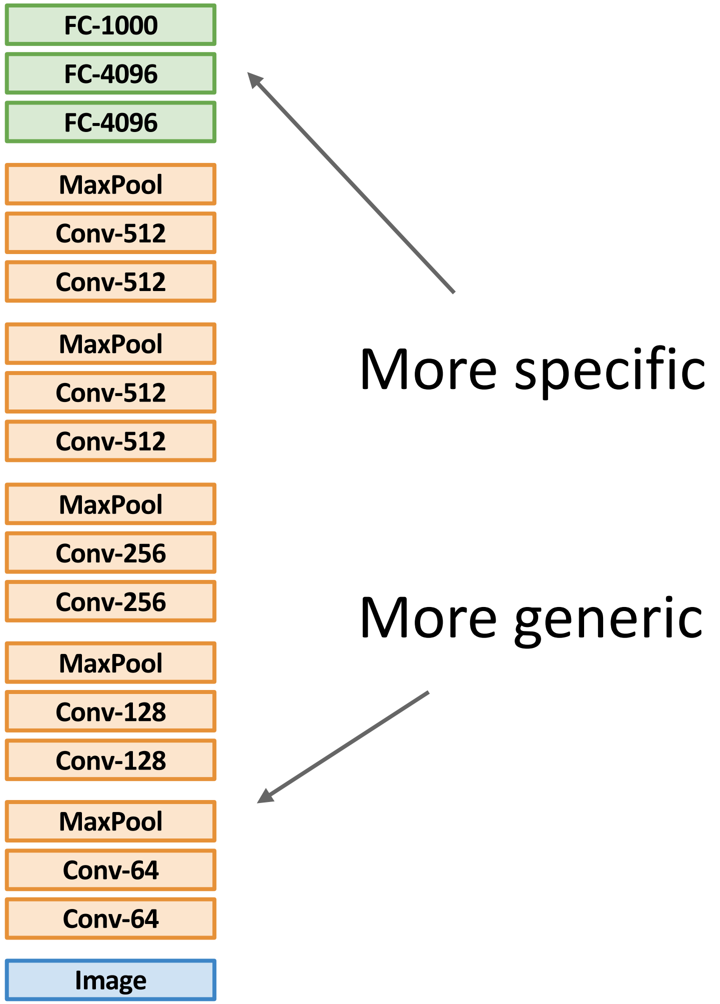
	Dataset similar to ImageNet	**Dataset very different from ImageNet**
very little data (10s to 100s)	Use Linear Classifier on top layer	?
quite a lot of data (100s to 1000s)	Finetune a few layers	?

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

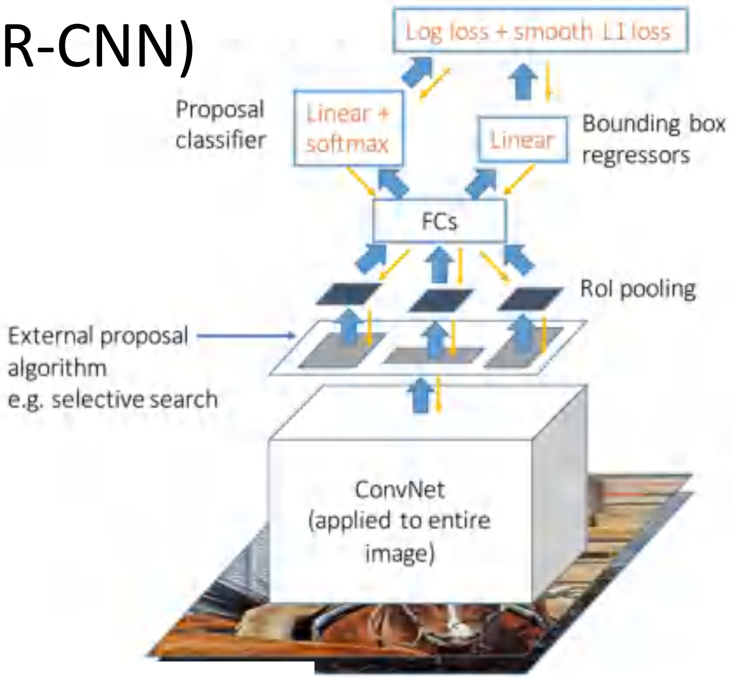
Transfer Learning with CNNs

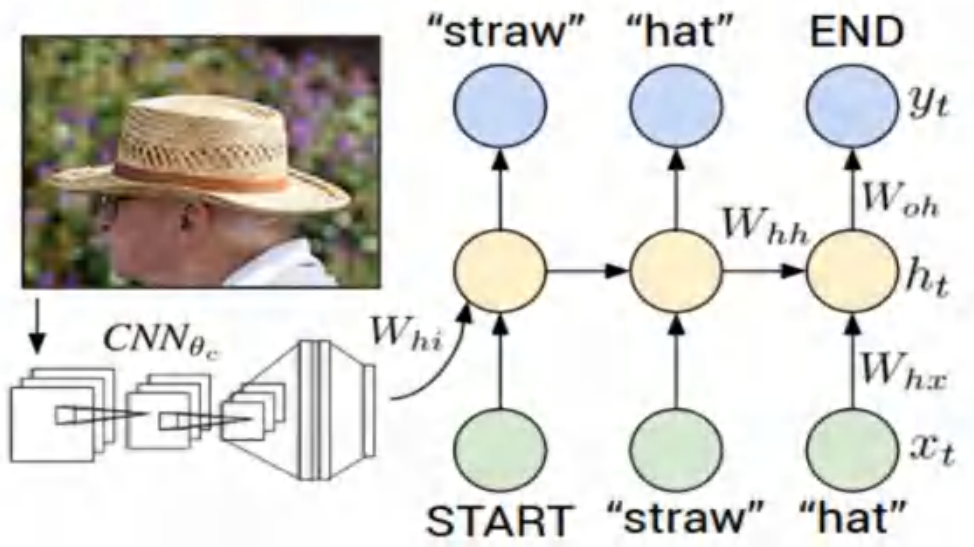


	Dataset similar to ImageNet	**Dataset very different from ImageNet**
very little data (10s to 100s)	Use Linear Classifier on top layer	You're in trouble… Try linear classifier from different stages
quite a lot of data (100s to 1000s)	Finetune a few layers	Finetune a larger number of layers

Transfer learning is pervasive!
It's the norm, not the exception

Object
Detection
(Fast R-CNN)





Girshick, "Fast R-CNN", ICCV 2015

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

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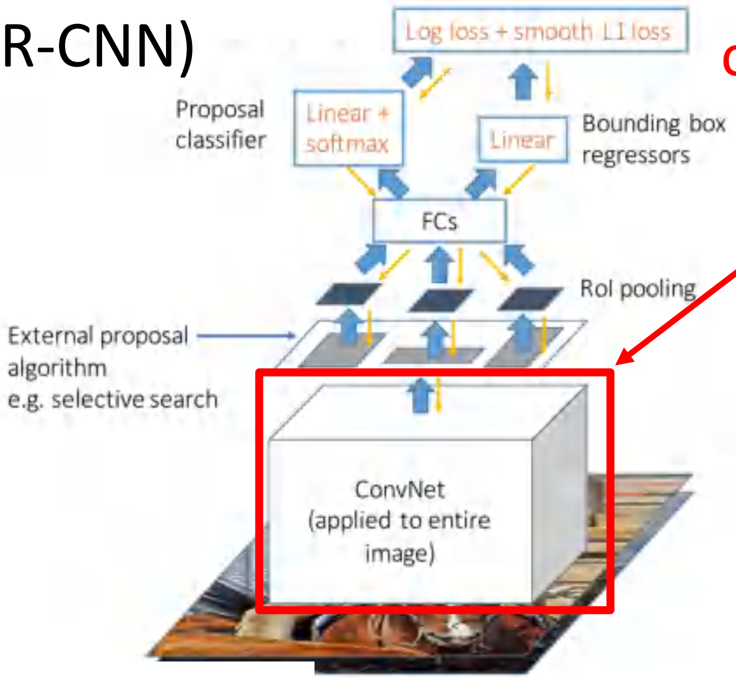
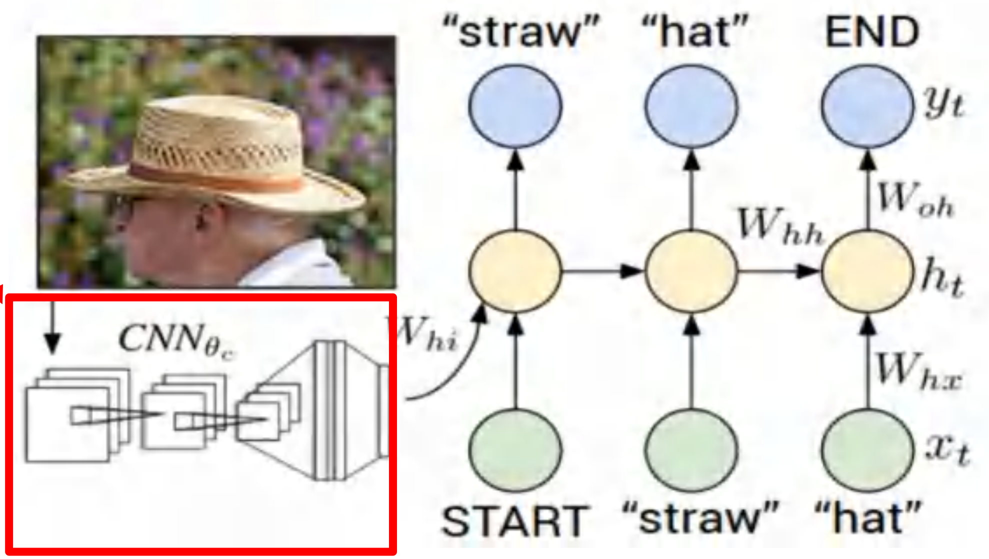
It's the norm, not the exception

Object Detection (Fast R-CNN)



CNN pretrained on ImageNet



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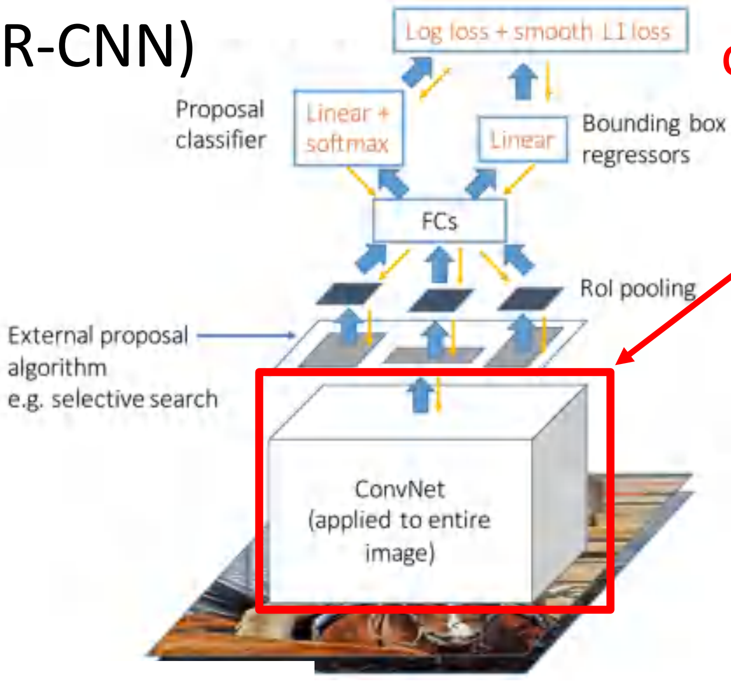
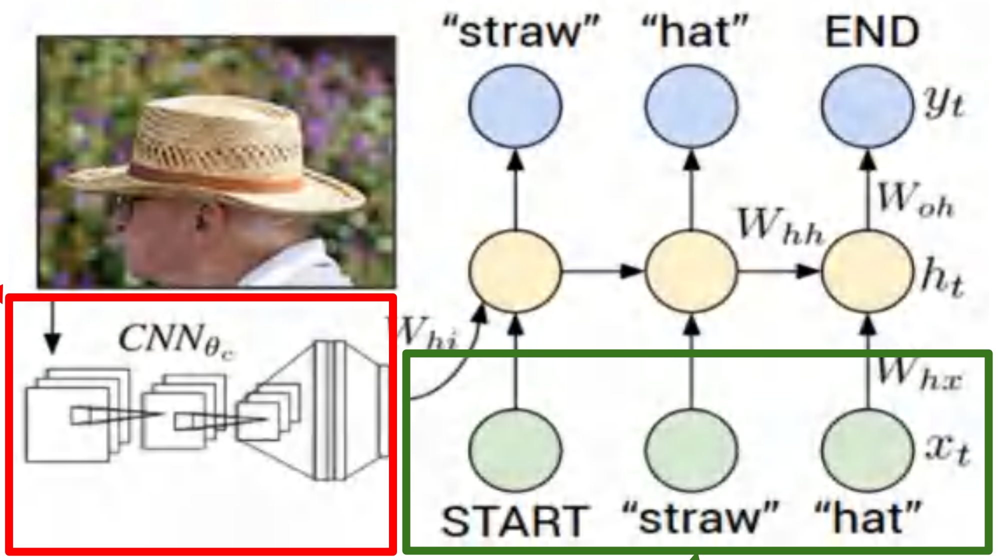
Object Detection (Fast R-CNN)



CNN pretrained on ImageNet

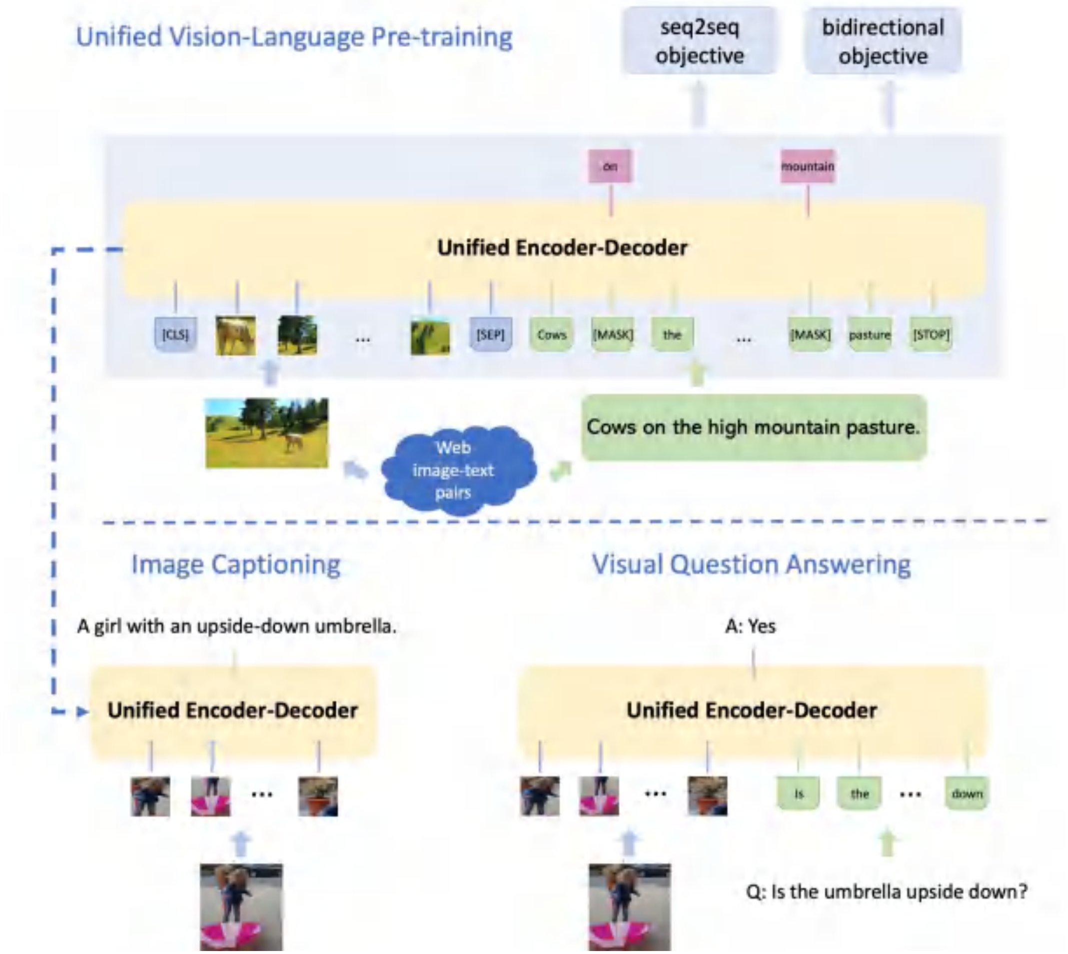


Word vectors pretrained with word2vec

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

Transfer learning is pervasive!
It’s the norm, not the exception

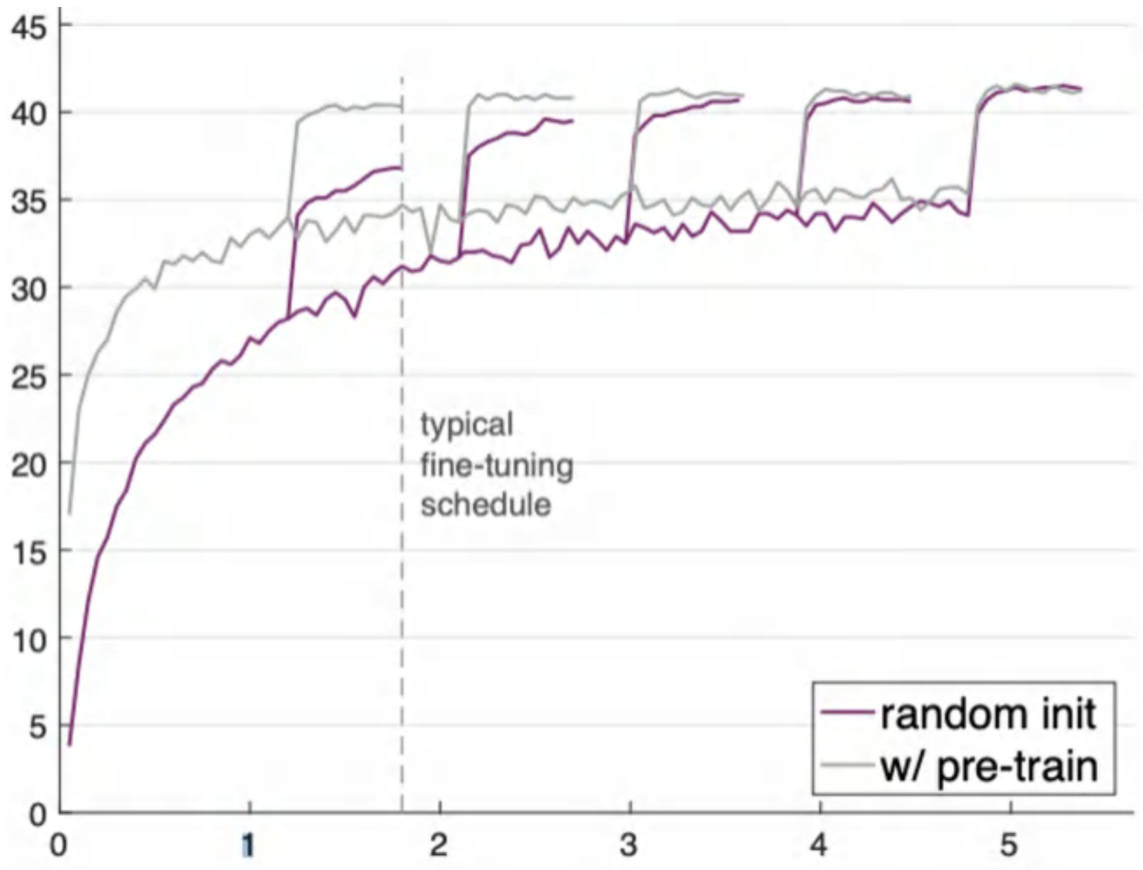


1. Train CNN on ImageNet
2. Fine-Tune (1) for object detection on Visual Genome
3. Train BERT language model on lots of text
4. Combine (2) and (3), train for joint image / language modeling
5. Fine-tune (5) for image captioning, visual question answering, etc.

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



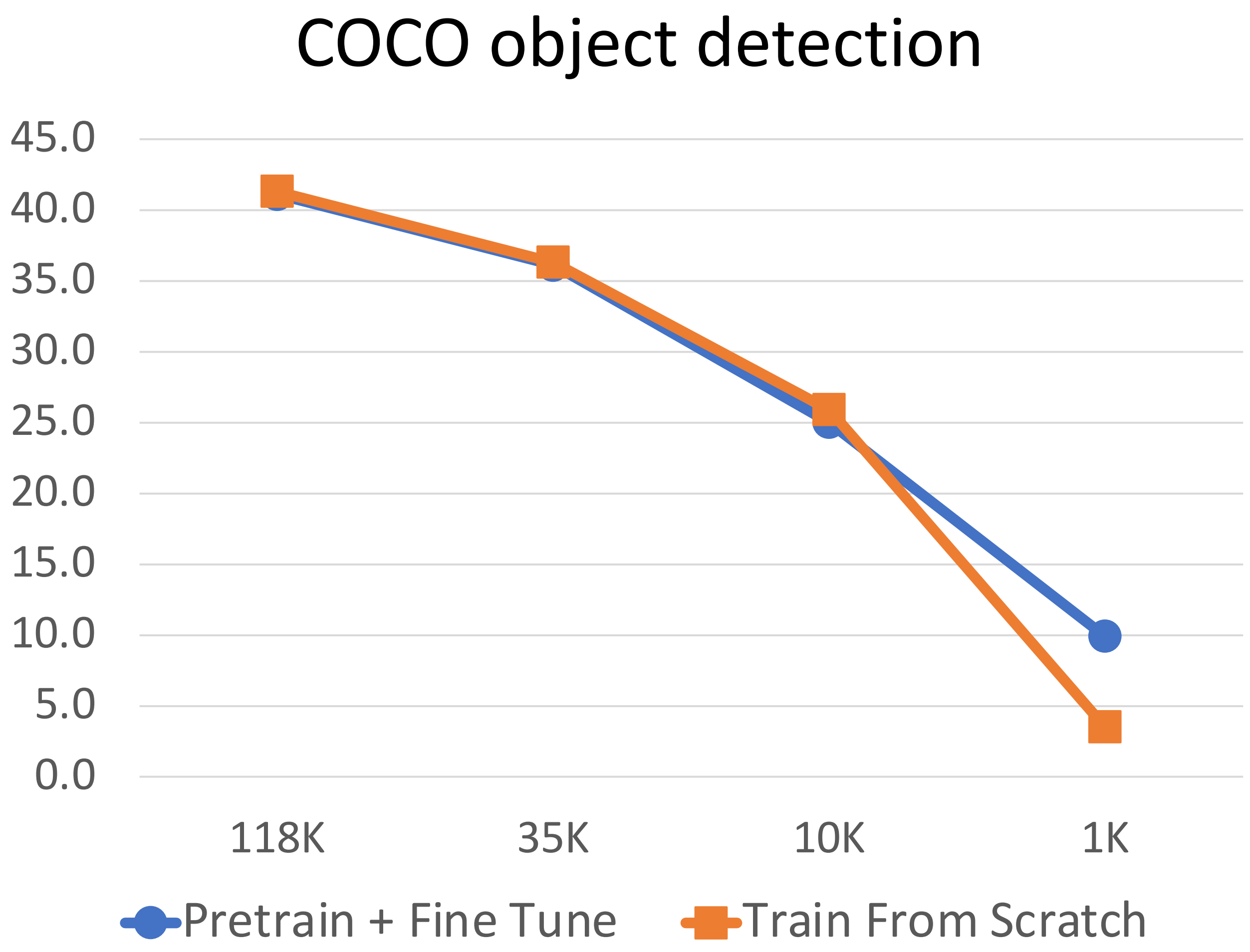
Training from scratch can work as well as pretraining on ImageNet!

… 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

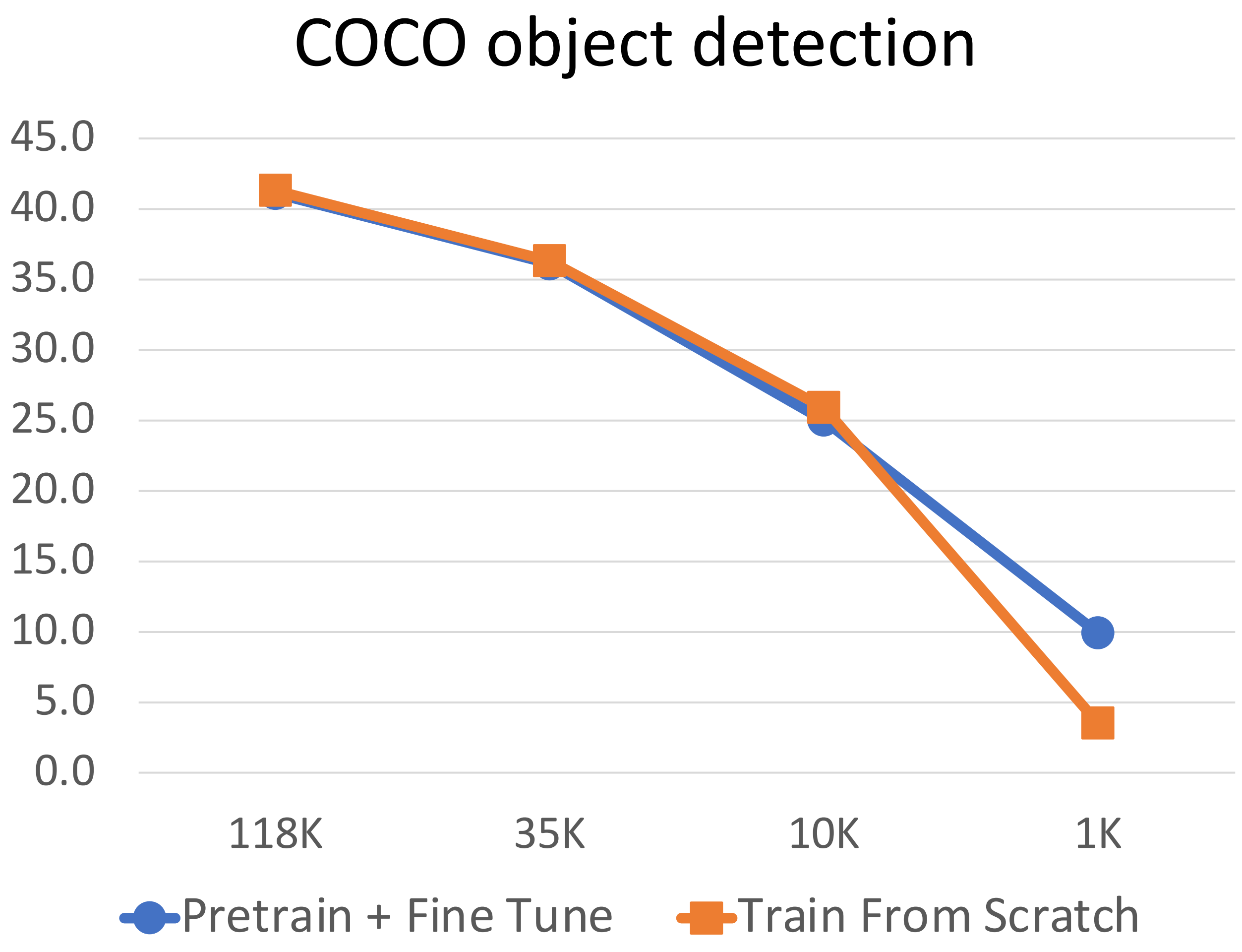


Pretraining + Finetuning beats training from scratch when dataset size is very small

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

Recap

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,

Last Time

Today

Next Time:
More CNN Architectures