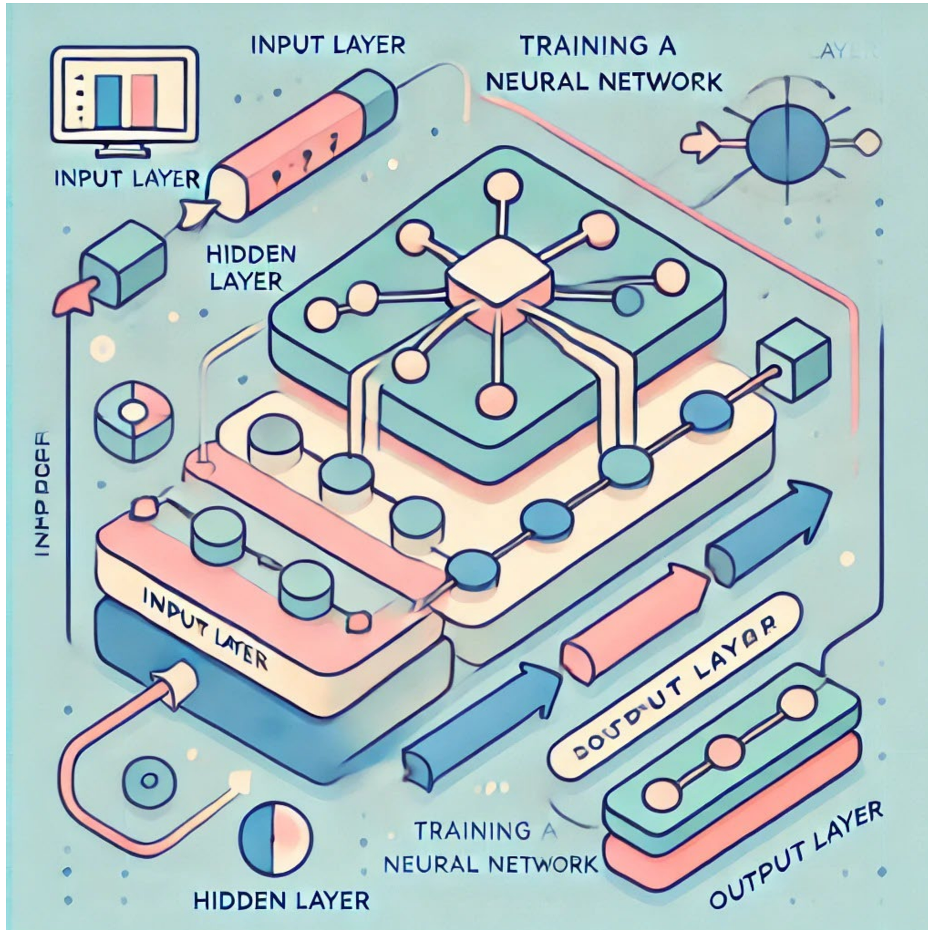
Training Recipes for Neural Nets II



AI604 Deep Learning for Computer Vision

Prof. Hyunjung Shim

Slide credit: Justin Johnson, Fei-Fei Li, Ehsan Adeli

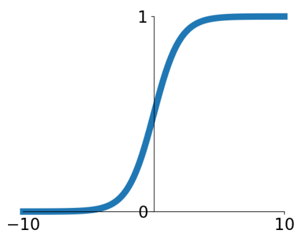
Topics

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

Recap: Activation Functions

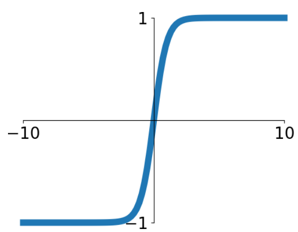
Sigmoid

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



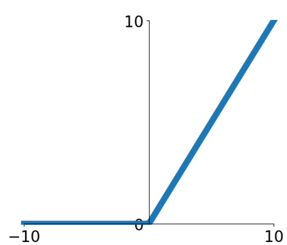
tanh

$\tanh(x)$



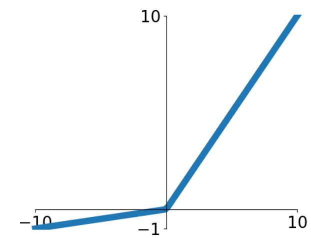
ReLU

$\max(0, x)$



Leaky ReLU

$\max(0.1x, x)$

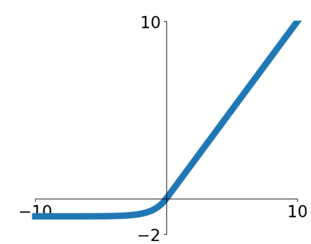


Maxout

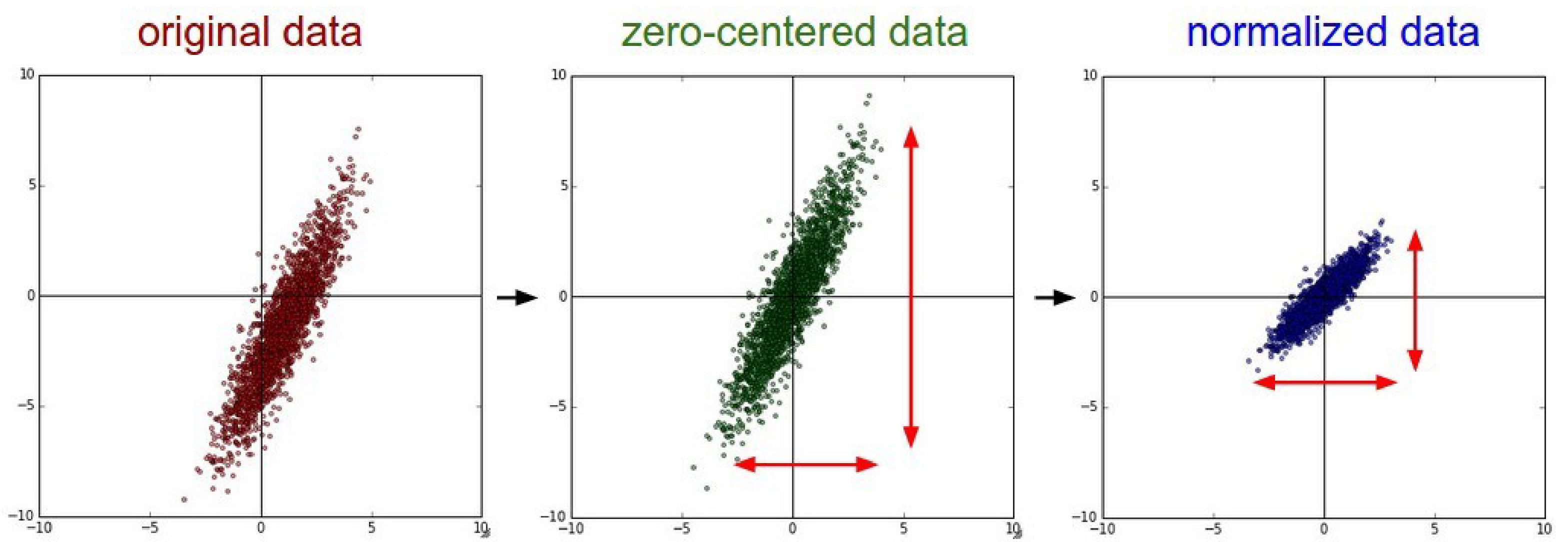
$\max(w_1^T x + b_1, w_2^T x + b_2)$

ELU

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



Recap: Data Preprocessing

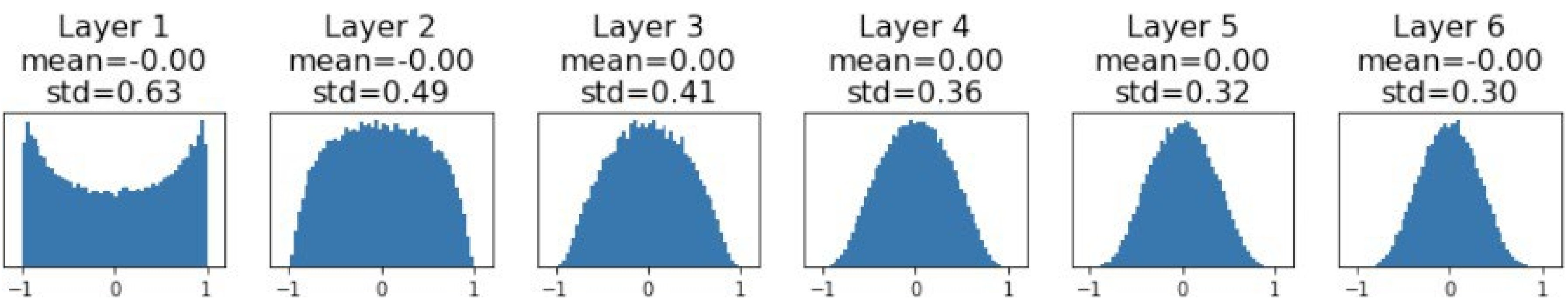


Recap: Weight Initialization

```
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)
```

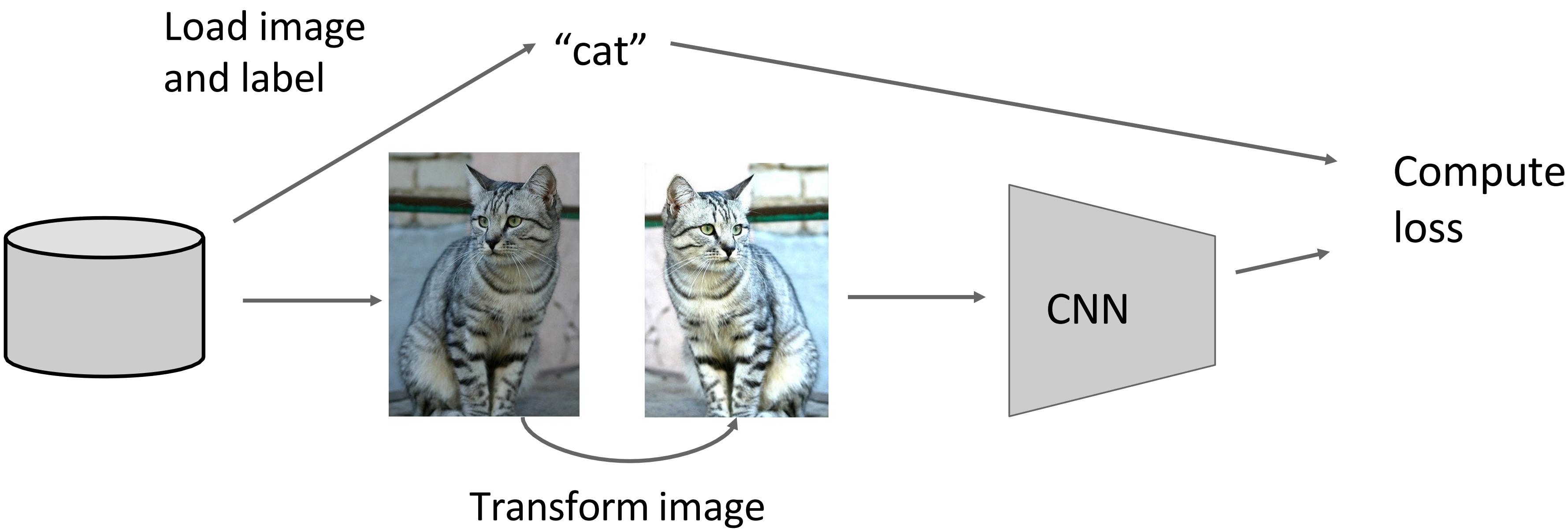
"Xavier" initialization:
std = 1/sqrt(Din)

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



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

Recap: Data Augmentation

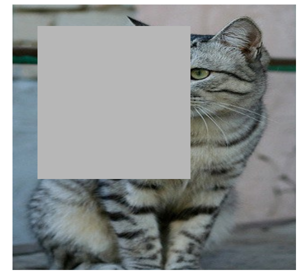


Recap: Regularization

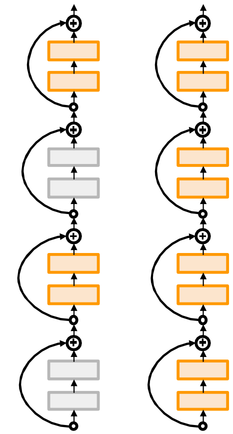
Training: Add randomness
Testing: Marginalize out randomness

Examples:
Batch Normalization
Data Augmentation

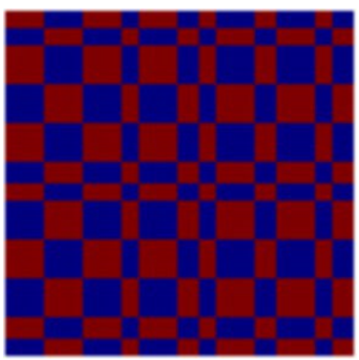
Cutout



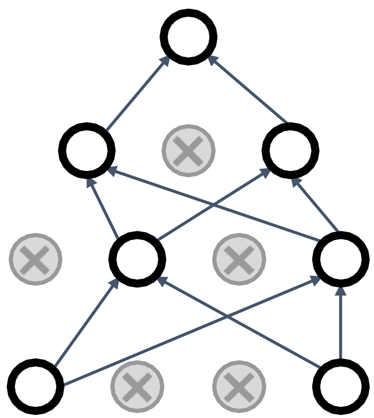
Stochastic Depth



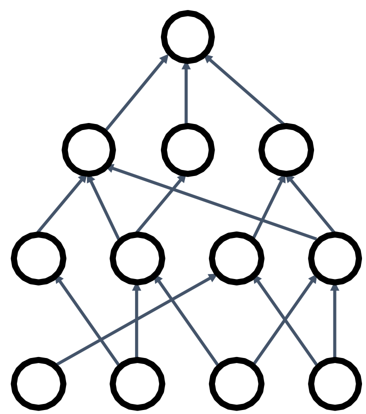
Fractional pooling



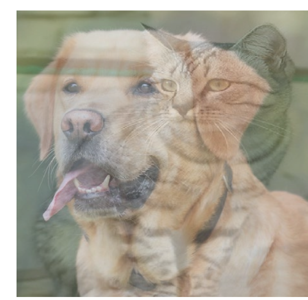
Dropout



DropConnect



Mixup



Topics

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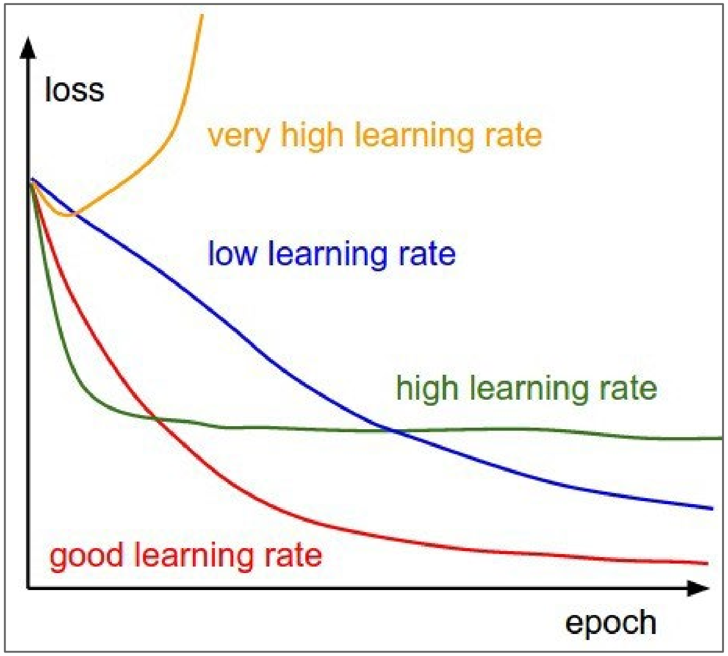
Learning Rate Schedules

SGD, SGD+Momentum, Adagrad, RMSProp, Adam

all have **learning rate** as a hyperparameter.



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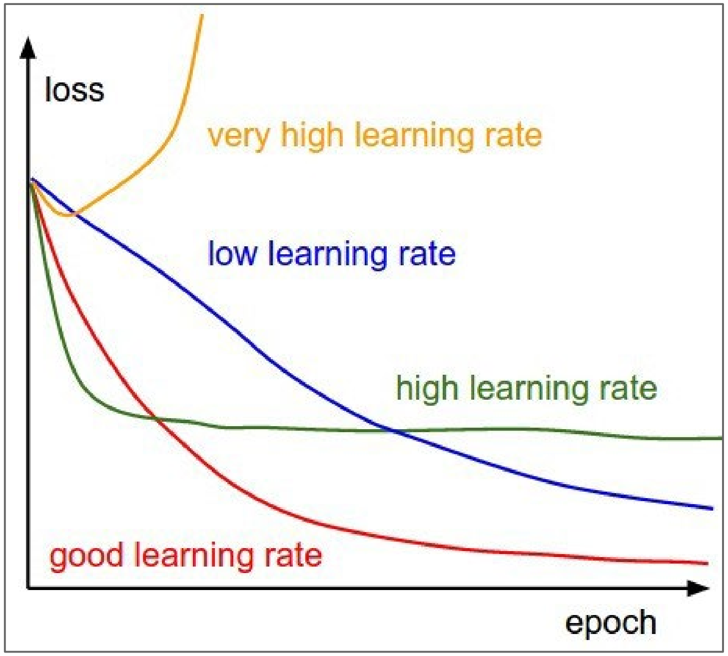
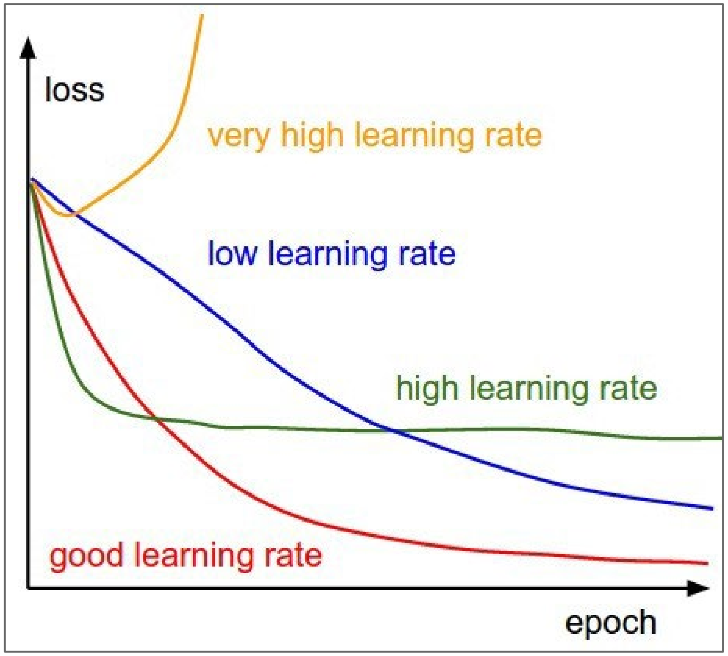


Q: Which one of these learning rates is best to use?

SGD, SGD+Momentum, Adagrad, RMSProp, Adam

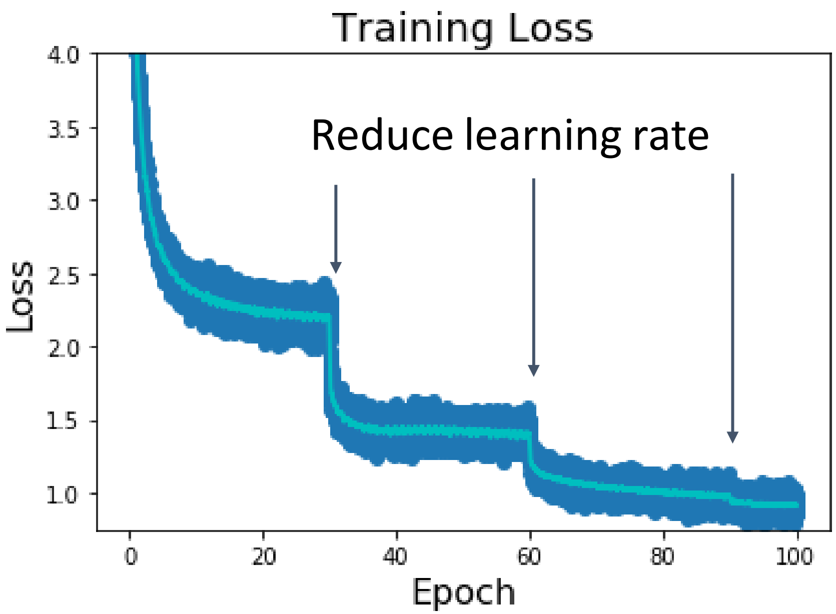
all have **learning rate** as a hyperparameter.



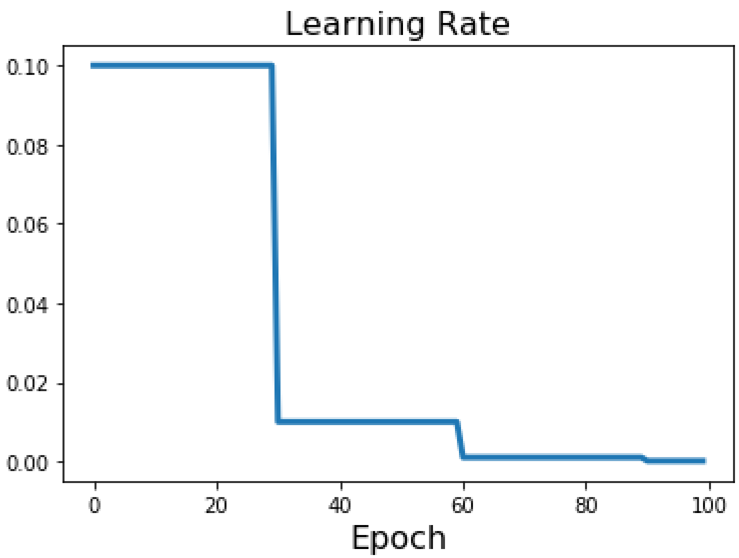
Q: Which one of these learning rates is best to use?

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

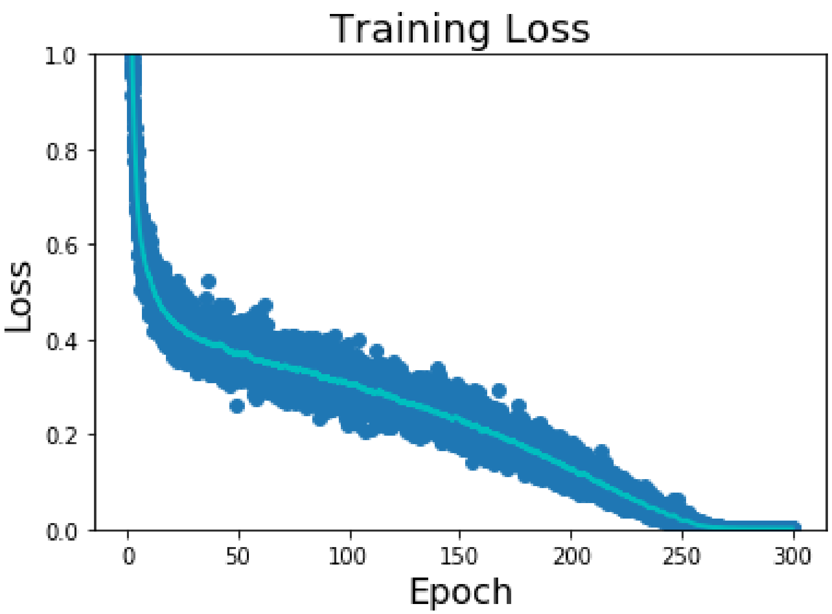
Learning Rate Decay: Step



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

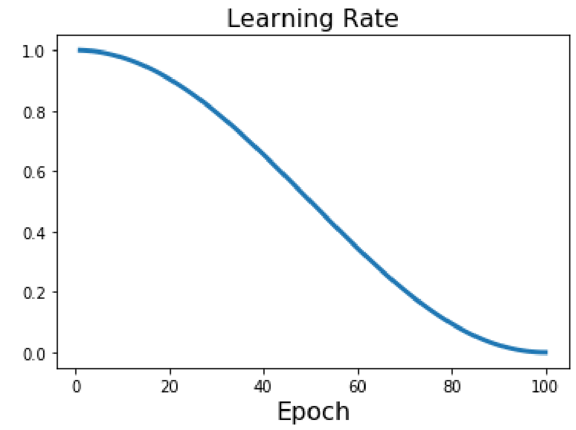


Learning Rate Decay: Cosine



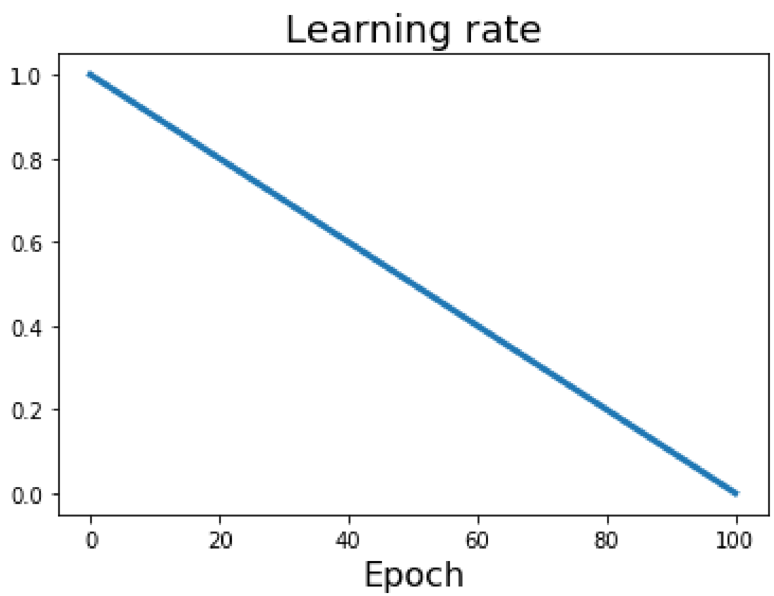
Step: Reduce learning rate at a few fixed points. E.g. for ResNets, multiply LR by 0.1 after epochs 30, 60, and 90.

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



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



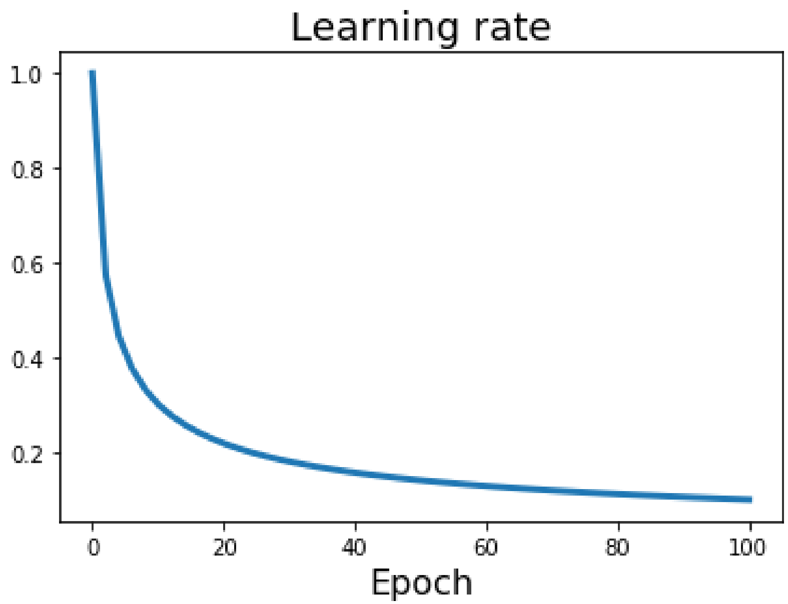
Step: Reduce learning rate at a few fixed points. E.g. for ResNets, multiply LR by 0.1 after epochs 30, 60, and 90.

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

Linear: $$\alpha_t = \alpha_0(1 - t/T)$$

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.

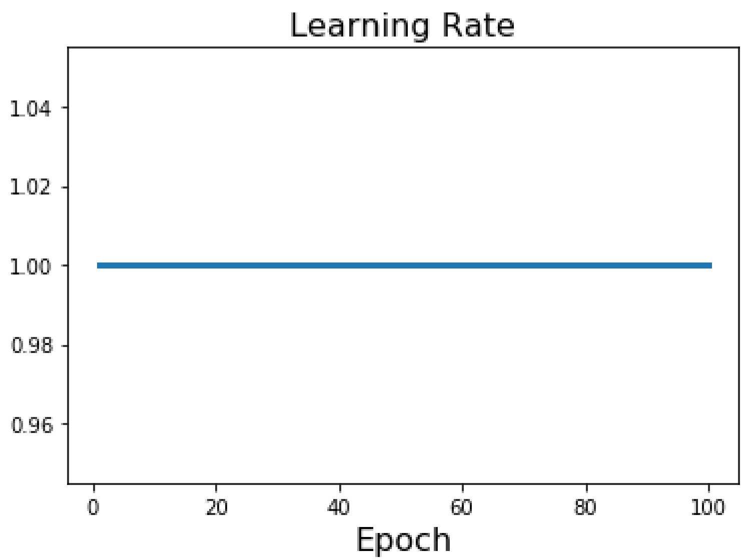
Cosine: $\alpha_t = \frac{1}{2}\alpha_0 \left(1 + \cos(t\pi/T)\right)$

Linear: $\alpha_t = \alpha_0(1 - t/T)$

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

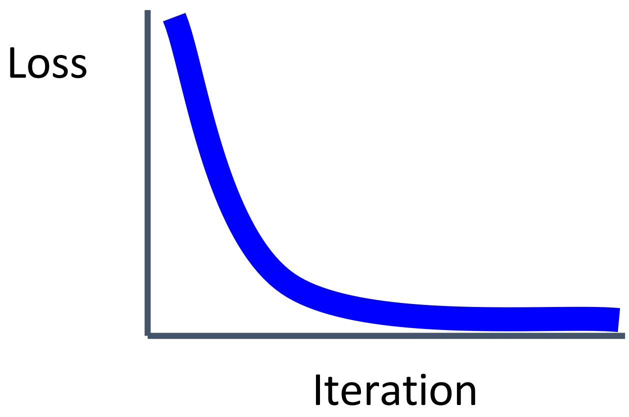
Linear: $$\alpha_t = \alpha_0(1 - t/T)$$

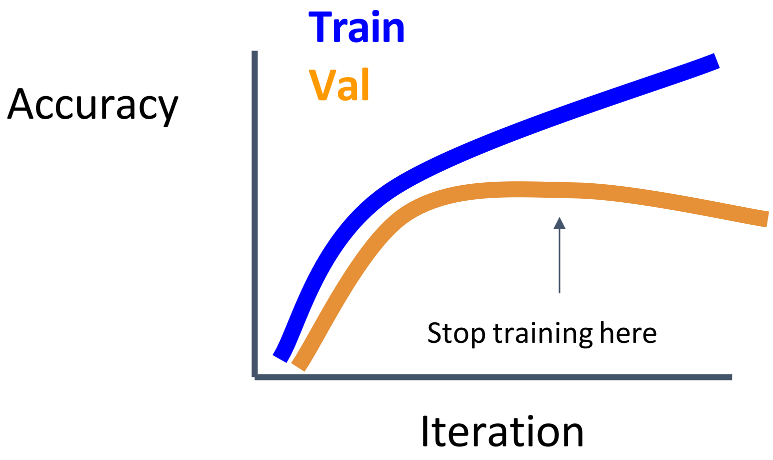
Inverse sqrt: $$\alpha_t = \alpha_0/\sqrt{t}$$

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 hyperparameter
(Often space choices log-linearly)

Example:
Weight decay: [$1x10^{-4}$, $1x10^{-3}$, $1x10^{-2}$, $1x10^{-1}$]
Learning rate: [$1x10^{-4}$, $1x10^{-3}$, $1x10^{-2}$, $1x10^{-1}$]

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

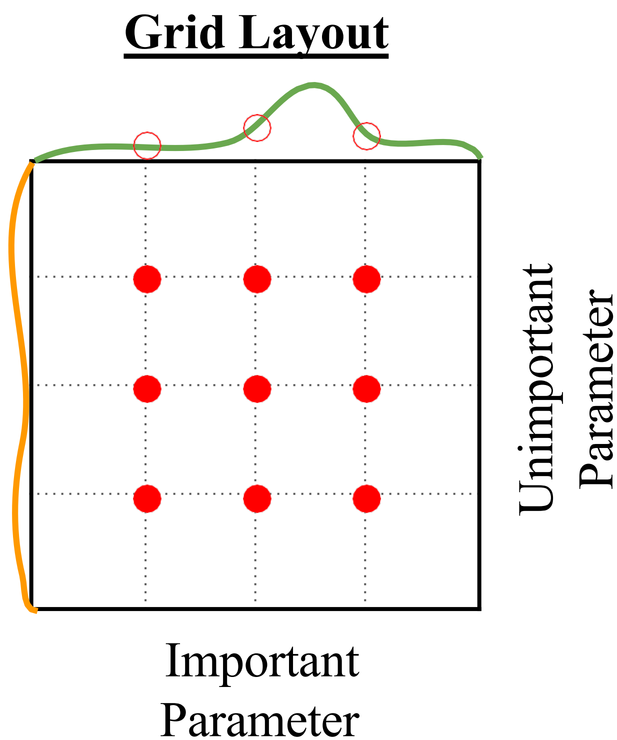
Choosing Hyperparameters: Random Search

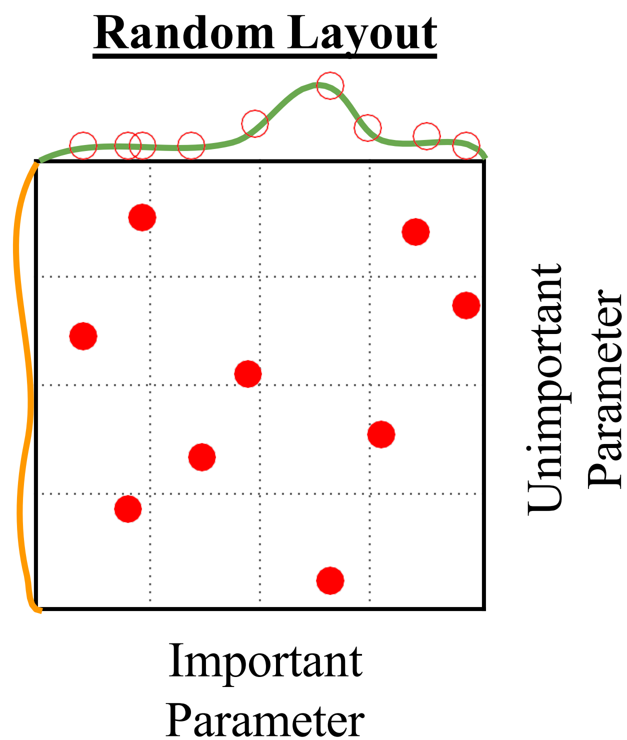
Choose several values for each hyperparameter
(Often space choices log-linearly)

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

Run many different trials

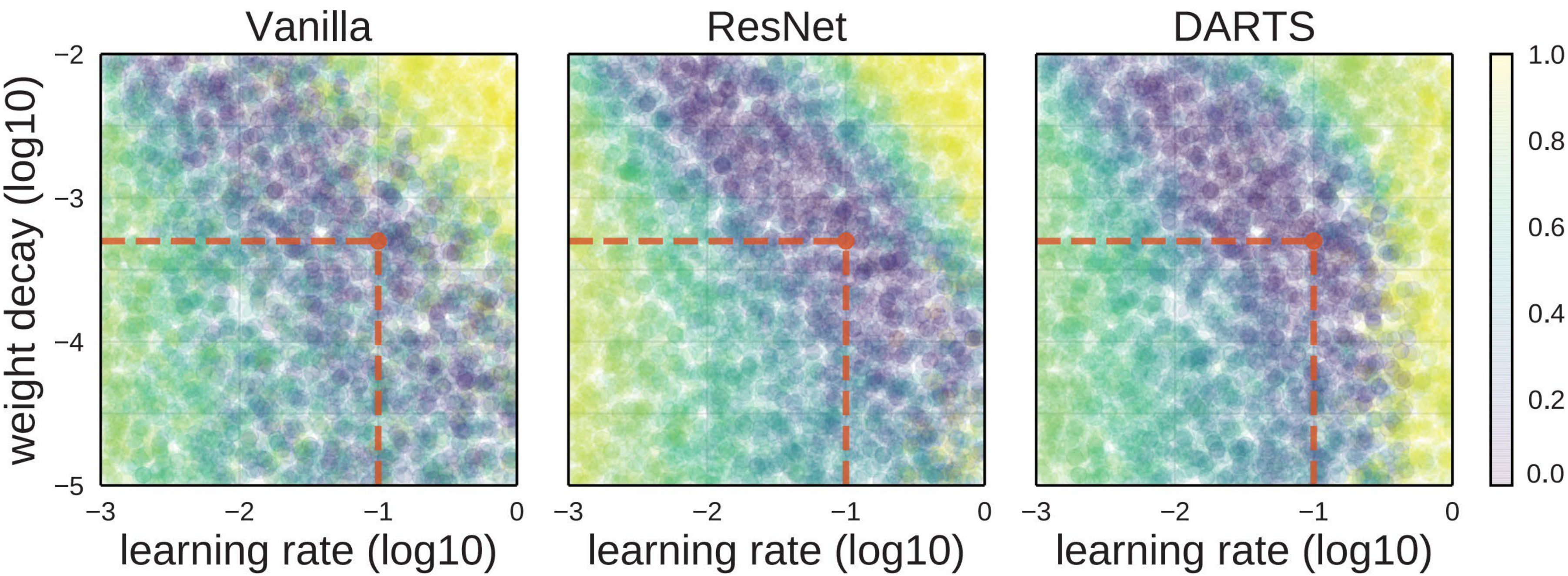
Choosing Hyperparameters: Random vs Grid Search





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

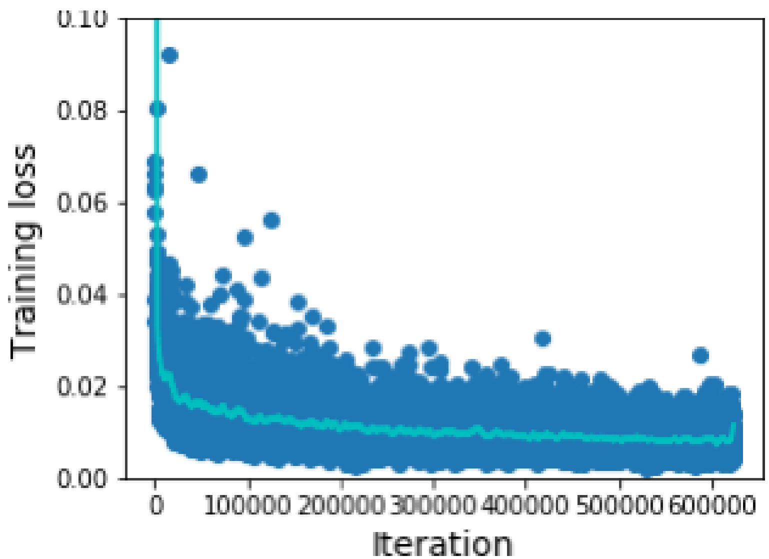
Step 1: Check initial loss
Step 2: Overfit a small sample
Step 3: Find LR that makes loss go down
Step 4: Coarse grid, train for ~1-5 epochs
Step 5: Refine grid, train longer

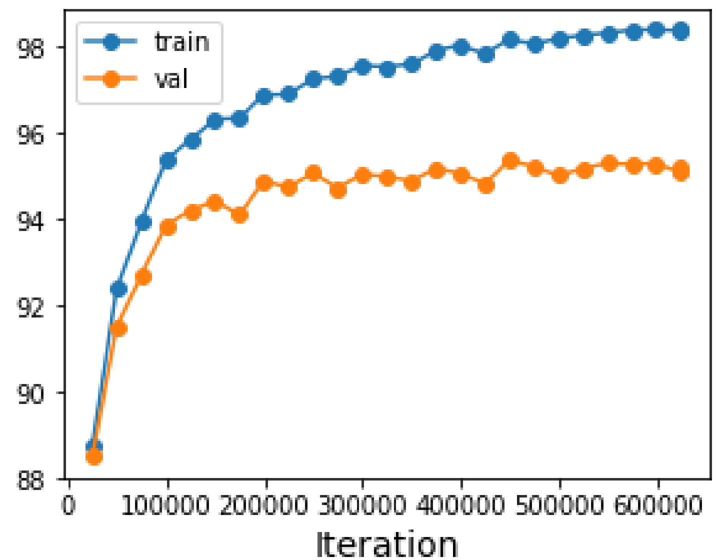
Pick best models from Step 4, train them for longer (~10-20 epochs) without learning rate decay

Choosing Hyperparameters

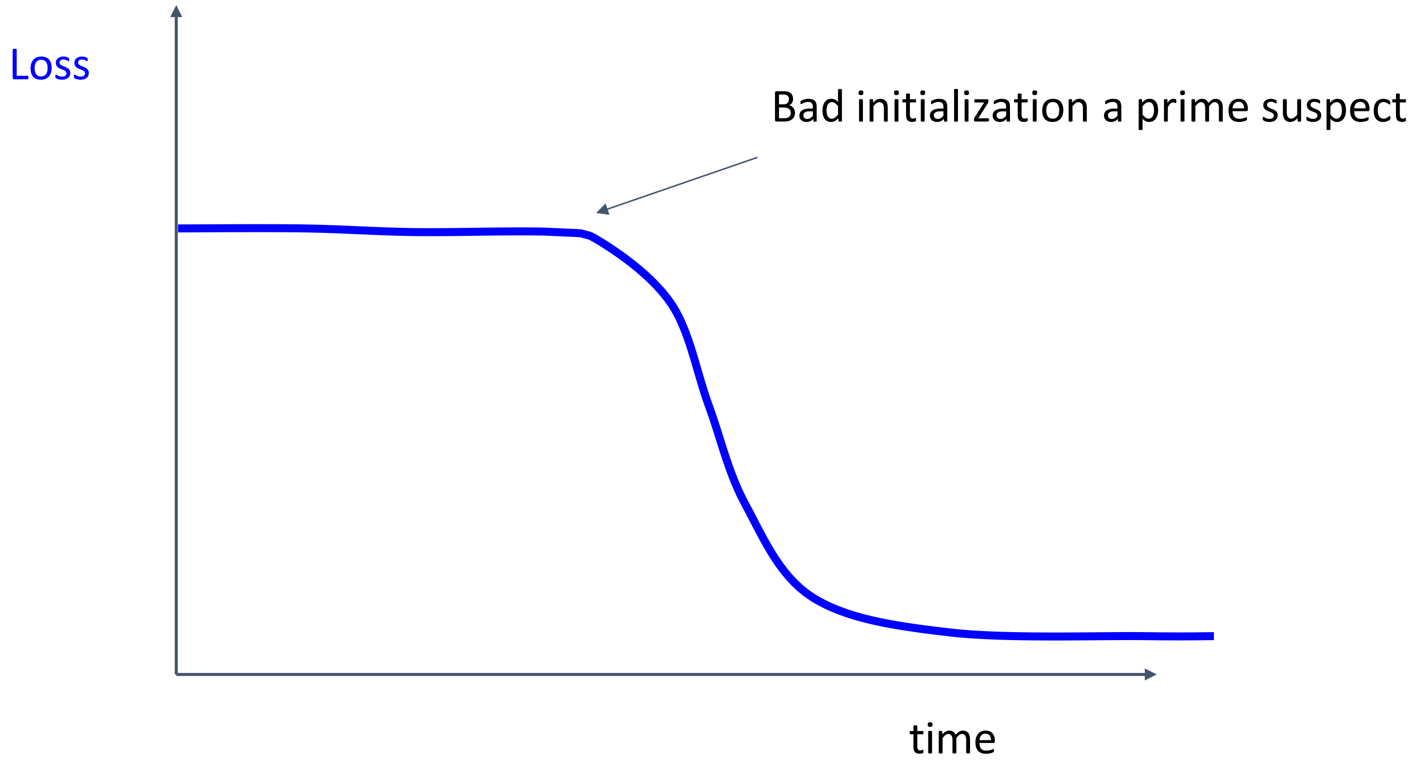
Step 1: Check initial loss
Step 2: Overfit a small sample
Step 3: Find LR that makes loss go down
Step 4: Coarse grid, train for ~1-5 epochs
Step 5: Refine grid, train longer
Step 6: Look at learning curves

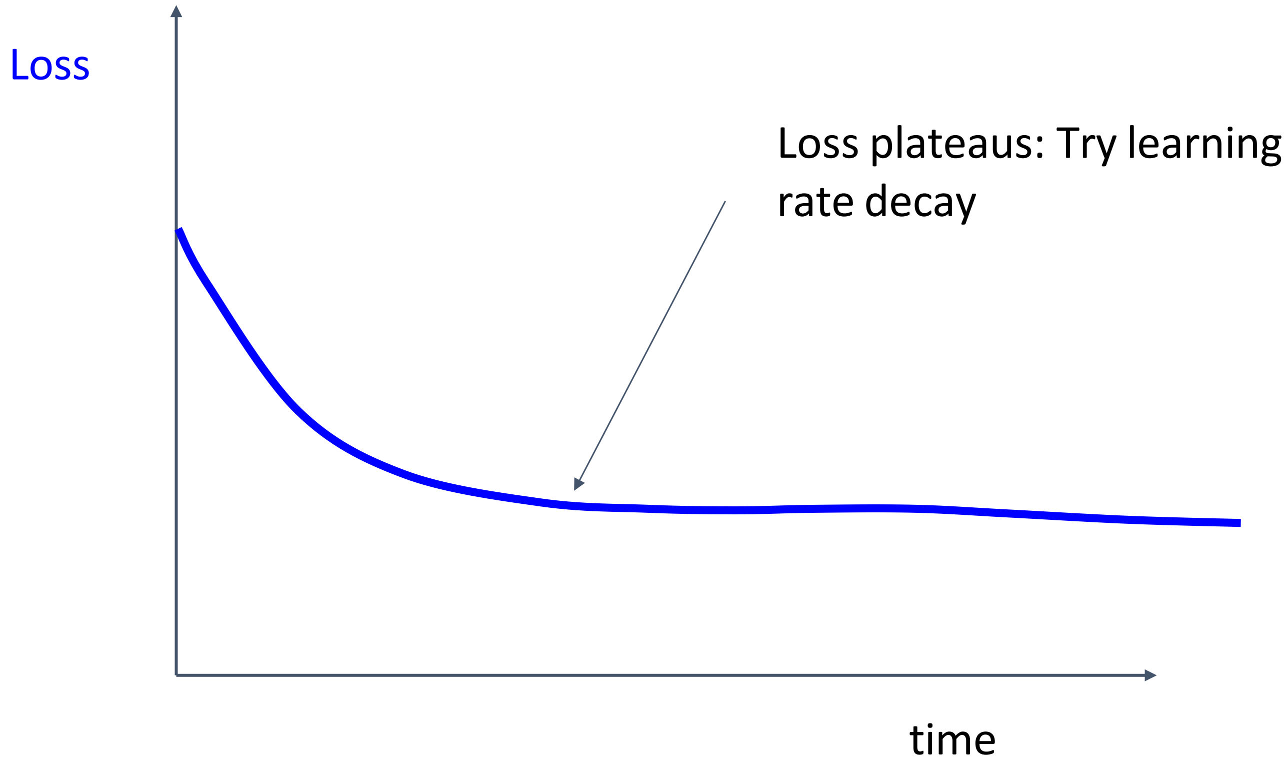
Look at Learning Curves!

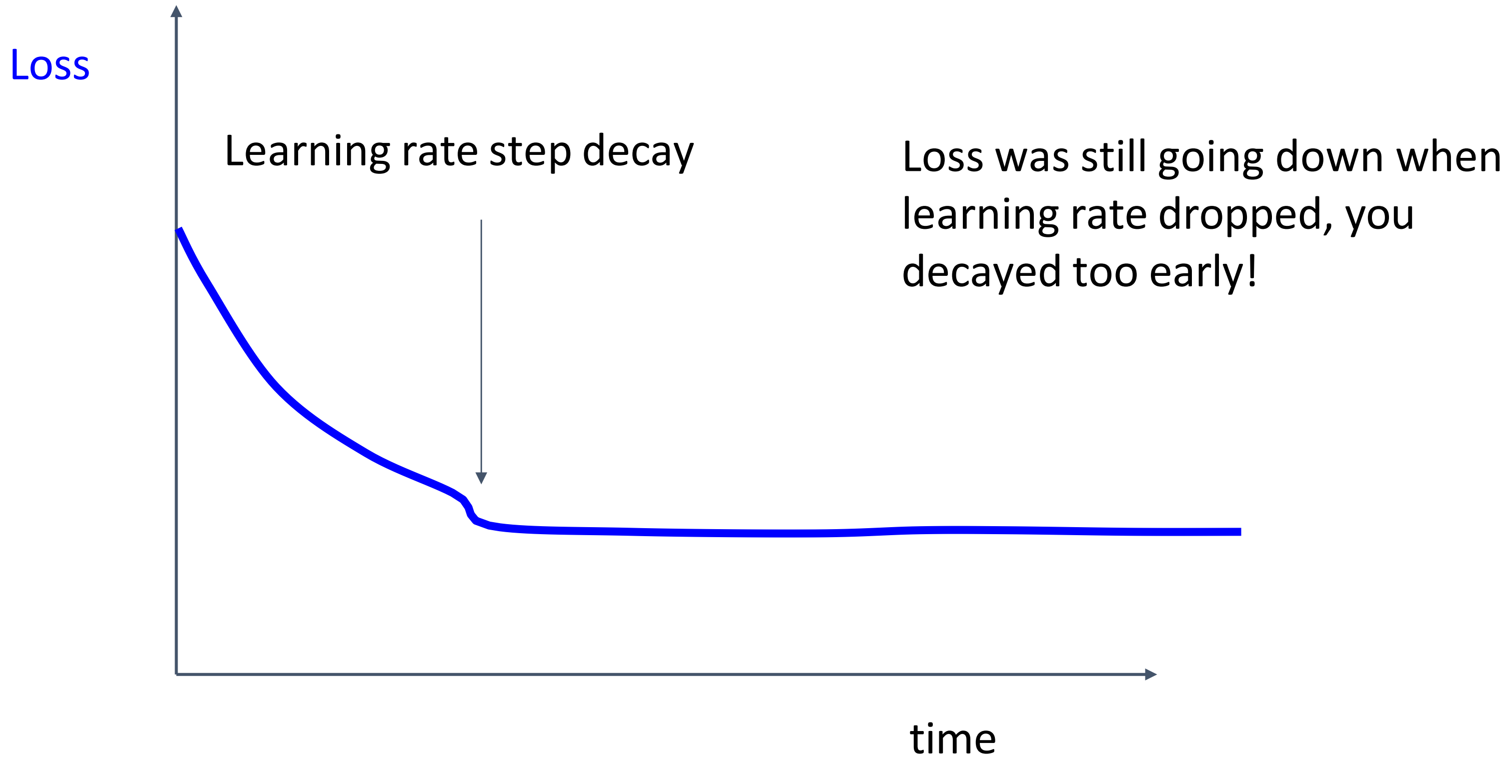


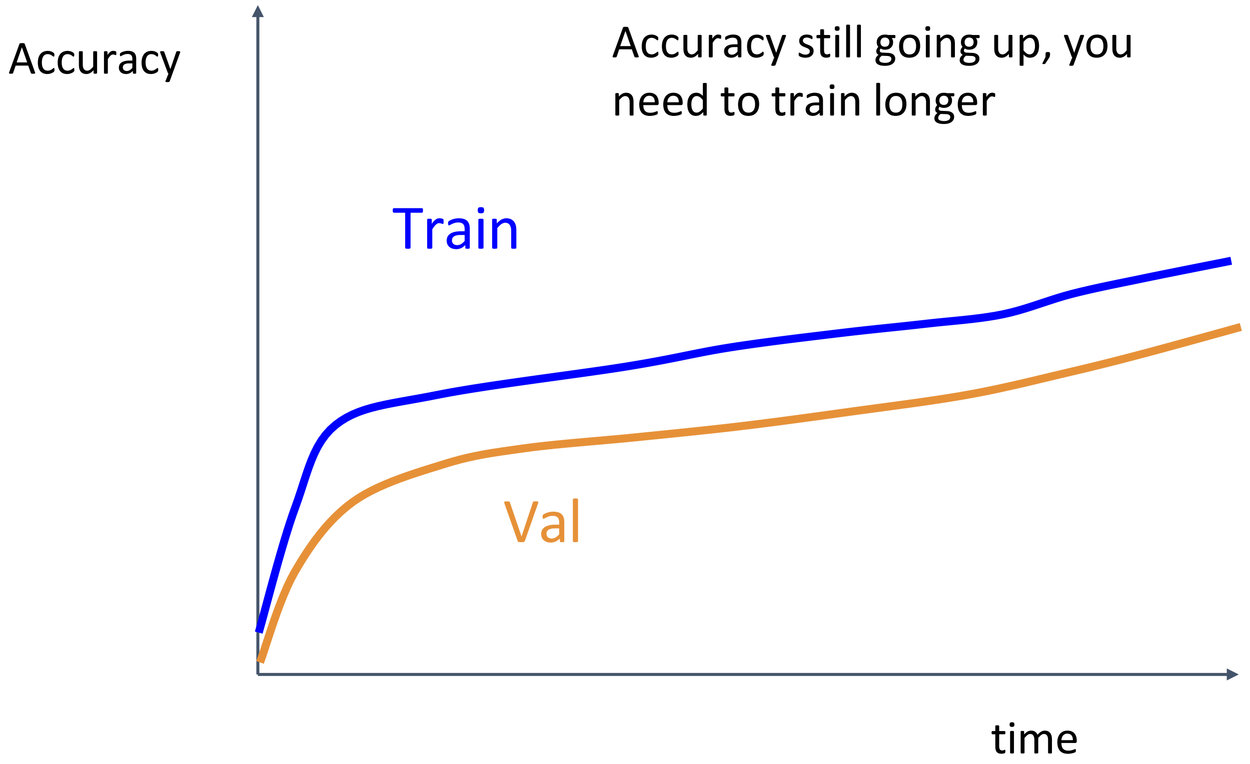


Losses may be noisy, use a scatter plot and also plot moving average to see trends better

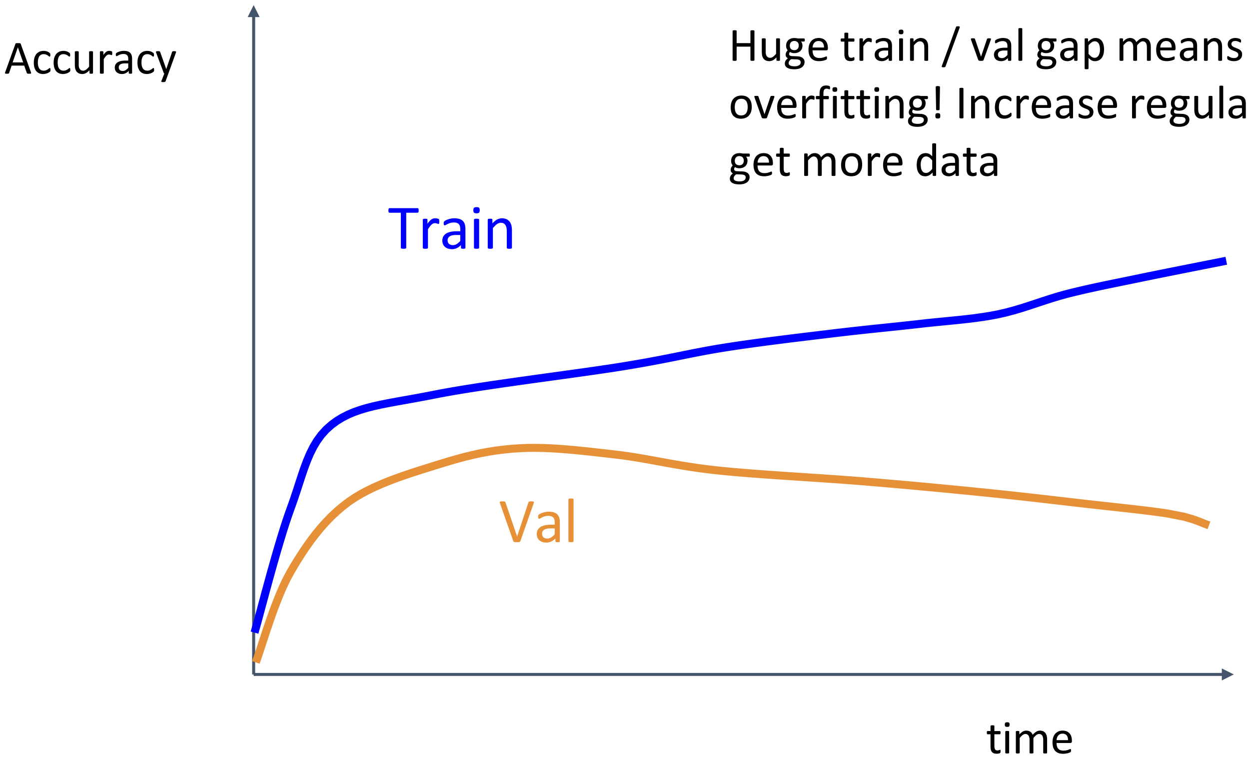

Loss
Bad initialization a prime suspect
time

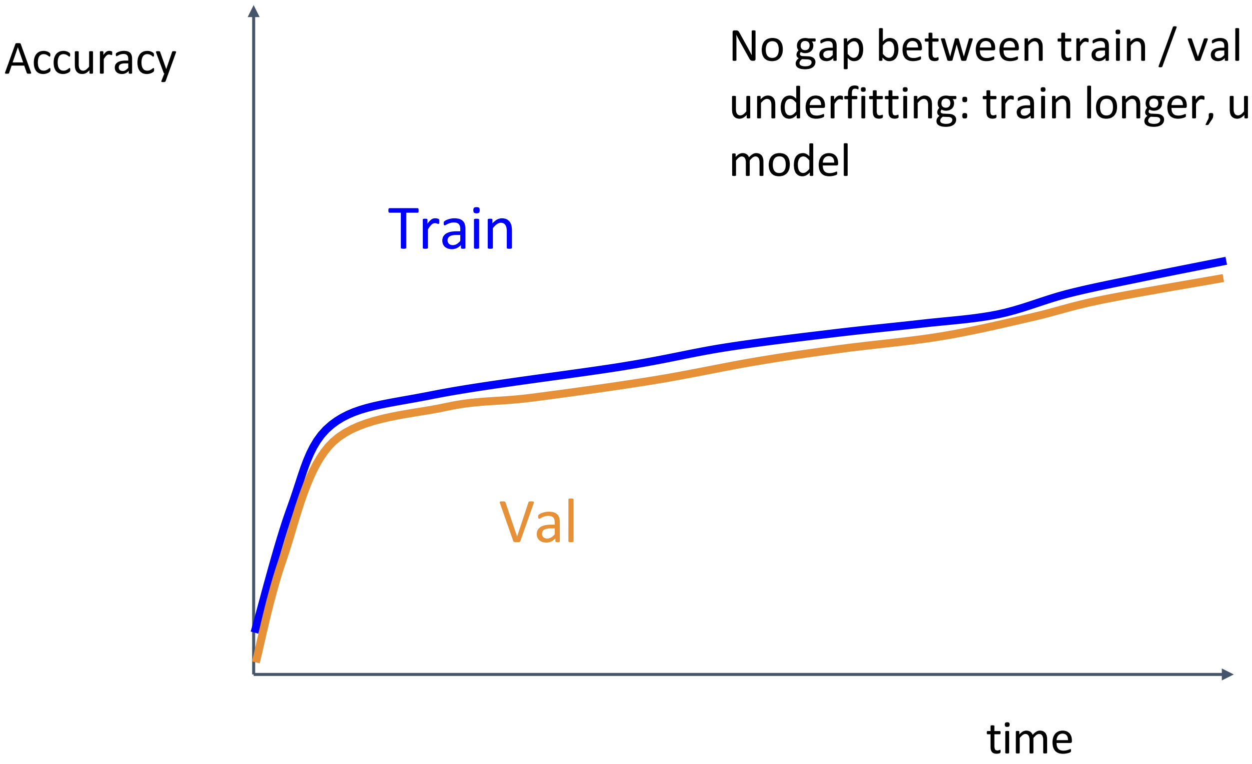

Loss
Loss plateaus: Try learning rate decay
time


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


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

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





No gap between train / val means underfitting: train longer, use a bigger model

Choosing Hyperparameters

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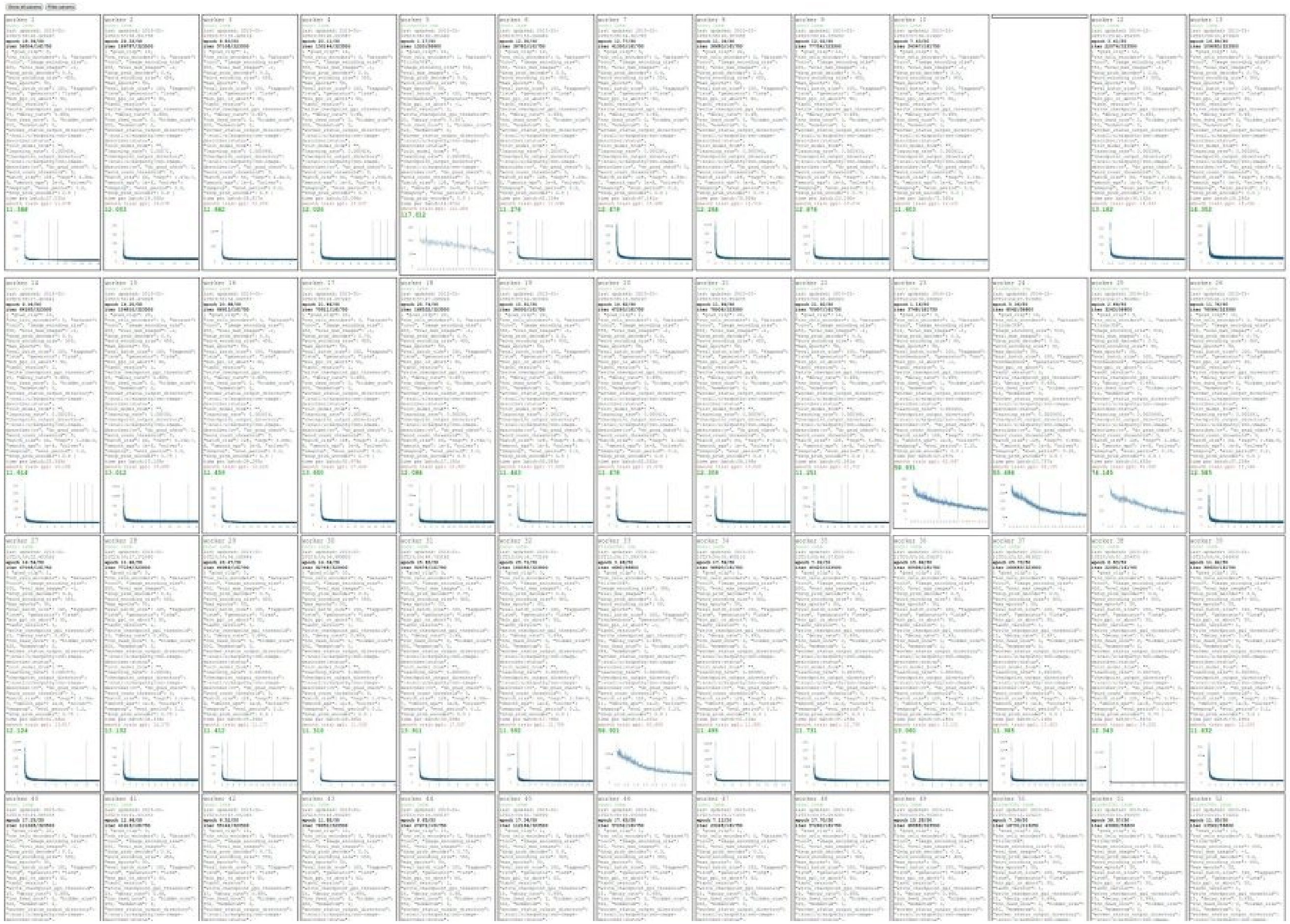
Step 5: Refine grid, train longer
Step 6: Look at loss curves
Step 7: GOTO step 5

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

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Model Ensembles

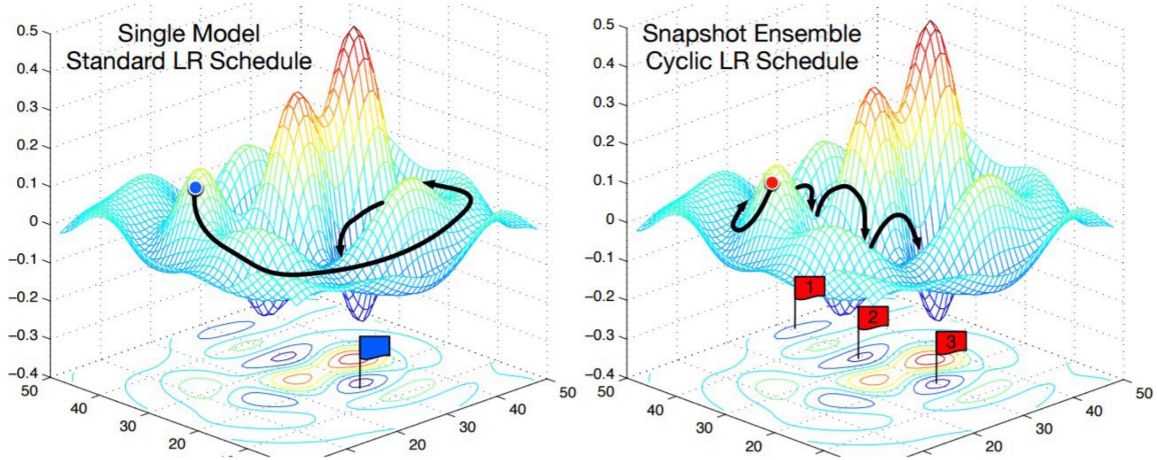
1. Train multiple independent models
2. At test time average their results

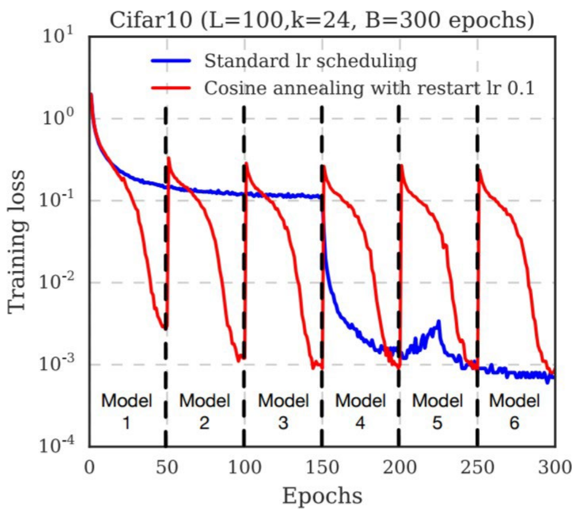
   (Take average of predicted probability distributions, then choose argmax)

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

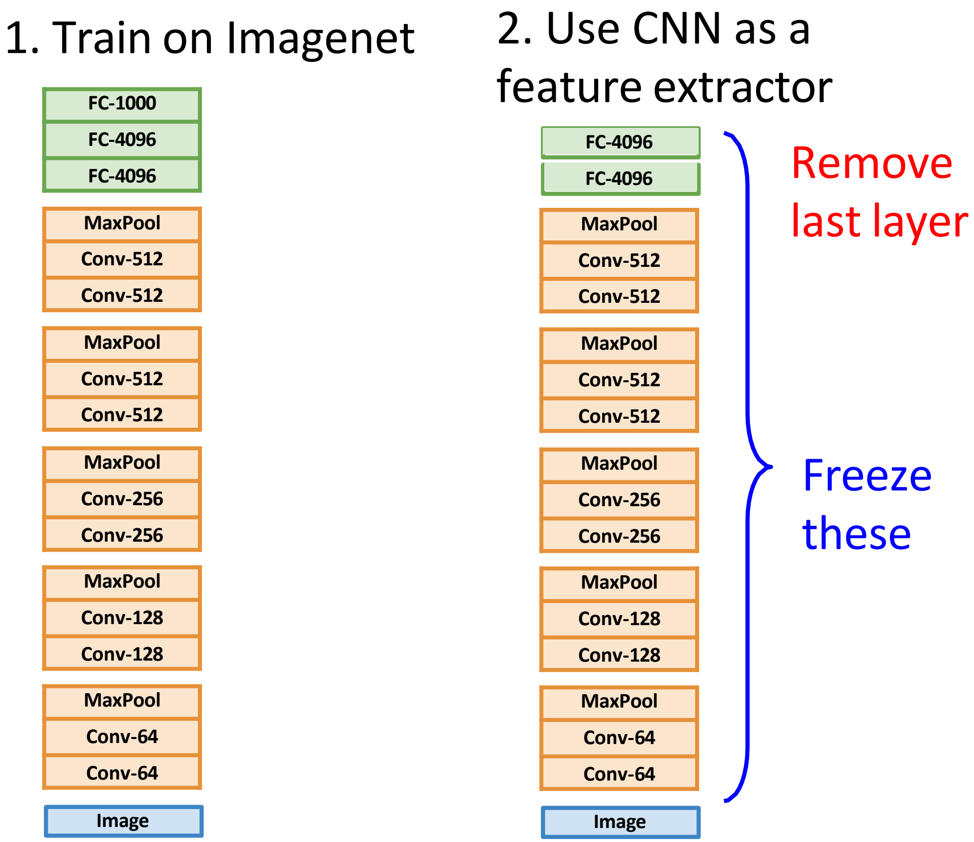
"You need a lot of a data if you want to train/use CNNs"

Transfer Learning

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

BUSTED

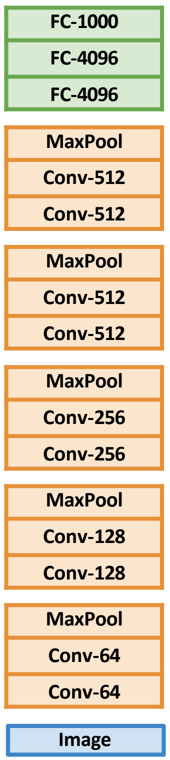
Transfer Learning with CNNs



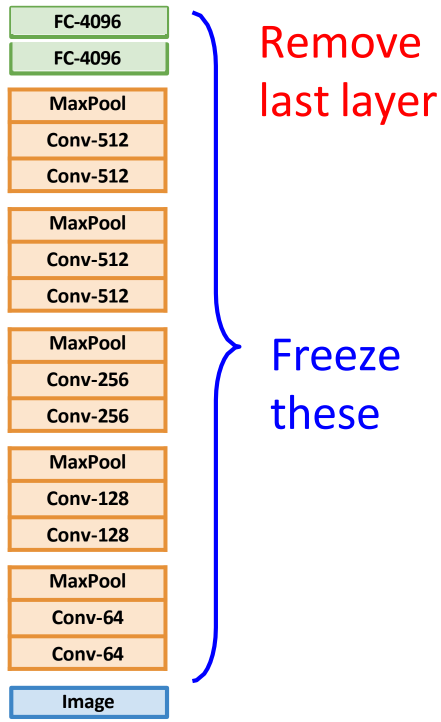
Donahue et al, "DeCAF: A Deep Convolutional Activation Feature for Generic Visual Recognition", ICML 2014

Transfer Learning with CNNs

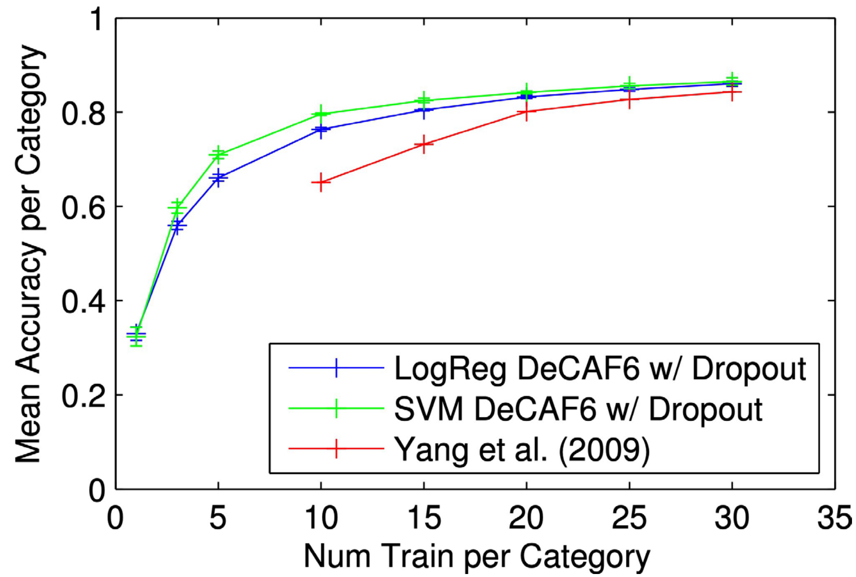
1. Train on Imagenet



2. Use CNN as a feature extractor



Classification on Caltech-101



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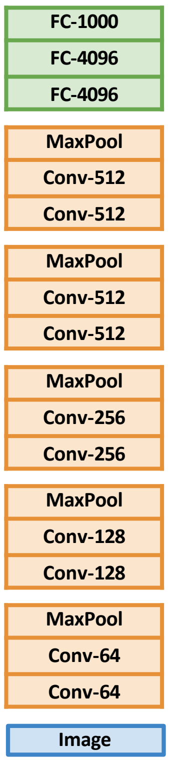
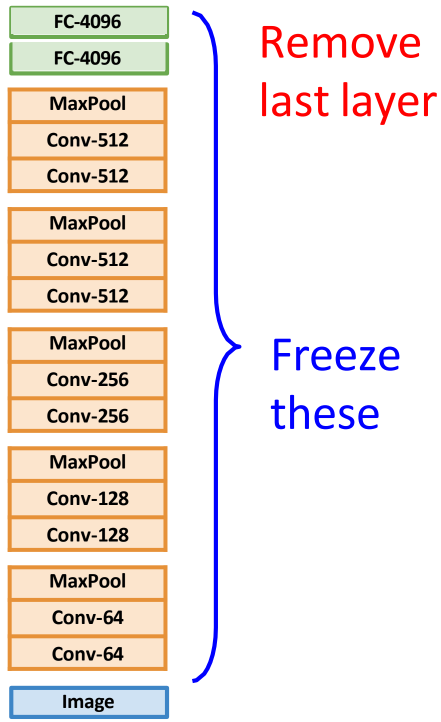
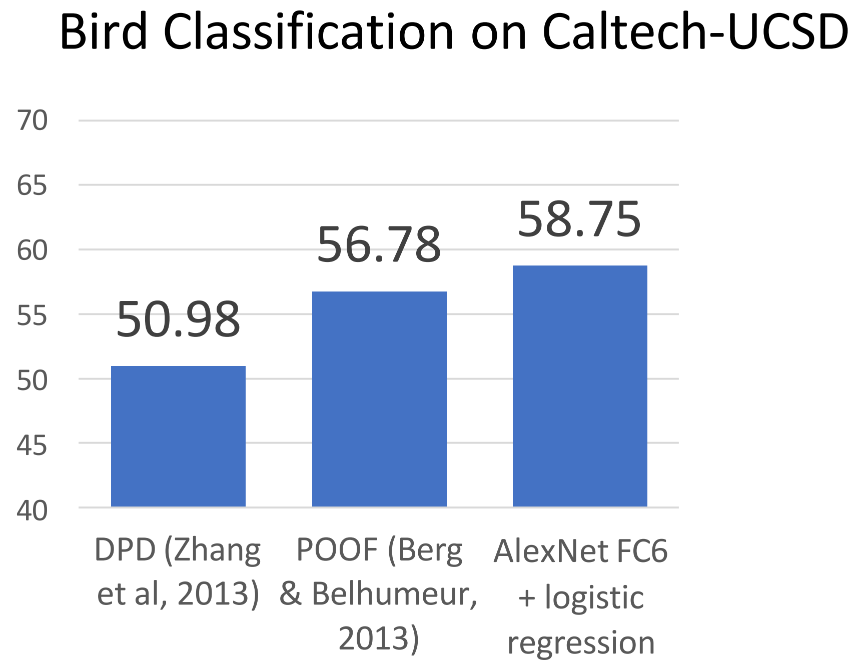


2. Use CNN as a feature extractor

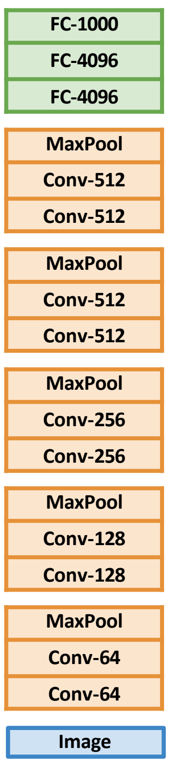




Donahue et al, "DeCAF: A Deep Convolutional Activation Feature for Generic Visual Recognition", ICML 2014

Transfer Learning with CNNs

1. Train on Imagenet



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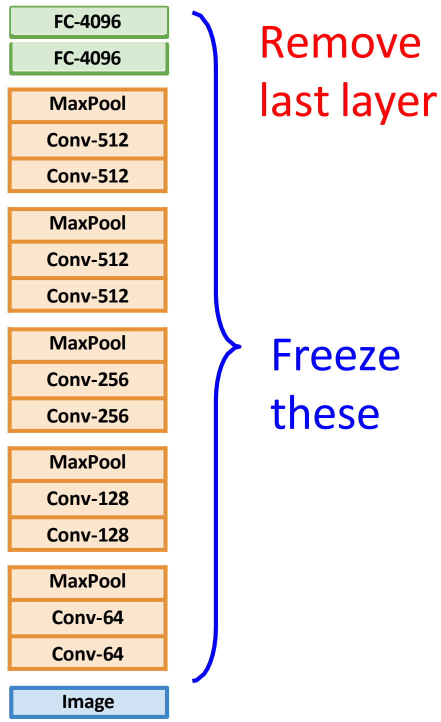
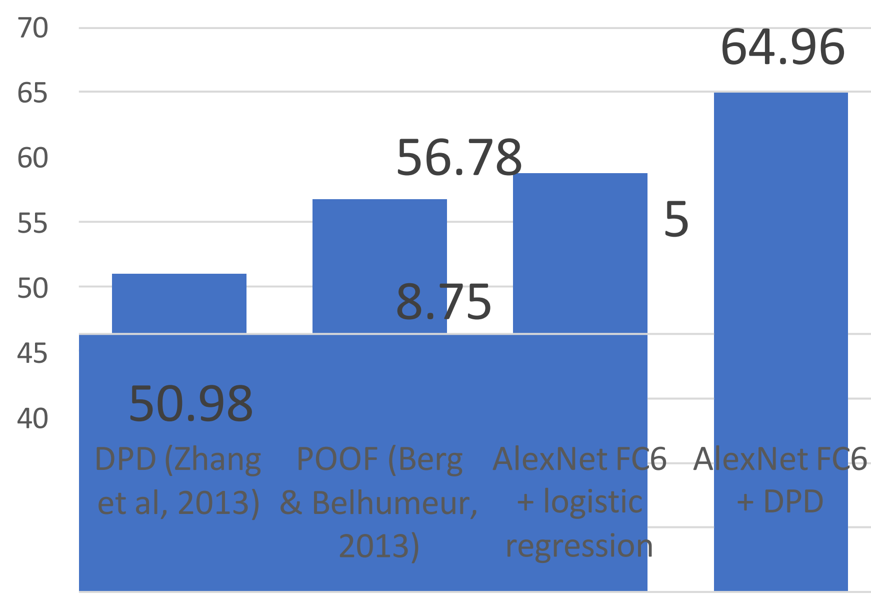


Bird Classification on Caltech-UCSD



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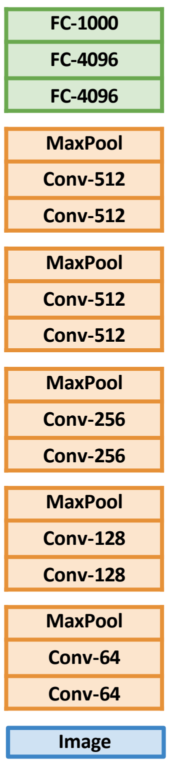

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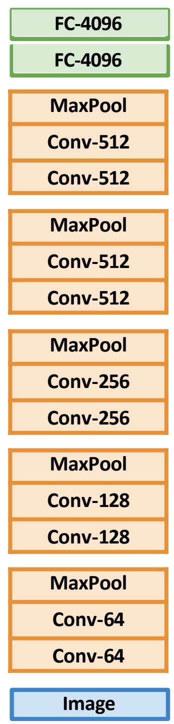

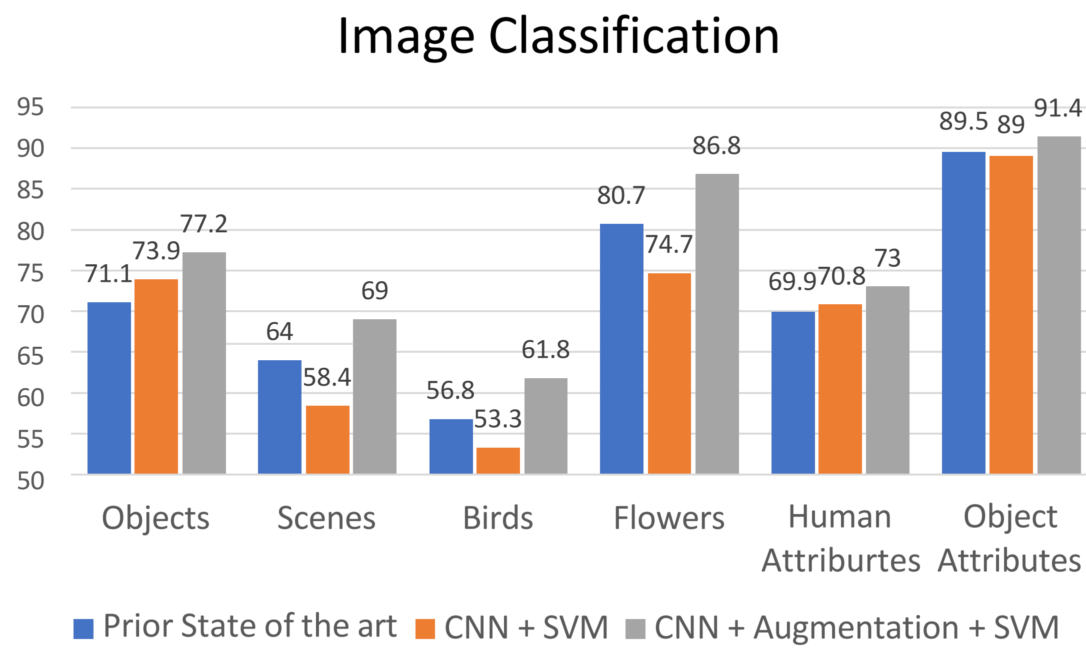

Razavian et al, "CNN Features Off-the-Shelf: An Astounding Baseline for Recognition", CVPR Workshops 2014

Transfer Learning with CNNs

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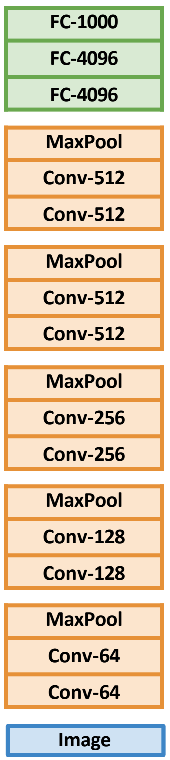

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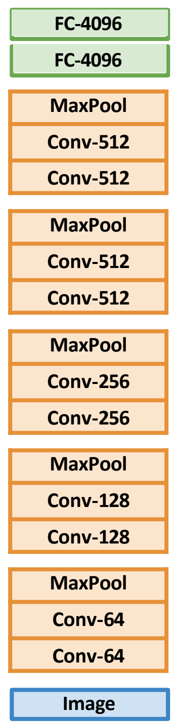
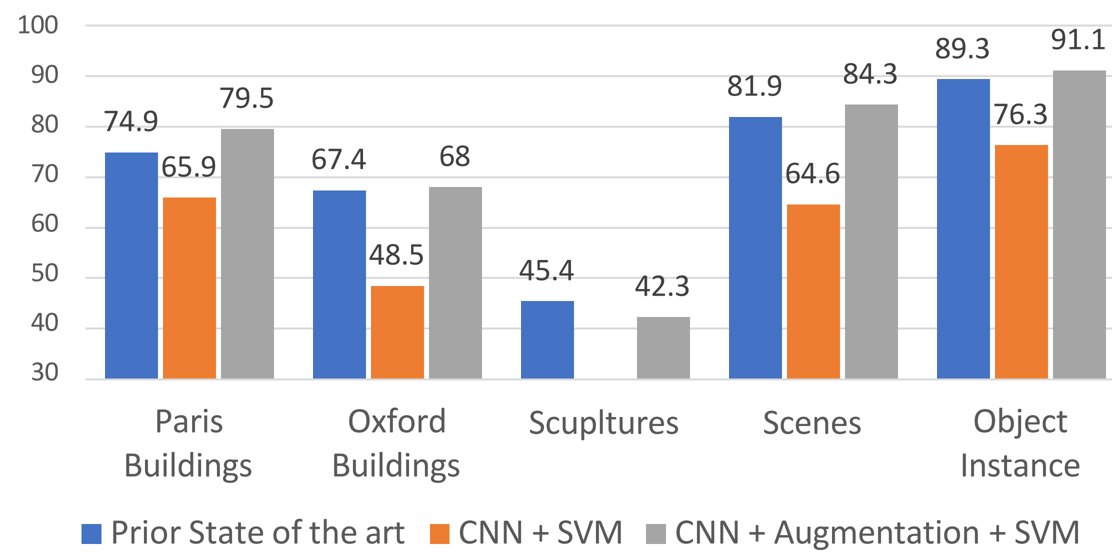
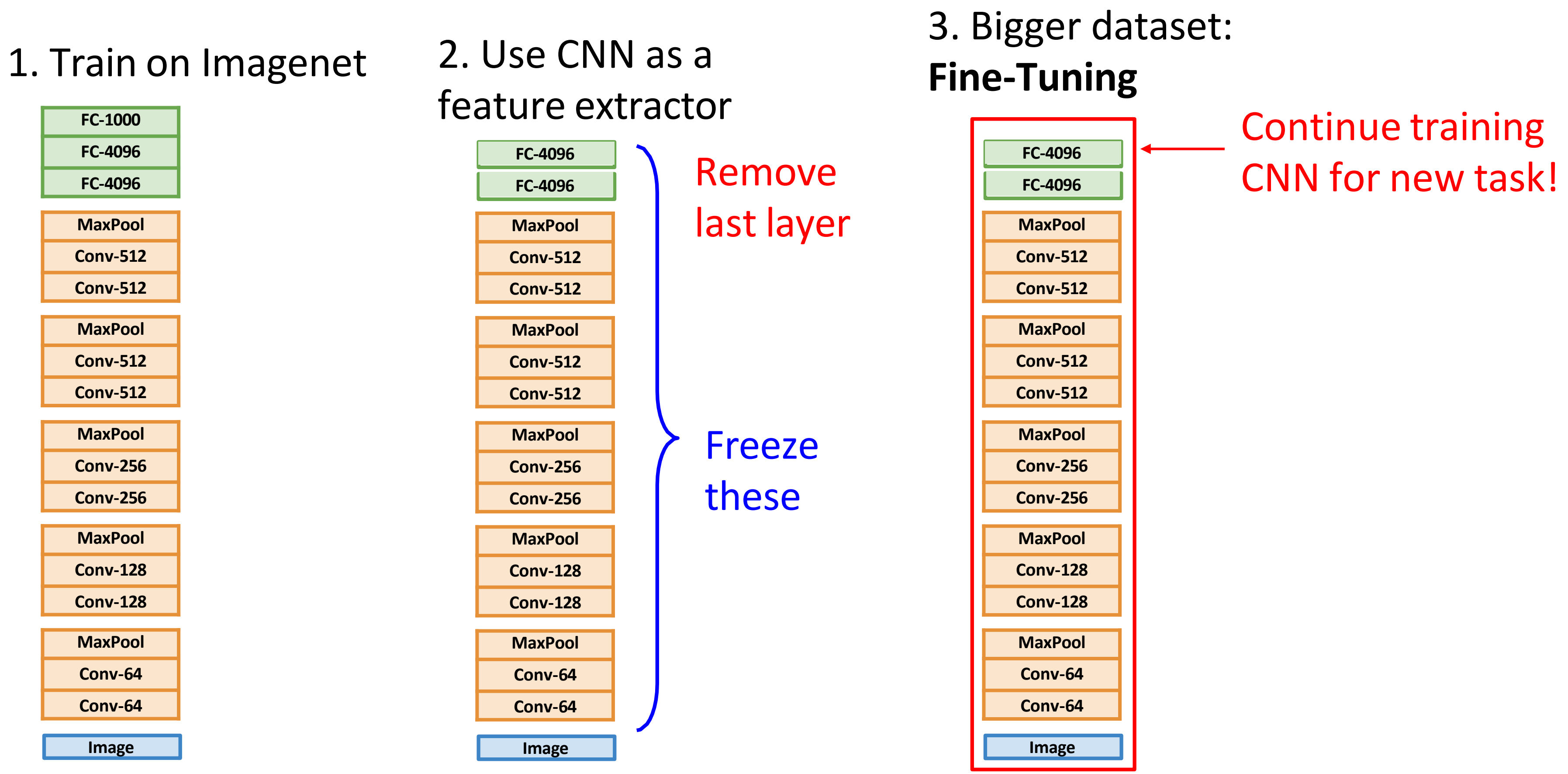


Image Retrieval: Nearest-Neighbor



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

Transfer Learning with CNNs



Transfer Learning with CNNs

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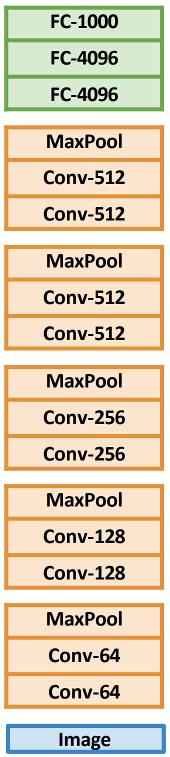

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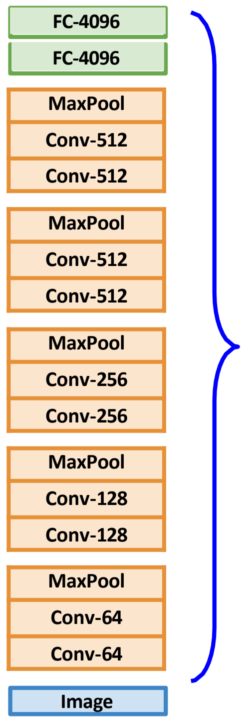
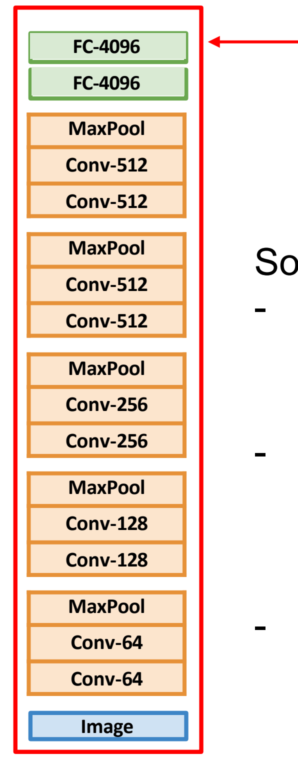


Remove last layer

Freeze these

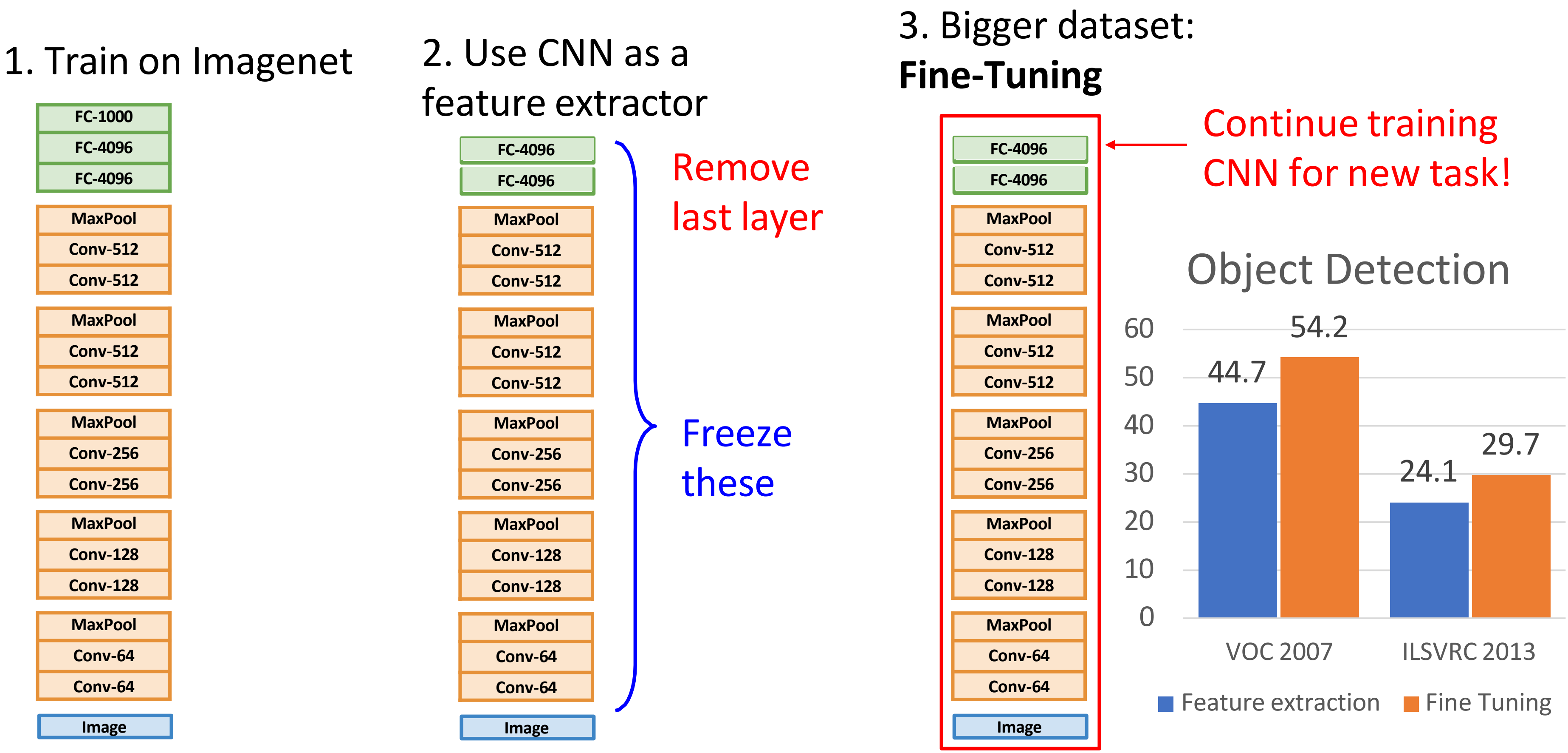
3. Bigger dataset: **Fine-Tuning**



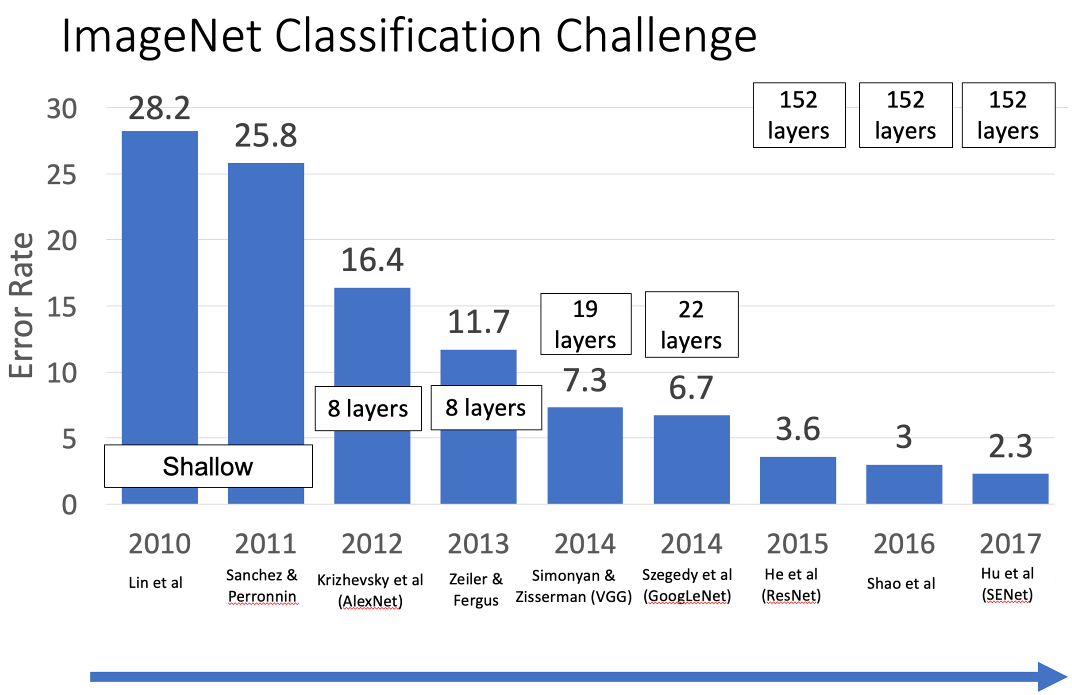
Continue training CNN for new task!

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

Transfer Learning with CNNs

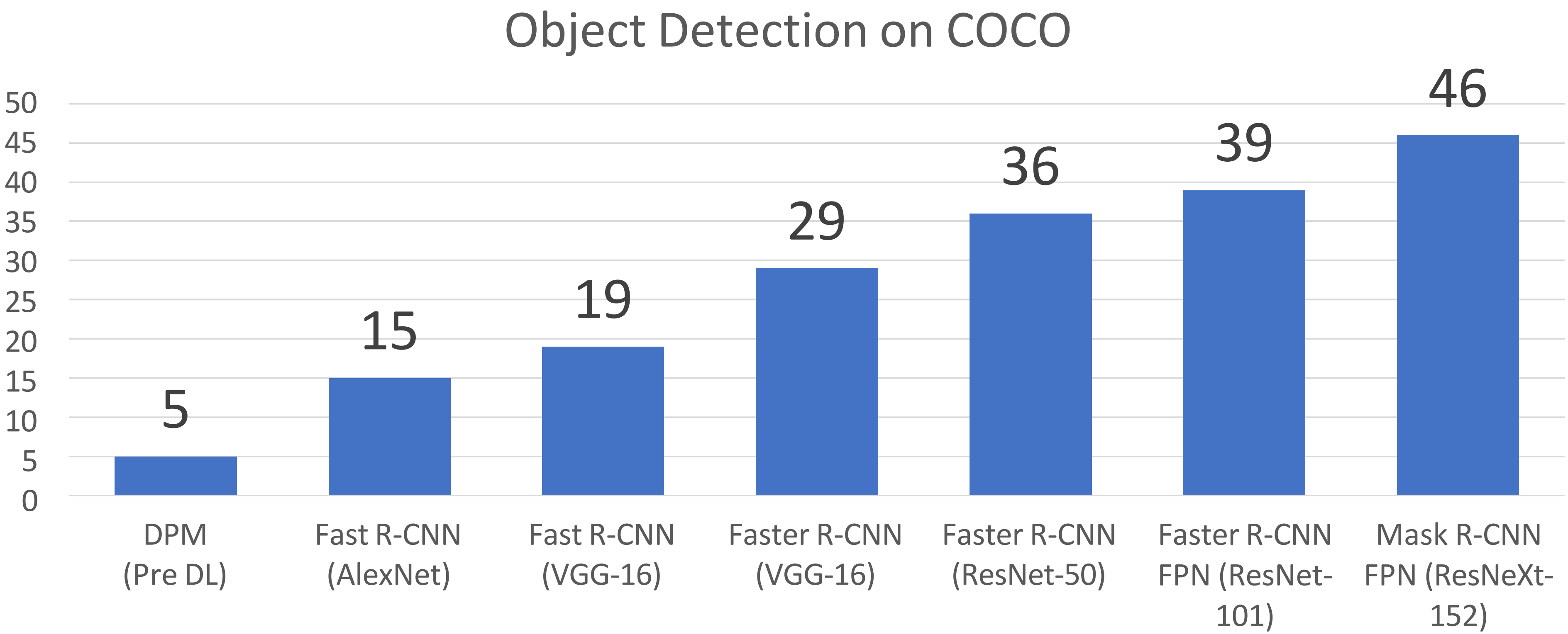


Transfer Learning with CNNs: Architecture Matters!



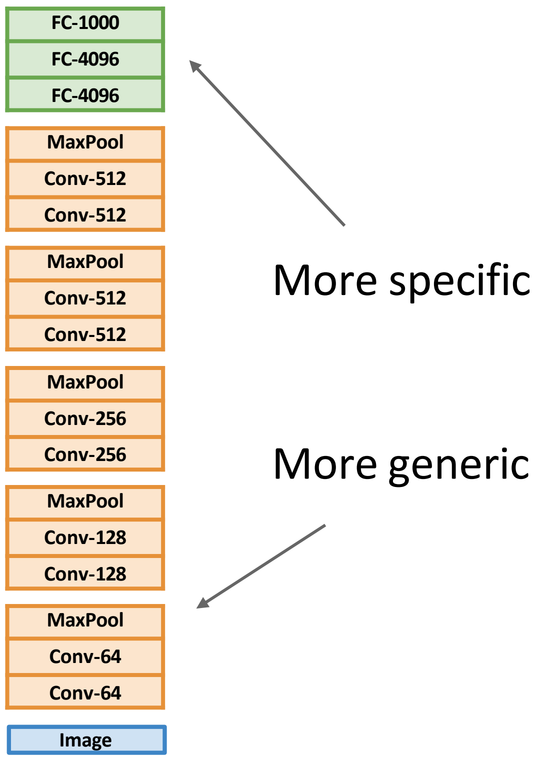
Improvements in CNN architectures lead to improvements in many downstream tasks thanks to transfer learning!

Transfer Learning with CNNs: Architecture Matters!



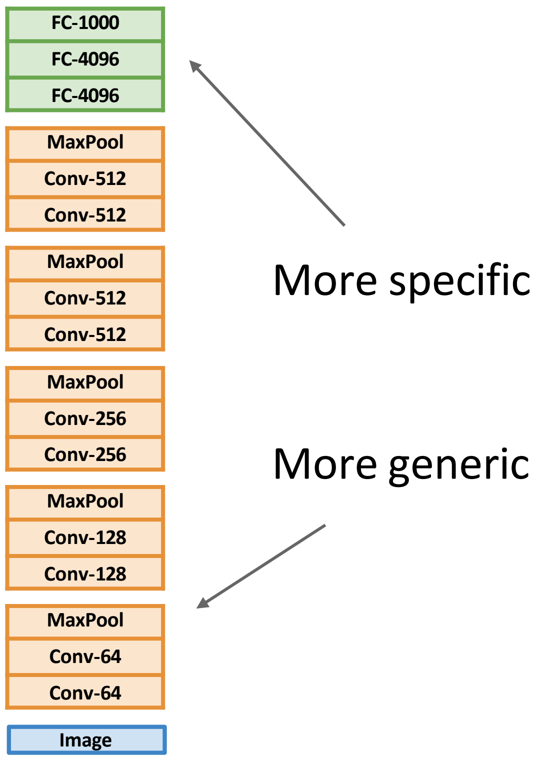
Ross Girshick, "The Generalized R-CNN Framework for Object Detection", ICCV 2017 Tutorial on Instance-Level Visual Recognition

Transfer Learning with CNNs



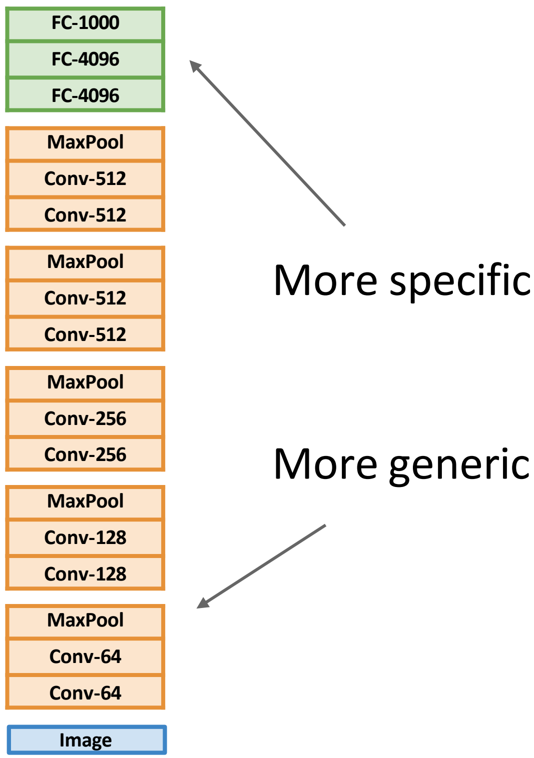
	Dataset similar to ImageNet	Dataset very different from ImageNet
very little data (10s to 100s)	?	?
quite a lot of data (100s to 1000s)	?	?

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	?
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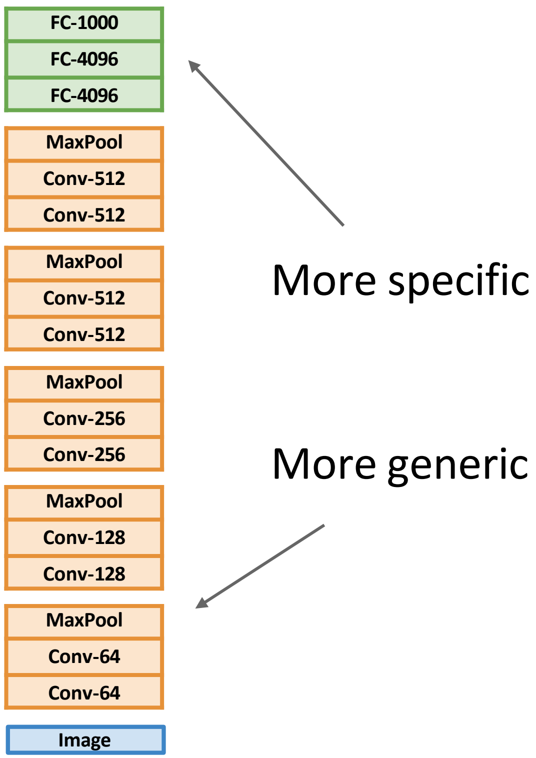
Transfer Learning with CNNs

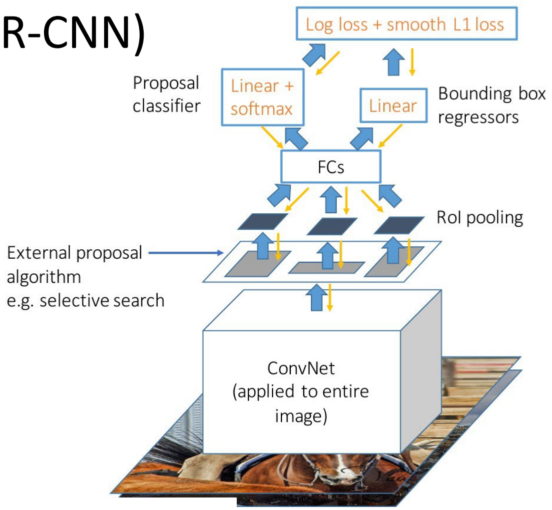


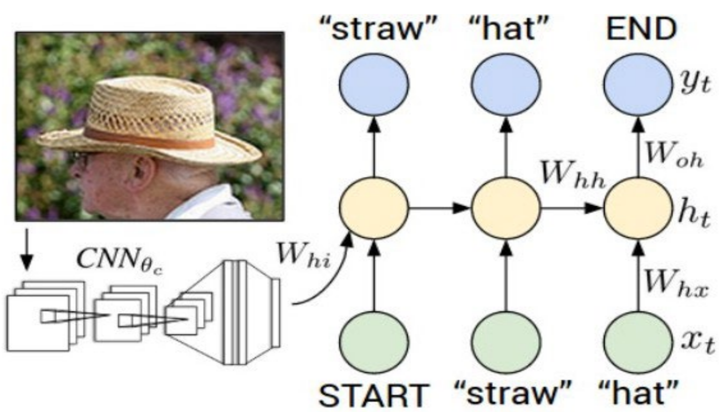
	Dataset similar to ImageNet	**Dataset very different from ImageNet**
very little data (10s to 100s)	Use Linear Classifier on top layer	You're in trouble… Try linear classifier from different stages
quite a lot of data (100s to 1000s)	Finetune a few layers	Finetune a larger number of layers

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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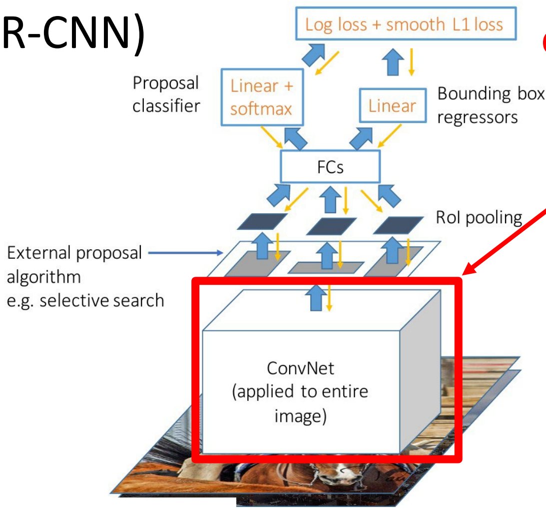
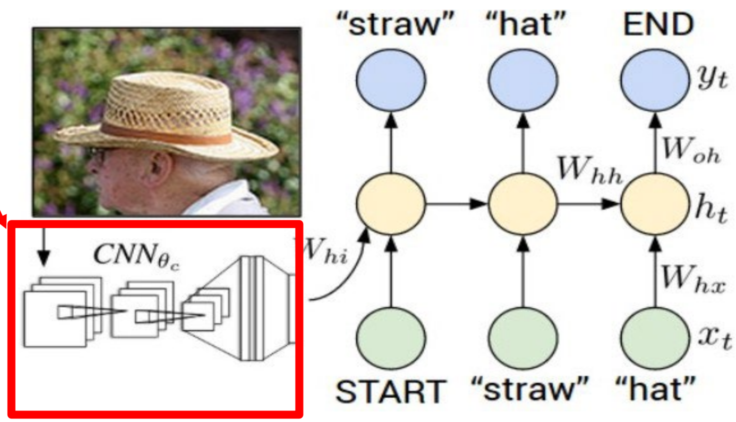
Object Detection (Fast R-CNN)

CNN pretrained on ImageNet





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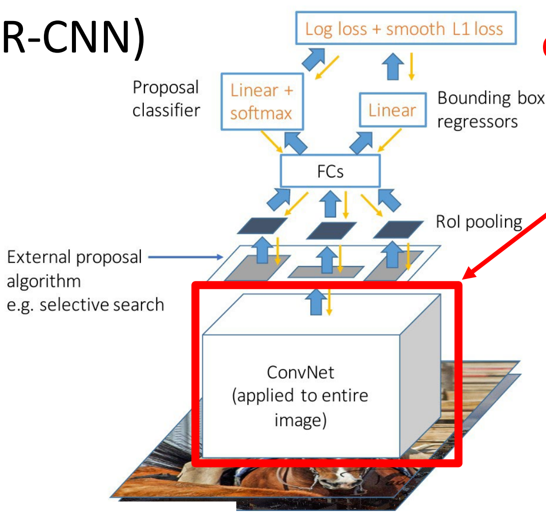
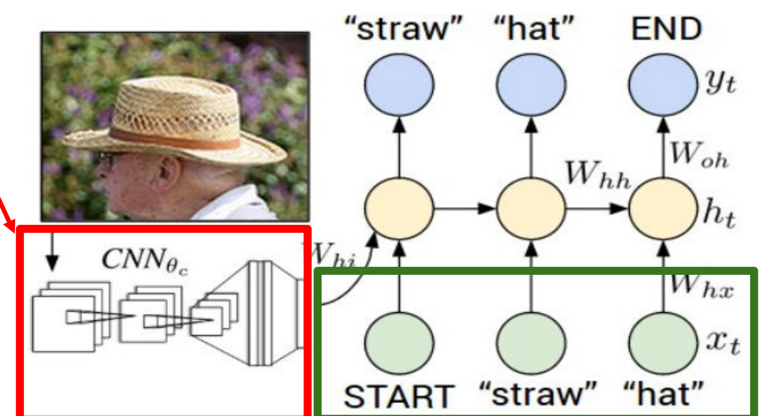


CNN pretrained on ImageNet



Word vectors pretrained with word2vec

Girshick, “Fast R-CNN”, ICCV 2015

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

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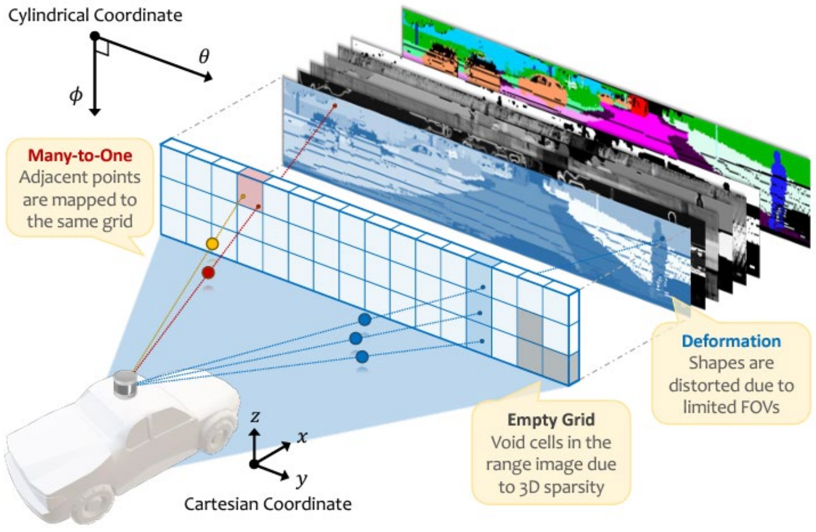


For LiDAR semantic segmentation task, Cityscapes pre-trained models are used as powerful encoder.

- Cityscapes: 2D RGB datasets consisting of driving scenes

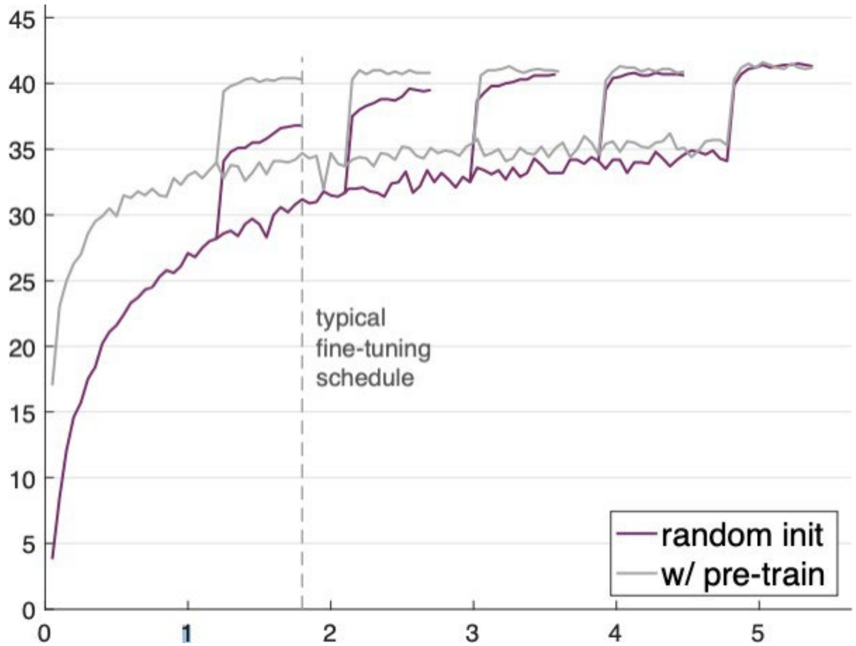
- Despite huge modality gaps between 2D and 3D data, the power of pre-trained model offers meaningful feature representations.

Kong et al, "Rethinking Range View Representation for LiDAR Segmentation", ICCV 2023.

Transfer learning is pervasive!

Some very recent results have questioned it

COCO object detection



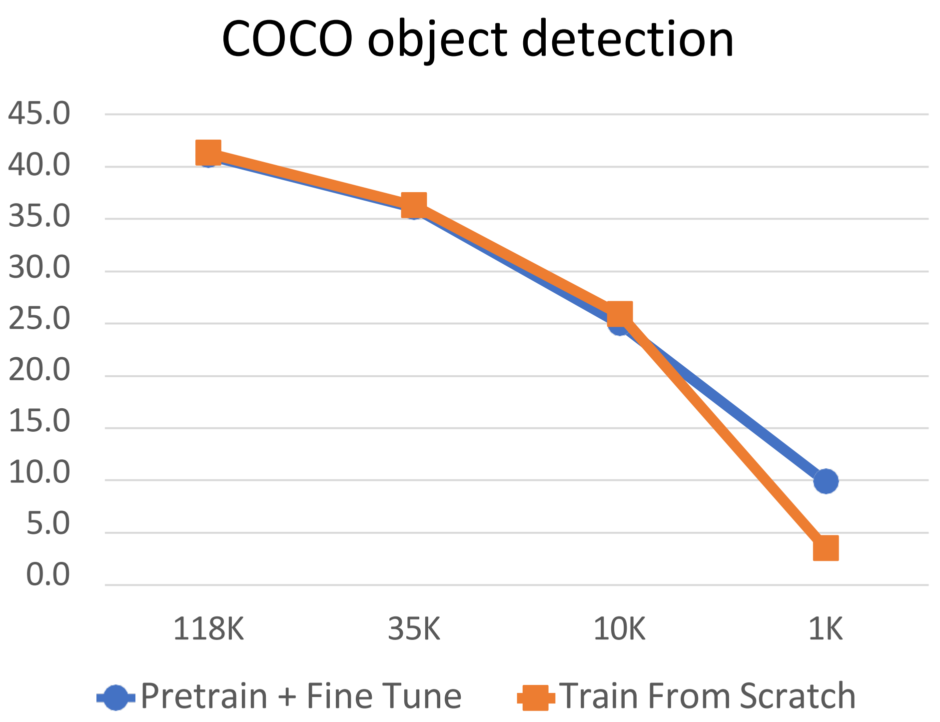
Training from scratch can work as well as pretraining on ImageNet!

… 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



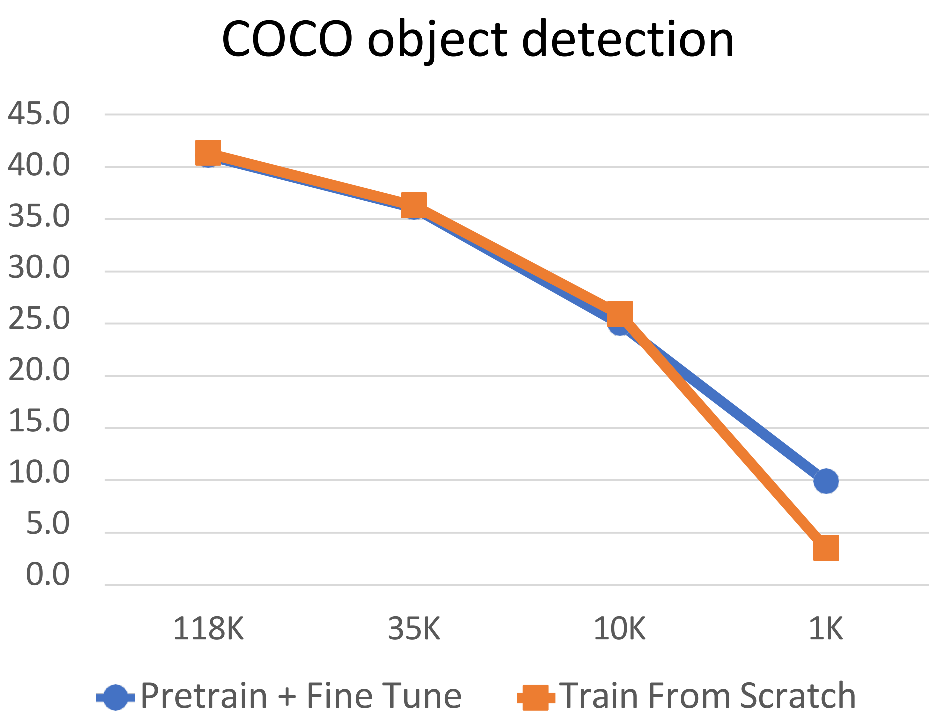
Pretraining + Finetuning beats training from scratch when dataset size is very small

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

Next Time:
Midterm