CS5670: Computer Vision

Training Deep Networks

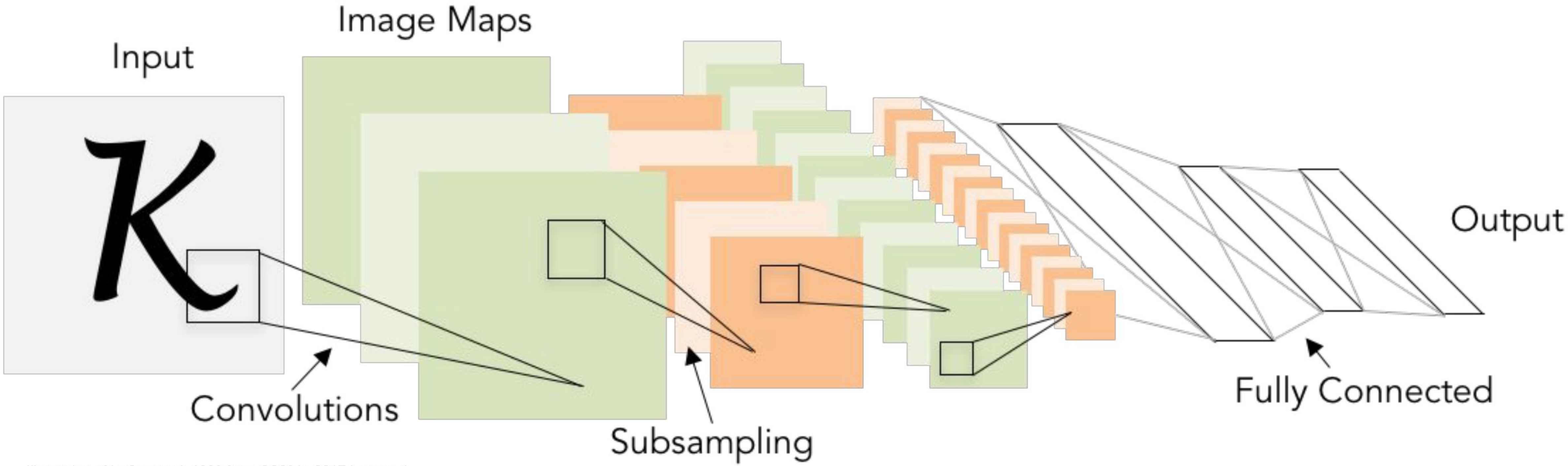


Illustration of LeCun et al. 1998 from CS231n 2017 Lecture 1

Slides from Fei-Fei Li, Justin Johnson, Serena Yeung
http://vision.stanford.edu/teaching/cs231n/

Announcements

- In class final on May 10
  - Open book, open note
- Project 5 (Neural Radiance Fields) due Weds, May 4, 2022 (by 8:00 pm)
- Course evaluations are open starting Tuesday, May 3
  - We would love your feedback!
  - Small amount of extra credit for filling out
    - What you write is still anonymous, instructors only see whether students filled it out
  - Link coming soon

Readings

- Convolutional neural networks
  - http://cs231n.github.io/convolutional-networks/
- Stochastic Gradient Descent & Backpropagation
  - http://cs231n.github.io/optimization-1/
  - http://cs231n.github.io/optimization-2/
- Best practices for training CNNs
  - http://cs231n.github.io/neural-networks-2/
  - http://cs231n.github.io/neural-networks-3/

Deep networks can be used for...

Image classification

f() = "apple"

f() = "tomato"

f() = "cow"

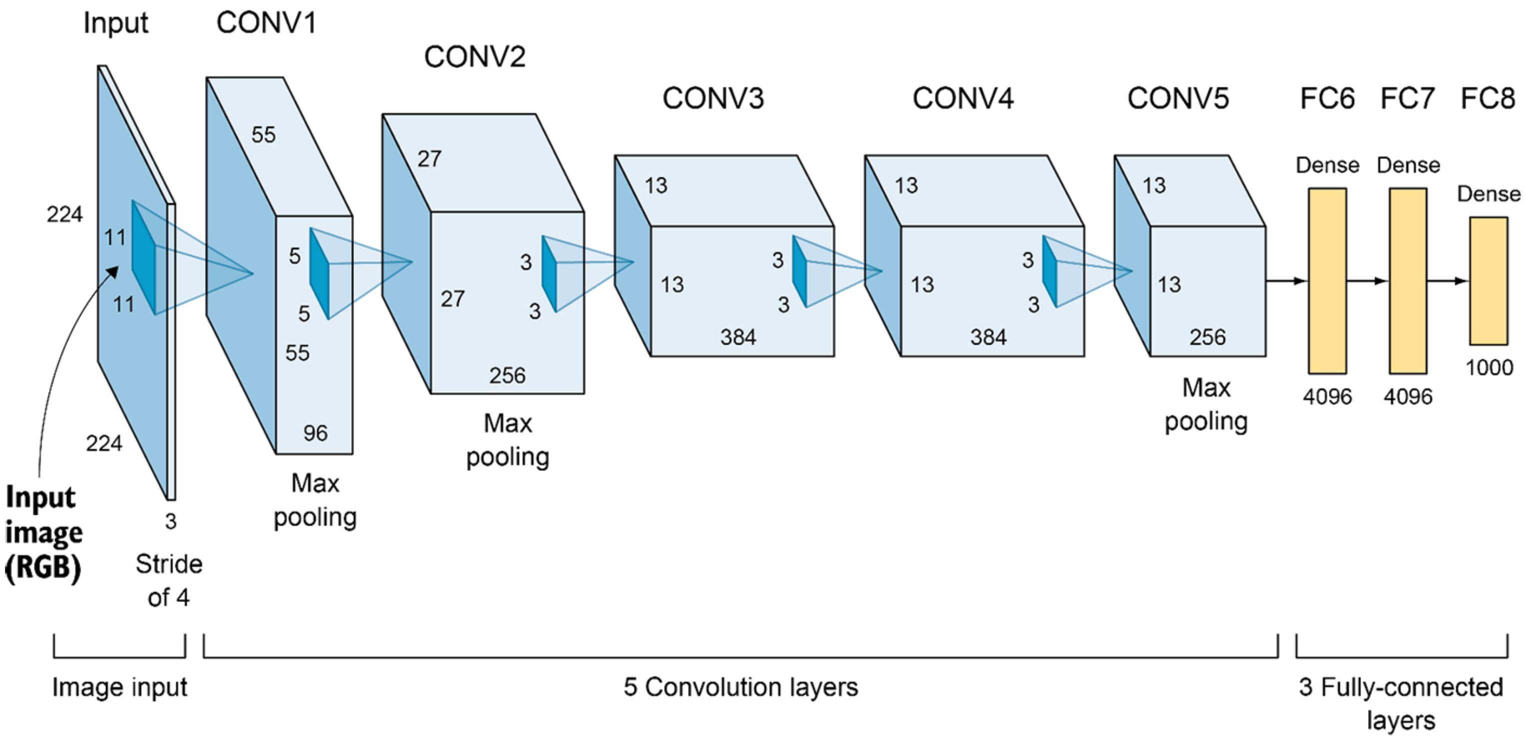
View synthesis

And much more!

Convolutional neural networks

Layer types:

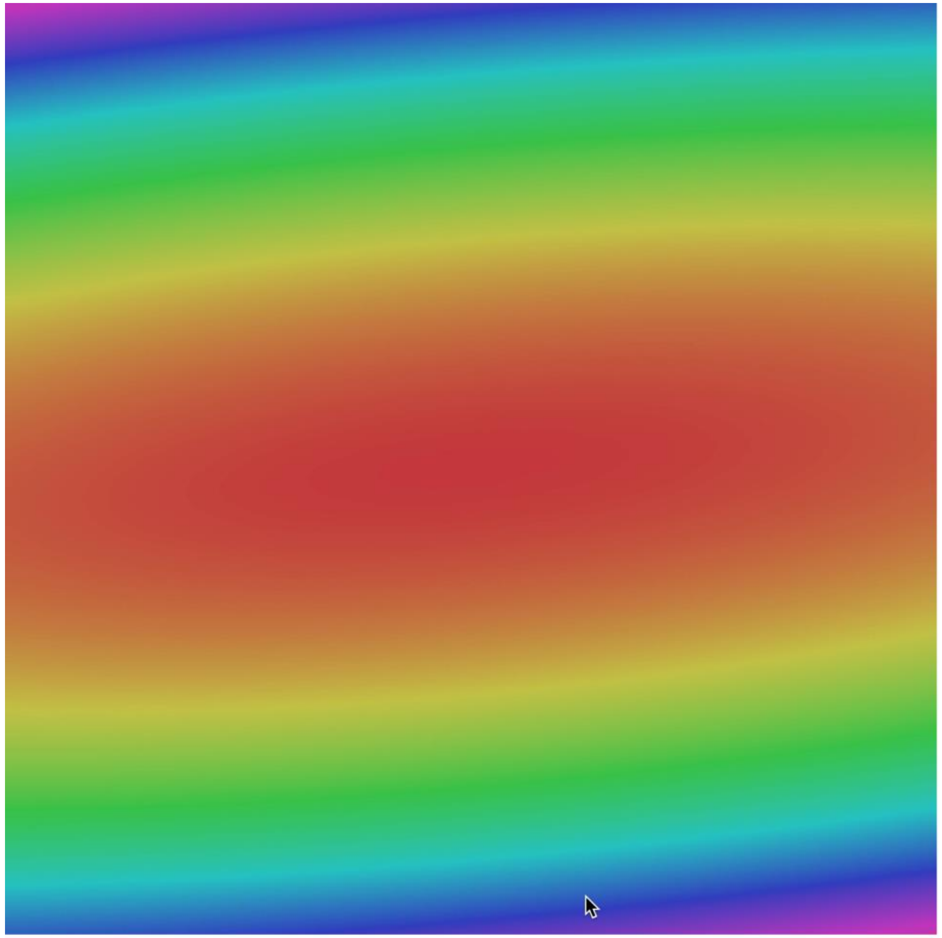
- *Convolutional layer*
- Pooling layer
- Fully-connected layer



Training the network

- Given a network architecture (CNN, MLP, etc) and some training data, how do we actually set the weights of the network?

Gradient descent: iteratively follow the slope



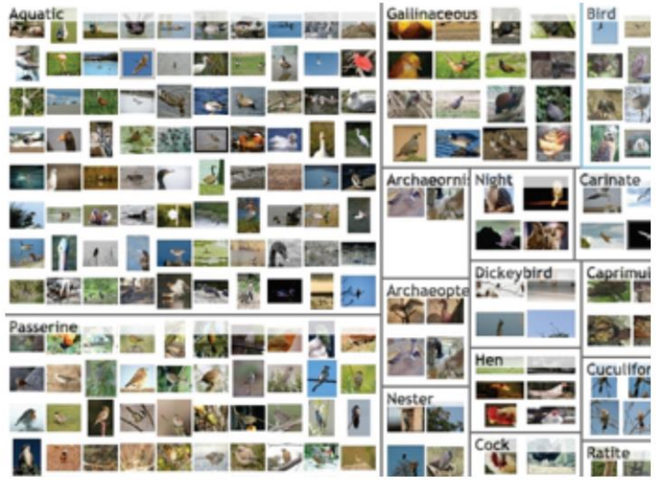
Stochastic gradient descent (SGD)

- Train on batches of data (e.g., 32 images or 32 rays) at a time
- A full pass through the dataset (i.e., using batches that cover the training data) is called an **epoch**
- Usually need to train for multiple epochs, i.e., multiple full passes through the dataset to converge
- Stochastic gradient descent approximates the true gradient, but works remarkably well in practice
- Use **backpropagation** to automatically compute gradients on each batch

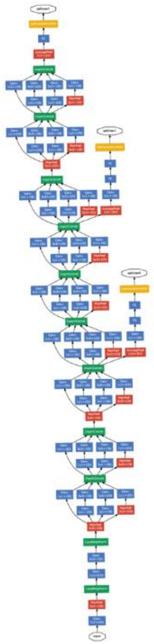
How do you actually train these things?

Roughly speaking:

Gather labeled data



Find a ConvNet architecture



Minimize the loss

Training a convolutional neural network

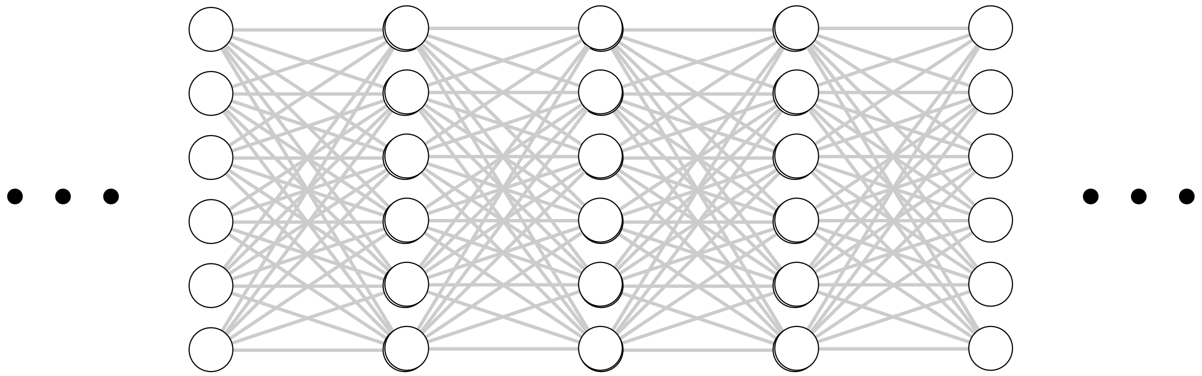
- Split and preprocess your data
- Choose your network architecture
- Initialize the weights
- Find a learning rate and regularization strength
- Minimize the loss and monitor progress
- Fiddle with knobs

Why so complicated?

- Training deep networks can be finicky – lots of parameters to learn, complex, non-linear optimization function

What Makes Training Deep Nets Hard?

- It's easy to get high training accuracy:
  - Use a huge, fully connected network with tons of layers
  - Let it memorize your training data

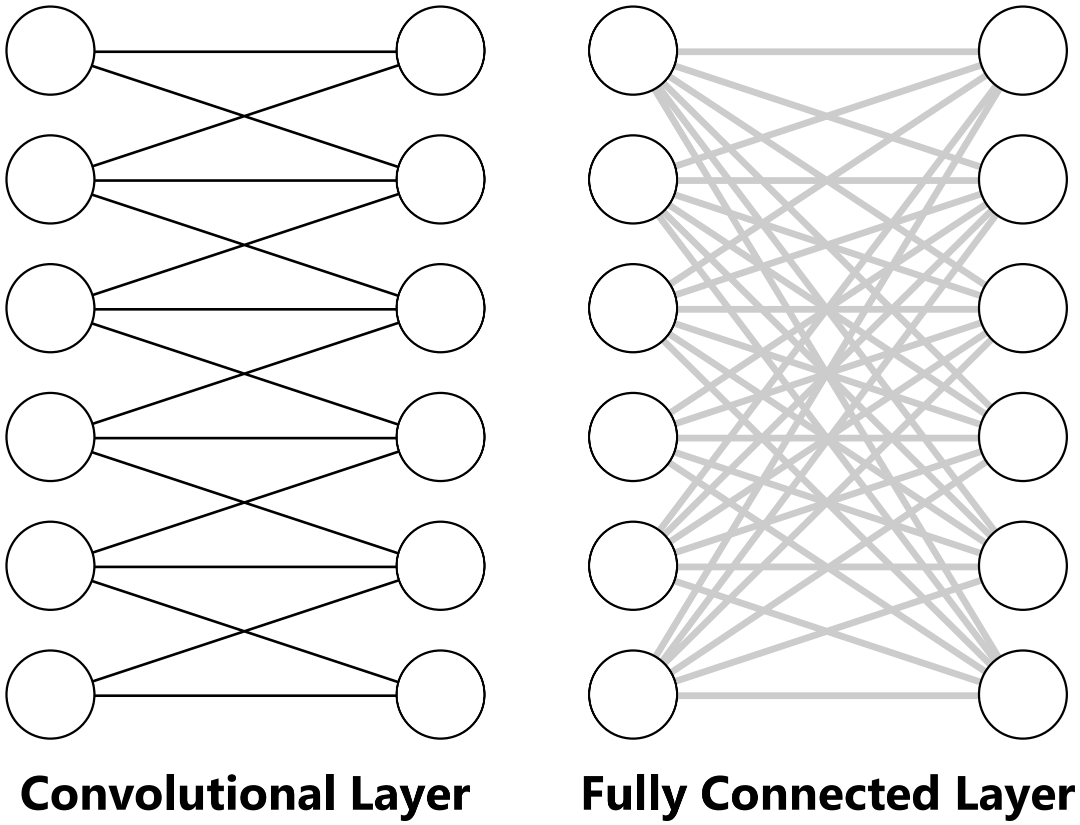


- Its hard to get high *test* accuracy

This would be an example of *overfitting*

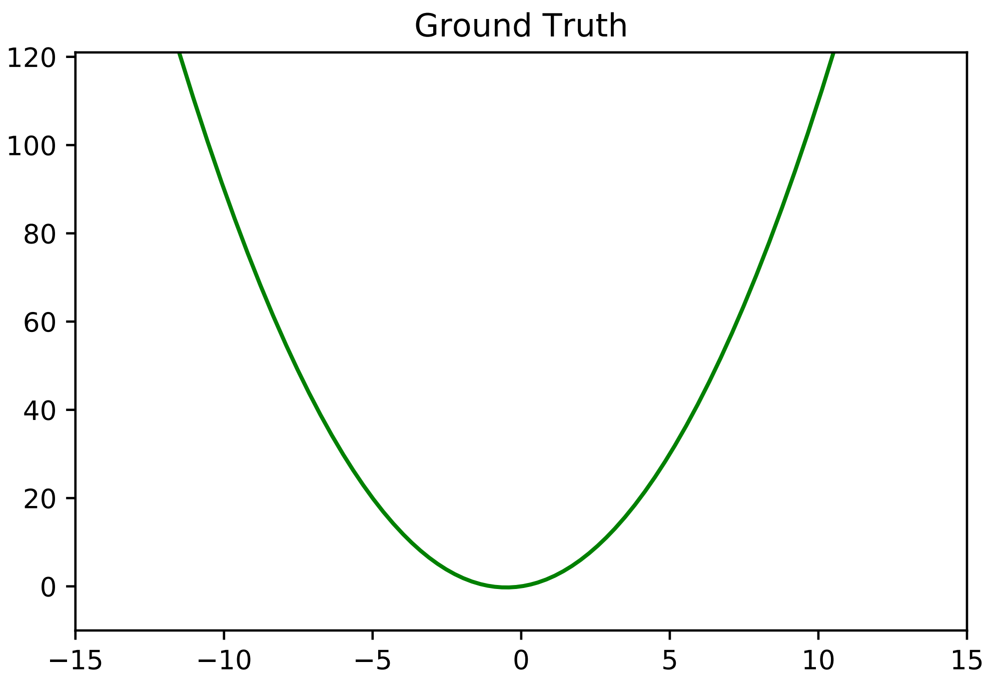
Related Question: Why Convolutional Layers?

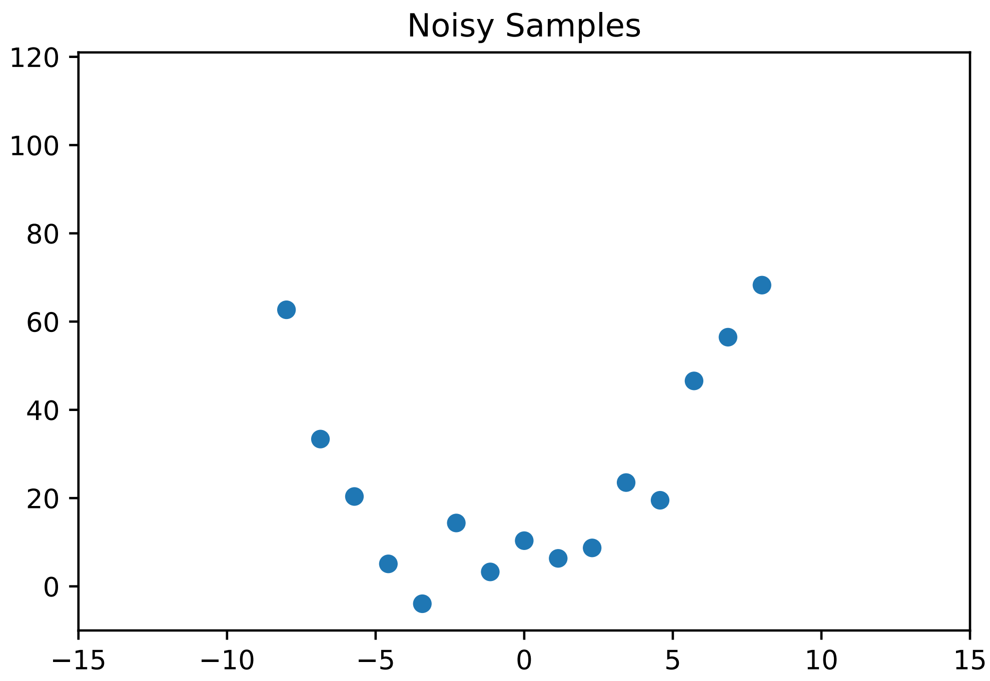
- A fully connected layer can generally represent the same functions as a convolutional one
  - Think of the convolutional layer as a version of the FC layer with constraints on parameters
- What is the advantage of CNNs?



Overfitting: More Parameters, More Problems

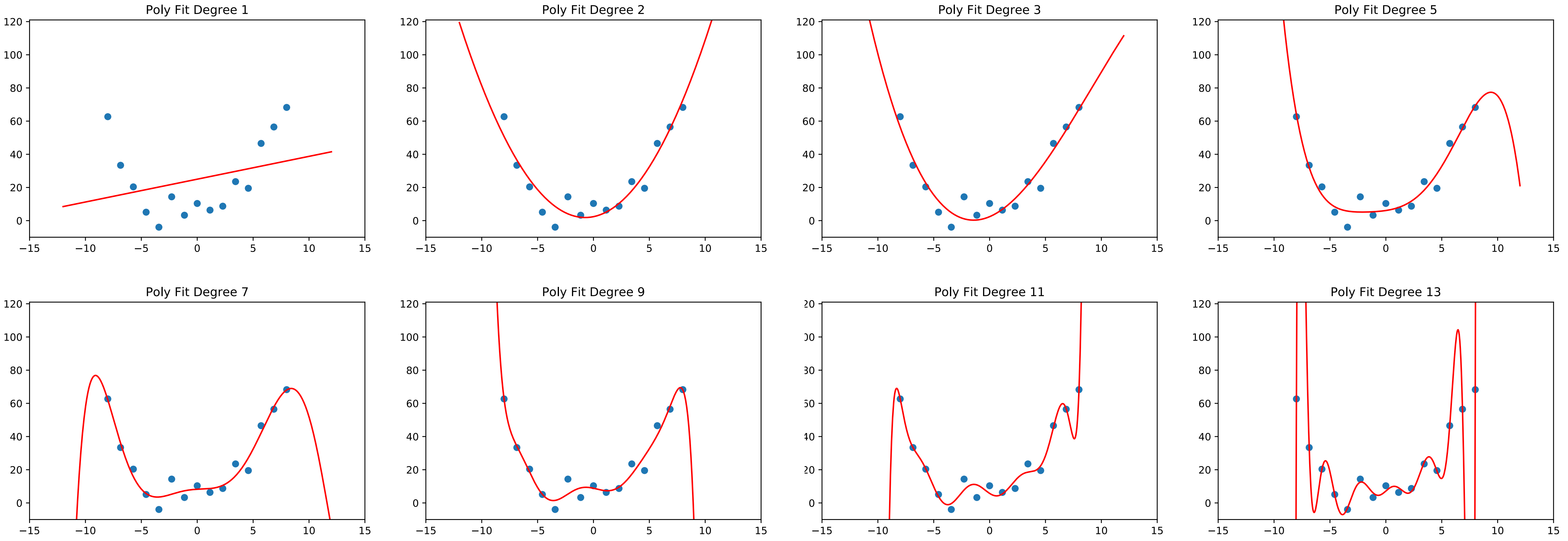
- Non-Deep Example: consider the function $x^2 + x$
- Let's take some noisy samples of the function…





Overfitting: More Parameters, More Problems

- Now lets fit a polynomial to our samples of the form $P_N(x) = \sum_{k=0}^{N} x^k p_k$



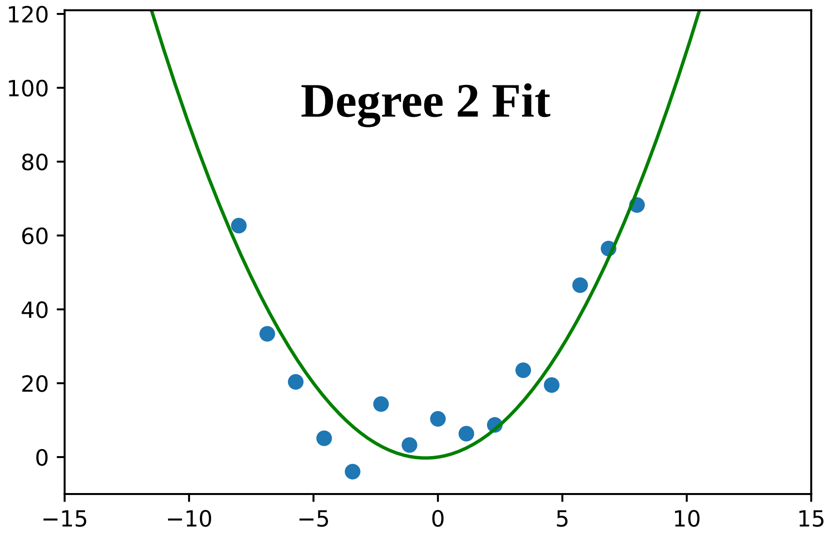
Overfitting: More Parameters, More Problems

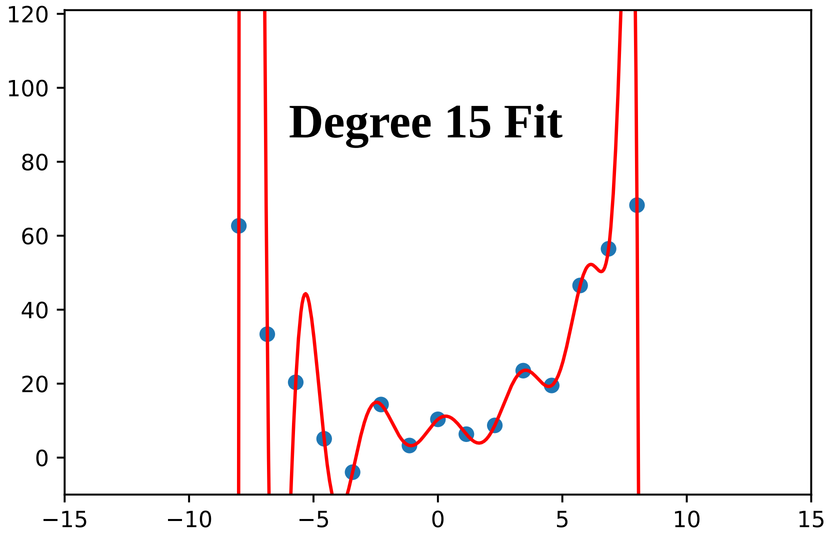
- A model with more parameters can represent more functions

- E.g.,: if $P_N(x) = \sum_{k=0}^{N} x^k p_k$ then $P_2 \in P_{15}$

- More parameters will often **reduce training error** but **increase testing error**. This is *overfitting*.

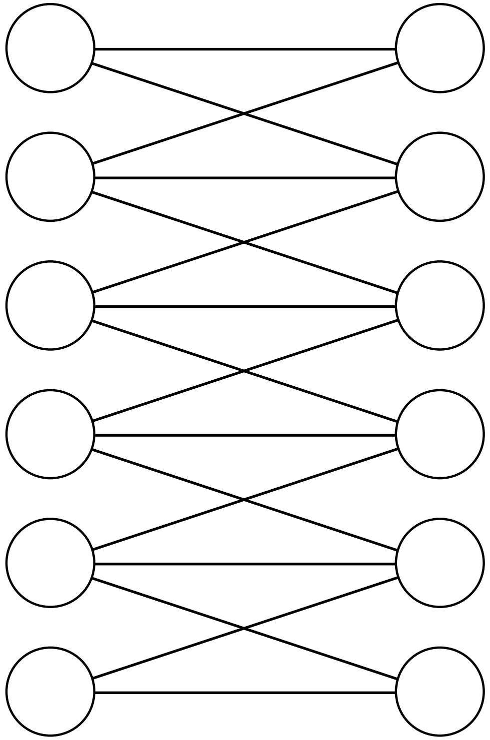
- When overfitting happens, models do not generalize well.



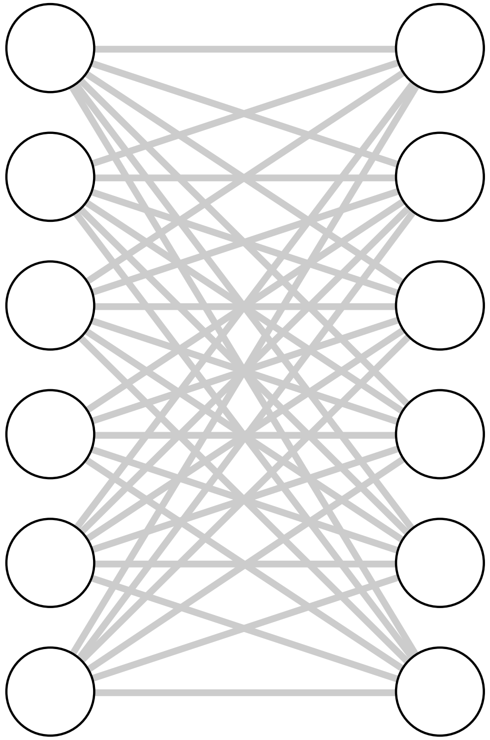


Deep Learning: More Parameters, More Problems?

- More parameters let us represent a larger space of functions
- The larger that space is, the harder our optimization becomes
- This means we need:
  - More data
  - More compute resources
  - Etc.



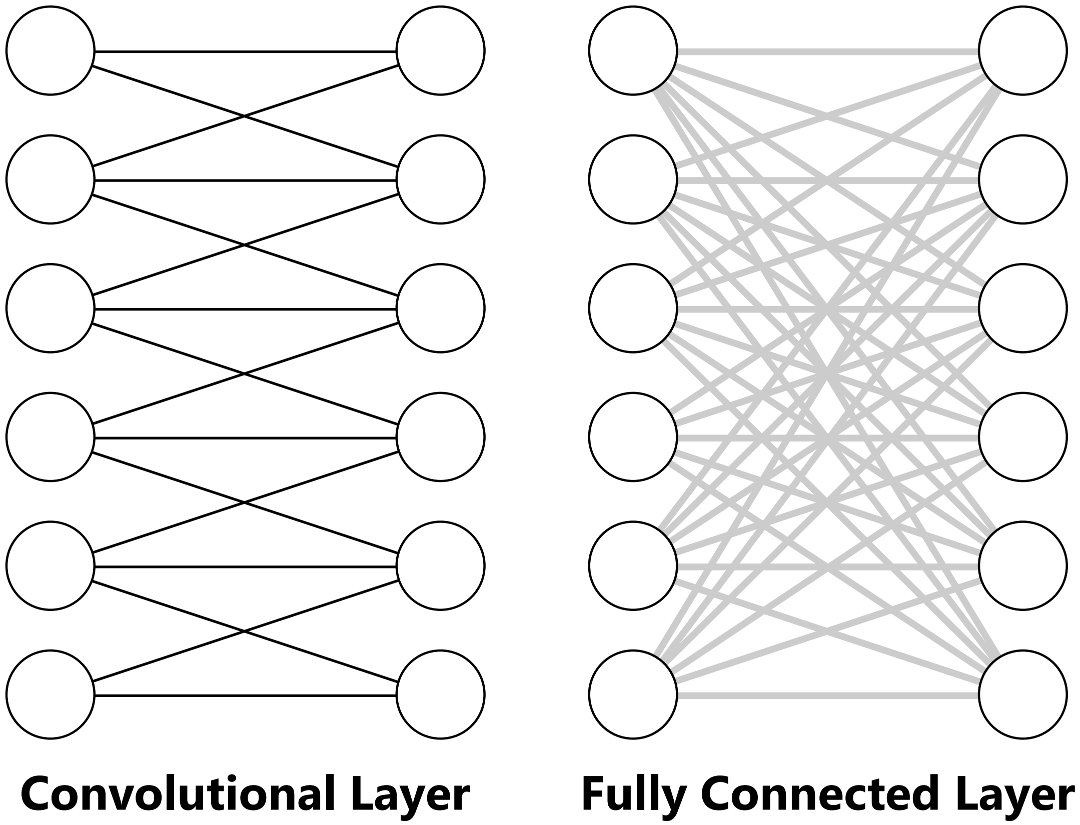
Convolutional Layer



Fully Connected Layer

Deep Learning: More Parameters, More Problems?

A convolutional layer looks for components of a function that are spatially-invariant



How to Avoid Overfitting: Regularization

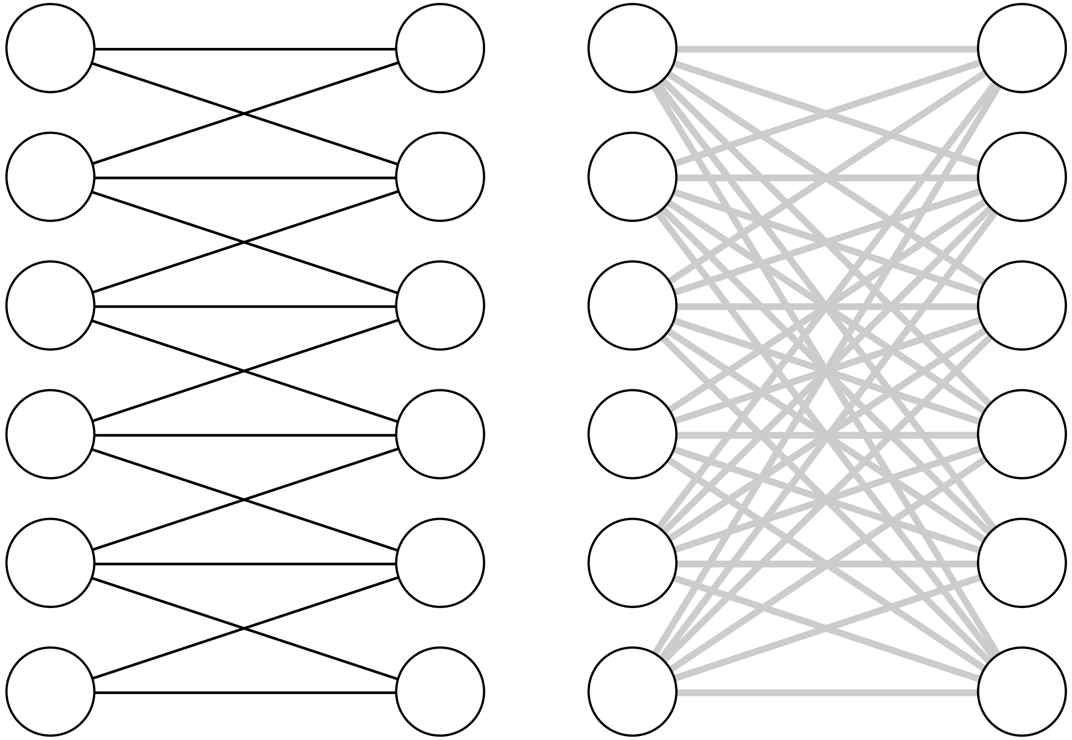
- In general:
  - More parameters means higher risk of overfitting
  - More constraints/conditions on parameters can help

- If a model is overfitting, we can
  - Collect more data to train on
  - *Regularize*: add some additional information or assumptions to better constrain learning

- Regularization can be done through:
  - the design of architecture
  - the choice of loss function
  - the preparation of data
  - …

Regularization: Architecture Choice

- "Bigger" architectures (typically, those with more parameters) tend to be more at risk of overfitting.



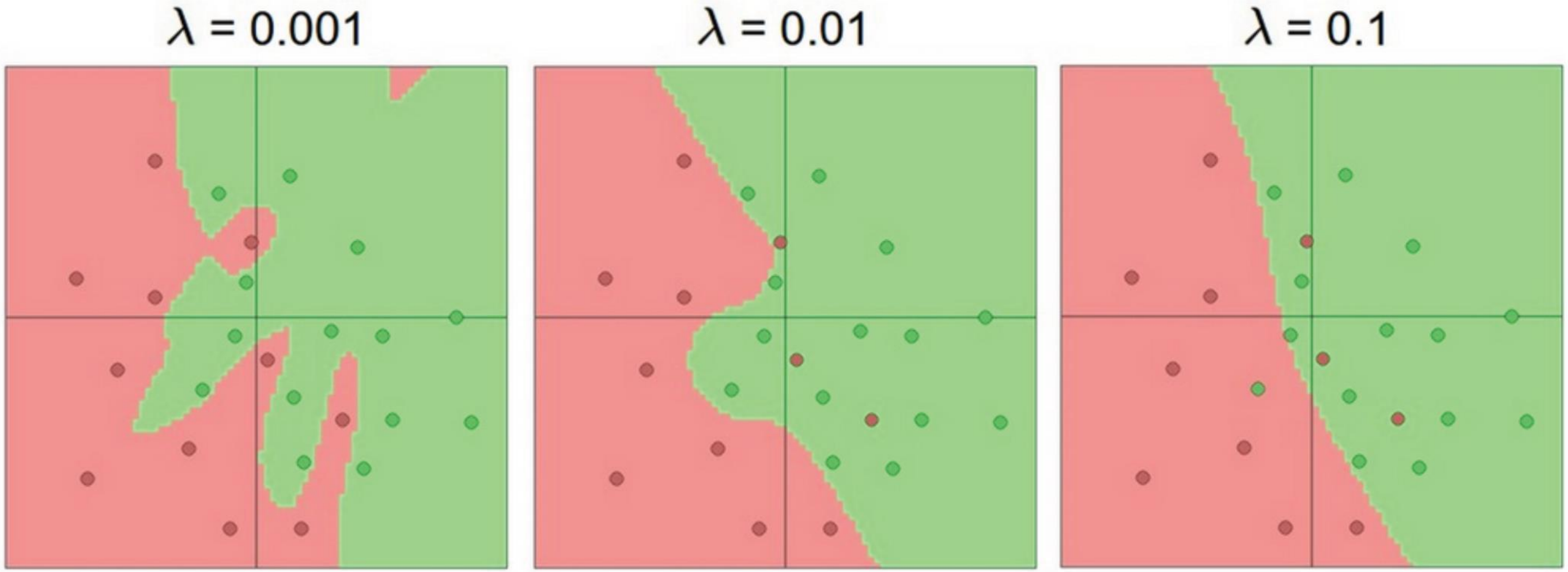
Convolutional Layer

Fully Connected Layer

Regularization

Regularization reduces overfitting:

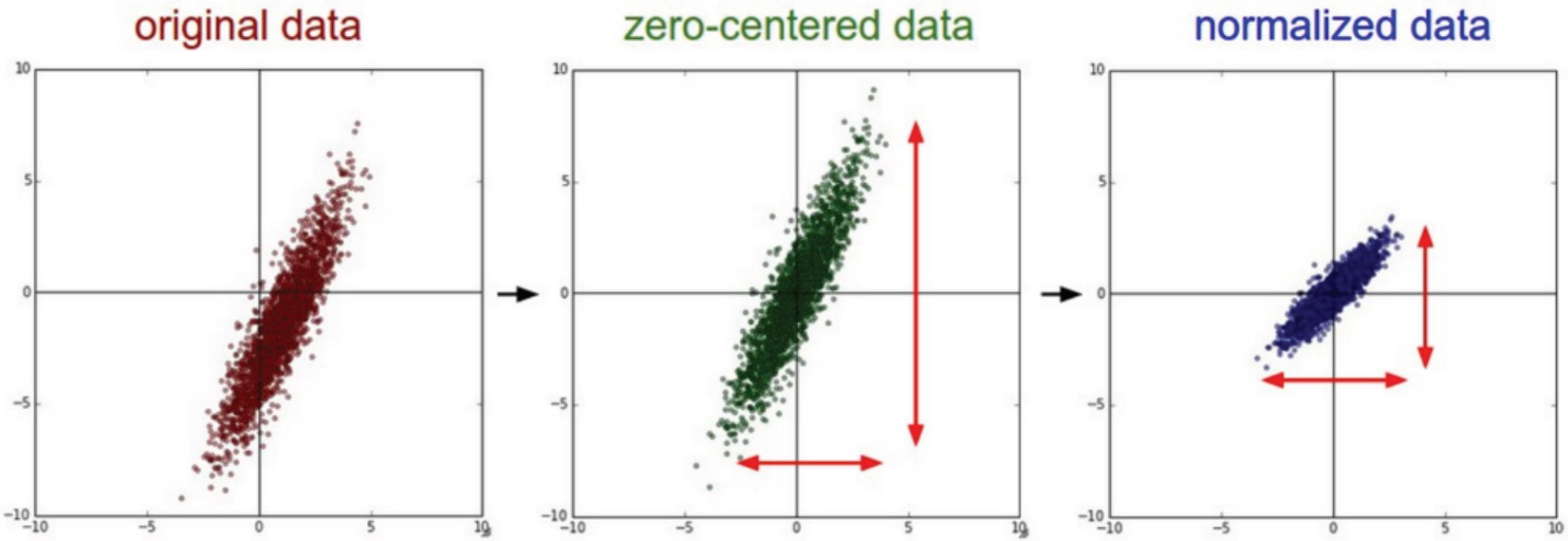
$$L = L_{\text{data}} + L_{\text{reg}} \qquad L_{\text{reg}} = \lambda \frac{1}{2} \|W\|_2^2$$



[Andrej Karpathy http://cs.stanford.edu/people/karpathy/convnetjs/demo/classify2d.html]

(1) Data preprocessing

Preprocess the data so that learning is better conditioned:



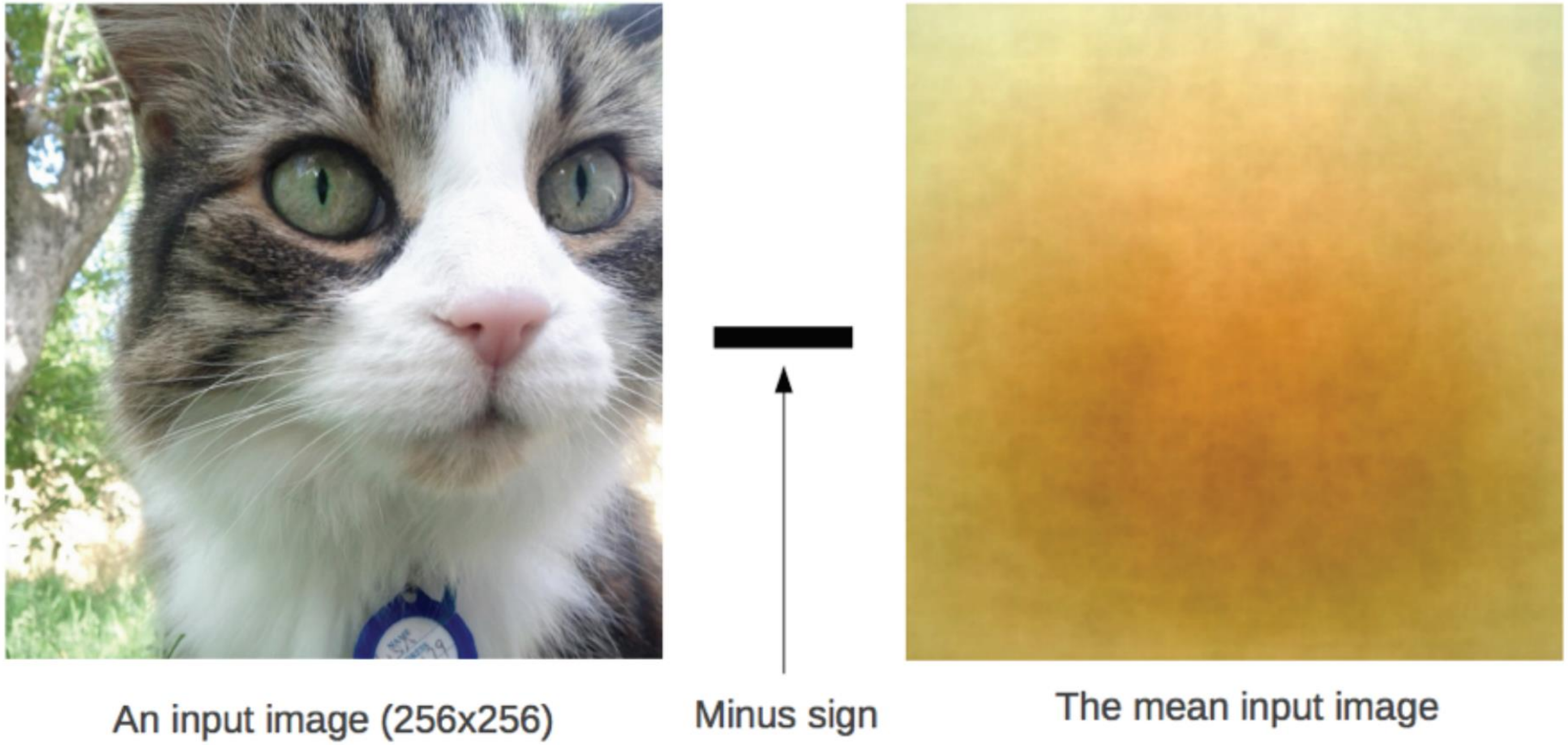

```
X -= np.mean(axis=0, keepdims=True)
```

```
X /= np.std(axis=0, keepdims=True)
```

Figure: Andrej Karpathy

(1) Data preprocessing

For ConvNets, typically only the mean is subtracted.



A per-channel mean also works (one value per R,G,B).

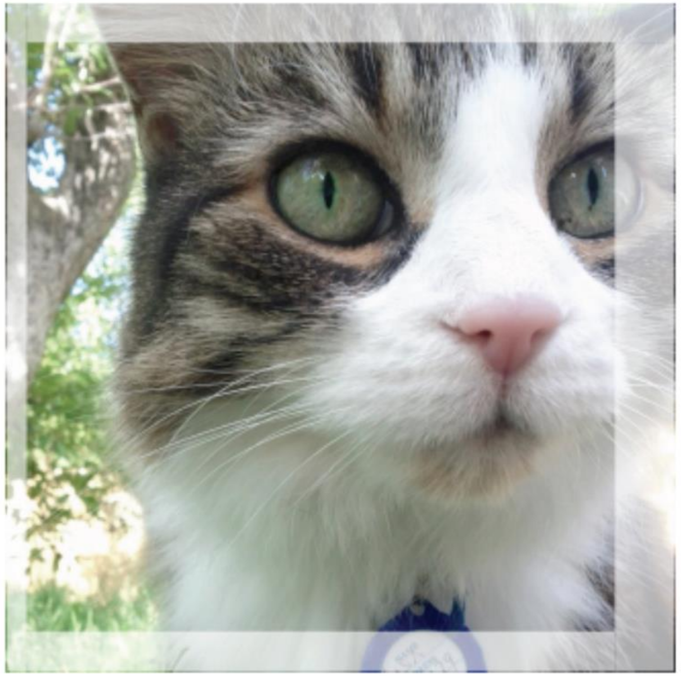
Figure: Alex Krizhevsky

Batch normalization

- Side note – can also perform normalization after each layer of the network to stabilize network training ("*batch normalization*")

(1) Data preprocessing

Augment the data — extract random crops from the input, with slightly jittered offsets. Without this, typical ConvNets (e.g. [Krizhevsky 2012]) overfit the data.



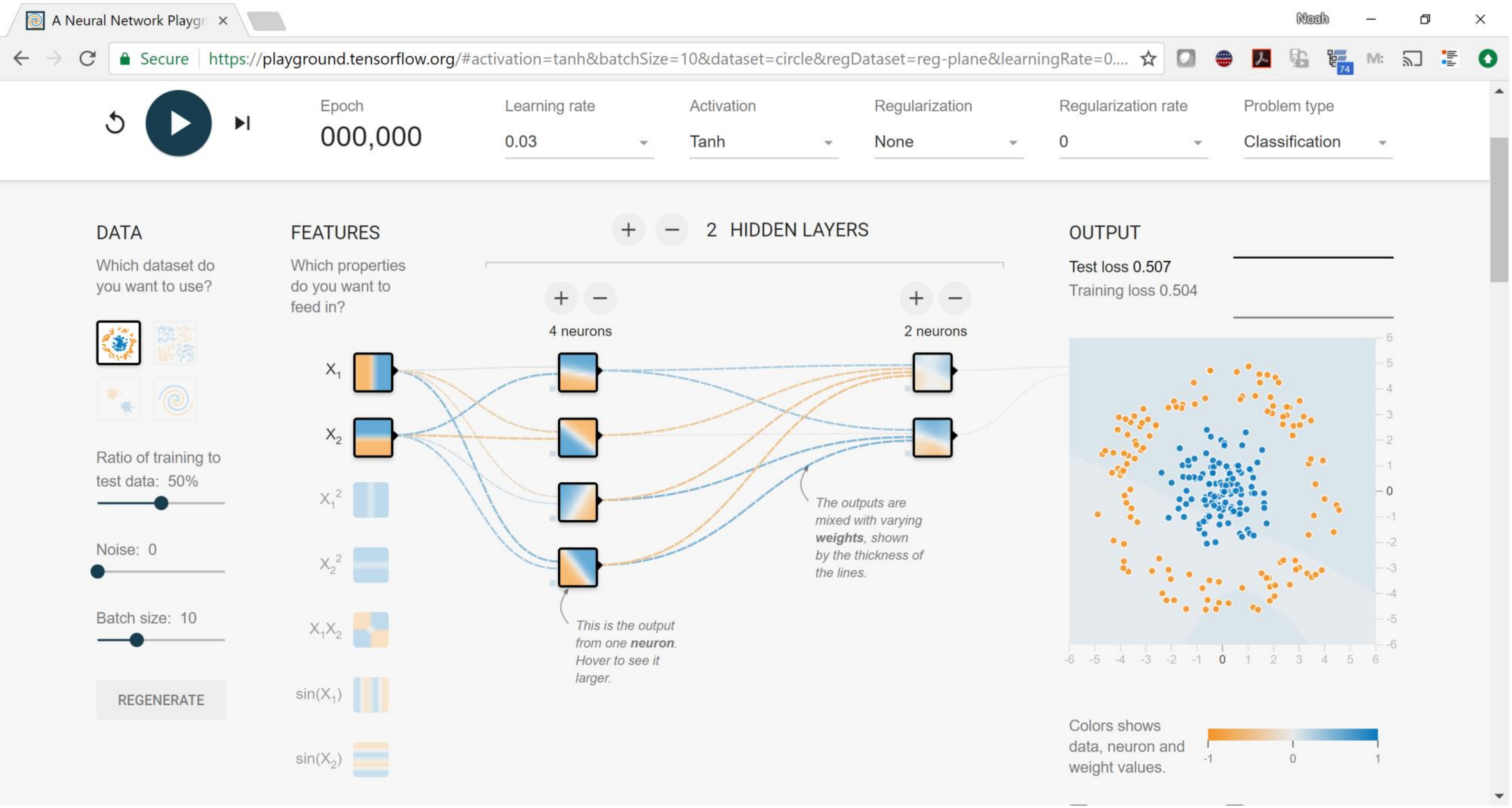
E.g. 224x224 patches extracted from 256x256 images

Randomly reflect horizontally

Perform the augmentation live during training

Figure: Alex Krizhevsky

(2) Choose your architecture

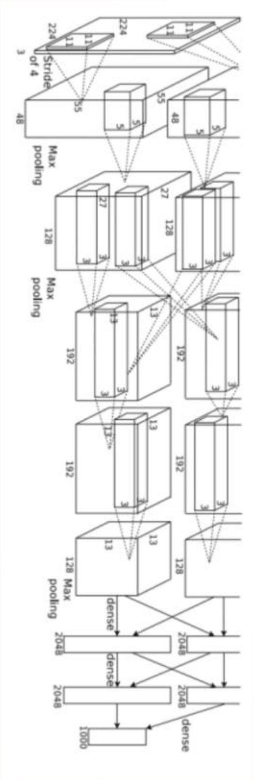


https://playground.tensorflow.org/

(2) Choose your architecture

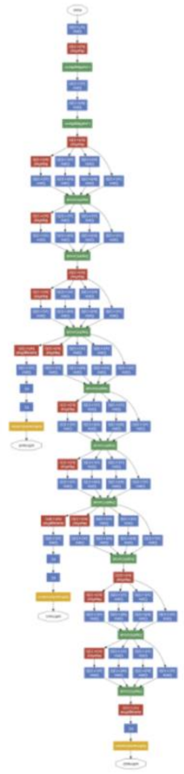
Very common modern choice

"AlexNet"



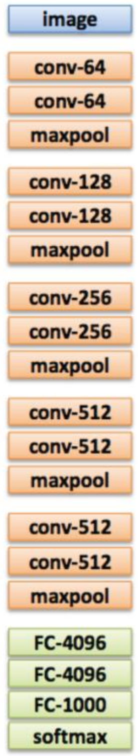
[Krizhevsky et al. NIPS 2012]

"GoogLeNet"



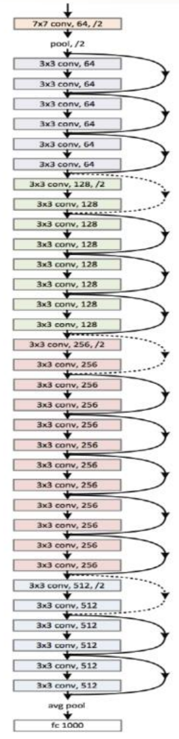
[Szegedy et al. CVPR 2015]

"VGG Net"



[Simonyan & Zisserman, ICLR 2015]

"ResNet"



[He et al. CVPR 2016]

(3) Initialize your weights

Set the weights to small random numbers:

```
W = np.random.randn(D, H) * 0.001
```

(matrix of small random numbers drawn from a Gaussian distribution)

Set the bias to zero (or small nonzero):

```
b = np.zeros(H)
```

(if you use ReLU activations, folks tend to initialize bias to small positive number)

Slide: Andrej Karpathy

(4) Overfit a small portion of the data

```
model = init_two_layer_model(32*32*3, 50, 10) # input size, hidden size, number of classes
trainer = ClassifierTrainer()
X_tiny = X_train[:20] # take 20 examples
y_tiny = y_train[:20]
best_model, stats = trainer.train(X_tiny, y_tiny, X_tiny, y_tiny,
                                  model, two_layer_net,
                                  num_epochs=200, reg=0.0,
                                  update='sgd', learning_rate_decay=1,
                                  sample_batches = False,
                                  learning_rate=1e-3, verbose=True)
```

The above code:

- take the first 20 examples from CIFAR-10
- turn off regularization (reg = 0.0)
- use simple vanilla ‘sgd’

(4) Overfit a small portion of the data

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```

Details:

'sgd': vanilla gradient descent (no momentum etc)

learning_rate_decay = 1: constant learning rate

sample_batches = False (full gradient descent, no batches)

epochs = 200: number of passes through the data

Slide: Andrej Karpathy

(4) Overfit a small portion of the data

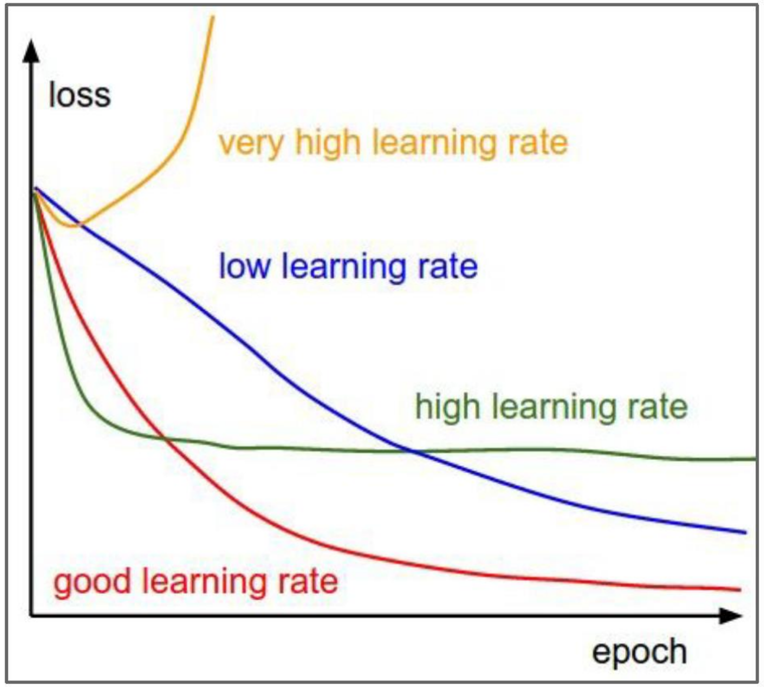
100% accuracy on the training set (good)

```
Finished epoch 1 / 200: cost 2.302603, train: 0.400000, val 0.400000, lr 1.000000e-03
Finished epoch 2 / 200: cost 2.302258, train: 0.450000, val 0.450000, lr 1.000000e-03
Finished epoch 3 / 200: cost 2.301849, train: 0.600000, val 0.600000, lr 1.000000e-03
Finished epoch 4 / 200: cost 2.301196, train: 0.650000, val 0.650000, lr 1.000000e-03
Finished epoch 5 / 200: cost 2.300044, train: 0.650000, val 0.650000, lr 1.000000e-03
Finished epoch 6 / 200: cost 2.297864, train: 0.550000, val 0.550000, lr 1.000000e-03
Finished epoch 7 / 200: cost 2.293595, train: 0.600000, val 0.600000, lr 1.000000e-03
Finished epoch 8 / 200: cost 2.285096, train: 0.550000, val 0.550000, lr 1.000000e-03
Finished epoch 9 / 200: cost 2.268094, train: 0.550000, val 0.550000, lr 1.000000e-03
Finished epoch 10 / 200: cost 2.234787, train: 0.500000, val 0.500000, lr 1.000000e-03
Finished epoch 11 / 200: cost 2.173187, train: 0.500000, val 0.500000, lr 1.000000e-03
Finished epoch 12 / 200: cost 2.076862, train: 0.500000, val 0.500000, lr 1.000000e-03
Finished epoch 13 / 200: cost 1.974090, train: 0.400000, val 0.400000, lr 1.000000e-03
Finished epoch 14 / 200: cost 1.895885, train: 0.400000, val 0.400000, lr 1.000000e-03
Finished epoch 15 / 200: cost 1.820876, train: 0.450000, val 0.450000, lr 1.000000e-03
Finished epoch 16 / 200: cost 1.737430, train: 0.450000, val 0.450000, lr 1.000000e-03
Finished epoch 17 / 200: cost 1.642356, train: 0.500000, val 0.500000, lr 1.000000e-03
Finished epoch 18 / 200: cost 1.535239, train: 0.600000, val 0.600000, lr 1.000000e-03
Finished epoch 19 / 200: cost 1.421527, train: 0.600000, val 0.600000, lr 1.000000e-03
```

```
Finished epoch 195 / 200: cost 0.002694, train: 1.000000, val 1.000000, lr 1.000000e-03
Finished epoch 196 / 200: cost 0.002674, train: 1.000000, val 1.000000, lr 1.000000e-03
Finished epoch 197 / 200: cost 0.002655, train: 1.000000, val 1.000000, lr 1.000000e-03
Finished epoch 198 / 200: cost 0.002635, train: 1.000000, val 1.000000, lr 1.000000e-03
Finished epoch 199 / 200: cost 0.002617, train: 1.000000, val 1.000000, lr 1.000000e-03
Finished epoch 200 / 200: cost 0.002597, train: 1.000000, val 1.000000, lr 1.000000e-03
finished optimization. best validation accuracy: 1.000000
```

Slide: Andrej Karpathy

(4) Find a learning rate



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

Learning rate schedule

How do we change the learning rate over time?

Various choices:

- Step down by a factor of 0.1 every 50,000 mini-batches (used by SuperVision [Krizhevsky 2012])
- Decrease by a factor of 0.97 every epoch (used by GoogLeNet [Szegedy 2014])
- Scale by sqrt(1-t/max_t) (used by BVLC to re-implement GoogLeNet)
- Scale by 1/t
- Scale by exp(-t)

Summary of things to fiddle

- Network architecture
- Learning rate, decay schedule, update type
- Regularization (L2, L1, maxnorm, dropout, …)
- Loss function (softmax, SVM, …)
- Weight initialization

Neural network parameters

Summary of things to fiddle

- Network architecture
- Learning rate, decay schedule, update type (+batch size)
- Regularization (L2, L1, maxnorm, dropout, …)
- Loss function (softmax, SVM, …)
- Weight initialization

Neural network parameters

Questions?

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

1. Train on Imagenet

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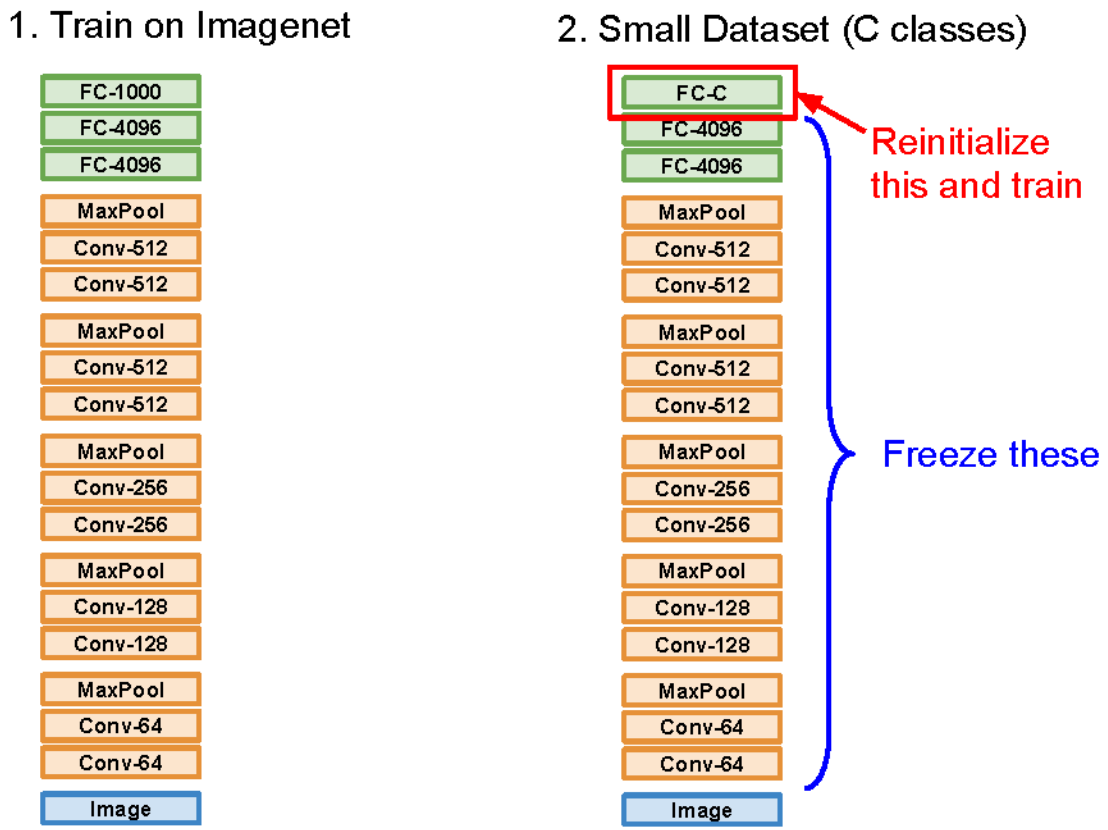

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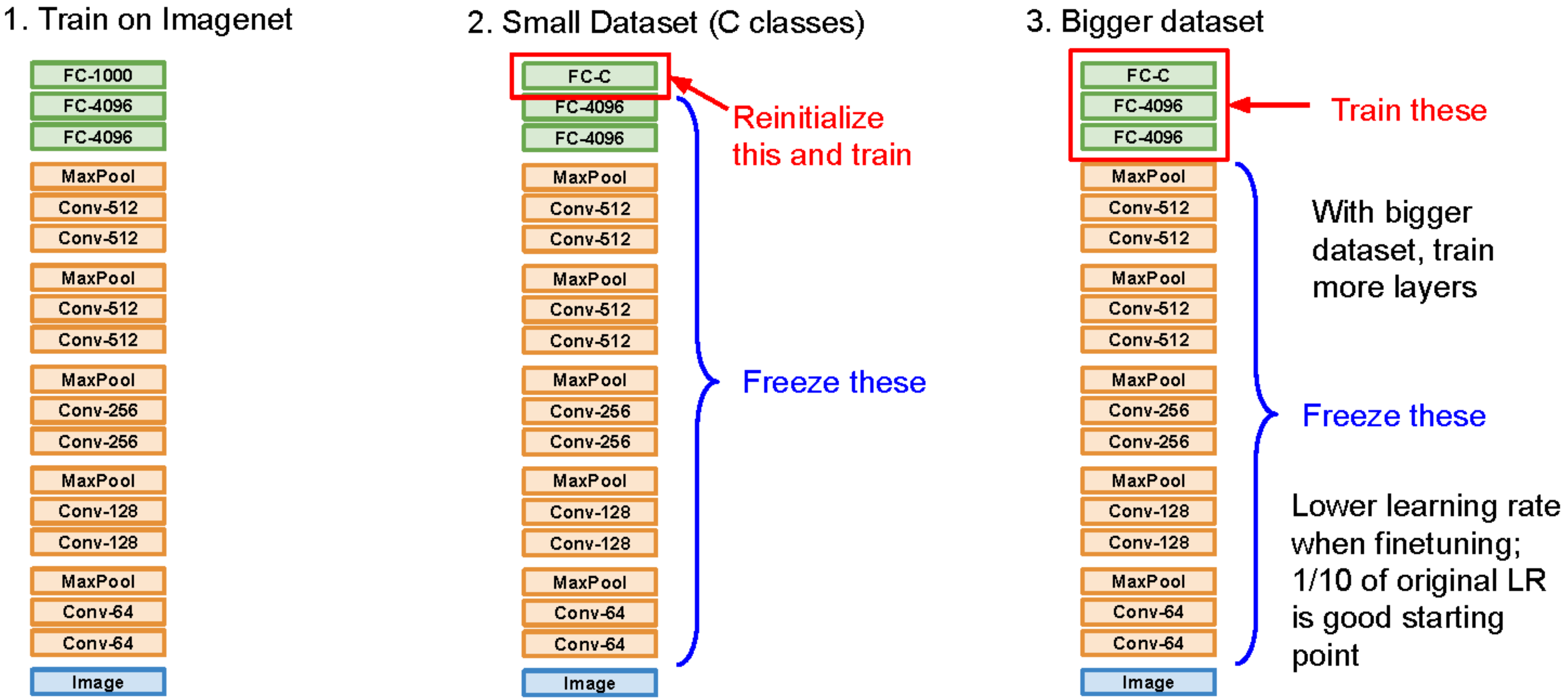
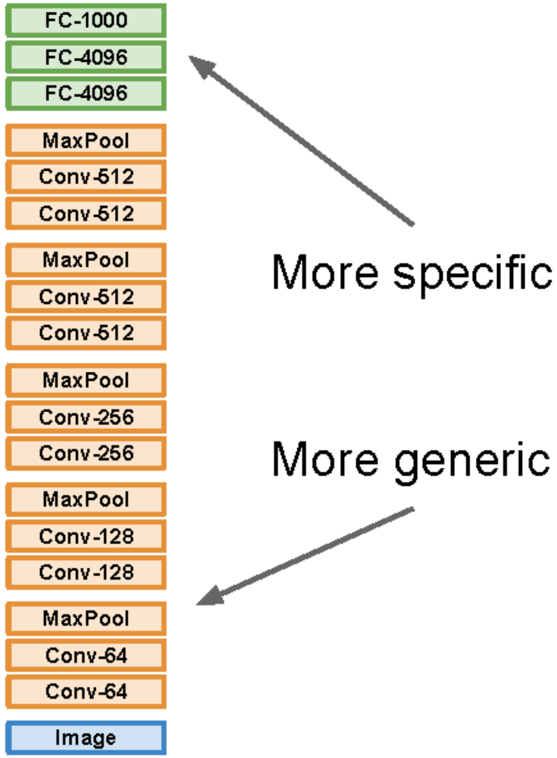
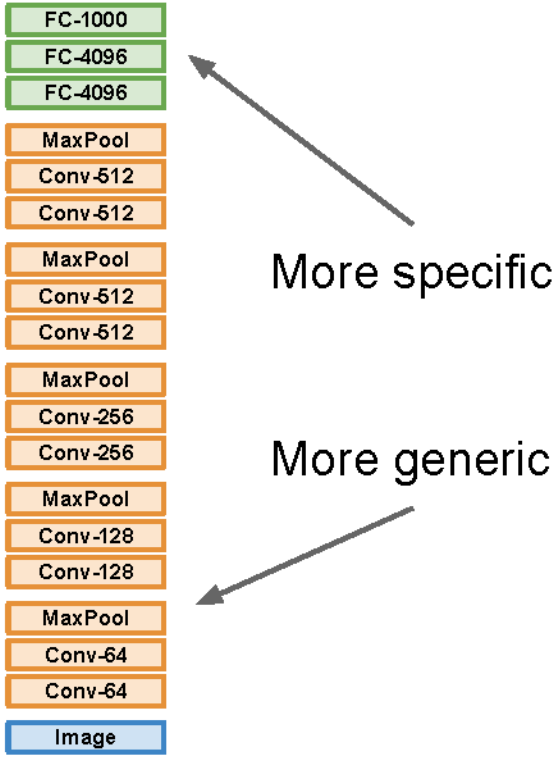
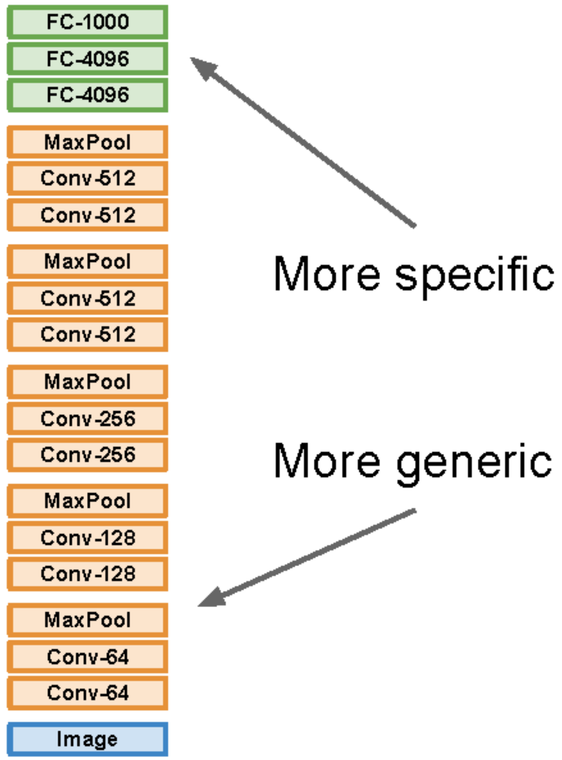




	very similar dataset	very different dataset
very little data	?	?
quite a lot of data	?	?



	very similar dataset	very different dataset
very little data	Use Linear Classifier on top layer	?
quite a lot of data	Finetune a few layers	?



	very similar dataset	very different dataset
very little data	Use Linear Classifier on top layer	You're in trouble… Try linear classifier from different stages
quite a lot of data	Finetune a few layers	Finetune a larger number of layers

Transfer learning with CNNs is pervasive…
(it's the norm, not an exception)

Object Detection
(Fast R-CNN)

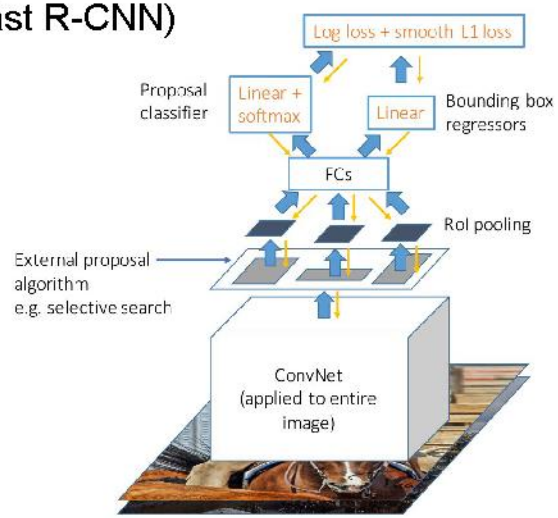
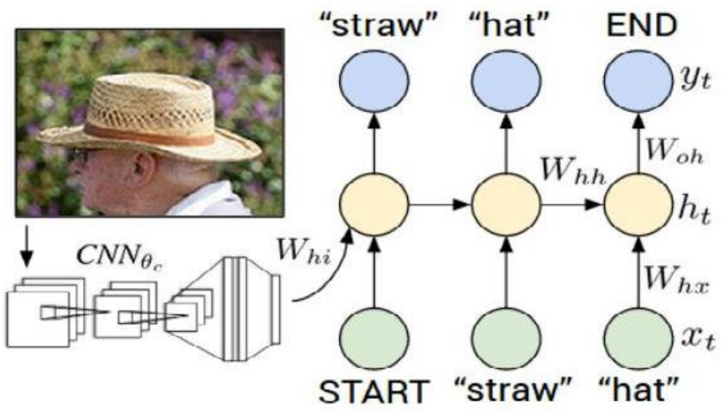


Image Captioning: CNN + RNN



Girshick, "Fast R-CNN", ICCV 2015
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Karpathy and Fei-Fei, "Deep Visual-Semantic Alignments for Generating Image Descriptions", CVPR 2015
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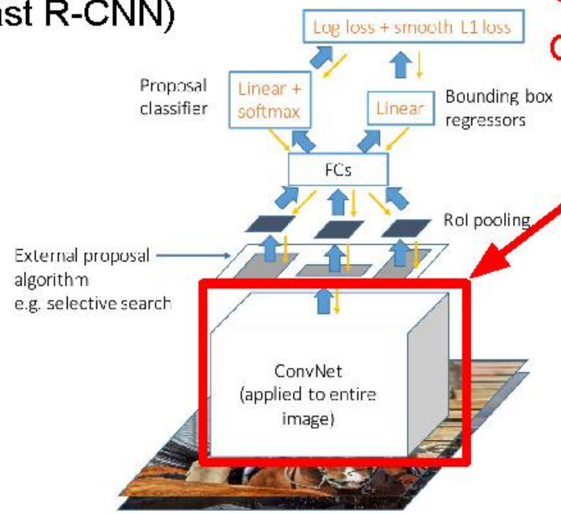

CNN pretrained on ImageNet

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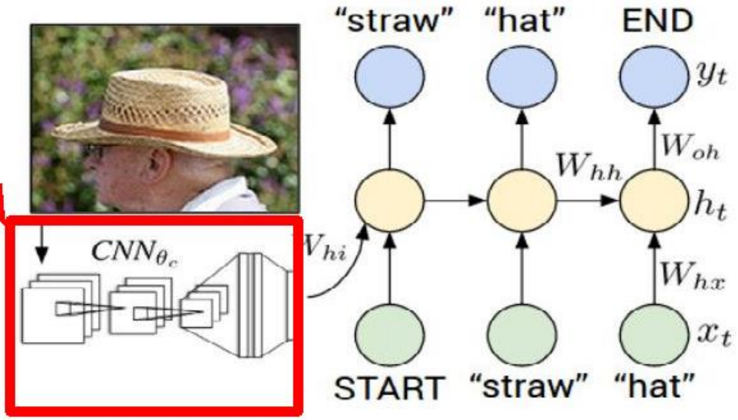

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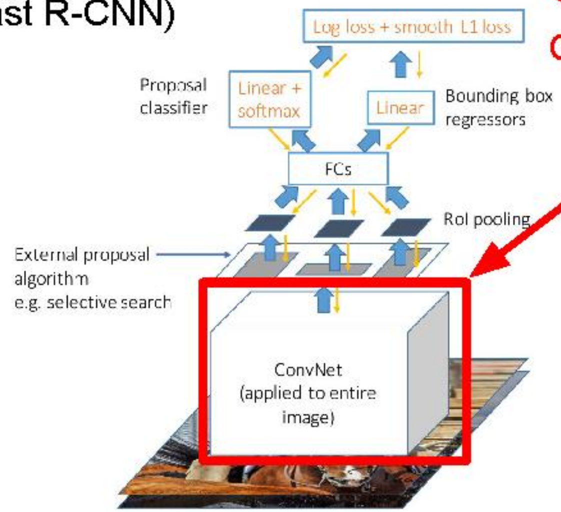

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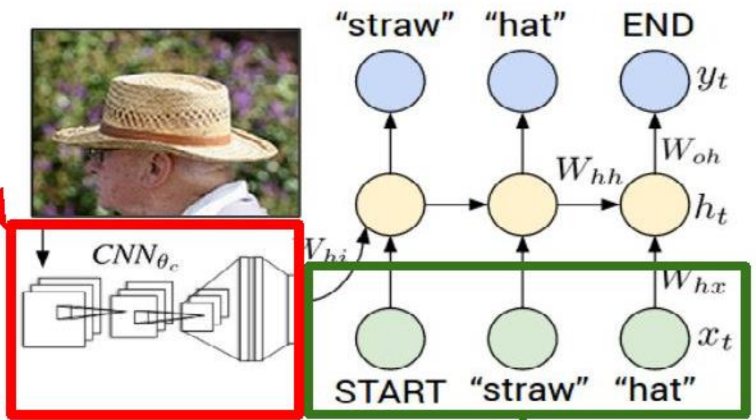

Word vectors pretrained with word2vec

Girshick, "Fast R-CNN", ICCV 2015
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Karpathy and Fei-Fei, "Deep Visual-Semantic Alignments for Generating Image Descriptions", CVPR 2015
Figure copyright IEEE, 2015. Reproduced for educational purposes.

Takeaway for your projects and beyond:

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

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

Deep learning frameworks provide a "Model Zoo" of pretrained models so you don't need to train your own

TensorFlow: https://github.com/tensorflow/models
PyTorch: https://github.com/pytorch/vision

Common modern approach: start with a ResNet architecture pre-trained on ImageNet, and fine-tune on your (smaller) dataset

Questions?