CS5670: Computer Vision

Training Deep Networks

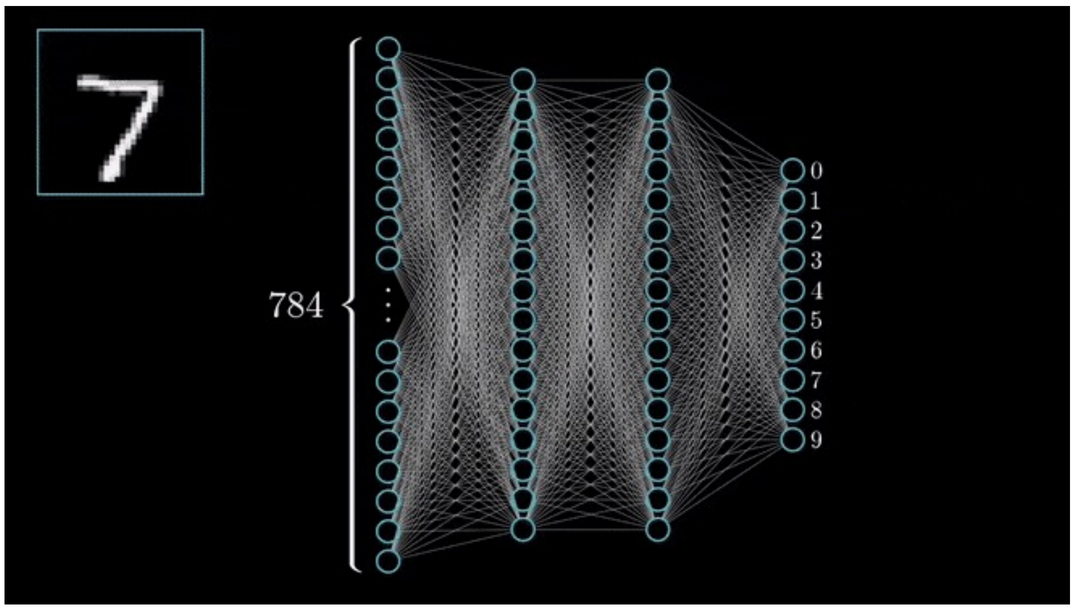


Image credit: https://blog.imarticus.org/what-are-some-tips-and-tricks-for-training-deep-neural-networks/

Some content adapted from material from Andrej Karpathy, Sean Bell, Kavita Bala, and

Announcements

- Project 5 (Neural Radiance Fields) due Weds, May 1 by 8pm
- In class final on May 7
  - Allowed two sheets of notes (front and back sides)
- Course evaluations are open starting Monday, April 29
  - 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
  - Szeliski (2nd Edition) Chapter 5.4
- 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”

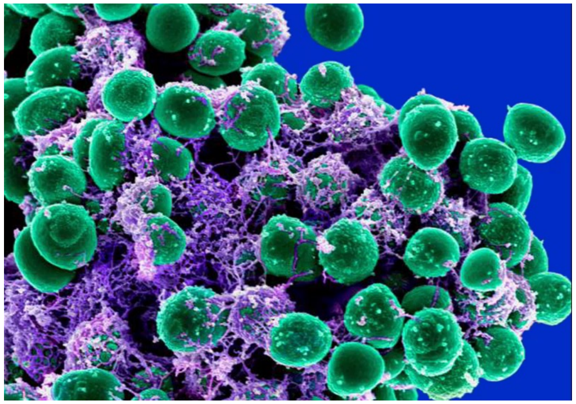
f() = “tomato”

f() = “cow”

View synthesis

And much more!

A Recent Example: *Segment Anything*



[Segment Anything]
Alexander Kirillov, Eric Mintun, Nikhila Ravi, Hanzi Mao, Chloe Rolland, Laura Gustafson, Tete Xiao, Spencer Whitehead, Alexander C. Berg, Wan-Yen Lo, Piotr Dollár, Ross Girshick

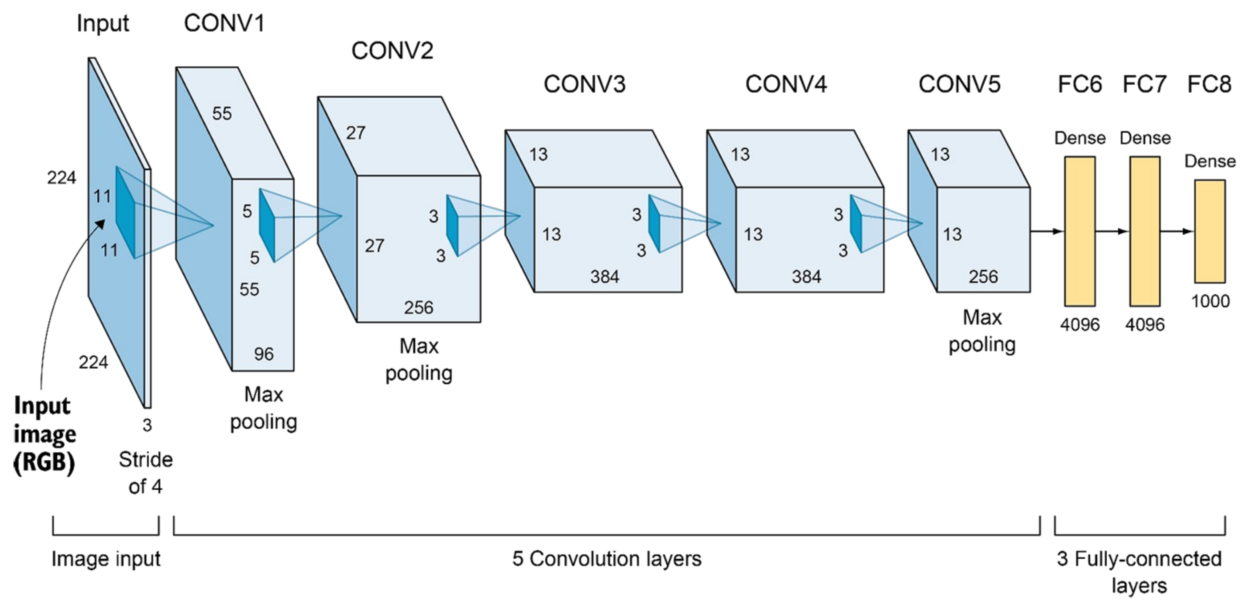
Another Recent Example: Tracking Everything Everywhere All at Once

Tracking Everything Everywhere All At Once
Qianqian Wang, Yen-Yu Chang, Ruojin Cai, Zhengqi Li, Bharath Hariharan, Aleksander Holynski, Noah Snavely

Back to convolutional neural networks

Layer types:

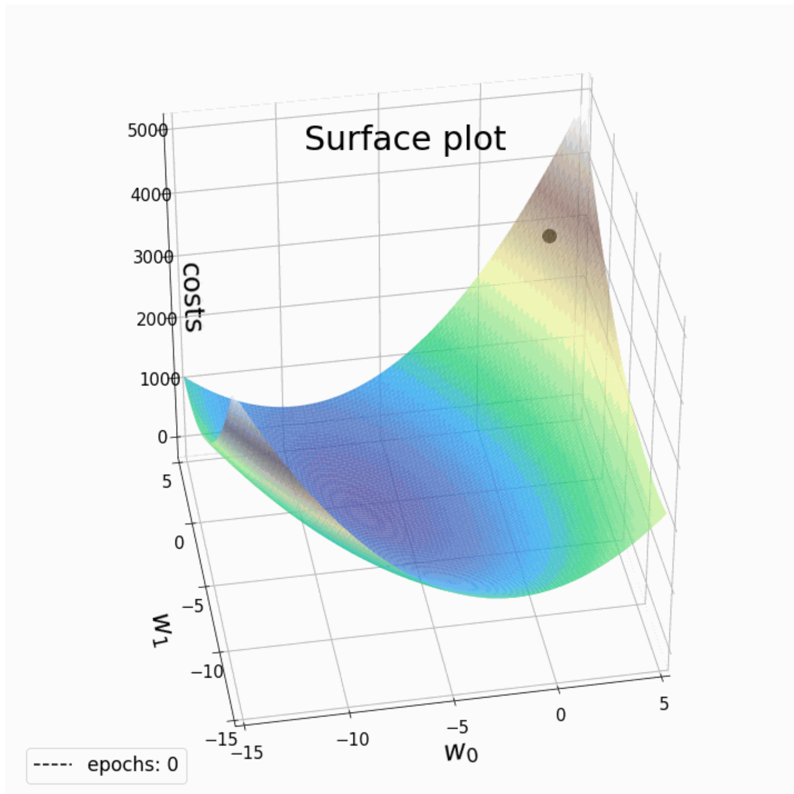
- Convolutional layer
- Pooling layer
- Fully-connected layer



Training a 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



https://laptrinhx.com/gradient-descent-animation-2-multiple-linear-regression-3070246823/

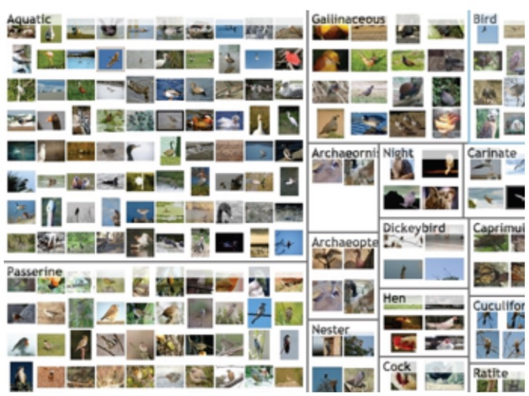
Stochastic gradient descent (SGD)

- Computing the exact gradient over the training set is expensive
- 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 only approximates the true gradient, but works remarkably well in practice
- Use **backpropagation** to automatically compute gradients on each batch

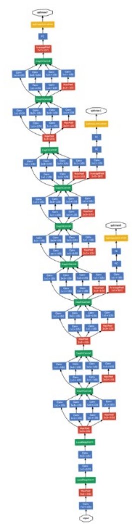
How do you actually train these things?

Roughly speaking:

Gather labeled data



Find a ConvNet architecture



Minimize the loss

But lots of details to get right!

Training a convolutional neural network

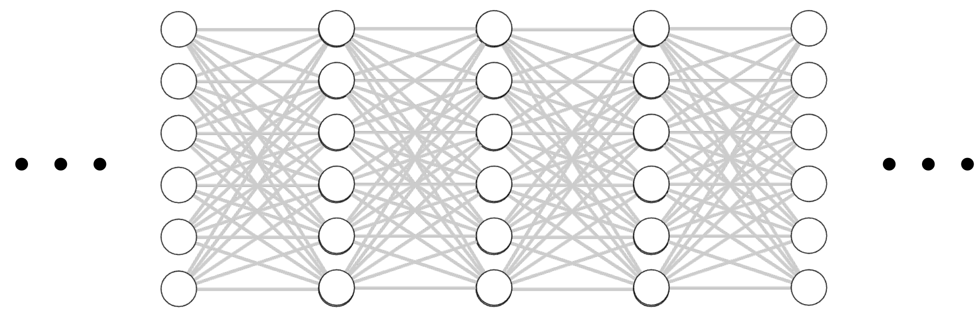
- Split and preprocess your data
- Choose your network architecture
- Initialize your network weights
- Find a learning rate and regularization weight
- Minimize the loss and monitor progress
- Fiddle with knobs…

Why so complicated?

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

What makes training deep networks 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
- It's harder to get high *test* accuracy

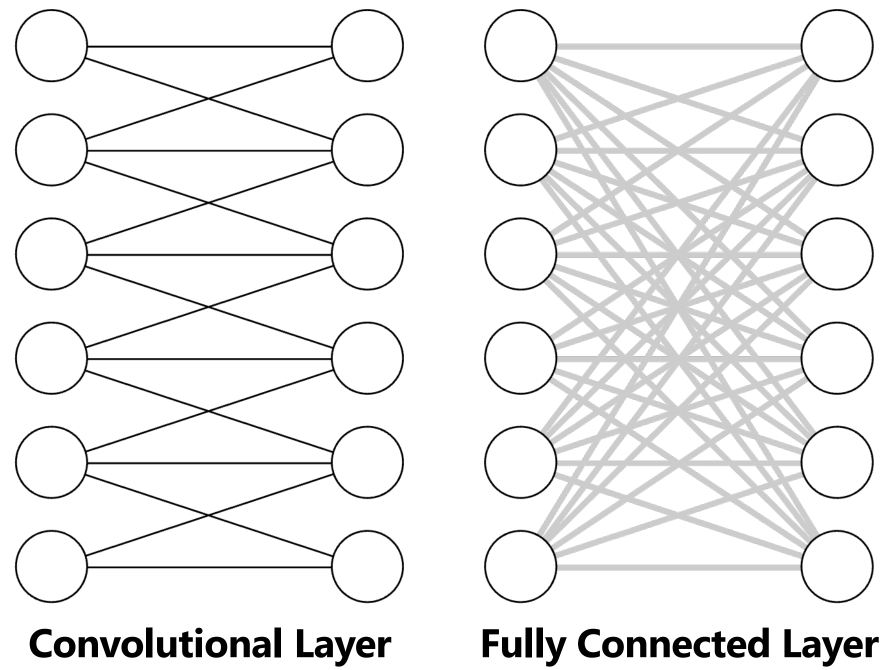


This would be an example of *overfitting*

Related Question: Why Convolutional Layers?

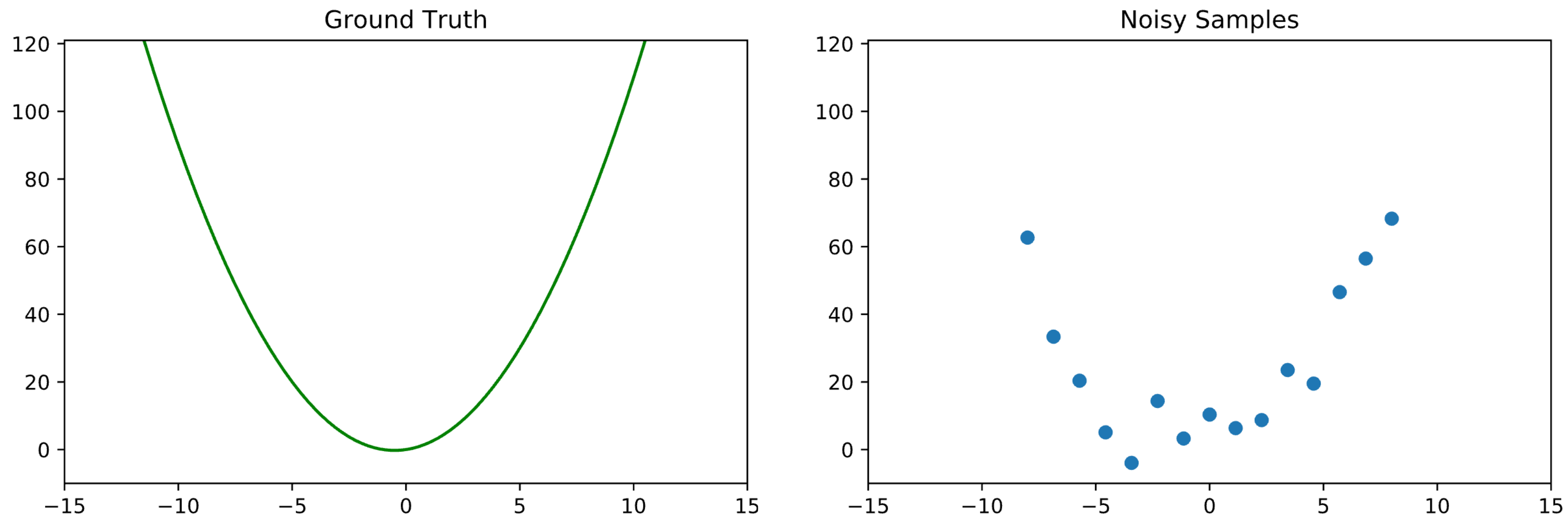
- A fully connected layer can generally represent the same functions as a convolutional one
    - Think of the convolutional layer as a version of the FC layer with constraints on parameters

- What is the advantage of CNNs?



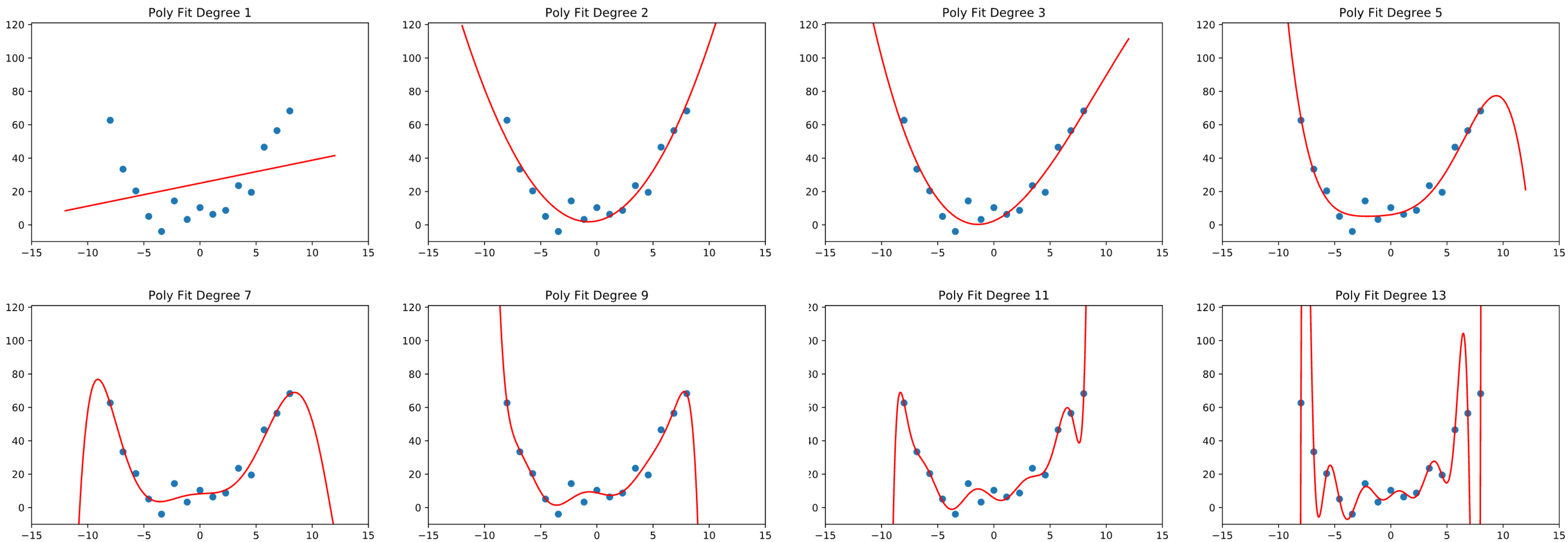
Overfitting: More Parameters, More Problems

- 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 $P_N(x) = \sum_{k=0}^{N} x^k p_k$



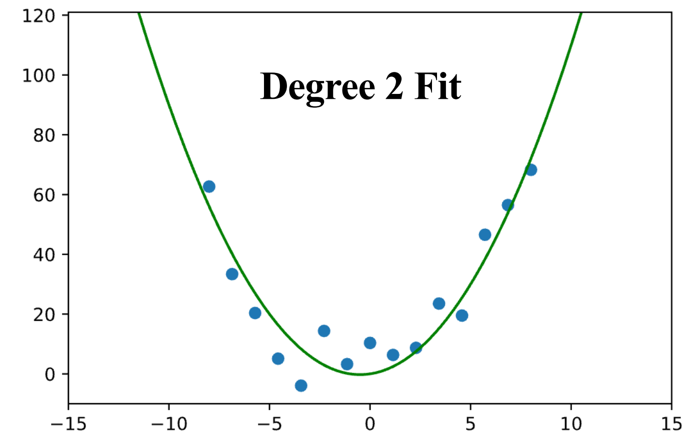
Overfitting: More Parameters, More Problems

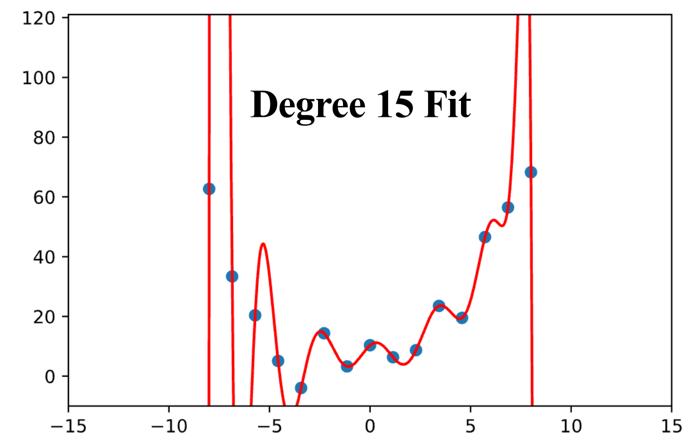
- A model with more parameters can represent more functions

- 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*.

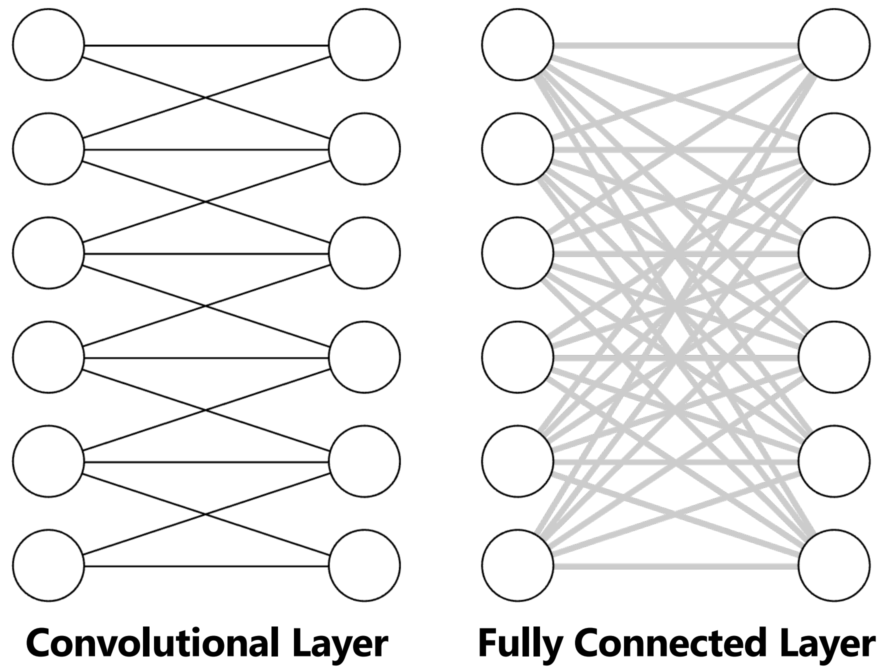
- When overfitting happens, models do not generalize well





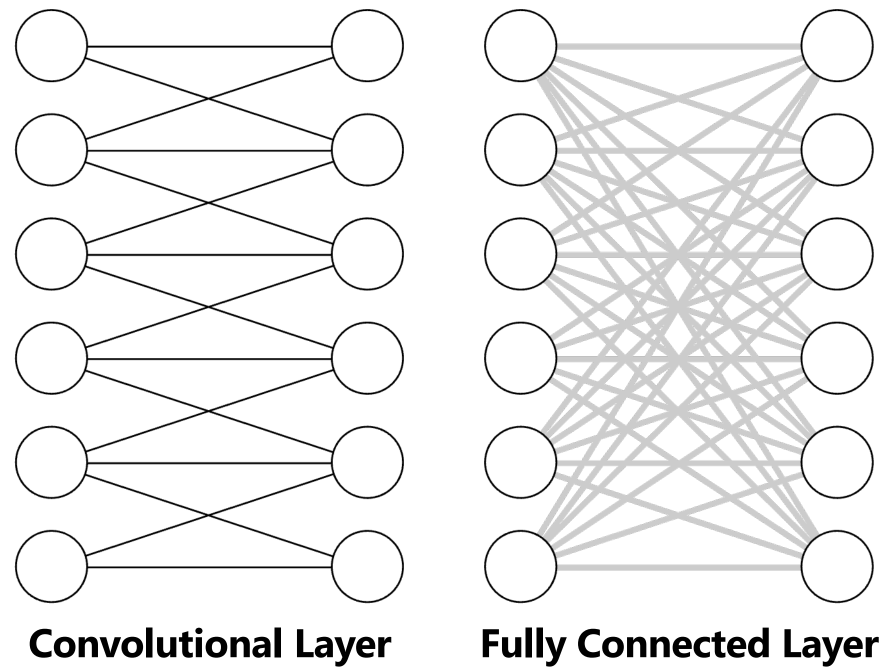
Deep Learning: More Parameters, More Problems?

- 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.



Deep Learning: More Parameters, More Problems?

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

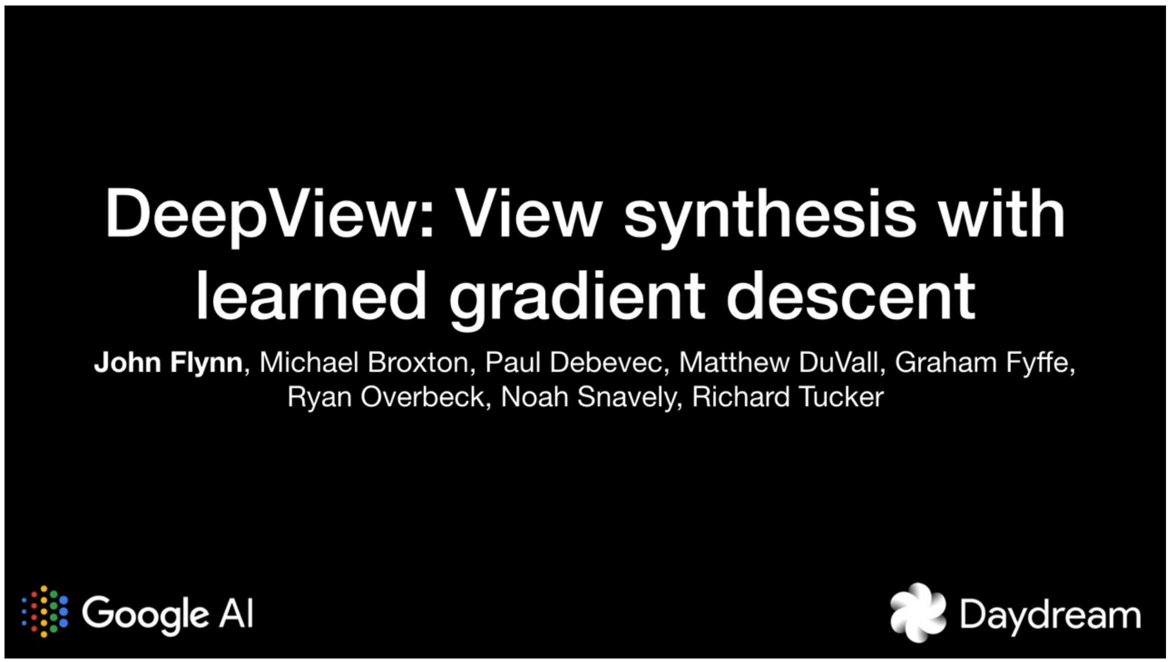


Overfitting in view synthesis

- What happens if you directly optimize an MPI to reconstruct a small set of input views?

Overfitting in view synthesis

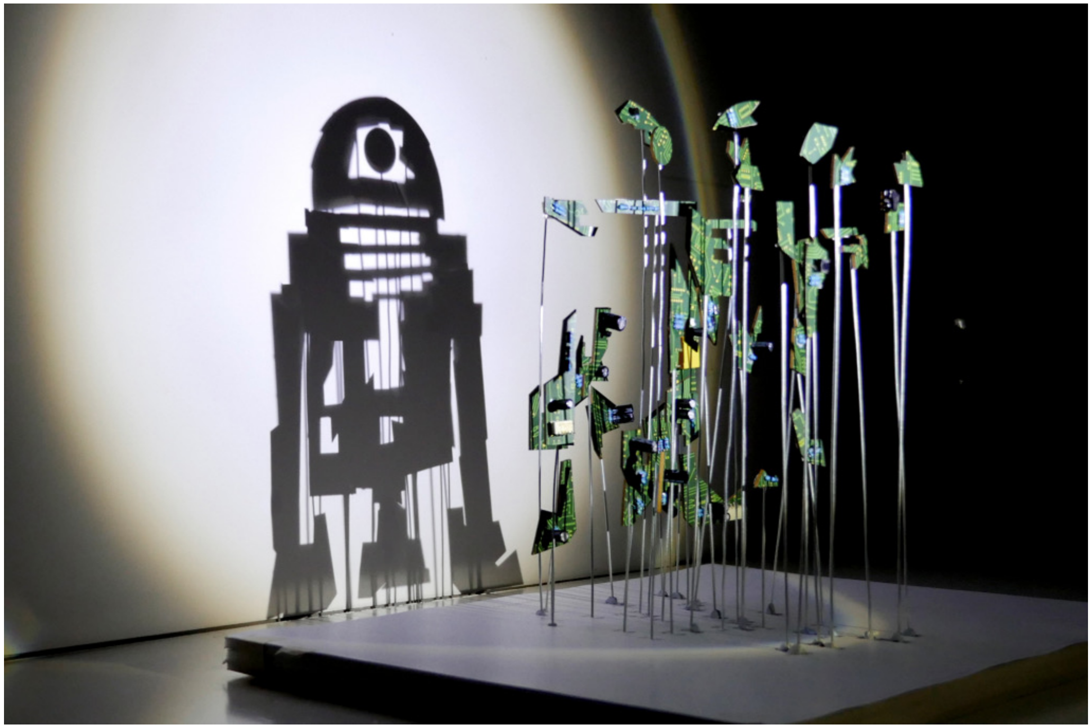
- Answer: you can exactly reconstruct the input views, but produce garbage for new views



Fitting a multi-plane image to a set of views using gradient descent

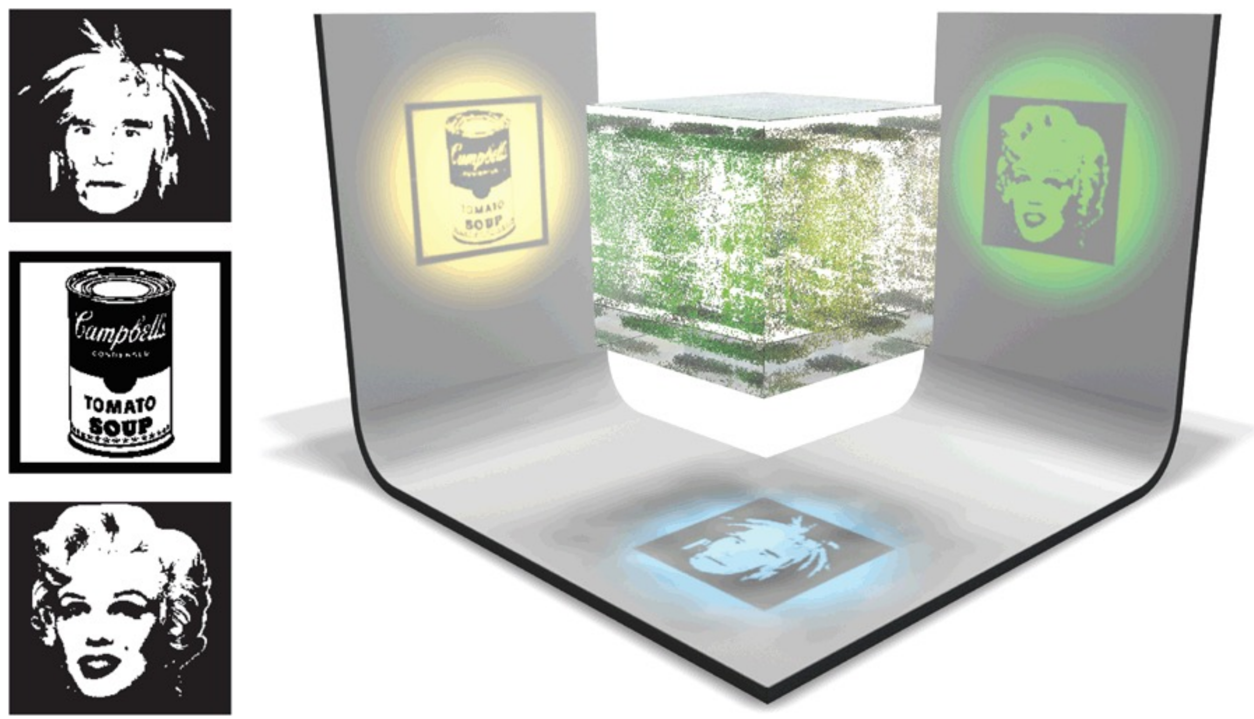
Overfitting in view synthesis

- Reminiscent of *shadow sculptures*



Anamorphic Star Wars Shadow Art by Red Hong Yi, via TKSST

Overfitting in view synthesis



[SHADOW ART](#)
Niloy J. Mitra, Mark Pauly
ACM SIGGRAPH Asia 2009

Overfitting in view sythesis

- MPI with 64 layers, each storing a 1024 x 768 RGBA image → ~200M parameters
- If we have 32 input RGB images of 1024x768 resolution → ~75M inputs
- **Many more parameters than measurements** → risk of overfitting

- Compare to NeRF: ~500K - 1M parameters

How to Avoid Overfitting: Regularization

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

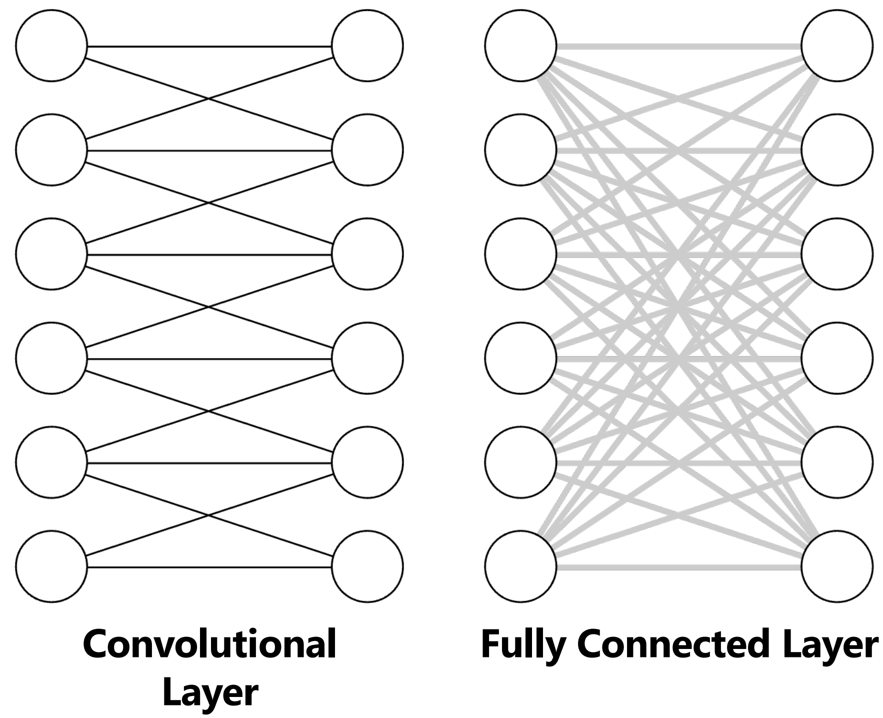
- If a model is overfitting, we can
  - Collect more data to train on
  - *Regularize*: add some additional information or assumptions to better constrain learning

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

Regularization: Architecture Choice

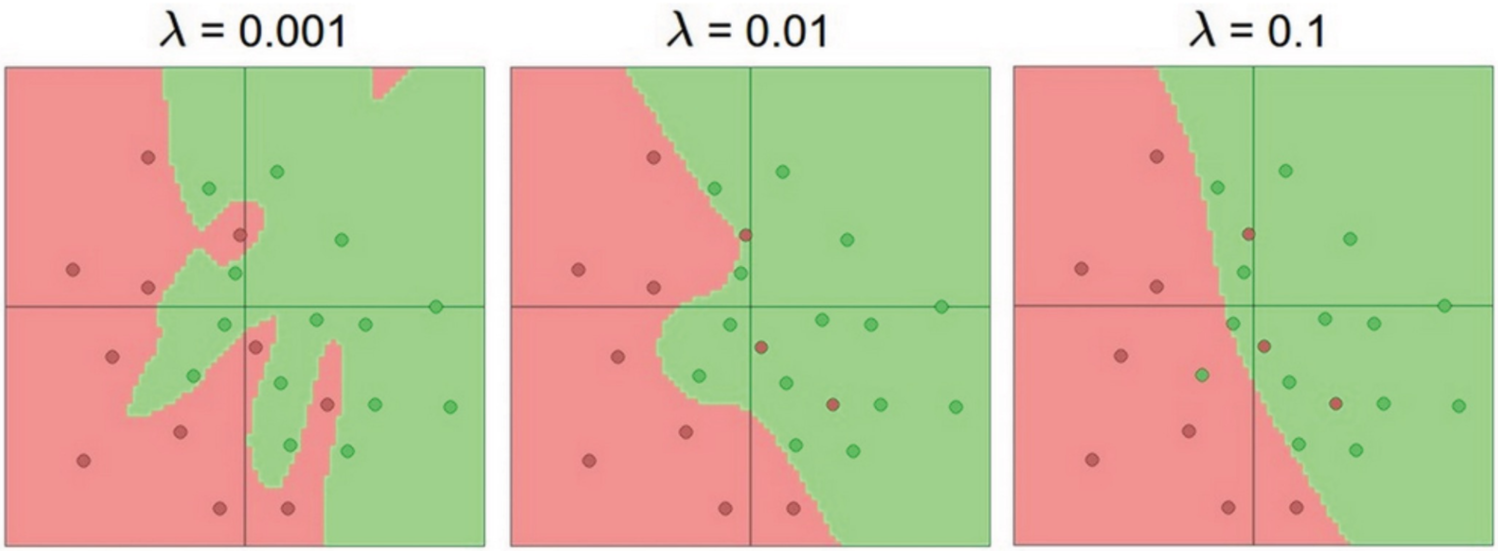
- “Bigger” architectures (typically, those with more parameters) tend to be more at risk of overfitting.

- But, we’ll see much bigger architectures (transformers) soon that work well when given lots of training data



Regularization reduces overfitting

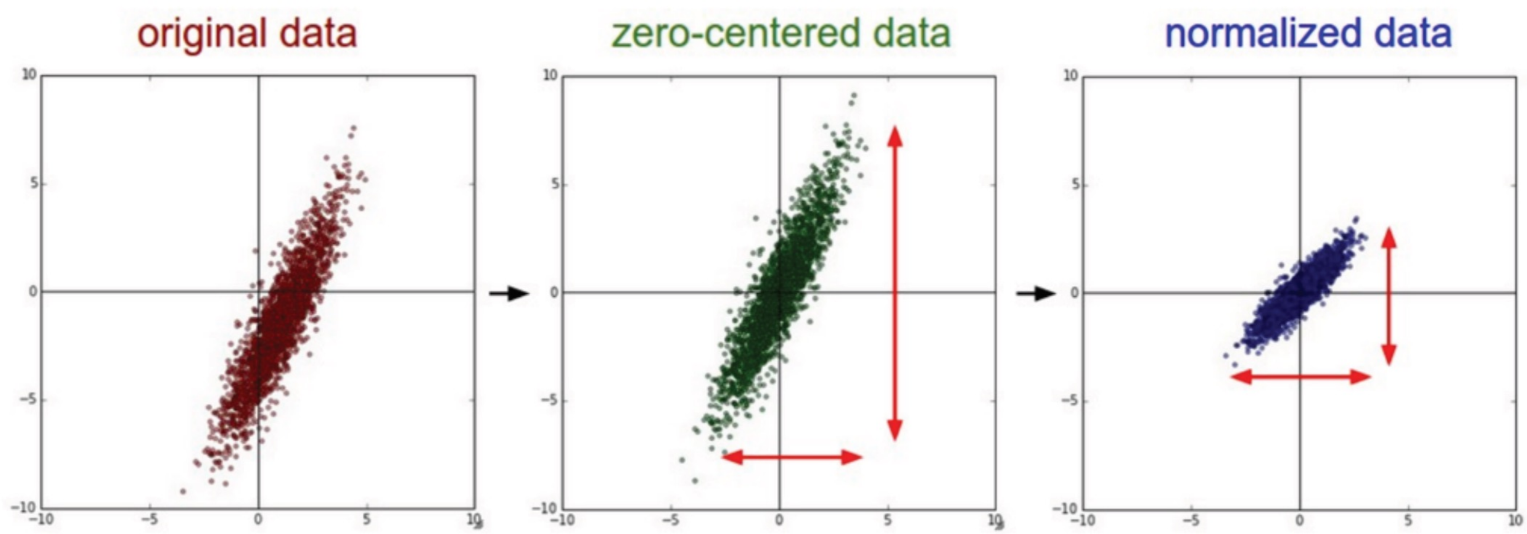
$$L = L_{\text{data}} + L_{\text{reg}} \qquad L_{\text{reg}} = \lambda \frac{1}{2} \|W\|_2^2$$



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

(1) Data proprocessing

Preprocess the data so that learning is better conditioned:

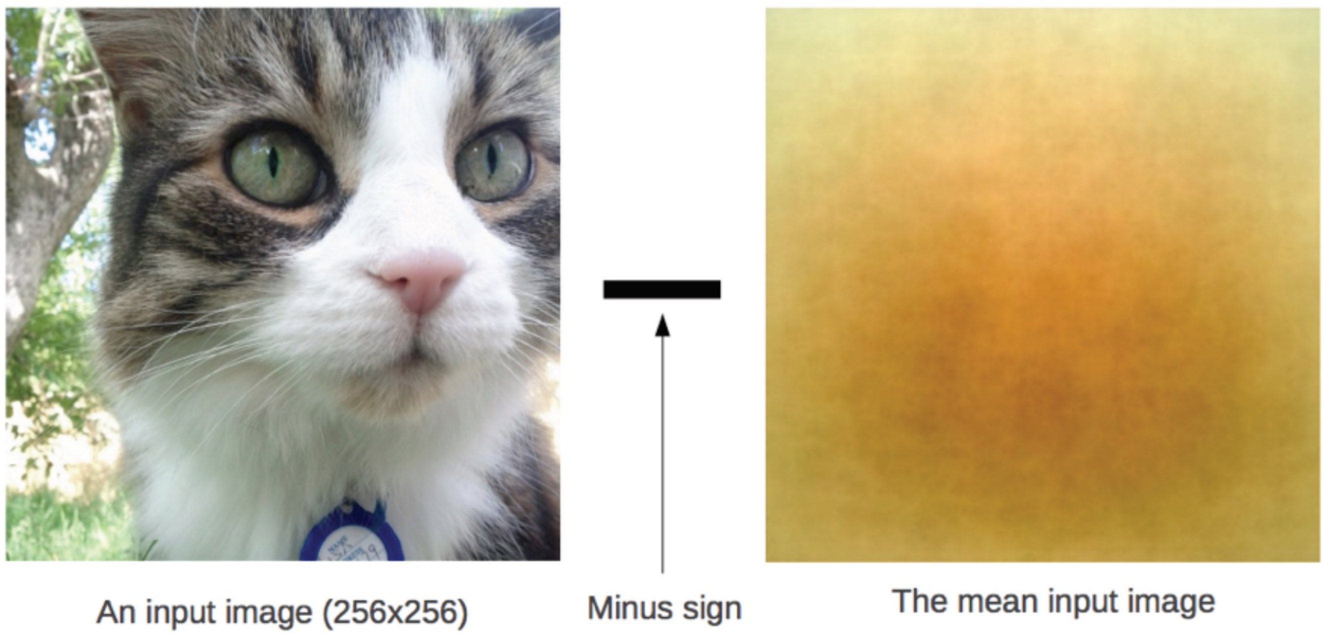



```
X -= np.mean(axis=0, keepdims=True)
```

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

Figure: Andrej Karpathy

(1) Data proprocessing



In practice, often perform a single mean RGB value, and divide by a per-channel standard deviation (recall MOPS, Normalized 8-Point Algorithm)

(1) Data proprocessing

```python
    # Data loading code
    if args.dummy:
        print("=> Dummy data is used!")
        train_dataset = datasets.FakeData(1281167, (3, 224, 224), 1000, transforms.ToTensor())
        val_dataset = datasets.FakeData(50000, (3, 224, 224), 1000, transforms.ToTensor())
    else:
        traindir = os.path.join(args.data, 'train')
        valdir = os.path.join(args.data, 'val')
        normalize = transforms.Normalize(mean=[0.485, 0.456, 0.406],
                                         std=[0.229, 0.224, 0.225])

        train_dataset = datasets.ImageFolder(
            traindir,
            transforms.Compose([
                transforms.RandomResizedCrop(224),
```

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.

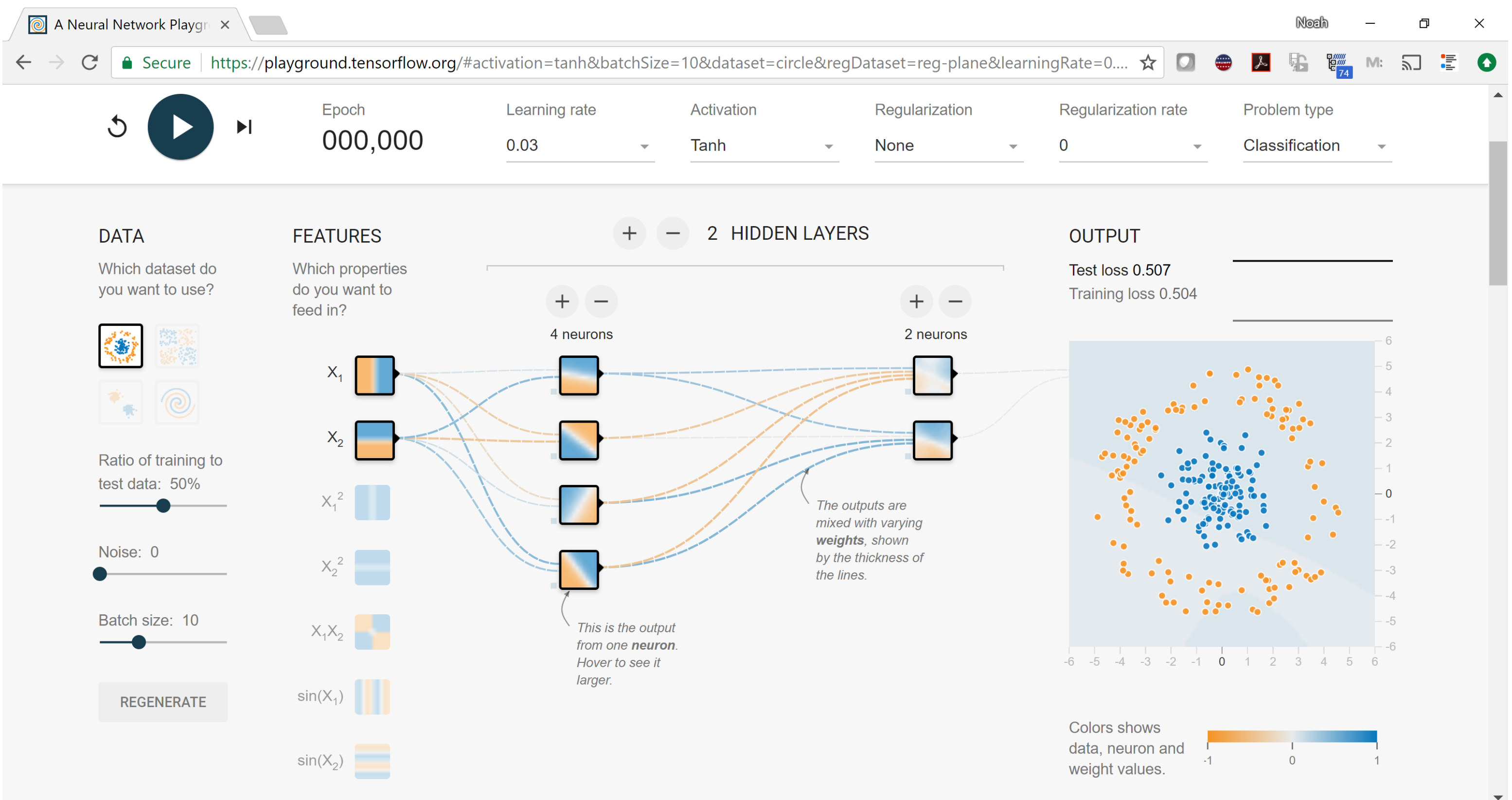
E.g. 224x224 patches extracted from 256x256 images

Randomly reflect horizontally

Perform the augmentation live during training

Figure: Alex Krizhevsky

(2) Choose your architecture

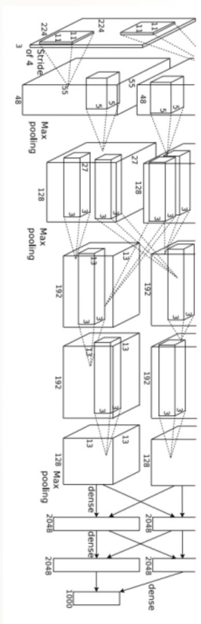


https://playground.tensorflow.org/

(2) Choose your architecture

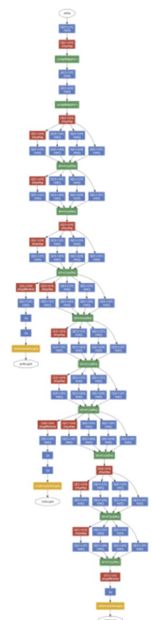
Very common modern choice
for classification problems

"AlexNet"



[Krizhevsky et al. NIPS 2012]

"GoogLeNet"

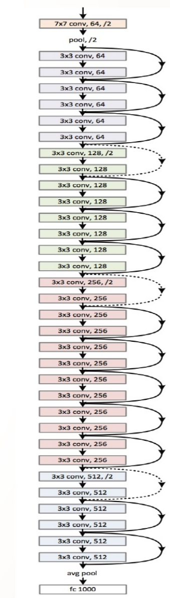


[Szegedy et al. CVPR 2015]

"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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                                  sample_batches = False,
                                  learning_rate=1e-3, verbose=True)
```

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

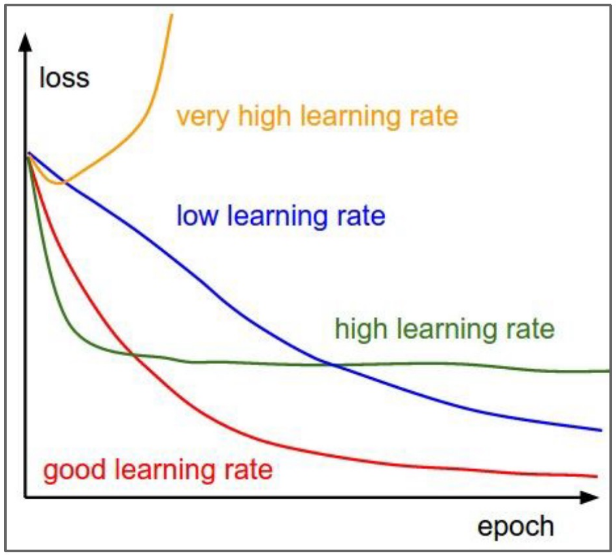
100% accuracy on the training set (good)

```
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 with

- 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 data if you want to train/use CNNs for a new classification task"

Slide credit: Fei-Fei Li, Justin Johnson, and Serena Yeun

Transfer learning

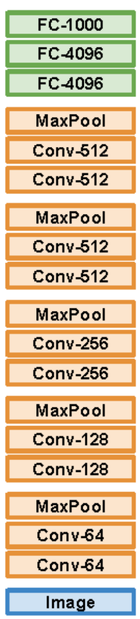
"You need a lot of data if you want to train/use CNNs for a new classification task"

BUSTED

Slide credit: Fei-Fei Li, Justin Johnson, and Serena Yeun

Transfer learning with CNNs

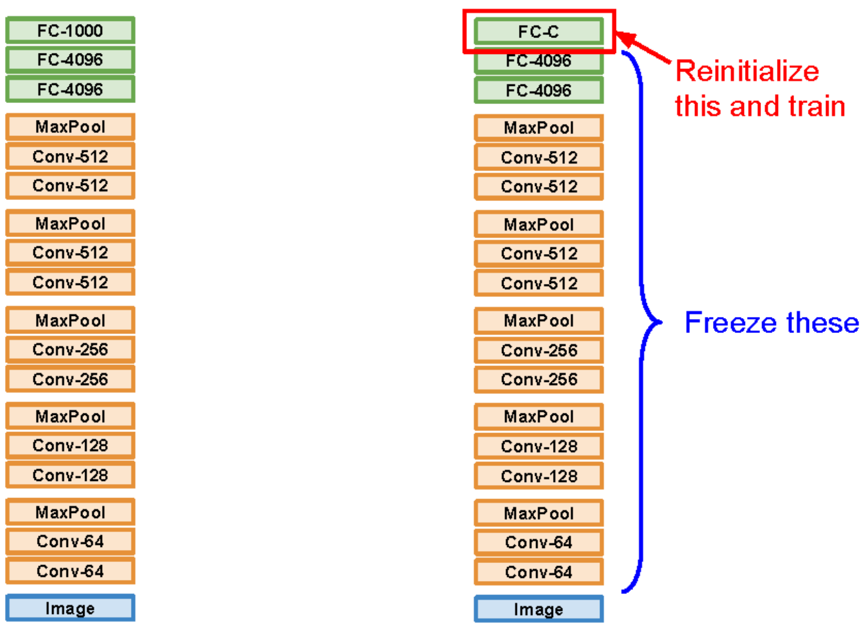
Step 1: Take a model trained on ImageNet



Slide credit: Fei-Fei Li, Justin Johnson, and Serena Yeur

Transfer learning with CNNs

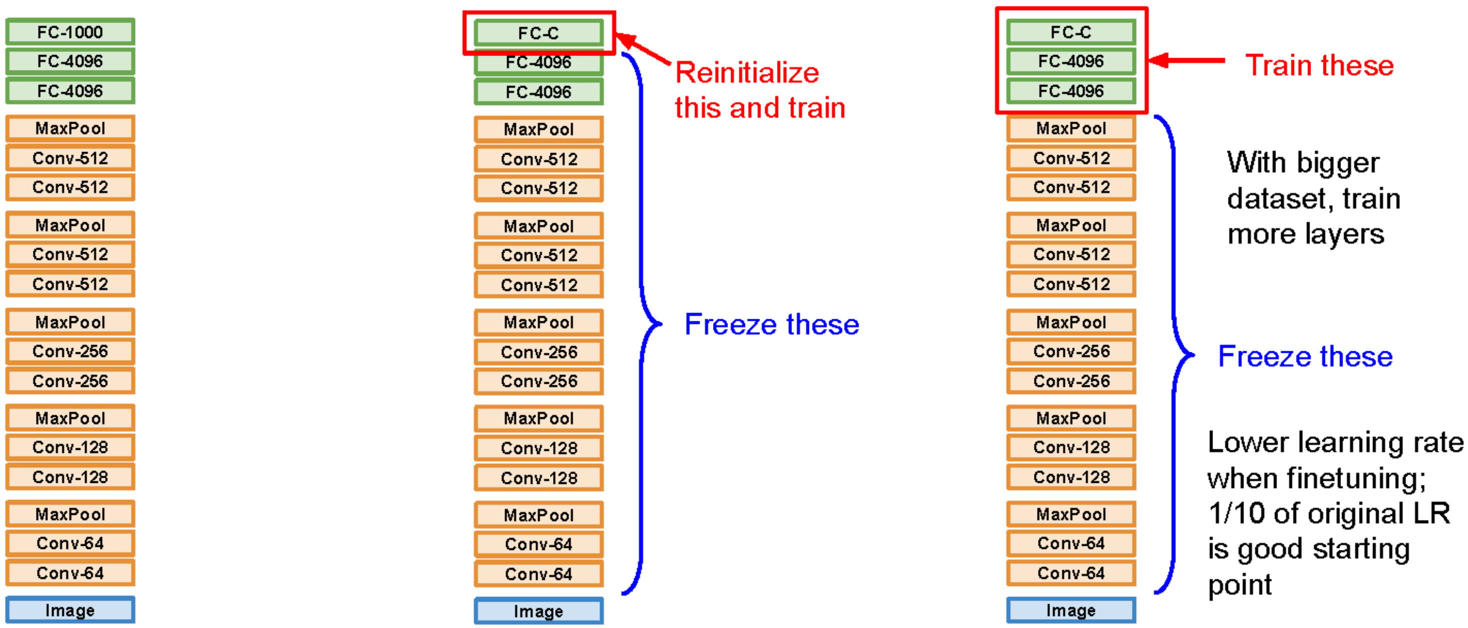
Step 2a: If you have a small amount of new data, adjust a small number of network weights



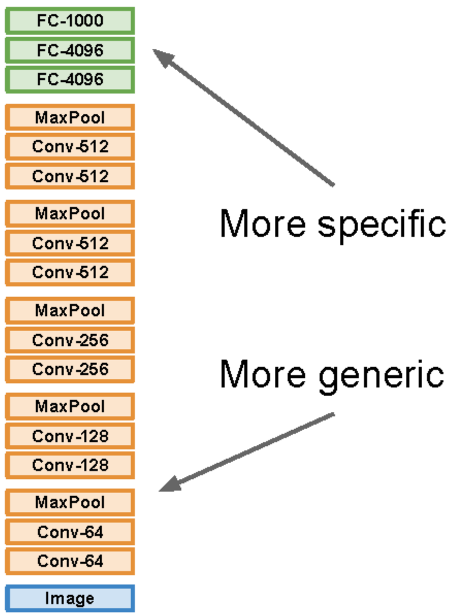
Slide credit: Fei-Fei Li, Justin Johnson, and Serena Yeun

Transfer learning with CNNs

Step 2b: If you have a larger amount of new data, adjust a larger number of network weights

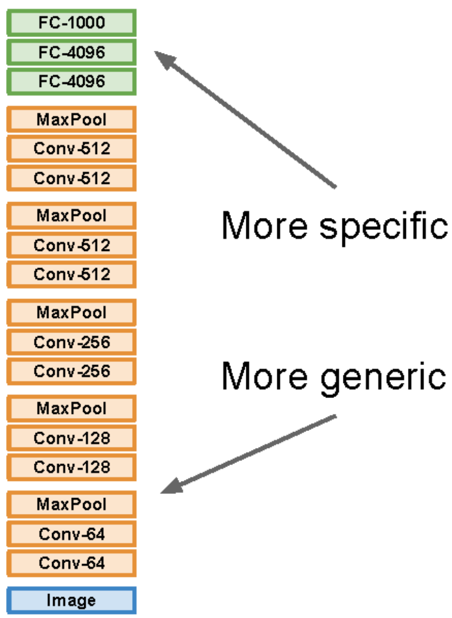


Slide credit: Fei-Fei Li, Justin Johnson, and Serena Yeun



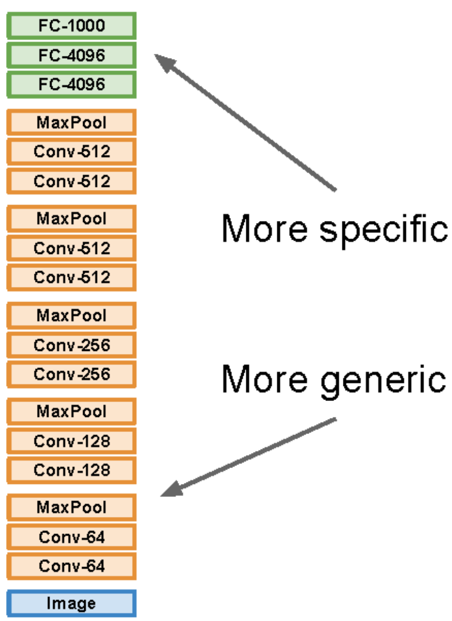
	very similar dataset	**very different dataset**
very little data	?	?
quite a lot of data	?	?

Slide credit: Fei-Fei Li, Justin Johnson, and Serena Yeur



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

Slide credit: Fei-Fei Li, Justin Johnson, and Serena Yeun

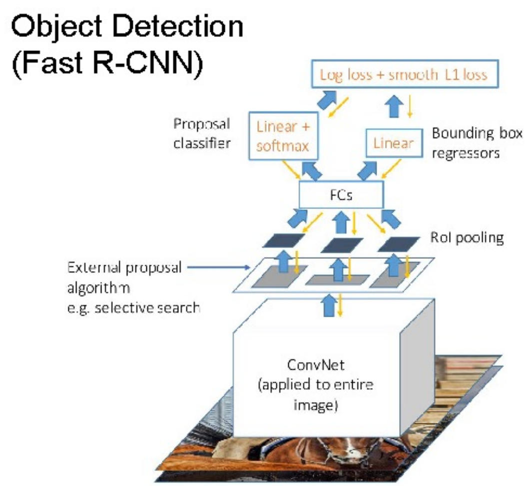


	very similar dataset	**very different dataset**
very little data	Use Linear Classifier on top layer	You're in trouble… Try linear classifier from different stages
quite a lot of data	Finetune a few layers	Finetune a larger number of layers

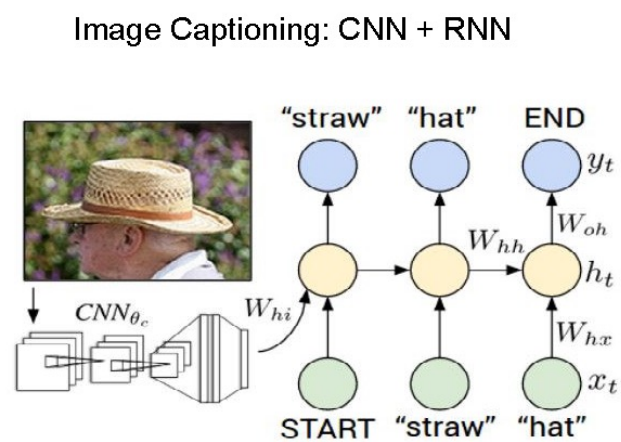
Slide credit: Fei-Fei Li, Justin Johnson, and Serena Yeun

Transfer learning with CNNs is pervasive

- It's the norm, not the exception



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

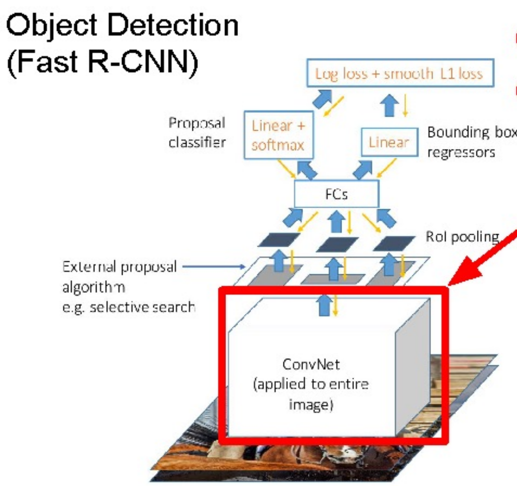


Karpathy and Fei-Fei, "Deep Visual-Semantic Alignments for Generating Image Descriptions", CVPR 2015
Figure copyright IEEE, 2015. Reproduced for educational purposes.

Slide credit: Fei-Fei Li, Justin Johnson, and Serena Yeun

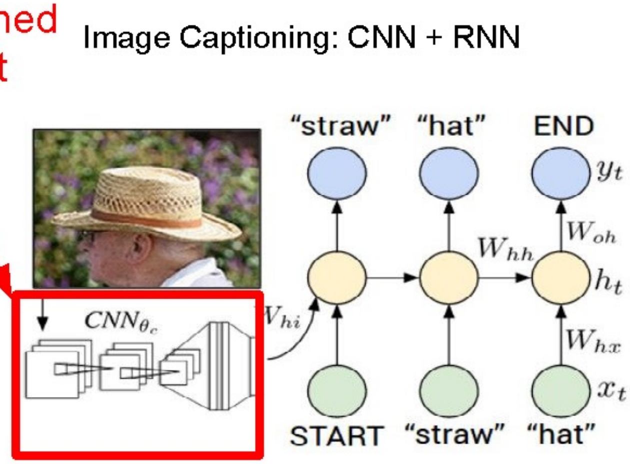
Transfer learning with CNNs is pervasive

- It's the norm, not the exception



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

CNN pretrained on ImageNet



Karpathy and Fei-Fei, "Deep Visual-Semantic Alignments for Generating Image Descriptions", CVPR 2015
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Other pre-trained models are starting to become standard

- Swin-transformer pre-trained on ImageNet-21K
- DINO features
- Foundation models (Stable Diffusion, etc)

Takeaway for your projects and beyond

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

1. Find a large dataset with similar data (e.g., ImageNet), train a large CNN
2. Apply transfer learning to fine-tune on your data

For step 1, many existing models exist in “Model Zoos”

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

Slide credit: Fei-Fei Li, Justin Johnson, and Serena Yeun

Questions?