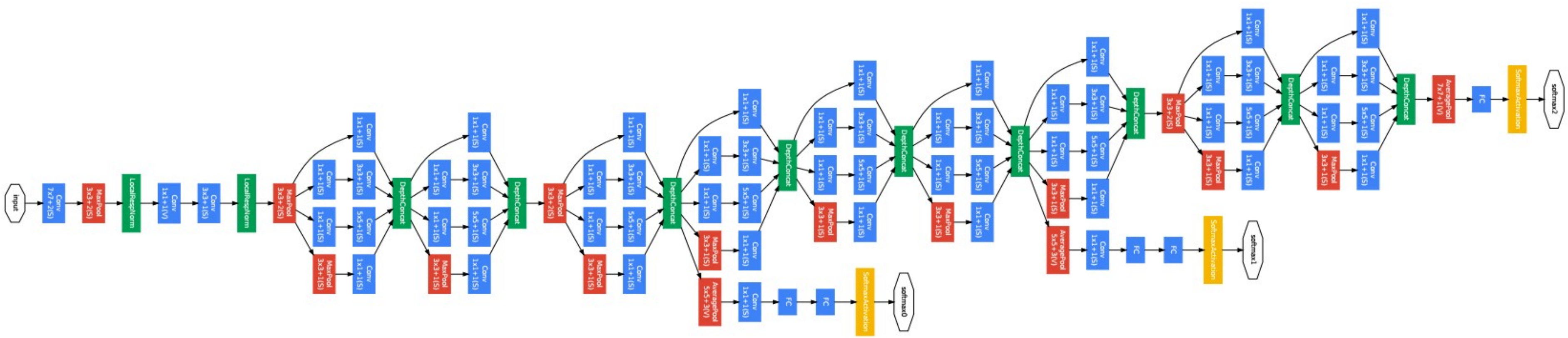
CSCI 497P/597P: Computer Vision

Regularization

CNNs: Interpretation, Practicalities



Readings

with a great deal more detail…

- https://cs231n.github.io/neural-networks-2/
- https://cs231n.github.io/neural-networks-3/
- https://cs231n.github.io/convolutional-networks/

Goals (Last Lecture)

- Understand why we need activation functions.
- Understand the motivation and behavior of convolutional layers in neural networks.
- Understand the degrees of freedom available in setting up a convolution layer:
  - Output channels, kernel size, padding, stride
- Know the meaning of the various basic layers involved in standard CNN architectures
  - Conv, ReLU, Pool, Fully Connected

Goals (Today)

- Understand the purpose of applying regularization in machine learning training.
- Know what overfitting means and why it’s bad.
- Gain intuition for the meaning of intermediate layers in CNNs.
- Know the idea and purpose of each of the following tricks used when training CNNs:
  - Batched training
  - Preprocessing / data augmentation
  - Momentum
  - Learning rate decay
  - Dropout
  - Weight initialization and batch normalization

Announcements

- HW5 still doesn't exist. It will be short, optional, or both, with the goal of helping you prepare for the final.
- P2 grading is in progress.

Announcements

- P4 is out. You will:
  - Modify a trained 1000-class classifier to turn it into a 2-class "dog vs food" classifier.
  - Misuse backpropagation to:
    - see which input pixels are most influential in classifying it
    - trick the classifier into predicting the wrong class
    - synthesize images that maximize a chosen class score

Announcements

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    - see which input pixels are most influential in classifying it
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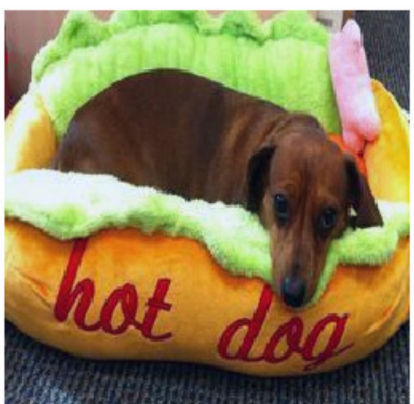
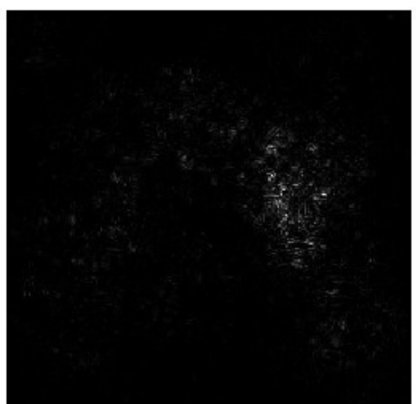
    - synthesize images that maximize a chosen class score

Announcements

– Misuse backpropagation to:
  - **see which input pixels are most influential (saliency)**
  - trick the classifier into predicting the wrong class
  - synthesize images that maximize a chosen class score





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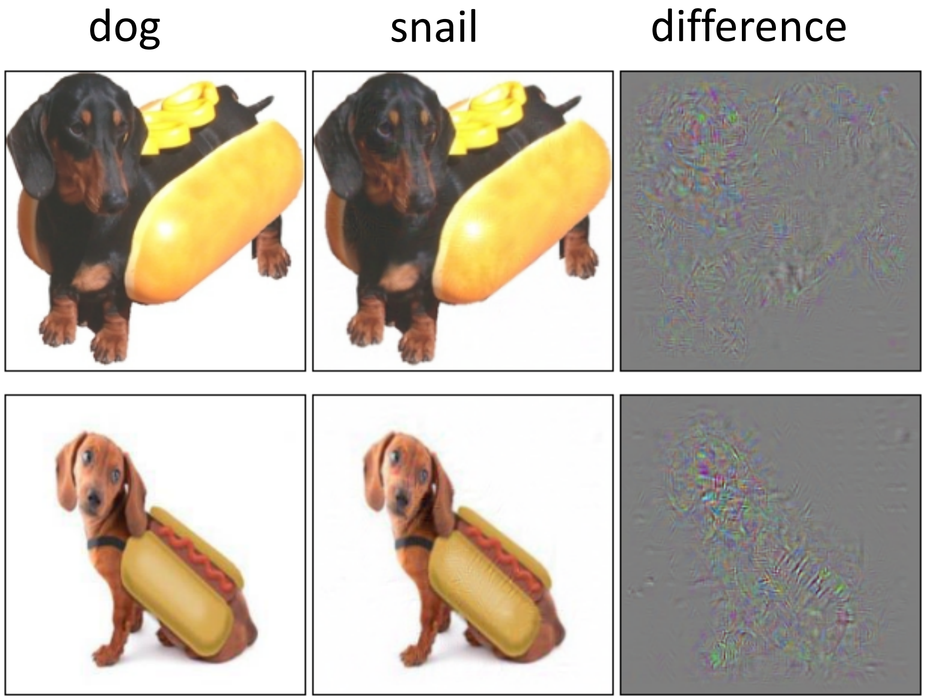

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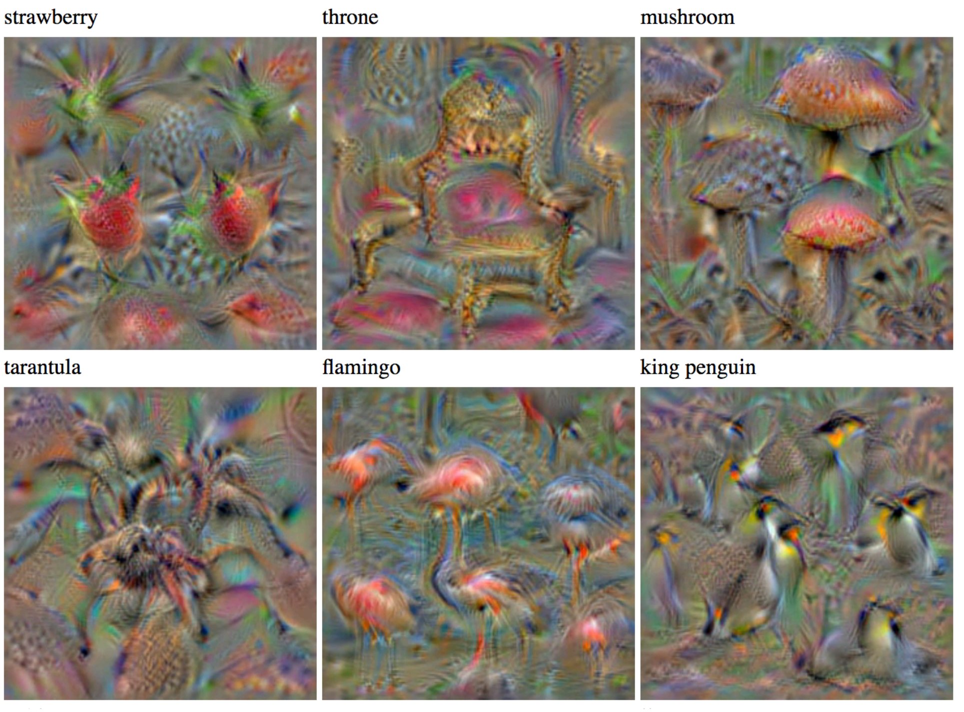


Machine Learning Aside: Regularization

- Suppose we've learned a linear classifier W such that L = 0: it classifies everything perfectly.

- Is this W unique?

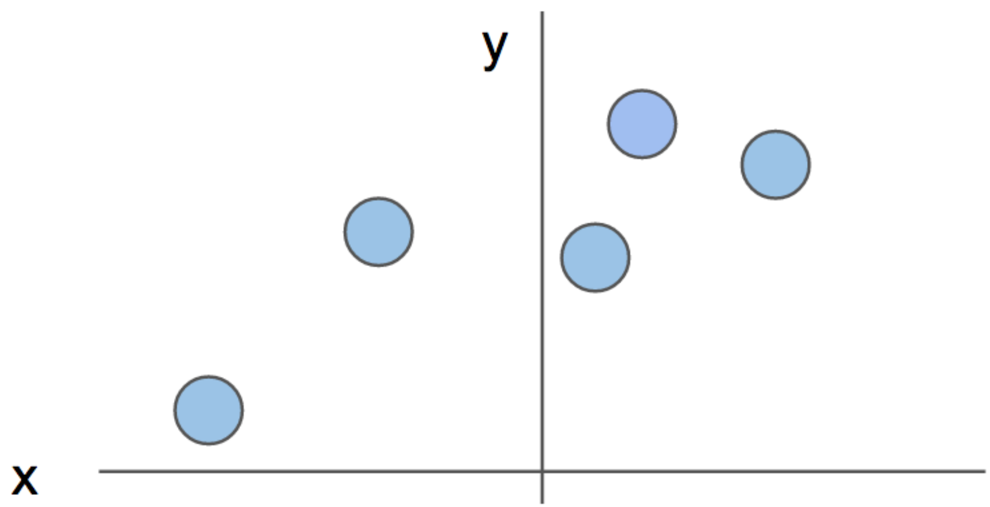
Regularization

- Suppose we've learned a linear classifier W such that L = 0: it classifies everything perfectly.

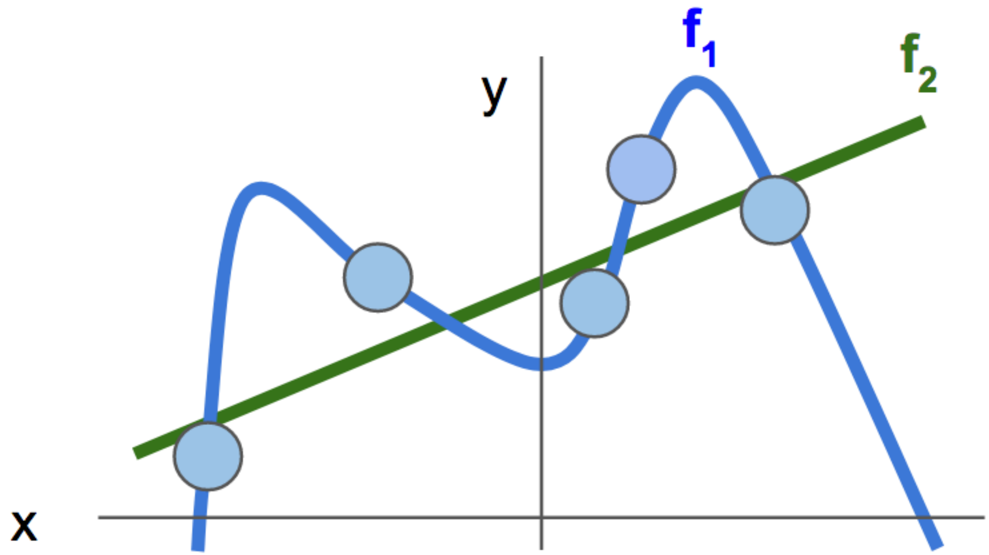
- Is this W unique?

No! 2W is also has L = 0!
Which do we prefer – W, or 2W?

Regularization: Prefer Simpler Models



Regularization: Prefer Simpler Models



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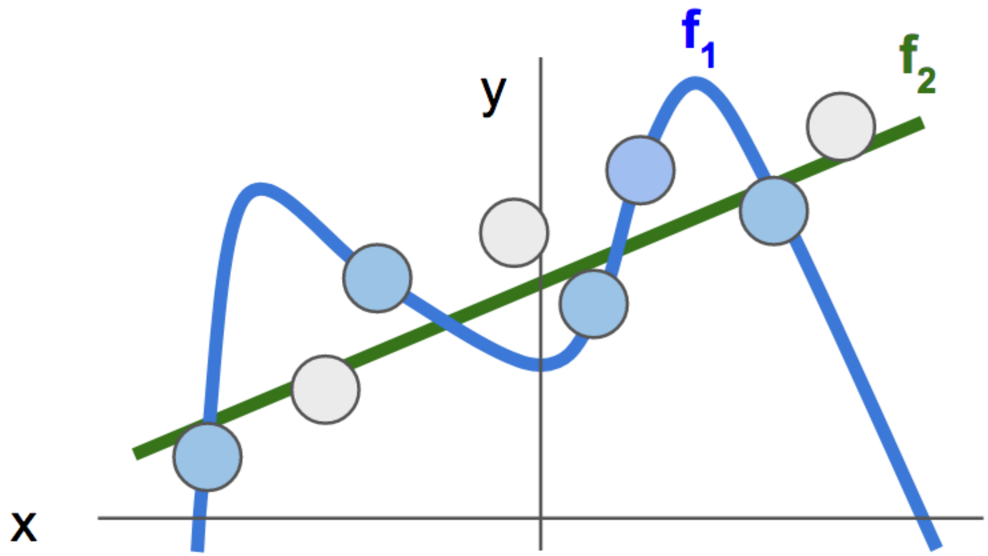
Regularization: Prefer Simpler Models



Regularization pushes against fitting the data *too* well so we don't fit noise in the data

overfitting: learning the training data **too** well, to the detriment of performance on unseen data

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A more interesting example of non-uniqueness…

Regularization

$$\underbrace{L(W) = \frac{1}{N}\sum_{i=1}^{N} L_i(f(x_i, W), y_i)}$$

Data loss: Model predictions should match training data

Regularization

$$L(W) = \underbrace{\frac{1}{N}\sum_{i=1}^{N} L_i(f(x_i, W), y_i)}_{\text{Data loss}} + \underbrace{\lambda R(W)}_{\text{Regularization}}$$

Data loss: Model predictions should match training data

Regularization: Prevent the model from doing *too* well on training data

Regularization

λ = regularization strength (hyperparameter)

$$L(W) = \underbrace{\frac{1}{N} \sum_{i=1}^{N} L_i(f(x_i, W), y_i)}_{\text{Data loss}} + \underbrace{\lambda R(W)}_{\text{Regularization}}$$

Data loss: Model predictions should match training data

Regularization: Prevent the model from doing *too* well on training data

Simple examples

<u>L2 regularization:</u> $R(W) = \sum_k \sum_l W_{k,l}^2$

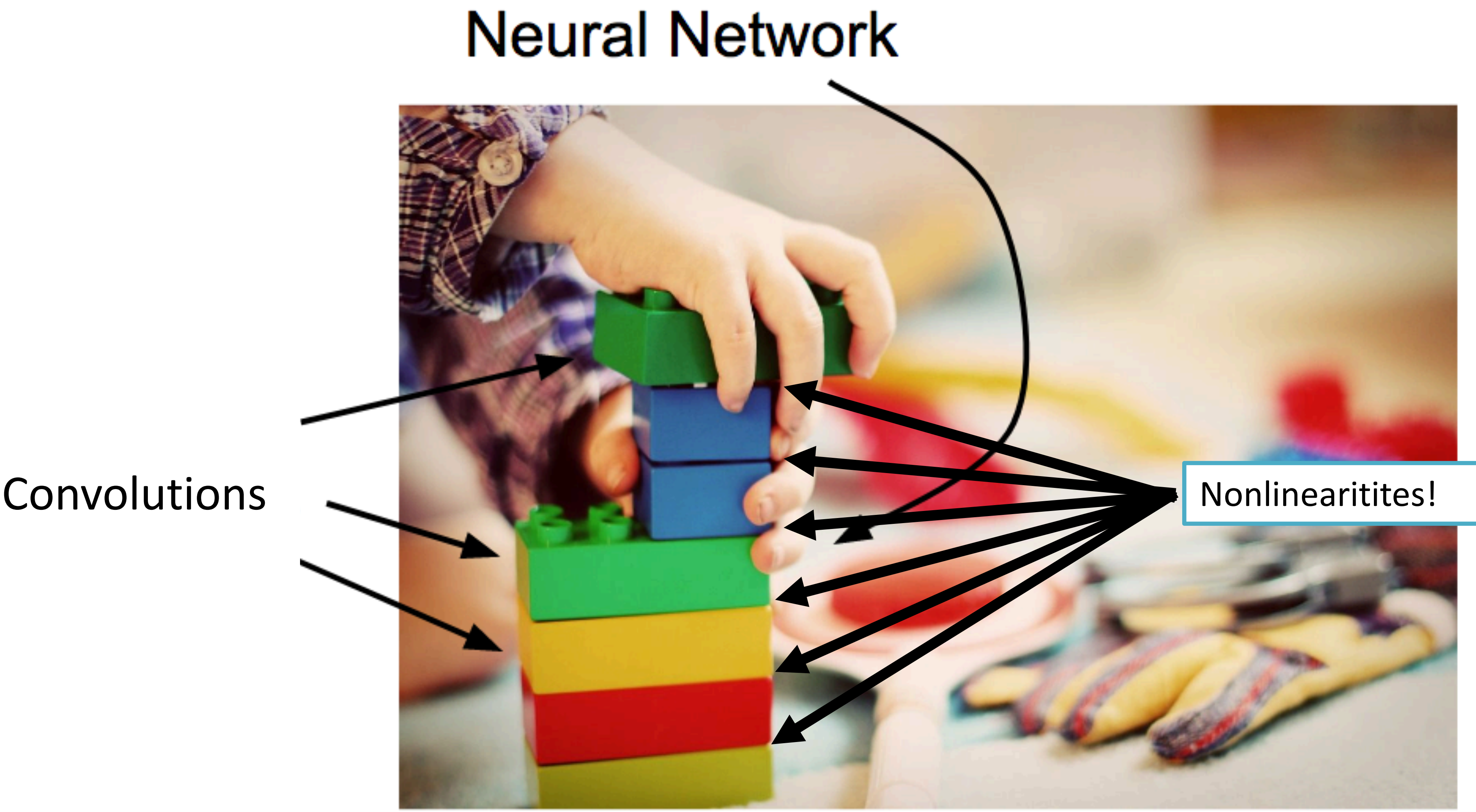
L1 regularization: $R(W) = \sum_k \sum_l |W_{k,l}|$

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

Regularization in CNNs

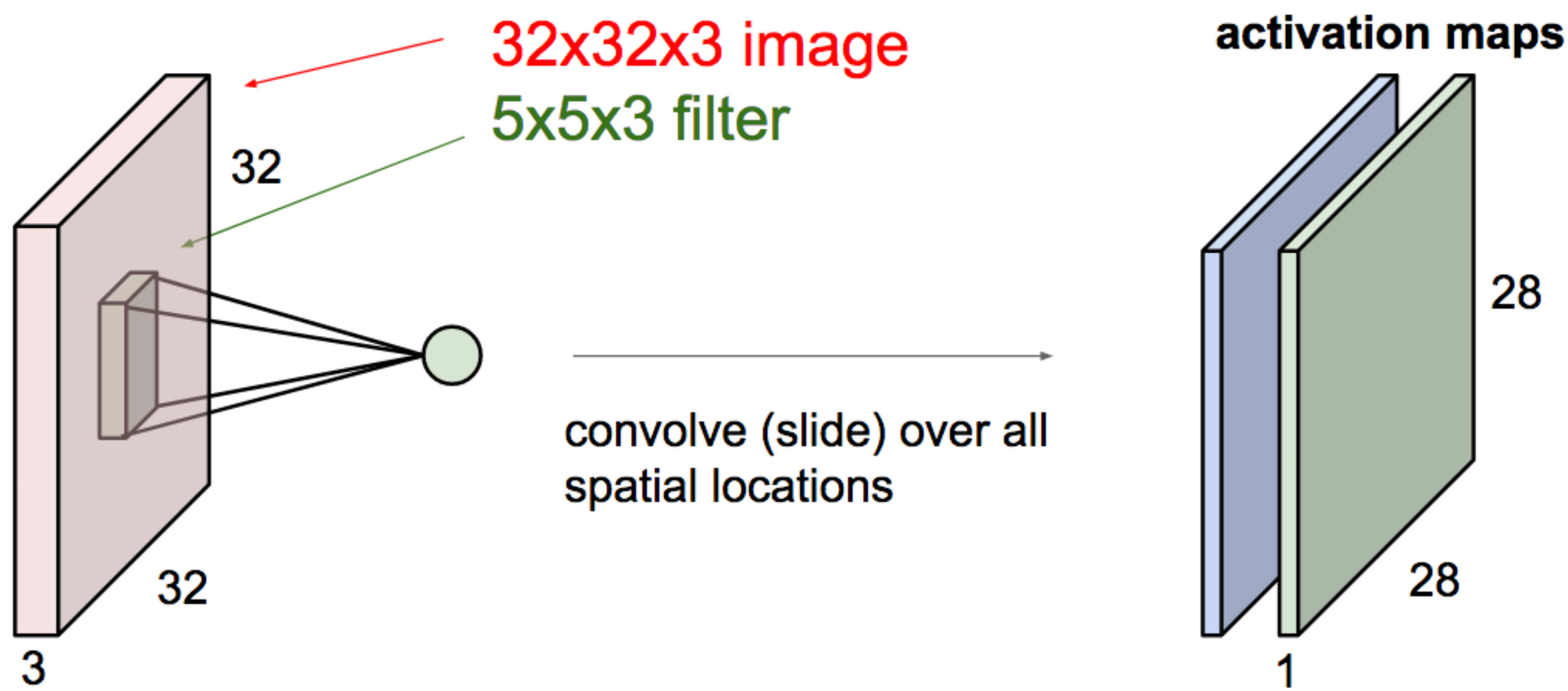
- AKA “weight decay”

Convolutional Neural Networks

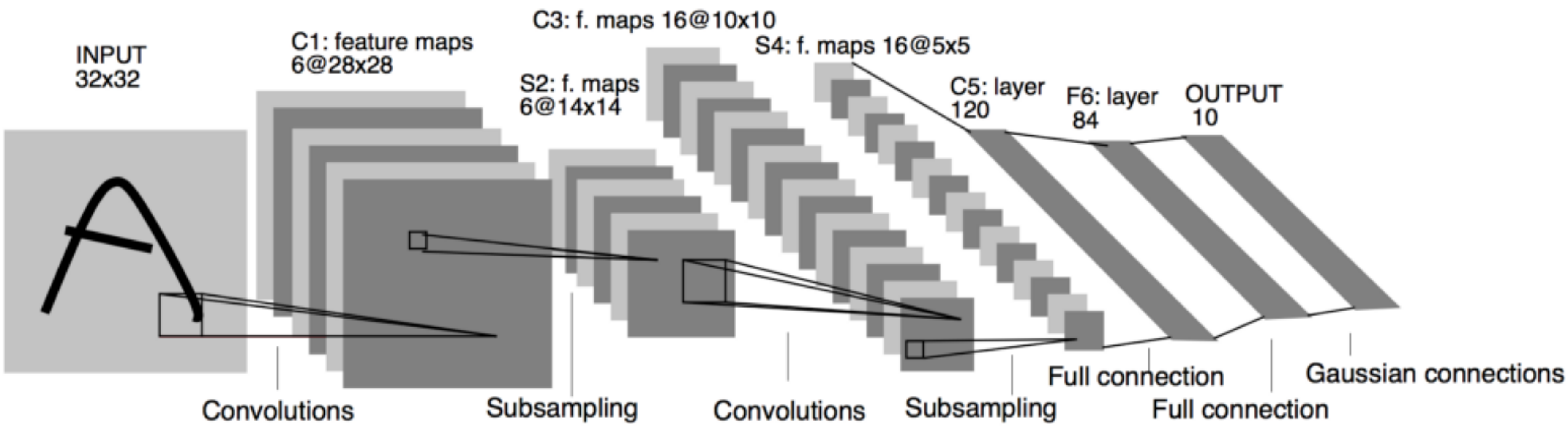


Convolution Layer

consider a second, green filter

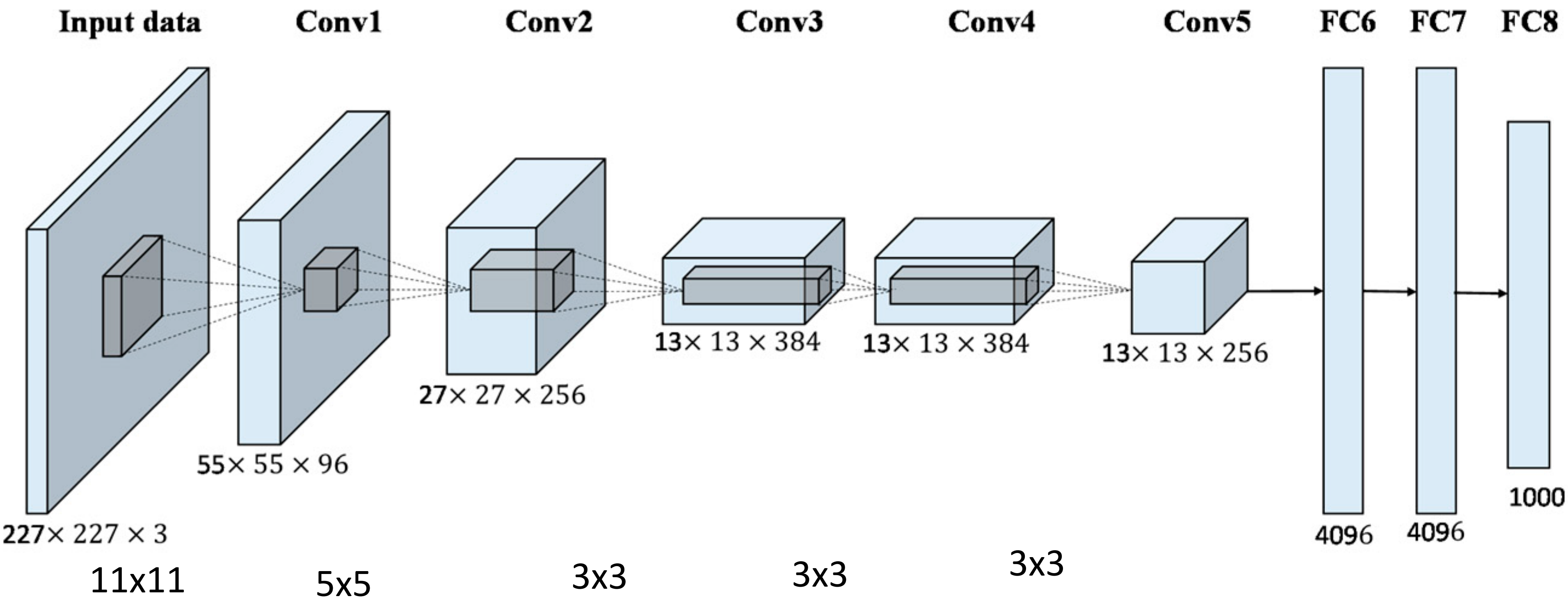


CNNs before they were cool: LeNet-5 [LeCun et al., 1998]



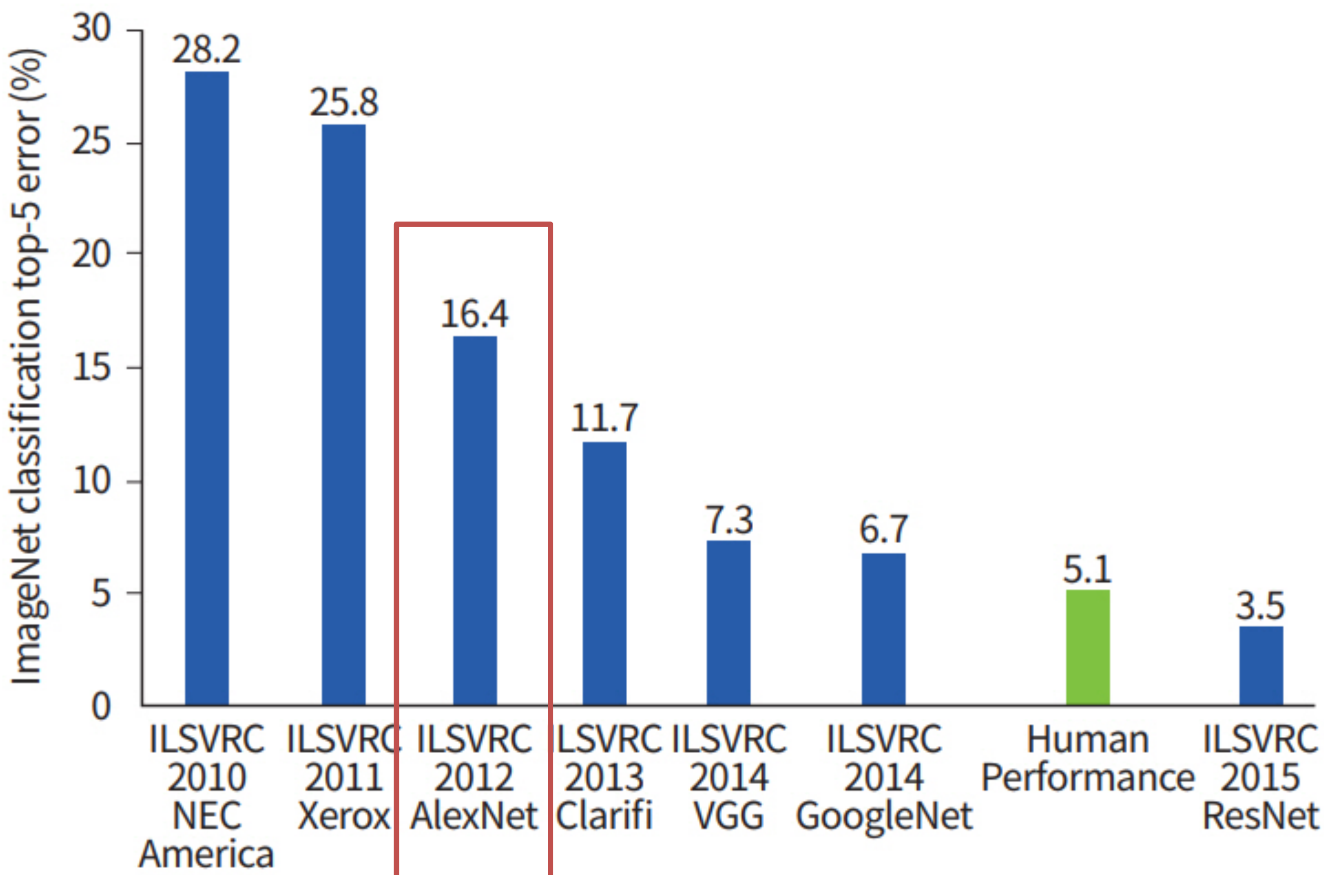
- Today's architectures still look a lot like this!

The CNN that made them cool: AlexNet [Krizhevsky et al. 2012]



The CNN that made them cool: AlexNet [Krizhevsky et al. 2012]

- What happened?

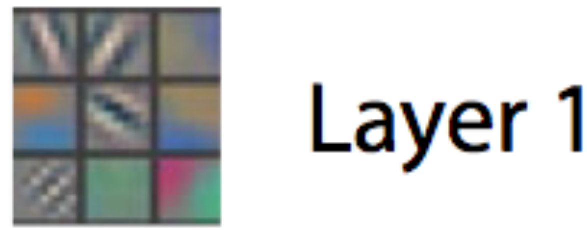


The CNN that made them cool: AlexNet [Krizhevsky et al. 2012]

- What changed?
  - Bigger training data: ImageNet has 14 million images and 20,000 categories.
    - (performance numbers are on a 1000-category subset)
  - GPU implementation of ConvNets
    - Train bigger, deeper networks for longer than before
  - ReLU
    - Not new in AlexNet, but a necessary design choice to avoid vanishing gradients in deep network
- Hence “deep learning”:
  - a rebranding of formerly unfashionable neural networks

What do all these feature maps *mean?*

The filters:

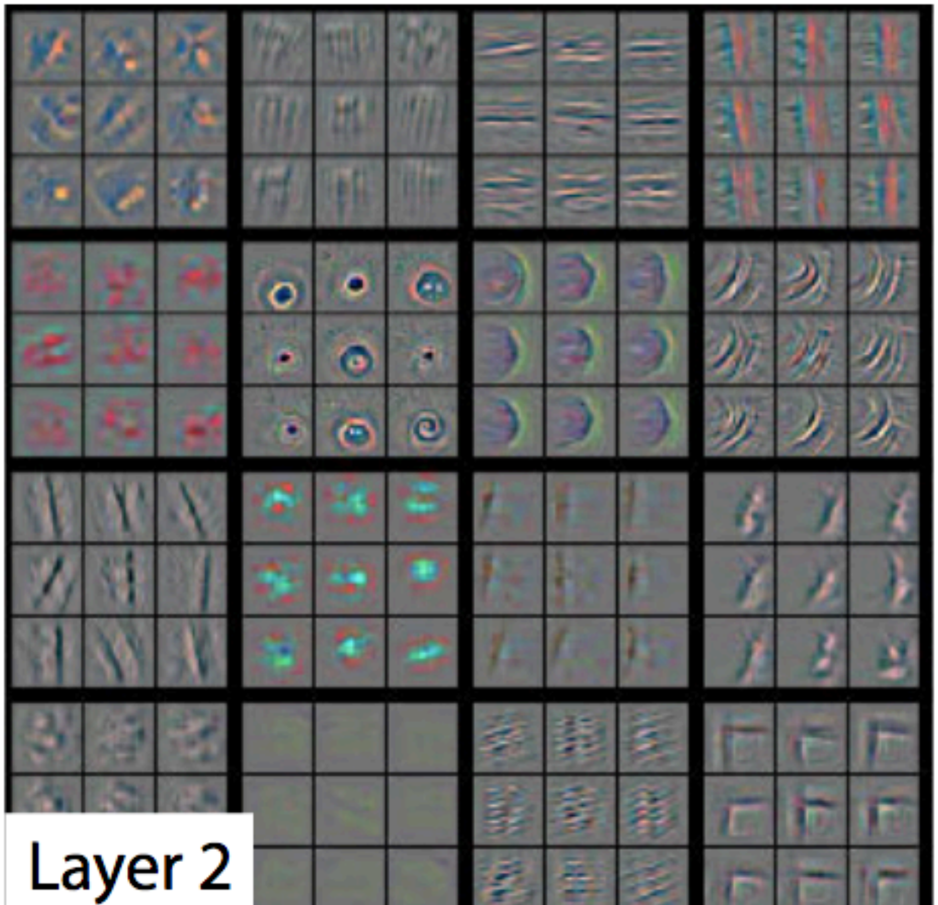


Some image patches that have high activations on those filters:

Visualizations from
[M.D. Zeiler and R. Fergus: Visualizing and Understanding Convolutional Networks, ECCV 2014]

What do all these feature maps *mean?*

The filters, “deconvolved” back into pixel space (see the paper):



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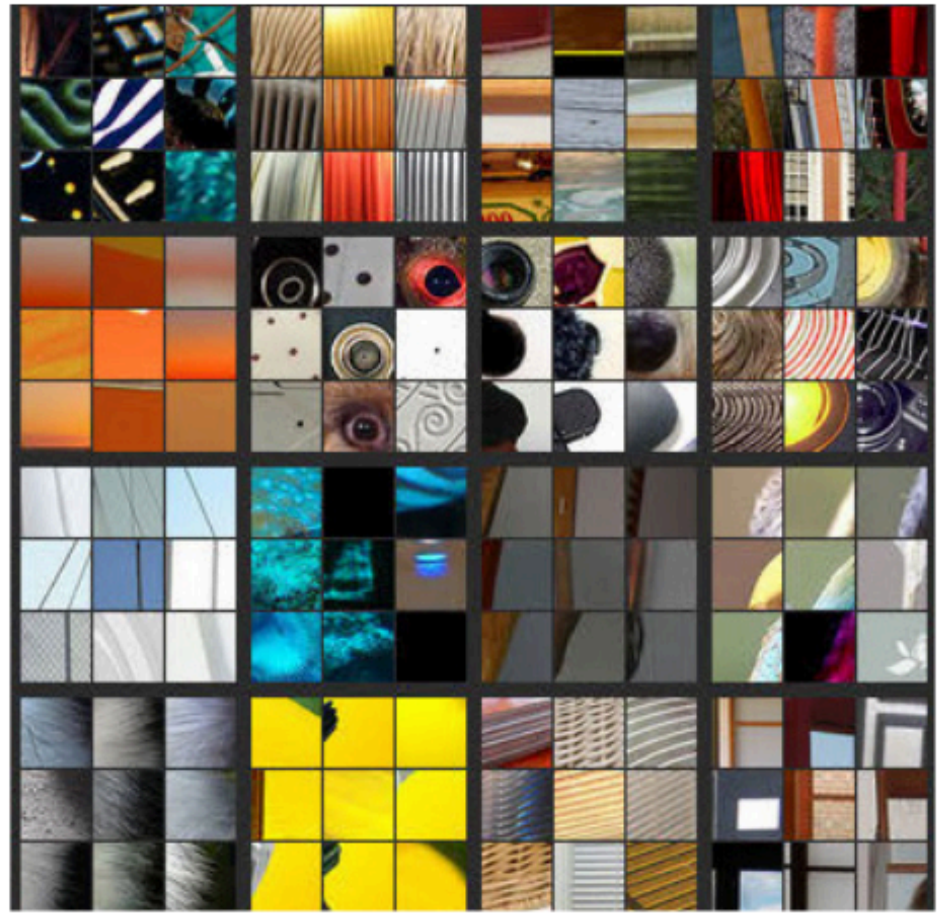

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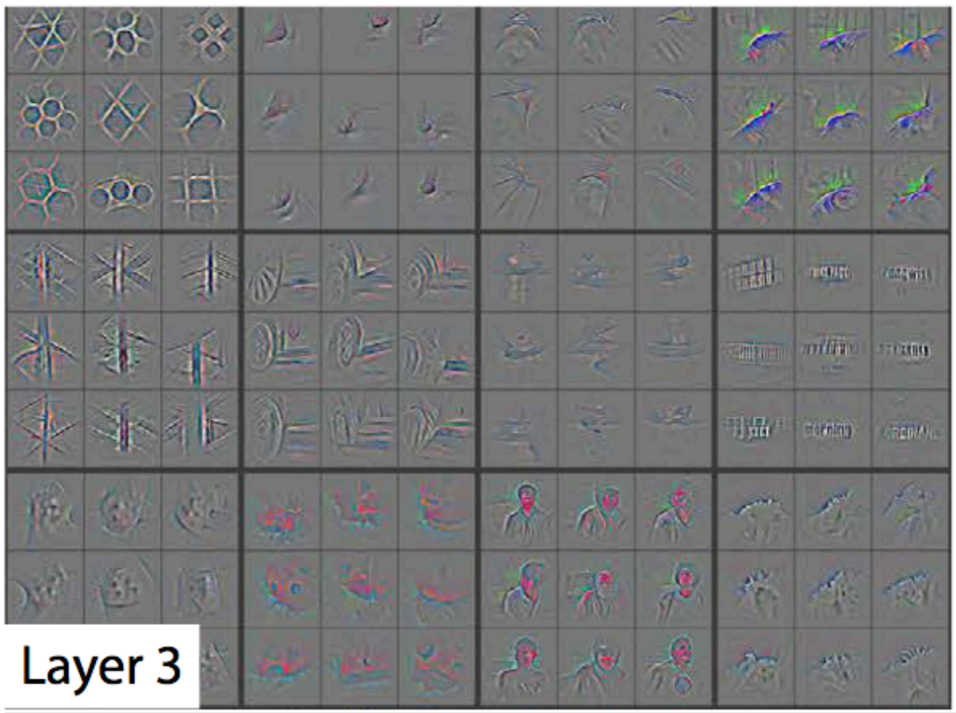

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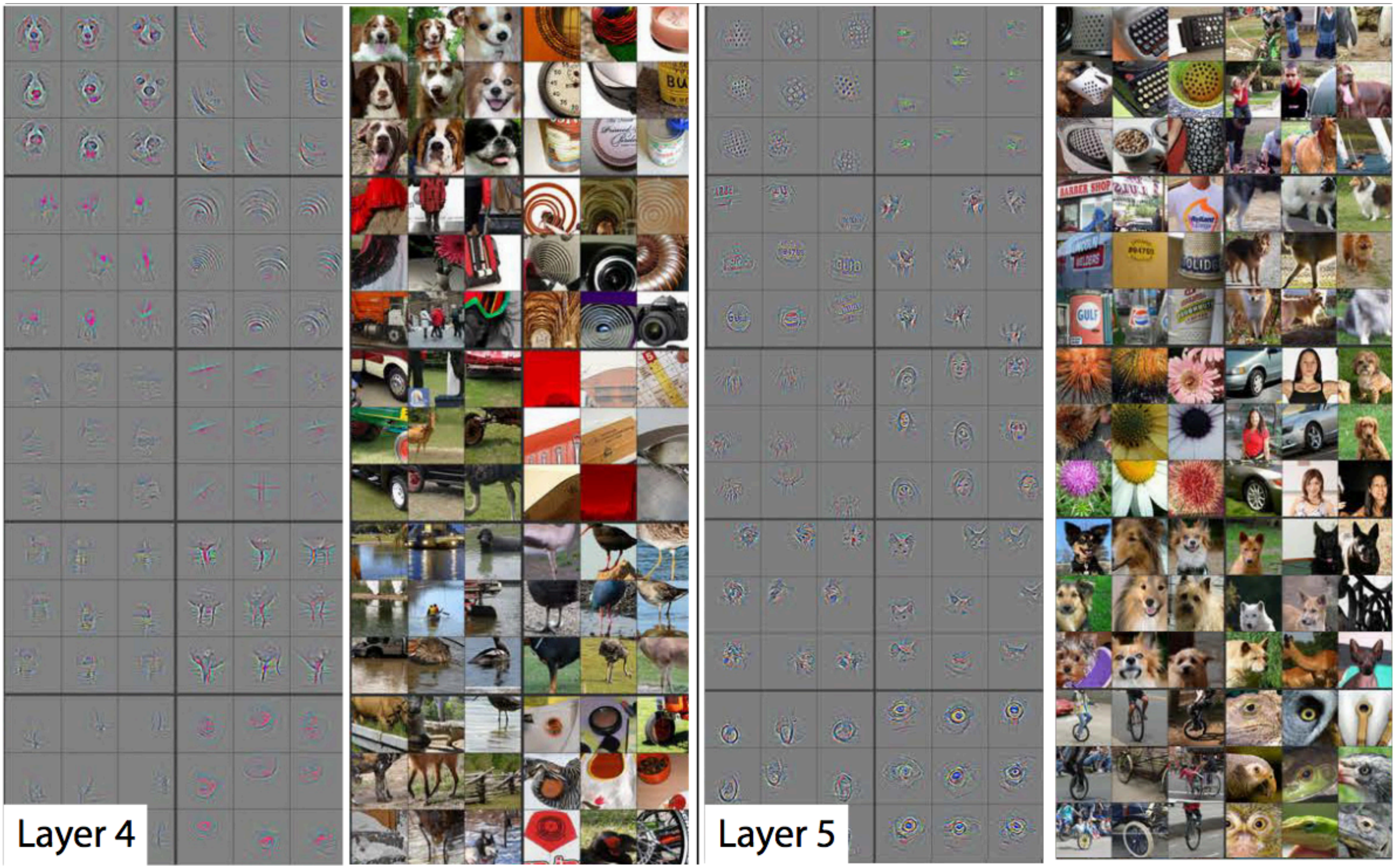

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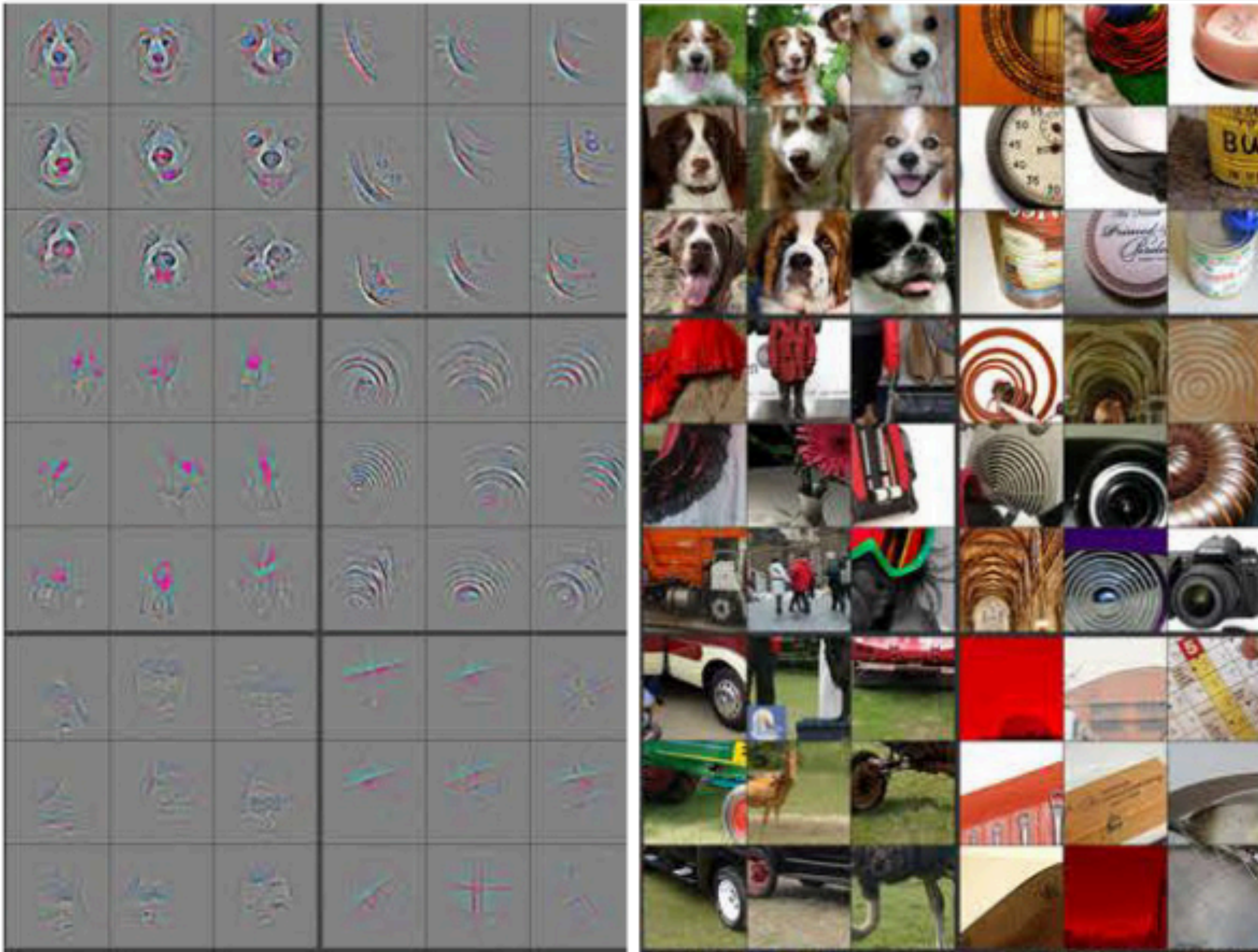
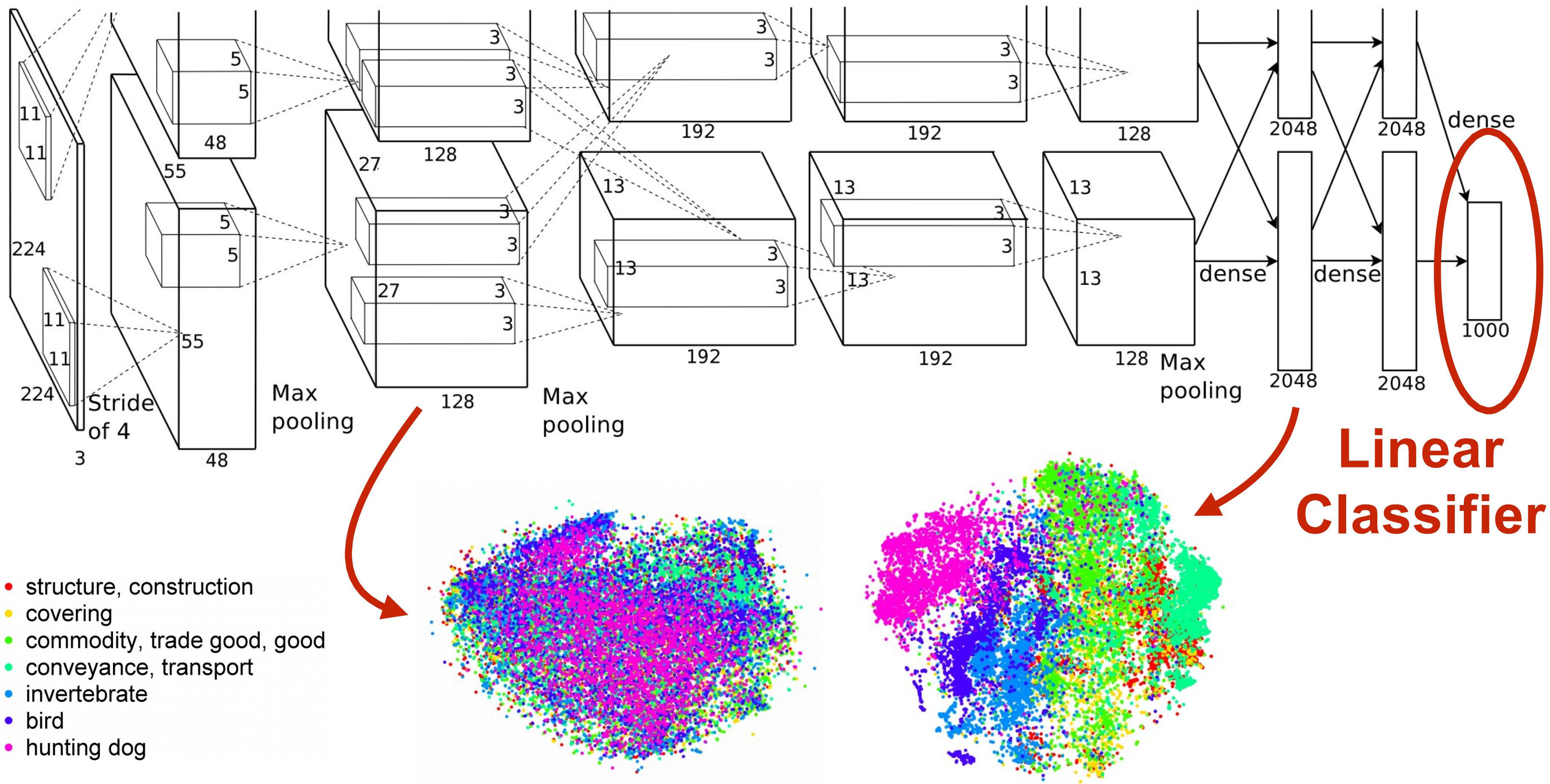


Another View: Visualizing AlexNet in 2D with t-SNE



(c) DeCAF_1 (d) DeCAF_6

(2D visualization using t-SNE)

[Donahue, "DeCAF: DeCAF: A Deep Convolutional …", arXiv 2013]

How do you get this to work?

- Basic version:
  - Download the 1281167 images in ImageNet
  - Feed an image into network, compute gradient of loss wrt parameters, update parameters.
  - Repeat a few times (1.5 billion should do it)

There's a bit more to it.

- Most of these things are practical heuristics that have been empirically discovered to work well:
  - Batched training
  - Preprocessing / data augmentation
  - Momentum
  - Learning rate decay
  - Dropout
  - Weight initialization and batch normalization

How do you get this to work?

Mini-batch SGD

Loop:

1. **Sample** a batch of data
2. **Forward** prop it through the graph (network), get loss
3. **Backprop** to calculate the gradients
4. **Update** the parameters using the gradient

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Batched Training

- Stochastic gradient descent, technically:
  - Sample a single random datapoint
  - Compute the loss
  - Update the parameters
- What people actually mean when they say SGD: Minibatch Gradient Descent
  - Shuffle your dataset
  - Iterate over batches of (batch_size) images:
    - Feed the whole batch through the network
    - Compute loss and update parameters
- What size batches?
  - Whatever your GPU can push through the model at once. 16, 32, 64, 256, …

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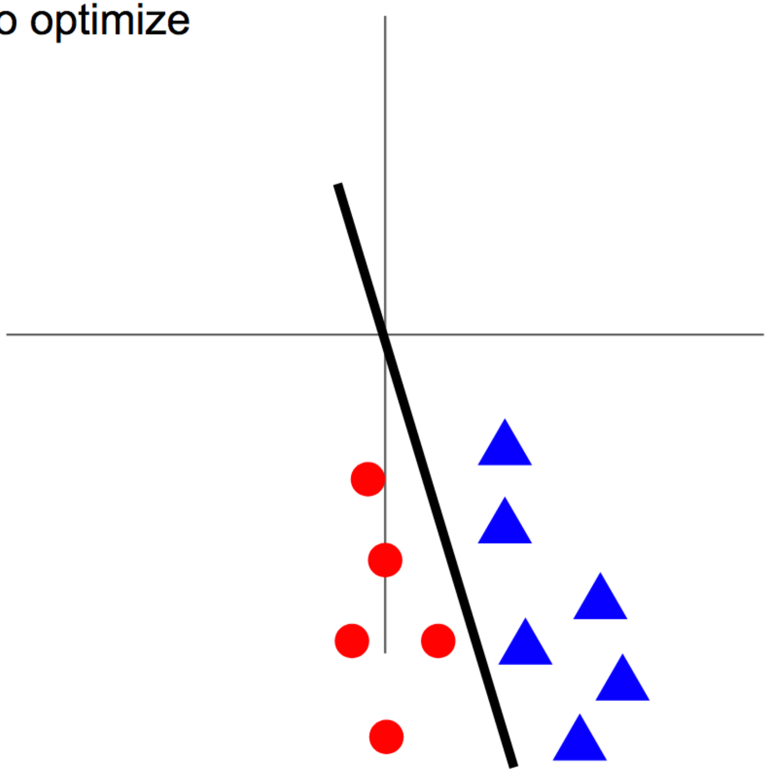
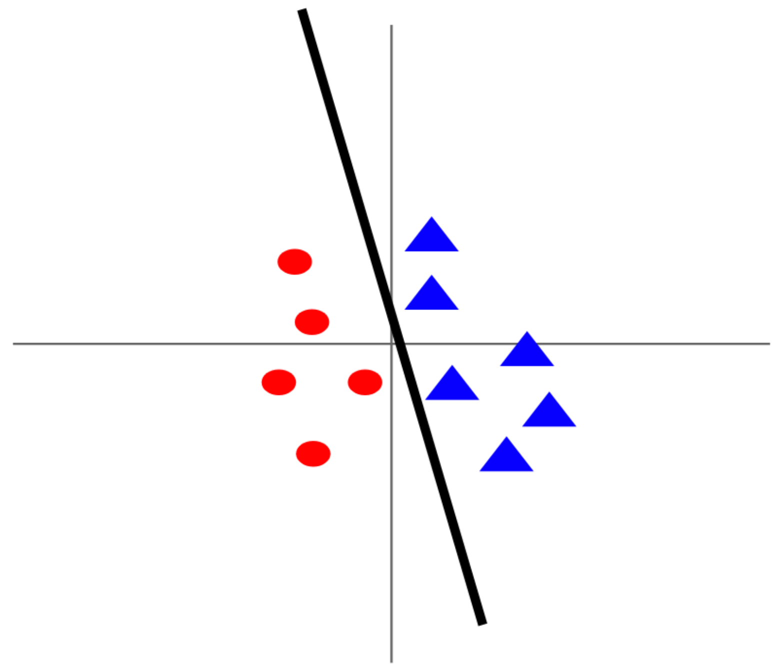
Networks learn better on zero-centered data.

Before normalization: classification loss very sensitive to changes in weight matrix; hard to optimize



After normalization: less sensitive to small changes in weights; easier to optimize



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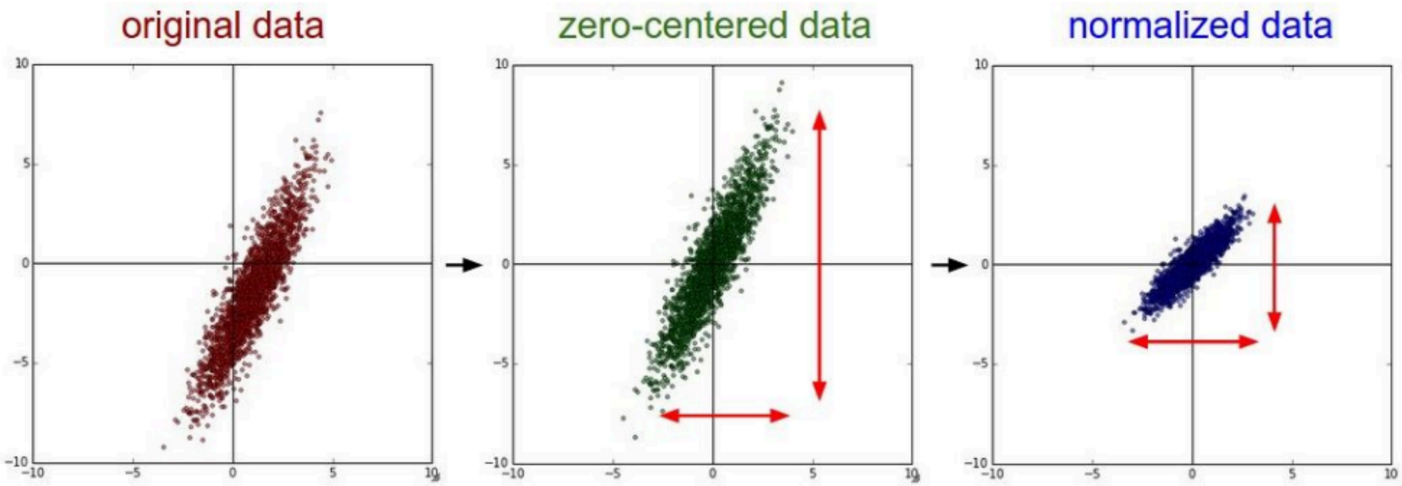
Preprocessing

Step 1: Preprocess the data




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

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

(Assume X [NxD] is data matrix, each example in a row)

In practice: Average all images in the dataset and subtract that from each input.

Dividing by stdev isn't usually done.

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Data Augmentation

- When >1 million training images is not enough:
  – Randomly Flip, Scale, Crop, Rotate, Perturb brightness and color
  – Example:

```
import torchvision.transforms as tvt
transforms = tvt.Compose([
    tvt.Resize((224,224)),
    tvt.ColorJitter(hue=.05, saturation=.05),
    tvt.RandomHorizontalFlip(),
    tvt.RandomRotation(20, resample=PIL.Image.BILINEAR)
])
```

Data Augmentation


pixers

There's a bit more to it.

- Most of these things are practical heuristics that have been empirically discovered to work well:
  - Batched training
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Mini-batch SGD

Loop:

1. **Sample** a batch of data
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4. **Update** the parameters using the gradient

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Updating Parameters

```
# Vanilla update
x += - learning_rate * dx
```

```
# Momentum update
v = mu * v - learning_rate * dx # integrate velocity
x += v # integrate position
```

Momentum combines the gradient update with a direction based on the average of recent update direction.

Update on v is usually something like:

```
v = (1 – b) v  +  b * dx
```

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Updating Parameters

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```

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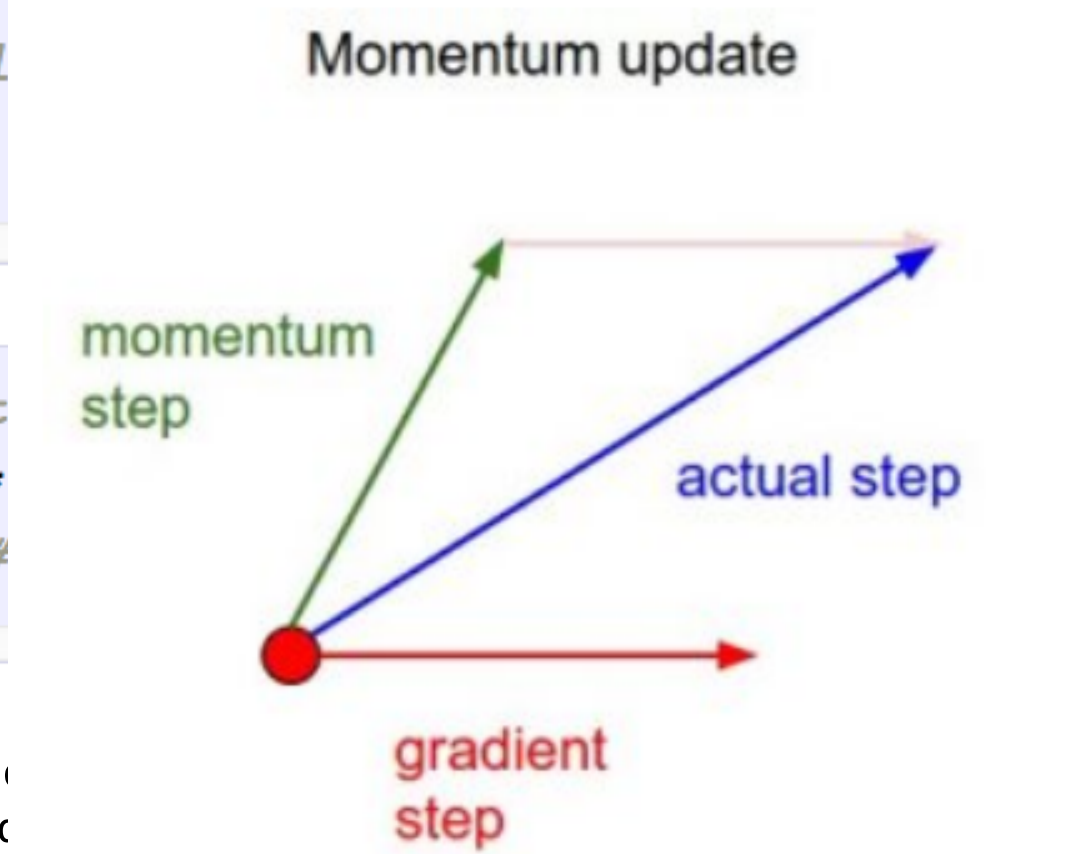

velocity

Momentum the average of recent upc

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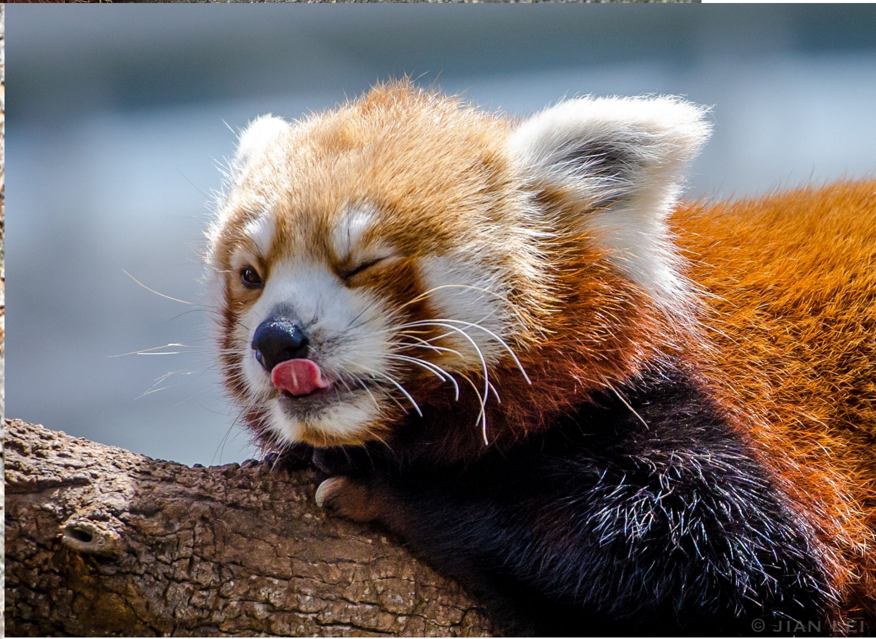
30 Second Red Panda Break



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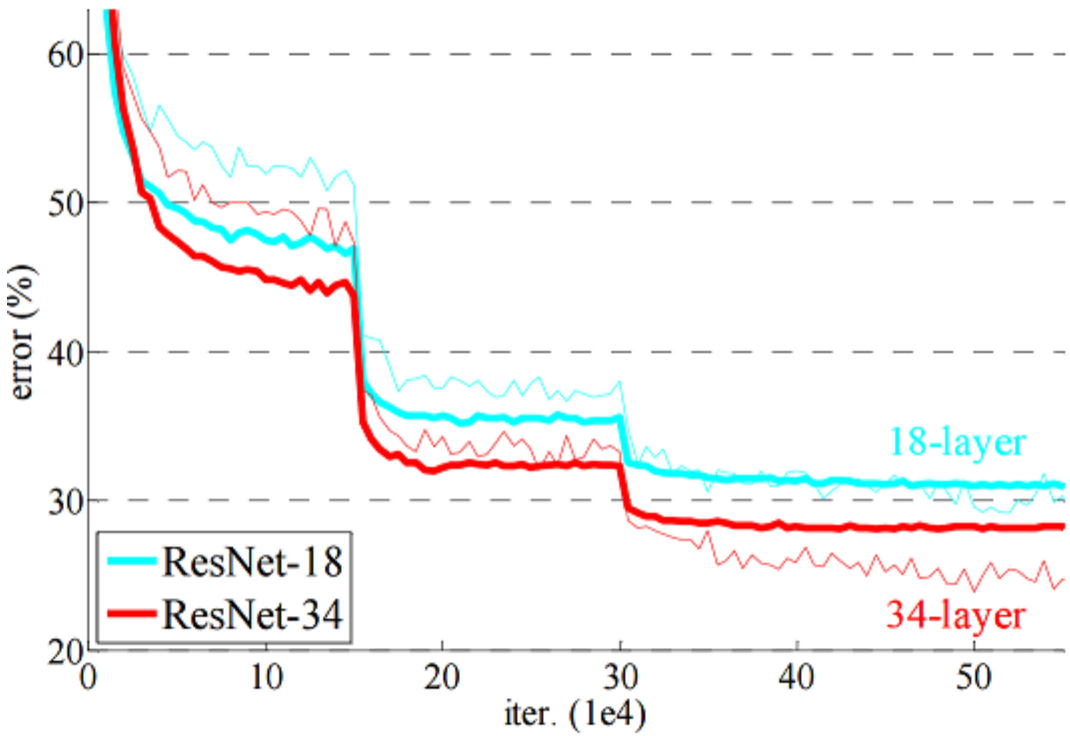
  - Dropout

Learning Rate Decay (Annealing)

- Reduce learning rate as training continues.
  – Step decay:

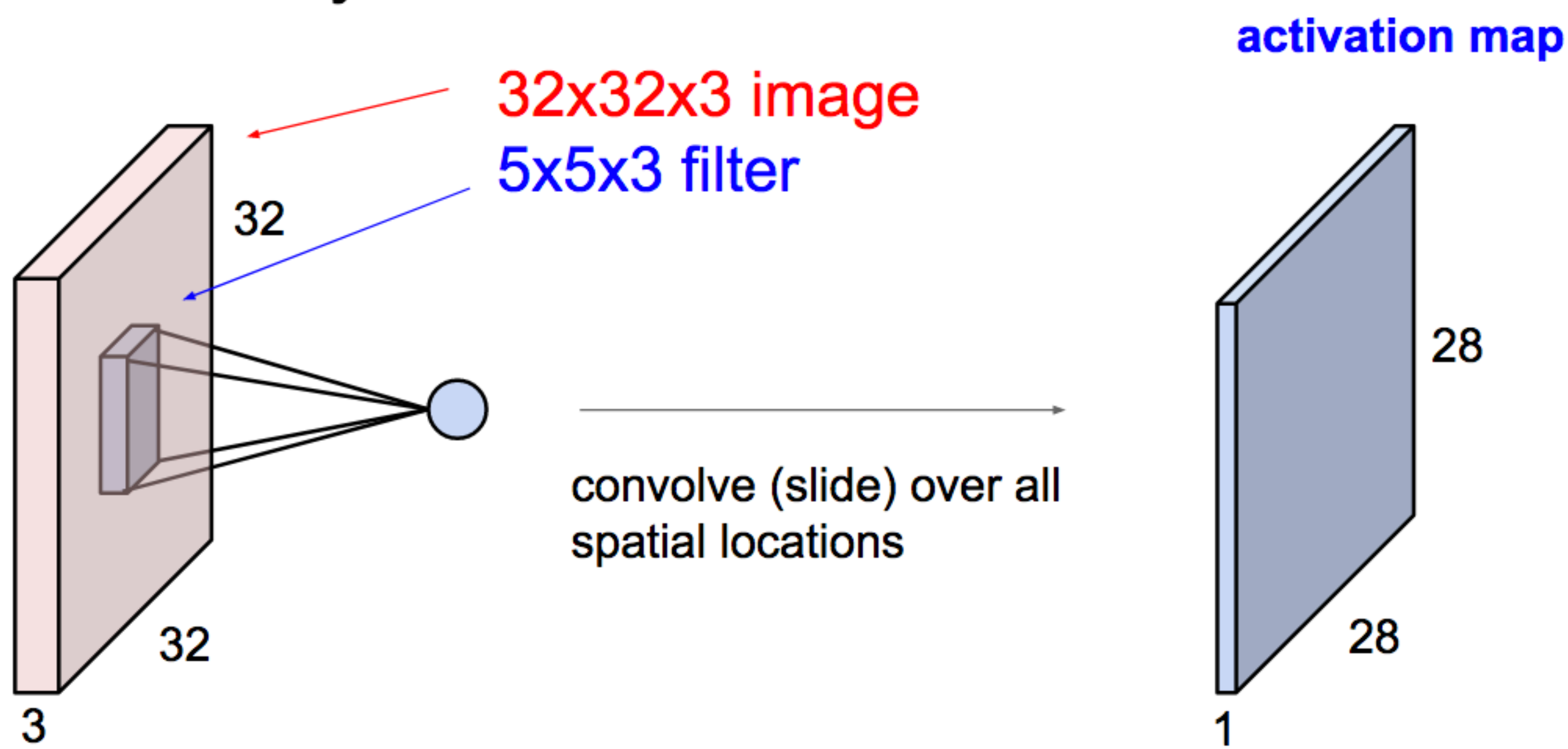


  – Exponential decay
  – 1/t decay

Question for you

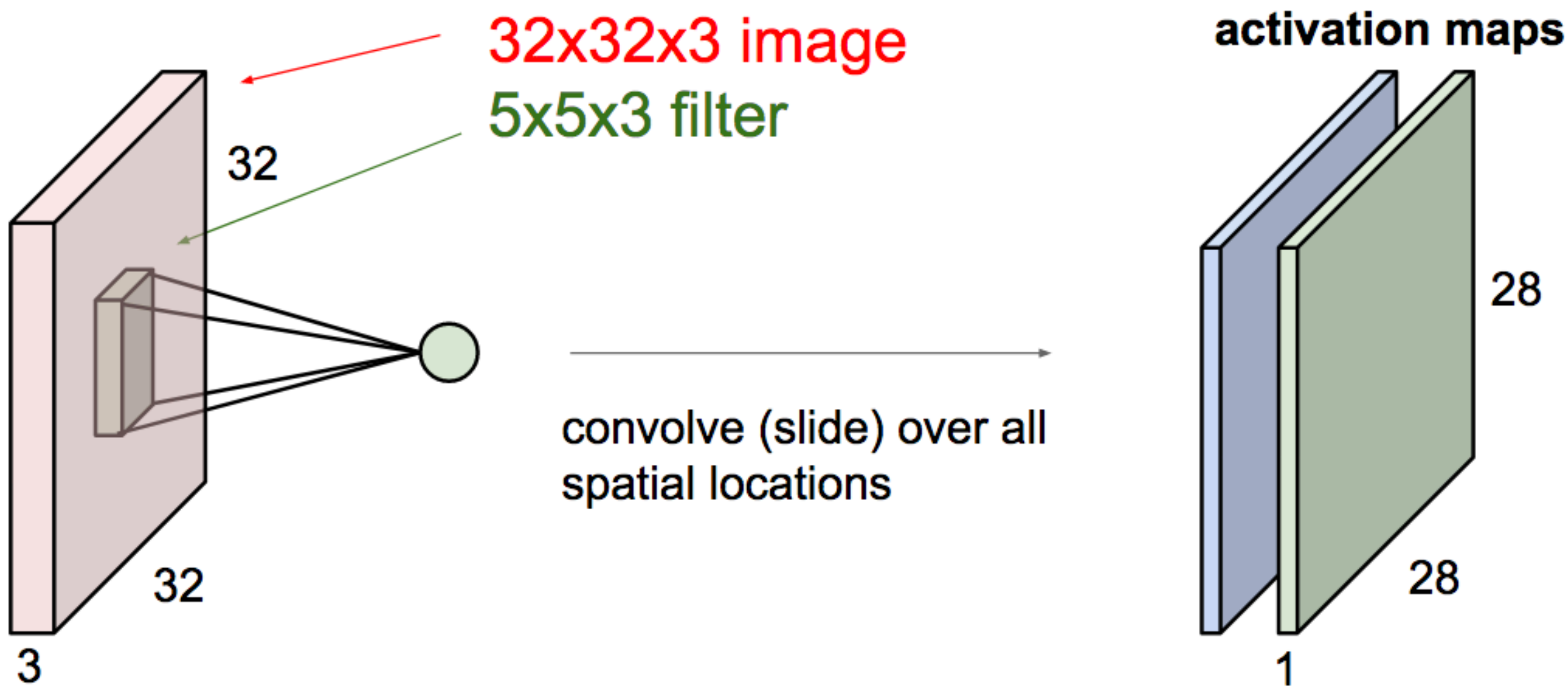
- 2 questions on Socrative: How do convolution layers work?
- Breakout groups of 3
  - socrative.com
  - room name: CSCI497P

Convolution Layer



Convolution Layer

consider a second, green filter

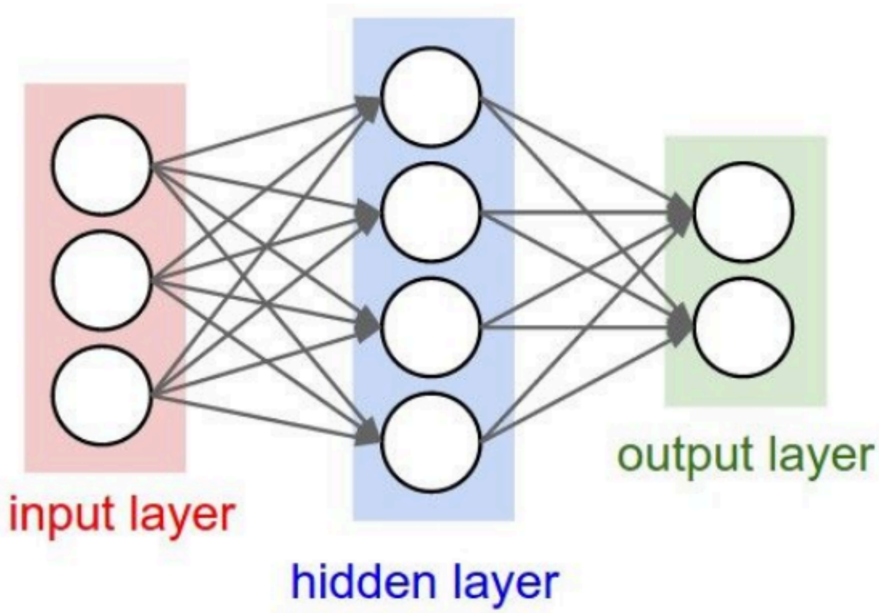


Training CNNs

- Most of these things are practical heuristics that have been empirically discovered to work well:
  - Batched training
  - Preprocessing / data augmentation
  - Momentum
  - Learning rate decay
  - Weight initialization and batch normalization
  - Ensembling
  - Dropout

Weight Initialization

- Q: what happens when W=constant init is used?



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Weight Initialization

- First idea: **Small random numbers**
(gaussian with zero mean and 1e-2 standard deviation)

```
W = 0.01* np.random.randn(D,H)
```

Weight Initialization

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Works ~okay for small networks, but problems with deeper networks.

Lets look at some activation statistics

E.g. 10-layer net with 500 neurons on each layer, using tanh non-linearities, and initializing as described in last slide.

```
# assume some unit gaussian 10-D input data
D = np.random.randn(1000, 500)
hidden_layer_sizes = [500]*10
nonlinearities = ['tanh']*len(hidden_layer_sizes)

act = {'relu':lambda x:np.maximum(0,x), 'tanh':lambda x:np.tanh(x)}
Hs = {}
for i in xrange(len(hidden_layer_sizes)):
    X = D if i == 0 else Hs[i-1] # input at this layer
    fan_in = X.shape[1]
    fan_out = hidden_layer_sizes[i]
    W = np.random.randn(fan_in, fan_out) * 0.01 # layer initialization

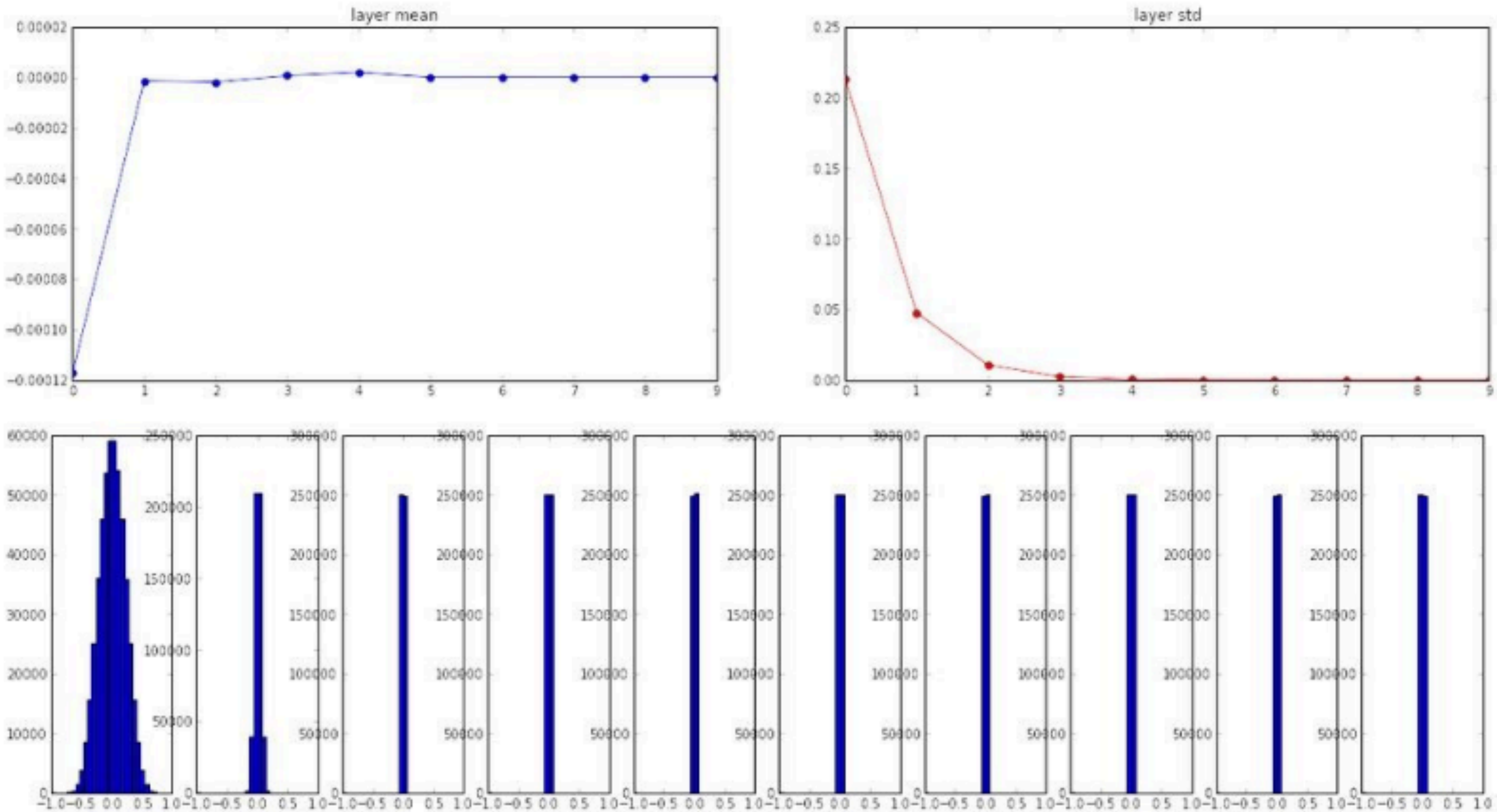
    H = np.dot(X, W) # matrix multiply
    H = act[nonlinearities[i]](H) # nonlinearity
    Hs[i] = H # cache result on this layer

# look at distributions at each layer
print 'input layer had mean %f and std %f' % (np.mean(D), np.std(D))
layer_means = [np.mean(H) for i,H in Hs.iteritems()]
layer_stds = [np.std(H) for i,H in Hs.iteritems()]
for i,H in Hs.iteritems():
    print 'hidden layer %d had mean %f and std %f' % (i+1, layer_means[i], layer_stds[i])

# plot the means and standard deviations
plt.figure()
plt.subplot(121)
plt.plot(Hs.keys(), layer_means, 'ob-')
plt.title('layer mean')
plt.subplot(122)
plt.plot(Hs.keys(), layer_stds, 'or-')
plt.title('layer std')

# plot the raw distributions
plt.figure()
for i,H in Hs.iteritems():
    plt.subplot(1,len(Hs),i+1)
    plt.hist(H.ravel(), 30, range=(-1,1))
```

```
input layer had mean 0.000927 and std 0.998388
hidden layer 1 had mean -0.000117 and std 0.213081
hidden layer 2 had mean -0.000001 and std 0.047551
hidden layer 3 had mean -0.000002 and std 0.010630
hidden layer 4 had mean 0.000001 and std 0.002378
hidden layer 5 had mean 0.000002 and std 0.000532
hidden layer 6 had mean -0.000000 and std 0.000119
hidden layer 7 had mean 0.000000 and std 0.000026
hidden layer 8 had mean -0.000000 and std 0.000006
hidden layer 9 had mean 0.000000 and std 0.000001
hidden layer 10 had mean -0.000000 and std 0.000000
```



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hidden layer 8 had mean -0.000000 and std 0.000006
hidden layer 9 had mean 0.000000 and std 0.000001
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```
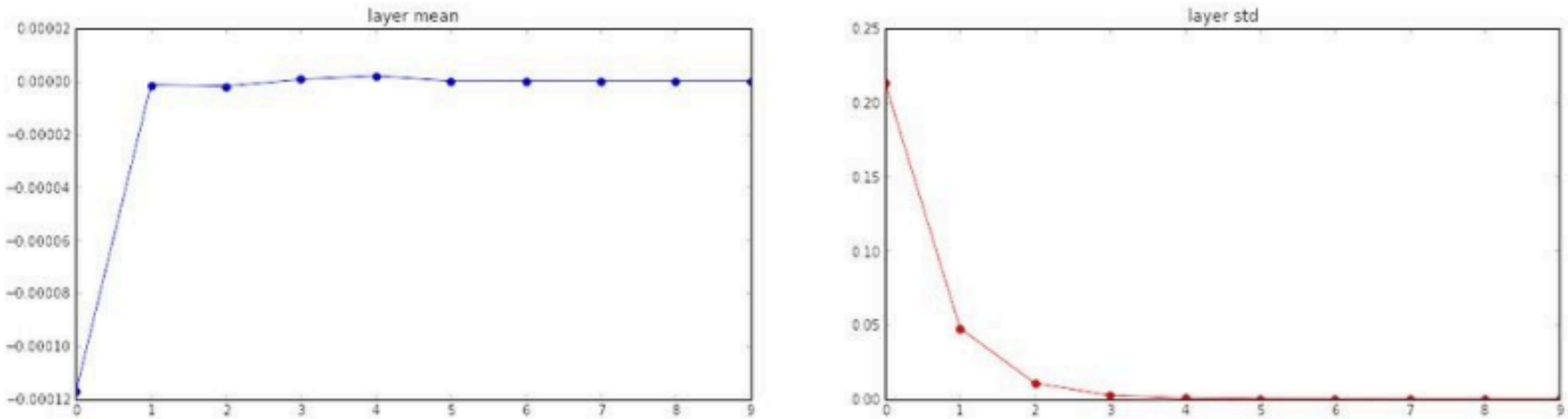
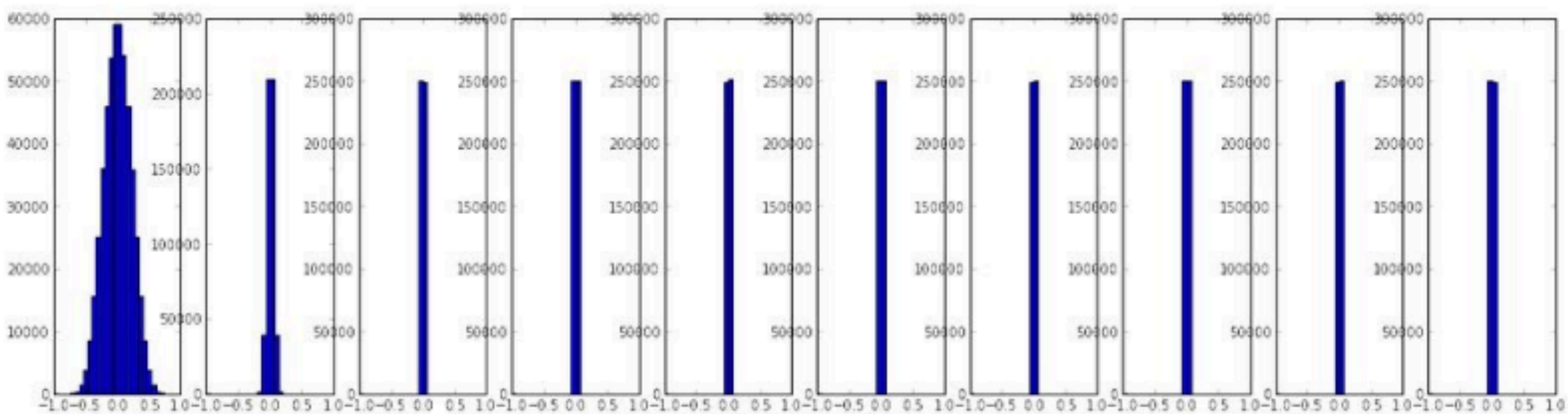

Activations become zero!

What do the gradients look like?





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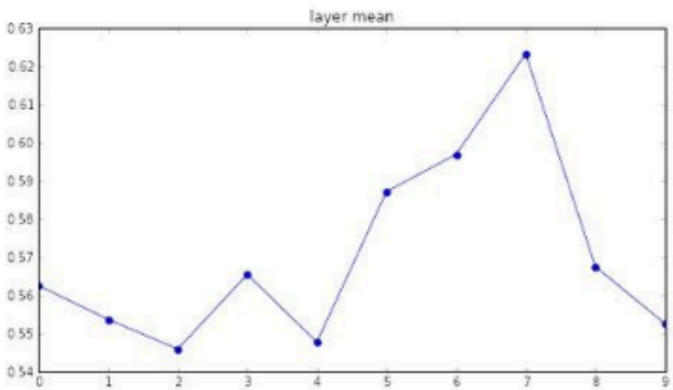
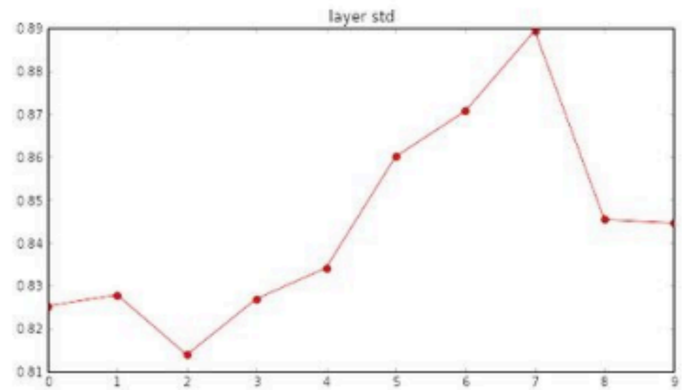
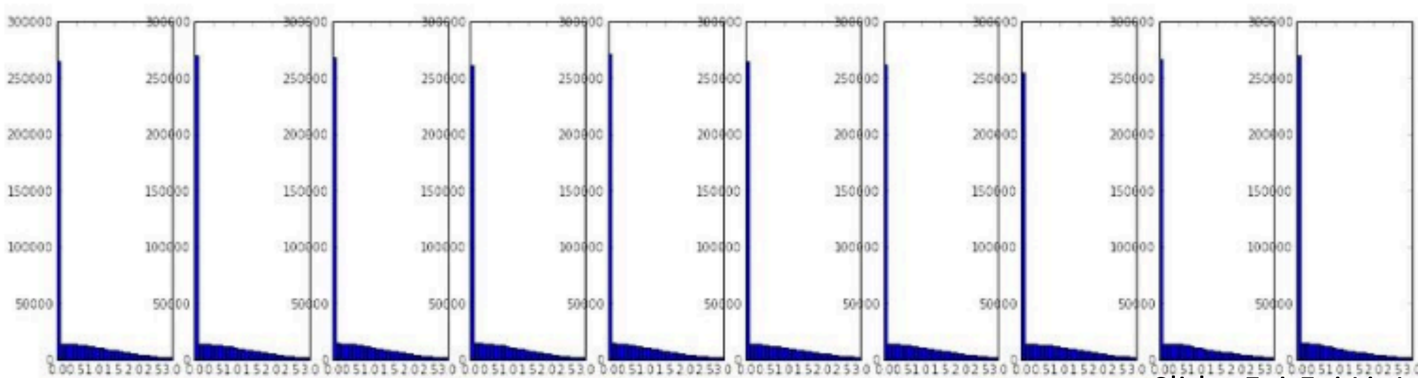
Weight Initialization

```
W = np.random.randn(fan_in, fan_out) / np.sqrt(2/fan_in)
                                        # fan_in = numel(input)
                                        # fan_out = numel(output)
```

```
input layer had mean 0.000501 and std 0.999444
hidden layer 1 had mean 0.562488 and std 0.825232
hidden layer 2 had mean 0.553614 and std 0.827835
hidden layer 3 had mean 0.545867 and std 0.813855
hidden layer 4 had mean 0.565396 and std 0.826902
hidden layer 5 had mean 0.547678 and std 0.834092
hidden layer 6 had mean 0.587103 and std 0.860035
hidden layer 7 had mean 0.596867 and std 0.870610
hidden layer 8 had mean 0.623214 and std 0.889348
hidden layer 9 had mean 0.567498 and std 0.845357
hidden layer 10 had mean 0.552531 and std 0.844523
```







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Proper initialization is an active area of research…

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

Exact solutions to the nonlinear dynamics of learning in deep linear neural networks by Saxe et al, 2013

Random walk initialization for training very deep feedforward networks by Sussillo and Abbott, 2014

Delving deep into rectifiers: Surpassing human-level performance on ImageNet classification by He et al., 2015

Data-dependent Initializations of Convolutional Neural Networks by Krähenbühl et al., 2015

All you need is a good init, Mishkin and Matas, 2015

Fixup Initialization: Residual Learning Without Normalization, Zhang et al, 2019

The Lottery Ticket Hypothesis: Finding Sparse, Trainable Neural Networks, Frankle and Carbin, 2019

…

Training CNNs

- Most of these things are practical heuristics that have been empirically discovered to work well:
  - Batched training
  - Preprocessing / data augmentation
  - Momentum
  - Learning rate decay
  - Weight initialization and batch normalization
  - Ensembling
  - Dropout

Batch Normalization

[Ioffe and Szegedy, 2015]

"you want zero-mean unit-variance activations? just make them so."

consider a batch of activations at some layer. To make each dimension zero-mean unit-variance, apply:

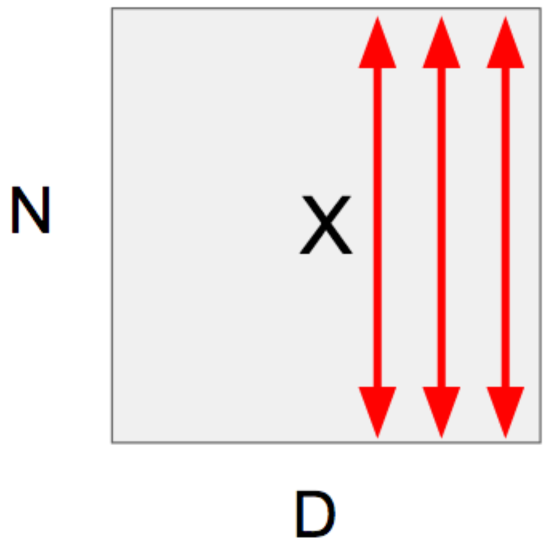
$$\widehat{x}^{(k)} = \frac{x^{(k)} - \mathrm{E}[x^{(k)}]}{\sqrt{\mathrm{Var}[x^{(k)}]}}$$

this is a vanilla differentiable function...

Batch Normalization

[Ioffe and Szegedy, 2015]

"you want zero-mean unit-variance activations? just make them so."



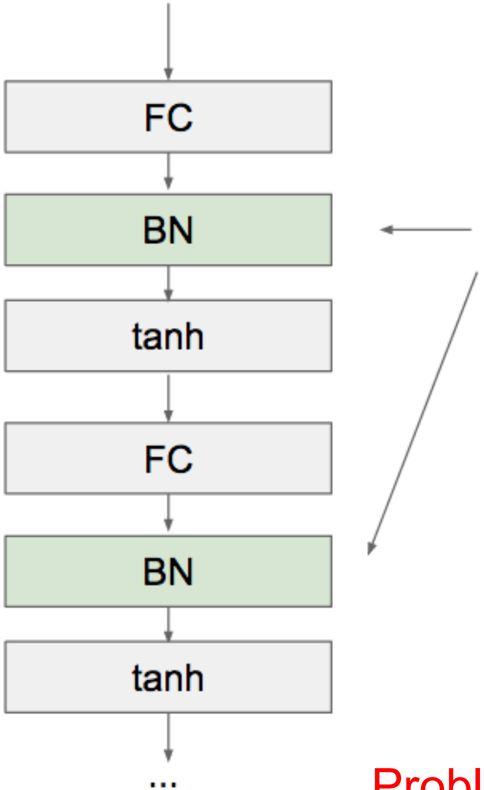
1. compute the empirical mean and variance independently for each dimension.

2. Normalize

$$\widehat{x}^{(k)} = \frac{x^{(k)} - \mathrm{E}[x^{(k)}]}{\sqrt{\mathrm{Var}[x^{(k)}]}}$$

Batch Normalization

[Ioffe and Szegedy, 2015]



Usually inserted after Fully Connected or Convolutional layers, and before nonlinearity.

$$\widehat{x}^{(k)} = \frac{x^{(k)} - \mathrm{E}[x^{(k)}]}{\sqrt{\mathrm{Var}[x^{(k)}]}}$$

Problem: do we necessarily want a zero-mean unit-variance input?

Batch Normalization

[Ioffe and Szegedy, 2015]

Normalize:

$$\boxed{\widehat{x}^{(k)} = \frac{x^{(k)} - \mathrm{E}[x^{(k)}]}{\sqrt{\mathrm{Var}[x^{(k)}]}}}$$

And then allow the network to squash the range if it wants to:

$$\boxed{y^{(k)} = \gamma^{(k)}\widehat{x}^{(k)} + \beta^{(k)}}$$

Details in the batchorm paper:
https://arxiv.org/pdf/1502.03167.pdf

Note, the network can learn:

$$\gamma^{(k)} = \sqrt{\mathrm{Var}[x^{(k)}]}$$

$$\beta^{(k)} = \mathrm{E}[x^{(k)}]$$

to recover the identity mapping.

- At test time, the answer shouldn't depend on the batch:
  - Instead, use a global average (computed during training) of activation means and variances

Batch Normalization

BatchNorm2d

CLASS `torch.nn.BatchNorm2d(num_features, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)` [SOURCE]

Applies Batch Normalization over a 4D input (a mini-batch of 2D inputs with additional channel dimension) as described in the paper Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift .

$$y = \frac{x - \mathrm{E}[x]}{\sqrt{\mathrm{Var}[x] + \epsilon}} * \gamma + \beta$$

TL;DR: Using batch normalization speeds up training and makes it less sensitive to weight initialization.

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  - Dropout

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

Why would this work?

- Using different random initializations results in training arriving at different local minima.
- Remarkable (empirical) fact: performance of each one is similar!

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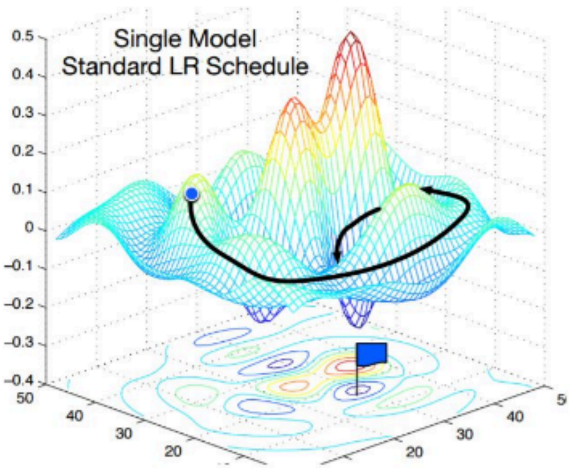
Model Ensembles: Tips and Tricks

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



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

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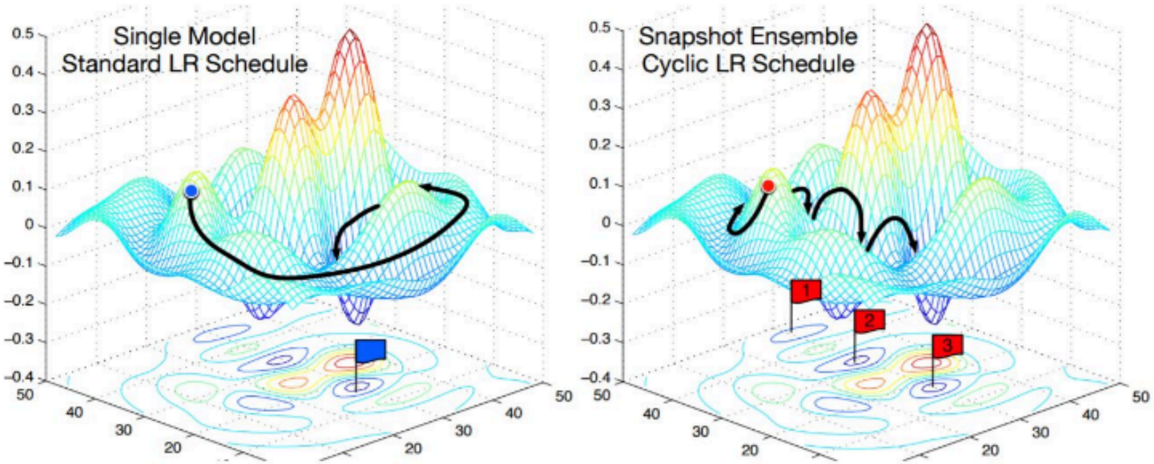

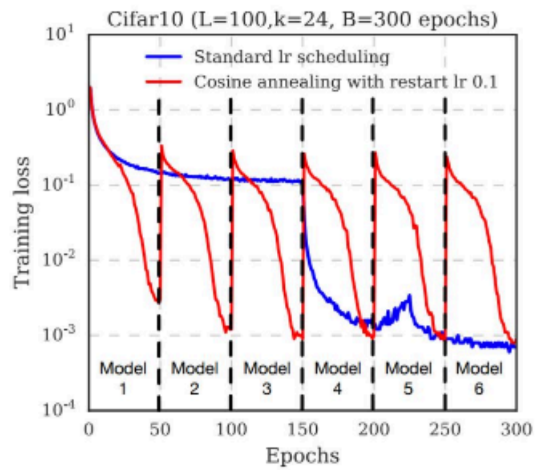

Loshchilov and Hutter, "SGDR: Stochastic gradient descent with restarts", arXiv 2016
Huang et al, "Snapshot ensembles: train 1, get M for free", ICLR 2017
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Cyclic learning rate schedules can make this work even better!

Training CNNs

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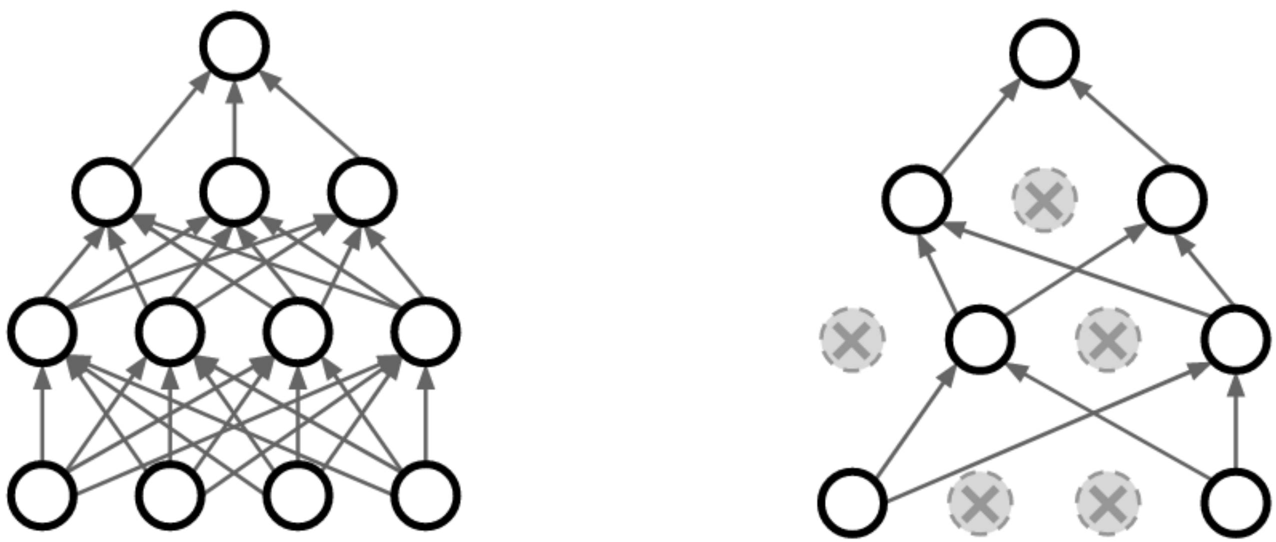
Regularization: Reminder

- Penalizes large weights to prevent the model from fitting training data *too* closely **(overfitting)**
  - Helps network generalize to unseen data
- L2 regularization forces parameters to be used "equally"
  - parameters with similar magnitudes will have a lower regularization cost than mostly zero with a few huge values.
- Another way to force the network to use all its parameters equally: randomly drop parameters each training iteration!

Another way to force the network to use all its parameters equally: **randomly drop parameters** each training iteration!

Regularization: Dropout

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



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

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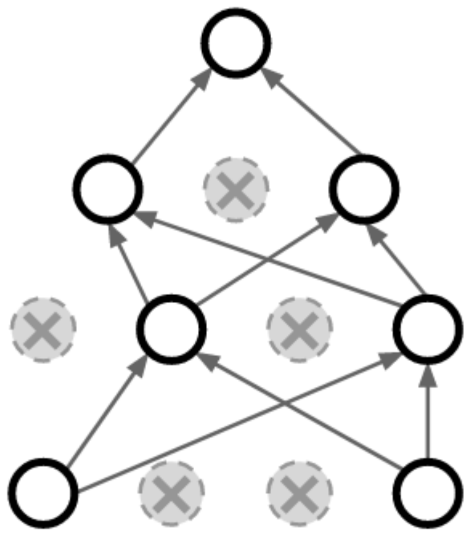
Regularization: Dropout

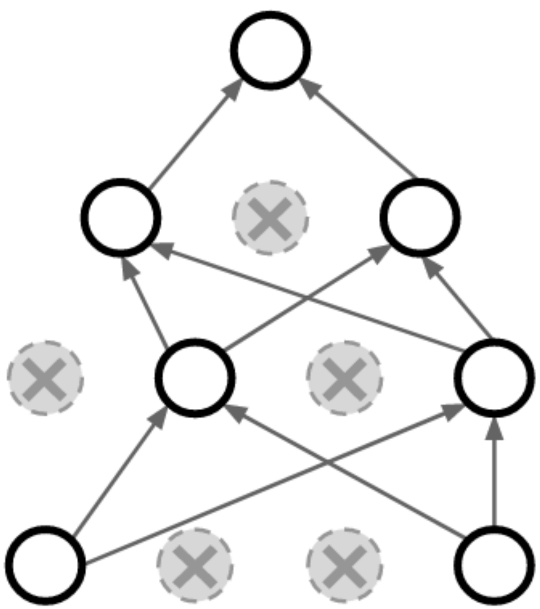
```
p = 0.5 # probability of keeping a unit active. higher = less dropout

def train_step(X):
  """ X contains the data """

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

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

Example forward pass with a 3-layer network using dropout



Regularization: Dropout

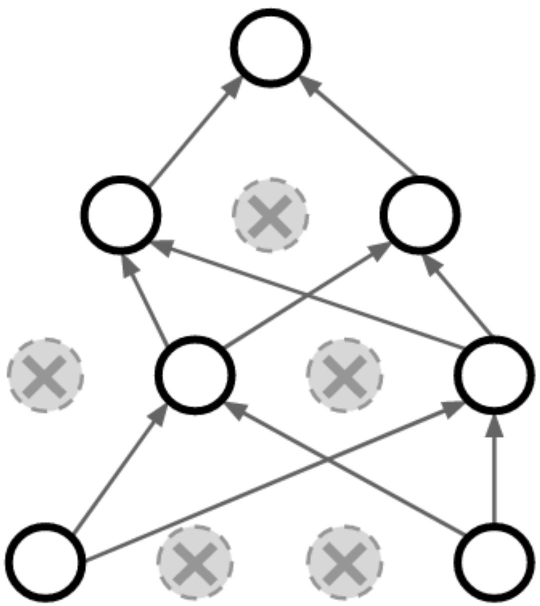
How can this possibly be a good idea?



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

Regularization: Dropout

How can this possibly be a good idea?



Another interpretation:

Dropout is training a large **ensemble** of models (that share parameters).

Each binary mask is one model

An FC layer with 4096 units has $2^{4096} \sim 10^{1233}$ possible masks!
Only $\sim 10^{82}$ atoms in the universe...

Dropout: Test time

```
def predict(X):
  # ensembled forward pass
  H1 = np.maximum(0, np.dot(W1, X) + b1) * p # NOTE: scale the activations
  H2 = np.maximum(0, np.dot(W2, H1) + b2) * p # NOTE: scale the activations
  out = np.dot(W3, H2) + b3
```

At test time all neurons are active always
=> We must scale the activations so that for each neuron:
<u>output at test time</u> = <u>expected output at training time</u>

Dropout Summary

```python
""" Vanilla Dropout: Not recommended implementation (see notes below) """

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

def train_step(X):
  """ X contains the data """

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

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

def predict(X):
  # ensembled forward pass
  H1 = np.maximum(0, np.dot(W1, X) + b1) * p # NOTE: scale the activations
  H2 = np.maximum(0, np.dot(W2, H1) + b2) * p # NOTE: scale the activations
  out = np.dot(W3, H2) + b3
```

drop in forward pass

scale at test time

More common: "Inverted dropout"

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

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

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

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

test time is unchanged!

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Next Up: CNN Architecture Tour

- What happened since AlexNet?
- There's a general theme: