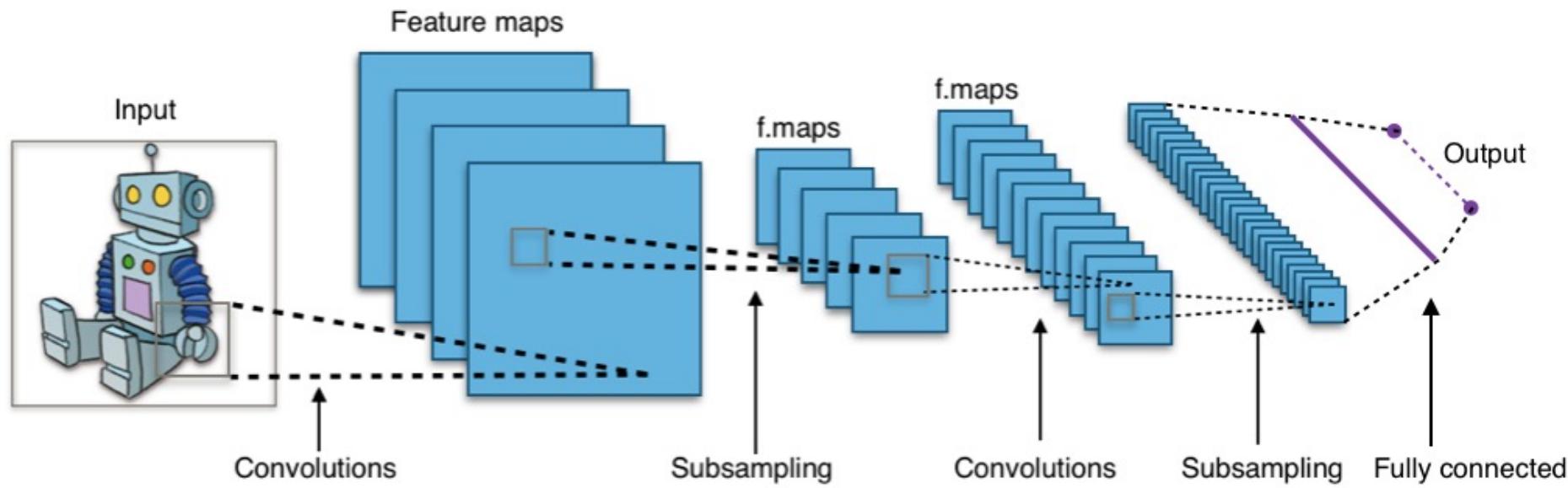


# Convolutional neural networks



# Overview of today's lecture

- Convolutional neural networks.
- Training ConvNets.

# Slide credits

Most of these slides were adapted from:

- Noah Snavely (Cornell University).
- Fei-Fei Li (Stanford University).
- Andrej Karpathy (Stanford University).

# Convolutional Neural Networks

# Aside: “CNN” vs “ConvNet”

## Note:

- There are many papers that use either phrase, but
- “ConvNet” is the preferred term, since “CNN” clashes with other things called CNN



Yann LeCun

# Motivation

T

HOME

MENU

CONNECT

THE LATEST

POPULAR

MOST SHARED



MIT  
Technology  
Review

## 10 BREAKTHROUGH TECHNOLOGIES 2013

Introduction

The 10 Technologies

Past Years

### Deep Learning

With massive amounts of computational power, machines can now recognize objects and translate speech in real time. Artificial intelligence is finally getting smart.

### Temporary Social Media

Messages that quickly self-destruct could enhance the privacy of online communications and make people freer to be spontaneous.

### Prenatal DNA Sequencing

Reading the DNA of fetuses will be the next frontier of the genomic revolution. But do you really want to know about the genetic problems or musical aptitude of your unborn child?

### Additive Manufacturing

Skeptical about 3-D printing? GE, the world's largest manufacturer, is on the verge of using the technology to make jet parts.

### Baxter: The Blue-Collar Robot

Rodney Brooks's newest creation is easy to interact with, but the complex innovations behind the robot show just how hard it is to get along with people.

Memory Implants

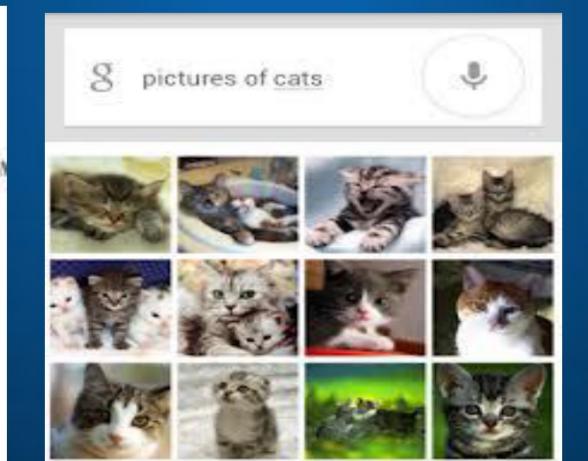
Smart Watches

Ultra-Efficient Solar

Big Data from

Supergrids

# Products



# CNNs in 2012: “SuperVision” (aka “AlexNet”)

“AlexNet” — Won the ILSVRC2012 Challenge

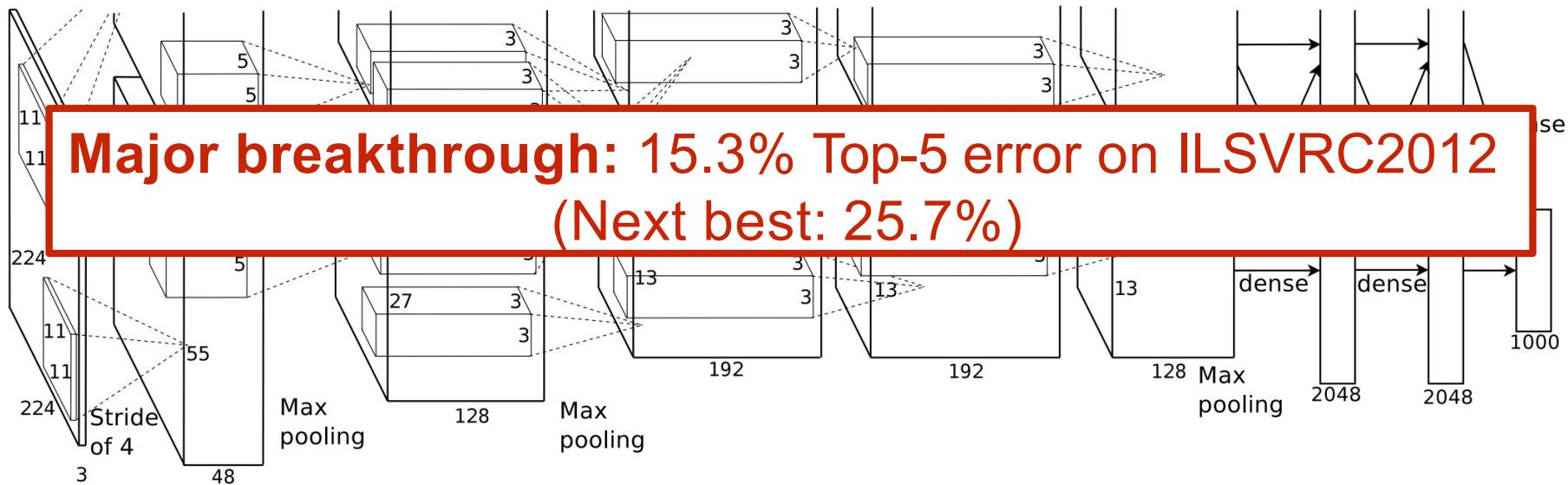


Figure 2: An illustration of the architecture of our CNN, explicitly showing the delineation of responsibilities between the two GPUs. One GPU runs the layer-parts at the top of the figure while the other runs the layer-parts at the bottom. The GPUs communicate only at certain layers. The network’s input is 150,528-dimensional, and the number of neurons in the network’s remaining layers is given by 253,440–186,624–64,896–64,896–43,264–4096–4096–1000.

[Krizhevsky, Sutskever, Hinton. NIPS 2012]

# Recap: Before Deep Learning

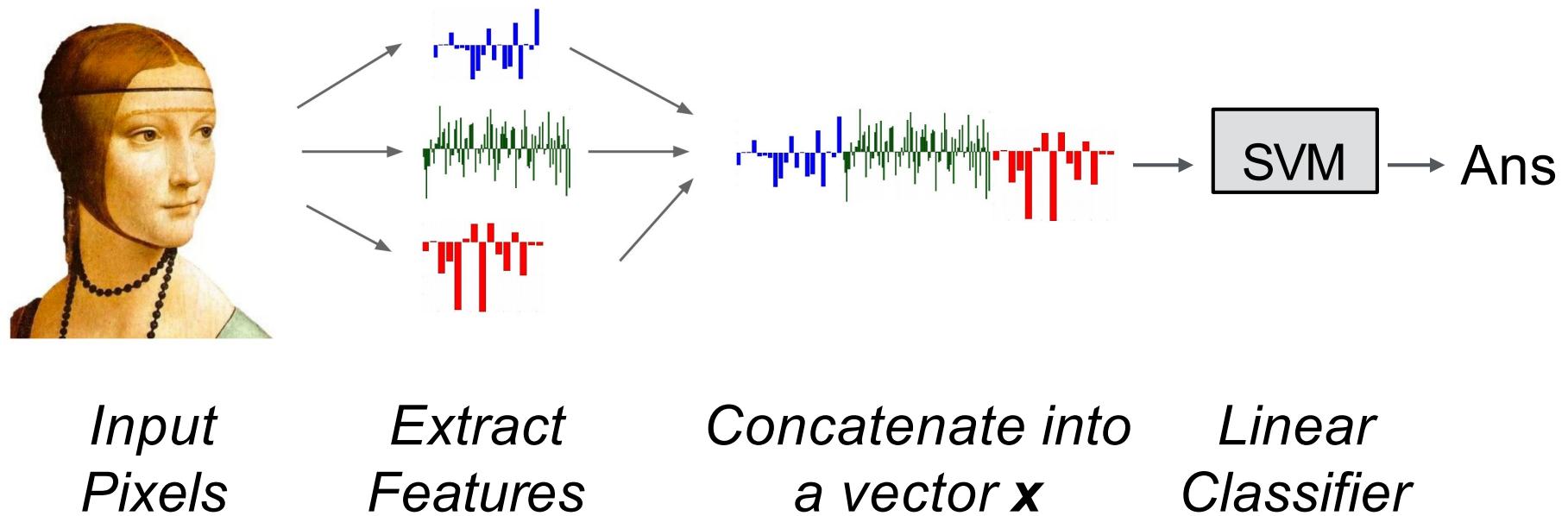
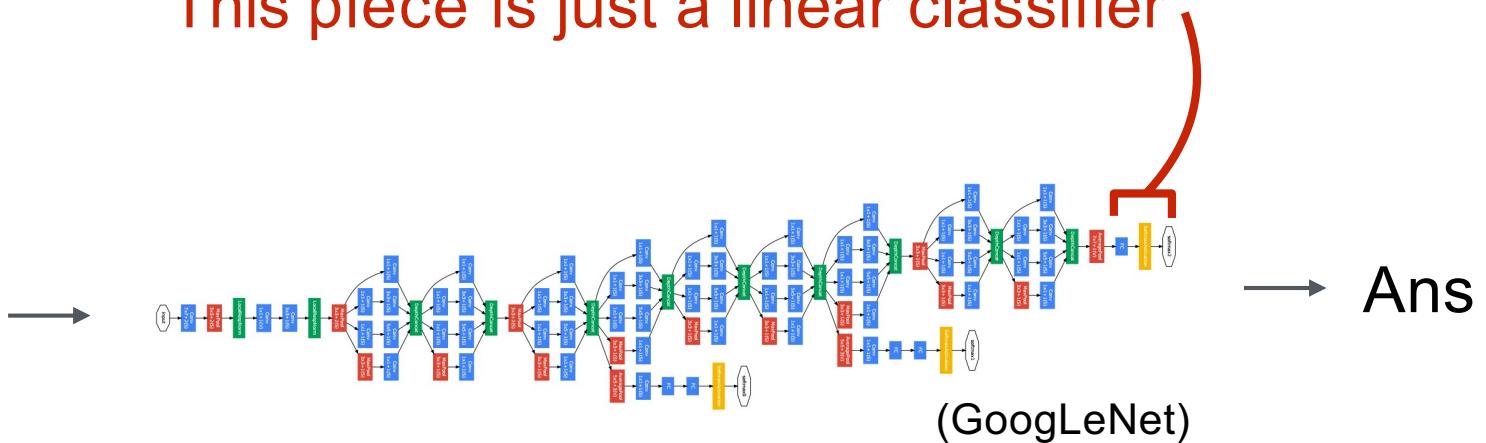


Figure: Karpathy 2016

# The last layer of (most) CNNs are linear classifiers



This piece is just a linear classifier



*Input  
Pixels*

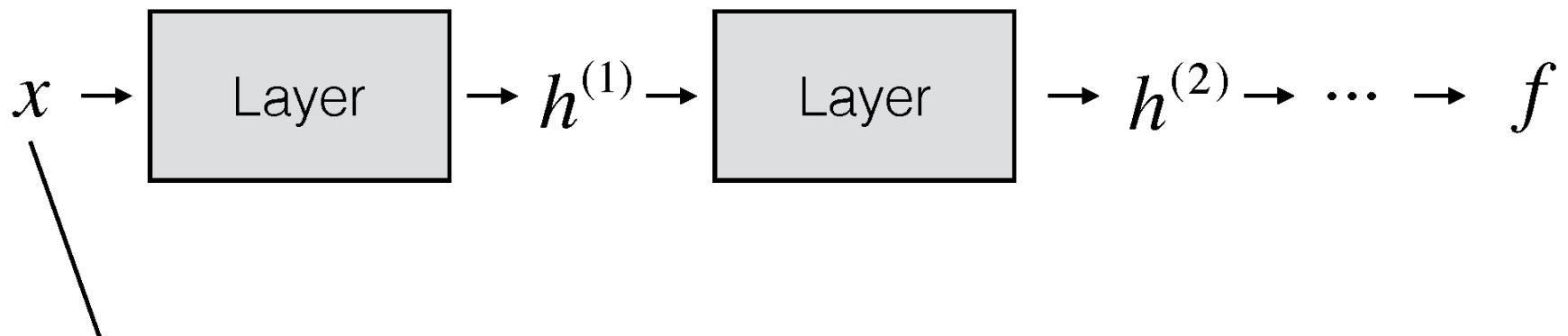
*Perform everything with a big neural  
network, trained end-to-end*

**Key:** perform enough processing so that by the time you get to the end of the network, the classes are linearly separable

# ConvNets

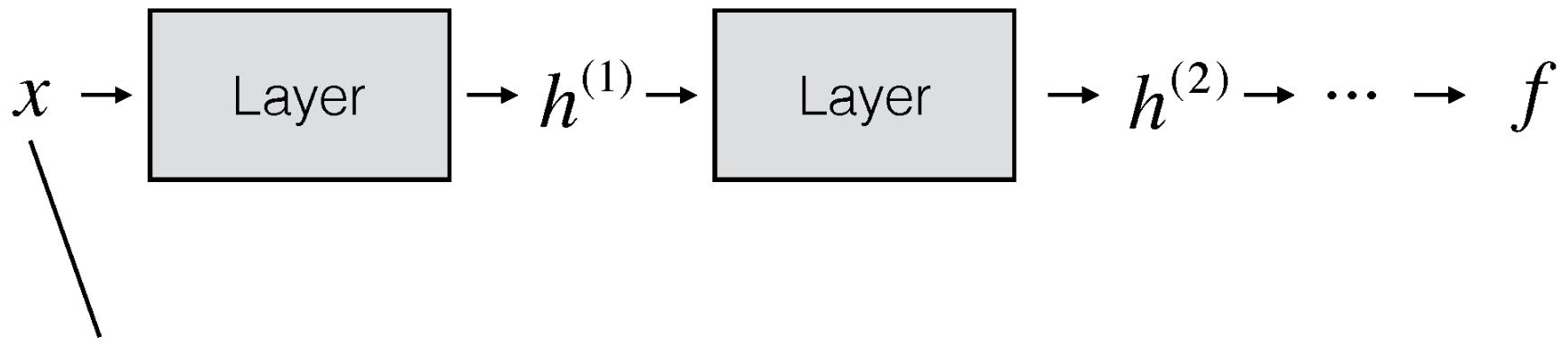
They're just neural networks with  
3D activations and weight sharing

# What shape should the activations have?



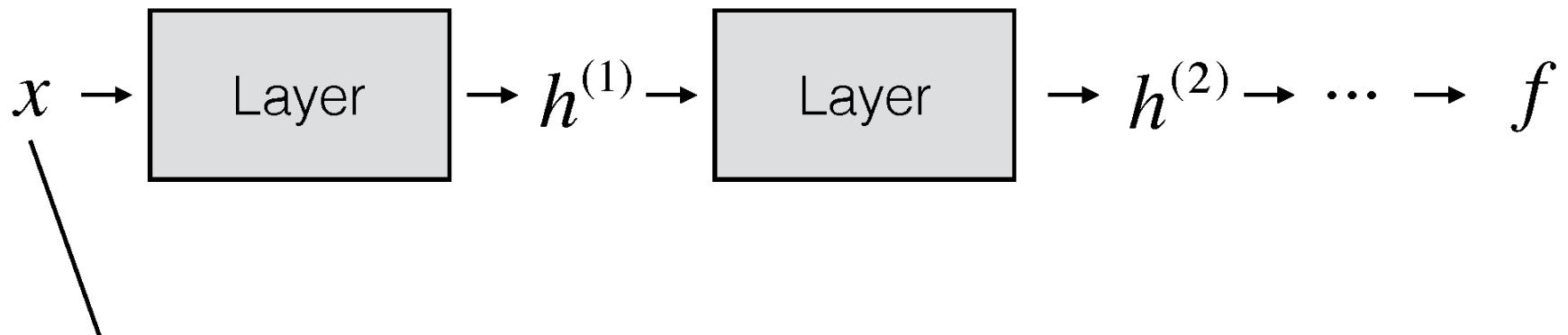
- The input is an image, which is 3D (RGB channel, height, width)

# What shape should the activations have?



- The input is an image, which is 3D (RGB channel, height, width)
- We could flatten it to a 1D vector, but then we lose structure

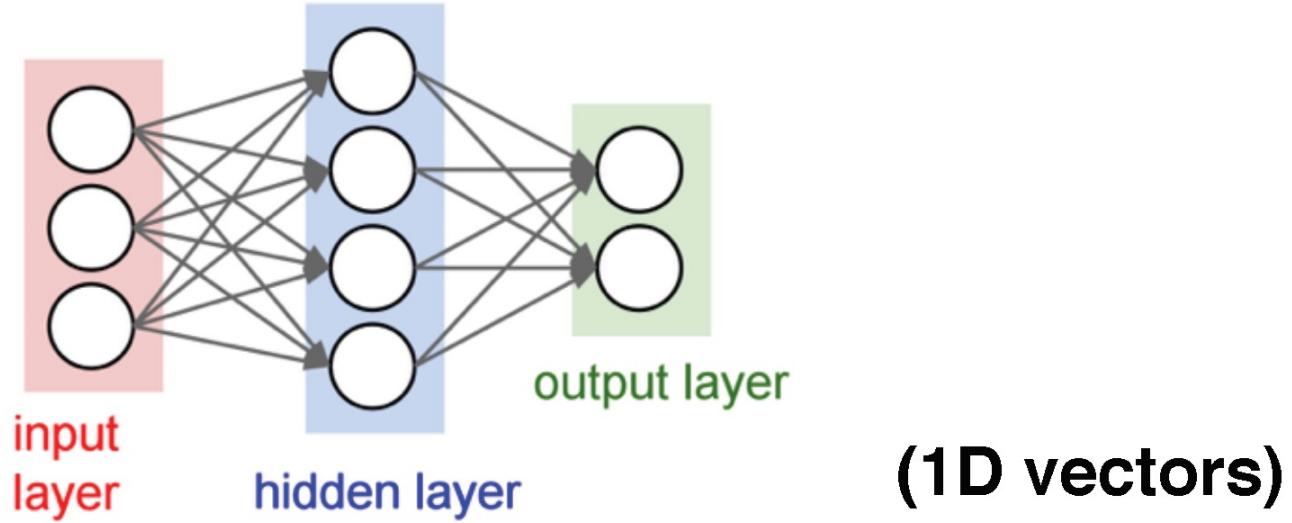
# What shape should the activations have?



- The input is an image, which is 3D (RGB channel, height, width)
- We could flatten it to a 1D vector, but then we lose structure
- What about keeping everything in 3D?

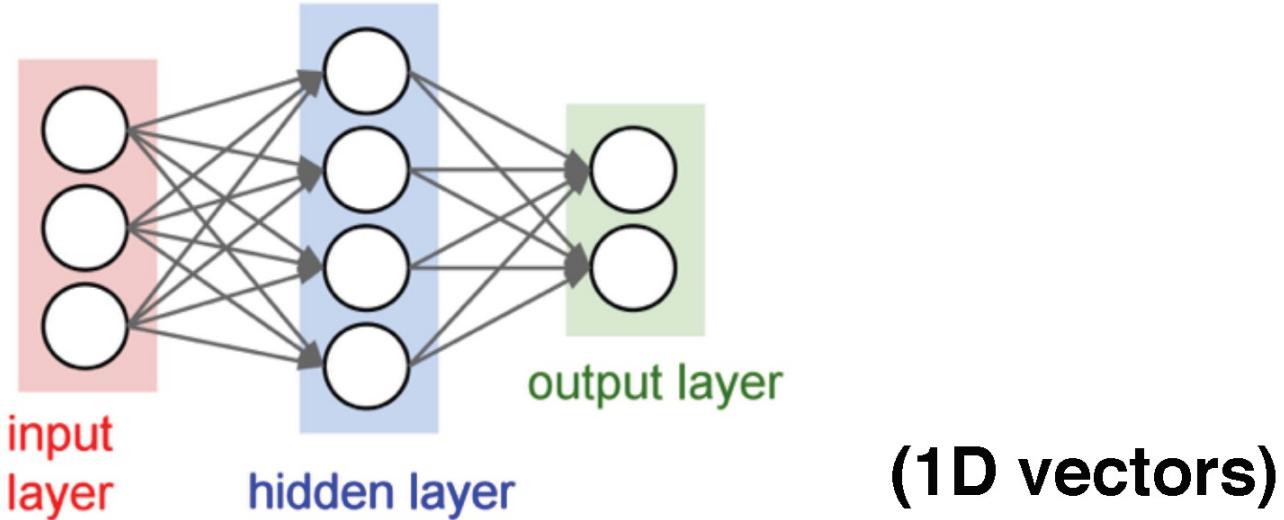
# 3D Activations

before:

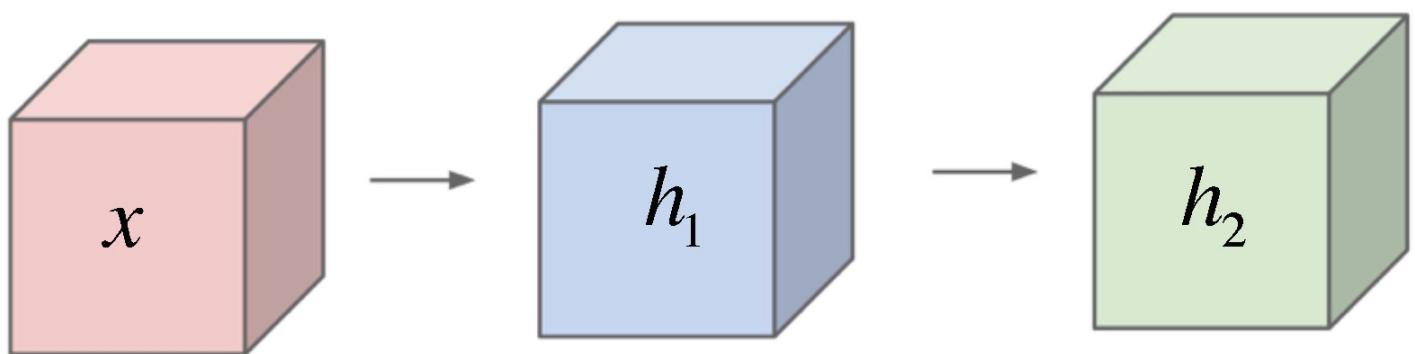


# 3D Activations

before:

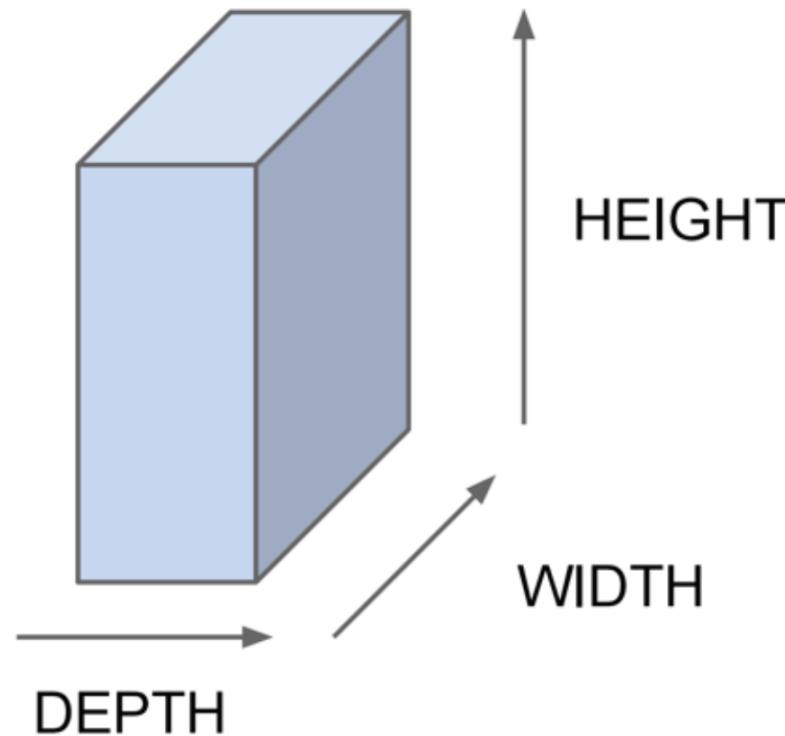


now:



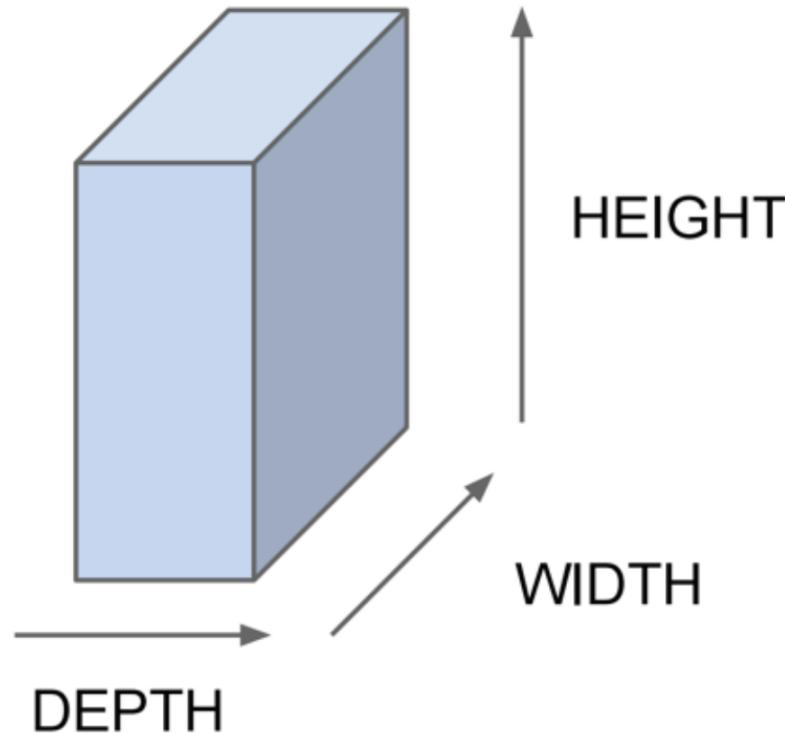
# 3D Activations

All Neural Net  
activations  
arranged in **3 dimensions**:



# 3D Activations

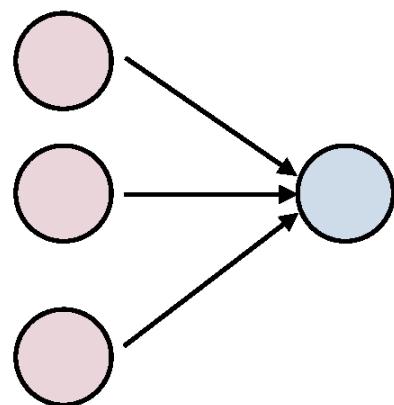
All Neural Net activations arranged in **3 dimensions**:



For example, a CIFAR-10 image is a  $3 \times 32 \times 32$  volume (3 depth — RGB channels, 32 height, 32 width)

# 3D Activations

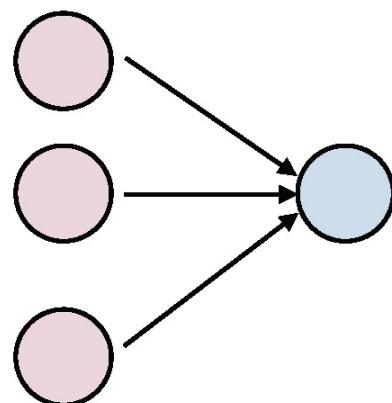
## 1D Activations:



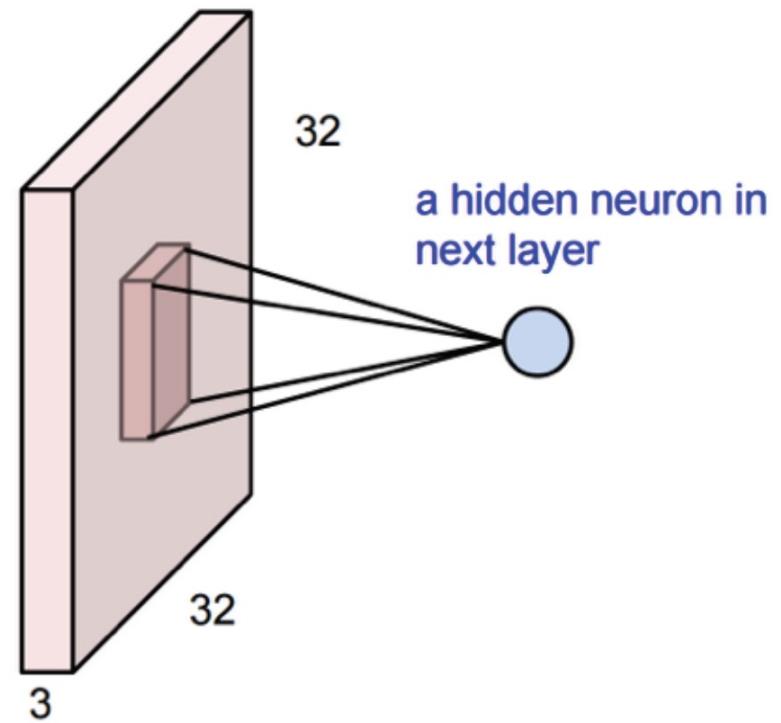
*Figure: Andrej Karpathy*

# 3D Activations

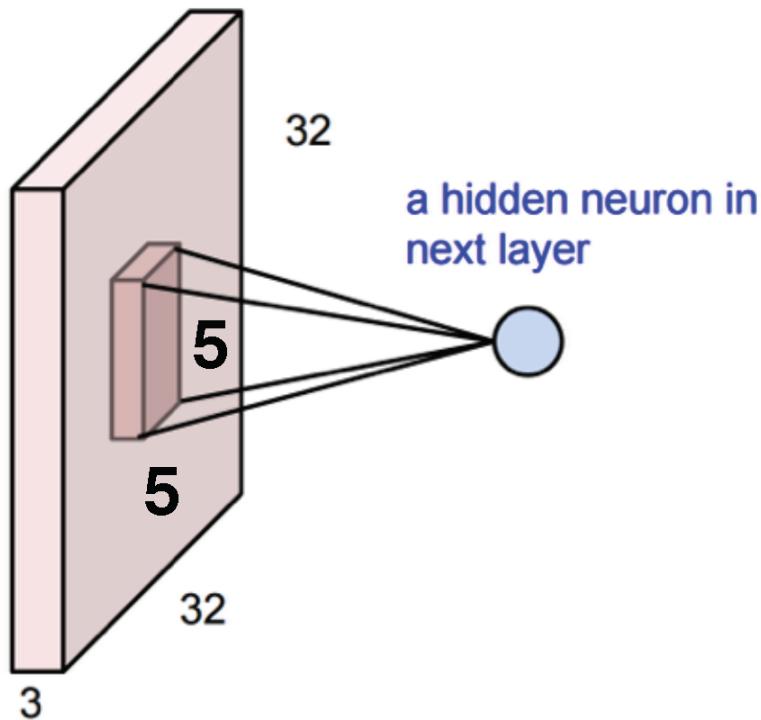
**1D Activations:**



**3D Activations:**

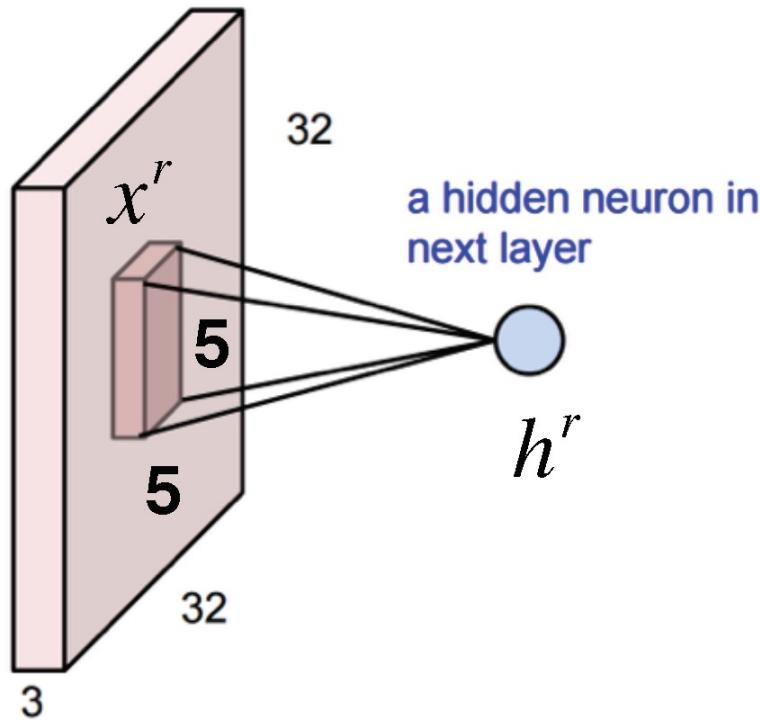


# 3D Activations



- The input is  $3 \times 32 \times 32$
- This neuron depends on a  $3 \times 5 \times 5$  chunk of the input
- The neuron also has a  $3 \times 5 \times 5$  set of weights and a bias (scalar)

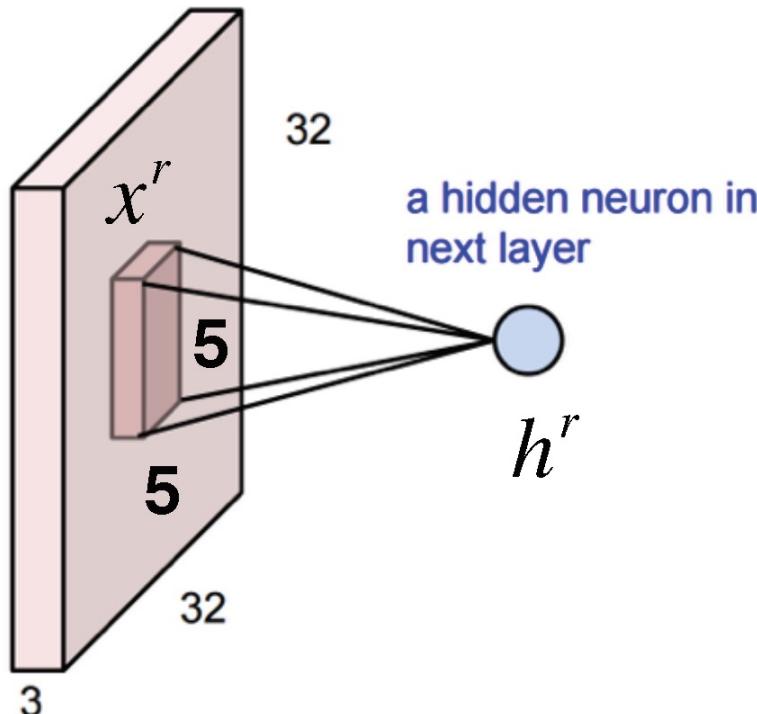
# 3D Activations



Example: consider the region of the input " $x^r$ "

With output neuron  $h^r$

# 3D Activations



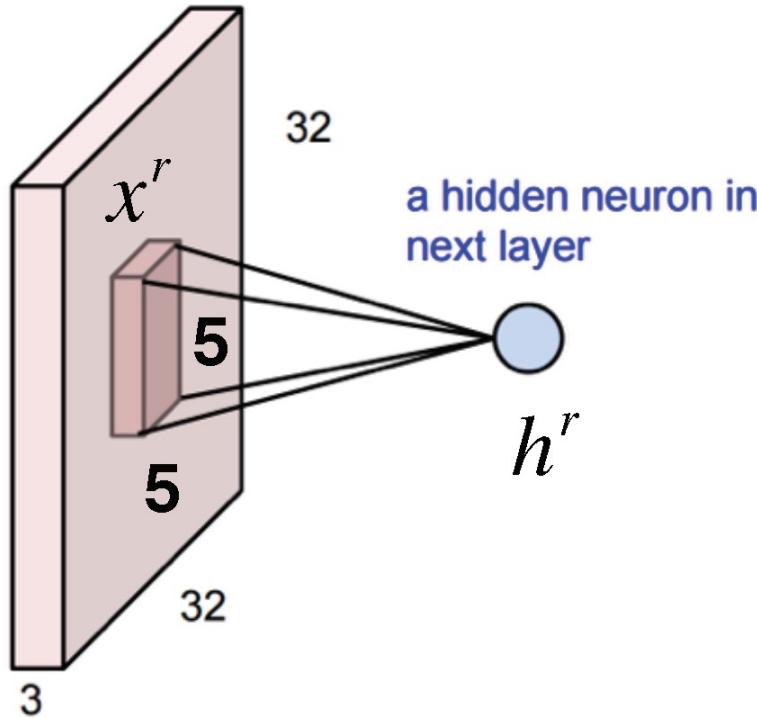
Example: consider the region of the input " $x^r$ "

With output neuron  $h^r$

Then the output is:

$$h^r = \sum_{ijk} x^r_{ijk} W_{ijk} + b$$

# 3D Activations



Example: consider the region of the input " $x^r$ "

With output neuron  $h^r$

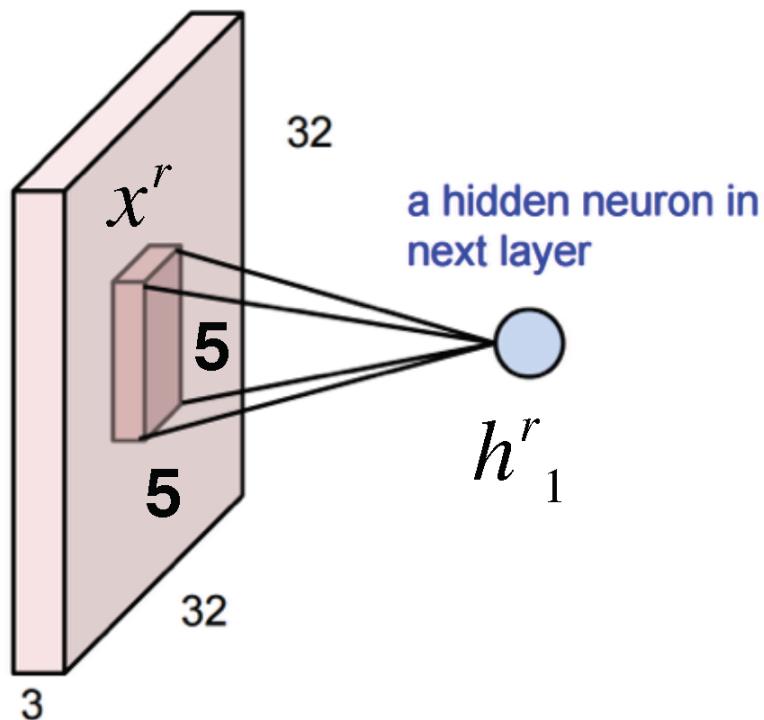
Then the output is:

$$h^r = \sum_{ijk} x^r_{ijk} W_{ijk} + b$$

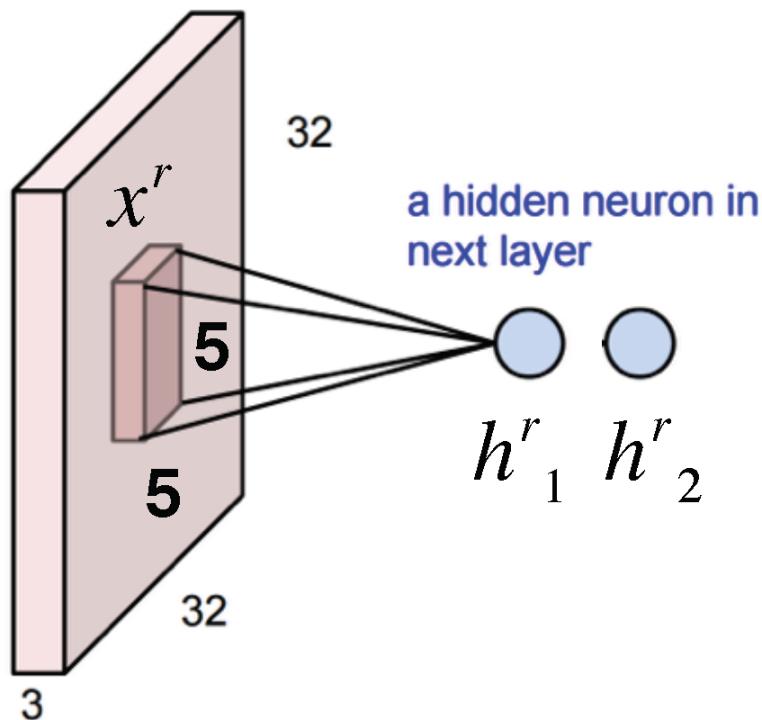


Sum over 3 axes

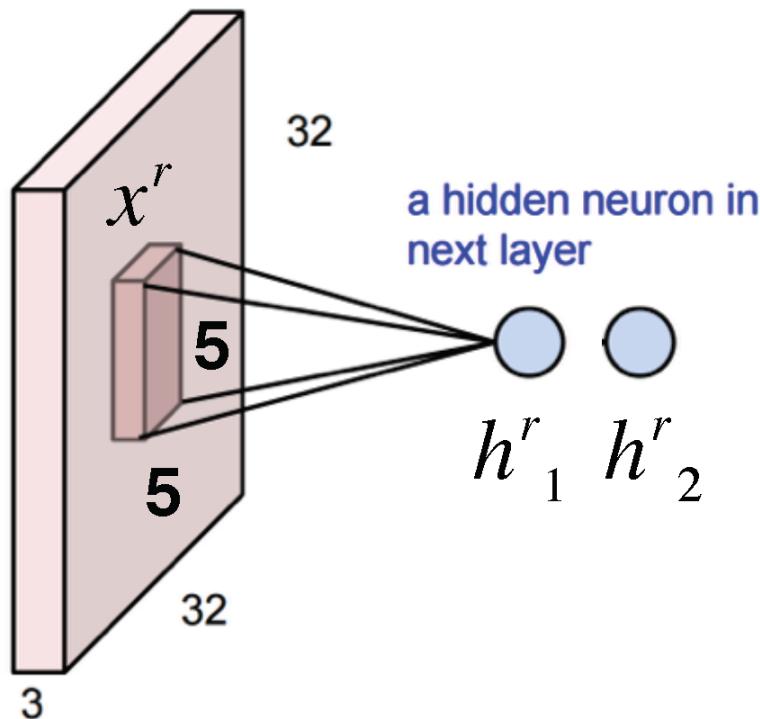
# 3D Activations



# 3D Activations



# 3D Activations

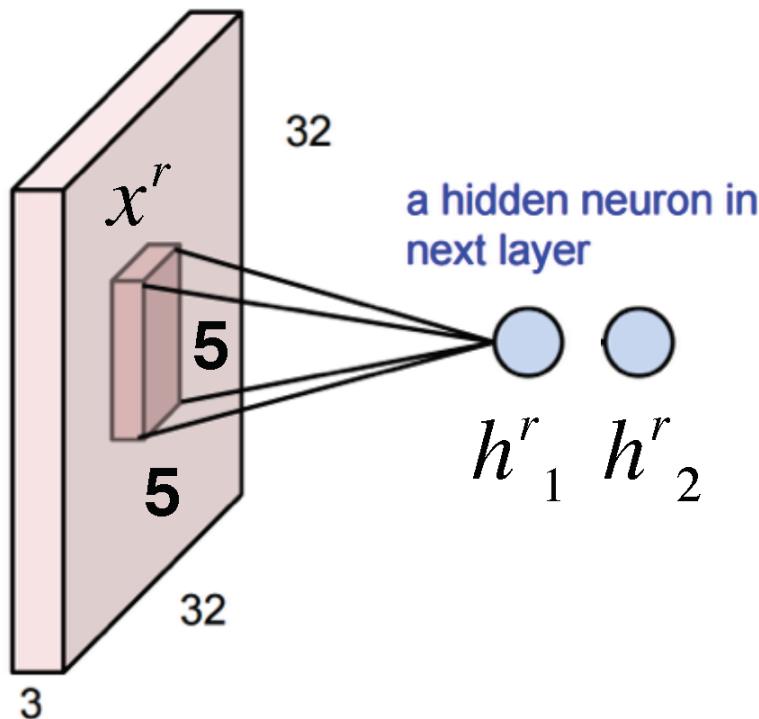


With **2** output neurons

$$h^r_1 = \sum_{ijk} x^r_{ijk} W_{1ijk} + b_1$$

$$h^r_2 = \sum_{ijk} x^r_{ijk} W_{2ijk} + b_2$$

# 3D Activations



With **2** output neurons

$$h^r_1 = \sum_{ijk} x^r_{ijk} W_{1ijk} + b_1$$

$$h^r_2 = \sum_{ijk} x^r_{ijk} W_{2ijk} + b_2$$

# 3D Activations

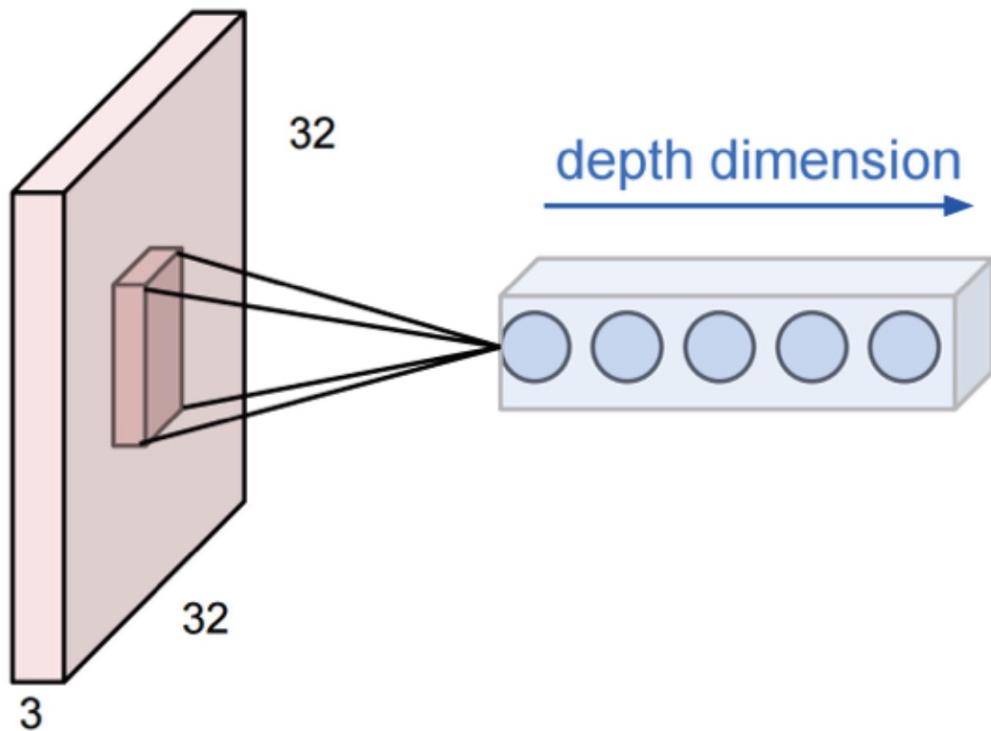
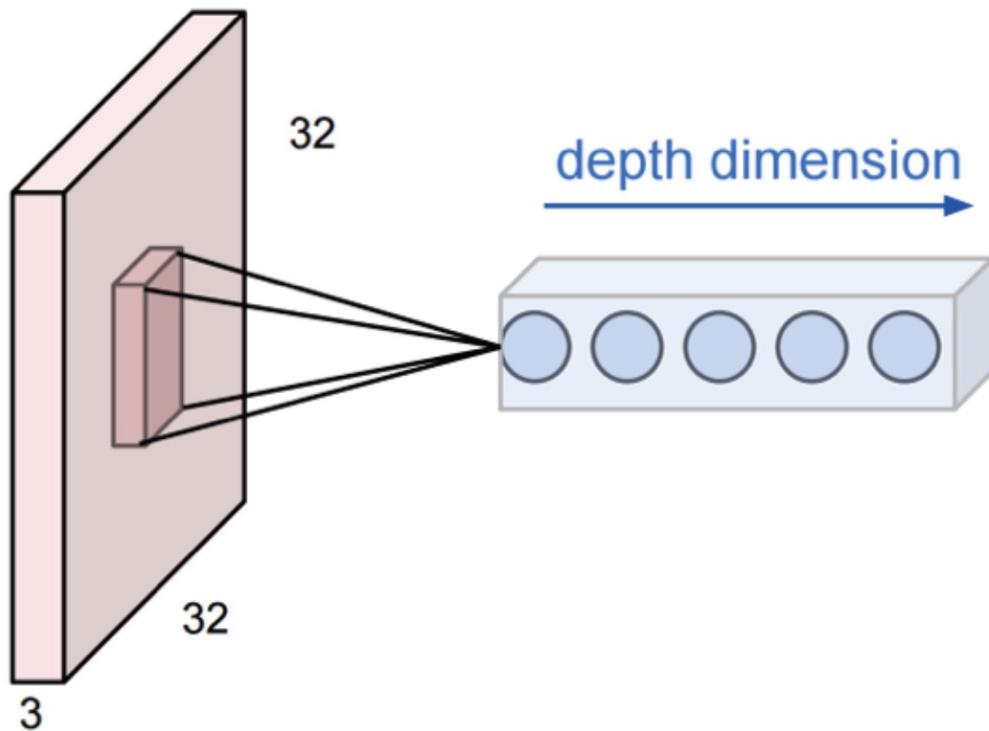


Figure: Andrej Karpathy

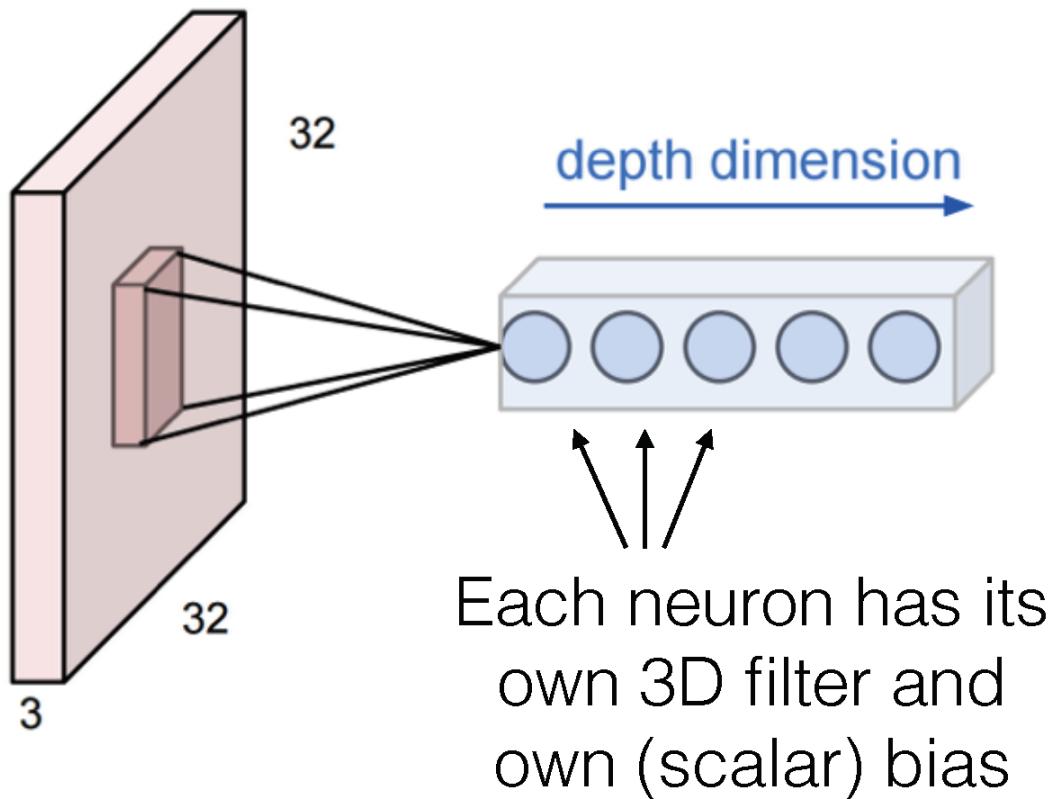
# 3D Activations



We can keep adding more outputs

These form a column in the output volume:  
[depth x 1 x 1]

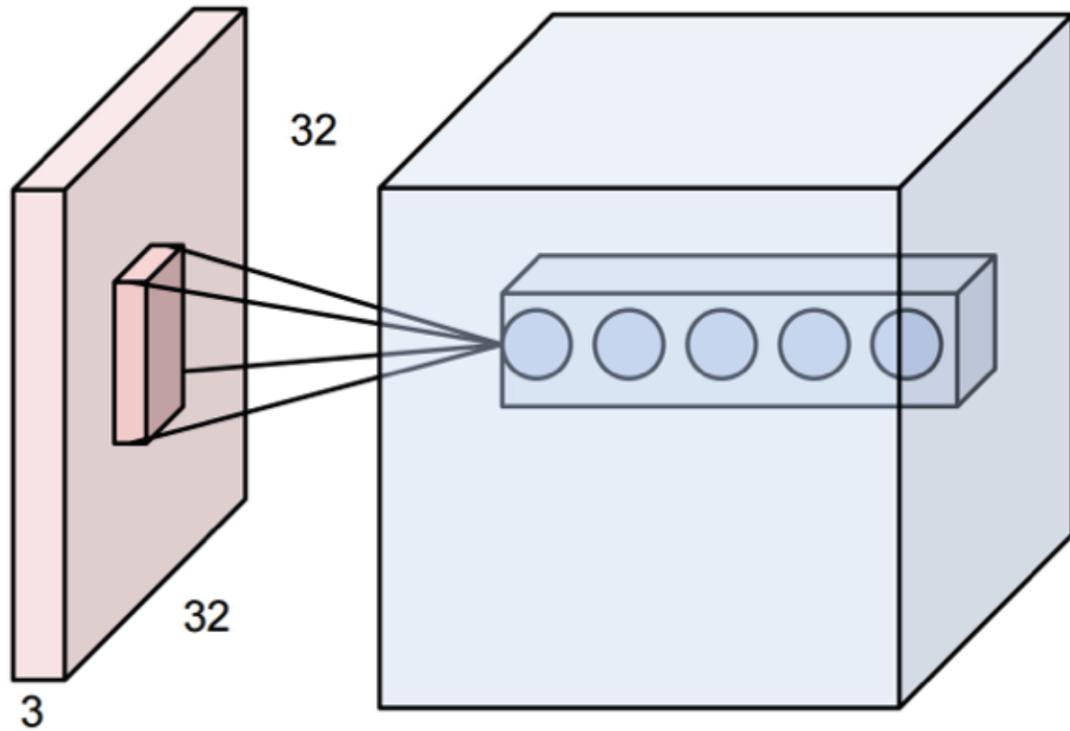
# 3D Activations



We can keep adding more outputs

These form a column in the output volume:  
[depth x 1 x 1]

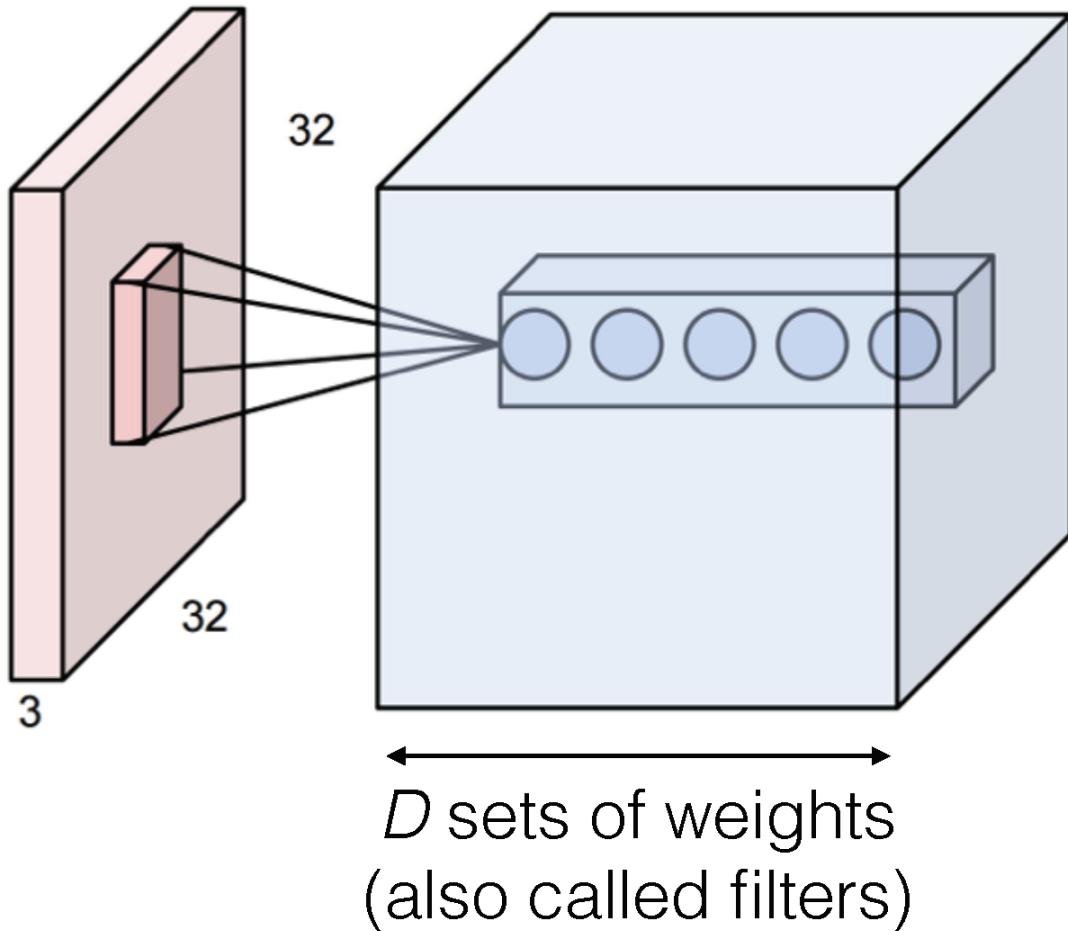
# 3D Activations



Now repeat this across the input

$\leftarrow \rightarrow$   
 $D$  sets of weights  
(also called filters)

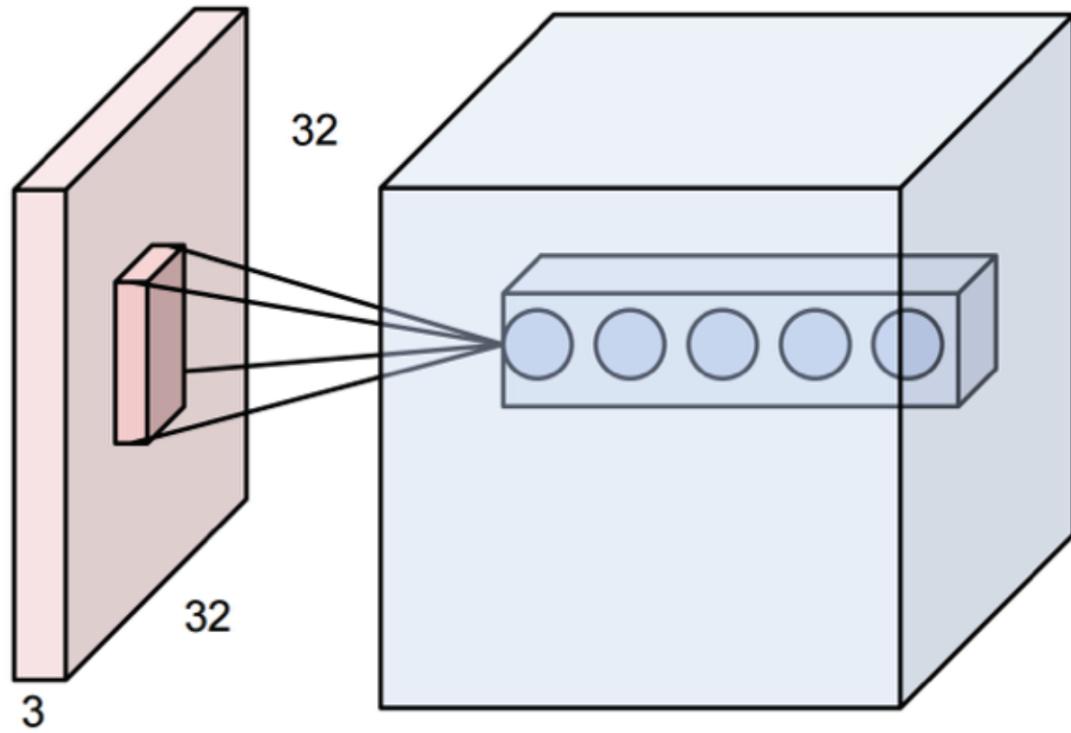
# 3D Activations



Now repeat this  
across the input

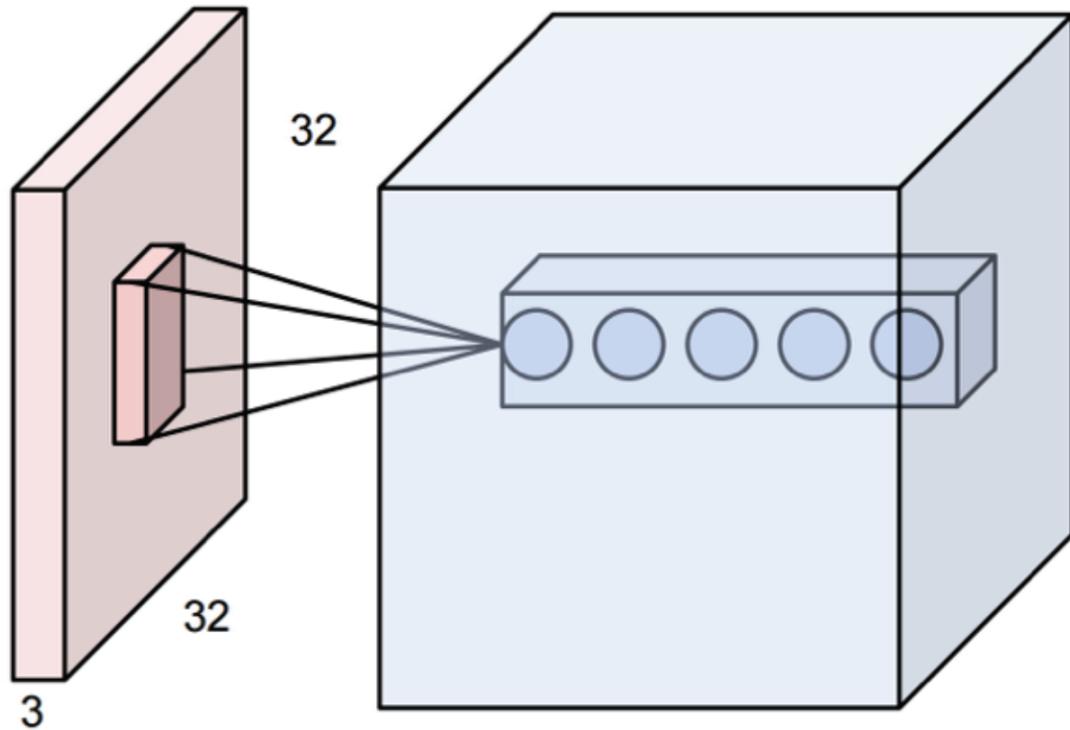
**Weight sharing:**  
Each filter shares  
the same weights  
(but each depth  
index has its own  
set of weights)

# 3D Activations



$D$  sets of weights  
(also called filters)

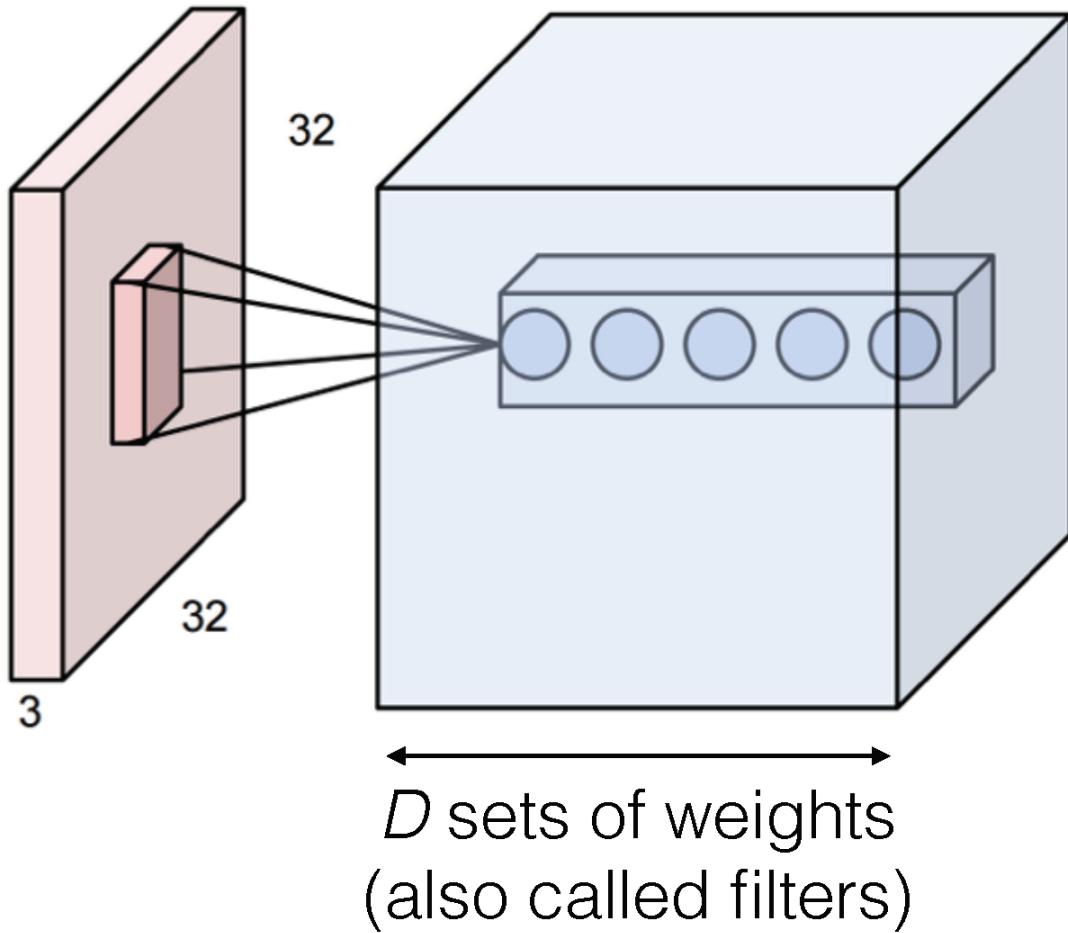
# 3D Activations



With weight sharing,  
this is called  
**convolution**

$D$  sets of weights  
(also called filters)

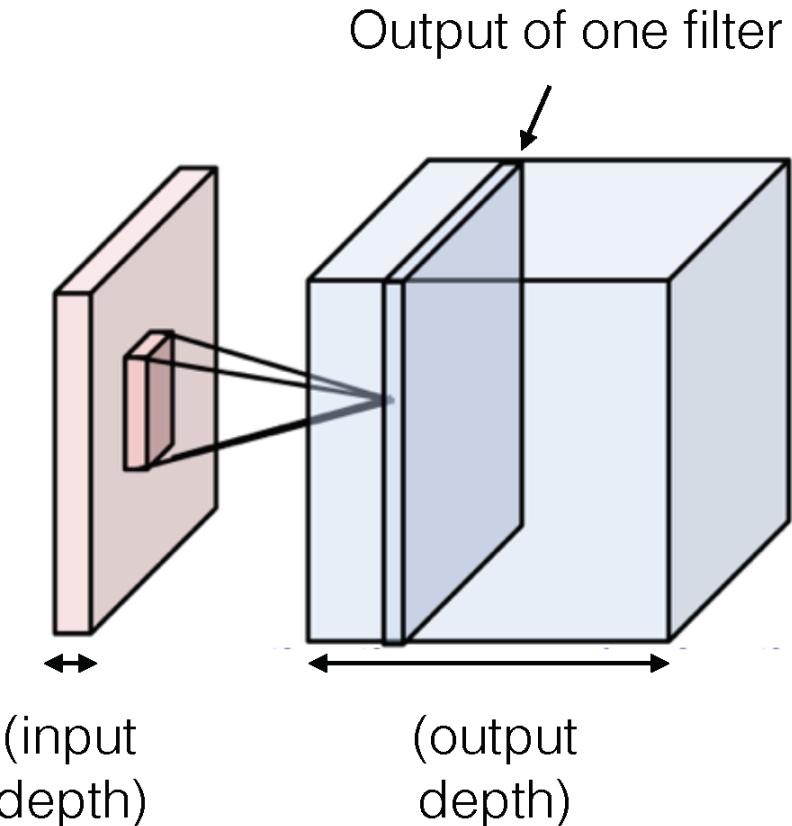
# 3D Activations



With weight sharing,  
this is called  
**convolution**

Without weight sharing,  
this is called a  
**locally connected layer**

# 3D Activations

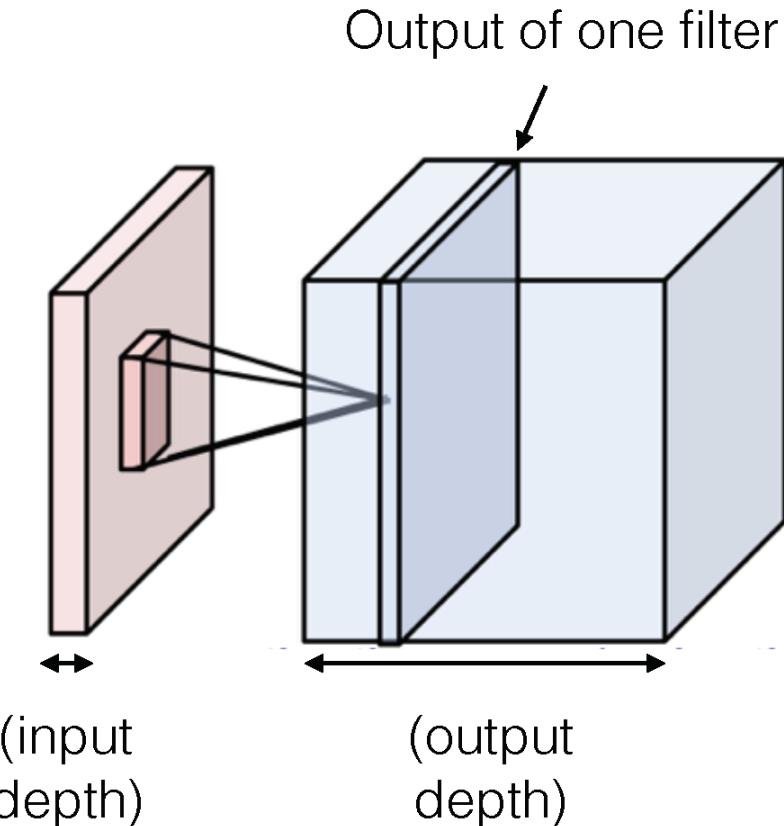


One set of weights gives  
one slice in the output

To get a 3D output of depth  $D$ ,  
use  $D$  different filters

In practice, ConvNets use  
many filters (~64 to 1024)

# 3D Activations



One set of weights gives  
one slice in the output

To get a 3D output of depth  $D$ ,  
use  $D$  different filters

In practice, ConvNets use  
many filters (~64 to 1024)

All together, the weights are **4** dimensional:  
(output depth, input depth, kernel height, kernel width)

# 3D Activations

We can unravel the 3D cube and show each layer separately:

(Input)



one filter = one depth slice (or activation map)

(32 filters, each 3x5x5)



Figure: Andrej Karpathy

# 3D Activations

We can unravel the 3D cube and show each layer separately:

(Input)



one filter = one depth slice (or activation map)

(32 filters, each 3x5x5)

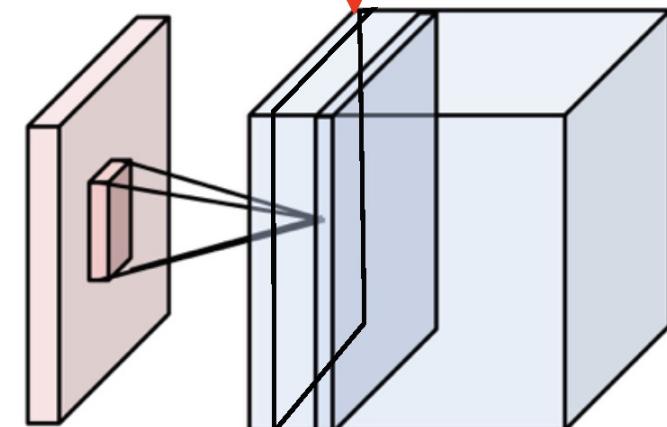
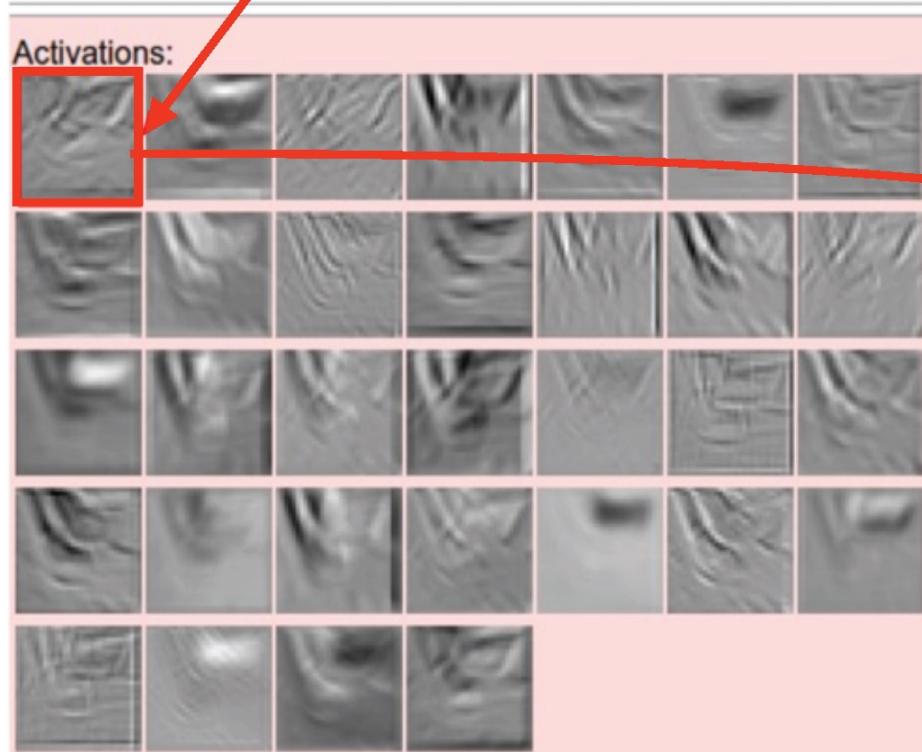


Figure: Andrej Karpathy

# 3D Activations

We can unravel the 3D cube and show each layer separately:

(Input)

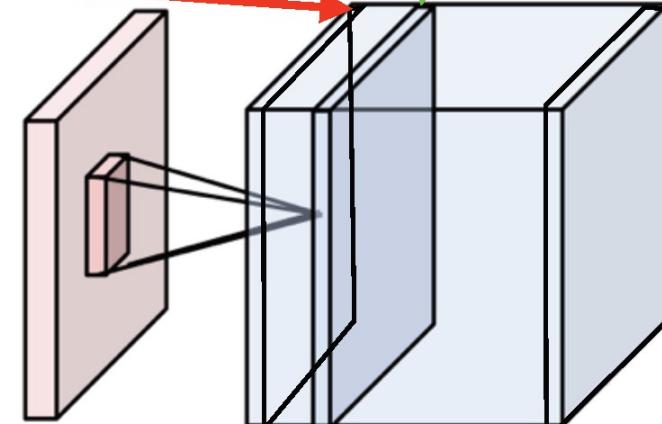
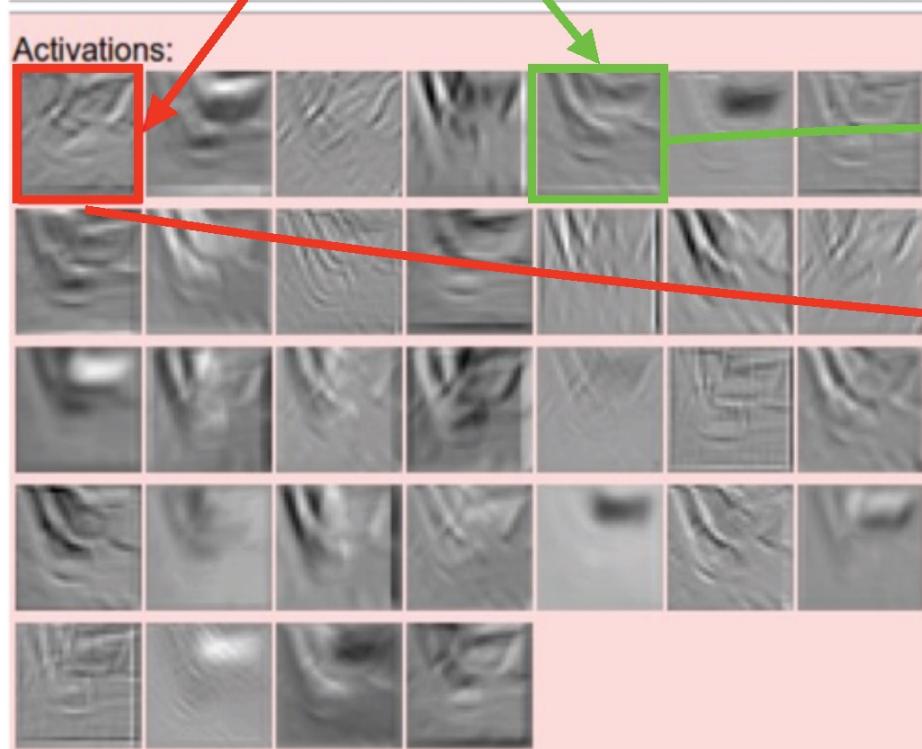


Figure: Andrej Karpathy

# 3D Activations

We can unravel the 3D cube and show each layer separately:

(Input)



one filter = one depth slice (or activation map) (32 filters, each 3x5x5)

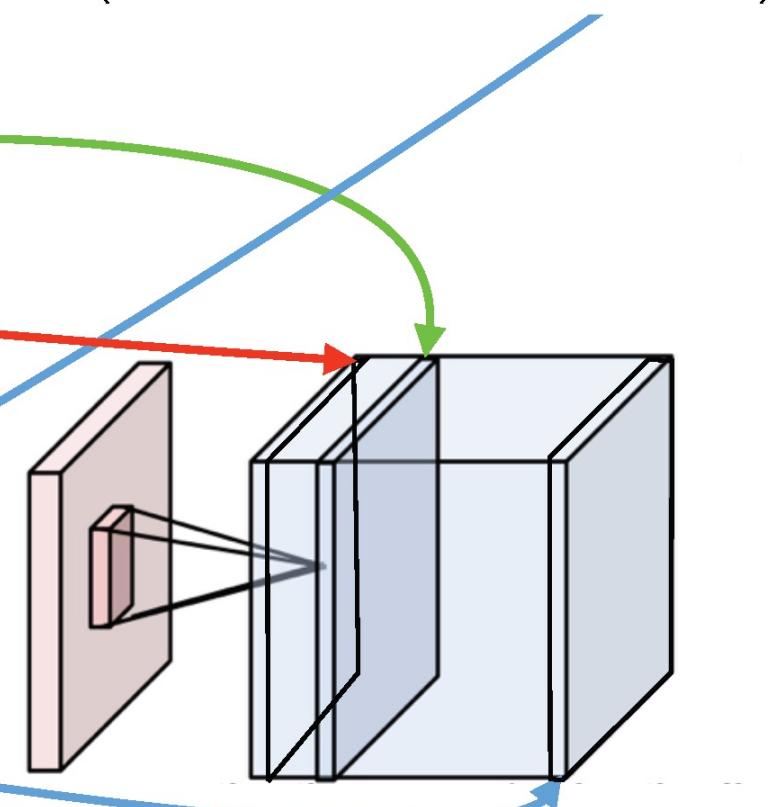
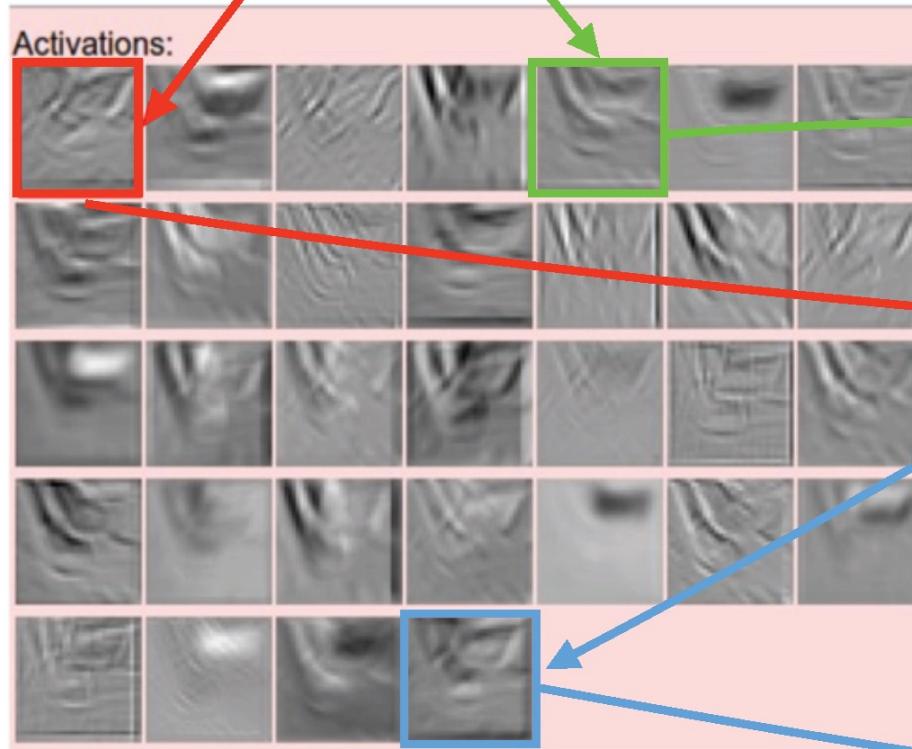
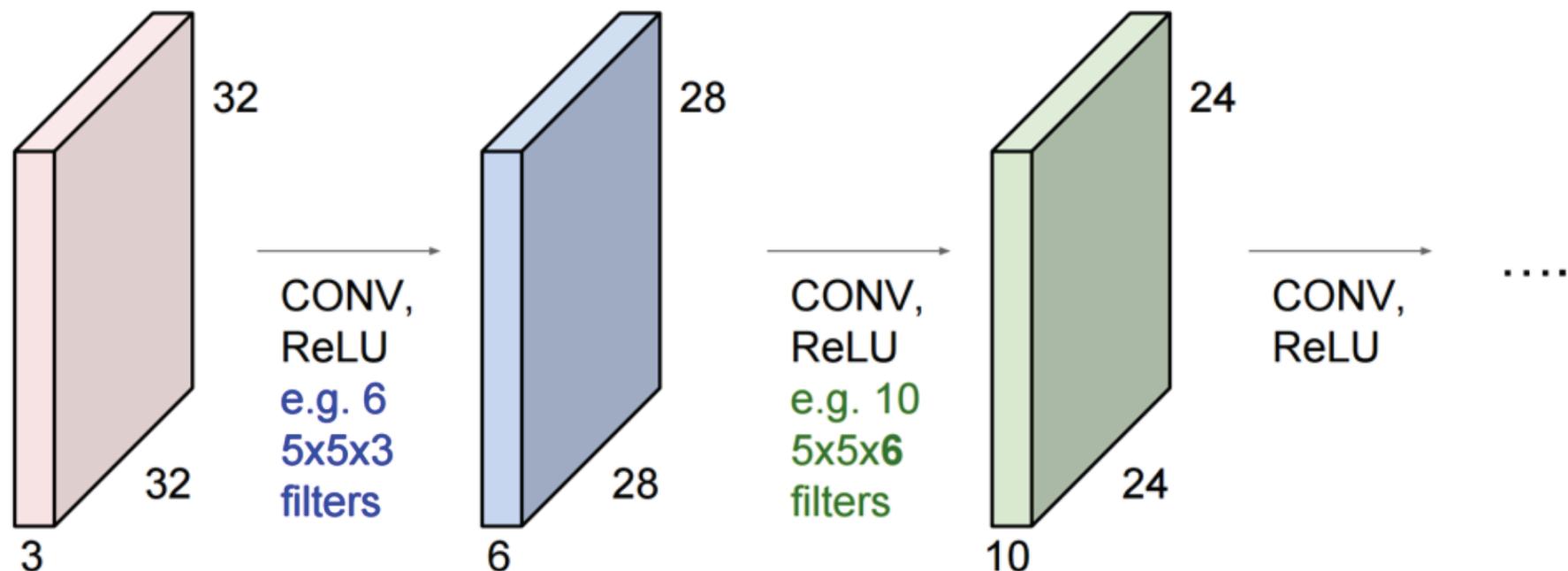


Figure: Andrej Karpathy

# (Recap)

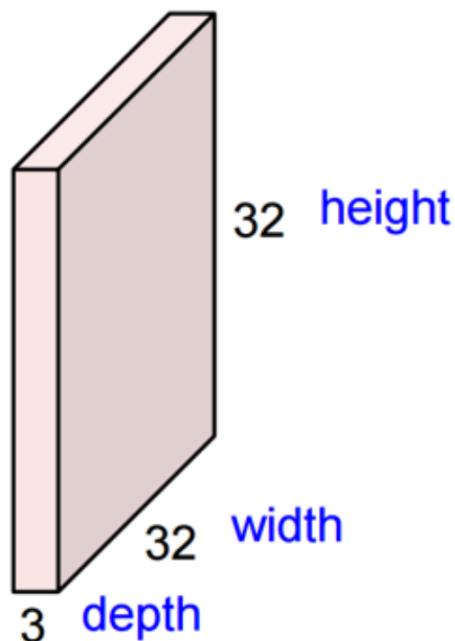
A **ConvNet** is a sequence of convolutional layers, interspersed with activation functions (and possibly other layer types)



# (Recap)

## Convolution Layer

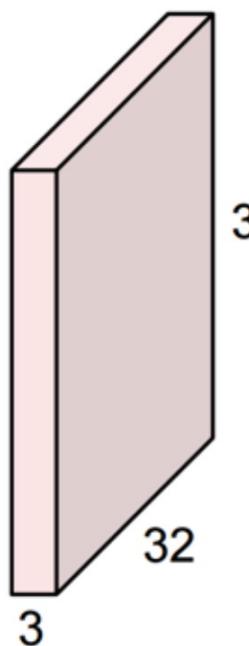
32x32x3 image



# (Recap)

## Convolution Layer

32x32x3 image



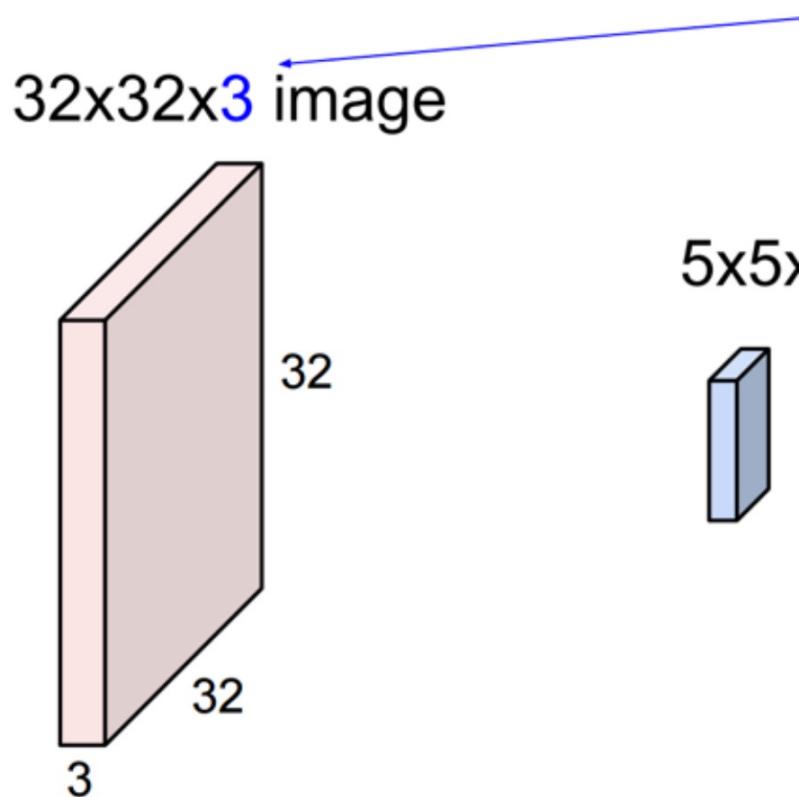
5x5x3 filter



**Convolve** the filter with the image  
i.e. “slide over the image spatially,  
computing dot products”

# (Recap)

## Convolution Layer



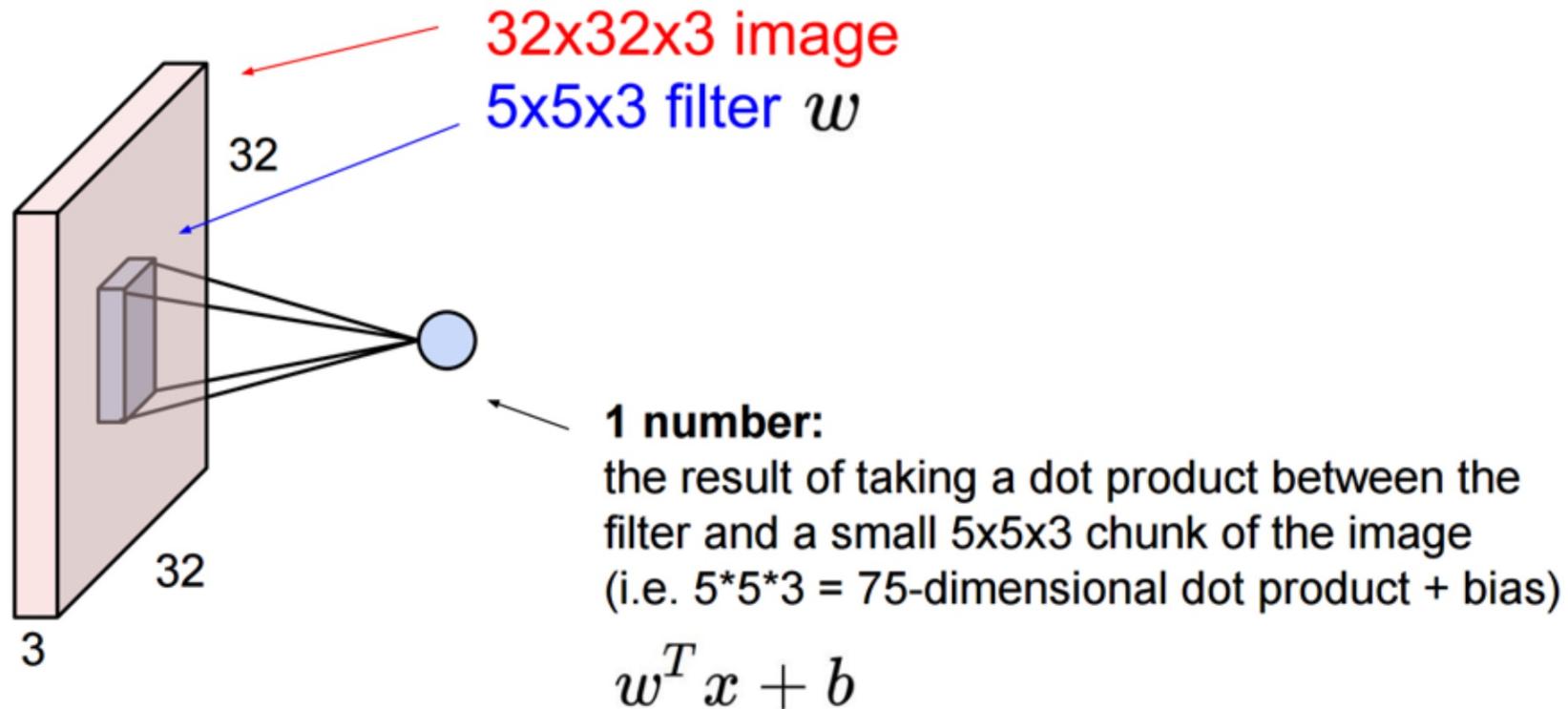
Filters always extend the full depth of the input volume

5x5x3 filter

**Convolve** the filter with the image  
i.e. “slide over the image spatially,  
computing dot products”

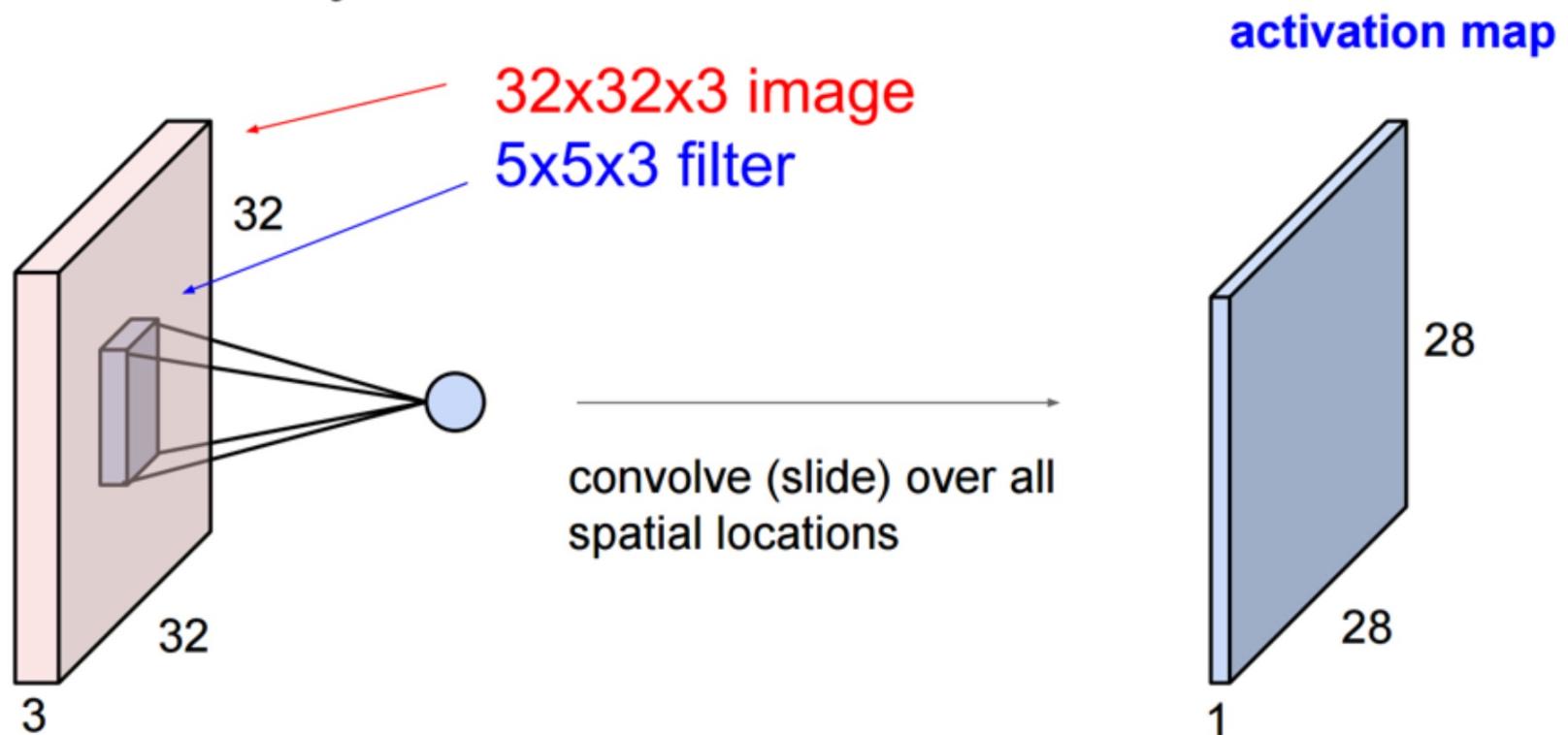
# (Recap)

## Convolution Layer



# (Recap)

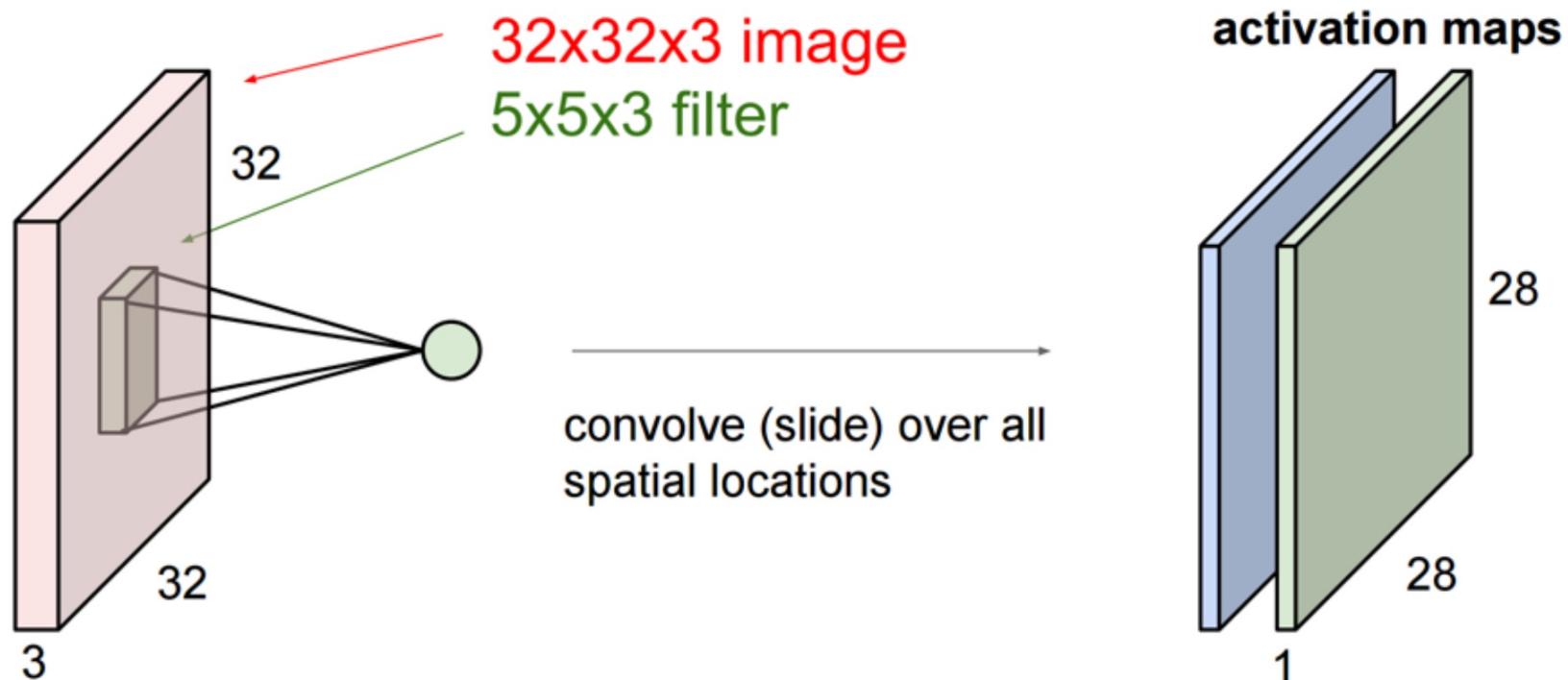
## Convolution Layer



# (Recap)

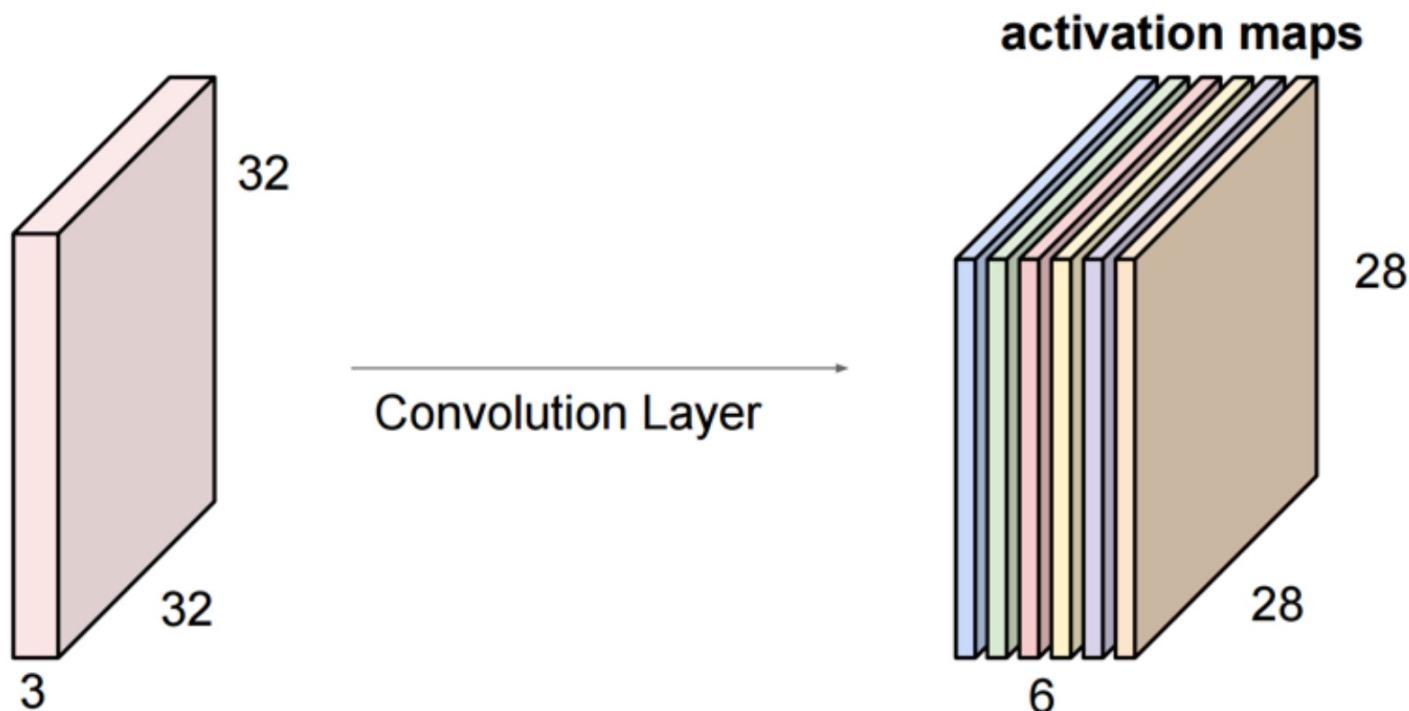
## Convolution Layer

consider a second, green filter



# (Recap)

For example, if we had 6 5x5 filters, we'll get 6 separate activation maps:



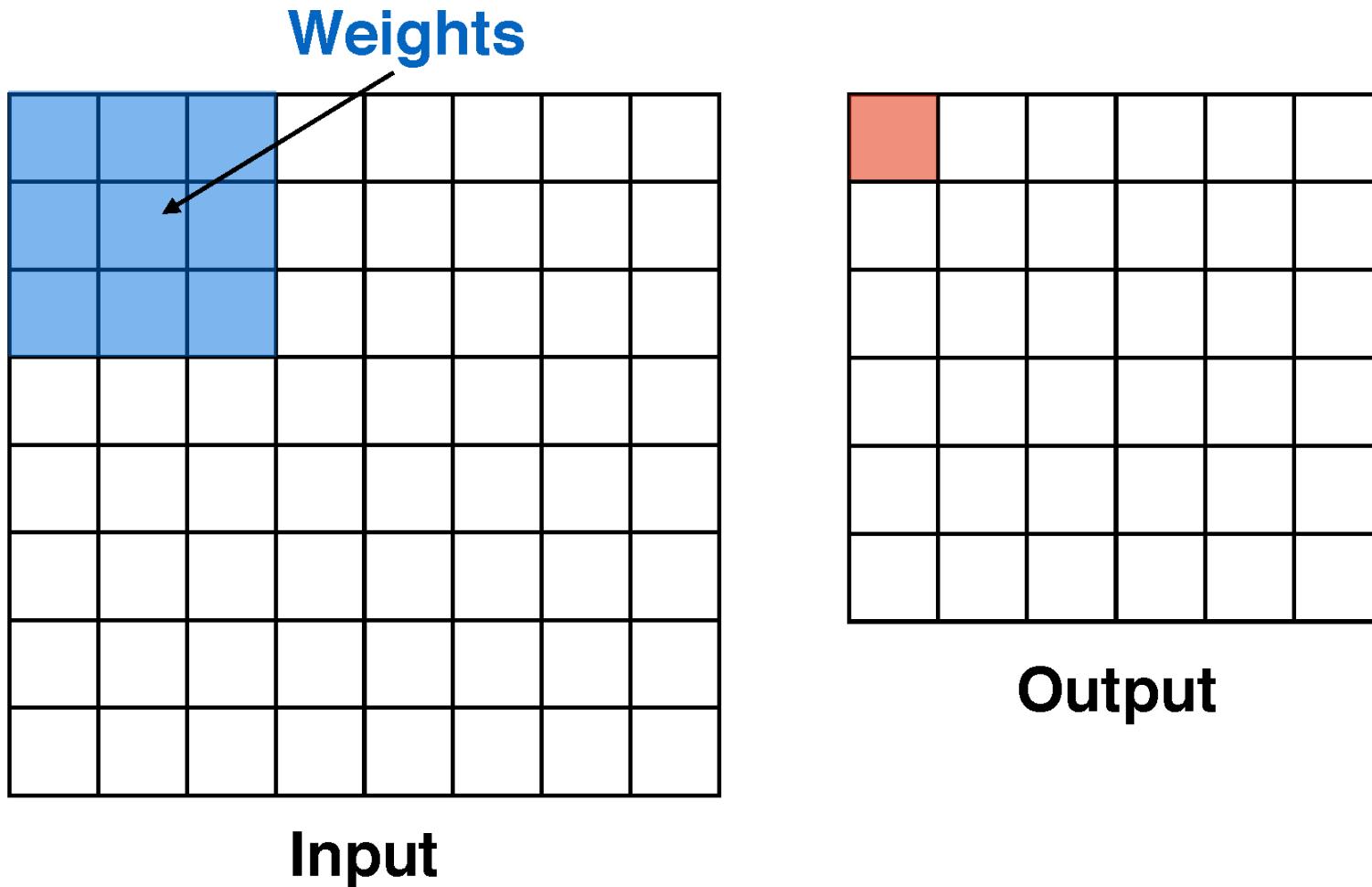
We stack these up to get a “new image” of size 28x28x6!

# Demos

- <http://cs231n.stanford.edu/>
- <http://cs.stanford.edu/people/karpathy/convnetjs/demo/mnist.html>

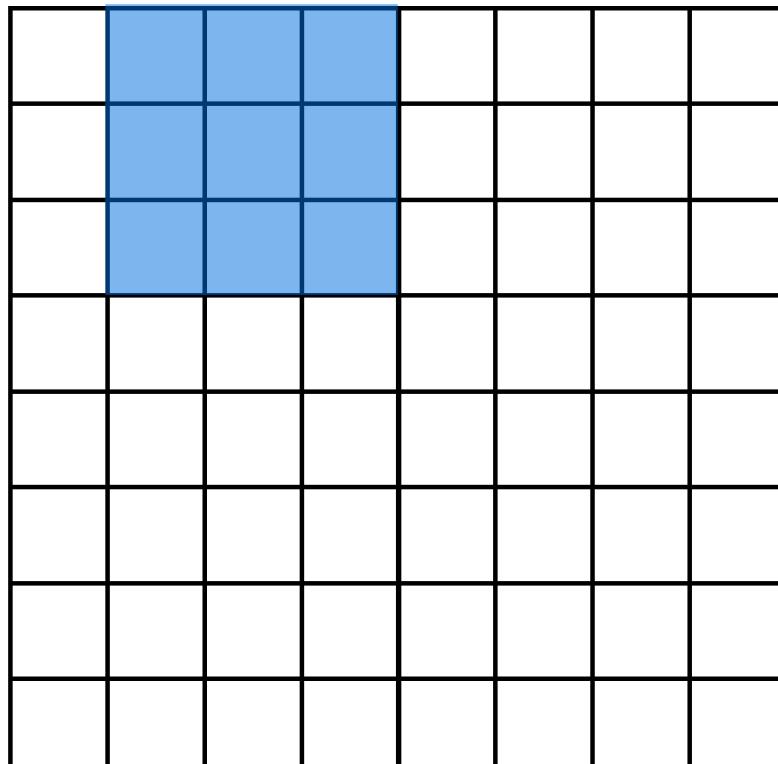
# Convolution: Stride

During convolution, the weights “slide” along the input to generate each output

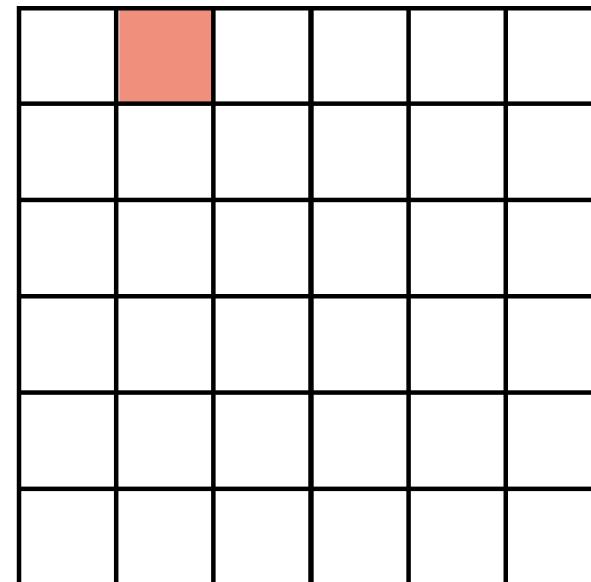


# Convolution: Stride

During convolution, the weights “slide” along the input to generate each output



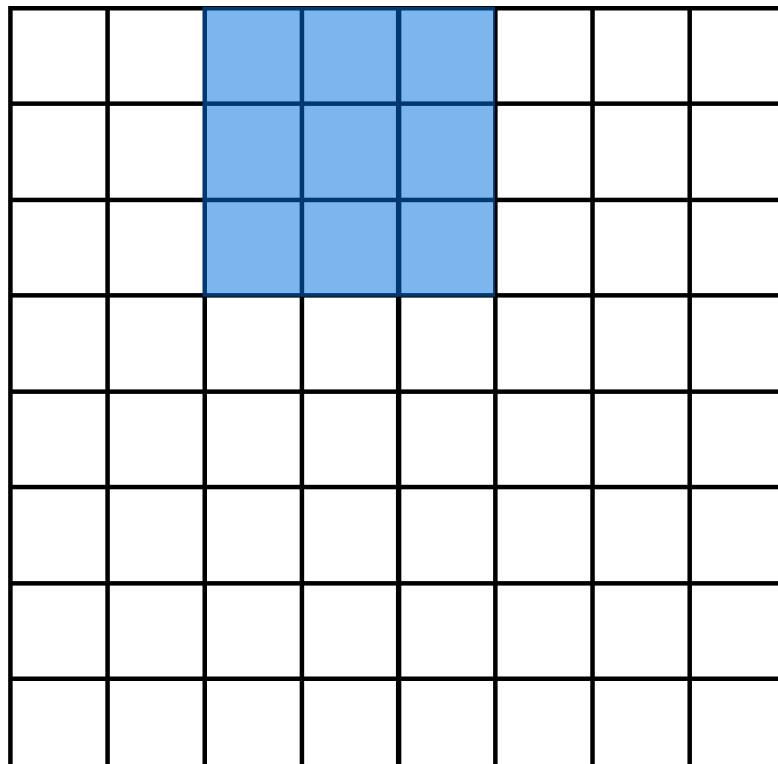
**Input**



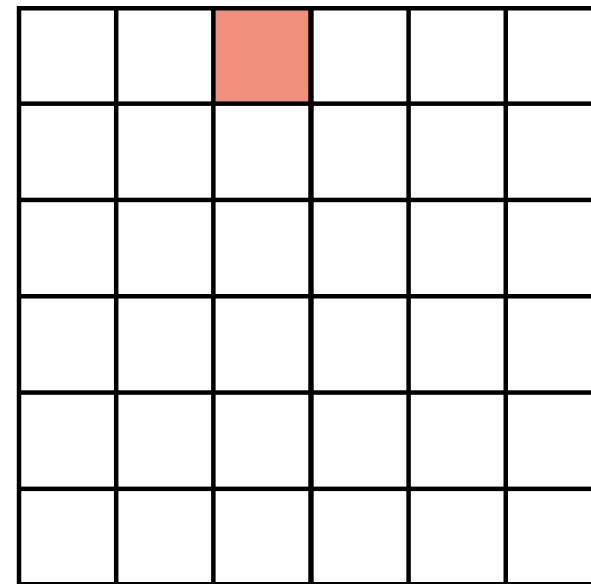
**Output**

# Convolution: Stride

During convolution, the weights “slide” along the input to generate each output



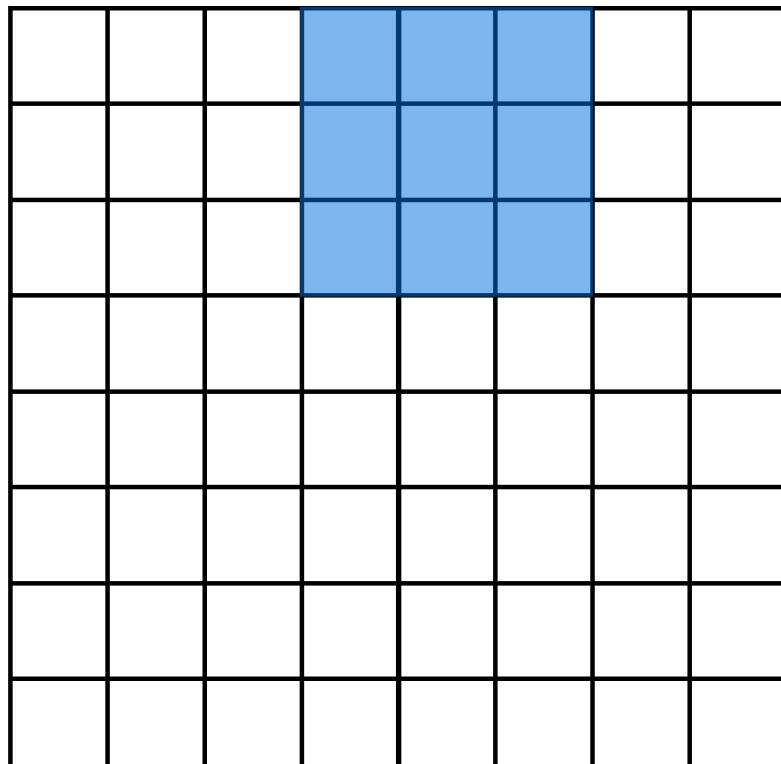
**Input**



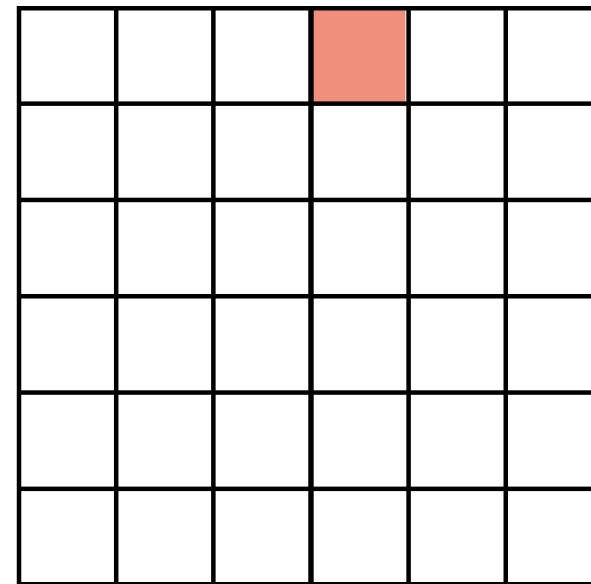
**Output**

# Convolution: Stride

During convolution, the weights “slide” along the input to generate each output



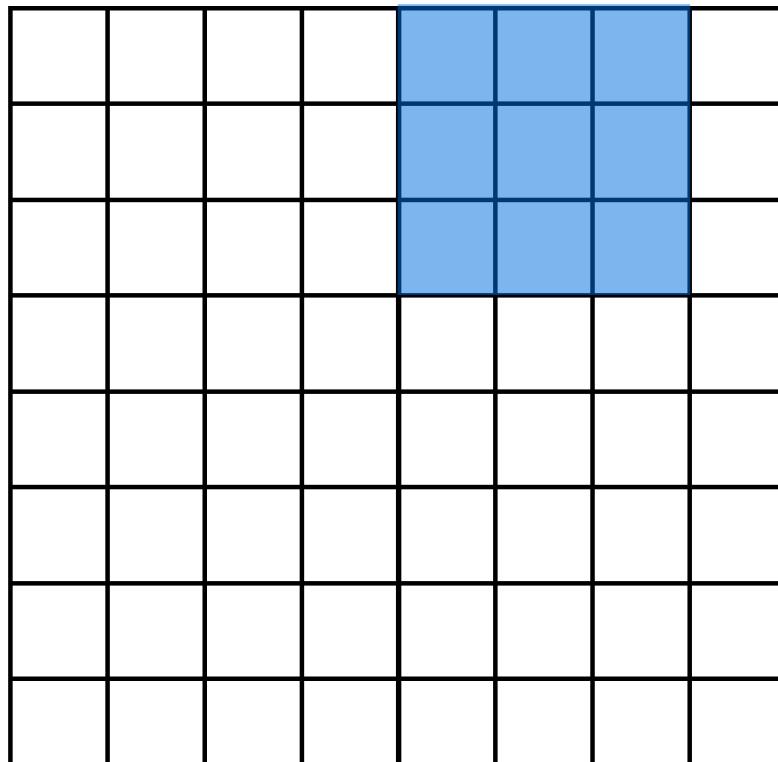
**Input**



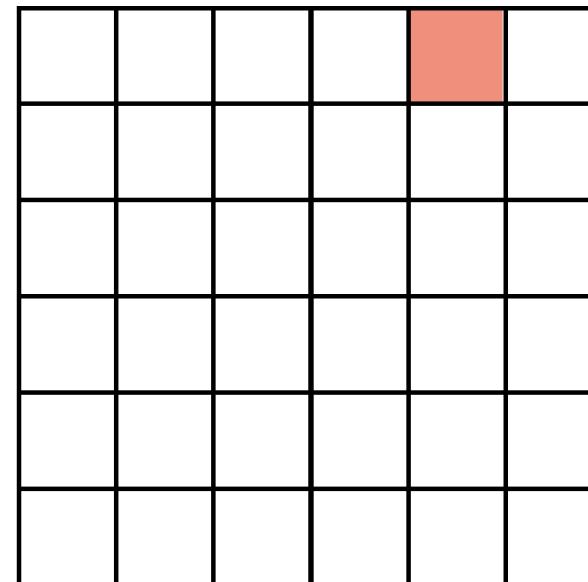
**Output**

# Convolution: Stride

During convolution, the weights “slide” along the input to generate each output



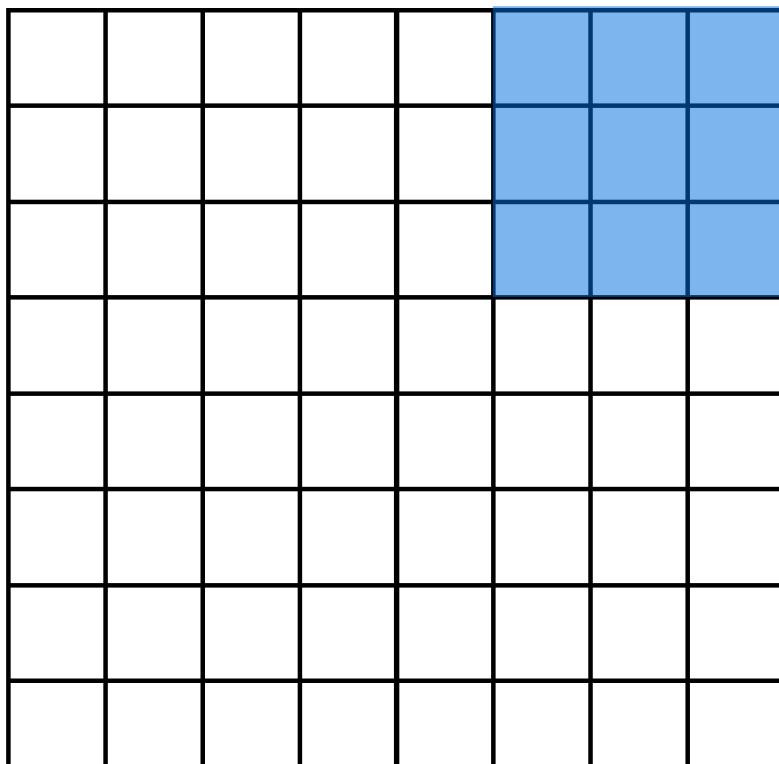
**Input**



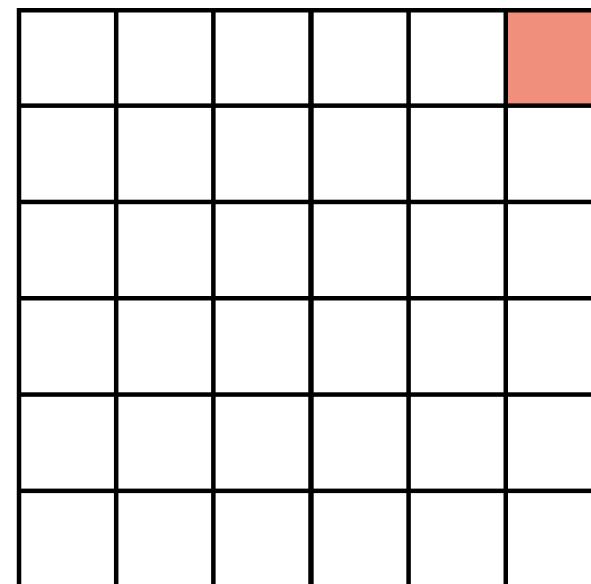
**Output**

# Convolution: Stride

During convolution, the weights “slide” along the input to generate each output



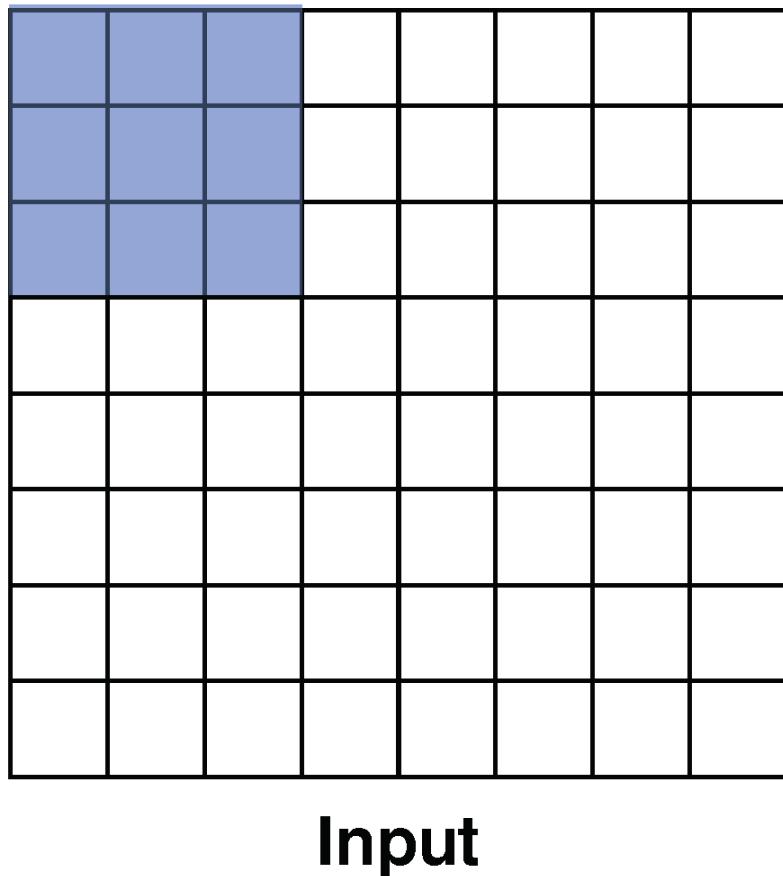
**Input**



**Output**

# Convolution: Stride

During convolution, the weights “slide” along the input to generate each output



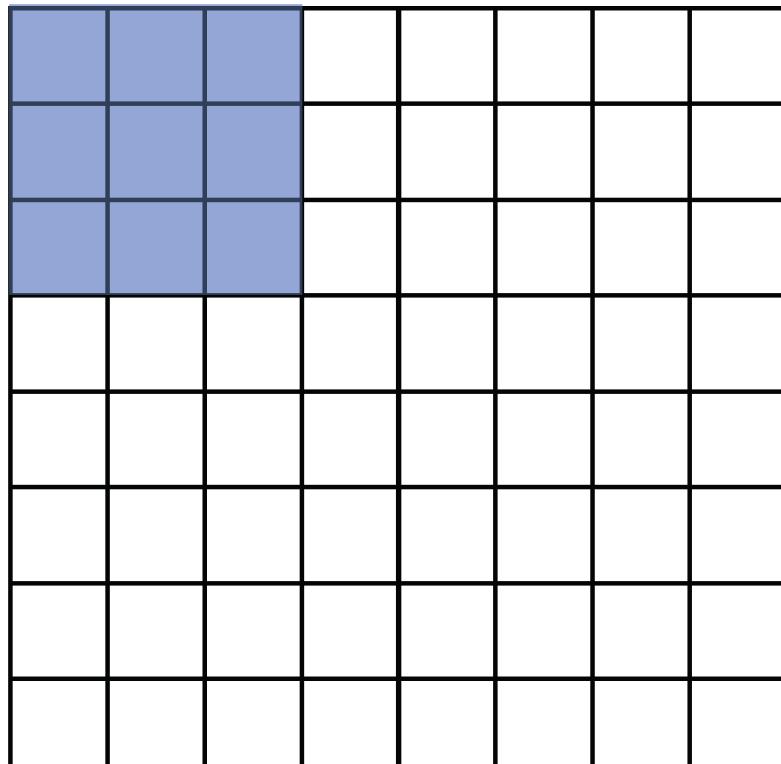
Recall that at each position,  
we are doing a **3D** sum:

$$h^r = \sum_{ijk} x^r_{ijk} W_{ijk} + b$$

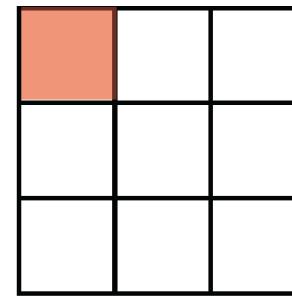
*(channel, row, column)*

# Convolution: Stride

But we can also convolve with a **stride**, e.g. stride = 2



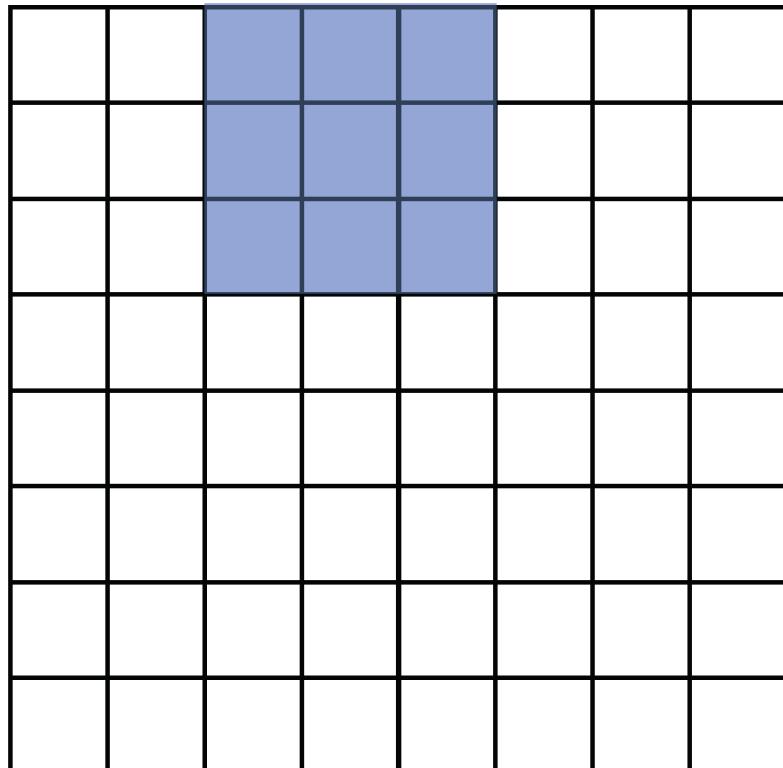
**Input**



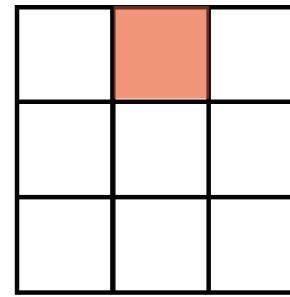
**Output**

# Convolution: Stride

But we can also convolve with a **stride**, e.g. stride = 2



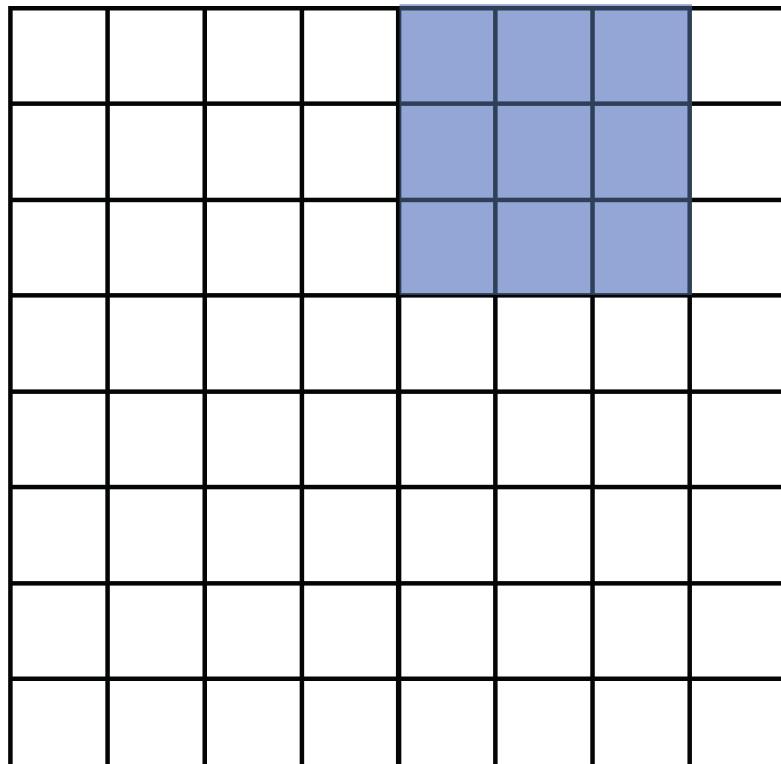
**Input**



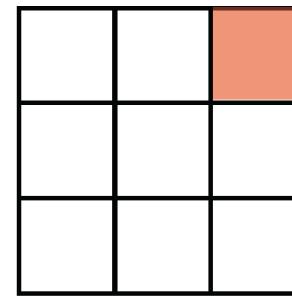
**Output**

# Convolution: Stride

But we can also convolve with a **stride**, e.g. stride = 2



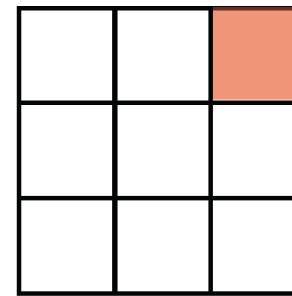
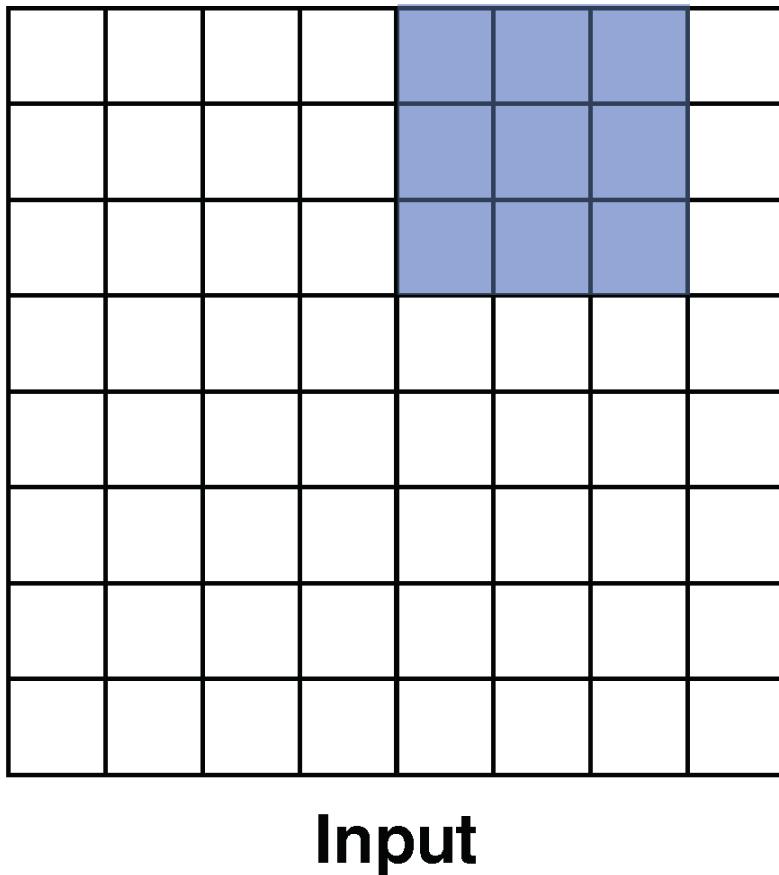
**Input**



**Output**

# Convolution: Stride

But we can also convolve with a **stride**, e.g. stride = 2



**Output**

- Notice that with certain strides, we may not be able to cover all of the input
- The output is also half the size of the input

# Convolution: Padding

We can also pad the input with zeros.

Here, **pad = 1, stride = 2**

0	0	0	0	0	0	0	0	0
0								0
0								0
0								0
0								0
0								0
0								0
0								0
0	0	0	0	0	0	0	0	0

**Input**


**Output**

# Convolution: Padding

We can also pad the input with zeros.

Here, **pad = 1, stride = 2**

0	0	0	0	0	0	0	0	0
0								0
0								0
0								0
0								0
0								0
0								0
0								0
0	0	0	0	0	0	0	0	0

**Input**


**Output**

# Convolution: Padding

We can also pad the input with zeros.

Here, **pad = 1, stride = 2**

0	0	0	0	0	0	0	0	0
0								0
0								0
0								0
0								0
0								0
0								0
0								0
0	0	0	0	0	0	0	0	0

**Input**


**Output**

# Convolution: Padding

We can also pad the input with zeros.

Here, **pad = 1, stride = 2**

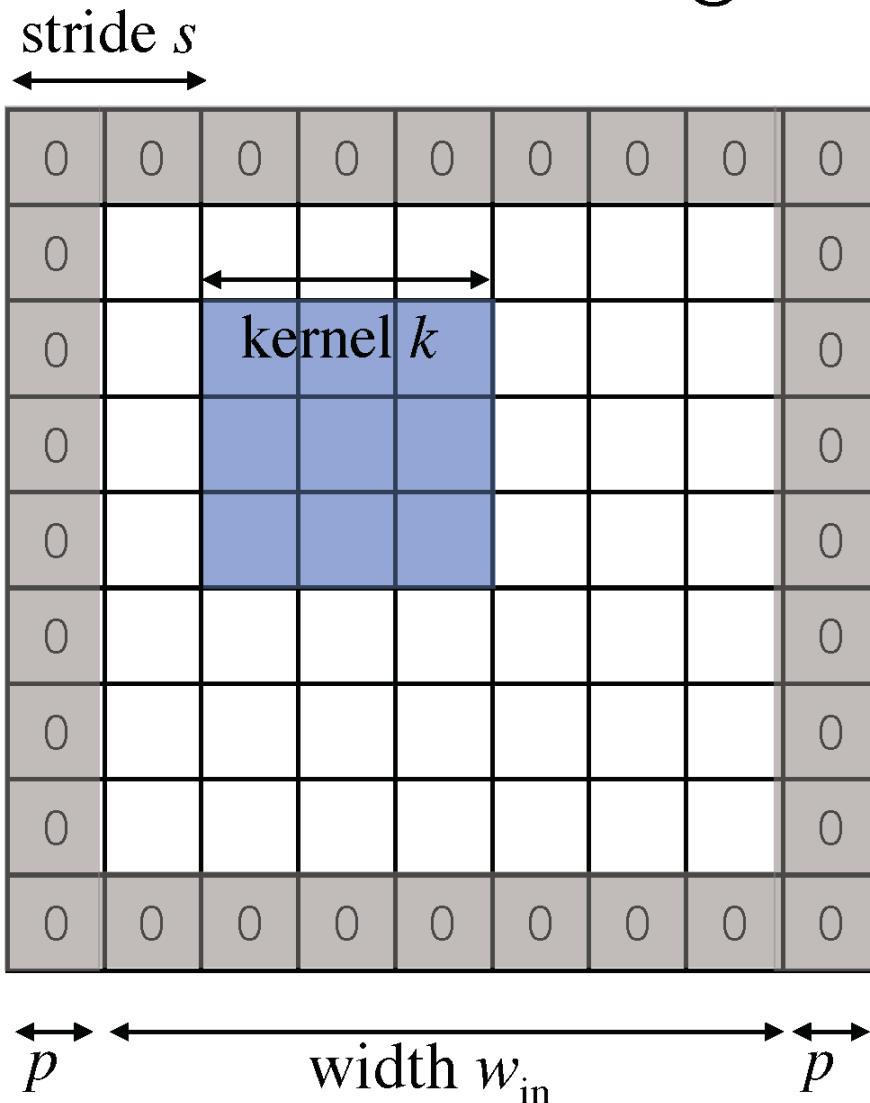
0	0	0	0	0	0	0	0	0
0								0
0								0
0								0
0								0
0								0
0								0
0								0
0	0	0	0	0	0	0	0	0

**Input**


**Output**

# Convolution:

## How big is the output?

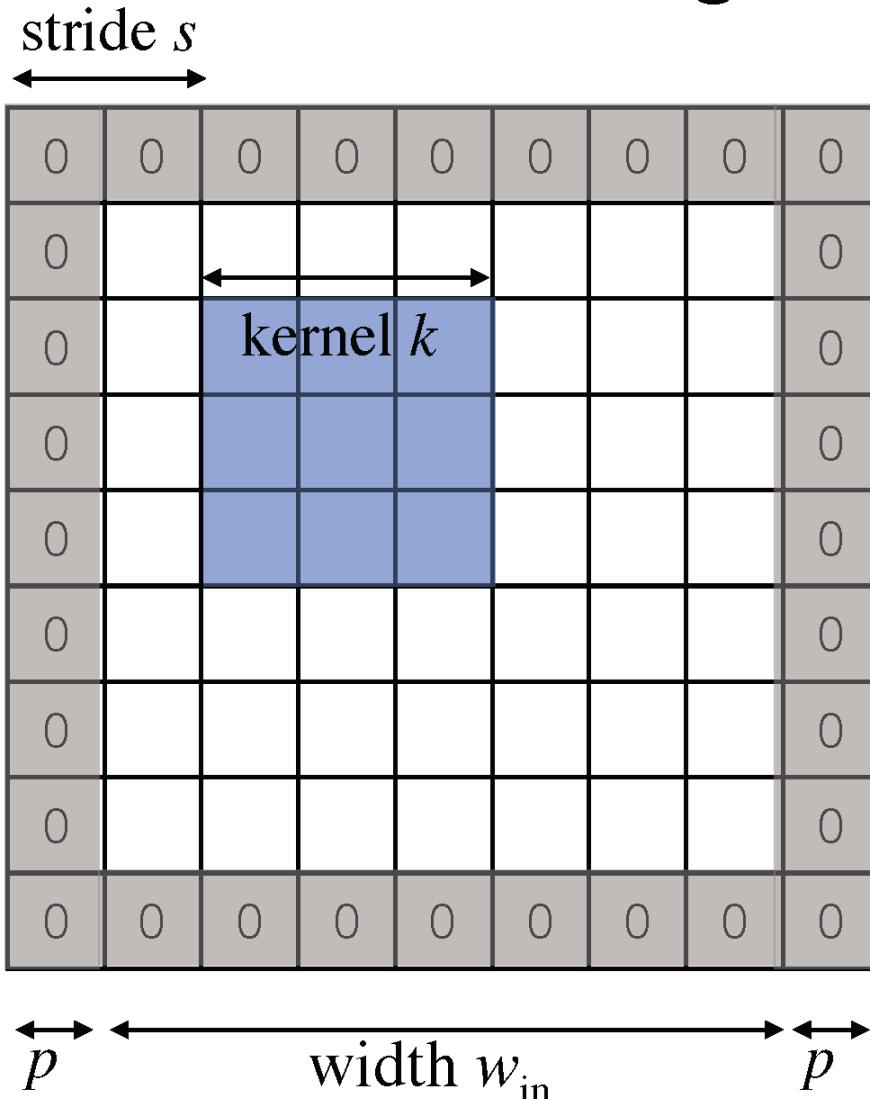


In general, the output has size:

$$w_{\text{out}} = \left\lfloor \frac{w_{\text{in}} + 2p - k}{s} \right\rfloor + 1$$

# Convolution:

## How big is the output?



**Example:**  $k=3$ ,  $s=1$ ,  $p=1$

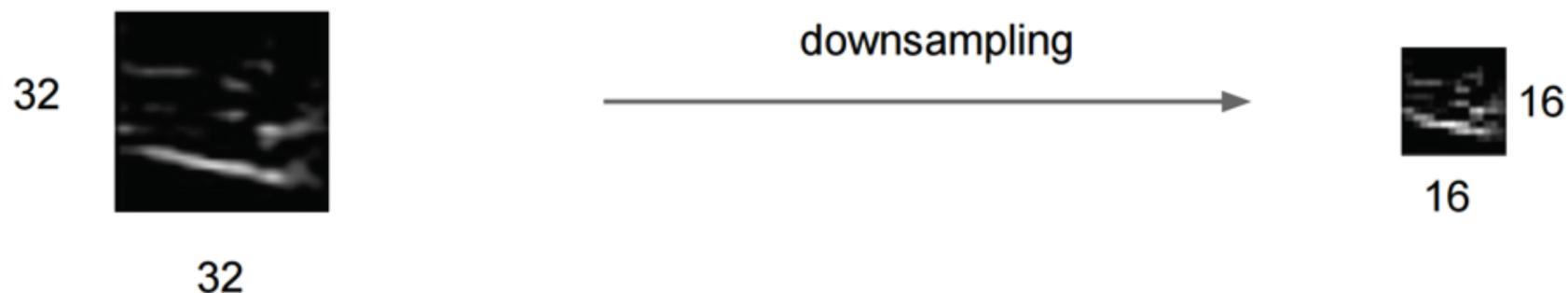
$$\begin{aligned}w_{out} &= \left\lfloor \frac{w_{in} + 2p - k}{s} \right\rfloor + 1 \\&= \left\lfloor \frac{w_{in} + 2 - 3}{1} \right\rfloor + 1 \\&= w_{in}\end{aligned}$$

VGGNet [Simonyan 2014]  
uses filters of this shape

# Pooling

For most ConvNets, **convolution** is often followed by **pooling**:

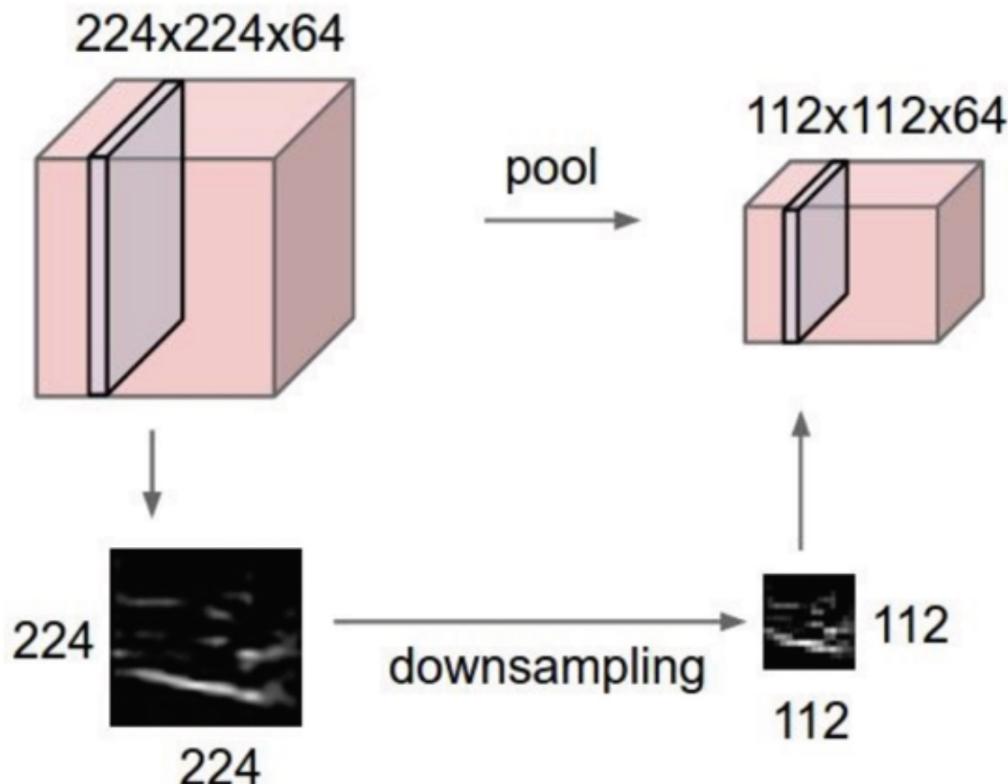
- Creates a smaller representation while retaining the most important information
- The “max” operation is the most common
- Why might “avg” be a poor choice?



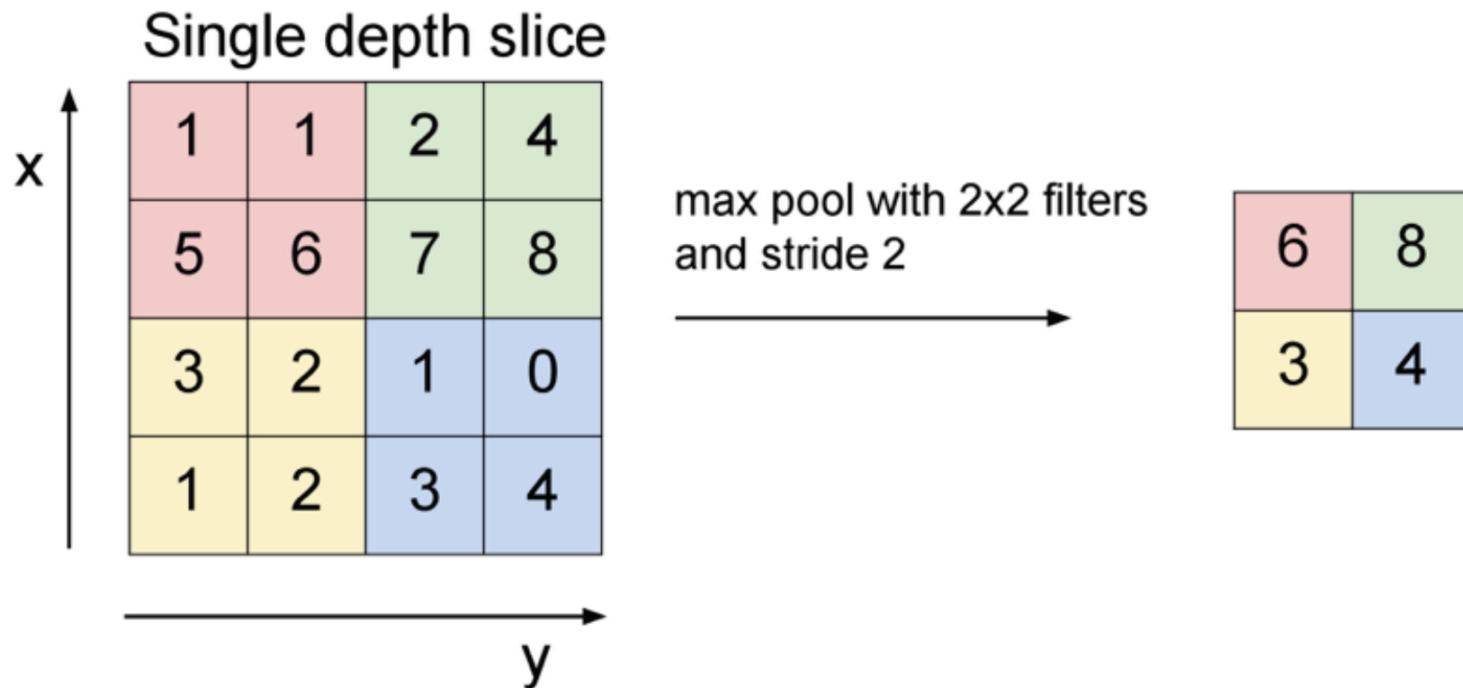
*Figure: Andrej Karpathy*

# Pooling

- makes the representations smaller and more manageable
- operates over each activation map independently:



# Max Pooling



What's the backprop rule for max pooling?

- In the forward pass, store the index that took the max
- The backprop gradient is the input gradient at that index

# Example ConvNet

CONV      CONV      POOL  
↓            ↓            ↓  
ReLU          ReLU

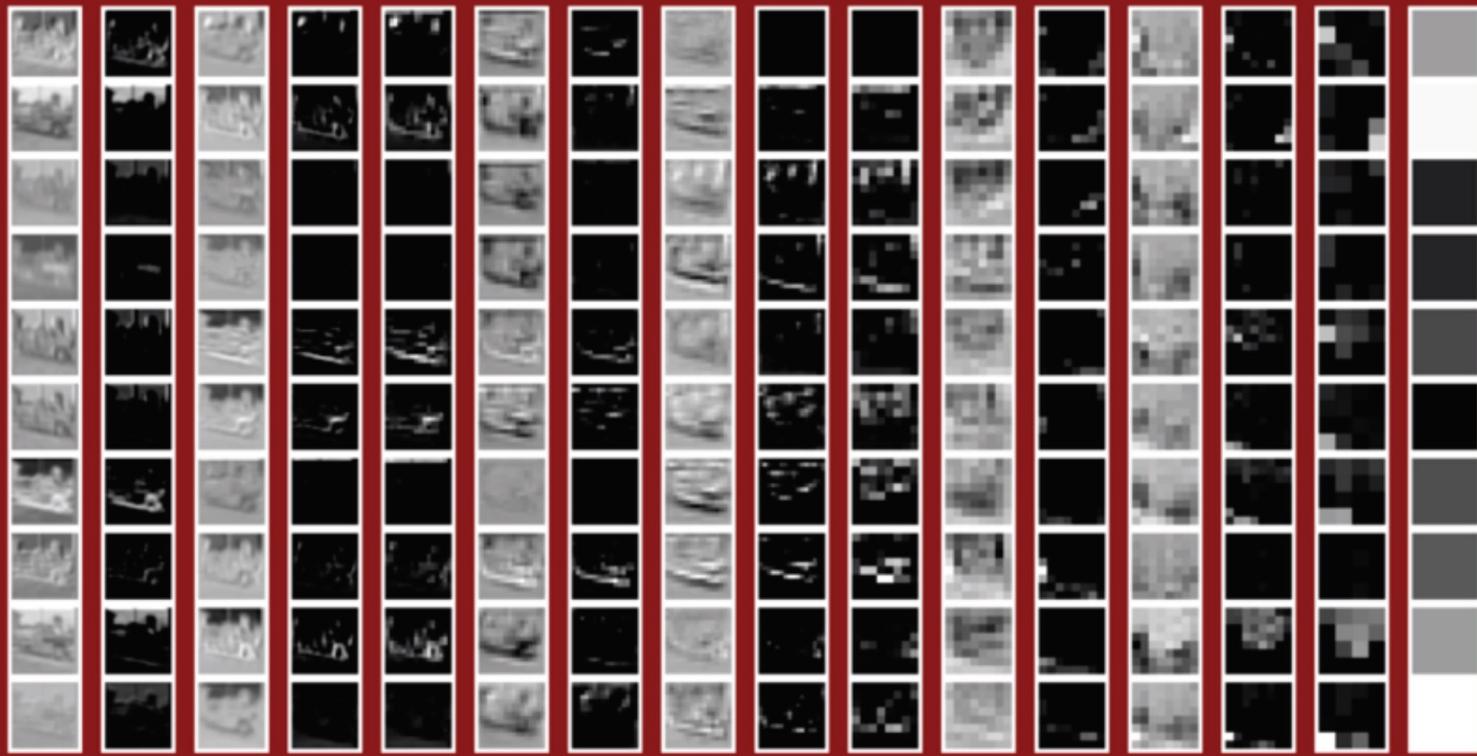


Figure: Andrej Karpathy

# Example ConvNet

CONV    CONV    **POOL** CONV    CONV    **POOL** CONV    CONV    **POOL**

↓            ↓            ↓            ↓            ↓            ↓            ↓

ReLU          ReLU       ReLU       ReLU       ReLU       ReLU       ReLU

↓            ↓            ↓            ↓            ↓            ↓            ↓



truck  
car  
airplane  
ship  
horse

Figure: Andrej Karpathy

# Example ConvNet

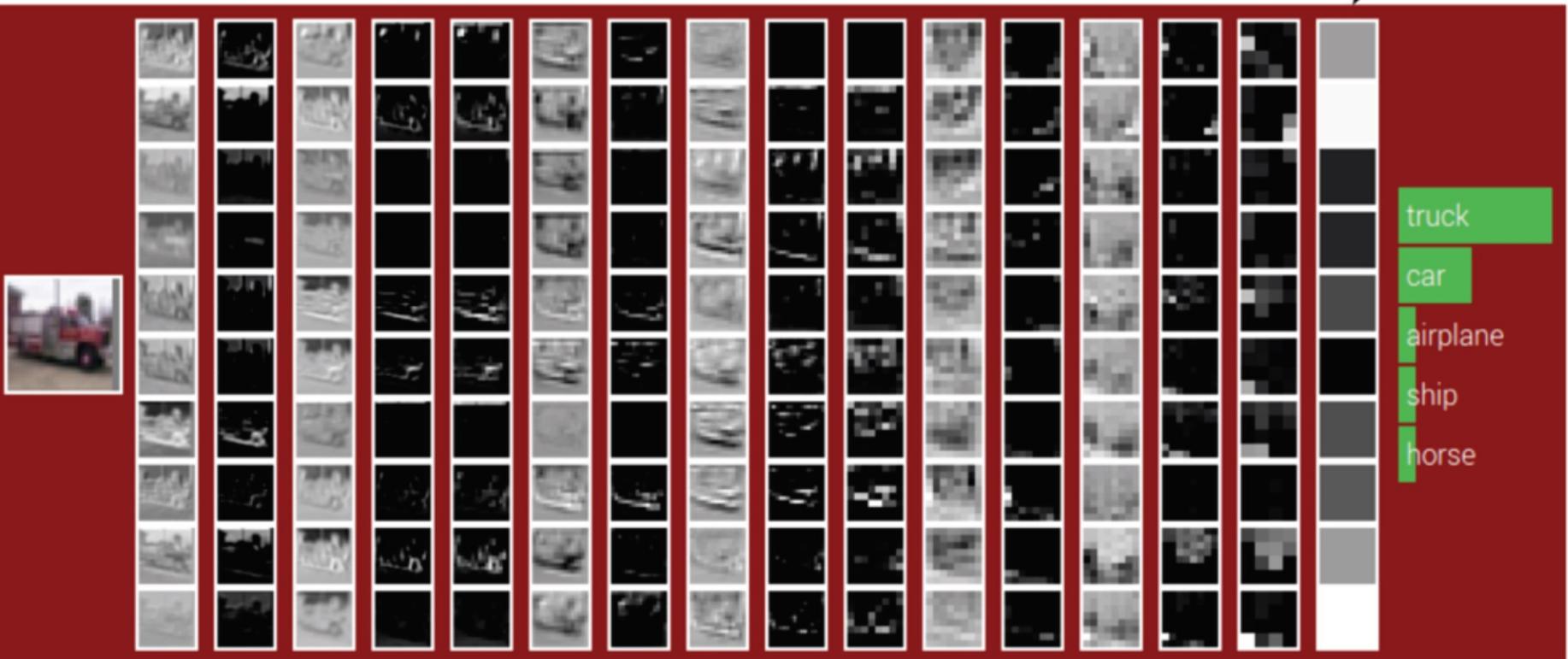
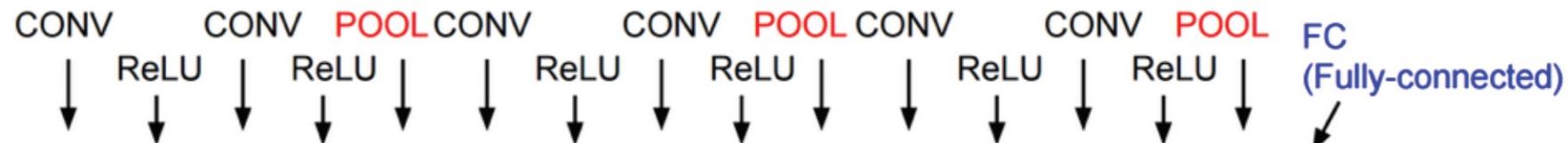
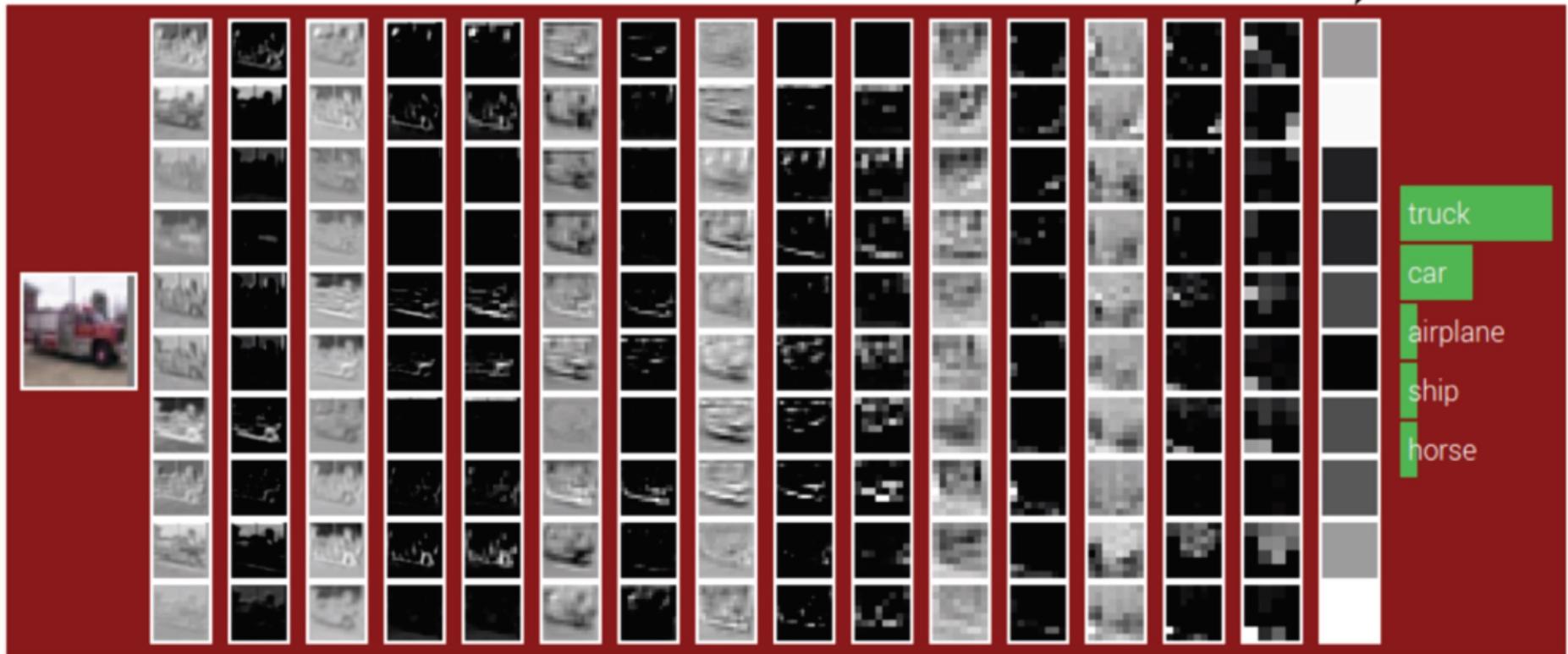


Figure: Andrej Karpathy

# Example ConvNet

CONV    CONV    POOL    CONV    CONV    POOL    CONV    CONV    POOL  
↓            ↓            ↓            ↓            ↓            ↓            ↓            ↓            ↓  
ReLU        ReLU        ReLU        ReLU        ReLU        ReLU        ReLU        ReLU

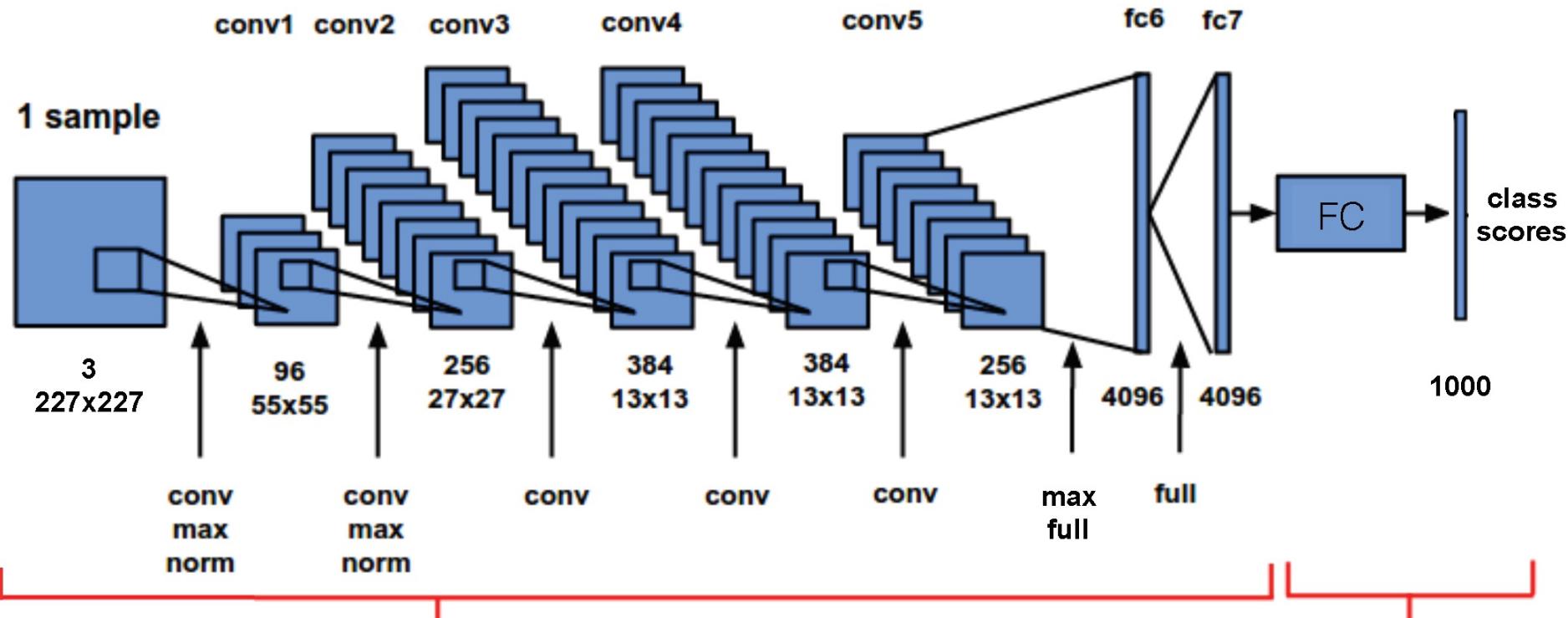


10x3x3 conv filters, stride 1, pad 1

2x2 pool filters, stride 2

*Figure: Andrej Karpathy*

# Example: AlexNet [Krizhevsky 2012]



**Extract high level features**

**Classify each sample**

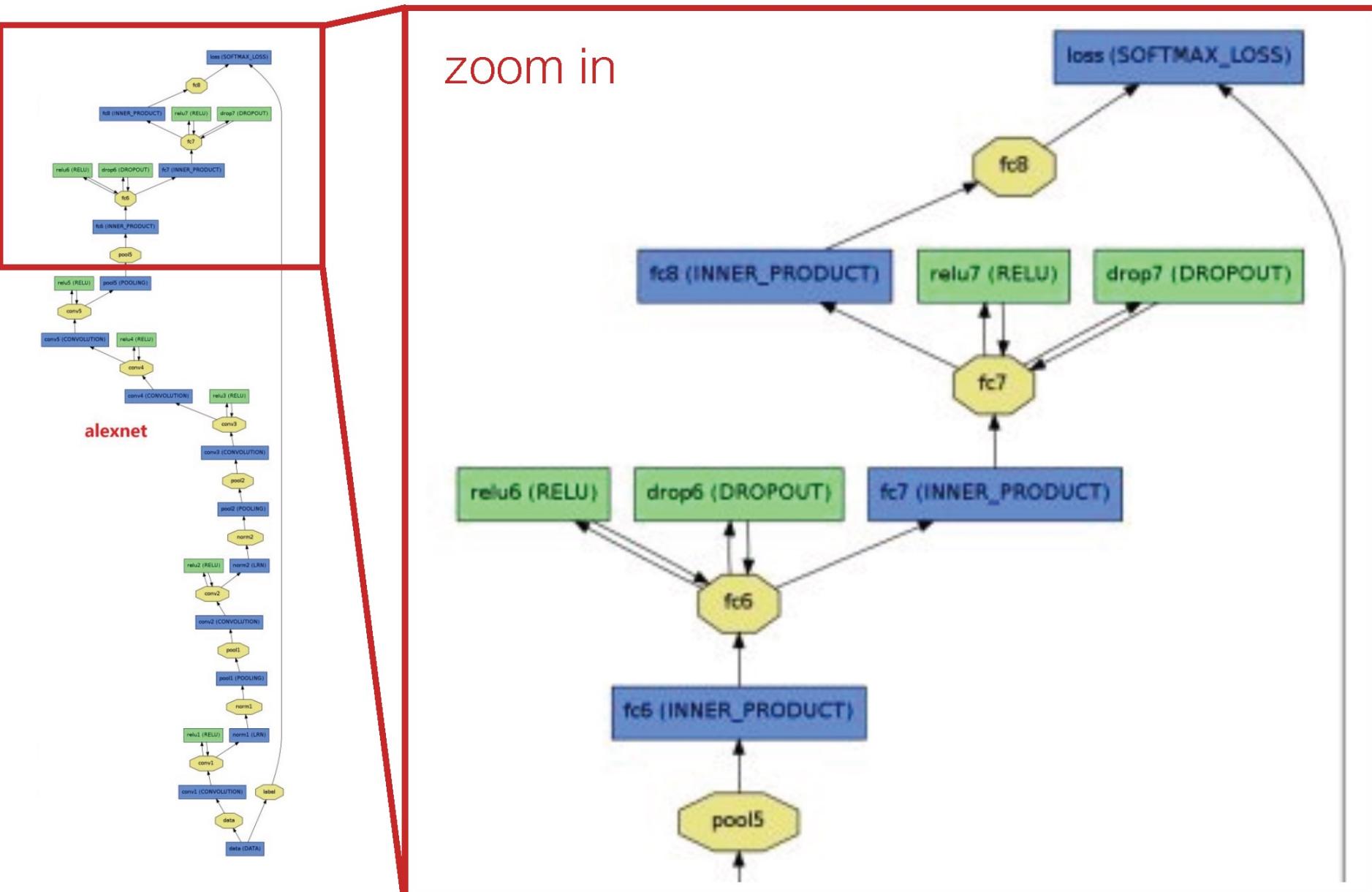
“max”: max pooling

“norm”: local response normalization

“full”: fully connected

Figure: [Karnowski 2015] (with corrections)

# Example: AlexNet [Krizhevsky 2012]

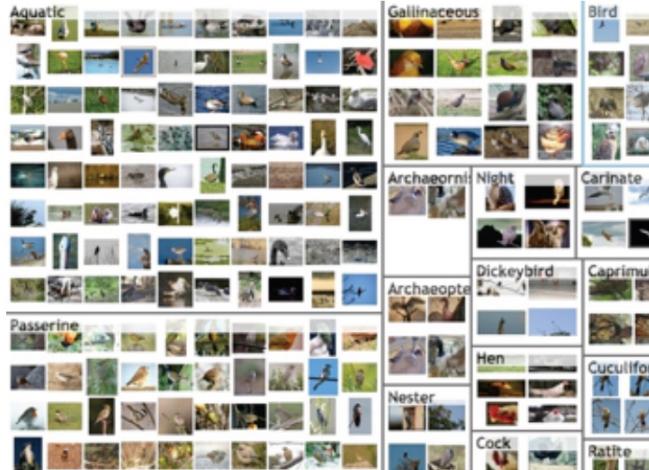


# Training ConvNets

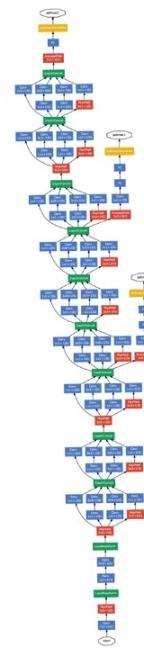
# How do you actually train these things?

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

# Mini-batch Gradient Descent

## Loop:

1. Sample a batch of training data (~100 images)
2. Forwards pass: compute loss (avg. over batch)
3. Backwards pass: compute gradient
4. Update all parameters

**Note:** usually called “stochastic gradient descent” even though SGD has a batch size of 1

# Regularization

**Regularization reduces overfitting:**

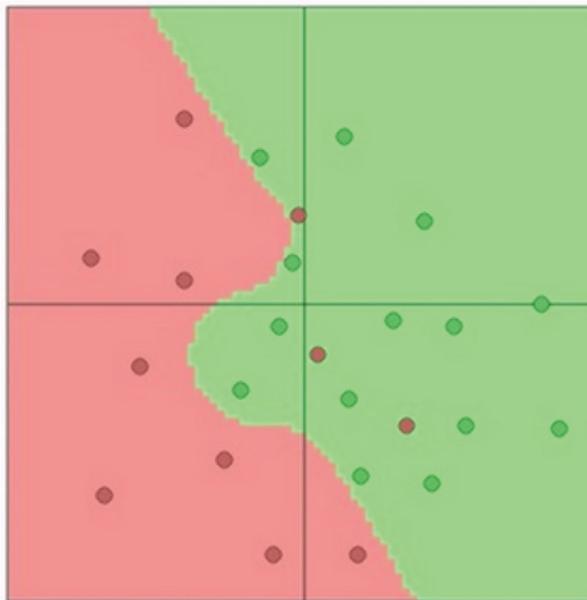
$$L = L_{\text{data}} + L_{\text{reg}}$$

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

$\lambda = 0.001$



$\lambda = 0.01$



$\lambda = 0.1$

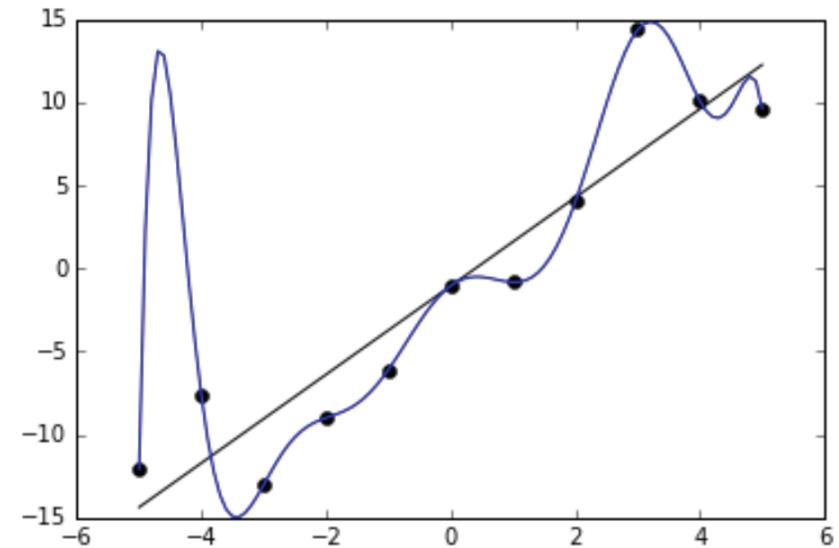


# Overfitting

**Overfitting:** modeling noise in the training set instead of the “true” underlying relationship

**Underfitting:** insufficiently modeling the relationship in the training set

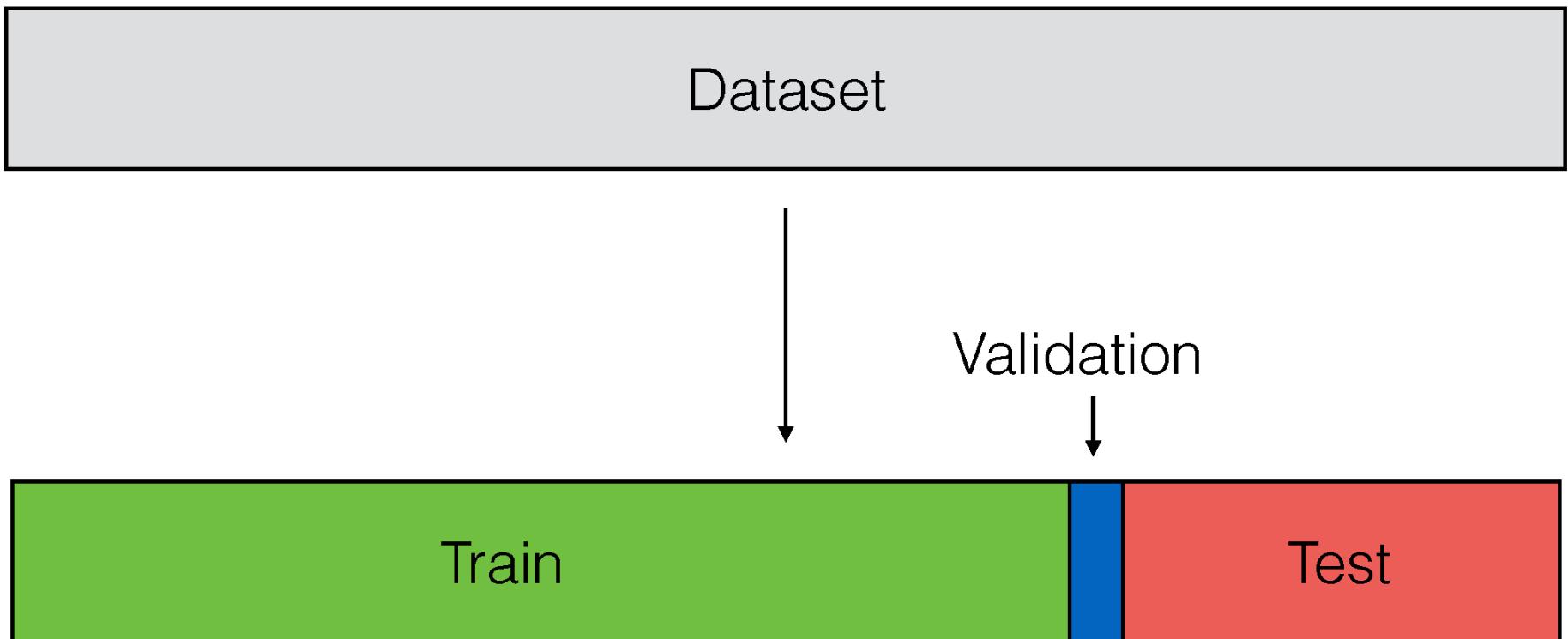
**General rule:** models that are “bigger” or have more capacity are more likely to overfit



[Image: [https://en.wikipedia.org/wiki/File:Overfitted\\_Data.png](https://en.wikipedia.org/wiki/File:Overfitted_Data.png)]

# (0) Dataset split

**Split your data into “train”, “validation”, and “test”:**



# (0) Dataset split



**Train:** gradient descent and fine-tuning of parameters

**Validation:** determining hyper-parameters (learning rate, regularization strength, etc) and picking an architecture

**Test:** estimate real-world performance  
(e.g. accuracy = fraction correctly classified)

# (0) Dataset split



**Be careful with false discovery:**

To avoid false discovery, once we have used a test set once, we should *not use it again* (but nobody follows this rule, since it's expensive to collect datasets)

Instead, try and avoid looking at the test score until the end

# (1) Data preprocessing

Preprocess the data so that learning is better conditioned:

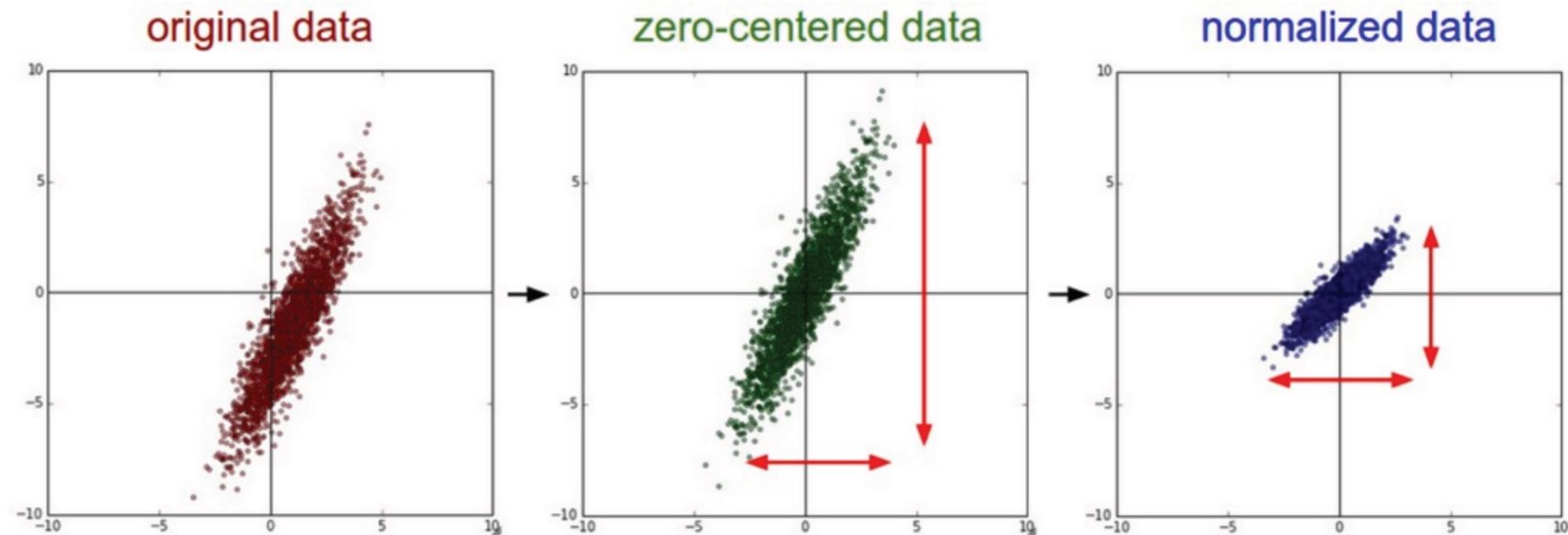
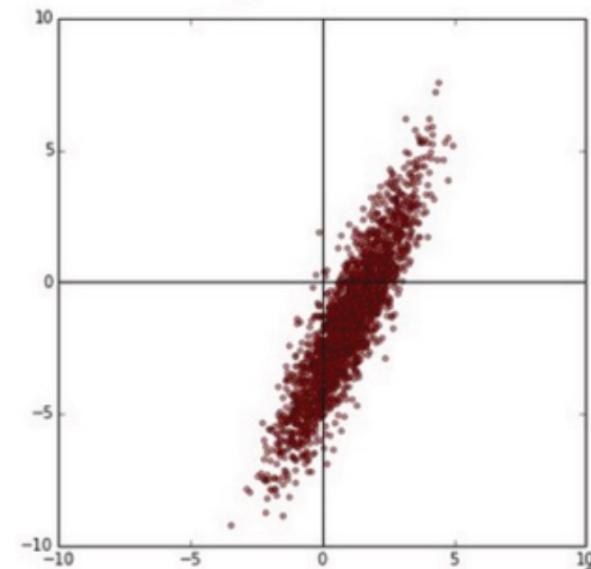


Figure: Andrej Karpathy

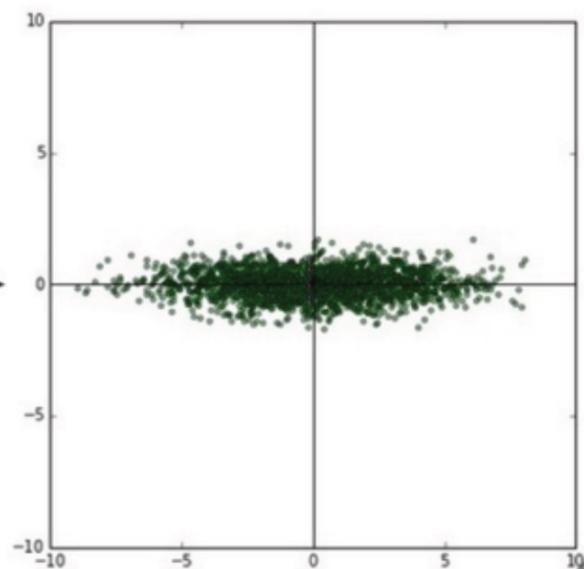
# (1) Data preprocessing

In practice, you may also see **PCA** and **Whitening** of the data:

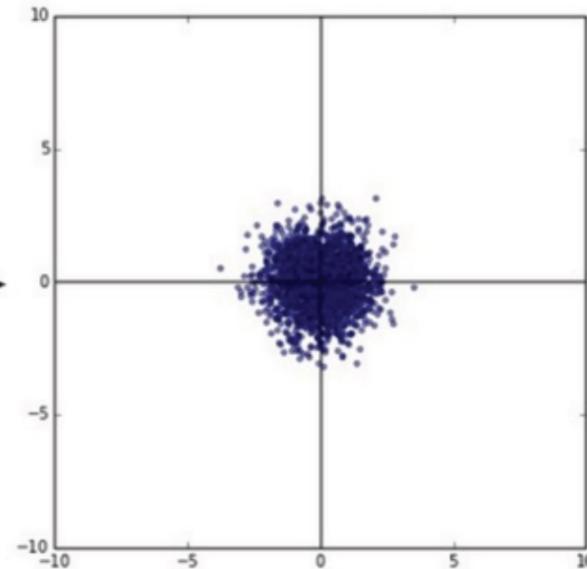
original data



decorrelated data



whitened data

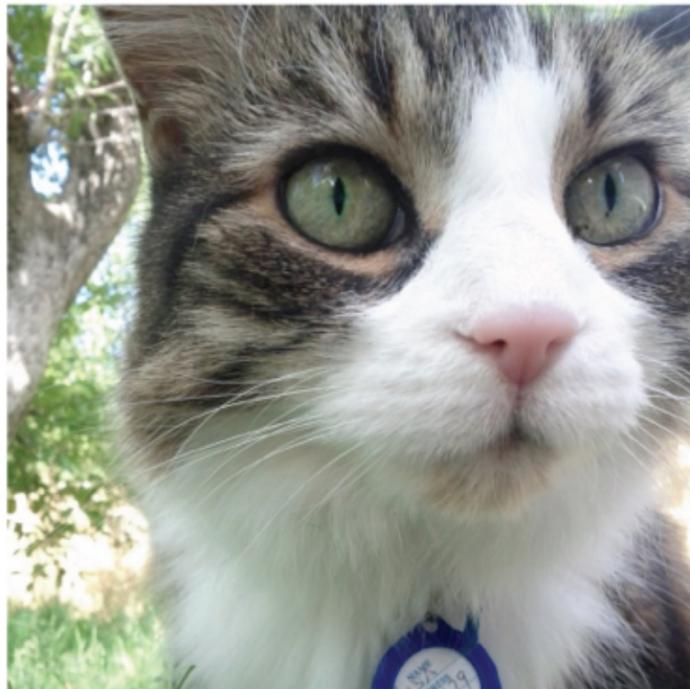


(data has diagonal covariance matrix)

(covariance matrix is the identity matrix)

# (1) Data preprocessing

For ConvNets, typically only the mean is subtracted.



An input image (256x256)



Minus sign



The mean input image

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

*Figure: Alex Krizhevsky*

# (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

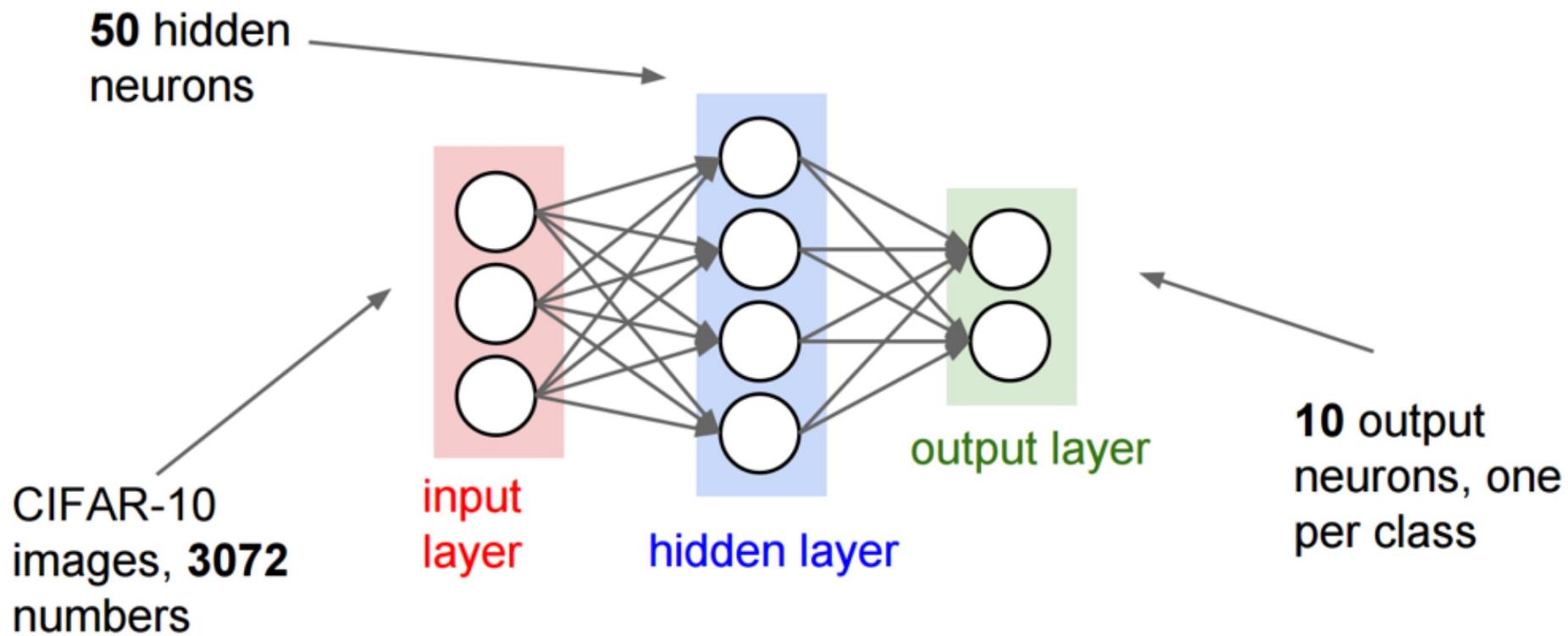
Randomly reflect horizontally

Perform the augmentation live  
during training

*Figure: Alex Krizhevsky*

# (2) Choose your architecture

**Toy example: one hidden layer of size 50**



# (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)

(the magnitude is important and this is not optimal — more on this later)

**Set the bias to zero (or small nonzero):**

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

# (3) Check that the loss is reasonable

```
def init_two_layer_model(input_size, hidden_size, output_size):  
    # initialize a model  
    model = {}  
    model['W1'] = 0.0001 * np.random.randn(input_size, hidden_size)  
    model['b1'] = np.zeros(hidden_size)  
    model['W2'] = 0.0001 * np.random.randn(hidden_size, output_size)  
    model['b2'] = np.zeros(output_size)  
    return model
```

```
model = init_two_layer_model(32*32*3, 50, 10) # input size, hidden size, number of classes  
loss, grad = two_layer_net(X_train, model, y_train 0.0) disable regularization  
print loss
```



returns the loss and the  
gradient for all parameters

# (3) Check that the loss is reasonable

```
def init_two_layer_model(input_size, hidden_size, output_size):  
    # initialize a model  
    model = {}  
    model['W1'] = 0.0001 * np.random.randn(input_size, hidden_size)  
    model['b1'] = np.zeros(hidden_size)  
    model['W2'] = 0.0001 * np.random.randn(hidden_size, output_size)  
    model['b2'] = np.zeros(output_size)  
    return model
```

```
model = init_two_layer_model(32*32*3, 50, 10) # input size, hidden size, number of classes  
loss, grad = two_layer_net(X_train, model, y_train, 1e3)    crank up regularization  
print loss
```



loss went up, good. (sanity check)

# (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)
```

## 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

# (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 20 / 200: cost 1.305760, train: 0.550000, val 0.550000, 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
```

(4) Find a learning rate

Let's start with small regularization and find the learning rate that makes the loss decrease:

# (4) Find a learning rate

```
model = init_two_layer_model(32*32*3, 50, 10) # input size, hidden size, number of classes
trainer = ClassifierTrainer()
best_model, stats = trainer.train(X_train, y_train, X_val, y_val,
                                  model, two_layer_net,
                                  num_epochs=10, reg=0.000001,
                                  update='sgd', learning_rate_decay=1,
                                  sample_batches = True,
                                  learning_rate=1e-6, verbose=True)
```

```
Finished epoch 1 / 10: cost 2.302576, train: 0.080000, val 0.103000, lr 1.000000e-06
Finished epoch 2 / 10: cost 2.302582, train: 0.121000, val 0.124000, lr 1.000000e-06
Finished epoch 3 / 10: cost 2.302558, train: 0.119000, val 0.138000, lr 1.000000e-06
Finished epoch 4 / 10: cost 2.302519, train: 0.127000, val 0.151000, lr 1.000000e-06
Finished epoch 5 / 10: cost 2.302517, train: 0.158000, val 0.171000, lr 1.000000e-06
Finished epoch 6 / 10: cost 2.302518, train: 0.179000, val 0.172000, lr 1.000000e-06
Finished epoch 7 / 10: cost 2.302466, train: 0.180000, val 0.176000, lr 1.000000e-06
Finished epoch 8 / 10: cost 2.302452, train: 0.175000, val 0.185000, lr 1.000000e-06
Finished epoch 9 / 10: cost 2.302459, train: 0.206000, val 0.192000, lr 1.000000e-06
Finished epoch 10 / 10: cost 2.302420, train: 0.190000, val 0.192000, lr 1.000000e-06
finished optimization. best validation accuracy: 0.192000
```

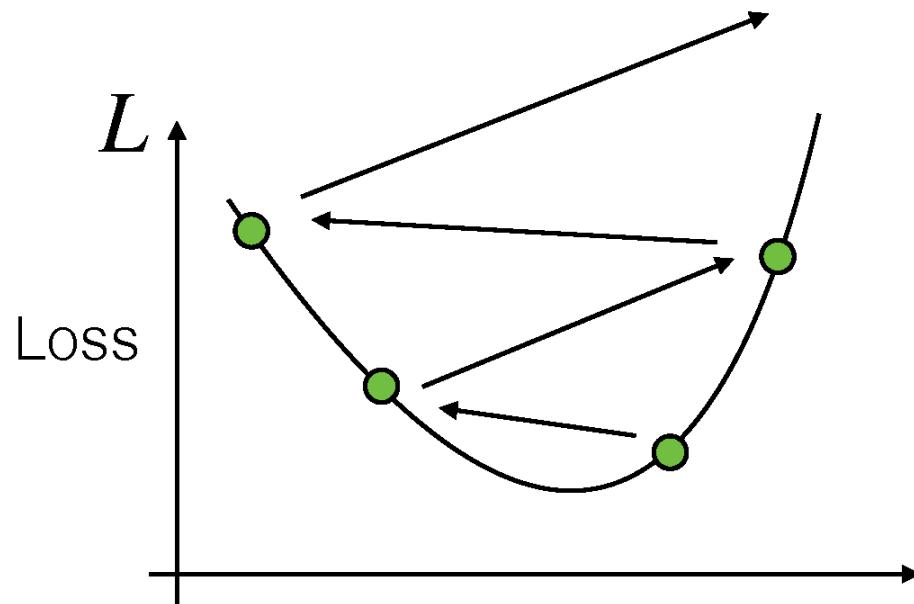
**Loss barely changes**

(learning rate is too low or regularization too high)

**Why is the accuracy 20%?**

# (4) Find a learning rate

Learning rate: 1e6 — what could go wrong?



A weight somewhere in the network

# (4) Find a learning rate

## **Coarse to fine search**

First stage: only a few epochs (passes through the data) to get a rough idea

Second stage: longer running time, finer search

**Tip:** if  $\text{loss} > 3 * \text{original loss}$ , quit early  
(learning rate too high)

# (4) Find a learning rate

**Normally, you don't have the budget for lots of cross-validation** —> visualize as you go

## Plot the loss

For very small learning rates, the loss decreases linearly and slowly

*(Why linear?)*

Larger learning rates tend to look more exponential

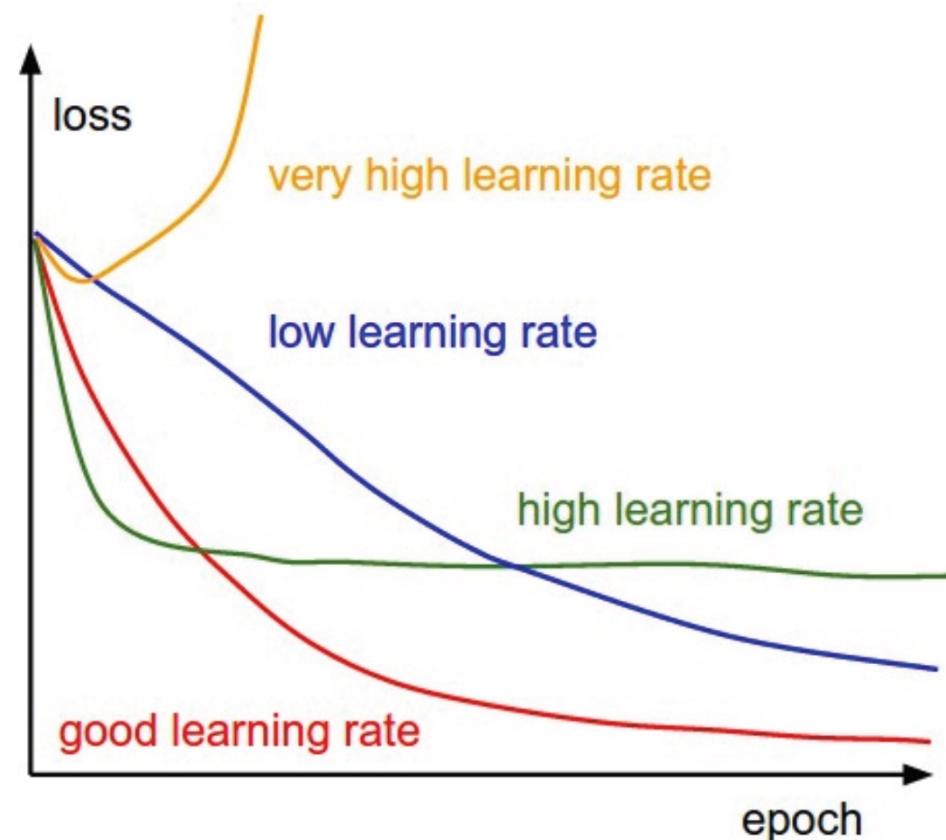


Figure: Andrej Karpathy

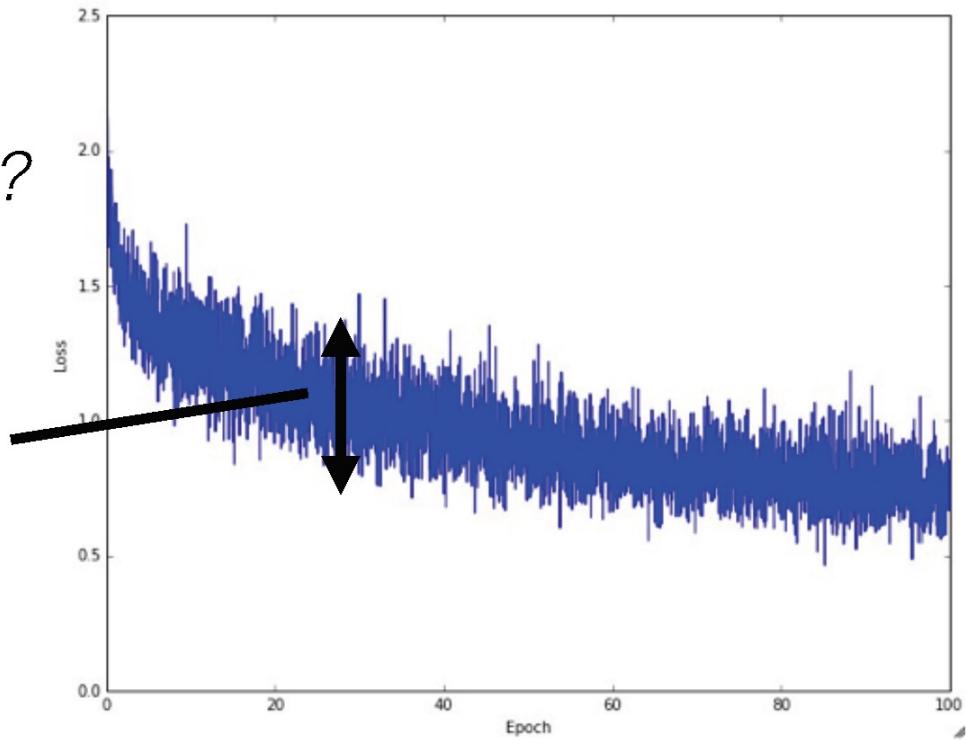
# (4) Find a learning rate

**Normally, you don't have the budget for lots of cross-validation** —> visualize as you go

**Typical training loss:**

*Why is it varying so rapidly?*

The width of the curve is related to the batchsize — if too noisy, increase the batch size

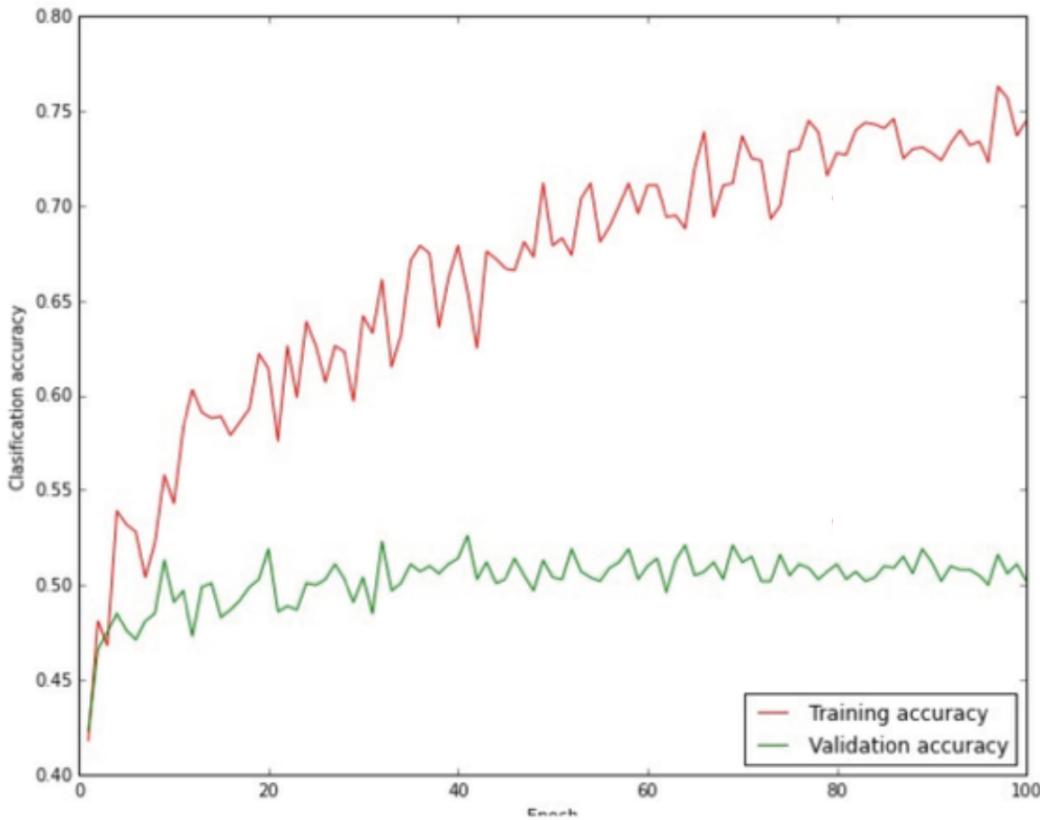


Possibly too linear  
(learning rate too small)

*Figure: Andrey Karpathy*

# (4) Find a learning rate

## Visualize the accuracy



**Big gap:** overfitting  
(increase regularization)

**No gap:** underfitting  
(increase model capacity,  
make layers bigger  
or decrease regularization)

# (4) Find a learning rate

## Visualize the weights

Noisy weights: possibly regularization not strong enough

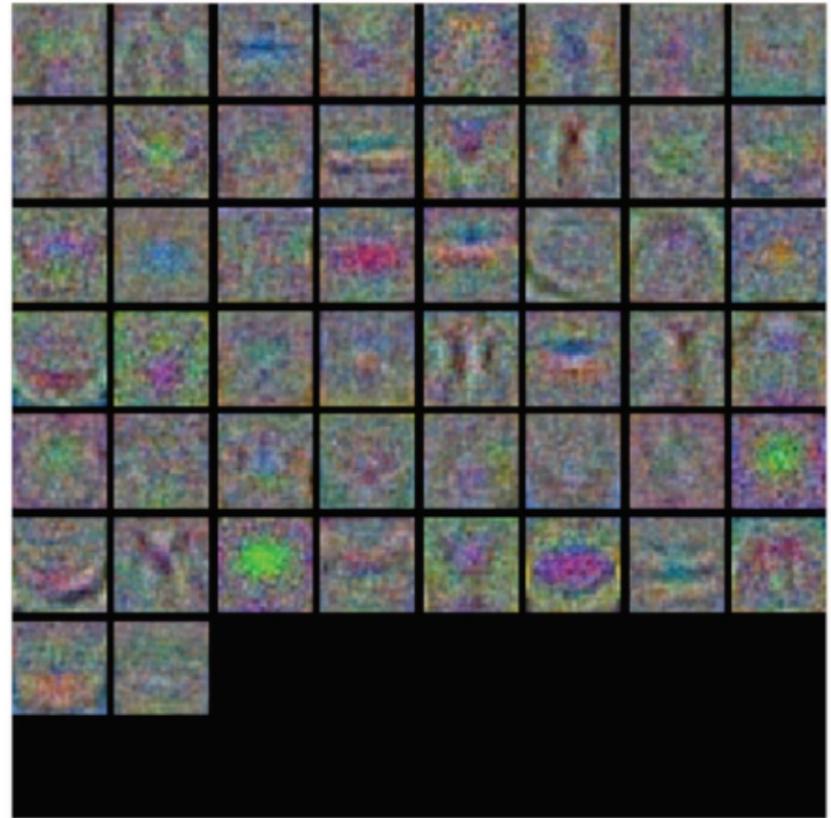


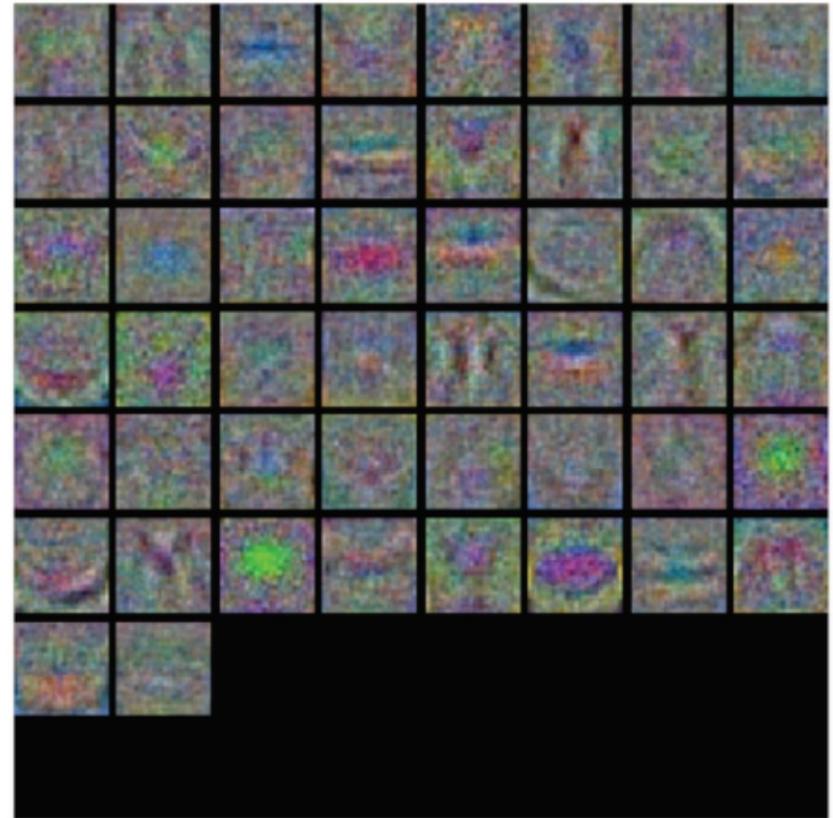
Figure: Andrej Karpathy

# (4) Find a learning rate

## Visualize the weights



Nice clean weights:  
training is proceeding well



*Figure: Alex Krizhevsky , Andrej Karpathy*

# 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

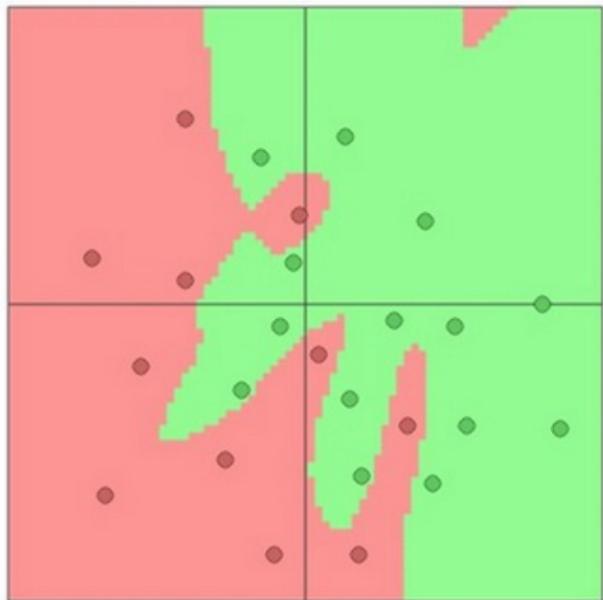


# (Recall) Regularization reduces overfitting

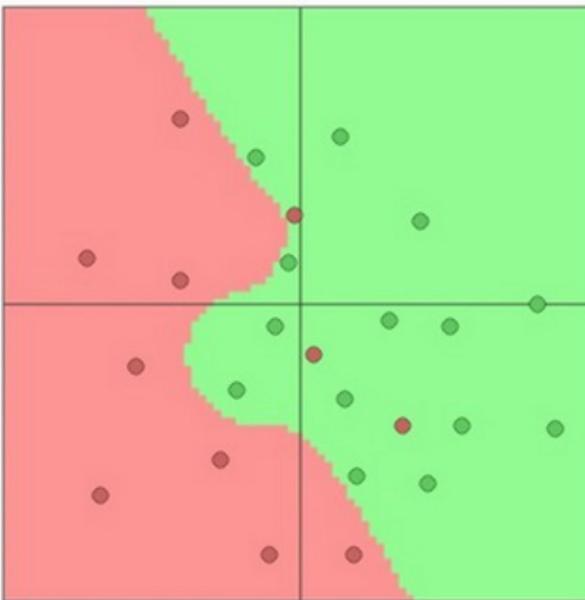
$$L = L_{\text{data}} + L_{\text{reg}}$$

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

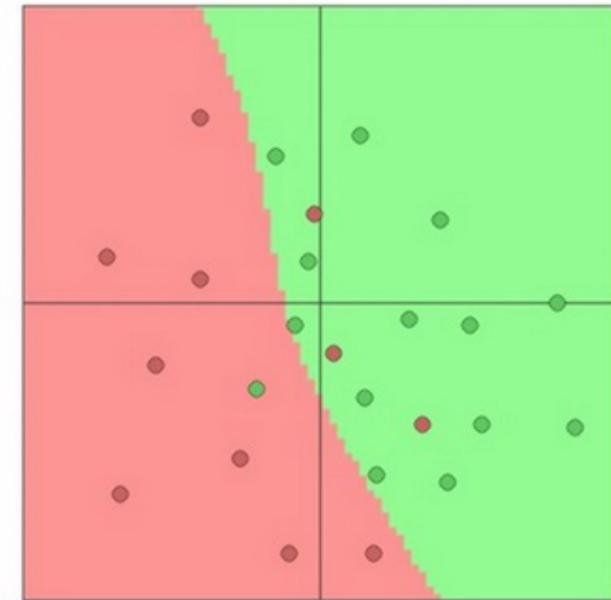
$\lambda = 0.001$



$\lambda = 0.01$



$\lambda = 0.1$



# Example Regularizers

## L2 regularization

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

(L2 regularization encourages small weights)

## L1 regularization

$$L_{\text{reg}} = \lambda \|W\|_1 = \lambda \sum_{ij} |W_{ij}|$$

(L1 regularization encourages sparse weights:  
weights are encouraged to reduce to exactly zero)

## “Elastic net”

$$L_{\text{reg}} = \lambda_1 \|W\|_1 + \lambda_2 \|W\|_2^2$$

(combine L1 and L2 regularization)

## Max norm

Clamp weights to some max norm

$$\|W\|_2^2 \leq c$$

# “Weight decay”

**Regularization is also called “weight decay” because the weights “decay” each iteration:**

$$L_{\text{reg}} = \lambda \frac{1}{2} \|W\|_2^2 \longrightarrow \frac{\partial L}{\partial W} = \lambda W$$

Gradient descent step:

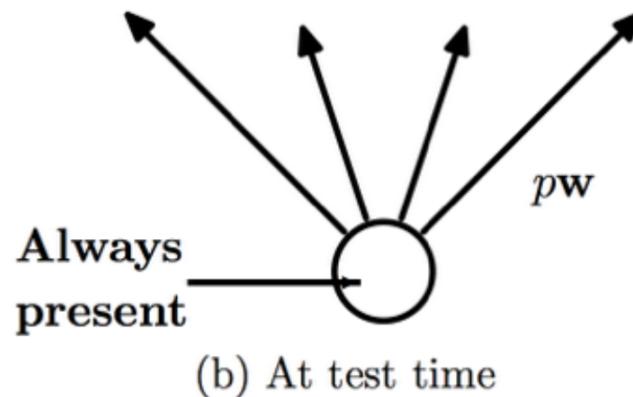
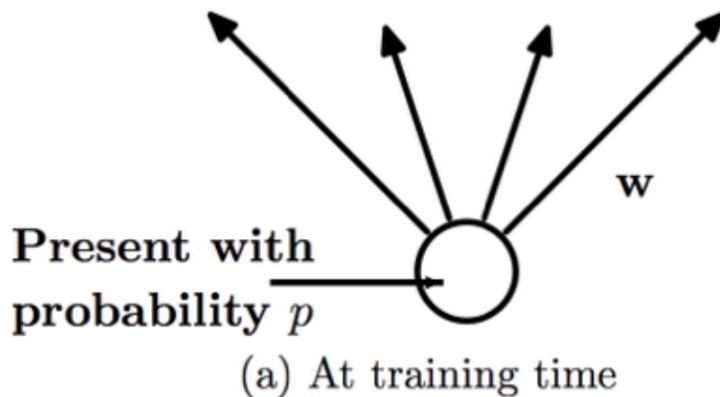
$$W \leftarrow W - \alpha \lambda W - \frac{\partial L_{\text{data}}}{\partial W}$$

Weight decay:  $\alpha \lambda$  (weights always decay by this amount)

**Note:** biases are sometimes excluded from regularization

# Dropout

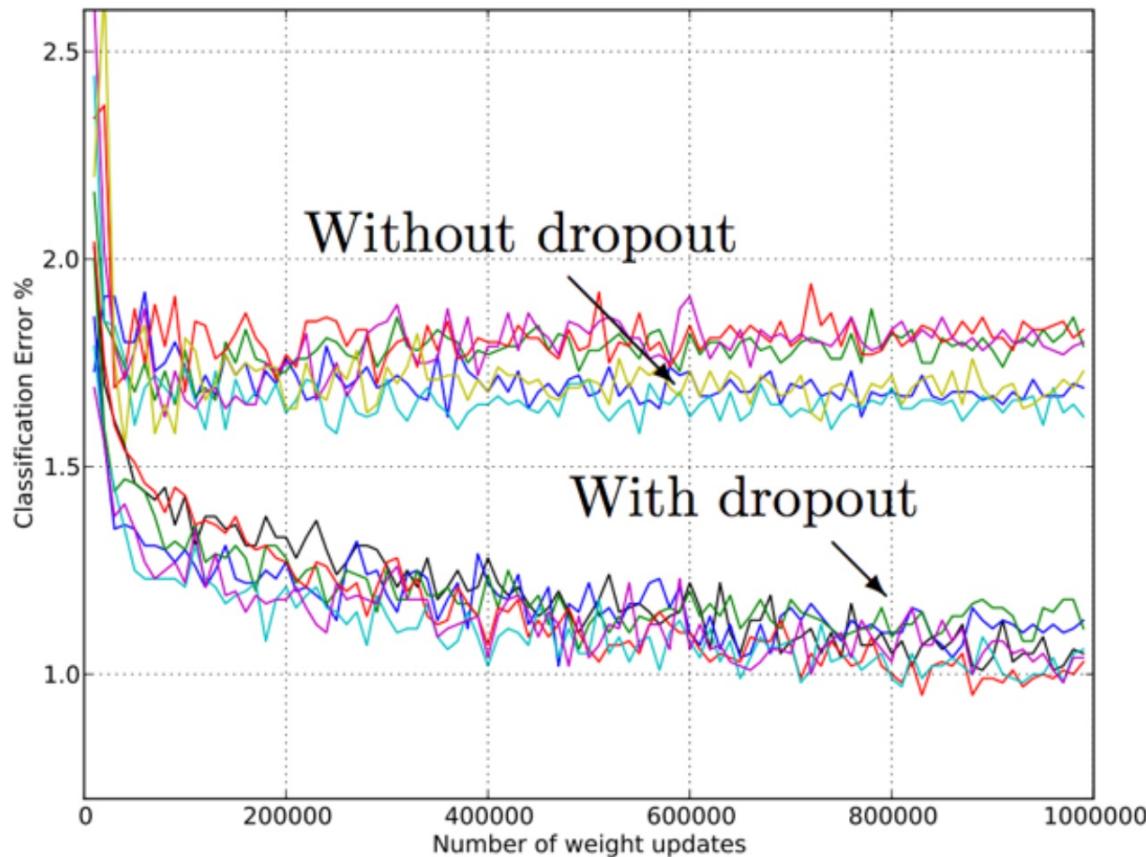
**Simple but powerful technique to reduce overfitting:**



[Srivasta et al, “Dropout: A Simple Way to Prevent Neural Networks from Overfitting”, JMLR 2014]

# Dropout

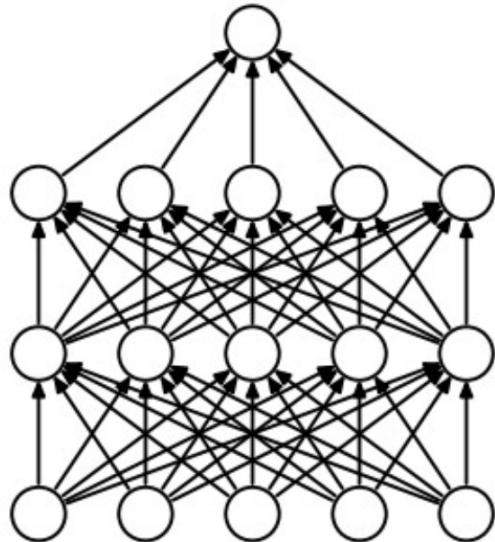
**Simple but powerful technique to reduce overfitting:**



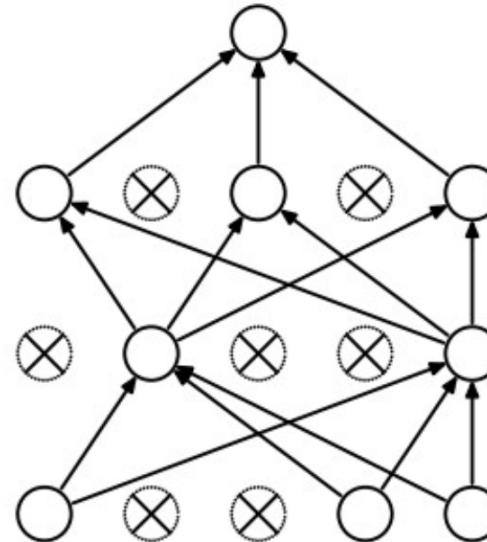
[Srivasta et al, "Dropout: A Simple Way to Prevent Neural Networks from Overfitting", JMLR 2014]

# Dropout

**Simple but powerful technique to reduce overfitting:**



(a) Standard Neural Net



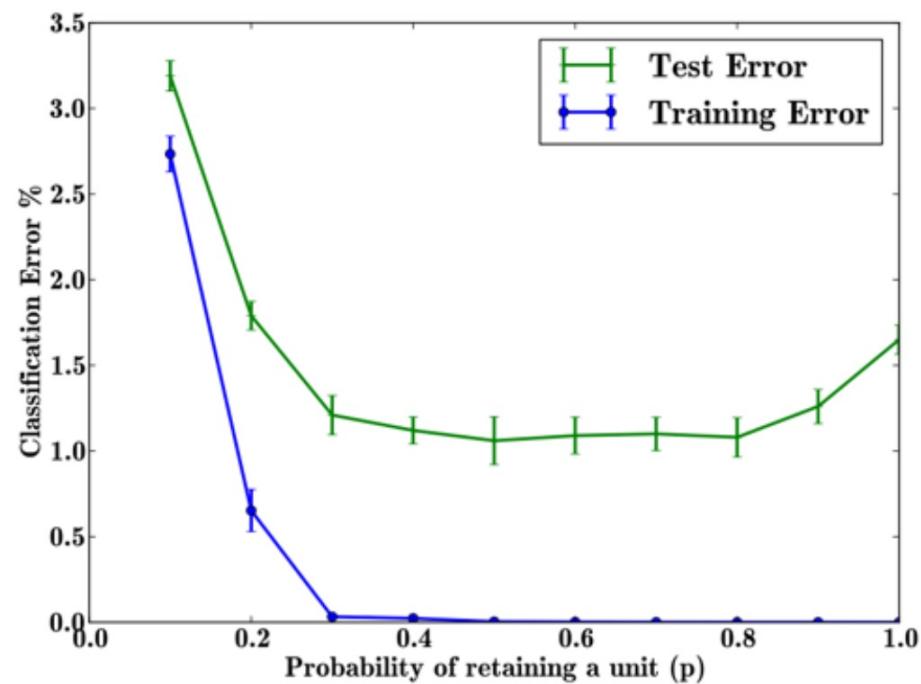
(b) After applying dropout.

**Note:** Dropout can be interpreted as an approximation to taking the geometric mean of an ensemble of exponentially many models

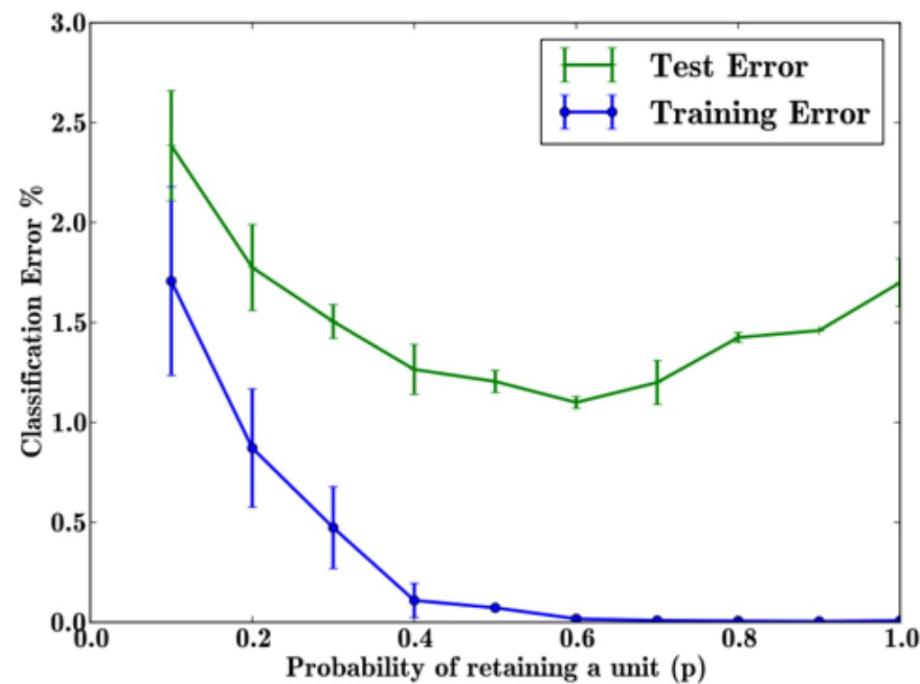
[Srivasta et al, “Dropout: A Simple Way to Prevent Neural Networks from Overfitting”, JMLR 2014]

# Dropout

**How much dropout?** Around  $p = 0.5$



(a) Keeping  $n$  fixed.



(b) Keeping  $pn$  fixed.

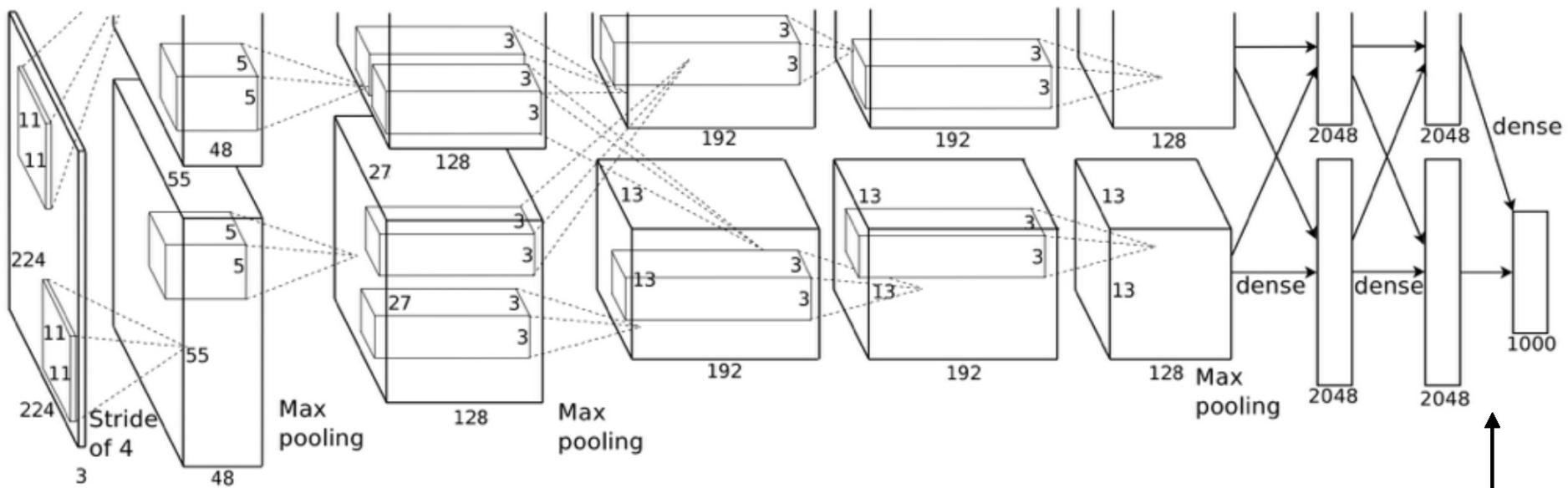
[Srivasta et al, “Dropout: A Simple Way to Prevent Neural Networks from Overfitting”, JMLR 2014]

# Dropout

## Case study: [Krizhevsky 2012]

*“Without dropout, our network exhibits substantial overfitting.”*

Dropout here  
↓  
↓



**But not here — why?**

[Krizhevsky et al, “ImageNet Classification with Deep Convolutional Neural Networks”, NIPS 2012]

# 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)
```

(note, here  $X$  is a single input)

Example forward pass with a 3-layer network using dropout

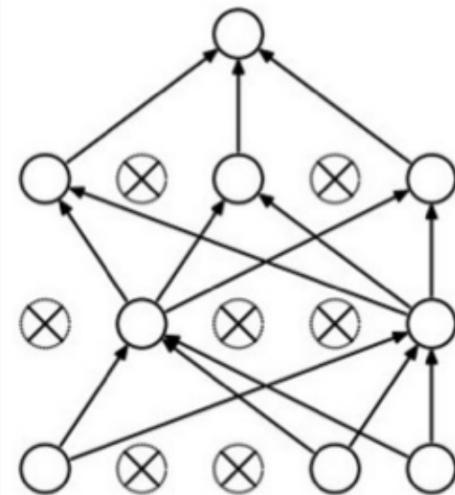


Figure: Andrej Karpathy

# Dropout

**Test time:** scale the activations

Expected value of a neuron  $h$  with dropout:

$$E[h] = ph + (1 - p)0 = ph$$

```
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
```

We want to keep the same expected value

# Summary

- Preprocess the data (subtract mean, sub-crops)
- Initialize weights carefully
- Use Dropout
- Use SGD + Momentum
- Fine-tune from ImageNet
- Babysit the network as it trains