# Deep Learning 1

#### Pointers from Last Time

- Saving your models
  - Just need to save parameters
  - Can Use it anywhere
  - E.g. in linear regression with y=w1x1 + w2 you can just save w1 and w2 forever!
  - No data dependence after training
- Cost function is only used during training. Prediction function is eternal.
- Linear regression can be made non linear just by adding multiple powers of the same feature

# Motivation: ImageNet

### Image Classification Dataset





# ~1,000,000 images ~1,000 classes

Ground truths prepared manually through Amazon Mechanical Turk

You score if ground truth class is one your top 5 predictions

ImageNet Top-5 challenge:

Best approaches used hand-crafted features (SIFT, HOGs, Fisher vectors, etc) + classifier

Top-5 error rate: ~25%



The Game Has Changed...

Krizhevsky, Sutskever and Hinton;

ImageNet Classification with

Deep Convolutional Neural networks [Krizhevsky12]

Top-5 error rate of ~15%

In the last few years, more modern networks have achieved better results.

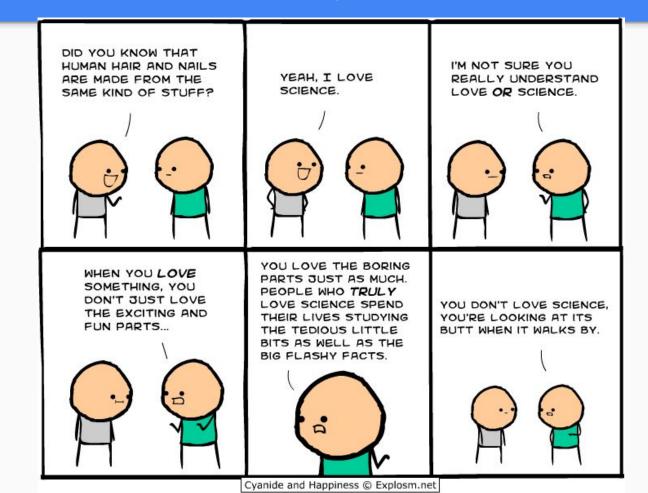
[Simonyan14, He15]

Top-5 error rates of ~5-7%

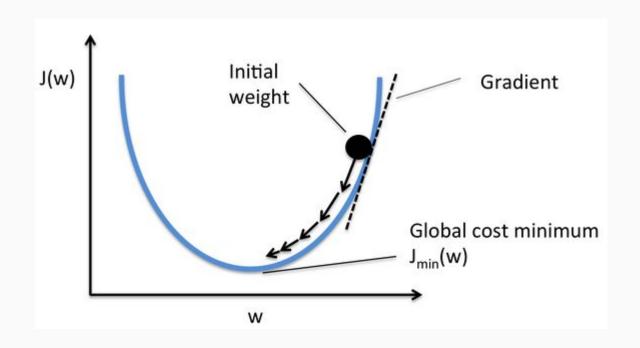
#### **Gradient Descent: Understanding the Math**

- We talked about loss functions (i.e. cost functions)
  - Absolute Loss | h(x) y |
  - Quadrative Loss (h(x) -y)<sup>2</sup>
- Real world is not so generous.
- The following cycle goes on and on until we have a reasonable model
  - Predict using current hypothesis (last time)
  - Find how good the prediction was (last time)
  - Update the hypothesis. (this time)
- Q: How Does the update step happen?
  - A: Gradient Descent

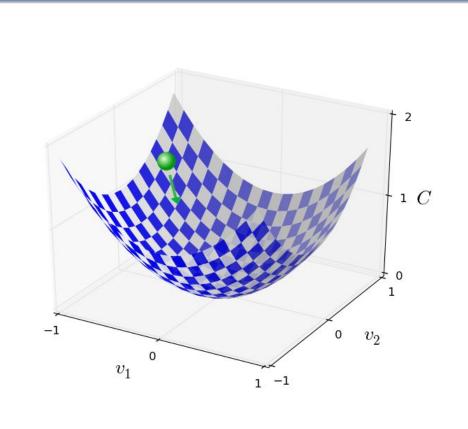
### Motivation (http://explosm.net/comics/3557/)



### **Gradient Descent (Cont.)**



### Gradient Descent (cont.)



### Algorithm

### Gradient descent algorithm

repeat until convergence { 
$$\theta_j := \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta_0, \theta_1)$$
 (for  $j = 1$  and  $j = 0$ )

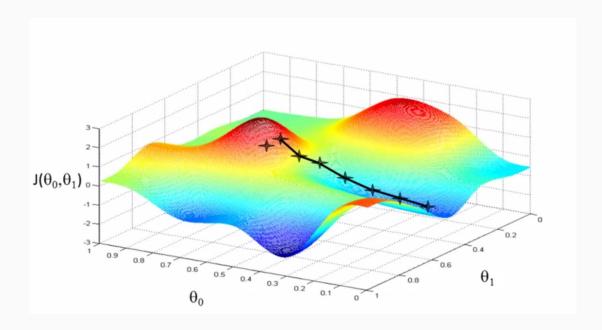
### Repeat until convergence

{ 
$$\theta_j := \theta_j - \alpha \frac{1}{m} \sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)}) x_j^{(i)}$$
 }

 $\label{local-equation-equation} $$ $$ https://2.bp.blogspot.com/-AdV-O-MoZHE/TtLibFTaf9I/AAAA AAAAAVM/aOxUGP7zl98/s1600/gradient+descent+algorithm +OLS.png$ 

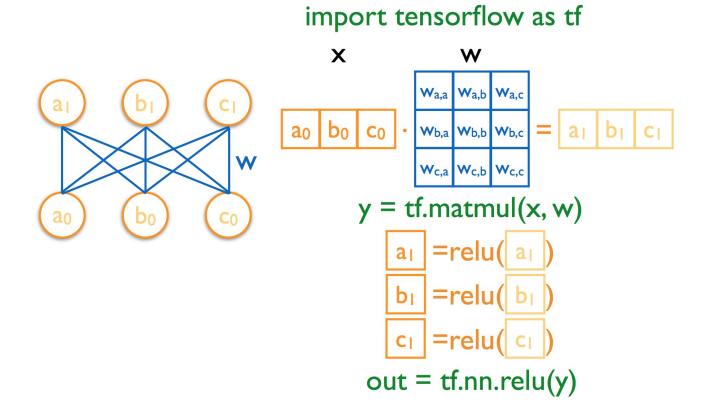
http://2.bp.blogspot.com/-ZxJ87cWjPJ8/TtLtwqv0hCl/AAAAAAAAAV0/9FYqcxJ6dNY/s1600/gradient+descent+algorithm+OLS.png

### Real world is ugly



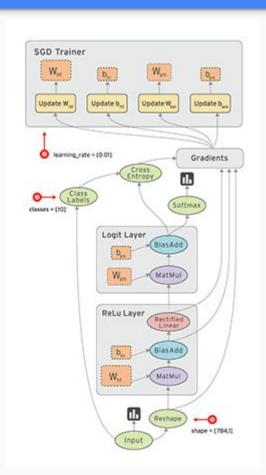
## TensorFlow

#### TensorFlow: Introduction



### **Data Flow Graph**

- Describe mathematical computation with a directed graph of <u>nodes</u> & <u>edges</u>.
  - Nodes in the graph represent mathematical operations.
  - Edges describe the i/o relationships between nodes.
  - Data edges carry dynamically-sized multidimensional data arrays, or tensors.
- Nodes are assigned to computational devices and execute asynchronously and in parallel once all the tensors on their incoming edges becomes available.



# TensorFlow Playground

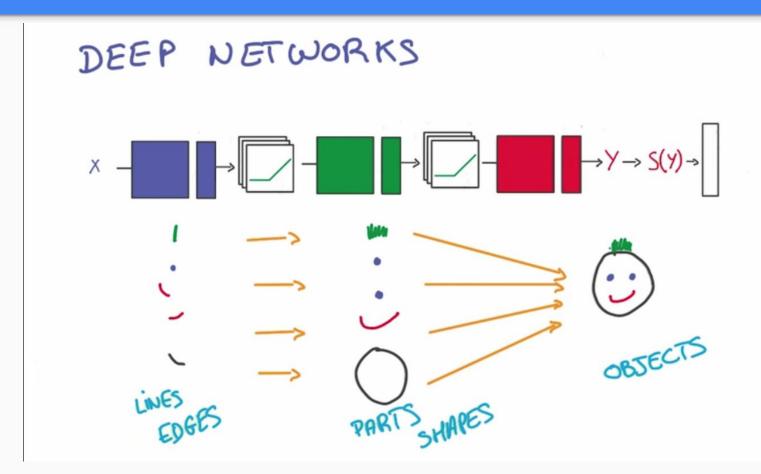
http://playground.tensorflow.org/

## Back to Code: Hello Tensor

What is Neural Network?

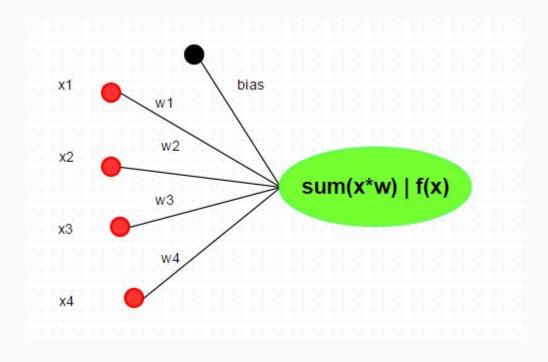
- Multiple layers
- Data propagates through layers
- ☐ Transformed by each layer

### Possible Reasoning behind effectiveness of NN's



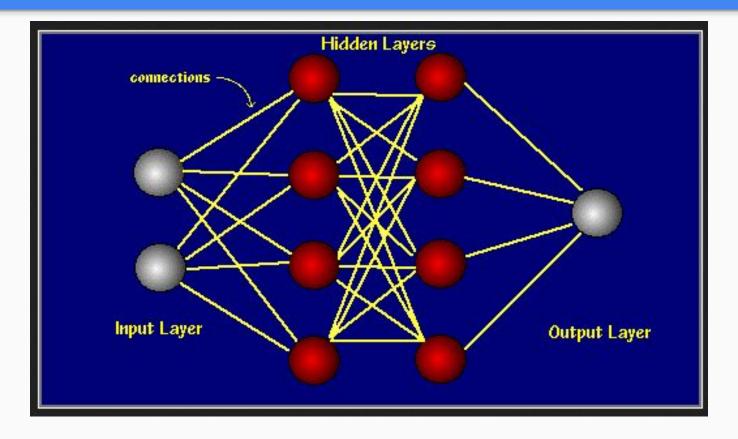
DeepLearning udacity.com

### A Perceptron: (Logistic Regression)

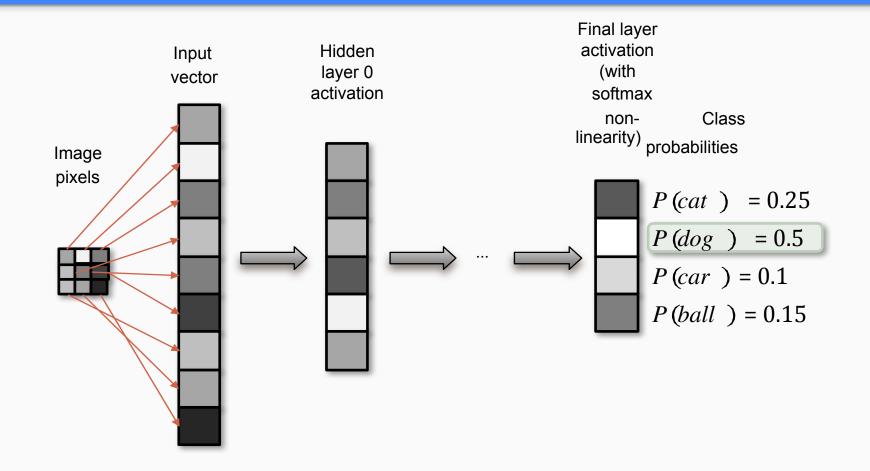


http://www.parallelr.com/wp-content/uploads/2016/02/neuron.png

### Increasing The classifiers



#### As a classifier



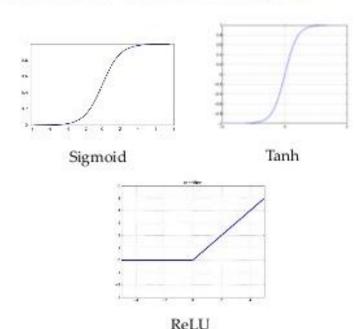
#### Types of Nonlinearities

### Non-Linear Activation Function

- Sigmoid:  $S(t) = \frac{1}{1 + e^{-t}}$ .
- Tanh:  $\tanh x = \frac{\sinh x}{\cosh x} = \frac{e^x e^{-x}}{e^x + e^{-x}}$
- Rectified Linear Unit (ReLU):

$$f(x) = \max(0, x)$$

Most popular activation function for DNN as of 2015, avoids saturation issues, makes learning faster

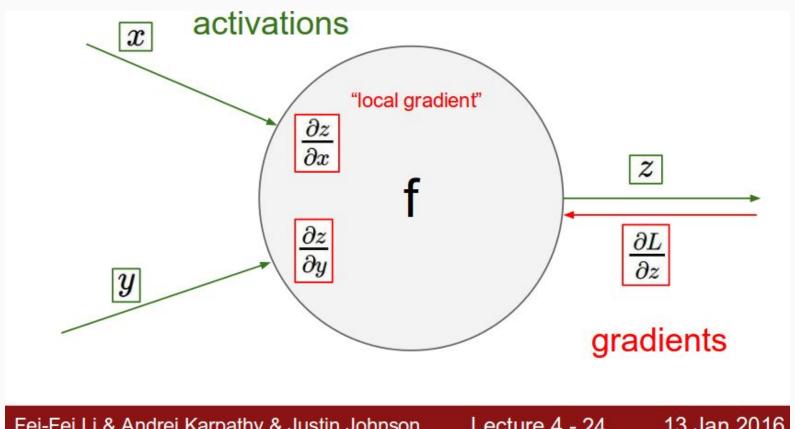


### Training a Network

- Forward Propagation
  - Multiply Weights by inputs and add them up
  - Pass the result through a nonlinearity (ReLU, Sigmoid)
  - Repeat for next layer until the end layer

- Backward Propagation
  - Each node contributes to a certain degree of error
  - Final errors is a combination of everything
  - Disperse the error to respective nodes
  - Until you reach the starting node

### Toy Example Intuition



Fei-Fei Li & Andrej Karpathy & Justin Johnson

Lecture 4 - 24

13 Jan 2016

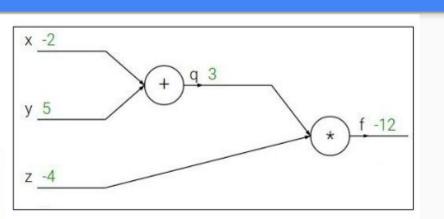
### Toy Example

$$f(x, y, z) = (x + y)z$$
  
e.g. x = -2, y = 5, z = -4

$$q=x+y \qquad rac{\partial q}{\partial x}=1, rac{\partial q}{\partial y}=1$$

$$f=qz$$
  $rac{\partial f}{\partial q}=z, rac{\partial f}{\partial z}=q$ 

Want:  $\frac{\partial f}{\partial x}$ ,  $\frac{\partial f}{\partial y}$ ,  $\frac{\partial f}{\partial z}$ 



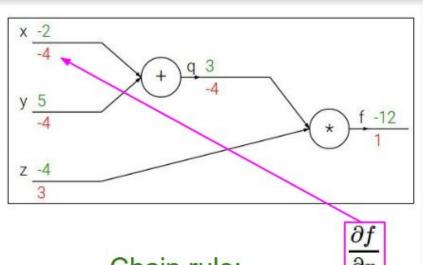
### Toy Example (Cont.)

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Want:  $\frac{\partial f}{\partial x}$ ,  $\frac{\partial f}{\partial y}$ ,  $\frac{\partial f}{\partial z}$ 



Chain rule:

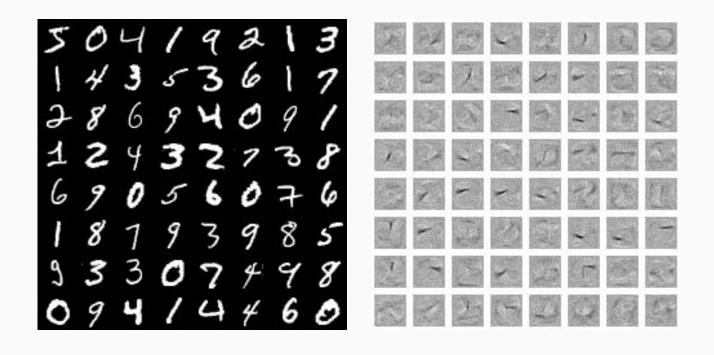
$$\frac{\partial f}{\partial x} = \frac{\partial f}{\partial q} \frac{\partial q}{\partial x}$$

Break (10 Min)

Hands On After That

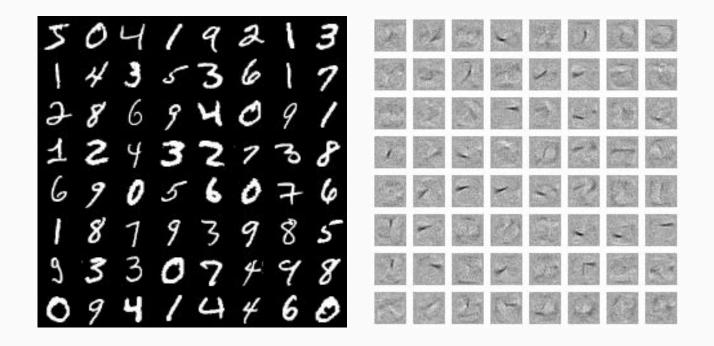
## A Problem

### Visualising the learned weights can be educational



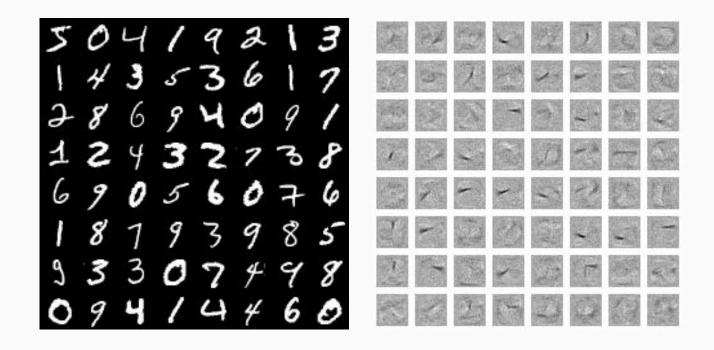
Each image visualises the weights connecting pixels to a specific unit in the first hidden layer.

Note the stroke features detected by the various units



#### The fully connected networks so far have a weakness:

# No translation invariance; learned features are position dependent



#### How do you solve this?

### For more general imagery:

- Requires a training set large enough to see all features in all possible positions...
- Requires network with enough units to represent this...

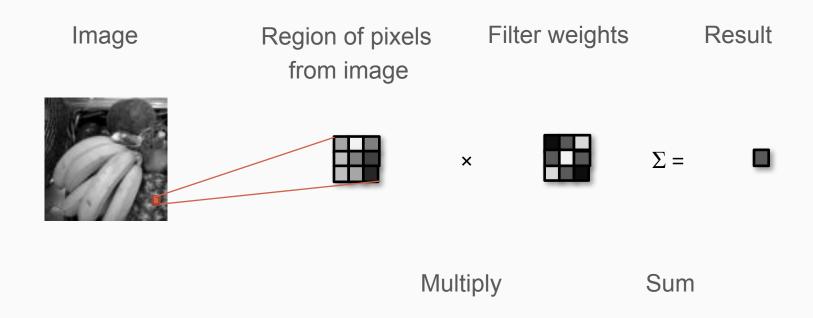
# Convolutional Networks

Convolution

Often used for feature detection

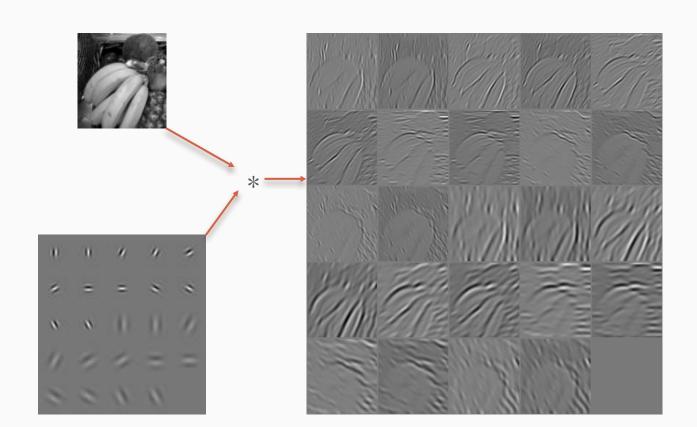
Slide a convolutional filter over an image...

#### Multiply image pixels by filter weights and sum



Do this for all possible positions in the image

#### Convolution: Gabor filters

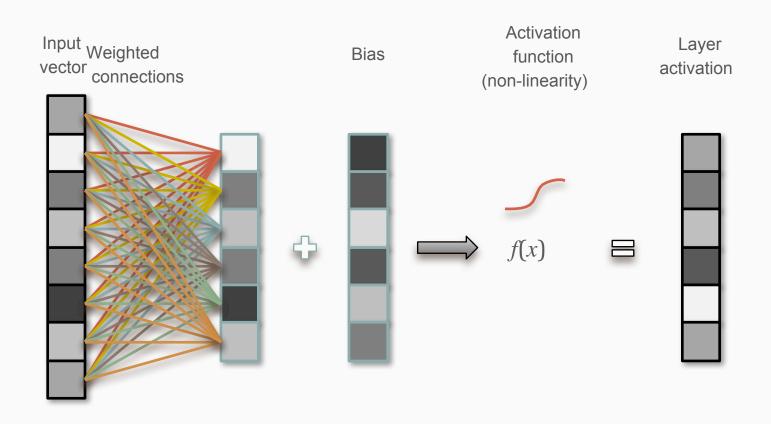


# Convolution detects features in a position independent manner

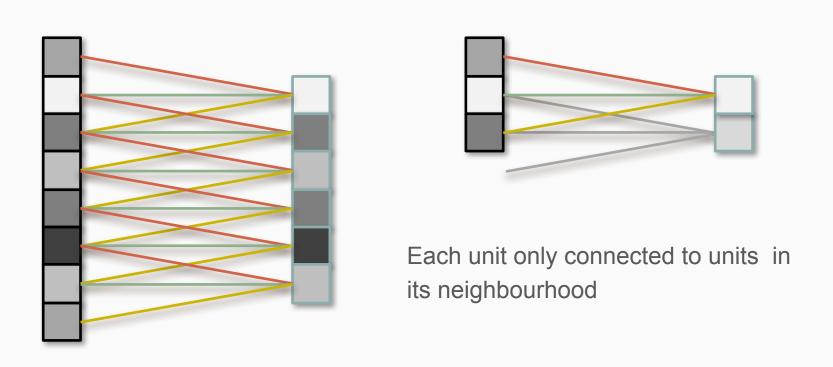
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Convolutional neural networks learn position independent filters (feature detectors)

### Recap: FC (fully-connected) layer



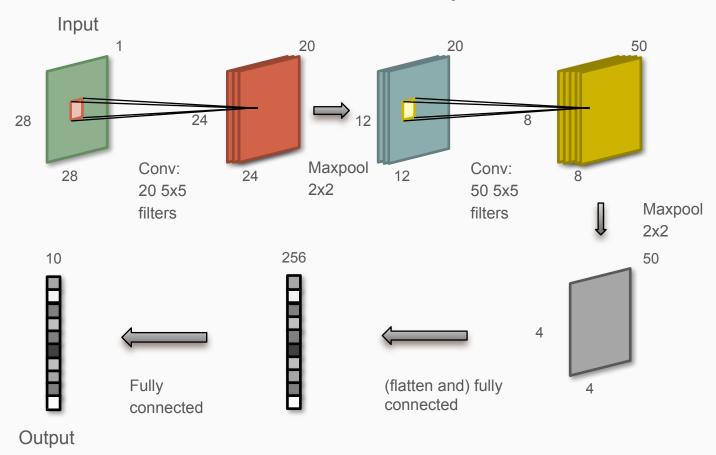
#### Convolutional layer



Example:

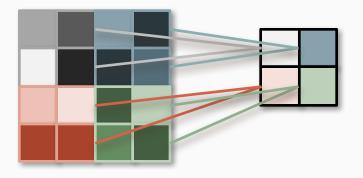
A Simplified LeNet [LeCun95] for MNIST digits

#### Convolutional layer



#### Max-pooling 'layer' [Ciresan12]

Take maximum value from each 2 x 2 pooling region  $(p \times p)$  in the general case



after 300 iterations over training set:

99.21% validation accuracy

## Thanks

#### Adapted from:

- https://github.com/Britefury
- https://github.com/nlintz/TensorFlow-Tutorials