Computer Vision
Neural Network:

*(Before)* Linear score function:

\[ f = Wx \]
Neural Network:

(Before) Linear score function:

(Now) 2-layer Neural Network

\[ f = Wx \]

\[ f = W_2 \max(0, W_1 x) \]
Neural Network:

(Before) Linear score function:

(Now) 2-layer Neural Network

$$f = Wx$$

$$f = W_2 \max(0, W_1x)$$
Neural Network:

(Before) Linear score function:

\[ f = W \mathbf{x} \]

(Now) 2-layer Neural Network or 3-layer Neural Network

\[ f = W_2 \max(0, W_1 \mathbf{x}) \]
\[ f = W_3 \max(0, W_2 \max(0, W_1 \mathbf{x})) \]
impulses carried toward cell body

impulses carried away from cell body

dendrites

nucleus

cell body

branches of axon

axon

axon terminals
impulses carried toward cell body

branches of axon

impulses carried away from cell body

sigmoid activation function

\[
\frac{1}{1 + e^{-x}}
\]
Be very careful with your Brain analogies:

**Biological Neurons:**
- Many different types
- Dendrites can perform complex non-linear computations
- Synapses are not a single weight but a complex non-linear dynamical system
- Rate code may not be adequate
Neural Networks: Architectures

“2-layer Neural Net”, or “1-hidden-layer Neural Net”

“3-layer Neural Net”, or “2-hidden-layer Neural Net”

“Fully-connected” layers
Setting the number of layers and their sizes

more neurons = more capacity
Loss Functions
1. Network Flow ---- forward pass
2. How much did I miss? (loss function)
3. Backward propagation (update weights)
**Forward Pass**

**image parameters**

\[ f(x, W) \]

- **input image**
- **array of numbers 0...1** (3072 numbers total)
- **stretch pixels into single column**

**Matrix**

\[
\begin{bmatrix}
0.2 & -0.5 & 0.1 & 2.0 \\
1.5 & 1.3 & 2.1 & 0.0 \\
0 & 0.25 & 0.2 & -0.3 \\
\end{bmatrix}
\]

- **W**

\[
\begin{bmatrix}
56 \\
231 \\
24 \\
2 \\
\end{bmatrix}
\]

- **b**

\[
\begin{bmatrix}
1.1 \\
3.2 \\
-1.2 \\
\end{bmatrix}
\]

\[
f(x_i; W, b) = -96.8 + 437.9 + 61.95 = 305.05
\]
Softmax Classifier (Multinomial Logistic Regression)

\[ L_i = -\log\left( \frac{e^{s_{y_i}}}{\sum_j e^{s_j}} \right) \]

<table>
<thead>
<tr>
<th>Category</th>
<th>Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>cat</td>
<td>3.2</td>
</tr>
<tr>
<td>car</td>
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<tr>
<td>frog</td>
<td>-1.7</td>
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**Softmax Classifier** (Multinomial Logistic Regression)

$$L_i = - \log \left( \frac{e^{s_{y_i}}}{\sum_j e^{s_j}} \right)$$

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unnormalized log probabilities
**Softmax Classifier** (Multinomial Logistic Regression)

\[ L_i = -\log\left( \frac{e^{s_{i,y_i}}}{\sum_j e^{s_j}} \right) \]

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<tr>
<th>Class</th>
<th>Unnormalized Probabilities</th>
<th>Unnormalized Log Probabilities</th>
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</tr>
<tr>
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<td>5.1</td>
<td>164.0</td>
</tr>
<tr>
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**Softmax Classifier** (Multinomial Logistic Regression)

\[
L_i = -\log \left( \frac{e^{sy_i}}{\sum_j e^{s_j}} \right)
\]

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unnormalized log probabilities

unnormalized probabilities

probabilities
**Softmax Classifier** (Multinomial Logistic Regression)

\[
L_i = - \log \left( \frac{e^{s_{y_i}}}{\sum_j e^{s_j}} \right)
\]

<table>
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<tr>
<th>cat</th>
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<th>0.13</th>
</tr>
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<tbody>
<tr>
<td>car</td>
<td>5.1</td>
<td>164.0</td>
<td>0.87</td>
</tr>
<tr>
<td>frog</td>
<td>-1.7</td>
<td>0.18</td>
<td>0.00</td>
</tr>
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</table>

unnormalized log probabilities

\[
ex^\text{cat} = 20.81, \quad ex^\text{car} = 158.9, \quad ex^\text{frog} = 0.18
\]

unnormalized probabilities

\[
\frac{e^{24.5}}{20.81 + 158.9 + 0.18} = 0.13
\]

probabilities

\[
L_i = -\log(0.13) = 0.89
\]
Follow the slope

In 1-dimensional, the derivative of a function:

\[
\frac{df(x)}{dx} = \lim_{h \to 0} \frac{f(x + h) - f(x)}{h}
\]

In multiple dimensions, the **gradient** is the vector of (partial derivatives).
current $W$: 

$$[0.34,\ -1.11,\ 0.78,\ 0.12,\ 0.55,\ 2.81,\ -3.1,\ -1.5,\ -1.5,\ 0.33,...]$$

**loss 1.25347**

gradient $dW$: 

$$[?,\ ?,\ ?,\ ?,\ ?,\ ?,\ ?,\ ?,\ ?,\ ?,\ ?,\ ?,\ ?,\ ?,\ ?,\ ?,\ ?,\ ?,\ ?,\ ?,\ ?,\ ?,\ ?,\ ?,\ ?,\ ?,\ ?,\ ?,\ ?,\ ?,\ ?,\ ?,\ ?,\ ?,\ ?,\ ?,\ ?,\ ?,\ ?,\ ?,\ ?,\ ?,\ ?,\ ?,\ ?,\ ?,\ ?,\ ?,\ ?,\ ?,\ ?,\ ?,...]$$
<table>
<thead>
<tr>
<th>current $W$:</th>
<th>$W + h$ (first dim):</th>
<th>gradient $dW$:</th>
</tr>
</thead>
<tbody>
<tr>
<td>[0.34, -1.11, 0.78, 0.12, 0.55, 2.81, -3.1, -1.5, 0.33, ...]</td>
<td>[0.34 + 0.0001, -1.11, 0.78, 0.12, 0.55, 2.81, -3.1, -1.5, 0.33, ...]</td>
<td>[?, ?, ?, ?, ?, ?, ?, ?, ?, ..., ?]</td>
</tr>
<tr>
<td>loss 1.25347</td>
<td>loss 1.25322</td>
<td></td>
</tr>
<tr>
<td>current $W$:</td>
<td>$W + h$ (first dim):</td>
<td>gradient $dW$:</td>
</tr>
<tr>
<td>----------------</td>
<td></td>
<td></td>
</tr>
<tr>
<td>[0.34, -1.11, 0.78, 0.12, 0.55, 2.81, -3.1, -1.5, 0.33,...]</td>
<td>[0.34 + <strong>0.0001</strong>, -1.11, 0.78, 0.12, 0.55, 2.81, -3.1, -1.5, 0.33,...]</td>
<td><strong>[-2.5, ?, ?, (1.25322 - 1.25347)/0.0001] = -2.5</strong></td>
</tr>
<tr>
<td><strong>loss 1.25347</strong></td>
<td><strong>loss 1.25322</strong></td>
<td><strong>...</strong></td>
</tr>
<tr>
<td>current W:</td>
<td>W + h (second dim):</td>
<td>gradient dW:</td>
</tr>
<tr>
<td>-----------</td>
<td>------------------</td>
<td>-------------</td>
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<tr>
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<tr>
<td>loss 1.25347</td>
<td>loss 1.25353</td>
<td></td>
</tr>
<tr>
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<td>[0.34, -1.11 + 0.0001, 0.78, 0.12, 0.55, 2.81, -3.1, -1.5, 0.33,...]</td>
<td>[-2.5, 0.6, ?, ?, ?,?,...]</td>
</tr>
<tr>
<td>loss 1.25347</td>
<td>loss 1.25353</td>
<td>[\frac{1.25353 - 1.25347}{0.0001} = 0.6]</td>
</tr>
</tbody>
</table>

\[
\frac{df(x)}{dx} = \lim_{h \to 0} \frac{f(x + h) - f(x)}{h}
\]
<table>
<thead>
<tr>
<th>current W:</th>
<th>( W + h ) (third dim):</th>
<th>gradient ( dW ):</th>
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<td>0.34, -1.11, 0.78, 0.12, 0.55, 2.81, -3.1, -1.5, 0.33,...</td>
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current $W$:  

[0.34, 
-1.11, 
0.78, 
0.12, 
0.55, 
2.81, 
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-1.5, 
0.33,...]  

loss 1.25347

$W + h$ (third dim):  

[0.34, 
-1.11, 
0.78 + 0.0001, 
0.12, 
0.55, 
2.81, 
-3.1, 
-1.5, 
0.33,...]  

loss 1.25347

gradient $dW$:  

[-2.5, 
0.6, 
0, 
?, 
?, 
?, 
?, 
?, 
?, 
?,...]

$(1.25347 - 1.25347)/0.0001 = 0$

\[
\frac{df(x)}{dx} = \lim_{h \to 0} \frac{f(x+h) - f(x)}{h}
\]
Numeric vs Analytic Gradient
\[ f(x, y, z) = (x + y)z \]

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

e.g. \( x = -2, \ y = 5, \ z = -4 \)

\[
q = x + y \quad \frac{\partial q}{\partial x} = 1, \ \frac{\partial q}{\partial y} = 1
\]

\[
f = qz \quad \frac{\partial f}{\partial q} = z, \ \frac{\partial f}{\partial z} = q
\]

Want: \( \frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}, \frac{\partial f}{\partial z} \)
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*Example: \( x = -2, \ y = 5, \ z = -4 \)*

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\[ f(x, y, z) = (x + y)z \]

e.g. \( x = -2, \ y = 5, \ z = -4 \)

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

Chain rule:

\[ \frac{\partial f}{\partial y} = \frac{\partial f}{\partial q} \frac{\partial q}{\partial y} \]
\[ f(x, y, z) = (x + y)z \]

e.g. \( x = -2, \ y = 5, \ z = -4 \)

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

Chain rule:

\[
\frac{\partial f}{\partial x} = \frac{\partial f}{\partial q} \frac{\partial q}{\partial x}
\]
activations

\[ \frac{\partial z}{\partial x} \]

\[ \frac{\partial z}{\partial y} \]

“local gradient”
activations

\[ \frac{\partial z}{\partial x} \]

"local gradient"

\[ \frac{\partial z}{\partial y} \]

\[ \frac{\partial L}{\partial z} \]

gradients
activations

\[ \frac{\partial L}{\partial x} = \frac{\partial L}{\partial z} \frac{\partial z}{\partial x} \]

"local gradient"

\[ \frac{\partial z}{\partial x} \]

\[ \frac{\partial z}{\partial y} \]

\[ \frac{\partial L}{\partial z} \]

gradients
activations

\( \frac{\partial L}{\partial x} = \frac{\partial L}{\partial z} \frac{\partial z}{\partial x} \)

\( \frac{\partial L}{\partial y} = \frac{\partial L}{\partial z} \frac{\partial z}{\partial y} \)

"local gradient"

gradients

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Activation Functions
Activation Functions

Sigmoid
\[ \sigma(x) = \frac{1}{1 + e^{-x}} \]

\[ \text{tanh} \quad \text{tanh}(x) \]

ReLU  \[ \text{max}(0, x) \]

Leaky ReLU
\[ \text{max}(0.1x, x) \]

Maxout
\[ \text{max}(w_1^T x + b_1, w_2^T x + b_2) \]

ELU
\[ f(x) = \begin{cases} 
    x & \text{if } x > 0 \\
    \alpha \left( \exp(x) - 1 \right) & \text{if } x \leq 0
\end{cases} \]
Activation Functions
Activation Functions

$\sigma(x) = \frac{1}{1 + e^{-x}}$

- Squashes numbers to range [0,1]
- Historically popular since they have nice interpretation as a saturating “firing rate” of a neuron
Activation Functions

Sigmoid

\[ \sigma(x) = \frac{1}{1 + e^{-x}} \]

- Squashes numbers to range [0,1]
- Historically popular since they have nice interpretation as a saturating “firing rate” of a neuron

3 problems:

1. Saturated neurons “kill” the gradients
What happens when $x = -10$?
What happens when $x = 0$?
What happens when $x = 10$?
Activation Functions

Sigmoid

\[ \sigma(x) = \frac{1}{1 + e^{-x}} \]

- Squashes numbers to range [0,1]
- Historically popular since they have nice interpretation as a saturating “firing rate” of a neuron

3 problems:

1. Saturated neurons “kill” the gradients
2. Sigmoid outputs are not zero-centered
Activation Functions

Sigmoid

\[ \sigma(x) = \frac{1}{1 + e^{-x}} \]

- Squashes numbers to range [0,1]
- Historically popular since they have nice interpretation as a saturating “firing rate” of a neuron

3 problems:

1. Saturated neurons “kill” the gradients
2. Sigmoid outputs are not zero-centered
3. \( \exp() \) is a bit compute expensive
Activation Functions

- Squashes numbers to range \([-1, 1]\)
- zero centered (nice)
- still kills gradients when saturated :(

\[ \tanh(x) \]

[LeCun et al., 1991]
Activation Functions

- Computes $f(x) = \max(0,x)$
- Does not saturate (in +region)
- Very computationally efficient
- Converges much faster than sigmoid/tanh in practice (e.g. 6x)

ReLU
(Rectified Linear Unit)

[Krizhevsky et al., 2012]
Activation Functions

ReLU (Rectified Linear Unit)

- Computes $f(x) = \max(0, x)$
- Does not saturate (in +region)
- Very computationally efficient
- Converges much faster than sigmoid/tanh in practice (e.g. 6x)
- Not zero-centered output
- An annoyance:

    hint: what is the gradient when $x < 0$?
Convolutional Neural Networks

[LeNet-5, LeCun 1980]
A bit of history:

Hubel & Wiesel, 1959
RECEPTIVE FIELDS OF SINGLE NEURONES IN THE CAT'S STRIATE CORTEX

1962
RECEPTIVE FIELDS, BINOCULAR INTERACTION AND FUNCTIONAL ARCHITECTURE IN THE CAT'S VISUAL CORTEX

1968...
Video time https://youtu.be/8VdFf3egwfg?t=1m10s
A bit of history

Topographical mapping in the cortex: nearby cells in cortex represented nearby regions in the visual field
Hierarchical organization

Hubel & Weisel
- topographical mapping

Featural hierarchy
- hyper-complex cells
- complex cells
- simple cells

High level
Mid level
Low level
A bit of history:

Neurocognitron

[Fukushima 1980]
A bit of history:
Gradient-based learning applied to document recognition
[LeCun, Bottou, Bengio, Haffner 1998]
A bit of history:

ImageNet Classification with Deep Convolutional Neural Networks

[Krizhevsky, Sutskever, Hinton, 2012]

“AlexNet”
Fast-forward to today: ConvNets are everywhere

Classification

Retrieval

[Krizhevsky 2012]
Fast-forward to today: ConvNets are everywhere

Detection

Segmentation

[Faster R-CNN: Ren, He, Girshick, Sun 2015]  [Farabet et al., 2012]
Fast-forward to today: ConvNets are everywhere

self-driving cars

NVIDIA Tegra X1
Fast-forward to today: ConvNets are everywhere

[Simonyan et al. 2014]

[Goodfellow 2014]

[Simonyan et al. 2014]

[Goodfellow 2014]

[Taigman et al. 2014]
Fast-forward to today: ConvNets are everywhere

I caught this movie on the Sci-Fi channel recently. It actually turned out to be pretty decent as far as an 8-bit horror/romance film goes. Two guys, one male and one female (who’s not). The hero (the female) takes a road trip to stop a serial killer who has been using her ex-boyfriend to escape. Her ex-boyfriend is an evil genius who’s been tracking her and deciding to play cat-and-mouse with them. Things are further complicated when they pick up a ridiculously shrill little girl. What makes this film unique is that the combination of comedy and terror actually works in this movie, unlike so many others. The two girls are likable enough and there are some good 8-bit horror scenes. Nice pacing and comic timing make this movie more than possible for the horror-obsessed fan. Definitely worth rewatching.

I just saw there was a local independent station in the New York City area. The film elected president last time I saw the district. George Bush, of course, I thought unnecessary. Having enough, I was more interested in how they took the votes and stupid as ever. George Bush won the election. He’s like a stupid man a Michael Mey – with all the awareness that accumulated promise. There’s no point to the conspiracy, no cunning means that sign the conspirators. We are left to understand to connect the dots from one bit of gossip to another track in the film to the next. The current budget crisis, the rise in Iraq, Islamic extremism, the current events all add up to a plot that includes a new president in the USA who wants to make all Americans without health care, stagnating wages, and the death of the middle class are all subsumed by the latest terror of global. A truly, stunningly 8-bit film.

Graphics is far from the best part of the game. This is the number one best 8-bit game in the series. Next is Underground. If it were done right, it is a new genre. There are massive levels, massive action, the characters... it’s just a really good game. Want your money on this game. This is the kind of money that is serious property. And even though graphics suck, this doesn’t make a game good. Actually, the graphics were good at the time. Today the graphics are crap. WHO CARES as they say in Canada. This is the best game, yes. You get to go to Canadian TUPP! Well, I don’t care if they say that, but they might, who knows. Well, Canadian people do. Wait a minute, I’m getting off topic. This game rocks. Buy it, play it, enjoy it, love it. It’s PURE BRILLIANCE.

The film was good and original. I was a semi-hit horror/romance movie. So I heard a second was made and I had to watch it. What really makes this movie work is half-ATAR’s character and the sometimes clever script. Better good script for a genre that the Four Elements plus and the money was when sometimes there’s music when it looks like it was played using a home video camera with a pony – look. Great mood – TV series. If was worth the rental but portable worth being just to get that once time feeling and maybe Bob’s Teachers doing what he should. I suggest newcomers to watch the first one before watching the sequel, just so you’ll have an idea what Stanley is like and get a little history background.

[Denil et al. 2014]

[Turaga et al., 2010]
Whale recognition, Kaggle Challenge

Mnih and Hinton, 2010
Image Captioning

A person riding a motorcycle on a dirt road.

Two dogs play in the grass.

A skateboarder does a trick on a ramp.

A dog is jumping to catch a frisbee.

A group of young people playing a game of frisbee.

Two hockey players are fighting over the puck.

A little girl in a pink hat is blowing bubbles.

A refrigerator filled with lots of food and drinks.

A herd of elephants walking across a dry grass field.

A close up of a cat laying on a couch.

A red motorcycle parked on the side of the road.

A yellow school bus parked in a parking lot.

[Vinyals et al., 2015]
Convolution Layer

32x32x3 image

32  height
32  width
3   depth
Convolution Layer

32x32x3 image

5x5x3 filter

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

32x32x3 image

5x5x3 filter

Filters always extend the full depth of the input volume

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

1 number:
the result of taking a dot product between the filter and a small 5x5x3 chunk of the image
(i.e. $5 \times 5 \times 3 = 75$-dimensional dot product + bias)

$$w^T x + b$$
Convolution Layer

32x32x3 image
5x5x3 filter

convolve (slide) over all spatial locations

activation map
Convolution Layer

32x32x3 image
5x5x3 filter

convolve (slide) over all spatial locations

consider a second, green filter

activation maps
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!
**Preview:** ConvNet is a sequence of Convolution Layers, interspersed with activation functions.

- CONV, ReLU
- e.g. 6 5x5x3 filters
ConvNet is a sequence of Convolutional Layers, interspersed with activation functions.

- **CONV, ReLU**
  - e.g. 6
  - 5x5x3 filters

- **CONV, ReLU**
  - e.g. 10
  - 5x5x6 filters

- **CONV, ReLU**
  - ....
Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]
Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]
We call the layer convolutional because it is related to convolution of two signals:

\[ f[x,y] \ast g[x,y] = \sum_{n_1=-\infty}^{\infty} \sum_{n_2=-\infty}^{\infty} f[n_1,n_2] \cdot g[x-n_1,y-n_2] \]

elementwise multiplication and sum of a filter and the signal (image)
A closer look at spatial dimensions:

32x32x3 image
5x5x3 filter

convolve (slide) over all spatial locations

activation map
A closer look at spatial dimensions:

7x7 input (spatially)
assume 3x3 filter
A closer look at spatial dimensions:

7x7 input (spatially)
assume 3x3 filter
A closer look at spatial dimensions:

7x7 input (spatially) assume 3x3 filter
A closer look at spatial dimensions:

7x7 input (spatially)
assume 3x3 filter
A closer look at spatial dimensions:

7x7 input (spatially) assume 3x3 filter

=> 5x5 output
A closer look at spatial dimensions:

7x7 input (spatially) assume 3x3 filter applied with stride 2
A closer look at spatial dimensions:

7x7 input (spatially) assume 3x3 filter applied with stride 2
A closer look at spatial dimensions:

7x7 input (spatially) assume 3x3 filter applied \textit{with stride 2}
=> 3x3 output!
A closer look at spatial dimensions:

7x7 input (spatially) assume 3x3 filter applied with stride 3?
A closer look at spatial dimensions:

7x7 input (spatially) assume 3x3 filter applied with stride 3?

doesn’t fit! cannot apply 3x3 filter on 7x7 input with stride 3.
In practice: Common to zero pad the border

e.g. input 7x7
3x3 filter, applied with **stride 1**
**pad with 1 pixel** border => what is the output?

(recall:)
(N - F) / stride + 1
In practice: Common to zero pad the border

- e.g. input 7x7
- 3x3 filter, applied with **stride 1**
- **pad with 1 pixel** border => what is the output?

7x7 output!
In practice: Common to zero pad the border

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e.g. input 7x7

3x3 filter, applied with **stride 1**

**pad with 1 pixel** border => what is the output?

**7x7 output!**

in general, common to see CONV layers with stride 1, filters of size FxF, and zero-padding with (F-1)/2. (will preserve size spatially)

e.g. F = 3 => zero pad with 1

F = 5 => zero pad with 2

F = 7 => zero pad with 3