

CSC321 Neural Networks and Machine Learning

Lecture 6

February 12, 2020

Agenda

- ▶ Projects 1 and 2
- ▶ Project 3 data collection
- ▶ Midterm
- ▶ Convolutional Neural Networks

Announcements

- ▶ Project 1 is released
 - ▶ If you received more than 4 points off due to your answers being cut off, please submit a remark request
 - ▶ Remarks are for possible TA mistakes
 - ▶ Feedback on common issues available on Quercus
- ▶ Project 2 is due tomorrow
 - ▶ FAQ on Piazza
 - ▶ Pouria has office hours later today

Project 3 Data Collection

For project 3, we'll be collecting our own data as a class.

Right Shoe	Left Shoe
 A white athletic shoe with black accents and laces, viewed from the top-left angle.	 A white athletic shoe with black accents and laces, viewed from the top-right angle.
 A black athletic shoe with a textured upper and laces, viewed from the top-left angle.	 A black athletic shoe with a textured upper and laces, viewed from the top-right angle.

If you submit your data by **Monday Feb 17th, 9pm** we will award you 3 extra grace tokens. (Why? So that we have more time to develop a fun assignment with this data set!)

Midterm

Midterm Logistics

The midterm will take place after reading week on **Feb 26th**

- ▶ 50 minutes midterm during the first half of the hour
 - ▶ 9:10am - 10:00am (LEC0101)
 - ▶ 11:10am - 12:00pm (LEC0101)
- ▶ We'll have a short lecture after
 - ▶ 10:20am-11am (LEC0101)
 - ▶ 12:20pm-1pm (LEC0102)

Midterm Coverage

- ▶ Weeks 1-6 materials, including convolutional neural networks forward pass
- ▶ Tutorials 2-6, Homeworks 1-3, Projects 1-2
- ▶ No aids will be permitted
- ▶ You won't need a calculator
- ▶ You may be asked to work with code, for example reason about issues with code that we give you
 - ▶ You don't need to memorize the numpy or PyTorch API
 - ▶ You do need to recognize (for example) a that trying to multiply a 3×4 matrix and a 5×2 matrix will fail

How to study?

- ▶ Previous midterms (available on the course website)
- ▶ Midterms from related courses (to see what multiple choice questions might look like)
- ▶ Review homework questions
- ▶ Review projects 1 and 2 (especially if you worked with a partner)

If you post study resources to share on Piazza (notes, solutions to posted problems, etc), we'll pin it.

Office Hours

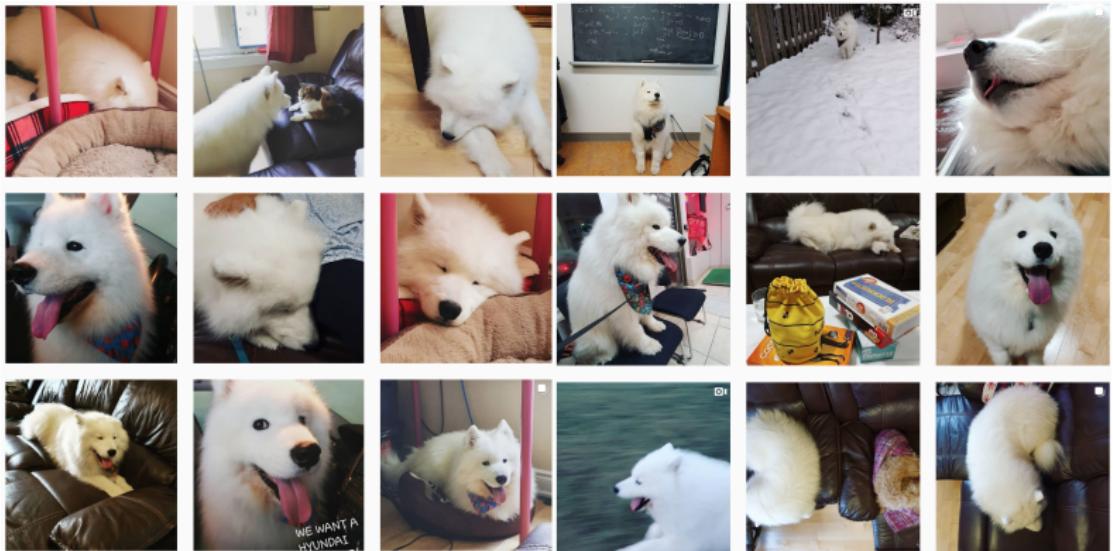
- ▶ No office hours during reading week
- ▶ Pouria will have an online office hour during reading week (to be announced)
- ▶ Lisa has office hours Monday Feb 24th
- ▶ Tuesday's tutorial time will be turned into office hours
- ▶ CANCELLED Pouria's office hours Wednesday Feb 26th

Questions?

Working with Images

Computer vision is hard

- ▶ Object change in pose, size, viewpoint, background
- ▶ Some objects are hidden behind others: *occlusion*



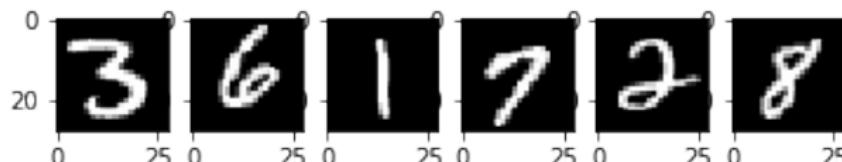
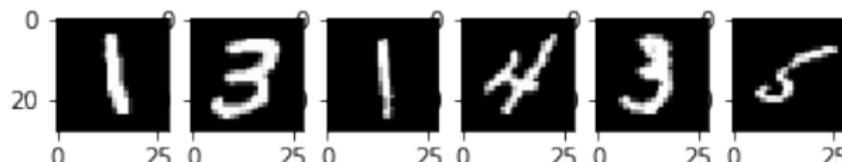
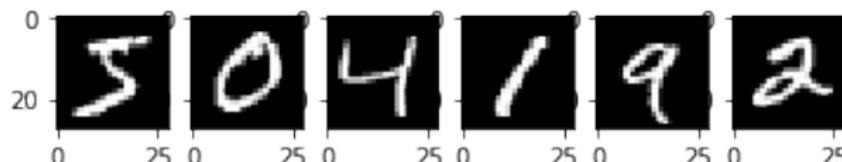
Computer vision is really hard



How can you “hard code” an algorithm that still recognizes that this is a cat?

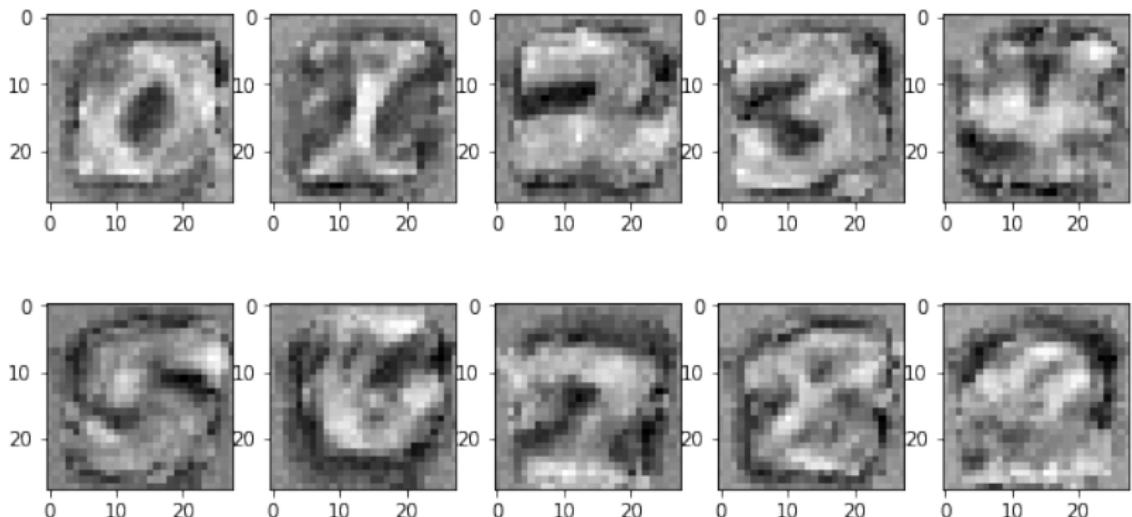
Working with Small Images

In tutorials 4 and 6, we worked with small images: 28×28 pixels, black and white.

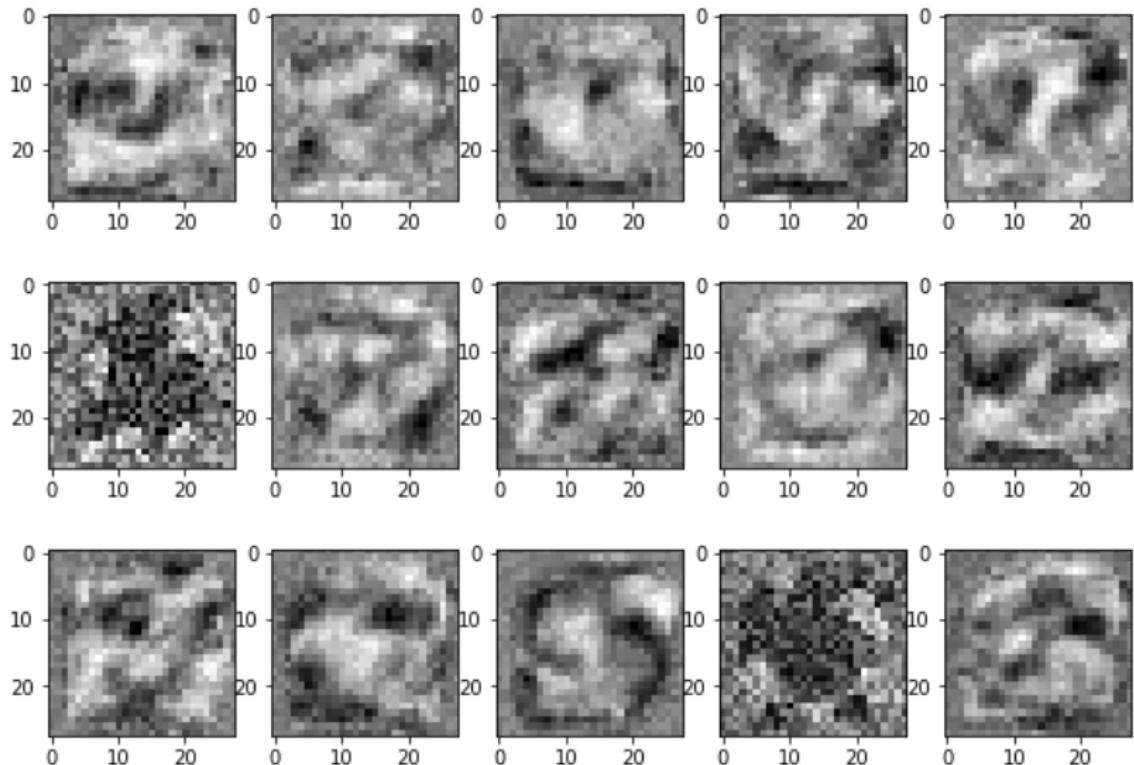


How do our models work?

Notebook Demo - Logistic Regression Weights



Notebook Demo - MLP Weights (first layer)



Working with Large Images

- ▶ Suppose you have an image that is 200 pixels x 200 pixels
- ▶ There are 500 units in the first hidden layer

Q: How many **parameters** will there be in the first layer?

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A: $200 \times 200 \times 500 + 500 = \text{over 20 million!}$

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Q: Why might using a fully connected layer be problematic?

Working with Large Images

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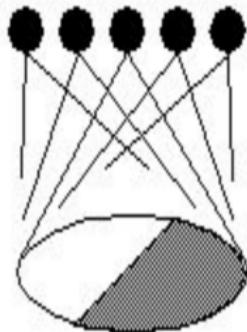
- ▶ computing predictions (forward pass) will take a long time
- ▶ large number of weights requires a lot of training data to avoid overfitting
- ▶ small shift in image can result in large change in prediction

Convolutions

Biological Influence

Hubel & Weisel

topographical mapping

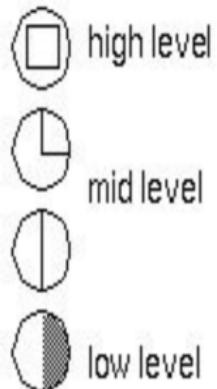
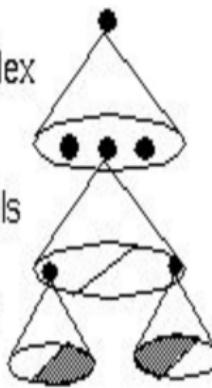


featural hierarchy

hyper-complex cells

complex cells

simple cells



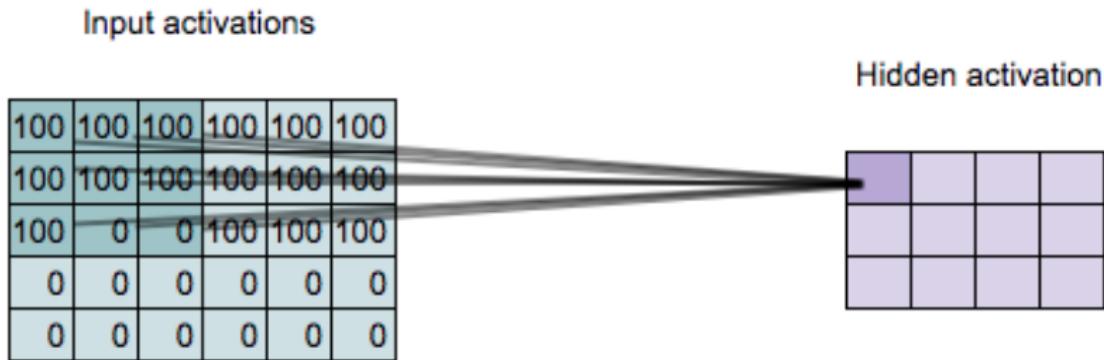
There is evidence that biological neurons in the visual cortex have *locally-connected* connections

Convolutional Neural Network

Ideas:

- ▶ **Locally-connected layers:** compute *local* features based on small regions of the image
 - ▶ Examples of *features*:
 - ▶ a horizontal edge in an area
 - ▶ a vertical edge in an area
 - ▶ a blob (no edges) in the area
 - ▶ a circular shape in the area
- ▶ **Weight-sharing:** detect the *same* local features across the entire image

Locally Connected Layers



Each hidden unit connects to a small region of the input (in this case a 3×3 region)

Locally Connected Layers

Input activations

100	100	100	100	100	100
100	100	100	100	100	100
100	0	0	100	100	100
0	0	0	0	0	0
0	0	0	0	0	0

Hidden activation

purple			

(Remove lines for readability)

Locally Connected Layers

Input activations

100	100	100	100	100	100
100	100	100	100	100	100
100	0	0	100	100	100
0	0	0	0	0	0
0	0	0	0	0	0

Hidden activation

Hidden unit geometry has a 2D geometry consistent with the input

Locally Connected Layers

Input activations

100	100	100	100	100	100
100	100	100	100	100	100
100	0	0	100	100	100
0	0	0	0	0	0
0	0	0	0	0	0

Hidden activation

Locally Connected Layers

Input activations

100	100	100	100	100	100
100	100	100	100	100	100
100	0	0	100	100	100
0	0	0	0	0	0
0	0	0	0	0	0

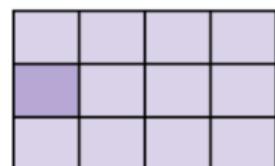
Hidden activation

Locally Connected Layers

Input activations

100	100	100	100	100	100
100	100	100	100	100	100
100	0	0	100	100	100
0	0	0	0	0	0
0	0	0	0	0	0

Hidden activation



Locally Connected Layers

Input activations

100	100	100	100	100	100
100	100	100	100	100	100
100	0	0	100	100	100
0	0	0	0	0	0
0	0	0	0	0	0

Hidden activation

Locally Connected Layers

Input activations

100	100	100	100	100	100
100	100	100	100	100	100
100	0	0	100	100	100
0	0	0	0	0	0
0	0	0	0	0	0

Hidden activation

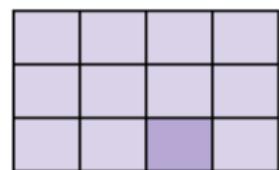
Q: Which region of the input is this hidden unit connected to?

Locally Connected Layers

Input activations

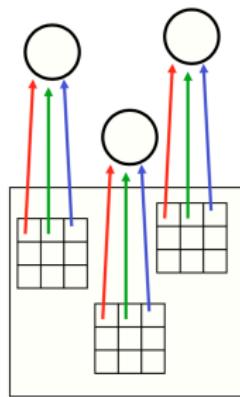
100	100	100	100	100	100
100	100	100	100	100	100
100	0	0	100	100	100
0	0	0	0	0	0
0	0	0	0	0	0

Hidden activation



Weight Sharing

Use the *same weights* across each region (each colour represents the same weight)



Each neuron on the higher layer is detecting the same feature, but in different locations on the lower layer

“Detecting” = output (activation) is high if feature is present

“Feature” = something in a part of the image, like an edge or shape

Convolution Computation

Input activations

100	100	100	100	100	100
100	100	100	100	100	100
100	0	0	100	100	100
0	0	0	0	0	0
0	0	0	0	0	0

Kernel

1	2	1
0	0	0
-1	-2	-1

Hidden activation

300			

$$\begin{aligned}300 = & 100 \times 1 + 100 \times 2 + 100 \times 1 + \\& 100 \times 0 + 100 \times 0 + 100 \times 0 + \\& 100 \times (-1) + 0 \times (-2) + 0 \times (-1)\end{aligned}$$

- ▶ The **kernel** or **filter** (middle) contains the trainable weights
- ▶ In our example, the **kernel size** is 3×3
- ▶ The “**convolved features**” or “**feature map**” are other terms for the output hidden activation

Convolution Computation

Input activations

100	100	100	100	100	100
100	100	100	100	100	100
100	0	0	100	100	100
0	0	0	0	0	0
0	0	0	0	0	0

Kernel

1	2	1
0	0	0
-1	-2	-1

Hidden activation

300	300		

$$300 = 100 \times 1 + 100 \times 2 + 100 \times 1 + \\ 100 \times 0 + 100 \times 0 + 100 \times 0 + \\ 0 \times (-1) + 0 \times (-2) + 100 \times (-1)$$

Convolution Computation (Your Turn!)

Input activations

100	100	100	100	100	100
100	100	100	100	100	100
100	0	0	100	100	100
0	0	0	0	0	0
0	0	0	0	0	0

Weights

1	2	1
0	0	0
-1	-2	-1

Hidden activation

300	300	?	

Q: What is the value of the highlighted hidden activation?

Convolution Computation

Input activations

100	100	100	100	100	100
100	100	100	100	100	100
100	0	0	100	100	100
0	0	0	0	0	0
0	0	0	0	0	0

Kernel

1	2	1
0	0	0
-1	-2	-1

Hidden activation

300	300	100	

$$\begin{aligned}100 = & 100 \times 1 + 100 \times 2 + 100 \times 1 + \\& 100 \times 0 + 100 \times 0 + 100 \times 0 + \\& 0 \times (-1) + 100 \times (-2) + 100 \times (-1)\end{aligned}$$

Convolution Computation

Input activations

100	100	100	100	100	100
100	100	100	100	100	100
100	0	0	100	100	100
0	0	0	0	0	0
0	0	0	0	0	0

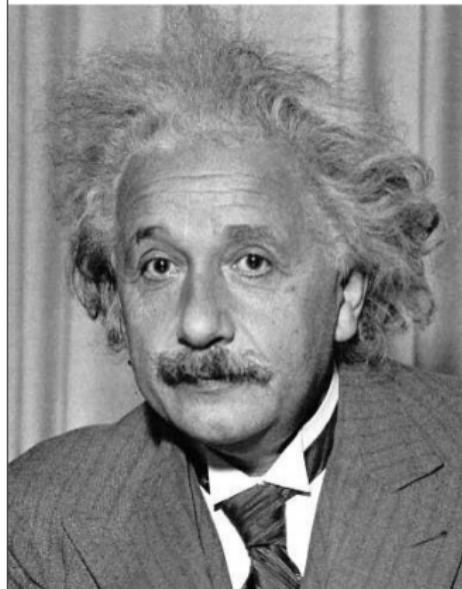
Kernel

1	2	1
0	0	0
-1	-2	-1

Hidden activation

300	300	100	0
400	400	400	400
100	100	300	300

Sobel Filter - Weights to Detect Horizontal Edges

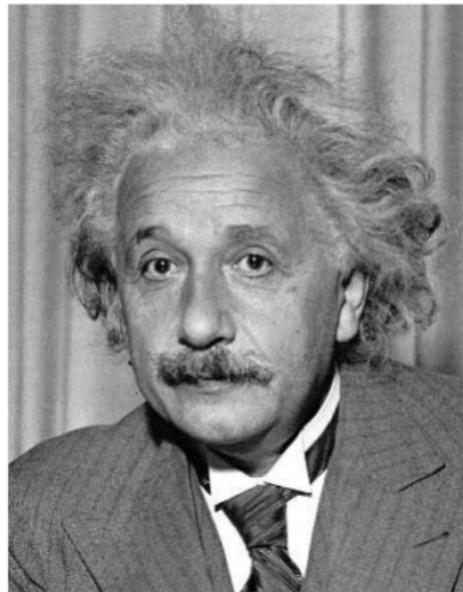


$$\begin{matrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{matrix}$$



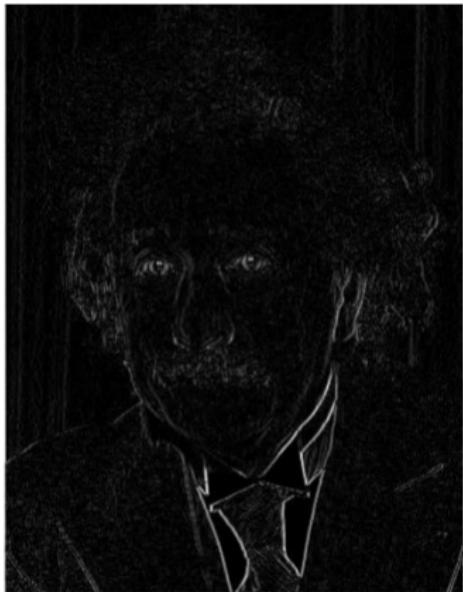
Horizontal Edge
(absolute value)⁸

Sobel Filter - Weights to Detect Vertical Edges



$$\begin{matrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{matrix}$$

*



Vertical Edge
(absolute value)
7

Weights to Detect Blobs



$$* \begin{pmatrix} 0 & 0 & 3 & 2 & 2 & 2 & 3 & 0 & 0 \\ 0 & 2 & 3 & 5 & 5 & 5 & 3 & 2 & 0 \\ 3 & 3 & 5 & 3 & 0 & 3 & 5 & 3 & 3 \\ 2 & 5 & 3 & -12 & -23 & -12 & 3 & 5 & 2 \\ 2 & 5 & 0 & -23 & -40 & -23 & 0 & 5 & 2 \\ 2 & 5 & 3 & -12 & -23 & -12 & 3 & 5 & 2 \\ 3 & 3 & 5 & 3 & 0 & 3 & 5 & 3 & 3 \\ 0 & 2 & 3 & 5 & 5 & 5 & 3 & 2 & 0 \\ 0 & 0 & 3 & 2 & 2 & 2 & 3 & 0 & 0 \end{pmatrix}$$



Q: What is the *kernel size* of this convolution?

Example:

Greyscale input image: 8×8

Convolution **kernel**: 5×5

Q: How many hidden units are in the output of this convolution?

Q: How many trainable parameters are there?

Example:

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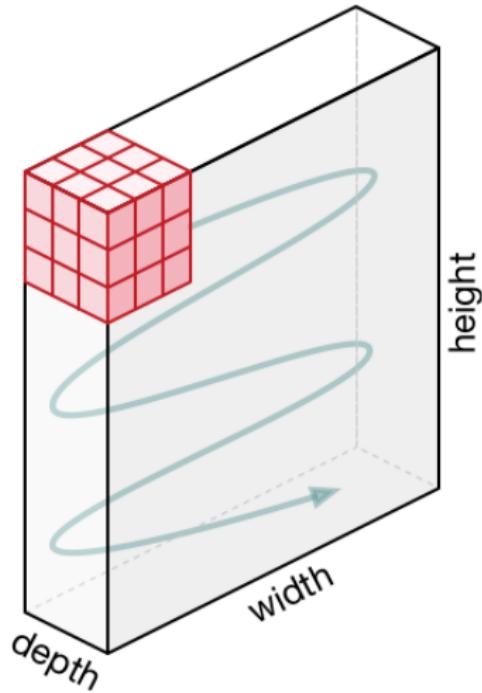
There are $5 \times 5 + 1$ trainable parameters. We have been ignoring the bias, but there is a bias applied.

Convolutions in Practice

What if we have a coloured image?

What if we want to compute *multiple* features?

Convolution in RGB



The kernel becomes a 3-dimensional tensor!

In this example, the kernel has size $3 \times 5 \times 5$

Convolutions: RGB Input

Colour input image: $3 \times 8 \times 8$

Convolution kernel: $3 \times 5 \times 5$

Questions:

- ▶ How many units are in the **output** of this convolution?
- ▶ How many trainable parameters are there?

Convolutions: RGB Input

Colour input image: $3 \times 8 \times 8$

Convolution kernel: $3 \times 5 \times 5$

Questions:

- ▶ How many units are in the **output** of this convolution?
- ▶ How many trainable parameters are there?

There are $3 \times 5 \times 5 + 1$ trainable parameters.

Terminology

Input image: $3 \times 8 \times 8$

Convolution kernel: $3 \times 5 \times 5$

- ▶ The number 3 is the number of **input channels** or **input feature maps**

Detecting Multiple Features

Q: What if we want to detect many features of the input? (i.e. **both** horizontal edges and vertical edges, and maybe even other features?)

Detecting Multiple Features

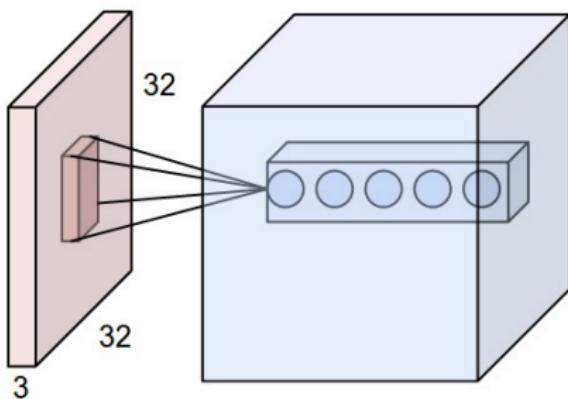
Q: What if we want to detect many features of the input? (i.e. **both** horizontal edges and vertical edges, and maybe even other features?)

A: Have many convolutional filters!

Detecting Multiple Features

Q: What if we want to detect many features of the input? (i.e. **both** horizontal edges and vertical edges, and maybe even other features?)

A: Have many convolutional filters!



Many Convolutional Filters

Input image: $3 \times 8 \times 8$

Convolution kernel: **10** $\times 3 \times 5 \times 5$

Q:

- ▶ How many units are in the output of this convolution?
- ▶ How many trainable weights are there?

Many Convolutional Filters

Input image: $3 \times 8 \times 8$

Convolution kernel: **10** $\times 3 \times 5 \times 5$

Q:

- ▶ How many units are in the output of this convolution?
- ▶ How many trainable weights are there?

There are $10 \times (3 \times 5 \times 5 + 1)$ trainable parameters.

More Terminology

Input image of size $3 \times 8 \times 8$

Convolution kernel of $10 \times 3 \times 5 \times 5$

- ▶ The number 10 is the number of **output channels** or **output feature maps**
- ▶ The number 3 is the number of **input channels** or **input feature maps**

Example

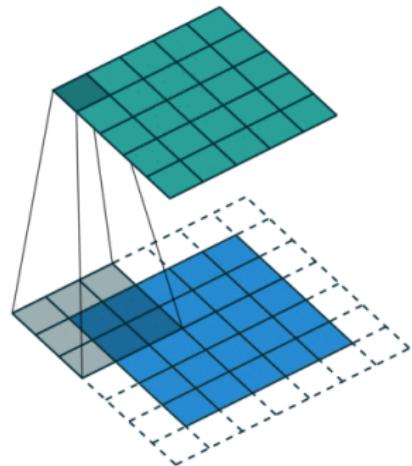
Input features: $5 \times 32 \times 32$

Convolution kernel: $8 \times 5 \times 3 \times 3$

Questions:

- ▶ How many input channels are there?
- ▶ How many output channels are there?
- ▶ How many units are in the higher layer?
- ▶ How many trainable weights are there?

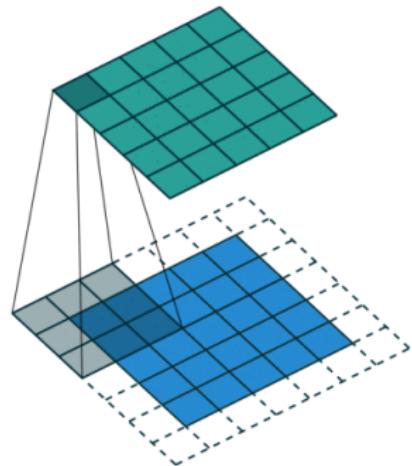
Zero Padding



- ▶ Add zeros around the border of the image
- ▶ (Can add more than one pixel of zeros)

Q: Why might we want to add zero padding?

Zero Padding



- ▶ Add zeros around the border of the image
- ▶ (Can add more than one pixel of zeros)

Q: Why might we want to add zero padding?

- ▶ Keep the next layer's width and height consistent with the previous
- ▶ Keep the information around the border of the image

Convolutional Layers in PyTorch

Let's take a look at convolutional layers in PyTorch!

Consolidating Information

In a neural network with fully-connected layers, we reduced the number of units in each hidden layer

Q: Why?

Consolidating Information

In a neural network with fully-connected layers, we reduced the number of units in each hidden layer

Q: Why?

- ▶ To be able to consolidate information, and remove out information not useful for the current task

Q: How can we consolidate information in a neural network with convolutional layers?

Consolidating Information

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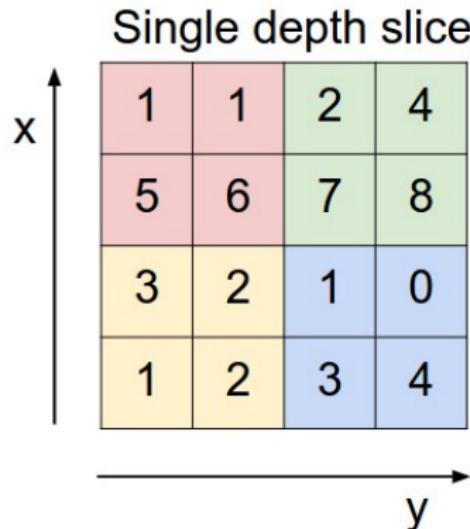
- ▶ To be able to consolidate information, and remove out information not useful for the current task

Q: How can we consolidate information in a neural network with convolutional layers?

- ▶ max pooling, average pooling, strided convolutions

Max-Pooling

Idea: take the **maximum value** in each 2×2 grid.



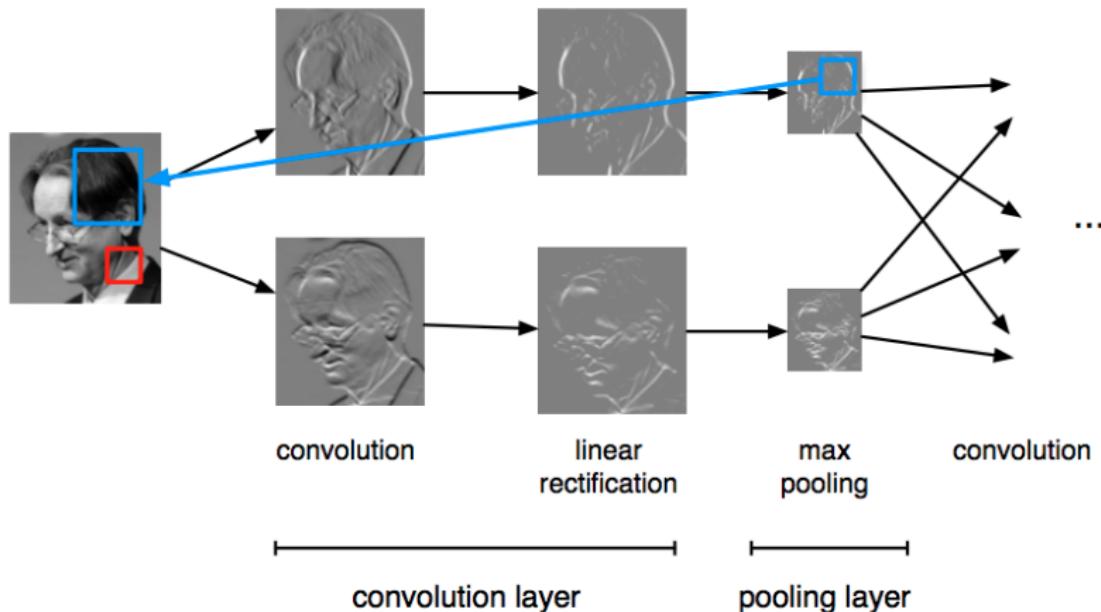
max pool with 2x2 filters
and stride 2

The output grid has 2 rows and 2 columns. The top-left cell contains 6 (from the top-left 2x2 block of the input), the top-right cell contains 8 (from the top-right 2x2 block), the bottom-left cell contains 3 (from the bottom-left 2x2 block), and the bottom-right cell contains 4 (from the bottom-right 2x2 block). The output grid is colored in a 2x2 block pattern: the top-left block is pink, the top-right block is green, the bottom-left block is yellow, and the bottom-right block is blue.

6	8
3	4

Max-Pooling Example

We can add a max-pooling layer *after* each convolutional layer



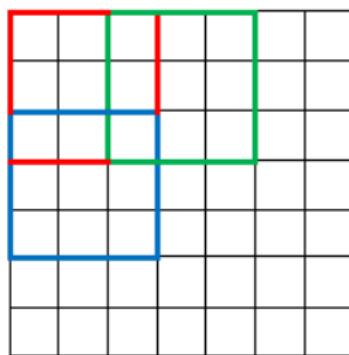
Average Pooling

- ▶ Average pooling (compute the average activation of a region)
- ▶ Max pooling generally works better

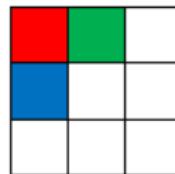
Strided Convolution

More recently people are doing away with pooling operations, using **strided** convolutions instead:

7×7 Input Volume



3×3 Output Volume



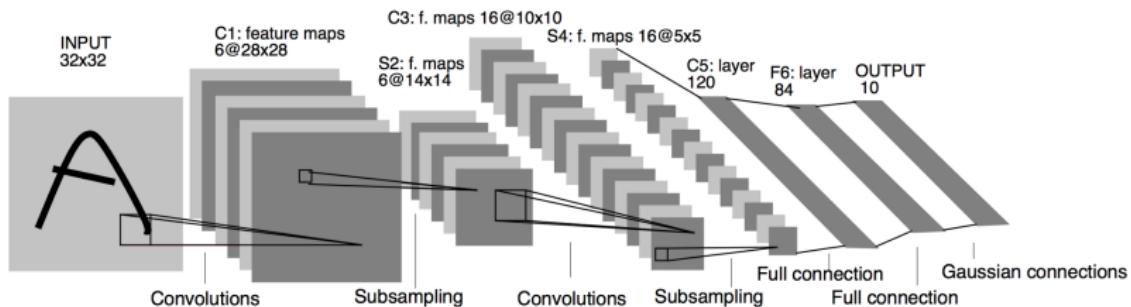
Shift the kernel by **2** (stride=2) when computing the next output feature.

Visuals

<https://arxiv.org/pdf/1603.07285.pdf>

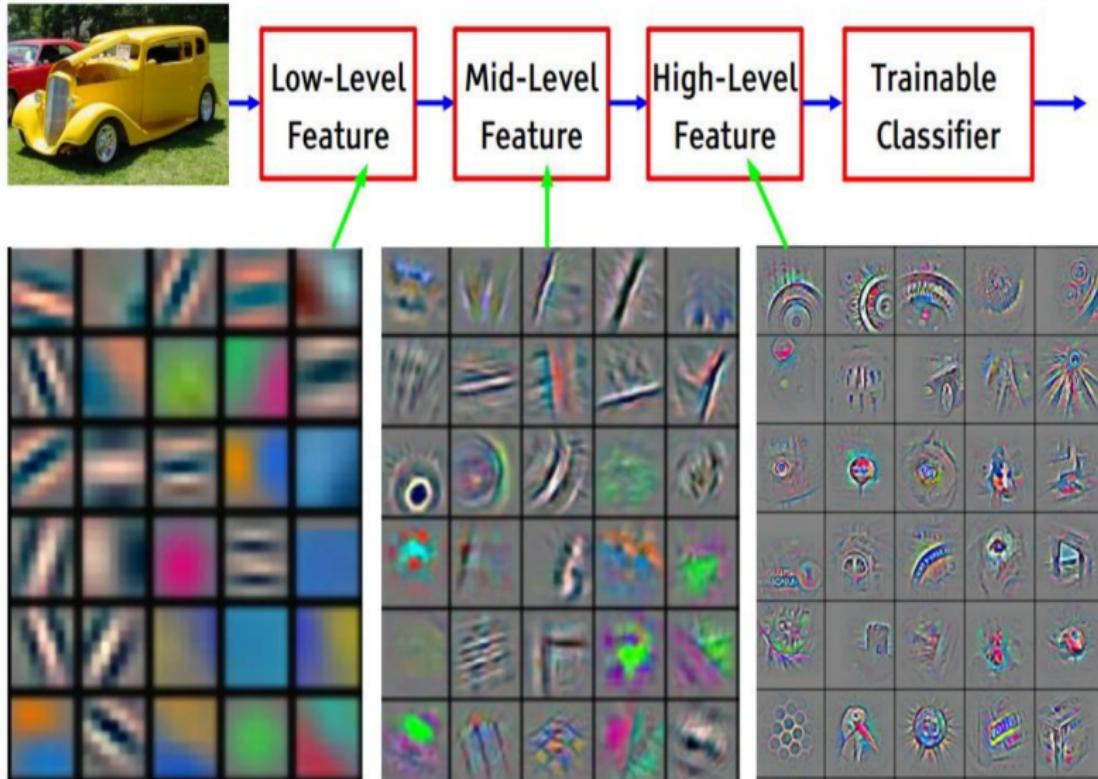
https://github.com/vdumoulin/conv_arithmetic

Early Convolutional Architecture: LeNet Architecture



- ▶ Input: 32×32 pixel, greyscale image
- ▶ First convolution has 6 output features (5x5 convolution?)
- ▶ First subsampling is probably a max-pooling operation
- ▶ Second convolution has 16 output features (5x5 convolution?)
- ▶ ...
- ▶ Some number of fully-connected layers at the end

What features do CNN's detect?



Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]

Training a CNN

- ▶ We train using backpropagation!
- ▶ We already know how to work with shared weights (project 2), and computing CNN weight updates works the same way