CSC321 Lecture 12: Image Classification

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Midterm

- Tuesday, March 6, during class
- 50 minutes
- What you're responsible for:
  - Lectures, up through L12 (this one)
  - Tutorials, up through T4 (this week)
  - Weekly homeworks, up through HW6
  - Programming assignments, up through PA2
- Emphasis on concepts covered in multiple of the above
- There will be some conceptual questions and some mathematical questions (similar to individual steps of the weekly homeworks)
- No formal proofs necessary, but you should justify your answers.
- Practice exams will be posted.

Overview

- Object recognition is the task of identifying which object category is present in an image.
- It's challenging because objects can differ widely in position, size, shape, appearance, etc., and we have to deal with occlusions, lighting changes, etc.
- Why we care about it
  - Direct applications to image search
  - Closely related to object detection, the task of locating all instances of an object in an image
    - E.g., a self-driving car detecting pedestrians or stop signs
- For the past 5 years, all of the best object recognizers have been various kinds of conv nets.

Recognition Datasets

- In order to train and evaluate a machine learning system, we need to collect a dataset. The design of the dataset can have major implications.
- Some questions to consider:
  - Which categories to include?
  - Where should the images come from?
  - How many images to collect?
  - How to normalize (preprocess) the images?

Image Classification

- Conv nets are just one of many possible approaches to image classification. However, they have been by far the most successful for the last 5 years.
- Biggest image classification "advances" of the last two decades
  - Datasets have gotten much larger (because of digital cameras and the Internet)
  - Computers got much faster
    - Graphics processing units (GPUs) turned out to be really good at training big neural nets; they're generally about 30 times faster than CPUs.
  - As a result, we could fit bigger and bigger neural nets.

MNIST Dataset

- MNIST dataset of handwritten digits
  - **Categories:** 10 digit classes
  - **Source:** Scans of handwritten zip codes from envelopes
  - **Size:** 60,000 training images and 10,000 test images, grayscale, of size 28×28
  - **Normalization:** centered within in the image, scaled to a consistent size
    - The assumption is that the digit recognizer would be part of a larger pipeline that segments and normalizes images.
- In 1998, Yann LeCun and colleagues built a conv net called LeNet which was able to classify digits with 98.9% test accuracy.
  - It was good enough to be used in a system for automatically reading numbers on checks.

ImageNet

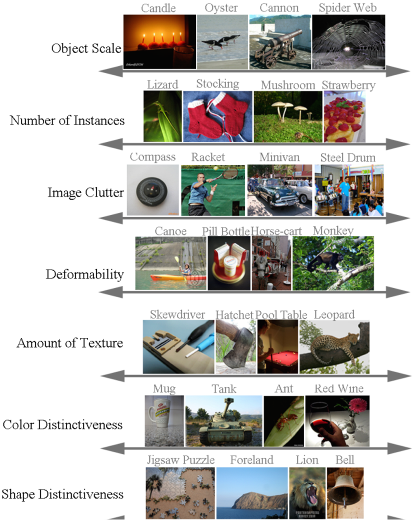
ImageNet is the modern object recognition benchmark dataset. It was introduced in 2009, and has led to amazing progress in object recognition since then.

ImageNet

- Used for the ImageNet Large Scale Visual Recognition Challenge (ILSVRC), an annual benchmark competition for object recognition algorithms
- Design decisions
  - **Categories:** Taken from a lexical database called WordNet
    - WordNet consists of "synsets", or sets of synonymous words
    - They tried to use as many of these as possible; almost 22,000 as of 2010
    - Of these, they chose the 1000 most common for the ILSVRC
    - The categories are really specific, e.g. hundreds of kinds of dogs
  - **Size:** 1.2 million full-sized images for the ILSVRC
  - **Source:** Results from image search engines, hand-labeled by Mechanical Turkers
    - Labeling such specific categories was challenging; annotators had to be given the WordNet hierarchy, Wikipedia, etc.
  - **Normalization:** none, although the contestants are free to do preprocessing

ImageNet

Images and object categories vary on a lot of dimensions



Russakovsky et al.

ImageNet

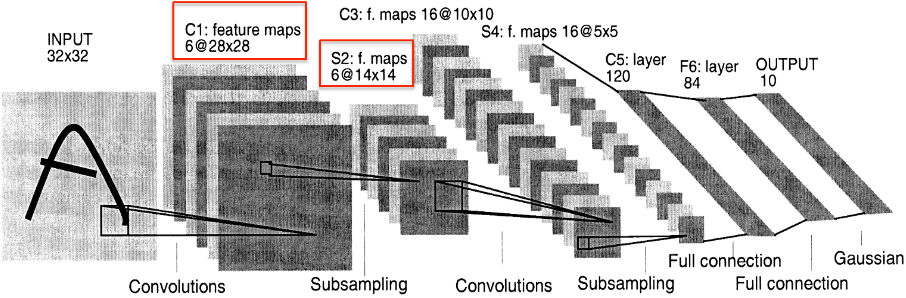
Size on disk:

MNIST
60 MB

ImageNet
50 GB

LeNet

Here's the LeNet architecture, which was applied to handwritten digit recognition on MNIST in 1998:



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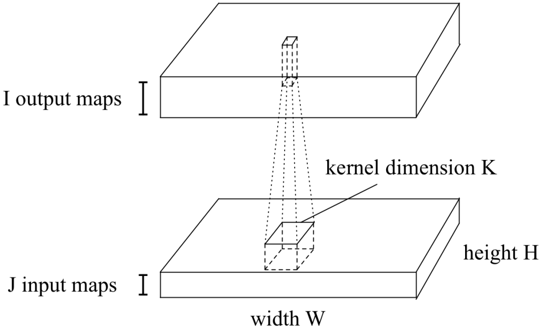
- We saw that a fully connected layer with M input units and N output units has MN connections and MN weights.
- The story for conv nets is more complicated.

Size of a Conv Net



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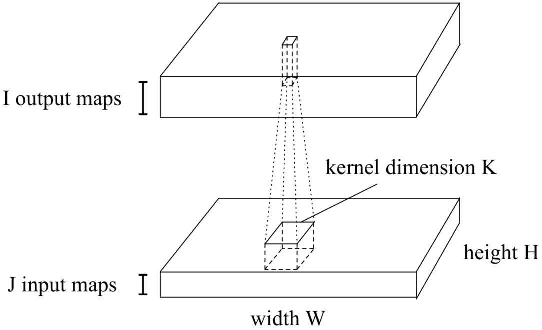

	fully connected layer	convolution layer
# output units		

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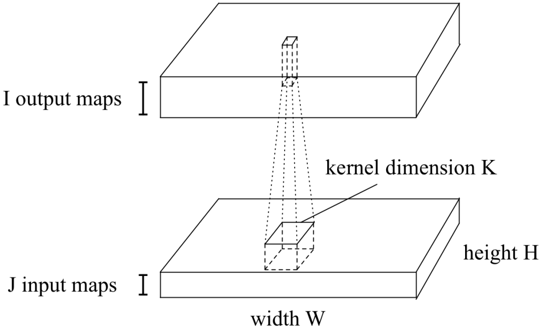

	fully connected layer	**convolution layer**
# output units	WHI	WHI

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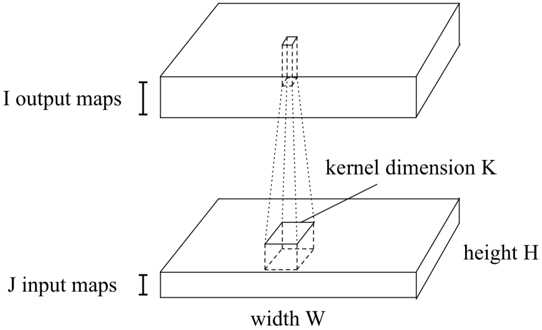

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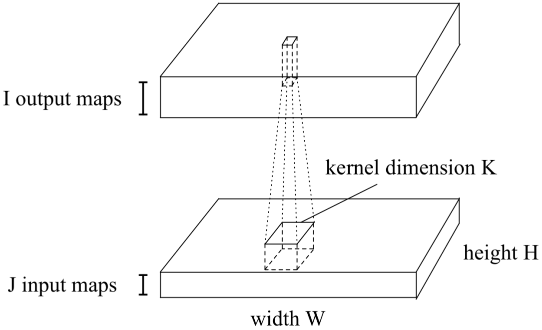

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# output units	WHI	WHI
# weights	W^2H^2IJ	

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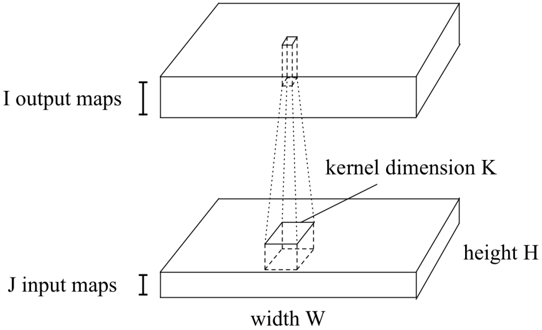

	fully connected layer	**convolution layer**
# output units	WHI	WHI
# weights	W^2H^2IJ	K^2IJ

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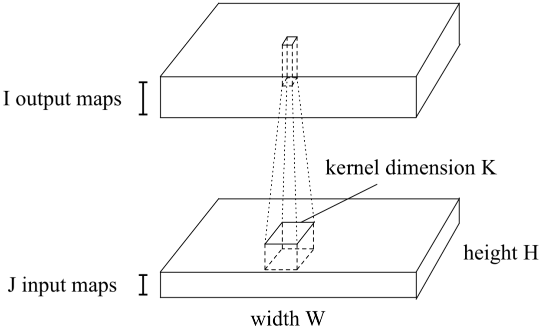

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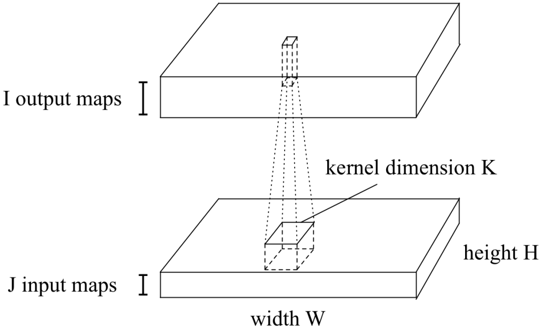

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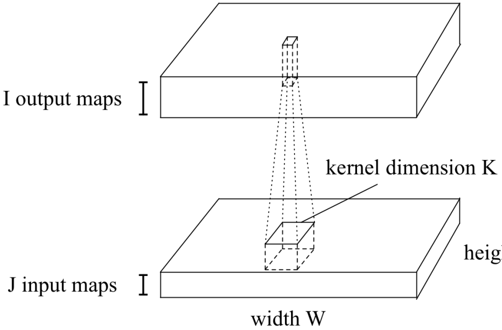

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# connections	W^2H^2IJ	WHK^2IJ

Size of a Conv Net

Sizes of layers in LeNet:

Layer	Type	# units	# connections	# weights
C1	convolution	4704	117,600	150
S2	pooling	1176	4704	0
C3	convolution	1600	240,000	2400
S4	pooling	400	1600	0
F5	fully connected	120	48,000	48,000
F6	fully connected	84	10,080	10,080
output	fully connected	10	840	840

Conclusions?

Size of a Conv Net

- Rules of thumb:
  - Most of the units and connections are in the convolution layers.
  - Most of the weights are in the fully connected layers.
- If you try to make layers larger, you'll run up against various resource limitations (i.e. computation time, memory)
- Conv nets have gotten a LOT larger since 1998!

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classification task	digits	digits	objects

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parameters	9,760	60,000	60 million

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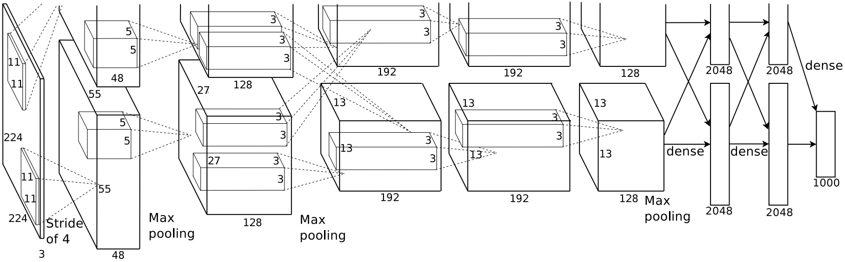
connections	65,000	344,000	652 million
total operations	11 billion	412 billion	200 quadrillion (est.)

AlexNet

- AlexNet, 2012. 8 weight layers. 16.4% top-5 error (i.e. the network gets 5 tries to guess the right category).



(Krizhevsky et al., 2012)

- They used lots of tricks we've covered in this course (ReLU units, weight decay, data augmentation, SGD with momentum, dropout)
- AlexNet's stunning performance on the ILSVRC is what set off the deep learning boom of the last 5 years.

GoogLeNet

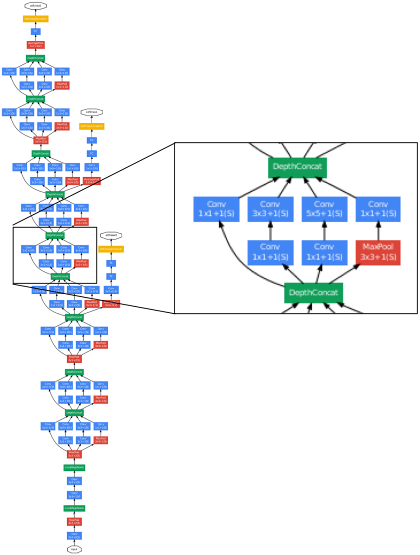
GoogLeNet, 2014.

22 weight layers

Fully convolutional (no fully connected layers)

Convolutions are broken down into a bunch of smaller convolutions

6.6% test error on ImageNet



GoogLeNet

- They were really aggressive about cutting the number of parameters.
  - Motivation: train the network on a large cluster, run it on a cell phone
    - Memory at test time is the big constraint.
    - Having lots of units is OK, since the activations only need to be stored at training time (for backpropagation).
    - Parameters need to be stored both at training and test time, so these are the memory bottleneck.
  - How they did it
    - No fully connected layers (remember, these have most of the weights)
    - Break down convolutions into multiple smaller convolutions (since this requires fewer parameters total)
  - GoogLeNet has "only" 2 million parameters, compared with 60 million for AlexNet
  - This turned out to improve generalization as well. (Overfitting can still be a problem, even with over a million images!)

Classification

ImageNet results over the years. Note that errors are top-5 errors (the network gets to make 5 guesses).

Year	**Model**	**Top-5 error**
2010	Hand-designed descriptors + SVM	28.2%
2011	Compressed Fisher Vectors + SVM	25.8%
2012	AlexNet	16.4%
2013	a variant of AlexNet	11.7%
2014	GoogLeNet	6.6%
2015	deep residual nets	4.5%

We'll cover deep residual nets later in the course, since they require an idea we haven't covered yet.

Human-performance is around 5.1%.

They stopped running the object recognition competition because the performance is already so good.