CSC 411: Lecture 11: Neural Networks II

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Today

- Deep learning for Object Recognition
People are very good at recognizing shapes
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- Intrinsically difficult, computers are bad at it
People are very good at recognizing shapes
  - Intrinsically difficult, computers are bad at it

Why is it difficult?
Why is it a Problem?

- Difficult scene conditions

[From: Grauman & Leibe]
Why is it a Problem?

- Huge within-class variations. Recognition is mainly about modeling variation.

[Pic from: S. Lazebnik]
Why is it a Problem?

- Tones of classes

\[ \approx 10,000 \text{ to } 30,000 \]

[Biederman]
People are very good at recognizing shapes
  - Intrinsically difficult, computers are bad at it

Some reasons why it is difficult:

- Segmentation: Real scenes are cluttered
- Invariances: We are very good at ignoring all sorts of variations that do not affect shape
- Deformations: Natural shape classes allow variations (faces, letters, chairs)
- A huge amount of computation is required
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Neural Nets for Object Recognition

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How to Deal with Large Input Spaces

- How can we apply neural nets to images?
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How many parameters do I have?
How to Deal with Large Input Spaces

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- Images can have millions of pixels, i.e., \( x \) is very high dimensional
- How many parameters do I have?
- Prohibitive to have fully-connected layers
How can we apply neural nets to images?

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What can we do?
How to Deal with Large Input Spaces

- How can we apply neural nets to images?
- Images can have millions of pixels, i.e., $x$ is very high dimensional
- How many parameters do I have?
- Prohibitive to have fully-connected layers
- What can we do?
- We can use a locally connected layer
Locally Connected Layer

Example: 200x200 image
40K hidden units
Filter size: 10x10
4M parameters

Note: This parameterization is good when input image is registered (e.g., face recognition).
When Will this Work?

- This is good when the input is (roughly) registered.
The object can be anywhere
The object can be anywhere
General Images

- The object can be anywhere

[Slide: Y. Zhu]
STATIONARITY? Statistics is similar at different locations

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40K hidden units
Filter size: 10x10
4M parameters

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The replicated feature approach

- Adopt approach apparently used in monkey visual systems
- Use many different copies of the same feature detector.
  - Copies have slightly different positions.
  - Could also replicate across scale and orientation.
    - Tricky and expensive
  - Replication reduces number of free parameters to be learned.
- Use several different feature types, each with its own replicated pool of detectors.
  - Allows each patch of image to be represented in several ways.
Convolutional Neural Net

- Idea: statistics are similar at different locations (Lecun 1998)
- Connect each hidden unit to a small input patch and share the weight across space
- This is called a convolution layer and the network is a convolutional network

Share the same parameters across different locations (assuming input is stationary):
Convolutions with learned kernels
Convolutional Layer

\[ h_j^n = \max(0, \sum_{k=1}^{K} h_{k}^{n-1} \ast w_{jk}^n) \]
Convolutional Layer

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Convolutional Layer

\[ h^n_j = \max(0, \sum_{k=1}^{K} h^{n-1}_k * w^n_{jk}) \]
Convolutional Layer

\[ h_j^n = \max(0, \sum_{k=1}^{K} h_{k}^{n-1} \ast w_{jk}^n) \]
Learn multiple filters.

E.g.: 200x200 image
100 Filters
Filter size: 10x10
10K parameters
Convolutional Layer

Figure: **Left:** CNN, **right:** Each neuron computes a linear and activation function.
Convolutional Layer

Figure: Left: CNN, right: Each neuron computes a linear and activation function

Hyperparameters of a convolutional layer:
Convolutional Layer

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- The number of filters (controls the **depth** of the output volume)
- The **stride**: how many units apart do we apply a filter spatially (this controls the spatial size of the output volume)
Figure: **Left:** CNN, **right:** Each neuron computes a linear and activation function

Hyperparameters of a convolutional layer:

- The number of filters (controls the **depth** of the output volume)
- The **stride**: how many units apart do we apply a filter spatially (this controls the spatial size of the output volume)
- The size $w \times h$ of the filters
MLP vs ConvNet

Figure: Top: MLP, bottom: Convolutional neural network

[Zemel, Urtasun, Fidler (UofT)]
By “pooling” (e.g., taking max) filter responses at different locations we gain robustness to the exact spatial location of features.
Pooling Options

- **Max Pooling**: return the maximal argument
- **Average Pooling**: return the average of the arguments
- Other types of pooling exist.
Pooling

Figure: **Left:** Pooling, **right:** max pooling example
Pooling

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Hyperparameters of a pooling layer:
Hyperparameters of a pooling layer:

- The spatial extent $F$

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Pooling

Hyperparameters of a pooling layer:

- The spatial extent $F$
- The stride

[http://cs231n.github.io/convolutional-networks/]
If convolutional filters have size $K \times K$ and stride 1, and pooling layer has pools of size $P \times P$, then each unit in the pooling layer depends upon a patch (at the input of the preceding conv. layer) of size: $(P+K-1) \times (P+K-1)$
It is easy to modify the backpropagation algorithm to incorporate linear constraints between the weights.

To constrain: \( w_1 = w_2 \)

we need: \( \Delta w_1 = \Delta w_2 \)
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We compute the gradients as usual, and then modify the gradients so that they satisfy the constraints.

compute: \( \frac{\partial E}{\partial w_1} \) and \( \frac{\partial E}{\partial w_2} \)
use: \( \frac{\partial E}{\partial w_1} + \frac{\partial E}{\partial w_2} \) for \( w_1 \) and \( w_2 \)
Backpropagation with Weight Constraints

- It is easy to modify the backpropagation algorithm to incorporate linear constraints between the weights.

  
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- So if the weights started off satisfying the constraints, they will continue to satisfy them.
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So if the weights started off satisfying the constraints, they will continue to satisfy them.

This is an intuition behind the backprop. In practice, write down the equations and compute derivatives (it’s a nice exercise, do it at home)
Now let’s make this very deep to get a real state-of-the-art object recognition system
Convolutional Neural Networks (CNN)

- Remember from your image processing / computer vision course about filtering?

**Input “image”**

**Filter**
If our filter is \([-1, 1]\), you get a vertical edge detector.
Now imagine we want to have many filters (e.g., vertical, horizontal, corners, one for dots). We will use a filterbank.
Convolutional Neural Networks (CNN)

- So applying a filterbank to an image yields a cube-like output, a 3D matrix in which each slice is an output of convolution with one filter. We apply an activation function on each hidden unit (typically a ReLU).

image (3 channels: R, G, B)

Each slice in this cube is the output of convolution of the image and a filter (in this example an 11x11 filter)

In this example there are 96 filters

In this example our network will always expect a 224x224x3 image.
So applying a filterbank to an image yields a cube-like output, a 3D matrix in which each slice is an output of convolution with one filter. We apply an activation function on each hidden unit (typically a ReLU).

Each slice in this cube is the output of convolution of the image and a filter.

In this example the filter size is 11x11x3.

We don’t do convolution in every pixel, but in every 4th pixel (in x and y direction)
Convolutional Neural Networks (CNN)

- Do some additional tricks. A popular one is called max pooling. Any idea why you would do this?

\[ O(i, j) = \max_{k \in \{i-1, i, i+1\}, l \in \{j-1, j, j+1\}} O(k, l) \]

Take each slice in the output cube, and in each pixel compute a max over a small patch around it. This is called max pooling.
Do some additional tricks. A popular one is called max pooling. Any idea why you would do this? To get invariance to small shifts in position.

\[
O(i, j) = \max_{k \in \{i-1, i, i+1\}} \max_{l \in \{j-1, j, j+1\}} O(k, l)
\]

Take each slice in the output cube, and in each pixel compute a max over a small patch around it. This is called max pooling.
Now add another “layer” of filters. For each filter again do convolution, but this time with the output cube of the previous layer.

Add one more layer of filters

These filters are convolved with the output of the previous layer. The results of each convolution is again a slice in the cube on the right.

What is the dimension of each of these filters?
Convolutional Neural Networks (CNN)

- Keep adding a few layers. Any idea what’s the purpose of more layers? Why can’t we just have a full bunch of filters in one layer?

Do it recursively
Have multiple "layers"
Convolutional Neural Networks (CNN)

- In the end add one or two **fully** (or **densely**) connected layers. In this layer, we don’t do convolution we just do a dot-product between the “filter” and the output of the previous layer.

  In the top, most networks add a `densely` connected layer. You can think of this as a filter, and the output value is a dot product between the filter and the output cube of the previous layer.

  What are the dimensions of this filter in this example? How many such filters are on this layer?
Convolutional Neural Networks (CNN)

- Add one final layer: a **classification** layer. Each dimension of this vector tells us the probability of the input image being of a certain class.

Add a **classification** `\"layer\"`.

For an input image, the value in a particular dimension of this vector tells you the probability of the corresponding object class.
The trick is to not hand-fix the weights, but to **train** them. Train them such that when the network sees a picture of a dog, the last layer will say “dog”.
Convolutional Neural Networks (CNN)

- Or when the network sees a picture of a cat, the last layer will say “cat”.

**Train the weights of filters**
Convolutional Neural Networks (CNN)

- Or when the network sees a picture of a boat, the last layer will say "boat"... The more pictures the network sees, the better.

Train on **lots** of examples. Millions. Tens of millions. Wait a week for training to finish.

Share your network (the weights) with others who are not fortunate enough with GPU power.
Classification

- Once trained we feed in an image or a crop, run through the network, and read out the class with the highest probability in the last (classif) layer.

What’s the class of this object?
Example

[http://cs231n.github.io/convolutional-networks/]

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Krizhevsky et al. “ImageNet Classification with deep CNNs” NIPS 2012
Architecture for Classification

Total nr. params: 60M

Total nr. flops: 832M

Krizhevsky et al. “ImageNet Classification with deep CNNs” NIPS 2012
Imagenet, biggest dataset for object classification: http://image-net.org/

- 1000 classes, 1.2M training images, 150K for test
The 2012 Computer Vision Crisis

Zemel, Urtasun, Fidler (UofT)

(Classification)

(Detection)
So Neural Networks are Great

- So networks turn out to be great.
- Everything is deep, even if it’s shallow!
- Companies leading the competitions as they have more computational power
- At this point Google, Facebook, Microsoft, Baidu “steal” most neural network professors/students from academia
So Neural Networks are Great

- But to train the networks you need quite a bit of computational power (e.g., GPU farm). So what do you do?
So Neural Networks are Great

- Buy even more.
So Neural Networks are Great

- And train **more layers**. 16 instead of 7 before. 144 million parameters.

**add more layers**

*Figure*: K. Simonyan, A. Zisserman, *Very Deep Convolutional Networks for Large-Scale Image Recognition*. arXiv 2014
150 Layers!

- Networks are now at 150 layers
- They use a skip connections with special form
- In fact, they don’t fit on this screen
- Amazing performance!
- A lot of “mistakes” are due to wrong ground-truth

\[ H(x) = F(x) + x \]

Results: Object Classification

Revolution of Depth

152 layers

ImageNet Classification top-5 error (%)

ILSVRC'15 ResNet 3.57
ILSVRC'14 GoogleNet 6.7
ILSVRC'14 VGG 7.3
ILSVRC'13 11.7
ILSVRC'12 AlexNet 16.4
ILSVRC'11 25.8
ILSVRC'10 28.2

Results: Object Detection

Revolution of Depth

Engines of visual recognition

- HOG, DPM: 34
- AlexNet (RCNN): 58 (8 layers)
- VGG (RCNN): 66 (16 layers)
- ResNet (Faster RCNN)*: 101 layers

Results: Object Detection

Results: Object Detection

![Object Detection Result]

- Person: 0.989
- Refrigerator: 0.979
- Bottle: 0.792
- Oven: 0.969
- Knife: 0.739
- Spoon: 0.727
- Cup: 0.881
- Bowl: 0.927

Results: Object Detection

What do CNNs Learn?

Figure: Filters in the first convolutional layer of Krizhevsky et al
What do CNNs Learn?

Figure: Filters in the second layer

What do CNNs Learn?

Figure: Filters in the third layer

How to Train Good CNNs

- Normalize your data (standard trick: subtract mean, divide by standard deviation)
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- In training: Random initialization of weights with proper variance
- Monitor your loss function, and accuracy (performance) on validation
- If your labeled image dataset is small: pre-train your CNN on a large dataset (eg Imagenet), and fine-tune on your dataset

Tricking a Neural Net

Read about it here (and try it!): https://codewords.recurse.com/issues/five/why-do-neural-networks-think-a-panda-is-a-vulture

Watch: https://www.youtube.com/watch?v=M2IebCN9Ht4
More on NNs

More on NNs

A man is eating a hot dog in a crowd.

More on NNs

Figure: Compose music: https://www.youtube.com/watch?v=0VTI1BBLydE
Links

- **NNs for computer vision:**
  [https://github.com/kjw0612/awesome-deep-vision](https://github.com/kjw0612/awesome-deep-vision)

- **Recurrent neural networks:** [https://github.com/kjw0612/awesome-rnn](https://github.com/kjw0612/awesome-rnn)

- **Lots of code, models, tutorials:**
  [https://github.com/carpedm20/awesome-torch](https://github.com/carpedm20/awesome-torch)

- **More links on our class webpage**