Video 1

Recap Neural Networks
A lot of the buzz about ML recently has come from recent advancements in **deep learning**.

When people talk about “deep learning” they are generally talking about a class of models called **neural networks** that are a loose approximation of how our brains work.
Compute the output for input (0, 1). There is a sign activation function on the hidden layers and output layer.
NNs to the Rescue

Neural Networks implicitly find these low level features for us!

Example detectors learned

Example interest points detected

[Zeiler & Fergus ‘13]

Each layer learns more and more complex features
Hyperparameter Optimization

How do we choose hyperparameters to train and evaluate?

Grid search:
Hyperparameters on 2d uniform grid

Random search:
Hyperparameters randomly chosen

Bayesian Optimization:
Hyperparameters \textit{adaptively} chosen
Video 2

Convolutions
Images are extremely high dimensional

CIFAR-10 dataset are very small: 3@32x32
  - # inputs:

For moderate sized images: 3@200x200
  - # inputs:

Images are structured, we should leverage this
Idea: Reduce the number of weights that need to be learned by looking at local neighborhoods of image.

Use the idea of a convolution to reduce the number of inputs by combing information about local pixels.
Convolution

Use a **kernel** that slides across the image, computing the sum of the element-wise product between the kernel and the overlapping part of the image.

<table>
<thead>
<tr>
<th>Image</th>
<th>Kernel</th>
</tr>
</thead>
<tbody>
<tr>
<td>3 3 2 1 0</td>
<td>0 1 2</td>
</tr>
<tr>
<td>0 0 1 3 1</td>
<td>2 2 0</td>
</tr>
<tr>
<td>3 1 2 2 3</td>
<td>0 1 2</td>
</tr>
<tr>
<td>2 0 0 2 2</td>
<td></td>
</tr>
<tr>
<td>2 0 0 0 1</td>
<td></td>
</tr>
</tbody>
</table>
Convolution

The input image (blue), the kernel (dark blue, numbers lower right) slide over the image to produce a result (green)
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Special Kernels

The numbers in the kernels determine special properties.

<table>
<thead>
<tr>
<th>Identity</th>
<th>Edge Detection</th>
</tr>
</thead>
</table>
| \[
\begin{bmatrix}
0 & 0 & 0 \\
0 & 1 & 0 \\
0 & 0 & 0 \\
\end{bmatrix}
\] | \[
\begin{bmatrix}
-1 & -1 & -1 \\
-1 & 8 & -1 \\
-1 & -1 & -1 \\
\end{bmatrix}
\] |

<table>
<thead>
<tr>
<th>Sharpen</th>
<th>Box Blur</th>
</tr>
</thead>
</table>
| \[
\begin{bmatrix}
0 & -1 & 0 \\
-1 & 5 & -1 \\
0 & -1 & 0 \\
\end{bmatrix}
\] | \[
\frac{1}{9}
\begin{bmatrix}
1 & 1 & 1 \\
1 & 1 & 1 \\
1 & 1 & 1 \\
\end{bmatrix}
\] |

Convolutional Neural Networks (CNNs) learn the right weights for each kernel they use! Generally not interpretable!
Hyper-parameters of a Single Convolution

You can specify a few more things about a kernel:

- Kernel dimensions
- Padding size and padding values
- Stride (how far to jump) values

For example, a 3x3 kernel applied to a 5x5 image with 1x1 zero padding and a 2x2 stride
CSE/STAT 416

Convolutional Neural Networks

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Paul G. Allen School of Computer Science & Engineering
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May 3, 2024
- Nobody
- Google Colab:

You get a GPU and you get a GPU

Everyone gets a GPU
A lot of the buzz about ML recently has come from recent advancements in **deep learning**.

When people talk about “deep learning” they are generally talking about a class of models called **neural networks** that are a loose approximation of how our brains work.
Features in computer vision are local detectors. Combine features to make prediction.

In reality, these features are much more low level (e.g., Corner?)
A popular approach to computer vision was to make hand-crafted features for object detection.

Input

Extract features

Use simple classifier

e.g., logistic regression, SVMs

Face?

Relies on coming up with these features by hand (yuck!)
NNs to the Rescue

Neural Networks implicitly find these low level features for us!

Each layer learns more and more complex features
Idea: Reduce the number of weights that need to be learned by looking at local neighborhoods of image.

Use the idea of a convolution to reduce the number of inputs by combing information about local pixels.
You can specify a few more things about a kernel:

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For example, a 3x3 kernel applied to a 5x5 image with 1x1 zero padding and a 2x2 stride.
What is the result of applying a convolution using this kernel on this input image?
Use 1x1 zero padding and a 2x2 stride

<table>
<thead>
<tr>
<th>Image</th>
<th>Kernel</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 2 3 4</td>
<td></td>
</tr>
<tr>
<td>5 6 7 8</td>
<td></td>
</tr>
<tr>
<td>9 10 11 12</td>
<td></td>
</tr>
<tr>
<td>13 14 15 16</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1 1 0 2</td>
</tr>
</tbody>
</table>
Convolutional Neural Networks
Another core operation that is similar to a convolution is a pool. Idea is to down sample an image using some operation. Combine local pixels using some operation (e.g. max, min, average, median, etc.)

Typical to use max pool with 2x2 filter and stride 2. Tends to work better than average pool.
Combine convolutions and pools into pre-processing layers on image to learn a smaller, information dense representation.

Example architecture for hand-written digit recognition

Each convolution section uses many different kernels (increasing depth of channels)

Pooling layers downsample each channel separately

Usually ends with fully connected neural network
Convolutional Neural Network

Why does this help?

- Only need to learn a small number of values (kernel weights) that get applied to the entire image region by region
- This is called weight-sharing
- Gives efficiency + shift invariance

Pooling lets us focus on features from larger and larger regions of the original image.
Input: 10x10x1 image (grayscale image of 10x10 pixels)
Convolution: 5x5 kernel, stride 1
MaxPool: 2x2, stride 2
What is the size of the resulting image?
Input: 10x10x1 image (grayscale image of 10x10 pixels)

Convolution: 5x5 kernel, stride 1

MaxPool: 2x2, stride 2

What is the size of the resulting image?
Brain Break
Number of Weights / Parameters

38
CNN with Color Images

How does this work if there is more than one input channel?

Usually, use a 3-dimensional **tensor** as the kernel to combine information from each input channel.
Another way of thinking about this process is each kernel is a (hidden-layer) neuron that looks at the kernel-size pixels in a neighborhood.

If there are 5 output channels in a conv layer, only need to learn the weights for the 5 neurons.

These neurons are a bit different since they look at the pixels that overlap with the window at each position.
Consider a plain neural network below, how many weights need to be learned?

Completely ignore intercept terms

15  10  5  2
Consider solving a digit recognition task on 28x28 grayscale images. Suppose I wanted to use a fully connected hidden layer with 84 neurons

**Without Convolutions:**
Consider solving a digit recognition task on 28x28 images. Suppose I wanted to use a fully connected hidden layer with 84 neurons *With Convolutions* (assume $n_1=10$, $n_2=20$) (not counting intercepts)
CNN
Applications & Transfer Learning
CNNs usually* have architectures that look like the following:

A series of Convolution + Activation Functions and Pooling layers. It’s very common to do a pool after each convolution.

Each set of operations lowers the size of the image but increases the number of features.

Then after some number of these operations, flatten the image to work with the final neural network.
The learned kernels are exactly the “features” for computer vision! They start simple (corners, edges) and get more complex after more layers.
Brain Break
CNNs have had remarkable success in practice

LeNet, 1990s
LeNet made 82 errors on MNIST (popular hand-written digit dataset of size 60K). 99.86% accuracy
CNN Success

ImageNet 2012 competition:
- 1.2M training images
- 1000 categories

Winner: SuperVision
- 8 layers, 60M parameters
- [Krizhevsky et al. ‘12]
- Top-5 Error: 17%
CNN Success

**Won 2014 ImageNet challenge with 6.66% top-5 error rate**

Huge CNN depth has proven helpful in recognition systems... Maybe because images contain hierarchical structure (faces contain eyes contain edges, etc.)

GoogLeNet, 2014
Applications

Image Classification

- **Input:** $x$
  - Image pixels

- **Output:** $y$
  - Predicted object

Scene Parsing [Farabet et al. ‘13]
Applications


Product Recommendation
For each of the Computer Vision Tasks below, what do you think the output layer of the neural network would look like? What would each output neuron represent?

**Image Classification**: Given an image with a single object, output the class of the object.

**Object Localization**: Given an image with a single object, output the class and bounding box \((x,y,w,h)\) of the object.

**Object Detection**: Given an image with possibly multiple objects, output the bounding box and class for **each** object.
**Image Classification:** Given an image with a single object, output the class of the object.

**Object Localization:** Given an image with a single object, output the class **and** bounding box \((x,y,w,h)\) of the object.

**Object Detection:** Given an image with possibly multiple objects, output the bounding box **and** class for **each** object.
If we don’t have a lot of data for Task 2, what can we do?

**Idea:** Use a model that was trained for one task to help learn another task.

An old idea, explored for deep learning by Donahue et al. ‘14 & others
CNNs

What is learned in a neural network?

Initial layers are low-level and very general.
Usually not sensitive/specific to the task at hand

Neural net trained for Task 1: cat vs. dog

More generic
Can be used as feature extractor

Very specific
to Task 1
Should be ignored
for other tasks
Transfer Learning

Share the weights for the general part of the network

Use simple classifier e.g., logistic regression, SVMs, nearest neighbor, ...

Keep weights fixed!

Re-train
If done successfully, transfer learning can really help. Can give you

- A higher *start*
- A higher *slope*
- A higher *asymptote*
Pros

No need to manually engineer features, enable automated learning of features

Impressive performance gains
  Image processing
  Natural Language Processing
  Speech recognition

Making huge impacts in most fields
Cons

- Requires a LOT of data
- Computationally really expensive
  - Environmentally, extremely expensive ([Green AI](#))
- Hard to tune hyper-parameters
  - Choice of architecture (we’ve added even more hyper-parameters)
    - Size of kernels, stride, 0 padding, number of conv layers, depth of outputs of conv layers,
  - Learning algorithm
- Still not very interpretable
NN Failures

While NNs have had amazing success, they also have some baffling failures.

“No one adds noise to things in real applications”

Not true!

Hackers will hack

Sensors (cameras) are noisy!
NN Failures

They even fail with “natural” transformations of images

Objects can be created to trick neural networks!
Datasets, like ImageNet, are generally biased. One approach is to augment your dataset to add random permutations of data to avoid bias.
Demo: Adversarial Neural Networks to Promote Fairness


Dataset: Adult UCI

- Predict whether a person’s income will be > $50K or ≤ $50K based on factors like:
  - Age
  - Education level
  - Marital status
  - Served in Armed Services?
  - Hours per week worked
  - Occupation sector
  - Etc.
Further Readings on Deep Learning

Dealing with Variable Length Sequences (e.g. language)
- Recurrent Neural Networks (RNNs)
- Long Short Term Memory Nets (LSTMs)
  [http://colah.github.io/posts/2015-08-Understanding-LSTMs/](http://colah.github.io/posts/2015-08-Understanding-LSTMs/)

Reinforcement Learning
- [Google DeepMind AlphaGo Zero](https://www.deepmind.com/blog/alphago-zero)

Generative Adversarial Networks
- [How to learn synthetic data](https://arxiv.org/abs/1511.06434)

Green AI
Recap

**Theme:** Details of convolutional neural networks

**Ideas:**

- Convolutions
- MaxPool
- Number of Parameters in a (C)NN
- Weight Sharing
- CNN Applications
- Transfer Learning
- NN Failures
- Using NNs to promote algorithmic fairness