CAP 4453
Robot Vision
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Credits

• Some slides comes directly from:
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  • Justin Johnson
  • Andrew Ng
Robot Vision

14. Introduction to Deep Learning I
Outline

• What is Machine Learning?
  • Main basic problems: regression, classification
  • Supervised vs unsupervised
  • Generalization, overfitting

• What is Deep learning?
  • What is Neural network
  • Activation functions
  • Define error
  • What are you optimizing?
  • Chain rule
  • Back-propagation
  • Why deep? How deep?
    • Hyper-parameters
  • Problems with NN. What happened in the 80’s?
    • Vanishing gradient problem
    • Number of parameters

• What kind of problems DN can solve?
  • Regression, classification
  • Computer vision: object detection, semantic segmentation, super-resolution,
  • Time series: NLP, visual questioning/answering
  • Generative models: impersonators ()
Introduction
Hubel and Wiesel

- In 1959, David H. Hubel and Torsten N. Wiesel conducted groundbreaking experiments that significantly expanded our understanding of sensory processing (visual system).
- Experiments on cats and kittens as models for humans, and in the 1970s they repeated the experiments on primates.
- In 1981 they won Nobel Prize.
- Each cell fires when you shine light in a specific small circular area of the visual field, with different cells responding to light in different places.
- Record the activity of neurons in cat brains while presenting various visual stimuli.
Hubel and Wiesel

- Trying respond to traditional visual stimuli such as dots: No response.
- Showed pictures of beautiful women from a magazine: No response.

- they were recording from a silent neuron, it suddenly started firing like crazy as they changed the projection slide that they were using to present the stimuli.
- Turns out, the cell was responding to the edge of the slide. That’s when Hubel and Wiesel discovered that there are cells specialized for detecting lines.
Hubel and Wiesel

They discovered another type of cell in the visual cortex, which they called a complex cell. Complex cells were activated by lines of a specific orientation, but many of them responded best to a line that was moving steadily through space.

So now the brain can detect a totally new feature: movement.

The visual system goes from detecting individual photons to detecting circles, lines, and movement!

The brain isn’t just a collection of neurons doing their own thing with their precious dendrites and axons; it’s a network of cells that talk to each other and trade information.
Larry Roberts (1963)

- Computer recognition of three-dimensional objects from image capture
- Edge finding (the first edge operator), line fitting, and model-based object recognition.
- First computer vision thesis
- Roberts is considered one of the fathers of the modern internet
  - Help invent Packet Switching
  - Distributed control (multiple computers)
  - Idea of satellite connections
The ICCV best-paper award is the Marr Prize, named after British neuroscientist David Marr.
Generalized cylinders

• Model complex objects from simpler parts
Edges (canny)

- Recognize objects from edges
Normalized cuts (1997)
SIFT (1999)
Voila and Jones (2001): Face detection

Figure 5. The first and second features selected by AdaBoost. The two features are shown in the top row and then overlayed on a typical training face in the bottom row. The first feature measures the difference in intensity between the region of the eyes and a region across the upper cheeks. The feature capitalizes on the observation that the eye region is often darker than the cheeks. The second feature compares the intensities in the eye regions to the intensity across the bridge of the nose.
Pascal Challenge: Object detection (2005-2012)

Classification: person, motorcycle

Action: riding bicycle

Large Scale Visual Recognition Challenge (ILSVRC) 2010-2014

- 200 object classes: 517,840 images
- 1000 object classes: 1,431,167 images

http://image-net.org/challenges/LSVRC/
Perceptron 1958

- One of the earliest algorithms could learn from data
  - Linear classifier
- Implemented in hardware. Weights stored in potentiometers updated with electric motors during learning
- Connected to a 20x20 camera
- Could learn to recognize letters
Mutilayer Perceptron idea

Minsky and Papert, 1969

<table>
<thead>
<tr>
<th>X</th>
<th>Y</th>
<th>F(x,y)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
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<td>0</td>
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<td>1</td>
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</tr>
</tbody>
</table>

Showed that Perceptrons could not learn the XOR function
Caused a lot of disillusionment in the field
Convolutional Networks

Neocognitron: Fukushima, 1980

Computational model the visual system, directly inspired by Hubel and Wiesel’s hierarchy of complex and simple cells

Interleaved simple cells (convolution) and complex cells (pooling)

No practical training algorithm
Back propagation

Lenet: First trainable convolutional neural network

Deep learning

2000s: “Deep Learning”

People tried to train neural networks that were deeper and deeper

Not a mainstream research topic at this time

Hinton and Salakhutdinov, 2006
Bengio et al, 2007
Lee et al, 2009
Glorot and Bengio, 2010
AlexNet

- 1.2 million high-resolution images from ImageNet LSVRC-2010 contest
- 1000 different classes (softmax layer)
- NN configuration
  - NN contains 60 million parameters and 650,000 neurons,
  - 5 convolutional layers, some of which are followed by max-pooling layers
  - 3 fully-connected layers

Some feature representations

SIFT

Spin image

HoG

RIFT

Textons

GLOH
Some feature representations

Coming up with features is often difficult, time-consuming, and requires expert knowledge.
What is Machine Learning?

• *machine learning* is using data to detect patterns. It is the same thing as *AI*. *

• What is new?
  • faster
  • cheaper
  • Bigger
  • Feature engineering is generally replaced by Feature learning

• What is the goal of the algorithms?
  • make predictions about future observations of data in the same format (generalization)
  • *input data + weights → f (weights)*

Today

Feature engineering (Expert knowledge) -> Feature learning (Data)
The machine learning framework

• Apply a prediction function to a feature representation of the image to get the desired output:

\[ f(\text{apple}) = \text{“apple”} \]
\[ f(\text{tomato}) = \text{“tomato”} \]
\[ f(\text{cow}) = \text{“cow”} \]
The machine learning framework

\[ f(x) = y \]

Prediction function or classifier \hspace{2cm} Image feature \hspace{2cm} Output (label)

**Training:** Given a *training set* of labeled examples:

\[ \{(x_1, y_1), \ldots, (x_N, y_N)\} \]

Estimate the prediction function \( f \) by minimizing the prediction error on the training set.

**Testing:** Apply \( f \) to an unseen *test example* \( x_u \) and output the predicted value \( y_u = f(x_u) \) to classify \( x_u \).
What is machine learning?

• If let’s say $f$ is a linear function in $N$ dimensions, $X = [x_1, x_2, ..., x_N]$, what do you learn?
  • $f(w_1, w_2, ..., w_{N+1}) = w_1 x_1 + w_2 x_2 + \cdots w_N x_N + w_{N+1}$
  • You learn the weights $w$ that match better that function

• Simplest case $N=1$,
  • Input Data is number (X axis)
  • output value is the Y axis
  • $f(w_1, w_2) = w_1 x_1 + w_2$

Finding these values is called training
Basic problems in machine learning

• You can break most of the machine learning problems in 2 categories:
  • **Regression**: predicting a value (such as price or time to failure)
  • **Classification** — predicting the category of something (dog/cat, good/bad, wolf/cow)
Basic problems in machine learning

- Supervised
- Unsupervised
- Semi-supervised

FROM SCIKIT-LEARN LIBRARY

scikit-learn algorithm cheat-sheet

classification
- SVC
- Ensemble Classifiers
- KNeighbors Classifier
- SGD Classifier

classification
- Naive Bayes
- Test Data
- Linear SVC
- get more data

clustering
- Spectral Clustering
- GMM
- KMeans
- MiniBatch KMeans
- MeanShift
- DBSCAN

clustering
- number of categories known
- <10K samples

regression
- SGD Regressor
- Lasso
- ElasticNet
- Ridge Regression
- SVR(kernel='linear')

dimensionality reduction
- Randomized PCA
- Isomap
- Spectral Embedding
- LLE

predicting a quantity
- <100K samples
- few features should be important

predicting a category
- >100K samples
- >50 samples

Looking
- <10K samples

Structure
- >10K samples
- predicting structure

Tough luck
- <10K samples

Labeled data
- <10K samples
- >10K samples
- predicting a category

START
Generalization AND overfitting
WITH TRAINING DATA

Overfitting in regression

Overfitting in classification
Generalization AND overfitting
WITH NEW TESTING DATA

Overfitting in regression

Overfitting in classification
Generalization AND overfitting
WITH NEW TESTING DATA

- Overfitting in regression
  ![Overfitting in regression](image)

- Overfitting in classification
  ![Overfitting in classification](image)
So far ...

- Machine learning = AI
- Goal: general function for input data
- Training process: Find parameters for the model
- Supervised: you have labeled data
- Unsupervised: you do not have labeled data
- Semi-supervised: some of your data is labeled
- Overfitting: training adjust very well to your training data, but do not generalize
What is deep learning?
What is deep learning?

• A machine learning technique that solves problems with enormous amount of data.
  • Huge number of tunable parameters
  • Highly non-linear
  • Based on neural networks
    • A stack of neural networks layers
  • It is data driven (not hand-crafted features)
Neurons in the Brain

- Brain is composed of neurons
- A neuron receives input from other neurons (generally thousands) from its dendrites
- Inputs are approximately summed
- When the input exceeds a threshold, the neuron sends an electrical spike that travels from the body, down the axon, to the next neuron(s)
What is a neuron?

\[ z = w^T x \]

\[ a = \sigma(z) \]

\[ a = \hat{y} \]
What is a neural network?
It’s all just matrix multiplication!

GPUs -> special hardware for fast/large matrix multiplication.
Composition: activation function

• Activation function must be a non-linear function.
  • Other case the output will be a linear function
    • Image you have 2 layers

\[
\begin{align*}
\mathbf{z}^{[1]} &= \mathbf{W}^{[1]} \mathbf{x} + \mathbf{b}^{[1]} \\
\mathbf{z}^{[2]} &= \mathbf{W}^{[2]} \mathbf{z}^{[1]} + \mathbf{b}^{[2]} \\
\mathbf{z}^{[2]} &= \mathbf{W}^{[2]} \mathbf{z}^{[1]} + \mathbf{b}^{[2]} \\
&= \mathbf{W}^{[2]} \left[ \mathbf{W}^{[1]} \mathbf{x} + \mathbf{b}^{[1]} \right] + \mathbf{b}^{[2]} \\
&= \mathbf{W}^{[2]} \mathbf{W}^{[1]} \mathbf{x} + \mathbf{W}^{[2]} \mathbf{b}^{[1]} + \mathbf{b}^{[2]} \\
&= \mathbf{W} \mathbf{x} + \mathbf{b} \\
\hat{y} &= \mathbf{z}^{[2]} = \mathbf{W} \mathbf{x} + \mathbf{b}
\end{align*}
\]

The output is always a linear function of the input!
Problem 1 with all linear functions

• We have formed chains of linear functions.
• We know that linear functions can be reduced
  • $g = f(h(x))$

Our composition of functions is really just a single function : ( 
Problem 2 with all linear functions

Linear classifiers:

small change in input can cause large change in binary output.

We want:

\[ w + \Delta w \]

causes a small change in the output

\[ \text{output} + \Delta \text{output} \]
Activation function

Pros and cons of activation functions

sigmoid: \( a = \frac{1}{1 + e^{-z}} \)

\[
tanh: a = \frac{e^z - e^{-z}}{e^z + e^{-z}}
\]

ReLU \( a = \max(0, z) \)

Leaky ReLU \( a = \max(0.01z, z) \)

Andrew Ng
Mark 1 Perceptron
c.1960

20x20 pixel camera feed
Loss function

• Error: Difference between expected value and obtained value

• Example: Image classification

• Loss: sum errors in the training dataset

\[ J_1 = \frac{1}{m} \sum_{\text{train}} |\hat{y}_i - y_i| \]

\[ J_2 = \frac{1}{m} \sum_{\text{train}} (\hat{y}_i - y_i)^2 \]
What are you optimizing?

- Goal: Minimize the loss function!!

The network is a function $f()$ with parameters $W$ which must be set to the appropriate values to get the desired behavior from the net.

- **Given:** the architecture of the network
- **The parameters of the network:** The weights and biases
  - The weights associated with the blue arrows in the picture
- **Learning the network:** Determining the values of these parameters such that the network computes the desired function
How to minimize a function?

In our case the loss function

\[ w_{\text{new}} = w_{\text{prev}} - \alpha \frac{dJ}{dW} \]

Repeat until there is almost not change

How to compute this gradient?
Gradient descent

\[ f(x) \]
General approach

Pick random starting point.
General approach

Compute gradient at point (analytically or by finite differences)
General approach

Move along parameter space in direction of negative gradient

\[ f(x) \]

\[ a_2 = a_1 - \gamma \nabla f(a_1) \]

\( \gamma \) = amount to move = learning rate
General approach

Move along parameter space in direction of negative gradient.

\[ a_3 = a_2 - \gamma \nabla f(a_2) \]

\( \gamma \) = amount to move
  = learning rate
General approach

Stop when we don’t move any more.

\[ a_{stop} : \quad a_{n-1} - \gamma \nabla f(a_{n-1}) = 0 \]
Back-propagation

• It is a technique to compute the gradient
• Gradients are necessary to get closer to the solution
• FORWARD PASS: You take the inputs, compute the outputs and loss(saving intermedia results)
• From the loss, you start computing backwards to estimate the values of the gradients for all the parameters \( w \)

\[
\begin{align*}
  x_1 & \\
  x_2 & \\
  x_3 & \\
\end{align*}
\]
Back-propagation

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\[
\frac{dj}{dw_{11}^2}, \frac{dj}{dw_{12}^2}, \frac{dj}{dw_{13}^2}, \frac{dj}{dw_{14}^2}, \frac{dj}{dw_{31}^3}, \frac{dj}{dw_{32}^3}, \ldots, \frac{dj}{dw_{33}^3}, \frac{dj}{dw_{34}^3}
\]

Goal: find

\( \hat{y} \)
What is a deep network?

- A neural network with many layers
- Highly nonlinear
An example
What is a deep network?

- A neural network with many layers
- Highly non linear
So far …

• A deep network is a neural network with many layers
• A neuron in a linear function followed for an activation function
• Activation function must be non-linear
• A loss function measures how close is the created function (network) from a desired output
• The “training” is the process of find parameters (‘weights’) that reduces the loss functions
• Updating the weights as $w_{new} = w_{prev} - \alpha \frac{dJ}{dW}$ reduces the loss
• An algorithm named back-propagation allows to compute $\frac{dJ}{dW}$ for all the weights of the network in 2 steps: 1 forward, 1 backward
What kind of problems deep learning can solve?
What problems you can solve?

• The fundamental ones:
  • Regression: predict values
  • Classification: predict labels

• Computer vision:
  • object detection
  • semantic segmentation
  • super-resolution,

• Time series:
  • NLP
  • visual questioning/answering

• Generative models
  • impersonators ()
Computer vision

- Find region of interest (regression)
- Find a class label (classification)
Computer vision

• Find a class for each pixel
Computer vision

SUPER-RESOLUTION FROM A SINGLE IMAGE

Figure 5: Sketch of several deep architectures for SISR.
Computer vision

OTHER PROBLEMS

• Super resolution from multiple images
• Denoising
Time series (RNN, LSTM, Attention models)

USE MEASUREMENT TO CHANGE STATE, USE STATE TO PREDICT FUTURE

• Natural language Processing
  • Translation
  • Check Google Bert
  • Visual Questioning answer

• Stocks
• Signals
  • ECG

Who is wearing glasses?
  man
  woman

Where is the child sitting?
  fridge
  arms

Is the umbrella upside down?
  yes
  no

How many children are in the bed?
  2
  1
Generative models
GAN (GENERATIVE ADVERSARIAL NETWORKS)

• Predict the data based on some loose input.
• Looks like the network is able to create something
Generative models

Figure 1: Many problems in image processing, graphics, and vision involve translating an input image into a corresponding output image. These problems are often treated with application-specific algorithms, even though the setting is always the same: map pixels to pixels. Conditional adversarial nets are a general-purpose solution that appears to work well on a wide variety of these problems. Here we show results of the method on several. In each case we use the same architecture and objective, and simply train on different data.

Generative models

IMAGE CREATION FROM TEXT

• Generative Adversarial Text to Image Synthesis. Scott Reed, Zeynep Akata, Xinchen Yan, Lajanugen Logeswaran, Bernt Schiele, Honglak Lee. ICML 2016

![Figure 1](image.png)

Figure 1. Examples of generated images from text descriptions. Left: captions are from zero-shot (held out) categories, unseen text. Right: captions are from the training set.
Generative models

CREATE FAKE MODELS

- https://youtu.be/p1b5aiTrGzY
NERF: NEURAL RADIANCE FIELD (3D RENDERING)

(11) NeRF: Neural Radiance Fields - YouTube
Questions?