CSC321 Lecture 1: Introduction

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  - recognizing people and objects
  - understanding human speech

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  - recognizing people and objects
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- Machine learning approach: program an algorithm to automatically learn from data, or from experience
- Some reasons you might want to use a learning algorithm:
  - hard to code up a solution by hand (e.g. vision, speech)
  - system needs to adapt to a changing environment (e.g. spam detection)
  - want the system to perform *better* than the human programmers
  - privacy/fairness (e.g. ranking search results)

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- But it's not statistics!
  - Stats is more concerned with helping scientists and policymakers draw good conclusions; ML is more concerned with building autonomous agents
  - Stats puts more emphasis on interpretability and mathematical rigor; ML puts more emphasis on predictive performance, scalability, and autonomy

What is machine learning?

- Types of machine learning
  - **Supervised learning:** have labeled examples of the correct behavior
  - **Reinforcement learning:** learning system receives a reward signal, tries to learn to maximize the reward signal
  - **Unsupervised learning:** no labeled examples – instead, looking for interesting patterns in the data

Course information

- Course about machine learning, with a focus on neural networks
  - Independent of CSC411, and CSC412, with about 25% overlap in topics
  - First 2/3: supervised learning
  - Last 1/3: unsupervised learning
  - Maybe a bit of reinforcement learning, time permitting
- Two sections
  - Equivalent content, same assignments and exams
  - Both sections are full, so please attend your own.

Course information

- Formal prerequisites:
  - **Calculus:** (MAT136H1 with a minimum mark of 77)/(MAT137Y1 with a minimum mark of 73)/(MAT157Y1 with a minimum mark of 67)/MAT235Y1/MAT237Y1/MAT257Y1
  - **Linear Algebra:** MAT221H1/MAT223H1/MAT240H1
  - **Probability:** STA247H1/STA255H1/STA257H1
  - **Multivariable calculus (recommended):** MAT235Y1/MAT237Y1/MAT257Y1
  - **Programming experience (recommended)**

Course information

- Expectations and marking
  - Weekly homeworks (10% of total mark)
    - Due Monday nights at 11:59pm, starting 1/16
    - 2-3 short conceptual questions
    - Use material covered up through Tuesday of the preceding week
  - 4 programming assignments (10% each)
    - Python
    - 10-15 lines of code
    - may also involve some mathematical derivations
    - give you a chance to experiment with the algorithms
  - Exams
    - midterm (15%)
    - final (35%)
- See Course Information handout for detailed policies

Course information

- Textbooks
  - None, but we link to lots of free online resources. (see syllabus)
    - Professor Geoffrey Hinton's Coursera lectures
    - the Deep Learning textbook by Goodfellow et al.
    - Metacademy
  - I will *try* to post detailed lecture notes, but I will not have time to cover every lecture.
- Tutorials
  - Roughly every week
  - Programming background; worked-through examples

Course information

Course web page:

`http://www.cs.toronto.edu/~rgrosse/courses/csc321_2017/`

Includes detailed course information handout

Supervised learning examples

Supervised learning: have labeled examples of the correct behavior

e.g. Handwritten digit classification with the MNIST dataset

- **Task:** given an image of a handwritten digit, predict the digit class
  - **Input:** the image
  - **Target:** the digit class

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- **Data:** 70,000 images of handwritten digits labeled by humans
  - **Training set:** first 60,000 images, used to train the network
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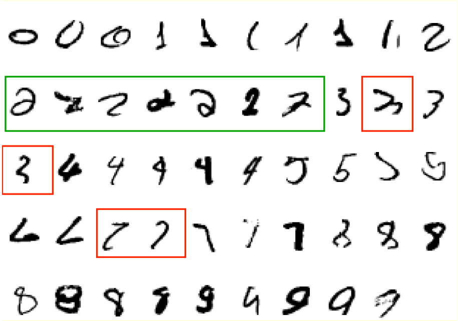
- This dataset is the "fruit fly" of neural net research
- Current best algorithm has only 0.23% error rate on the test set!

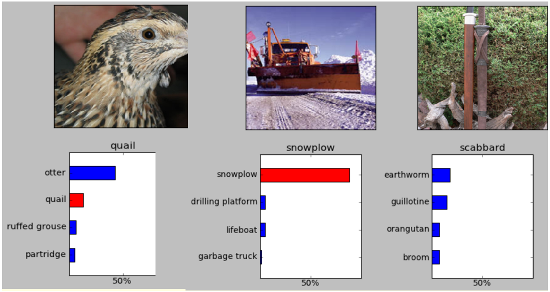
Supervised learning examples

What makes a “2”?



Supervised learning examples

Object recognition



(Krizhevsky and Hinton, 2012)

ImageNet dataset: thousands of categories, millions of labeled images

Lots of variability in viewpoint, lighting, etc.

Error rate dropped from 25.7% to 5.7% over the course of a few years!

Supervised learning examples

Caption generation

TAGS:

frisbees frisbee pushups golfers kickball

Nearest Neighbor Sentence:

- several people that are playing in a frisbee game .

Top-5 Generated:

- a group of girls are playing a game of frisbee .
- a group of girls are playing a soccer game .
- a group of girls playing on a soccer game .
- a group of people playing a game of frisbee .
- the young people are playing a game of frisbee .

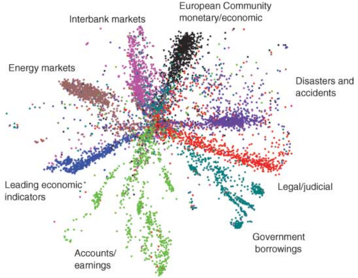
Given: dataset of Flickr images with captions

More examples at `http://deeplearning.cs.toronto.edu/i2t`

Unsupervised learning examples

Unsupervised learning: no labeled examples – instead, looking for interesting patterns in the data

E.g. visualization of documents; algorithm was given 800,000 newswire stories, and learned to represent these documents as points in two-dimensional space



Colors are based on human labels, but these weren't given to the algorithm

Unsupervised learning examples

Automatic mouse tracking

- When biologists do behavioral genetics researchers on mice, it's very time consuming for a person to sit and label everything a mouse does
- The Datta lab at Harvard is building a system for automatically tracking mouse behaviors
- Goal: show the researchers a summary of how much time different mice spend on various behaviors, so they can determine the effects of the genetic manipulations
- One of the major challenges is that we don't know the right "vocabulary" for describing the behaviors — clustering the observations into meaningful groups is an unsupervised learning task
- **video:** `http://www.sciencedirect.com/science/article/pii/S0896627315010375`

Reinforcement learning

- An **agent** interacts with an **environment** (e.g. game of Breakout)
- In each time step,
  - the agent receives **observations** (e.g. pixels) which give it information about the **state** (e.g. positions of the ball and paddle)
  - the agent picks an **action** (e.g. keystrokes) which affects the state
- The agent periodically receives a **reward** (e.g. points)
- The agent wants to learn a **policy**, or mapping from observations to actions, which maximizes its average reward over time

Reinforcement learning

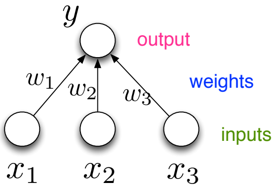
DeepMind trained neural networks to play many different Atari games

- given the raw screen as input, plus the score as a reward
- single network architecture shared between all the games
- in many cases, the networks learned to play better than humans (in terms of points in the first minute)

https://www.youtube.com/watch?v=V1eYniJ0Rnk

What are neural networks?

- Most of the biological details aren't essential, so we use vastly simplified models of neurons.
- While neural nets originally drew inspiration from the brain, nowadays we mostly think about math, statistics, etc.



output bias i'th weight

$$y = g\left(b + \sum_i x_i w_i\right)$$

nonlinearity i'th input

- Neural networks are collections of thousands (or millions) of these simple processing units that together perform useful computations.

What are neural networks?

Why neural nets?

- inspiration from the brain
  - proof of concept that a neural architecture can see and hear!
- very effective across a range of applications (vision, text, speech, medicine, robotics, etc.)
- widely used in both academia and the tech industry
- powerful software frameworks (Torch, Theano, Caffe, TensorFlow) let us quickly implement sophisticated algorithms

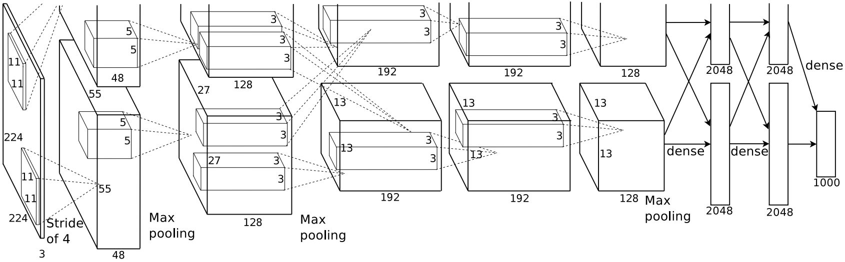
What are neural networks?

- Some near-synonyms for neural networks
  - “Deep learning”
    - Emphasizes that the algorithms often involve hierarchies with many stages of processing

"Deep learning"

Deep learning: many layers (stages) of processing

E.g. this network which recognizes objects in images:

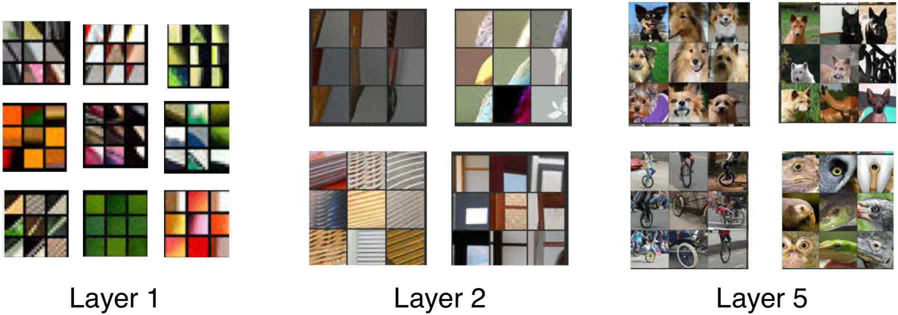


(Krizhevsky et al., 2012)

Each of the boxes consists of many neuron-like units similar to the one on the previous slide!

“Deep learning”

Here are the image regions that most strongly activate various neurons at different layers of the network. (Zeiler and Fergus, 2014)



Higher layers capture more abstract semantic information.

What are neural networks?

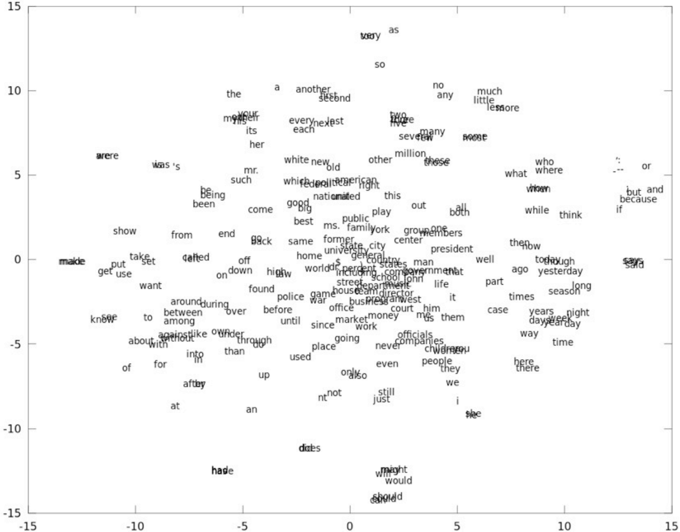
- Some near-synonyms for neural networks
  - "Deep learning"
    - Emphasizes that the algorithms often involve hierarchies with many stages of processing
  - "Representation learning"
    - The algorithms typically map the raw data into some other space which makes the relationships between different things more explicit

What is a representation?

- How you represent your data determines what questions are easy to answer.
  - E.g. a dict of word counts is good for questions like "What is the most common word in *Hamlet*?"
  - It's not so good for semantic questions like "if Alice liked *Harry Potter*, will she like *The Hunger Games*?"

What is a representation?

Idea: represent words as vectors



What is a representation?

- Mathematical relationships between vectors encode semantic relationships between words
  - Measure semantic similarity using the dot product (or dissimilarity using Euclidean distance)
  - Represent a web page with the average of its word vectors
  - Complete analogies by doing arithmetic on word vectors
    - e.g. "Paris is to France as London is to ____"
    - France – Paris + London = ____

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- It's very hard to construct representations like these by hand, so we need to learn them from data
  - This is a big part of what neural nets do, whether it's supervised, unsupervised, or reinforcement learning!

Software frameworks

- Array processing (NumPy)
  - **vectorize** computations (express them in terms of matrix/vector operations) to exploit hardware efficiency
- Neural net frameworks: Torch, Theano, Caffe, TensorFlow
  - automatic differentiation
  - compiling computation graphs
  - libraries of algorithms and network primitives
  - support for graphics processing units (GPUs)
- For this course:
  - Python, NumPy
  - **Autograd**, a lightweight automatic differentiation package written by Professor David Duvenaud and colleagues

Software frameworks

Why this class, and why Autograd?

So you know what do to if something goes wrong!

- Debugging learning algorithms requires sophisticated detective work, which requires understanding what goes on beneath the hood.
- That's why we derive things by hand in this class!

Next time

Next lecture: linear regression