

CSC421 Lecture 1: Introduction

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Course information

- Second course in machine learning, with a focus on neural networks
 - Replaces CSC321; similar content, but less introductory material and more cutting-edge topics
 - Assumes knowledge of basic ML algorithms: linear regression, logistic regression, maximum likelihood, PCA, EM, etc.
 - First 2/3: supervised learning
 - Last 1/3: unsupervised learning and reinforcement learning
- Two sections
 - Equivalent content, same assignments and exams

Course information

- Formal prerequisites:
 - **Multivariable Calculus:** MAT235/MAT237/MAT257
 - **Linear Algebra:** MAT221H1/MAT223H1/MAT240H1
 - **Machine Learning:** CSC411/STA314
- Prerequisites will be enforced, including for grad students.

Course information

- Expectations and marking (**undergrads**)
 - Written homeworks (20% of total mark)
 - Due Wednesday nights at 11:59pm, starting 1/24
 - 2-3 short conceptual questions
 - Use material covered up through Tuesday of the preceding week
 - 4 programming assignments (30% of total mark)
 - Python, PyTorch
 - 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

- Expectations and marking (**grad students**)
 - Same as undergrads:
 - Written homeworks: 20%
 - Programming assignments: 30%
 - Midterm: 15%
 - **Final project: 35%**
- See Course Information handout for detailed policies

How to get free GPUs

- **Colab (Recommended)** Google Colab is a web-based iPython Notebook service that has access to a free Nvidia K80 GPU per Google account.
- **GCE (Recommended)** Google Compute Engine delivers virtual machines running in Google's data center. You get \$300 free credit when you sign up.
- **CS Teaching Lab** There are some very old GPUs in our CS Teaching Labs / CDF labs
- See Course Information handout for the details

Course information

Course web page:

http://www.cs.toronto.edu/~rgrosse/courses/csc421_2019/

Includes detailed course information handout

What is machine learning?

- For many problems, it's difficult to program the correct behavior by hand
 - recognizing people and objects
 - understanding human speech

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 - recognizing people and objects
 - understanding human speech
- 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)

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

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

Supervised learning examples

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- **Task:** given an image of a handwritten digit, predict 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
 - **Test set:** last 10,000 images, not available during training, used to evaluate performance

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- This dataset is the “fruit fly” of neural net research
- Neural nets already achieved $> 99\%$ accuracy in the 1990s, but we still continue to learn a lot from it

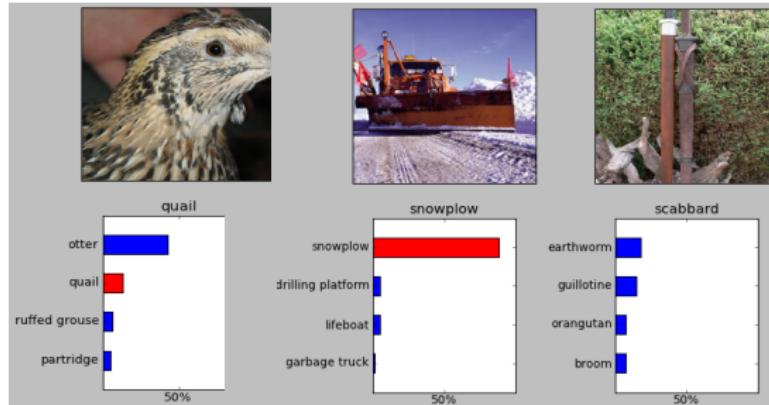
Supervised learning examples

What makes a “2”?



Supervised learning examples

Object recognition



(Krizhevsky and Hinton, 2012)

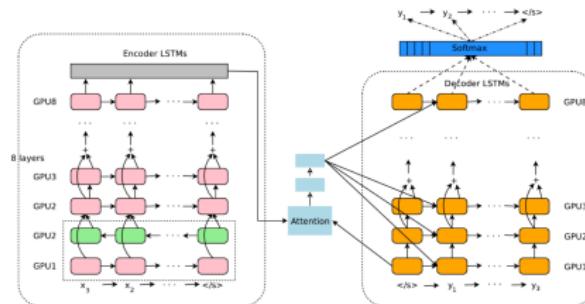
ImageNet dataset: thousands of categories, millions of labeled images

Lots of variability in viewpoint, lighting, etc.

Error rate dropped from 26% to under 4% over the course of a few years!

Supervised learning examples

Neural Machine Translation



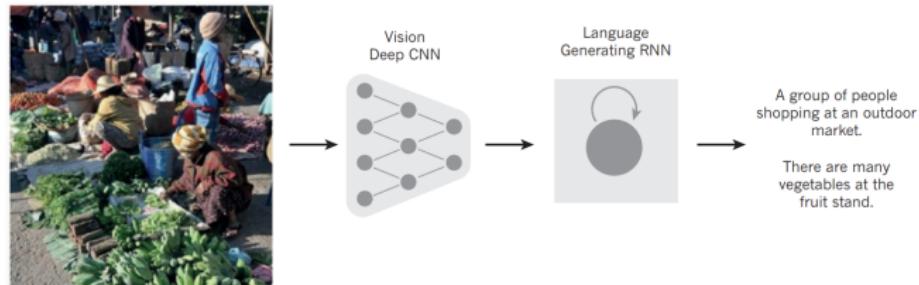
(Wu et al., 2016)

| <i>Input sentence:</i> | <i>Translation (PBMT):</i> | <i>Translation (GNMT):</i> | <i>Translation (human):</i> |
|---|---|--|---|
| 李克強此行將啟動中加總理年度對話機制，與加拿大總理杜魯多舉行兩國總理首次年度對話。 | Li Keqiang premier added this line to start the annual dialogue mechanism with the Canadian Prime Minister Trudeau two prime ministers held its first annual session. | Li Keqiang will start the annual dialogue mechanism with Prime Minister Trudeau of Canada and hold the first annual dialogue between the two premiers. | Li Keqiang will initiate the annual dialogue mechanism between premiers of China and Canada during this visit, and hold the first annual dialogue with Premier Trudeau of Canada. |

Now the production model on Google Translate

Supervised learning examples

Caption generation



A woman is throwing a **frisbee** in a park.



A **dog** is standing on a hardwood floor.



A **stop** sign is on a road with mountain in the background

(Xu et al., 2015)

Given: dataset of Flickr images with captions

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

Unsupervised learning examples

- In **generative modeling**, we want to learn a distribution over some dataset, such as natural images.
- We can evaluate a generative model by sampling from the model and seeing if it looks like the data.
- These results were considered impressive in 2014:



Denton et al., 2014, Deep generative image models using a Laplacian pyramid of adversarial networks

Unsupervised learning examples

- Fast-forward to 2017:



Unsupervised learning examples

- The progress of generative models:

Odena et al

2016



Miyato et al

2017



Zhang et al

2018



Unsupervised learning examples

- Recent exciting result: a model called the CycleGAN takes lots of images of one category (e.g. horses) and lots of images of another category (e.g. zebras) and learns to translate between them.



<https://github.com/junyanz/CycleGAN>



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>

Reinforcement learning for control

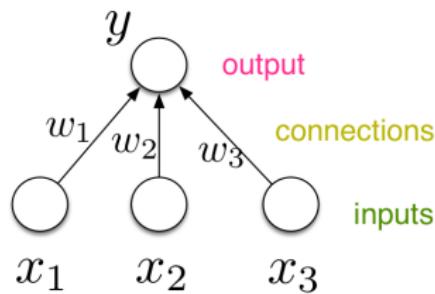
Learning locomotion control from scratch

- The reward is to run as far as possible over all the obstacles
- single control policy that learns to adapt to different terrains

https://www.youtube.com/watch?v=hx_bgoTF7bs

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.



An equation for a linear model with bias:

$$y = \phi(\mathbf{w}^\top \mathbf{x} + b)$$

Annotations explain the components:

- "output" points to the variable y .
- "weights" points to the term $\mathbf{w}^\top \mathbf{x}$.
- "bias" points to the term b .
- "activation function" points to the term ϕ .
- "inputs" points to the term \mathbf{x} .

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

What are neural networks?

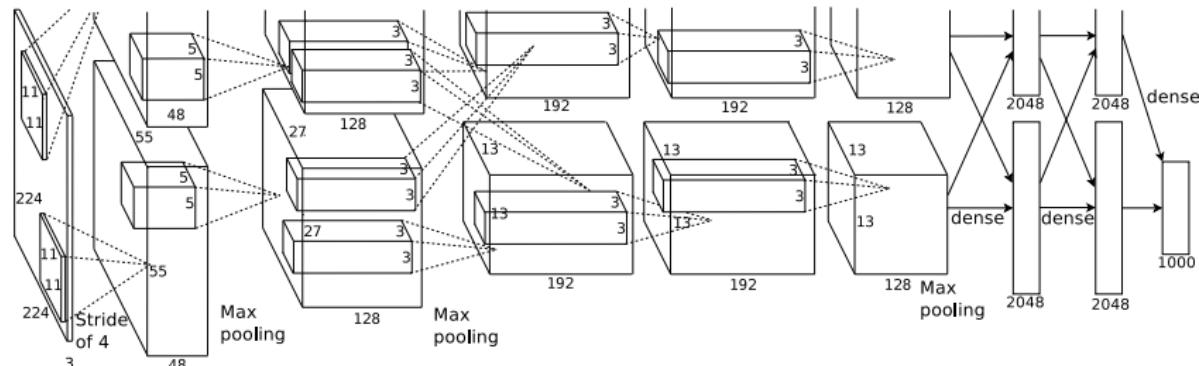
Why neural nets?

- 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 (PyTorch, TensorFlow, etc.) let us quickly implement sophisticated algorithms

“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”

- You can visualize what a learned feature is responding to by finding an image that excites it. (We'll see how to do this.)
- Higher layers in the network often learn higher-level, more interpretable representations



Edges (layer conv2d0)

Textures (layer mixed3a)

Patterns (layer mixed4a)

<https://distill.pub/2017/feature-visualization/>



“Deep learning”

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Parts (layers mixed4b & mixed4c) Objects (layers mixed4d & mixed4e)

<https://distill.pub/2017/feature-visualization/>

Software frameworks

- Array processing (NumPy)
 - **vectorize** computations (express them in terms of matrix/vector operations) to exploit hardware efficiency
- Neural net frameworks: PyTorch, TensorFlow, etc.
 - 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
 - **PyTorch**, a widely used neural net framework

Software frameworks

Why take this class, if PyTorch does so much for you?

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!