CSC 411: Lecture 01: Introduction

Richard Zemel, Raquel Urtasun and Sanja Fidler

University of Toronto

Today

- Administration details
- Why is machine learning so cool?

The Team I

- **Instructors**:
  - Raquel Urtasun
  - Richard Zemel
- **Email**:
  - csc411prof@cs.toronto.edu
- **Offices**:
  - Raquel: 290E in Pratt
  - Richard: 290D in Pratt
- **Office hours**: TBA

The Team II

- **TA's**:
  - Siddharth Ancha
  - Azin Asgarian
  - Min Bai
  - Lluis Castrejon Subira
  - Kaustav Kundu
  - Hao-Wei Lee
  - Renjie Liao
  - Shun Liao
  - Wenjie Luo
  - David Madras
  - Seyed Parsa Mirdehghan
  - Mengye Ren
  - Geoffrey Roeder
  - Yulia Rubanova
  - Elias Tragas
  - Eleni Triantafillou
  - Shenlong Wang
  - Ayazhan Zhakhan
- **Email**:
  - csc411ta@cs.toronto.edu

Admin Details

- Liberal wrt waiving pre-requisites
  - But it is up to you to determine if you have the appropriate background
- Do I have the appropriate background?
  - Linear algebra: vector/matrix manipulations, properties
  - Calculus: partial derivatives
  - Probability: common distributions; Bayes Rule
  - Statistics: mean/median/mode; maximum likelihood
  - Sheldon Ross: A First Course in Probability

Course Information (Section 1)

- **Class**: Mondays at 11-1pm in AH 400
- **Instructor**: Raquel Urtasun
- **Tutorials**: Monday, 3-4pm, same classroom
- **Class Website**:

  http://www.cs.toronto.edu/~urtasun/courses/CSC411_Fall16/CSC411_Fall16.html
- The class will use Piazza for **announcements** and **discussions**:

  https://piazza.com/utoronto.ca/fall2016/csc411/home
- First time, sign up here:

  https://piazza.com/utoronto.ca/fall2016/csc411
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Course Information (Section 2)

- **Class**: Wednesdays at 11-1pm in MS 2170
- **Instructor**: Raquel Urtasun
- **Tutorials**: Wednesday, 3-4pm, BA 1170
- **Class Website**:

  http://www.cs.toronto.edu/~urtasun/courses/CSC411_Fall16/CSC411_Fall16.html
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Course Information (Section 3)

- **Class**: Thursdays at 4-6pm in KP 108
- **Instructor**: Richard Zemel
- **Tutorials**: Thursday, 6-7pm, same class
- **Class Website**:

  http://www.cs.toronto.edu/~urtasun/courses/CSC411_Fall16/CSC411_Fall16.html
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Course Information (Section 4)

- **Class**: Fridays at 11-1pm in MS 2172
- **Instructor**: Richard Zemel
- **Tutorials**: Thursday, 3-4pm, same class
- **Class Website**:

  http://www.cs.toronto.edu/~urtasun/courses/CSC411_Fall16/CSC411_Fall16.html
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Textbook(s)

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- Other Textbooks:
  - Kevin Murphy: *"Machine Learning: a Probabilistic Perspective"*
  - David Mackay: *"Information Theory, Inference, and Learning Algorithms"*
  - Ethem Alpaydin: *"Introduction to Machine Learning"*, 2nd edition, 2010.

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- Do the readings!

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More on Assigments

- Collaboration on the assignments is not allowed. Each student is responsible for his/her own work. Discussion of assignments should be limited to clarification of the handout itself, and should not involve any sharing of pseudocode or code or simulation results. Violation of this policy is grounds for a semester grade of F, in accordance with university regulations.

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- Final assignment is a bake-off: competition between ML algorithms. We will give you some data for training a ML system, and you will try to develop the best method. We will then determine which system performs best on unseen test data. Grads can do own project.

Provisional Calendar (Section 1)

- Intro + Linear Regression
- Linear Classif. + Logistic Regression
- Non-parametric + Decision trees
- Multi-class + Prob. Classif I
- Thanksgiving
- Prob. Classif II + NNets I
- Nnet II + Clustering
- Midterm + Mixt. of Gaussians
- Reading Week
- PCA/Autoencoders + SVM
- Kernels + Ensemble I
- Ensemble II + RL

Provisional Calendar (Sections 2,3,4)

- Intro + Linear Regression
- Linear Classif. + Logistic Regression
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Figure: How can we make a robot cook?

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  - Want to implement unknown function, only have access e.g., to sample input-output pairs (training examples)

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- Different than standard CS:
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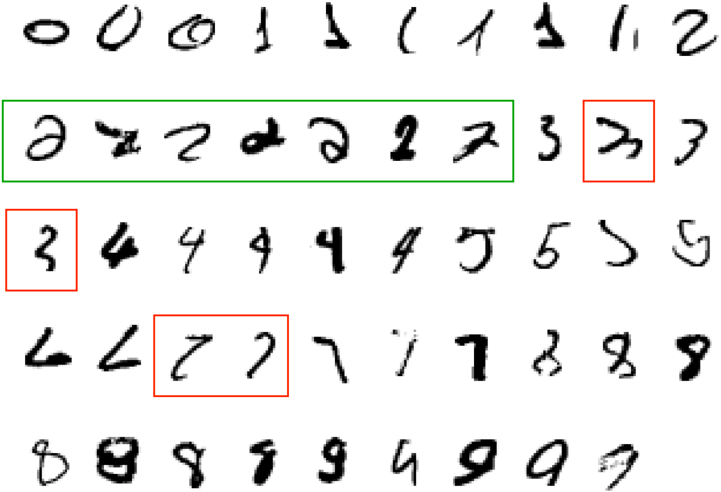
- Learning simply means incorporating information from the training examples into the system

Tasks that requires machine learning: What makes a 2?



Tasks that benefits from machine learning: cooking!

Robots learn to cook by watching YouTube

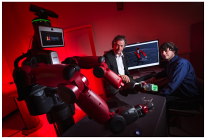
When it comes to learning how to cook, it turns out that robots may not be so different from humans after all... or are they?

Sci-Tech

January 20, 2015
4:26 PM PST

by Michelle Starr
@riding_red

When it comes to teaching robots how to do things, there are some very key differences. A human knows what you mean when you say "I need a cup". A robot needs to be taught that that means it has to turn around, go to the cupboard, open it, take out the cup, close the cupboard, turn back around, return to you, manoeuvre the cup over the bench, and release the cup.



John T. Consoli, UMD

This is one of the key parts of figuring out machine learning: How can you program a robot so that it can intuit that a plastic cup, a glass and a mug may all be classified under the general term "cup"? How can you design a robot that is able to teach itself?

One way, as researchers at the University of Maryland Institute for Advanced Computer Studies are finding out, is YouTube. More specifically, cooking tutorials on YouTube. By watching these videos,
...arn the complicated series of grasping and manipulation motions required for

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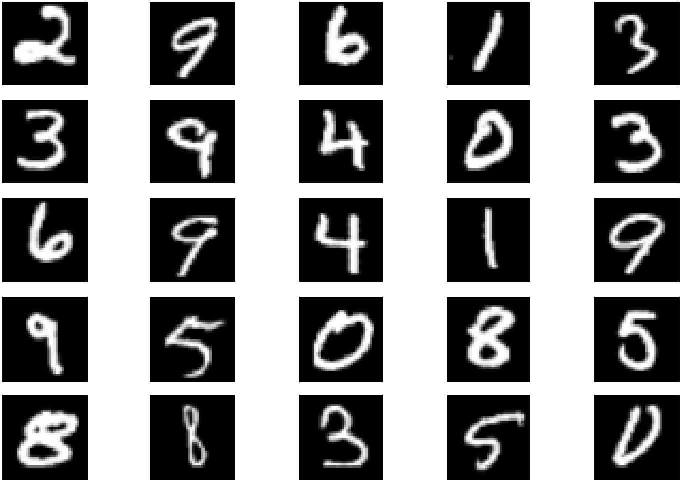
- A machine learning algorithm then takes these examples and produces a program that does the job
  - The program produced by the learning algorithm may look very different from a typical hand-written program. It may contain millions of numbers.
  - If we do it right, the program works for new cases as well as the ones we trained it on.

Learning algorithms are useful in many tasks

1. Classification: Determine which discrete category the example is

Examples of Classification



What digit is this?

Examples of Classification

Is this a dog?

Examples of Classification

what about this one?

Examples of Classification

Am I going to pass the exam?

Examples of Classification

Do I have diabetes?

Learning algorithms are useful in many tasks

1. Classification: Determine which discrete category the example is
2. Recognizing patterns: Speech Recognition, facial identity, etc

Examples of Recognizing patterns

Figure: Siri: https://www.youtube.com/watch?v=8ciagGASro0

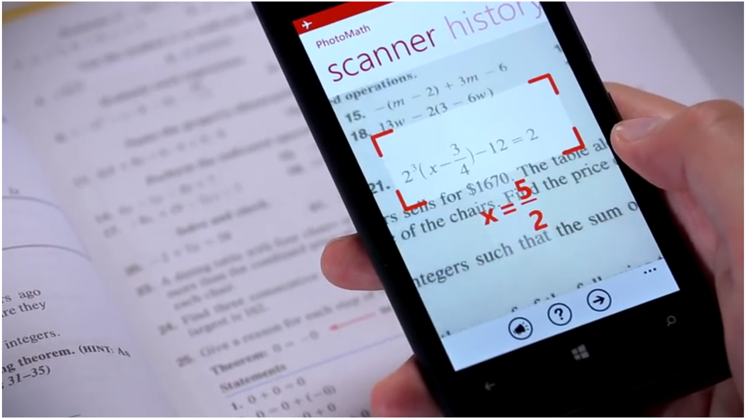
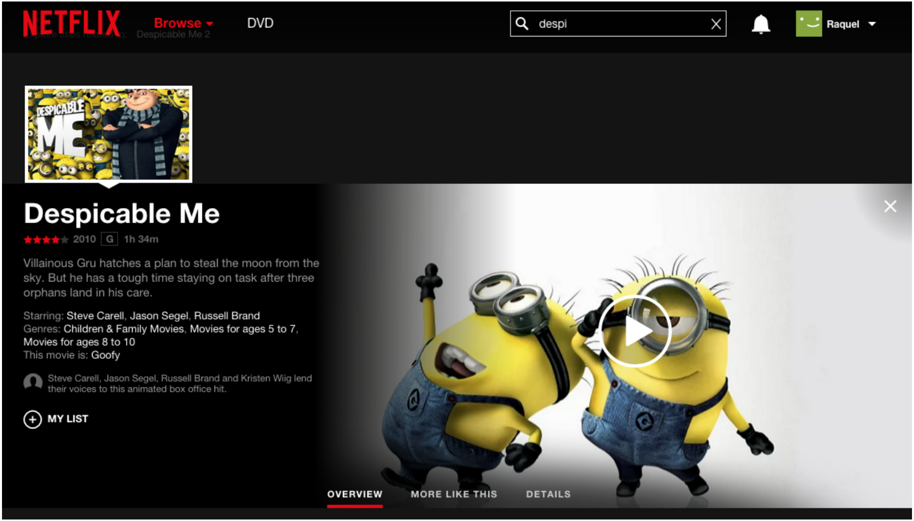


Figure: Photomath: https://photomath.net/

Learning algorithms are useful in other tasks

1. Classification: Determine which discrete category the example is
2. Recognizing patterns: Speech Recognition, facial identity, etc
3. Recommender Systems: Noisy data, commercial pay-off (e.g., Amazon, Netflix).

Examples of Recommendation systems



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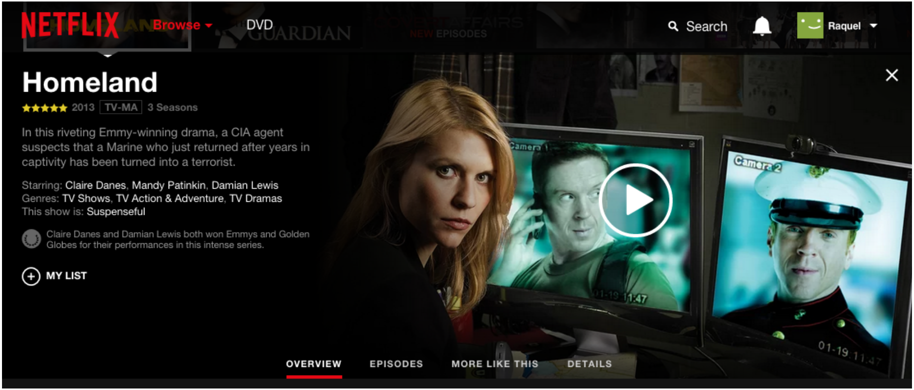

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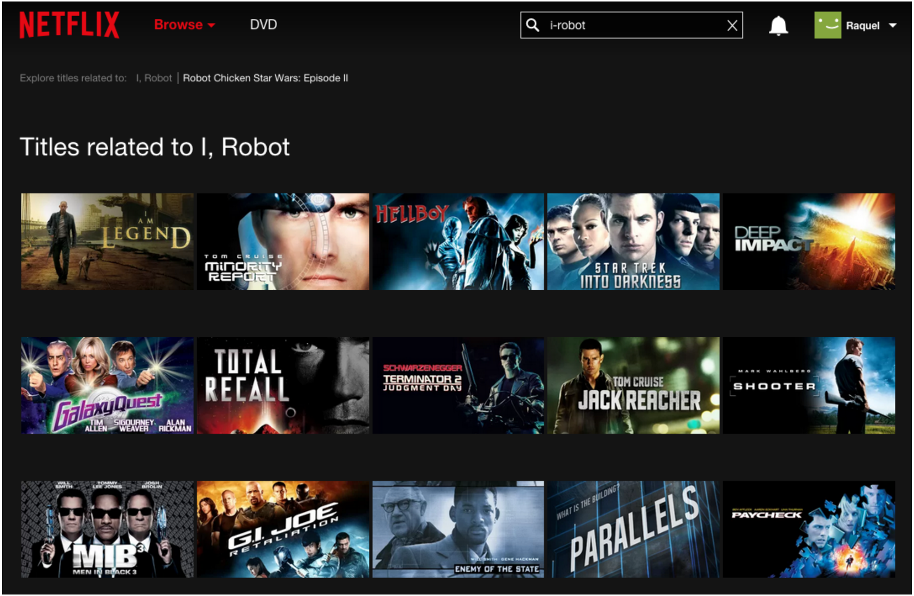

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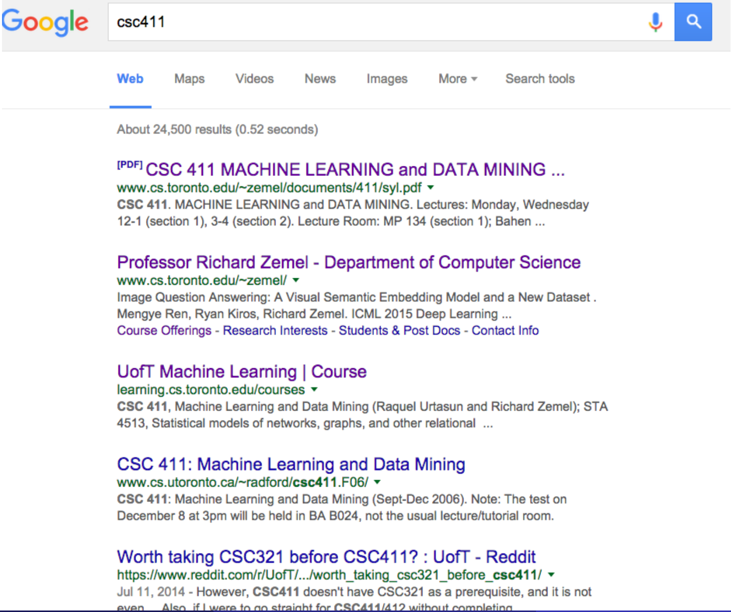
4. Information retrieval: Find documents or images with similar content

Examples of Information Retrieval



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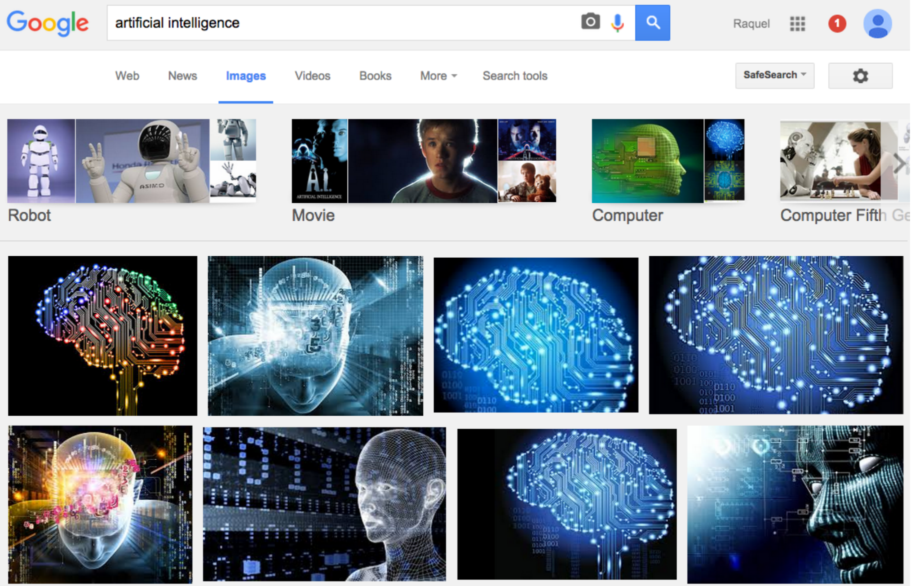


Examples of Information Retrieval

Google

artificial intelligence

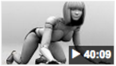
Web | News | Images | **Videos** | Books | More | Search tools

About 2,830,000 results (0.29 seconds)

'Artificial Intelligence is as dangerous as NUCLEAR ...

www.dailymail.co.uk/.../**Artificial-Intelligence**-dangero...
Jul 17, 2015
Artificial intelligence has the potential to be as dangerous to mankind as nuclear weapons, a leading pioneer ...

Rise of Future Technology | Artificial Intelligence - New ...



www.youtube.com/watch?v=YUvDBGYk17Y
Dec 6, 2014 - Uploaded by Incredible Documentaries
Rise of Future Technology | **Artificial Intelligence** - New Documentary(2015)

Why You Shouldn't Fear Artificial Intelligence - YouTube

www.youtube.com/watch?v=uEWGjQ0nTm4
Jan 19, 2015 - Uploaded by DNews
Stephen Hawking and Elon Musk have warned us of the dangers of **Artificial Intelligence**, but is AI really ...

Artificial Intelligence - YouTube

www.youtube.com/watch?v=9TRv0cXUVQw
Aug 17, 2015 - Uploaded by The School of Life
Should we be scared of **artificial intelligence** and all it will bring us? Not so long as we remember to make sure ...

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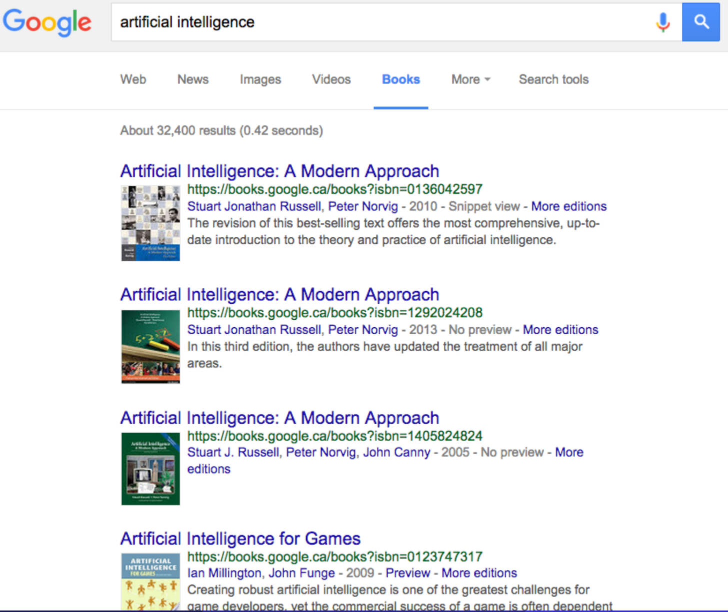

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5. Computer vision: detection, segmentation, depth estimation, optical flow, etc

Computer Vision

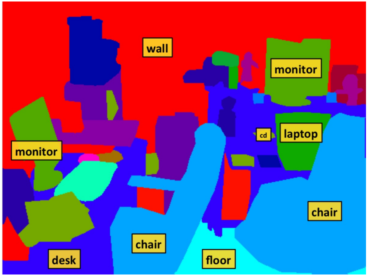
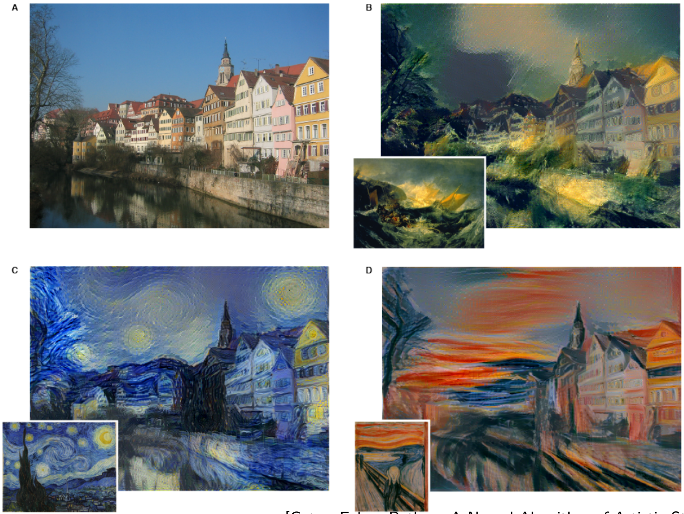


Figure: Kinect: https://www.youtube.com/watch?v=op82fDRRqSY

Computer Vision



[Gatys, Ecker, Bethge. A Neural Algorithm of Artistic Style. Arxiv'15.]

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6. Robotics: perception, planning, etc

Autonomous Driving

Flying Robots

Figure: Video: https://www.youtube.com/watch?v=YQIMGV5vtd4

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7. Learning to play games

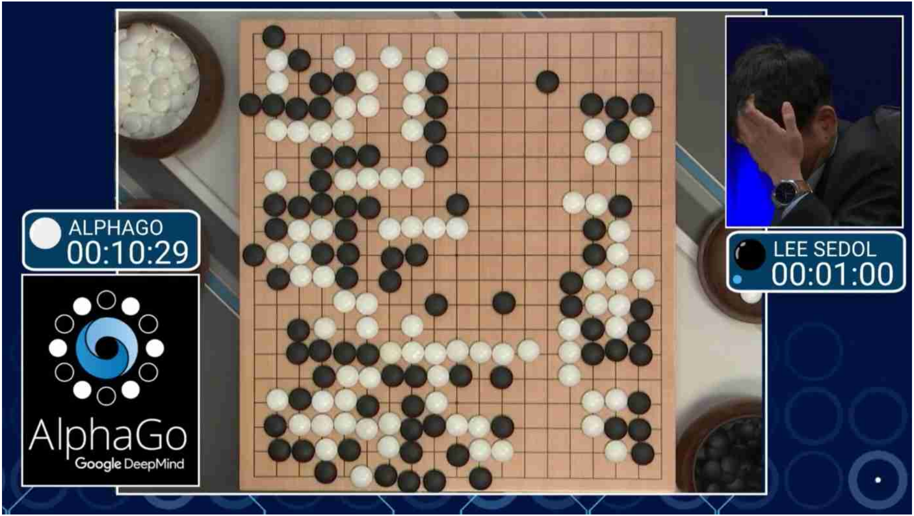
Playing Games: Atari

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

Playing Games: Super Mario

Figure: Video: https://www.youtube.com/watch?v=wfL4L_l4U9A

Playing Games: Alpha Go



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10. Many more!

Human Learning

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  - Learn to predict output when given an input vector

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    - Regression: real-valued output (predicting market prices, customer rating)

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  - Learn to predict output when given an input vector
    - Classification: 1-of-N output (speech recognition, object recognition, medical diagnosis)
    - Regression: real-valued output (predicting market prices, customer rating)
- Unsupervised learning
  - Create an internal representation of the input, capturing regularities/structure in data

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- Reinforcement learning
  - Learn action to maximize payoff
    - Not much information in a payoff signal
    - Payoff is often delayed

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- But problems with AI flavor (e.g., recognition, robot navigation) still domain of ML

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  - Good piece of ML: Demo that a complicated algorithm produces impressive results on a specific task.
- Can view ML as applying computational techniques to statistical problems. But go beyond typical statistics problems, with different aims (speed vs. accuracy).

Cultural gap (Tibshirani)

MACHINE LEARNING

- weights
- learning
- generalization
- supervised learning
- unsupervised learning
- large grant: \$1,000,000
- conference location: Snowbird, French Alps

STATISTICS

- parameters
- fitting
- test set performance
- regression/classification
- density estimation, clustering
- large grant: \$50,000
- conference location: Las Vegas in August

Course Survey

Please complete the following survey this week:
https://docs.google.com/forms/d/e/1FAIpQLScd5JwTrh55gW-O-5UKXLidFPvvH-XhVxr36AqfQzsrdDNxGQ/viewform?usp=send_form

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- Evaluate on test set: generalization