CSC 411: Lecture 01: Introduction

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University of Toronto

Today

- Administration details
- Why is machine learning so cool?

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

Textbook(s)

- Christopher Bishop: *"Pattern Recognition and Machine Learning"*, 2006

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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.

Requirements (Undergrads)

- Do the readings!

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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Figure : How can we make a robot cook?

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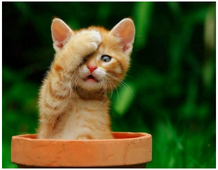



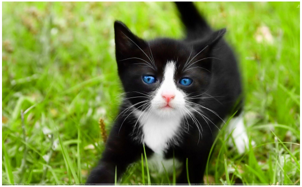

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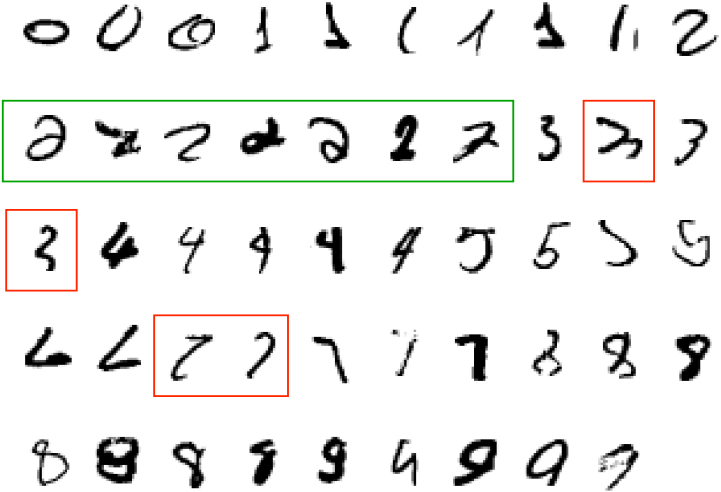
- Learning simply means incorporating information from the training examples into the system

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

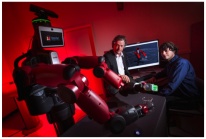
January 20, 2015

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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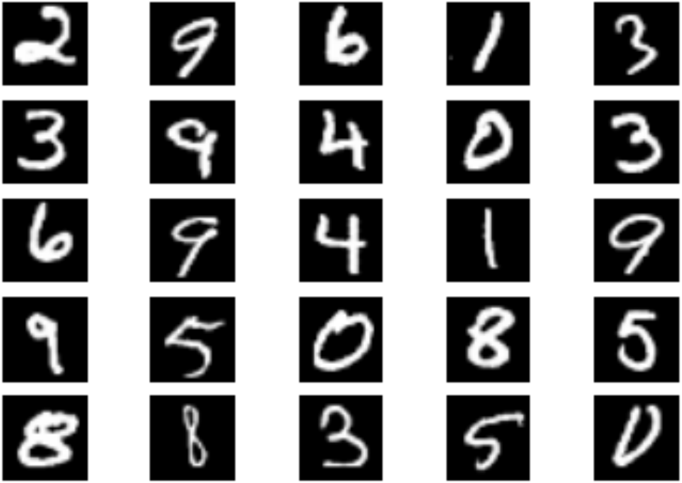
  - The program produced by the learning algorithm may look very different from a typical hand-written program. It may contain millions of numbers.
  - If we do it right, the program works for new cases as well as the ones we trained it on.

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

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2. Recognizing patterns: Speech Recognition, facial identity, etc

Examples of Recognizing patterns

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

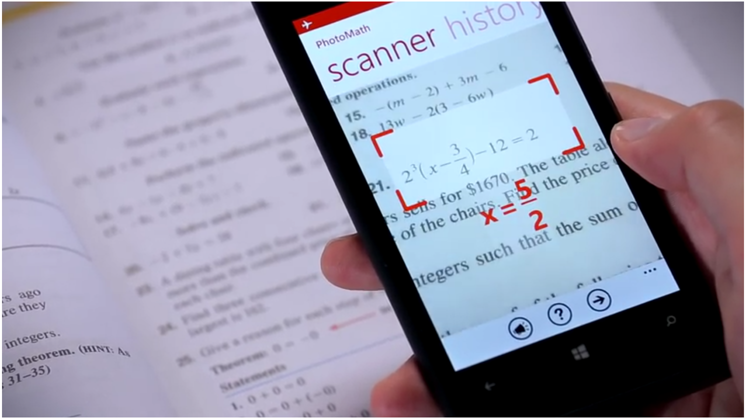

Figure : Photomath: https://photomath.net/

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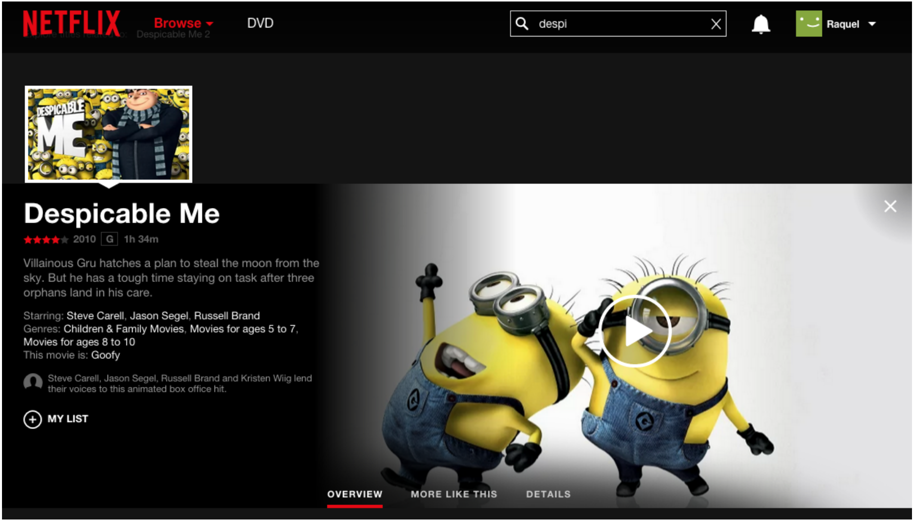
3. Recommender Systems: Noisy data, commercial pay-off (e.g., Amazon, Netflix).

Examples of Recommendation systems



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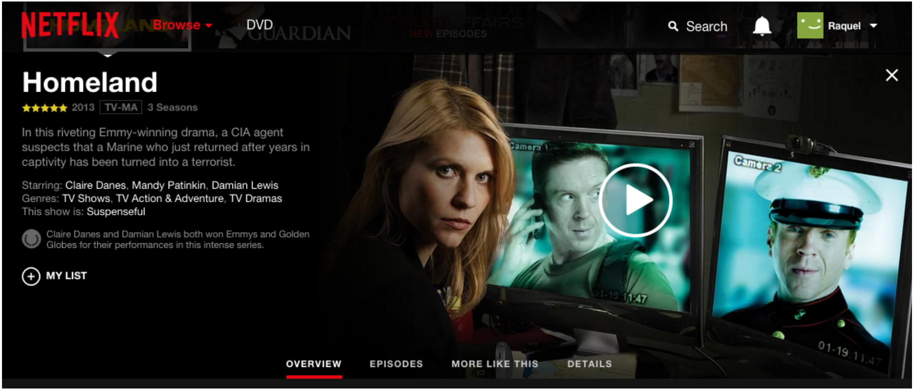

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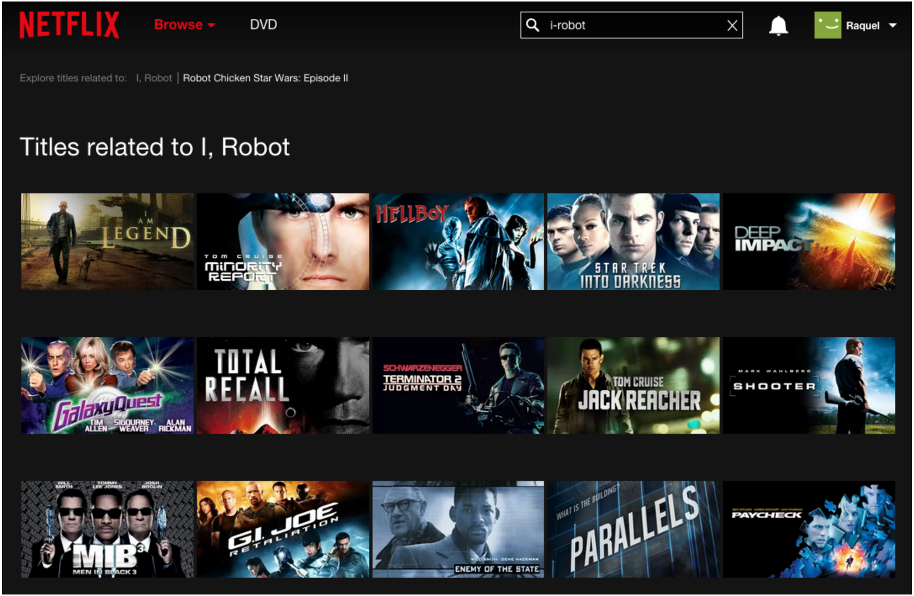

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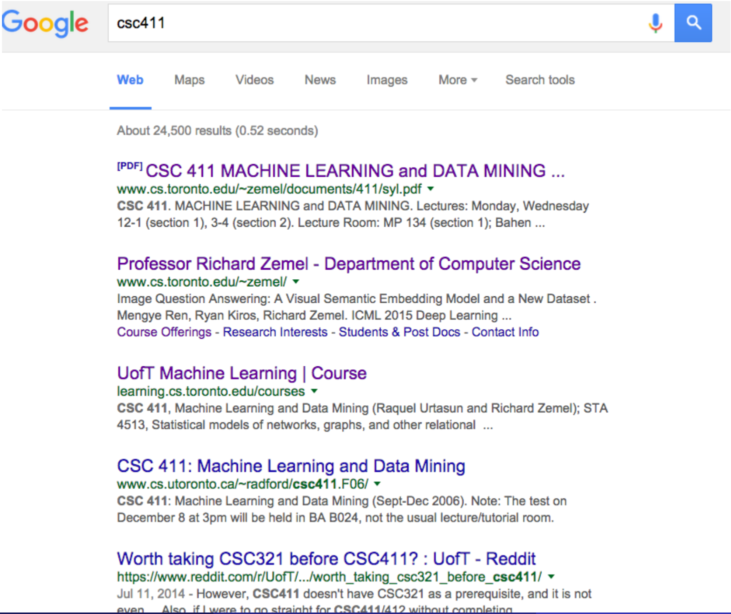

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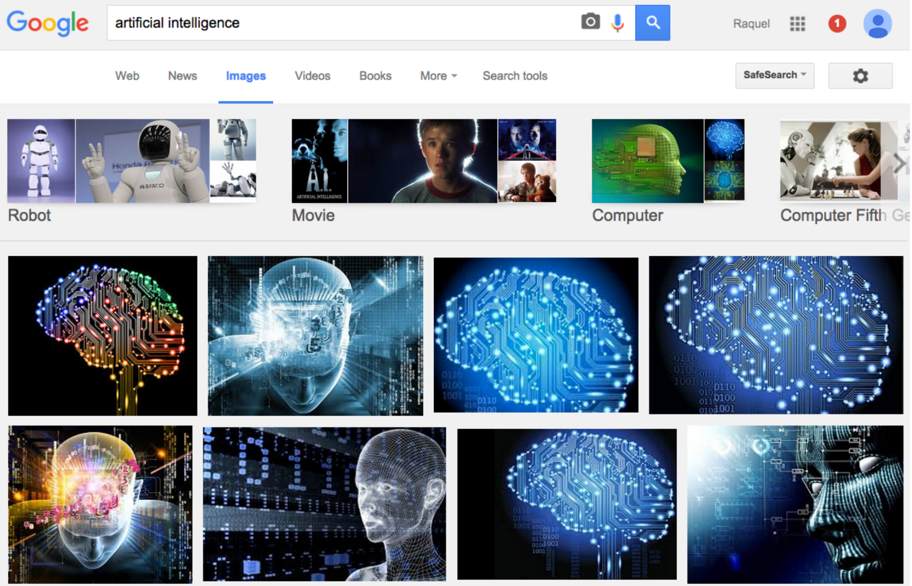

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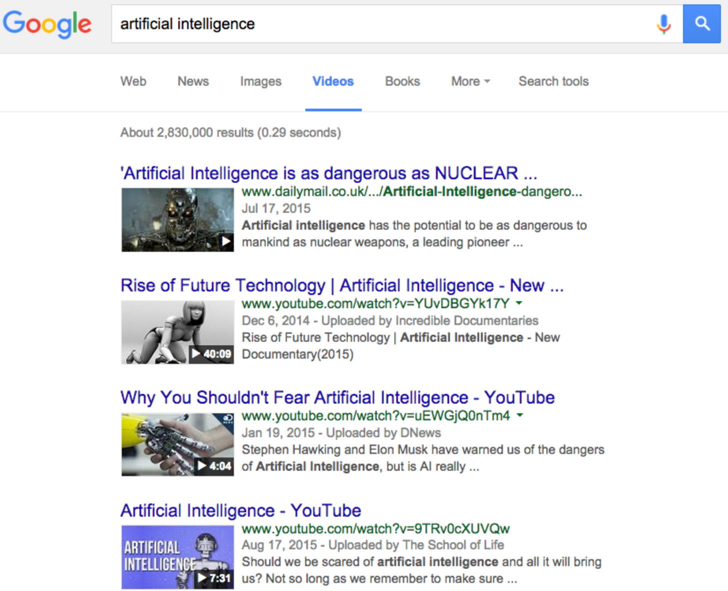

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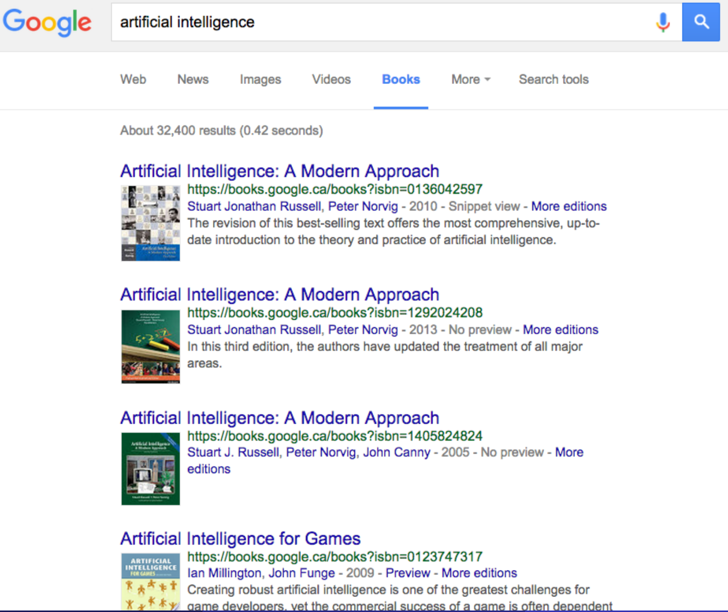

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Computer Vision

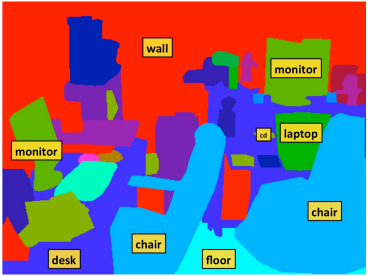

Figure : Kinect: https://www.youtube.com/watch?v=op82fDRRqSY

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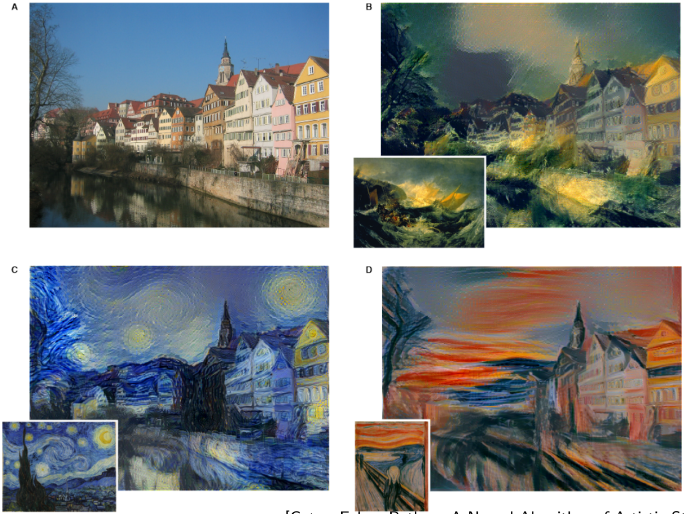

[Gatys, Ecker, Bethge. A Neural Algorithm of Artistic Style. Arxiv'15.]

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Autonomous Driving

Flying Robots

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

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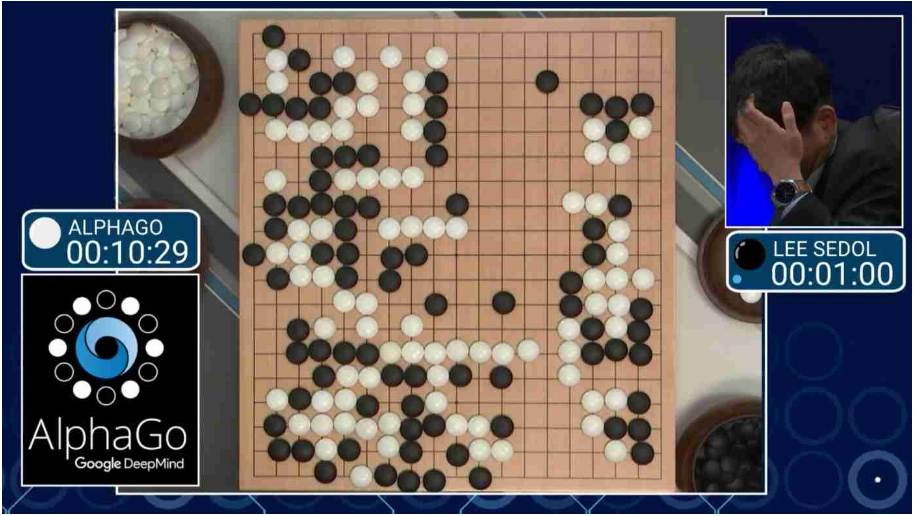
Playing Games: Atari

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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    - How do we know if a representation is good?
- 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