

CSC 411: Lecture 01: Introduction

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University of Toronto

Today

- Administration details
- Why is machine learning so cool?

- 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 Assignments

- **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.

What is Machine Learning?

- How can we solve a specific problem?

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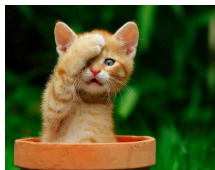
- How can we solve a specific problem?
 - ▶ As computer scientists we **write a program** that encodes a set of rules that are useful to solve the problem



Figure : How can we make a robot cook?

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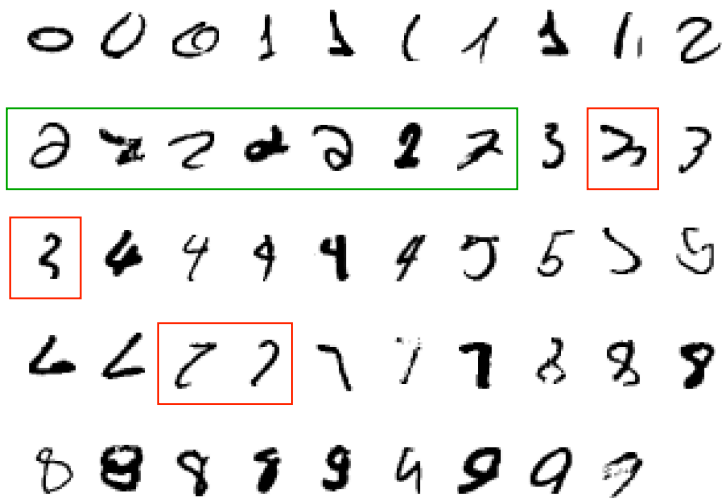
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- Learning simply means incorporating information from the training examples into the system

Tasks that requires machine learning: What makes a 2?



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, robots learn the complicated series of grasping and manipulation motions required for

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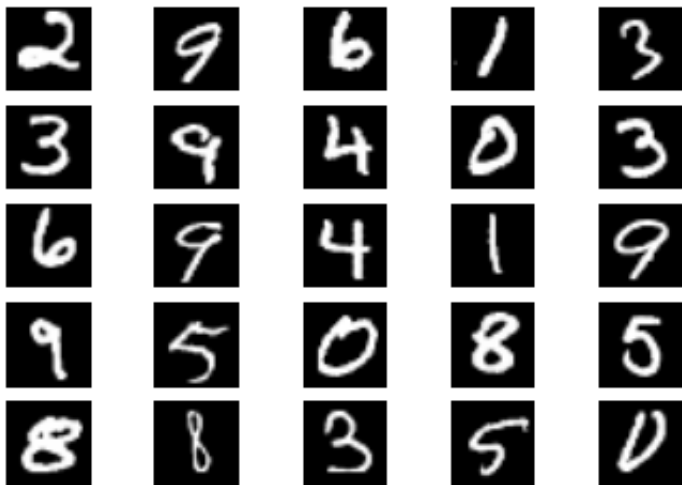
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 - ▶ The program produced by the learning algorithm may look very different from a typical hand-written program. It may contain millions of numbers.
 - ▶ If we do it right, the program works for new cases as well as the ones we trained it on.

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?

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Examples of Recognizing patterns



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

Examples of Recognizing patterns

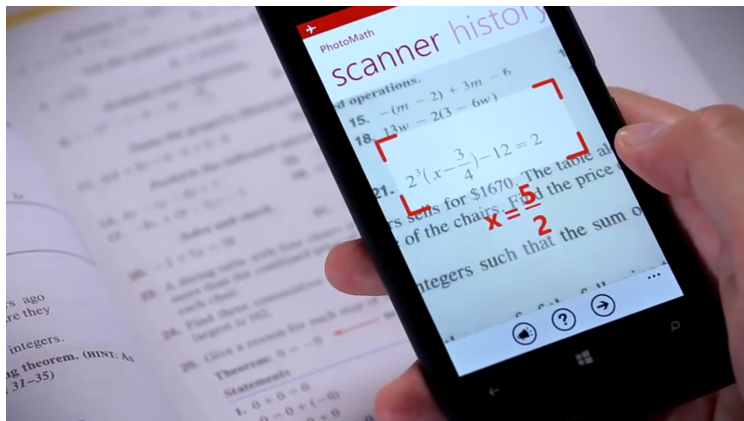


Figure : Photomath: <https://photomath.net/>

Learning algorithms are useful in other tasks

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

Examples of Recommendation systems

NETFLIX Browse ▾ Despicable Me 2

DVD

Q despi X

🔔

😊 Raquel ▾



Despicable Me

★★★★☆ 2010 [G] 1h 34m

Villainous Gru hatches a plan to steal the moon from the sky. But he has a tough time staying on task after three orphans land in his care.

Starring: Steve Carell, Jason Segel, Russell Brand
Genres: Children & Family Movies, Movies for ages 5 to 7,
Movies for ages 8 to 10
This movie is: Goofy

 Steve Carell, Jason Segel, Russell Brand and Kristen Wiig lend their voices to this animated box office hit.

 MY LIST

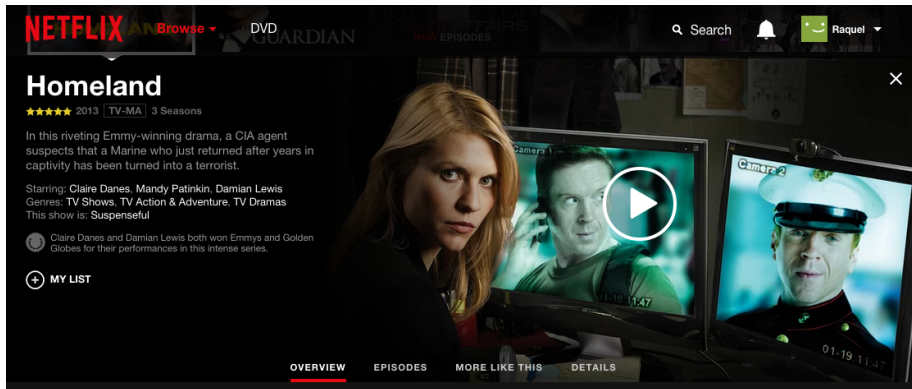


OVERVIEW

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DETAILS

Examples of Recommendation systems



Examples of Recommendation systems

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Notifications: Profile: Raquel ▾

Explore titles related to: [I, Robot](#) | [Robot Chicken Star Wars: Episode II](#)




Titles related to I, Robot

The grid displays 15 movie posters arranged in three rows of five. The titles include: I AM LEGEND, TOM CRUISE MINORITY REPORT, HELLBOY, STAR TREK INTO DARKNESS, DEEP IMPACT, Galaxy Quest, TOTAL RECALL, SCHWARZENEGGER TERMINATOR 2 JUDGMENT DAY, JACK REACHER, SHOOTER, MIB MEN IN BLACK 3, GI JOE RETALIATION, ENEMY OF THE STATE, PARALLELS, and PAYCHECK.

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Examples of Information Retrieval



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[\[PDF\] CSC 411 MACHINE LEARNING and DATA MINING ...](#)
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CSC 411. MACHINE LEARNING and DATA MINING. Lectures: Monday, Wednesday 12-1 (section 1), 3-4 (section 2). Lecture Room: MP 134 (section 1); Bahen ...

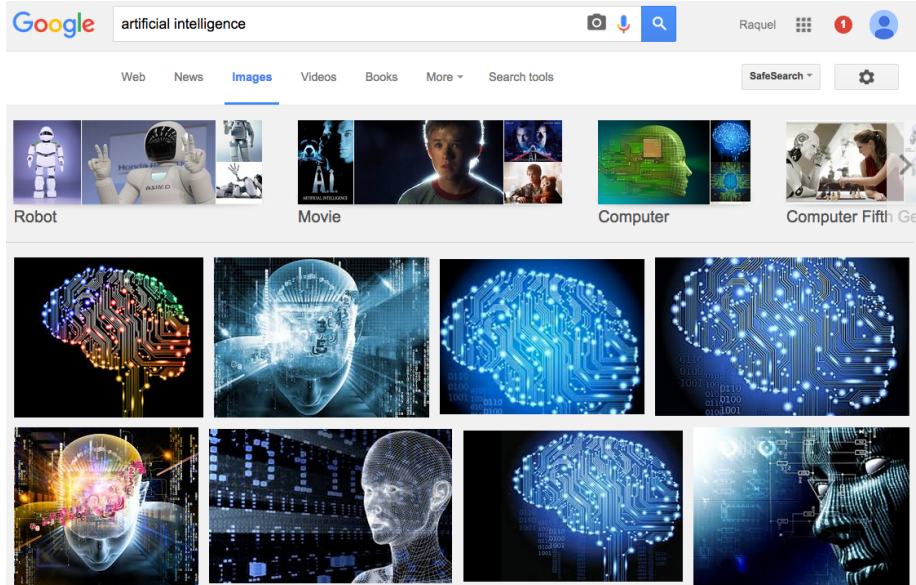
[Professor Richard Zemel - Department of Computer Science](#)
www.cs.toronto.edu/~zemel/ ▾
Image Question Answering: A Visual Semantic Embedding Model and a New Dataset . Mengye Ren, Ryan Kiros, Richard Zemel. ICML 2015 Deep Learning ...
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[UofT Machine Learning | Course](#)
learning.cs.toronto.edu/courses ▾
CSC 411, Machine Learning and Data Mining (Raquel Urtasun and Richard Zemel); STA 4513, Statistical models of networks, graphs, and other relational ...


[CSC 411: Machine Learning and Data Mining](#)
www.cs.utoronto.ca/~radford/csc411.F06/ ▾
CSC 411: Machine Learning and Data Mining (Sept-Dec 2006). Note: The test on December 8 at 3pm will be held in BA B024, not the usual lecture/tutorial room.

[Worth taking CSC321 before CSC411? : UofT - Reddit](#)
https://www.reddit.com/r/UofT/.../worth_taking_csc321_before_csc411/ ▾
Jul 11, 2014 - However, **CSC411** doesn't have CSC321 as a prerequisite, and it is not even ... Also, if I were to go straight for **CSC411/412** without completing

Examples of Information Retrieval




Examples of Information Retrieval



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'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



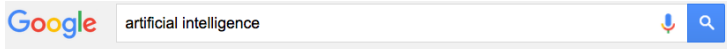
www.youtube.com/watch?v=uEWGjQ0nTm4 ▾
Jan 19, 2015 - Uploaded by DNews
Stephen Hawking and Elon Musk have warned us of the dangers of **Artificial Intelligence**, but is AI really ...

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 ...

Examples of Information Retrieval



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Artificial Intelligence: A Modern Approach



<https://books.google.ca/books?isbn=0136042597>

Stuart Jonathan Russell, Peter Norvig - 2010 - Snippet view - [More editions](#)

The revision of this best-selling text offers the most comprehensive, up-to-date introduction to the theory and practice of artificial intelligence.

Artificial Intelligence: A Modern Approach



<https://books.google.ca/books?isbn=1292024208>

Stuart Jonathan Russell, Peter Norvig - 2013 - No preview - [More editions](#)

In this third edition, the authors have updated the treatment of all major areas.

Artificial Intelligence: A Modern Approach



<https://books.google.ca/books?isbn=1405824824>

Stuart J. Russell, Peter Norvig, John Canny - 2005 - No preview - [More editions](#)

Artificial Intelligence for Games



<https://books.google.ca/books?isbn=0123747317>

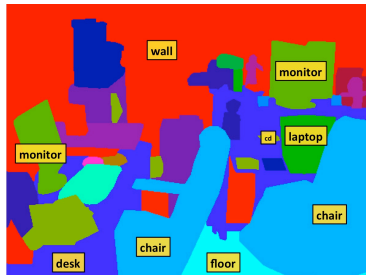
Ian Millington, John Funge - 2009 - Preview - [More editions](#)

Creating robust artificial intelligence is one of the greatest challenges for game developers, yet the commercial success of a game is often dependent

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Computer Vision



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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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7. **Learning to play games**

Playing Games: Atari



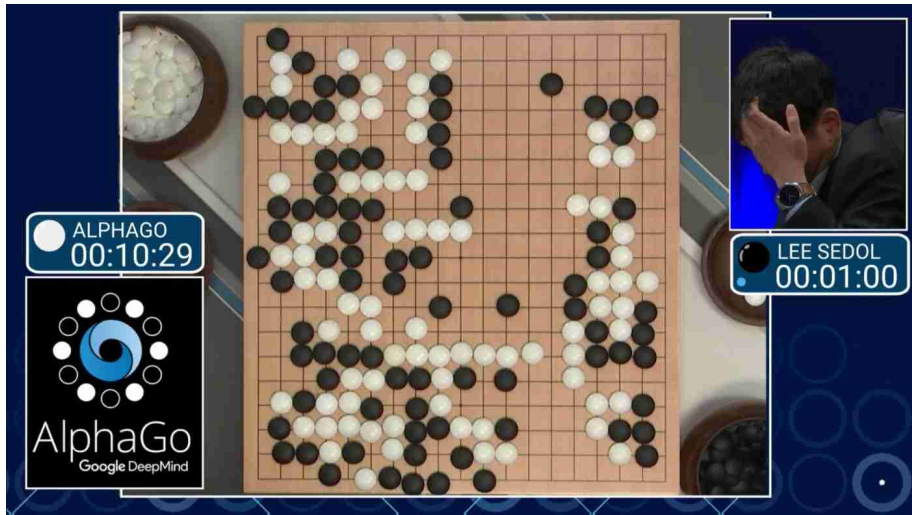
Figure : Video: <https://www.youtube.com/watch?v=V1eYniJ0Rnk>

Playing Games: Super Mario



Figure : Video: https://www.youtube.com/watch?v=wFL4L_14U9A

Playing Games: Alpha Go



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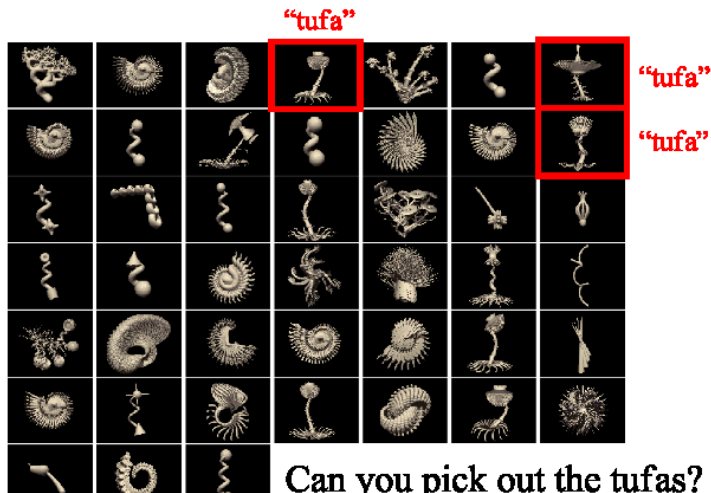
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10. **Many more!**

Human Learning



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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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- Now lines are blurred: many ML problems involve tons of data
- 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