CSC 411: Lecture 01: Introduction

Class based on Raquel Urtasun & Rich Zemel's lectures

Sanja Fidler

University of Toronto

Jan 11, 2016

Today

- Administration details
- Why is machine learning so cool?

The Team

- **Instructor**:

Sanja Fidler (fidler@cs.toronto.edu)

- **Office**: 283B in Pratt
- **Office hours**: Mon 1.15-2.30pm, or by appointment
- **TAs**:

Shenlong Wang (slwang@cs.toronto.edu)

Ladislav Rampasek (rampasek@cs.toronto.edu)

Boris Ivanovic (boris.ivanovic@mail.utoronto.ca)

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

- **Class**: Mondays and Wednesday at noon-1pm in LM158
- **Tutorials**: Fridays, same hour as lecture, same classroom
- **Class Website**:

  http://www.cs.toronto.edu/~fidler/teaching/2015/CSC411.html
- The class will use Piazza for **announcements** and **discussions**:

  https://piazza.com/utoronto.ca/winter2016/csc411/home
- First time, sign up here:

  https://piazza.com/utoronto.ca/winter2016/csc411
- Your grade will **not depend on your participation on Piazza**. It's just a good way for asking questions, discussing with your instructor, TAs and your peers

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.

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- Final:
  - Focused on second half of course
  - Worth 35% of course mark

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.

Calendar

Date	Topic	Assignments
Jan 11	Introduction	
Jan 13	Linear Regression	
Jan 15	*Probability for ML & Linear regression*	
Jan 18	Linear Classification	
Jan 20	Logistic Regression	
Jan 22	*Optimization for ML*	
Jan 25	Nonparametric Methods	
Jan 27	Decision Trees	
Jan 29	*kNN & Decision Trees*	Asst 1 Out
Feb 1	Multi-class Classification	
Feb 3	Probabilistic Classifiers	
Feb 5	Probabilistic Classifiers II	
Feb 8	Neural Networks I	
Feb 10	Neural Networks II	Asst 1 In
Feb 22	*Naive Bayes and Gaussian Bayes Classifier*	
Feb 24	*Neural Networks Tutorial*	
Feb 26	*Mid-term review*	
Feb 29	MIDTERM	

Date	Topic	Assignments
Mar 2	Clustering	Assit 2 Out
Mar 4	*Clustering*	
Mar 7	Mixture of Gaussians & EM	
Mar 9	PCA & Autoencoders	
Mar 11	*PCA Tutorial*	
Mar 14	Kernels and Margins	Asst 2 In
Mar 16	Support Vector Machines	
Mar 18	*SVM Tutorial*	Asst3 Out
Mar 21	Ensemble Methods I	
Mar 23	Ensemble Methods II	
Mar 28	Bayesian Methods	
Mar 30	Reinforcement Learning I	
Apr 1	*Bagging & Boosting*	
Apr 4	Reinforcement Learning II	
Apr 6	Final & Wrap-up	Ass 3 In

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Figure: How can we make a robot cook?

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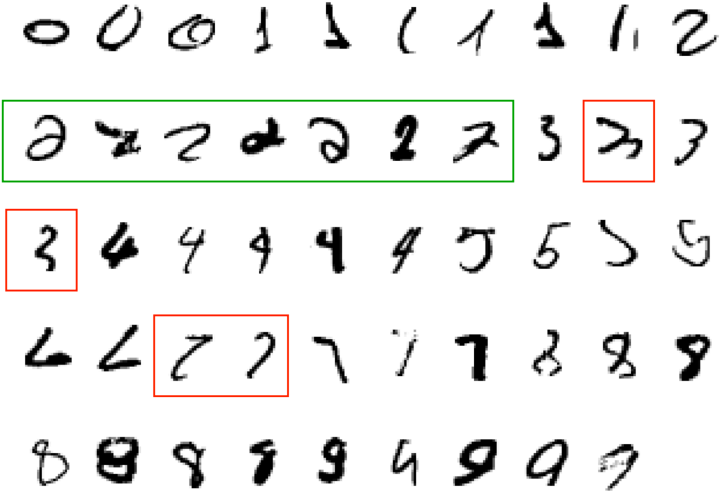
- Learning simply means incorporating information from the training examples into the system

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

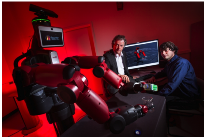
January 20, 2015

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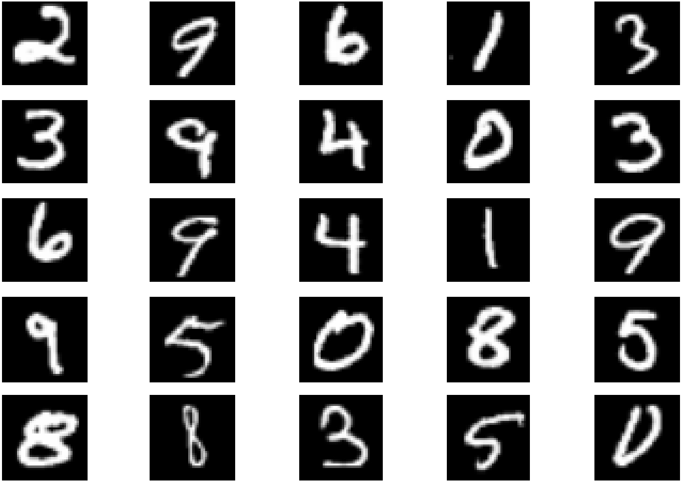
  - The program produced by the learning algorithm may look very different from a typical hand-written program. It may contain millions of numbers.
  - If we do it right, the program works for new cases as well as the ones we trained it on.

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

Examples of Recognizing patterns

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

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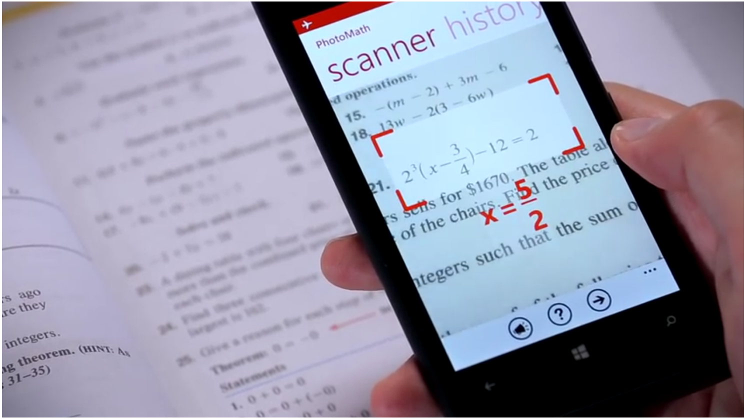

Figure: Photomath: https://photomath.net/

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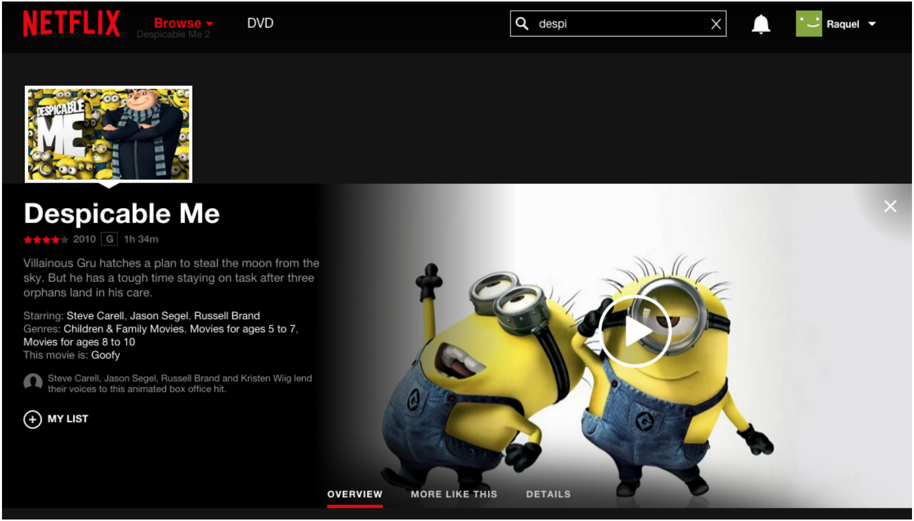
Examples of Recommendation systems



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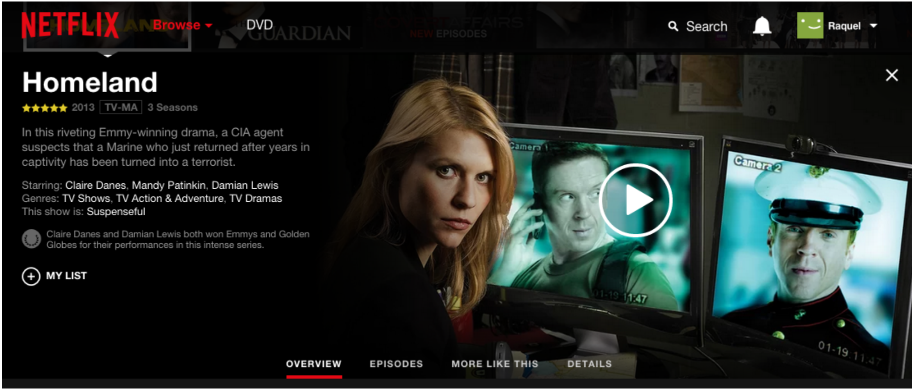

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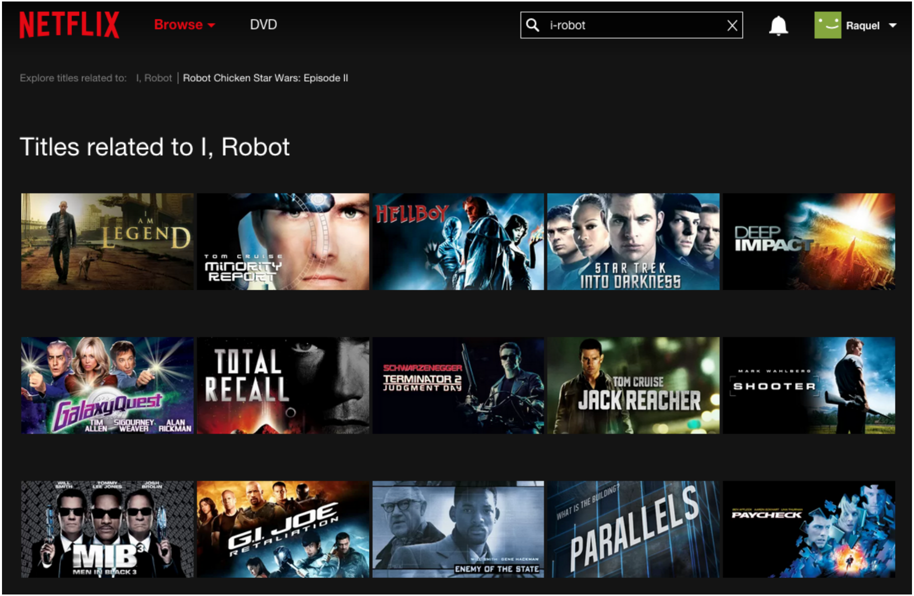

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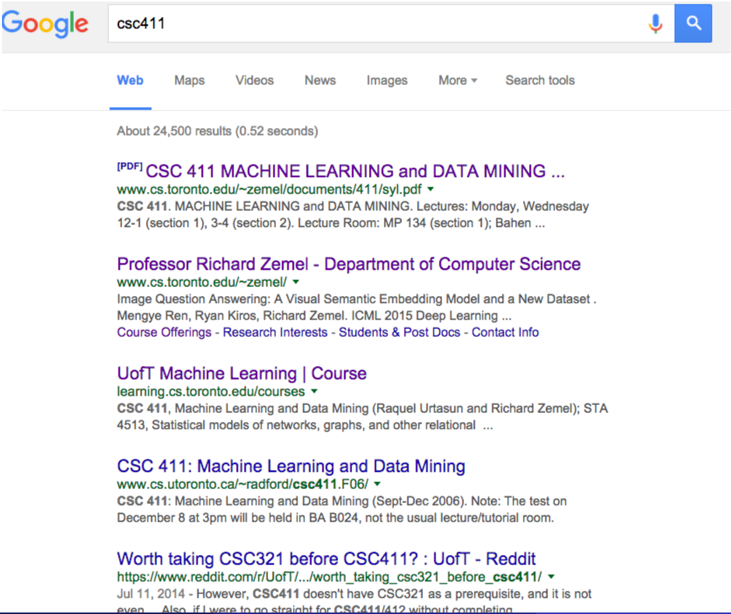
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[PDF] CSC 411 MACHINE LEARNING and DATA MINING ...
www.cs.toronto.edu/~zemel/documents/411/syl.pdf ▾
CSC 411. MACHINE LEARNING and DATA MINING. Lectures: Monday, Wednesday 12-1 (section 1), 3-4 (section 2). Lecture Room: MP 134 (section 1); Bahen ...

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 ...
Course Offerings - Research Interests - Students & Post Docs - Contact Info

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

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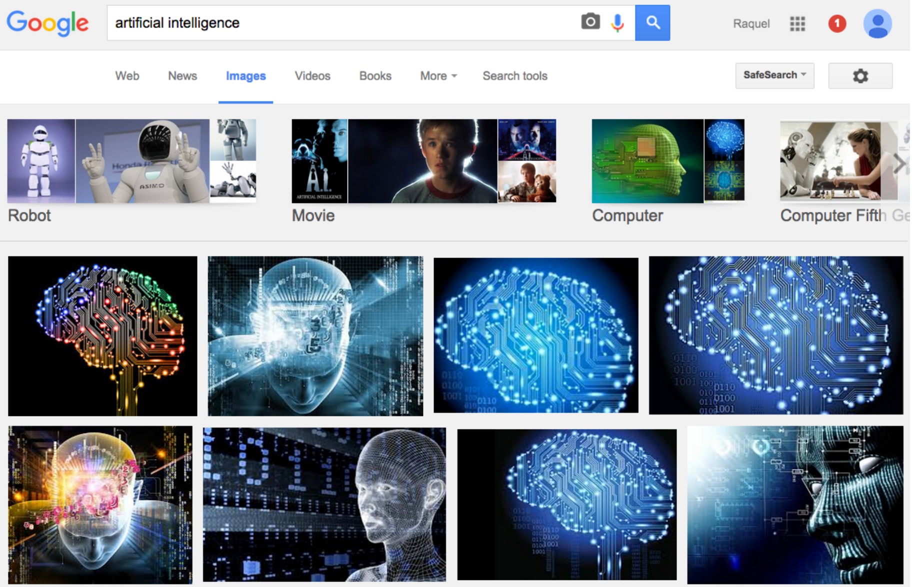

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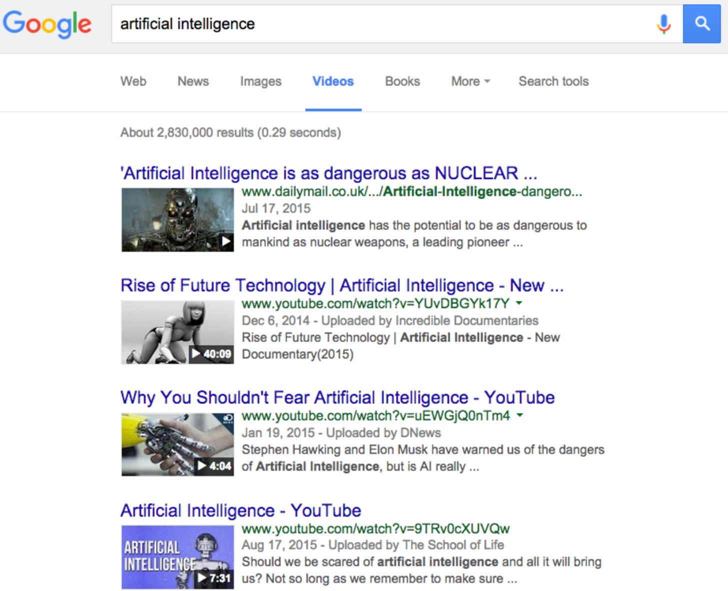

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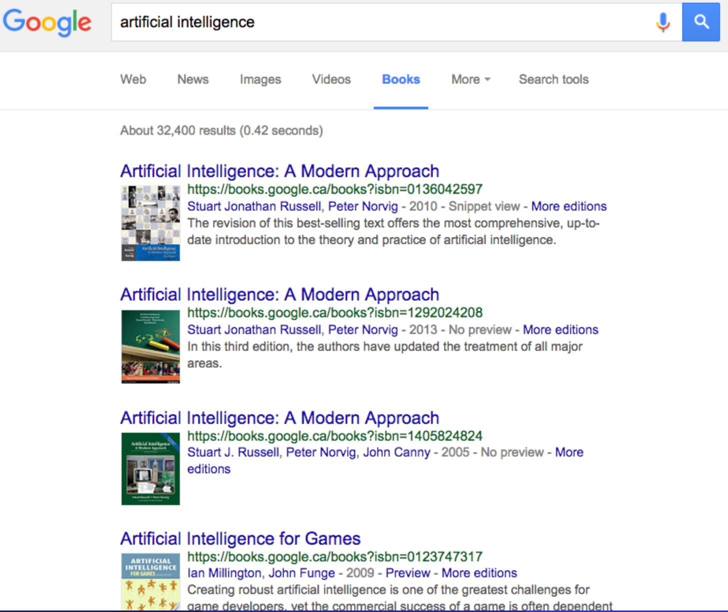

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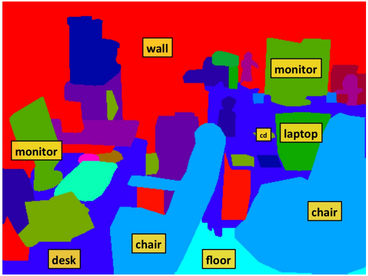
Computer Vision



Computer Vision

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

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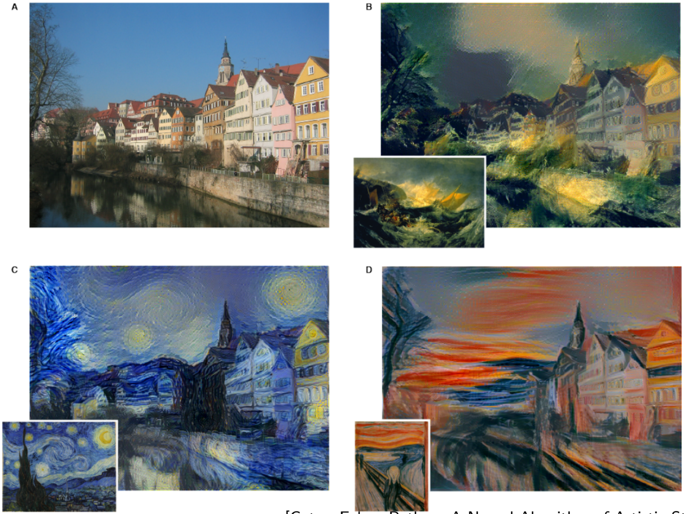

[Gatys, Ecker, Bethge. A Neural Algorithm of Artistic Style. Arxiv'15.]

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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

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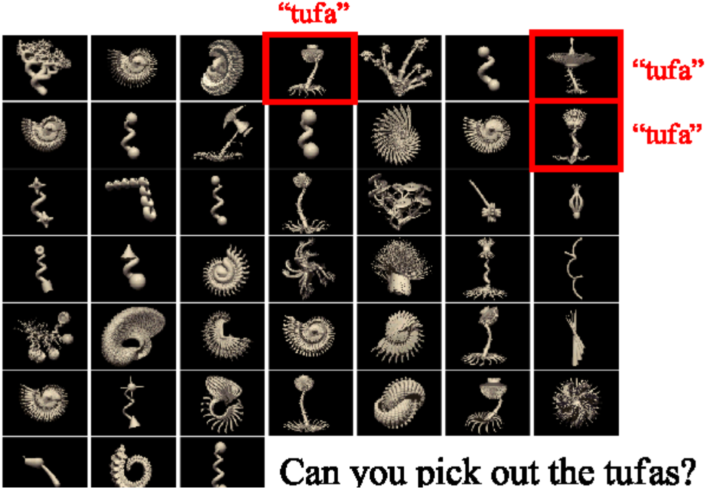
10. Many more!

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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- 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.

Machine Learning vs Statistics

- ML uses statistical theory to build models
- A lot of ML is rediscovery of things statisticians already knew; often disguised by differences in terminology
- But the emphasis is very different:
  - Good piece of statistics: Clever proof that relatively simple estimation procedure is asymptotically unbiased.
  - 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/1O6xRNnKp87GrDM74tkvOMhMIJmwz271TgWdYb6ZitKO/viewform?usp=send_form

Initial Case Study

- What grade will I get in this course?

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  - Split into training set; test set
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- Set model parameters to optimize performance
- Evaluate on test set: generalization