

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.

Requirements

- Do the [readings!](#)

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 - ▶ One hour exam on Feb 29th
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- [Final:](#)
 - ▶ Focused on second half of course
 - ▶ Worth 35% of course mark

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.

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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	<i>Probability for ML & Linear regression</i>	
Jan 18	Linear Classification	
Jan 20	Logistic Regression	
Jan 22	<i>Optimization for ML</i>	
Jan 25	Nonparametric Methods	
Jan 27	Decision Trees	
Jan 29	<i>kNN & Decision Trees</i>	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	<i>Naive Bayes and Gaussian Bayes Classifier</i>	
Feb 24	<i>Neural Networks Tutorial</i>	
Feb 26	<i>Mid-term review</i>	
Feb 29	MIDTERM	

Date	Topic	Assignments
Mar 2	Clustering	Assit 2 Out
Mar 4	<i>Clustering</i>	
Mar 7	Mixture of Gaussians & EM	
Mar 9	PCA & Autoencoders	
Mar 11	<i>PCA Tutorial</i>	
Mar 14	Kernels and Margins	Asst 2 In
Mar 16	Support Vector Machines	
Mar 18	<i>SVM Tutorial</i>	Asst3 Out
Mar 21	Ensemble Methods I	
Mar 23	Ensemble Methods II	
Mar 28	Bayesian Methods	
Mar 30	Reinforcement Learning I	
Apr 1	<i>Bagging & Boosting</i>	
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?

0 0 0 1 1 (1 1 1 2

2 2 2 2 2 2 3 3 3

3 4 4 4 4 4 5 5 5

6 6 7 7 7 7 1 8 8 8

8 8 8 8 9 4 9 9 9

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](#)
 @ridingred



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, learn 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.

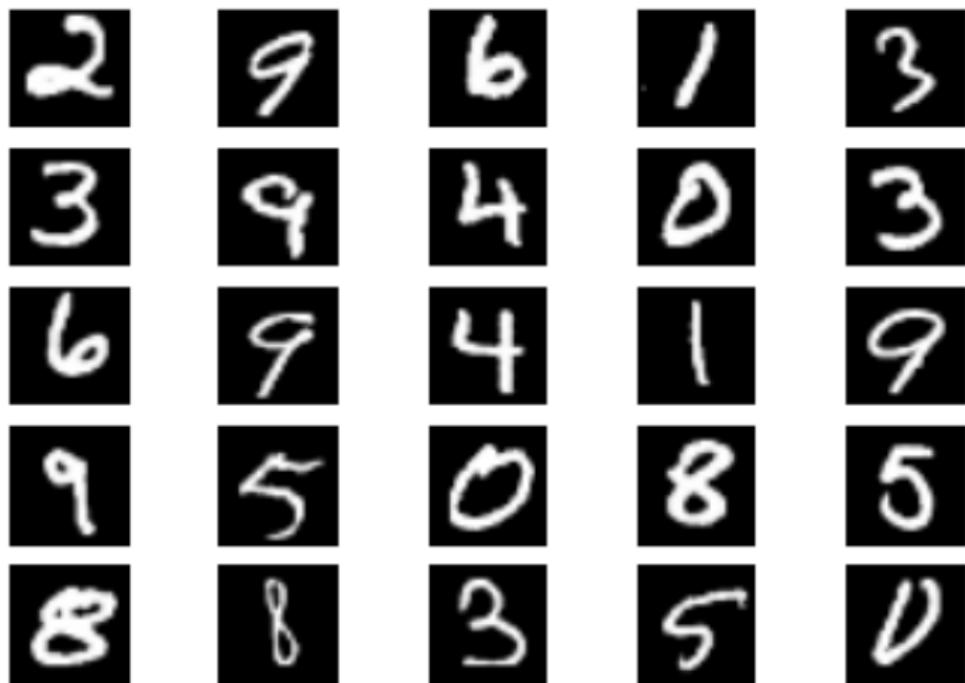
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 - ▶ The program produced by the learning algorithm may look very different from a typical hand-written program. It may contain millions of numbers.
 - ▶ If we do it right, the program works for new cases as well as the ones we trained it on.

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

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>

Examples of Recognizing patterns

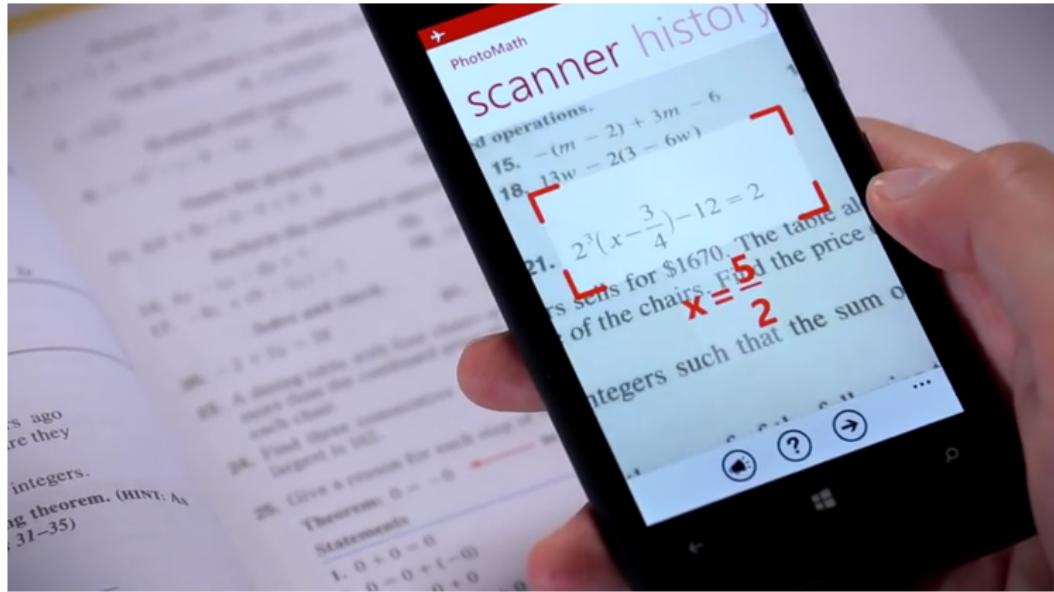


Figure: Photomath: <https://photomath.net/>

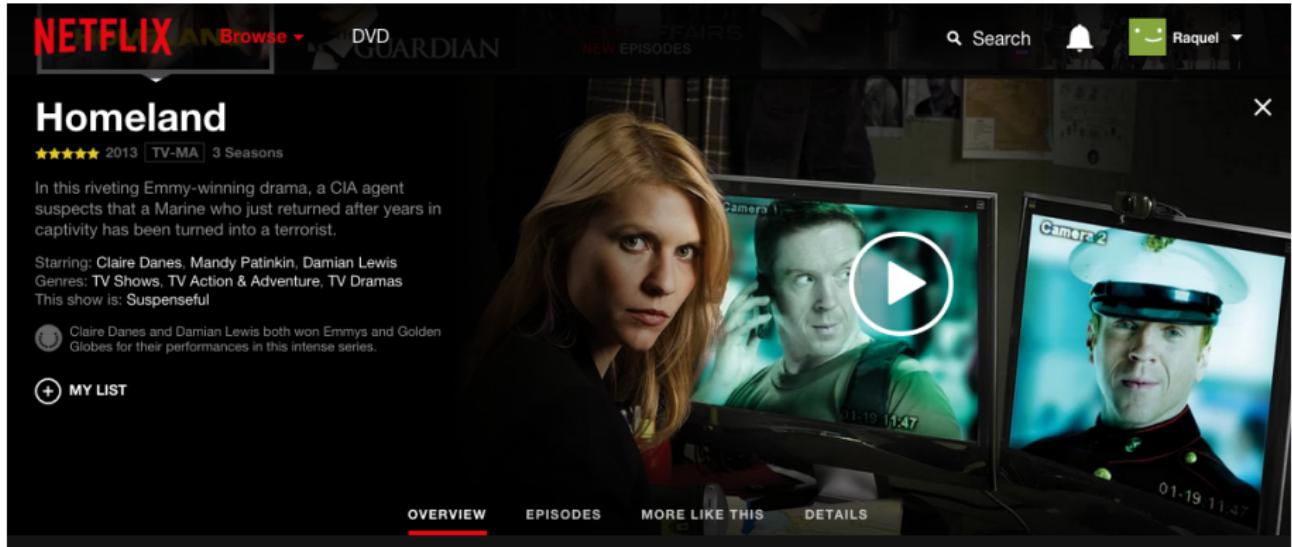
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3. **Recommender Systems:** Noisy data, commercial pay-off (e.g., Amazon, Netflix).

Examples of Recommendation systems

The screenshot shows the Netflix interface. At the top, there's a search bar with the query "despi". Below it, the movie poster for "Despicable Me" is displayed, featuring Gru surrounded by yellow minions. The title "Despicable Me" is prominently shown in large letters. Below the poster, the movie's details are listed: a 4-star rating, the year 2010, a G rating, and a runtime of 1h 34m. The plot summary describes Gru's plan to steal the moon. The cast includes Steve Carell, Jason Segel, and Russell Brand. The genres listed are Children & Family Movies and Movies for ages 5 to 7. It also notes that the movie is suitable for ages 8 to 10 and is described as "Goofy". A bio for Kristen Wiig is present, stating she voices the character. There are buttons for "MY LIST" and a play button overlaid on the image of two minions. At the bottom, there are tabs for "OVERVIEW" (which is selected), "MORE LIKE THIS", and "DETAILS".

Examples of Recommendation systems



Examples of Recommendation systems

The screenshot shows the Netflix homepage with a search bar containing "i-robot". Below the search bar, it says "Explore titles related to: I, Robot | Robot Chicken Star Wars: Episode II". The main content area displays a grid of movie posters for related titles:

- I, Robot** (Top Row, First)
- A.I. Artificial Intelligence** (Top Row, Second)
- Minority Report** (Top Row, Third)
- Hellboy** (Top Row, Fourth)
- Star Trek Into Darkness** (Top Row, Fifth)
- Deep Impact** (Top Row, Sixth)
- Galaxy Quest** (Second Row, First)
- Total Recall** (Second Row, Second)
- Schwarzenegger Terminator 2 Judgment Day** (Second Row, Third)
- Jack Reacher** (Second Row, Fourth)
- Shooter** (Second Row, Fifth)
- MIB: Men in Black 3** (Third Row, First)
- G.I. Joe: Retaliation** (Third Row, Second)
- Enemy of the State** (Third Row, Third)
- What Is the Building Parallels** (Third Row, Fourth)
- Paycheck** (Third Row, Fifth)

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

Examples of Information Retrieval

A screenshot of a Google search results page. The search bar at the top contains the query "csc411". Below the search bar, there are tabs for "Web", "Maps", "Videos", "News", "Images", "More", and "Search tools". The "Web" tab is selected. Below the tabs, it says "About 24,500 results (0.52 seconds)". The first result is a PDF link: "[PDF] CSC 411 MACHINE LEARNING and DATA MINING ...". The second result is a link to a professor's page: "Professor Richard Zemel - Department of Computer Science". The third result is a link to a university course page: "UofT Machine Learning | Course". The fourth result is another university course page: "CSC 411: Machine Learning and Data Mining". The fifth result is a link from Reddit: "Worth taking CSC321 before CSC411? : UofT - Reddit".

Web Maps Videos News Images More Search tools

About 24,500 results (0.52 seconds)

[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

Examples of Information Retrieval

A screenshot of a Google search results page for the query "artificial intelligence". The search bar shows the query. The interface includes the Google logo, camera, microphone, and search icons, and user information for Raquel. Below the search bar, navigation tabs are visible: Web, News, Images (selected), Videos, Books, More, and Search tools. A SafeSearch dropdown and a settings gear icon are also present.

The main content area displays four categories of images:

- Robot:** Three images showing various robots, including a white humanoid and a blue robot arm.
- Movie:** Three images related to science fiction movies, featuring a robot hand, a boy in a dark setting, and a couple in a futuristic setting.
- Computer:** Two images: one showing a green digital brain and another showing a blue digital brain.
- Computer Fifth Ge**: An image showing a person interacting with a white humanoid robot at a chessboard.

Below these categories, there are four rows of additional images, each showing a stylized brain composed of glowing circuit boards or digital data.

Examples of Information Retrieval

Google search results for "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-dangerous...
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)
4:09

Why You Shouldn't Fear Artificial Intelligence - YouTube



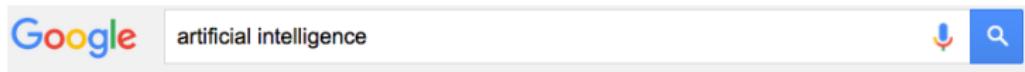
www.youtube.com/watch?v=uEWGjQ0nTm4 ▾
Jan 19, 2015 - Uploaded by DNews
Stephen Hawking and Elon Musk have warned us of the dangers of Artificial Intelligence, but is AI really ...
4:04

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 ...
7:31

Examples of Information Retrieval



Web News Images Videos Books More Search tools

About 32,400 results (0.42 seconds)

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>

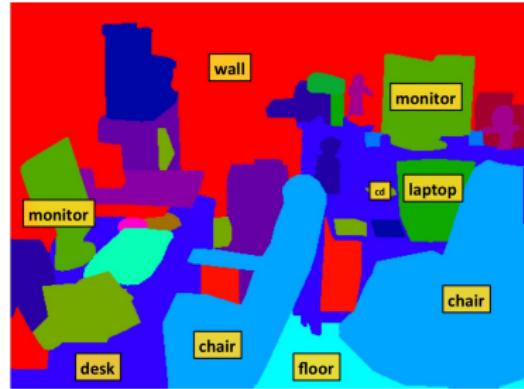
Ian Millington, John Funge - 2009 - Preview - [More editions](#)

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

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).
4. **Information retrieval:** Find documents or images with similar content
5. **Computer vision:** detection, segmentation, depth estimation, optical flow, etc

Computer Vision



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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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

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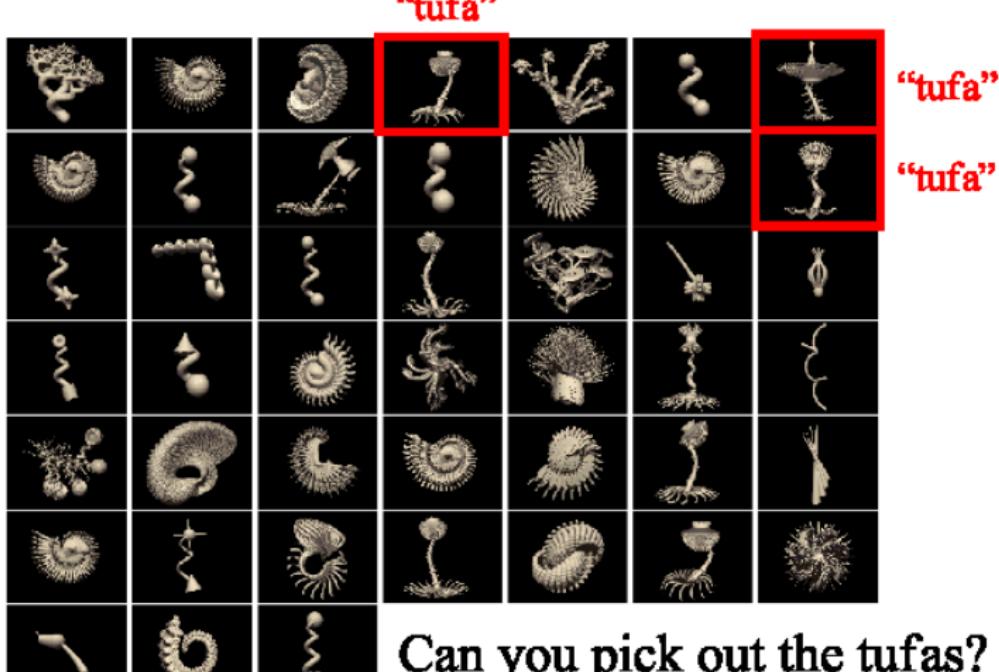
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9. **Spam filtering, fraud detection:** The enemy adapts so we must adapt too

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10. **Many more!**

Human Learning



Types of learning tasks

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 - ▶ **Classification**: 1-of-N output (speech recognition, object recognition, medical diagnosis)
 - ▶ **Regression**: real-valued output (predicting market prices, customer rating)

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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 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/>

[106xRNnKp87GrDM74tkvOMhMIJmwz271TgWdYb6ZitK0/viewform?usp=send_form](https://docs.google.com/forms/d/106xRNnKp87GrDM74tkvOMhMIJmwz271TgWdYb6ZitK0/viewform?usp=send_form)

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- Evaluate on test set: generalization