Lecture-1
Introduction

CS 277:
Machine Learning
and
Data Science

By:
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Dept. of CSE, IIT Patna

Tentative course plan

- Week 1: Introduction, Probability Distributions, Density Estimation
- Week 2: Density Estimation, Linear Regression
- Week 3: Logistic Regression, Linear Discriminant Analysis
- Week 4: Naïve Bayes, Decision trees
- Week 5: Support Vector Machines, Quiz 1
- Week 6: Feature selection techniques, Wrapper and Filter approaches
- Week 7: Mid semester exam
- Week 8: Mid semester break
- Week 9: Feature selection techniques, Forward and Backward selection, PCA
- Week 10: Unsupervised learning, K means, K medoid, hierarchical techniques, Expectation Maximization
- Week 11: Density based methods, Validity indices and similarity measures
- Week 12: Advanced clustering techniques
- Week 13: Graphical models
- Week 14: Graphical models, Quiz 2
- Week 15: Semi supervised learning, Active learning
- Week 16: Topic Modelling, LDA
- Week 17: End Sem Exam

Course Books

- Pattern Recognition and Machine Learning by Christopher M. Bishop
- The elements of statistical learning by Hastie, Tibshirani and Friedman

Course grading

- Programming assignments: 10%
- Quizzes: 15%
- Mid sem: 25%
- End sem 50%

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Figure: How can we make a robot cook?

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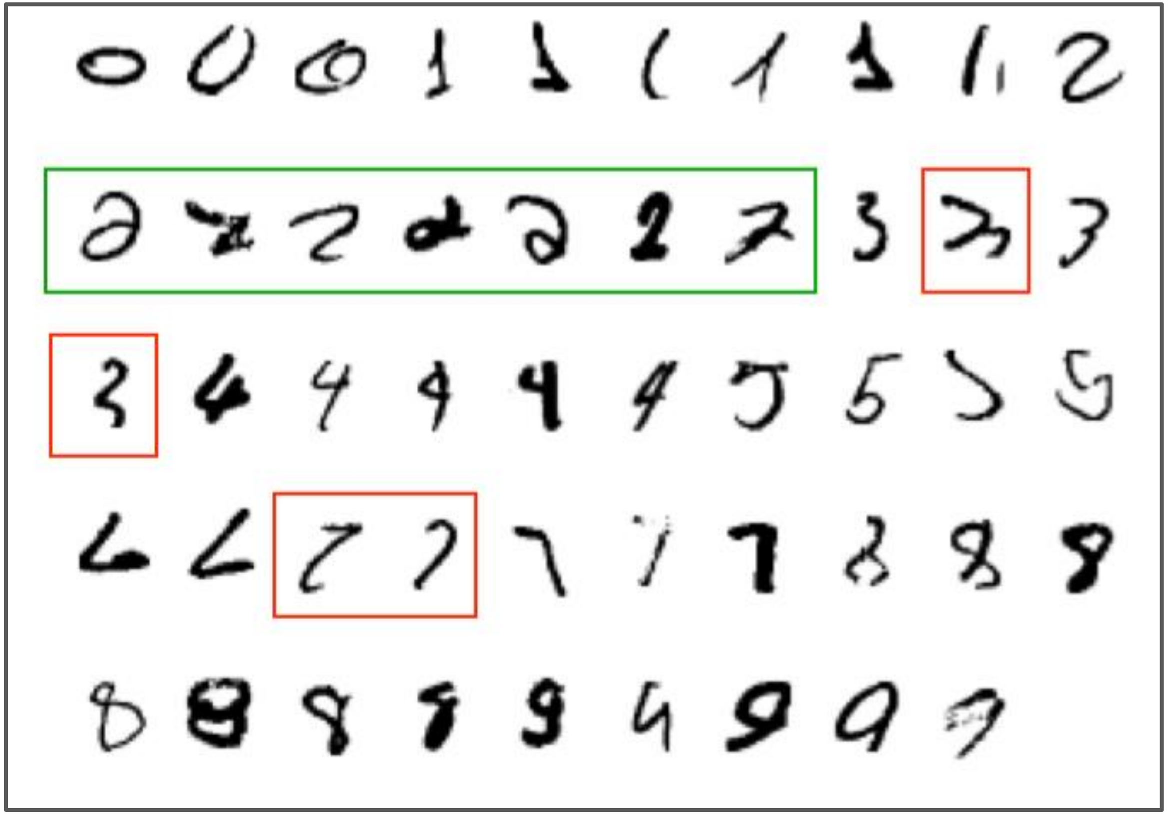
  - input-output pairs (training examples)
- Learning simply means incorporating information from the training examples into the system

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, [illegible] arn the complicated series of grasping and manipulation motions required for

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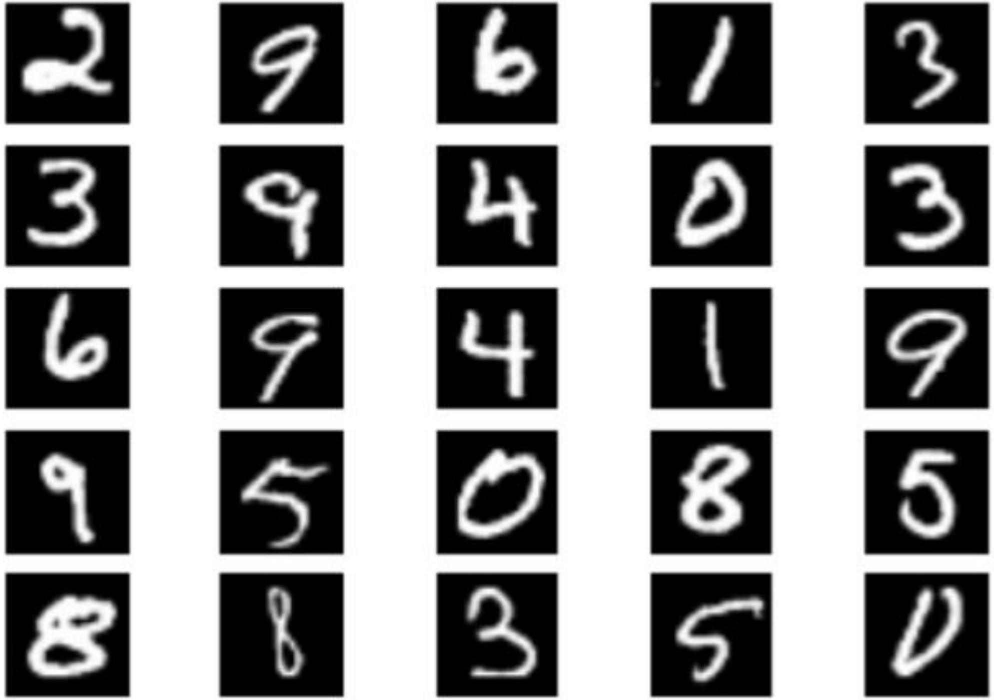
  - The program produced by the learning algorithm may look very different from a typical hand-written program. It may contain millions of numbers.
  - If we do it right, the program works for new cases as well as the ones we trained it on.

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?

Do I have diabetes?

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Examples of Recognizing patterns

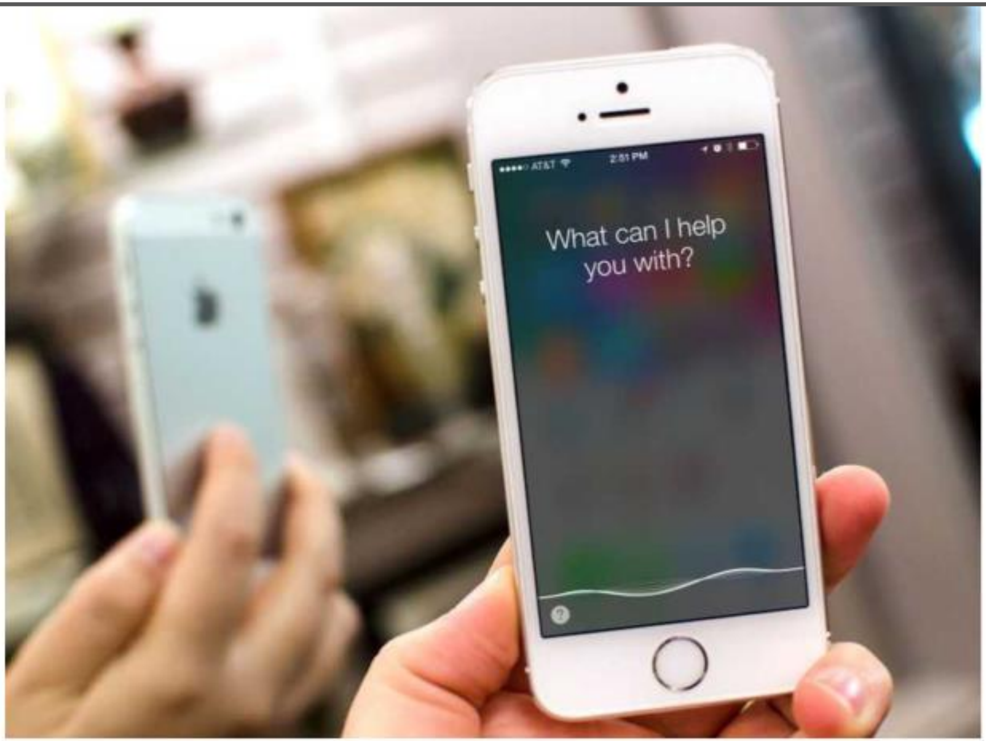

Figure: Siri: https://www.youtube.com/watch?v=8ciagGASro0

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

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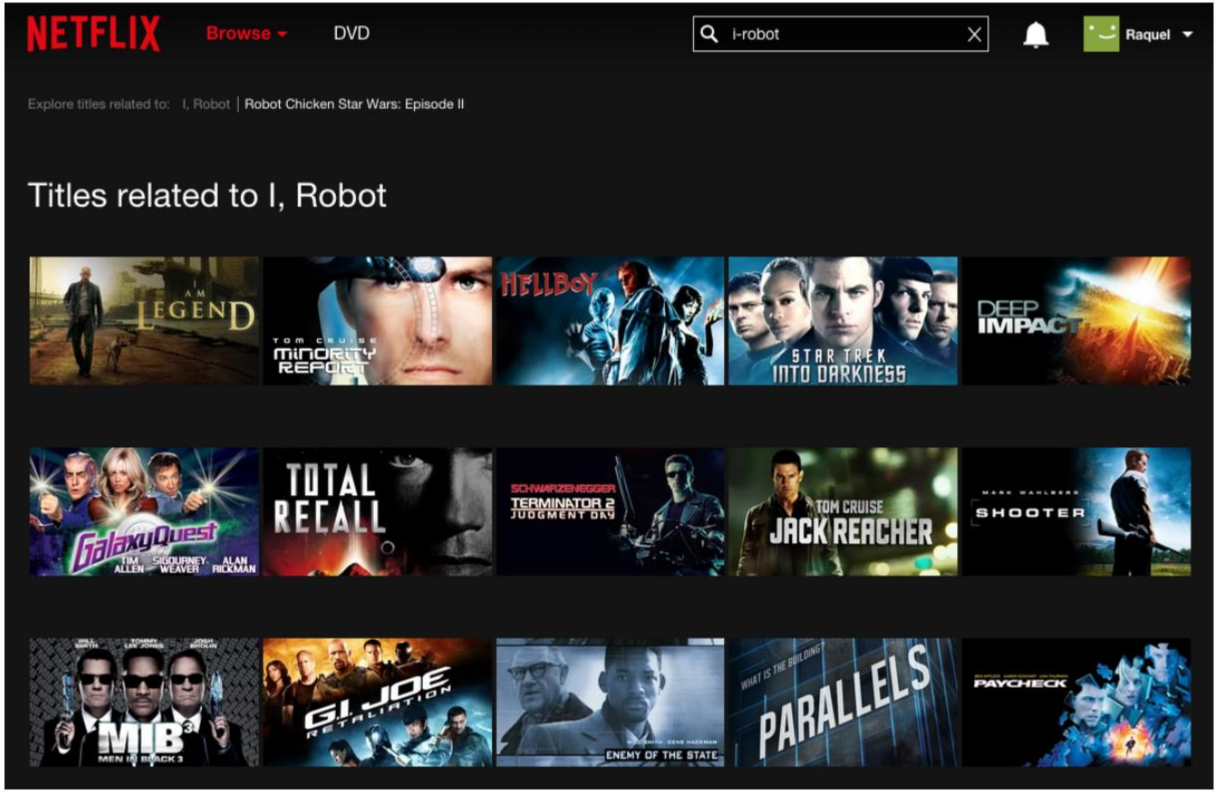

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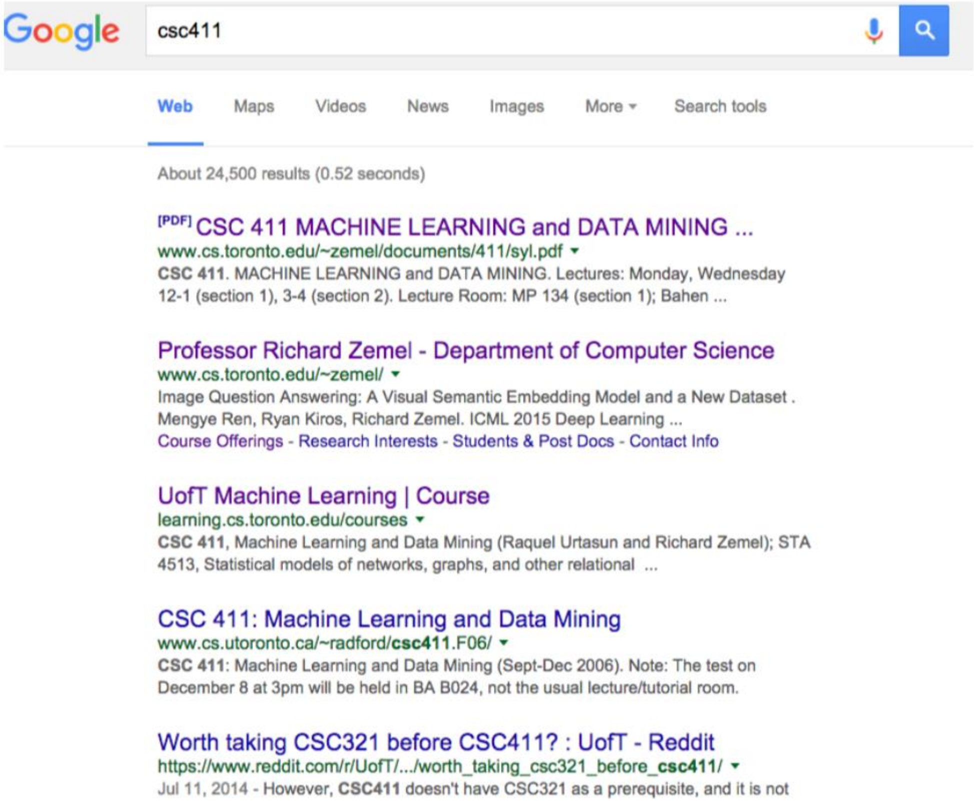

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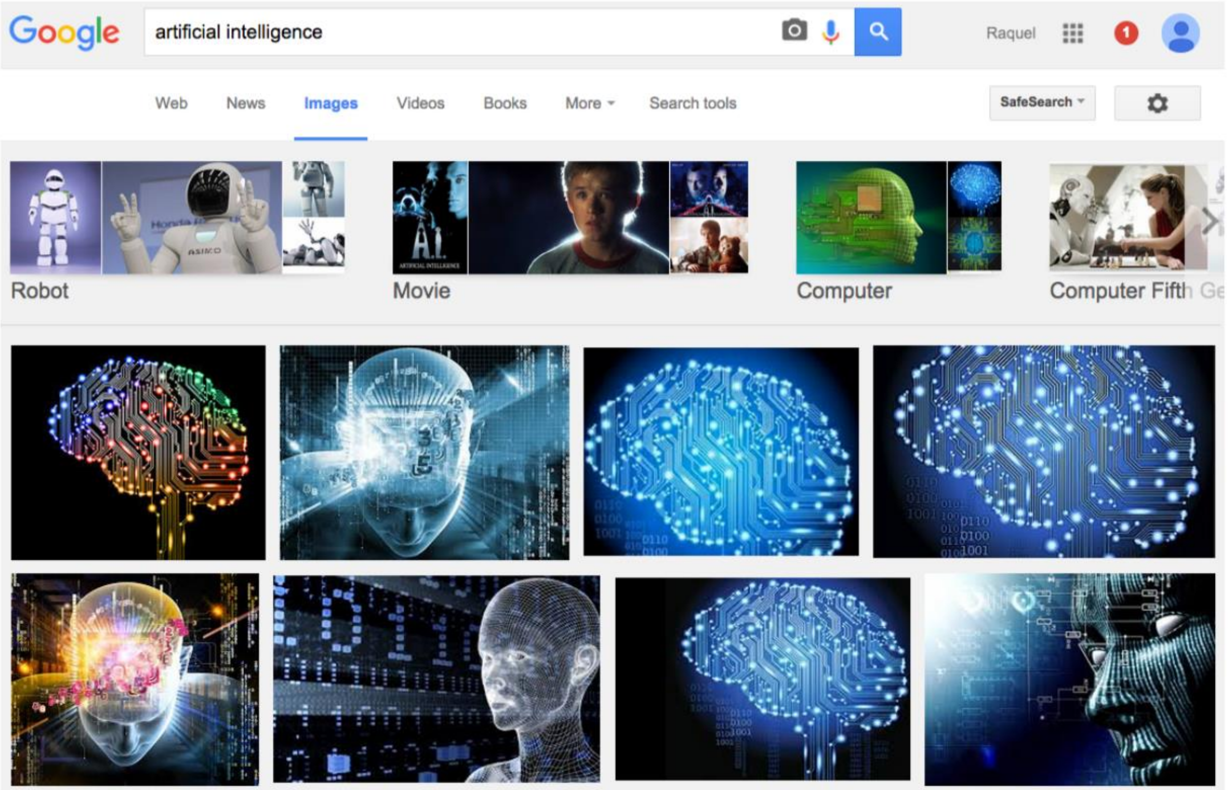

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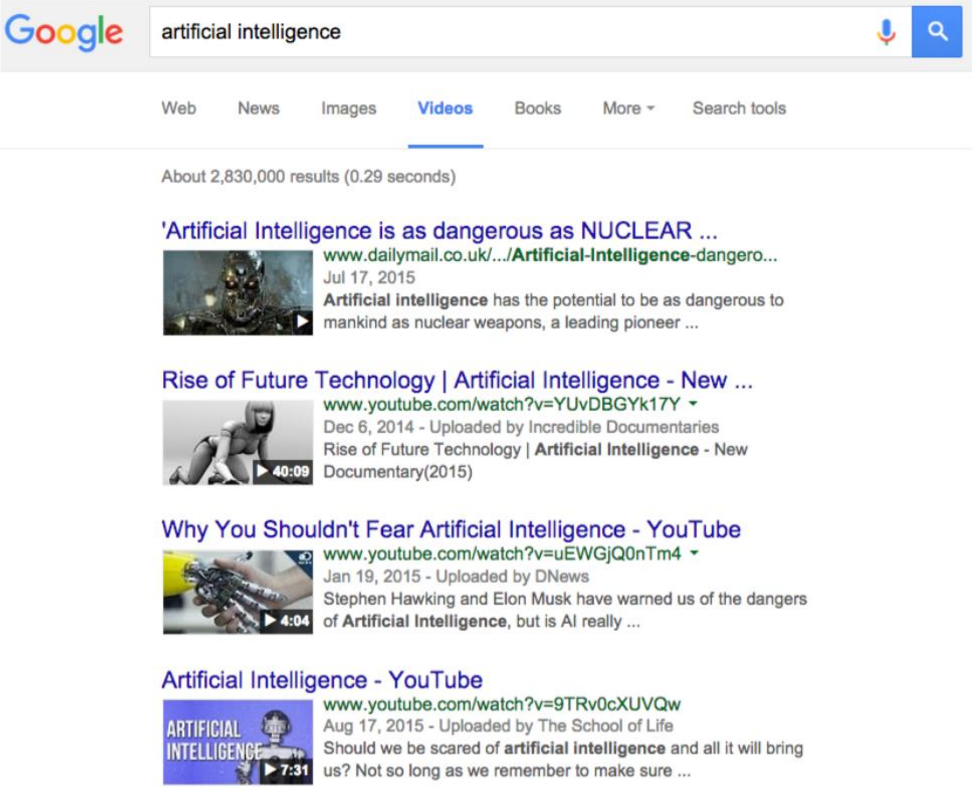

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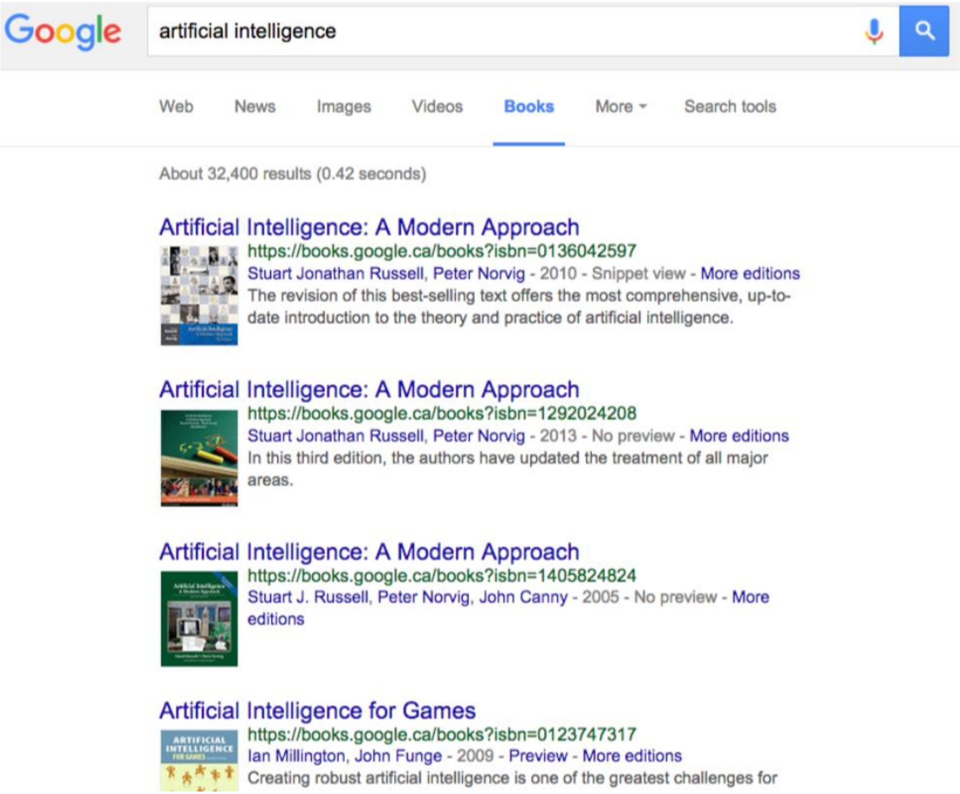

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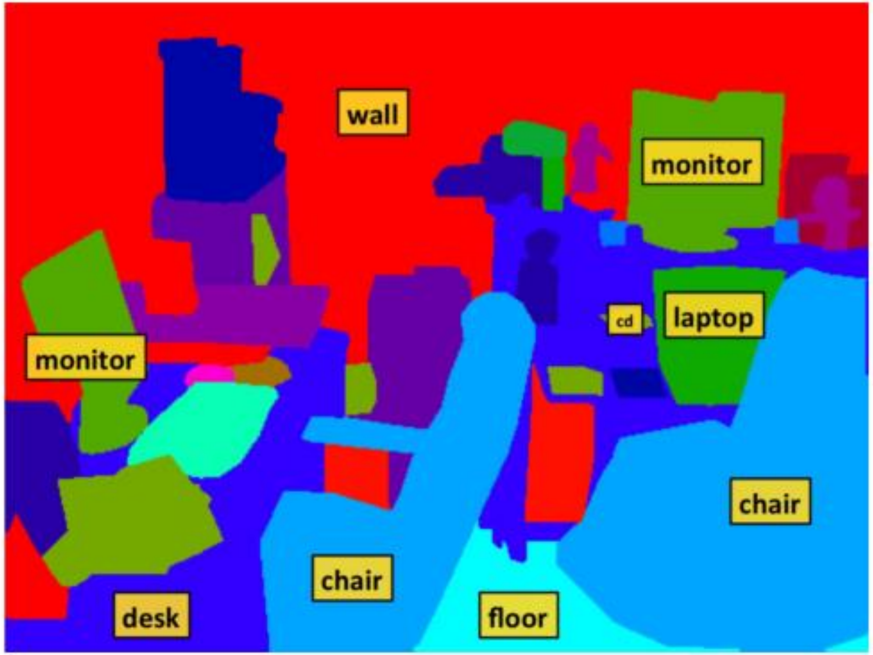
Computer Vision



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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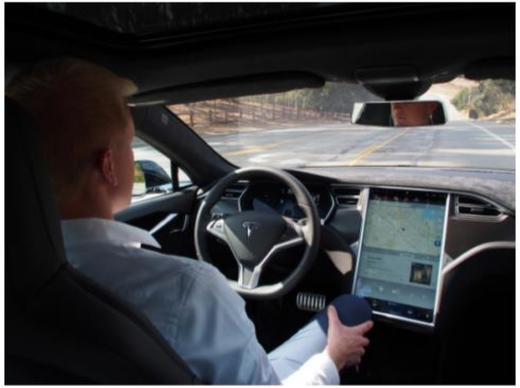
Autonomous Driving



Flying Robots

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

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7. **Learning to play games**

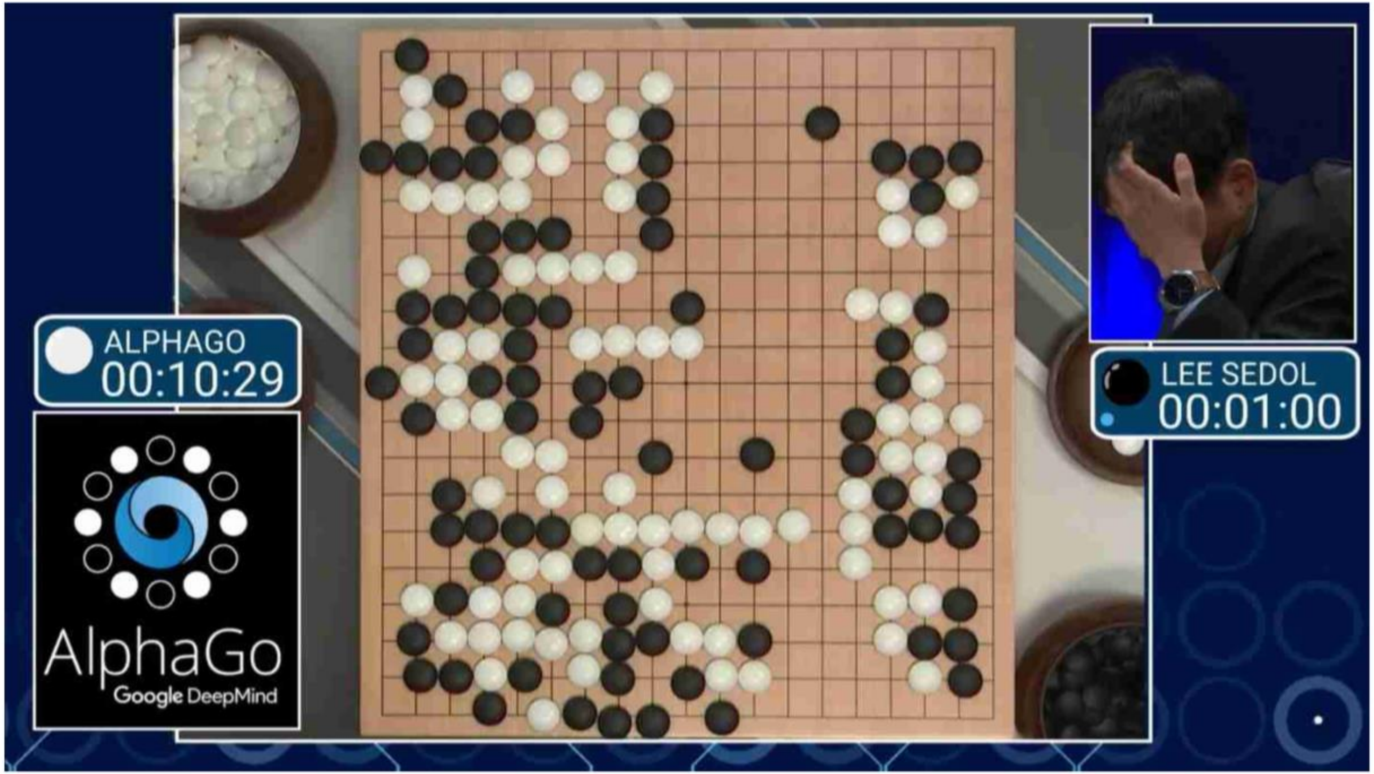
Playing Games: Atari

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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10. **Many more!**

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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

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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).

Any Questions??