COMPUTATIONAL INTELLIGENCE LECTURE 4-1: INTRODUCTION TO MACHINE LEARNING

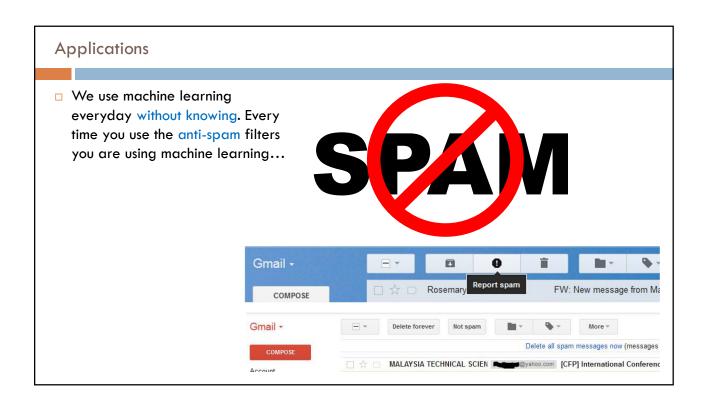
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A Few Quotes

- "A breakthrough in machine learning would be worth ten Microsofts" (Bill Gates, Chairman, Microsoft)
- □ "Machine learning is the next Internet" (Tony Tether, Director, DARPA)
- □ "Machine learning is the hot new thing"(John Hennessy, President, Stanford)
- "Machine learning is going to result in a real revolution" (Greg Papadopoulos, Former CTO, Sun)
- "Machine learning today is one of the hottest aspects of computer science" (Steve Ballmer, CEO, Microsoft)

Sample Applications

- Web search
- □ Finance (e.g. stock price prediction)
- □ **E-commerce** (e.g. fraud detection)
- □ Computational biology (e.g. gene and DNA data analysis)
- □ Space exploration (control, image processing, ...)
- □ **Robotics** (e.g. control, sensory data processing, decision making)
- Information extraction (and Data Mining)
- □ Social networks (e.g. friend and membership suggestions)
- Software Debugging
- □ [Your favorite area]

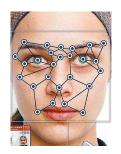


Applications – Face Detection and Recognition

■ Every time you use iPhoto, Google+, Facebook to automatically recognize you and your friends, you are using machine learning...









Applications – Self Driving Cars

□ Self driving cars which will come to market this year are using machine learning... (Video)













Applications - Robots Robots are coming ... military, surveillance, service... (See Boston Dynamics ...) - Video PETMAN Roston Dynamics ...) - Video 28.0 mph Roston Dynamics ...) - Video



Applications - UAVs

□ Self learning, self driving aircrafts.... Self piloted drones... Drone control in the absence of satellite communications ... (Video)







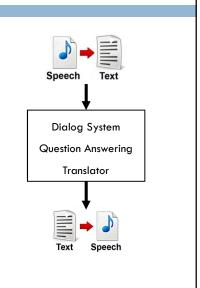




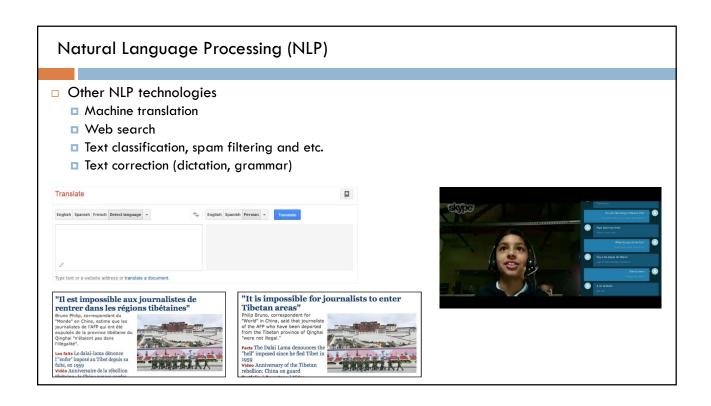
Natural Language Processing (NLP)

- □ Speech technologies (e.g. Cortana, Siri)
 - Automatic speech recognition (ASR) or Speech to Text (STT)
 - Text-to-speech synthesis (TTS)
 - Dialog systems
 - Question answering





Natural Language Processing (NLP) Question Answering, Dialogue systems ... Mostly use Deep Neural Networks (Video) **The Company of the Co



Machine Learning (vs. Normal Programs and Classic Al)

- □ Writing software is the bottleneck of building computer systems
- □ So, how about getting computers to program themselves
- ☐ Give the data to computer, Let it create the program itself
- □ This is in fact automating automation

Traditional Programming:



Machine Learning:



Classic Al vs. Machine Learning vs. Traditional Programming

□ Traditional Programming vs. Machine Learning

- In some situations we don't know how to design an algorithm to solve the problem (e.g. face detection)
- Traditional programming methods are incapable when it comes to very complicated scenarios... learning is the way forward

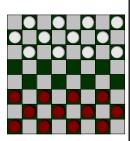
Classic AI vs. Machine Learning

- Classic Al (i.e. search, logic and symbolic methods) has not been very successful in building
 General Al
- □ Classic AI does not work well in dynamic, uncertain and non-deterministic environments
- The best bet is to mimic natural Al and the way it works (aka. Neural networks)

Machine Learning definition

Arthur Samuel's (1959) definition of machine learning: Field of study that gives computers the ability to <u>learn</u> without being explicitly programmed for the task.

He created a checkers program that played the game tens of thousands of times against itself (randomly at the start) and learned what positions are good or bad. It was then able to play much better than an average human (reinforcement learning).



Checkers, Chess, ...

- □ Tom Mitchell's (1998) description of Learning:
 - Assume we have a "task T".
 - □ A <u>program</u> gathers "experience E" by doing T (or by watching someone doing it)
 - The performance is measured by a "performance measure P"
 - If "performance measure P" improves by experience E, then the <u>program</u> is learning.

Quiz

- □ "A computer program is said to learn from experience E with respect to some task T and some performance measure P, if its performance on T, as measured by P, improves with experience E."
- Suppose your email program watches which emails you do or do not mark as spam, and based on that learns how to better filter spam. Which items match T, P, and E?
 - Classifying emails as spam or not spam.
 - Watching you label emails as spam or not spam.
 - □ The number (or fraction) of emails correctly classified as spam/not spam.
 - None of the above—this is not a machine learning problem.

Types of Learning

Supervised/inductive learning (classification or regression)

■ Training data includes desired outputs. We provide a series of "input->output" pairs. The algorithm learns from them. We then provide inputs and the trained algorithm tries to guess an output.

Unsupervised learning (clustering)

■ Training data does not include desired outputs. We only adjust the algorithm parameters in a way that the inputs are clustered into separate groups based on specific similarities

Semi-supervised learning

■ Training data for clustering includes a few desired outputs (labels)

Reinforcement learning

■ We only provide a performance measure. The algorithm randomly tries different things (looking at their performance). It will then repeat those actions that produce better results.

□ Recommender system

■ Looks into the selections we make, it tries to select the same way (can be done using clustering, so could be an application of above)

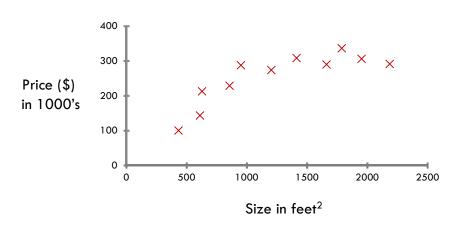
Supervised Learning

Inductive (Supervised) Learning

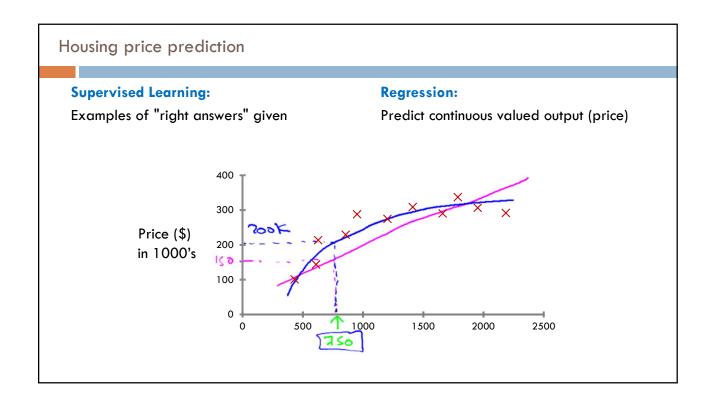
- If we use examples of a function (i.e. some x and F(x) values) to build a function (or model) that can predict F(x) for new values x ... then we have performed supervised learning.
 - □ **Discrete F(x)**: Classification
 - □ Continuous F(x): Regression
 - \blacksquare **F**(X) = **Probability**(X) : Probability estimation
 - in fact a regression with output value in the range of [0,1]

Housing price prediction

□ Having this data, assume you want to predict the price of your friend's 750 ft² house for him... How a learning algorithm help you?

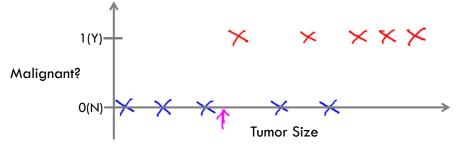


Housing price prediction □ The learning algorithm can use a linear fit □ Or better, it can fit a more accurate curve (e.g. a quadratic function) and do a better prediction... 400 300 Price (\$) 200 in 1000's 6 21 100 500 1000 1500 2000 2500 1750



Breast cancer (malignant, benign)

Assume you look into medical records and you want to predict whether a Tumor with the specified size is malignant or benign based on its size...



Classification:

Discrete valued output (0 or 1)

Not necessarily limited to two classes:

0: Benign

1: Type 1

2: Type2

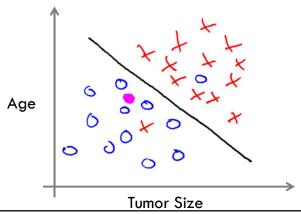
3: Type3

Alternative presentation:



Multiple Parameters

- In previous example, the prediction was based on only one parameter (tumor size). Let's assume we have extracted two parameters from the medical records. If the new parameter is relevant, it might help in better classification.
- The algorithm again tries to find a line (or barrier) that separates the two classes (malignant, benign).



Other potential parameters:

- Clump Thickness
- Uniformity of Cell Size
- Uniformity of Cell Shape

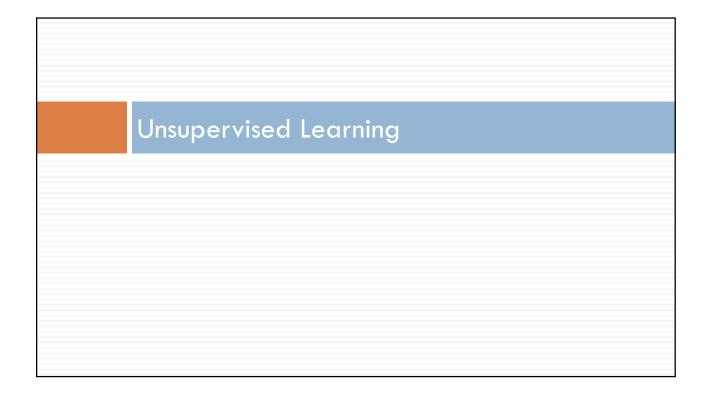
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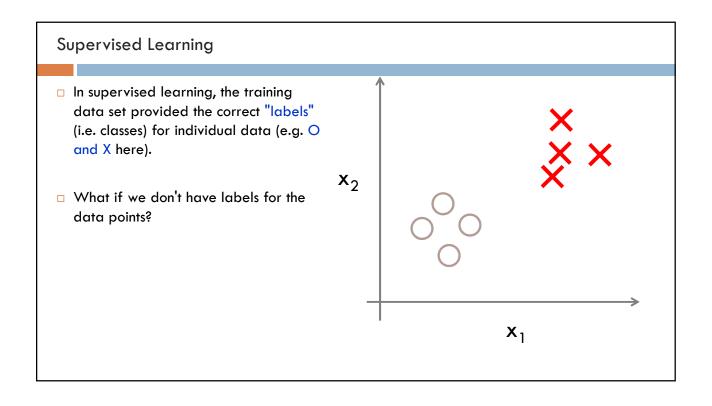
How supervised learning typically works

- \square We start by choosing a model-class: $y = f(\mathbf{x}; \mathbf{W})$
 - \blacksquare A model-class, f, is a way of using some numerical parameters, \mathbf{W} , to map each input vector, \mathbf{x} , into a predicted output \mathbf{y} .
- □ Learning usually means adjusting the parameters to reduce the difference between the target output, t, on each training case and the actual output, y, produced by the model.
 - We use numerical measures to minimize the difference between predicted output and the actual output
 - For regression, we will see later that $\frac{1}{2}(y-t)^2$ is often a suitable measure.
 - For classification there are other measures that are generally more sensible (they also work better).

Recap

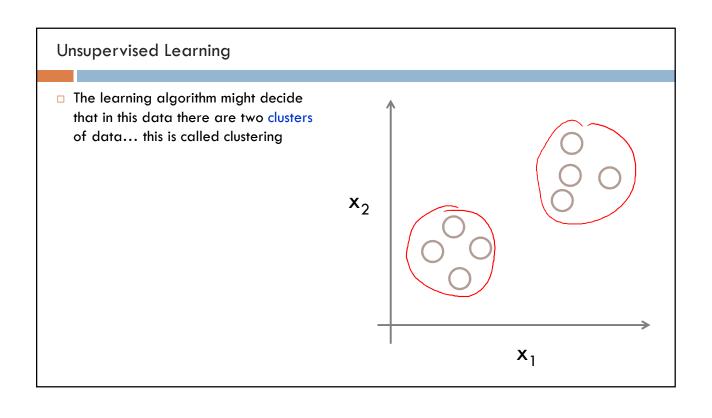
- □ In this course we will be looking at supervised learning methods. The idea is that in our training data set, we are going to give the algorithm some correct answers.
- □ The algorithm will learn from the training set and it will generalize what it has learned to the questions it has not seen.
- □ Learning is done by adjusting the model parameters (e.g. using optimization methods).
- □ It will guess the answers for new questions, based on what it has learned in past.
- Classification: discrete
- Regression: continuous





Unsupervised Learning In these kind of problems, we are given some data but we don't know how different they are and there are no labeled examples We are asked to find a structure in data.

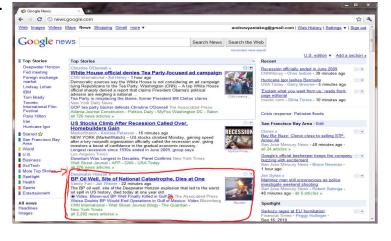
 \mathbf{x}_1

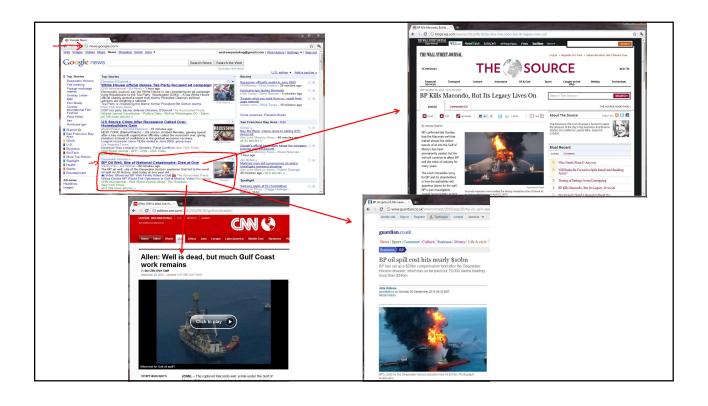


Unsupervised Learning - Applications

 One example of clustering is used in Google news. News items of the same topic are clustered into separate subjects (headlines). No label or supervision is provided ... It just

recognizes clusters of news... (using words in the article)

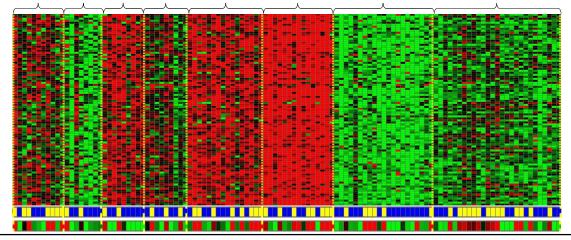




Clustering - Applications

Genes

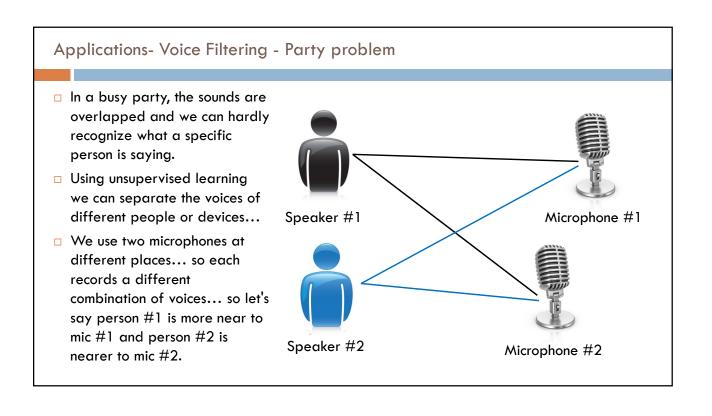
Here is another example of clustering. We have gathered gene information of different individuals. We want to see whether different people have specific genes... and then we want to divide people into different categories or types ... note that we don't know what exactly are those genes... we just cluster the individuals based on their gene data...
 Individuals



Why called unsupervised

- Because we don't provide the right answer (labels) to the algorithm, and the algorithm finds similarities in them automatically, it is called unsupervised learning....
- □ It is the given examples that supervise the learning in supervised methods.

Applications Organize jobs on clusters Social network analysis Market segmentation Astronomical data analysis



Applications- Voice Filtering Microphone #1: Output #1: Microphone #2: Output #2: Microphone #1: Output #1: Microphone #2: Output #1: Microphone #2: Output #3: Microphone #3: Output #3: Microphone #3: Output #3: