

Applied Machine Learning

Introduction

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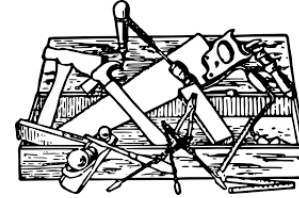
COMP 551 (winter 2020)

Objectives

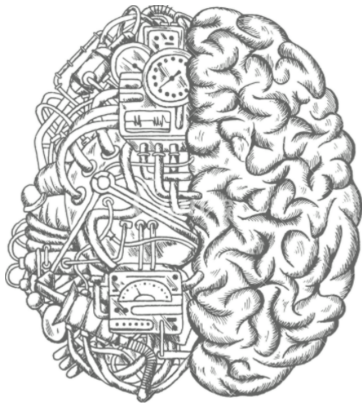
- understanding the scope of machine learning
 - relation to other areas
- understanding types of machine learning

What is Machine Learning?

ML is the set of "algorithms and statistical models that computer systems use to perform a specific task without using explicit instructions"



an inadequate **history of ML**



- 1950: Turing test
- 1956: checker player that learned as it played (Arthur Samuel)
 - coined the term Machine Learning
- 1958: first artificial neural networks called Perceptron (Frank Rosenblatt),
 - 1959: ADELIN (Widrow and Hoff)
- 1963: support vector machines (Vapnick & Ya)
- 1969: Minsky and Pappert show the limitations of single-layer neural networks
- 1970-80s rule-based and symbolic AI dominates (two AI winters)
- 1980's Bayesian networks (Judea Pearl)
- 1986 Backpropagation rediscovered (Rumelhart, Hinton & Williams)
- 1991 Kernel trick for SVM
- 2012 AlexNet wins Imagenet by a large margin
- 2012 - now deep learning explosion...
- next? AI winter? AGI?

Placing ML: overlapping fields

- **Artificial Intelligence:** its a broader domain (includes search, planning, multiagent systems, robotics, etc.)
- **Statistics:** historically precedes ML. ML is more focused on algorithmic, practical and powerful models (e.g., neural networks) and is built around AI
- **Vision & Natural Language Processing:** use many ML algorithms and ideas
- **Optimization:** extensively used in ML
- **Data mining:** scalability, and performance comes before having strong theoretical foundations, more space for using heuristics, exploratory analysis, and unsupervised algorithms
- **Data science:** an umbrella term for the above mostly used in industry when the output is knowledge/information to be used for decision making

Placing ML: main venues

top computer science conferences

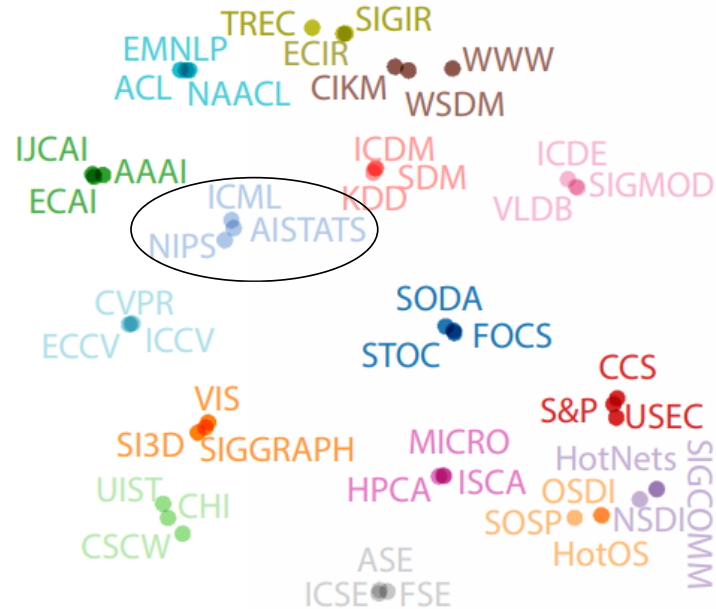
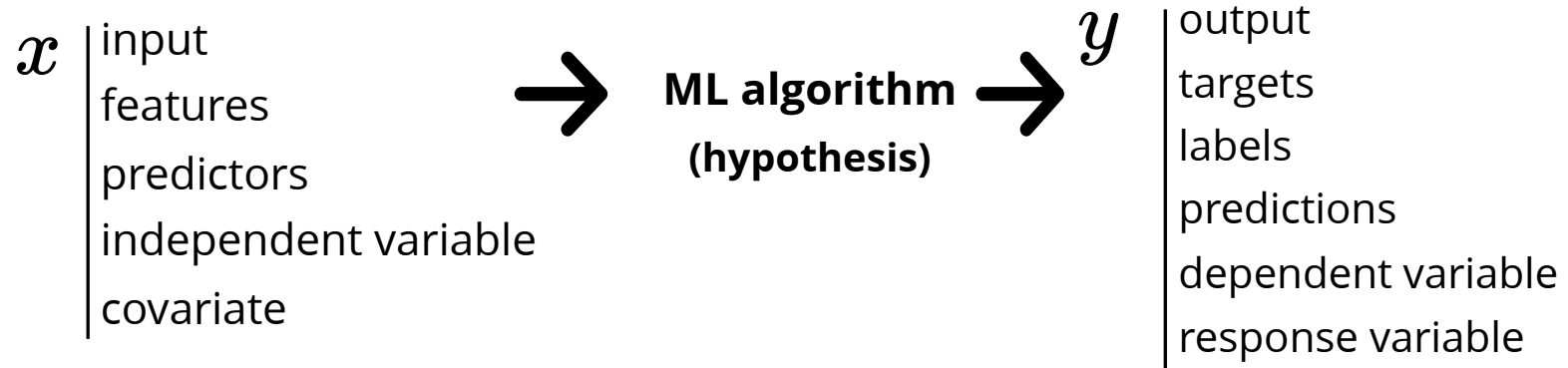


Figure from Dong et al.

Some terminology



example

<tumorsize, texture, perimeter> = <18.2, 27.6, 117.5> → cancer = No

Some terminology

(labelled) **datasets**: consist of many training examples or **instances**

<tumorsize, texture, perimeter> , <cancer, size change>

<18.2, 27.6, 117.5> , < No , +2 > $x^{(1)}$

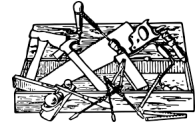
<17.9, 10.3, 122.8> , < No , -4 > $x^{(2)}$ one instance

<20.2, 14.3, 111.2> , < Yes , +3 > $x^{(3)}$

⋮
⋮

<15.5, 15.2, 135.5> , < No , 0 > $x^{(N)}$

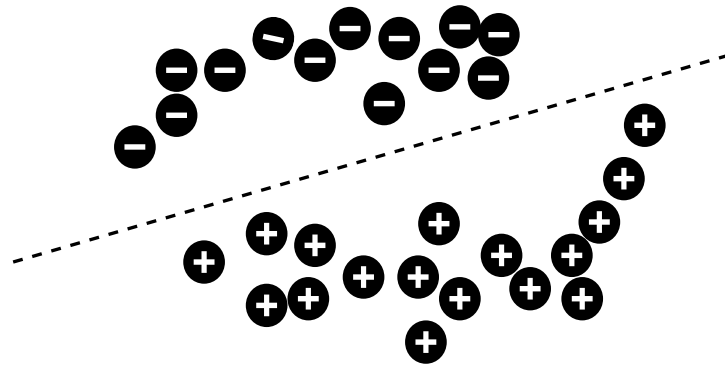
"Types" of Machine Learning



Supervised Learning: we have labeled data

- classification
- regression
- structured prediction

most of this course!



Supervised Learning

Classification: categorical/discrete output

<tumorsize, texture, perimeter>	,	<cancer>
<18.2, 27.6, 117.5>	,	< No >
<17.9, 10.3, 122.8>	,	< No >
<20.2, 14.3, 111.2>	,	< Yes >
<15.5, 15.2, 135.5>	,	< No >

target

Regression: continuous output

<tumorsize, texture, perimeter>	,	<size change>
<18.2, 27.6, 117.5>	,	< +2 >
<17.9, 10.3, 122.8>	,	< -4 >
<20.2, 14.3, 111.2>	,	< +3 >
<15.5, 15.2, 135.5>	,	< 0 >

target

Supervised Learning: Example

MIT
Technology
Review

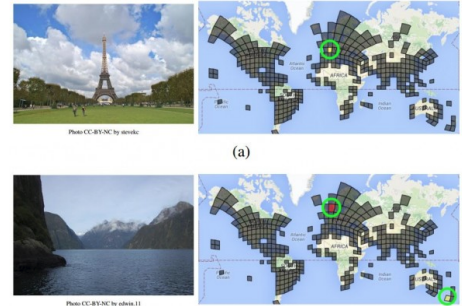
Intelligent Machines

Google Unveils Neural Network with “Superhuman” Ability to Determine the Location of Almost Any Image

Guessing the location of a randomly chosen Street View image is hard, even for well-traveled humans. But Google’s latest artificial-intelligence machine manages it with relative ease.

by Emerging Technology from the arXiv February 24, 2016

Topics+ TI



Supervised Learning: **Example**

Machine Translation:

data consists of input-output sentence pairs (x,y)

DeepL schools other online translators with clever machine learning

Devin Coldewey, Frederic Lardinois / 1:57 pm EDT • August 29, 2017

[Comment](#)



[Image Credits: H. Armstrong Roberts/Getty Images](#)

Supervised Learning: **Example**

Image captioning

input: image

output: text



The man at bat readies to swing at the pitch while the umpire looks on.



A large bus sitting next to a very tall building.

image: COCO dataset

Supervised Learning: Example

Object detection

input: image

output: a set of bounding box coordinates

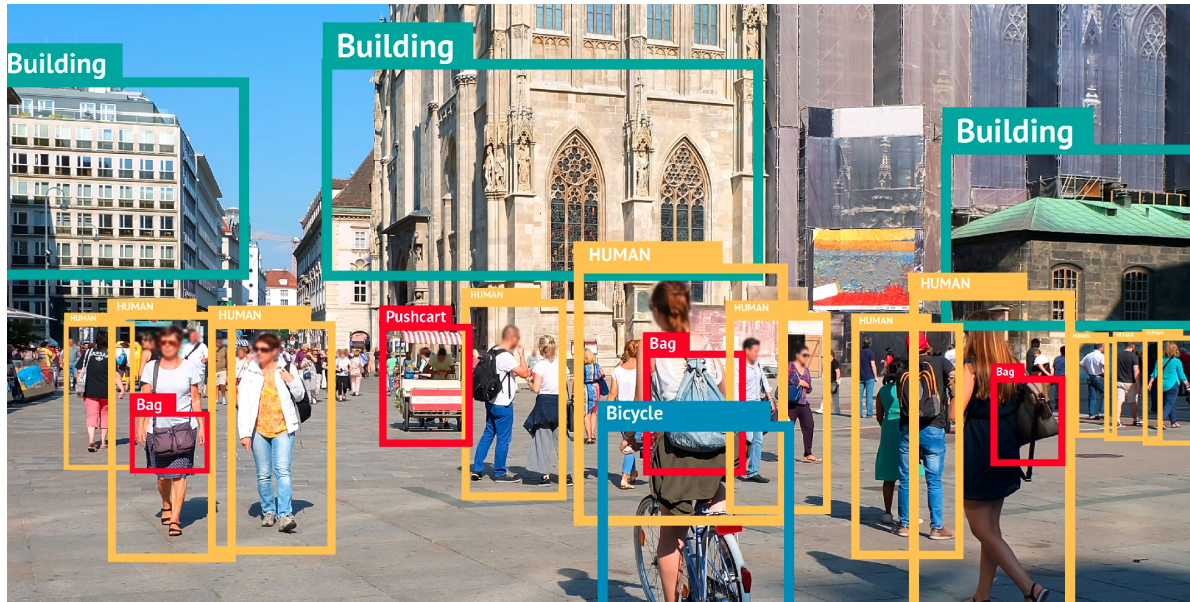


image: <https://bitmovin.com/object-detection/>

"Types" of Machine Learning



Unsupervised Learning: only unlabeled data

- clustering
- dimensionality reduction
- density estimation / generative modeling
- anomaly detection
- discovering latent factors and structures

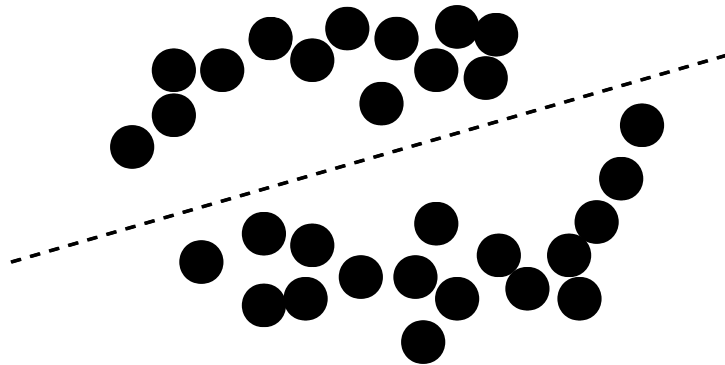
helps explore and understand the data
closer to data mining
we have much more unlabeled data
more open challenges

Unsupervised Learning: **Example**

clustering

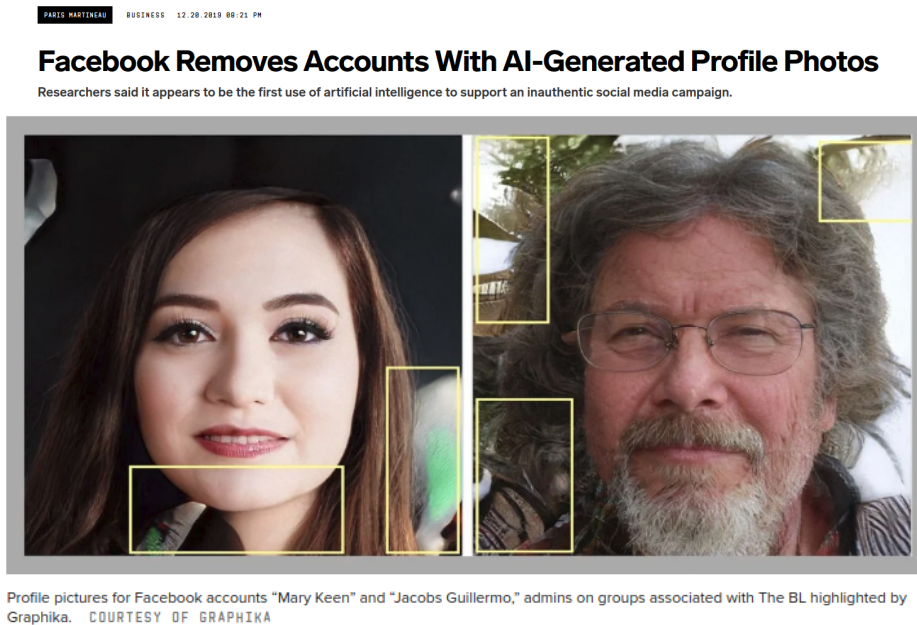
similar to classification but labels/classes should be inferred and are not given to the algorithm

<tumorsize, texture, perimeter>		
<18.2,	27.6,	117.5>
<17.9,	10.3,	122.8>
<20.2,	14.3,	111.2>
<15.5,	15.2,	135.5>



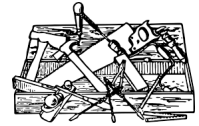
Unsupervised Learning: Example

Generative modeling (density estimation):
learn the data distribution $p(x)$

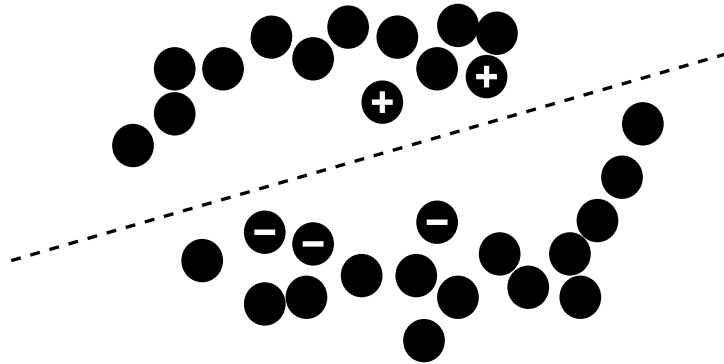


"Types" of Machine Learning

Semisupervised learning: a few labeled examples

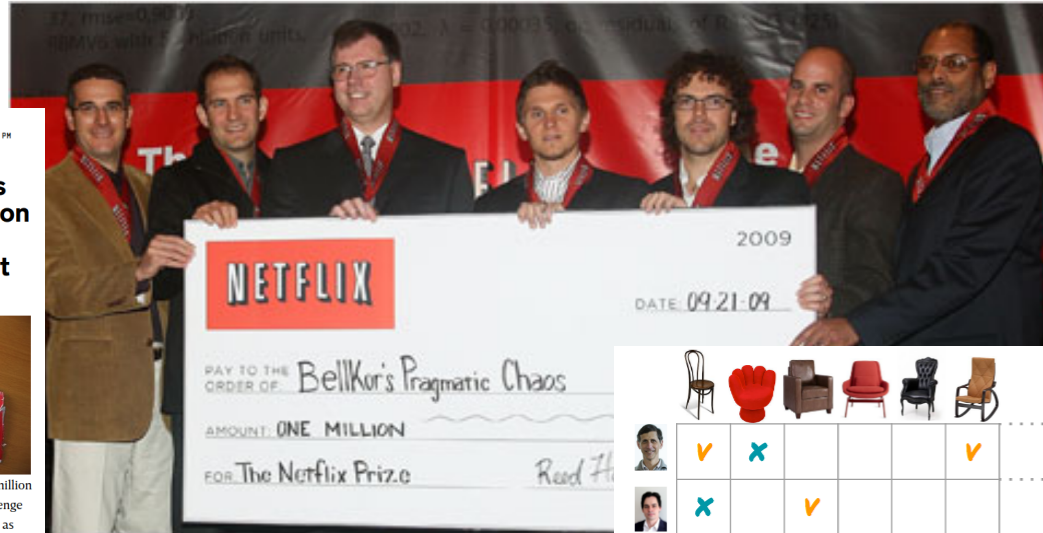


- we can include structured problems such as
 - matrix completion (a few entries are observed)
 - link prediction



Netflix Awards \$1 Million Prize and Starts a New Contest

BY STEVE LOHR SEPTEMBER 21, 2009 10:15 AM



RYAN STANGEL SECURITY 03.12.10 02:48 PM

NetFlix Cancels Recommendation Contest After Privacy Lawsuit



Netflix is canceling its second \$1 million Netflix Prize to settle a legal challenge that it breached customer privacy as part of the first contest's race for a better movie-recommendation engine.

on Kempin/Getty Images Netflix prize winners, f Chabbert, Martin Piotte, Michael Jahrer, Andreas To

Update | 1:45 p.m. Adding details announced close finish to the contest.

	✓	✗				✓				
	✗		✓				✓			✗
					✓			✗		
		✓		✓	✗					
			✓	✗	✓					✗

"Types" of Machine Learning

Reinforcement Learning:

- weak supervision through the reward signal
- sequential decision making
- biologically motivated

also related:

imitation learning: learning from demonstrations

- behavior cloning (is supervised learning!)
- inverse reinforcement learning (learning the reward function)



Reinforcement Learning: Example



Human Level Control Through Deep Reinforcement Learning

Abstract

The theory of reinforcement learning provides a normative account deeply rooted in psychological and neuroscientific perspectives on animal behaviour, of how agents may optimize their control of an environment. To use reinforcement learning successfully in situations approaching real-world complexity, however, agents are confronted with a difficult task: they must derive efficient representations of the environment from high-dimensional sensory inputs, and use these to generalize

Reinforcement Learning: **Example**

Google's AlphaGo Defeats Chinese Go Master in Win for A.I.

[点击查看本文中文版](#)

By PAUL MOZUR MAY 23, 2017



Ke Jie, the world's top Go player, reacting during his match on Tuesday against AlphaGo, artificial intelligence software developed by a Google affiliate. China Stringer Network, via Reuters

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Summary

- **Supervised Learning:** we have labeled data
 - classification
 - regression
 - structured prediction
- **Unsupervised Learning:** only unlabeled data
 - clustering
 - dimensionality reduction
 - density estimation / generative modeling
 - anomaly detection
 - discovering latent factors and structures
- **Semisupervised learning:** a few labeled examples
- **Reinforcement Learning:** reward signal