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: ADELINE (Widrow and Hoff)
- 1963: support vector machines (Vapnick & Ya)
- 1969: Minskey 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.)
Placing ML: overlapping fields

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- **Statistics**: historically precedes ML. ML is more focused on algorithmic, practical and powerful models (e.g., neural networks) and is built around AI
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- **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

$\mathbf{x}$

- input
- features
- predictors
- independent variable
- covariate
Some terminology

\( x \) | input
- features
- predictors
- independent variable
- covariate

\[ \rightarrow \quad \text{ML algorithm} \quad \rightarrow \quad y \]

\( y \) | output
- targets
- labels
- predictions
- dependent variable
- response variable
Some terminology

`x` | input features predictors independent variable covariate
---|---
`y` | output targets labels predictions dependent variable response variable

ML algorithm (hypothesis)

Example:

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

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

<table>
<thead>
<tr>
<th>Tumor Size</th>
<th>Texture</th>
<th>Perimeter</th>
<th>Cancer Status</th>
<th>Size Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>18.2</td>
<td>27.6</td>
<td>117.5</td>
<td>No</td>
<td>+2</td>
</tr>
<tr>
<td>17.9</td>
<td>10.3</td>
<td>122.8</td>
<td>No</td>
<td>-4</td>
</tr>
<tr>
<td>20.2</td>
<td>14.3</td>
<td>111.2</td>
<td>Yes</td>
<td>+3</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>15.5</td>
<td>15.2</td>
<td>135.5</td>
<td>No</td>
<td>0</td>
</tr>
</tbody>
</table>
### Some terminology

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

<table>
<thead>
<tr>
<th>Tumorsize, Texture, Perimeter</th>
<th>Cancer, Size Change</th>
<th>Instance</th>
</tr>
</thead>
<tbody>
<tr>
<td>18.2, 27.6, 117.5</td>
<td>&lt; No, 2 &gt;</td>
<td>$x^{(1)}$</td>
</tr>
<tr>
<td>17.9, 10.3, 122.8</td>
<td>&lt; No, -4 &gt;</td>
<td>$x^{(2)}$</td>
</tr>
<tr>
<td>20.2, 14.3, 111.2</td>
<td>&lt; Yes, 3 &gt;</td>
<td>$x^{(3)}$</td>
</tr>
<tr>
<td>15.5, 15.2, 135.5</td>
<td>&lt; No, 0 &gt;</td>
<td>$x^{(N)}$</td>
</tr>
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</table>

\[ x_{(1)} \cdot x_{(2)} \cdot \ldots \cdot x_{(N)} \]
"Types" of Machine Learning

**Supervised Learning:** we have labeled data

- classification
- regression
- structured prediction

most of this course!
Supervised Learning

**Regression:** continuous output

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target
# Supervised Learning

**Classification:** categorical/discrete output

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<th>&lt;cancer&gt;</th>
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Supervised Learning: Example

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
Supervised Learning: Example

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

\[
\begin{array}{ccc}
\text{tumorsize, texture, perimeter} & \text{cancer} \\
<18.2, & 27.6, & 117.5> & \text{No} \\
<17.9, & 10.3, & 122.8> & \text{No} \\
<20.2, & 14.3, & 111.2> & \text{Yes} \\
<15.5, & 15.2, & 135.5> & \text{No} \\
\end{array}
\]
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

Jason Kempin/Getty Images Netflix prize winners, from left, Greg Chabbert, Martin Piotte, Michael Jahrer, Andreas To

Update | 1:45 p.m. Adding details announced close finish to the contest.
Netflix Awards $1 Million Prize and Starts a New Contest

BY STEVE LOHR    SEPTEMBER 21, 2009 10:15 AM

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.

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"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.

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

A.I. Is Doing Legal Work. But It Won't Replace Lawyers, Yet.  MARCH 20, 2017

China's Intelligent Weaponry Gets Smarter  FEB. 3, 2017

The Future of Work  FEB. 23, 2017

Master of Go Board Game Is Walloped by Google Computer Program  MARCH 13, 2016
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