Lecture 1 Introduction - Part 1

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Introduction

Machine learning: what and why?

Types of machine learning

- Supervised learning
- Unsupervised learning

Supervised Learning - Classification

- Different types of Classification
- Function Approximation and Generalization
- The need for Probabilistic Predictions
- Real World Applications

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Lezioni Giorni, Orari e Contatti

Aula A7

- Martedì 12:00 13:30 (Teoria)
- Giovedì 8:30 10:00 (Teoria)
- Giovedì 10:15 11:45 (Esercitazione)

Contatti

- Prof. Fiora Pirri Stanza B110 http://www.dis.uniroma1.it/~pirri mail: pirri@dis.uniroma1.it
- Tutor: Luigi Freda mail: freda@dis.uniroma1.it
- Tutor: Francesco Puja mail: puja@dis.uniroma1.it

Sito web

http://www.dis.uniroma1.it/~alcor/site/index.php/courses.html



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• Kevin Murphy "Machine Learning, A Probabilistic Perspective"



• MATLAB software package: **PMTK**

https://github.com/probml/pmtk3

PMTK was used to generate many of the **figures** in the book; the source code for these figures is included on the PMTK website, you can play with it and easily see the effects of changing the data or algorithm or parameter settings

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- Learning denotes changes in the system that are adaptive in the sense that they enable the system to do the task or tasks drawn from the same population more efficiently and more effectively the next time[Herbert Simon]
- closely related to
 - statistics (fitting models to data and testing them)
 - data mining/ exploratory data analysis (discovering models)
 - adaptive control theory
 - AI (building intelligent machines by hand)

- the goal of machine learning is to develop methods that can automatically detect patterns in data, and then to use the uncovered patterns to predict future data or other outcomes of interest.
- in machine learning, **uncertainty** comes in many forms:
 - what is the **best prediction** (or decision) given some data?
 - what is the best model given some data?
 - what measurement should I perform next? (planning how to collect more data)

- in practice machine learning is programming computers to **optimize a performance criterion** using example data or past experience
- there is no need to "learn" to calculate payroll
- learning is used when:
 - Human expertise does not exist (navigating on Mars)
 - Humans are unable to explain their expertise (speech recognition)
 - Solution changes in time (routing on a computer network)
 - Solution needs to be adapted to particular cases (user biometrics)

supervised learning

- predict output y from input x

e unsupervised learning

- find patterns in data x

reinforcement learning

- learn how to behave in novel environments (e.g. robot navigation)

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Supervised learning

the goal is to learn a **mapping** from inputs **x** to outputs *y*, given a labeled set of input-output pairs $\mathcal{D} = \{(\mathbf{x}_i, y_i)\}_{i=1}^N$

- the set $\mathcal{D} = \{(\mathbf{x}_i, y_i)\}_{i=1}^N$ is the training set
- N is the number of training examples
- x_i is the **training input** and it is a *D*-dimensional vector of numbers
- the components of the vector x_i are called **features**
- the vector x_i are usually stored row by row in the N × D design matrix X
- y is the training output

in order to evaluate the estimated mapping we can compare our prediction \hat{y} for a given ${\bf x}$ to the actual observed value y

Supervised learning

given the training set $\mathcal{D} = \{(\mathbf{x}_i, y_i)\}_{i=1}^N$, we have two types of supervised learning:

classification

if $y \in \{1, 2, ..., C\}$ where C is the cardinality of a finite set of labels/classes/categories

egression

if $y \in \mathbb{R}$

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Unsupervised learning

- In this case, the training set is $\mathcal{D} = \{\mathbf{x}_i\}_{i=1}^N$ and the goal is to find "interesting patterns" in it
- This is sometimes called knowledge discovery
- We are not told what kinds of patterns to look for, and there is no obvious error metric to use (unlike supervised learning, where we can compare our prediction of y for a given x to the observed value)

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Different types of Classification

- binary classification: $y \in \{0, 1\}$
- multiclass classification: $y \in \{1, 2, ... C\}$
- multi-output classification: $\mathbf{y} = [y_1, y_2, ..., y_M]^T$ where $y_i \in \{0, 1\}$

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Function approximation

- we assume $y = f(\mathbf{x})$ for some unknown function f
- the goal of learning is to estimate the function f given a labeled training set $\mathcal{D} = \{(\mathbf{x}_i, y_i)\}_{i=1}^N$
 - binary classification: $y \in \{0, 1\}$
 - multiclass classification: $y \in \{1, 2, ... C\}$
- then to make predictions using $\hat{y} = \hat{f}(\mathbf{x})$ (the hat symbol to denotes an estimate)

Generalization

- our main goal is to make **predictions** on **novel inputs**, meaning ones that we have not seen before
- predicting the response on the training set is easy (we can just look up the answer).

Classification Example



	• D1	D features (attributes)		
	Color	Shape	Size (cm)	Label
ses	Blue	Square	10	1
N	Red	Ellipse	2.4	1
,	Red	Ellipse	20.7	0

input features x can be discrete, continuous or a combination of the two. In addition to the inputs, we have a vector of training labels y

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The need for Probabilistic Predictions



- to handle ambiguous cases, such as the yellow circle above, it is desirable to return a **probability**
- we will denote the probability distribution over possible labels, given the input vector x and training set D by p(y|x, D)
- when choosing between different **models** M_i , we will make this assumption explicit by writing $p(y|\mathbf{x}, \mathcal{D}, M_i)$

given a probabilistic output, we can always compute our "**best guess**" as to the "true label" using

$$\hat{y} = \hat{f}(\mathbf{x}) = \operatorname*{argmax}_{c=1}^{C} p(y = c | \mathbf{x}, \mathcal{D})$$

- this corresponds to the most probable class label, and is called the mode of the distribution p(y|x, D) it is also known as a MAP estimate (MAP stands for maximum a posteriori)
- using the most probable label makes intuitive sense
- this will be justified



- now consider a case such as the yellow circle, where $p(\hat{y}|\mathbf{x}, D)$ is far from 1
- in such a case we are not very confident of our answer, so it might be better to say "I don't know" instead of returning an answer that we don't really trust

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Document classification and email spam filtering

- the goal is to classify a document (e.g. web page or email message) into one of *C* classes
- that is, compute $p(y|\mathbf{x}, D)$, where x is some representation of the text
- a special case of this is email spam filtering, where the classes are spam y = 1 or no-spam y = 0

Problem: most classifiers assume that the input vector x has a fixed size. But we have variable-length documents.

Solution: **bag of words** representation. Basic idea: define $x_{ij} = 1$ iff word *j* occurs in document *i*

Real World Applications

Classifying flowers



- rather than working directly with images, a botanist has already extracted 4 useful **features**/characteristics: sepal length and width, and petal length and width.
- such feature extraction is an important, but difficult, task
- most machine learning methods use features chosen by some human
- there are methods that can automatically **learn good features** from the data

Real World Applications

Classifying flowers



- scatter plot of the iris data
- $\bullet\,$ on the above plot: different colors $\rightarrow\,$ different flowers
- rule of thumb: it is always a good idea to perform exploratory data analysis, such as plotting the data, before applying a machine learning method = .

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Image classification and handwriting recognition we might want to classify an image as a whole, e.g.

- it an indoors or outdoors scene?
- is it a horizontal or vertical photo?
- does it contain a human or not?
- does it contain a dog or a cat?

Real World Applications

Image classification and handwriting recognition



- in the special case that the images consist of isolated handwritten letters and digits, for example, in a postal or ZIP code on a letter, we can use classification to perform handwriting recognition
- a standard dataset used in this area is known as **MNIST**, which stands for "Modified National Institute of Standards"
- many generic classification methods ignore any structure in the input features, such as **spatial layout**
- this **flexibility** is both a blessing (since the methods are general purpose) and a curse (since the methods ignore an obviously useful **source of information**)

Real World Applications

Object Detection

• find objects within an image; this is called object detection or object localization

Face Detection and Recognition





- an important special case is face detection
- a very simple approach to this problem is the **sliding window detector**: divide the image into many small overlapping patches at different locations, scales and orientations, and to classify each such patch based on whether it contains face-like texture or not
- having found the faces, one can then proceed to perform face recognition

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Regression

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- here $y \in \mathbb{R}$
- then make predictions using $\hat{y} = \hat{f}(\mathbf{x})$ (the hat symbol to denotes an estimate)

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a simple example: we have a single real-valued input $x_i \in \mathbb{R}$ and a single real-valued response $y \in \mathbb{R}$

Some examples of real-world regression problems

- predict tomorrow's **stock market price** given current market conditions and other possible side information
- predict the age of a viewer watching a given video on YouTube
- predict the location in 3D space of a mobile robot (robot localization), given wheel rotations and laser sensory information
- predict the amount of prostate specific antigen (PSA) in the body as a function of a number of different clinical measurements
- predict the **temperature at any location** inside a building using weather data, time, door sensors, etc

N.B.: is prediction an important word in the above applications?

• Kevin Murphy's book and slides for CS340 and CS540