Machine Learning

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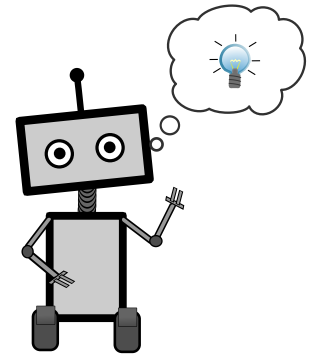
Spring 2015

Machine Learning

Subfield of AI concerned with *learning from data*.

Broadly, using:
- ***Experience***
- To Improve ***Performance***
- On Some ***Task***

(Tom Mitchell, 1997)



vs …

ML

vs

Statistics

vs

Data Mining

Why?

Developing effective learning methods has proved difficult.
Why bother?

Autonomous discovery
- We don't know something, want to find out.

Hard to program
- Easier to specify task, collect data.

Adaptive behavior
- Our agents should adapt to new data, unforeseen circumstances.

Types

Depends on *feedback available*:

Labeled data:

- Supervised learning

No feedback, just data:

- Unsupervised learning.

Sequential data, weak labels:

- Reinforcement learning

Supervised Learning

Input:

$X = \{x_1, \ldots, x_n\}$ inputs

$Y = \{y_1, \ldots, y_n\}$ labels

training data

Learn to *predict new labels*.

Given x: y?

Unsupervised Learning

Input:

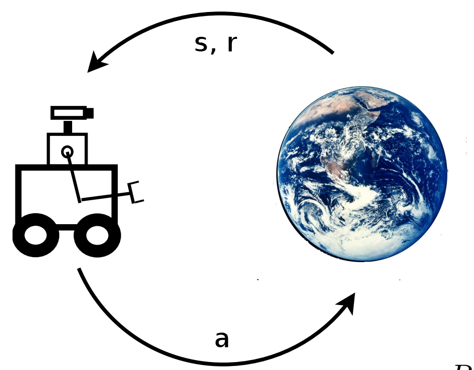
$X = \{x_1, \ldots, x_n\}$ inputs

Try to understand the *structure of the data.*

E.g., how many types of cars? How can they vary?

Reinforcement Learning

Learning counterpart of planning.



$\pi : S \rightarrow A$

$$\max_{\pi} R = \sum_{t=0}^{\infty} \gamma^t r_t$$

Today: Supervised Learning

Formal definition:

Given training data:
$X = \{x_1, \ldots, x_n\}$ inputs
$Y = \{y_1, \ldots, y_n\}$ labels

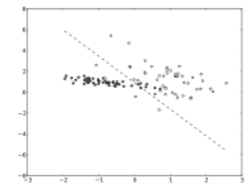
Produce:
Decision function $f : X \rightarrow Y$

That minimizes error:

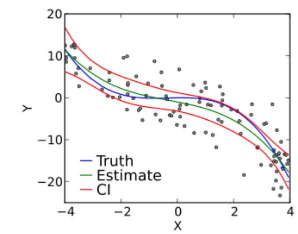
$$\sum_i err(f(x_i), y_i)$$

Classification vs. Regression

If the set of labels Y is discrete:
- Classification
- Minimize number of errors



If Y is real-valued:
- Regression
- Minimize sum squared error



Today we focus on classification.

Key Ideas

Class of functions *F*, from which to find *f*.
- *F* is known as the **hypothesis space**.

Learning:
- Search over *F* to find *f* that minimizes error.

Minimize error measured on what?
- Don't get to see future data.
- Could use test data … but! **may not generalize.**

Test/Train Split

General principle:
Do not measure error on the data you train on!

Methodology:
- Split data into **training set** and **test set**.
- Fit *f* using *training set.*
- Measure error on *test set.*

Always do this.

Decision Trees

Let's assume:

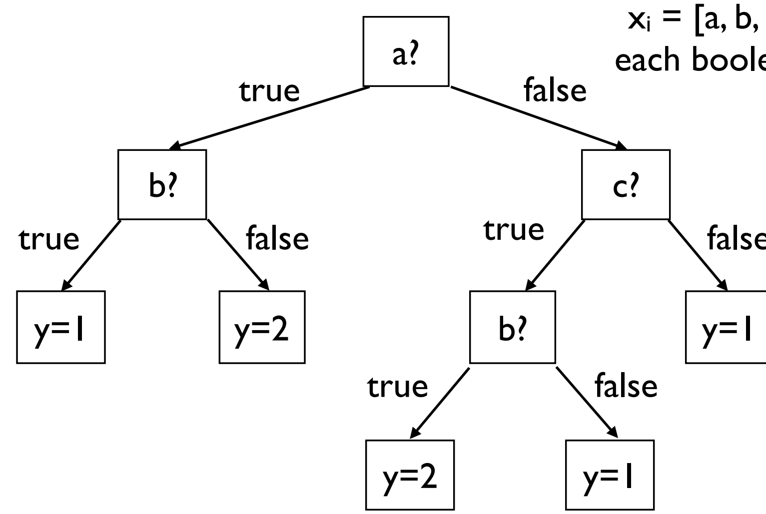
- Discrete inputs.
- Two classes (*true* and *false*).
- Input X is a vector of values.

Relatively simple classifier:

- Tree of *tests*.
- Evaluate test for for each x_i, follow branch.
- Leaves are class labels.

Decision Trees

x_i = [a, b, c]
each boolean



Decision Trees

How to make one?

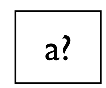
Given
$X = \{x_1, \ldots, x_n\}$
$Y = \{y_1, \ldots, y_n\}$

repeat:

- if all the labels are the same, we have a leaf node.
- pick an attribute and split data on it.
- recurse on each half.

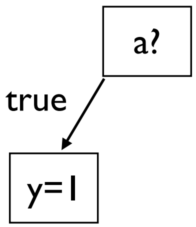
If we run out of splits, and data not perfectly in one class, then take a max.

Decision Trees



A	B	C	L
T	F	T	1
T	T	F	1
T	F	F	1
F	T	F	2
F	T	T	2
F	T	F	2
F	F	T	1
F	F	F	1

Decision Trees



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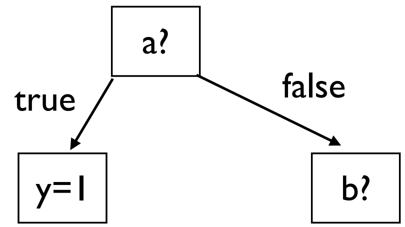
Decision Trees



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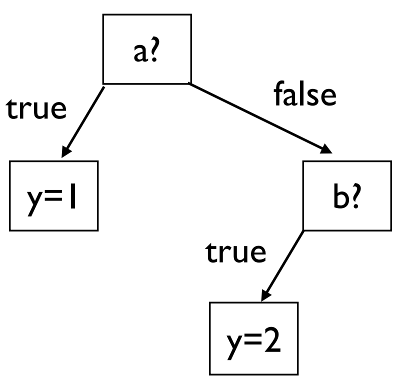
Decision Trees



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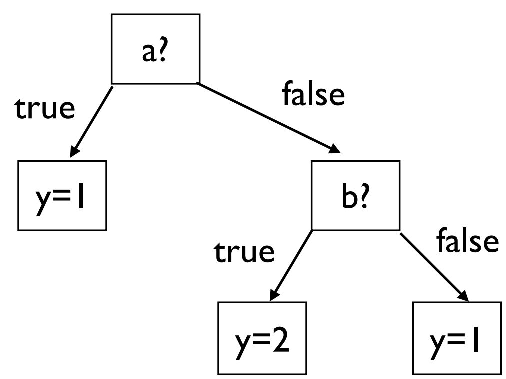
Decision Trees



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Attribute Picking

Key question:

- Which attribute to split over?

Information contained in a data set:

$$I(A) = -f_1 \log_2 f_1 - f_2 \log_2 f_2$$

How many "bits" of information do we need to determine the label in a dataset?

Pick the attribute with the max information gain:

$$Gain(B) = I(A) - \sum_i f_i I(B_i)$$

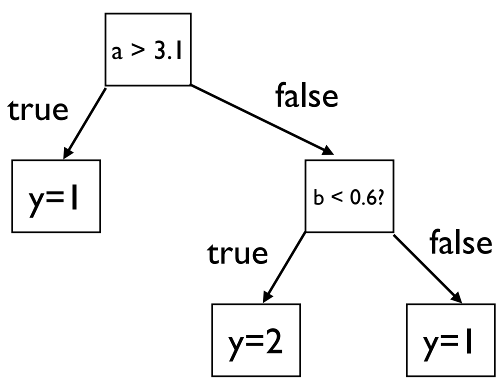
Example

A	B	C	L
T	F	T	1
T	T	F	1
T	F	F	1
F	T	F	2
F	T	T	2
F	T	F	2
F	F	T	1
F	F	F	1

Decision Trees

What if the inputs are real-valued?

- Have inequalities rather than equalities.



Hypothesis Class

What is the hypothesis class for a decision tree?

- Discrete inputs?
- Real-valued inputs?