Machine Learning - Lecture 8: Decision trees

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Introduction to bias

Modeling involves finding and representing patterns in the data.

This means deciding what sort of pattern to look for, and how to represent it.

Learning methods always have a **bias** towards certain forms of pattern and representation.

A bias that is very specific is said to be **strong**.

Otherwise it is **weak**.

Because strongly biased methods are more focussed, they tend to be faster.

Weakly biased methods are more general.

The problem of bias-mismatch

A common problem in machine learning is **bias mismatch**.

This happens when the learning method is biased towards the wrong form of pattern, i.e., a form that does not feature in the data.

The result can be extremely bad performance in training or testing, or both.

Clustering methods

Clustering methods look for patterns which take the form of (hyper-)spherical groupings of similarly classified datapoints.

This is a common form of regularity.

But there are many contexts in which it is not seen.

Applying clustering methods in such cases is likely to be ineffective.

Demo

Demo involving ebaySales data with k-means clustering.

Ebay-Sales dataset

Rectangle structure

In the ebay data, we see data bunching-up in *rectangular* patterns.

This happens whenever specific values are significant in the classification of datapoints.

The effect is highly likely in categorical data.

It's also likely with numeric data whenever there are significant ranges or threshold values.

The wrong way to sort out bias mismatch

Applying centroid-based methods to data exibiting non-spherical forms of patterning, we have a bias mismatch that guarantees unsatisfactory results.

If we're not aware of what's going wrong, though, we may assume the answer is simply to increase the representational power of the method, i.e., increase the number of centroids.

The outcome can be then be confusing.

As we get closer to the situation of having one centroid per datapoint, performance on the training set improves.

But performance on testing data stays the same.

The ‘lookup table’ effect

If we take this approach far enough, we end up with one centroid for each datapoint.

Performance on the training set is perfect.

But generalization is likely to be no better than would be achieved by random guessing.

We’ve fully replicated the data within the model.

The model then works as a kind of ‘lookup table’ for the data.

Decision-tree learning

Methods that are better suited for rectangular patterning are the decision-tree methods ID3, C4.5 and CART.

These incrementally construct a decision-tree, by repeatedly dividing up the data.

The aim at each stage is to associate specific targets (i.e., desired output values) with specific values of a particular variable.

The result is a decision-tree in which each path identifies a *combination* of values associated with a particular prediction.

The effect achieved is representation of rectangular patterns.

Worked example

The data represent files on a computer system.

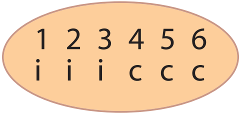
The task is to derive a model for virus identification.

Possible values of the CLASS variable are ‘infected’, which implies the file has a virus infection, or ‘clean’ which implies that it doesn’t.

DATASET

	WRITABLE	UPDATED	SIZE	CLASS
1	yes	no	small	infected
2	yes	yes	large	infected
3	no	yes	med	infected
4	no	no	med	clean
5	yes	no	large	clean
6	no	no	large	clean

Initialisation of tree



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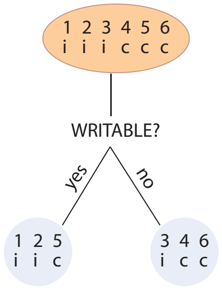
Evaluating possible splits



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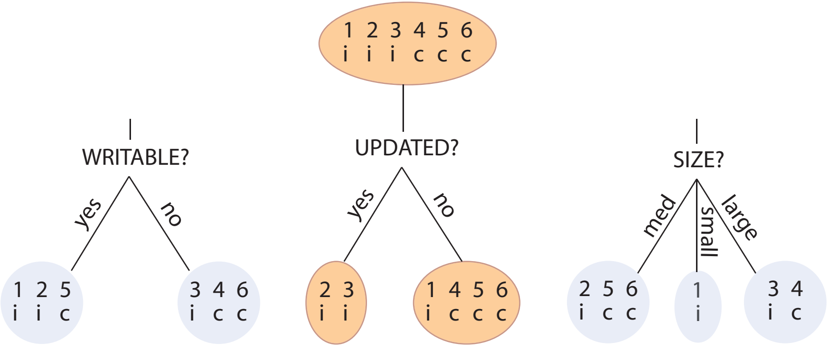
Selecting the optimal split



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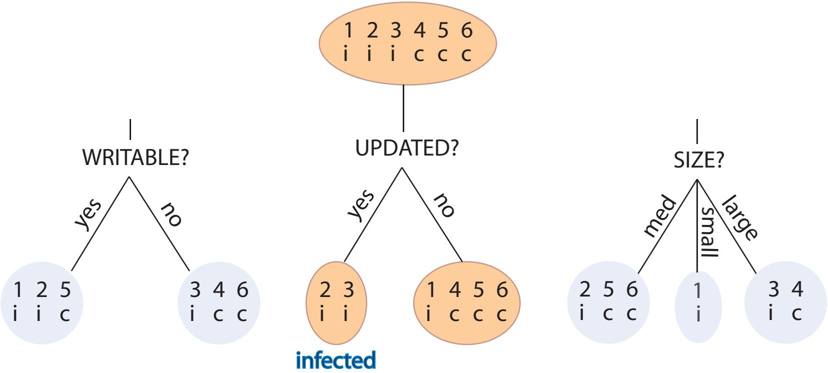
Creation of a terminal node



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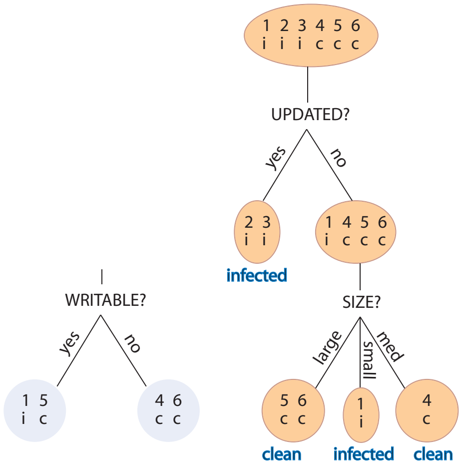
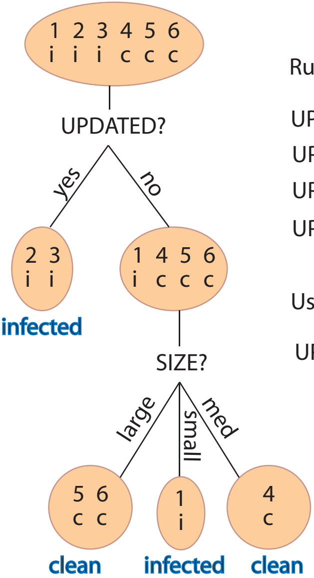
Finalised decision tree



Derived rules and implied facts



Rules derived from complete paths:

UPDATED=yes $\longrightarrow$ CLASS=infected

UPDATED=no $\wedge$ SIZE=large $\longrightarrow$ CLASS=clean

UPDATED=no $\wedge$ SIZE=small $\longrightarrow$ CLASS=infected

UPDATED=no $\wedge$ SIZE=med $\longrightarrow$ CLASS=clean

Using these rules we can infer facts such as

UPDATED=yes $\wedge$ WRITABLE=no $\wedge$ CLASS=infected

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Golfing dataset

```
type data\golf

"Outlook     Temp   Humidity  Windy    Decision
sunny        75     70        true     Play
sunny        80     90        true     NoPlay
sunny        85     85        false    NoPlay
sunny        72     95        false    NoPlay
sunny        69     70        false    Play
overcast     72     90        true     Play
overcast     83     78        false    Play
overcast     64     65        true     Play
overcast     81     75        false    Play
rain         71     80        true     NoPlay
rain         65     70        true     NoPlay
rain         75     80        false    Play
rain         68     80        false    Play
rain         70     96        false    Play
```

ID3 on the golfing data

```
java Id3 golf
Data: 10+4
Variable names: [Outlook Temp Humidity Windy Decision]
Most frequent output: Play

 Temp?
 |-- <=83.0
 |    |-- Play
 |-- >83.0
      |-- NoPlay

Id3 #0 on golf R(10+4) 1.0 (100.0%)
```

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