Machine Learning - Lecture 9: Generalized decision-tree learning

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Use information gain

A key question in decision-tree learning is how to identify the 'best split' of data at each point.

Decision-tree methods often use information theory for this.

The frequency with which an output appears can be seen as the probability of it being correct for all members of the group.

Frequency counts then become probability distributions.

To find the best split, we take all the possible splits, and choose the one that gives the biggest reduction in uncertainty.

This is also the split that gives the biggest **gain** of information, i.e., the biggest improvement in the model.

Methods which work this way are said to use an **information-gain** heuristic.

Expected gains

One difficulty, here, is the fact that each split produces several subgroups, each of which has a distinct size and uncertainty.

How do we calculate an uncertainty for the split as a whole?

The solution is to calculate an **expected uncertainty** by weighting the uncertainty for each subgroup by its relative size (i.e., by the probability of it containing an arbitrary datapoint).

We then select the split that produces the biggest reduction in *expected* uncertainty.

Or equivalently, the biggest expected information gain.

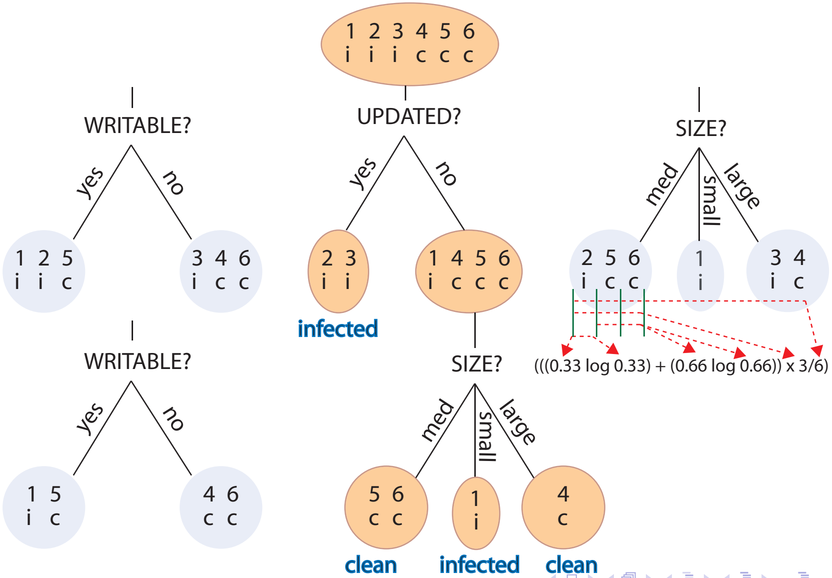
Expected entropy formula

The expected uncertainty for a split is calculated using this formula.

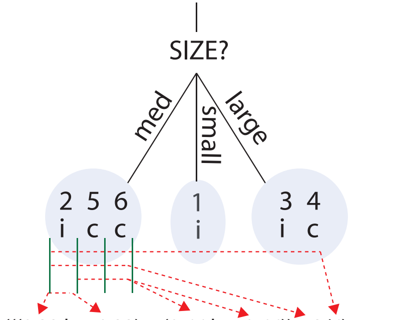
Here, the p_i values are the probabilities of classes in the j'th subgroup, and p_j is the probability of a datapoint appearing in the j'th group.

$$\sum_j p_j \left(- \sum_i p_i \log p_i \right)$$

Computation of entropy values



Expected entropy



(((0.33 log 0.33) + (0.66 log 0.66)) x 3/6)

+ ((1.0 log 1.0) x 1/6)

+ ((0.5 log 0.5) + (0.5 log 0.5)) x 2/6)

= expected entropy for SIZE split

Application to numeric data

The decision-tree algorithm is defined in terms of operations on categorical data.

Can it be used with numeric data?

In the standard algorithm, a split is constructed on a particular variable by creating one branch for each distinct value observed.

If we apply this to a numeric variable, we get one branch for each distinct *number*.

This may be fine with integer data.

Application to real-valued data

The problem is that with real-valued data, each numeric value is likely to be unique.

The result may be a split with a huge number of branches, each of which creates a subset of just one datapoint!

The algorithm terminates immediately, having generated a lookup table in the form of a single branch.

Worst-case generalisation ensues, and there's a good chance the tree will not even classify an unseen example.

Using single thresholds (C4.5 approach)

In order to handle real-valued data, we need splits to be made on the basis of threshold values.

A simple idea is to find the observed value which when treated as a theshold gives the best split.

The resulting tree defines ‘large’ generalisations in which each range of variable values is divided into two parts.

There is no risk of an unseen example being unclassified.

What about multiple thresholds?

Situations can occur where a single threshold seems inappropriate.

Imagine we have a variable representing age. The implicit structure may then be all to do with the four significant age groupings (0-20, 20-40, 40-60, 60+).

To deal with such situations, we really need the algorithm to put in a threshold wherever one is needed.

But how is this to be done?

Ideally, we should consider all possible ways of dividing the variable into subranges, and use the information heuristic to choose the best.

But the combinatorial costs are just too great.

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