# **Decision Trees**

Course: Data Mining

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Subject: Decision Trees and Overfitting

## How to Address Overfitting

### Pre-Pruning (Early Stopping Rule)

- Stop the algorithm before it becomes a fully-grown tree.
- Typical stopping conditions for a node:
  - Stop if all instances belong to the same class.
  - Stop if all the attribute values are the same.
- More restrictive conditions:
  - Stop if number of instances is less than some user-specified threshold.
  - Stop if class distribution of instances is independent of the available features (e.g., using  $\chi^2$  test).
  - Stop if expanding the current node does not improve impurity measures (e.g., Gini or information gain).

### Post-pruning

- Grow the decision tree to its entirety.
- Trim the nodes of the decision tree in a bottom-up fashion.
- If generalization error improves after trimming, replace sub-tree by a leaf node.
- The class label of the leaf node is determined from the majority class of instances in the sub-tree.
- Can use MDL (Minimum Description Length) for post-pruning.

## **Example of Post-Pruning**

Class = Yes	20
Class = No	10
Error = 10/30	

Training Error (Before splitting) = 10 / 30Pessimistic error = (10 + 0.5) / 30 = 10.5 / 30Training Error (After splitting) = 9 / 30Pessimistic error (After splitting) =

$$(9+4\times0.5)/30=11/30$$

#### PRUNE!

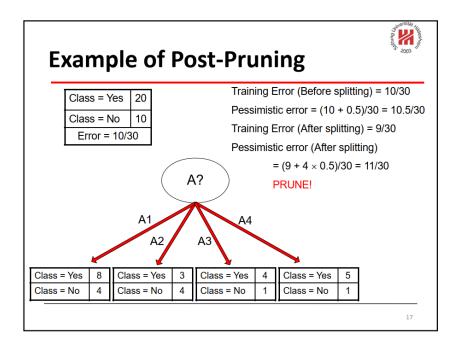
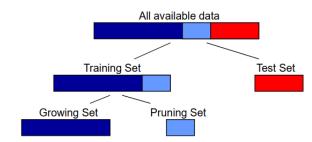


Figure 1: Example of Post-Pruning

## Partitioning Data in Tree Induction

Estimating the accuracy of a tree on new data: "Test Set". Some post-pruning methods need an independent data set: "Pruning Set".

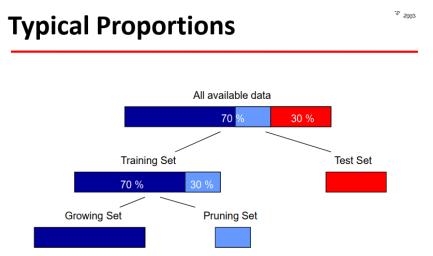


To evaluate the classification technique, experiment with repeated random splits of data

Figure 2: Partitioning Data in Tree Induction

## **Typical Proportions**

Problem with using "Pruning Set": less data for "Growing Set".



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Figure 3: Typical Proportions in Data Splitting

## Reduced Error Pruning (REP)

- Use pruning set to estimate accuracy of sub-trees and accuracy at individual nodes.
- Let T be a sub-tree rooted at node v.
- Define the gain from pruning at v:

Gain from pruning at v = misclassification in T - misclassification at v

- Repeat: prune at node with largest gain until only negative gain nodes remain.
- $\bullet$  "Bottom-up restriction": T can only be pruned if it does not contain a sub-tree with lower error than T.

## **REP Example**

$$E(T_{v_2}) = 3$$
,  $E(v_2) = 2$ ,  $E(T_{v_3}) = 1$ ,  $E(v_3) = 3$ 

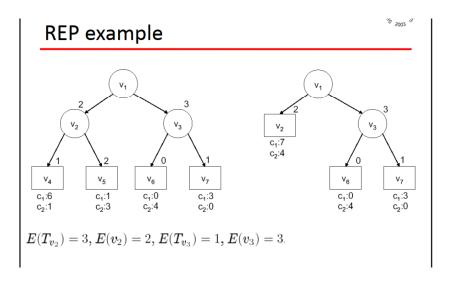


Figure 4: Example of Reduced Error Pruning (REP)