Classification: Decision Trees & Overfitting

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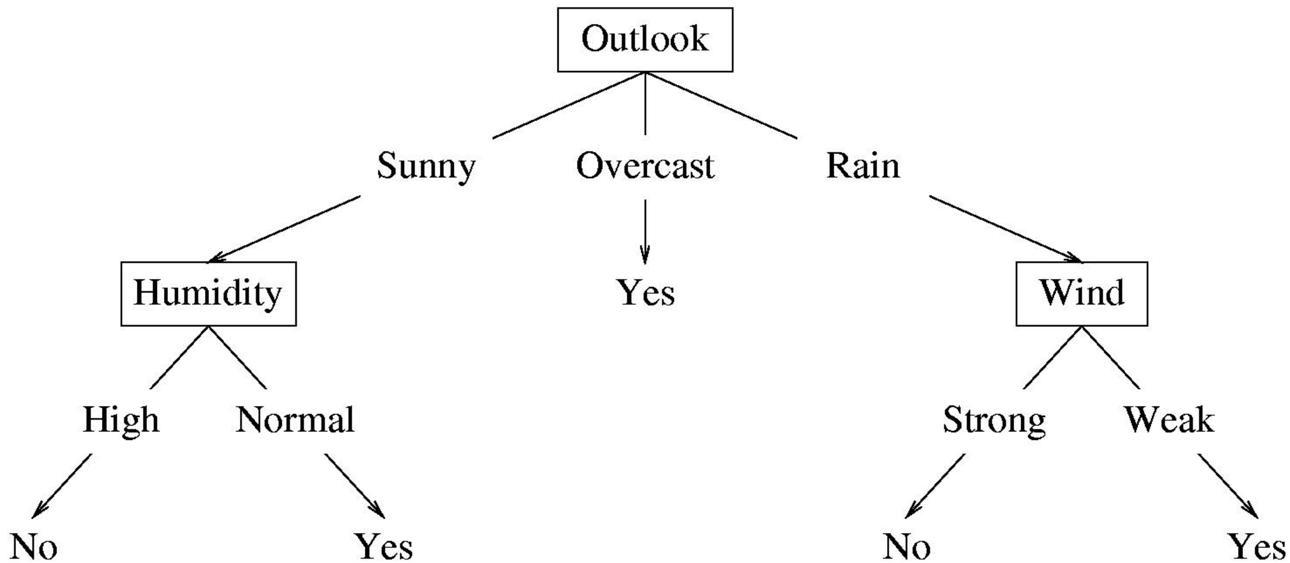
Summary of Decision Trees (so far)



- Decision tree induction → choose the best attribute
  - Choose split via information gain
  - Build tree greedily, recursing on children of split
  - Stop when we achieve homogeny
    - i.e., when all instance in a child have the same class

Noisy Data

- Many kinds of “noise” can occur in the examples:
  – Two examples have same attribute/value pairs, but different classifications
  – Some values of attributes are incorrect because of errors in the data acquisition process or the preprocessing phase
  – The instance was labeled incorrectly (+ instead of -)

- Also, some attributes are irrelevant to the decision-making process
  – e.g., color of a die is irrelevant to its outcome

Overfitting in Decision Trees

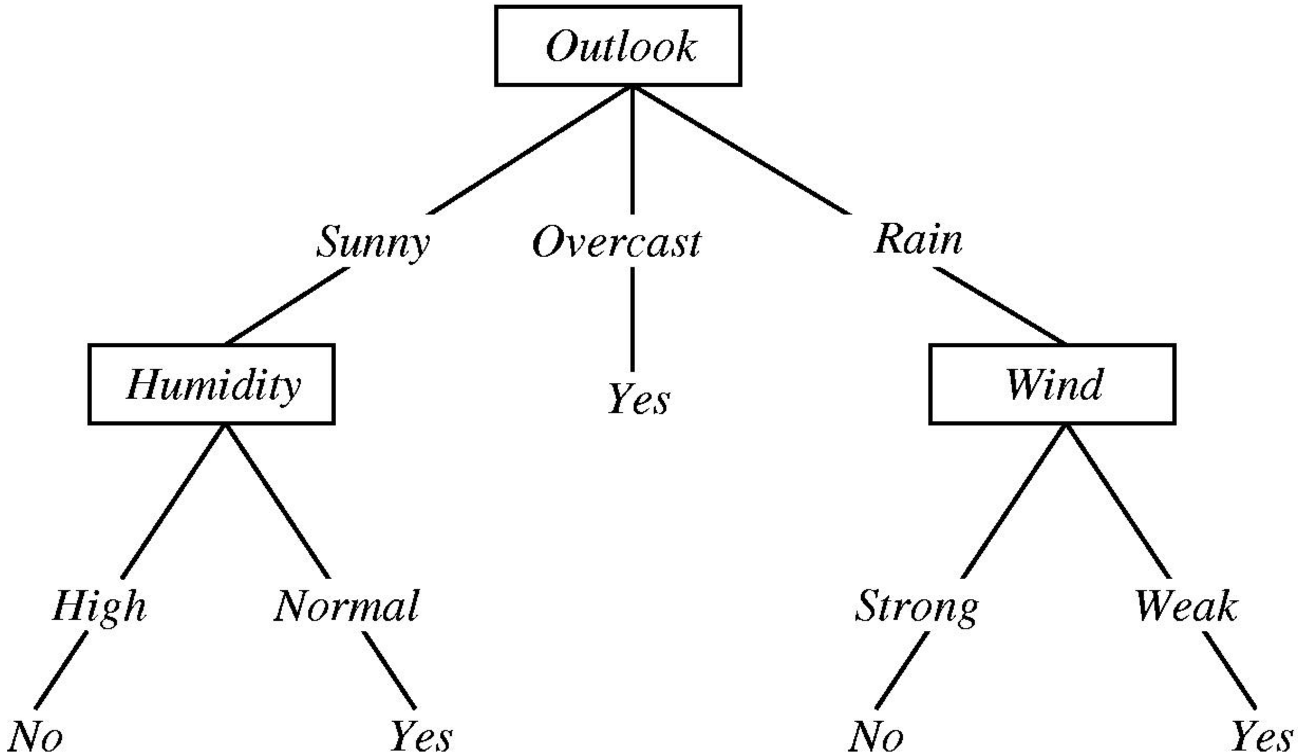
- Irrelevant attributes can result in *overfitting* the training example data
  - If hypothesis space has many dimensions (large number of attributes), we may find **meaningless regularity** in the data that is irrelevant to the true, important, distinguishing features

- If we have too little training data, even a reasonable hypothesis space will 'overfit'

Based on Slide from M. desJardins & T. Finin

Overfitting in Decision Trees

Consider adding a noisy training example to the following tree:



What would be the effect of adding:

<outlook=sunny, temperature=hot, humidity=normal, wind=strong, playTennis=No> ?

Overfitting in Decision Trees

Consider error of hypothesis h over

- training data: $error_{train}(h)$
- entire distribution $\mathcal{D}$ of data: $error_{\mathcal{D}}(h)$

Hypothesis $h \in H$ **overfits** training data if there is an alternative hypothesis $h' \in H$ such that

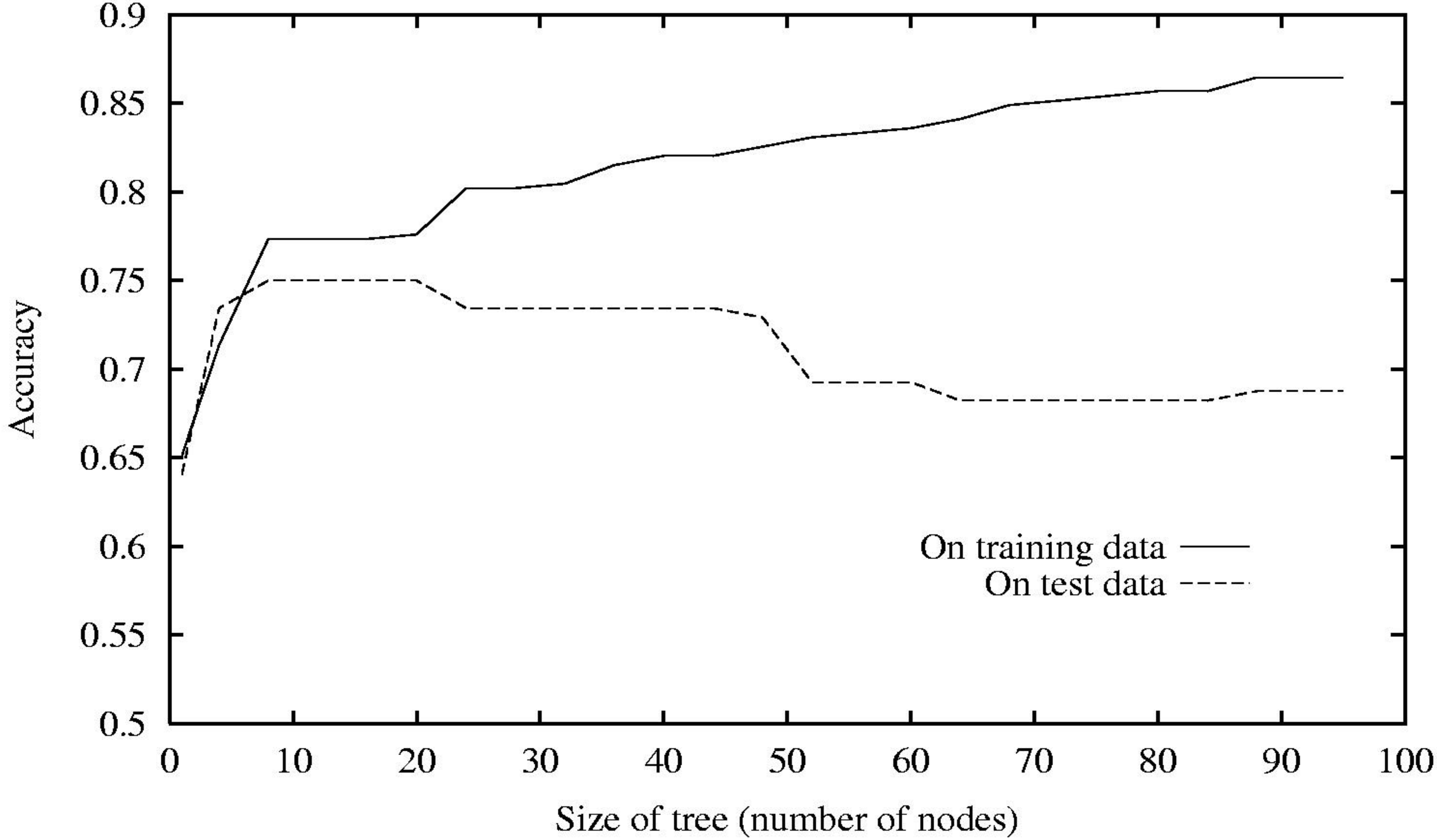
$$error_{train}(h) < error_{train}(h')$$

and

$$error_{\mathcal{D}}(h) > error_{\mathcal{D}}(h')$$

Slide by Pedro Domingos

Overfitting in Decision Trees



Slide by Pedro Domingos

Avoiding Overfitting in Decision Trees

How can we avoid overfitting?

- Stop growing when data split is not statistically significant
- Acquire more training data
- Remove irrelevant attributes (manual process – not always possible)
- Grow full tree, then post-prune

How to select "best" tree:

- Measure performance over training data
- Measure performance over separate validation data set
- Add complexity penalty to performance measure

Based on Slide by Pedro Domingos

Reduced-Error Pruning

Split data into *training* and *validation* sets

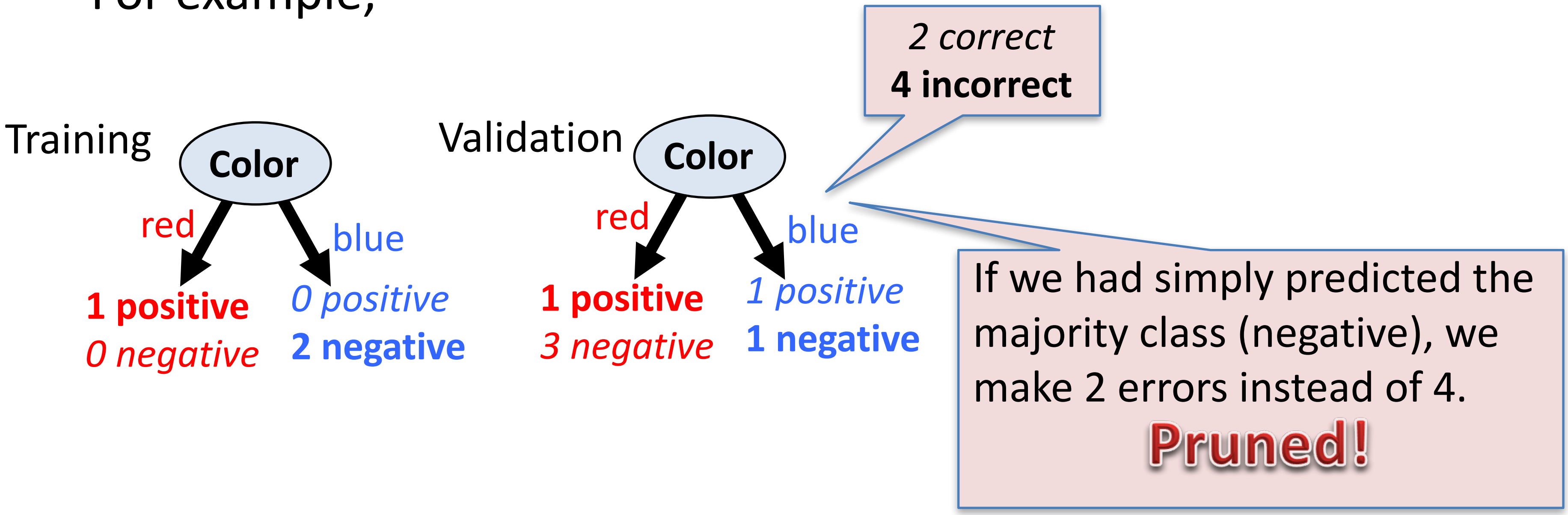
Grow tree based on *training set*

Do until further pruning is harmful:

1. Evaluate impact on validation set of pruning each possible node (plus those below it)
2. Greedily remove the node that most improves *validation set* accuracy

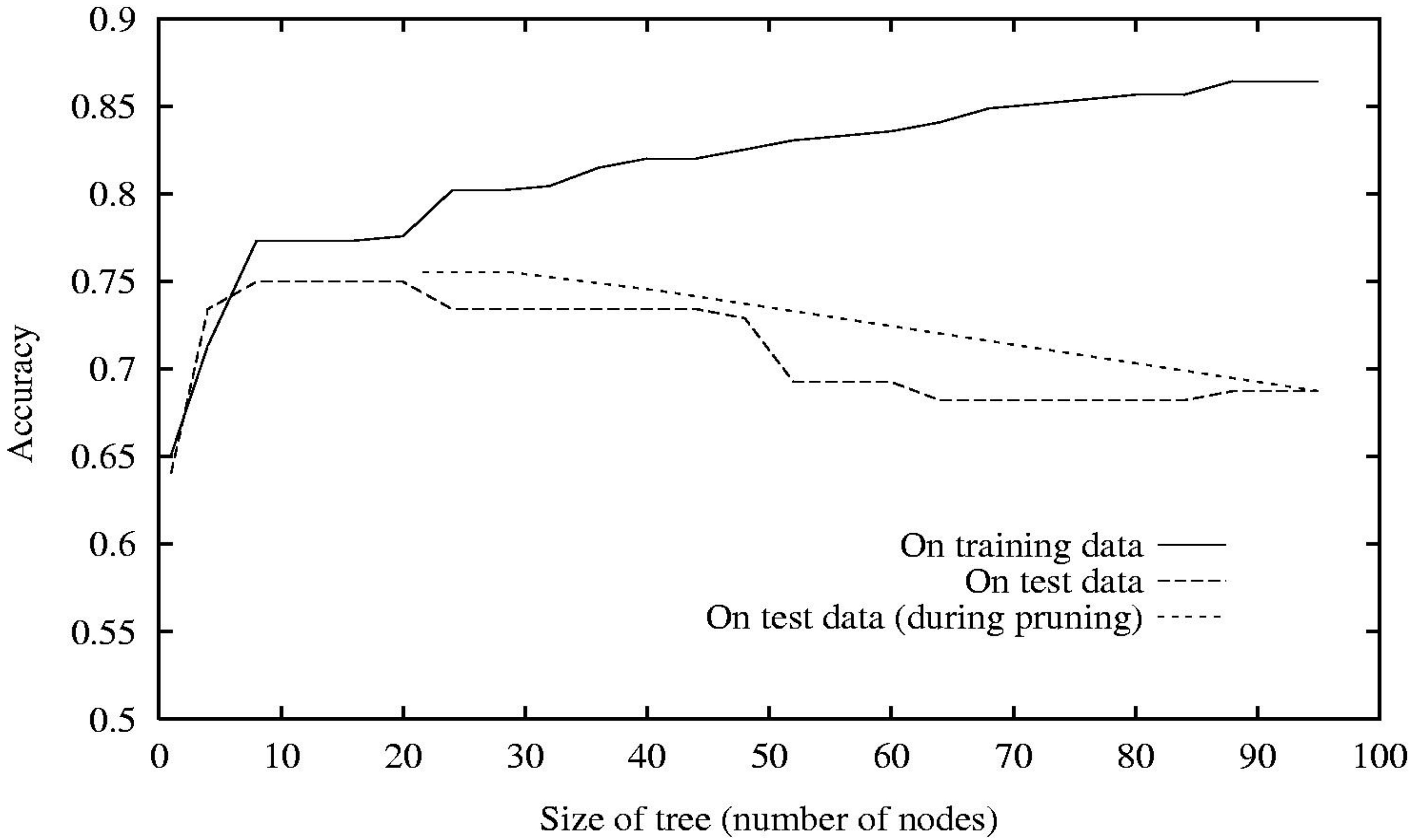
Pruning Decision Trees

- Pruning of the decision tree is done by replacing a whole subtree by a leaf node.
- The replacement takes place if a decision rule establishes that the expected error rate in the subtree is greater than in the single leaf.
- For example,



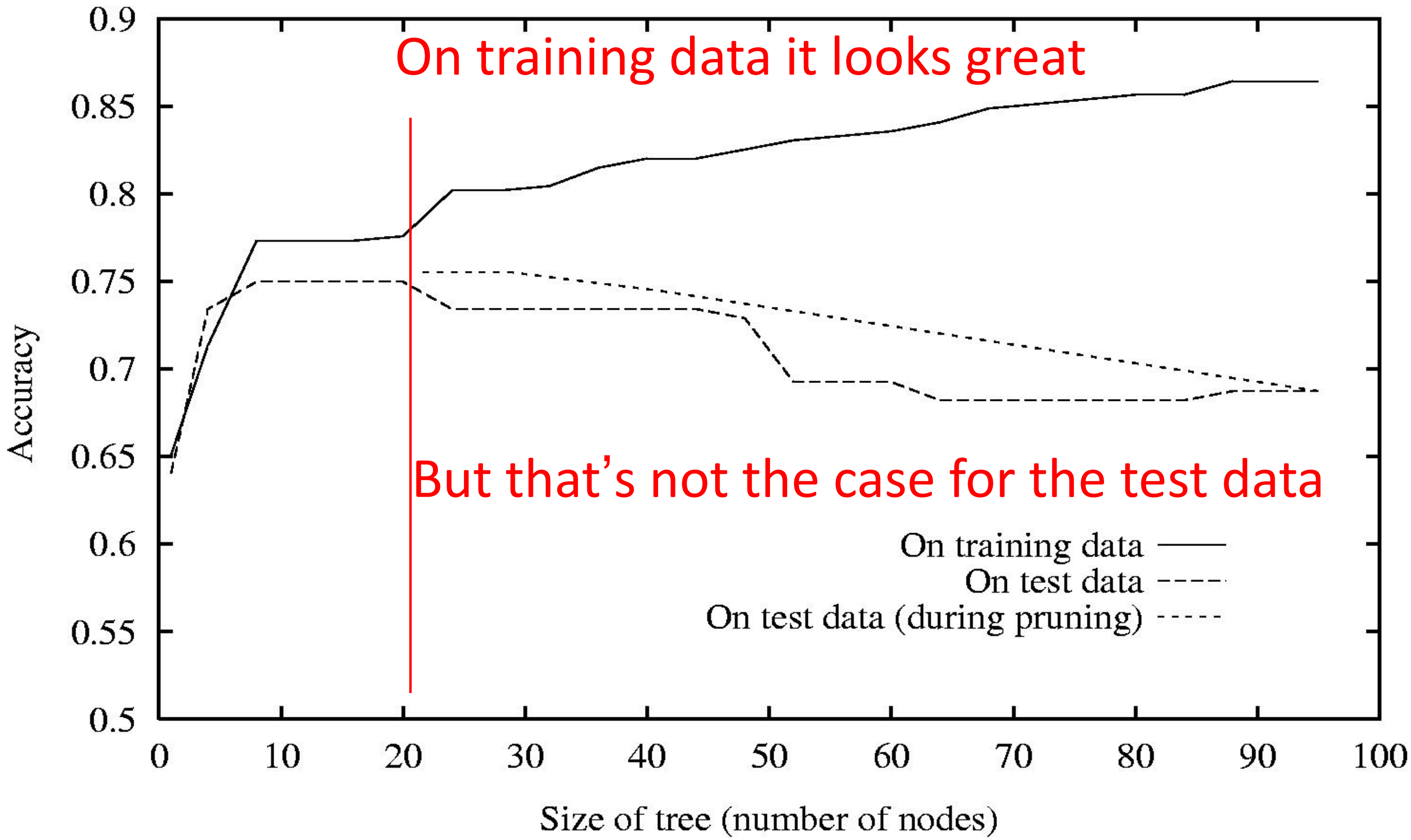
Based on Example from M. desJardins & T. Finin

Effect of Reduced-Error Pruning



Based on Slide by Pedro Domingos

Effect of Reduced-Error Pruning



The tree is pruned back to the red line where it gives more accurate results on the test data

Based on Slide by Pedro Domingos

Summary: Decision Tree Learning

- Widely used in practice
- Strengths include
  - Fast and simple to implement
  - Can convert to rules
  - Handles noisy data
- Weaknesses include
  - Univariate splits/partitioning using only one attribute at a time --- limits types of possible trees
  - Large decision trees may be hard to understand
  - Requires fixed-length feature vectors
  - Non-incremental (i.e., batch method)

Summary: Decision Tree Learning

- Representation: decision trees
- Bias: prefer small decision trees
- Search algorithm: greedy
- Heuristic function: information gain or information content or others
- Overfitting / pruning

Comparison of Learning Methods

Characteristic	Neural Nets	SVM	Trees	MARS	k-NN, Kernels
Natural handling of data of “mixed” type	▼	▼	▲	▲	▼
Handling of missing values	▼	▼	▲	▲	▲
Robustness to outliers in input space	▼	▼	▲	▼	▲
Insensitive to monotone transformations of inputs	▼	▼	▲	▼	▼
Computational scalability (large N)	▼	▼	▲	▲	▼
Ability to deal with irrelevant inputs	▼	▼	▲	▲	▼
Ability to extract linear combinations of features	▲	▲	▼	▼	◆
Interpretability	▼	▼	◆	▲	▼
Predictive power	▲	▲	▼	◆	▲

[Table 10.3 from Hastie, et al. Elements of Statistical Learning, 2nd Edition]