Decision Tree: Issues

CSE 4334 / 5334 Data Mining
Spring 2019

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(Slides courtesy of Pang-Ning Tan, Michael Steinbach and Vipin Kumar, and Jiawei Han, Micheline Kamber and Jian Pei)

Practical Issues of Classification

- Underfitting and Overfitting
- Missing Values
- Costs of Classification

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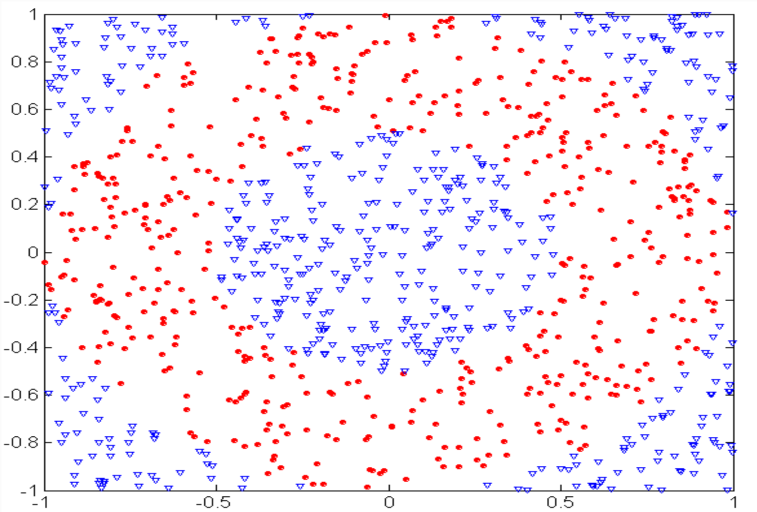
Underfitting and Overfitting (Example)



500 circular and 500 triangular data points.

Circular points:

$0.5 \le \text{sqrt}(x_1^2+x_2^2) \le 1$

Triangular points:

$\text{sqrt}(x_1^2+x_2^2) < 0.5$ or

$\text{sqrt}(x_1^2+x_2^2) > 1$

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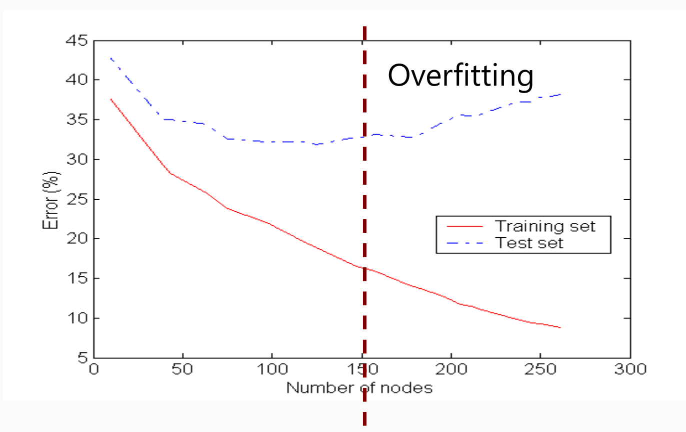
Underfitting and Overfitting



Underfitting: when model is too simple, both training and test errors are large

Overfitting: when model is too complex, test error increases even though training error decreases

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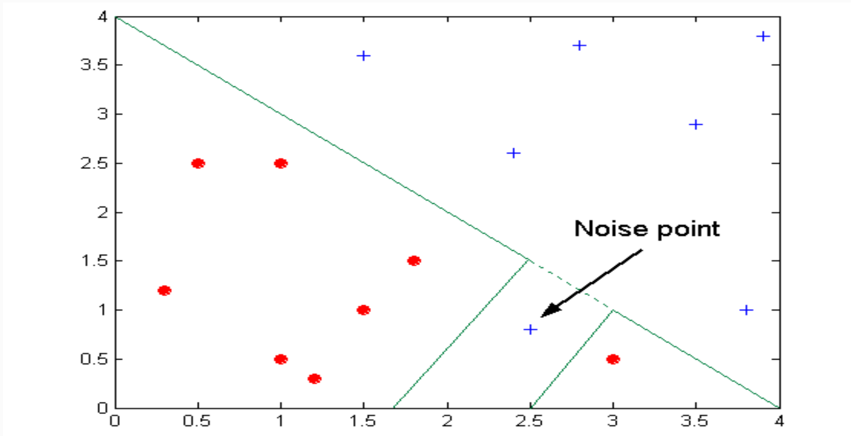
Overfitting due to Noise



Decision boundary is distorted by noise point

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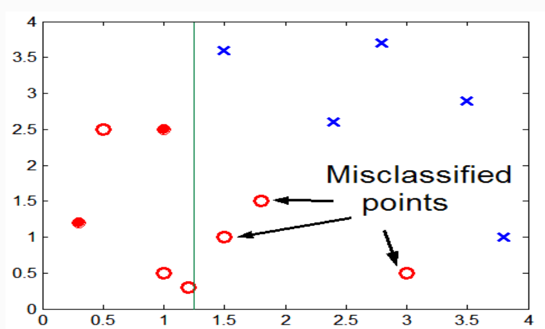
Overfitting due to Insufficient Examples



Lack of data points in the lower half of the diagram makes it difficult to predict correctly the class labels of that region

- Insufficient number of training records in the region causes the decision tree to predict the test examples using other training records that are irrelevant to the classification task

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Notes on Overfitting

Overfitting results in decision trees that are more complex than necessary

Training error no longer provides a good estimate of how well the tree will perform on previously unseen records

Need new ways for estimating errors

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Estimating Generalization Errors

Re-substitution errors: error on training (Σ e(t))
Generalization errors: error on testing (Σ e'(t))

Methods for estimating generalization errors:

- Optimistic approach: e'(t) = e(t)
- Pessimistic approach:
  - For each leaf node: e'(t) = (e(t)+0.5)
  - Total errors: e'(T) = e(T) + N × 0.5 (N: number of leaf nodes)
  - For a tree with 30 leaf nodes and 10 errors on training (out of 1000 instances):

    Training error = 10/1000 = 1%

    Generalization error = (10 + 30×0.5)/1000 = 2.5%
- Reduced error pruning (REP):
  - uses validation data set to estimate generalization error

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Occam's Razor

Given two models of similar generalization errors, one should prefer the **simpler model** over the more complex model

For complex models, there is a greater chance that it was fitted accidentally by errors in data

Therefore, one should include model complexity when evaluating a model

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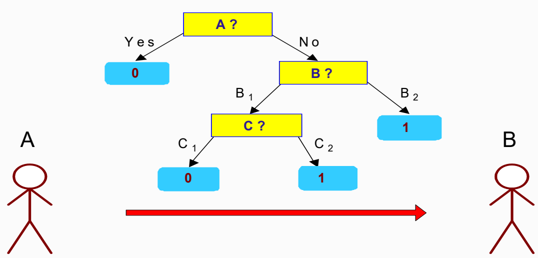
Minimum Description Length (MDL)

X	y
X_1	1
X_2	0
X_3	0
X_4	1
…	…
X_n	1



X	y
X_1	?
X_2	?
X_3	?
X_4	?
…	…
X_n	?

Cost(Model,Data) = Cost(Data|Model) + Cost(Model)

- Cost is the number of bits needed for encoding.
- Search for the least costly model.

Cost(Data|Model) encodes the misclassification errors.

Cost(Model) uses node encoding (number of children) plus splitting condition encoding.

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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 are independent of the available features (e.g., using χ^2 test)
  - Stop if expanding the current node does not improve impurity measures (e.g., Gini or information gain).

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How to Address Overfitting…

Post-pruning

- Grow 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.
- Class label of leaf node is determined from majority class of instances in the sub-tree
- Can use MDL for post-pruning

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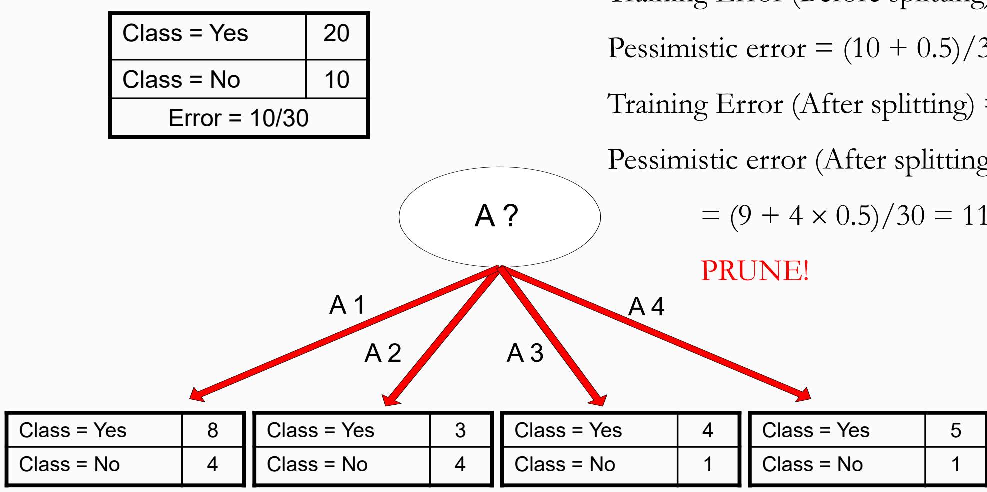
Example of Post-Pruning



Training Error (Before splitting) = 10/30

Pessimistic error = (10 + 0.5)/30 = 10.5/30

Training Error (After splitting) = 9/30

Pessimistic error (After splitting)

$= (9 + 4 \times 0.5)/30 = 11/30$

PRUNE!

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Examples of Post-pruning

- Optimistic error?

  Don't prune for both cases

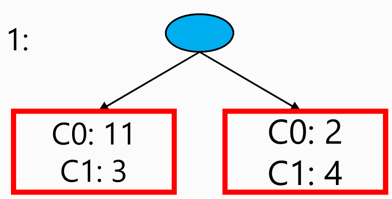
- Pessimistic error?

  Don't prune case 1, prune case 2

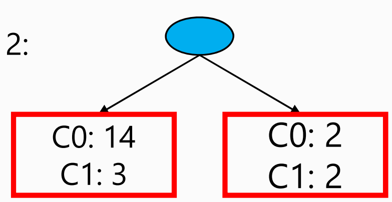
- Reduced error pruning?

  Depends on validation set

Case 1:



Case 2:



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Handling Missing Attribute Values

Missing values affect decision tree construction in three different ways:

- Affects how impurity measures are computed
- Affects how to distribute instance with missing value to child nodes
- Affects how a test instance with missing value is classified

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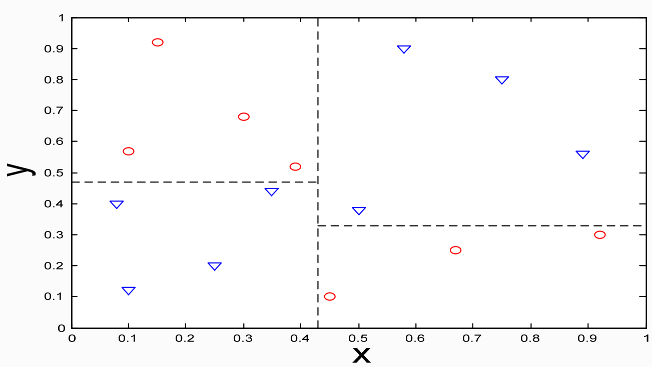
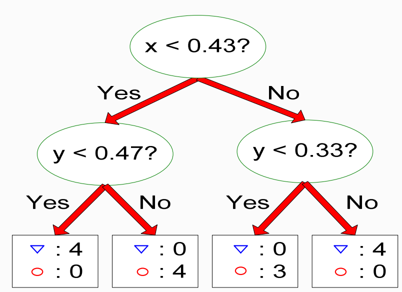
Decision Boundary





- Border line between two neighboring regions of different classes is known as decision boundary
- Decision boundary is parallel to axes because test condition involves a single attribute at-a-time

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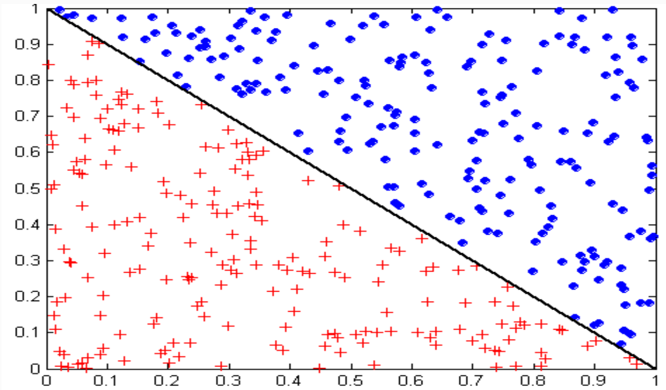
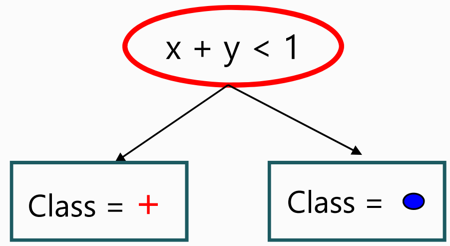
Oblique Decision Trees





- Test condition may involve multiple attributes
- More expressive representation
- Finding optimal test condition is computationally expensive

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