GENERAL ASSEMBLY

INTRO TO DATA SCIENCE

LECTURE 10: TREE BASED CLASSIFIERS

YUCHEN ZHAO / DAT-14

LAST TIME:

I. CLUSTERING SUMMARY
II. DECISION TREES
III. BUILDING DECISION TREES

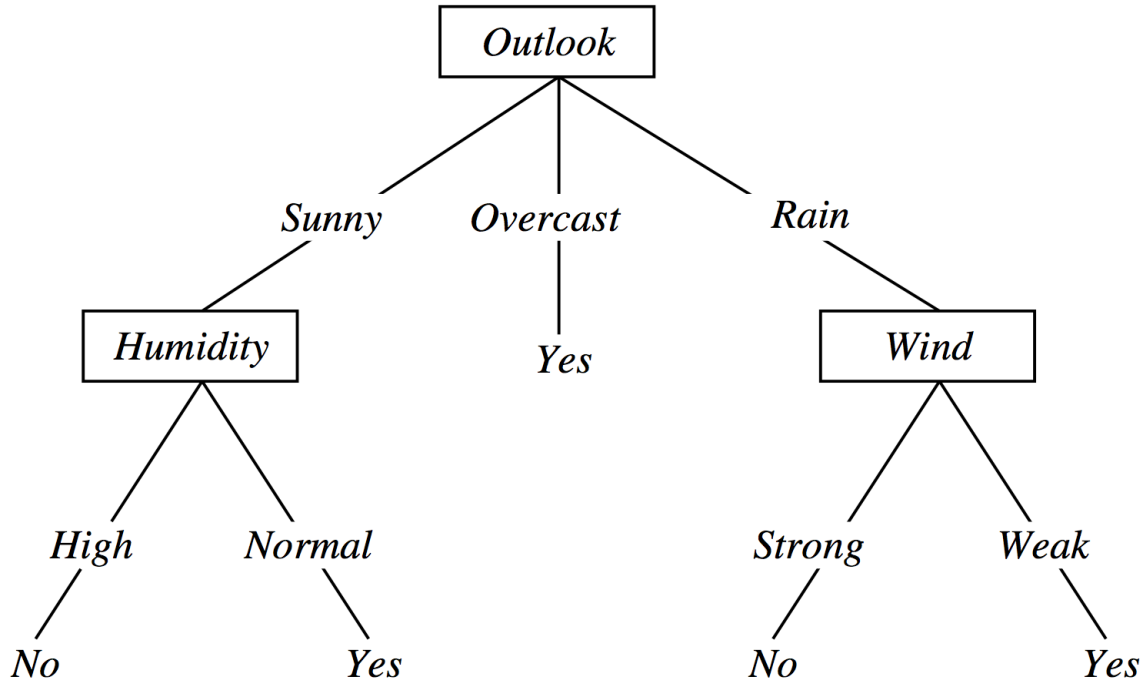
QUESTIONS?

I. BUILDING TREES
II. OPTIMIZATION FUNCTIONS
III. PREVENTING OVERFITTING

EXERCISE:
V. DECISION TREES WITH SCIKIT-LEARN

DECISION TREES

DECISION TREE CLASSIFIERS



Classify an instance: <outlook=Sunny, temp = Hot, humidity=High, wind = Strong>

EXAMPLE – DECISION TREE

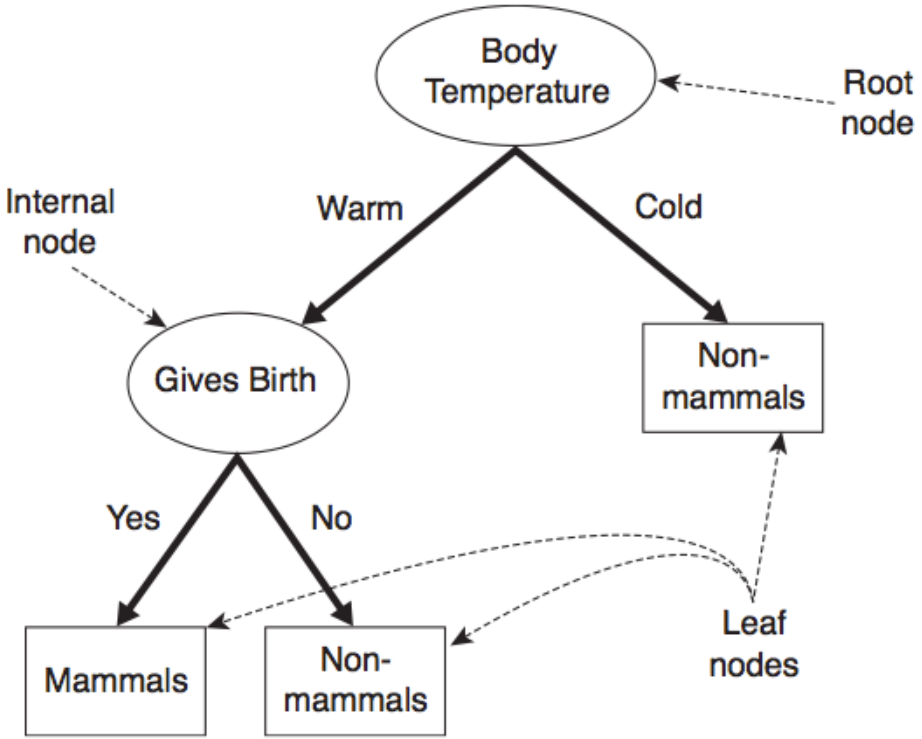


Figure 4.4. A decision tree for the mammal classification problem.

source: http://www-users.cs.umn.edu/~kumar/dmbook/ch4.pdf

NOTE

Internal nodes represent test conditions which partition the records at that node.

I. BUILDING DECISION TREES

The basic method used to build (or "grow") a decision tree is **Hunt's algorithm**.

This is a **greedy recursive** *algorithm that leads to a* **local optimum**.

greedy – *algorithm makes locally optimal decision at each step*
recursive – *splits task into subtasks, solves each the same way*
local optimum – *solution for a given neighborhood of points*

Hunt's algorithm builds a decision tree by recursively partitioning records into smaller & smaller subsets.

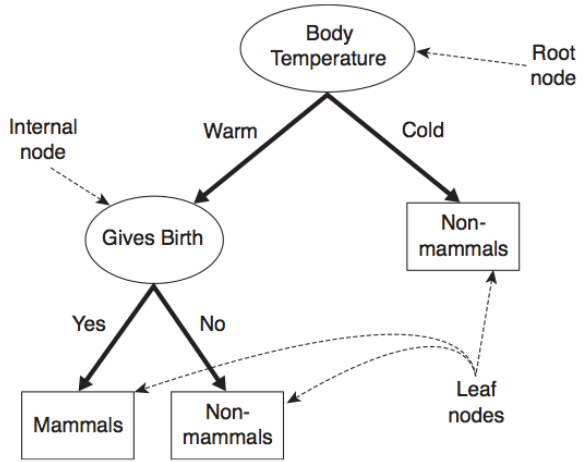


Figure 4.4. A decision tree for the mammal classification problem.

BUILDING A DECISION TREE

Hunt's algorithm builds a decision tree by recursively partitioning records into smaller & smaller subsets.

The partitioning decision is made at each node according to a metric called **purity**.

A partition is 100% pure when all of its records belong to a single class.

Table 4.1. The vertebrate data set.

Name	Body Temperature	Skin Cover	Gives Birth	Aquatic Creature	Aerial Creature	Has Legs	Hiber-nates	Class Label
human	warm-blooded	hair	yes	no	no	yes	no	mammal
python	cold-blooded	scales	no	no	no	no	yes	reptile
salmon	cold-blooded	scales	no	yes	no	no	no	fish
whale	warm-blooded	hair	yes	yes	no	no	no	mammal
frog	cold-blooded	none	no	semi	no	yes	yes	amphibian
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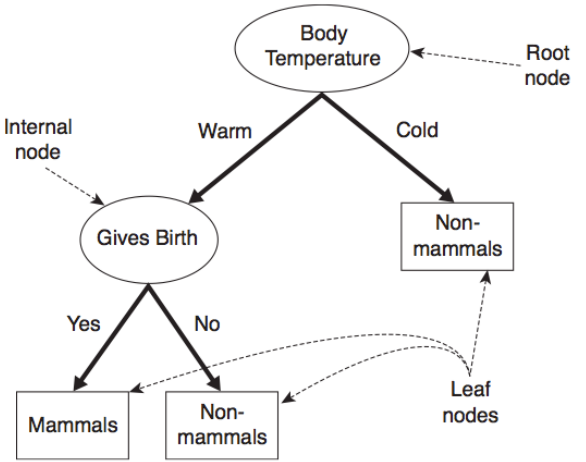

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NOTE

This is the base case for the recursive algorithm.

Consider a binary classification problem with classes X, Y. Given a set of records D_t at node t, Hunt's algorithm proceeds as follows:

2) If D_t contains records from both classes, then a test condition is created to partition the records further. In this case, t is an internal node whose outgoing edges correspond to the possible outcomes of this test condition.

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2) If D_t contains records from both classes, then a test condition is created to partition the records further. In this case, t is an internal node whose outgoing edges correspond to the possible outcomes of this test condition.

These outgoing edges terminate in **child nodes**. *A record d in D_t is assigned to one of these child nodes based on the outcome of the test condition applied to d.*

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NOTE

Decision trees are easy to interpret, but the algorithms to create them are a bit complicated.

Q: How do we partition the training records?

CREATING PARTITIONS

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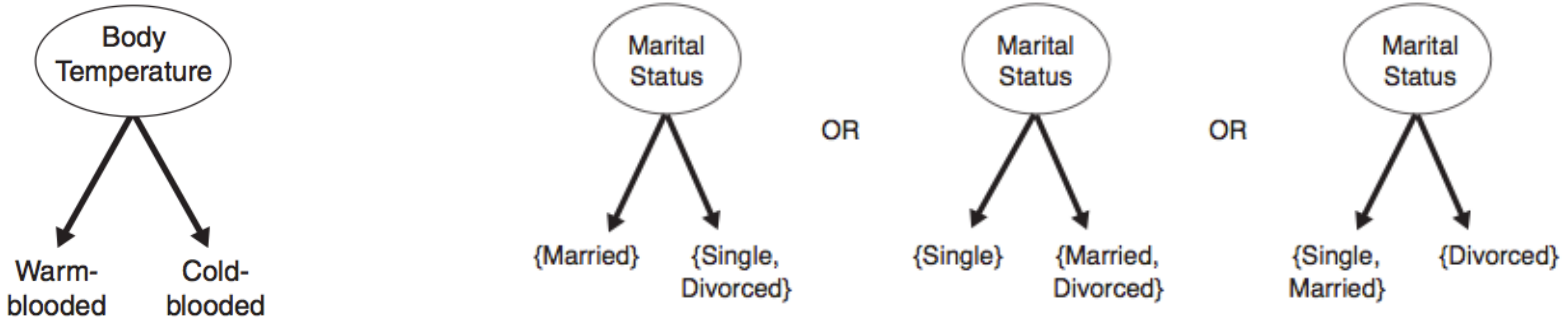


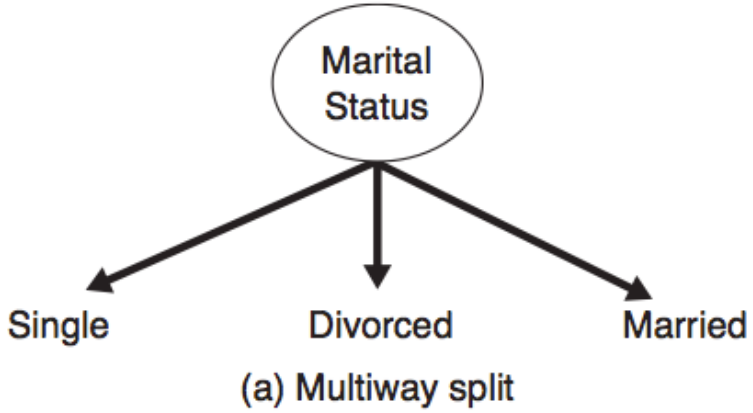
Figure 4.8. Test condition for binary attributes.

(b) Binary split {by grouping attribute values}

Q: How do we partition the training records?

A: There are a few ways to do this.

Alternatively, we can create **multiway splits***:*



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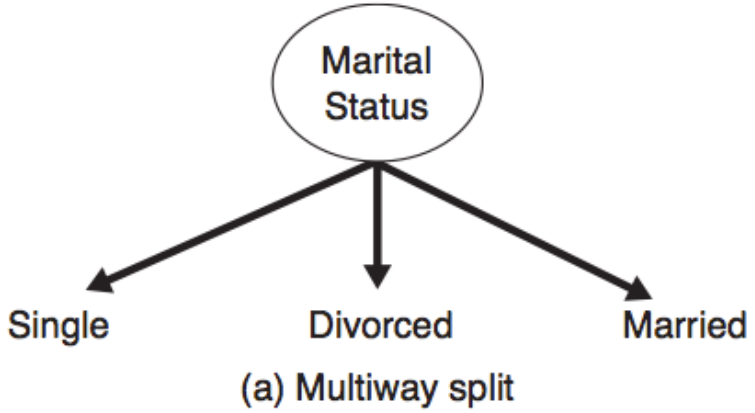


(a) Multiway split

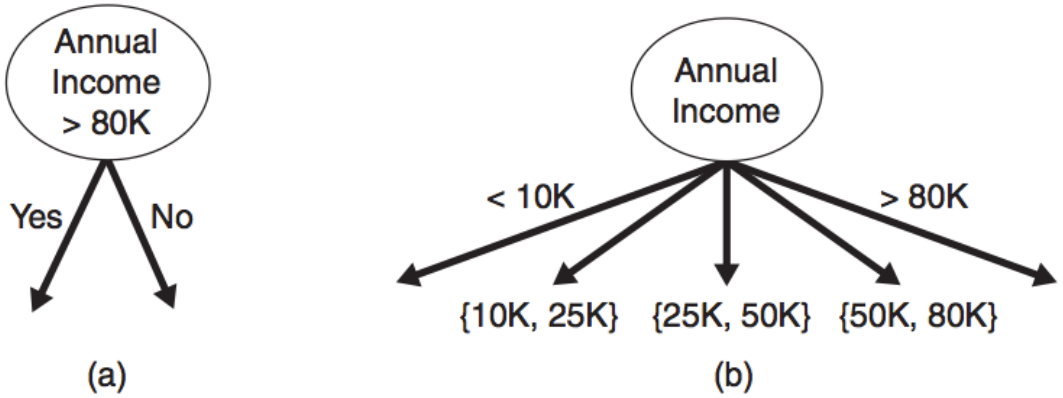
NOTE

Multiway splits can produce purer subsets, but may lead to overfitting!

Q: How do we partition the training records?

A: There are a few ways to do this.

For continuous features, we can use either method:



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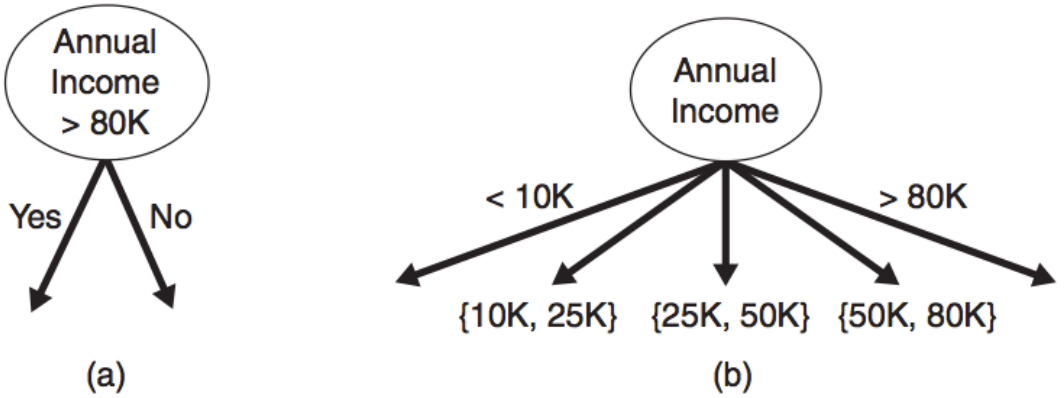

Figure 4.11. Test condition for continuous attributes.

NOTE

There are optimizations that can improve the naïve quadratic complexity of determining the optimum split point for continuous atrributes.

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We need an objective function to optimize!

II. OPTIMIZATION FUNCTIONS

We want our objective function to measure the gain in purity from a particular split.

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Name	Body Temperature	Skin Cover	Gives Birth	Aquatic Creature	Aerial Creature	Has Legs	Hiber-nates	Class Label
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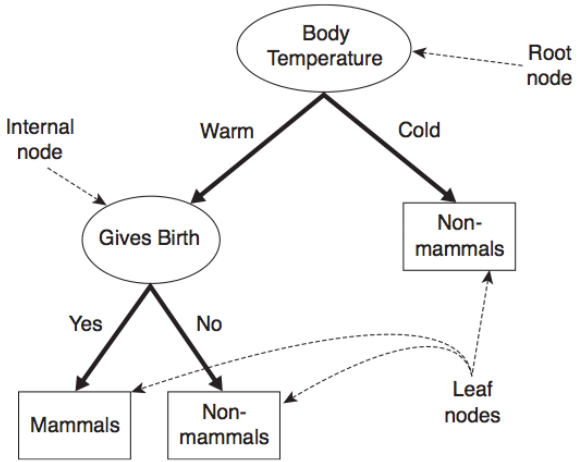

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OBJECTIVE FUNCTIONS

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For example, let $p(i|t)$ *be the probability of class* i *at node* t *(eg, the fraction of records labeled* i *at node* t*).*

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The maximum purity partition is given (eg) by the distribution:

$$p(0|t) = 1 - p(1|t) = 1$$

how to measure the value of information?

*Some measures of **impurity** include:*

$$\text{Entropy}(t) = -\sum_{i=0}^{c-1} p(i|t) \log_2 p(i|t),$$

$$\text{Gini}(t) = 1 - \sum_{i=0}^{c-1} [p(i|t)]^2,$$

$$\text{Classification error}(t) = 1 - \max_i [p(i|t)],$$

$$\text{Entropy}(t) \quad = \quad -\sum_{i=0}^{c-1} p(i|t) \log_2 p(i|t)$$

Use entropy as a measure of impurity or disorder of the data set

ENTROPY

$$\text{Entropy}(t) \quad = \quad -\sum_{i=0}^{c-1} p(i|t) \log_2 p(i|t)$$

1. The data set D has 50% positive examples (Pr(*positive*) = 0.5) and 50% negative examples (Pr(*negative*) = 0.5).

2. The data set D has 20% positive examples (Pr(*positive*) = 0.2) and 80% negative examples (Pr(*negative*) = 0.8).

3. The data set D has 100% positive examples (Pr(*positive*) = 1) and no negative examples, (Pr(*negative*) = 0).

source: http://www.cs.uic.edu/~liub/teach/cs583-spring-12/CS583-supervised-learning.ppt

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$$entropy(D) = -0.5 \times \log_2 0.5 - 0.5 \times \log_2 0.5 = 1$$

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$$entropy(D) = -0.2 \times \log_2 0.2 - 0.8 \times \log_2 0.8 = 0.722$$

3. The data set D has 100% positive examples (Pr(*positive*) = 1) and no negative examples, (Pr(*negative*) = 0).

$$entropy(D) = -1 \times \log_2 1 - 0 \times \log_2 0 = 0$$

As the data become purer and purer, the entropy value becomes smaller and smaller.

CONSISTENCY OF OBJECTIVE FUNCTIONS

Note that each measure achieves its max at 0.5, min at 0 & 1.

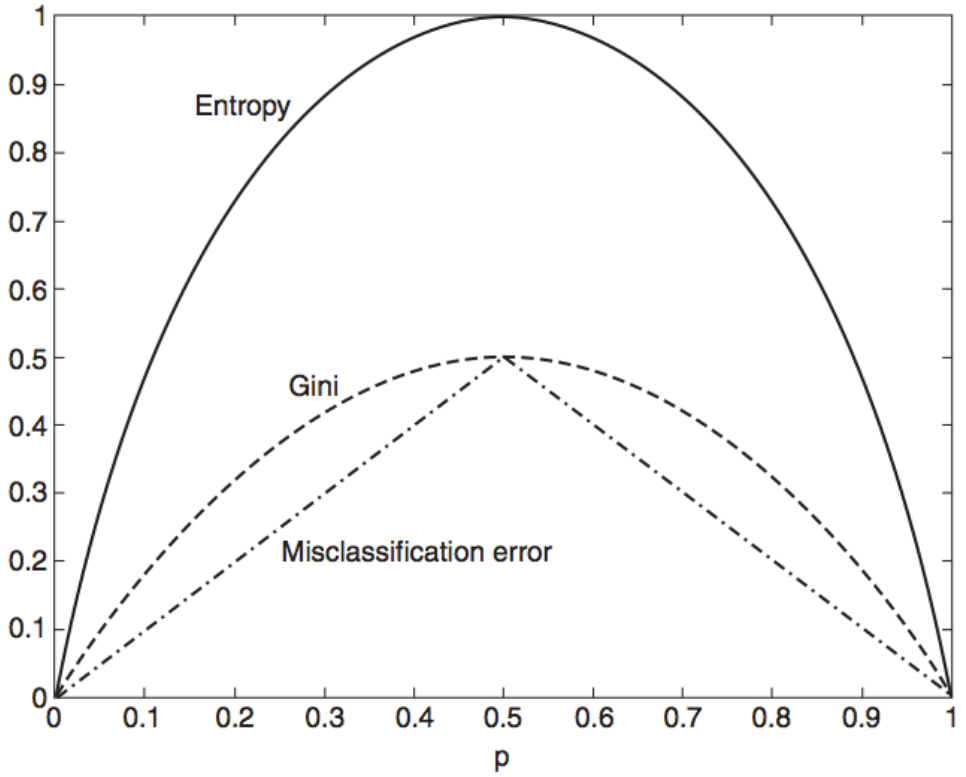

Figure 4.13. Comparison among the impurity measures for binary classification problems.

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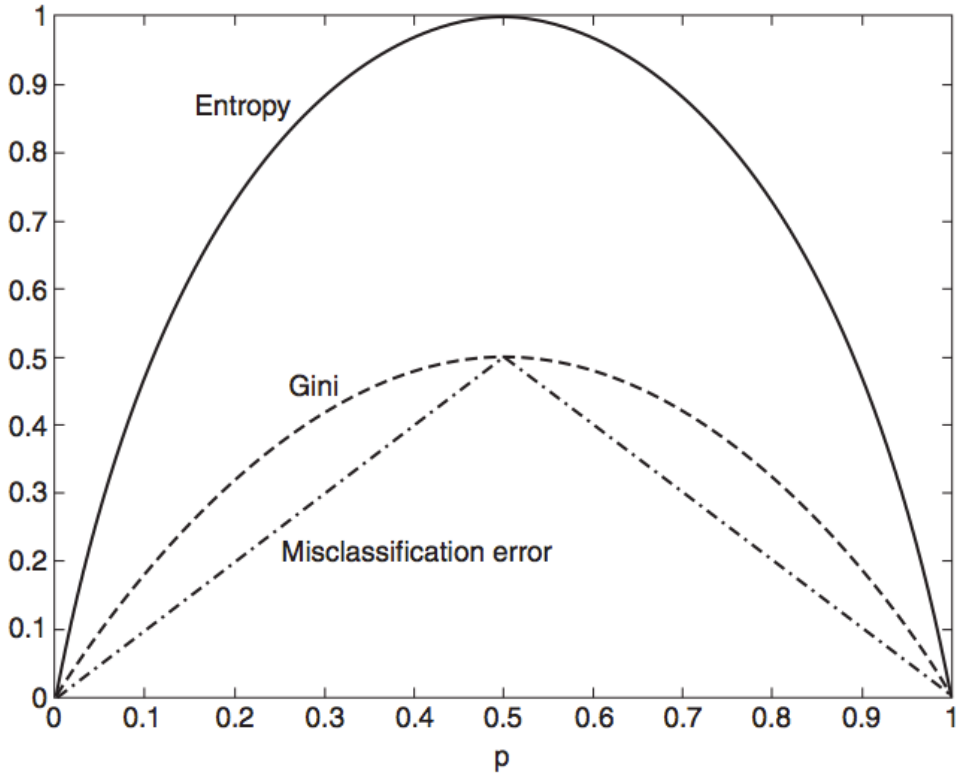
NOTE

Despite consistency, different measures may create different splits.



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Q: Why is this true?

Impurity measures put us on the right track, but on their own they are not enough to tell us how our split will do.

Q: Why is this true?
A: We still need to look at impurity before & after the split.

We can make this comparison using the **gain**:

$$\Delta = I(\text{parent}) - \sum_{\text{children } j} \frac{N_j}{N} I(\text{child } j)$$

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(Here I *is the impurity measure,* $\mathrm{N_j}$ *denotes the number of records at child node* j*, and* N *denotes the number of records at the parent node.)*

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When I *is the entropy, this quantity is called the* **information gain**.

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One way of dealing with this is to restrict the algorithm to binary splits only (CART).

Another way is to use a splitting criterion which explicitly penalizes the number of outcomes (C4.5)

We can use a function of the information gain called the **gain ratio** *to explicitly penalize high numbers of outcomes:*

$$\text{gain ratio} = \frac{\Delta_{info}}{-\sum p(v_i) log_2 p(v_i)}$$

(Where $\mathrm{p}(\mathrm{v_i})$ *refers to the probability of label* i *at node* v*)*

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NOTE

This is a form of regularization!

(Where $\mathrm{p}(\mathrm{v_i})$ *refers to the probability of label* i *at node* v*)*

II. PREVENTING OVERFITTING

In addition to determining splits, we also need a stopping criterion to tell us when we're done.

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This is correct in principle, but would likely lead to overfitting.

One possibility is **pre-pruning**, *which involves setting a minimum threshold on the gain, and stopping when no split achieves a gain above this threshold.*

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This prevents overfitting, but is difficult to calibrate in practice (may preserve bias!)

Alternatively we could build the full tree, and then perform **pruning** *as a post-processing step.*

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To prune a tree, we examine the nodes from the bottom-up and simplify pieces of the tree (according to some criteria).

Complicated subtrees can be replaced either with a single node, or with a simpler (child) subtree.

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The first approach is called **subtree replacement**, *and the second is* **subtree raising**.

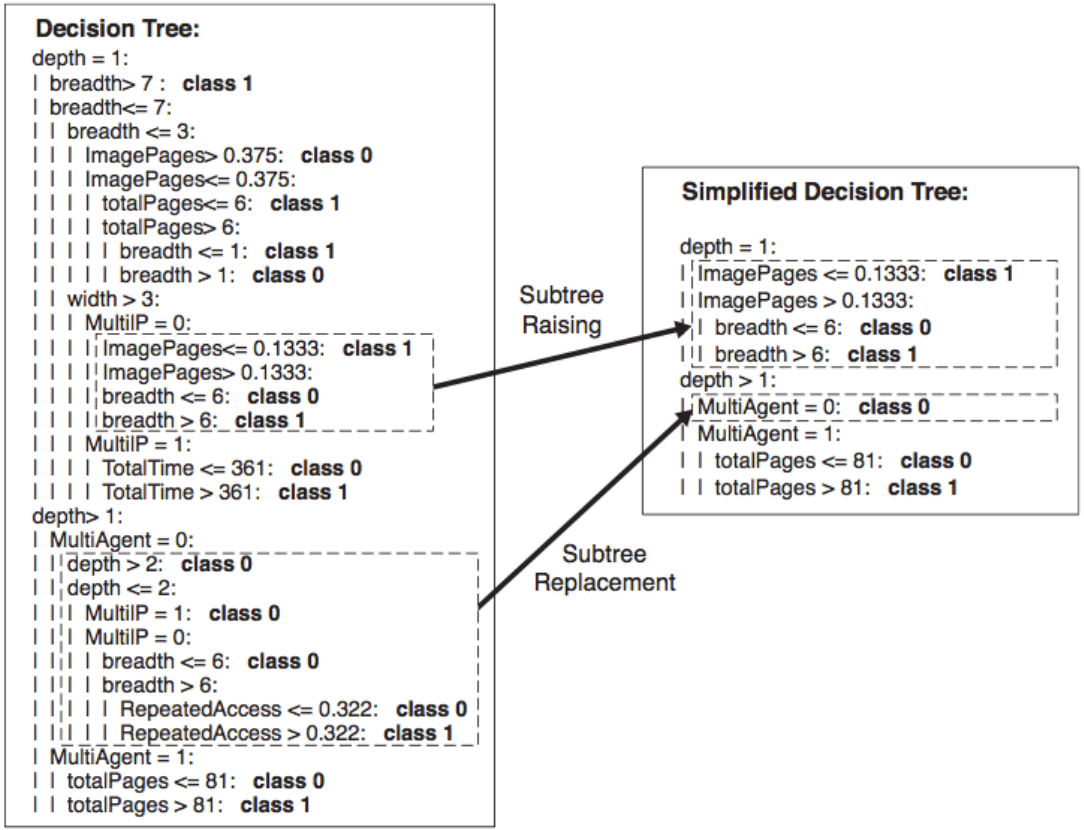

Figure 4.29. Post-pruning of the decision tree for Web robot detection.

EX: DECISION TREES IN PYTHON