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

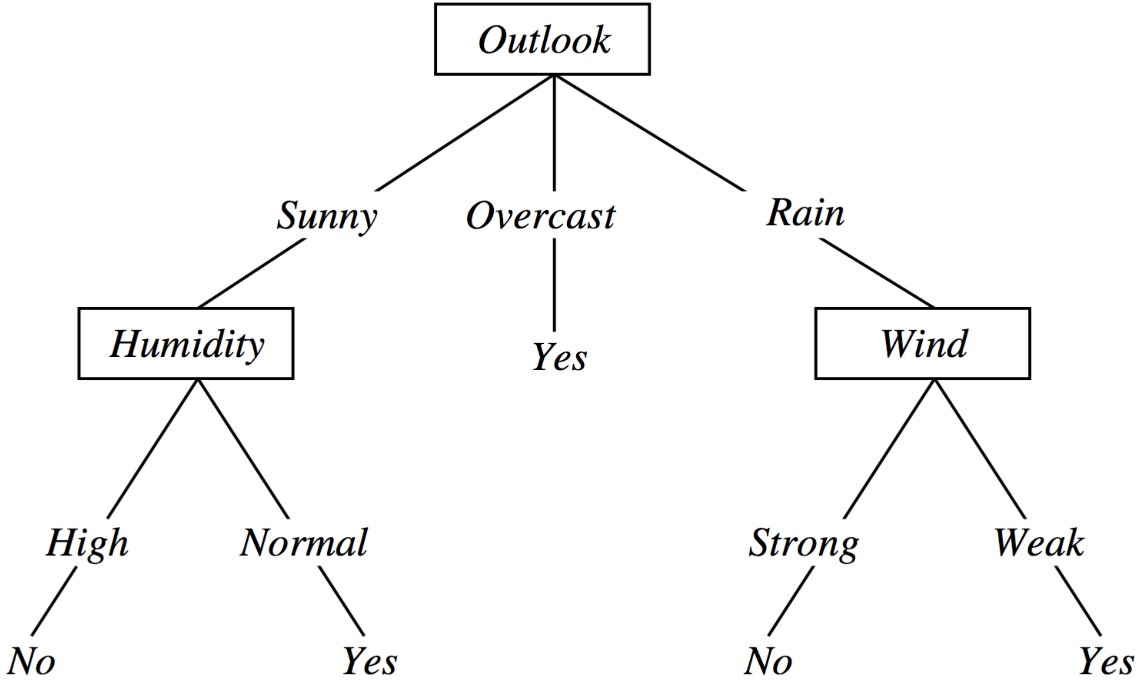
QUESTIONS?

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

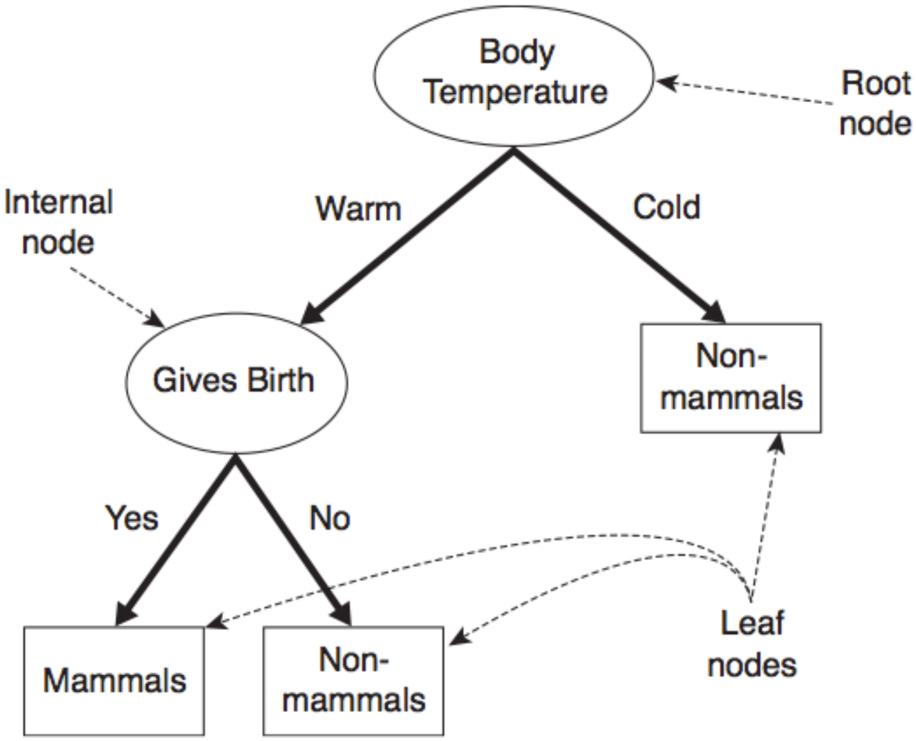


Figure 4.4. A decision tree for the mammal classification problem.

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.

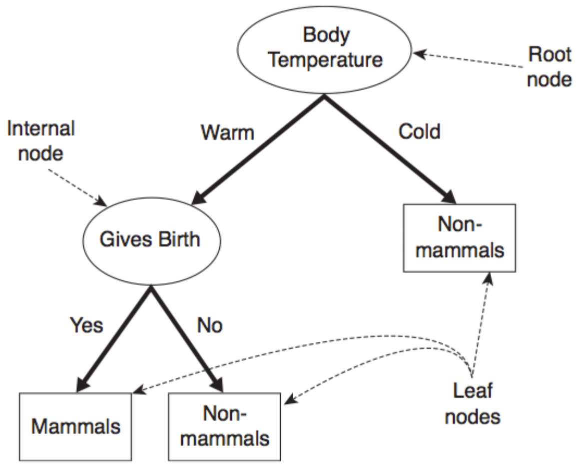


Figure 4.4. A decision tree for the mammal classification problem.

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

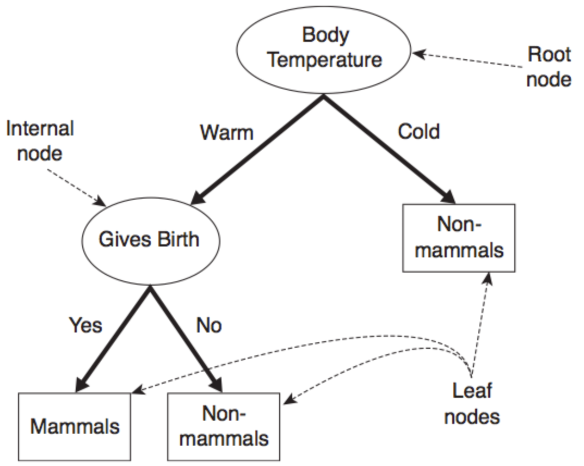
The partitioning decision is made at each node according to a metric called **purity**.

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

PURITY

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
komodo dragon	cold-blooded	scales	no	no	no	yes	no	reptile
bat	warm-blooded	hair	yes	no	yes	yes	yes	mammal
pigeon	warm-blooded	feathers	no	no	yes	yes	no	bird
cat	warm-blooded	fur	yes	no	no	yes	no	mammal
leopard shark	cold-blooded	scales	yes	yes	no	no	no	fish
turtle	cold-blooded	scales	no	semi	no	yes	no	reptile
penguin	warm-blooded	feathers	no	semi	no	yes	no	bird
porcupine	warm-blooded	quills	yes	no	no	yes	yes	mammal
eel	cold-blooded	scales	no	yes	no	no	no	fish
salamander	cold-blooded	none	no	semi	no	yes	yes	amphibian



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BUILDING A DECISION TREE

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:

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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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3) *These steps are then recursively applied to each child node.*

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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?

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A: There are a few ways to do this.

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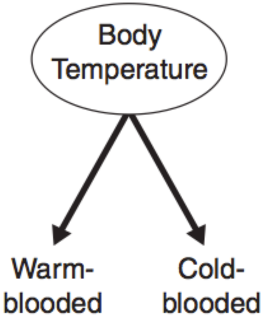
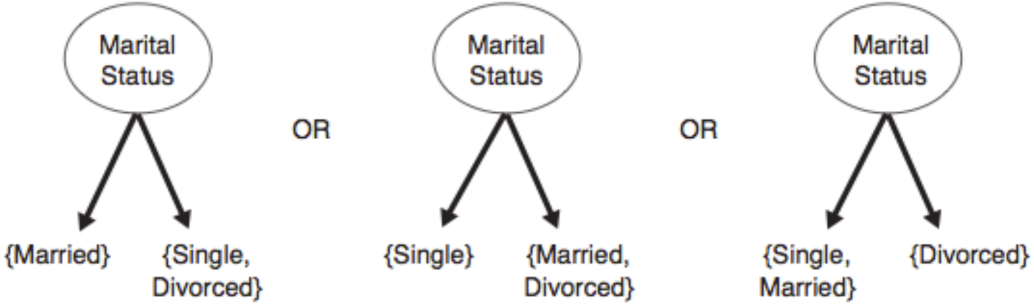


Figure 4.8. Test condition for binary attributes.

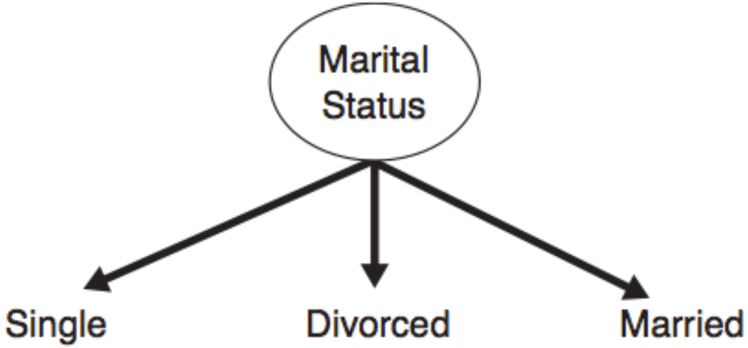


(b) Binary split {by grouping attribute values}

Q: How do we partition the training records?

A: There are a few ways to do this.

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



(a) Multiway split

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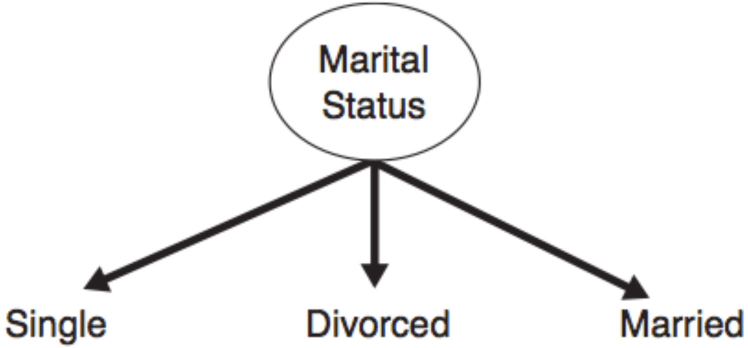

(a) Multiway split

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:

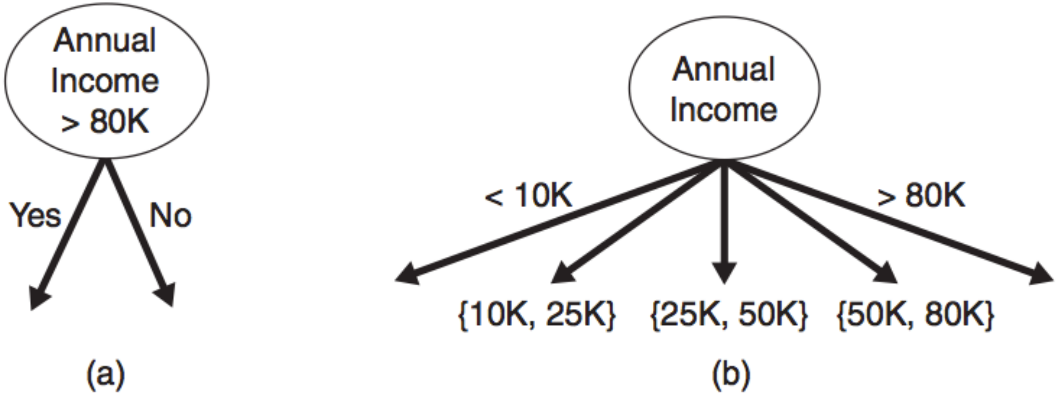

Figure 4.11. Test condition for continuous attributes.

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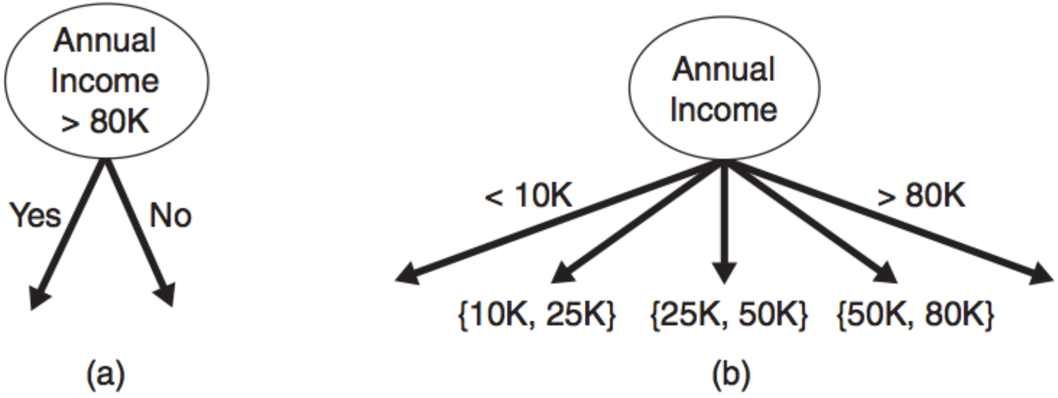

Figure 4.11. Test condition for continuous attributes.

NOTE

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

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Therefore we want each step to create the partition with the highest possible purity.

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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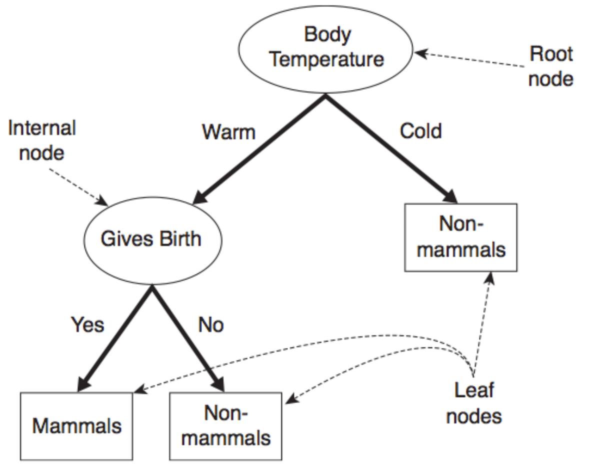

Figure 4.4. A decision tree for the mammal classification problem.

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Therefore we want it to depend on the class distribution over the nodes (before and after the split).

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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*).*

Then for a binary (0/1) classification problem,

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The minimum purity partition is given by the distribution:

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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:*

$$\begin{aligned}
\text{Entropy}(t) &= -\sum_{i=0}^{c-1} p(i|t) \log_2 p(i|t), \\
\text{Gini}(t) &= 1 - \sum_{i=0}^{c-1} [p(i|t)]^2, \\
\text{Classification error}(t) &= 1 - \max_i [p(i|t)],
\end{aligned}$$

OBJECTIVE FUNCTIONS

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

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

ENTROPY

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

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

ENTROPY

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

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

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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.

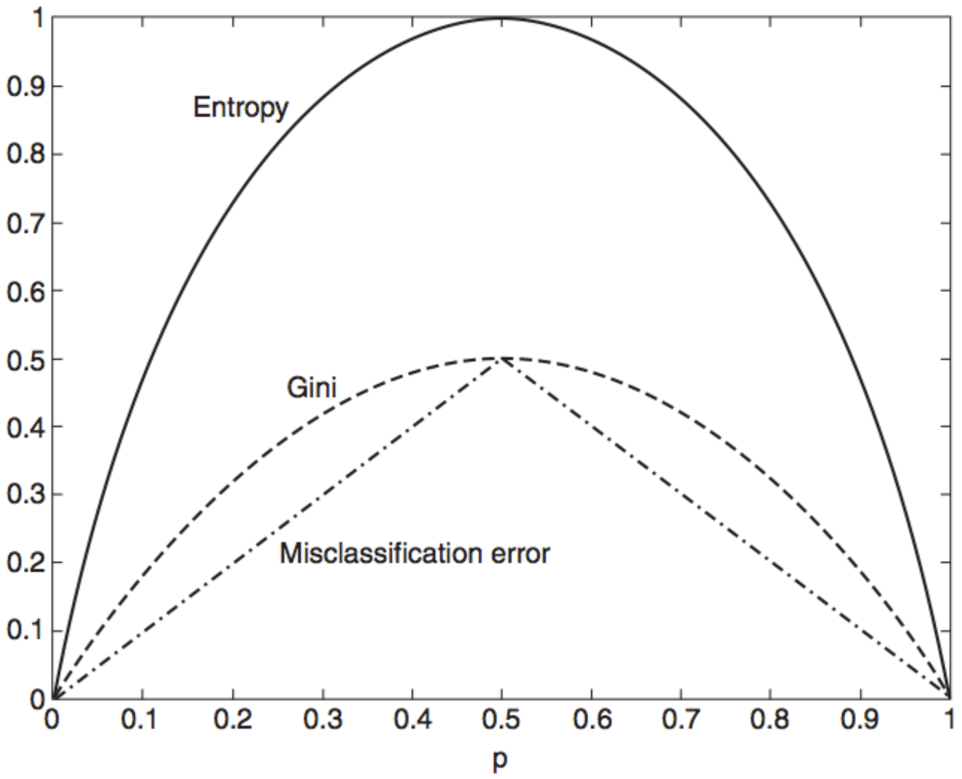

Figure 4.13. Comparison among the impurity measures for binary classification problems.

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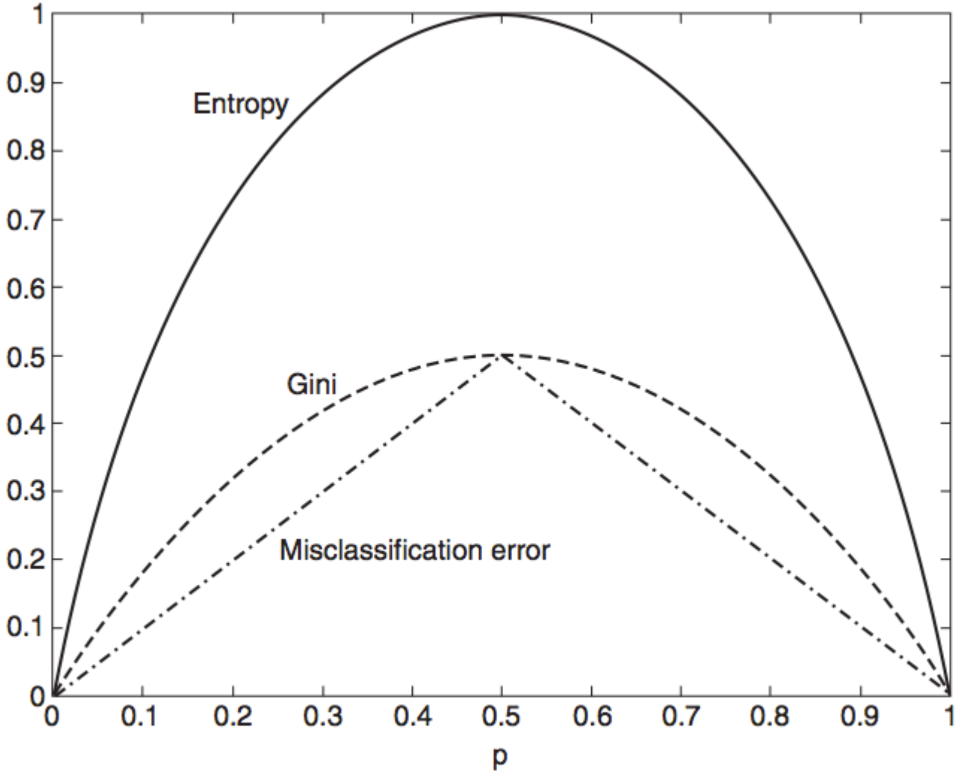
NOTE

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

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

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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 $p(v_i)$ *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**.

PREVENTING OVERFITTING

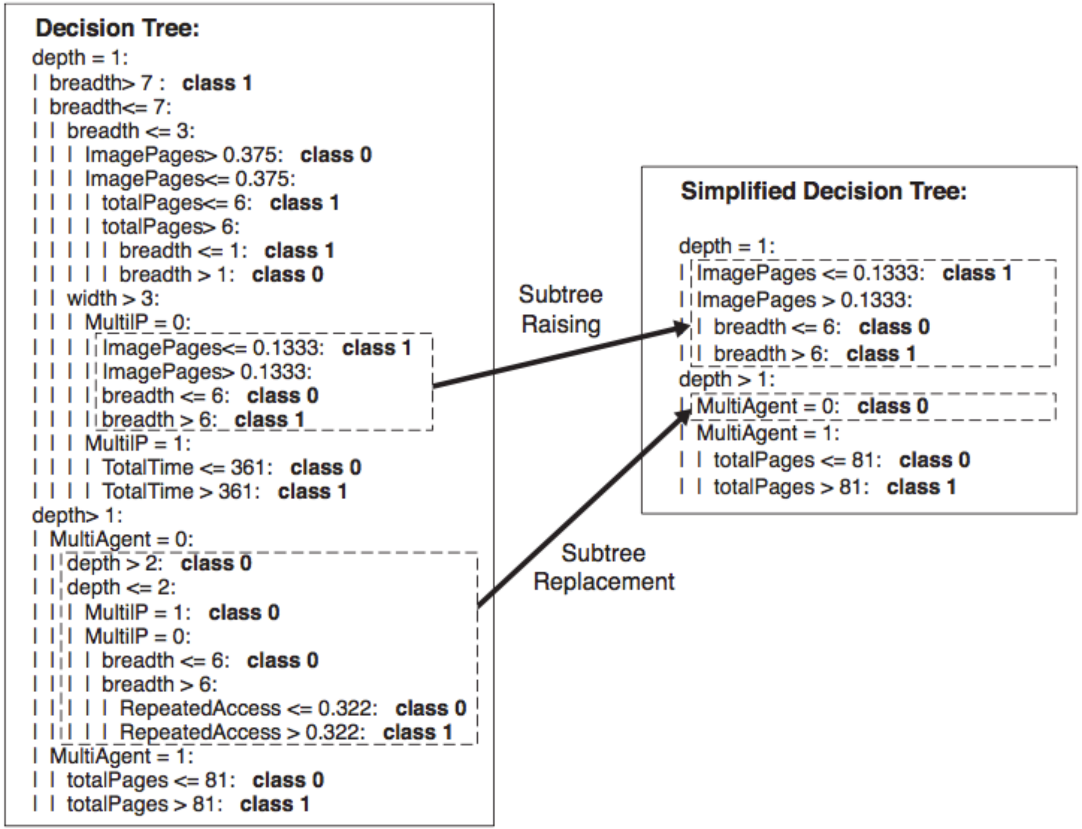

Figure 4.29. Post-pruning of the decision tree for Web robot detection.

EX: DECISION TREES IN PYTHON