

Information Extraction

Lecture 5 – Decision Trees (Basic Machine Learning)

CIS, LMU München

Winter Semester 2020-2021

Prof. Dr. Alexander Fraser, CIS

Administravia

- I cancelled the seminar on January 7th
(now January 21st)

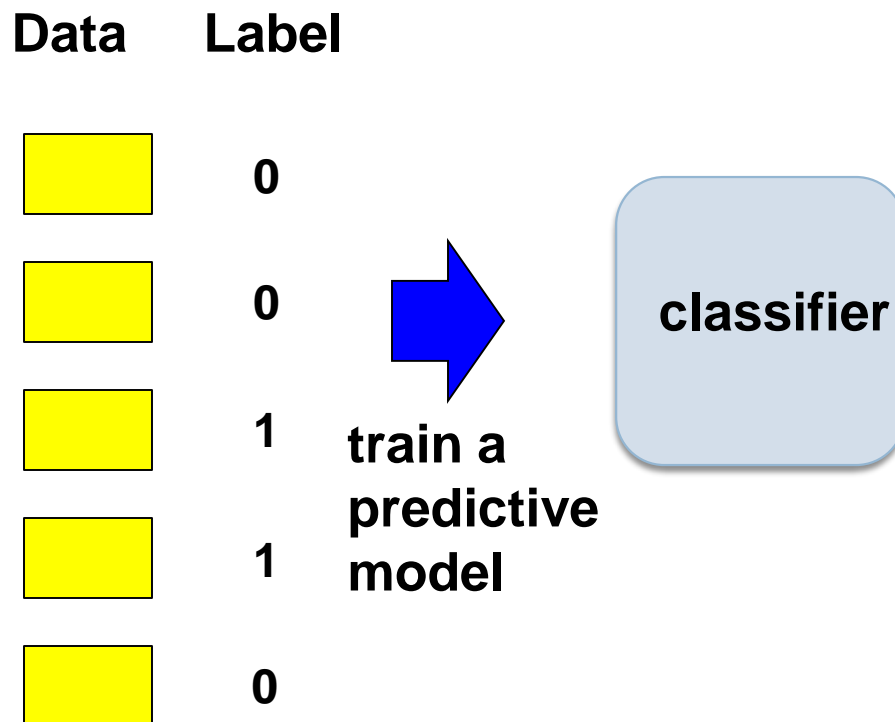
Lecture Today

- Last week, we covered a basic idea of how NER classification works
 - We talked about sliding windows and features
 - Today I will complete this introduction by comparing sliding windows with boundary detection
- After that, we'll spend the rest of the lecture on an important topic in machine learning

How can we pose this as a classification (or learning) problem?

... 00 : pm Place : Wean Hall Rm 5409 Speaker : Sebastian Thrun ...

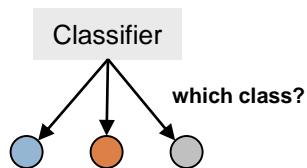
prefix contents suffix



Lots of possible techniques

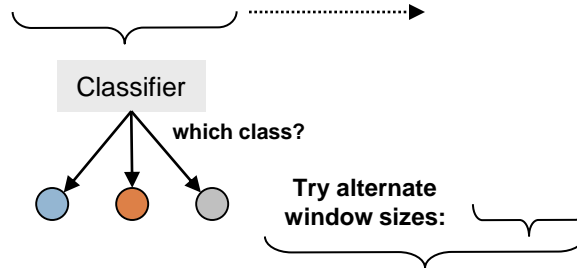
Classify Candidates

Abraham Lincoln was born in Kentucky.

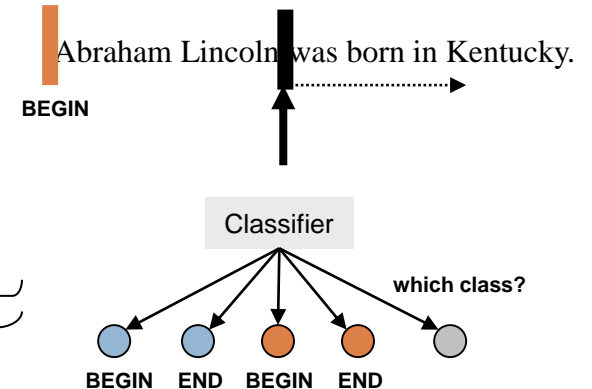


Sliding Window

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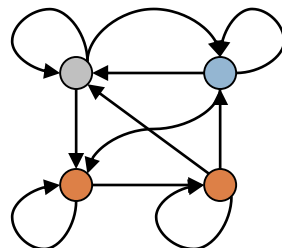


Boundary Models



Finite State Machines

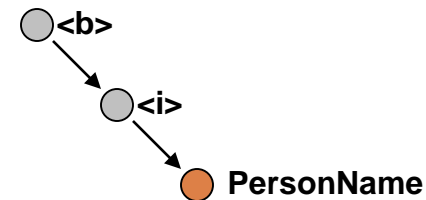
Abraham Lincoln was born in Kentucky.



Wrapper Induction

Abraham Lincoln was born in Kentucky.

Learn and apply pattern for a website



Any of these models can be used to capture words, formatting or both.

Information Extraction by Sliding Window

**E.g.
Looking for
seminar
location**

GRAND CHALLENGES FOR MACHINE LEARNING



Jaime Carbonell
School of Computer Science
Carnegie Mellon University

3:30 pm
7500 Wean Hall

Machine learning has evolved from obscurity in the 1970s into a vibrant and popular discipline in artificial intelligence during the 1980s and 1990s. As a result of its success and growth, machine learning is evolving into a collection of related disciplines: inductive concept acquisition, analytic learning in problem solving (e.g. analogy, explanation-based learning), learning theory (e.g. PAC learning), genetic algorithms, connectionist learning, hybrid systems, and so on.

CMU UseNet Seminar Announcement

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Information Extraction by Sliding Window



- Standard supervised learning setting
 - Positive instances?
 - Negative instances?

Information Extraction by Sliding Window



- Standard supervised learning setting
 - Positive instances: Windows with real label
 - Negative instances: All other windows
 - Features based on candidate, prefix and suffix

IE by Boundary Detection

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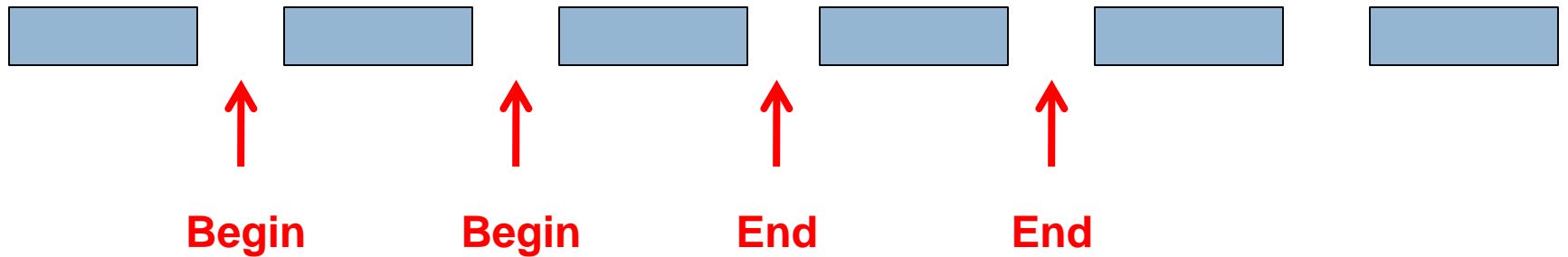
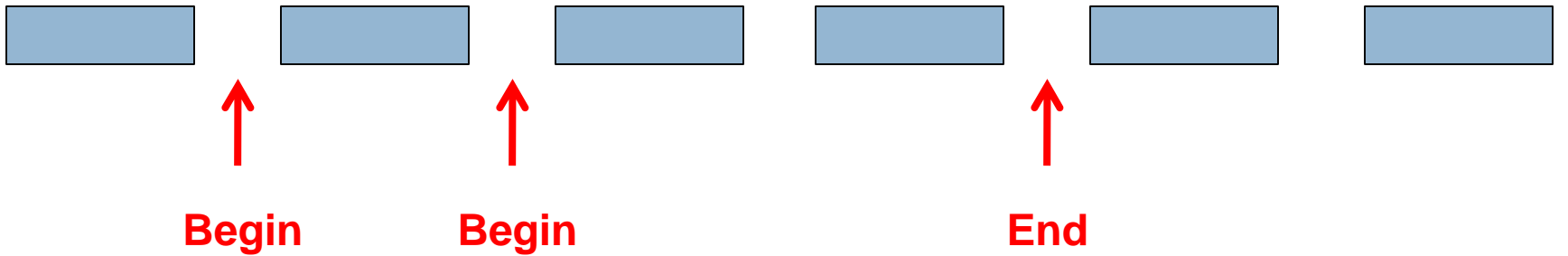
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CMU UseNet Seminar Announcement

Some concerns



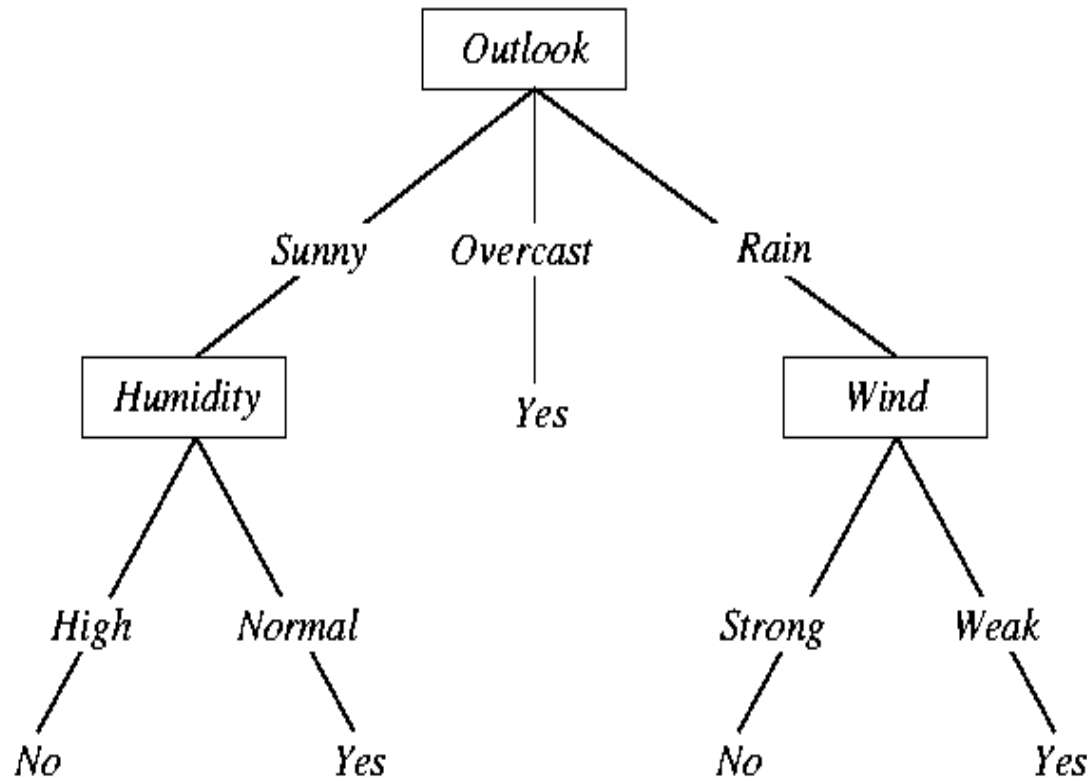
Problems with Sliding Windows and Boundary Finders

- Decisions in neighboring parts of the input are made independently from each other.
 - Sliding Window may predict a “seminar end time” before the “seminar start time”.
 - It is possible for two overlapping windows to both be above threshold.
 - In a Boundary-Finding system, left boundaries are laid down independently from right boundaries

Where we are going

- What we just completed: introduction to NER using classifiers
 - Features, sliding windows vs. boundaries
- Rest of today: look at decision trees as part of a general introduction to machine learning
 - I will present a different perspective from the Statistical Methods course
 - Necessary background to linear models, which I will present next week
 - Next week, I will connect linear models with NER
 - The rest of this lecture is a short break from NER

Decision Tree Representation for 'Play Tennis?'



- Internal node
~ test an attribute
- Branch
~ attribute value
- Leaf
~ classification result

When is it useful?

- Medical diagnosis
- Equipment diagnosis
- Credit risk analysis
- etc

Outline

- Contingency tables
 - Census data set
- Information gain
 - Beach data set
- Learning an unpruned decision tree recursively
 - Gasoline usage data set
- Training error
- Test error
- Overfitting
- Avoiding overfitting

Here is a dataset

age	employe	education	edun	marital	...	job	relation	race	gender	hour	country	wealth
					...							
39	State_gov	Bachelors	13	Never_mar	...	Adm_cleric	Not_in_fan	White	Male	40	United_Stat	poor
51	Self_emp_	Bachelors	13	Married	...	Exec_man	Husband	White	Male	13	United_Stat	poor
39	Private	HS_grad	9	Divorced	...	Handlers_(Not_in_fan	White	Male	40	United_Stat	poor
54	Private	11th	7	Married	...	Handlers_(Husband	Black	Male	40	United_Stat	poor
28	Private	Bachelors	13	Married	...	Prof_speci	Wife	Black	Female	40	Cuba	poor
38	Private	Masters	14	Married	...	Exec_man	Wife	White	Female	40	United_Stat	poor
50	Private	9th	5	Married_sp	...	Other_ser	Not_in_fan	Black	Female	16	Jamaica	poor
52	Self_emp_	HS_grad	9	Married	...	Exec_man	Husband	White	Male	45	United_Stat	rich
31	Private	Masters	14	Never_mar	...	Prof_speci	Not_in_fan	White	Female	50	United_Stat	rich
42	Private	Bachelors	13	Married	...	Exec_man	Husband	White	Male	40	United_Stat	rich
37	Private	Some_coll	10	Married	...	Exec_man	Husband	Black	Male	80	United_Stat	rich
30	State_gov	Bachelors	13	Married	...	Prof_speci	Husband	Asian	Male	40	India	rich
24	Private	Bachelors	13	Never_mar	...	Adm_cleric	Own_child	White	Female	30	United_Stat	poor
33	Private	Assoc_acc	12	Never_mar	...	Sales	Not_in_fan	Black	Male	50	United_Stat	poor
41	Private	Assoc_voc	11	Married	...	Craft_repa	Husband	Asian	Male	40	*MissingV	rich
34	Private	7th_8th	4	Married	...	Transport_	Husband	Amer_India	Male	45	Mexico	poor
26	Self_emp_	HS_grad	9	Never_mar	...	Farming_fi	Own_child	White	Male	35	United_Stat	poor
33	Private	HS_grad	9	Never_mar	...	Machine_c	Unmarried	White	Male	40	United_Stat	poor
38	Private	11th	7	Married	...	Sales	Husband	White	Male	50	United_Stat	poor
44	Self_emp_	Masters	14	Divorced	...	Exec_man	Unmarried	White	Female	45	United_Stat	rich
41	Private	Doctorate	16	Married	...	Prof_speci	Husband	White	Male	60	United_Stat	rich
:	:	:	:	:	:	:	:	:	:	:	:	:

48,000 records, 16 attributes [Kohavi 1995]

About this dataset

- It is a tiny subset of the 1990 US Census.
- It is publicly available online from the UCI Machine Learning Datasets repository

Used Attributes

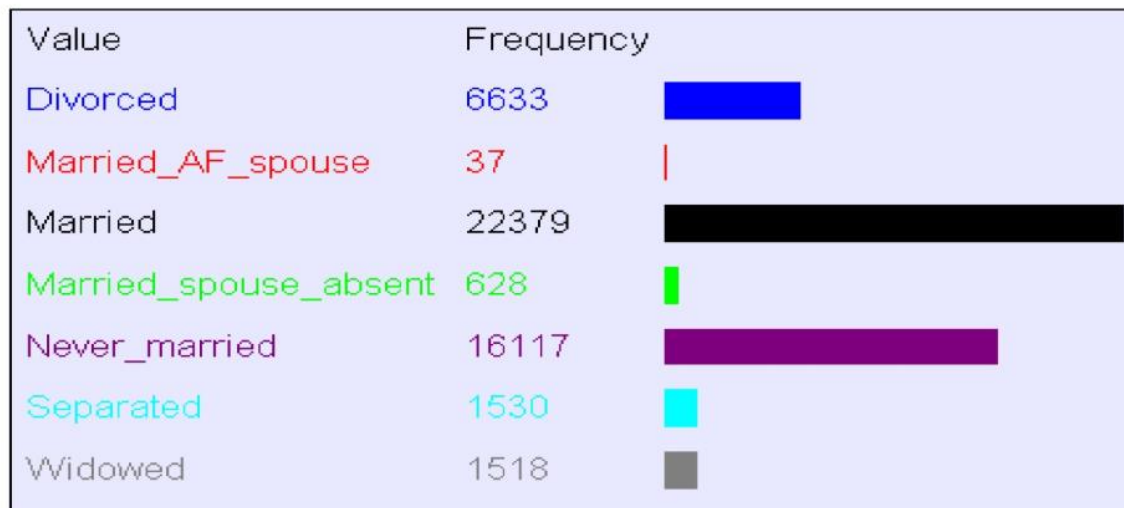
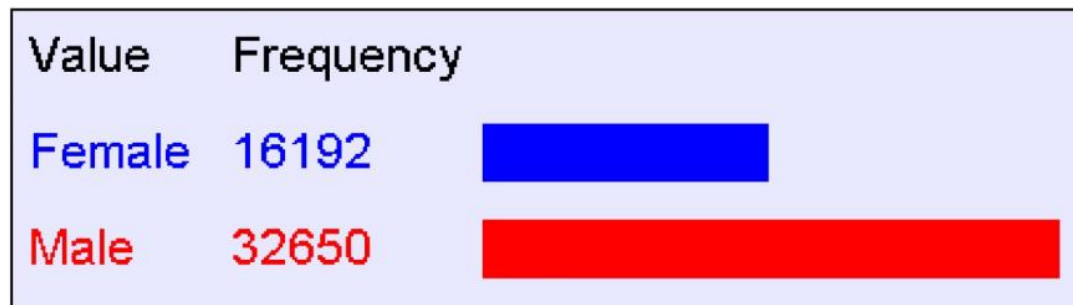
age	edunum	race	hours_worked
employment	marital	gender	country
taxweighting	job	capitalgain	wealth
education	relation	capitalloss	agegroup

This color = Real-valued This color = Symbol-valued

Successfully loaded a new dataset from the file \tadult.fds. It has 16 attributes and 48842 records.

What can you do with a dataset?

- Well, you can look at histograms...





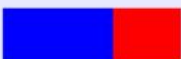




A 2-d Contingency Table

wealth values:		poor	rich
agegroup	10s	2507	3
	20s	11262	743
	30s	9468	3461
	40s	6738	3986
	50s	4110	2509
	60s	2245	809
	70s	668	147
	80s	115	16
	90s	42	13










- For each pair of values for attributes (agegroup, wealth) we can see how many records match.

A 2-d Contingency Table

wealth values:		poor	rich	
agegroup	10s	2507	3	
	20s	11262	743	
	30s	9468	3461	
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	60s	2245	809	
	70s	668	147	
	80s	115	16	
	90s	42	13	

- Easier to appreciate graphically

A 2-d Contingency Table

wealth values:		poor	rich	
agegroup	10s	2507	3	
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	90s	42	13	

- Easier to see “interesting” things if we stretch out the histogram bars

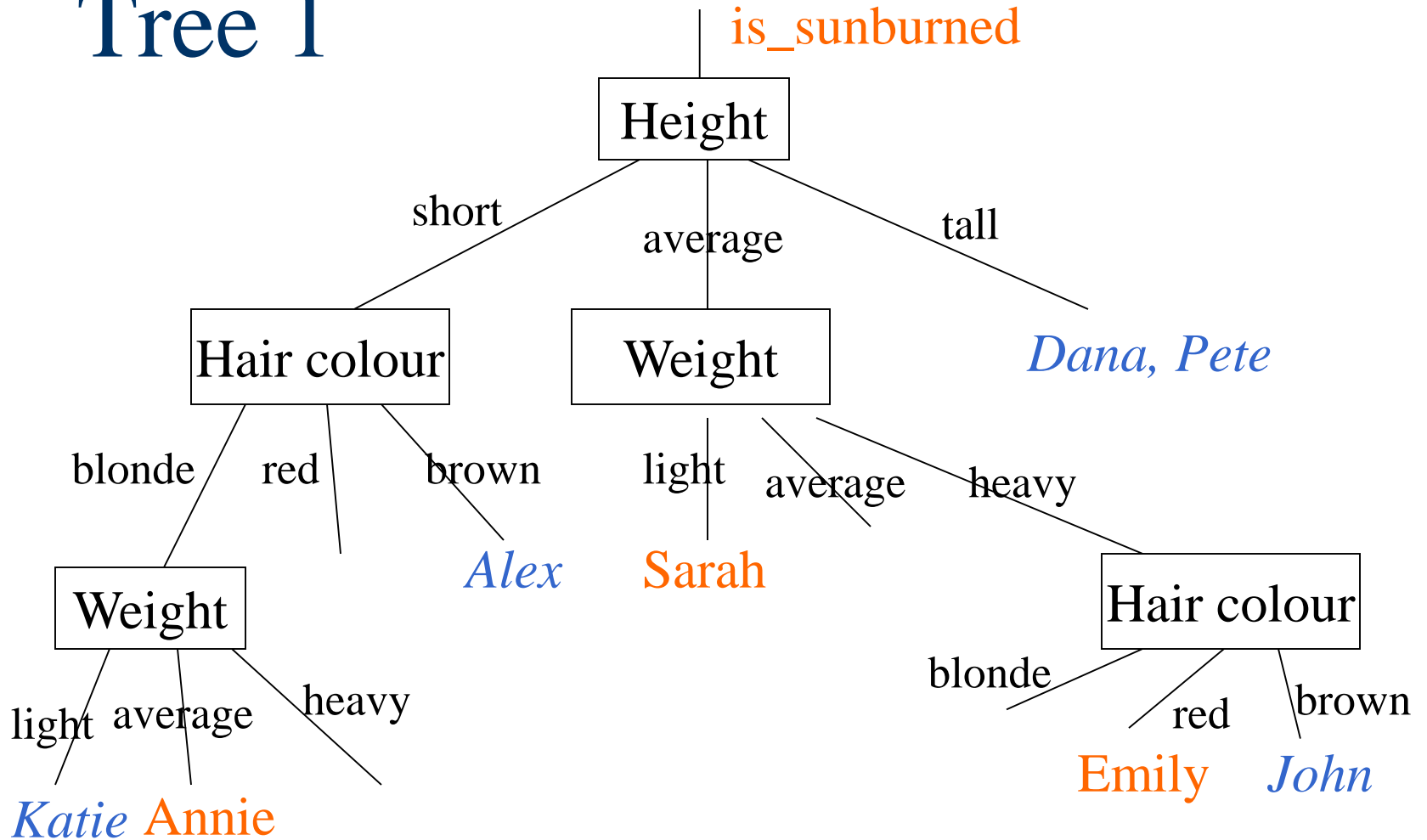
Using this idea for classification

- We will now look at a (toy) dataset presented in Winston's Artificial Intelligence textbook
- It is often used when explaining decision trees
- The variable we are trying to pick is "got_a_sunburn" (or "is_sunburned" if you like)
- We will look at different decision trees that can be used to correctly classify this data

Sunburn Data Collected

Name	Hair	Height	Weight	Lotion	Result
<i>Sarah</i>	Blonde	Average	Light	No	<i>Sunburned</i>
<i>Dana</i>	Blonde	Tall	Average	Yes	<i>None</i>
<i>Alex</i>	Brown	Short	Average	Yes	<i>None</i>
<i>Annie</i>	Blonde	Short	Average	No	<i>Sunburned</i>
<i>Emily</i>	Red	Average	Heavy	No	<i>Sunburned</i>
<i>Pete</i>	Brown	Tall	Heavy	No	<i>None</i>
<i>John</i>	Brown	Average	Heavy	No	<i>None</i>
<i>Kate</i>	Blonde	Short	Light	Yes	<i>None</i>

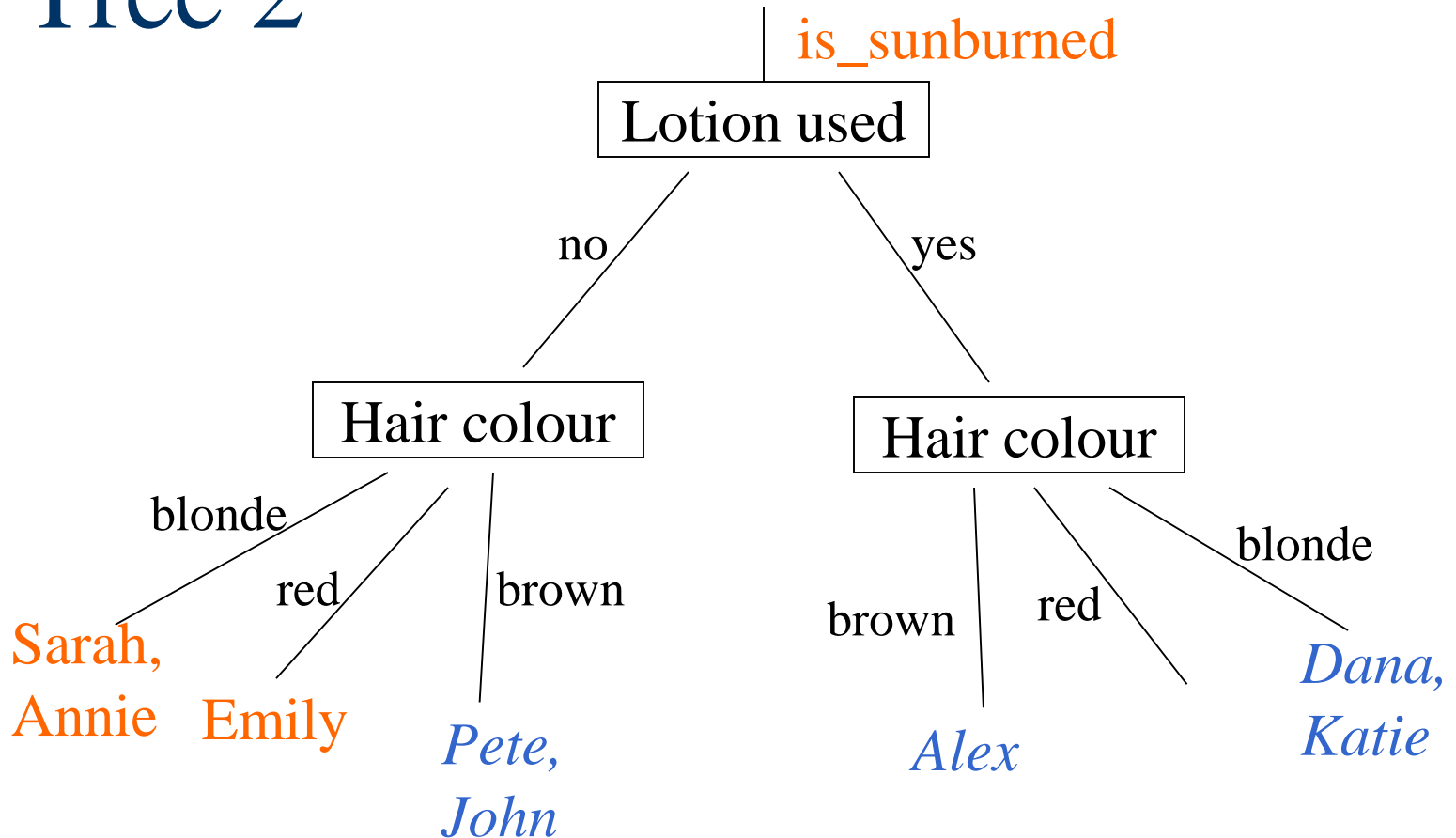
Decision Tree 1



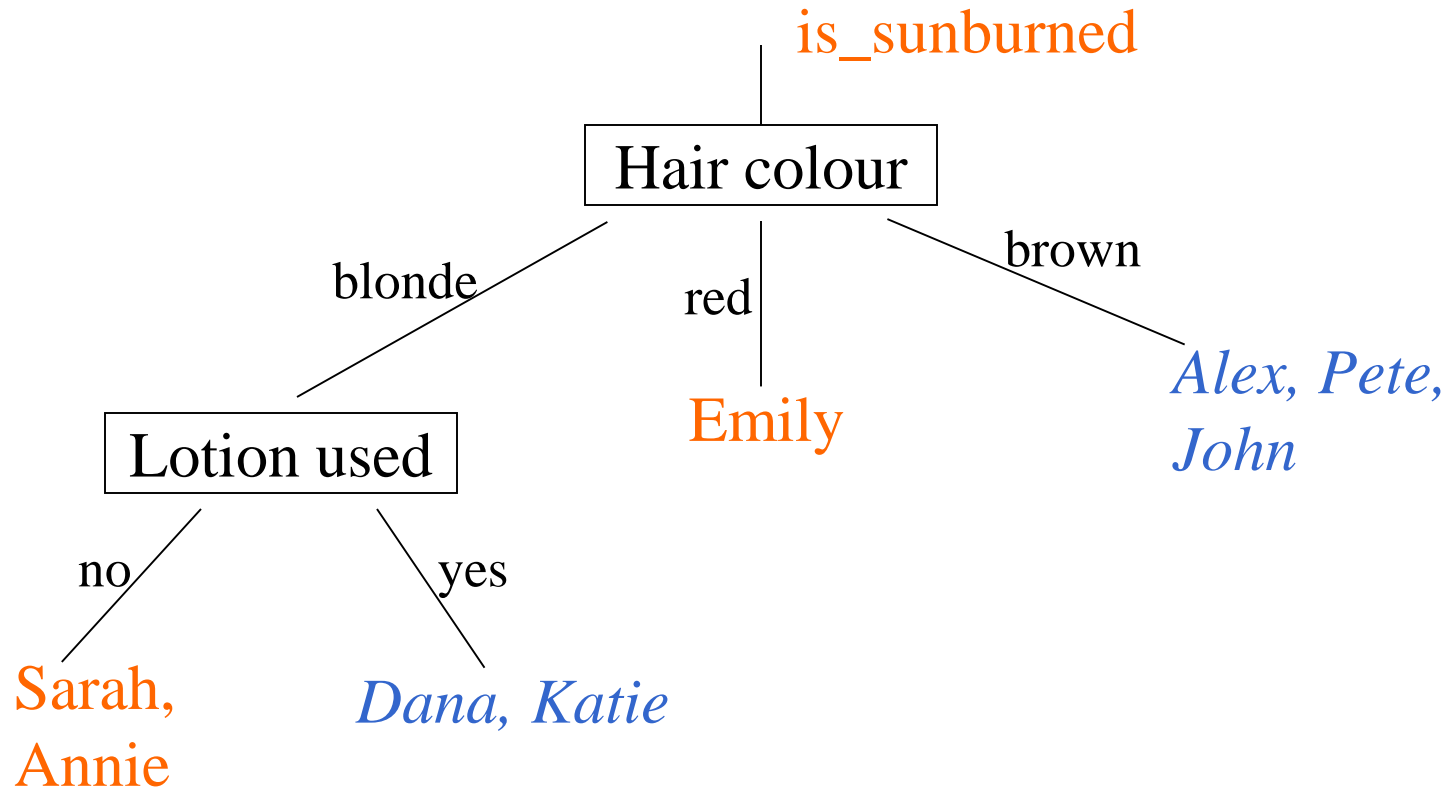
Sunburn sufferers are ...

- If height="average" then
 - if weight="light" then
 - `return(true) ;;; Sarah`
 - elseif weight="heavy" then
 - if hair_colour="red" then
 - `return(true) ;;; Emily`
- elseif height="short" then
 - if hair_colour="blonde" then
 - if weight="average" then
 - `return(true) ;;; Annie`
- else *`return(false) ;;;everyone else`*

Decision Tree 2



Decision Tree 3



Summing up

- Irrelevant attributes do not classify the data well
- Using irrelevant attributes thus causes larger decision trees
- a computer could look for simpler decision trees
- Q: How?

A: How WE did it?

- Q: Which is the best attribute for splitting up the data?
- A: The one which is *most informative* for the classification we want to get.
- Q: What does it mean 'more informative'?
- A: The attribute which best *reduces the uncertainty* or the disorder

- We need a quantity to measure the *disorder* in a set of examples

$$S = \{s_1, s_2, s_3, \dots, s_n\}$$

where $s_1 = \text{"Sarah"}$, $s_2 = \text{"Dana"}$, ...

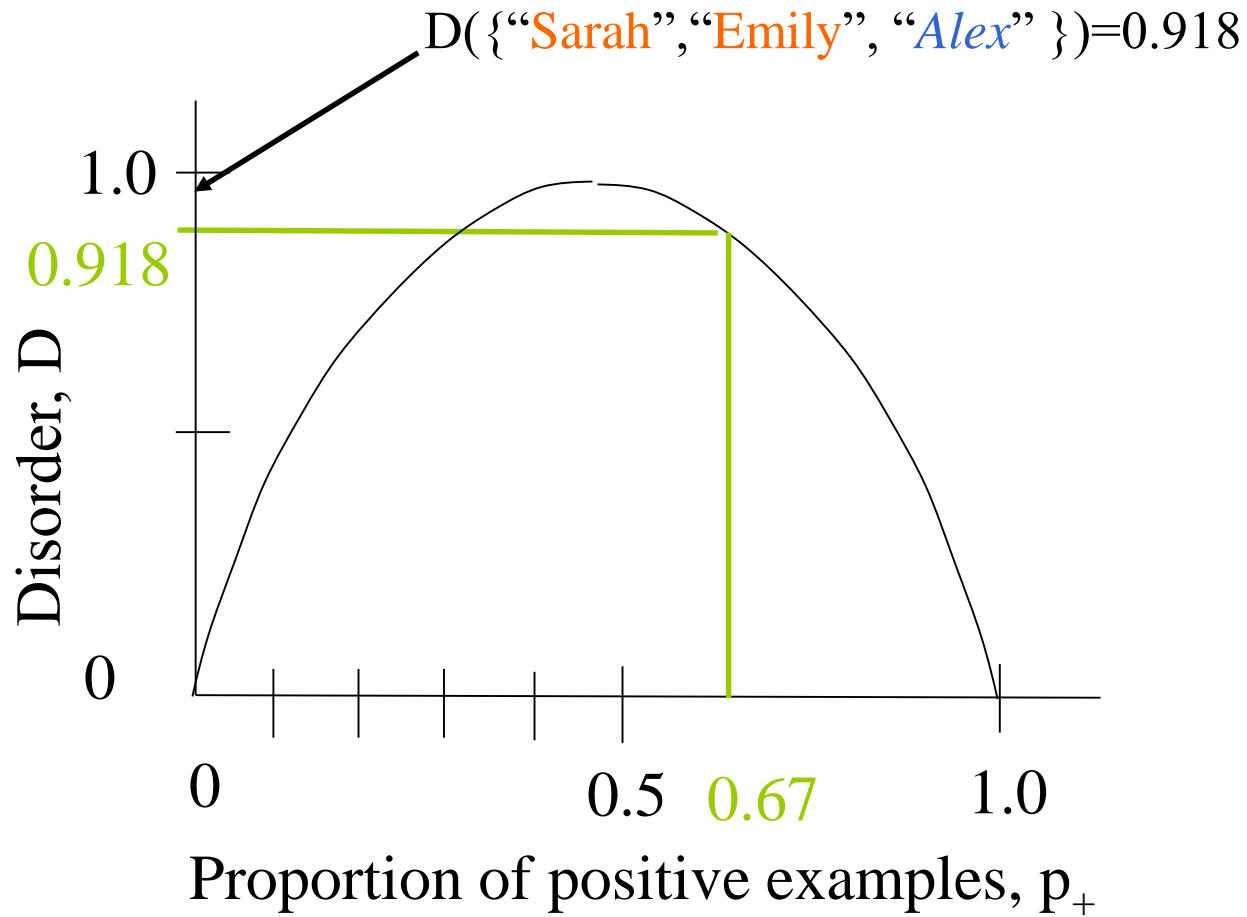
- Then we need a quantity to measure the amount of *reduction of the disorder* level in the instance of knowing the value of a particular attribute

What properties should the *Disorder* (D) have?

- Suppose that $D(S)=0$ means that all the examples in S have the same class
- Suppose that $D(S)=1$ means that half the examples in S are of one class and half are the opposite class

Examples

- $D(\{\text{"Dana"}, \text{"Pete"}\}) = 0$
- $D(\{\text{"Sarah"}, \text{"Annie"}, \text{"Emily"}\}) = 0$
- $D(\{\text{"Sarah"}, \text{"Emily"}, \text{"Alex"}, \text{"John"}\}) = 1$
- $D(\{\text{"Sarah"}, \text{"Emily"}, \text{"Alex"}\}) = ?$



Definition of Disorder

The **Entropy** measures the disorder of a set S containing a total of n examples of which n_+ are positive and n_- are negative and it is given by

$$D(n_+, n_-) = -\frac{n_+}{n} \log_2 \frac{n_+}{n} - \frac{n_-}{n} \log_2 \frac{n_-}{n} = \text{Entropy}(S)$$

where

$$\log_2 x \text{ means } 2^? = x$$

Check it!

$$D(0,1) = ? \quad D(1,0)=? \quad D(0.5,0.5)=?$$

Back to the beach (or the disorder of sunbathers)!

$D(\{ \text{“Sarah”}, \text{“Dana”}, \text{“Alex”}, \text{“Annie”}, \text{“Emily”}, \text{“Pete”}, \text{“John”}, \text{“Katie”} \})$

$$= D(3,5) = -\frac{3}{8} \log_2 \frac{3}{8} - \frac{5}{8} \log_2 \frac{5}{8}$$

$$= 0.954$$

Some more useful properties of the Entropy

$$D(n, m) = D(m, n)$$

$$D(0, m) = 0$$

$$D(m, m) = 1$$

- So: We can measure the disorder 😊
- What's left:
 - We want to measure how much by knowing the value of a particular attribute the disorder of a set would reduce.

- The **Information Gain** measures the expected reduction in entropy due to splitting on an attribute A

$$Gain(S, A) = Entropy(S) - \underbrace{\sum_{v \in Values(A)} \frac{|S_v|}{|S|} Entropy(S_v)}$$

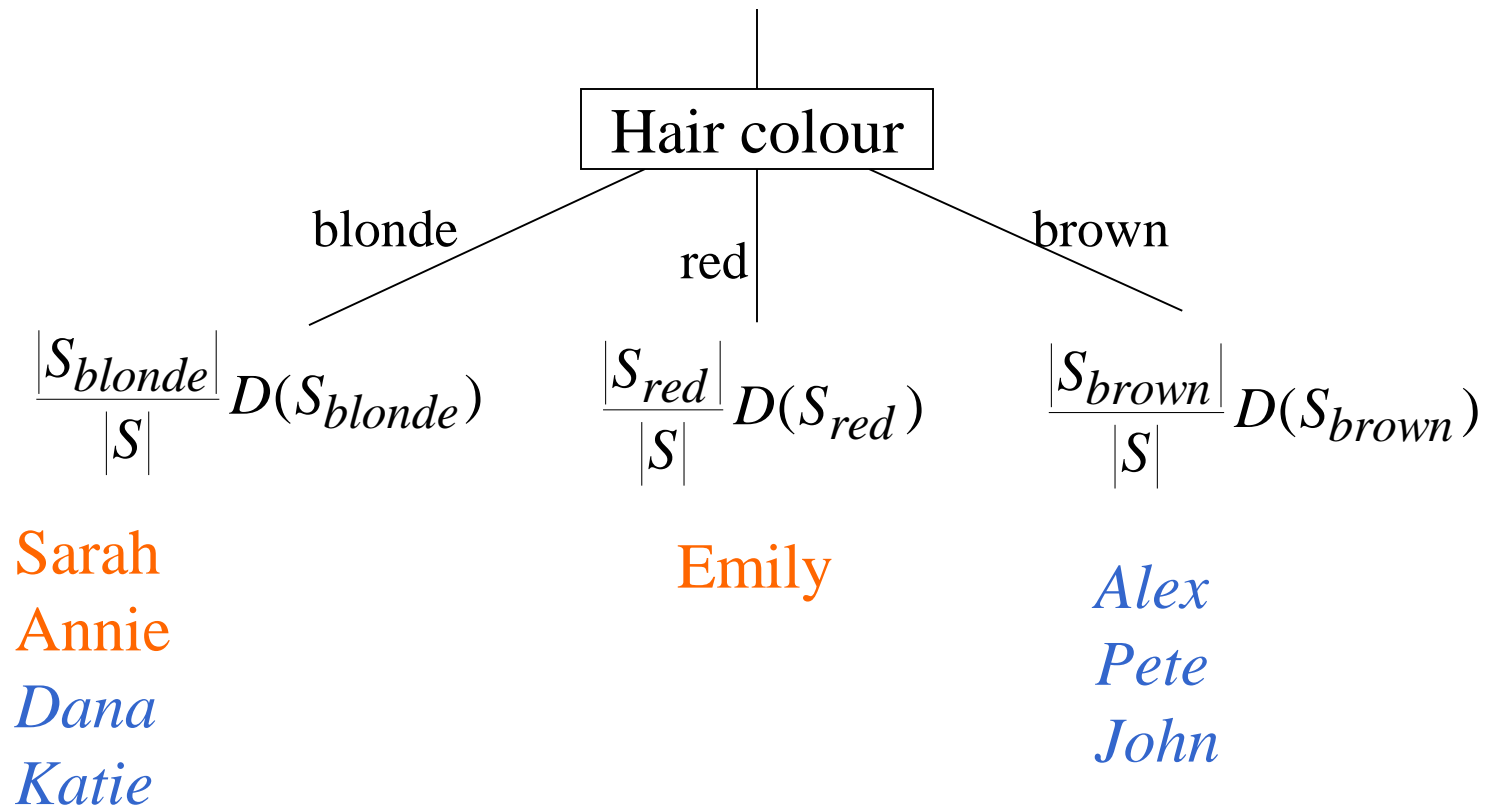
We want:

-large Gain

-same as: small avg
disorder created

the **average disorder** is just the weighted sum of the disorders in the branches (subsets) created by the values of A.

Back to the beach: calculate the Average Disorder associated with Hair Colour



...Calculating the Disorder of the “blondes”

The first term of the sum:

- $D(S_{blonde}) =$
 $D(\{ \text{“Sarah”}, \text{“Annie”}, \text{“Dana”}, \text{“Katie”} \}) = D(2,2)$
 $= 1$

$$\frac{|S_{blonde}|}{|S|} D(S_{blonde}) = \frac{|S_{blonde}|}{|S|} = \frac{4}{8} = 0.5$$

...Calculating the disorder of the others

The second and third terms of the sum:

- $S_{\text{red}} = \{ \text{“Emily”} \}$
- $S_{\text{brown}} = \{ \text{“Alex”}, \text{“Pete”}, \text{“John”} \}$.

These are both 0 because within each set
all the examples have the same class

So the avg disorder created when splitting
on ‘hair colour’ is $0.5+0+0=0.5$

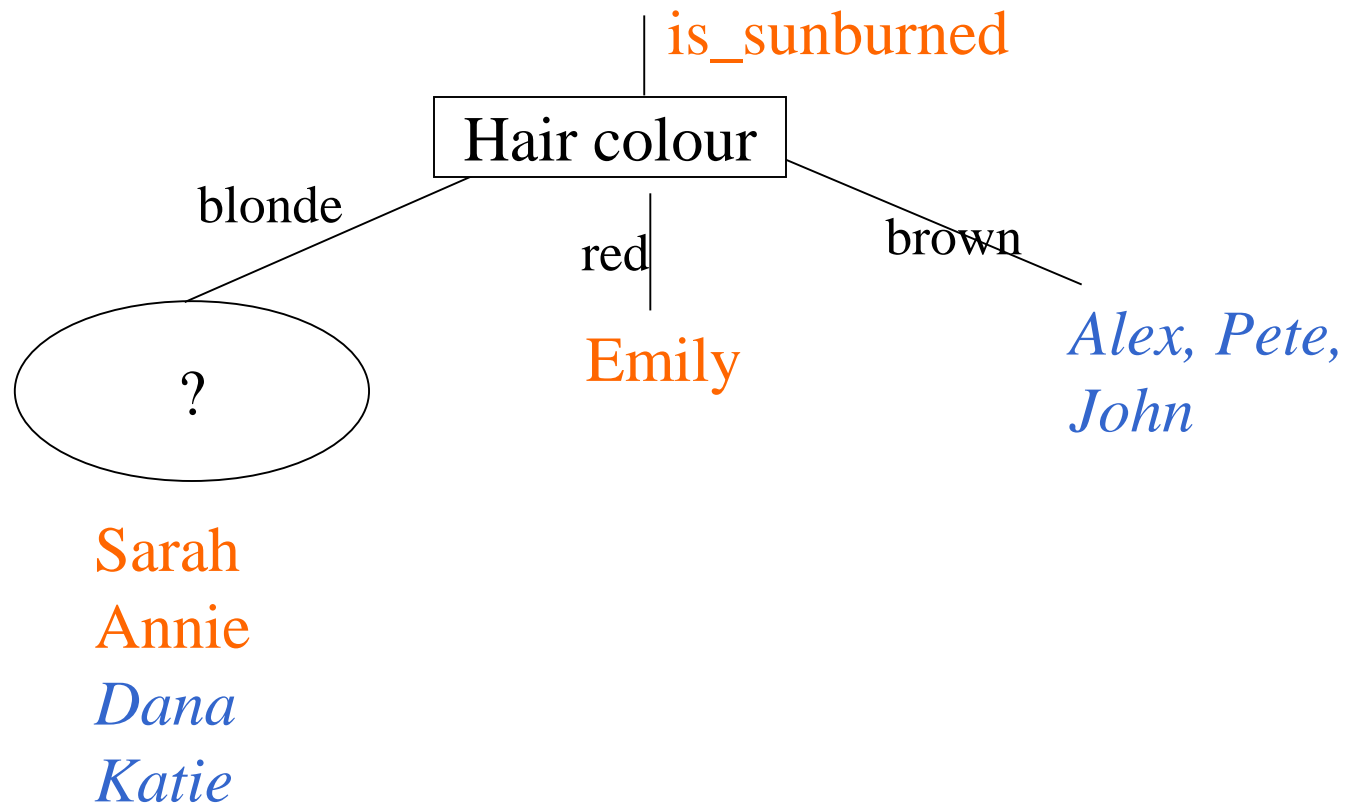
Which decision variable minimises the disorder?

Test	Disorder	
Hair	0.5	– this what we just computed
height	0.69	} these are the avg disorders of the other attributes, computed in the same way
weight	0.94	
lotion	0.61	

Which decision variable maximises the Info Gain then?

Remember it's the one which minimises the avg disorder (see slide 46 for memory refreshing).

So what is the best decision tree?



Outline

- Contingency tables
 - Census data set
- Information gain
 - Beach data set
- Learning an unpruned decision tree recursively
 - Good/bad gasoline usage = "miles per gallon" data set
- Training error
- Test error
- Overfitting
- Avoiding overfitting

Learning Decision Trees

- A Decision Tree is a tree-structured plan of a set of attributes to test in order to predict the output.
- To decide which attribute should be tested first, simply find the one with the highest information gain.
- Then recurse...

A small dataset: Miles Per Gallon

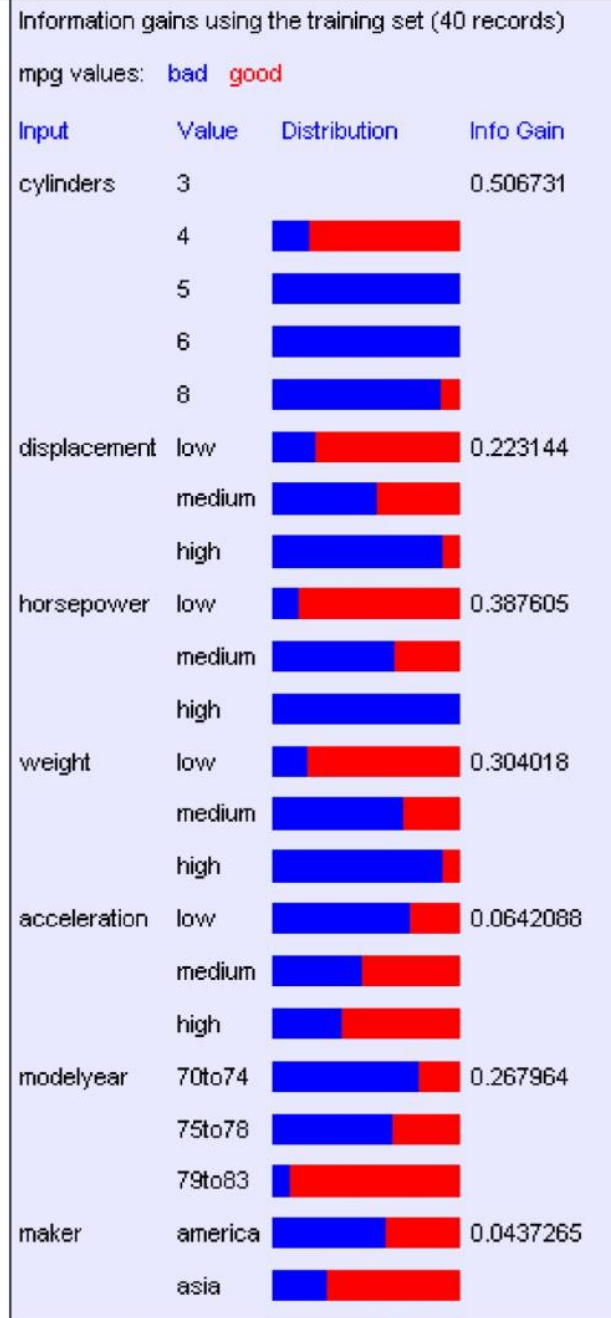
40
Records

mpg	cylinders	displacement	horsepower	weight	acceleration	modelyear	maker
good	4	low	low	low	high	75to78	asia
bad	6	medium	medium	medium	medium	70to74	america
bad	4	medium	medium	medium	low	75to78	europa
bad	8	high	high	high	low	70to74	america
bad	6	medium	medium	medium	medium	70to74	america
bad	4	low	medium	low	medium	70to74	asia
bad	4	low	medium	low	low	70to74	asia
bad	8	high	high	high	low	75to78	america
:	:	:	:	:	:	:	:
:	:	:	:	:	:	:	:
:	:	:	:	:	:	:	:
bad	8	high	high	high	low	70to74	america
good	8	high	medium	high	high	79to83	america
bad	8	high	high	high	low	75to78	america
good	4	low	low	low	low	79to83	america
bad	6	medium	medium	medium	high	75to78	america
good	4	medium	low	low	low	79to83	america
good	4	low	low	medium	high	79to83	america
bad	8	high	high	high	low	70to74	america
good	4	low	medium	low	medium	75to78	europa
bad	5	medium	medium	medium	medium	75to78	europa

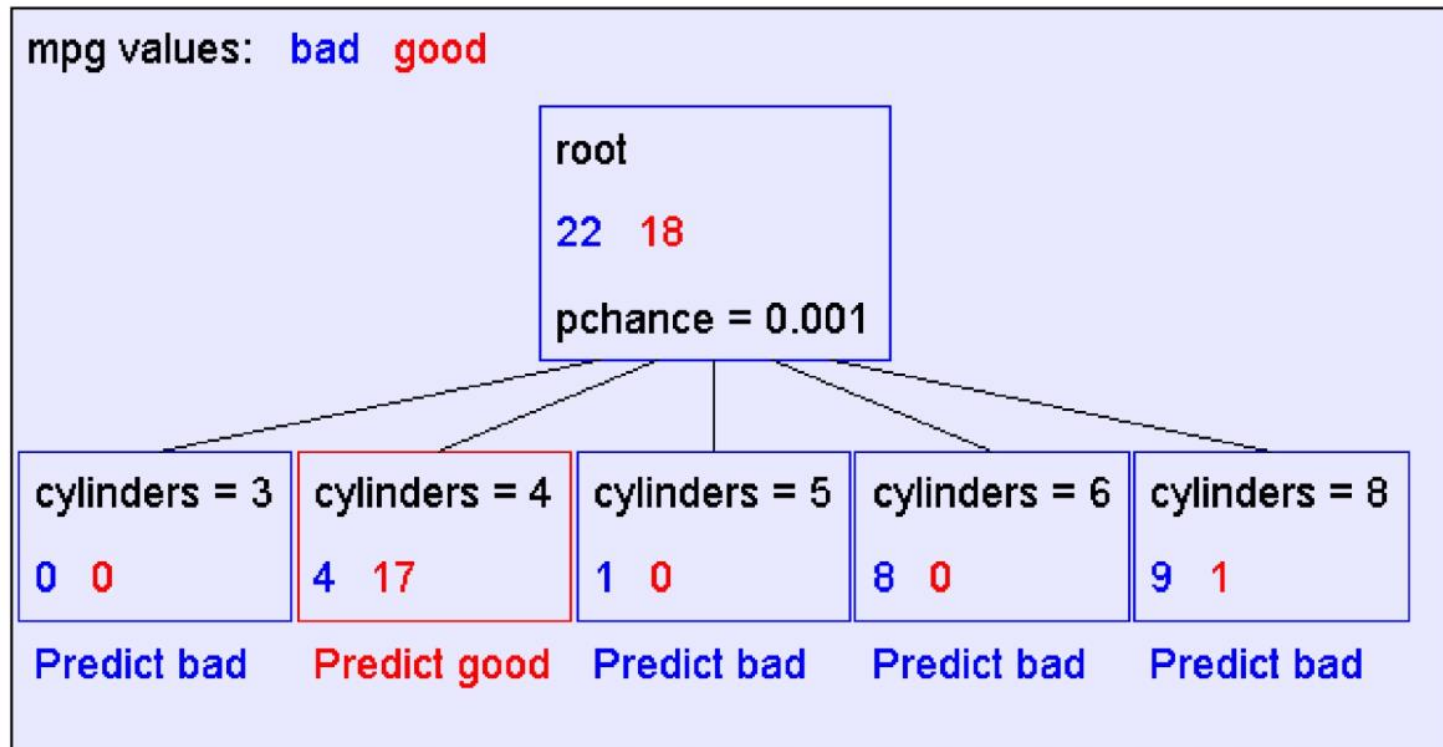
From the UCI repository (thanks to Ross Quinlan)

Suppose we want to predict MPG.

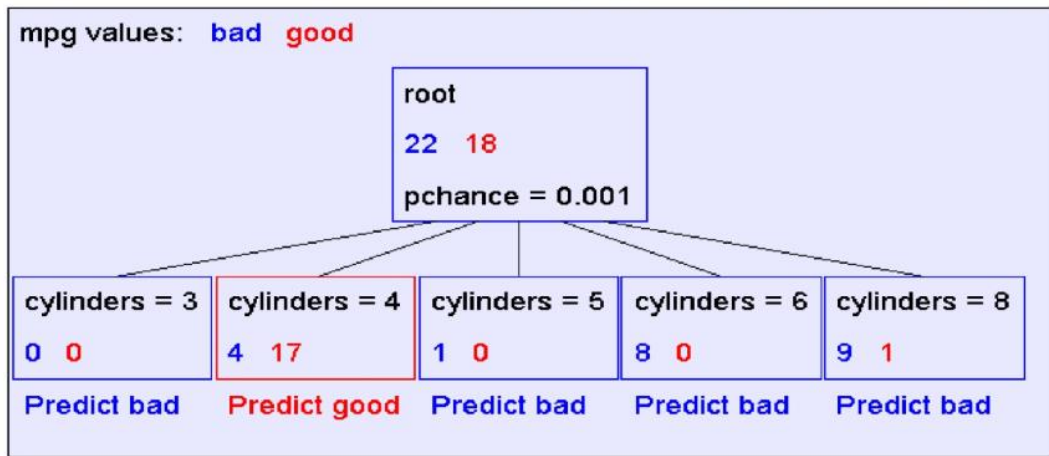
Look at all the information gains...



A Decision Stump



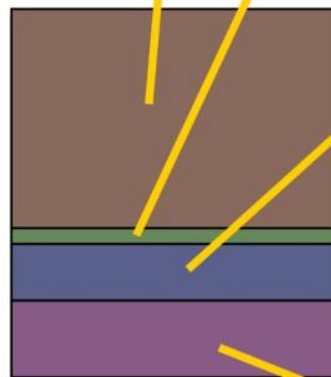
Recursion Step



Take the
Original
Dataset..



And partition it
according
to the value of
the attribute
we split on



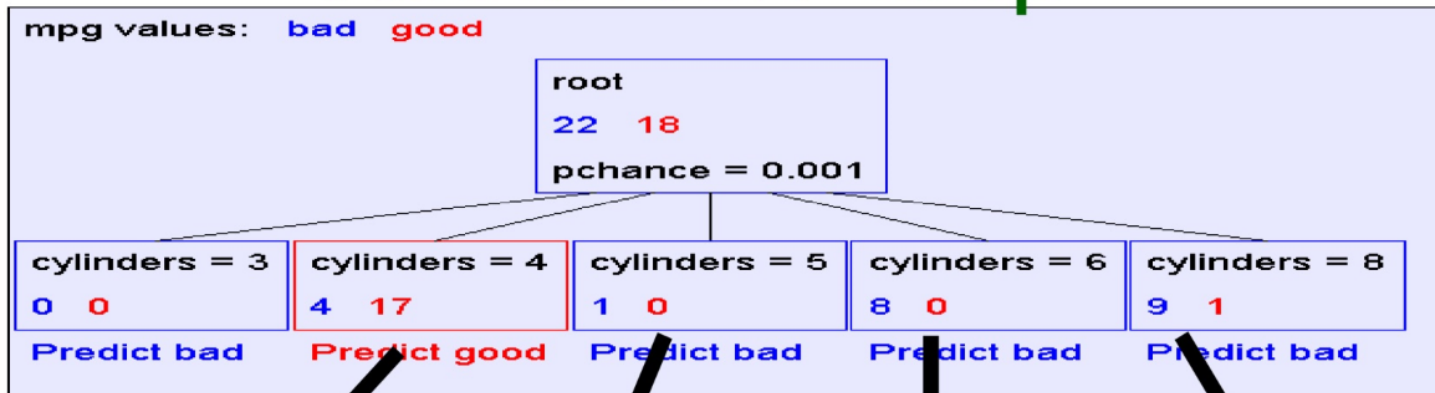
Records
in which
cylinders
= 4

Records
in which
cylinders
= 5

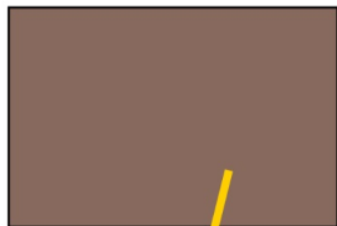
Records
in which
cylinders
= 6

Records
in which
cylinders
= 8

Recursion Step



Build tree from
These records..



Records in
which
cylinders = 4

Build tree from
These records..



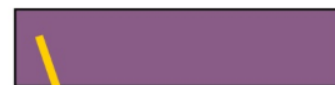
Records in
which
cylinders = 5

Build tree from
These records..



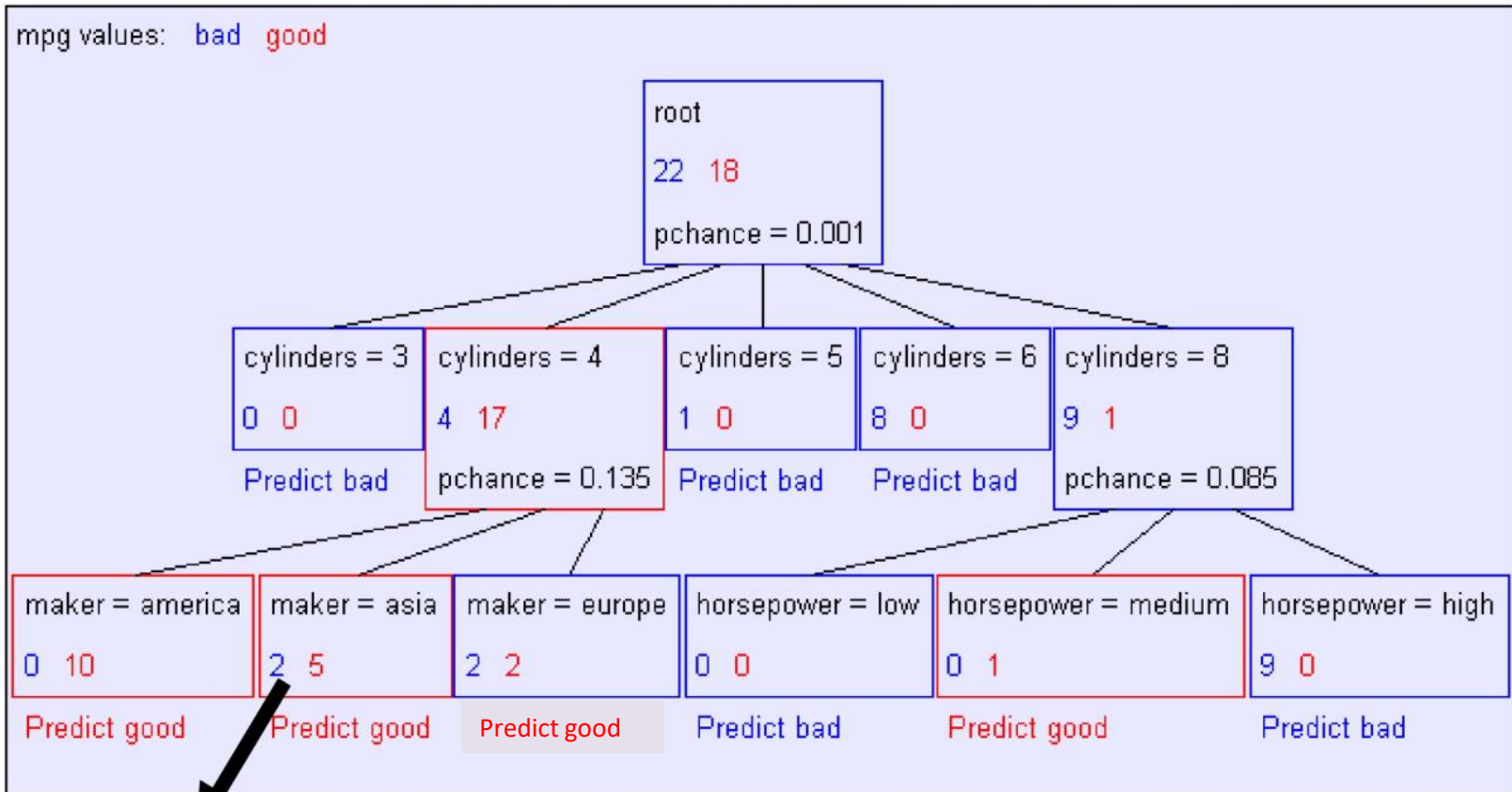
Records in
which
cylinders = 6

Build tree from
These records..



Records in
which
cylinders = 8

Second level of tree

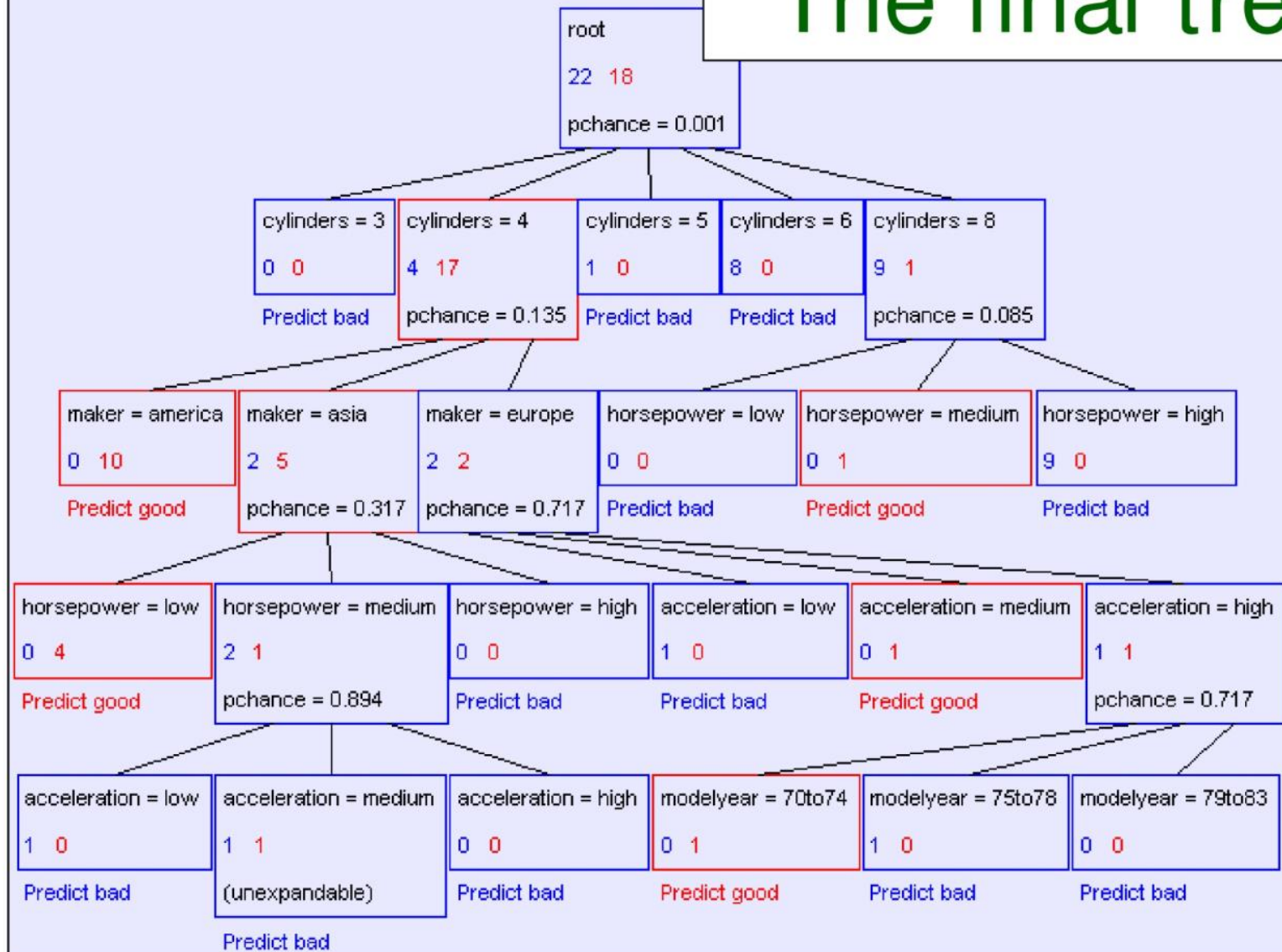


Recursively build a tree from the seven records in which there are four cylinders and the maker was based in Asia

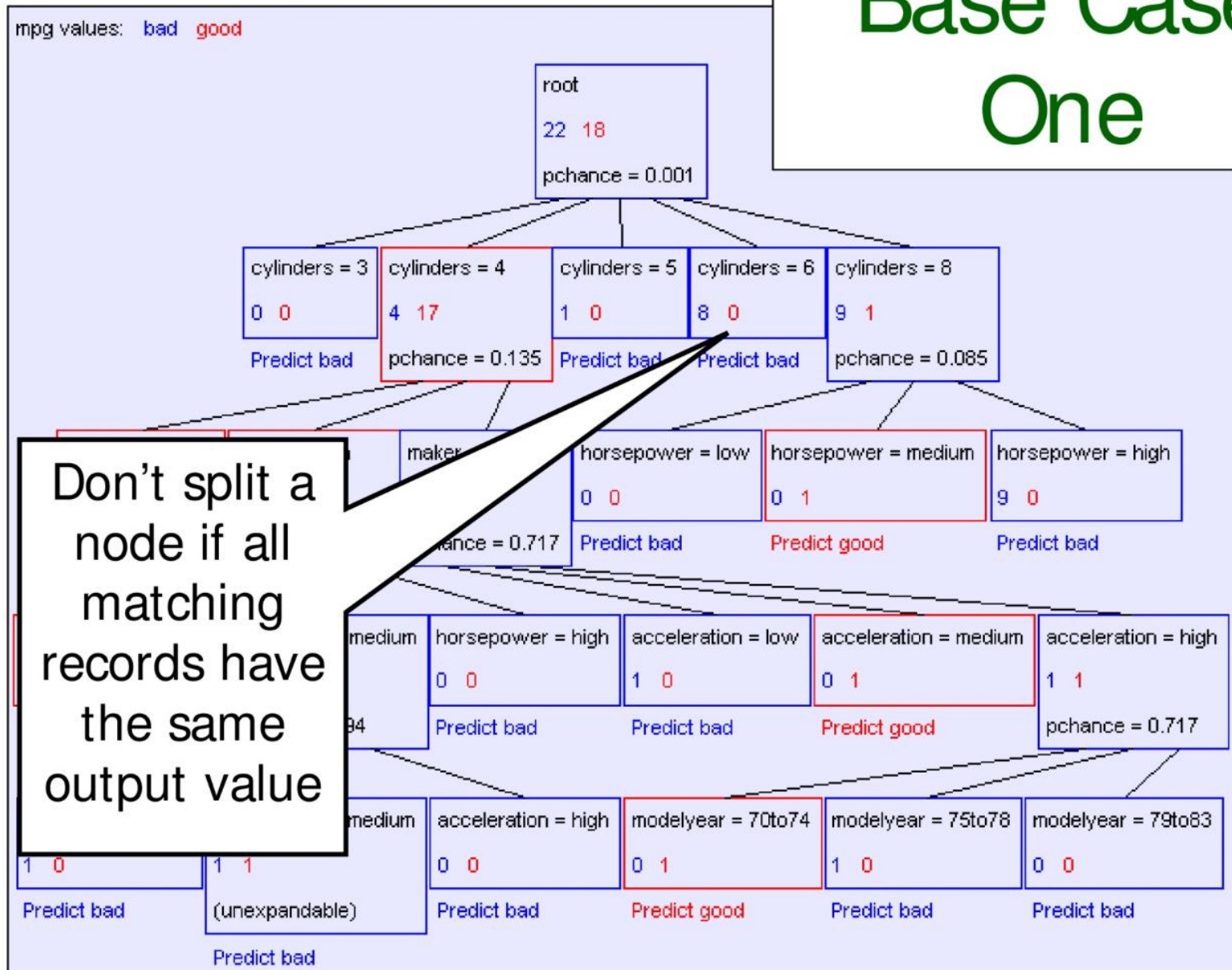
(Similar recursion in the other cases)

The final tree

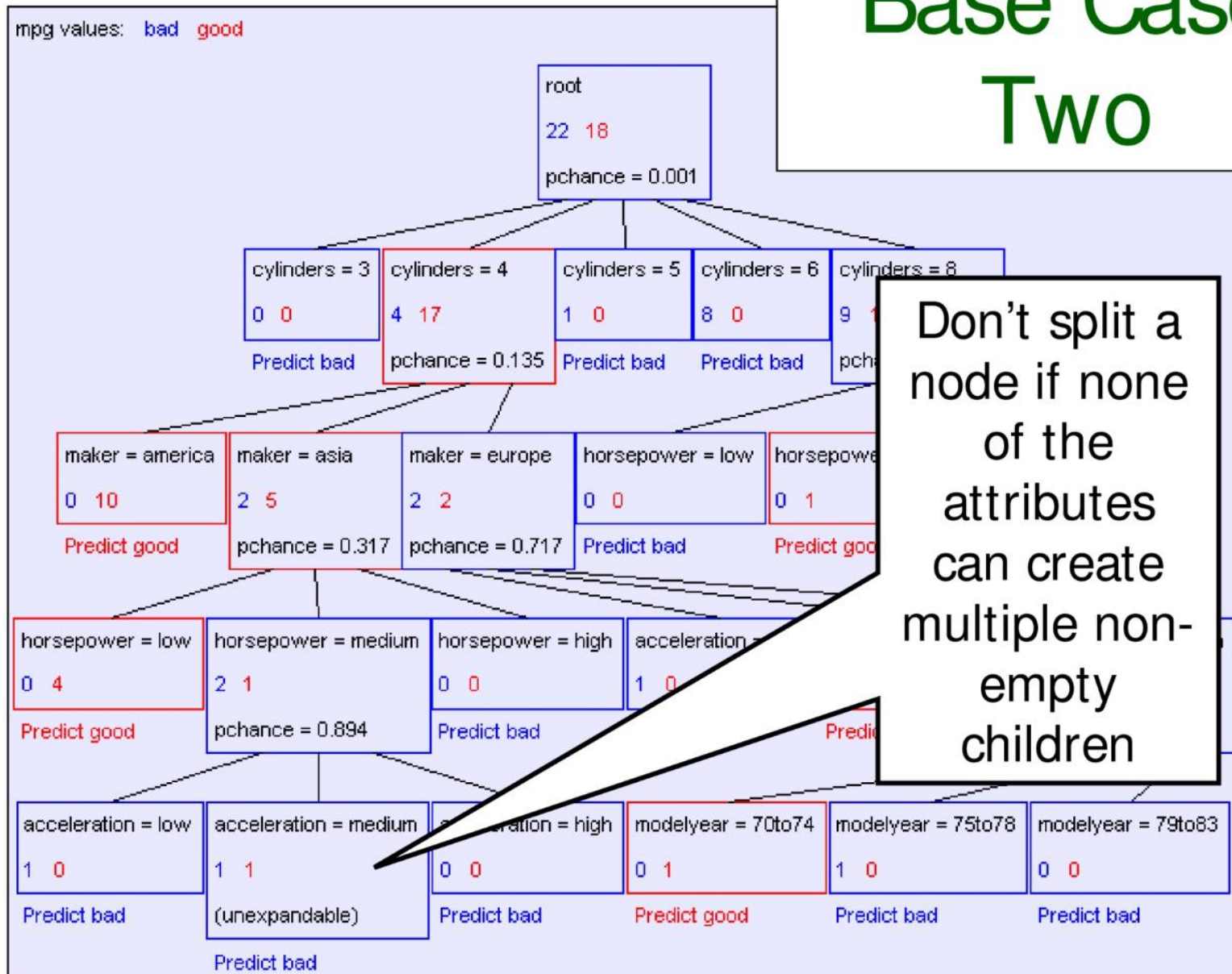
mpg values: bad good



Base Case One

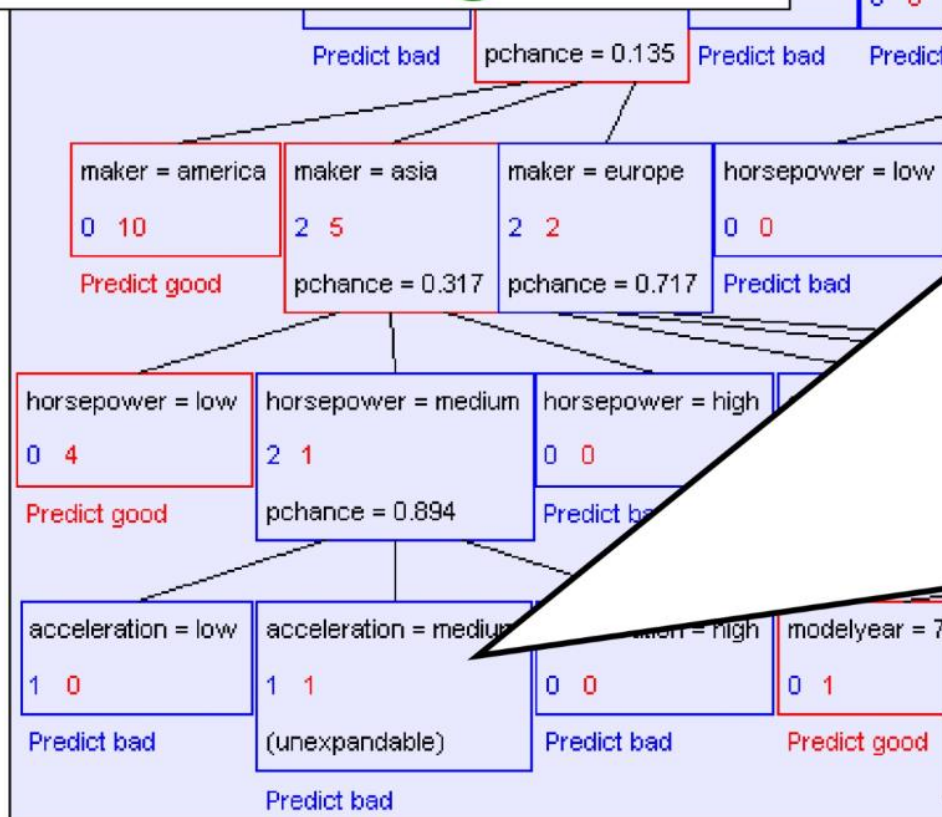


Base Case Two



Don't split a node if none of the attributes can create multiple non-empty children

Base Case Two: No attributes can distinguish



Information gains using the training set (2 records)

mpg values: bad good

Input	Value	Distribution	Info Gain
cylinders	3		0
	4		
	5		
	6		
displacement	low		0
	medium		
	high		
horsepower	low		0
	medium		
	high		
weight	low		0
	medium		
	high		
acceleration	low		0
	medium		
	high		
modelyear	70to74		0
	75to78		
	79to83		
maker	america		0
	asia		
	europe		

Base Cases

- Base Case One: If all records in current data subset have the same output then **don't recurse**
- Base Case Two: If all records have exactly the same set of input attributes then **don't recurse**

Basic Decision Tree Building

Summarized

BuildTree(*DataSet*, *Output*)

- If all output values are the same in *DataSet*, return a leaf node that says “predict this unique output”
- If all input values are the same, return a leaf node that says “predict the majority output”
- Else find attribute X with highest Info Gain
- Suppose X has n_X distinct values (i.e. X has arity n_X).
 - Create and return a non-leaf node with n_X children.
 - The i th child should be built by calling

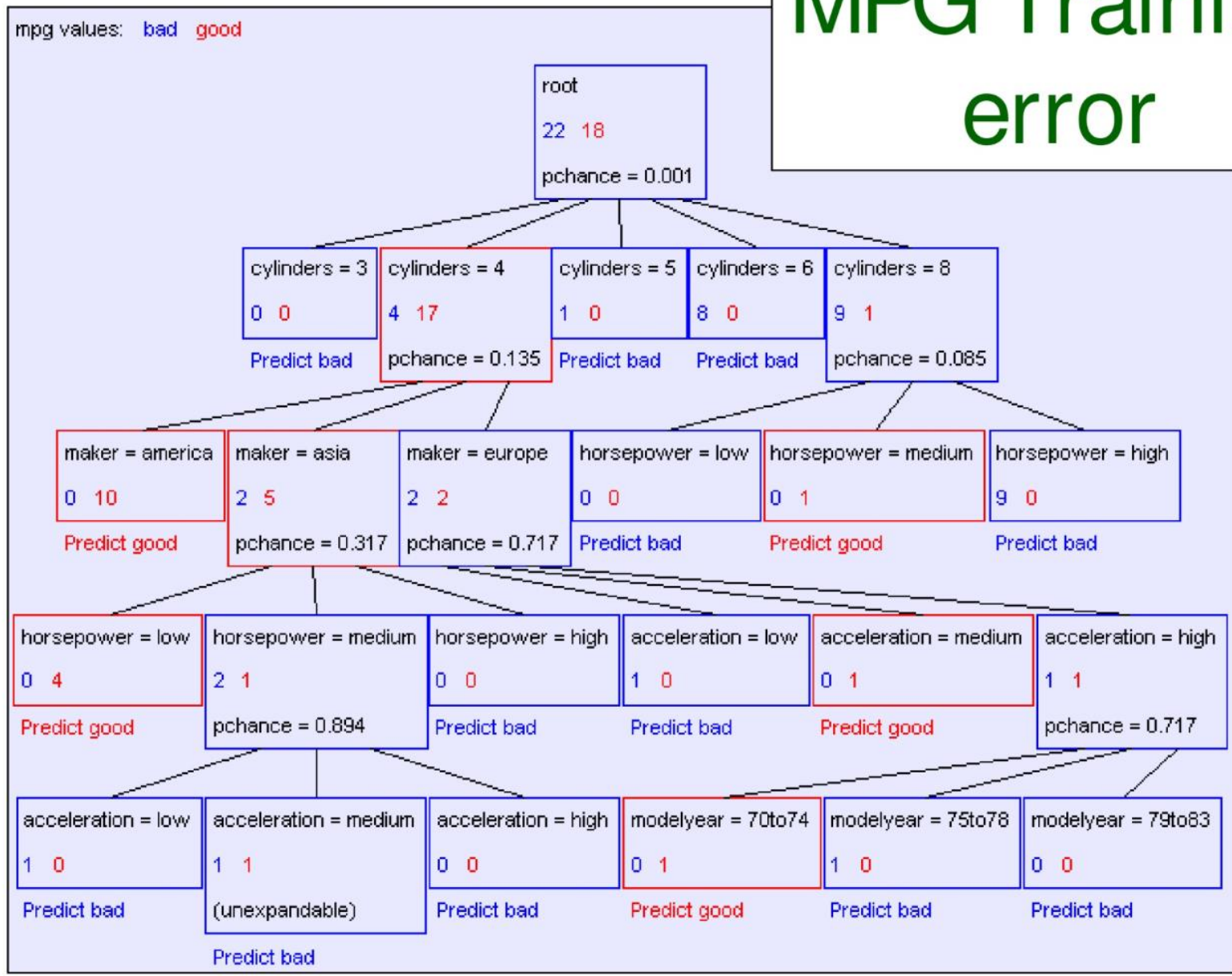
BuildTree(DS_i , *Output*)

Where DS_i built consists of all those records in *DataSet* for which $X = i$ th distinct value of X .

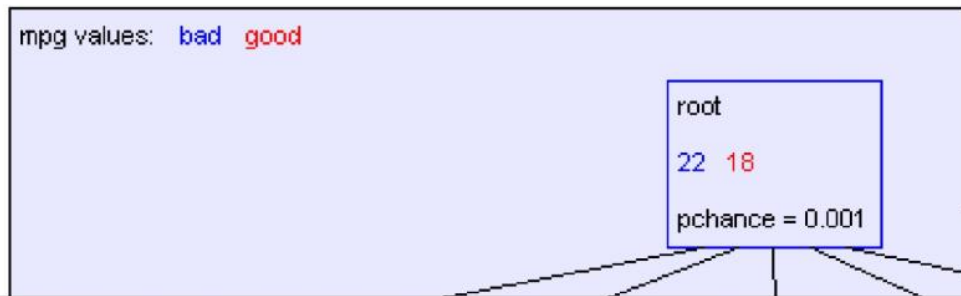
Training Set Error

- For each record, follow the decision tree to see what it would predict
For what number of records does the decision tree's prediction disagree with the true value in the database?
- This quantity is called the *training set error*. The smaller the better.

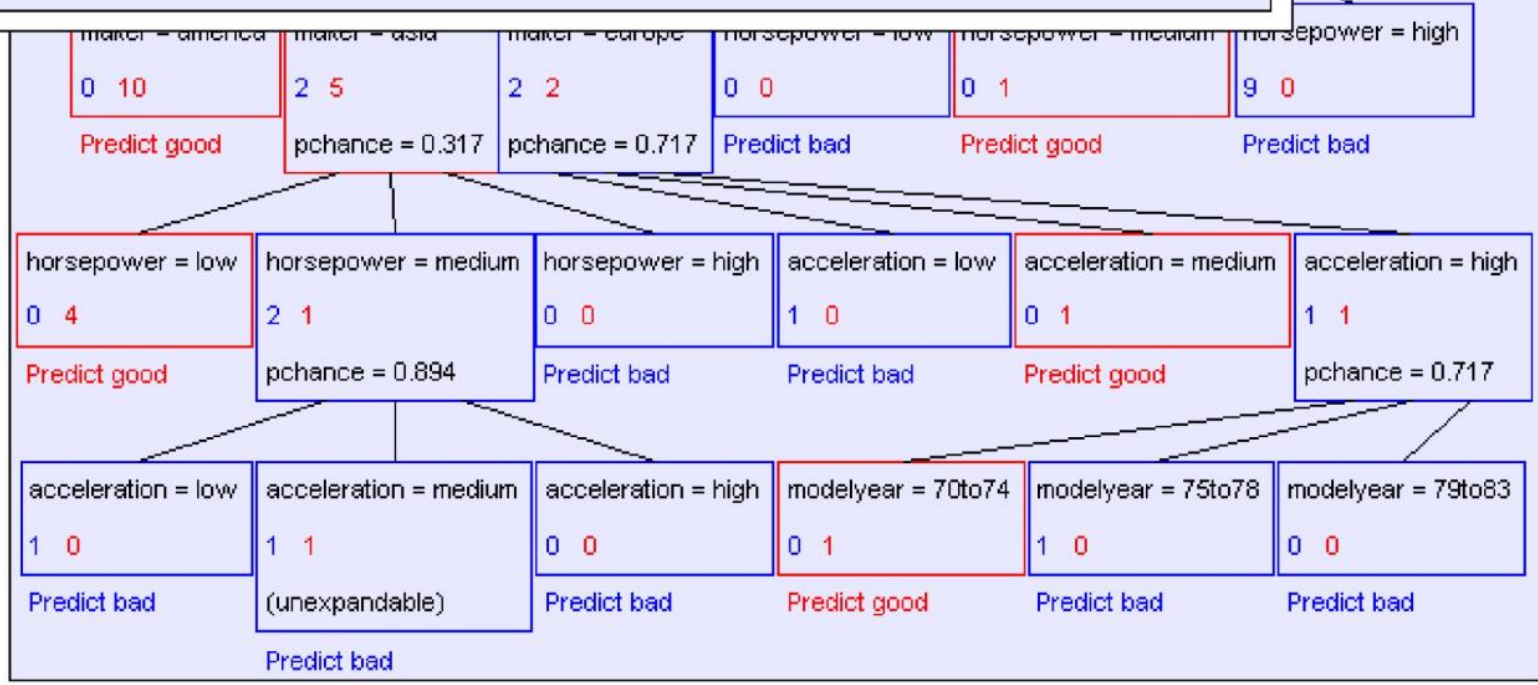
MPG Training error



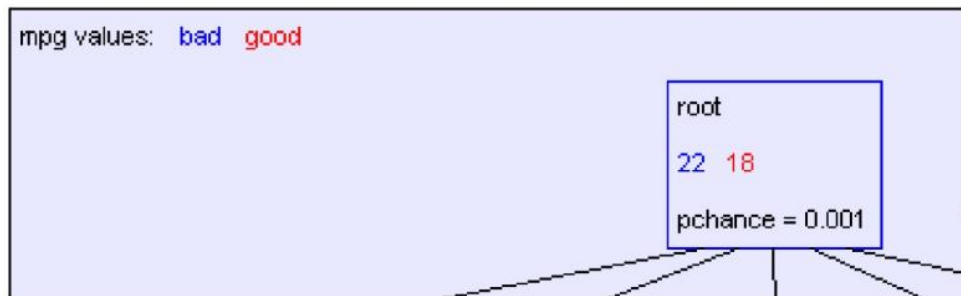
MPG Training error



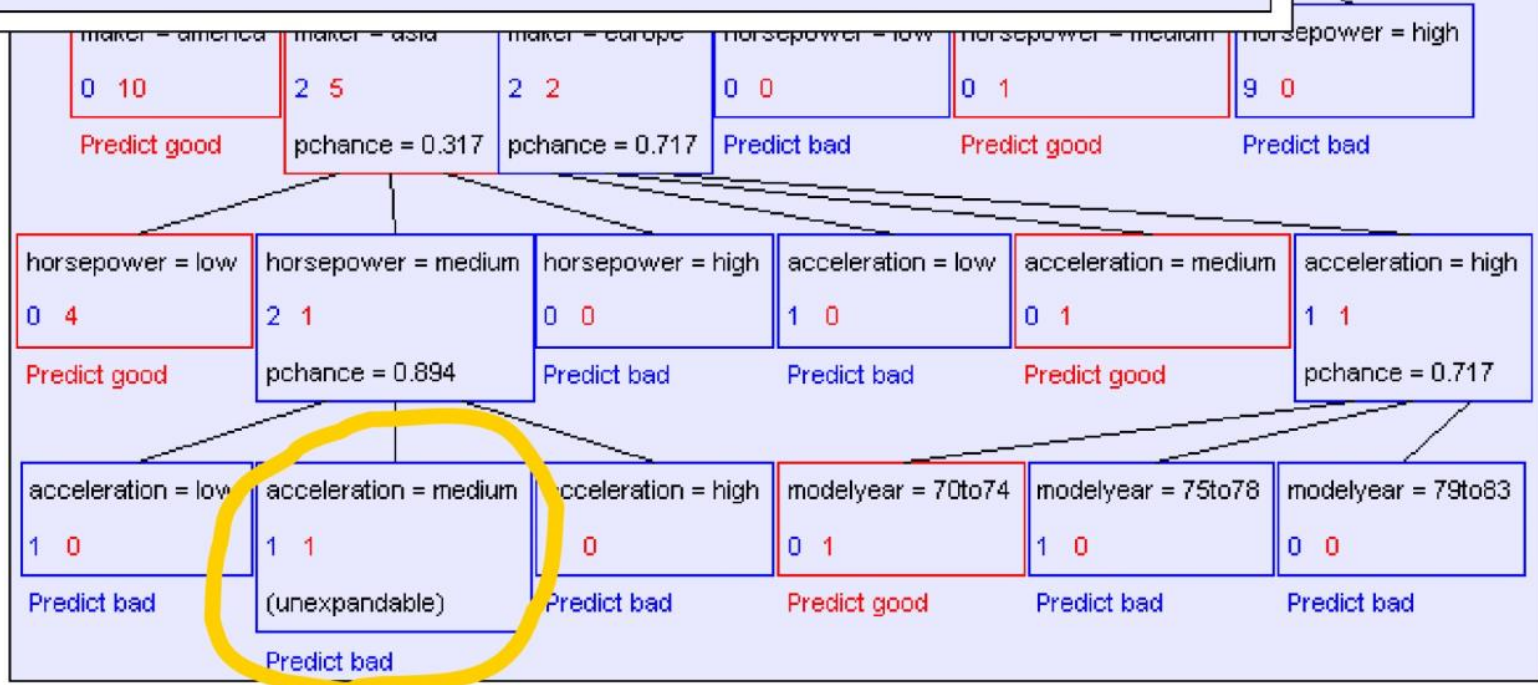
	Num Errors	Set Size	Percent Wrong
Training Set 1	1	40	2.50



MPG Training error



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Stop and reflect: Why are we doing this learning anyway?

- It is not usually in order to predict the training data's output on data we have already seen.

Stop and reflect: Why are we doing this learning anyway?

- It is not usually in order to predict the training data's output on data we have already seen.
- It is more commonly in order to predict the output value for **future data** we have not yet seen.

Test Set Error

- Suppose we are forward thinking.
- We hide some data away when we learn the decision tree.
- But once learned, we see how well the tree predicts that data.
- This is a good simulation of what happens when we try to predict future data.
- And it is called **Test Set Error**.

MPG Test set error

mpg values: bad good

root
22 18
pchance = 0.001

	Num Errors	Set Size	Percent Wrong
Training Set	1	40	2.50
Test Set	74	352	21.02

horsepower = high

predict bad

horsepower = low
0 4
Predict good

horsepower = medium
2 1
pchance = 0.894

horsepower = high
0 0
Predict bad

acceleration = low
1 0
Predict bad

acceleration = medium
0 1
Predict good

acceleration = high
1 1
pchance = 0.717

acceleration = low
1 0
Predict bad

acceleration = medium
1 1
(unexpandable)
Predict bad

acceleration = high
0 0
Predict bad

modelyear = 70to74
0 1
Predict good

modelyear = 75to78
1 0
Predict bad

modelyear = 79to83
0 0
Predict bad

Overfitting

- Definition: If your machine learning algorithm fits noise (i.e. pays attention to parts of the data that are irrelevant) it is **overfitting**.
- Fact (theoretical and empirical): If your machine learning algorithm is overfitting then it may perform less well on test set data.

How do I know I am overfitting?

- The best way is to have a held-out "development" test set to measure generalization performance on
 - This should be held separate from the final test set
- An interesting empirical fact about decision trees, is that larger trees tend to overfit more, so trying to create small trees is a good idea
 - It is easy to see that very small trees can't overfit
 - for instance, always choosing majority class is a very small tree
- People often talk about the depth of the tree (distance of the longest path from root to leaf) because of this

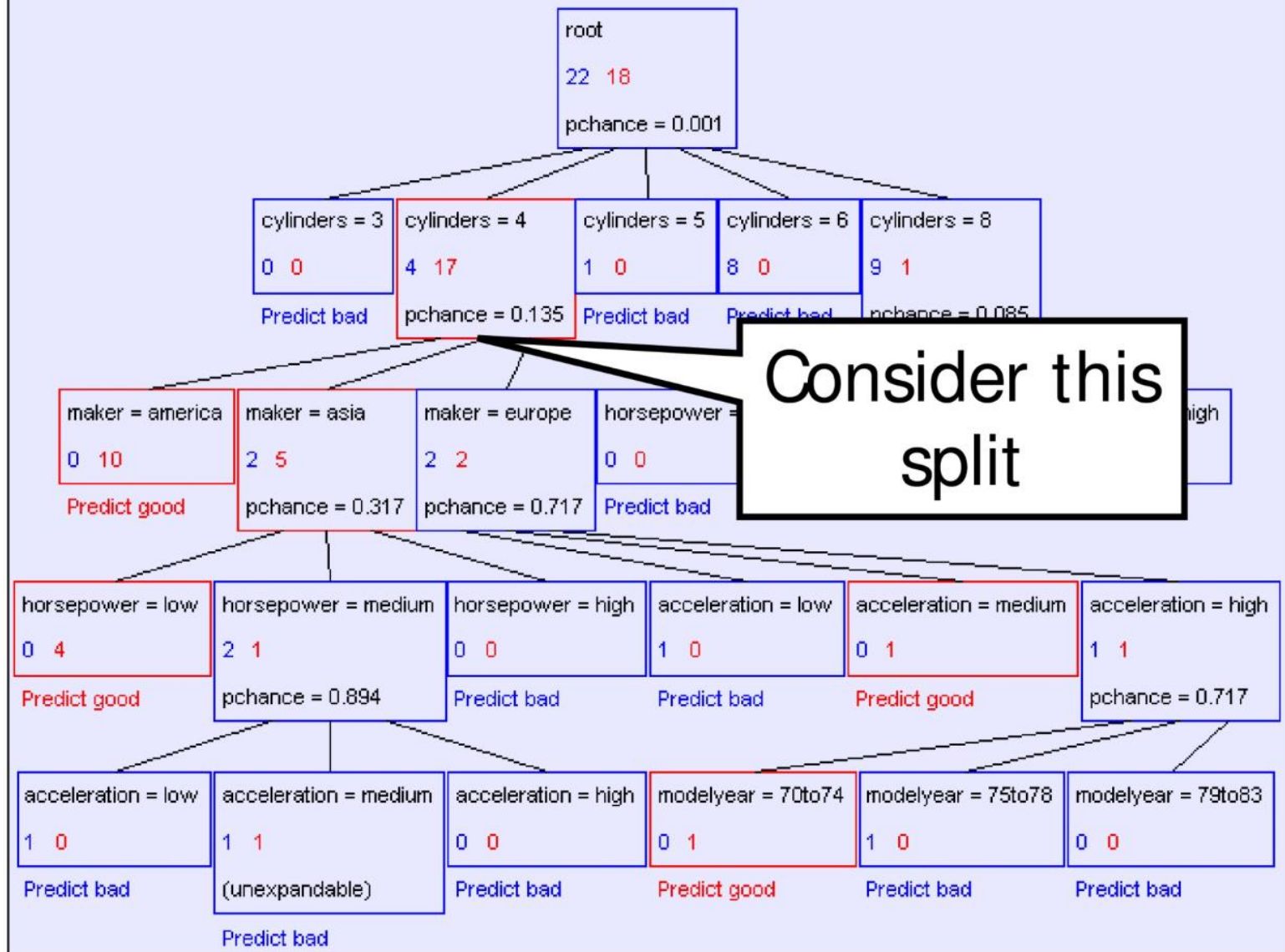
Avoiding overfitting

- Usually we do not know in advance which are the irrelevant variables
- ...and it may depend on the context

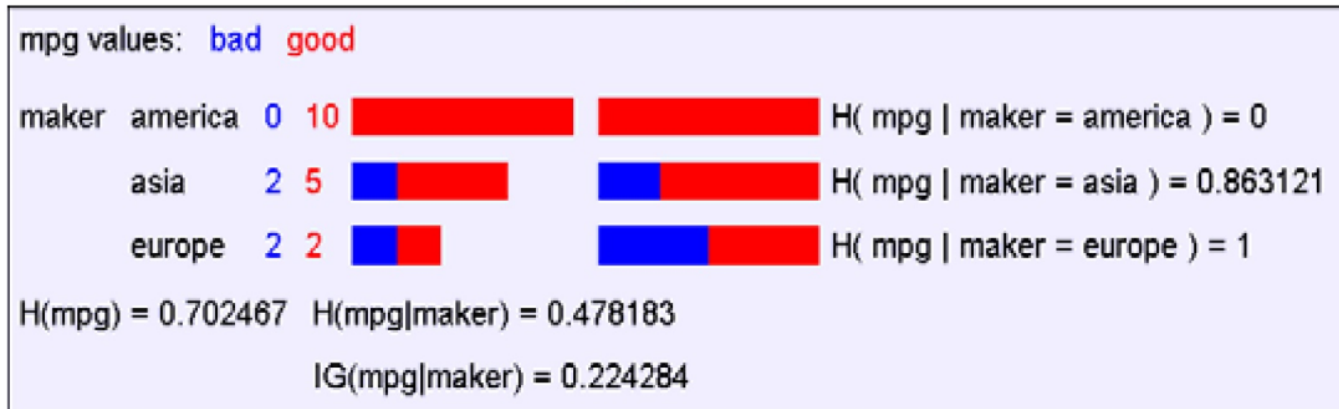
For example, if $y = a \text{ AND } b$ then b is an irrelevant variable only in the portion of the tree in which $a=0$

But we can use simple statistics to warn us that we might be overfitting.

mpg values: bad good

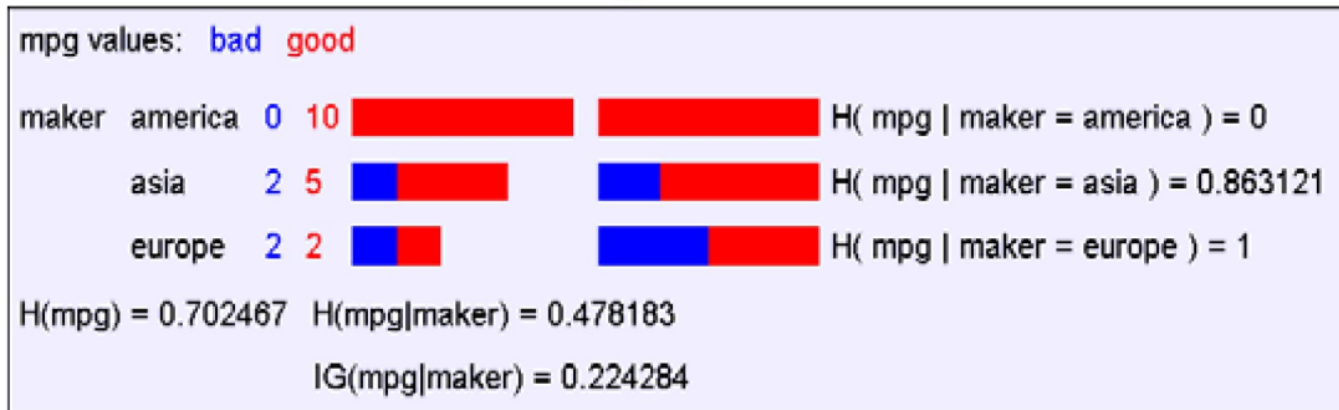


A chi-squared test



- Suppose that mpg was completely uncorrelated with maker.
- What is the chance we'd have seen data of at least this apparent level of association anyway?

A chi-squared test



- Suppose that mpg was completely uncorrelated with maker.
- What is the chance we'd have seen data of at least this apparent level of association anyway?

By using a particular kind of chi-squared test, the answer is 13.5%.

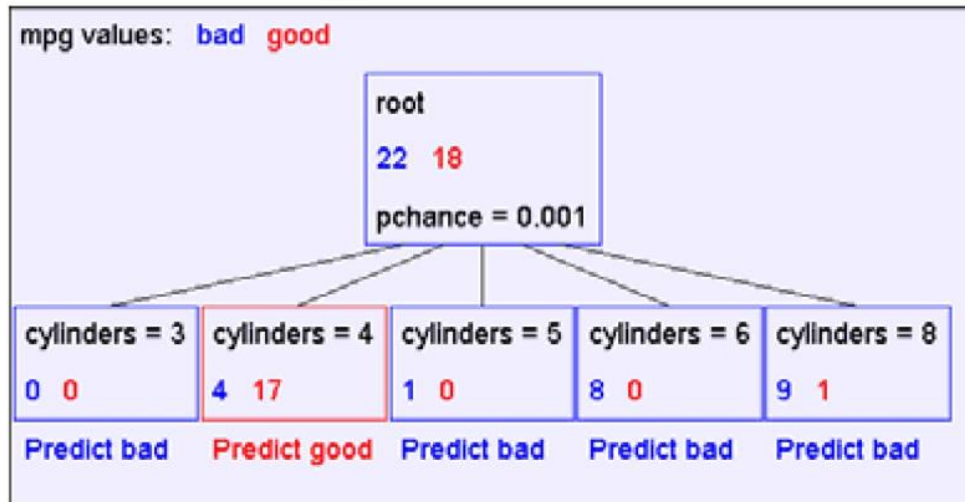
Using Chi-squared to avoid overfitting

- Build the full decision tree as before.
- But when you can grow it no more, start to prune:
 - Beginning at the bottom of the tree, delete splits in which $p_{chance} > MaxPchance$.
 - Continue working your way up until there are no more prunable nodes.

MaxPchance is a magic parameter you must specify to the decision tree, indicating your willingness to risk fitting noise.

Pruning example

- With $\text{MaxPchance} = 0.1$, you will see the following MPG decision tree:



Note the improved test set accuracy compared with the unpruned tree

	Num Errors	Set Size	Percent Wrong
Training Set	5	40	12.50
Test Set	56	352	15.91

More on pruning

- Another way to prune is to work with a special pruning set, which is separate from the data used to grow the tree
- This algorithm is called **Reduced Error Pruning**, and it is due to Quinlan
 - First grow the tree completely (as we did in our example)
 - Then, starting with each split at the bottom, classify the pruning set, compare:
 - 1) the accuracy of your current tree
 - 2) the accuracy of your current tree with this split removed (i.e., with the decision being the majority class before the split)
 - If (2) wins, then remove the split
 - Then move on to examine each node in the tree in turn, applying the same test
- This approach is very easy to understand, and can also be efficiently applied
- Big disadvantage: must separate data into data for growing tree, and data used to control pruning
- See Esposito et al. 1997 for an influential study of pruning techniques for decision trees

Conclusions

- Decision trees are the single most popular data mining tool
 - Easy to understand
 - Easy to implement
 - Easy to use
 - Computationally cheap
- It's possible to get in trouble with overfitting
- They do classification: predict a categorical output from categorical and/or real inputs

Things I didn't discuss - I

- How to deal with **real-valued inputs**
 - Either: discretize these into buckets before building a decision tree
 - As was done on the gasoline usage data set we just saw
 - Or: while building the decision tree, use less-than checks
 - E.g., try all of **age < 24** versus **age < 25** versus **age < 26** (etc...) and find the best split of the **age** variable (according to information gain)
 - But the details are complex and this requires many assumptions
- Information Gain can sometimes incorrectly favor splitting on **features which have many possible values**
 - There are alternative criteria that are sometimes preferred
 - There are also ways to correct Information Gain for this problem

Things I didn't discuss - II

- There are very interesting techniques for further improving on decision trees
 - One way is to build a "random forest" of decision trees on different subsets of the data and even different subsets of the features
 - Then have the trees in the forest vote on the final classification
 - This often works really well!
- Finally, there are also **very different solutions** that work well for classification like this
 - For instance, consider Naive Bayes or **linear models** in general
 - Linear models associate one weight with each feature value as we saw in the previous lecture
 - The same basic ideas about generalization and overfitting apply!
 - We'll discuss these in detail in the next lecture
 - Following that, we'll discuss deep learning (non-linear models)

- Some credits:
 - See Ata Kaban's (Birmingham) machine learning class particularly for the intuitive discussion of the Winston sunburn problem and Information Gain
 - See Andrew W. Moore's (Carnegie Mellon) website for a longer presentation of his slides on decision trees, and slides on many other machine learning topics:
<http://www.autonlab.org/tutorials>

- Thank you for your attention!