Information Extraction

Lecture 5 – Decision Trees (Basic Machine Learning)

CIS, LMU München
Winter Semester 2021-2022

Prof. Dr. Alexander Fraser, CIS

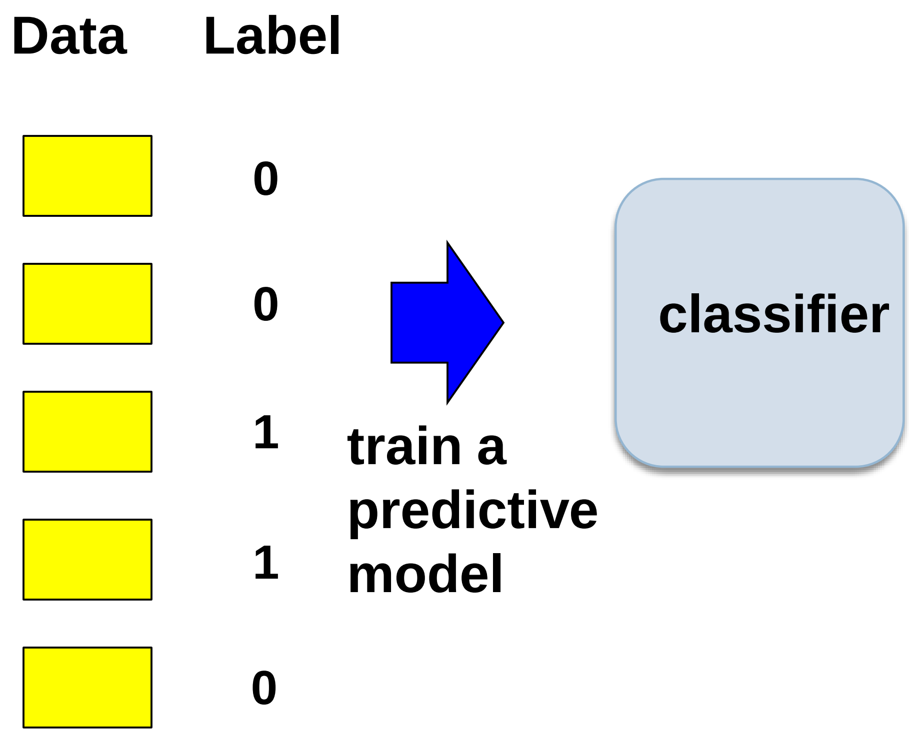
Lecture Today

- 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

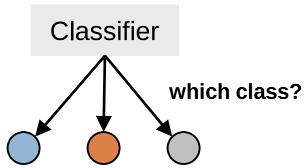


Slide from Kauchak

Lots of possible techniques

Classify Candidates

<u>Abraham Lincoln</u> was born in <u>Kentucky</u>.



Sliding Window

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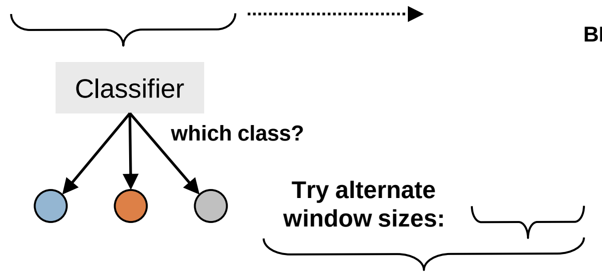
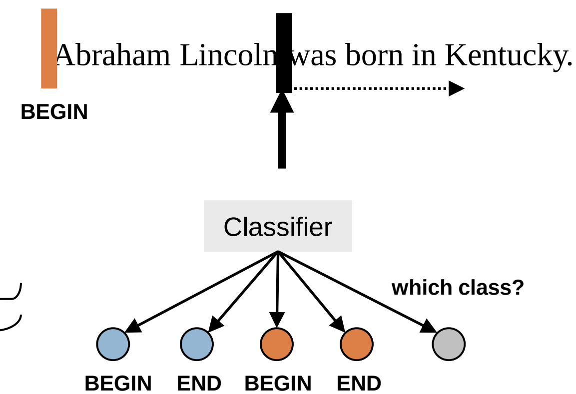


Boundary Models



Finite State Machines

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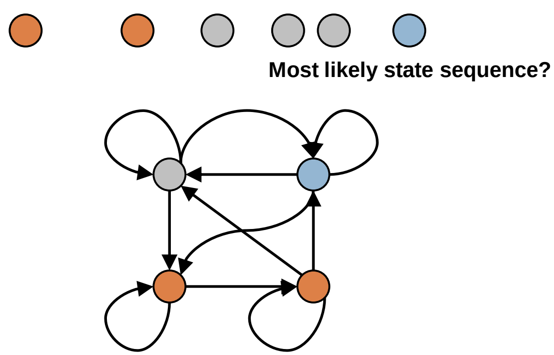
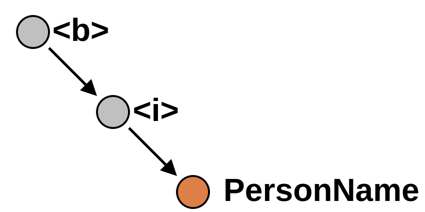


Wrapper Induction

<i>***Abraham Lincoln***</i> was born in Kentucky.

Learn and apply pattern for a website



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

Slide from Kauchak

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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$\underbrace{w_{t-m} \quad \cdots \quad w_{t-1}}_{\text{prefix}} \quad \underbrace{w_{t} \quad \cdots \quad w_{t+n}}_{\text{contents}} \quad \underbrace{w_{t+n+1} \quad \cdots \quad w_{t+n+m}}_{\text{suffix}}$

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

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$\underbrace{w_{t-m} \quad \ldots \quad w_{t-1}}_{\text{prefix}} \quad \underbrace{w_{t} \quad \ldots \quad w_{t+n}}_{\text{contents}} \quad \underbrace{w_{t+n+1} \quad \ldots \quad w_{t+n+m}}_{\text{suffix}}$

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

Slide from Kauchak

IE by Boundary Detection

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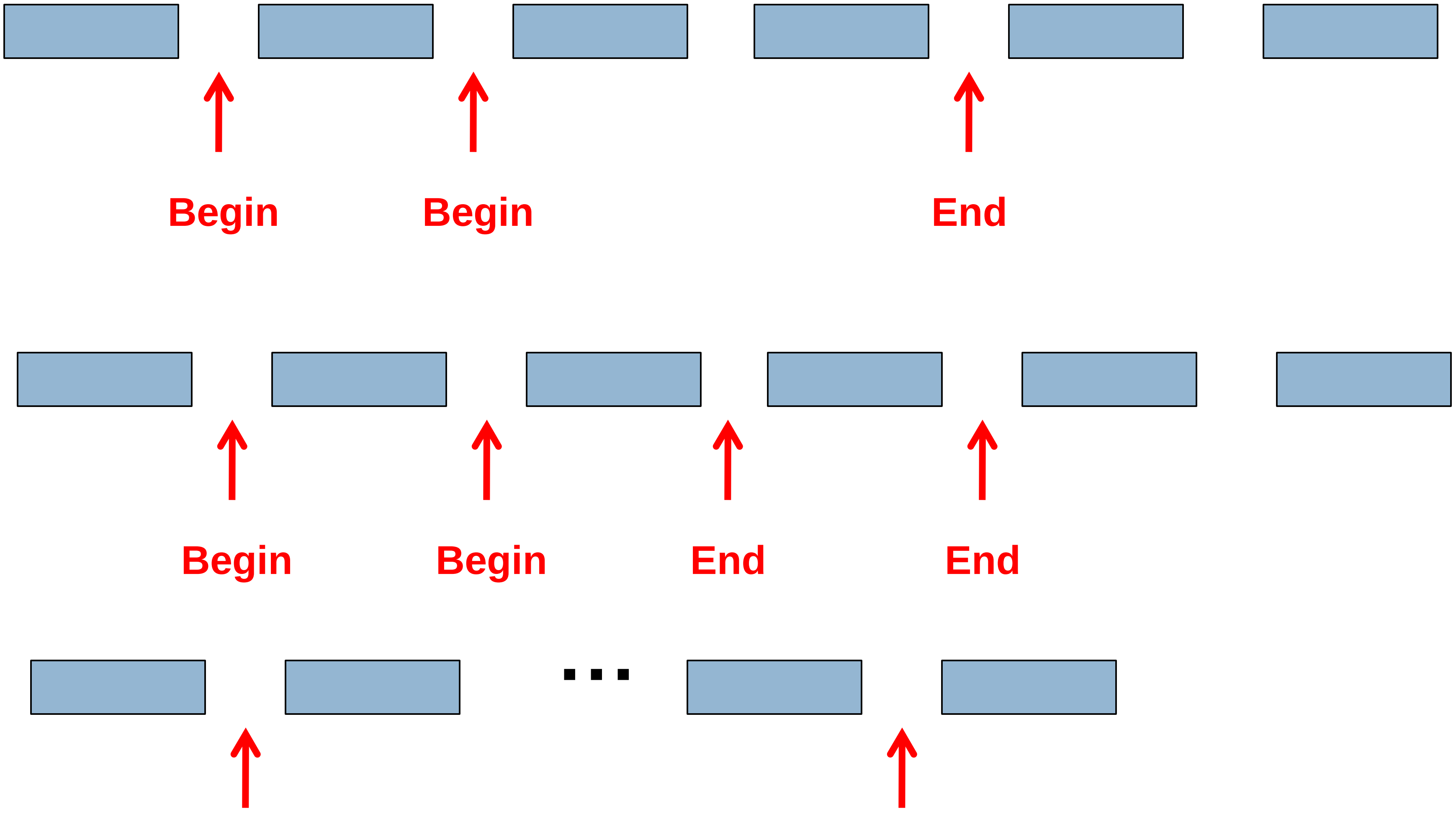
Slide from Kauchak

Some concerns



Slide from Kauchak

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.

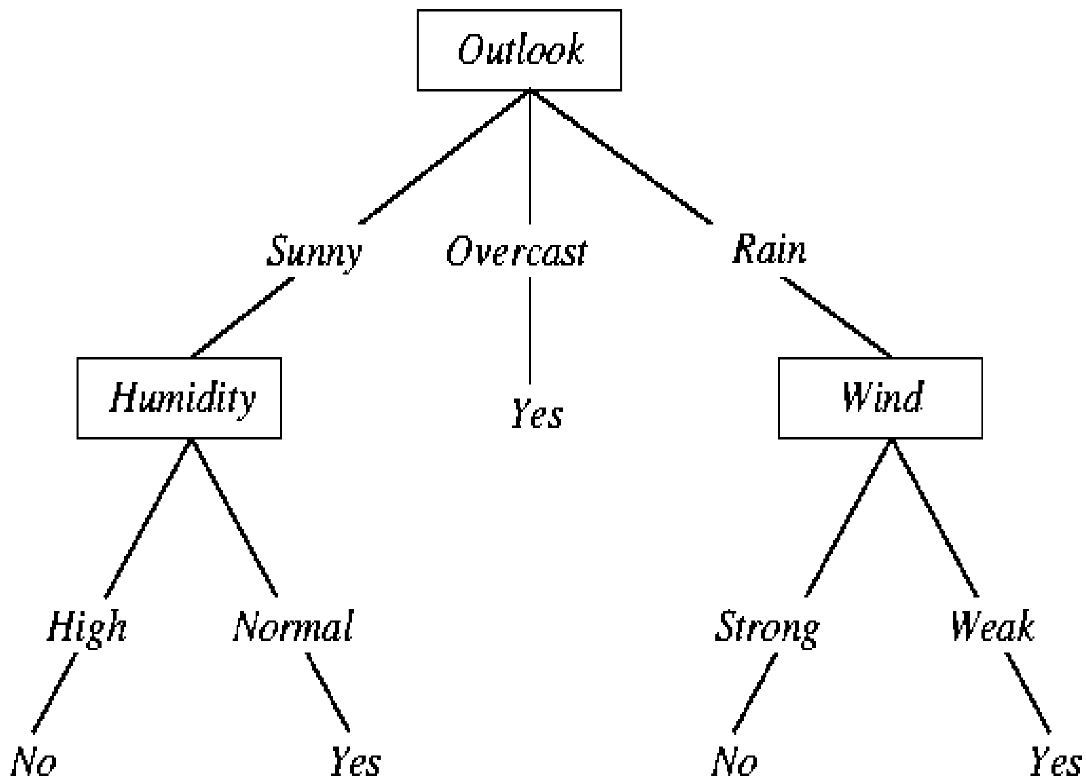
  - In a Boundary-Finding system, left boundaries are laid down independently from right boundaries

Slide from Kauchak

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

Slide from A. Kaban

When is it useful?

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

Slide from A. Kaban

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	employme	education	edun	marital	...	job	relation	race	gender	hour	country	wealth
					...							
39	State_gov	Bachelors	13	Never_mar	...	Adm_cleric	Not_in_fam	White	Male	40	United_Sta	poor
51	Self_emp_	Bachelors	13	Married	...	Exec_man	Husband	White	Male	13	United_Sta	poor
39	Private	HS_grad	9	Divorced	...	Handlers_c	Not_in_fam	White	Male	40	United_Sta	poor
54	Private	11th	7	Married	...	Handlers_c	Husband	Black	Male	40	United_Sta	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_Sta	poor
50	Private	9th	5	Married_sp	...	Other_serv	Not_in_fam	Black	Female	16	Jamaica	poor
52	Self_emp_	HS_grad	9	Married	...	Exec_man	Husband	White	Male	45	United_Sta	rich
31	Private	Masters	14	Never_mar	...	Prof_speci	Not_in_fam	White	Female	50	United_Sta	rich
42	Private	Bachelors	13	Married	...	Exec_man	Husband	White	Male	40	United_Sta	rich
37	Private	Some_coll	10	Married	...	Exec_man	Husband	Black	Male	80	United_Sta	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_Sta	poor
33	Private	Assoc_acc	12	Never_mar	...	Sales	Not_in_fam	Black	Male	50	United_Sta	poor
41	Private	Assoc_voc	11	Married	...	Craft_repai	Husband	Asian	Male	40	*MissingVa	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_Sta	poor
33	Private	HS_grad	9	Never_mar	...	Machine_o	Unmarried	White	Male	40	United_Sta	poor
38	Private	11th	7	Married	...	Sales	Husband	White	Male	50	United_Sta	poor
44	Self_emp_	Masters	14	Divorced	...	Exec_man	Unmarried	White	Female	45	United_Sta	rich
41	Private	Doctorate	16	Married	...	Prof_speci	Husband	White	Male	60	United_Sta	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…

Gender

Value	Frequency
Female	16192
Male	32650

Marital Status

Value	Frequency
Divorced	6633
Married_AF_spouse	37
Married	22379
Married_spouse_absent	628
Never_married	16117
Separated	1530
Widowed	1518

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

		poor	rich
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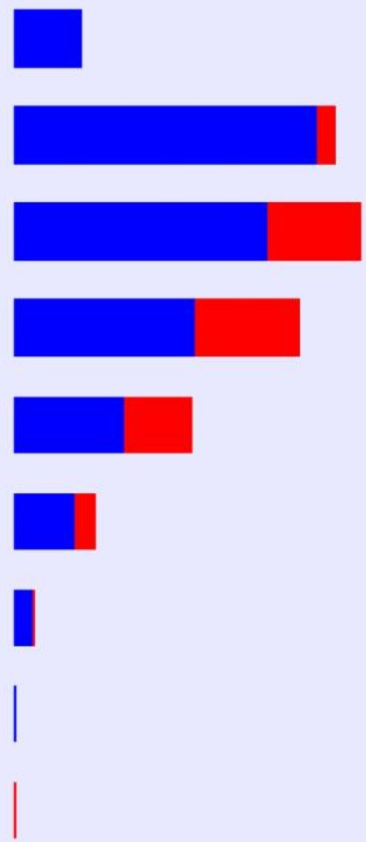

- Easier to appreciate graphically

A 2-d Contingency Table

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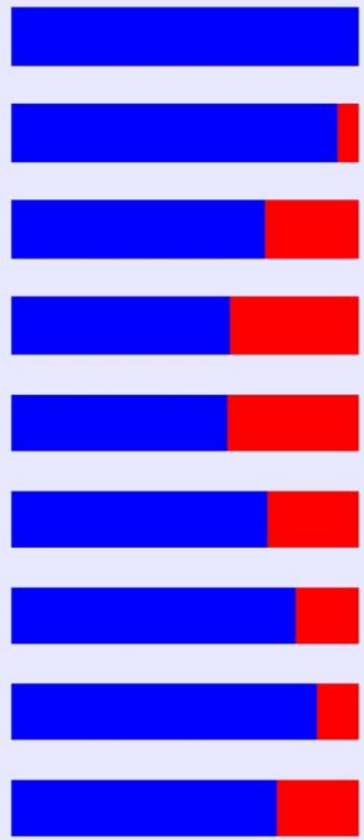


- Easier to see "interesting" things if we stretch out the histogram bars

Using this idea for classification

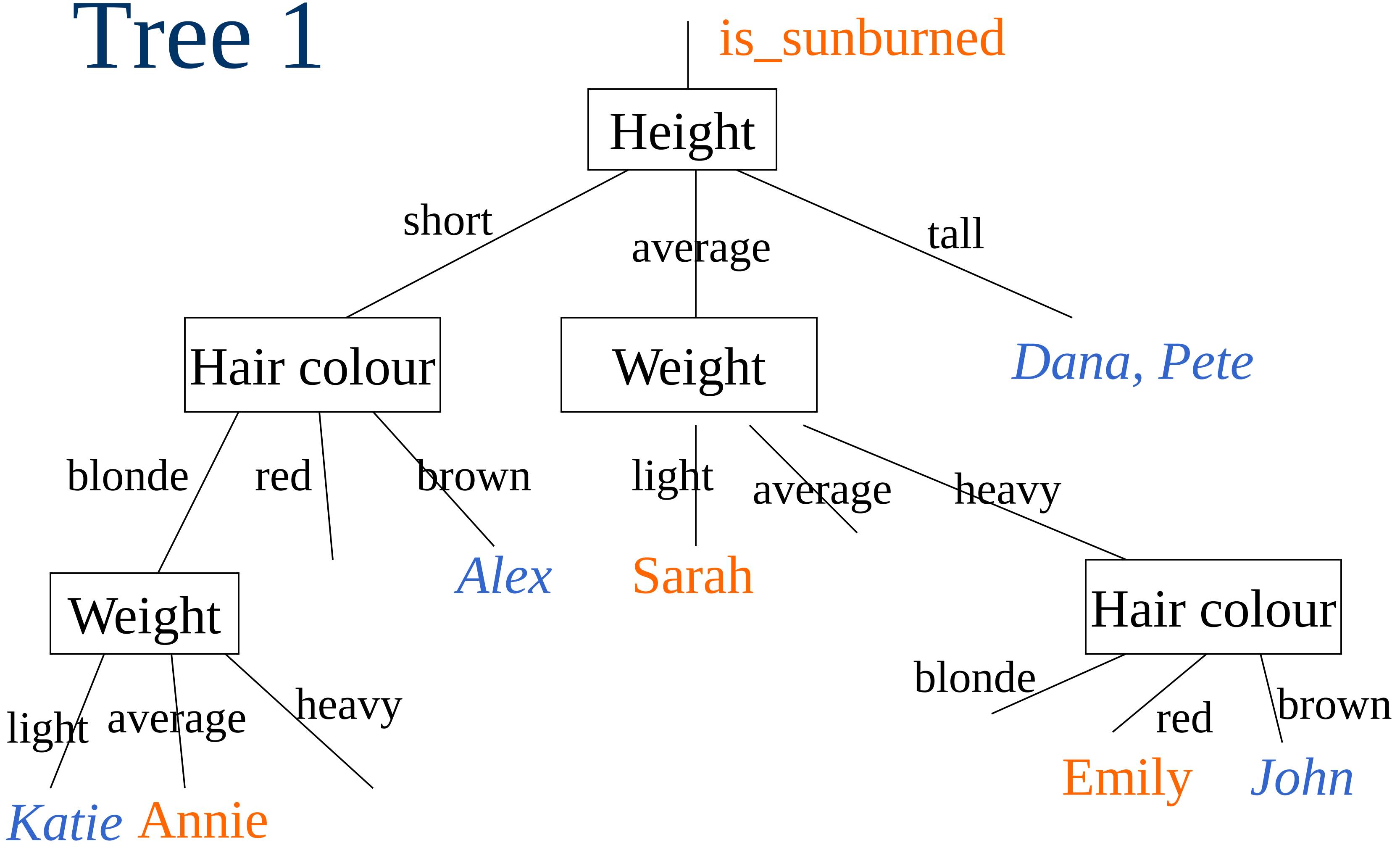
- We will now look at a (toy) dataset presented in Winston's Artificial Intelligence textbook
- It is often used when explaining decision trees
- The variable we are trying to pick is "got_a_sunburn" (or "is_sunburned" if you like)
- We will look at different decision trees that can be used to correctly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

Sunburn Data Collected

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

Slide from A. Kaban

Decision Tree 1



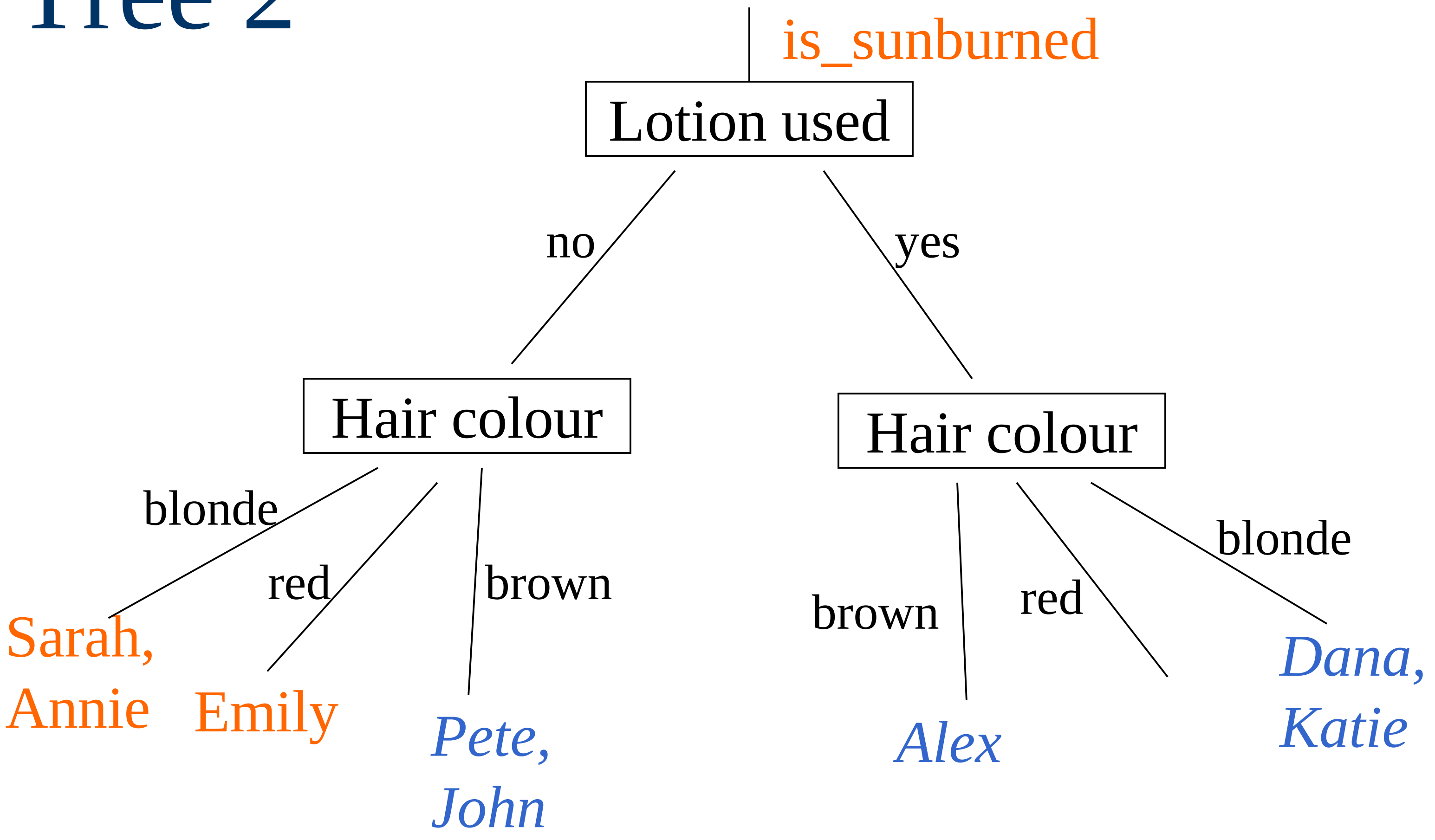
Slide from A. Kaban

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*

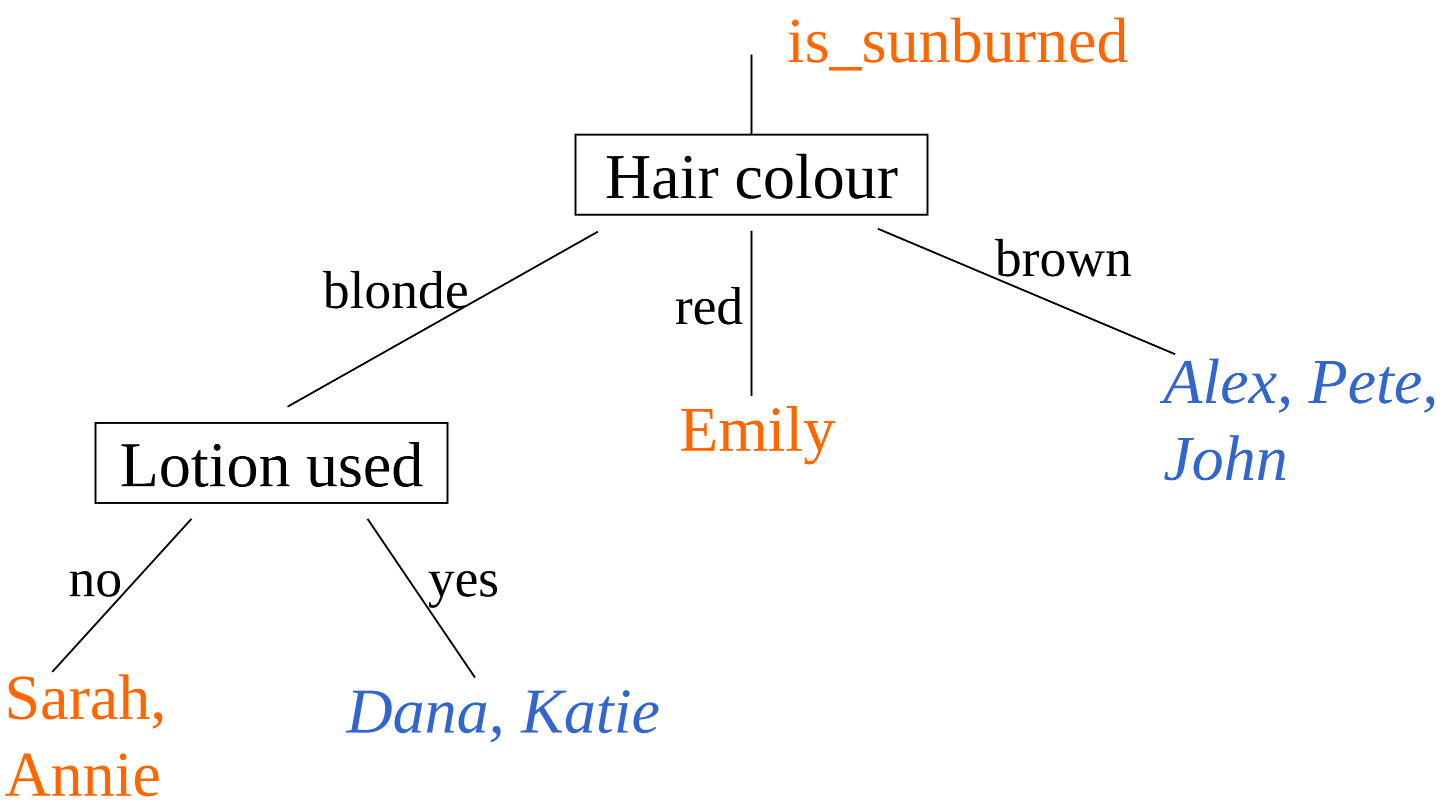
Slide from A. Kaban

Decision Tree 2



Slide from A. Kaban

Decision Tree 3



Slide from A. Kaban

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?

Slide from A. Kaban

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

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

  where *s1*="Sarah", *s2*="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?

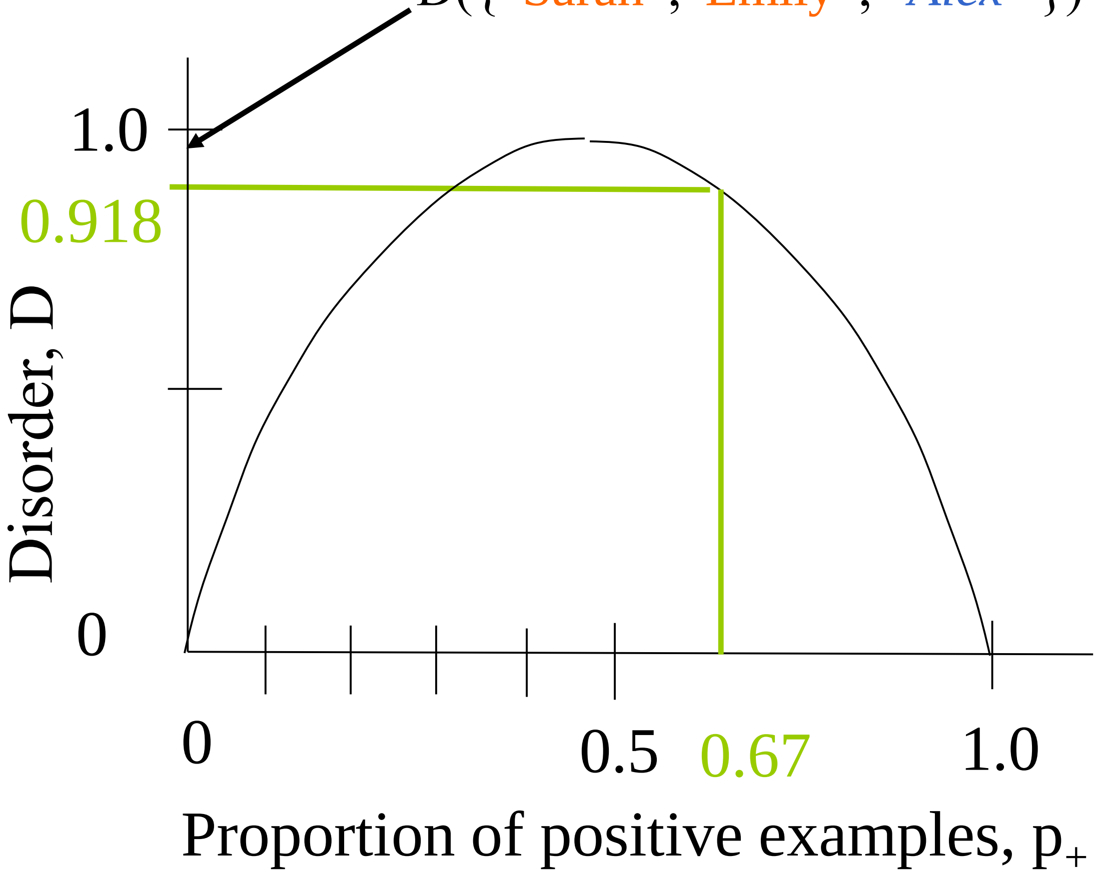
- Suppose that *D(S)=0* means that all the examples in *S* have the same class
- Suppose that *D(S)=1* means that half the examples in *S* are of one class and half are the opposite class

Examples

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

Slide from A. Kaban

D({"Sarah","Emily", "*Alex*" })=0.918



Slide from A. Kaban

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

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

where

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

Check it!

D(0,1) = ? D(1,0)=? D(0.5,0.5)=?

Slide from A. Kaban

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

D({ "Sarah","*Dana*","*Alex*","Annie", "Emily","*Pete*","*John*","*Katie*"})

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

$$= 0.954$$

Slide from A. Kaban

Some more useful properties of the Entropy

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

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

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

Slide from A. Kaban

- 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

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

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

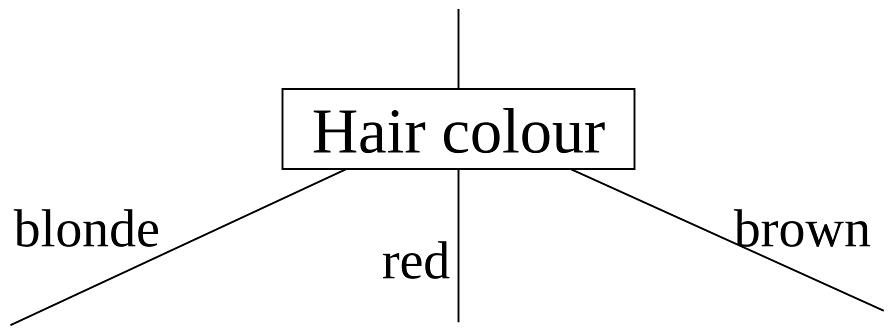
We want:

-large Gain

-same as: small avg disorder created

Slide from A. Kaban

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



$\frac{|S_{blonde}|}{|S|} D(S_{blonde})$ $\frac{|S_{red}|}{|S|} D(S_{red})$ $\frac{|S_{brown}|}{|S|} D(S_{brown})$

Sarah
Annie
Dana
Katie

Emily

Alex
Pete
John

Slide from A. Kaban

…Calculating the Disorder of the "blondes"

The first term of the sum:

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

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

Slide from A. Kaban

…Calculating the disorder of the others

The second and third terms of the sum:

- S_{red}={"Emily"}
- S_{brown}={ "*Alex*", "*Pete*", "*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

Slide from A. Kaban

Which decision variable minimises the disorder?

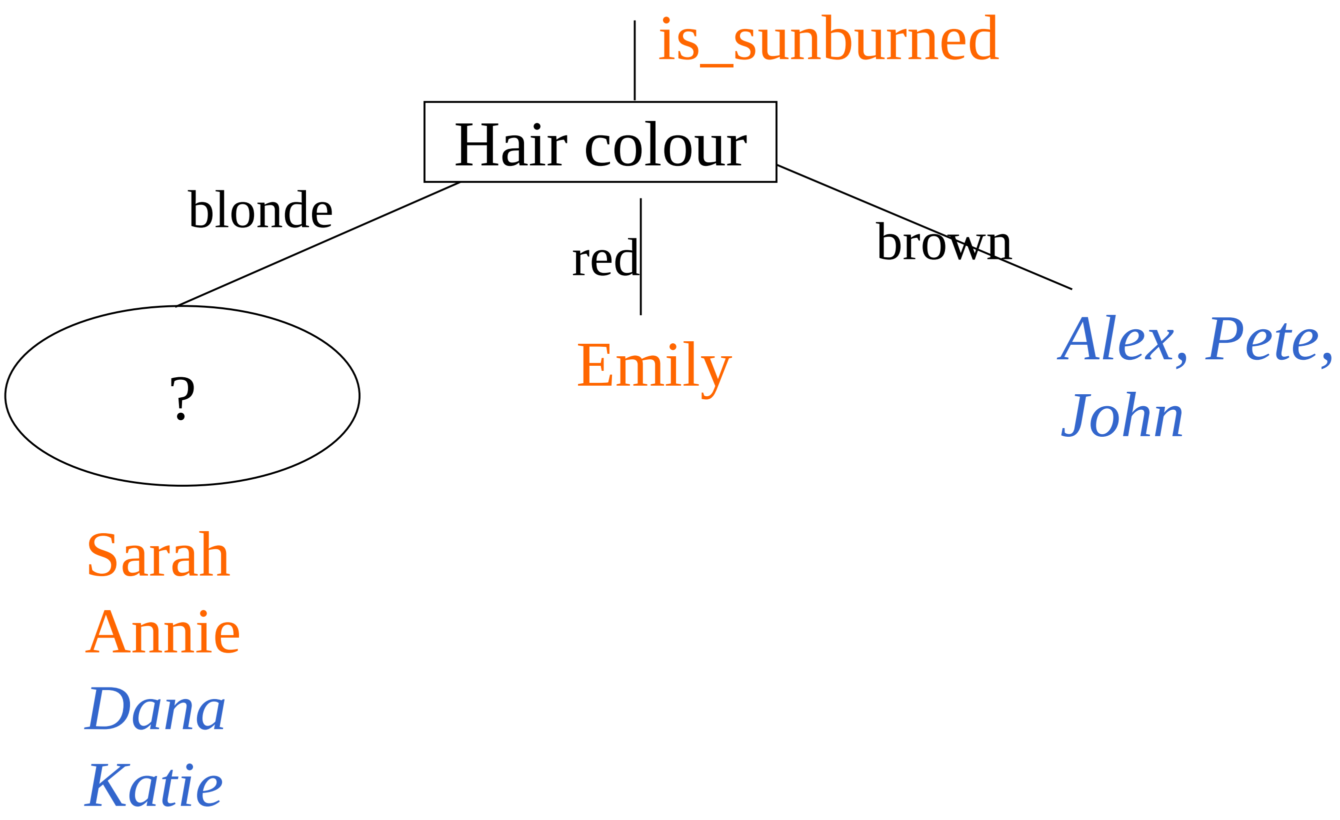
Test	Disorder	
Hair	0.5 – this what we just computed	
height	0.69	these are the avg disorders of the other attributes, computed in the same way
weight	0.94	
lotion	0.61	

Which decision variable maximises the Info Gain then?

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

Slide from A. Kaban

So what is the best decision tree?



Slide from A. Kaban

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

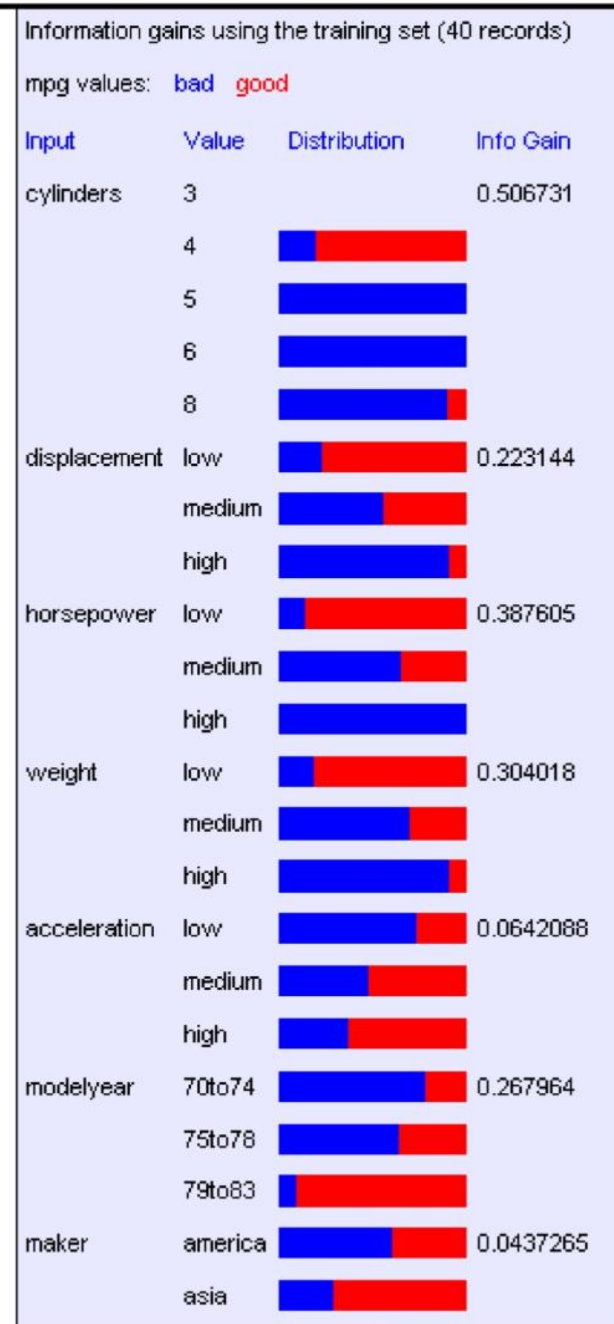
40 Records

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	europe
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	europe
bad	5	medium	medium	medium	medium	75to78	europe

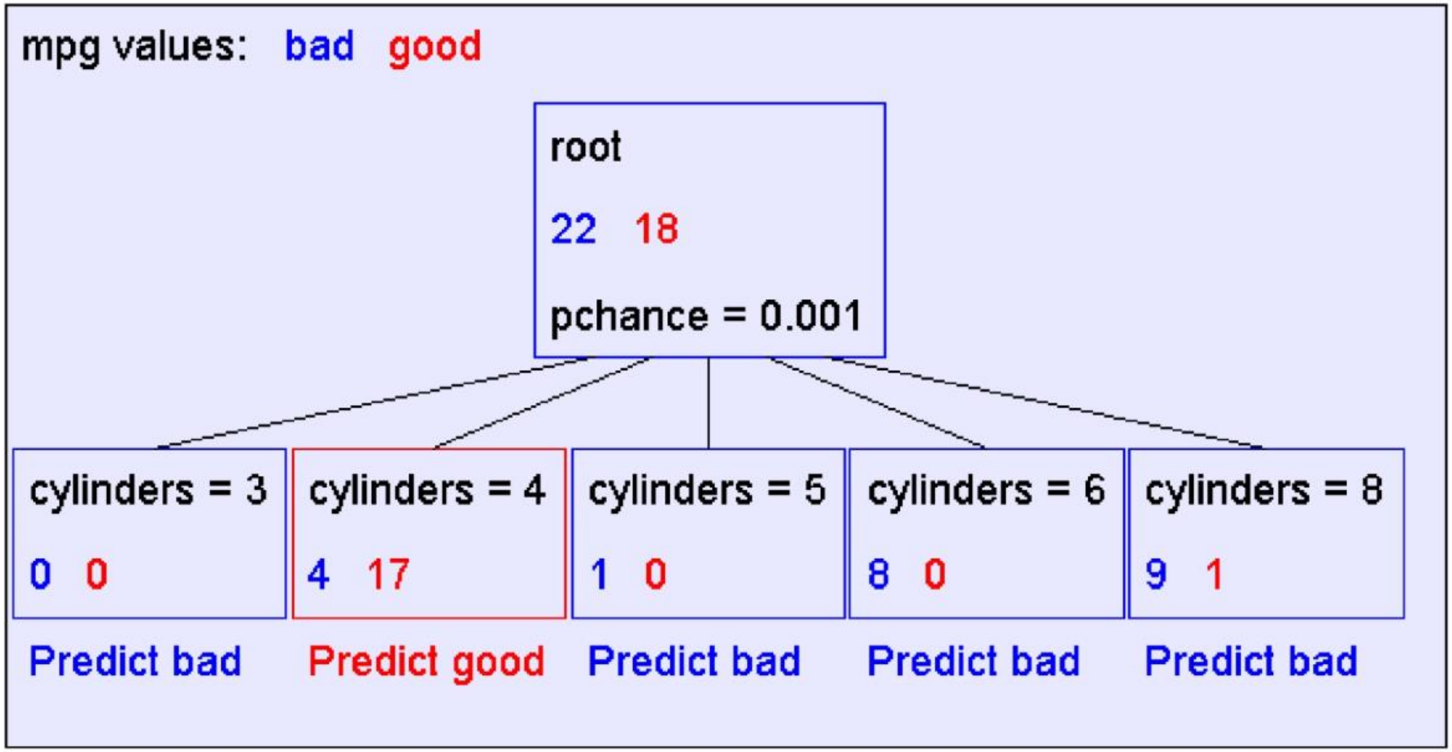
From the UCI repository (thanks to Ross Quinlan)

Suppose we want to predict MPG.

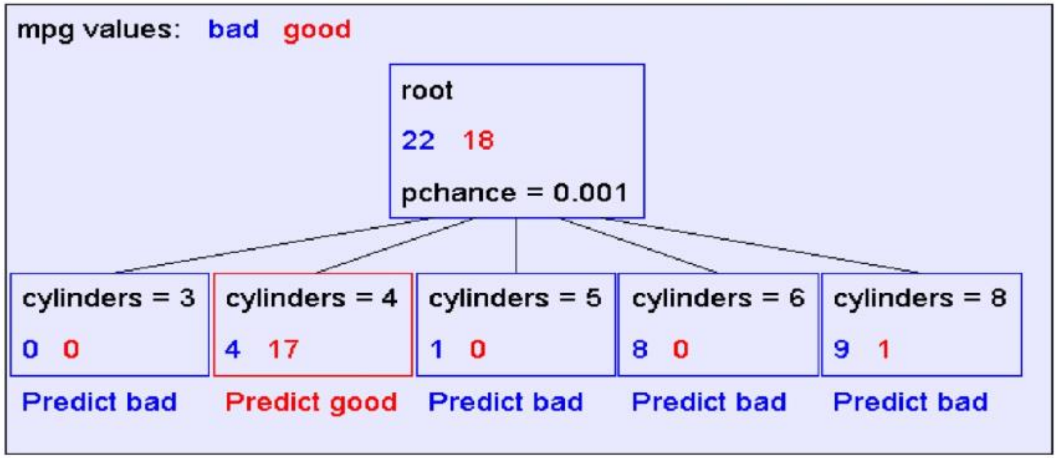
Look at all the information gains…



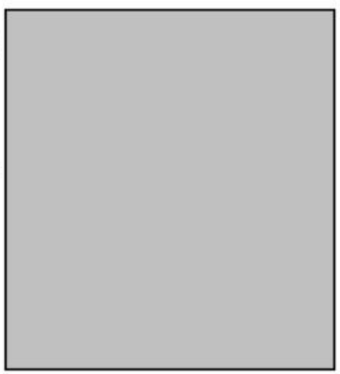
A Decision Stump



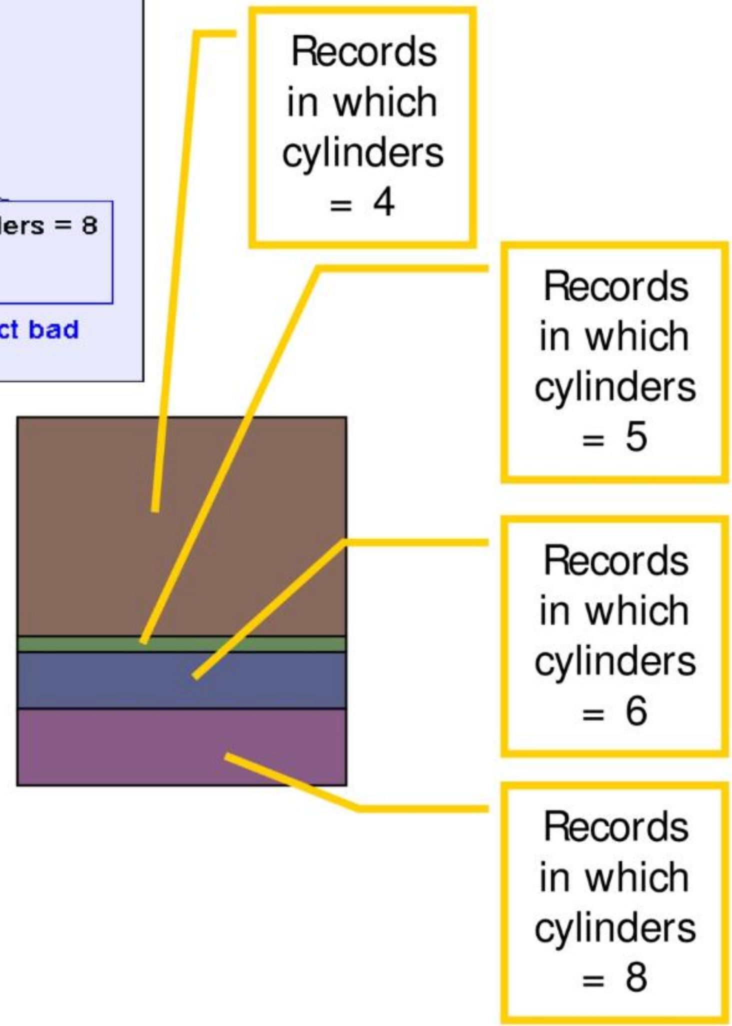
Recursion Step



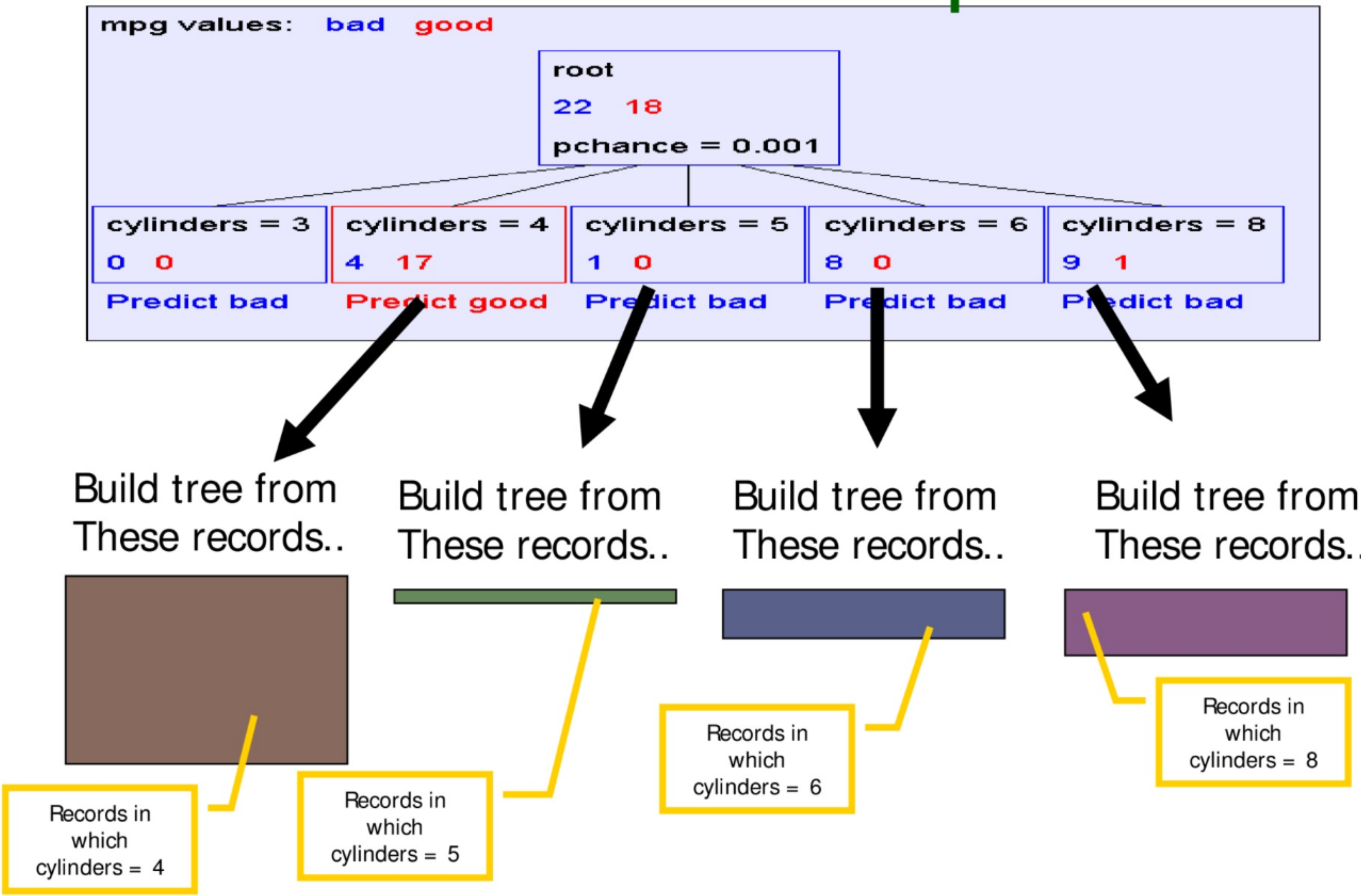
Take the Original Dataset..



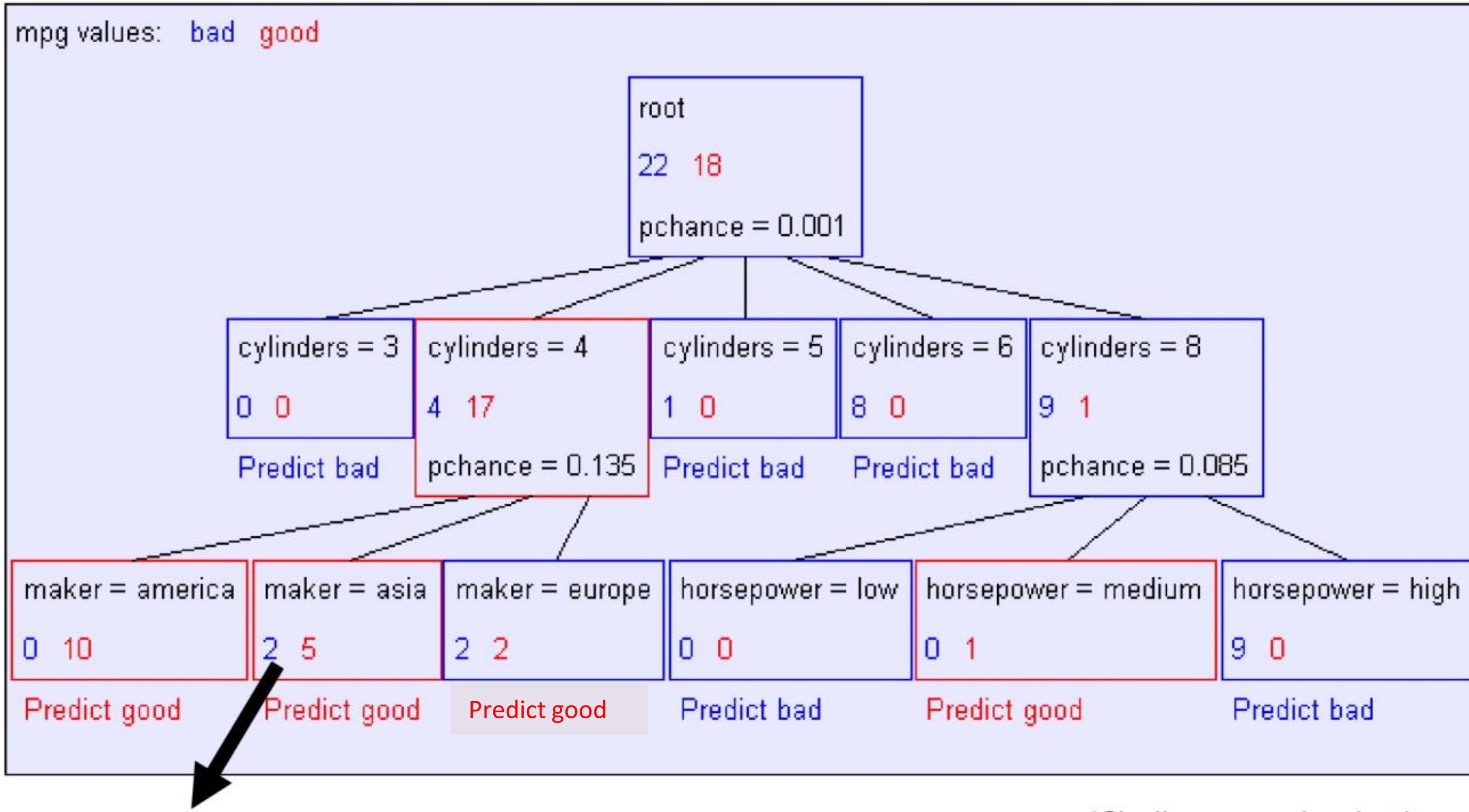
And partition it according to the value of the attribute we split on



Recursion Step



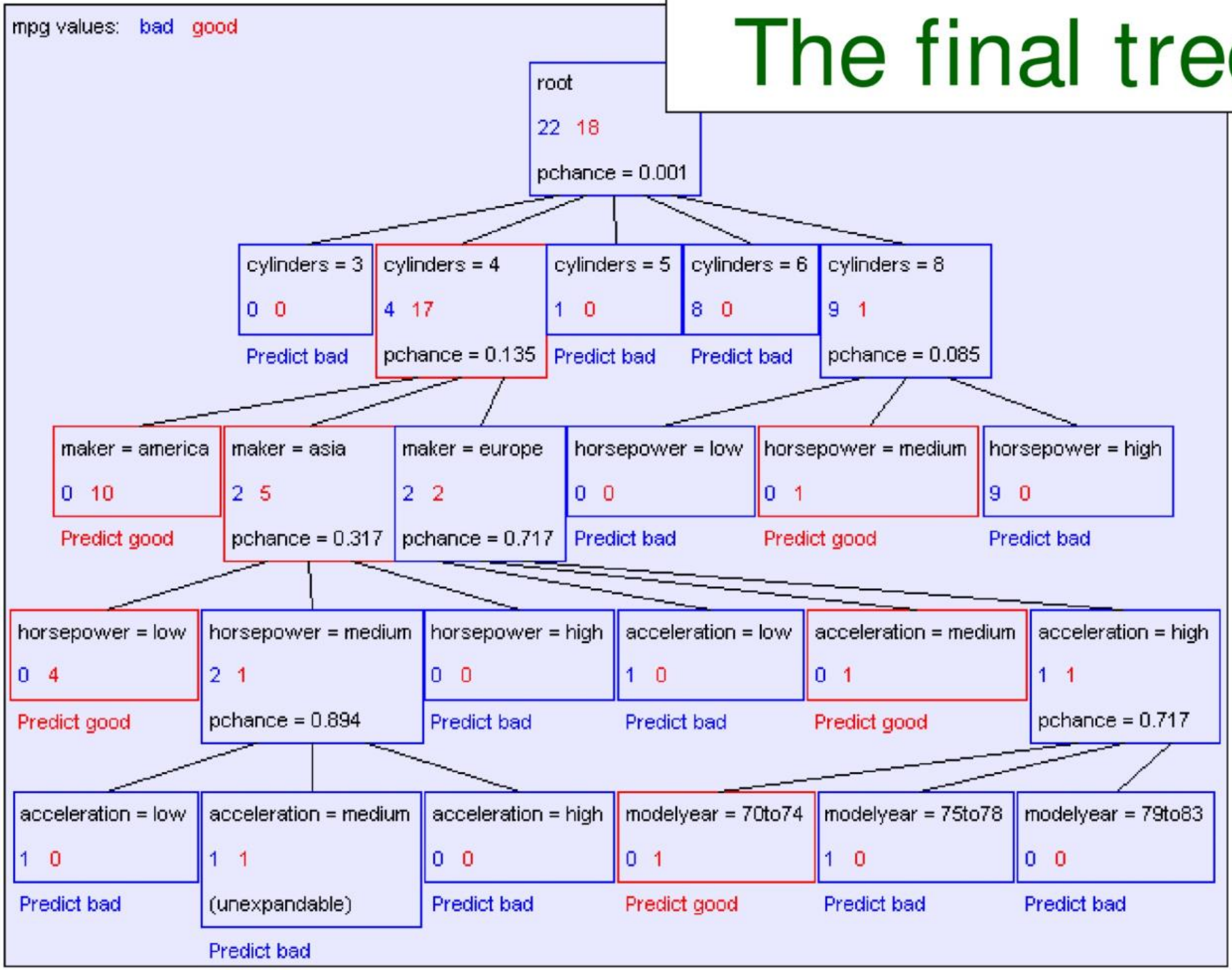
Second level of tree



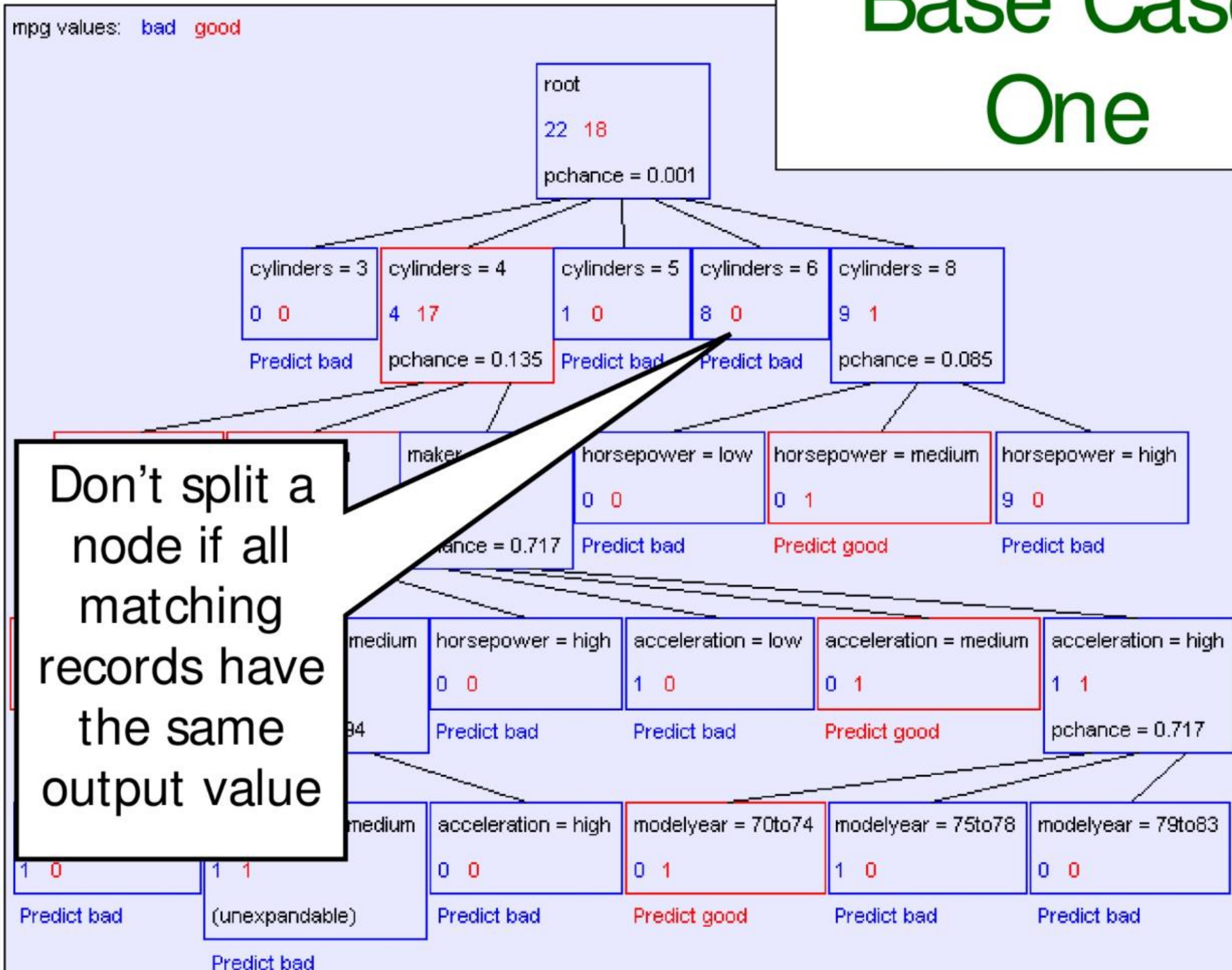
Recursively build a tree from the seven records in which there are four cylinders and the maker was based in Asia

(Similar recursion in the other cases)

The final tree

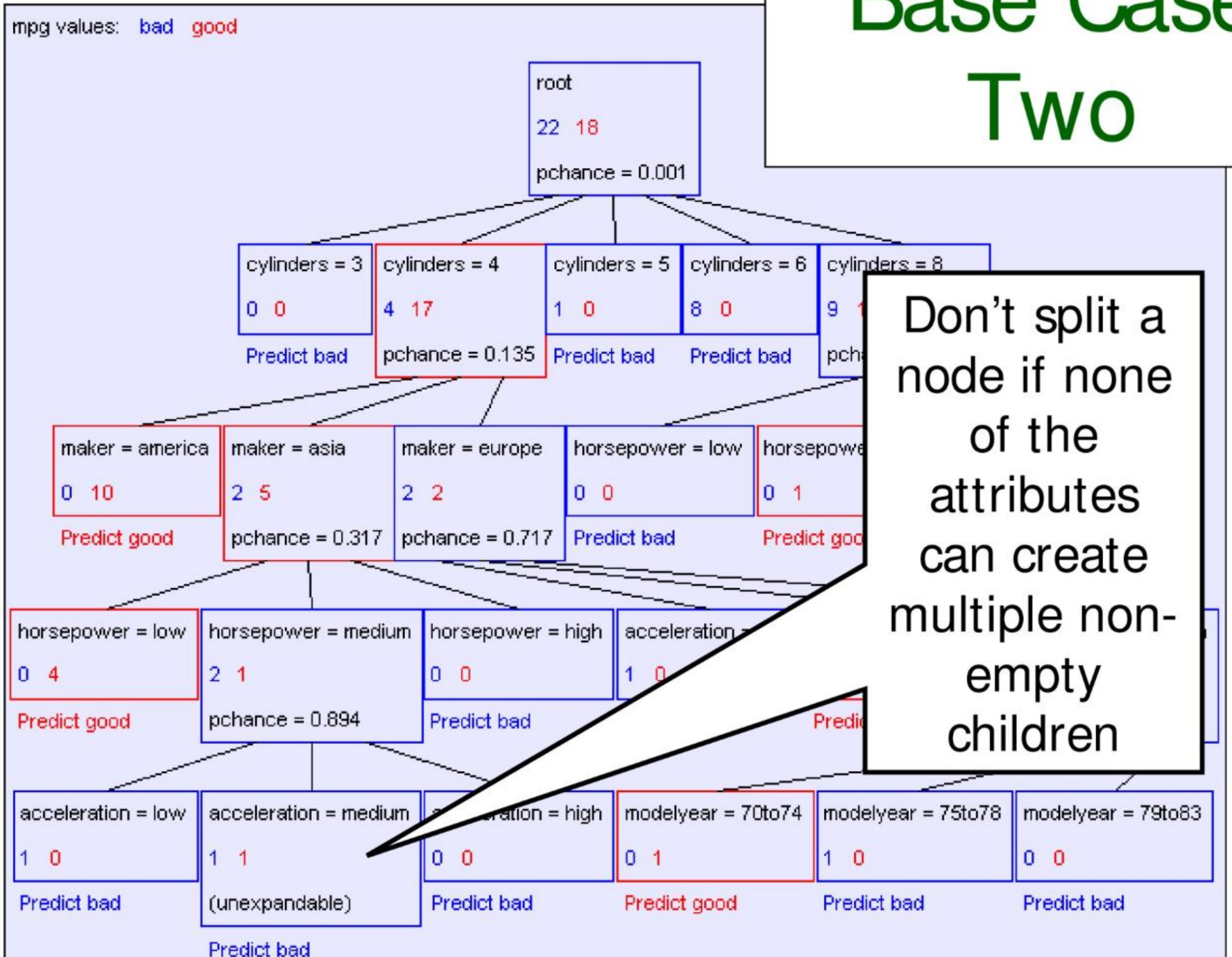


Base Case One



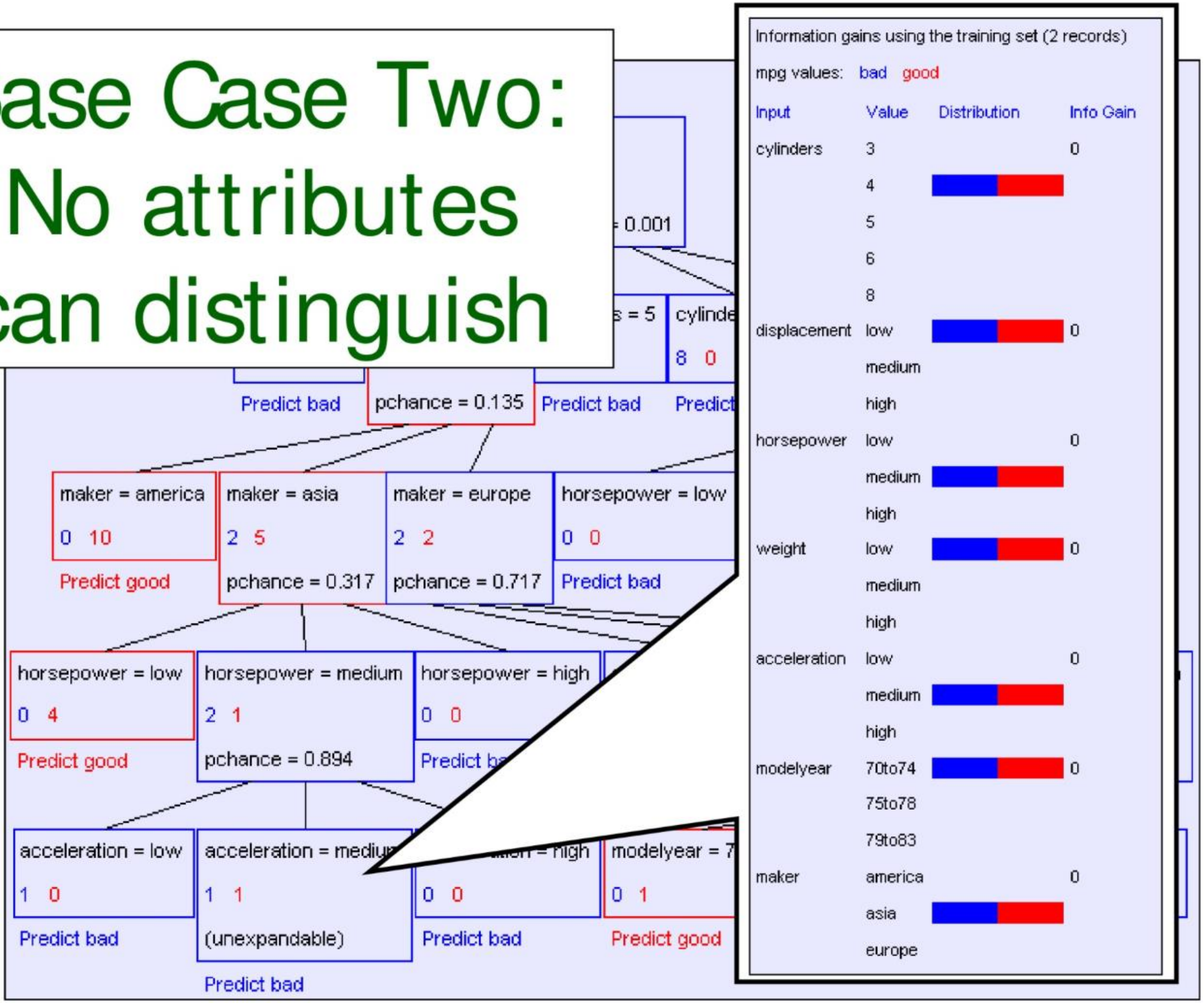
Don't split a node if all matching records have the same output value

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



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.

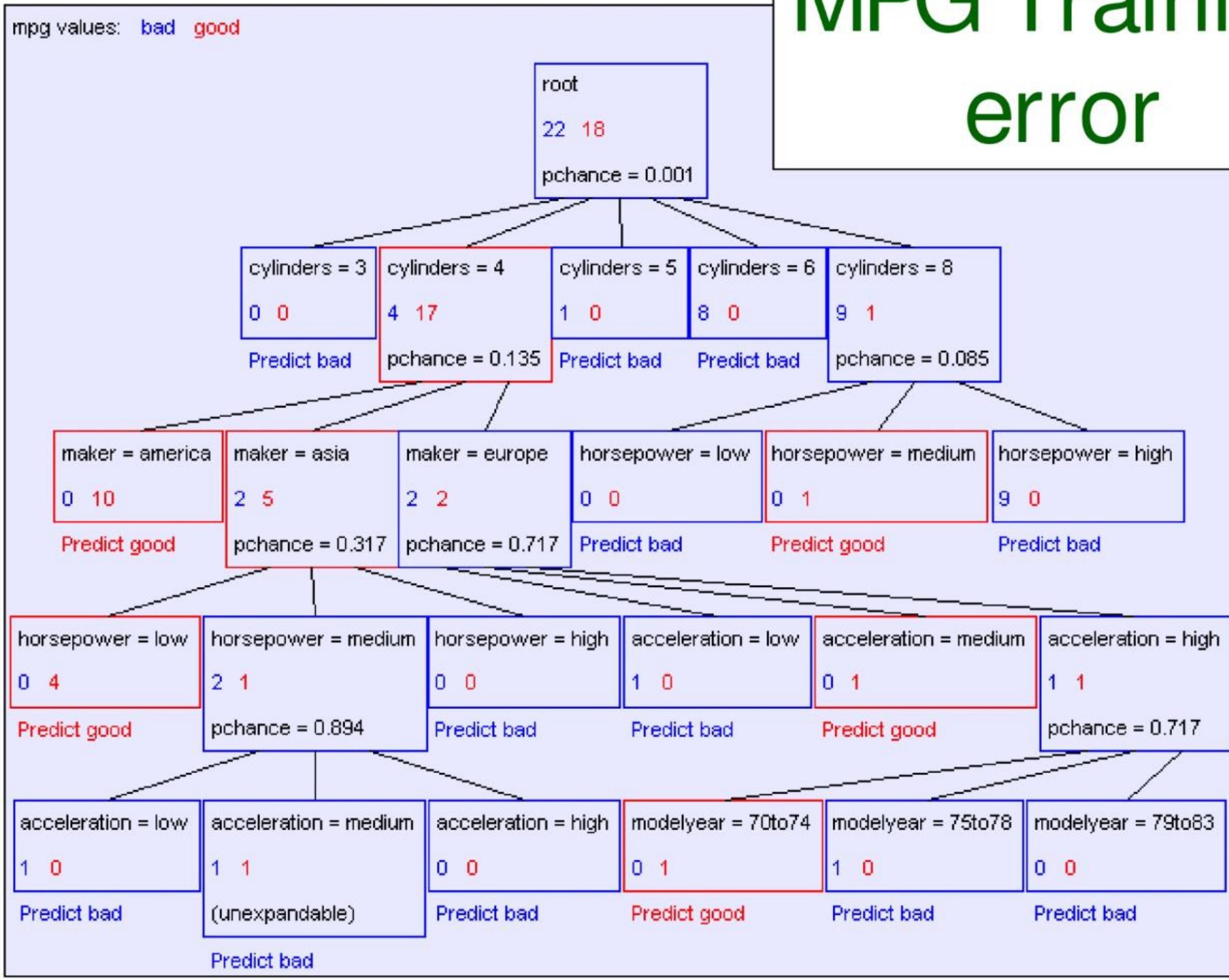
Training Set Error

- 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?

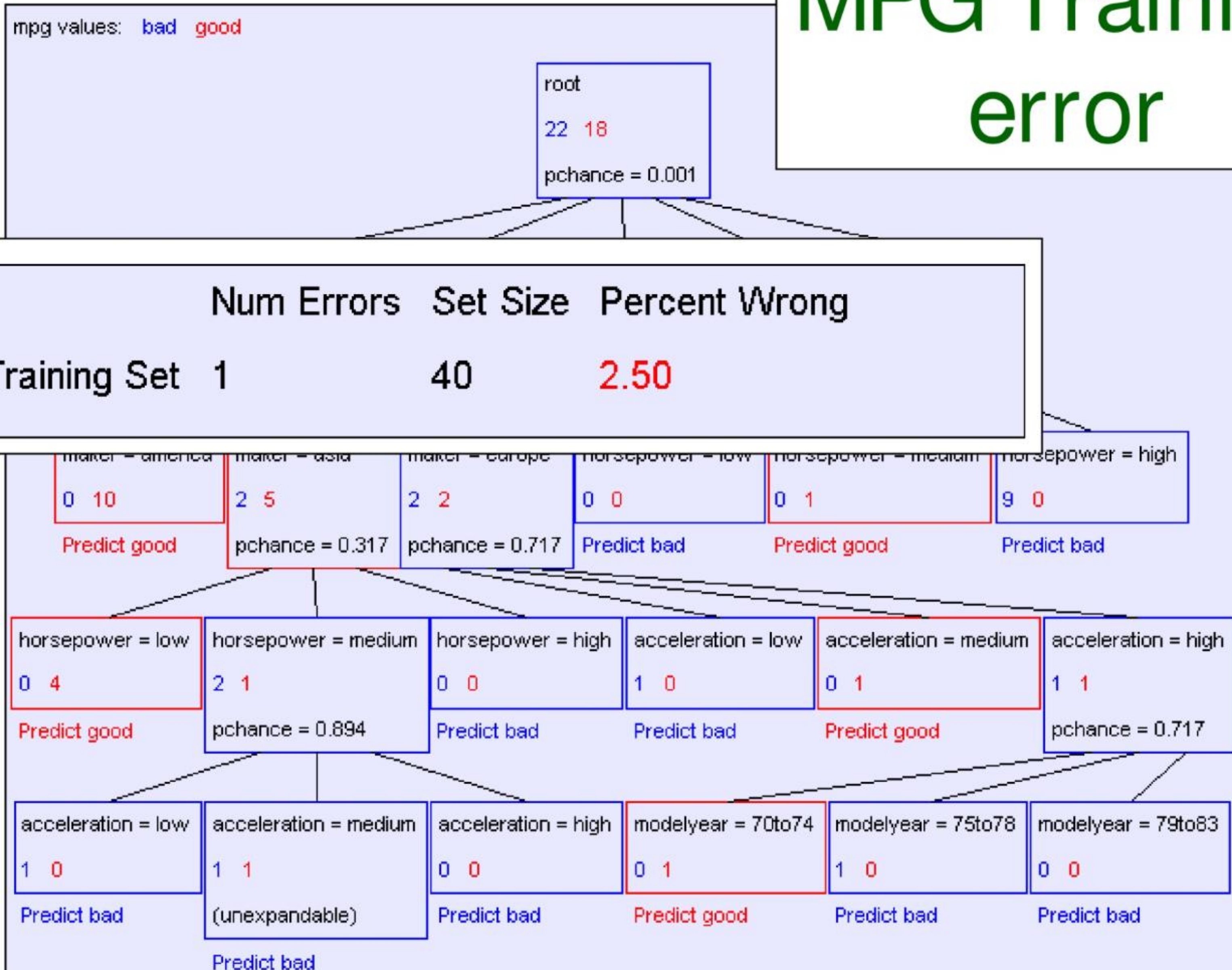
- This quantity is called the *training set error*. The smaller the better.

MPG Training error



MPG Training error

	Num Errors	Set Size	Percent Wrong
Training Set	1	40	2.50



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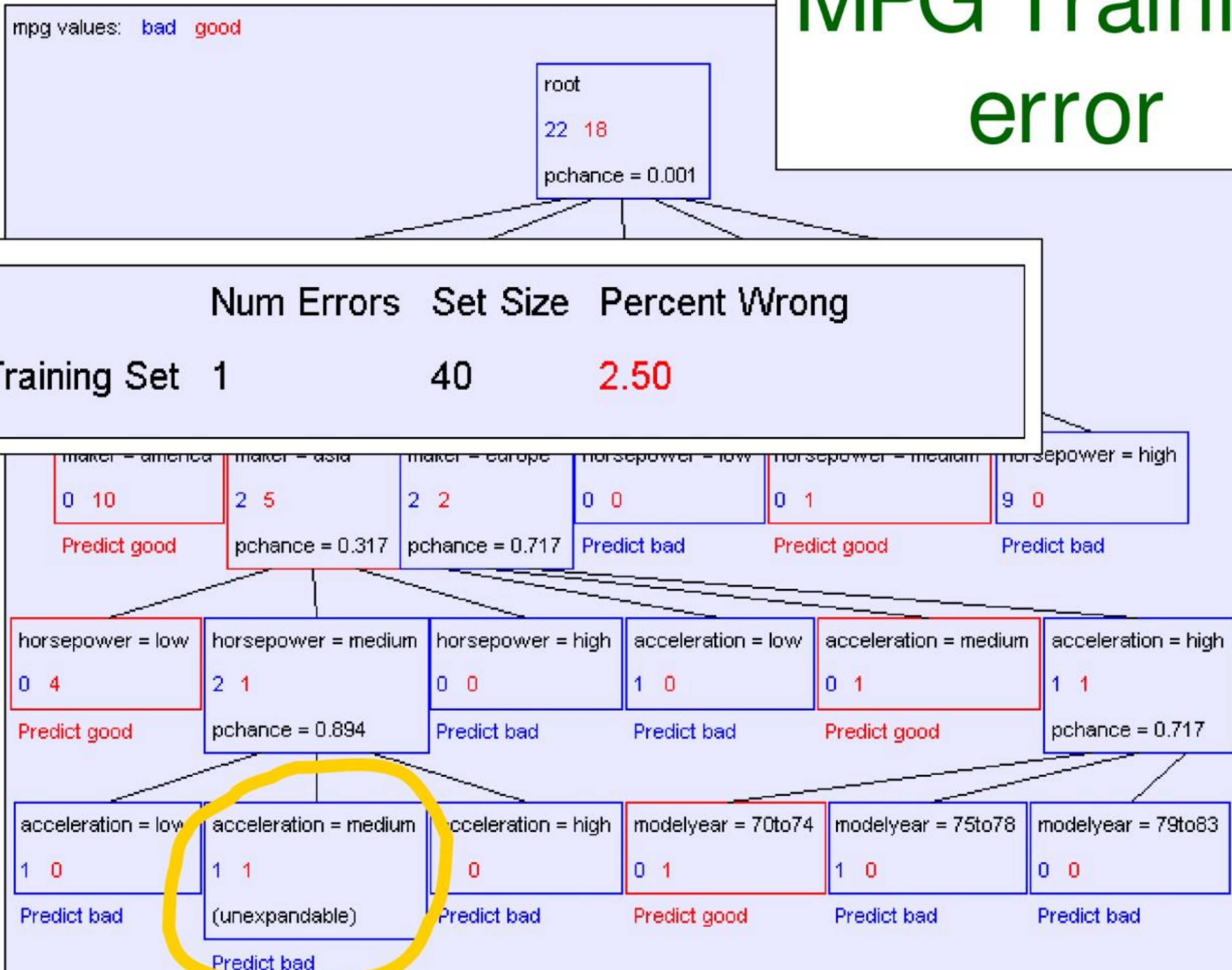


Stop and reflect: Why are we doing this learning anyway?

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

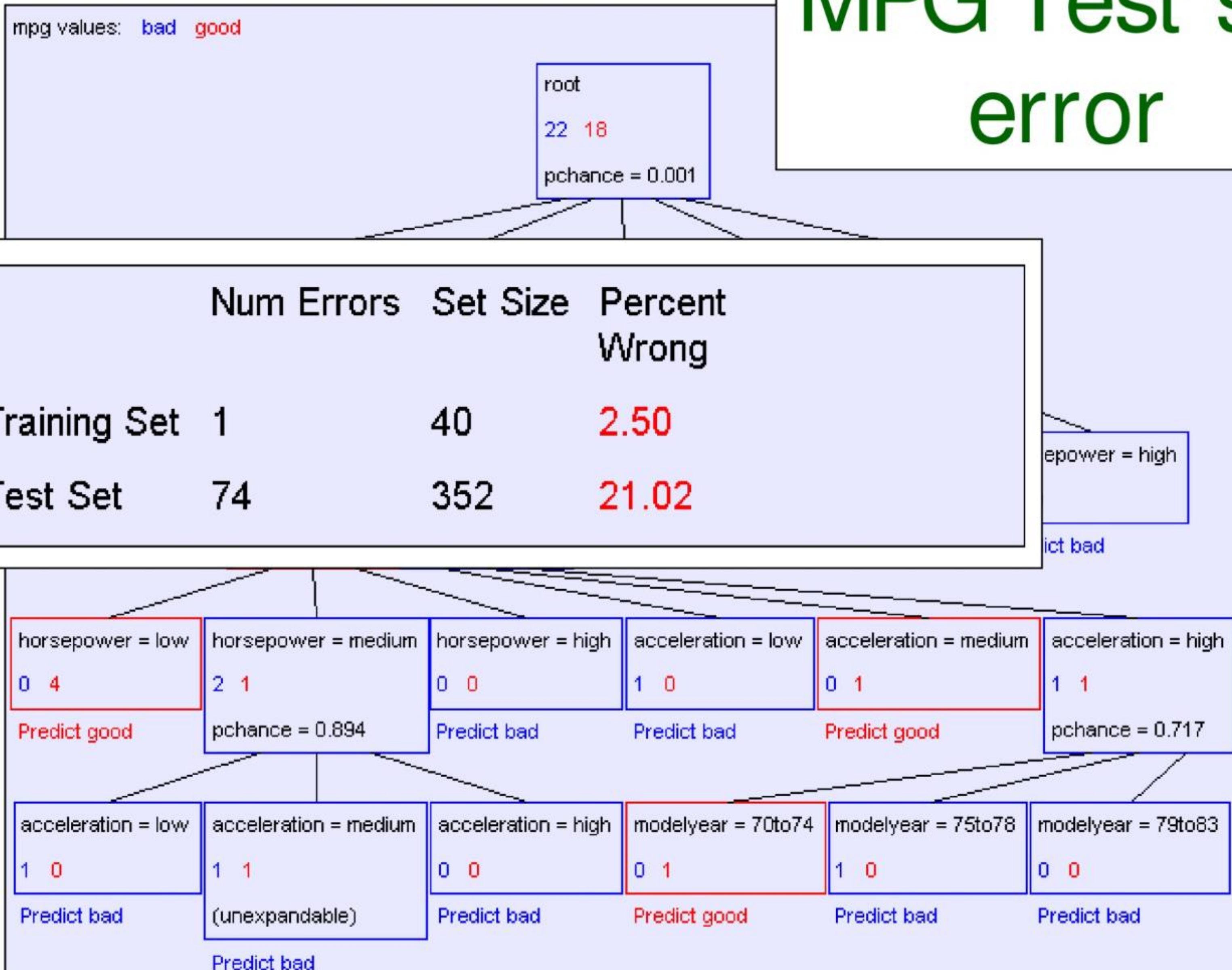
Stop and reflect: Why are we doing this learning anyway?

- 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



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

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?

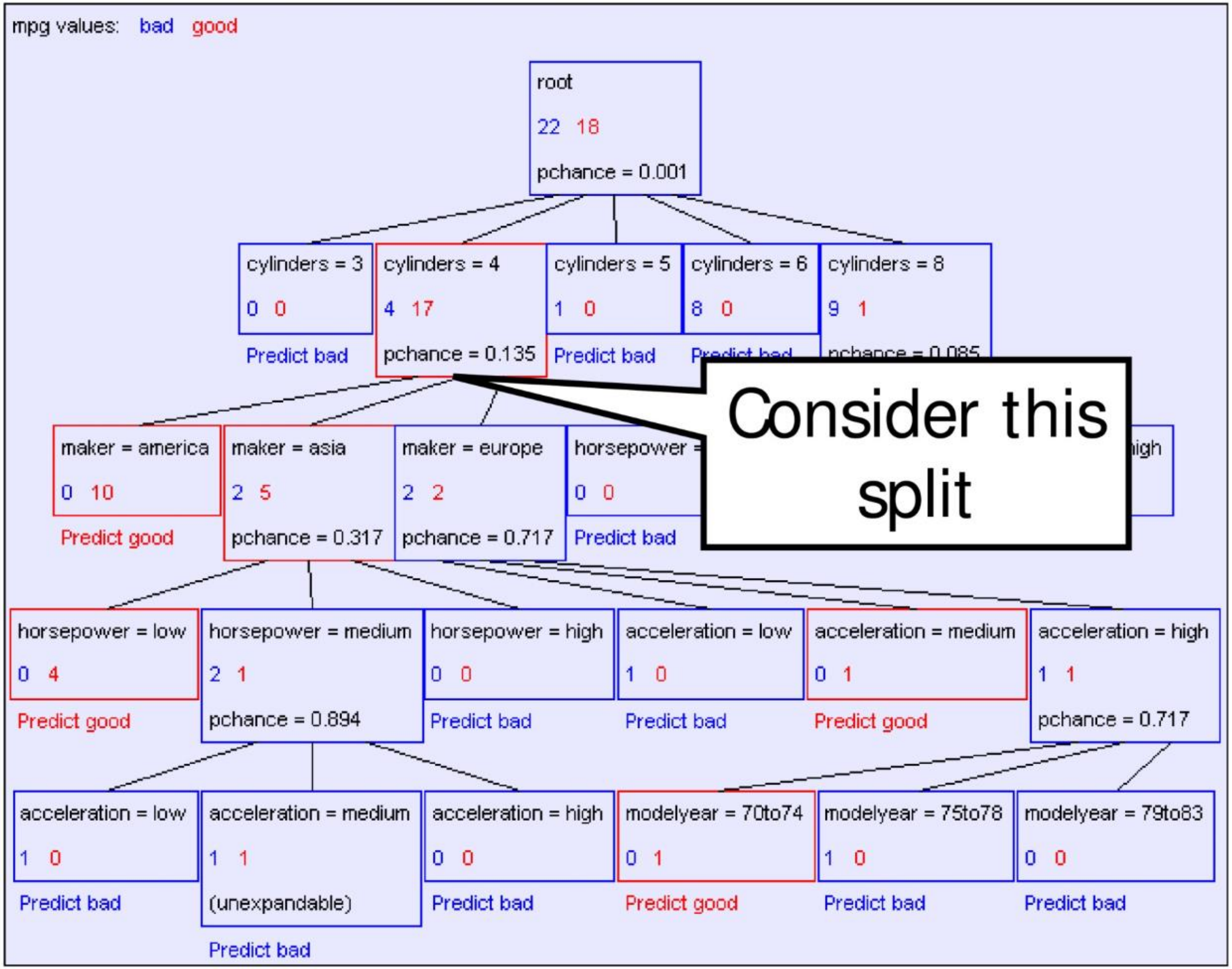
- The best way is to have a held-out "development" test set to measure generalization performance on
  - This should be held separate from the final test set
- An interesting empirical fact about decision trees, is that larger trees tend to overfit more, so trying to create small trees is a good idea
  - 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

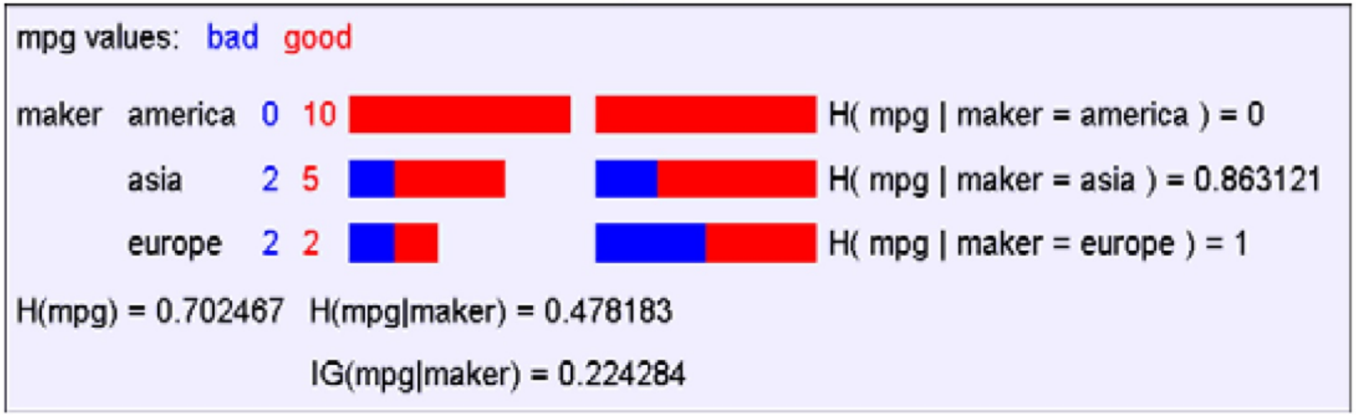
- Usually we do not know in advance which are the irrelevant variables
- …and it may depend on the context

  For example, if y = a 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.

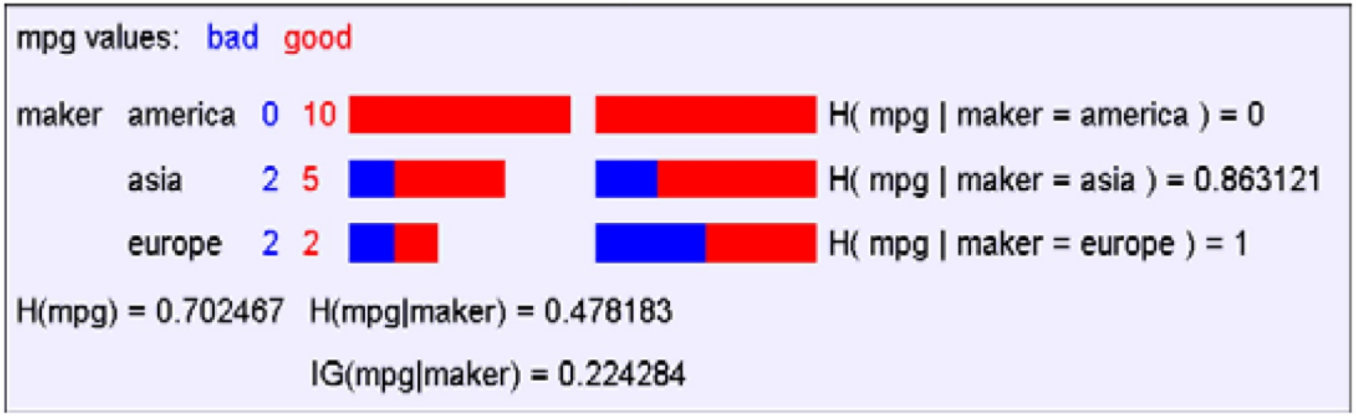

mpg values: bad good
root
22 18
pchance = 0.001
cylinders = 3
0 0
Predict bad
cylinders = 4
4 17
pchance = 0.135
cylinders = 5
1 0
Predict bad
cylinders = 6
8 0
cylinders = 8
9 1
Consider this split
maker = america
0 10
Predict good
maker = asia
2 5
pchance = 0.317
maker = europe
2 2
pchance = 0.717
horsepower
0 0
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

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%.

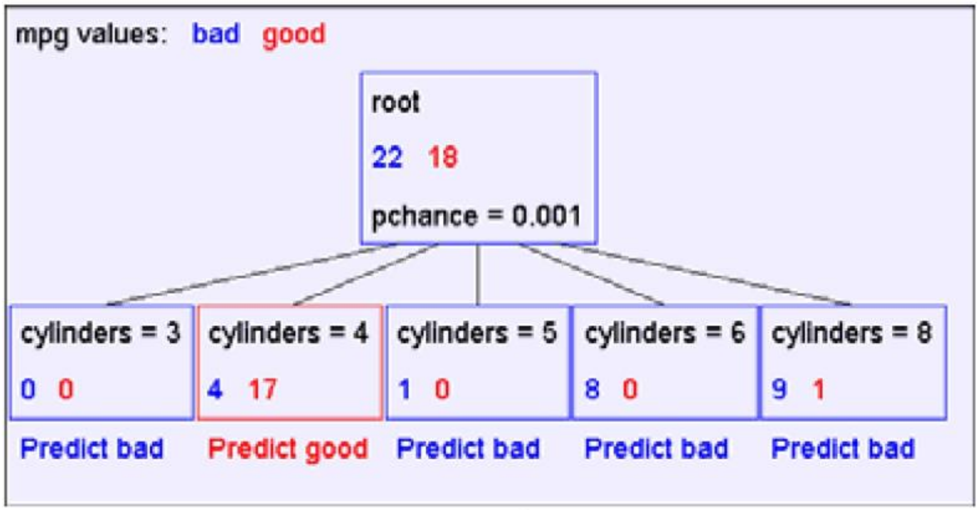
Using Chi-squared to avoid overfitting

- 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 you 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 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!