FIT3152 Data analytics – Lecture 7

Introduction to decision trees

- Assignment Q & A
- Regression Review Questions
- Overview: data mining and machine learning
- Introduction to classification and decision trees
- A specific decision tree algorithm: ID3
- Entropy and information gain
- Model accuracy; training and testing
- Decision trees in R

Week-by-week

Week Starting	Lecture	Topic	Tutorial	A1	A2
2/3/21	1	Intro to Data Science, review of basic statistics using R	...		
9/3/21	2	Exploring data using graphics in R	T1		
16/3/21	3	Data manipulation in R	T2	Released	
23/3/21	4	Data Science methodologies, dirty/clean/tidy data, data manipulation	T3		
30/3/21	5	Network analysis	T4		
6/4/21		Mid-semester Break			
13/4/21	6	Regression modelling	T5		
20/4/21	7	Classification using decision trees	T6	Submitted	
27/4/21	8	Naïve Bayes, evaluating classifiers	T7		Released
4/5/21	9	Ensemble methods, artificial neural networks	T8		
11/5/21	10	Clustering	T9		
18/5/21	11	Text analysis	T10		Submitted
25/5/21	12	Review of course, Exam preparation	T11		

Assignment 1

FIT3152 Data analytics: Assignment 1

This assignment is worth 20% of your final marks in FIT3152. Due: Friday 23rd April 2021.

Activity, language use and social interactions in an on-line community. Analyse the metadata and linguistic summary from a real on-line forum and submit a report of your findings. Do the following:

Assignment 1

a. Analyse activity and language on the forum over time. Some starting points:

- Describe your data: How active are participants, and are there periods where this increases or decreases? Is there a trend over time?
- Looking at the linguistic variables, do these change over time? Is there a relationship between variables?

b. Analyse the language used by groups. Some starting points:

- Threads indicate groups of participants communicating on the same topic. Describe the threads present in your data.
- By analysing the linguistic variables for all or some of the threads, is it possible to see a difference in the language used by different groups?
- Does the language used within threads (or between threads) change over time? How consistent or variable is the language used within threads?

Assignment 1

c. Challenge: Social networks online. We can think of participants posting to the same thread at similar times (for example during the same month) as forming a social network. When these participants also post to other threads over the same period, their social network extends.

- Can you define, graph and describe the social network that exists at a particular point in time, for example over one month? How does this change in the following months?
- Note: you only need to analyse a small portion of the social network over a short time period. We will cover social network analysis in Lecture 5.

d. Reflection on your investigation. What did you first investigate? How did you then modify your research based on the results of your first investigation?

- Using one of the data science methodologies in Lecture 4, illustrate your research process.

Assignment 1

Data

The data is contained in the file webforum.csv and consists of the metadata and linguistic analysis of posts over the years 2002 to 2011. You will each work with 20,000 posts, randomly selected from the original file. The linguistic analysis was conducted using Linguistic Inquiry and Word Count (LIWC), which assesses the prevalence of certain thoughts, feelings and motivations by calculating the proportion of key words used in communication. See http://liwc.wpengine.com/ for more information, including the language manual http://liwc.wpengine.com/wp-content/uploads/2015/11/LIWC2015_LanguageManual.pdf

Create your individual data as follows:

```
rm(list = ls())
set.seed(XXXXXXXX) # XXXXXXXX = your student ID
webforum <- read.csv("webforum.csv")
webforum <- webforum [sample(nrow(webforum), 20000), ] # 20000 rows
```

Assignment 1

ThreadID	AuthorID	Date	Time	WC	Analytic	Clout	Authentic	Tone	WPS	i	we	you	they	number	affect	posemo	negemo	anx
659289	193537	24/11/2009	5:36	53	82.26	71.43	25.14	25.77	26.5	0	1.89	0	3.77	3.77	3.77	1.89	1.89	0
432269	136196	26/11/2007	23:42	216	25.71	94.73	45.81	33.77	24	1.85	6.48	0.46	5.09	0.46	6.02	3.24	2.78	0
572531	170305	17/02/2009	7:31	136	31.61	67.04	28.81	79.41	13.6	3.68	0	5.15	2.94	0.74	9.56	5.88	2.94	0.74
230003	32359	7/09/2005	21:25	29	39.74	91.6	3.81	85.87	14.5	3.45	0	6.9	0	6.9	3.45	3.45	0	0
459059	47875	19/02/2008	5:23	108	80.75	60.95	23.51	88.52	13.5	2.78	0	0	0	0.93	9.26	6.48	2.78	0
635953	181593	28/09/2009	8:40	86	64.98	45.37	57.24	1	43	1.16	0	0	5.81	3.49	3.49	0	3.49	0
235116	51993	29/09/2005	15:59	49	33.33	20.71	13.15	25.77	16.33	6.12	0	0	2.04	0	8.16	4.08	4.08	0
593767	169459	23/04/2009	19:21	368	85.91	63.82	19.13	7.15	24.53	1.36	2.17	0	0.54	0.54	5.43	1.9	3.53	0.54
532649	248548	25/12/2011	8:28	13	92.84	50	1	25.77	13	0	0	0	0	61.54	0	0	0	0
517685	65	20/02/2005	10:50	65	91.21	62.1	33.6	81.28	13	7.69	0	0	0	0	9.23	6.15	3.08	0
588291	158329	23/04/2009	23:40	265	55.7	73.95	45.85	11.21	44.17	1.89	1.13	0.38	3.4	5.66	3.4	1.13	2.26	0
29936	194	25/07/2002	4:29	106	80.44	80.2	20.42	98.46	15.14	1.89	0	4.72	0	0.94	7.55	6.6	0.94	0.94
199787	47875	20/05/2005	16:48	160	94.48	73.4	2.07	5.64	22.86	1.25	0	0	0	5.62	8.12	3.12	5	1.88
545552	143229	24/11/2008	23:39	33	79.25	18.16	98.01	80.64	8.25	6.06	0	0	0	3.03	3.03	3.03	0	0
303058	88912	25/07/2006	23:57	244	44.21	65.92	33.49	7.09	27.11	2.87	0.82	0.41	4.51	1.64	6.56	2.46	4.1	0
772248	75628	16/01/2011	2:24	108	39.91	57.35	45.81	25.77	13.5	5.56	0	2.78	0	0.93	1.85	0.93	0.93	0
761807	227011	4/12/2010	23:48	104	73.9	57.63	74.76	62.24	34.67	0.96	0	2.88	3.85	2.88	5.77	3.85	1.92	0
110837	34501	24/01/2004	2:53	49	90.62	20.71	46.05	1	24.5	2.04	0	0	0	0	6.12	0	6.12	0
636255	180475	3/09/2009	22:25	2	92.84	99	1	99	2	0	0	0	0	0	50	50	0	0
178736	43291	18/01/2005	2:40	75	69.57	92.87	1	1	15	0	0	2.67	6.67	0	10.67	1.33	9.33	1.33
275754	-1	6/03/2006	18:01	56	92.84	70.4	41.07	6.15	18.67	1.79	0	1.79	0	1.79	1.79	0	1.79	0
833308	231141	21/09/2011	21:39	32	78.67	82.58	74.76	25.77	16	0	0	6.25	0	0	0	0	0	0
642657	180098	13/11/2009	16:34	13	92.84	6.21	99	1	13	23.08	0	0	0	0	7.69	0	7.69	7.69
365246	116735	17/02/2007	9:48	48	49.05	33.83	62.53	1	48	2.08	0	2.08	2.08	0	10.42	2.08	8.33	4.17
279233	84070	21/03/2006	1:59	51	77.76	50	66.34	25.77	51	3.92	0	1.96	0	1.96	7.84	3.92	3.92	0
300539	-1	8/06/2006	22:43	24	49.05	33.83	23.51	92.4	6	8.33	0	0	4.17	8.33	4.17	4.17	0	0
277955	32925	14/03/2006	23:45	87	55.99	78.96	62.98	3.63	43.5	0	0	1.15	4.6	2.3	2.3	0	2.3	1.15
90325	32485	25/09/2003	3:30	48	94.65	79.76	3.9	25.77	12	0	0	0	2.08	2.08	12.5	6.25	6.25	0
321495	90627	12/09/2006	1:40	42	40.66	68.29	37.24	70.57	21	4.76	4.76	2.38	2.38	0	2.38	2.38	0	0
281667	79878	28/03/2006	2:45	60	32.98	56.63	65.14	1.03	20	1.67	1.67	0	3.33	0	3.33	0	3.33	0
294983	75902	21/05/2006	0:07	60	56.15	25.24	32.84	25.77	60	3.33	0	0	0	0	6.67	3.33	3.33	0
397699	125170	21/06/2007	21:41	34	92.84	92.92	14.7	25.77	17	0	2.94	2.94	0	0	5.88	2.94	2.94	0
313191	101368	30/07/2006	17:53	25	81.4	2.31	43.37	25.77	25	0	0	0	0	12	0	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...

Assignment 1

Data fields are (see the language manual for more detail and examples):

Column	Brief Descriptor
ThreadID	Unique ID for each thread
AuthorID	Unique ID for each author
Date	Date
Time	Time
WC	Word count of the text of the post
Analytic	LIWC Summary (Analytical thinking)
Clout	LIWC Summary (Power, force, impact)
Authentic	LIWC Summary (Using an authentic tone of voice)
Tone	LIWC Summary (Emotional tone)
WPS	LIWC (Words per sentence)
i	LIWC ("I, me, mine" words) First person singular
we	LIWC ("We, us, our" words) First person plural
you	LIWC ("You" words) Second person
they	LIWC ("They" words) Third person plural
number	LIWC(Quantities and ranks)
affect	LIWC (Expressing sentiment)
posemo	LIWC (Positive emotions)
negemo	LIWC (Negative emotions)
anx	LIWC (Indicating anxiety)

Assignment 1

Submission. Due Friday 23rd April 2021 11:55pm GMT+10.
Suggested length: 6–8 A4 pages + appendix.
Submit the results of your analysis, answering the research questions and report anything else you discover of relevance. If you choose to analyse only a subset of your data, you should explain why.

You are expected to include at least one multivariate graphic summarising key results. You may also include simpler graphs and tables. Report any assumptions you've made in modelling, and include your R code as an appendix. Submit your report as a single PDF with the file name *FirstnameSecondnameID.pdf* on Moodle.

Software

It is expected that you will use R for your data analysis and graphics and tables. You are free to use any R packages you need but please document these in your report and include in your R code.

Assignment 1

Assessment criteria will include:

The quality of your analysis and description of your analytical process; Graphics and tables supporting your analysis; The quality of graphics used in the report. Justification of your findings and the degree of proof you can offer (for example statistical tests); Readability and quality of your written report; Insights gained from the data; Novelty of your approach.

Factors you should consider (starting points, not a complete list):

Techniques: summary/descriptive statistics, identification of important variables, networks, etc.
Major grouping variables: author, thread, date and/or time, or a combination of these.
Time window (days, weeks, months, years…); Subsets of the data to be analysed.
Graphics to communicate your analysis and insights (histograms, scatterplots, heat maps, time series are some basic starting points, but see https://datavizproject.com/ for inspiration.

Response to student questions

- Being aware that each student receives 20,000 random rows (posts) of the original webforum dataset, we may not get a representative distribution of the 'real' data.
  - > Treat your sample as the population for your assignment. We are aware that each student will be working with a slightly different subset of the original data and we are ready to assess students on that basis.

Response to student questions

- Should we put plots in the appendix or in the main report? If multiple plots are inserted in the report, it will account for some space.
  - > Put plots in the report if possible. If you have a lot of plots, then put some in the Appendix - if your report is a bit longer than 6-8 due to plots taking up a few pages then that will be ok.

Quick review from regression lecture:

Feel free to answer in the Zoom chat...

mtcars

The (inbuilt) data set Motor Trend Car Road Tests gives summary statistics including fuel usage (mpg), engine size (disp), number of cylinders (cyl), power (hp), body weight (wt) and the number of gears for a variety of cars.

How well do these variables predict fuel economy?

Summary data

```
> head(mtcars)
                   mpg cyl disp  hp drat   wt qsec vs am gear
Mazda RX4         21.0   6  160 110 3.90 2.62 16.5  0  1    4
Mazda RX4 Wag     21.0   6  160 110 3.90 2.88 17.0  0  1    4
Datsun 710        22.8   4  108  93 3.85 2.32 18.6  1  1    4
Hornet 4 Drive    21.4   6  258 110 3.08 3.21 19.4  1  0    3
Hornet Sportabout 18.7   8  360 175 3.15 3.44 17.0  0  0    3
Valiant           18.1   6  225 105 2.76 3.46 20.2  1  0    3
```

Model

```
> attach(mtcars)
> fitted = lm(mpg ~ cyl + disp + hp + wt + gear)
> fitted

Call:
lm(formula = mpg ~ cyl + disp + hp + wt + gear)

Coefficients:
(Intercept)          cyl         disp           hp           wt
    37.3626      -1.1186       0.0138      -0.0279      -3.7143
       gear
     0.6788
```

Summary (a)

```
Call:
lm(formula = mpg ~ cyl + disp + hp + wt + gear)

Residuals:
   Min     1Q Median     3Q    Max
-3.223 -1.686 -0.383  1.293  5.943
```

Summary (b)

```
Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  37.3626     5.9725    6.26  1.3e-06 ***
cyl          -1.1186     0.7144   -1.57   0.1295
disp          0.0138     0.0123    1.12   0.2727
hp           -0.0279     0.0166   -1.68   0.1052
wt           -3.7143     1.0482   -3.54   0.0015 **
gear          0.6788     1.0345    0.66   0.5175
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘
’ 1

Residual standard error: 2.54 on 26 degrees of freedom
Multiple R-squared:  0.851,   Adjusted R-squared:  0.822
F-statistic: 29.7 on 5 and 26 DF,  p-value: 5.72e-10
```

Question 1

Ignoring the constant term, the best predictor of fuel economy (mpg) is:

		Estimate	Std. Error	t value	Pr(>|t|)	
	(Intercept)	37.3626	5.9725	6.26	1.3e-06	***
(a)	cyl	-1.1186	0.7144	-1.57	0.1295	
(b)	disp	0.0138	0.0123	1.12	0.2727	
(c)	hp	-0.0279	0.0166	-1.68	0.1052	
(d)	wt	-3.7143	1.0482	-3.54	0.0015	**
(e)	gear	0.6788	1.0345	0.66	0.5175	

Question 2

The worst predictor of fuel economy is:

		Estimate	Std. Error	t value	Pr(>|t|)	
	(Intercept)	37.3626	5.9725	6.26	1.3e-06	***
(a)	cyl	-1.1186	0.7144	-1.57	0.1295	
(b)	disp	0.0138	0.0123	1.12	0.2727	
(c)	hp	-0.0279	0.0166	-1.68	0.1052	
(d)	wt	-3.7143	1.0482	-3.54	0.0015	**
(e)	gear	0.6788	1.0345	0.66	0.5175	

Question 3

Cars with more gears are more economical:

A. True
B. False
C. Can't tell

		Estimate	Std. Error	t value	Pr(>|t|)	
	(Intercept)	37.3626	5.9725	6.26	1.3e-06	***
(a)	cyl	-1.1186	0.7144	-1.57	0.1295	
(b)	disp	0.0138	0.0123	1.12	0.2727	
(c)	hp	-0.0279	0.0166	-1.68	0.1052	
(d)	wt	-3.7143	1.0482	-3.54	0.0015	**
(e)	gear	0.6788	1.0345	0.66	0.5175	

Question 4

Heaver cars are less economical:

A. True
B. False
C. Can't tell

		Estimate	Std. Error	t value	Pr(>|t|)	
	(Intercept)	37.3626	5.9725	6.26	1.3e-06	***
(a)	cyl	-1.1186	0.7144	-1.57	0.1295	
(b)	disp	0.0138	0.0123	1.12	0.2727	
(c)	hp	-0.0279	0.0166	-1.68	0.1052	
(d)	wt	-3.7143	1.0482	-3.54	0.0015	**
(e)	gear	0.6788	1.0345	0.66	0.5175	

Question 5

Overall, the predictive power of the model is high:

A. True (better than 70%)
B. False (worse than 30%)
C. Can't tell

```
Residual standard error: 2.54 on 26 degrees of freedom
Multiple R-squared:  0.851,   Adjusted R-squared:  0.822
F-statistic: 29.7 on 5 and 26 DF,  p-value: 5.72e-10
```

Machine learning

Machine Learning

Automated (statistical) learning of a concept from labelled sample data.

- For example: Spam filtering with an algorithm that takes some examples of spam and makes a rule to predict whether an email should go to the spam folder.

How can a model learn a concept?

- Descriptive: captures the training data;
- Predictive: generalizes to unseen data;
- Explanatory: describes the concept to be learned.

Classification example – tax return

- Given the following data about people who submitted a tax return, we want to automatically create a model that will classify people into cheats or non-cheats.
- We then want to be able to Use the model to classify 'new' people into cheats or non-cheats.

	categorical	categorical	continuous	class
Tid	**Refund**	**Marital Status**	**Taxable Income**	**Cheat**
1	Yes	Single	125K	**No**
2	No	Married	100K	**No**
3	No	Single	70K	**No**
4	Yes	Married	120K	**No**
5	No	Divorced	95K	**Yes**
6	No	Married	60K	**No**
7	Yes	Divorced	220K	**No**
8	No	Single	85K	**Yes**
9	No	Married	75K	**No**
10	No	Single	90K	**Yes**

Classification

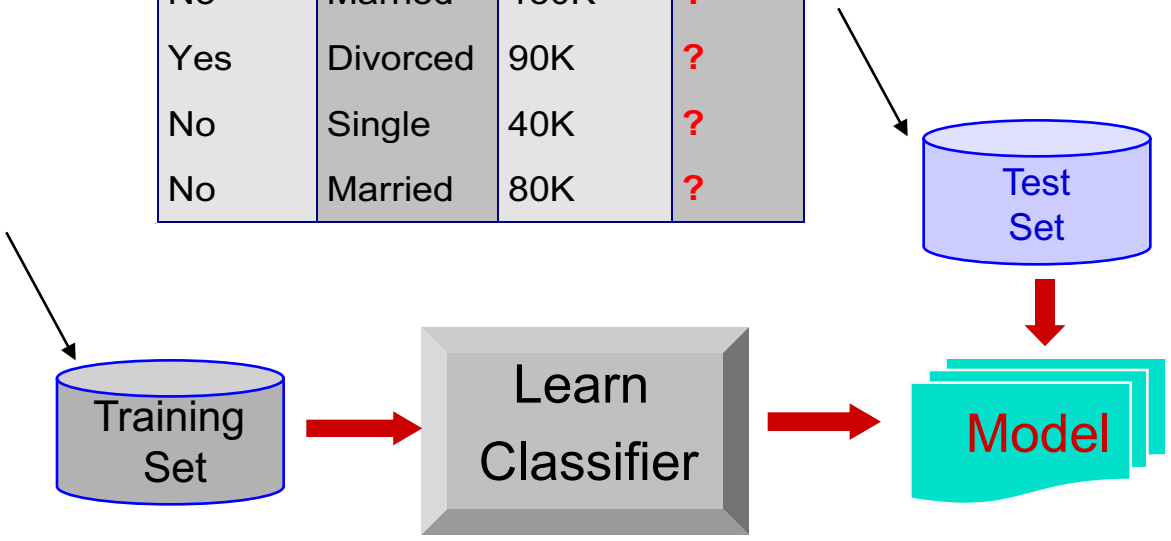
Using a collection of records containing a set of *attributes* where one of the attributes is the *class*, find a model to predict class as a function of the other attributes.

- Goal: previously unseen records should be assigned a class as accurately as possible.
- Data is usually divided into a *training set* to build the model, and a *test set* used to validate (test the accuracy) of the model.

Classification example – tax return

Tid	Refund (categorical)	Marital Status (categorical)	Taxable Income (continuous)	Cheat (class)
1	Yes	Single	125K	No
2	No	Married	100K	No
3	No	Single	70K	No
4	Yes	Married	120K	No
5	No	Divorced	95K	Yes
6	No	Married	60K	No
7	Yes	Divorced	220K	No
8	No	Single	85K	Yes
9	No	Married	75K	No
10	No	Single	90K	Yes

Refund	Marital Status	Taxable Income	Cheat
No	Single	75K	?
Yes	Married	50K	?
No	Married	150K	?
Yes	Divorced	90K	?
No	Single	40K	?
No	Married	80K	?

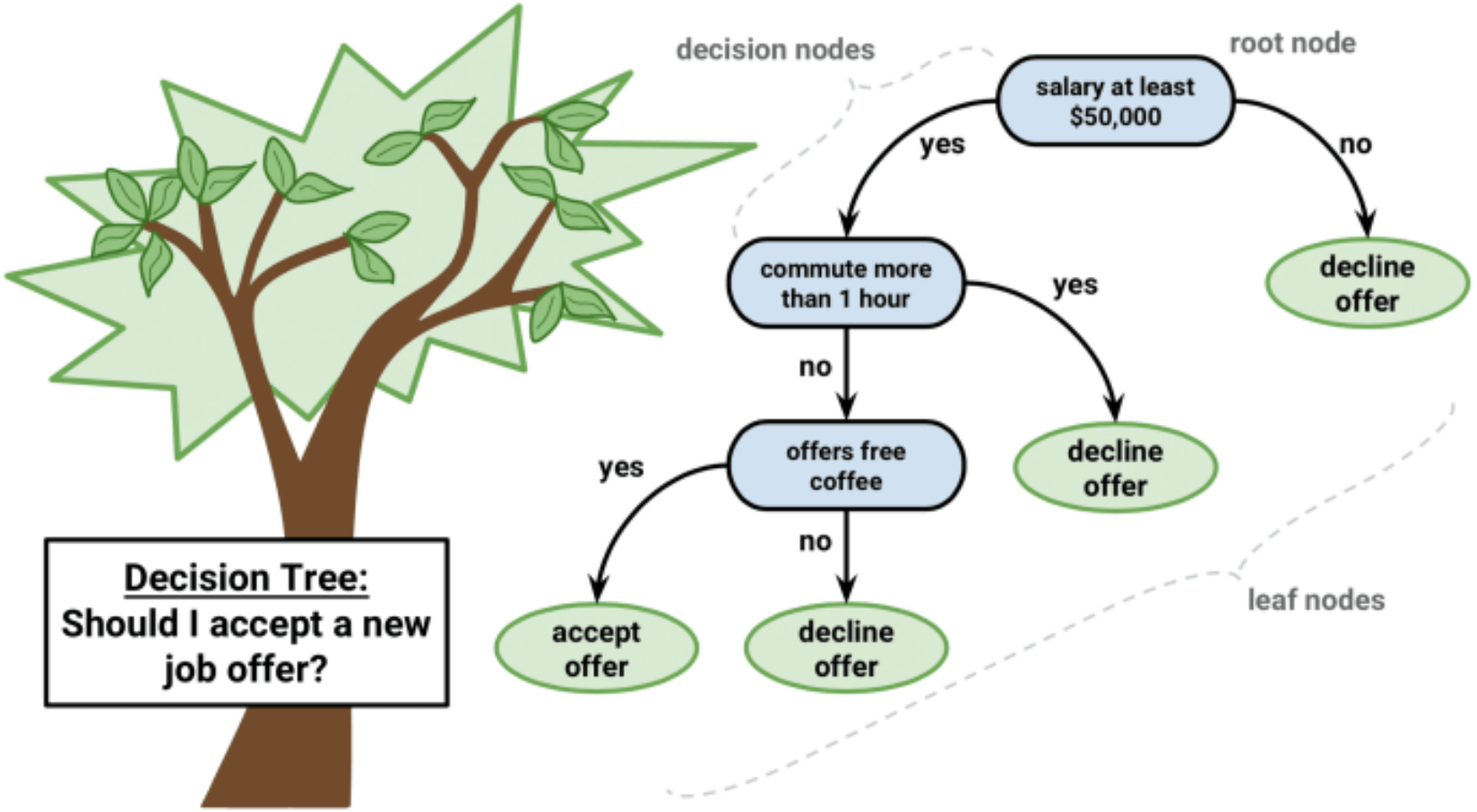


Classification

Classification techniques include:

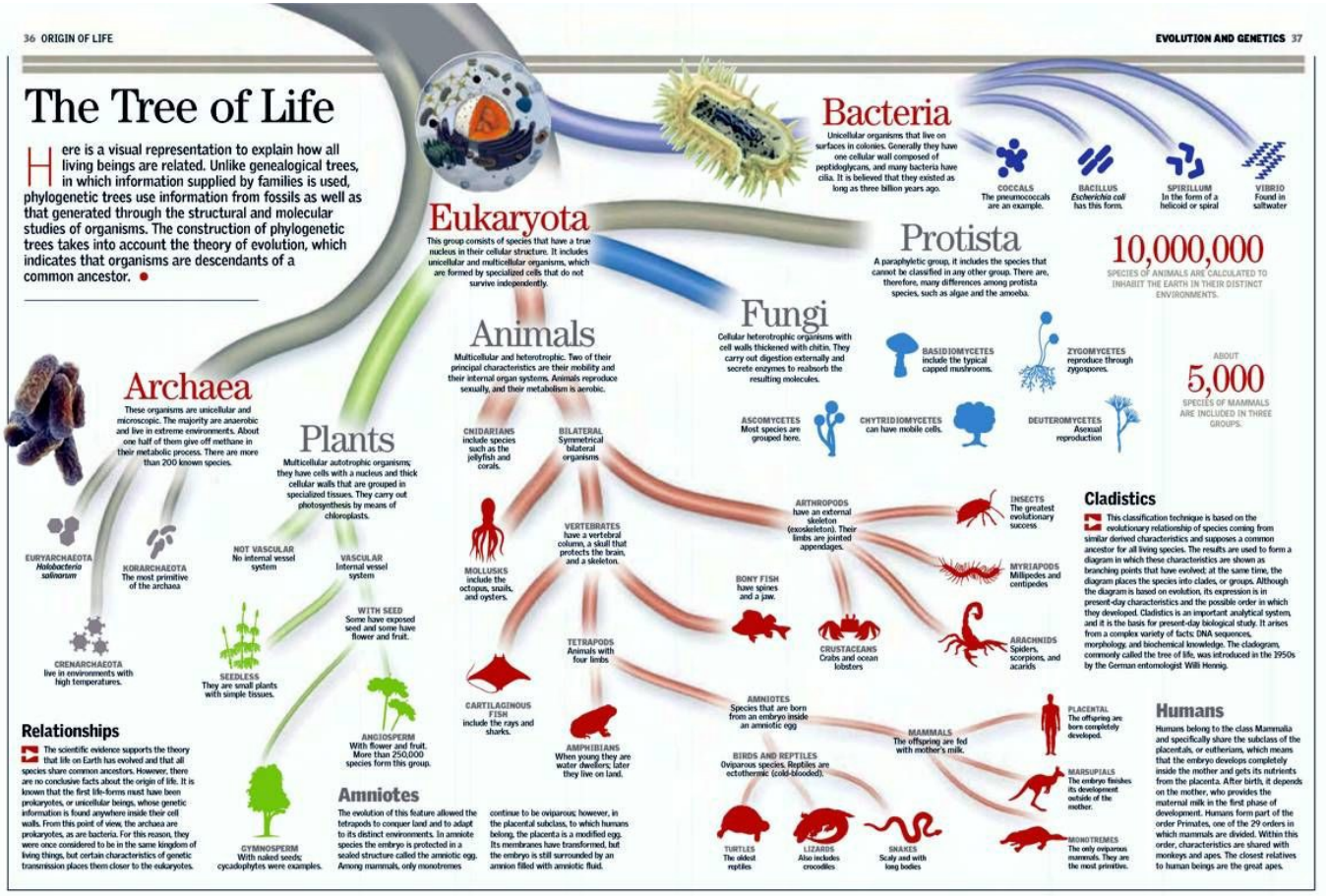
- Decision Tree based methods
- Naïve Bayes and Bayesian Belief Networks
- Ensemble methods
- Artificial neural networks
- Rule-based methods
- Memory based reasoning
- Support Vector Machines

Decision tree: should I accept job?



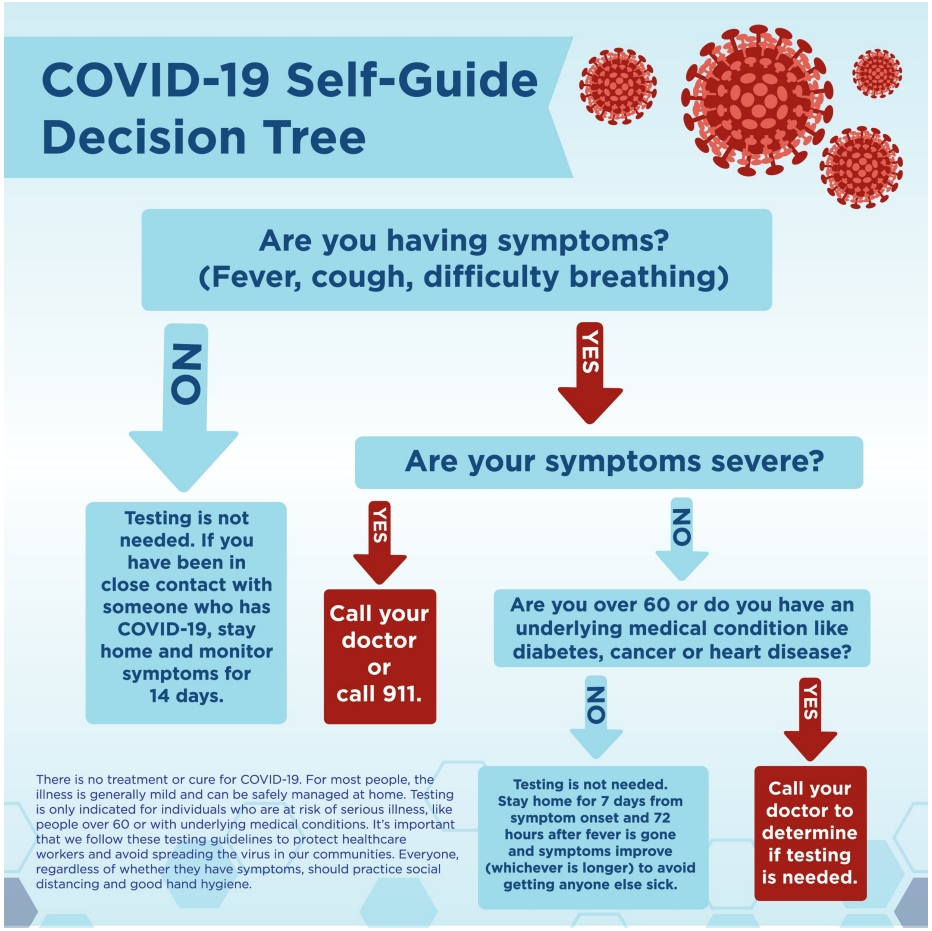
https://towardsdatascience.com/decision-tree-hugging-b8851f853486

Classification tree: life forms



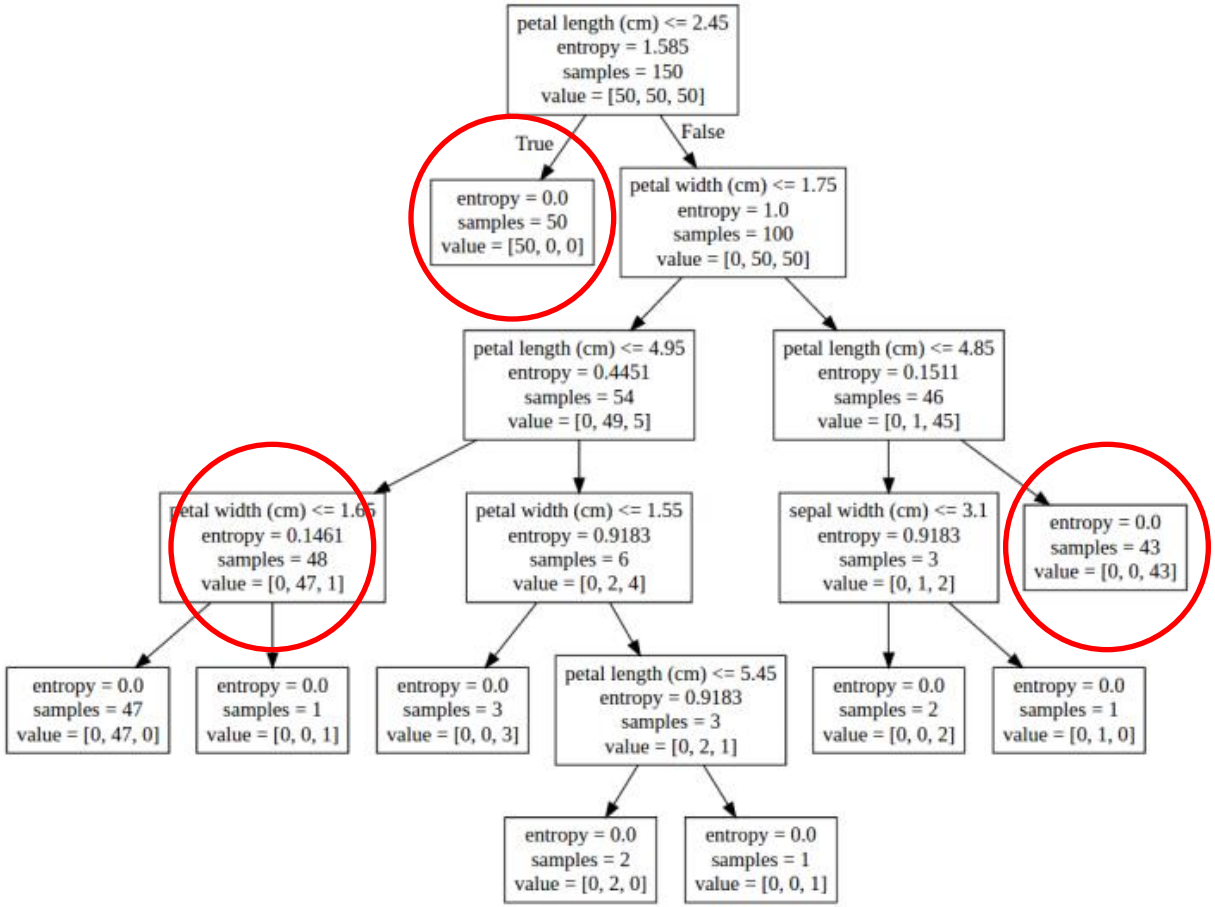
https://medium.com/cracking-the-data-science-interview/decision-trees-how-to-optimize-my-decision-making-process-e1f327999c7a

COVID-19 Self-diagnosis



https://www.holzer.org/coronavirus-covid-19-updates/

Iris species classification



https://www.kdnuggets.com/2017/05/simplifying-decision-tree-interpretation-decision-rules-python.html

Decision Trees

Decision trees are one of the most widely used and practical methods in machine learning:

- Model uses existing data attributes and values
- Can be used to classify new instances
- Can be used to profile existing data
- Robust to noise and missing values
- Each tree can be viewed as a sequence of "if – then – else" statements, this readability is highly desirable.
- *We can construct simple decision trees by hand!*

Decision Trees

Tree constitutes:

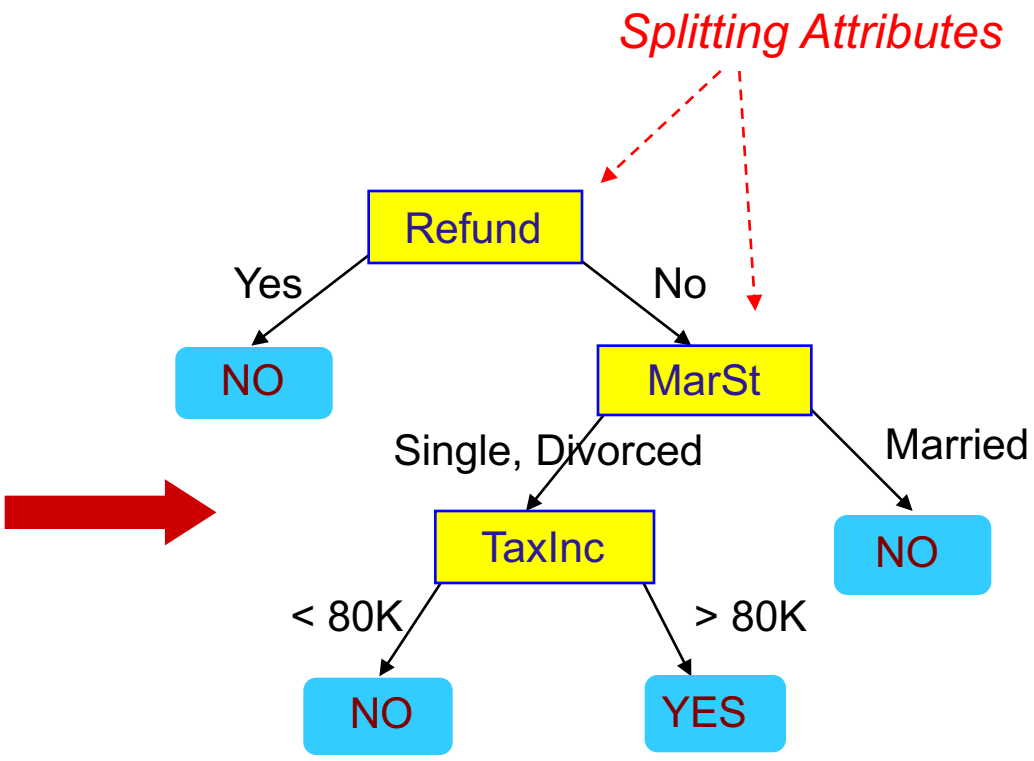
- leaf nodes (class) and non-leaf nodes, corresponding to the decision attributes,
- Branches – corresponding to the values of the decision attributes having either binary or multi-way splits.
- To classify an object, each decision node (starting from the root) compares an attribute of the object with a specific attribute value (or range) and takes the corresponding branch.
- A path from the root to a leaf node gives the class of the object.

Classification example – tax return

Tid	Refund	Marital Status	Taxable Income	Cheat
1	Yes	Single	125K	No
2	No	Married	100K	No
3	No	Single	70K	No
4	Yes	Married	120K	No
5	No	Divorced	95K	Yes
6	No	Married	60K	No
7	Yes	Divorced	220K	No
8	No	Single	85K	Yes
9	No	Married	75K	No
10	No	Single	90K	Yes

categorical categorical continuous class

Training Data

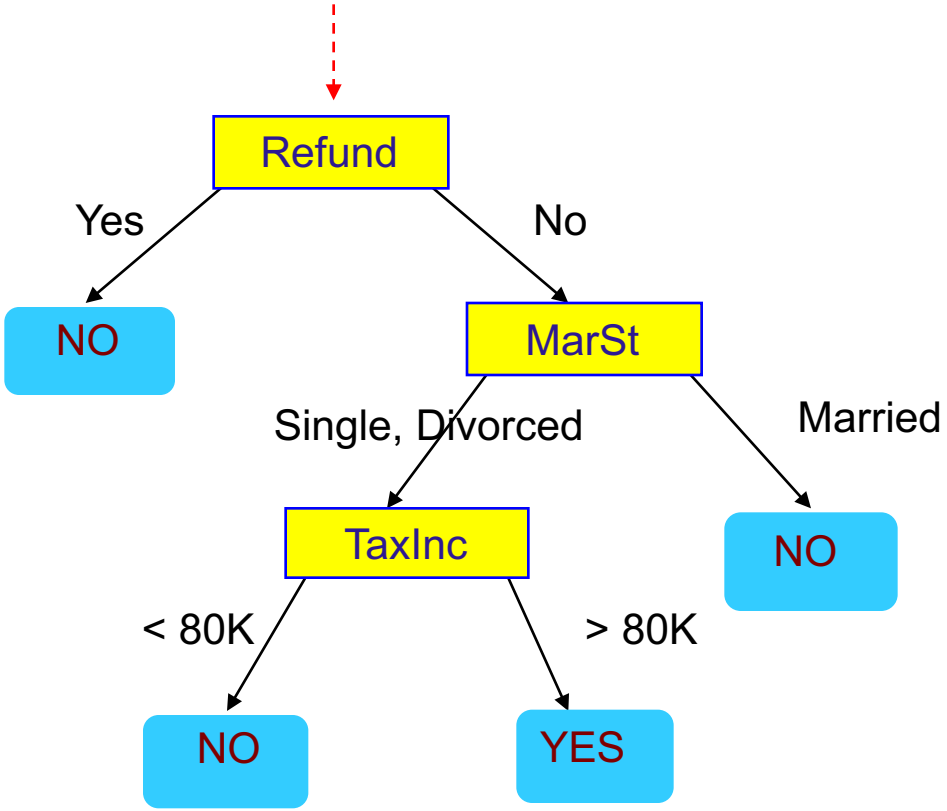


Model: Decision Tree

(One of many possible trees)

Apply Model to Test Data

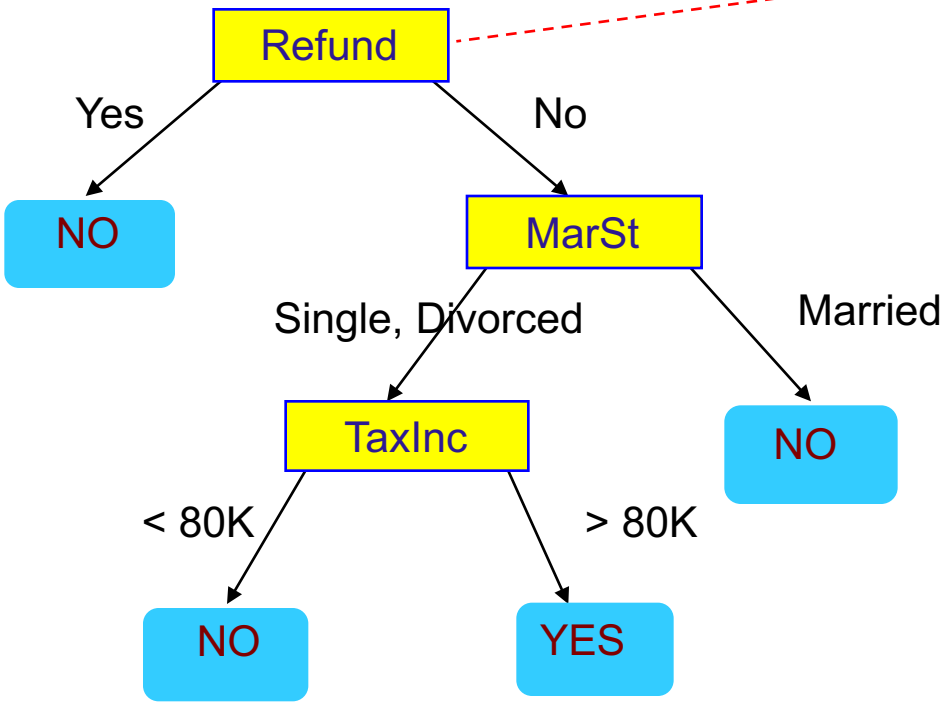
Start from the root of tree.



Test Data

Refund	Marital Status	Taxable Income	Cheat
No	Married	80K	?

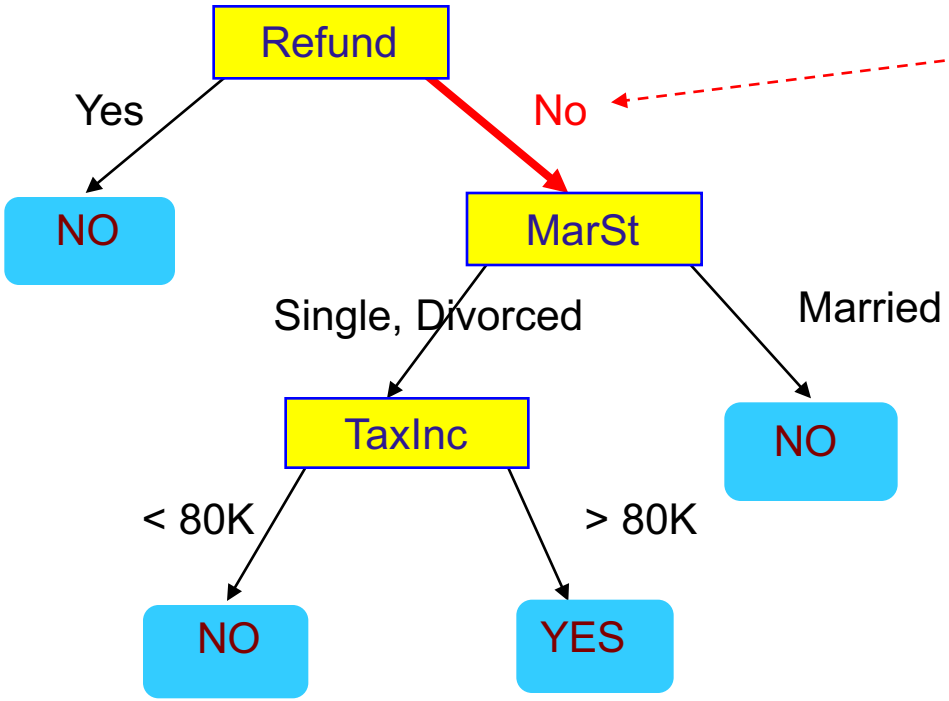
Apply Model to Test Data



Test Data

Refund	Marital Status	Taxable Income	Cheat
No	Married	80K	?

Apply Model to Test Data



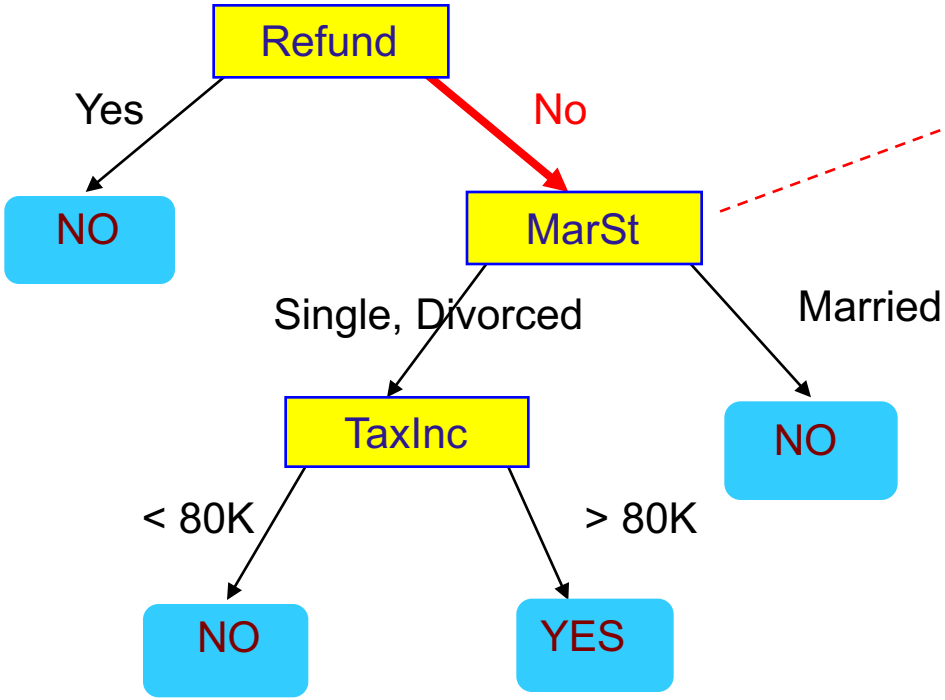
Test Data

Refund	Marital Status	Taxable Income	Cheat
No	Married	80K	?

Apply Model to Test Data

Test Data

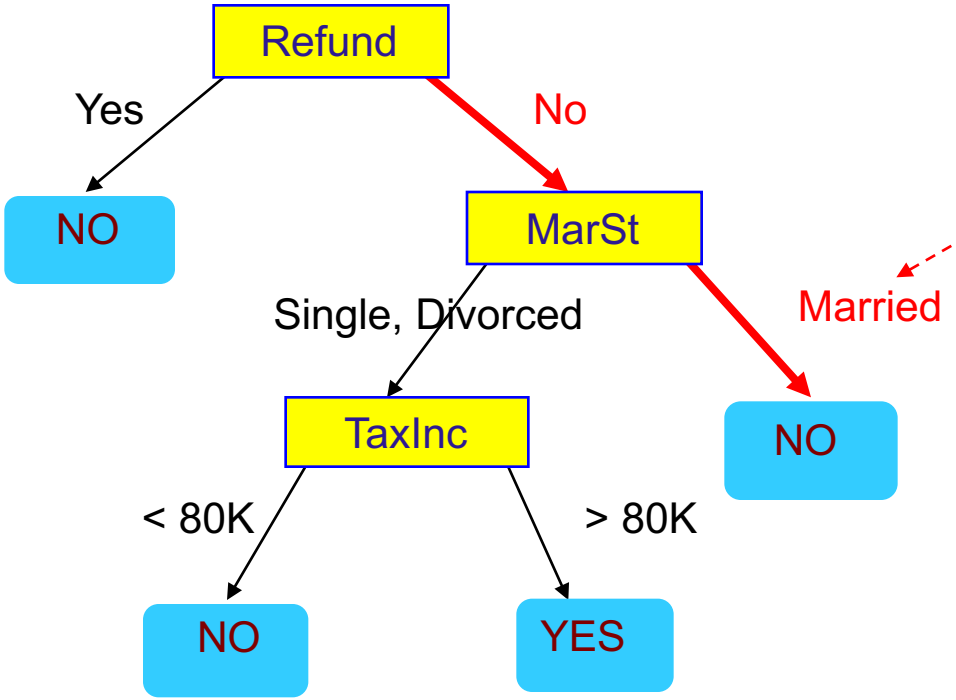
Refund	Marital Status	Taxable Income	Cheat
No	Married	80K	?



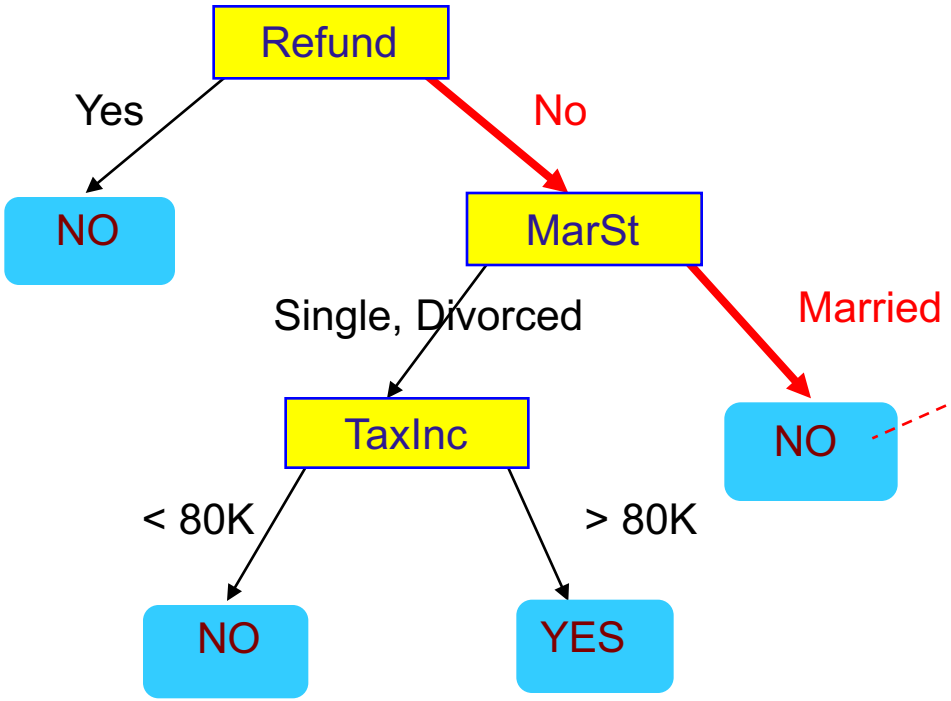
Apply Model to Test Data

Test Data

Refund	Marital Status	Taxable Income	Cheat
No	Married	80K	?



Apply Model to Test Data



Test Data

Refund	Marital Status	Taxable Income	Cheat
No	Married	80K	?

Assign Cheat to “No”

Building a decision tree

Building a decision tree requires answering:

- Which attribute should be tested at a node?
- When should a node be declared a leaf?
- What if tree becomes too large?
- How to handle missing values?
- Should the properties be restricted to binary-valued or allowed to be multi-valued?
- Answering these questions leads to different variants of decision trees, ID3, C4.5, C5, CART, etc.

Building a decision tree

Many decision tree learning algorithms are variations on a core algorithm that employs *top-down*, *greedy search* through the space of possible decision trees.

The algorithm aims to create *homogeneous* leaf nodes.

Top-down induction: ID3

The algorithm (*Iterative Dichotomiser 3*):

- At each step, determine the "best" decision attribute, A, for next node
- Assign A as decision attribute for node
- For each value of A create new descendant
- Sort training examples to that node according to the attribute value of the branch
- If all training examples are perfectly classified (same value of target attribute) stop, else iterate over new leaf nodes.

For this algorithm assume class attribute is categorical.

https://en.wikipedia.org/wiki/ID3_algorithm

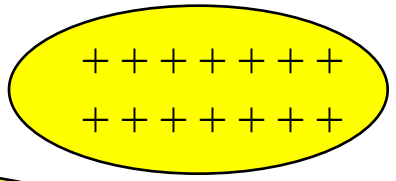
Which attribute to split on?

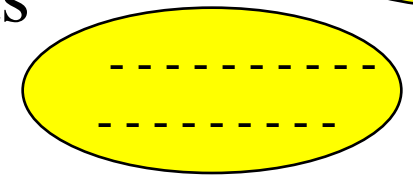
- At each stage of the process, we try to find the 'best' attribute and split to partition the data.
- That decision may not be the best overall – but once it is made we stay with it for the rest of the tree.
- This is generally called a *greedy* approach and may not result in the best overall decision tree.
- At each split the goal is to increase the *homogeneity* of the resulting datasets with respect to the *class* or *target* variable (which we are trying to classify).

Homogeneity

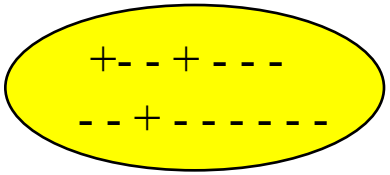
Suppose we have a binary target attribute with values '+' and '–'.

- These two sets are homogeneous

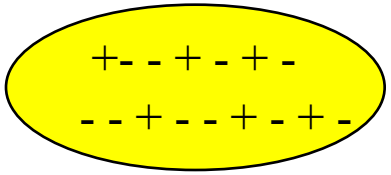




- This one is not



- This one even less so



Information gain

Which attribute to choose for splitting?

- A statistical property called *information gain* measures how well a given attribute separates the training examples into homogeneous groups according to target classification.
- ID3 uses information gain as the splitting criteria for building a tree and chooses the attribute which provides the greatest information gain.
- Information gain is determined using a measure from Information Theory called *Entropy*.

Entropy

In thermodynamics:

- It gives a measure of the amount of chaos present in a system (or a measure of the disorder in a system).

In Information Theory:

- Entropy measures the uncertainty in a random variable – or message, or indicates how much information (or impurity) there is in an event.
- In general, the more uncertain or random the event is, the more information it will contain.

Entropy cont…

See Wikipedia:

https://en.wikipedia.org/wiki/Entropy_(information_theory)

- In information theory, systems are modeled by a transmitter, channel, and receiver… The receiver attempts to infer which message was sent. In this context, entropy (more specifically, Shannon entropy) is the expected value (average) of the information contained in each message. 'Messages' can be modeled by any flow of information…

Calculating entropy

For a two class problem: c_1 and c_2:

- P indicates the probability of belonging to each class, the number in each class is $N_{c1} + N_{c2} = N$.

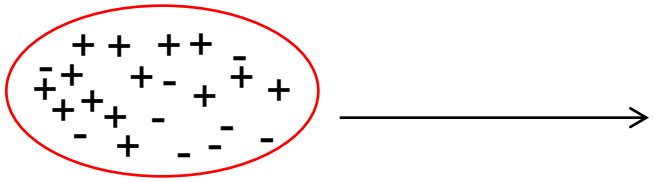
$$\begin{aligned} \text{Entropy(S)} &= -P_{c1}\log_2(P_{c1}) - P_{c2}\log_2(P_{c2}) \\ &= -\frac{N_{c1}}{N}\log_2(\frac{N_{c1}}{N}) - \frac{N_{c2}}{N}\log_2(\frac{N_{c2}}{N}) \end{aligned}$$

For a multi-class problem

$$\begin{aligned} \text{Entropy(S)} &= -\sum_{i=1}^{C} P_i \log_2(P_i) \\ &= -\sum_{i=1}^{C} \frac{N_i}{N}\log_2(\frac{N_i}{N}) \end{aligned}$$

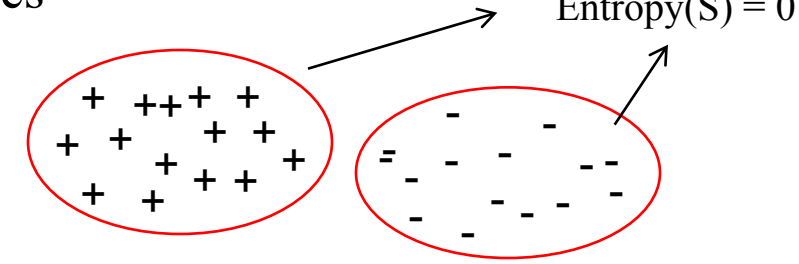
Calculating entropy

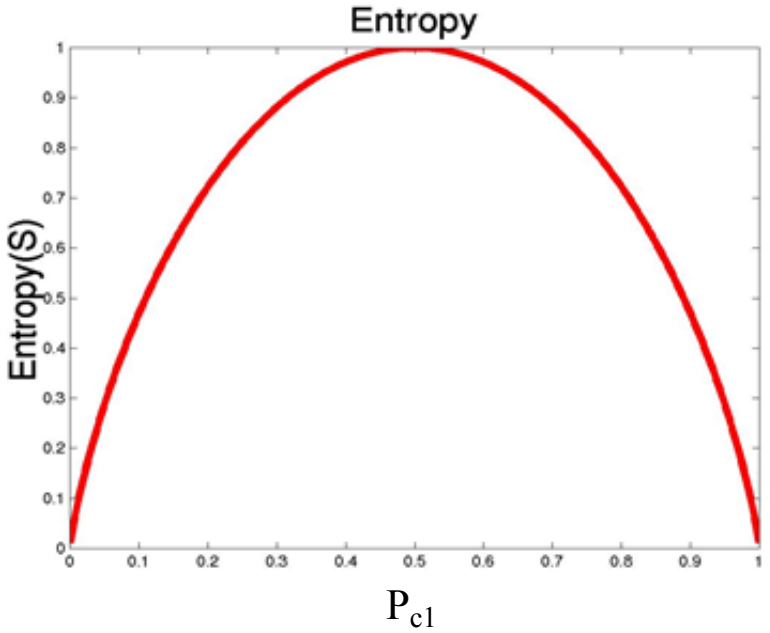
E.g. Suppose S is a collection of 14 examples, 9 positive and 5 negative → [9+,5-]



$$\begin{aligned} \text{Entropy(S)} &= -P_{c1}\log_2(P_{c1}) - P_{c2}\log_2(P_{c2}) \\ &= -\frac{9}{14}\log_2(\frac{9}{14}) - \frac{5}{14}\log_2(\frac{5}{14}) \\ &= 0.940 \end{aligned}$$

E.g. suppose S has all positive or all negative examples





Entropy is 0 (minimum) if all members belong to the same class. Entropy is 1 (maximum) if the collection consists of equal number of positive and negative examples. Note: $0\text{Log}_2 0 = 0$

Calculating entropy

The previous example as a spreadsheet:

- If your calculator can't work out logs to base 2 then use the following:

$$\log_2(x) = \frac{\log_{10}(x)}{\log_{10}(2)} \approx \frac{\log_{10}(x)}{0.3010}$$

Yes	No	P(Yes)	Log2(Yes)	P(No)	Log2(No)	Entropy
9	5	0.6429	-0.6374	0.3571	-1.4854	0.9403

- Note: $\log_2$ yields entropy in units called "shannons"

Information gain

Information gain is the expected reduction in entropy caused by partitioning the examples according to an attribute A.

- Gain(S,A) of an attribute A, relative to a collection of examples S (with v groups having $|S_v|$ elements) is:

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

Entropy before split

Expected entropy after split

How ID3 uses information gain

The algorithm ‘splits’ on the attribute that provides the most information gain – i.e. gives the purest class breakdown at each step in the decision tree.

Recall: purer class = entropy reduction!

How ID3 uses information gain

The algorithm:

- At each step, determine the “best” decision attribute, A, for next node.
- Assign A as decision attribute for node.
- For each value of A create a new descendant.
- Sort training examples to that node according to the attribute value of the branch.
- If all training examples are perfectly classified (same value of target attribute) stop, else iterate over new leaf nodes.

Example: playing tennis

Build a decision tree for playing tennis based on weather conditions.

Training set (S): What would you choose?

Day	Outlook	Temperature	Humidity	Wind	Play
D1	Sunny	Hot	High	Weak	No
D2	Sunny	Hot	High	Strong	No
D3	Overcast	Hot	High	Weak	Yes
D4	Rain	Mild	High	Weak	Yes
D5	Rain	Cool	Normal	Weak	Yes
D6	Rain	Cool	Normal	Strong	No
D7	Overcast	Cool	Normal	Strong	Yes
D8	Sunny	Mild	High	Weak	No
D9	Sunny	Cool	Normal	Weak	Yes
D10	Rain	Mild	Normal	Weak	Yes
D11	Sunny	Mild	Normal	Strong	Yes
D12	Overcast	Mild	High	Strong	Yes
D13	Overcast	Hot	Normal	Weak	Yes
D14	Rain	Mild	High	Strong	No

First split on: Outlook, Temperature, Humidity or Wind?

Terminology

- *Instance*: single row in a data set. Also called an example or object.
- *Attribute*: an aspect of an instance. Also called feature, variable. These can be categorical or numerical.
- *Value*: category that an attribute can take.
- *Class*: the thing to be learned. Also called *Concept* or *Target.*
- It is usual to have several decision attributes and one target attribute.

Playing tennis: initial entropy

Training set (*S*): Initial entropy before splitting based on 9 Yes/5 No:

Day	Outlook	Temperature	Humidity	Wind	Play
D1	Sunny	Hot	High	Weak	No
D2	Sunny	Hot	High	Strong	No
D3	Overcast	Hot	High	Weak	Yes
D4	Rain	Mild	High	Weak	Yes
D5	Rain	Cool	Normal	Weak	Yes
D6	Rain	Cool	Normal	Strong	No
D7	Overcast	Cool	Normal	Strong	Yes
D8	Sunny	Mild	High	Weak	No
D9	Sunny	Cool	Normal	Weak	Yes
D10	Rain	Mild	Normal	Weak	Yes
D11	Sunny	Mild	Normal	Strong	Yes
D12	Overcast	Mild	High	Strong	Yes
D13	Overcast	Hot	Normal	Weak	Yes
D14	Rain	Mild	High	Strong	No

Yes	No	P(Yes)	Log2(Yes)	P(No)	Log2(No)	Entropy
9	5	0.6429	-0.6374	0.3571	-1.4854	0.9403

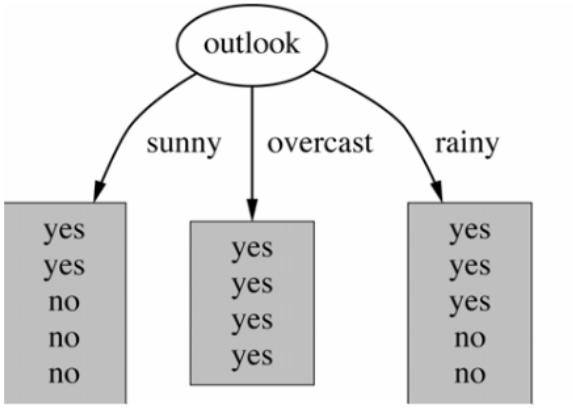
Initial entropy

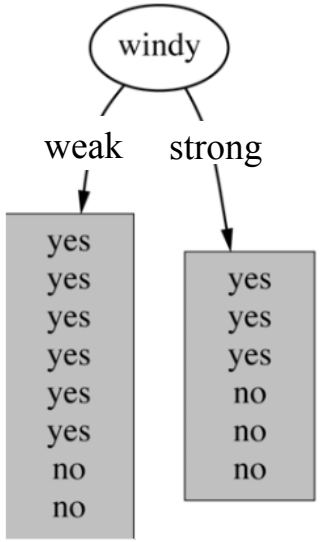
- Without any knowledge of the weather there are 9 Yes and 5 No cases. Initial entropy is:
- $E(S) = -\frac{9}{14} \cdot log_2\left(\frac{9}{14}\right) - \frac{5}{14} \cdot log_2\left(\frac{5}{14}\right)$
- $E(S) = 0.9403$

Which attribute to select?

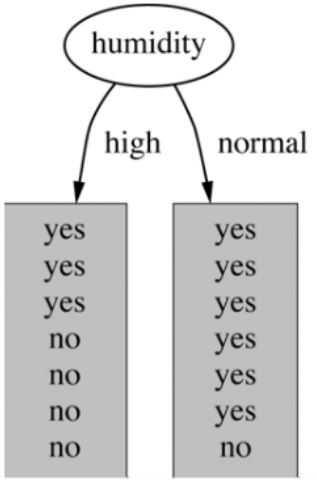
Remember - ID3 chooses the attribute which gives the greatest information gain (reduction in Entropy), or the 'purest' result.

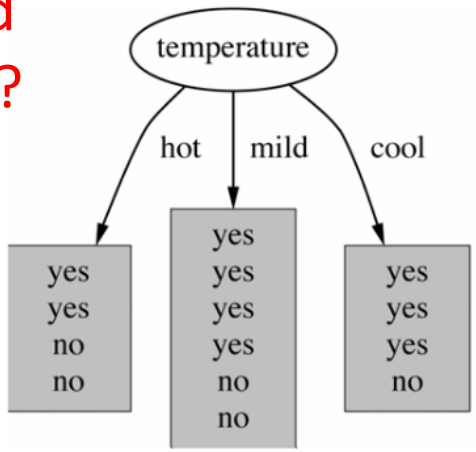
We next calculate the information gain for each attribute in turn.





What would you choose?

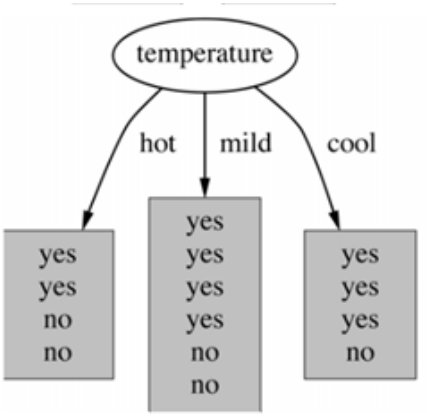




Information gain: Temperature

Calculate entropy for each branch first:

- $E(S_{hot}) = -\frac{2}{4} \cdot log_2\left(\frac{2}{4}\right) - \frac{2}{4} \cdot log_2\left(\frac{2}{4}\right) = 1$
- $E(S_{mild}) = -\frac{4}{6} \cdot log_2\left(\frac{4}{6}\right) - \frac{2}{6} \cdot log_2\left(\frac{2}{6}\right) = 0.918$
- $E(S_{cool}) = -\frac{3}{4} \cdot log_2\left(\frac{3}{4}\right) - \frac{1}{4} \cdot log_2\left(\frac{1}{4}\right) = 0.811$



Now calculate expected entropy and information gain

- $Gain(S, Temp) = E(S) - E(S, Temp)$
- $Gain(S, Temp) = E(S) - \left(\frac{4}{14}1 + \frac{6}{14}0.918 + \frac{4}{14}0.811\right)$
- $= 0.9403 - 0.910$
- $= 0.0292$

Information gain: Temperature

As a spreadsheet showing initial entropy and subsequent information gain:

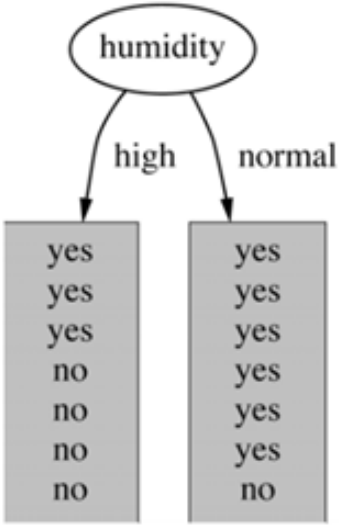
Initial State	Yes	No	P(Yes)	Log2(Yes)	P(No)	Log2(No)	Entropy
Entropy(S)	9	5	0.6429	-0.6374	0.3571	-1.4854	0.9403

Temperature	Yes	No	P(Yes)	Log2(Yes)	P(No)	Log2(No)	Entropy
Hot	2	2	0.5000	-1.0000	0.5000	-1.0000	1.0000
Mild	4	2	0.6667	-0.5850	0.3333	-1.5850	0.9183
Cool	3	1	0.7500	-0.4150	0.2500	-2.0000	0.8113
EEntropy(Temp)							0.9111
Gain(S, Temp)							**0.0292**

Information gain: Humidity

Calculate entropy for each branch first:

- $E(S_{high}) = -\frac{3}{7} \cdot log_2\left(\frac{3}{7}\right) - \frac{4}{7} \cdot log_2\left(\frac{4}{7}\right) = 0.9852$
- $E(S_{normal}) = -\frac{6}{7} \cdot log_2\left(\frac{6}{7}\right) - \frac{1}{7} \cdot log_2\left(\frac{1}{7}\right) = 0.5917$



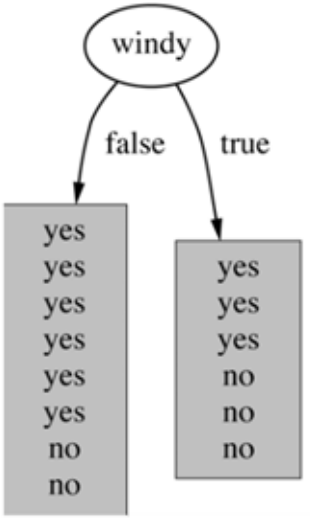
Now calculate expected entropy and information gain

- $Gain(S, Humidity) = E(S) - E(S, Humidity)$
- $Gain(S, Humidity) = E(S) - \left(\frac{7}{14}0.9852 + \frac{7}{14}0.5917\right)$
- $= 0.9403 - 0.7885$
- $= 0.1518$

Information gain: Windy (for you to do)

Calculate entropy for each branch first:

- $E(S_{false}) = -\frac{6}{8} \cdot log_2\left(\frac{6}{8}\right) - \frac{2}{8} \cdot log_2\left(\frac{2}{8}\right) =$ ☐
- $E(S_{true}) = -\frac{3}{6} \cdot log_2\left(\frac{3}{6}\right) - \frac{3}{6} \cdot log_2\left(\frac{3}{6}\right) =$ ☐



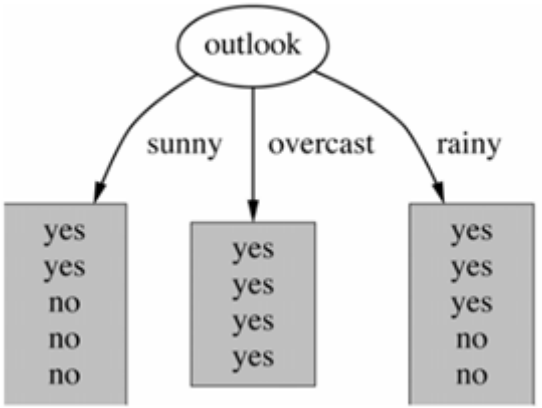
Now calculate expected entropy and information gain

- $Gain(S, Windy) = E(S) - E(S, Windy)$
- $Gain(S, Windy) = E(S) - \left(\frac{8}{14}$ ☐ $+ \frac{6}{14}$ ☐ $\right)$
- $= 0.9403 -$ ☐ $=$ ☐

Information gain: Outlook (for you to do)

Calculate entropy for each branch first:

- $E(S_{sunny}) = -\frac{2}{5} \cdot log_2\left(\frac{2}{5}\right) - \frac{3}{5} \cdot log_2\left(\frac{3}{5}\right) =$ ☐
- $E(S_{overcast}) = 0$
- $E(S_{rainy}) = -\frac{3}{5} \cdot log_2\left(\frac{3}{5}\right) - \frac{2}{5} \cdot log_2\left(\frac{2}{5}\right) =$ ☐



Now calculate expected entropy and information gain

- $Gain(S, Outlook) = E(S) - E(S, Outlook)$
- $Gain(S, Outlook) = E(S) - \left(\frac{5}{14}$ ☐ $+ \frac{4}{14}$ ☐ $+ \frac{5}{14}$ ☐ $\right)$
- $= 0.9403 -$ ☐ $=$ ☐

Calcs: Humidity, Windy, Outlook

Humidity	**Yes**	**No**	**P(Yes)**	**Log2(Yes)**	**P(No)**	**Log2(No)**	**Entropy**
High	3	4	0.4286	-1.2224	0.5714	-0.8074	0.9852
Normal	6	1	0.8571	-0.2224	0.1429	-2.8074	0.5917
EEntropy(Humidity)							0.7885
Gain(S, Humidity)							**0.1518**

Wind	**Yes**	**No**	**P(Yes)**	**Log2(Yes)**	**P(No)**	**Log2(No)**	**Entropy**
Weak	6	2	0.7500	-0.4150	0.2500	-2.0000	0.8113
Strong	3	3	0.5000	-1.0000	0.5000	-1.0000	1.0000
EEntropyWind)							0.8922
Gain(S, Wind)							**0.0481**

Outlook	**Yes**	**No**	**P(Yes)**	**Log2(Yes)**	**P(No)**	**Log2(No)**	**Entropy**
Sunny	2	3	0.4000	-1.3219	0.6000	-0.7370	0.9710
Overcast	4	0	1.0000	0.0000	0.0000	0.0000	0.0000
Rain	3	2	0.6000	-0.7370	0.4000	-1.3219	0.9710
EEntropy(Outlook)							0.6935
Gain(S, Outlook)							**0.2467**

Attribute giving greatest information gain

Which attribute to choose? Outlook, Temperature, Humidity or Wind?

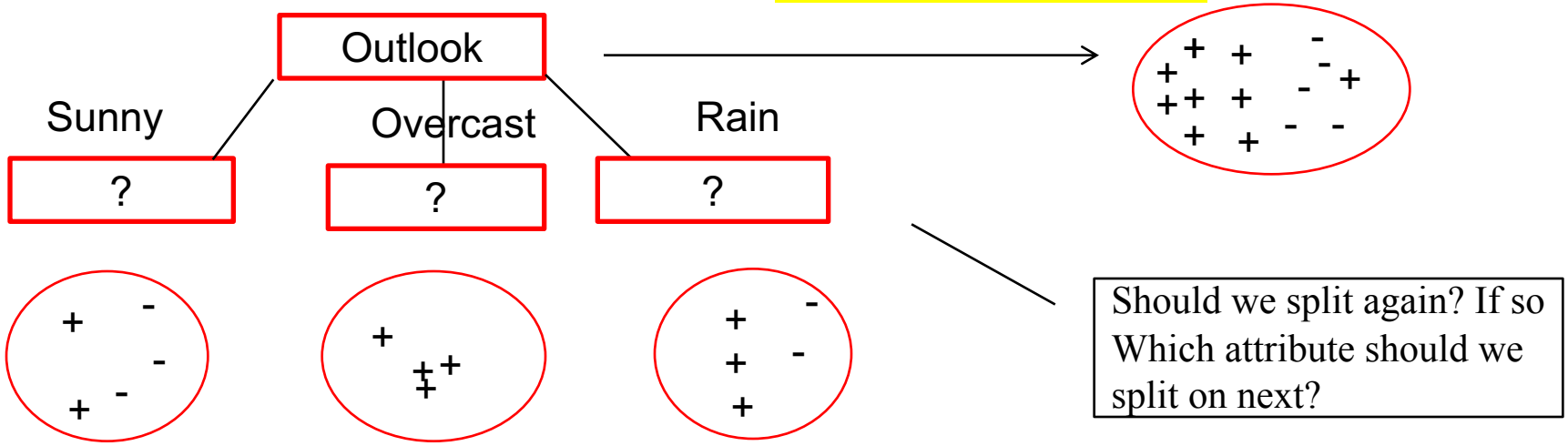
Gain(S, Temperature) = 0.029

Gain(S, Humidity) = 0.151

Gain(S, Wind) = 0.048

Gain(S, Outlook) = 0.247

Choose this one!



Entropy after "Outlook"

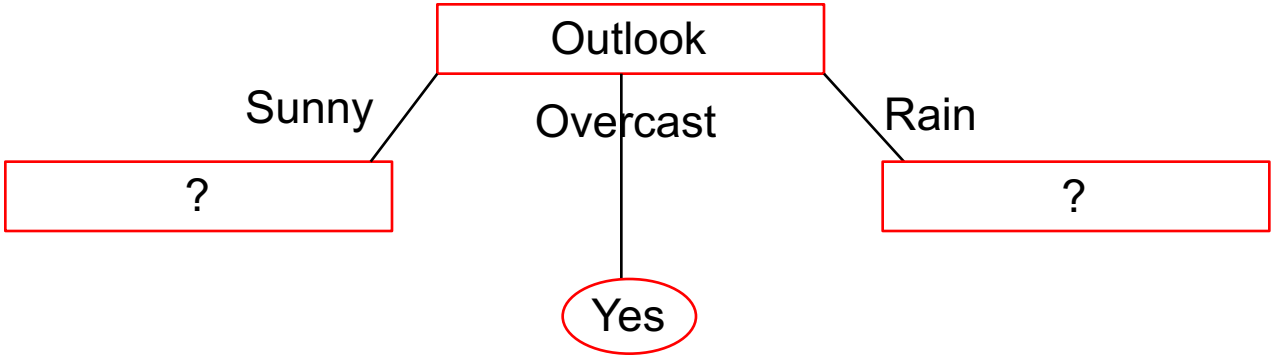
The entropy of each branch of the decision tree after split on Outlook is shown below.

- Information gain in descendent trees is now measured as change in the entropy of each branch
- For example Entropy(Sunny) = 0.971

Outlook	Yes	No	P(Yes)	og2(Yes)	P(No)	.og2(No)	Entropy
Sunny	2	3	0.400	-1.322	0.600	-0.737	0.971
Overcast	4	0	1.000	0.000	0.000	0.000	0.000
Rain	3	2	0.600	-0.737	0.400	-1.322	0.971
EEntropy(Outlook)							0.694

Which attribute to split on next?

Now, starting with Sunny, which attribute should be split on next? Temperature, Humidity or Wind?

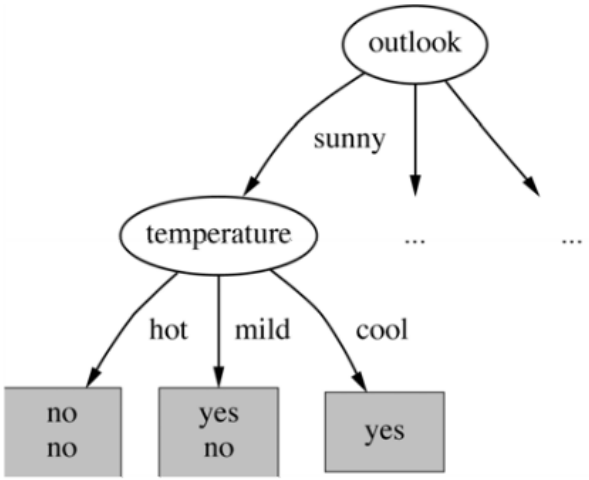


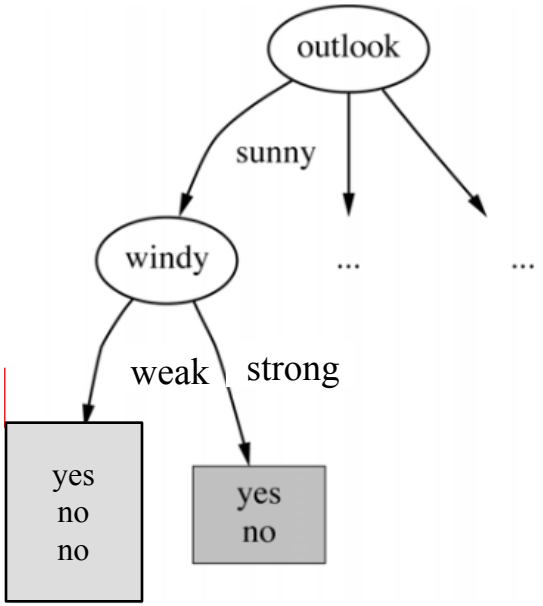
ID3 Step 2: gain(S_sunny, ???)

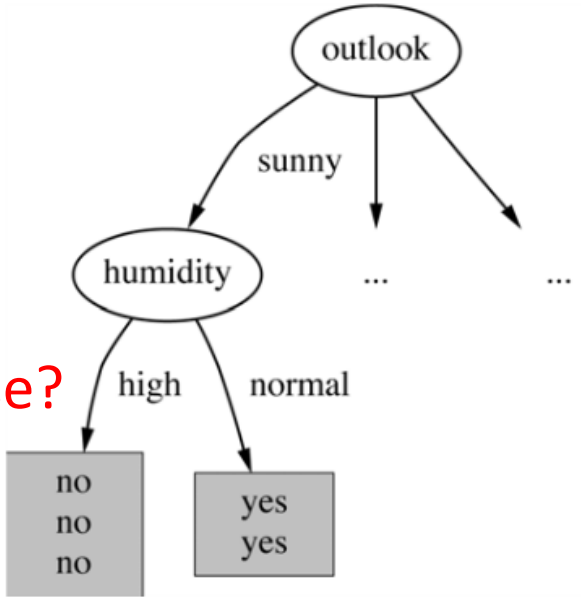
Now consider subset corresponding to “Sunny”:

Day	Outlook	Temperature	Humidity	Wind	Play
D1	Sunny	Hot	High	Weak	No
D2	Sunny	Hot	High	Strong	No
~~D3~~	~~Overcast~~	~~Hot~~	~~High~~	~~Weak~~	~~Yes~~
~~D4~~	~~Rain~~	~~Mild~~	~~High~~	~~Weak~~	~~Yes~~
~~D5~~	~~Rain~~	~~Cool~~	~~Normal~~	~~Weak~~	~~Yes~~
~~D6~~	~~Rain~~	~~Cool~~	~~Normal~~	~~Strong~~	~~No~~
~~D7~~	~~Overcast~~	~~Cool~~	~~Normal~~	~~Strong~~	~~Yes~~
D8	Sunny	Mild	High	Weak	No
D9	Sunny	Cool	Normal	Weak	Yes
~~D10~~	~~Rain~~	~~Mild~~	~~Normal~~	~~Weak~~	~~Yes~~
D11	Sunny	Mild	Normal	Strong	Yes
~~D12~~	~~Overcast~~	~~Mild~~	~~High~~	~~Strong~~	~~Yes~~
~~D13~~	~~Overcast~~	~~Hot~~	~~Normal~~	~~Weak~~	~~Yes~~
~~D14~~	~~Rain~~	~~Mild~~	~~High~~	~~Strong~~	~~No~~

Which attribute to split on next?





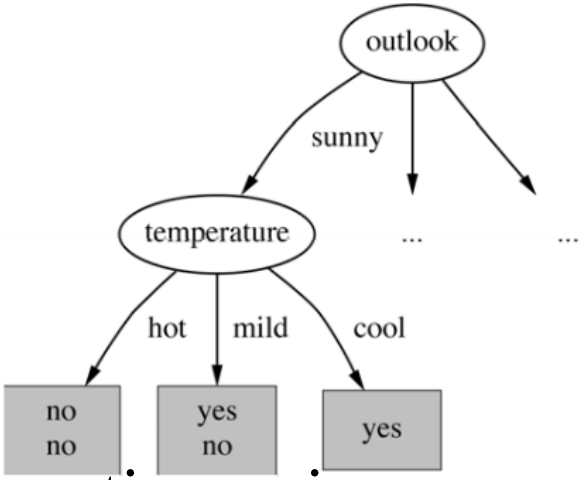


What attribute would you choose?

ID3 Step 2: Gain Sunny, Temperature

Calculate entropy for each branch first:

- $E(S_{sunny,\,hot}) = -\frac{0}{2} \cdot log_2\left(\frac{0}{2}\right) - \frac{2}{2} \cdot log_2\left(\frac{2}{2}\right) = 0$
- $E(S_{sunny,mild}) = -\frac{1}{2} \cdot log_2\left(\frac{1}{2}\right) - \frac{1}{2} \cdot log_2\left(\frac{1}{2}\right) = 1$
- $E(S_{sunny,cool}) = -\frac{1}{1} \cdot log_2\left(\frac{1}{1}\right) - \frac{0}{1} \cdot log_2\left(\frac{0}{1}\right) = 0$



Now calculate expected entropy and information gain

- $Gain(S, Sunny, Temp) = E(S, Sunny) - E(S, Sunny, Temp)$
- $Gain(S, Sunny, Temp) = E(S, Sunny) - \left(\frac{2}{5}0 + \frac{2}{5}1 + \frac{1}{5}0\right)$
- $= 0.971 - 0.4 = 0.571$

Calculations for all attributes shown on the next slide…

ID3 Step 2: Gain for Sunny Outlook

Sunny, Temp	Yes	No	P(Yes)	Log2(Yes)	P(No)	Log2(No)	Entropy
Hot	0	2	0.0000	0.0000	1.0000	0.0000	0.0000
Mild	1	1	0.5000	-1.0000	0.5000	-1.0000	1.0000
Cool	1	0	1.0000	0.0000	0.0000	0.0000	0.0000
EEntropy(Temp)							0.4000
Gain(Sunny, Temp)							**0.5710**

Sunny, Humid	Yes	No	P(Yes)	Log2(Yes)	P(No)	Log2(No)	Entropy
High	0	3	0.0000	0.0000	1.0000	0.0000	0.0000
Normal	2	0	1.0000	0.0000	0.0000	0.0000	0.0000
EEntropy(Temp)							0.0000
Gain(Sunny, Humid)							**0.9710**

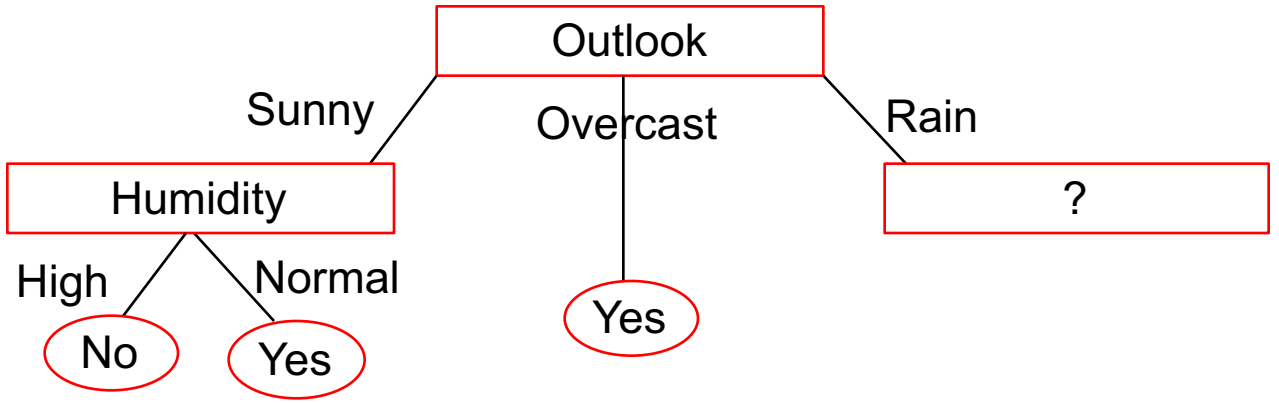
Sunny, Wind	Yes	No	P(Yes)	Log2(Yes)	P(No)	Log2(No)	Entropy
Weak	1	2	0.3333	-1.5850	0.6667	-0.5850	0.9183
Strong	1	1	0.5000	-1.0000	0.5000	-1.0000	1.0000
EEntropyWind)							0.9510
Gain(Sunny, Wind)							**0.0200**

ID3 Step 2: Gain for Sunny Outlook

Which attribute to choose? Temperature, Humidity or Wind?

- $Gain(S_{sunny}, Wind) = 0.020$
- $Gain(S_{sunny}, Humidity) = 0.971$
- $Gain(S_{sunny}, Temperature) = 0.570$

Choose this one!



Repeat the process to find which attribute is the best to split on at this step

Not all leaves need to be 'pure'.
Splitting stops when the data can't be split any further.

Class activity

Now consider subset after “Rain Outlook”:

Day	Outlook	Temperature	Humidity	Wind	Play
~~D1~~	~~Sunny~~	~~Hot~~	~~High~~	~~Weak~~	~~No~~
~~D2~~	~~Sunny~~	~~Hot~~	~~High~~	~~Strong~~	~~No~~
~~D3~~	~~Overcast~~	~~Hot~~	~~High~~	~~Weak~~	~~Yes~~
D4	Rain	Mild	High	Weak	Yes
D5	Rain	Cool	Normal	Weak	Yes
D6	Rain	Cool	Normal	Strong	No
~~D7~~	~~Overcast~~	~~Cool~~	~~Normal~~	~~Strong~~	~~Yes~~
~~D8~~	~~Sunny~~	~~Mild~~	~~High~~	~~Weak~~	~~No~~
~~D9~~	~~Sunny~~	~~Cool~~	~~Normal~~	~~Weak~~	~~Yes~~
D10	Rain	Mild	Normal	Weak	Yes
~~D11~~	~~Sunny~~	~~Mild~~	~~Normal~~	~~Strong~~	~~Yes~~
~~D12~~	~~Overcast~~	~~Mild~~	~~High~~	~~Strong~~	~~Yes~~
~~D13~~	~~Overcast~~	~~Hot~~	~~Normal~~	~~Weak~~	~~Yes~~
D14	Rain	Mild	High	Strong	No

Class activity

Class counts and expected entropy after rain outlook.

Day	Outlook	Temperature	Humidity	Wind	Play
D1	Sunny	Hot	High	Weak	No
D2	Sunny	Hot	High	Strong	No
D3	Overcast	Hot	High	Weak	Yes
D4	Rain	Mild	High	Weak	Yes
D5	Rain	Cool	Normal	Weak	Yes
D6	Rain	Cool	Normal	Strong	No
D7	Overcast	Cool	Normal	Strong	Yes
D8	Sunny	Mild	High	Weak	No
D9	Sunny	Cool	Normal	Weak	Yes
D10	Rain	Mild	Normal	Weak	Yes
D11	Sunny	Mild	Normal	Strong	Yes
D12	Overcast	Mild	High	Strong	Yes
D13	Overcast	Hot	Normal	Weak	Yes
D14	Rain	Mild	High	Strong	No

Rain, Temp	Yes	No
Hot		
Mild		
Cool		

Rain, Humid	Yes	No
High		
Normal		

Rain, Wind	Yes	No
Weak	3	0
Strong	0	2

What would you choose?

ID3 Step 3: Gain for Rain Outlook

Rain, Temp	Yes	No	P(Yes)	Log2(Yes)	P(No)	Log2(No)	Entropy
Hot							
Mild							
Cool							
EEntropy(Temp)							
Gain(Rain, Temp)							

$$\text{Entropy}(S) = -P_{C_1}\log_2\left(P_{C_1}\right) - P_{C_2}\log_2\left(P_{C_2}\right) = -\frac{N_{C_1}}{N}\log_2\left(\frac{N_{C_1}}{N}\right) - \frac{N_{C_2}}{N}\log_2\left(\frac{N_{C_2}}{N}\right)$$

Rain, Humid	Yes	No	P(Yes)	Log2(Yes)	P(No)	Log2(No)	Entropy
High							
Normal							
EEntropy(Temp)							
Gain(Rain, Humid)							

$$\log_2(x) = \frac{\log_{10}(x)}{\log_{10}(2)} \approx \frac{\log_{10}(x)}{0.3010}$$

Rain, Wind	Yes	No	P(Yes)	Log2(Yes)	P(No)	Log2(No)	Entropy
Weak							
Strong							
EEntropyWind)							
Gain(Rain, Wind)							

ID3 Step 3: Gain for Rain Outlook

Rain, Temp	Yes	No	P(Yes)	Log2(Yes)	P(No)	Log2(No)	Entropy
Hot	0	0	0.0000	0.0000	0.0000	0.0000	0.0000
Mild	2	1	0.6667	-0.5850	0.3333	-1.5850	0.9183
Cool	1	1	0.5000	-1.0000	0.5000	-1.0000	1.0000
EEntropy(Temp)							0.9510
Gain(Rain, Temp)							**0.0200**

Rain, Humid	Yes	No	P(Yes)	Log2(Yes)	P(No)	Log2(No)	Entropy
High	1	1	0.5000	-1.0000	0.5000	-1.0000	1.0000
Normal	2	1	0.6667	-0.5850	0.3333	-1.5850	0.9183
EEntropy(Temp)							0.9510
Gain(Rain, Humid)							**0.0200**

Rain, Wind	Yes	No	P(Yes)	Log2(Yes)	P(No)	Log2(No)	Entropy
Weak	3	0	1.0000	0.0000	0.0000	0.0000	0.0000
Strong	0	2	0.0000	0.0000	1.0000	0.0000	0.0000
EEntropyWind)							0.0000
Gain(Rain, Wind)							**0.9710**

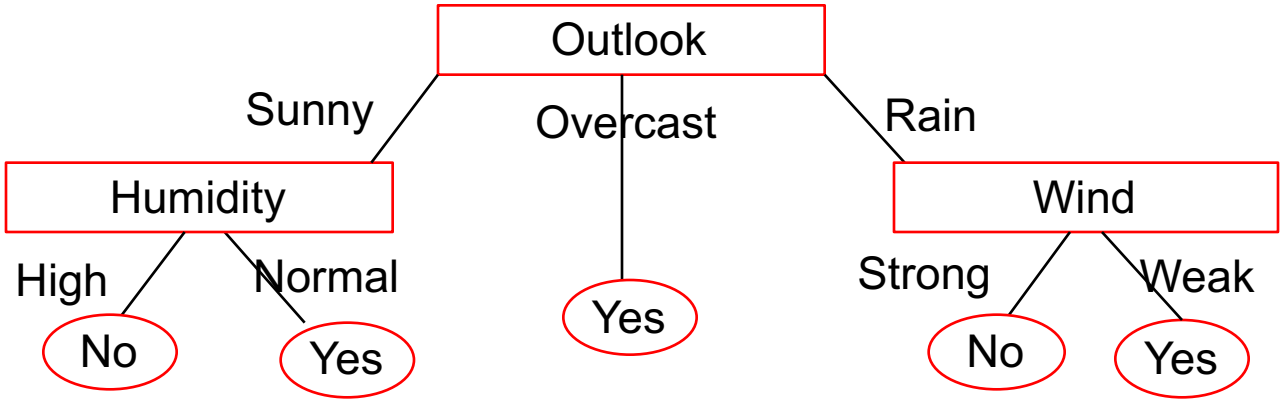
The Final tree

The process of selecting a new attribute and partitioning the training examples is repeated for each non-leaf node, this time only using the examples associated with that node.

Attributes that have been incorporated higher in the tree are excluded, so that any given attribute can appear at most once along any path through the tree.

The process continues for each leaf node until:

- every attribute has been included along that path through the tree or
- the training examples associated with this leaf node all have the same class.



The Decision Tree Rules

In addition to generating a tree structure, explicit rules for classifying 'play/don't play' are also generated:

If outlook = Overcast Then Play= Yes {No=0, Yes=4}

If outlook = Rain And wind = Strong Then Play= No {No=2, Yes=0}

If outlook = Rain And wind = Weak Then Play = Yes {No=0, Yes=3}

If outlook = Sunny And humidity = High Then Play = No {No=3, Yes=0}

If outlook = Sunny And humidity = Normal Then Play = Yes {No=0, Yes=2}

Further considerations

Types of decision trees?

- Classification Trees (categorical – nominal attributes)
- Regression Trees (numerical – continuous attributes)

How do we specify the splitting conditions?

How do we evaluate the decision tree model?

Some other decision tree algorithms

Classification Trees *vs* Regression Trees

- Target variable types

Splitting criteria:

- Information gain
- Gain ratio (reduces bias for highly branched attributes)
- Gini index

Decision tree algorithms

- ID3 (discrete), C4.5, C5 (continuous) target attributes
- CART, Chaid etc.
- See: https://en.wikipedia.org/wiki/Decision_tree_learning

Metrics for Performance Evaluation

How to evaluate the performance of a model?

- Training and testing
- Confusion matrix
- Cross validation

Training and testing

- You can measure a classifier's performance in terms of the error rate (proportion of errors made over a whole set of instances).
- Due to desirability of generalization, low error on the training data is not a good measure.
- To predict the performance of a classifier on a new data, we need to assess its error on data that was not used to build the model.
- In general, the data set is divided into two subsets: training and testing. Training for learning the model and testing for determining how well it will do on unseen data.

Performance evaluation of the Model

Focus on the predictive capability of a model

- Rather than how fast it takes to classify or build models, scalability, etc.

How to determine accuracy of decision tree in classifying/predicting?

- Usual to have two data sets:
  - A *Training Set* and a *Test Set*
  - This can be created by dividing the data set into two sets – e.g. 70%/30%
- We create the decision tree model using the training set.
- Then run the test set through the model to find out what the predicted class is.
- Then compare the predicted class with the actual class to see how accurate the model is.

Metrics for Performance Evaluation

One way of assessing performance is to calculate accuracy based on a *confusion matrix* (for the test data classification).

		PREDICTED CLASS	
		Class=Yes	Class=No
ACTUAL CLASS	Class=Yes	a	b
	Class=No	c	d

a: TP (true positive) b: FN (false negative)

c: FP (false positive) d: TN (true negative)

Metrics for Performance Evaluation

		PREDICTED CLASS	
		Class=Yes	Class=No
ACTUAL CLASS	Class=Yes	a (TP)	b (FN)
	Class=No	c (FP)	d (TN)

Most widely-used metric:

$$\text{Accuracy} = \frac{a+d}{a+b+c+d} = \frac{TP+TN}{TP+TN+FP+FN}$$

Also:

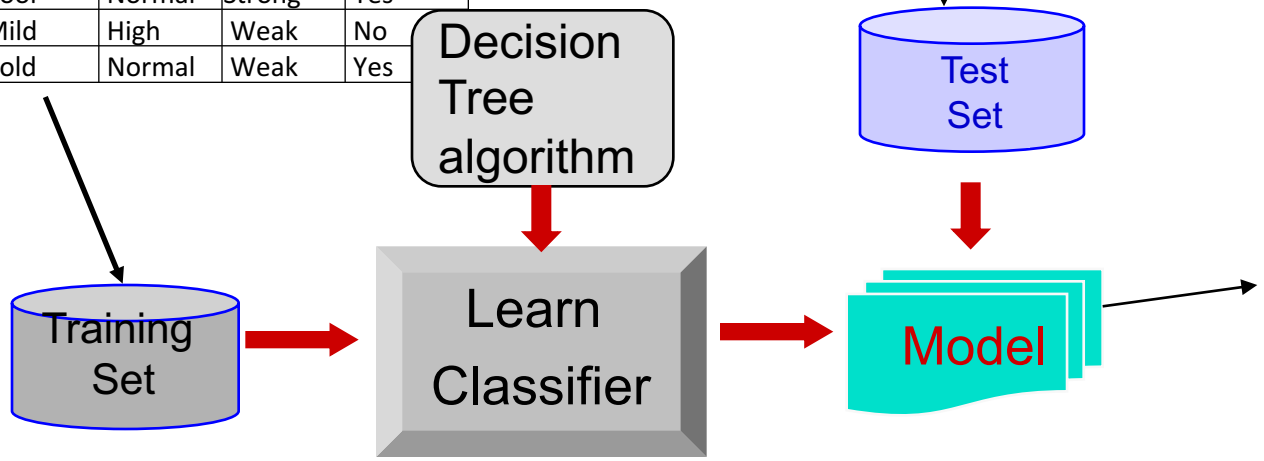
Precision = TP/(TP + FP)

Sensitivity = TP /(TP + FN)

The Play Tennis example

ID	outlook	temp	humidity	wind	play
D1	Sunny	Hot	High	Weak	No
D10	Rain	Mild	Normal	Weak	Yes
D11	Sunny	Mild	Normal	Strong	Yes
D12	Overcast	Mild	High	Strong	Yes
D13	Overcast	Hot	Normal	Weak	Yes
D14	Rain	Mild	High	Strong	No
D2	Sunny	Hot	High	Strong	No
D3	Overcast	Hot	High	Weak	Yes
D4	Rain	Mild	High	Weak	Yes
D5	Rain	Cool	Normal	Weak	Yes
D6	Rain	Cool	Normal	Strong	No
D7	Overcast	Cool	Normal	Strong	Yes
D8	Sunny	Mild	High	Weak	No
D9	Sunny	Cold	Normal	Weak	Yes

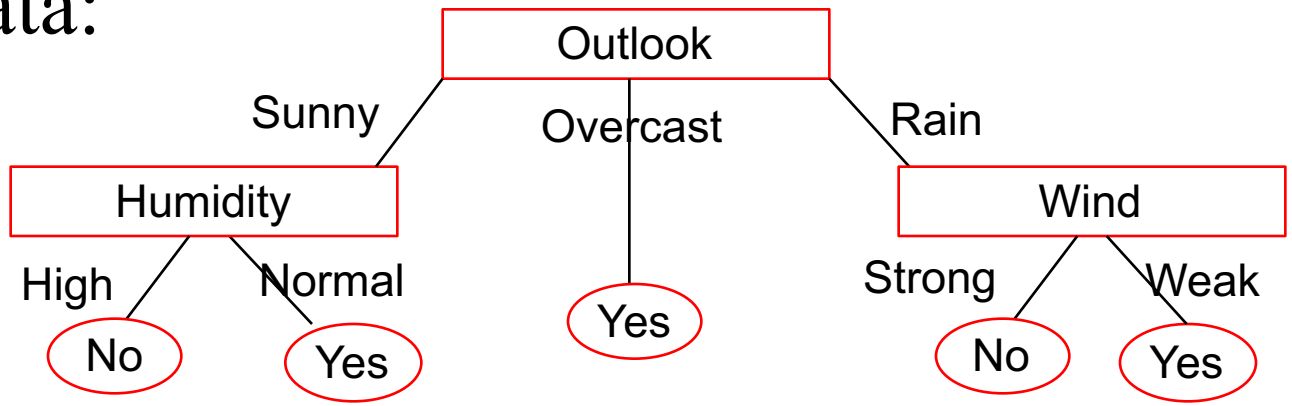
ID	outlook	temp	humidity	wind	play
D15	Sunny	Mild	Normal	Strong	No
D16	Sunny	Hot	High	Weak	Yes
D17	Rain	Hot	High	Weak	No
D18	Overcast	Cool	High	Strong	No
D19	Overcast	Mild	Normal	Weak	Yes
D20	Rain	Mild	Normal	Weak	Yes



actual class	Predicted class		
		Class=Yes	Class=No
	Class=Yes	a	b
	Class=No	c	d

The play tennis example

Let's see what our model would predict using the test data:



Day	Outlook	Temperature	Humidity	Wind	Play	Predict
D15	Sunny	Mild	Normal	Strong	No	yes
D16	Sunny	Hot	High	Weak	Yes	no
D17	Rain	Hot	High	Weak	No	yes
D18	Overcast	Cool	High	Strong	No	yes
D19	Overcast	Mild	Normal	Weak	Yes	yes
D20	Rain	Mild	Normal	Weak	Yes	yes

Metrics for Performance Evaluation…

		PREDICTED CLASS	
ACTUAL CLASS		Class=Yes	Class=No
	Class=Yes	2 (TP)	1 (FN)
	Class=No	3 (FP)	0 (TN)

Most widely-used metric:

$$Accuracy = \frac{a+d}{a+b+c+d} = \frac{TP+TN}{TP+TN+FP+FN} = \frac{2+0}{6} = 33.3\%$$

More ways to measure classification performance next lecture...

Decision trees in R

Decision trees in R

There are a number of packages to create decision trees in R. We will start with the "tree" package.

```
> install.packages("tree")
> library(tree)
```

Note: "tree" aims to minimise 'impurity' by binary splitting. Similar, but not identical, to ID3 in effect.

https://cran.r-project.org/web/packages/tree/index.html

tree: details

- A tree is grown by binary recursive partitioning using the response in the specified formula and choosing splits from the terms of the right-hand-side. Numeric variables are divided into X < a and X > a;
- The levels of an unordered factor are divided into two non-empty groups.
- The split which maximizes the reduction in impurity is chosen, the data set split and the process repeated.
- Splitting continues until the terminal nodes are too small or too few to be split.

https://cran.r-project.org/web/packages/tree/index.html

Classification tree: data

Build and test a model using the playtennis data.

Day	Outlook	Temperature	Humidity	Wind	Play
D1	Sunny	Hot	High	Weak	No
D2	Sunny	Hot	High	Strong	No
D3	Overcast	Hot	High	Weak	Yes
D4	Rain	Mild	High	Weak	Yes
D5	Rain	Cool	Normal	Weak	Yes
D6	Rain	Cool	Normal	Strong	No
D7	Overcast	Cool	Normal	Strong	Yes
D8	Sunny	Mild	High	Weak	No
D9	Sunny	Cool	Normal	Weak	Yes
D10	Rain	Mild	Normal	Weak	Yes
D11	Sunny	Mild	Normal	Strong	Yes
D12	Overcast	Mild	High	Strong	Yes
D13	Overcast	Hot	Normal	Weak	Yes
D14	Rain	Mild	High	Strong	No

Classification tree: data

Build and test a model using the playtennis data.

As the training set is small, a larger synthetic data set is created by resampling with replacement.

```
> ptt <- read.csv("playtennistrain.csv")
> set.seed(9999) #make random selection repeatable
> # resampling with replacement
> pttrain = ptt[sample(nrow(ptt), 100, replace = TRUE),]
```

Classification tree: building the tree

Build the tree using “Play” as the response and all input variables except “Day” as predictors.

Syntax is very similar to linear model function.

Output is a list.

```
> ptfit = tree(Play ~. -Day, data = pttrain)
```

? tree

- Description

  A tree is grown by binary recursive partitioning using the response in the specified formula and choosing splits from the terms of the right-hand-side.

- Usage

```
tree(formula, data, weights, subset,
na.action = na.pass, control =
tree.control(nobs, ...),
method = "recursive.partition",
split = c("deviance", "gini"),
model = FALSE, x = FALSE, y = TRUE, wts = TRUE,
...)
```

Classification tree: summary

Use “summary” to get a basic idea of model performance: terminal nodes, variables actually used, error measures.

```
> summary(ptfit)
Classification tree:
tree(formula = Play ~ . - Day, data = pttrain)
Variables actually used in tree construction:
[1] "Outlook"  "Humidity" "Wind"
Number of terminal nodes:  7
Residual mean deviance:  0 = 0 / 93
Misclassification error rate: 0 = 0 / 100
```

Classification tree: details

Details of each split, root to leaf, left to right.

> ptfit

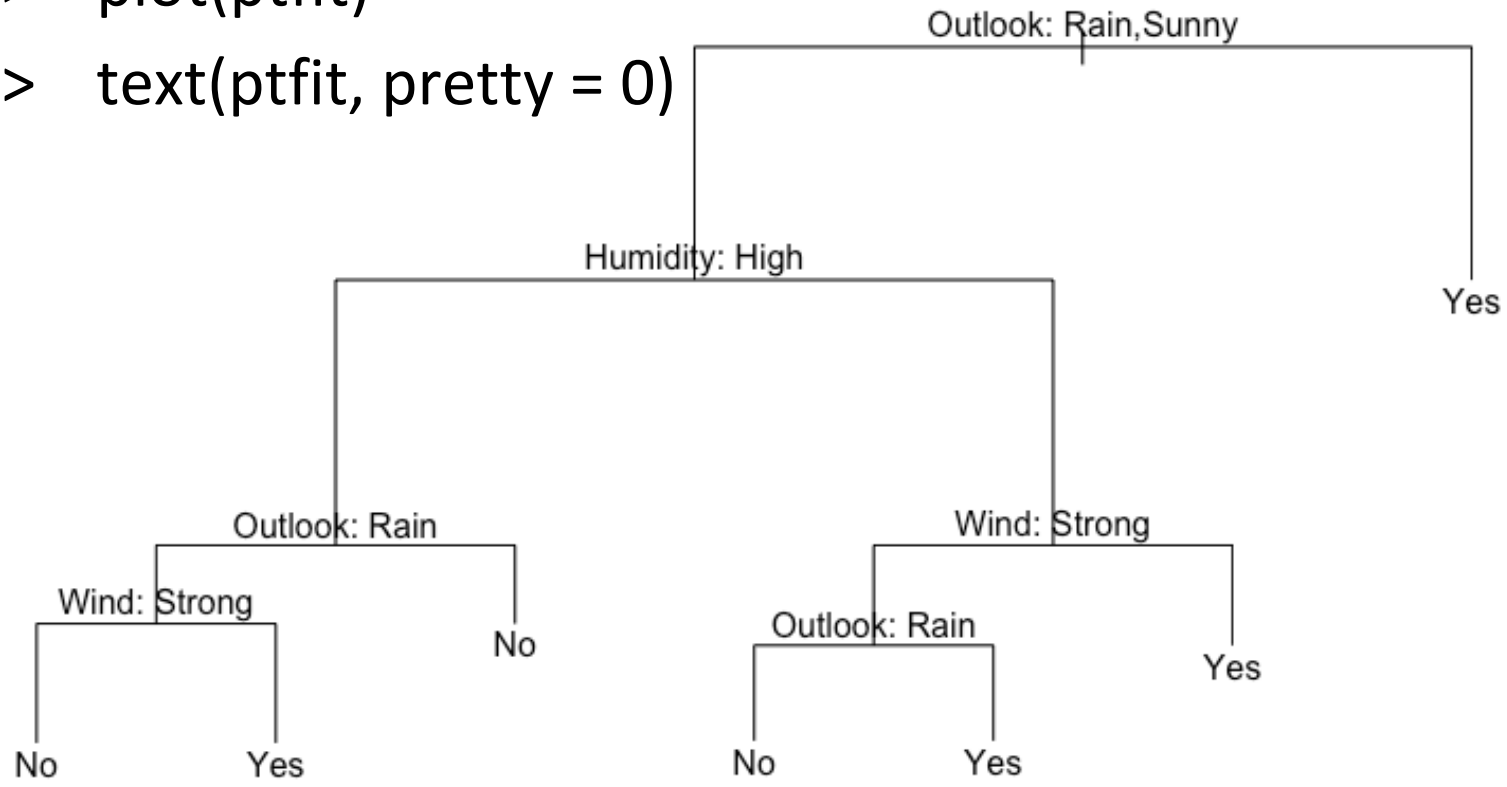
```
node), split, n, deviance, yval, (yprob)
      * denotes terminal node

 1) root 100 129.50 Yes ( 0.3500 0.6500 )
   2) Outlook: Rain,Sunny 69  95.64 No ( 0.5072 0.4928 )
     4) Humidity: High 35  28.71 No ( 0.8571 0.1429 )
       8) Outlook: Rain 13  17.32 No ( 0.6154 0.3846 )
        16) Wind: Strong 8   0.00 No ( 1.0000 0.0000 ) *
        17) Wind: Weak 5   0.00 Yes ( 0.0000 1.0000 ) *
       9) Outlook: Sunny 22   0.00 No ( 1.0000 0.0000 ) *
     5) Humidity: Normal 34  28.39 Yes ( 0.1471 0.8529 )
      10) Wind: Strong 10  13.86 Yes ( 0.5000 0.5000 )
        20) Outlook: Rain 5   0.00 No ( 1.0000 0.0000 ) *
        21) Outlook: Sunny 5   0.00 Yes ( 0.0000 1.0000 ) *
      11) Wind: Weak 24   0.00 Yes ( 0.0000 1.0000 ) *
   3) Outlook: Overcast 31   0.00 Yes ( 0.0000 1.0000 ) *
```

Classification tree: plot

Headers give rule for left branching.

```
> plot(ptfit)
> text(ptfit, pretty = 0)
```



Classification tree: testing the model

To test the model, make a prediction for each input from the test data set and cross tabulate with the actual classification in the test data:

```
> pttest <- read.csv("playtennistest.csv")
> tpredict = predict(ptfit, pttest, type = "class")
> Tpredict
[1] Yes No  Yes Yes Yes Yes
Levels: No Yes
```

Classification tree: testing the model

Comparing predicted with actual values as a Confusion Matrix:

```
> tpredict
[1] Yes No  Yes Yes Yes Yes
> pttest$Play
[1] No  Yes No  No  Yes Yes
> table(observed = pttest$Play, predicted = tpredict)
          predicted
observed No Yes
     No   0   3
     Yes  1   2
```

Edgar Anderson's Iris data

50 samples from 3 species:

- Iris setosa, – virginica, – versicolor

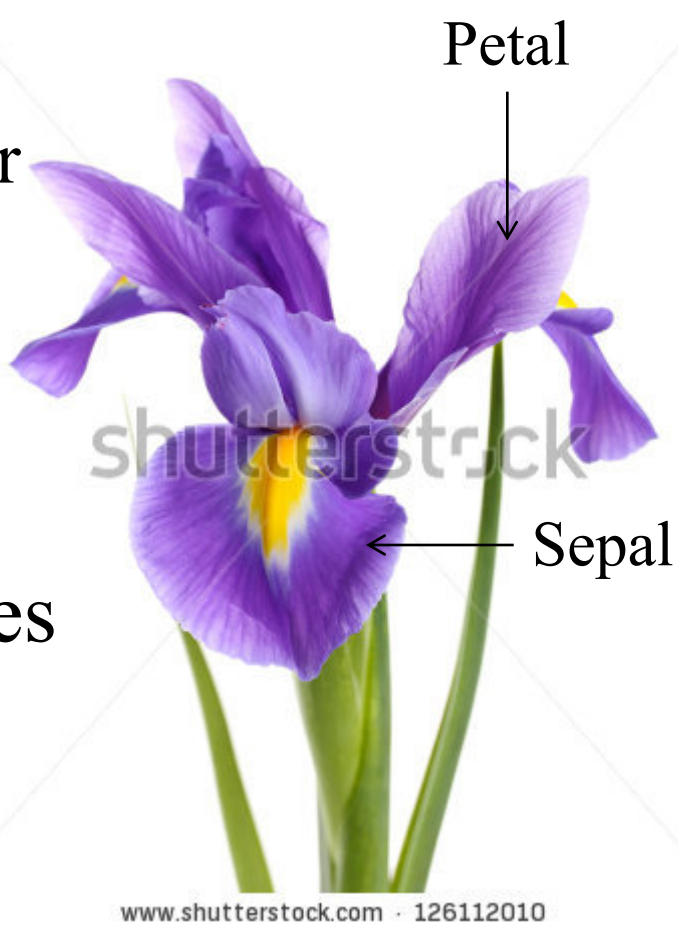
Four features measured:

- Sepal width and length
- Petal width and length

Is it possible to distinguish species using physical measurements?

- Data is packaged with R: "iris"

http://en.wikipedia.org/wiki/Iris_flower_data_set



Regression tree: data

Build and test a model using the iris data.

Subset the data into training and test data sets.

```
> # to select 70% of rows
> set.seed(9999) # make random selection repeatable
> train.row = sample(1:nrow(iris), 0.7*nrow(iris))
> iris.train = iris[train.row,]
> iris.test = iris[-train.row,]
```

Regression tree: building and testing

Adapting the same commands used for the tennis example:

```
> itree = tree(Species ~., data = iris.train)
> itree
> summary(itree)
> plot(itree)
> text(itree, pretty = 0)
> ipredict = predict(itree, iris.test, type = "class")
> table(observed = iris.test$Species, predicted = ipredict)
```

Regression tree: summary

Summary of terminal nodes, variables actually used, error measures.

```
> summary(itree)
Classification tree:
tree(formula = Species ~ ., data = iris.train)
Variables actually used in tree construction:
[1] "Petal.Length" "Petal.Width"
Number of terminal nodes:  5
Residual mean deviance:  0.1332 = 13.32 / 100
Misclassification error rate: 0.0381 = 4 / 105
```

Regression tree: details

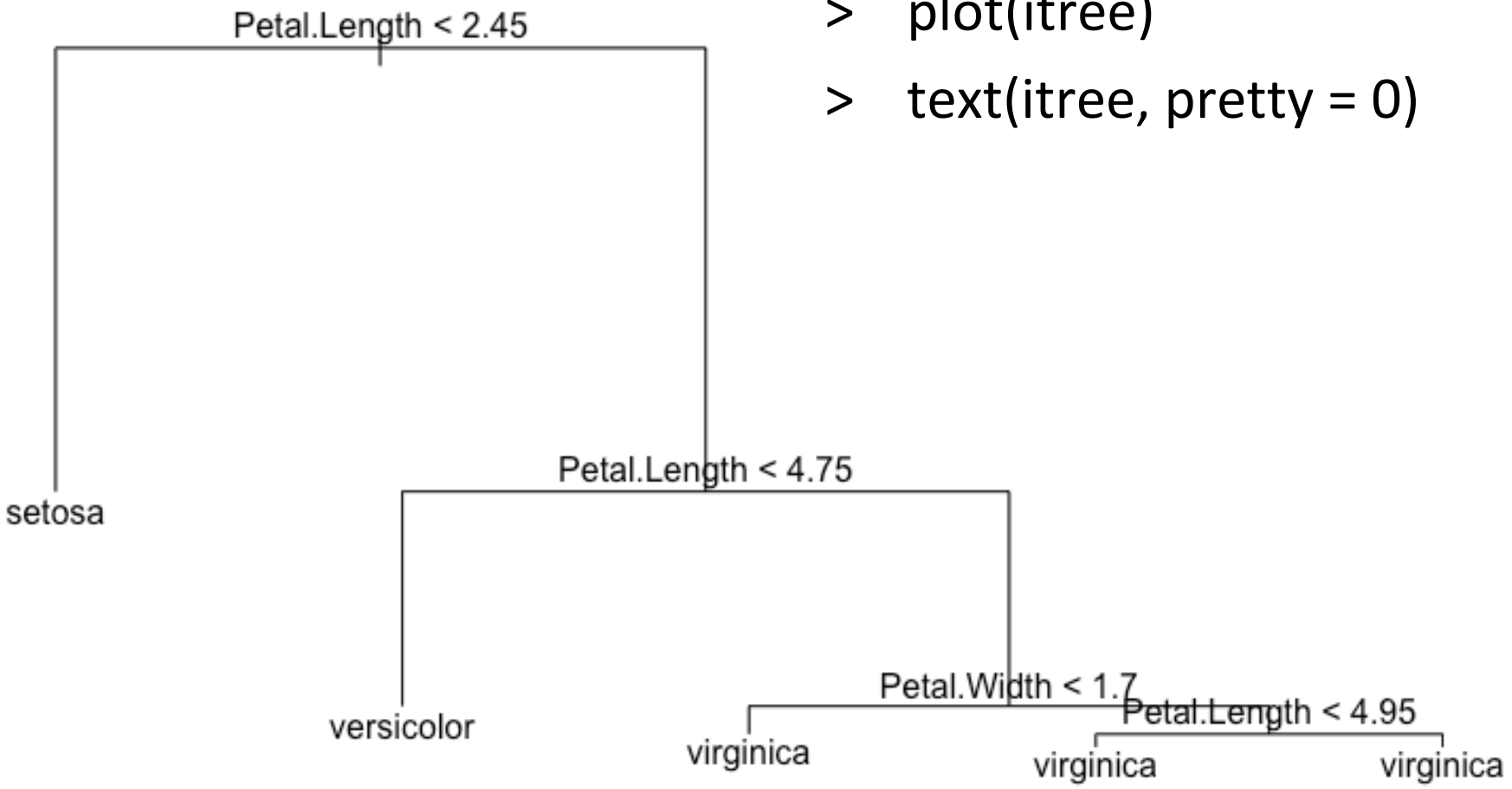
> itree

```
node), split, n, deviance, yval, (yprob)
      * denotes terminal node

 1) root 105 200 setosa ( 0.36 0.30 0.34 )
   2) Petal.Length < 2.45 38   0 setosa ( 1.00 0.00 0.00 ) *
   3) Petal.Length > 2.45 67  90 virginica ( 0.00 0.46 0.54 )
     6) Petal.Length < 4.75 27   0 versicolor ( 0.00 1.00 0.00 ) *
     7) Petal.Length > 4.75 40  30 virginica ( 0.00 0.10 0.90 )
      14) Petal.Width < 1.7 6   8 virginica ( 0.00 0.50 0.50 ) *
      15) Petal.Width > 1.7 34   9 virginica ( 0.00 0.03 0.97 )
        30) Petal.Length < 4.95 5   5 virginica ( 0.00 0.20 0.80 ) *
        31) Petal.Length > 4.95 29   0 virginica ( 0.00 0.00 1.00 ) *
```

Regression tree: plot

```
> plot(itree)
> text(itree, pretty = 0)
```



Classification tree: testing the model

To test the model, make a prediction for each and draw the confusion matrix.

```
> table(observed = iris.test$Species, predicted = ipredict)
                predicted
observed     setosa versicolor virginica
 setosa          13          0         0
 versicolor       0         14         3
 virginica        0          1        14
```

Discussion

How good is each model?

Could the models be improved?

Are they too specific, based on the training set?

Note that previous examples are sensitive to the value of the random seed. If this changed the decision tree model and/or accuracy may change.

More on decision devlopment and testing as well as other classifcation methods next lecture.

Answers to the quiz questions

1. D
2. E
3. C
4. A
5. A

Reading/Notes on the presentation

Further Reading:

- An Introduction to Statistical Learning with applications in R (Springer Texts in Statistics), James, Witten, Hastie and Tibshirani, Chapter 8 (available on-line from Monash Library)

Notes:

- This presentation contains some slides created to accompany: *Introduction to Data Mining*, Tan, Steinbach, Kumar. Pearson Education Inc., 2006.
- Presentation originally created by Dr. Sue Bedingfield.