FIT3152 Data analytics – Lecture 12

Revision and Exam Preparation

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		

SETU

Student Evaluation of Teaching and Units (SETU) has opened for Semester 1.

- All students are encouraged to participate. Your feedback is very important.
- You will see a block in Moodle linking you to the survey.
- There are 100, $50 vouchers for students to win.
- The University will email students a weekly reminder with links to the survey.

End of semester exam

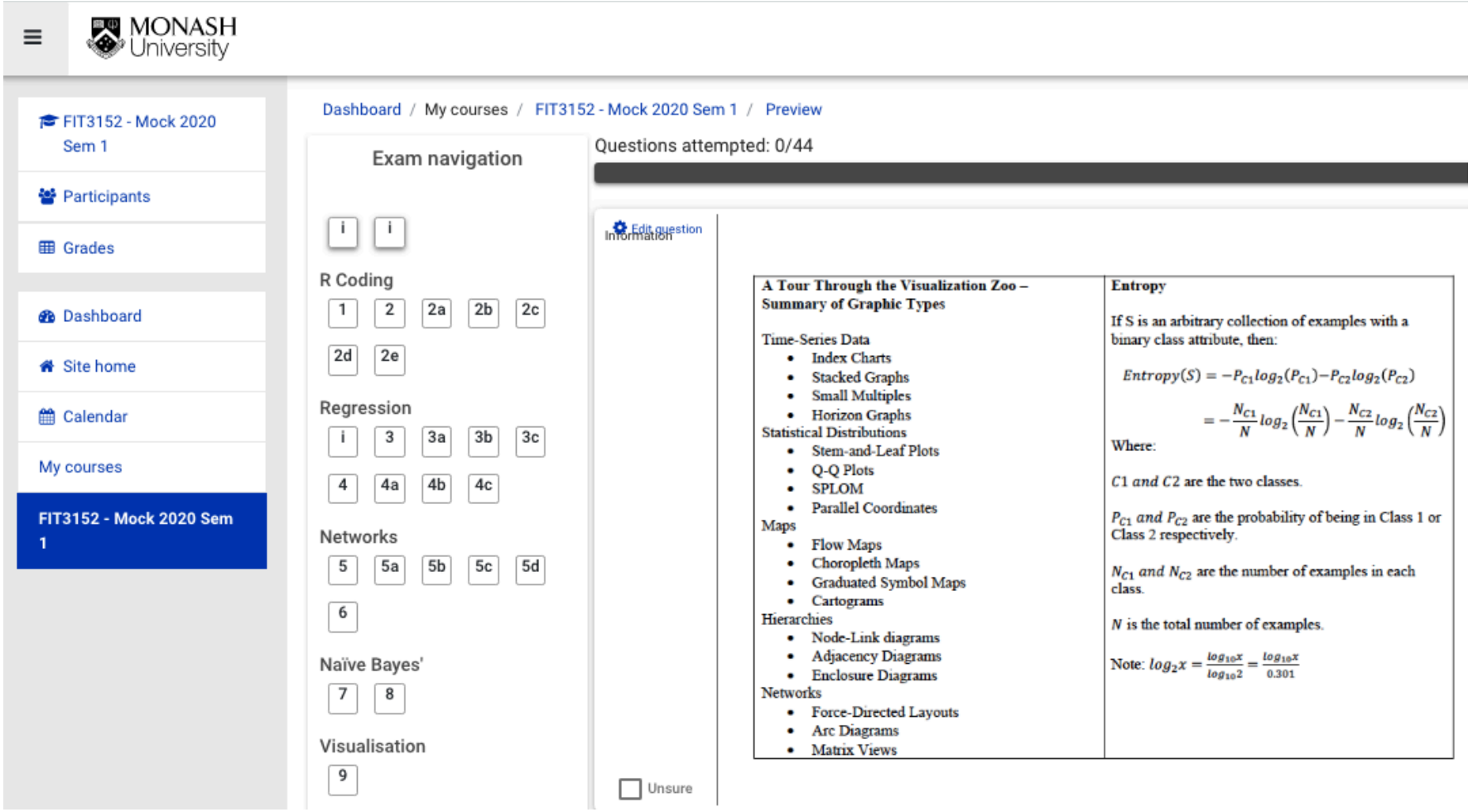
The end of semester exam:

- Will be online, e-vigilated. The university will advise you of the arrangements for sitting the exam.
- The exam is closed book. You can have two sheets for working, which you do not hand in.
- You may use a calculator: graphing, scientific or CAS are permitted.
- The practice exam has been setup as a mock exam. It is a good indicator of length/complexity. Link:
  https://student-eassessment.monash.edu/mod/quiz/view.php?id=3863
- Solutions will be released Week 13.

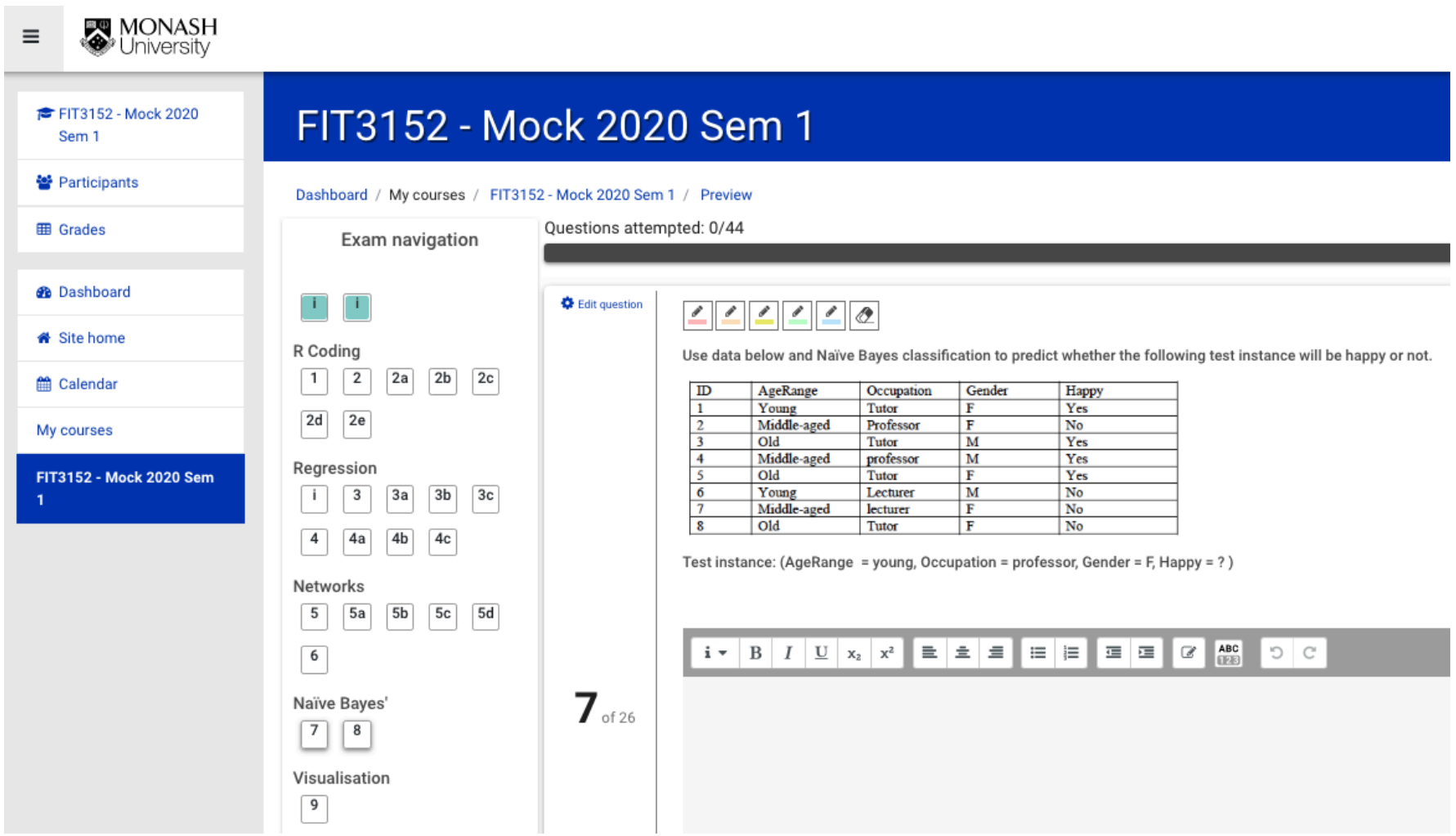
The eExam

- 10 Question groups in the final exam.
- Format of the eExam makes it seem like there are more questions than a paper exam (but there are not).
- You will write answers in spaces provided.
- Attempt all questions in any order you like.
- You can commence writing at the start of the exam.
- You do not have to finish the paper to pass.
- *Do the easy questions first and get them right!*

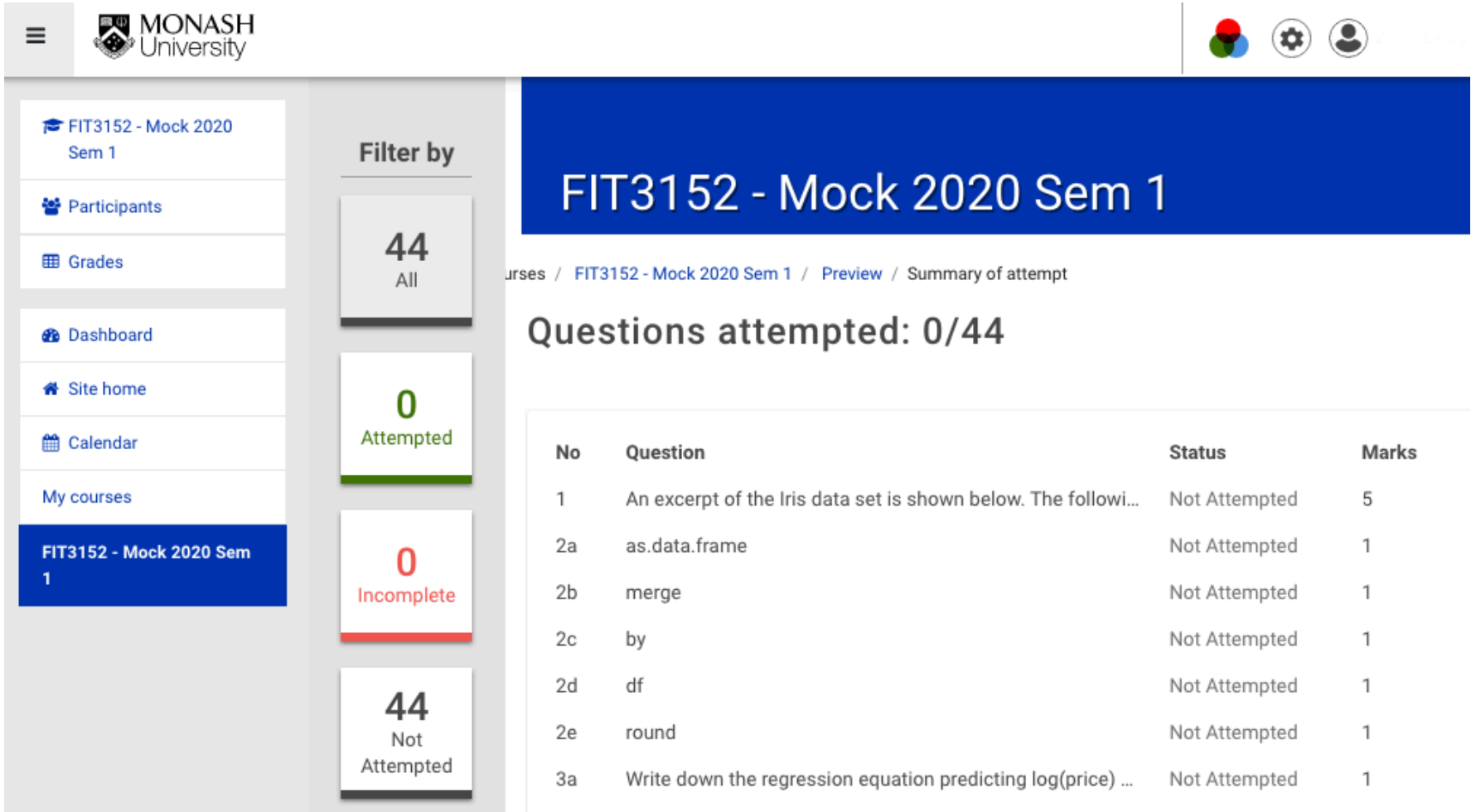
eExam sample: formulas



eExam sample: question



eExam sample: summary page



Consultations

Current consultation schedule will be continued.

More consultations will open up for during Swot Vac and the exam period.

We'll notify you of these on Moodle.

Lecture 1 – Introduction to Data Science

Recent examples:

- crime, food webs, global warming

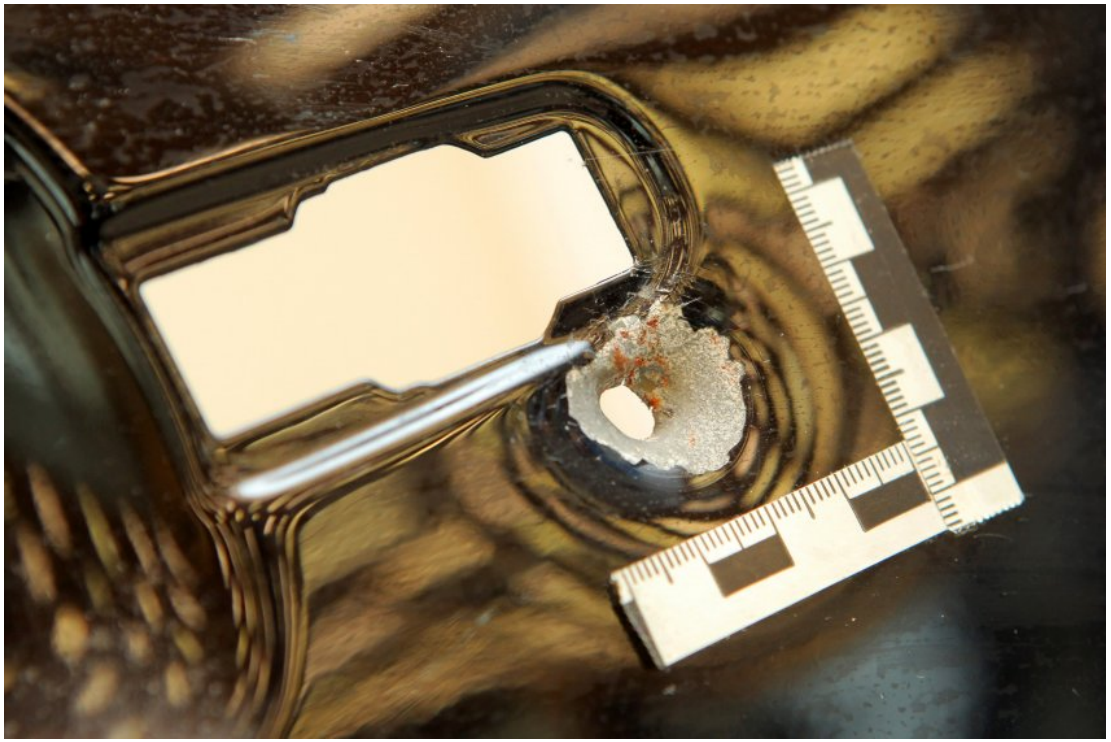
Common themes:

- large data sets with complex interactions within the data. Importance of graphics for analysis and to display results

Review of basic statistics using R

Criminal investigation

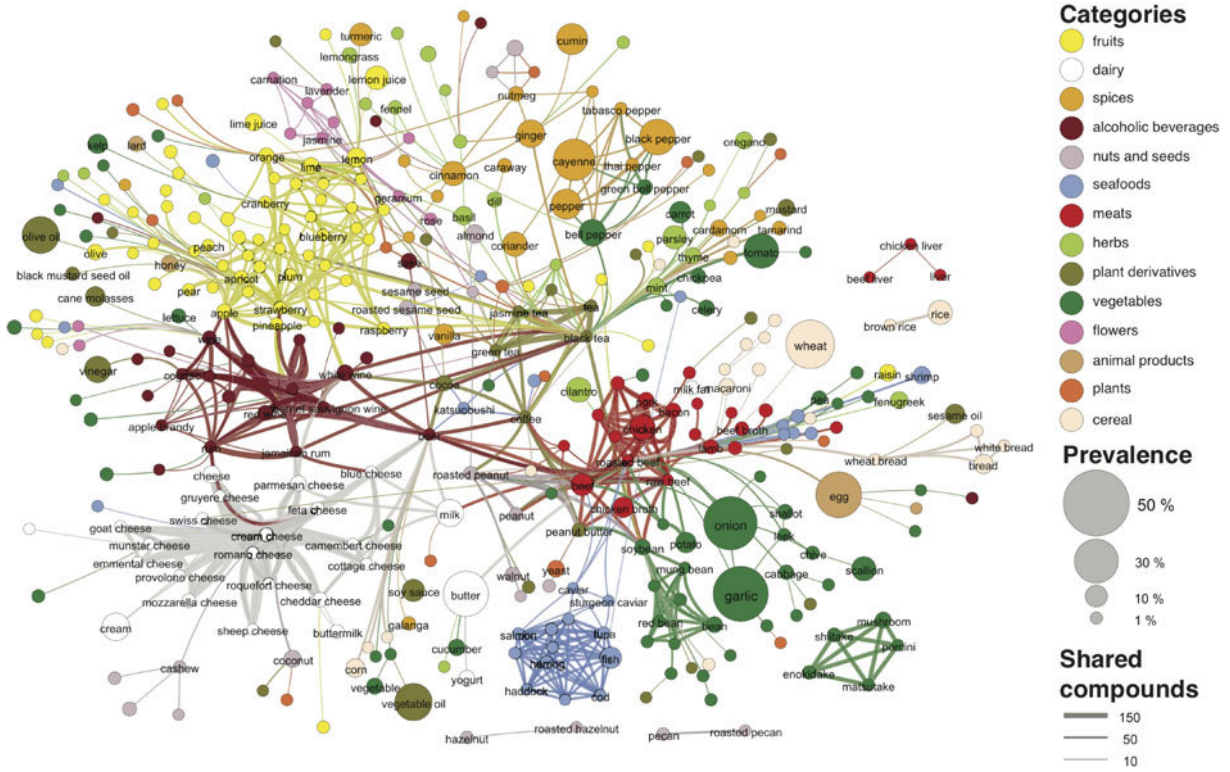
Road Shooter Found Via Mass Data Collection



http://www.spiegel.de/international/germany/spectacular-highway-shooter-investigation-raises-data-privacy-concerns-a-908006.html

Food networks

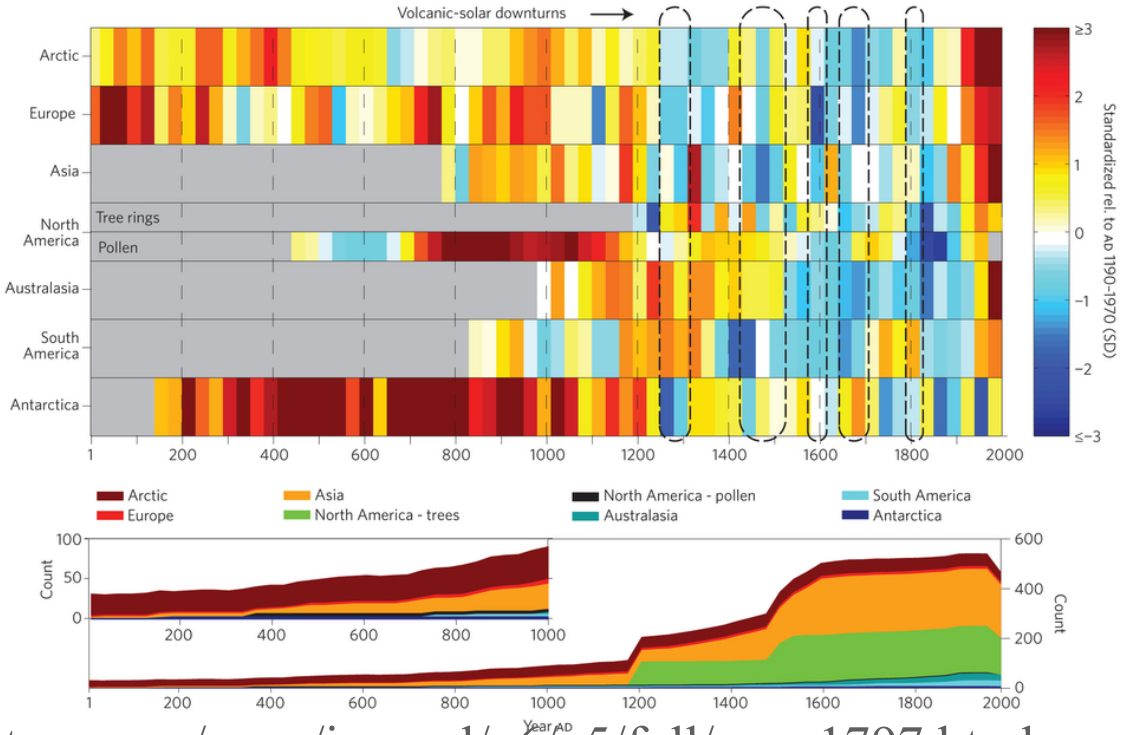
Flavor network and the principles of food pairing



http://www.nature.com/srep/2011/111215/srep00196/full/srep00196.html

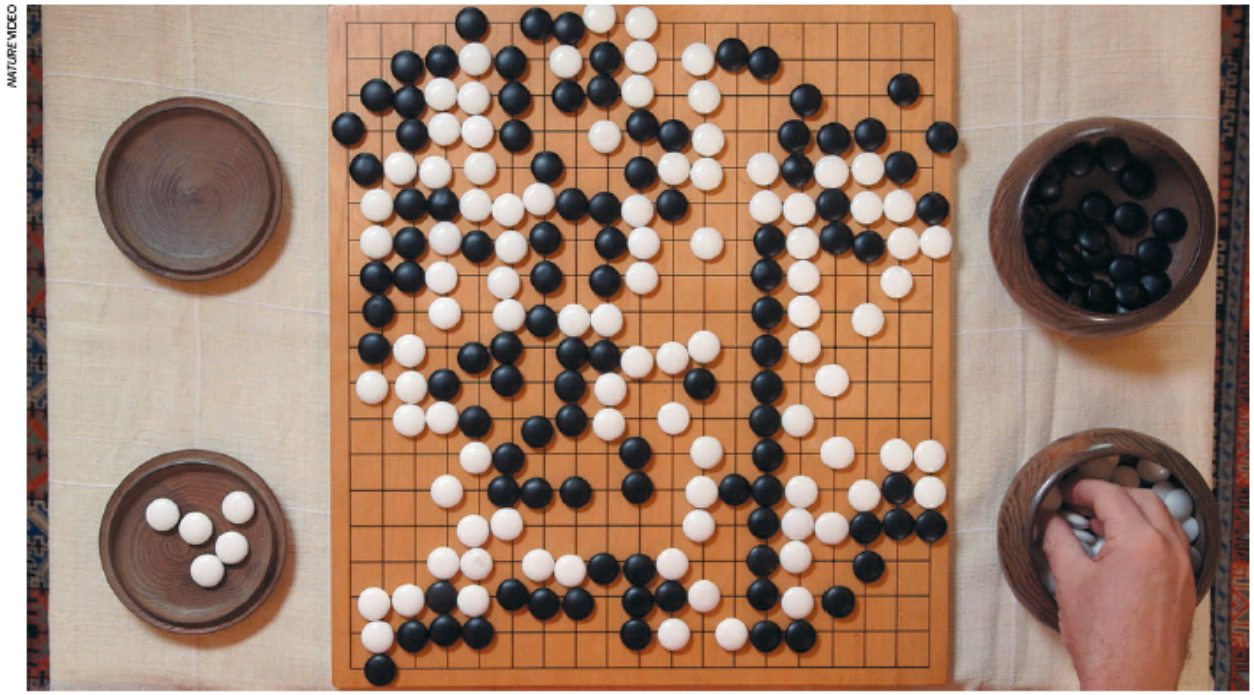
Climate change

Continental-scale temperature variability during the past two millennia



http://www.nature.com/ngeo/journal/v6/n5/full/ngeo1797.html

Deep learning



Go, a complex game popular in Asia, has frustrated the efforts of artificial-intelligence researchers for decades.

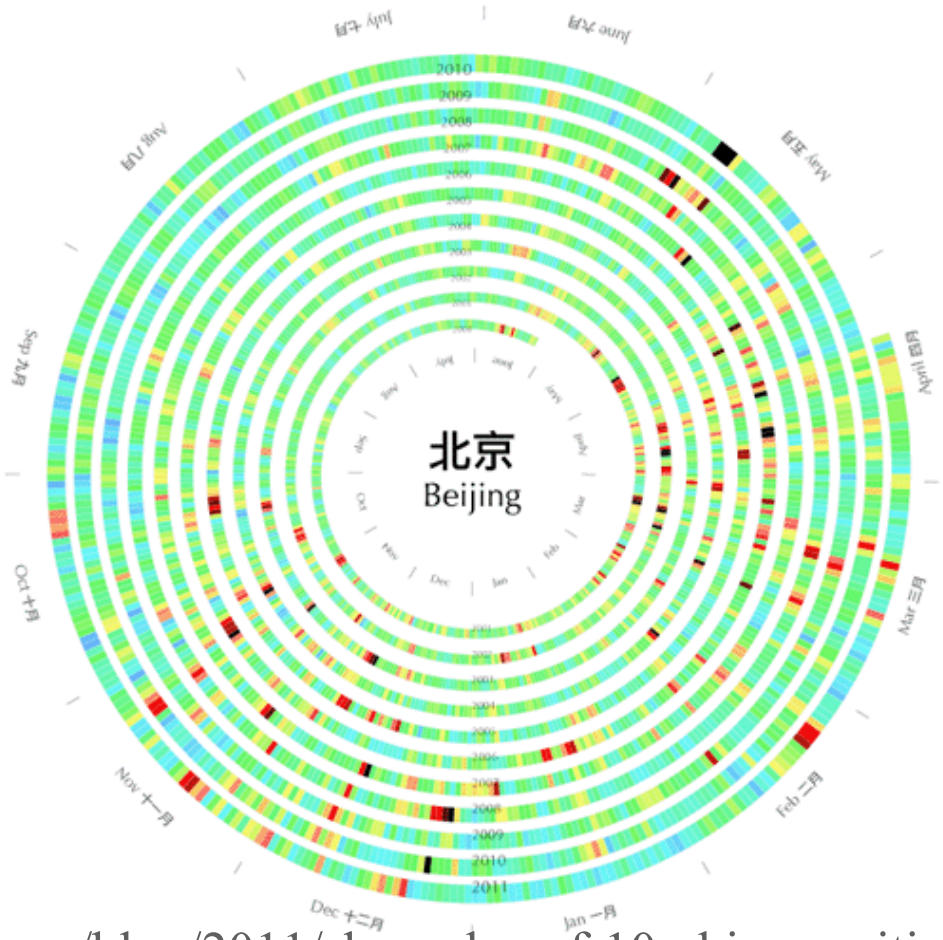
ARTIFICIAL INTELLIGENCE

Google masters Go

Deep-learning software excels at complex ancient board game.

https://www.nature.com/news/google-ai-algorithm-masters-ancient-game-of-go-1.19234

Beautiful graphic design



http://xiaoji-chen.com/blog/2011/sky-color-of-10-chinese-cities/

Data science: some common themes

Previous examples illustrate:

- Complex problems, of societal concern.
- Large data sets, multiple data sets (mashups), messy, incomplete, heterogeneous, non-traditional, open data.
- Often using data repositories created for another purpose (food network): One description of Data Science is making a product out of data…
- Data collection and analysis on a scale that would have been unthinkable 15 years ago.
- Use of high quality graphics for communicating results!

Data science: high-level skills

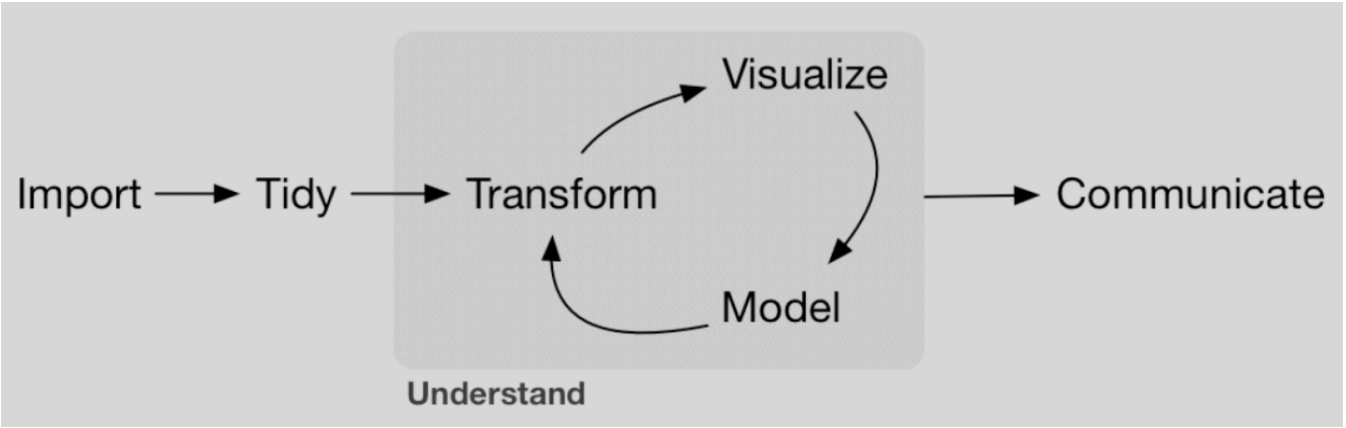
Some necessary skills for a data scientist:

- Understand a problem from client's perspective,
- Collect, cleanse, manage and combine data – which may come from disparate sources,
- Understand the data, most likely using visualization tools as a starting point,
- Analyze and model the data using statistical and (AI) machine learning techniques,
- Communicate the results simply and effectively.

The data science process

Generic methodologies for data analysis:

- For example, the data analysis process from Wickham and Gromelund:



https://r4ds.had.co.nz/

R

Rationale for using R, some background.

Obtaining and installing R and R studio,

Using R: syntax, data types, functions,

Data structures: data frames, arrays etc.,

Packages,

Help and References in R,

Review of basic statistics using R.

Lecture 2 – Visualization of data

Recent examples, common themes:

- Graphics present many dimensions using: colour, size, position, adjacency, connection, shape…

Visualization using R

- First steps: looking at the data (Iris data)
- Visualization for analysis – base graphics
- Presentation quality graphics – ggplot2, lattice

A tour through the visualization zoo

Summary of Graphic Types

- Time-Series Data
  - > Index Charts, Stacked Graphs, Small Multiples, Horizon Graphs
- Statistical Distributions
  - > Stem-and-Leaf Plots, Q-Q Plots, SPLOM, Parallel Coordinates
- Maps
  - > Flow Maps, Choropleth Maps, Graduated Symbol Maps, Cartograms
- Hierarchies
  - > Node-Link diagrams, Adjacency Diagrams, Enclosure Diagrams
- Networks
  - > Force-Directed Layouts, Arc Diagrams, Matrix Views

Edgar Anderson's Iris data

50 samples from 3 species:

- Iris setosa, – virginica, – versicolor

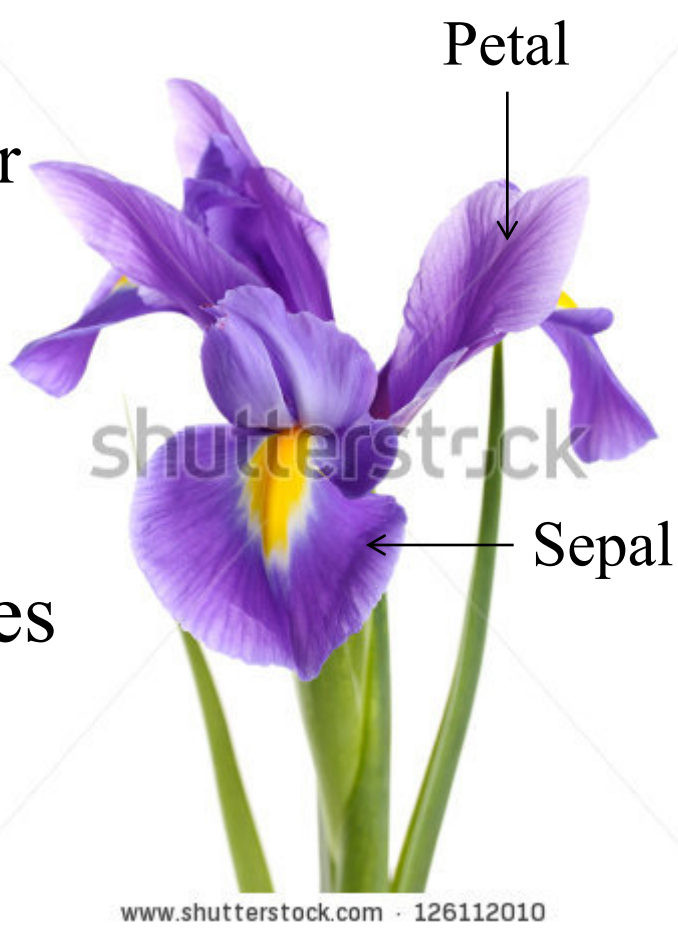
Four features measured:

- 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



Print

> iris *# = print(iris)*

```
    Sepal.Length Sepal.Width Petal.Length Petal.Width    Species
1            5.1         3.5          1.4         0.2     setosa
2            4.9         3.0          1.4         0.2     setosa
3            4.7         3.2          1.3         0.2     setosa
4            4.6         3.1          1.5         0.2     setosa
5            5.0         3.6          1.4         0.2     setosa
6            5.4         3.9          1.7         0.4     setosa
7            4.6         3.4          1.4         0.3     setosa
8            5.0         3.4          1.5         0.2     setosa
9            4.4         2.9          1.4         0.2     setosa
10           4.9         3.1          1.5         0.1     setosa
...
```

Sample exam question:

6 Marks

A World Health study is examining how life expectancy varies between men and women in different countries and at different times in history. The table below shows a sample of the data that has been recorded. There are approximately 15,000 records in all.

Country	Year of Birth	Gender	Age at Death
Australia	1818	M	9
Afghanistan	1944	F	40
USA	1846	F	12
India	1926	F	6
China	1860	F	32
India	1868	M	54
Australia	1900	F	37
China	1875	F	75
England	1807	M	15
France	1933	M	52
Egypt	1836	M	19
USA	1906	M	58

Using one of the graphic types from the Visualization Zoo (see formulae and references for a list of types) suggest a suitable graphic to help the researcher display as many variables as clearly as possible.

Explain your decision. Which graph elements correspond to the variables you want to display?

Lecture 3 – Data Manipulation in R

Making tables and summaries

Working with factors

- E.g. to apply functions by groups (species in iris data)

Transforming data: analysis + reformatting output

- aggregate, cor, by, as.table, as.data.frame, colnames, merge, cbind, rbind, max, which.max, do.call

High level view

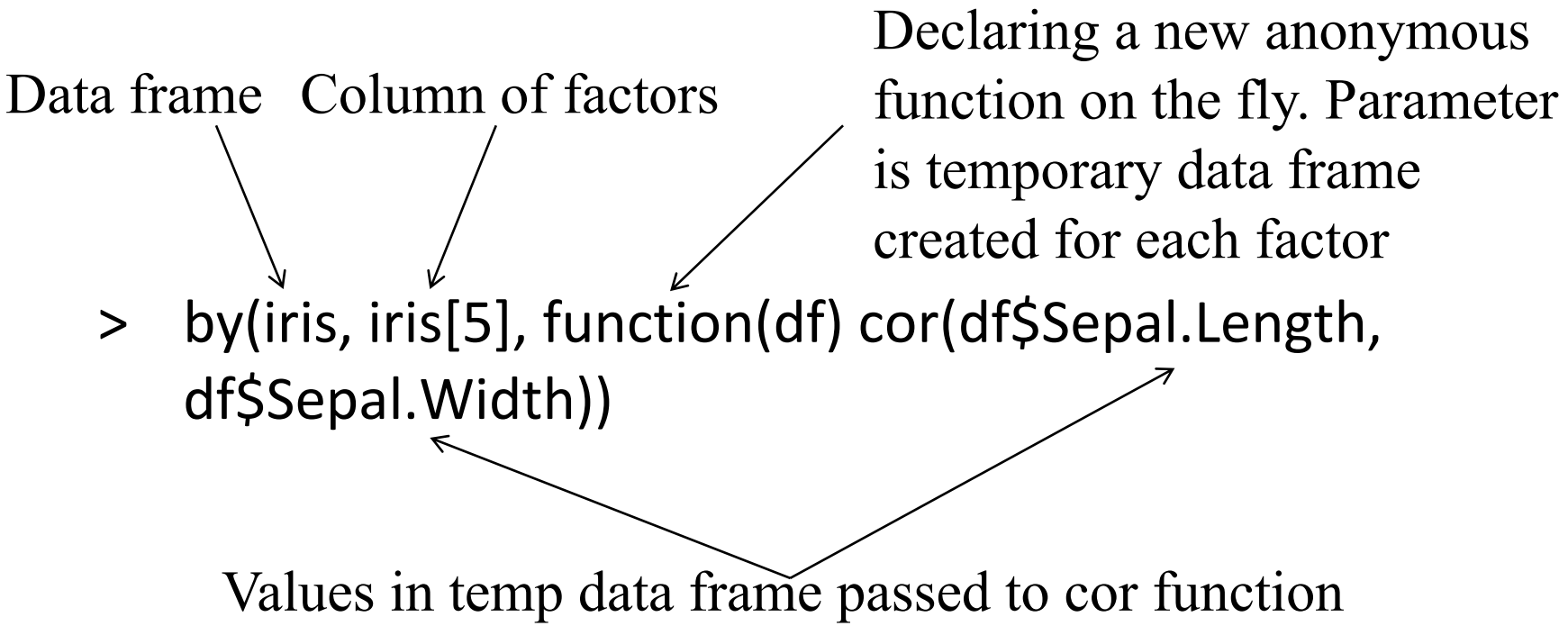
Data analysis is easier if you have a high level view of the data:

- 4 columns + 1 factor (Species)
- Two pairs of related columns: sepals & petals

Sepal.Length	Sepal.Width	Petal.Length	Petal.Width	Setosa
Sepal.Length	Sepal.Width	Petal.Length	Petal.Width	Virginica
Sepal.Length	Sepal.Width	Petal.Length	Petal.Width	Versicolor

?by: applying the cor function

Looking more closely at the way correlation is calculated:



Sample exam question:

5 Marks

An excerpt of the Iris data set is shown below.

```
> head(iris)
  Sepal.Length Sepal.Width Petal.Length Petal.Width Species
1          5.1         3.5          1.4         0.2  setosa
2          4.9         3.0          1.4         0.2  setosa
3          4.7         3.2          1.3         0.2  setosa
4          4.6         3.1          1.5         0.2  setosa
5          5.0         3.6          1.4         0.2  setosa
6          5.4         3.9          1.7         0.4  setosa
```

The following code is run:

```
Petal.cor <- as.data.frame(as.table(by(iris, iris[5], function(df)
    cor(df[3], df[4]))))
colnames(Petal.cor) <- c("Species", "Petal.cor")
Sepal.cor <- as.data.frame(as.table(by(iris, iris[5], function(df)
    cor(df[1], df[2]))))
colnames(Sepal.cor) <- c("Species", "Sepal.cor")
iris.cor <- merge(Sepal.cor, Petal.cor, by = "Species")
iris.cor[,2] = round(iris.cor[,2], digits = 3)
iris.cor[,3] = round(iris.cor[,3], digits = 3)
write.csv(iris.cor, file = "Iris.cor.csv", row.names=FALSE)
```

Describe the action and outputs of the R code.

Lecture 4 – Data science industry

The data science industry

Data science workflow models

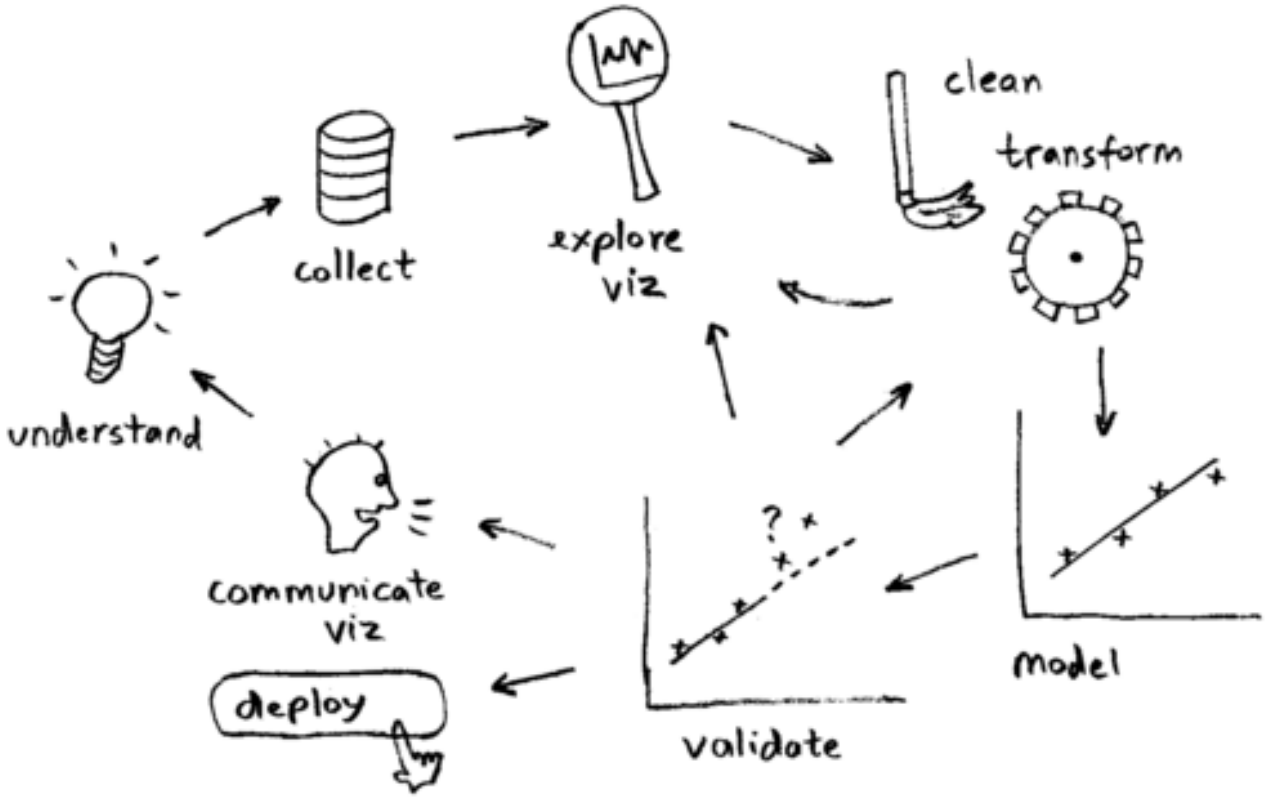
Dirty, and Tidy data

Transforming data: recoding, extracting subsets, working with dates.

The data science industry

- What is a Data Scientist?
  - > What skills are required?
- The data mining process and need for a consistent analytics methodology:
  - > KDD, SEMMA, CRISP-DM
  - > Business understanding, Data understanding, Data preparation, Modelling, Evaluation, Deployment
- Data preparation and pre-processing, visualization
  - > Sampling, impute missing variables, transformations...

The data science workflow



http://datascience.la/data-science-toolbox-survey-results-surprise-r-and-python-win/

Dirty Data

Data in the real world is dirty:

- Incorrect data
- Inaccurate data
- Business rule violations
- Inconsistent data
- Incomplete data
- Non-integrated data

See: A taxonomy of dirty data

Sample exam question:

6 Marks

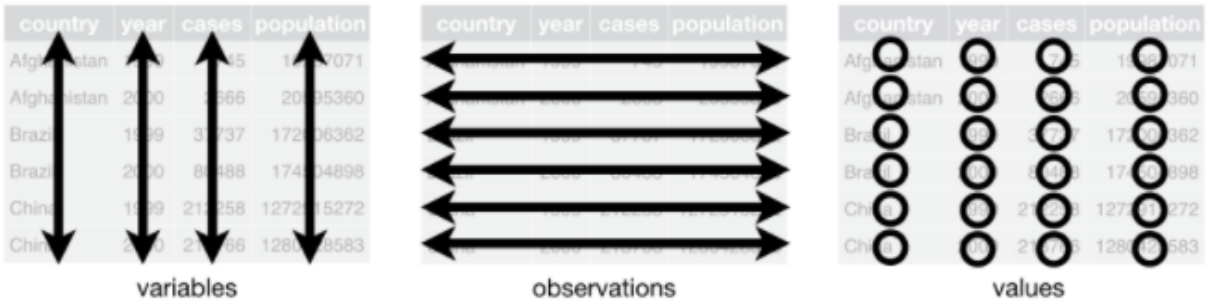
The table below is an extract from the list of books in the British Library. Identify the instances of dirty data present, stating the way in which the data is dirty.

Identifier	Edition Statement	Place of Publication	Date of Publication	Publisher	Title	Author	Contributors
206		London	1879 [1878]	S. Tinsley & Co.	Walter Forbes. [A novel.] By A. A	A. A.	FORBES, Walter.
216		London; Virtue & Yo	1868	Virtue & Co.	All for Greed. [A novel. The dedication s	A., A. A.	BLAZE DE BURY, Ma
218		London	1869	Bradbury, Evans & C	Love the Avenger. By the author of â€œe	A., A. A.	BLAZE DE BURY, Ma
472		London	1851	James Darling	Welsh Sketches, chiefly ecclesiastical, to	A., E. S.	Appleyard, Ernest Si
480	A new edition, revis	London	1857	Wertheim & Macint	[The World in which I live, and my place	A., E. S.	BROOME, John Hen
481	Fourth edition, revis	London	1875	William Macintosh	[The World in which I live, and my place	A., E. S.	BROOME, John Hen
519		London	1872	The Author	Lagonells. By the author of Darmayne (R	A., F. E.	ASHLEY, Florence En
667		pp. 40. G. Bryan & Co: Oxford, 1898			The Coming of Spring, and other poems	A., J. [A., J.	ANDREWS, J. - Write
874		London]	1676		A Warning to the inhabitants of England	RemaÊ¿.	ADAMS, Mary.
1143		London	1679		A Satyr against Vertue. (A poem: suppos	A., T.	OLDHAM, John.
1280		Coventry	1802	Printed by J. Turner	An Account of the many and great Loan		CARTE, Samuel. [JAC
1808		Christiania	1859		Erindringer som Bidrag til Norges Histor	AALL, Jacob.	AALL, J. C. [LANGE, C
1905		Firenze	1888		Gli Studi storici in terra d'Otranto ... Fra	AAR, Ermanno - pse	S., L. G. D. [SIMONE,
1929		Amsterdam	1839, 38-54		De Aardbol. Magazijn van hedendaagsch		WITKAMP, Pieter Hz
2836		Savona	1897		Cronache Savonesi dal 1500 al 1570 ... A	ABATE, Giovanni Ag	ASSERETO, Giovanni
2854		London	1865	E. Moxon & Co.	See-Saw; a novel ... Edited [or rather, w	ABATI, Francesco.	READE, William Win
2956		Paris	1860-63		Gellodellsie d'une partie de la Haute E	ABBADIE, Antoine T	RADAU, Rodolphe.
2957		Paris	1873		[With eleven maps.]	ABBADIE, Antoine T	RADAU, Rodolphe.
3017	Nueva edicion, anot	Puerto-Rico	1866		[Historia geografÏfica, civil y politica de	ABBAD Y LASIERRA,	ACOSTA Y CALBO, Jo
3131		New York	1899	W. Abbatt	The Crisis of the Revolution, being the s	ABBATT, William.	ANDREÏl, John - Ma
4598		Hull	1814	The Author	Peace: a lyric poem. [With prefatory ad	ABBOTT, Thomas Ea	WRANGHAM, Franc
4884		London	1820	J. Hatchard & Son	Abdallah; or, The Arabian Martyr: a Chr		BARHAM, Thomas F
4976	[Another edition.] A	Oxonii	1800	J. Cooke, etc.	[Abdollatiphi HistoriÃ¦ Ã†gypti compen		WHITE, Joseph - Can
5382		London	1847, 48 [1846-48]	Punch Office	The Comic History of England ... With ...	A'BECKETT, Gilbert A	LEECH, John - Artist
5385	[Another edition.] Il	London	[1897?]	Bradbury, Agnew &	[The comic history of England ... With tw	A'BECKETT, Gilbert A	LEECH, John - Artist
5389	[Another edition.]	London	[1897?]	Bradbury, Agnew &	[The Comic History of Rome ... Illustrate	A'BECKETT, Gilbert A	LEECH, John - Artist
5432		Milano	1893		Signa: opera in tre atti [founded on the	A'BECKETT, Gilbert A	MAZZUCATO, Giova
6036		London	1805	C. & R. Baldwin	The Venetian Outlaw, a drama in three		ELLISTON, Robert W
6821		Aberdeen	1837	J. Davidson & Co.	Description of the Coast between Aberd		DUNCAN, William -

Tidy data

Tidy data seeks a consistent format that has:

- Each variable in its own column.
- Each observation in its own row.
- Each value in its own cell.



- 2 benefits: consistency and exploits R's vector nature

http://www.jstatsoft.org/v59/i10/paper

Lecture 5 – Networks

Structure

- Nodes (vertices) and edges (arcs), directed – undirected, weighted – unweighted.
- Walk, Path, Cycle, Geodesic, Length, Connected,
- Loop, Complete, Subgraph, Clique, Simple.

Network Statistics

- Diameter, Average path length, Degree distribution, Density and Clustering coefficient.

Vertex Characteristics

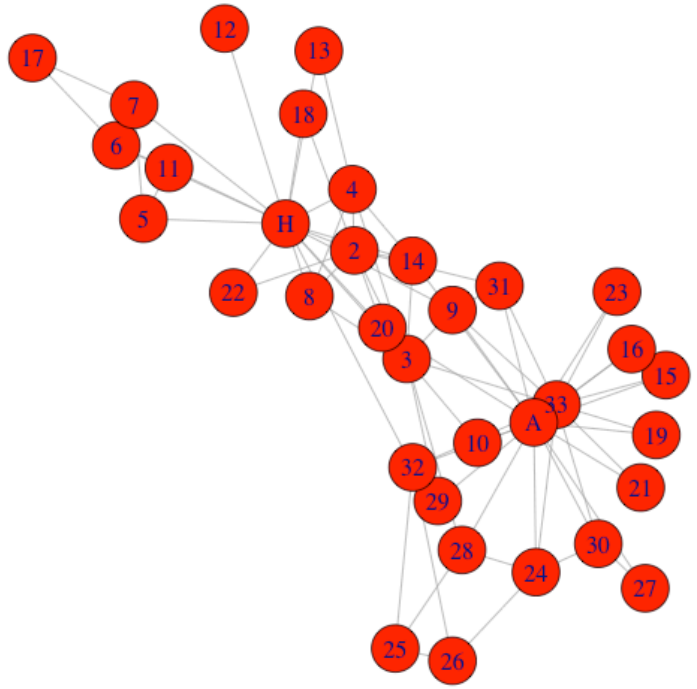
- Degree, Centrality: Betweenness, Closeness, Eigenvector.

Analysis

- Igraph package in R
- Graph data object. Creating graphs in R. Data entry using different methods, edge list, csv, etc.
- Plots
- Detecting the most important actors in a network using centrality measures.
- Theoretical graph types (E-R (random), B-A (scale-free), W-S (small world)).

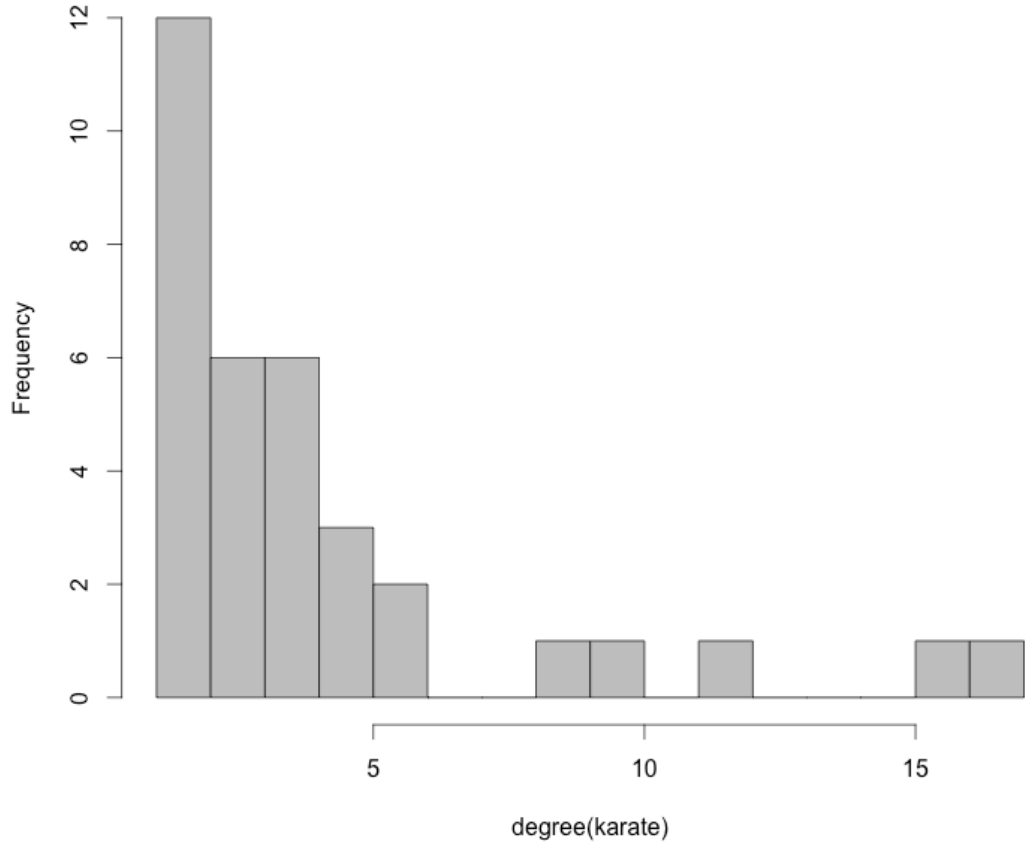
Karate club – force-directed plot

```
> plot(karate, layout = layout.fruchterman.reingold)
```



Karate club – degree distribution

```
> hist(degree(karate), breaks = 18, col = "grey")
```



Karate club – vertex statistics

Actor	Degree	Closeness	Betweenness
Mr Hi	16	0.0077	250.1
Actor 2	9	0.0061	33.8
Actor 3	10	0.0060	36.6
Actor 4	6	0.0053	1.3
Actor 5	3	0.0046	0.5
Actor 6	4	0.0046	15.5
Actor 7	4	0.0047	15.5
Actor 8	4	0.0055	0.0
Actor 9	5	0.0060	13.1
Actor 10	2	0.0058	7.3
Actor 11	3	0.0053	0.5
Actor 12	1	0.0044	0.0
Actor 13	2	0.0062	0.0
Actor 14	5	0.0058	1.2
Actor 15	2	0.0052	0.0
Actor 16	2	0.0042	0.0
Actor 17	2	0.0033	0.0

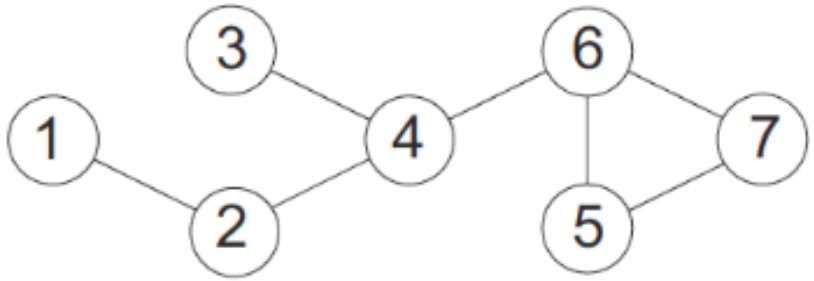
Actor	Degree	Closeness	Betweenness
Actor 18	2	0.0058	16.1
Actor 19	2	0.0057	3.0
Actor 20	3	0.0075	127.1
Actor 21	2	0.0062	0.0
Actor 22	2	0.0053	0.0
Actor 23	2	0.0048	0.0
Actor 24	5	0.0042	1.0
Actor 25	3	0.0048	33.8
Actor 26	3	0.0037	0.5
Actor 27	2	0.0051	0.0
Actor 28	4	0.0047	6.5
Actor 29	3	0.0061	10.1
Actor 30	4	0.0053	0.0
Actor 31	4	0.0053	3.0
Actor 32	6	0.0063	66.3
Actor 33	12	0.0061	38.1
John A	17	0.0076	209.5

What can we conclude about the structure of this network? Who are the most important people?

Sample exam question

The social network of a group of friends (numbered from 1 – 7) is drawn below.

2 Marks



Write down the adjacency matrix for the network. (Use only the cells you need)

Lecture 6 – Linear regression

Fitting the regression

- Assumptions, LOBF, linear model object: coefficients & residuals, prediction

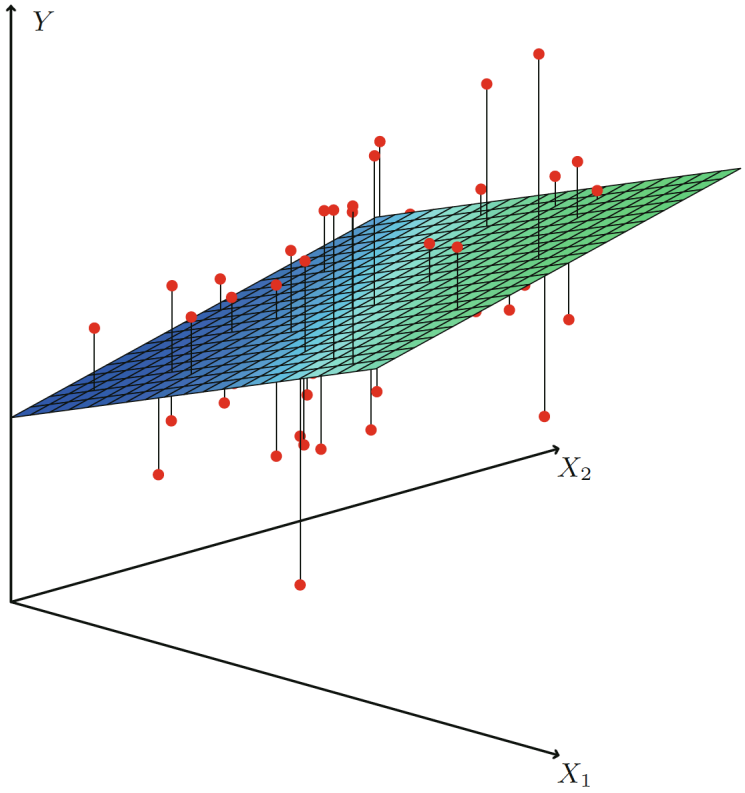
Regression diagnostics.

Multiple linear regression

Regression with qualitative variables

- Using non-numerical factors

Multiple linear regression



From: G. James et al., An Introduction to Statistical Learning: with Applications in R (2013).

Diagnostics – summary

```
> summary(fit)
Call:
lm(formula = Function ~ Price)

Residuals:
     Min       1Q   Median       3Q      Max
-19.3839  -6.8347   0.0382   8.1903  13.4312

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   44.020      4.565   9.642 3.09e-10 ***
Price          6.942      1.502   4.621 8.43e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 9.185 on 27 degrees of freedom
Multiple R-squared:  0.4416,    Adjusted R-squared:  0.421
F-statistic: 21.36 on 1 and 27 DF,  p-value: 8.428e-05
```

Median close to 0

Coefficients: α, β

Hypothesis test that $\alpha, \beta = 0$ vs $\alpha, \beta \neq 0$

Coefficient of Determination: r^2

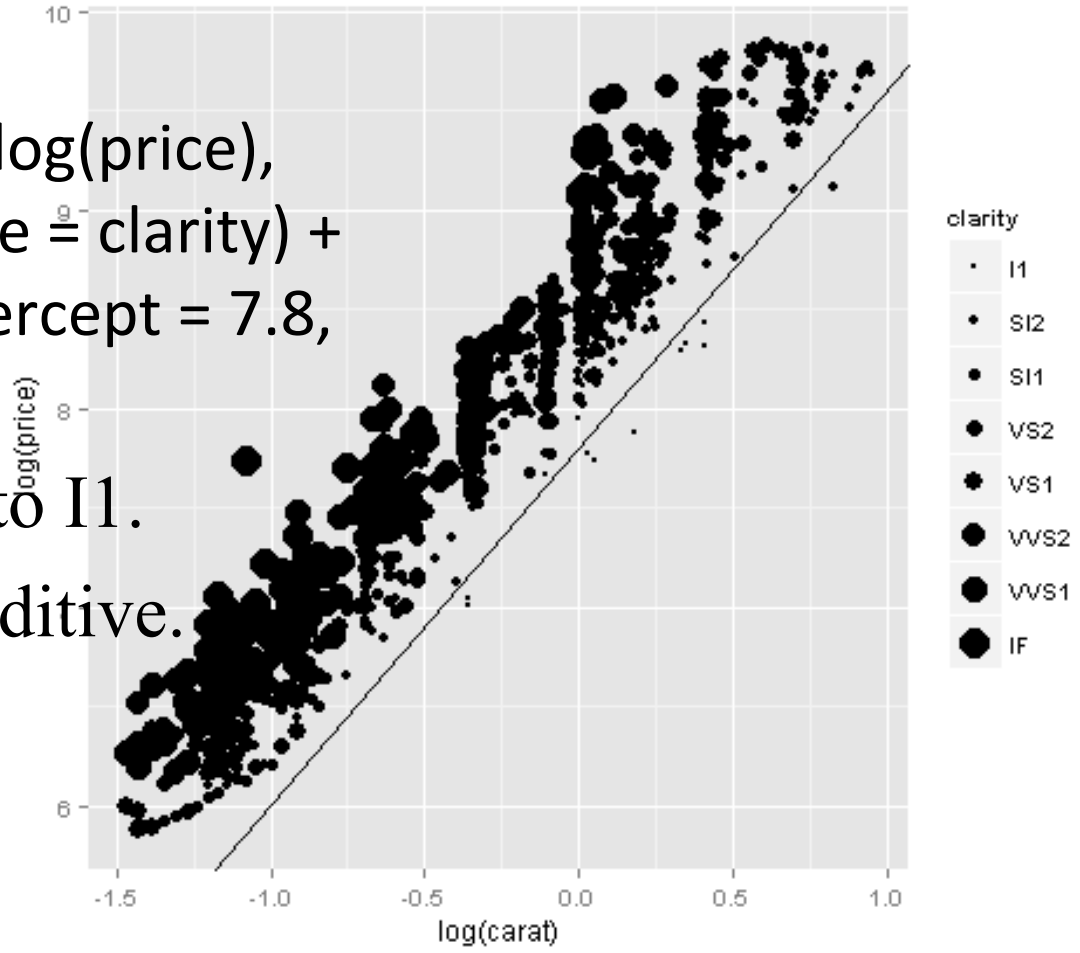
Overall significance of regression: that at least one coefficient $\neq 0$

Fitted model

ln(price) v ln(carat)

> qplot(log(carat), log(price),
> data = dsmall, size = clarity) +
> geom_abline(intercept = 7.8,
> slope = 1.8)

- Basic model fitted to I1.
- Quality increase additive.



Sample exam question:

4 Marks

The least squares regression of log(price) on log(size) and color is given below. Note that 'log' in this context means '$\text{Log}_e(X)$.' Based on this output, answer the following questions.

```
> library(ggplot2)
> set.seed(9999) # Random seed
> dsmall <- diamonds[sample(nrow(diamonds), 1000), ] # sample of 1000 rows
> attach(dsmall)
> contrasts(color) = contr.treatment(7)

> d.fit <- lm(log(price) ~ log(carat) + color)
> d.fit

> summary(d.fit)

Call:
lm(formula = log(price) ~ log(carat) + color)

Residuals:
     Min       1Q   Median       3Q      Max
-0.97535 -0.16001  0.01106  0.15500  0.99937

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  8.61356    0.02289 376.259  < 2e-16 ***
log(carat)   1.74075    0.01365 127.529  < 2e-16 ***
color2      -0.06717    0.02833  -2.371   0.0179 *
color3      -0.05469    0.02783  -1.965   0.0496 *
color4      -0.07139    0.02770  -2.578   0.0101 *
color5      -0.21255    0.02973  -7.148  1.7e-12 ***
color6      -0.32995    0.03175 -10.393  < 2e-16 ***
color7      -0.50842    0.04563 -11.143  < 2e-16 ***
---
Residual standard error: 0.2393 on 992 degrees of freedom
Multiple R-squared: 0.9446,   Adjusted R-squared: 0.9443
F-statistic:  2418 on 7 and 992 DF,  p-value: < 2.2e-16
```

Write down the regression equation predicting log(price) as a function of size and color.

Explain the different data types present in the variables: **carat** and **color**. What is the effect of this difference on the regression equation?

Lecture 7 – Decision Trees

Overview of data mining and machine learning

Introduction to classification and decision trees:

- Leaf nodes, Branches, Tree nodes…

A specific decision tree algorithm: ID3

Entropy and information gain

- Decision attributes, Attribute splitting

Model accuracy; training and performance evaluation

Implementing a decision tree using R

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

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

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 | | 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

Playing tennis: initial entropy

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

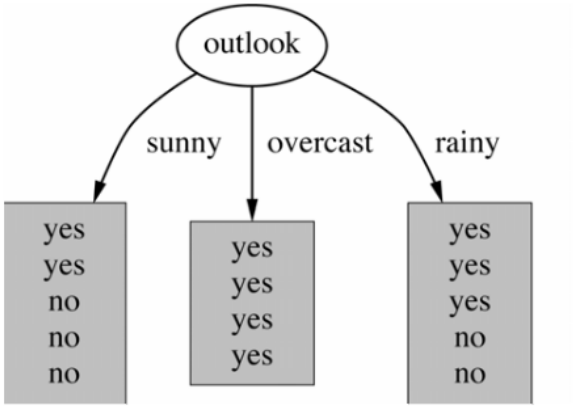
Day	Outlook	Temperature	Humidity	Wind	Play
D1	Sunny	Hot	High	Weak	No
D2	Sunny	Hot	High	Strong	No
D3	Overcast	Hot	High	Weak	Yes
D4	Rain	Mild	High	Weak	Yes
D5	Rain	Cool	Normal	Weak	Yes
D6	Rain	Cool	Normal	Strong	No
D7	Overcast	Cool	Normal	Strong	Yes
D8	Sunny	Mild	High	Weak	No
D9	Sunny	Cool	Normal	Weak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

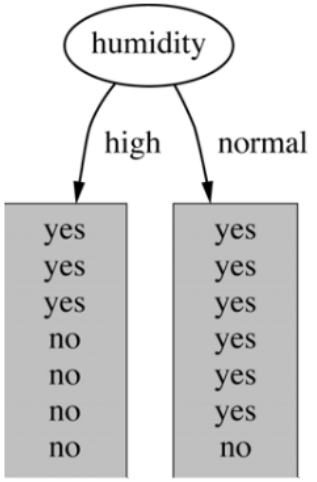
Yes	No	P(Yes)	Log2(Yes)	P(No)	Log2(No)	Entropy
9	5	0.6429	-0.6374	0.3571	-1.4854	0.9403

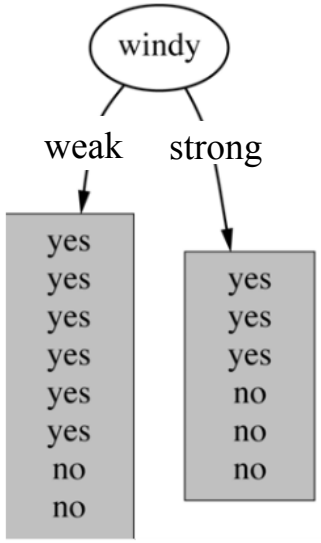
Which attribute to select?

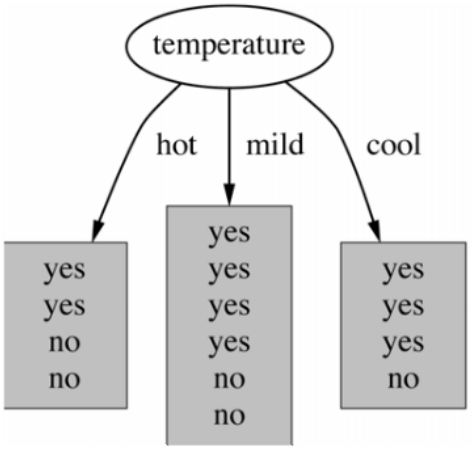
Remember - ID3 chooses the attribute which gives the greatest information gain (reduction in Entropy), or the 'purest' result.

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









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)

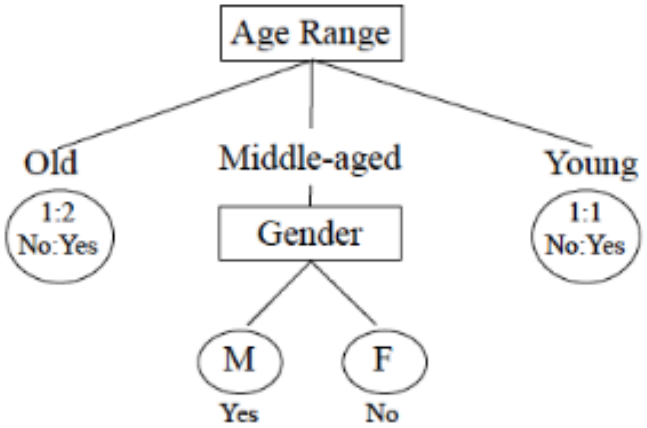
Sample exam question

4 Marks

Eight university staff completed a questionnaire on happiness. The results are given below.

ID	Age Range	Occupation	Gender	Happy
1	Young	Tutor	F	Yes
2	Middle-aged	Professor	F	No
3	Old	Tutor	M	Yes
4	Middle-aged	Professor	M	Yes
5	Old	Tutor	F	Yes
6	Young	Lecturer	M	No
7	Middle-aged	Lecturer	F	No
8	Old	Tutor	F	No

A decision tree was generated from the data.



Sample exam question

Using the decision tree generated from the data provided, assuming a required confidence level greater than 60% to classify as 'Happy', what is the predicted classification for the following instances:

Instance 1: (Age Range = Young, Occupation = Professor, Gender = F, Happy = ?)

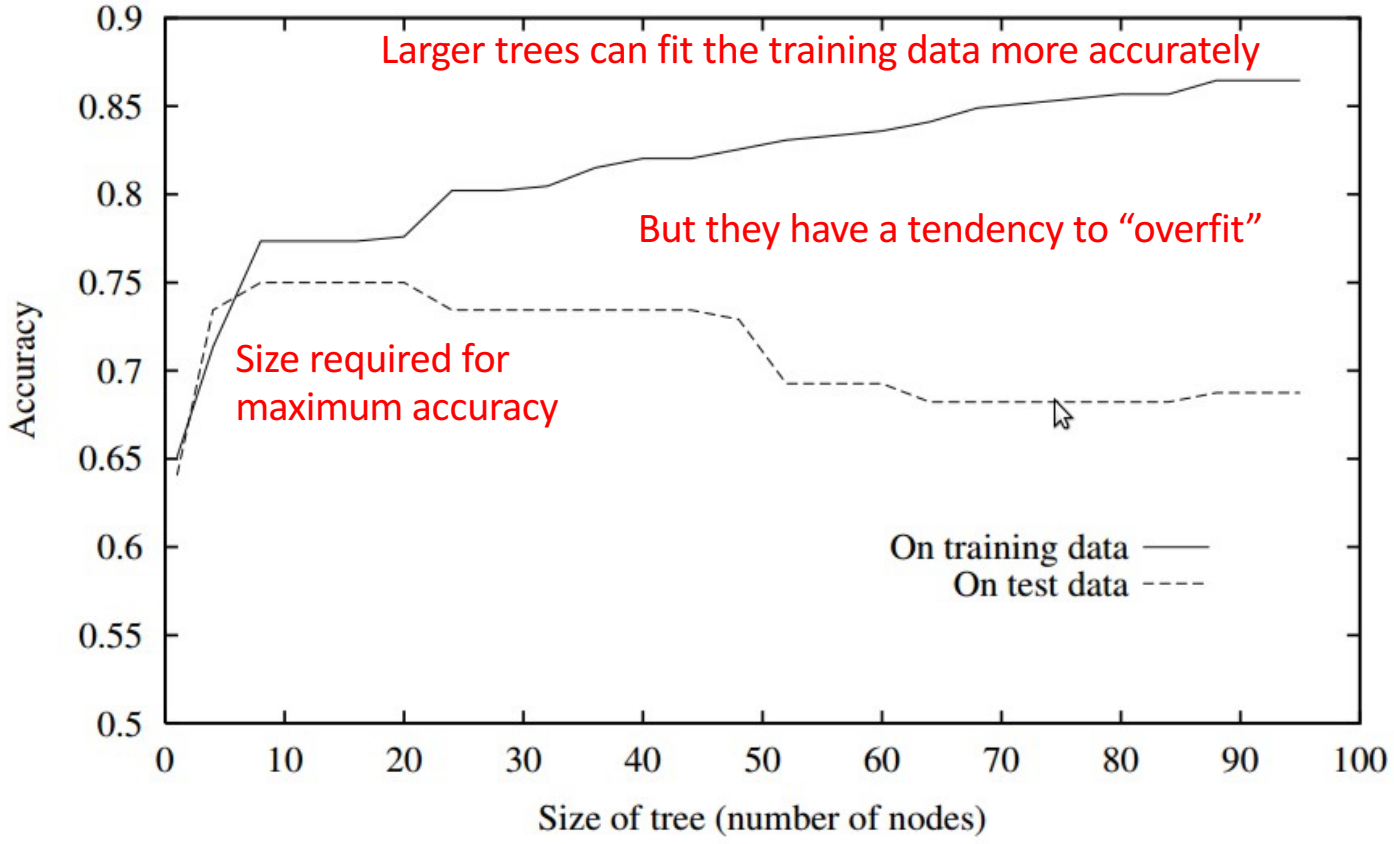
Instance 2: (Age Range = Old, Occupation = Professor, Gender = F, Happy = ?)

Lecture 8 – Classification continued

Classification Continued:

- Improving the basic decision tree: pruning and cross-validation,
- Naïve Bayes classification,
- Classifier model evaluation: ROC evaluation,
- Lift.

Example: size of tree vs accuracy



Avoiding over-fitting

Two approaches:

1. Pre-pruning: stop growing the tree earlier, before it reaches the point where it over fits on the training data.

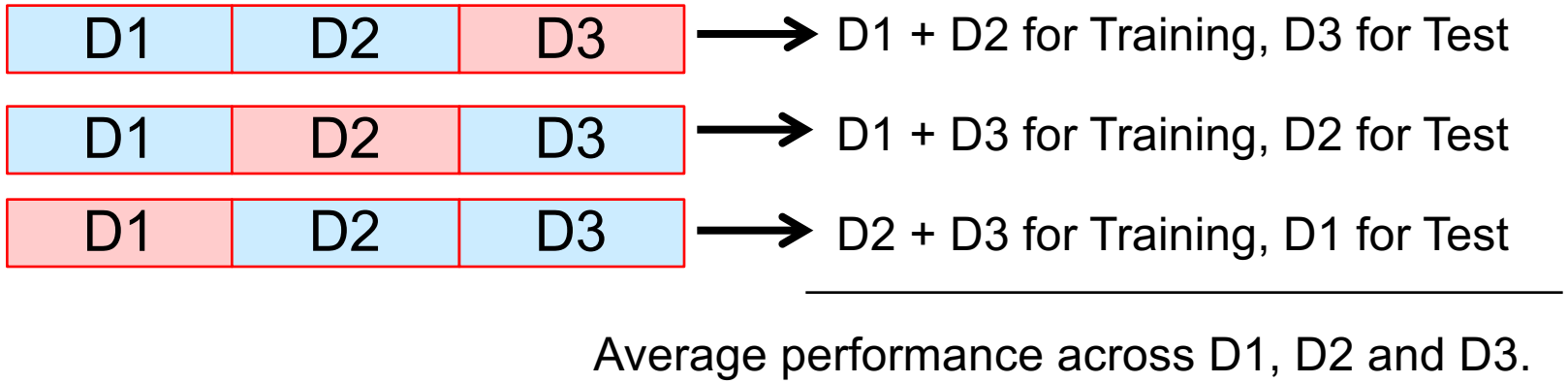
2. Post-pruning: allow the tree to overfit the data, and then post-prune the tree. (more effective in practice).

Example: 3 fold cross validation

Partitioning:

- *2/3* training (making the model)
- *1/3* testing (measuring performance of model)

Repeat the procedure three times so that every case has been used exactly once for testing.



Bayesian Classifiers

Approach:

- Compute the posterior probability for all values of C_j using Bayes theorem

$$P(C_j|A_1 \cap A_2 \cap A_3 \ldots \cap A_n) = \frac{P(C_j) \cdot P(A_1 \cap A_2 \cap A_3 \ldots \cap A_n|C_j)}{P(A_1 \cap A_2 \cap A_3 \ldots \cap A_n)}$$

- Choose the value of C_j that maximises this posterior probability $P(C_j|A_1 \cap A_2 \cap A_3 \ldots \cap A_n)$

- Is equivalent to maximising $P(C_j) \cdot P(A_1 \cap A_2 \cap A_3 \ldots \cap A_n|C_j)$, since $P(A_1 \cap A_2 \cap A_3 \ldots \cap A_n)$ is the same for all C_j.

Naïve Bayes classifier

- Assume independence among attributes A_i when class is given, thus

$$P(A_1 \cap A_2 \cap A_3 \ldots \cap A_n | C_j) = P(A_1|C_j) \times P(A_2|C_j) \times \ \ldots \ \times P(A_n|C_j)$$

- Estimate $P(A_i|C_j)$ for all A_i

- A new point is classified to the C_j which maximises

$$P(C_j) \times P(A_1|C_j) \times P(A_2|C_j) \times \ \ldots \ \times P(A_n|C_j)$$

- Classification confidence (probability) is given by

$$P(C_j|A_1 \cap A_2 \cap A_3 \ldots \cap A_n) = \frac{P(C_j) \cdot P(A_1 \cap A_2 \cap A_3 \ldots \cap A_n|C_j)}{P(A_1 \cap A_2 \cap A_3 \ldots \cap A_n)}$$

Sample exam question

3 Marks

Use data below and Naïve Bayes classification to predict whether the following test instance will be happy or not.

ID	AgeRange	Occupation	Gender	Happy
1	Young	Tutor	F	Yes
2	Middle-aged	Professor	F	No
3	Old	Tutor	M	Yes
4	Middle-aged	professor	M	Yes
5	Old	Tutor	F	Yes
6	Young	Lecturer	M	No
7	Middle-aged	lecturer	F	No
8	Old	Tutor	F	No

Test instance: (AgeRange = young, Occupation = professor, Gender = F, Happy = ?)

Sample exam question

1 Mark

Use the complete Naïve Bayes formula to evaluate the confidence of predicting Happy = yes, based on the same attributes as the previous question: (AgeRange = young, Occupation = professor, Gender = F).

Hint: adapt $P(C_j|A_1 \cap A_2 \cap A_3 \ldots \cap A_n) = \frac{P(C_j) \cdot P(A_1 \cap A_2 \cap A_3 \ldots \cap A_n|C_j)}{P(A_1 \cap A_2 \cap A_3 \ldots \cap A_n)}$ for independent events.

Notes

Receiver Operating Characteristic

Developed in the 1950s for signal detection - to analyse noisy signal transmission.

- Characterises the tradeoff between positive hits and false alarms.
- ROC plots True Positive Rate, TPR, (on y axis) against False Positive Rate, FPR, (on x axis).
- Performance of a single classifier presented as a single point of ROC curve.
- Changing the threshold of algorithm, sample distribution or cost matrix etc. changes that point: this lets a profile of classifier to be developed.

Receiver Operating Characteristic

Calculating TPR and FPR

- True Positive Rate, TPR, also called *sensitivity* indicates how good a test is for correctly predicting "yes" when it should predict "yes". (Think of confidence)

$$True\ Positive\ Rate\text{: } TPR = \frac{TP}{TP + FN}$$

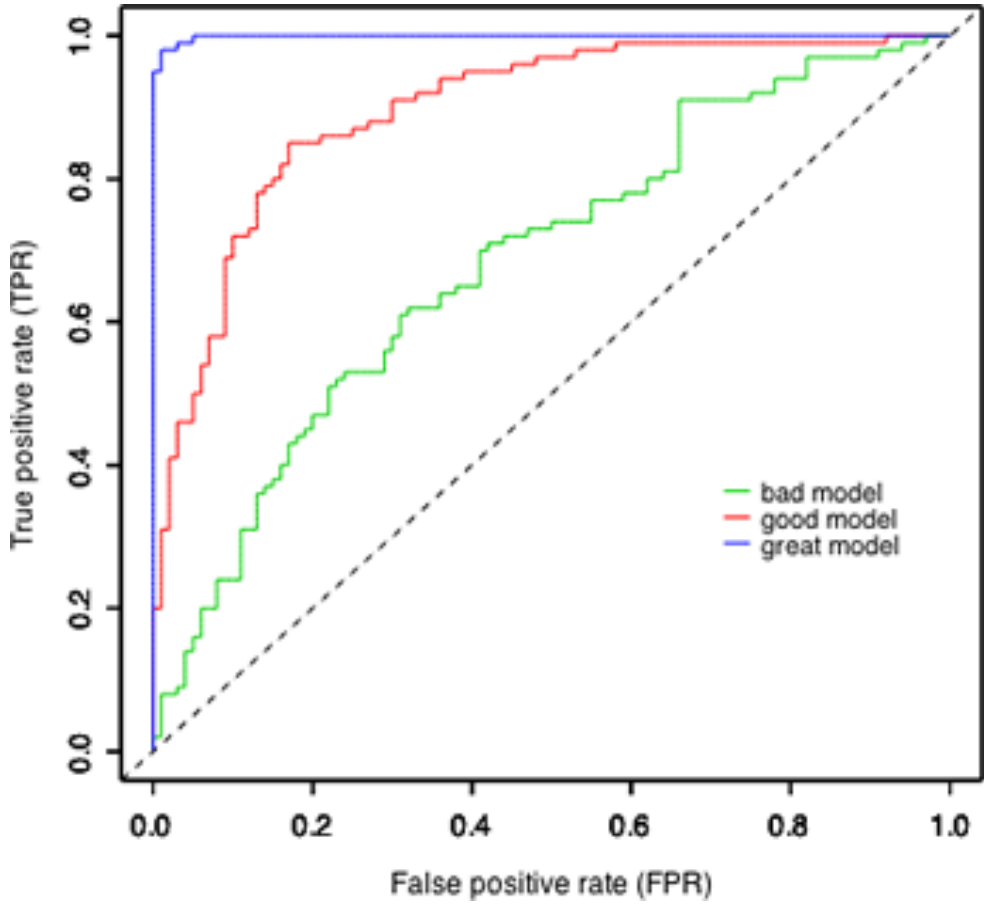
- False Positive Rate, FPR, also known as a '*false alarm*' is:

$$False\ Positive\ Rate\text{: } TPR = \frac{FP}{FP + TN}$$

- ROC plots TPR against FPR

Using ROC for Model Comparison

ROC curves for three different classifiers



Sample exam question

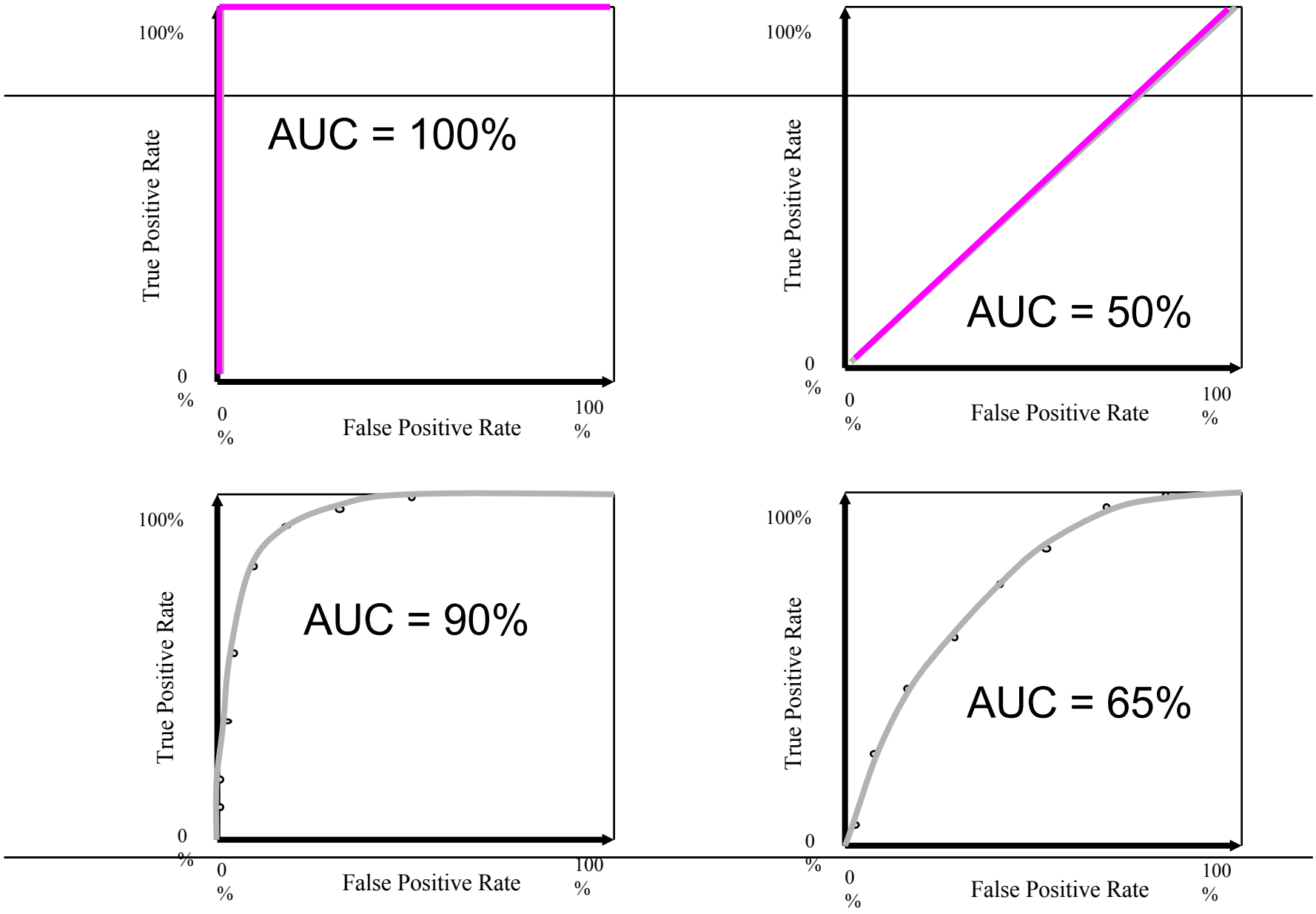
4 Marks

The following table shows the outcome of a classification model for customer data. The table lists customers by code and provides the following information: The model confidence of a customer buying/not buying a new product (confidence-buy); whether in fact the customer did or did not buy the product (buy = 1 if the customer purchased the model, buy = 0 if the customer did not buy the model).

customer	confidence-buy	buy-not-buy
c1	0.9	1
c2	0.8	1
c3	0.7	0
c4	0.7	1
c5	0.6	1
c6	0.5	1
c7	0.4	0
c8	0.4	1
c9	0.2	0
c10	0.1	0

Calculate the **True Positive Rate** and the **False Positive Rate** when a confidence level of 20% is required for a positive classification.

AUC for ROC curves

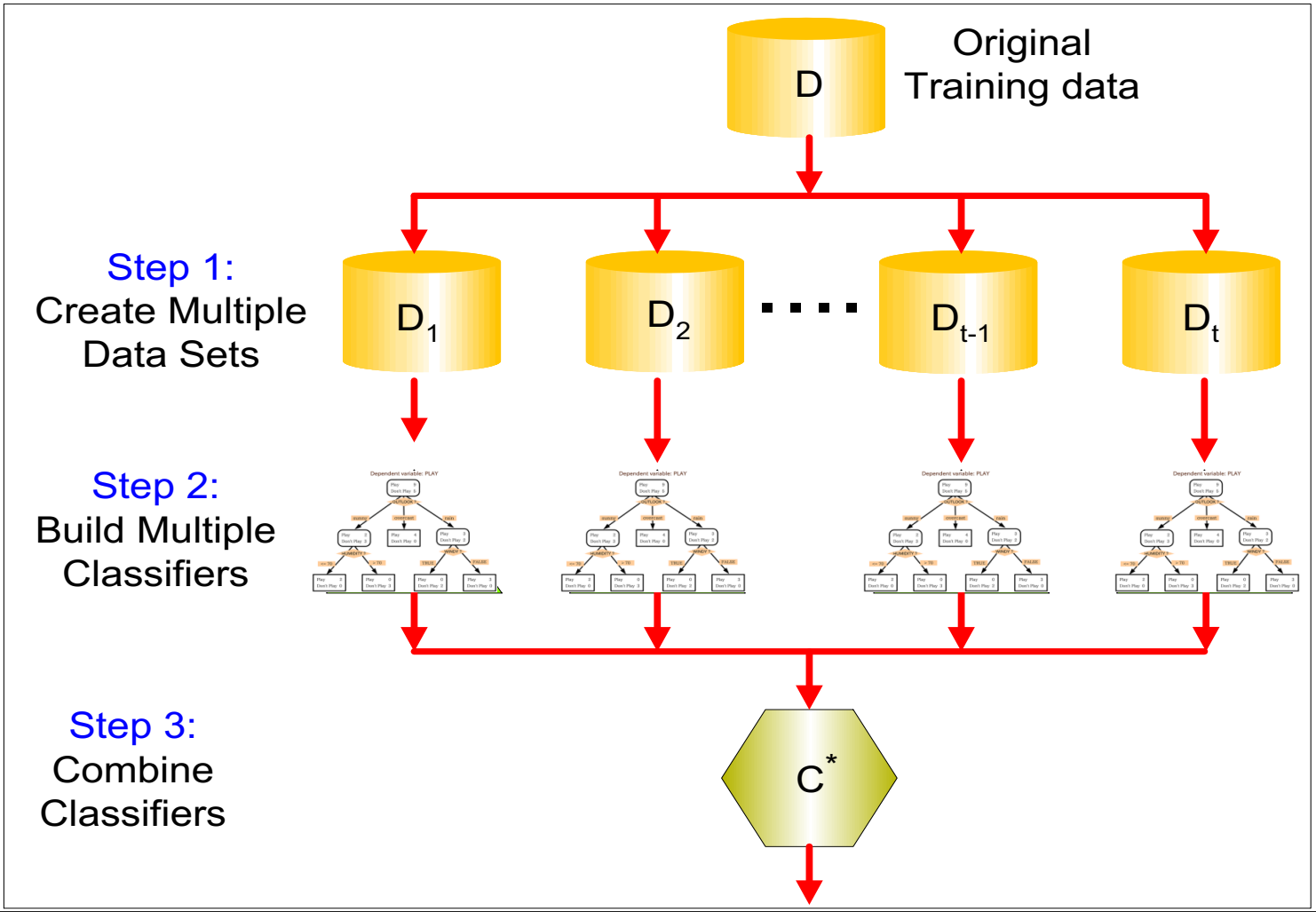


Lift

For binary classification and prediction models:

- Lift is a measure of the effectiveness of a predictive model calculated as the ratio between the results obtained with and without the predictive model.
- Lift charts are visual aids for measuring model performance
- Lift factor = success rate with model / success rate without model

Lecture 9 Ensemble methods + ANN



Bagging (Bootstrap Aggregating)

- Bootstrapping: resampling the original data set to produce multiple synthetic data sets.
- Sampling is uniform, each bootstrap replicate may have multiple instances of the original data points, and contains approximately 63% of the original data set.
- Build a classifier on each of the replicates and combine results by voting. Multiple classifiers reduce the (high) variance of individual decision trees, (recall: sample variance is $\frac{\sigma}{\sqrt{n}}$).

Boosting

Multiple trees are grown slowly, using incremental improvement.

Data set is not bootstrap sampled, but training examples are weighted, with a higher weight given to hard to classify examples at each step.

Classification is by a weighted sum from each classifier, with more accurate classifiers having a greater weight.

Random Forest

A refinement of bagged decision trees.

Specifically designed for decision trees.

Random Forest Algorithm

- Create multiple data sets from the original training set using subsets of data points and subsets of attributes.
- Build a decision tree classifier for each new data.
- Combine the classifiers by taking a majority vote to produce the final decision.

Artificial Neural Networks, ANNs

- Are computer models of neural behaviour in the (human) brain.
- Are applicable to wide range of problems
- Have the ability to ‘learn’ by weighting the contribution of each neuron to a decision (output).
- They are accurate, can handle redundant attributes and noisy data.
- Large ANNs give rise to ‘deep learning’.

Setting up ANNs

Pre-processing

- One input neuron for each input variable,
- One output neuron for each output class,
- Inputs can only be numerical (R will accept binary TRUE FALSE),
- Data should be normalised,
- Categorical, data needs to be converted to binary columns as indicator variables,
- No missing values.

Lecture 10 – Clustering

k-Means clustering

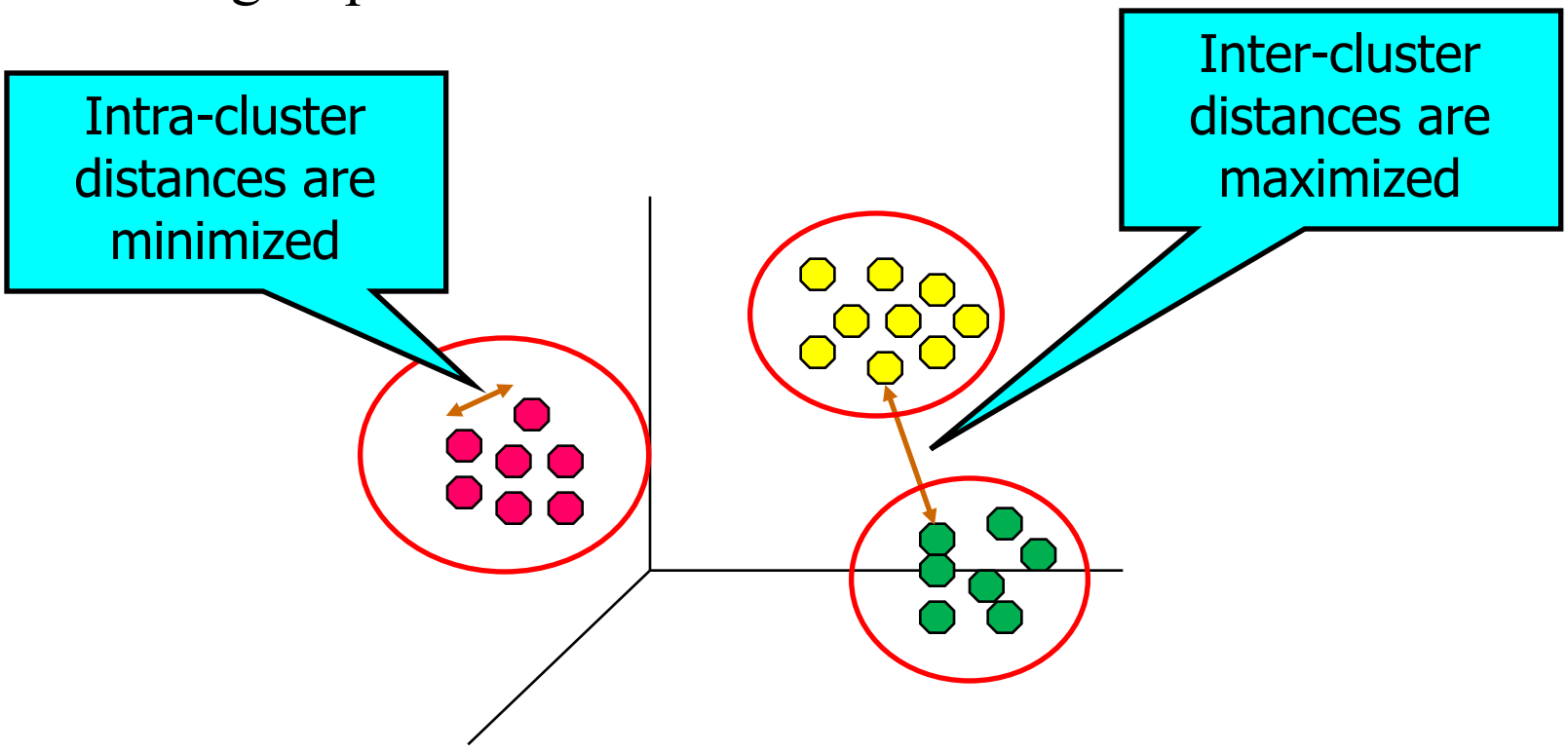
Hierarchical clustering

Clustering using R

Recall: clustering is unsupervised learning!

What is Cluster Analysis?

Finding groups of objects such that the objects in a group will be similar (or related) to one another and different from (or unrelated to) the objects in other groups



k-Means Clustering

Partitional clustering approach

Each cluster is associated with a **centroid** (center point)

Each point is assigned to the cluster with the closest centroid

Number of clusters, *k*, must be specified

The basic algorithm is very simple:

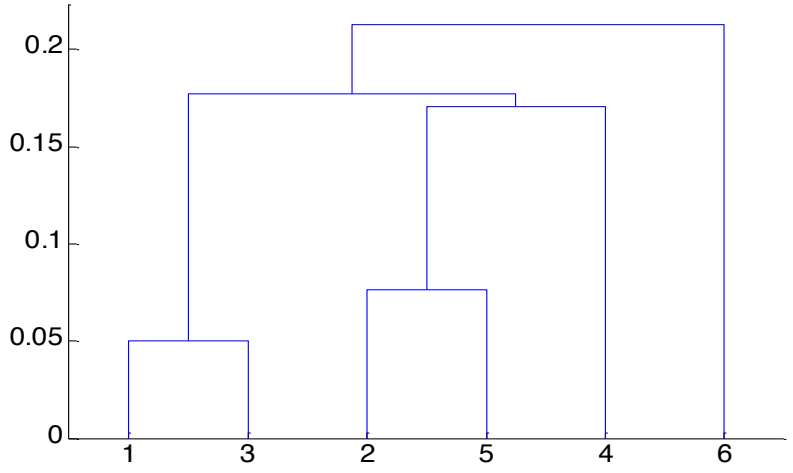
1. Select *k* points (at random) as the initial centroids
2. **Repeat**
    3. Form *k* clusters by assigning all points to the closest centroid
    4. Re-compute the centroid of each cluster
5. **Until** the centroids don't change

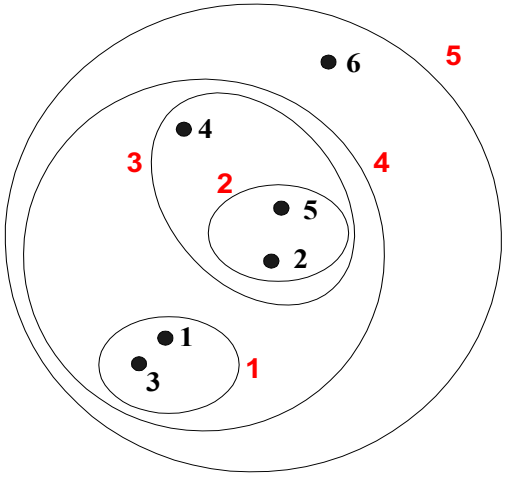
Sample exam question

Hierarchical Clustering

Produces a set of nested clusters organized as a **hierarchical tree**

- Records the sequences of merges or splits.
- Can be visualized as a dendrogram or enclosure diagram.

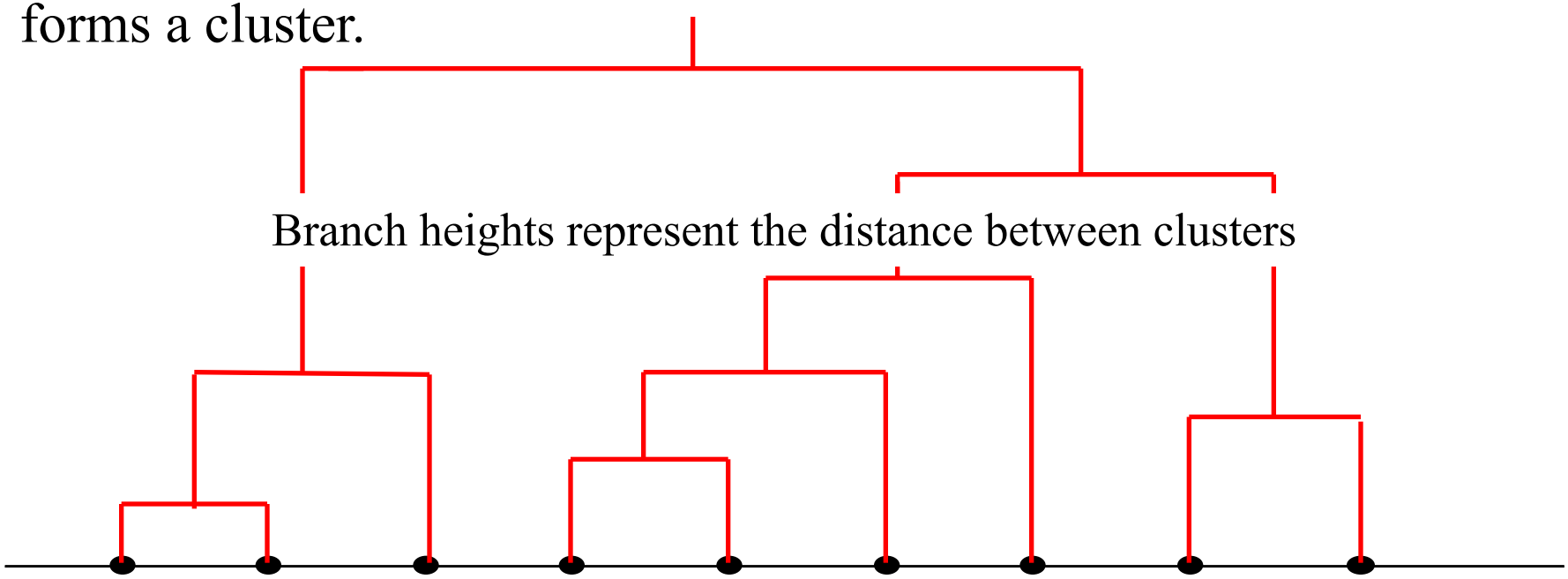




Dendrogram and hierarchies

Decompose data objects into a several levels of nested partitioning (**tree** of clusters), called a **dendrogram**.

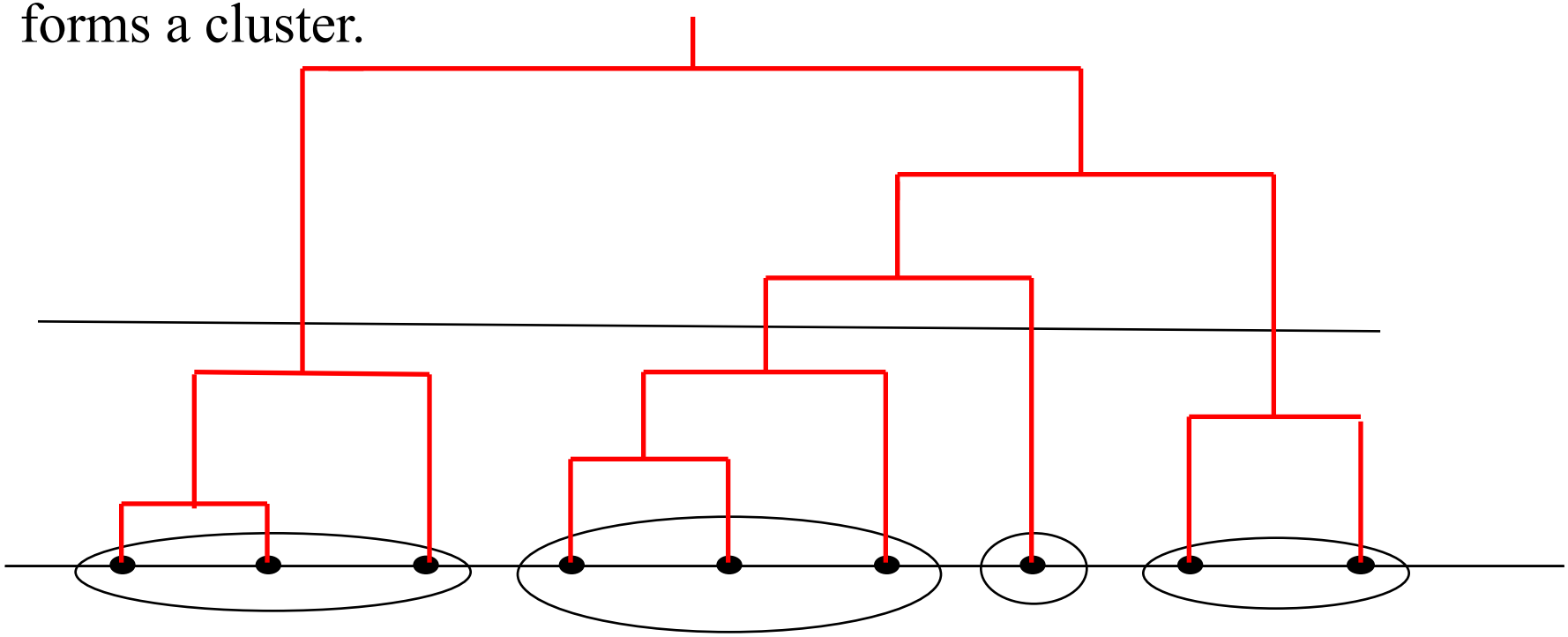
A **clustering** of the data objects is obtained by **cutting** the dendrogram at the desired level, then each **connected component** forms a cluster.



Dendrogram and hierarchies

Decompose data objects into a several levels of nested partitioning (**tree** of clusters), called a **dendrogram**.

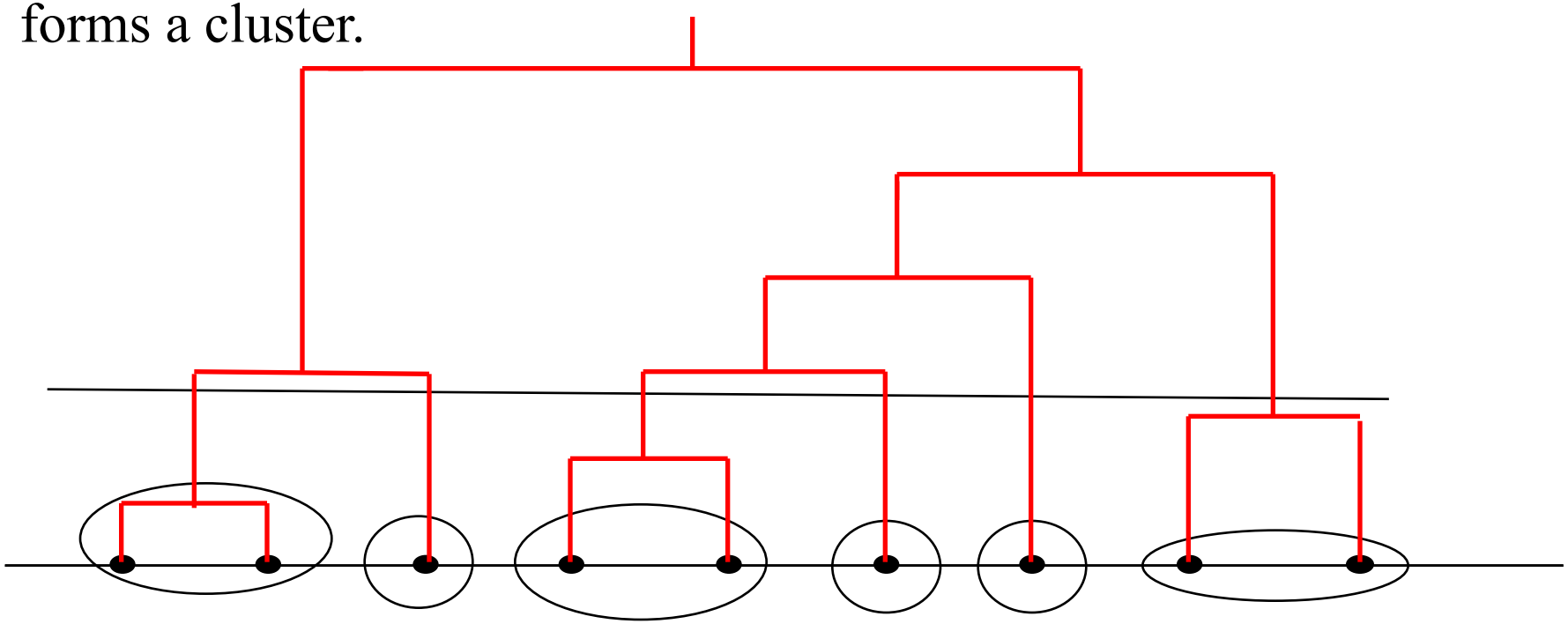
A **clustering** of the data objects is obtained by **cutting** the dendrogram at the desired level, then each **connected component** forms a cluster.



Dendrogram and hierarchies

Decompose data objects into a several levels of nested partitioning (**tree** of clusters), called a **dendrogram**.

A **clustering** of the data objects is obtained by **cutting** the dendrogram at the desired level, then each **connected component** forms a cluster.



Lecture 11 – Text analytics

Text analytics

- Processing text for analysis,
- Representing text by a Term-Document Matrix,
- Weighting factors for document similarity calculations,
- Vector space model and cosine distance.

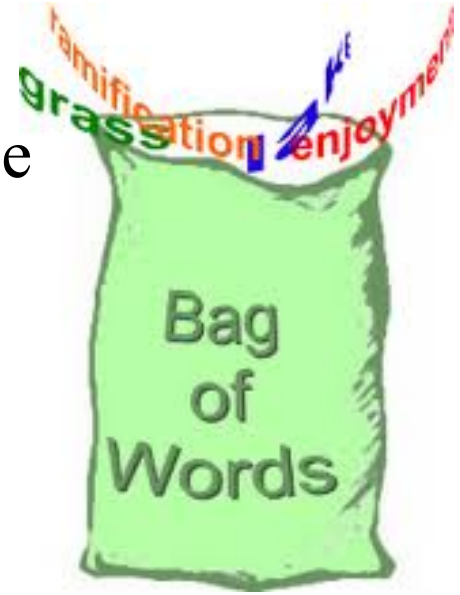
Text analytics in R

- Text processing,
- Document clustering.

Vector Space Model

Uses a ‘bag of words’ approach

- Each document assumed to be just a collection of words
- Makes implicit assumptions that the order of the words in a document does not matter
- Syntactically similar documents are semantically similar – which is often the case



These assumptions not always valid e.g.

- ‘James and the giant ate a peach.’
- ‘The giant ate James and a peach.’

But works well in practice

Extracting structure from text

Several steps:

- Tokenise
- Convert case
- Remove stop words
- Stem
- Lemmatize
- Create n-grams

TDM for processed documents

The Corpus:

- Doc1: {dog | dog_eat | eat | eat_homework | homework}
- Doc2: {cat | cat_eat | eat | eat_sandwich | sandwich}
- Doc3: {dolphin | dolphin_eat | eat | eat_homework | homework}

Term-Document (Frequency) Matrix

Document	eat	eat_homework	eat_sandwich	cat	cat_eat	dog	dog_eat	dolphin	dolphin_eat	homework	sandwich
Doc 1	1	1	0	0	0	1	1	0	0	1	0
Doc 2	1	0	1	1	1	0	0	0	0	0	1
Doc 3	1	1	0	0	0	0	0	1	1	1	0

Sample exam question

2 Marks

Apply the five main steps required to pre-process text documents for analysis to the corpus below. Write your processed documents in the space provided.

Doc1 = { The choir sang loudly. }

Doc2 = { The boys were singing in church. }

Doc3 = { The boy asked to sing a song. }

2 Marks

Construct the term document frequency matrix for the processed text documents above. Use as many cells as you require below.

FIT3152 Data analytics

Summary

Unit objectives (from Lecture 1)

What the course is trying to achieve:

- We are concentrating on fundamental, generic, skills for a data scientist that are independent of software platform or problem domain.
- Problem solving skills, independence and ingenuity. Good communication skills.

What it is not trying to achieve:

- Introduction to the vast range of software, techniques and computing platforms available to data scientists.

Technical skills

Using R as a platform we have covered:

- Basic statistics
- Exploring data using graphics
- Data manipulation
- Linear regression
- Network analysis
- Decision trees, ensemble methods, ANNs (supervised)
- Clustering (unsupervised)
- Text analysis

High-level skills (Lecture 1)

Some necessary skills for a data scientist:

- Understand a problem from client's perspective
- Collect, cleanse, manage and combine data – which may come from disparate sources
- Understand the data, most likely using visualization tools as a starting point
- Analyze and model the data using statistical and (AI) machine learning techniques
- Communicate the results simply and effectively.

Where to next?

If you want to take data science further:

- Kaggle competitions

  www.kaggle.com
- MeetUp groups

  https://www.meetup.com/Data-Science-Melbourne/
- Employment: business, finance, government, all areas of industry, science, consulting ...
- Further study (FIT has Master of Data Science)

Good Luck!