GG 501 SPATIAL KNOWLEDGE MOBILIZATION

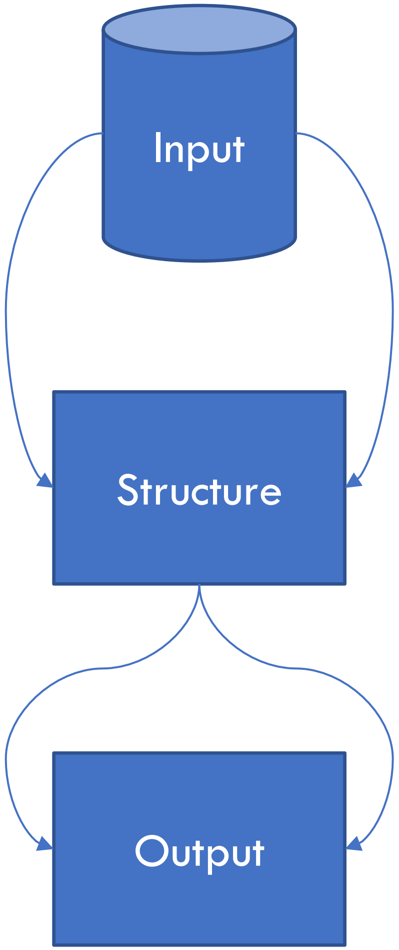
Mar 1: Parameterization and validation I

MODELS – parameterization and validation

- Any time we fit a model, we have to make choices
  - What data goes in
  - What settings or configutations need to be set to run the model
    - this is parameterization
    - these are model-dependent
  -

MODELS COME IN MANY VARIETIES

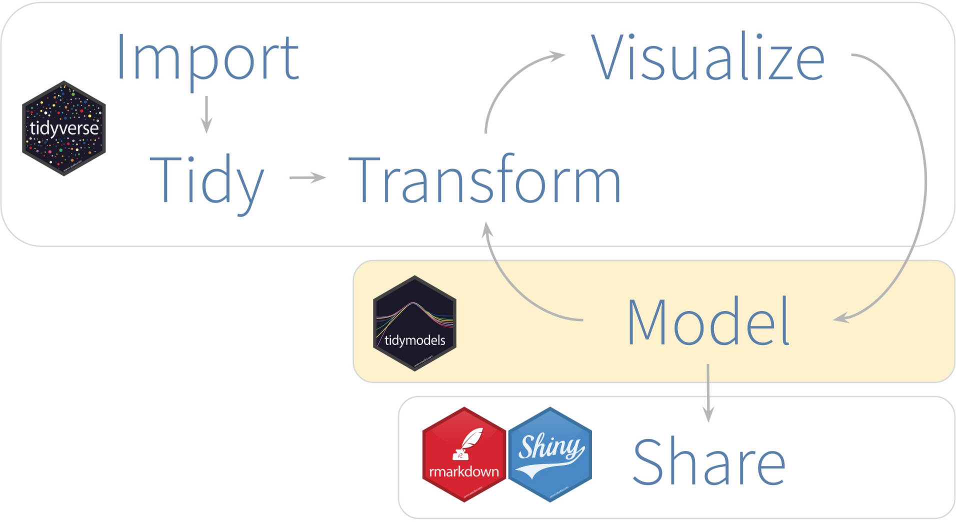
- Each take some input data
- Attempt to generalize about the underling data-generating-process
- Can be used for a variety of purposes –
  - description
  - explanation
  - prediction



TIDYMODELS

- provide a clean and unified interface for modelling in data as part of an overall tidy workflow

- a collection of packages that focus on common aspects of statistical modelling and support many different versions of models implemented in different packages

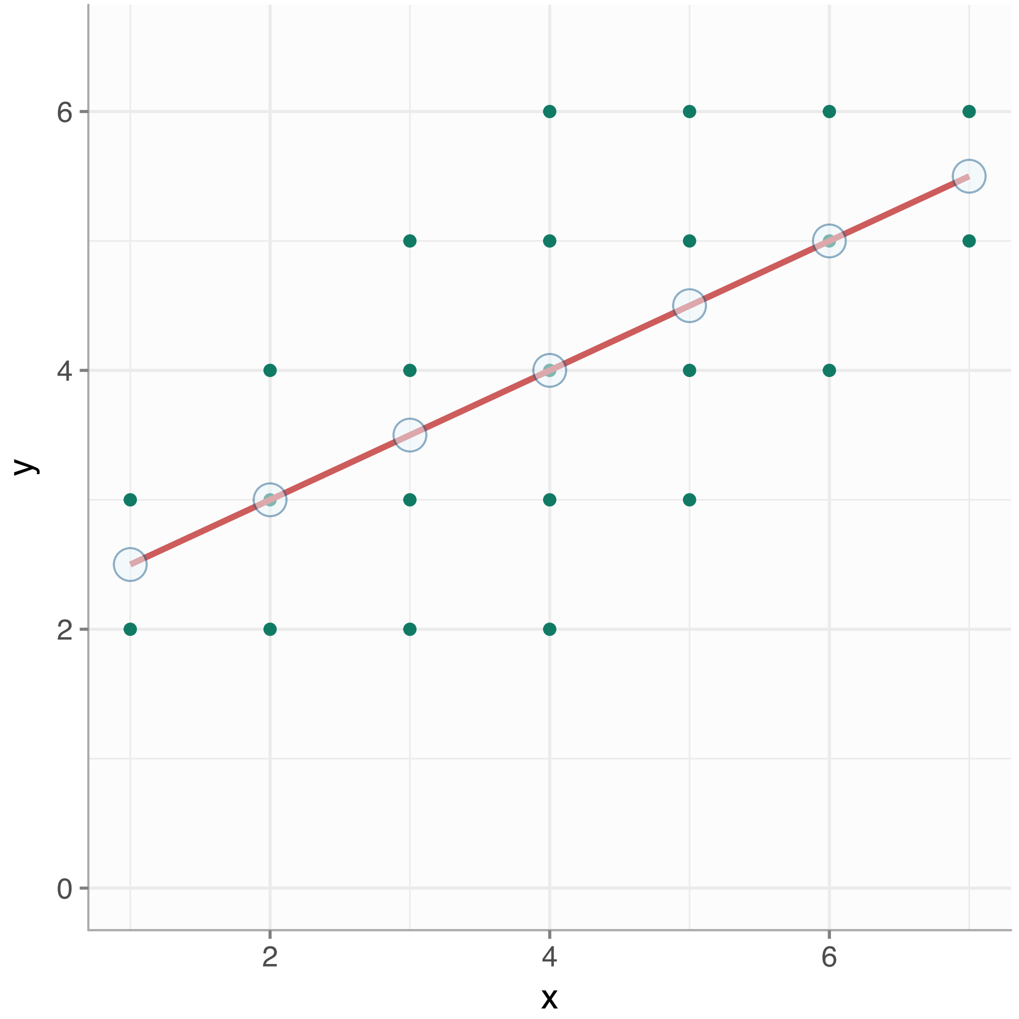


LINEAR MODEL IN R `lm`

- simple linear regression model available in r runction `lm`
- linear model fits a relationship between covariates and the conditional mean of the response or dependent variable
- has strict assumptions regarding independence of error terms which have implicaitons for using with spatial / environmental data (and temporally correlated data)

LINEAR REGRESSION IN R

- Recalling `lm` in r
- Each point represents a single observation
- The red line is the **line of best fit**
  - all predicted values from this model will fall on the line of best fit
- The line goes through each *conditional mean*
  - It goes through the mean at each value of x
    - E.g. When x = 1, mean of y = 2.5 (the conditional mean of y at x = 1 is 2.5)



GENERALIZED LINEAR MODELS

- Flexible generalization of ordinary linear regression.
- Allows for outcomes that have other than a normal distribution.
- R implementation considers all models and link functions implemented in the R function glm

Linear	Normally distributed outcome
Logistic	Binary outcome
Multi-nomial	Multi-class outcome
Poisson	Count outcome

glm IN R

```
## an example with offsets from Venables & Ripley (2002,
p.189)
utils::data(anorexia, package = "MASS")
anorex.1 <- glm(Postwt ~ Prewt + Treat + offset(Prewt),
family = gaussian, data = anorexia)
summary(anorex.1)
```

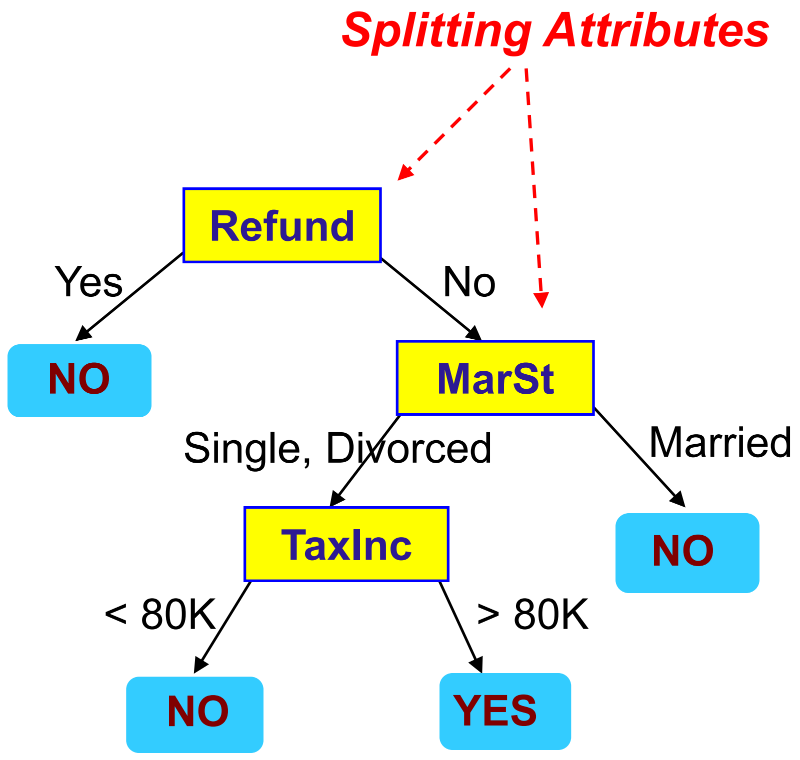
```
## Dobson (1990) Page 93: Randomized Controlled Trial :
counts <- c(18,17,15,20,10,20,25,13,12)
outcome <- gl(3,1,9)
treatment <- gl(3,3)
data.frame(treatment, outcome, counts)
# showing data
glm.D93 <- glm(counts ~ outcome + treatment, family =
poisson())
```

```
> summary(anorex.1)

Call:
glm(formula = Postwt ~ Prewt + Treat + offset(Prewt),
family = gaussian,
    data = anorexia)

Deviance Residuals:
     Min         1Q     Median         3Q        Max
-14.1083   -4.2773   -0.5484     5.4838    15.2922

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  49.7711    13.3910   3.717 0.000410 ***
Prewt        -0.5655     0.1612  -3.509 0.000803 ***
TreatCont    -4.0971     1.8935  -2.164 0.033999 *
TreatFT       4.5631     2.1333   2.139 0.036035 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.'
0.1 ' ' 1

(Dispersion parameter for gaussian family taken to be
48.69504)

    Null deviance: 4525.4  on 71  degrees of freedom
Residual deviance: 3311.3  on 68  degrees of freedom
AIC: 489.97

Number of Fisher Scoring iterations: 2
```

EXAMPLE OF A DECISION TREE

	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

Training Data

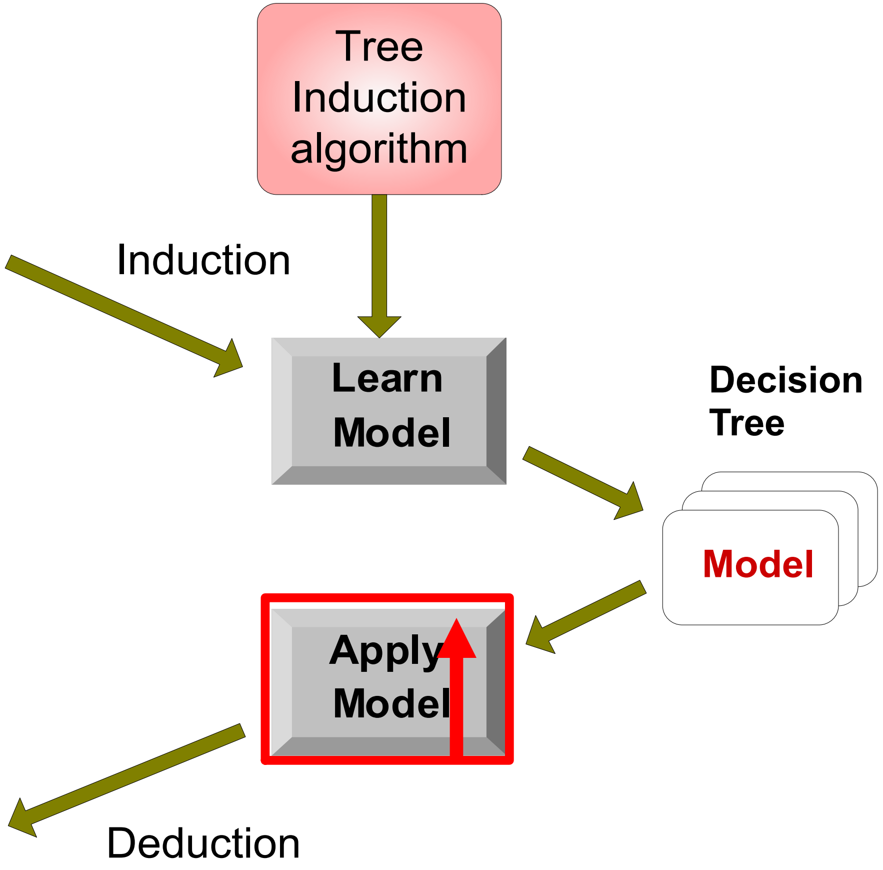


Model: Decision Tree

DECISION TREE CLASSIFICATION TASK

Tid	Attrib1	Attrib2	Attrib3	Class
1	Yes	Large	125K	No
2	No	Medium	100K	No
3	No	Small	70K	No
4	Yes	Medium	120K	No
5	No	Large	95K	Yes
6	No	Medium	60K	No
7	Yes	Large	220K	No
8	No	Small	85K	Yes
9	No	Medium	75K	No
10	No	Small	90K	Yes

Training Set

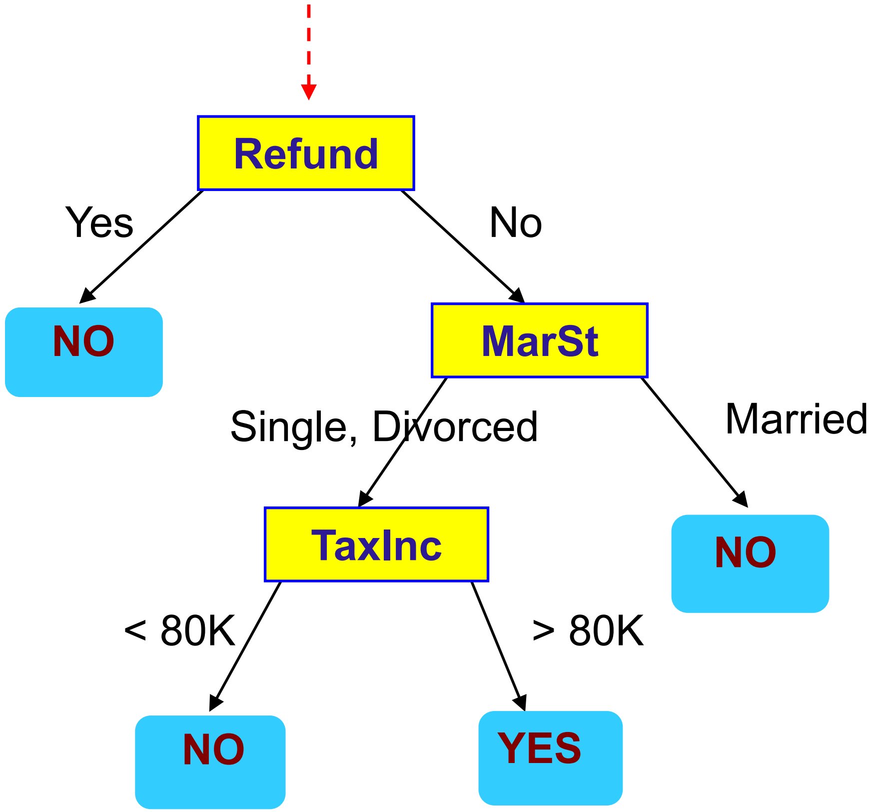


Tid	Attrib1	Attrib2	Attrib3	Class
11	No	Small	55K	?
12	Yes	Medium	80K	?
13	Yes	Large	110K	?
14	No	Small	95K	?
15	No	Large	67K	?

Test Set

APPLY MODEL TO TEST DATA

Start from the root of tree.



Test Data

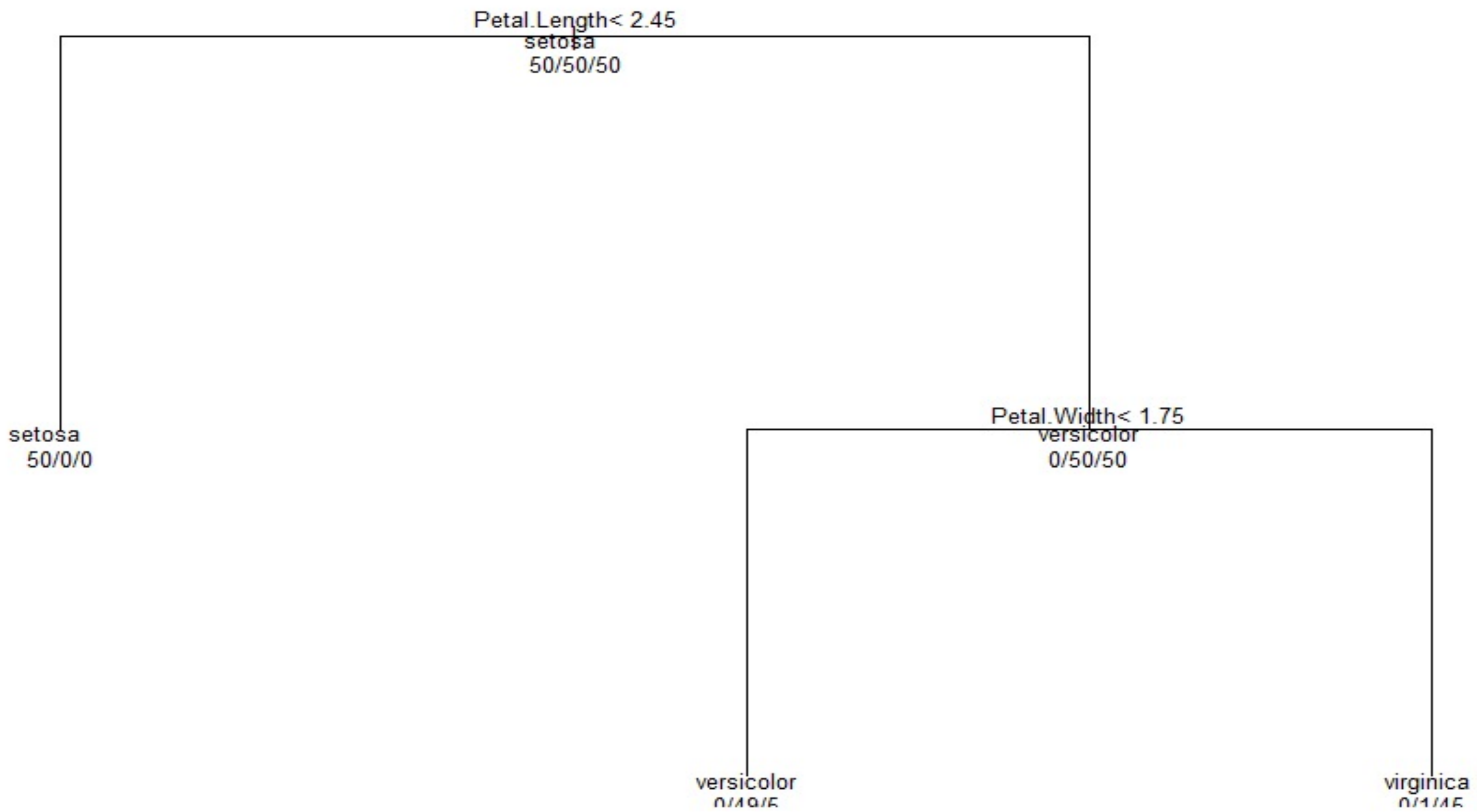
Refund	Marital Status	Taxable Income	Cheat
No	Married	80K	?

DECISION TREES

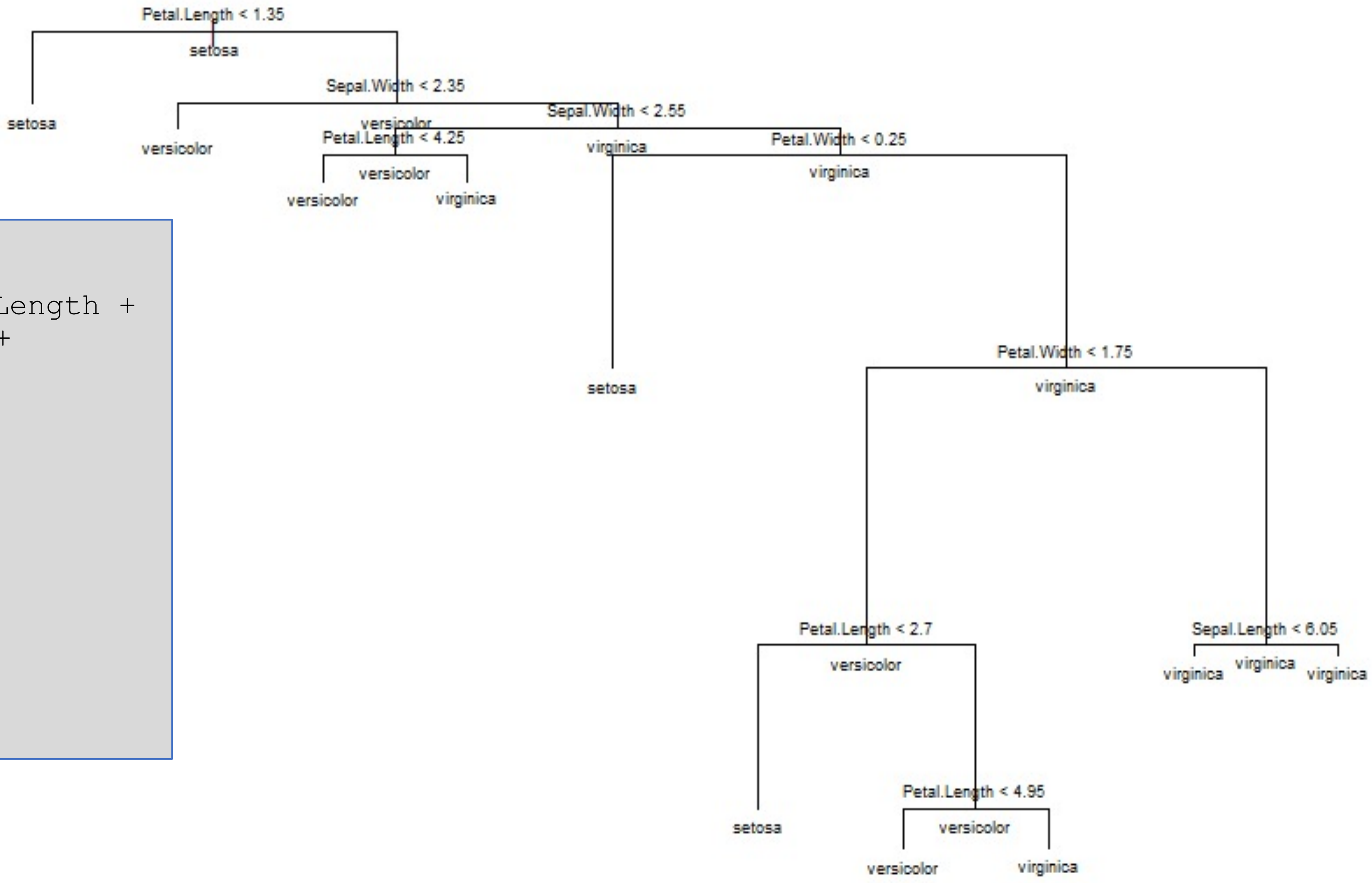
- Used for classifying data by partitioning attribute space
- Tries to find decision boundaries for specified optimality criteria
- Leaf nodes contain class labels, representing classification decisions
- Keeps splitting nodes based on split criterion, such as
  - GINI index, information gain or entropy
- Pruning necessary to avoid overfitting

DECISION TREES IN R

```
mydata<-data.frame(iris)

attach(mydata)



library(rpart)

model<-rpart(Species ~ Sepal.Length +
  Sepal.Width + Petal.Length +
  Petal.Width,

  data=mydata,

  method="class")

plot(model)

text(model,use.n=TRUE,all=TRUE,cex=0.8)
```



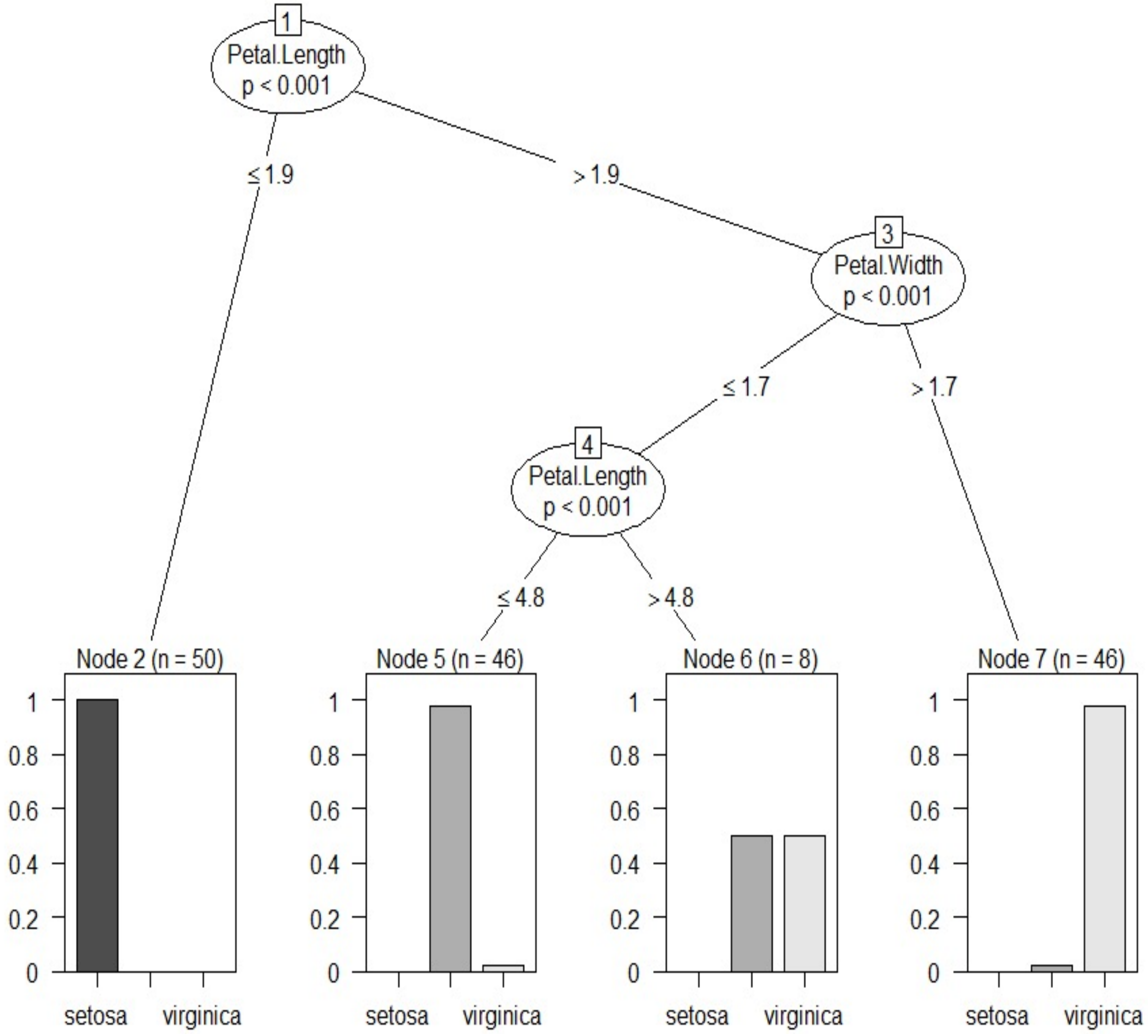
DECISION TREES IN R




```
library(tree)

model1<-tree(Species ~ Sepal.Length +
  Sepal.Width + Petal.Length +
  Petal.Width,

  data=mydata,

  method="class",

  split="gini")

plot(model1)

text(model1,all=TRUE,cex=0.6)
```

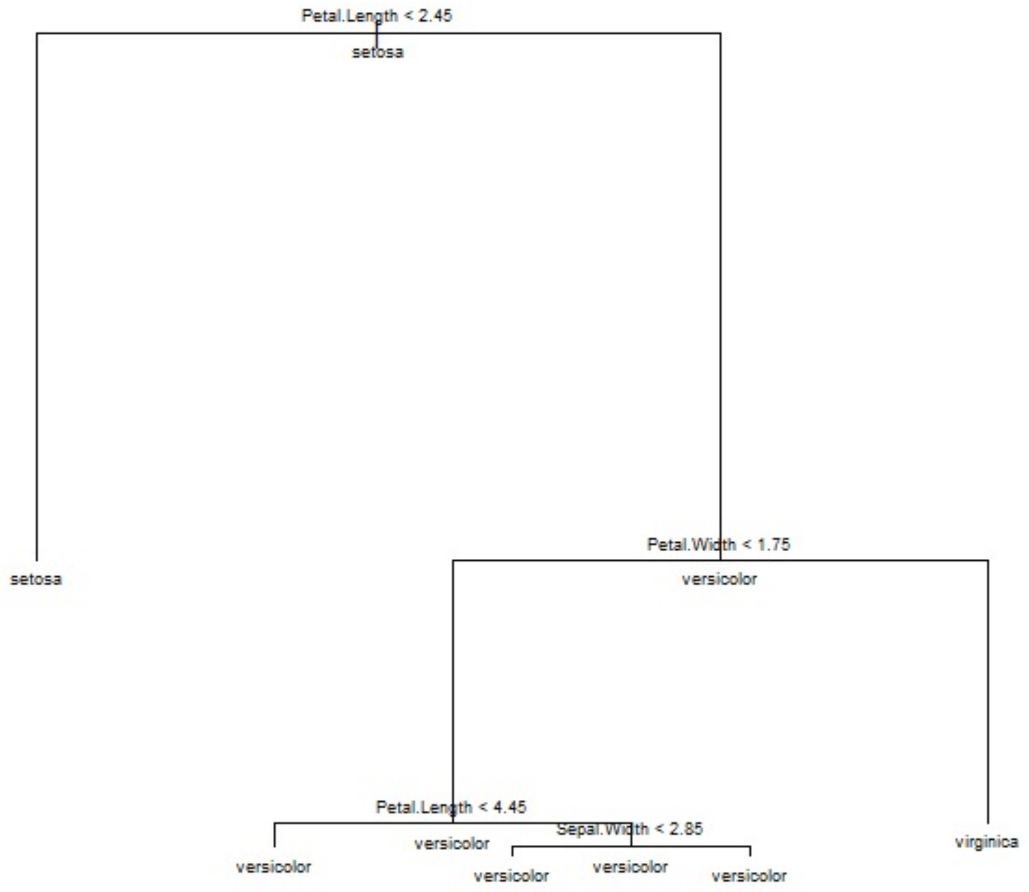
DECISION TREES IN R

```
library(party)

model2<-ctree(Species ~
  Sepal.Length +
  Sepal.Width +
  Petal.Length +
  Petal.Width,

  data=mydata)

plot(model2)
```



CONTROLLING NUMBER OF NODES

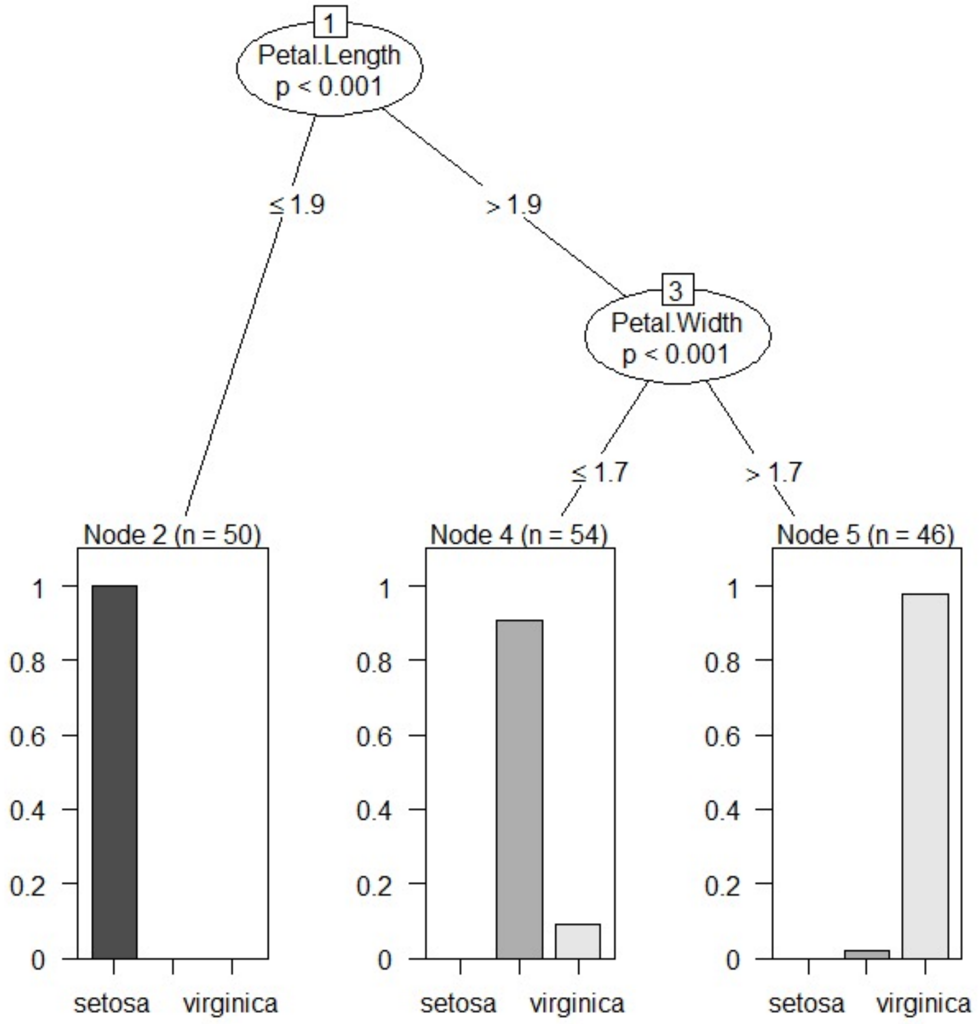
```
library(tree)
mydata<-data.frame(iris)
attach(mydata)
model1<-tree(Species ~ Sepal.Length +
Sepal.Width + Petal.Length +
Petal.Width,
     data=mydata,
     method="class",
     control =    tree.control(nobs =
     150, mincut = 10))
plot(model1)
text(model1,all=TRUE,cex=0.6)
predict(model1,iris)
```



Note how the number of nodes is reduced by increasing the minimum number of observations in a child node!

CONTROLLING NUMBER OF NODES

```
model2<-ctree(Species ~
Sepal.Length + Sepal.Width +
Petal.Length + Petal.Width,
data = mydata, controls =
ctree_control(maxdepth=2))

plot(model2)
```

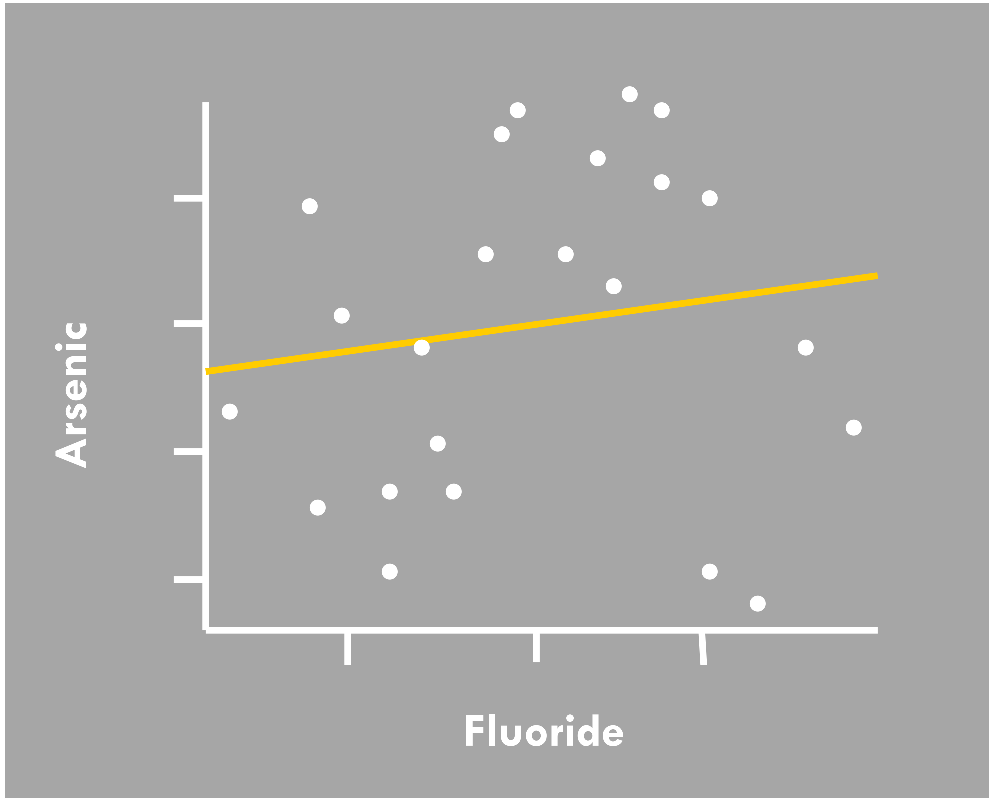


Note that setting the maximum depth to 2 has reduced the number of nodes!

SPATIAL VARIATION IN MODEL FIT

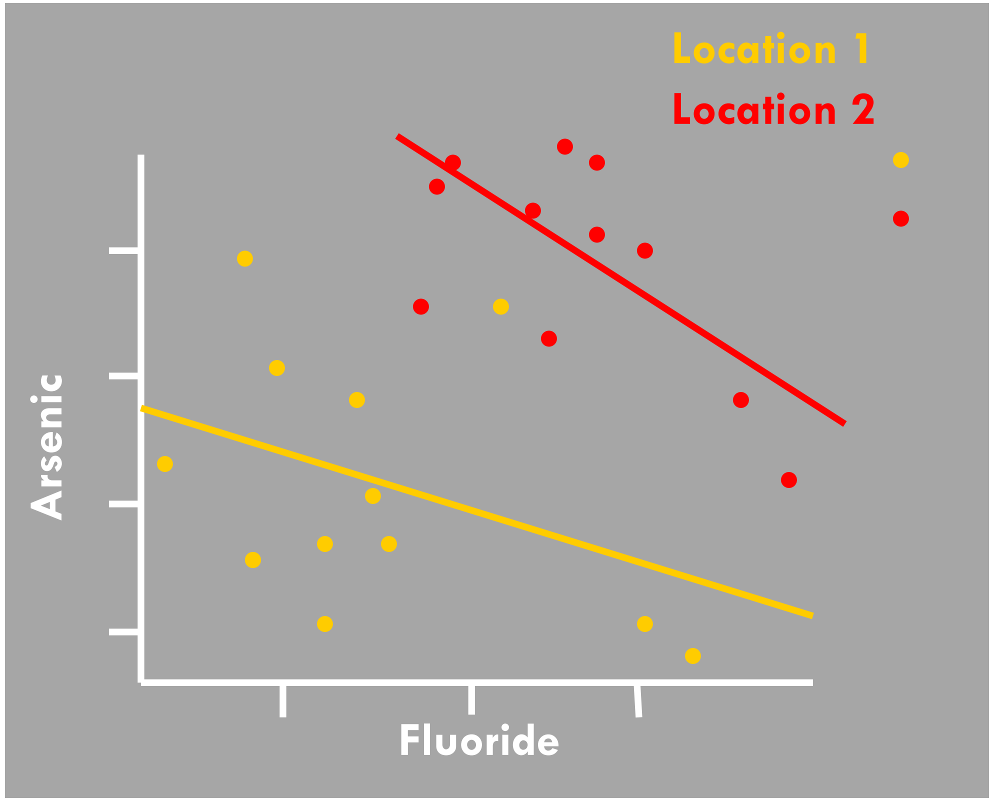
- When fitting a 'global' model (i.e., a single model) for a process observed over different spatial locations, we must assume that the relationship(s) are constant over space
  - this is often an incorrect assumption

- Here we have a line of best fit through two variables of water quality parameters, `fluoride` and `arsenic`



SPATIAL VARIATION IN MODEL FIT

- Split up global data into regions and fit separate models for each region
- The challenge is how to define homogeneous regions
  - neighbourhoods
  - ecological zones
  - spatially-constrained cluster analysis
- The extreme is to estimate a new model at each location with a subset of neighbouring observations as the dataset
  - this is called 'geographically-weighted regression'



KEY CONCEPTS TO CONSIDER WHEN WORKING WITH ENVIRONMENTAL MODELS

- **Data input**: quality, sources of bias, errors, consistency, training vs. testing
- **Model characteristics**: number of parameters, complexity, assumptions, representations
- **Model evaluation**: model fit, overfitting / generalizability
- **Model use**: how will models results be used, how can they be misused, etc.

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