# HUDK 4051: LEARNING ANALYTICS: PROCESS & THEORY

2/12/19 12:04 PM

# Today

- Prediction background
- The five tribes
- Caret (Weka)
- Activity

# Prediction

- There are times when we want to automate a process in education

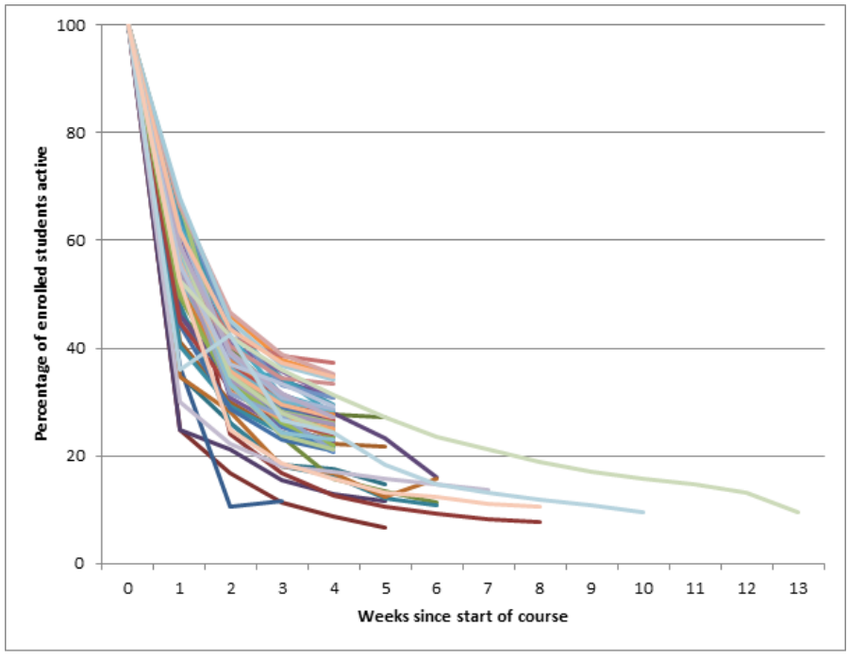
- Action oriented

- Sometimes this is a supervised learning problem

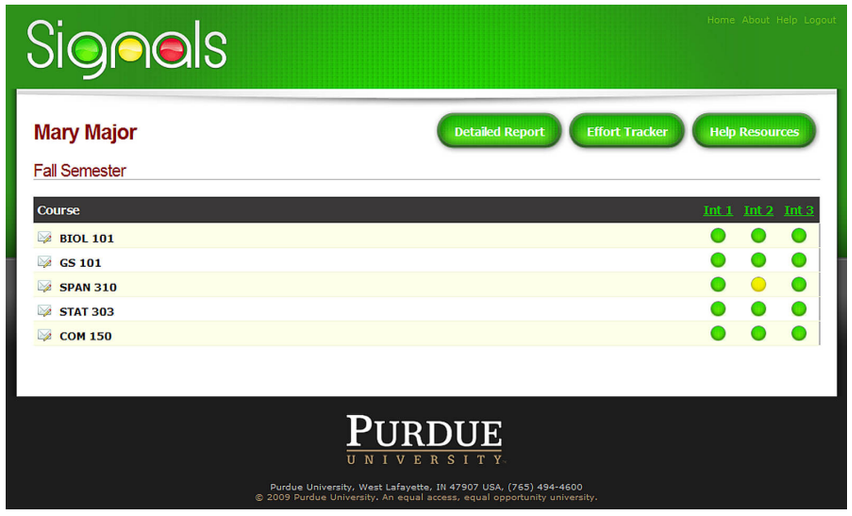
- (Sometimes it is not)

# Prediction

- Common supervised learning problems:
- Drop out, attendance, payment
- Correct/incorrect




K Jordan, Open University, 2013



# Prediction

- The aim of prediction is to predict the future and intervene

**Predictive Modelling in Teaching and Learning**

Christopher Brooks & Craig Thompson

- Key metric is the accuracy of the prediction and how generalizable it is (Purdue)

- JEDM

**PREDICTING STUDENTS' PERFORMANCE USING ID3 AND C4.5 CLASSIFICATION ALGORITHMS**

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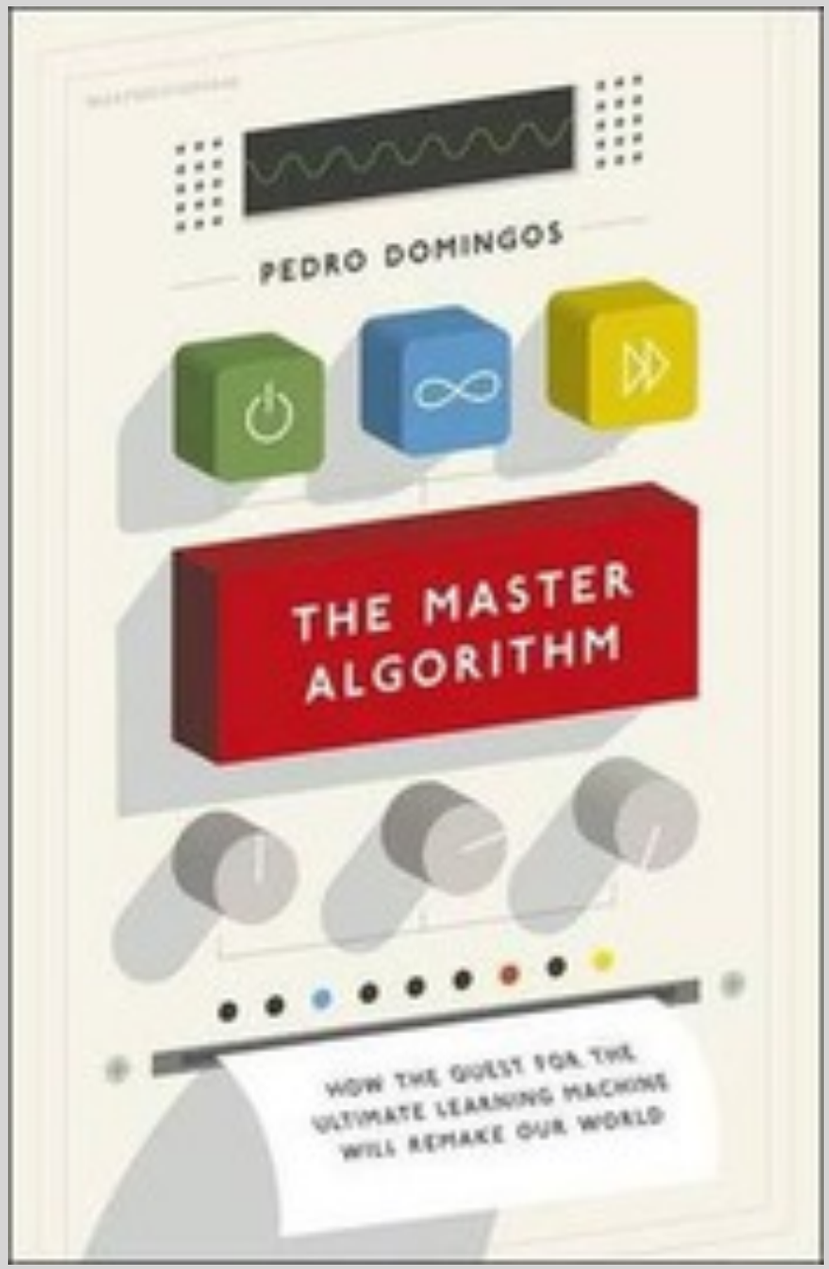
# Five Tribes

- Symbolists
- Connectionists
- Evolutionaries
- Bayesians
- Analogizers



# Symbolists

# Symbolists

- Inverse deduction (deduction)

*Socrates is human*

*……..?*

*Therefore Socrates is mortal*

- Decision trees

# Symbolists

- Manipulating symbols with an algorithm and choose the ones that work
- It is about learning “rules” that can be applied

# Symbolists

Positives:

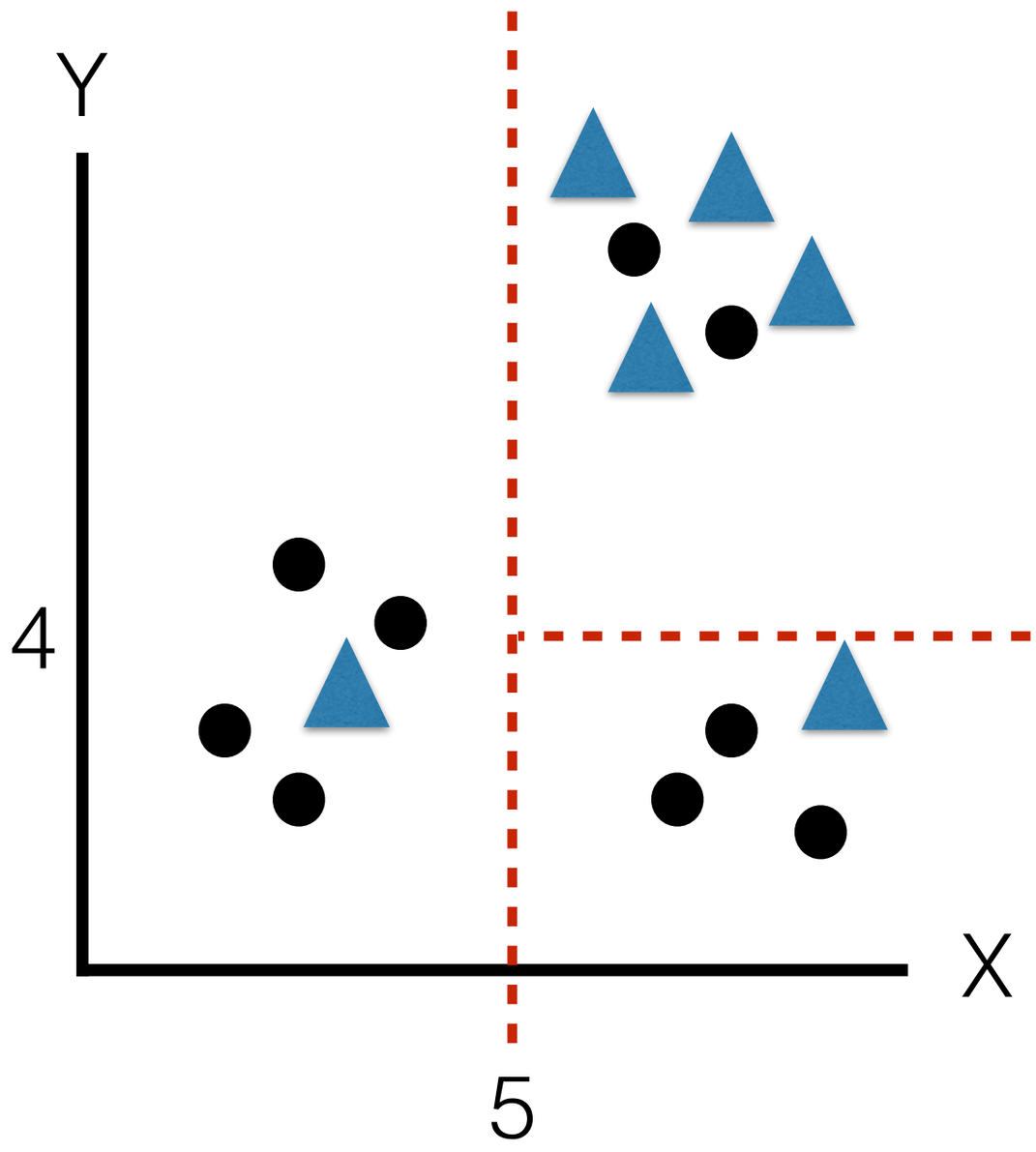
- Easy to interpret
- Fast
- Makes “sense”

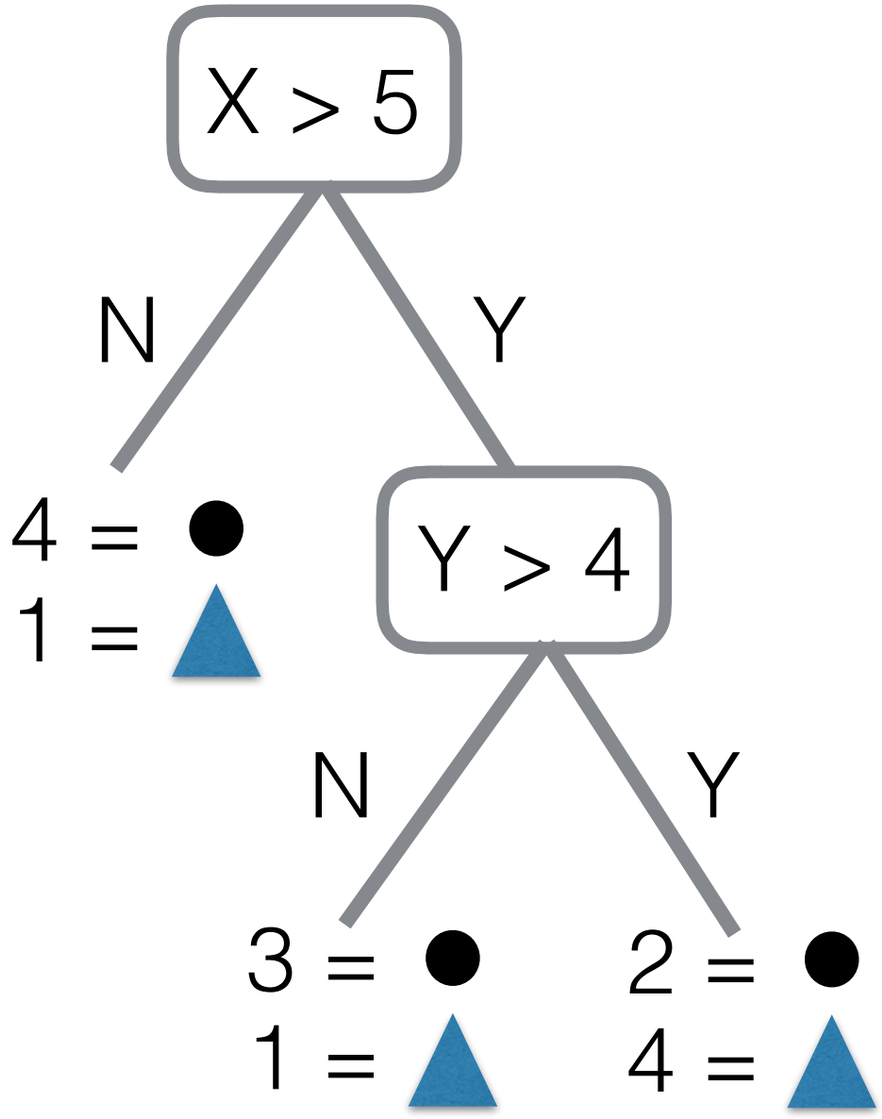
Drawbacks:

- The number of possible inductions is practically infinite - need to be very specific about the problem space
- If the premise or conclusion are wrong it is over
- Overfitting
- Concepts are rarely cleanly defined: female/male, spam/non-spam - can’t incorporate grey areas

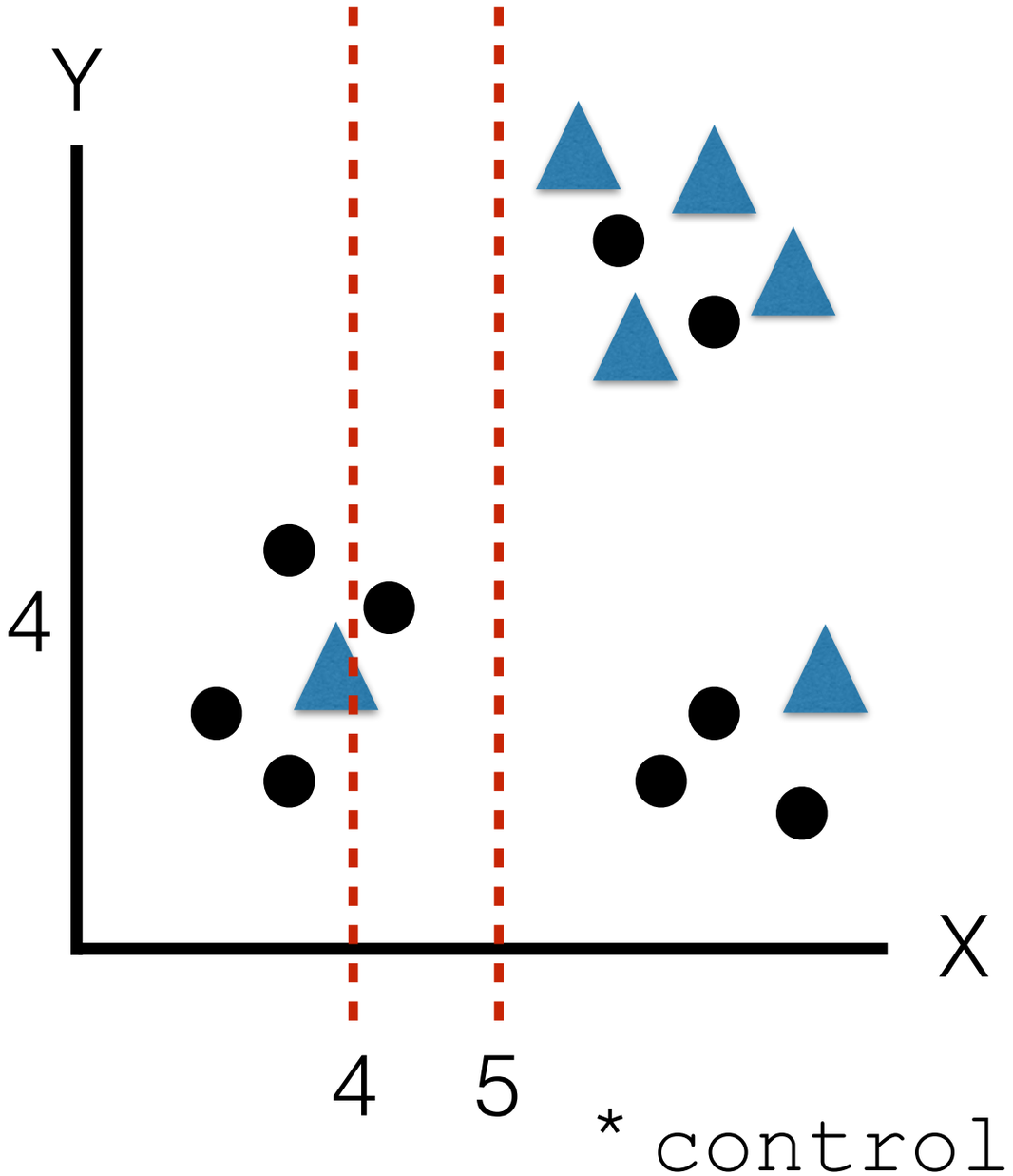
# Binary Classification Tree

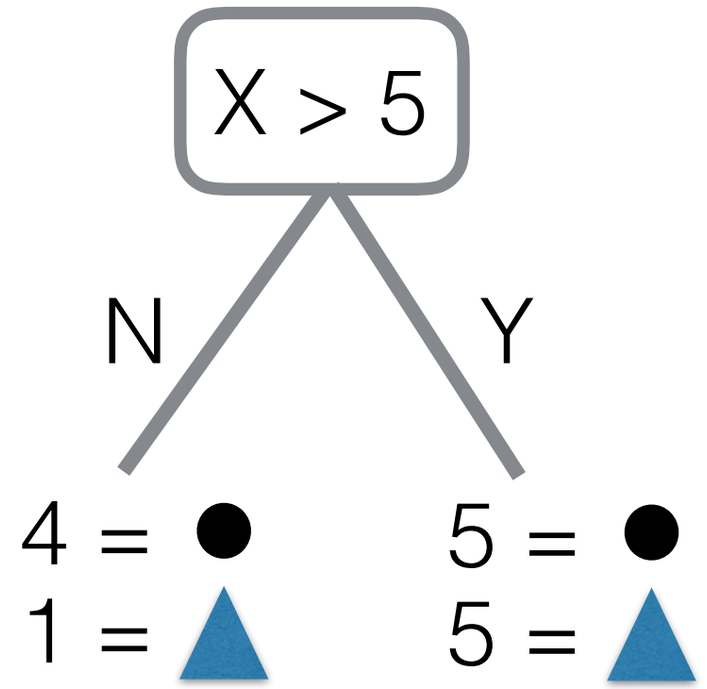
* Minimize the error



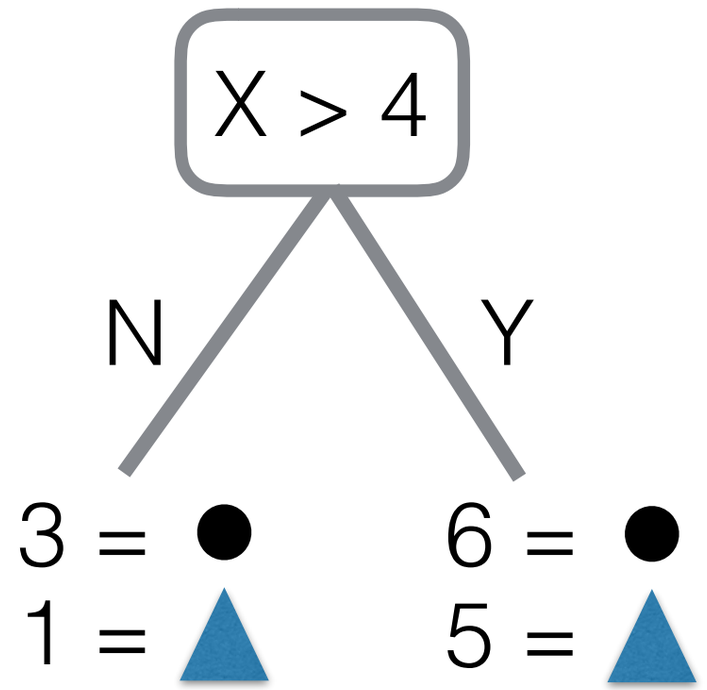



# RPART




$ENT_5 = -0.8*\log_2(0.8) + -0.5*\log_2(0.5) = 0.75$




$ENT_4 = -0.75*\log_2(0.75) + -0.55*\log_2(0.55) = 0.76$

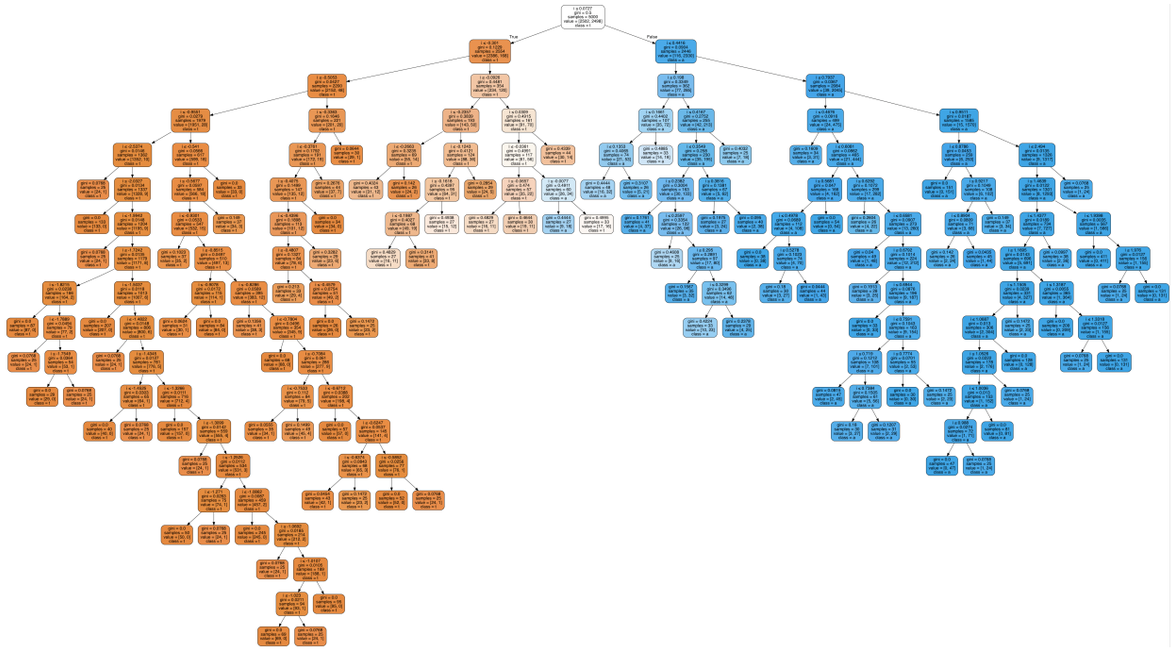
# RPART

- Tree chooses the optimal fit at each leaf - NOT the overall best fit for the data

- Therefore, there is a danger of overfitting the tree

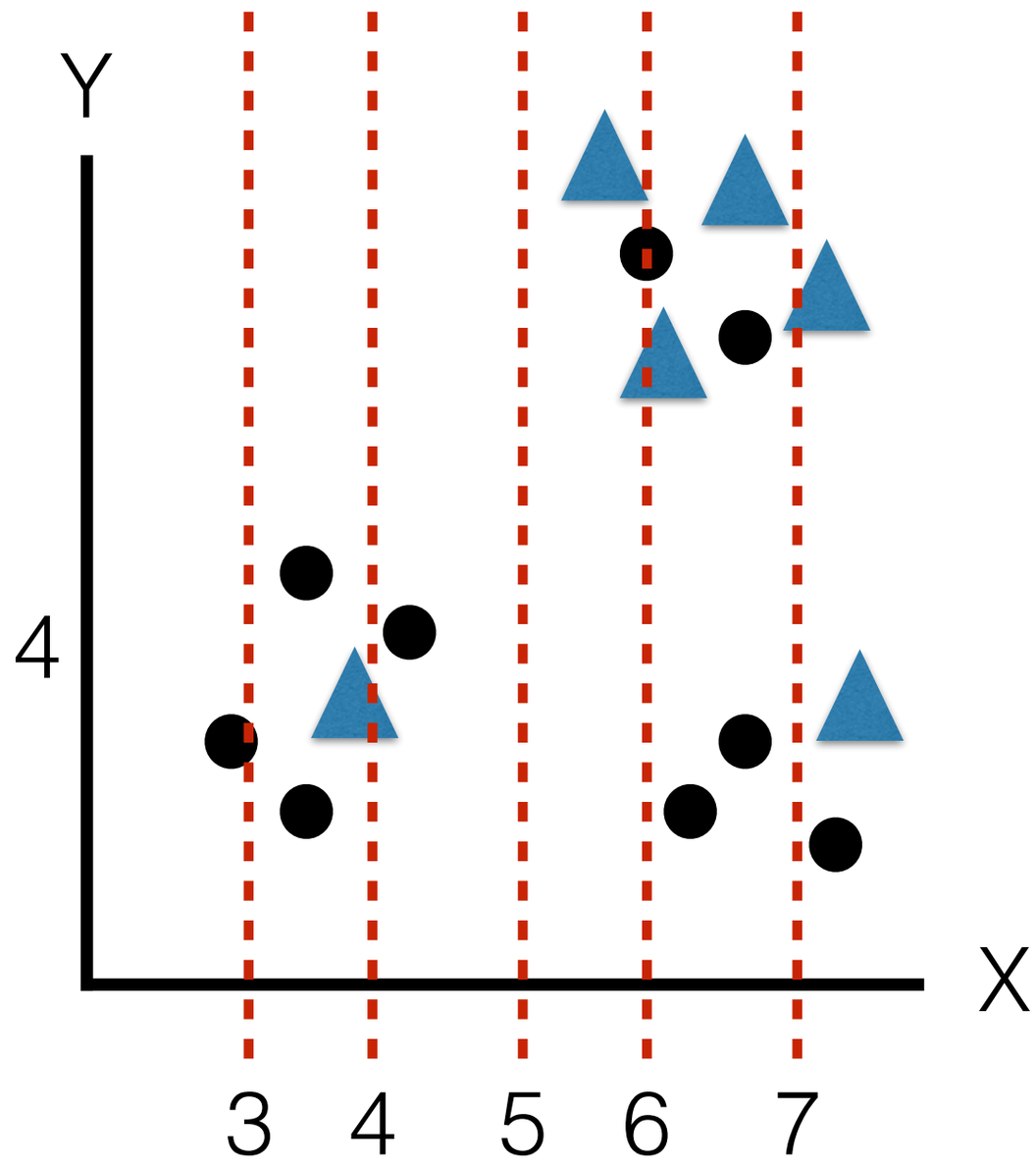
- Tree is too specific to training data to be able to predict new data

- Therefore: stop the tree at a certain number of nodes OR prune



# PARTY

- “part(y)itioning” 😎
- Conditional Inference Tree
- Look at correlation between X and shape and Y and shape
- Statistically test $H_0$: there is no relationship
- Choose the variable with the highest correlation
- Split on that variable
- Stop when $H_0$ cannot be rejected



# Bayesians

# Bayesians

$$P(\theta \mid \mathbf{D}) = P(\theta)\frac{P(\mathbf{D} \mid \theta)}{P(\mathbf{D})}$$

- Probabilistic (just grey areas)
- Conditional probabilities shrink the problem space
- Often we know the probabilities of the effects given causes, what we want is the probabilities of the causes given the effects (EG - medical diagnoses)
- Conditional independence assumption

# Bayesians

Positives

- Computationally simple
- Empirically accurate
- Can handle ambiguity

Negatives

- Conditional independence assumption
- Susceptible to exponential blowup/Bayesian networks become intractable as variables ↑
- There is no true hypothesis = have to calculate everything
- Can’t generate new hypotheses on the fly

# Analogizers

# Analogizers

- Representation = your data
- Find the thing closest to the thing you are looking for: nearest neighbor
- EG - John Snow Cholera Map (1854)
- Collaborative Filters
- k-nearest neighbors, Support Vector Machines, stepwise regression

# Analogizers

Positives

- Fast and at one time accurate as Neural Nets for complex feature sets OTB
- Can do transfer learning
- High dimensional space works well

Negatives

- Can’t handle class overlap well
- Run time is dependent on data size
- Probabilities are generated by cross validation

# Connectionists

# Connectionists

- Hebb's Rule: neuron's that fire together, wire together
- One concept = many neurons
- Sigmoid curve
- Backpropagation

# Connectionists

Positives

- Can learn very complex data sets

Negatives

- Hyperspace is ~infinite, you will likely find a local minima
- Weights are not interpretable
- Can’t do adaptive reasoning (rule chaining)

# Evolutionaries

# Evolutionaries

- John Holland (first PhD in CS)
- Objective, program, fitness function, sex
- Selective breeding + immortality
- EG - Spam filter that looks at every word in an email
- Mostly work at the sub-routine level

# Evolutionaries

Positives

- Combines neural nets with rule based system
- Maybe it can create any kind of machine?

Negatives

- No empirical reason to have the sex step
  - And maybe a reason not to (mixability)
- Is it the evolutionary nature or just brute force that leads to success?
- Needs a lot of computing power

# caret

- Standard syntax for comparing many models
- Generate training and testing data sets
- Run several model types
- Run resampling algorithms and alter parameters to generate the best model
- Compare using the same diagnostic metrics
- https://topepo.github.io/caret/

# caret

## Generate Training/Test Data Sets

```
trainData <- createDataPartition(
  y = data$thing, ## the outcome data are needed
  p = .75, ## The percentage of data in the
training set
  list = FALSE)

#Generates a list of index numbers for the sample

training <- DATA[ trainData,]
testing  <-DATA[-trainData,]
```

# caret

## K-Fold Cross Validation

```
ctrl <- trainControl(method = "cv", repeats = 3)
```

# caret

## Train Model

```
fit1 <- train(
  thing ~ .,
  data = training,
  method = “model", ## Center and scale the
predictors for the training set and all future
samples.
  preProc = c("center", “scale")
  trControl = ctrl #add cross validation specs
  metric = "ROC"
)
```

# caret

Test Model

```
pred1 <- predict(fit1, newdata = testing)

confusionMatrix(data = pred1, DATA$thing)
```

la-process-and-theory/prediction-activity