FIT3152 Data analytics. Tutorial 07: Decision Trees

Objectives:
- Understand entropy and information gain in relation to decision tree algorithms
- Create decision trees using R
- Using decision trees for profiling
- Using decision trees for classifying unseen instances
- Evaluation of decision tree models – confusion matrices

References: Introduction to Data Mining, Tan, Steinbach and Kumar (available from Hargrave-Andrew library); 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)

1 Work through the examples in the lecture slides. For the examples using R you will need to download and install the 'tree' package using the following code.

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

2 Calculation of entropy and information gain

Table 1 below includes data for 10 different types of aliens. The data is to be used to determine which aliens are friendly and which are not.

a. What is the entropy of the IsFriendly class?
b. Which decision attribute should you choose as the root of the decision tree – you can work this out without doing any calculations. Explain why you chose that attribute.
c. What is the information gain of the attribute you chose in b.?
d. Using the attribute you chose in b. as the root node, and using examples 1 to 10, build a decision tree for classifying aliens as friendly or not.
e. Using your decision tree, what are the predictions for aliens 11, 12, 13 in table 2?

Table 1: Training Set

ID	colour	size	teeth	IsFriendly
1	red	medium	yes	no
2	blue	big	no	yes
3	green	medium	no	no
4	green	small	yes	no
5	blue	big	yes	yes
6	blue	small	yes	yes
7	red	small	no	yes
8	red	medium	no	yes
9	blue	medium	yes	yes
10	green	small	no	no

Table 2: Test Set

ID	colour	size	teeth	IsFriendly
11	red	big	yes	?
12	green	big	yes	?
13	blue	small	no	?

```
# Calculations for decision tree using lecture template
```

For Aliens Data			Log Base	2	0.3010		
Initial State	**Yes**	**No**	**P(Yes)**	**Log2(Yes)**	**P(No)**	**Log2(No)**	**Entropy**
Entropy(S)	6	4	0.6000	-0.7370	0.4000	-1.3219	0.9710
colour	**Yes**	**No**	**P(Yes)**	**Log2(Yes)**	**P(No)**	**Log2(No)**	**Entropy**
red	2	1	0.6667	-0.5850	0.3333	-1.5850	0.9183
blue	4	0	1.0000	0.0000	0.0000	0.0000	0.0000
green	0	3	0.0000	0.0000	1.0000	0.0000	0.0000
EEntropy(colour)							0.2755
Gain(S, colour)							**0.6955**
size	**Yes**	**No**	**P(Yes)**	**Log2(Yes)**	**P(No)**	**Log2(No)**	**Entropy**
medium	2	2	0.5000	-1.0000	0.5000	-1.0000	1.0000
big	2	0	1.0000	0.0000	0.0000	0.0000	0.0000
small	2	2	0.5000	-1.0000	0.5000	-1.0000	1.0000
EEntropy(size)							0.8000
Gain(S, size)							**0.1710**
teeth	**Yes**	**No**	**P(Yes)**	**Log2(Yes)**	**P(No)**	**Log2(No)**	**Entropy**
yes	3	2	0.6000	-0.7370	0.4000	-1.3219	0.9710
no	2	3	0.4000	-1.3219	0.6000	-0.7370	0.9710
Eentropy(teeth)							0.9710
Gain(S, teeth)							**0.0000**
After splitting on colour: blue and green branches terminate as leaf nodes. Evaluate red branch:							
red, size	**Yes**	**No**	**P(Yes)**	**Log2(Yes)**	**P(No)**	**Log2(No)**	**Entropy**
medium	1	1	0.5000	-1.0000	0.5000	-1.0000	1.0000
small	1	0	1.0000	0.0000	0.0000	0.0000	0.0000
EEntropy(size)							0.6667
Gain(S, size)							**0.2516**
red, teeth	**Yes**	**No**	**P(Yes)**	**Log2(Yes)**	**P(No)**	**Log2(No)**	**Entropy**
yes	0	1	0.0000	0.0000	1.0000	0.0000	0.0000
no	2	0	1.0000	0.0000	0.0000	0.0000	0.0000
Eentropy(teeth)							0.0000
Gain(S, teeth)							**0.9183**
So split on teeth and tree finished.							

3 The built-in data set mtcars describes the fuel consumption and 10 other variables for 32 cars produced during 1973 – 1974. Fuel consumption is determined as miles per gallon (mpg). Create a decision tree to classify cars as either high consumption (greater than the median), or low consumption. To do this, follow the steps below.

a. Convert the mpg variables in to a class using the script below and create new data set: carsclass.

```
data(mtcars)
attach(mtcars)
summary(mpg)
cons = ifelse(mpg >= 19.20, "yes", "no")
cons = as.factor(cons)
carsclass = cbind(cons, mtcars)
head(carsclass)
```

b. Partition your new data set into 70% training and 30% test.

```
# partition on to training and test data
set.seed(9999)
train.row = sample(1:nrow(carsclass), 0.7*nrow(carsclass))
c.train = carsclass[train.row,]
c.test = carsclass[-train.row,]
```

c. Fit the 'tree' model to your data. Make sure you don't include mpg as an attribute. You may need to first create a synthetically larger training data set using resampling with replacement as was done for the playtennis example.

```
# get larger training data set
set.seed(9999)
cl.train = c.train[sample(nrow(c.train), 100, replace = TRUE),]

# fit tree model
library(tree)
c.fit=tree(cons~.-mpg, data=cl.train)
```

d. Examine your decision tree using summary and plot functions. What are the important attributes for determining fuel economy?

```
summary(c.fit)
plot(c.fit)
text(c.fit, pretty = 0)
```

e. Using the test data set, calculate the accuracy of your model. How well does it predict fuel economy?

```
# test accuracy
c.predict = predict(c.fit, c.test, type = "class")
table(actual = c.test$cons, predicted = c.predict)
```

Outputs

```
> summary(c.fit)

Classification tree:
tree(formula = cons ~ . - mpg, data = cl.train)
Variables actually used in tree construction:
```

```
[1] "disp" "cyl"  "qsec"
Number of terminal nodes:  4
Residual mean deviance:  0.06773 = 6.502 / 96
Misclassification error rate: 0.01 = 1 / 100

# This shows that weight and displacement are the important
attributes for building the tree. Misclassification rate on the
training data is 2/100 or 2%

> table(actual = c.test$cons, predicted = c.predict)
      predicted
actual no yes
   no    7   0
   yes   1   2
> (7 + 2)/10
[1] 0.9

# Accuracy on the test data is 90%
```

4 The Zoo data set (zoo.data.csv) contains data relating to seven classes of animals.

Using all the data, construct a decision tree to predict class "type" based on the other attributes. Note that you will need to specify that "type" is a factor. Which attributes are most influential in determining the class of an animal. What classes have less than 100% accuracy?

```
# set working directory to desktop
setwd("~/Desktop")
# clean up the environment before starting
rm(list = ls())

# read in data
zoo=read.csv("zoo.data.csv", stringsAsFactors = TRUE)
zoo[,2:18]=lapply(zoo[,2:18] , factor

# fit tree model
library(tree)
z.fit=tree(type~.-animal_name, data = zoo)
summary(z.fit)
plot(z.fit)
text(z.fit, pretty=0)
```

```
Outputs

> summary(z.fit)

Classification tree:
tree(formula = type ~ . - animal_name, data = zoo)
Variables actually used in tree construction:
[1] "milk"     "feathers" "backbone" "legs"     "fins"
Number of terminal nodes:  6
Residual mean deviance:  0.2355 = 22.37 / 95
Misclassification error rate: 0.05941 = 6 / 10

# The accuracy on whole data set (training) is 1-(6/101)=0.94 or 94%
You can see the important attributes in the summary.
```

Now split your data into a training set 70% and test set 30% and refit the model. What is the overall accuracy of the model when measured on the test set?

```
zt.fit = tree(formula = type ~ . -animal_name, data = z.train)
summary(zt.fit)

z.predict = predict(zt.fit, z.test, type="class")
table(actual = z.test$type, predicted = z.predict)

Outputs

summary(zt.fit)

Classification tree:
tree(formula = type ~ . - animal_name, data = z.train)
Variables actually used in tree construction:
[1] "milk"     "backbone" "legs"     "feathers" "fins"
Number of terminal nodes:  6
Residual mean deviance:  0.2135 = 13.67 / 64
Misclassification error rate: 0.04286 = 3 / 70

# The accuracy on test data is 1-(3/70)=0.95 or 95%

Important attributes are mile, tail, aquatic, feathers

> table(actual = z.test$type, predicted = z.predict)
      predicted
actual  1  2  3  4  5  6  7
     1 12  0  0  0  0  0  0
     2  0  8  0  0  0  0  0
     3  0  0  1  0  0  0  0
     4  0  0  0  5  0  0  0
     5  0  0  2  0  0  0  0
     6  0  0  0  0  0  1  0
     7  0  0  0  0  0  1  1

>(12+8+1+5+1+1)/31
[1] 0.9032258
```

5 The Mushroom data set (mushroom.data.csv) contains 22 pieces of information about 8000+ species of mushrooms. This data set was obtained from the UCI Machine Learning Repository. Further information about the data can be obtained from: https://archive.ics.uci.edu/ml/datasets/Mushroom

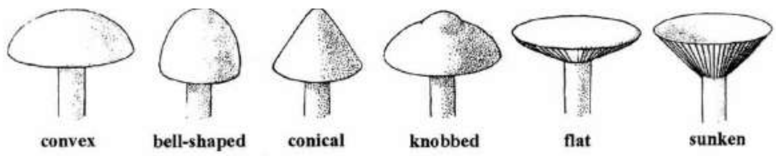
Using the data, construct a decision tree to predict whether an unclassified mushroom is of "class" poisonous or edible based on the other attributes:

1. cap-shape: bell=b,conical=c,convex=x,flat=f, knobbed=k,sunken=s
2. cap-surface: fibrous=f,grooves=g,scaly=y,smooth=s
3. cap-color: brown=n,buff=b,cinnamon=c,gray=g,green=r, pink=p, purple=u, red=e, white=w, yellow=y
4. bruises?: bruises=t,no=f
5. odor: almond=a,anise=l,creosote=c,fishy=y,foul=f, musty=m,none=n,pungent=p,spicy=s

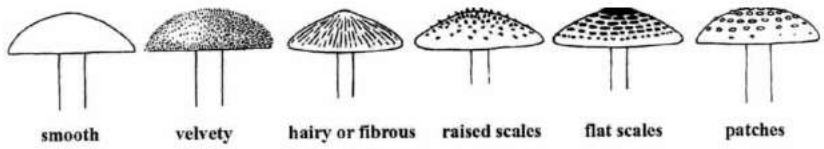
…

You should create a training and test data set and report the accuracy of your model. Which attributes are most important in distinguishing between poisonous and edible mushrooms?

Mushroom cap shapes



Mushroom cap surfaces




```
# read in data
m = read.csv("mushroom.data.csv", stringsAsFactors = TRUE)

# partition on to training and test data
set.seed(9999)
train.row = sample(1:nrow(m), 0.7*nrow(m))
m.train = m[train.row,]
m.test = m[-train.row,]

# fit tree model on training data
library(tree)
m.fit=tree(class~., data = m.train)
summary(m.fit)
plot(m.fit)
text(m.fit, pretty=0)

# test accuracy
m.predict = predict(m.fit, m.test, type = "class")
table(actual = m.test$class, predicted = m.predict)
```

```
Outputs

> summary(m.fit)

Classification tree:
tree(formula = class ~ ., data = m.train)
Variables actually used in tree construction:
[1]
"odor"                    "spore.print.color"      "stalk.color.below
.ring"
Number of terminal nodes:  4
Residual mean deviance:  0.02936 = 166.8 / 5682
Misclassification error rate: 0.002286 = 13 / 5686

> plot(m.fit)
> text(m.fit, pretty=0)

> #test accuracy
> m.predict = predict(m.fit, m.test, type = "class")

> table(actual = m.test$class, predicted = m.predict)
      predicted
actual    e    p
     e 1287    0
     p   11 1140
```

6 Using data from the Kaggle competition: Titanic: Machine Learning from Disaster (ref https://www.kaggle.com/c/titanic/data) develop a decision tree model to predict whether a passenger would have or have not survived. The data has been portioned into a training and a test set: (Kaggle.Titanic.train.csv, Kaggle.Titanic.test.csv) The main details of the attributes, from the Kaggle site, are:

```
VARIABLE DESCRIPTIONS:
survival        Survival
                (0 = No; 1 = Yes)
pclass          Passenger Class
                (1 = 1st; 2 = 2nd; 3 = 3rd)
name            Name
sex             Sex
age             Age
sibsp           Number of Siblings/Spouses Aboard
parch           Number of Parents/Children Aboard
ticket          Ticket Number
fare            Passenger Fare
cabin           Cabin
embarked        Port of Embarkation
                (C = Cherbourg; Q = Queenstown; S = Southampton)
```

How accurate is your model? Based on your model, what are the most important predictors for survival?

```
# clean up the environment before starting
rm(list = ls())

#read in data
t.train=read.csv("Kaggle.Titanic.train.csv")
t.test=read.csv("Kaggle.Titanic.test.csv")

t.train$PassengerId=NULL
t.train$Ticket=NULL
t.train$Name=NULL
t.test$PassengerId=NULL
t.test$Ticket=NULL
t.test$Name=NULL

#Make Survived a factor (otherwise model fits a regression tree)
t.train$Survived = as.factor(t.train$Survived)

#fit tree model on training data
library(tree)
t.fit=tree(Survived~.-Cabin, data=t.train)
summary(t.fit)
plot(t.fit)
text(t.fit, pretty=0)

#tpredict = predict(t.fit, t.test, type = "vector")
tpredict = predict(t.fit, t.test, type = "class")

> summary(t.fit)

Classification tree:
tree(formula = Survived ~ . - Cabin, data = t.train)
Variables actually used in tree construction:
[1] "Sex"    "Pclass" "Fare"   "Age"    "SibSp"
Number of terminal nodes:  7
Residual mean deviance:  0.7975 = 563.9 / 707
Misclassification error rate: 0.1737 = 124 / 714
```