

Decision Tree using R

```
> setwd("C:/Users/home/Desktop")
```

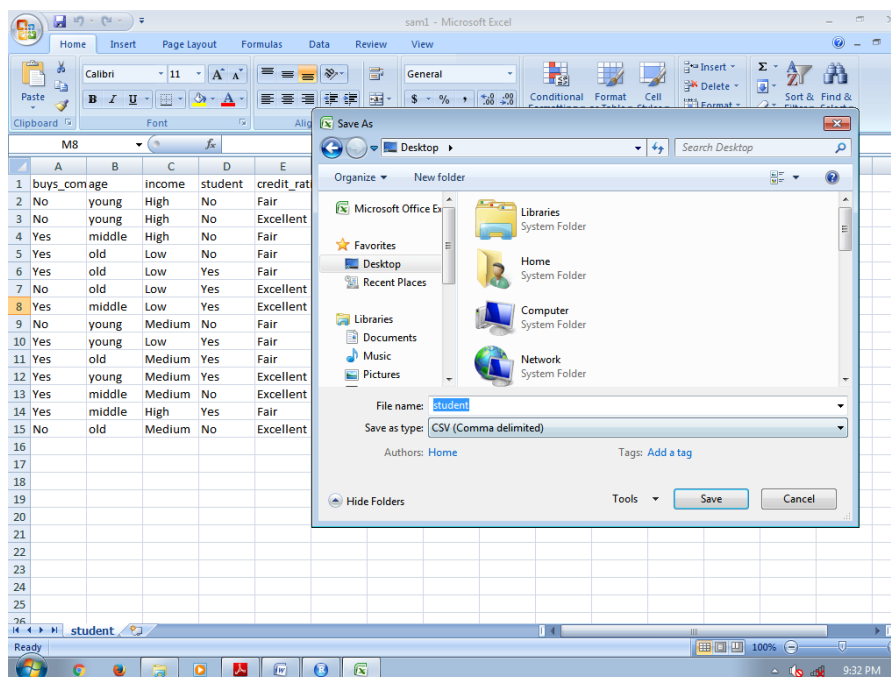
```
> library("rpart")
```

```
> library("rpart.plot")
```

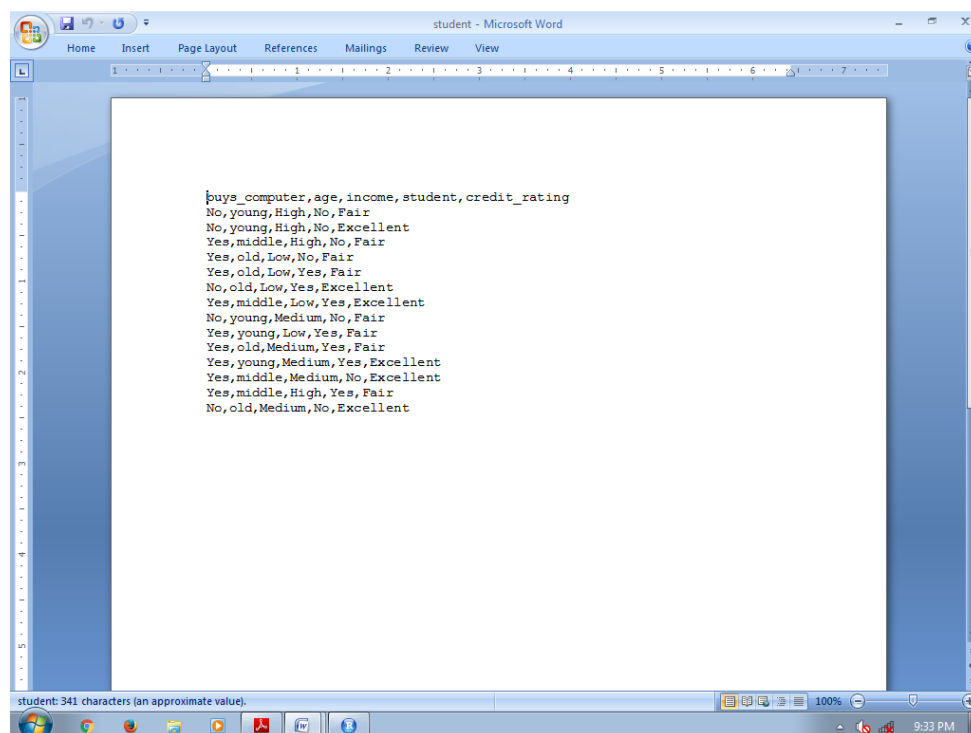
Step 1: Making as an Excel Format

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1	buys_comage	income	student	credit_rating											
2	No	young	High	No	Fair										
3	No	young	High	No	Excellent										
4	Yes	middle	High	No	Fair										
5	Yes	old	Low	No	Fair										
6	Yes	old	Low	Yes	Fair										
7	No	old	Low	Yes	Excellent										
8	Yes	middle	Low	Yes	Excellent										
9	No	young	Medium	No	Fair										
10	Yes	young	Low	Yes	Fair										
11	Yes	old	Medium	Yes	Fair										
12	Yes	young	Medium	Yes	Excellent										
13	Yes	middle	Medium	No	Excellent										
14	Yes	middle	High	Yes	Fair										
15	No	old	Medium	No	Excellent										

Step 2: Saving the File as CSV - File->save as ->student.csv(comma delimited) as shown below.



To open the CSV file(student.csv) in Ms-Word



```
>play_decision <- read.table ("C:/Users/home/Desktop/student.csv", header=TRUE,  
sep=",")
```

```
> play_decision
```

```
buys_computer  age income student credit_rating
```

```
1      No young  High   No    Fair  
2      No young  High   No    Excellent  
3      Yes middle High   No    Fair  
4      Yes  old   Low    No    Fair  
5      Yes  old   Low   Yes    Fair  
6      No  old   Low   Yes    Excellent  
7      Yes middle Low   Yes    Excellent  
8      No young Medium  No    Fair  
9      Yes young  Low   Yes    Fair  
10     Yes  old Medium  Yes    Fair  
11     Yes young Medium  Yes    Excellent  
12     Yes middle Medium No    Excellent  
13     Yes middle High   Yes    Fair  
14     No  old Medium  No    Excellent
```

> summary(play_decision)

```
buys_computer  age    income student credit_rating
No :5      middle:4 High :4 No :7 Excellent:6
Yes:9      old :5 Low :5 Yes:7 Fair :8
      young :5 Medium:5
```

**> fit <- rpart(buys_computer ~ age + income + student + credit_rating,
+ method = "class",
+ data = play_decision,
+ control = rpart.control(minsplit = 1),
+ parms = list(split = 'information'))**

> summary(fit)

Call:

```
rpart(formula = buys_computer ~ age + income + student + credit_rating,
      data = play_decision, method = "class", parms = list(split = "information"),
      control = rpart.control(minsplit = 1, data = play_decision, method = "class", parms = list(split =
"information"), t = 1))
n= 14
```

	CP	nsplit	rel error	xerror	xstd
1	0.30	0	1.0	1.0	0.3585686
2	0.20	2	0.4	1.8	0.3585686
3	0.10	3	0.2	1.0	0.3585686
4	0.01	5	0.0	1.2	0.3703280

Variable importance

age	income	student	credit_rating
39	32	19	11

Node number 1: 14 observations, complexity param=0.3

predicted class=Yes expected loss=0.3571429 P(node) =1

class counts: 5 9

probabilities: 0.357 0.643

left son=2 (10 obs) right son=3 (4 obs)

Primary splits:

age splits as RLL, improve=2.1931200, (0 missing)

student splits as LR, improve=1.4734210, (0 missing)

credit_rating splits as LR, improve=0.4670276, (0 missing)

income splits as LRL, improve=0.4399255, (0 missing)

Node number 2: 10 observations, complexity param=0.3

predicted class=No expected loss=0.5 P(node) =0.7142857

class counts: 5 5

probabilities: 0.500 0.500

left son=4 (5 obs) right son=5 (5 obs)

Primary splits:

student splits as LR, improve=1.9274480, (0 missing)
income splits as LRR, improve=1.6389660, (0 missing)
credit_rating splits as LR, improve=0.8630462, (0 missing)
age splits as -RL, improve=0.2013551, (0 missing)

Surrogate splits:

income splits as LRR, agree=0.7, adj=0.4, (0 split)
age splits as -RL, agree=0.6, adj=0.2, (0 split)

Node number 3: 4 observations

predicted class=Yes expected loss=0 P(node) =0.2857143
class counts: 0 4
probabilities: 0.000 1.000

Node number 4: 5 observations, complexity param=0.2

predicted class=No expected loss=0.2 P(node) =0.3571429
class counts: 4 1
probabilities: 0.800 0.200

left son=8 (4 obs) right son=9 (1 obs)

Primary splits:

income splits as LRL, improve=2.5020120, (0 missing)
age splits as -RL, improve=1.1157180, (0 missing)
credit_rating splits as LR, improve=0.5924696, (0 missing)

Node number 5: 5 observations, complexity param=0.1

predicted class=Yes expected loss=0.2 P(node) =0.3571429
class counts: 1 4
probabilities: 0.200 0.800

left son=10 (2 obs) right son=11 (3 obs)

Primary splits:

credit_rating splits as LR, improve=1.1157180, (0 missing)
age splits as -LR, improve=0.5924696, (0 missing)
income splits as -LR, improve=0.5924696, (0 missing)

Node number 8: 4 observations

predicted class=No expected loss=0 P(node) =0.2857143
class counts: 4 0
probabilities: 1.000 0.000

Node number 9: 1 observations

predicted class=Yes expected loss=0 P(node) =0.07142857
class counts: 0 1
probabilities: 0.000 1.000

Node number 10: 2 observations, complexity param=0.1

predicted class=No expected loss=0.5 P(node) =0.1428571
class counts: 1 1
probabilities: 0.500 0.500

left son=20 (1 obs) right son=21 (1 obs)

Primary splits:

age splits as -LR, improve=1.386294, (0 missing)
income splits as -LR, improve=1.386294, (0 missing)

Node number 11: 3 observations

predicted class=Yes expected loss=0 P(node) =0.2142857
 class counts: 0 3
 probabilities: 0.000 1.000

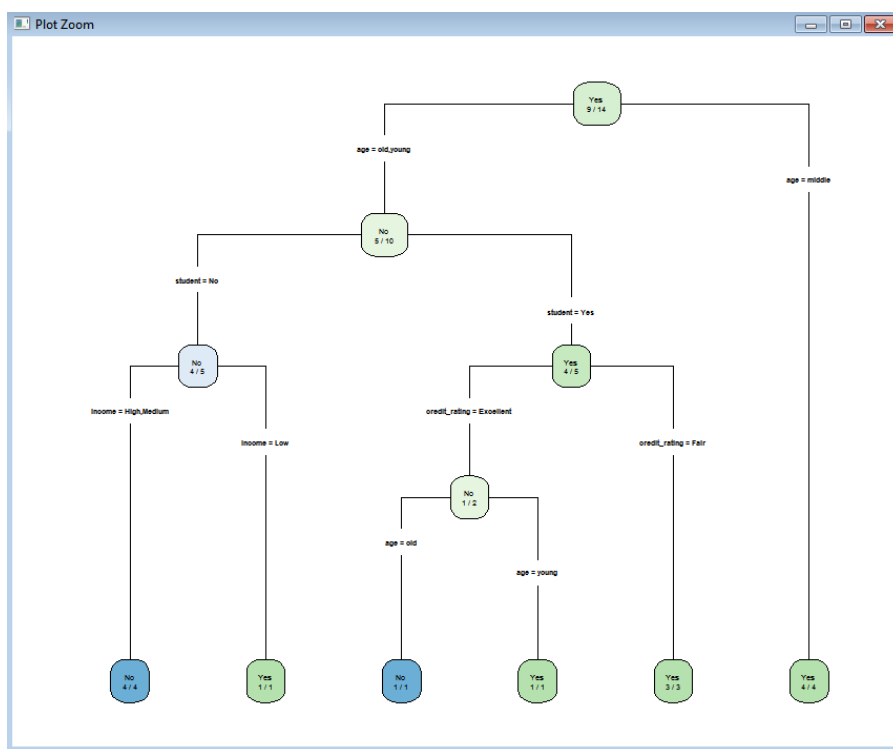
Node number 20: 1 observations

predicted class=No expected loss=0 P(node) =0.07142857
 class counts: 1 0
 probabilities: 1.000 0.000

Node number 21: 1 observations

predicted class=Yes expected loss=0 P(node) =0.07142857
 class counts: 0 1
 probabilities: 0.000 1.000

**> rpart.plot(fit,type=4,extra=2,clip.right.labs=FALSE,
 + varlen =0, faclen=0)**



Sample data

**> newdata <- data.frame(age="middle",income="High",student="No",credit_rating="Fair")
 > newdata**

Age income student credit_rating

1 middle High No Fair

> predict (fit,newdata=newdata, type= "prob")

No Yes

1 0 1

> predict (fit,newdata=newdata, type= "class")

1

Yes

Levels: No Yes