K2 Analytics
Building Skills, Building Individuals

Business Analytics using Data Mining (BADM)
- Rajesh Jakhotia

12-Oct-2015

Earning is in Learning
- Rajesh Jakhotia

Agenda

Introduction
Data Mining in a nut shell
Basic number skills
Classification Tree
CHAID, CART, C4.5 & Random Forest

About K2 Analytics

At K2 Analytics, we believe that skill development is very important for the growth of an individual, which in turn leads to the growth of Society & Industry and ultimately the Nation as a whole. For this it is important that access to knowledge and skill development trainings should be made available easily and economically to every individual.

Our Vision: *“To be the preferred partner for training and skill development”*

Our Mission: *“To provide training and skill development training to individuals, make them skilled & industry ready and create a pool of skilled resources readily available for the industry”*

*We have chosen Business Intelligence and Analytics as our focus area. With this endeavour we make this presentation on “**Business Analytics using Data Mining (BADM)**” accessible to all those who wish to learn Analytics. We hope it is of help to you. For any feedback / suggestion or if you are looking for job in analytics then feel free to write back to us at ar.jakhotia@k2analytics.co.in*

Welcome to BADM!!!

Data Mining in a nut shell

Statistics Vs. Data Mining

Statistics

- the practice or science of collecting and analysing numerical data in large quantities, especially for the purpose of inferring proportions in a whole from those in a representative sample.

- Infer / Describe
- Data Collection
- Large Dataset implies hundred / thousand data points
- Population / Sample Level
- Charts & Table
- Makes many assumptions

Data Mining

- Data mining is the analysis of (often large) observational data sets to find unsuspected relationships and to summarize the data in novel ways that are both understandable and useful to the data owner.

- Predict
- Data Preparation
- Large Datasets implies millions / billions data points
- Customer (Granular) Level
- Visualizations
- Makes few / no assumptions

http://www.cs.csi.cuny.edu/~imberman/DataMining/Statistics%20vs.pdf

Types of Data Mining Techniques

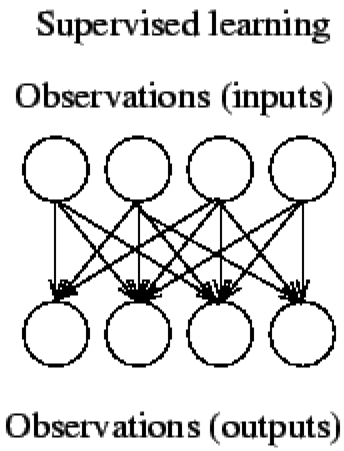
- Supervised learning: The target output expected is clearly defined

- Unsupervised learning: The data have no target attribute.
  - We want to explore the data to find some intrinsic structures in them.

Types of Data Mining techniques

Supervised Techniques

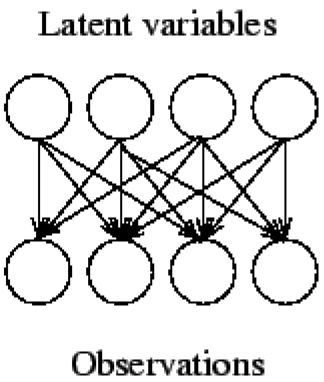
- In supervised learning, the model defines the effect one set of observations, called inputs, has on another set of observations, called outputs



- Prediction (numerical Y)
- Classification (Categorical Y)

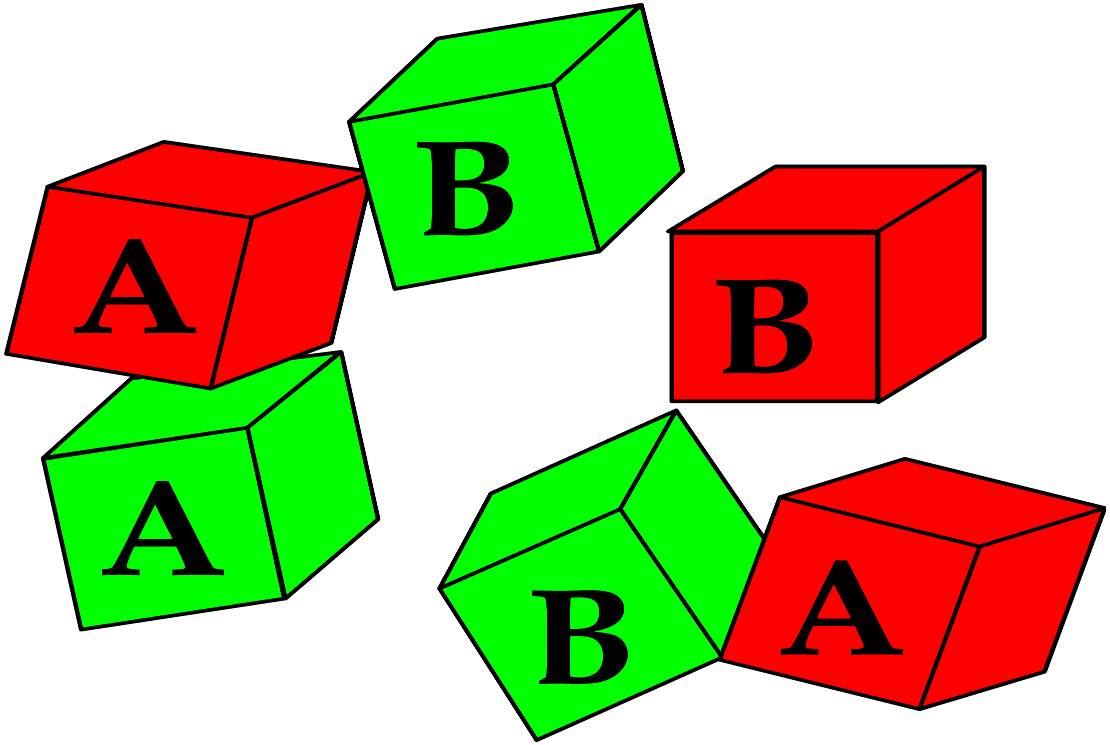
Unsupervised Techniques

- In unsupervised learning, all the observations are assumed to be caused by latent variables, that is, the observations are assumed to be at the end of the causal chain

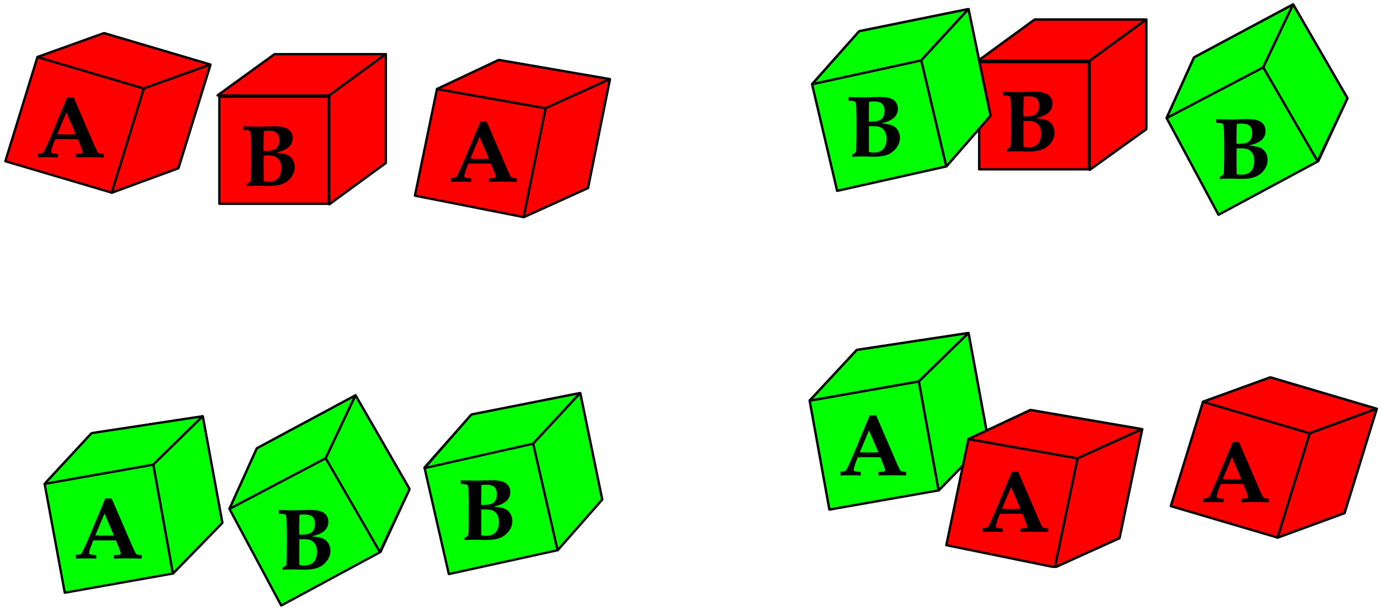


- Dimension Reduction
- Clustering
- Association Analysis

Understanding Supervised and Unsupervised Learning

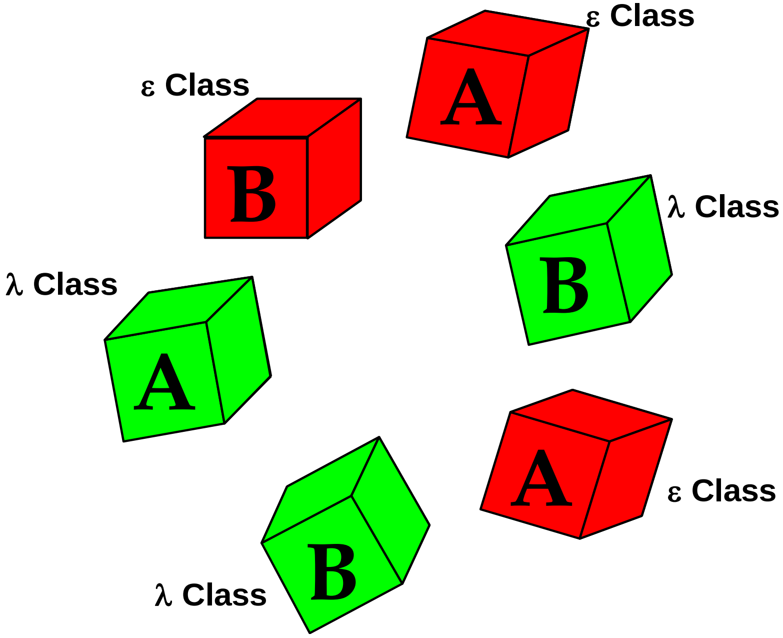


Two Possible Solutions



Supervised Learning

- It is based on a labeled training set.
- The class of each piece of data in training set is known.
- Class labels are pre-determined and provided in the training phase.



Modeling Process: CRISP-DM

- CRISP – DM stands for Cross Industry Standard Process for Data Mining

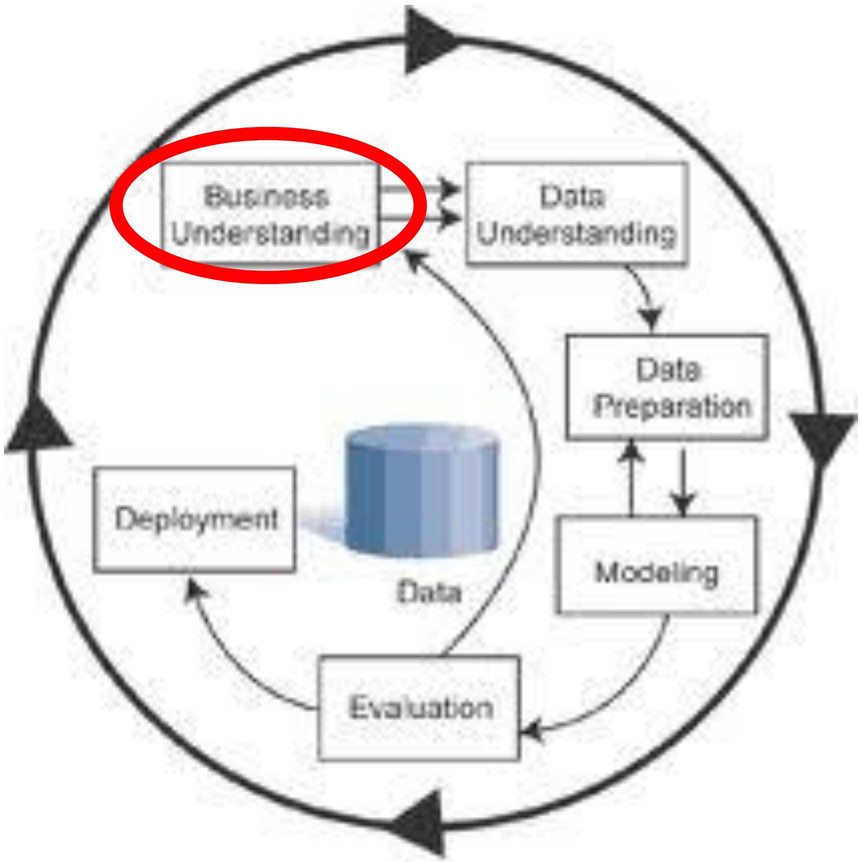
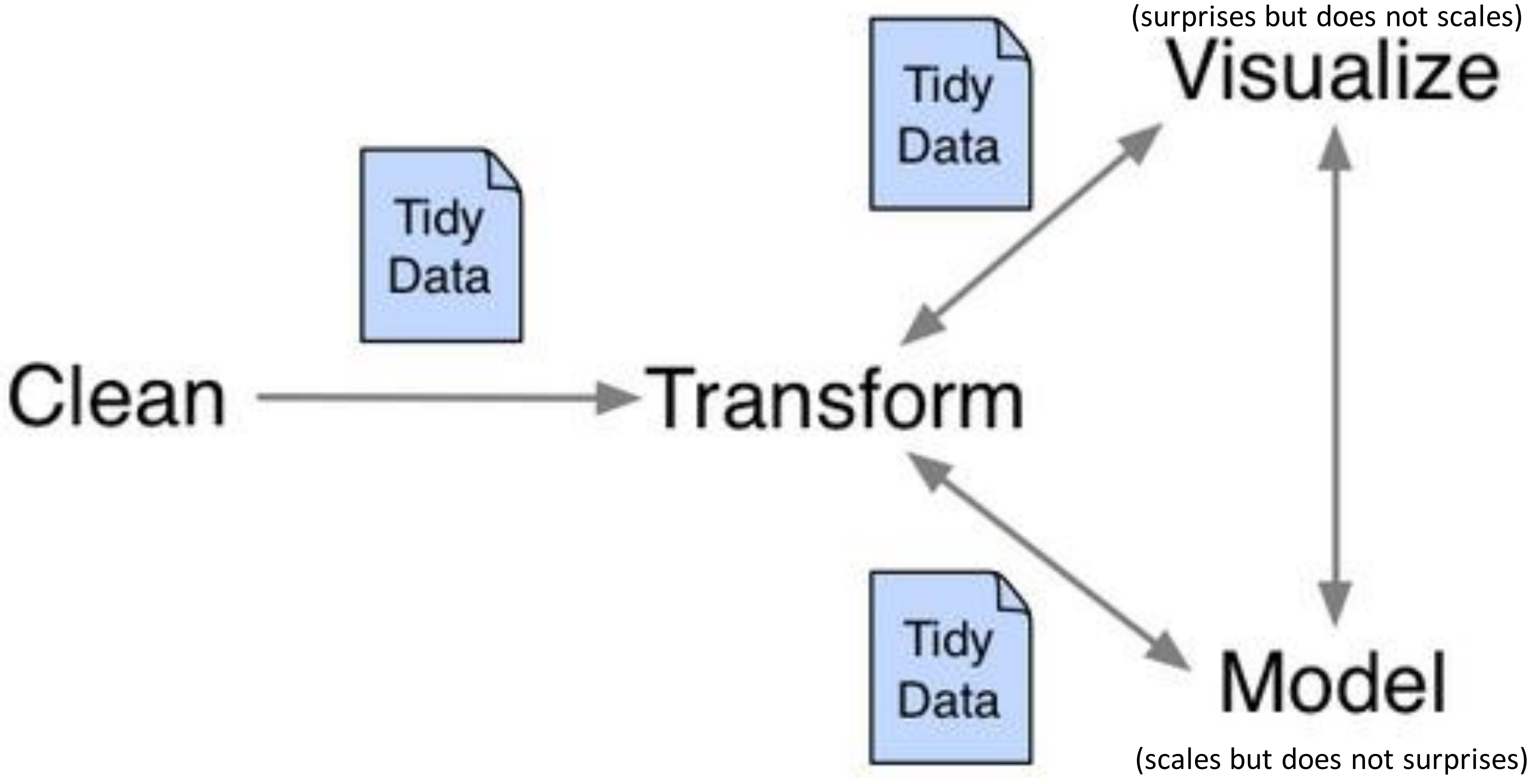


FIGURE 1 Data-Mining Process Model

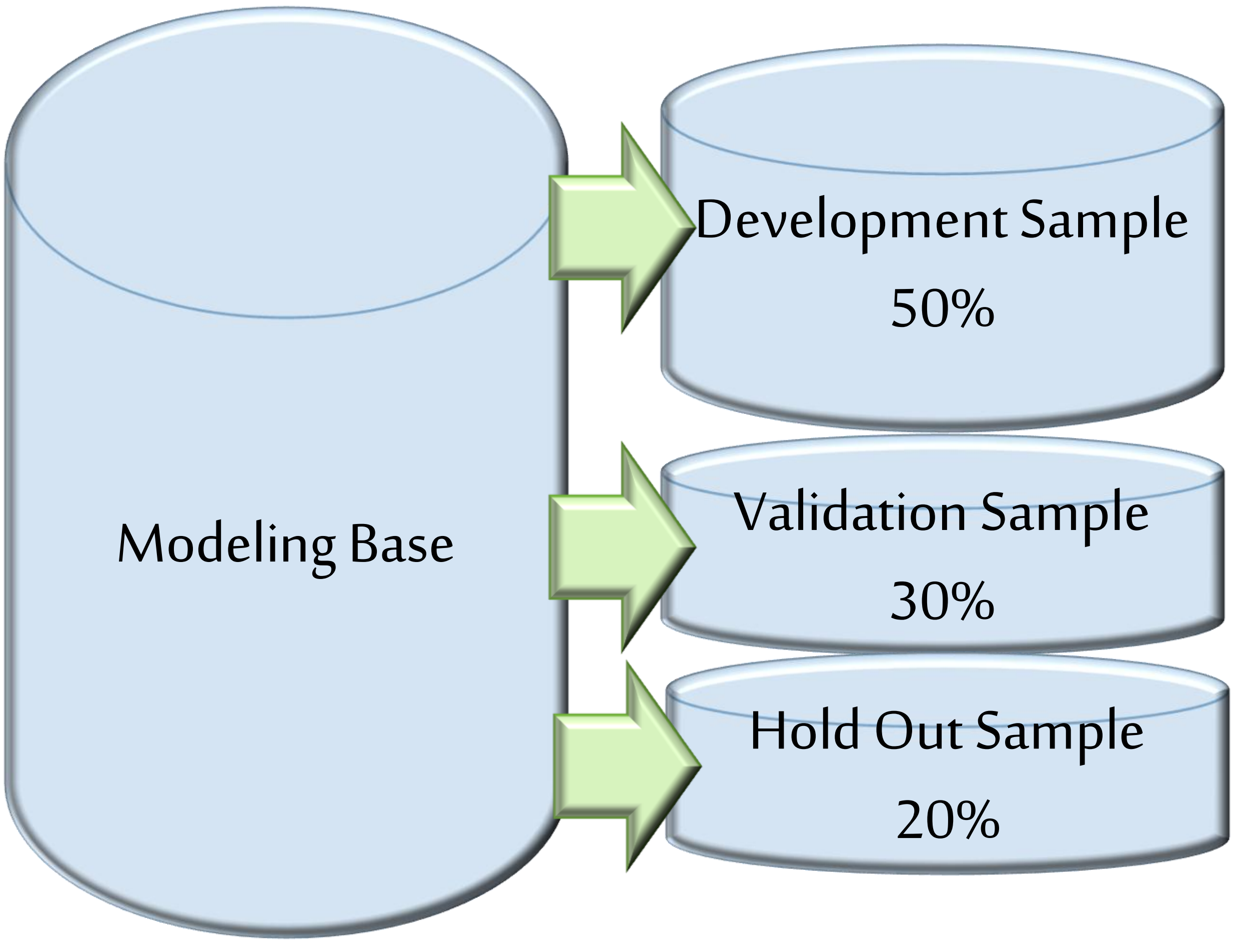
Most challenging part in modeling is defining the objective

Data Preparation & Modeling Process



Note: Figure adapted and modified from a presentation by Hadley Wickham.

Hold Out concept in Model Evaluation



K2 Analytics

Building Skills, Building Individuals

Basic Number Skills
Modeling Techniques

Basic Number Skills

- Measures of Central Tendency
  - Mean, Median, Mode
- Measures of Dispersion
  - Std. Deviation, Variance
- Correlation and Covariance
- Chi-Sq Test
- Additive Variables, Count and Ratio

Standardization & Normalization

- Standardization & Normalization are 2 commonly used method for rescaling
- *Normalization*, which scales all numeric variables in the range [0,1]. One possible formula is given below:

$$x_{new} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

- Standardization transforms data to mean zero and unit variance

$$x_{new} = \frac{x - \mu}{\sigma}$$

Hypothesis Testing

Hypothesis testing is the use of statistics to determine the probability that a given hypothesis is true. The usual process of hypothesis testing consists of four steps.

1. Formulate the **null hypothesis** (commonly, that the observations are the result of pure chance) and the **alternate hypothesis** (commonly, that the observations show a real effect combined with a component of chance variation).

2. Identify a **test statistic** that can be used to assess the truth of the **null hypothesis**

3. Compute the **p-value**, which is the probability that a test statistic at least as significant as the one observed would be obtained assuming that the **null hypothesis** were true. The smaller the p-value, the stronger the evidence against the null hypothesis.

4. Compare the p-value to an acceptable significance value α (sometimes called an **alpha value**). If $\alpha <= p$, that the observed effect is statistically significant, the null hypothesis is ruled out, and the alternative hypothesis is valid.

Uni, Bi & Multi-variate analysis

- Univariate Analysis – Descriptive statistics like Mean, Median, Mode, STD Deviation, Variance, Frequency Distribution

- Bi & Multi-variate analysis –
  - Differences of Group (Chi-Sq, t-Test, ANOVA)
  - Relationship (Correlation & Regression)

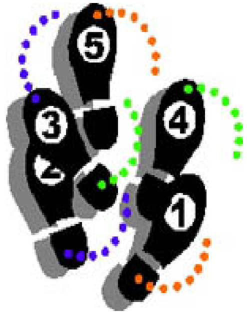
Cardinal, Ordinal, & Nominal Numbers

A **cardinal number** tells **"how many."** Cardinal numbers are also known as "counting numbers," because they **show quantity.**

Here are some examples using cardinal numbers:

- 8 puppies
- 14 friends

Ordinal numbers tell the **order of things in a set**—first, second, third, etc. Ordinal numbers do not show quantity. They only **show rank or position.**



Here are some examples using ordinal numbers:

- 3rd fastest
- 6th in line

A **nominal number names something**—a telephone number, a player on a team. Nominal numbers do not show quantity or rank. They are used only to **identify something.**

Here are some examples using nominal numbers:

- jersey number 4
- zip code 02116

http://www.factmonster.com/ipka/A0875618.html

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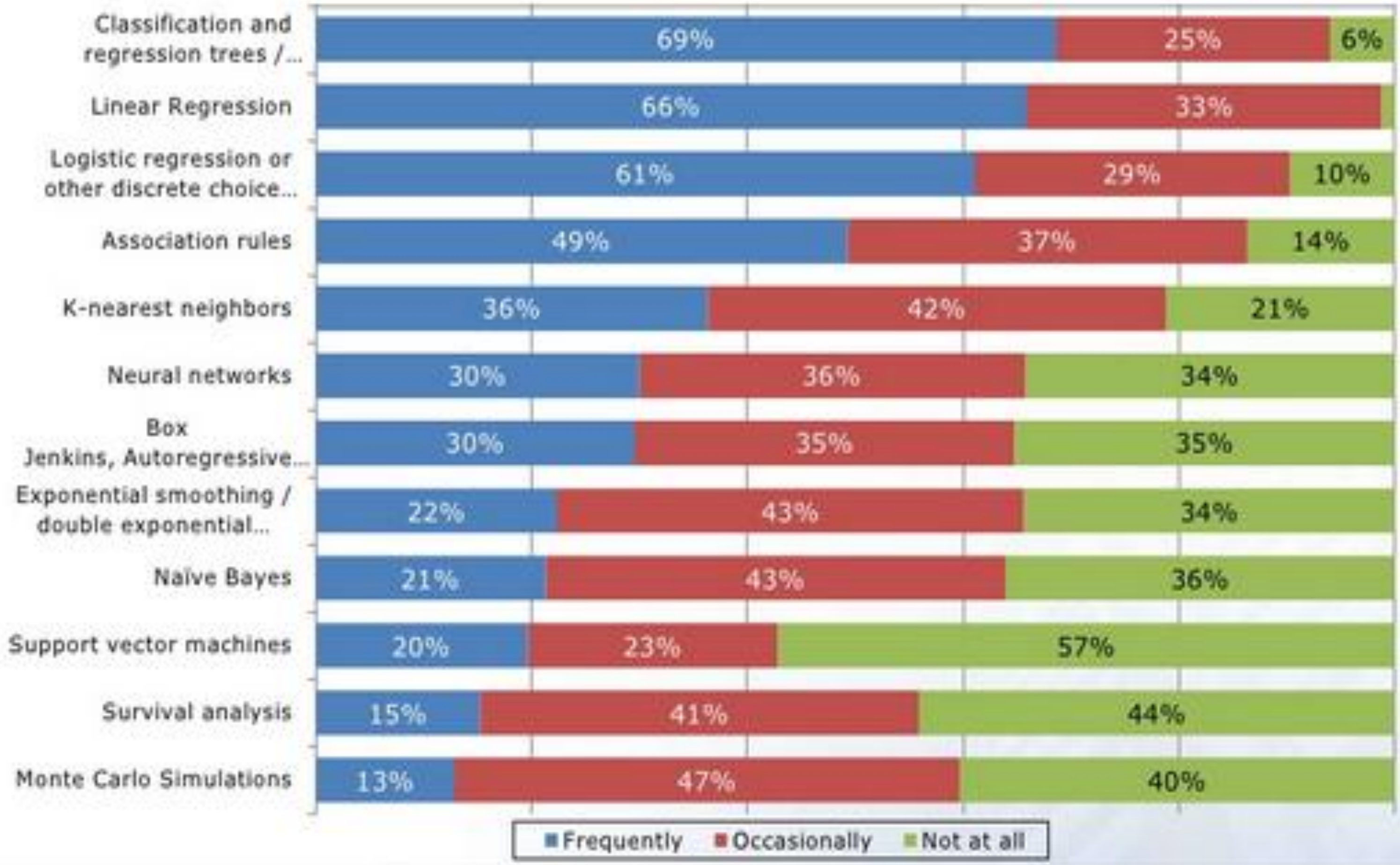
Classification Techniques

CHAID
CART

Analytics that are Actually Used

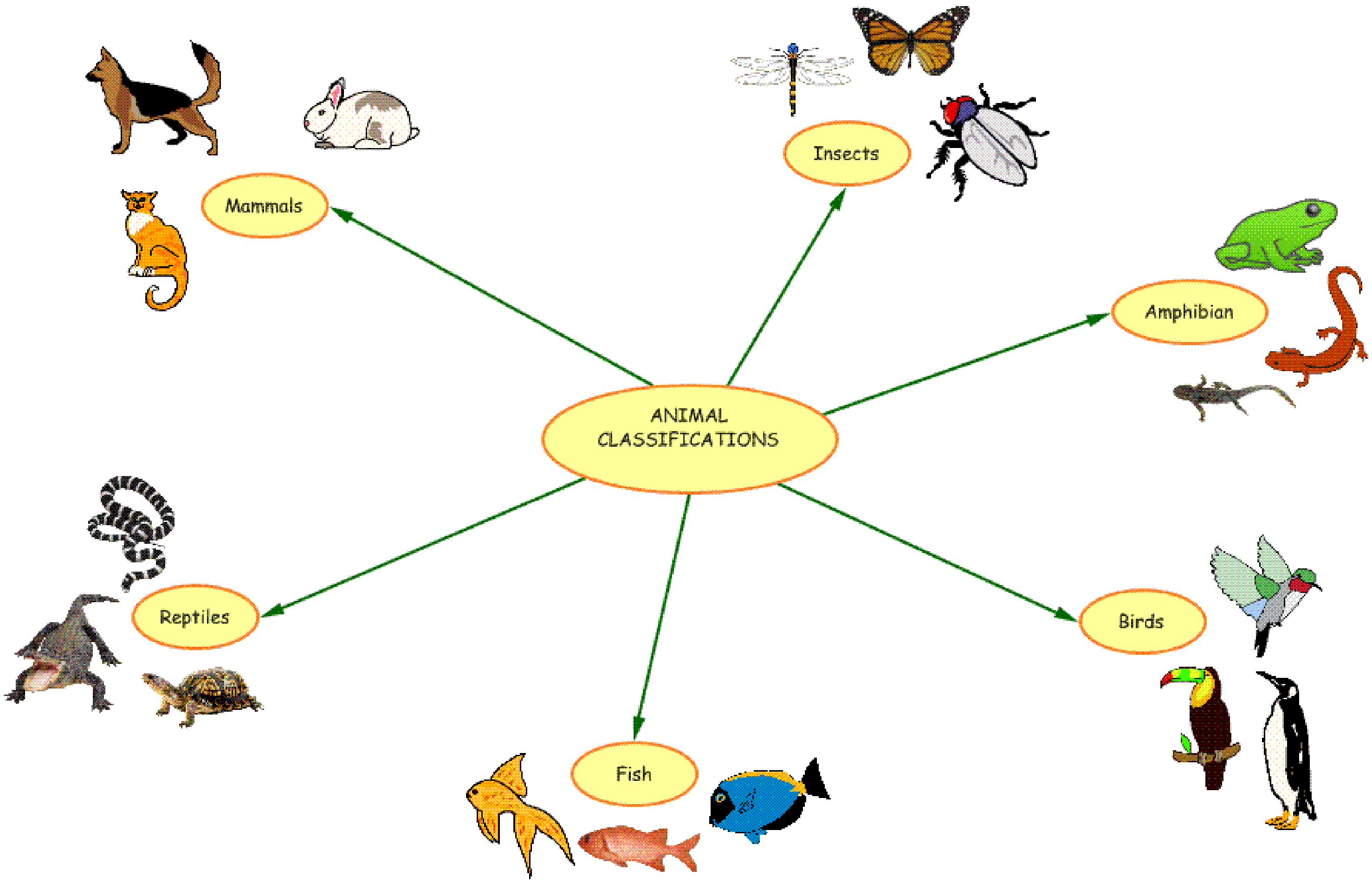


Classification and regression trees / decision trees and Linear Regression are the most popular predictive analytics techniques used.

Source: Ventana Research Predictive Analytics Benchmark Research

What is Classification?

The action or process of classifying something according to shared qualities or characteristics.



Defining Characteristics of each animal classification

- Mammals – Mammals are vertebrates (backboned animals). Mammals are warm-blooded and have hair. Mammals are able to move around using limbs
- Birds – Birds are warm-blooded vertebrates, having a body covered with feathers, forelimbs modified into wings, scaly legs, a beak, and no teeth, and bearing young ones in a hard-shelled egg
- Insects – any of small invertebrate animals which typically have a well defined head, thorax, and abdomen, only three pairs of legs, and typically one or two pair of wings
- Amphibian - any cold-blooded vertebrate that live on land but breed in water
- Reptiles - class of cold-blooded air-breathing vertebrates with completely ossified skeleton and a body usually covered with scales or horny plates
- Fish - A limbless cold-blooded vertebrate animal with gills and fins and living wholly in water

Why Classify?

To Explain (Profile)

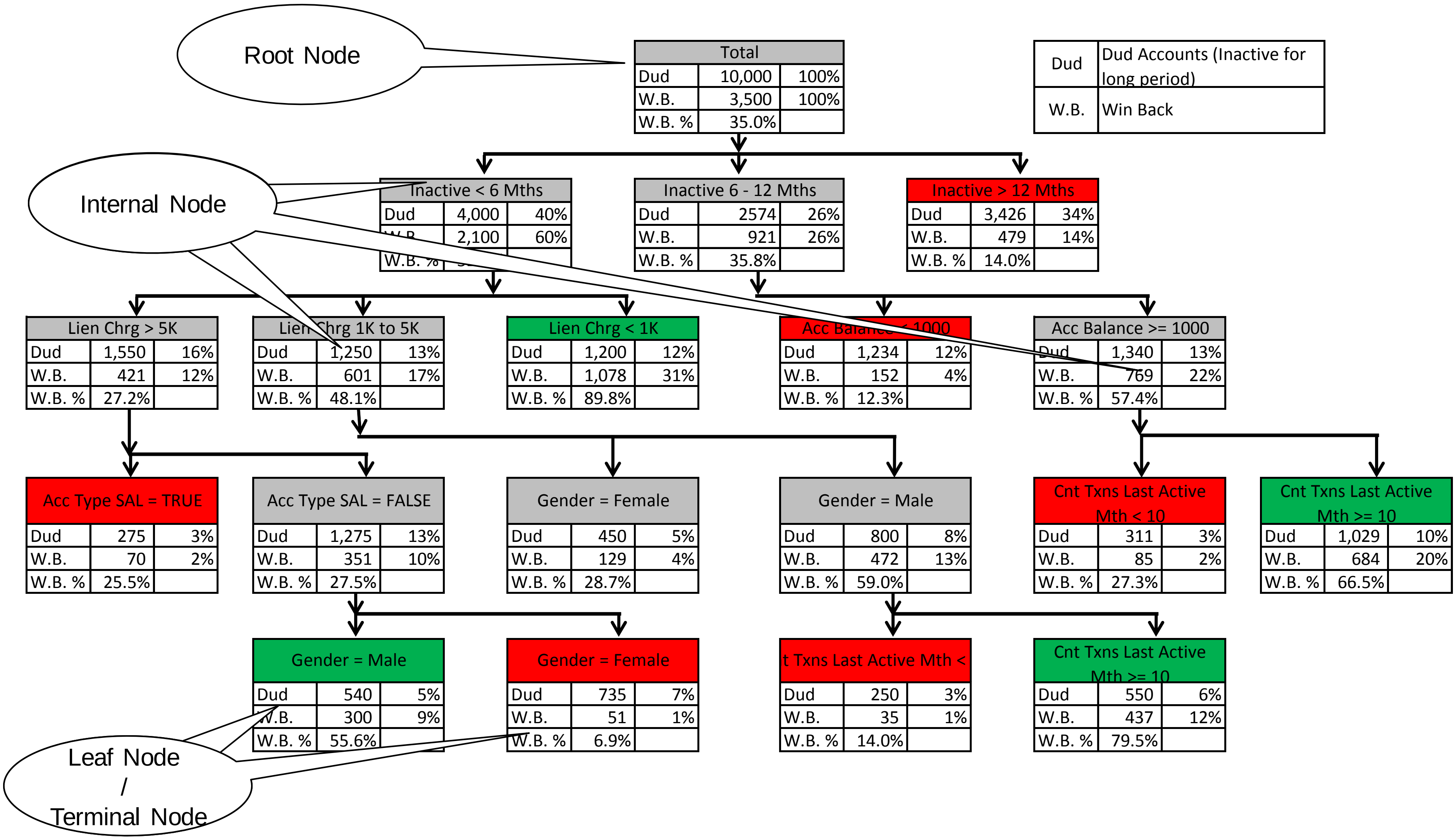
Explaining in the classification world is called Profiling

or

To Predict (Classify)

Predicting the class of new records is called Classifying

Win Back Campaign Classification Analysis



Main issues of classification tree learning

- Choosing the splitting criterion
  - Impurity based criteria
  - Information gain
  - Statistical measures of association

- Binary or multiway splits
  - Multiway split
  - Binary split

- Finding the right sized tree
  - Pre-pruning
  - Post-pruning

Popular Classification Techniques

- **CHAID - CHi-squared Automatic Interaction Detector**. The “*Chi-squared” part of the name arises because the technique* essentially involves automatically constructing many cross-tabs, and working out statistical significance of the proportions. The most significant relationships are used to control the structure of a tree diagram
  - CHAID is a non-binary decision tree; **Recursive Partitioning Algorithm**
  - Continuous variables must be grouped into a finite number of bins to create categories.
- **CLASSIFICATION AND REGRESSION TREES (CART)** are binary decision trees, which split a single variable at each node.
  - The CART algorithm recursively goes though an exhaustive search of all variables and split values to find the optimal splitting rule for each node.
- **C4.5** builds decision trees from a set of training data using the concept of information entropy

CHAID | Splitting Criteria

Contingency table

Cross tabulation between Y and X

Y / X	x_1	x_l	x_L	Σ
y_1		$\vdots$		
y_k	$\cdots$	n_{kl}	$\cdots$	$n_{k.}$
		$\vdots$		
y_K				
Σ		$n_{.l}$		n

Measures of association

Comparing the observed and theoretical frequencies
(under the null hypothesis : Y and X are independent)

$$\chi^2 = \sum_{k=1}^{K} \sum_{l=1}^{L} \frac{\left(n_{kl} - \frac{n_{k.} \times n_{.l}}{n}\right)^2}{\frac{n_{k.} \times n_{.l}}{n}}$$

CHAID | Merging Criteria

Cust_ID	Occupation	Target
C16505	SELF-EMP	1
C17241	SAL	0
C18802	SENP	1
C19289	PROF	0
C14028	SELF-EMP	0
C17960	SAL	
C10216	SENP	
C4575	P	
C6171		
C4		
C		

Example:

Should we Merge the Occupation Categories or treat each separately?

- Cycle through predictors to determine for each predictor the pair of categories that is least significantly different with respect to the dependent variable
- It will compute a Chi-Square test; if the respective test for a given pair of categorical variables is not statistically significant as defined by alpha-to-merge, then it will merge the respective predictor categories
- Repeat the steps to find next pair of categories, which now may include previously merged categories

R Code … Data Import & Data Understanding

Let us first set the working directory path

```
setwd ("C:/K2-Analytics/Colleges/GLIM/")
getwd()
```

Let us import the data that we intend to use for modeling

```
CTDF <- read.table("datafile/CF_TREE_SAMPLE.csv", sep = ",", header = T)
head(CTDF)
```

Let us quickly understand the structure of our data

```
str(CTDF)
CTDF$Target = as.factor(CTDF$Target)



summary(CTDF)
```

CHI-SQ Calculation…e.g.

Cross Tab between Occupation and Target

```
tbl <- table(CTDF$Occupation, CTDF$Target)
tbl
chisq.test(tbl)
```

```
             0    1
PROF      5028  435
SAL       5426  413
SELF-EMP  2858  508
SENP      4955  377

        Pearson's Chi-squared test

data:  tbl
X-squared = 214.92, df = 3, p-value < 2.2e-16
```

CHI-SQ Calculations	Observed		Row Total	Expected		(O - E)^2/E	
	0	1		0	1	0	1
PROF	5,028	435	5,463	4,990	473	0.30	3.11
SAL	5,426	413	5,839	5,333	506	1.62	17.08
SELF-EMP	2,858	508	3,366	3,074	292	15.22	160.46
SENP	4,955	377	5,332	4,870	462	1.48	15.64
Total	18,267	1,733	20,000	18,267	1,733	CHI-SQ	215
Total Proportions	0.913	0.087					

Degree of Freedom = (m-1) * (n-1) = (4-1) * (2-1) = 3
p-value is arrived by seeing the CHI Sq Table based on CHI-SQ and Degree of Freedom

R Code

Let us first set the working directory path

```
setwd ("C:/K2-Analytics/Colleges/GLIM/")
getwd()
```

Let us import the data that we intend to use for modeling

```
CTDF <- read.table("datafile/CF_TREE_SAMPLE.csv", sep = ",", header = T)
head(CTDF)
```

Let us quickly understand the structure of our data

```
str(CTDF)
CTDF$Target = as.factor(CTDF$Target)
```

Merging Threshold: merge sub-categories in predictor variable if p-value is above alpha2 threshold

Installing the CHAID package

install.packages("partykit")

install.packages("CHAID", repos="http://R-Forge.R-project.org")

Splitting Threshold: If p-value below alpha4 consider the predictor for splitting of the node

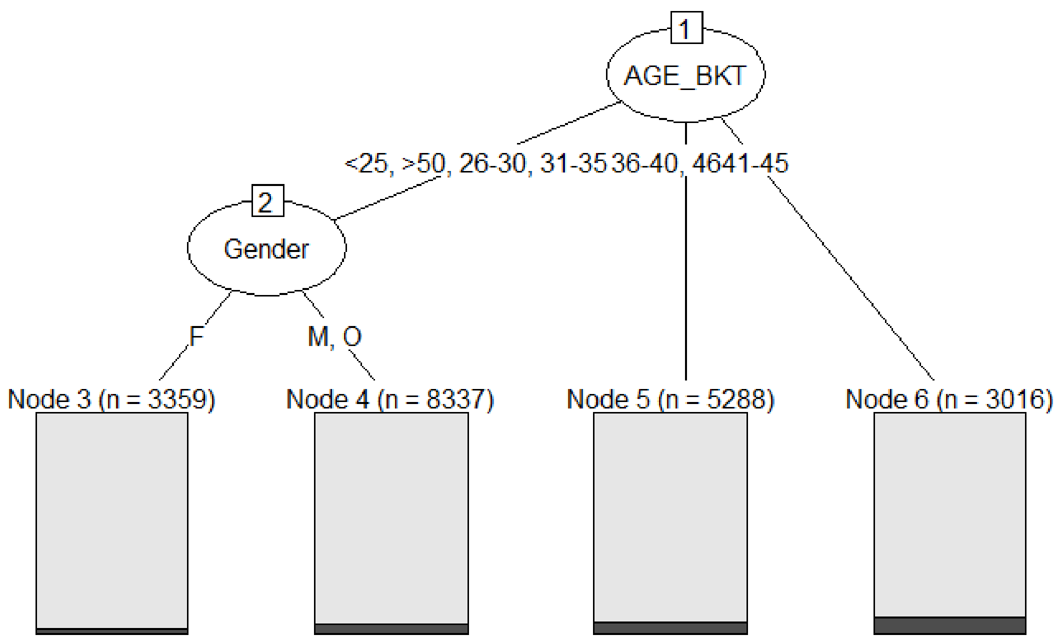
```
library(CHAID)
ctrl <- chaid_control(minbucket = 100, minsplit = 100, alpha2=.05, alpha4 = .05)
chaid.tree <-chaid(Target~Gender+AGE_BKT,data=CTDF, control = ctrl)
print(chaid.tree)
plot(chaid.tree)
```

CHAID Output

```
Model formula:
Target ~ Gender + AGE_BKT

Fitted party:
[1] root
|   [2] AGE_BKT <25, >50, 26-30, 31-35
|   |   [3] Gender in F: 0 (n = 3359, err = 2.1%)
|   |   [4] Gender in M, O: 0 (n = 8337, err = 4.0%)
|   [5] AGE_BKT in 36-40, 46-50: 0 (n = 5288, err = 5.0%)
|   [6] AGE_BKT in 41-45: 0 (n = 3016, err = 7.3%)

Number of inner nodes:    2
Number of terminal nodes: 4
```



Note:

- CHAID package in R is still not full developed… as such we will move on to another technique

CART

Run the CHAID with **Occupation** field also and see this plot

CART | Splitting Criteria

- CART uses the Gini Index as measure of impurity
- Gini of a Node

$$GINI(t) = 1 - \sum_j [p(j \mid t)]^2$$

(NOTE: $p(j \mid t)$ is the relative frequency of class j at node t).

- Gini of Split Node is computed as Weighted Avg Gini of each Node at Split Node level

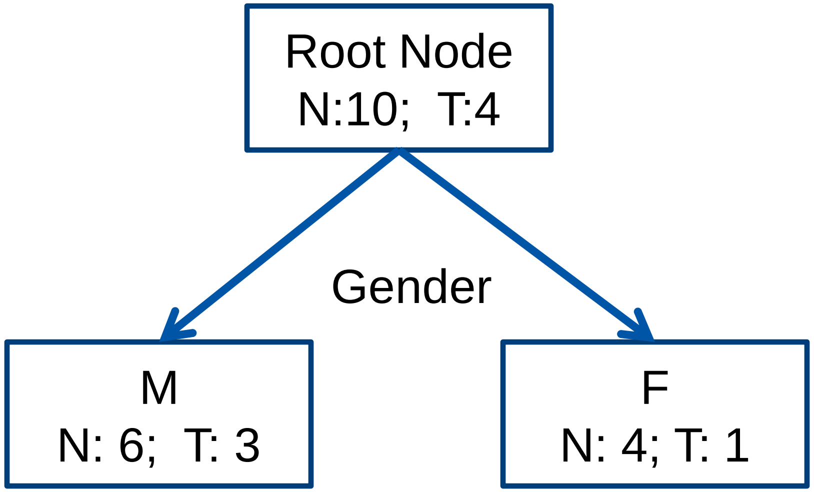
$$GINI_{split} = \sum_{i=1}^{k} \frac{n_i}{n} GINI(i)$$

n_i = number of records at child i,
n = Total number of records in parent node

- Gini Gain = Gini(t) – Gini(split)

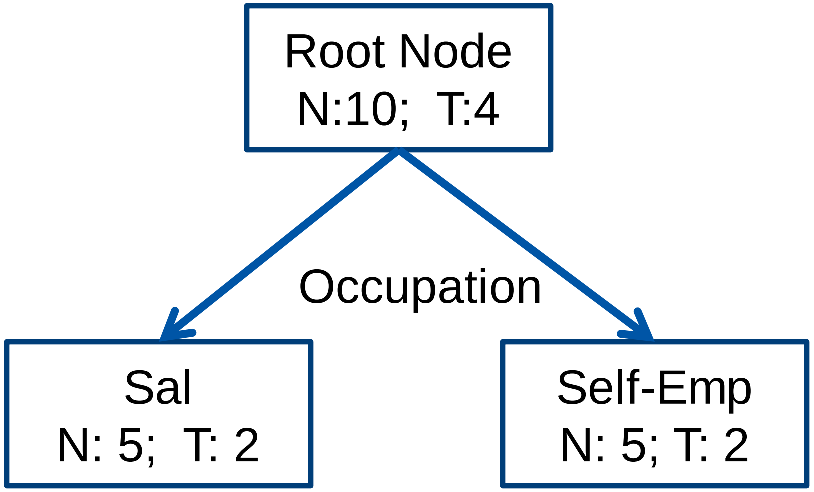
Gini calculations

Cust_ID	Gender	Occupation	Age	Target
1	M	Sal	22	1
2	M	Sal	22	0
3	M	Self-Emp	23	1
4	M	Self-Emp	23	0
5	M	Self-Emp	24	1
6	M	Self-Emp	24	0
7	F	Sal	25	1
8	F	Sal	25	0
9	F	Sal	26	0
10	F	Self-Emp	26	0



Node	Gini Computation Formula	Gini Index
Overall	= 1 - ((4/10)^2 + (6/10)^2)	0.48
Gender = M	= 1 - ((3/6)^2 + (3/6)^2)	0.50
Gender = F	= 1 - ((1/4)^2 + (3/4)^2)	0.375
Gender	= (6/10) * 0.5 + (4/10) * 0.375	0.45
Gini Gain	= Gini (Overall) – Gini (Gender)	0.03

Gini calculations



Node	Gini Computation Formula	Gini Index
Overall	= 1 - ((4/10)^2 + (6/10)^2)	0.48
Occ = Sal	= 1 - ((2/5)^2 + (2/5)^2)	0.48
Occ = Self-Emp	= 1 - ((2/5)^2 + (2/5)^2)	0.48
Occupation	= (5/10) * 0.48 + (5/10) * 0.48	0.48
Gini Gain	= Gini (Overall) – Gini (Occupation)	0.0

Age	<=22	<=23	<=24	<=25
Gini (Left)	0.5	0.5	0.5	0.5
Gini (Right)	0.47	0.44	0.38	0
Gini Split	0.48	0.47	0.45	0.40
Gini Gain	0.0	0.01	0.03	0.08

Sampling…

```
## Creating Development and Validation Sample
## CTDF$random <- runif (nrow(CTDF), 0, 1);
## CTDF.dev <- CTDF [which(CTDF$random <= 0.7),]
## CTDF.holdout <- CTDF [which(CTDF$random > 0.7),]
## c (nrow(CTDF.dev), nrow(CTDF.holdout))
```

Sampling Code

Separate Dev & Val samples are provided as such we will directly import them rather than use sampling code

```
CTDF.dev <- read.table ("datafile/DEV_SAMPLE.csv", sep = ",", header = T)
CTDF.holdout <- read.table ("datafile/HOLDOUT_SAMPLE.csv", sep = ",", header = T)
```

rpart code to build CART Tree

```
## installing rpart package for CART
## install.packages("rpart")
## install.packages("rpart.plot")

## loading the library
library(rpart)
library(rpart.plot)

## setting the control parameter inputs for rpart
r.ctrl = rpart.control(minsplit=100, minbucket = 10, cp = 0, xval = 10)

## calling the rpart function to build the tree
m1 <- rpart(formula = Target ~ ., data = CTDF.dev[,-1], method = "class", control = r.ctrl)
m1
```

Complexity Parameter Initially set to Zero to allow the full tree to be grown

Cross Validation Parameter

rpart.control arguments

- **minsplit:** the minimum number of observations that must exist in a node in order for a split to be attempted.
- **minbucket**: the minimum number of observations in any terminal leaf node. If only one of minbucket or minsplit is specified, the code either sets minsplit to minbucket*3 or minbucket to minsplit/3, as appropriate.
- **cp complexity parameter**: Any split that does not decrease the overall lack of fit by a factor of cp is not attempted. The main role of this parameter is to save computing time by pruning off splits that are obviously not worthwhile. Essentially,the user informs the program that any split which does not improve the fit by cp will likely be pruned off by cross-validation, and that hence the program need not pursue it.
- **xval**: number of cross-validations

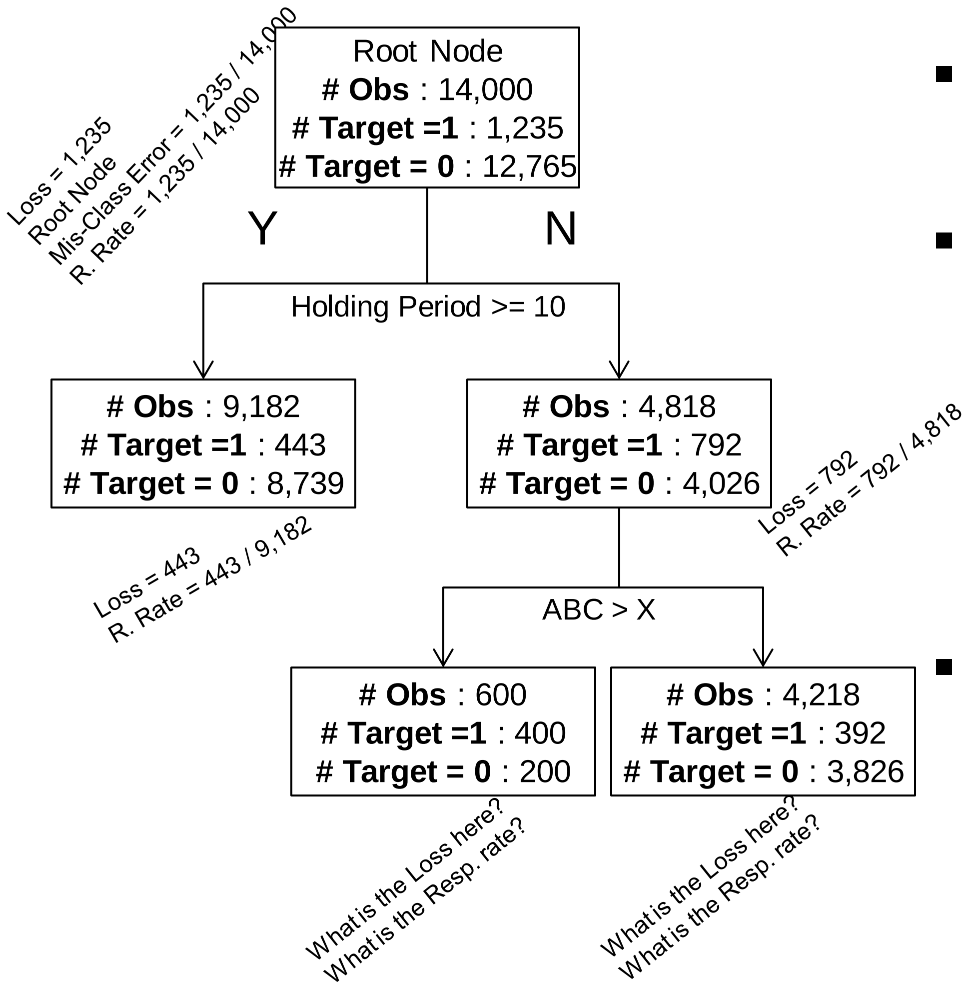
rpart output

```
n= 14000

node), split, n, loss, yval, (yprob)
      * denotes terminal node

 1) root 14000 1235 0 (0.91178571 0.08821429)
   2) Holding_Period>=10.5 9182  443 0 (0.95175343 0.04824657)
     4) NO_OF_CR_TXNS< 20.5 6858  212 0 (0.96908720 0.03091280) *
     5) NO_OF_CR_TXNS>=20.5 2324  231 0 (0.90060241 0.09939759)
      10) Occupation=PROF,SAL 1814  124 0 (0.93164278 0.06835722) *
      11) Occupation=SELF-EMP,SENP 510  107 0 (0.79019608 0.20980392)
        22) SCR< 334.5 120    9 0 (0.92500000 0.07500000) *
        23) SCR>=334.5 390   98 0 (0.74871795 0.25128205)
          46) Gender=M,O 370   85 0 (0.77027027 0.22972973) *
          47) Gender=F 20    7 1 (0.35000000 0.65000000) *
   3) Holding_Period< 10.5 4818  792 0 (0.83561644 0.16438356)
     6) Occupation=PROF,SAL,SENP 3971  546 0 (0.86250315 0.13749685)
      12) NO_OF_CR_TXNS< 20.5 2832  317 0 (0.88806497 0.11193503)
        24) Balance>=10853.5 2551  259 0 (0.89847119 0.10152881)
          48) SCR< 697.5 1618  129 0 (0.92027194 0.07972806) *
          49) SCR>=697.5 933  130 0 (0.86066452 0.13933548)
            98) Holding_Period>=1.5 791   98 0 (0.87610619 0.12389381)
             196) SCR>=732.5 712   81 0 (0.88623596 0.11376404)
               392) AGE_BKT=>50,26-30,31-35 358   30 0 (0.91620112 0.08379888) *
               393) AGE_BKT=<25,36-40,41-45,46-50 354   51 0 (0.85593220 0.14406780)
                 786) Balance>=34458.97 278   33 0 (0.88129496 0.11870504)
                  1572) Balance< 48554.42 28    0 0 (1.00000000 0.00000000) *
                  1573) Balance>=48554.42 250   33 0 (0.86800000 0.13200000)
                    3146) Balance>=212700.4 103    8 0 (0.92233010 0.07766990) *
                    3147) Balance< 212700.4 147   25 0 (0.82993197 0.17006803)
                      6294) Holding_Period< 2.5 23    0 0 (1.00000000 0.00000000) *
                      6295) Holding_Period>=2.5 124   25 0 (0.79838710 0.20161290)
                       12590) Holding_Period>=3.5 108   16 0 (0.85185185 0.14814815) *
                       12591) Holding_Period< 3.5 16    7 1 (0.43750000 0.56250000) *
                 787) Balance< 34458.97 76   18 0 (0.76315789 0.23684211) *
             197) SCR< 732.5 79   17 0 (0.78481013 0.21518987) *
            99) Holding_Period< 1.5 142   32 0 (0.77464789 0.22535211) *
        25) Balance< 10853.5 281   58 0 (0.79359431 0.20640569) *
      13) NO_OF_CR_TXNS>=20.5 1139  229 0 (0.79894644 0.20105356)
        26) Occupation=PROF,SAL 1048  174 0 (0.83396947 0.16603053) *
        27) Occupation=SENP 91   36 1 (0.39560440 0.60439560) *
     7) Occupation=SELF-EMP 847  246 0 (0.70956316 0.29043684)
      14) SCR< 725 538  107 0 (0.80111524 0.19888476)
        28) NO_OF_CR_TXNS< 29.5 434   68 0 (0.84331797 0.15668203) *
        29) NO_OF_CR_TXNS>=29.5 104   39 0 (0.62500000 0.37500000)
          58) Balance>=4171.13 93   31 0 (0.66666667 0.33333333) *
          59) Balance< 4171.13 11    3 1 (0.27272727 0.72727273) *
      15) SCR>=725 309  139 0 (0.55016181 0.44983819)
        30) Balance>=13166.99 205   72 0 (0.64878049 0.35121951)
          60) NO_OF_CR_TXNS< 20.5 149   39 0 (0.73825503 0.26174497) *
          61) NO_OF_CR_TXNS>=20.5 56   23 1 (0.41071429 0.58928571) *
        31) Balance< 13166.99 104   37 1 (0.35576923 0.64423077)
          62) Age>=48 17    6 0 (0.64705882 0.35294118) *
          63) Age< 48 87   26 1 (0.29885057 0.70114943) *
```

Loss, Mis-Classification Error and Response Rate



What is the mis-classification error for the above tree?

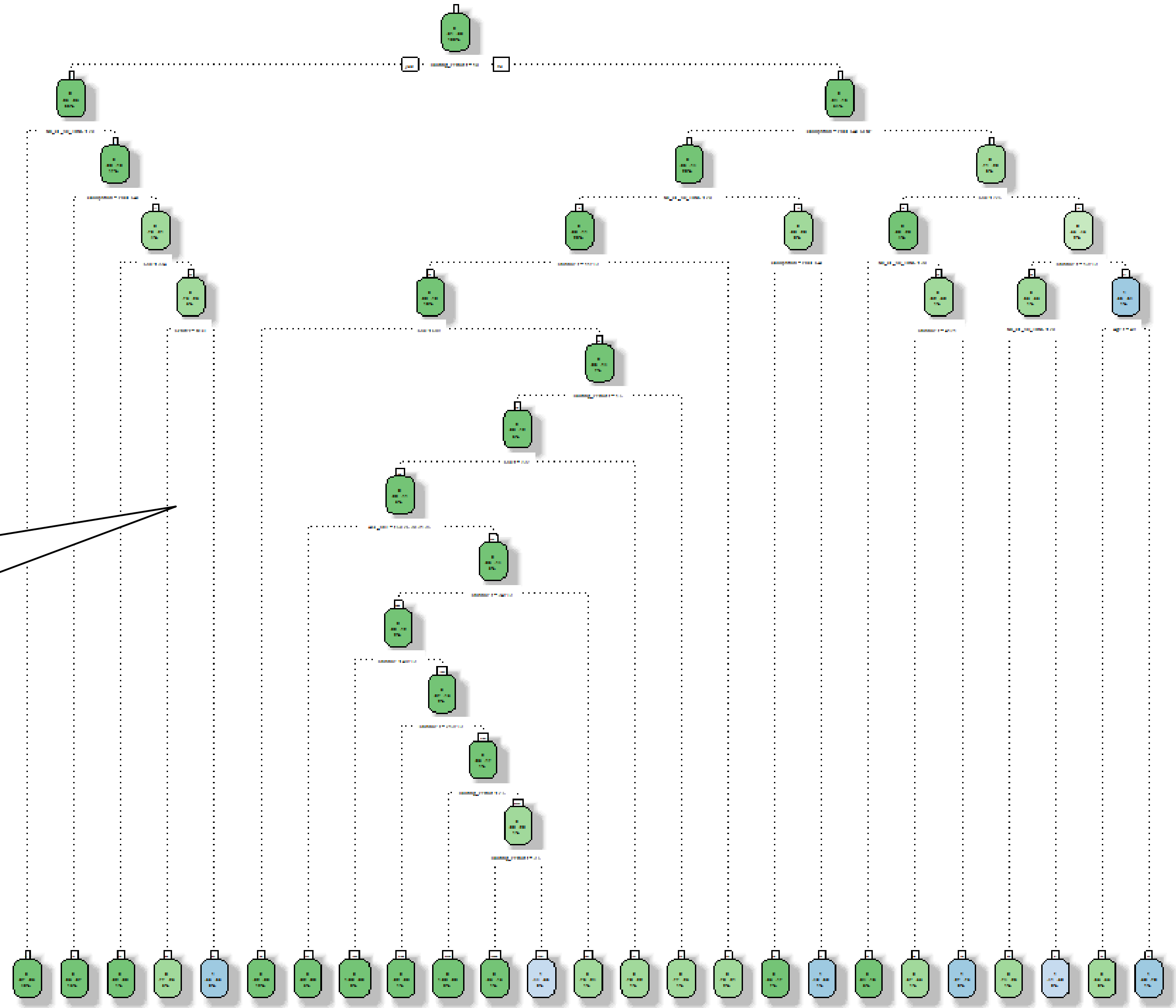
- Loss is the number of cases mis-classified in a given node
- Mis-Classification Error is the ratio of total number of cases mis-classified to total number of cases
  – We are interested in mis-classification error for the full tree
- Response Rate is the ratio of number of responders (Target = 1) to the total number of cases
  – We are interested in finding nodes where the response rate is very high

Plotting the Classification Tree

library(rattle)

library(RColorBrewer

fancyRpartPlot(m1)



Let us export the output to PDF format to have a clear view of the tree

Concepts | Greedy Algorithm

Make 31 Paise using any combination of above coins

Optimal solution with few coins : 25 + 5 + 1

What if the 5 paise coin is not there?

Optimal solution with few coins : 10 * 3 + 1

Greedy Algorithm solution: 25 + 1 * 6

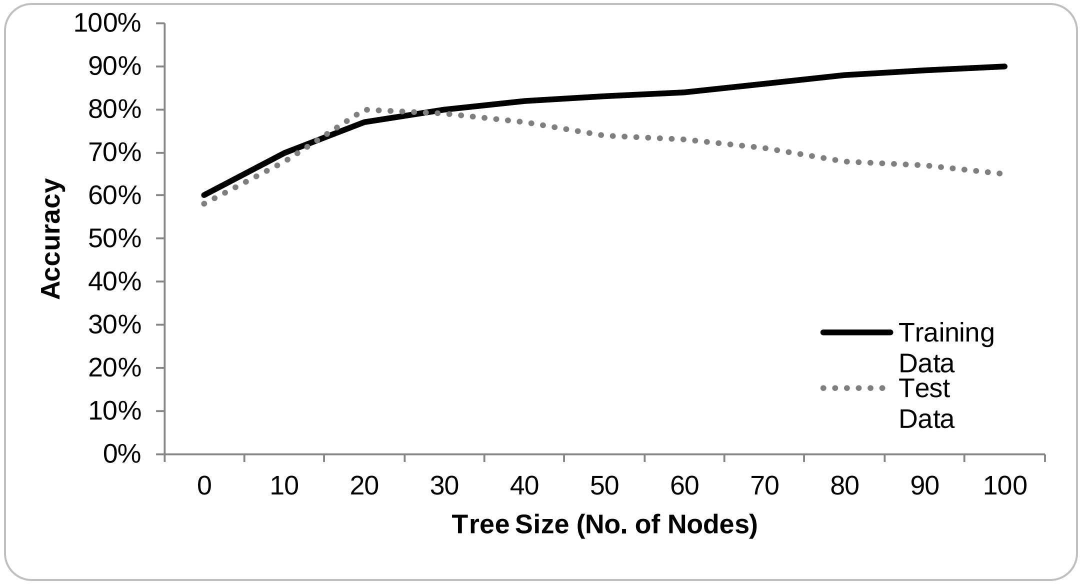
Concepts | Cross Validation

K Fold CV	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
Fold 1	Train	Train	Train	Train	Train	Train	Train	Train	Train	Test
Fold 2	Train	Train	Train	Train	Train	Train	Train	Train	Test	Train
Fold 3	Train	Train	Train	Train	Train	Train	Train	Test	Train	Train
Fold 4	Train	Train	Train	Train	Train	Train	Test	Train	Train	Train
Fold 5	Train	Train	Train	Train	Train	Test	Train	Train	Train	Train
Fold 6	Train	Train	Train	Train	Test	Train	Train	Train	Train	Train
Fold 7	Train	Train	Train	Test	Train	Train	Train	Train	Train	Train
Fold 8	Train	Train	Test	Train	Train	Train	Train	Train	Train	Train
Fold 9	Train	Test	Train	Train	Train	Train	Train	Train	Train	Train
Fold 10	Test	Train	Train	Train	Train	Train	Train	Train	Train	Train

- Cross Validation is part of the CART algorithm
- Method to see how well the model performs to unseen data
- Typically xval parameter for cross-validation is set to 10

Concepts | Over-fitting

- If you grow the tree too long you will run the risk of over-fitting
- Classification model may not work well on unseen data



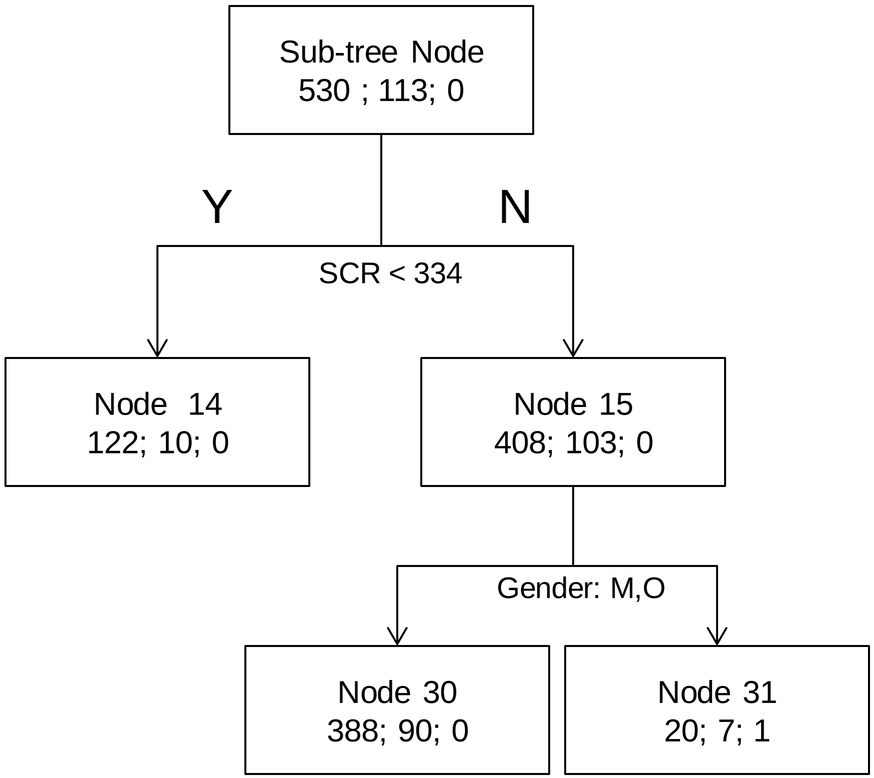
How do we avoid Over-fitting?

Stopping Rule: don't expand a node if the impurity reduction of the best split is below some threshold

Pruning: grow a very large tree and merge back nodes

Concepts | Parsimony Principle & Re-substitution Error

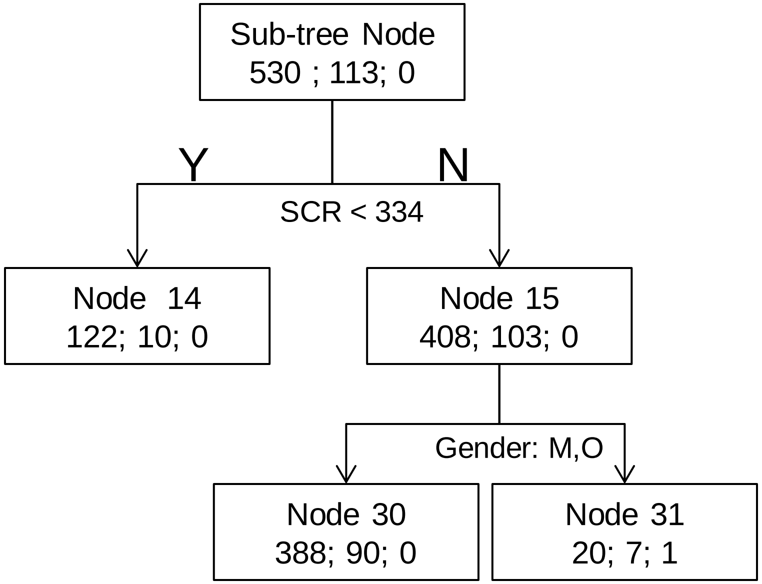
- **Parsimony principle** is basic to all science and tells us to choose the simplest scientific explanation that fits the evidence.
- **Resubstitution Error**: It measures what fraction of the cases in a node is classified incorrectly if we assign every case to the majority class in that node; It always favours large tree
- To counter balance the resubstitution error we need a penalty component that favours smaller tree



Re (prunded) = 113 / 530
Re (leaves) = 107 / 530

Cost Component Pruning

- “cost-complexity” – a measure of avg. error reduced per leaf
- Calculate number of errors for each node if collapsed to leaf
- Compare to errors in leaves, taking into account more nodes used



$$\text{Re (prunded)} + 1\,\alpha = \text{Re (leaves)} + 3\,\alpha$$

$$113 / 530 + 1\,\alpha = 107 / 530 + 3\,\alpha$$

$$\alpha = 0.0056$$

Print Optimal Pruning table based on Complexity Parameter

to find how the tree performs

printcp(m1)

plotcp(m1)

```
> printcp(m1)

Classification tree:
rpart(formula = Target ~ ., data = CT_DF.dev[, -1], method = "class",
    control = r.ctrl)

Variables actually used in tree construction:
[1] Age            AGE_BKT        Balance        Gender         Holding_Period No_OF_CR_TXNS
[7] Occupation     SCR

Root node error: 1235/14000 = 0.088214

n= 14000

          CP nsplit rel error  xerror     xstd
1 0.00607287      0   1.00000 1.00000 0.027171
2 0.00404858      7   0.95223 0.98138 0.026941
3 0.00202429      8   0.94818 0.98057 0.026931
4 0.00121457     10   0.94413 0.97895 0.026911
5 0.00016194     14   0.93927 0.99514 0.027112
6 0.00000000     24   0.93765 0.99676 0.027132
```

Pruning criteria based on cp table

	CP	nsplit	rel error	xerror	xstd
1	0.00607287	0	1.00000	1.00000	0.027171
2	0.00404858	7	0.95223	0.98138	0.026941
3	0.00202429	8	0.94818	0.98057	0.026931
4	0.00121457	10	0.94413	0.97895	0.026911
5	0.00016194	14	0.93927	0.99514	0.027112
6	0.00000000	24	0.93765	0.99676	0.027132

- xerror – Prune the tree at cp where xerror is minimum
- 1 SE Rule : Look form minimum xerror and then
- … or probably use business rule to decide the number of nodes

```
## Pruning Code
ptree<- prune(m1, cp= 0.0015,"CP")
printcp(ptree)
fancyRpartPlot(ptree, uniform=TRUE,  main="Pruned Classification Tree")
```

1 SE rule example

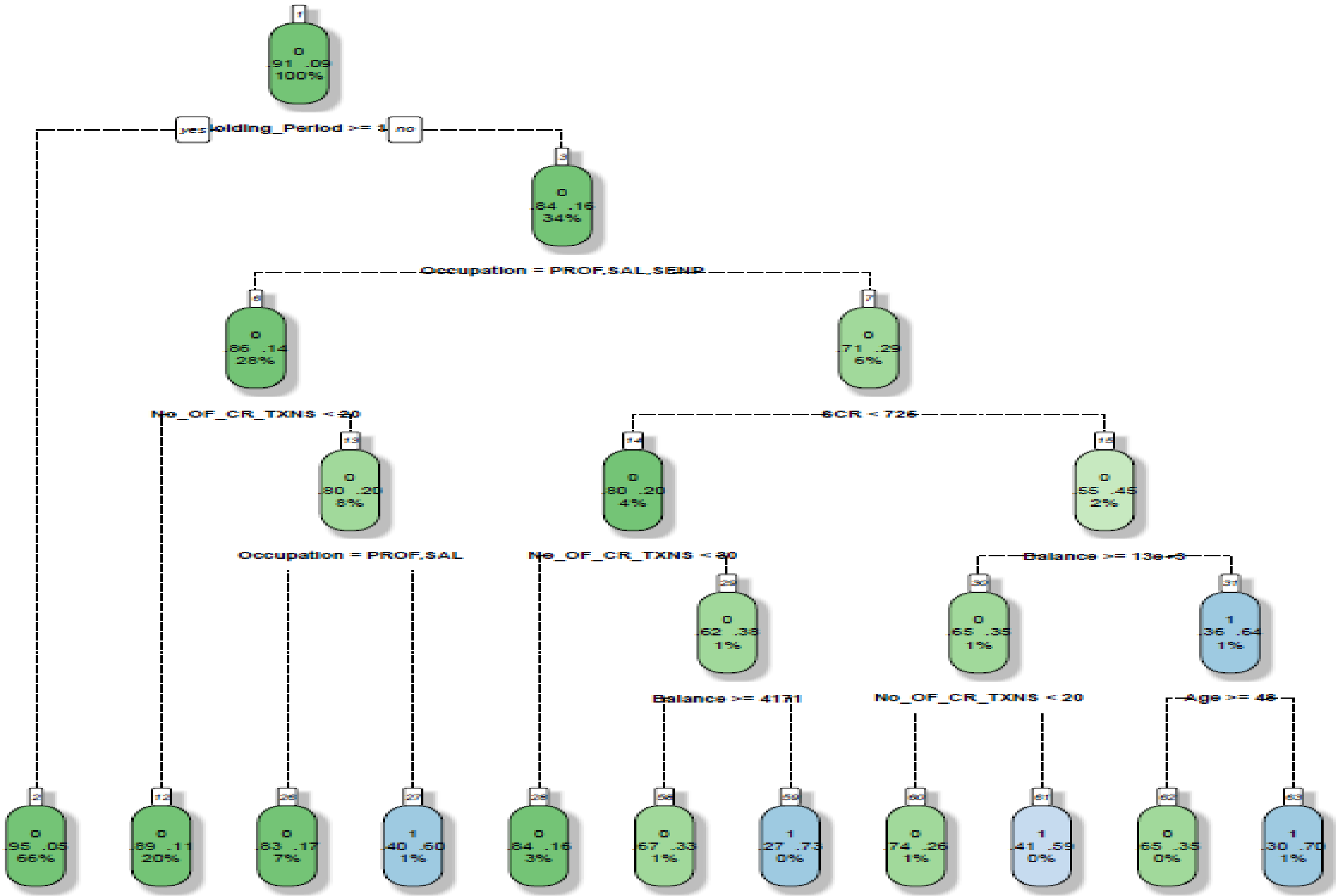
	CP	nsplit	rel error	xerror	xstd
1	0.161992664	0	1.0000000	1.0002790	0.01853630
2	0.043985638	1	0.8380073	0.8385070	0.01749290
3	0.030278222	2	0.7940217	0.7963870	0.01709283
4	0.013881619	3	0.7637435	0.7695997	0.01653832
5	0.010181164	4	0.7498619	0.7560406	0.01606136
6	0.008004043	5	0.7396807	0.7466449	0.01600352
7	0.007026176	6	0.7316767	0.7356289	0.01549501
8	0.006614587	8	0.7176243	0.7388091	0.01559568
9	0.005312278	10	0.7043951	0.7254237	0.01522645
10	0.004883811	11	0.6990828	0.7248227	0.01526605

e.g. taken for explanation purpose only

- Based on xerror criteria we will stop at row 10
- Using column xstd, that would suggest using 0.7248227 + 1*0.01526605 = 0.7400887 and thus pruning should occur at row 7

http://stats.stackexchange.com/questions/92547/r-rpart-cross-validation-and-1-se-rule-why-is-the-column-in-cptable-called-xst
https://stats.stackexchange.com/questions/13471/how-to-choose-the-number-of-splits-in-rpart

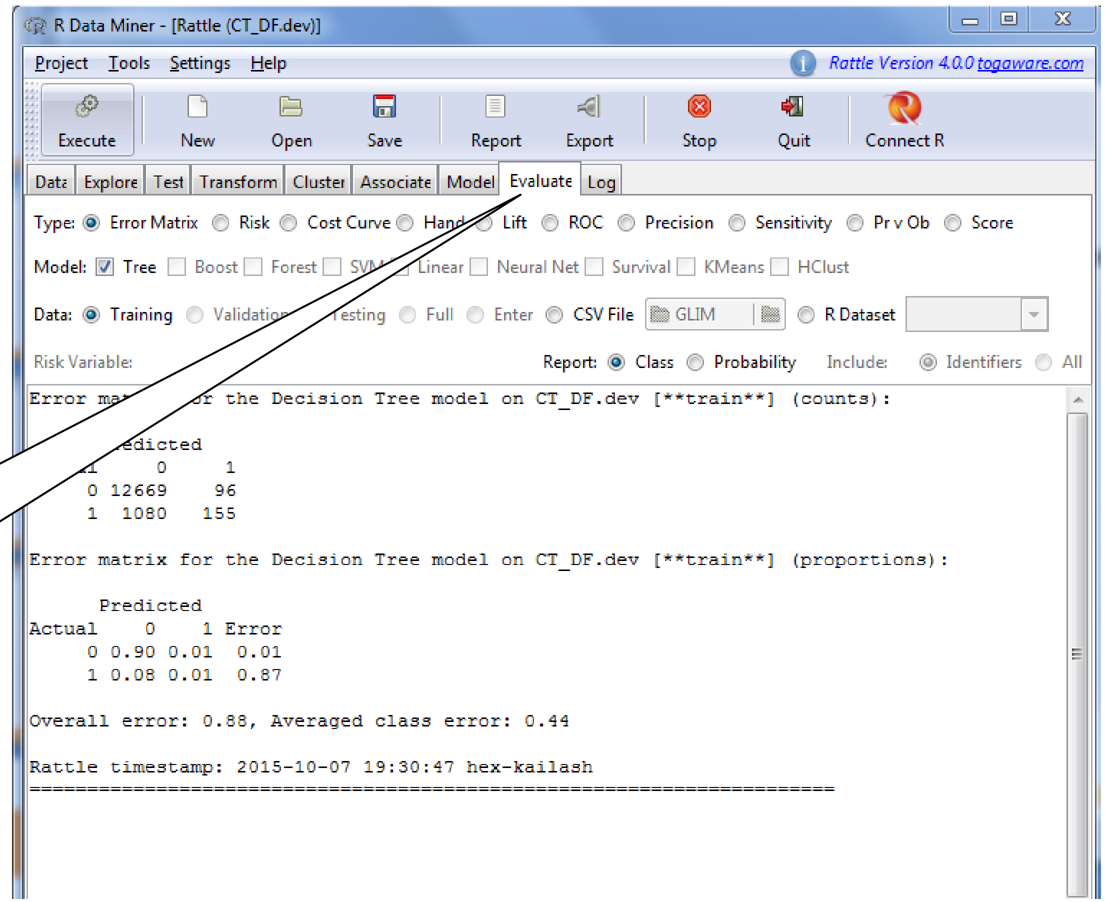
Pruned Classification Tree



Model Evaluation

Various measures to see the model performance

- Error Matrix
- Gini Coefficient
- AUC
- KS
- Lift Chart



Demo of Rattle interface to build model and generate various model evaluation measures

https://www.youtube.com/watch?v=OAl6eAyP-yo

Just in case you are interested in coding… ☺☺☺

```
## scoring step
CTDF.dev$predict.score <- predict(m1, CTDF.dev)

## deciling code
decile <- function(x){
  deciles <- vector(length=10)
  for (i in seq(0.1,1,.1)){
    deciles[i*10] <- quantile(x, i, na.rm=T)
  }
  return (
  ifelse(x<deciles[1], 1,
  ifelse(x<deciles[2], 2,
  ifelse(x<deciles[3], 3,
  ifelse(x<deciles[4], 4,
  ifelse(x<deciles[5], 5,
  ifelse(x<deciles[6], 6,
  ifelse(x<deciles[7], 7,
  ifelse(x<deciles[8], 8,
  ifelse(x<deciles[9], 9, 10
  ))))))))))
}

## deciling
CTDF.dev$deciles <- decile(CTDF.dev$predict.score[,2])
```

Some coding continued… ☺☺☺

```
## Ranking code
library(data.table)
tmp_DT = data.table(CTDF.dev)
rank <- tmp_DT[, list(
  cnt = length(Target),
  cnt_resp = sum(Target),
  cnt_non_resp = sum(Target == 0)) ,
  by=deciles][order(deciles)]
rank$rrate <- rank$cnt_resp * 100 / rank$cnt;
rank$cum_resp <- cumsum(rank$cnt_resp)
rank$cum_non_resp <- cumsum(rank$cnt_non_resp)
rank$cum_rel_resp <- rank$cum_resp / sum(rank$cnt_resp);
rank$cum_rel_non_resp <- rank$cum_non_resp /
sum(rank$cnt_non_resp);
rank$ks <- abs(rank$cum_rel_resp -
rank$cum_rel_non_resp);
rank
```

```
## Plotting ROC Curve and AUC
library(ROCR)
pred <- prediction(CTDF.dev$predict.score[,2],
CTDF.dev$Target)
perf <- performance(pred, "tpr", "fpr")
plot(perf)
KS <- max(attr(perf, 'y.values')[[1]]-attr(perf, 'x.values')[[1]])
auc <- performance(pred,"auc");
auc <- as.numeric(auc@y.values)
```

```
## Computing Gini Index
library(ineq)
gini = ineq(CTDF.dev$predict.score[,2], type="Gini")
```

```
## Output all the values
with(CTDF.dev, table(Target, predict.class))
auc
KS
gini
```

```
> with(CTDF.dev, table(Target, predict.class))
      predict.class
Target     0     1
     0 12663   102
     1  1056   179
> auc
[1] 0.7578043
> KS
[1] 0.4009363
> gini
[1] 0.4701245
```

Mis-Class = 8.3%

Area Under Curve

Classification Matrix		Predicted	
		Y	N
Actual	Y	a	b
	N	c	d

Sensitivity = True Positive Rate

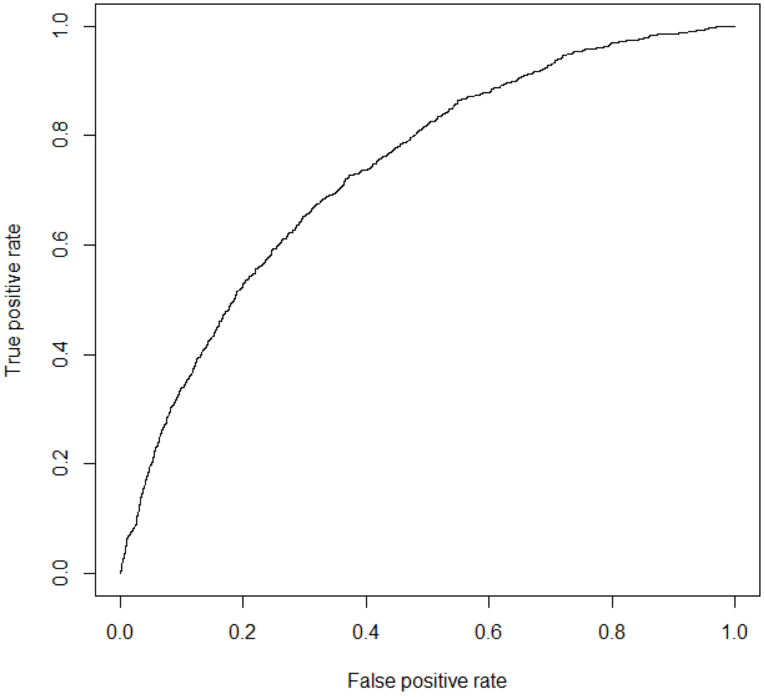
= True Positive / Total Positive

= a / (a + b)

Specificity = True Negative / Total Negative

= d / (c + d)

False Positive Rate = 1 - Specificity



Scoring

Syntax to get the node path

tree.path <- path.rpart (ptree, node = c(2, 12))

Scoring syntax

CTDF.dev$predict.class <- predict(m1, CTDF.dev, type="class")

CTDF.dev$predict.score <- predict(m1, CTDF.dev)

We can use the above syntax for scoring the Hold Out Sample also

CTDF.holdout$predict.class <- predict(m1, CTDF.holdout, type="class")

CTDF.holdout$predict.score <- predict(m1, CTDF.holdout)

Checking performance of mode on Hold Out Sample

with(CTDF.holdout, table(Target, predict.class))

What to ensure when scoring a new dataset?

The **predictor variables** which are included in the final classification model should be present in the dataset to be scored

```
> with(CTDF.holdout, table(Target, predict.class))
      predict.class
Target    0    1
     0 5454   48
     1  443   55
```

Mis-Class = 8.2%

K2 Analytics

Building Skills, Building Individuals

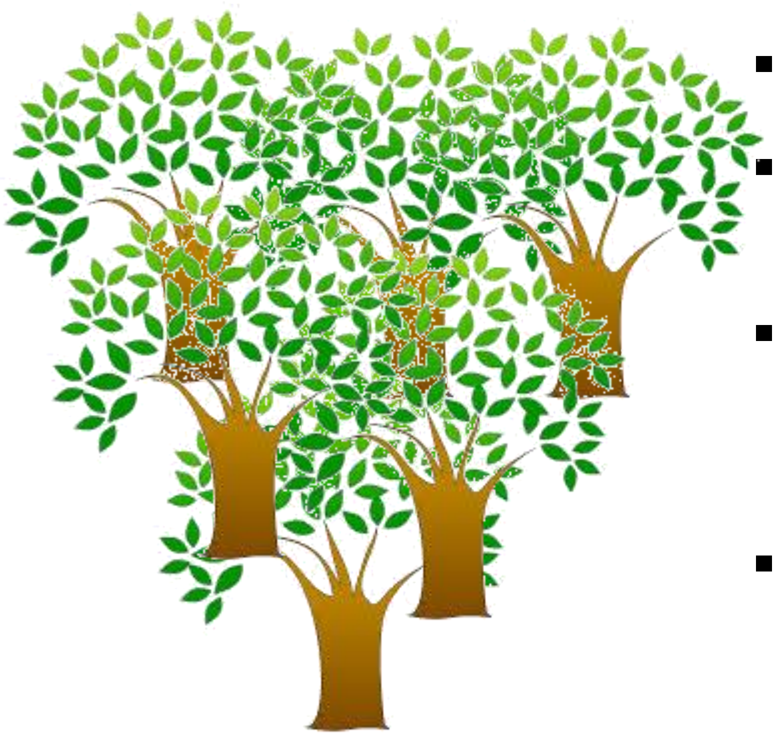
Random Forest

Some Concepts

- **Ensemble** : use of ***multiple learning algorithms*** to obtain better ***predictive performance*** than could be obtained from any of the constituent learning algorithms

- **Bootstrap aggregating**, also called **bagging:** Given a standard training set *D* of size *n*, bagging generates *m* new training sets D_i, each of size *n′*, by sampling from D uniformly with replacement. By sampling with replacement, some observations may be repeated in each D_i

Random Forest



- Ensemble Technique
- Involves constructing multitude of decision trees at training time
- Prediction is based on mode for classification tree and mean for regression tree
- Help reduce over-fitting
  – Note: there is possibility of high over-fitting at individual tree level but averaging removes the bias

RF Algorithm

- Step 1: Random Sampling with replacement

ID	A1	A2	A3	…	A(M)	Class
R1						
R2						
R3						
.						
.						
.						
Rn						

D_1

ID	A1	A2	A3	…	A(M)	Class
R10						
R3						
R15						
R4						
.						
.						

D_2

ID	A1	A2	A3	…	A(M)	Class
R1						
R1						
R100						
R500						
.						
.						

$D_{\dots}$

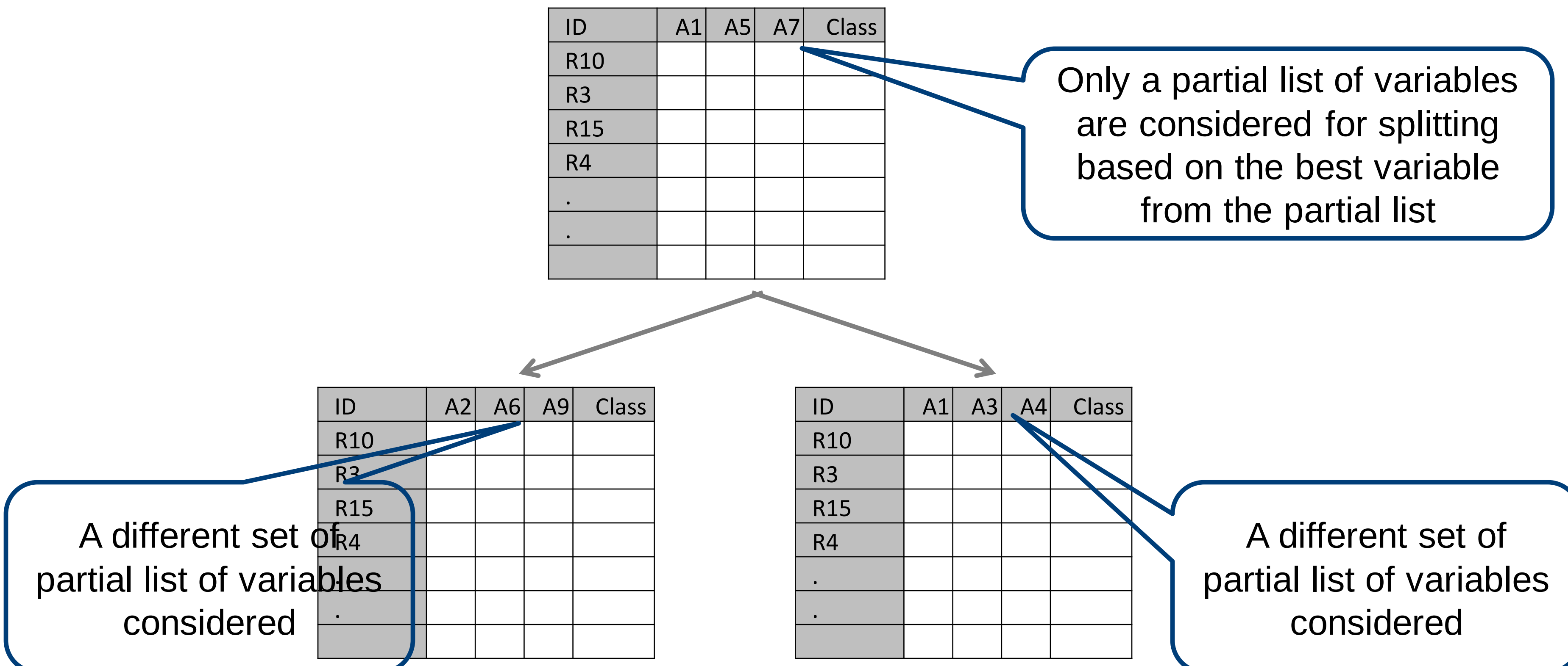
ID	A1	A2	A3	…	A(M)	Class
R1						
R1						
R100						
R500						
.						
.						

D_n

ID	A1	A2	A3	…	A(M)	Class
R1						
R1						
R100						
R500						
.						
.						

RF Algorithm… contd

- Step 2: Building the tree for each sample with only partial set of ‘m’ variable being considered at each node
- m << M where M is total number of predictor variables



RF Algorithm… contd

Step 3: Classifying

- Based on ‘n’ samples… ‘n’ tree are built
- Each records is classified based on the n tree
- Final class for each record is decided based on voting

Note: We do not have the pruning step in RF

Some original papers on RF proved that the RF error rate depends on two factors

1. The *correlation* between any two trees in the forest. Increasing the correlation increases the forest error rate.

2. The *strength* of each individual tree in the forest. A tree with a low error rate is a strong classifier. Increasing the strength of the individual trees decreases the forest error rate.

3. Reducing m reduces both the correlation and the strength. Increasing it increases both. Somewhere in between is an "optimal" range of m - usually quite wide

https://www.stat.berkeley.edu/~breiman/RandomForests/cc_home.htm

Building Random Forest in R

```
## Building the model using Random Forest

## importing the data
RFDF.dev <- read.table("datafile/DEV_SAMPLE.csv", sep = ",", header = T)
RFDF.holdout <- read.table("datafile/HOLDOUT_SAMPLE.csv", sep = ",", header = T)
c(nrow(RFDF.dev), nrow(RFDF.holdout))

##install.packages("randomForest")
library(randomForest)

## Calling syntax to build the Random Forest
RF <- randomForest(as.factor(Target) ~ ., data = RFDF.dev[,-1],
    ntree=100,            ## number of trees to be built
    mtry = 3,             ## number of variables randomly sampled as candidate at each split
    nodesize = 10,        ## minimum number of records in terminal node
    importance=TRUE )     ## should importance of predictors be assessed
print(RF)
```

OOB Estimate of error rate

```
> print(RF)

Call:
 randomForest(formula = as.factor(Target) ~ ., data = RFDF.dev[,      -1], 
ntree = 100, mtry = 3, importance = TRUE)
               Type of random forest: classification
                     Number of trees: 100
No. of variables tried at each split: 3

        OOB estimate of  error rate: 8.29%
Confusion matrix:
      0   1 class.error
0 12667  98 0.007677242
1  1063 172 0.860728745
```

RF does not need cross-validation

<u>OOB Error Rate Computation Steps</u>

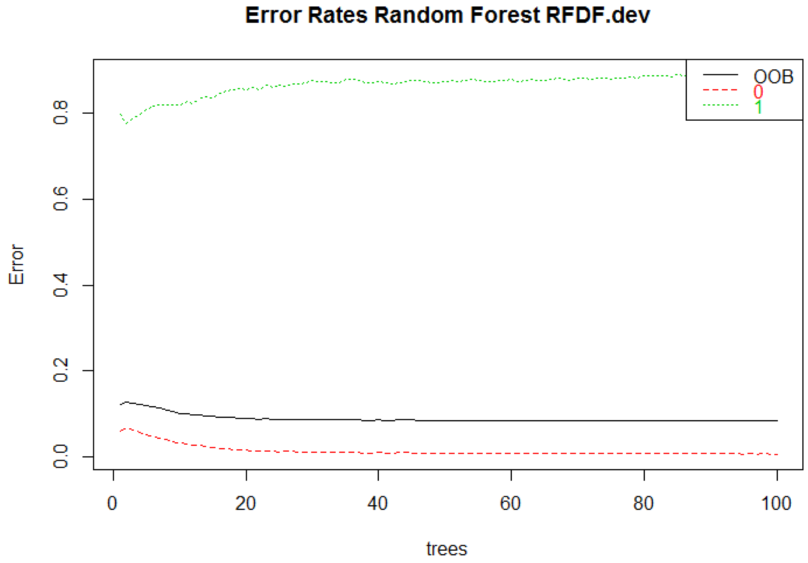
- Sample left out (out-of-bag) in K^{th} tree is classified using the K^{th} tree
- Assume j cases are mis-classified
- Proportion of time that j is not equal to true class averaged over all cases is the oob estimate of error rate

OOB Error Rate … contd

- OOB Estimate of Error Rate is dependent on two key factors
  - nTree
  - Mtry

```
plot(RF, main="")
legend("topright", c("OOB", "0", "1"), text.col=1:6, lty=1:3, col=1:3)
title(main="Error Rates Random Forest RFDF.dev")
```

Tip: One easy way to get these code scripts is to work on rattle and then copy-paste-alter the code generated in its log

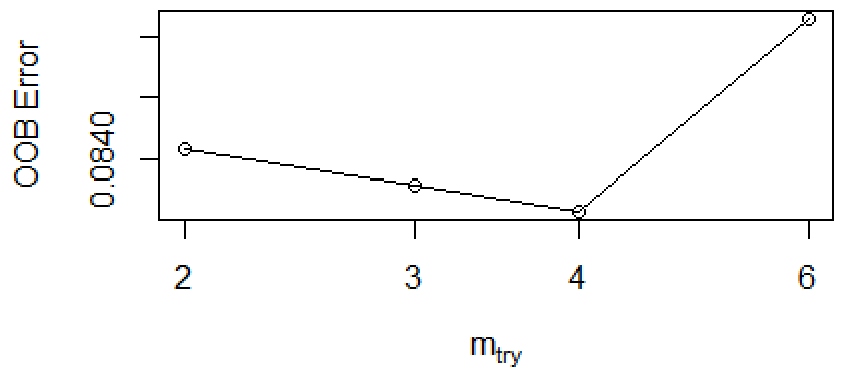


Finding optimal mtry value

```
## Tuning Random Forest
tRF <- tuneRF(x = RFDF.dev[,-c(1,2)],
              y=as.factor(RFDF.dev$Target),
              mtryStart = 3,
              ntreeTry=100,
              stepFactor = 1.5,
              improve = 0.0001,
              trace=TRUE,
              plot = TRUE,
              doBest = TRUE,
              nodesize = 10,
              importance=TRUE
              )
```

Parameter Explanation
x – predictor variables
y – Target Variable
mtryStart – starting value of mtry
ntreeTry – No of tree used for tuning
stepFactor – steps to increase (deflate) mtry
improve – the relative oob by atleast this much
trace – print the trace or not
plot – plot OOB vs mtry graph or not
doBest – Finally build the RF using optimal mtry
nodesize – min terminal node size
importance – compute variable importance or not

```
mtry = 3  OOB error = 8.38%
Searching left ...
mtry = 2        OOB error = 8.41%
-0.00341006 0.0001
Searching right ...
mtry = 4        OOB error = 8.36%
0.002557545 0.0001
mtry = 6        OOB error = 8.51%
-0.01880342 0.0001
```



Measuring RF Model performance

Syntax remains same as for the earlier model

```
## Scoring syntax
RFDF.dev$predict.class <- predict(tRF, RFDF.dev, type="class")
RFDF.dev$predict.score <- predict(tRF, RFDF.dev, type=“prob")

## deciling
RFDF.dev$deciles <- decile(RFDF.dev$predict.score[,2])

## Ranking code
library(data.table)
tmp_DT = data.table(RFDF.dev)
rank <- tmp_DT[, list(
  cnt = length(Target),
  cnt_resp = sum(Target),
  cnt_non_resp = sum(Target == 0)) ,
  by=deciles][order(deciles)]
rank$rrate <- rank$cnt_resp * 100 / rank$cnt;
rank$cum_resp <- cumsum(rank$cnt_resp)
rank$cum_non_resp <- cumsum(rank$cnt_non_resp)
rank$cum_rel_resp <- rank$cum_resp / sum(rank$cnt_resp);
rank$cum_rel_non_resp <- rank$cum_non_resp /
sum(rank$cnt_non_resp);
rank$ks <- abs(rank$cum_rel_resp - rank$cum_rel_non_resp);
rank
```

…contd

```
## AUC Computation
library(ROCR)
pred <- prediction(RFDF.dev$predict.score[,2],
RFDF.dev$Target)
perf <- performance(pred, "tpr", "fpr")
plot(perf)
KS <- max(attr(perf, 'y.values')[[1]]-attr(perf, 'x.values')[[1]])
auc <- performance(pred,"auc");
auc <- as.numeric(auc@y.values)

## Gini Compuation
library(ineq)
gini = ineq(RFDF.dev$predict.score[,2], type="Gini")

## Printing the model performance statistics
with(RFDF.dev, table(Target, predict.class))
auc
KS
gini
```

Compare RF Model Performance with CART Model

```
> with(RFDF.dev, table(Target, predict.class))
      predict.class
Target     0     1
     0 12758     7
     1   797   438
> auc
[1] 0.9949836
> KS
[1] 0.9571465
> gini
[1] 0.7276404
```

Mis-Class = 5.7%

Hold Out Sample Testing

Scoring syntax

RFDF.holdout$predict.class <- predict(tRF, RFDF.holdout, type="class")

RFDF.holdout$predict.score <- predict(tRF, RFDF.holdout, type="prob")

with(RFDF.holdout, table(Target, predict.class))

```
> with(RFDF.holdout, table(Target, predict.class))
      predict.class
Target    0    1
     0 5474   28
     1  437   61
```

Mis-Class = 7.8%

Comparing Mis-Classification Rate of Dev & Hold Out we can say that there is Over-Fitting… however, this mis-classification would have been low if we would have many predictor variables

Why I like RF technique?

- … very good technique to pacify Business Users

Variable Category	Variable Name	Variable Description	Variable Name	Variable Description
TxnMode	no_of_csh_dep_txns_in_mth_	Number of cash deposit transactions	tot_csh_dep_amt_in_mth_	Total cash deposit amount
	no_of_l_u_non_csh_cr_txns_in_mth_	Number of all user inititated non-cash credit (deposit) transactions	tot_u_non_csh_cr_amt_in_mth_	Total cheque deposit amount
	no_of_chq_cr_txns_in_mth_	Number of cheque deposit transactions	tot_chq_cr_amt_in_mth_	Total user inititated non-cash credit (deposit) amount
	no_of_csh_wdl_txns_in_mth_	Number of cash withdrawal transactions	tot_csh_wdl_amt_in_mth_	Total cash withdrawal amount
	no_of_l_u_non_csh_dr_txns_in_mth_	Number of all user inititated non-cash debit transactions	tot_u_non_csh_dr_amt_in_mth_	Total cheque issued amount
	no_of_chq_dr_txns_in_mth_	Number of cheque issued transactions	tot_chq_dr_amt_in_mth_	Total user inititated non-cash debit amount
Cr Dr	no_of_l_cr_txns_in_mth_	Number of all credit transactions in month	tot_cr_amt_in_mth_	Total Credit Amount in month
	no_of_l_dr_txns_in_mth_	Number of all debit transactions in month	to_dr_amt_in_mth_	Total Debit Amount in month
	no_of_l_u_cr_txns_in_mth_	Number of all user initiated credit transactions	tot_l_u_cr_amt_in_mth_	Total user initiated credit deposit
	no_of_l_u_dr_txns_in_mth_	Number of all user initiated debit transactions		Total user initiated debit amount
Channel	no_of_atm_csh_wdl_txns_in_mth_	Number of ATM cash withdrawal transactions		
	no_of_atm_csh_dep_txns_in_mth_	Number of ATM cash deposit transactions		
	no_of_br_csh_wdl_txns_in_mth_	Number of Branch cash withdrawal transactio		
	no_of_br_csh_dep_txns_in_mth_	Number of Branch cash deposit transactio		
	no_of_atm_chq_dep_txns_in_mth_	Number of ATM cheque deposit transa		
	no_of_atm_cr_txns_in_mth_	Number of deposits (Cash or cheq		
	no_of_br_cr_txns_in_mth_	Number of credit transaction d		
	no_of_net_cr_txns_in_mth_	Number of credits received		
	no_of_net_dr_txns_in_mth_	Number of transfers do		
	no_of_br_dr_txns_in_mth_	Number of debit tr		
	no_of_mb_txns_in_mth_	Number of Mob		
	no_of_pb_txns_in_mth_	Number of P		
	no_of_si_txns_in_mth_	Number		
	no_of_pos_txns_in_mth_	Num		
Purpose (Reml Charges)	no_of_aqb_chq_txns_in_mth_			
	no_of_iw_chq_bno_txns_in_mth_			
	no_of_ow_chq_bno_txns_in_mth_			

- Typically you will have 300 – 500 variables for modeling
- With techniques like Logistic Regression you will be forced to drop variables because of multi-collinarity
- Business users will have their own hypothesis and would want collinear variables to be part of the model
- Ensemble techniques like RF helps you build models by considering multitude of predictor variable permutations

Challenges

- **You do not get a Equation**
- **Somewhat of Black Box and hence not used in some industries like Banks for Risk Modeling**

K2 Analytics
Building Skills, Building Individuals

Classification Technique

C4.5

C4.5 | Splitting Criteria

- C4.5 makes use of Entropy and Information Gain as splitting criteria
- Entropy of a Node

$$Entropy(t) = -\sum_j p(j \mid t) \log p(j \mid t)$$

(NOTE: $p(j \mid t)$ is the relative frequency of class j at node t).

- Entropy of Split Node is computed as Weighted Avg Entropy of each Node at Split Node level
- Gain also called **Information Gain** is Difference of Entropy Parent Node and Entropy Split Node

$$GAIN_{split} = Entropy(p) - \left(\sum_{i=1}^{k} \frac{n_i}{n} Entropy(i) \right)$$

n_i = number of records at child i,
n = Total number of records in parent node p

www.cs.kent.edu/~jin/DM07/**ClassificationDecisionTree**.ppt

Information Gain Ratio

- Information Gain tends to prefer large number of partitions, each being small and pure

- Gain Ratio: Adjustment to Information Gain; Penalizes more splits

$$GainRATIO_{split} = \frac{GAIN_{Split}}{SplitINFO}$$

$$SplitINFO = -\sum_{i=1}^{k} \frac{n_i}{n} \log \frac{n_i}{n}$$

Parent Node, p is split into k partitions
n_i is the number of records in partition i

R Code

```
m1 <- rpart(formula = Target ~ .,
        data = CTDF.dev[,-1],
        method = "class",
        control = r.ctrl
        parms = list(split = "information")
        )
```

C5.0 an extension of C4.5

Exercise: Self-Study the usage of C5.0 Algorithm and Package usage

```
## C50
##install.packages("C50")
library(C50)
C50DF.dev <- read.table("datafile/DEV_SAMPLE.csv", sep = ",", header = T)
C50model <- C5.0(x = C50DF.dev[,-c(1,2)],
                 y=as.factor(C50DF.dev$Target))
summary(C50model)
plot(C50model)

predict.class <- predict(C50model, C50DF.dev, type="class")
table(C50DF.dev$Target, predict.class)
```

Questions??   … Thankyou

Contact Us

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