Data Analytics and Business Intelligence (8696/8697)

Ensemble Decision Trees

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Overview

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Building Multiple Models

- General idea developed in Multiple Inductive Learning algorithm (Williams 1987).
- Ideas were developed (ACJ 1987, PhD 1990) in the context of:
  - observe that variable selection methods don't discriminate;
  - so build multiple decision trees;
  - then combine into a single model.
- Basic idea is that multiple models, like multiple experts, may produce better results when working together, rather than in isolation
- Two approaches covered: **Boosting** and **Random Forests**.
- Meta learners.

Overview

Boosting Algorithms

Basic idea: boost observations that are "hard to model."

Algorithm: iteratively build weak models using a poor learner:

- Build an initial model;
- Identify mis-classified cases in the training dataset;
- Boost (over-represent) training observations modelled incorrectly;
- Build a new model on the boosted training dataset;
- Repeat.

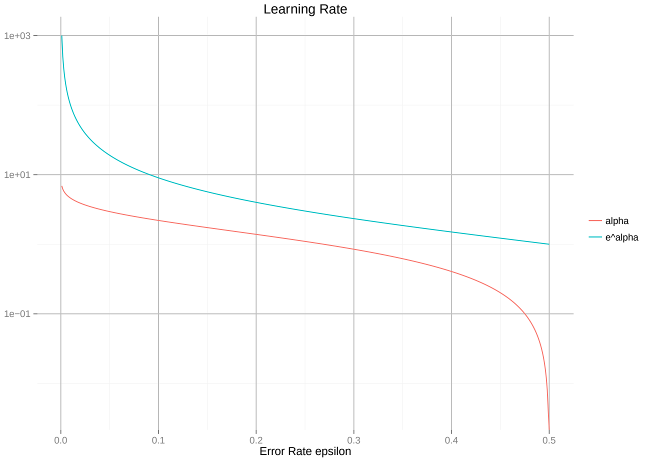
The result is an ensemble of weighted models.

Best off the shelf model builder. (Leo Brieman)

Algorithm in Pseudo Code

```
adaBoost <- function(form, data, learner)
{
  w <- rep(1/nrows(data), nrows(data))
  e <- NULL
  a <- NULL
  m <- list()
  i <- 0
  repeat
  {
    i <- i + 1
    m <- c(m, learner(form, data, w))
    ms <- which(predict(m[i], data) != data[target(form)])
    e <- c(e, sum(w[ms])/sum(w))
    a <- c(a, log((1-e[i])/e[i]))
    w[ms] <- w[ms] * exp(a[i])
    if (e[i] >= 0.5) break
  }
  return(sum(a * sapply(m, predict, data)))
}
```

Distributions



Example: First Iteration

```
n <- 10
w <- rep(1/n, n)           # 0.1 0.1 ...
ms <- c(7, 8, 9, 10)
e <- sum(w[ms])/sum(w)     # 0.4
a <- log((1-e)/e)          # 0.4055
w[ms] <- w[ms] * exp(a)    # 0.15 0.15 0.15 0.15
```

Example: Second Iteration

```
ms <- c(1, 8)                 # 0.10 0.15
w[ms]

## [1] 0.10 0.15

e <- sum(w[ms])/sum(w)        # 0.2083
a <- log((1-e)/e)             # 1.335
(w[ms] <- w[ms] * exp(a))

## [1] 0.38 0.57
```

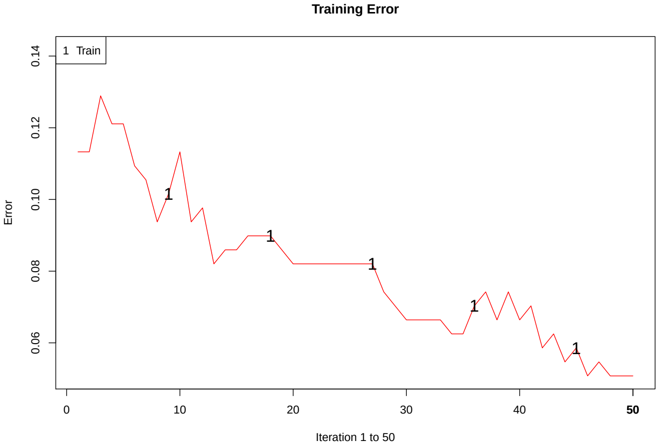
Example: Ada on Weather Data

```
head(weather[c(1:5, 23, 24)], 3)

##         Date Location MinTemp MaxTemp Rainfall RISK_MM...
## 1 2007-11-01 Canberra     8.0    24.3      0.0     3.6...
## 2 2007-11-02 Canberra    14.0    26.9      3.6     3.6...
## 3 2007-11-03 Canberra    13.7    23.4      3.6    39.8...
....

set.seed(42)
train <- sample(1:nrow(weather), 0.7 * nrow(weather))
(m <- ada(RainTomorrow ~ ., weather[train, -c(1:2, 23)]))

## Call:
## ada(RainTomorrow ~ ., data=weather[train, -c(1:2, 23)])
##
## Loss: exponential Method: discrete   Iteration: 50
....
```

Example: Error Rate

Notice error rate decreases quickly then flattens.

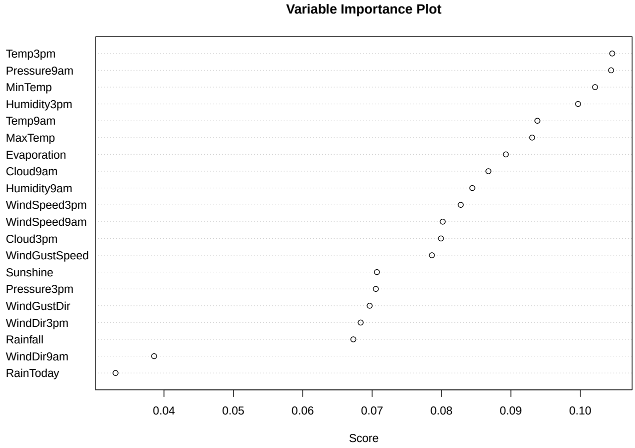
```
plot(m)
```



Example: Variable Importance

Helps understand the *knowledge* captured.

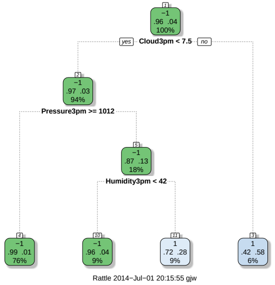
```
varplot(m)
```

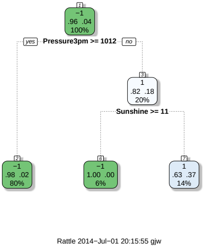


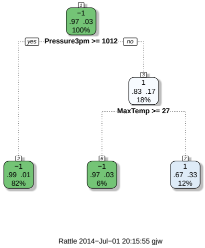
Example: Sample Trees

There are 50 trees in all. Here's the first 3.

```
fancyRpartPlot(m$model$trees[[1]])
fancyRpartPlot(m$model$trees[[2]])
fancyRpartPlot(m$model$trees[[3]])
```

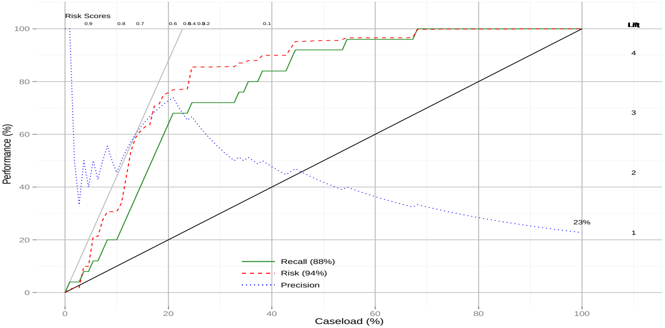






Example: Performance

```
predicted <- predict(m, weather[-train,], type="prob")[,2]
actual <-  weather[-train,]$RainTomorrow
risks <- weather[-train,]$RISK_MM
riskchart(predicted, actual, risks)
```



Example Applications

- ATO Application: What life events affect compliance?
  - First application of the technology — 1995
  - Decision Stumps: Age > NN; Change in Marital Status

- Boosted Neural Networks
  - OCR using neural networks as base learners
  - Drucker, Schapire, Simard, 1993

Summary

1. Boosting is implemented in R in the `ada` library
2. AdaBoost uses e^{-m}; LogitBoost uses $log(1 + e^{-m})$; Doom II uses $1 - tanh(m)$
3. AdaBoost tends to be sensitive to noise (addressed by BrownBoost)
4. AdaBoost tends not to overfit, and as new models are added, generalisation error tends to improve.
5. Can be proved to converge to a perfect model if the learners are always better than chance.

Overview

Random Forests

- Original idea from Leo Brieman and Adele Cutler.
- The name is Licensed to Salford Systems!
- Hence, R package is randomForest.
- Typically presented in context of decision trees.
- Random Multinomial Logit uses multiple multinomial logit models.

Random Forests

- Build many decision trees (e.g., 500).
- For each tree:
  - Select a random subset of the training set (N);
  - Choose different subsets of variables for each node of the decision tree ($m << M$);
  - Build the tree without pruning (i.e., overfit)
- Classify a new entity using every decision tree:
  - Each tree "votes" for the entity.
  - The decision with the largest number of votes wins!
  - The proportion of votes is the resulting score.

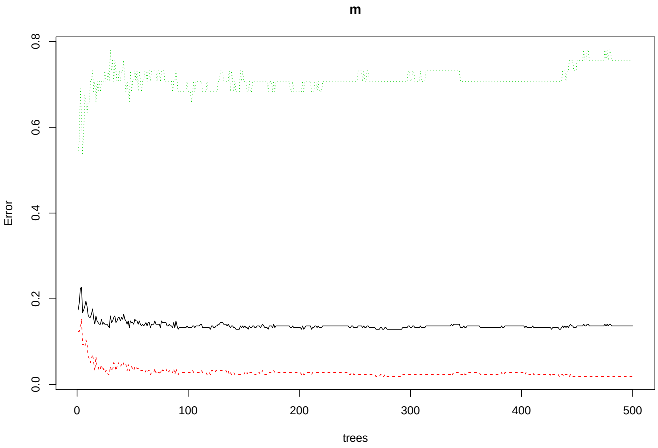
Example: RF on Weather Data

```
set.seed(42)
(m <- randomForest(RainTomorrow ~ ., weather[train, -c(1:2, 23)],
                   na.action=na.roughfix,
                   importance=TRUE))

##
## Call:
##  randomForest(formula=RainTomorrow ~ ., data=weath...
##               Type of random forest: classification
##                     Number of trees: 500
## No. of variables tried at each split: 4
##
##         OOB estimate of  error rate: 13.67%
## Confusion matrix:
##      No Yes class.error
## No  211   4      0.0186
## Yes  31  10      0.7561
```


Example: Error Rate

Error rate decreases quickly then flattens over the 500 trees.

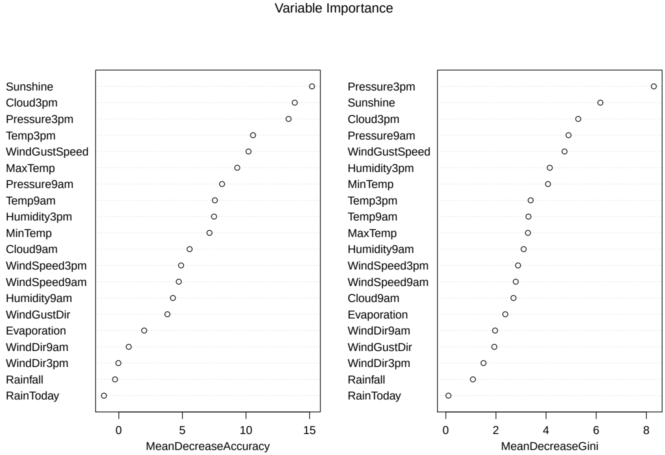
```
plot(m)
```



Example: Variable Importance

Helps understand the *knowledge* captured.

```
varImpPlot(m, main="Variable Importance")
```



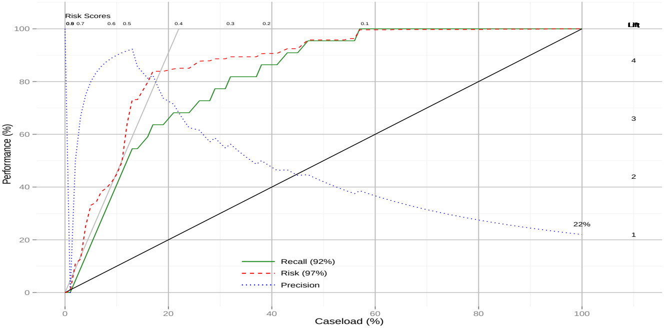
Example: Sample Trees

There are 500 trees in all. Here's some rules from the first tree.

```
## Random Forest Model 1
##
## -------------------------------------------------------...
## Tree 1 Rule 1 Node 30 Decision No
##
## 1: Evaporation <= 9
## 2: Humidity3pm <= 71
## 3: Cloud3pm <= 2.5
## 4: WindDir9am IN ("NNE")
## 5: Sunshine <= 10.25
## 6: Temp3pm <= 17.55
## -------------------------------------------------------...
## Tree 1 Rule 2 Node 31 Decision Yes
##
## 1: Evaporation <= 9
## 2: Humidity3pm <= 71
....
```

Example: Performance

```
predicted <- predict(m, weather[-train,], type="prob")[,2]
actual <-  weather[-train,]$RainTomorrow
risks <- weather[-train,]$RISK_MM
riskchart(predicted, actual, risks)
```



Features of Random Forests: By Brieman

- Most accurate of current algorithms.
- Runs efficiently on large data sets.
- Can handle thousands of input variables.
- Gives estimates of variable importance.

Overview

Other Ensembles

- Netflix
  - Movie rental business - 100M customer movie ratings
  - $1M for 10% improved root mean square error
  - First annual award (Dec '07) to KorBell (AT&T) 8.43% $50K
  - Aggregate of the best other models!
  - Linear combination of 107 other models
  - `http://stat-computing.org/newsletter/v182.pdf`
- A lot of the different model builders deliver similar performance.
- So why not build one of each model and combine!
- In Rattle: Generate a Score file from all the models, and reload that into Rattle to explore.

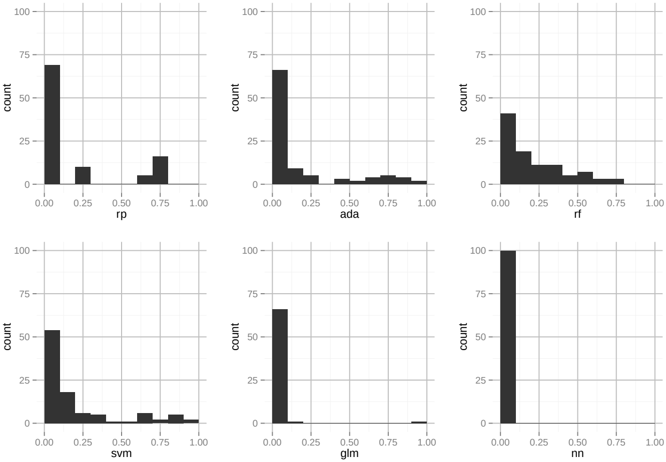
Build a Model of Each Type

```
ds <- weather[train, -c(1:2, 23)]
form <- RainTomorrow ~ .
m.rp  <- rpart(form, data=ds)
m.ada <- ada(form, data=ds)
m.rf  <- randomForest(form, data=ds, na.action=na.roughfix,
                      importance=TRUE)
m.svm <- ksvm(form, data=ds, kernel="rbfdot", prob.model=TRUE)
m.glm <- glm(form, data=ds, family=binomial(link="logit"))
m.nn  <- nnet(form, data=ds, size=10, skip=TRUE,
              MaxNWts=10000, trace=FALSE, maxit=100)
```

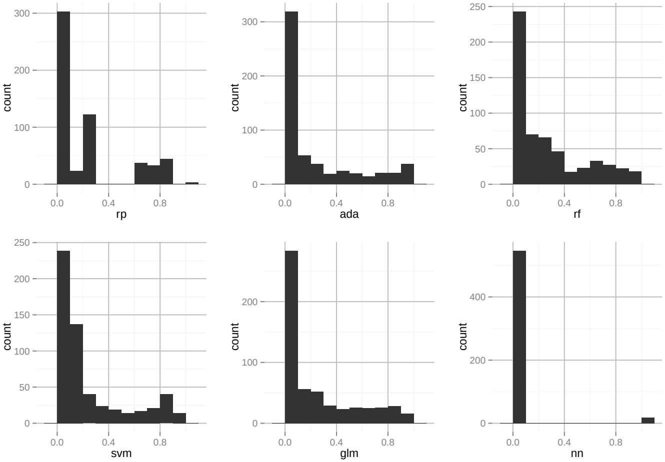
Calculate Probabilities

```
ds <- weather[-train, -c(1:2, 23)]
ds <- na.omit(ds, "na.action")
pr <- data.frame(
        obs=row.names(ds),
        rp=predict(m.rp, ds)[,2],
        ada=predict(m.ada, ds, type="prob")[,2],
        rf=predict(m.rf, ds, type="prob")[,2],
        svm=predict(m.svm, ds, type="probabilities")[,2],
        glm=predict(m.glm, type="response", ds),
        nn=predict(m.nn, ds))
prw <- pr
```


Plots—Weather Dataset

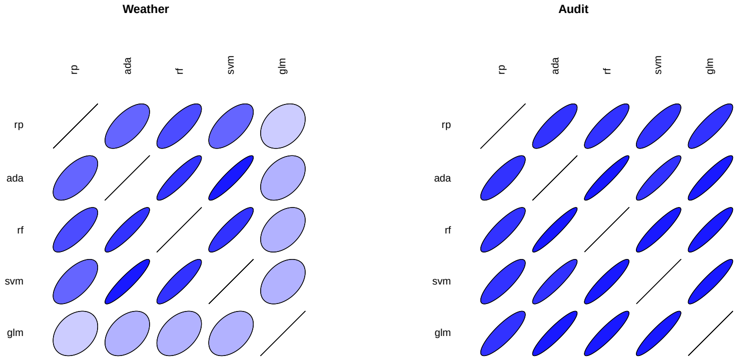


Plots—Audit Dataset



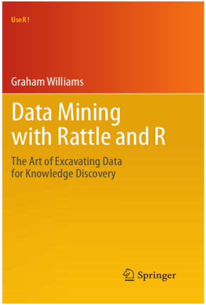
Correlation of Scores

The correlations between scores obtained by the different models suggest quite an overlap in their abilities to extract the same knowledge.



Overview

Reference Book



Data Mining with Rattle and R
Graham Williams
2011, Springer, Use R!
ISBN: 978-1-4419-9889-7.
Chapters 12 and 13.

Summary

- Ensemble: Multiple models working together
- Often better than a single model
- Variance and bias of the model are reduced
- The best available models today - accurate and robust
- In daily use in very many areas of application

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