# 模型预测的利器 — 随机森林

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# Introduction

## Definition

Random Forests grows many classification trees. To classify a new object from an input vector, put the input vector down each of the trees in the forest. Each tree gives a classification, and we say the tree "votes" for that class. The forest chooses the classification having the most votes (over all the trees in the forest)[Brieman 2001]

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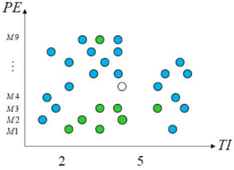
- the most successful general-purpose and good-performance algorithm in modern times
- are used not only for prediction ,but also to assess variable importance,outlier detection,clustering data etc.
- can handle "small n large p" -problem,high-order interactions,correlated predictor variable

# Decision Tree

binary-class with two predictor

| TI | PE | Response |
|---|---|---|
| 1.0 | M2 | good |
| 2.0 | M1 | bad |
| ... | ... | ... |
| 4.5 | M5 | ? |



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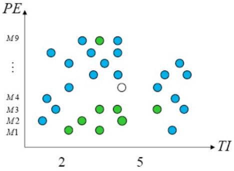
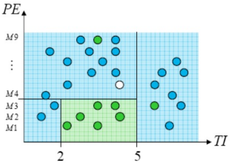
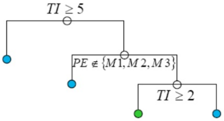



A simpler recursive partitioning tree



# Tree-Based Models

- Classification and regression trees (CART) can be generated through the rpart package.tend to select variables that have many possible splits or many missing values
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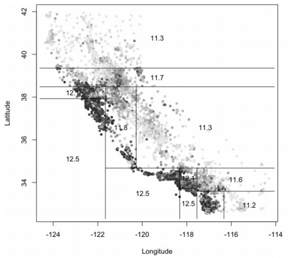
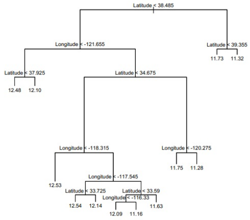
- other trees. such as oblique tree,rotation tree etc.

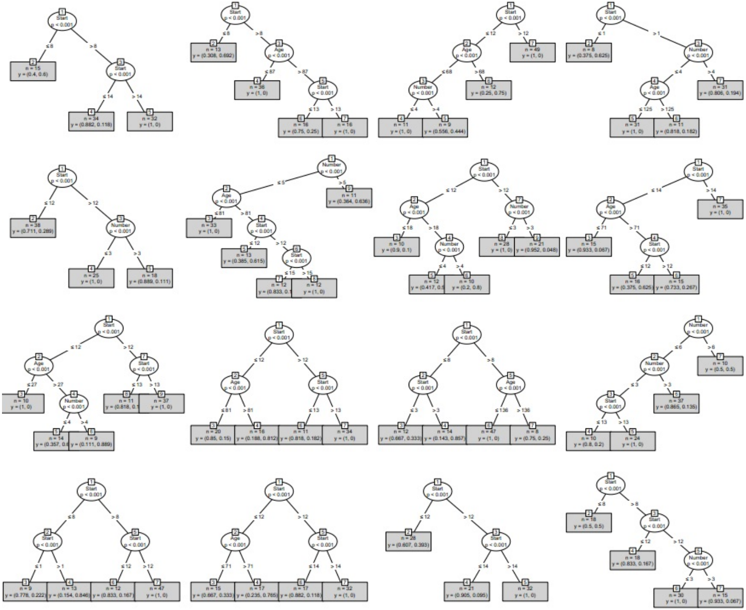
# A single tree can work?

- High variance.depend vary strongly on the particular learning sample used
- quite large and complex
- solution:pruning the tree with cross-validate



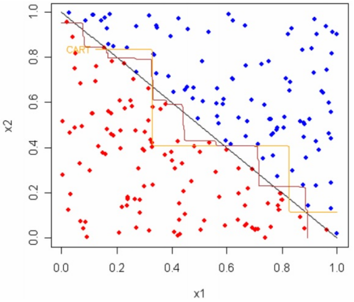


# what about a number of trees together?



# First idea — randomization with Bagging(Bagging Tree)

- create new training sets by random sampling with replacement
- reduce variance



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- Bagging is a special case for randomforest when $m_{try} = K$ . $m_{try} = \sqrt{k}$ for classification and $m_{try} = \frac{k}{3}$ for regression . Empirically ,stronger than Bagging tree,especially K is small.

# Third idea — Extremely randomized tree

- higher randomization levels can improve the accuracy with respect to existing ensemble methods.
  each tree is built from the complete learning sample (no bootstrap copying).
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  each tree is built from the complete learning sample (no bootstrap copying).
  randomly selected at each interior node(cut-point is selected at random to define a split).
- $m_{try} = \sqrt{k}$ for classification and $m_{try} = k$ for regression
  $n_{min}$ the number of samples required for splitting a node.Larger $n_{min}$ lead to smaller trees,higher bias and smaller variance
  $M$ denote the number of trees.compromise between computational requirement and accuracy.

# Random forest in R

- randomForest (pkg:randomForest)
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  unbiased conditional inference tree
- obliqueRF (pkg:obliqueRF)
  the optimal split is sought in the subspace spanned by those features

# cforest

a covariate selection scheme based on statistical theory.
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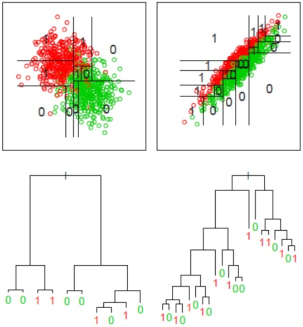
```
require(gtools)
dv <- c(1,3,4,5,5); covariate <- c(2,2,5,4,5)
# all possible permutations of dv, length(120):
perms <- permutations(5,5,dv,set=FALSE)
# now calculate correlations for all perms with covariate:
cors <- apply(perms, 1, function(perms_row) cor(perms_row,covariate))
cors <- cors[order(cors)]
# now p-value: compare cor(dv,covariate) with the
# sorted vector of all permutation correlations
length(cors[cors>=cor(dv,covariate)])/length(cors)
# result: [1] 0.1, i.e. a p-value of .1
# note that this is a one-sided test
```

# oblique Randomforest

- base learner: orthogonal split
- correlated feature values



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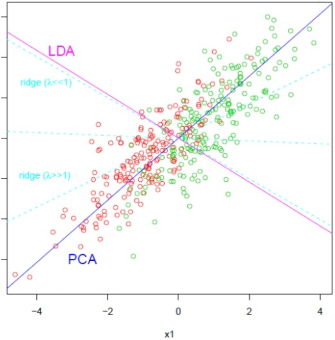


**Recursive binary splits** :

$$f_m(\mathbf{x}) : \beta_m^T \mathbf{x} > c_m$$

with coefficients $\beta_m$ and threshold $c_m$

**Coefficients** $\beta_m$ : ridge regression

$$\beta_{ridge}(\lambda) \sim \underset{\beta}{\operatorname{argmin}} \sum_{i=1}^{N} \left( y_i - \sum_{j=1}^{2} x_{ij}\beta_j \right)^2 + \lambda \sum_{j=1}^{P} |\beta_j|^2$$

$$\beta_{ridge}(\lambda') \sim \underset{||\beta=1||}{\operatorname{argmax}}\, corr^2(\beta X, Y) * \frac{var(\beta X)}{var(\beta X) + \lambda'}$$

# oblique Randomforest

oblique random forest with recursive linear model split:

- oRF outperforms RF on spectral data or nominal data especially on few samples,many irrelevant features and correlated predictors
- simpler feature importance/proximity measure

# Variable importance

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- Permutation importance: decrease in classification accuracy after permuting $X_j$ over all trees
- oRF importance:calculate ANOVA at every split
- Conditional importance: Some Variable has no effect of its own,but correlated with a relevant predictor

# Variable importance code

```
# pkg :randomForest
# type = 1 Permutation importance,2 Gini importance
obj <- randomForest(...,importance=TURE)
importance(obj,type=1)
# pkg :party
# Permutation importance
obj <- cforest(...)
varimp(obj)
# oRF importance
obj <- obluqyeRF(...,bImportance=TRUE)
importance(obj)
# pkg :party
# Conditional importance
obj <- cforest(...)
varimp(obj,conditional = TRUE)
```

# Imbalance problem

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- down-sampling the majority,over-sampling the minority
- cost-sensitive learning.place a heavier penalty on misclassifying the minority class.weights for finding splits (weighted loss function) and weights in the terminal node(weighted majority vote)

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- pkg:randomForest need to impute the missing data
  - impute with median or maximum category
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  - Impute missing values in predictor data using proximityrfImpute(x, y, iter=5, ntree=300, ...
- pkg:party can handle missing value with surrogate split
- other impute methods
  - knnimpute,multiply imputationpkg:mice
  - pkg:missForest.don't need response variable

# missForest

1. The observed values of variable $\mathbf{X}_s$, denoted by $\mathbf{y}_{obs}^{(s)}$;
2. the missing values of variable $\mathbf{X}_s$, denoted by $\mathbf{y}_{mis}^{(s)}$;
3. the variables other than $\mathbf{X}_s$ with observations $\mathbf{i}_{obs}^{(s)} = \{1, \dots, n\} \setminus \mathbf{i}_{mis}^{(s)}$ denoted by $\mathbf{x}_{obs}^{(s)}$;
4. the variables other than $\mathbf{X}_s$ with observations $\mathbf{i}_{mis}^{(s)}$ denoted by $\mathbf{x}_{mis}^{(s)}$.

**Require:** $\mathbf{X}$ an $n \times p$ matrix, stopping criterion $\gamma$

Make initial guess for missing values;
$\mathbf{k} \leftarrow$ vector of sorted indices of columns in $\mathbf{X}$ w.r.t. increasing amount of missing values;
**while** not $\gamma$ **do**
    $\mathbf{X}_{old}^{imp} \leftarrow$ store previously imputed matrix;
    **for** $s$ in $\mathbf{k}$ **do**
        Fit a random forest: $\mathbf{y}_{obs}^{(s)} \sim \mathbf{x}_{obs}^{(s)}$;
        Predict $\mathbf{y}_{mis}^{(s)}$ using $\mathbf{x}_{mis}^{(s)}$;
        $\mathbf{X}_{new}^{imp} \leftarrow$ update imputed matrix, using predicted $\mathbf{y}_{mis}^{(s)}$;
    **end for**
    update $\gamma$.
**end while**
**return** the imputed matrix $\mathbf{X}^{imp}$

Thank you!