Random Forest for Classification Problems

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Overview

Intro

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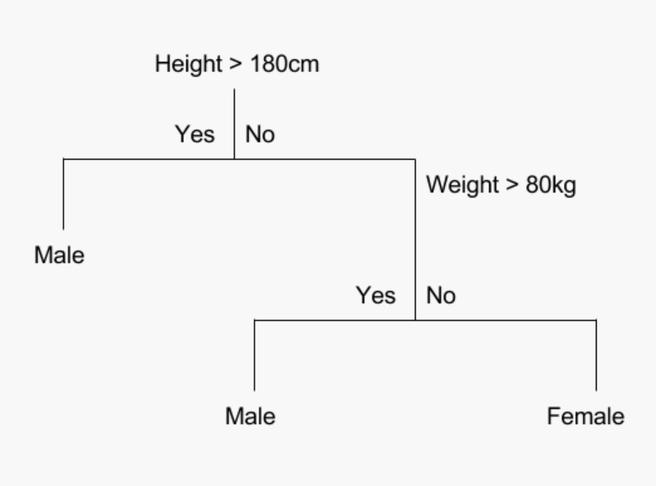
Decision Tree: Example



Decision Tree: Tree Building Process

A tree is grown starting from the root node by repeatedly using the following steps on each node (also called binary splitting):

(i) **Find best split s for each feature X_m:** For each feature X_m, there exist $K-1$-many potiential splits whereas K is the number of different values for the respective feature. Evaluate each value $X_{m,i}$ at the current node t as a candidate split point (for $x \in X_m$, if $x \leq X_{m,i} = s$, then x goes to left child node t_L else to right child node t_R). The best split point is the one that maximize the splitting criterion $\Delta i(s,t)$ the most when the node is split according to it. The different splitting criteria will be covered in the next chapter.

(ii) **Find the node's best split:** Among the best splits for each feature from Step (i) find the one s^*, which maximizes the splitting criterion $\Delta i(s,t)$.

(iii) **Satisfy stopping criterion:** Split the node t using best node split s^* from Step (ii) and repeat from Step (i) until stopping criterion is satisfied.

Decision Tree: Purity Measures

Gini Measure

$$i(t) = \sum_{c \in C} p(c|t)(1 - p(c|t)) = 1 - \sum_{c \in C} p_c^2 \tag{1}$$

Information Entropy

$$i(t) = \sum_{c \in C} p(c|t) log(p(c|t)) \tag{2}$$

Bias Variance

Heading

1. Statement
2. Explanation
3. Example

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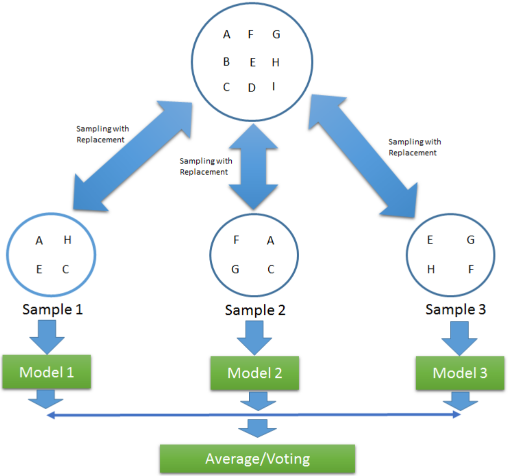
Bagging

1. created for methods with high variance
2. reduces variance and gives better predictions
3. improvement of bagging: Random Forest



Random Forest

Treatments	Response 1	Response 2
Treatment 1	0.0003262	0.562
Treatment 2	0.0015681	0.910
Treatment 3	0.0009271	0.296

Table: Table caption

Bias Variance

Example (Theorem Slide Code)

```
\begin{frame}
\frametitle{Theorem}
\begin{theorem}[Mass--energy equivalence]
$E = mc^2$
\end{theorem}
\end{frame}
```

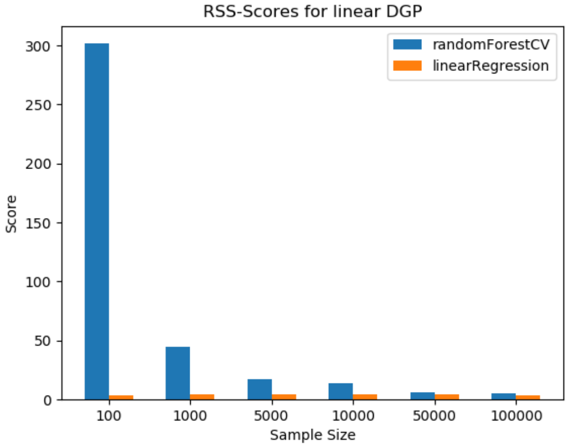
Simulation Study: Linear DGP

The linear DGP generates the data tuples (y, x_1, x_2, x_3) as follows:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \epsilon, \tag{3}$$

whereas $(\beta_0, \beta_1, \beta_2, \beta_3) = (0.3, 5, 10, 15)$, $x_1, x_2, x_3 \sim \mathcal{N}(0,\, 3)$, and $\epsilon \sim \mathcal{N}(0,\, 1)$.

Decision Tree: Linear DGP Results



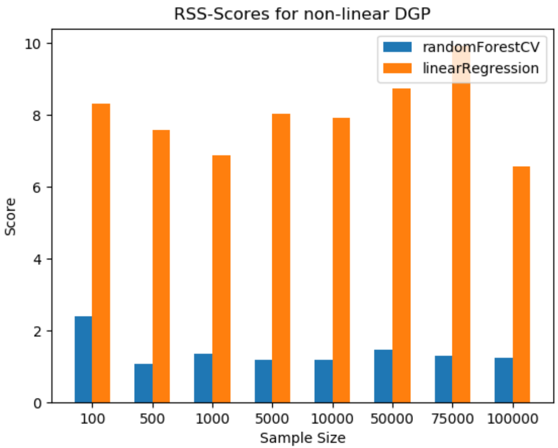
Simulation Study: Non-Linear DGP

The non-linear DGP generates the data tuples (y, x_1, x_2) as follows:

$$y = \beta_0 + \beta_1 \mathbb{1}(x_1 \geq 0, x_2 \geq 0) + \beta_2 \mathbb{1}(x_1 \geq 0, x_2 < 0) + \beta_3 \mathbb{1}(x_1 < 0) + \epsilon, \quad (4)$$

whereas $(\beta_0, \beta_1, \beta_2, \beta_3)$, x_1, x_2 and ϵ are the same as in the previous DGP.

Simulation Study: Non-Linear DGP Results



Real Data

An example of the `\cite` command to cite within the presentation:

This statement requires citation [**breiman1984classification**].

The End

References