Regression Trees

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Introduction: Tree Based Algorithms or **CARTs**

- Tree-Based models or algorithms can be applied to both regression and classification projects.
- Tree-Based models refer to many algorithms such, Regression Trees, Decision Trees, and ensemble models such as Random Forest, Bagging, and Gradient Boosting Machines (or GBMs).
- These algorithms involve **stratifying or segmenting** the predictor space into a number of regions.
- Tree-Based models: are simple to understand, easy-to-use, easy to interpret, and, when used in ensembles, the have excellent accuracy.
- They are used to make decisions, explore the data and make predictions. (Even by non-data scientists like managers)
- They do not need pre-processing, which make them a good start for beginners. And they are Flexible or non-linear models.

Terminology

- A Decision tree is a hierarchical structure with nodes and directed edges.
- **Node**: A question or prediction
- Root node: The top node at the top with no parent, it involves a question that gives two answers (children).
- leaf nodes or terminal nodes. The nodes at the bottom. The have one parent and no children. (The leaves are used for prediction)
- Internal nodes the nodes that are neither the root node or the leaf nodes. The have one **parent** and give two **children**.
- **Branch**: The segments connecting the parent with the children nodes.
- Maximum Depth: the distance between the root node (depth = 0) and the final leaf.

Diagram Showing the Terminology 01

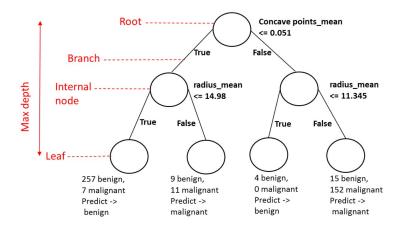
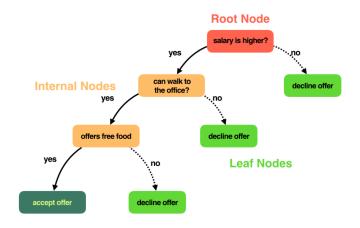


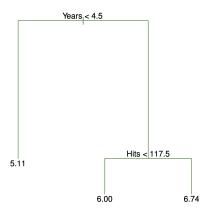
Diagram Showing the Terminology 02

Decision tree terminology: nodes



How Regression Tree Works

Baseball data, with three variables, years, Hits, to predict the Salary.



Fitting Regression Tree (Motivation Example)

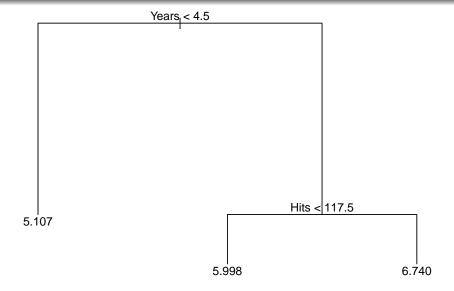
```
library(ISLR)
library(tree)
data("fitters")
str(Hitters)
```

```
## 'data frame':
                 322 obs. of 20 variables:
## $ AtBat : int 293 315 479 496 321 594 185 298 323 401 ...
## $ Hits
             : int 66 81 130 141 87 169 37 73 81 92 ...
## $ HmRun
             : int 1 7 18 20 10 4 1 0 6 17 ...
## $ Runs
              : int 30 24 66 65 39 74 23 24 26 49 ...
##
   $ RBI
             : int 29 38 72 78 42 51 8 24 32 66 ...
## $ Walks : int 14 39 76 37 30 35 21 7 8 65 ...
## $ Years : int 1 14 3 11 2 11 2 3 2 13 ...
## $ CAtBat : int 293 3449 1624 5628 396 4408 214 509 341 5206 ...
## $ CHits
            : int 66 835 457 1575 101 1133 42 108 86 1332 ...
## $ CHmRun : int 1 69 63 225 12 19 1 0 6 253 ...
## $ CRuns : int 30 321 224 828 48 501 30 41 32 784 ...
##
   $ CRBI : int 29 414 266 838 46 336 9 37 34 890 ...
## $ CWalks : int 14 375 263 354 33 194 24 12 8 866 ...
   $ League : Factor w/ 2 levels "A"."N": 1 2 1 2 2 1 2 1 2 1 ...
##
## $ Division : Factor w/ 2 levels "E","W": 1 2 2 1 1 2 1 2 2 1 ...
## $ PutOuts : int 446 632 880 200 805 282 76 121 143 0 ...
## $ Assists : int 33 43 82 11 40 421 127 283 290 0 ...
## $ Errors : int 20 10 14 3 4 25 7 9 19 0 ...
## $ Salary : num NA 475 480 500 91.5 750 70 100 75 1100 ...
##
   $ NewLeague: Factor w/ 2 levels "A"."N": 1 2 1 2 2 1 1 1 2 1 ...
```

```
## node), split, n, deviance, yval
## * denotes terminal node
## 1) root 263 207.20 5.927
## 2) Years < 4.5 90 42.35 5.107 *
## 3) Years > 4.5 173 72.71 6.354
6) Hits < 117.5 90 28.09 5.998 *
## 7) Hits > 117.5 83 20.88 6.740 *
```

summary(tree_model)

```
##
## Regression tree:
## Tree(formula = log(Salary) - Years + Hits, data = my_data, control = tree.control(nobs = nrow(my_data),
## number of terminal nodes: 3
## Residual mean deviance: 0.3513 = 91.33 / 260
## Distribution of residuals:
## Distribution of residuals:
## Min. 1st Qu. Median Mean 3rd Qu. Max.
## 2.24000 - 0.39580 - 0.03162 0.00000 0.33380 2.55600
```



Fitting Regression Tree (No control)

```
## node), split, n, deviance, yval
##
         * denotes terminal node
##
##
    1) root 263 207.200 5.927
##
      2) Years < 4.5 90 42.350 5.107
##
        4) Years < 3.5 62 23.010 4.892
         8) Hits < 114 43 17.150 4.727
##
##
          16) Hits < 40.5 5 10.400 5.511 *
##
          17) Hits > 40.5 38 3.280 4.624 *
         9) Hits > 114 19 2.069 5.264 *
##
##
        5) Years > 3.5 28 10.130 5.583 *
##
      3) Years > 4.5 173 72.710 6.354
##
        6) Hits < 117.5 90 28.090 5.998
##
        12) Years < 6.5 26 7.238 5.689 *
##
        13) Years > 6.5 64 17.350 6.124
##
           26) Hits < 50.5 12 2.689 5.730 *
##
           27) Hits > 50.5 52 12.370 6.215 *
##
       7) Hits > 117.5 83 20.880 6.740 *
```

