

Hyperparameter tuning in caret

Dr. Shirin Glander
Data Scientist



Voter dataset from US 2016 election

Split intro training and test set

```
library(tidyverse)
glimpse(voters train data)
Observations: 6,692
Variables: 42
$ turnout16 2016
                       <chr> "Did not vote", "Did not vote", "Did not vote", "Di
$ RIGGED SYSTEM 1 2016 <int> 2, 2, 3, 2, 2, 3, 3, 1, 2, 3, 4, 4, 4, 3, 1, 2, 2,
$ RIGGED SYSTEM 2 2016 <int> 3, 3, 2, 2, 3, 3, 2, 2, 1, 2, 4, 2, 3, 2, 3, 4, 3,
$ RIGGED SYSTEM 3 2016 <int> 1, 1, 3, 1, 1, 1, 2, 1, 1, 2, 1, 2, 1, 2, 1, 1, 1,
$ RIGGED SYSTEM 4 2016 <int> 2, 1, 2, 2, 2, 2, 2, 1, 3, 3, 1, 3, 3, 1, 3, 3,
 RIGGED SYSTEM 5 2016 <int> 1, 2, 2, 2, 2, 3, 1, 1, 2, 3, 2, 2, 1, 3, 1, 1, 2,
 RIGGED SYSTEM 6 2016 <int> 1, 1, 2, 1, 2, 2, 2, 1, 2, 2, 1, 3, 1, 3, 1, 1, 1,
 track 2016
                       <int> 2, 2, 2, 1, 2, 2, 2, 2, 1, 2, 1, 2, 1, 1, 2, 2,
 persfinretro 2016
                      <int> 2, 2, 2, 2, 1, 2, 2, 3, 2, 3, 2, 2, 2, 2, 3, 3,
                      <int> 2, 2, 2, 3, 1, 2, 2, 2, 3, 2, 4, 1, 1, 2, 2, 2, 3,
$ econtrend 2016
 Americatrend 2016
                      <int> 2, 3, 1, 1, 3, 3, 2, 2, 1, 2, 3, 1, 1, 2, 3, 3, 3,
 futuretrend 2016
                      <int> 3, 3, 3, 4, 4, 3, 2, 2, 3, 2, 4, 1, 1, 3, 3, 3, 3,
$ wealth 2016
                      <int> 2, 2, 1, 2, 2, 8, 2, 8, 2, 2, 2, 2, 2, 2, 1, 2, 2,
```



Let's train another model with caret

Stochastic Gradient Boosting



Let's train another model with caret



Cartesian grid search with caret

Define a Cartesian grid of hyperparameters:

```
man grid \leftarrow expand.grid(n.trees = c(100, 200, 250),
                          interaction.depth = c(1, 4, 6),
                          shrinkage = 0.1,
                          n.minobsinnode = 10)
fitControl <- trainControl (method = "repeatedcv",</pre>
                            number = 3,
                            repeats = 5)
tic()
set.seed(42)
gbm model voters grid <- train(turnout16 2016 ~ .,
                    data = voters train data,
                    method = "gbm",
                    trControl = fitControl,
                    verbose = FALSE,
                    tuneGrid = man grid)
toc()
85.745 sec elapsed
```



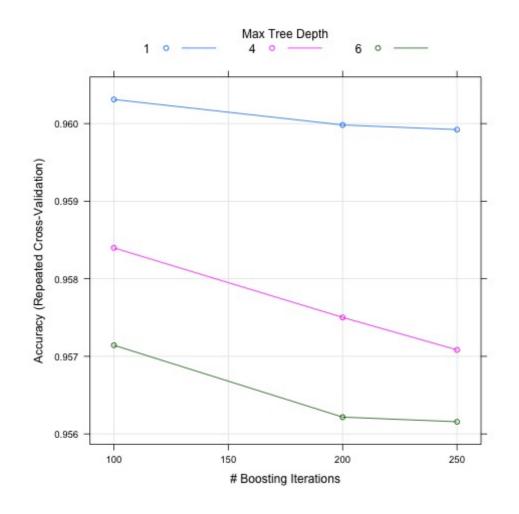
Cartesian grid search with caret

```
gbm model voters grid
Stochastic Gradient Boosting
. . .
Resampling results across tuning parameters:
  interaction.depth n.trees Accuracy Kappa
                    100
                              0.9603108 0.000912769
Tuning parameter 'shrinkage' was held constant at a value of 0.1
Tuning parameter 'n.minobsinnode' was held constant at a value of 10
Accuracy was used to select the optimal model using the largest value.
The final values used for the model were n.trees = 100,
interaction.depth = 1, shrinkage = 0.1 and n.minobsinnode = 10.
```

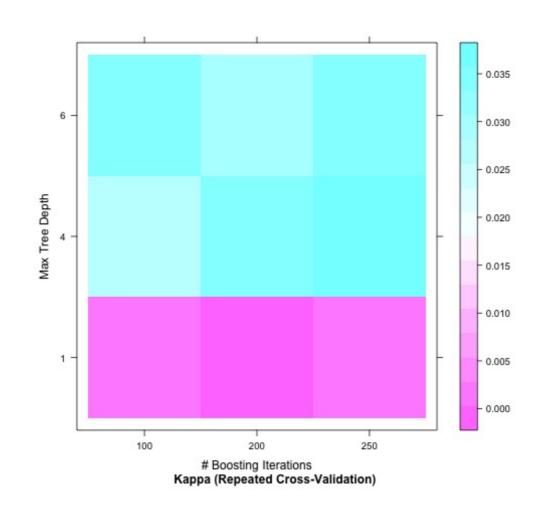


Plot hyperparameter models

```
plot(gbm_model_voters_grid)
```



```
plot(gbm_model_voters_grid,
    metric = "Kappa",
    plotType = "level")
```







Test it out for yourself!





Hyperparameter tuning with Grid vs. Random Search

Dr. Shirin Glander
Data Scientist

Grid search continued

```
man grid \leftarrow expand.grid(n.trees = c(100, 200, 250),
                          interaction.depth = c(1, 4, 6),
                          shrinkage = 0.1,
                          n.minobsinnode = 10)
fitControl <- trainControl(method = "repeatedcv",</pre>
                            number = 3,
                            repeats = 5,
                            search = "grid")
tic()
set.seed(42)
gbm model voters grid <- train(turnout16 2016 ~ .,
                    data = voters train data,
                    method = "gbm",
                    trControl = fitControl,
                    verbose= FALSE,
                    tuneGrid = man grid)
toc()
85.745 sec elapsed
```



Grid Search with hyperparameter ranges

```
big grid \leftarrow expand.grid(n.trees = seq(from = 10, to = 300, by = 50),
                           interaction.depth = seq(from = 1, to = 10,
                                                      length.out = 6),
                           shrinkage = 0.1,
                           n.minobsinnode = 10)
big grid
   n.trees interaction.depth shrinkage n.minobsinnode
        10
                           1.0
                                      0.1
        60
                           1.0
                                      0.1
                                                        10
       110
                           1.0
                                      0.1
                                                        10
       160
                           1.0
                                      0.1
                                                        10
                           1.0
                                      0.1
       210
                                                        10
       260
                           1.0
                                      0.1
                                                        10
                           2.8
       10
                                      0.1
                                                        10
        60
                           2.8
                                      0.1
                                                        10
                           2.8
       110
                                      0.1
                                                        10
10
                           2.8
       160
                                      0.1
                                                        10
11
                           2.8
       210
                                      0.1
                                                        10
12
                           2.8
       260
                                      0.1
                                                        10
13
        10
                           4.6
                                      0.1
                                                        10
. . .
36
       260
                          10.0
                                      0.1
                                                        10
```



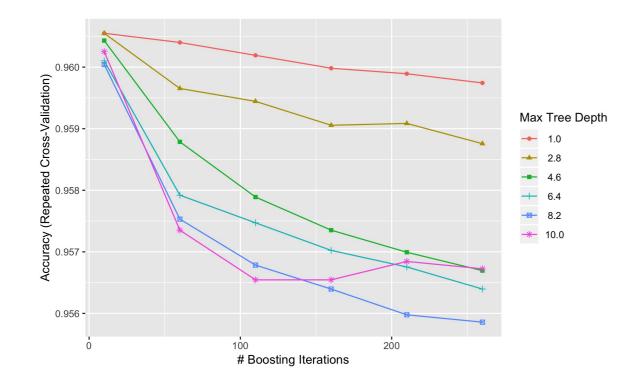
Grid Search with many hyperparameter options

```
big grid \leftarrow expand.grid(n.trees = seq(from = 10, to = 300, by = 50),
                          interaction.depth = seq(from = 1, to = 10,
                                                   length.out = 6),
                          shrinkage = 0.1,
                          n.minobsinnode = 10)
fitControl <- trainControl (method = "repeatedcv",
                            number = 3,
                            repeats = 5,
                            search = "grid")
tic()
set.seed(42)
gbm model voters big grid <- train(turnout16 2016 ~ .,
                   data = voters train data,
                   method = "gbm",
                   trControl = fitControl,
                   verbose = FALSE,
                   tuneGrid = big grid)
toc()
240.698 sec elapsed
```



Cartesian grid vs random search

ggplot(gbm_model_voters_big_grid)



- Grid search can get slow and computationally expensive very quickly!
- Therefore, in reality, we often use random search.



Random Search in caret

• Define random search in trainControl function

• Set tuneLength

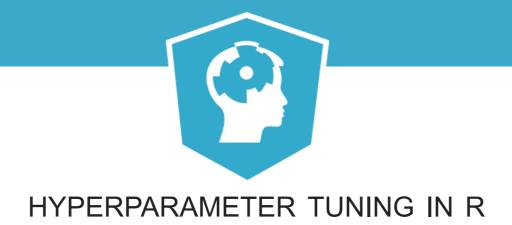


Random Search in caret

```
gbm model voters random
Stochastic Gradient Boosting
. . .
Resampling results across tuning parameters:
  shrinkage interaction.depth n.minobsinnode n.trees Accuracy Kappa
 0.08841129
                                               4396
                                                        0.9670737 - 0.00853312
 0.09255042
                                               540
                                                        0.9630635 -0.01329168
                                               3154
                                                       0.9570179 -0.01397025
 0.14484962 3
                                               2566
                                                       0.9610734 -0.01572681
 0.34935098 10
                               10
                                               2094
 0.43341085 1
                               13
                                                        0.9460727 - 0.02479105
Accuracy was used to select the optimal model using the largest value.
The final values used for the model were n.trees = 4396,
interaction.depth = 4, shrinkage = 0.08841129 and n.minobsinnode = 6.
```

Beware: in caret random search can NOT be combined with grid search!





Let's get coding!





Adaptive Resampling

Dr. Shirin Glander
Data Scientist



What is Adaptive Resampling?

Grid Search

All hyperparameter combinations are computed.

Random Search

- Random subsets of hyperparameter combinations are computed.
- => Evaluation of best combination is done at the end.

Adaptive Resampling

- Hyperparameter combinations are resampled with values near combinations that performed well.
- Adaptive Resampling is, therefore,
 faster and more efficient!

"Futility Analysis in the Cross-Validation of Machine Learning Models." Max Kuhn; ARXIV 2014

Adaptive Resampling in caret

```
trainControl:method = "adaptive cv" + search = "random" + adaptive =
```

- *min*: minimum number of resamples per hyperparameter
- alpha: confidence level for removing hyperparameters
- *method*: "gls" for linear model or "BT" for Bradley-Terry
- complete: if TRUE generates full resampling set

Adaptive Resampling in caret

• trainControl() + tuneLength = x

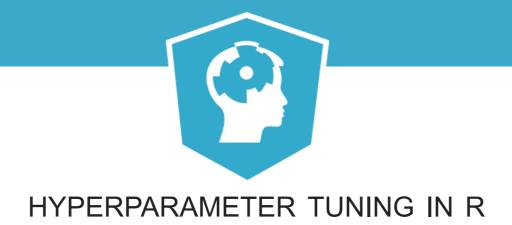
```
fitControl <- trainControl (method = "adaptive cv",
                             number = 3,
                             repeats = 3,
                              adaptive = list(min = 2,
                                              alpha = 0.05,
                                              method = "qls",
                                              complete = TRUE),
                              search = "random")
tic()
set.seed(42)
gbm model voters adaptive <- train(turnout16 2016 ~ .,
                                    data = voters train data,
                                    method = "gbm",
                                    trControl = fitControl,
                                    verbose = FALSE,
                                    tuneLength = 7)
toc()
1239.837 sec elapsed
```



Adaptive Resampling

```
gbm model voters adaptive
Resampling results across tuning parameters:
 shrinkage interaction.depth n.minobsinnode n.trees Accuracy
                                                                 Kappa
 0.07137493
                                               4152
                                                       0.9564654 0.02856571
 0.08408739
                               14
                                              674
                                                       0.9547185 0.02098853
 0.28552325
                               15
                                              3209
                                                       0.9568141 0.03024238
 0.33663932 10
                               13
                                              2595
                                                      0.9571130 0.04250979
 0.54251480 3
                                              3683
                                                      0.9482171 0.03568586
                               24
                                              4685
                               25
                                                       0.9549898 0.05284333
 0.56406870 7
                                                       0.9520286 0.02742592
 0.58695763
                               2.4
                                              1431
Accuracy was used to select the optimal model using the largest value.
The final values used for the model were n.trees = 2595,
interaction.depth = 10, shrinkage = 0.3366393 and n.minobsinnode = 13.
```





Let's get coding!