The big picture

useR - July 2019



The modeling ecosystem

Case study

The R Modeling Ecosystem

It's like the Wild West, the Internet. There are no rules.

Steven Wright



It's like the Wild West, the Litternet. There are no rules.

Modeling Ecosystem

Steven Wright



But I thought R was good at modeling?

But I thought R was good at modeling?

It is.

But I thought R was good at modeling?

It is.

But...

A problem of consistency

Function	Package	Code
lda	MASS	predict(obj)
glm	stats	<pre>predict(obj, type = "response")</pre>
gbm	gbm	<pre>predict(obj, type = "response", n.trees)</pre>
mda	mda	<pre>predict(obj, type = "posterior")</pre>
rpart	rpart	<pre>predict(obj, type = "prob")</pre>
Weka	RWeka	<pre>predict(obj, type = "probability")</pre>
logitboost	LogitBoost	<pre>predict(obj, type = "raw", nIter)</pre>
pamr.train	pamr	<pre>pamr.predict(obj, type = "posterior", threshold)</pre>

A problem of consistency

Function	Package	Code
•	MASS	predict(obj)
h	h	<pre>predict(obj, type = "response")</pre>
gbm	redict	(Ob:
mda	mda	type - type
rpart	rpart	(Obj, type = "response", n.trees) (obj, type = "response", n.trees) predict(obj, type = "probability") predict(obj, type = "probability")
Weka	RWeka	<pre>predict(obj, type = "probability")</pre>
		<pre>predict(obj, type = "raw", nIter)</pre>
pamr.train	pamr	<pre>pamr.predict(obj, type = "posterior", threshold)</pre>

tidymodels

```
library(parsnip)
train ← mtcars[1:20,]
test ← mtcars[21:32,]
```

```
linear_reg(penalty = .01) %>%
                                        rand_forest(mode = "regression") %>%
  set_engine("glmnet") %>%
                                          set_engine("ranger") %>%
  fit(mpg ~ cyl + disp, train) %>%
                                          fit(mpg ~ cyl + disp, train) %>%
  predict(test)
                                          predict(test)
#> # A tibble: 12 x 1
                                        #> # A tibble: 12 x 1
     .pred
#>
                                              .pred
                                        #>
   <dbl>
                                           <dbl>
                                        #>
#>
#> 1 26.5
                                        #> 1 25.0
#> 2 15.1
                                        #> 2 15.6
   3 15.5
                                        #> 3 15.7
#>
#> 4 14.4
                                        #> 4 15.6
#> 5 13.2
                                        #> 5 15.5
#> 6 27.5
                                        #> 6 30.2
#> 7 26.5
                                        #> 7 25.0
   8 27.1
#>
                                        #> 8 26.7
#> 9 14.4
                                        #> 9 15.6
#> 10 22.6
                                        #> 10 21.5
#> 11 15.6
                                        #> 11 15.7
#> 12
     26.5
                                        #> 12 25.0
```



Gradient boosting is a machine learning technique for <u>regression</u> and <u>classification</u> problems, which produces a prediction model in the form of an <u>ensemble</u> of weak prediction models, typically <u>decision trees</u>.

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https://en.wikipedia.org/wiki/Gradient_boosting

Written by C developers as an R interface to a C library

```
library(xgboost)
library(dplyr)
outcome ← pull(iris, Species)
predictors ← select(iris, -Species)
head(outcome)
#> [1] setosa setosa setosa setosa setosa
#> Levels: setosa versicolor virginica
head(predictors)
#> Sepal.Length Sepal.Width Petal.Length Petal.Width
             5.1
                        3.5
                                     1.4 0.2
```

4.9 3.0

5.4 3.9

#> 4 4.6 3.1

#> 5 5.0 3.6

4.7 3.2

1.4

1.3

1.5

1.4 0.2

1.7

0.2

0.2

0.2

#> 1

#> 2

#> 3

#> 6

```
model ← xgboost(
  data = predictors,
  label = outcome,
  objective = "multi:softprob"
)
```

```
model \( \times \text{xgboost}(\)
  data = predictors,
  label = outcome,
  objective = "multi:softprob"
)

#> Warning in xgb.get.DMatrix(data, label, missing,
#> weight): xgboost: label will be ignored.

#> Error in xgb.get.DMatrix(data, label, missing,
#> weight): xgboost doesn't support data.frame as
#> input. Convert it to matrix first.
```

```
model ← xgboost(
  data = as.matrix(predictors),
  label = outcome,
  objective = "multi:softprob"
)
```

```
model 		 xgboost(
    data = as.matrix(predictors),
    label = outcome,
    objective = "multi:softprob"
)

#> Error in check.booster.params(params, ...):
#> 'num_class' > 1 parameter must be set for
#> multiclass classification
```

```
model ← xgboost(
  data = as.matrix(predictors),
  label = outcome,
  objective = "multi:softprob"
)

#> Error in check.booster.params(params, ...):
    'num_class' > 1 parameter must be set for
    #> multiclass classification
```

num_class set the number of classes.
To use only with multiclass objectives.

```
model ← xgboost(
  data = as.matrix(predictors),
  label = outcome,
  objective = "multi:softprob",
  num_class = 3
)
```

```
model ← xgboost(
  data = as.matrix(predictors),
  label = outcome,
  objective = "multi:softprob",
  num_class = 3,
  nrounds = 10
)
```

```
model \leftarrow xgboost(
  data = as.matrix(predictors),
 label = outcome,
  objective = "multi:softprob",
  num_class = 3,
  nrounds = 10
#> Error in xgb.iter.update(bst$handle, dtrain,
#> iteration - 1, obj): [12:15:39] amalgamation/../
#> src/objective multiclass_obj.cu:110:
#> SoftmaxMultiClassObj: label must be in
#> [0, num class).
#>
#> Stack trace returned 10 entries:
#> [bt] (0) 0 xgboost.so
#> 0×000000010f7bb23c dmlc::StackTrace(unsigned long)
#> + 460
#> .. BLAHHHHHHH
```

```
model \leftarrow xgboost(
  data = as.matrix(predictors),
  label = outcome,
  objective = "multi:softprob",
  num_class = 3,
  nrounds = 10
#> Error in xgb.iter.update(bst$handle, dtrain,
#> iteration - 1, obj): [12:15:39] amalgamation/../
#> src/objective multiclass_obj.cu:110:
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#> [0, num class).
#>
#> Stack trace returned 10 entries:
#> [bt] (0) 0 xgboost.so
#> 0×000000010f7bb23c dmlc::StackTrace(unsigned long)
#> + 460
#> .. BLAHHHHHHH
```

```
model \leftarrow xgboost(
            = as.matrix(predictors),
  data
 label = as.numeric(outcome) - 1L,
  objective = "multi:softprob",
  num_class = 3,
  nrounds = 10
#> [1] train-merror:0.020000
#> [2] train-merror:0.026667
#> [3] train-merror:0.020000
#> [4] train-merror:0.020000
#> [5] train-merror:0.013333
#> [6] train-merror:0.013333
#> [7] train-merror:0.013333
#> [8] train-merror:0.013333
#> [9] train-merror:0.013333
#> [10] train-merror:0.013333
```

Constructive feedback 😌



Why can't predictors be a data frame?

Why force me to specify num_class?

Why do I always have to set nrounds?

Why can't outcome be a factor?

Why does outcome have to be a 0-based integer?

Constructive feedback 🤪



Why can't predictors be a data frame?

Principle: Familiar interface

Why force me to specify num_class?

Principle: Good defaults

Why do I always have to set nrounds?

Principle: Good defaults

Why can't outcome be a factor?

Principle: Familiar interface

Why does outcome have to be a 0-based integer?

Principle: Familiar interface

predict(model, as.matrix(predictors))

```
#> [1] 0.95302665 0.02447842 0.02249493 0.95302665 0.02447842
#> [6] 0.95302665 0.02447842 0.02249493 0.95302665 0.02447842
#> ...
```

```
predict(model, as.matrix(predictors))
```

```
#> [1] 0.95302665 0.02447842 0.02249493 0.95302665 0.02447842 #> [6] 0.95302665 0.02447842 0.02249493 0.95302665 0.02447842 #> ...
```

```
0.95302665 + 0.02447842 + 0.02249493
#> [1] 1
```

Constructive feedback 😌

Why can't newdata be a data frame?

Principle: Familiar interface

Why is the default multiclass prob output a vector?

Principle: Predictable output

Note: If factors were allowed, the column names of

the output could actually be meaningful!

Principle: User burden

In summary:

"I feel like I'm working for xgboost rather than having xgboost work for me."

What makes a modeling package "good"?

What makes a modeling package "good"? intuitive to use

Familiar interfaces

Good defaults

Familiar output types

Standardized arguments

Familiar interfaces

Good defaults

Familiar output types

Standardized arguments

Think about the R <u>interface</u> in addition to the <u>implementation</u>

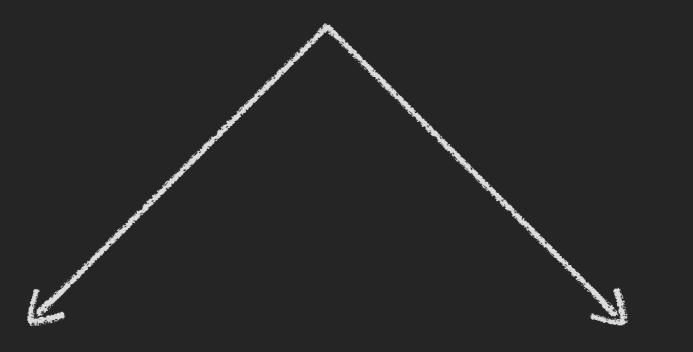
Think about the R <u>interface</u> in addition to the <u>implementation</u>





High barrier of required knowledge

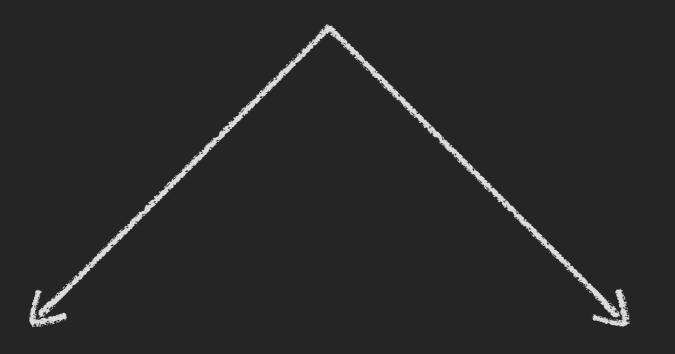
Low amount of tooling



High barrier of required knowledge

Low amount of tooling





High barrier of required knowledge

Low amount of tooling



hardhat

"A toolkit for the construction of modeling packages"

- Opinionated
- Handles preprocessing
- Robust at prediction time
- S3 method advice
- Validation