compboost

Fast and Flexible Component-Wise Boosting

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Use-Case

- We own a small booth at the Christmas market that sells mulled wine.
- As we are very interested in our customers' health, we only sell to customers who we expect to drink less than 15 liters per season.
- To estimate how much a customer drinks, we have collected data from 200 customers in recent years.
- These data include mulled wine consumption (in liter and cups), age, sex, country of origin, weight, body size, and 200 characteristics (that have absolutely no influence).

mw_consumption	mw_consumption_cups	gender	country	age	weight	height	noise1
12.6	42	f	Seychelles	21	119.25	157.9	0.1680
2.1	7	f	Poland	57	67.72	157.5	0.8075
12.6	42	m	Seychelles	25	65.54	181.6	0.3849
9.3	31	f	Germany	68	84.81	195.9	0.3277
4.8	16	m	Ireland	39	85.30	163.9	0.6021
9.3	31	f	Germany	19	102.75	173.8	0.6044
5.1	17	f	Poland	66	98.54	199.7	0.1246
7.5	25	f	Seychelles	62	108.21	198.1	0.2946
15.0	50	m	Seychelles	22	62.08	180.1	0.5776
8.4	28	m	Germany	52	75.42	170.0	0.6310

With these data we want to answer the following questions:

- Which of the customers' characteristics are important to be able to determine the consumption?
- How does the effect of important features look like?
- How does the model behave on unseen data?

What can we do to answer all the questions?

- Fit a linear model?
- Fit a linear model on each feature and build the ensemble?
- Fit a regularized linear model?
- Train a random forest?

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- Fit a linear model?
  $\rightarrow$ Not possible $p > n$

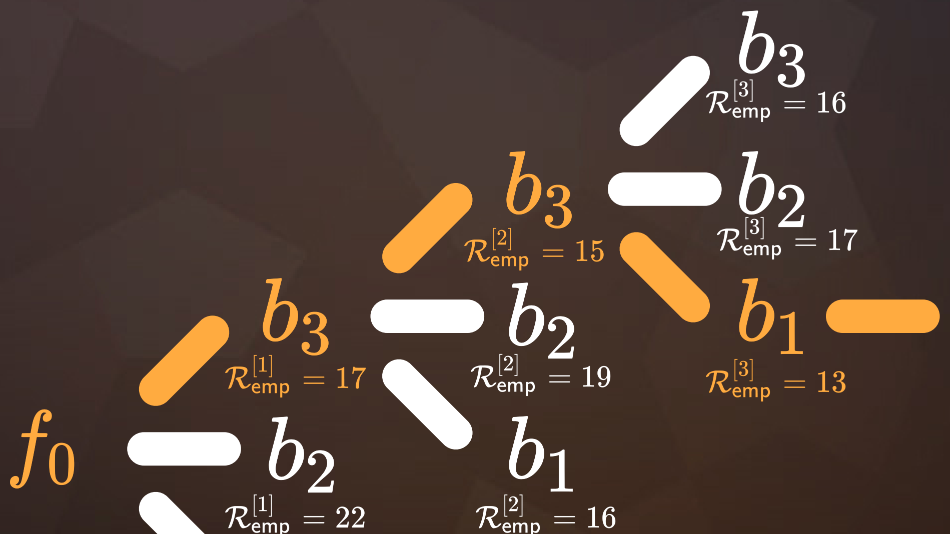
- Fit a linear model on each feature and build the ensemble?
  $\rightarrow$ Possible, but how should we determine important effects?

- Train a random forest?
  $\rightarrow$ Possible, but we want to interpret the effects.

- Fit a regularized linear model?
  $\rightarrow$ Possible, and basically the same as component-wise boosting.

Component-Wise Boosting

The Idea of Component-Wise Boosting



$$f_3 = f_0 + \beta \sum_{(3,3,1)} b_i$$

Why Component-Wise Boosting?

- Inherent (unbiased) feature selection.
- Resulting model is sparse since important effects are selected first and therefore it is able to learn in high-dimensional feature spaces ($p \gg n$).
- Parameters are updated iteratively. Therefore, the whole trace of how the model evolves is available.

About `compboost`

The `compboost` package is a fast and flexible framework for model-based boosting completely written in `C++`:

- With `mboost` as standard, we want to keep the modular principle of defining custom base-learner and losses.
- Completely written in `C++` and exposed by `Rcpp` to obtain high performance and full memory control.
- `R` API is written in `R6` to provide convenient wrapper.
- Major parts of the `compboost` functionality are unit tested against `mboost` to ensure correctness.

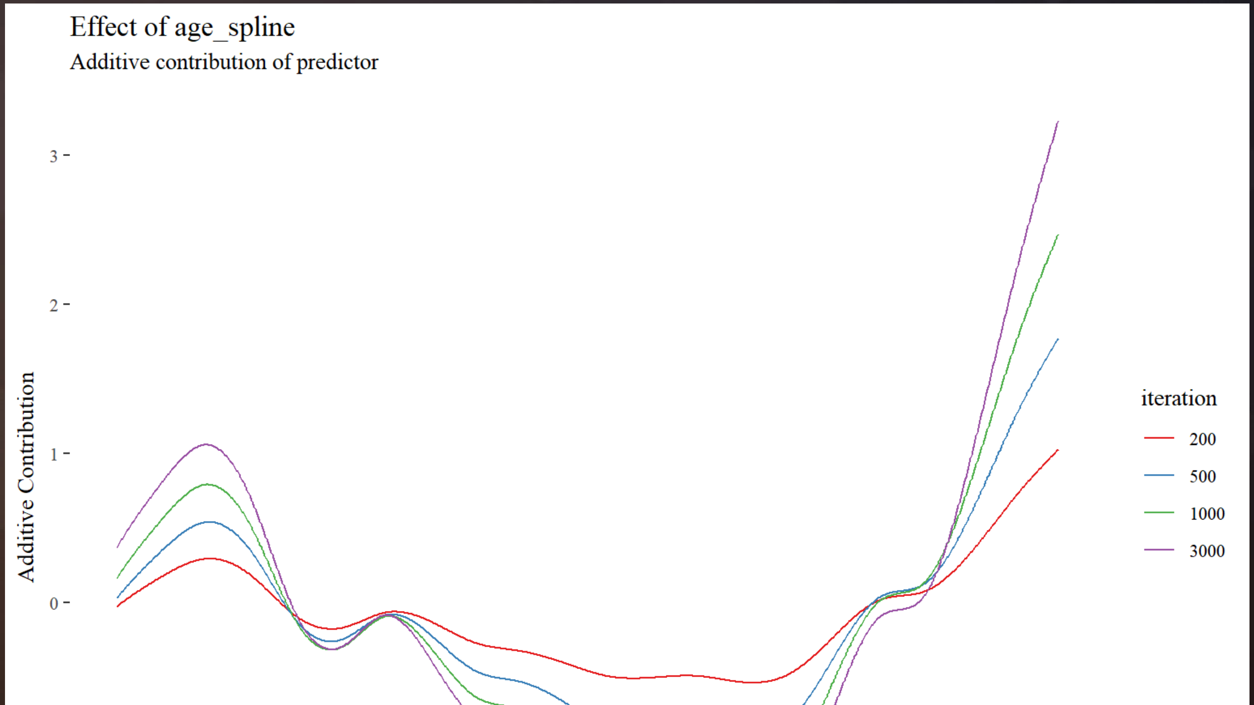
Applying `compboost` to the Use-Case

Quick Start With Wrapper Functions

```
cboost = boostSplines(data = mulled_wine_data[,-2], target = "mw_consumptic
  loss = LossQuadratic$new(), learning.rate = 0.005, iterations = 6000,
  trace = 600)
##    1/6000   risk = 5.6
##  600/6000   risk = 2.5
## 1200/6000   risk = 1.3
## 1800/6000   risk = 0.8
## 2400/6000   risk = 0.51
## 3000/6000   risk = 0.34

## 3600/6000   risk = 0.24
## 4200/6000   risk = 0.17
## 4800/6000   risk = 0.12
## 5400/6000   risk = 0.087
## 6000/6000   risk = 0.064
##
##
## Train 6000 iterations in 9 Seconds.
## Final risk based on the train set: 0.064
```

Effect Visualization

```
cboost$plot("age_spline", iters = c(200, 500, 1000, 3000))
```



Inbag and OOB Behavior

To get an idea, how the model behaves on unseen data we use 75 % as training data and the other 25 % of the data to calculate the out of bag (OOB) risk:

```r
n_data = nrow(mulled_wine_data)
idx_train = sample(x = seq_len(n_data), size = n_data * 0.75)
idx_test = setdiff(x = seq_len(n_data), idx_train)
```

Define Model and Base-Learner the “Object-Oriented Style”

```r
cboost = Compboost$new(data = mulled_wine_data[idx_train,-2],
  target = "mw_consumption", loss = LossQuadratic$new(),
  learning.rate = 0.005)

for (feature_name in setdiff(names(mulled_wine_data[,-2]), target)) {
  if (feature_name %in% c("gender", "country")) {

    cboost$addBaselearner(feature = feature_name, id = "category",
      bl.factory = BaselearnerPolynomial, intercept = FALSE)
  } else {
    cboost$addBaselearner(feature = feature_name, id = "spline",
      bl.factory = BaselearnerPSpline, degree = 3, n.knots = 10)
  }
}
```

OOB Data

To track the OOB risk we have to prepare the new data so that `compboost` knows the new data sources:

```
oob_data = cboost$prepareData(mulled_wine_data[idx_test,])
oob_response = mulled_wine_data$mw_consumption[idx_test]
```

Define Logger

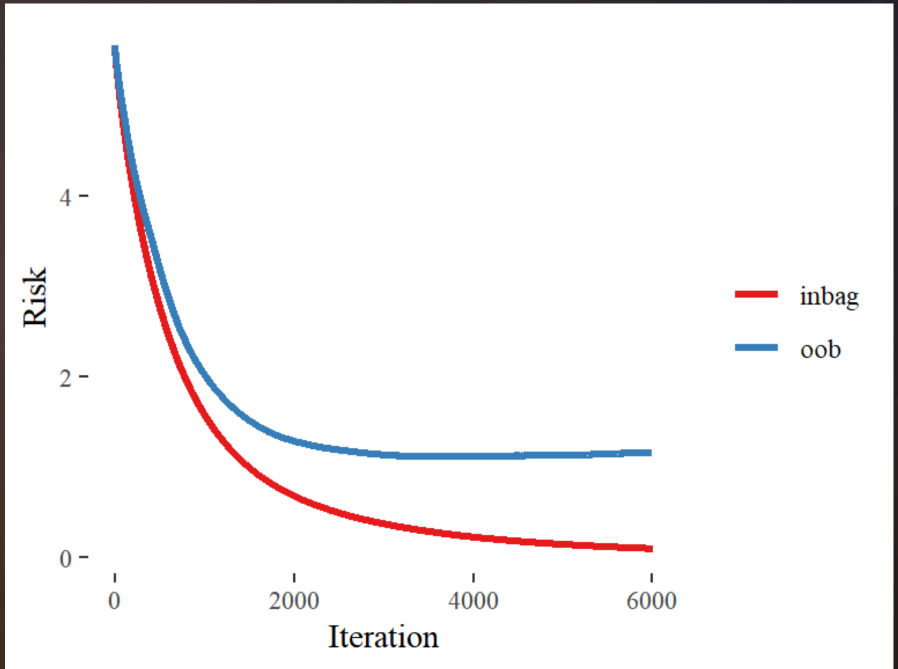
```r
cboost$addLogger(logger = LoggerOobRisk, logger.id = "oob_risk",
  used.loss = LossQuadratic$new(), eps.for.break = 0,
  oob.data = oob_data, oob.response = oob_response)

cboost$addLogger(logger = LoggerTime, logger.id = "microseconds",
  max.time = 0, time.unit = "microseconds")

cboost$train(6000, trace = 1500)

##    1/6000   risk = 5.6  microseconds = 1   oob_risk = 5.7
## 1500/6000   risk = 0.99  microseconds = 2518925   oob_risk = 1.5
## 3000/6000   risk = 0.37  microseconds = 4848996   oob_risk = 1.1
## 4500/6000   risk = 0.17  microseconds = 7171435   oob_risk = 1.1
## 6000/6000   risk = 0.092  microseconds = 9495656   oob_risk = 1.2
##
##
## Train 6000 iterations in 9 Seconds.
## Final risk based on the train set: 0.092
```

Extract Inbag and OOB Data

```r
inbag_trace = cboost$getInbagRisk()
head(inbag_trace)
## [1] 5.659 5.647 5.635 5.623 5.612 5.600

logger_data = cboost$getLoggerData()
head(logger_data)

##   _iterations microseconds oob_risk
## 1           1            1    5.671
## 2           2         1728    5.660
## 3           3         3374    5.649
## 4           4         5043    5.639
## 5           5         6697    5.628
## 6           6         8428    5.618
```

Visualization of Inbag and OOB Risk

```r
oob_trace = logger_data[["oob_risk"]]

risk_data = data.frame(
  risk = c(inbag_trace, oob_trace),
  type = rep(c("inbag", "oob"), times = c(length(inbag_trace),
    length(oob_trace))),
  iter = c(seq_along(inbag_trace), seq_along(oob_trace))
)
ggplot(risk_data, aes(x = iter, y = risk, color = type)) + geom_line()
```

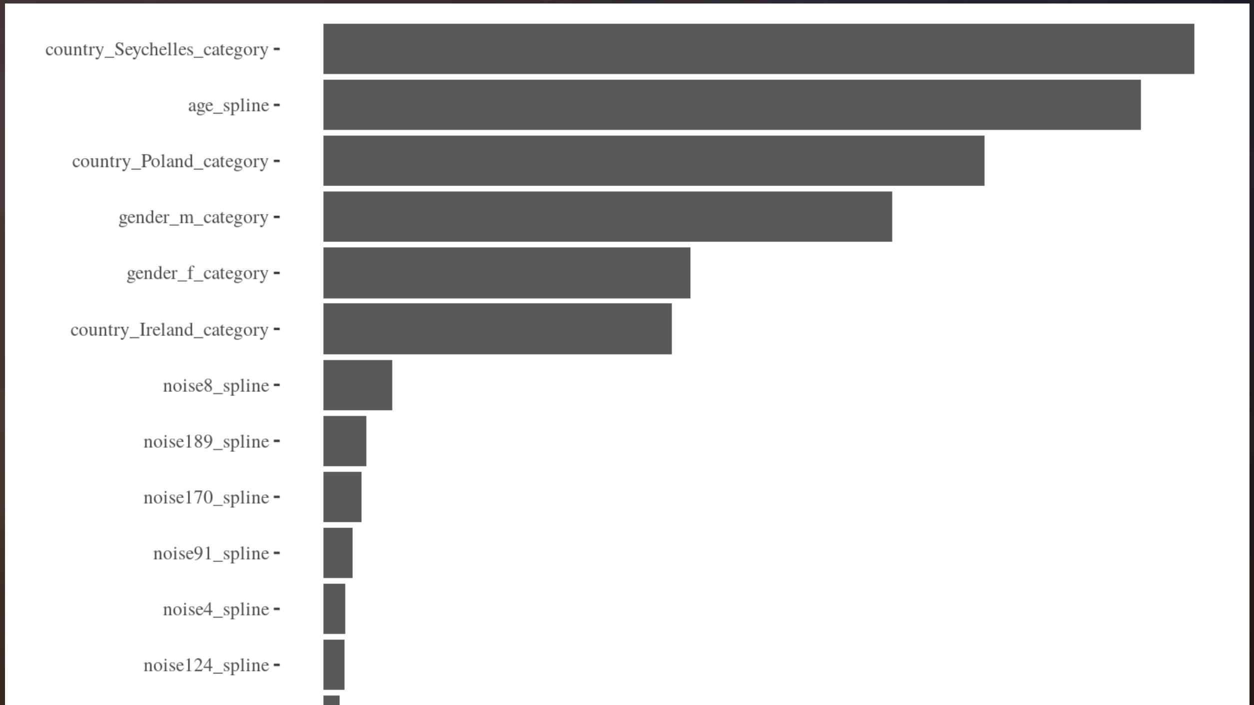


Set Model to a Specific Iteration

```r
cboost$train(2200)
cboost
## Component-Wise Gradient Boosting
##
## Trained on mulled_wine_data[idx_train, -2] with target mw_consumption
## Number of base-learners: 210
## Learning rate: 0.005

## Iterations: 2200
## Offset: 6.65
##
## LossQuadratic Loss:
##
##   Loss function: L(y,x) = 0.5 * (y - f(x))^2
##
##
```

Feature Importance

```r
cboost$plotFeatureImportance(num.feat = 15L)
```



Using Custom Losses - Defining a Loss

Now we recognize that the customers do not buy the wine in liters but per cup, therefore it might be better to use a Poisson loss to take the counting data into account. For that reason we define a new custom loss:

```r
lossPoi = function (truth, pred) {
  return (-log(exp(pred)^truth * exp(-exp(pred)) / gamma(truth + 1)))
}
gradPoi = function (truth, pred) {
  return (exp(pred) - truth)
}
constInitPoi = function (truth) {
  return (log(mean.default(truth)))
}
# Define custom loss:
my_custom_loss = LossCustom$new(lossPoi, gradPoi, constInitPoi)
```

Using Custom Losses - Using the Loss

```
cboost = boostSplines(data = mulled_wine_data[,-1],
  target = "mw_consumption_cups", loss = my_custom_loss,
  optimizer = OptimizerCoordinateDescent$new(),
  learning.rate = 0.005, iterations = 500, trace = 100,
  n.knots = 10, degree = 3)
##   1/500   risk = 5.3
## 100/500   risk = 3

## 200/500   risk = 2.7
## 300/500   risk = 2.6
## 400/500   risk = 2.6
## 500/500   risk = 2.5
##
##
## Train 500 iterations in 0 Seconds.
## Final risk based on the train set: 2.5
```

Further Functionalities

- Each logger can also be used as stopper, therefore we can use them for early stopping
- In combination with the custom loss, we can use the OOB logger to track performance measures like the AUC (in binary classification)
- Losses and base-learner can also be directly extended using `C++` (see `getCustomCppExample()`)

From C++ to R

Rcpp

- Automated conversion between `R` and `C++` data structures, such as vectors, matrices, or even whole classes
- Seamless integration of Armadillo for linear algebra
- Complicated stuff like compilation, or again, the conversion between `R` and `C++` are handled automatically

C++ to R Wrap Up of `compboost`

R	C++

`> cboost = Compboost$new(...)`	`> bl_list = BaselearnerFactoryList(...)`
	`> l_list  = LoggerList(...)`
	`> loss    = new LossQuadratic(...)`
	`> optim   = new OptimizerCoordinateDesc(...)`

`> cboost$addBaselearner(feat)`	`> source = InMemoryData(feat)`
	`> target = InMemoryData()`
	`> bl_feat = BaselearnerPSpline(source, target)`
	`> bl_list.registerBaselearner(bl_feat)`

`> cboost$addLogger(logger)`	`> logger = LoggerOOBRisk(...)` `> l_list.registerLogger(logger)`

Challenges When Using C++ and Rcpp

- Saving object is not possible at the moment
- Memory managing is not easy $\Rightarrow$ Segmentation folds or memory leaks may happen
- Exported API of classes is not very informative
- Debugging of `C++` from `R` can be very annoying and time-consuming

What’s Next?

- Better selection process of base-learner
- Speed up the training by parallel computations
- Greater functionality:
    - Functional data structures and loss functions
    - Unbiased feature selection
    - Effect decomposition into constant, linear, and non-linear

Thanks for your attention!

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- Actively developed on GitHub:

  https://github.com/schalkdaniel/compboost

- Project page:

  https://compboost.org/

Credits

Slides were created with:

- revealjs
- Font-Awesome:
- rmarkdown
- revealjs (R Package)
- Google Fonts