compboost

Fast and Flexible Component-Wise Boosting Framework

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Use-Case

The Situation

- We own a small booth at the city center that sells beer.
- As we are very interested in our customers' health, we only sell to customers who we expect to drink less than 110 liters per year.
- To estimate how much a customer drinks, we have collected data from 200 customers in recent years.
- These data include the beer consumption (in liter), age, sex, country of origin, weight, body size, and 200 characteristics gained from app usage (that have absolutely no influence).

Overview of the Data

beer_consumption	gender	country	age	weight	height	app_usage1	...	app_usage200
106.5	m	Seychelles	33	87.17	172.9	0.1680	...	0.1313
85.5	f	Seychelles	52	89.38	200.4	0.8075	...	0.6087
116.5	f	Czechia	54	92.03	178.7	0.3849	...	0.5786
67.0	m	Australia	32	63.53	186.3	0.3277	...	0.3594
43.0	f	Australia	51	64.73	175.0	0.6021	...	0.7406
85.0	m	Austria	43	95.74	173.2	0.6044	...	0.4181
79.0	f	Austria	55	87.65	156.3	0.1246	...	0.4398
107.0	f	Austria	24	93.17	161.4	0.2946	...	0.6130
57.0	m	USA	55	76.27	182.5	0.5776	...	0.4927
89.0	m	USA	16	72.21	203.3	0.6310	...	0.0735

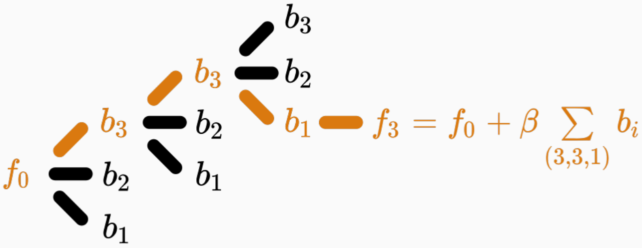
Our Goals

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 is Component-Wise Boosting?

General Idea



- Sequential refitting of the base-learner b_1, b_2, b_3 on the error of the current ensemble.
- The base-learner with the best fit on the error (measured as mean squared error) is added to the ensemble.

Advantages of 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

Current Standard

Most popular package for model-based boosting is `mboost`:

- Large number of available base-learner and losses.
- Extended to more complex problems:
  - Functional data
  - GAMLSS models
  - Survival analysis
- Extendible with custom base-learner and losses.

So, why another boosting implementation?

- Main parts of `mboost` are written in `R` and gets slow for large datasets.
- Complex implementation:
  - Nested scopes
  - Mixture of different `R` class systems

About Compboost

Fast and flexible framework for model-based boosting:

- 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.

Small Demonstration

Starting With Convenience Wrapper

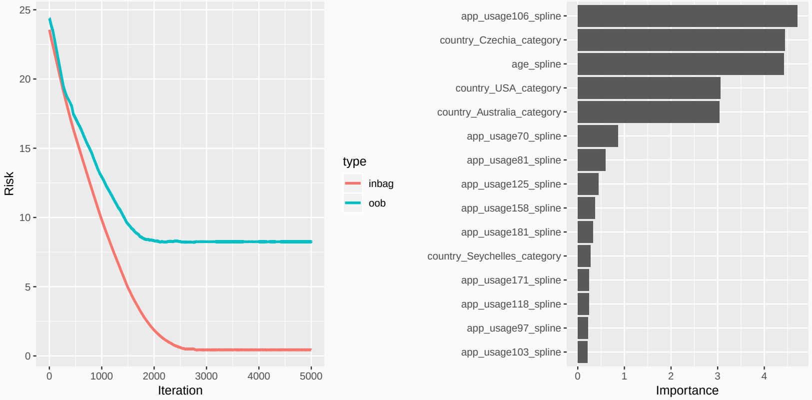
`boostLinear()` and `boostSplines()` automatically adds univariate linear models or a GAM for all features.

```
set.seed(618)
cboost = boostSplines(data = beer_data, target = "beer_consumption",
  loss = LossAbsolute$new(), learning_rate = 0.1, iterations = 5000L,
  penalty = 10, oob_fraction = 0.3, trace = 2500L)
```

```
##    1/5000   risk = 24  oob_risk = 24
## 2500/5000   risk = 0.6  oob_risk = 8.3
## 5000/5000   risk = 0.44  oob_risk = 8.3
##
##
## Train 5000 iterations in 13 Seconds.
## Final risk based on the train set: 0.44
```

Visualizing the Results

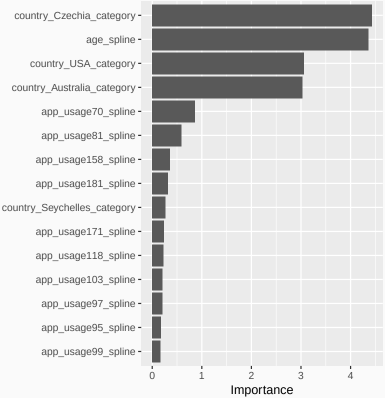
```
gg1 = cboost$plotInbagVsOobRisk()
gg2 = cboost$plotFeatureImportance()
```

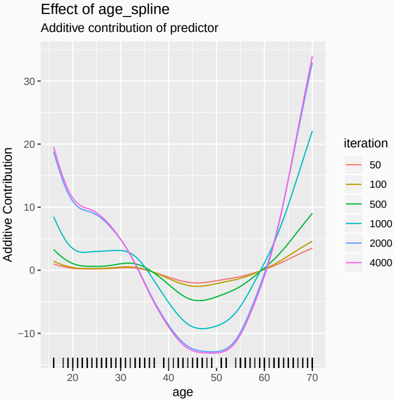


Visualizing the Results

```r
cboost$train(2000L)

gg1 = cboost$plotFeatureImportance()
gg2 = cboost$plot("age_spline", iters = c(50, 100, 500, 1000, 2000, 4000))
```





Using the R6 Interface

```
cboost = Compboost$new(data = beer_data, target = "beer_consumption",
  loss = LossQuantile$new(0.9), learning_rate = 0.1, oob_fraction = 0.3)

cboost$addBaselearner("age", "spline", BaselearnerPSpline)
cboost$addBaselearner("country", "category", BaselearnerPolynomial)

cboost$addLogger(logger = LoggerTime, use_as_stopper = TRUE, logger_id = "time",
  max_time = 2e5, time_unit = "microseconds")

cboost$train(10000, trace = 500)


##     1/10000   risk = 11  oob_risk = 10   time = 0
##   500/10000   risk = 7.9  oob_risk = 8.2   time = 18930
##  1000/10000   risk = 6.3  oob_risk = 6.6   time = 46725
##  1500/10000   risk = 5.1  oob_risk = 5.4   time = 94017
##  2000/10000   risk = 4.2  oob_risk = 4.5   time = 134416
##  2500/10000   risk = 3.5  oob_risk = 3.8   time = 179140
##
##
## Train 2721 iterations in 0 Seconds.
## Final risk based on the train set: 3.3
```

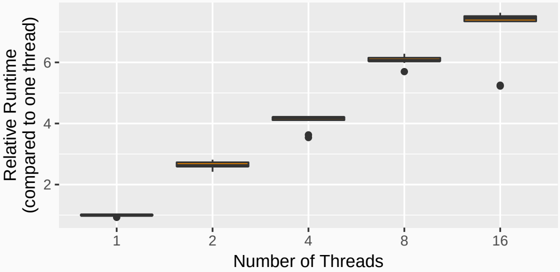
Overview of the Functionality

- **Base-learner:** `BaselearnerPolynomial`, `BaselearnerSpline`, `BaselearnerCustom`, and `BaselearnerCustomCpp`
- **Loss functions:** `LossQuadratic`, `LossAbsolute`, `LossQuantile`, `LossHuber`, `LossBinomial`, `LossCustom`, and `LossCustomCpp`
- **Logger/Stopper:** `LoggerIteration`, `LoggerInbagRisk`, `LoggerOobRisk`, and `LoggerTime`

Performance Considerations

Performance Considerations

- Optimizer are parallelized via openmp:



- Take advantage of the matrix structure to speed up the algorithm by reducing the number of repetitive or too expensive calculations.
- Matrices are stored (if possible) as a sparse matrix.

Small Comparison With Mboost

- Runtime (numbers are given in minutes):

nrows / ncols	mboost	compboost	compboost (16 threads)
20000 / 200	21.10 (1)	10.47 (2.02)	0.95 (22.21)
20000 / 2000	216.70 (1)	83.95 (2.58)	8.15 (26.59)

- Memory (numbers are given in GB):

nrows / ncols	mboost	compboost	compboost (16 threads)
20000 / 200	1.04 (1)	0.28 (3.71)	0.30 (3.47)
20000 / 2000	8.70 (1)	2.60 (3.35)	2.98 (2.92)

(Comparison was made by just using spline base-learner with 20 knots and and 5000 iterations. The numbers in the brackets are the relative values compared to `mboost`.)

What's Next?

What's Next?

- Research on computational aspects of the algorithm:
  - More stable base-learner selection process via resampling
  - Base-learner selection for arbitrary performance measures
  - Smarter and faster optimizers
- Greater functionality:
  - Functional data structures and loss functions
  - Unbiased feature selection
  - Effect decomposition into constant, linear, and non-linear
- Reducing the memory load by applying binning on numerical features.
- Exposing `C++` classes to python.

- Actively developed on GitHub:

  www.github.com/schalkdaniel/compboost

- Project page:

  www.compboost.org

- JOSS DOI:

  10.21105/joss.00967