#### compboost

Fast and Flexible Component-Wise Boosting Framework

Daniel Schalk July 12, 2019

LMU Munich Working Group Computational Statistics



#### **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**

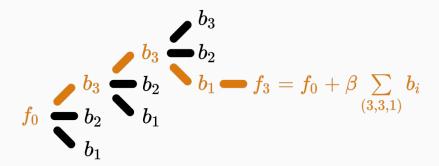
With these data we want to answer the following questions:

- 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**



#### **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

#### **About Compboost**

The compboost package is a 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.

**A Small Demonstration** 

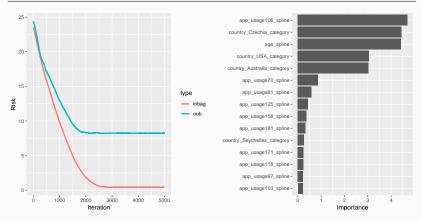
#### **Starting With Convenience Wrapper**

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)

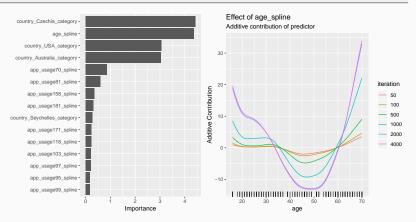
## 1/5000 risk = 24 oob_risk = 24
## 2500/5000 risk = 0.6 oob_risk = 8.3
## 5000/5000 risk = 0.44 oob_risk = 8.3
##
## Train 5000 iterations in 14 Seconds.
## Final risk based on the train set: 0.44
```

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



```
cboost$train(2000L)

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



```
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 = 21216
   1000/10000
               risk = 6.3 oob_risk = 6.6 time = 44665
##
##
   1500/10000 risk = 5.1 oob_risk = 5.4 time = 74519
##
   2000/10000
               risk = 4.2 oob risk = 4.5 time = 111910
##
   2500/10000
               risk = 3.5 oob risk = 3.8 time = 155150
##
##
## Train 2964 iterations in O Seconds.
## Final risk based on the train set: 3.2
```

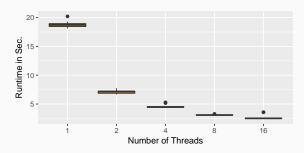
#### Overview of the Functionality

- 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.

Thanks for your attention!
Questions?

• Actively developed on GitHub:

www.github.com/schalkdaniel/compboost

• Project page:

www.compboost.org

• JOSS DOI:

10.21105/joss.00967