Compboost

Modular framework for component-wise boosting

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10 July 2018

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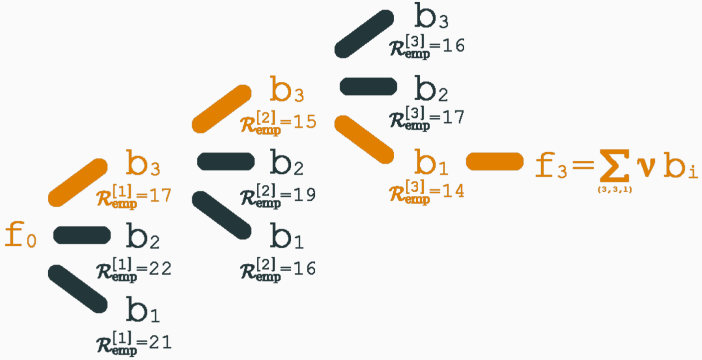
Why Component-Wise Boosting

Why Component-Wise Boosting?



Why Component-Wise Boosting?

- Inherent (unbiased) feature selection [HHKS11].
- The resulting model is sparse since important effects are selected first and therefore it is able to learn in high-dimensional feature spaces ($p \gg n$).
- The parameters are updated iteratively. Therefore, the whole trace of how the model evolves is available.

Available R Packages

Most popular package for model-based boosting is `mboost` [HBK+17]:

- Large number of available base-learner and losses.
- Suited for more complex problems:
  - Functional data [BRG17]
  - GAMLSS models [MFH+12]
  - Survival analysis
- Extendible with custom base-learner and losses.

So, why another boosting implementation?

- Main algorithm is implemented in `R` which is not the best choice for expensive algorithms.
- Complex implementation:
  - Nested scopes
  - Mixture of different `R` class systems.

About Compboost

About Compboost

- 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` [Edd13, EF17] to obtain high performance and full memory control.
- `R` API is written with `R6` to provide convenient wrapper.
- Major parts of the `compboost` functionality are unit tested against `mboost` to ensure correct use.

Compboost: Functionality

Main components:

- Base-learner and loss classes.
- Logger class for early stopping and logging mechanisms.

Possible extensions:

- Custom `R` or `C++` base-learner.
- Custom `R` or `C++` loss objects.
- Custom logging and stopping rules via custom losses.

Custom classes can be defined without recompiling the whole package, even when using `C++` functions.

Small Usecase

Initializing Model

```r
library(compboost)

data(PimaIndiansDiabetes, package = "mlbench")

cboost = Compboost$new(PimaIndiansDiabetes, "diabetes",
  loss = BinomialLoss$new())

cboost$addBaselearner("age", "spline", PSplineBlearner,
  degree = 3, n.knots = 10, penalty = 2, differences = 2)
cboost$addBaselearner("mass", "linear", PolynomialBlearner,
  degree = 1, intercept = TRUE)
```

Initializing Model

```r
cboost$train(2000, trace = FALSE)
cboost
```

```
## Component-Wise Gradient Boosting
##
## Trained on PimaIndiansDiabetes with target diabetes
## Number of base-learners: 2
## Learning rate: 0.05
## Iterations: 2000
## Positive class: neg
## Offset: 0.3118
##
## BinomialLoss Loss:
##
##   Loss function: L(y,x) = log(1 + exp(-2yf(x))
##
##
```

Access Results

```
table(cboost$selected())
```

```
##
##  age_spline mass_linear
##        1511         489
```

```
head(cboost$risk())
```

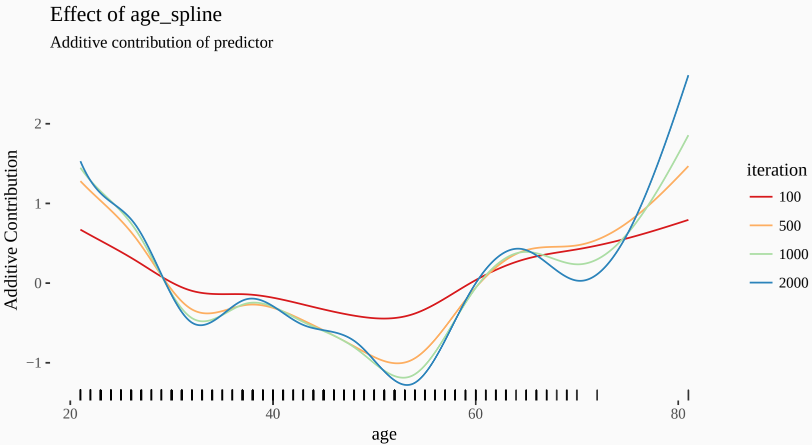
```
## [1] 0.6582 0.6565 0.6549 0.6533 0.6518 0.6503
```

```
str(cboost$coef())
```

```
## List of 3
##  $ age_spline : num [1:14, 1] 4.407 0.913 1.124 -1.044 0.126 ...
##  $ mass_linear: num [1:2, 1] 3.0352 -0.0886
##  $ offset     : num 0.312
```

Plot Results

```
cboost$plot("age_spline", iters = c(100, 500, 1000, 2000))
```



Custom Poisson Loss: Definition

```r
lossPoisson = function (truth, response) {
  return (-log(exp(response)^truth * exp(-exp(response)) / gamma(truth + 1)))
}
gradPoisson = function (truth, response) {
  return (exp(response) - truth)
}
constInitPoisson = function (truth) {
  return (log(mean.default(truth)))
}
# Define custom loss:
my.poisson.loss = CustomLoss$new(lossPoisson, gradPoisson, constInitPoisson)
```

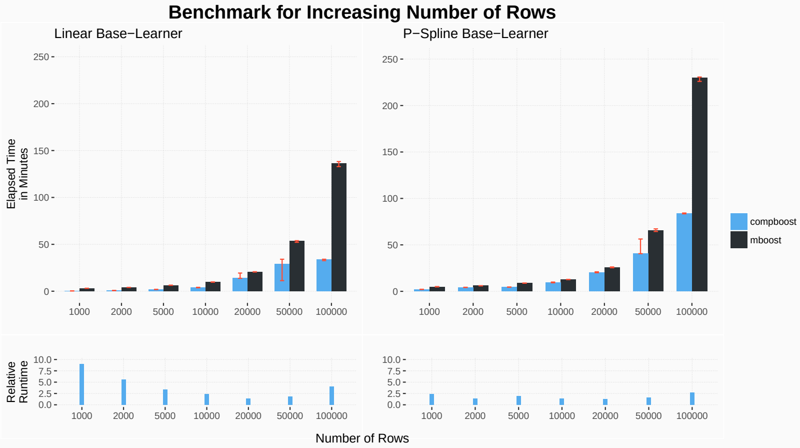
Custom Poisson Loss: Train Model

```r
data(VonBort, package = "vcd")

cboost = Compboost$new(VonBort, "deaths", loss = my.poisson.loss)
cboost$addBaselearner("year", "spline", PSplineBlearner)
cboost$train(100, trace = FALSE)

mod = mboost(deaths ~ bbs(year, lambda = 2), data = VonBort, family = Poisson(),
  control = boost_control(mstop = 100, nu = 0.05))

head(cbind(
  compboost = as.numeric(cboost$coef()[[1]]),
  mboost = as.numeric(coef(mod)[[1]])))
```

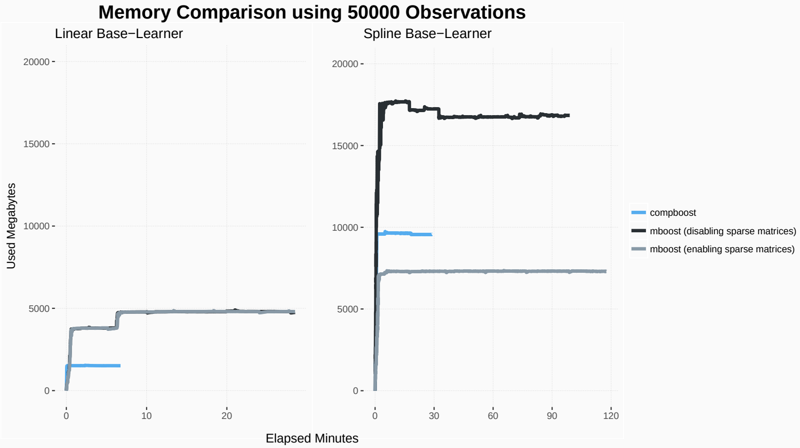
```
##      compboost  mboost
## [1,]   -1.2233 -1.2233
## [2,]   -0.9133 -0.9133
## [3,]   -0.6078 -0.6078
## [4,]   -0.3389 -0.3389
## [5,]   -0.1809 -0.1809
## [6,]   -0.0788 -0.0788
```

Small Benchmark

Runtime Comparison Against Mboost



Memory Comparison Against Mboost



Next Steps

Next Steps

- Implementing more base-learner and loss functions.
- Support for multiclass classification.
- Parallel computations.
- Using sparse matrices to store, e.g., spline data matrices.

Where to Find

- Developed on *GitHub*:

  www.github.com/schalkdaniel/compboost

- Additional resources on the project page:

  www.compboost.org

- Bug reports via the issue tracker.

Contributions are highly welcome!

Questions?

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