

Compboost

Modular framework for component-wise boosting

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Table of contents

1. What is Component-Wise Boosting
2. About Compboost
3. Small Usecase
4. Next Steps

What is Component-Wise Boosting

Component-Wise Boosting: Terminology

- Loss Function:

$$L : \mathcal{Y} \times \mathcal{X} \rightarrow \mathbb{R}$$

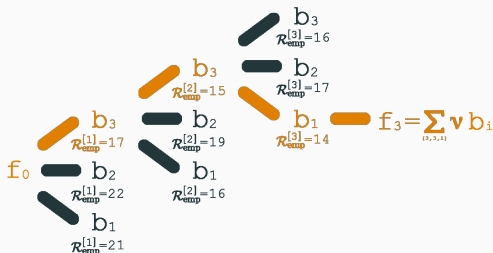
- Empirical Risk:

$$\mathcal{R}_{\text{emp}}(\theta) = \frac{1}{n} \sum_{i=1}^n L\left(y^{(i)}, f(x^{(i)})\right)$$

- Estimated model/parameter at iteration m :

$$\hat{f}^{[m]}, \theta^{[m]}$$

Component-Wise Boosting: The Idea



Iteration 1: $\hat{f}^{[1]}(x) = \beta b_3(x_3, \theta^{[1]})$

Iteration 2: $\hat{f}^{[2]}(x) = \beta b_3(x_3, \theta^{[1]}) + \beta b_3(x_3, \theta^{[2]})$

Iteration 2: $\hat{f}^{[3]}(x) = \beta b_3(x_3, \theta^{[1]}) + \beta b_3(x_3, \theta^{[2]}) + \beta b_1(x_1, \theta^{[3]})$

$$\Rightarrow \hat{f}^{[3]}(x) = \beta \left(b_3(x_3, \theta^{[1]} + \theta^{[2]}) + b_1(x_1, \theta^{[3]}) \right)$$

Component-Wise Boosting: The Algorithm

Result: Component-wise boosting model $\hat{f}(x)$

Initialize $\hat{f}^{[0]}(x) = \arg \min_{c \in \mathbb{R}} \mathcal{R}_{\text{emp}}(c)$;

for $m \in \{1, \dots, M\}$ **do**

 // Update pseudo residuals:

$$r^{[m](i)} = - \left[\frac{\delta}{\delta f(x^{(i)})} L \left(y^{(i)}, f(x^{(i)}) \right) \right]_{f=f^{[m-1]}}, \quad \forall i \in \{1, \dots, n\} ;$$

 // Get index j^* of m -th base-learner from optimizer:

for $j \in \{1, \dots, J\}$ **do**

 // Fit each base-learner $b_j^{[m]}$ to the pseudo residuals:

$$\hat{\theta}_j^{[m]} = \arg \min_{\theta_j} \sum_{i=1}^n \left(r^{[m](i)} - b_j^{[m]}(x^{(i)}, \theta_j) \right)^2 ;$$

 // Calculate the SSE of the fitted base-learner:

$$\text{SSE}_j = \sum_{i=1}^n \left(r^{[m](i)} - b_j^{[m]}(x^{(i)}, \hat{\theta}_j) \right)^2 ;$$

end

 // Add selected component to model:

$$\hat{f}^{[m]}(x) = \hat{f}^{[m-1]}(x) + \beta b_{j^*}^{[m]}(x, \theta_{j^*}^{[m]})$$

end

Returns: $\hat{f}(x) = \hat{f}^{[m]}(x)$;

Available R Packages

- Tree-based implementations:
 - `xgboost`
 - `catboost`
 - `gbm`
- Model-based implementations:
 - `mboost`

So, why another boosting implementation?

About Comboost

- Installation

```
devtools::install_github("schalkdaniel/compboost")  
library(compboost)
```

Compboost Members and Member Functions

- **Member Functions:**

- `addBaselearner()`
- `addLogger()`
- `train()`
- `coef()`
- `predict()`
- `risk()`
- `selected()`
- `plot()`
- `...`

- **Public Members:**

- `model`
- `bl.factory.list`
- `loss`
- `optimizer`
- `...`

Small Usecase

Initializng Model

```
mtcars$mpg_cat = ifelse(mtcars$mpg > 15, "A", "B")
cboost = Comboost$new(mtcars, "mpg", loss = QuadraticLoss$new())

cboost$addBaselearner("wt", "spline", PSplineBlearnerFactory,
  degree = 3, knots = 10, penalty = 2, differences = 2)
cboost$addBaselearner("mpg_cat", "linear", PolynomialBlearnerFactory,
  degree = 1, intercept = FALSE)

cboost$train(2000, trace=FALSE)
cboost

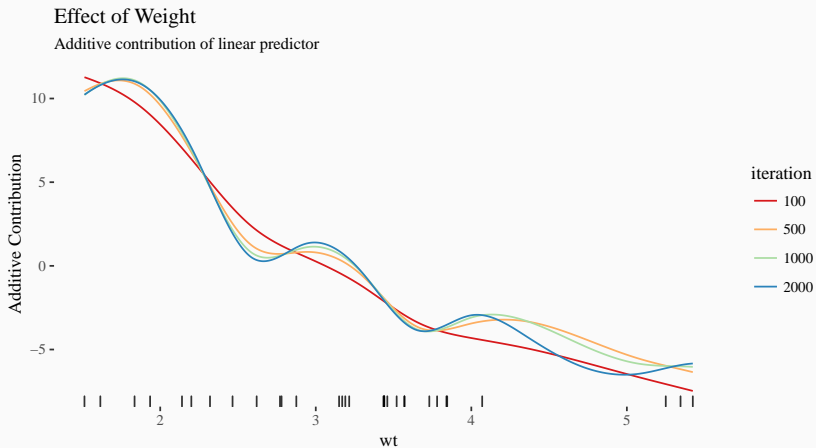
## Componentwise Gradient Boosting
##
## Trained on mtcars with target mpg
## Number of base-learners: 3
## Learning rate: 0.05
## Iterations: 2000
## Offset:20.090625
##
## QuadraticLoss Loss:
##
## Loss function:  $y = (y - f(x))^2$ 
##
##
```

Plot Results

```
library(ggplot2)
library(ggthemes)

cboost$plot("wt_spline", iters = c(100, 500, 1000, 2000)) +
  labs(title = "Effect of Weight",
       subtitle = "Additive contribution of linear predictor") +
  theme_tufte() +
  scale_color_brewer(palette = "Spectral")
```

Plot Results



Next Steps

Questions?