Introduction to Machine Learning

Boosting

Gradient Boosting: CWB Basics 2

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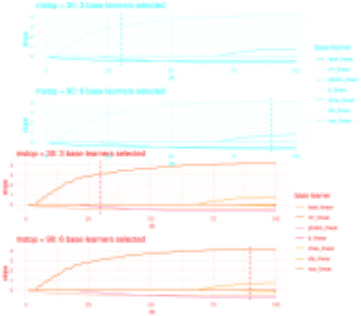

Learning goals

- Handling of categorical features
- Intercept handling
- Practical example

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HANDLING OF CATEGORICAL FEATURES / 2

Advantages of simultaneously handling all categories in CWB:

- Much faster estimation compared to using individual binary BLs
- Explicit solution of $\hat{\theta} = \arg\min_{\theta \in \mathbb{R}^G} \sum_{i=1}^{n} (y^{(i)} - b_j(x_j^{(i)} | \theta))^2$:

$$\hat{\theta}_g = n_g^{-1} \sum_{i=1}^{n} y^{(i)} \mathbb{1}_{\{x_j^{(i)} = g\}}$$

- For features with many categories we usually add a ridge penalty

HANDLING OF CATEGORICAL FEATURES / 3

Advantages of including categories individually in CWB:

- Enables finer selection since non-informative categories are simply not included in the model.
- Explicit solution of $\hat{\theta}_{j,g} = \arg\min_{\theta \in \mathbb{R}} \sum_{i=1}^{n} (y^{(i)} - b_g(x_j^{(i)} | \theta))^2$ with:

$$\hat{\theta}_{j,g} = n_g^{-1} \sum_{i=1}^{n} y^{(i)} \mathbb{1}_{\{x_j^{(i)} = g\}}$$

Disadvantage of individually handling all categories in CWB:

- Fitting CWB is slower
- Penalization and selection become difficult since base learner has exactly one degree of freedom.

INTERCEPT HANDLING

There are two options to handle the intercept in CWB. In both, the loss-optimal constant $f^{[0]}(\mathbf{x})$ is an initial model intercept.

1. Include an intercept BL:
   - Add BL $b_{int} = \theta$ as potential candidate considered in each iteration and remove intercept from all linear BLs, i.e., $b_j(\mathbf{x}) = \theta_j x_j$.
   - Final intercept is given as $f^{[0]}(\mathbf{x}) + \hat{\theta}$. Linear BLs without intercept only make sense if covariates are centered (see Hofner et al. 2014 tutorial, p. 7)
2. Include intercept in each linear BL and aggregate into global intercept post-hoc:
   - Assume linear base learners $b_j(\mathbf{x}) = \theta_{j1} + \theta_{j2} x_j$. If base learner $\hat{b}_j$ with parameter $\hat{\boldsymbol{\theta}}^{[1]} = (\hat{\theta}_{j1}^{[1]}, \hat{\theta}_{j1}^{[1]})$ is selected in first iteration, model intercept is updated to $f^{[0]}(\mathbf{x}) + \hat{\theta}_{j1}^{[1]}$.
   - During training, intercept is adjusted M times to yield $f^{[0]}(\mathbf{x}) + \sum_{m=1}^{M} \hat{\theta}_{j1}^{[m]}$

EXAMPLE: LIFE EXPECTANCY

- Consider the `life expectancy` data set (WHO, available on Kaggle): regression task to predict life expectancy.
- We fit a CWB model with linear BLs (with intercept)

variable	description
`Life.expectancy`	Life expectancy in years
`Country`	The country (just a selection GER, USE, SWE, ZAF, and ETH)
`Year`	The recorded year
`BMI`	Average BMI $= \frac{\text{body weight in kg}}{(\text{Height in m})^2}$ in a year and country
`Adult.Mortality`	Adult mortality rates per 1000 population

- Using `compboost` with $M = 150$ iterations, we can visualize which BL was selected when and how the estimated feature effects evolve over time.