Gradient Boosting

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Gradient Boosting

- Extremely popular, successful across many domains and one of the leading methods for winning Kaggle competitions.
- GBMs build an ensemble of shallow and weak successive trees with each tree learning and improving on the previous.
- When combined, these many weak successive trees produce a powerful "committee" that are often hard to beat with other algorithms.

Preparation

- The following slides are based on UC Business Analytics R Programming Guide on **gbm regression**

```
library(rsample)      # data splitting
library(gbm)          # basic implementation
library(xgboost)      # a faster implementation of gbm
library(caret)        # an aggregator package for machine learni
library(h2o)          # a java-based platform
library(pdp)          # model visualization
library(ggplot2)      # model visualization
library(lime)         # model visualization
```

The dataset

```
set.seed(123)
ames_split <- initial_split(AmesHousing::make_ames(), prop = .7)
ames_train <- training(ames_split)
ames_test  <- testing(ames_split)
```

Advantages

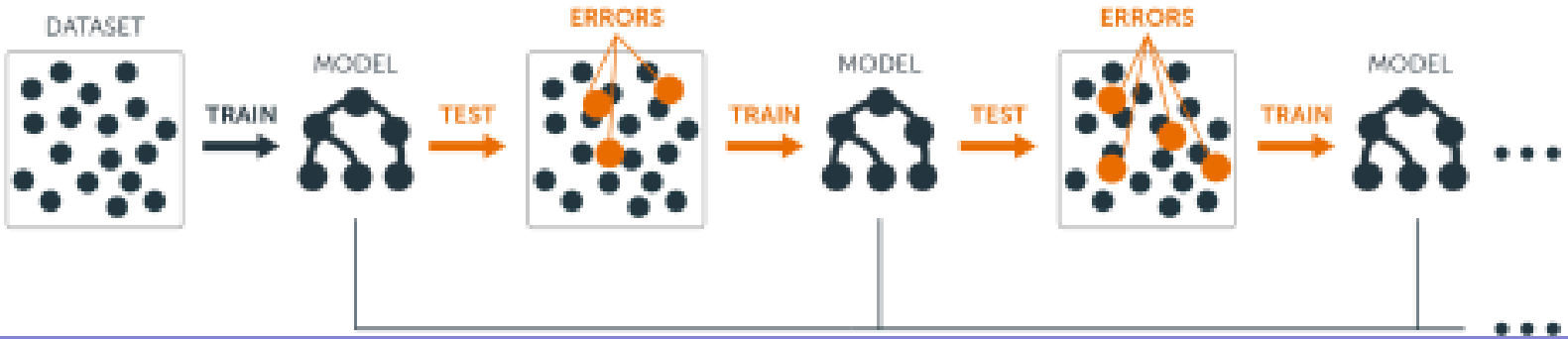
- Often provides predictive accuracy that cannot be beat.
- Lots of flexibility - can optimize on different loss functions and provides several hyperparameter tuning options that make the function fit very flexible.
- No data pre-processing required - often works great with categorical and numerical values as is.
- Handles missing data - imputation not required.

Disdvantages

- GBMs will continue improving to minimize all errors. This can overemphasize outliers and cause overfitting. Must use cross-validation to neutralize.
- Computationally expensive - GBMs often require many trees ($>$1000) which can be time and memory exhaustive.
- The high flexibility results in many parameters that interact and influence heavily the behavior of the approach (number of iterations, tree depth, regularization parameters, etc.). This requires a large grid search during tuning.
- Less interpretable although this is easily addressed with various tools (variable importance, partial dependence plots, LIME, etc.).

The idea

- Several supervised machine learning models are founded on a single predictive model (i.e. linear regression, penalized models, naive Bayes, support vector machines).
- Other approaches such as bagging and random forests are built on the idea of building an ensemble of models where each individual model predicts the outcome and then the ensemble simply averages the predicted values.
- The main idea of boosting is to add new models to the ensemble sequentially.
- At each particular iteration, a new weak, base-learner model is trained with respect to the error of the whole ensemble learnt so far.



Important concepts

Base-learning models

- Boosting is a framework that iteratively improves any weak learning model.
- Many gradient boosting applications allow you to "plug in" various classes of weak learners at your disposal.
- In practice, boosted algorithms often use decision trees as the base-learner.

Training weak models

- A weak model is one whose error rate is only slightly better than random guessing.
- The idea behind boosting is that each sequential model builds a simple weak model to slightly improve the remaining errors.
- Shallow trees represent a weak learner.
- Trees with only 1-6 splits are used.

Sequential training with respect to errors

- Boosted trees are grown sequentially;
- each tree is grown using information from previously grown trees.
- The basic algorithm for boosted regression trees can be generalized to the following where x represents our features and y represents our response:

1.) Fit a decission tree: $F_1(x) = y$

2.) the next decission tree is fixed to the residuals of the previous: $h_1(x) = y - F_1(x)$

3.) Add this new tree to our algorithm: $F_2(x) = F_1(x) + h_1(x)$

4.) The next decission tree is fixed to the residuals of $F_2 : h_2(x) = y - F_2(x)$

5.) Add the new tree to the algorithm: $F_3(x) = F_2(x) + h_1(x)$

Continue this process until some mechanism (i.e. cross validation) tells us to stop.