

# Advanced Tree-Based Methods (MSBA 7027)

## GBM, Stochastic GBM, XGBoost

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2023

# Gradient Boosting Machines (GBMs)

Extremely popular ML algorithm

Successful across many domains

Leading methods for winning ML competitions

Builds shallow trees in sequence

Each tree learns and improves on the previous one

# How Boosting Works

Main idea: add new models (decision trees) sequentially

Start with a weak model,

**Note: the textbook uses “base learner” for weak model, we reserve this term for the Stacking topic to avoid confusion**

Sequentially boosts performance by adding new weak models,

Each new weak model fixes mistakes from previous ones

Main steps

1. Specify the weak model (e.g. max depth / min. node size)
2. Sequential training of weak model

# How Boosting Works

1. Specify the weak model (e.g. max depth / min. node size)

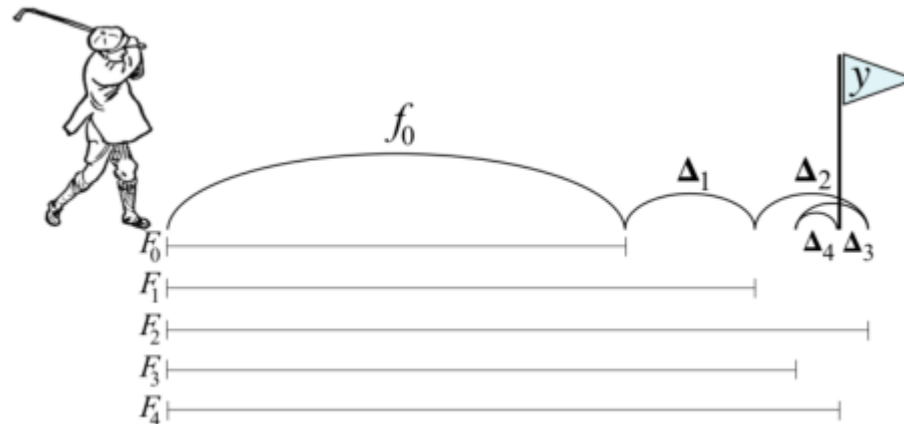
Usually: small-size decision trees

Most common: Trees with depth  $\leq 8$

2. Sequential training of weak model

Each weak model tries to fix mistakes of previous ones

In sequential manner



**Sequential model ensemble:** each iter. gradually nudges predicted values to target

# GBM Numerical Example

Assume Learning Rate = 1

X	Y	Pred aft 1 <sup>st</sup> T	Residual aft 1 <sup>st</sup> T	Pred aft 2 <sup>nd</sup> T	Residual aft 2 <sup>nd</sup> T	Pred aft 3 <sup>rd</sup> T	Residual aft 3 <sup>rd</sup> T
2	6	20/3	- 2/3				
5	10	20/3	10/3				
6	4	20/3	- 8/3				

Note: Residual = true value – predict value

# GBM Numerical Example

Assume Learning Rate = 0.5

X	Y	Pred aft 1 <sup>st</sup> T	Residual aft 1 <sup>st</sup> T	Pred aft 2 <sup>nd</sup> T	Residual aft 2 <sup>nd</sup> T	Pred aft 3 <sup>rd</sup> T	Residual aft 3 <sup>rd</sup> T
2	6	20/3	- 2/3				
5	10	20/3	10/3				
6	4	20/3	- 8/3				

Note: Residual = true value – predict value

# Ames Housing Example – Basic GBM

## Basic Implementation

### Hyperparameters

- Boosting Hyperparameters: #Trees, Learning rate
- Tree Hyperparameters: Tree depth, Min Node size

# Ames Housing Example – Basic GBM

## Basic Implementation

### **Boosting Hyperparameters:**

**#Trees:** total #trees in the boosting sequence

GBM requires many trees

Can overfit – find best #trees by CV

**Learning rate:** Controls how quickly GBM algorithm proceeds

Also called “shrinkage”

Value ranges from (0, 1), typical values between (0.001, 0.3)

Smaller values: typically model more accurate, but algorithm takes longer



# Ames Housing Example – Basic GBM

## Basic Implementation

### **Tree Hyperparameters:**

**Tree depth:** Controls the complexity (depth) of individual trees

Typical value 3-8

High depth: model more accurate, but algorithm takes longer, more prone to overfitting

**Min Node size:** min. #observations in terminal nodes

Also controls the complexity of each tree

Typical value 5-15

# Ames Housing Example – Basic GBM

## Basic Implementation

### gbm package in R

Start with: Learning rate 0.1, # Trees = 5000, Tree depth = 3,  
min node size = 10 (default), 10-fold CV

```
library(gbm) ~ # for original implementation
```

```
# Run a basic GBM model  
# RUNTIME: 2 minutes on i7 CPU  
set.seed(123) # for reproducibility  
system.time( ames_gbm1 <- gbm(  
  formula = Sale_Price ~ .,  
  data = ames_train,  
  distribution = "gaussian",  
  n.trees = 5000,  
  shrinkage = 0.1,  
  interaction.depth = 3,  
  n.minobsinnode = 10,  
  cv.folds = 10  
))
```

**For Classification Problem, use  
distribution = “Bernoulli”**

**Boosting hyperpara.**

**Tree hyperpara.**

{  
{

```
# SSE loss function  
# number of trees  
# learning rate, default is 0.001  
# depth of each tree  
  
# 10-fold cv
```

**Above code returns model\_object ames\_gbm1, with CV errors for all #trees up to 5000**

# Ames Housing Example – Basic GBM

## Basic Implementation

### gbm package in R

Start with: Learning rate 0.1, # Trees = 5000, Tree depth = 3,  
min Node size = 10 (default), 10-fold CV

```
# find index for number trees with minimum CV error  
best <- which.min(ames_gbm1$cv.error)
```

```
# get MSE and compute RMSE  
sqrt(ames_gbm1$cv.error[best])      22402
```

```
# Plot error curve - Figure 12.6
```

```
# Training and cross-validated MSE as n trees are added to the GBM algorithm.
```

```
gbm.perf(ames_gbm1, method = "cv")
```

```
# NOTE: Our results show a cross-validated SSE of 22402 which was achieved with 1119 trees.
```

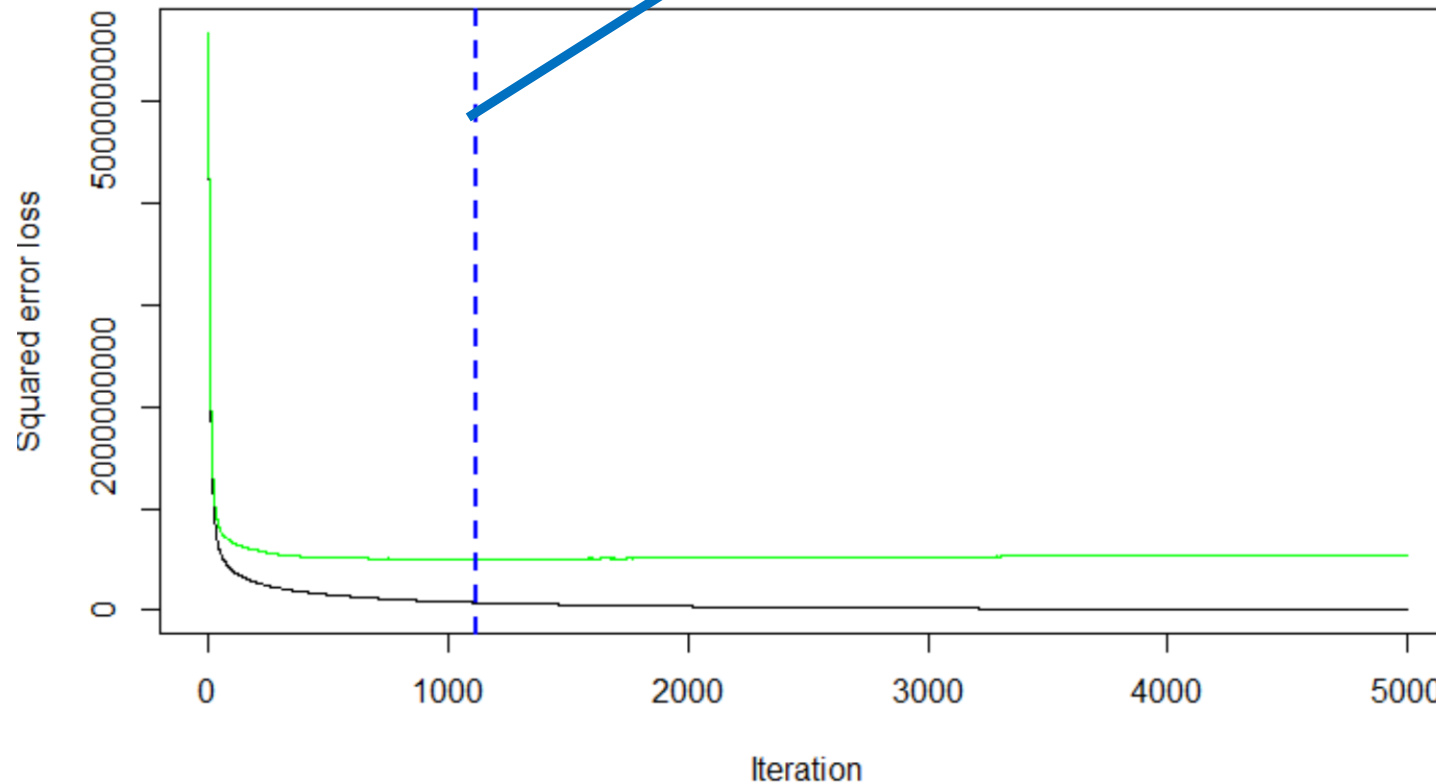
```
#      Gray and green line: Training and cross-validated MSE
```

```
#      Blue line - Achieved with 1119 trees
```

# Ames Housing Example – Basic GBM

## Basic Implementation

Achieve min CV MSE: About 1000 trees



Green curve: cross-validated MSE

Grey curve: training MSE

# Ames Housing Example – Basic GBM

## Tuning Hyperparameters

- Simple way: full grid-search (more details refer to RF)
- More advanced (from book): alternating optimization between learning rate & tree hyperpara.

# Ames Housing Example – Basic GBM

## Tuning Hyperparameters: Alternating Optimization

1. Set learning rate = 0.1 (always a good start value) and determine best #trees
2. Fix tree hyperparameters & tune learning rate → assess speed vs. performance
3. Fix learning rate & tune tree-specific hyperparameters