BOOSTING

Boosting

- What is boosting?
- Benefit of boosting
- How boosting works
- Clarify things about weak learner
- Adaboost
- Gradient boosting
- LightGBM, XGBoost, CatBoost
- Further reading

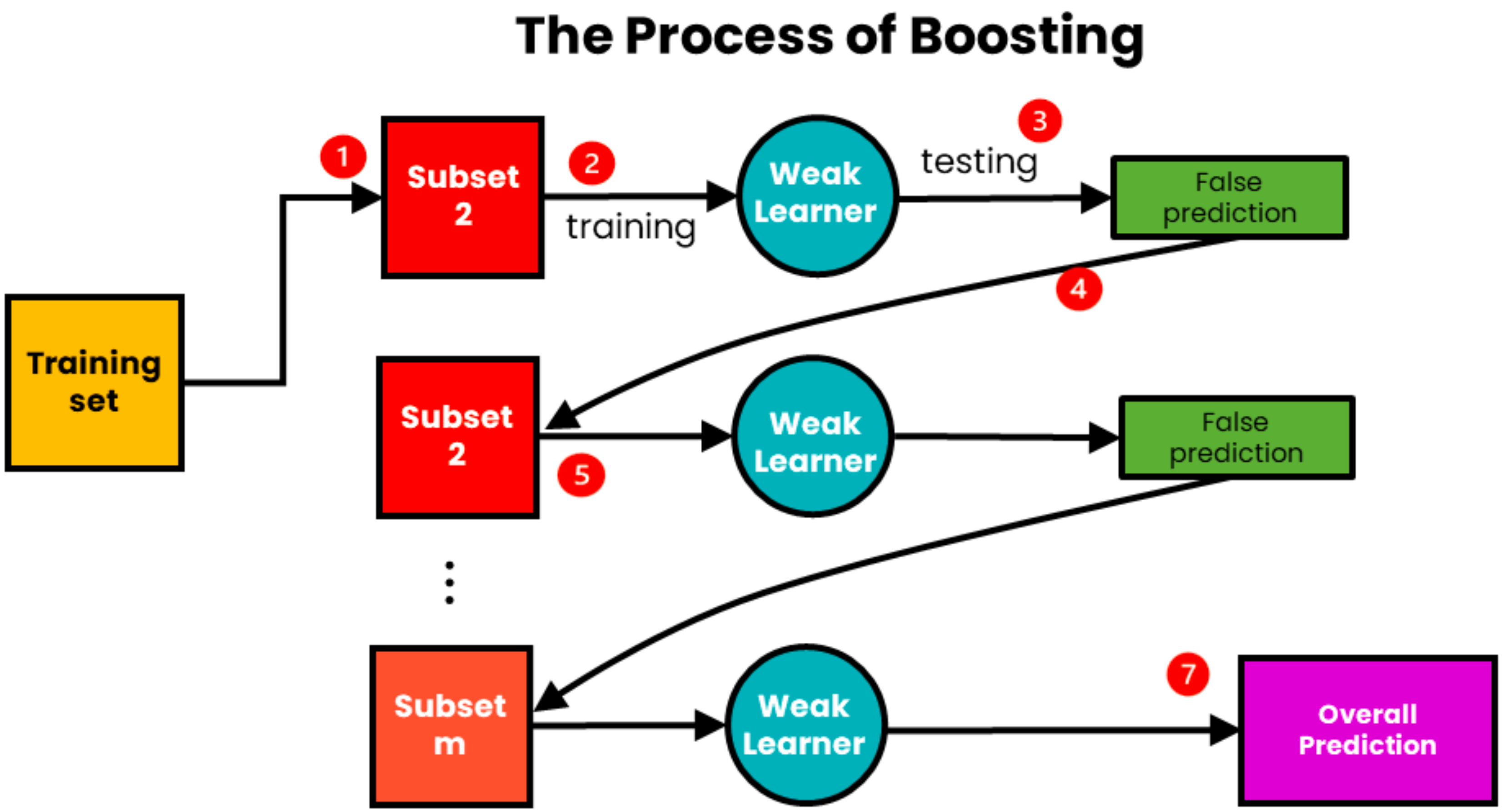
What is boosting?

Boosting is a machine learning ensemble technique that aims to improve the predictive performance of a model by combining multiple weak learners to create a strong learner. The primary goal of boosting is to reduce both bias and variance in supervised learning.

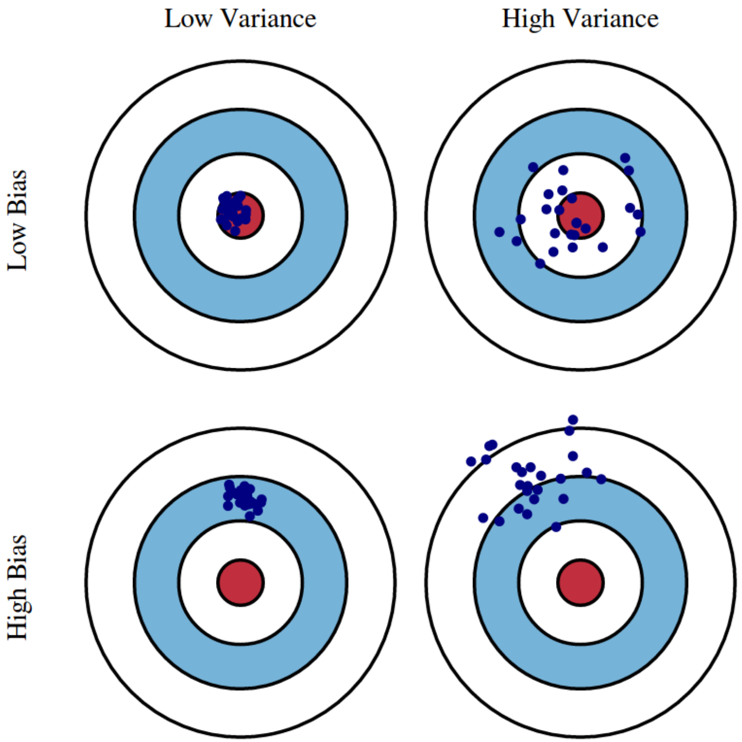
Benefit of boosting (with SL)

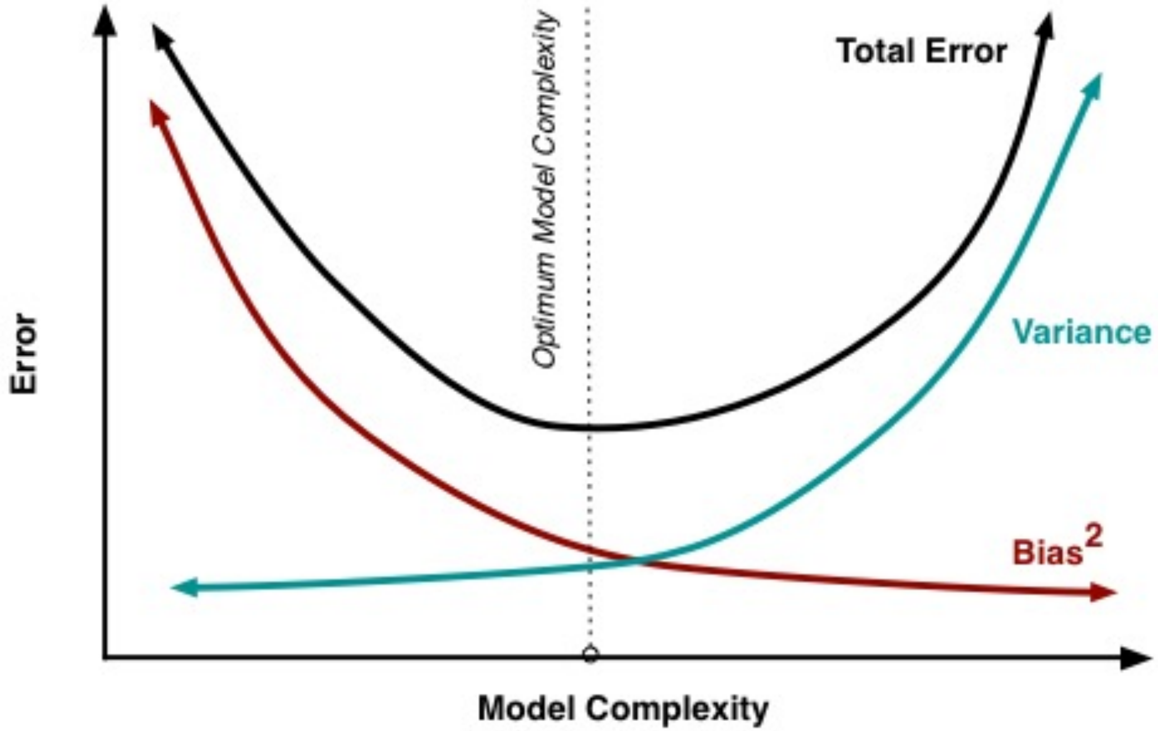
- Improve predictive performance
- Reduction of bias (and variance)
- Robust to overfitting
- Sensitive to outliers

How boosting works



How boosting works





Clarify things about weak learner

Clarify things about weak learner

AdaBoost

AdaBoost

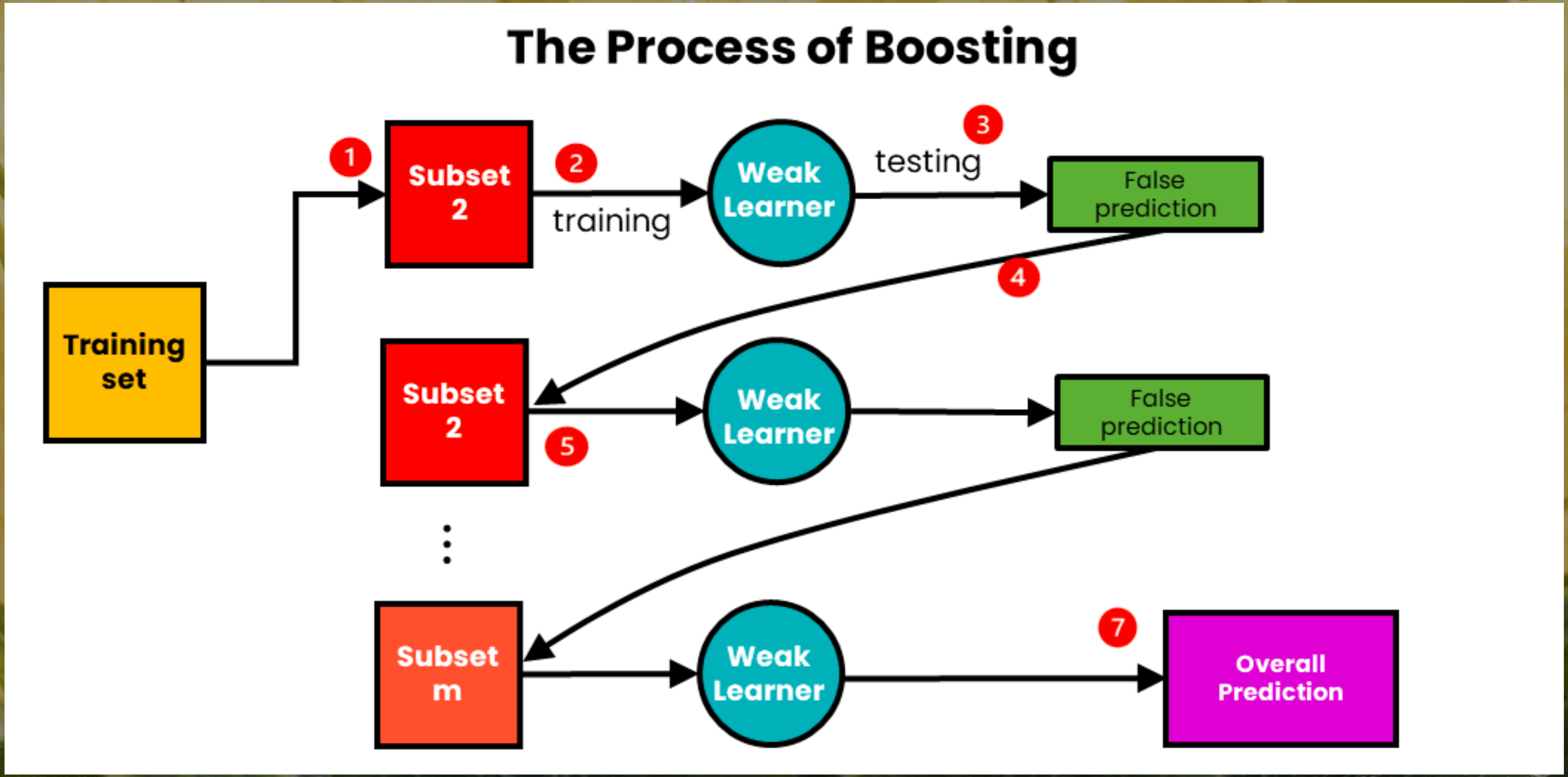
- What is AdaBoost?
- Calculation step
- Calculation concept
- Calculation example
- Discussion about AdaBoost
- Code

What is AdaBoost?

AdaBoost, short for Adaptive Boosting, is a popular ensemble learning technique used primarily for classification tasks. It works by combining multiple weak classifiers to create a strong classifier.

Calculation step

1. Initialize weights
2. Train weak learner
3. Calculate Total Error
4. Calculate influence
5. Update sample weights
6. Normalize sample weights
7. Repeat step 2-6 until meet stopping criteria


The Process of Boosting
Training set
1
Subset 2
2
training
Weak Learner
3
testing
False prediction
4
Subset 2
5
Weak Learner
False prediction
Subset m
Weak Learner
7
Overall Prediction

Initial weights = $\frac{1}{n}$

$n = \text{number of samples}$

$$\text{Total Error} = \frac{n\_errors}{n\_samples}$$

$$\text{Influence} = \alpha = \frac{1}{2}\log\left(\frac{1 - Total\ Error}{Total\ Error}\right)$$

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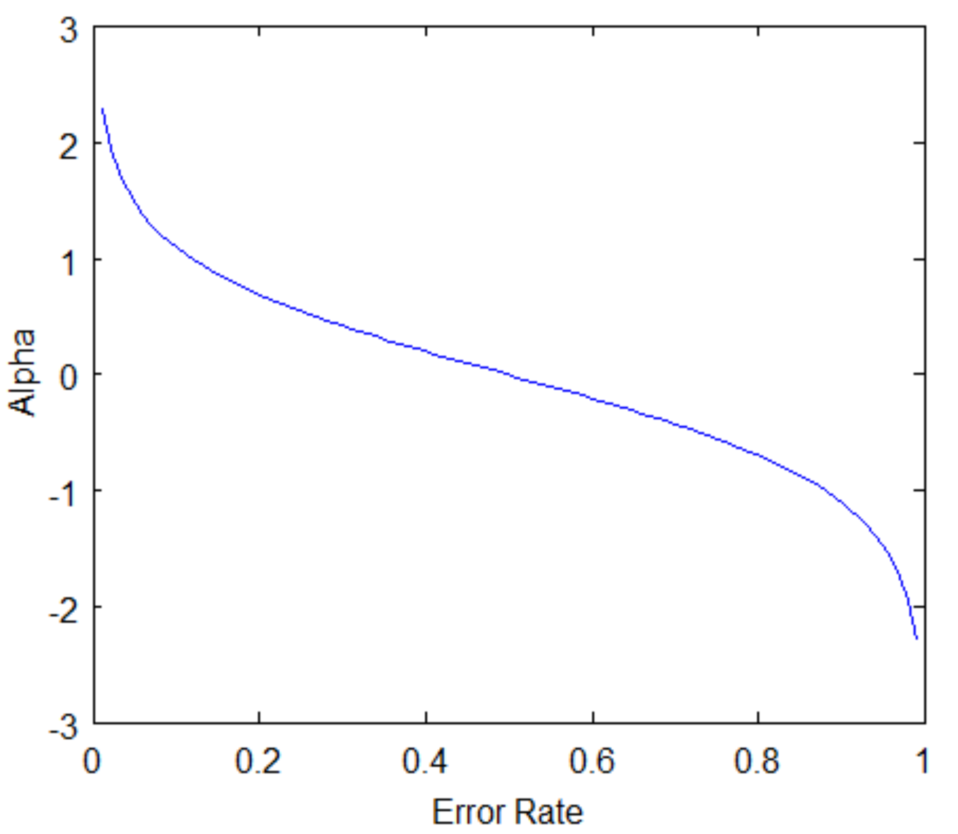


$$new\ sample\ weight = old\ weight\ x\ e^{\alpha}$$

miss-classified

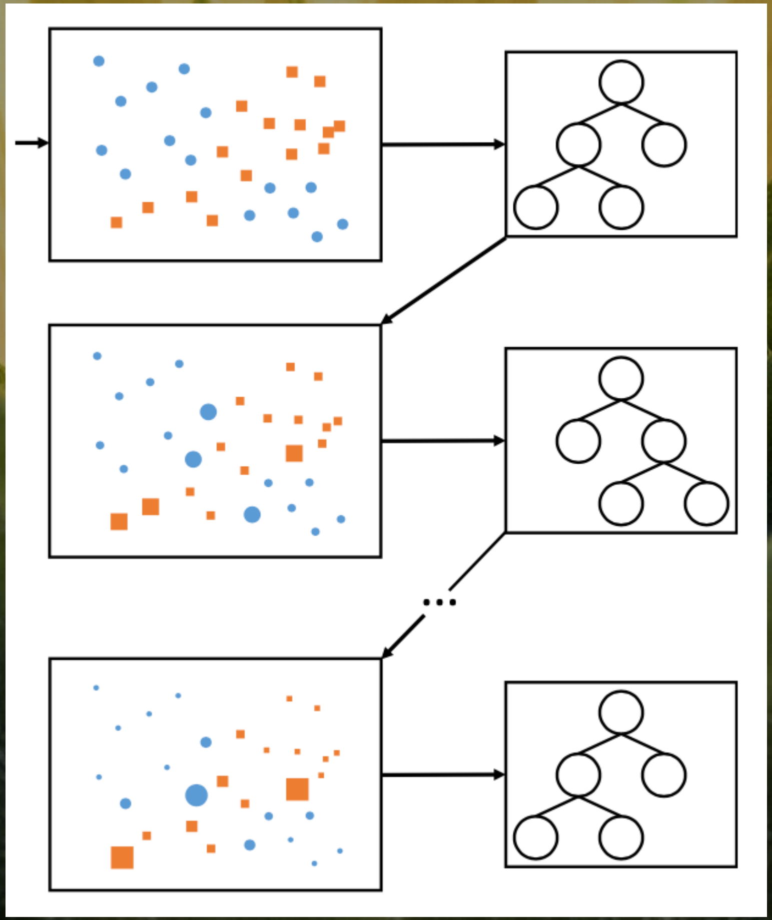
$$new\ sample\ weight = old\ weight\ x\ e^{-\alpha}$$

correctly classified

$$H(x) = \alpha_1 h_1(x) + \alpha_2 h_2(x) + \cdots + \alpha_m h_m(x)$$

$$final\ prediction = sign(H(x))$$

Calculation concept



Calculation example

Initialize weights

x_1	x_2	x_3	x_4	y	weight
$x_{1,1}$	$x_{1,2}$	$x_{1,3}$	$x_{1,4}$	$True$	1/6
$x_{2,1}$	$x_{2,2}$	$x_{2,3}$	$x_{2,4}$	$True$	1/6
$x_{3,1}$	$x_{3,2}$	$x_{3,3}$	$x_{3,4}$	$False$	1/6
$x_{4,1}$	$x_{4,2}$	$x_{4,3}$	$x_{4,4}$	$True$	1/6
$x_{5,1}$	$x_{5,2}$	$x_{5,3}$	$x_{5,4}$	$False$	1/6
$x_{6,1}$	$x_{6,2}$	$x_{6,3}$	$x_{6,4}$	$False$	1/6

Iteration1 – train weak learner

x_1	x_2	x_3	x_4	y	$h_1(x) \Rightarrow \hat{y}$	weight
$x_{1,1}$	$x_{1,2}$	$x_{1,3}$	$x_{1,4}$	$True$	$True$	1/6
$x_{2,1}$	$x_{2,2}$	$x_{2,3}$	$x_{2,4}$	$True$	$True$	1/6
$x_{3,1}$	$x_{3,2}$	$x_{3,3}$	$x_{3,4}$	$False$	$True$	1/6
$x_{4,1}$	$x_{4,2}$	$x_{4,3}$	$x_{4,4}$	$True$	$False$	1/6
$x_{5,1}$	$x_{5,2}$	$x_{5,3}$	$x_{5,4}$	$False$	$False$	1/6
$x_{6,1}$	$x_{6,2}$	$x_{6,3}$	$x_{6,4}$	$False$	$False$	1/6

Iteration1 – Calculate Total Error

x_1	x_2	x_3	x_4	y	$h_1(x) \Rightarrow \hat{y}$	weight
$x_{1,1}$	$x_{1,2}$	$x_{1,3}$	$x_{1,4}$	$True$	$True$	1/6
$x_{2,1}$	$x_{2,2}$	$x_{2,3}$	$x_{2,4}$	$True$	$True$	1/6
$x_{3,1}$	$x_{3,2}$	$x_{3,3}$	$x_{3,4}$	$False$	$True$	1/6
$x_{4,1}$	$x_{4,2}$	$x_{4,3}$	$x_{4,4}$	$True$	$False$	1/6
$x_{5,1}$	$x_{5,2}$	$x_{5,3}$	$x_{5,4}$	$False$	$False$	1/6
$x_{6,1}$	$x_{6,2}$	$x_{6,3}$	$x_{6,4}$	$False$	$False$	1/6

$$Total\ Error = \frac{n\_errors}{n\_samples} = \frac{2}{6} = \frac{1}{3}$$

Iteration1 – Calculate influence

x_1	x_2	x_3	x_4	y	$h_1(x) \Rightarrow \hat{y}$	weight
$x_{1,1}$	$x_{1,2}$	$x_{1,3}$	$x_{1,4}$	$True$	$True$	1/6
$x_{2,1}$	$x_{2,2}$	$x_{2,3}$	$x_{2,4}$	$True$	$True$	1/6
$x_{3,1}$	$x_{3,2}$	$x_{3,3}$	$x_{3,4}$	$False$	$True$	1/6
$x_{4,1}$	$x_{4,2}$	$x_{4,3}$	$x_{4,4}$	$True$	$False$	1/6
$x_{5,1}$	$x_{5,2}$	$x_{5,3}$	$x_{5,4}$	$False$	$False$	1/6
$x_{6,1}$	$x_{6,2}$	$x_{6,3}$	$x_{6,4}$	$False$	$False$	1/6

$$Influence = \alpha_1 = \frac{1}{2}\log\left(\frac{1 - Total\ Error}{Total\ Error}\right) = \frac{1}{2}\log\frac{(1-\frac{1}{3})}{\frac{1}{3}} = 0.35$$

Iteration1 – update sample weights

x_1	x_2	x_3	x_4	y	$h_1(x) \Rightarrow \hat{y}$	weight
$x_{1,1}$	$x_{1,2}$	$x_{1,3}$	$x_{1,4}$	$True$	$True$	$\frac{1}{6}e^{-0.35}$
$x_{2,1}$	$x_{2,2}$	$x_{2,3}$	$x_{2,4}$	$True$	$True$	$\frac{1}{6}e^{-0.35}$
$x_{3,1}$	$x_{3,2}$	$x_{3,3}$	$x_{3,4}$	$False$	$True$	$\frac{1}{6}e^{0.35}$
$x_{4,1}$	$x_{4,2}$	$x_{4,3}$	$x_{4,4}$	$True$	$False$	$\frac{1}{6}e^{0.35}$
$x_{5,1}$	$x_{5,2}$	$x_{5,3}$	$x_{5,4}$	$False$	$False$	$\frac{1}{6}e^{-0.35}$
$x_{6,1}$	$x_{6,2}$	$x_{6,3}$	$x_{6,4}$	$False$	$False$	$\frac{1}{6}e^{-0.35}$

$$new\ sample\ weight = old\ weight\ x\ e^{\alpha}$$

miss-classified

$$new\ sample\ weight = old\ weight\ x\ e^{-\alpha}$$

correctly classified

Iteration1 – update sample weights

x_1	x_2	x_3	x_4	y	$h_1(x) \Rightarrow \hat{y}$	weight
$x_{1,1}$	$x_{1,2}$	$x_{1,3}$	$x_{1,4}$	$True$	$True$	0.70
$x_{2,1}$	$x_{2,2}$	$x_{2,3}$	$x_{2,4}$	$True$	$True$	0.70
$x_{3,1}$	$x_{3,2}$	$x_{3,3}$	$x_{3,4}$	$False$	$True$	1.42
$x_{4,1}$	$x_{4,2}$	$x_{4,3}$	$x_{4,4}$	$True$	$False$	1.42
$x_{5,1}$	$x_{5,2}$	$x_{5,3}$	$x_{5,4}$	$False$	$False$	0.70
$x_{6,1}$	$x_{6,2}$	$x_{6,3}$	$x_{6,4}$	$False$	$False$	0.70

Iteration1 – Normalize sample weights

x_1	x_2	x_3	x_4	y	$h_1(x) \Rightarrow \hat{y}$	weight
$x_{1,1}$	$x_{1,2}$	$x_{1,3}$	$x_{1,4}$	$True$	$True$	0.12
$x_{2,1}$	$x_{2,2}$	$x_{2,3}$	$x_{2,4}$	$True$	$True$	0.12
$x_{3,1}$	$x_{3,2}$	$x_{3,3}$	$x_{3,4}$	$False$	$True$	0.25
$x_{4,1}$	$x_{4,2}$	$x_{4,3}$	$x_{4,4}$	$True$	$False$	0.25
$x_{5,1}$	$x_{5,2}$	$x_{5,3}$	$x_{5,4}$	$False$	$False$	0.12
$x_{6,1}$	$x_{6,2}$	$x_{6,3}$	$x_{6,4}$	$False$	$False$	0.12

Iteration2

Iteration2 – train weak learner

x_1	x_2	x_3	x_4	y	$h_2(x) \Rightarrow \hat{y}$	weight
$x_{1,1}$	$x_{1,2}$	$x_{1,3}$	$x_{1,4}$	$True$	$False$	0.12
$x_{2,1}$	$x_{2,2}$	$x_{2,3}$	$x_{2,4}$	$True$	$True$	0.12
$x_{3,1}$	$x_{3,2}$	$x_{3,3}$	$x_{3,4}$	$False$	$False$	0.25
$x_{4,1}$	$x_{4,2}$	$x_{4,3}$	$x_{4,4}$	$True$	$True$	0.25
$x_{5,1}$	$x_{5,2}$	$x_{5,3}$	$x_{5,4}$	$False$	$False$	0.12
$x_{6,1}$	$x_{6,2}$	$x_{6,3}$	$x_{6,4}$	$False$	$False$	0.12

Iteration2 – Calculate Total Error

x_1	x_2	x_3	x_4	y	$h_2(x) \Rightarrow \hat{y}$	weight
$x_{1,1}$	$x_{1,2}$	$x_{1,3}$	$x_{1,4}$	$True$	$False$	0.12
$x_{2,1}$	$x_{2,2}$	$x_{2,3}$	$x_{2,4}$	$True$	$True$	0.12
$x_{3,1}$	$x_{3,2}$	$x_{3,3}$	$x_{3,4}$	$False$	$False$	0.25
$x_{4,1}$	$x_{4,2}$	$x_{4,3}$	$x_{4,4}$	$True$	$True$	0.25
$x_{5,1}$	$x_{5,2}$	$x_{5,3}$	$x_{5,4}$	$False$	$False$	0.12
$x_{6,1}$	$x_{6,2}$	$x_{6,3}$	$x_{6,4}$	$False$	$False$	0.12

$$Total\ Error = \frac{n\_errors}{n\_samples} = \frac{1}{6}$$

Iteration2 – Calculate influence

x_1	x_2	x_3	x_4	y	$h_2(x) \Rightarrow \hat{y}$	weight
$x_{1,1}$	$x_{1,2}$	$x_{1,3}$	$x_{1,4}$	$True$	$False$	0.12
$x_{2,1}$	$x_{2,2}$	$x_{2,3}$	$x_{2,4}$	$True$	$True$	0.12
$x_{3,1}$	$x_{3,2}$	$x_{3,3}$	$x_{3,4}$	$False$	$False$	0.25
$x_{4,1}$	$x_{4,2}$	$x_{4,3}$	$x_{4,4}$	$True$	$True$	0.25
$x_{5,1}$	$x_{5,2}$	$x_{5,3}$	$x_{5,4}$	$False$	$False$	0.12
$x_{6,1}$	$x_{6,2}$	$x_{6,3}$	$x_{6,4}$	$False$	$False$	0.12

$$Influence = \alpha_2 = \frac{1}{2}\log\left(\frac{1 - Total\ Error}{Total\ Error}\right) = \frac{1}{2}\log\frac{(1-\frac{1}{6})}{\frac{1}{6}} = 0.80$$

Iteration2 – update sample weights

x_1	x_2	x_3	x_4	y	$h_2(x) \Rightarrow \hat{y}$	weight
$x_{1,1}$	$x_{1,2}$	$x_{1,3}$	$x_{1,4}$	$True$	$False$	$0.12e^{0.80}$
$x_{2,1}$	$x_{2,2}$	$x_{2,3}$	$x_{2,4}$	$True$	$True$	$0.12e^{-0.80}$
$x_{3,1}$	$x_{3,2}$	$x_{3,3}$	$x_{3,4}$	$False$	$False$	$0.25e^{-0.80}$
$x_{4,1}$	$x_{4,2}$	$x_{4,3}$	$x_{4,4}$	$True$	$True$	$0.25e^{-0.80}$
$x_{5,1}$	$x_{5,2}$	$x_{5,3}$	$x_{5,4}$	$False$	$False$	$0.12e^{-0.80}$
$x_{6,1}$	$x_{6,2}$	$x_{6,3}$	$x_{6,4}$	$False$	$False$	$0.12e^{-0.80}$

$$new\ sample\ weight = old\ weight\ x\ e^{\alpha}$$

miss-classified

$$new\ sample\ weight = old\ weight\ x\ e^{-\alpha}$$

correctly classified

Iteration2 – update sample weights

x_1	x_2	x_3	x_4	y	$h_2(x) \Rightarrow \hat{y}$	weight
$x_{1,1}$	$x_{1,2}$	$x_{1,3}$	$x_{1,4}$	$True$	$False$	0.27
$x_{2,1}$	$x_{2,2}$	$x_{2,3}$	$x_{2,4}$	$True$	$True$	0.05
$x_{3,1}$	$x_{3,2}$	$x_{3,3}$	$x_{3,4}$	$False$	$False$	0.17
$x_{4,1}$	$x_{4,2}$	$x_{4,3}$	$x_{4,4}$	$True$	$True$	0.17
$x_{5,1}$	$x_{5,2}$	$x_{5,3}$	$x_{5,4}$	$False$	$False$	0.05
$x_{6,1}$	$x_{6,2}$	$x_{6,3}$	$x_{6,4}$	$False$	$False$	0.05

Iteration2 – Normalize sample weights

x_1	x_2	x_3	x_4	y	$h_2(x) \Rightarrow \hat{y}$	weight
$x_{1,1}$	$x_{1,2}$	$x_{1,3}$	$x_{1,4}$	$True$	$False$	0.42
$x_{2,1}$	$x_{2,2}$	$x_{2,3}$	$x_{2,4}$	$True$	$True$	0.0.8
$x_{3,1}$	$x_{3,2}$	$x_{3,3}$	$x_{3,4}$	$False$	$False$	0.25
$x_{4,1}$	$x_{4,2}$	$x_{4,3}$	$x_{4,4}$	$True$	$True$	0.25
$x_{5,1}$	$x_{5,2}$	$x_{5,3}$	$x_{5,4}$	$False$	$False$	0.08
$x_{6,1}$	$x_{6,2}$	$x_{6,3}$	$x_{6,4}$	$False$	$False$	0.08

$$H(x) = 0.35h_1(x) + 0.80h_2(x)$$

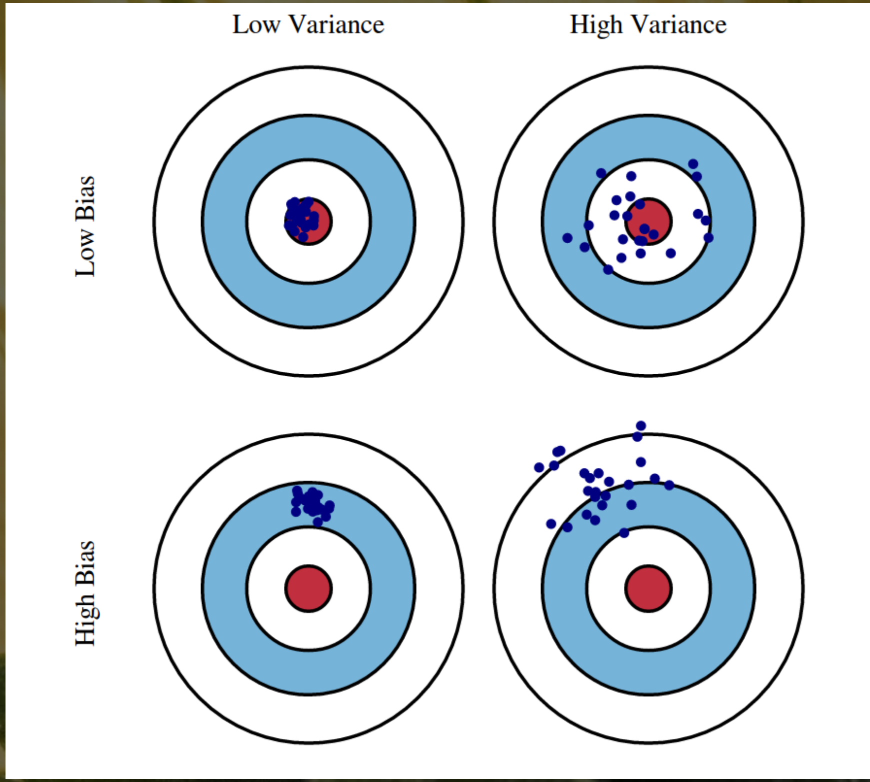
$$final\ prediction = sign(H(x))$$

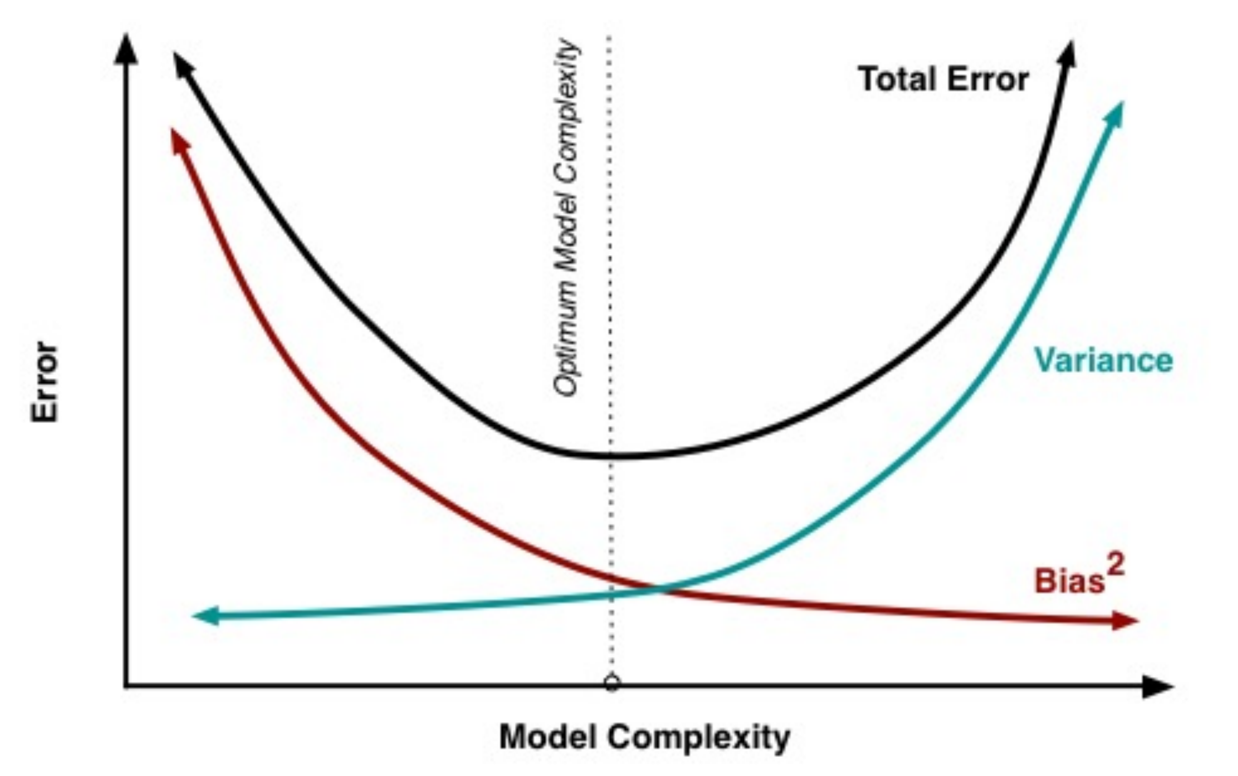
Discussion about AdaBoost

Discussion about AdaBoost

- Mechanism behind AdaBoost
- Why weak learner?
- Extension from AdaBoost
- Suitable n_iterations for AdaBoost

Discussion about AdaBoost





Code

AdaBoost.ipynb

Gradient boosting

Gradient Boosting

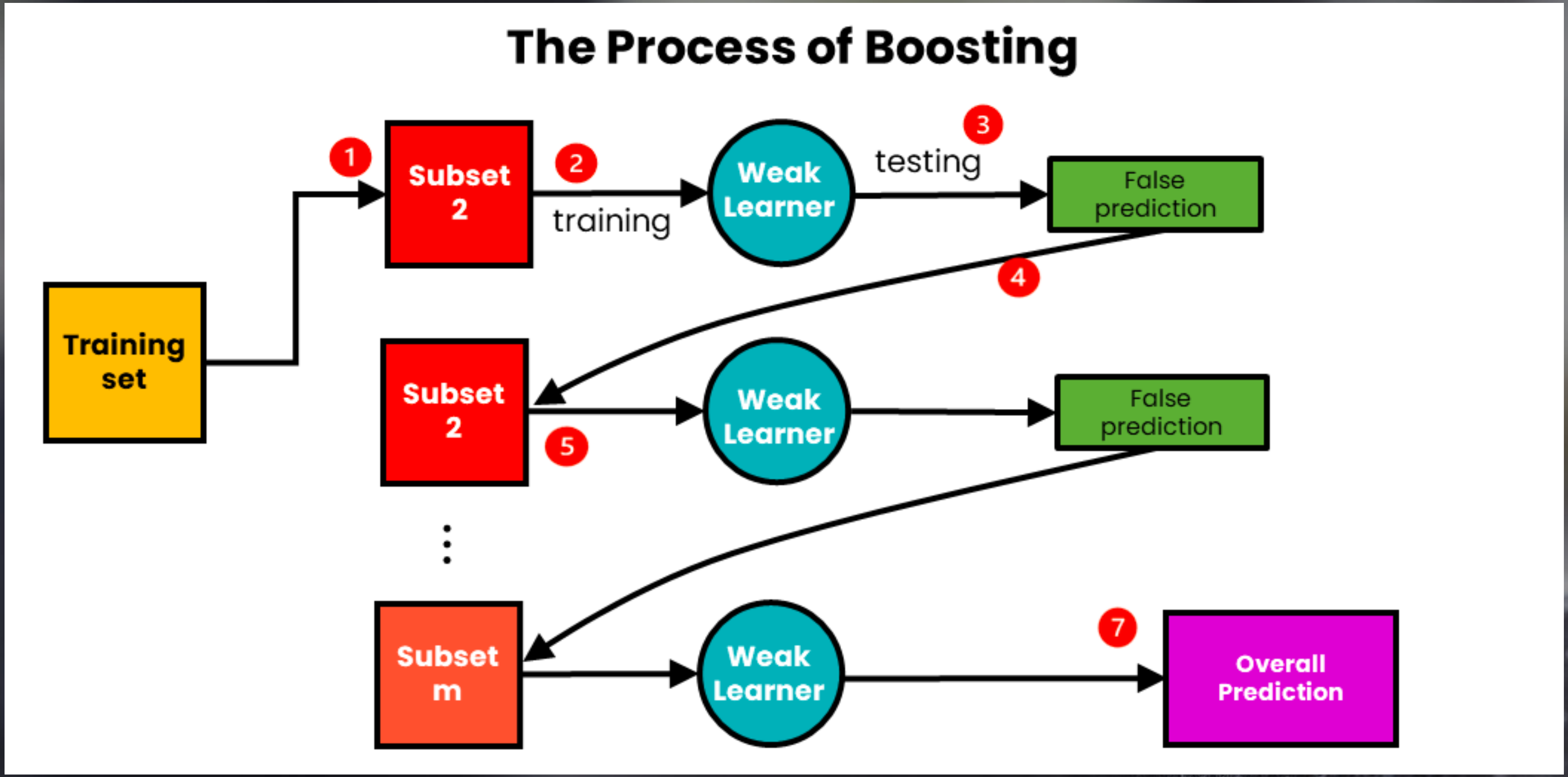
- What is gradient boosting?
- Calculation step
- Calculation concept
- Calculation example
- Discussion about gradient boosting
- Code

What is Gradient boosting?

Gradient Boosting for regression is a machine learning technique that constructs a predictive model by sequentially adding weak learners to minimize the errors of previous models.

Calculation step

1. Initialize the model
2. Calculate pseudo residuals
3. Train weak learner
4. Update the model
5. Repeat step 2-4 until meet stopping criteria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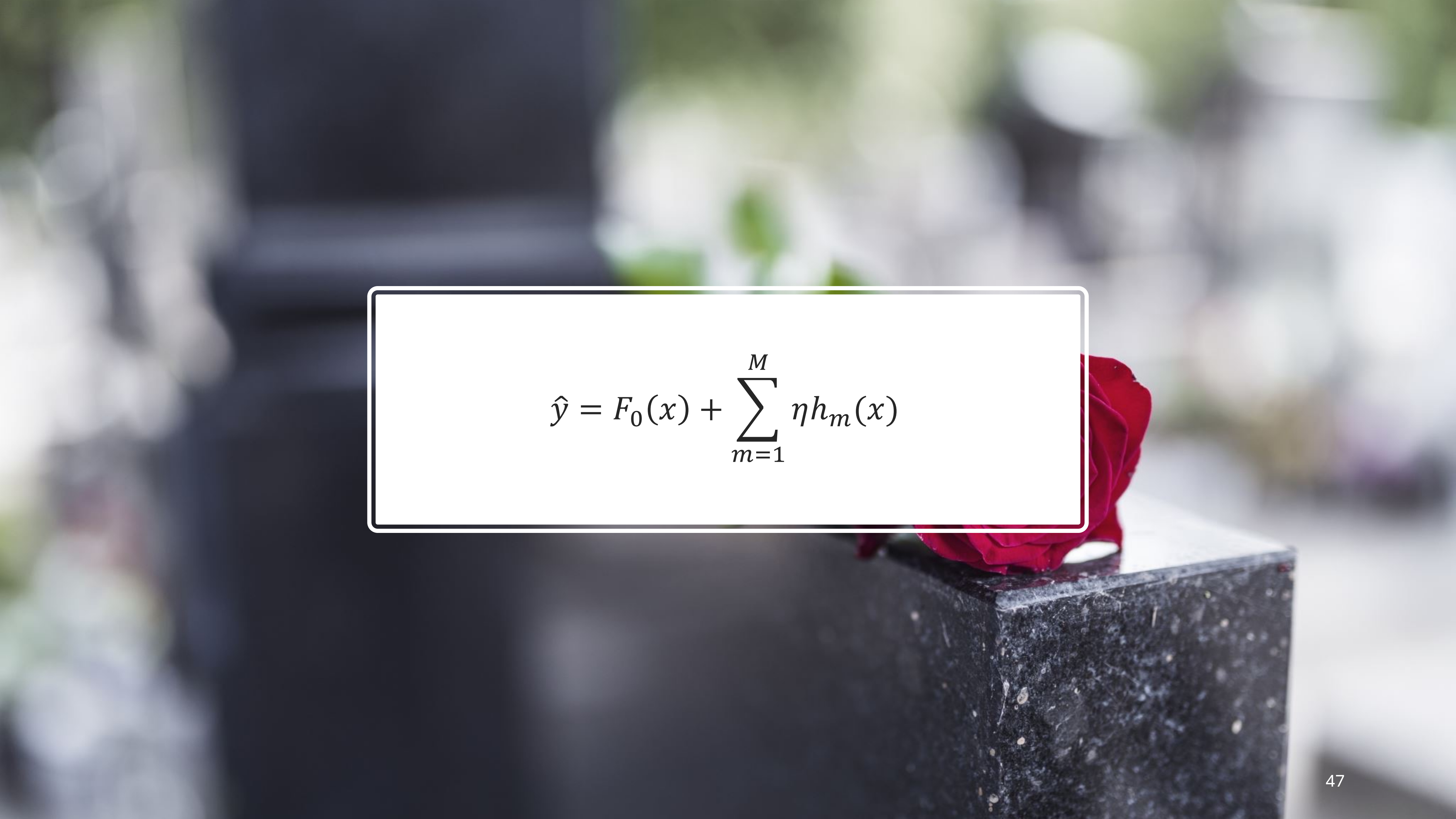
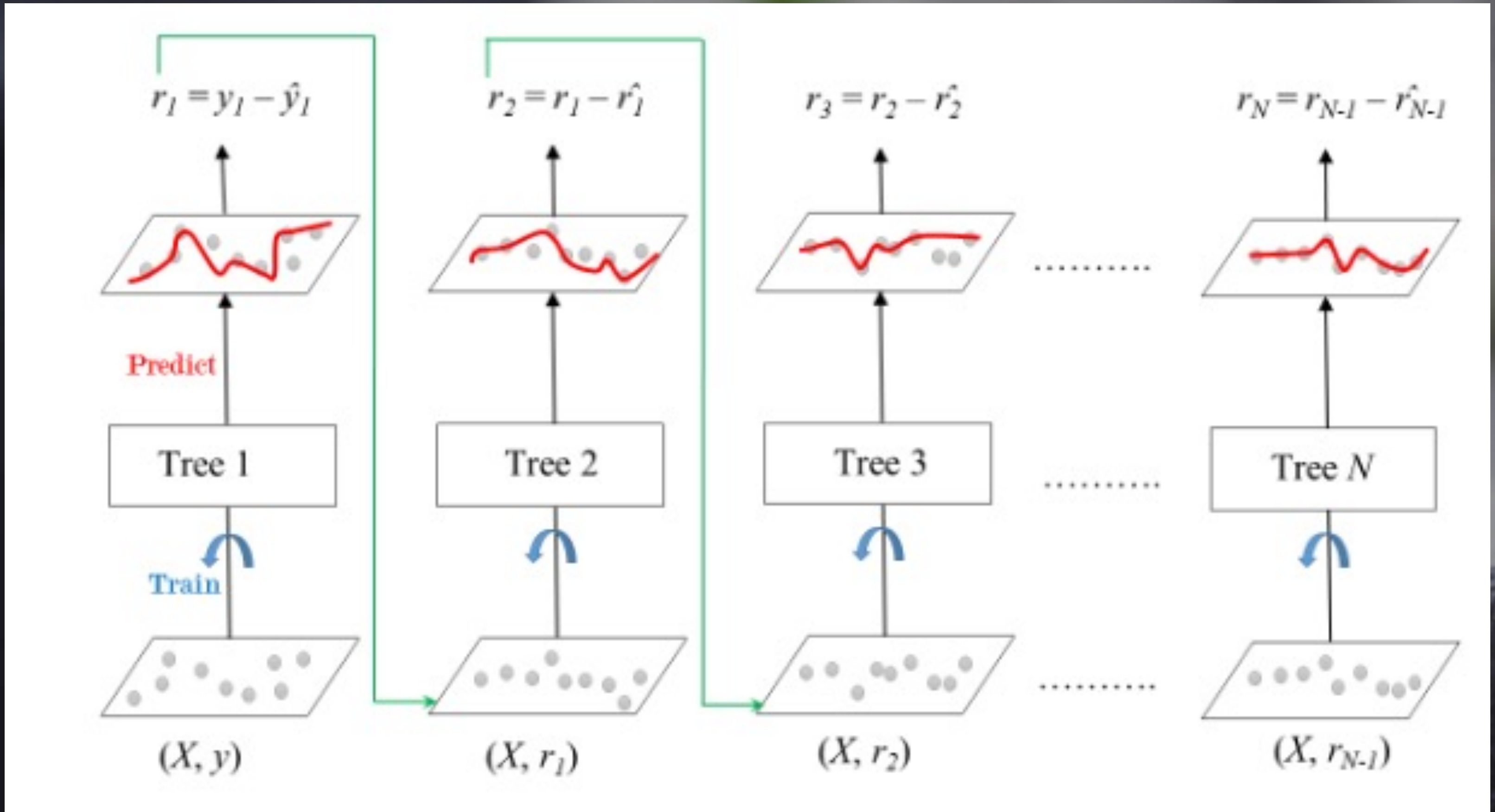
Overall Prediction



$$\hat{y} = F_0(x) + \sum_{m=1}^{M} \eta h_m(x)$$

Calculation concept



Calculation example

Initialize the model

x_1	x_2	x_3	y	$\hat{y} = F_0(x)$
$x_{1,1}$	$x_{1,2}$	$x_{1,3}$	35,000	30,000
$x_{2,1}$	$x_{2,2}$	$x_{2,3}$	10,000	30,000
$x_{3,1}$	$x_{3,2}$	$x_{3,3}$	15,000	30,000
$x_{4,1}$	$x_{4,2}$	$x_{4,3}$	20,000	30,000
$x_{5,1}$	$x_{5,2}$	$x_{5,3}$	40,000	30,000
$x_{6,1}$	$x_{6,2}$	$x_{6,3}$	60,000	30,000

Iteration1 – calculate pseudo residuals

x_1	x_2	x_3	y	$F_0(x)$	r_1
$x_{1,1}$	$x_{1,2}$	$x_{1,3}$	35,000	30,000	5,000
$x_{2,1}$	$x_{2,2}$	$x_{2,3}$	10,000	30,000	-20,000
$x_{3,1}$	$x_{3,2}$	$x_{3,3}$	15,000	30,000	-15,000
$x_{4,1}$	$x_{4,2}$	$x_{4,3}$	20,000	30,000	-10,000
$x_{5,1}$	$x_{5,2}$	$x_{5,3}$	40,000	30,000	10,000
$x_{6,1}$	$x_{6,2}$	$x_{6,3}$	60,000	30,000	30,000

Iteration1 – train weak learner

x_1	x_2	x_3	r_1	$h_1(x)$
$x_{1,1}$	$x_{1,2}$	$x_{1,3}$	5,000	4,800
$x_{2,1}$	$x_{2,2}$	$x_{2,3}$	-20,000	-21,000
$x_{3,1}$	$x_{3,2}$	$x_{3,3}$	-15,000	-16,000
$x_{4,1}$	$x_{4,2}$	$x_{4,3}$	-10,000	-10,000
$x_{5,1}$	$x_{5,2}$	$x_{5,3}$	10,000	11,000
$x_{6,1}$	$x_{6,2}$	$x_{6,3}$	30,000	29,000

Iteration1 – update the model

กำหนดให้ $\eta = 0.1$

จาก $\hat{y} = F_0(x) + \sum_{m=1}^{M} \eta h_m(x)$

ณ iteration1 จะได้ว่า

$$\hat{y} = F_0(x) + 0.1h_m(x)$$

Iteration1 – update the model

x_1	x_2	x_3	y	$\hat{y} = F_0(x) + 0.1h_1(x)$
$x_{1,1}$	$x_{1,2}$	$x_{1,3}$	35,000	30,480
$x_{2,1}$	$x_{2,2}$	$x_{2,3}$	10,000	27,900
$x_{3,1}$	$x_{3,2}$	$x_{3,3}$	15,000	28,400
$x_{4,1}$	$x_{4,2}$	$x_{4,3}$	20,000	29,000
$x_{5,1}$	$x_{5,2}$	$x_{5,3}$	40,000	31,000
$x_{6,1}$	$x_{6,2}$	$x_{6,3}$	60,000	32,900

iteration2

Iteration2 - calculate pseudo residuals

x_1	x_2	x_3	y	$\hat{y} = F_0(x) + 0.1h_1(x)$	r_2
$x_{1,1}$	$x_{1,2}$	$x_{1,3}$	35,000	30,480	4,520
$x_{2,1}$	$x_{2,2}$	$x_{2,3}$	10,000	27,900	-17,900
$x_{3,1}$	$x_{3,2}$	$x_{3,3}$	15,000	28,400	-13,400
$x_{4,1}$	$x_{4,2}$	$x_{4,3}$	20,000	29,000	-9,000
$x_{5,1}$	$x_{5,2}$	$x_{5,3}$	40,000	31,000	9,000
$x_{6,1}$	$x_{6,2}$	$x_{6,3}$	60,000	32,900	27,100

Iteration2 – train weak learner

x_1	x_2	x_3	r_2	$h_1(x)$
$x_{1,1}$	$x_{1,2}$	$x_{1,3}$	4,520	4,500
$x_{2,1}$	$x_{2,2}$	$x_{2,3}$	-17,900	-18,000
$x_{3,1}$	$x_{3,2}$	$x_{3,3}$	-13,400	-13,000
$x_{4,1}$	$x_{4,2}$	$x_{4,3}$	-9,000	-9,000
$x_{5,1}$	$x_{5,2}$	$x_{5,3}$	9,000	10,000
$x_{6,1}$	$x_{6,2}$	$x_{6,3}$	27,100	27,000

Iteration2 – update the model

กำหนดให้ $\eta = 0.1$

จาก $\hat{y} = F_0(x) + \sum_{m=1}^{M} \eta h_m(x)$

ณ iteration1 จะได้ว่า

$$\hat{y} = F_0(x) + 0.1h_1(x) + 0.1h_2(x)$$

Iteration2 – update the model

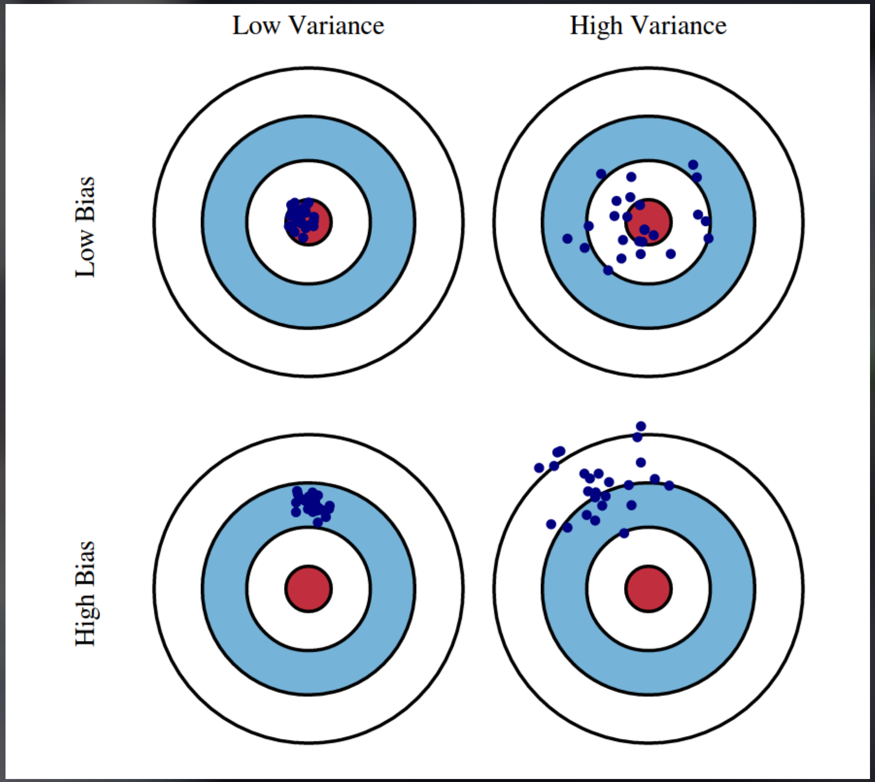
x_1	x_2	x_3	y	$\hat{y} = F_0(x) + 0.1h_1(x) + 0.1h_2(x)$
$x_{1,1}$	$x_{1,2}$	$x_{1,3}$	35,000	30,930
$x_{2,1}$	$x_{2,2}$	$x_{2,3}$	10,000	26,100
$x_{3,1}$	$x_{3,2}$	$x_{3,3}$	15,000	27,100
$x_{4,1}$	$x_{4,2}$	$x_{4,3}$	20,000	28,100
$x_{5,1}$	$x_{5,2}$	$x_{5,3}$	40,000	32,000
$x_{6,1}$	$x_{6,2}$	$x_{6,3}$	60,000	35,600

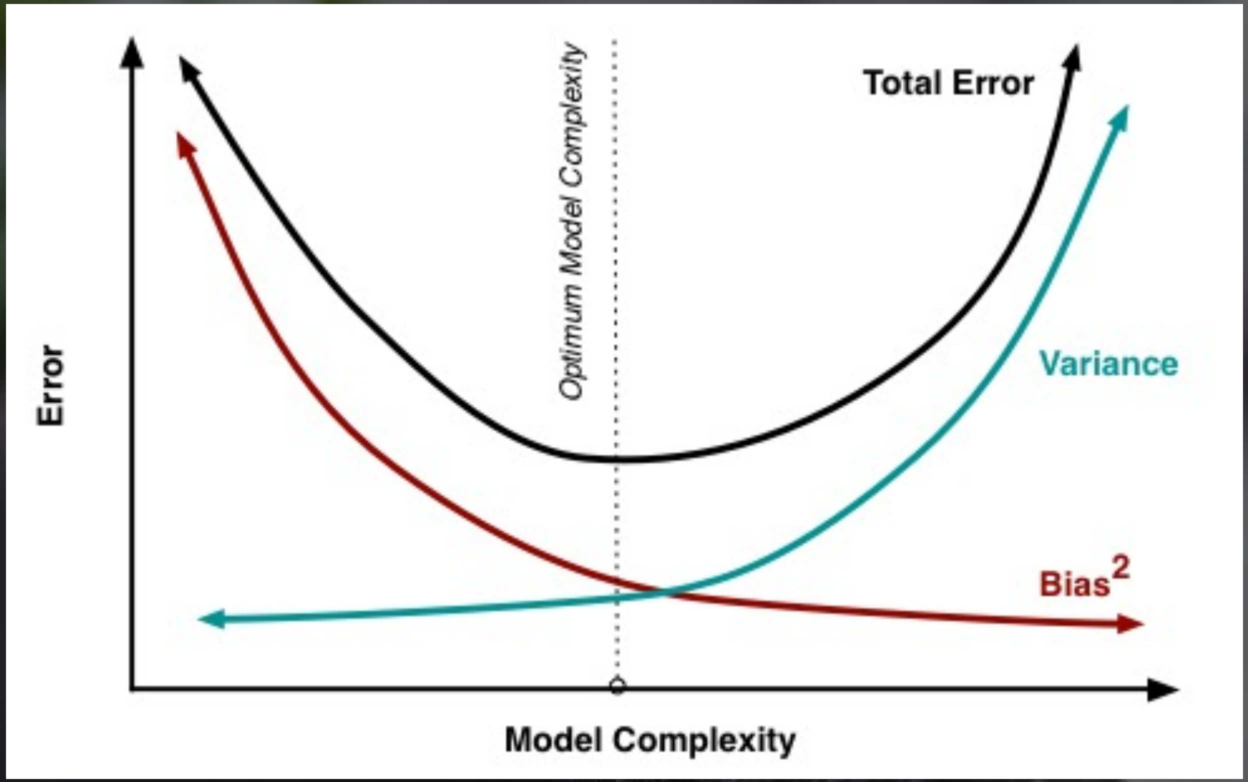
Discussion about gradient boosting

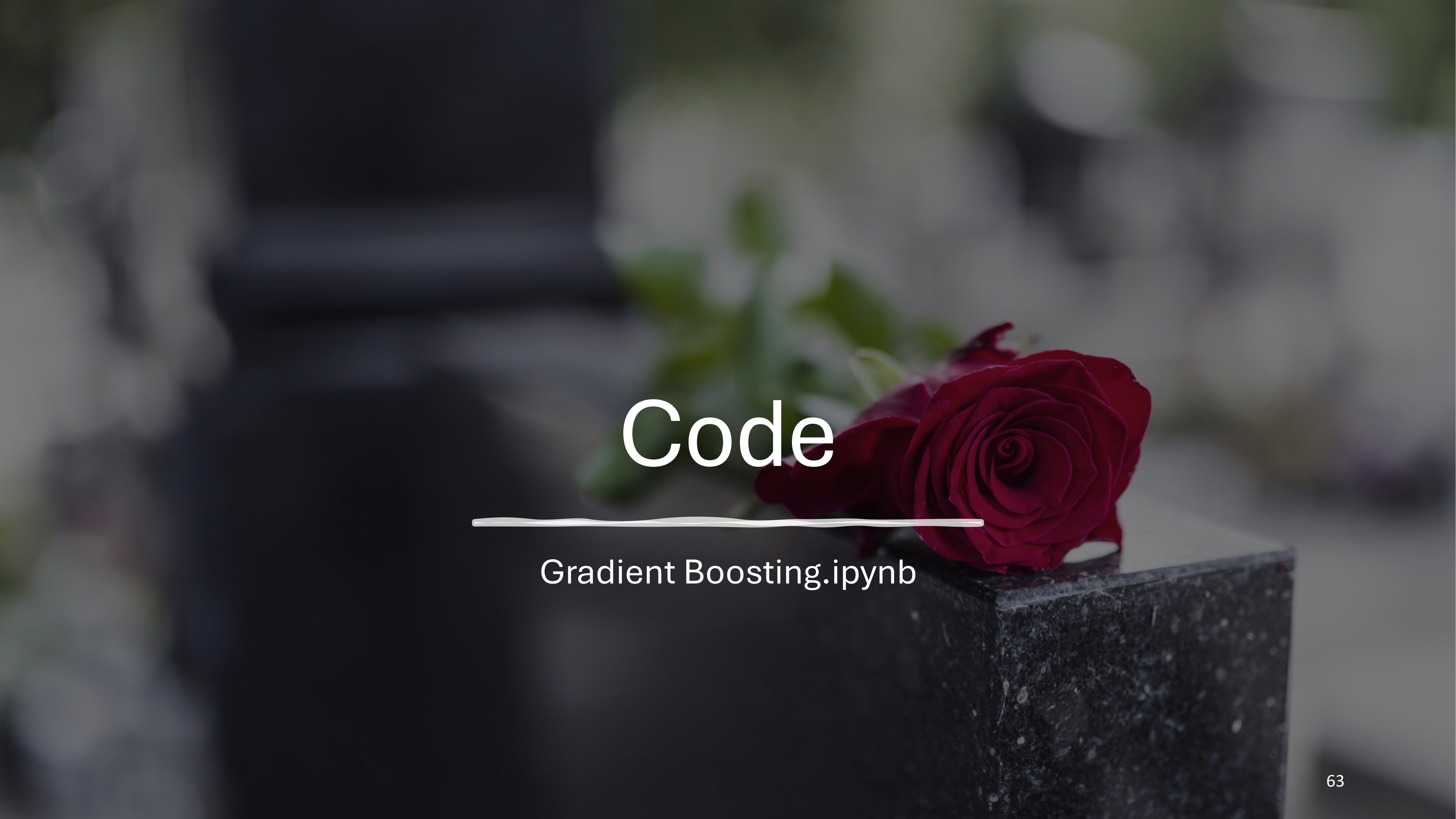
Discussion about gradient boosting

- Why don't we fit pseudo residuals with strong learner?
- What is the intuition behind gradient boosting?
- Why weak learner?
- Suitable n_iterations for gradient boosting

Discussion about gradient boosting







Code

Gradient Boosting.ipynb

LightGBM, XGBoost, CatBoost

LightGBM, XGBoost, CatBoost

Gradient boosting

+ regularization

+ approximate greedy algorithm

+ weighted quantile sketch

+ sparsity-aware split finding

+ parallel learning

+ cache-aware access

+ blocks for out-of-core computation

+ etc

Further reading

- AdaBoost for regression
- Gradient boost for classification

QUESTION & ANSWER

Reference

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