XgBoost → (R, C)

$w_n = w_0 + \eta \left(\frac{\partial L}{\partial w}\right) \rightarrow GD$

RF

$T_1 \quad T_2 \quad T_3$

$T_4 \quad T_5$

T_6

1. Ensemble → DT

2. Boosting → Tree will be built in a seq order.

$$T_1 \xrightarrow{L} T_2 \rightarrow T_3 \rightarrow T_4 \cdots$$

3. Gradient Descent.

R → MSE,

C → Logloss.

4. Regularization → L1, L2,

$$\boxed{L(\theta) = \underbrace{\sum_{i=1}^{n} l(y_i, \hat{y})}_{\text{loss}} + \underbrace{\sum_{k=1}^{K} \Omega(f_k)}_{\text{Regularization term}} \rightarrow \text{Objective fun.}}$$

↓

(Taylor Expansion)

$$L(\theta) = \sum_{i=1}^{n} \left[g_i \cdot d_t(x_i) + \frac{1}{2} h_i\, d_t^2(x_i) \right] + \Omega(f_t)$$

$$g_i = \frac{\partial l(y_i, \hat{y}_i)}{\partial \hat{y}_i} \quad \text{(Gradient)} \qquad \left(\frac{1}{2n} \sum_i (y_i - \hat{y}_i)^2 \right)$$

$$h_i = \frac{\partial^2 l(y_i, \hat{y}_i)}{\partial \hat{y}_i} \quad \text{(Hessian)}$$

$$\Omega(f) = \left(\gamma T + \frac{1}{2} \lambda \sum w_i^2 \right)$$

$T \rightarrow$ Number of leaves in tree.

$\gamma \rightarrow$ It controles the depth of the tree.

$\lambda \rightarrow$ L2

$(0, 1)$

$T_1 \rightarrow \hat{y}_1 = 0.5$

$g_i = \frac{\partial L}{\partial \hat{y}} = (\hat{y} - y)$

$h_i = \frac{\partial^2 L}{\partial \hat{y}^2} = \hat{y}(1 - \hat{y})$

$y = 0, 1$

$\hat{y}$ = Prediction Probability.

$T_2 \rightarrow$

$$\text{Gain} = \frac{1}{2}\left[\frac{G_L^2}{H_L + \lambda} + \frac{G_R^2}{H_R + \lambda} - \frac{(G_L + G_R)^2}{H_L + H_R + \lambda}\right] - \gamma$$

$G_L \rightarrow G_R \rightarrow$ Sum of Gradient of left and Right child Node

$H_L, H_R \rightarrow$ Sum of Hessians of left and right Node

$\lambda \rightarrow$ L2 Reg.

$\gamma \rightarrow$ Penalty term

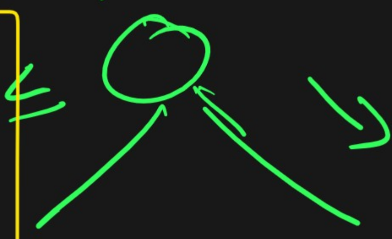
$$W = \frac{-G}{H + \lambda}$$

$$\hat{y}_n = \hat{y}_0 + \eta f(x)$$

T_1

$$= 0.5 + \eta$$

X = 12



ID	X	y (C)
1	10	1
2	15	0
3	20	1
4	17	? (0, 1)

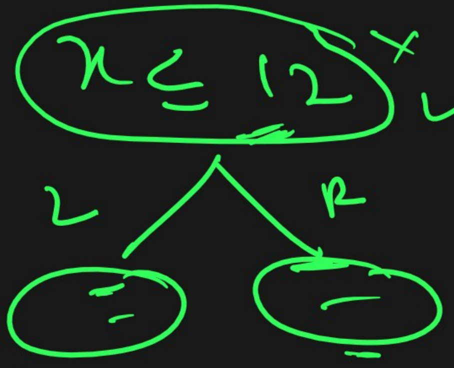
$T_1 \rightarrow \hat{y}_{17} = 0.5$

$$g_i = (\hat{y} - y)$$

$$h_i = \hat{y}(1 - \hat{y})$$

ID	X	$\hat{y}_1$	g_i	h_i
1	10	0.5	−0.5	0.25
✓ 2	15	0.5	0.5	0.25
✓ 3	20	0.5	−0.5	0.25

T2



$G_L = -0.5 \quad H_L = 0.25$

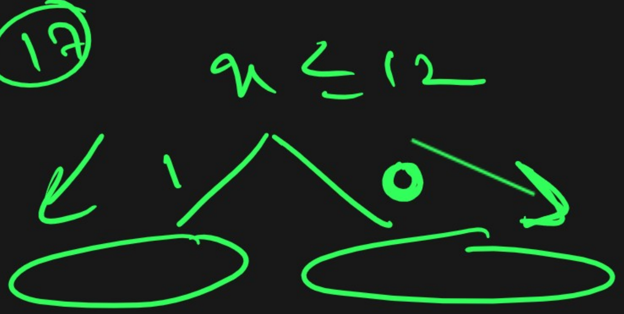
1 $\quad x > 12 \quad$ 0

$G_R = 0 \quad H_R = 0.5$

$$\text{Gain} = \frac{1}{2}\left[\frac{(-0.5)^2}{0.25+\lambda} + \frac{0^2}{0.5+\lambda} - \frac{(-0.5+0)^2}{0.75+\lambda}\right] - \gamma$$

$$w_L = -\left(\frac{-0.5}{0.25+\lambda}\right) \qquad w_R = -\frac{0}{0.5+\lambda} = 0$$

12



$w_2 =$ $\quad w_R =$ $\quad 0$

$$w_L = \frac{0.5}{0.25+\lambda} \qquad w_R = 0$$

0.1

$w_L = (1.42) \qquad w_R = 0$

$$\hat{y} = y_0 + \eta(f(x))$$

$\hat{y}_{17} = 0.5 + 0.01 \times 0$

$= 0.5$

KNN → K nearest neighbours

→ classification ✓

→ Reg ✓

① choose the value of K. →

② calculate distance between new data points and all the existing one.

③ Identify the K nearest →

④ Go for prediction.

10m

	Weight	Sweetness (1-10)	Fruit	Distance
1	150	8	Apple	$\sqrt{(150-145)^2 + (8.5-8)^2} \approx 5.02$
2	160	7	Apple	≈ 15.08
3	180	6	Apple	≈ 35.08
4	130	9	orange	≈ 15.01
5	120	10	orange	≈ 25.04
6	140	9	Orange	≈ 5.02
P	145	8.5	? (orange)	

165   12

P_1 P_2

(x_1, y_1) (x_2, y_2)

$$d = \sqrt{(x_1-x_2)^2 + (y_1-y_2)^2}$$

$$K = \sqrt{N} = \sqrt{6} = 2.44 \approx (2, 3)$$

(2 - NN) - X

(3 - NN)

$K = 2$