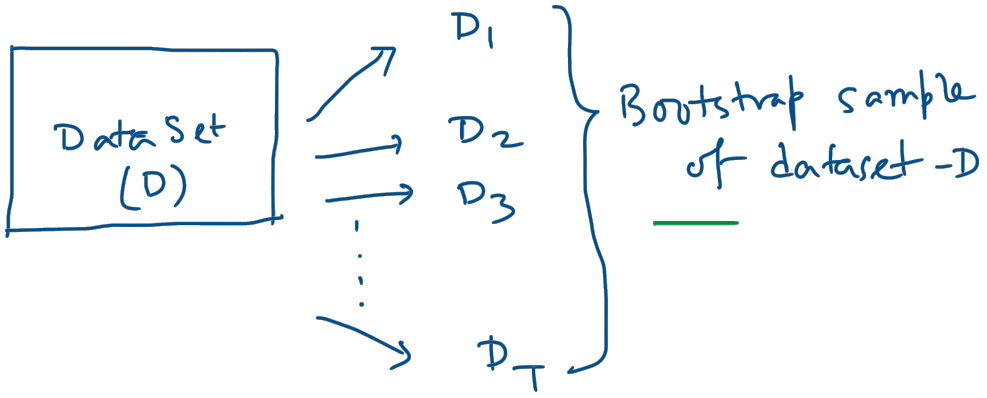
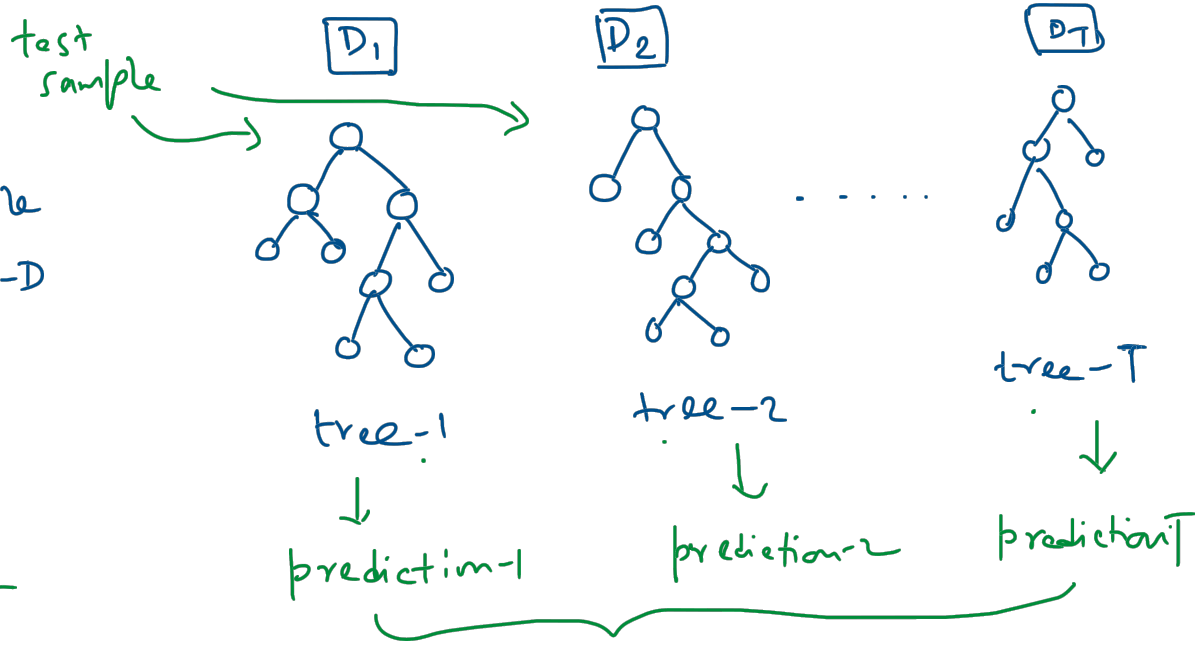
Random Forest Revisit :-





1) We create full size tree for each of the bootstrapped sample data

2) majority voting : Each DT has equal 'say' in the final outcome.

3) Order of the DT creation doesn't matter.

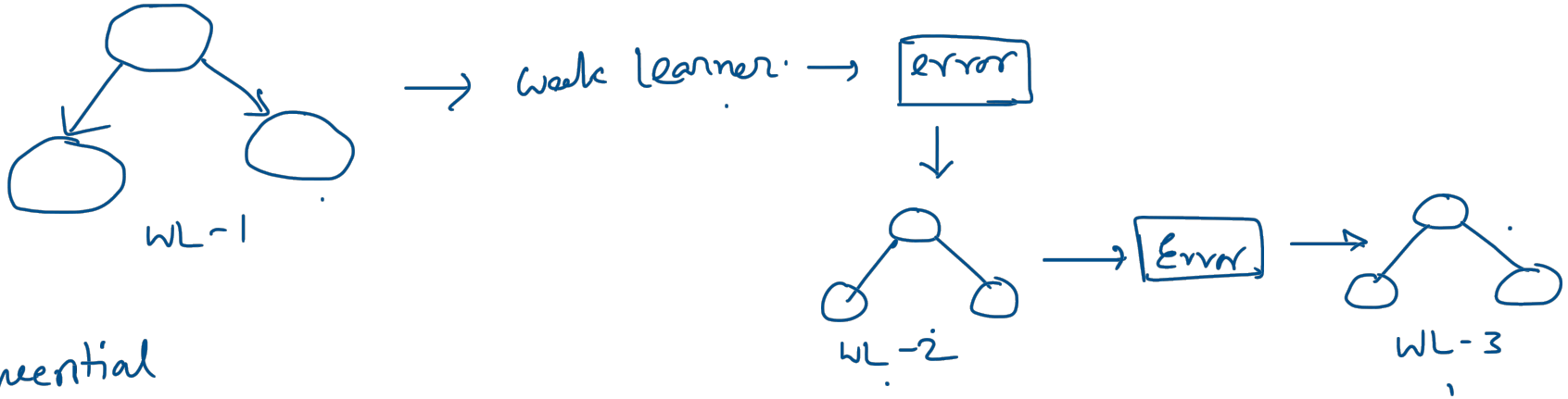
Boosting: An ensemble of multiple weak classifiers.

(AdaBoosting)

↓

Decision stumps

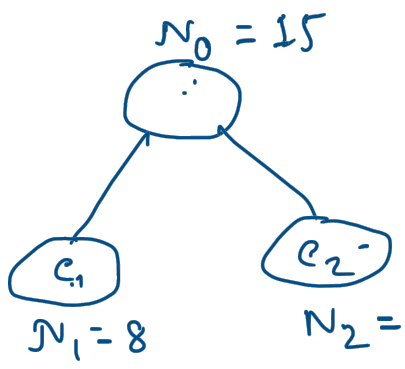
Single depth decision tree



Sequential

The 'say' of WL will depend on their error rate

GINI :-



Class:0 | 5
Class:1 | 3

Class:0 | 2
Class:1 | 5

$$\left(5 \times \frac{1}{15}\right) - \left(8 \times \frac{1}{15}\right)$$

weight ratio of class-0 in node-1

$$\left(\frac{3 \times \frac{1}{15}}{8 \times \frac{1}{15}}\right)$$

weight ratio of class-1 in node-1

$$\left(1 - \sum_{j=1}^{K} p_j^2\right)$$

$p_j \rightarrow$ frequency of class-j

$$GINI(Split) = \frac{N_1}{N_0} \times GINI(C_1) + \frac{N_2}{N_0} GINI(C_2)$$

1 → 0.1
2 → 0.01 ✓ -
3 → 0.05 ✓
4 → 0.07 ✓ -
⋮
⋮
15 → 0.2 ✓ -

$\sum w_i = 1$

Sl No	feature-1	class	Sample weight
1	x_1	1	0.1
2	x_2	0	0.2
3	x_3	1	0.4
4	x_4	1	0.2
5	x_5	0	0.1

N_1 : Sl No 1, 2, 3 — N_2 : Sl No 4, 5

$\sum w_i = 1$

Class -0

$$\sum_{y=0} w_i = 0.2 + 0.1 = 0.3$$

Class -1

$$\sum_{y=1} w_i = 0.7$$

$$\frac{\sum_{y=0} w_i}{\sum_i w_i} = 0.3 \qquad \frac{\sum_{y=1} w_i}{\sum w_i} = 0.7$$

Weighted Gini $= 1 - (0.3^2 + 0.7^2) = 1 - (0.09 + 0.49)$

$= 1 - 0.58 = 0.42.$

Normal Gini $= 1 - \sum p_j^2 = 1 - \left[\left(\frac{2}{5}\right)^2 + \left(\frac{3}{5}\right)^2\right] = 1 - \frac{4+9}{25} = \frac{12}{25} = 0.48.$

Weighted Gini of node-1

$\sum_{Node(N_1)} w_i = 0.7$,

class -0 $\sum_{N_1, y=0} w_i = 0.2$

class -1 $\sum_{N_1, y=1} w_i = 0.5$

$$1 - \left(\frac{0.2}{0.7}\right)^2 - \left(\frac{0.5}{0.7}\right)^2$$

$$w_i^{(new)} = w_i^{(old)} \times e^{-\alpha_m \boxed{y_i \cdot h_m(x_i)} = z_i}$$

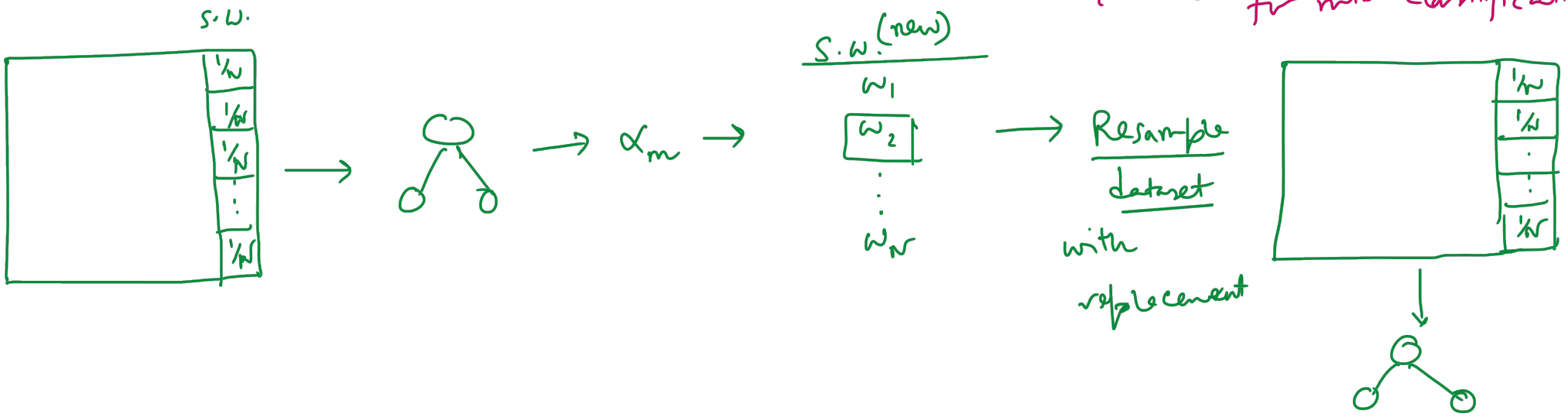
$$= w_i^{(old)} \cdot e^{-\alpha_m z_i}$$

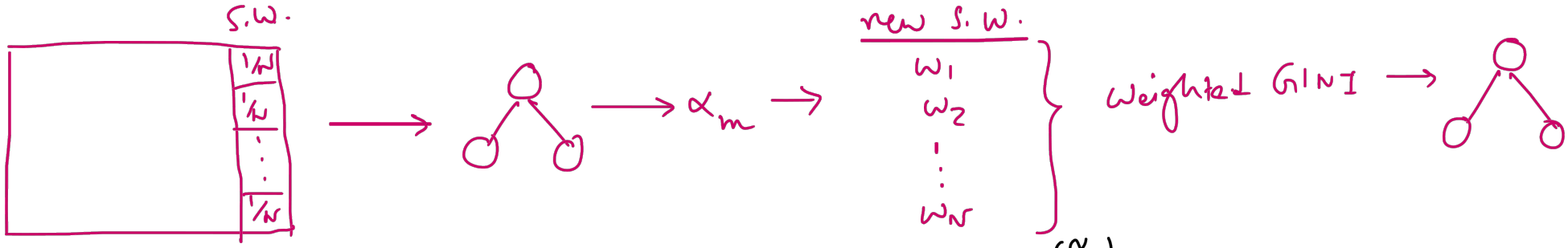
$$z_i = y_i \cdot h_m(x_i)$$

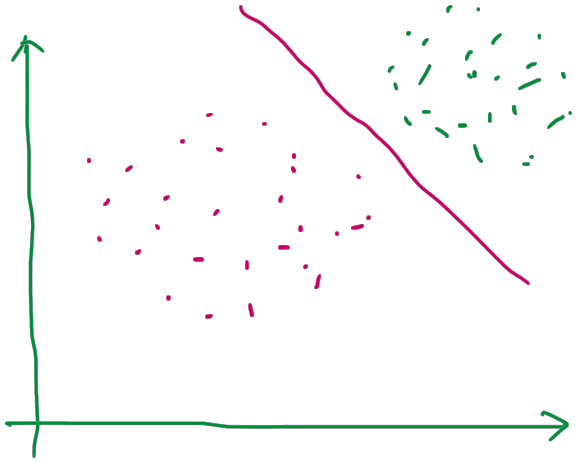
where, $z_i = +1$ if $\hat{y}_i = y_i$ (correct classification)

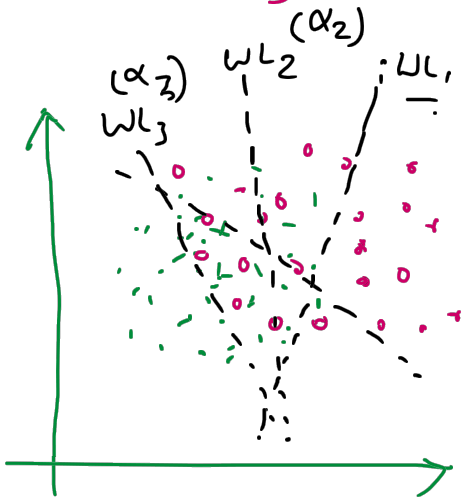
$z_i = -1$ for mis classification.

$$\alpha_m \rightarrow \text{importance} = \frac{1}{2} \ln\left(\frac{1-\varepsilon_m}{\varepsilon_m}\right)$$









.fit(X, y, sample_weight = w)

$$\text{BCE Loss} = -\frac{1}{m}\sum_{i=1}^{m}\left[y^{(i)}\log\hat{y}^{(i)} + (1-y^{(i)})\cdot\log(1-\hat{y}^{(i)})\right]$$

$$\text{Weighted BCE loss} = -\frac{1}{m}\sum_{i=1}^{m} w_i\left[y^{(i)}\log\hat{y}^{(i)} + (1-y^{(i)})\log(1-\hat{y}^{(i)})\right]$$