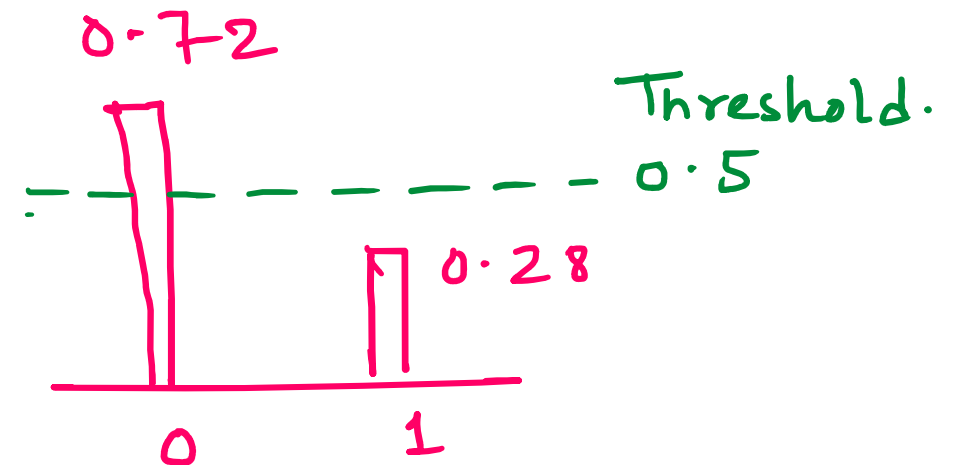
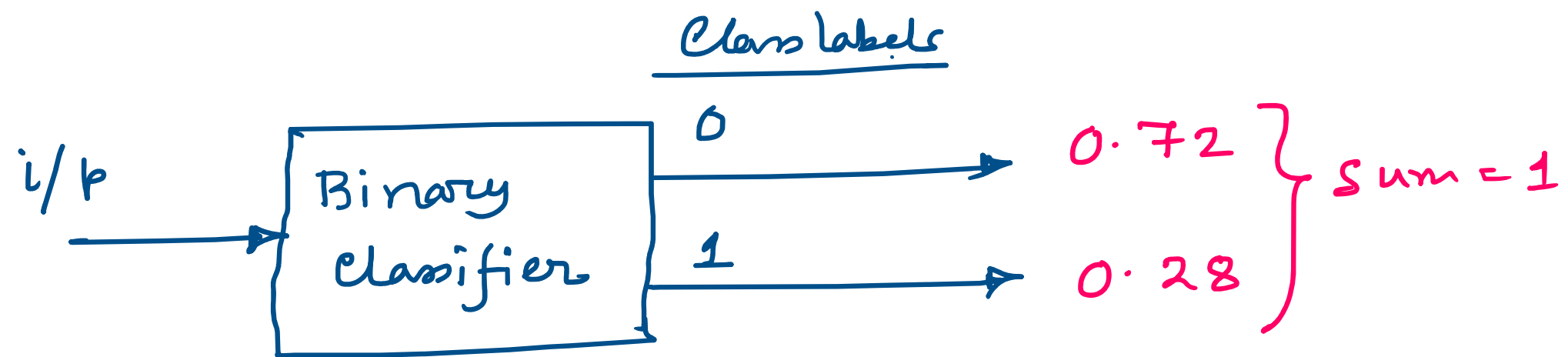


Binary Vs. Multiclass Classifier :-

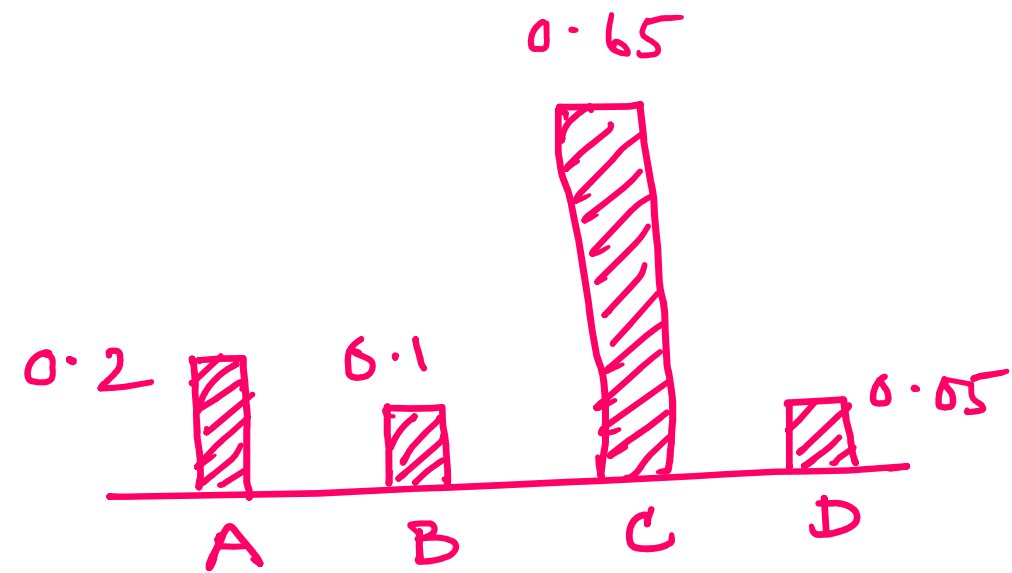
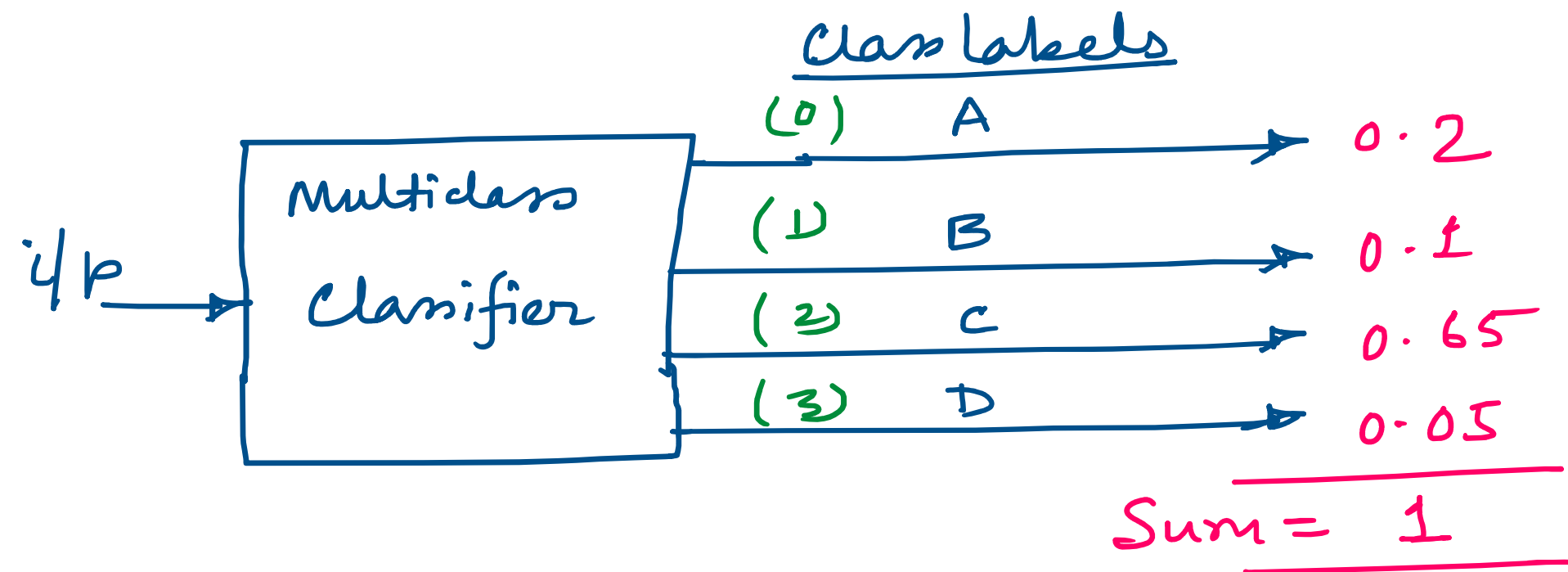


$\text{clf} = \text{fit}(X_{\text{train}}, y_{\text{train}})$

$\text{clf.predict_proba}(X_{\text{test}}) \rightarrow [0.72, 0.28]$

$\text{clf.predict}(X_{\text{test}}, \text{th} = 0.5) \rightarrow 0$

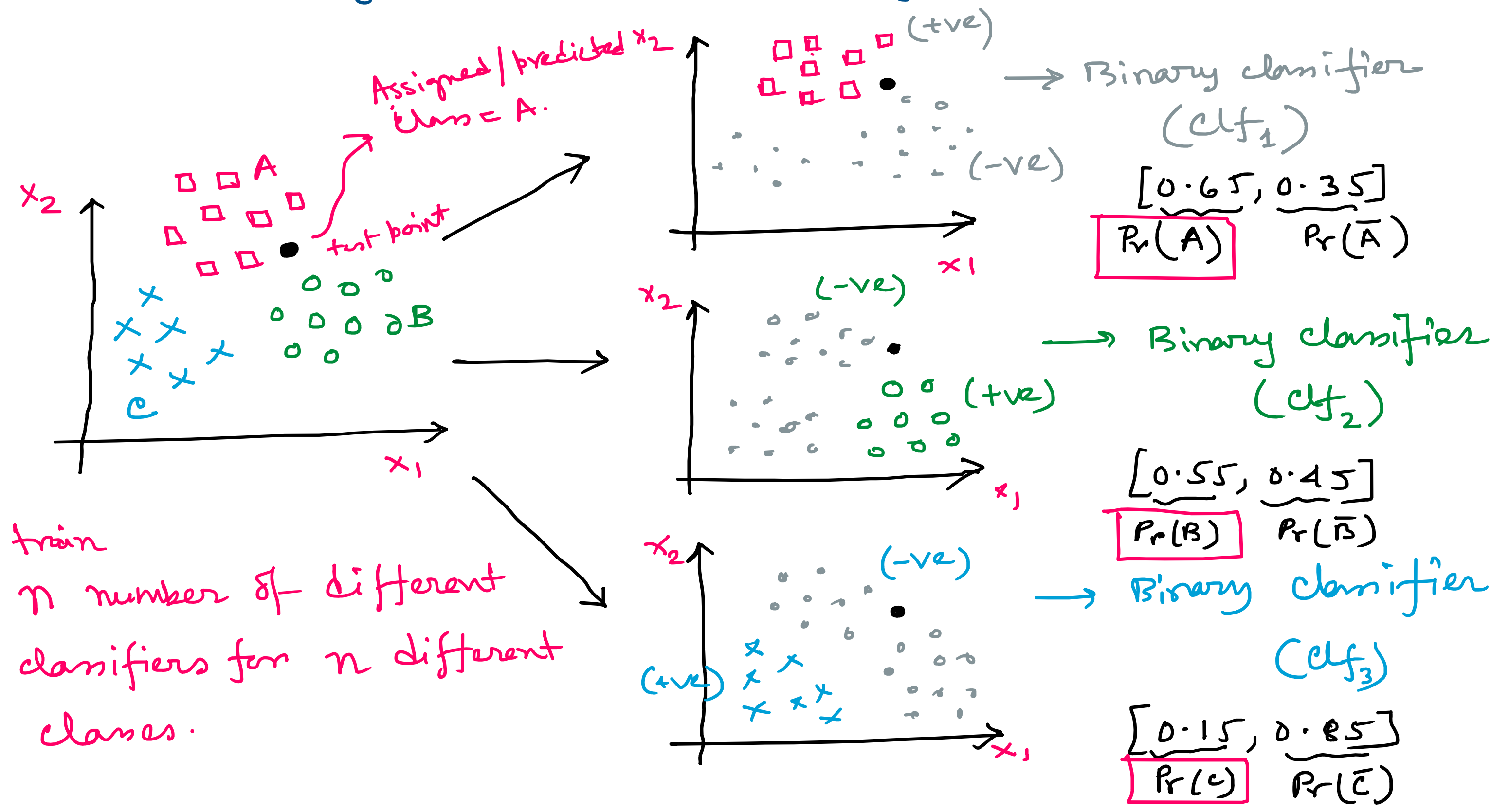
Note: If we change the threshold that might affect classifier's performance.



`clf.fit(x_train, y_train)`
`clf.predict_proba(x_test)` $\rightarrow [0.2, 0.1, 0.65, 0.05]$
`clf.predict(x_test)` $\rightarrow 2 \rightarrow \underline{\text{class-c}}$

An arrow points from the value 0.65 in the array $[0.2, 0.1, 0.65, 0.05]$ to the underlined text class-c.

One-vs-Rest (OVR) Multiclass classification



Confusion Matrix for multiclass classifier

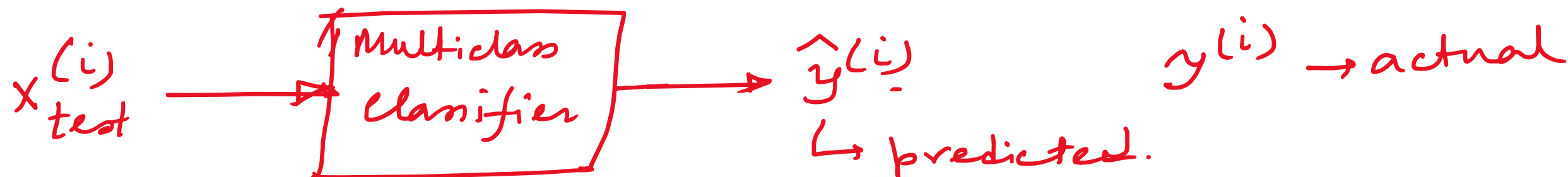
There are total ' C ' classes ($C = 5$ for ex.)

		<u>Actual</u>	
		0	1
Predicted	0	TP	
	1		TN

2x2 matrix for binary clf.

		<u>Actual</u>				
		0	1	2	3	4
Predicted	0					
	1					
	2					
	3					
	4					

(i, j)
 \downarrow
 no of outputs whose predicted class label is ' i ' & actual class label is ' j '.



Actual.

	0	1	2	3	4
0	C_{00}	C_{01}	C_{02}	C_{03}	C_{04}
1	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}
2	C_{20}	C_{21}	C_{22}	C_{23}	C_{24}
3					
4					

Predicted

C_{03} = number of instances which are incorrectly classified as '0' but actually belong to class-3.

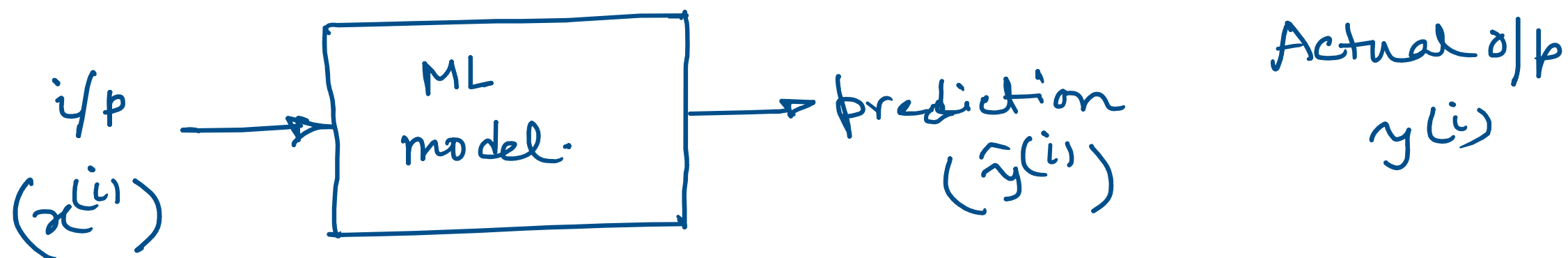
C_{0j} $j \neq 0$ = number of instances which are classified as '0' but actually belong to class-j

C_{ij} $i \neq j$ = number of instances which are classified as 'i' but actually belong to class-j

$\sum_j C_{ij}$ $i \neq j$ = total number of instances those are wrongly classified as class-i

$$\text{Precision of - Class}(i) = \frac{C_{ii}}{C_{ii} + \sum_{j, j \neq i} C_{ij}} = \frac{C_{ii}}{\sum_j C_{ij}} = \frac{\text{Recall}(i)}{\sum_i C_{ij}}$$

Gradient Boosting:-



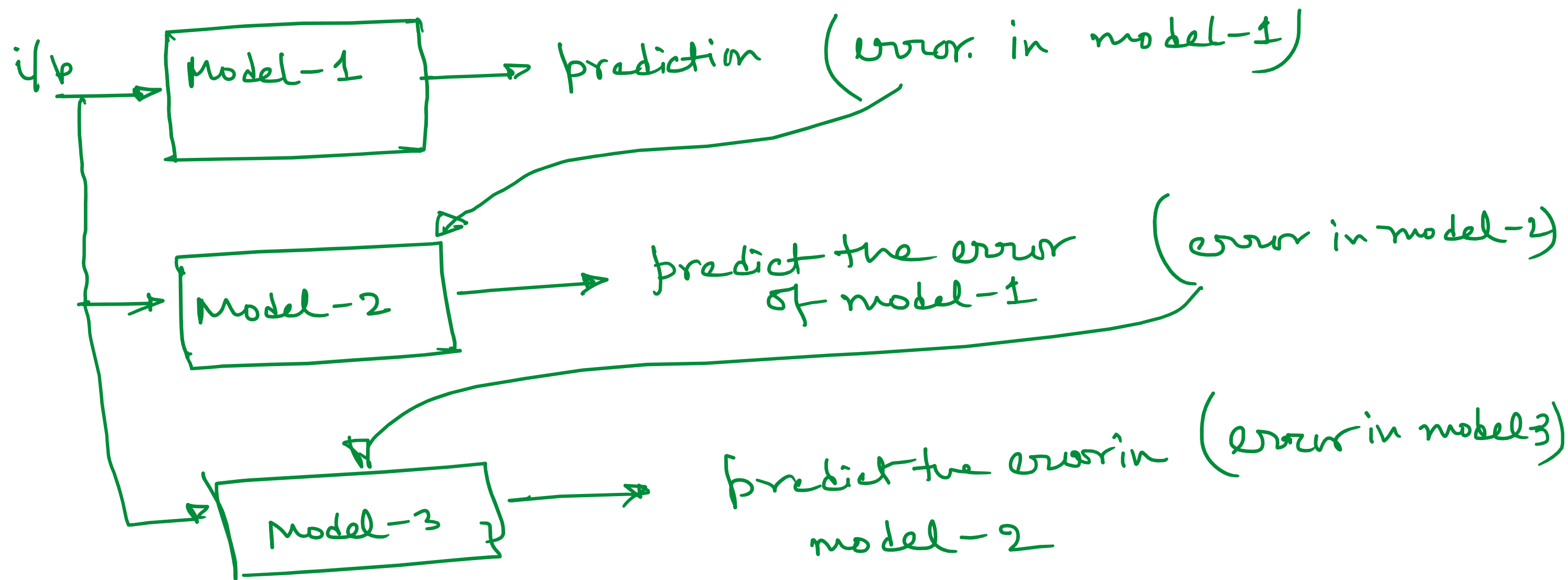
Suppose considering regression problem.

$$\text{mean square error } (e^{(i)}) = \frac{1}{2} (y^{(i)} - \hat{y}^{(i)})^2$$

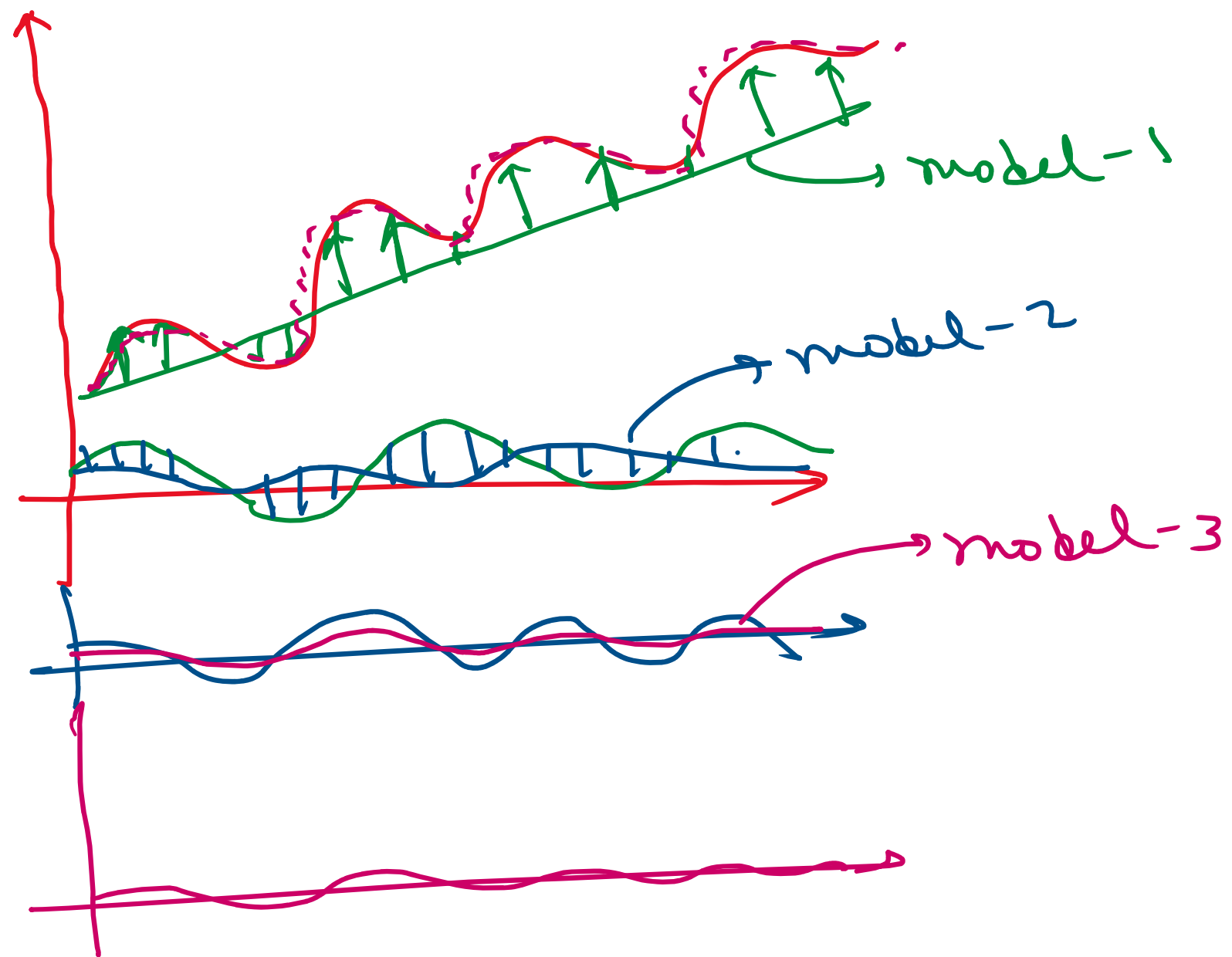
$$\frac{\Delta e^{(i)}}{\Delta \theta} \propto \underline{(\hat{y}^{(i)} - y^{(i)})}$$

$$\begin{aligned} \underline{\Delta e^{(i)}} &= - (y^{(i)} - \hat{y}^{(i)}) \left(\frac{\partial \hat{y}^{(i)}}{\partial \theta} \right) \Delta \theta \\ &= \underbrace{(\hat{y}^{(i)} - y^{(i)})}_{\text{difference between actual \& predicted (error in prediction)}} \frac{\partial \hat{y}^{(i)}}{\partial \theta} \cdot \Delta \theta \end{aligned}$$

difference between actual
& predicted
(error in prediction)

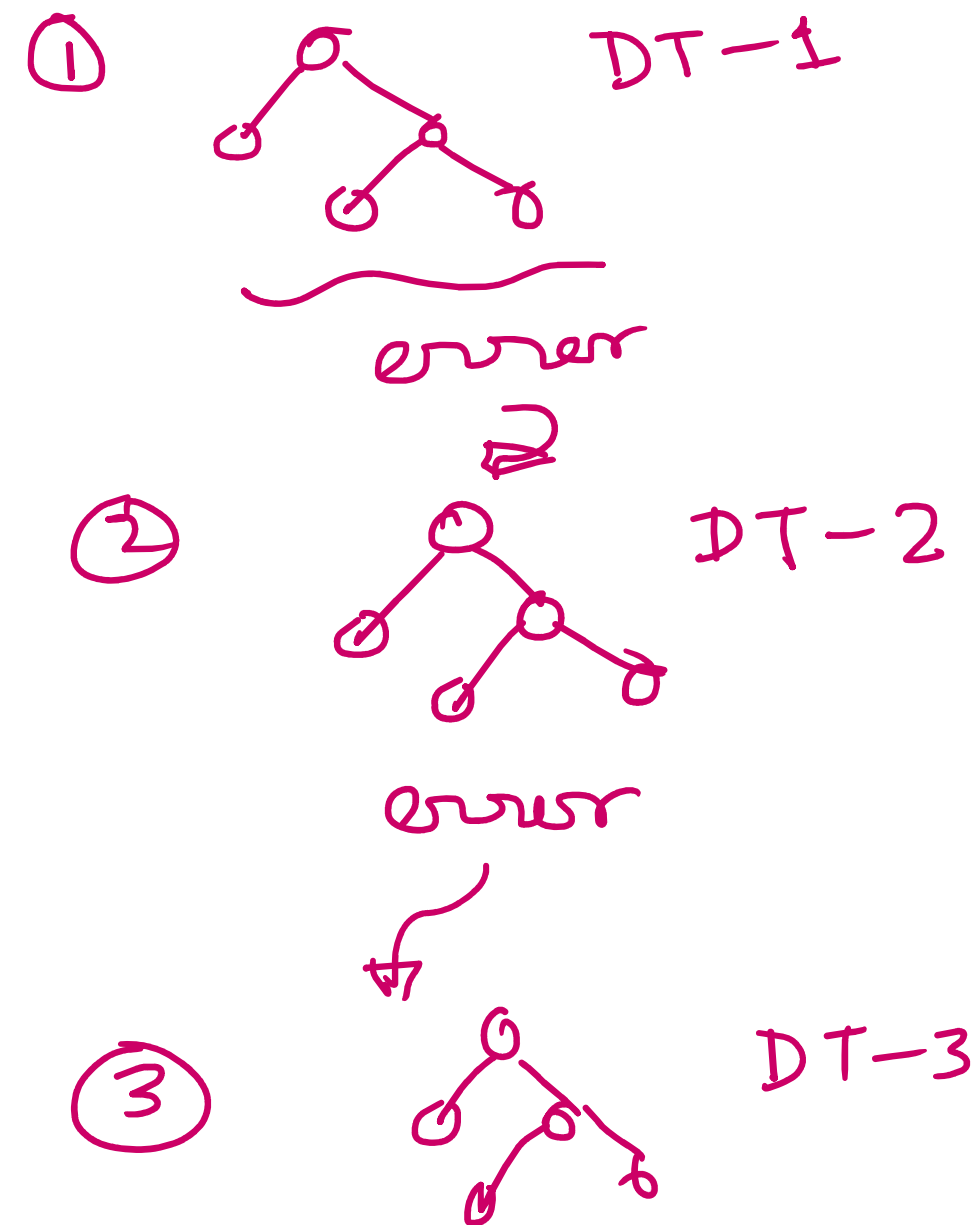


Model : $\text{Model-1} + \eta \times \text{Model-2} + \eta \times \text{model-3} + \dots + \eta \times \text{model-k}$
 learning rate.



Gradient Boosted Trees.

For classification:-



Extreme Gradient Boosting (XGBoost)

→ XGBoost is a very high performing ML algorithm that outperforms most of the traditional ML algorithms in case of tabular data.

→ We have both XGBoost Regressor & XGBoost Classifier.

Salient features of XGBoost:-

1. Regularization: XGBoost uses regularization (L_1, L_2) to reduce overfitting.
i.e. Why XGBoost is called regularized boosting technique.
2. Parallel Processing: GBM is sequential, whereas XGBoost core algorithm implements parallel processing. & is very fast.

The parallel processing is actually happening in building the tree (not in boosting).

parallelize \rightarrow node building at each level.

parallelize split finding on each node.

3. High flexibility: XGBoost allows users to define custom optimization objectives & evaluation criteria.

4. Handling missing values:- XGBoost can handle missing values by inbuilt algorithm.

5. Tree Pruning , 6. It has Built in cross validation