$y(x) =$

⇒ Gradient Boosting Algorithm

① Regression

Let we have dataset

Independent | Dependent | Predicted by base model

Experience	Degree	y (Salary)	$\hat{y}$
2	B.E	50K	75K
3	Masters	70K	75K
5	Masters	80K	75K
6	PHD	100K	75K

Steps:

① Create a base model:

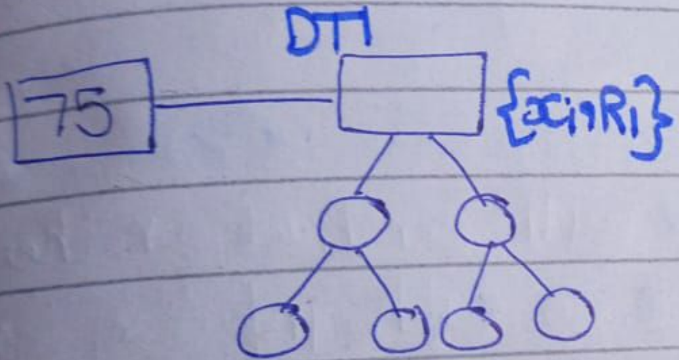
The output of this base model is equal to average of salary

$$\text{Average} = \frac{50+70+80+100}{4} = 75K$$

(2) Calculate residuals, Errors

Experience	Degree	y(salary)	$\hat{y}$	Residual $\hat{r}$ (R1) $y-\hat{y}$
2	B.E	50K	75K	-25K
3	Masters	70K	75K	-5K
5	Masters	80K	75K	5K
6	PHD	100K	75K	25K

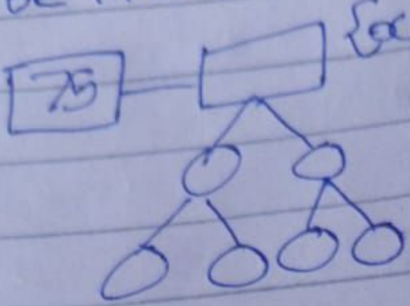
(3) Construct a decision tree considering inputs x_i (Experience, degree) and output R_i (residual)



Now let's say we pass all inputs to this DT1 and it gives outputs. $\hat{y} - \hat{y}$

Degree	y	$\hat{y}$	$R_1(y-\hat{y})$	R_2	$\hat{y}'$	R_3	R_4
B.E	50K	75K	-25K	-23	72.7	-22.7	—
Masters	70K	75K	-5K	-3	74.7	-4.7	—
Masters	80K	75K	5K	3	—	—	—
PHD	100K	75K	25K	20	—		

where R_2 are value of DT1
And the prediction will now
be like

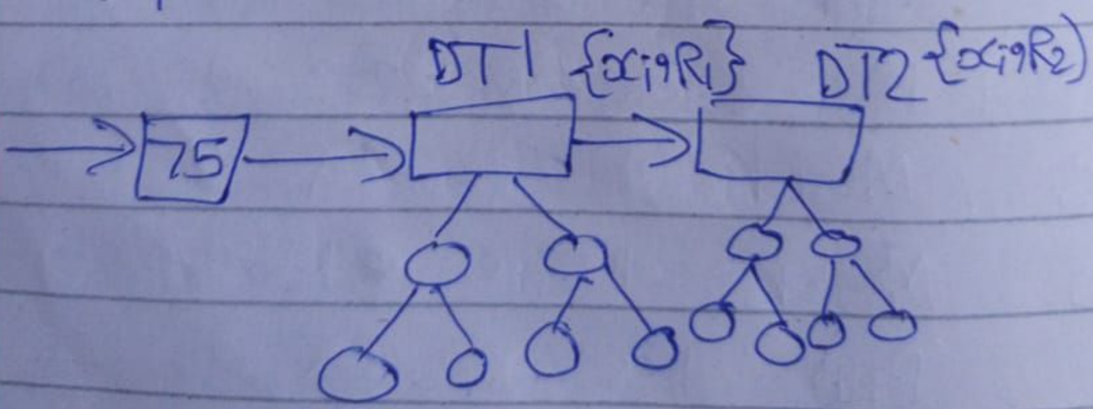


predicted outputs
$75 + DT_1 = 75 + (-23)$
$= 52$ (overfitting so added α)

predicted output $\Rightarrow 75 + \alpha(DT_1)$
$= 75 + 0.1(-23)$
$= \boxed{72.7}$

where

$\alpha \Rightarrow$ Learning Rate ([redacted] 0 to 1)
Now we will construct another decision tree with input x_i and output R_3 and the output of that Decision Tree will be R_4.



Now the final Function for gradient boost will be

$$F(x) = \alpha_0 h_0(x) + \alpha_1 (h(x)) + \alpha_2 (h(x)) + \alpha_3 (h(x)) + \dots + \alpha_n (h(x))$$

where $\alpha = 0 - 1$ (Learning rate)

$$\boxed{F(x) = \sum_{i=0}^{n} (\alpha_i h_i(x))}$$

$\Downarrow$

Final Function for gradient boosting

where $\alpha(h_0(x)) \Rightarrow$ base model $\Rightarrow 75$