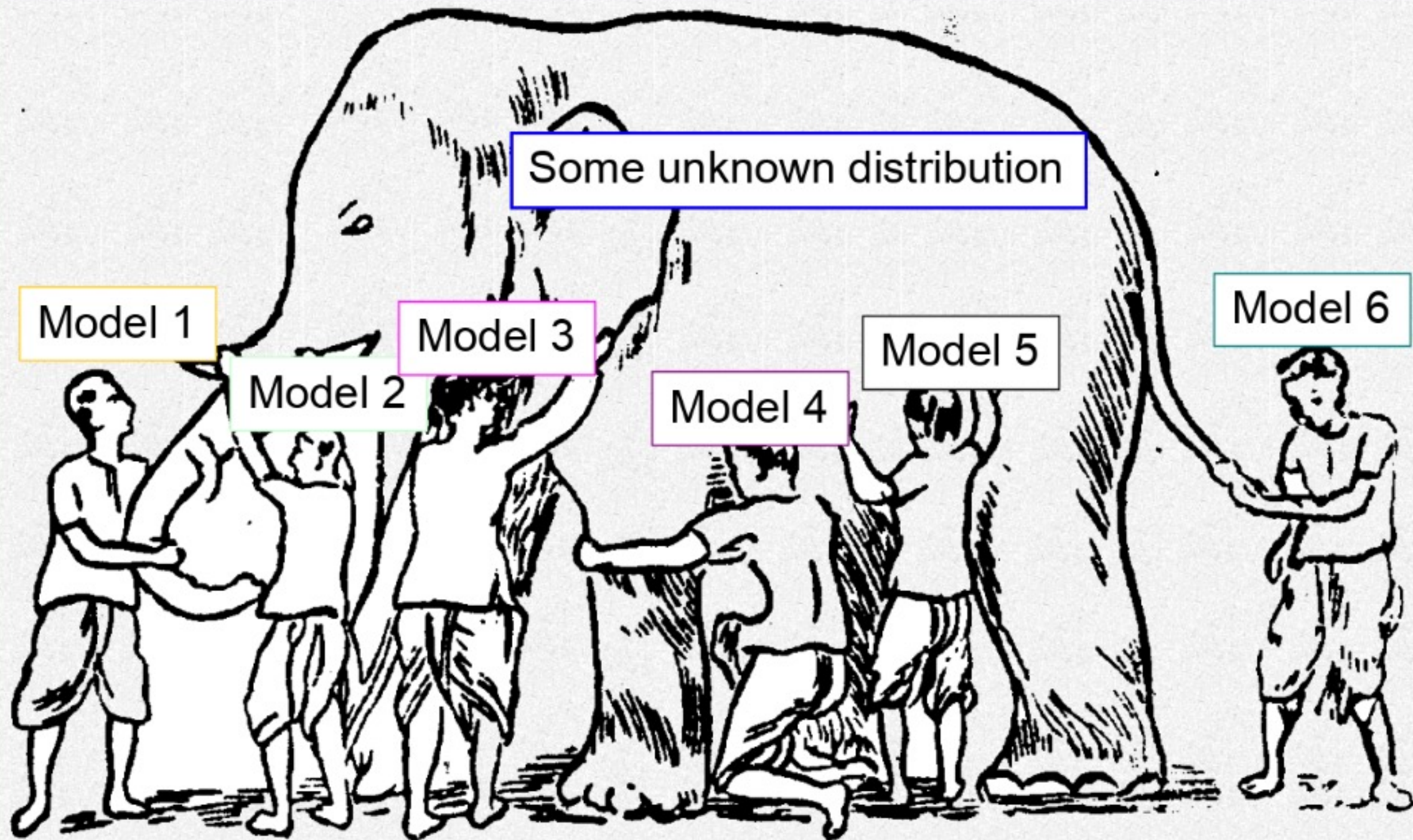
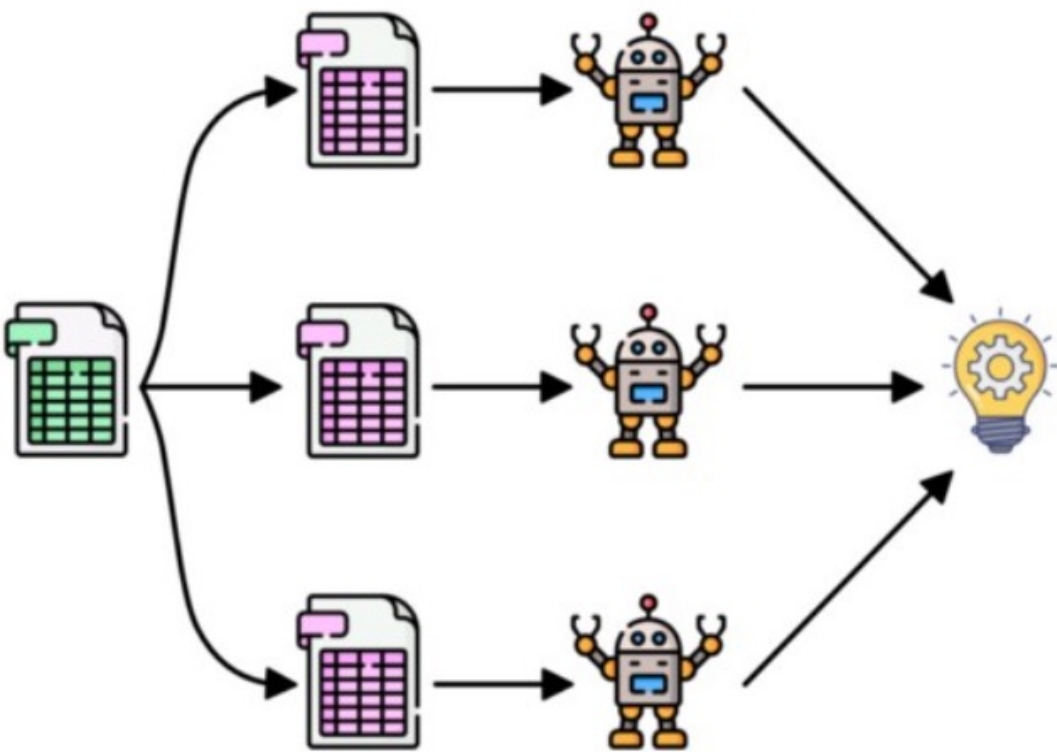


Gradient Boosting

TUAN NGUYEN

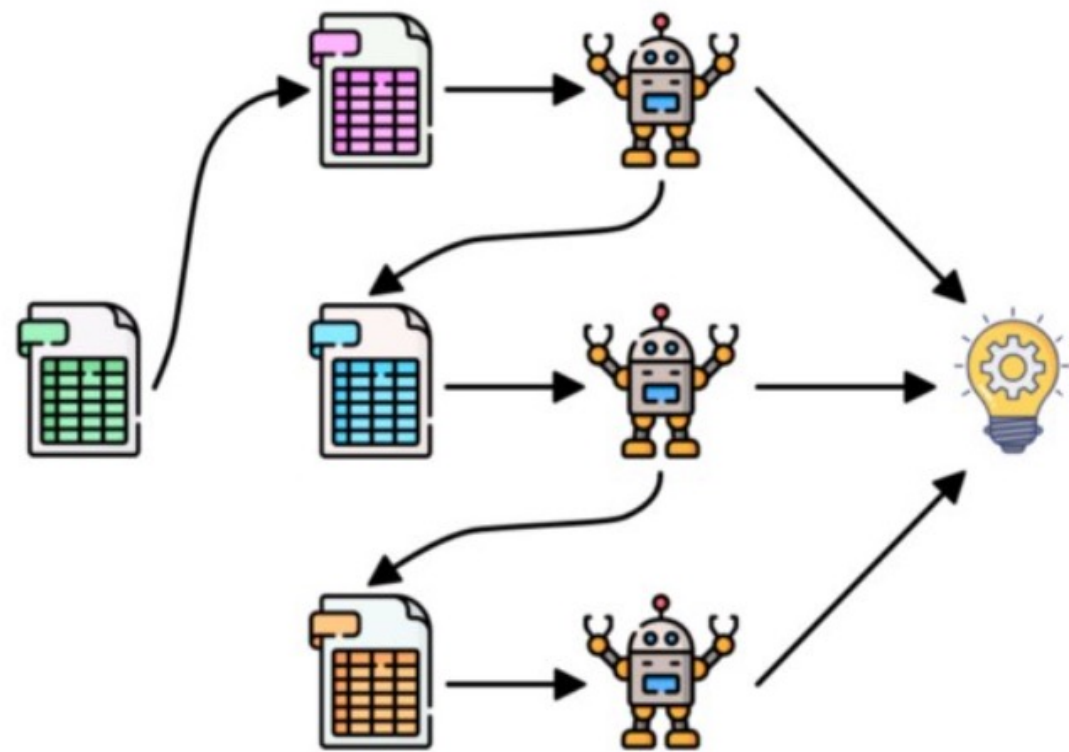


Bagging



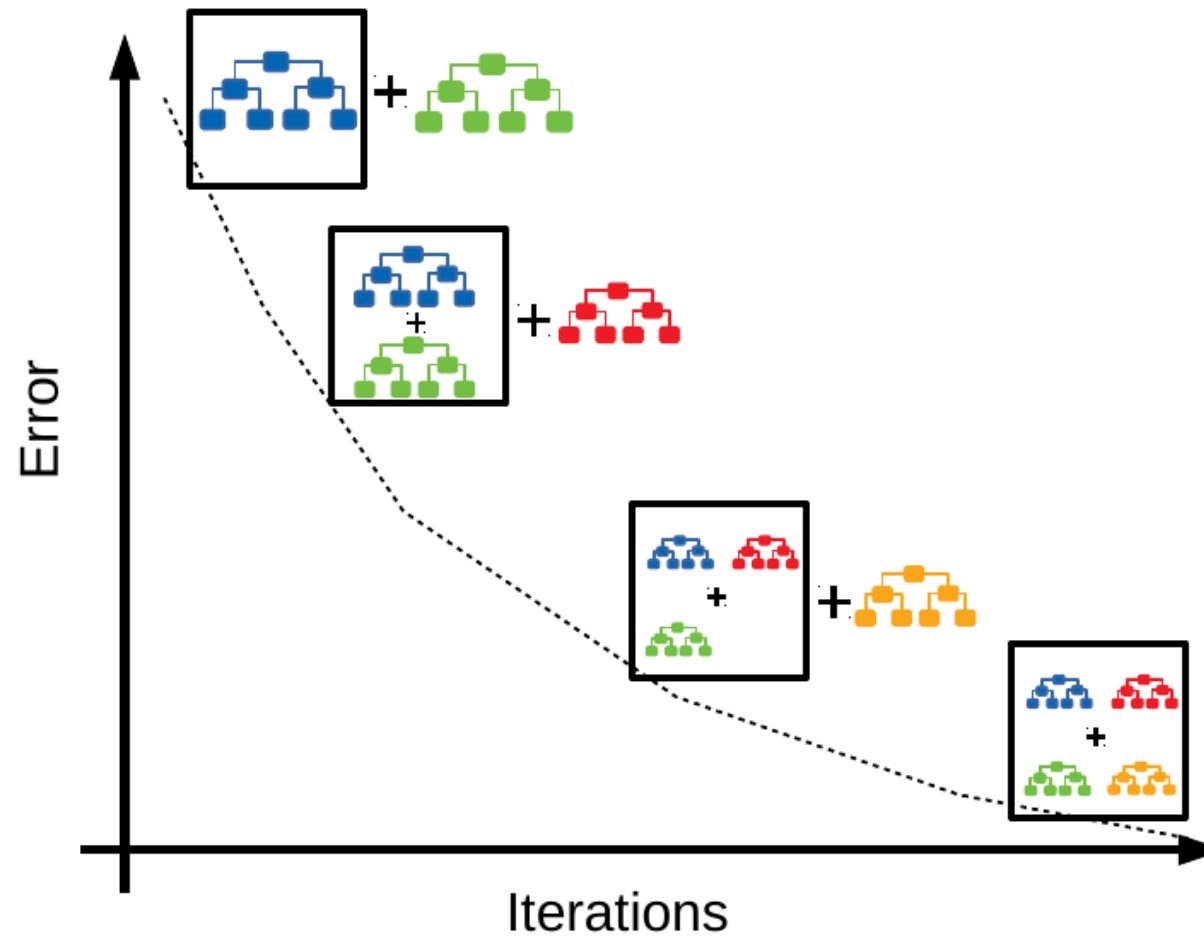
Parallel

Boosting

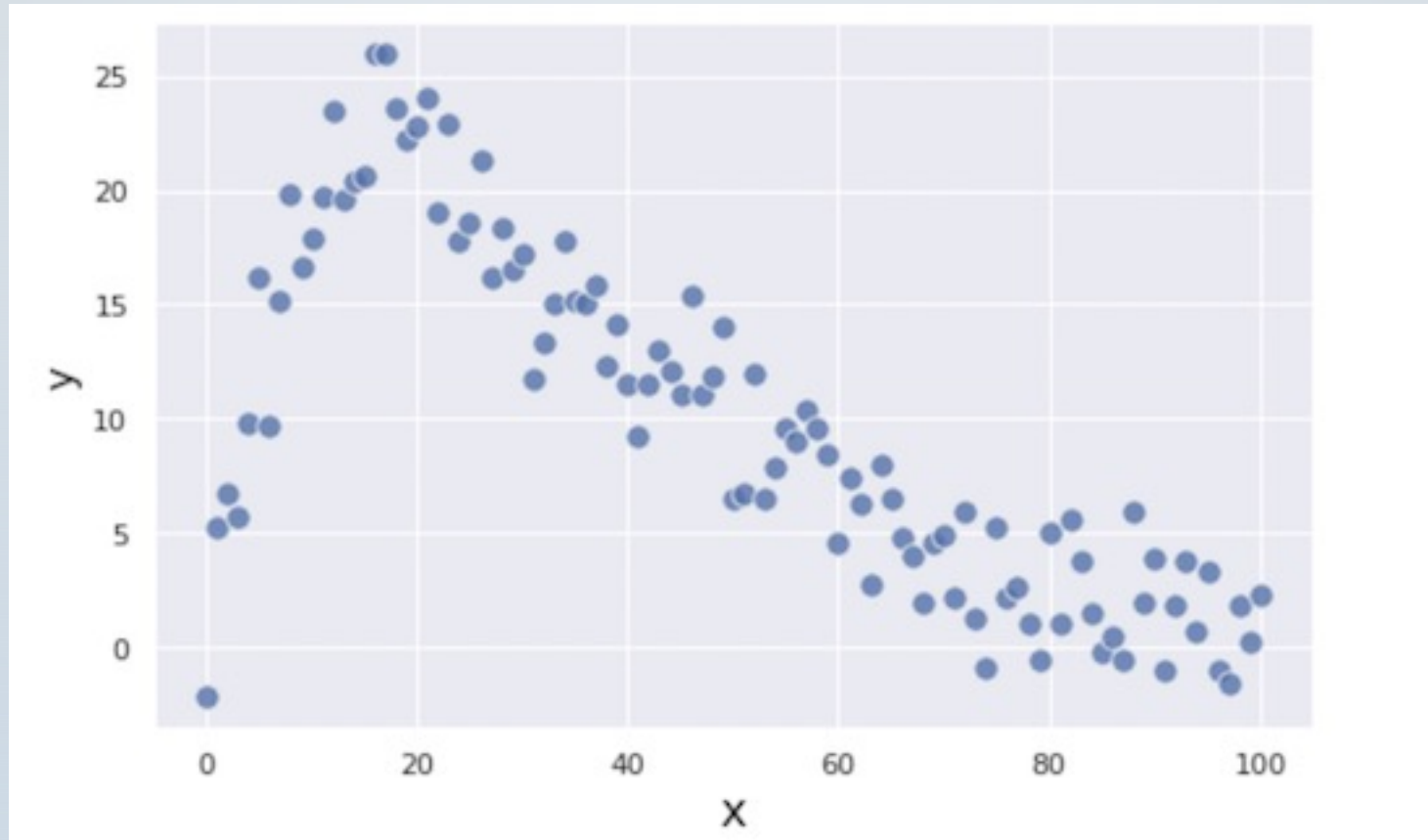


Sequential

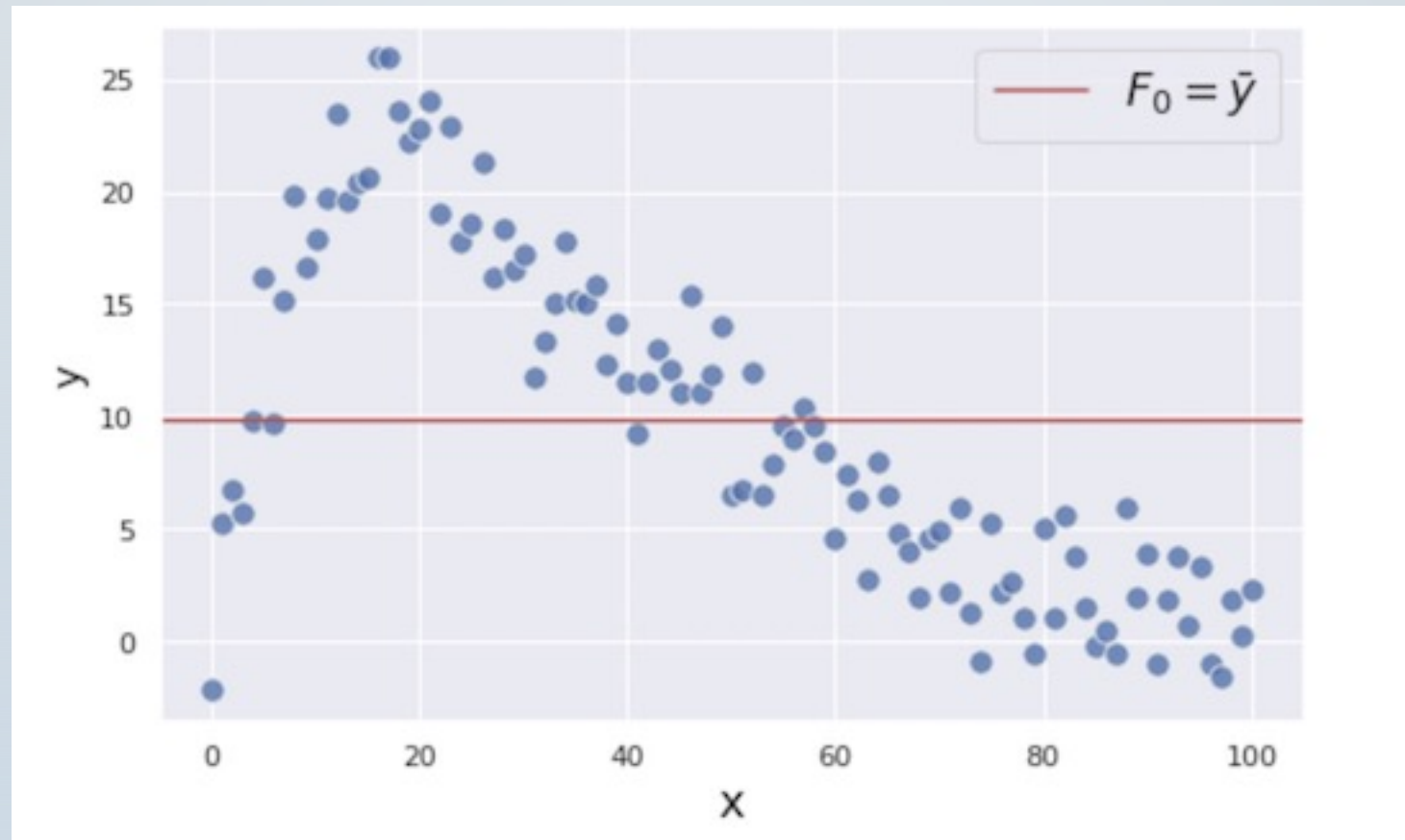
Gradient Boosting



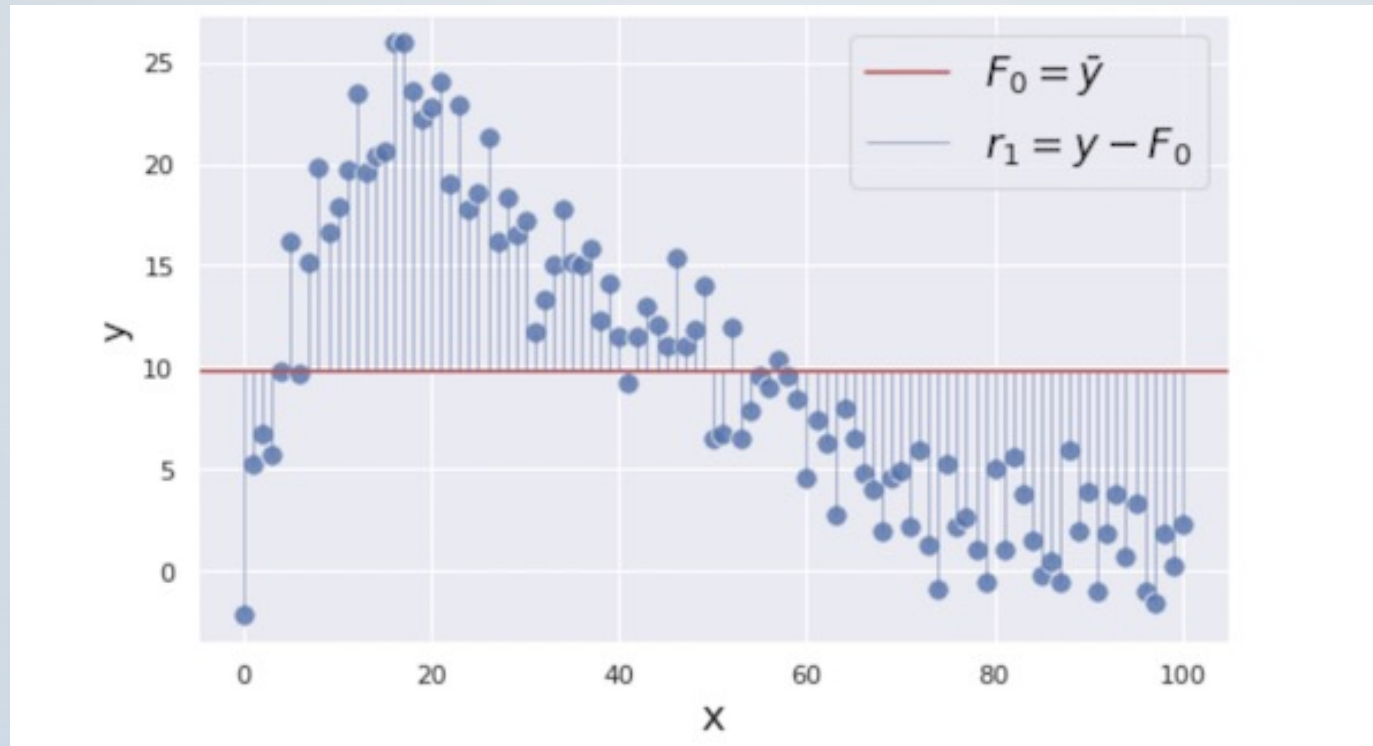
Dataset



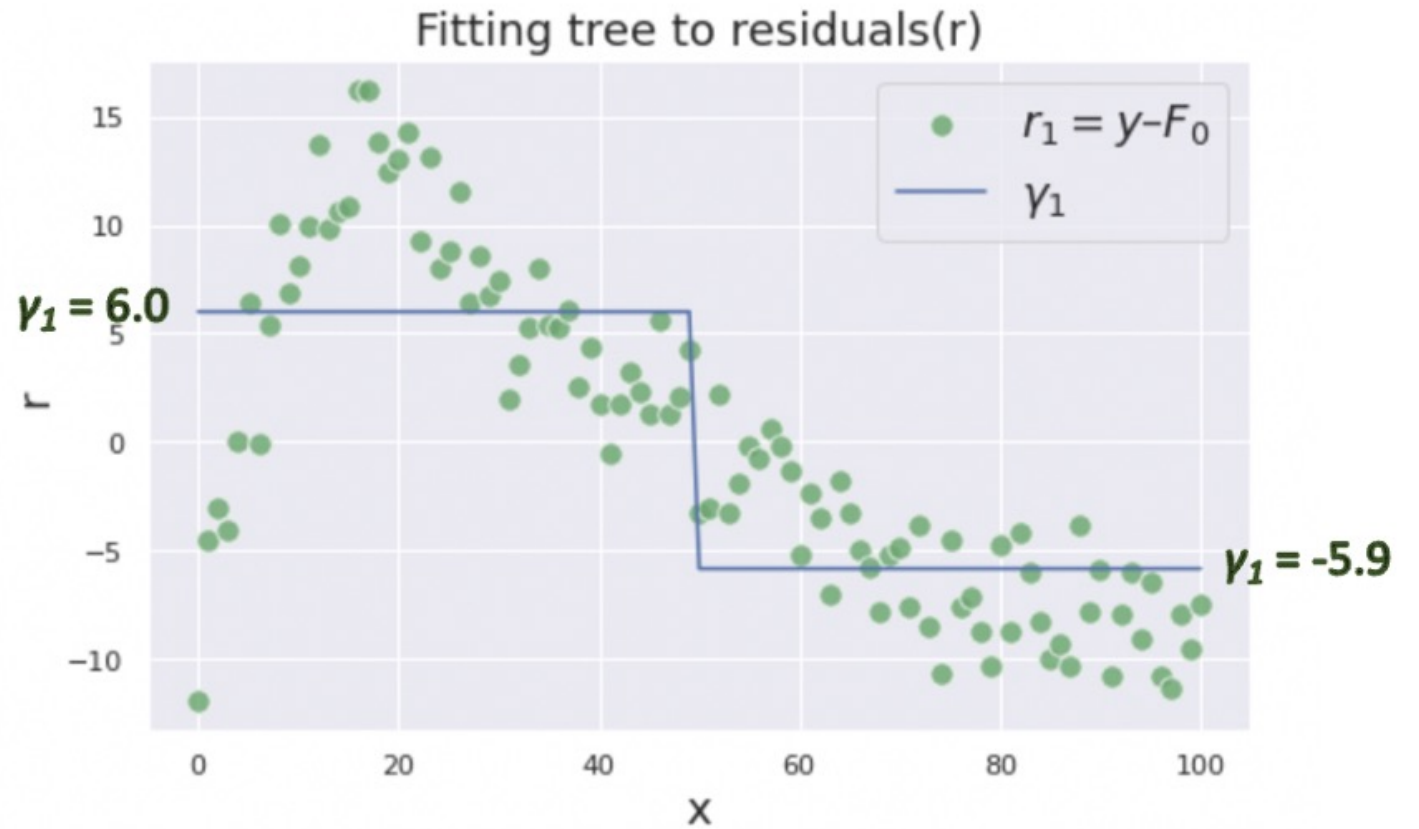
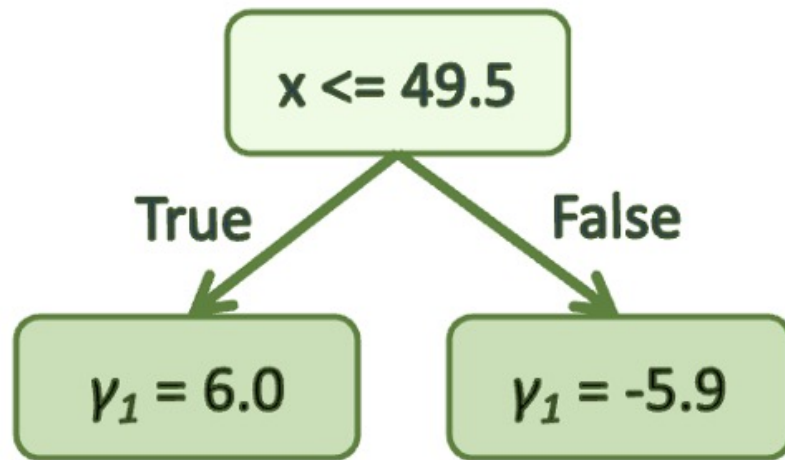
Simple prediction



Residual data



Residual model



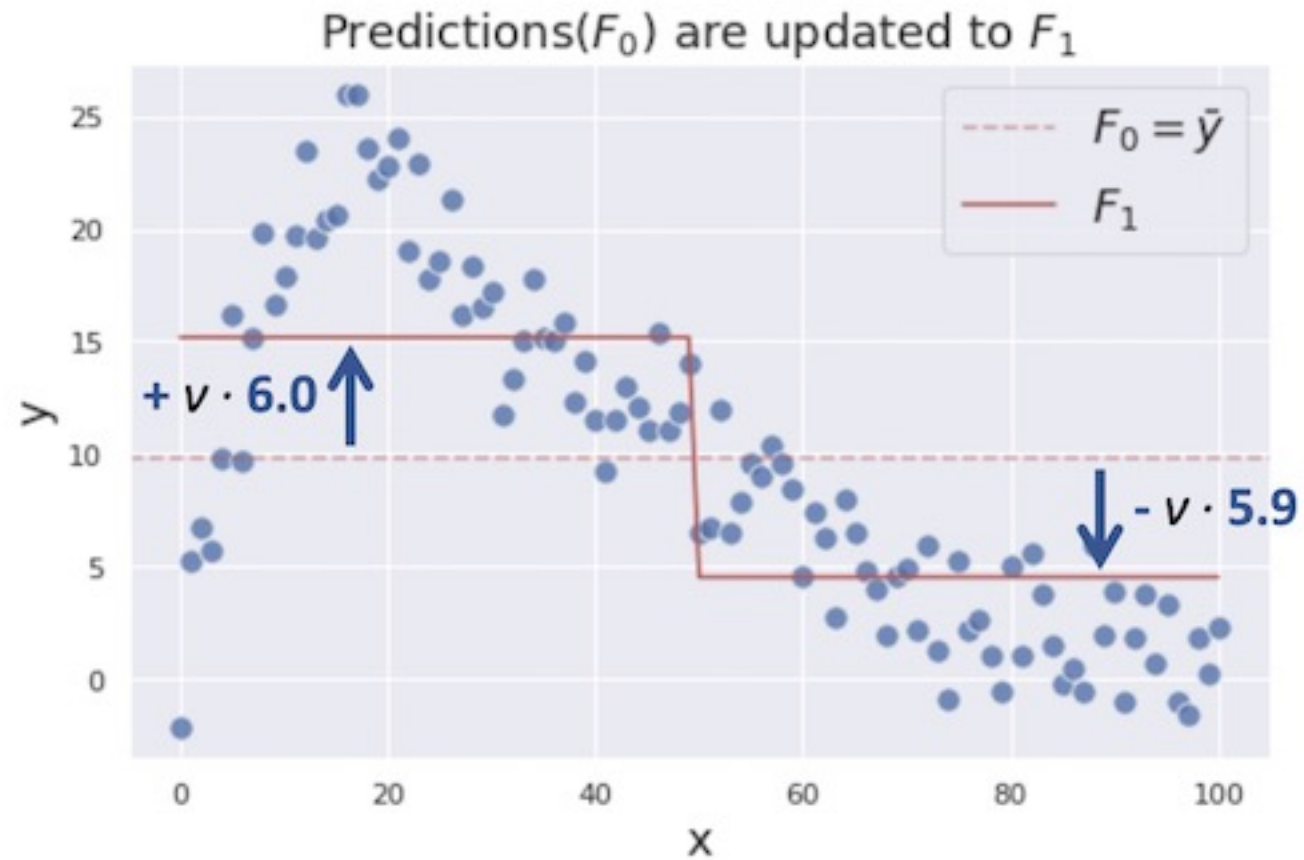
Prediction change

$$F_1 = F_0 + v \cdot \gamma_1$$

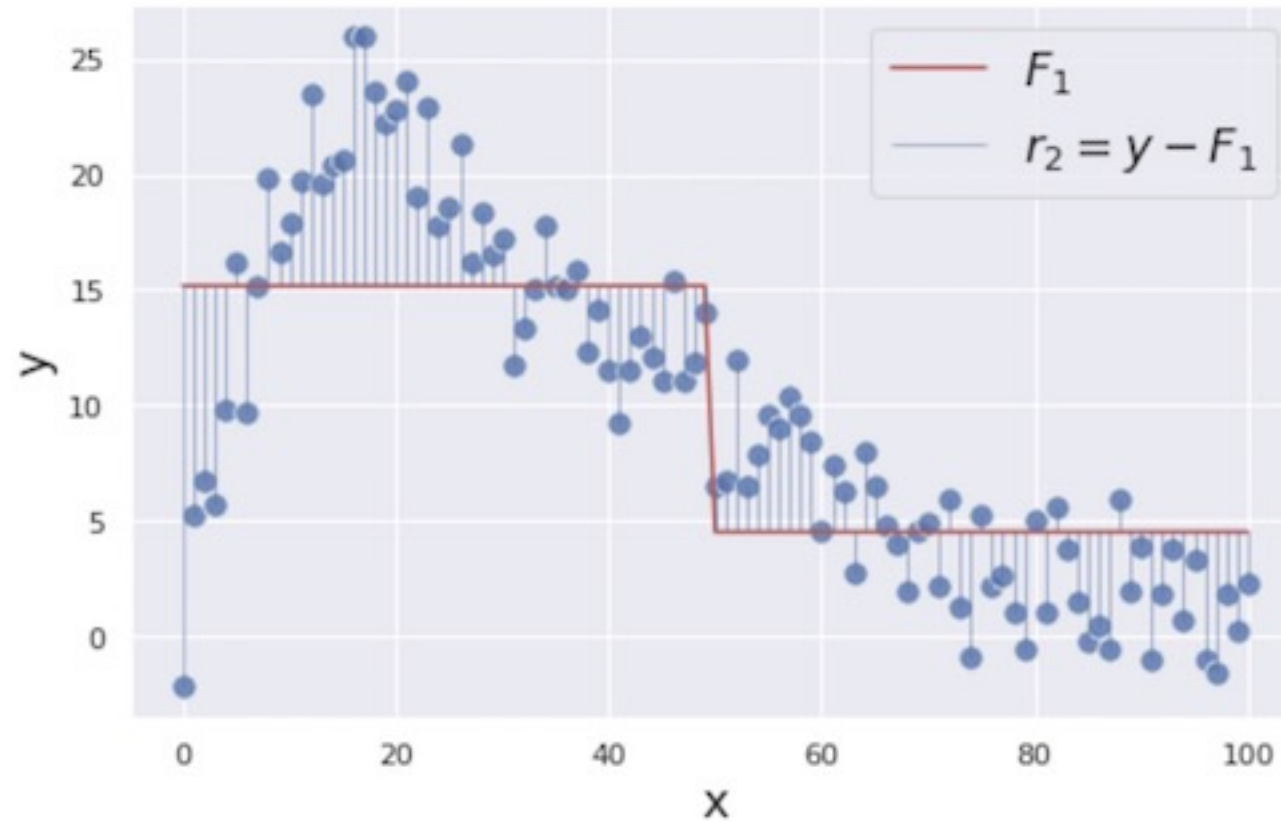
In fact, gradient boosting algorithm does not simply add γ to F as it makes the model overfit to the training data. Instead, γ is scaled down by **learning rate** v which ranges between 0 and 1

$$F_1 = \begin{cases} F_0 + v \cdot 6.0 & \text{if } x \leq 49.5 \\ F_0 - v \cdot 5.9 & \text{otherwise} \end{cases}$$

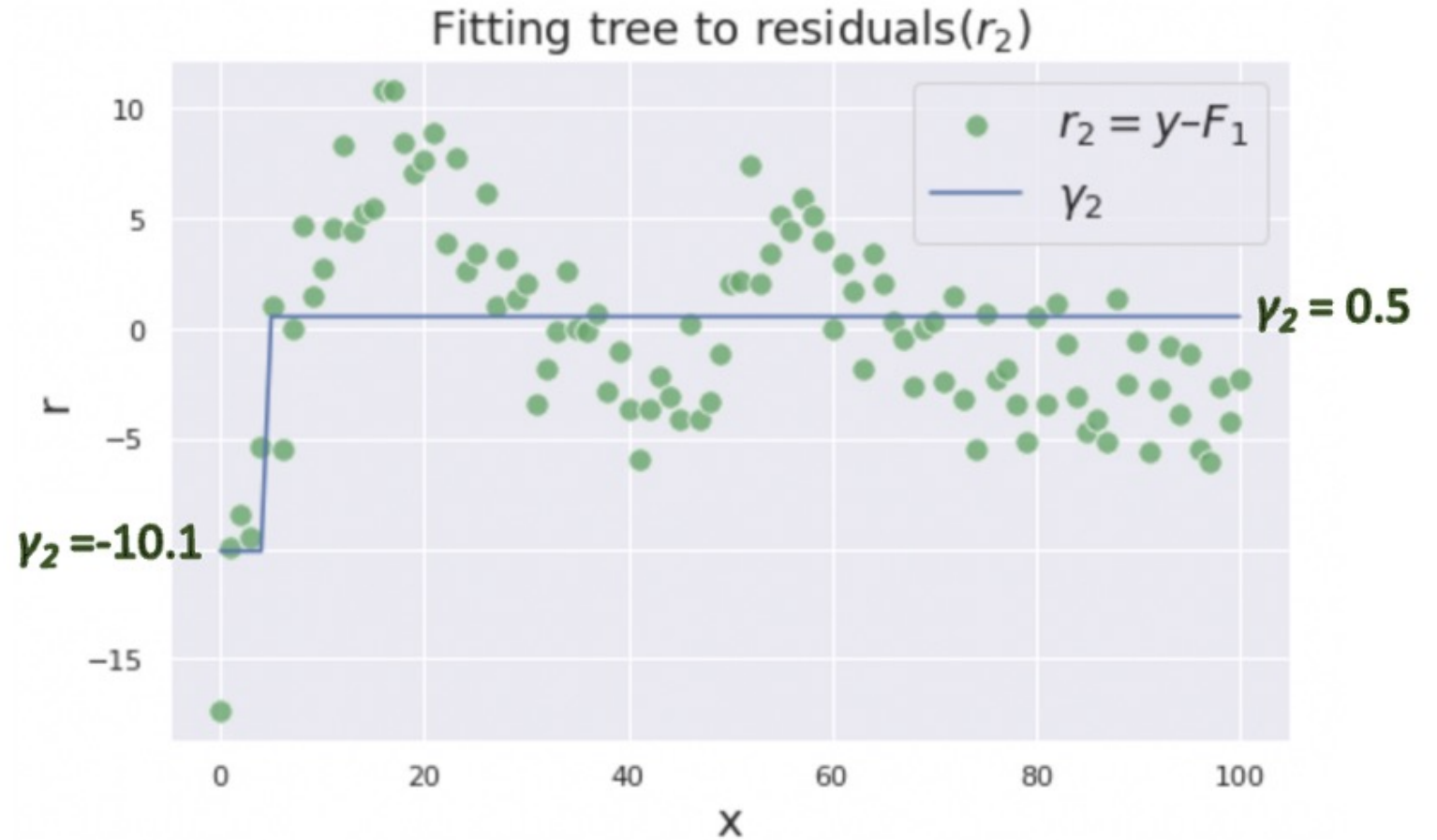
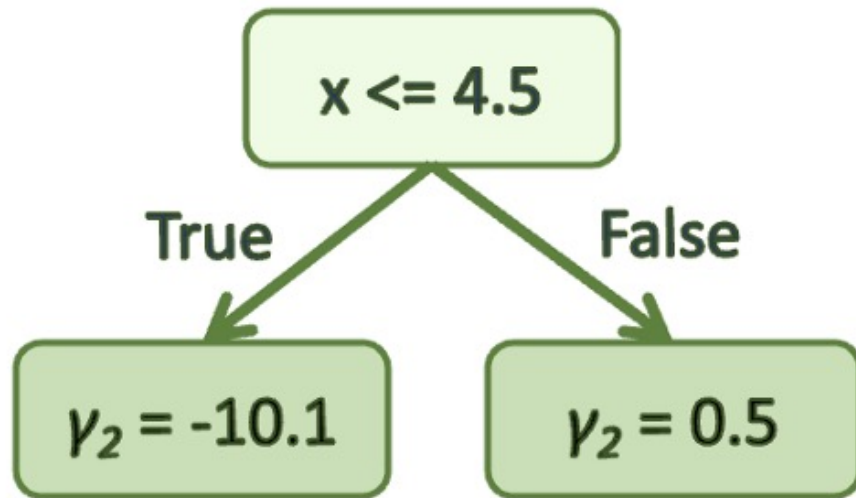
Model prediction update



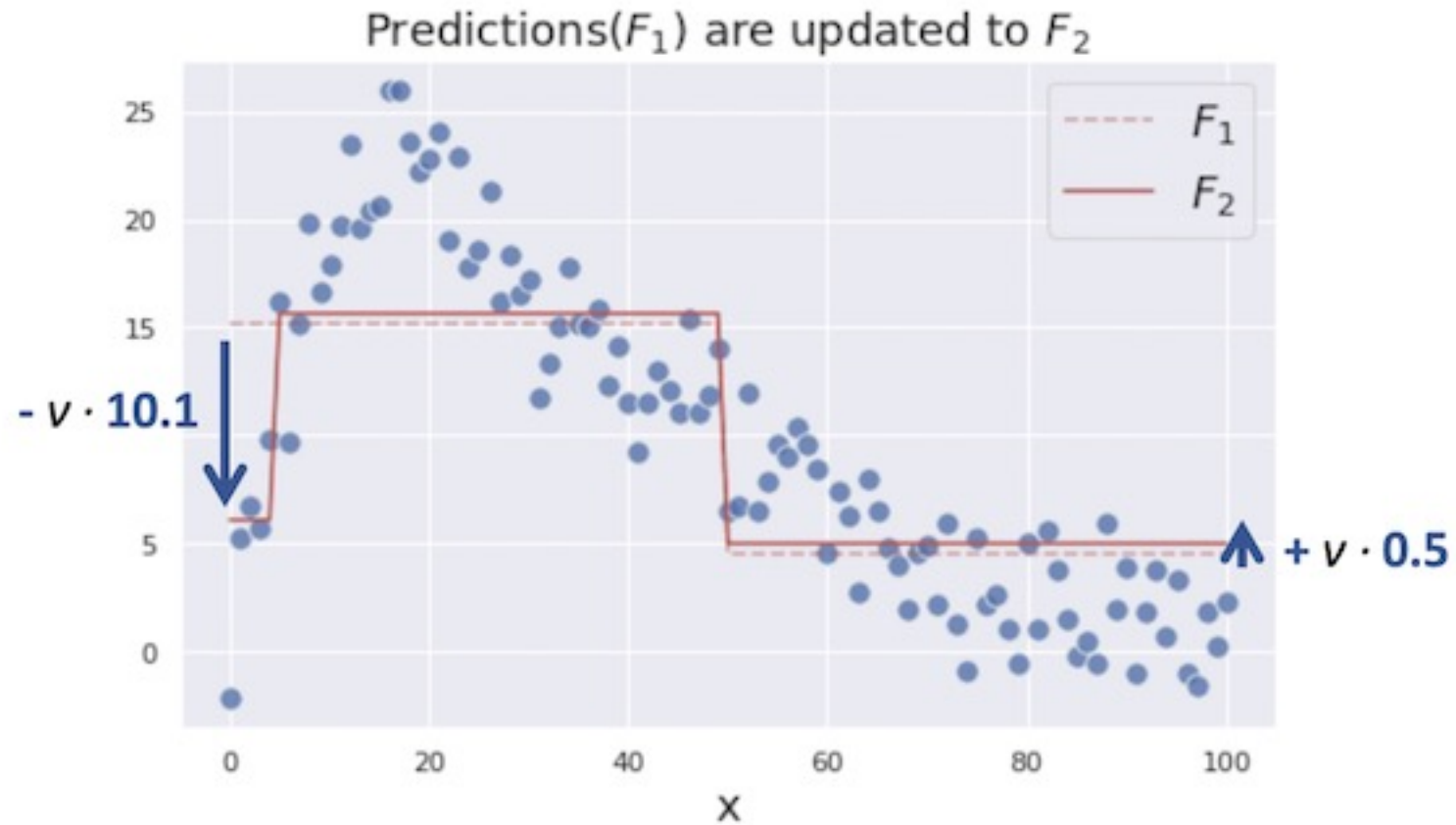
Residual update



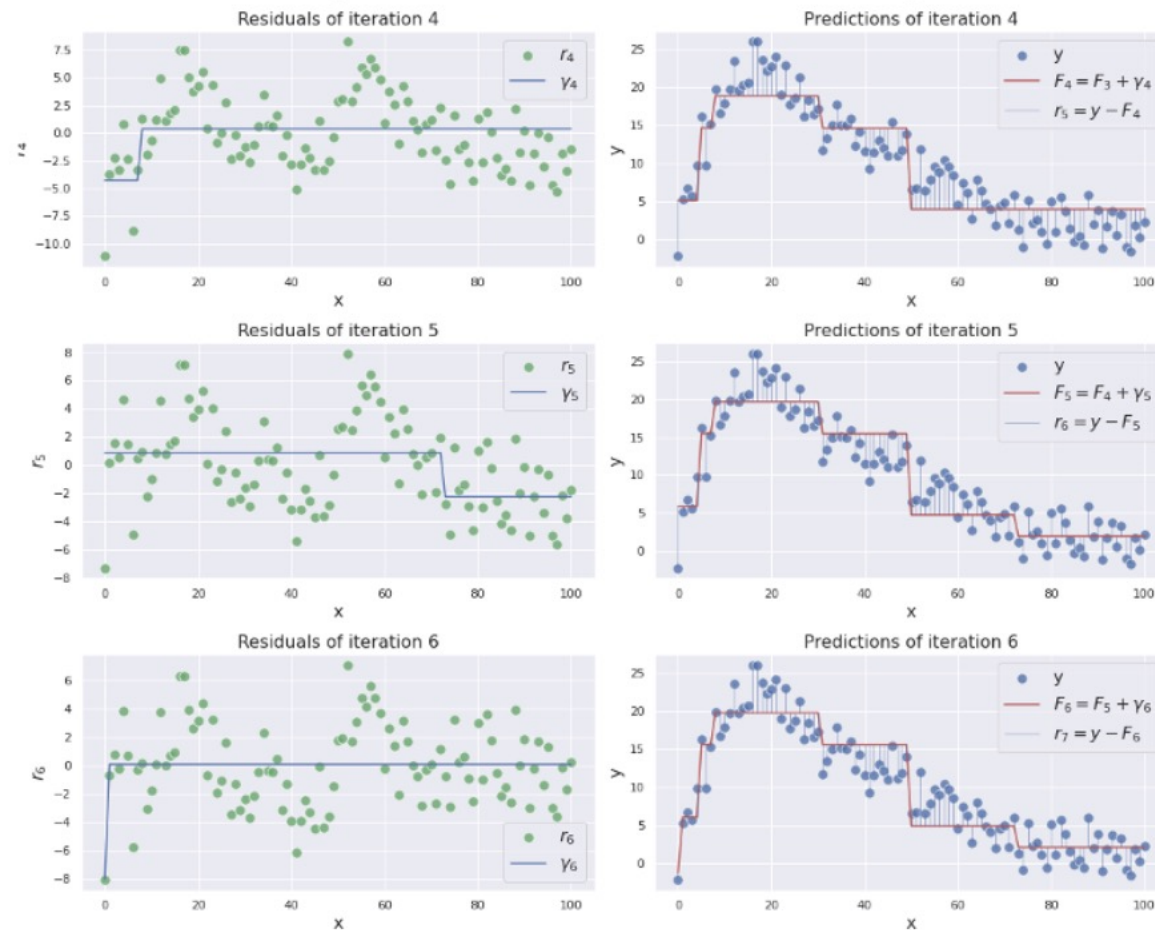
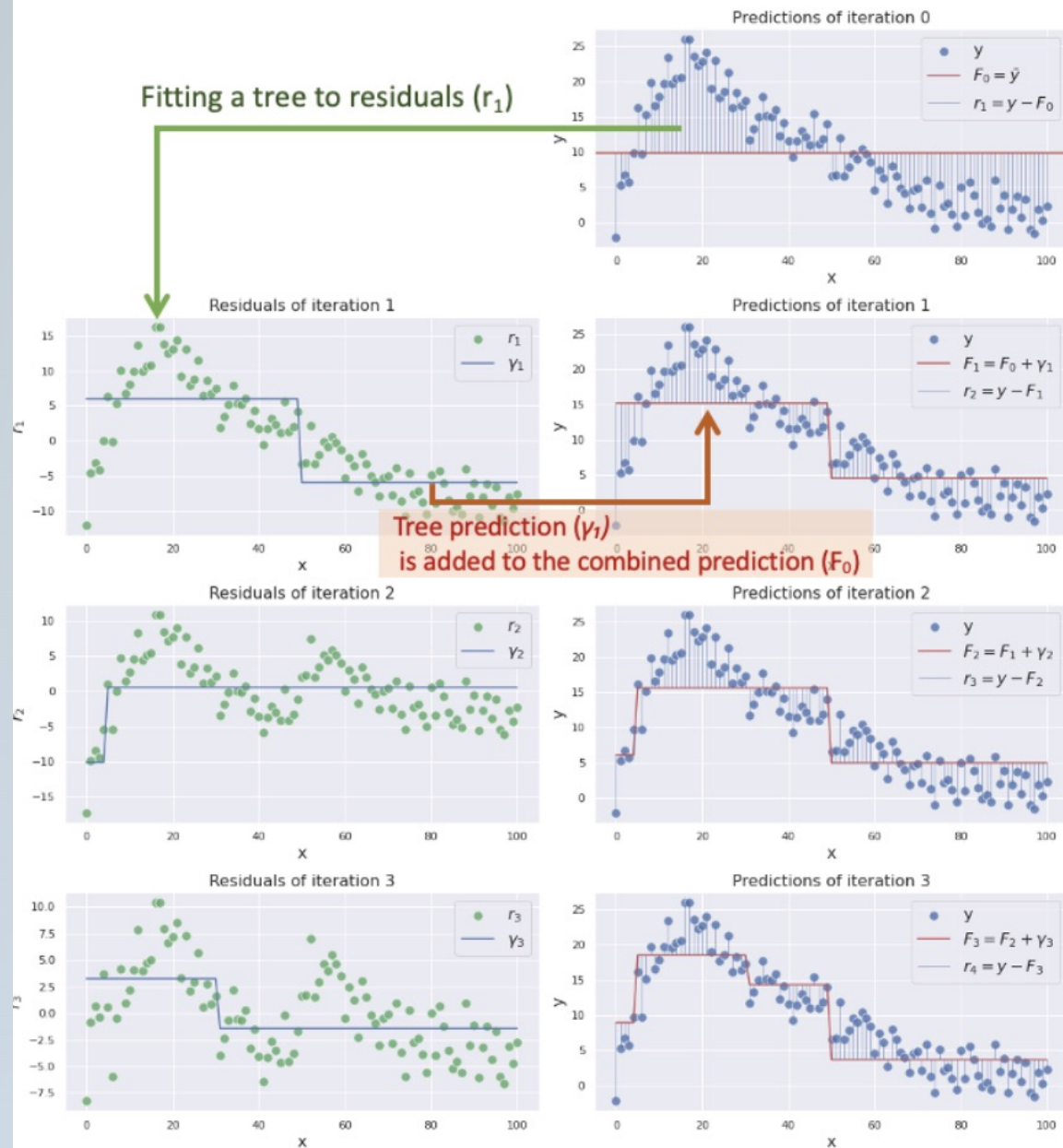
Residual model (2)



Model prediction update



Fitting a tree to residuals (r_1)



Algorithms

Gradient Boosting Algorithm

1. Initialize model with a constant value:

$$F_0(x) = \underset{\gamma}{\operatorname{argmin}} \sum_{i=1}^n L(y_i, \gamma)$$

2. for $m = 1$ to M :

2-1. Compute residuals $r_{im} = - \left[\frac{\partial L(y_i, F(x_i))}{\partial F(x_i)} \right]_{F(x)=F_{m-1}(x)}$ for $i = 1, \dots, n$

2-2. Train regression tree with features x against r and create terminal node regions R_{jm} for $j = 1, \dots, J_m$

2-3. Compute $\gamma_{jm} = \underset{\gamma}{\operatorname{argmin}} \sum_{x_i \in R_{jm}} L(y_i, F_{m-1}(x_i) + \gamma)$ for $j = 1, \dots, J_m$

2-4. Update the model:

$$F_m(x) = F_{m-1}(x) + \nu \sum_{j=1}^{J_m} \gamma_{jm} 1(x \in R_{jm})$$

More...

- <https://towardsdatascience.com/all-you-need-to-know-about-gradient-boosting-algorithm-part-1-regression-2520a34a502>
- <https://towardsdatascience.com/all-you-need-to-know-about-gradient-boosting-algorithm-part-2-classification-d3ed8f56541e>