An Introduction to Machine Learning with Python Programming

11 Sep 2023 - 20 Oct 2023

Boosting

Conducted by:

iHUB Divya Sampark, IIT Roorkee

and

Ritvij Bharat Private Limited (RBPL)

Presented by:

Shreyas Shukla

fig ref: pierian data

Boosting

- We’ve have seeked to improve upon single Decision Trees with Random Forest models.
- Let’s now explore how to improve on the single decision tree, known as **boosting**.

fig ref: pierian data

- Boosting and Meta-Learning
- AdaBoost (Adaptive Boosting) Theory
- Example of AdaBoost
- Gradient Boosting Theory
- Example of Gradient Boosting

fig ref: pierian data

Boosting is not actually a machine learning algorithm, it is methodology *applied* to an existing machine learning algorithm, most commonly applied to the decision tree.

Let’s explore this idea of a meta-learning algorithm by reviewing a simple application and formula.

fig ref: pierian data

Main formula for boosting:

$$F_T(x) = \sum_{t=1}^{T} f_t(x)$$

fig ref: pierian data

$$F_T(x) = \sum_{t=1}^{T} \boxed{f_t(x)} \qquad \boxed{f_t(x) = \alpha_t h(x)}$$

fig ref: pierian data

$$F_T(x) = \sum_{t=1}^{T} \boxed{f_t(x)} \qquad \boxed{f_t(x) = \alpha_t h(x)}$$

A combination of **estimators** with an applied **coefficient** could act as an effective **ensemble estimator**.

$$F_T(x) = \sum_{t=1}^{T} \boxed{f_t(x)} \qquad \boxed{f_t(x) = \alpha_t h(x)}$$

Note **h(x)** can in theory be **any** machine learning algorithm (estimator/learner).

fig ref: pierian data

$$F_T(x) = \sum_{t=1}^{T} \boxed{f_t(x)} \qquad \boxed{f_t(x) = \alpha_t h(x)}$$

Can an ensemble of **weak learners** (very simple models) be a **strong learner** when combined?

fig ref: pierian data

$$F_T(x) = \sum_{t=1}^{T} \boxed{f_t(x)} \qquad \boxed{f_t(x) = \alpha_t h(x)}$$

For decision tree models, we can use simple trees in place of h(x) and combine them with the coefficients on each model.

fig ref: pierian data

Let’s focus on AdaBoost and understand how to combine weak learners to create a strong estimator

We will also explore why Decision Trees are so well suited for boosting.

fig ref: pierian data

AdaBoost

Intuition and Theory

fig ref: pierian data

AdaBoost (Adaptive Boosting) works by using an ensemble of **weak learners** and then combining them through the use of a weighted sum.

It uses previously created **weak learners** in order to adjust misclassified instances for the next created **weak learner.**

fig ref: pierian data

weak learner

A model that is too simple to perform well on its own.

fig ref: pierian data

Weak learner

- A model that is too simple to perform well on its own.
- The weakest decision tree possible would be a **stump**, one node and two leaves!

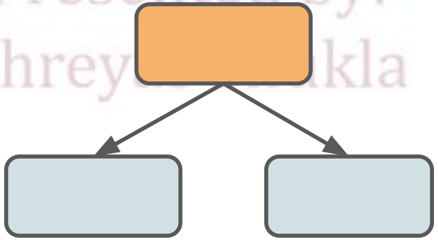


fig ref: pierian data

Unlike a single decision tree which fits to all the data at once (*fitting the data hard*), AdaBoost aggregates multiple weak learners, allowing the overall **ensemble** model to *learn slowly* from the features.

Let’s first understand how this works from a data perspective!

fig ref: pierian data

Imagine a classification task:

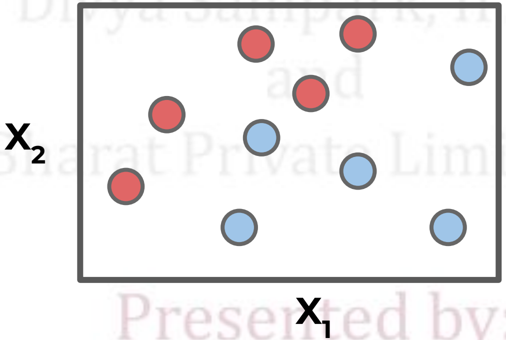


fig ref: pierian data

What would a stump classification look like?

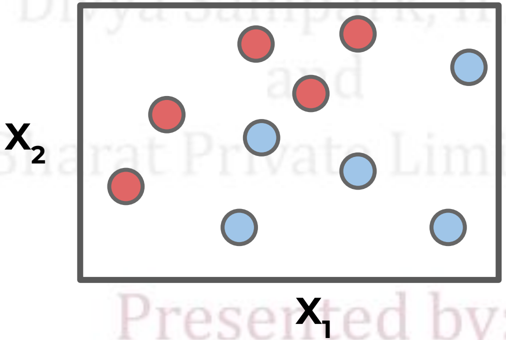
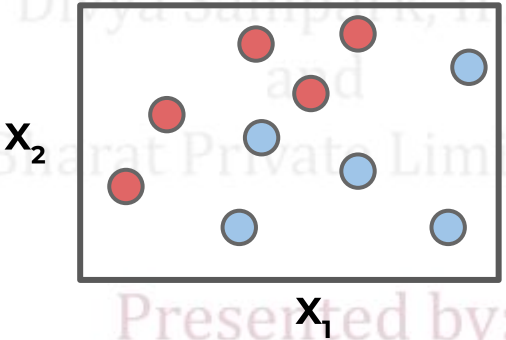


fig ref: pierian data



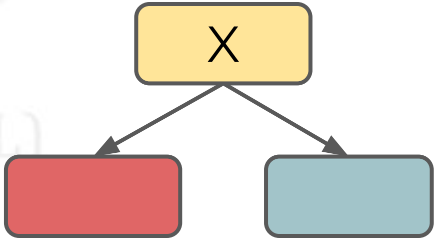
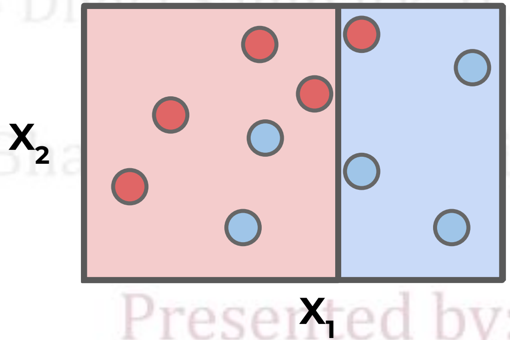


fig ref: pierian data



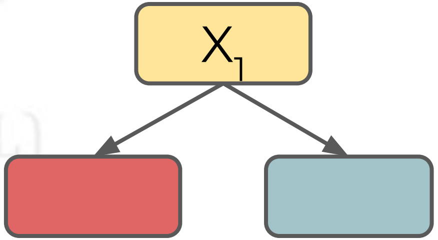
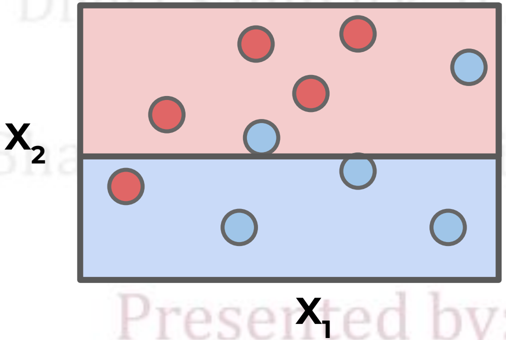


fig ref: pierian data



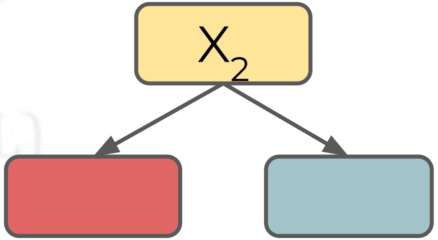


fig ref: pierian data

How can we combine stumps? How to improve performance with an ensemble?

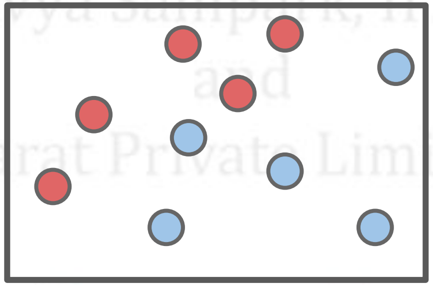
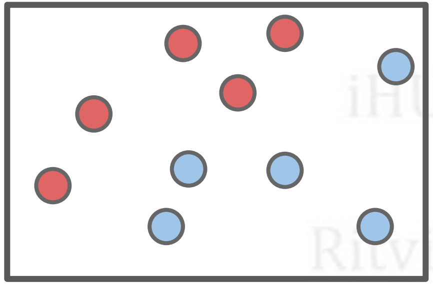


fig ref: pierian data

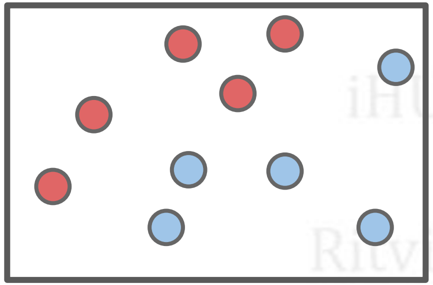
AdaBoost Process:



- Main Formulas
- Algorithmic Steps
- Visual Walkthrough of Algorithm

fig ref: pierian data

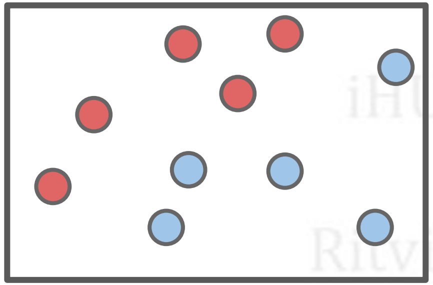
Main Formulas



$$F_T(x) = \sum_{t=1}^{T} f_t(x)$$

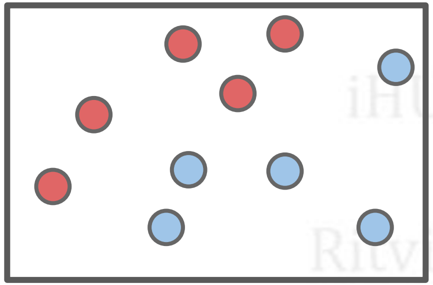
fig ref: pierian data

AdaBoost Process:



$$F_T(x) = \sum_{t=1}^{T} \boxed{f_t(x)} \qquad \boxed{f_t(x) = \alpha_t h(x)}$$

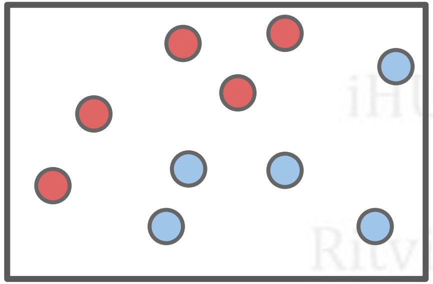
fig ref: pierian data



$$F_T(x) = \sum_{t=1}^{T} f_t(x)$$

$$f_t(x) = \boxed{\alpha_t} h(x)$$

fig ref: pierian data

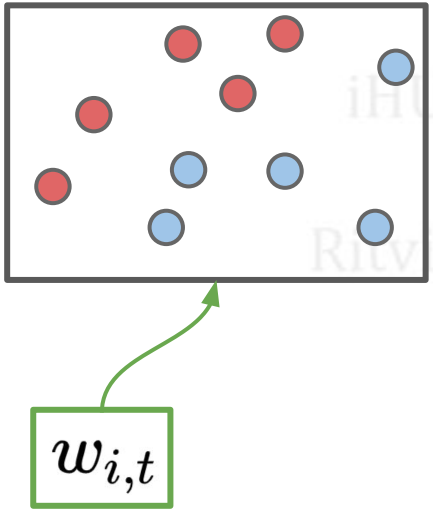


$$F_T(x) = \sum_{t=1}^{T} f_t(x)$$

$$f_t(x) = \boxed{\alpha_t} h(x)$$

$$E_t = \sum_i E[F_{t-1}(x_i) + \boxed{\alpha_t} h(x_i)]$$

fig ref: pierian data



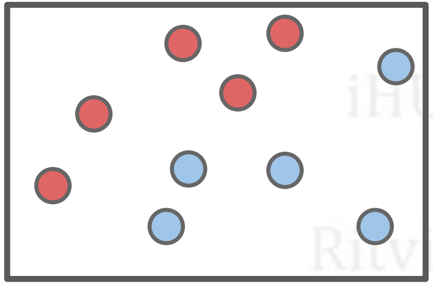
$$F_T(x) = \sum_{t=1}^{T} f_t(x)$$

$$f_t(x) = \alpha_t h(x)$$

$$E_t = \sum_i E[F_{t-1}(x_i) + \alpha_t h(x_i)]$$

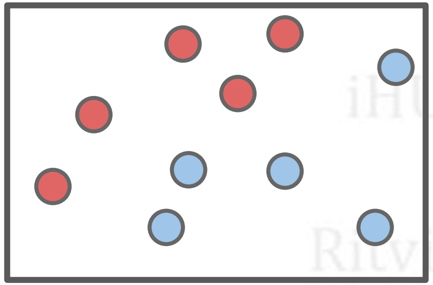
fig ref: pierian data

Algorithm Steps



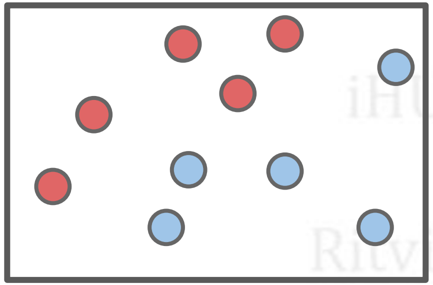
With:

- Samples $x_1 \ldots x_n$
- Desired outputs $y_1 \ldots y_n, y \in \{-1, 1\}$
- Initial weights $w_{1,1} \ldots w_{n,1}$ set to $\dfrac{1}{n}$
- Error function $E(f(x), y, i) = e^{-y_i f(x_i)}$
- Weak learners $h \colon x \rightarrow \{-1, 1\}$



For t in $1 \ldots T$:

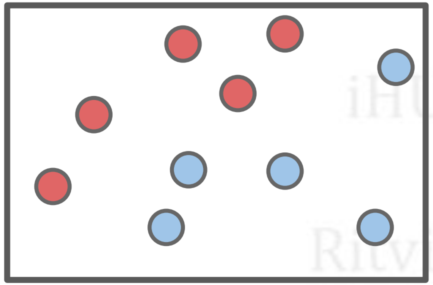
- Choose $h_t(x)$:
  - Find weak learner $h_t(x)$ that minimizes ϵ_t, the weighted sum error for misclassified points $\epsilon_t = \sum_{\substack{i=1 \\ h_t(x_i) \neq y_i}}^{n} w_{i,t}$
  - Choose $\alpha_t = \frac{1}{2} \ln\left(\frac{1-\epsilon_t}{\epsilon_t}\right)$



For t in $1 \ldots T$:

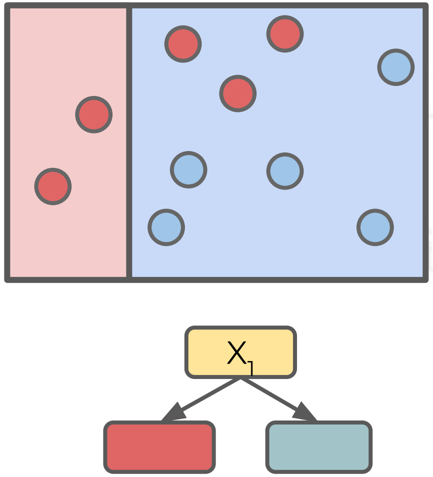
- Add to ensemble:
  - $F_t(x) = F_{t-1}(x) + \alpha_t h_t(x)$
- Update weights:
  - $w_{i,t+1} = w_{i,t} e^{-y_i \alpha_t h_t(x_i)}$ for i in $1 \ldots n$
  - Renormalize $w_{i,t+1}$ such that $\sum_i w_{i,t+1} = 1$

Visual Walkthrough



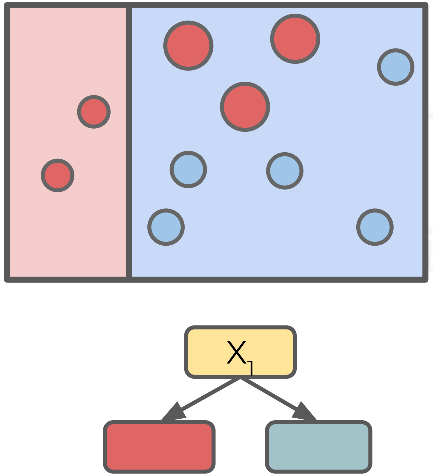
With:

- Samples $x_1 \ldots x_n$
- Desired outputs $y_1 \ldots y_n, y \in \{-1, 1\}$
- Initial weights $w_{1,1} \ldots w_{n,1}$ set to $\frac{1}{n}$
- Error function $E(f(x), y, i) = e^{-y_i f(x_i)}$
- Weak learners $h: x \to \{-1, 1\}$

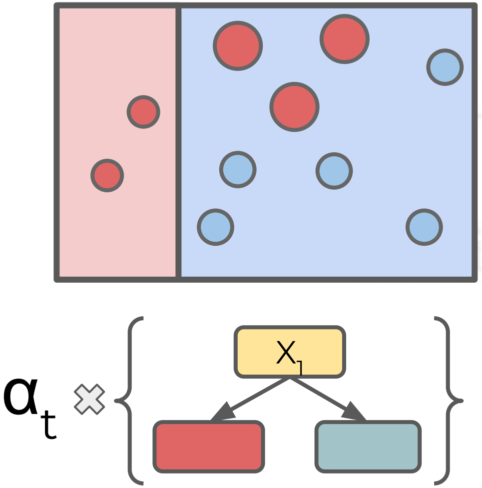


- Choose $h_t(x)$:
  - Find weak learner $h_t(x)$ that minimizes ϵ_t, the weighted sum error for misclassified points $\epsilon_t = \sum_{\substack{i=1 \\ h_t(x_i) \neq y_i}}^{n} w_{i,t}$

fig ref: pierian data



- Choose $h_t(x)$:
  - Find weak learner $h_t(x)$ that minimizes ϵ_t, the weighted sum error for misclassified points $\epsilon_t = \sum_{\substack{i=1 \\ h_t(x_i) \neq y_i}}^{n} w_{i,t}$



- Choose $h_t(x)$:
  - Find weak learner $h_t(x)$ that minimizes ϵ_t, the weighted sum error for misclassified points $\epsilon_t = \sum_{\substack{i=1 \\ h_t(x_i) \neq y_i}}^{n} w_{i,t}$
  - Choose $\alpha_t = \frac{1}{2} \ln\left(\frac{1-\epsilon_t}{\epsilon_t}\right)$

fig ref: pierian data

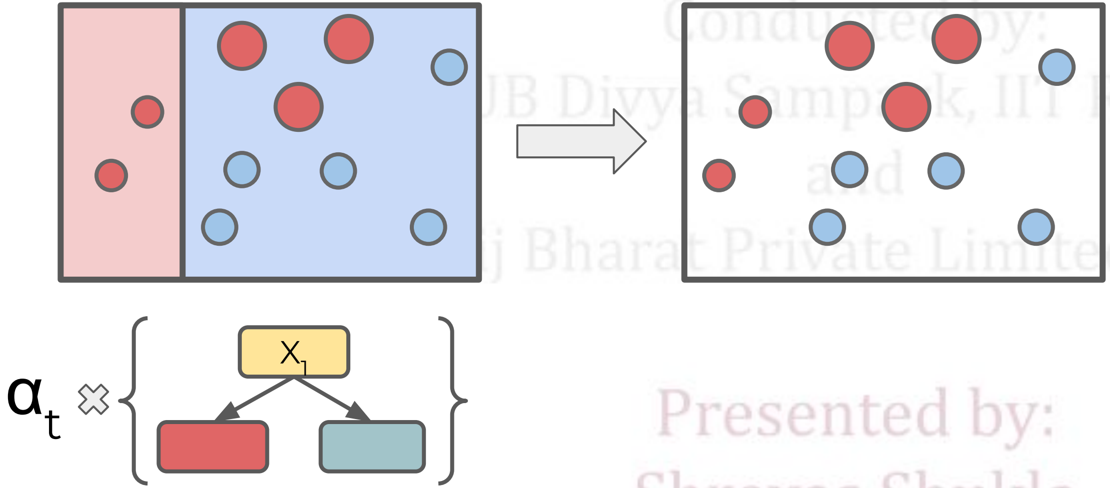


fig ref: pierian data

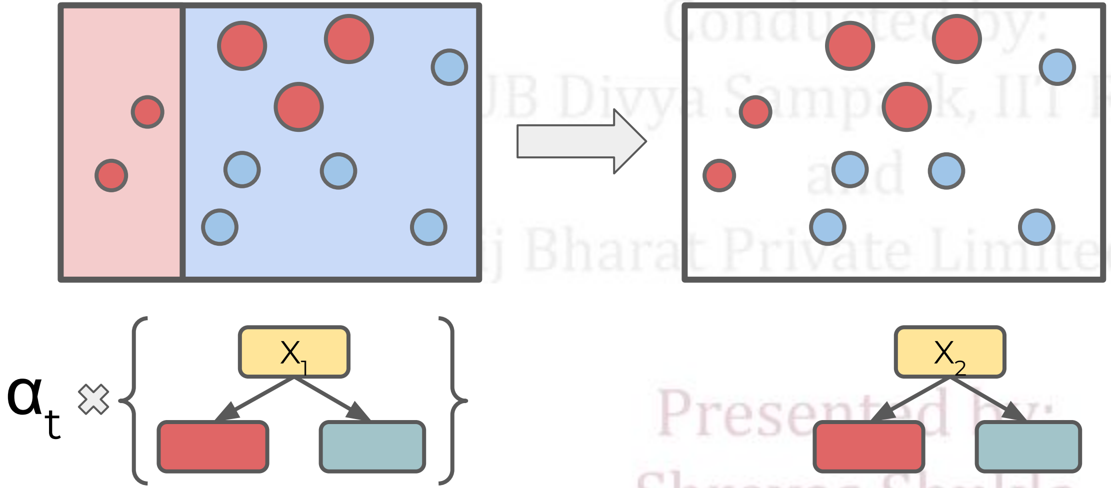


fig ref: pierian data

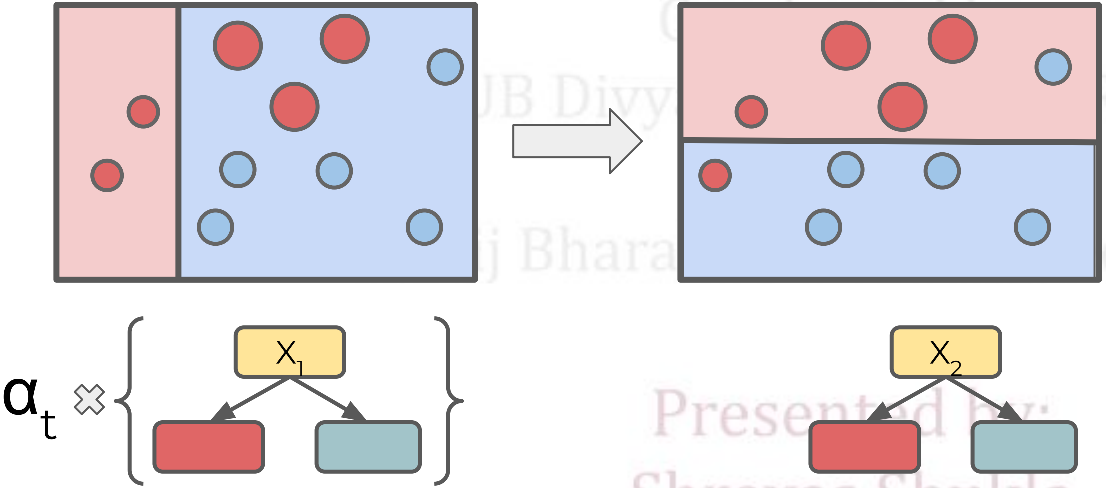


fig ref: pierian data

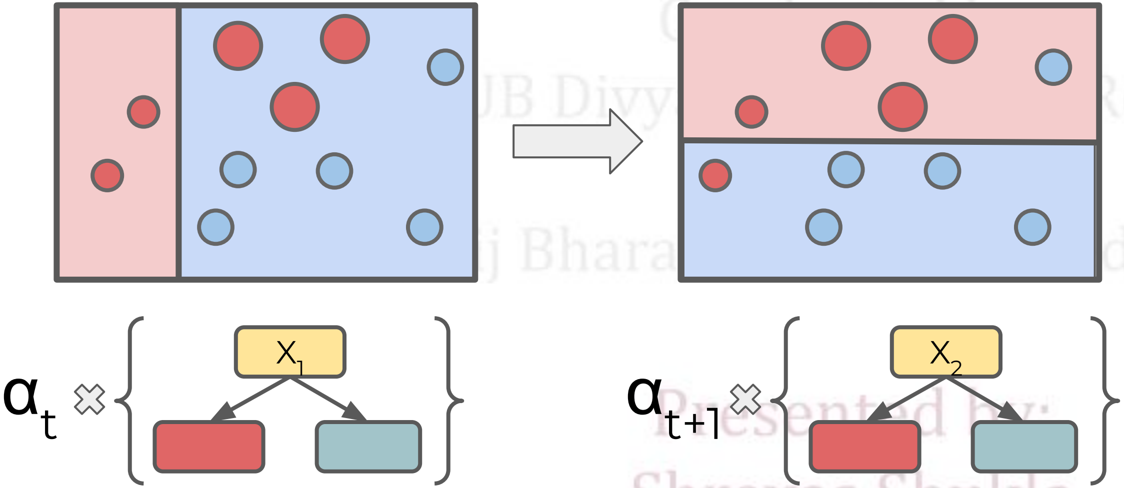


fig ref: pierian data

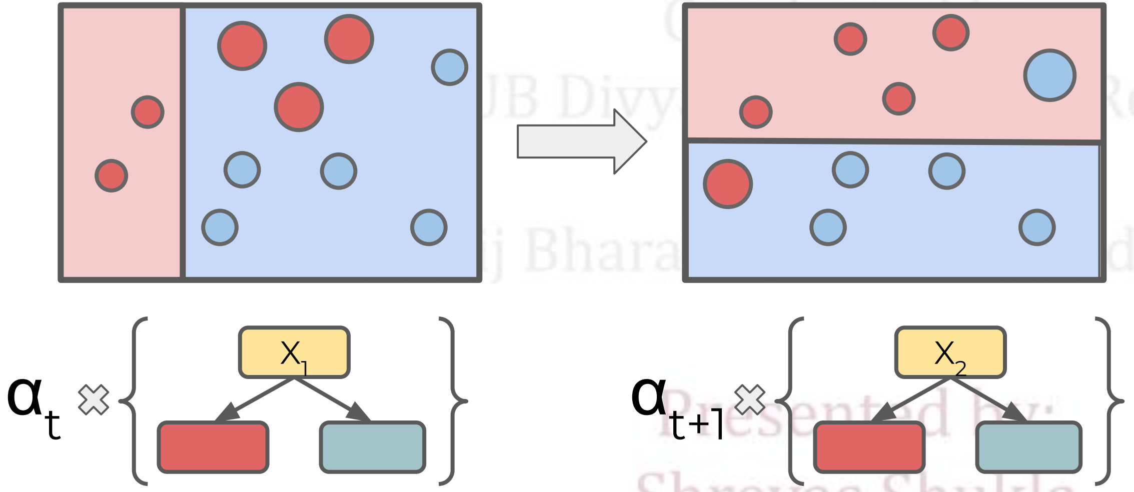


fig ref: pierian data

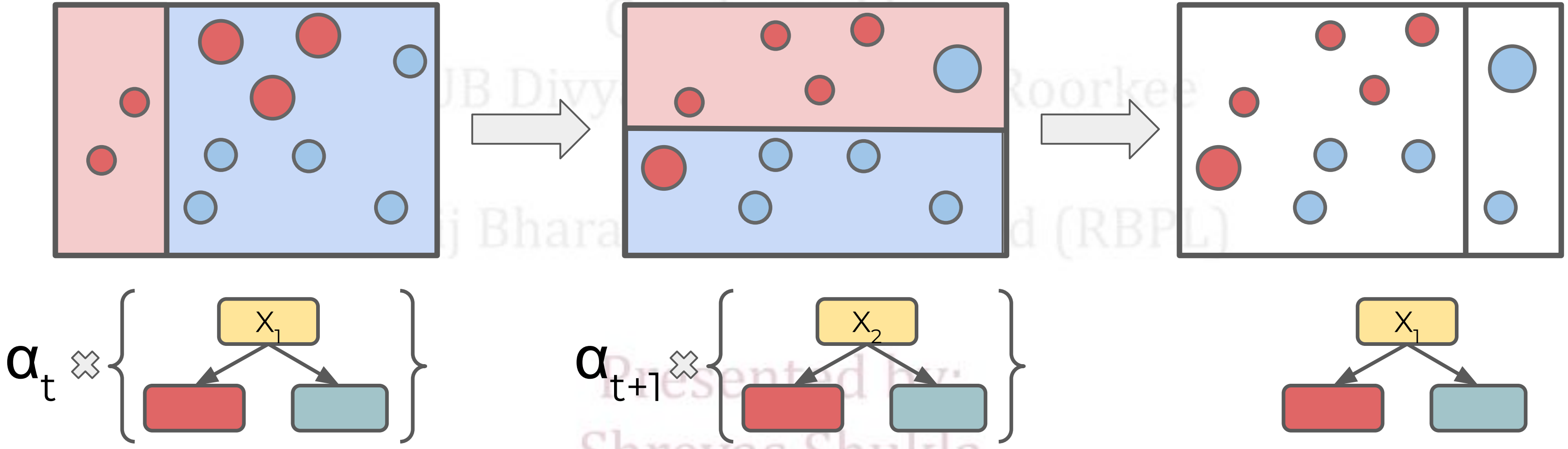


fig ref: pierian data

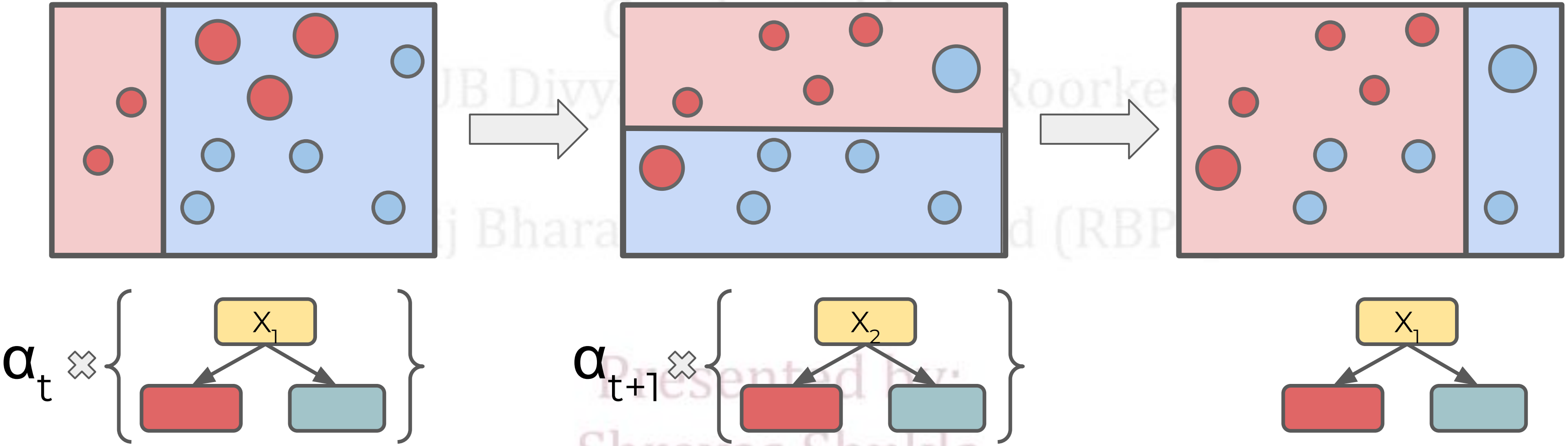
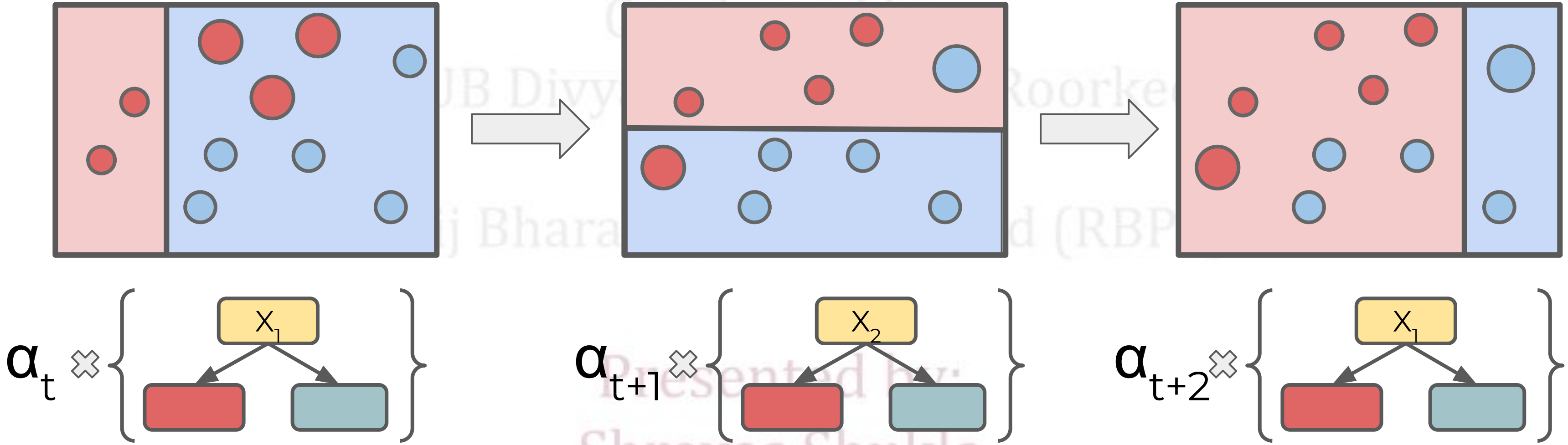
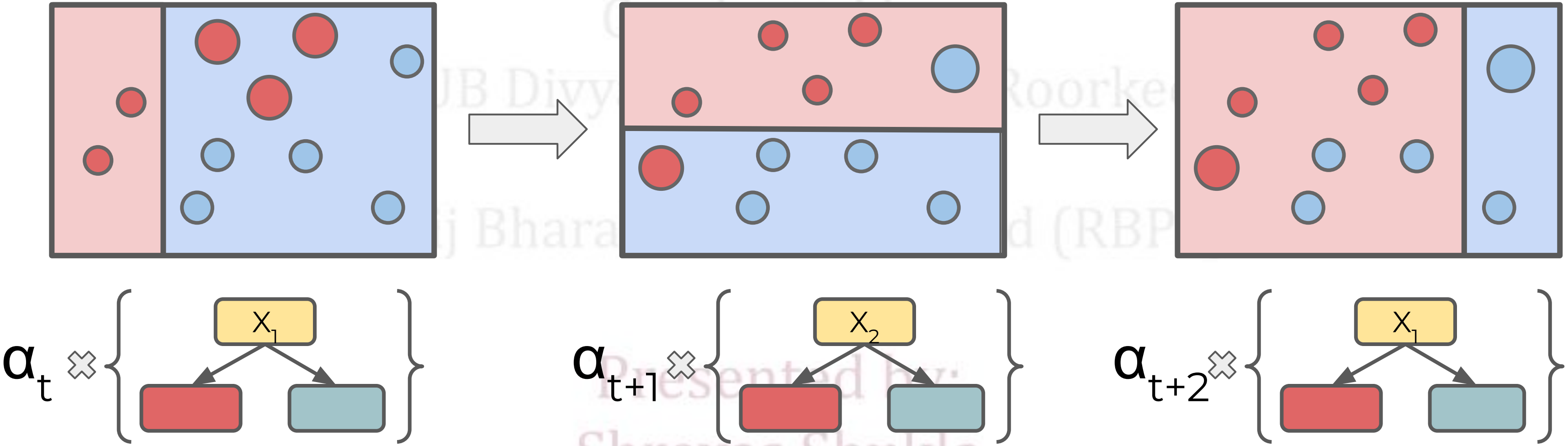


fig ref: pierian data


α_t
X_1
α_{t+1}
X_2
α_{t+2}
X_1



$$F_T(x) = \sum_{t=1}^{T} f_t(x) \qquad f_t(x) = \alpha_t h(x)$$

fig ref: pierian data

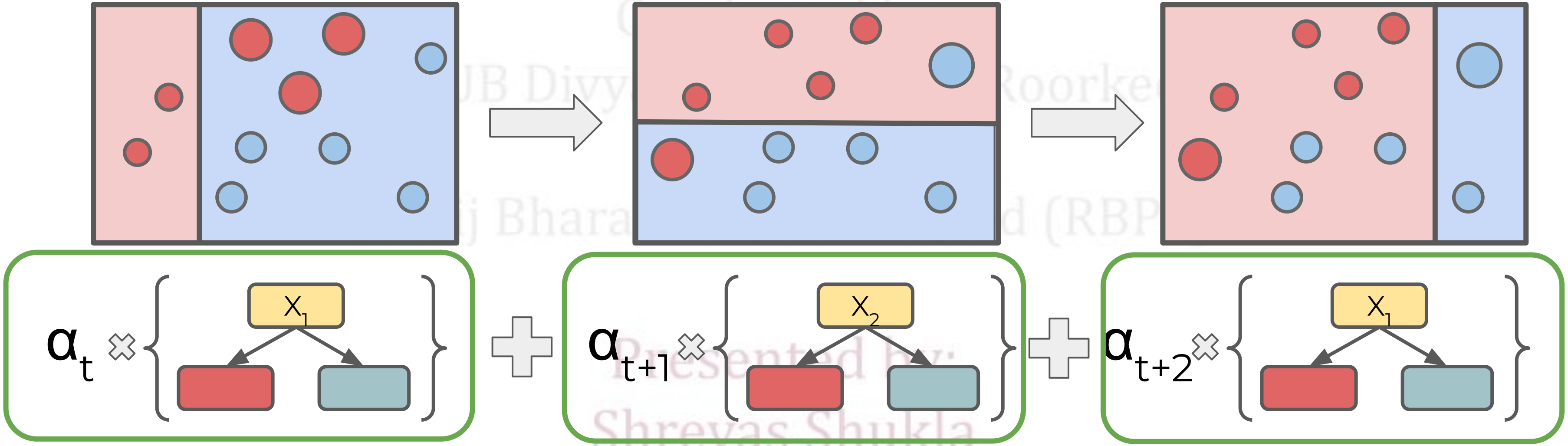


fig ref: pierian data

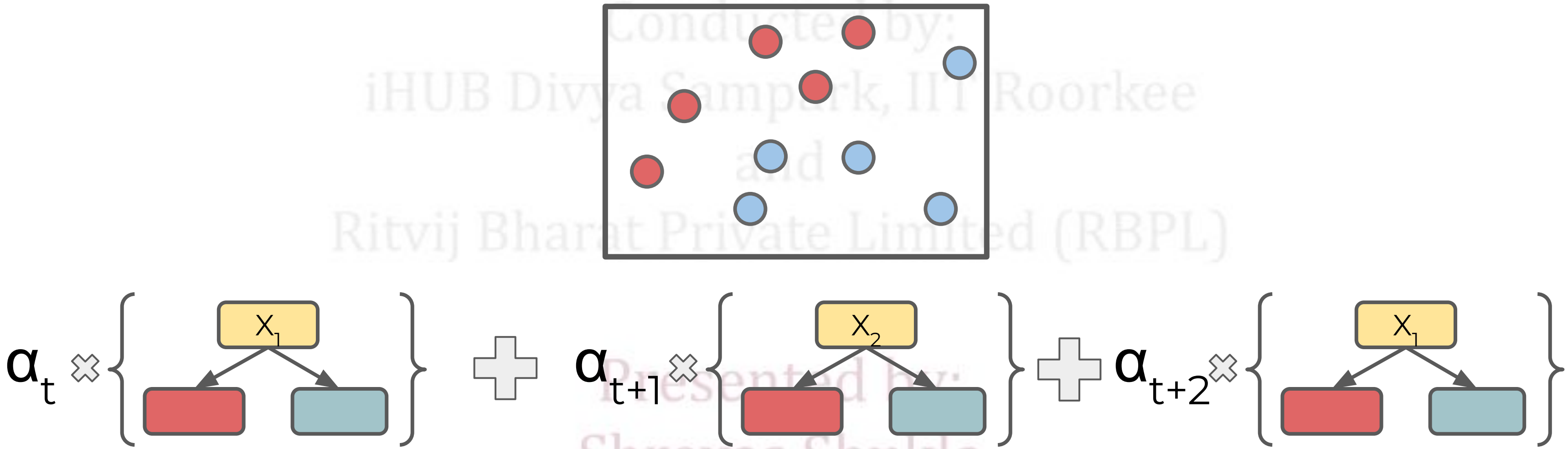


fig ref: pierian data

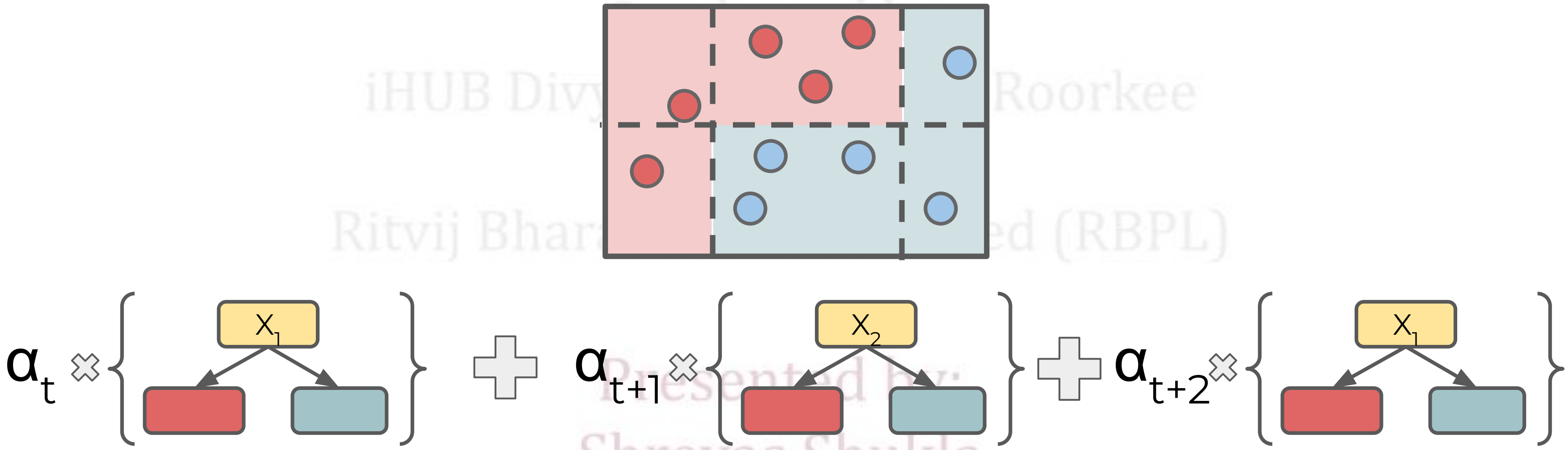


fig ref: pierian data

AdaBoost uses an ensemble of **weak learners** that learn slowly in series.

Certain weak learners have more weightage in in the final output than others due to the multiplied alpha parameter.

Each subsequent **t** weak learner is built using a reweighted data set from the **t-1** weak learner.

fig ref: pierian data

Intuition of Adaptive Boosting:

- Each stump essentially represents the strength of a feature to predict.
- Building these stumps in series and adding in the alpha parameter allows us to intelligently combine the importance of each feature together.

fig ref: pierian data

Unlike Random Forest, it is possible to overfit with AdaBoost, however it takes many trees to do this.

Usually error has already stabilized way before enough trees are added to cause overfitting.

Let’s put to practice!

An Introduction to Machine Learning with Python Programming
11 Sep 2023 - 20 Oct 2023

Conducted by:
iHUB Divya Sampark, IIT Roorkee
and
Ritvij Bharat Private Limited (RBPL)

Presented by:
Shreyas Shukla

fig ref: pierian data