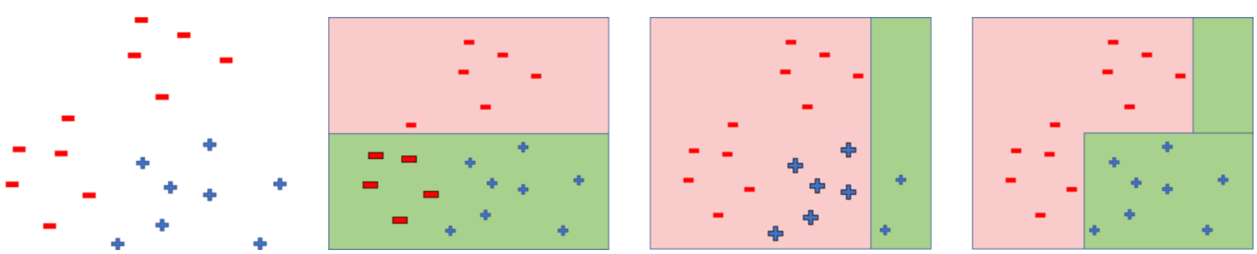
# BOOSTING



## 1. ADABOOST

- Classes should be +1 and -1
- Train N weak learners
- Build 1st weak learner
  - get misclassified points
  - increase the weight of these points
  - weight increasing helps in increasing the probability of getting picked for building the model
- Build 2nd weak learner
  - Hope the above misclassified points get classified correctly
  - get misclassified points
  - increase the weight of these points
  - weight increasing helps in increasing the probability of getting picked for building the model
- and so on
- Build Nth weak learner
  - Hope the above misclassified points get classified correctly
  - get misclassified points
  - increase the weight of these points
  - weight increasing helps in increasing the probability of getting picked for building the model
- Ensemble them.

- **Formulae:**

$$\alpha_t = \frac{1}{2}\log_e\left(\frac{1 - error_t}{error_t}\right);\ Where, error_t = 1 - accuracy_t$$

$\boldsymbol{Weights\ Updation}$:

$$D(t) = D(t) *\ e^{(\alpha_t * Y * h_t(x))}$$

$$D(t) = \frac{D(t)}{\sum D(t)}$$

$\boldsymbol{Final\ model}$ :

$$H(x) = sign(\sum_{t=1}^{T} \alpha_t * h_t(x))$$

$Where,$

$\alpha_t = Weight\ of\ the\ model_t$

$h_t(x) = model_t\ Predictions$

$T = number\ of\ learners$

- **Algorithm:**

Initialize mean weights to each point

i.e. $\frac{1}{N}$ for all the N points in the sample data

$For\ i\ \ in\ \ [T]\ Trees$

Build $i^{th}$ Tree on the weighted data points

Calculate $accuracy_i = \frac{(TP+FP)}{(TP+FP+TN+FN)}$

Calculate $error_i = 1 - accuracy_i$

Calculate $alpha_i = \frac{1}{2}\ log_e\left(\frac{(1 - error_i)}{error_i}\right)$

Update Weights

$$D(t) = D(t) * \ e^{(\alpha_t * Y * h_t(x))}$$

$$D(t) = \frac{D(t)}{\sum D(t)}$$

End For Loop

Final Model

$$H(x) = sign(\sum_{t=1}^{T} \alpha_t * h_t(x))$$

- **Note:**
  - $\alpha_t$ is $+ve$ for a good classifier (more the better)
  - $\alpha_t$ is 0 for 50% accurate classifier
  - $\alpha_t$ is $-ve$ for bad classifier (less the weaker)
  - If $\alpha_t$ is $-ve$ (weak learner):
    - if a point is wrongly classified: $D(t)$ increases a little
    - if a point is correctly classified: $D(t)$ decreases by a lot
  - If $\alpha_t$ is $+ve$ (strong learner):
    - if a point is wrongly classified: $D(t)$ increases a lot
    - if a point is correctly classified: $D(t)$decreases a little

## 2. GRADIENT BOOSTING

- **STEP: 1 (BUILDING)**
  - Build Decision Stump Classifier and Predict or Predict as mean value of train target value
  - For each iteration
    - Calculate gradient
      - $gradient = sigmoid(y_{pred}) - Y$
    - $cbind(X, gradient)$ - build Decision Stump Regressor with $maxdepth = 2$ and $minsplit = 2$
    - store the model in a list
    - predict the gradient on X ($predictedGradient$)
    - update the prediction using learning rate:
      - $y_{pred} = y_{pred} - learningRate * predictedGradient$
- **STEP: 2 (PREDICTION)**
  - For each tree
    - predict the gradient
    - update the gradient using learning rate:
      - $gradient = gradient * learningRate$
    - update the final prediction as:
      - $y_{pred} - gradient$
  - squash it using soft max
    - $\frac{e^x}{\sum e^x}$
- **Link**
  - https://github.com/kartheekpnsn/machine-learning-from-scratch/blob/master/R/gradient-boosting.R

## 3. GBM vs ADABOOST

- In GBM, first learner to classify the points then Calculates loss then Builds second to predict the loss after first step then Adjusts predictions, Builds loss after second step… and so on…
- If a learner misclassifies a sample, the weight of the learner is reduced and the weight of the sample point increases. It will repeat such process until converge.

## 4. GBM vs XGBOOST

- parallelized inside each tree
- handles missing values
- regularization
- tree pruned from maximum $depth$