Machine Learning I

Mohamed Hussien

Ensemble Learning

What Is Ensemble Learning?

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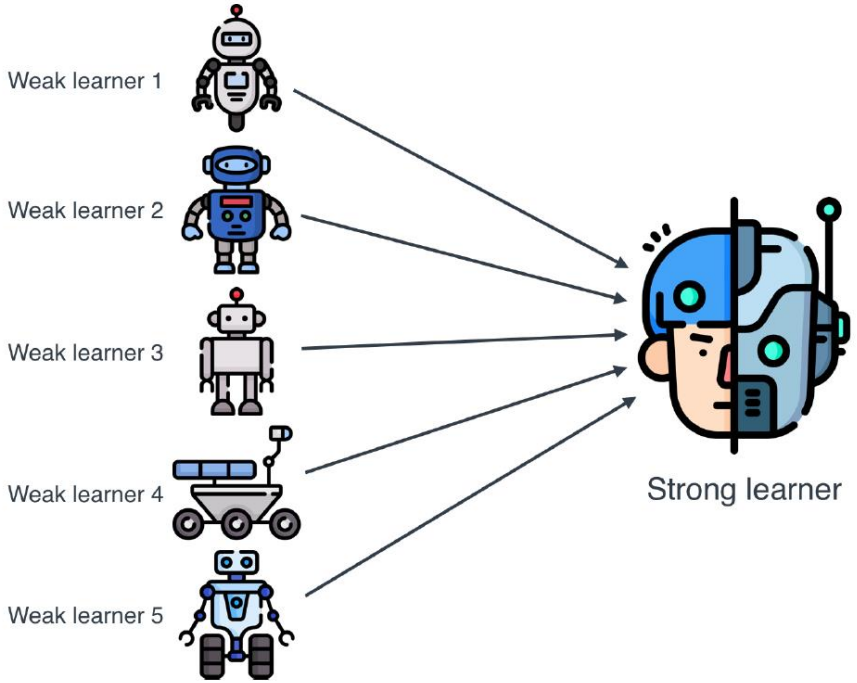
What Is Ensemble Learning?

Ensemble Learning:
Combine weak learners to form a strong one.

Learners could be any type of
machine learning model.

Ensemble Learning types:
- Bagging
- Boosting



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A technique in which we build a strong learner based on a set of weak learners **trained on data splitted randomly** and making predictions by **voting**.

If these learners are **decision trees**, then our model is called **Random Forest**.

Random Forest Steps:

- Split data **randomly** into sets:
- Train each decision tree at one of these sets.
- Take decision based on **vote** between these models.

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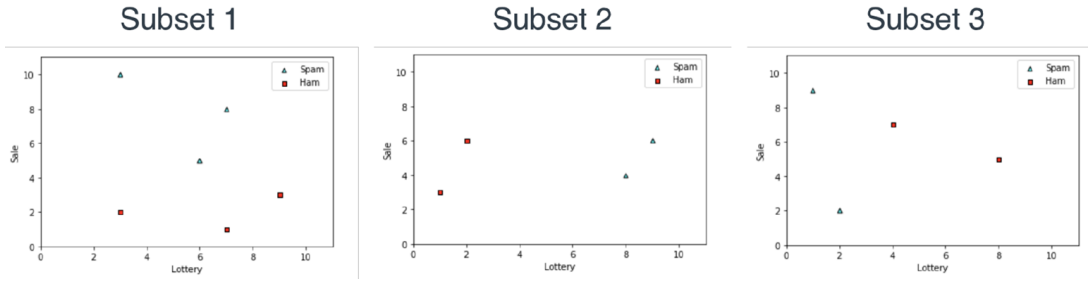

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A technique in which we build a strong learner based on a set of weak learners **not randomly selected,but trained in a smarter way** and making predictions by **voting**. Ex: AdaBoost, XGBoost

Each model trained to **cover the weakness of the previous ones**.

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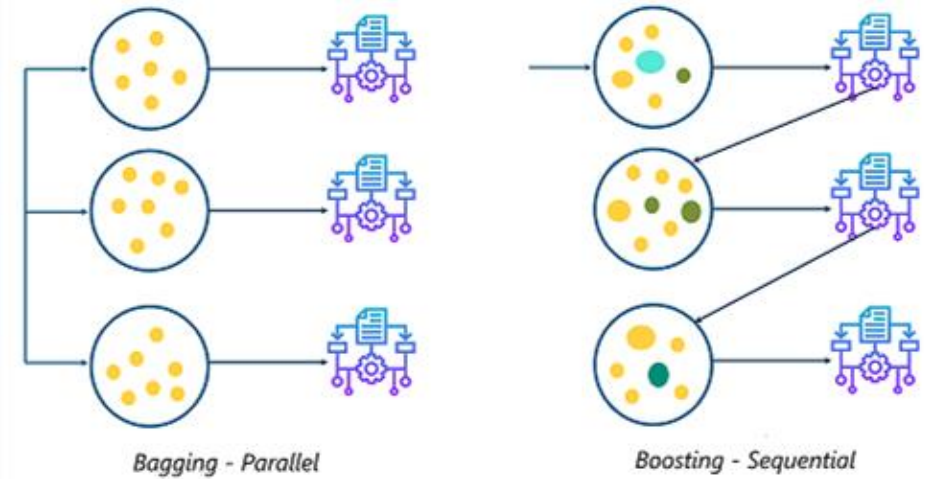

AdaBoost(Adaptive Boosting)

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Using very simple learners (1-depth decision tree) to build a strong learner

Steps:

- Train the first learner
- **Increase the weight** of the data samples that learner **predicts incorrectly**
- **Decrease the weight** of the data samples that learner **predicts correctly**
- Train another learner using **the modified dataset**
- Repeat steps 2,3,4 for all other learners
- Make the prediction using the weighted voting based on the performance of each learner

AdaBoost could be used for classification or regression. Our example is a classification problem.

AdaBoost [Big Picture]

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Our learners are very simple.
Ex: 1-Depth Decision Tree

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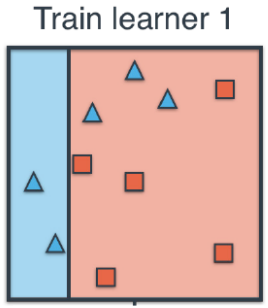

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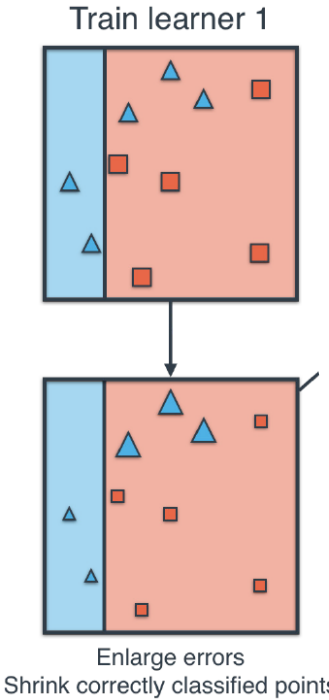

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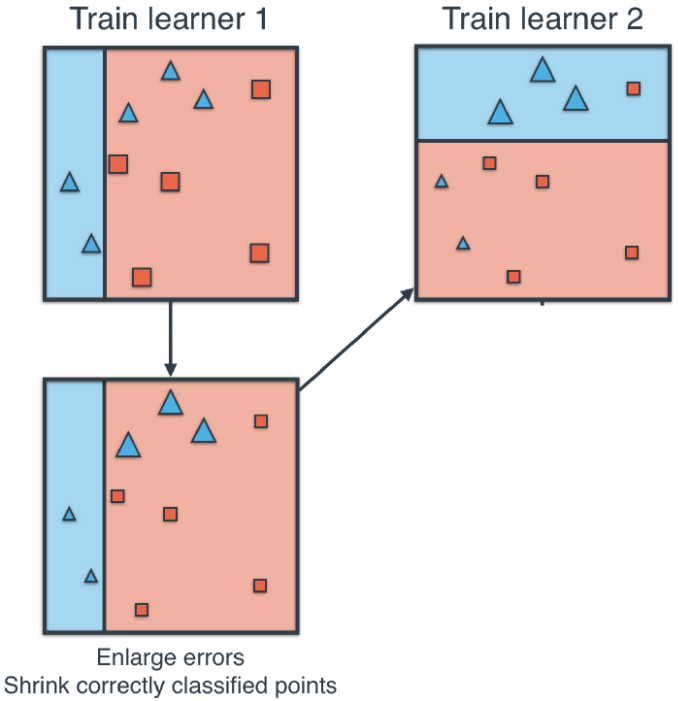

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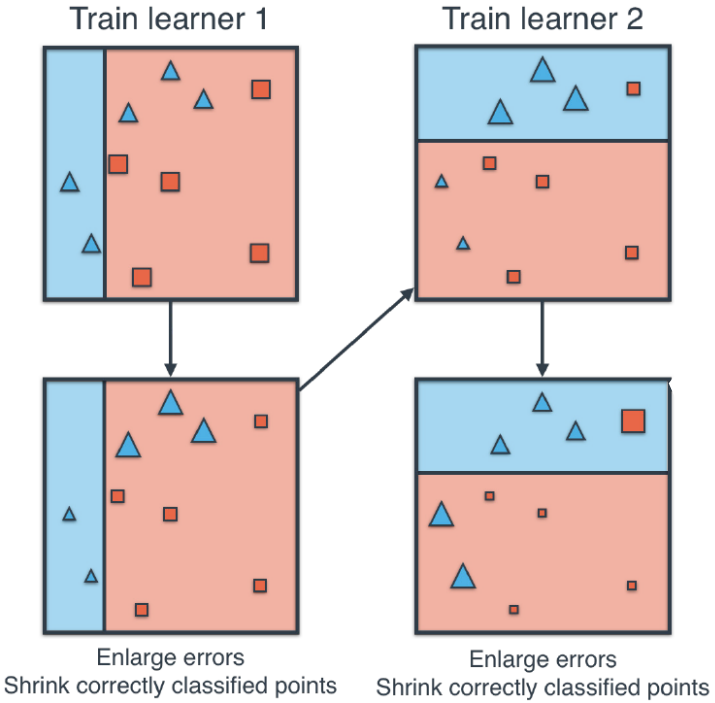

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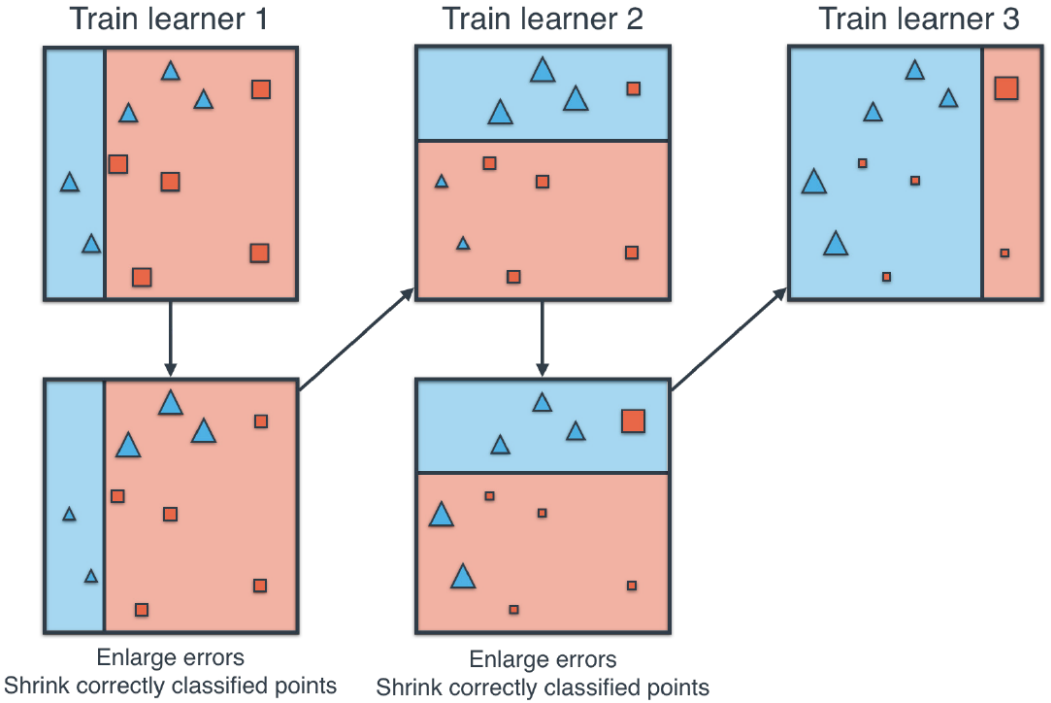

AdaBoost [Big Picture]

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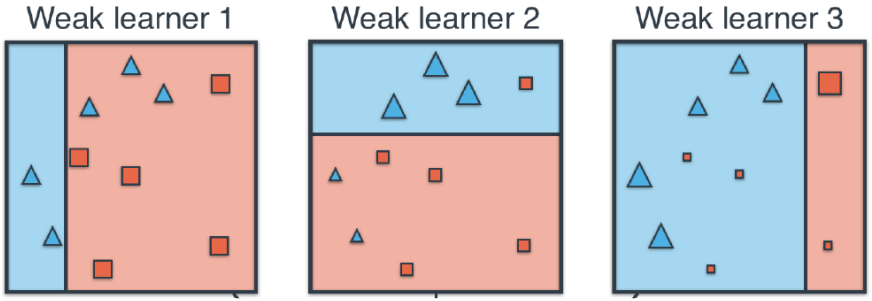

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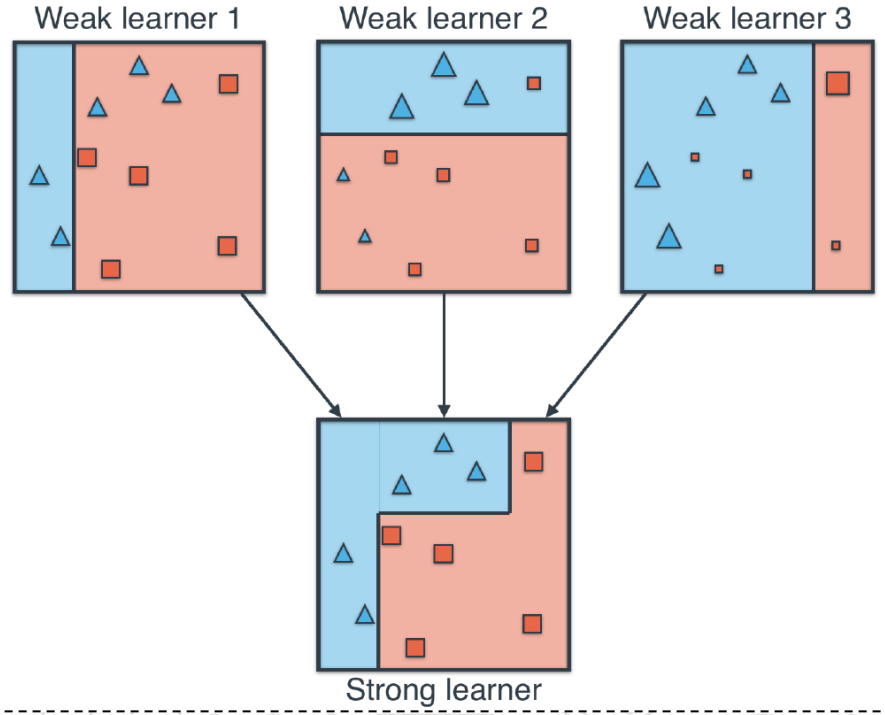

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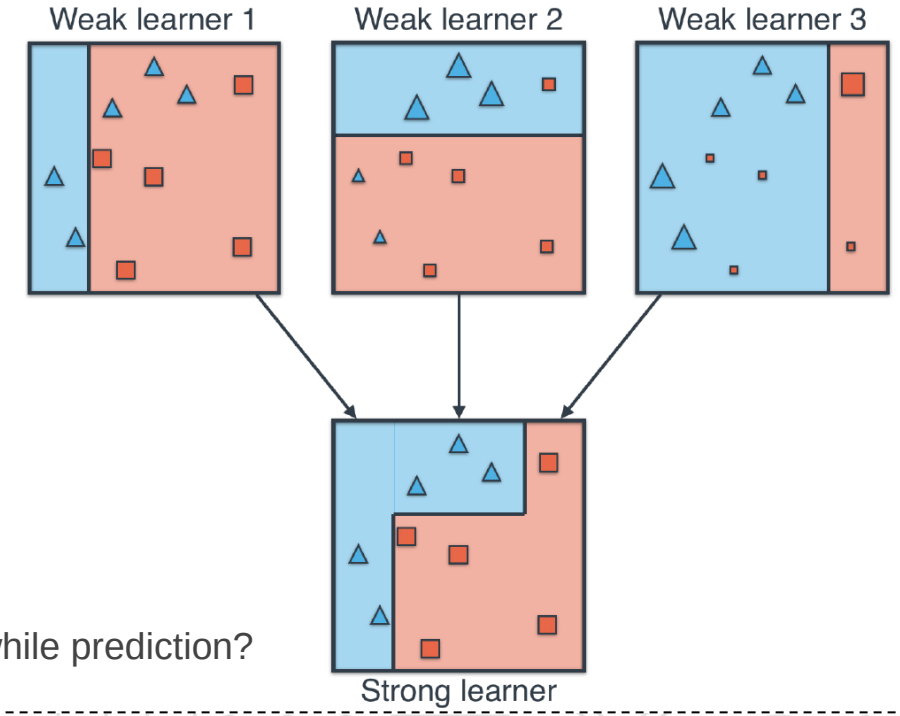

Need to answer two questions:

- How to change the points weights?
- How to choose the weight of each learner while prediction?

AdaBoost [In Details]

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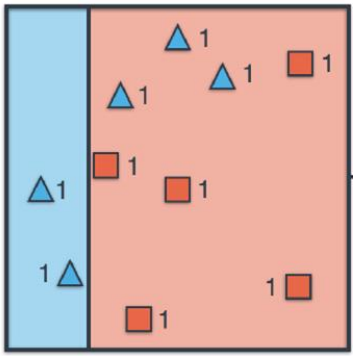

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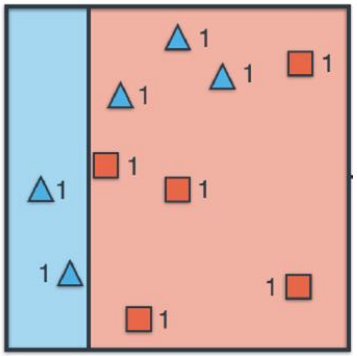

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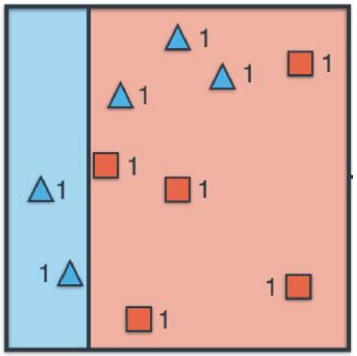

Rescaling Factor = 7/3 = 2.33

Could rescaling factor be < 1?

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How to update the weights? [Steps]

- Train the learner
- Calculate the rescaling factor
- Multiply incorrected classified Points by the rescaling factor
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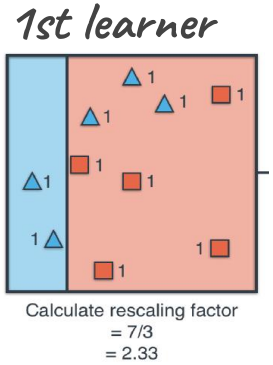

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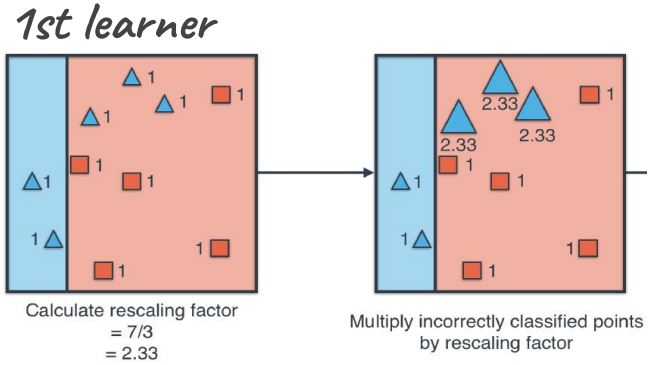

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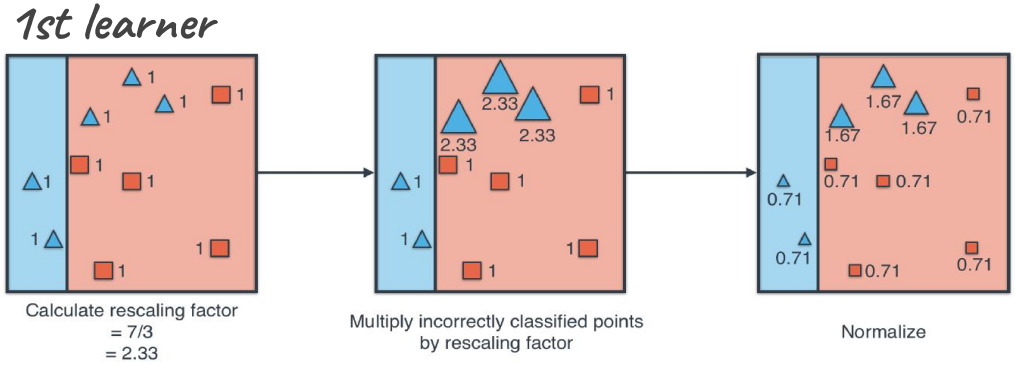

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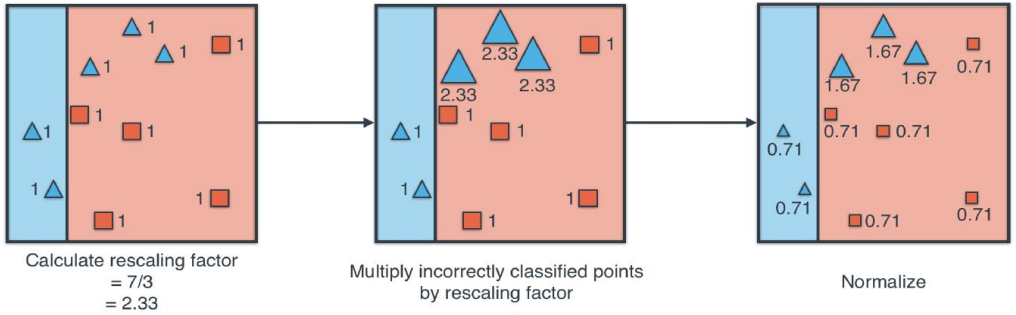
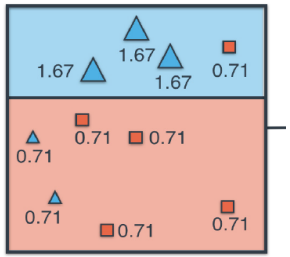


2nd learner



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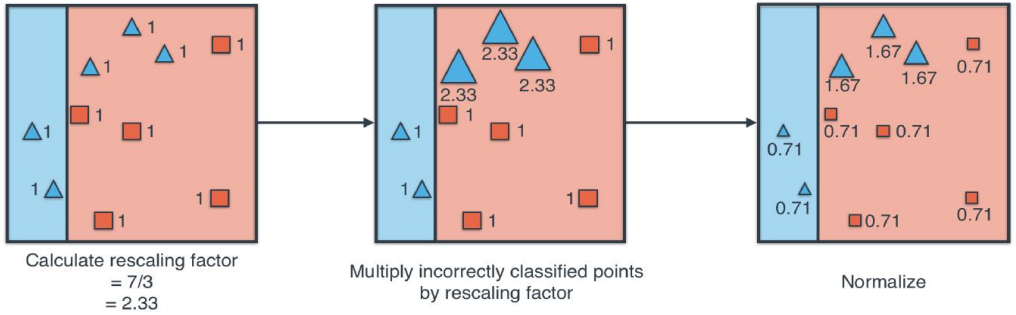

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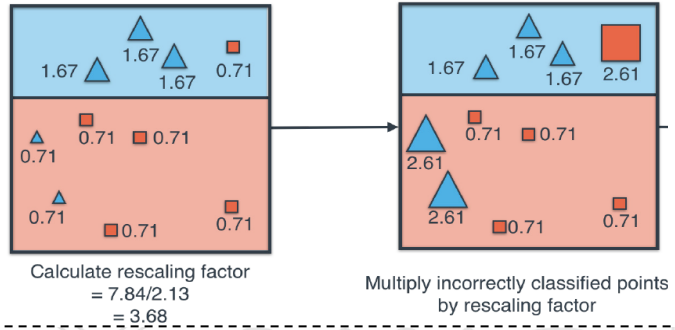

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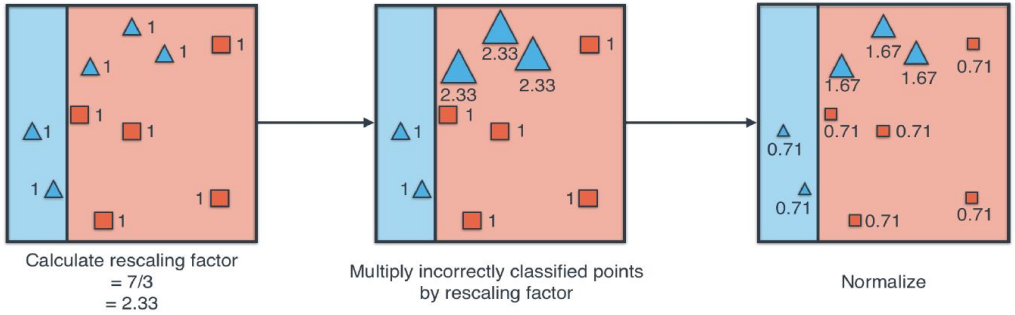

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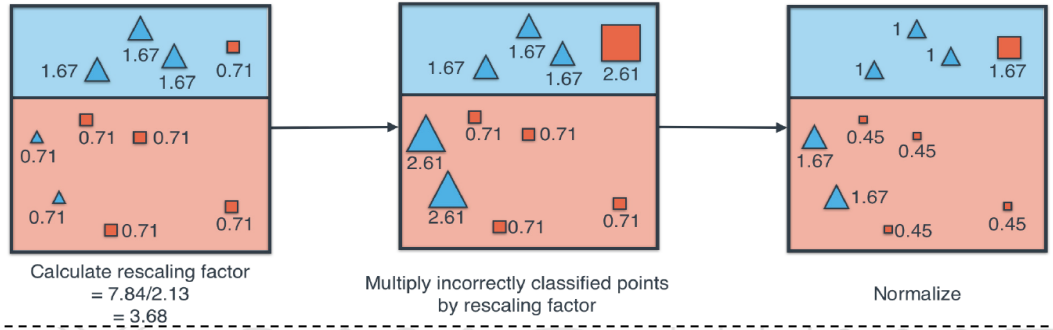

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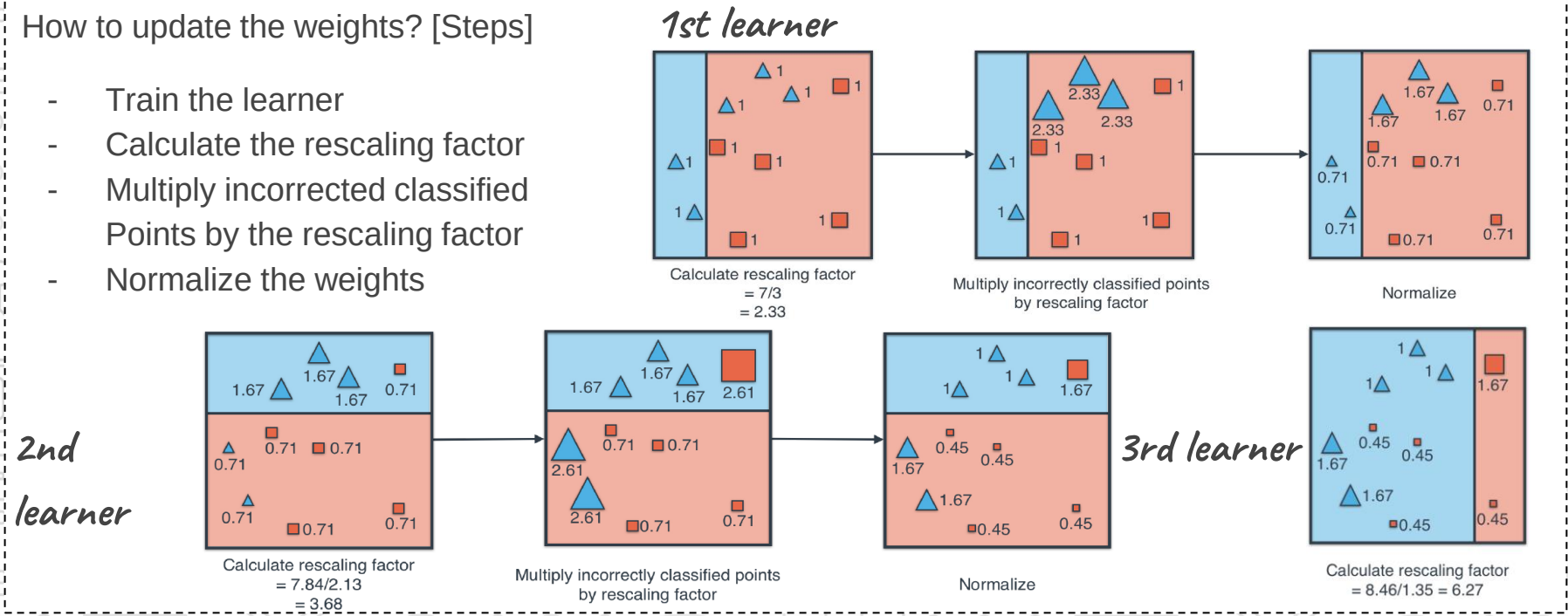

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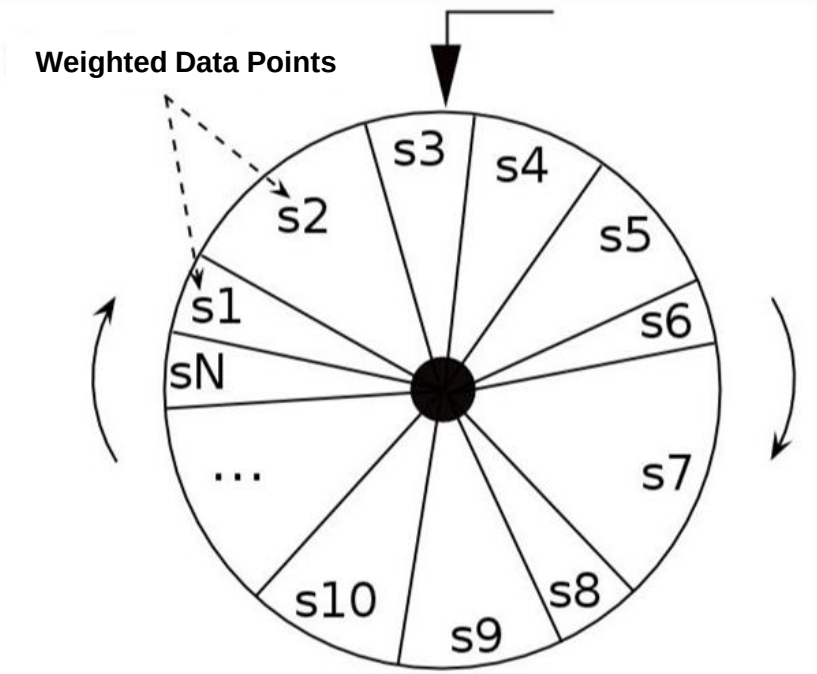

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Weight of each learner while prediction?

We can use **odd ratio** of the learner as a weight for that learner

BUT, Which model is better accuracy?
99%, 70%, 50%, 30%, 1%

If we inverted the 1% accuracy model predictions.
It will equal to the 99% accuracy.

We need a function that
multiply the weight by (-) if accuracy<50 (odd ratio<1)
And multiply the weight by (+) if accuracy>50 (odd ratio>1)

So we use the **ln(odd ratio)** of the learner to be the weight of this learner

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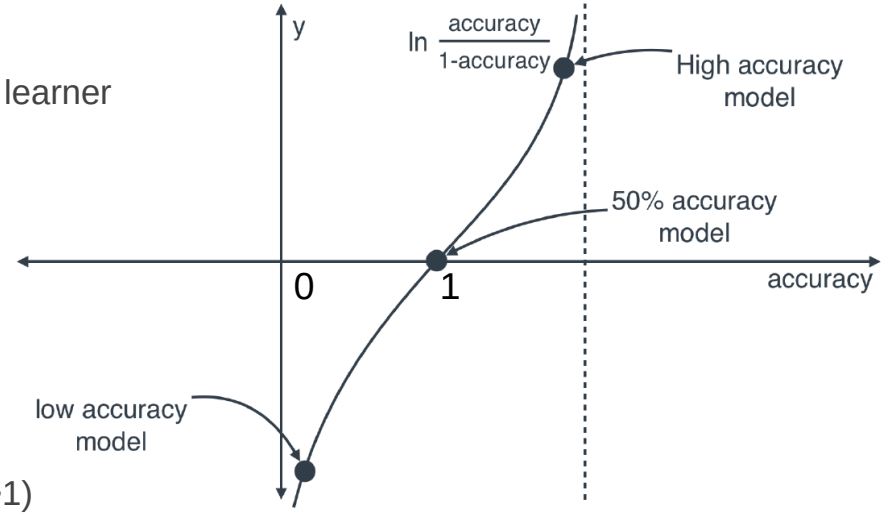

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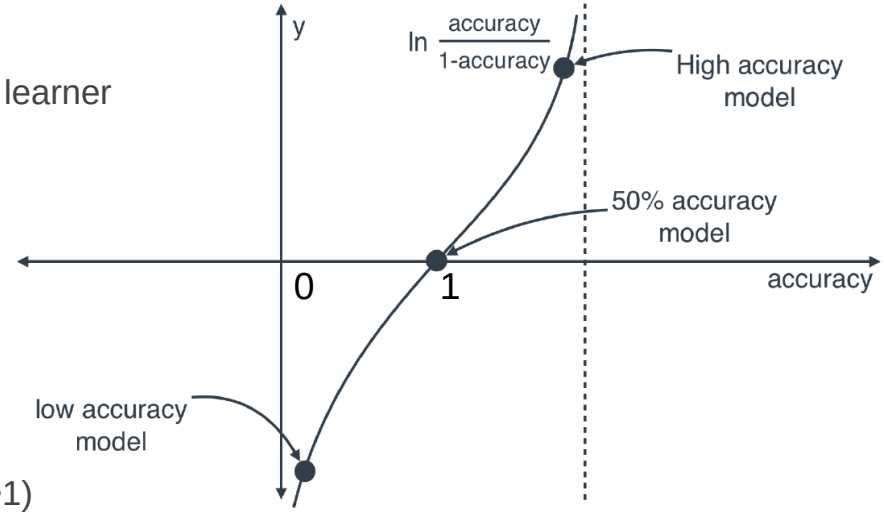

Notice that for the low-accuracy models we **increased the weight of the true points** then we **inverted the prediction**

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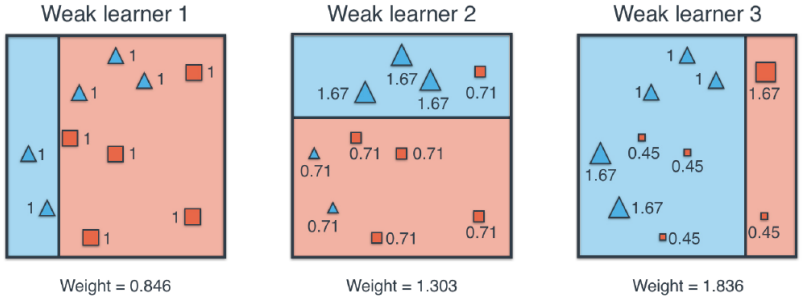

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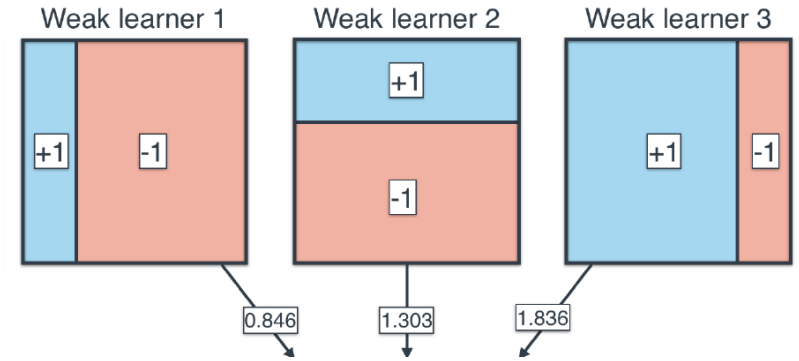

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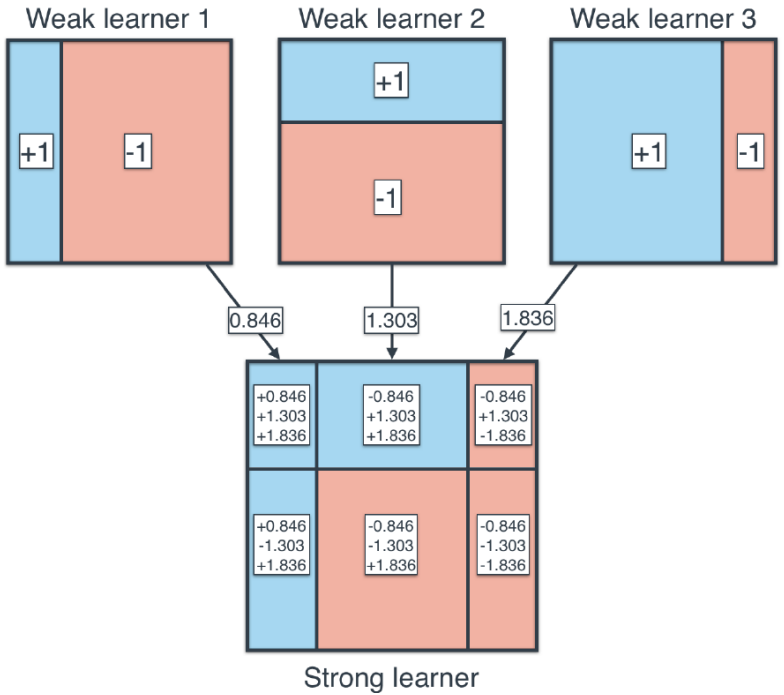

Coding AdaBoost

Use colab to open this github notebook:

“s7s/machine_learning_1/ensemble_methods/AdaBoost.ipynb”

XGBoost

XGBoost

AdaBoost consists of 1-depth weak learners. What if we build a similar algorithm with deeper trees?

XGBoost could be used for classification or regression. Our example is a regression problem.

Steps:

- Start with a naive learner that predicts 0.5 in all cases
- Calculate residual between predicted and label
- Build a new learner to predict the residual
- Repeat step 2,3 for other learners
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Need to answer two questions:

- How to build the learner?
- How to combine the learners to make the prediction?

XGBoost

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$$\text{Similarity} = \frac{\text{Square of sum of labels of the set}}{\text{Number of points of the set} + \lambda} \qquad \text{let } \lambda = 0$$

Example: If we have three sets with these labels {10, -10, 4}, {7, 7, 7}, {7}

XGBoost

How to build the learner?

In XGBoost we use a similarity instead of Gini and Entropy

$$Similarity = \frac{\text{Square of sum of labels of the set}}{\text{Number of points of the set} + \lambda} \qquad let\ \lambda = 0$$

Example: If we have three sets with these labels {10, -10, 4}, {7, 7, 7}, {7}

Set 1: $Similarity = \frac{(10-10+4)^2}{3} = \frac{16}{3}$.

XGBoost

How to build the learner?

In XGBoost we use a similarity instead of Gini and Entropy

$$Similarity = \frac{\text{Square of sum of labels of the set}}{\text{Number of points of the set} + \lambda} \qquad let\ \lambda = 0$$

Example: If we have three sets with these labels {10, -10, 4}, {7, 7, 7}, {7}

Set 1: $Similarity = \frac{(10-10+4)^2}{3} = \frac{16}{3}.$

Set 2: $Similarity = \frac{(7+7+7)^2}{3} = 147$

XGBoost

How to build the learner?

In XGBoost we use a similarity instead of Gini and Entropy

$$\text{Similarity} = \frac{\text{Square of sum of labels of the set}}{\text{Number of points of the set} + \lambda} \qquad \text{let } \lambda = 0$$

Example: If we have three sets with these labels {10, -10, 4}, {7, 7, 7}, {7}

Set 1: $Similarity = \frac{(10-10+4)^2}{3} = \frac{16}{3}$.

Set 2: $Similarity = \frac{(7+7+7)^2}{3} = 147$

Set 3: $Similarity = \frac{7^2}{1} = 49$

XGBoost

How to build the learner?

In XGBoost we use a similarity instead of Gini and Entropy

$$\text{Similarity} = \frac{\text{Square of sum of labels of the set}}{\text{Number of points of the set} + \lambda} \qquad \text{let } \lambda = 0$$

Example: If we have three sets with these labels {10, -10, 4}, {7, 7, 7}, {7}

Set 1: $Similarity = \frac{(10-10+4)^2}{3} = \frac{16}{3}$.

Set 2: $Similarity = \frac{(7+7+7)^2}{3} = 147$

Set 3: $Similarity = \frac{7^2}{1} = 49$

This is **not a perfect similarity metric** as it gives **high priority for high values**, but this is **good for our purpose** as we will see.

XGBoost

Age (feature)	Engagement (label)
10	7
20	5
30	6
40	0
50	1
60	0
70	4
80	3

XGBoost

Building the learners

Step1:
Start with a naive learner that predicts 0.5 in all cases

Age (feature)	Engagement (label)
10	7
20	5
30	6
40	0
50	1
60	0
70	4
80	3

XGBoost

Building the learners

Step1:
Start with a naive learner that predicts 0.5 in all cases

Age (feature)	Engagement (label)	Predicted label
10	7	0.5
20	5	0.5
30	6	0.5
40	0	0.5
50	1	0.5
60	0	0.5
70	4	0.5
80	3	0.5

XGBoost

Building the learners

Step1:
Start with a naive learner that predicts 0.5 in all cases

Step2:
Calculate residual between predicted and label

Age (feature)	Engagement (label)	Predicted label
10	7	0.5
20	5	0.5
30	6	0.5
40	0	0.5
50	1	0.5
60	0	0.5
70	4	0.5
80	3	0.5

XGBoost

Building the learners

Step1:
Start with a naive learner that predicts 0.5 in all cases

Step2:
Calculate residual between predicted and label

Age (feature)	Engagement (label)	Predicted label	Residual
10	7	0.5	6.5
20	5	0.5	4.5
30	6	0.5	5.5
40	0	0.5	-0.5
50	1	0.5	0.5
60	0	0.5	-0.5
70	4	0.5	3.5
80	3	0.5	2.5

XGBoost

Age (feature)	Residual
10	6.5
20	4.5
30	5.5
40	-0.5
50	0.5
60	-0.5
70	3.5
80	2.5

XGBoost

Building the learners

Step3:
Build a decision tree to predict the residual based on similarity gain

Base similarity:

Age (feature)	Residual
10	6.5
20	4.5
30	5.5
40	-0.5
50	0.5
60	-0.5
70	3.5
80	2.5

XGBoost

Building the learners

Step3:
Build a decision tree to predict the residual based on similarity gain

Base similarity:

Age (feature)	Residual
10	6.5
20	4.5
30	5.5
40	-0.5
50	0.5
60	-0.5
70	3.5
80	2.5

XGBoost

Building the learners

Step3:

Build a decision tree to predict the residual based on similarity gain

Base similarity: $\frac{(6.5 + 4.5 + 5.5 - 0.5 + 0.5 - 0.5 + 3.5 + 2.5)^2}{8} = 60.5$

Age (feature)	Residual
10	6.5
20	4.5
30	5.5
40	-0.5
50	0.5
60	-0.5
70	3.5
80	2.5

XGBoost

Building the learners

Step3:

Build a decision tree to predict the residual based on similarity gain

Base similarity: $\frac{(6.5 + 4.5 + 5.5 - 0.5 + 0.5 - 0.5 + 3.5 + 2.5)^2}{8} = 60.5$

Split at 15: Similarity Score = 76.57
Split at 25: Similarity Score = 80.67
Split at 35: Similarity Score = 96.8
Split at 45: Similarity Score = 73
Split at 55: Similarity Score = 64.53
Split at 65: Similarity Score = 60.67
Split at 75: Similarity Score = 60.57

Age (feature)	Residual
10	6.5
20	4.5
30	5.5
40	-0.5
50	0.5
60	-0.5
70	3.5
80	2.5

XGBoost

Building the learners

Step3:

Build a decision tree to predict the residual based on similarity gain

Base similarity: $\frac{(6.5 + 4.5 + 5.5 - 0.5 + 0.5 - 0.5 + 3.5 + 2.5)^2}{8} = 60.5$

Split at 15: Similarity Score = 76.57
Split at 25: Similarity Score = 80.67
Split at 35: Similarity Score = 96.8
Split at 45: Similarity Score = 73
Split at 55: Similarity Score = 64.53
Split at 65: Similarity Score = 60.67
Split at 75: Similarity Score = 60.57

Split at 15: Similarity Gain = 16.07
Split at 25: Similarity Gain = 20.16
Split at 35: Similarity Gain = 36.3
Split at 45: Similarity Gain = 12.5
Split at 55: Similarity Gain = 4.03
Split at 65: Similarity Gain = 0.17
Split at 75: Similarity Gain = 0.07

Age (feature)	Residual
10	6.5
20	4.5
30	5.5
40	-0.5
50	0.5
60	-0.5
70	3.5
80	2.5

XGBoost

Age (feature)	Residual
10	6.5
20	4.5
30	5.5
40	-0.5
50	0.5
60	-0.5
70	3.5
80	2.5

XGBoost

Building the learners

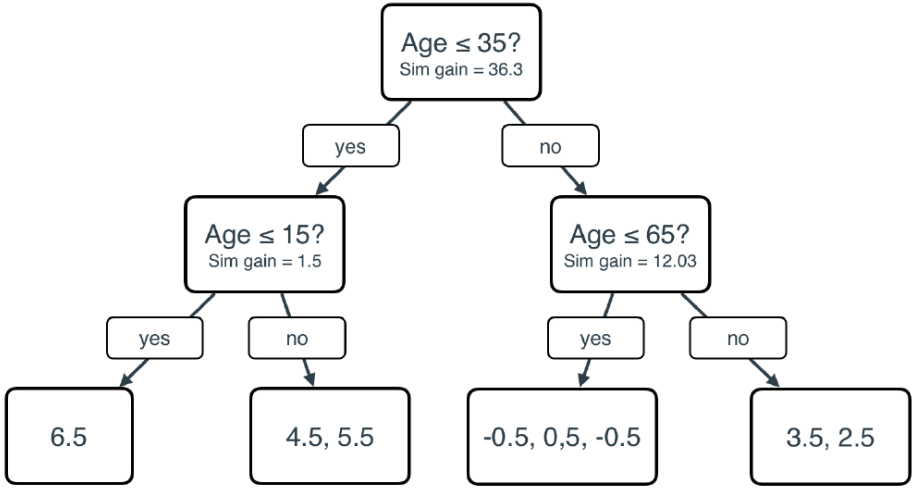
Step3:
Build a decision tree to predict the residual based on similarity gain

Age (feature)	Residual
10	6.5
20	4.5
30	5.5
40	-0.5
50	0.5
60	-0.5
70	3.5
80	2.5

XGBoost

Building the learners

Step3:
Build a decision tree to predict the residual based on similarity gain



Age (feature)	Residual
10	6.5
20	4.5
30	5.5
40	-0.5
50	0.5
60	-0.5
70	3.5
80	2.5

XGBoost

XGBoost

Hyperparameters:

Maximum Tree Depth: If increased, Overfitting increased.

Number Of Trees: Number of learners (estimators)

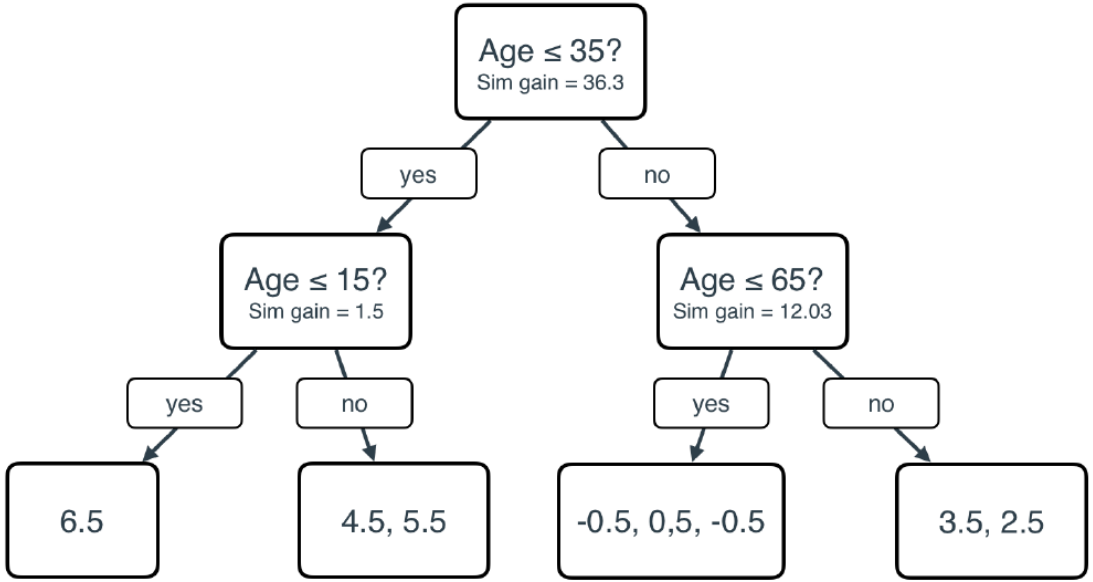
Minimum Number Of Elements Per Leaf: If increased, Overfitting decreased.

Minimum Similarity Gain (gamma γ): Minimum gain to split. If increased, Overfitting decreased.

Lambda λ: If increased, similarity gain decrease, overfitting decreased.

Learning Rate (eta η): The percentage of prediction that we take to not take the full step of decreasing.

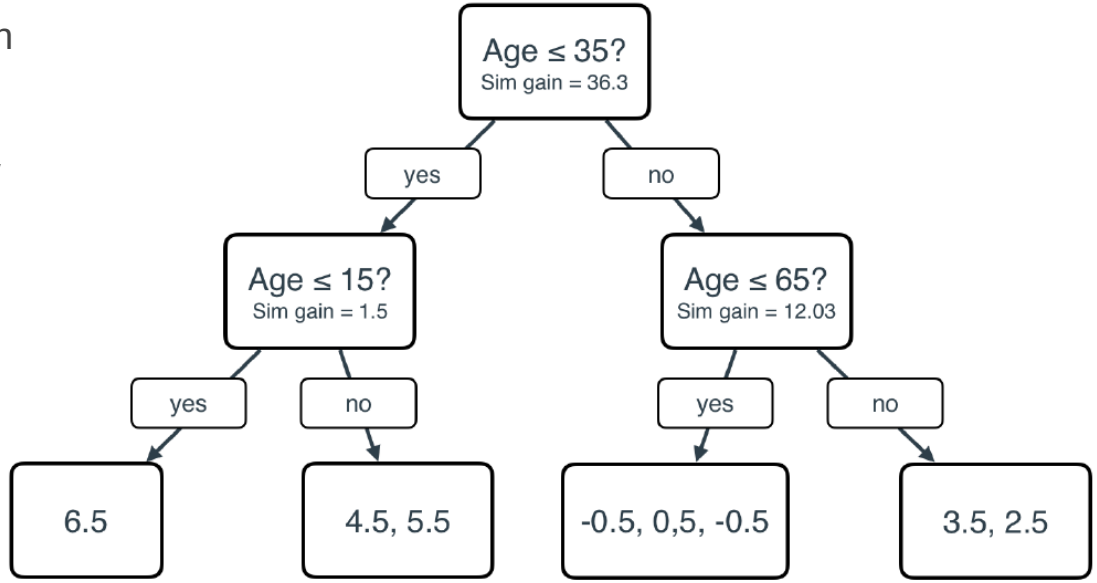
XGBoost


Age ≤ 35?
Sim gain = 36.3
yes
no
Age ≤ 15?
Sim gain = 1.5
Age ≤ 65?
Sim gain = 12.03
yes
no
yes
no
6.5
4.5, 5.5
-0.5, 0,5, -0.5
3.5, 2.5

XGBoost

Tree Pruning:
Stop splitting or remove leaves based on the above hyperparameters.

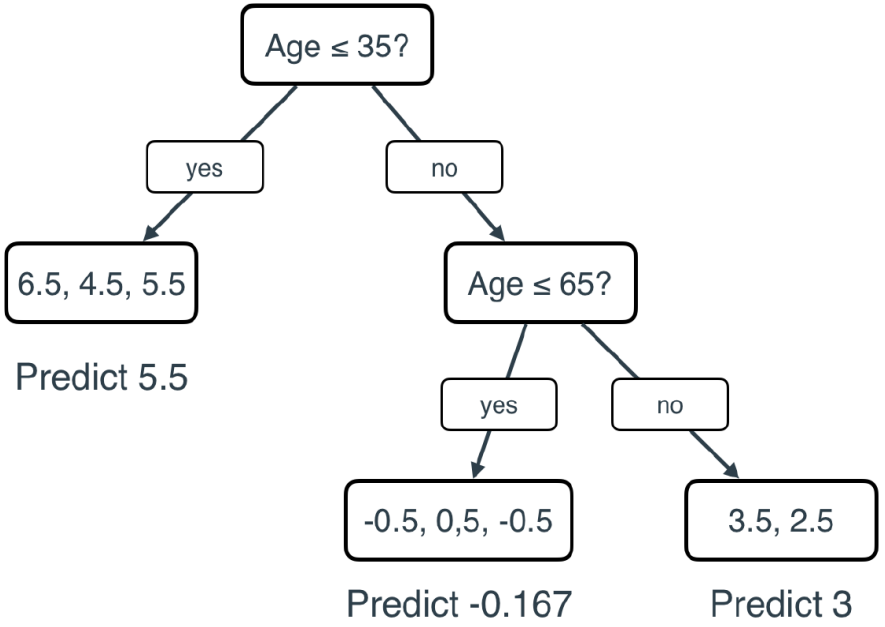
For example we set “Minimum Similarity Gain (gamma γ)” to 5



XGBoost

Tree Pruning:
Stop splitting or remove leaves based on the above hyperparameters.

For example we set “Minimum Similarity Gain (gamma γ)” to 5



XGBoost

XGBoost

Steps till now:

- Start with a naive learner that predicts 0.5 in all cases
- Calculate residual of learner 1
- Build learner 2 to fit the residual
- Multiply the predictions of learner 2 by learning rate (η), say 0.7
- Calculate the new predictions (learner 1 preds + learner 2 preds) Why?
- Calculate the new resuals

XGBoost

Steps till now:

- Start with a naive learner that predicts 0.5 in all cases
- Calculate residual of learner 1
- Build learner 2 to fit the residual
- Multiply the predictions of learner 2 by learning rate (η), say 0.7
- Calculate the new predictions (learner 1 preds + learner 2 preds) Why?
- Calculate the new resuals

Age (feature)	Engagement (label)
10	7
20	5
30	6
40	0
50	1
60	0
70	4
80	3

XGBoost

Steps till now:

- Start with a naive learner that predicts 0.5 in all cases
- Calculate residual of learner 1
- Build learner 2 to fit the residual
- Multiply the predictions of learner 2 by learning rate (η), say 0.7
- Calculate the new predictions (learner 1 preds + learner 2 preds) Why?
- Calculate the new resuals

Age (feature)	Engagement (label)	Prediction 1 (First tree)
10	7	0.5
20	5	0.5
30	6	0.5
40	0	0.5
50	1	0.5
60	0	0.5
70	4	0.5
80	3	0.5

XGBoost

Steps till now:

- Start with a naive learner that predicts 0.5 in all cases
- Calculate residual of learner 1
- Build learner 2 to fit the residual
- Multiply the predictions of learner 2 by learning rate (η), say 0.7
- Calculate the new predictions (learner 1 preds + learner 2 preds) Why?
- Calculate the new resuals

Age (feature)	Engagement (label)	Prediction 1 (First tree)	First residual
10	7	0.5	6.5
20	5	0.5	4.5
30	6	0.5	5.5
40	0	0.5	-0.5
50	1	0.5	0.5
60	0	0.5	-0.5
70	4	0.5	3.5
80	3	0.5	2.5

XGBoost

Steps till now:

- Start with a naive learner that predicts 0.5 in all cases
- Calculate residual of learner 1
- Build learner 2 to fit the residual
- Multiply the predictions of learner 2 by learning rate (η), say 0.7
- Calculate the new predictions (learner 1 preds + learner 2 preds) Why?
- Calculate the new resuals

Age (feature)	Engagement (label)	Prediction 1 (First tree)	First residual	Prediction 2 (Second tree)
10	7	0.5	6.5	5.5
20	5	0.5	4.5	5.5
30	6	0.5	5.5	5.5
40	0	0.5	-0.5	-0.167
50	1	0.5	0.5	-0.167
60	0	0.5	-0.5	-0.167
70	4	0.5	3.5	3
80	3	0.5	2.5	3

XGBoost

Steps till now:

- Start with a naive learner that predicts 0.5 in all cases
- Calculate residual of learner 1
- Build learner 2 to fit the residual
- Multiply the predictions of learner 2 by learning rate (η), say 0.7
- Calculate the new predictions (learner 1 preds + learner 2 preds) Why?
- Calculate the new resuals

Age (feature)	Engagement (label)	Prediction 1 (First tree)	First residual	Prediction 2 (Second tree)	Prediction 2 times learning rate
10	7	0.5	6.5	5.5	4.4
20	5	0.5	4.5	5.5	4.4
30	6	0.5	5.5	5.5	4.4
40	0	0.5	-0.5	-0.167	-0.134
50	1	0.5	0.5	-0.167	-0.134
60	0	0.5	-0.5	-0.167	-0.134
70	4	0.5	3.5	3	2.4
80	3	0.5	2.5	3	2.4

XGBoost

Steps till now:

- Start with a naive learner that predicts 0.5 in all cases
- Calculate residual of learner 1
- Build learner 2 to fit the residual
- Multiply the predictions of learner 2 by learning rate (η), say 0.7
- Calculate the new predictions (learner 1 preds + learner 2 preds) Why?
- Calculate the new resuals

Age (feature)	Engagement (label)	Prediction 1 (First tree)	First residual	Prediction 2 (Second tree)	Prediction 2 times learning rate	Total prediction (pred 1 + pred 2)
10	7	0.5	6.5	5.5	4.4	4.9
20	5	0.5	4.5	5.5	4.4	4.9
30	6	0.5	5.5	5.5	4.4	4.9
40	0	0.5	-0.5	-0.167	-0.134	0.366
50	1	0.5	0.5	-0.167	-0.134	0.366
60	0	0.5	-0.5	-0.167	-0.134	0.366
70	4	0.5	3.5	3	2.4	2.9
80	3	0.5	2.5	3	2.4	2.9

XGBoost

Steps till now:

- Start with a naive learner that predicts 0.5 in all cases
- Calculate residual of learner 1
- Build learner 2 to fit the residual
- Multiply the predictions of learner 2 by learning rate (η), say 0.7
- Calculate the new predictions (learner 1 preds + learner 2 preds) Why?
- Calculate the new resuals

Age (feature)	Engagement (label)	Prediction 1 (First tree)	First residual	Prediction 2 (Second tree)	Prediction 2 times learning rate	Total prediction (pred 1 + pred 2)	Second residual
10	7	0.5	6.5	5.5	4.4	4.9	2.1
20	5	0.5	4.5	5.5	4.4	4.9	0.1
30	6	0.5	5.5	5.5	4.4	4.9	1.1
40	0	0.5	-0.5	-0.167	-0.134	0.366	-0.366
50	1	0.5	0.5	-0.167	-0.134	0.366	0.636
60	0	0.5	-0.5	-0.167	-0.134	0.366	-0.366
70	4	0.5	3.5	3	2.4	2.9	1.1
80	3	0.5	2.5	3	2.4	2.9	0.1

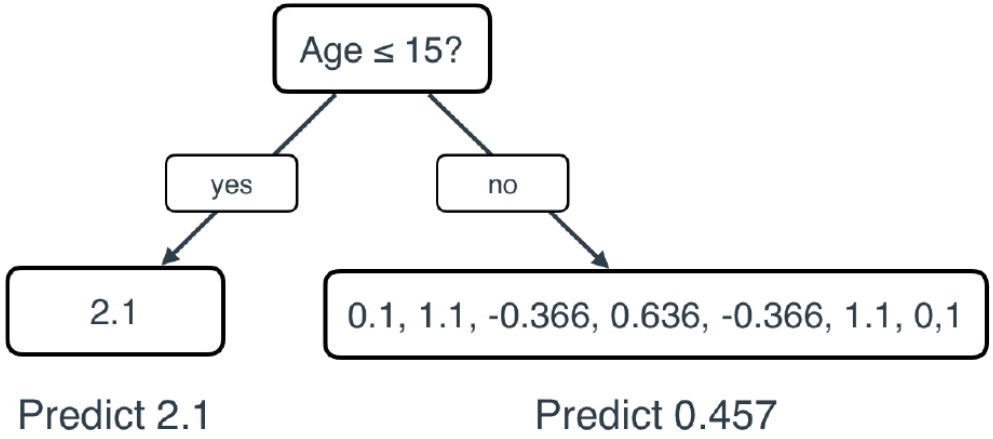
XGBoost

Time to build learner 3 with the same way

Age (feature)	Second residual
10	2.1
20	0.1
30	1.1
40	-0.366
50	0.636
60	-0.366
70	1.1
80	0.1

XGBoost

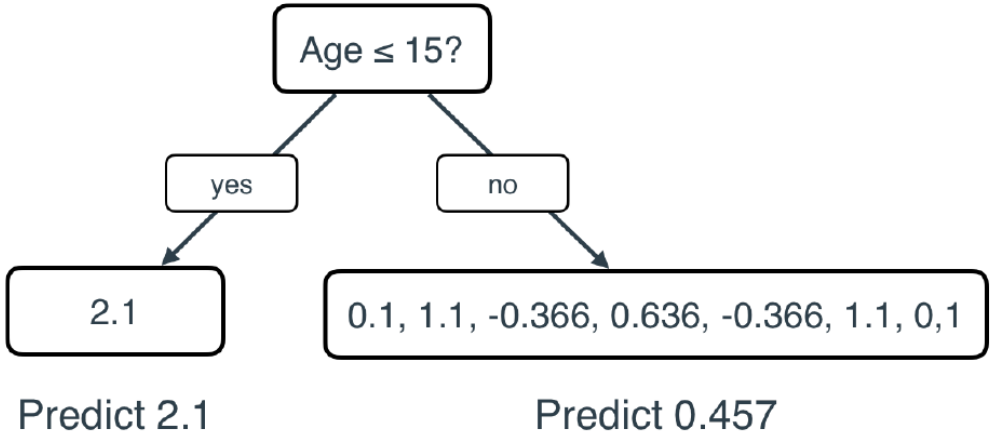
Time to build learner 3 with the same way



Age (feature)	Second residual
10	2.1
20	0.1
30	1.1
40	-0.366
50	0.636
60	-0.366
70	1.1
80	0.1

XGBoost

Time to build learner 3 with the same way



Age (feature)	Second residual
10	2.1
20	0.1
30	1.1
40	-0.366
50	0.636
60	-0.366
70	1.1
80	0.1

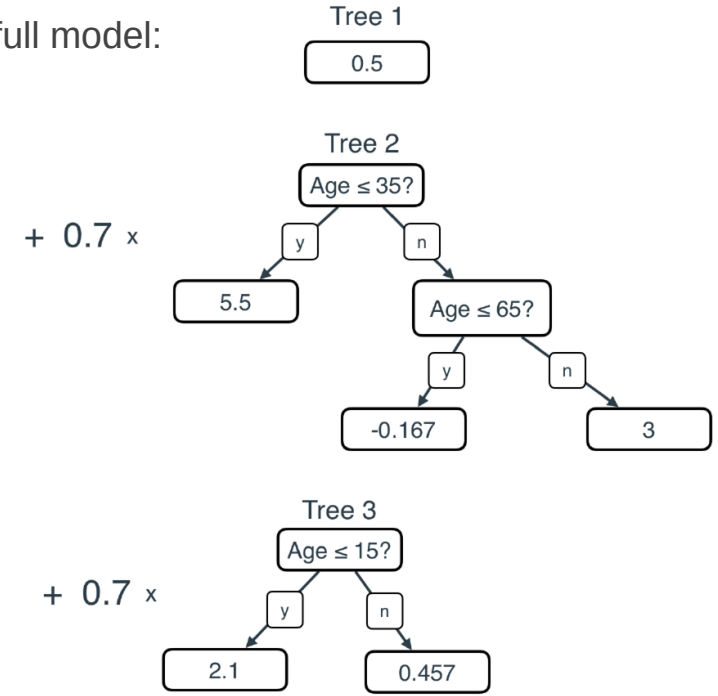
To get the predictions from learner 3, we multiply the output by the learning rate (0.7)

XGBoost

The full model:

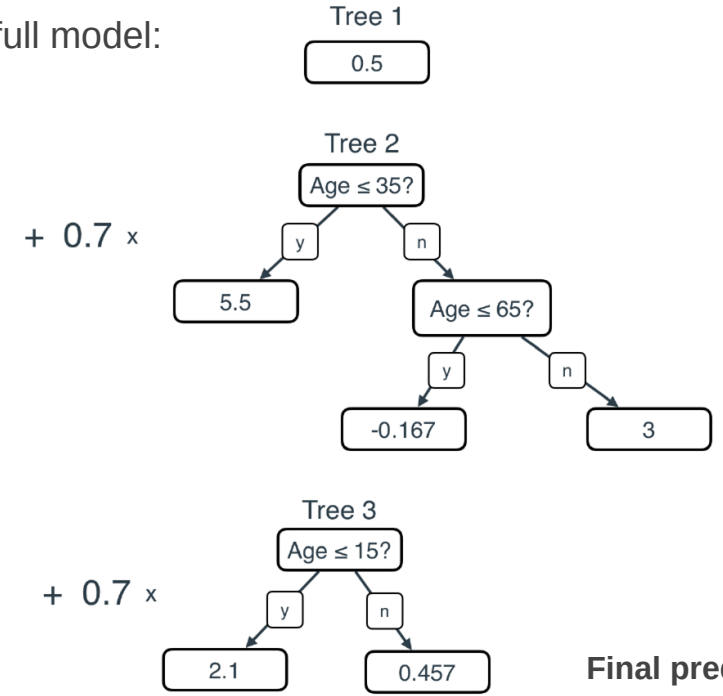
XGBoost

The full model:



XGBoost

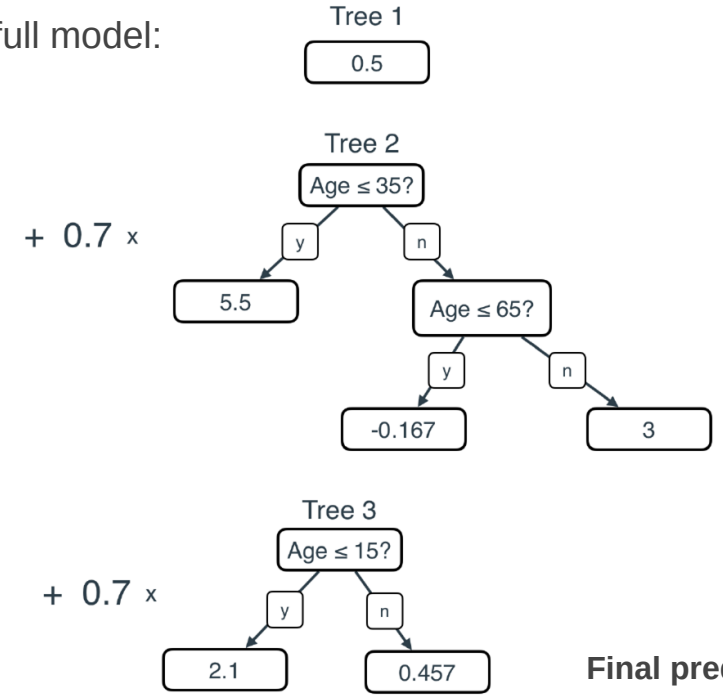
The full model:



Final prediction = Prediction 1 + 0.7 * Prediction 2 + 0.7 * Prediction 3

XGBoost

The full model:



Age (feature)	Engagement (label)	Prediction 1 (First tree)	Prediction 2 (Second tree)	Prediction 3 (Third tree)	Final prediction
10	7	0.5	5.5	2.1	5.82
20	5	0.5	5.5	0.457	4.67
30	6	0.5	5.5	0.457	4.67
40	0	0.5	-0.167	0.457	0.7
50	1	0.5	-0.167	0.457	0.7
60	0	0.5	-0.167	0.457	0.7
70	4	0.5	3	0.457	2.9
80	3	0.5	3	0.457	2.9

Final prediction = Prediction 1 + 0.7 * Prediction 2 + 0.7 * Prediction 3

Coding XGBoost

Use colab to open this github notebook:

“s7s/machine_learning_1/ensemble_methods/XGBoost.ipynb”