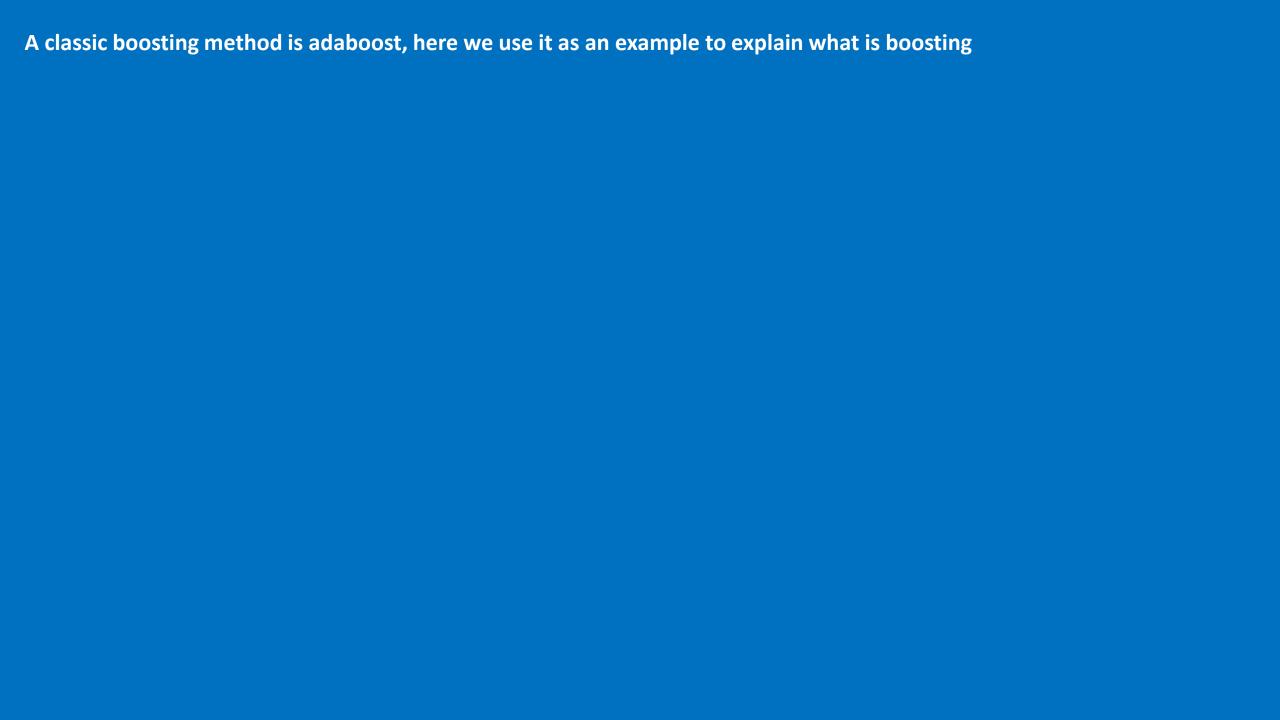
Boosting



Chest Pain	Blocked Arteries	Patient Weight	Heart Disease
Yes	Yes	205	Yes
No	Yes	180	Yes
Yes	No	210	Yes
Yes	Yes	167	Yes
No	Yes	156	No
No	Yes	125	No
Yes	No	168	No
Yes	Yes	172	No

Assuming we have the above dataset

Chest Pain	Blocked Arteries	Patient Weight	Heart Disease	Sample weight
Yes	Yes	205	Yes	<mark>1/8</mark>
No	Yes	180	Yes	1/8
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Step 1: we give weights for each sample (e.g., as an initial guess, it can be $\frac{1}{total \ samples}$)

Assuming we have the above dataset

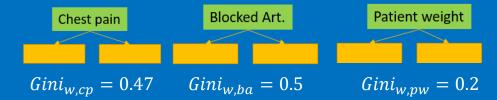
Chest Pain	Blocked Arteries	Patient Weight	Heart Disease	Sample weight
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Assuming we have the above dataset

Step 1: we give weights for each sample (e.g., as an initial guess, it can be $\frac{1}{total \ samples}$)

Step 2: determine the "root" tree

we go through each feature, grow trees and calculate "weighted Gini index"



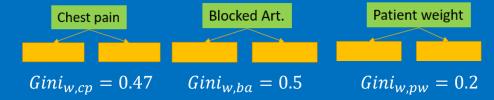
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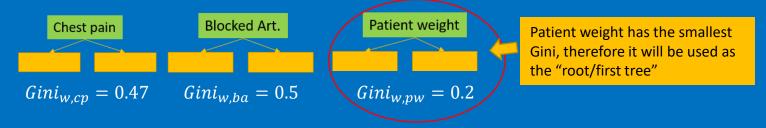
Chest Pain	Blocked Arteries	Patient Weight	Heart Disease	Sample weight
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Patient weight

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Yes	Yes	205	Yes	1/8
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Assuming we have the above dataset

Step 1: we give weights for each sample (e.g., as an initial guess, it can be $\frac{1}{total \ samples}$)

Step 2: determine the "root" tree

Step 3: determine how much the above tree will contribute to the final results

- Calculating the weighted prediction error for the tree, which is 0.125 (see Adaboost tutorial for the details)
- Calculating the "amount of say" for the tree, which is 0.97 (see Adaboost tutorial for the details)

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Assuming we have the above dataset

Step 1: we give weights for each sample (e.g., as an initial guess, it can be $\frac{1}{total \ samples}$)

Step 2: determine the "root" tree

Step 3: determine how much the above tree will contribute to the final results ("amount of say")

- Calculating the weighted prediction error for the tree, which is 0.125 (see Adaboost tutorial for the details)
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Step 4: Update the sample weight depending on the "amount of say"

Chest Pain	Blocked Arteries	Patient Weight	Heart Disease	San wei	Sample weight
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Step 5: Go back to "step 2", using the updated weight, and repeat the processes between "step 2" and "step 4"

Chest Pain	Blocked Arteries	Patient Weight	Heart Disease	San wei	Sample weight
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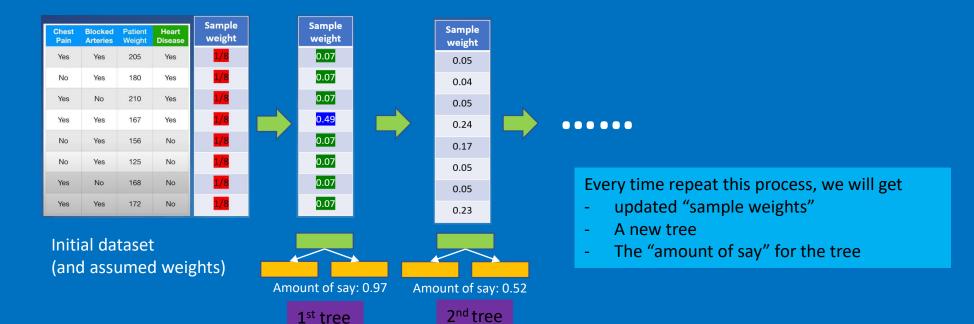
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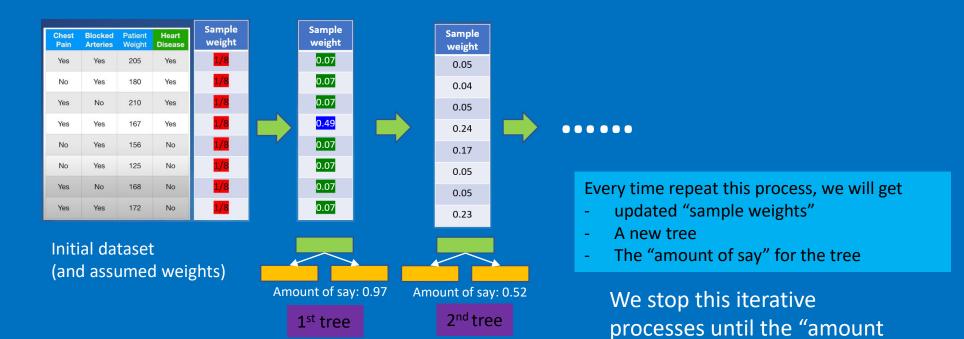
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of say" is small enough

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When we have a testing data

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Patient weight

Step 3: determine how much the above tree will contribute to the final results ("amount of say")

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When we have a testing data

We use the testing data to go through all the trees

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Step 3: determine how much the above tree will contribute to the final results ("amount of say")

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When we have a testing data





We use the testing data to go through all the trees

- When the tree output is "YES", we take it as "1".
- When the tree output is "NO", we take it as "0"

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Patient weight

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When we have a testing data





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The tree output is multiplied by the "amount of say" w_i

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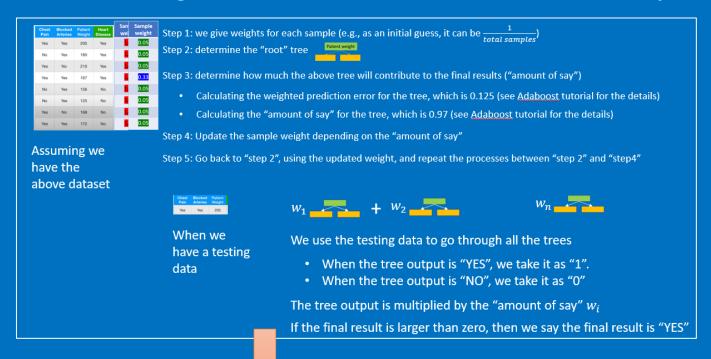




We use the testing data to go through all the trees

- When the tree output is "YES", we take it as "1".
- When the tree output is "NO", we take it as "0"

The tree output is multiplied by the "amount of say" w_i If the final result is larger than zero, then we say the final result is "YES"

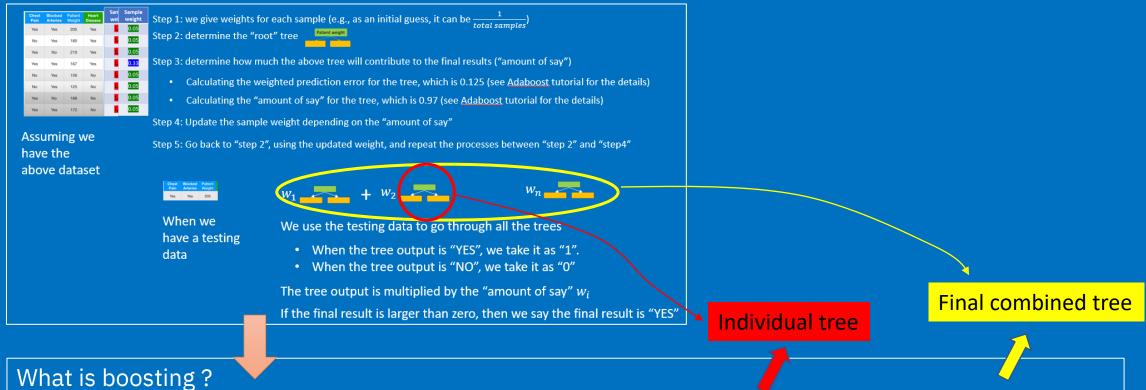


What is boosting?

Boosting is an ensemble learning method that combines a set of weak learners into a strong learner to minimize training errors.

In boosting, the sample data is fitted with a model and then trained sequentially—that is, each model tries to compensate for the weaknesses of its predecessor (so models are interconnected).

With each iteration, the weak rules from each individual classifier are combined to form one, strong prediction rule.



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