

# Statistical Methods in AI (CSE 471)

## Ensemble Methods

Vineet Gandhi



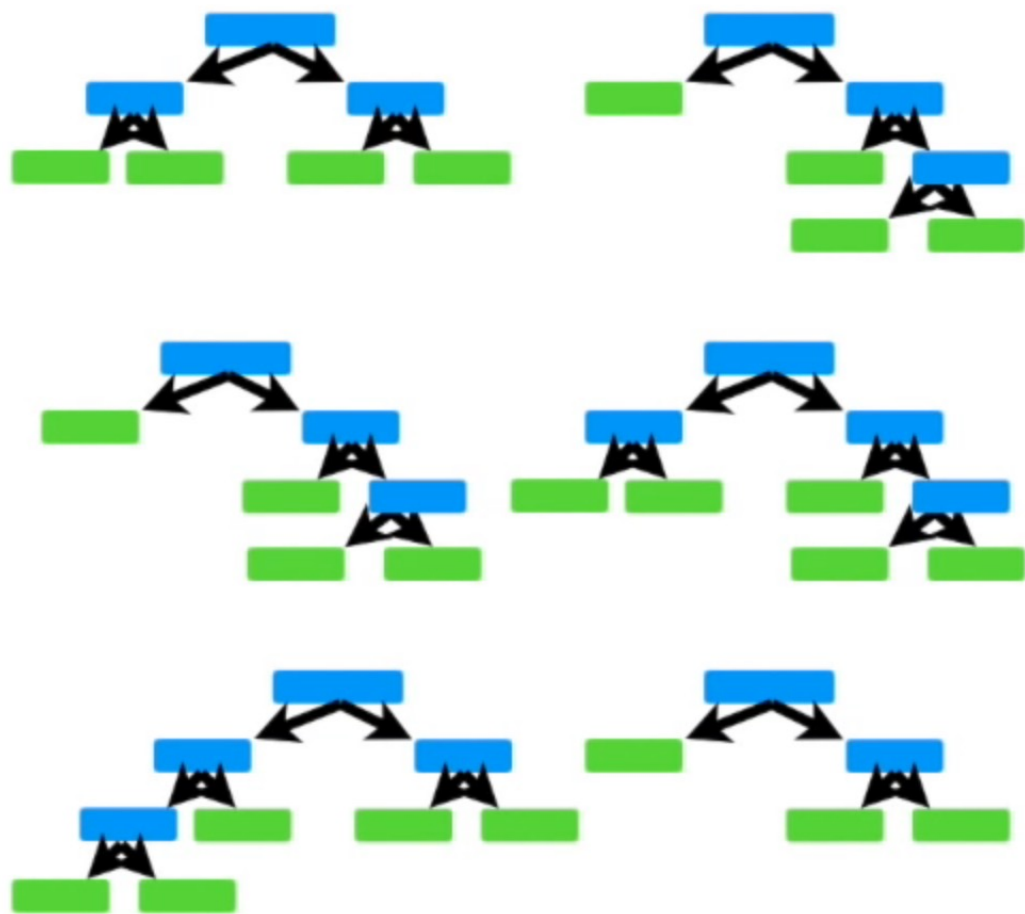
Many slides and figures from: Dr. Markus Kalisch ETH Zurich, Criminisi et al. Microsoft Research, StatQuest with Josh Starmer

# Boosting

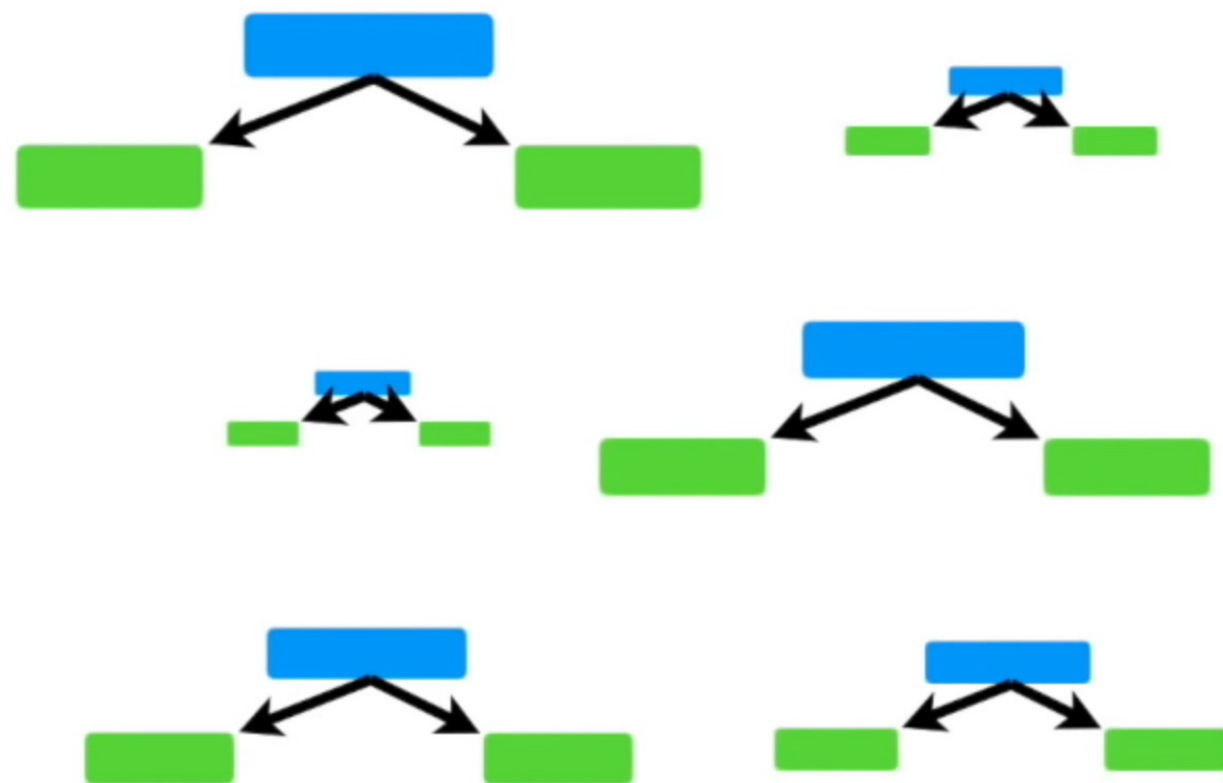
# The idea of probabilistic sampling

Chest Pain	Blocked Arteries	Patient Weight	Heart Disease	Sample Weight
Yes	Yes	205	Yes	$\frac{1}{8}$
No	Yes	180	Yes	$\frac{1}{8}$
Yes	No	210	Yes	$\frac{1}{8}$
Yes	Yes	167	Yes	$\frac{1}{8}$
No	Yes	156	No	$\frac{1}{8}$
No	Yes	125	No	$\frac{1}{8}$
Yes	No	168	No	$\frac{1}{8}$
Yes	Yes	172	No	$\frac{1}{8}$

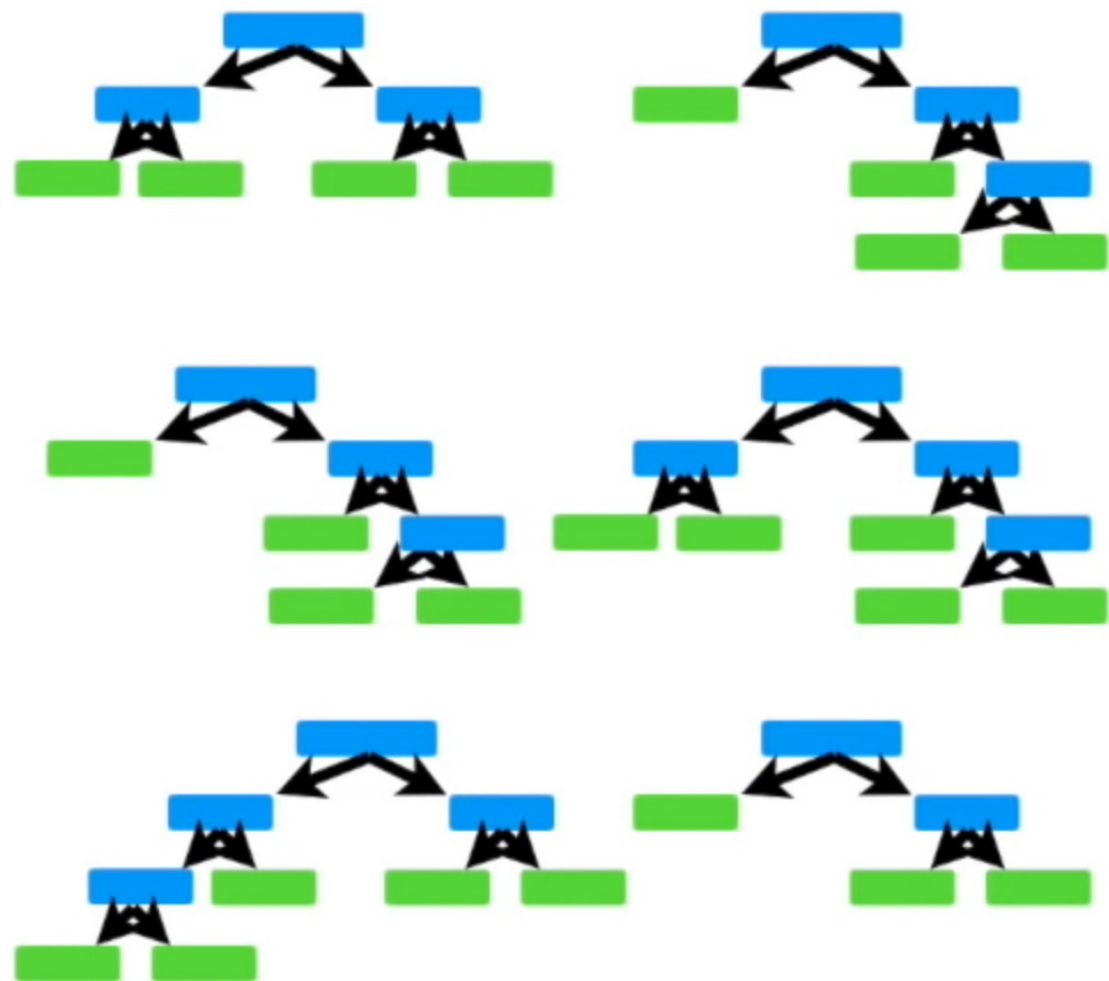
In a **Random Forest**, each tree has an equal vote on the final classification.



In contrast, in a **Forest of Stumps** made with **AdaBoost**, some stumps get more say in the final classification than others.

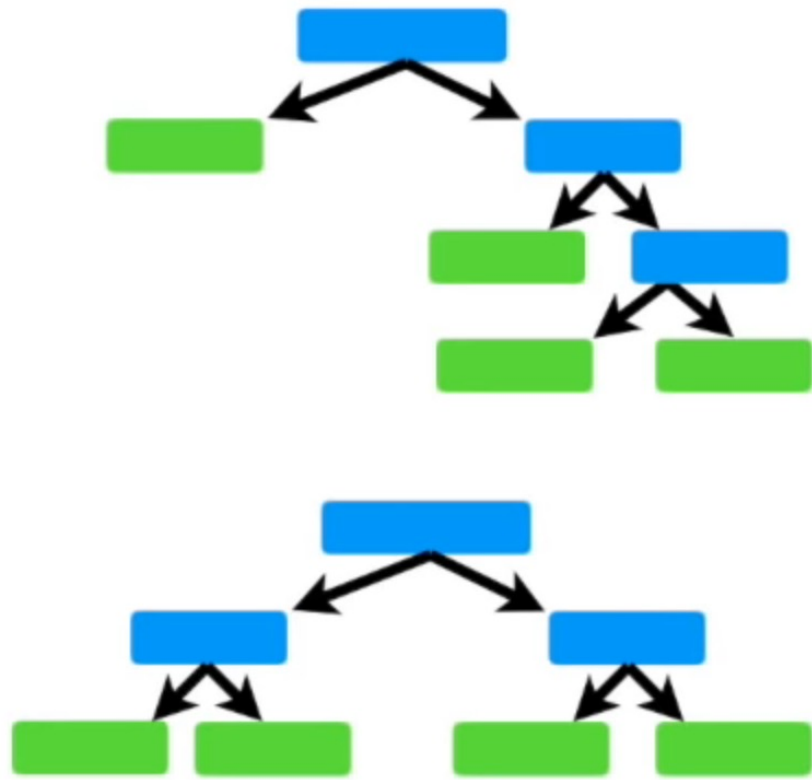


Lastly, in a **Random Forest**, each decision tree is made independently of the others.

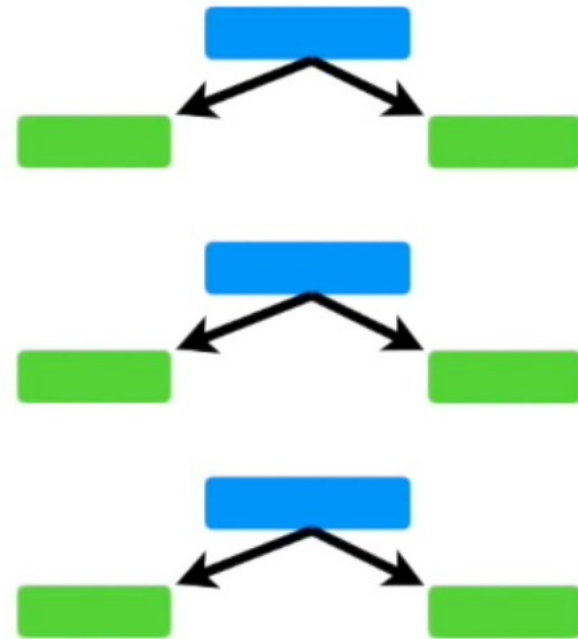


In contrast, in a **Forest of Stumps** made with **AdaBoost**, order is important.

In a **Random Forest**, each time you make a tree, you make a full sized tree.



In contrast, in a **Forest of Trees** made with **AdaBoost**, the trees are usually just a **node** and two **leaves**.



# Adaboost

- In Adaboost we assign (non-negative) weights to points in the data set, which are then normalised so that they sum to one
- Iteratively learn new classifier
- In each iteration, we generate a training set by sampling from the data using the weights
- After learning the current classifier, we increase the (relative) weights of the data points which are misclassified by the current classifier
- The final classifier is the weighted majority voting by all classifiers

# Adaboost

- Let  $\{(X_1, y_1), \dots, (X_n, y_n)\}$  be the data. We take  $y_i$  in  $\{-1, +1\}$
- Let  $w_i(k)$  denote the weight for the  $i$ th data point at  $k$ th iteration
- Let  $h_k$  be the classifier learnt at  $k$ th iteration, we take  $h_k(X)$  in  $\{-1, +1\}$
- We assume error rate of each classifier on its training data is less than 0.5



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Given:  $(x_1, y_1), \dots, (x_m, y_m)$  where  $x_i \in \mathcal{X}$ ,  $y_i \in \{-1, +1\}$ .

Initialize:  $D_1(i) = 1/m$  for  $i = 1, \dots, m$ .

For  $t = 1, \dots, T$ :

- Train weak learner using distribution  $D_t$ .
- Get weak hypothesis  $h_t : \mathcal{X} \rightarrow \{-1, +1\}$ .
- Aim: select  $h_t$  with low weighted error:

$$\varepsilon_t = \Pr_{i \sim D_t} [h_t(x_i) \neq y_i].$$

- Choose  $\alpha_t = \frac{1}{2} \ln \left( \frac{1 - \varepsilon_t}{\varepsilon_t} \right)$ .
- Update, for  $i = 1, \dots, m$ :

$$D_{t+1}(i) = \frac{D_t(i) \exp(-\alpha_t y_i h_t(x_i))}{Z_t}$$

where  $Z_t$  is a normalization factor (chosen so that  $D_{t+1}$  will be a distribution).

Output the final hypothesis:

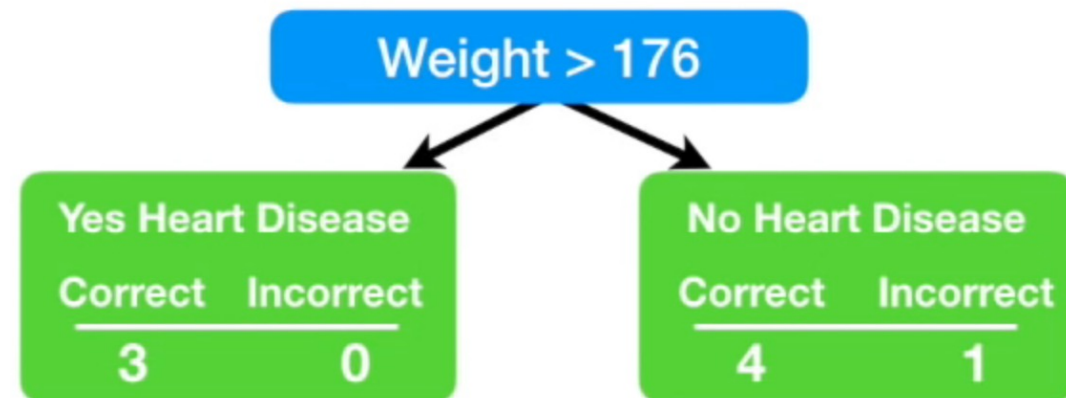
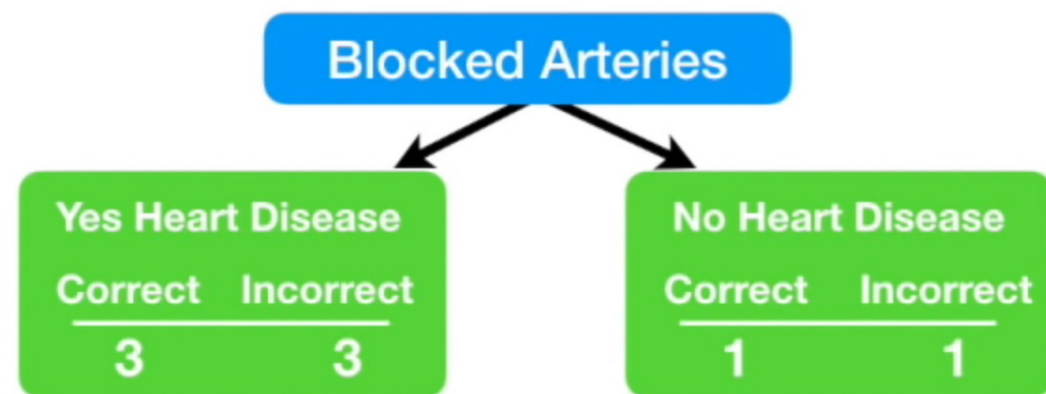
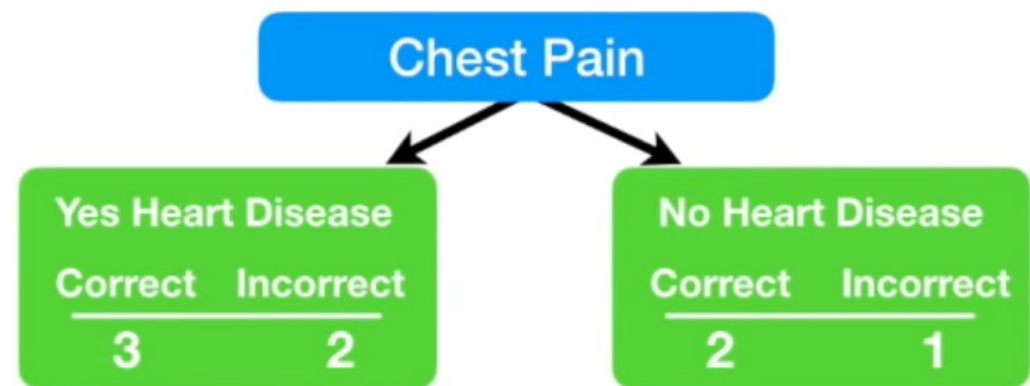
$$H(x) = \text{sign} \left( \sum_{t=1}^T \alpha_t h_t(x) \right).$$

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**Fig. 1** The boosting algorithm AdaBoost.

Lets take an example

Chest Pain	Blocked Arteries	Patient Weight	Heart Disease	Sample Weight
Yes	Yes	205	Yes	1/8
No	Yes	180	Yes	1/8
Yes	No	210	Yes	1/8
Yes	Yes	167	Yes	1/8
No	Yes	156	No	1/8
No	Yes	125	No	1/8
Yes	No	168	No	1/8
Yes	Yes	172	No	1/8



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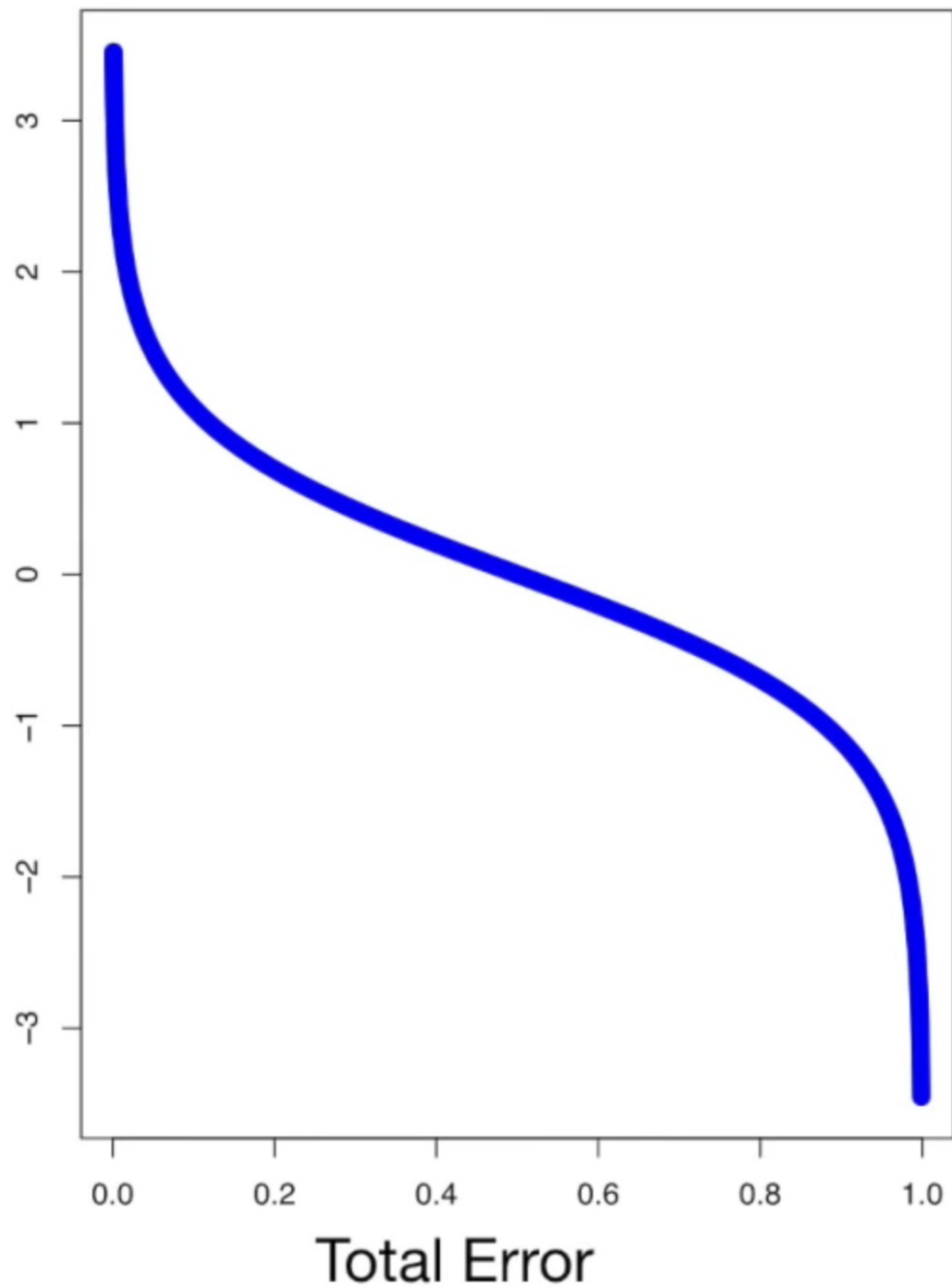
Thus, in this case, the **Total Error** is **1/8**.

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**Total Error is 1/8.**

$$\text{Amount of Say} = \frac{1}{2} \log\left(\frac{1 - \text{Total Error}}{\text{Total Error}}\right)$$



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$$\text{Amount of Say} = \frac{1}{2} \log(7) = 0.97$$

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No	Yes	156	No	1/8
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Yes	No	168	No	1/8
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New Sample Weight = sample weight  $\times e^{\text{amount of say}}$

$$= \frac{1}{8} e^{0.97} = \frac{1}{8} \times 2.64 = 0.33$$

New Sample Weight = sample weight  $\times e^{-\text{amount of say}}$

$$= \frac{1}{8} e^{-0.97} = \frac{1}{8} \times 0.38 = 0.05$$

Chest Pain	Blocked Arteries	Patient Weight	Heart Disease	Sample Weight	New Weight	Norm. Weight
Yes	Yes	205	Yes	1/8	0.05	0.07
No	Yes	180	Yes	1/8	0.05	0.07
Yes	No	210	Yes	1/8	0.05	0.07
Yes	Yes	167	Yes	1/8	0.33	0.49
No	Yes	156	No	1/8	0.05	0.07
No	Yes	125	No	1/8	0.05	0.07
Yes	No	168	No	1/8	0.05	0.07
Yes	Yes	172	No	1/8	0.05	0.07



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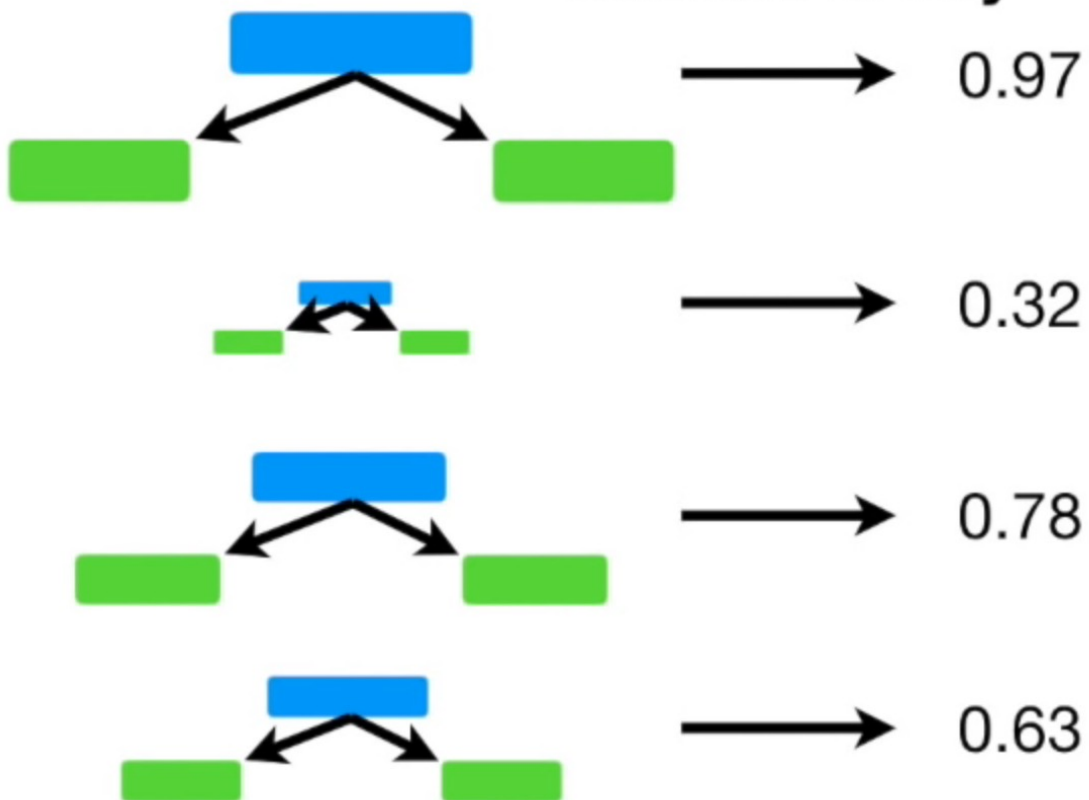
Chest Pain	Blocked Arteries	Patient Weight	Heart Disease
No	Yes	156	No
Yes	Yes	167	Yes
No	Yes	125	No
Yes	Yes	167	Yes
Yes	Yes	167	Yes
Yes	Yes	172	No
Yes	Yes	205	Yes
Yes	Yes	167	Yes

Ultimately, the patient is classified  
as **Has Heart Disease** because  
this is the larger sum.

Has Heart Disease

**Total = 2.7**

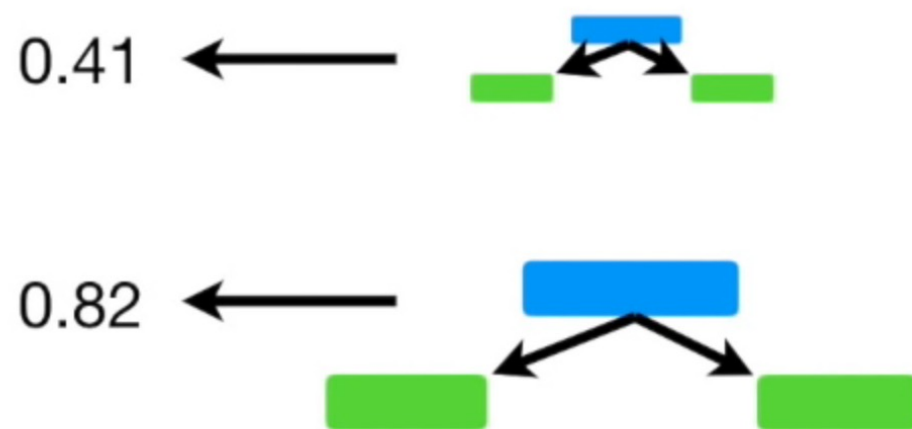
**Amount of Say**

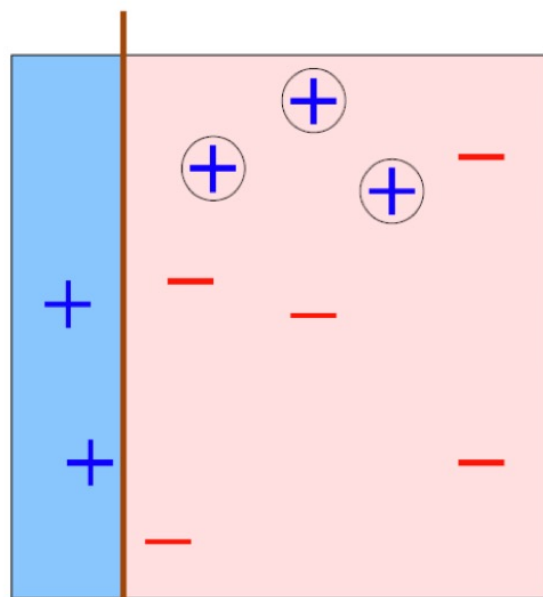
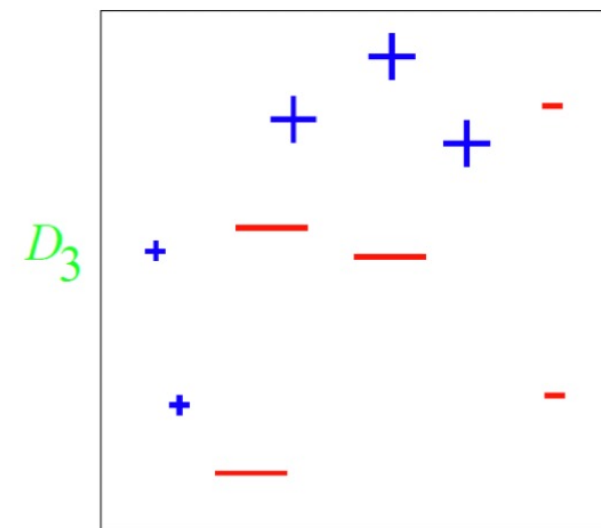
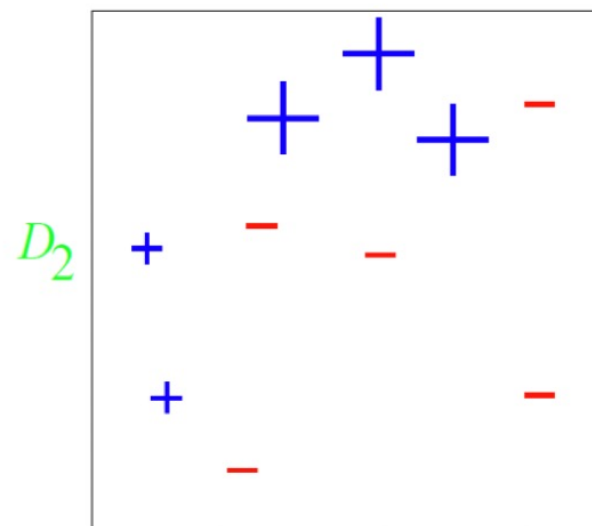
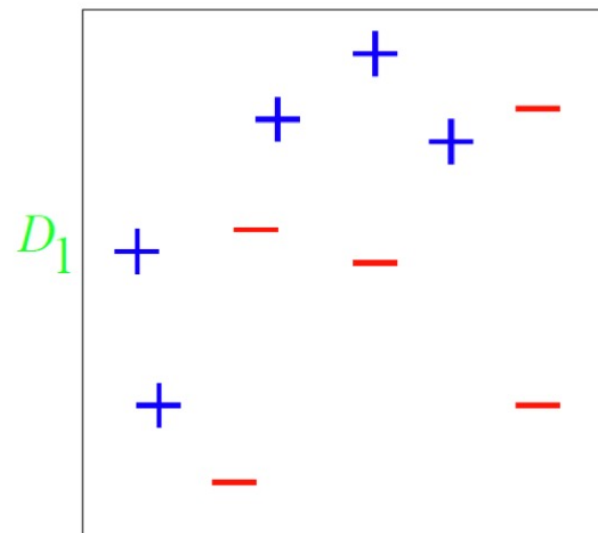


**Total = 1.23**

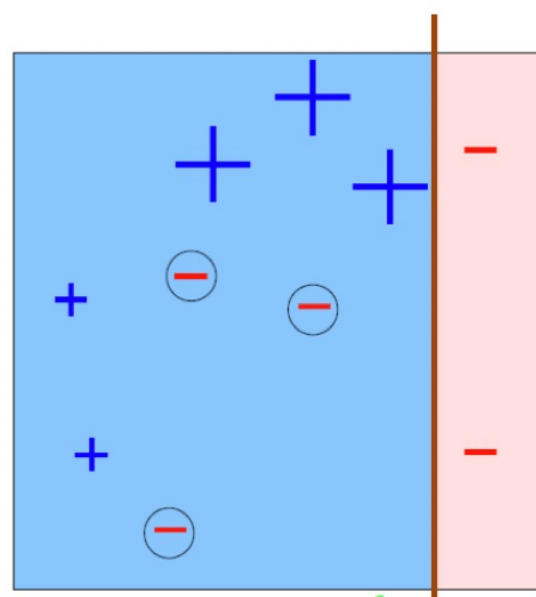
Does Not Have  
Heart Disease

**Amount of Say**

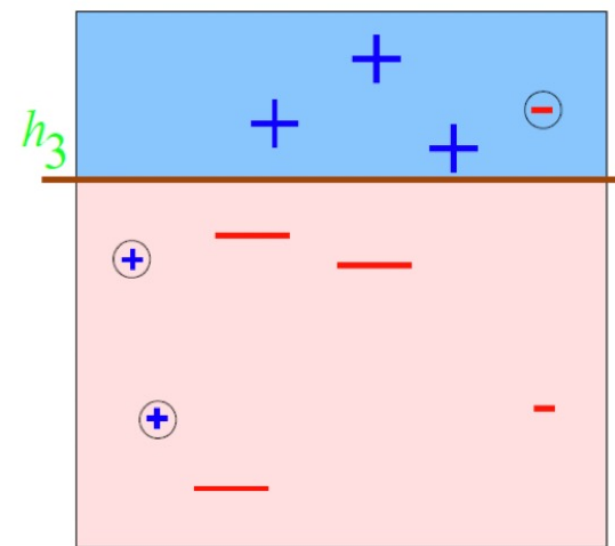




$h_1$   
 $\epsilon_1=0.30$   
 $\alpha_1=0.42$



$\epsilon_2=0.21$   
 $\alpha_2=0.65$   
 $h_2$



$\epsilon_3=0.14$   
 $\alpha_3=0.92$

$$H_{\text{final}} = \text{sign} \left( 0.42 \begin{array}{|c|} \hline \text{blue} \\ \hline \text{red} \end{array} + 0.65 \begin{array}{|c|} \hline \text{blue} \\ \hline \text{red} \end{array} + 0.92 \begin{array}{|c|} \hline \text{blue} \\ \hline \text{red} \end{array} \right)$$

