CSCI567 Machine Learning (Spring 2021)

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March 10, 2021

Outline

1. Logistics
2. Review of last lecture
3. Boosting

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Logistics

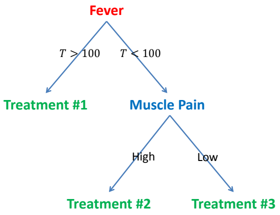
- Checkpoint 1 for project is due today. We will be tracking Kaggle submissions starting March 11, 2021.
- Quiz 1 has been graded. The mean, median, and standard deviation were 60.3, 62.3 and 17.4, respectively.
- March 12, 2021 is a **Wellness Day**, there will be no class.

Outline

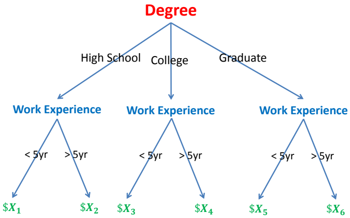
Decision Trees

Many decisions are made based on some tree structure

Medical treatment



Salary in a company



Learning Decision Trees

DecisionTreeLearning(Examples, Features)

- if Examples have the same class, return a leaf with this class
- else if Features is empty, return a leaf with the majority class
- else if Examples is empty, return a leaf with majority class of parent
- else

  find the best feature A to split (e.g. based on conditional entropy)

  Tree $\leftarrow$ a root with test on A

  For each value a of A:

  Child $\leftarrow$ **DecisionTreeLearning**(Examples with $A = a$, Features$\setminus\{A\}$)
  add **Child** to **Tree** as a new branch
- return **Tree**

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We again focus on binary classification.

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- repeat ...
- final classifier is the (weighted) majority vote of all weak classifiers

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- many algorithms can deal with a weighted training set (e.g. for algorithm that minimizes some loss, we can simply replace "total loss" by "weighted total loss")
- even if it's not obvious how to deal with weight directly, we can always resample according to D to create a new unweighted dataset

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AdaBoost is one of the most successful boosting algorithms.

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- obtain a weak classifier $h_t \leftarrow \mathcal{A}(S, D_t)$
- calculate the importance of h_t as

$$\beta_t = \frac{1}{2} \ln \left(\frac{1 - \epsilon_t}{\epsilon_t} \right) \qquad (\beta_t > 0 \Leftrightarrow \epsilon_t < 0.5)$$

where $\epsilon_t = \sum_{n: h_t(\boldsymbol{x}_n) \neq y_n} D_t(n)$ is the weighted error of h_t.

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- update distributions

$$D_{t+1}(n) \propto D_t(n) e^{-\beta_t y_n h_t(\boldsymbol{x}_n)} = \begin{cases} D_t(n) e^{-\beta_t} & \text{if } h_t(x_n) = y_n \\ D_t(n) e^{\beta_t} & \text{else} \end{cases}$$

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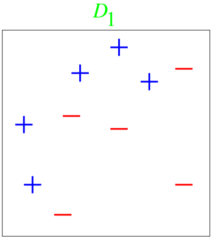
Output the final classifier $H(\boldsymbol{x}) = \text{sgn}\left(\sum_{t=1}^{T} \beta_t h_t(\boldsymbol{x}) \right)$

Example

10 data points in $\mathbb{R}^2$

The size of $+$ or - indicates the weight, which starts from uniform D_1



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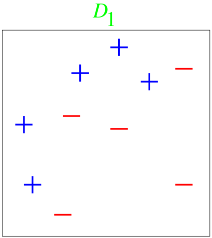

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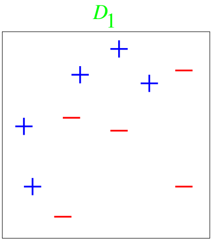

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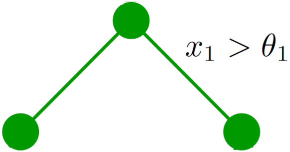
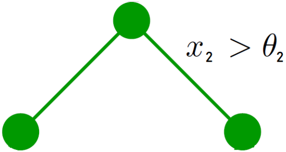
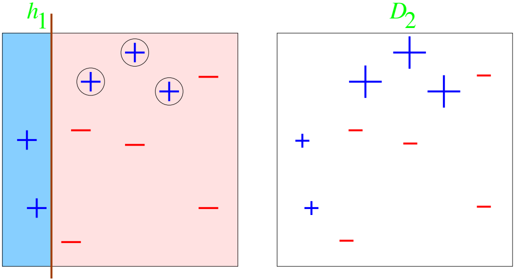




Observe that *no stump can predict very accurately for this dataset*

Round 1: $t = 1$



- 3 misclassified (circled): $\epsilon_1 = 0.3 \rightarrow \beta_1 = \frac{1}{2} \ln \left(\frac{1-\epsilon_t}{\epsilon_t} \right) \approx 0.42.$

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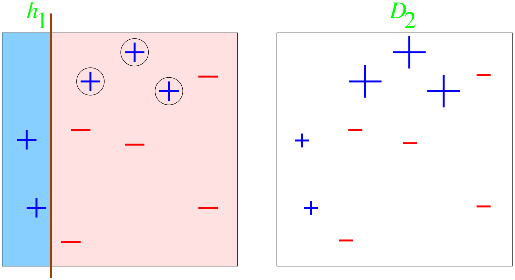

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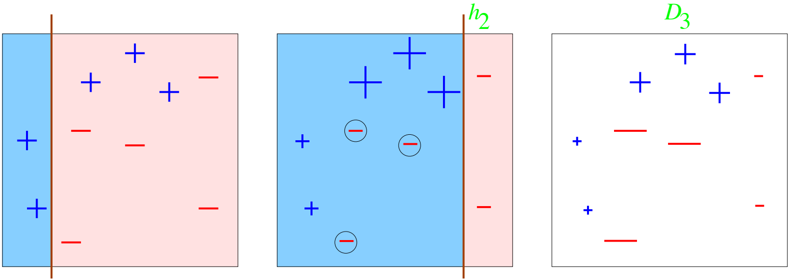

- 3 misclassified (circled): $\epsilon_2 = 0.21 \rightarrow \beta_2 = 0.65$.

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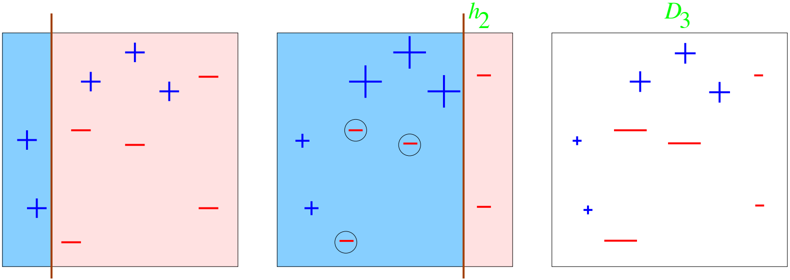

- 3 misclassified (circled): $\epsilon_2 = 0.21 \to \beta_2 = 0.65$.
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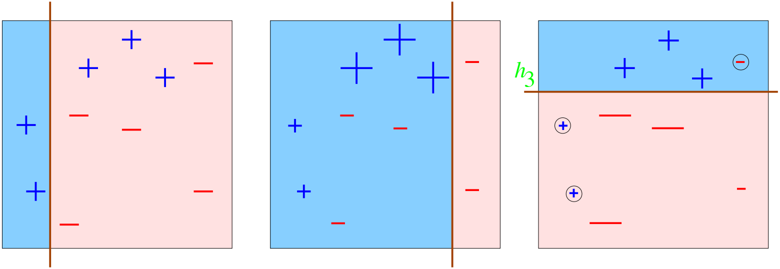
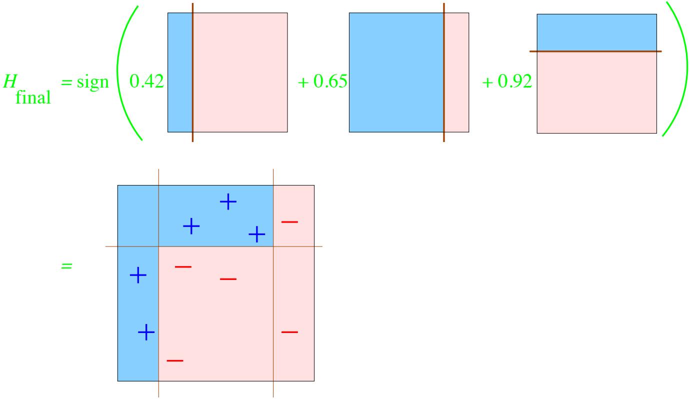
Round 3: $t = 3$



- again 3 misclassified (circled): $\epsilon_3 = 0.14 \rightarrow \beta_3 = 0.92$.

Final classifier: combining 3 classifiers



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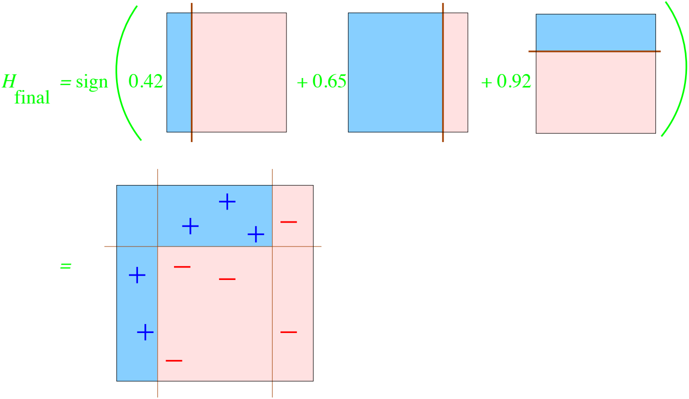

All data points are now classified correctly, even though each weak classifier makes 3 mistakes.

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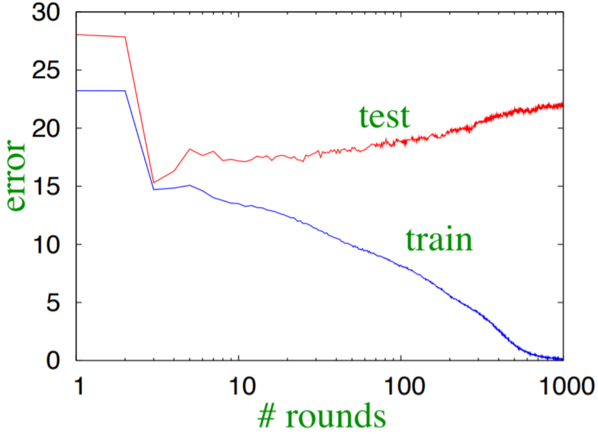

(boosting "stumps" on heart-disease dataset)

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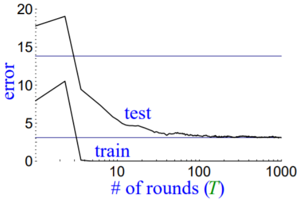

(boosting C4.5 on "letter" dataset)

- test error does not increase, even after 1000 rounds
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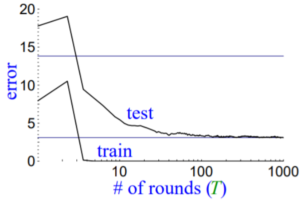

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Used to be a mystery, but by now rigorous theory has been developed to explain this phenomenon.

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Step 2: the loss that AdaBoost minimizes is the exponential loss

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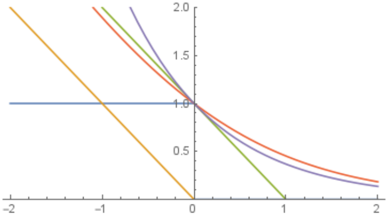

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where the last step is by the definition of weights

$$D_t(n) \propto D_{t-1}(n) \exp\left(-y_n \beta_{t-1} h_{t-1}(\boldsymbol{x}_n)\right) \propto \cdots \propto \exp\left(-y_n f_{t-1}(\boldsymbol{x}_n)\right)$$

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(recall $\epsilon_t = \sum_{n: y_n \neq h_t(\boldsymbol{x}_n)} D_t(n)$)

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&= \epsilon_t (e^{\beta_t} - e^{-\beta_t}) + e^{-\beta_t}
\end{aligned}
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$$= \epsilon_t (e^{\beta_t} - e^{-\beta_t}) + e^{-\beta_t}$$

It is now clear we should find h_t to minimize the weighted classification error ϵ_t, *exactly what the base algorithm should do intuitively!*

Greedy minimization

So the goal becomes finding $\beta_t, h_t \in \mathcal{H}$ that minimize

$$\sum_{n=1}^{\mathsf{N}} D_t(n) \exp\left(-y_n \beta_t h_t(\boldsymbol{x}_n)\right)$$

$$= \sum_{n: y_n \neq h_t(\boldsymbol{x}_n)} D_t(n) e^{\beta_t} + \sum_{n: y_n = h_t(\boldsymbol{x}_n)} D_t(n) e^{-\beta_t}$$

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This greedy step is abstracted out through a base algorithm.

Greedy minimization

When h_t (and thus ϵ_t) is fixed, we then find β_t to minimize

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Keep doing this greedy minimization gives the AdaBoost algorithm.

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