

Ensemble Methods

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Class Meeting: Mon & Wed, 4:00 PM - 5:15 PM, CHHS 376



Boosting (AdaBoost)

- Also works by manipulating training set, but classifiers trained sequentially
- Each classifier trained given knowledge of the performance of previously trained classifiers: focus on hard examples
- Final classifier: weighted sum of component classifiers

Making Weak Learners Stronger

- Suppose you have a weak learning module (a base classifier) that can always get $(0.5 + \epsilon)$ correct when given a two-way classification task
 - That seems like a weak assumption but beware!
- Can you apply this learning module many times to get a strong learner that can get close to zero error rate on the training data?
 - ► Theorists showed how to do this and it actually led to an effective new learning procedure (Freund & Shapire, 1996)

Boosting (AdaBoost)

- First train the base classifier on all the training data with equal importance weights on each case.
- Then re-weight the training data to emphasize the hard cases and train a second model.
 - How do we re-weight the data?
- Keep training new models on re-weighted data
- Finally, use a weighted committee of all the models for the test data.
 - How do we weight the models in the committee?

Train Each Classifier

- Input: \mathbf{x} , Output: $y(\mathbf{x}) \in \{1, -1\}$
- Target $t \in \{-1, 1\}$
- Weight on example n for classifier m: \mathbf{w}_n^m
- Cost function for classifier m

$$J_m = \sum_{n=1}^{N} w_n^m \underbrace{[y_m(\mathbf{x}^n) \neq t^{(n)}]}_{1 \text{ if error, 0 o.w.}} = \sum_{m=1}^{N} \text{weighted errors}$$

Weight each training case for classifier m

Recall cost function is

$$J_m = \sum_{n=1}^N w_n^m \underbrace{[y_m(\mathbf{x}^n) \neq t^{(n)}]}_{\text{1 if error, 0 o.w.}} = \sum_{m=1}^N \text{weighted errors}$$

Weighted error rate of a classifier

$$\epsilon_m = \frac{J_m}{\sum w_n^m}$$

The quality of the classifier is

$$\alpha_m = \ln\left(\frac{1 - \epsilon_m}{\epsilon_m}\right)$$

It is zero if the classifier has weighted error rate of 0.5 and infinity if the classifier is perfect

The weights for the next round are then

$$w_n^{m+1} = \exp\left(-\frac{1}{2}t^{(n)}\sum_{i=1}^m \alpha_i y_i(\mathbf{x}^{(n)})\right) = w_n^m \exp\left(-\frac{1}{2}t^{(n)}\alpha_m y_m(\mathbf{x}^{(n)})\right)$$

Make predictions using a committee of classifiers

Weight the binary prediction of each classifier by the quality of that classifier:

$$y_M(\mathbf{x}) = \operatorname{sign}\left(\sum_{m=1}^M \frac{1}{2}\alpha_m y_m(\mathbf{x})\right)$$

 This is how to do inference, i.e., how to compute the prediction for each new example.

AdaBoost Algorithm

- Input: $\{\mathbf{x}^{(n)}, t^{(n)}\}_{n=1}^{N}$, and WeakLearn: learning procedure, produces classifier $y(\mathbf{x})$
- Initialize example weights: $w_n^m(\mathbf{x}) = 1/N$
- For m=1:M
 - $y_m(\mathbf{x}) = WeakLearn(\{\mathbf{x}\}, \mathbf{t}, \mathbf{w})$, fit classifier by minimizing

$$J_m = \sum_{n=1}^N w_n^m [y_m(\mathbf{x}^n) \neq t^{(n)}]$$

Compute unnormalized error rate

$$\epsilon_m = \frac{J_m}{\sum w_n^m}$$

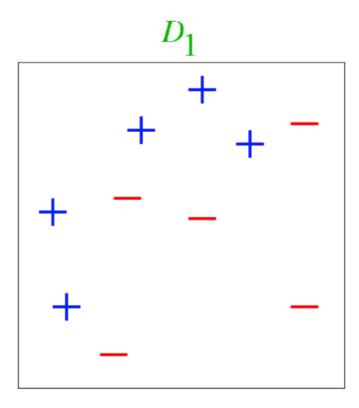
- Compute classifier coefficient $\alpha_m = \log \frac{1 \epsilon_m}{\epsilon_m}$
- Update data weights

$$w_n^{m+1} = w_n^m \exp\left(-\frac{1}{2}t^{(n)}\alpha_m y_m(\mathbf{x}^{(n)})\right)$$

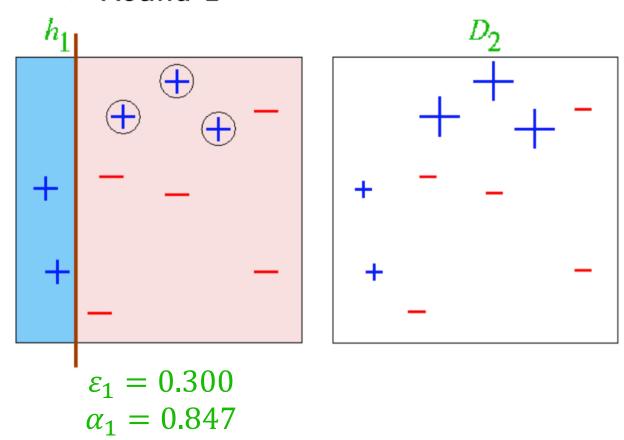
Final model

$$Y(\mathbf{x}) = sign(y_M(\mathbf{x})) = sign(\sum_{m=1}^{M} \alpha_m y_m(\mathbf{x}))$$

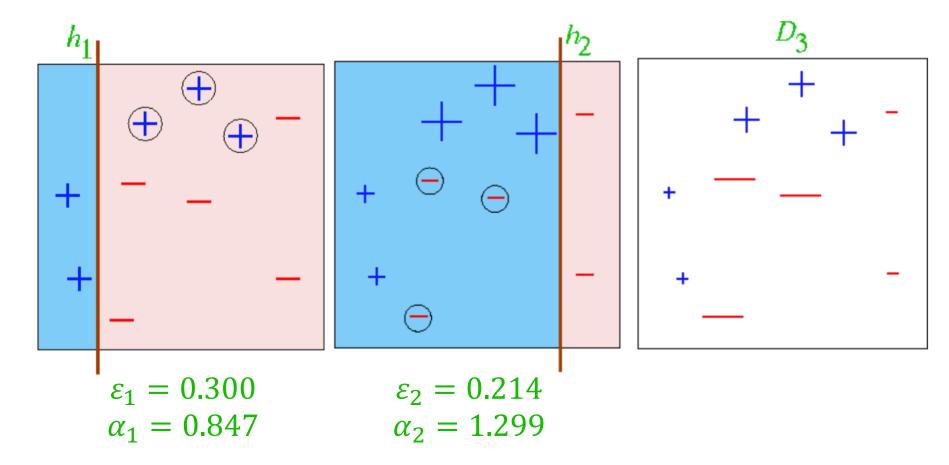
Training data



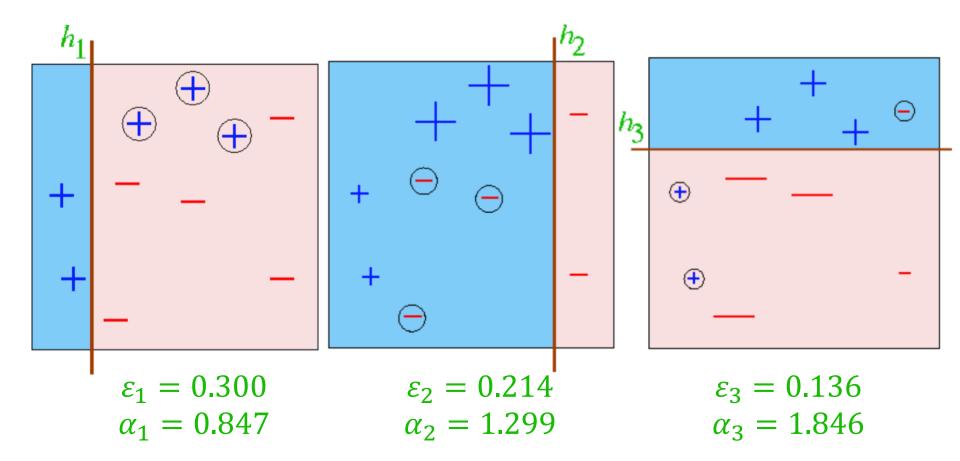
• Round 1



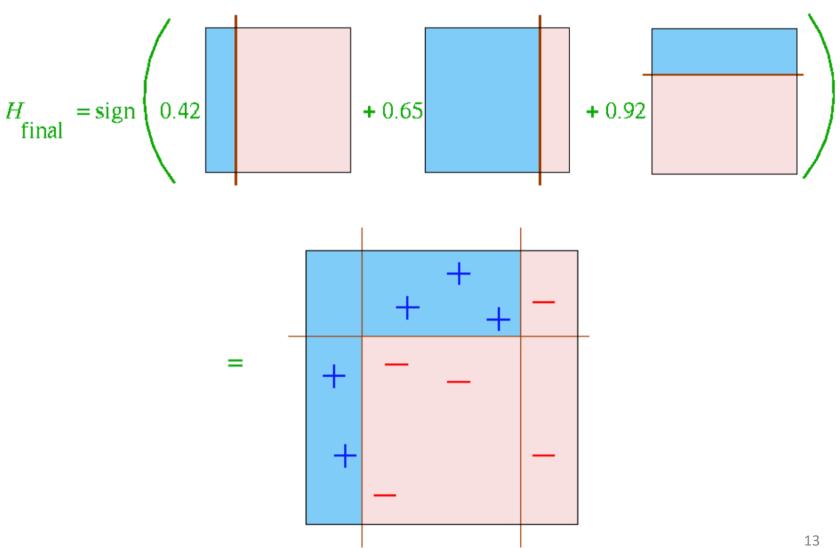
Round 2

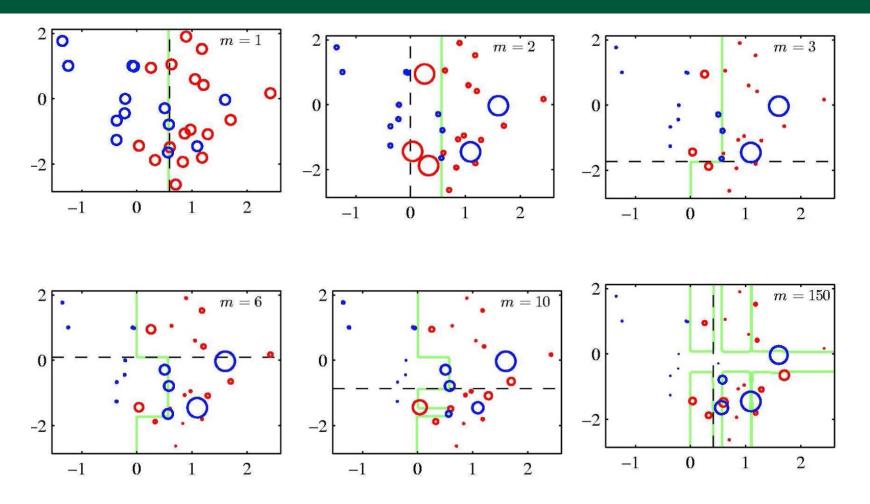


Round 3



Final classifier





 Each figure shows the number m of base learners trained so far, the decision of the most recent learner (dashed black), and the boundary of the ensemble (green)

Questions?

