

## The AdaBoost algorithm

**Input to AdaBoost:**  $m$  labelled examples  $S = (x_1, y_1), \dots, (x_m, y_m)$  where each label  $y_i \in \pm 1$

**Notation:**

- $\mathcal{D}_t$  denotes the  $t$ -th distribution AdaBoost constructs over the  $m$  examples.  $\mathcal{D}_t(i)$  denotes  $\Pr_{\mathcal{D}_t}(x_i)$ . *what weak learner gives when we run it on  $\mathcal{D}_t$*
- $h_t$  is the  $t$ -th hypothesis.
- $\epsilon_t$  denotes  $\Pr_{i \in \mathcal{D}_t}[h_t(x_i) \neq y_i]$  the error of  $h_t$  w.r.t.  $\mathcal{D}_t$   $= \sum_{i \in [m]} \mathcal{D}_t(i) \cdot h_t(x_i) \neq y_i$

**The algorithm:**

1. Initialize  $\mathcal{D}_1(i) = \frac{1}{m}$  for each  $i = 1, \dots, m$ .
2. For  $t = 1$  to  $T$  do:
  - (a) Run weak learner  $L$  on  $\mathcal{D}_t$  to get hypothesis  $h_t$  which has error  $\epsilon_t$  w.r.t.  $\mathcal{D}_t$ .
  - (b) Let  $\alpha_t = \frac{1}{2} \ln \left( \frac{1-\epsilon_t}{\epsilon_t} \right)$
  - (c) Update

$$\mathcal{D}_{t+1}(i) = \frac{\mathcal{D}_t(i) \cdot \exp(-\alpha_t y_i h_t(x_i))}{Z_t}$$

where  $Z_t$  is a normalization factor so that  $\sum_{i=1}^m \mathcal{D}_{t+1}(i) = 1$ .

3. Final hypothesis is  $H(x) = \text{sign}(f(x))$  where  $f(x) = \sum_{t=1}^T \alpha_t h_t(x)$ .

*weighted sum*  
*weighted*  
*major vote*  
*of weak hyp's.*