

# Adaboost Implementation

David Torpey

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## 1 Introduction

In order to perform the Adaboost (Adaptive Boosting) algorithm, we need to define two hyper-parameters:

1.  $M$  - number of models in the Adaboost cascade.
2.  $C_i$  - a base classifier to use in the Adaboost cascade.

Usually,  $C_i$  is some simple classifier such as a decision stump (a decision tree of depth one). An optimal  $M$  can be chosen through cross-validation.

## 2 Algorithm

Below is pseudocode for the Adaboost algorithm.

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**Algorithm 1** Adaboost

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Initialize observation weights  $D_t(i) = \frac{1}{m}, \forall i = 1, \dots, m$ .

**for**  $t = 1$  to  $T$  **do**

(1) Train weak learner  $h_t$  using distribution  $D_t$  (sample  $m$  samples from  $X$  using  $D_t$ ).

(2) Given above weak hypothesis  $h_t : X \rightarrow \{-1, +1\}$ , find  $\epsilon_t = P_{i \sim D_t}[h_t(x_i) \neq y_i]$ .

(3) Calculate  $\alpha_t = \frac{1}{2} \ln(\frac{1-\epsilon_t}{\epsilon_t})$ .

Update the weight distribution for the samples:  $D_{t+1}(i) = \frac{D_t(i) \exp(-\alpha_t y_i h_t(x_i))}{Z_t}$ , where  $Z_t$  is a normalization factor that ensures  $D_{t+1}$  is a distribution. This can be, for example,  $Z_t = \sum_{i=1}^m (D_t(i))$ .

**end for**

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The final classifier/hypothesis will then be:

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