

# Chapter 16

## Adaptive basis function models

### 16.1 AdaBoost

#### 16.1.1 Representation

$$y = \text{sign}(f(x)) = \text{sign}\left(\sum_{i=1}^m \alpha_i G_i(x)\right) \quad (16.1)$$

where  $G_m(x)$  are sub classifiers.

#### 16.1.2 Evaluation

$L(y, f(x)) = \exp[-yf(x)]$  i.e., exponential loss function

$$(\alpha_m, G_m(x)) = \arg \min_{\alpha, G} \sum_{i=1}^N \exp[-y_i(f_{m-1}(x_i) + \alpha G(x_i))] \quad (16.2)$$

Define  $\bar{w}_{mi} = \exp[-y_i(f_{m-1}(x_i))]$ , which is constant w.r.t.  $\alpha, G$

$$(\alpha_m, G_m(x)) = \arg \min_{\alpha, G} \sum_{i=1}^N \bar{w}_{mi} \exp(-y_i \alpha G(x_i)) \quad (16.3)$$

#### 16.1.3 Optimization

##### 16.1.3.1 Input

$$\begin{aligned} \mathcal{D} &= \{(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2), \dots, (\mathbf{x}_N, y_N)\} \\ &\text{where } \mathbf{x}_i \in \mathbb{R}^D, y_i \in \{-1, +1\} \\ &\text{Weak classifiers } \{G_1, G_2, \dots, G_m\} \end{aligned}$$

##### 16.1.3.2 Output

Final classifier:  $G(x)$

##### 16.1.3.3 Algorithm

1. Initialize the weights' distribution of training data (when  $m = 1$ )

$$\mathcal{D}_0 = (w_{11}, w_{12}, \dots, w_{1n}) = \left(\frac{1}{N}, \frac{1}{N}, \dots, \frac{1}{N}\right)$$

2. Iterate over  $m = 1, 2, \dots, M$ 
  - (a) Use training data with current weights' distribution  $\mathcal{D}_m$  to get a classifier  $G_m(x)$
  - (b) Compute the error rate of  $G_m(x)$  over the training data

$$e_m = P(G_m(x_i) \neq y_i) = \sum_{i=1}^N w_{mi} \mathbb{I}(G_m(x_i) \neq y_i) \quad (16.4)$$

- (c) Compute the coefficient of classifier  $G_m(x)$

$$\alpha_m = \frac{1}{2} \log \frac{1 - e_m}{e_m} \quad (16.5)$$

- (d) Update the weights' distribution of training data

$$w_{m+1,i} = \frac{w_{mi}}{Z_m} \exp(-\alpha_m y_i G_m(x_i)) \quad (16.6)$$

where  $Z_m$  is the normalizing constant

$$Z_m = \sum_{i=1}^N w_{mi} \exp(-\alpha_m y_i G_m(x_i)) \quad (16.7)$$

3. Ensemble  $M$  weak classifiers

$$G(x) = \text{sign} f(x) = \text{sign} \left[ \sum_{m=1}^M \alpha_m G_m(x) \right] \quad (16.8)$$

#### 16.1.4 The upper bound of the training error of AdaBoost

**Theorem 16.1.** *The upper bound of the training error of AdaBoost is*

$$\frac{1}{N} \sum_{i=1}^N \mathbb{I}(G(x_i) \neq y_i) \leq \frac{1}{N} \sum_{i=1}^N \exp(-y_i f(x_i)) = \prod_{m=1}^M Z_m \quad (16.9)$$

*Note: the following equation would help proof this theorem*

$$w_{mi} \exp(-\alpha_m y_i G_m(\mathbf{x}_i)) = Z_m w_{m+1,i} \quad (16.10)$$