

1. Machine Learning Algorithms Pseudocode

Algorithm 1 k-Nearest Neighbor

Input: X: training data, Y: Class labels of X, x : unknown sample

Output: Class with the highest number of occurrence

```
1: function CLASSIFY( $X, Y, x$ )
2:   for  $i = 1$  to  $m$  do
3:     Compute distance  $d(X_i, x)$ 
4:   end for
5:   Compute set  $I$  containing indices for the  $k$  smallest distances  $d(X_i, x)$ 
6:   Return majority label  $\{Y_i \text{ where } i \in I\}$ 
7: end function
```

1. Ensemble Algorithm

Algorithm 2 Adaboost

Input:

Training data $\{(x_i, y_i)_{i=1}^N$ where $x_i \in \mathbb{R}^k$ and $y_i \in \{-1, 1\}\}$

Large number of classifiers denoted by $f_m(x) \in \{-1, 1\}$

0-1 loss function I defined as

$$I(f_m(x, y)) = \begin{cases} 0, & \text{if } f_m(x_i) = y_i \\ 1, & \text{if } f_m(x_i) \neq y_i \end{cases} \quad (1)$$

(2)

Output: The final classifier

```
1: for  $i = 1$  to  $N$  do
2:   for  $i = 1$  to  $M$  do
3:     Fit weak classifier  $m$  to minimize the objective function:
4:      $\epsilon_m = \frac{\sum_{i=1}^N w_i^m I(f_m(x_i) \neq y_i)}{x^2 + 2x + 1}$ 
5:     where  $I(f_m(x_i) \neq y_i) = 1$  if  $f_m(x_i) \neq y_i$  and 0 otherwise
6:      $\alpha_m = \ln \frac{1 - \epsilon_m}{\epsilon_m}$ 
7:   end for
8:   for all  $i$  do
9:      $w_i^{m+1} = w_i^{(m)} e^{\alpha_m I(f_m(x_i) \neq y_i)}$ 
10:  end for
11: end for
```

1. Another Pseudocode for Adaboost

1. Machine Learning Algorithms Pseudocode

Algorithm 3 Adaboost

Input:Training data $\{(x_i, y_i)_{i=1}^N$ where $x_i \in \mathbb{R}^k$ and $y_i \in \{-1, 1\}\}$ **Output:** The final classifier

- 1: Given Training data $\{(x_i, y_i) \text{ where } y_i \in \{-1, 1\}\}$
- 2: initialize D_1 = uniform distribution on training examples
- 3: **for** $t = 1$ to T **do**
- 4: Train weak classifier h_t on D_t
- 5: choose $\alpha_t > 0$
- 6: compute new distribution D_{t+1} :
- 7: **for** all i **do**
- 8: multiply $D_t(x)$ by

$$\begin{cases} e^{-\alpha_t}, & (< 1) \text{ if } y_i = h_t(x_i) \\ e^{\alpha_t}, & (> 1) \text{ if } y_i \neq h_t(x_i) \end{cases} \quad (3)$$

- 9: renormalize
 - 10: **end for**
 - 11: output final classifier $H_{final}(x) = \text{sign}(\sum \alpha_t h_t(x))$
 - 12: **end for**
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Algorithm 4 Random forest

Input: S: training set, F:Features and number of trees in forest B **Output:** Constructed tree

- 1: **function** RANDOMFOREST(S, F)
 - 2: $H \leftarrow \emptyset$
 - 3: **for** $i \in 1, \dots, B$ **do**
 - 4: $S^{(i)} \leftarrow$ A bootstrap sample from S
 - 5: $h_i \leftarrow \text{RANDOMIZEDTREELEARN}(S^{(i)}, F)$
 - 6: $H \leftarrow H \cup \{h_i\}$
 - 7: **end for**
 - 8: return H
 - 9: **end function**
 - 10: **function** RANDOMIZEDTREELEARN(S, F)
 - 11: At each node:
 - 12: $f \leftarrow$ a very small subset of F
 - 13: Split on best feature in f
 - 14: return The learned tree
 - 15: **end function**
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