

1. Logistic Regression

Input: Training data X , labels Y , learning rate α , epochs E

Initialize weights W and bias b

For epoch = 1 to E

For each training example (x, y)

$$z = W \cdot x + b$$

$$y_{\text{hat}} = 1 / (1 + e^{(-z)})$$

$$dw = (y_{\text{hat}} - y) \cdot x$$

$$db = (y_{\text{hat}} - y)$$

$$W = W - \alpha \cdot dw$$

$$b = b - \alpha \cdot db$$

Return W, b

2. K-Nearest Neighbors (KNN)

Input: Training data X , labels Y , test sample x_{test} , k

For each x in X

distance = compute_distance(x, x_{test})

Sort distances in ascending order

Select first k samples

Get labels of selected samples

$y_{\text{pred}} = \text{most_frequent_label}(\text{labels})$

Return y_{pred}

3. Naive Bayes

Input: Training data X , labels Y , test sample x_{test}

For each class c in Y

$$\text{prior}[c] = \text{count}(c) / \text{total_samples}$$

$$\text{likelihood}[c] = 1$$

For each feature i

$$\text{likelihood}[c] *= P(x_{\text{test}}[i] | c)$$

$$\text{posterior}[c] = \text{prior}[c] * \text{likelihood}[c]$$

$y_{\text{pred}} = \text{class with maximum posterior}$

Return y_{pred}

4. Decision Tree

Input: Training data X , labels Y

If all labels are same

Return label

If no features left

Return majority_label

Select best_feature using information_gain

Create node with best_feature

For each value v of best_feature

Subset = samples where best_feature == v

Child = build_tree(Subsets)

Add Child to node

Return node