



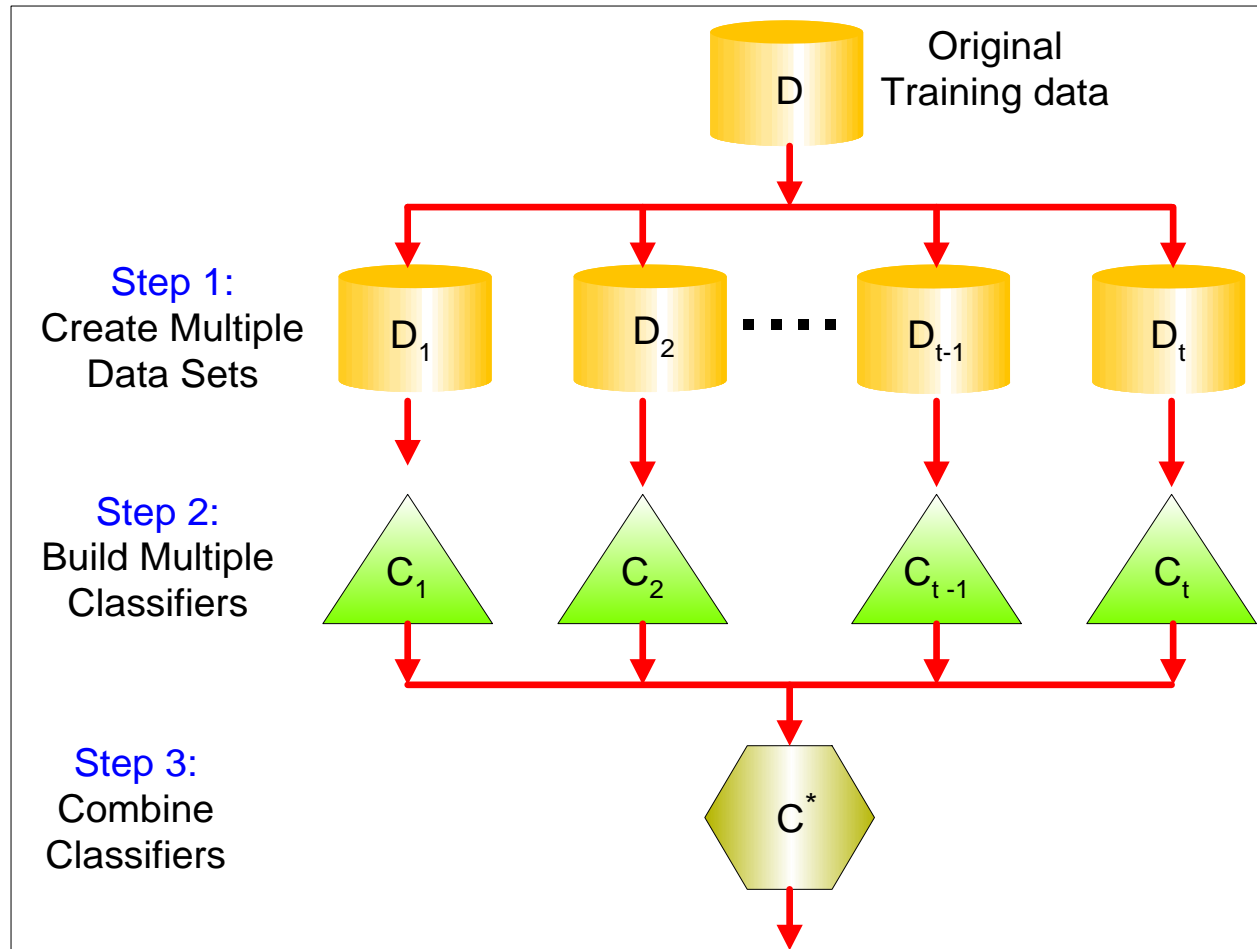
Rule Based Classifiers

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Ensemble Methods

- Construct a set of classifiers from the training data
- Predict class label of previously unseen records by aggregating predictions made by multiple classifiers

General Idea



Why does it work?

- Suppose there are 25 base classifiers
 - Each classifier has error rate, $\varepsilon = 0.35$
 - Assume classifiers are independent
 - Probability that the ensemble classifier makes a wrong prediction by **majority voting**:

$$\sum_{i=13}^{25} \binom{25}{i} \varepsilon^i (1 - \varepsilon)^{25-i} = 0.06$$

Methods for Ensemble Classifiers

- By manipulating the training data:
 - Bagging
 - Boosting
- By manipulating the input features
 - Random forest
- By manipulating the class labels
 - Error correcting output coding
- By manipulating the learning algorithm

Bagging

- Create multiple samples of original data (almost of same size) with replacement

Original Data	1	2	3	4	5	6	7	8	9	10
Bagging (Round 1)	7	8	10	8	2	5	10	10	5	9
Bagging (Round 2)	1	4	9	1	2	3	2	7	3	2
Bagging (Round 3)	1	8	5	10	5	5	9	6	3	7

- Each sample, D_i , is called bootstrap sample
- Build classifier on each bootstrap sample

Bagging Algorithm

Algorithm 5.6 Bagging algorithm.

- 1: Let k be the number of bootstrap samples.
 - 2: **for** $i = 1$ to k **do**
 - 3: Create a bootstrap sample of size N , D_i .
 - 4: Train a base classifier C_i on the bootstrap sample D_i .
 - 5: **end for**
 - 6: $C^*(x) = \underset{y}{\operatorname{argmax}} \sum_i \delta(C_i(x) = y)$.
 $\{\delta(\cdot) = 1 \text{ if its argument is true and } 0 \text{ otherwise}\}.$
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Boosting

- An iterative procedure to adaptively change distribution of training data by focusing more on previously misclassified records
 - Initially, all N records are assigned equal weights
 - Unlike bagging, weights may change at the end of boosting round

Boosting

- Records that are wrongly classified will have their weights increased
- Records that are classified correctly will have their weights decreased

Original Data	1	2	3	4	5	6	7	8	9	10
Boosting (Round 1)	7	3	2	8	7	9	4	10	6	3
Boosting (Round 2)	5	4	9	4	2	5	1	7	4	2
Boosting (Round 3)	4	4	8	10	4	5	4	6	3	4

- Example 4 is hard to classify
- Its weight is increased, therefore it is more likely to be chosen again in subsequent rounds

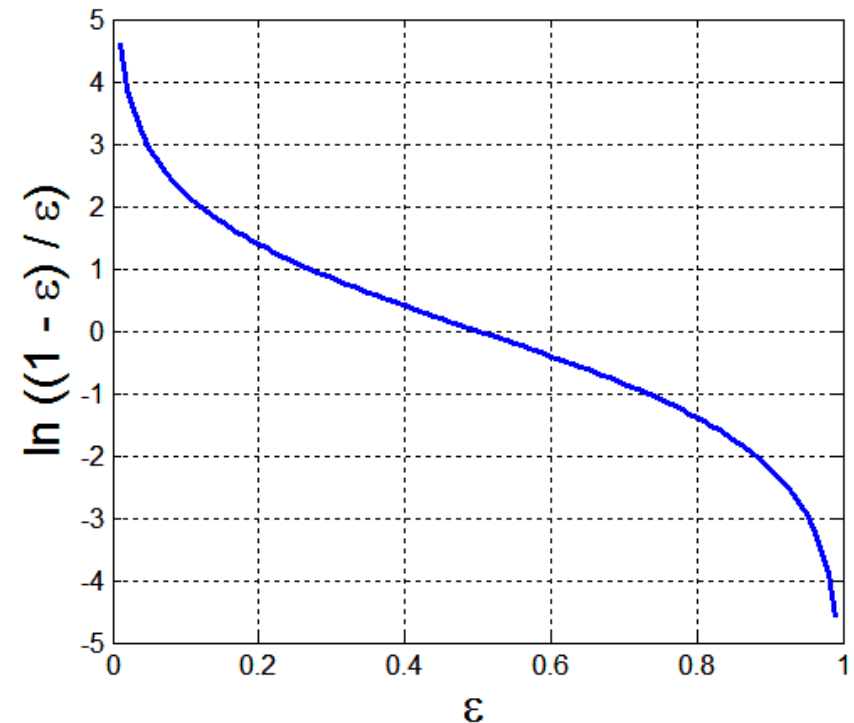
Example: AdaBoost

- Base classifiers: C_1, C_2, \dots, C_T
- Error rate:

$$\varepsilon_i = \frac{1}{N} \sum_{j=1}^N w_j \delta(C_i(x_j) \neq y_j)$$

- Importance of a classifier:

$$\alpha_i = \frac{1}{2} \ln \left(\frac{1 - \varepsilon_i}{\varepsilon_i} \right)$$



Example: AdaBoost

- Weight update:

$$w_i^{(j+1)} = \frac{w_i^{(j)}}{Z_j} \begin{cases} \exp^{-\alpha_j} & \text{if } C_j(x_i) = y_i \\ \exp^{\alpha_j} & \text{if } C_j(x_i) \neq y_i \end{cases}$$

where Z_j is the normalization factor

- If any intermediate rounds produce error rate higher than 50%, the weights are reverted back to $1/n$ and the resampling procedure is repeated
- Classification: $C^*(x) = \arg \max_y \sum_{j=1}^T \alpha_j \delta(C_j(x) = y)$

AdaBoost Algorithm

Algorithm 5.7 AdaBoost algorithm.

- 1: $\mathbf{w} = \{w_j = 1/N \mid j = 1, 2, \dots, N\}$. {Initialize the weights for all N examples.}
 - 2: Let k be the number of boosting rounds.
 - 3: **for** $i = 1$ to k **do**
 - 4: Create training set D_i by sampling (with replacement) from D according to \mathbf{w} .
 - 5: Train a base classifier C_i on D_i .
 - 6: Apply C_i to all examples in the original training set, D .
 - 7: $\epsilon_i = \frac{1}{N} [\sum_j w_j \delta(C_i(x_j) \neq y_j)]$ {Calculate the weighted error.}
 - 8: **if** $\epsilon_i > 0.5$ **then**
 - 9: $\mathbf{w} = \{w_j = 1/N \mid j = 1, 2, \dots, N\}$. {Reset the weights for all N examples.}
 - 10: Go back to Step 4.
 - 11: **end if**
 - 12: $\alpha_i = \frac{1}{2} \ln \frac{1-\epsilon_i}{\epsilon_i}$.
 - 13: Update the weight of each example according to Equation 5 ^{given on the prev slide}
 - 14: **end for**
 - 15: $C^*(\mathbf{x}) = \operatorname{argmax}_y \sum_{j=1}^T \alpha_j \delta(C_j(\mathbf{x}) = y)$.
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