10_Ensemble_Learning

Bagging Algorithm

Reduce variance .Effective on non-prouning desicion tree,ANN

- **inputs**:
  Traing dataset : $D = \{(x_1, y_1), (x_2, y_2), \dots (x_m, y_m)\}$
  Use *Bootstrap Sampling to generate bootstrap replicas* : random sampling with replacement. Sampling subsets could have intersections with others.
  Base Learning Algorithm: L
  Training turns: T i.e. T sampling sets. Based on each sampling set, train a model(Base Learner). Then combine all the models.
- **procedure**:
  for $t = 1, 2, \dots, T$ do: #iration
  $h_t = L(D, D_{bs})$
  end for
- **outputs**:
  $H(x) = argmax_y \in Y \sum_{t=1}^{T} ind(h_t(x) = y)$

Random Forest

Two Randomness : Bootstrap sampling. Featrue selection at each node
On the basis of Bagging-Decision Tree, import random attribution selection in the process of training decision tree.

Boosting

- **inputs**:
  Given dataset: : $D = \{(x_1, y_1), (x_2, y_2), \dots (x_m, y_m)\}, y_i \in \{-1, 1\}$
  Base Learning Algorithm: L
  Training turns: T i.e. T possible weak learners.
- **procedure**:
  Initialize: $\omega_t = \frac{1}{m}$
  for $t = 1, 2, \dots, T$ do: *iration*
  $h_t = L(D, D_{bs})$ *train weak classifier*
  ϵ_t *sum of the weights for misclassified samples*
  $if\ \epsilon_t > 0.5, then\ break$
  $\alpha_t = ln(\frac{1-\epsilon_t}{\epsilon_t})$ *compute the reliability coefficient*
  $\omega_{t+1} = \omega_t\ e^{-\epsilon_t y_t h_t}$ *update weight*