



CS 329P: Practical Machine Learning (2021 Fall)

5.3 Boosting

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https://c.d2l.ai/stanford-cs329p

Boosting



- Learn n weak learners sequentially, combine to reduce model bias
- At step *i*, repeat:
 - Evaluate the existing learners' errors ϵ_t
 - Train a weak learner h_i , focus on wrongly predicted examples
 - AdaBoost: Re-sample data according to ϵ_t
 - Gradient boosting: Train learner to predict ϵ_t
 - Additively combining existing weak learners with h_i

Gradient Boosting



- Supports arbitrary differentiable loss
- $H_t(x)$: output of combined model at time t, with $H_1(x) = 0$
- For each step t, repeat:
 - Train a new learner h_t on residuals: $\{(x_i, y_i H_t(x_i))\}_{i=1,...,m}$
 - Combine: $H_{t+1}(x) = H_t(x) + \eta h_t(x)$ shrinkage parameter η for regularization
- MSE $L = \frac{1}{2}(H(x) y)^2$, residual equals negative gradient $y H(x) = -\frac{\partial L}{\partial H}$
 - For other loss L, learner $h_t = \arg\min \frac{1}{2} \left(h_t(x) + \frac{\partial L(x)}{\partial H_t} \right)^2$
- Avoid overfitting: subsampling, shrinkage, early-stopping

Gradient Boosting Code

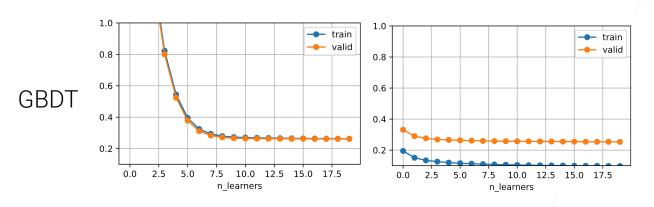


```
class GradientBoosting:
def __init__(self, base_learner, n_learners, learning_rate):
    self.learners = [clone(base_learner) for _ in range(n_learners)]
    self.lr = learning rate
def fit(self, X, y):
    residual = y.copy()
    for learner in self.learners:
        learner.fit(X, residual)
        residual -= self.lr * learner.predict(X)
def predict(self,X):
    preds = [learner.predict(X) for learner in self.learners]
    return np.array(preds).sum(axis=0) * self.lr
```

Gradient Boosting Decision Trees (GBDT)



- Use decision tree as the weak learner
 - Regularize by a small max_depth and randomly sampling features
- Sequentially constructing trees runs slow
 - Popular libraries use accelerated algorithms, e.g. XGBoost, lightGBM



Random Forest