

Boosting

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Introduction to Boosting

Boosting encompasses a highly successful set of learning algorithms.

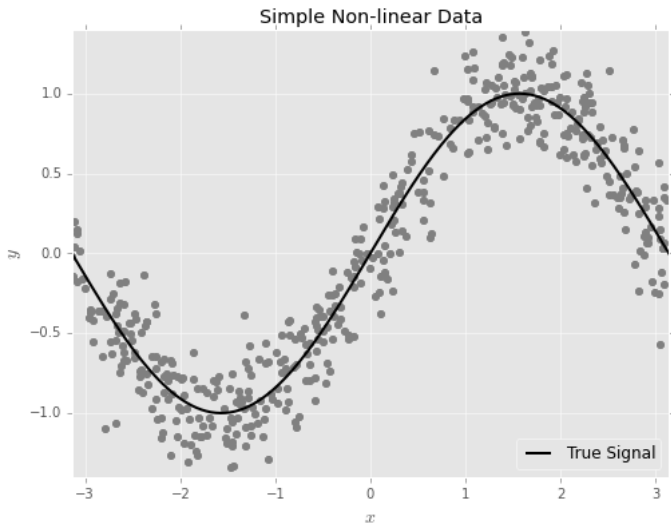
Boosting encompasses a highly successful set of learning algorithms.

- ▶ Allstate has held three Kaggle competitions. All three were won by algorithms incorporating gradient boosting as a fundamental component.

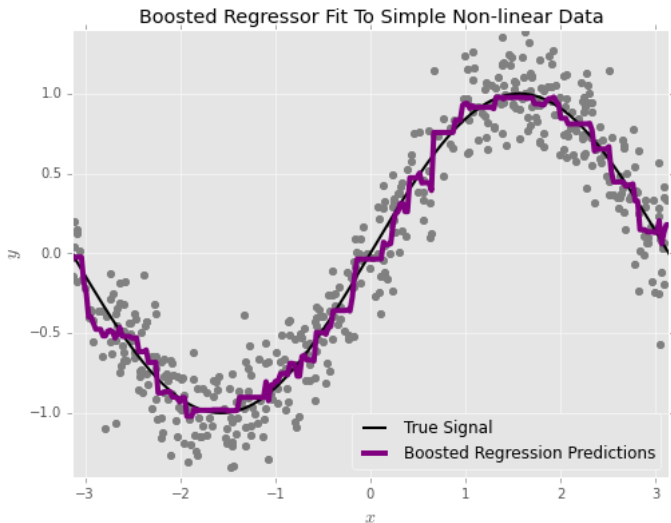
Boosting encompasses a highly successful set of learning algorithms.

- ▶ Allstate has held three Kaggle competitions. All three were won by algorithms incorporating gradient boosting as a fundamental component.
- ▶ In the 1990's insurance company's discovered that incorporating consumers credit information into pricing greatly increased the accuracy of prices, which revolutionized the industry. Using a boosted model in place of a (generalized) linear model when setting prices gives roughly the same increase in predictive power.

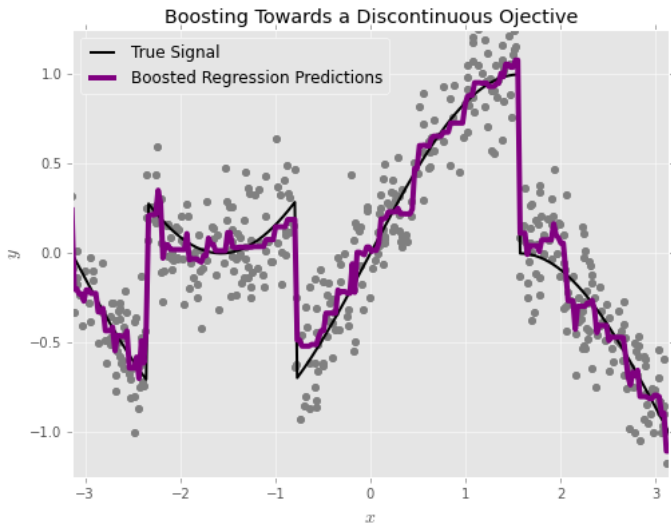
Boosting can adapt itself effortlessly to very non-linear objectives



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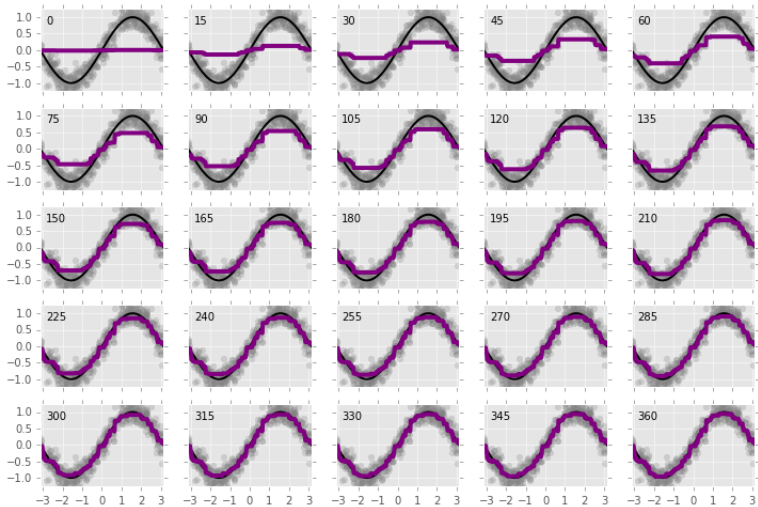


Boosting can adapt itself effortlessly to very non-linear objectives

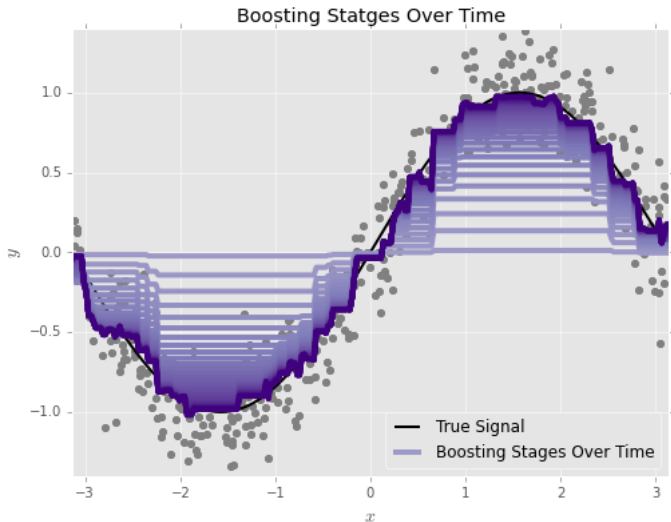


Boosting accomplishes this by *growing the model gradually*

Boosting Stages Over Time



At each stage of the growth, the next model is built as an adjustment to the previous model



Compared to:

Linear Models:

Lowers variance by using a regularization penalty.

Lowers bias by including more predictors.

Compared to:

Random Forest:

Lowers variance by growing many learners on different subsamples of the data and predictors, then averaging them.

Lowers bias by growing really big trees.

Compared to:

SVM:

Lowers variance by maximizing the margin between positive and negative cases.

Lowers bias by using a kernel, which projects the data into a very high dimensional space.

Boosting:

Lowers variance by growing the model slowly over time (along with a few other tricks).

Lowers bias by stacking many non-parametric models into the final result.

Outline of the Lesson

Agenda:

- ▶ Introduction
- ▶ You Could Have Invented Gradient Boosting
- ▶ Practical Gradient Boosted Regression
- ▶ Interpreting Gradient Boosted Regression
- ▶ Gradient Boosted Classification
- ▶ Adaboost
- ▶ Drawbacks of Boosting

Objectives:

- ▶ Understand the conceptual foundation of Boosting
- ▶ Understand the algorithm's hyperparameters, and how to tune them.
- ▶ Understand how to create a booster for your own loss function.
- ▶ Understand some basic strategies for interpreting a booster.
- ▶ Understand the drawbacks of boosting.

You Could Have Invented Gradient Boosting

Let's start with our usual basic setup.

$\{x_i, y_i\}$ is a data set, where i indexes the samples we have available for training our model.

Each x_i may be a vector, in which case I'll refer to it's components (if needed) as x_{ij} .

Our goal is to construct a function f so that

$$y_i \approx f(x_i) \text{ for all } i$$

Question: What should the domain of f be?

Degenerate Choice:

$$\text{Domain}(f) = \{x_i\}$$

That is, let's only attempt to define f on our training samples.

"But Matt. This is silly. The answer is obvious."

Define: $f(x_i) = y_i$

True.

But let's try to derive this in a creative way.

Recall: Gradient descent is a general purpose algorithm for optimizing any objective function $L(x)$.

How does this go?

Algorithm: Gradient Descent to Minimize a function L .

Inputs: A function f .

Outputs: A point x_{optim} that minimizes f .

- ▶ Compute $\nabla L(x)$ somehow, on paper is good.
- ▶ Initialize $x_0 = 0$ (arbitrary, there may be more principled choices).
- ▶ Iterate until convergence:
 - ▶ Set $x_{i+1} = x_i - \nabla L(x_i)$.

Let's focus on a *single point in our domain*, and try to minimize the classic squared error loss function

$$L(f, y) = \frac{1}{2}(y - f)^2$$

Here f is not a function yet, it is just a number.

Initialize f to the average value of y_i

$$f_0 = \frac{1}{N} \sum_i y_i$$

Compute the gradient with respect to f by hand

$$\nabla_f(f, y) = \frac{\partial}{\partial f} \left(\frac{1}{2}(y - f)^2 \right) = f - y$$

...and apply the update rule

$$f_1 = f_0 - \nabla_f(f_0, y) = f_0 - (f_0 - y) = y$$

So this (admittedly quite bizarre) application of gradient descent immediately recovers the correct solution

$$f(x_i) = y_i$$

for every data point.

Question:

What is stopping up from applying this scheme in the more realistic situation where we want to construct a function f with domain \mathbb{R}^n so that

$$f(x_i) \approx y_i$$

The **first step works**, we can certainly define f_0 to be a constant function

$$f_0(x) = \frac{1}{N} \sum_i y_i \text{ for all } x \in \mathbb{R}^n$$

The **update step fails**.

We cannot evaluate the gradient at any point where we have not observed a value of y .

$$\nabla_f(f, y) = f - y$$

We need to extend the gradient to points where we have not observed a value of y .

Fundamental Idea Of Gradient Boosting:

Replace the response y in our dataset with the **gradient of the loss evaluated at y**

$$\{x_i, \nabla_f L(f_0(x_i), y_i)\} = \{x_i, f_0(x_i) - y_i\}$$

Then, fit a model to this new **working response**.

The **predictions from this model** can be viewed as an (approximate) extension of the gradient to all of \mathbb{R}^n .

Algorithm: Gradient Boosting to Minimize Sum of Squared Errors.

Inputs: A data set $\{x_i, y_i\}$.

Returns: A function f such that $f(x_i) \approx y_i$.

- ▶ Initialize $f_0(x) = \frac{1}{N} \sum_i y_i$.
- ▶ Iterate (parameter k) until satisfied:
 - ▶ Create the working data set $W_k = \{x_i, f_k(x_i) - y_i\}$.
 - ▶ Fit a decision tree to W_k , minimizing least squares (though most anything would work here). Call this tree T_k .
 - ▶ Set $f_{k+1}(x) = f_k(x) - T_k(x)$.
- ▶ Return $f_{\max}(x) = f_0(x) - T_1(x) - T_2(x) - \dots - T_{\max}(x)$.

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- ▶ Just like in other algorithms, we can introduce a *learning rate* to make the gradient descent more robust

$$x_{i+1} = x_i - \lambda \nabla L(x_i)$$

This is particularly important in boosting, to prevent overfitting.

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$$x_{i+1} = x_i - \lambda \nabla L(x_i)$$

This is particularly important in boosting, to prevent overfitting.

- ▶ We could have fit the tree to the negative gradient, which would have resulted in the more aesthetically appealing

$$f_{\max}(x) = f_0(x) + T_1(x) + T_2(x) + \cdots + T_{\max}(x)$$

Practical Gradient Boosted Regression

Scikit-learn includes the gradient boosted regression algorithm in the `ensembles` module

```
from sklearn.ensemble import GradientBoostedRegressor
```

A GradientBoostingRegressor object is fit in the same way as every other leaning model in sklearn

```
model = GradientBoostingRegressor()  
model.fit(X, y)
```

The `predict` method returns predictions on new data

```
preds = model.predict(X_new)
```

Especially useful is the iterator `staged_predict` which creates predictions from models created by truncating series of trees

```
for preds in model.staged_predict(X_new):  
    # Do something interesting, used heavily in the plots to  
    follow.
```

GradientBoostingRegressor has many knobs to turn.

```
GradientBoostingRegressor(loss='ls',  
                           n_estimators=100,  
                           learning_rate=0.1,  
                           max_depth=3,  
                           subsample=1.0,  
                           min_samples_split=2,  
                           min_samples_leaf=1,  
                           min_weight_fraction_leaf=0.0,  
                           ...)
```

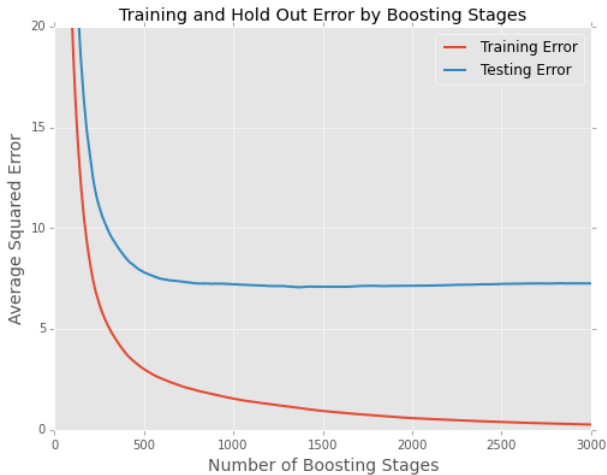
The most important options to `GradientBoostedRegressor` are

- ▶ `loss` controls the loss function to minimize. `ls` is the least squares minimization algorithm we discussed in the previous section.
- ▶ `n_estimators` is how many boosting stages to compute, i.e. how many regression trees to grow.
- ▶ `learning_rate` is the learning rate for the gradient update.
- ▶ `max_depth` controls how deep to grow each individual tree.
- ▶ `subsample` allows to fit each tree on a random sample of the training data (like bagging in random forests).

Tuning the Number of Estimators

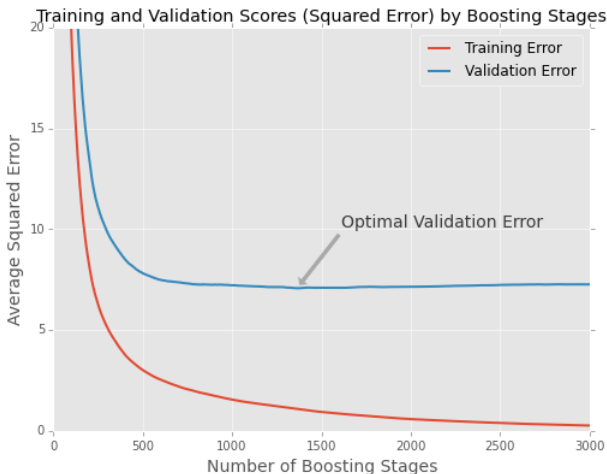
As more and more trees are added to the model the training set error will be driven down monotonically, but the same is not true for the testing error





This means that it is essential to determine the proper number of trees to grow, as too many may lead to overfitting

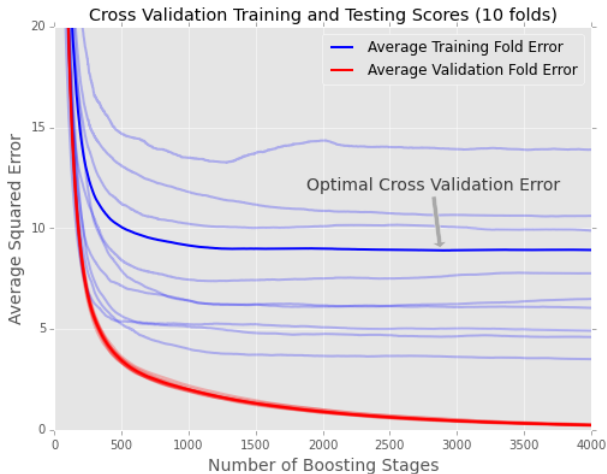
One way to tune the number of trees is to make use of a validation set, held out from both training and testing

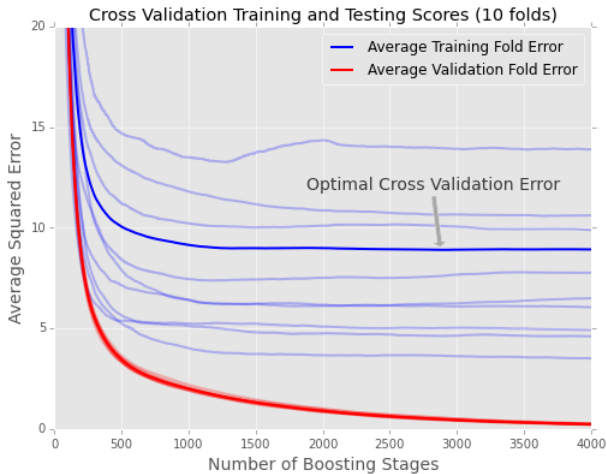


The `loss_` method is important here, it allows us to compute the loss function on held out data

```
validation_loss = np.zeros(model.get_params('n_estimators'))  
for i, preds in enumerate(model.staged_predict(X_new)):  
    validation_loss[i] = model.loss_(preds, y_new)  
  
optimal_tree = np.argmin(validation_loss)  
optimal_loss = validation_loss[optimal_tree]
```

Another way to choose the optimal number of trees is to replace the validation set with cross validation





We generally choose the number of trees minimizing the *average* out validation fold error.

Tuning the Learning Rate

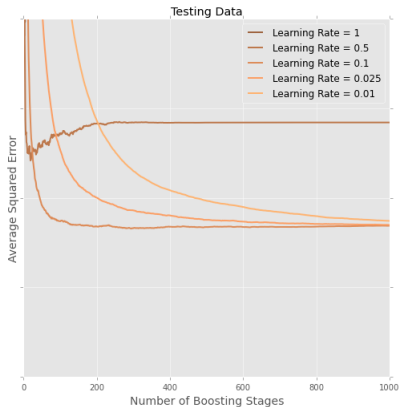
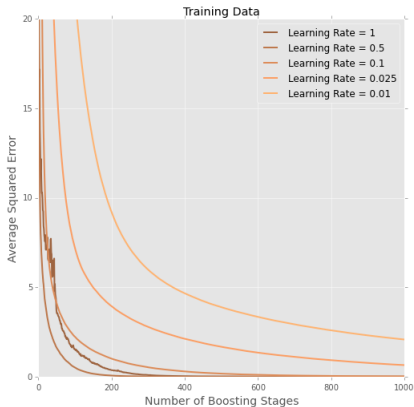
The learning rate allows us to grow our boosted model slowly.

A large learning rate will cause the model to fit hard to the training data, which creates a *high variance* situation.

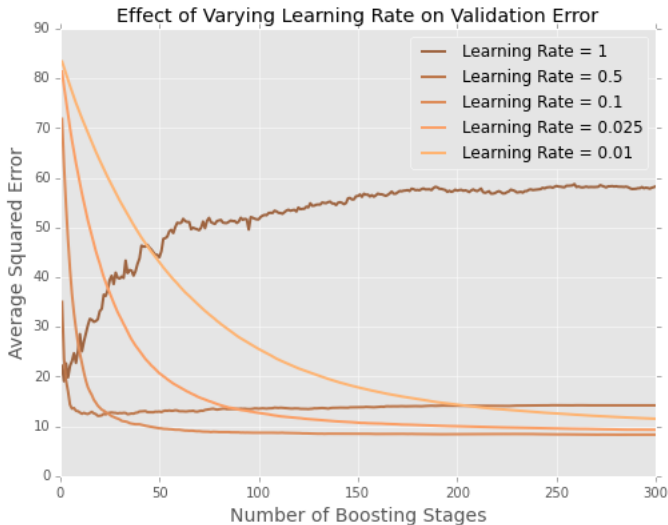
A smaller learning rate reduces the boosted models sensitivity to the training data.

Decreasing the learning rate reduces how fast the booster drives down the training error rate

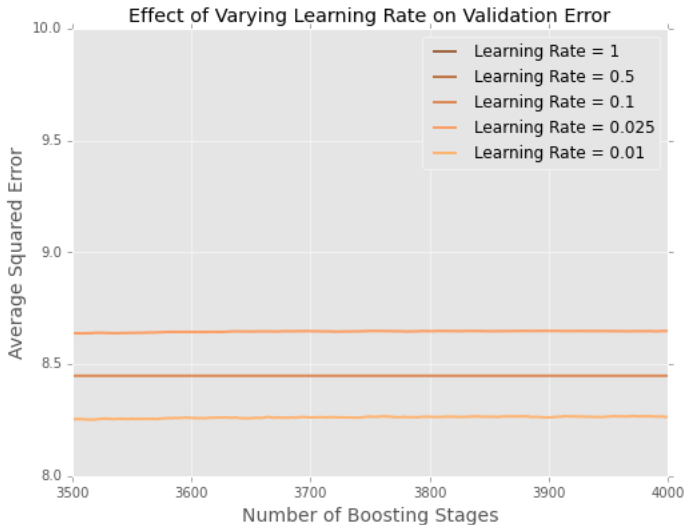
Effect of Varying the Learning Rate



On the other hand, a smaller learning rate means more trees are needed to reach the optimal point



In general, a smaller learning rate eventually (over enough time) results in a superior model



Strategy for Learning Rate:

- ▶ In the initial exploratory phases of modeling, set the learning rate to some large value, say 0.1. This allows you to iterate through ideas quickly.
- ▶ When tuning other parameters using grid search, decrease the learning rate to a more sensible value, 0.01 works well.
- ▶ When fitting the *final* production model, set the learning rate to a very small value, 0.001 or 0.0005, smaller is better.

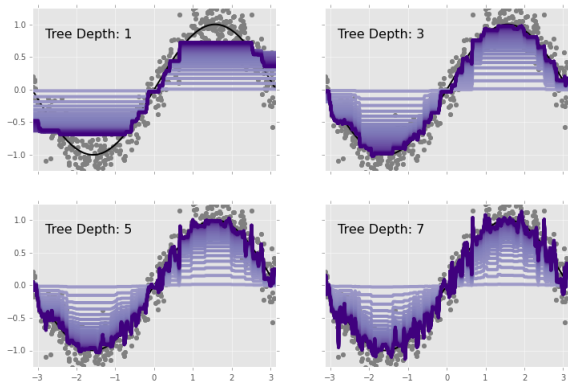
Run the final model overnight! It will fit while you are sleeping!

Make sure you've written all your analysis code up front, based on your initial models. Then all that's left is to run your final model through and see your final plots and statistics.

Tuning the Tree Depth

A larger tree depth allows the model to capture deeper interactions between the predictors, resulting in lower bias.

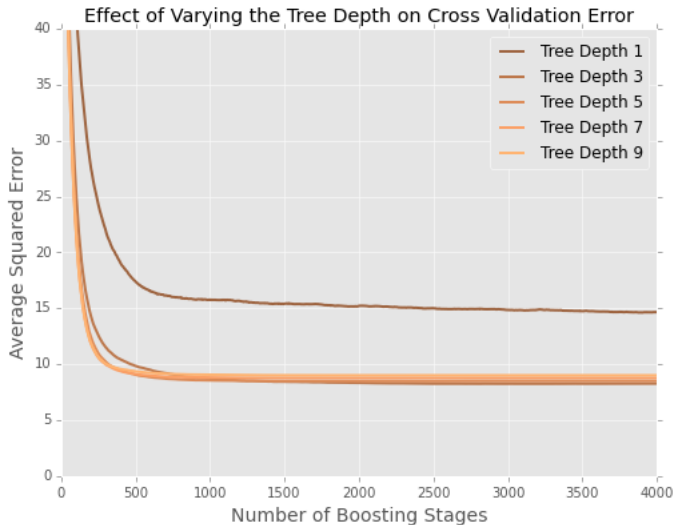
Effect of Tree Depth on Boosting

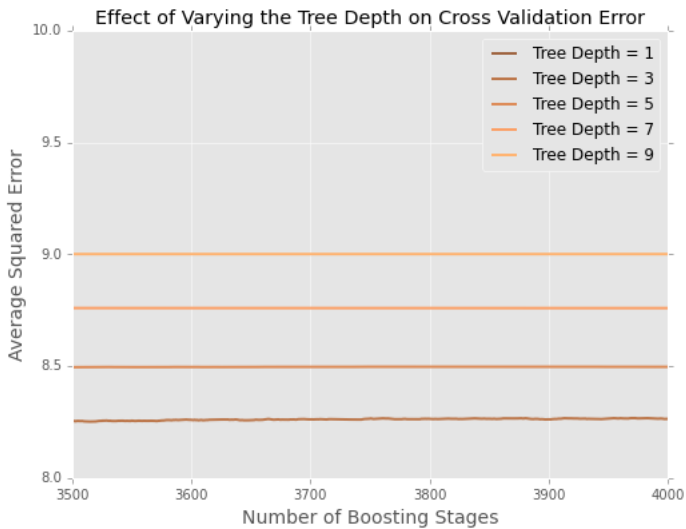


Unfortunately, a deeper tree depth also

- ▶ Causes the model to fit faster, increasing the variance and somewhat combating the effect of the learning rate.
- ▶ Allows the model to assume a more complex for at the same number of trees. This is a blessing (low bias) and curse (high variance).

It's never obvious up front what tree depth is best for a given problem, so a grid search is needed to determine the best value





Strategy for Tree Depth:

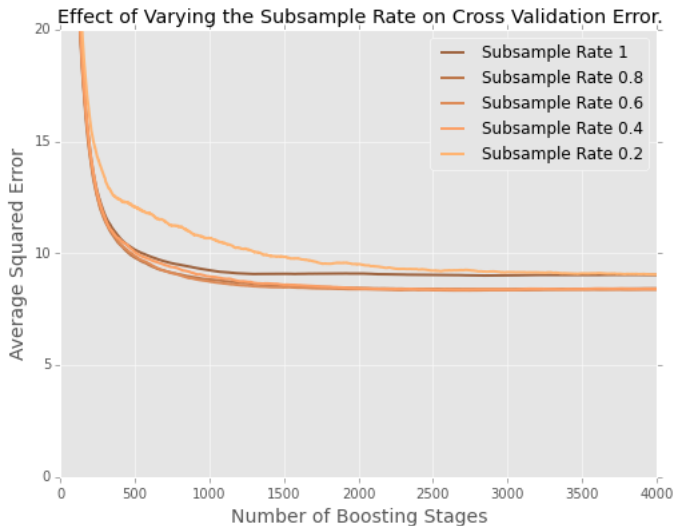
Tune with a grid search and cross validation.

Tuning the Subsample Rate

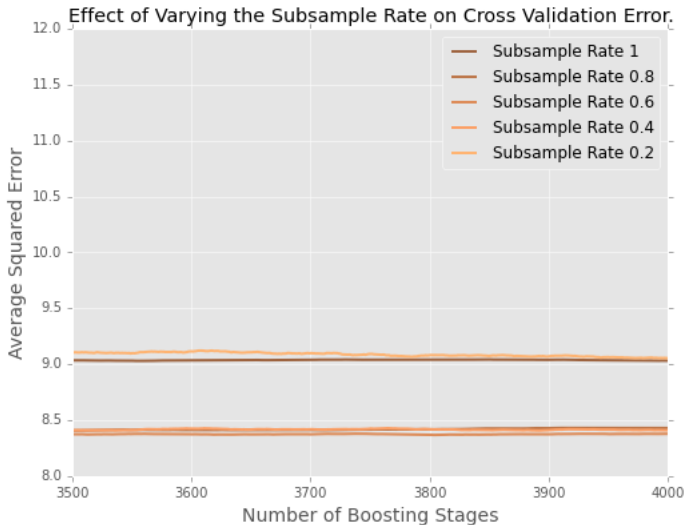
The `subsample` parameter allows one to train each tree on a subsample of the training data.

This is similar to bagging in the random forest algorithms, and has the same result: it lowers the variance of the resulting model.

Not subsampling at all, or over subsampling are both bad ideas



Between these two extremes, different levels of subsampling generally give the same performance



Strategy For Subsample:

Set to 0.5, it almost always works well.