17.9.3

Boosting in Practice

Armed with an understanding of boosting, you're excited to put this technique into practice. Jill encourages you to dive into gradient boosting. Your next step is to apply your knowledge to Python code.

Let's look at an example of using a gradient boosted tree model to enhance the performance of weak learners by combining them into an ensemble.

Start by downloading the files you'll need for this section.

[Download 17-9-3-gradient_boosted_tree.zip](https://2u-data-curriculum-team.s3.amazonaws.com/dataviz-online/module_17/17-9-3-gradient_boosted_tree.zip) (https://2u-data-curriculum-team.s3.amazonaws.com/dataviz-online/module_17/17-9-3-gradient_boosted_tree.zip)

Open `gradient_boosted_tree.ipynb`, or if you like, create a new notebook in the same location, and place the following code.

```
import pandas as pd
from path import Path
file_path = Path("../Resources/loans_data_encoded.csv")
loans_df = pd.read_csv(file_path)
loans_df.head()
```

A preview of the DataFrame reveals that the dataset again contains information on loan applications. The bad column is the target column, with 0 indicating a good loan application and 1 indicating a bad loan application.

	amount	term	age	bad	month_num	education_Bachelor	education_High School or Below	education_Master or Above	education_college	gender_female	gender_male
0	1000	30	45	0	6	0	1	0	0	0	1
1	1000	30	50	0	7	1	0	0	0	1	0
2	1000	30	33	0	8	1	0	0	0	1	0
3	1000	15	27	0	9	0	0	0	1	0	1
4	1000	30	28	0	10	0	0	0	1	1	0

Then, separate the feature columns from the target column.

```
X = loans_df.copy()
X = X.drop("bad", axis=1)
y = loans_df["bad"].values
```

Next, split the dataset into training and testing sets. Again, the `random_state` argument is optional.

```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
X_train, X_test, y_train, y_test = train_test_split(X,
   y, random_state=1)
```

The data is scaled in the next step. Scaling is typically necessary when using models that calculate distances between data points, such as SVM. While not strictly required for tree-based models, it can be a good idea to scale the data, especially when comparing the performances of different models.

```
scaler = StandardScaler()
X_scaler = scaler.fit(X_train)
X_train_scaled = X_scaler.transform(X_train)
X_test_scaled = X_scaler.transform(X_test)
```

In the next step, a `for` loop is used to identify the learning rate that yields the best performance.

```
from sklearn.ensemble import GradientBoostingClassifier
learning_rates = [0.05, 0.1, 0.25, 0.5, 0.75, 1]
for learning_rate in learning_rates:
   classifier = GradientBoostingClassifier(n_estimators=20,
   learning_rate=learning_rate,
   max_features=5,
   max_depth=3,
   random_state=0)
   classifier.fit(X_train_scaled, y_train.ravel)
```

The `GradientBoostingClassifier` includes the following:

- An array called `learning_rates` is manually created and contains a range of values.
- For each learning rate value, a `GradientBoostingClassifier` model is instantiated.
- The `max_depth` argument refers to the size of the decision tree stumps used in gradient boosting.
- The `n_estimators` argument refers to the number of trees used.
- The `n_estimators`, `max_features`, and `max_depth` parameters are fixed at the defined values. These, like the learning rate, can be optimized, but we'll stick to the default values used in the example above.

During each iteration of the `for` loop, the accuracy scores of the training and testing sets are also printed for each learning rate.

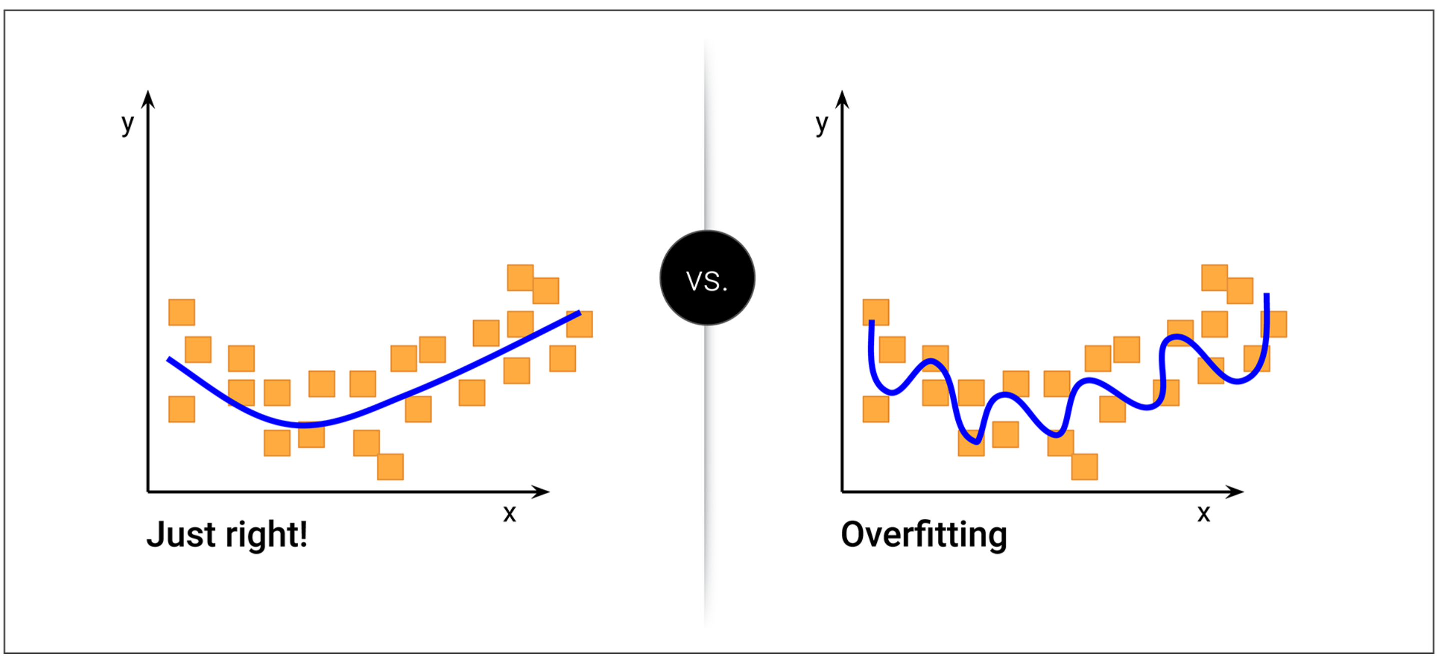
```
   print("Learning rate: ", learning_rate)
   print("Accuracy score (training): {0:.3f}".format(
       classifier.score(
           X_train_scaled,
           y_train)))
   print("Accuracy score (validation): {0:.3f}".format(
       classifier.score(
           X_test_scaled,
           y_test)))
```

Previously, we used Scikit-learn's `accuracy_score` module to validate a model. The method used here is `classifier.score()`, which yields the same result.

Of the learning rates used, 0.5 yields the best accuracy score for the testing set and a high accuracy score for the training set. This is the value we'll implement in the final model. Also, note that the testing accuracy is more important here than the training accuracy.

```
Learning rate:  0.05
Accuracy score (training): 0.627
Accuracy score (validation): 0.520

Learning rate:  0.1
Accuracy score (training): 0.667
Accuracy score (validation): 0.528

Learning rate:  0.25
Accuracy score (training): 0.723
Accuracy score (validation): 0.536

Learning rate:  0.5
Accuracy score (training): 0.755
Accuracy score (validation): 0.560

Learning rate:  0.75
Accuracy score (training): 0.781
Accuracy score (validation): 0.520

Learning rate:  1
Accuracy score (training): 0.792
Accuracy score (validation): 0.480
```

A model that performs well on the training set but poorly on the testing set is said to be "overfit." Overfitting is akin to memorizing the answers to an exam: It will help on that particular exam, but not on any others. In other words, overfitting occurs when a model gives undue importance to patterns within a particular dataset that are not found in other, similar datasets. Instead of learning a general pattern that can be applied to other similar datasets, it learns the patterns specific to one dataset.



Which of the following is an example of overfitting?

- Training score: 0.9; testing score: 0.9
- Training score: 0.9; testing score: 0.6
- Training score: 0.8; testing score: 0.85

Check Answer

Finish

Using the `learning_rate` value obtained from the `for` loop, we instantiate a model, train it, then create predictions.

```
classifier = GradientBoostingClassifier(n_estimators=20,
   learning_rate=0.5, max_features=5, max_depth=3, random_state=0)

classifier.fit(X_train_scaled, y_train)
predictions = classifier.predict(X_test_scaled)
```

Having created predictions with the gradient boosted tree model, we can assess the model's performance. This time, the `accuracy_score()` method is used.

```
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report
acc_score = accuracy_score(y_test, predictions)
print(f"Accuracy Score : {acc_score}")
```

Predictably, the `accuracy_score()` method returns the same score as that of the `classifier.score()` method.

```
Accuracy Score: 0.56
```

Next, we generate a `confusion_matrix` of the results.

```
cm = confusion_matrix(y_test, predictions)
cm_df = pd.DataFrame(
   cm, index=["Actual 0", "Actual 1"],
   columns=["Predicted 0", "Predicted 1"]
)
display(cm_df)
```

	Predicted 0	Predicted 1
Actual 0	49	16
Actual 1	39	21

Finally, we can generate a classification report to evaluate the precision, recall, and F1 scores.

```
print("Classification Report")
print(classification_report(y_test, predictions))
```

```
Classification Report
              precision    recall  f1-score   support

           0       0.56      0.75      0.64        65
           1       0.57      0.35      0.43        60

    accuracy                           0.56       125
   macro avg       0.56      0.55      0.54       125
weighted avg       0.56      0.56      0.54       125
```

SKILL DRILL

How would you interpret the results of this classification report?