

subsets for training and validation. We'll also apply a *stratification* technique when splitting the data to maintain the proportion of each label value in the training and validation datasets.

```
from sklearn.model_selection import train_test_split

# Separate features and labels
penguins_X, penguins_y = penguins[penguin_features].values, penguins[penguin_label].values

# Split data 70%-30% into training set and test set
x_penguin_train, x_penguin_test, y_penguin_train, y_penguin_test = train_test_split(penguins_X,
                                                                                      penguins_y,
                                                                                      test_size=0.3,
                                                                                      random_state=42,
                                                                                      stratify=penguins_y)

print ('Training Set: %d, Test Set: %d \n' % (x_penguin_train.shape[0], x_penguin_test.shape[0])
```

## Train and evaluate a multiclass classifier

Now that we have a set of training features and corresponding training labels, we can fit a multiclass classification algorithm to the data to create a model. Most scikit-learn classification algorithms inherently support multiclass classification. We'll try a logistic

Now we can use the trained model to predict the labels for the test features, and compare the predicted labels to the actual labels:

Let's look at a classification report.

As with binary classification, the report includes *precision* and *recall* metrics for each class. However, while with binary classification we could focus on the scores for the *positive* class; in this case, there are multiple classes so we need to look at an overall metric (either the macro or weighted average) to get a sense of how well the model performs across all three classes.

You can get the overall metrics separately from the report using the scikit-learn metrics score classes, but with multiclass results you must specify which average metric you want to use for precision and recall.

Now let's look at the confusion matrix for our model:

The confusion matrix shows the intersection of predicted and actual label values for each class - in simple terms, the diagonal intersections from top-left to bottom-right indicate the number of correct predictions.

When dealing with multiple classes, it's generally more intuitive to visualize this as a heat map, like this:

The darker squares in the confusion matrix plot indicate high numbers of cases, and you can hopefully see a diagonal line of darker squares indicating cases where the predicted and actual label are the same.

In the case of a multiclass classification model, a single ROC curve showing true positive rate vs false positive rate is not possible. However, you can use the rates for each class in a One vs Rest (OVR) comparison to create a ROC chart for each class.

To quantify the ROC performance, you can calculate an aggregate area under the curve score that is averaged across all of the OVR curves.

## Preprocess data in a pipeline

Again, just like with binary classification, you can use a pipeline to apply preprocessing steps to the data before fitting it to an algorithm to train a model. Let's see if we can improve the penguin predictor by scaling the numeric features in a transformation steps before training. We'll also try a different algorithm (a support vector machine), just to show that we can!

Now we can evaluate the new model.

## Use the model with new data observations

Now let's save our trained model so we can use it again later.

OK, so now we have a trained model. Let's use it to predict the class of a new penguin observation:

You can also submit a batch of penguin observations to the model, and get back a prediction for each one.

## Summary

Classification is one of the most common forms of machine learning, and by following the basic principles we've discussed in this notebook you should be able to train and evaluate classification models with scikit-learn. It's worth spending some time investigating

classification algorithms in more depth, and a good starting point is the [Scikit-Learn documentation](#).

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