In sklearn, different machine learning models are represented as classes. Below, we see a LogisticRegression classifier imported to use at our disposal.

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns # imports seaborn class as an alias 'sns';
import sklearn.datasets # imports 'classical' machine learning data
sets
from sklearn.linear_model import LogisticRegression # imports Logis
ticRegression class
from sklearn.decomposition import PCA # imports the PCA class, allo
wing us to reduce the dimensionality of our data
from sklearn.model_selection import train_test_split # imports the
function train_test_split,
                                                     # which allows
us to easily split our X and y into training and testing sets
```

The [iris dataset (https://archive.ics.uci.edu/ml/datasets/iris)](https://archive.ics.uci.edu/ml/datasets/iris) is built into sklearn and can be loaded with the function `sklearn.datasets.load_iris()` . However, `load_iris()` returns a dictionary, which contains both our input, `X` , and our target output, `y` , with the keys `'data'` and `'target'` , respectively.

In [4]:
```
iris_data = sklearn.datasets.load_iris()  # loads in the Iris datas
et through sklearn.datasets
X = iris_data['data']  # gets the input values, our input X, from i
ris_data
y = iris_data['target'] # gets the target values, our output y, fro
m iris_data
```

Note in the output of the cell below that X has 150 rows and 4 columns, while y is a 1D array with 150 values.

In [5]:
```
print(type(iris_data)) # prints the type of iris_data, which says '
sklearn.utils.Bunch',
                       # but is very similar to a Python dictionary
print(X.shape) # prints the shape of X
print(y.shape) # prints the shape of y
```

```
<class 'sklearn.utils.Bunch'>
(150, 4)
(150,)
```

This dataset is commonly used in classification tasks as there are three different classes: Iris Setosa, Iris Versicolour, and Iris Virginica.

We have 4 different 'features' or dimensions in our dataset: sepal length in cm, sepal width in cm, petal length in cm, and petal width in cm.

We'd like to visualize these 4 features to get an intuition for the differences between the classes. However, we cannot see past 3 dimensions, so we will have to reduce the dimensionality of our dataset. To do this we use Principal Component Analysis or PCA to reduce our dimensions from 4 to 2.

In [14]:
```
pca = PCA(n_components=2)  # initialize a PCA class to reduce our d
ata to 2 dimensions, which is n_components
```

In [15]:
```
X.shape
```

Out[15]:
```
(150, 4)
```

In [16]:
```
X_pca = pca.fit_transform(X)  # we fit PCA to our dataset X and tra
nsform X from 4 dimensions to 2
```

In [17]:
```
print(X.shape) # the shape of our original dataset (150 rows, 4 col
umns)
print(X_pca.shape) # the shape of our PCA-transformed dataset (150
rows, 2 columns)
```

```
(150, 4)
(150, 2)
```

In [18]:
```
iris_df = pd.DataFrame(np.insert(X_pca, 2, y, axis=1), columns=['fe
at_1', 'feat_2', 'class'])
```

In [19]:
```
iris_df['class'].value_counts()
```

Out[19]:
```
2.0    50
1.0    50
0.0    50
Name: class, dtype: int64
```

In [21]:
```
iris_df
```

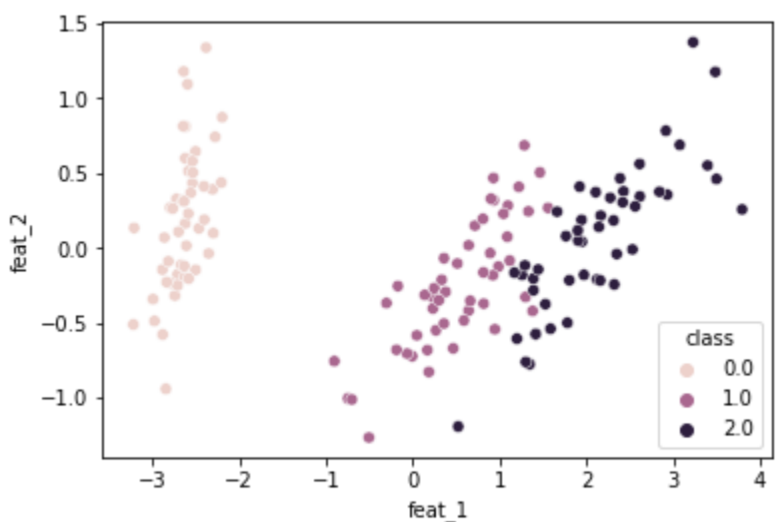
Out[21]:

	feat_1	feat_2	class
0	-2.684126	0.319397	0.0
1	-2.714142	-0.177001	0.0
2	-2.888991	-0.144949	0.0
3	-2.745343	-0.318299	0.0
4	-2.728717	0.326755	0.0
...	...	...	...
145	1.944110	0.187532	2.0
146	1.527167	-0.375317	2.0
147	1.764346	0.078859	2.0
148	1.900942	0.116628	2.0
149	1.390189	-0.282661	2.0

150 rows × 3 columns

In [20]:
```
sns.scatterplot(data=iris_df, x='feat_1', y='feat_2', hue='class')
```

Out[20]: <AxesSubplot:xlabel='feat_1', ylabel='feat_2'>



Before training our model, we will split our model into a training set and testing set, so that we can check the accuracy of our model on unseen data.

In [22]:
```
train_test_split?
```

In [24]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size
=0.3) # splits our X and y into train and test sets,

# with the testing data being 30% of the size

# of the training set
```

In [26]:
```
clf = LogisticRegression()  # initializes a LogisticRegression clas
s,
                           # which will allow us to train and test
a Logistic Regression model
```

`clf.fit(X, y)` will train our LogisticRegression classifier to our training dataset.
In other words, the `fit` function updates our LogisticRegression object with the set of parameters W and bias vector B needed to make predictions.

In [27]:
```
clf.fit(X_train, y_train) # fits or trains our LogisticRegression m
odel on our training data
```

Out[27]:
```
LogisticRegression()
```

Once we fit our model, we have a set of weights and biases that we then apply to our test data to measure the accuracy of our model.

In [30]:
```
y_pred = clf.predict(X_test)  # predicts the y_test values based on
our trained model and given inputs X_test
y_pred[:5] # outputs our first 5 predictions (our output is either
class 0, 1, or 2)
```

Out[30]:
```
array([2, 2, 1, 0, 1])
```

To evaluate our model's accuracy, we will see how many values from `y_pred` are equal to `y_test`, divided by the length of either array.

In [31]:
```
sum(y_pred == y_test) / len(y_pred)  # gets the accuracy of our mod
el by summing all the times y_pred equals y_test
                                     # divided by the length of y_p
red
```

Out[31]:
```
0.9777777777777777
```

In [ ]:
```

```