logistic_regression

May 29, 2021

1 Linear model for classification

In regression, we saw that the target to be predicted was a continuous variable. In classification, this target will be discrete (e.g. categorical).

We will go back to our penguin dataset. However, this time we will try to predict the penguin species using the culmen information. We will also simplify our classification problem by selecting only 2 of the penguin species to solve a binary classification problem.

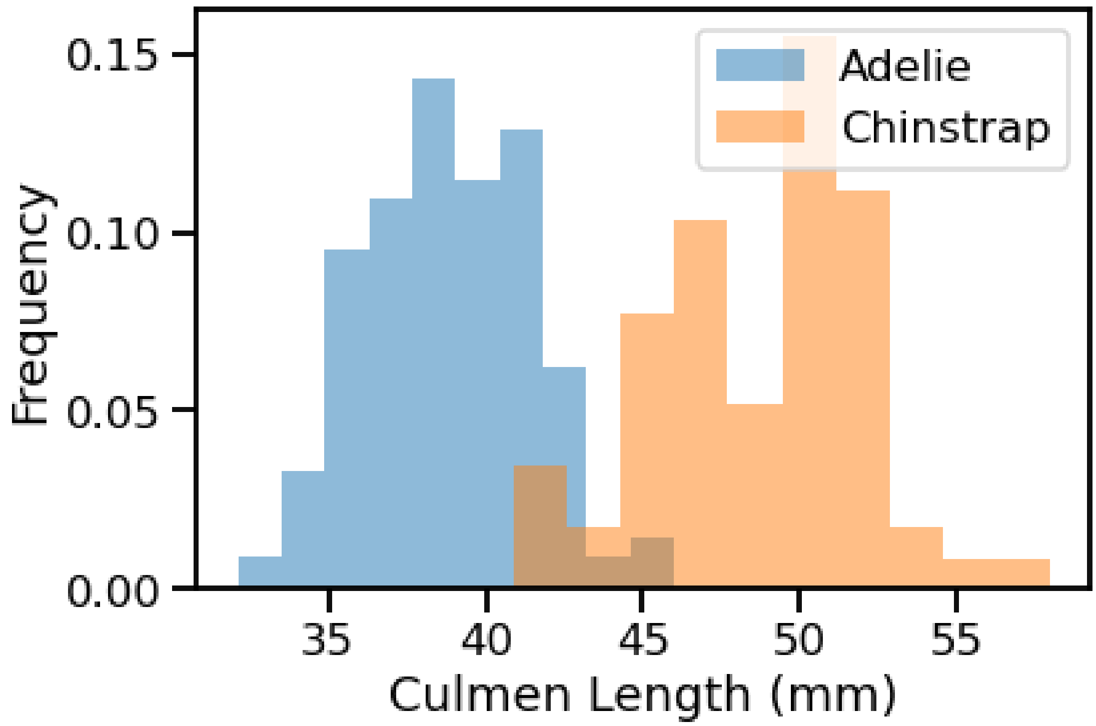
Note

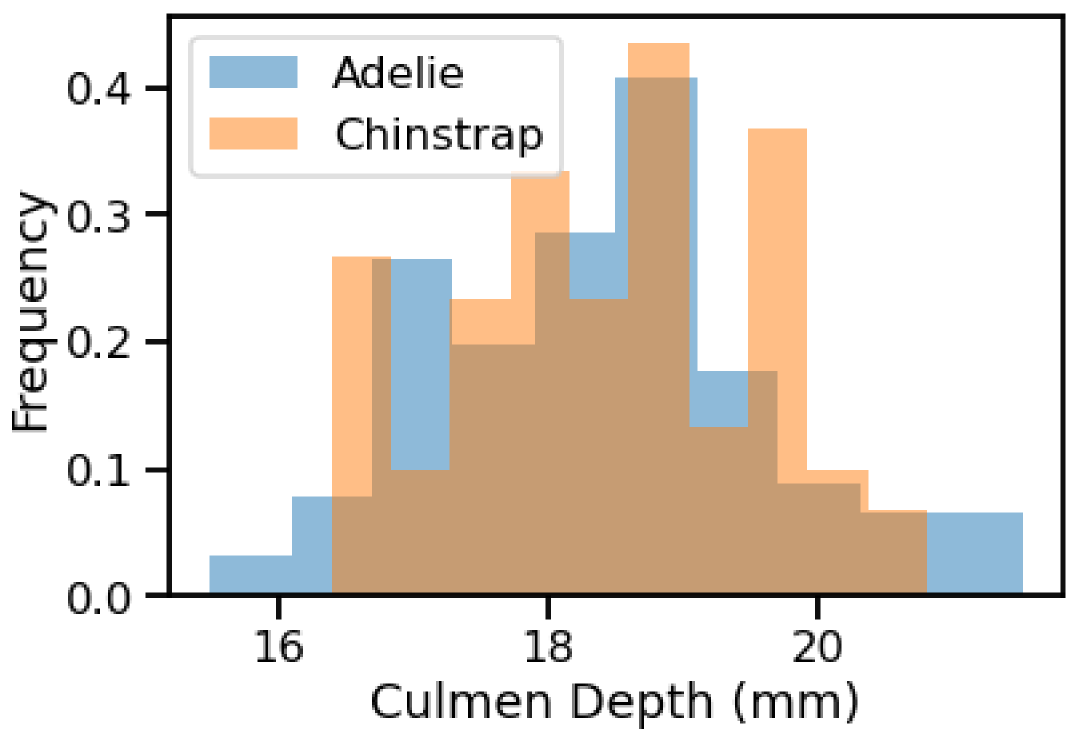
If you want a deeper overview regarding this dataset, you can refer to the Appendix - Datasets description section at the end of this MOOC.

[1]:
```python
import pandas as pd

penguins = pd.read_csv("../datasets/penguins_classification.csv")

# only keep the Adelie and Chinstrap classes
penguins = penguins.set_index("Species").loc[
    ["Adelie", "Chinstrap"]].reset_index()
culmen_columns = ["Culmen Length (mm)", "Culmen Depth (mm)"]
target_column = "Species"
```

We can quickly start by visualizing the feature distribution by class:

[2]:
```python
import matplotlib.pyplot as plt

for feature_name in culmen_columns:
    plt.figure()
    # plot the histogram for each specie
    penguins.groupby("Species")[feature_name].plot.hist(
        alpha=0.5, density=True, legend=True)
    plt.xlabel(feature_name)
```


Adelie
Chinstrap
0.15
0.10
0.05
0.00
Frequency
35
40
45
50
55
Culmen Length (mm)


Adelie
Chinstrap
0.4
0.3
0.2
0.1
0.0
Frequency
16
18
20
Culmen Depth (mm)

We can observe that we have quite a simple problem. When the culmen length increases, the probability that the penguin is a Chinstrap is closer to 1. However, the culmen depth is not helpful for predicting the penguin species.

For model fitting, we will separate the target from the data and we will create a training and a testing set.

[3]:
```
from sklearn.model_selection import train_test_split

penguins_train, penguins_test = train_test_split(penguins, random_state=0)

data_train = penguins_train[culmen_columns]
data_test = penguins_test[culmen_columns]

target_train = penguins_train[target_column]
target_test = penguins_test[target_column]

range_features = {
    feature_name: (penguins[feature_name].min() - 1,
                   penguins[feature_name].max() + 1)
    for feature_name in culmen_columns
}
```

To visualize the separation found by our classifier, we will define an helper function `plot_decision_function`. In short, this function will plot the edge of the decision function, where the probability to be an Adelie or Chinstrap will be equal (p=0.5).

[4]:
```
import numpy as np


def plot_decision_function(fitted_classifier, range_features, ax=None):
    """Plot the boundary of the decision function of a classifier."""
    from sklearn.preprocessing import LabelEncoder

    feature_names = list(range_features.keys())
    # create a grid to evaluate all possible samples
    plot_step = 0.02
    xx, yy = np.meshgrid(
        np.arange(*range_features[feature_names[0]], plot_step),
        np.arange(*range_features[feature_names[1]], plot_step),
    )

    # compute the associated prediction
    Z = fitted_classifier.predict(np.c_[xx.ravel(), yy.ravel()])
    Z = LabelEncoder().fit_transform(Z)
    Z = Z.reshape(xx.shape)

    # make the plot of the boundary and the data samples
```

```python
    if ax is None:
        _, ax = plt.subplots()
    ax.contourf(xx, yy, Z, alpha=0.4, cmap="RdBu_r")

    return ax
```

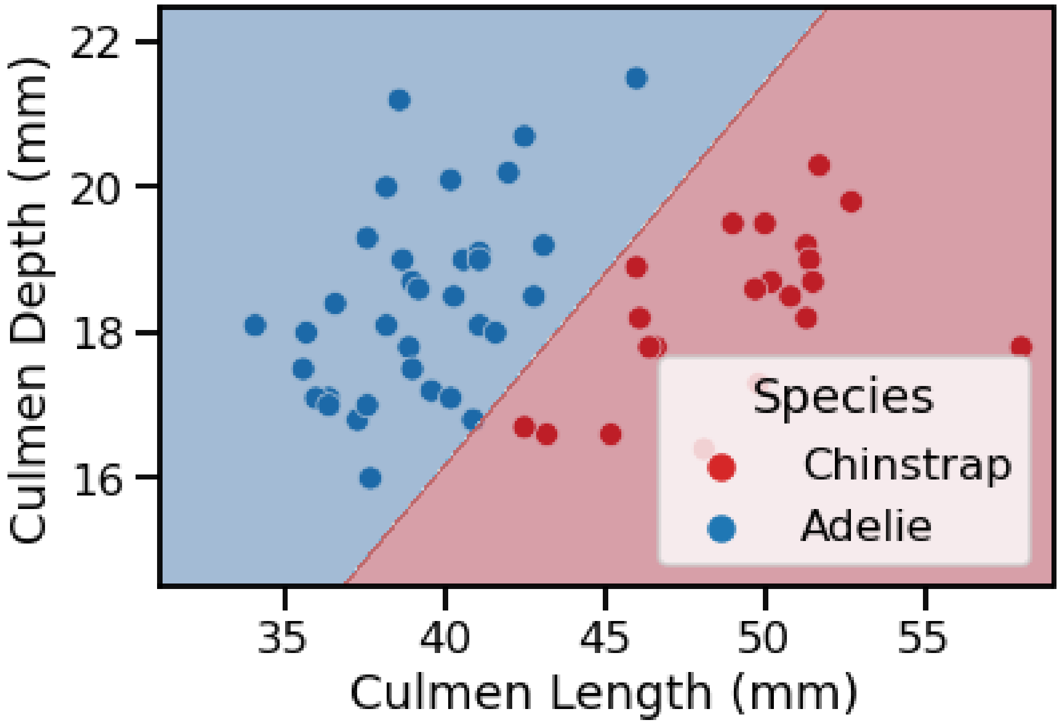
The linear regression that we previously saw will predict a continuous output. When the target is a binary outcome, one can use the logistic function to model the probability. This model is known as logistic regression.

Scikit-learn provides the class `LogisticRegression` which implements this algorithm.

[5]:
```python
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression

logistic_regression = make_pipeline(
    StandardScaler(), LogisticRegression(penalty="none")
)
logistic_regression.fit(data_train, target_train)
```

[5]:
```
Pipeline(steps=[('standardscaler', StandardScaler()),
                ('logisticregression', LogisticRegression(penalty='none'))])
```

[6]:
```python
import seaborn as sns

ax = sns.scatterplot(
    data=penguins_test, x=culmen_columns[0], y=culmen_columns[1],
    hue=target_column, palette=["tab:red", "tab:blue"])
_ = plot_decision_function(logistic_regression, range_features, ax=ax)
```



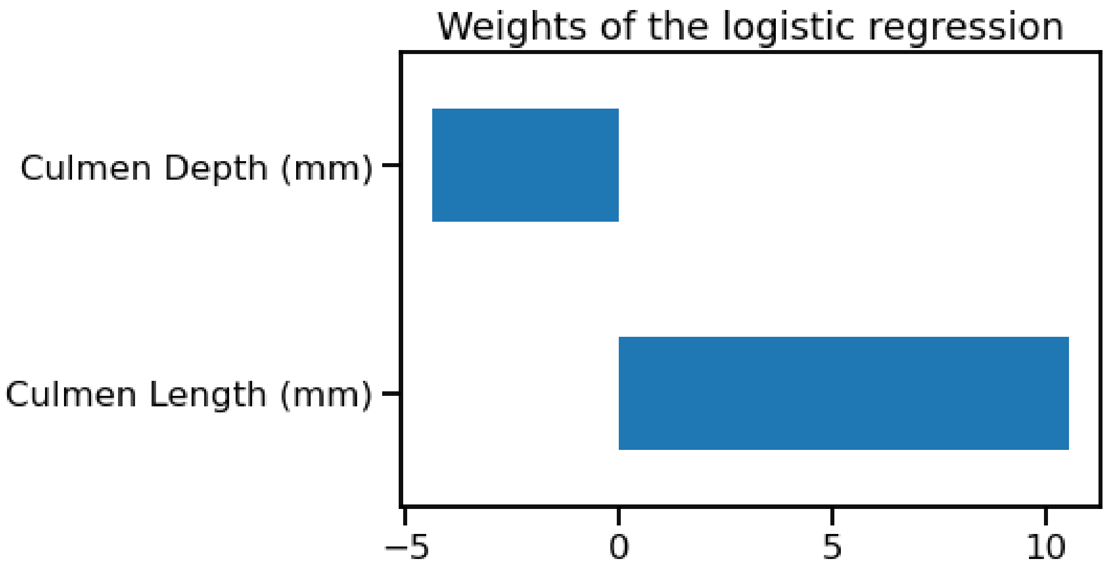
Thus, we see that our decision function is represented by a line separating the 2 classes. We should also note that we did not impose any regularization by setting the parameter `penalty` to `'none'`.

Since the line is oblique, it means that we used a combination of both features:

[7]:
```
coefs = logistic_regression[-1].coef_[0]  # the coefficients is a 2d array
weights = pd.Series(coefs, index=culmen_columns)
```

[8]:
```
weights.plot.barh()
plt.title("Weights of the logistic regression")
```

[8]: `Text(0.5, 1.0, 'Weights of the logistic regression')`



Indeed, both coefficients are non-null.