

[https://github.com/IrishRugbyman/QuentinLambolez\\_IrisProject](https://github.com/IrishRugbyman/QuentinLambolez_IrisProject)

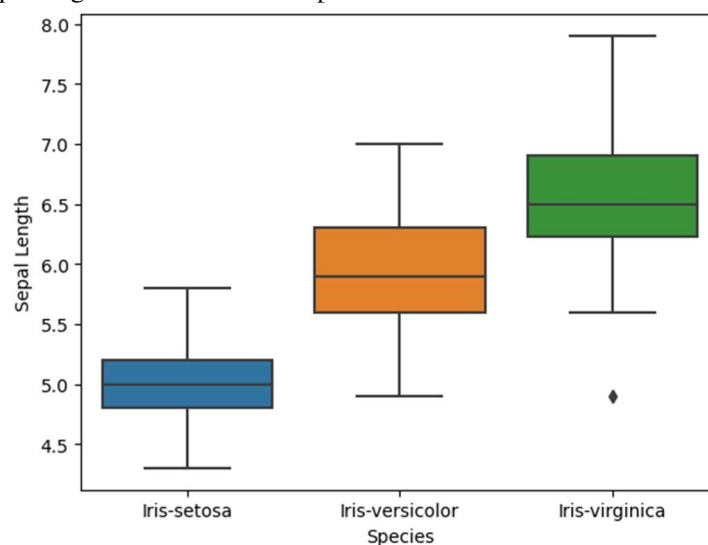
I made a Python script that performs a k-NN classification on the IRIS flower dataset. I first load the dataset, perform some data analysis (including graphs), pre-process the data, train a k-NN classifier using a pipeline, and evaluate the.

## Data Analysis

It's necessary to perform some data analysis to get a better understanding of the data. In this script, I used the `seaborn` library to create visualizations of the dataset.

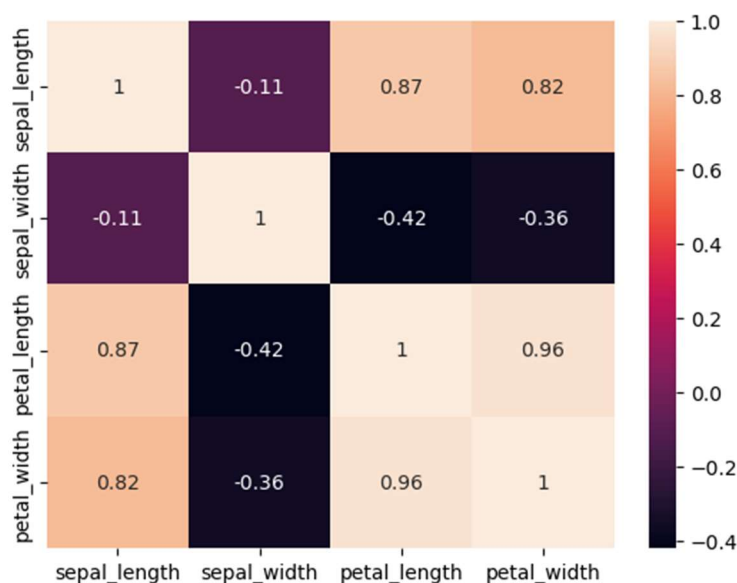
First, I created a box plot to compare the sepal length across the three different species of flowers. The `"sns.boxplot()"` function from the `seaborn` library is used for this.

We can see that the sepal length for the Iris Setosa species is much smaller than the other two species.

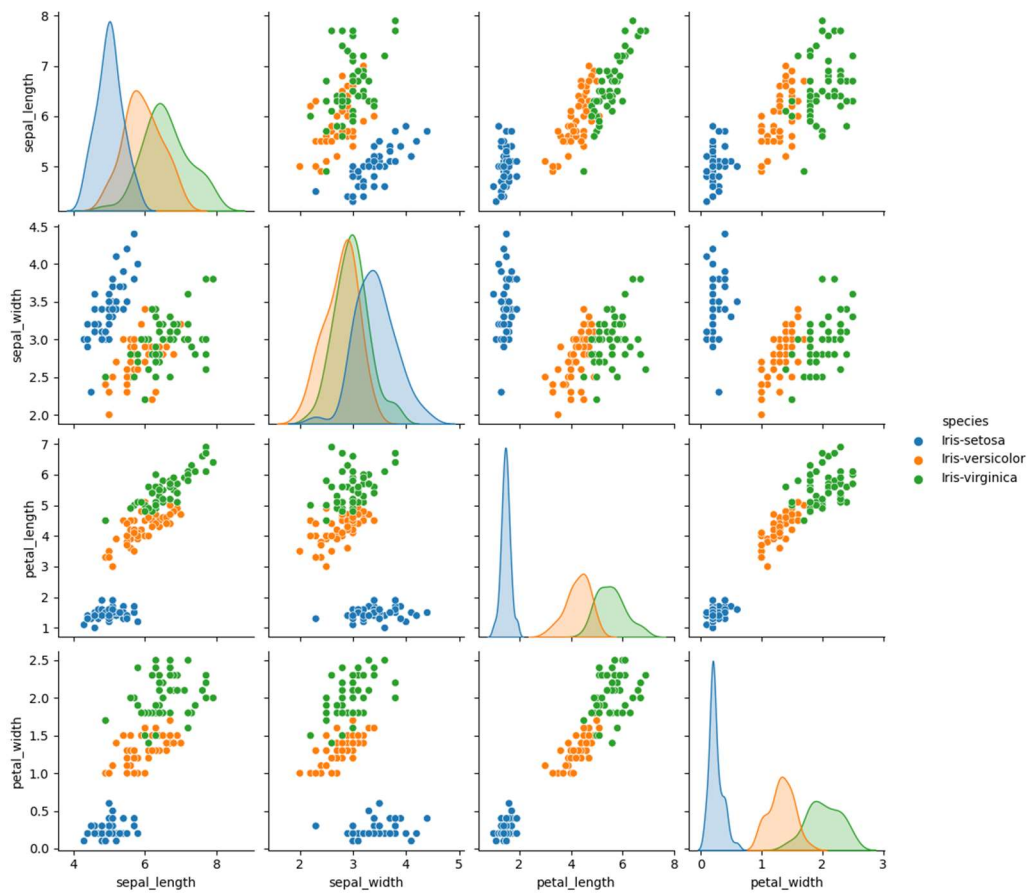


Next, I created a heatmap to visualize the correlation between the features. The `sns.heatmap()` function is used again.

It's clear that the petal length and petal width are highly correlated with each other, while the sepal length and sepal width are less correlated.

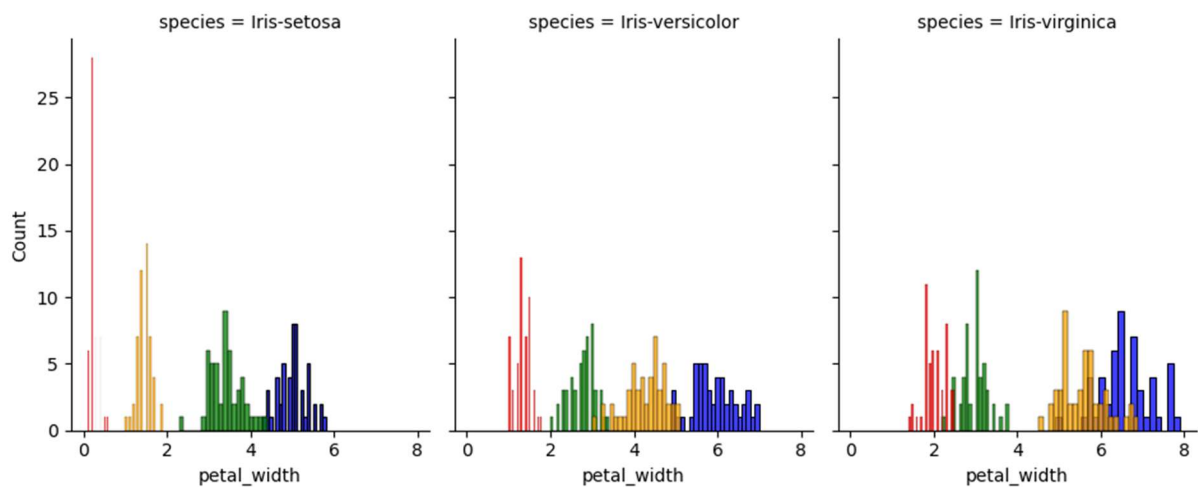


Then, I made a pairplot to visualize the relationships between the features and the target variable. The `sns.pairplot()` function is used once again. We learn that the petal length and petal width are the most important features for distinguishing between the three different species of flowers.



Finally, I created a FacetGrid plot to visualize the distribution of each feature for each species of flower. I first created a FacetGrid using the `sns.FacetGrid()` function, passing in the dataset and the 'species' column as the variable.

Then, I used the `g.map()` function to apply a histogram plot using the `sns.histplot()` function to each column. The resulting plot allows us to easily compare the distribution of each feature for each species of flower.



## Pre-processing

After performing some data analysis, the next step is to pre-process the data:

- Splitting the data into features and target variables.
- Encoding the target variable.
- Splitting the data into training and test sets.

The *iloc()* function from the pandas library is used to split the data into features (X) and target (y).

Then, the *LabelEncoder* class from the sklearn.preprocessing library is used to encode the target variable.

And, lastly, the *train\_test\_split()* function from the sklearn.model\_selection library is used to split the data into training and test sets.

## Training the k-NN classifier

After pre-processing the data, the next step is to train the k-NN classifier. In this code, I used a pipeline to connect the steps of getting the data ready and the actual classification process.

The k-NN classifier is trained using the training set. The *GridSearchCV* class is used to perform a grid search over the hyperparameters of the k-NN classifier. The hyperparameters include the number of neighbors, the weight, and the distance.

## Evaluating the classifier

After training the k-NN classifier, the next step is to evaluate its performance on the test set. In this script, the *classification\_report()* function and the *accuracy\_score()* function to evaluate the classifier.

	precision	recall	f1-score	support
Iris-setosa	1.00	1.00	1.00	10
Iris-versicolor	1.00	1.00	1.00	9
Iris-virginica	1.00	1.00	1.00	11
accuracy			1.00	30
macro avg	1.00	1.00	1.00	30
weighted avg	1.00	1.00	1.00	30

Accuracy: 1.0000

We can see that the precision, the recall, the f1-score are all equal to 1. This may come from the fact that the dataset does not have a lot of data so the model does not have enough data to work with.