University of St. Gallen Fall Semester 2022

Implementing Machine Learning in Python

Group Project

Programming with Advanced Computer Languages

Submitted by:

Marco Birchler (21-615-711)

Xuan Zhao (22-605-356)

Mathieu Youssef (18-408-385)

December 23, 2022

Table of Contents

Why a Machine Learning Project?

Machine learning is a powerful tool for solving a wide range of problems in fields such as computer science, statistics, and data science. By training machine learning models on large datasets, we can enable them to learn patterns and relationships in the data that allow them to make informed predictions or decisions.

Machine learning projects can be a valuable tool for solving real-world problems and driving innovation. Whether you are a student, researcher, or professional, working on a machine learning project can be a rewarding and challenging experience that can help you develop valuable skills and advance your career.

Overview and goal of the project

The project aims to train a machine learning model to accurately predict the species of Iris flower (Iris setosa, Iris virginica, or Iris versicolor) based on four features: sepal length, sepal width, petal length, and petal width, all measured in centimeters.

In machine learning, classification is the process of predicting a class label for a given input data. In this case, the input data is the measurements of an Iris flower, and the class label is the species of the flower. The goal is to train a model that can learn the relationship between the measurements and the species and then use that knowledge to accurately predict the species of new, unseen flowers based on their measurements.

To accomplish this goal, we will need to follow a series of steps, such as loading the data, splitting it into training and testing sets, building and training a model, making predictions on the test data, and evaluating the model's performance. By following these steps, we can train a machine learning model that is capable of accurately classifying Iris flowers based on their measurements.

The Dataset

The dataset consists of 150 instances, or data points, each with four features (attributes) and one class label. The four features are:

- Sepal length: the length of the sepal, measured in centimeters
- Sepal width: the width of the sepal, measured in centimeters
- Petal length: the length of the petal, measured in centimeters
- Petal width: the width of the petal, measured in centimeters

The class label is the species of Iris flower: Iris setosa, Iris virginica, or Iris versicolor.

Credit

Aier, S. & Mayer, S. (2022, September 24-28). Data Science. *Fundamentals and Methods of Computer Science*. University of St. Gallen, Switzerland.

In [1]:
```python
# These are the necessary imports for the following code
%matplotlib inline
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.datasets import load_iris
```

In [2]:
```python
# As an example dataset we use the Iris dataset (https://archive.ics.uci.edu) loaded through sklearn.datasets:
iris = load_iris()
```

In [3]:
```python
# In the following lines we prepare the dataframe as well as the right labels
df = pd.DataFrame(iris.data, columns = iris.feature_names)
df['target'] = iris.target
df['target'].replace(0, "setosa", inplace=True)
df['target'].replace(1, "versicolor", inplace=True)
df['target'].replace(2, "virginica", inplace=True)
X = iris.data
df.head()
```

Out[3]:

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	target
0	5.1	3.5	1.4	0.2	setosa
1	4.9	3.0	1.4	0.2	setosa
2	4.7	3.2	1.3	0.2	setosa
3	4.6	3.1	1.5	0.2	setosa
4	5.0	3.6	1.4	0.2	setosa

In [4]:
```python
# Here we show the dimensions of the Dataframe
# The output is in the format (lines, columns)
df.shape
```

Out[4]:
```
(150, 5)
```

In [5]:
```python
# Creating a dictionary for the species to make later results easier to interpret
lookup_iris_target = dict(enumerate(df.target.unique()))
lookup_iris_target
```

Out[5]:
```
{0: 'setosa', 1: 'versicolor', 2: 'virginica'}
```

In [6]:
```python
# In the following cells we create a test split:
```

In [7]:
```python
# Preparing a variable for the feature columns
X = df[['sepal length (cm)', 'sepal width (cm)', 'petal length (cm)', 'petal width (cm)']]

# Preparing a variable for the species ('target') column
y = df['target']
```

In [8]:
```python
# Actually creating the split
# We use a test split size of 30% at first and a random state of 0
X_train, X_test, y_train, y_test =  train_test_split(X, y, test_size=0.30, random_state=0)
```

In [9]:
```python
# In the following cells we implement the k-NN-algorithm which is a non-parametric supervised learning method:
```

In [10]:
```python
from sklearn.neighbors import KNeighborsClassifier

# We go for the next 3 Neighbours, but it would be possible to set other values to n_neighbors
knn = KNeighborsClassifier(n_neighbors = 3)
```

In [11]:
```python
# Here we train the the classifier using the fit()-method
knn.fit(X_train, y_train)
```

Out[11]:
```
KNeighborsClassifier(n_neighbors=3)
```

In [12]:
```python
# Here we test the performance of the classifier
# The output is the percentage of correctly guessed test samples
knn.score(X_test, y_test)
```

Out[12]:
```
0.9777777777777777
```

In [13]:
```python
# In the next cells we create a confusion matrix which allows us to track exactly how many of which species were guessed right:
```

In [14]:
```python
from sklearn.metrics import confusion_matrix
```

In [15]:
```python
# Here we prepare the needed variables
predicted = knn.predict(X=X_test)
expected = y_test
```

In [16]:
```python
# Here we create the confusion matrix
confusion = confusion_matrix(y_true=expected, y_pred=predicted)
```

In [17]:
```python
# For more info on confusion matrixes go to: https://towardsdatascience.com/understanding-confusion-matrix-a9ad42dcfd62
# The Output is structered like the following example:
# 1st column: which were predicted as setosa?
# 1st row: which are actually setosa?
confusion
```

Out[17]:
```
array([[16,  0,  0],
       [ 0, 17,  1],
       [ 0,  0, 11]], dtype=int64)
```

In [18]:
```python
# In the following cells we create a classification_report:
```

In [19]:
```python
from sklearn.metrics import classification_report
```

In [20]:
```python
# Here we use the previously created dictionary for the species names in preparation of the report
names = [lookup_iris_target[i] for i in range(len(lookup_iris_target))]
names
```

Out[20]:
```
['setosa', 'versicolor', 'virginica']
```

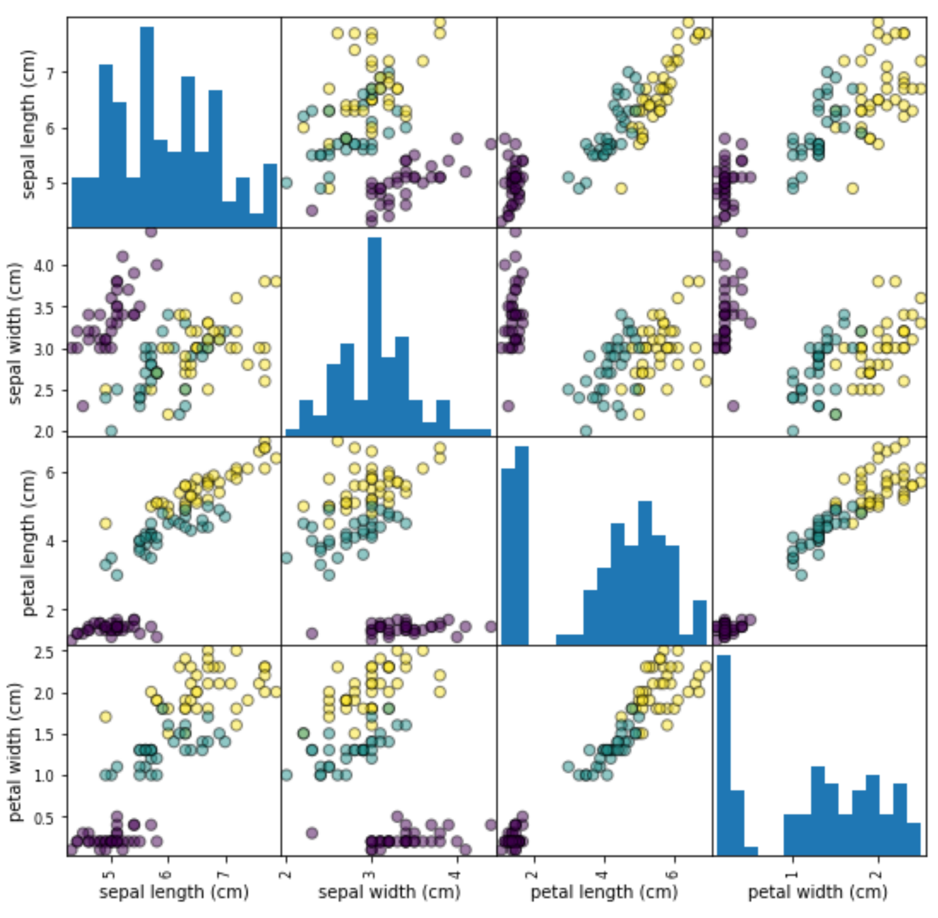
In [21]:
```python
# Here we print out the classification report using the method imported above
print(classification_report(expected, predicted,
       target_names=names))
```

```
              precision    recall  f1-score   support

      setosa       1.00      1.00      1.00        16
  versicolor       1.00      0.94      0.97        18
   virginica       0.92      1.00      0.96        11

    accuracy                           0.98        45
   macro avg       0.97      0.98      0.98        45
weighted avg       0.98      0.98      0.98        45
```

In [22]:
```python
# About the Output:
# precision: from all the observations we have predicted, which are actually right? --> 100%
# recall: from all the versicolor, how many have been predicted as versicolor? --> 94 %
# macro avg = (1.00+0.97+0.96+)/3 => 0.9766
# weighted avg = 1.00 x 16/45 + 0.97 x 18/45 + 0.96 x 11/45 => 0.98
```

In [23]:
```python
# In the following cells we examine the data and plot it through various methods:
```

In [24]:
```python
import seaborn as sns
import matplotlib.pylab as plt
import numpy as np

# Plotting the scatter matrix
y_train_local = y_train.replace({'setosa' : 0, 'versicolor' : 1, 'virginica' : 2})
scatter = pd.plotting.scatter_matrix(X_train, c= y_train_local, s=40,  marker = 'o', edgecolor='black', hist_kwds={'bins':15}, figsize=(9,9))
```



In [25]:
```python
# In the next part of the project we classify new, previously unseen objects:
```

In [26]:
```python
# Now we are creating data for a plant

my_columns=['sepal length (cm)', 'sepal width (cm)', 'petal length (cm)', 'petal width (cm)']

# The measurements used shouldnt be mistaken for real data
example_iris_1 = pd.DataFrame([[5.4, 4.1, 1.36, 0.18]], columns=my_columns)

print(example_iris_1)
```

```
   sepal length (cm)  sepal width (cm)  petal length (cm)  petal width (cm)
0                5.4               4.1               1.36              0.18
```

In [27]:
```python
# Now we can let the algorithm guess the species

iris_prediction = knn.predict(example_iris_1)
print(iris_prediction)
```

```
['setosa']
```

In [28]:
```python
# Another example with different plant data

example_iris_2 = pd.DataFrame([[6.15, 3.56, 4.98, 1.95]], columns=my_columns) # the measurements used shouldnt be mistaken for actual data
print(example_iris_2)
```

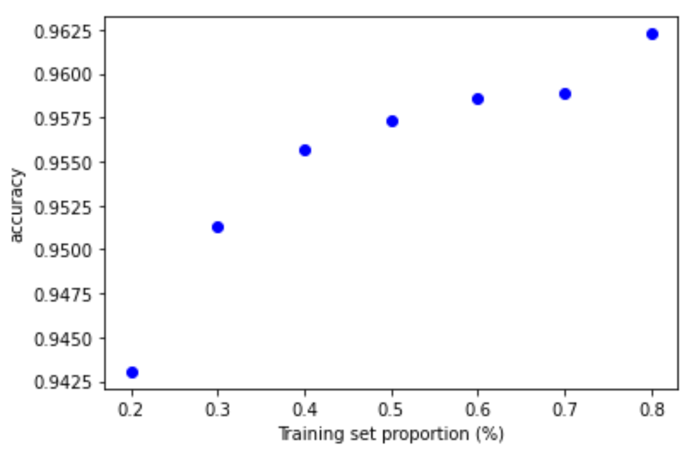
```
   sepal length (cm)  sepal width (cm)  petal length (cm)  petal width (cm)
0               6.15              3.56               4.98              1.95
```

In [29]:
```python
# Now we can let the algorithm also guess this species

iris_prediction = knn.predict(example_iris_2)
print(iris_prediction)
```

```
['versicolor']
```

In [30]:
```python
# In the following part we visualise the outcomes with different split proportions:
```

In [31]:
```python
# Creating a needed Variable
t = [0.8, 0.7, 0.6, 0.5, 0.4, 0.3, 0.2]

# Here we use k = 3 for simplicity
knn = KNeighborsClassifier(n_neighbors = 3)

plt.figure()

# Appending different scores for different test splits
for s in t:
    scores = []
    for i in range(1,1000):
        X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 1-s)
        knn.fit(X_train, y_train)
        scores.append(knn.score(X_test, y_test))
    plt.plot(s, np.mean(scores), 'bo')

# Adding the right labels
plt.xlabel('Training set proportion (%)')
plt.ylabel('accuracy');
```



In [32]:
```python
# In the following part we visualise the different outcomes with different values for k:
```

In [33]:
```python
# Creating needed variables
k_range = range(1,20)
scores = []

# Appending the different scores for different k-values
for k in k_range:
    knn = KNeighborsClassifier(n_neighbors = k)
    knn.fit(X_train, y_train)
    scores.append(knn.score(X_test, y_test))

# Preparing the format of the figure
plt.figure()
plt.xlabel('k')
plt.ylabel('accuracy')
plt.scatter(k_range, scores)
plt.xticks([0,5,10,15,20]);
```