Modelling of Cognitive Processes

Delta learning

Lesson 08
12/11/2019
Pieter Huycke

Overview

Theoretical

- $scikit - learn?$

Practical

1. Florence + the machine: novice
2. The iris dataset: journeyman
3. The iris dataset: adept
4. The digits dataset: expert

Theory

What?

Let's take a look at their own definition of what this package is about ⬇

In [1]:
```python
import sklearn

print(sklearn.__doc__)
```

```
Machine learning module for Python
==================================

sklearn is a Python module integrating classical machine
learning algorithms in the tightly-knit world of scientific Python
packages (numpy, scipy, matplotlib).

It aims to provide simple and efficient solutions to learning problems
that are accessible to everybody and reusable in various contexts:
machine-learning as a versatile tool for science and engineering.

See http://scikit-learn.org for complete documentation.
```

Why?

Advantages

- One can use $scikit-learn$ for modelling purposes, as we will be doing in a moment
  - $scikit-learn$ was originally built for machine learning efforts though
- It can be used for larger scale problems (e.g. process large amounts of input to the model)
- As it is a well-known package in (computational) science, knowledge of this package is a valuable skill to have

Disadvantages

- Sometimes $scikit-learn$ operates like a black box
- The functions are predefined, so you might not find what you are looking for exactly

How?

You can install $scikit - learn$ in your Anaconda environment using the following steps:

1. Check if $scikit - learn$ is already installed by executing the following in your **Spyder console**

```
import sklearn
```

2. If this throws no errors, you can stop reading
3. If you are here, this means that you should close spyder, and open an **Anaconda prompt**
4. In the prompt, type the following:

```
conda install -c anaconda scikit-learn
```

5. Now type

```
spyder
```

6. In the new instance of Spyder, try *step 2* and *step 3* again

If this did not work out for you, raise your hand and ask for help

Practical

1. Florence + the machine: novice

Florence: the recap

Quick recap of the previous practical session:

- We had two patterns we wanted to associated with each other using Delta learning
  - We had a pattern which represented an image of florence + the machine
    - `image_florence = [.99, .01, .99, .01, .99, .01]`
  - Additionally, we had a pattern which represented an song of the same group
    - `song_stand_by_me = [.99, .99, .01, .01]`
- To perform the Delta learning, we used custom-made code
- We succeeded to learn the association between the two patterns using Delta learning

Making the old code work

Now, we will adapt and extend the code from the previous practical and use $scikit-learn$ to perform learning.
Below, we define a list of adaptations that has to be completed to make sure the code from the previous practical works using $scikit-learn$

Adaptations to be done

1. The output should be a 1D array, meaning that we cannot work with patterns like `song_florence` anymore.
   Instead, we should work with integer values (i.e. `song_florence = 1`).
   To convert an array to a 1D array, use the NumPy function `np.ravel()`.
2. Note that $scikit-learn$ works best with NumPy arrays.
   So, the variables `image_florence` and `song_florence` should be converted to NumPy arrays.
3. The input should be an $N \times P$ array.
   Here, N represents how many times the pattern is shown to the model.
   In contrast, P is the length of the pattern.

    - So, if we showed the image 50 times, this would result in an array with dimensions 50×6.

Extensions to be done

1. Because `scikit-learn` works only when instances from several **different** classes are offered, we will add another group image, and their associated label.
   - Add a variabel refering to the image of your favorite group: `groupname = np.array([.01, .99, .01, .99, .01, .99])`
2. Add a label associated with this new group: `songname = 0`.
3. We will use $N = 50$, meaning that we will show each image 50 times to the model.
4. Link the associated label with each image, meaning that the model should react 0 if the image of florence is shown, and 1 if the image of the other group is presented.
5. Comply with the needed array notation defined in *steps 2 & 3* from the *Adaptations* list.
6. Find a way to shuffle the input array and the output array **together**.
7. Use 75% of the input array to train your model, and test performance on the other 25%.

Florence: the modelling aproach

Our action plan:

1. Open **'ch4_florence_sklearn_exercise.py'**
2. Fill in the blanks using the aforementioned explanation and the comments
    - Mind that *how* you fill in the blanks does not matter, **what matters is that it works...**
3. Stuck? Google is your friend 😉
4. Really stuck? Ask us!

2. The iris dataset: journeyman

Iris dataset?

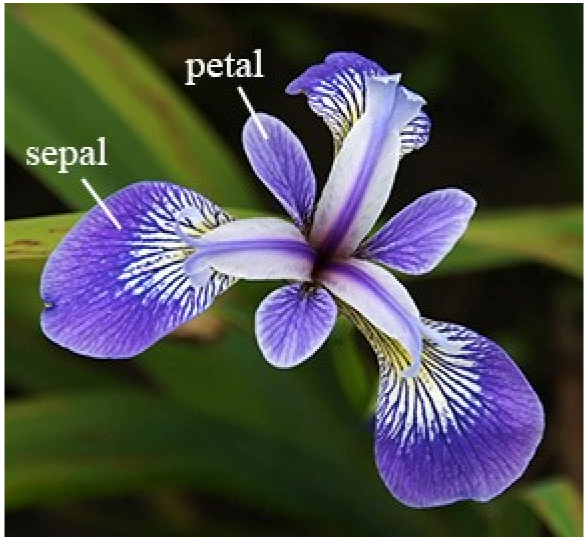
In this exercise, we will use the iris dataset [(Fisher, 1936) (https://onlinelibrary.wiley.com/doi/epdf/10.1111/j.1469-1809.1936.tb02137.x)](https://onlinelibrary.wiley.com/doi/epdf/10.1111/j.1469-1809.1936.tb02137.x).
More specifically, we will use this dataset to **predict the species** of the flower **based on the features** of the flower.

The dataset consists of 150 rows, where each row represents measurements of 150 different flowers.
Each flower is different, but they all belong to the same family: "iris".
There are 3 different species in the dataset, so we have 50 different flowers for each family.

The data available 🌹

- Features of the flower
    - Sepal width
    - Sepal length
    - Petal width
    - Petal length
- The name of the flower
    - Iris setosa
    - Iris vericolor
    - Iris virginica

An example of the provided features



Our question

What iris *type (setosa*, *virginica or versicolor?)* is this based on the provided measures?

In [6]:

```
# import modules
import pandas as     pd
from   sklearn import datasets

# import the Iris flower dataset
iris        = datasets.load_iris()
X           = iris.data
y           = iris.target
class_names = iris.target_names

# glue data together
y           = np.reshape(y,
                          (150, 1))
data_shown  = np.concatenate((X, y),
                              axis = 1)
iris_visual = pd.DataFrame(data_shown)

# make column names
colnames            = ['sep len', 'sep wid',
                       'pet len', 'pet wid',
                       'family']
iris_visual.columns = colnames
```

In [7]:

```python
# show me the way (first 10 rows)
print('First 5 observations:\n', iris_visual[:5])
print('\nLast 5 observations:\n',iris_visual[-5:])
```

```
First 5 observations:
    sep len  sep wid  pet len  pet wid  family
0       5.1      3.5      1.4      0.2     0.0
1       4.9      3.0      1.4      0.2     0.0
2       4.7      3.2      1.3      0.2     0.0
3       4.6      3.1      1.5      0.2     0.0
4       5.0      3.6      1.4      0.2     0.0

Last 5 observations:
      sep len  sep wid  pet len  pet wid  family
145       6.7      3.0      5.2      2.3     2.0
146       6.3      2.5      5.0      1.9     2.0
147       6.5      3.0      5.2      2.0     2.0
148       6.2      3.4      5.4      2.3     2.0
149       5.9      3.0      5.1      1.8     2.0
```

...?

Our goal is to predict the family based on the provided features.
So, if we see the following:

```
In [9]: X[10,:]
Out[9]: array([5.4, 3.7, 1.5, 0.2])

In [10]:y[10]
Out[10]: 0
```

We know that flower 11 has a sepal length of 5.4 cm, sepal width of 3.7 cm ... .
We also know that flower 11 belongs to family 0 (i.e. setosa).

Ideally, our model would be able to predict the family based on the features for every flower.
So, if we give the model the features for flower 62:

```
In [16]: X[61,:]
Out[16]: array([5.9, 3. , 4.2, 1.5])
```

we want to output of the model to be equal to 1 (i.e. versicolor), which is the observed family for flower 62.

The modelling perspective

So, why the iris dataset?
When doing computational modelling, we might be interested in the processes behind object recognition.
In that case, we might train a model that is able to recognize flowers based on certain flower characteristics.
Additionally, we might even go further, and model how someone becomes an expert in recognizing flowers, what happens when we presents other objects to a flower expert ...

Now that the reason we use the iris dataset is (hopefully) clear, we move on to the actual exercise.

The iris dataset: journeyman

Problem statement

Your task is to implement an algorithm in Python that is able to successfully separate flowers belonging to the **setosa** and **virginica** family, and to find out whether this task is linearly separable or not.
For now, we will use the entire Iris dataset, but we ask you to relabel the observations belonging to the 'versicolor' family to 'virginica'.

In line with the previous exercise, you should train your model on part of the data, and after training test the model on the rest of the data (extra: look for a built-in function in $scikit - learn$ that is able to shuffle and split the data in a training - and a testing part).

Print your classification accuracy at the end of your script, and infer based on your results whether your algorithm succeeded or not.

The iris dataset: adept

The iris dataset: adept

Note: no start script is provided as this script relies partly on the code from previous exercises.

<u>Problem statement</u>

As we already saw in the theoretical part about delta learning, this learning algorithm only works when the provided inputs are linearly separable. For this assignment, we ask you to find out which flower families are linearly separable. Thus, can a delta learning algorithm separate setosa from virginica, or setosa from versicolor...?

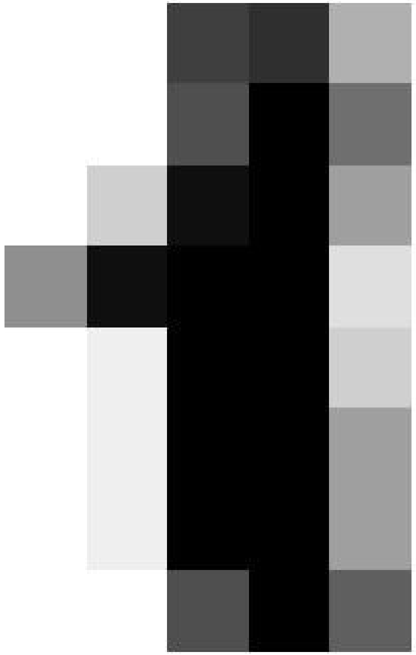
Write a script that loops over each family comparison 50 times to account for variability in data shuffling and data splitting (in line with this, *don't use a random seed*). Store the accuracies of your model predictions in a `Pandas.DataFrame`. Compute the minimal accuracy across simulations for each family comparison, and determine based on this which flower families are linearly separable, and which ones are not.

The desired output DataFrame should be of the form 50×3, where 50 represents the amount of simulations, and 3 represents the amount of category comparisons that are made.

The digits dataset: expert

The digits dataset

This dataset is made up of 1797 8×8 images.
Each image, like the one shown below (representing number 1), is of a hand-written digit.
The dataset is included in `sklearn.datasets`. Additional information can be found on [this webpage (https://archive.ics.uci.edu/ml/datasets/Pen-Based+Recognition+of+Handwritten+Digits)](https://archive.ics.uci.edu/ml/datasets/Pen-Based+Recognition+of+Handwritten+Digits).



The digits dataset

We can see that this array $1797 \times 8 \times 8$ represents 1797 images, each image being a square of 8×8 representing pixel values.
Here, larger values represent darker pixels, so:

- `image[0, 0, 0] == 0.0` ➡️ this pixel will be plotted in white
- `image[0, 4, 2] == 8.0` ➡️ this pixel will be plotted in gray
- `image[0, 1, 3] == 15.0` ➡️ this pixel will be plotted in black

We illustrate this point immediately below

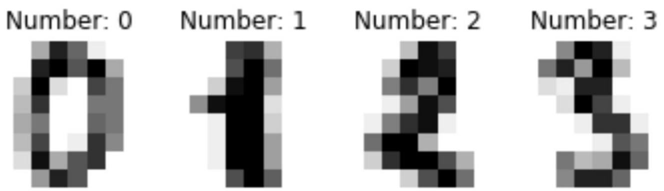
In [27]:

```
# showing dims
print("Dimensions of the input data: ", X.shape)

# concatenate elements row wise + select first four
images_and_labels = list(zip(X, y))
first_four        = images_and_labels[:4]

# plot the first four elements in the dataset
for index, (image, label) in enumerate(first_four):
    plt.subplot(1, 4, index + 1)
    plt.axis('off')
    plt.imshow(image,
               cmap          = plt.cm.gray_r,
               interpolation = 'nearest')
    plt.title('Number: %i' % label)
```

```
Dimensions of the input data:  (1797, 8, 8)
```



The digits dataset: expert

Note: no start script is provided as this is an expert exercise, good luck! 🤖

Problem statement

Image processing is a valuable skill to have, so in this exercise, we ask you to load in the digits dataset available in the standard version of $scikit - learn$. Your goal is straightforward: process the images, feed them to a delta learning algorithm, and check whether your model is able to say the correct number for each inputted image.

Think about the logical steps that you should take to succeed in this exercise.
What does your delta learning model need? How should the input to the model look like?

Is classification of images a linearly separable problem or not?