PALMER PENGUINS DATABASE MACHINE LEARNING IMPLEMENTATION WITH NEURAL NETWORKS IN PYTHON

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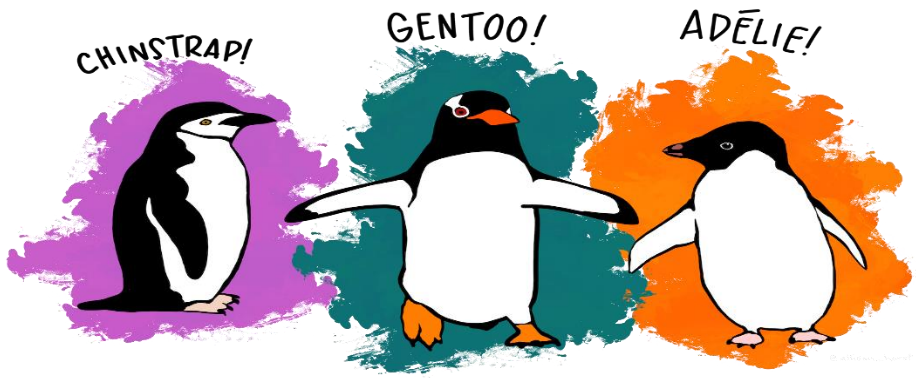
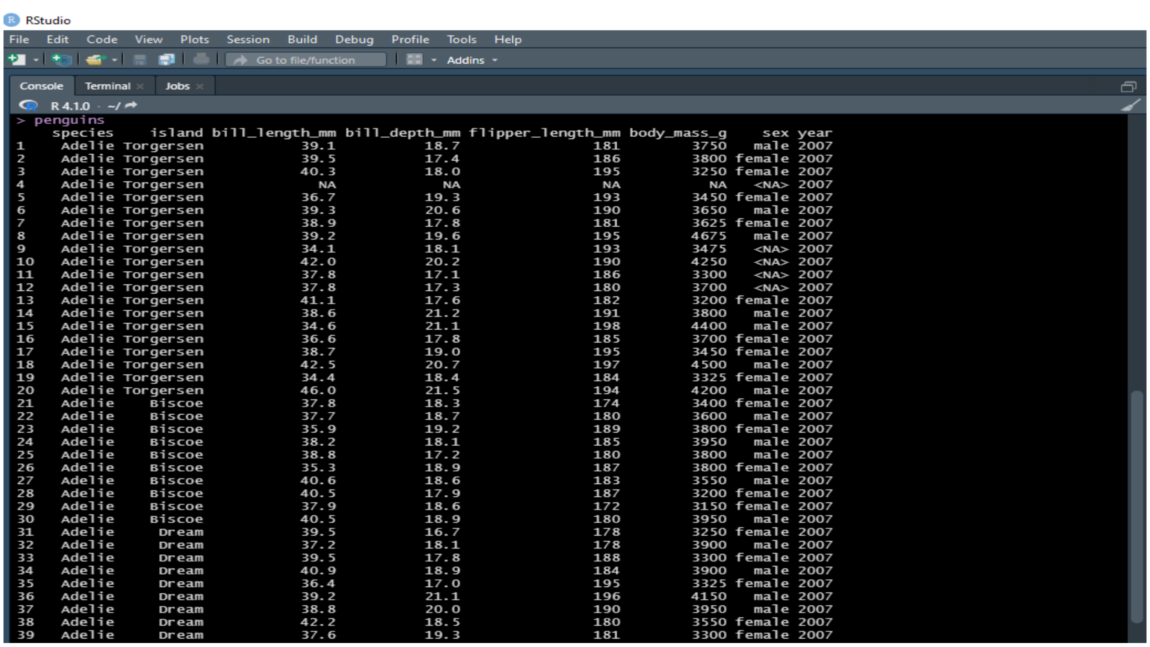


INTRODUCTION

The Palmer Penguins' dataset is a nice alternative to the Iris dataset commonly used in all machine learning examples. This dataset has data for 3 penguin species: Adélie, Chinstrap and Gentoo. By taking bill and flipper length measured in millimeters it is possible to classify a penguin. In this report I'll explain how my model works and the steps to clean, preprocess and train the dataset and finally predict and get precision percentage with train and test data.

DATA EXTRACTION FROM R FILE

I used RStudio to download the database in order to export it as a .CSV file.



Then looked for the .CSV path and opened it.

```
> path_to_file("penguins.csv")
[1] "D:/Documentos/R/win-library/4.1/palmerpenguins/extdata/penguins.csv"
> |
```

DATABASE ANALYSIS

Decided to check the dataset and noticed there were 8 columns with 344 rows. According to theory this is a small dataset and some parameters for the implemented neural network should be changed. But first I created a Jupyter Notebook for my Python program.

IMPLEMENTED MODEL

Neural networks are without a doubt one of the best models from Machine Learning to predict data so I needed to use *sklearn* library and a few others like *pandas* and *numpy*.

The neural network has 3 hidden layers with 15 neurons in each one with two X1 and X2 input values (bill length and flipper length).

TRAINING DATA AND TEST DATA

Data was cleaned because it had NaN values in some rows and got 333 rows with valid data as my 100%. I could have taken 60% or 80% but I finally took 70% as my training data which has 233 rows.

The dataset was split into two: **data** and **backup**. 'data' is 70% of the original dataframe and 'backup' 100%. Before splitting I shuffled the rows to get a better extraction of data and not mostly Adélie and Gentoo rows, that will help a lot to get a better trained model.

I highly recommend checking the program comments to get a better understanding of every single step to clean, split and backup the dataframe but here's a list of functions I used to make this work.

- pd.isnull(data["bill_length_mm])
- data.dropna()
- sk.utils.shuffle()
- data.reset_index(inplace = True, drop =True)
- data.copy()

After that I needed to set my X and Y values for input and expected predictions so I took the species column and used a LabelEncoder() to assign numerical values instead of words, this gave me a set of 3 ID's for species: 0-Adélie, 1-Chinstrap, 2-Gentoo stored in sp column.

Both bill length and flipper length already have float values, so those rows won't be changed. Encoding was applied for <u>backup</u> and <u>data</u> because I needed that column for both datasets and get my precision percentage at the end of my program.

MULTI-LAYER PERCEPTRON SETTING

Train and test data are stored in Xtrain and Xtest, <u>sp</u> column (which has species id's) is stored in Ytrain and Ytest. Preprocessing that data was important so I used a StandardScaler to fit Xtrain and Xtest to get better predictions.

My neural network was created with MLPClassifier with a few modified parameters (check program for more details) and then trained the model.

PREDICTIONS WITH 70% TRAINED DATA

After training with only 70% original data, I stored all predictions for every pair of values in <u>predictions</u>, then checked if first and last element predictions were correct, and finally a prediction with random values and the model predicted it perfectly, it was a Gentoo.

```
[0 1]
[2]
[0 2 1 1 1 2 0 0 0 2 2 2 2 0 1 2 0 2 2 1 2 1 1 0 0 1 2 0 1 2 0 0 2 2 2 2 2
 2 2 0 2 1 0 0 1 2 2 2 0 2 1 2 1 0 2 0 0 0 2 2 2 2 2 0 1 2 0 0 1 0 2 0 0 0
 2 0 2 2 2 1 1 2 0 2 1 2 0 1 2 0 0 1 0 0 2 1 0 0 2 2 2 0 2 0 2 0 2 0 0 0 1
 0 2 0 0 0 2 2 1 0 1 2 0 2 1 0 2 1 2 2 1 0 0 0 0 2 2 2 0 2 0 2 2 0 0 1 0 0
 2 0 1 2 0 1 0 2 2 2 2 0 0 2 0 0 1 2 0 1 2 1 1 2 0 0 0 1 2 2 0 0 1 0 2 1 0
 0 2 2 0 1 1 1 1 0 0 0 0 0 2 0 2 0 2 0 0 2 0 0 0 2 0 1 2 1 1 0 0 1 0 0 1 0
 1 2 2 0 0 2 1 1 0 0 1]
```

MODEL PRECISION WITH 70% DATA

To get my precision values for the model I used a classification_report with Ytrain and my predictions list.

This is the output:

```
              precision    recall  f1-score   support

           0       0.99      0.99      0.99        97
           1       0.98      0.98      0.98        50
           2       1.00      1.00      1.00        86

   micro avg       0.99      0.99      0.99       233
   macro avg       0.99      0.99      0.99       233
weighted avg       0.99      0.99      0.99       233
```

PREDICTIONS WITH 100% TEST DATA

I stored my final predictions with test data (Xtest and Ytest) in final_predictions

This is the output (remember this is for 333 rows):

```
[2 2 2 0 1 2 0 0 2 2 0 1 1 0 2 1 2 1 0 2 2 2 1 1 2 0 0 0 1 2 0 0 2 1 0 0 2
 1 2 0 1 1 0 0 0 2 2 2 0 2 0 0 2 2 0 2 0 0 1 0 2 1 0 0 0 2 1 2 2 2 1 2 0 1
 2 2 0 2 2 0 1 2 0 2 2 2 1 1 2 0 0 0 2 2 0 1 1 0 0 0 0 2 2 2 0 1 0 2 2 0 0
 0 1 0 2 0 1 2 2 0 2 0 2 0 2 2 2 0 0 0 1 0 0 0 2 0 0 2 1 2 0 2 1 0 0 2 2 2
 1 1 0 0 0 1 2 2 0 1 0 2 0 2 2 0 1 0 2 0 2 0 0 2 0 2 0 2 0 0 0 0 2 2 0 0 1
 1 0 2 2 0 2 0 0 0 0 0 1 1 2 2 1 0 0 2 0 0 0 1 2 2 2 1 1 1 0 2 2 0 2 0 0 2
 2 0 0 1 0 1 1 0 2 0 2 0 2 2 0 2 0 2 1 2 0 2 2 0 2 0 0 0 1 0 0 2 0 0 0 0 2
 1 0 2 1 0 2 2 0 2 2 2 0 1 2 1 0 0 2 0 0 1 0 2 1 1 0 0 2 0 2 1 1 2 2 2 2 0
 2 0 0 2 0 0 0 0 2 1 1 2 0 0 2 0 1 0 2 1 1 0 1 0 0 0 0 2 0 0 1 0 1 2 0 1 2]
```

MODEL PRECISION WITH 100% TEST DATA

My classification report showed that precision was slightly changed but it was without a doubt a good percentage.

```
              precision    recall  f1-score   support

           0       0.97      0.98      0.97       146
           1       0.94      0.93      0.93        68
           2       0.99      0.98      0.99       119

   micro avg       0.97      0.97      0.97       333
   macro avg       0.97      0.96      0.96       333
weighted avg       0.97      0.97      0.97       333
```

MAKING A LIST WITH INPUT VALUES AND PREDICTED SPECIES

Just wrote a bit of code to store backup's bill length, flipper length and predicted species values in _list[] and then just printed it.

```
[[35.1, 193.0, 0], [46.3, 215.0, 2], [46.5, 213.0, 2], [41.1, 189.0, 0], [37.5, 199.0, 0], [48.7, 208.0, 2], [52.5, 221.0, 2],
[46.5, 192.0, 1], [39.0, 191.0, 0], [50.0, 218.0, 2], [40.8, 195.0, 0], [46.8, 189.0, 1], [46.4, 191.0, 1], [51.0, 203.0, 1],
[40.3, 195.0, 0], [42.0, 200.0, 0], [49.6, 225.0, 2], [36.0, 190.0, 0], [39.6, 186.0, 0], [42.6, 213.0, 2], [47.3, 222.0, 2],
[47.2, 214.0, 2], [40.6, 183.0, 0], [37.8, 193.0, 0], [37.7, 180.0, 0], [38.6, 199.0, 0], [38.6, 188.0, 0], [35.0, 192.0, 0],
[47.4, 212.0, 2], [46.5, 217.0, 2], [50.8, 201.0, 1], [55.8, 207.0, 1], [42.9, 215.0, 2], [48.4, 213.0, 2], [50.4, 224.0, 2],
[37.6, 185.0, 0], [45.7, 193.0, 1], [45.5, 214.0, 2], [48.1, 199.0, 1], [45.8, 210.0, 2], [45.7, 195.0, 1], [38.9, 190.0, 0],
[43.2, 187.0, 1], [49.2, 195.0, 1], [41.1, 188.0, 0], [36.5, 182.0, 0], [43.5, 213.0, 2], [51.5, 230.0, 2], [39.6, 186.0, 0],
[45.3, 210.0, 2], [46.2, 217.0, 2], [35.2, 186.0, 0], [44.9, 212.0, 2], [42.5, 187.0, 1], [34.0, 185.0, 0], [36.5, 181.0, 0],
[47.5, 212.0, 2], [39.7, 190.0, 0], [39.5, 178.0, 0], [53.4, 219.0, 2], [42.1, 195.0, 0], [50.0, 230.0, 2], [37.9, 172.0, 0],
[50.9, 196.0, 1], [46.4, 221.0, 2], [50.8, 210.0, 1], [43.2, 192.0, 0], [41.5, 201.0, 0], [36.7, 193.0, 0], [51.7, 194.0, 1],
[36.0, 195.0, 0], [46.0, 194.0, 0], [51.3, 197.0, 1], [47.2, 215.0, 2], [39.6, 190.0, 0], [41.4, 202.0, 0], [50.8, 228.0, 2],
[46.8, 215.0, 2], [39.8, 184.0, 0], [50.5, 216.0, 2], [49.0, 212.0, 1], [45.2, 191.0, 1], [46.9, 222.0, 2], [40.8, 208.0, 0],
[55.9, 228.0, 2], [45.2, 223.0, 2], [48.5, 219.0, 2], [40.9, 187.0, 1], [41.5, 195.0, 0], [40.5, 187.0, 0], [37.0, 185.0, 0],
[39.6, 196.0, 0], [46.1, 215.0, 2], [38.7, 195.0, 0], [45.0, 220.0, 2], [47.6, 215.0, 2], [50.2, 198.0, 1], [42.3, 191.0, 0],
[41.1, 182.0, 0], [40.2, 193.0, 0], [40.9, 184.0, 0], [41.4, 191.0, 0], [54.2, 201.0, 1], [49.5, 200.0, 1], [45.5, 212.0, 2],
[50.9, 196.0, 1], [46.8, 215.0, 2], [41.8, 198.0, 0], [36.2, 187.0, 0], [45.9, 190.0, 1], [37.3, 199.0, 0], [52.1, 230.0, 2],
[42.5, 197.0, 0], [51.4, 201.0, 1], [59.6, 230.0, 2], [39.3, 190.0, 0], [42.7, 208.0, 2], [39.6, 191.0, 0], [36.6, 184.0, 0],
[46.7, 219.0, 2], [44.0, 208.0, 2], [38.1, 187.0, 0], [35.5, 190.0, 0], [46.4, 216.0, 2], [45.5, 196.0, 1], [50.0, 196.0, 1],
[47.5, 209.0, 2], [35.5, 195.0, 0], [48.2, 210.0, 2], [49.0, 216.0, 2], [38.5, 190.0, 0], [40.2, 200.0, 0], [45.7, 214.0, 2],
[51.5, 187.0, 1], [45.4, 188.0, 1], [40.5, 180.0, 0], [46.6, 193.0, 1], [50.0, 220.0, 2], [42.8, 209.0, 2], [42.5, 187.0, 1],
[44.5, 214.0, 2], [38.8, 191.0, 0], [49.6, 193.0, 1], [32.1, 188.0, 0], [45.1, 207.0, 2], [38.6, 191.0, 0], [41.3, 195.0, 0],
[37.0, 185.0, 0], [48.4, 203.0, 2], [39.7, 184.0, 0], [52.0, 201.0, 1], [47.8, 215.0, 2], [45.8, 219.0, 2], [52.0, 210.0, 1],
[35.7, 202.0, 0], [44.4, 219.0, 2], [33.1, 178.0, 0], [50.1, 190.0, 1], [41.6, 192.0, 0], [46.2, 187.0, 1], [50.7, 223.0, 2],
[52.2, 228.0, 2], [47.6, 195.0, 1], [48.5, 191.0, 1], [51.3, 193.0, 1], [36.4, 195.0, 0], [35.9, 189.0, 0], [47.0, 185.0, 1],
[47.7, 216.0, 2], [39.2, 190.0, 0], [43.6, 217.0, 2], [51.3, 198.0, 1], [49.2, 221.0, 2], [40.3, 196.0, 0], [46.6, 210.0, 2],
[49.8, 229.0, 2], [41.7, 210.0, 2], [34.6, 198.0, 0], [35.6, 191.0, 0], [50.5, 200.0, 1], [38.8, 180.0, 0], [36.8, 193.0, 0],
[36.3, 190.0, 0], [45.2, 215.0, 2], [37.6, 194.0, 0], [42.9, 196.0, 0], [34.6, 189.0, 0], [50.0, 224.0, 2], [43.3, 208.0, 2],
[48.5, 220.0, 2], [41.1, 192.0, 0], [41.1, 182.0, 0], [38.3, 189.0, 0], [37.7, 198.0, 0], [44.1, 210.0, 0], [33.5, 190.0, 0],
[50.7, 203.0, 1], [46.0, 195.0, 1], [40.9, 191.0, 0], [48.1, 209.0, 2], [50.5, 222.0, 2], [46.4, 190.0, 1], [45.3, 208.0, 2],
[48.7, 210.0, 2], [50.1, 225.0, 2], [38.2, 185.0, 0], [41.1, 205.0, 0], [48.4, 220.0, 2], [42.7, 196.0, 0], [39.7, 193.0, 0],
[43.2, 197.0, 0], [48.2, 221.0, 2], [50.3, 197.0, 1], [49.1, 220.0, 2], [36.2, 187.0, 0], [36.6, 185.0, 0], [46.2, 221.0, 2],
[39.1, 181.0, 0], [54.3, 231.0, 2], [45.1, 215.0, 2], [41.3, 194.0, 0], [38.9, 181.0, 0], [46.1, 178.0, 1], [49.1, 228.0, 2],
[47.5, 218.0, 2], [49.3, 203.0, 1], [39.5, 186.0, 0], [46.7, 195.0, 1], [34.5, 187.0, 0], [51.1, 225.0, 2], [46.2, 209.0, 2],
[50.5, 225.0, 2], [45.4, 211.0, 2], [41.1, 190.0, 0], [51.1, 220.0, 2], [49.5, 224.0, 2], [52.2, 197.0, 1], [37.7, 183.0, 0],
[39.5, 188.0, 0], [38.1, 181.0, 0], [49.9, 213.0, 2], [39.7, 193.0, 0], [45.2, 198.0, 1], [50.6, 193.0, 1], [45.8, 197.0, 0],
[42.2, 180.0, 0], [40.6, 187.0, 0], [42.8, 195.0, 0], [42.4, 181.0, 1], [49.7, 195.0, 1], [36.2, 187.0, 0], [48.8, 222.0, 2],
[52.8, 205.0, 1], [58.0, 181.0, 1], [50.5, 201.0, 1], [34.4, 184.0, 0], [40.2, 176.0, 0], [50.8, 226.0, 2], [40.6, 199.0, 0],
```

PRECISION PERCENTAGE

And finally I compared both final_predictions list (which has all predicted species from the original dataset) and species_backup (which has only the species numerical value from the original dataset) to get my final precision percentage.

```
percentage = len(set(final_predictions) & set(species_backup)) / float(len(set(final_predictions) | set(species_backup))) * 100
print("Precision percentage amongst lists: ",percentage)

Precision percentage amongst lists:  100.0
```

All penguins from the original dataset (100%) were perfectly classified according to the 70% trained data.

Precision percentage is equal to 100%.

CONCLUSION

Working with neural networks in Python to classify individuals is a great way to predict future data. With this code it is possible to process a bigger dataset and get good results. It is possible to change the neural networks architecture but with 3 hidden layers and less than 1000 max iterations works perfectly fine.