Ai_lab05_TahaAbbas_P200119

March 2, 2023

Lab 05 - Task

Perceptron algorithm to the Iris dataset

Load the iris dataset using scikit-learn library

Create a Pandas DataFrame with the dataset and add column names

Convert the problem into a binary classification problem by only considering two classes and removing the third one. For example, we can keep only "setosa" and "versicolor" classes and remove "virginica". Visualize the data using a scatter plot.

Split the data into train and test sets

Remove the target column from the train and test sets

Apply the built-in Perceptron algorithm from scikit-learn

Evaluate the accuracy, precision, recall, and F1 score of the model.

Apply the Perceptron algorithm from scratch using above code snippets

Evaluate the accuracy, precision, recall, and F1 score of the model.

[52]:
```
#imports
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.linear_model import Perceptron
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
 ↪f1_score
import pandas as pd
import numpy as np



# Visualization imports
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

[53]:
```
data = load_iris()
data
```

[53]:
```
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 'frame': None,
 'target_names': array(['setosa', 'versicolor', 'virginica'], dtype='<U10'),
 'DESCR': '.. _iris_dataset:\n\nIris plants
dataset\n--------------------\n\n**Data Set Characteristics:**\n\n    :Number of
Instances: 150 (50 in each of three classes)\n    :Number of Attributes: 4
numeric, predictive attributes and the class\n    :Attribute Information:\n
- sepal length in cm\n        - sepal width in cm\n        - petal length in
cm\n        - petal width in cm\n        - class:\n                - Iris-
Setosa\n                - Iris-Versicolour\n                - Iris-Virginica\n
\n    :Summary Statistics:\n\n    ============== ==== ==== ======= =====
====================\n                    Min  Max   Mean    SD   Class
Correlation\n    ============== ==== ==== ======= ===== ====================\n
sepal length:   4.3  7.9   5.84   0.83    0.7826\n    sepal width:    2.0  4.4
3.05   0.43   -0.4194\n    petal length:   1.0  6.9   3.76   1.76    0.9490
(high!)\n    petal width:    0.1  2.5   1.20   0.76    0.9565  (high!)\n
============== ==== ==== ======= ===== ====================\n\n    :Missing
Attribute Values: None\n    :Class Distribution: 33.3% for each of 3 classes.\n
:Creator: R.A. Fisher\n    :Donor: Michael Marshall
(MARSHALL%PLU@io.arc.nasa.gov)\n    :Date: July, 1988\n\nThe famous Iris
database, first used by Sir R.A. Fisher. The dataset is taken\nfrom Fisher\'s
paper. Note that it\'s the same as in R, but not as in the UCI\nMachine Learning
Repository, which has two wrong data points.\n\nThis is perhaps the best known
database to be found in the\npattern recognition literature.  Fisher\'s paper is
a classic in the field and\nis referenced frequently to this day.  (See Duda &
Hart, for example.)  The\ndata set contains 3 classes of 50 instances each,
where each class refers to a\ntype of iris plant.  One class is linearly
separable from the other 2; the\nlatter are NOT linearly separable from each
```

```
other.\n\n.. topic:: References\n\n   - Fisher, R.A. "The use of multiple
measurements in taxonomic problems"\n     Annual Eugenics, 7, Part II, 179-188
(1936); also in "Contributions to\n     Mathematical Statistics" (John Wiley,
NY, 1950).\n   - Duda, R.O., & Hart, P.E. (1973) Pattern Classification and
Scene Analysis.\n     (Q327.D83) John Wiley & Sons.  ISBN 0-471-22361-1.  See
page 218.\n   - Dasarathy, B.V. (1980) "Nosing Around the Neighborhood: A New
System\n     Structure and Classification Rule for Recognition in Partially
Exposed\n     Environments".  IEEE Transactions on Pattern Analysis and
Machine\n     Intelligence, Vol. PAMI-2, No. 1, 67-71.\n   - Gates, G.W. (1972)
"The Reduced Nearest Neighbor Rule".  IEEE Transactions\n     on Information
Theory, May 1972, 431-433.\n   - See also: 1988 MLC Proceedings, 54-64.
Cheeseman et al"s AUTOCLASS II\n     conceptual clustering system finds 3
classes in the data.\n   - Many, many more …',
 'feature_names': ['sepal length (cm)',
  'sepal width (cm)',
  'petal length (cm)',
  'petal width (cm)'],
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```

[54]:
```
data.keys()
```

[54]:
```
dict_keys(['data', 'target', 'frame', 'target_names', 'DESCR', 'feature_names',
'filename', 'data_module'])
```

[55]:
```
data.data
```

[55]:
```
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       [5.9, 3. , 5.1, 1.8]])
```

[56]:
```
data.feature_names
```

[56]:
```
['sepal length (cm)',
 'sepal width (cm)',
 'petal length (cm)',
 'petal width (cm)']
```

[57]:
```
df = pd.DataFrame(data.data, columns = data.feature_names)
#df['target'] = data.target
```

```
df.head()
```

[57]:

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

[58]:
```
#columns= data['feature_names'] + ['target']
```

[59]:
```
category=[]
for i in data.target:
    category.append(data.target_names[i])

print(category)
```

```
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'versicolor', 'versicolor', 'versicolor', 'versicolor', 'versicolor',
'versicolor', 'versicolor', 'versicolor', 'versicolor', 'versicolor',
'versicolor', 'versicolor', 'versicolor', 'versicolor', 'versicolor',
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'versicolor', 'versicolor', 'versicolor', 'versicolor', 'versicolor',
'versicolor', 'versicolor', 'versicolor', 'versicolor', 'versicolor',
'versicolor', 'virginica', 'virginica', 'virginica', 'virginica', 'virginica',
'virginica', 'virginica', 'virginica', 'virginica', 'virginica', 'virginica',
'virginica', 'virginica', 'virginica', 'virginica', 'virginica', 'virginica',
'virginica', 'virginica', 'virginica', 'virginica', 'virginica', 'virginica',
'virginica', 'virginica', 'virginica', 'virginica', 'virginica', 'virginica',
'virginica', 'virginica', 'virginica', 'virginica', 'virginica', 'virginica',
'virginica', 'virginica', 'virginica', 'virginica', 'virginica', 'virginica',
'virginica', 'virginica', 'virginica', 'virginica', 'virginica', 'virginica',
'virginica', 'virginica', 'virginica']
```

[60]:
```
len(category)
```

[60]: 150

[61]:
```
len(df)
```

[61]:
```
150
```

[62]:
```
df['labels'] = category
```

[63]:
```
df.head()
```

[63]:
```
   sepal length (cm)  sepal width (cm)  petal length (cm)  petal width (cm)  \
0                5.1               3.5                1.4               0.2
1                4.9               3.0                1.4               0.2
2                4.7               3.2                1.3               0.2
3                4.6               3.1                1.5               0.2
4                5.0               3.6                1.4               0.2

   labels
0  setosa
1  setosa
2  setosa
3  setosa
4  setosa
```

[64]:
```
len(df)
```

[64]:
```
150
```

[65]:
```
df.shape
```

[65]:
```
(150, 5)
```

[66]:
```
#df.iloc[start_row_index:end_row_index, start_column_index:end_column_index]
df.iloc[0:100, :]
```

[66]:
```
    sepal length (cm)  sepal width (cm)  petal length (cm)  petal width (cm)  \
0                 5.1               3.5                1.4               0.2
1                 4.9               3.0                1.4               0.2
2                 4.7               3.2                1.3               0.2
3                 4.6               3.1                1.5               0.2
4                 5.0               3.6                1.4               0.2
..                ...               ...                ...               ...
95                5.7               3.0                4.2               1.2
96                5.7               2.9                4.2               1.3
97                6.2               2.9                4.3               1.3
98                5.1               2.5                3.0               1.1
99                5.7               2.8                4.1               1.3

        labels
```

```
0       setosa
1       setosa
2       setosa
3       setosa
4       setosa
..         …
95  versicolor
96  versicolor
97  versicolor
98  versicolor
99  versicolor

[100 rows x 5 columns]
```

[67]:
```
dfcopy = (df.iloc[0:100, :].copy())
```

[68]:
```
df.head()
```

[68]:
```
   sepal length (cm)  sepal width (cm)  petal length (cm)  petal width (cm)  \
0                5.1               3.5                1.4               0.2
1                4.9               3.0                1.4               0.2
2                4.7               3.2                1.3               0.2
3                4.6               3.1                1.5               0.2
4                5.0               3.6                1.4               0.2

   labels
0  setosa
1  setosa
2  setosa
3  setosa
4  setosa
```

[69]:
```
dfcopy.head()
```

[69]:
```
   sepal length (cm)  sepal width (cm)  petal length (cm)  petal width (cm)  \
0                5.1               3.5                1.4               0.2
1                4.9               3.0                1.4               0.2
2                4.7               3.2                1.3               0.2
3                4.6               3.1                1.5               0.2
4                5.0               3.6                1.4               0.2

   labels
0  setosa
1  setosa
2  setosa
3  setosa
4  setosa
```

[70]:
```
# Separate features and target
X = dfcopy.iloc[:,0:4].values
Y = dfcopy.iloc[:,4].values
```

[71]:
```
X
```

[71]:
```
array([[5.1, 3.5, 1.4, 0.2],
       [4.9, 3. , 1.4, 0.2],
       [4.7, 3.2, 1.3, 0.2],
       [4.6, 3.1, 1.5, 0.2],
       [5. , 3.6, 1.4, 0.2],
       [5.4, 3.9, 1.7, 0.4],
       [4.6, 3.4, 1.4, 0.3],
       [5. , 3.4, 1.5, 0.2],
       [4.4, 2.9, 1.4, 0.2],
       [4.9, 3.1, 1.5, 0.1],
       [5.4, 3.7, 1.5, 0.2],
       [4.8, 3.4, 1.6, 0.2],
       [4.8, 3. , 1.4, 0.1],
       [4.3, 3. , 1.1, 0.1],
       [5.8, 4. , 1.2, 0.2],
       [5.7, 4.4, 1.5, 0.4],
       [5.4, 3.9, 1.3, 0.4],
       [5.1, 3.5, 1.4, 0.3],
       [5.7, 3.8, 1.7, 0.3],
       [5.1, 3.8, 1.5, 0.3],
       [5.4, 3.4, 1.7, 0.2],
       [5.1, 3.7, 1.5, 0.4],
       [4.6, 3.6, 1. , 0.2],
       [5.1, 3.3, 1.7, 0.5],
       [4.8, 3.4, 1.9, 0.2],
       [5. , 3. , 1.6, 0.2],
       [5. , 3.4, 1.6, 0.4],
       [5.2, 3.5, 1.5, 0.2],
       [5.2, 3.4, 1.4, 0.2],
       [4.7, 3.2, 1.6, 0.2],
       [4.8, 3.1, 1.6, 0.2],
       [5.4, 3.4, 1.5, 0.4],
       [5.2, 4.1, 1.5, 0.1],
       [5.5, 4.2, 1.4, 0.2],
       [4.9, 3.1, 1.5, 0.2],
       [5. , 3.2, 1.2, 0.2],
       [5.5, 3.5, 1.3, 0.2],
       [4.9, 3.6, 1.4, 0.1],
       [4.4, 3. , 1.3, 0.2],
       [5.1, 3.4, 1.5, 0.2],
       [5. , 3.5, 1.3, 0.3],
```

```
[4.5, 2.3, 1.3, 0.3],
[4.4, 3.2, 1.3, 0.2],
[5. , 3.5, 1.6, 0.6],
[5.1, 3.8, 1.9, 0.4],
[4.8, 3. , 1.4, 0.3],
[5.1, 3.8, 1.6, 0.2],
[4.6, 3.2, 1.4, 0.2],
[5.3, 3.7, 1.5, 0.2],
[5. , 3.3, 1.4, 0.2],
[7. , 3.2, 4.7, 1.4],
[6.4, 3.2, 4.5, 1.5],
[6.9, 3.1, 4.9, 1.5],
[5.5, 2.3, 4. , 1.3],
[6.5, 2.8, 4.6, 1.5],
[5.7, 2.8, 4.5, 1.3],
[6.3, 3.3, 4.7, 1.6],
[4.9, 2.4, 3.3, 1. ],
[6.6, 2.9, 4.6, 1.3],
[5.2, 2.7, 3.9, 1.4],
[5. , 2. , 3.5, 1. ],
[5.9, 3. , 4.2, 1.5],
[6. , 2.2, 4. , 1. ],
[6.1, 2.9, 4.7, 1.4],
[5.6, 2.9, 3.6, 1.3],
[6.7, 3.1, 4.4, 1.4],
[5.6, 3. , 4.5, 1.5],
[5.8, 2.7, 4.1, 1. ],
[6.2, 2.2, 4.5, 1.5],
[5.6, 2.5, 3.9, 1.1],
[5.9, 3.2, 4.8, 1.8],
[6.1, 2.8, 4. , 1.3],
[6.3, 2.5, 4.9, 1.5],
[6.1, 2.8, 4.7, 1.2],
[6.4, 2.9, 4.3, 1.3],
[6.6, 3. , 4.4, 1.4],
[6.8, 2.8, 4.8, 1.4],
[6.7, 3. , 5. , 1.7],
[6. , 2.9, 4.5, 1.5],
[5.7, 2.6, 3.5, 1. ],
[5.5, 2.4, 3.8, 1.1],
[5.5, 2.4, 3.7, 1. ],
[5.8, 2.7, 3.9, 1.2],
[6. , 2.7, 5.1, 1.6],
[5.4, 3. , 4.5, 1.5],
[6. , 3.4, 4.5, 1.6],
[6.7, 3.1, 4.7, 1.5],
[6.3, 2.3, 4.4, 1.3],
```

```
       [5.6, 3. , 4.1, 1.3],
       [5.5, 2.5, 4. , 1.3],
       [5.5, 2.6, 4.4, 1.2],
       [6.1, 3. , 4.6, 1.4],
       [5.8, 2.6, 4. , 1.2],
       [5. , 2.3, 3.3, 1. ],
       [5.6, 2.7, 4.2, 1.3],
       [5.7, 3. , 4.2, 1.2],
       [5.7, 2.9, 4.2, 1.3],
       [6.2, 2.9, 4.3, 1.3],
       [5.1, 2.5, 3. , 1.1],
       [5.7, 2.8, 4.1, 1.3]])
```

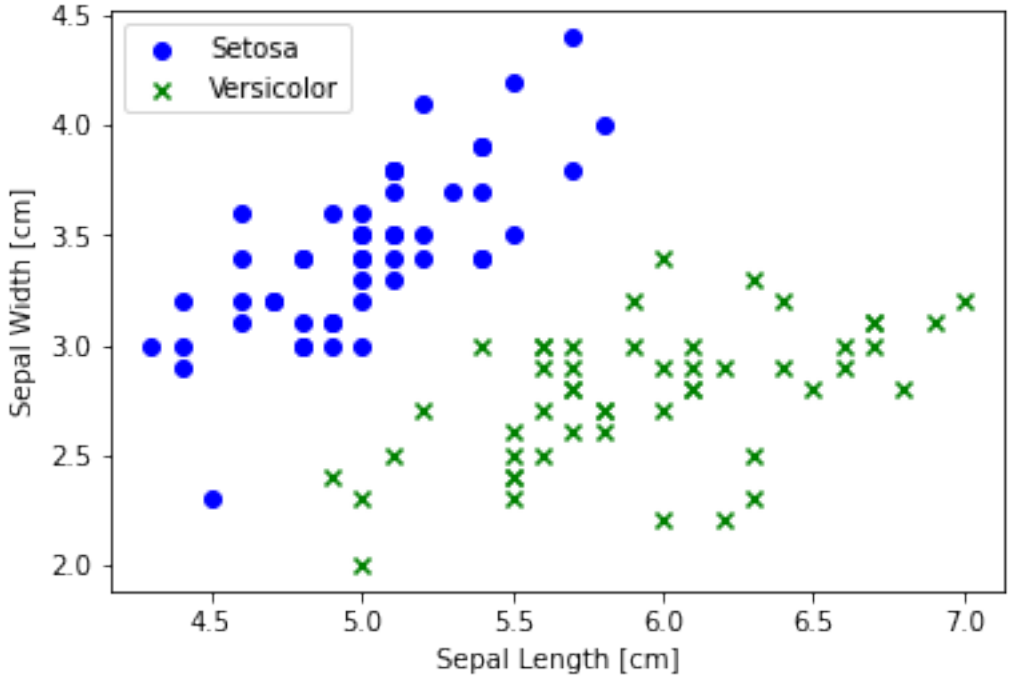
[72]:
```
Y
```

[72]:
```
array(['setosa', 'setosa', 'setosa', 'setosa', 'setosa', 'setosa',
       'setosa', 'setosa', 'setosa', 'setosa', 'setosa', 'setosa',
       'setosa', 'setosa', 'setosa', 'setosa', 'setosa', 'setosa',
       'setosa', 'setosa', 'setosa', 'setosa', 'setosa', 'setosa',
       'setosa', 'setosa', 'setosa', 'setosa', 'setosa', 'setosa',
       'setosa', 'setosa', 'setosa', 'setosa', 'setosa', 'setosa',
       'setosa', 'setosa', 'setosa', 'setosa', 'setosa', 'setosa',
       'setosa', 'setosa', 'setosa', 'setosa', 'setosa', 'setosa',
       'setosa', 'setosa', 'versicolor', 'versicolor', 'versicolor',
       'versicolor', 'versicolor', 'versicolor', 'versicolor',
       'versicolor', 'versicolor', 'versicolor', 'versicolor',
       'versicolor', 'versicolor', 'versicolor', 'versicolor',
       'versicolor', 'versicolor', 'versicolor', 'versicolor',
       'versicolor', 'versicolor', 'versicolor', 'versicolor',
       'versicolor', 'versicolor', 'versicolor', 'versicolor',
       'versicolor', 'versicolor', 'versicolor', 'versicolor',
       'versicolor', 'versicolor', 'versicolor', 'versicolor',
       'versicolor', 'versicolor', 'versicolor', 'versicolor',
       'versicolor', 'versicolor', 'versicolor', 'versicolor',
       'versicolor', 'versicolor', 'versicolor', 'versicolor',
       'versicolor', 'versicolor', 'versicolor'], dtype=object)
```

[73]:
```
# Plot the data points
plt.scatter(X[:50, 0], X[:50, 1],
            color='blue', marker='o', label='Setosa')
plt.scatter(X[50:100, 0], X[50:100, 1],
            color='green', marker='x', label='Versicolor')

plt.xlabel('Sepal Length [cm]')
plt.ylabel('Sepal Width [cm]')
plt.legend(loc='upper left')
```

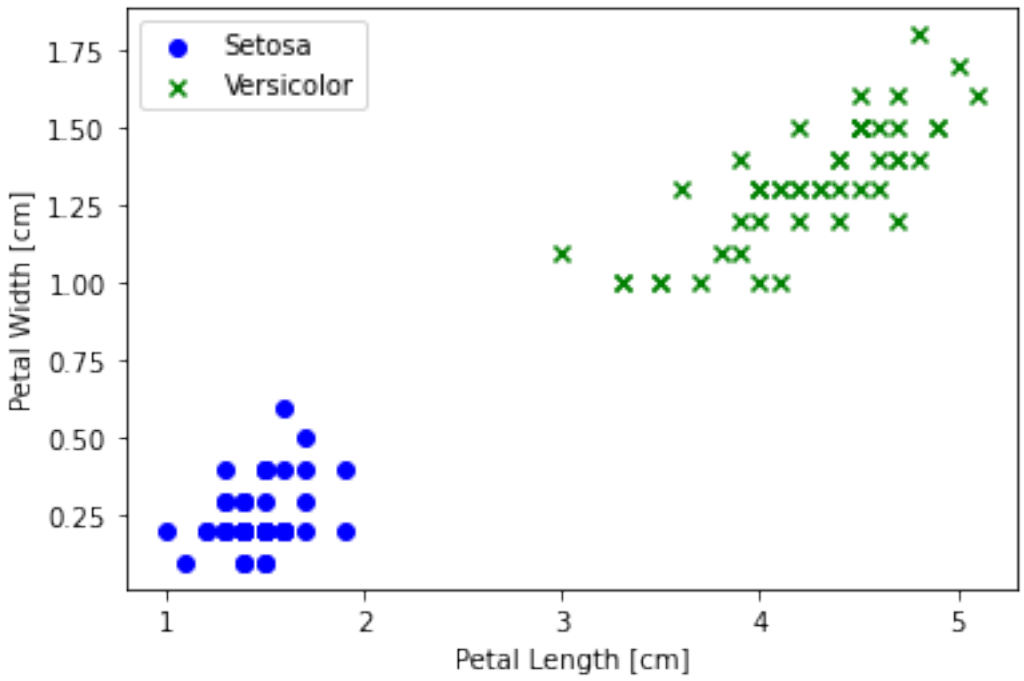
[73]: <matplotlib.legend.Legend at 0x7f139bada910>



[74]:
```
plt.scatter(X[:50, 2], X[:50, 3],
            color='blue', marker='o', label='Setosa')
plt.scatter(X[50:100, 2], X[50:100, 3],
            color='green', marker='x', label='Versicolor')

plt.xlabel('Petal Length [cm]')
plt.ylabel('Petal Width [cm]')
plt.legend(loc='upper left')
```

[74]: <matplotlib.legend.Legend at 0x7f139ba49670>



[75]:
```
print(X)
```

```
[[5.1 3.5 1.4 0.2]
 [4.9 3.  1.4 0.2]
 [4.7 3.2 1.3 0.2]
 [4.6 3.1 1.5 0.2]
 [5.  3.6 1.4 0.2]
 [5.4 3.9 1.7 0.4]
 [4.6 3.4 1.4 0.3]
 [5.  3.4 1.5 0.2]
 [4.4 2.9 1.4 0.2]
 [4.9 3.1 1.5 0.1]
 [5.4 3.7 1.5 0.2]
 [4.8 3.4 1.6 0.2]
 [4.8 3.  1.4 0.1]
 [4.3 3.  1.1 0.1]
 [5.8 4.  1.2 0.2]
 [5.7 4.4 1.5 0.4]
 [5.4 3.9 1.3 0.4]
 [5.1 3.5 1.4 0.3]
 [5.7 3.8 1.7 0.3]
 [5.1 3.8 1.5 0.3]
 [5.4 3.4 1.7 0.2]
 [5.1 3.7 1.5 0.4]
 [4.6 3.6 1.  0.2]
```

```
[5.1 3.3 1.7 0.5]
[4.8 3.4 1.9 0.2]
[5.  3.  1.6 0.2]
[5.  3.4 1.6 0.4]
[5.2 3.5 1.5 0.2]
[5.2 3.4 1.4 0.2]
[4.7 3.2 1.6 0.2]
[4.8 3.1 1.6 0.2]
[5.4 3.4 1.5 0.4]
[5.2 4.1 1.5 0.1]
[5.5 4.2 1.4 0.2]
[4.9 3.1 1.5 0.2]
[5.  3.2 1.2 0.2]
[5.5 3.5 1.3 0.2]
[4.9 3.6 1.4 0.1]
[4.4 3.  1.3 0.2]
[5.1 3.4 1.5 0.2]
[5.  3.5 1.3 0.3]
[4.5 2.3 1.3 0.3]
[4.4 3.2 1.3 0.2]
[5.  3.5 1.6 0.6]
[5.1 3.8 1.9 0.4]
[4.8 3.  1.4 0.3]
[5.1 3.8 1.6 0.2]
[4.6 3.2 1.4 0.2]
[5.3 3.7 1.5 0.2]
[5.  3.3 1.4 0.2]
[7.  3.2 4.7 1.4]
[6.4 3.2 4.5 1.5]
[6.9 3.1 4.9 1.5]
[5.5 2.3 4.  1.3]
[6.5 2.8 4.6 1.5]
[5.7 2.8 4.5 1.3]
[6.3 3.3 4.7 1.6]
[4.9 2.4 3.3 1. ]
[6.6 2.9 4.6 1.3]
[5.2 2.7 3.9 1.4]
[5.  2.  3.5 1. ]
[5.9 3.  4.2 1.5]
[6.  2.2 4.  1. ]
[6.1 2.9 4.7 1.4]
[5.6 2.9 3.6 1.3]
[6.7 3.1 4.4 1.4]
[5.6 3.  4.5 1.5]
[5.8 2.7 4.1 1. ]
[6.2 2.2 4.5 1.5]
[5.6 2.5 3.9 1.1]
[5.9 3.2 4.8 1.8]
```

```
[6.1 2.8 4.  1.3]
[6.3 2.5 4.9 1.5]
[6.1 2.8 4.7 1.2]
[6.4 2.9 4.3 1.3]
[6.6 3.  4.4 1.4]
[6.8 2.8 4.8 1.4]
[6.7 3.  5.  1.7]
[6.  2.9 4.5 1.5]
[5.7 2.6 3.5 1. ]
[5.5 2.4 3.8 1.1]
[5.5 2.4 3.7 1. ]
[5.8 2.7 3.9 1.2]
[6.  2.7 5.1 1.6]
[5.4 3.  4.5 1.5]
[6.  3.4 4.5 1.6]
[6.7 3.1 4.7 1.5]
[6.3 2.3 4.4 1.3]
[5.6 3.  4.1 1.3]
[5.5 2.5 4.  1.3]
[5.5 2.6 4.4 1.2]
[6.1 3.  4.6 1.4]
[5.8 2.6 4.  1.2]
[5.  2.3 3.3 1. ]
[5.6 2.7 4.2 1.3]
[5.7 3.  4.2 1.2]
[5.7 2.9 4.2 1.3]
[6.2 2.9 4.3 1.3]
[5.1 2.5 3.  1.1]
[5.7 2.8 4.1 1.3]]
```

[76]:
```
Y
```

[76]:
```
array(['setosa', 'setosa', 'setosa', 'setosa', 'setosa', 'setosa',
       'setosa', 'setosa', 'setosa', 'setosa', 'setosa', 'setosa',
       'setosa', 'setosa', 'setosa', 'setosa', 'setosa', 'setosa',
       'setosa', 'setosa', 'setosa', 'setosa', 'setosa', 'setosa',
       'setosa', 'setosa', 'setosa', 'setosa', 'setosa', 'setosa',
       'setosa', 'setosa', 'setosa', 'setosa', 'setosa', 'setosa',
       'setosa', 'setosa', 'setosa', 'setosa', 'setosa', 'setosa',
       'setosa', 'setosa', 'versicolor', 'versicolor', 'versicolor',
       'versicolor', 'versicolor', 'versicolor', 'versicolor',
       'versicolor', 'versicolor', 'versicolor', 'versicolor',
       'versicolor', 'versicolor', 'versicolor', 'versicolor',
       'versicolor', 'versicolor', 'versicolor', 'versicolor',
       'versicolor', 'versicolor', 'versicolor', 'versicolor',
```

```
       'versicolor', 'versicolor', 'versicolor', 'versicolor',
       'versicolor', 'versicolor', 'versicolor', 'versicolor',
       'versicolor', 'versicolor', 'versicolor', 'versicolor',
       'versicolor', 'versicolor', 'versicolor', 'versicolor',
       'versicolor', 'versicolor', 'versicolor', 'versicolor',
       'versicolor', 'versicolor', 'versicolor'], dtype=object)
```

[77]:
```
X.shape
```

[77]:
```
(100, 4)
```

[78]:
```
Y.shape
```

[78]:
```
(100,)
```

[79]:
```
dfcopy
```

[79]:
```
    sepal length (cm)  sepal width (cm)  petal length (cm)  petal width (cm)  \
0                 5.1               3.5                1.4               0.2
1                 4.9               3.0                1.4               0.2
2                 4.7               3.2                1.3               0.2
3                 4.6               3.1                1.5               0.2
4                 5.0               3.6                1.4               0.2
..                ...               ...                ...               ...
95                5.7               3.0                4.2               1.2
96                5.7               2.9                4.2               1.3
97                6.2               2.9                4.3               1.3
98                5.1               2.5                3.0               1.1
99                5.7               2.8                4.1               1.3

        labels
0       setosa
1       setosa
2       setosa
3       setosa
4       setosa
..         ...
95  versicolor
96  versicolor
97  versicolor
98  versicolor
99  versicolor

[100 rows x 5 columns]
```

[80]:
```
# Split the data into training and testing sets with 70% of the data for␣
↪training and 30% for testing
```

```
X_train, X_test, y_train, y_test = train_test_split(dfcopy.iloc[:, :-1], dfcopy.
↪iloc[:, -1], test_size=0.3, random_state=0)
```

[81]:
```
X_train.head()
```

[81]:

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)
60	5.0	2.0	3.5	1.0
80	5.5	2.4	3.8	1.1
90	5.5	2.6	4.4	1.2
68	6.2	2.2	4.5	1.5
51	6.4	3.2	4.5	1.5

[82]:
```
len(X_train)
```

[82]:
```
70
```

[83]:
```
X_test.head()
```

[83]:

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)
26	5.0	3.4	1.6	0.4
86	6.7	3.1	4.7	1.5
2	4.7	3.2	1.3	0.2
55	5.7	2.8	4.5	1.3
75	6.6	3.0	4.4	1.4

[84]:
```
len(X_test)
```

[84]:
```
30
```

[85]:
```
y_train
```

[85]:
```
60    versicolor
80    versicolor
90    versicolor
68    versicolor
51    versicolor
         …
96    versicolor
67    versicolor
64    versicolor
47        setosa
44        setosa
Name: labels, Length: 70, dtype: object
```

[86]:
```
len(y_train)
```

[86]:
```
70
```

[87]:
```
len(y_test)
```

[87]: 30

[88]:
```
print(type(X_train), X_train.shape )
print(type(X_test), X_test.shape )

print(type(y_train), y_train.shape )
print(type(y_test), y_test.shape )
```

```
<class 'pandas.core.frame.DataFrame'> (70, 4)
<class 'pandas.core.frame.DataFrame'> (30, 4)
<class 'pandas.core.series.Series'> (70,)
<class 'pandas.core.series.Series'> (30,)
```

[89]:
```
perceptron = Perceptron()
perceptron.fit(X_train, y_train)
y_pred = perceptron.predict(X_test)
```

[90]:
```
print("Stats for different metrics of Setosa!")
print('Accuracy:', accuracy_score(y_test, y_pred))
print('Precision:', precision_score(y_test, y_pred, pos_label='setosa'))
print('Recall:', recall_score(y_test, y_pred, pos_label='setosa'))
print('F1 score:', f1_score(y_test, y_pred, pos_label='setosa'))
```

```
Stats for different metrics of Setosa!
Accuracy: 1.0
Precision: 1.0
Recall: 1.0
F1 score: 1.0
```

[91]:
```
print("Stats for different metrics of Versicolor!")
print('Accuracy:', accuracy_score(y_test, y_pred))
print('Precision:', precision_score(y_test, y_pred, pos_label='versicolor'))
print('Recall:', recall_score(y_test, y_pred, pos_label='versicolor'))
print('F1 score:', f1_score(y_test, y_pred, pos_label='versicolor'))
```

```
Stats for different metrics of Versicolor!
Accuracy: 1.0
Precision: 1.0
Recall: 1.0
F1 score: 1.0
```

[92]:
```
X.shape[0]
```

[92]: 100

[93]:
```
X.shape[1]
```

[93]: 4

[94]:
```
# Apply the Perceptron algorithm from scratch using above code snippets
class MyPerceptron:
    def __init__(self, _learningRate=0.1, _epochs=1000):
        self.learningRate = _learningRate
        self.epochs = _epochs

    def fit(self, X, y):
        self.weights = np.zeros(X.shape[1])
        self.bias = 0
        for i in range(self.epochs):
            for j in range(X.shape[0]):
                if y[j] * (np.dot(X[j], self.weights) + self.bias) <= 0:
                    self.weights += self.learningRate * y[j] * X[j]
                    self.bias += self.learningRate * y[j]

        print(self.weights)
        print(self.bias)

    def predict(self, X):
        y_pred = np.sign(np.dot(X, self.weights) + self.bias)
        return np.where(y_pred == -1, 'setosa', 'versicolor')

P = MyPerceptron()
P.fit(X_train.values, y_train.replace({'setosa': -1, 'versicolor': 1}).values)

y_pred = P.predict(X_test.values)
print('Accuracy:', accuracy_score(y_test, y_pred))
```

```
[-0.02 -0.15  0.2   0.08]
0.0
Accuracy: 1.0
```

[95]:
```
print("Stats for different metrics of Setosa!")
print('Accuracy:', accuracy_score(y_test, y_pred))
print('Precision:', precision_score(y_test, y_pred, pos_label='setosa'))
print('Recall:', recall_score(y_test, y_pred, pos_label='setosa'))
print('F1 score:', f1_score(y_test, y_pred, pos_label='setosa'))
```

```
Stats for different metrics of Setosa!
Accuracy: 1.0
Precision: 1.0
Recall: 1.0
F1 score: 1.0
```

[96]:
```
print("Stats for different metrics of Versicolor!")
print('Accuracy:', accuracy_score(y_test, y_pred))
print('Precision:', precision_score(y_test, y_pred, pos_label='versicolor'))
print('Recall:', recall_score(y_test, y_pred, pos_label='versicolor'))
print('F1 score:', f1_score(y_test, y_pred, pos_label='versicolor'))
```

```
Stats for different metrics of Versicolor!
Accuracy: 1.0
Precision: 1.0
Recall: 1.0
F1 score: 1.0
```