Perceptron

September 18, 2020

1 Perceptron

[1]:
```python
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.datasets import load_iris
```

[2]:
```python
iris = load_iris()
iris
```

[2]:
```
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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)'],
 'filename':
'/Library/Frameworks/Python.framework/Versions/3.7/lib/python3.7/site-
packages/sklearn/datasets/data/iris.csv'}
```

[3]:

```python
data = pd.DataFrame(iris['data'], columns = ['petal length', 'petal width',␣
 ↪'sepal length', 'sepal width'])
data['species'] = iris['target']
data['species'] = data['species'].apply(lambda x: iris['target_names'][x])
data
```

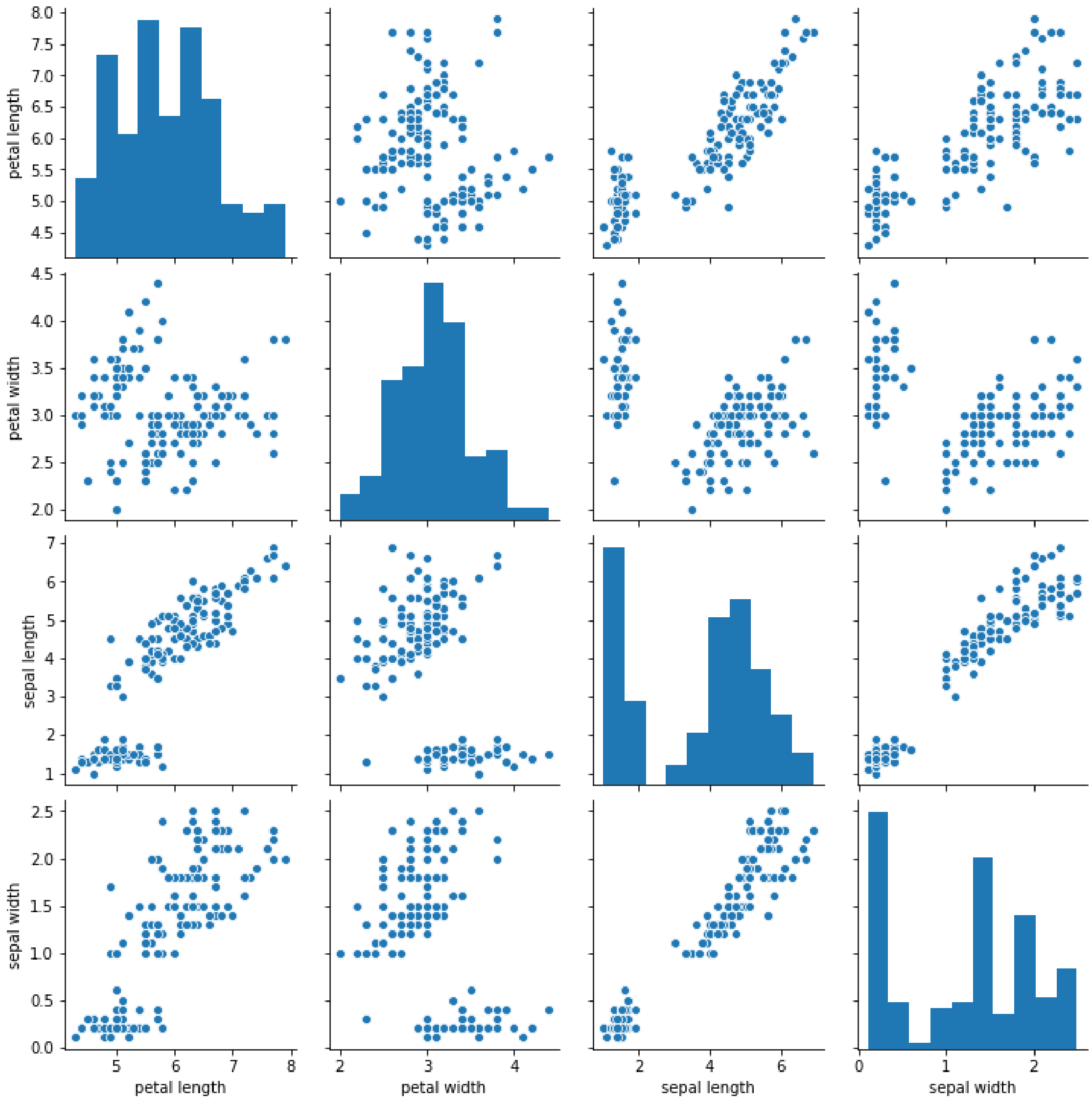
[3]:
```
     petal length  petal width  sepal length  sepal width    species
0             5.1          3.5           1.4          0.2     setosa
1             4.9          3.0           1.4          0.2     setosa
2             4.7          3.2           1.3          0.2     setosa
3             4.6          3.1           1.5          0.2     setosa
4             5.0          3.6           1.4          0.2     setosa
..            …            …             …            …          …
145           6.7          3.0           5.2          2.3  virginica
146           6.3          2.5           5.0          1.9  virginica
147           6.5          3.0           5.2          2.0  virginica
148           6.2          3.4           5.4          2.3  virginica
149           5.9          3.0           5.1          1.8  virginica

[150 rows x 5 columns]
```

[4]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 5 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   petal length  150 non-null    float64
 1   petal width   150 non-null    float64
 2   sepal length  150 non-null    float64
 3   sepal width   150 non-null    float64
 4   species       150 non-null    object
dtypes: float64(4), object(1)
memory usage: 6.0+ KB
```

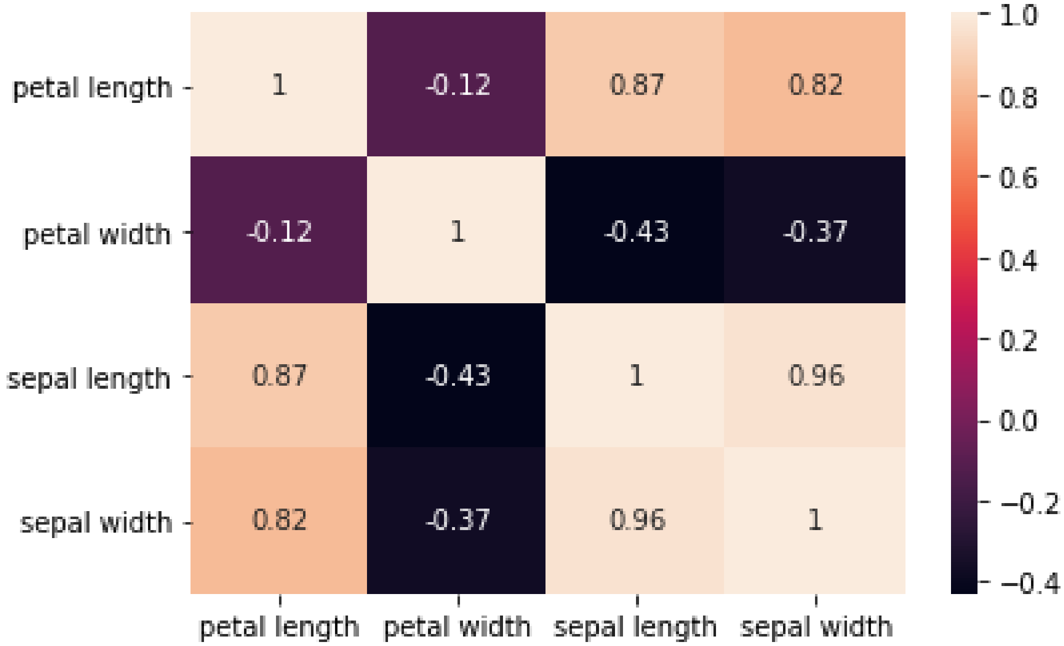
[5]:
```
sns.pairplot(data)
```

[5]: `<seaborn.axisgrid.PairGrid at 0x7fb17c5de908>`

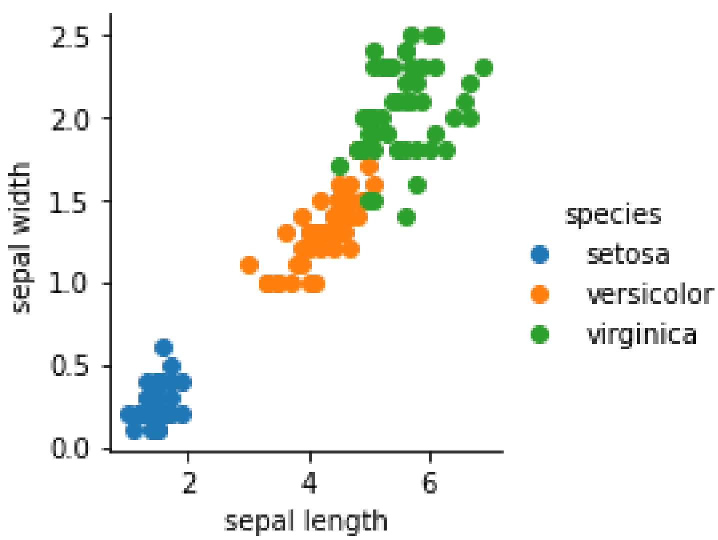



```
[6]: sns.heatmap(data.corr(), annot = True)
```

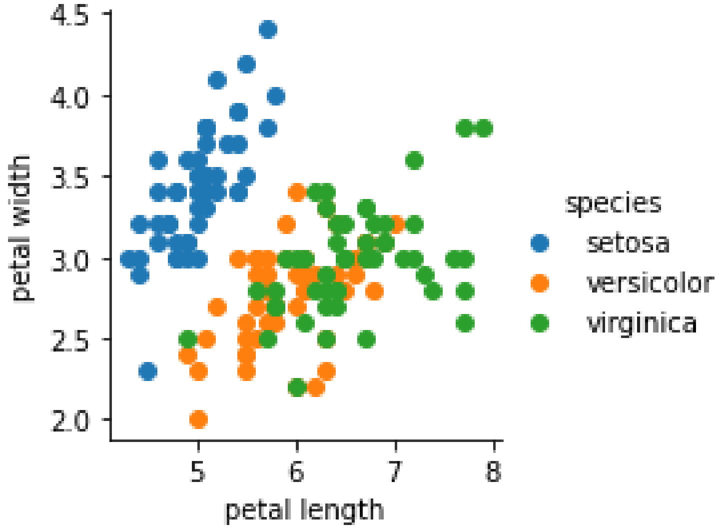
```
[6]: <matplotlib.axes._subplots.AxesSubplot at 0x7fb17d0f7828>
```



[7]:
```
sns.FacetGrid(data, hue = 'species').map(plt.scatter, 'sepal length', 'sepal␣
↪width').add_legend()
plt.show()
```

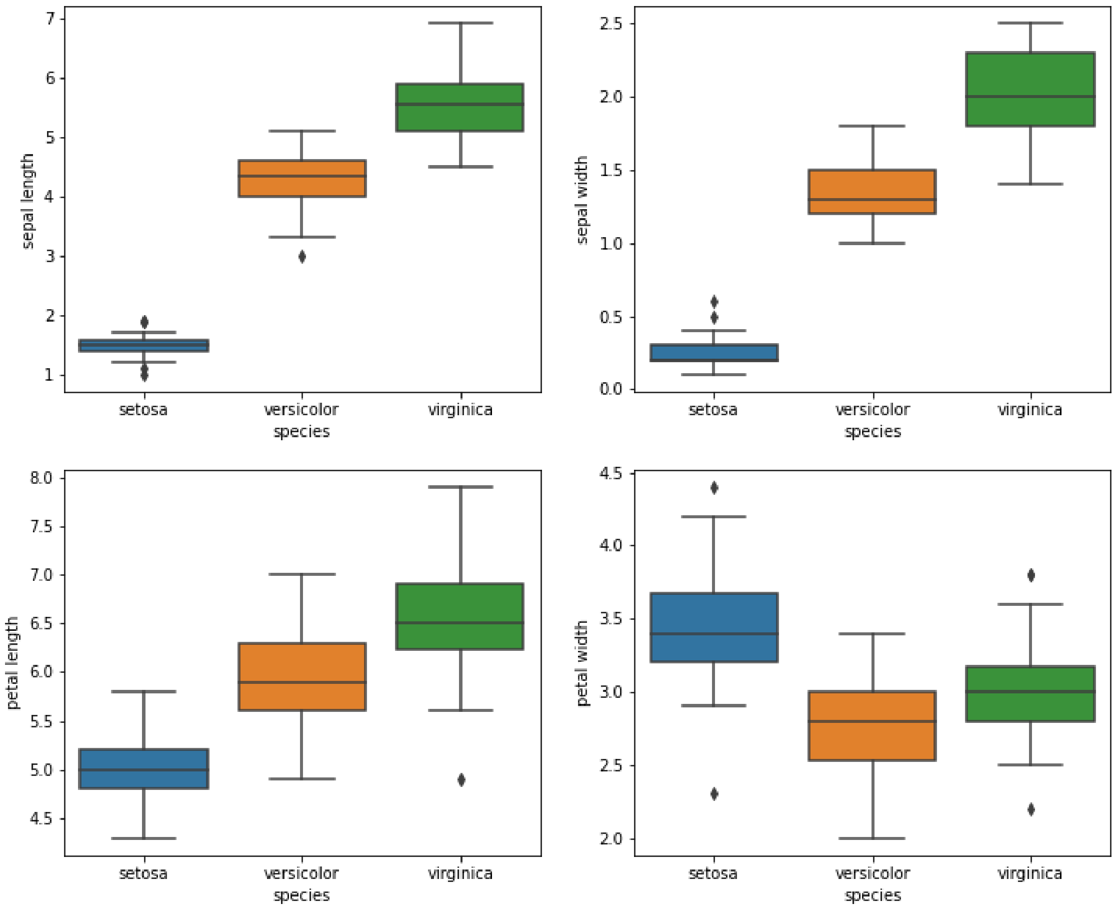


[8]:
```
sns.FacetGrid(data, hue = 'species').map(plt.scatter, 'petal length', 'petal␣
↪width').add_legend()
plt.show()
```



[9]:
```
plt.figure(figsize = (12, 10))
plt.subplot(2, 2, 1)
sns.boxplot(x = 'species', y = 'sepal length', data = data)
plt.subplot(2, 2, 2)
sns.boxplot(x = 'species', y = 'sepal width', data = data)
plt.subplot(2, 2, 3)
sns.boxplot(x = 'species', y = 'petal length', data = data)
plt.subplot(2, 2, 4)
sns.boxplot(x = 'species', y = 'petal width', data = data)
```

[9]: <matplotlib.axes._subplots.AxesSubplot at 0x7fb17cf8c588>



There are three types of iris. Each time, we pick two types of them to run.

[10]:
```
X = iris.data[:100]
Y = iris.target[:100]
Y = np.where(Y == 1, 1, -1)
```

[11]:
```
trainX, testX, trainY, testY = train_test_split(X, Y, test_size = 0.4)
```

[12]:
```
def evaluation(x, y, w, b):
    p = np.dot(x, w) + b
    pred = np.where(p <= 0, -1, 1)
    correct_count = (pred == y).sum()
    total_count = x.shape[0]
    accuracy = 1.0 * correct_count / total_count
    return accuracy
```

[13]:
```
def perceptron(x, y, eta_learning_rate, n_epoch):
    w = np.zeros(x.shape[1])
    b = 0
```

```
    errors = []
    for i in range(n_epoch):
        error = 0
        for xi, yi in zip(x, y):
            p = np.dot(xi, w) + b
            if p * yi <= 0:
                delta_w = yi * xi * eta_learning_rate
                delta_b = yi * eta_learning_rate
                w = w + delta_w
                b = b + delta_b
                error = error + 1

        errors.append(error)
        accuracy = evaluation(testX, testY, w, b)
        info = '[{0}] Training_Error: {error_count:d} Accuracy:␣
↪{accuracy_percentage:.4f}'.format(i, error_count = error,␣
↪accuracy_percentage = accuracy)
        print(info)
    return w, b
```

[14]:
```
w, b = perceptron(trainX, trainY, 0.01, 10)
```

```
[0] Training_Error: 9 Accuracy: 1.0000
[1] Training_Error: 0 Accuracy: 1.0000
[2] Training_Error: 0 Accuracy: 1.0000
[3] Training_Error: 0 Accuracy: 1.0000
[4] Training_Error: 0 Accuracy: 1.0000
[5] Training_Error: 0 Accuracy: 1.0000
[6] Training_Error: 0 Accuracy: 1.0000
[7] Training_Error: 0 Accuracy: 1.0000
[8] Training_Error: 0 Accuracy: 1.0000
[9] Training_Error: 0 Accuracy: 1.0000
```

[ ]:
```

```