## 1-experiment-1-dlvs-lab

August 29, 2024

## 1 \*\*\*\*1. DESIGN SINGLE UNIT PERCEPTRON FOR CLAS-SIFICATION OF IRIS DATASET WITHOUT USING PRE-DEFINED MODELS\*

```
[45]: # This Python 3 environment comes with many helpful analytics libraries.
       \hookrightarrow installed
      # It is defined by the kaggle/python Docker image: https://github.com/kaggle/
       \rightarrow docker-python
      # For example, here's several helpful packages to load
      import numpy as np # linear algebra
      import pandas as pd # data processing, CSV file I/O (e.g. pd.read csv)
      # Input data files are available in the read-only "../input/" directory
      # For example, running this (by clicking run or pressing Shift+Enter) will list⊔
       ⇔all files under the input directory
      import os
      for dirname, _, filenames in os.walk('/kaggle/input'):
          for filename in filenames:
              print(os.path.join(dirname, filename))
      # You can write up to 20GB to the current directory (/kaqqle/working/) that
       ⇒gets preserved as output when you create a version using "Save & Run All"
      # You can also write temporary files to /kaggle/temp/, but they won't be saved
       ⇔outside of the current session
```

/kaggle/input/iris-dataset/iris.csv

iris

```
[46]: import numpy as np
    from sklearn.datasets import load_iris
    from sklearn.model_selection import train_test_split
[47]: iris=pd.read_csv("/kaggle/input/iris-dataset/iris.csv")
```

```
[47]:
           sepal_length sepal_width petal_length petal_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
                                                               0.2
      4
                     5.0
                                   3.6
                                                  1.4
                                                                        setosa
                     6.7
                                                  5.2
      145
                                   3.0
                                                               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
```

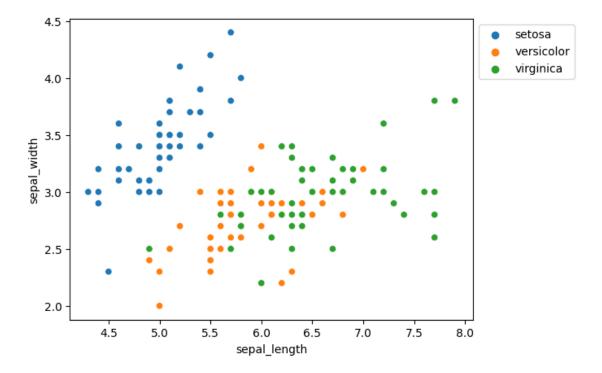
[150 rows x 5 columns]

```
[48]: import seaborn as sns
import matplotlib.pyplot as plt

sns.scatterplot(x='sepal_length', y='sepal_width', hue='species', data=iris,)

# Placing Legend outside the Figure
plt.legend(bbox_to_anchor=(1, 1), loc=2)

plt.show()
```



```
[49]: iris['species'].unique()
[49]: array(['setosa', 'versicolor', 'virginica'], dtype=object)
[50]: iris.groupby('species').size()
[50]: species
               setosa
                                                   50
               versicolor
                                                  50
               virginica
                                                  50
               dtype: int64
[51]: \#iris = load iris()
               iris = load_iris()
               X = iris.data[:100, :2] # Use only two features and two classes (Setosa and
                \hookrightarrow Versicolor)
               y = iris.target[:100]
[52]: y
1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1])
[53]: # Convert labels to -1 and 1
               y = np.where(y == 0, -1, 1)
               У
-1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1,
                                -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1, -1,
                                   1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
[54]: # Split the data into training and testing sets
               X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,_
                  →random_state=42)
[55]: # Initialize weights and bias
               weights = np.zeros(X_train.shape[1])
               bias = 0
               learning_rate = 0.1
```

```
epochs = 10
[56]: # Perceptron training
      for epoch in range(epochs):
          for i in range(X_train.shape[0]):
              linear_output = np.dot(X_train[i], weights) + bias
              y_pred = np.where(linear_output > 0, 1, -1)
              # Update weights and bias
              if y_train[i] != y_pred:
                  weights += learning_rate * y_train[i] * X_train[i]
                  bias += learning_rate * y_train[i]
[57]: # Testing the perceptron
      correct_predictions = 0
      for i in range(X_test.shape[0]):
          linear_output = np.dot(X_test[i], weights) + bias
          y_pred = np.where(linear_output > 0, 1, -1)
          if y_pred == y_test[i]:
```

[58]: accuracy = correct\_predictions / X\_test.shape[0]
print(f"Accuracy: {accuracy \* 100:.2f}%")

Accuracy: 100.00%

correct\_predictions += 1