# Machine Learning Lab/Even Sem 2023-23/Experiment 1b

Grade:

Class/Roll No.:

Name:

**Description / Theory:** 

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	Dyotak Kachare	D11AD/26		
Title of Experiment :				
Introduction to scikit learn, matplotlib, seaborn library				
Objective of Experiment :				
To introduce platforms such as Anaconda, COLAB suitable to Machine learning.				
Outcome of Experiment :				
Implement various Machine learning models				
Problem Statement :				
	Introduction to scikit learn, matplotlib, seaborn library			

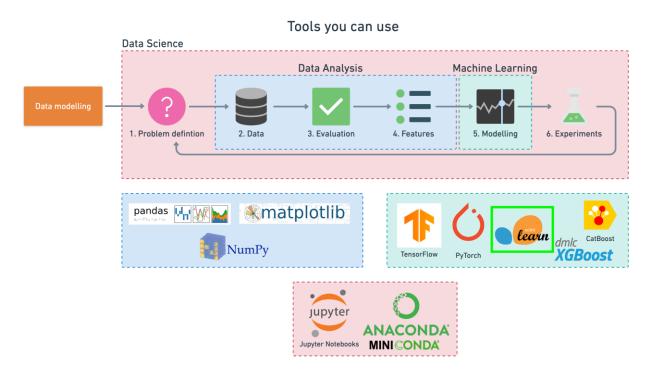


## Machine Learning Lab/Even Sem 2023-23/Experiment 1b

## What is Scikit-Learn (sklearn)?

Scikit-Learn, also referred to as sklearn, is an open-source Python machine learning library.

It's built on top on NumPy (Python library for numerical computing) and Matplotlib (Python library for data visualization).



#### Why Scikit-Learn?

Although the fields of data science and machine learning are vast, the main goal is finding patterns within data and then using those patterns to make predictions.

And there are certain categories which a majority of problems fall into.

If you're trying to create a machine learning model to predict whether an email is spam and or not spam, you're working on a classification problem (whether something is one thing or another).

If you're trying to create a machine learning model to predict the price of houses given their characteristics, you're working on a regression problem (predicting a number).

If you're trying to get a machine learning algorithm to group together similar samples (that you don't necessarily know which should go together), you're working on a clustering problem.



## Machine Learning Lab/Even Sem 2023-23/Experiment 1b

Once you know what kind of problem you're working on, there are also similar steps you'll take for each. Steps like splitting the data into different sets, one for your machine learning algorithms to learn on (the training set) and another to test them on (the testing set).

Choosing a machine learning model and then evaluating whether or not your model has learned anything.

Scikit-Learn offers Python implementations for doing all of these kinds of tasks (from preparing data to modelling data). Saving you from having to build them from scratch.

# What is matplotlib?

Matplotlib is a visualization library for Python.

As in, if you want to display something in a chart or graph, matplotlib can help you do that programmatically.

Many of the graphics you'll see in machine learning research papers or presentations are made with matplotlib.

#### Why matplotlib?

Matplotlib is part of the standard Python data stack (pandas, NumPy, matplotlib, Jupyter).

It has terrific integration with many other Python libraries.

pandas uses matplotlib as a backend to help visualize data in DataFrames.

#### What is seaborn?

Seaborn is a library for making statistical graphics in Python. It builds on top of matplotlib and integrates closely with pandas data structures.

Seaborn helps you explore and understand your data. Its plotting functions operate on dataframes and arrays containing whole datasets and internally perform the necessary semantic mapping and statistical aggregation to produce informative plots. Its dataset-oriented, declarative API lets you focus on what the different elements of your plots mean, rather than on the details of how to draw them.

#### 0.1 Introduction to Scikit Learn

```
[1]: # Importing required libraries
      import pandas as pd
      import numpy as np
      import matplotlib.pyplot as plt
      import sklearn
      import seaborn as sns
[20]: # Reading data
      heart_disease = pd.read_csv('../data/cleaned/heart.csv')
      heart_disease.head()
                                               restecg
[20]:
         age
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                    ср
                        trestbps
                                   chol
                                        fbs
                                                        thalach exang oldpeak slope
          52
                     0
                              125
                                    212
                                                     1
                                                             168
                                                                              1.0
                                                                                       2
      1
          53
                 1
                     0
                              140
                                    203
                                           1
                                                     0
                                                             155
                                                                      1
                                                                              3.1
                                                                                       0
      2
          70
                 1
                     0
                              145
                                    174
                                           0
                                                     1
                                                             125
                                                                      1
                                                                              2.6
                                                                                       0
                     0
                              148
                                    203
                                           0
                                                     1
                                                             161
                                                                      0
                                                                              0.0
                                                                                       2
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          61
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          62
                              138
                                    294
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                                                             106
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          0
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                         0
      3
          1
                 3
                         0
      4
          3
                 2
                         0
[21]: # Create X (all the feature columns)
      X = heart_disease.drop("target", axis=1)
      # Create y (the target column)
      y = heart_disease["target"]
      # Check the head of the features DataFrame
      X.head()
[21]:
                                         fbs
                        trestbps
                                   chol
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                                                        thalach
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                                                                         oldpeak
                                                                                   slope \
         age
               sex
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                                    212
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                                                                              1.0
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          53
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          70
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                              145
                                    174
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                                                     1
                                                             125
                                                                      1
                                                                              2.6
                                                                                       0
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          61
                 1
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                              148
                                    203
                                           0
                                                     1
                                                             161
                                                                      0
                                                                              0.0
                                                                                       2
                                    294
                                                     1
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      4
          62
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             thal
         ca
      0
          2
                 3
      1
          0
                 3
      2
          0
                 3
      3
          1
                 3
      4
          3
[22]: # Check the head and the value counts of the labels
      y.head(), y.value_counts()
```

```
[22]: (0
            0
            0
       1
       2
            0
       3
            0
       4
       Name: target, dtype: int64,
       target
            526
       0
            499
       Name: count, dtype: int64)
[23]: # Split the data into training and test sets
      from sklearn.model_selection import train_test_split
      X_train, X_test, y_train, y_test = train_test_split(X,
                                                           test size=0.25) # by default₽
        →train_test_split uses 25% of the data for the test set
      X_train.shape, X_test.shape, y_train.shape, y_test.shape
[23]: ((768, 13), (257, 13), (768,), (257,))
[24]: from sklearn.ensemble import RandomForestClassifier
      clf = RandomForestClassifier()
[25]: clf.get_params()
[25]: {'bootstrap': True,
       'ccp_alpha': 0.0,
       'class_weight': None,
       'criterion': 'gini',
       'max_depth': None,
       'max_features': 'sqrt',
       'max_leaf_nodes': None,
       'max_samples': None,
       'min_impurity_decrease': 0.0,
       'min_samples_leaf': 1,
       'min_samples_split': 2,
       'min_weight_fraction_leaf': 0.0,
       'n_estimators': 100,
       'n jobs': None,
       'oob score': False,
       'random_state': None,
       'verbose': 0,
       'warm_start': False}
[26]: clf.fit(X=X_train, y=y_train)
[26]: RandomForestClassifier()
[27]: X_test.head()
```

```
149
                                                                             0.8
      81
            49
                  1
                      2
                               118
                                            0
                                                             126
                                                                      0
                                                     0
      706
            57
                  1
                      2
                               128
                                     229
                                            0
                                                     0
                                                             150
                                                                      0
                                                                             0.4
      792
                               144
                                     193
                                                                      0
                                                                             3.4
            68
                      0
                                                     1
                                                             141
                  1
                                            1
      113
            57
                  1
                      0
                               110
                                     335
                                            0
                                                     1
                                                             143
                                                                      1
                                                                             3.0
      643
            65
                  1
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                               120
                                     177
                                            0
                                                     1
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                                                                      0
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                 ca
      81
               2
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                          2
      706
                   1
                          3
               1
      792
               1
                   2
                          3
      113
               1
                   1
                          3
      643
               2
                   0
                          3
[28]: y_preds = clf.predict(X=X_test)
      y_preds
[28]: array([0, 0, 0, 0, 1, 0, 1, 0, 1, 1, 1, 0, 1, 1, 0, 0, 1, 1, 0, 1, 1,
             1, 0, 1, 0, 1, 0, 1, 1, 0, 1, 1, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 1,
             0, 1, 1, 1, 1, 0, 1, 0, 1, 0, 0, 0, 1, 0, 1, 1, 1, 0, 0, 0, 0, 0,
             1, 1, 1, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1,
             0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 1, 0, 1, 1, 1, 0, 0, 1, 1, 1, 0,
             0, 1, 1, 1, 0, 0, 0, 0, 1, 1, 0, 1, 1, 1, 1, 0, 1, 0, 0, 0, 1, 0,
             1, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1, 1, 0, 1, 0, 0, 1, 1, 1, 0,
             0, 1, 0, 1, 1, 0, 0, 0, 0, 1, 0, 1, 1, 1, 0, 1, 0, 1, 1, 0, 1,
             0, 0, 1, 0, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 1, 0, 0, 0, 0, 1, 0, 0,
             1, 1, 0, 1, 1, 1, 0, 0, 1, 0, 1, 1, 0, 1, 0, 1, 0, 0, 0, 0, 1, 1,
             0, 1, 1, 1, 1, 0, 1, 1, 0, 0, 1, 1, 0, 0, 1, 0, 1, 1, 0, 0, 1,
             1, 1, 0, 0, 0, 1, 1, 0, 1, 0, 1, 1, 0, 0, 1], dtype=int64)
[29]: from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
      # Create a classification report
      print(classification report(y test, y preds))
                    precision
                                 recall f1-score
                                                     support
                 0
                         0.98
                                   1.00
                                             0.99
                                                         124
                 1
                         1.00
                                   0.98
                                             0.99
                                                         133
                                             0.99
                                                         257
         accuracy
                         0.99
                                   0.99
                                             0.99
                                                         257
        macro avg
                         0.99
                                   0.99
                                             0.99
                                                         257
     weighted avg
[30]: # Create a confusion matrix
      conf_mat = confusion_matrix(y_test, y_preds)
      conf_mat
[30]: array([[124,
                     0],
             [ 3, 130]], dtype=int64)
```

cp trestbps chol fbs

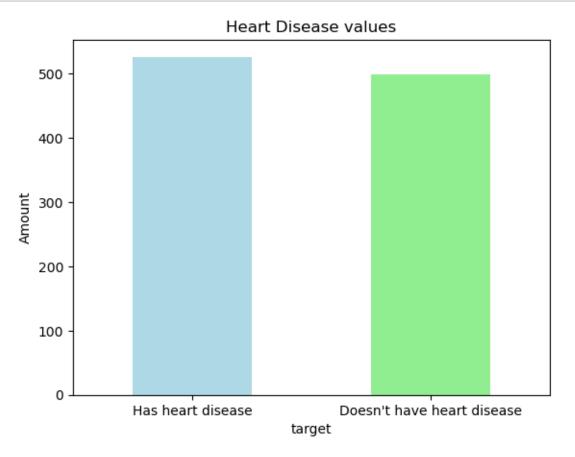
[27]:

age sex

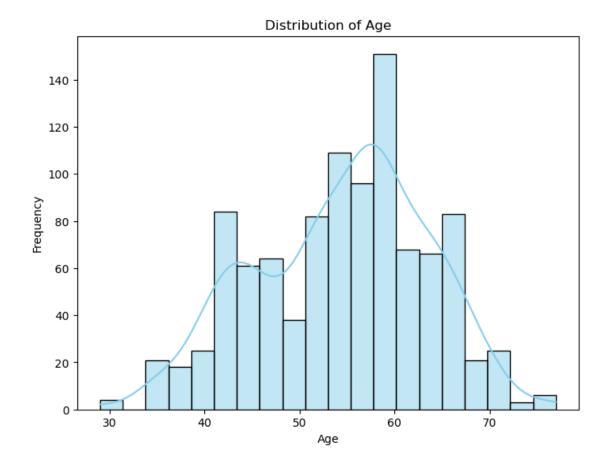
oldpeak \

restecg thalach exang

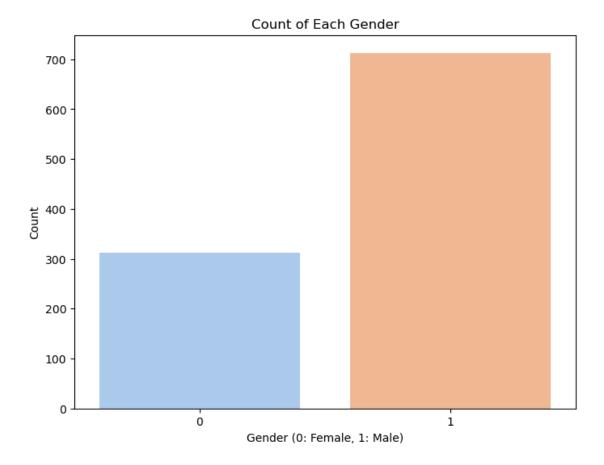
# 0.2 Matplotlib and SnS



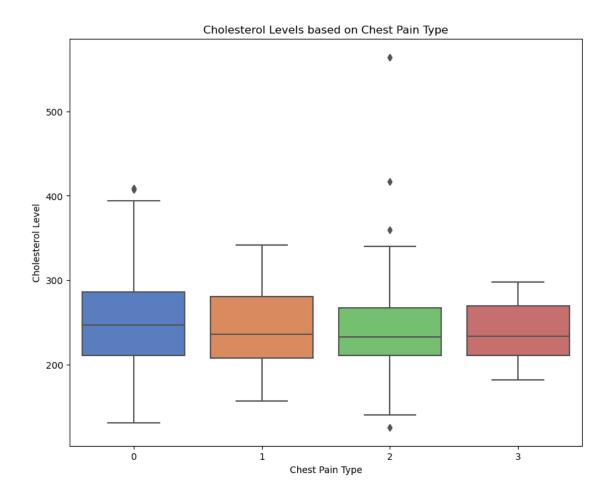
```
plt.figure(figsize=(8, 6))
sns.histplot(heart_disease['age'], bins=20, kde=True, color='skyblue')
plt.title('Distribution of Age')
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.show()
```

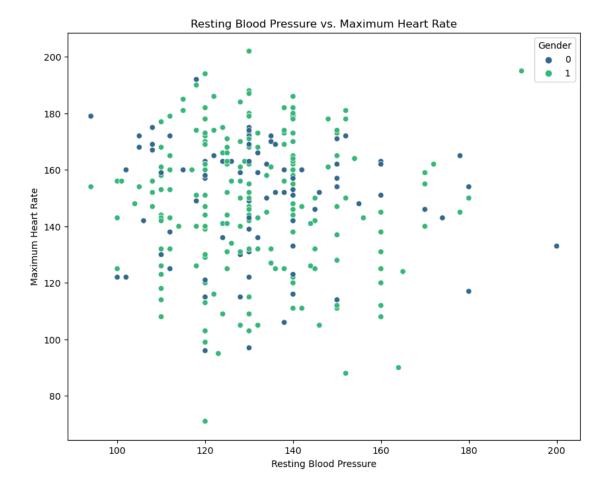


```
[33]: plt.figure(figsize=(8, 6))
    sns.countplot(x='sex', data=heart_disease, palette='pastel')
    plt.title('Count of Each Gender')
    plt.xlabel('Gender (0: Female, 1: Male)')
    plt.ylabel('Count')
    plt.show()
```



```
[34]: plt.figure(figsize=(10, 8))
    sns.boxplot(x='cp', y='chol', data=heart_disease, palette='muted')
    plt.title('Cholesterol Levels based on Chest Pain Type')
    plt.xlabel('Chest Pain Type')
    plt.ylabel('Cholesterol Level')
    plt.show()
```





Machine Learning Lab/Even Sem 2023-23/Experiment 1b

# **Result and Discussion:**

Thus we have successfully used the python libraries.