Lab-1 : Logistic Regression

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Objective

1. Logistic Regression Using Single Feature

2. Logistic Regression Using Multiple Features

Background

Artificial Intelligence (AI):

- A broad field focused on creating systems that can perform tasks requiring human-like intelligence, such as learning, reasoning, and decision-making.

Machine Learning (ML):

- The system learns from data and finds patterns instead of being fully hard-coded.

Deep Learning (DL):

- A subset of ML that uses multi-layer neural networks to model complex patterns, commonly applied in image, speech, and text processing.

Data Science:

- The broader process that involves collecting, cleaning, exploring, visualizing, and modeling data to extract meaningful insights and support decision-making.

Task 1: Logistic Regression with a Single Feature

1. Data Retrieval and Collection

```
import pandas as pd

data = pd.read_csv("Heart_Disease_Prediction.csv")

data.shape, data.columns
```

```
((270, 14),
 Index(['Age', 'Sex', 'Chest pain type', 'BP', 'Cholesterol', 'FBS over 120',
        'EKG results', 'Max HR', 'Exercise angina', 'ST depression',
        'Slope of ST', 'Number of vessels fluro', 'Thallium', 'Heart Disease'],
       dtype='str'))
```

2. Data Cleaning

```
# checking for missing values
data.isnull().sum()
```

```
Age                            0
Sex                            0
Chest pain type                0
BP                             0
Cholesterol                    0
FBS over 120                   0
EKG results                    0
Max HR                         0
Exercise angina                0
ST depression                  0
Slope of ST                    0
Number of vessels fluro        0
Thallium                       0
Heart Disease                  0
dtype: int64
```

```
#remove invalid values <=0
data = data[data["Cholesterol"] > 0]

print(data["Heart Disease"].unique())
#target value is binary or not
```

```
<StringArray>
['Presence', 'Absence']
Length: 2, dtype: str
```

```
# Convert target variable to binary numeric form
data["Heart Disease"] = data["Heart Disease"].map({
    "Absence": 0,
    "Presence": 1
})

print(data["Heart Disease"].unique())
#target value is binary or not
```

```
[1 0]
```

```
data.dtypes
```

```
Age                              int64
Sex                              int64
Chest pain type                  int64
BP                               int64
Cholesterol                      int64
FBS over 120                     int64
EKG results                      int64
```

```
Max HR                             int64
Exercise angina                    int64
ST depression                    float64
Slope of ST                        int64
Number of vessels fluro            int64
Thallium                           int64
Heart Disease                      int64
dtype: object
```

3. Feature Design

```
X = data[["Cholesterol"]]  # Feature (input)
y = data["Heart Disease"]  # Target (output)
```

Cholestrol is used as a feature because it is a strongly associated factor with cardiovascular diseases.

4. Algorithm Selection

Logistic Regression is chosen because it is designed for binary classification. It is easy to intrepret and the outputs probabilities are between 0 and 1.

5. Loss Function Selection

Binary Cross-Entropy (Log Loss)

$L=-[y\log(p)+(1-y)\log(1-p)]$

Penalizes confident but incorrect predictions and is ideal for probabilistic classifiers.

6. Model Learning(Training)

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42
)

# Train model
model_single = LogisticRegression()
model_single.fit(X_train, y_train)

LogisticRegression()
```

7. Model Evaluation

```
from sklearn.metrics import accuracy_score, precision_score,
recall_score, f1_score, confusion_matrix
```

```
y_pred = model_single.predict(X_test)

print("Accuracy :", accuracy_score(y_test, y_pred))
print("Precision:", precision_score(y_test, y_pred))
print("Recall   :", recall_score(y_test, y_pred))
print("F1-score :", f1_score(y_test, y_pred))
```

```
Accuracy : 0.6111111111111112
Precision: 0.5
Recall   : 0.23809523809523808
F1-score : 0.3225806451612903
```

```
confusion_matrix(y_test, y_pred)
```

```
array([[28,  5],
       [16,  5]])
```

Interpretation

Accuracy: Overall correctness

Precision: How many predicted positives are correct

Recall: Ability to detect heart disease

F1-score: Balance between precision and recall

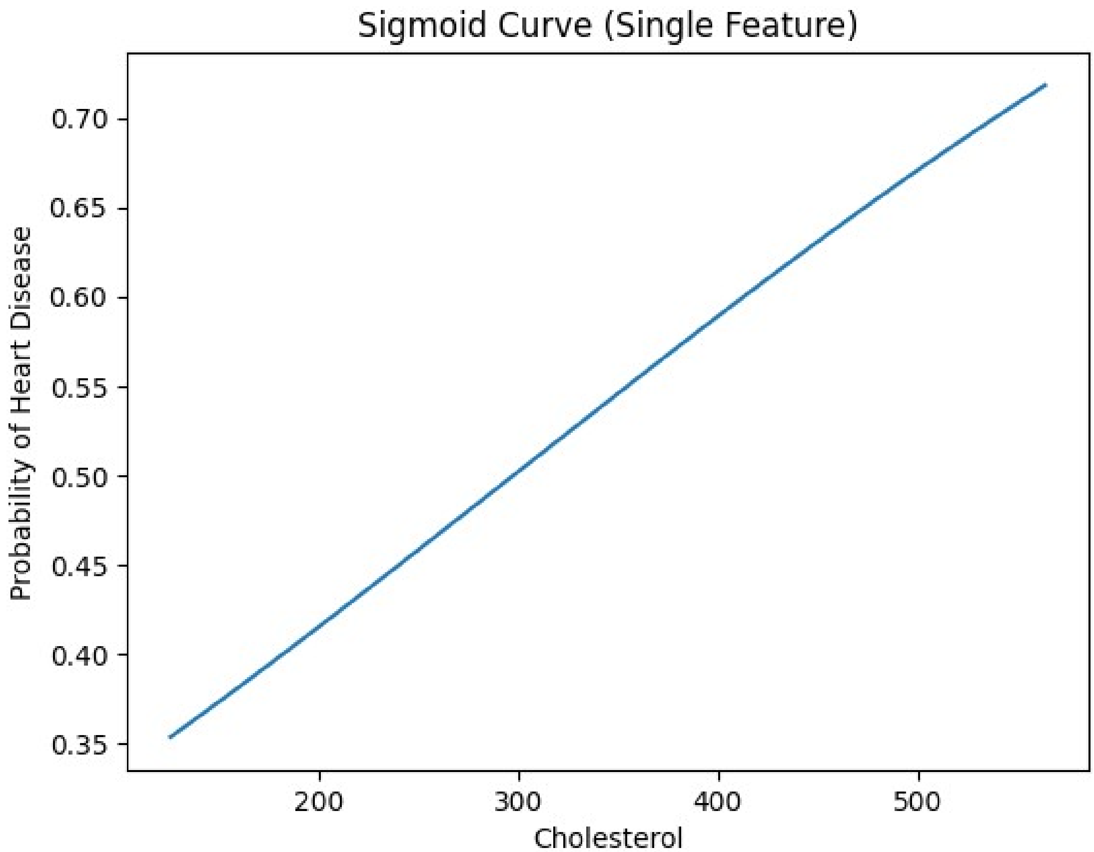
Sigmoid Curve

```
import numpy as np
import matplotlib.pyplot as plt

X_range = np.linspace(X.min(), X.max(), 300).reshape(-1, 1)
y_prob = model_single.predict_proba(X_range)[:, 1]

plt.plot(X_range, y_prob)
plt.xlabel("Cholesterol")
plt.ylabel("Probability of Heart Disease")
plt.title("Sigmoid Curve (Single Feature)")
plt.show()
```

```
c:\Users\blood\Desktop\AI-LAB\lab_env\Lib\site-packages\sklearn\utils\
validation.py:2691: UserWarning: X does not have valid feature names,
but LogisticRegression was fitted with feature names
  warnings.warn(
```



Task 2: Logistic Regression Using Multiple Features

Data retrieval,collection and cleaning are already done (same as task 1).

3. Feature Design

```
# Features and target
X_multi = data.drop("Heart Disease", axis=1)
y = data["Heart Disease"]

#Encoding & Scaling
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
X_multi_scaled = scaler.fit_transform(X_multi)
```

Multiple features are needed because:

Heart disease depends on multiple medical factors.

Multiple features capture complex relationships and improves predictive power.

4. Algorithm Selection

Logistic Regression still suitable:

Works well with multiple features

Interpretable coefficients

5. Loss Function

Binary Cross-Entropy (Log Loss)

$L=-[y\log(p)+(1-y)\log(1-p)]$

6. Model Learning

```
X_train, X_test, y_train, y_test = train_test_split(
    X_multi_scaled, y, test_size=0.2, random_state=42
)

model_multi = LogisticRegression(max_iter=1000)
model_multi.fit(X_train, y_train)
```

```
LogisticRegression(max_iter=1000)
```

7. Model Evaluation

```
y_pred_multi = model_multi.predict(X_test)

print("Accuracy:", accuracy_score(y_test, y_pred_multi))
print("Precision:", precision_score(y_test, y_pred_multi))
print("Recall:", recall_score(y_test, y_pred_multi))
print("F1 Score:", f1_score(y_test, y_pred_multi))
```

```
Accuracy: 0.9074074074074074
Precision: 0.9
Recall: 0.8571428571428571
F1 Score: 0.8780487804878049
```

```
confusion_matrix(y_test, y_pred_multi)
```

```
array([[31,  2],
       [ 3, 18]])
```

Model Comparision

Logistic regression predicts probabilities.

Single-feature models are interpretable but limited with lower accuracy.

Multi-feature models capture real-world complexity with higher accuracy and improved recalling features.

DISCUSSION AND CONCLUSION

In this lab, we studied how to build a Machine Learning pipeline using logistic regression. We started with a breast cancer dataset to understand the basics and then moved on to a heart disease dataset. The main goal was to see how well we could predict if a patient has heart disease by following the standard ML steps: collecting data, cleaning it (like removing invalid cholesterol values), choosing features, and training the model.We tested two different models. The first one was a single-feature model that only used cholesterol levels to make predictions. We chose cholesterol because it's a known risk factor, but it didn't work very well on its own. It ended up with a very low F1-score of 0.32 and a recall of 24%. In a real hospital, this would be dangerous because it would miss 16 out of 21 sick patients, which is a huge risk.The second model used multiple features like age, blood pressure, and max heart rate. This model was much better because it could see the more complex patterns in the data. Its F1-score jumped to 0.88 and its recall hit 86%. This time, the model only missed 3 patients instead of 16. It also had a high precision of 90%, meaning it didn't cause many false alarms.

Overall, this lab showed that while single-feature models are easy to understand, they aren't accurate enough for something as important as healthcare. Using multiple features makes the model much more reliable. Even though the multi-feature model is more complex, its ability to save lives by not missing cases makes it the better choice for clinical use.