National University of Computer & Emerging Sciences, Karachi

# FALL 2024, LAB MANUAL – 09

# LOGISTIC REGRESSION AND NEURAL NETWORK

| | |
|---|---|
| COURSE CODE : | AL3002 |
| INSTRUCTOR : | ALISHBA SUBHANI |

## OBJECTIVE

1. Implementation of Logistic Regression
2. Parameters of Logistic Regression
3. Gradient Descent and Cost Function

## LOGISTIC REGRESSION

Logistic regression is the appropriate regression analysis to conduct when the dependent variable is dichotomous (binary). Like all regression analyses, logistic regression is a predictive analysis. Logistic regression is used to describe data and to explain the relationship between one dependent binary variable and one or more nominal, ordinal, interval or ratio-level independent variables.

## TYPES OF LOGISTIC REGRESSION

- Ordinal Logistic Regression
- Binary Logistic Regression
- Multinomial Logistic Regression

### Binary logistic regression

Binary logistic regression is used to predict the probability of a binary outcome, such as yes or no, true or false, or 0 or 1. For example, it could be used to predict whether a customer will churn or not, whether a patient has a disease or not, or whether a loan will be repaid or not.

### Multinomial logistic regression

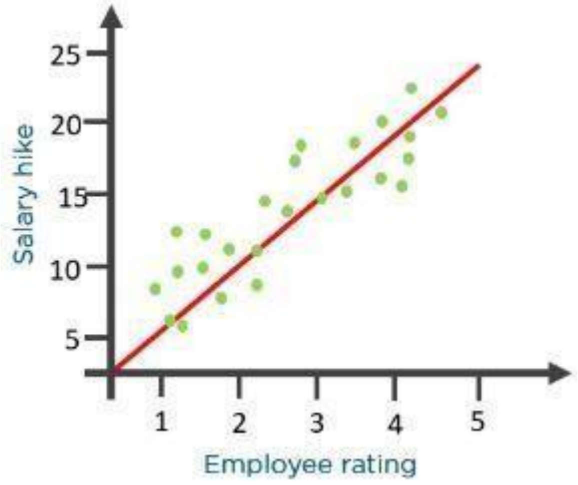
Multinomial logistic regression is used to predict the probability of one of three or more possible outcomes, such as the type of product a customer will buy, the rating a customer will give a product, or the political party a person will vote for.

**Ordinal logistic regression**

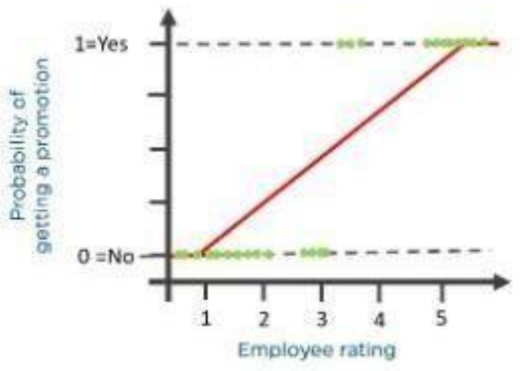
Ordinal Logistic Regression is used to predict the probability of an outcome that falls into a predetermined order, such as the level of customer satisfaction, the severity of a disease, or the stage of cancer.

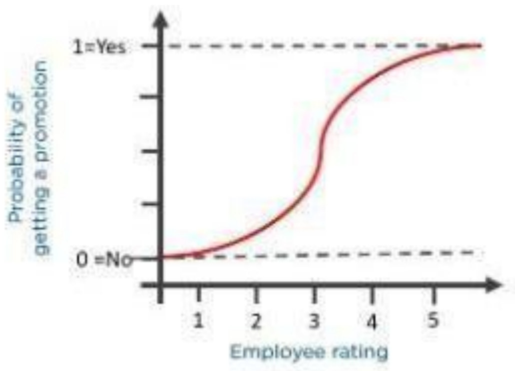
**HOW DOES THE LOGISTIC REGRESSION ALGORITHM WORK?**

Consider the following example: An organization wants to determine an employee's salary increase based on their performance.
For this purpose, a linear regression algorithm will help them decide. Plotting a regression line by considering the employee's performance as the independent variable, and the salary increase as the dependent variable will make their task easier.



Now, what if the organization wants to know whether an employee would get a promotion or not based on their performance? The above linear graph won't be suitable in this case. As such, we clip the line at zero and one, and convert it into a sigmoid curve (S curve).

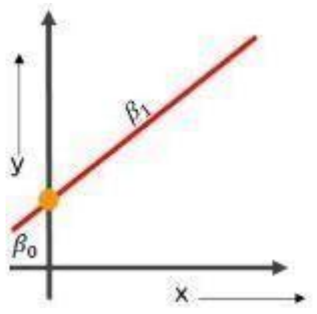




Based on the threshold values, the organization can decide whether an employee will get a salary increase or not.

To understand logistic regression, let’s go over the odds of success.
Odds ($\theta$) = Probability of an event happening / Probability of an event not happening
**□ = p / 1 - p**
The values of odds range from zero to ∞ and the values of probability lies between zero and one.

Consider the equation of a straight line:
**□ = □0 + □1* □**



Here, $\beta 0$ is the y-intercept
$\beta 1$ is the slope of the line
x is the value of the x coordinate
y is the value of the prediction
Now to predict the odds of success, we use the following formula:

$$\log\left(\frac{p(x)}{1-P(x)}\right) = \beta_0 + \beta_1 x$$

Exponentiation both the sides, we have:

$$\mathrm{e}^{ln\left(\frac{p(x)}{1-p(x)}\right)} = \mathrm{e}^{\beta_0+\beta_1 x}$$

$$\left(\frac{p(x)}{1-p(x)}\right) = \mathrm{e}^{\beta_0+\beta_1 x}$$

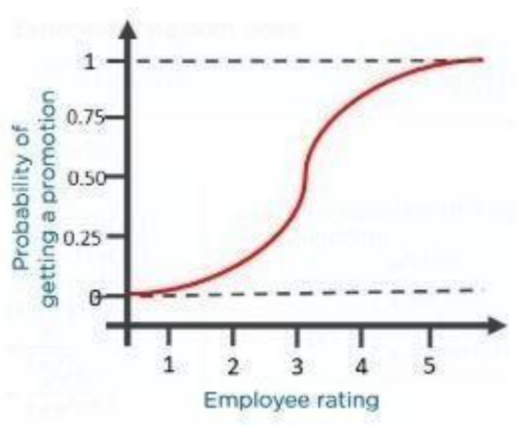
Let Y = e $\beta 0+\beta 1 * x$
Then p(x) / 1 - p(x) = Y
p(x) = Y(1 - p(x))
p(x) = Y - Y(p(x))
p(x) + Y(p(x)) = Y
p(x)(1+Y) = Y
p(x) = Y / 1+Y

$$p(x) = \frac{e^{\beta_0+\beta_1 x}}{1 + e^{\beta_0+\beta_1 x}}$$

The equation of the sigmoid function is:

$$p(x) = \frac{1}{1 + e^{-(\beta_0+\beta_1 x)}}$$

The sigmoid curve obtained from the above equation is as follows:



**SIGMOID FUNCTION:**

- The sigmoid function is a mathematical function used to map the predicted values to probabilities.
- It maps any real value into another value within a range of 0 and 1.
- The value of the logistic regression must be between 0 and 1, which cannot go beyond this limit, so it forms a curve like the "S" form. The S-form curve is called the Sigmoid function or the logistic function.

- In logistic regression, we use the concept of the threshold value, which defines the probability of either 0 or 1. Such as values above the threshold value tends to 1, and a value below the threshold values tends to 0.

We apply the sigmoid activation function on the hypothetical function of linear regression. So the resultant hypothetical function for logistic regression is given below:

```
h( x ) = sigmoid( wx + b )

Here, w is the weight vector.
x is the feature vector.
b is the bias.

sigmoid( z ) = 1 / ( 1 + e( - z ) )
```

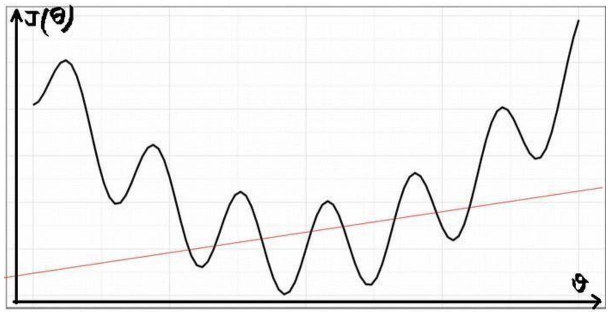
## COST FUNCTION

The cost function represents optimization objective i.e. we create a cost function and minimize it so that we can develop an accurate model with minimum error.

$$J(\theta) = \frac{1}{2}\sum_{i=1}^{m}(h_\theta(x^{(i)}) - y^{(i)})^2.$$

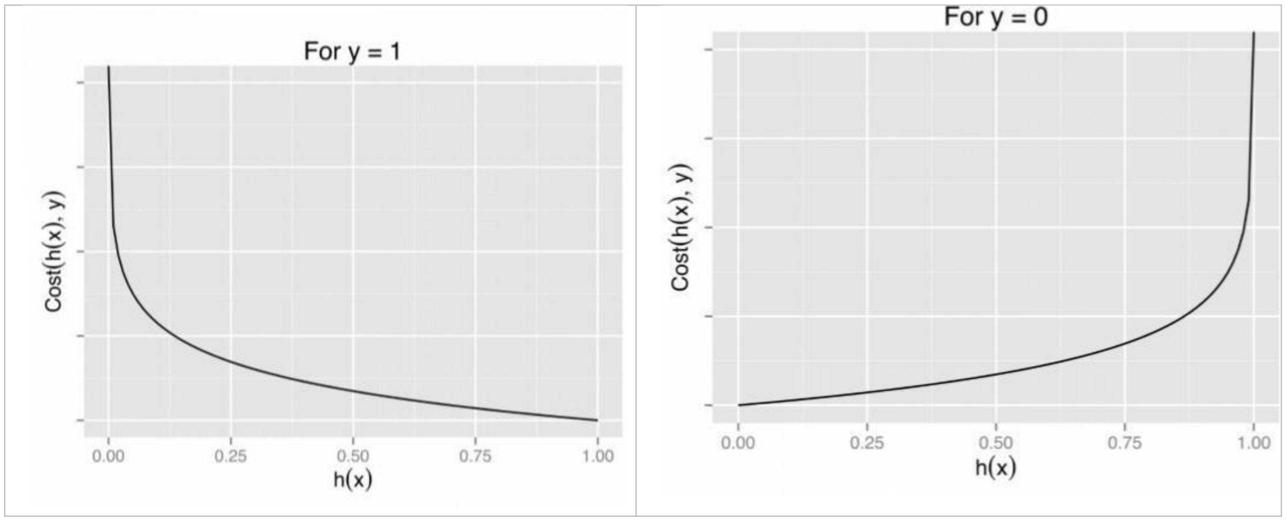
*Figure 1Cost Function of Linear regression*

If we try to use the cost function of the linear regression in ‘Logistic Regression’ then it would be of no use as it would end up being a **non-convex** function with many local minimums, in which it would be very **difficult** to **minimize the cost value** and find the global minimum.



For logistic regression, the Cost function is defined as:

$$Cost(h_\theta(x), y) = \begin{cases} -log(h_\theta(x)) & \text{if } y = 1 \\ -log(1 - h_\theta(x)) & \text{if } y = 0 \end{cases}$$



The above two functions can be compressed into a single function i.e.

$$J(\theta) = -\frac{1}{m}\sum\left[y^{(i)}\log(h\theta(x(i))) + \left(1 - y^{(i)}\right)\log(1 - h\theta(x(i)))\right]$$

**GRADIENT DESCENT**

Now the question arises, how do we reduce the cost value. Well, this can be done by using **Gradient Descent.** The main goal of Gradient descent is to **minimize the cost value.** i.e. min J($\theta$).
Now to minimize our cost function we need to run the gradient descent function on each parameter i.e.

$$\theta j := \theta j - \alpha \frac{\partial}{\partial \theta j} J(\theta)$$

**Objective:** To minimize the cost function we have to run the gradient descent function on each parameter

Want $\min_\theta J(\theta)$:

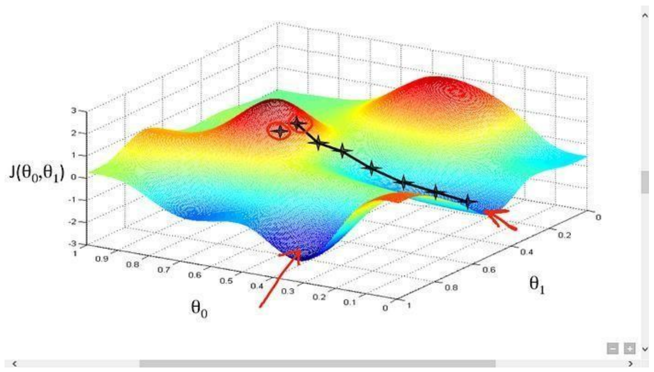
Repeat $\{$

$$\theta_j := \theta_j - \alpha \sum_{i=1}^{m} (h_\theta(x^{(i)}) - y^{(i)}) x_j^{(i)}$$

(simultaneously update all $\theta_j$)

$\}$

Gradient descent has an analogy in which we have to imagine ourselves at the top of a mountain valley and left stranded and blindfolded, our objective is to reach the bottom of the hill. Feeling the slope of the terrain around you is what everyone would do. Well, this action is analogous to calculating the gradient descent, and taking a step is analogous to one iteration of the update to the parameters.



## Logistic Regression

```
from sklearn.linear_model import LogisticRegression
LR = LogisticRegression()
modelLR = LR.fit(x_train,y_train)
prediction= modelLR.predict(x_test)

from sklearn.metrics import accuracy_score
print("=====================Training Accuarcy=============")
trac=LR.score(x_train,y_train)
print(trac)
print("=====================Testing Accuarcy=============")
teacLR=accuracy_score(y_test,prediction)
print(teacLR)
```

## Exploring Slope and Coefficients

```
print(modelLR.coef_)
print(modelLR.intercept_)
```

**Multinomial logistic regression,** also known as softmax regression or maximum entropy classifier, is an extension of binary logistic regression to handle problems with more than two categories. It is a classification algorithm used when the dependent variable is categorical with more than two levels.

In multinomial logistic regression, the model predicts the probability of each category and assigns the observation to the category with the highest probability. The output is a probability distribution over multiple classes, and the probabilities sum to 1

## Multinomial Logistic Regression

```
MLR = LogisticRegression(multi_class='multinomial')
modelMLR = MLR.fit(x_train,y_train)
prediction= modelMLR.predict(x_test)
```

In scikit-learn's Logistic Regression, the **multi_class='auto'** parameter is used as default to automatically determine the multi-class strategy based on the nature of the problem and the solver selected. Specifically, it selects the appropriate strategy based on the number of unique classes in the target variable. The behavior of multi_class='auto' can be understood as follows:

**Binary Classification (Two Classes):**

If there are only two unique classes in the target variable, logistic regression defaults to the binary classification strategy ('ovr' or 'ovr_balanced' depending on the value of the class_weight parameter).

**Multiclass Classification (More than Two Classes):**

If there are more than two unique classes, logistic regression automatically switches to the "multinomial" strategy. In this strategy, the model is trained to handle multiple classes simultaneously, and it optimizes a single objective function.

## Solver in Logistic Regression

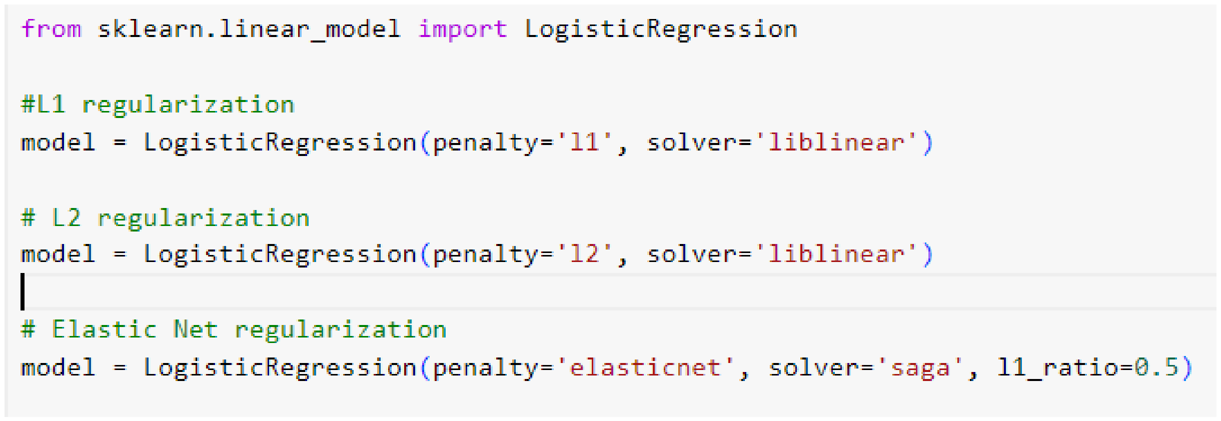
```
model1 = LogisticRegression(solver='newton-cg')
model1.fit(x_train,y_train)
```

The solver parameter also plays a role in determining the behavior. If solver='liblinear', it is designed for binary classification and uses the 'ovr' strategy for multiclass problems. If solver is set to other algorithms like 'lbfgs', 'newton-cg', or 'sag', logistic regression

The choice of the solver depends on various factors, including the size of the dataset, the number of features, and the regularization requirements. Here are some considerations:

- For small to medium-sized datasets, 'liblinear' is often a good choice.
- For high-dimensional datasets, 'lbfgs' or 'newton-cg' might be more efficient.
- For large datasets, especially when the number of samples is much larger than the number of features, 'sag' or 'saga' could be beneficial.

## Penalty in Logistic Regression



```python
from sklearn.linear_model import LogisticRegression

#L1 regularization
model = LogisticRegression(penalty='l1', solver='liblinear')

# L2 regularization
model = LogisticRegression(penalty='l2', solver='liblinear')

# Elastic Net regularization
model = LogisticRegression(penalty='elasticnet', solver='saga', l1_ratio=0.5)
```

In scikit-learn's Logistic Regression model, the penalty parameter is used to specify the type of regularization applied to the model. Regularization is a technique used to prevent overfitting by adding a penalty term to the loss function. The penalty parameter has two main options: 'l1' and 'l2', each corresponding to a different type of regularization.

**L1 Regularization ('l1'):**

- Also known as Lasso regularization.
- Adds the absolute values of the coefficients as a penalty term to the loss function.
- Encourages sparsity in the feature coefficients, leading to some coefficients being exactly zero.
- Useful for feature selection if you suspect that many features are irrelevant.

**L2 Regularization ('l2'):**

- Also known as Ridge regularization.
- Adds the squared values of the coefficients as a penalty term to the loss function.

- Encourages small, but non-zero, coefficients for all features.
- Generally used when all features are expected to contribute to the prediction.

**Elastic Net Regularization ('elasticnet'):**

- A combination of L1 and L2 regularization.
- The l1_ratio parameter controls the balance between L1 and L2 regularization.
- Useful when there are many features, and some of them are expected to be irrelevant.

By default, the penalty parameter is set to 'l2'. The choice between 'l1' and 'l2' (or 'elasticnet') depends on the characteristics of your data and the problem at hand. Experimenting with different penalties and regularization strengths can help determine the optimal configuration for your logistic regression model.

**Click here to explore more Logistic Regression Parameters**

**PERCEPTRON**

A perceptron is a fundamental building block of artificial neural networks and serves as a basic computational unit. It was developed by Frank Rosenblatt in 1957. The perceptron is a type of linear classifier that takes a set of binary inputs and produces a binary output. It's a simple mathematical model inspired by the way biological neurons work.

Here are the key components and concepts related to perceptrons:

**Inputs and Weights:**

The perceptron receives multiple binary inputs (0 or 1).

Each input is associated with a weight, which determines the influence of that input on the perceptron's output.

**Weighted Sum:**

The weighted sum of inputs and weights is calculated.

The perceptron performs a weighted sum: $\text{sum}=\sum_{i}^{n}{=}_{1}\ \text{input}_i \text{ x } \text{weight}_i$

**Activation Function:**

The weighted sum is passed through an activation function.

The result is typically compared to a threshold.

If the result exceeds the threshold, the perceptron outputs 1; otherwise, it outputs 0.

**Thresholding**:

The activation function acts as a thresholding function.

A common choice is a step function: output

$$\begin{cases} 1 & \text{if sum} \geq \text{threshold} \\ 0 & \text{otherwise} \end{cases}.$$

Mathematically, the output (output) of a perceptron can be represented as:

$$\text{output} = \begin{cases} 1 & \text{if } \sum_{i=1}^{n} \text{input}_i \times \text{weight}_i \geq \text{threshold} \\ 0 & \text{otherwise} \end{cases}$$

Perceptron have limitations, particularly their inability to learn more complex patterns and relationships. However, they form the basis for more advanced neural network architectures. Multilayer perceptron (MLPs) and other neural network structures were later developed to address the limitations of single-layer perceptron, allowing for the learning of more complex functions.

## NEURAL NETWORK

A neural network is a computational model inspired by the way biological neural networks in the human brain work. It consists of interconnected nodes, often referred to as neurons or artificial neurons, organized into layers. Neural networks are a fundamental component of machine learning, particularly in the field of deep learning.

## COMPONENTS OF NEURAL NETWORK

Here are the key components and concepts related to neural networks:

**Neurons (Nodes):**

Neurons are the basic computational units in a neural network.

Each neuron receives one or more inputs, performs a computation, and produces an output.

**Layers:**

Neurons are organized into layers. The three main types of layers are:

**Input Layer:** Receives the initial input data.

**Hidden Layers**: Intermediate layers between the input and output layers. Deep neural networks have multiple hidden layers.

**Output Layer:** Produces the final output or prediction.

**Weights and Connections:**

Connections between neurons are associated with weights.

Weights determine the strength of the connection between neurons.

Learning in a neural network involves adjusting these weights based on training data.

**Activation Function:**

Each neuron typically applies an activation function to its weighted sum of inputs.

Common activation functions include sigmoid, hyperbolic tangent (tanh), and rectified linear unit (ReLU).

**Feedforward and Backpropagation:**

In a feedforward neural network, information flows from the input layer through the hidden layers to the output layer.

Backpropagation is a training algorithm used to adjust weights based on the error between predicted and actual outputs.

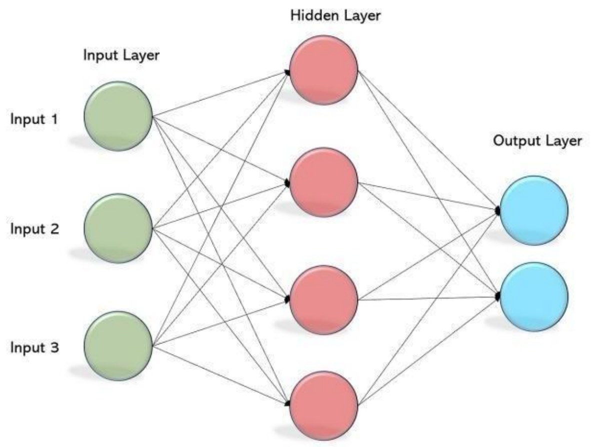
**Training and Learning:**

Neural networks learn from data by adjusting their weights during the training process.

Training involves presenting input data with known outputs and updating weights to minimize prediction errors.

## MULTI LAYER PERCEPTRON

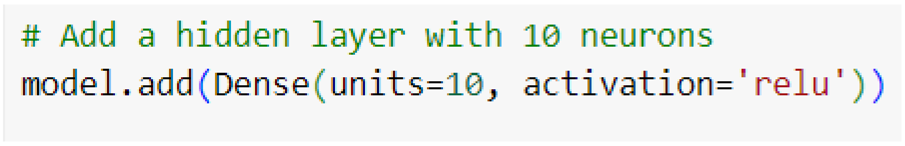
MLP stands for "Multilayer Perceptron," and it refers to a type of neural network architecture. An MLP is a class of feedforward artificial neural networks characterized by having multiple layers of nodes (neurons), including an input layer, one or more hidden layers, and an output layer. Each layer is fully connected to the next layer.



### Input Layer with One Hidden Layer

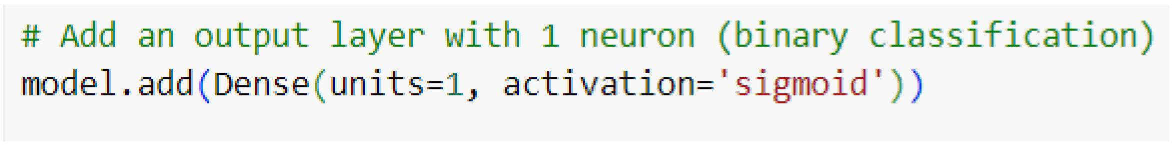
```
# Add an input layer with 20 neurons (input features)
model.add(Dense(units=20, input_dim=20, activation='relu'))
```

## 2nd Hidden Layer



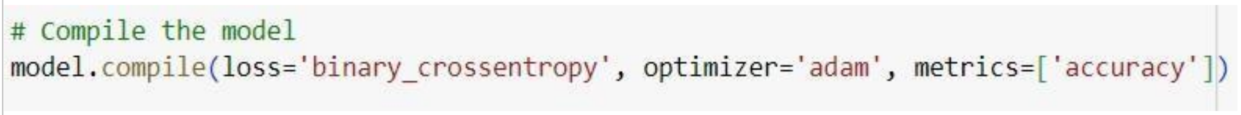
```
# Add a hidden layer with 10 neurons
model.add(Dense(units=10, activation='relu'))
```

## Output Layer



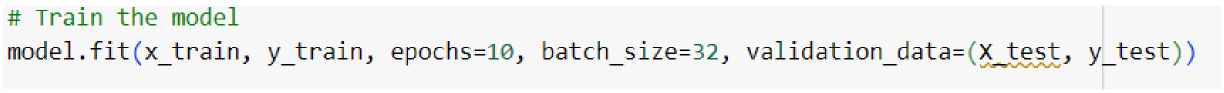
```
# Add an output layer with 1 neuron (binary classification)
model.add(Dense(units=1, activation='sigmoid'))
```

## Compile MLP



```
# Compile the model
model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
```

## Model Training



```
# Train the model
model.fit(x_train, y_train, epochs=10, batch_size=32, validation_data=(X_test, y_test))
```

**What are Activation Functions?**

An **activation function** decides **whether a neuron should be “activated” or not**, i.e., whether it should pass its signal to the next layer.

- Without activation functions, a neural network would just be a **linear model**, no matter how many layers it has.
- Activation functions **introduce non-linearity**, allowing the network to learn **complex patterns**.

Mathematically:

$$\text{output} = f\left(\sum_i w_i x_i + b\right)$$

where *f* is the **activation function**.

### Common Activation Functions

| Function | Formula | Output Range | Pros | Drawbacks |
|---|---|---|---|---|
| **Sigmoid** | $\sigma(x) = \frac{1}{1+e^{-x}}$ | (0,1) | Smooth, interpretable as probability | Saturates → vanishing gradients for large |
| **Tanh** | $\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$ | (-1,1) | Zero-centered, stronger gradients than sigmoid | Saturates → vanishing gradients, slower convergence |
| **ReLU** | $f(x) = \max(0, x)$ | [0,∞) | Fast, avoids vanishing gradient for positive x | "Dying ReLU": neurons can get stuck at 0 |
| **Leaky ReLU** | $f(x) = x \text{ if } x > 0, \alpha x \text{ if } x < 0$ | (-∞,∞) | Fixes dying ReLU problem | Slightly more computation, choice of α |
| **Softmax** | $f_i(x) = \frac{e^{x_i}}{\sum_j e^{x_j}}$ | (0,1), sum = 1 | Converts vector to probability distribution | Not for hidden layers, only output classification |

**1. Sigmoid**

- For very large or very small inputs, derivative → 0 → **vanishing gradient**.
- Example: If z = 10 → gradient ≈ 0 → learning slows down.

**2. Tanh**

- Also suffers from **vanishing gradient** at large |z|.
- Slightly better than sigmoid because output is zero-centered.

**3. ReLU**

- Positive side → great, gradient = 1
- Negative side → gradient = 0 → neuron **can die** (never activate again).
- Fix: Leaky ReLU or Parametric ReLU

**4. Softmax**

- Great for classification outputs, but **cannot be used in hidden layers**.
- Sensitive to very large input values (overflow) → can use `log-softmax`.

## Choosing Activation Functions

- **Hidden layers:** usually ReLU or Leaky ReLU (fast, non-linear)
- **Output layer:** depends on the task
  - Regression → Linear activation (no function)
  - Binary classification → Sigmoid
  - Multi-class classification → Softmax

```
from tensorflow.keras.layers import Dense, LeakyReLU

model = Sequential([
    Dense(64, activation=None, input_shape=(20,)),
    LeakyReLU(alpha=0.01),
    Dense(32, activation=None),
    LeakyReLU(alpha=0.01),
    Dense(1)
])
```

**Note:** You cannot pass `activation='leaky_relu'` directly to `Dense` — must use the `LeakyReLU` layer.

## Choosing Loss Function

| Task | Common Loss | Formula | Notes |
|---|---|---|---|
| **Regression** | MSE | $\frac{1}{n}\sum(y-\hat{y})^2$ | Penalizes large errors |
| **Regression** | MAE | $\frac{1}{n}\sum_{i=1}^{n}\lvert y_i-\hat{y}_i\rvert$ | y-\hat{y} |
| **Classification (binary)** | Binary Cross-Entropy | $-\frac{1}{n}\sum[y\log\hat{y}+(1-y)\log(1-\hat{y})]$ | Sigmoid output |
| **Classification (multi-class)** | Categorical Cross-Entropy | $-\sum y\log\hat{y}$ | Softmax output |
| **Classification (multi-class, integer)** | Sparse Categorical Cross-Entropy | Same as above | Integer labels |

## Gradient Descent — the big idea

The goal of **gradient descent** is to minimize the **loss function** (e.g., MSE, cross-entropy) by adjusting the model's parameters (weights, biases).
At each step, we move **in the opposite direction** of the gradient (because it points toward the steepest increase).

$$\theta_{\text{new}} = \theta_{\text{old}} - \eta \, \nabla_\theta J(\theta)$$

Where

- $\theta$= model parameters (weights)
- $\eta$= learning rate
- $\nabla_\theta J(\theta)$= gradient of the loss

### Types of Gradient Descent

The difference lies in **how much data** we use to compute the gradient each step.

#### (a) Batch Gradient Descent

- Uses **the entire training dataset** to compute the gradient before taking one update step.
- One iteration = one forward + backward pass over **all samples**.

$$\theta = \theta - \eta \, \nabla_\theta J(\theta; \text{all data})$$

#### (b) Stochastic Gradient Descent (SGD)

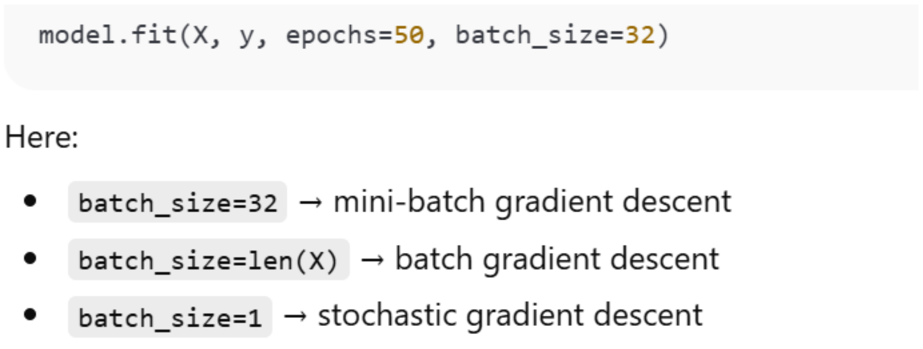
- Updates parameters **after every single sample**.

$$\theta = \theta - \eta \, \nabla_\theta J(\theta; x_i, y_i)$$

#### (c) Mini-Batch Gradient Descent

- Uses a **small batch of samples (e.g., 32, 64)** to compute the gradient each step.
- Most commonly used in practice.

$$\theta = \theta - \eta \, \nabla_\theta J(\theta; \text{batch})$$



```
model.fit(X, y, epochs=50, batch_size=32)
```

Here:

- `batch_size=32` → mini-batch gradient descent
- `batch_size=len(X)` → batch gradient descent
- `batch_size=1` → stochastic gradient descent

```
model.fit(X, y, validation_split=0.2, epochs=10, batch_size=32)
```

Then with **1000 rows:**

| Parameter | Meaning | Calculation | Result |
|---|---|---|---|
| validation_split=0.2 | Reserve 20% for validation | 1000 × 0.2 | 200 validation rows |
| | | 1000 × 0.8 | 800 training rows |
| batch_size=32 | Number of samples per batch | 800 ÷ 32 | 25 batches per epoch |
| epochs=10 | Full passes over training data | 10 × 25 batches | 250 weight updates total |

## What is Regularization?

**Regularization** is a technique to **prevent overfitting** in machine learning models.

- **Overfitting** happens when a model learns **not just the true pattern**, but also the **noise in the training data**.
- Regularization adds a **penalty** to the model's complexity to encourage **simpler models** that generalize better to new data.

Imagine your neural network is trying to **predict an output from 20 features**.

- Without regularization → the network might assign **huge weights** to some features just to perfectly fit your training data.
- Regularization → encourages the network to **keep weights smaller and balanced**, so it doesn't overreact to small noise in the dataset.

## Types of Regularization

### (a) L1 Regularization (Lasso)

- Adds the **absolute value of weights** to the loss:

$$Loss_{new} = Loss_{original} + \lambda \sum |w_i|$$

- Encourages **sparsity** → some weights become **exactly 0**, effectively removing irrelevant features.
- Useful if you suspect some of your 20 features are **not important**.

## (b) L2 Regularization (Ridge)

- Adds the **squared value of weights** to the loss:

$$Loss_{new} = Loss_{original} + \lambda \sum w_i^2$$

- Encourages **small weights** but rarely zero.
- Makes the model **less sensitive to any single feature**, reducing overfitting.

```
Dense(64, activation='relu', input_shape=(20,), kernel_regularizer=l2(0.01)),
Dense(32, activation='relu', kernel_regularizer=l2(0.01)),
```

- `kernel_regularizer=l2(0.01)` → adds L2 penalty to the loss.
- You can also use `l1()` for L1 or combine them with `l1_l2()`.

## (c) Dropout

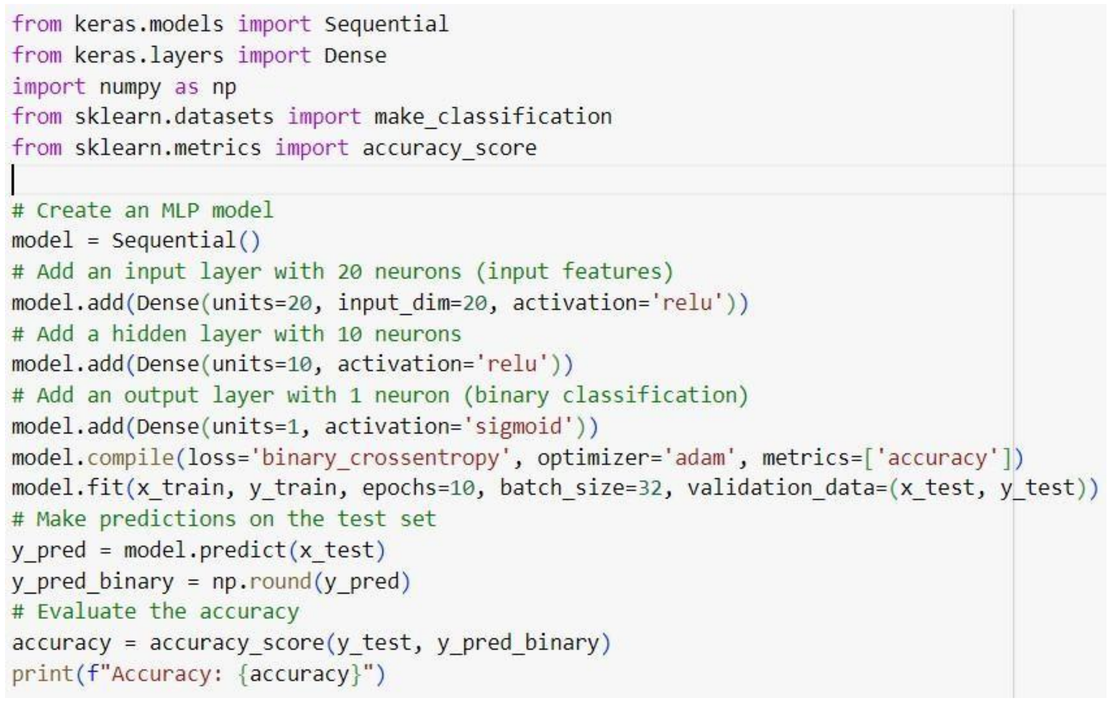
**Dropout** is a method where, during **training**, we **randomly "drop" (ignore)** a fraction of neurons in a layer.

- Dropped neurons **do not participate** in forward pass or backpropagation for that training step.
- Each training step uses a **different random subset** of neurons.
- During **testing/inference**, all neurons are used, but their outputs are **scaled** to match the effect of dropout.

**Purpose:** Prevent the network from **relying too heavily on specific neurons** — encourages it to learn redundant, robust representations**.**

```
model = Sequential([
    Dense(64, activation='relu', input_shape=(20,)),
    Dropout(0.2),  # Drop 20% of neurons randomly
    Dense(32, activation='relu'),
    Dropout(0.2),
    Dense(1)       # Regression output
])
```

## MLP For Binary Classification

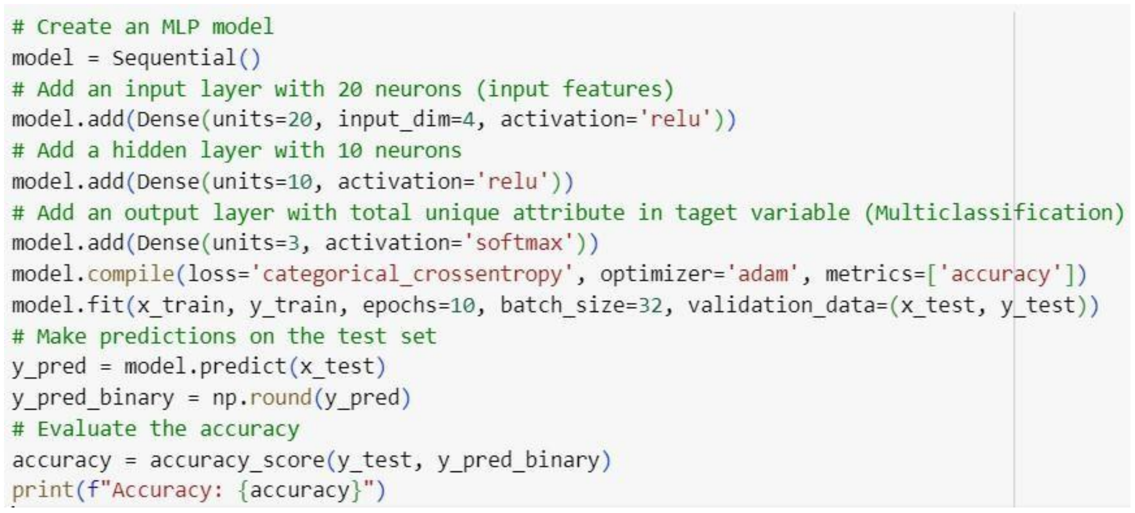


```
from keras.models import Sequential
from keras.layers import Dense
import numpy as np
from sklearn.datasets import make_classification
from sklearn.metrics import accuracy_score

# Create an MLP model
model = Sequential()
# Add an input layer with 20 neurons (input features)
model.add(Dense(units=20, input_dim=20, activation='relu'))
# Add a hidden layer with 10 neurons
model.add(Dense(units=10, activation='relu'))
# Add an output layer with 1 neuron (binary classification)
model.add(Dense(units=1, activation='sigmoid'))
model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
model.fit(x_train, y_train, epochs=10, batch_size=32, validation_data=(x_test, y_test))
# Make predictions on the test set
y_pred = model.predict(x_test)
y_pred_binary = np.round(y_pred)
# Evaluate the accuracy
accuracy = accuracy_score(y_test, y_pred_binary)
print(f"Accuracy: {accuracy}")
```

For Training a binary classification model , the input dim should be equal to the number of featurtes, activation function in input and hidden can be choosen as Relu or any other. But in Output Layer we have to choose Sigmoid for Binary Classification. The loss parameter in compile should be Binary Cross entropy for Binary Classification. The number of nodes in Output Layer should be One for Binary Classification.

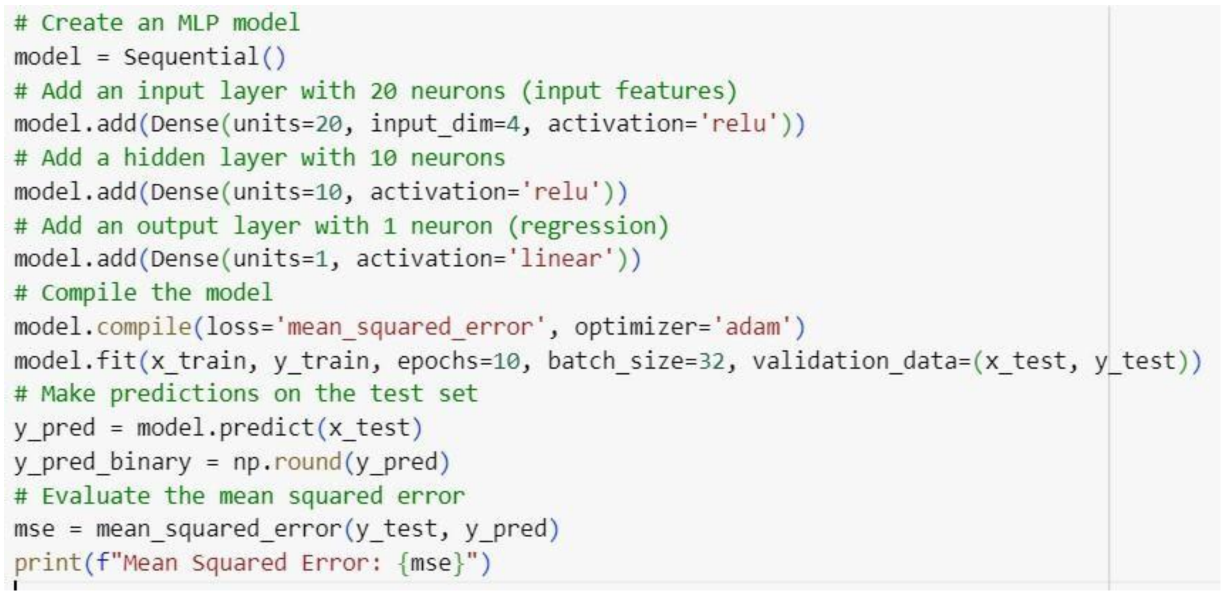
## MLP For Multi Classification



```
# Create an MLP model
model = Sequential()
# Add an input layer with 20 neurons (input features)
model.add(Dense(units=20, input_dim=4, activation='relu'))
# Add a hidden layer with 10 neurons
model.add(Dense(units=10, activation='relu'))
# Add an output layer with total unique attribute in taget variable (Multiclassification)
model.add(Dense(units=3, activation='softmax'))
model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
model.fit(x_train, y_train, epochs=10, batch_size=32, validation_data=(x_test, y_test))
# Make predictions on the test set
y_pred = model.predict(x_test)
y_pred_binary = np.round(y_pred)
# Evaluate the accuracy
accuracy = accuracy_score(y_test, y_pred_binary)
print(f"Accuracy: {accuracy}")
```

For Training a Multi classification model , the input dim should be equal to the number of features, activation function in input and hidden can be choosen as Relu or any other. But in Output Layer we have to choose Softmax for Multi Classification. The loss parameter in compile should be Categorical Cross entropy for Multi Classification. The number of nodes in Output layer should be equal to the unique records found in Class/Target Variable.

## MLP For Regression



```
# Create an MLP model
model = Sequential()
# Add an input layer with 20 neurons (input features)
model.add(Dense(units=20, input_dim=4, activation='relu'))
# Add a hidden layer with 10 neurons
model.add(Dense(units=10, activation='relu'))
# Add an output layer with 1 neuron (regression)
model.add(Dense(units=1, activation='linear'))
# Compile the model
model.compile(loss='mean_squared_error', optimizer='adam')
model.fit(x_train, y_train, epochs=10, batch_size=32, validation_data=(x_test, y_test))
# Make predictions on the test set
y_pred = model.predict(x_test)
y_pred_binary = np.round(y_pred)
# Evaluate the mean squared error
mse = mean_squared_error(y_test, y_pred)
print(f"Mean Squared Error: {mse}")
```

For Training a Regression model , the input dim should be equal to the number of features, activation function in input and hidden can be choosen as Relu or any other. But in Output Layer we have to choose Linear for Regression. The loss parameter in compile should be Mean Square Error for Regression. The number of nodes in Output layer should be equal to 1.

## TASKS

**TASK 1:**

Load the heart disease dataset

- Perform necessary EDA and Data Wrangling and Implement Logistic Regression
- First train your model using penalty as l1 regularization
- Train your model with l2 regularization
- Train your model with penalty = elastic net
- Now compare the results of training and testing accuracy
- Discuss in a text cell, what error you have gone through while implementing this penalty, Have you changed other parameter to apply these Penalties??
- What additional parameter you have changed while implementing the mentioned penalty, what is the relationship between these?

### TASK 2:

Implement Logistic regression on the **Iris dataset** , now choose different solvers
***lbfgs', 'liblinear', 'newton-cg', 'newton-cholesky', 'sag', 'saga'***

Compare the results of Training and testing accuracy in a Dataframe like this

| **Solver** | **Training Accuracy** | **Testing Accuracy** |
|---|---|---|
| | | |

- Briefly discuss the effect of solver on your dataset ,
- Have you found the similarity as mentioned by Sklearn that which solver is best for small, medium or larger dataset.
- Which solver is best in your case and why?
- Now copy this file and apply a new Dataset (Heart Disease) and compare, Does it really affected by the size of dataset??

### TASK 3:

- Implement Perceptron on Iris Data and the Compare the Results of Logistic Regression (Sklearn) model with Perceptron model. Compare Training and Testing results of Perceptron and LR
- What is the difference between Perceptron and LR

**TASK 4**

You are tasked with developing a more sophisticated MLP model for fraud detection in financial transactions. The dataset contains information about various transactions, and the goal is to classify each transaction as either fraudulent (1) or not fraudulent (0).

Your tasks are as follows:

- Load the dataset.
- Explore the dataset to understand its structure and characteristics.
- Preprocess the data if necessary.
- Split the dataset into training and testing sets.
- Create an MLP model for classification with the following Hidden Layer architecture:
    - Hidden Layer 1: 128 neurons, ReLU activation function.
    - Hidden Layer 2: 64 neurons, Tanh activation function.
    - Hidden Layer 3: 32 neurons, ReLU activation function.
    - Decide input and output by yourself
- Compile the model with the appropriate loss function and the Adam optimizer.
- Train the model on the training data for 50 epochs.
- Evaluate the model on the testing data.
- Additionally, monitor key metrics like accuracy, precision, recall, or F1 score during training and testing phases.

**TASK 5**

Implement MLP on these Dataset
Dataset 1
Dataset 2