# Regression Analysis



Nisal Mihiranga



### **Facilitator**

### **Nisal Mihiranga**



Al, Technology, Science, Teaching, Consulting, Mentoring



Head of AI and Data Science, Architect at Zone24x7 pvt Ltd Corporate Trainer

12 Years of Industry exposure to Data Engineering, Data Science and Business Intelligence

#### **Credentials:**

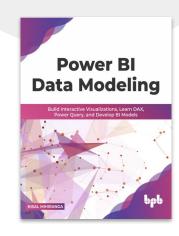
M.Sc in Data Science

B.Sc in Information Technology

Microsoft Certified Trainer







## Curriculum



Week	Module		
Week 1	Python for Machine Learning		
Week 2	Introduction to Machine Learning		
Week 3	Data Transformation and Analysis		
Week 4	Classification		
Week 5	Regression		
Week 6	Clustering Algorithms		
Week 7	Neural Networks		
Week 8	MLOPS, Machine Learning in Cloud		

### **Learning Outcomes**



- Understand the Purpose and Types of Regression Analysis: Learn the fundamental purpose of regression, which is to model and analyze relationships between variables, and differentiate between types (e.g., linear, multiple, logistic) based on use cases and data types.
- Evaluate Model Performance and Fit: Learn to use performance metrics (e.g., Mean Squared Error, R-squared, Adjusted R-squared) to assess the quality of a regression model, determining how well it explains the variability in the data.

# Regression Analysis

## Regression



How much or How many?



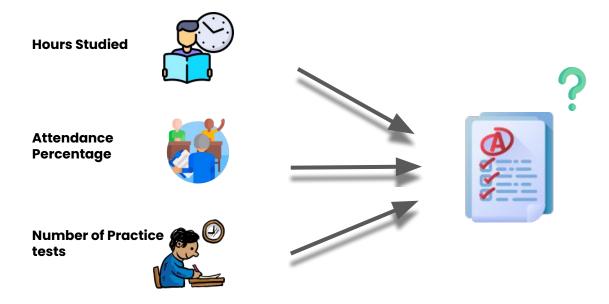


How much will this cost?

## What Is Regression Analysis?



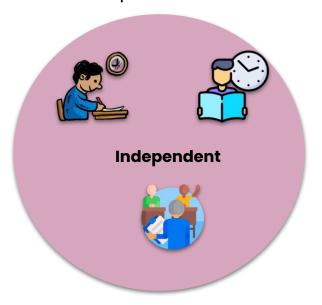
Regression analysis is statistical method that can allow to infer or predict one variable basis on one or more other variables.



## Dependent and Independent variable



 Variables used for prediction are called Independent variables.



 Variable to be inferred is called Dependent variable.



## When do we use Regression Analysis?



Regression analysis can be used to achieve two goals,

- Measurement of the influence of one or more variables on other variables.
  - Economics Analysis

     (Impact factors: Inflation, Interest Rate, etc...)
  - Medical Research
     (Blood pressure, cholesterol level, etc...)



Marketing
(Advertising spread, Pricing Strategies, etc...)





- Regression analysis is also valuable for making predictions based on known data.
  - Stock Market (Predict stock price)
  - Weather Forecasting (Predict weather pattern)



Customer Behaviors
 (Predict customers behaviours)





## Types of Regression Analysis

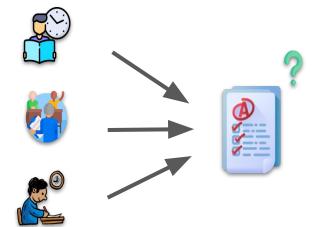


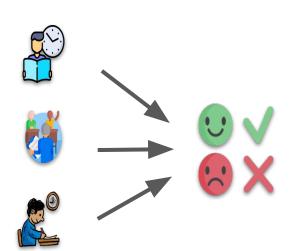
## 1. Simple Linear Regression

2. Multiple Linear Regression

3. Logistic Regression







## Simple Linear Regression

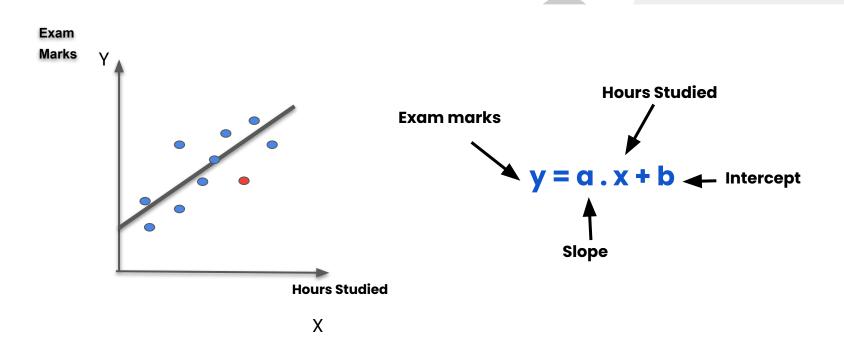


Linear Regression is used to find a relationship between a *dependent variable* (**Y**) and one or more *independent variables* (**X**). In simple linear regression, you have one independent variable, while in multiple linear regression, you have more than one.

Suppose you want to predict a student's test score (Y) based on the number of hours they study (X). The relationship can be represented as: **Y = aX + b**, where 'a' is the **slope** and 'b' is the **y-intercept**.

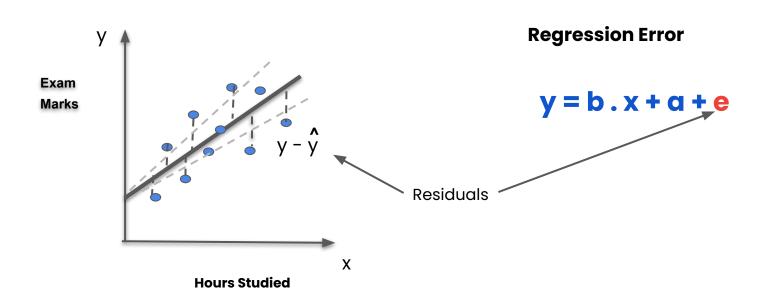
## Simple Linear Regression





## Fitting a line to data

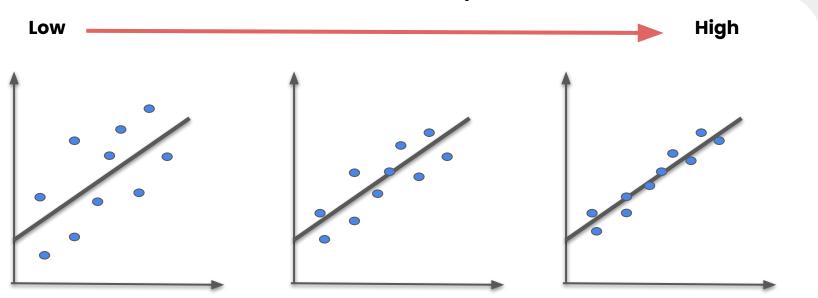




## Simple Linear Regression



#### **Linear Relationship**



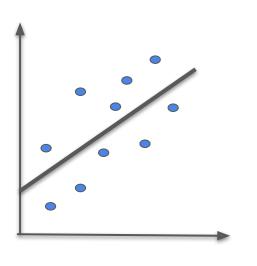
## **Regression Coefficient**

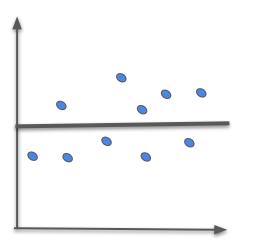


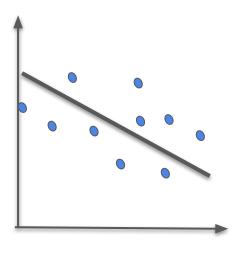
There is positive correlation between x and y

There is no correlation between x and y

There is negative correlation between x and y







b > 0

b = 0

b < 0





https://mlu-explain.github.io/linear-regression

## **Implement Regression Model**



There are several ways to implement linear regression, depending on the programming language and libraries you prefer

**Method 1**: Using sklearn library



Method 2: Using Statsmodels



Get familiar with **numpy** 



## Simple Linear Regression - code



```
import numpy as np
from sklearn.linear model import LinearRegression
# Sample data
hours studied = np.array([1, 2, 3, 4, 5])
exam scores = np.array([50, 60, 70, 80, 90])
# Reshape the data
hours studied = hours studied.reshape(-1, 1)
# Create a Linear Regression model
model = LinearRegression()
# Fit the model to the data
model.fit(hours studied, exam scores)
# Predict the exam score for a student who studies 6 hours
predicted score = model.predict([[6]])
print("Predicted exam score:", predicted_score[0])
```

# What is Mean Absolute Error (MAE), Mean Squared Error (MSE) and R Squared?



**Mean Absolute Error(MAE):** measures the average absolute error between actual and predicted values.

#### MAE = Actual values - Predicted values

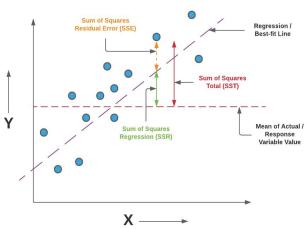
The Mean Squared Error (MSE): measures the average squared error between actual and

predicted values.

MSE = 
$$\frac{1}{\sum_{N = 1}^{n} \Sigma \text{ (actual values - predicted values)}^2}$$

R- Squared score represents the goodness of fit, with values closer to 1 indicating a better fit. Determine the X and Y are correlated

$$R^2 = \frac{SSR}{SST}$$



# What is Mean Absolute Error (MAE), Mean Squared Error (MSE) and R Squared?



**Mean Absolute Error(MAE)** is the mean size of the mistakes in collected predictions. We know that an error basically is the absolute difference between the actual or true values and the values that are predicted. The absolute difference means that if the result has a negative sign, it is ignored.

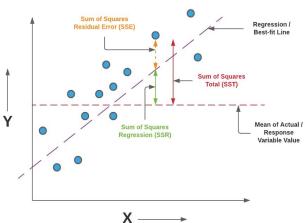
#### MAE = Actual values - Predicted values

**The Mean Squared Error** is the squared mean of the difference between the actual values and predictable values.

$$MSE = \frac{1}{N} \sum_{i=1}^{n} (\text{ actual values - predicted values})^{2}$$

**R- Squared** is the proportion of the total variation in the dependent variable that can be explained by the independent variables in the model.

$$R^2 = \frac{SSR}{SST}$$



## Simple Linear Regression - code



```
# Calculate the metrics
mae = mean absolute error(exam scores, predicted scores)
mse = mean squared error(exam scores, predicted scores)
r2 = r2 score(exam scores, predicted scores)
print("Mean Absolute Error:", mae)
print("Mean Squared Error:", mse)
print("R-squared Score:", r2)
# Plot the data and the regression line
plt.scatter(hours studied, exam scores, label="Actual Scores")
plt.plot(hours studied, predicted scores, color='red', label="Regression
Line")
plt.xlabel("Hours Studied")
plt.ylabel("Exam Scores")
plt.legend()
plt.show()
```



Multiple Linear Regression is an extension of Linear Regression that allows you to predict a continuous target variable based on multiple input features. Instead of a line, it fits a hyperplane to the data.

#### Ex:

Suppose you want to predict a house's price based on its size (in square feet), the number of bedrooms, and the number of bathrooms.

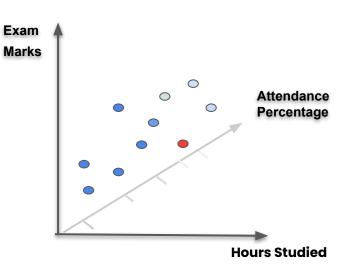


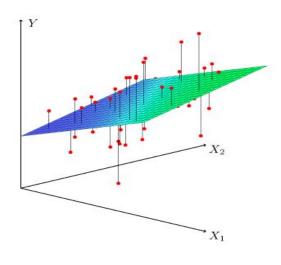


#### **Multiple**

$$y = b \cdot x + a \longrightarrow$$

$$y = b1.x1 + b2.x2 + .....bk.xk + a$$







	<b>Study Hours</b>	<b>Prep Exams</b>	Final Exam Score
Student 1	3	2	76
Student 2	7	6	88
Student 3	16	5	96
Student 4	14	2	90
Student 5	12	7	98
Student 6	7	4	80
Student 7	4	4	86
Student 8	19	2	89
Student 9	4	8	68
Student 10	8	4	75
Student 11	8	1	72
Student 12	3	3	76



```
import numpy as np
from sklearn.linear model import LinearRegression
# Sample data
sizes = np.array([1200, 1500, 1800, 2000, 2200, 2400, 2600, 2800, 3000,
3500])
bedrooms = np.array([2, 3, 3, 4, 4, 3, 4, 3, 4, 5])
bathrooms = np.array([1, 2, 2, 2, 3, 2, 3, 2, 3, 4])
prices = np.array([140000, 210000, 220000, 270000, 330000, 250000, 310000,
280000, 350000, 4000001)
# Create a matrix of input features
X = np.column_stack((sizes, bedrooms, bathrooms))
# Create a Multiple Linear Regression model
model = LinearRegression()
# Fit the model to the data
model.fit(X, prices)
# Predict the price of a house with 2500 sq. ft., 3 bedrooms, and 2
bathrooms
predicted_price = model.predict([[2500, 3, 2]])
print("Predicted house price:", predicted price[0])
```

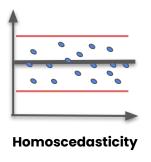
## **Assumptions of Linear Regression**

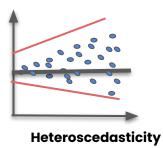


 Linearity - In linear regression, a straight line is drawn through the data. The straight line should represented all data points as good as possible, If it is can not represented its called non linear.



Homoscedasticity - The residuals must have a constant variance.

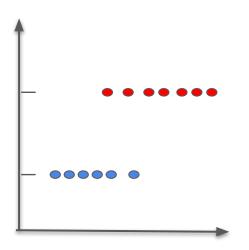




## **Logistic Regression**



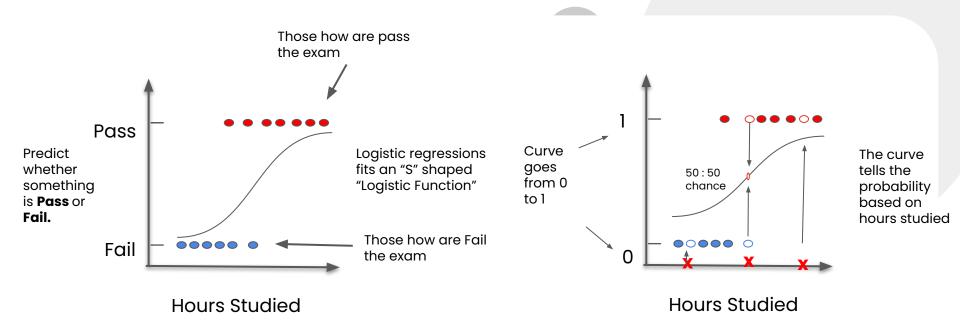
Logistic regression predicts whether something is Yes/No, Win/Loss, Negative/Positive, True/False and so on.



- Risk of a patient developing diabetes or not, (based on age, weight and other factors...)
- Likelihood of a borrower defaulting on a loan,
   (Based on their income, monthly payments, and other financial factors...)
- Detect fraudulent transactions,
   (Based on amount of transactions, the time of transactions and other factors...)

## **Logistic Regression**

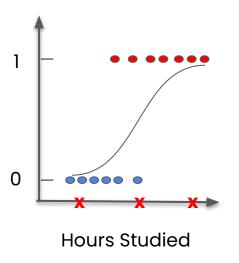


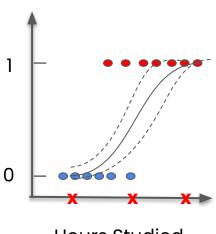


### How the line is fit to the data?



Logistic regression doesn't have the same concept "Residual". Instead it uses "maximum likelihood".





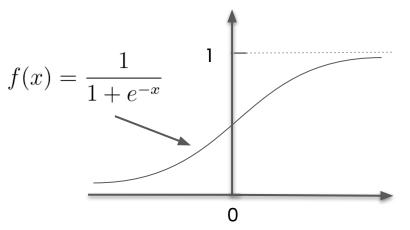
**Hours Studied** 

### How the line is fit to the data?



The logistic model is based on the logistic function.

The important thing about the logistic function is only values between 0 and 1.

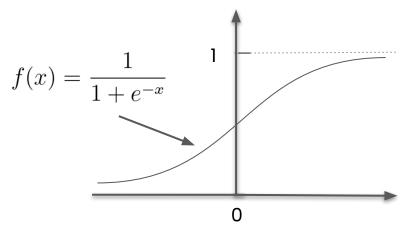


$$\hat{y} = \underbrace{b_1 \cdot x_1 + b_2 \cdot x_2 + \ldots + b_k \cdot x_k + a}_{1 + e^{-z}} = rac{1}{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + a)}_{1$$

## How to Train a Logistic Regression Model PDU

The logistic model is based on the logistic function.

The important thing about the logistic function is only values between 0 and 1.



$$\hat{y} = \underbrace{b_1 \cdot x_1 + b_2 \cdot x_2 + \ldots + b_k \cdot x_k + a}_{1 + e^{-z}} = rac{1}{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + \ldots + b_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + a)_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + a)_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + a)_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + a)_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + a)_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + a)_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + a)_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + a)_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + a)_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + a)_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + a)_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + a)_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + a)_k \cdot x_k + a)}_{1 + e^{-\underbrace{(b_1 \cdot x_1 + a)_k$$





https://mlu-explain.github.io/logistic-regression/







### **Thank You**



Nisal Mihiranga Head of AI & DS at Zone24x7 Consultant, Trainer **M:** +94 71 726 3044







