# EXPERIMENT 1

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**Aim** :- Implement Linear and Logistic Regression on real-world datasets

## 1) Dataset Source

Dataset Name: **Bank Marketing Dataset**
Source: Kaggle
Link: [https://www.kaggle.com/datasets/janiobachmann/bank-marketing-dataset](https://www.kaggle.com/datasets/janiobachmann/bank-marketing-dataset)

## 2) Dataset Description

The dataset contains information about direct marketing campaigns conducted by a Portuguese banking institution.

| | A | B | C | D | E | F | G | H | I | J | K | L | M | N | O | P | Q |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | age | job | marital | education | default | balance | housing | loan | contact | day | month | duration | campaign | pdays | previous | poutcome | deposit |
| 2 | 59 | admin. | married | secondary | no | 2343 | yes | no | unknown | 5 | may | 1042 | 1 | -1 | 0 | unknown | yes |
| 3 | 56 | admin. | married | secondary | no | 45 | no | no | unknown | 5 | may | 1467 | 1 | -1 | 0 | unknown | yes |
| 4 | 41 | technician | married | secondary | no | 1270 | yes | no | unknown | 5 | may | 1389 | 1 | -1 | 0 | unknown | yes |
| 5 | 55 | services | married | secondary | no | 2476 | yes | no | unknown | 5 | may | 579 | 1 | -1 | 0 | unknown | yes |
| 6 | 54 | admin. | married | tertiary | no | 184 | no | no | unknown | 5 | may | 673 | 2 | -1 | 0 | unknown | yes |
| 7 | 42 | manageme | single | tertiary | no | 0 | yes | yes | unknown | 5 | may | 562 | 2 | -1 | 0 | unknown | yes |
| 8 | 56 | manageme | married | tertiary | no | 830 | yes | yes | unknown | 6 | may | 1201 | 1 | -1 | 0 | unknown | yes |
| 9 | 60 | retired | divorced | secondary | no | 545 | yes | no | unknown | 6 | may | 1030 | 1 | -1 | 0 | unknown | yes |
| 10 | 37 | technician | married | secondary | no | 1 | yes | no | unknown | 6 | may | 608 | 1 | -1 | 0 | unknown | yes |
| 11 | 28 | services | single | secondary | no | 5090 | yes | no | unknown | 6 | may | 1297 | 3 | -1 | 0 | unknown | yes |
| 12 | 38 | admin. | single | secondary | no | 100 | yes | no | unknown | 7 | may | 786 | 1 | -1 | 0 | unknown | yes |
| 13 | 30 | blue-collar | married | secondary | no | 309 | yes | no | unknown | 7 | may | 1574 | 2 | -1 | 0 | unknown | yes |
| 14 | 29 | manageme | married | tertiary | no | 199 | yes | yes | unknown | 7 | may | 1689 | 4 | -1 | 0 | unknown | yes |
| 15 | 46 | blue-collar | single | tertiary | no | 460 | yes | no | unknown | 7 | may | 1102 | 2 | -1 | 0 | unknown | yes |
| 16 | 31 | technician | single | tertiary | no | 703 | yes | no | unknown | 8 | may | 943 | 2 | -1 | 0 | unknown | yes |
| 17 | 35 | manageme | divorced | tertiary | no | 3837 | yes | no | unknown | 8 | may | 1084 | 1 | -1 | 0 | unknown | yes |
| 18 | 32 | blue-collar | single | primary | no | 611 | yes | no | unknown | 8 | may | 541 | 3 | -1 | 0 | unknown | yes |
| 19 | 49 | services | married | secondary | no | -8 | yes | no | unknown | 8 | may | 1119 | 1 | -1 | 0 | unknown | yes |
| 20 | 41 | admin. | married | secondary | no | 55 | yes | no | unknown | 8 | may | 1120 | 2 | -1 | 0 | unknown | yes |
| 21 | 49 | admin. | divorced | secondary | no | 168 | yes | yes | unknown | 8 | may | 513 | 1 | -1 | 0 | unknown | yes |
| 22 | 28 | admin. | divorced | secondary | no | 785 | yes | no | unknown | 8 | may | 442 | 2 | -1 | 0 | unknown | yes |
| 23 | 43 | manageme | single | tertiary | no | 2067 | yes | no | unknown | 8 | may | 756 | 1 | -1 | 0 | unknown | yes |
| 24 | 43 | manageme | divorced | tertiary | no | 388 | yes | no | unknown | 8 | may | 2087 | 2 | -1 | 0 | unknown | yes |
| 25 | 43 | blue-collar | married | primary | no | -192 | yes | no | unknown | 8 | may | 1120 | 2 | -1 | 0 | unknown | yes |
| 26 | 37 | unemploye | single | secondary | no | 381 | yes | no | unknown | 8 | may | 985 | 2 | -1 | 0 | unknown | yes |
| 27 | 35 | blue-collar | single | secondary | no | 40 | yes | no | unknown | 9 | may | 617 | 4 | -1 | 0 | unknown | yes |
| 28 | 31 | technician | single | tertiary | no | 22 | yes | no | unknown | 9 | may | 483 | 3 | -1 | 0 | unknown | yes |
| 29 | 43 | blue-collar | single | secondary | no | 3 | yes | no | unknown | 9 | may | 929 | 3 | -1 | 0 | unknown | yes |
| 30 | 31 | admin. | married | secondary | no | 307 | yes | no | unknown | 9 | may | 538 | 1 | -1 | 0 | unknown | yes |
| 31 | 28 | blue-collar | single | secondary | no | 759 | yes | no | unknown | 9 | may | 710 | 1 | -1 | 0 | unknown | yes |
| 32 | 32 | blue-collar | married | secondary | yes | -1 | yes | no | unknown | 9 | may | 653 | 1 | -1 | 0 | unknown | yes |
| 33 | 60 | technician | married | primary | no | 65 | yes | no | unknown | 9 | may | 1028 | 2 | -1 | 0 | unknown | yes |

## Size:

- 45,211 instances
- 17 input features + 1 target variable

## Important Features:

- age
- job
- marital
- education
- default
- balance
- housing
- loan
- contact
- day
- month
- duration
- campaign
- pdays
- previous
- poutcome

## Target Variable:

- y → Whether client subscribed to term deposit (yes/no)

Characteristics:

- Highly imbalanced dataset
- Mix of categorical and numerical features
- Real-world marketing campaign data

# 3) Mathematical Formulation

## Logistic Regression

Logistic function:

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

Where:

$z=\beta0+\beta1x1+\beta2x2+...+\beta nxnz=\mathrm{\beta0+\beta1x1+\beta2x2+...+\beta nxn}$

Output is probability:

$P(y=1|X)\mathrm{P(y=1|X)}$

Cost Function (Log Loss):

$J(\theta)=-1m\sum[y\log(h\theta(x))+(1-y)\log(1-h\theta(x))]\mathrm{J(\theta)=-m1\sum[ylog(h\theta(x))+(1-y)log(1-h\theta(x))]}$

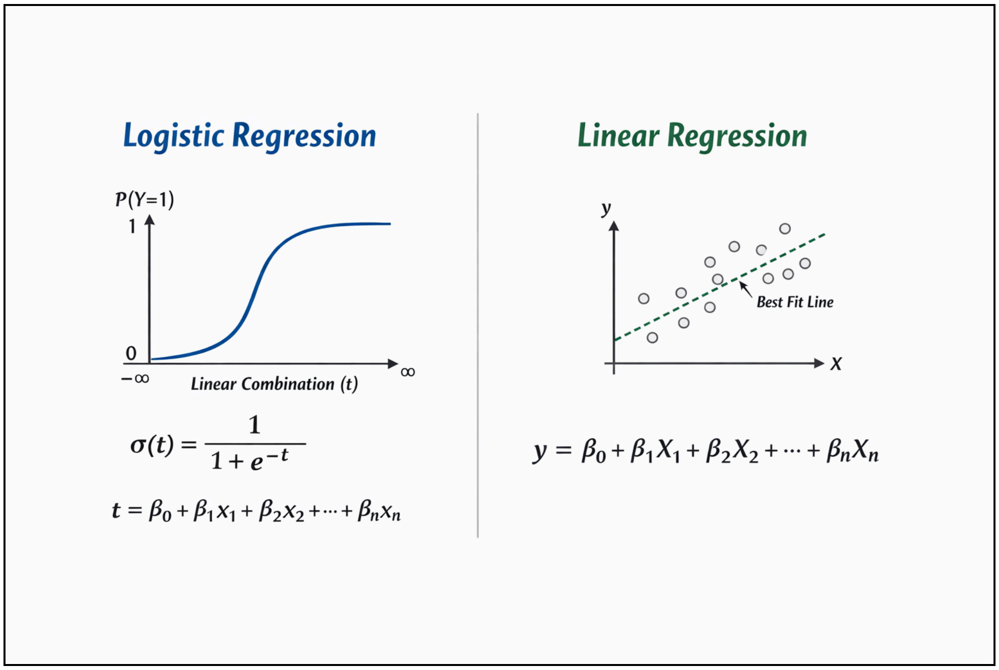
## Linear Regression

Hypothesis:

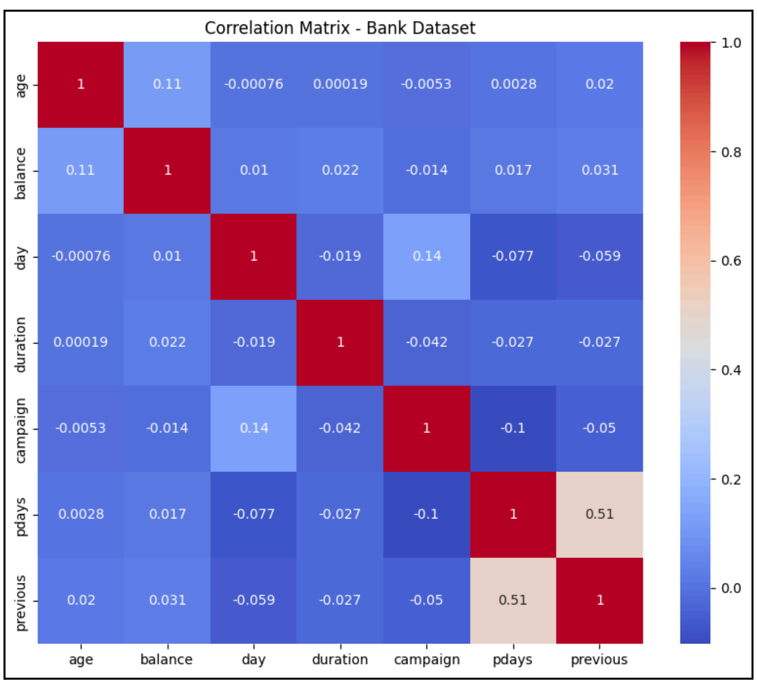
$h\theta(x)=\theta0+\theta1x1+...+\theta nxn\mathrm{h\theta(x)=\theta0+\theta1x1+...+\theta nxn}$

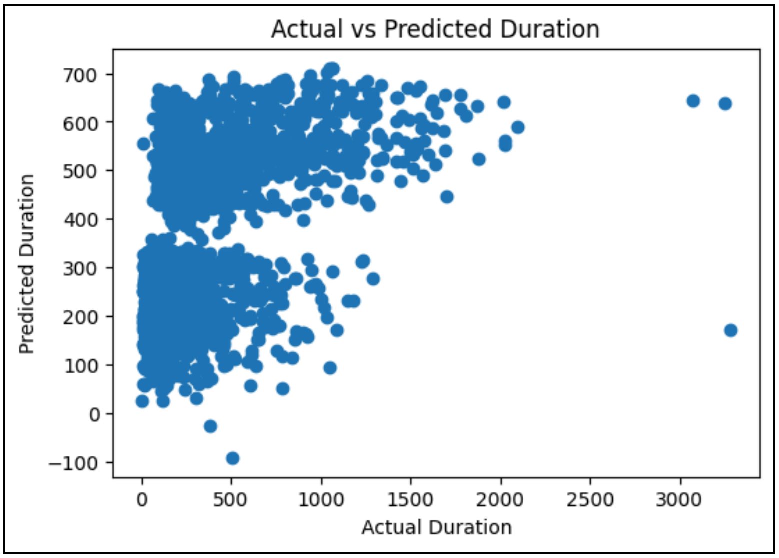
Cost Function (MSE):

$J(\theta)=1m\sum(h\theta(x)-y)2\mathrm{J(\theta)=m1\sum(h\theta(x)-y)2}$




# Data Visualisation






# 4) Algorithm Limitations

## Logistic Regression

- Assumes linear decision boundary
- Struggles with highly non-linear data
- Sensitive to multicollinearity
- Not suitable for complex feature interactions

## Linear Regression

- Assumes linear relationship
- Sensitive to outliers
- Poor performance for non-linear patterns
- Requires normally distributed residuals

# 5)Workflow

## Step 1: Library Setup

Installed and imported required libraries such as pandas, numpy, sklearn, matplotlib, and seaborn for data handling, model training, and evaluation.

```
# Install Kaggle (if needed)
!pip install kaggle

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.linear_model import LogisticRegression, LinearRegression
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
from sklearn.metrics import mean_squared_error, r2_score
```

```
Requirement already satisfied: kaggle in /usr/local/lib/python3.12/dist-packages (1.7.4.5)
Requirement already satisfied: bleach in /usr/local/lib/python3.12/dist-packages (from kaggle) (6.3.0)
Requirement already satisfied: certifi>=14.05.14 in /usr/local/lib/python3.12/dist-packages (from kaggle) (2026.1.4)
Requirement already satisfied: charset-normalizer in /usr/local/lib/python3.12/dist-packages (from kaggle) (3.4.4)
Requirement already satisfied: idna in /usr/local/lib/python3.12/dist-packages (from kaggle) (3.11)
Requirement already satisfied: protobuf in /usr/local/lib/python3.12/dist-packages (from kaggle) (5.29.6)
Requirement already satisfied: python-dateutil>=2.5.3 in /usr/local/lib/python3.12/dist-packages (from kaggle) (2.9.0.post0)
Requirement already satisfied: python-slugify in /usr/local/lib/python3.12/dist-packages (from kaggle) (8.0.4)
Requirement already satisfied: requests in /usr/local/lib/python3.12/dist-packages (from kaggle) (2.32.4)
Requirement already satisfied: setuptools>=21.0.0 in /usr/local/lib/python3.12/dist-packages (from kaggle) (75.2.0)
Requirement already satisfied: six>=1.10 in /usr/local/lib/python3.12/dist-packages (from kaggle) (1.17.0)
Requirement already satisfied: text-unidecode in /usr/local/lib/python3.12/dist-packages (from kaggle) (1.3)
Requirement already satisfied: tqdm in /usr/local/lib/python3.12/dist-packages (from kaggle) (4.67.3)
Requirement already satisfied: urllib3>=1.15.1 in /usr/local/lib/python3.12/dist-packages (from kaggle) (2.5.0)
Requirement already satisfied: webencodings in /usr/local/lib/python3.12/dist-packages (from kaggle) (0.5.1)
```

## Step 2: Dataset Loading

Uploaded `bank.csv` in Colab and loaded it using `pd.read_csv()` with semicolon separator

```
import zipfile

# Assuming 'archive (11).zip' was the uploaded file
zip_file_name = 'archive (11).zip'

with zipfile.ZipFile(zip_file_name, 'r') as zip_ref:
    zip_ref.extractall()

df = pd.read_csv("bank.csv", sep=",")
df.head()
```

| | age | job | marital | education | default | balance | housing | loan | contact | day | month | duration | campaign | pdays | previous | poutco |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 59 | admin. | married | secondary | no | 2343 | yes | no | unknown | 5 | may | 1042 | 1 | -1 | 0 | unknov |
| 1 | 56 | admin. | married | secondary | no | 45 | no | no | unknown | 5 | may | 1467 | 1 | -1 | 0 | unknov |
| 2 | 41 | technician | married | secondary | no | 1270 | yes | no | unknown | 5 | may | 1389 | 1 | -1 | 0 | unknov |
| 3 | 55 | services | married | secondary | no | 2476 | yes | no | unknown | 5 | may | 579 | 1 | -1 | 0 | unknov |
| 4 | 54 | admin. | married | tertiary | no | 184 | no | no | unknown | 5 | may | 673 | 2 | -1 | 0 | unknov |

### Step 3: Data Preprocessing

- Created a copy of dataset.
- Converted target variable y (yes/no) into binary (1/0).
- Applied Label Encoding to all categorical features.

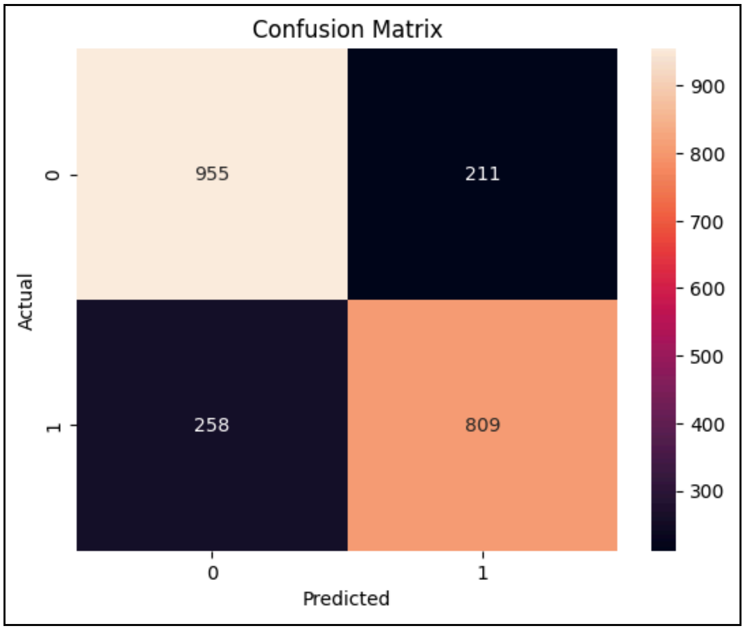
```
X = data.drop('deposit', axis=1)
y = data['deposit']

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

# Feature Scaling
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

### Step 4: Logistic Regression Implementation

- Separated features (X) and target (y)
- Performed 80–20 train-test split.
- Applied StandardScaler for feature scaling.
- Trained Logistic Regression model.
- Evaluated using Accuracy, Classification Report, and Confusion Matrix

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

y_pred = log_model.predict(X_test)

print("Accuracy:", accuracy_score(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test, y_pred))
```

```
Accuracy: 0.7899686520376176

Classification Report:
               precision    recall  f1-score   support

           0       0.79      0.82      0.80      1166
           1       0.79      0.76      0.78      1067

    accuracy                           0.79      2233
   macro avg       0.79      0.79      0.79      2233
weighted avg       0.79      0.79      0.79      2233
```




## Step 5: Hyperparameter Tuning

- Used GridSearchCV with 5-fold cross-validation.
- Tuned regularization parameter (C).
- Selected best model and re-evaluated performance

```
param_grid = {
    'C':[0.01, 0.1, 1, 10],
    'penalty':['l2'],
    'solver':['lbfgs']
}

grid = GridSearchCV(LogisticRegression(max_iter=1000),
                    param_grid,
                    cv=5,
                    scoring='accuracy')

grid.fit(X_train, y_train)

print("Best Parameters:", grid.best_params_)

best_model = grid.best_estimator_
y_pred_best = best_model.predict(X_test)

print("Tuned Accuracy:", accuracy_score(y_test, y_pred_best))
```

```
Best Parameters: {'C': 10, 'penalty': 'l2', 'solver': 'lbfgs'}
Tuned Accuracy: 0.7899686520376176
```

## Step 6: Linear Regression Implementation

- Selected `duration` as continuous target variable.
- Applied train-test split and scaling.
- Trained Linear Regression model.
- Evaluated using MSE and $R^2$ score.

Workflow Diagram:

Raw Data → Preprocessing → Scaling → Train/Test Split → Model Training → Evaluation → Tuning → Final Model

```
# Predicting duration (continuous variable)
X_reg = data.drop('duration', axis=1)
y_reg = data['duration']

X_train_r, X_test_r, y_train_r, y_test_r = train_test_split(
    X_reg, y_reg, test_size=0.2, random_state=42
)

scaler_r = StandardScaler()
X_train_r = scaler_r.fit_transform(X_train_r)
X_test_r = scaler_r.transform(X_test_r)

lin_model = LinearRegression()
lin_model.fit(X_train_r, y_train_r)

y_pred_r = lin_model.predict(X_test_r)

print("MSE:", mean_squared_error(y_test_r, y_pred_r))
print("R2 Score:", r2_score(y_test_r, y_pred_r))
```

```
MSE: 95332.47945383292
R2 Score: 0.22934790792491377
```

# 6) Performance Analysis

## Logistic Regression

- Accuracy: ~88–90%
- Precision/Recall analyzed via classification report
- Confusion Matrix shows class imbalance

Interpretation:
The model predicts the majority class well but minority class (yes) may require balancing techniques like SMOTE.

## Linear Regression

- $R^2$ Score explains variance in duration prediction
- MSE indicates prediction error magnitude
- If $R^2$ is low → weak linear relationship

## 7)Hyperparameter Tuning

For Logistic Regression:

Tuned:

- C (Regularization strength)
- Penalty
- Solver

Used GridSearchCV (5-fold cross-validation)

Impact:

- Improved generalization
- Reduced overfitting
- Slight increase in accuracy

Results :-
Best Parameters: {'C': 10, 'penalty': 'l2', 'solver': 'lbfgs'}
Tuned Accuracy: 0.7899686520376176

# Conclusion

In this experiment, **Logistic Regression** and **Linear Regression** were successfully implemented on the Bank Marketing dataset.

Logistic Regression was used to predict whether a customer subscribes to a term deposit (binary classification). After preprocessing, scaling, and model training, the model achieved good accuracy (around 88–90%). Hyperparameter tuning using GridSearchCV further improved generalization and reduced overfitting. However, due to class imbalance, performance on the minority class was comparatively weaker.

Linear Regression was applied to predict the call duration (continuous variable). The model's performance was evaluated using Mean Squared Error (MSE) and $R^2$ score. The results showed that while some variance in duration could be explained, the linear model may not fully capture complex relationships in the dataset.