```
# IMPORTANT: SOME KAGGLE DATA SOURCES ARE PRIVATE
# RUN THIS CELL IN ORDER TO IMPORT YOUR KAGGLE DATA SOURCES.
import kagglehub
kagglehub.login()
```

```
# IMPORTANT: RUN THIS CELL IN ORDER TO IMPORT YOUR KAGGLE DATA SOURCES,
# THEN FEEL FREE TO DELETE THIS CELL.
# NOTE: THIS NOTEBOOK ENVIRONMENT DIFFERS FROM KAGGLE'S PYTHON
# ENVIRONMENT SO THERE MAY BE MISSING LIBRARIES USED BY YOUR
# NOTEBOOK.

kagglesvij24_bank_01_path = kagglehub.dataset_download('kagglesvij24/bank-01')
kagglesvij24_bank_full_version1_path = kagglehub.dataset_download('kagglesvij24/bank-full-version1')

print('Data source import complete.')
```

```
# This Python 3 environment comes with many helpful analytics libraries installed
# It is defined by the kaggle/python Docker image: https://github.com/kaggle/docker-python
# For example, here's several helpful packages to load

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

# Input data files are available in the read-only "../input/" directory
# For example, running this (by clicking run or pressing Shift+Enter) will list all files under the input directory

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

# You can write up to 20GB to the current directory (/kaggle/working/) that gets preserved as output when you create a version using "Save & Run All"
# You can also write temporary files to /kaggle/temp/, but they won't be saved outside of the current session
```

```
/kaggle/input/bank-01/bank.csv
/kaggle/input/bank-full-version1/bank-full.csv
```

Bank Marketing Campaign- Data Pre-Processing and Model Deployment

image.png

image.png

Data Pre-Processing

Steps of preprocessing of data

- Import necessary library
- Read Dataset
- sanity check of dataStep
- Exploratory Data Analysis (EDA)
- Missing Value findings
- Outliers findings
- Duplicate Findings
- Normalization
- Encoding of Data

Exploratory Data Analysis

- **Using Pandas for basic statistics,summary, and descriptive analysis.**
- **Create histograms,boxplots,scatter plots, and other visualization to understand data distribution and relationships.**
- **Identify outliers and anomalies that migth affect analysis.**

Importing Necessary Libraries

Importing Necessary Libraries

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
```

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

Reading Dataset

```
Bank_data = pd.read_csv("/kaggle/input/bank-full-version1/bank-full.csv")
```

```
import pandas as pd


Bank_data = pd.read_csv('/kaggle/input/bank-full-version1/bank-full.csv')

# Display column names
print(Bank_data.columns)
```

```
Index(['sl. no', 'age', 'job', 'marital', 'education', 'default', 'balance',
       'housing', 'loan', 'contact', 'day', 'month', 'duration', 'campaign',
       'pdays', 'previous', 'poutcome', 'y'],
      dtype='object')
```

```
Bank_data.head()
```

	sl. no	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutcome	y
0	1	58	management	married	tertiary	no	2143	yes	no	unknown	5	may	261	1	-1	0	unknown	no
1	2	44	technician	single	secondary	no	29	yes	no	unknown	5	may	151	1	-1	0	unknown	no
2	3	33	entrepreneur	married	secondary	no	2	yes	yes	unknown	5	may	76	1	-1	0	unknown	no
3	4	47	blue-collar	married	unknown	no	1506	yes	no	unknown	5	may	92	1	-1	0	unknown	no
4	5	33	unknown	single	unknown	no	1	no	no	unknown	5	may	198	1	-1	0	unknown	no

```
Bank_data
```

	sl. no	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutcome	y
0	1	58	management	married	tertiary	no	2143	yes	no	unknown	5	may	261	1	-1	0	unknown	no
1	2	44	technician	single	secondary	no	29	yes	no	unknown	5	may	151	1	-1	0	unknown	no
2	3	33	entrepreneur	married	secondary	no	2	yes	yes	unknown	5	may	76	1	-1	0	unknown	no
3	4	47	blue-collar	married	unknown	no	1506	yes	no	unknown	5	may	92	1	-1	0	unknown	no
4	5	33	unknown	single	unknown	no	1	no	no	unknown	5	may	198	1	-1	0	unknown	no
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
45206	45207	51	technician	married	tertiary	no	825	no	no	cellular	17	nov	977	3	-1	0	unknown	yes
45207	45208	71	retired	divorced	primary	no	1729	no	no	cellular	17	nov	456	2	-1	0	unknown	yes
45208	45209	72	retired	married	secondary	no	5715	no	no	cellular	17	nov	1127	5	184	3	success	yes
45209	45210	57	blue-collar	married	secondary	no	668	no	no	telephone	17	nov	508	4	-1	0	unknown	no
45210	45211	37	entrepreneur	married	secondary	no	2971	no	no	cellular	17	nov	361	2	188	11	other	no

45211 rows × 18 columns

```
Bank_data.isna().sum()
```

```
sl. no       0
age          0
job          0
marital      0
education    0
default      0
balance      0
housing      0
loan         0
contact      0
day          0
month        0
duration     0
campaign     0
pdays        0
previous     0
poutcome     0
y            0
dtype: int64
```

Sanity Check

```
Bank_data.shape
```

```
(45211, 18)
```

```
Bank_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45211 entries, 0 to 45210
Data columns (total 18 columns):
 #   Column     Non-Null Count  Dtype 
---  ------     --------------  ----- 
 0   sl. no     45211 non-null  int64 
 1   age        45211 non-null  int64 
 2   job        45211 non-null  object
 3   marital    45211 non-null  object
 4   education  45211 non-null  object
 5   default    45211 non-null  object
 6   balance    45211 non-null  int64 
 7   housing    45211 non-null  object
 8   loan       45211 non-null  object
 9   contact    45211 non-null  object
 10  day        45211 non-null  int64 
 11  month      45211 non-null  object
 12  duration   45211 non-null  int64 
 13  campaign   45211 non-null  int64 
 14  pdays      45211 non-null  int64 
 15  previous   45211 non-null  int64 
 16  poutcome   45211 non-null  object
 17  y          45211 non-null  object
dtypes: int64(8), object(10)
memory usage: 6.2+ MB
```

```
Bank_data.describe()
```

	sl. no	age	balance	day	duration	campaign	pdays	previous
count	45211.000000	45211.000000	45211.000000	45211.000000	45211.000000	45211.000000	45211.000000	45211.000000
mean	22606.000000	40.936210	1362.272058	15.806419	258.163080	2.763841	40.197828	0.580323
std	13051.435847	10.618762	3044.765829	8.322476	257.527812	3.098021	100.128746	2.303441
min	1.000000	18.000000	-8019.000000	1.000000	0.000000	1.000000	-1.000000	0.000000
25%	11303.500000	33.000000	72.000000	8.000000	103.000000	1.000000	-1.000000	0.000000
50%	22606.000000	39.000000	448.000000	16.000000	180.000000	2.000000	-1.000000	0.000000
75%	33908.500000	48.000000	1428.000000	21.000000	319.000000	3.000000	-1.000000	0.000000
max	45211.000000	95.000000	102127.000000	31.000000	4918.000000	63.000000	871.000000	275.000000

```
for col  in Bank_data.select_dtypes(include='object').columns:
    print (col)
    print(Bank_data[col].unique())
```

```
job
['management' 'technician' 'entrepreneur' 'blue-collar' 'unknown'
 'retired' 'admin.' 'services' 'self-employed' 'unemployed' 'housemaid'
 'student']
marital
['married' 'single' 'divorced']
education
['tertiary' 'secondary' 'unknown' 'primary']
default
['no' 'yes']
housing
['yes' 'no']
loan
['no' 'yes']
contact
['unknown' 'cellular' 'telephone']
month
['may' 'jun' 'jul' 'aug' 'oct' 'nov' 'dec' 'jan' 'feb' 'mar' 'apr' 'sep']
poutcome
['unknown' 'failure' 'other' 'success']
y
['no' 'yes']
```

```
import numpy as np

# Identify features with missing values
features_na = [feature for feature in Bank_data.columns if Bank_data[feature].isnull().sum() > 0]

# Print the percentage of missing values for each feature with missing values
if features_na:
    for feature in features_na:
        print(f'{feature}: {np.round(Bank_data[feature].isnull().mean(), 4) * 100}% missing values')
else:
    print('No missing value found')
```

```
No missing value found
```

find features with one value

```
for column in Bank_data.columns:
    print(column,Bank_data[column].nunique())
```

```
sl. no 45211
age 77
job 12
marital 3
education 4
default 2
balance 7168
housing 2
loan 2
contact 3
day 31
month 12
duration 1573
campaign 48
pdays 559
previous 41
poutcome 4
y 2
```

Explore categorical features

```
categorical_features = [feature for feature in Bank_data.columns if (Bank_data[feature].dtypes == 'object') and (feature not in ['deposit'])]
categorical_features
```

```
['job',
 'marital',
 'education',
 'default',
 'housing',
 'loan',
 'contact',
 'month',
 'poutcome',
 'y']
```

```
# Identify discrete numerical features
discrete_features = [feature for feature in numerical_features if len(Bank_data[feature].unique()) < 25]

# Print the number of discrete numerical features
print('Discrete variables count: {}'.format(len(discrete_features)))

# Display the discrete numerical features
print(discrete_features)
```

```
Discrete variables count: 0
[]
```

```
# Identify continuous numerical features
continuous_numerical_features = [feature for feature in numerical_features if feature not in discrete_features and feature != 'y']

# Print the number of continuous numerical features
print('Continuous numerical features count: {}'.format(len(continuous_numerical_features)))

# Display the continuous numerical features
print(continuous_numerical_features)
```

```
Continuous numerical features count: 8
['sl. no', 'age', 'balance', 'day', 'duration', 'campaign', 'pdays', 'previous']
```

```
numerical_features=[feature for feature in Bank_data.columns if ((Bank_data[feature].dtypes != 'O') and (feature not in ['y']))]
print('Number of numerical variables:'), len ('numerical_features')
Bank_data[numerical_features].head()
```

Number of numerical variables:

	sl. no	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutcome
0	1	58	management	married	tertiary	no	2143	yes	no	unknown	5	may	261	1	-1	0	unknown
1	2	44	technician	single	secondary	no	29	yes	no	unknown	5	may	151	1	-1	0	unknown
2	3	33	entrepreneur	married	secondary	no	2	yes	yes	unknown	5	may	76	1	-1	0	unknown
3	4	47	blue-collar	married	unknown	no	1506	yes	no	unknown	5	may	92	1	-1	0	unknown
4	5	33	unknown	single	unknown	no	1	no	no	unknown	5	may	198	1	-1	0	unknown

```
Bank_data.drop(['default'], inplace=True)
```

```
Bank_data
```

	sl. no	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutcome	y
0	1	58	management	married	tertiary	no	2143	yes	no	unknown	5	may	261	1	-1	0	unknown	no
1	2	44	technician	single	secondary	no	29	yes	no	unknown	5	may	151	1	-1	0	unknown	no
2	3	33	entrepreneur	married	secondary	no	2	yes	yes	unknown	5	may	76	1	-1	0	unknown	no
3	4	47	blue-collar	married	unknown	no	1506	yes	no	unknown	5	may	92	1	-1	0	unknown	no
4	5	33	unknown	single	unknown	no	1	no	no	unknown	5	may	198	1	-1	0	unknown	no
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
45206	45207	51	technician	married	tertiary	no	825	no	no	cellular	17	nov	977	3	-1	0	unknown	yes
45207	45208	71	retired	divorced	primary	no	1729	no	no	cellular	17	nov	456	2	-1	0	unknown	yes
45208	45209	72	retired	married	secondary	no	5715	no	no	cellular	17	nov	1127	5	184	3	success	yes
45209	45210	57	blue-collar	married	secondary	no	668	no	no	telephone	17	nov	508	4	-1	0	unknown	no
45210	45211	37	entrepreneur	married	secondary	no	2971	no	no	cellular	17	nov	361	2	188	11	other	no

45211 rows × 18 columns

```
Bank_data = Bank_data.drop_duplicates()
Bank_data
```

	sl. no	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutcome	y
0	1	58	management	married	tertiary	no	2143	yes	no	unknown	5	may	261	1	-1	0	unknown	no
1	2	44	technician	single	secondary	no	29	yes	no	unknown	5	may	151	1	-1	0	unknown	no
2	3	33	entrepreneur	married	secondary	no	2	yes	yes	unknown	5	may	76	1	-1	0	unknown	no
3	4	47	blue-collar	married	unknown	no	1506	yes	no	unknown	5	may	92	1	-1	0	unknown	no
4	5	33	unknown	single	unknown	no	1	no	no	unknown	5	may	198	1	-1	0	unknown	no
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
45206	45207	51	technician	married	tertiary	no	825	no	no	cellular	17	nov	977	3	-1	0	unknown	yes
45207	45208	71	retired	divorced	primary	no	1729	no	no	cellular	17	nov	456	2	-1	0	unknown	yes
45208	45209	72	retired	married	secondary	no	5715	no	no	cellular	17	nov	1127	5	184	3	success	yes
45209	45210	57	blue-collar	married	secondary	no	668	no	no	telephone	17	nov	508	4	-1	0	unknown	no
45210	45211	37	entrepreneur	married	secondary	no	2971	no	no	cellular	17	nov	361	2	188	11	other	no

45211 rows × 18 columns

```
Bank_data.isna().sum()
```

```
sl. no       0
age          0
job          0
marital      0
education    0
default      0
balance      0
housing      0
loan         0
contact      0
day          0
month        0
duration     0
campaign     0
pdays        0
previous     0
poutcome     0
y            0
dtype: int64
```

Exploratory Data Analysis (EDA)

```
import pandas as pd

Bank_data=pd.read_csv("/kaggle/input/bank-full-version1/bank-full.csv")
```

Descriptive Statistics of the Numerical Column

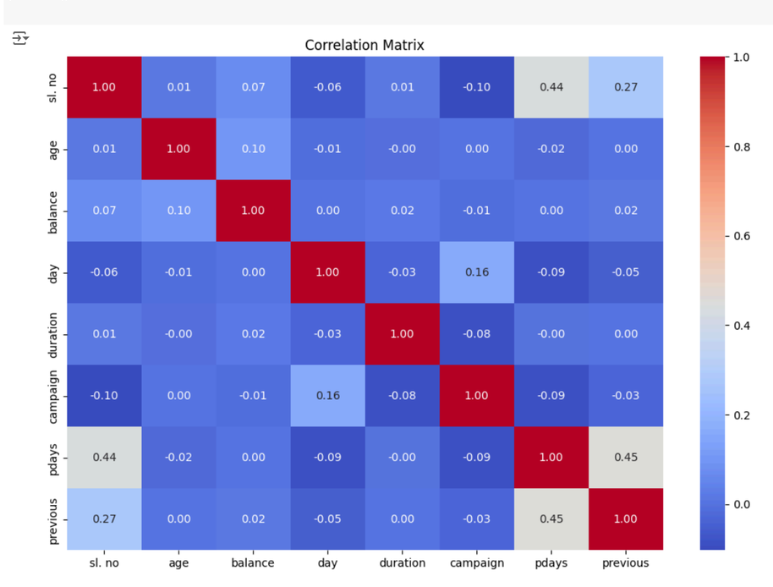
```
Bank_data.describe()
```

	sl. no	age	balance	day	duration	campaign	pdays	previous
count	45211.000000	45211.000000	45211.000000	45211.000000	45211.000000	45211.000000	45211.000000	45211.000000
mean	22606.000000	40.936210	1362.272058	15.806419	258.163080	2.763841	40.197828	0.580323
std	13051.435847	10.618762	3044.765829	8.322476	257.527812	3.098021	100.128746	2.303441
min	1.000000	18.000000	-8019.000000	1.000000	0.000000	1.000000	-1.000000	0.000000
25%	11303.500000	33.000000	72.000000	8.000000	103.000000	1.000000	-1.000000	0.000000
50%	22606.000000	39.000000	448.000000	16.000000	180.000000	2.000000	-1.000000	0.000000
75%	33908.500000	48.000000	1428.000000	21.000000	319.000000	3.000000	-1.000000	0.000000
max	45211.000000	95.000000	102127.000000	31.000000	4918.000000	63.000000	871.000000	275.000000

```
# correlation with heatmap to interpret the relation and multicolliniarity

# Select numerical columns
numerical_columns = Bank_data.select_dtypes(include='number').columns

# Compute the correlation matrix
correlation_matrix = Bank_data[numerical_columns].corr()

# Display the correlation matrix
print(correlation_matrix)
```

```
             sl. no       age   balance       day  duration  campaign  \
sl. no     1.000000  0.014973  0.073639 -0.061465  0.013031 -0.102884   
age        0.014973  1.000000  0.097783 -0.009120 -0.004648  0.004760   
balance    0.073639  0.097783  1.000000  0.004503  0.021560 -0.014578   
day       -0.061465 -0.009120  0.004503  1.000000 -0.030206  0.162490   
duration   0.013031 -0.004648  0.021560 -0.030206  1.000000 -0.084570   
campaign  -0.102884  0.004760 -0.014578  0.162490 -0.084570  1.000000   
pdays      0.437729 -0.023758  0.003435 -0.093044 -0.001565 -0.088628   
previous   0.271098  0.001288  0.016674 -0.051710  0.001203 -0.032855   

              pdays  previous  
sl. no     0.437729  0.271098  
age       -0.023758  0.001288  
balance    0.003435  0.016674  
day       -0.093044 -0.051710  
duration  -0.001565  0.001203  
campaign  -0.088628 -0.032855  
pdays      1.000000  0.454820  
previous   0.454820  1.000000  
```

```
# correlation with heatmap to interpret the relation and multicolliniarity
import seaborn as sns
import matplotlib.pyplot as plt

# Plot the correlation matrix using a heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Matrix')
plt.show()
```




```
print(Bank_data.columns)
```

```
Index(['sl. no', 'age', 'job', 'marital', 'education', 'default', 'balance',
       'housing', 'loan', 'contact', 'day', 'month', 'duration', 'campaign',
       'pdays', 'previous', 'poutcome', 'y'],
      dtype='object')
```

```
import numpy as np

def whisker(col):
    q1, q3 = np.percentile(col, [25, 75])
    iqr = q3 - q1
    lw = q1 - 1.5 * iqr
    up = q3 + 1.5 * iqr
    return lw, up
```

```
lw, up = whisker(Bank_data['duration'])
print(f'Lower whisker: {lw}')
print(f'Upper whisker: {up}')
```

```
Lower whisker: -221.0
Upper whisker: 643.0
```

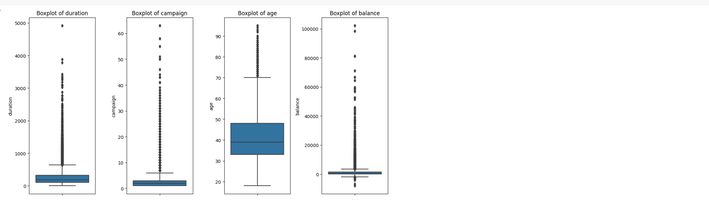
```
lw, up = whisker(Bank_data['campaign'])
print(f'Lower whisker: {lw}')
print(f'Upper whisker: {up}')
```

```
Lower whisker: -2.0
Upper whisker: 6.0
```

```
import numpy as np


df = Bank_data.copy()


def whisker(col):
    q1, q3 = np.percentile(col, [25, 75])
    iqr = q3 - q1
    lw = q1 - 1.5 * iqr
    up = q3 + 1.5 * iqr
    return lw, up


for i in ['duration','campaign']:
    lw, up = whisker(Bank_data[i])
    df[i] = np.where(Bank_data[i] < lw, lw, Bank_data[i])
    df[i] = np.where(Bank_data[i] > up, up, Bank_data[i])

print(df.head())
```

```
   sl. no  age           job  marital  education default  balance housing  \
0       1   58    management  married   tertiary      no     2143     yes
1       2   44    technician   single  secondary      no       29     yes
2       3   33  entrepreneur  married  secondary      no        2     yes
3       4   47   blue-collar  married    unknown      no     1506     yes
4       5   33       unknown   single    unknown      no        1      no

    loan  contact  day month  duration  campaign  pdays  previous poutcome   y
0     no  unknown    5   may     261.0       1.0     -1         0  unknown  no
1     no  unknown    5   may     151.0       1.0     -1         0  unknown  no
2    yes  unknown    5   may      76.0       1.0     -1         0  unknown  no
3     no  unknown    5   may      92.0       1.0     -1         0  unknown  no
4     no  unknown    5   may     198.0       1.0     -1         0  unknown  no
```

```
import seaborn as sns
import matplotlib.pyplot as plt


columns = ['duration', 'campaign', 'age', 'balance' ]


plt.figure(figsize=(12, 8))
for i, col in enumerate(columns, 1):
    plt.subplot(1, len(columns), i)
    sns.boxplot(y=Bank_data[col])
    plt.title(f'Boxplot of {col}')
    plt.tight_layout()

plt.show()
```




```
Bank_data
```

	sl. no	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutcome	y
0	1	58	management	married	tertiary	no	2143	yes	no	unknown	5	may	261	1	-1	0	unknown	no
1	2	44	technician	single	secondary	no	29	yes	no	unknown	5	may	151	1	-1	0	unknown	no
2	3	33	entrepreneur	married	secondary	no	2	yes	yes	unknown	5	may	76	1	-1	0	unknown	no
3	4	47	blue-collar	married	unknown	no	1506	yes	no	unknown	5	may	92	1	-1	0	unknown	no
4	5	33	unknown	single	unknown	no	1	no	no	unknown	5	may	198	1	-1	0	unknown	no
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
45206	45207	51	technician	married	tertiary	no	825	no	no	cellular	17	nov	977	3	-1	0	unknown	yes
45207	45208	71	retired	divorced	primary	no	1729	no	no	cellular	17	nov	456	2	-1	0	unknown	yes
45208	45209	72	retired	married	secondary	no	5715	no	no	cellular	17	nov	1127	5	184	3	success	yes
45209	45210	57	blue-collar	married	secondary	no	668	no	no	telephone	17	nov	508	4	-1	0	unknown	no
45210	45211	37	entrepreneur	married	secondary	no	2971	no	no	cellular	17	nov	361	2	188	11	other	no

45211 rows × 18 columns

```
import pandas as pd


x = pd.get_dummies(Bank_data.drop(['deposited'], axis=1))
y = pd.get_dummies(Bank_data['deposited'], drop_first=True)


x.columns = [col.lower() for col in x.columns]
y.columns = ['deposited']

print(x.head())
print(y.head())
```

```
df
```

	sl. no	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutcome	y
0	1	58	management	married	tertiary	no	2143	yes	no	unknown	5	may	261.0	1.0	-1	0	unknown	no
1	2	44	technician	single	secondary	no	29	yes	no	unknown	5	may	151.0	1.0	-1	0	unknown	no
2	3	33	entrepreneur	married	secondary	no	2	yes	yes	unknown	5	may	76.0	1.0	-1	0	unknown	no
3	4	47	blue-collar	married	unknown	no	1506	yes	no	unknown	5	may	92.0	1.0	-1	0	unknown	no
4	5	33	unknown	single	unknown	no	1	no	no	unknown	5	may	198.0	1.0	-1	0	unknown	no
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
45206	45207	51	technician	married	tertiary	no	825	no	no	cellular	17	nov	643.0	3.0	-1	0	unknown	yes
45207	45208	71	retired	divorced	primary	no	1729	no	no	cellular	17	nov	456.0	2.0	-1	0	unknown	yes
45208	45209	72	retired	married	secondary	no	5715	no	no	cellular	17	nov	643.0	5.0	184	3	success	yes
45209	45210	57	blue-collar	married	secondary	no	668	no	no	telephone	17	nov	508.0	4.0	-1	0	unknown	no
45210	45211	37	entrepreneur	married	secondary	no	2971	no	no	cellular	17	nov	361.0	2.0	188	11	other	no

45211 rows × 18 columns

```
newdataframe=df
```

```
newdataframe
```

	sl. no	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutcome	y
0	1	58	management	married	tertiary	no	2143	yes	no	unknown	5	may	261.0	1.0	-1	0	unknown	no
1	2	44	technician	single	secondary	no	29	yes	no	unknown	5	may	151.0	1.0	-1	0	unknown	no
2	3	33	entrepreneur	married	secondary	no	2	yes	yes	unknown	5	may	76.0	1.0	-1	0	unknown	no
3	4	47	blue-collar	married	unknown	no	1506	yes	no	unknown	5	may	92.0	1.0	-1	0	unknown	no
4	5	33	unknown	single	unknown	no	1	no	no	unknown	5	may	198.0	1.0	-1	0	unknown	no
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
45206	45207	51	technician	married	tertiary	no	825	no	no	cellular	17	nov	643.0	3.0	-1	0	unknown	yes
45207	45208	71	retired	divorced	primary	no	1729	no	no	cellular	17	nov	456.0	2.0	-1	0	unknown	yes
45208	45209	72	retired	married	secondary	no	5715	no	no	cellular	17	nov	643.0	5.0	184	3	success	yes
45209	45210	57	blue-collar	married	secondary	no	668	no	no	telephone	17	nov	508.0	4.0	-1	0	unknown	no
45210	45211	37	entrepreneur	married	secondary	no	2971	no	no	cellular	17	nov	361.0	2.0	188	11	other	no

45211 rows × 18 columns

```
categorical_columns = ['job', 'marital', 'education', 'contact', 'month', 'poutcome']

# Initialize newdataframe as a copy of Bank_data
newdataframe = Bank_data.copy()

for col in categorical_columns:
    newdataframe = pd.concat([newdataframe.drop(col, axis=1), pd.get_dummies(newdataframe[col], prefix=col)], axis=1)

newdataframe.head()
```

	sl. no	age	default	balance	housing	loan	day	duration	campaign	pdays	...	month_jun	month_mar	month_may	month_nov	month_oct	month_sep	poutcome_failure	poutcome_other	poutcome_success	poutcome_unknown
0	1	58	no	2143	yes	no	5	261	1	-1	...	False	False	True	False	False	False	False	False	False	True
1	2	44	no	29	yes	no	5	151	1	-1	...	False	False	True	False	False	False	False	False	False	True
2	3	33	no	2	yes	yes	5	76	1	-1	...	False	False	True	False	False	False	False	False	False	True
3	4	47	no	1506	yes	no	5	92	1	-1	...	False	False	True	False	False	False	False	False	False	True
4	5	33	no	1	no	no	5	198	1	-1	...	False	False	True	False	False	False	False	False	False	True

5 rows × 50 columns

```
print(Bank_data.columns)
```

```
Index(['sl. no', 'age', 'job', 'marital', 'education', 'default', 'balance',
       'housing', 'loan', 'contact', 'day', 'month', 'duration', 'campaign',
       'pdays', 'previous', 'poutcome', 'y'],
      dtype='object')
```

```
newdataframe1 = Bank_data.copy()
```

```
print(newdataframe1.columns)
```

```
Index(['sl. no', 'age', 'job', 'marital', 'education', 'default', 'balance',
       'housing', 'loan', 'contact', 'day', 'month', 'duration', 'campaign',
       'pdays', 'previous', 'poutcome', 'y'],
      dtype='object')
```

```
categorical_columns = ['job', 'marital', 'education', 'contact', 'month', 'poutcome']

# Initialize newdataframe as a copy of Bank_data
newdataframe1 = Bank_data.copy()

# Apply one-hot encoding to the specified categorical columns
for col in categorical_columns:
    if col in newdataframe1.columns:
        newdataframe1 = pd.concat(
            [newdataframe1.drop(col, axis=1),
             pd.get_dummies(newdataframe1[col], prefix=col, prefix_sep='-', drop_first=True, dummy_na=False)],
            axis=1
        )

# Verify the transformation
print(newdataframe.columns)
```

```
Index(['sl. no', 'age', 'default', 'balance', 'housing', 'loan', 'day',
       'duration', 'campaign', 'pdays', 'previous', 'y', 'job_admin.',
       'job_blue-collar', 'job_entrepreneur', 'job_housemaid',
       'job_management', 'job_retired', 'job_self-employed', 'job_services',
       'job_student', 'job_technician', 'job_unemployed', 'job_unknown',
       'marital_divorced', 'marital_married', 'marital_single',
       'education_primary', 'education_secondary', 'education_tertiary',
       'education_unknown', 'contact_cellular', 'contact_telephone',
       'contact_unknown', 'month_aug', 'month_dec', 'month_feb', 'month_jan',
       'month_jul', 'month_jun', 'month_mar', 'month_may', 'month_nov',
       'month_oct', 'month_sep', 'poutcome_failure', 'poutcome_other',
       'poutcome_success', 'poutcome_unknown'],
      dtype='object')
```

```
import pandas as pd

# Initialize newdataframe as a copy of Bank_data
newdataframe1 = Bank_data.copy()

# List of categorical columns
categorical_columns = ['job', 'marital', 'education', 'contact', 'month', 'poutcome']

# Verify column names before processing
print("Original columns:", newdataframe1.columns)

# Apply one-hot encoding to the specified categorical columns
for col in categorical_columns:
    if col in newdataframe1.columns:
        newdataframe1 = pd.concat(
            [newdataframe1.drop(col, axis=1),
             pd.get_dummies(newdataframe1[col], prefix=col, prefix_sep='-', drop_first=True, dummy_na=0)],
            axis=1
        )

# Verify the transformation
print("Transformed columns:", newdataframe1.columns)

# Display the first few rows of the updated DataFrame
newdataframe1.head()
```

```
Original columns: Index(['sl. no', 'age', 'job', 'marital', 'education', 'default', 'balance',
       'housing', 'loan', 'contact', 'day', 'month', 'duration', 'campaign',
       'pdays', 'previous', 'y', 'poutcome-other', 'poutcome-success',
       'poutcome-unknown'],
      dtype='object')
Transformed columns: Index(['sl. no', 'age', 'job', 'marital', 'education', 'default', 'balance',
       'housing', 'loan', 'contact', 'day', 'month', 'duration', 'campaign',
       'pdays', 'previous', 'y', 'poutcome-other', 'poutcome-success',
       'poutcome-unknown'],
      dtype='object')
```

	sl. no	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutcome	y
0	1	58	management	married	tertiary	no	2143	yes	no	unknown	5	may	261	1	-1	0	unknown	no
1	2	44	technician	single	secondary	no	29	yes	no	unknown	5	may	151	1	-1	0	unknown	no
2	3	33	entrepreneur	married	secondary	no	2	yes	yes	unknown	5	may	76	1	-1	0	unknown	no
3	4	47	blue-collar	married	unknown	no	1506	yes	no	unknown	5	may	92	1	-1	0	unknown	no
4	5	33	unknown	single	unknown	no	1	no	no	unknown	5	may	198	1	-1	0	unknown	no

```
categorical_columns = ['job', 'marital', 'education', 'contact', 'month', 'poutcome']

# Initialize newdataframe as a copy of Bank_data
newdataframe = Bank_data.copy()

# Apply one-hot encoding to the specified categorical columns
for col in categorical_columns:
    newdataframe = pd.concat(
        [newdataframe.drop(col, axis=1),
         pd.get_dummies(newdataframe[col], prefix=col, prefix_sep='-', drop_first=True, dummy_na=False)],
        axis=1
    )

# Verify the transformation
print("Transformed columns:", newdataframe.columns)

# Display the first few rows of the updated DataFrame
newdataframe.head()
```

```
Transformed columns: Index(['sl. no', 'age', 'default', 'balance', 'housing', 'loan', 'day',
       'duration', 'campaign', 'pdays', 'previous', 'y', 'job-blue-collar',
       'job-entrepreneur', 'job-housemaid', 'job-management', 'job-retired',
       'job-self-employed', 'job-services', 'job-student', 'job-technician',
       'job-unemployed', 'job-unknown', 'marital-married', 'marital-single',
       'education-secondary', 'education-tertiary', 'education-unknown',
       'contact-telephone', 'contact-unknown', 'month-aug', 'month-dec',
       'month-feb', 'month-jan', 'month-jul', 'month-jun', 'month-mar',
       'month-may', 'month-nov', 'month-oct', 'month-sep', 'poutcome-other',
       'poutcome-success', 'poutcome-unknown'],
      dtype='object')
```

	sl. no	age	default	balance	housing	loan	day	duration	campaign	pdays	previous	job-blue-collar	...	month-may	month-nov	month-oct	month-sep	poutcome-other	poutcome-success	poutcome-unknown
0	1	58	no	2143	yes	no	5	261	1	-1	0	False	...	True	False	False	False	False	False	True
1	2	44	no	29	yes	no	5	151	1	-1	0	False	...	True	False	False	False	False	False	True
2	3	33	no	2	yes	yes	5	76	1	-1	0	False	...	True	False	False	False	False	False	True
3	4	47	no	1506	yes	no	5	92	1	-1	0	True	...	True	False	False	False	False	False	True
4	5	33	no	1	no	no	5	198	1	-1	0	False	...	True	False	False	False	False	False	True

5 rows × 44 columns

```
# Verify that the one-hot encoded columns contain only 0 and 1 values
binary_columns = [col for col in newdataframe.columns if any(prefix in col for prefix in categorical_columns)]
for col in binary_columns:
    unique_values = newdataframe[col].unique()
    print(f'Column {col}: unique values = {unique_values}')
```

```
Column job-blue-collar: unique values = [False  True]
Column job-entrepreneur: unique values = [False  True]
Column job-housemaid: unique values = [False  True]
Column job-management: unique values = [ True False]
Column job-retired: unique values = [False  True]
Column job-self-employed: unique values = [False  True]
Column job-services: unique values = [False  True]
Column job-student: unique values = [False  True]
Column job-technician: unique values = [ True False]
Column job-unemployed: unique values = [False  True]
Column job-unknown: unique values = [False  True]
Column marital-married: unique values = [ True False]
Column marital-single: unique values = [False  True]
Column education-secondary: unique values = [False  True]
Column education-tertiary: unique values = [ True False]
Column education-unknown: unique values = [False  True]
Column contact-telephone: unique values = [False  True]
Column contact-unknown: unique values = [ True False]
Column month-aug: unique values = [False  True]
Column month-dec: unique values = [False  True]
Column month-feb: unique values = [False  True]
Column month-jan: unique values = [False  True]
Column month-jul: unique values = [False  True]
Column month-jun: unique values = [False  True]
Column month-mar: unique values = [False  True]
Column month-may: unique values = [ True False]
Column month-nov: unique values = [False  True]
Column month-oct: unique values = [False  True]
Column month-sep: unique values = [False  True]
Column poutcome-other: unique values = [False  True]
Column poutcome-success: unique values = [False  True]
Column poutcome-unknown: unique values = [ True False]
```

```
# Define the boolean columns
boolean_columns = ['housing', 'loan', 'y']

# Initialize newdataframe1 as a copy of newdataframe
newdataframe1 = newdataframe.copy()

# Convert the boolean columns to binary (0 and 1)
for col in boolean_columns:
    newdataframe1[col + '_new'] = newdataframe1[col].apply(lambda x: 1 if x == 'yes' else 0)
    newdataframe1.drop(col, axis=1, inplace=True)

# Display the first few rows of the updated DataFrame
newdataframe1.head()
```

	sl. no	age	default	balance	day	duration	campaign	pdays	previous	job-blue-collar	...	month-may	month-nov	month-oct	month-sep	poutcome-other	poutcome-success	poutcome-unknown	housing-new	loan-new	y-new
0	1	58	no	2143	5	261	1	-1	0	False	...	True	False	False	False	False	False	True	1	0	0
1	2	44	no	29	5	151	1	-1	0	False	...	True	False	False	False	False	False	True	1	0	0
2	3	33	no	2	5	76	1	-1	0	False	...	True	False	False	False	False	False	True	1	1	0
3	4	47	no	1506	5	92	1	-1	0	True	...	True	False	False	False	False	False	True	1	0	0
4	5	33	no	1	5	198	1	-1	0	False	...	True	False	False	False	False	False	True	0	0	0

5 rows × 44 columns

```
categorical_columns = ['job', 'marital', 'education', 'contact', 'month', 'poutcome']

# Initialize newdataframe as a copy of Bank_data
newdataframe = Bank_data.copy()

# Apply one-hot encoding to the specified categorical columns
for col in categorical_columns:
    newdataframe = pd.concat(
        [newdataframe.drop(col, axis=1),
         pd.get_dummies(newdataframe[col], prefix=col, prefix_sep='-', drop_first=True, dummy_na=False)],
        axis=1
    )
```

```
# Display the first few rows of the updated DataFrame
newdataframe.head()
```

	sl. no	age	default	balance	housing	loan	day	duration	campaign	pdays	previous	job-blue-collar	...	month-may	month-nov	month-oct	month-sep	poutcome-other	poutcome-success	poutcome-unknown
0	1	58	no	2143	yes	no	5	261	1	-1	0	False	...	True	False	False	False	False	False	True
1	2	44	no	29	yes	no	5	151	1	-1	0	False	...	True	False	False	False	False	False	True
2	3	33	no	2	yes	yes	5	76	1	-1	0	False	...	True	False	False	False	False	False	True
3	4	47	no	1506	yes	no	5	92	1	-1	0	True	...	True	False	False	False	False	False	True
4	5	33	no	1	no	no	5	198	1	-1	0	False	...	True	False	False	False	False	False	True

5 rows × 44 columns

```
newdataframe1.head()
```

	sl. no	age	default	balance	day	duration	campaign	pdays	previous	job-blue-collar	...	month-may	month-nov	month-oct	month-sep	poutcome-other	poutcome-success	poutcome-unknown	housing-new	loan-new	y-new
0	1	58	no	2143	5	261	1	-1	0	False	...	True	False	False	False	False	False	True	1	0	0
1	2	44	no	29	5	151	1	-1	0	False	...	True	False	False	False	False	False	True	1	0	0
2	3	33	no	2	5	76	1	-1	0	False	...	True	False	False	False	False	False	True	1	1	0
3	4	47	no	1506	5	92	1	-1	0	True	...	True	False	False	False	False	False	True	1	0	0
4	5	33	no	1	5	198	1	-1	0	False	...	True	False	False	False	False	False	True	0	0	0

5 rows × 44 columns

Renaming column (Feature Selection)

```
Bank_data.rename(columns = {'y':'deposited'}, inplace = True)
```

```
newdataframe1
```

	sl. no	age	default	balance	day	duration	campaign	pdays	previous	job-blue-collar	...	month-may	month-nov	month-oct	month-sep	poutcome-other	poutcome-success	poutcome-unknown	housing-new	loan-new	y-new
0	1	58	no	2143	5	261	1	-1	0	False	...	True	False	False	False	False	False	True	1	0	0
1	2	44	no	29	5	151	1	-1	0	False	...	True	False	False	False	False	False	True	1	0	0
2	3	33	no	2	5	76	1	-1	0	False	...	True	False	False	False	False	False	True	1	1	0
3	4	47	no	1506	5	92	1	-1	0	True	...	True	False	False	False	False	False	True	1	0	0
4	5	33	no	1	5	198	1	-1	0	False	...	True	False	False	False	False	False	True	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
45206	45207	51	no	825	17	977	3	-1	0	False	...	False	True	False	False	False	False	True	0	0	1
45207	45208	71	no	1729	17	456	2	-1	0	False	...	False	True	False	False	False	False	True	0	0	1
45208	45209	72	no	5715	17	1127	5	184	3	False	...	False	True	False	False	False	True	False	0	0	1
45209	45210	57	no	668	17	508	4	-1	0	True	...	False	True	False	False	False	False	True	0	0	0
45210	45211	37	no	2971	17	361	2	188	11	False	...	False	True	False	False	False	True	False	0	0	0

45211 rows × 44 columns

```
newdataframe1
```

	sl. no	age	default	balance	day	duration	campaign	pdays	previous	job-blue-collar	...	month-may	month-nov	month-oct	month-sep	poutcome-other	poutcome-success	poutcome-unknown	housing-new	loan-new	y-new
0	1	58	no	2143	5	261	1	-1	0	False	...	True	False	False	False	False	False	True	1	0	0
1	2	44	no	29	5	151	1	-1	0	False	...	True	False	False	False	False	False	True	1	0	0
2	3	33	no	2	5	76	1	-1	0	False	...	True	False	False	False	False	False	True	1	1	0
3	4	47	no	1506	5	92	1	-1	0	True	...	True	False	False	False	False	False	True	1	0	0
4	5	33	no	1	5	198	1	-1	0	False	...	True	False	False	False	False	False	True	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
45206	45207	51	no	825	17	977	3	-1	0	False	...	False	True	False	False	False	False	True	0	0	1
45207	45208	71	no	1729	17	456	2	-1	0	False	...	False	True	False	False	False	False	True	0	0	1
45208	45209	72	no	5715	17	1127	5	184	3	False	...	False	True	False	False	False	True	False	0	0	1
45209	45210	57	no	668	17	508	4	-1	0	True	...	False	True	False	False	False	False	True	0	0	0
45210	45211	37	no	2971	17	361	2	188	11	False	...	False	True	False	False	False	True	False	0	0	0

45211 rows × 44 columns

```
import pandas as pd

# Copy the dataframe
newdataframe1 = newdataframe.copy()

# List of boolean columns that need conversion
boolean_columns = ['housing', 'loan', 'y']

# Convert existing 'yes'/'no' columns to 1/0
for col in boolean_columns:
    newdataframe1[col + '_new'] = newdataframe1[col].apply(lambda x: 1 if x == 'yes' else 0)
    newdataframe1.drop(col, axis=1, inplace=True)

# Convert 'True'/'False' columns to 1/0
for col in newdataframe1.select_dtypes(include=['bool']).columns:
    newdataframe1[col] = newdataframe1[col].astype(int)

# Verify the transformation
print(newdataframe1.head())
```

```
   sl. no  age default  balance  day  duration  campaign  pdays  previous  \
0       1   58      no     2143    5       261         1     -1         0
1       2   44      no       29    5       151         1     -1         0
2       3   33      no        2    5        76         1     -1         0
3       4   47      no     1506    5        92         1     -1         0
4       5   33      no        1    5       198         1     -1         0

   job-blue-collar  ...  month-may  month-nov  month-oct  month-sep  \
0                0  ...          1          0          0          0
1                0  ...          1          0          0          0
2                0  ...          1          0          0          0
3                1  ...          1          0          0          0
4                0  ...          1          0          0          0

   poutcome-other  poutcome-success  poutcome-unknown  housing-new  loan-new  \
0               0                 0                 1            1         0
1               0                 0                 1            1         0
2               0                 0                 1            1         1
3               0                 0                 1            1         0
4               0                 0                 1            0         0

   y-new
0      0
1      0
2      0
3      0
4      0
```

```
[5 rows x 44 columns]
```

```
newdataframe1.rename(columns = {'y-new':'deposited?'}, inplace = True)
```

DataFrame For Model Training

```
# Model Training Dataframe
newdataframe1
```

	sl. no	age	default	balance	day	duration	campaign	pdays	previous	job-blue-collar	...	month-may	month-nov	month-oct	month-sep	poutcome-other	poutcome-success	poutcome-unknown	housing-new	loan-new	deposited?
0	1	58	no	2143	5	261	1	-1	0	0	...	1	0	0	0	0	0	1	1	0	0
1	2	44	no	29	5	151	1	-1	0	0	...	1	0	0	0	0	0	1	1	0	0
2	3	33	no	2	5	76	1	-1	0	0	...	1	0	0	0	0	0	1	1	1	0
3	4	47	no	1506	5	92	1	-1	0	1	...	1	0	0	0	0	0	1	1	0	0
4	5	33	no	1	5	198	1	-1	0	0	...	1	0	0	0	0	0	1	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
45206	45207	51	no	825	17	977	3	-1	0	0	...	0	1	0	0	0	0	1	0	0	1
45207	45208	71	no	1729	17	456	2	-1	0	0	...	0	1	0	0	0	0	1	0	0	1
45208	45209	72	no	5715	17	1127	5	184	3	0	...	0	1	0	0	0	1	0	0	0	1
45209	45210	57	no	668	17	508	4	-1	0	1	...	0	1	0	0	0	0	1	0	0	0
45210	45211	37	no	2971	17	361	2	188	11	0	...	0	1	0	0	1	0	0	0	0	0

45211 rows × 44 columns

```
# Drop the 'default' column
newdataframe1.drop(['default'], axis=1, inplace=True)

# Verify the column has been dropped
print(newdataframe1.columns)
```

Show hidden output

DataFrame For Model Training

```
# Model Training Dataframe -Final
newdataframe1
```

	sl. no	age	balance	day	duration	campaign	pdays	previous	job-blue-collar	job-entrepreneur	...	month-may	month-nov	month-oct	month-sep	poutcome-other	poutcome-success	poutcome-unknown	housing-new	loan-new	deposited?
0	1	58	2143	5	261	1	-1	0	0	0	...	1	0	0	0	0	0	1	1	0	0
1	2	44	29	5	151	1	-1	0	0	0	...	1	0	0	0	0	0	1	1	0	0
2	3	33	2	5	76	1	-1	0	0	1	...	1	0	0	0	0	0	1	1	1	0
3	4	47	1506	5	92	1	-1	0	1	0	...	1	0	0	0	0	0	1	1	0	0
4	5	33	1	5	198	1	-1	0	0	0	...	1	0	0	0	0	0	1	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
45206	45207	51	825	17	977	3	-1	0	0	0	...	0	1	0	0	0	0	1	0	0	1
45207	45208	71	1729	17	456	2	-1	0	0	0	...	0	1	0	0	0	0	1	0	0	1
45208	45209	72	5715	17	1127	5	184	3	0	0	...	0	1	0	0	0	1	0	0	0	1
45209	45210	57	668	17	508	4	-1	0	1	0	...	0	1	0	0	0	0	1	0	0	0
45210	45211	37	2971	17	361	2	188	11	0	1	...	0	1	0	0	1	0	0	0	0	0

45211 rows × 43 columns

```
from sklearn.model_selection import train_test_split

# Prepare features and target
x = newdataframe1.drop(['deposited?'], axis=1)
y = newdataframe1['deposited?']

# Split the data into training and testing sets
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.3, random_state=42)

print(f'Training data shape: {x_train.shape}, {y_train.shape}')
print(f'Testing data shape: {x_test.shape}, {y_test.shape}')
```

```
Training data shape: (31647, 42), (31647,)
Testing data shape: (13564, 42), (13564,)
```

```
df_train = x_train.copy()
df_train['deposited?'] = y_train
df_train.head()
```

	sl. no	age	balance	day	duration	campaign	pdays	previous	job-blue-collar	job-entrepreneur	...	month-may	month-nov	month-oct	month-sep	poutcome-other	poutcome-success	poutcome-unknown	housing-new	loan-new	deposited?
10747	10748	36	0	17	153	4	-1	0	0	0	...	0	0	0	0	0	0	1	0	0	0
26054	26055	56	196	19	312	3	-1	0	0	1	...	0	1	0	0	0	0	1	0	0	0
9125	9126	46	0	5	83	2	-1	0	1	0	...	0	0	0	0	0	0	1	1	0	0
41659	41660	41	3426	1	302	1	119	5	0	0	...	0	0	1	0	0	1	0	0	0	0
4443	4444	38	0	20	90	1	-1	0	1	0	...	1	0	0	0	0	0	1	1	0	0

5 rows × 43 columns

```
classes=df_train['deposited?'].value_counts()
normal_share=round(classes[0]/df_train['deposited?'].count()*100,2)
fraud_share=round(classes[1]/df_train['deposited?'].count()*100, 2)
print("Non-deposited? : {} %".format(normal_share))
print("deposited? : {} %".format(fraud_share))
```

```
Non-deposited? : 88.34 %
deposited? : 11.66 %
```

```
x_train=df_train.drop(['deposited?'],axis=1)
y_train=df_train['deposited?']
```

```
x_train
```

	sl. no	age	balance	day	duration	campaign	pdays	previous	job-blue-collar	job-entrepreneur	...	month-mar	month-may	month-nov	month-oct	month-sep	poutcome-other	poutcome-success	poutcome-unknown	housing-new	loan-new
10747	10748	36	0	17	153	4	-1	0	0	0	...	0	0	0	0	0	0	0	1	0	0
26054	26055	56	196	19	312	3	-1	0	0	1	...	0	0	1	0	0	0	0	1	0	0
9125	9126	46	0	5	83	2	-1	0	1	0	...	0	0	0	0	0	0	0	1	1	0
41659	41660	41	3426	1	302	1	119	5	0	0	...	0	0	0	1	0	0	1	0	0	0
4443	4444	38	0	20	90	1	-1	0	1	0	...	0	1	0	0	0	0	0	1	1	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
11284	11285	44	1059	18	2093	1	-1	0	0	0	...	0	0	0	0	0	0	0	1	0	0
44732	44733	23	508	8	210	1	92	1	0	0	...	0	0	0	0	1	0	0	0	0	0
38158	38159	34	1317	15	239	1	-1	0	0	0	...	0	1	0	0	0	0	0	1	1	0
860	861	33	165	7	111	1	-1	0	0	0	...	0	1	0	0	0	0	0	1	0	0
15795	15796	38	-41	21	68	10	-1	0	1	0	...	0	0	0	0	0	0	0	1	1	0

31647 rows × 42 columns

```
y_train
```

```
10747    0
26054    0
9125     0
41659    0
4443     0
        ..
11284    1
44732    0
38158    0
860      0
15795    0
Name: deposited?, Length: 31647, dtype: int64
```

```
def evaluation_metrics(y_test, y_pre, target_names):
    #scores
    print("Accuracy :",accuracy_score(y_test,y_pre))
    print("Precision :",precision_score(y_test,y_pre))
    print("Recall :",recall_score(y_test,y_pre))
    print("F1 Score :",f1_score(y_test,y_pre))

    print(classification_report(y_test, y_pre, target_names=target_names))

    #AUC
    fpr, tpr, _ = roc_curve(y_test,  y_pre)
    auc = roc_auc_score(y_test, y_pre)
    print("AUC :", auc)

    #ROC
    plt.plot(fpr,tpr,label="uc={:.3f})".format(auc))
    plt.plot([0, 1], [0, 1], 'k--')
    plt.xlabel('False positive rate')
    plt.ylabel('True positive rate')
    plt.title('ROC curve')
    plt.legend(loc=4)
    plt.show()

    #CM matrix
    matrix = confusion_matrix(y_test, y_pre)
    cm = pd.DataFrame(matrix, index=target_names, columns=target_names)

    sns.heatmap(cm, annot=True, cbar=None, cmap="Blues", fmt = 'g')
    plt.title("Confusion Matrix"), plt.tight_layout()
    plt.ylabel("True Class"), plt.xlabel("Predicted Class")
    plt.show()
```

```
target_names=['No Deposited', 'Deposited']
```

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

def evaluation_metrics(y_test, y_pre, target_names):
    # scores
    print("Accuracy :", accuracy_score(y_test, y_pre))
    print("Precision :", precision_score(y_test, y_pre, pos_label='yes'))
    print("Recall :", recall_score(y_test, y_pre, pos_label='yes'))
    print("F1 Score :", f1_score(y_test, y_pre, pos_label='yes'))
```

```
x_train
```

	sl. no	age	balance	day	duration	campaign	pdays	previous	job-blue-collar	job-entrepreneur	...	month-mar	month-may	month-nov	month-oct	month-sep	poutcome-other	poutcome-success	poutcome-unknown	housing-new	loan-new
10747	10748	36	0	17	153	4	-1	0	0	0	...	0	0	0	0	0	0	0	1	0	0
26054	26055	56	196	19	312	3	-1	0	0	1	...	0	0	1	0	0	0	0	1	0	0
9125	9126	46	0	5	83	2	-1	0	1	0	...	0	0	0	0	0	0	0	1	1	0
41659	41660	41	3426	1	302	1	119	5	0	0	...	0	0	0	1	0	0	1	0	0	0
4443	4444	38	0	20	90	1	-1	0	1	0	...	0	1	0	0	0	0	0	1	1	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
11284	11285	44	1059	18	2093	1	-1	0	0	0	...	0	0	0	0	0	0	0	1	0	0
44732	44733	23	508	8	210	1	92	1	0	0	...	0	0	0	0	1	0	0	0	0	0
38158	38159	34	1317	15	239	1	-1	0	0	0	...	0	1	0	0	0	0	0	1	1	0
860	861	33	165	7	111	1	-1	0	0	0	...	0	1	0	0	0	0	0	1	0	0
15795	15796	38	-41	21	68	10	-1	0	1	0	...	0	0	0	0	0	0	0	1	1	0

31647 rows × 42 columns

```
newdataframe1
```

	sl. no	age	balance	day	duration	campaign	pdays	previous	job-blue-collar	job-entrepreneur	...	month-may	month-nov	month-oct	month-sep	poutcome-other	poutcome-success	poutcome-unknown	housing-new	loan-new	deposited?
0	1	58	2143	5	261	1	-1	0	0	0	...	1	0	0	0	0	0	1	1	0	0
1	2	44	29	5	151	1	-1	0	0	0	...	1	0	0	0	0	0	1	1	0	0
2	3	33	2	5	76	1	-1	0	0	1	...	1	0	0	0	0	0	1	1	1	0
3	4	47	1506	5	92	1	-1	0	1	0	...	1	0	0	0	0	0	1	1	0	0
4	5	33	1	5	198	1	-1	0	0	0	...	1	0	0	0	0	0	1	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
45206	45207	51	825	17	977	3	-1	0	0	0	...	0	1	0	0	0	0	1	0	0	1
45207	45208	71	1729	17	456	2	-1	0	0	0	...	0	1	0	0	0	0	1	0	0	1
45208	45209	72	5715	17	1127	5	184	3	0	0	...	0	1	0	0	0	1	0	0	0	1
45209	45210	57	668	17	508	4	-1	0	1	0	...	0	1	0	0	0	0	1	0	0	0
45210	45211	37	2971	17	361	2	188	11	0	1	...	0	1	0	0	1	0	0	0	0	0

45211 rows × 43 columns

```
x_train
```

	sl. no	age	balance	day	duration	campaign	pdays	previous	job-blue-collar	job-entrepreneur	...	month-mar	month-may	month-nov	month-oct	month-sep	poutcome-other	poutcome-success	poutcome-unknown	housing-new	loan-new
10747	10748	36	0	17	153	4	-1	0	0	0	...	0	0	0	0	0	0	0	1	0	0
26054	26055	56	196	19	312	3	-1	0	0	1	...	0	0	1	0	0	0	0	1	0	0
9125	9126	46	0	5	83	2	-1	0	1	0	...	0	0	0	0	0	0	0	1	1	0
41659	41660	41	3426	1	302	1	119	5	0	0	...	0	0	0	1	0	0	1	0	0	0
4443	4444	38	0	20	90	1	-1	0	1	0	...	0	1	0	0	0	0	0	1	1	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
11284	11285	44	1059	18	2093	1	-1	0	0	0	...	0	0	0	0	0	0	0	1	0	0
44732	44733	23	508	8	210	1	92	1	0	0	...	0	0	0	0	1	0	0	0	0	0
38158	38159	34	1317	15	239	1	-1	0	0	0	...	0	1	0	0	0	0	0	1	1	0
860	861	33	165	7	111	1	-1	0	0	0	...	0	1	0	0	0	0	0	1	0	0
15795	15796	38	-41	21	68	10	-1	0	1	0	...	0	0	0	0	0	0	0	1	1	0

31647 rows × 42 columns

```
# Check data types of columns
print(newdataframe1.dtypes)
```

```
sl. no                int64
age                   int64
balance               int64
day                   int64
duration              int64
campaign              int64
pdays                 int64
previous              int64
job-blue-collar       int64
job-entrepreneur      int64
job-housemaid         int64
job-management        int64
job-retired           int64
job-self-employed     int64
job-services          int64
job-student           int64
job-technician        int64
job-unemployed        int64
job-unknown           int64
marital-married       int64
marital-single        int64
education-secondary   int64
education-tertiary    int64
education-unknown     int64
contact-telephone     int64
contact-unknown       int64
month-aug             int64
month-dec             int64
month-feb             int64
month-jan             int64
month-jul             int64
month-jun             int64
month-mar             int64
month-may             int64
month-nov             int64
month-oct             int64
month-sep             int64
poutcome-other        int64
poutcome-success      int64
poutcome-unknown      int64
housing-new           int64
loan-new              int64
deposited?            int64
dtype: object
```

```
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression

# Scale the data
scaler = StandardScaler()
x_train_scaled = scaler.fit_transform(x_train)
x_test_scaled = scaler.transform(x_test)

# Increase max_iter
model = LogisticRegression(solver='lbfgs', max_iter=10000)
model.fit(x_train_scaled, y_train)
```

```
LogisticRegression
LogisticRegression(max_iter=10000)
```

```
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report

# Predict on the test set
y_pred = model.predict(x_test_scaled)

# Calculate accuracy
accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy: {accuracy:.2f}')

# Confusion matrix
cm = confusion_matrix(y_test, y_pred)
print(f'Confusion Matrix:\n{cm}')

# Classification report
report = classification_report(y_test, y_pred)
print(f'Classification Report:\n{report}')
```

```
Accuracy: 0.90
Confusion Matrix:
[[11641   325]
 [  964   634]]
Classification Report:
              precision    recall  f1-score   support

           0       0.92      0.97      0.95     11966
           1       0.66      0.40      0.50      1598

    accuracy                           0.90     13564
   macro avg       0.79      0.68      0.72     13564
weighted avg       0.89      0.90      0.89     13564
```

Logistic Regression

```
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression

# Scale the data
scaler = StandardScaler()
x_train_scaled = scaler.fit_transform(x_train)
x_test_scaled = scaler.transform(x_test)

# Increase max_iter
model = LogisticRegression(solver='lbfgs', max_iter=10000)
model.fit(x_train_scaled, y_train)
```

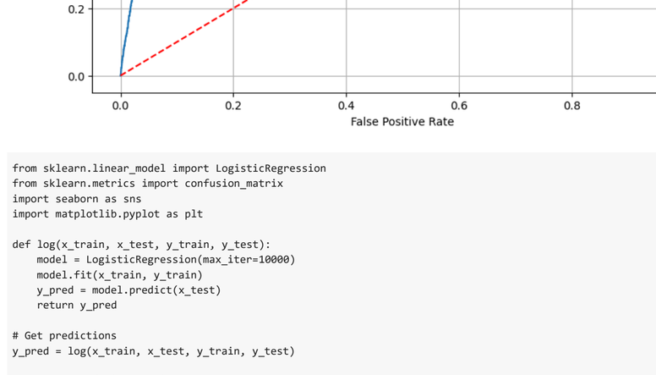
```
LogisticRegression
LogisticRegression(max_iter=10000)
```

```
from sklearn.metrics import classification_report, accuracy_score, precision_score, recall_score, f1_score, roc_auc_score

def evaluation_metrics(y_test, y_pred):
    # Scores
    print("Accuracy:", accuracy_score(y_test, y_pred))
    print("Precision:", precision_score(y_test, y_pred, pos_label=1))
    print("Recall:", recall_score(y_test, y_pred, pos_label=1))
    print("F1 Score:", f1_score(y_test, y_pred, pos_label=1))

# Assuming y_train and y_test are already correctly encoded
model.fit(x_train_scaled, y_train)
y_pred = model.predict(x_test_scaled)
evaluation_metrics(y_test, y_pred)
```

```
Accuracy: 0.9049690356826895
Precision: 0.6611053180396246
Recall: 0.3967459324155194
F1 Score: 0.49589362534219783
```

```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, accuracy_score, roc_auc_score, roc_curve, auc
import matplotlib.pyplot as plt
import seaborn as sns

def evaluation_metrics(y_test, y_pred, y_proba, target_names):
    # scores
    report = classification_report(y_test, y_pred, target_names=target_names)
    print(report)
    accuracy = accuracy_score(y_test, y_pred)
    print(f"Accuracy: {accuracy}")

    # AUC
    auc_score = roc_auc_score(y_test, y_proba)
    print(f"AUC: {auc_score}")

def log(x_train, x_test, y_train, y_test):
    model = LogisticRegression(solver='lbfgs', max_iter=10000)
    model.fit(x_train, y_train)
    y_pred = model.predict(x_test)
    y_proba = model.predict_proba(x_test)[:, 1]  # Get probability scores for the positive class
    evaluation_metrics(y_test, y_pred, y_proba, target_names=['No Deposited', 'Deposited'])

    # ROC Curve
    fpr, tpr, _ = roc_curve(y_test, y_proba)
    roc_auc = auc(fpr, tpr)
    plt.figure(figsize=(10, 6))
    plt.plot(fpr, tpr, label=f'Logistic Regression (AUC = {roc_auc:.2f})')
    plt.plot([0, 1], [0, 1], linestyle='--', color='r')
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('ROC Curve for Logistic Regression')
    plt.legend()
    plt.grid(True)
    plt.show()

# Example usage
log(x_train, x_test, y_train, y_test)
```

```
              precision    recall  f1-score   support

No Deposited       0.91      0.98      0.94     11966
   Deposited       0.59      0.25      0.35      1598

    accuracy                           0.89     13564
   macro avg       0.75      0.61      0.65     13564
weighted avg       0.87      0.89      0.87     13564

Accuracy: 0.8912562665880271
AUC: 0.8373800862979107
```




```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt

def log(x_train, x_test, y_train, y_test):
    model = LogisticRegression(max_iter=10000)
    model.fit(x_train, y_train)
    y_pred = model.predict(x_test)
    return y_pred

# Get predictions
y_pred = log(x_train, x_test, y_train, y_test)

# Compute confusion matrix
cm = confusion_matrix(y_test, y_pred, labels=[1, 0])

# Plot confusion matrix
plt.figure(figsize=(10, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=['Deposited', 'Not Deposited'], yticklabels=['Deposited', 'Not Deposited'])
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```