```
# 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')
kagglesvij24__sav_scikitlearn_default_1_path = kagglehub.model_download('kagglesvij24/.sav/ScikitLearn/default/1')

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/.sav/scikitlearn/default/1/final_model.sav
/kaggle/input/bank-full-version1/bank-full.csv
/kaggle/input/bank-01/bank.csv
```

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

```
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.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 = 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

```
# Check for missing values
print(Bank_data.isnull().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
```

```
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	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	NaN	no	1506	yes	no	unknown	5	may	92	1	-1	0	unknown	no
4	5	33	NaN	single	NaN	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

```
pd.DataFrame(Bank_data['education'].value_counts())
```

	count
education	
secondary	23202
tertiary	13301
primary	6851

```
newdataframe.isna().sum()
```

```
sl. no          0
age             0
job           288
marital         0
education    1857
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
```

```
newdataframe = newdataframe.sort_values(by='age', ascending=True)
```

```
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	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	NaN	no	1506	yes	no	unknown	5	may	92	1	-1	0	unknown	no
4	5	33	NaN	single	NaN	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

```
newdataframe['job'].unique()
```

```
array(['management', 'technician', 'entrepreneur', 'blue-collar', nan,
       'retired', 'admin.', 'services', 'self-employed', 'unemployed',
       'housemaid', 'student'], dtype=object)
```

```
data_marital
```

	student	blue-collar	admin.	services	unemployed	technician	retired	management	entrepreneur	self-employed	housemaid	nan
marital												
single	878	2014	1728	1198	401	2620	108	2947	238	446	144	NaN
married	54	6968	2693	2407	731	4052	1731	5400	1070	993	912	NaN
divorced	6	750	750	549	171	925	425	1111	179	140	184	NaN

```
import pandas as pd
```

```
agetomarital = pd.DataFrame()
agetomarital['married'] = newdataframe[newdataframe['marital'] == 'married']['age'].value_counts()
agetomarital['single'] = newdataframe[newdataframe['marital'] == 'single']['age'].value_counts()
agetomarital['divorced'] = newdataframe[newdataframe['marital'] == 'divorced']['age'].value_counts()
```

```
print(agetomarital)
```

```
     married  single  divorced
age
34      1131   650.0     149.0
35      1077   631.0     186.0
36      1076   538.0     192.0
33      1075   746.0     151.0
37      1073   453.0     170.0
..       ...     ...       ...
89         2     NaN       1.0
92         2     NaN       NaN
93         2     NaN       NaN
88         2     NaN       NaN
95         1     NaN       1.0

[73 rows x 3 columns]
```

```
agetomarital.sort_index()
```

	married	single	divorced
age			
20	3	47.0	NaN
21	5	74.0	NaN
22	9	120.0	NaN
23	27	175.0	NaN
24	53	248.0	1.0
...	...	...	...
88	2	NaN	NaN
89	2	NaN	1.0
92	2	NaN	NaN
93	2	NaN	NaN
95	1	NaN	1.0

73 rows × 3 columns

```
newdataframe['education'].unique()
```

```
array(['tertiary', 'secondary', nan, 'primary'], dtype=object)
```

```
import pandas as pd
```

```
agetoeducation = pd.DataFrame()
agetoeducation['tertiary'] = newdataframe[newdataframe['education'] == 'tertiary']['age'].value_counts()
agetoeducation['secondary'] = newdataframe[newdataframe['education'] == 'secondary']['age'].value_counts()
agetoeducation['unknown'] = newdataframe[newdataframe['education'] == 'unknown']['age'].value_counts()
agetoeducation['primary'] = newdataframe[newdataframe['education'] == 'primary']['age'].value_counts()
```

```
print(agetoeducation)
```

```
     tertiary  secondary  unknown  primary
age
32        776     1088.0      NaN      179
33        760     1011.0      NaN      167
31        749     1065.0      NaN      139
34        718     1000.0      NaN      166
30        686      913.0      NaN      124
..        ...        ...      ...      ...
82          2        3.0      NaN       12
81          2        3.0      NaN       10
80          1       12.0      NaN       17
89          1        NaN      NaN        2
84          1        3.0      NaN        5

[65 rows x 4 columns]
```

```
agetoeducation.sort_index()
```

	tertiary	secondary	unknown	primary
age				
20	3	26.0	NaN	6
21	6	54.0	NaN	10
22	14	96.0	NaN	8
23	33	143.0	NaN	17
24	44	219.0	NaN	19
...	...	...	...	...
81	2	3.0	NaN	10
82	2	3.0	NaN	12
83	5	2.0	NaN	14
84	1	3.0	NaN	5
89	1	NaN	NaN	2

65 rows × 4 columns

```
print(data_marital.columns)
```

```
Index(['student', 'blue-collar', 'admin.', 'services', 'unemployed',
       'technician', 'retired', 'management', 'entrepreneur', 'self-employed',
       'housemaid', 'nan'],
      dtype='object')
```

```
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	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	NaN	no	1506	yes	no	unknown	5	may	92	1	-1	0	unknown	no
4	5	33	NaN	single	NaN	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

```
print(newdataframe.columns)
```

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

```
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	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	NaN	no	1506	yes	no	unknown	5	may	92	1	-1	0	unknown	no
4	5	33	NaN	single	NaN	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

```
# Check unique values in the 'deposited?' column
print(newdataframe['y'].unique())

# Check for any missing values in the 'job' and 'deposited?' columns
print(newdataframe[['job', 'y']].isna().sum())
```

```
['no' 'yes']
job    288
y        0
dtype: int64
```

```
old_age = newdataframe[newdataframe['age'] > 61]
```

```
old_age
```

	sl. no	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutcome	y
28906	28907	66	housemaid	married	secondary	no	1929	no	no	cellular	2	feb	169	1	-1	0	unknown	no
28924	28925	62	technician	married	secondary	no	973	no	no	cellular	2	feb	326	1	-1	0	unknown	yes
28965	28966	62	retired	married	secondary	no	1495	no	no	cellular	2	feb	265	1	-1	0	unknown	yes
29158	29159	83	retired	married	primary	no	425	no	no	telephone	2	feb	912	1	-1	0	unknown	no
29261	29262	75	retired	divorced	primary	no	46	no	no	cellular	2	feb	294	1	-1	0	unknown	no
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
45191	45192	75	retired	divorced	tertiary	no	3810	yes	no	cellular	16	nov	262	1	183	1	failure	yes
45195	45196	68	retired	married	secondary	no	1146	no	no	cellular	16	nov	212	1	187	6	success	yes
45204	45205	73	retired	married	secondary	no	2850	no	no	cellular	17	nov	300	1	40	8	failure	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

1041 rows × 18 columns

```
old_age[old_age['y'] == 'yes']
```

	sl. no	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutcome	y
28924	28925	62	technician	married	secondary	no	973	no	no	cellular	2	feb	326	1	-1	0	unknown	yes
28965	28966	62	retired	married	secondary	no	1495	no	no	cellular	2	feb	265	1	-1	0	unknown	yes
29464	29465	68	retired	divorced	primary	no	250	no	no	cellular	3	feb	360	1	-1	0	unknown	yes
29865	29866	75	retired	divorced	primary	no	3881	yes	no	cellular	4	feb	136	3	-1	0	unknown	yes
29961	29962	69	retired	married	primary	no	324	no	no	cellular	4	feb	136	4	-1	0	unknown	yes
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
45191	45192	75	retired	divorced	tertiary	no	3810	yes	no	cellular	16	nov	262	1	183	1	failure	yes
45195	45196	68	retired	married	secondary	no	1146	no	no	cellular	16	nov	212	1	187	6	success	yes
45204	45205	73	retired	married	secondary	no	2850	no	no	cellular	17	nov	300	1	40	8	failure	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

445 rows × 18 columns

```
old_age
```

	sl. no	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutcome	y
28906	28907	66	housemaid	married	secondary	no	1929	no	no	cellular	2	feb	169	1	-1	0	unknown	no
28924	28925	62	technician	married	secondary	no	973	no	no	cellular	2	feb	326	1	-1	0	unknown	yes
28965	28966	62	retired	married	secondary	no	1495	no	no	cellular	2	feb	265	1	-1	0	unknown	yes
29158	29159	83	retired	married	primary	no	425	no	no	telephone	2	feb	912	1	-1	0	unknown	no
29261	29262	75	retired	divorced	primary	no	46	no	no	cellular	2	feb	294	1	-1	0	unknown	no
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
45191	45192	75	retired	divorced	tertiary	no	3810	yes	no	cellular	16	nov	262	1	183	1	failure	yes
45195	45196	68	retired	married	secondary	no	1146	no	no	cellular	16	nov	212	1	187	6	success	yes
45204	45205	73	retired	married	secondary	no	2850	no	no	cellular	17	nov	300	1	40	8	failure	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

1041 rows × 18 columns

```
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	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	NaN	no	1506	yes	no	unknown	5	may	92	1	-1	0	unknown	no
4	5	33	NaN	single	NaN	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

```
newdataframe
```

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

45211 rows × 18 columns

```
newdataframe
```

	sl. no	age	job	marital	education	default	balance	housing	loan	contact	day	month	campaign	pdays	previous	poutcome	deposited?
0	1	58	management	married	tertiary	0	2143	1	0	unknown	5	may	1	-1	0	unknown	0
1	2	44	technician	single	secondary	0	29	1	0	unknown	5	may	1	-1	0	unknown	0
2	3	33	entrepreneur	married	secondary	0	2	1	1	unknown	5	may	1	-1	0	unknown	0
5	6	35	management	married	tertiary	0	231	1	0	unknown	5	may	1	-1	0	unknown	0
6	7	28	management	single	tertiary	0	447	1	1	unknown	5	may	1	-1	0	unknown	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
45206	45207	51	technician	married	tertiary	0	825	0	0	cellular	17	nov	3	-1	0	unknown	1
45207	45208	71	retired	divorced	primary	0	1729	0	0	cellular	17	nov	2	-1	0	unknown	1
45208	45209	72	retired	married	secondary	0	5715	0	0	cellular	17	nov	5	184	3	success	1
45209	45210	57	blue-collar	married	secondary	0	668	0	0	telephone	17	nov	4	-1	0	unknown	0
45210	45211	37	entrepreneur	married	secondary	0	2971	0	0	cellular	17	nov	2	188	11	other	0

43193 rows × 17 columns

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

```
print(newdataframe.columns)
```

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

```
x=newdataframe.drop(['deposited?'],axis=1)
y=newdataframe['deposited?']
```

```
import pandas as pd
from sklearn.model_selection import train_test_split

x = pd.get_dummies(x)
x.columns = [col.lower() for col in x.columns]

x_train, x_test, y_train, y_test = train_test_split(x, y, random_state=42, test_size=0.3, stratify=y)
```

```
x = pd.get_dummies(x)
x.columns=[x.lower() for x in x.columns]
x_train,x_test,y_train,y_test=train_test_split(x,y,random_state=42,test_size=0.3, stratify=y)
```

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

	sl. no	age	default	balance	housing	loan	day	campaign	pdays	previous	...	month_mar	month_may	month_nov	month_oct	month_sep	poutcome_failure	poutcome_other	poutcome_success	poutcome_unknown	deposited?
8279	8280	35	0	532	1	0	2	1	-1	0	...	False	False	False	False	False	False	False	False	True	0
35520	35521	57	0	1577	1	0	7	2	357	1	...	False	True	False	False	False	False	True	False	False	0
41793	41794	32	0	2688	0	0	14	1	57	1	...	False	False	False	True	False	True	False	False	False	1
11500	11501	46	0	2441	0	0	19	2	-1	0	...	False	False	False	False	False	False	False	False	True	0
22837	22838	34	0	280	0	0	25	11	-1	0	...	False	False	False	False	False	False	False	False	True	0

5 rows × 47 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? : 88.3 %
deposited? : 11.7 %
/tmp/ipykernel_30/2674631261.py:2: FutureWarning: Series.__getitem__ treating keys as positions is deprecated. In a future version, integer keys will always be treated as labels (consistent with DataFrame behavior). To access a value by position, use `ser.iloc[pos]`
  normal_share=round(classes[0]/df_train['deposited?'].count()*100,2)
/tmp/ipykernel_30/2674631261.py:3: FutureWarning: Series.__getitem__ treating keys as positions is deprecated. In a future version, integer keys will always be treated as labels (consistent with DataFrame behavior). To access a value by position, use `ser.iloc[pos]`
  fraud_share=round(classes[1]/df_train['deposited?'].count()*100, 2)
```

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

```
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']
```

Logistic Regression

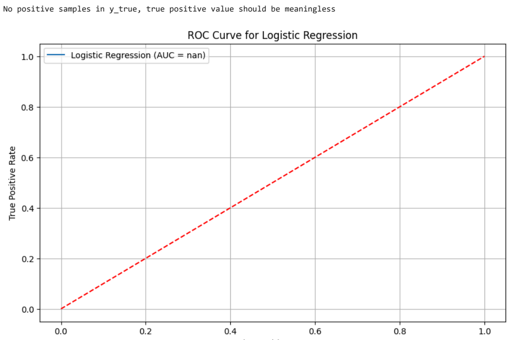
```
from sklearn.metrics import precision_score, recall_score, f1_score, accuracy_score

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'))
```

```
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 log(x_train,x_test,y_train,y_test):
    model=LogisticRegression()
    model.fit(x_train,y_train)
    y_pre=model.predict(x_test)
    evaluation_metrics(y_test, y_pre, target_names)

log(x_train,x_test,y_train,y_test)
```

```
/opt/conda/lib/python3.10/site-packages/sklearn/linear_model/_logistic.py:458: ConvergenceWarning:

lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression

Accuracy : 0.8883810085520495
Precision : 0.5516265912305516
Recall : 0.24574669187145556
F1 Score : 0.3400174367916303
```

```
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_pre, y_proba, target_names):
    # scores
    report = classification_report(y_test, y_pre, target_names=target_names)
    print(report)
    accuracy = accuracy_score(y_test, y_pre)
    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()
    model.fit(x_train, y_train)
    y_pre = model.predict(x_test)
    y_proba = model.predict_proba(x_test)[:, 1]  # Get probability scores for the positive class
    evaluation_metrics(y_test, y_pre, y_proba, target_names=['No Deposited', 'Deposited'])

    # ROC Curve
    fpr, tpr, _ = roc_curve(y_test, y_proba, pos_label='Deposited')
    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)
```

```
/opt/conda/lib/python3.10/site-packages/sklearn/linear_model/_logistic.py:458: ConvergenceWarning:

lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression

              precision    recall  f1-score   support

No Deposited       0.91      0.97      0.94     11977
   Deposited       0.55      0.25      0.34      1587

    accuracy                           0.89     13564
   macro avg       0.73      0.61      0.64     13564
weighted avg       0.87      0.89      0.87     13564

Accuracy: 0.8883810085520495
AUC: 0.8054506276706893
/opt/conda/lib/python3.10/site-packages/sklearn/metrics/_ranking.py:1029: UndefinedMetricWarning:

No positive samples in y_true, true positive value should be meaningless
```



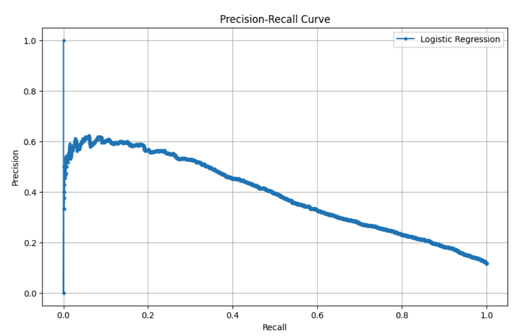

```
from sklearn.metrics import classification_report, accuracy_score, roc_auc_score
import numpy as np

def evaluation_metrics(y_test, y_pre, y_proba, target_names):
    # scores
    report = classification_report(y_test, y_pre, target_names=target_names)
    print(report)
    accuracy = accuracy_score(y_test, y_pre)
    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()
    model.fit(x_train, y_train)
    y_pre = model.predict(x_test)
```

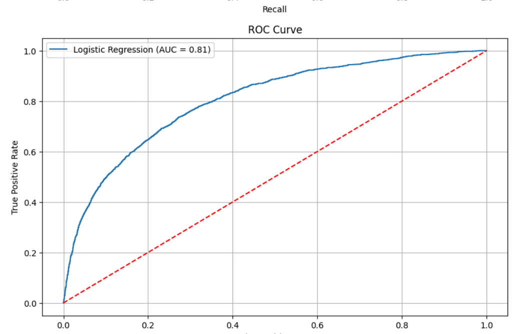
```
    y_proba = model.predict_proba(x_test)[:, 1]  # Get probability scores for the positive class
    evaluation_metrics(y_test, y_pre, y_proba, target_names=['No Deposited', 'Deposited'])

# Classification Report
report = classification_report(y_test, y_pre, target_names=['No Deposited', 'Deposited'])
print(report)

# Accuracy
accuracy = accuracy_score(y_test, y_pre)
print(f"Accuracy: {accuracy}")

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

# Display the results
results = classification_report(y_test, y_pre, target_names=['No Deposited', 'Deposited'], output_dict=True)
print(f"Precision (No Deposited): {results['No Deposited']['precision']}")
print(f"Recall (No Deposited): {results['No Deposited']['recall']}")
print(f"F1 Score (No Deposited): {results['No Deposited']['f1-score']}")
print(f"Support (No Deposited): {results['No Deposited']['support']}")
print(f"Precision (Deposited): {results['Deposited']['precision']}")
print(f"Recall (Deposited): {results['Deposited']['recall']}")
print(f"F1 Score (Deposited): {results['Deposited']['f1-score']}")
print(f"Support (Deposited): {results['Deposited']['support']}")
print(f"Accuracy: {accuracy}")
print(f"Macro Avg: {results['macro avg']}")
print(f"Weighted Avg: {results['weighted avg']}")
print(f"AUC: {auc_score}")
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
Cell In[63], line 23
     20     evaluation_metrics(y_test, y_pre, y_proba, target_names=['No Deposited', 'Deposited'])
     22 # Classification Report
---> 23 report = classification_report(y_test, y_pre, target_names=['No Deposited', 'Deposited'])
     24 print(report)
     26 # Accuracy

NameError: name 'y_pre' is not defined
```

```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import precision_recall_curve, roc_curve, auc
import matplotlib.pyplot as plt

def log(x_train, x_test, y_train, y_test):
    model = LogisticRegression()
    model.fit(x_train, y_train)
    y_proba = model.predict_proba(x_test)[:, 1]  # Get probability scores for the positive class
    return y_proba

# Get probability scores
y_proba = log(x_train, x_test, y_train, y_test)

# Precision-Recall Curve
precision, recall, _ = precision_recall_curve(y_test, y_proba, pos_label='yes')
plt.figure(figsize=(10, 6))
plt.plot(recall, precision, marker='.', label='Logistic Regression')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.title('Precision-Recall Curve')
plt.legend()
plt.grid(True)
plt.show()

# ROC Curve
fpr, tpr, _ = roc_curve(y_test, y_proba, pos_label='yes')
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')
plt.legend()
plt.grid(True)
plt.show()
```

```
/opt/conda/lib/python3.10/site-packages/sklearn/linear_model/_logistic.py:458: ConvergenceWarning:

lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
```

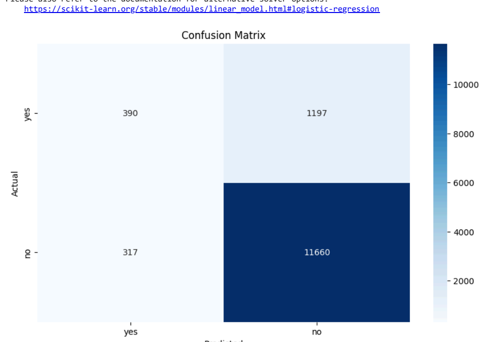





```
x_train=df_train.drop(['deposited?'],axis=1)
y_train=df_train['deposited?']
```

```
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()
    model.fit(x_train, y_train)
    y_pre = model.predict(x_test)
    return y_pre

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

# Compute confusion matrix
cm = confusion_matrix(y_test, y_pre, labels=['yes', 'no'])

# Plot confusion matrix
plt.figure(figsize=(10, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=['yes', 'no'], yticklabels=['yes', 'no'])
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```

```
/opt/conda/lib/python3.10/site-packages/sklearn/linear_model/_logistic.py:458: ConvergenceWarning:

lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
```



RidgeClassifier

Start coding or generate with AI.

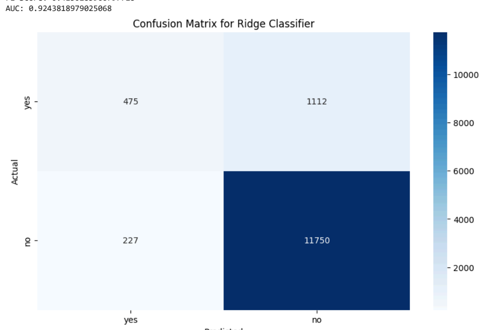
```
def evaluation_metrics(y_test, y_pre, target_names):
    #scores
    print("Accuracy :",accuracy_score(y_test,y_pre))
    print("Precision :",precision_score(y_test,y_pre))
    print("Recall :",recall_score(y_test,y_pre))
    print("F1 Score :",f1_score(y_test,y_pre))

    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()
```

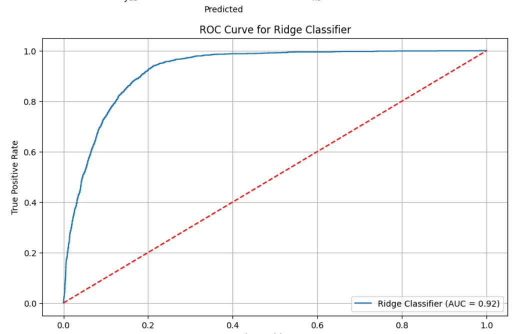
```
def Ridge(x_train,x_test,y_train,y_test):
    #train the model
    model = RidgeClassifier(random_state=2)
    model.fit(x_train, y_train)
    #predictions
    y_pre = model.predict(x_test)
    evaluation_metrics(y_test, y_pre, target_names)
```

```
print(y_test.unique())
```

```
from sklearn.linear_model import RidgeClassifier
from sklearn.metrics import classification_report, accuracy_score, roc_auc_score, roc_curve, auc, confusion_matrix, precision_score, recall_score, f1_score
import matplotlib.pyplot as plt
import seaborn as sns

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

    # Precision, Recall, F1 Score
    print(f"Precision: {precision_score(y_test, y_pre, pos_label='yes')}")
    print(f"Recall: {recall_score(y_test, y_pre, pos_label='yes')}")
    print(f"F1 Score: {f1_score(y_test, y_pre, pos_label='yes')}")

def Ridge(x_train, x_test, y_train, y_test):
    # Train the model
    model = RidgeClassifier(random_state=2)
    model.fit(x_train, y_train)
    # Predictions
    y_pre = model.predict(x_test)

    # Print evaluation metrics
    evaluation_metrics(y_test, y_pre, target_names=['no', 'yes'])

    # Compute AUC
    y_scores = model.decision_function(x_test)
    auc_score = roc_auc_score(y_test, y_scores)
    print(f"AUC: {auc_score}")

    # Plot confusion matrix
    unique_labels = y_test.unique()
    cm = confusion_matrix(y_test, y_pre, labels=unique_labels)
    plt.figure(figsize=(10, 6))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=unique_labels, yticklabels=unique_labels)
    plt.title('Confusion Matrix for Ridge Classifier')
    plt.xlabel('Predicted')
    plt.ylabel('Actual')
    plt.show()

    # ROC Curve
    fpr, tpr, _ = roc_curve(y_test, y_scores, pos_label='yes')
    roc_auc = auc(fpr, tpr)
    plt.figure(figsize=(10, 6))
    plt.plot(fpr, tpr, label=f'Ridge Classifier (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 Ridge Classifier')
    plt.legend()
    plt.grid(True)
    plt.show()

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

```
              precision    recall  f1-score   support

          no       0.91      0.98      0.95     11977
         yes       0.68      0.30      0.42      1587

    accuracy                           0.90     13564
   macro avg       0.80      0.64      0.68     13564
weighted avg       0.89      0.90      0.88     13564

Accuracy: 0.9012828074314362
Precision: 0.6766381766381766
Recall: 0.29930686830497794
F1 Score: 0.4150283966797728
AUC: 0.9243818979025068
```





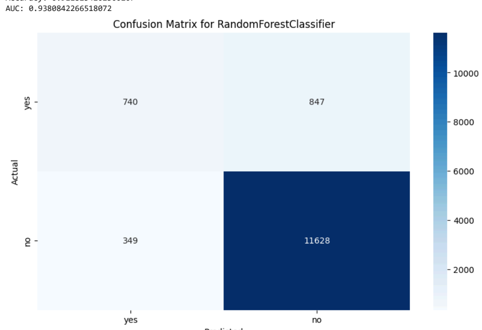
Random forest Classifier

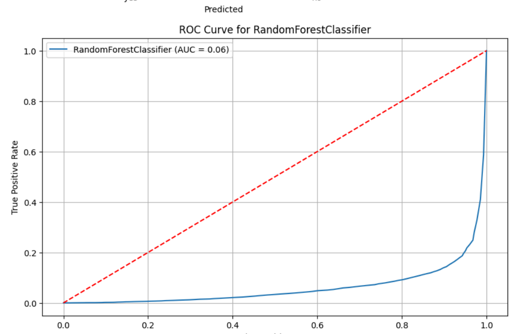
```
def RF(x_train,x_test,y_train,y_test):
  #train the model
  model = RandomForestClassifier(random_state=2)
  model.fit(x_train, y_train)
  #predictions
  y_pre = model.predict(x_test)
  evaluation_metrics(y_test, y_pre, target_names)
```

```
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, classification_report, roc_curve, roc_auc_score, confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd

def evaluation_metrics(y_test, y_pre, y_proba, target_names):
    # Scores
    print("Accuracy:", accuracy_score(y_test, y_pre))
    print("Precision:", precision_score(y_test, y_pre, pos_label='Deposited'))
    print("Recall:", recall_score(y_test, y_pre, pos_label='Deposited'))
    print("F1 Score:", f1_score(y_test, y_pre, pos_label='Deposited'))
    print(classification_report(y_test, y_pre, target_names=target_names))

    # AUC
    fpr, tpr, _ = roc_curve(y_test, y_proba, pos_label='Deposited')
    auc = roc_auc_score(y_test, y_proba)
    print("AUC:", auc)

    # ROC
    plt.plot(fpr, tpr, label="AUC={:.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()

    # Confusion 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()


from sklearn.metrics import classification_report, accuracy_score, roc_auc_score, roc_curve, auc, confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd


def evaluation_metrics(y_test, y_pre, y_proba, target_names):
    # Print Scores
    print("Accuracy:", accuracy_score(y_test, y_pre))
    print("Precision:", precision_score(y_test, y_pre, pos_label='Deposited'))
    print("Recall:", recall_score(y_test, y_pre, pos_label='Deposited'))
    print("F1 Score:", f1_score(y_test, y_pre, pos_label='Deposited'))
    print(classification_report(y_test, y_pre, target_names=target_names))

    # AUC
    fpr, tpr, _ = roc_curve(y_test, y_proba, pos_label='Deposited')
    auc_score = roc_auc_score(y_test, y_proba)
    print("AUC:", auc_score)

    # ROC Curve
    plt.figure(figsize=(10, 6))
    plt.plot(fpr, tpr, label=f"AUC = {auc_score:.3f}")
    plt.plot([0, 1], [0, 1], 'k--')
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('ROC Curve')
    plt.legend(loc='lower right')
    plt.grid(True)
    plt.show()

    # Confusion Matrix
    cm = confusion_matrix(y_test, y_pre, labels=['Deposited', 'No Deposited'])
    cm_df = pd.DataFrame(cm, index=['Deposited', 'No Deposited'], columns=['Deposited', 'No Deposited'])
    plt.figure(figsize=(10, 6))
    sns.heatmap(cm_df, annot=True, fmt='d', cmap='Blues')
    plt.title('Confusion Matrix')
    plt.xlabel('Predicted')
    plt.ylabel('Actual')
    plt.show()

# Ensure your model fits and predictions are done before calling evaluation_metrics
# Example usage:
# RF(x_train, x_test, y_train, y_test) should call evaluation_metrics with y_test, y_pre, y_proba



def RF(x_train,x_test,y_train,y_test):
  #train the model
  model = RandomForestClassifier(random_state=2)
  model.fit(x_train, y_train)
  #predictions
  y_pre = model.predict(x_test)
  evaluation_metrics(y_test, y_pre, target_names)


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


from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, accuracy_score, roc_auc_score, roc_curve, auc, confusion_matrix, precision_recall_curve
import matplotlib.pyplot as plt
import seaborn as sns

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

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

def RF(X_train, X_test, y_train, y_test):
    # Train the model
    model = RandomForestClassifier(random_state=2)
    model.fit(X_train, y_train)
    # Predictions
    y_pre = model.predict(X_test)
    y_proba = model.predict_proba(X_test)[:, 1]  # Get probability scores for the positive class
    # Print evaluation metrics
    evaluation_metrics(y_test, y_pre, y_proba, target_names=['No Deposited', 'Deposited'])

    # Plot confusion matrix
    unique_labels = y_test.unique()
    cm = confusion_matrix(y_test, y_pre, labels=unique_labels)
    plt.figure(figsize=(10, 6))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=unique_labels, yticklabels=unique_labels)
    plt.title('Confusion Matrix for RandomForestClassifier')
    plt.xlabel('Predicted')
    plt.ylabel('Actual')
    plt.show()

    # ROC Curve
    fpr, tpr, _ = roc_curve(y_test, y_proba, pos_label=unique_labels[1])
    roc_auc = auc(fpr, tpr)
    plt.figure(figsize=(10, 6))
    plt.plot(fpr, tpr, label=f'RandomForestClassifier (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 RandomForestClassifier')
    plt.legend()
    plt.grid(True)
    plt.show()

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

```
              precision    recall  f1-score   support

No Deposited       0.93      0.97      0.95     11977
   Deposited       0.68      0.47      0.55      1587

    accuracy                           0.91     13564
   macro avg       0.81      0.72      0.75     13564
weighted avg       0.90      0.91      0.90     13564

Accuracy: 0.9118254202300207
AUC: 0.9380842266518072
```





Conclusion

- Approximately all the classifiers have same result, but Random Forest was the best one.
- The model has around 91% Accuracy.
- Random Forest has 93% Precision, 95% Recall, & 95% F1 Score.
- We can also see the results for each classifier as well.