Banks Classification

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from ucimlrepo import fetch_ucirepo
from sklearn.cluster import KMeans
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix, ConfusionMatrixDisplay

random_state = np.random.seed(12)
pd.set_option('display.max_columns', None)
```

1 - Obtaining the Initial Dataset

In [2]:
```
bank_marketing = fetch_ucirepo(id=222)
```

In [3]:
```
initial_features = bank_marketing.data.features
initial_targets = bank_marketing.data.targets

processed_features = initial_features.copy()
processed_targets = initial_targets.copy()
```

In [4]:
```
initial_features
```

Out[4]:

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

45211 rows × 16 columns

In [5]:
```
initial_targets
```

Out[5]:

	y
0	no
1	no
2	no
3	no
4	no
...	...
45206	yes
45207	yes
45208	yes
45209	no
45210	no

45211 rows × 1 columns

2 - Processing the Dataset

2.1 - Processing Ordinal Categorical Feature Values

In [6]:
```
def ordinal(initial, key, values, is_object=False, default=0):
    data = initial.copy()
    data[key] = initial[key].apply(lambda value: values.index(value) if not is_object else values.get(value) if values.get
    return data
```

2.1.1 - Education

In [7]:
```
print(f"Initial Value Counts\n{processed_features['education'].value_counts()}\n")
processed_features = ordinal(processed_features, 'education', {"primary": 1, "secondary": 2, "tertiary": 3}, is_object=Tru
print(f"Final Value Counts\n{processed_features['education'].value_counts()}")
```

```
Initial Value Counts
education
secondary    23202
tertiary     13301
primary       6851
Name: count, dtype: int64

Final Value Counts
education
2    23202
3    13301
1     6851
0     1857
Name: count, dtype: int64
```

2.1.2 - Default

In [8]:
```
print(f"Initial Value Counts\n{processed_features['default'].value_counts()}\n")
processed_features = ordinal(processed_features, 'default', ['no', 'yes'])
print(f"Final Value Counts\n{processed_features['default'].value_counts()}")
```

```
Initial Value Counts
default
no     44396
yes      815
Name: count, dtype: int64

Final Value Counts
default
0    44396
1      815
Name: count, dtype: int64
```

2.1.3 - Housing

In [9]:
```
print(f"Initial Value Counts\n{processed_features['housing'].value_counts()}\n")
processed_features = ordinal(processed_features, 'housing', ['no', 'yes'])
print(f"Final Value Counts\n{processed_features['housing'].value_counts()}")
```

```
Initial Value Counts
housing
yes    25130
no     20081
Name: count, dtype: int64

Final Value Counts
housing
1    25130
0    20081
Name: count, dtype: int64
```

2.1.4 - Loan

In [10]:
```
print(f"Initial Value Counts\n{processed_features['loan'].value_counts()}\n")
processed_features = ordinal(processed_features, 'loan', ['no', 'yes'])
print(f"Final Value Counts\n{processed_features['loan'].value_counts()}")
```

```
Initial Value Counts
loan
no     37967
yes     7244
Name: count, dtype: int64

Final Value Counts
loan
0    37967
1     7244
Name: count, dtype: int64
```

2.1.5 - Month

In [11]:
```
print(f"Initial Value Counts\n{processed_features['month'].value_counts()}\n")
processed_features = ordinal(processed_features, 'month', ["jan", "feb", "mar", "apr", "may", "jun", "jul", "aug", "sep",
print(f"Final Value Counts\n{processed_features['month'].value_counts()}")
```

```
Initial Value Counts
month
may    13766
jul     6895
aug     6247
jun     5341
nov     3970
apr     2932
feb     2649
jan     1403
oct      738
sep      579
mar      477
dec      214
Name: count, dtype: int64

Final Value Counts
month
4     13766
6      6895
7      6247
5      5341
10     3970
3      2932
1      2649
0      1403
9       738
8       579
2       477
11      214
Name: count, dtype: int64
```

2.1.6 - POutcome

In [12]:
```
print(f"Initial Value Counts\n{processed_features['poutcome'].value_counts()}\n")
processed_features = ordinal(processed_features, 'poutcome', {"other": -1, "failure": 0, "success": 1}, is_object=True, de
print(f"Final Value Counts\n{processed_features['poutcome'].value_counts()}")
```

```
Initial Value Counts
poutcome
failure    4901
other      1840
success    1511
Name: count, dtype: int64

Final Value Counts
poutcome
-2    36959
 0     4901
-1     1840
 1     1511
Name: count, dtype: int64
```

2.2 - Processing Non-Ordinal Categorical Feature Values

In [13]:
```
def non_ordinal(initial, key, values):
    data = initial.copy()
    for value in values:
        data[f"{value}-{key}"] = (initial[key] == value).astype(int)
    data.drop([key], axis=1, inplace=True)
    return data
```

2.2.1 - Job

In [14]:
```
processed_features = non_ordinal(processed_features, 'job', ["admin.", "unemployed", "management", "housemaid", "entrepren
```

2.2.2 - Marital

In [15]:
```
processed_features = non_ordinal(processed_features, 'marital', ["married", "divorced", "single"])
```

2.2.3 - Contact

In [16]:
```
processed_features = non_ordinal(processed_features, 'contact', ["telephone", "cellular"])
```

2.3 - Validating the Processed Feature Values

In [17]:
```
print("Shape =", initial_features.shape)
initial_features
```

```
Shape = (45211, 16)
```

Out[17]:

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

45211 rows × 16 columns

In [18]:
```
print("Shape =", processed_features.shape)
processed_features
```

```
Shape = (45211, 29)
```

Out[18]:

	age	education	default	balance	housing	loan	day_of_week	month	duration	campaign	pdays	previous	poutcome	adr
0	58	3	0	2143	1	0	5	4	261	1	-1	0	-2	
1	44	2	0	29	1	0	5	4	151	1	-1	0	-2	
2	33	2	0	2	1	1	5	4	76	1	-1	0	-2	
3	47	0	0	1506	1	0	5	4	92	1	-1	0	-2	
4	33	0	0	1	0	0	5	4	198	1	-1	0	-2	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
45206	51	3	0	825	0	0	17	10	977	3	-1	0	-2	
45207	71	1	0	1729	0	0	17	10	456	2	-1	0	-2	
45208	72	2	0	5715	0	0	17	10	1127	5	184	3	1	
45209	57	2	0	668	0	0	17	10	508	4	-1	0	-2	
45210	37	2	0	2971	0	0	17	10	361	2	188	11	-1	

45211 rows × 29 columns

2.4 - Processing Binary Target Values

In [19]:
```
print(f"Initial Value Counts\n{processed_targets['y'].value_counts()}\n")
processed_targets = ordinal(processed_targets, 'y', ['no', 'yes'])
print(f"Final Value Counts\n{processed_targets['y'].value_counts()}")
```

```
Initial Value Counts
y
no     39922
yes     5289
Name: count, dtype: int64

Final Value Counts
y
0    39922
1     5289
Name: count, dtype: int64
```

2.5 - Validating the Processed Target Values

In [20]:
```
print("Shape =", initial_targets.shape)
initial_targets
```

```
Shape = (45211, 1)
```

Out[20]:

	y
0	no
1	no
2	no
3	no
4	no
...	...
45206	yes
45207	yes
45208	yes
45209	no
45210	no

45211 rows × 1 columns

In [21]:
```
print("Shape =", processed_targets.shape)
processed_targets
```

```
Shape = (45211, 1)
```

Out[21]:

	y
0	0
1	0
2	0
3	0
4	0
...	...
45206	1
45207	1
45208	1
45209	0
45210	0

45211 rows × 1 columns

3 - Splitting the Dataset

In [22]:
```
split_proportion = 0.7
dataset_size = processed_features.shape[0]
train_size = int(dataset_size * split_proportion)
test_size = dataset_size - train_size
```

In [23]:
```
x_train, y_train = processed_features.iloc[train_size:], processed_targets.iloc[train_size:]['y']
x_test, y_test = processed_features.iloc[:train_size], processed_targets.iloc[:train_size]['y']

print(f"Shape of x_train = {x_train.shape}")
print(f"Shape of y_train = {y_train.shape}")
print(f"Shape of x_test = {x_test.shape}")
print(f"Shape of y_test = {y_test.shape}")
```

```
Shape of x_train = (13564, 29)
Shape of y_train = (13564,)
Shape of x_test = (31647, 29)
Shape of y_test = (31647,)
```

4 - Supervised Model

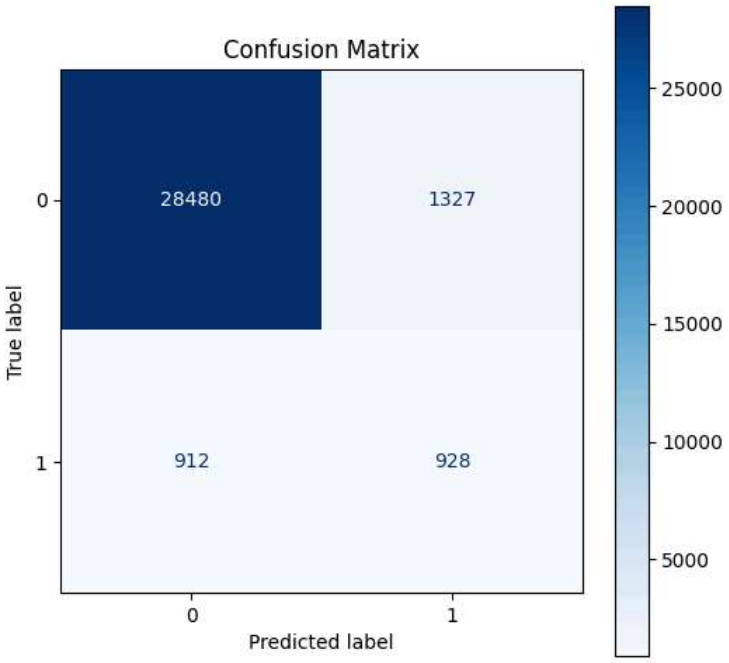
Accuracy = 0.92925

In [24]:
```
def display_results(accuracy, confusion_matrix, classification_report, predictions):
    print(f"Accuracy = {accuracy:.5f}\n")

    fig, ax = plt.subplots(figsize=(6, 6))
    disp = ConfusionMatrixDisplay(confusion_matrix=confusion_matrix, display_labels=np.unique(predictions))
    disp.plot(ax=ax, cmap='Blues', values_format='d')
    plt.title("Confusion Matrix")
    plt.show()

    print(classification_report)
```

In [25]:
```
def train_test_eval(model, x_train_set, y_train_set, x_test_set, y_test_set):
    model.fit(x_train_set, y_train_set)
    y_pred_set = model.predict(x_test_set).astype(int)
    results = (y_pred_set == y_test_set).value_counts()
    accuracy = float(results[True] / y_test_set.shape[0])
    return {
        "predictions": y_pred_set,
        "accuracy": accuracy,
        "confusion_matrix": confusion_matrix(y_test_set, y_pred_set),
        "classification_report": classification_report(y_test_set, y_pred_set)
    }
```

In [26]:
```
logistic_regression_model = LogisticRegression(n_jobs=-1)
logistic_regression_results = train_test_eval(logistic_regression_model, x_train, y_train, x_test, y_test)
display_results(**logistic_regression_results)
```

```
Accuracy = 0.92925
```



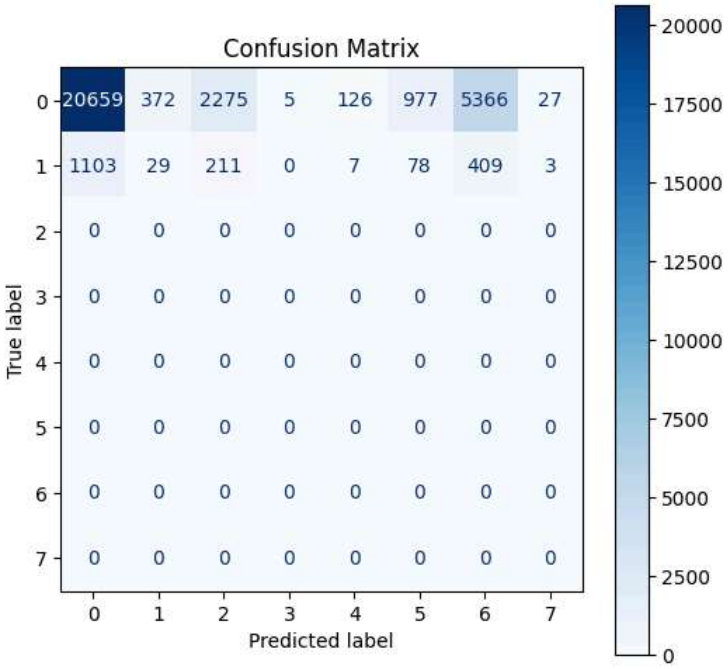

```
              precision    recall  f1-score   support

           0       0.97      0.96      0.96     29807
           1       0.41      0.50      0.45      1840

    accuracy                           0.93     31647
   macro avg       0.69      0.73      0.71     31647
weighted avg       0.94      0.93      0.93     31647
```

5 - Unsupervised Model

Accuracy = 0.65371

In [27]:
```
k_means_model = KMeans()
k_means_results = train_test_eval(k_means_model, x_train, y_train, x_test, y_test)
display_results(**k_means_results)
```

```
Accuracy = 0.65371
```



	precision	recall	f1-score	support
0	0.95	0.69	0.80	29807
1	0.07	0.02	0.03	1840
2	0.00	0.00	0.00	0
3	0.00	0.00	0.00	0
4	0.00	0.00	0.00	0
5	0.00	0.00	0.00	0
6	0.00	0.00	0.00	0
7	0.00	0.00	0.00	0
accuracy			0.65	31647
macro avg	0.13	0.09	0.10	31647
weighted avg	0.90	0.65	0.76	31647