Predicting Marketing Campaign Response Using Logistic Regression

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Summary

In this project, we developed a machine-learning pipeline using logistic regression to predict whether a customer will subscribe to a marketing campaign. The workflow combined a preprocessing stage (StandardScaler and OneHotEncoder) with a logistic regression classifier, followed by training and evaluation using a train/test split.

After applying class-weighting to address the dataset's imbalance, the model achieved an accuracy of approximately 85% and a ROC-AUC of ~0.91, indicating strong overall discrimination between the subscribed ("yes") and not-subscribed ("no") classes. Importantly, class-weighting significantly improved the model's ability to detect positive cases, giving the "yes" class a recall of 0.81. This shows that the weighted logistic regression approach is better suited for imbalanced marketing data, where correctly identifying potential subscribers is more valuable than simply maximizing accuracy.

Introduction

Background:

Financial institutions frequently rely on direct marketing campaigns to promote new products and services to potential clients. One common approach is telephone-based marketing, where bank representatives call customers to inform them about financial offerings, such as long-term deposits and attempt to persuade them to subscribe. Although this method can be effective, it is also resource-intensive calling uninterested or unlikely customers wastes time, labor, and operational costs. As a result, banks increasingly turn to data-driven decision-making to identify which individuals are most likely to respond positively to a campaign.

The Bank Marketing Dataset was created within this context. Compiled by researchers at the University of Minho in Portugal, it captures detailed information from a series of telephone marketing campaigns run by a Portuguese banking institution. The dataset includes demographic attributes (such as age, employment type, and marital status), financial indicators (such as credit defaults and loan status), and campaign-specific variables (including previous contact outcomes and call duration). The target variable indicates whether a customer ultimately subscribed to a term deposit, making the dataset a classic example of a binary classification problem.

The main question explored in this project is:

"Can we predict whether a bank customer will subscribe to a term deposit based on their demographic characteristics, financial information, and interactions with previous marketing campaigns?"

The dataset includes three main categories of features:

1. Client demographics and personal information

- age
- job
- marital
- education
- default (has credit in default)
- housing (has housing loan)
- loan (has personal loan)

2. Current campaign interaction

- contact — type of communication (cellular/telephone)
- day_of_week — day of contact
- month — month of campaign
- duration — call duration in seconds
- campaign — number of contacts during this campaign

3. Past campaign and historical interaction

- pdays — number of days since last contact
- previous — number of previous contacts
- poutcome — outcome of previous campaign

Methods

Data

The dataset used in this project is the Bank Marketing Dataset, created by Moro, Cortez, and Rita (2014) at the University of Minho in Portugal. The data was sourced from the UCI Machine Learning Repository, and can be accessed online at https://archive.ics.uci.edu/dataset/222/bank+marketing. Each row in the dataset represents a single customer contacted during a direct marketing phone campaign, and includes information such as demographic attributes, financial status, call details, previous campaign interactions, and the final outcome indicating whether the customer subscribed to a term deposit.

Analysis

A logistic regression model was used to predict whether a marketing campaign will be successful or not. All original variables from the dataset were included in the analysis. Before fitting, numerical features were standardized with a StandardScaler, and categorical variables were converted to binary indicators via OneHotEncoder. The dataset was split into 80% training and 20% testing, and class imbalance was addressed by balancing class weights during model training. The model's performance was evaluated using accuracy and ROC-AUC scores.

The code used to perform this analysis and generate the accompanying report can be found here:
https://github.com/Roccolee18/bank_marketing_group_24/blob/main/marketing_campain_pr

Results & Discussion

The logistic regression model developed for this analysis provides meaningful insight into the factors associated with customer subscription, but it also highlights the intrinsic challenges of modeling imbalanced marketing data. Our pipeline combined appropriate preprocessing steps—StandardScaler for numerical features and One-Hot Encoding for categorical variables—with a LogisticRegression classifier to ensure proper handling of the heterogeneous dataset while respecting the Golden Rule and avoiding data leakage.

The performance metrics indicate that the model performs reasonably well overall. The ROC-AUC score of approximately 0.91 suggests strong ability to distinguish between subscribers ("yes") and non-subscribers ("no"). Although overall accuracy is around 0.85, accuracy alone is not an appropriate metric for this imbalanced context, because the majority class dominates the dataset.

More importantly, the class-weighted logistic regression successfully shifts the model's focus toward the minority class. The recall for the "yes" class reaches 0.81, a substantial improvement compared to what a non-weighted model would typically achieve on an imbalanced dataset. This indicates that the model is able to identify most customers who eventually subscribe—an outcome that aligns with the core business objective, where failing to detect potential subscribers is far more costly than incorrectly flagging non-subscribers. The precision for the “yes” class is lower (0.42), which is an expected trade-off: by increasing recall and giving more weight to positive cases, the classifier becomes more permissive and produces more false positives. However, in a marketing context—where the cost of contacting an uninterested customer is low compared to the value of identifying a true potential subscriber—this trade-off is acceptable and strategically desirable.

The confusion matrix supports this interpretation. Out of 1,058 actual subscribers, the model correctly identifies 862 true positives while misclassifying 196 as non-subscribers. On the other hand, among the majority class, 6,786 non-subscribers are correctly classified, with 1,199 false positives. These numbers reflect a deliberate shift in the decision boundary due to class balancing: the model becomes more sensitive to the minority class at the expense of increasing false positives.

Overall, the balanced logistic regression model is appropriate for this business problem. Its ability to capture a large portion of true subscribers, even with lower precision, aligns with the strategic goal of maximizing successful marketing outreach. By prioritizing recall in the positive class, the model supports proactive customer engagement and provides a meaningful foundation for future marketing campaigns.

These results show that using a class-weighted logistic regression helps the model catch many more people who are likely to subscribe. This can be useful for marketing teams because it means they can focus their efforts on customers who are more likely to say “yes.” It also shows which factors—like the success of previous campaigns, the month of contact, or call duration—matter most, which can help improve how future campaigns are planned.

These results also bring up a number of future questions. For example, it is unclear whether another type of model, such as a tree-based method, could perform even better than logistic regression on this imbalanced data. Another question is whether the same patterns would appear if we ran this analysis on a different marketing campaign or a different time period. Finally, it would be useful to understand which types of customers the model tends to misclassify most often, and whether adding more customer information could help the model make more reliable predictions.

The following code reads the data programatically and saves it to the data folder:

In [1]:
```
from ucimlrepo import fetch_ucirepo
import pandas as pd
import altair as alt
import os
```

```python
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.metrics import (
    accuracy_score, classification_report,
    roc_auc_score, confusion_matrix
)
from sklearn.linear_model import LogisticRegression
import matplotlib.pyplot as plt
import seaborn as sns

# Create the data folder if it doesn't exist
os.makedirs("data", exist_ok=True)

# fetch dataset
bank_marketing = fetch_ucirepo(id=222)

# Convert the data into a pd dataframe
X = bank_marketing.data.features
y = bank_marketing.data.targets

df = pd.concat([X, y], axis=1)

# Save combined dataset to data folder
df.to_csv("data/bank_marketing.csv", index=False)

print(df.shape)
print(df.head())
```

```
(45211, 17)
   age           job  marital  education default  balance housing loan  \
0   58    management  married   tertiary      no     2143     yes   no   
1   44    technician   single  secondary      no       29     yes   no   
2   33  entrepreneur  married  secondary      no        2     yes  yes   
3   47   blue-collar  married        NaN      no     1506     yes   no   
4   33           NaN   single        NaN      no        1      no   no   

  contact  day_of_week month  duration  campaign  pdays  previous poutcome  
y
0     NaN            5   may       261         1     -1         0      NaN  
no
1     NaN            5   may       151         1     -1         0      NaN  
no
2     NaN            5   may        76         1     -1         0      NaN  
no
3     NaN            5   may        92         1     -1         0      NaN  
no
4     NaN            5   may       198         1     -1         0      NaN  
no
```

DATA VALIDATION

Before working on the dataset, we need to perform some validation checks to make sure that raw data meet the required format. The validation will be performed on the following points:

- Correct data file format
- Correct column names
- No empty observations
- Missingness not beyond expected threshold
- Correct data types in each column
- No duplicate observations
- No outlier or anomalous values
- Correct category levels (i.e., no string mismatches or single values)
- Target/response variable follows expected distribution
- No anomalous correlations between target/response variable and features/explanatory variables
- No anomalous correlations between features/explanatory variables

Correct data file format

In [2]:
```
from pathlib import Path
import pandera as pa
from pandera import Column, DataFrameSchema

def validate_correct_data_format(df, file_path):
    """
    Validate that the data format matches .csv.

    Parameters
    ----------
    df : pandas.DataFrame
        The used dataset.
    file_path : str or Path
        Path to the raw data file.

    """

    file_path = Path(file_path)

    if file_path.suffix.lower() != ".csv":
        raise ValueError(
            f"File format is not correct: expected '.csv', got '{file_path.s
```

```
        )

    print("The file format validation passed: .csv file detected")

validate_correct_data_format(df, "data/bank_marketing.csv")
```

```
The file format validation passed: .csv file detected
```

Correct column names

In [3]:
```
from pandera import Column, DataFrameSchema

columns = [
    "age", "job", "marital", "education", "default",
    "balance", "housing", "loan", "contact",
    "day_of_week", "month", "duration", "campaign",
    "pdays", "previous", "poutcome", "y"
]
column_schema=DataFrameSchema(
    columns={c: Column(nullable=True) for c in columns},
    strict=True,
    ordered=False
)
def column_names(df):
    """
    Validate of the correct column names.
    """

    column_schema.validate(df)
    print("Correct column names were passed")

column_names(df)
```

```
Correct column names were passed
```

No empty observations

In [4]:
```
def no_empty_observations(df):
    """
    Validation to make sure there are no empty observations (row where all v
    """
    n_obs=df.isna().all(axis=1).sum()

    empty_obs=pa.DataFrameSchema(
        columns=None,
        checks=[
            pa.Check(
            lambda df: ~(df.isna().all(axis=1)).any(),
            element_wise=False,
            error="Found one or more completely empty rows in the dataset."
        )
        ])
    empty_obs.validate(df)
    print(f"{n_obs} empty observations found in dataset.")
```

```
no_empty_observations(df)
```

```
0 empty observations found in dataset.
```

No anomalous correlations between target/response variable and features/explanatory variables

In [5]:
```
from deepchecks.tabular import Dataset
from deepchecks.tabular.checks import FeatureLabelCorrelation

bank_train_ds = Dataset(
    df, label="y",
    cat_features=['job',
                  'marital',
                  'education',
                  'default',
                  'housing',
                  'loan',
                  'contact',
                  'month',
                  'poutcome']
)

# Trigger a warning if any feature has a predictive power score (correlatior
check_feat_lab_corr = FeatureLabelCorrelation().add_condition_feature_pps_le
check_feat_lab_corr_result = check_feat_lab_corr.run(dataset=bank_train_ds)

if not check_feat_lab_corr_result.passed_conditions():
    raise ValueError("Feature-Label correlation exceeds the maximum acceptab
```

```
/Users/rabin/miniforge3/envs/522/lib/python3.12/site-packages/deepchecks/cor
e/serialization/dataframe/html.py:16: UserWarning:

pkg_resources is deprecated as an API. See https://setuptools.pypa.io/en/lat
est/pkg_resources.html. The pkg_resources package is slated for removal as e
arly as 2025-11-30. Refrain from using this package or pin to Setuptools<81.
```

No anomalous correlations between features/explanatory variables

In [6]:
```
from deepchecks.tabular.checks import FeatureFeatureCorrelation

check_feat_feat_corr = FeatureFeatureCorrelation().add_condition_max_number_
    threshold=0.99,
)

# Run the check
check_feat_feat_corr_result = check_feat_feat_corr.run(dataset=bank_train_ds

# Uncomment to print the actual values
#print(check_feat_feat_corr_result.value)
```

```python
# Trigger a warning if features have a predictive power (correlation) greate
if not check_feat_feat_corr_result.passed_conditions():
    raise ValueError("Feature-feature correlation exceeds the maximum accept
```

EDA

The following code performs some preliminary EDA:

In [7]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45211 entries, 0 to 45210
Data columns (total 17 columns):
 #   Column       Non-Null Count  Dtype 
---  ------       --------------  ----- 
 0   age          45211 non-null  int64 
 1   job          44923 non-null  object
 2   marital      45211 non-null  object
 3   education    43354 non-null  object
 4   default      45211 non-null  object
 5   balance      45211 non-null  int64 
 6   housing      45211 non-null  object
 7   loan         45211 non-null  object
 8   contact      32191 non-null  object
 9   day_of_week  45211 non-null  int64 
 10  month        45211 non-null  object
 11  duration     45211 non-null  int64 
 12  campaign     45211 non-null  int64 
 13  pdays        45211 non-null  int64 
 14  previous     45211 non-null  int64 
 15  poutcome     8252 non-null   object
 16  y            45211 non-null  object
dtypes: int64(7), object(10)
memory usage: 5.9+ MB
```

In [8]:
```python
df.describe()
```

Out[8]:

	age	balance	day_of_week	duration	campaign	
count	45211.000000	45211.000000	45211.000000	45211.000000	45211.000000	4521
mean	40.936210	1362.272058	15.806419	258.163080	2.763841	4
std	10.618762	3044.765829	8.322476	257.527812	3.098021	10
min	18.000000	-8019.000000	1.000000	0.000000	1.000000	-
25%	33.000000	72.000000	8.000000	103.000000	1.000000	-
50%	39.000000	448.000000	16.000000	180.000000	2.000000	-
75%	48.000000	1428.000000	21.000000	319.000000	3.000000	-
max	95.000000	102127.000000	31.000000	4918.000000	63.000000	87

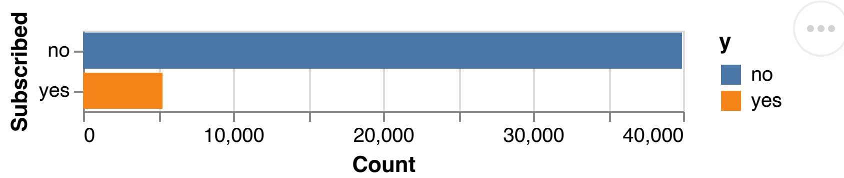
In [9]:
```
df.value_counts()
```

Out[9]:
```
age  job          marital   education  default  balance  housing  loan  con
tact     day_of_week  month  duration  campaign  pdays  previous  poutcome
y
18   student      single    primary    no        608     no       no    cel
lular   13           nov    210        1         93     1         success
yes     1
44   blue-collar  married   secondary  no        6491    yes      no    cel
lular   19           nov    126        2         174    1         failure
no      1
                                                 3060    yes      no    cel
lular   20           apr    87         2         151    3         failure
no      1
                                                 2979    yes      no    cel
lular   18           may    18         5         178    3         other
no      1
                                                 1495    yes      no    cel
lular   1            oct    82         1         142    1         failure
no      1

..
34   management   single    tertiary   no        -444    yes      yes   cel
lular   17           apr    129        2         148    4         other
no      1
                  married   tertiary   no        8000    no       no    cel
lular   12           feb    291        1         260    2         failure
yes     1
                                                 5878    no       no    cel
lular   29           jan    159        7         98     3         success
no      1
                                                 4859    no       no    cel
lular   30           apr    113        1         37     1         other
no      1
89   retired      divorced  primary    no        1323    no       no    tel
ephone  29           dec    207        4         189    1         other
no      1
Name: count, Length: 7842, dtype: int64
```

The distribution of people who subscribed and didn't subscribe can be found below:

In [10]:
```
# Simplify working with large datasets in Altair
alt.data_transformers.enable('vegafusion')

alt.Chart(df).mark_bar().encode(
    y=alt.Y("y:N", title="Subscribed"),
    x=alt.X("count()", title="Count"),
    color="y:N"
)
```

Out[10]:

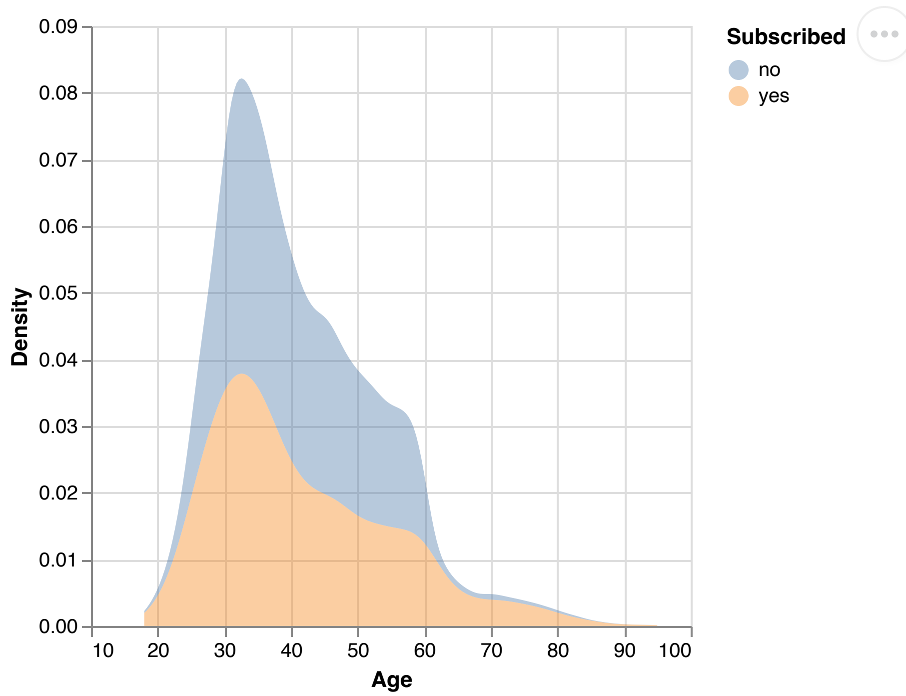


A comparison of the distribution of subscribed people among age can be found below:

In [11]:

```
(
alt.Chart(df)
.transform_density(
    density="age",
    groupby=["y"],
    as_=["age", "density"]
)
.mark_area(opacity=0.4)
.encode(
    x=alt.X("age:Q", title="Age"),
    y=alt.Y("density:Q", title="Density"),
    color=alt.Color("y:N", title="Subscribed")
)
)
```

Out[11]:



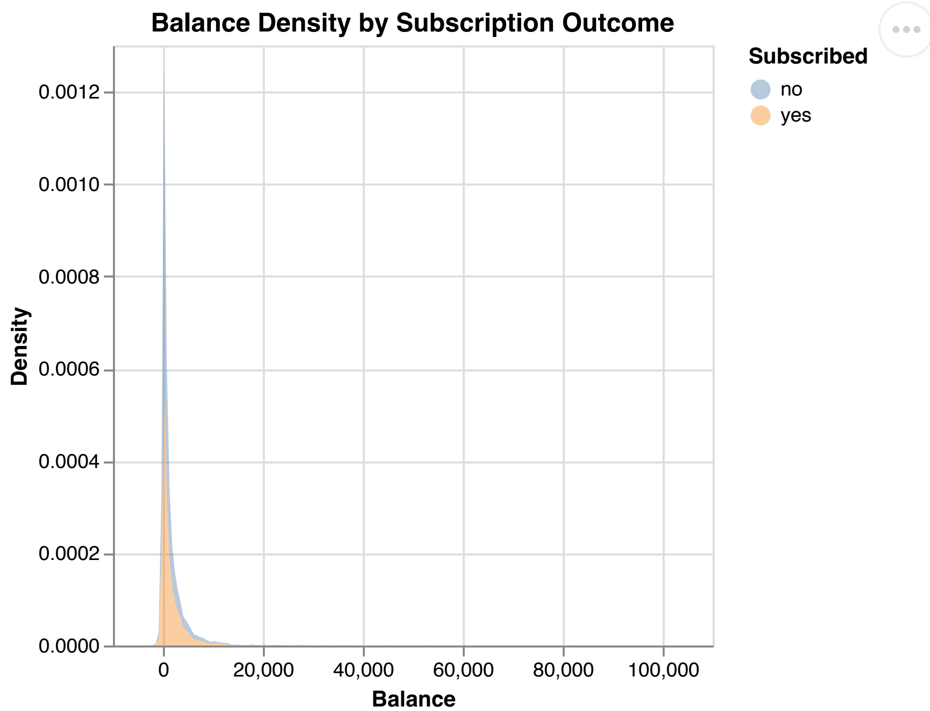
This shows that age can be a very good predictor for subsciption when used on its own.

In [12]:

```
(
alt.Chart(df)
.transform_density(
    density="balance",
    groupby=["y"],
    as_=["balance", "density"]
)
.mark_area(opacity=0.4)
```

```
.encode(
    x=alt.X("balance:Q", title="Balance"),
    y=alt.Y("density:Q", title="Density"),
    color=alt.Color("y:N", title="Subscribed")
)
.properties(title="Balance Density by Subscription Outcome")
)
```

Out[12]:



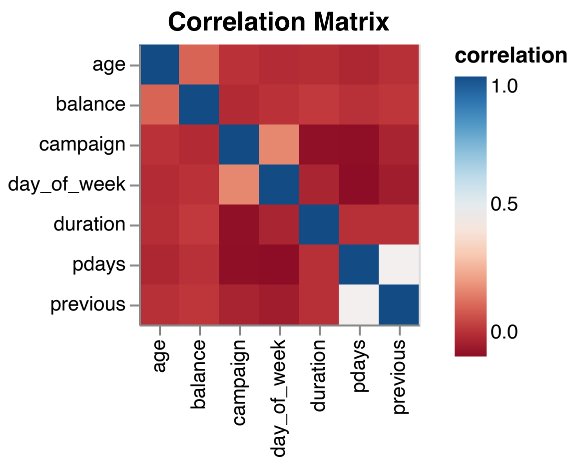
In the plot above we can see that the distribution of balance is right skwed and it might not be a good predictor on its own for subscription. However, when considering other variables, it might be useful.

The following shows a heatmap of the correlation among all the variables:

In [13]:

```
numeric_cols = df.select_dtypes(include='number').columns
corr_df = df[numeric_cols].corr().stack().reset_index()
corr_df.columns = ['var1', 'var2', 'correlation']

alt.Chart(corr_df).mark_rect().encode(
    x=alt.X('var1:N', title=""),
    y=alt.Y('var2:N', title=""),
    color=alt.Color('correlation:Q', scale=alt.Scale(scheme='redblue')),
    tooltip=['var1', 'var2', 'correlation']
).properties(
    title="Correlation Matrix"
)
```

Out[13]:



We can see that there is no multicolinearity among different variables.

In [14]:

```
print(df['education'].unique())
print(df['marital'].unique())
```

```
['tertiary' 'secondary' nan 'primary']
['married' 'single' 'divorced']
```

Preprocessing

In [15]:

```
df = df.dropna()
df = df[df['education'] != 'unknown']
df = df[df['job'] != 'unknown']
df = df[df['marital'] != 'unknown']

print(df.head())
print(df.info())
```

```
       age         job  marital  education default  balance housing loan  \
24060   33      admin.  married   tertiary      no      882      no   no
24062   42      admin.   single  secondary      no     -247     yes  yes
24064   33    services  married  secondary      no     3444     yes   no
24072   36  management  married   tertiary      no     2415     yes   no
24077   36  management  married   tertiary      no        0     yes   no

         contact  day_of_week month  duration  campaign  pdays  previous  \
24060  telephone           21   oct        39         1    151         3
24062  telephone           21   oct       519         1    166         1
24064  telephone           21   oct       144         1     91         4
24072  telephone           22   oct        73         1     86         4
24077  telephone           23   oct       140         1    143         3

      poutcome    y
24060  failure   no
24062    other  yes
24064  failure  yes
24072    other   no
24077  failure  yes
<class 'pandas.core.frame.DataFrame'>
Index: 7842 entries, 24060 to 45210
Data columns (total 17 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   age          7842 non-null   int64
 1   job          7842 non-null   object
 2   marital      7842 non-null   object
 3   education    7842 non-null   object
 4   default      7842 non-null   object
 5   balance      7842 non-null   int64
 6   housing      7842 non-null   object
 7   loan         7842 non-null   object
 8   contact      7842 non-null   object
 9   day_of_week  7842 non-null   int64
 10  month        7842 non-null   object
 11  duration     7842 non-null   int64
 12  campaign     7842 non-null   int64
 13  pdays        7842 non-null   int64
 14  previous     7842 non-null   int64
 15  poutcome     7842 non-null   object
 16  y            7842 non-null   object
dtypes: int64(7), object(10)
memory usage: 1.1+ MB
None
```

In [16]:

```
# Target variable: y = "yes" or "no"
df["y"] = df["y"].map({"yes": 1, "no": 0})
df["housing"] = df["housing"].map({"yes": 1, "no": 0})
df["loan"] = df["loan"].map({"yes": 1, "no": 0})
```

Missingness not beyond threshold, Correct datatypes in each column, and No duplicate observations

In [17]:
```python
# Before validation, check actual missingness
MISSINGNESS_THRESHOLDS = {
    "age": 0.01,
    "job": 0.5,
    "marital": 0.05,
    "education": 0.05,
    "default": 0.05,
    "balance": 0.05,
    "housing": 0.05,
    "loan": 0.05,
    "contact": 0.05,
    "day_of_week": 0.05,
    "month": 0.05,
    "duration": 0.05,
    "campaign": 0.05,
    "pdays": 0.05,
    "previous": 0.05,
    "poutcome": 0.05,
    "y": 0.05,
}

COLUMN_TYPES = {
    "age": pa.Int,
    "job": pa.String,
    "marital": pa.String,
    "education": pa.String,
    "default": pa.Bool,
    "balance": pa.Int,
    "housing": pa.Bool,
    "loan": pa.Bool,
    "contact": pa.String,
    "day_of_week": pa.Int,
    "month": pa.String,
    "duration": pa.Int,
    "campaign": pa.Int,
    "pdays": pa.Int,
    "previous": pa.Int,
    "poutcome": pa.String,
    "y": pa.Bool,
}

for col in df.columns:
    missing_pct = df[col].isna().mean()
    threshold = MISSINGNESS_THRESHOLDS.get(col, 0.05)
    print(f"{col}: {missing_pct:.2%} missing (threshold: {threshold:.2%})")
```

```
age: 0.00% missing (threshold: 1.00%)
job: 0.00% missing (threshold: 50.00%)
marital: 0.00% missing (threshold: 5.00%)
education: 0.00% missing (threshold: 5.00%)
default: 0.00% missing (threshold: 5.00%)
balance: 0.00% missing (threshold: 5.00%)
housing: 0.00% missing (threshold: 5.00%)
loan: 0.00% missing (threshold: 5.00%)
contact: 0.00% missing (threshold: 5.00%)
day_of_week: 0.00% missing (threshold: 5.00%)
month: 0.00% missing (threshold: 5.00%)
duration: 0.00% missing (threshold: 5.00%)
campaign: 0.00% missing (threshold: 5.00%)
pdays: 0.00% missing (threshold: 5.00%)
previous: 0.00% missing (threshold: 5.00%)
poutcome: 0.00% missing (threshold: 5.00%)
y: 0.00% missing (threshold: 5.00%)
```

In [18]:

```
import pandera as pa
from pandera import Column, DataFrameSchema, Check

# Helper function to create column schema
def create_column_schema(col_name, col_type, threshold):
    """Create a column schema with missingness check."""
    return Column(
        col_type,  # to validates the data type
        checks=[
            Check(
                lambda s: s.isna().mean() <= threshold,
                error=f"Missing value rate exceeds {threshold:.1%}",
                element_wise=False,
                ignore_na=False
            )
        ],
        nullable=True,
        coerce=True  # Attempt to coerce to the correct type
    )

# Build schema dynamically
columns_schema = {
    col_name: create_column_schema(col_name, COLUMN_TYPES[col_name], MISSING
    for col_name in MISSINGNESS_THRESHOLDS.keys()
}

schema = DataFrameSchema(
    columns_schema,
    strict=True,  # Ensures only defined columns are present
    unique=None,  # Will be used for duplicate check below
    coerce=True   # Attempt to coerce types across the dataframe
)

# Validate with lazy=True to collect ALL errors
try:
    # First validate schema (types and missingness)
    validated_df = schema.validate(df, lazy=True)
```

```python
    # Then check for duplicates
    duplicates = validated_df.duplicated()
    if duplicates.any():
        num_duplicates = duplicates.sum()
        duplicate_rows = validated_df[duplicates]

        print(f"✗ Found {num_duplicates} duplicate row(s):\n")
        print(duplicate_rows)
        print("\nDuplicate row indices:", duplicate_rows.index.tolist())

        # Optionally raise an error
        raise ValueError(f"DataFrame contains {num_duplicates} duplicate row

    print("PASSED: All validation checks passed!")
    print("- Data types are correct")
    print("- Missing value rates are within thresholds")
    print("- No duplicate rows found")
    print(f"\nValidated DataFrame shape: {validated_df.shape}")
    print(validated_df.head())

except pa.errors.SchemaErrors as e:
    print("ERROR: Schema validation failed with the following errors:\n")

    # Display a summary of all failures
    print(f"Total errors found: {len(e.failure_cases)}\n")

    # Check for data type errors
    if 'schema_context' in e.failure_cases.columns:
        type_errors = e.failure_cases[e.failure_cases['check'].str.contains(
        if not type_errors.empty:
            print("Data Type Errors:")
            for _, error in type_errors.iterrows():
                print(f"  • Column '{error['column']}': {error['check']}")
            print()

    # Show which columns failed missingness checks
    failed_columns = e.failure_cases['column'].unique()
    missingness_failures = [col for col in failed_columns
                            if col in MISSINGNESS_THRESHOLDS]

    if missingness_failures:
        print(f"Columns with missingness errors: {missingness_failures}\n")

        # Show detailed error information for each column
        for col in missingness_failures:
            col_errors = e.failure_cases[e.failure_cases['column'] == col]
            actual_missing = df[col].isna().mean()
            threshold = MISSINGNESS_THRESHOLDS.get(col, 0.05)
            print(f"  • {col}:")
            print(f"    - Actual missing rate: {actual_missing:.2%}")
            print(f"    - Threshold: {threshold:.2%}")
            print()

    # Show full error details
    print("\nFull error report:")
    print(e.failure_cases[['schema_context', 'column', 'check', 'check_numbe
```

```
except ValueError as e:
    # Catch duplicate row errors
    print(f"\n✗ {e}")

except Exception as e:
    print(f"\n✗ Unexpected error: {e}")
```

```
PASSED: All validation checks passed!
- Data types are correct
- Missing value rates are within thresholds
- No duplicate rows found

Validated DataFrame shape: (7842, 17)
       age         job  marital  education  default  balance  housing   loan  \
24060   33      admin.  married   tertiary     True      882    False  False
24062   42      admin.   single  secondary     True     -247     True   True
24064   33    services  married  secondary     True     3444     True  False
24072   36  management  married   tertiary     True     2415     True  False
24077   36  management  married   tertiary     True        0     True  False

         contact  day_of_week month  duration  campaign  pdays  previous  \
24060  telephone           21   oct        39         1    151         3
24062  telephone           21   oct       519         1    166         1
24064  telephone           21   oct       144         1     91         4
24072  telephone           22   oct        73         1     86         4
24077  telephone           23   oct       140         1    143         3

      poutcome      y
24060  failure  False
24062    other   True
24064  failure   True
24072    other  False
24077  failure   True
```

Outlier/Anomaly Validation

In [19]:

```
import pandera as pa
from pandera import Column, Check, DataFrameSchema


schema = DataFrameSchema(
    {
        "age": Column(
            int,
            checks=[
                Check.in_range(0, 120, include_min=True, include_max=True),
            ],
        ),
        "job": Column(
            str,
            checks=[
                Check(lambda s: s.str.len().between(2, 50, inclusive='both')
                error="Job title must be between 2 and 50 characters"),
```

```
            ],
            nullable = True
        ),
        "marital": Column(
            str,
            checks=[
                Check.isin(["married", "single", "divorced"])
            ],
        ),
        "education": Column(
            str,
            checks=[
                Check.isin(["tertiary", "secondary", "primary"]),
            ],
            nullable = True
        ),
        "default": Column(
            str,
            checks=[
                Check.isin(["no", "yes"]),
            ],
        ),
        "balance": Column(
            int,
            checks=[
                Check.in_range(-100000, 1000000000000, include_min=True, inc
            ],
        ),
        "housing": Column(
            int,
            checks=[
                Check.in_range(0, 1, include_min=True, include_max=True),
            ],
        ),
        "loan": Column(
            int,
            checks=[
               Check.in_range(0, 1, include_min=True, include_max=True),
            ],
        ),
        "contact": Column(
            str,
            checks=[
                Check.isin(["cellular", "telephone"]),
            ],
            nullable = True
        ),
        "day_of_week": Column(
            int,
            checks=[
                Check.in_range(1, 31, include_min=True, include_max=True),
            ],
        ),
        "month": Column(
            str,
            checks=[
```

```
                Check.isin(["jan", "feb", "mar", "apr", "may", "jun", "jul",
            ],
        ),
        "duration": Column(
            int,
            checks=[
                Check.in_range(0, 21600, include_min=True, include_max=True)
            ],
        ),
        "campaign": Column(
            int,
            checks=[
                Check.in_range(1, 100, include_min=True, include_max=True),
            ],
        ),
        "pdays": Column(
            int,
            checks=[
                Check.in_range(-1, 10000, include_min=True, include_max=True
            ],
        ),
        "previous": Column(
            int,
            checks=[
                Check.in_range(0, 10000000, include_min=True, include_max=Tr
            ]
        ),
        "poutcome": Column(
            str,
            checks=[
                Check.isin(["failure", "other", "success"]),
            ],
            nullable = True
        ),
        "y": Column(
            int,
            checks=[
                Check.in_range(0, 1, include_min=True, include_max=True),
            ],
        ),
    },
    strict=True,
    coerce=True,
)

def is_outlier_iqr(series, multiplier=1.5):
    Q1 = series.quantile(0.25)
    Q3 = series.quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - multiplier * IQR
    upper_bound = Q3 + multiplier * IQR
    return (series < lower_bound) | (series > upper_bound)

try:
    validated_df = schema.validate(df)
    print("✓ Data validation passed!")
```

```
    print(validated_df)

except pa.errors.SchemaError as e:
        print("✗ Data validation failed!")
        print(f"\nError summary: {e}")
        print("\nDetailed failure cases:")
        print(e.failure_cases)
```

```
✓ Data validation passed!
       age           job  marital  education default  balance  housing  loan  \
24060   33        admin.  married   tertiary      no      882        0     0
24062   42        admin.   single  secondary      no     -247        1     1
24064   33      services  married  secondary      no     3444        1     0
24072   36    management  married   tertiary      no     2415        1     0
24077   36    management  married   tertiary      no        0        1     0
...    ...           ...      ...        ...     ...      ...      ...   ...
45199   34   blue-collar   single  secondary      no     1475        1     0
45201   53    management  married   tertiary      no      583        0     0
45204   73       retired  married  secondary      no     2850        0     0
45208   72       retired  married  secondary      no     5715        0     0
45210   37  entrepreneur  married  secondary      no     2971        0     0

         contact  day_of_week month  duration  campaign  pdays  previous  \
24060  telephone           21   oct        39         1    151         3
24062  telephone           21   oct       519         1    166         1
24064  telephone           21   oct       144         1     91         4
24072  telephone           22   oct        73         1     86         4
24077  telephone           23   oct       140         1    143         3
...          ...          ...   ...       ...       ...    ...       ...
45199   cellular           16   nov      1166         3    530        12
45201   cellular           17   nov       226         1    184         4
45204   cellular           17   nov       300         1     40         8
45208   cellular           17   nov      1127         5    184         3
45210   cellular           17   nov       361         2    188        11

      poutcome  y
24060  failure  0
24062    other  1
24064  failure  1
24072    other  0
24077  failure  1
...        ... ..
45199    other  0
45201  success  1
45204  failure  1
45208  success  1
45210    other  0

[7842 rows x 17 columns]
```

Correct category levels (i.e., no string mismatches or single values)

In [20]:

```
categorical_df = df[["job", "marital", "education", "contact", "month", "pou

schema = DataFrameSchema(
    {
        "job": Column(
            str,
            checks=[
                Check(lambda s: s.str.len().between(2, 50, inclusive='both')
                error="Job title must be between 2 and 50 characters"),
            ],
            nullable = True
        ),
        "marital": Column(
            str,
            checks=[
                Check.isin(["married", "single", "divorced"])
            ],
        ),
        "education": Column(
            str,
            checks=[
                Check.isin(["tertiary", "secondary", "primary"]),
            ],
            nullable = True
        ),
        "contact": Column(
            str,
            checks=[
                Check.isin(["cellular", "telephone"]),
            ],
            nullable = True
        ),
        "month": Column(
            str,
            checks=[
                Check.isin(["jan", "feb", "mar", "apr", "may", "jun", "jul",
            ],
        ),
        "poutcome": Column(
            str,
            checks=[
                Check.isin(["failure", "other", "success"]),
            ],
            nullable = True
        ),
    },
    strict=True,
    coerce=True,
)

try:
    validated_df = schema.validate(categorical_df)
    print("✓ Data validation passed!")
    print(validated_df)
```

```python
except pa.errors.SchemaError as e:
        print("✗ Data validation failed!")
        print(f"\nError summary: {e}")
        print("\nDetailed failure cases:")
        print(e.failure_cases)
```

```
✓ Data validation passed!
                job  marital  education    contact month poutcome
24060        admin.  married   tertiary  telephone   oct  failure
24062        admin.   single  secondary  telephone   oct    other
24064      services  married  secondary  telephone   oct  failure
24072    management  married   tertiary  telephone   oct    other
24077    management  married   tertiary  telephone   oct  failure
...             ...      ...        ...        ...   ...      ...
45199   blue-collar   single  secondary   cellular   nov    other
45201    management  married   tertiary   cellular   nov  success
45204       retired  married  secondary   cellular   nov  failure
45208       retired  married  secondary   cellular   nov  success
45210  entrepreneur  married  secondary   cellular   nov    other

[7842 rows x 6 columns]
```

In [21]:

```python
# 4. Split features and target


# Identify numerical and categorical columns
numerical_cols = X.select_dtypes(include=["int64", "float64"]).columns
categorical_cols = X.select_dtypes(include=["object"]).columns

print(numerical_cols)
print(categorical_cols)
```

```
Index(['age', 'balance', 'day_of_week', 'duration', 'campaign', 'pdays',
       'previous'],
      dtype='object')
Index(['job', 'marital', 'education', 'default', 'housing', 'loan', 'contac
t',
       'month', 'poutcome'],
      dtype='object')
```

In [22]:
```
# 5. Preprocessing pipeline
numeric_transformer = Pipeline(
    steps=[
    ("scaler", StandardScaler())
])

categorical_transformer = Pipeline(
    steps=[
    ("onehot", OneHotEncoder(handle_unknown="ignore"))
])

preprocessor = ColumnTransformer(
    transformers=[
        ("num", numeric_transformer, numerical_cols),
        ("cat", categorical_transformer, categorical_cols)
    ]
)
```

Fitting the model and making predictions

In [23]:
```
# 6. Build model pipeline
model = Pipeline(steps=[
    ("preprocessor", preprocessor),
    ("classifier", LogisticRegression(max_iter=1000, class_weight ="balanced
])
```

In [24]:
```
# 7. Train/test split
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)
```

Data Validation - Target/Response Variable Follows Expected Distribution

In [25]:
```
from deepchecks.tabular.checks import LabelDrift , TrainTestFeatureDrift, Mu
from deepchecks.tabular import Dataset, Suite

categorical_feats = ["job", "marital", "education", "contact", "month", "pou
training_dataset = Dataset(pd.concat([X_train, y_train]), label = "y", cat_f
testing_dataset = Dataset(pd.concat([X_test, y_test]), label = "y", cat_feat


distribution_check = Suite(
        'Drift Detection Suite',
        LabelDrift().add_condition_drift_score_less_than(0.15),
        MultivariateDrift().add_condition_overall_drift_value_less_than(0.15
    )

suite_result = distribution_check.run(training_dataset, testing_dataset)
has_drift = False
for check_result in suite_result.results:
```

```python
    print(f"\nCheck: {check_result.get_header()}")

    if check_result.conditions_results:
        for condition_result in check_result.conditions_results:
            status = "✓" if condition_result.is_pass() else "❌"
            print(f"  {status} {condition_result.name}")
            if not condition_result.is_pass():
                has_drift = True
                print(f"     Details: {condition_result.details}")
    else:
        print("  No conditions set for this check")
```

```
/Users/rabin/miniforge3/envs/522/lib/python3.12/site-packages/deepchecks/tab
ular/dataset.py:236: UserWarning:

Dataframe index has duplicate indexes, setting index to [0,1..,n-1].

/Users/rabin/miniforge3/envs/522/lib/python3.12/site-packages/deepchecks/tab
ular/dataset.py:236: UserWarning:

Dataframe index has duplicate indexes, setting index to [0,1..,n-1].
```

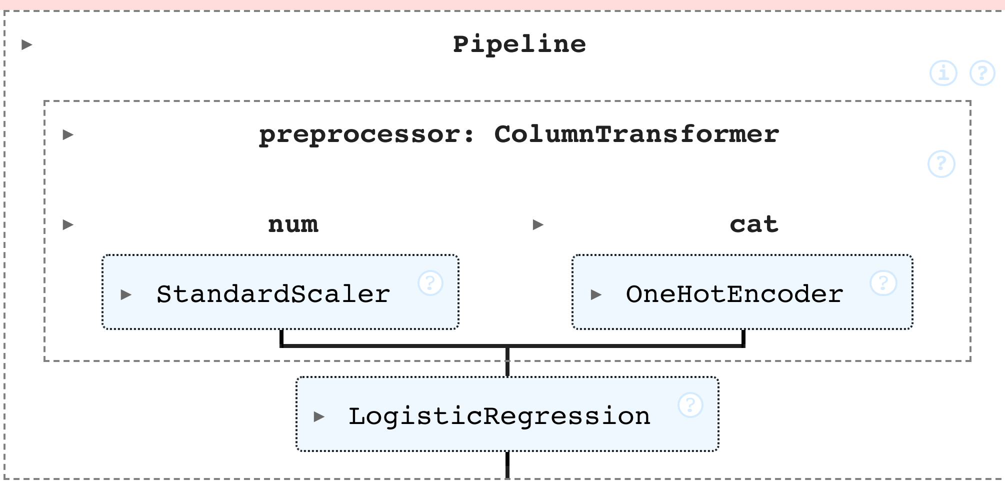
```
/Users/rabin/miniforge3/envs/522/lib/python3.12/multiprocessing/queues.py:12
2: UserWarning: pkg_resources is deprecated as an API. See https://setuptool
s.pypa.io/en/latest/pkg_resources.html. The pkg_resources package is slated
for removal as early as 2025-11-30. Refrain from using this package or pin t
o Setuptools<81.
  return _ForkingPickler.loads(res)
/Users/rabin/miniforge3/envs/522/lib/python3.12/multiprocessing/queues.py:12
2: UserWarning: pkg_resources is deprecated as an API. See https://setuptool
s.pypa.io/en/latest/pkg_resources.html. The pkg_resources package is slated
for removal as early as 2025-11-30. Refrain from using this package or pin t
o Setuptools<81.
  return _ForkingPickler.loads(res)
/Users/rabin/miniforge3/envs/522/lib/python3.12/multiprocessing/queues.py:12
2: UserWarning: pkg_resources is deprecated as an API. See https://setuptool
s.pypa.io/en/latest/pkg_resources.html. The pkg_resources package is slated
for removal as early as 2025-11-30. Refrain from using this package or pin t
o Setuptools<81.
  return _ForkingPickler.loads(res)
/Users/rabin/miniforge3/envs/522/lib/python3.12/multiprocessing/queues.py:12
2: UserWarning: pkg_resources is deprecated as an API. See https://setuptool
s.pypa.io/en/latest/pkg_resources.html. The pkg_resources package is slated
for removal as early as 2025-11-30. Refrain from using this package or pin t
o Setuptools<81.
  return _ForkingPickler.loads(res)
/Users/rabin/miniforge3/envs/522/lib/python3.12/multiprocessing/queues.py:12
2: UserWarning: pkg_resources is deprecated as an API. See https://setuptool
s.pypa.io/en/latest/pkg_resources.html. The pkg_resources package is slated
for removal as early as 2025-11-30. Refrain from using this package or pin t
o Setuptools<81.
  return _ForkingPickler.loads(res)
/Users/rabin/miniforge3/envs/522/lib/python3.12/multiprocessing/queues.py:12
2: UserWarning: pkg_resources is deprecated as an API. See https://setuptool
s.pypa.io/en/latest/pkg_resources.html. The pkg_resources package is slated
for removal as early as 2025-11-30. Refrain from using this package or pin t
o Setuptools<81.
  return _ForkingPickler.loads(res)
/Users/rabin/miniforge3/envs/522/lib/python3.12/multiprocessing/queues.py:12
2: UserWarning: pkg_resources is deprecated as an API. See https://setuptool
s.pypa.io/en/latest/pkg_resources.html. The pkg_resources package is slated
for removal as early as 2025-11-30. Refrain from using this package or pin t
o Setuptools<81.
  return _ForkingPickler.loads(res)
/Users/rabin/miniforge3/envs/522/lib/python3.12/multiprocessing/queues.py:12
2: UserWarning: pkg_resources is deprecated as an API. See https://setuptool
s.pypa.io/en/latest/pkg_resources.html. The pkg_resources package is slated
for removal as early as 2025-11-30. Refrain from using this package or pin t
o Setuptools<81.
  return _ForkingPickler.loads(res)
/Users/rabin/miniforge3/envs/522/lib/python3.12/multiprocessing/queues.py:12
2: UserWarning: pkg_resources is deprecated as an API. See https://setuptool
s.pypa.io/en/latest/pkg_resources.html. The pkg_resources package is slated
for removal as early as 2025-11-30. Refrain from using this package or pin t
o Setuptools<81.
  return _ForkingPickler.loads(res)
/Users/rabin/miniforge3/envs/522/lib/python3.12/multiprocessing/queues.py:12
2: UserWarning: pkg_resources is deprecated as an API. See https://setuptool
```

```
s.pypa.io/en/latest/pkg_resources.html. The pkg_resources package is slated
for removal as early as 2025-11-30. Refrain from using this package or pin t
o Setuptools<81.
  return _ForkingPickler.loads(res)
/Users/rabin/miniforge3/envs/522/lib/python3.12/multiprocessing/queues.py:12
2: UserWarning: pkg_resources is deprecated as an API. See https://setuptool
s.pypa.io/en/latest/pkg_resources.html. The pkg_resources package is slated
for removal as early as 2025-11-30. Refrain from using this package or pin t
o Setuptools<81.
  return _ForkingPickler.loads(res)
/Users/rabin/miniforge3/envs/522/lib/python3.12/multiprocessing/queues.py:12
2: UserWarning: pkg_resources is deprecated as an API. See https://setuptool
s.pypa.io/en/latest/pkg_resources.html. The pkg_resources package is slated
for removal as early as 2025-11-30. Refrain from using this package or pin t
o Setuptools<81.
  return _ForkingPickler.loads(res)
Check: Label Drift
  ✓ Label drift score < 0.15

Check: Multivariate Drift
  ✓ Drift value is less than 0.15
```

In [26]:
```python
# 8. Train model
model.fit(X_train, y_train)
```

```
/Users/rabin/miniforge3/envs/522/lib/python3.12/site-packages/sklearn/utils/
validation.py:1406: DataConversionWarning:

A column-vector y was passed when a 1d array was expected. Please change the
shape of y to (n_samples, ), for example using ravel().
```

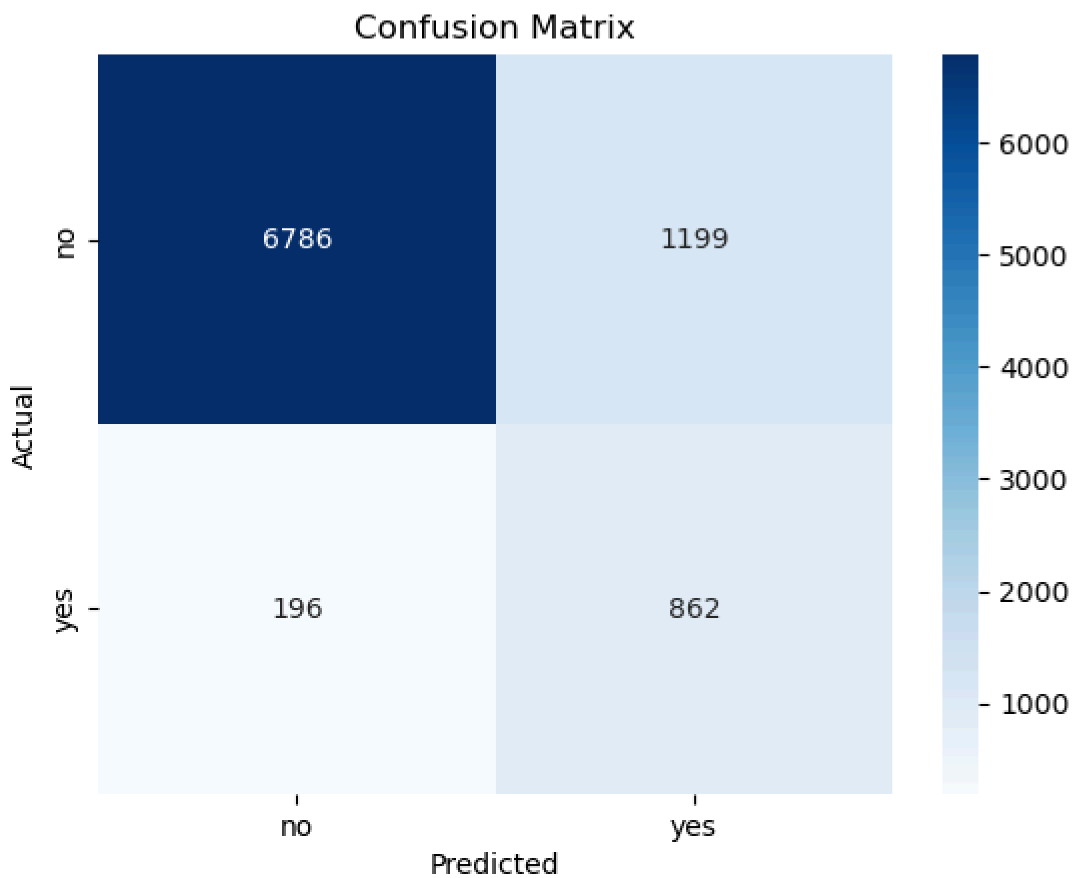
Out[26]:



In [27]:
```python
# 9. Predictions and evaluation
y_pred = model.predict(X_test)
y_prob = model.predict_proba(X_test)[:, 1]

print("Accuracy:", accuracy_score(y_test, y_pred))
print("ROC-AUC:", roc_auc_score(y_test, y_prob))
print("\nClassification Report:\n", classification_report(y_test, y_pred))

# Confusion matrix
cm = confusion_matrix(y_test, y_pred)
```

```
sns.heatmap(cm,
            annot=True,
            fmt="d",
            cmap="Blues",
            xticklabels=["no", "yes"],
            yticklabels=["no", "yes"]
            )
plt.title("Confusion Matrix")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```

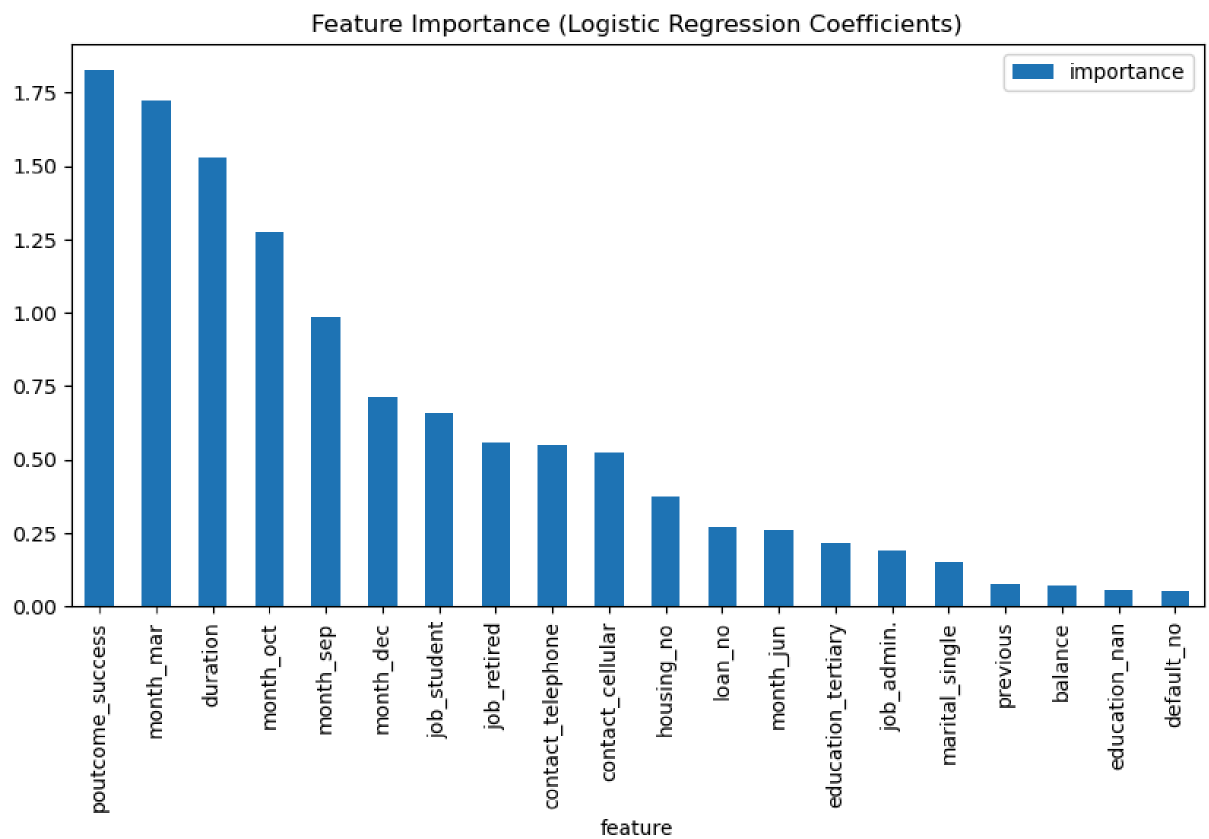
```
Accuracy: 0.8457370341700763
ROC-AUC: 0.9079218714674134

Classification Report:
              precision    recall  f1-score   support

          no       0.97      0.85      0.91      7985
         yes       0.42      0.81      0.55      1058

    accuracy                           0.85      9043
   macro avg       0.70      0.83      0.73      9043
weighted avg       0.91      0.85      0.87      9043
```



In [28]:
```
# 10. Feature Importance (for logistic regression)
# This is a bit tricky with pipelines — we extract processed feature names
ohe = model.named_steps["preprocessor"].named_transformers_["cat"]["onehot"]
cat_feature_names = ohe.get_feature_names_out(categorical_cols)
```

```
feature_names = np.concatenate([numerical_cols, cat_feature_names])

# Get coefficients
coeffs = model.named_steps["classifier"].coef_[0]

feat_imp = pd.DataFrame({
    "feature": feature_names,
    "importance": coeffs
}).sort_values(by="importance", ascending=False)

print(feat_imp.head(10))
feat_imp.head(20).plot(kind="bar", x="feature", y="importance", figsize=(10,
plt.title("Feature Importance (Logistic Regression Coefficients)")
plt.show()
```

```
               feature  importance
49    poutcome_success    1.824477
42           month_mar    1.722014
3             duration    1.525751
45           month_oct    1.276304
46           month_sep    0.984794
37           month_dec    0.713720
15         job_student    0.657311
12         job_retired    0.556467
33   contact_telephone    0.546549
32     contact_cellular    0.522132
```



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