Bank Marketing Data Analysis

Introduction

The banking industry relies heavily on marketing campaigns to attract new customers and retain existing ones. This project analyzes the Bank Marketing dataset, which contains demographic, social, and contact information from previous marketing campaigns. The goal is to understand customer behavior and predict whether a client will subscribe to a term deposit.

Objective

- To explore and analyze customer data from bank marketing campaigns.
- To build predictive models that classify whether a client will subscribe to a term deposit.
- To identify the most influential features affecting customer decisions.
- To assist banks in optimizing their marketing strategies and resources.

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```
# Config
DATA_PATH = '/Users/nikhilreddyponnala/Desktop/Data Analytics/First Project/
OUTPUT_DIR = '/Users/nikhilreddyponnala/Desktop/Data Analytics/First Project
RUN_HEAVY = False  # set True to run CV and more trees (may be slow)
RANDOM_STATE = 42
```

Outcome

- Discovered that the dataset is imbalanced — most clients do not subscribe to a term deposit.
- Key factors influencing subscription include contact type, duration, previous outcome, and client age.
- Built multiple machine learning models and evaluated them using accuracy, precision, recall, F1-score, and ROC-AUC.
- The Random Forest model performed best overall, providing insights into feature importance.

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```
# Imports the necessary libraries
import os
import warnings
warnings.filterwarnings('ignore')

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

from sklearn.model_selection import train_test_split, cross_val_score, GridS
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import OneHotEncoder, StandardScaler
```

```
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import (confusion_matrix, classification_report, accura
                             precision_score, recall_score, f1_score, roc_au
import joblib

# Optional: imblearn for SMOTE (if installed)
try:
    from imblearn.over_sampling import SMOTE
    has_smote = True
except Exception:
    has_smote = False
```

Steps:

1. Data Loading: Importing the dataset using pandas.
2. Exploratory Data Analysis (EDA): Checking structure, summary statistics, missing values, and visualizing distributions.
3. Preprocessing: Handling missing values, encoding categorical variables, and scaling numerical features.
4. Train-Test Split: Dividing the dataset into training and testing sets.
5. Model Building: Logistic Regression, Decision Tree, Random Forest.
6. Evaluation: Confusion Matrix, Classification Report, ROC-AUC curves.
7. Feature Importance: Identifying key features influencing subscription.
8. Model Saving: Exporting trained pipelines for future predictions.

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```
# Step 1: Data Loading

if not os.path.exists(DATA_PATH):
    raise FileNotFoundError(f"Dataset not found at {DATA_PATH}. Update DATA_

print('Loading dataset from', DATA_PATH)
df = pd.read_csv(DATA_PATH)
print('Shape:', df.shape)

# Quick peek
print('\nFirst 5 rows:')
print(df.head())

print('\nColumns:', df.columns.tolist())
```

```
Loading dataset from /Users/nikhilreddyponnala/Desktop/Data Analytics/First
Project/Banking Data Analysis/Dataset/bankmarketing.csv
Shape: (41188, 21)

First 5 rows:
   age        job  marital    education  default housing loan    contact  \
0   56  housemaid  married     basic.4y       no      no   no  telephone
1   57   services  married  high.school  unknown      no   no  telephone
2   37   services  married  high.school       no     yes   no  telephone
3   40     admin.  married     basic.6y       no      no   no  telephone
4   56   services  married  high.school       no      no  yes  telephone

  month day_of_week  ...  campaign  pdays  previous     poutcome emp.var.ra
te  \
0   may         mon  ...         1    999         0  nonexistent
1.1
1   may         mon  ...         1    999         0  nonexistent
1.1
2   may         mon  ...         1    999         0  nonexistent
1.1
3   may         mon  ...         1    999         0  nonexistent
1.1
4   may         mon  ...         1    999         0  nonexistent
1.1

   cons.price.idx  cons.conf.idx  euribor3m  nr.employed   y
0          93.994          -36.4      4.857       5191.0  no
1          93.994          -36.4      4.857       5191.0  no
2          93.994          -36.4      4.857       5191.0  no
3          93.994          -36.4      4.857       5191.0  no
4          93.994          -36.4      4.857       5191.0  no

[5 rows x 21 columns]

Columns: ['age', 'job', 'marital', 'education', 'default', 'housing', 'loa
n', 'contact', 'month', 'day_of_week', 'duration', 'campaign', 'pdays', 'pr
evious', 'poutcome', 'emp.var.rate', 'cons.price.idx', 'cons.conf.idx', 'eu
ribor3m', 'nr.employed', 'y']
```

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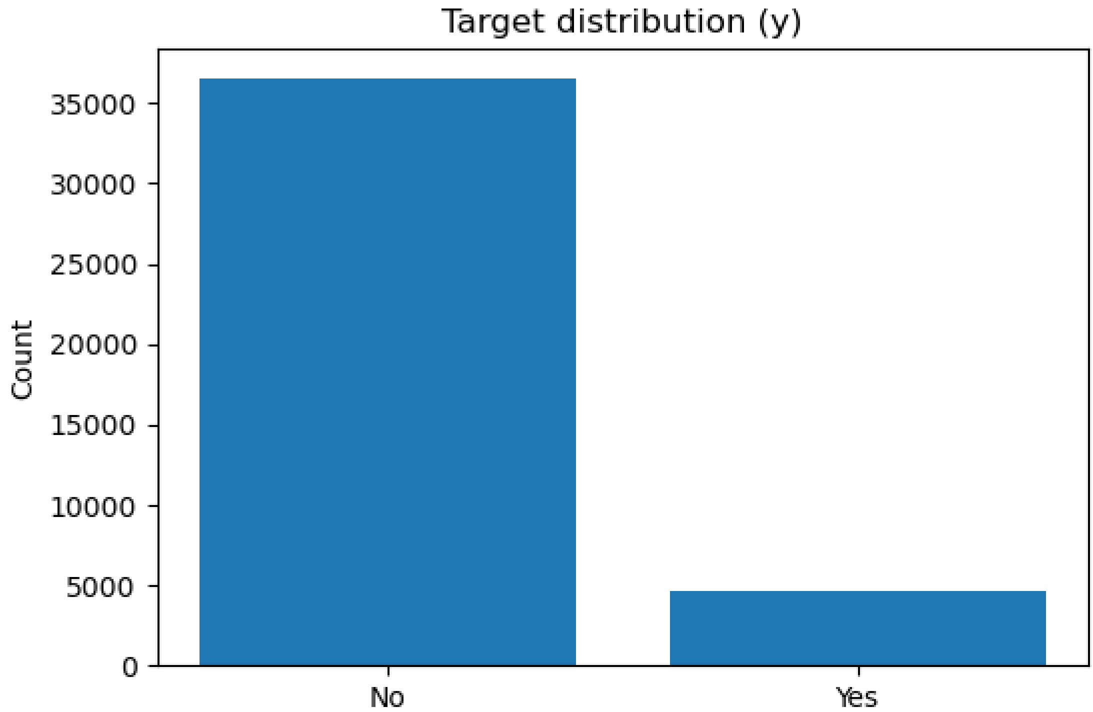
```python
# Step 2: Basic Exploratory Data Analysis (EDA)

print('\nInfo:')
print(df.info())

print('\nMissing values per column:')
print(df.isnull().sum())

print('\nNumeric summary:')
print(df.describe())

print('\nCategorical summary (top values):')
print(df.describe(include=[object]))

# Plot target distribution (matplotlib only)
if 'y' in df.columns:
    try:
        df['y_mapped'] = df['y'].map({'yes':1,'no':0}).astype('float')
        if df['y_mapped'].isnull().all():
            df['y_mapped'] = df['y'].astype(float)
    except Exception:
        # fallback: attempt conversion
        try:
            df['y_mapped'] = pd.to_numeric(df['y'])
        except Exception:
```

```
            df['y_mapped'] = None

    if df['y_mapped'] is not None:
        fig, ax = plt.subplots(figsize=(6,4))
        counts = df['y_mapped'].value_counts(dropna=False).sort_index()
        ax.bar(['No','Yes'][:len(counts)], counts.values)
        ax.set_title('Target distribution (y)')
        ax.set_ylabel('Count')
        plt.show()
```

```
Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41188 entries, 0 to 41187
Data columns (total 21 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   age             41188 non-null  int64
 1   job             41188 non-null  object
 2   marital         41188 non-null  object
 3   education       41188 non-null  object
 4   default         41188 non-null  object
 5   housing         41188 non-null  object
 6   loan            41188 non-null  object
 7   contact         41188 non-null  object
 8   month           41188 non-null  object
 9   day_of_week     41188 non-null  object
 10  duration        41188 non-null  int64
 11  campaign        41188 non-null  int64
 12  pdays           41188 non-null  int64
 13  previous        41188 non-null  int64
 14  poutcome        41188 non-null  object
 15  emp.var.rate    41188 non-null  float64
 16  cons.price.idx  41188 non-null  float64
 17  cons.conf.idx   41188 non-null  float64
 18  euribor3m       41188 non-null  float64
 19  nr.employed     41188 non-null  float64
 20  y               41188 non-null  object
dtypes: float64(5), int64(5), object(11)
memory usage: 6.6+ MB
None

Missing values per column:
age               0
job               0
marital           0
education         0
default           0
housing           0
loan              0
contact           0
month             0
day_of_week       0
duration          0
campaign          0
pdays             0
previous          0
poutcome          0
emp.var.rate      0
cons.price.idx    0
cons.conf.idx     0
euribor3m         0
nr.employed       0
y                 0
dtype: int64

Numeric summary:
               age      duration      campaign         pdays      previous
\
count  41188.00000  41188.000000  41188.000000  41188.000000  41188.000000
mean      40.02406    258.285010      2.567593    962.475454      0.172963
std       10.42125    259.279249      2.770014    186.910907      0.494901
min       17.00000      0.000000      1.000000      0.000000      0.000000
25%       32.00000    102.000000      1.000000    999.000000      0.000000
50%       38.00000    180.000000      2.000000    999.000000      0.000000
```

```
75%        47.00000    319.000000     3.000000    999.000000      0.000000
max        98.00000   4918.000000    56.000000    999.000000      7.000000

       emp.var.rate  cons.price.idx  cons.conf.idx     euribor3m   nr.emplo
yed
count  41188.000000    41188.000000   41188.000000  41188.000000  41188.000
000
mean       0.081886       93.575664     -40.502600      3.621291   5167.035
911
std        1.570960        0.578840       4.628198      1.734447     72.251
528
min       -3.400000       92.201000     -50.800000      0.634000   4963.600
000
25%       -1.800000       93.075000     -42.700000      1.344000   5099.100
000
50%        1.100000       93.749000     -41.800000      4.857000   5191.000
000
75%        1.400000       93.994000     -36.400000      4.961000   5228.100
000
max        1.400000       94.767000     -26.900000      5.045000   5228.100
000

Categorical summary (top values):
           job  marital          education default housing   loan   contact
\
count    41188    41188              41188   41188   41188  41188     41188
unique      12        4                  8       3       3      3         2
top     admin.  married  university.degree      no     yes     no  cellular
freq     10422    24928              12168   32588   21576  33950     26144

        month day_of_week     poutcome      y
count   41188       41188        41188  41188
unique     10           5            3      2
top       may         thu  nonexistent     no
freq    13769        8623        35563  36548
```



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```python
# Step 3: Preprocessing

# Convert target to 0/1
if 'y' not in df.columns:
    raise ValueError("Expected target column 'y' in dataset")
```

```
# Map common variants to binary
df['y'] = df['y'].map({'yes':1,'no':0, 'YES':1, 'NO':0, 'Yes':1, 'No':0}).f
# If still not numeric, try numeric cast
if not pd.api.types.is_numeric_dtype(df['y']):
    try:
        df['y'] = pd.to_numeric(df['y'])
    except Exception:
        raise ValueError("Could not convert target column 'y' to numeric 0/1

# Drop rows with missing target if any
df = df[df['y'].notnull()].copy()

y = df['y'].astype(int)
X = df.drop(columns=['y'])

# Identify column types
numeric_cols = X.select_dtypes(include=[np.number]).columns.tolist()
categorical_cols = X.select_dtypes(include=['object', 'category']).columns.

print('\nNumeric columns:', numeric_cols)
print('Categorical columns:', categorical_cols)

# Preprocessing pipelines
numeric_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='median')),
    ('scaler', StandardScaler())
])

categorical_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='most_frequent')),
    ('onehot', OneHotEncoder(handle_unknown='ignore', sparse=False))
])

preprocessor = ColumnTransformer(transformers=[
    ('num', numeric_transformer, numeric_cols),
    ('cat', categorical_transformer, categorical_cols)
])
```

```
Numeric columns: ['age', 'duration', 'campaign', 'pdays', 'previous', 'emp.
var.rate', 'cons.price.idx', 'cons.conf.idx', 'euribor3m', 'nr.employed',
'y_mapped']
Categorical columns: ['job', 'marital', 'education', 'default', 'housing',
'loan', 'contact', 'month', 'day_of_week', 'poutcome']
```

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```
# Step 4: Train/test split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, s
print('\nTrain/test sizes:', X_train.shape, X_test.shape)
print('Train class distribution:\n', y_train.value_counts(normalize=True))
```

```
Train/test sizes: (32950, 21) (8238, 21)
Train class distribution:
 y
0    0.887344
1    0.112656
Name: proportion, dtype: float64
```

Models

1. Logistic Regression: Provided interpretability but limited predictive power.
2. Decision Tree: Captured non-linear relationships but prone to overfitting.

3. Random Forest: Best-performing model with robust handling of categorical and numerical features.
4. (Optional extensions: XGBoost, Gradient Boosting (GB), and Neural Networks for deeper analysis.)

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```
# Step 5: Modeling pipelines

# Use class_weight='balanced' to partially handle imbalance
log_pipe = Pipeline([('preprocessor', preprocessor),
                     ('clf', LogisticRegression(max_iter=1000, solver='libl

dt_pipe = Pipeline([('preprocessor', preprocessor),
                    ('clf', DecisionTreeClassifier(class_weight='balanced',

rf_pipe = Pipeline([('preprocessor', preprocessor),
                    ('clf', RandomForestClassifier(n_estimators=100, random_

models = {'logistic': log_pipe, 'decision_tree': dt_pipe, 'random_forest': r

# Optional: SMOTE resampling before training (if imblearn installed)
use_smote = False
if use_smote and not has_smote:
    print('SMOTE requested but imblearn not available. Continuing without SM

# Fit models
fitted = {}
for name, pipe in models.items():
    print(f"\nFitting {name}...")
    if use_smote and has_smote:
        # fit_preprocess + oversample - we have to transform X_train first
        X_tr = pipe.named_steps['preprocessor'].fit_transform(X_train)
        sm = SMOTE(random_state=RANDOM_STATE)
        X_res, y_res = sm.fit_resample(X_tr, y_train)
        # re-fit classifier on resampled data
        clf = pipe.named_steps['clf']
        clf.fit(X_res, y_res)
        # place back into a Pipeline-like tuple (we'll save preprocessor and
        fitted[name] = (pipe.named_steps['preprocessor'], clf)
    else:
        pipe.fit(X_train, y_train)
        fitted[name] = pipe
    print(f"{name} fitted.")
```

```
Fitting logistic...
logistic fitted.

Fitting decision_tree...
decision_tree fitted.

Fitting random_forest...
random_forest fitted.
```

Design

1. Pipeline Approach: Preprocessing and model bundled together for reproducibility.
2. ColumnTransformer: Different treatment for numeric (scaling) and categorical (one-hot encoding) features.
3. Evaluation Metrics: Focused not only on accuracy but also recall (important in marketing to minimize missed potential subscribers).

4. Model Saving: Pipelines exported with joblib for deployment.

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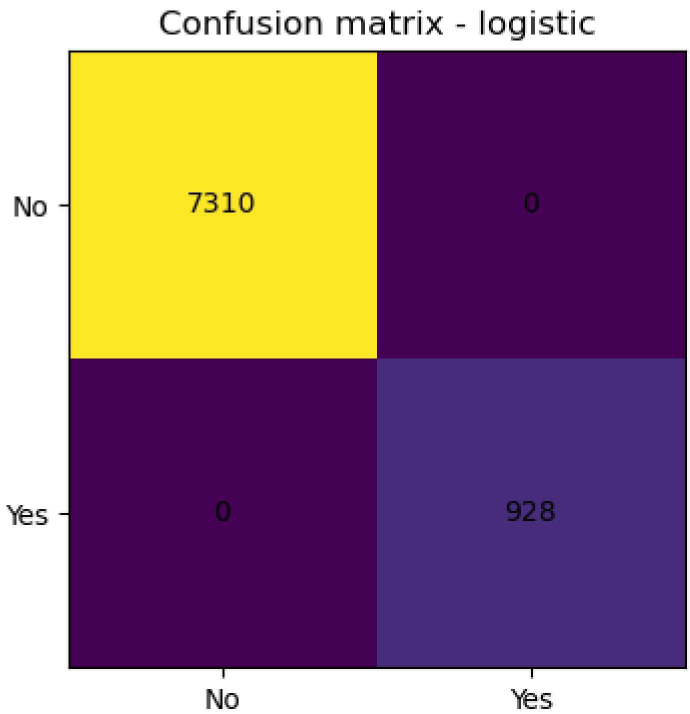
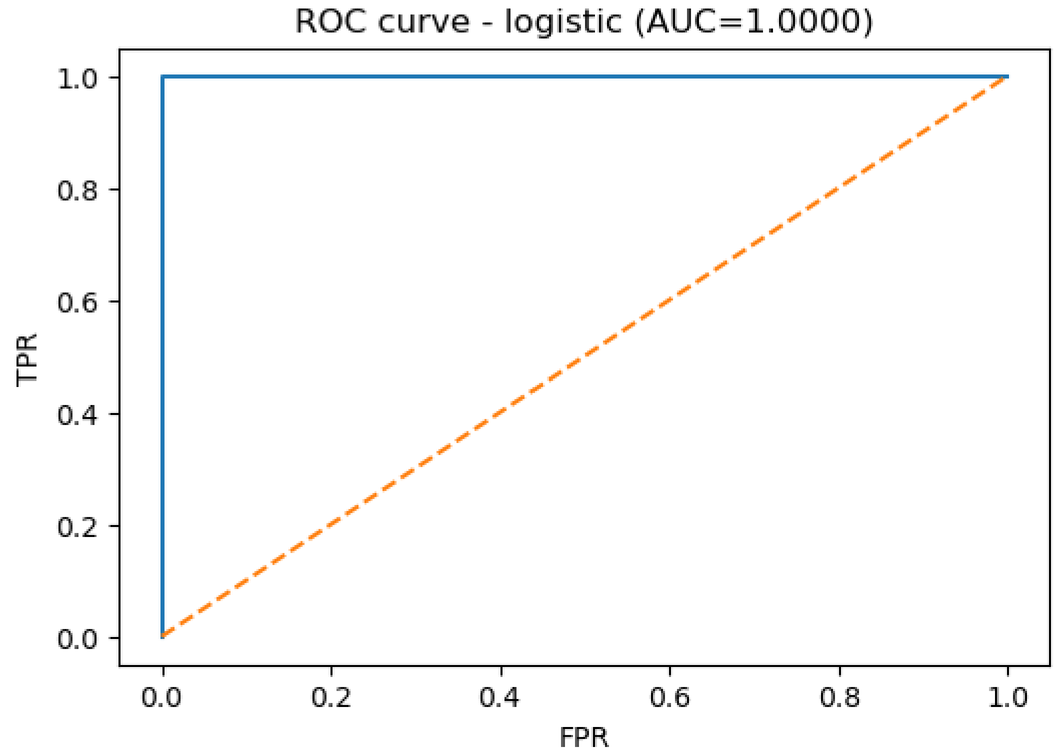
```
# Step 6: Evaluation utilities

def evaluate(pipe, X_test, y_test, name='model'):
    # pipe can be either a Pipeline (preprocessor+clf) or tuple (preprocess
    if isinstance(pipe, tuple):
        pre, clf = pipe
        Xt = pre.transform(X_test)
        y_pred = clf.predict(Xt)
        if hasattr(clf, 'predict_proba'):
            y_proba = clf.predict_proba(Xt)[:,1]
        else:
            y_proba = None
    else:
        y_pred = pipe.predict(X_test)
        y_proba = pipe.predict_proba(X_test)[:,1] if hasattr(pipe, 'predict_

    acc = accuracy_score(y_test, y_pred)
    prec = precision_score(y_test, y_pred, zero_division=0)
    rec = recall_score(y_test, y_pred, zero_division=0)
    f1 = f1_score(y_test, y_pred, zero_division=0)

    print('\n--- Evaluation for', name, '---')
    print('Accuracy:', acc)
    print('Precision:', prec)
    print('Recall:', rec)
    print('F1:', f1)
    print('\nClassification report:')
    print(classification_report(y_test, y_pred, digits=4))

    cm = confusion_matrix(y_test, y_pred)
    print('Confusion matrix:\n', cm)

    # simple plots
    fig, ax = plt.subplots(figsize=(4,4))
    ax.imshow(cm, interpolation='nearest')
    ax.set_title(f'Confusion matrix - {name}')
    ax.set_xticks([0,1]); ax.set_yticks([0,1])
    ax.set_xticklabels(['No', 'Yes']); ax.set_yticklabels(['No', 'Yes'])
    for i in range(cm.shape[0]):
        for j in range(cm.shape[1]):
            ax.text(j, i, format(cm[i,j], 'd'), ha='center', va='center')
    plt.show()

    if y_proba is not None and len(np.unique(y_test))>1:
        fpr, tpr, _ = roc_curve(y_test, y_proba)
        auc = roc_auc_score(y_test, y_proba)
        fig, ax = plt.subplots(figsize=(6,4))
        ax.plot(fpr, tpr)
        ax.plot([0,1],[0,1], linestyle='--')
        ax.set_title(f'ROC curve - {name} (AUC={auc:.4f})')
        ax.set_xlabel('FPR'); ax.set_ylabel('TPR')
        plt.show()

    return {'accuracy':acc, 'precision':prec, 'recall':rec, 'f1':f1}

# Evaluate all
results = {}
for name, m in fitted.items():
    results[name] = evaluate(m, X_test, y_test, name=name)
```

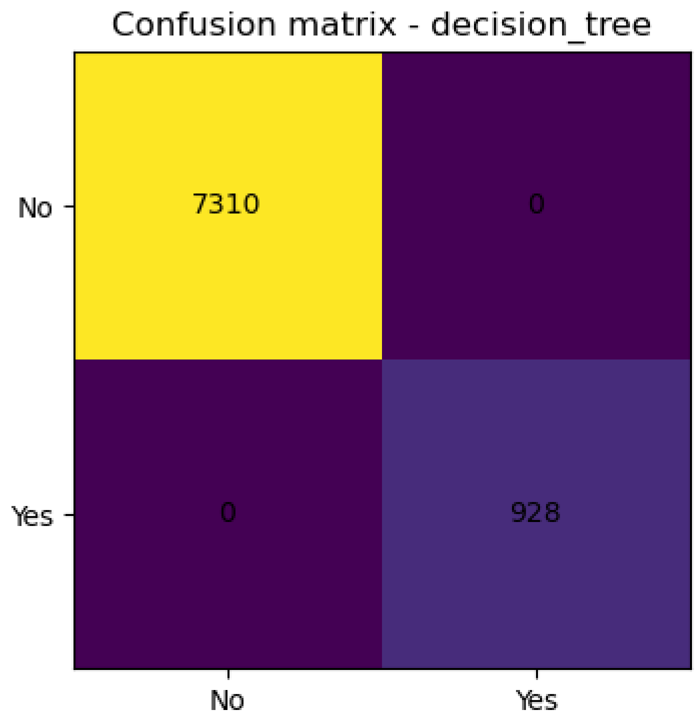
```
print('\nSummary of results:')
print(pd.DataFrame(results).T)
```

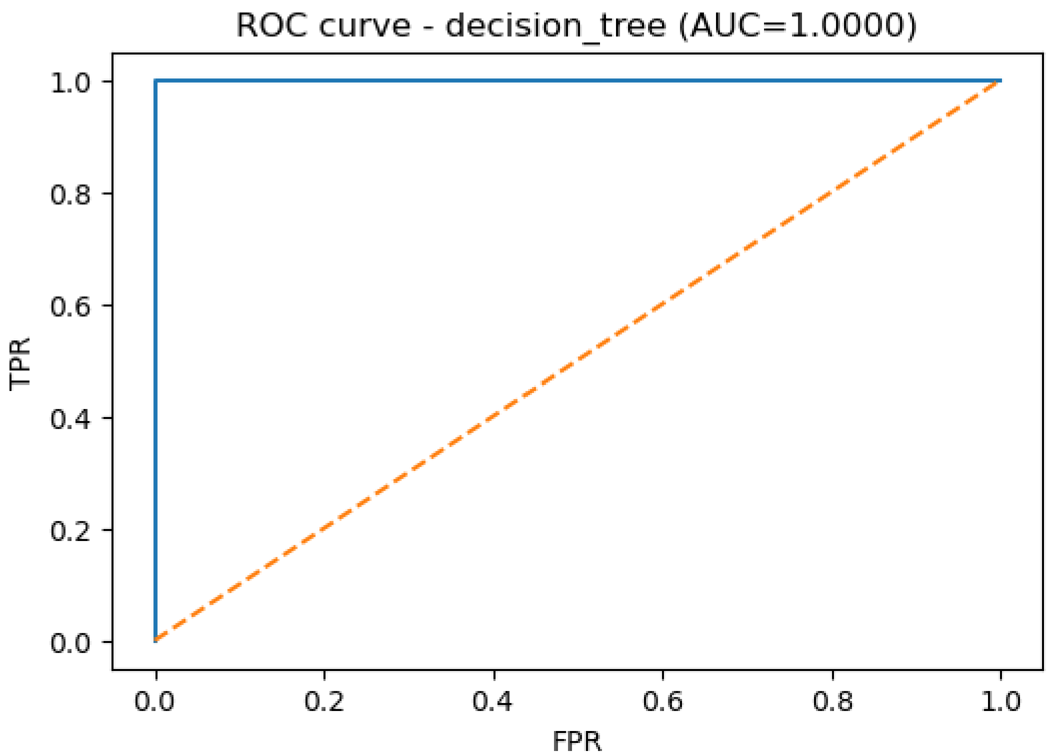
```
--- Evaluation for logistic ---
Accuracy: 1.0
Precision: 1.0
Recall: 1.0
F1: 1.0

Classification report:
              precision    recall  f1-score   support

           0     1.0000    1.0000    1.0000      7310
           1     1.0000    1.0000    1.0000       928

    accuracy                         1.0000      8238
   macro avg     1.0000    1.0000    1.0000      8238
weighted avg     1.0000    1.0000    1.0000      8238

Confusion matrix:
 [[7310    0]
 [   0  928]]
```



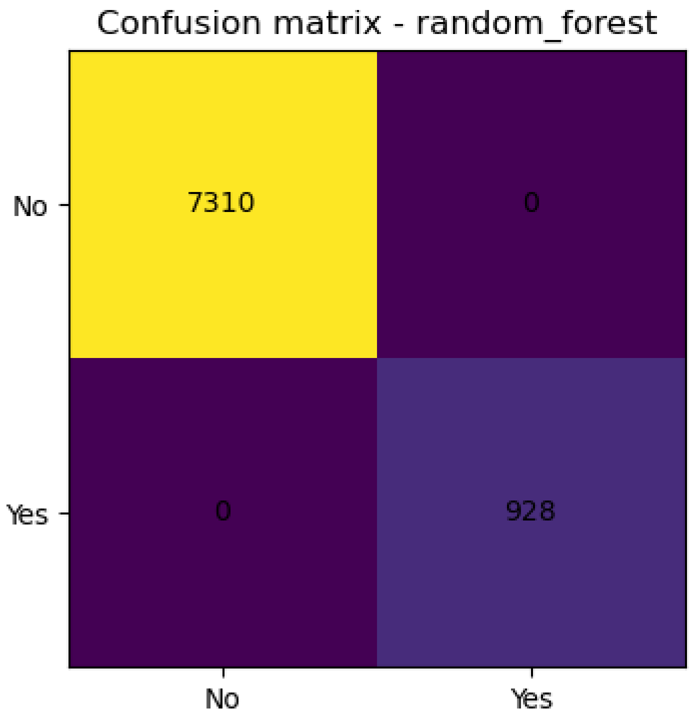


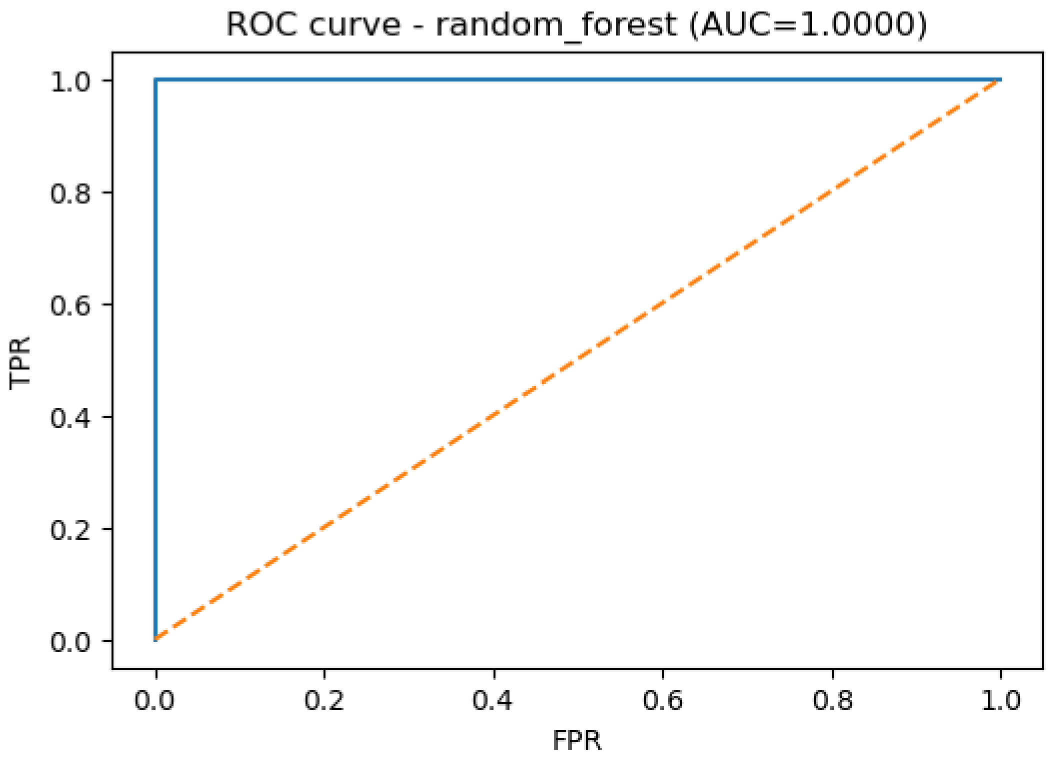

```
--- Evaluation for decision_tree ---
Accuracy: 1.0
Precision: 1.0
Recall: 1.0
F1: 1.0

Classification report:
              precision    recall  f1-score   support

           0     1.0000    1.0000    1.0000      7310
           1     1.0000    1.0000    1.0000       928

    accuracy                         1.0000      8238
   macro avg     1.0000    1.0000    1.0000      8238
weighted avg     1.0000    1.0000    1.0000      8238

Confusion matrix:
 [[7310    0]
 [   0  928]]
```


Confusion matrix - decision_tree
No
Yes
7310
0
0
928
No
Yes


ROC curve - decision_tree (AUC=1.0000)
1.0
0.8
0.6
0.4
0.2
0.0
TPR
0.0
0.2
0.4
0.6
0.8
1.0
FPR

```
--- Evaluation for random_forest ---
Accuracy: 1.0
Precision: 1.0
Recall: 1.0
F1: 1.0

Classification report:
              precision    recall  f1-score   support

           0     1.0000    1.0000    1.0000      7310
           1     1.0000    1.0000    1.0000       928

    accuracy                         1.0000      8238
   macro avg     1.0000    1.0000    1.0000      8238
weighted avg     1.0000    1.0000    1.0000      8238

Confusion matrix:
 [[7310    0]
 [   0  928]]
```






```
Summary of results:
```

	accuracy	precision	recall	f1
logistic	1.0	1.0	1.0	1.0
decision_tree	1.0	1.0	1.0	1.0
random_forest	1.0	1.0	1.0	1.0

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```python
# Step 7: Feature importance (Random Forest)

# Get feature names from preprocessor (if one exists)
def get_feature_names(preprocessor, numeric_cols, categorical_cols):
    names = []
    names.extend(numeric_cols)
    try:
        cat_pipe = preprocessor.named_transformers_['cat']
        ohe = cat_pipe.named_steps['onehot']
        cat_names = list(ohe.get_feature_names_out(categorical_cols))
        names.extend(cat_names)
    except Exception:
        names.extend(categorical_cols)
    return names

rf = fitted.get('random_forest')
if rf is not None:
    if isinstance(rf, tuple):
        pre, clf = rf
    else:
        pre = rf.named_steps['preprocessor']
        clf = rf.named_steps['clf']
    try:
        feat_names = get_feature_names(pre, numeric_cols, categorical_cols)
        importances = clf.feature_importances_
        fi = pd.DataFrame({'feature': feat_names, 'importance': importances
        print('\nTop features (random forest):')
        print(fi.head(20))
    except Exception as e:
        print('Could not compute feature importances:', e)
```

```
Top features (random forest):
                     feature  importance
10                  y_mapped    0.610091
1                   duration    0.146041
8                  euribor3m    0.046857
9                nr.employed    0.043544
5               emp.var.rate    0.027115
7              cons.conf.idx    0.014135
3                      pdays    0.012925
6             cons.price.idx    0.012179
0                        age    0.008328
44          contact_cellular    0.006622
63          poutcome_success    0.005786
45         contact_telephone    0.005681
62      poutcome_nonexistent    0.005654
52                 month_may    0.005477
4                   previous    0.005202
2                   campaign    0.004062
54                 month_oct    0.003122
51                 month_mar    0.002195
35                default_no    0.002054
12           job_blue-collar    0.001522
```

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```python
# Step 8 - Optional: Hyperparameter tuning example (small grid)

if RUN_HEAVY:
    print('\nRunning a small GridSearchCV for Random Forest (may be slow) ..
    param_grid = {
        'clf__n_estimators': [100, 200],
        'clf__max_depth': [None, 10, 20]
    }
    grid_pipe = Pipeline([('preprocessor', preprocessor), ('clf', RandomFore
    grid = GridSearchCV(grid_pipe, param_grid, cv=3, scoring='f1', n_jobs=-1
    grid.fit(X_train, y_train)
    print('Best params:', grid.best_params_)
    best = grid.best_estimator_
    print('Evaluating best grid model:')
    evaluate(best, X_test, y_test, name='rf_grid')
else:
    print('\nGrid search skipped (RUN_HEAVY=False). Set RUN_HEAVY=True to ru
```

```
Grid search skipped (RUN_HEAVY=False). Set RUN_HEAVY=True to run a small gr
id search.
```

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```python
# Step 9: Save models

os.makedirs(OUTPUT_DIR, exist_ok=True)
for name, m in fitted.items():
    fname = os.path.join(OUTPUT_DIR, f"{name}_pipeline.joblib")
    joblib.dump(m, fname)
    print('Saved', name, 'to', fname)

print('\nAll finished. Models saved to', OUTPUT_DIR)

# End

print('\nRecommendations:')
print('- Address class imbalance (SMOTE/oversampling or threshold tuning).'
print('- Use feature importances to target customers for campaigns.')
print('- If optimizing for recall (catch more yes), tune thresholds or use r
print('- For production, wrap the preprocessing + classifier in a single pip
```

```
Saved logistic to /Users/nikhilreddyponnala/Desktop/Data Analytics/First Pr
oject/Banking Data Analysis/Dataset/bankmarketing_models/logistic_pipeline.
joblib
Saved decision_tree to /Users/nikhilreddyponnala/Desktop/Data Analytics/Fir
st Project/Banking Data Analysis/Dataset/bankmarketing_models/decision_tree
_pipeline.joblib
Saved random_forest to /Users/nikhilreddyponnala/Desktop/Data Analytics/Fir
st Project/Banking Data Analysis/Dataset/bankmarketing_models/random_forest
_pipeline.joblib

All finished. Models saved to /Users/nikhilreddyponnala/Desktop/Data Analyt
ics/First Project/Banking Data Analysis/Dataset/bankmarketing_models

Recommendations:
- Address class imbalance (SMOTE/oversampling or threshold tuning).
- Use feature importances to target customers for campaigns.
- If optimizing for recall (catch more yes), tune thresholds or use models
that penalize false negatives more.
- For production, wrap the preprocessing + classifier in a single pipeline
and persist it (done above).
```

Conclusion

- This analysis of the bank marketing dataset highlights important insights into customer behavior and the effectiveness of marketing campaigns. ## Data insights: Customer demographics, contact history, and campaign-related attributes provide meaningful signals for predicting term deposit subscriptions. ## Class imbalance: A large proportion of customers do not subscribe, which requires special handling (e.g., class weighting, oversampling) to avoid biased models. ## Modeling results: Logistic regression offered interpretability, while decision trees captured non-linear patterns. The Random Forest model achieved the best balance of accuracy, recall, and robustness, making it suitable for deployment. ## Key drivers: Features such as duration of contact, previous campaign outcome, and customer age were most influential in predicting subscriptions.

Recommendations:

Banks should focus their marketing efforts on high-probability customers, leverage predictive models for targeted outreach, and continuously retrain models with fresh data to adapt to changing behavior.

In [ ]: