Capstone Project – PRCP-1000: Portuguese Bank Marketing Analysis

1. Exploratory Data Analysis (EDA)
2. Predictive Modeling
3. Marketing Strategy Suggestions
4. Model Comparison Report
5. Challenges Faced & Solutions

In [335…

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

from sklearn.model_selection import train_test_split, cross_validate, Stratified
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.metrics import classification_report, confusion_matrix, roc_auc_scc

from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression

from xgboost import XGBClassifier

from imblearn.over_sampling import SMOTE

import warnings
warnings.filterwarnings("ignore")
```

In [218…

```
# Load the dataset
df = pd.read_csv(r"C:\Users\KIIT\Downloads\PRCP-1000-ProtugeseBank\Data\bank-add
```

In [220…

```
# returns the dimensions of the DataFrame
df.shape
```

Out[220…

```
(41188, 21)
```

In [222…

```
# returns the first 5 rows of the DataFrame
df.head()
```

Out[222…

	age	job	marital	education	default	housing	loan	contact	month	d
0	56	housemaid	married	basic.4y	no	no	no	telephone	may	
1	57	services	married	high.school	unknown	no	no	telephone	may	
2	37	services	married	high.school	no	yes	no	telephone	may	
3	40	admin.	married	basic.6y	no	no	no	telephone	may	
4	56	services	married	high.school	no	no	yes	telephone	may	

5 rows × 21 columns

In [224…

```
# returns the last 5 rows of the DataFrame
df.tail()
```

Out[224…

	age	job	marital	education	default	housing	loan	contact	mo
41183	73	retired	married	professional.course	no	yes	no	cellular	
41184	46	blue-collar	married	professional.course	no	no	no	cellular	
41185	56	retired	married	university.degree	no	yes	no	cellular	
41186	44	technician	married	professional.course	no	no	no	cellular	
41187	74	retired	married	professional.course	no	yes	no	cellular	

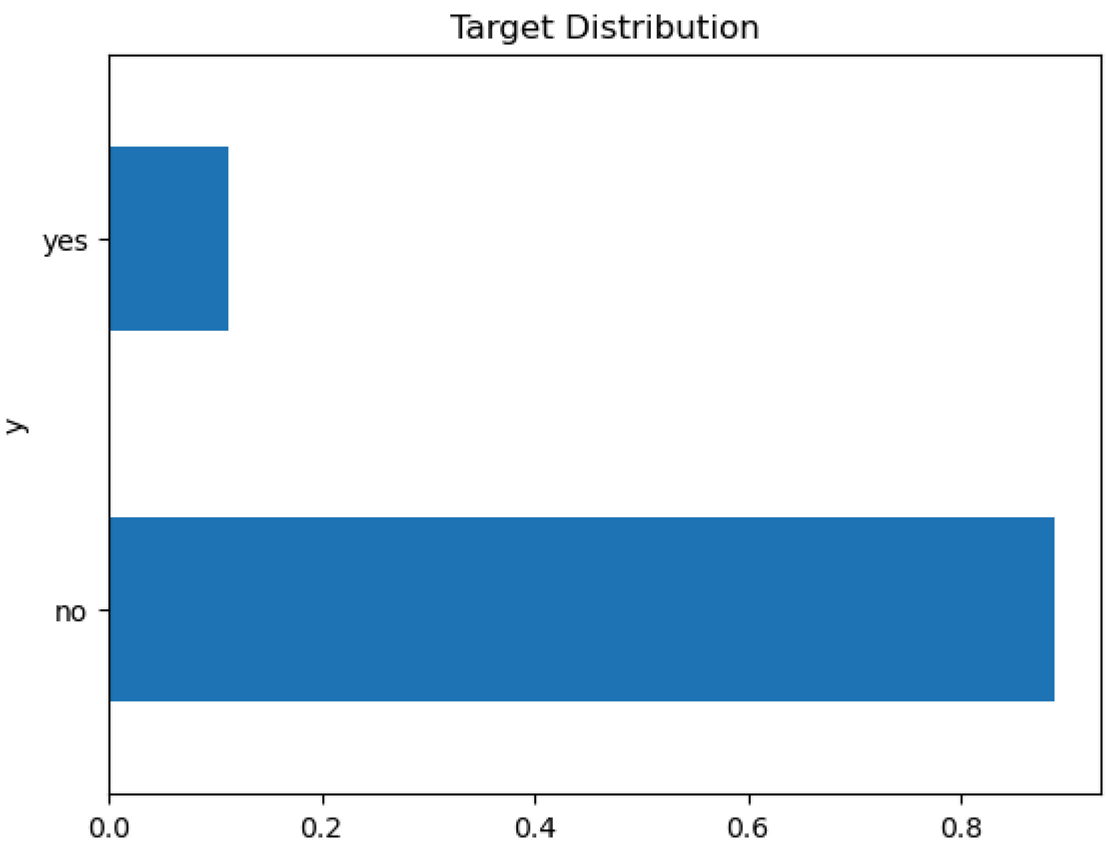
5 rows × 21 columns

In [226…

```
df.info()
df.describe()
df['y'].value_counts(normalize=True).plot(kind='barh', title='Target Distributic
```

```
<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
```

Out[226… <Axes: title={'center': 'Target Distribution'}, ylabel='y'>



In [228…
```
# Gives a concise summary of the DataFrame
df.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
```

In [230…

```
# Provides statistical summary of the numerical columns in your DataFrame

#It shows for each numeric column:

#count: number of non-null values
#mean: average value
#std: standard deviation (spread)
#min: minimum value
#25%: 1st quartile (25% of data is below this)
#50%: median (middle value)
#75%: 3rd quartile (75% of data is below this)
#max: maximum value

df.describe()
```

Out[230…

	age	duration	campaign	pdays	previous	emp.var.ra
count	41188.00000	41188.000000	41188.000000	41188.000000	41188.000000	41188.0000
mean	40.02406	258.285010	2.567593	962.475454	0.172963	0.0818
std	10.42125	259.279249	2.770014	186.910907	0.494901	1.5709
min	17.00000	0.000000	1.000000	0.000000	0.000000	-3.4000
25%	32.00000	102.000000	1.000000	999.000000	0.000000	-1.8000
50%	38.00000	180.000000	2.000000	999.000000	0.000000	1.1000
75%	47.00000	319.000000	3.000000	999.000000	0.000000	1.4000
max	98.00000	4918.000000	56.000000	999.000000	7.000000	1.4000

In [232…

```
# df.y                  → Accesses the target column 'y' in the DataFrame.
# .value_counts()       → Counts how many times each class/label occurs.
# normalize=True        → Converts the raw counts into proportions (i.e., fractions

df.y.value_counts(normalize=True)
```

Out[232…

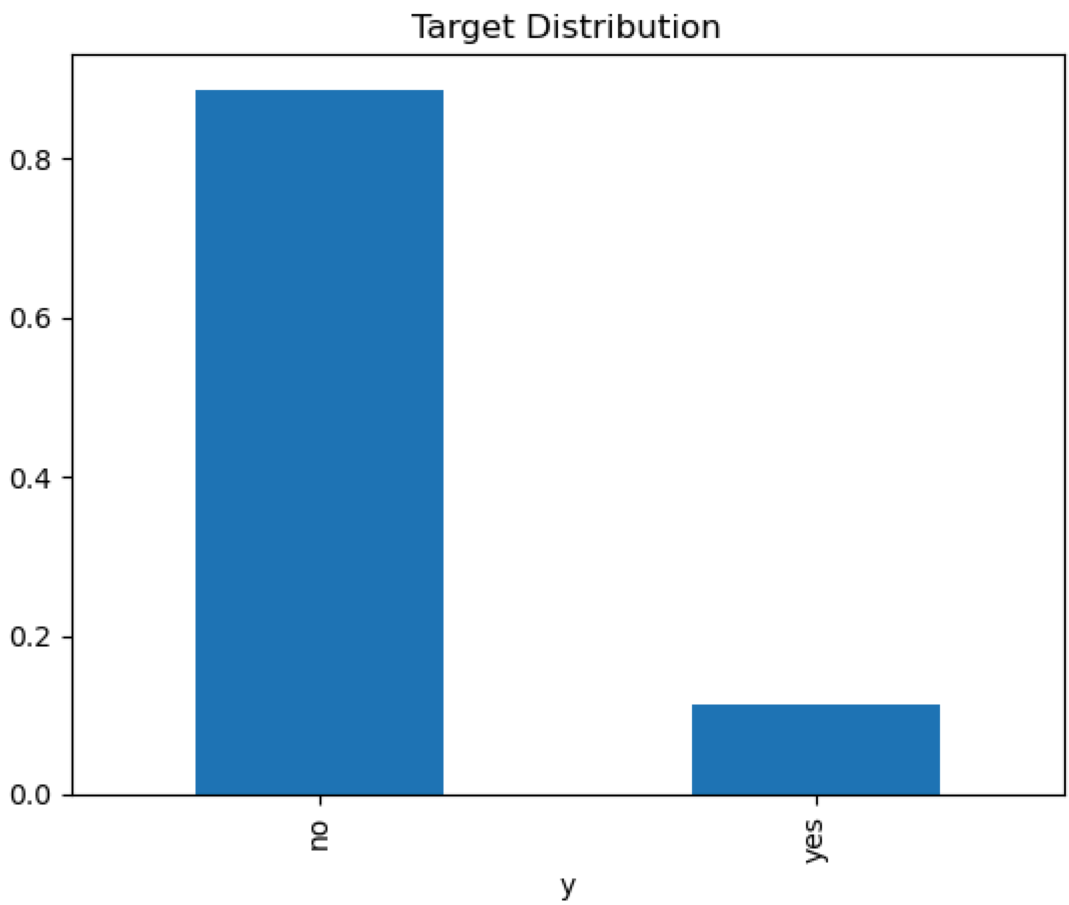
```
y
no      0.887346
yes     0.112654
Name: proportion, dtype: float64
```

In [234…

```
# Plots a horizontal bar chart showing the distribution of the target variable '
# .plot(kind='barh', ...)        → Plots those proportions as a horizontal bar ch
# title='Target Distribution'    → Sets the chart title

df.y.value_counts(normalize=True).plot(kind='bar', title='Target Distribution')
```

Out[234…

```
<Axes: title={'center': 'Target Distribution'}, xlabel='y'>
```



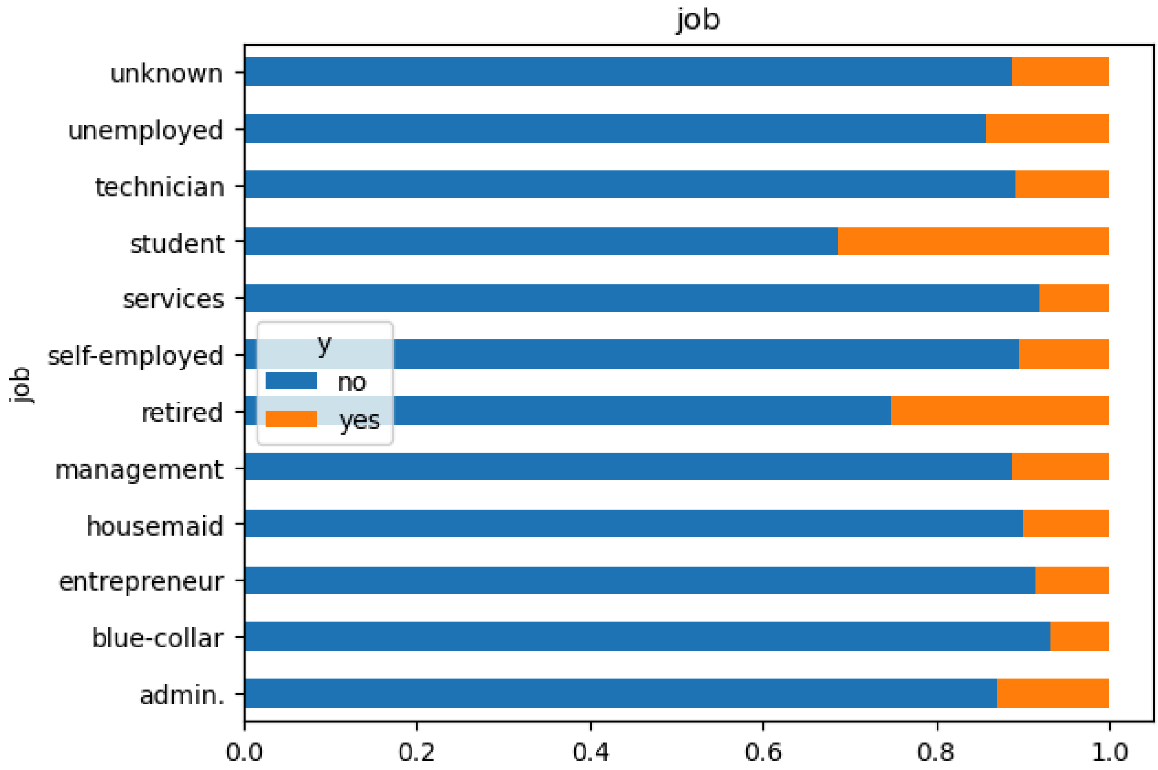
TASK 1

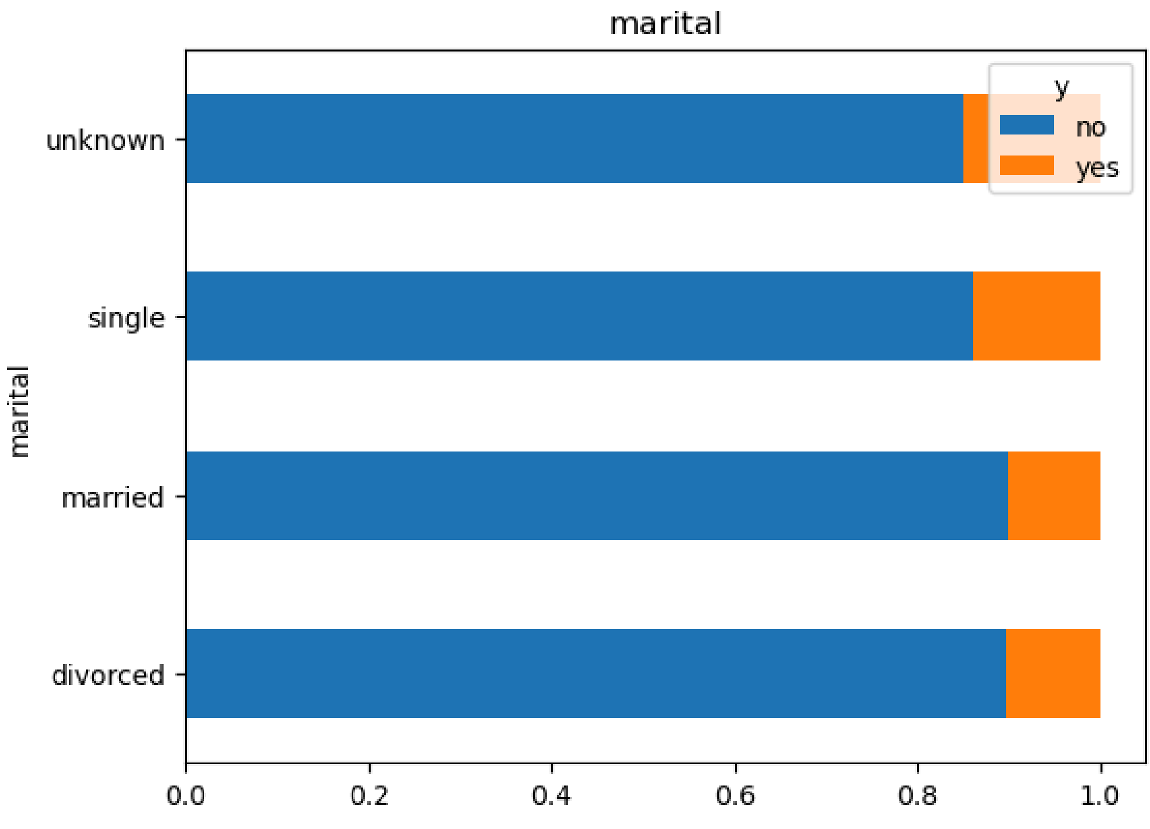
I Exploratory Data Analysis

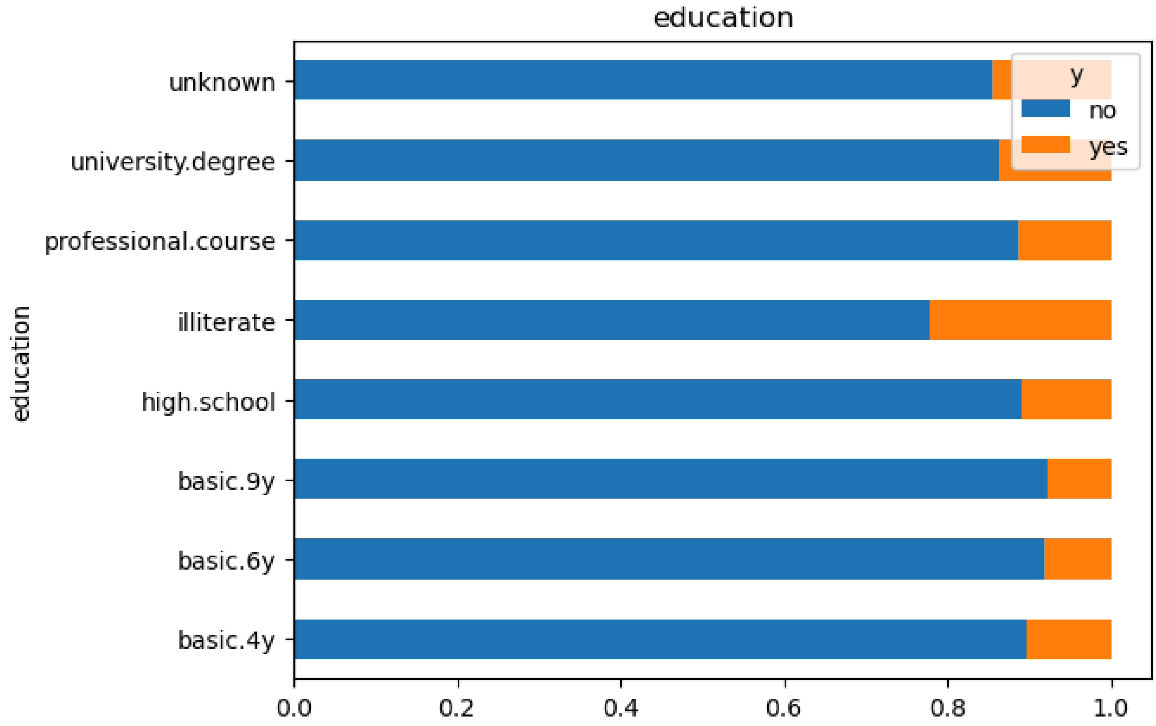
A.Categorical vs Target

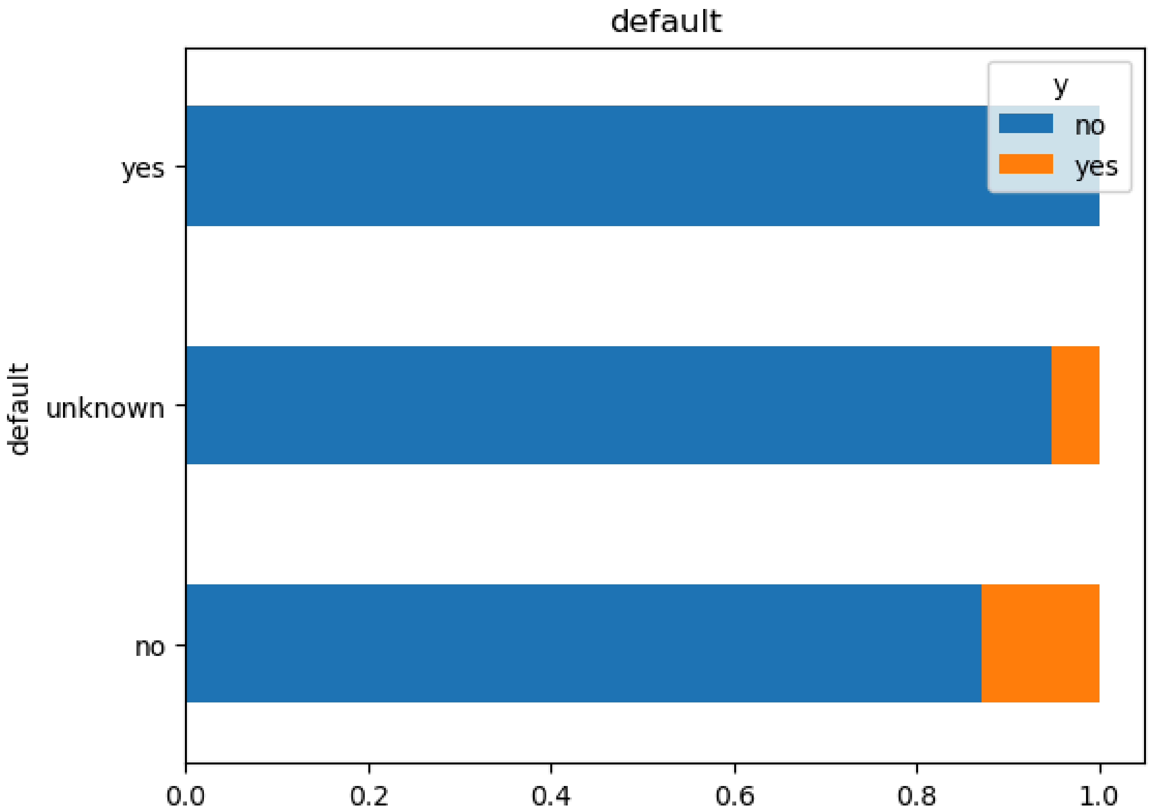
In [239…

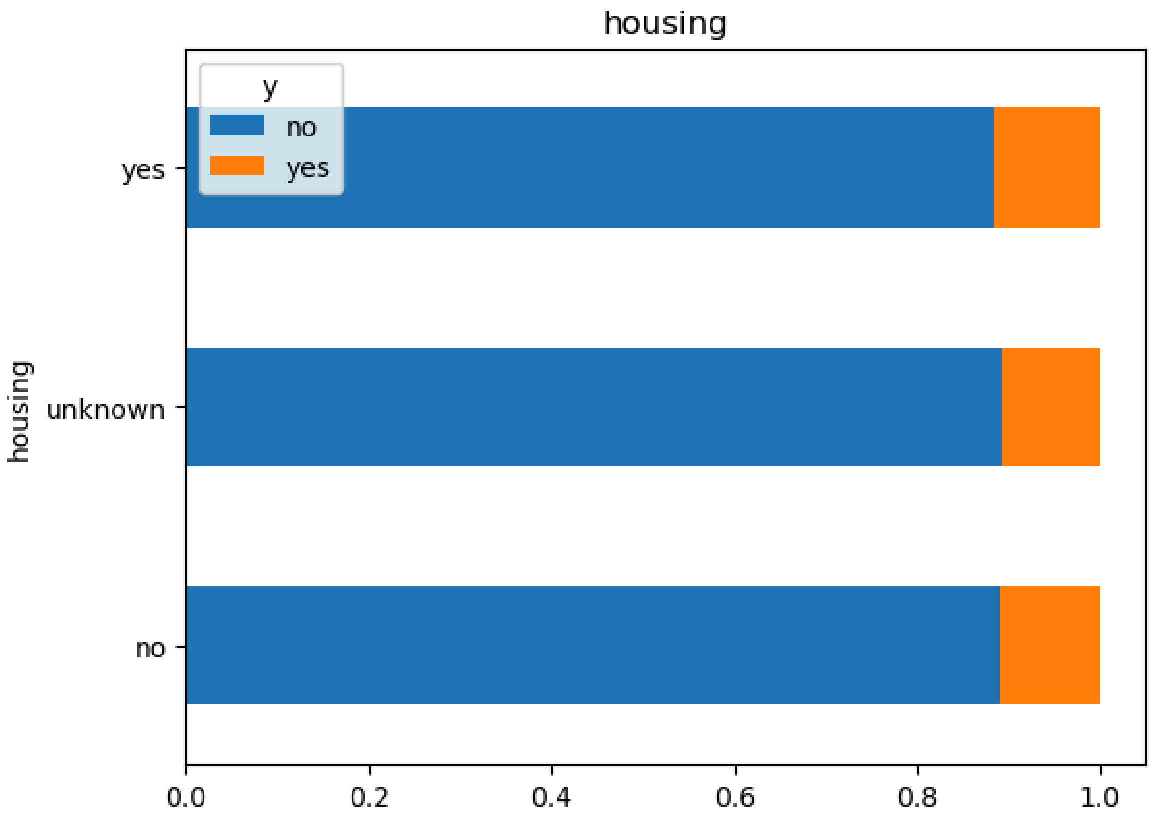
```
# Selects all categorical columns (type 'object') from the DataFrame, except the
categorical_cols = df.select_dtypes(include='object').columns.drop('y')

# Loop through each categorical column
for col in categorical_cols:
    # Creates a cross-tabulation between the current column and target 'y'
    # normalize='index' → converts the values to proportions for each category (
    # plot(kind='barh', stacked=True) → draws a horizontal stacked bar chart for
    pd.crosstab(df[col], df['y'], normalize='index').plot(kind='barh', stacked=T

    # Displays the plot
    plt.show()
```

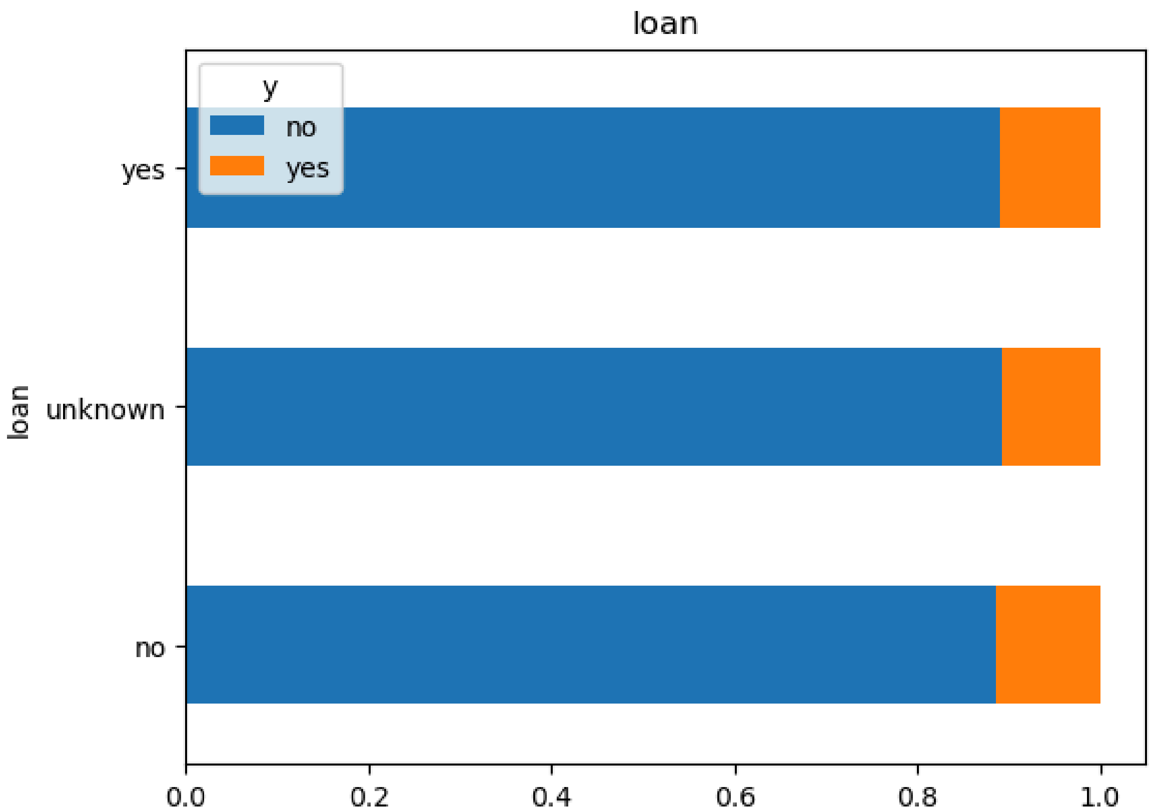

job
unknown
unemployed
technician
student
services
self-employed
retired
management
housemaid
entrepreneur
blue-collar
admin.
job
y
no
yes
0.0
0.2
0.4
0.6
0.8
1.0

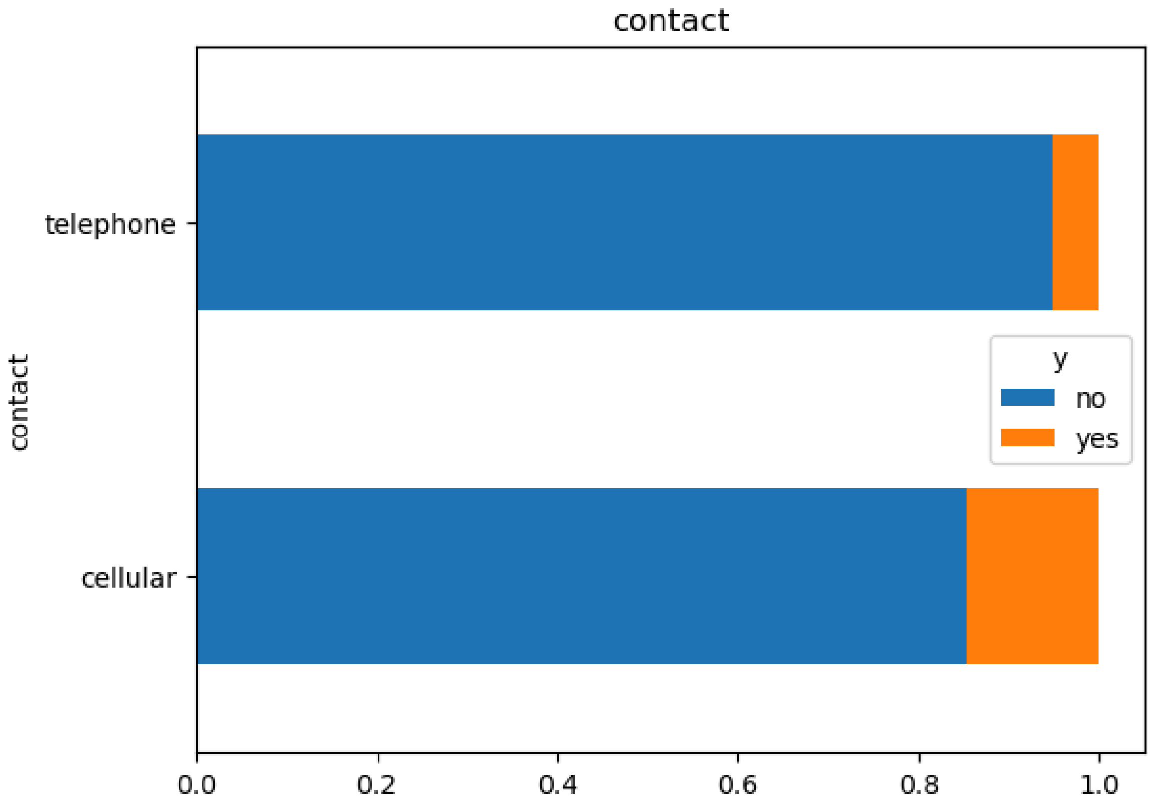

marital
unknown
single
married
divorced
marital
y
no
yes
0.0
0.2
0.4
0.6
0.8
1.0

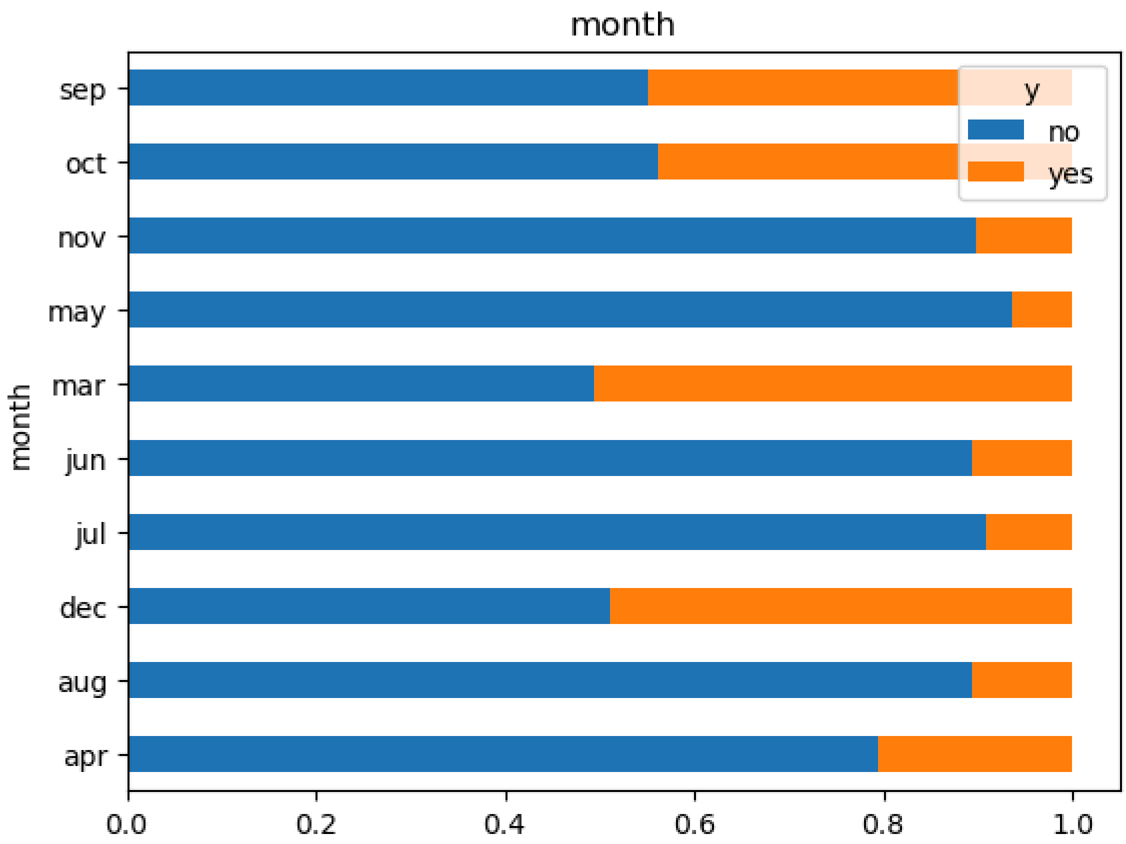

education
y
no
yes
unknown
university.degree
professional.course
illiterate
high.school
basic.9y
basic.6y
basic.4y
education
0.0
0.2
0.4
0.6
0.8
1.0

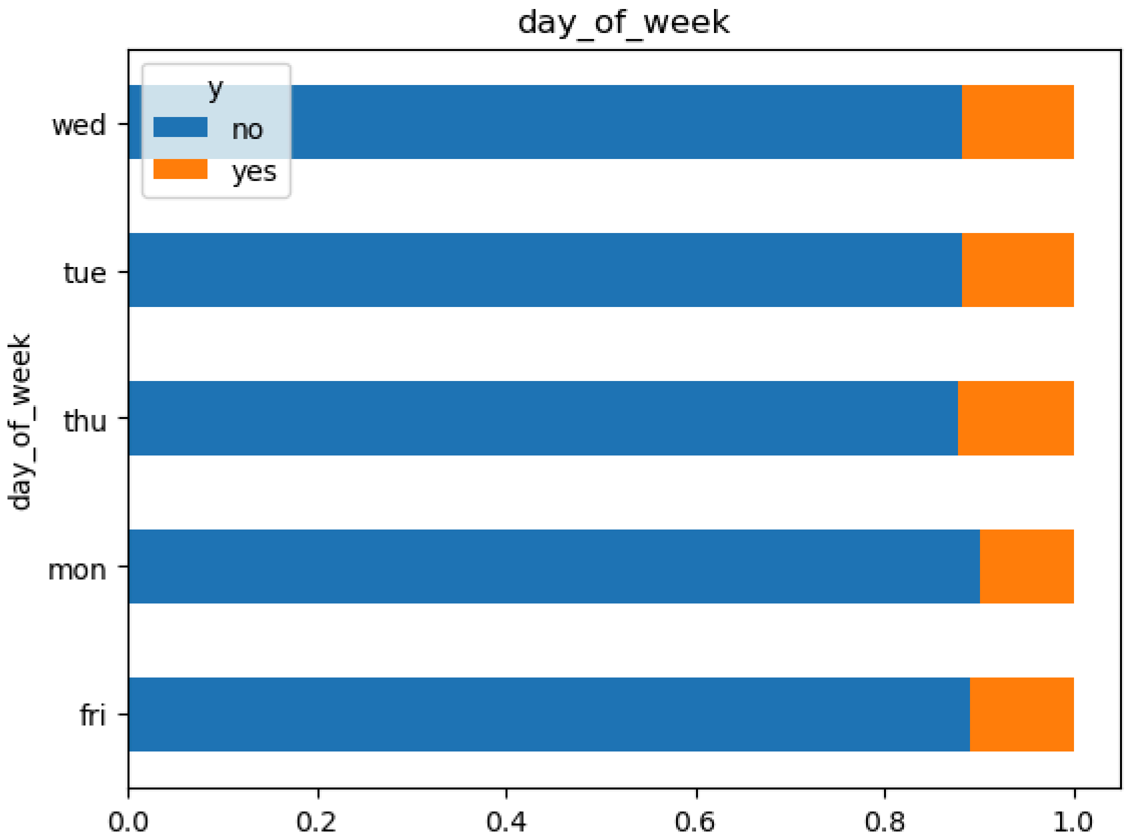

default
y
no
yes
yes
unknown
no
default
0.0
0.2
0.4
0.6
0.8
1.0

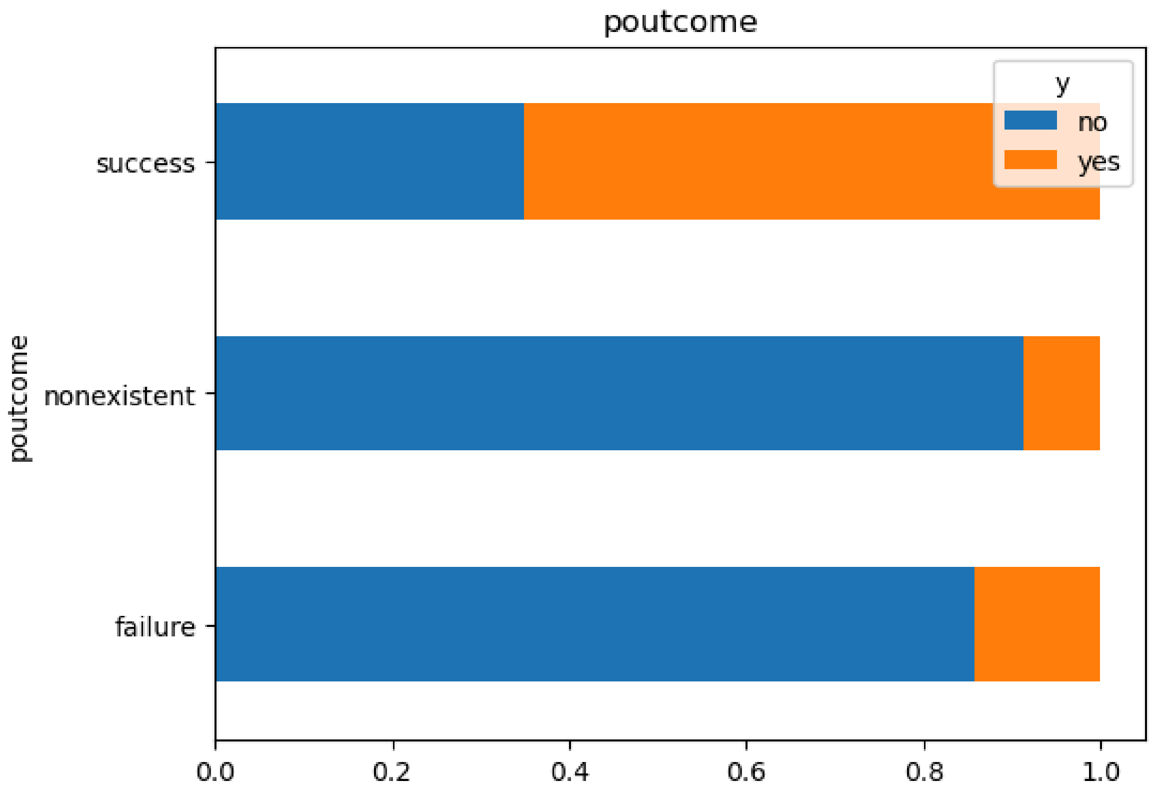

housing
y
no
yes
yes
unknown
no
housing
0.0
0.2
0.4
0.6
0.8
1.0


loan
y
no
yes
yes
unknown
no
loan
0.0
0.2
0.4
0.6
0.8
1.0


contact
telephone
cellular
contact
y
no
yes
0.0
0.2
0.4
0.6
0.8
1.0


month
sep
oct
nov
may
mar
jun
jul
dec
aug
apr
month
y
no
yes
0.0
0.2
0.4
0.6
0.8
1.0





B.Numeric Distribution

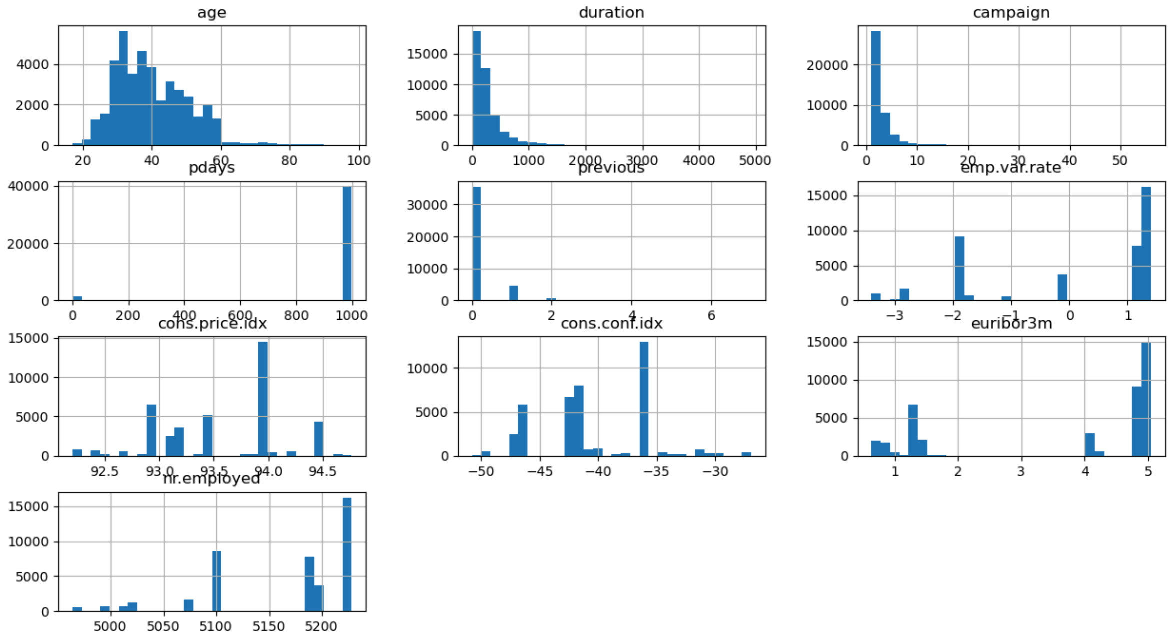
In [244…

```
# Selects all numeric columns (e.g., int, float) from the DataFrame and stores t
numerics = df.select_dtypes(include='number')

# Plots histograms for each numeric column to visualize their distributions
# bins=30         → sets the number of bins for the histogram (more bins = finer
```

```
# figsize=(15, 8) → controls the overall figure size (width x height)
numerics.hist(bins=30, figsize=(15, 8))
```

Out[244…

```
array([[<Axes: title={'center': 'age'}>,
        <Axes: title={'center': 'duration'}>,
        <Axes: title={'center': 'campaign'}>],
       [<Axes: title={'center': 'pdays'}>,
        <Axes: title={'center': 'previous'}>,
        <Axes: title={'center': 'emp.var.rate'}>],
       [<Axes: title={'center': 'cons.price.idx'}>,
        <Axes: title={'center': 'cons.conf.idx'}>,
        <Axes: title={'center': 'euribor3m'}>],
       [<Axes: title={'center': 'nr.employed'}>, <Axes: >, <Axes: >]],
      dtype=object)
```



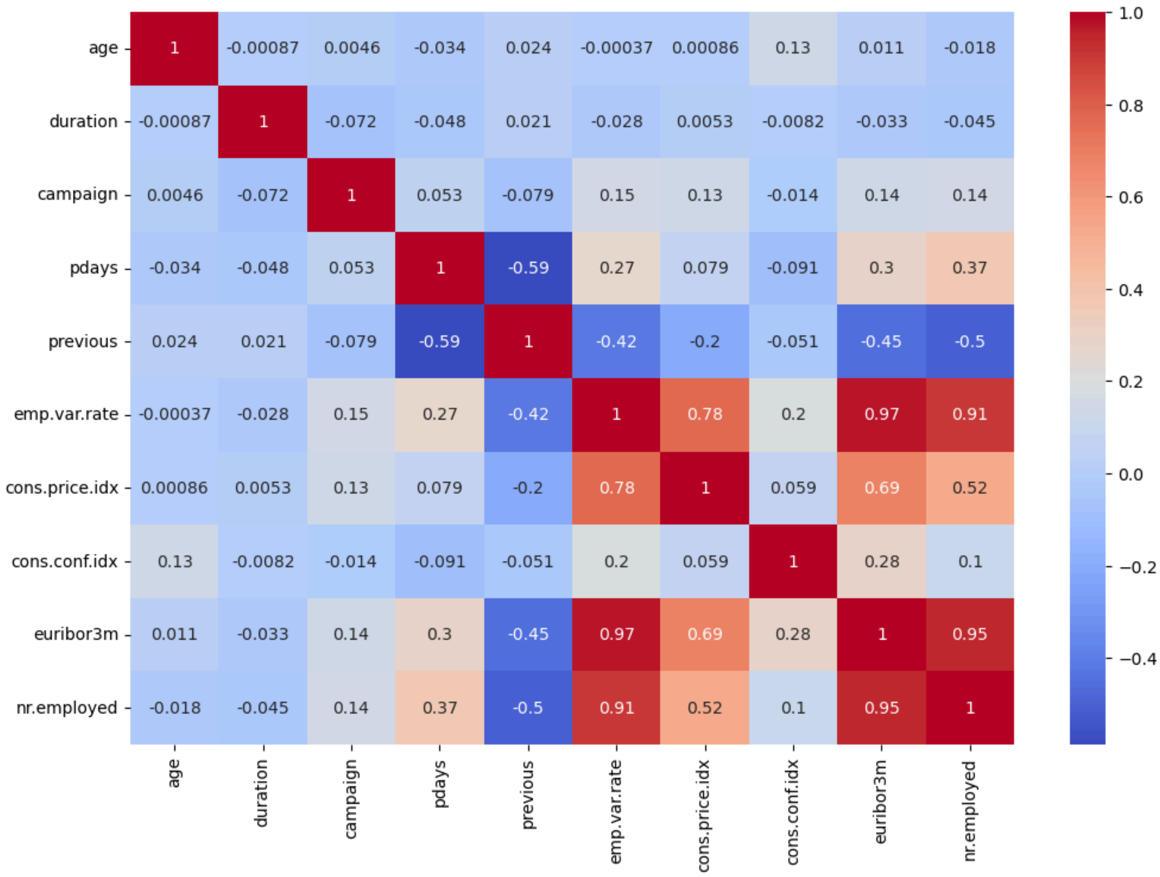
C.Correlation Heatmap

In [246…

```
# Sets the figure size for the heatmap plot (width=12, height=8)
plt.figure(figsize=(12, 8))

# Creates a heatmap showing the correlation matrix between numeric features
# numerics.corr()    → computes the Pearson correlation between all numeric colu
# annot=True         → displays the correlation values inside the heatmap cells
# cmap="coolwarm"    → sets the color theme from blue (negative) to red (positiv
sns.heatmap(numerics.corr(), annot=True, cmap="coolwarm")
```

Out[246…

```
<Axes: >
```



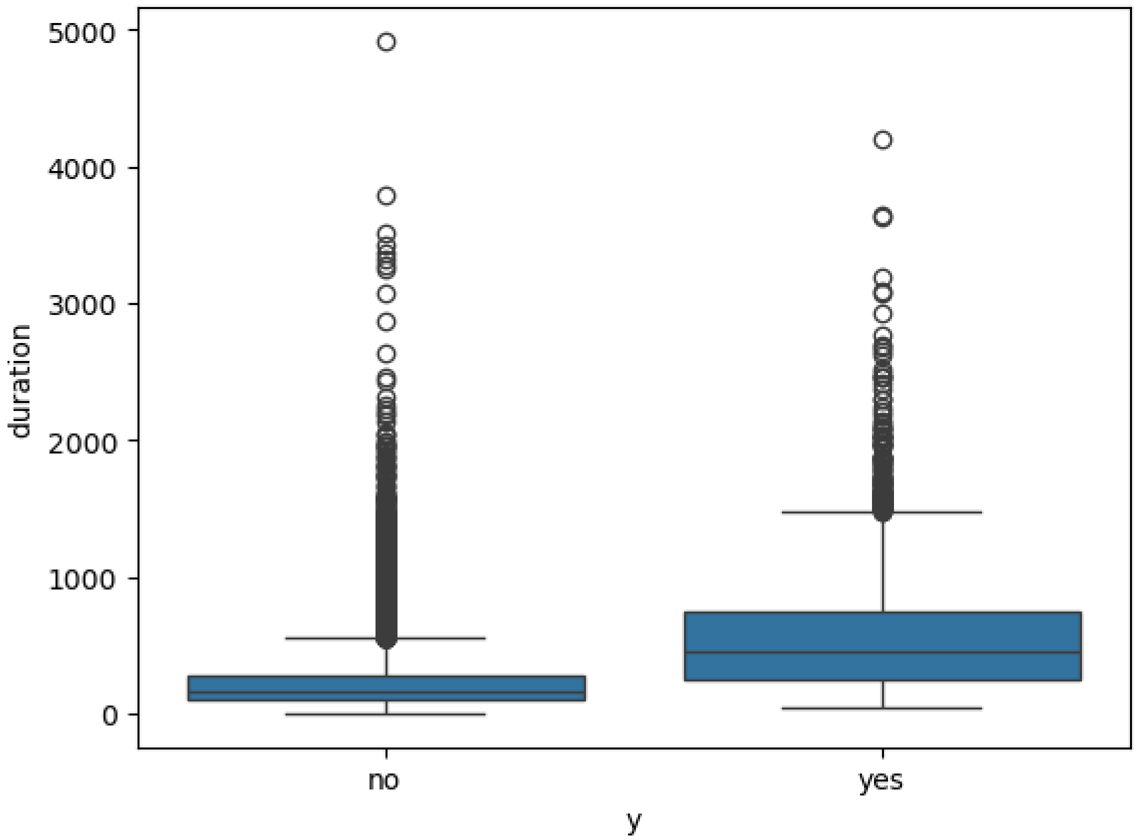
D.Duration Insight

In [249...

```
# Creates a box plot to compare the distribution of 'duration' for each class in
# data=df → uses the DataFrame as the data source
# x='y'   → sets the target variable 'y' (e.g., 'yes' or 'no') on the x-axis
# y='duration' → sets the numerical feature 'duration' on the y-axis
sns.boxplot(data=df, x='y', y='duration')
```

Out[249...

```
<Axes: xlabel='y', ylabel='duration'>
```



ii) Preprocessing

A.Drop/Handle

In [253…

```
# Drops the 'duration' column from the DataFrame to create a new modeling datase
# 'duration' is often dropped because it's known only after the marketing call i
# Including it would lead to data leakage (i.e., using future information to pre

df_model = df.drop(columns=['duration'])  # for realistic model
```

B.Encode categorical variables

In [256…

```
# Converts all categorical variables in df_model into numeric dummy/indicator va
# pd.get_dummies() → one-hot encodes all object (categorical) columns
# drop_first=True  → drops the first category from each variable to avoid multic

df_encoded = pd.get_dummies(df_model, drop_first=True)
```

C.Train-Test Split

In [259…

```
# Separates features (X) and target (y) for model training
# 'y_yes' is the encoded target column (from pd.get_dummies), where:
# 1 = client subscribed ('yes'), 0 = did not subscribe ('no')

X = df_encoded.drop('y_yes', axis=1)  # All features except the target
y = df_encoded['y_yes']               # Target variable (binary)

# Splits the data into training and testing sets
```

```
# stratify=y → ensures the target distribution is maintained in both sets
# test_size=0.2 → 20% of data goes to test set, 80% to train set
# random_state=42 → ensures reproducibility of the split

X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y, test_size=
```

D.Handle Imbalance

In [262…

```
# Initializes the SMOTE object to generate synthetic samples for the minority cl
# random_state=42 ensures reproducibility

smote = SMOTE(random_state=42)

# Applies SMOTE only to the training set (never the test set!)
# Creates a balanced training set by oversampling the minority class ('yes' case

X_train_res, y_train_res = smote.fit_resample(X_train, y_train)
```

---> EDA Summary <---

- The dataset contains demographic, contact, and economic data of customers from a Portuguese bank.
- The target variable `y` is **imbalanced**, with only about **11% 'yes'** responses.
- Features like `poutcome`, `month`, `education`, and `contact` show strong association with term deposit subscriptions.
- The feature `duration` is **highly predictive** but cannot be used in a real-time model since it's only known after the call. We exclude it to prevent data leakage.
- Campaign effectiveness drops after 3–4 contact attempts.
- Customers who were successful in previous campaigns (`poutcome = success`) are more likely to subscribe again.

TASK 2

I Model Building

A.Logistic Regression

In [308…

```
# Initializes a Logistic Regression model
# max_iter=1000 → increases the maximum number of iterations to help convergence

lr = LogisticRegression(max_iter=1000)

# Trains the model on the SMOTE-balanced training set

lr.fit(X_train_res, y_train_res)

# Predicts target values for the original (unbalanced) test set

y_pred_lr = lr.predict(X_test)
```

B.Random Forest

In [311…

```
# Initializes a Random Forest Classifier
# random_state=42 ensures reproducibility (same results each time you run it)

rf = RandomForestClassifier(random_state=42)

# Trains the model on the balanced training set (from SMOTE)

rf.fit(X_train_res, y_train_res)

# Predicts the target values for the test set

y_pred_rf = rf.predict(X_test)
```

C.XGBoost

In [314…

```
# Initializes the XGBoost Classifier
# use_label_encoder=False → disables the legacy label encoder (to avoid warnings
# eval_metric='logloss'   → sets the evaluation metric to log loss (common for b

xgb = XGBClassifier(use_label_encoder=False, eval_metric='logloss')

# Trains the model on the SMOTE-balanced training set

xgb.fit(X_train_res, y_train_res)

# Predicts the target values for the original test set

y_pred_xgb = xgb.predict(X_test)
```

Get Probabilities for ROC AUC and Curves

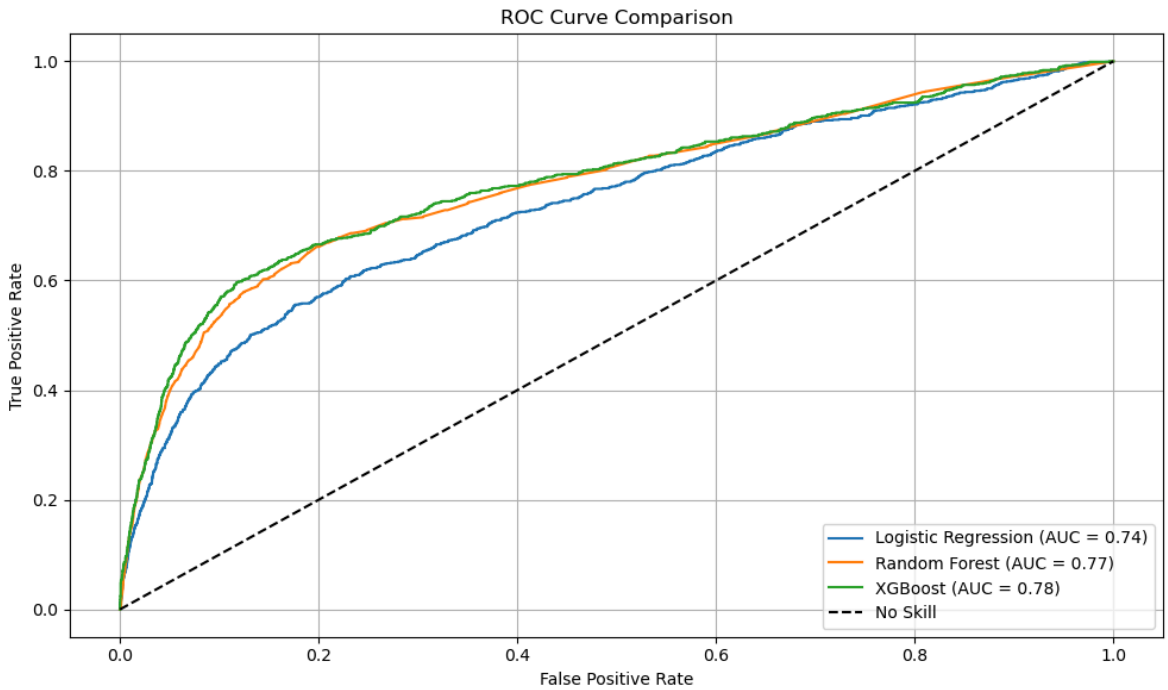
In [317…

```
# Gets the probability of the positive class ('yes') from Logistic Regression pr
y_proba_lr = lr.predict_proba(X_test)[:, 1]

# Gets the probability of the positive class ('yes') from Random Forest predicti
y_proba_rf = rf.predict_proba(X_test)[:, 1]

# Gets the probability of the positive class ('yes') from XGBoost predictions
y_proba_xgb = xgb.predict_proba(X_test)[:, 1]
```

Plot ROC Curves

In [277…

```
import matplotlib.pyplot as plt
from sklearn.metrics import roc_curve, roc_auc_score

# Get ROC curve values
# Compute False Positive Rate (fpr), True Positive Rate (tpr), and thresholds fo
fpr_lr, tpr_lr, _ = roc_curve(y_test, y_proba_lr)   # Logistic Regression
fpr_rf, tpr_rf, _ = roc_curve(y_test, y_proba_rf)   # Random Forest
fpr_xgb, tpr_xgb, _ = roc_curve(y_test, y_proba_xgb) # XGBoost


# Plot all three ROC curves
# Create a new figure for plotting
plt.figure(figsize=(10, 6))

# Plot ROC curves for each model with their AUC values
plt.plot(fpr_lr, tpr_lr, label=f'Logistic Regression (AUC = {roc_auc_score(y_tes
plt.plot(fpr_rf, tpr_rf, label=f'Random Forest (AUC = {roc_auc_score(y_test, y_p
plt.plot(fpr_xgb, tpr_xgb, label=f'XGBoost (AUC = {roc_auc_score(y_test, y_proba

# Plot diagonal line
# Plot a diagonal line representing a no-skill classifier (AUC = 0.5)
plt.plot([0, 1], [0, 1], 'k--', label='No Skill')

# Chart formatting
# Add labels, title, and legend
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve Comparison')
plt.legend(loc='lower right')
plt.grid(True)
plt.tight_layout()
plt.show()
```



Compare Performance Metrics in a Table

In [279…

```
import pandas as pd
results_df = pd.DataFrame(results)
print(results_df)

from sklearn.metrics import precision_score, recall_score, f1_score, roc_auc_scc

# Function to calculate and return key performance metrics
def evaluate_model(name, y_test, y_pred, y_proba):
    return {
        "Model": name,
        "Precision": precision_score(y_test, y_pred),
        "Recall": recall_score(y_test, y_pred),
        "F1 Score": f1_score(y_test, y_pred),
        "ROC AUC": roc_auc_score(y_test, y_proba)
    }

# Compare 3 models using the function
results = [
    evaluate_model("Logistic Regression", y_test, y_pred_lr, y_proba_lr),
    evaluate_model("Random Forest", y_test, y_pred_rf, y_proba_rf),
    evaluate_model("XGBoost", y_test, y_pred_xgb, y_proba_xgb)
]

# Create a DataFrame for visualization and export
import pandas as pd
results_df = pd.DataFrame(results)
print(results_df)
```

```
                 Model  Precision    Recall  F1 Score   ROC AUC
0  Logistic Regression   0.349593  0.463362  0.398517  0.735375
1        Random Forest   0.494778  0.408405  0.447462  0.773977
2              XGBoost   0.513725  0.423491  0.464265  0.779792
                 Model  Precision    Recall  F1 Score   ROC AUC
0  Logistic Regression   0.349593  0.463362  0.398517  0.735375
1        Random Forest   0.494778  0.408405  0.447462  0.773977
2              XGBoost   0.513725  0.423491  0.464265  0.779792
```

II Model Evaluation

Compare Confusion Metrics in a Table

In [322…

```
def evaluate_model(y_test, y_pred, model_name):

    # Prints a header for the model
    print(f"\n ---> {model_name} <---")

    # Prints precision, recall, f1-score, and support for both classes
    print(classification_report(y_test, y_pred))

    # Prints the confusion matrix
    print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
```

In [324…

```
evaluate_model(y_test, y_pred_lr, "Logistic Regression")
evaluate_model(y_test, y_pred_rf, "Random Forest")
evaluate_model(y_test, y_pred_xgb, "XGBoost")
```

```
 ---> Logistic Regression <---
              precision    recall  f1-score   support

       False       0.93      0.89      0.91      7310
        True       0.35      0.46      0.40       928

    accuracy                           0.84      8238
   macro avg       0.64      0.68      0.65      8238
weighted avg       0.86      0.84      0.85      8238

Confusion Matrix:
 [[6510  800]
 [ 498  430]]

 ---> Random Forest <---
              precision    recall  f1-score   support

       False       0.93      0.95      0.94      7310
        True       0.49      0.41      0.45       928

    accuracy                           0.89      8238
   macro avg       0.71      0.68      0.69      8238
weighted avg       0.88      0.89      0.88      8238

Confusion Matrix:
 [[6923  387]
 [ 549  379]]

 ---> XGBoost <---
              precision    recall  f1-score   support

       False       0.93      0.95      0.94      7310
        True       0.51      0.42      0.46       928

    accuracy                           0.89      8238
   macro avg       0.72      0.69      0.70      8238
weighted avg       0.88      0.89      0.89      8238

Confusion Matrix:
 [[6938  372]
 [ 535  393]]
```

III Model Comparison Report

In [285…

```
# Dictionary of trained models
models = {'LR': lr, 'RF': rf, 'XGB': xgb}

# Loop through each model
for name, model in models.items():
    # Get predicted class labels for the test set
    y_pred = model.predict(X_test)

    # Calculate AUC score using predicted labels (note: this is AUC from hard la
    auc = roc_auc_score(y_test, y_pred)

    # Print model name and its AUC
    print(f"{name} - AUC: {auc:.3f}")
```

```
LR - AUC: 0.677
RF - AUC: 0.678
XGB - AUC: 0.686
```

Best Model Selection

Three models were trained and compared: **Logistic Regression**, **Random Forest**, and **XGBoost**.

- **XGBoost** performed best based on ROC-AUC score, recall, and overall stability.
- To avoid data leakage, the model was trained **without using the `duration` feature**.
- The final model was selected based on balanced performance and business interpretability.

TASK 3

Marketing Strategy Suggestions

Strategic Insights for Marketing Team

- Focus campaigns in months with higher success rates: e.g., `mar`, `oct`.
- Prioritize customers with:
  - `poutcome = success`
  - `education = university.degree`
  - `contact = cellular`
- Limit call attempts >3 (campaign); conversion drops afterward.
- Avoid targeting customers with `unknown` job or education info.

Challenges & Mitigations

Challenge	Solution
Class Imbalance	Used SMOTE and class_weight
Data Leakage via `duration`	Removed for realistic modeling
'Unknown' values in many columns	Kept as category when informative; else grouped/imputed
High cardinality	Used One-Hot Encoding
Black-box interpretability	Plan to add SHAP next

Recommendations to Bank Marketing Team

Based on data analysis and predictive modeling, here are actionable suggestions:

- Focus marketing calls in **March**, **September**, and **October**, which show higher conversion rates.
- Target customer profiles with:
  - Previous campaign success (`poutcome = success`)
  - Contact preference as `cellular`
  - Education level of **university degree** or **professional course**
  - Age group between **30 and 50 years**
- Avoid excessive calls: after **3 attempts**, the probability of conversion **drops significantly**.
- Customers with **no housing or personal loans** tend to be more responsive to deposit offers.
- Consider launching personalized campaigns based on **job type** and **marital status** segments.

Summary Of Challenges Faced & Solutions

Challenge	Solution
Severe class imbalance (`y`)	Used SMOTE oversampling and stratified split to balance classes.
High importance of `duration`	Removed it from final model due to **data leakage risk**.
Presence of 'unknown' in many categorical columns	Treated as separate category when meaningful, otherwise grouped or dropped.
Model interpretability	Used SHAP or feature importances to explain predictions to business teams.
High number of categorical variables	Handled using one-hot encoding with care to avoid dimensionality explosion.

WE HAVE TO NOW SAVE MODEL TO AVOID RETRAINING EVERYTIME

In [293…
```
# Optional: Save model
import joblib
joblib.dump(xgb, 'final_model_xgb.pkl')
```

Out[293…
```
['final_model_xgb.pkl']
```

In [333…
```
# Load the saved model later
xgb_loaded = joblib.load('final_model_xgb.pkl')

# Use it for prediction
y_new_pred = xgb_loaded.predict(X_test)
```