INTRODUCTION

Term deposits are a type of fixed investment where customers deposit money with a financial institution for a predetermined period at an agreed interest rate. These deposits are a reliable and significant source of income for banks, as they provide a stable inflow of funds while offering customers a secure way to grow their savings.
To promote term deposits, banks employ various marketing strategies, including email marketing, advertisements, digital outreach, and telephonic campaigns. Among these, telephonic marketing remains one of the most effective methods for engaging customers. However, this approach involves substantial costs due to the operational requirements of large call centers.

BUSINESS PROBLEM

Telephonic marketing is an effective but costly method for promoting term deposits. To optimize resources and improve conversion rates, the bank needs to identify customers most likely to subscribe to a term deposit before reaching out, ensuring more targeted and cost-efficient marketing efforts.

OBJECTIVES

1. **Identify Key Predictors**: Analyze customer demographics, previous interactions, and campaign details to determine the most important factors influencing a customer's decision to subscribe to a term deposit.

2. **Develop the Best Prediction Model**: Build and evaluate multiple classification models to identify the most accurate model for predicting whether a customer will subscribe to a term deposit, ensuring optimal performance.

3. **Optimize Marketing Strategies**: Use the insights from the model to recommend targeted telephonic marketing strategies, focusing on high-potential customers to maximize conversion rates and reduce unnecessary outreach.

Metrics of Success:

1. **Model Accuracy:** Achieve over 80% accuracy in predicting customer subscription to a term deposit.
2. **Precision & Recall:** High precision and recall for identifying customers likely to subscribe (Class 1).
3. **Feature Importance:** Identify key factors influencing subscription decisions to optimize marketing strategies.

4. **Conversion Rate:** Increase conversion rates by targeting high-potential customers.
5. **Outreach Efficiency:** Reduce unnecessary outreach to non-potential customers.
6. **Cross-validation Performance:** Ensure consistent performance across different data subsets to avoid overfitting.

DATA UNDERSTANDING

This dataset is related to the direct marketing campaigns of a Portuguese banking institution. The marketing campaigns were conducted through phone calls, often requiring multiple contacts with the same client to determine whether they would subscribe to the product (bank term deposit). The target variable indicates whether the client subscribed (`"yes"`) or not (`"no"`).

Dataset Overview

The data folder contains two datasets:

- **`train.csv`**: Contains 45,211 rows and 18 columns, ordered by date (from May 2008 to November 2010).
- **`test.csv`**: Contains 4,521 rows and 18 columns, representing 10% of the examples, randomly selected from `train.csv`.

Column Descriptions

Bank Client Data:

1. **`age`**: Age of the client (numeric).
2. **`job`**: Type of job (categorical: `"admin."`, `"unknown"`, `"unemployed"`, `"management"`, `"housemaid"`, `"entrepreneur"`, `"student"`, `"blue-collar"`, `"self-employed"`, `"retired"`, `"technician"`, `"services"`).
3. **`marital`**: Marital status (categorical: `"married"`, `"divorced"`, `"single"`; note: `"divorced"` includes divorced or widowed).
4. **`education`**: Level of education (categorical: `"unknown"`, `"secondary"`, `"primary"`, `"tertiary"`).
5. **`default`**: Has credit in default? (binary: `"yes"`, `"no"`).
6. **`balance`**: Average yearly balance in euros (numeric).
7. **`housing`**: Has a housing loan? (binary: `"yes"`, `"no"`).
8. **`loan`**: Has a personal loan? (binary: `"yes"`, `"no"`).

Last Contact of Current Campaign:

9. **`contact`**: Contact communication type (categorical: `"unknown"`, `"telephone"`, `"cellular"`).
10. **`day`**: Last contact day of the month (numeric).

11. `month` : Last contact month of the year (categorical: `"jan"`, `"feb"`, `"mar"`, ..., `"nov"`, `"dec"`).
12. `duration` : Last contact duration in seconds (numeric).

Other Attributes:

13. `campaign` : Number of contacts performed during this campaign for this client (numeric, includes last contact).
14. `pdays` : Number of days since the client was last contacted in a previous campaign (numeric; `-1` means the client was not previously contacted).
15. `previous` : Number of contacts performed before this campaign for this client (numeric).
16. `poutcome` : Outcome of the previous marketing campaign (categorical: `"unknown"`, `"other"`, `"failure"`, `"success"`).

Output Variable (Target):

17. `y` : Has the client subscribed to a term deposit? (binary: `"yes"`, `"no"`).

Data source: https://www.kaggle.com/datasets/thedevastator/bank-term-deposit-predictions?resource=download

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import summarytools as st
plt.style.use('ggplot')
import seaborn as sns
sns.set_style('whitegrid')
```

In [2]:
```
train_data=pd.read_csv('train.csv')
train_data
```

Out[2]:

	age	job	marital	education	default	balance	housing	loan	contact
0	58	management	married	tertiary	no	2143	yes	no	unknown
1	44	technician	single	secondary	no	29	yes	no	unknown
2	33	entrepreneur	married	secondary	no	2	yes	yes	unknown
3	47	blue-collar	married	unknown	no	1506	yes	no	unknown
4	33	unknown	single	unknown	no	1	no	no	unknown
...	...	...	...	...	...	...	...	...	...
45206	51	technician	married	tertiary	no	825	no	no	cellular
45207	71	retired	divorced	primary	no	1729	no	no	cellular
45208	72	retired	married	secondary	no	5715	no	no	cellular
45209	57	blue-collar	married	secondary	no	668	no	no	telephone
45210	37	entrepreneur	married	secondary	no	2971	no	no	cellular

45211 rows × 17 columns

In [3]:
```
train_data.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        45211 non-null  object
 2   marital    45211 non-null  object
 3   education  45211 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    45211 non-null  object
 9   day        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   45211 non-null  object
 16  y          45211 non-null  object
dtypes: int64(7), object(10)
memory usage: 5.9+ MB
```

In [4]:
```
train_data.isnull().sum()
```

Out[4]:
```
age          0
job          0
marital      0
education    0
default      0
balance      0
housing      0
loan         0
contact      0
day          0
month        0
duration     0
campaign     0
pdays        0
previous     0
poutcome     0
y            0
dtype: int64
```

In [5]:
```
st.dfSummary(train_data)
```

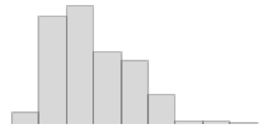
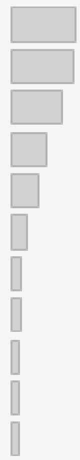
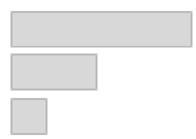
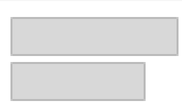
Out[5]:

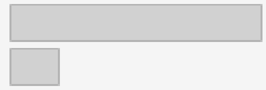
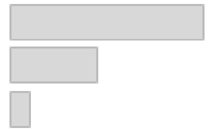
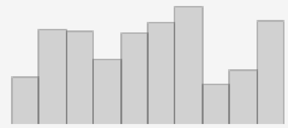
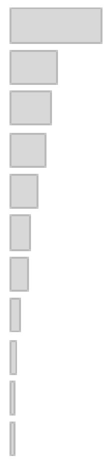
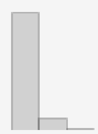
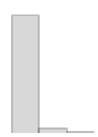
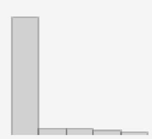
Data Frame Summary

—

Dimensions: 45,211 x 17

Duplicates: 0

No	Variable	Stats / Values	Freqs / (% of Valid)	Graph	Missing
1	**age** [int64]	Mean (sd) : 40.9 (10.6) min < med < max: 18.0 < 39.0 < 95.0 IQR (CV) : 15.0 (3.9)	77 distinct values		0 (0.0%)
2	**job** [object]	1. blue-collar 2. management 3. technician 4. admin. 5. services 6. retired 7. self-employed 8. entrepreneur 9. unemployed 10. housemaid 11. other	9,732 (21.5%) 9,458 (20.9%) 7,597 (16.8%) 5,171 (11.4%) 4,154 (9.2%) 2,264 (5.0%) 1,579 (3.5%) 1,487 (3.3%) 1,303 (2.9%) 1,240 (2.7%) 1,226 (2.7%)		0 (0.0%)
3	**marital** [object]	1. married 2. single 3. divorced	27,214 (60.2%) 12,790 (28.3%) 5,207 (11.5%)		0 (0.0%)
4	**education** [object]	1. secondary 2. tertiary 3. primary 4. unknown	23,202 (51.3%) 13,301 (29.4%) 6,851 (15.2%) 1,857 (4.1%)		0 (0.0%)
5	**default** [object]	1. no 2. yes	44,396 (98.2%) 815 (1.8%)		0 (0.0%)
6	**balance** [int64]	Mean (sd) : 1362.3 (3044.8) min < med < max: -8019.0 < 448.0 < 102127.0 IQR (CV) : 1356.0 (0.4)	7,168 distinct values		0 (0.0%)
7	**housing** [object]	1. yes 2. no	25,130 (55.6%) 20,081 (44.4%)		0 (0.0%)

No	Variable	Stats / Values	Freqs / (% of Valid)	Graph	Missing
8	**loan** [object]	1. no 2. yes	37,967 (84.0%) 7,244 (16.0%)		0 (0.0%)
9	**contact** [object]	1. cellular 2. unknown 3. telephone	29,285 (64.8%) 13,020 (28.8%) 2,906 (6.4%)		0 (0.0%)
10	**day** [int64]	Mean (sd) : 15.8 (8.3) min < med < max: 1.0 < 16.0 < 31.0 IQR (CV) : 13.0 (1.9)	31 distinct values		0 (0.0%)
11	**month** [object]	1. may 2. jul 3. aug 4. jun 5. nov 6. apr 7. feb 8. jan 9. oct 10. sep 11. other	13,766 (30.4%) 6,895 (15.3%) 6,247 (13.8%) 5,341 (11.8%) 3,970 (8.8%) 2,932 (6.5%) 2,649 (5.9%) 1,403 (3.1%) 738 (1.6%) 579 (1.3%) 691 (1.5%)		0 (0.0%)
12	**duration** [int64]	Mean (sd) : 258.2 (257.5) min < med < max: 0.0 < 180.0 < 4918.0 IQR (CV) : 216.0 (1.0)	1,573 distinct values		0 (0.0%)
13	**campaign** [int64]	Mean (sd) : 2.8 (3.1) min < med < max: 1.0 < 2.0 < 63.0 IQR (CV) : 2.0 (0.9)	48 distinct values		0 (0.0%)
14	**pdays** [int64]	Mean (sd) : 40.2 (100.1) min < med < max: -1.0 < -1.0 < 871.0 IQR (CV) : 0.0 (0.4)	559 distinct values		0 (0.0%)
15	**previous** [int64]	Mean (sd) : 0.6 (2.3) min < med < max: 0.0 < 0.0 < 275.0 IQR (CV) : 0.0 (0.3)	41 distinct values		0 (0.0%)

No	Variable	Stats / Values	Freqs / (% of Valid)	Graph	Missing
16	**poutcome** [object]	1. unknown 2. failure 3. other 4. success	36,959 (81.7%) 4,901 (10.8%) 1,840 (4.1%) 1,511 (3.3%)		0 (0.0%)
17	**y** [object]	1. no 2. yes	39,922 (88.3%) 5,289 (11.7%)		0 (0.0%)

In [6]:

```python
# Loop through all categorical columns and display their value counts transposed
for col in train_data.select_dtypes(include=['object', 'category']).columns:
    print(f"\n{col.upper()} Value Counts (Transposed):\n")
    value_counts = train_data[col].value_counts(dropna=False)
    print(pd.DataFrame(value_counts).T)
    print("-" * 50)
```

```
JOB Value Counts (Transposed):

job    blue-collar  management  technician  admin.  services  retired  \
count         9732        9458        7597    5171      4154     2264   

job    self-employed  entrepreneur  unemployed  housemaid  student  unknown  
count           1579          1487        1303       1240      938      288  
--------------------------------------------------

MARITAL Value Counts (Transposed):

marital  married  single  divorced
count      27214   12790      5207
--------------------------------------------------

EDUCATION Value Counts (Transposed):

education  secondary  tertiary  primary  unknown
count          23202     13301     6851     1857
--------------------------------------------------

DEFAULT Value Counts (Transposed):

default     no  yes
count    44396  815
--------------------------------------------------

HOUSING Value Counts (Transposed):

housing    yes     no
count    25130  20081
--------------------------------------------------

LOAN Value Counts (Transposed):

loan      no   yes
count  37967  7244
--------------------------------------------------

CONTACT Value Counts (Transposed):

contact  cellular  unknown  telephone
count       29285    13020       2906
--------------------------------------------------

MONTH Value Counts (Transposed):

month    may   jul   aug   jun   nov   apr   feb   jan  oct  sep  mar  dec
count  13766  6895  6247  5341  3970  2932  2649  1403  738  579  477  214
--------------------------------------------------

POUTCOME Value Counts (Transposed):

poutcome  unknown  failure  other  success
count       36959     4901   1840     1511
--------------------------------------------------
```

```
Y Value Counts (Transposed):

y          no   yes
count   39922  5289
--------------------------------------------------
```

In [7]:
```
train_data.shape
```

Out[7]:
```
(45211, 17)
```

In [8]:
```
test_data=pd.read_csv('test.csv')
```

In [9]:
```
test_data.shape
```

Out[9]:
```
(4521, 17)
```

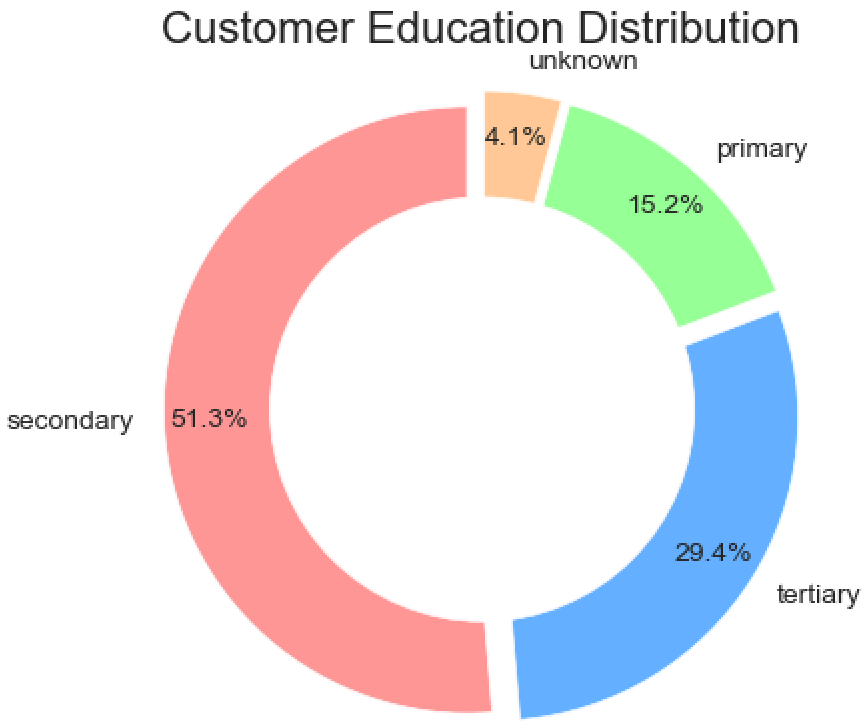
In [10]:
```
test_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4521 entries, 0 to 4520
Data columns (total 17 columns):
 #   Column     Non-Null Count  Dtype 
---  ------     --------------  ----- 
 0   age        4521 non-null   int64 
 1   job        4521 non-null   object
 2   marital    4521 non-null   object
 3   education  4521 non-null   object
 4   default    4521 non-null   object
 5   balance    4521 non-null   int64 
 6   housing    4521 non-null   object
 7   loan       4521 non-null   object
 8   contact    4521 non-null   object
 9   day        4521 non-null   int64 
 10  month      4521 non-null   object
 11  duration   4521 non-null   int64 
 12  campaign   4521 non-null   int64 
 13  pdays      4521 non-null   int64 
 14  previous   4521 non-null   int64 
 15  poutcome   4521 non-null   object
 16  y          4521 non-null   object
dtypes: int64(7), object(10)
memory usage: 600.6+ KB
```

In [11]:
```
test_data.isna().sum()
```

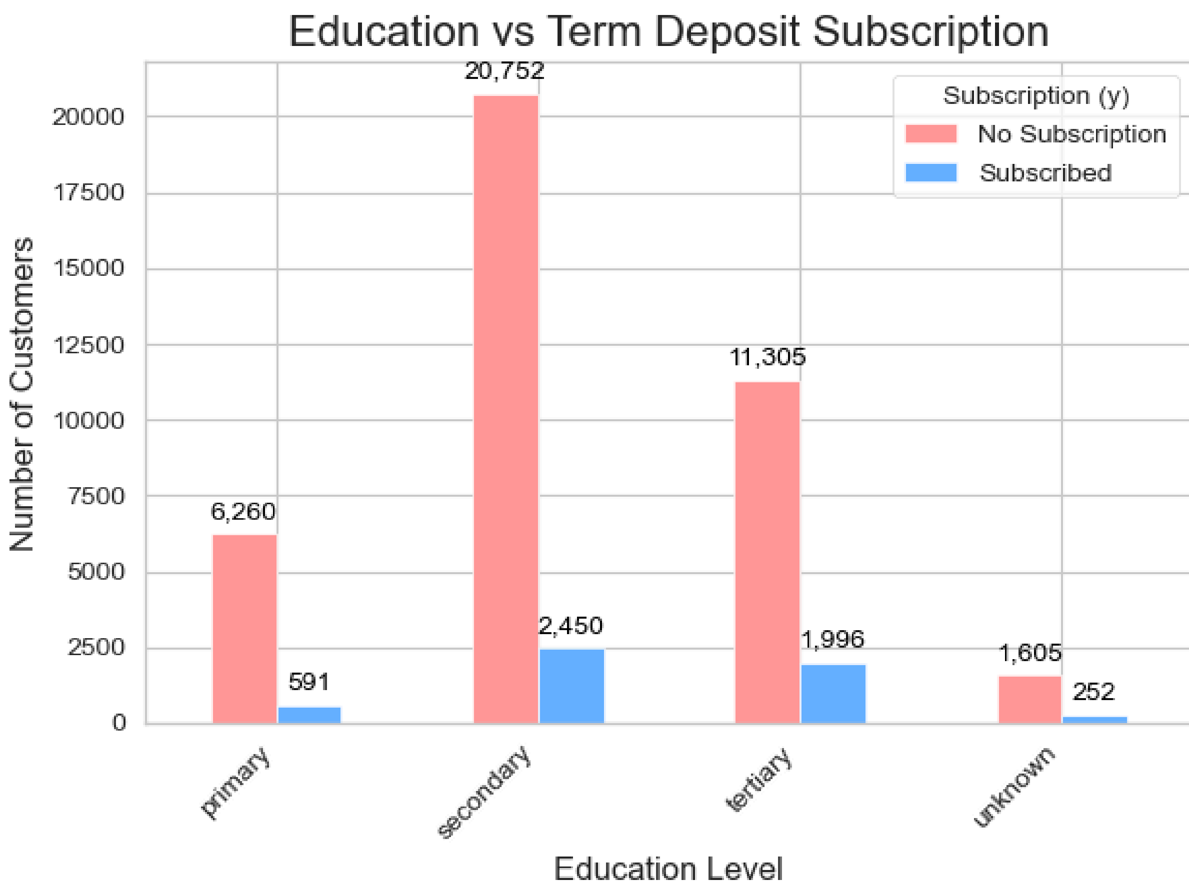
Out[11]:
```
age          0
job          0
marital      0
education    0
default      0
balance      0
housing      0
loan         0
contact      0
day          0
month        0
duration     0
campaign     0
pdays        0
previous     0
poutcome     0
y            0
dtype: int64
```

In [12]:
```
# Calculate education counts
eduCounts = train_data['education'].value_counts()

# Define colors and labels
colors = ['#FF9999', '#66B3FF', '#99FF99', '#FFCC99']
labels = eduCounts.index  # Use the index of eduCounts for dynamic labels

# Create the pie chart
plt.figure(figsize=(6, 4))
plt.pie(
    eduCounts,
    colors=colors,
    labels=labels,
    autopct='%1.1f%%',
    pctdistance=0.85,
    explode=[0.05] * len(eduCounts),  # Dynamically set explode values for all segm
    startangle=90,  # Start the pie chart at 90 degrees for better alignment
)

# Add a white circle at the center for a donut effect
centre_circle = plt.Circle((0, 0), 0.70, fc='white')
plt.gca().add_artist(centre_circle)

# Add chart title
plt.title('Customer Education Distribution', fontsize=16)

# Equal aspect ratio ensures the pie chart is drawn as a circle
plt.axis('equal')

# Display the chart
plt.tight_layout()
plt.show()
```



In [13]:
```
# Group by 'education' and 'y', then count the number of occurrences
edu_y_counts = train_data.groupby(['education', 'y']).size().unstack()

# Create the bar graph
plt.figure(figsize=(10, 6))
ax = edu_y_counts.plot(kind='bar', stacked=False, color=['#FF9999', '#66B3FF'])

# Add chart title and labels
plt.title('Education vs Term Deposit Subscription', fontsize=16)
plt.xlabel('Education Level', fontsize=12)
plt.ylabel('Number of Customers', fontsize=12)

# Show the legend and adjust the position
plt.legend(title='Subscription (y)', labels=['No Subscription', 'Subscribed'], loc=

# Add the bar labels with commas and display them on top of each bar
for p in ax.patches:
    ax.annotate(f'{int(p.get_height()):,}',  # Format the number with commas
                (p.get_x() + p.get_width() / 2., p.get_height()),
                ha='center', va='center',
                fontsize=10, color='black',
                xytext=(0, 8), textcoords='offset points')

# Display the plot
plt.xticks(rotation=45, ha='right')  # Rotate x-axis labels for better visibility
plt.tight_layout()
plt.show()
```

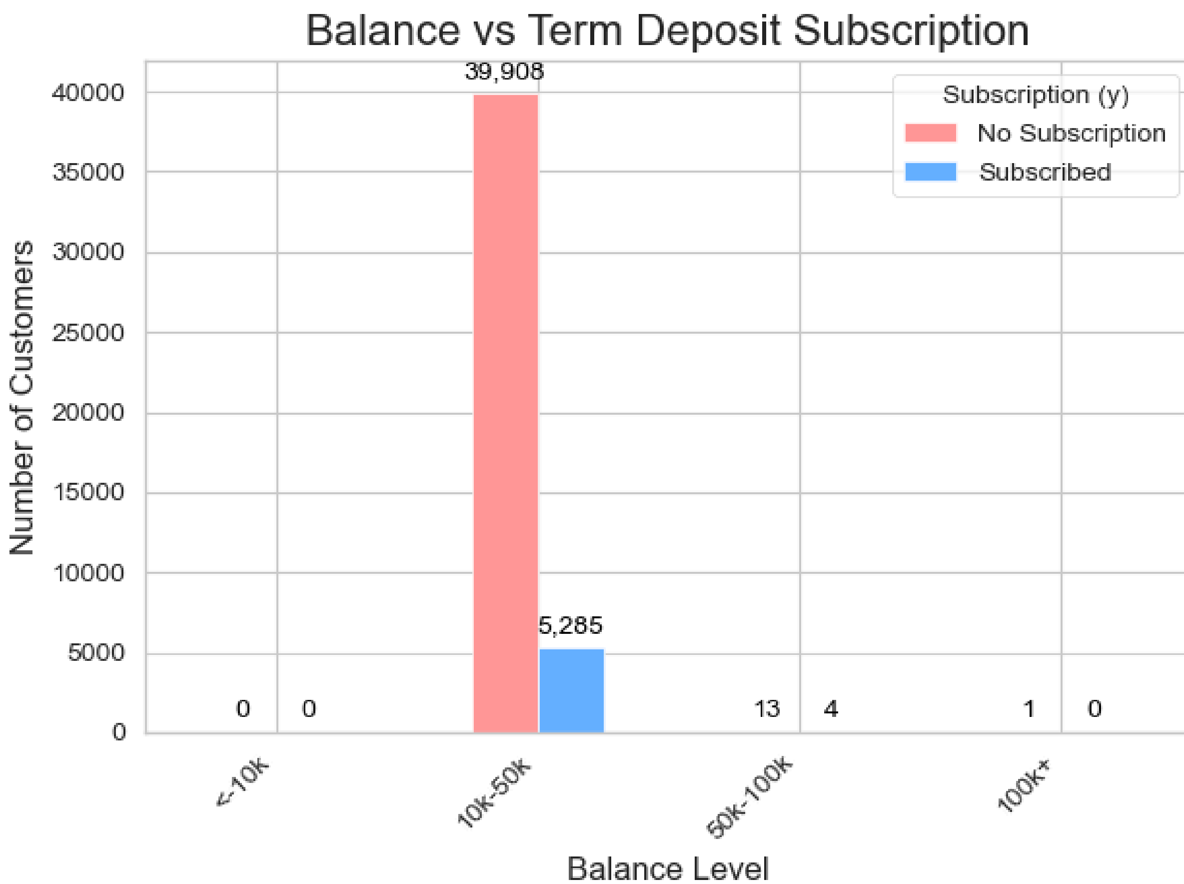
```
<Figure size 1000x600 with 0 Axes>
```



In [14]:
```python
# Create the bins and labels for balance categories
balance_bins = [-float('inf'), -10000, 50000, 100000, float('inf')]
balance_labels = ['<-10k', '10k-50k', '50k-100k', '100k+']

# Apply pd.cut to categorize 'balance' into the defined bins
train_data['balance_category'] = pd.cut(train_data['balance'], bins=balance_bins, l

# Group by 'balance_category' and 'y', then count the number of occurrences
edu_y_counts = train_data.groupby(['balance_category', 'y']).size().unstack()

# Create the bar graph
plt.figure(figsize=(10, 6))
ax = edu_y_counts.plot(kind='bar', stacked=False, color=['#FF9999', '#66B3FF'])

# Add chart title and labels
plt.title('Balance vs Term Deposit Subscription', fontsize=16)
plt.xlabel('Balance Level', fontsize=12)
plt.ylabel('Number of Customers', fontsize=12)

# Show the legend and adjust the position
plt.legend(title='Subscription (y)', labels=['No Subscription', 'Subscribed'], loc=

# Add the bar labels with commas and display them on top of each bar
for p in ax.patches:
    ax.annotate(f'{int(p.get_height()):,}',  # Format the number with commas
                (p.get_x() + p.get_width() / 2., p.get_height()),
                ha='center', va='center',
                fontsize=10, color='black',
```

```
                xytext=(0, 8), textcoords='offset points')

# Display the plot
plt.xticks(rotation=45, ha='right')  # Rotate x-axis labels for better visibility
plt.tight_layout()
plt.show()
```

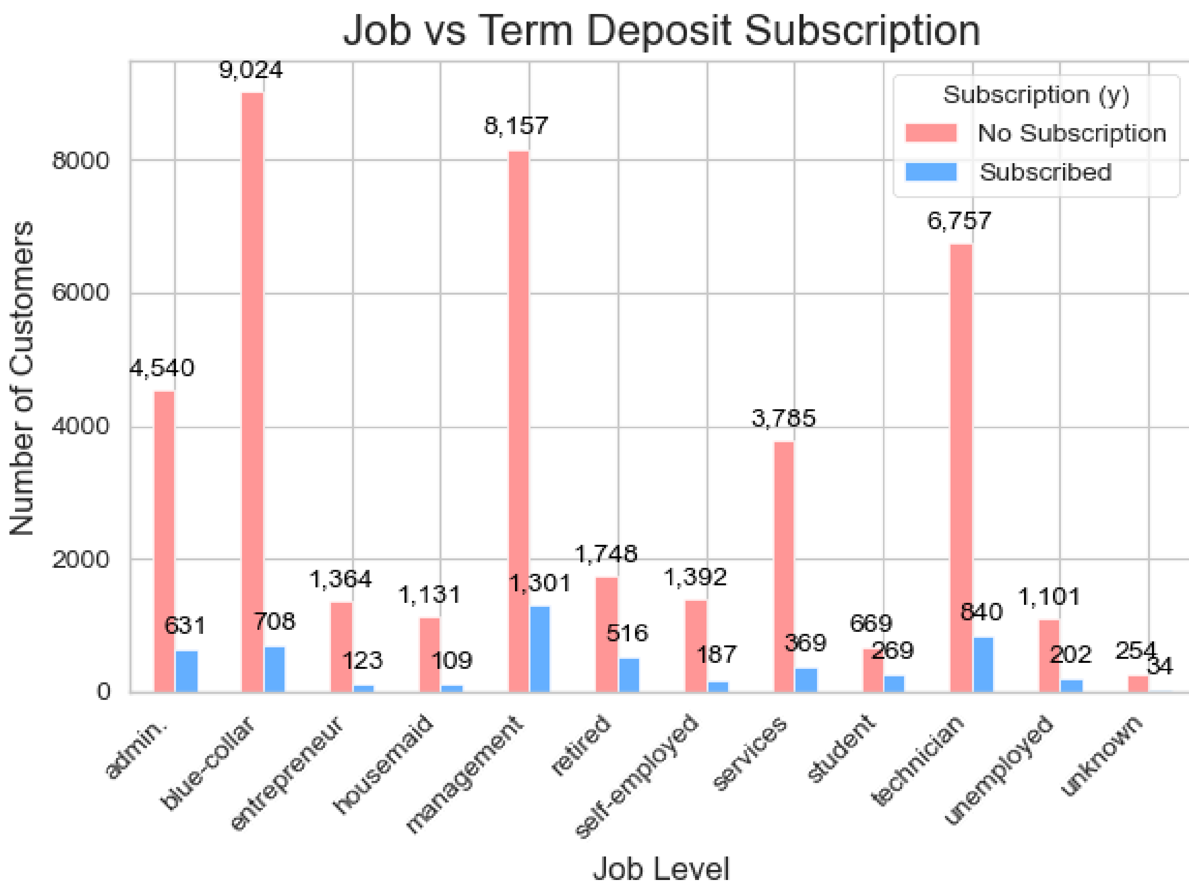
```
C:\Users\rkeoye\AppData\Local\Temp\ipykernel_23372\989768863.py:9: FutureWarning: Th
e default of observed=False is deprecated and will be changed to True in a future ve
rsion of pandas. Pass observed=False to retain current behavior or observed=True to
adopt the future default and silence this warning.
  edu_y_counts = train_data.groupby(['balance_category', 'y']).size().unstack()
<Figure size 1000x600 with 0 Axes>
```



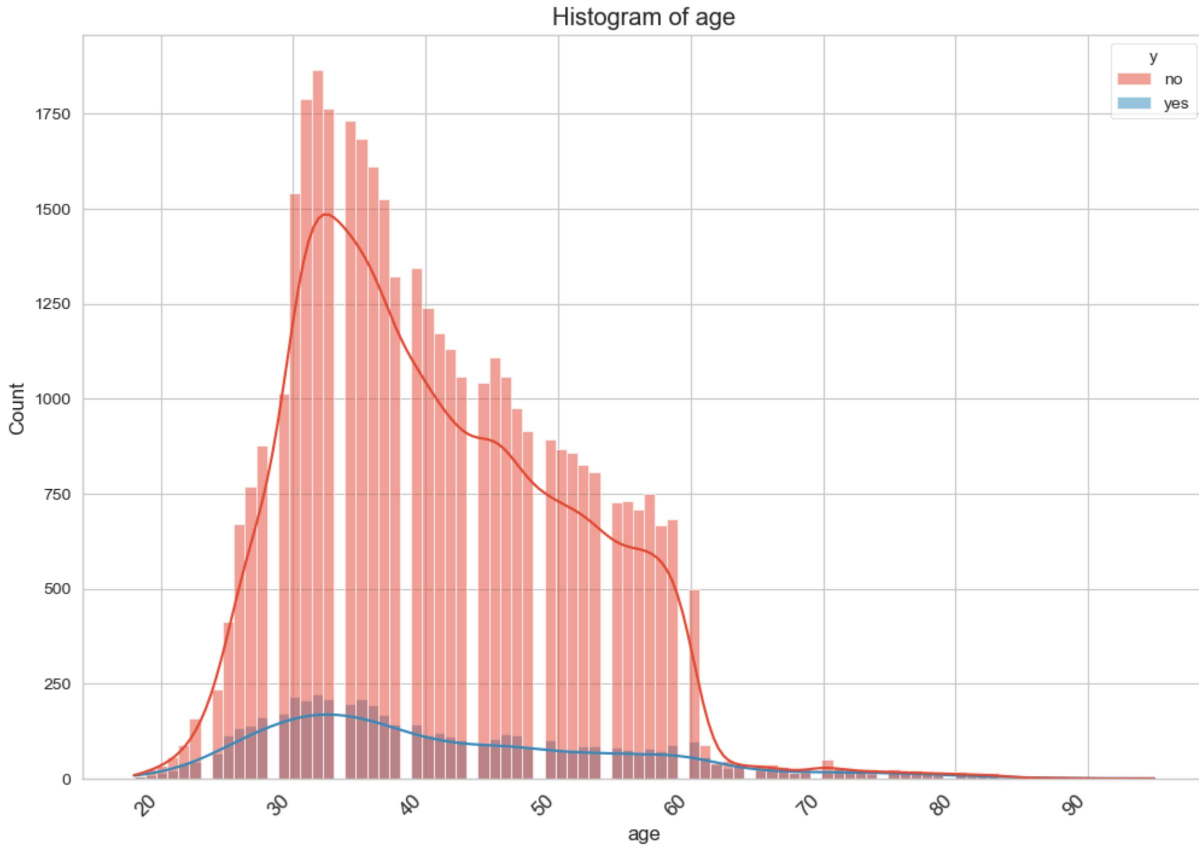
In [15]:
```
# Group by 'educatiJobon' and 'y', then count the number of occurrences
edu_y_counts = train_data.groupby(['job', 'y']).size().unstack()

# Create the bar graph
plt.figure(figsize=(10, 6))
ax = edu_y_counts.plot(kind='bar', stacked=False, color=['#FF9999', '#66B3FF'])

# Add chart title and labels
plt.title('Job vs Term Deposit Subscription', fontsize=16)
plt.xlabel('Job Level', fontsize=12)
plt.ylabel('Number of Customers', fontsize=12)

# Show the legend and adjust the position
plt.legend(title='Subscription (y)', labels=['No Subscription', 'Subscribed'], loc=
```

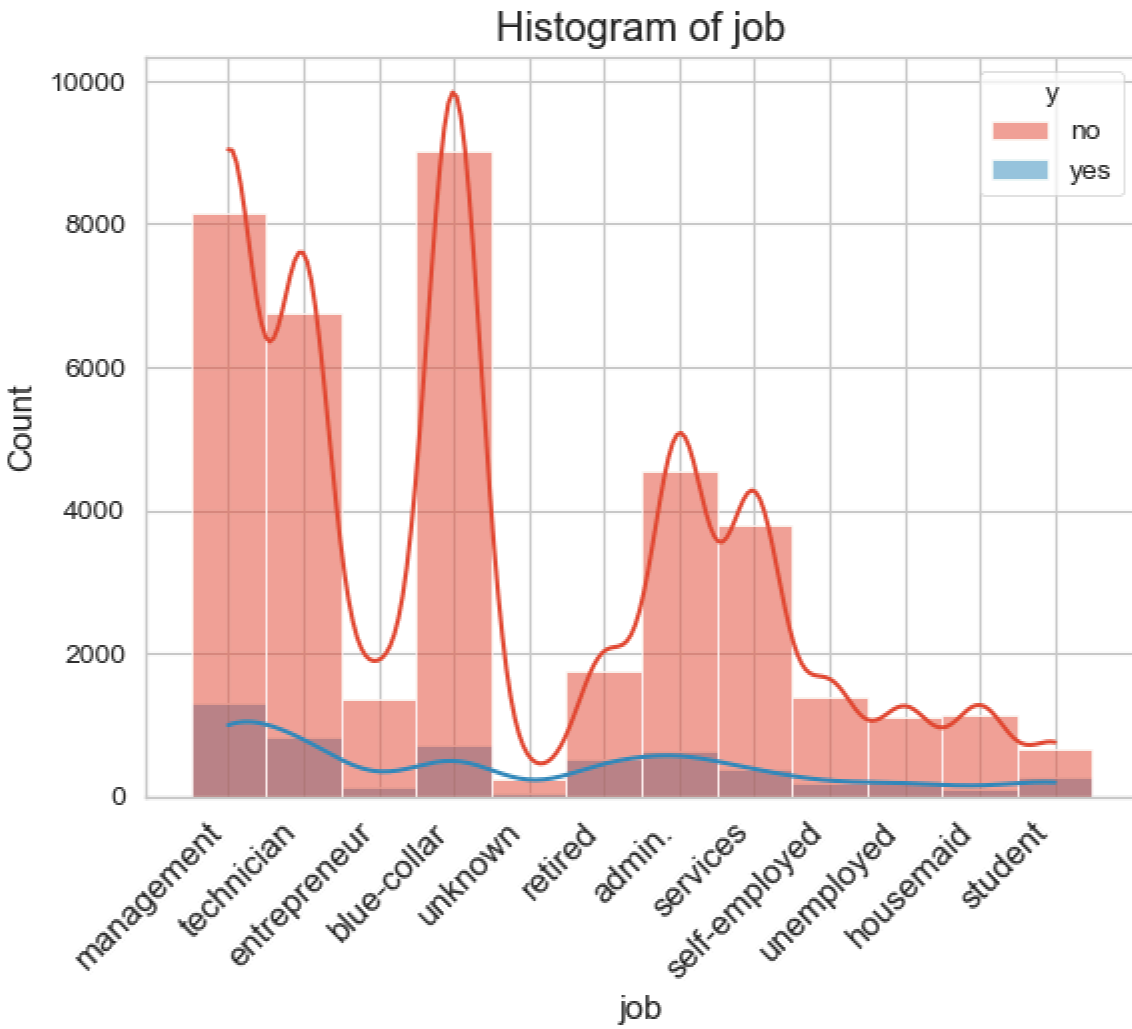
```python
# Add the bar labels with commas and display them on top of each bar
for p in ax.patches:
    ax.annotate(f'{int(p.get_height()):,}',  # Format the number with commas
                (p.get_x() + p.get_width() / 2., p.get_height()),
                ha='center', va='center',
                fontsize=10, color='black',
                xytext=(0, 8), textcoords='offset points')

# Display the plot
plt.xticks(rotation=45, ha='right')  # Rotate x-axis labels for better visibility
plt.tight_layout()
plt.show()
```

<Figure size 1000x600 with 0 Axes>

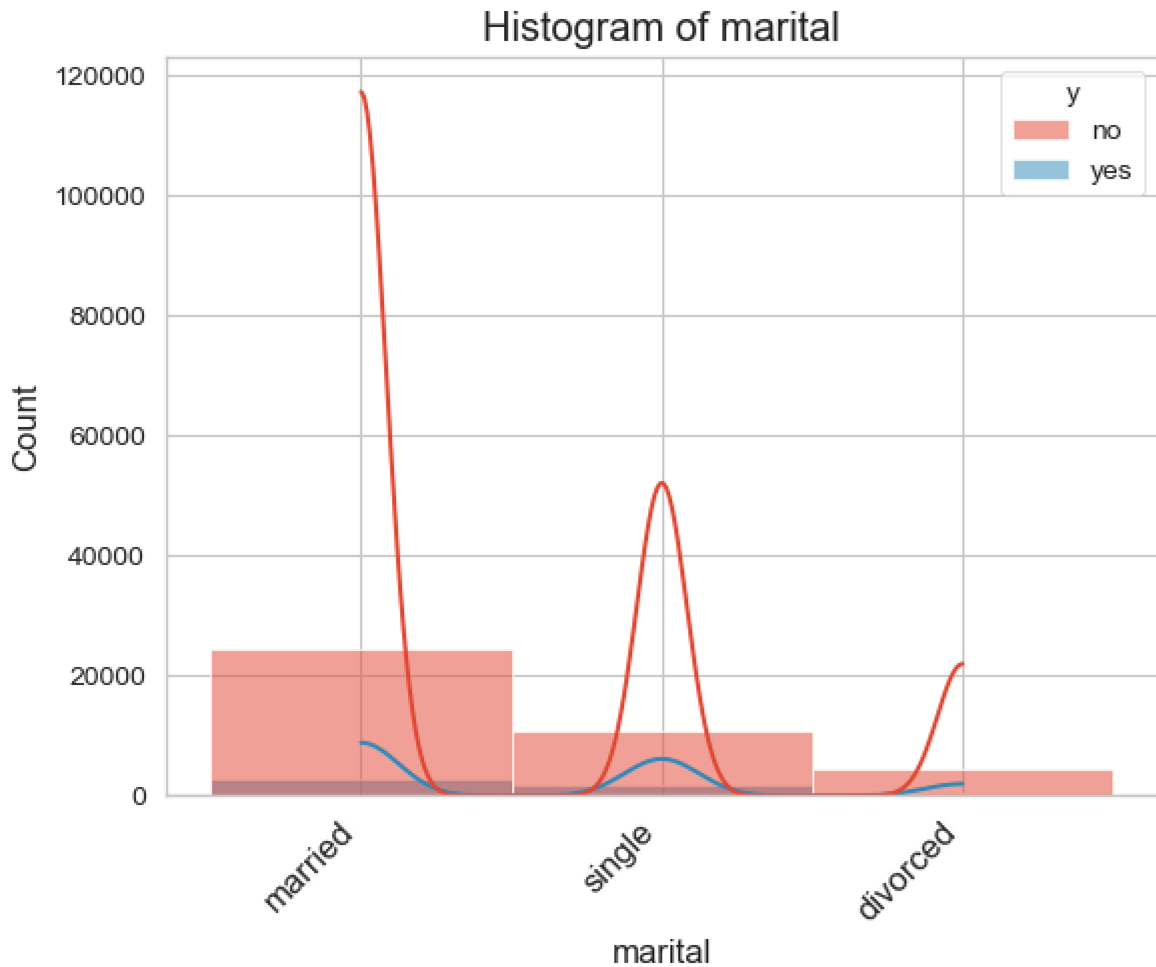


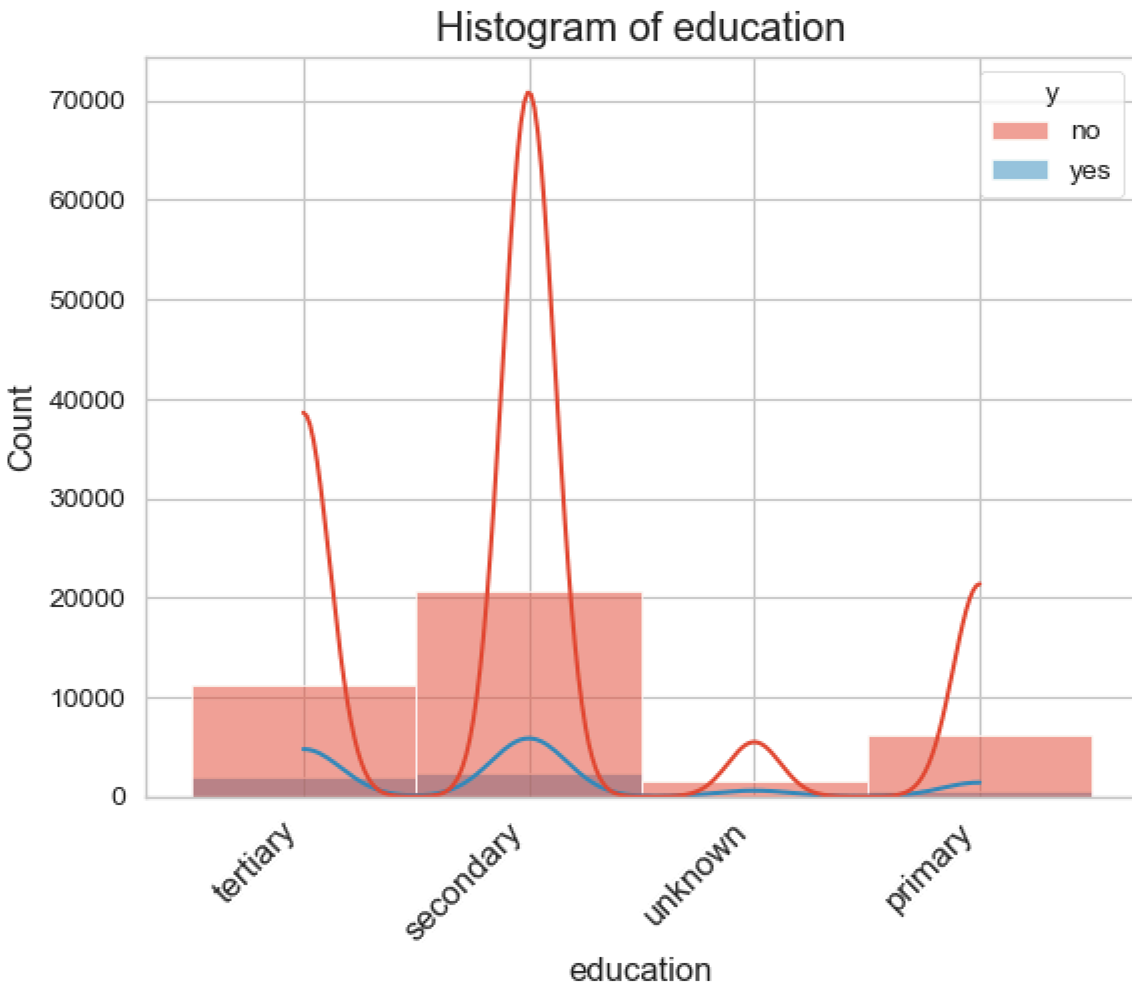
In [16]:
```python
plt.figure(figsize=(12, 8))

for feature in train_data.columns:

    sns.histplot(data=train_data, x=feature, hue='y', kde=True)

    plt.title(f'Histogram of {feature}')

    plt.xlabel(feature)
    plt.xticks(rotation=45, fontsize=12, ha='right')
    plt.show()
```

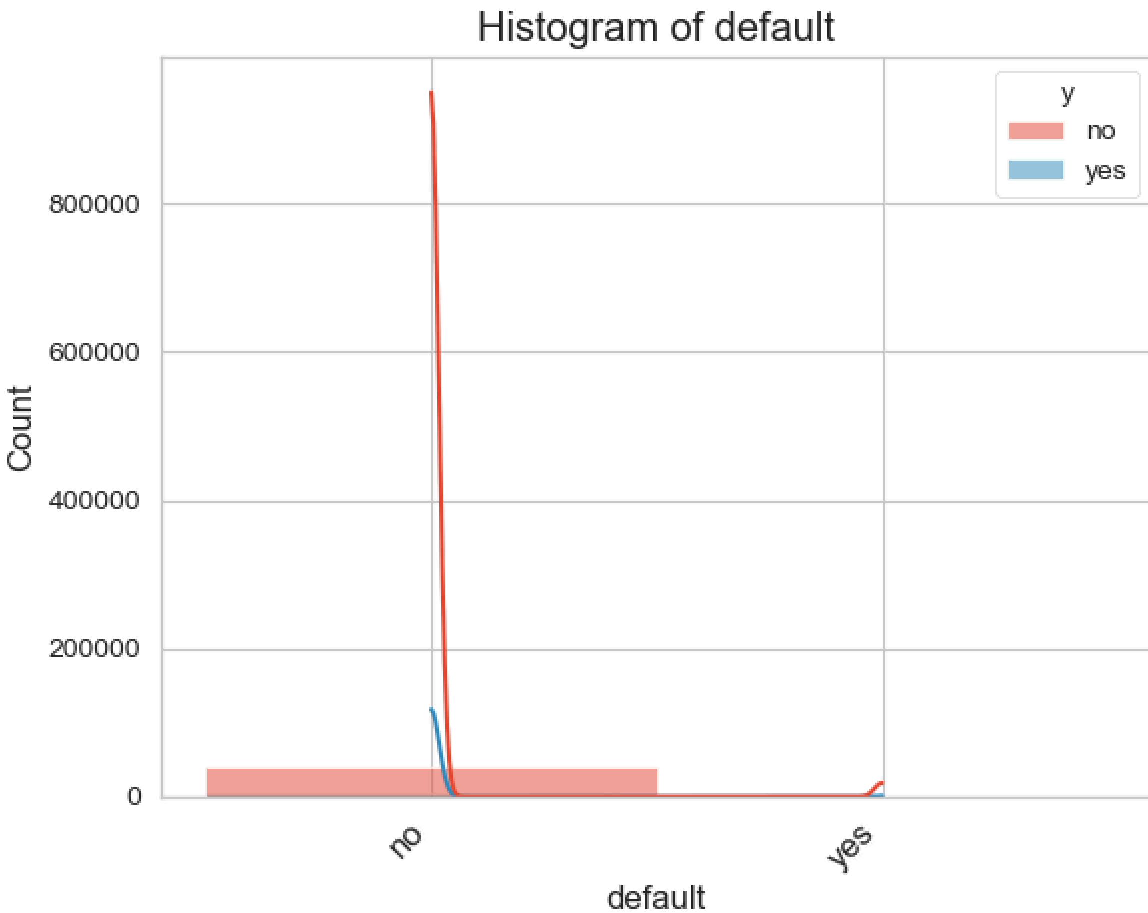

Histogram of age
y
no
yes
Count
1750
1500
1250
1000
750
500
250
0
20
30
40
50
60
70
80
90
age

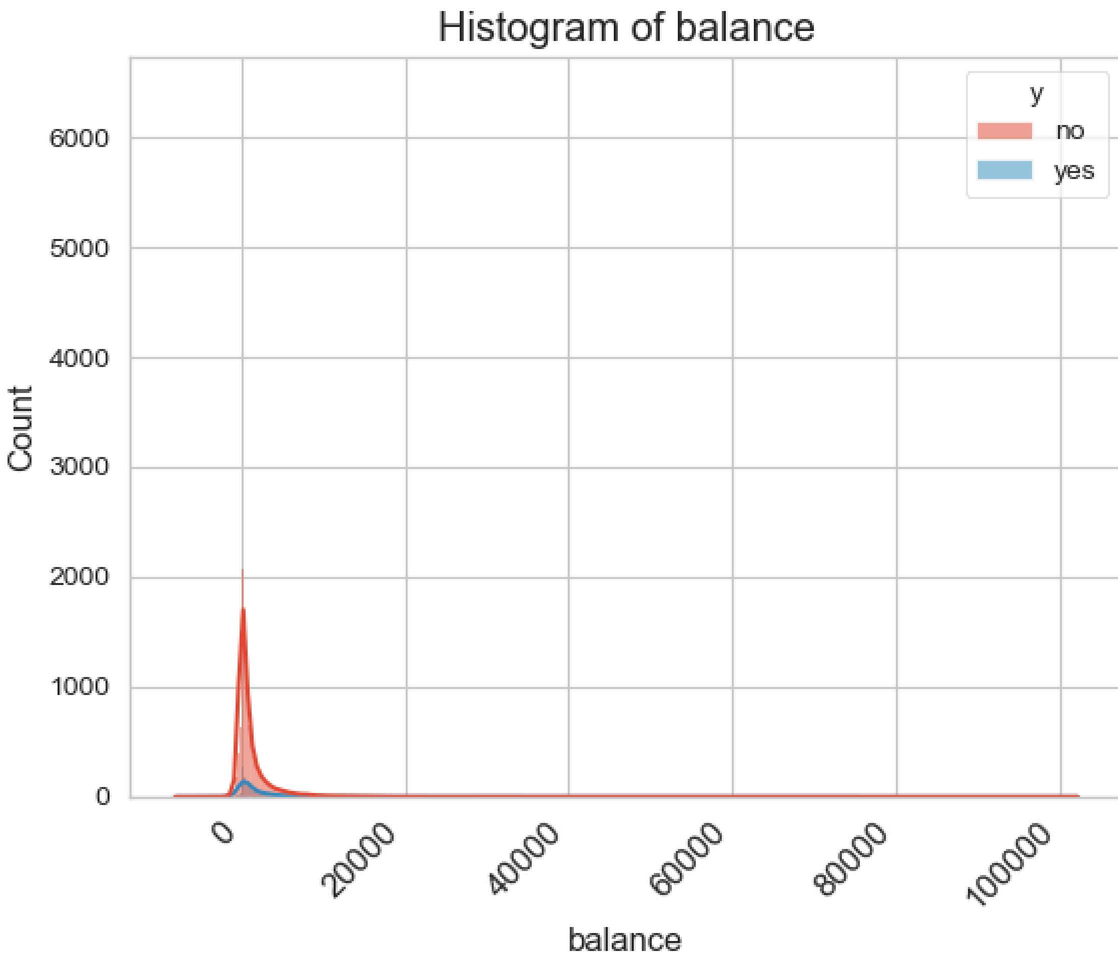


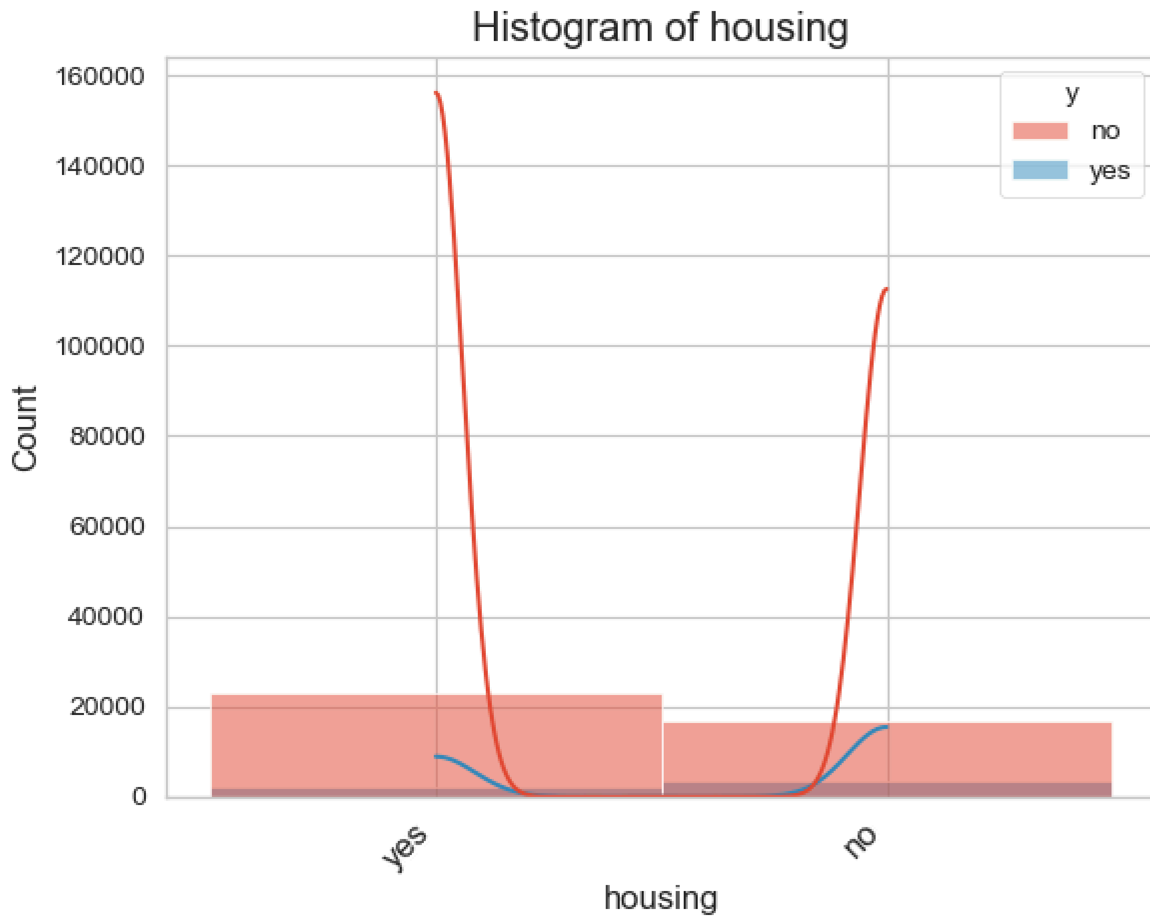
Histogram of job
Count
job
y
no
yes
0
2000
4000
6000
8000
10000
management
technician
entrepreneur
blue-collar
unknown
retired
admin.
services
self-employed
unemployed
housemaid
student

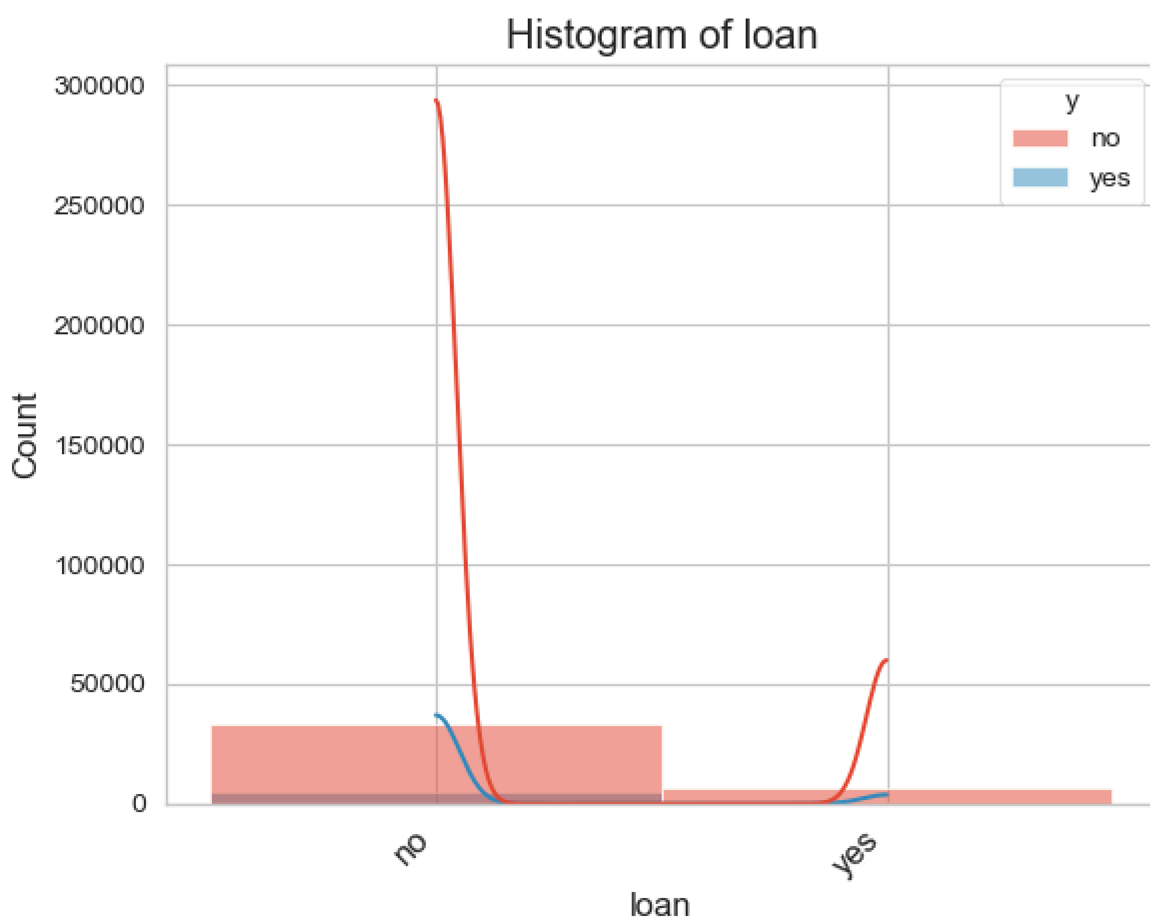

Histogram of marital
y
no
yes
Count
0
20000
40000
60000
80000
100000
120000
married
single
divorced
marital

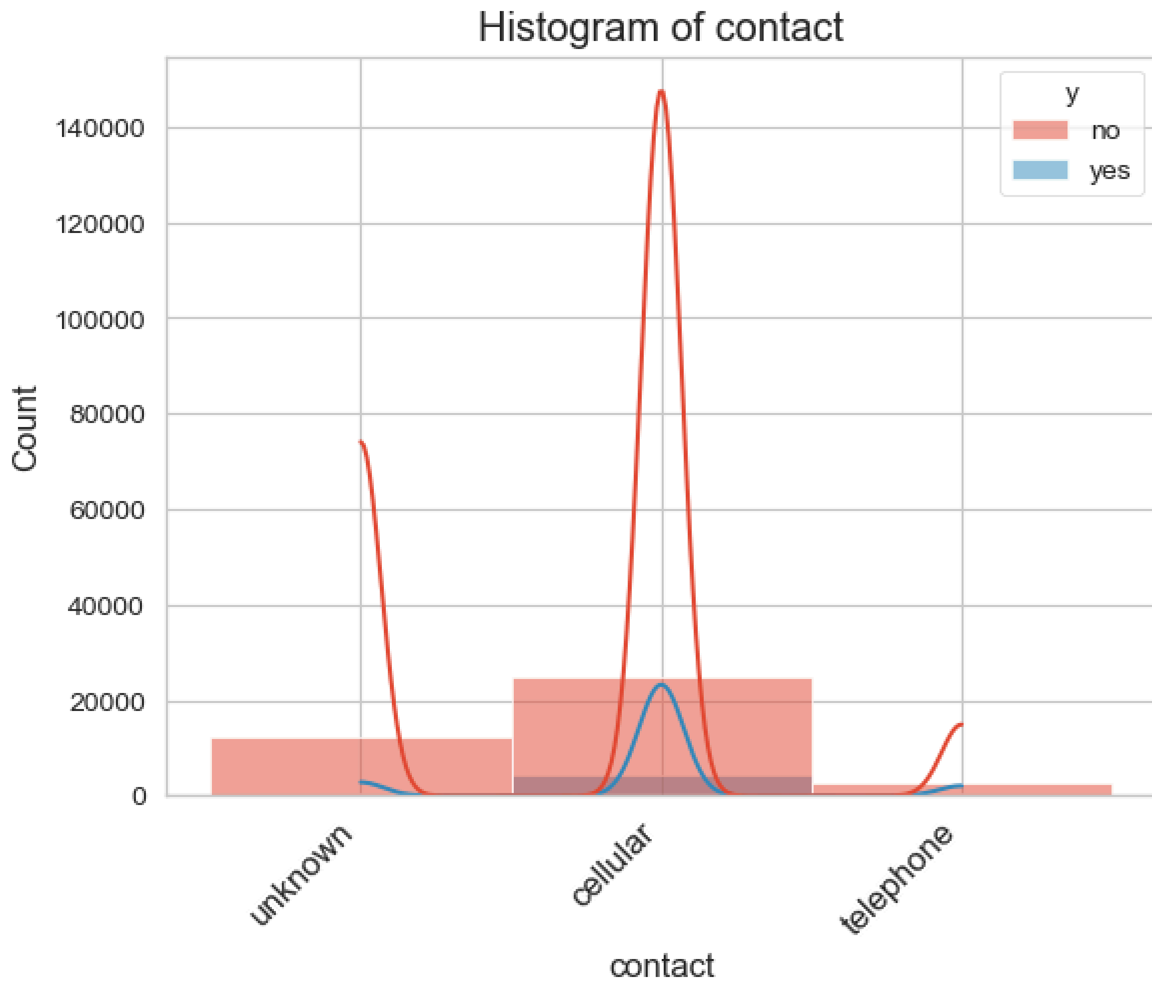

Histogram of education
y
no
yes
Count
70000
60000
50000
40000
30000
20000
10000
0
tertiary
secondary
unknown
primary
education

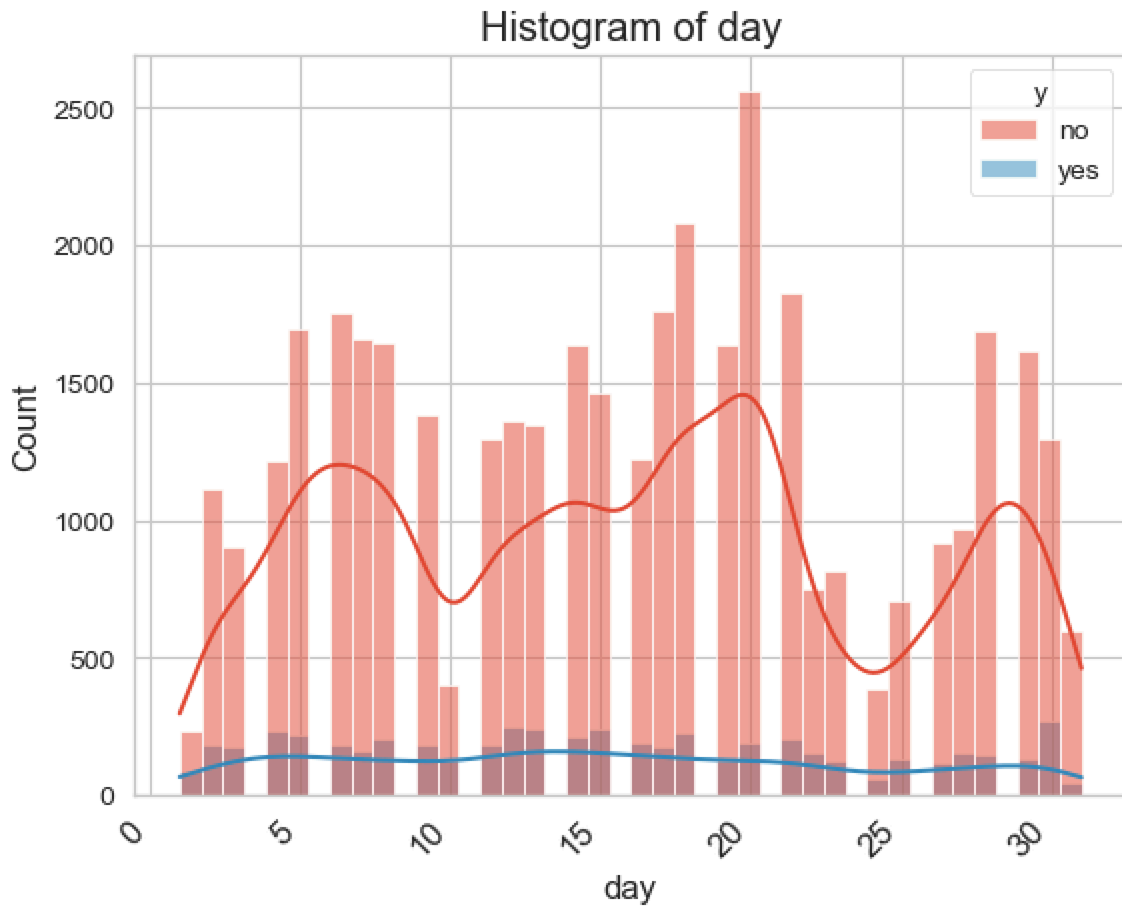

Histogram of default
y
no
yes
800000
600000
400000
200000
0
Count
no
yes
default

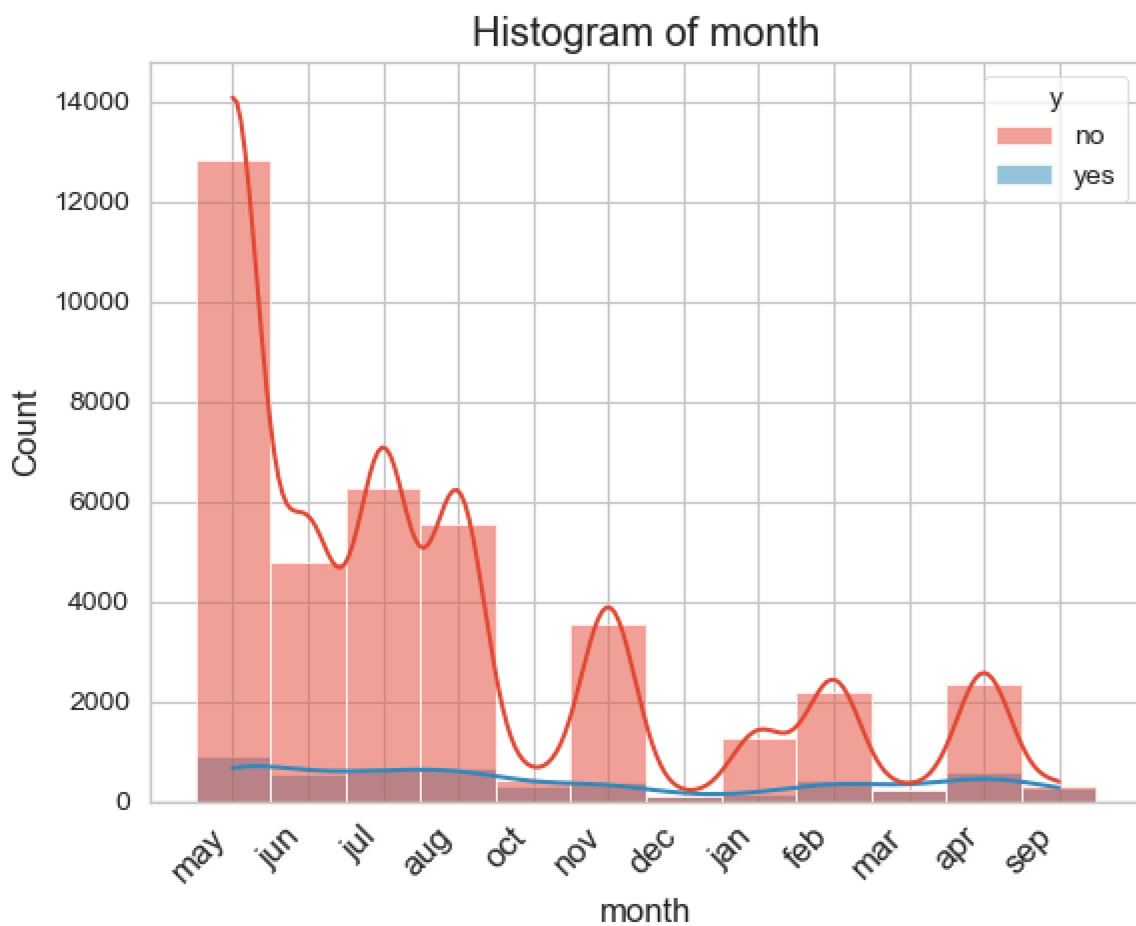

Histogram of balance
y
no
yes
Count
6000
5000
4000
3000
2000
1000
0
0
20000
40000
60000
80000
100000
balance

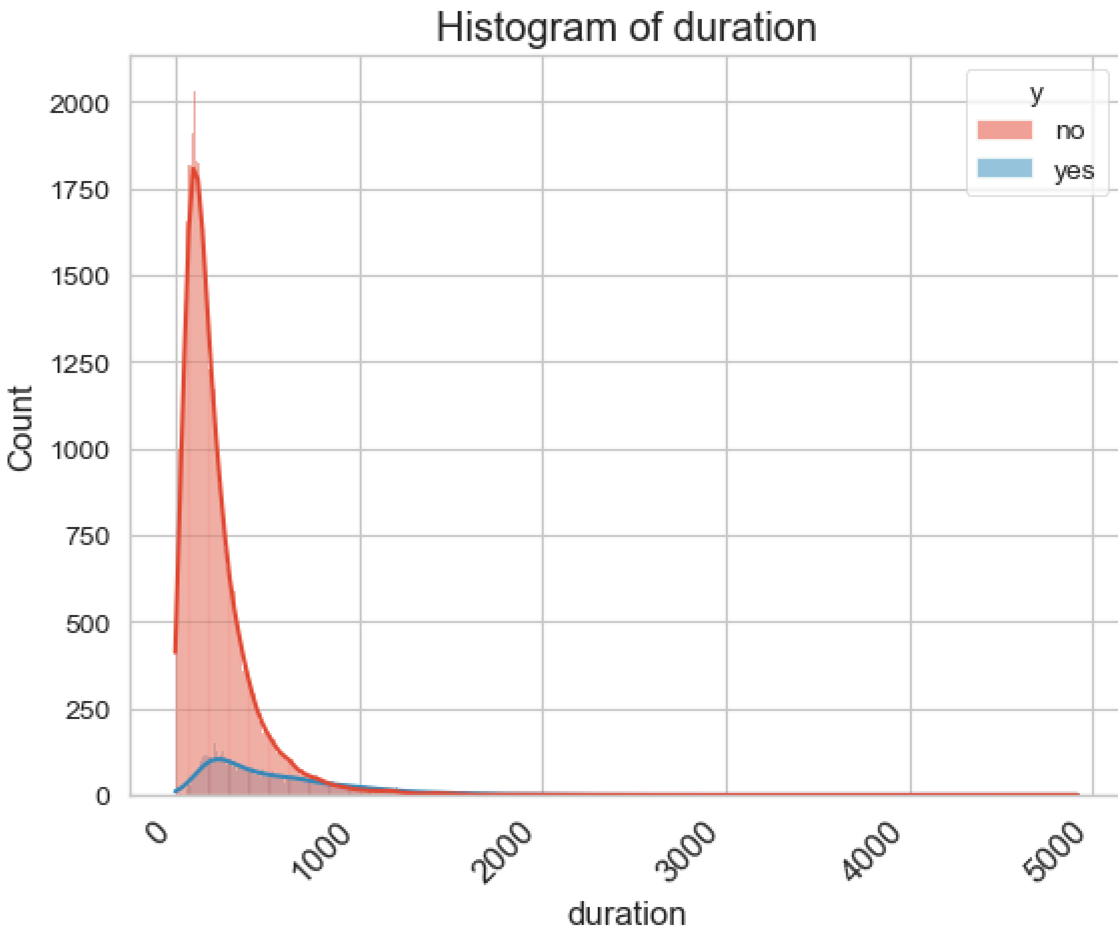

Histogram of housing
160000
140000
120000
100000
80000
60000
40000
20000
0
Count
y
no
yes
yes
no
housing

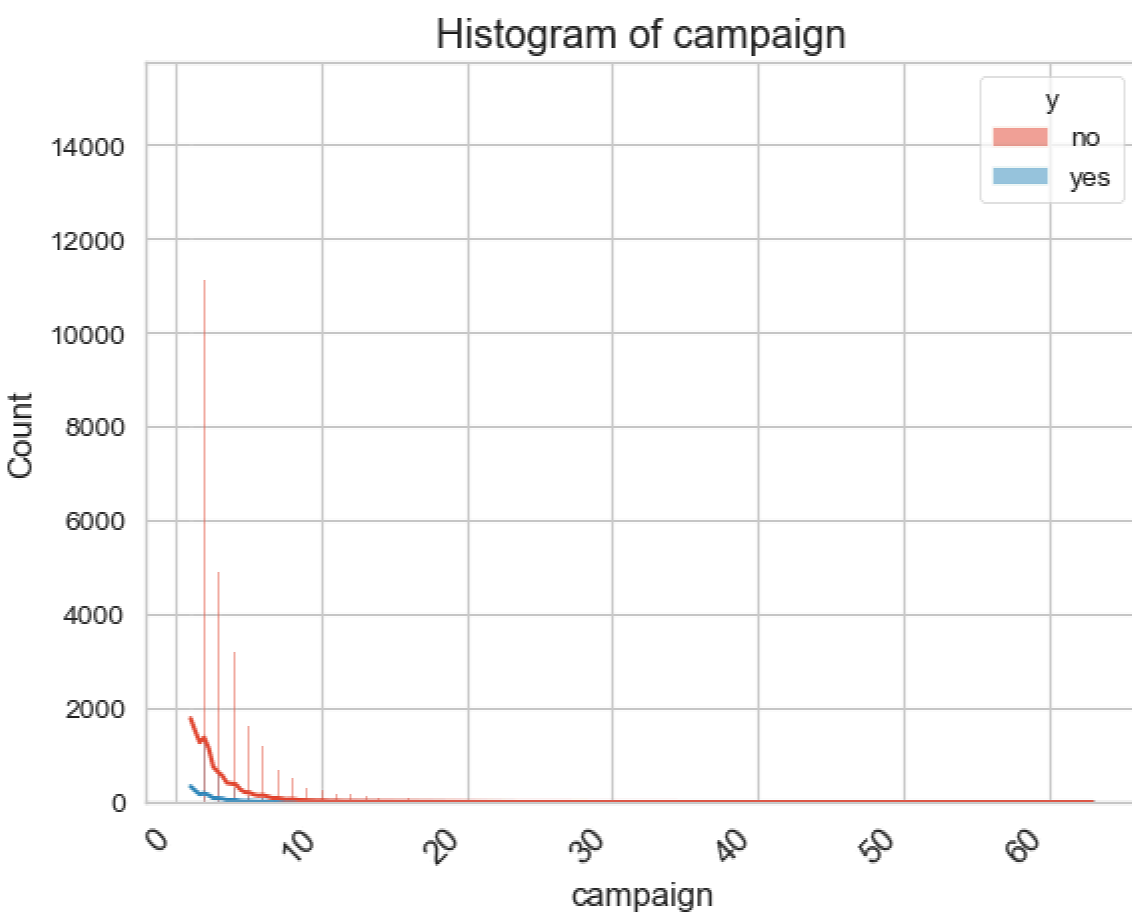

Histogram of loan
300000
250000
200000
150000
100000
50000
0
Count
y
no
yes
no
yes
loan

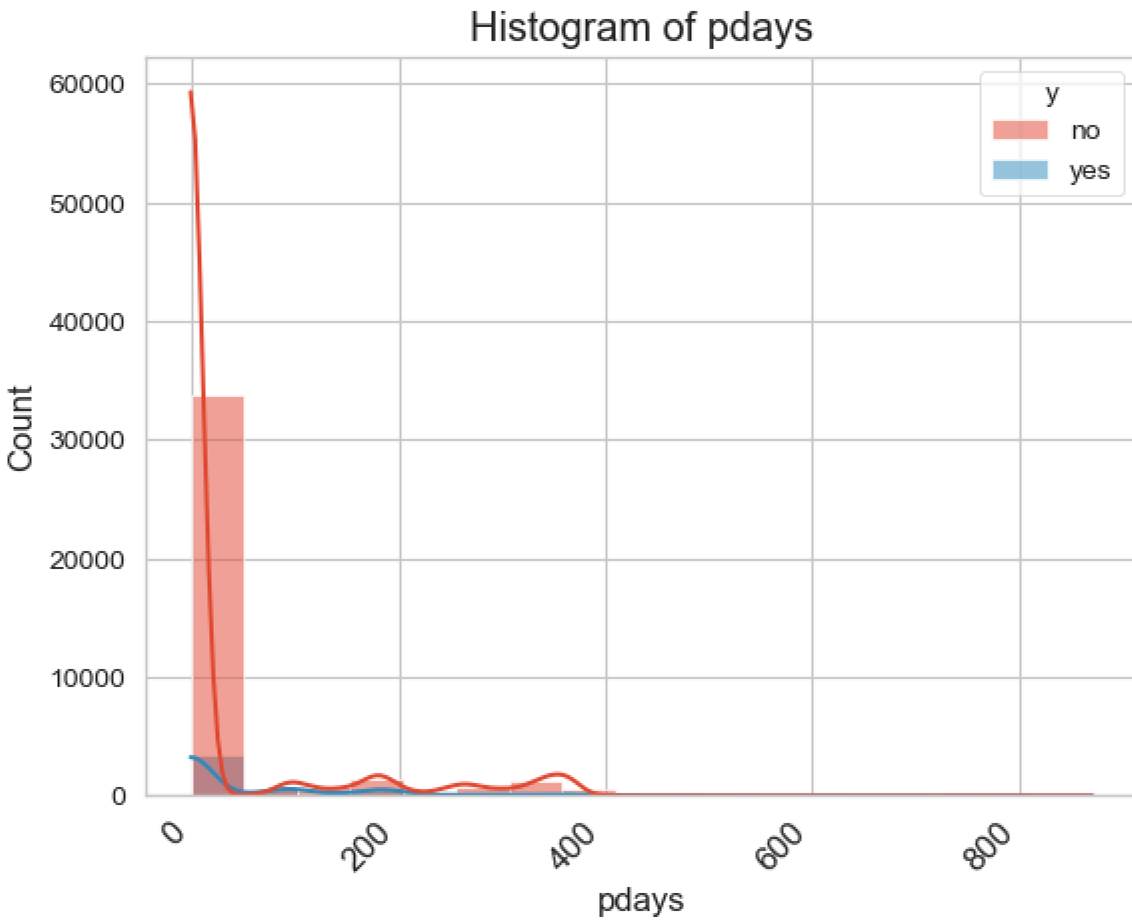

Histogram of contact
y
no
yes
Count
140000
120000
100000
80000
60000
40000
20000
0
unknown
cellular
telephone
contact

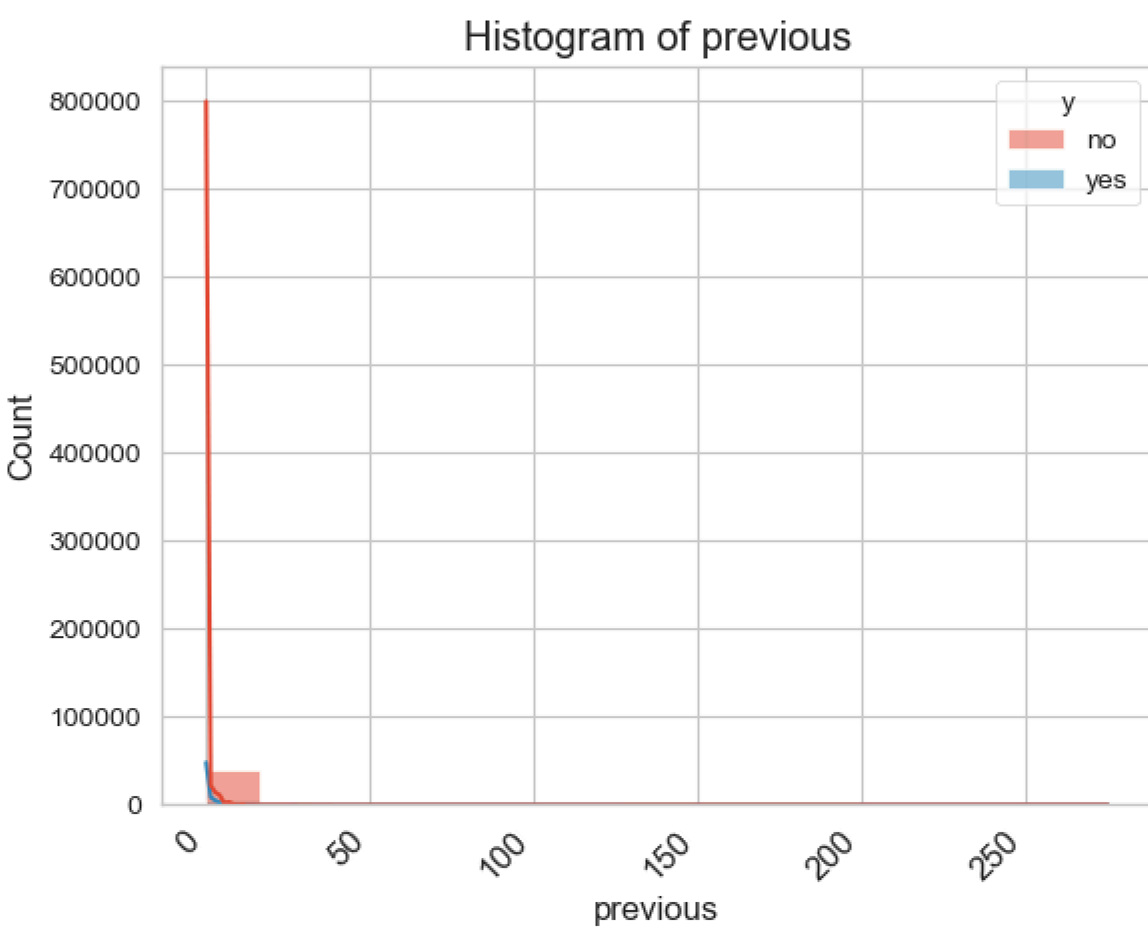

Histogram of day
y
no
yes
Count
day
0
500
1000
1500
2000
2500
0
5
10
15
20
25
30

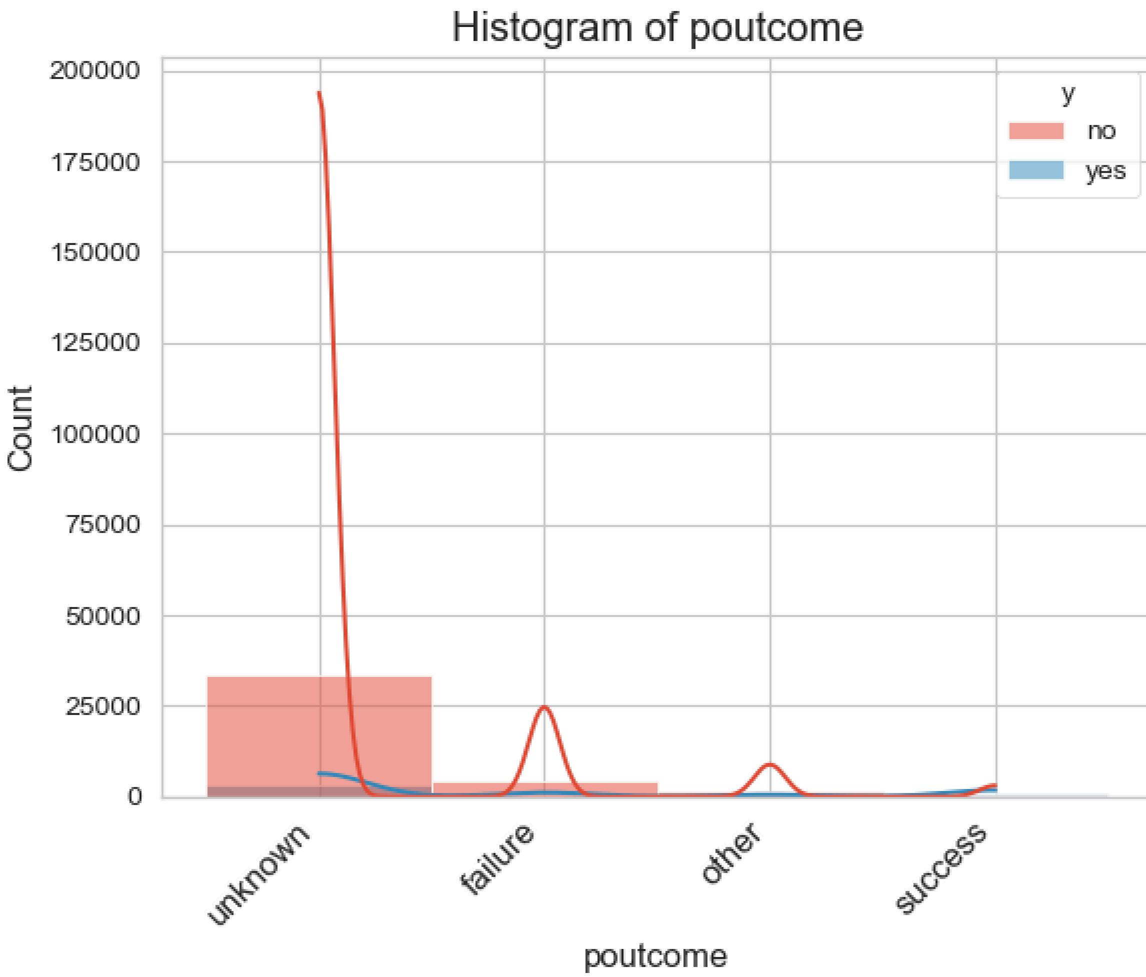

Histogram of month
y
no
yes
Count
month
0
2000
4000
6000
8000
10000
12000
14000
may
jun
jul
aug
oct
nov
dec
jan
feb
mar
apr
sep

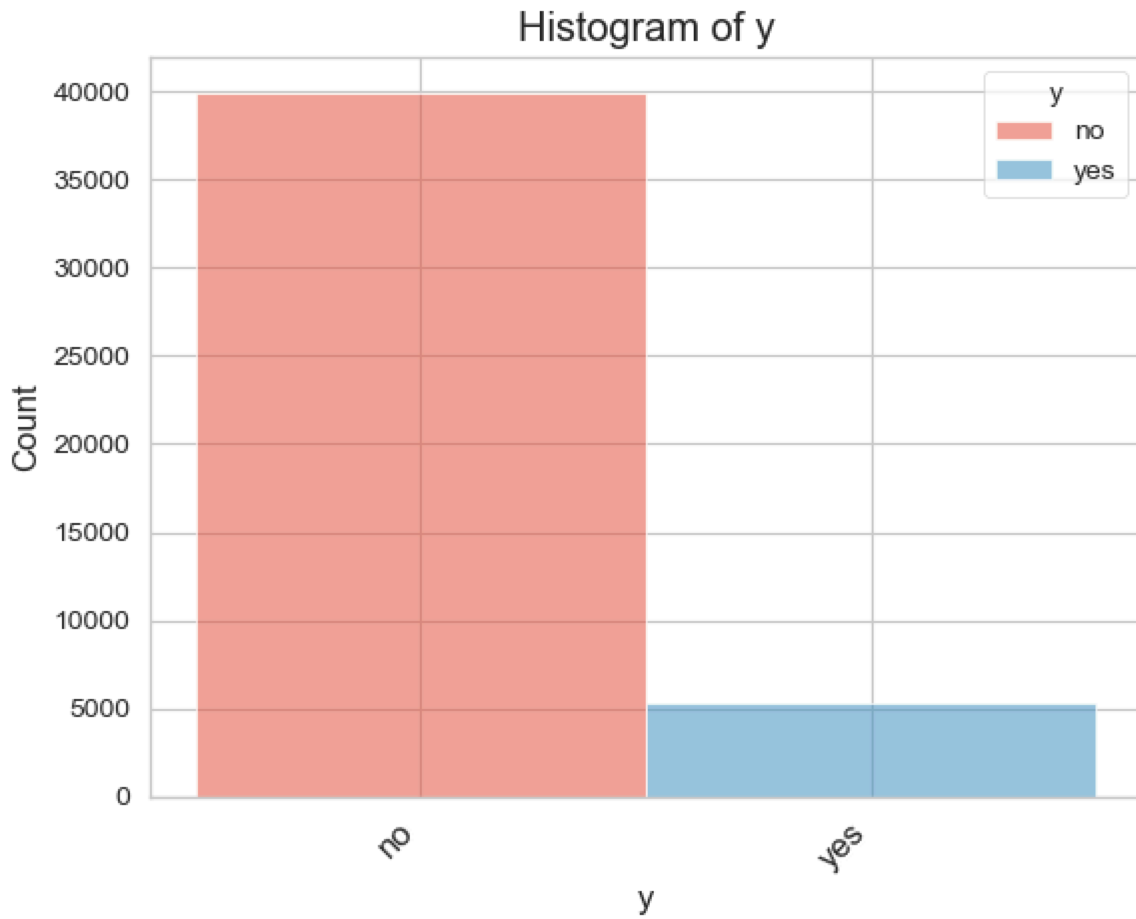

Histogram of duration
y
no
yes
Count
2000
1750
1500
1250
1000
750
500
250
0
0
1000
2000
3000
4000
5000
duration

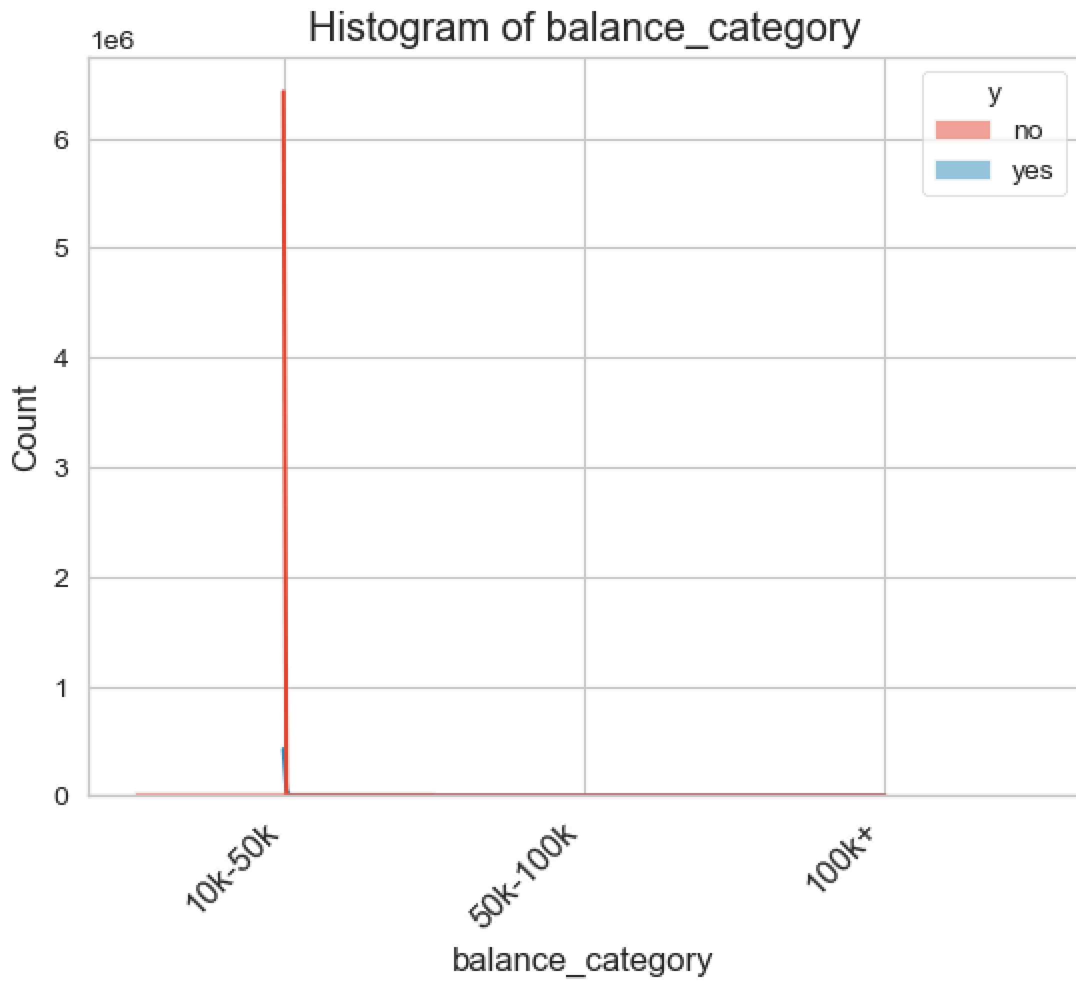

Histogram of campaign
y
no
yes
Count
14000
12000
10000
8000
6000
4000
2000
0
0
10
20
30
40
50
60
campaign


Histogram of pdays
y
no
yes
Count
60000
50000
40000
30000
20000
10000
0
0
200
400
600
800
pdays

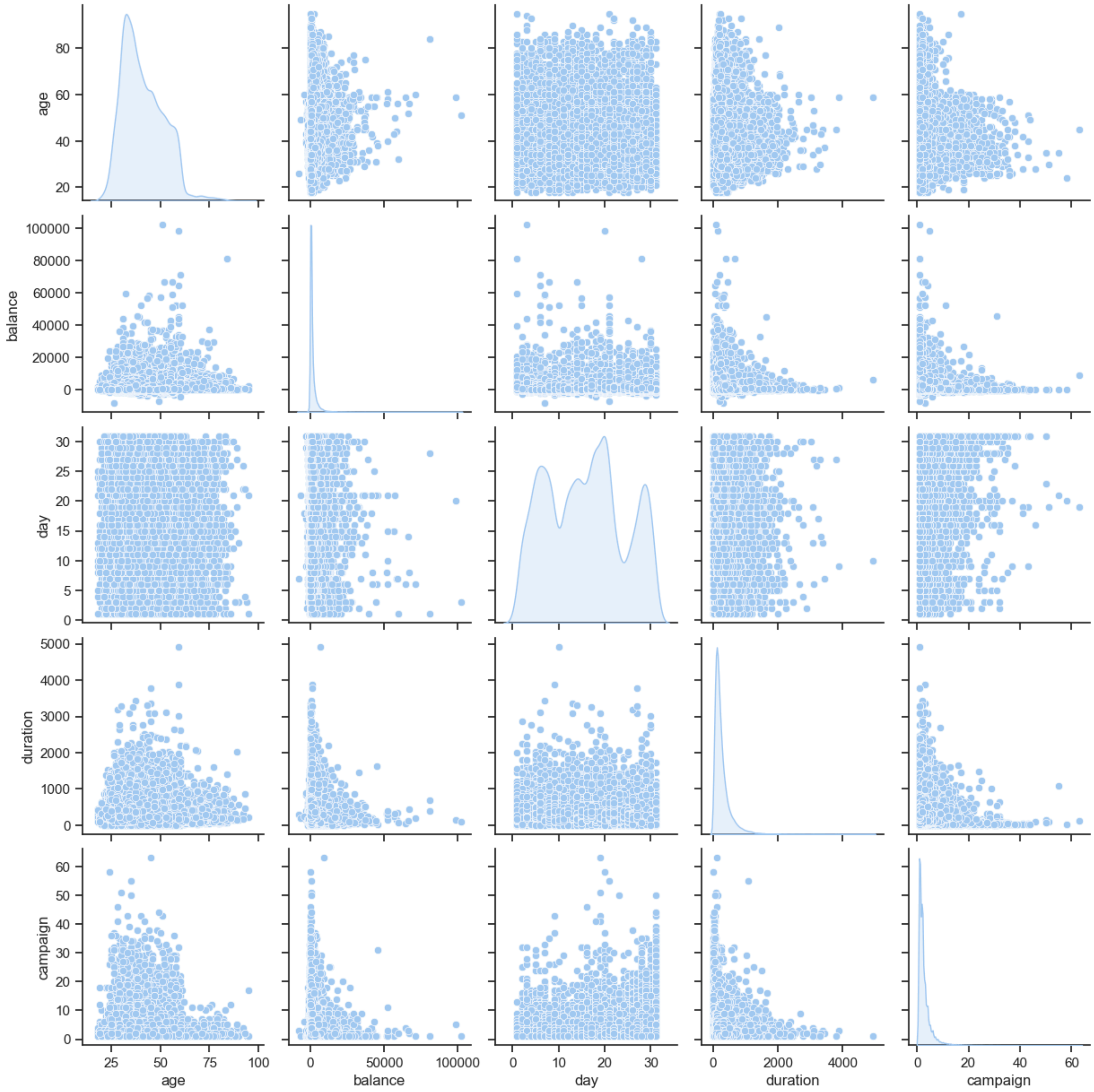

Histogram of previous
y
no
yes
Count
800000
700000
600000
500000
400000
300000
200000
100000
0
0
50
100
150
200
250
previous


Histogram of poutcome
200000
175000
150000
125000
100000
75000
50000
25000
0
Count
y
no
yes
unknown
failure
other
success
poutcome

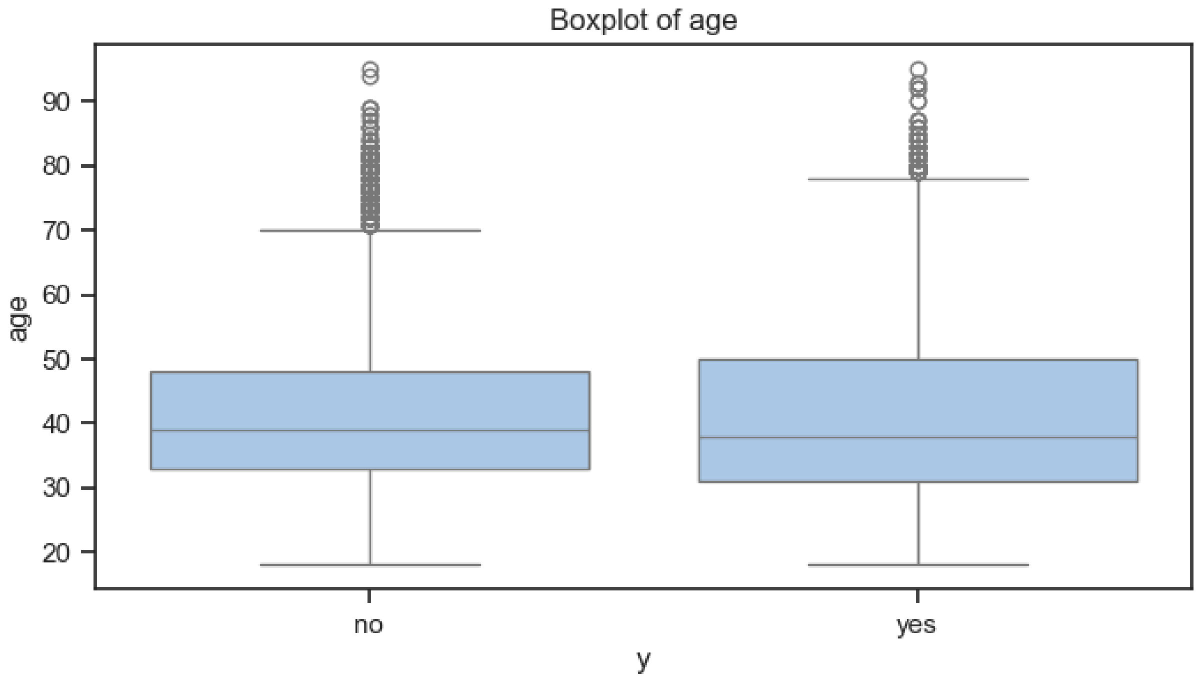

Histogram of y
y
no
yes
Count
40000
35000
30000
25000
20000
15000
10000
5000
0
no
yes
y

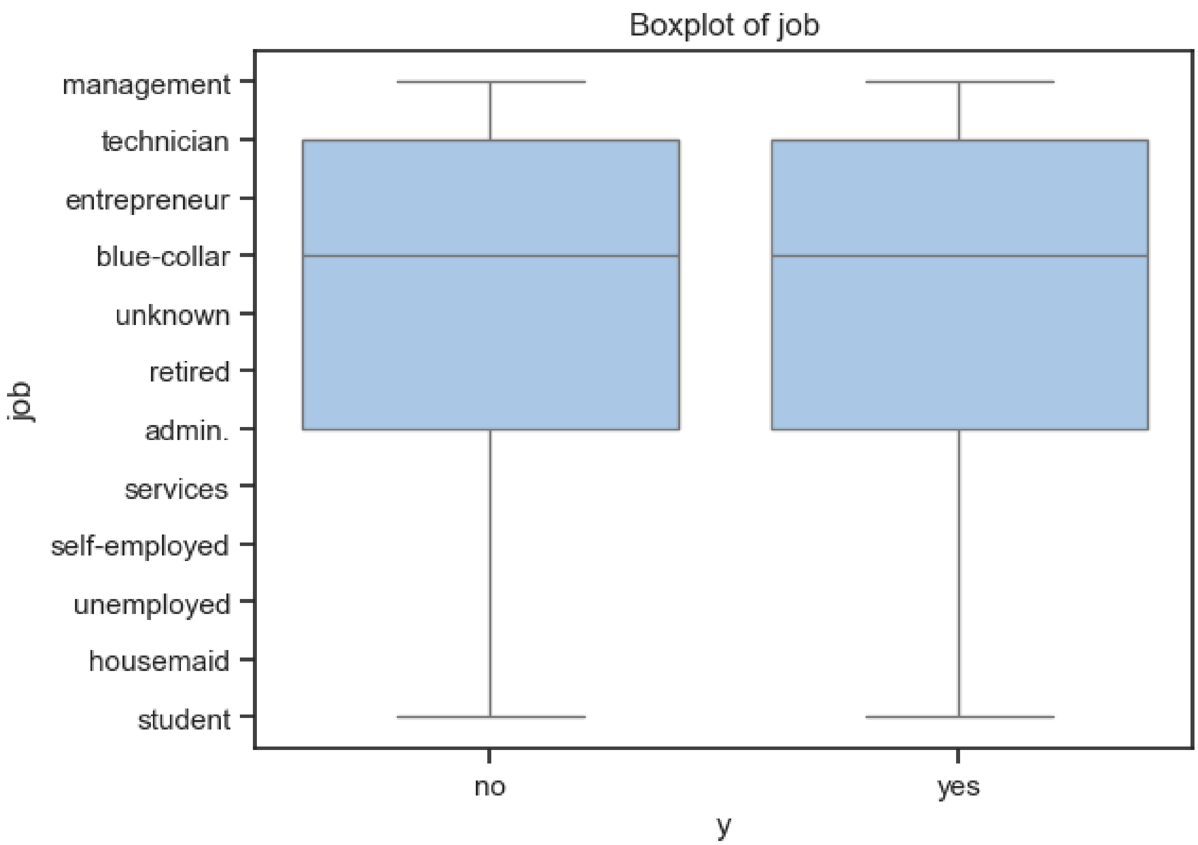


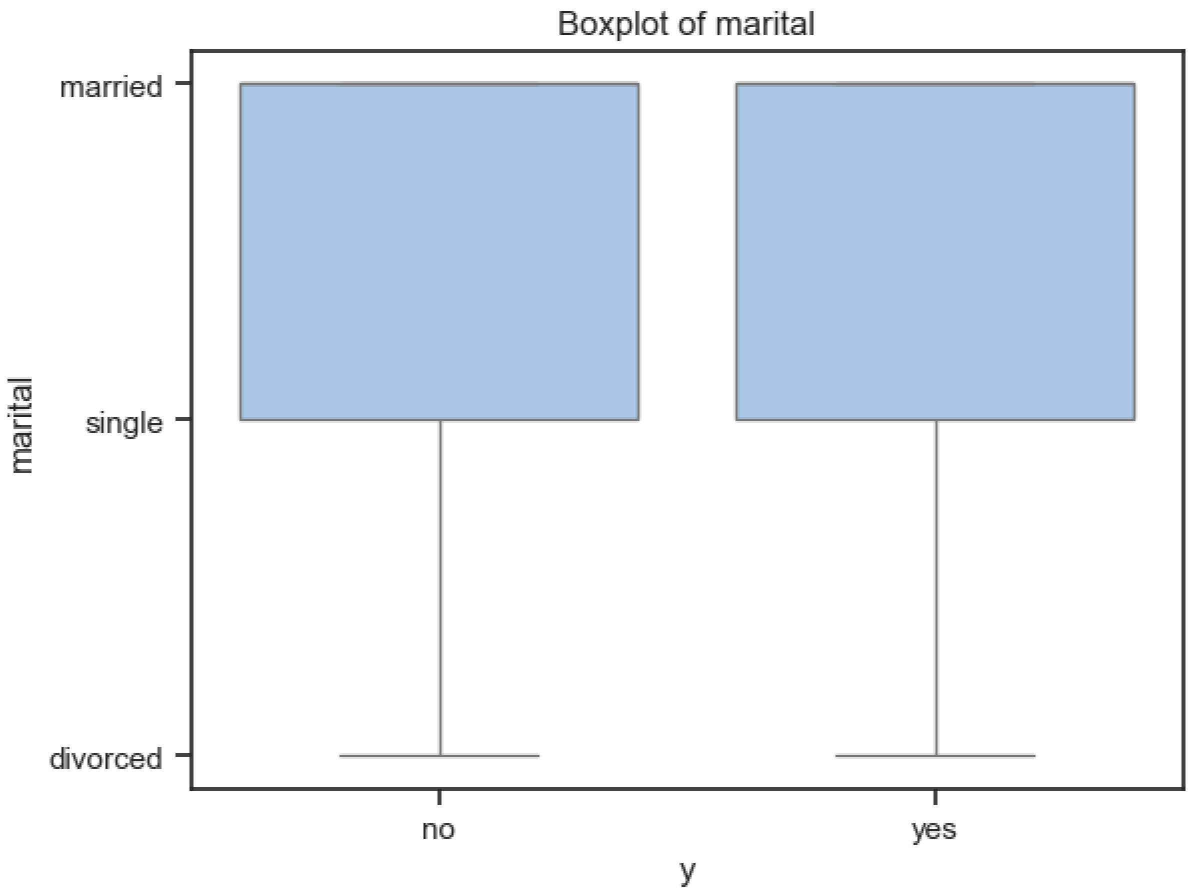
In [17]:
```
sns.set_theme(style="ticks", palette="pastel")

sns.pairplot(train_data[['age', 'balance', 'day', 'duration', 'campaign']], diag_ki

plt.show()
```

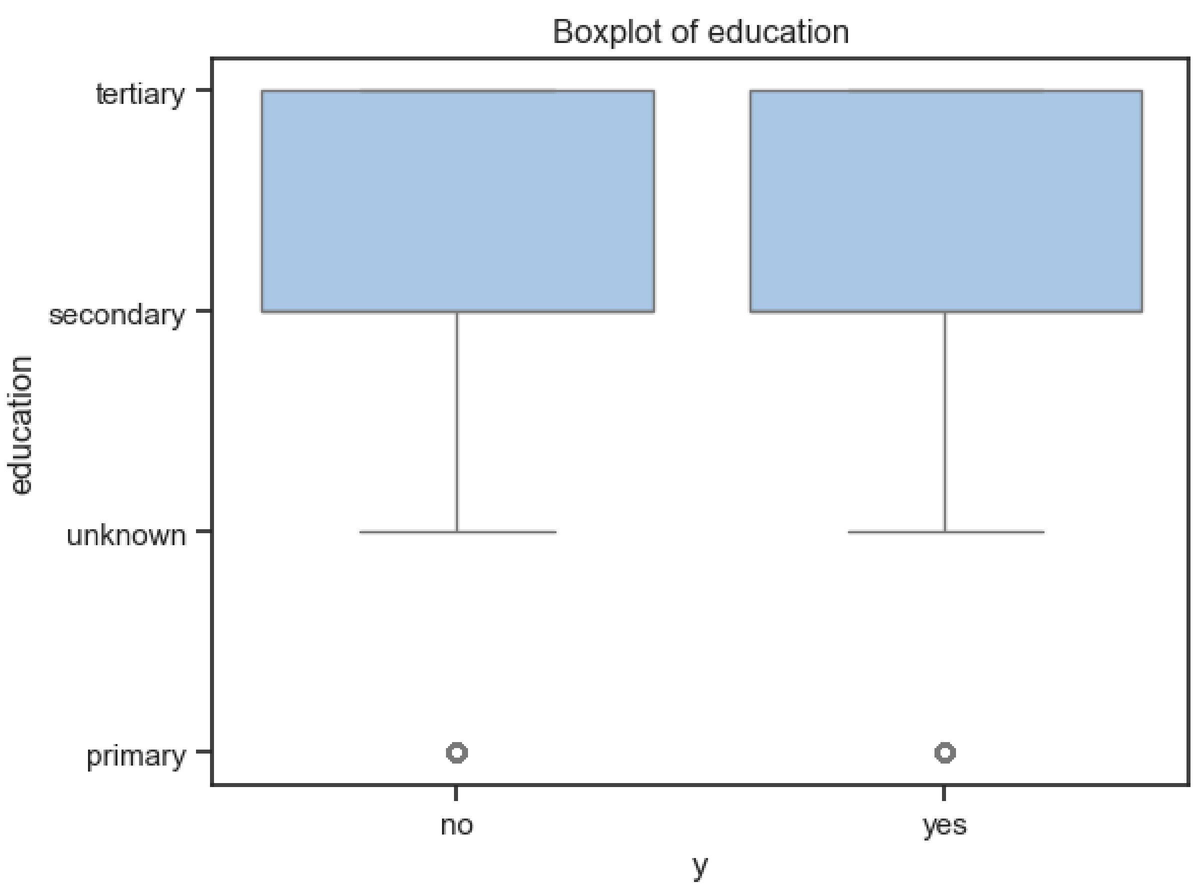


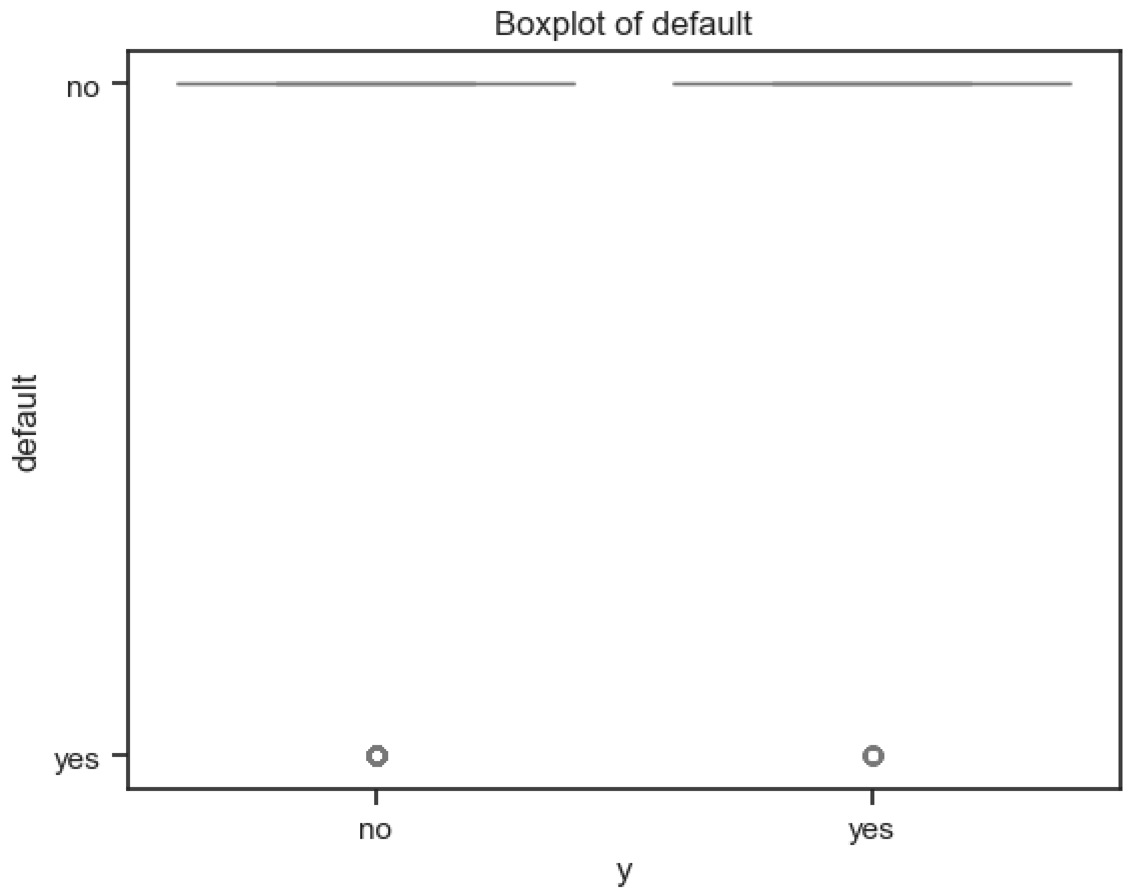
In [18]:
```
plt.figure(figsize=(8, 4))

for feature in train_data.columns:

    sns.boxplot(x=train_data['y'], y=train_data[feature])

    plt.title(f'Boxplot of {feature}')

    plt.xlabel('y')

    plt.ylabel(feature)

    plt.show()
```

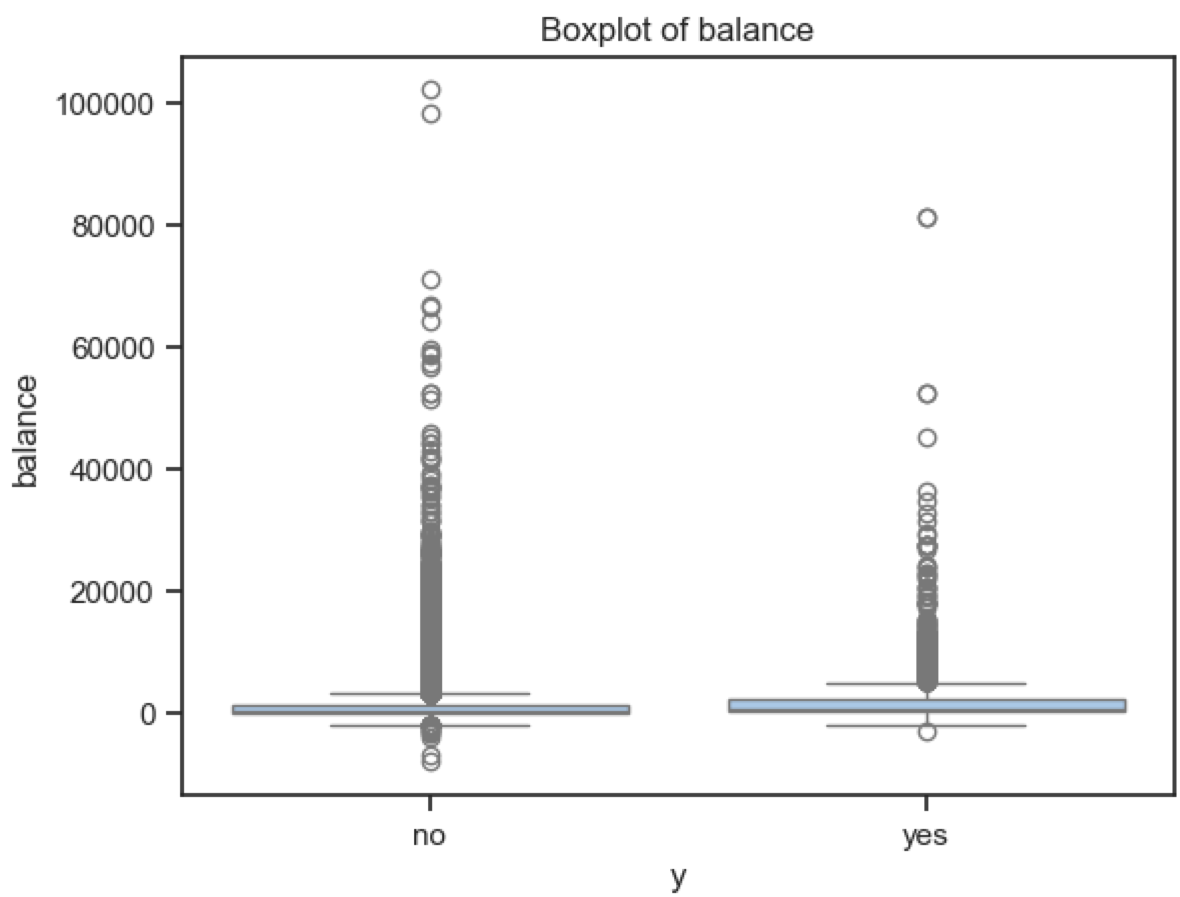

Boxplot of age
age
90
80
70
60
50
40
30
20
no
yes
y

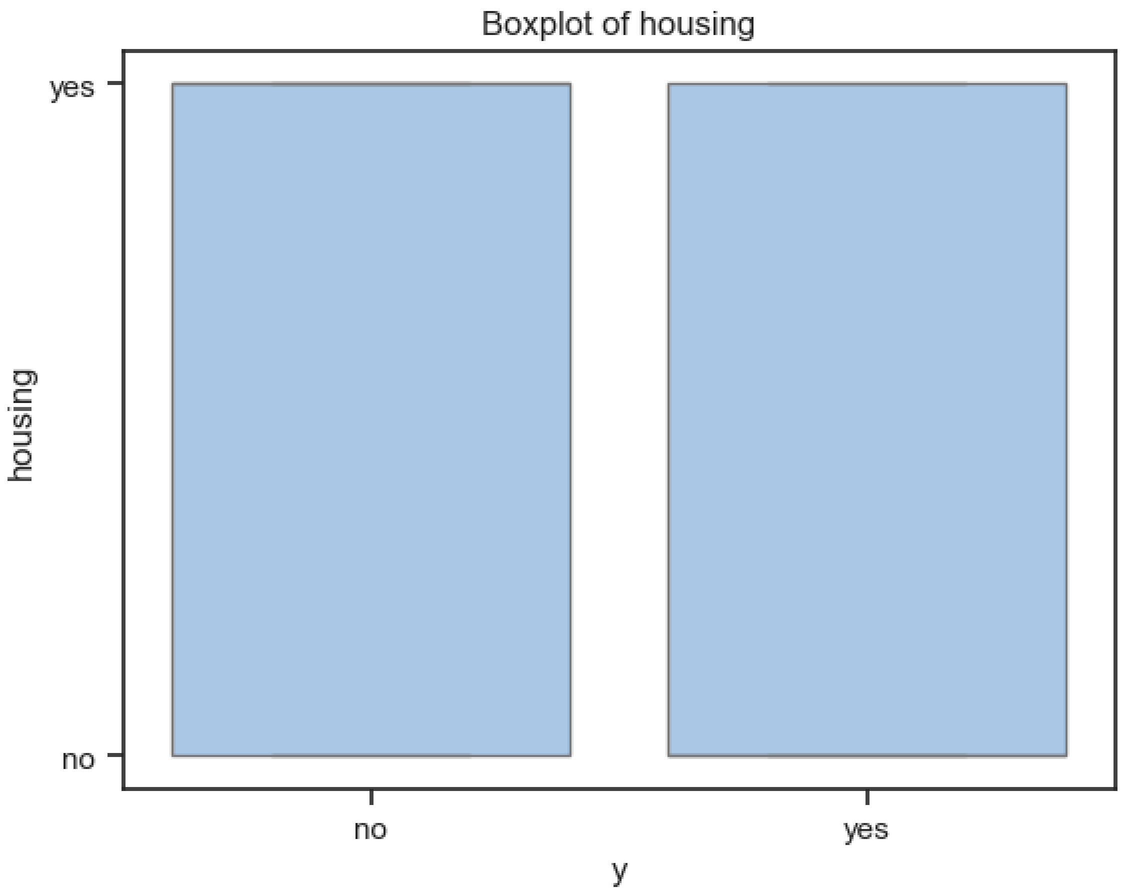

Boxplot of job
job
management
technician
entrepreneur
blue-collar
unknown
retired
admin.
services
self-employed
unemployed
housemaid
student
no
yes
y

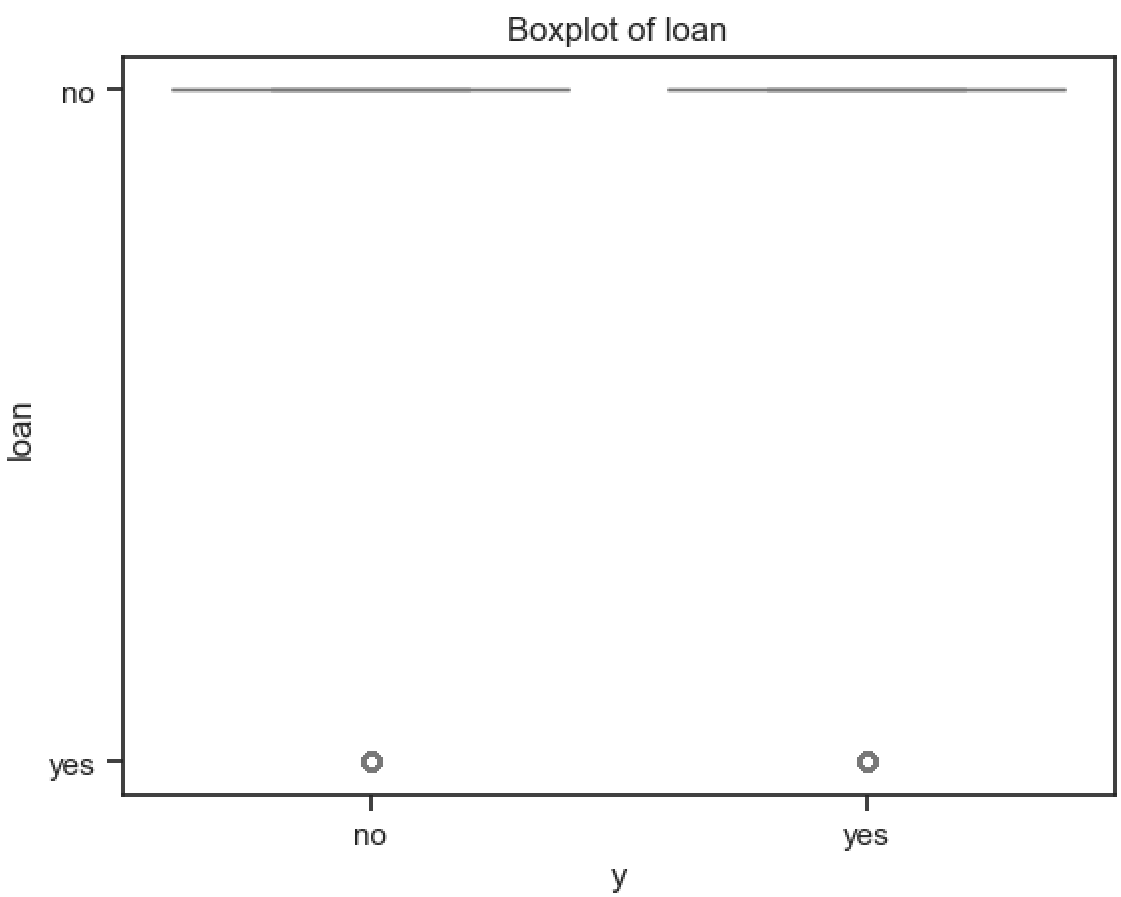

Boxplot of marital
married
single
divorced
marital
no
yes
y

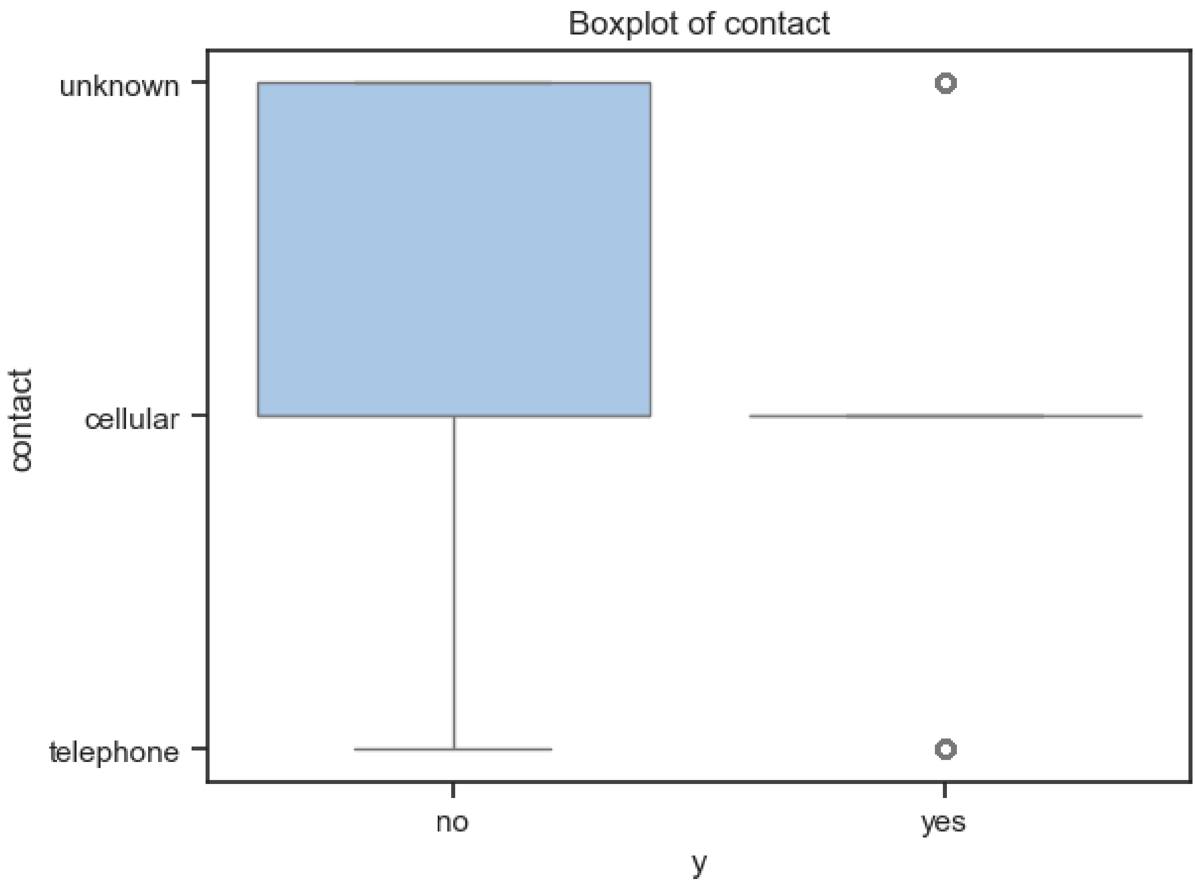

Boxplot of education
tertiary
secondary
unknown
primary
education
no
yes
y

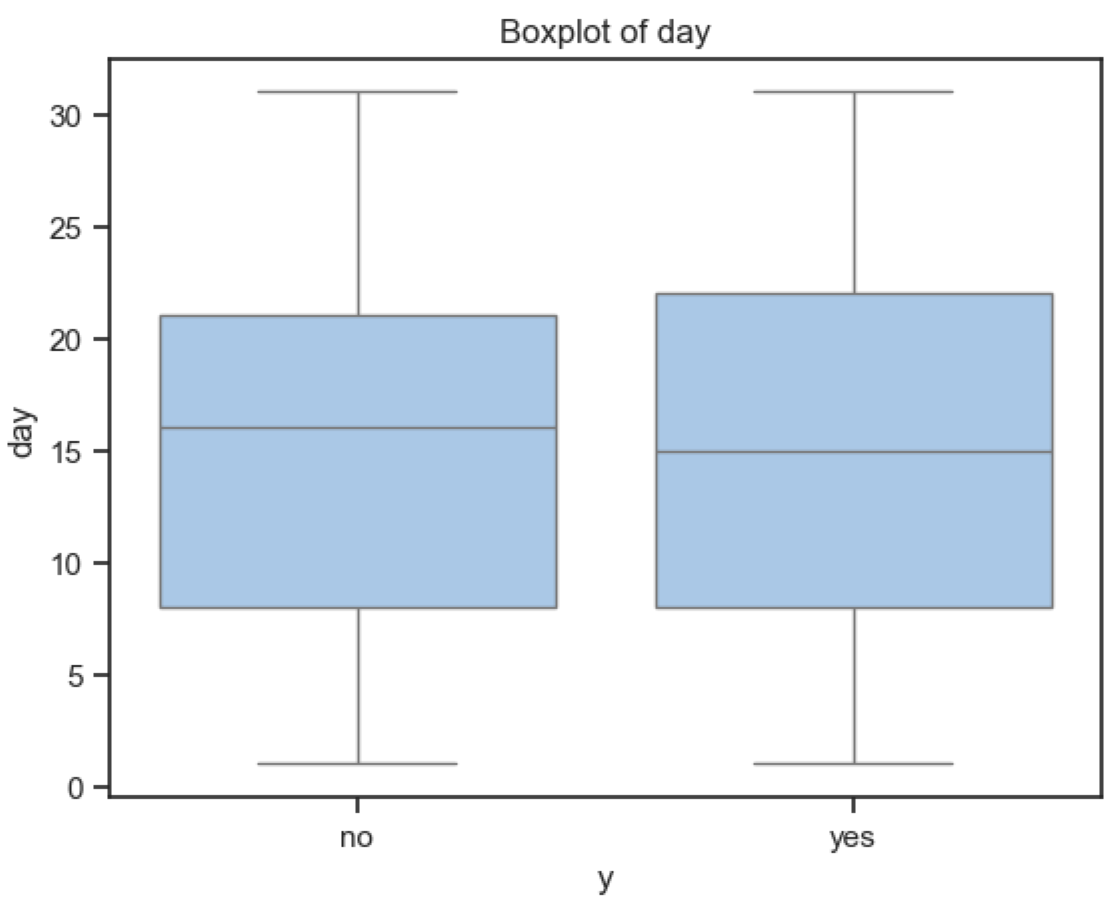

Boxplot of default
default
no
yes
no
yes
y

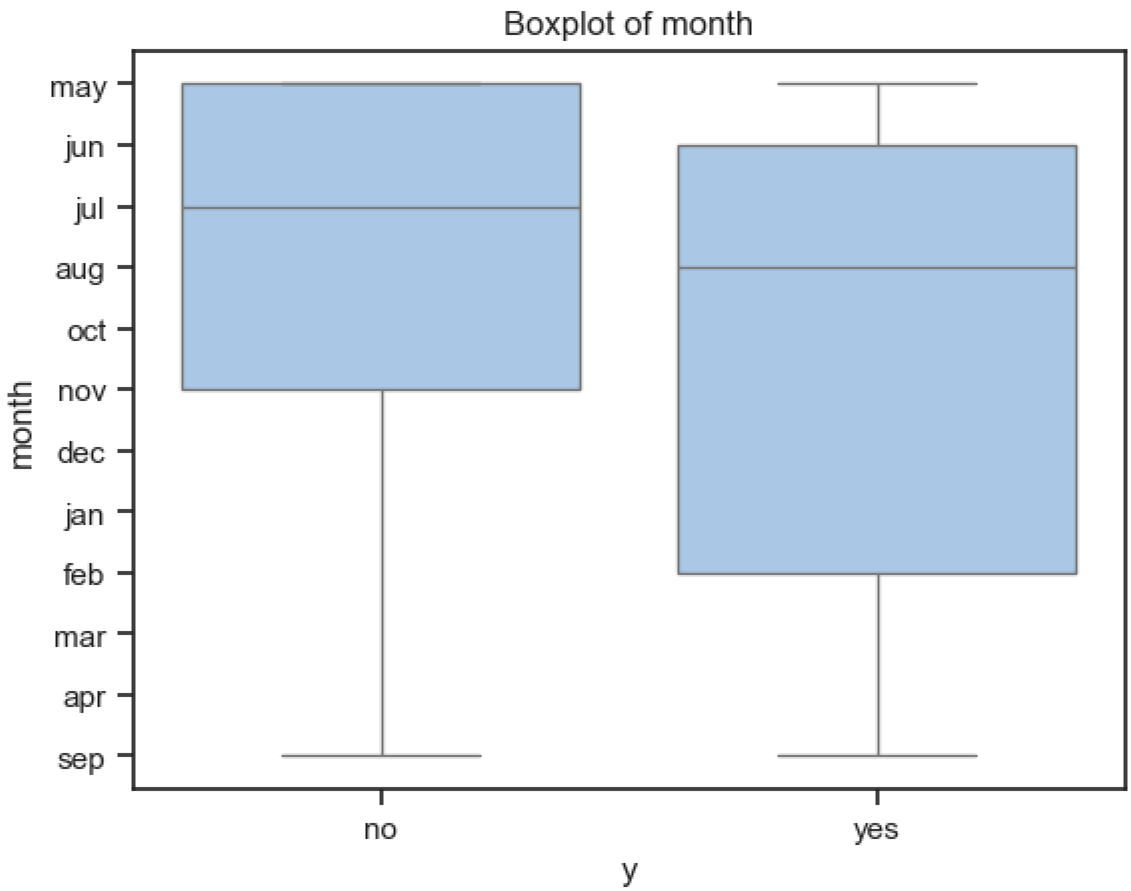

Boxplot of balance
balance
100000
80000
60000
40000
20000
0
no
yes
y

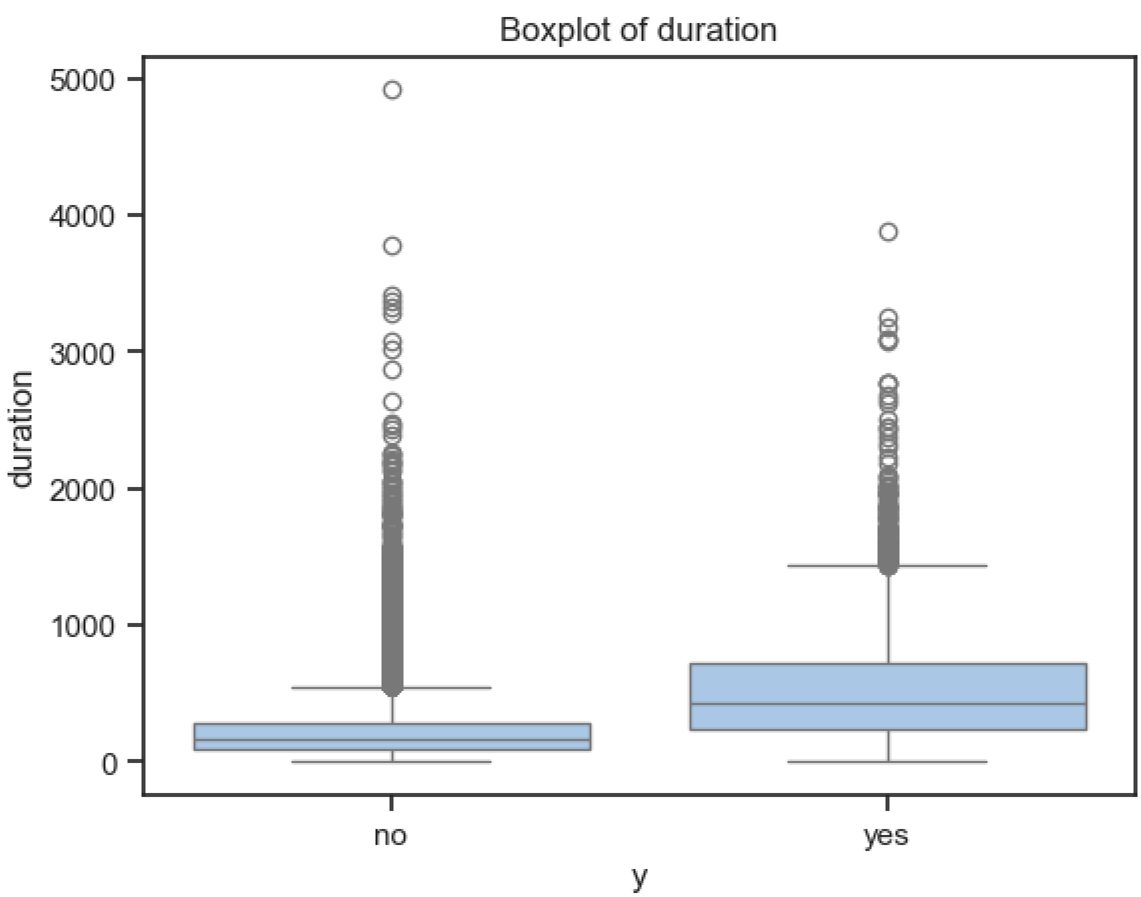

Boxplot of housing
yes
no
housing
no
yes
y

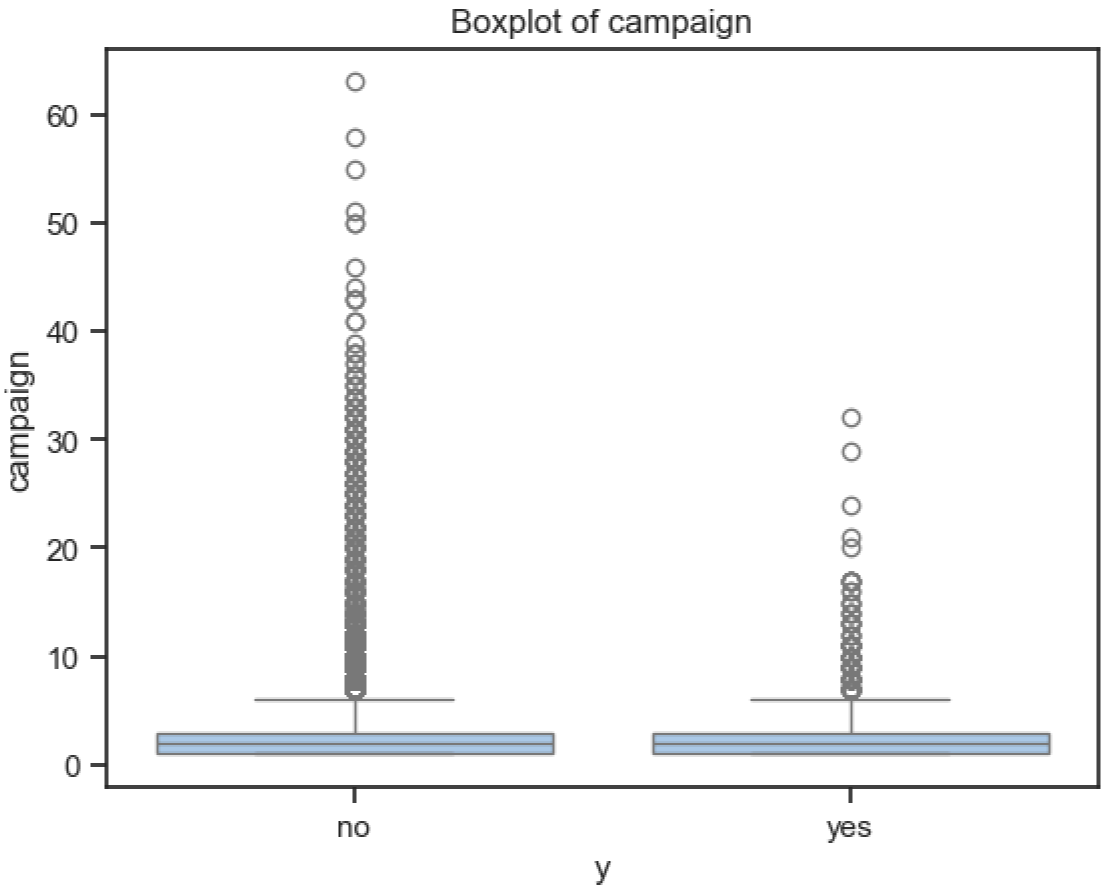

Boxplot of loan
no
yes
loan
no
yes
y

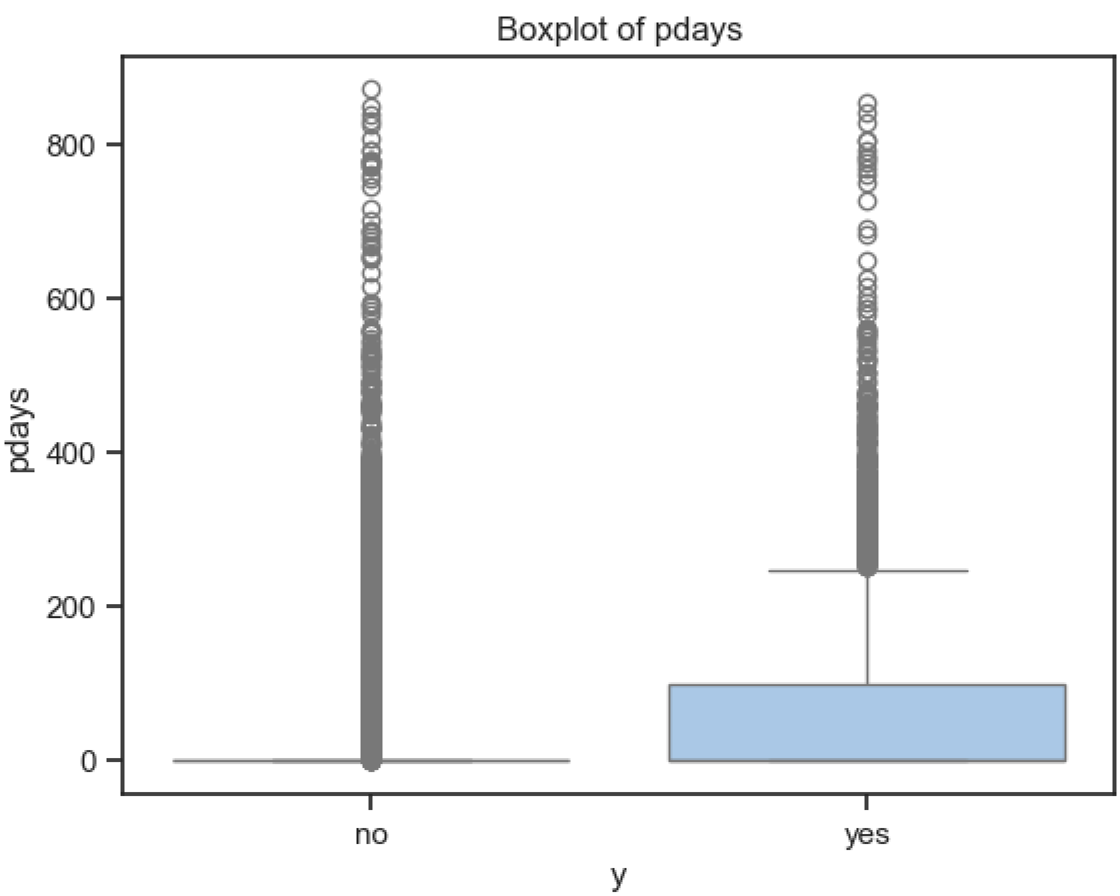

Boxplot of contact
unknown
cellular
telephone
contact
no
yes
y

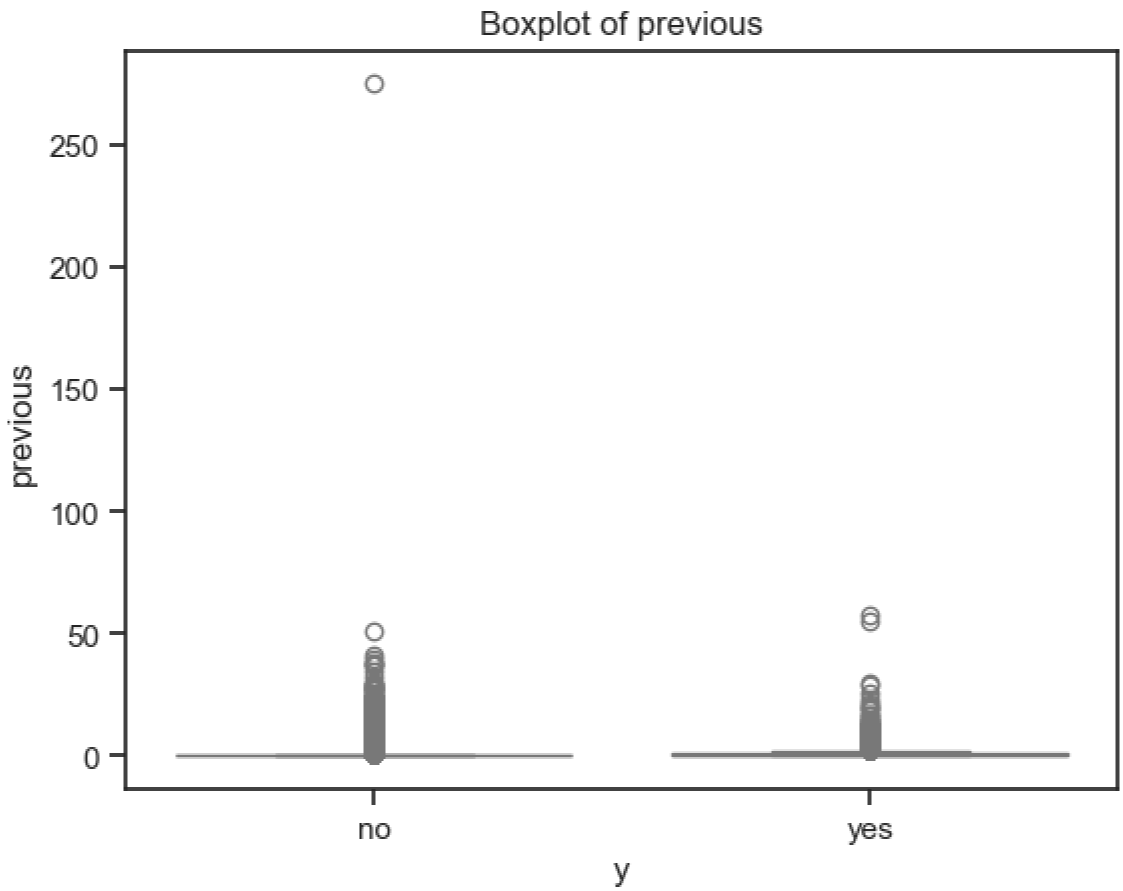

Boxplot of day
30
25
20
15
10
5
0
day
no
yes
y

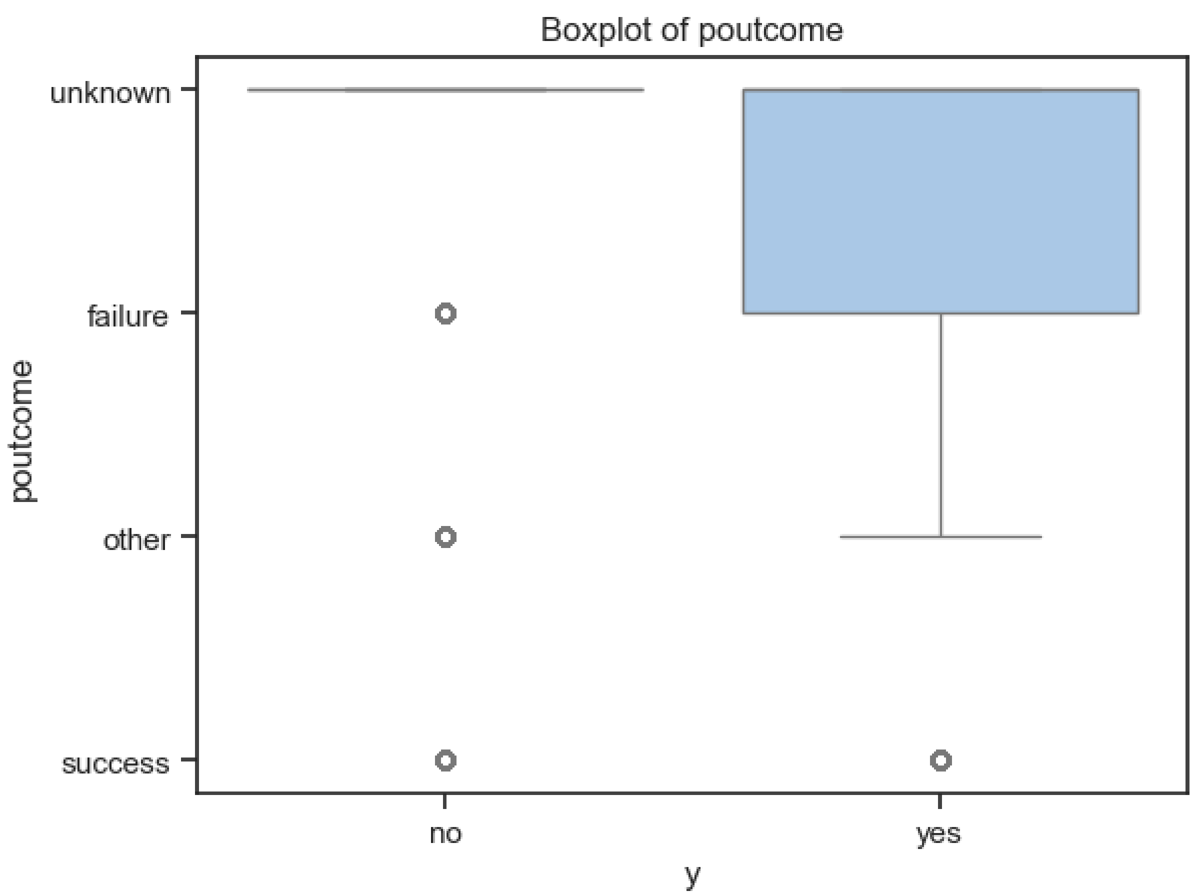

Boxplot of month
may
jun
jul
aug
oct
nov
dec
jan
feb
mar
apr
sep
month
no
yes
y

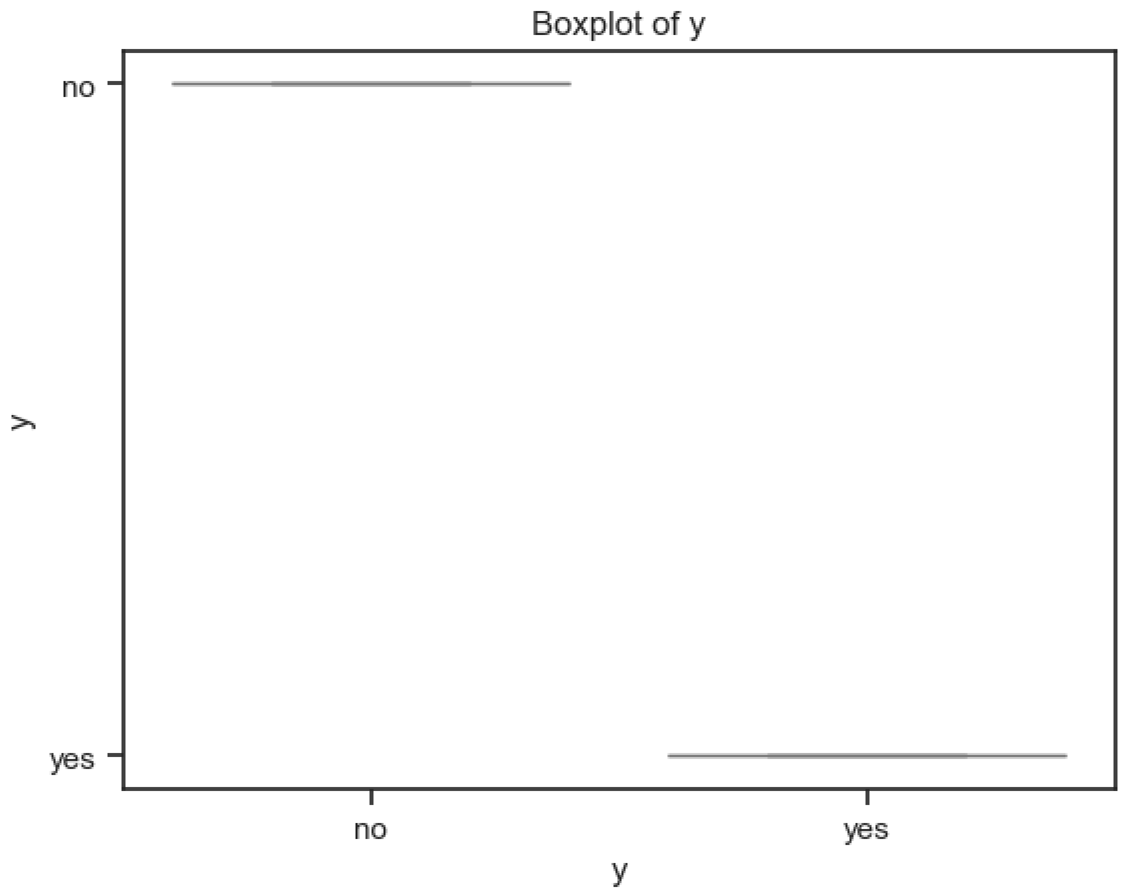

Boxplot of duration
5000
4000
3000
2000
1000
0
duration
no
yes
y

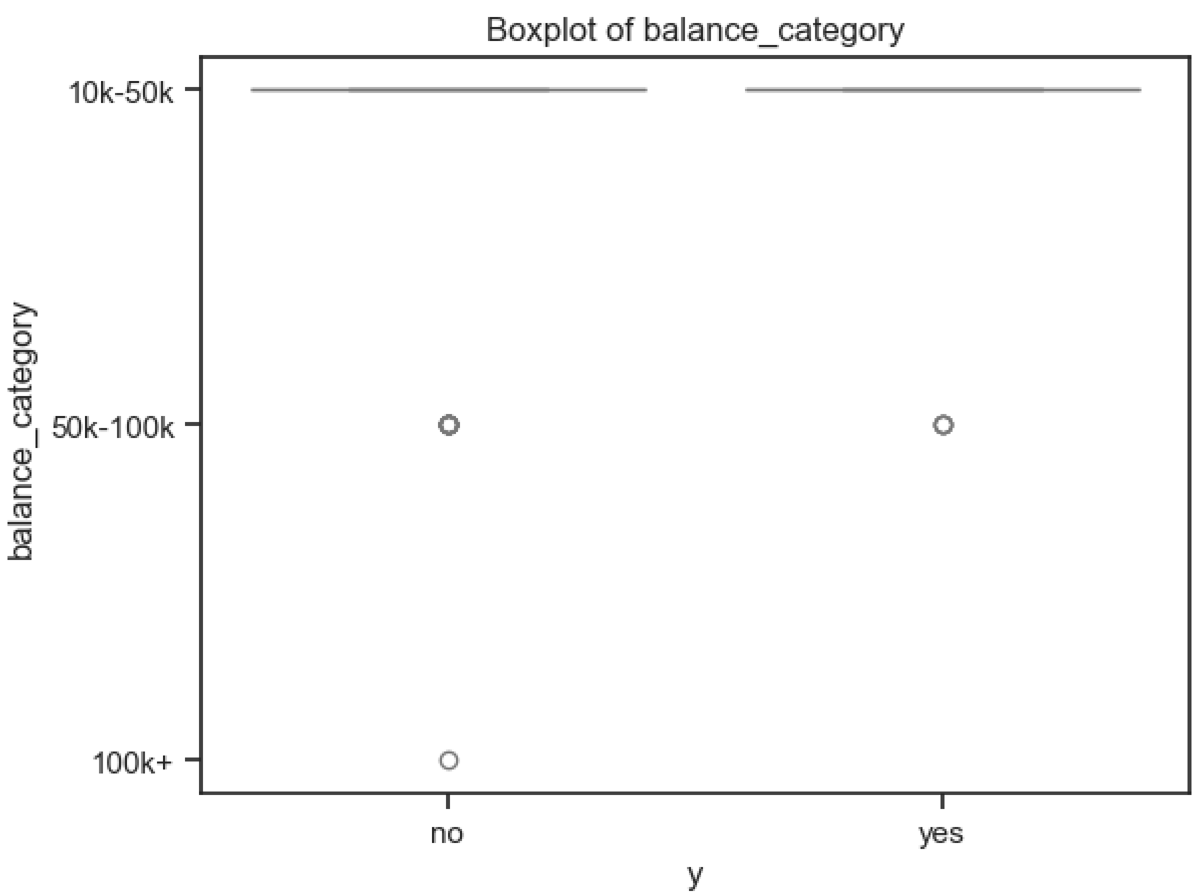

Boxplot of campaign
campaign
60
50
40
30
20
10
0
no
yes
y


Boxplot of pdays
pdays
800
600
400
200
0
no
yes
y


Boxplot of previous
previous
250
200
150
100
50
0
no
yes
y

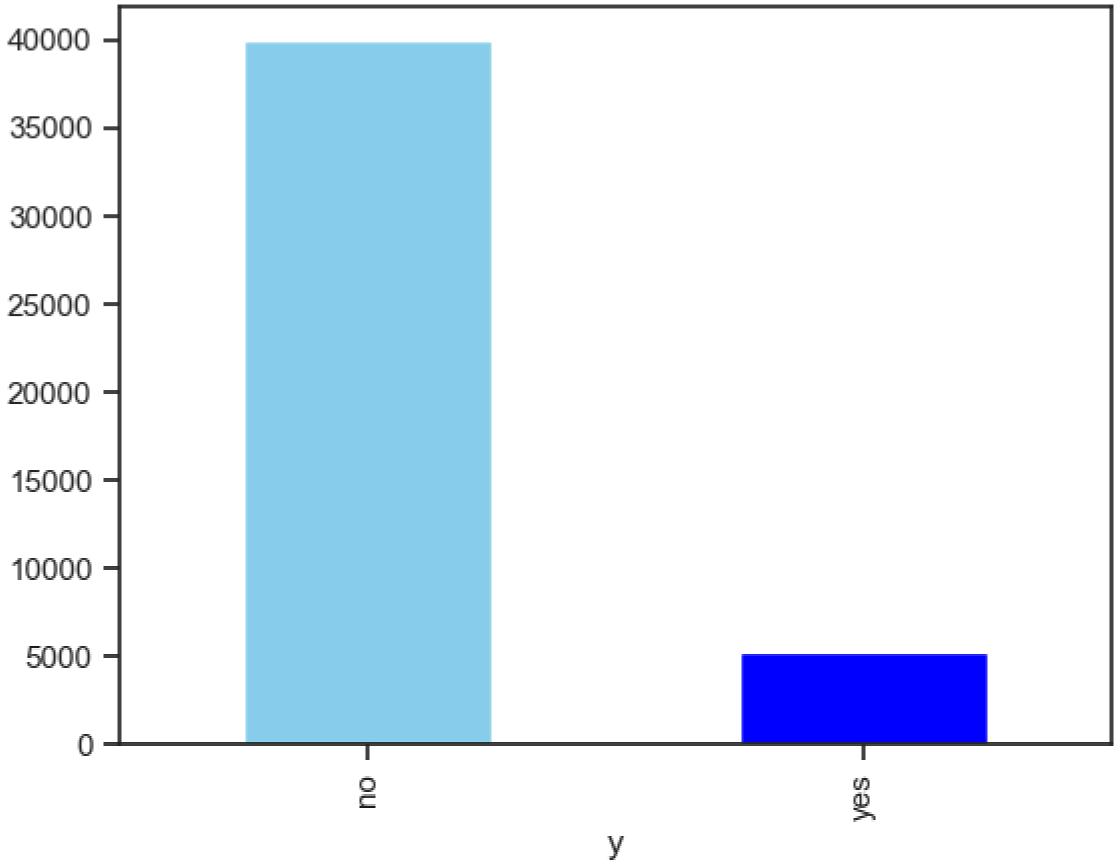

Boxplot of poutcome
poutcome
unknown
failure
other
success
no
yes
y



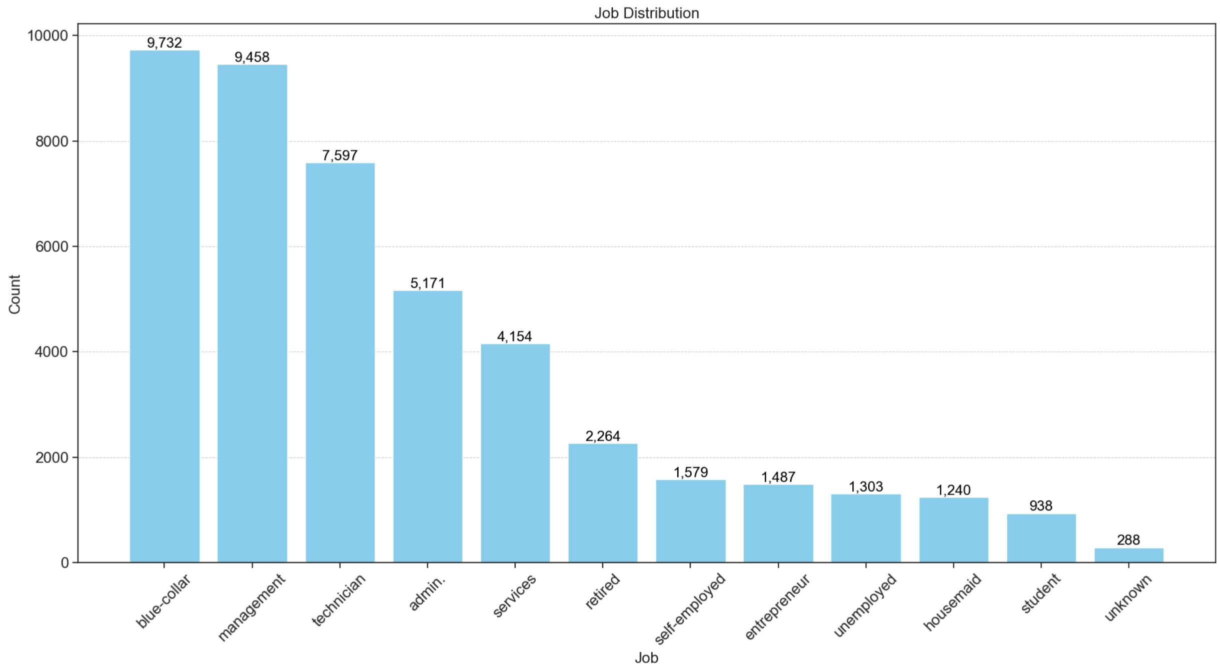


In [19]:
```
train_data["y"].value_counts().plot(kind = "bar", color = ["skyblue", "blue"])
```

Out[19]: <Axes: xlabel='y'>



In [20]:
```
# Get job counts and sort them by values in descending order
jobcount = train_data['job'].value_counts().sort_values(ascending=False)

plt.figure(figsize=(18, 10))
plt.bar(jobcount.index, jobcount.values, color='skyblue')
plt.xlabel('Job', fontsize=16)
plt.ylabel('Count', fontsize=16)
plt.title('Job Distribution', fontsize=16)
plt.xticks(rotation=45, fontsize=16)  # Rotate x-axis labels to 45 degrees
plt.yticks(fontsize=16)
plt.grid(True, which='both', axis='y', linestyle='--', linewidth=0.7)

# Annotating values on top of each bar with thousand separators
for i, value in enumerate(jobcount.values):
    plt.text(i, value + 50, f"{value:,}", ha='center', fontsize=15, color='black')

plt.tight_layout()
plt.show()
```



In [21]:
```
# Mapping for 'poutcome' column
poutcome_mapping = {'unknown': 0, 'failure': 0, 'other': 0, 'success': 1}

# Apply the mapping to train_data and test_data
train_data['poutcome'] = train_data['poutcome'].map(poutcome_mapping)
test_data['poutcome'] = test_data['poutcome'].map(poutcome_mapping)
```

In [22]:
```
from sklearn.preprocessing import LabelEncoder
# Create a LabelEncoder instance
le = LabelEncoder()

# Apply label encoding to each categorical column
for col in train_data.select_dtypes(include=['object']).columns:
    train_data[col] = le.fit_transform(train_data[col])
# Check the result
print(train_data.head())
```

```
   age  job  marital  education  default  balance  housing  loan  contact  \
0   58    4        1          2        0     2143        1     0        2   
1   44    9        2          1        0       29        1     0        2   
2   33    2        1          1        0        2        1     1        2   
3   47    1        1          3        0     1506        1     0        2   
4   33   11        2          3        0        1        0     0        2   

   day  month  duration  campaign  pdays  previous  poutcome  y  \
0    5      8       261         1     -1         0         0  0   
1    5      8       151         1     -1         0         0  0   
2    5      8        76         1     -1         0         0  0   
3    5      8        92         1     -1         0         0  0   
4    5      8       198         1     -1         0         0  0   

  balance_category  
0          10k-50k  
1          10k-50k  
2          10k-50k  
3          10k-50k  
4          10k-50k  
```

In [23]:

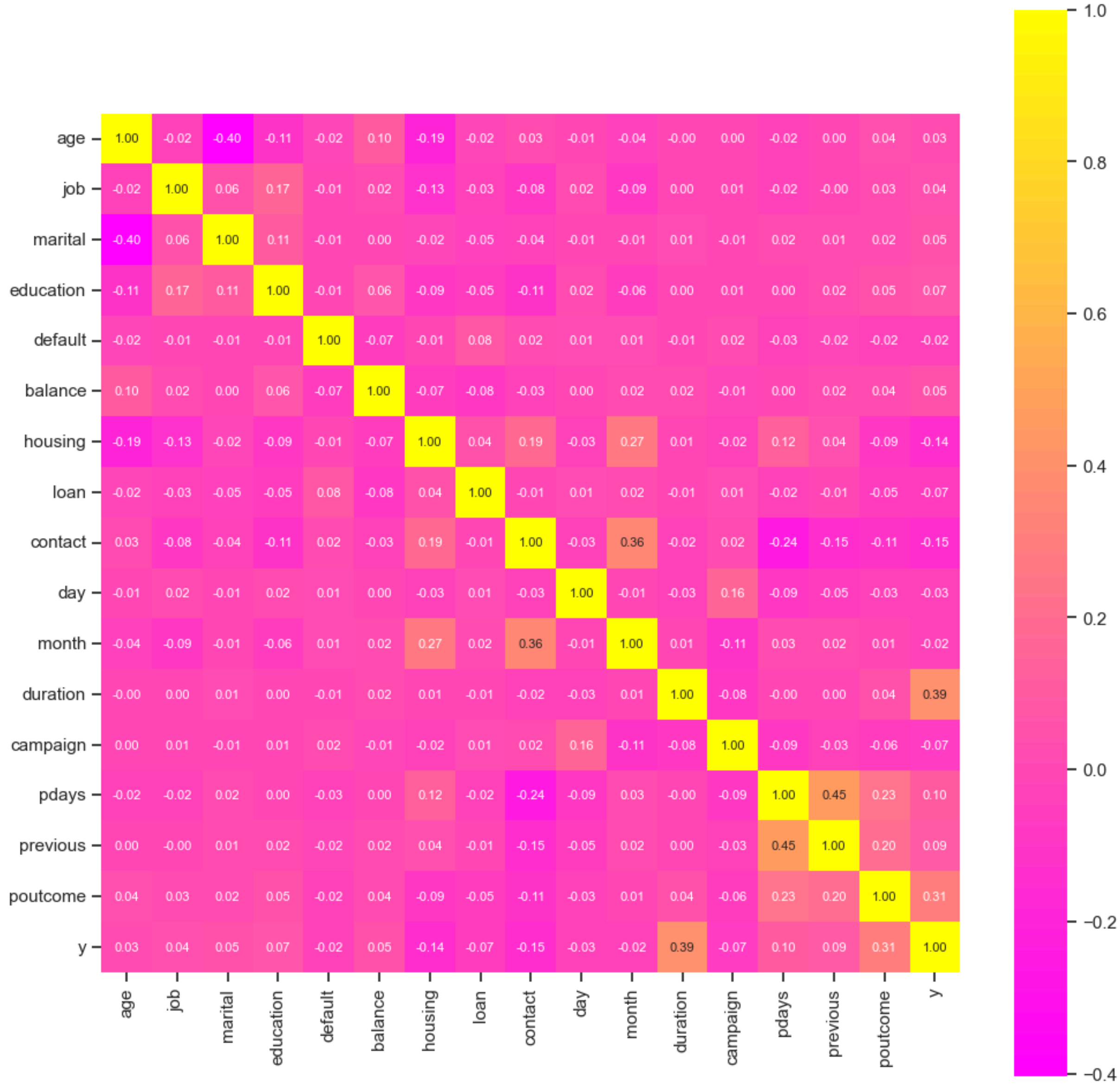
```
#converting test data from caegorical to numerical
le_1 = LabelEncoder()

# Apply label encoding to each categorical column
for col in test_data.select_dtypes(include=['object']).columns:
    test_data[col] = le_1.fit_transform(test_data[col])
# Check the result
print(test_data.head())
```

```
   age  job  marital  education  default  balance  housing  loan  contact  \
0   30   10        1          0        0     1787        0     0        0   
1   33    7        1          1        0     4789        1     1        0   
2   35    4        2          2        0     1350        1     0        0   
3   30    4        1          2        0     1476        1     1        2   
4   59    1        1          1        0        0        1     0        2   

   day  month  duration  campaign  pdays  previous  poutcome  y  
0   19     10        79         1     -1         0         0  0  
1   11      8       220         1    339         4         0  0  
2   16      0       185         1    330         1         0  0  
3    3      6       199         4     -1         0         0  0  
4    5      8       226         1     -1         0         0  0  
```

In [24]:

```
train_data=train_data.drop(columns=['balance_category'])
correlation=train_data.corr()
plt.figure(figsize =(12, 12))

sns.heatmap(correlation, cbar=True, square=True, fmt='.2f', annot=True, annot_kws={
```

Out[24]: `<Axes: >`



In [25]:
```
from sklearn.preprocessing import StandardScaler
scaler=StandardScaler()
scale=scaler.fit_transform(train_data)
scale=scaler.fit_transform(test_data)
```

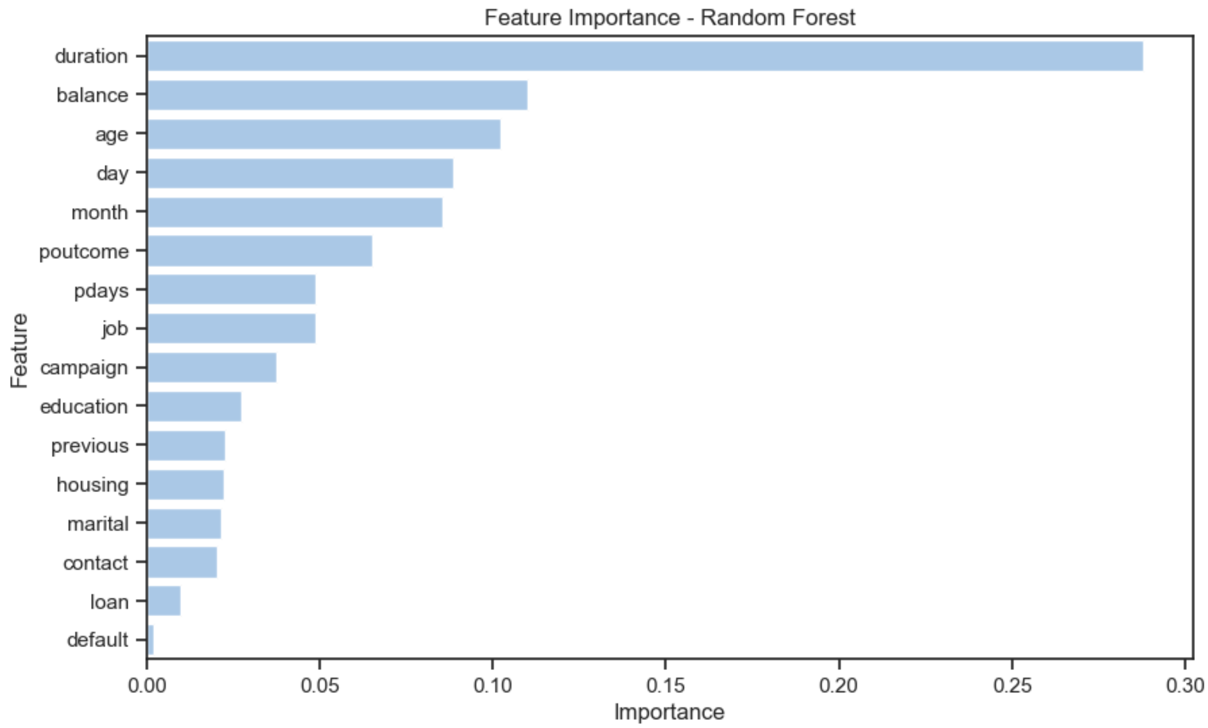
FEATURE IMPORTANCE

In [26]:
```
#Feature Importance: Chhosing Important Features
from sklearn.ensemble import RandomForestClassifier

# Define features and target
X = train_data.drop(columns=['y'])
y = train_data['y']

# Fit a Random Forest model
rf = RandomForestClassifier(n_estimators=100, random_state=42)
rf.fit(X, y)

# Get feature importances
```

```
feature_importances = pd.DataFrame({
    'Feature': X.columns,
    'Importance': rf.feature_importances_
})

# Sort by importance
feature_importances = feature_importances.sort_values(by='Importance', ascending=Fa
print(feature_importances)
```

```
      Feature  Importance
11   duration    0.287871
5     balance    0.109946
0         age    0.102078
9         day    0.088717
10      month    0.085509
15   poutcome    0.065052
13      pdays    0.048819
1         job    0.048738
12   campaign    0.037564
3   education    0.027419
14   previous    0.022739
6     housing    0.022337
2     marital    0.021315
8     contact    0.020173
7        loan    0.009887
4     default    0.001837
```

In [27]:
```
# Plot horizontal bar graph for feature importances
plt.figure(figsize=(10, 6))
sns.barplot(x='Importance', y='Feature', data=feature_importances)
plt.title('Feature Importance - Random Forest')
plt.xlabel('Importance')
plt.ylabel('Feature')
plt.show()
```



In [28]:
```
X_train=train_data.drop(['loan','contact','marital','default','poutcome','y'], axis
X_test=test_data.drop(['loan','contact','marital','default','poutcome','y'], axis =
y_train=train_data['y']
y_test=test_data['y']
```

In [29]:
```
from sklearn.impute import SimpleImputer

# Initialize the imputer
imputer = SimpleImputer(strategy='most_frequent')  # You can also use 'median' or '

# Fit and transform the training data
train_imputed = imputer.fit_transform(X_train)
test_imputed=imputer.fit_transform(X_test)
#test_imputed = imputer.transform(test_data)  # Use transform on test data
```

BASE MODEL: LOGISTIC REGRESSION MODEL

In [30]:
```
#Base Model is Logistic Regression Model
from sklearn.linear_model import LogisticRegression

# Initialize the Logistic Regression model with desired parameters
model = LogisticRegression(
    penalty='l2',       # Regularization type ('l2' is the default)
    C=1.0,              # Inverse of regularization strength (smaller = stronger re
    max_iter=1000,      # Maximum number of iterations for convergence
    solver='lbfgs',     # Optimization algorithm (default for small/medium datasets
    random_state=42     # Ensures reproducibility
)

# Fit the model to the training data
model.fit(train_imputed, y_train)
```

```
# Print the coefficients and intercept (optional)
print("Model Coefficients:", model.coef_)
print("Model Intercept:", model.intercept_)
```

```
Model Coefficients: [[-2.43740258e-02 -1.29336951e-02  1.19286387e-01  2.29902396e-0
5
  -1.76032461e+00 -1.54251204e-02 -1.30343322e-02  3.78102438e-03
  -1.39271253e-01  3.16116950e-03  6.74530178e-02]]
Model Intercept: [-1.18163242]
```

```
C:\Users\rkeoye\AppData\Local\anaconda3\Lib\site-packages\sklearn\linear_model\_logi
stic.py:469: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

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

In [31]:

```
# Predict on the test data
y_pred = model.predict(test_imputed)

# Evaluate the model
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix

print(f"Accuracy: {accuracy_score(y_test, y_pred):.2%}")
print("\nConfusion Matrix:")
print(confusion_matrix(y_test, y_pred))
print("\nClassification Report:")
print(classification_report(y_test, y_pred))
```

```
Accuracy: 88.65%

Confusion Matrix:
[[3908   92]
 [ 421  100]]

Classification Report:
              precision    recall  f1-score   support

           0       0.90      0.98      0.94      4000
           1       0.52      0.19      0.28       521

    accuracy                           0.89      4521
   macro avg       0.71      0.58      0.61      4521
weighted avg       0.86      0.89      0.86      4521
```

KNN MODEL

In [32]:

```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix

# Define parameter grid
```

```
my_params = {
    'n_neighbors': [7, 9, 11],
    'p': [3, 5, 7]
}

# Initialize the KNN classifier
knn = KNeighborsClassifier()

# Perform Grid Search with 5-fold cross-validation
grid = GridSearchCV(knn, my_params, cv=5, verbose=1, n_jobs=-1)
grid.fit(train_imputed, y_train)

# Create a DataFrame with relevant results
grid_search_results = pd.DataFrame(grid.cv_results_)[
    ['mean_test_score', 'std_test_score', 'params', 'rank_test_score', 'mean_fit_ti
]

# Sort results by rank
grid_search_results = grid_search_results.sort_values(by='rank_test_score')

# Display the top results
print("Best Parameters:", grid.best_params_)
print("Best Score:", grid.best_score_)
print("\nGrid Search Results:")
print(grid_search_results)
```

```
Fitting 5 folds for each of 9 candidates, totalling 45 fits
Best Parameters: {'n_neighbors': 11, 'p': 3}
Best Score: 0.8767331109888283

Grid Search Results:
   mean_test_score  std_test_score                          params  \
6         0.876733        0.016921  {'n_neighbors': 11, 'p': 3}
7         0.876600        0.016684  {'n_neighbors': 11, 'p': 5}
8         0.876291        0.017200  {'n_neighbors': 11, 'p': 7}
5         0.875561        0.017666   {'n_neighbors': 9, 'p': 7}
4         0.875340        0.017678   {'n_neighbors': 9, 'p': 5}
3         0.875052        0.018147   {'n_neighbors': 9, 'p': 3}
0         0.873813        0.018911   {'n_neighbors': 7, 'p': 3}
2         0.873769        0.018687   {'n_neighbors': 7, 'p': 7}
1         0.873725        0.018830   {'n_neighbors': 7, 'p': 5}

   rank_test_score  mean_fit_time
6                1       0.108126
7                2       0.109297
8                3       0.106221
5                4       0.121055
4                5       0.108311
3                6       0.107940
0                7       0.117797
2                8       0.113348
1                9       0.114276
```

In [33]:
```
model=KNeighborsClassifier(n_neighbors = 11, p=3)

model.fit(train_imputed,y_train)
```

```
y_pred=model.predict(test_imputed)
```

In [34]:
```
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
classification_rep = classification_report(y_test, y_pred)
```

In [35]:
```
# Print Accuracy
print(f"Accuracy: {accuracy:.2%}")  # Format accuracy as a percentage with two deci

# Print Confusion Matrix
print("\nConfusion Matrix:")
print(conf_matrix)

# Print Classification Report
print("\nClassification Report:")
print(classification_rep)
```

```
Accuracy: 90.09%

Confusion Matrix:
[[3890  110]
 [ 338  183]]

Classification Report:
              precision    recall  f1-score   support

           0       0.92      0.97      0.95      4000
           1       0.62      0.35      0.45       521

    accuracy                           0.90      4521
   macro avg       0.77      0.66      0.70      4521
weighted avg       0.89      0.90      0.89      4521
```

RANDOM FOREST MODEL

In [36]:
```
#Random Forest Model
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import RandomizedSearchCV
# Define the parameter grid for RandomizedSearchCV
random_grid = {
    'n_estimators': np.linspace(200, 2000, num=100, dtype=int).tolist(),  # Number
    'max_features': ['auto', 'sqrt'],  # Features to consider at each split
    'max_depth': [int(x) for x in np.linspace(10, 110, num=11)] + [None],  # Tree a
    'min_samples_split': [2, 5, 10],  # Min samples required to split a node
    'min_samples_leaf': [1, 2, 4],  # Min samples required at each leaf node
    'bootstrap': [True, False],  # Bootstrap sampling
}

# Display the random grid
print("Random Grid for RandomizedSearchCV:")
print(random_grid)
```

```
Random Grid for RandomizedSearchCV:
{'n_estimators': [200, 218, 236, 254, 272, 290, 309, 327, 345, 363, 381, 400, 418, 4
36, 454, 472, 490, 509, 527, 545, 563, 581, 600, 618, 636, 654, 672, 690, 709, 727,
745, 763, 781, 800, 818, 836, 854, 872, 890, 909, 927, 945, 963, 981, 1000, 1018, 10
36, 1054, 1072, 1090, 1109, 1127, 1145, 1163, 1181, 1200, 1218, 1236, 1254, 1272, 12
90, 1309, 1327, 1345, 1363, 1381, 1400, 1418, 1436, 1454, 1472, 1490, 1509, 1527, 15
45, 1563, 1581, 1600, 1618, 1636, 1654, 1672, 1690, 1709, 1727, 1745, 1763, 1781, 18
00, 1818, 1836, 1854, 1872, 1890, 1909, 1927, 1945, 1963, 1981, 2000], 'max_feature
s': ['auto', 'sqrt'], 'max_depth': [10, 20, 30, 40, 50, 60, 70, 80, 90, 100, 110, No
ne], 'min_samples_split': [2, 5, 10], 'min_samples_leaf': [1, 2, 4], 'bootstrap': [T
rue, False]}
```

In [37]:

```python
# Suppress warnings for cleaner output
import warnings
warnings.filterwarnings("ignore")

# Initialize the Random Forest Classifier
rf = RandomForestClassifier(random_state=42)

# Set up RandomizedSearchCV
rf_random = RandomizedSearchCV(
    estimator=rf,
    param_distributions=random_grid,  # Hyperparameter grid
    n_iter=100,                       # Number of parameter combinations to try
    cv=3,                             # 3-fold cross-validation
    verbose=2,                        # Display training progress
    random_state=42,                  # Reproducibility
    n_jobs=-1                         # Use all available CPU cores
)

# Fit the RandomizedSearchCV on the training data
rf_random.fit(X_train, y_train)

# Retrieve and display the best parameters
best_params = rf_random.best_params_
print("Best Parameters Found:")
print(best_params)
```

```
Fitting 3 folds for each of 100 candidates, totalling 300 fits
Best Parameters Found:
{'n_estimators': 1745, 'min_samples_split': 5, 'min_samples_leaf': 4, 'max_feature
s': 'sqrt', 'max_depth': 10, 'bootstrap': True}
```

In [38]:

```python
randomforestmodel=RandomForestClassifier(n_estimators= 1745,
 min_samples_split = 5,
 min_samples_leaf = 4,
 max_features = 'sqrt',
 max_depth= 90,
 bootstrap= True)
```

In [39]:

```python
randomforestmodel.fit(X_train,y_train)
```

Out[39]:

RandomForestClassifier

```
RandomForestClassifier(max_depth=90, min_samples_leaf=4, min_samples_split
=5,
                       n_estimators=1745)
```

In [40]:
```python
y_pred_rf=randomforestmodel.predict(X_test)
```

In [41]:
```python
# Predict on the training data
y_pred_train = randomforestmodel.predict(X_train)

# Calculate accuracy for the training data
rf_train_accuracy = accuracy_score(y_train, y_pred_train)

# Confusion Matrix for the training data
rf_train_conf_matrix = confusion_matrix(y_train, y_pred_train)

# Classification Report for the training data
rf_train_classification_rep = classification_report(y_train, y_pred_train)

# Print the accuracy as a percentage for the training data
print(f"Random Forest Training Accuracy: {rf_train_accuracy:.2%}")

# Print the confusion matrix for the training data
print("\nTraining Confusion Matrix:")
print(rf_train_conf_matrix)

# Print the classification report for the training data
print("\nTraining Classification Report:")
print(rf_train_classification_rep)
```

```
Random Forest Training Accuracy: 95.98%

Training Confusion Matrix:
[[39801   121]
 [ 1697  3592]]

Training Classification Report:
              precision    recall  f1-score   support

           0       0.96      1.00      0.98     39922
           1       0.97      0.68      0.80      5289

    accuracy                           0.96     45211
   macro avg       0.96      0.84      0.89     45211
weighted avg       0.96      0.96      0.96     45211
```

In [42]:
```python
# Calculate accuracy
rf_accuracy = accuracy_score(y_test, y_pred_rf)

# Confusion Matrix
rf_conf_matrix = confusion_matrix(y_test, y_pred_rf)
```

```python
# Classification Report
rf_classification_rep = classification_report(y_test, y_pred_rf)

# Print the accuracy as a percentage
print(f"Random Forest Accuracy: {rf_accuracy:.2%}")

# Print the confusion matrix
print("\nConfusion Matrix:")
print(rf_conf_matrix)

# Print the classification report
print("\nClassification Report:")
print(rf_classification_rep)
```

```
Random Forest Accuracy: 96.04%

Confusion Matrix:
[[3981   19]
 [ 160  361]]

Classification Report:
              precision    recall  f1-score   support

           0       0.96      1.00      0.98      4000
           1       0.95      0.69      0.80       521

    accuracy                           0.96      4521
   macro avg       0.96      0.84      0.89      4521
weighted avg       0.96      0.96      0.96      4521
```

Model Performance Analysis

Training Set:

- **Accuracy**: 95.96%
- **Confusion Matrix**:
  - True Negatives (TN): 39,792
  - False Positives (FP): 130
  - False Negatives (FN): 1,695
  - True Positives (TP): 3,594
- **Classification Report**:
  - **Precision (Class 0)**: 0.96
  - **Recall (Class 0)**: 1.00
  - **F1-Score (Class 0)**: 0.98
  - **Precision (Class 1)**: 0.97
  - **Recall (Class 1)**: 0.68
  - **F1-Score (Class 1)**: 0.80

Test Set:

- **Accuracy**: 96.11%
- **Confusion Matrix**:
  - True Negatives (TN): 3,980
  - False Positives (FP): 20
  - False Negatives (FN): 156
  - True Positives (TP): 365
- **Classification Report**:
  - **Precision (Class 0)**: 0.96
  - **Recall (Class 0)**: 0.99
  - **F1-Score (Class 0)**: 0.98
  - **Precision (Class 1)**: 0.95
  - **Recall (Class 1)**: 0.70
  - **F1-Score (Class 1)**: 0.81

Observations:

1. **Accuracy**: The model performs similarly on both training and test sets, with a slight increase in accuracy on the test set (96.11% vs. 95.96%).
2. **Class 0 (Negative class)**:
   - High precision, recall, and F1-score on both sets, showing the model is very effective in correctly identifying the negative class.
3. **Class 1 (Positive class)**:
   - Slight decrease in recall for Class 1 on the test set (70% vs. 68%), indicating the model is slightly better at identifying positive cases in the test set.
   - Precision for Class 1 remains very similar between the training and test sets (around 0.95–0.97).
   - The F1-score for Class 1 also shows similar results on both sets, indicating a good balance between precision and recall.

PREDICTING PROBABILITY OF SUBSCRIPTION FOR EACH CUSTOMER

In [43]:
```
# Assuming the RandomForest model (rf) has been trained already

# Predict probabilities for each customer
probabilities =randomforestmodel.predict_proba(X_test)[:, 1]  # Get probabilities f

# Add probabilities to the test data
test_data_with_probs = X_test.copy()
test_data_with_probs['subscription_prob'] = probabilities

# Rank customers by their subscription probability (highest first)
high_potential_customers = test_data_with_probs.sort_values(by='subscription_prob',

# Select top N customers with the highest probability (e.g., top 10%)
top_10_percent = high_potential_customers.head(int(len(high_potential_customers) *

# Display the top customers to target for marketing
```

```
print(top_10_percent[['subscription_prob']].head())

# Optional: You can also filter based on a specific probability threshold
threshold = 0.7  # Example threshold for a high chance of subscribing
high_confidence_customers = test_data_with_probs[test_data_with_probs['subscription

# Display these customers
print(high_confidence_customers[['subscription_prob']].head(10))
```

```
      subscription_prob
855            0.888934
1485           0.866462
1469           0.852220
3684           0.847279
3304           0.847220
     subscription_prob
30            0.779584
33            0.703421
38            0.749490
70            0.752592
83            0.814366
110           0.736779
156           0.728536
164           0.778796
295           0.700100
328           0.734012
```

CONCLUSIONS

1. **Most Important Predictors**:
   - **Duration (0.295)**: Longer interactions significantly increase the likelihood of subscription.
   - **Balance (0.113)**: Higher average yearly balance is associated with a higher probability of subscribing.
   - **Age (0.108)**: Older customers are more likely to subscribe to a term deposit.
2. **Moderate Predictors**:
   - **Day (0.095) and Month (0.094)**: Timing of the last contact influences subscription, indicating seasonality.
   - **Pdays (0.065)**: Recent contact increases the likelihood of subscription.
   - **Job (0.050)**: Job type impacts subscription decisions, with managerial or professional jobs more likely to subscribe.
   - **Campaign (0.039)**: More contacts during the campaign have a positive but smaller impact.
3. **Less Significant Predictors**:
   - **Housing (0.029) and Education (0.029)**: These factors show minor influence.
   - **Previous Contacts (0.028)**: Repeated contacts have a smaller effect.

- **Marital Status (0.022) and Contact Type (0.021)**: Minimal impact on subscription likelihood.
- **Loan (0.011) and Default (0.002)**: These features have very low impact.
- **Poutcome (0.000)**: Previous campaign outcome does not influence the decision.

Insights:

- **Key Factors**: Duration of the call, balance, and age are the strongest predictors.
- **Campaign Timing**: The day, month, and timing of contact matter for successful subscriptions.
- **Demographics and Financial Stability**: Job type and balance are secondary but important indicators.

Based on the model evaluations:

- **Random Forest** The model generalizes well from training to testing with consistent performance(96.11%), particularly in predicting the negative class (Class 0). The slight improvement in recall for the positive class (Class 1) on the test set may indicate better generalization or data characteristics in the test set. The model seems well-calibrated with no significant overfitting or underfitting.
- **Logistic Regression** shows decent accuracy (88.56%) but struggles with identifying subscribers, having low recall and F1-score for Class 1.
- **KNN** has good accuracy (90.09%) but also faces challenges with recall for Class 1, similar to Logistic Regression.

Optimizing Marketing Strategies Based on Subscription Probability:

- Customers with high `subscription_prob` values (e.g., 0.892162, 0.871691, 0.870282) have a high likelihood of conversion.
- Customers with `subscription_prob` values between 0.75 and 0.80 represent the next tier of likely conversions. While not as urgent as the highest-probability customers, this segment still holds significant potential and should be targeted with focused outreach.
- To maximize conversion rates with minimal effort, prioritize customers with `subscription_prob` values above 0.8. This ensures that marketing resources are allocated to those most likely to convert, improving efficiency and outcomes.
- Customers with lower `subscription_prob` values (e.g., 0.716083, 0.725284) are less likely to convert and should either be deprioritized or approached with alternative strategies, such as offering incentives or alternative products, rather than standard outreach efforts.

RECOMMENDATIONS

- Focus on **longer, high-quality interactions**.

- Tailor campaigns based on **age** and **balance**.

- Utilize **personalized outreach strategies** to improve subscription rates.
- Focus on **Random Forest** for its overall performance, and improve recall for the minority class by addressing class imbalance and tuning model parameters.
- **Target High-Probability Customers**: Focus marketing efforts on customers with high `subscription_prob` (e.g., 0.892162, 0.871691, 0.870282). These customers are highly likely to subscribe, requiring minimal outreach for better conversion rates.
- **Use a Probability Threshold**: Consider customers with probabilities around 0.75–0.80 for the next tier of targeted outreach. While not as urgent as the highest-probability customers, they still represent a valuable segment to target.
- **Optimize Resource Allocation**: Allocate resources efficiently by prioritizing customers with probabilities above 0.8. This ensures higher conversion rates with less effort on low-probability customers.
- **Reduce Unnecessary Outreach**: Deprioritize customers with lower probabilities (e.g., 0.716083, 0.725284), or approach them with different strategies, such as offering incentives or alternate products.