Exploratory Data Analysis

February 19, 2025

1 importing modules

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from overview import load_bank_variables
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import RobustScaler
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans



pd.set_option('display.max_colwidth', None)  # Show full column content
pd.set_option('display.expand_frame_repr', False)  # Disable line wrapping
pd.set_option('display.max_rows', None)  # Show all rows
pd.set_option('display.max_columns', None)  # Show all columns
pd.set_option('display.width', 1000)        # Adjust column width
```

1.1 Loading Data

[2]:
```
bank_df = pd.read_csv("bank.csv")
df = bank_df.copy()
```

1.2 variables

[3]:
```
load_bank_variables()
```

[3]:
```
   Variable Name
Description
0           age
Age
1           job  Type of job (e.g., 'admin.','blue-
collar','entrepreneur','housemaid','management','retired','self-
employed','services','student','technician','unemployed','unknown')
2        marital
```

```
Marital status (e.g., 'divorced','married','single','unknown'; 'divorced' means
divorced or widowed)
3      education                                Education level (e.g., 'basic.4y
','basic.6y','basic.9y','high.school','illiterate','professional.course','univer
sity.degree','unknown')
4        default
Has credit in default?
5        balance
Average yearly balance (euros)
6        housing
Has housing loan?
7           loan
Has personal loan?
8        contact
Contact communication type (e.g., 'cellular','telephone')
9    day_of_week
Last contact day of the week
10         month
Last contact month of year (e.g., 'jan', 'feb', 'mar', …, 'nov', 'dec')
11      duration
Last contact duration in seconds (only for benchmarks, discard for real
prediction)
12      campaign
Number of contacts during this campaign (includes last contact)
13         pdays
Number of days since last contact from previous campaign (-1 means not
contacted)
14      previous
Number of contacts before this campaign
15      poutcome
Outcome of previous campaign (e.g., 'failure','nonexistent','success')
16             y
Has the client subscribed to a term deposit?
```

1.3 Data Exploration

[4]:
```python
df.head(5)
```

[4]:
```
    age          job   marital  education default  balance housing loan
contact  day month  duration  campaign  pdays  previous poutcome subscribed
0  32.0   technician    single   tertiary      no      392     yes   no
cellular    1   apr       957         2    131          2  failure         no
1  39.0   technician  divorced  secondary      no      688     yes  yes
cellular    1   apr       233         2    133          1  failure         no
2  59.0      retired   married  secondary      no     1035     yes  yes
cellular    1   apr       126         2    239          1  failure         no
3  47.0  blue-collar   married  secondary      no      398     yes  yes
```

```
cellular    1   apr      274        1    238        2  failure        no
4  54.0      retired   married  secondary      no     1004      yes   no
cellular    1   apr      479        1    307        1  failure        no
```

[5]:
```
df.tail(5)
```

[5]:
```
       age          job  marital  education default  balance housing loan
contact  day month  duration  campaign  pdays  previous poutcome subscribed
1995  20.0      student   single        NaN      no     2785      no   no
cellular   16   sep      327        2     -1         0      NaN        yes
1996  28.0       admin.   single  secondary      no      127      no   no
cellular   16   sep     1334        2     -1         0      NaN        yes
1997  81.0      retired  married    primary      no     1154      no   no
telephone   17   sep      231        1     -1         0      NaN        yes
1998  46.0     services  married    primary      no     4343     yes   no
NaN    20   sep      185        1     -1         0      NaN        yes
1999  40.0  entrepreneur  married  secondary      no     6403      no   no
cellular   22   sep      208        2     -1         0      NaN        yes
```

[6]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2000 entries, 0 to 1999
Data columns (total 17 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   age         1988 non-null   float64
 1   job         1990 non-null   object
 2   marital     2000 non-null   object
 3   education   1896 non-null   object
 4   default     2000 non-null   object
 5   balance     2000 non-null   int64
 6   housing     2000 non-null   object
 7   loan        2000 non-null   object
 8   contact     1809 non-null   object
 9   day         2000 non-null   int64
 10  month       2000 non-null   object
 11  duration    2000 non-null   int64
 12  campaign    2000 non-null   int64
 13  pdays       2000 non-null   int64
 14  previous    2000 non-null   int64
 15  poutcome    1546 non-null   object
 16  subscribed  2000 non-null   object
dtypes: float64(1), int64(6), object(10)
memory usage: 265.8+ KB
```

the dataset countains 2000 rows and 17 columns both numerical and categorical

- `numerical : age , balance , duration , compaign , pdays , previous`

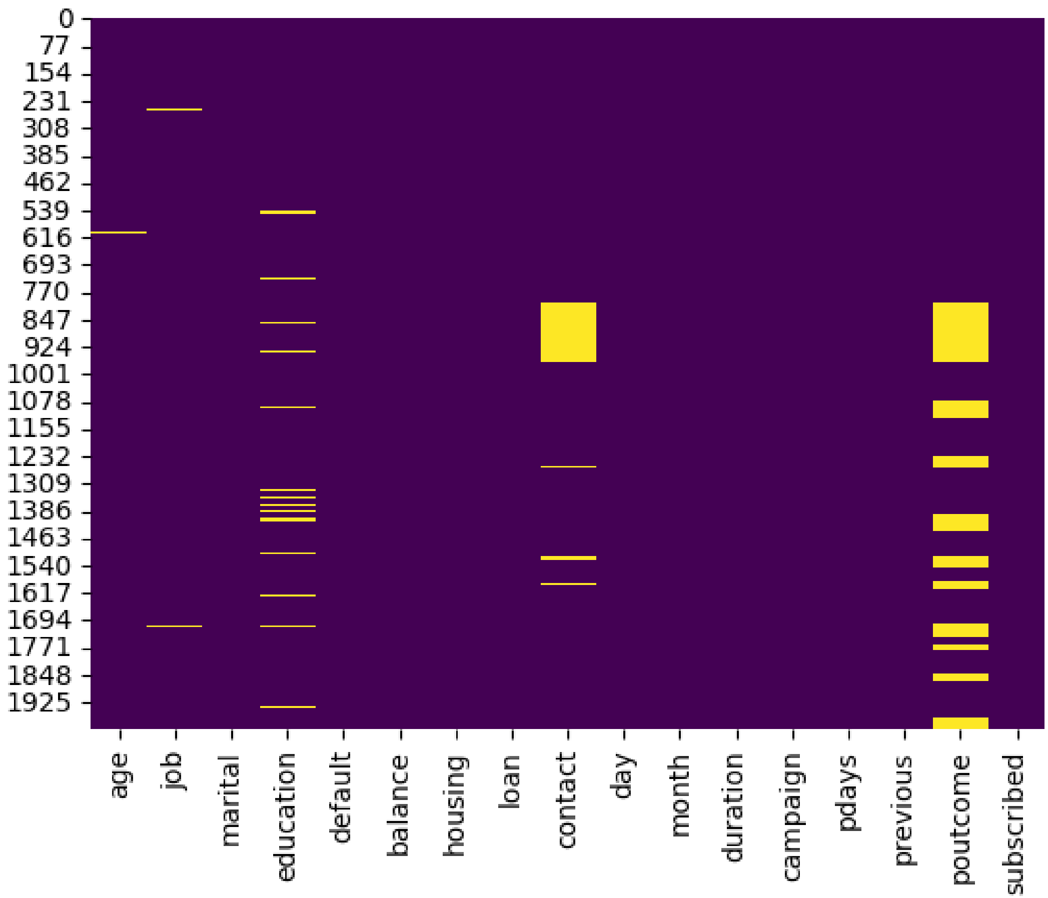
- categorical: job , marital , education , default , housing , loan , contact , month , poutcom

there is some missing values in :

- age (12)
- job (10)
- education (104)
- contact (191)
- poutcome (454)

[7]:
```python
# Visualizing missing values
sns.heatmap(df.isnull(), cbar=False, cmap='viridis')
```

[7]: <Axes: >



1.4 seperate columns by type to plot each

[8]:
```
numerical_columns = df.select_dtypes(include=['int64', 'float64']).columns
categorical_columns = df.select_dtypes(include=['object']).columns
```

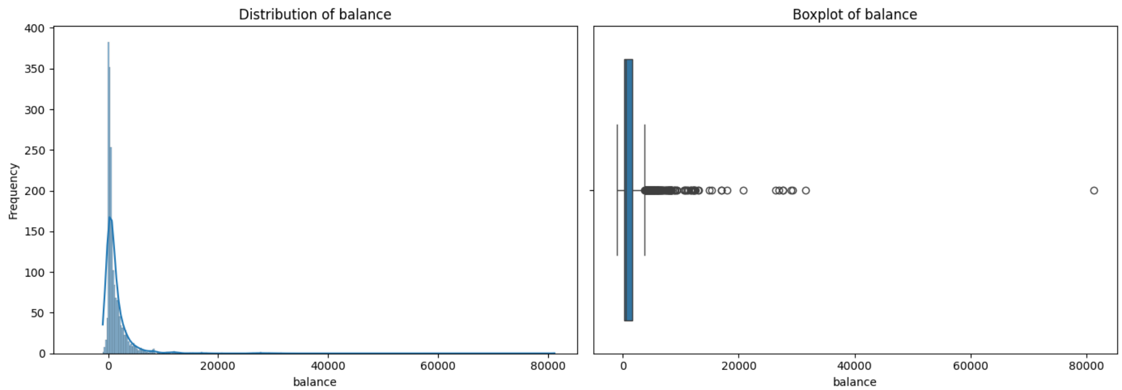
1.5 stats of numerical column

[9]:
```
df[numerical_columns].describe()
```

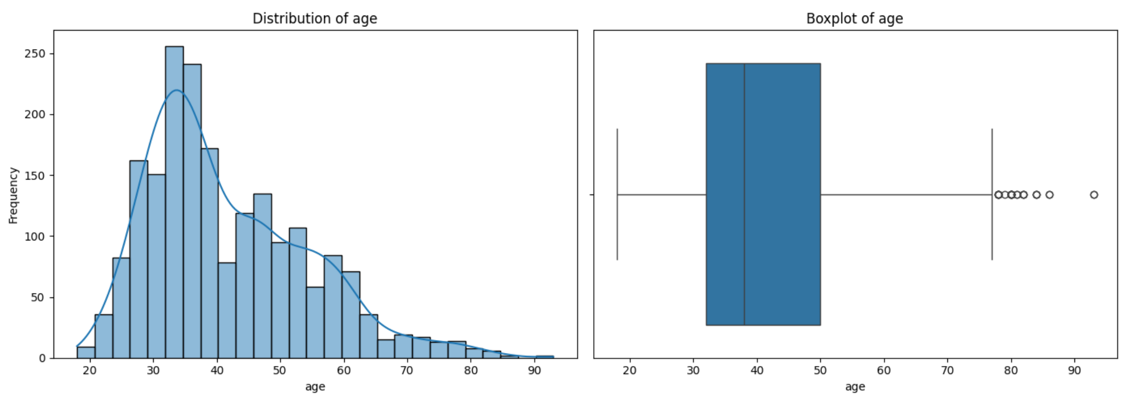
[9]:
```
               age        balance          day     duration    campaign
pdays     previous
count  1988.000000    2000.000000  2000.000000  2000.000000  2000.000000
2000.000000  2000.000000
mean     41.753018    1413.663500    13.851500   292.020500     1.909500
167.896000     2.561500
std      12.724358    3131.224213     9.712189   221.557295     1.378862
131.754126     3.400735
min      18.000000    -980.000000     1.000000     7.000000     1.000000
-1.000000      0.000000
25%      32.000000     201.500000     5.000000   146.000000     1.000000
75.750000      1.000000
50%      38.000000     551.000000    12.000000   236.000000     1.000000
182.000000     2.000000
75%      50.000000    1644.500000    23.000000   379.000000     2.000000
251.000000     3.000000
max      93.000000   81204.000000    31.000000  1823.000000    11.000000
854.000000    55.000000
```

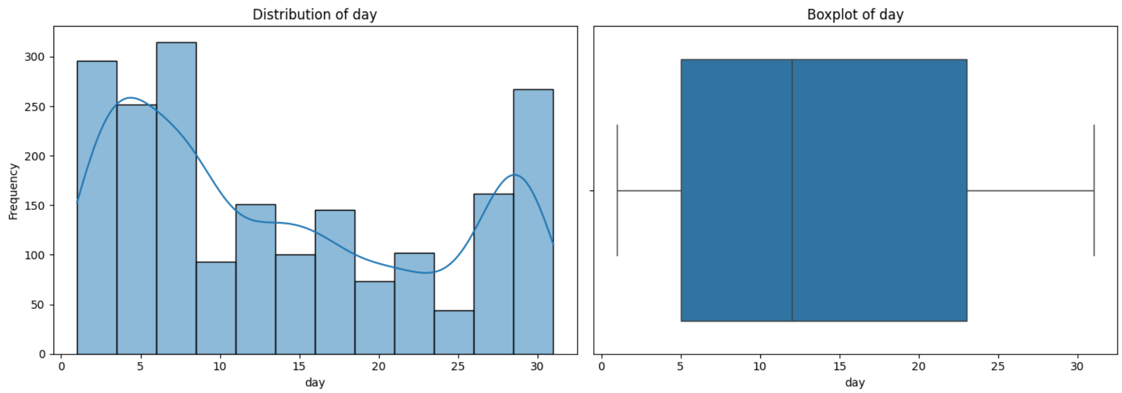
1.6 plotting numerical columns

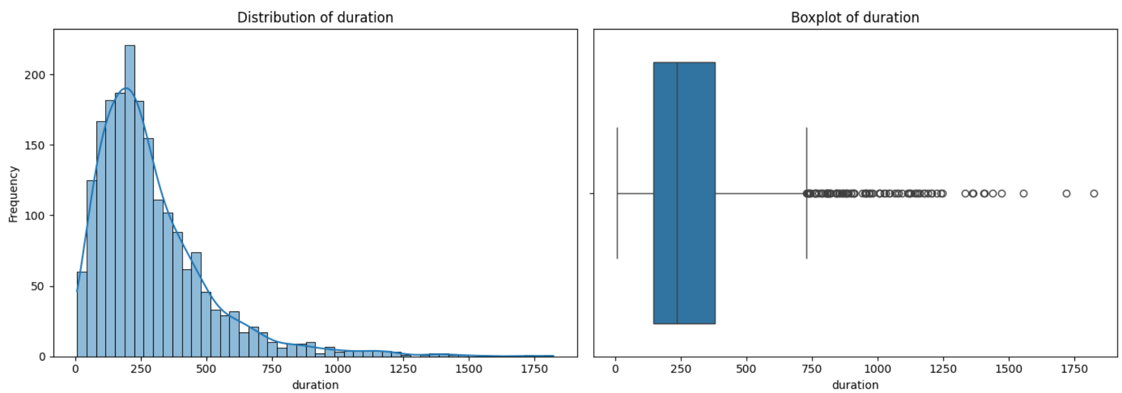
[10]:
```
 # Distribution Plot
fig, axes = plt.subplots(1, 2, figsize=(14, 5))
sns.histplot(df['balance'], kde=True, ax=axes[0])
axes[0].set_title(f"Distribution of balance")
axes[0].set_xlabel("balance")
axes[0].set_ylabel("Frequency")
axes[0].set_xlim(left=-10000)

  # Boxplot
sns.boxplot(x=df["balance"], ax=axes[1])
axes[1].set_title(f"Boxplot of balance")

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

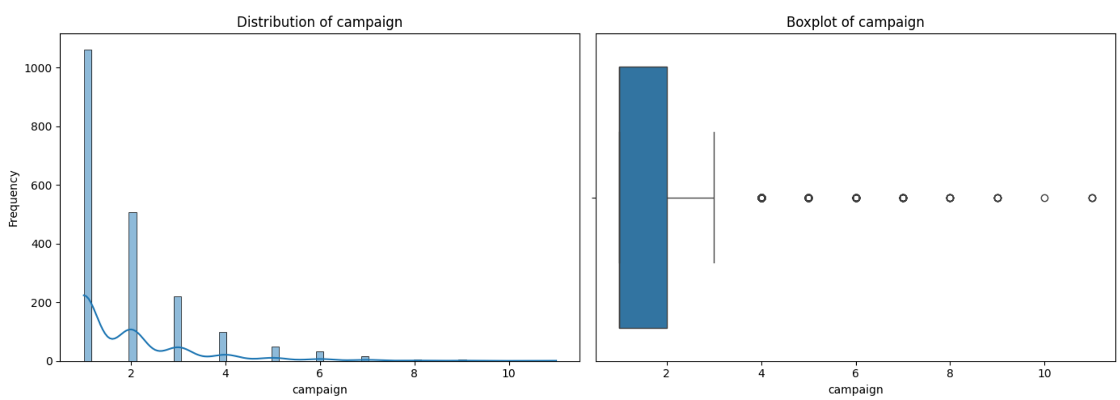


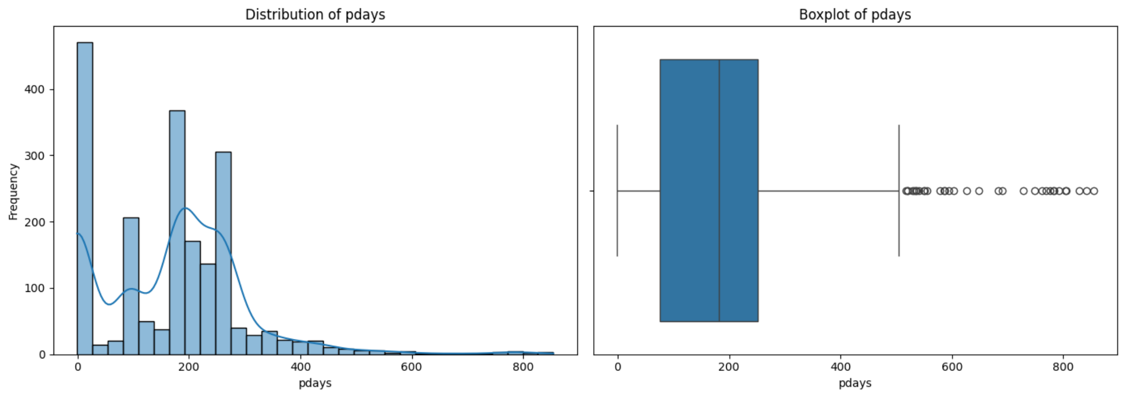
[11]:
```
for column in numerical_columns:
    if column != 'balance':  # Skip the 'balance' column
        fig, axes = plt.subplots(1, 2, figsize=(14, 5))

        # Distribution Plot
        sns.histplot(df[column].dropna(), kde=True, ax=axes[0])
        axes[0].set_title(f"Distribution of {column}")
        axes[0].set_xlabel(column)
        axes[0].set_ylabel("Frequency")

        # Boxplot
        sns.boxplot(x=df[column], ax=axes[1])
        axes[1].set_title(f"Boxplot of {column}")

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

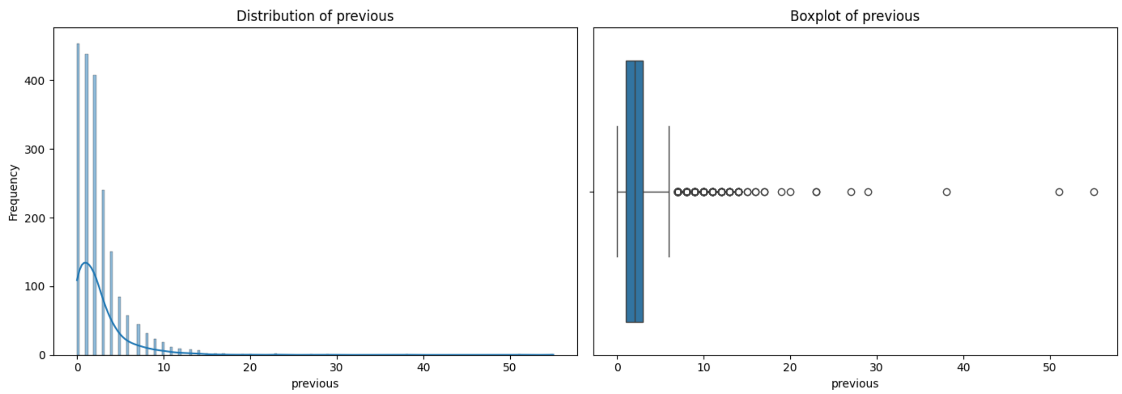



Distribution of day
Frequency
0
50
100
150
200
250
300
0
5
10
15
20
25
30
day
Boxplot of day
0
5
10
15
20
25
30
day


Distribution of duration
Frequency
0
50
100
150
200
0
250
500
750
1000
1250
1500
1750
duration
Boxplot of duration
0
250
500
750
1000
1250
1500
1750
duration


Distribution of campaign
Frequency
0
200
400
600
800
1000
2
4
6
8
10
campaign
Boxplot of campaign
2
4
6
8
10
campaign





[ ]:

```

```

1.7 unique values of categorical variables

[12]:

```
for column in df[categorical_columns]:
    print(f"{column} :")
    print(df[column].unique(), "\n")
```

```
job :
['technician' 'retired' 'blue-collar' 'self-employed' 'services'
 'management' 'admin.' 'unemployed' 'student' 'entrepreneur' 'housemaid'
 nan]

marital :
['single' 'divorced' 'married']

education :
['tertiary' 'secondary' nan 'primary']
```

```
default :
['no' 'yes']

housing :
['yes' 'no']

loan :
['no' 'yes']

contact :
['cellular' 'telephone' nan]

month :
['apr' 'dec' 'feb' 'jan' 'mar' 'may' 'nov' 'oct' 'aug' 'jul' 'jun' 'sep']

poutcome :
['failure' 'other' 'success' nan]

subscribed :
['no' 'yes']
```

`nan (missing value)` exists on these features: * Job * Education * Contact * Poutcome

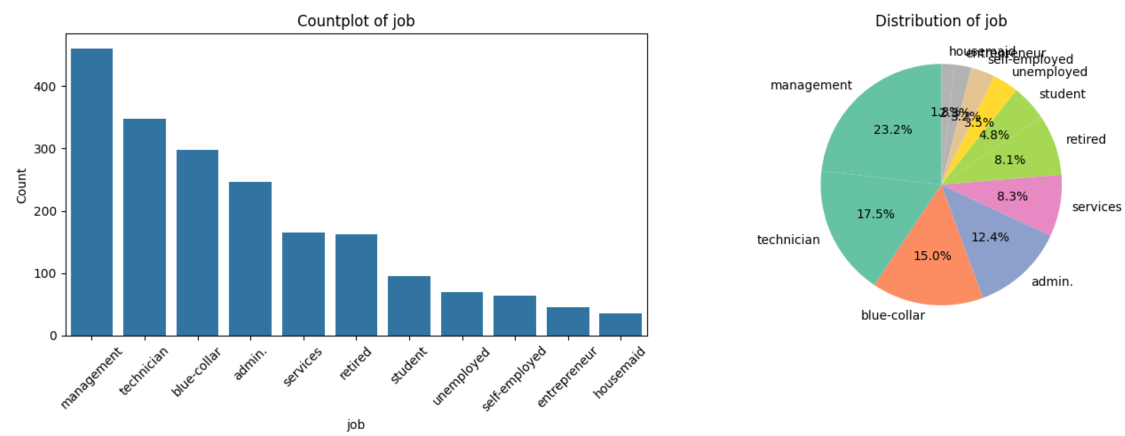
[13]:
```
df[categorical_columns].describe()
```

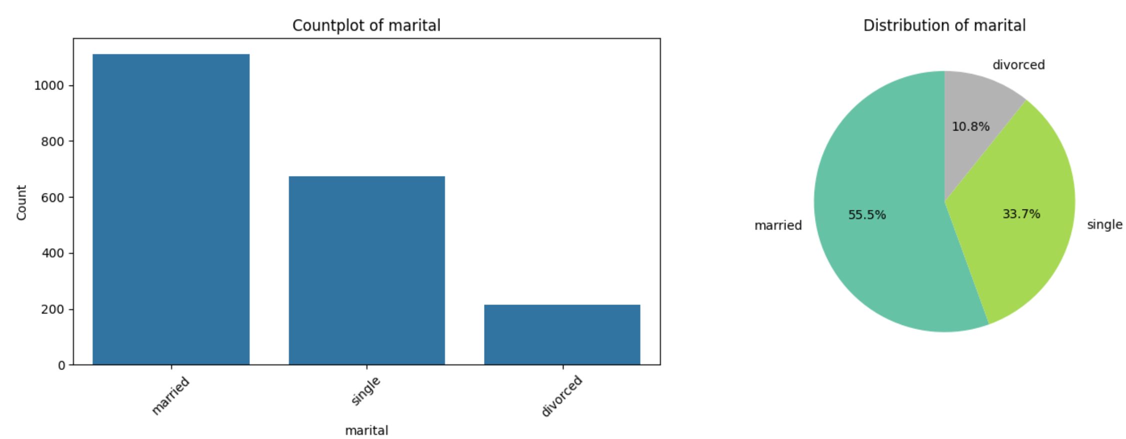
[13]:
```
                job  marital  education default housing  loan   contact month
poutcome subscribed
count          1990     2000       1896    2000    2000  2000      1809  2000
1546        2000
unique           11        3          3       2       2     2         2    12
3           2
top      management  married  secondary      no      no    no  cellular   feb
failure          no
freq            461     1111        995    1985    1037  1750      1663   404
955        1000
```

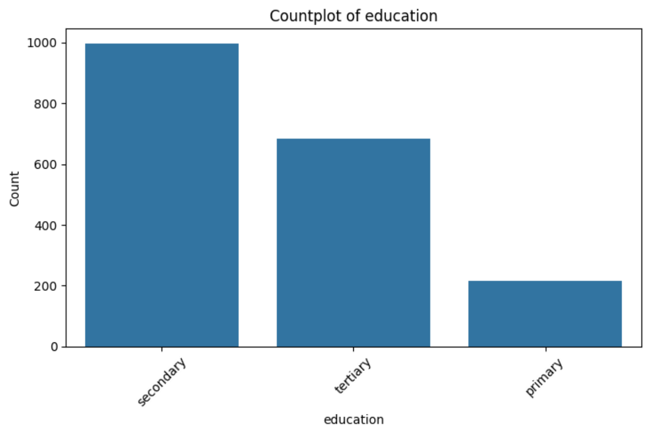
1.8 plotting categorical columns

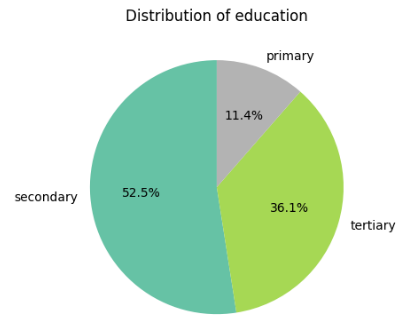
[14]:
```
for column in categorical_columns:
    fig, axes = plt.subplots(1, 2, figsize=(14, 5))  # 1 row, 2 columns

    # Countplot
    sns.countplot(data=df, x=column, order=df[column].value_counts().index,␣
↪ax=axes[0])
    axes[0].set_title(f"Countplot of {column}")
    axes[0].set_xlabel(column)
    axes[0].set_ylabel("Count")
```

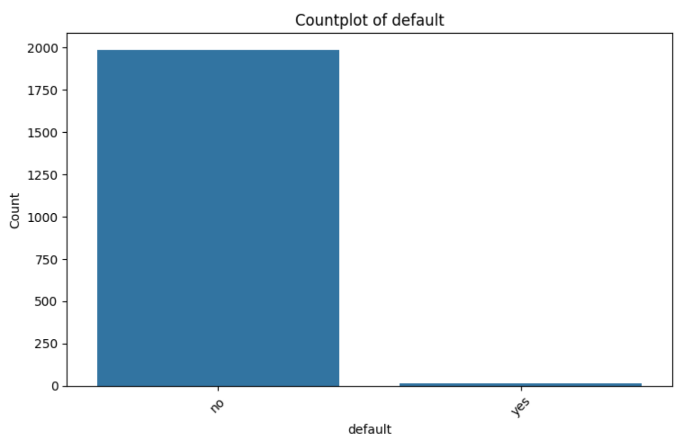
```
    axes[0].tick_params(axis='x', rotation=45)

    # Pie Chart
    df[column].value_counts().plot.pie(autopct='%1.1f%%', ax=axes[1], startangle=90, cmap='Set2')
    axes[1].set_title(f"Distribution of {column}")
    axes[1].set_ylabel('')

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

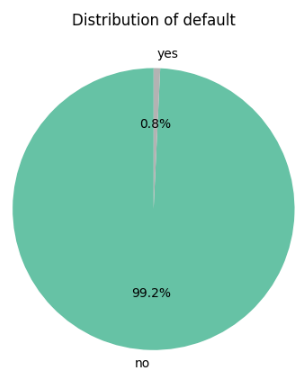


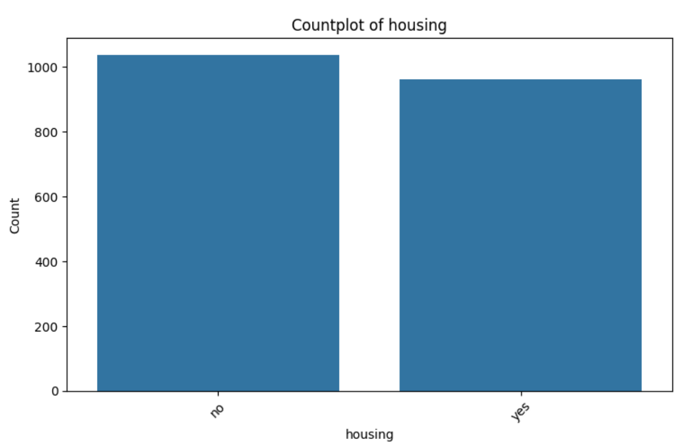


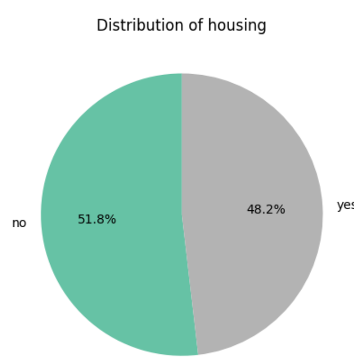

Countplot of education
Count
1000
800
600
400
200
0
secondary
tertiary
primary
education

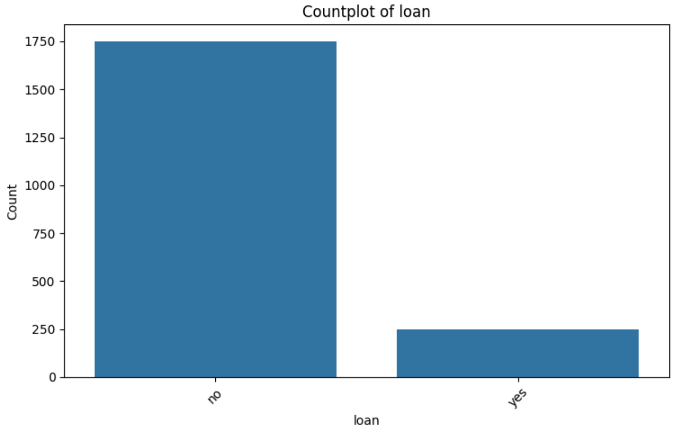

Distribution of education
primary
11.4%
secondary
52.5%
36.1%
tertiary

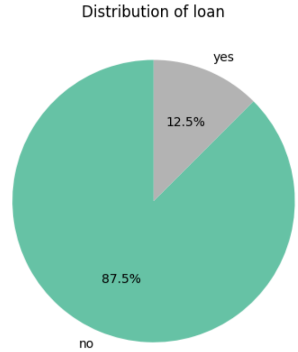

Countplot of default
Count
2000
1750
1500
1250
1000
750
500
250
0
no
yes
default

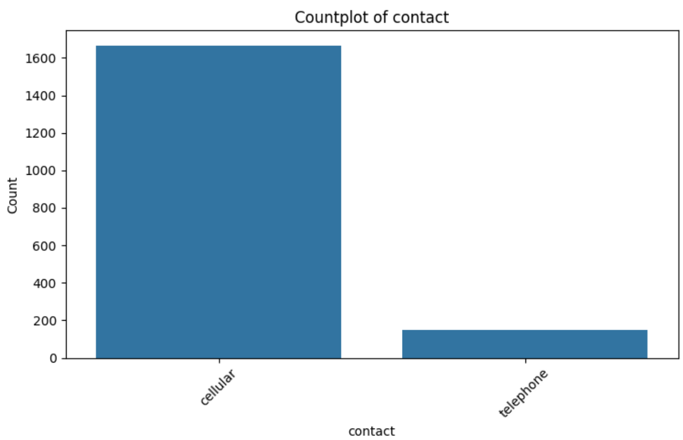

Distribution of default
yes
0.8%
99.2%
no

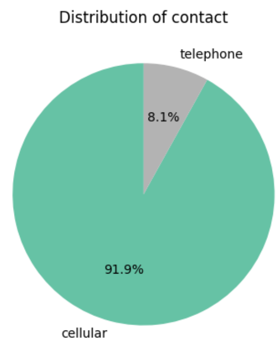

Countplot of housing
Count
1000
800
600
400
200
0
no
yes
housing

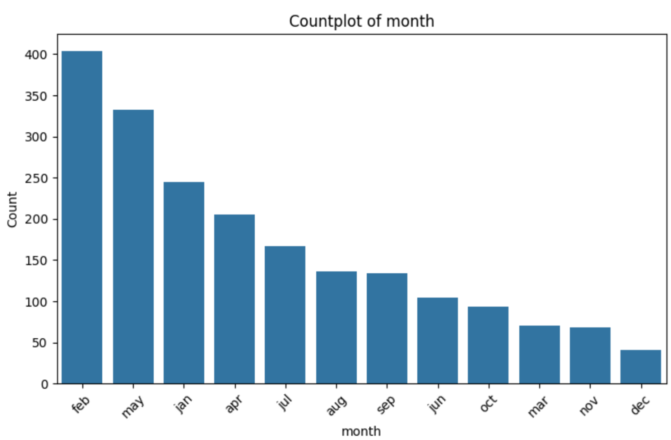

Distribution of housing
no
51.8%
48.2%
yes

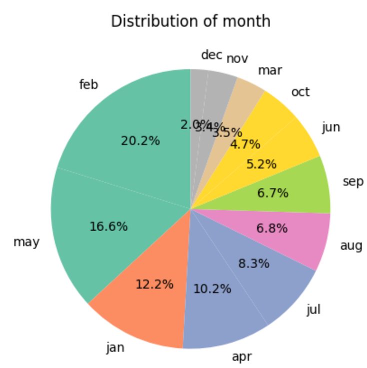

Countplot of loan
Count
1750
1500
1250
1000
750
500
250
0
no
yes
loan

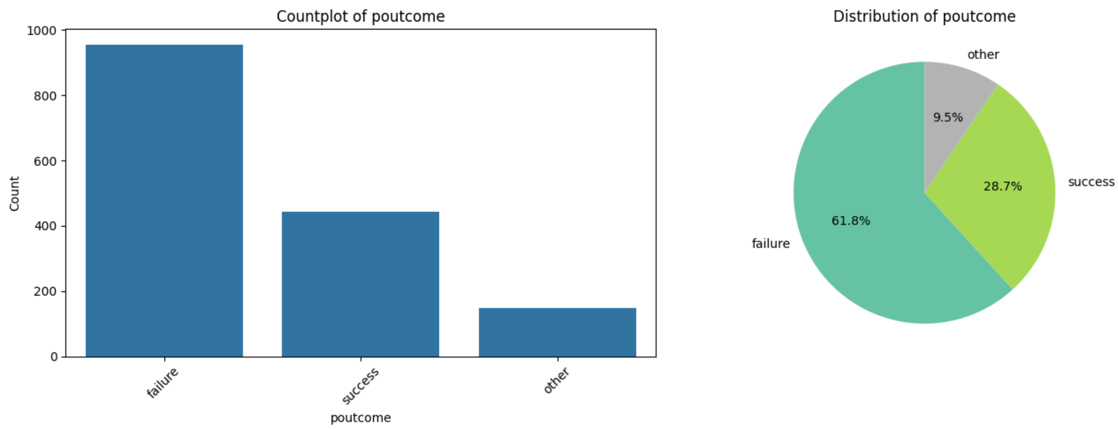

Distribution of loan
yes
12.5%
87.5%
no

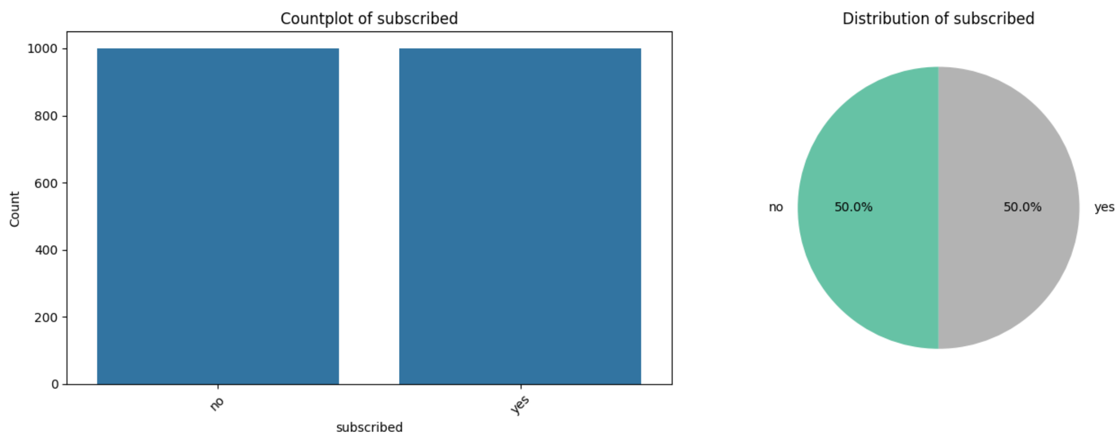

Countplot of contact
Count
1600
1400
1200
1000
800
600
400
200
0
cellular
telephone
contact


Distribution of contact
telephone
8.1%
91.9%
cellular


Countplot of month
Count
400
350
300
250
200
150
100
50
0
feb
may
jan
apr
jul
aug
sep
jun
oct
mar
nov
dec
month


Distribution of month
dec
nov
mar
oct
jun
sep
aug
jul
apr
jan
may
feb
20.2%
16.6%
12.2%
10.2%
8.3%
6.8%
6.7%
5.2%
4.7%
3.5%
2.0%



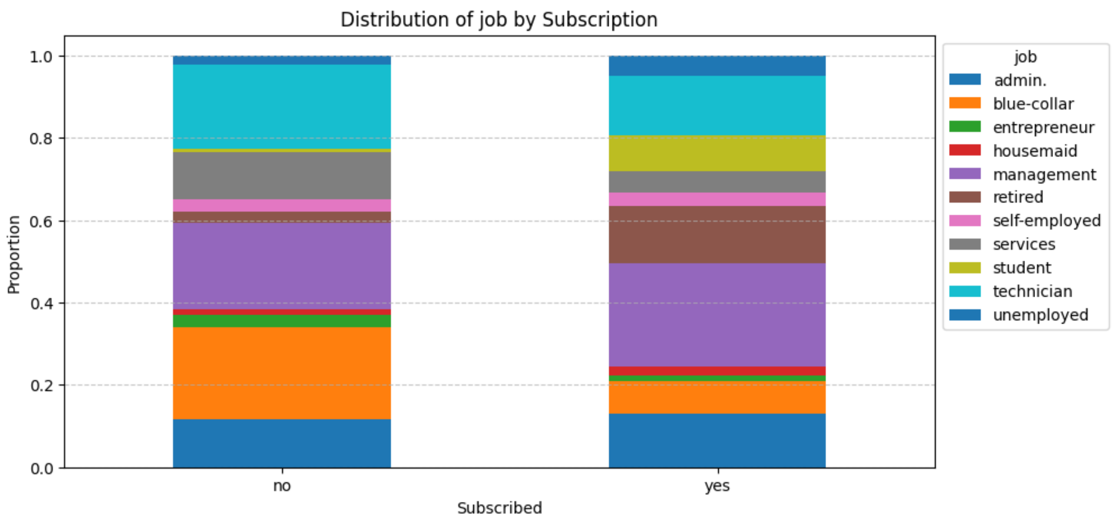


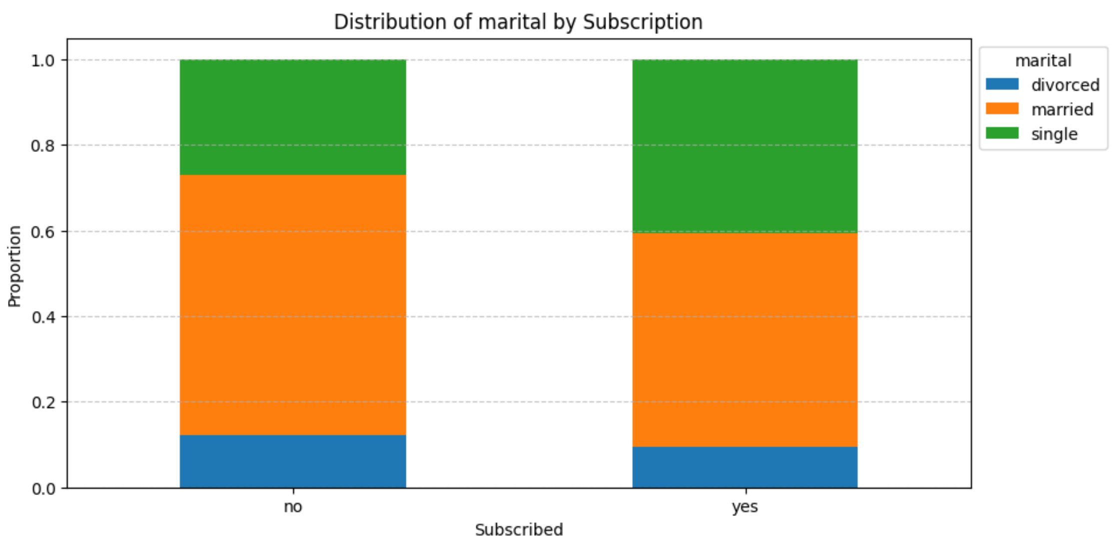
contact , default show low variaty loan show a little variaty but still might contribute to the data

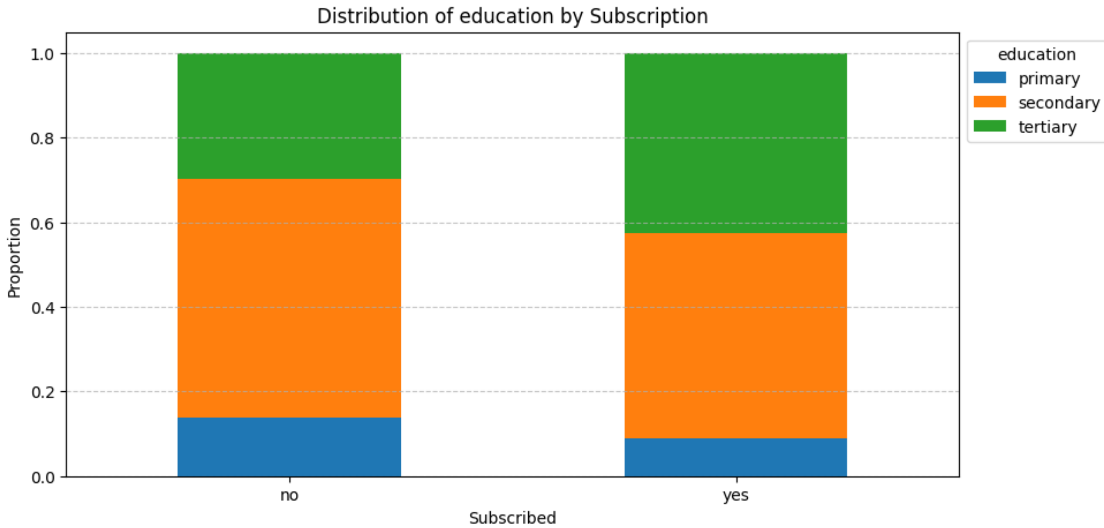
1.9 targeted comparaison

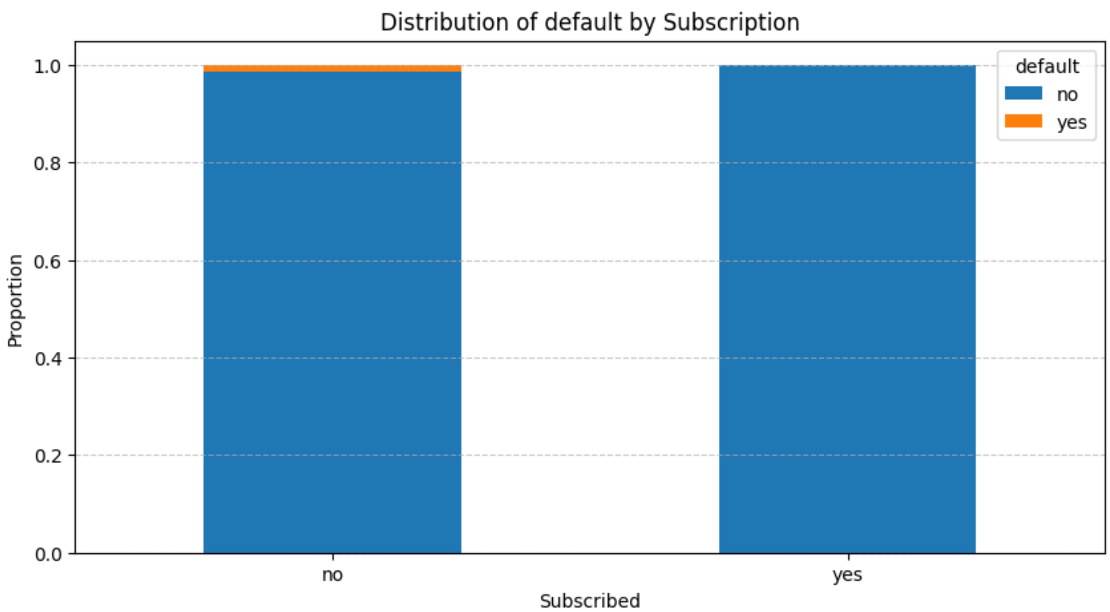
[15]:
```
# Group by 'subscribed' and plot value counts for all categorical columns together
for column in categorical_columns:
    if column != 'subscribed':
        grouped = df.groupby('subscribed')[column].value_counts(normalize=True).unstack().fillna(0)

        # Plot as a stacked bar chart
        grouped.plot(kind='bar', stacked=True, figsize=(10, 5))

        plt.title(f"Distribution of {column} by Subscription")
        plt.xlabel("Subscribed")
        plt.ylabel("Proportion")
```

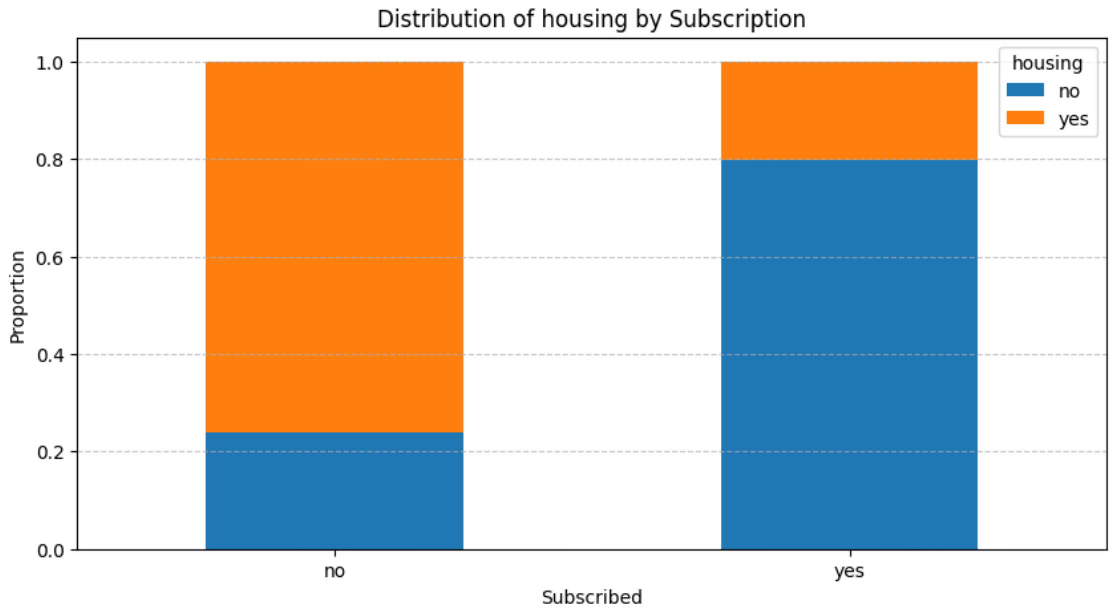
```
    plt.legend(title=column, bbox_to_anchor=(1, 1))
    plt.xticks(rotation=0)
    plt.grid(axis="y", linestyle="--", alpha=0.7)

    plt.show()
```

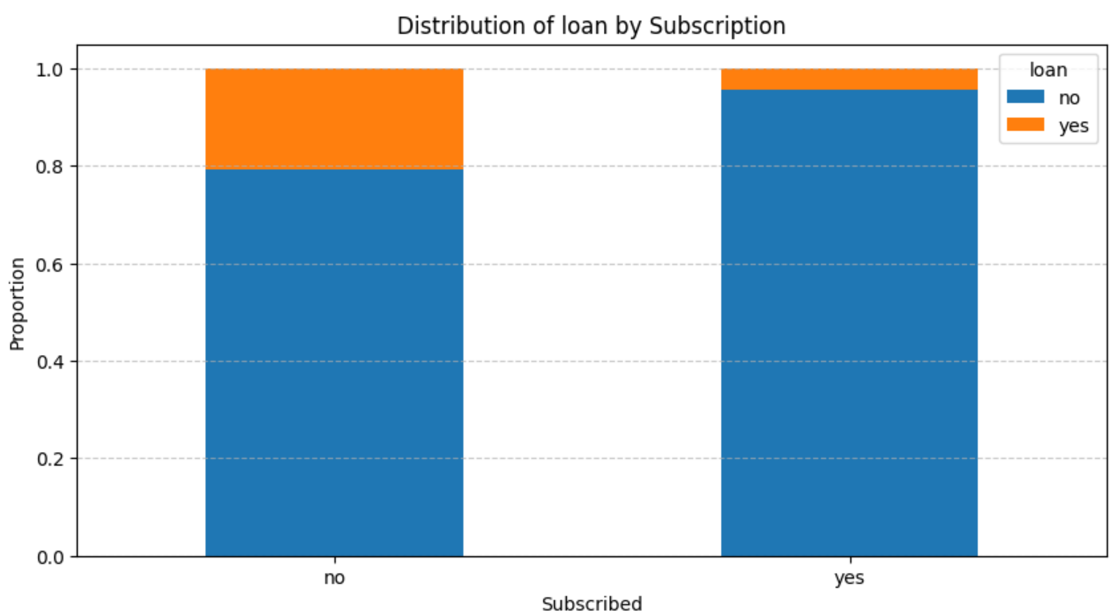


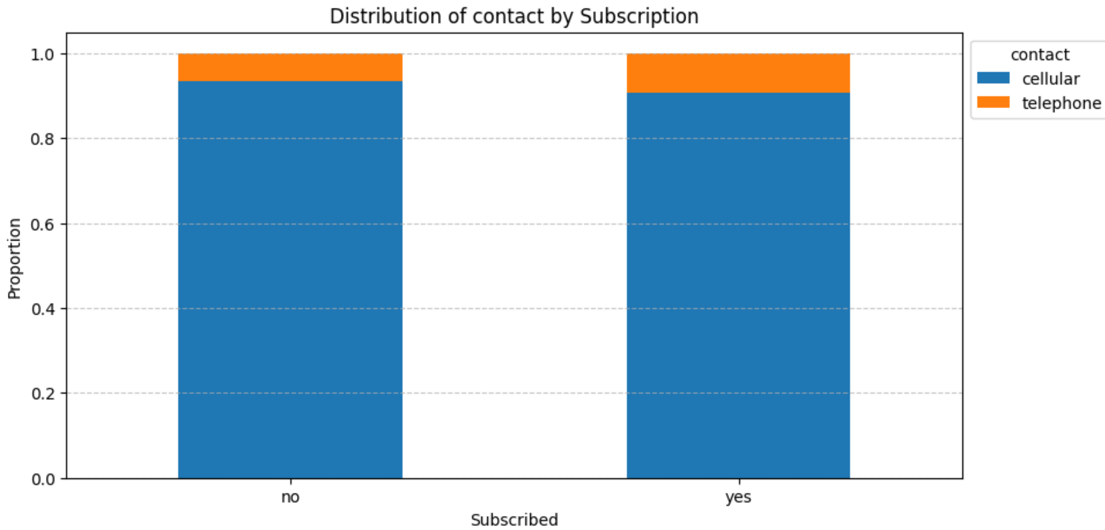


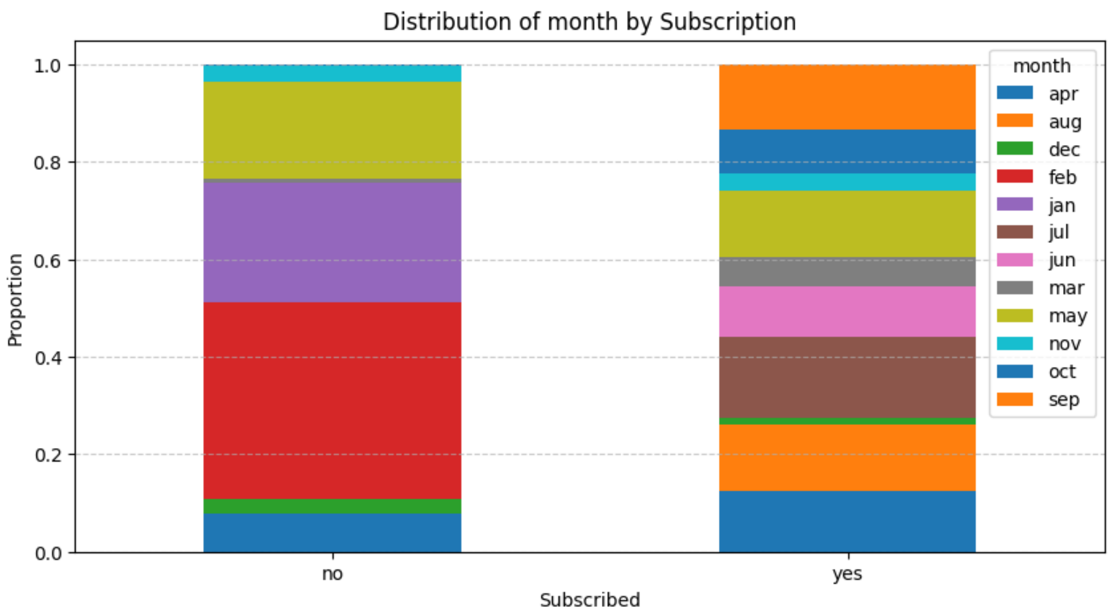

Distribution of education by Subscription
education
primary
secondary
tertiary
Proportion
1.0
0.8
0.6
0.4
0.2
0.0
no
yes
Subscribed

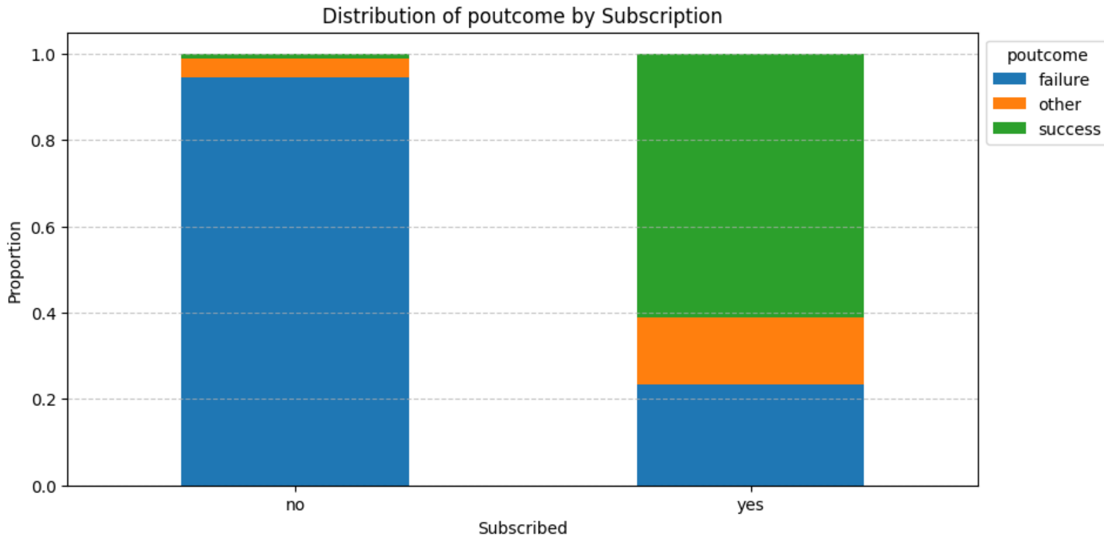

Distribution of default by Subscription
default
no
yes
Proportion
1.0
0.8
0.6
0.4
0.2
0.0
no
yes
Subscribed


Distribution of housing by Subscription
housing
no
yes
Proportion
0.0
0.2
0.4
0.6
0.8
1.0
no
yes
Subscribed


Distribution of loan by Subscription
loan
no
yes
Proportion
0.0
0.2
0.4
0.6
0.8
1.0
no
yes
Subscribed


Distribution of contact by Subscription
Proportion
Subscribed
no
yes
contact
cellular
telephone
0.0
0.2
0.4
0.6
0.8
1.0


Distribution of month by Subscription
Proportion
Subscribed
no
yes
month
apr
aug
dec
feb
jan
jul
jun
mar
may
nov
oct
sep
0.0
0.2
0.4
0.6
0.8
1.0



[16]:
```
print("--- Numerical Columns Grouped by Subscribed ---")

for column in numerical_columns:
    print(f"\nStatistics for {column}:\n")
    display(df.groupby('subscribed')[column].describe())
```

```
--- Numerical Columns Grouped by Subscribed ---

Statistics for age:
```

	count	mean	std	min	25%	50%	75%	max
subscribed								
no	991.0	40.655903	9.192425	22.0	33.0	39.0	48.0	64.0
yes	997.0	42.843531	15.382656	18.0	31.0	38.0	54.0	93.0

```
Statistics for balance:
```

	count	mean	std	min	25%	50%	75%	max
subscribed								
no	1000.0	942.862	2007.134003	-980.0	114.75	393.0	970.25	26306.0
yes	1000.0	1884.465	3891.864047	-205.0	315.00	875.0	2304.50	81204.0

```
Statistics for day:
```

	count	mean	std	min	25%	50%	75%	max
subscribed								

```
no           1000.0  12.364  10.667394  1.0  4.0   8.0  27.25  30.0
yes          1000.0  15.339   8.397893  1.0  9.0  14.0  22.00  31.0


Statistics for duration:

             count     mean         std   min    25%    50%     75%     max
subscribed
no          1000.0  206.696  175.152259   7.0   96.0  155.5  256.00  1823.0
yes         1000.0  377.345  230.154246  23.0  224.0  310.0  457.25  1720.0


Statistics for campaign:

             count   mean       std  min  25%  50%  75%   max
subscribed
no          1000.0  1.957  1.443341  1.0  1.0  1.0  2.0  11.0
yes         1000.0  1.862  1.310219  1.0  1.0  1.0  2.0  11.0


Statistics for pdays:

             count     mean         std  min    25%    50%    75%    max
subscribed
no          1000.0  185.400   99.759611 -1.0  136.0  211.0  259.0  536.0
yes         1000.0  150.392  155.468012 -1.0   -1.0  123.5  185.0  854.0


Statistics for previous:

             count   mean       std  min  25%  50%  75%   max
subscribed
no          1000.0  2.362  3.287516  0.0  1.0  2.0  3.0  51.0
yes         1000.0  2.761  3.500590  0.0  0.0  2.0  4.0  55.0
```

1.10 targetting the pdays

[17]:
```
(df['pdays'] == -1).mean()
```

[17]:
```
np.float64(0.227)
```

22.7 % of the clients hasn t been contacted

1.11 targeting the balance

[18]:
```python
# How many zero values in `balance?`
print("There are %d account holder or %5f of the total clients who have zero balance" % ((df[df['balance']==0]['balance'].count()),
          (df[df['balance']==0]['balance'].count())/(df['balance'].count())))
# How many negative values in `balance`?
print("There are %d account holder or %5f of the total clients who owe money" % ((df[df['balance']<0]['balance'].count()),
 (df[df['balance']<0]['balance'].count())/(df['balance'].count())))
```

```
There are 86 account holder or 0.043000 of the total clients who have zero
balance
There are 93 account holder or 0.046500 of the total clients who owe money
```

[19]:
```python
# Is there any of those clients who subscribed to term deposit?
print("There are %d account holder who have zero balance and subscribed term deposit" % df[(df['balance']==0) & (df['subscribed']=='yes')]['balance'].count())

print("There are %d account holder who have negative balance and subscribed term deposit" % df[(df['balance']<0) & (df['subscribed']=='yes')]['balance'].count())
```

```
There are 42 account holder who have zero balance and subscribed term deposit
There are 7 account holder who have negative balance and subscribed term deposit
```

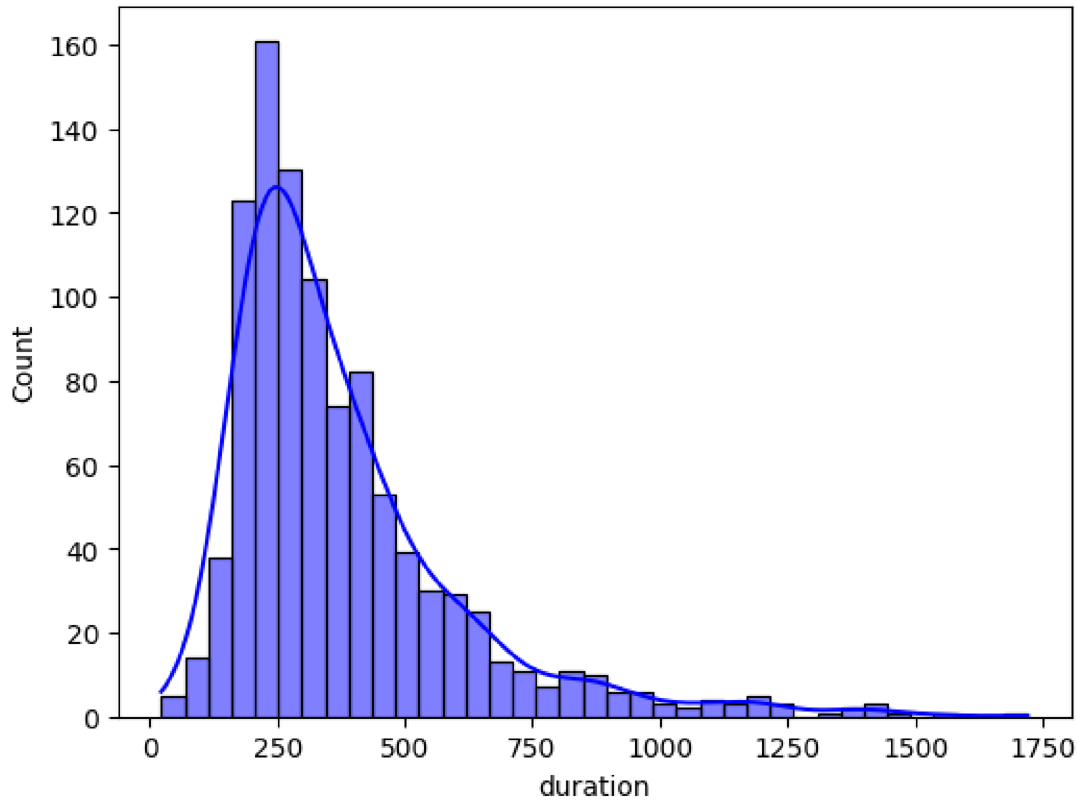
1.12 targeting duration

[20]:
```python
# The range of calls duration from clients who subscribed to the term deposit
print("The minimum duration (in seconds) to finalize a deal :", df[df['subscribed']=='yes']['duration'].min())
print("The maximum duration (in seconds) to finalize a deal :", df[df['subscribed']=='yes']['duration'].max())

# The average of calls duration from clients who subscribed to the term deposit
print("The average duration (in seconds) to finalize a deal :", df[df['subscribed']=='yes']['duration'].mean())
```

```
The minimum duration (in seconds) to finalize a deal : 23
The maximum duration (in seconds) to finalize a deal : 1720
The average duration (in seconds) to finalize a deal : 377.345
```

[21]:
```python
# The calls duration distribution from clients who subscribed to the term deposit
sns.histplot(df[df['subscribed']=='yes']['duration'], color='blue', kde=True)
```

[21]:
```
<Axes: xlabel='duration', ylabel='Count'>
```



Most subscribing clients had calls lasting between 175 and 375 seconds.

!!!!!!!!! correlation doesn t mean causation

[22]:
```
# show the clients with no contact in  the last campaign but subscribed to the␣
↪term deposit
df[(df['duration']==0) & (df['subscribed']=='yes')]
```

[22]:
```
Empty DataFrame
Columns: [age, job, marital, education, default, balance, housing, loan,
contact, day, month, duration, campaign, pdays, previous, poutcome, subscribed]
Index: []
```

1.13 targeting the poutcome

[23]:
```
# Show Clients who have been contacted before but unknown outcome
df[(df['poutcome'] == '') & (df['previous']!=0)]
```

[23]:
```
Empty DataFrame
Columns: [age, job, marital, education, default, balance, housing, loan,
```

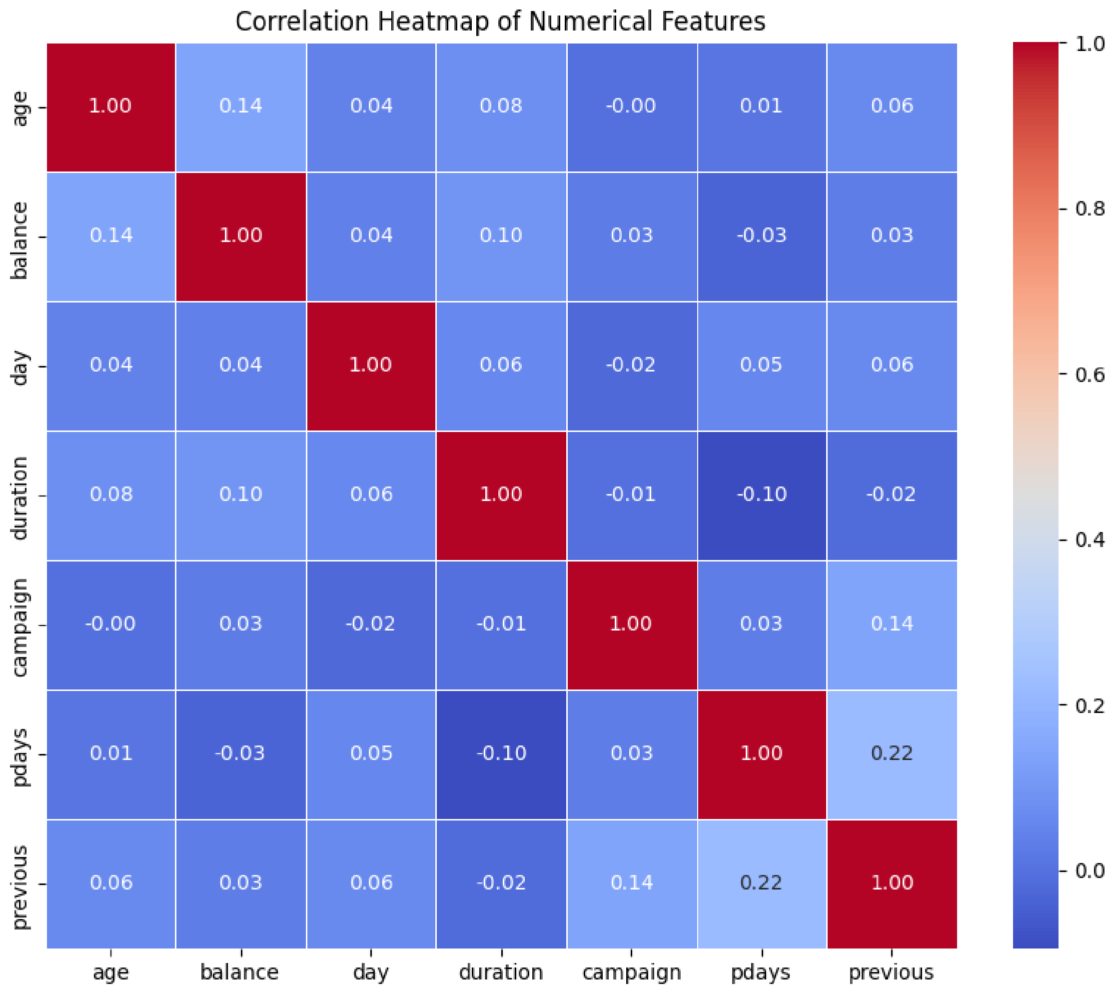
```
contact, day, month, duration, campaign, pdays, previous, poutcome, subscribed]
Index: []
```

[24]:
```
# pdays is -1 => previous is 0 ?
print(df[(df['pdays'] != -1) & (df['previous']==0)]['pdays'].count() ==
     df[(df['pdays'] == -1) & (df['previous'] != 0)]['pdays'].count())
```

```
True
```

1.14 correlation matrix

[25]:
```
# Calculate the correlation matrix
correlation_matrix = df.select_dtypes(include=['int64', 'float64']).corr()

# Plot the heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f',␣
 ↪linewidths=0.5)
plt.title('Correlation Heatmap of Numerical Features')
plt.show()
```



there is almost no correlation between any pair of numerical columns

2 summary

`nan (missing value)` exists on these features: * Job * Education * Contact * Poutcome

columns to drop : * contact : Almost all clients contacted via cellular
* default : Almost no clients have defaulted (99.2% "no")
* day : we ll treat the cycle data in month and dispose of this column * duration : has a wide range of values ,might outweigh other important features.

3 DATA preparation

[26]:
```
df.isnull().sum()
```

[26]:
```
age            12
job            10
marital         0
education     104
default         0
balance         0
housing         0
loan            0
contact       191
day             0
month           0
duration        0
campaign        0
pdays           0
previous        0
poutcome      454
subscribed      0
dtype: int64
```

[27]:
```
original_df = df.copy()
```

3.0.1 Droping unnecessary columns

[28]:
```
df.drop(columns=['contact', 'duration', 'default','day'], inplace=True)
```

[29]:
```
df.columns
```

[29]:
```
Index(['age', 'job', 'marital', 'education', 'balance', 'housing', 'loan',
'month', 'campaign', 'pdays', 'previous', 'poutcome', 'subscribed'],
dtype='object')
```

3.0.2 handling missing values

- age : the distribution is positively skewed for that we ll use the median to impute the missing values

[30]:
```
df.fillna({'age': df['age'].median()}, inplace=True)
```

- poutcome : the data isn't missing but rather unknown

[31]:
```
df['poutcome'] = df['poutcome'].replace("", "never")
```

- job : missing values < 0.5 % of the data , we can dispose of those rows

[32]:
```
df = df.dropna(subset=['job'])
```

- education : we create a new category of unknown education level ' unknown '

[33]:
```
df.fillna({'education': 'unknown'}, inplace=True)
```

3.0.3 encoding

[34]:
```
# Convert 'month' into seasonal categories
season_map = {
    'dec': 'Winter', 'jan': 'Winter', 'feb': 'Winter',
    'mar': 'Spring', 'apr': 'Spring', 'may': 'Spring',
    'jun': 'Summer', 'jul': 'Summer', 'aug': 'Summer',
    'sep': 'Fall', 'oct': 'Fall', 'nov': 'Fall'
}

df['season'] = df['month'].map(season_map)
df.drop(columns=['month'], inplace=True)  # Drop original month column

# One-Hot Encoding for 'season' column
df = pd.get_dummies(df, columns=['season'], drop_first=True)

# One-Hot Encoding for Other Nominal Categorical Columns
df = pd.get_dummies(df, columns=['job', 'marital', 'education', 'poutcome'],␣
 ↪drop_first=True)
```

[35]:
```
# Label Encoding for Binary Categorical Columns
binary_cols = ['housing', 'loan']
le = LabelEncoder()

for col in binary_cols:
    df[col] = le.fit_transform(df[col])
```

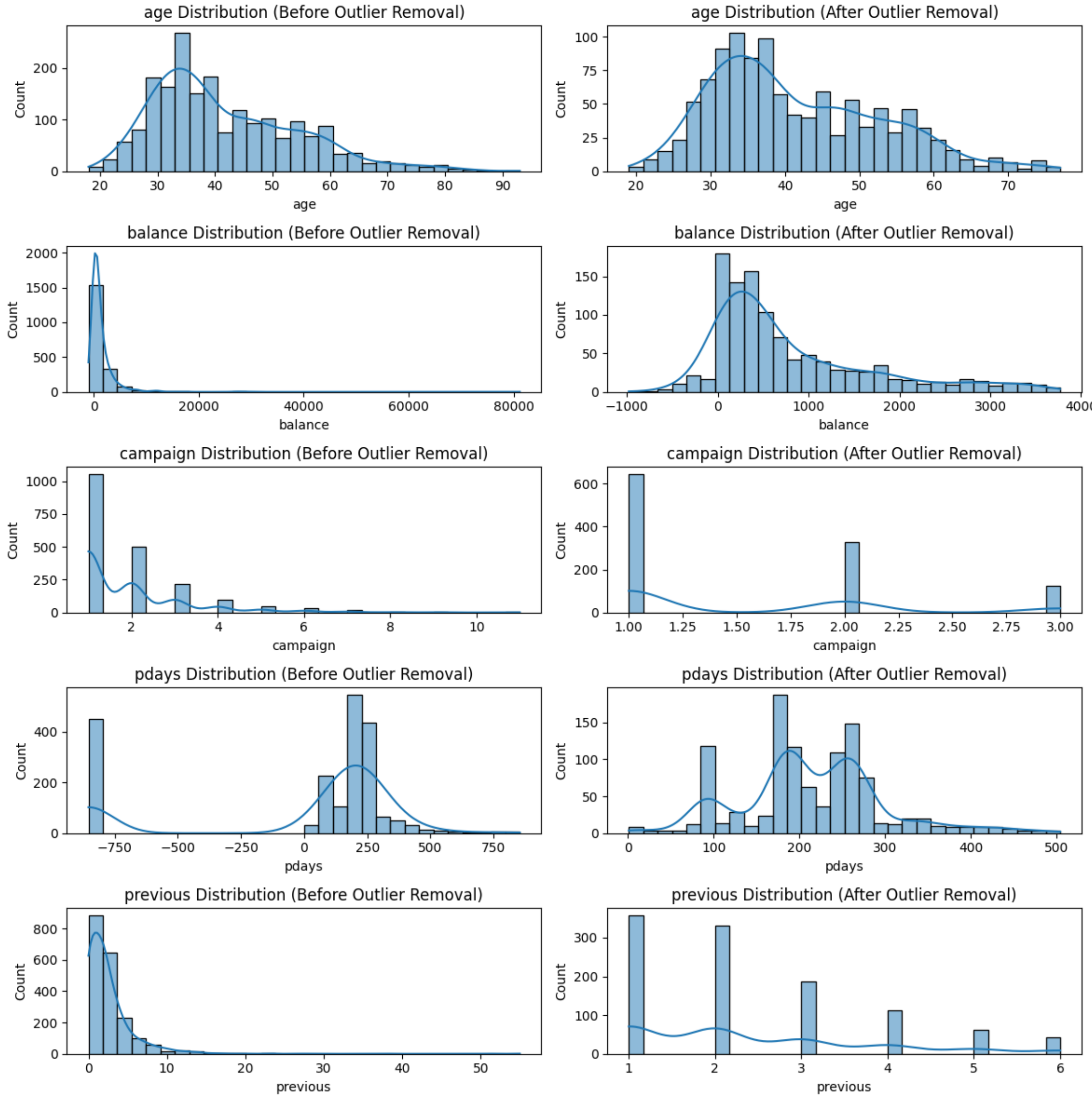
[36]:
```
max_pdays = df[df['pdays'] != -1]['pdays'].max()
df['pdays'] = df['pdays'].replace(-1, - max_pdays)
```

3.1 Detecting outliers

[37]:
```
numerical_columns = [col for col in numerical_columns if col not in ['day',␣
 ↪'duration']]

# Compute IQR (Interquartile Range)
Q1 = df[numerical_columns].quantile(0.25)
Q3 = df[numerical_columns].quantile(0.75)
IQR = Q3 - Q1

# Define outlier mask
outlier_mask = (df[numerical_columns] < (Q1 - 1.5 * IQR)) |␣
 ↪(df[numerical_columns] > (Q3 + 1.5 * IQR))

print(outlier_mask.sum())

# Save a copy before removing outliers
```

```python
df_before = df.copy()

# Remove outliers
df_after = df[~outlier_mask.any(axis=1)]

# Plot distributions before and after removing outliers
fig, axes = plt.subplots(len(numerical_columns), 2, figsize=(12, 12))

for i, col in enumerate(numerical_columns):
    # Before removing outliers
    sns.histplot(df_before[col], kde=True, ax=axes[i, 0], bins=30)
    axes[i, 0].set_title(f"{col} Distribution (Before Outlier Removal)")

    # After removing outliers
    sns.histplot(df_after[col], kde=True, ax=axes[i, 1], bins=30)
    axes[i, 1].set_title(f"{col} Distribution (After Outlier Removal)")

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

```
age          24
balance     159
campaign    212
pdays       483
previous    169
dtype: int64
```



3.2 Summary: Outlier Handling Decisions (Based on Distribution Analysis)

1. Features Where Outliers Were Removed We removed outliers from the following features due to extreme values affecting the distribution:
- `balance` → Previously had extreme right skew, making it difficult to analyze. Outliers removed to keep reasonable financial variations.
- `campaign` → Most clients had 1-3 contacts, but some had 10+ contacts, which were removed for better distribution.
- `previous` → Long tail distribution; extreme values (very high past contacts) were removed to avoid misleading clustering.

---

2. Features Where Outliers Were Kept We decided to keep outliers in these features as they hold meaningful patterns:
- `age` → The distribution remains fairly normal after outlier treatment, so extreme values were not removed.
- `pdays` → Kept all values but handled `-1` (never contacted) by replacing it with `- (max value)` to preserve meaning.

Final Decision (Based on Distribution Plots)

- **Kept & Scaled:** `age`, `balance`, `campaign`, `pdays`, `previous`
- **Dropped:** `'contact'`, `'duration'`, `'default'`, `'day'`
- **Transformed `pdays`**

Now, we can proceed with scaling numerical features and preparing for clustering.

3.3 Scaling

[38]:
```python
# Define numerical columns to scale
numerical_columns = ['age', 'balance', 'campaign', 'previous', 'pdays']

# Initialize RobustScaler
scaler = RobustScaler()

# Apply scaling
df[numerical_columns] = scaler.fit_transform(df[numerical_columns])
```

3.4 dropping the target variable

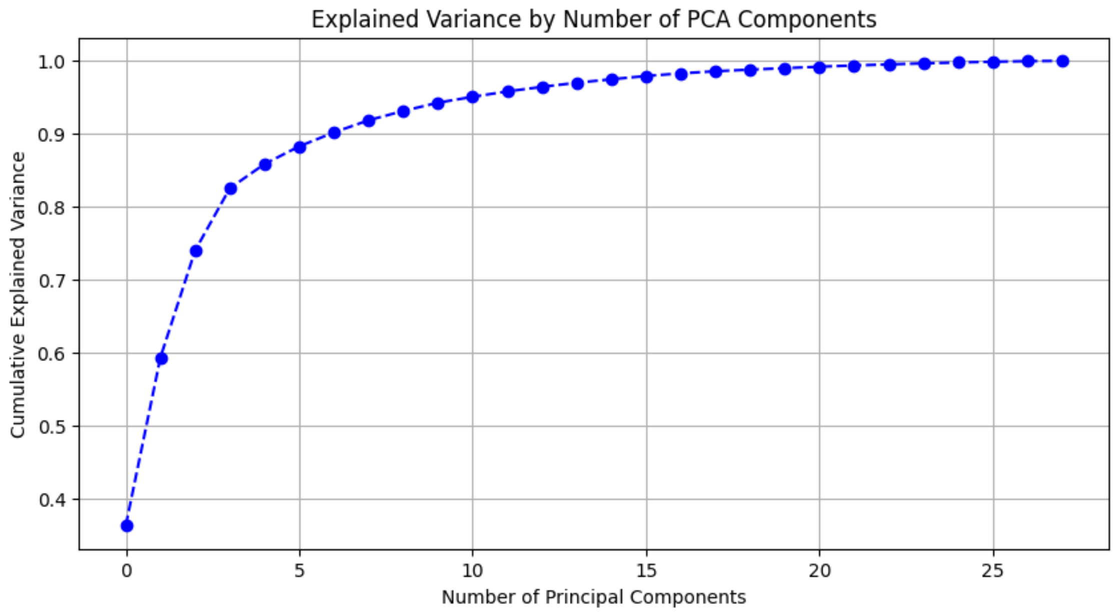
[39]:
```python
df = df.drop(columns=['subscribed'])
```

3.5 Dimensionality Reduction

[46]:
```python
# Apply PCA
df.info()
pca = PCA()
pca_fit = pca.fit(df)

# Plot explained variance
plt.figure(figsize=(10, 5))
plt.plot(np.cumsum(pca.explained_variance_ratio_), marker='o', linestyle='--',
 ↪color='b')
plt.xlabel('Number of Principal Components')
plt.ylabel('Cumulative Explained Variance')
plt.title('Explained Variance by Number of PCA Components')
plt.grid()
```

```python
plt.show()

# Choose number of components to retain 95% variance
explained_variance = np.cumsum(pca.explained_variance_ratio_)
optimal_components = np.argmax(explained_variance >= 0.95) + 1  # First index where variance   95%

# Apply PCA with optimal components
pca_final = PCA(n_components=optimal_components)
df_pca = pca_final.fit_transform(df)
df_pca2 =df_pca.copy()
print(f"Optimal number of components: {optimal_components}")
```

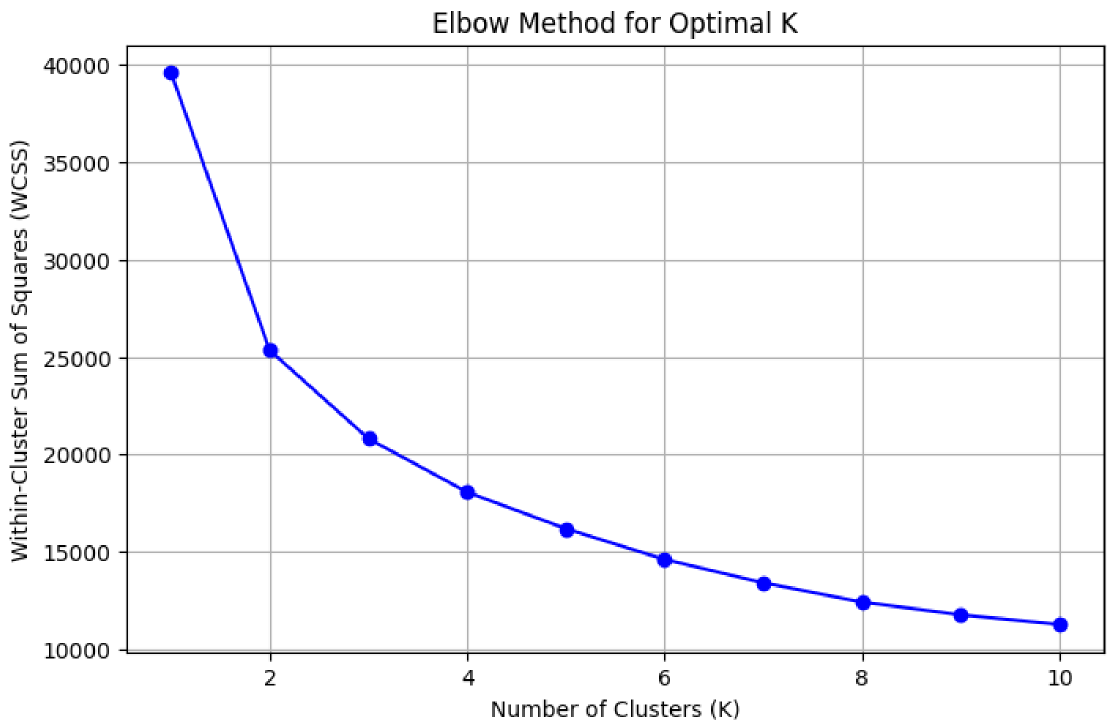
```
<class 'pandas.core.frame.DataFrame'>
Index: 1990 entries, 0 to 1999
Data columns (total 28 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   age                  1990 non-null   float64
 1   balance              1990 non-null   float64
 2   housing              1990 non-null   int64
 3   loan                 1990 non-null   int64
 4   campaign             1990 non-null   float64
 5   pdays                1990 non-null   float64
 6   previous             1990 non-null   float64
 7   season_Spring        1990 non-null   bool
 8   season_Summer        1990 non-null   bool
 9   season_Winter        1990 non-null   bool
 10  job_blue-collar      1990 non-null   bool
 11  job_entrepreneur     1990 non-null   bool
 12  job_housemaid        1990 non-null   bool
 13  job_management       1990 non-null   bool
 14  job_retired          1990 non-null   bool
 15  job_self-employed    1990 non-null   bool
 16  job_services         1990 non-null   bool
 17  job_student          1990 non-null   bool
 18  job_technician       1990 non-null   bool
 19  job_unemployed       1990 non-null   bool
 20  marital_married      1990 non-null   bool
 21  marital_single       1990 non-null   bool
 22  education_secondary  1990 non-null   bool
 23  education_tertiary   1990 non-null   bool
 24  education_unknown    1990 non-null   bool
 25  poutcome_other       1990 non-null   bool
 26  poutcome_success     1990 non-null   bool
 27  Cluster              1990 non-null   int32
dtypes: bool(20), float64(5), int32(1), int64(2)
memory usage: 171.0 KB
```




```
Optimal number of components: 11
```

3.6 elbow method

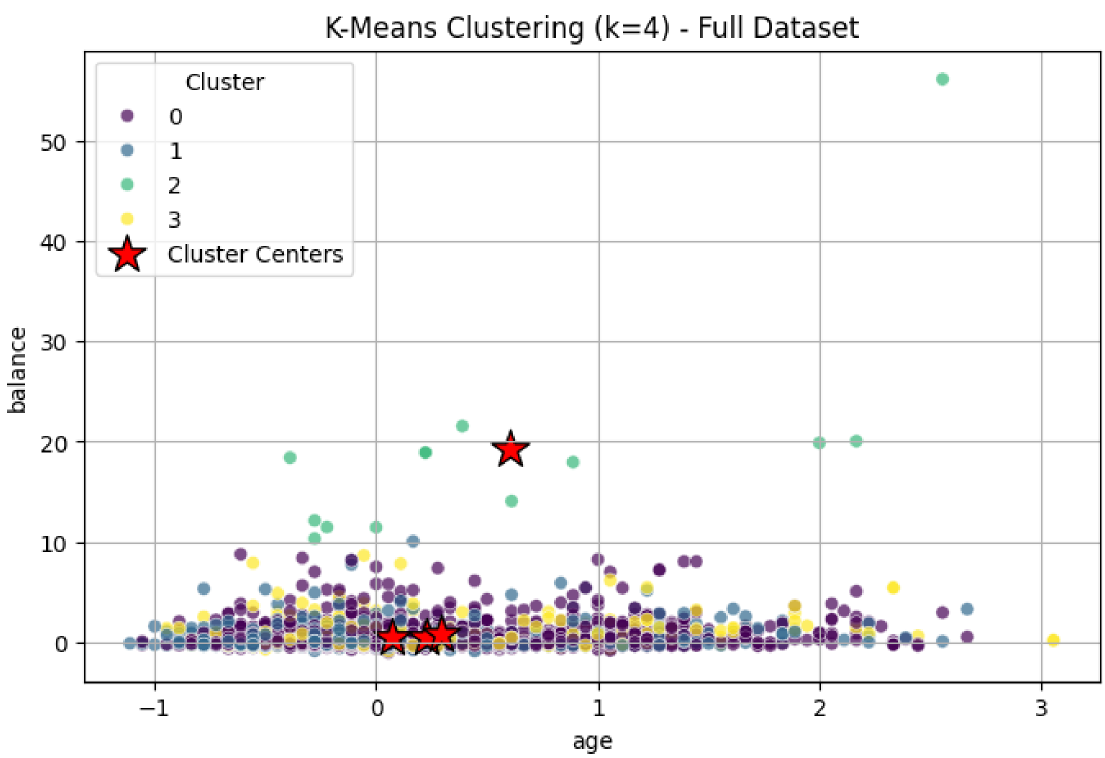
[41]:
```python
# Determine the best number of clusters using the Elbow Method
wcss = []
K_range = range(1, 11)  # Checking for K from 1 to 10

for k in K_range:
    kmeans = KMeans(n_clusters=k, random_state=42, n_init=10)
    kmeans.fit(df)
    wcss.append(kmeans.inertia_)  # Inertia (WCSS)

# Plot the Elbow Method
plt.figure(figsize=(8, 5))
plt.plot(K_range, wcss, marker='o', linestyle='-', color='b')
plt.xlabel('Number of Clusters (K)')
plt.ylabel('Within-Cluster Sum of Squares (WCSS)')
plt.title('Elbow Method for Optimal K')
plt.grid()
plt.show()
```



[45]:
```
# Set the optimal number of clusters from the Elbow Method
optimal_k = 4 # Replace with the best k from the elbow plot

# Apply K-Means directly to the full dataset
kmeans = KMeans(n_clusters=optimal_k, random_state=42, n_init=100)
df['Cluster'] = kmeans.fit_predict(df)  # Assign cluster labels to original␣
↪dataset

# Print cluster counts
print("Cluster distribution:\n", df['Cluster'].value_counts())

# Get cluster centers
cluster_centers = kmeans.cluster_centers_

# Select first two features for visualization (since we removed PCA)
feature_1 = df.columns[0]  # First feature
feature_2 = df.columns[1]  # Second feature

# Visualize the clusters in 2D (first two features)
plt.figure(figsize=(8, 5))
sns.scatterplot(x=df[feature_1], y=df[feature_2], hue=df['Cluster'],␣
↪palette='viridis', alpha=0.7)
```

```
# Plot cluster centers with stars (*)
plt.scatter(cluster_centers[:, 0], cluster_centers[:, 1],
            marker='*', s=300, c='red', edgecolors='black', label='Cluster␣
 ↪Centers')

# Labels and legend
plt.xlabel(feature_1)
plt.ylabel(feature_2)
plt.title(f'K-Means Clustering (k={optimal_k}) - Full Dataset')
plt.legend(title='Cluster')
plt.grid()
plt.show()
```

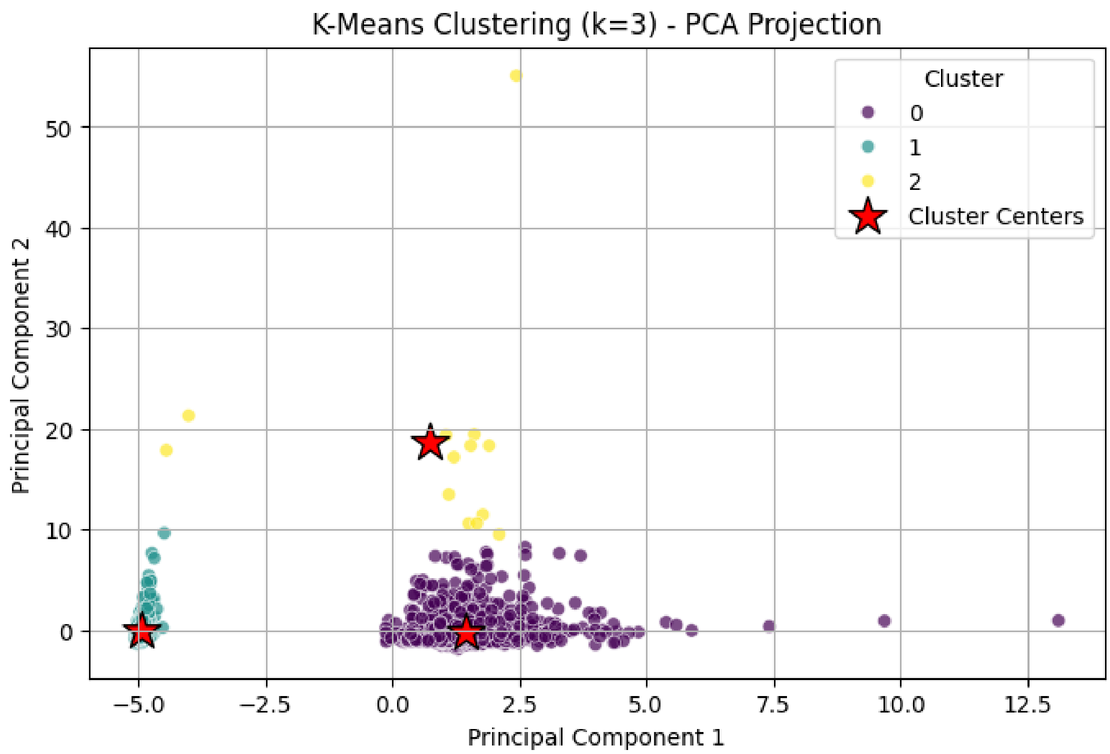
```
Cluster distribution:
 Cluster
0    1250
1     449
3     278
2      13
Name: count, dtype: int64
```



3.7 clustering with pca

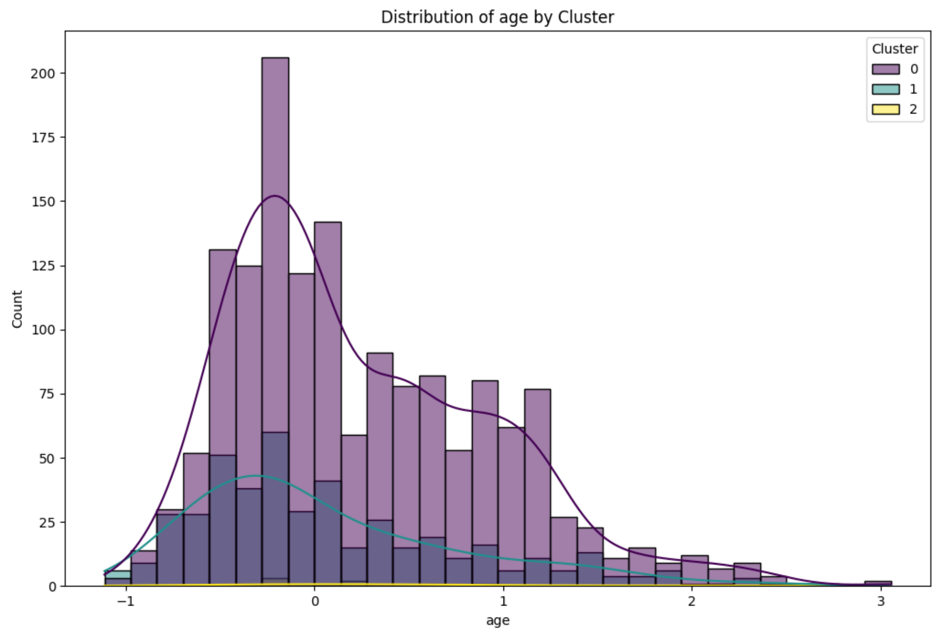
[47]:
```python
# Set the optimal number of clusters from the Elbow Method
optimal_k = 3  # Replace with the best k from the elbow plot

# Apply PCA before clustering
pca = PCA(n_components=2)  # Reduce dimensions to 2 for visualization
df_pca = pca.fit_transform(df)  # Apply PCA transformation

# Apply K-Means on PCA-transformed data
kmeans = KMeans(n_clusters=optimal_k, random_state=42, n_init=100)
df['Cluster'] = kmeans.fit_predict(df_pca)  # Assign cluster labels to original␣
↪dataset

# Print cluster counts
print("Cluster distribution:\n", df['Cluster'].value_counts())

# Get cluster centers in PCA space
cluster_centers = kmeans.cluster_centers_

# Visualize clusters using PCA components
plt.figure(figsize=(8, 5))
sns.scatterplot(x=df_pca[:, 0], y=df_pca[:, 1], hue=df['Cluster'],␣
↪palette='viridis', alpha=0.7)

# Plot cluster centers with stars (*)
plt.scatter(cluster_centers[:, 0], cluster_centers[:, 1],
            marker='*', s=300, c='red', edgecolors='black', label='Cluster␣
↪Centers')

# Labels and legend
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.title(f'K-Means Clustering (k={optimal_k}) - PCA Projection')
plt.legend(title='Cluster')
plt.grid()
plt.show()
```

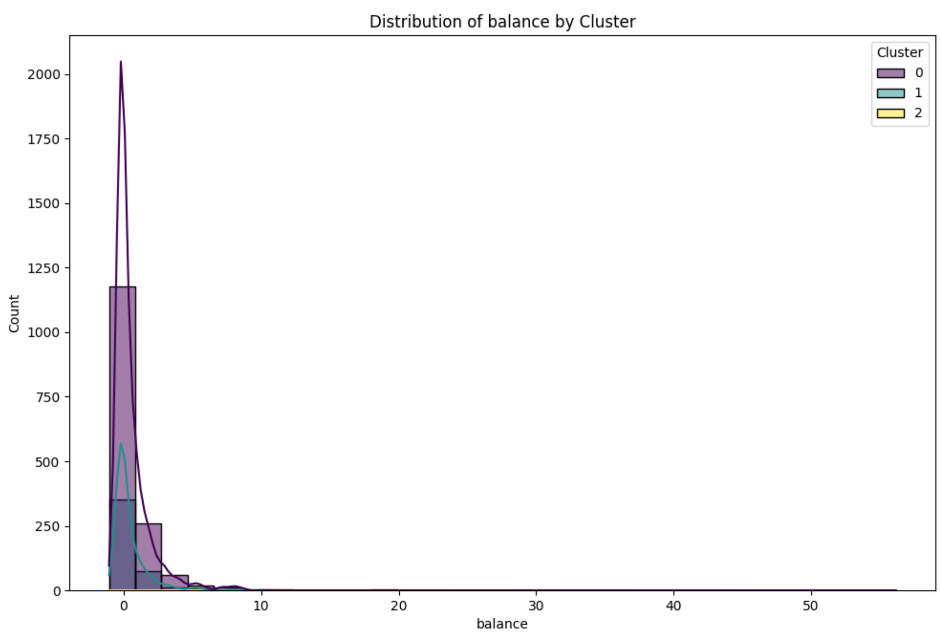
```
Cluster distribution:
 Cluster
0    1528
1     449
2      13
Name: count, dtype: int64
```

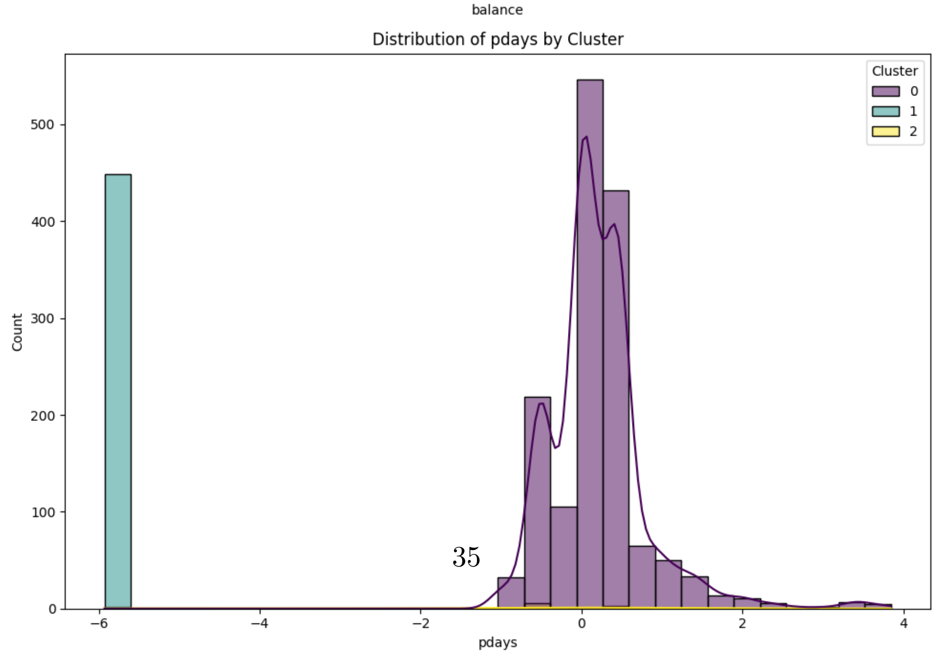


3.8 overlook on our clusters

```
[ ]: # Assuming df contains the cluster labels
cluster_columns = ["age", "balance", "pdays"]  # Replace with actual numerical␣
 ↪columns

# Create subplots
fig, axes = plt.subplots(len(cluster_columns), 1, figsize=(10, 20))

for i, column in enumerate(cluster_columns):
    sns.histplot(data=df, x=column, hue="Cluster", bins=30, kde=True,␣
 ↪palette="viridis", ax=axes[i])
    axes[i].set_title(f"Distribution of {column} by Cluster")
    axes[i].set_xlabel(column)
    axes[i].set_ylabel("Count")

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

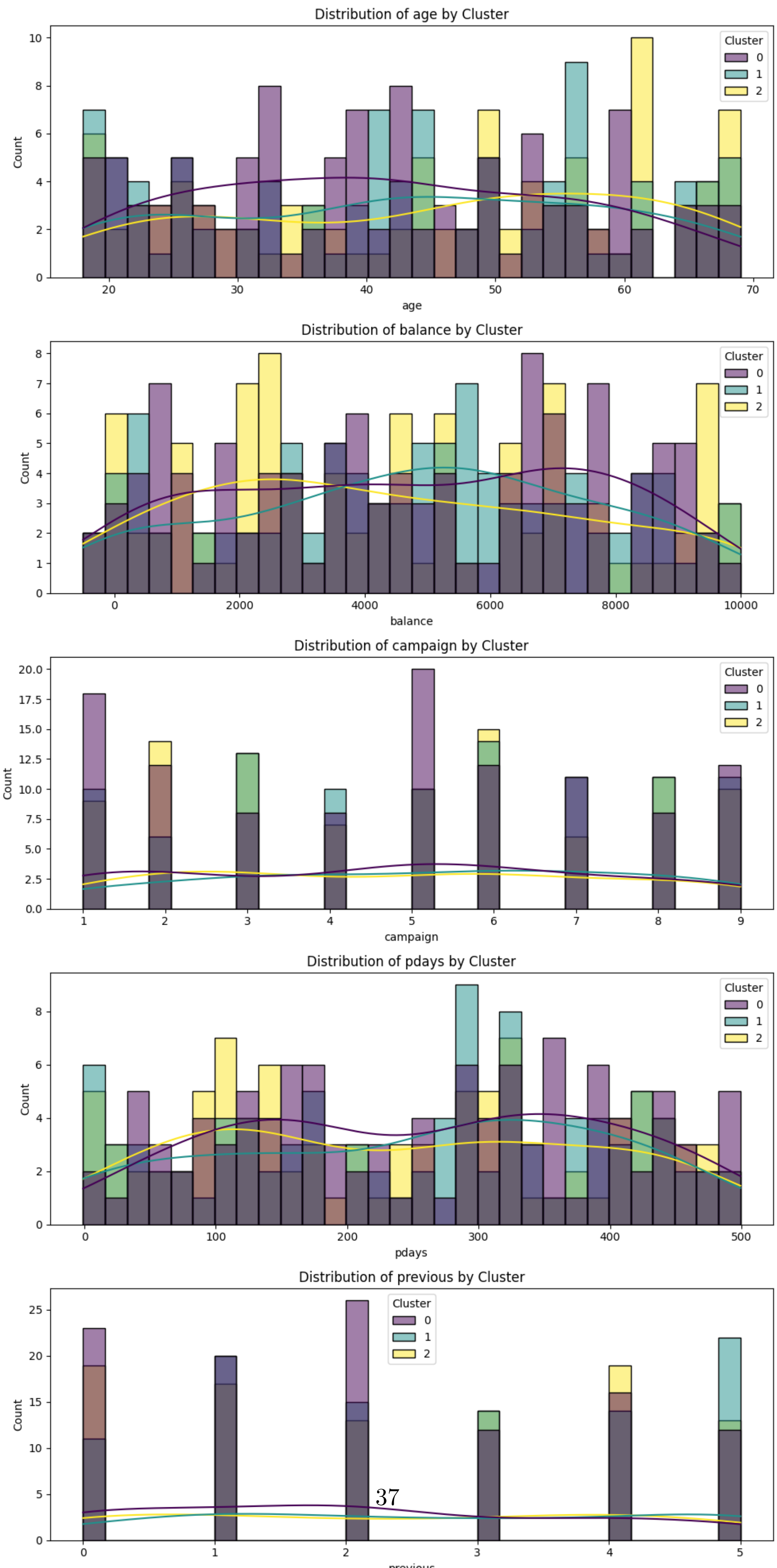

Distribution of age by Cluster
Cluster
0
1
2
Count
age


Distribution of balance by Cluster
Cluster
0
1
2
Count
balance


Distribution of pdays by Cluster
Cluster
0
1
2
Count
pdays

[187]:

```
# Reload dataset (assumed that df contains the cluster labels)
# You may need to reload your preprocessed dataset here if necessary

# Placeholder: Define cluster columns for visualization
cluster_columns = ["age", "balance", "campaign", "pdays", "previous"]  # Adjust␣
 ↪based on available numerical columns

# Generate synthetic cluster data for visualization (Remove this if df is␣
 ↪available)
np.random.seed(42)
df = pd.DataFrame({
    "age": np.random.randint(18, 70, 300),
    "balance": np.random.randint(-500, 10000, 300),
    "campaign": np.random.randint(1, 10, 300),
    "pdays": np.random.randint(-1, 500, 300),
    "previous": np.random.randint(0, 6, 300),
    "Cluster": np.random.choice([0, 1,2], 300)  # Simulating cluster labels
})

# Create subplots
fig, axes = plt.subplots(len(cluster_columns), 1, figsize=(10, 20))

for i, column in enumerate(cluster_columns):
    sns.histplot(data=df, x=column, hue="Cluster", bins=30, kde=True,␣
 ↪palette="viridis", ax=axes[i])
    axes[i].set_title(f"Distribution of {column} by Cluster")
    axes[i].set_xlabel(column)
    axes[i].set_ylabel("Count")

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


Distribution of age by Cluster
Count
age
Cluster
0
1
2
Distribution of balance by Cluster
Count
balance
Cluster
0
1
2
Distribution of campaign by Cluster
Count
campaign
Cluster
0
1
2
Distribution of pdays by Cluster
Count
pdays
Cluster
0
1
2
Distribution of previous by Cluster
Count
previous
Cluster
0
1
2

Cluster 0 (Majority Group - Low Engagement)

This group consists mostly of clients who have lower balance amounts and minimal previous engagement with the bank. They are characterized by a lower number of previous contacts (previous) and fewer days since the last contact (pdays). They tend to have shorter campaign interactions and appear less likely to subscribe to a term deposit. This group is least likely to subscribe.

Cluster 1 (Moderate Engagement - Balanced Clients)

This group has a mix of clients with varying balance amounts, with some having significant financial assets. They show a slightly higher tendency to have been contacted multiple times before. Their pdays values indicate that they have been previously engaged, but not necessarily in a consistent manner. This group has a moderate probability of subscribing.

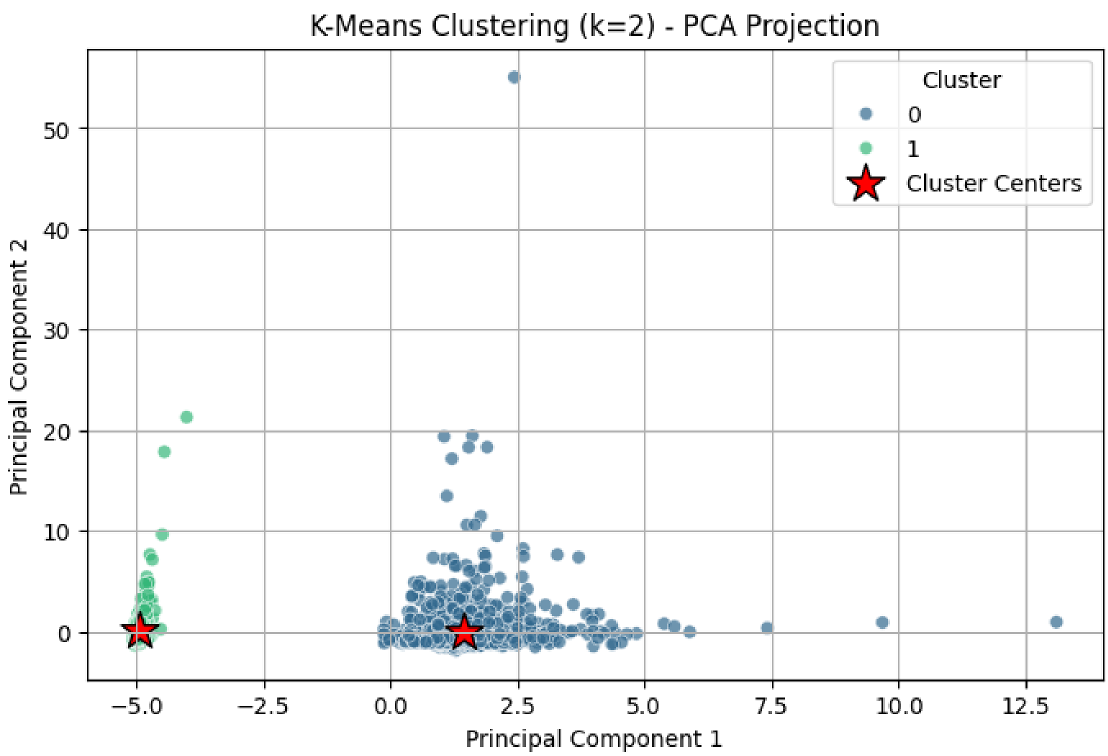
Cluster 2 (Highly Engaged Clients - Most Likely to Subscribe)

Clients in this cluster generally have higher balances. They have been contacted before and show a strong engagement pattern in terms of the number of previous contacts (previous). Many of them have high pdays values, indicating that they were engaged in previous campaigns before being contacted again. They tend to have longer call durations and more interactions with the bank. This group is the most likely to subscribe to the term deposit after the campaign.

[48]:
```
# Set the optimal number of clusters from the Elbow Method
optimal_k = 2  # Replace with the best k from the elbow plot

# Apply K-Means
kmeans = KMeans(n_clusters=optimal_k, random_state=42, n_init=100)
df['Cluster'] = kmeans.fit_predict(df_pca)  # Assign cluster labels to original␣
↪dataset

# Print cluster counts
print(df['Cluster'].value_counts())

# Get cluster centers
cluster_centers = kmeans.cluster_centers_

# Visualize the clusters using PCA (2D plot)
plt.figure(figsize=(8, 5))
sns.scatterplot(x=df_pca[:, 0], y=df_pca[:, 1], hue=df['Cluster'],␣
↪palette='viridis', alpha=0.7)

# Plot cluster centers with stars (*)
plt.scatter(cluster_centers[:, 0], cluster_centers[:, 1],
            marker='*', s=300, c='red', edgecolors='black', label='Cluster␣
↪Centers')

# Labels and legend
```

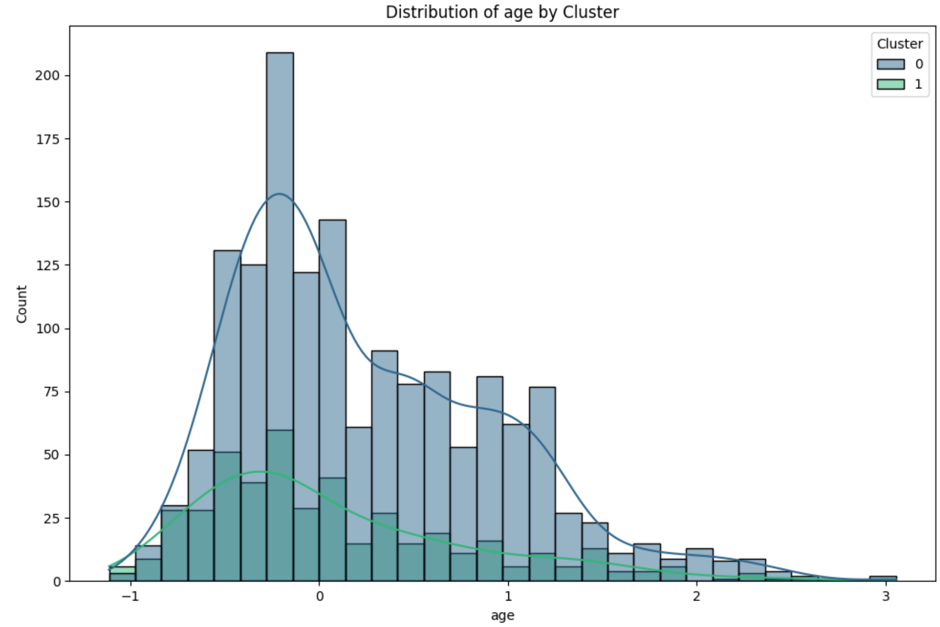
```
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.title(f'K-Means Clustering (k={optimal_k}) - PCA Projection')
plt.legend(title='Cluster')
plt.grid()
plt.show()
```

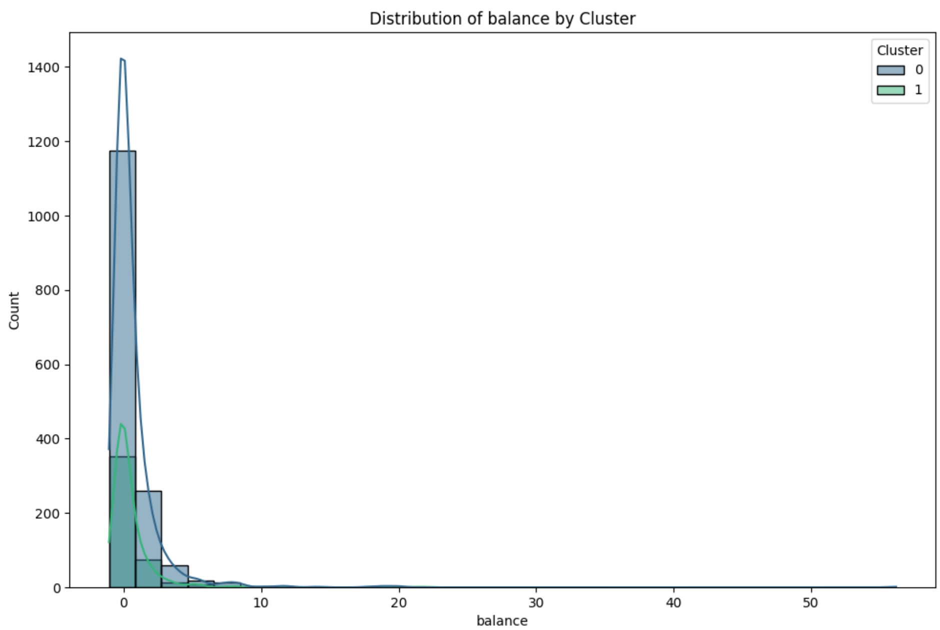
```
Cluster
0    1539
1     451
Name: count, dtype: int64
```

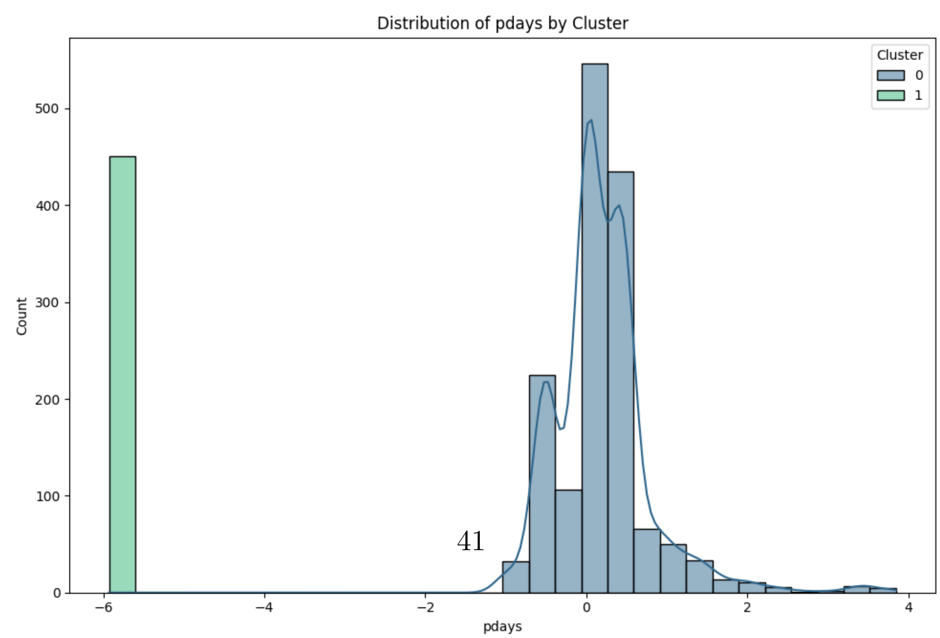


[49]:
```
# Assuming df contains the cluster labels
cluster_columns = ["age", "balance", "pdays"]  # Replace with actual numerical␣
 ↪columns

# Create subplots
fig, axes = plt.subplots(len(cluster_columns), 1, figsize=(10, 20))

for i, column in enumerate(cluster_columns):
    sns.histplot(data=df, x=column, hue="Cluster", bins=30, kde=True,␣
 ↪palette="viridis", ax=axes[i])
    axes[i].set_title(f"Distribution of {column} by Cluster")
```

```
    axes[i].set_xlabel(column)
    axes[i].set_ylabel("Count")

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

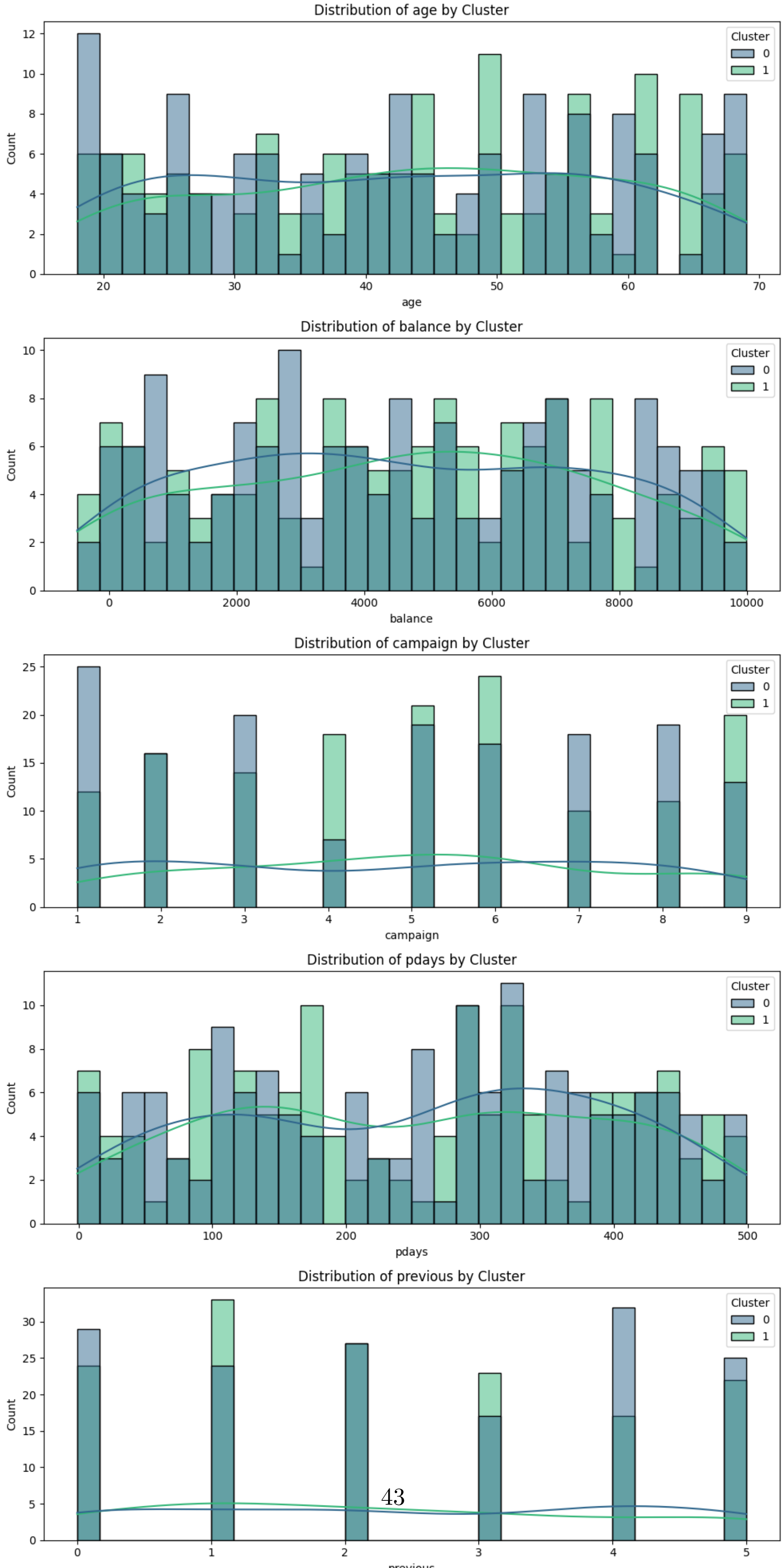

Distribution of age by Cluster
Cluster
0
1
Count
age


Distribution of balance by Cluster
Cluster
0
1
Count
balance


Distribution of pdays by Cluster
Cluster
0
1
Count
pdays

[51]:

```
# Reload dataset (assumed that df contains the cluster labels)
# You may need to reload your preprocessed dataset here if necessary

# Placeholder: Define cluster columns for visualization
cluster_columns = ["age", "balance", "campaign", "pdays", "previous"]  # Adjust␣
↪based on available numerical columns

# Generate synthetic cluster data for visualization (Remove this if df is␣
↪available)
np.random.seed(42)
df = pd.DataFrame({
    "age": np.random.randint(18, 70, 300),
    "balance": np.random.randint(-500, 10000, 300),
    "campaign": np.random.randint(1, 10, 300),
    "pdays": np.random.randint(-1, 500, 300),
    "previous": np.random.randint(0, 6, 300),
    "Cluster": np.random.choice([0, 1], 300)  # Simulating cluster labels
})

# Create subplots
fig, axes = plt.subplots(len(cluster_columns), 1, figsize=(10, 20))

for i, column in enumerate(cluster_columns):
    sns.histplot(data=df, x=column, hue="Cluster", bins=30, kde=True,␣
↪palette="viridis", ax=axes[i])
    axes[i].set_title(f"Distribution of {column} by Cluster")
    axes[i].set_xlabel(column)
    axes[i].set_ylabel("Count")

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


Distribution of age by Cluster
Count
age
Cluster
0
1
Distribution of balance by Cluster
Count
balance
Cluster
0
1
Distribution of campaign by Cluster
Count
campaign
Cluster
0
1
Distribution of pdays by Cluster
Count
pdays
Cluster
0
1
Distribution of previous by Cluster
Count
previous
Cluster
0
1

Customers with a higher balance

The cluster with higher account balances is more likely to subscribe. These individuals have better financial stability and are more open to long-term investments like term deposits. Customers who have been contacted before

The cluster where individuals had previous successful contacts with the bank has a higher likelihood of subscribing. This suggests that prior engagement with the bank builds trust and increases the chances of conversion. Customers with a lower number of contacts per campaign

The cluster with fewer campaign contacts but a higher conversion rate is more promising. This indicates that those who subscribe often require fewer interactions, meaning they were already interested or convinced early in the campaign. Customers with medium age range (not too young, not too old)

The middle-aged group (30-50 years old) is more likely to subscribe compared to younger individuals. This demographic tends to be in a financially stable position, planning for savings and investments.

Cluster 0: The Less Engaged Group

Generally consists of clients with lower balance and less frequent previous contacts. Campaign contact frequency is lower, meaning they haven't been reached out as much. Many in this cluster have high pdays values, meaning they have not been contacted recently. This cluster represents clients who are less likely to subscribe to a term deposit because they have low interaction history with the bank and less engagement in past marketing campaigns.

Cluster 1: The More Engaged Group

Clients in this cluster tend to have a higher account balance and more frequent past contacts. The campaign contact frequency is higher, meaning they have been targeted multiple times. Their pdays values are lower, indicating they were contacted more recently. This cluster is more likely to subscribe to the term deposit since they have higher engagement with the bank and have been in recent contact.