EDA - Assesment # 1 - Telecom

In [145…
```python
## First, let's import the libraries
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import csv
import dataprep
from dataprep.eda import plot
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm
from scipy.stats import pointbiserialr
import scipy.stats as ss
```

Data Reading & General Overview - Variable Definition

In [146…
```python
# Load the dataset with semicolon as the delimiter
marketing = pd.read_csv('TeleCom_Data-1.csv', sep=';')

# Display the first few rows of the dataframe
marketing.head()
```

Out[146…

	age;"job";"marital";"education";"default";"housing";"loan";"contact";"month";"day_o
0	
1	
2	
3	
4	

In [147…
```python
# lets find a different way to process the data reading because pd.read_csv
cleaned_data = []

with open('TeleCom_Data-1.csv', mode='r', encoding='utf-8') as file:
    reader = csv.reader(file, delimiter=';')
    for row in reader:
        cleaned_data.append(row)

# Manually split each row by semicolon and handle the quotes
split_data = [line[0].split(';') for line in cleaned_data]

# Convert the split data to a DataFrame
marketing = pd.DataFrame(split_data[1:], columns=split_data[0])
```

```
# Clean the column names and data by removing extra quotation marks
marketing.columns = [col.strip().replace('"', '').strip() for col in marketi
marketing = marketing.applymap(lambda x: x.strip().replace('"', '').strip())


original_data = marketing.copy()

# Display the first few rows of the cleaned DataFrame
marketing.head()
```

Out[147…

	age	job	marital	education	default	housing	loan	contact	mont
0	40	admin.	married	basic.6y	no	no	no	telephone	ma
1	56	services	married	high.school	no	no	yes	telephone	ma
2	45	services	married	basic.9y	unknown	no	no	telephone	ma
3	59	admin.	married	professional.course	no	no	no	telephone	ma
4	41	blue-collar	married	unknown	unknown	no	no	telephone	ma

5 rows × 21 columns

In [148…

```
marketing.shape
```

Out[148…

```
(41180, 21)
```

Variable dictionary definitions

In [149…

```
## I want to have here the dictionary of the columns and their data types
dict_market = pd.read_excel('Data_dictionary-1.xlsx')
dict_market
```

Out[149…

	Variable Name	Description
0	age	Age
1	job	Type of job
2	marital	Marital status
3	education	Level of education
4	default	Has credit in default
5	balance	Average yearly balance
6	housing	Has a housing loan
7	loan	Has a personal loan
8	contact	Contact communication type
9	day	Day of contact
10	month	Month of contact
11	duration	Last contact duration, in seconds (numeric). I...
12	campaign	Number of contacts performed during this campa...
13	pdays	Number of days that passed by after the client...
14	previous	Number of contacts performed before this campa...
15	poutcome	Outcome of the previous marketing campaign
16	emp.var.rate	employment variation rate - quarterly indicato...
17	cons.price.idx	consumer price index - monthly indicator (nume...
18	cons.conf.idx	consumer confidence index - monthly indicator ...
19	euribor3m	euribor 3 month rate - daily indicator (numeric)
20	nr.employed	number employed - quarterly indicator (numeric)
21	y	Did the client subscribe to a Telecom plan?

In [150…

```
marketing.shape
```

Out[150…

```
(41180, 21)
```

Information of dataset variables

In [151…

```
marketing.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41180 entries, 0 to 41179
Data columns (total 21 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   age             41180 non-null  object
 1   job             41180 non-null  object
 2   marital         41180 non-null  object
 3   education       41180 non-null  object
 4   default         41180 non-null  object
 5   housing         41180 non-null  object
 6   loan            41180 non-null  object
 7   contact         41180 non-null  object
 8   month           41180 non-null  object
 9   day_of_week     41180 non-null  object
 10  duration        41180 non-null  object
 11  campaign        41180 non-null  object
 12  pdays           41180 non-null  object
 13  previous        41180 non-null  object
 14  poutcome        41180 non-null  object
 15  emp.var.rate    41180 non-null  object
 16  cons.price.idx  41180 non-null  object
 17  cons.conf.idx   41180 non-null  object
 18  euribor3m       41180 non-null  object
 19  nr.employed     41180 non-null  object
 20  y               41180 non-null  object
dtypes: object(21)
memory usage: 6.6+ MB
```

In [152…

```
duplicate_rows = marketing.duplicated().sum()

# Display number of duplicate rows
print("\nNumber of duplicate rows:", duplicate_rows)
```

```
Number of duplicate rows: 12
```

However, these duplicates can be different entries because there is nothing that separates one client from another client. They can coincide in the same features

In [153…

```
## assigning correct type

numeric_columns = ['age', 'duration', 'campaign', 'pdays', 'previous',
                   'emp.var.rate', 'cons.price.idx', 'cons.conf.idx',
                   'euribor3m', 'nr.employed']

marketing[numeric_columns] = marketing[numeric_columns].apply(pd.to_numeric,

# Verify the changes
marketing.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41180 entries, 0 to 41179
Data columns (total 21 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   age             41180 non-null  int64  
 1   job             41180 non-null  object 
 2   marital         41180 non-null  object 
 3   education       41180 non-null  object 
 4   default         41180 non-null  object 
 5   housing         41180 non-null  object 
 6   loan            41180 non-null  object 
 7   contact         41180 non-null  object 
 8   month           41180 non-null  object 
 9   day_of_week     41180 non-null  object 
 10  duration        41180 non-null  int64  
 11  campaign        41180 non-null  int64  
 12  pdays           41180 non-null  int64  
 13  previous        41180 non-null  int64  
 14  poutcome        41180 non-null  object 
 15  emp.var.rate    41180 non-null  float64
 16  cons.price.idx  41180 non-null  float64
 17  cons.conf.idx   41180 non-null  float64
 18  euribor3m       41180 non-null  float64
 19  nr.employed     41180 non-null  float64
 20  y               41180 non-null  object 
dtypes: float64(5), int64(5), object(11)
memory usage: 6.6+ MB
```

Summary Statistics

In [154…

```python
## lets check the general description of the data using the describe methodc
marketing.describe()
```

Out[154…

	age	duration	campaign	pdays	previous	emp.
count	41180.000000	41180.000000	41180.000000	41180.000000	41180.000000	41180.
mean	40.021710	258.280427	2.567800	962.516707	0.172705	C
std	10.419593	259.299856	2.770225	186.809028	0.493719	'
min	17.000000	0.000000	1.000000	0.000000	0.000000	-3.
25%	32.000000	102.000000	1.000000	999.000000	0.000000	-1.
50%	38.000000	180.000000	2.000000	999.000000	0.000000	1
75%	47.000000	319.000000	3.000000	999.000000	0.000000	1.
max	98.000000	4918.000000	56.000000	999.000000	7.000000	1.

In [155…

```python
## lets check the statistics for the categorical variables
marketing.describe(include='object')
```

Out [155…

	job	marital	education	default	housing	loan	contact	month	da
count	41180	41180	41180	41180	41180	41180	41180	41180	
unique	12	4	8	3	3	3	2	10	
top	admin.	married	university.degree	no	yes	no	cellular	may	
freq	10422	24921	12166	32581	21571	33943	26140	13765	

Data Cleaning & Processing

In [156…

```
# Check for missing values
missing_values = marketing.isnull().sum()

# Display columns with missing values
missing_values[missing_values > 0]
```

Out [156…

```
Series([], dtype: int64)
```

In [157…

```
# Function to display unique values for a specific column
def inspect_column(column_name):
    print(f"Unique values in column '{column_name}':")
    print(marketing[column_name].unique())
    print("\n")

# Call this function for each column you're interested in inspecting
inspect_column('age')
inspect_column('job')
inspect_column('marital')
inspect_column('education')
inspect_column('default')
inspect_column('housing')
inspect_column('loan')
```

```
Unique values in column 'age':
[40 56 45 59 41 24 25 29 57 35 54 46 39 30 55 37 49 34 52 58 32 38 44 42
 60 53 50 47 51 48 33 31 43 36 28 27 26 22 23 20 21 61 19 18 70 66 76 67
 73 88 95 77 68 75 63 80 62 65 72 82 64 71 69 78 85 79 83 81 74 17 87 91
 86 98 94 84 92 89]


Unique values in column 'job':
['admin.' 'services' 'blue-collar' 'technician' 'housemaid' 'retired'
 'management' 'unemployed' 'self-employed' 'unknown' 'entrepreneur'
 'student']


Unique values in column 'marital':
['married' 'single' 'divorced' 'unknown']


Unique values in column 'education':
['basic.6y' 'high.school' 'basic.9y' 'professional.course' 'unknown'
 'basic.4y' 'university.degree' 'illiterate']


Unique values in column 'default':
['no' 'unknown' 'yes']


Unique values in column 'housing':
['no' 'yes' 'unknown']


Unique values in column 'loan':
['no' 'yes' 'unknown']
```

In [158…

```
inspect_column('contact')
inspect_column('month')
inspect_column('day_of_week')
inspect_column('duration')
inspect_column('campaign')
inspect_column('pdays')
```

```
Unique values in column 'contact':
['telephone' 'cellular']


Unique values in column 'month':
['may' 'jun' 'jul' 'aug' 'oct' 'nov' 'dec' 'mar' 'apr' 'sep']


Unique values in column 'day_of_week':
['mon' 'tue' 'wed' 'thu' 'fri']


Unique values in column 'duration':
[ 151  307  198 ... 1246 1556 1868]


Unique values in column 'campaign':
[ 1  2  3  4  5  6  7  8  9 10 11 12 13 19 18 23 14 22 25 16 17 15 20 56
 39 35 42 28 26 27 32 21 24 29 31 30 41 37 40 33 34 43]


Unique values in column 'pdays':
[999   6   4   3   5   1   0  10   7   8   9  11   2  12  13  14  15  16
  21  17  18  22  25  26  19  27  20]
```

In [159…

```
inspect_column('previous')
inspect_column('poutcome')
inspect_column('emp.var.rate')
inspect_column('cons.price.idx')
inspect_column('cons.conf.idx')
inspect_column('euribor3m')
inspect_column('nr.employed')
inspect_column('y')
```

```
Unique values in column 'previous':
[0 1 2 3 4 5 6 7]


Unique values in column 'poutcome':
['nonexistent' 'failure' 'success']


Unique values in column 'emp.var.rate':
[ 1.1  1.4 -0.1 -0.2 -1.8 -2.9 -3.4 -3.  -1.7 -1.1]


Unique values in column 'cons.price.idx':
[93.994 94.465 93.918 93.444 93.798 93.2   92.756 92.843 93.075 92.893
 92.963 92.469 92.201 92.379 92.431 92.649 92.713 93.369 93.749 93.876
 94.055 94.215 94.027 94.199 94.601 94.767]


Unique values in column 'cons.conf.idx':
[-36.4 -41.8 -42.7 -36.1 -40.4 -42.  -45.9 -50.  -47.1 -46.2 -40.8 -33.6
 -31.4 -29.8 -26.9 -30.1 -33.  -34.8 -34.6 -40.  -39.8 -40.3 -38.3 -37.5
 -49.5 -50.8]


Unique values in column 'euribor3m':
[4.857 4.856 4.855 4.859 4.86  4.858 4.864 4.865 4.866 4.967 4.961 4.959
 4.958 4.96  4.962 4.955 4.947 4.956 4.966 4.963 4.957 4.968 4.97  4.965
 4.964 5.045 5.    4.936 4.921 4.918 4.912 4.827 4.794 4.76  4.733 4.7
 4.663 4.592 4.474 4.406 4.343 4.286 4.245 4.223 4.191 4.153 4.12  4.076
 4.021 3.901 3.879 3.853 3.816 3.743 3.669 3.563 3.488 3.428 3.329 3.282
 3.053 1.811 1.799 1.778 1.757 1.726 1.703 1.687 1.663 1.65  1.64  1.629
 1.614 1.602 1.584 1.574 1.56  1.556 1.548 1.538 1.531 1.52  1.51  1.498
 1.483 1.479 1.466 1.453 1.445 1.435 1.423 1.415 1.41  1.405 1.406 1.4
 1.392 1.384 1.372 1.365 1.354 1.344 1.334 1.327 1.313 1.299 1.291 1.281
 1.266 1.25  1.244 1.259 1.264 1.27  1.262 1.26  1.268 1.286 1.252 1.235
 1.224 1.215 1.206 1.099 1.085 1.072 1.059 1.048 1.044 1.029 1.018 1.007
 0.996 0.979 0.969 0.944 0.937 0.933 0.927 0.921 0.914 0.908 0.903 0.899
 0.884 0.883 0.881 0.879 0.873 0.869 0.861 0.859 0.854 0.851 0.849 0.843
 0.838 0.834 0.829 0.825 0.821 0.819 0.813 0.809 0.803 0.797 0.788 0.781
 0.778 0.773 0.771 0.77  0.768 0.766 0.762 0.755 0.749 0.743 0.741 0.739
 0.75  0.753 0.754 0.752 0.744 0.74  0.742 0.737 0.735 0.733 0.73  0.731
 0.728 0.724 0.722 0.72  0.719 0.716 0.715 0.714 0.718 0.721 0.717 0.712
 0.71  0.709 0.708 0.706 0.707 0.7   0.655 0.654 0.653 0.652 0.651 0.65
 0.649 0.646 0.644 0.643 0.639 0.637 0.635 0.636 0.634 0.638 0.64  0.642
 0.645 0.659 0.663 0.668 0.672 0.677 0.682 0.683 0.684 0.685 0.688 0.69
 0.692 0.695 0.697 0.699 0.701 0.702 0.704 0.711 0.713 0.723 0.727 0.729
 0.732 0.748 0.761 0.767 0.782 0.79  0.793 0.802 0.81  0.822 0.827 0.835
 0.84  0.846 0.87  0.876 0.885 0.889 0.893 0.896 0.898 0.9   0.904 0.905
 0.895 0.894 0.891 0.89  0.888 0.886 0.882 0.88  0.878 0.877 0.942 0.953
 0.956 0.959 0.965 0.972 0.977 0.982 0.985 0.987 0.993 1.    1.008 1.016
 1.025 1.032 1.037 1.043 1.045 1.047 1.05  1.049 1.046 1.041 1.04  1.039
 1.035 1.03  1.031 1.028]


Unique values in column 'nr.employed':
[5191.  5228.1 5195.8 5176.3 5099.1 5076.2 5017.5 5023.5 5008.7 4991.6
```

```
4963.6]


Unique values in column 'y':
['no' 'yes']
```

In [160…

```
plot(marketing, 'y')
```

```
0%|          | 0/76 [00:00<?, ?it/s]
```

Out[160…

Stats Bar Chart Pie Chart Word Cloud Word Frequency Word Length Value Table

Overview

Approximate Distinct Count	2
Approximate Unique (%)	0.0%
Missing	0
Missing (%)	0.0%
Memory Size	2763698

Sample

1st row	no
2nd row	no
3rd row	no
4th row	no
5th row	no

Length

Mean	2.1126
Standard Deviation	0.3161
Median	2
Minimum	2
Maximum	3

Letter

Count	86998
Lowercase Letter	86998
Space Separator	0
Uppercase Letter	0
Dash Punctuation	0
Decimal Number	0

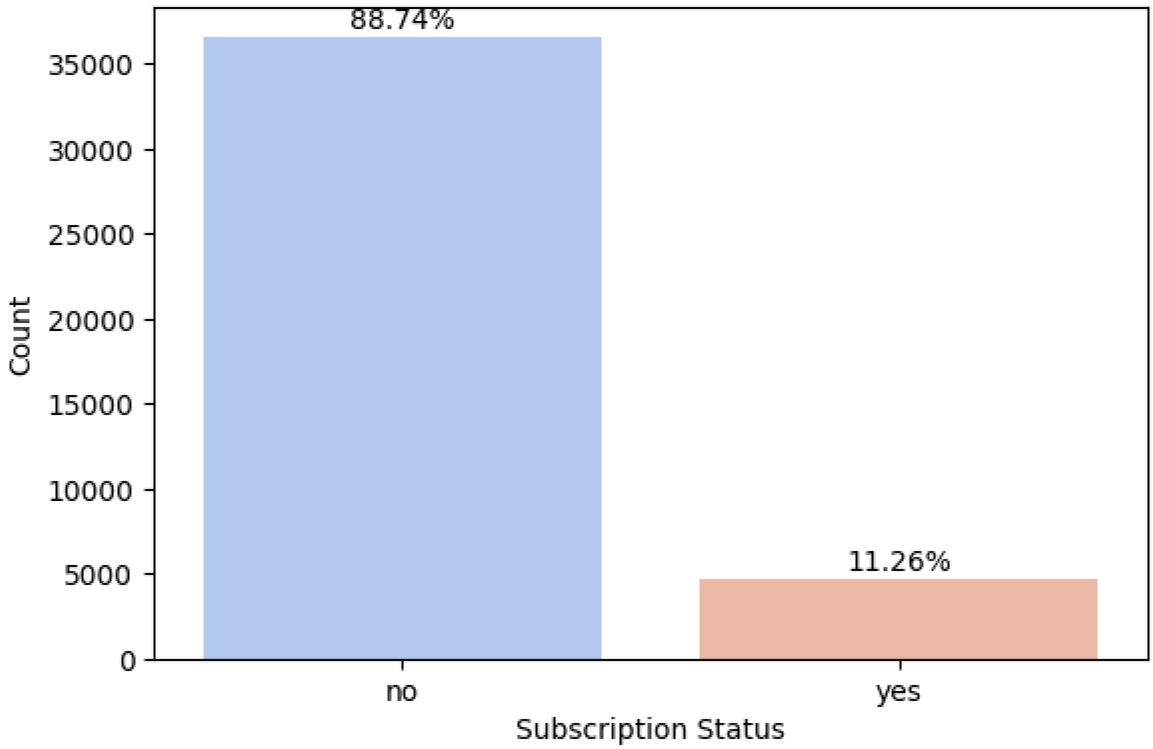
EDA Analysis

Target Variable

In [161…

```
# Plot distribution of the target variable 'y' with percentages
plt.figure(figsize=(6, 4))
ax = sns.countplot(data=marketing, x='y', palette='coolwarm')

# Calculate percentages
total = len(marketing['y'])
for p in ax.patches:
    percentage = f'{100 * p.get_height() / total:.2f}%'
    ax.annotate(percentage, (p.get_x() + p.get_width() / 2, p.get_height()),
                ha='center', va='center', xytext=(0, 6), textcoords='offset
```

```
plt.xlabel('Subscription Status')
plt.ylabel('Count')

# Show plot
plt.tight_layout()
plt.show()
```



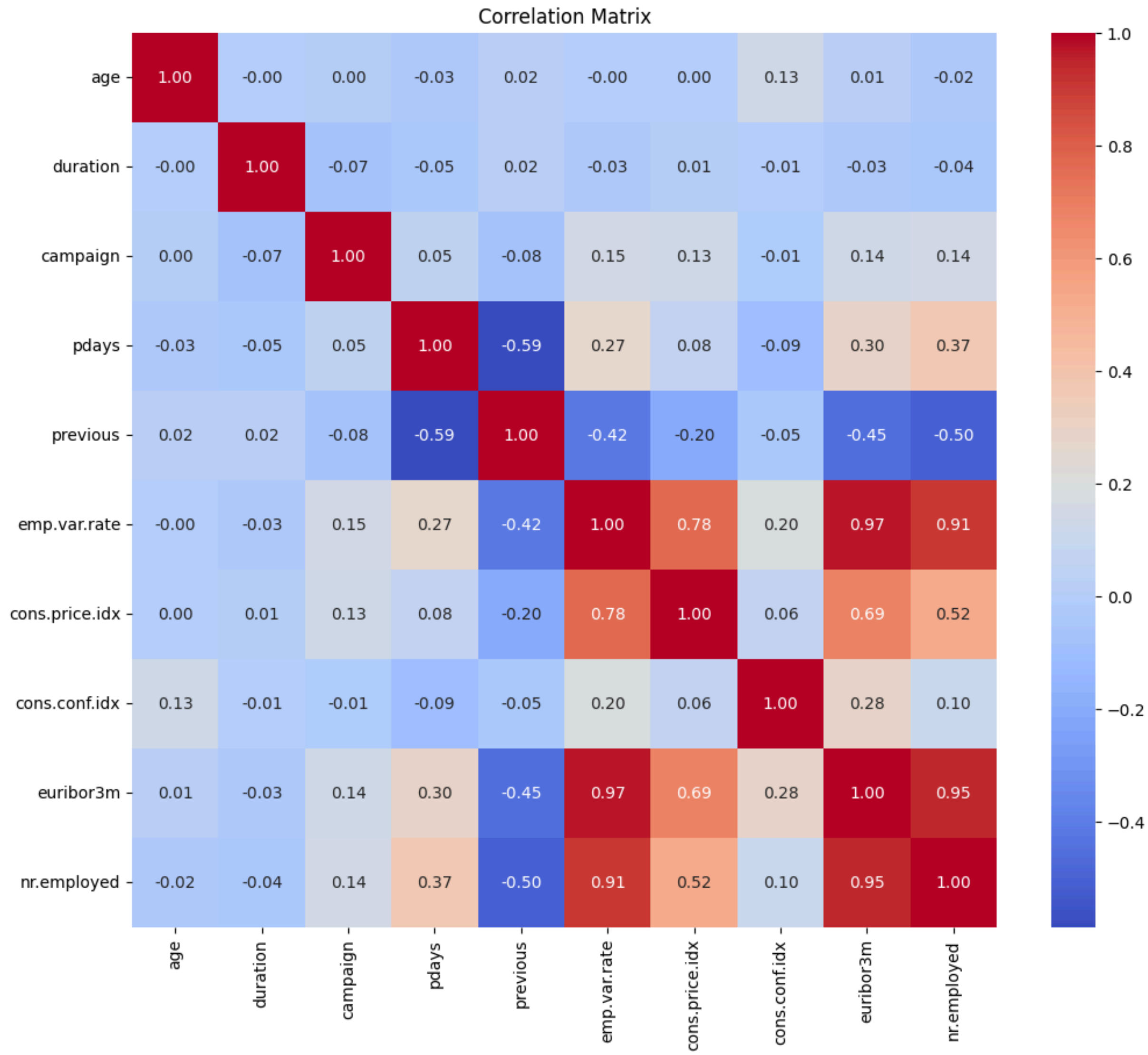
It is necessary to check variable by vvariable and analyze them individually and then what they relate with the y variable/

Heatmap for the numerical values

In [162…
```
corr_matrix = marketing.corr()
```

In [163…
```
## generate a heatmap of the correlation matrix
plt.figure(figsize=(12, 10))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Matrix')
```

Out[163…
```
Text(0.5, 1.0, 'Correlation Matrix')
```



Biserial correlation (Binary vs numerical values)

In [164...

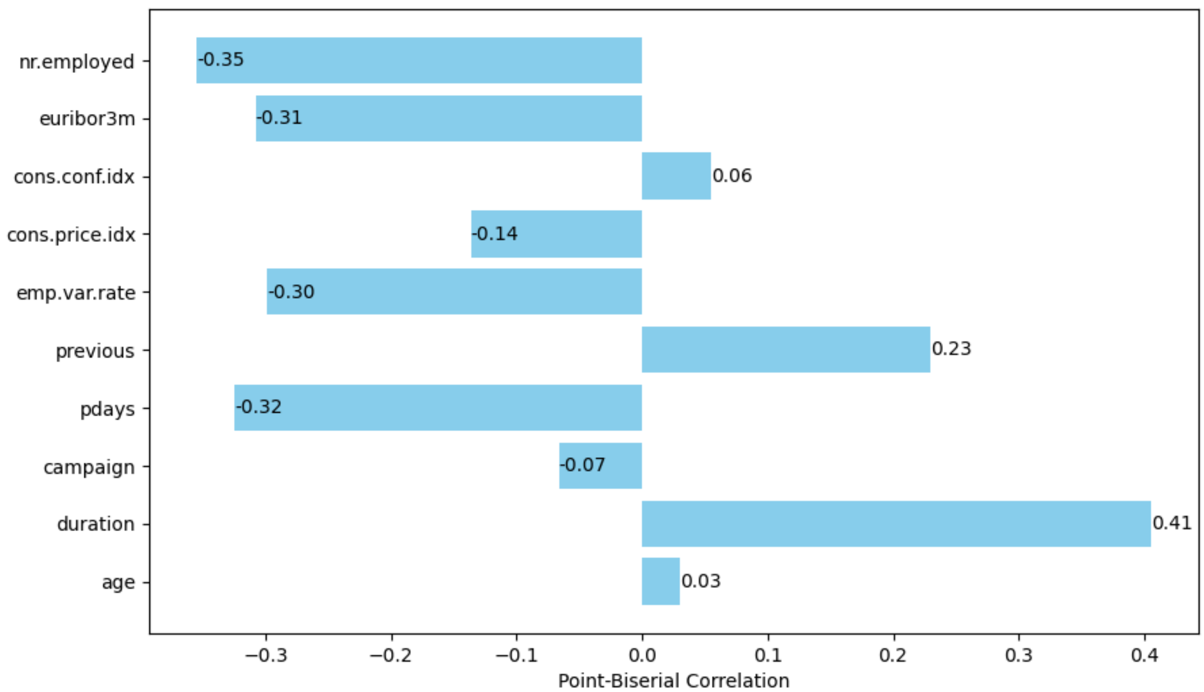
```
# Initialize LabelEncoder
label_encoder = LabelEncoder()

# Encode 'y' (target variable)
marketing['y'] = label_encoder.fit_transform(marketing['y'])

# Check the encoded values
print(marketing['y'].unique())  # Should output: [0, 1]
```

```
[0 1]
```

In [165...

```
# Calculate Point-Biserial Correlation for each numerical column
correlations = {}
for col in numeric_columns:
    corr, _ = pointbiserialr(marketing[col], marketing['y'])
    correlations[col] = corr

# Create a DataFrame for easy plotting
correlation_df = pd.DataFrame(list(correlations.items()), columns=['Variable
```

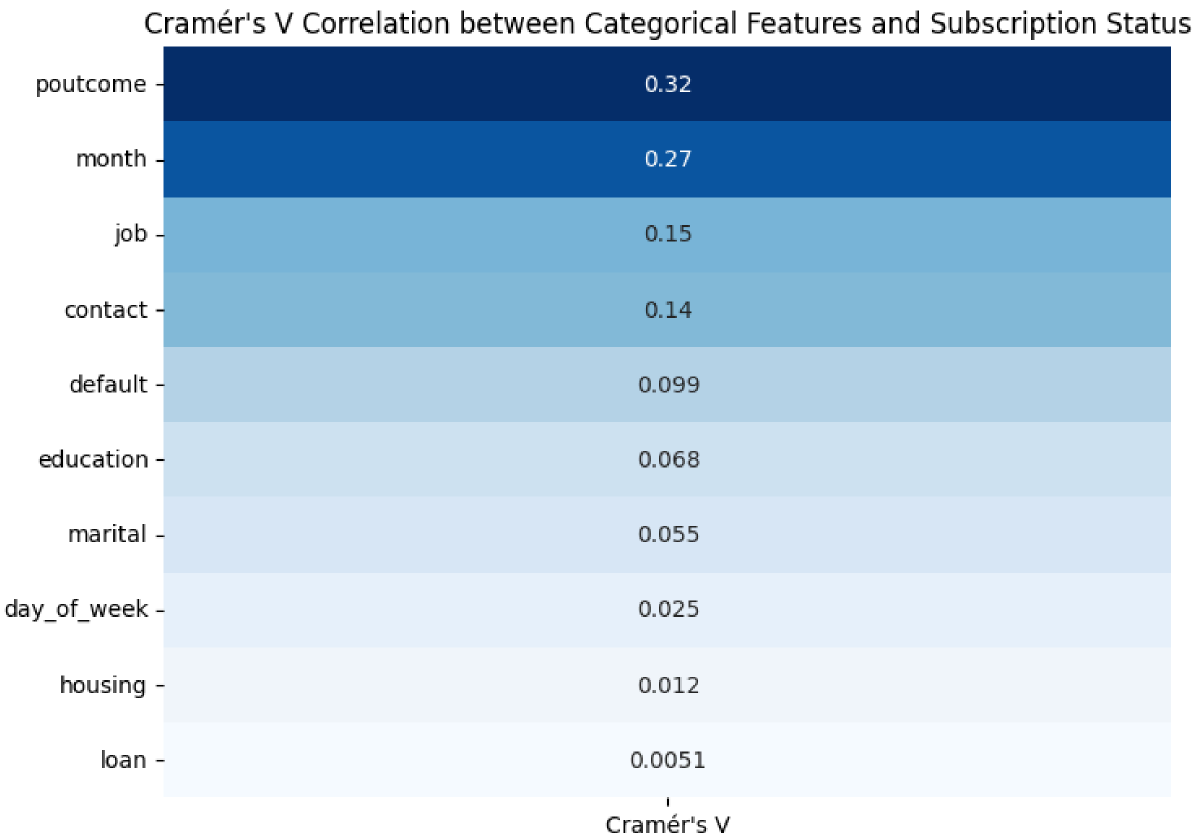
```
# Plot the results with values on the bars
plt.figure(figsize=(10, 6))
ax = plt.barh(correlation_df['Variable'], correlation_df['Point-Biserial Cor

# Annotate the values on the bars
for index, value in enumerate(correlation_df['Point-Biserial Correlation']):
    plt.text(value, index, f'{value:.2f}', va='center', ha='left')

# Labels and title
plt.xlabel('Point-Biserial Correlation')
#plt.title('Point-Biserial Correlation Between Target Variable and Numerical

# Show plot
plt.show()
```



In [213…

```
# Cramér's V calculation for categorical variables
def cramers_v(x, y):
    contingency_table = pd.crosstab(x, y)
    chi2 = ss.chi2_contingency(contingency_table)[0]
    n = contingency_table.sum().sum()
    r, k = contingency_table.shape
    return np.sqrt(chi2 / (n * (min(r - 1, k - 1))))

categorical_features = ['job', 'marital', 'education', 'default', 'housing',

# Calculate Cramér's V for each categorical feature
cramers_v_scores = {feature: cramers_v(marketing[feature], marketing['y']) f

# Convert results into DataFrame and plot heatmap
cramers_v_df = pd.DataFrame.from_dict(cramers_v_scores, orient='index', colu

plt.figure(figsize=(8, 6))
sns.heatmap(cramers_v_df, annot=True, cmap='Blues', cbar=False)
```

```
plt.title('Cramér\'s V Correlation between Categorical Features and Subscrip
plt.show()
```



Age

Univariate Analysis

In [166…

```
plot(marketing, 'age')
```

```
 0%|          | 0/122 [00:00<?, ?it/s]
```

Out [166…

Stats | Histogram | KDE Plot | Normal Q-Q Plot | Box Plot | Value Table

Overview

Approximate Distinct Count	78
Approximate Unique (%)	0.2%
Missing	0
Missing (%)	0.0%
Infinite	0
Infinite (%)	0.0%
Memory Size	658880
Mean	40.0217
Minimum	17
Maximum	98
Zeros	0
Zeros (%)	0.0%
Negatives	0
Negatives (%)	0.0%

Quantile Statistics

Minimum	17
5-th Percentile	26
Q1	32
Median	38
Q3	47
95-th Percentile	58
Maximum	98
Range	81
IQR	15

Descriptive Statisti

Mean	
Standard Deviation	
Variance	
Sum	1.6
Skewness	
Kurtosis	
Coefficient of Variation	

In [167…

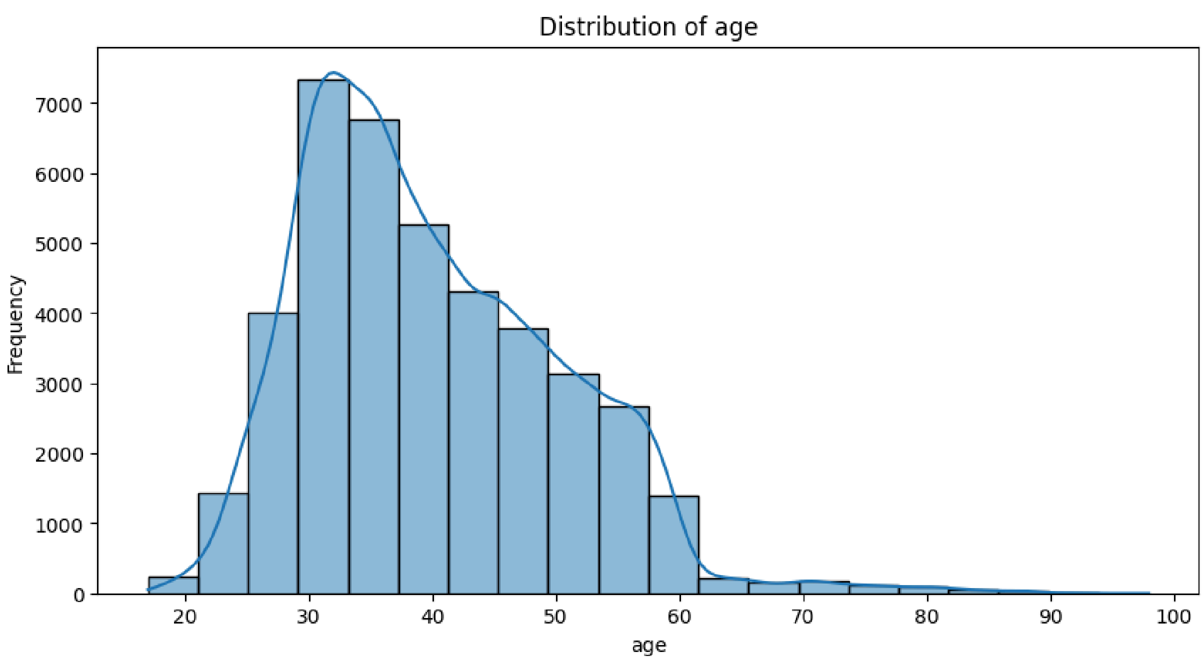
```
def analyze_column(df, column_name, chart_type='bar'):
    """
    Analyze and visualize a specific column in the DataFrame.

    Parameters:
    df (pd.DataFrame): The DataFrame containing the data.
    column_name (str): The name of the column to analyze.
    chart_type (str): The type of chart to display ('bar' or 'pie'). Default
    """
    # Summary of the column
    print(f"Summary of '{column_name}':\n{df[column_name].describe()}\n")

    # Unique values in the column
    print(f"Unique values in '{column_name}':\n{df[column_name].unique()}\n"

    # Visualization of the column distribution
    plt.figure(figsize=(10, 5))

    if df[column_name].dtype in ['int64', 'float64']:
        sns.histplot(df[column_name], kde=True, bins=20)
        plt.title(f'Distribution of {column_name}')
    else:
        if chart_type == 'bar':
            sns.countplot(y=df[column_name], order=df[column_name].value_cou
            plt.title(f'Distribution of {column_name} - Bar Chart')
```

```
        elif chart_type == 'pie':
            df[column_name].value_counts().plot.pie(autopct='%1.1f%%', start
            plt.title(f'Distribution of {column_name} - Pie Chart')
            plt.ylabel('')  # Hide the y-label for pie charts

    plt.xlabel(column_name)
    plt.ylabel('Frequency')
    plt.show()
```

In [168…

```
# Example usage with the 'age' column
analyze_column(marketing, 'age')
```

```
Summary of 'age':
count    41180.000000
mean        40.021710
std         10.419593
min         17.000000
25%         32.000000
50%         38.000000
75%         47.000000
max         98.000000
Name: age, dtype: float64

Unique values in 'age':
[40 56 45 59 41 24 25 29 57 35 54 46 39 30 55 37 49 34 52 58 32 38 44 42
 60 53 50 47 51 48 33 31 43 36 28 27 26 22 23 20 21 61 19 18 70 66 76 67
 73 88 95 77 68 75 63 80 62 65 72 82 64 71 69 78 85 79 83 81 74 17 87 91
 86 98 94 84 92 89]
```



BIvariate Analysis

In [169…

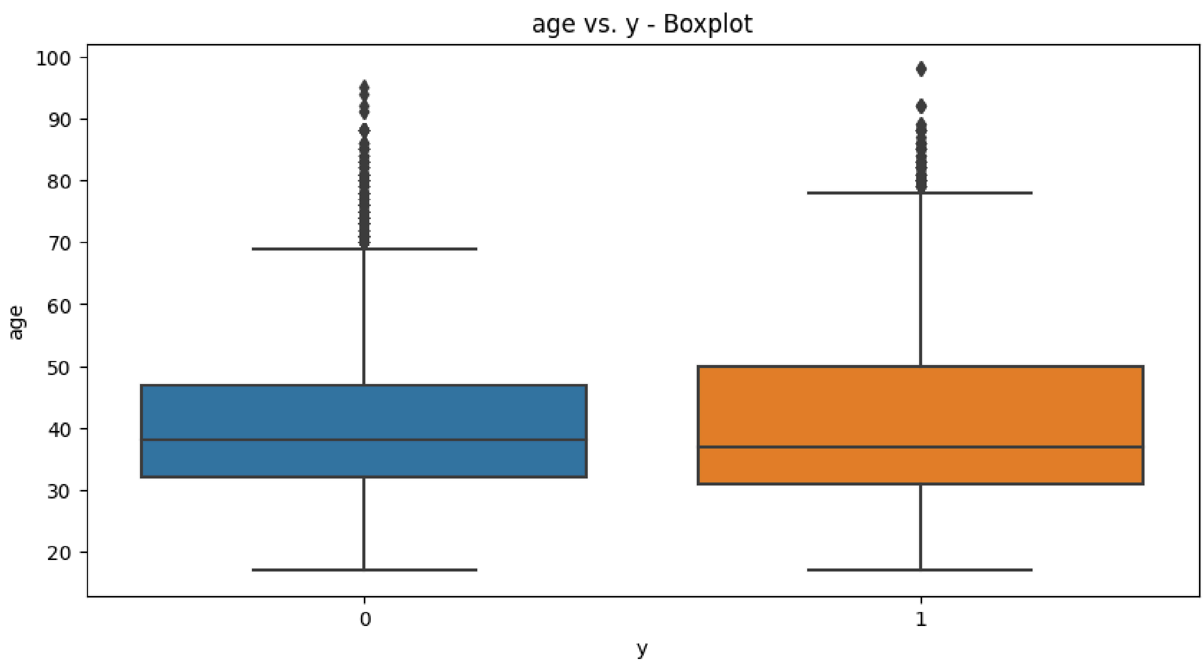
```
def bivariate_analysis(df, independent_var, target_var='y', chart_type='stac
    """
    Perform bivariate analysis between an independent variable and the targe
    including multiple plots to visualize the relationship.
```

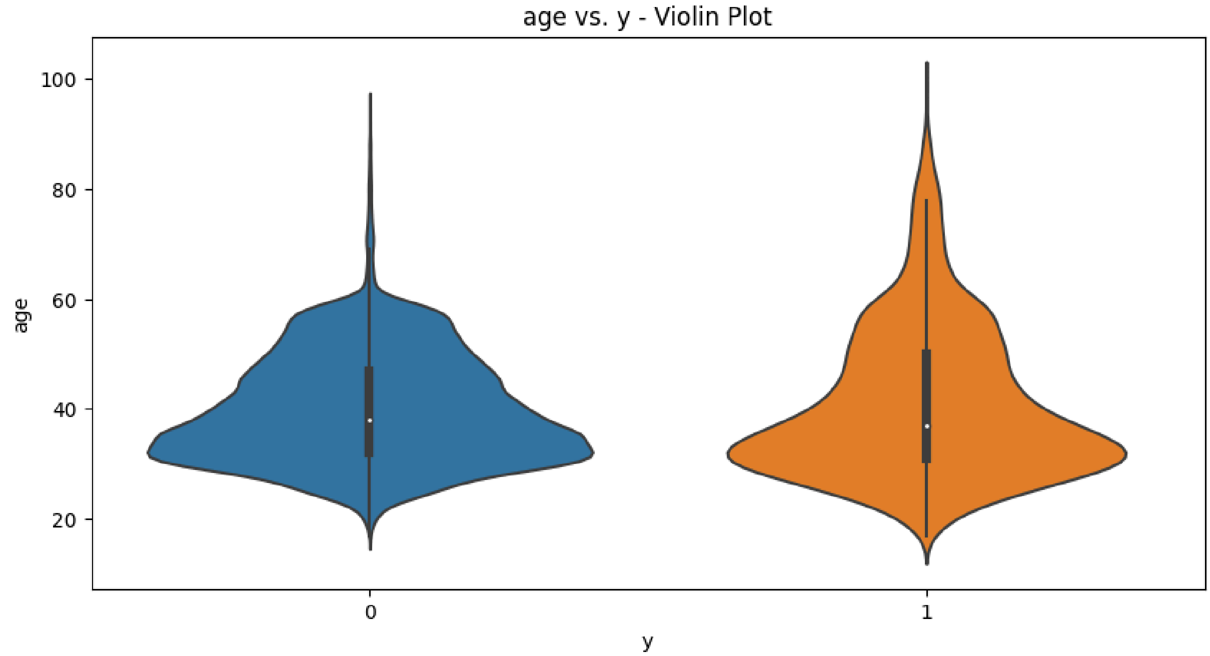
```
    Parameters:
    df (pd.DataFrame): The DataFrame containing the data.
    independent_var (str): The name of the independent variable to analyze.
    target_var (str): The name of the target variable (default is 'y').
    chart_type (str): The type of chart to display for categorical variables
                      ('stacked_bar', 'bar', 'pie'). Default is 'stacked_bar
    exclude_unknown (bool): Whether to exclude 'unknown' categories. Default
    """
    # Exclude 'unknown' values if required
    if exclude_unknown:
        df = df[df[independent_var] != 'unknown']

    print(f"Bivariate Analysis of '{independent_var}' and '{target_var}'\n")

    if df[independent_var].dtype in ['int64', 'float64']:
        # Numerical variable analysis

        # Boxplot
        plt.figure(figsize=(10, 5))
        sns.boxplot(x=target_var, y=independent_var, data=df)
        plt.title(f'{independent_var} vs. {target_var} - Boxplot')
        plt.xlabel(target_var)
        plt.ylabel(independent_var)
        plt.show()

        # Violin Plot
        plt.figure(figsize=(10, 5))
        sns.violinplot(x=target_var, y=independent_var, data=df)
        plt.title(f'{independent_var} vs. {target_var} - Violin Plot')
        plt.xlabel(target_var)
        plt.ylabel(independent_var)
        plt.show()

        # Histogram with KDE
        plt.figure(figsize=(10, 5))
        sns.histplot(df, x=independent_var, hue=target_var, kde=True, elemer
        plt.title(f'{independent_var} vs. {target_var} - Histogram with KDE'
        plt.xlabel(independent_var)
        plt.ylabel('Density')
        plt.show()

        # Strip Plot
        plt.figure(figsize=(10, 5))
        sns.stripplot(x=target_var, y=independent_var, data=df, jitter=True)
        plt.title(f'{independent_var} vs. {target_var} - Strip Plot')
        plt.xlabel(target_var)
        plt.ylabel(independent_var)
        plt.show()

    else:
        # Categorical variable analysis

        if chart_type == 'stacked_bar':
            # Stacked Bar plot of proportions
            prop_df = (df.groupby([independent_var, target_var]).size() /
```

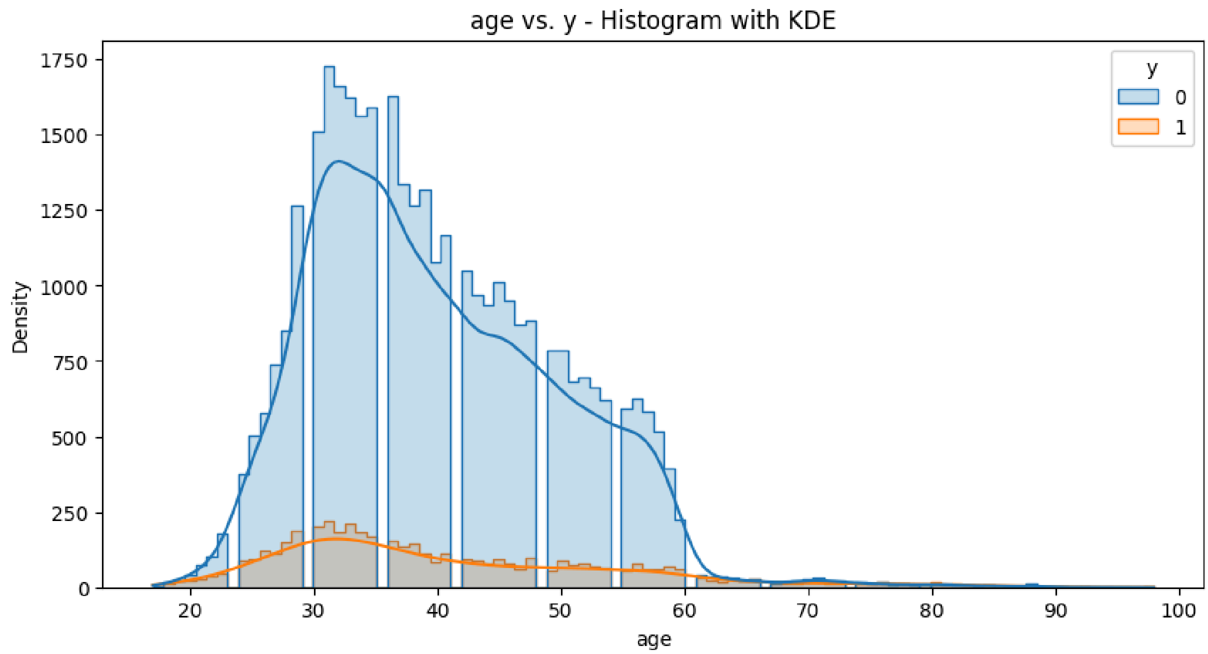
```
                     df.groupby([independent_var]).size()).unstack()
            prop_df.plot(kind='bar', stacked=True, figsize=(10, 5))
            plt.title(f'{independent_var} vs. {target_var} - Stacked Proport
            plt.xlabel(independent_var)
            plt.ylabel('Proportion')
            plt.show()

        elif chart_type == 'bar':
            # Countplot
            plt.figure(figsize=(10, 5))
            sns.countplot(x=independent_var, hue=target_var, data=df)
            plt.title(f'{independent_var} vs. {target_var} - Count Plot')
            plt.xlabel(independent_var)
            plt.ylabel('Count')
            plt.show()

        elif chart_type == 'pie':
            # Pie chart of proportions
            prop_df = df[target_var].groupby(df[independent_var]).value_cour
            for idx, row in prop_df.iterrows():
                plt.figure(figsize=(7, 7))
                row.plot(kind='pie', autopct='%1.1f%%', startangle=90)
                plt.title(f'{independent_var}: {idx}')
                plt.ylabel('')
                plt.show()
```

In [170…
```
# Example usage with the 'age' column
bivariate_analysis(marketing, 'age')
```

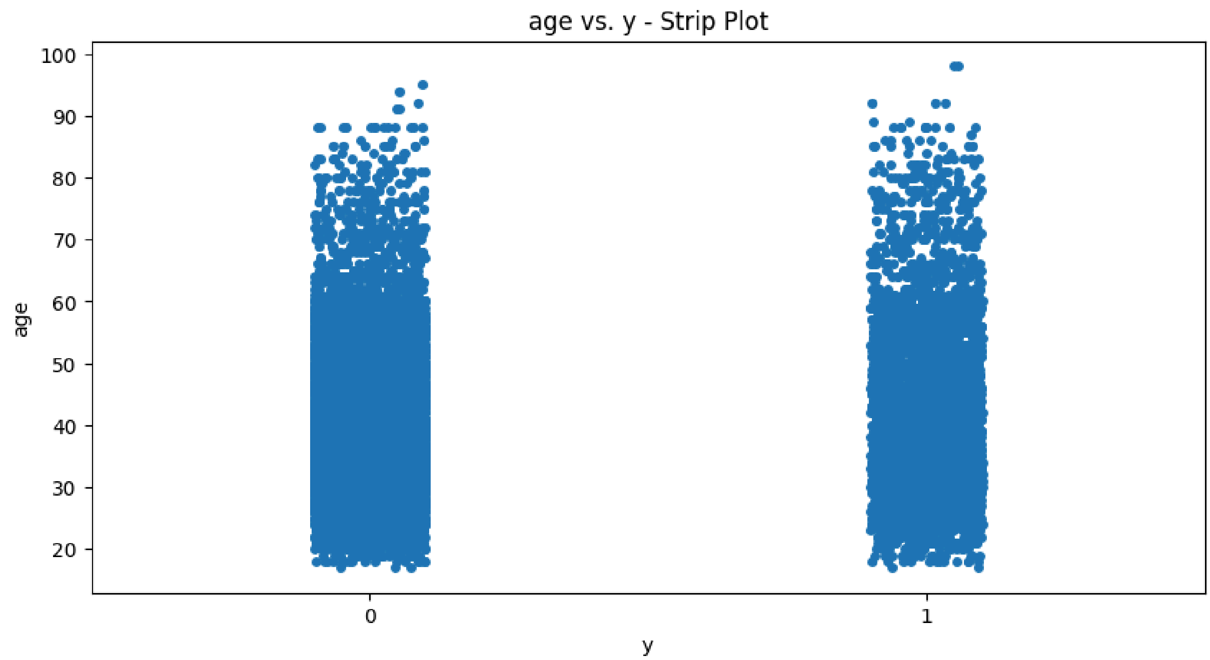
```
Bivariate Analysis of 'age' and 'y'
```





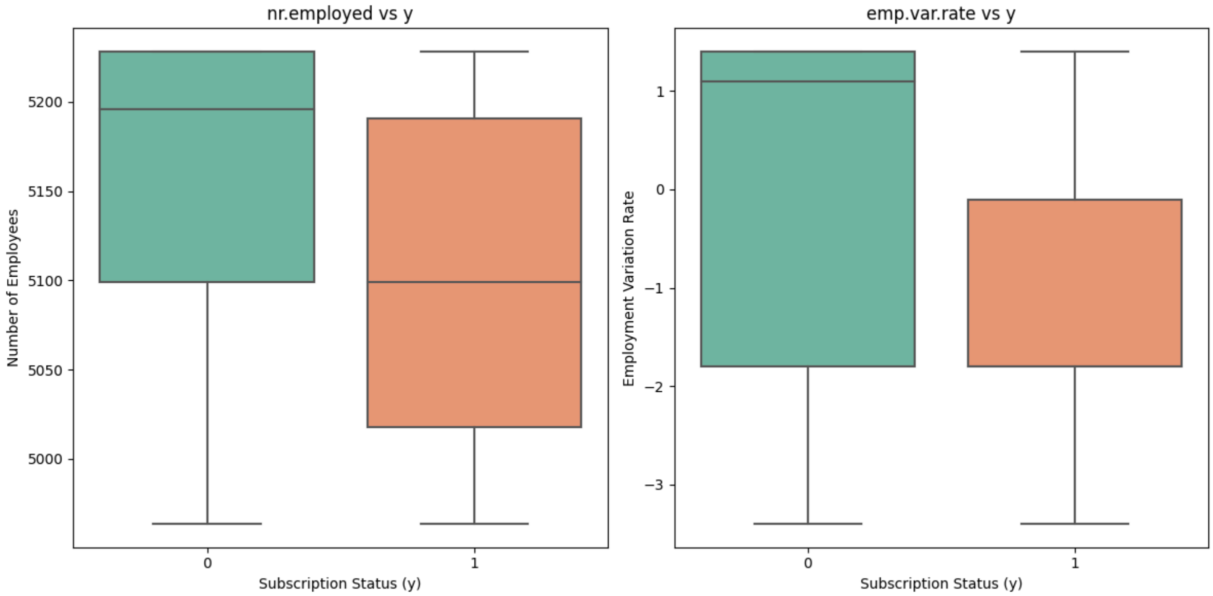



```
Using categorical units to plot a list of strings that are all parsable as f
loats or dates. If these strings should be plotted as numbers, cast to the a
ppropriate data type before plotting.
Using categorical units to plot a list of strings that are all parsable as f
loats or dates. If these strings should be plotted as numbers, cast to the a
ppropriate data type before plotting.
```



In [171…

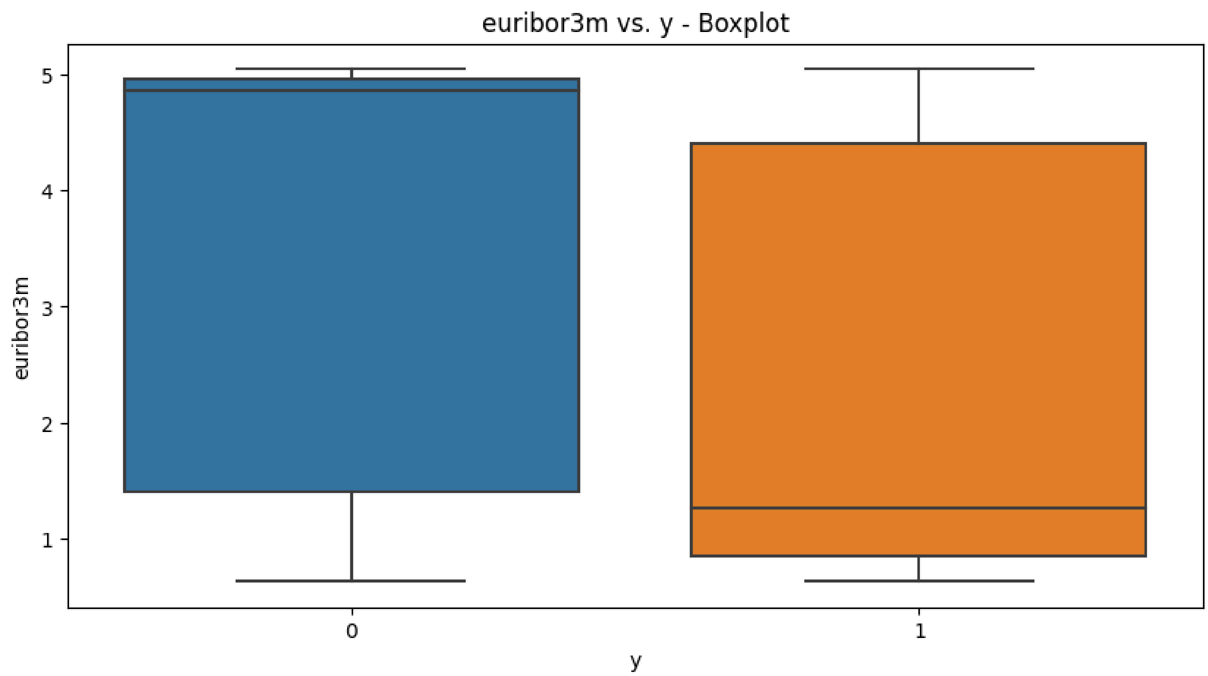
```
plt.figure(figsize=(12, 6))

# Subplot 1: nr.employed vs y
plt.subplot(1, 2, 1)
sns.boxplot(x='y', y='nr.employed', data=marketing, palette="Set2")
plt.title('nr.employed vs y')
plt.xlabel('Subscription Status (y)')
plt.ylabel('Number of Employees')

# Subplot 2: emp.var.rate vs y
plt.subplot(1, 2, 2)
sns.boxplot(x='y', y='emp.var.rate', data=marketing, palette="Set2")
plt.title('emp.var.rate vs y')
plt.xlabel('Subscription Status (y)')
plt.ylabel('Employment Variation Rate')

# Show the combined plots
plt.tight_layout()
plt.show()
```

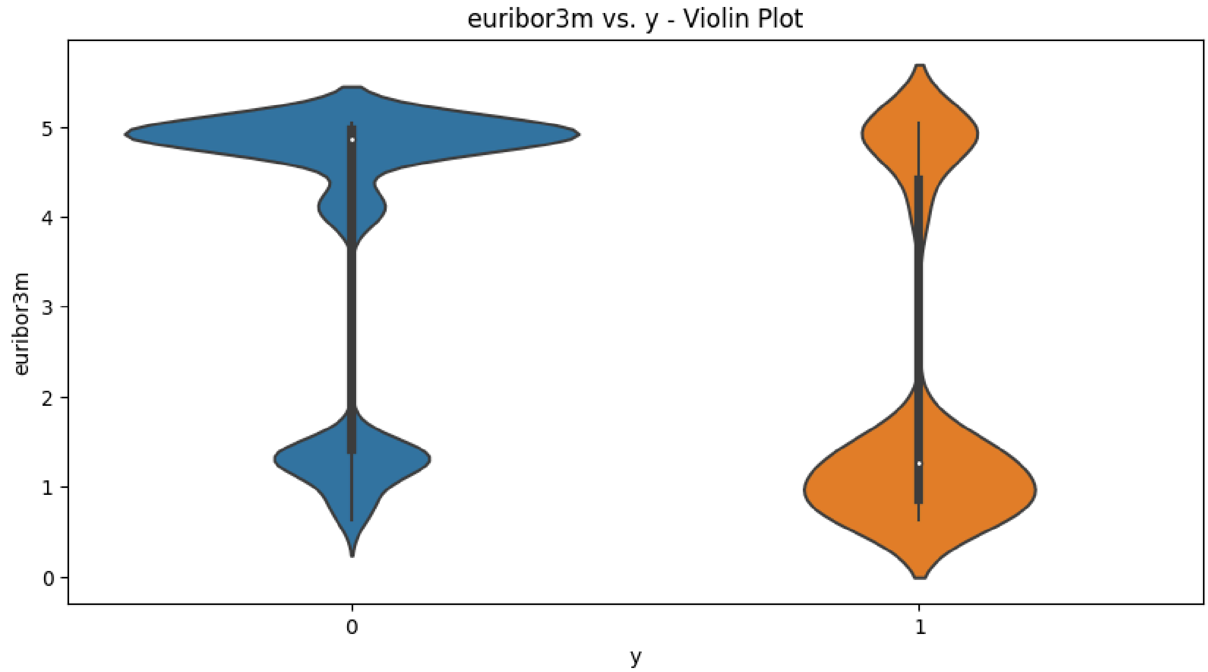


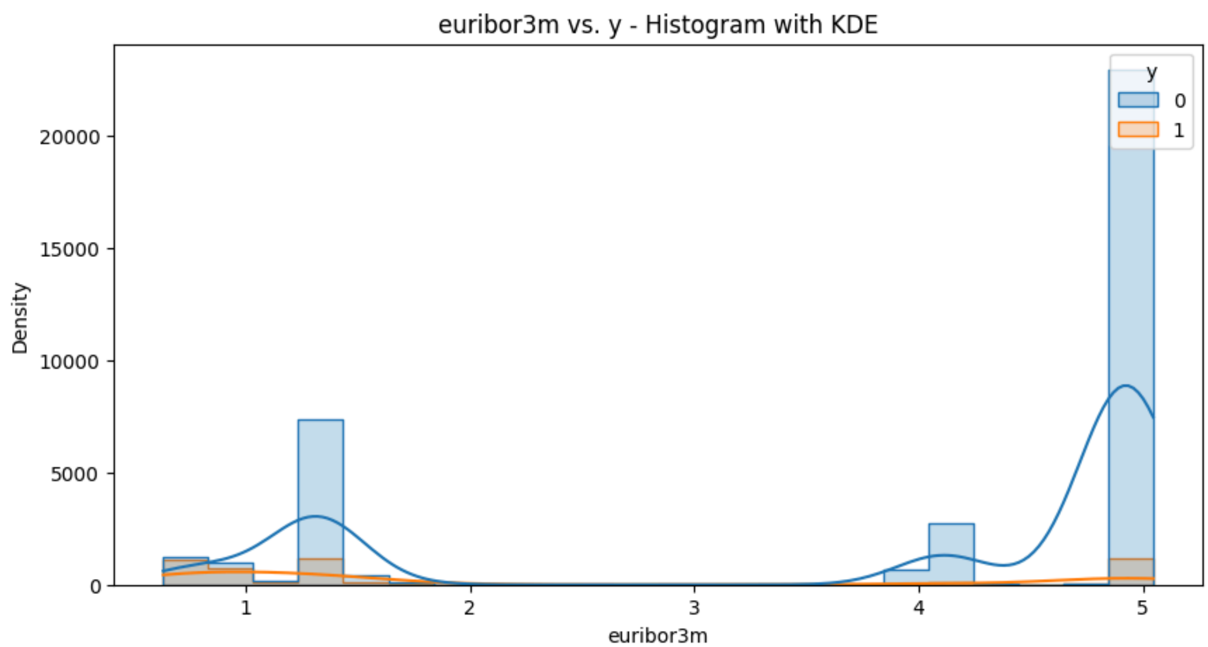
In [172…

```
## lets plot euoribor3m vs
bivariate_analysis(marketing, 'euribor3m')
```

```
Bivariate Analysis of 'euribor3m' and 'y'
```








```
Using categorical units to plot a list of strings that are all parsable as f
loats or dates. If these strings should be plotted as numbers, cast to the a
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Using categorical units to plot a list of strings that are all parsable as f
loats or dates. If these strings should be plotted as numbers, cast to the a
ppropriate data type before plotting.
```
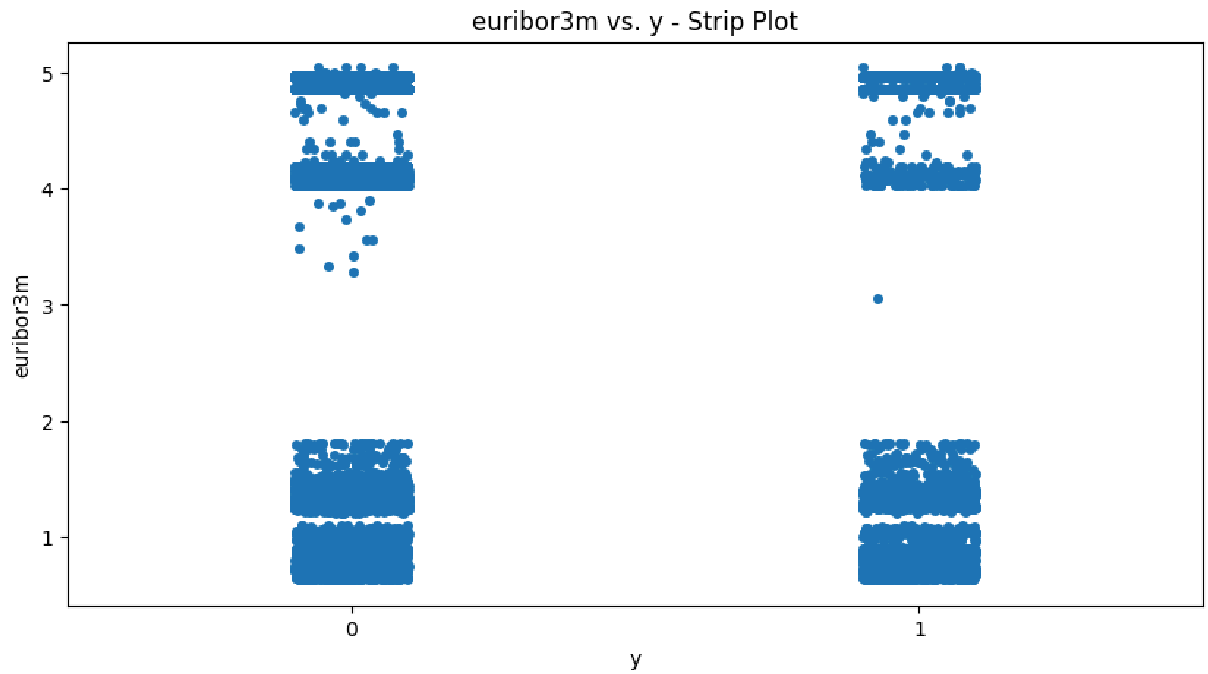
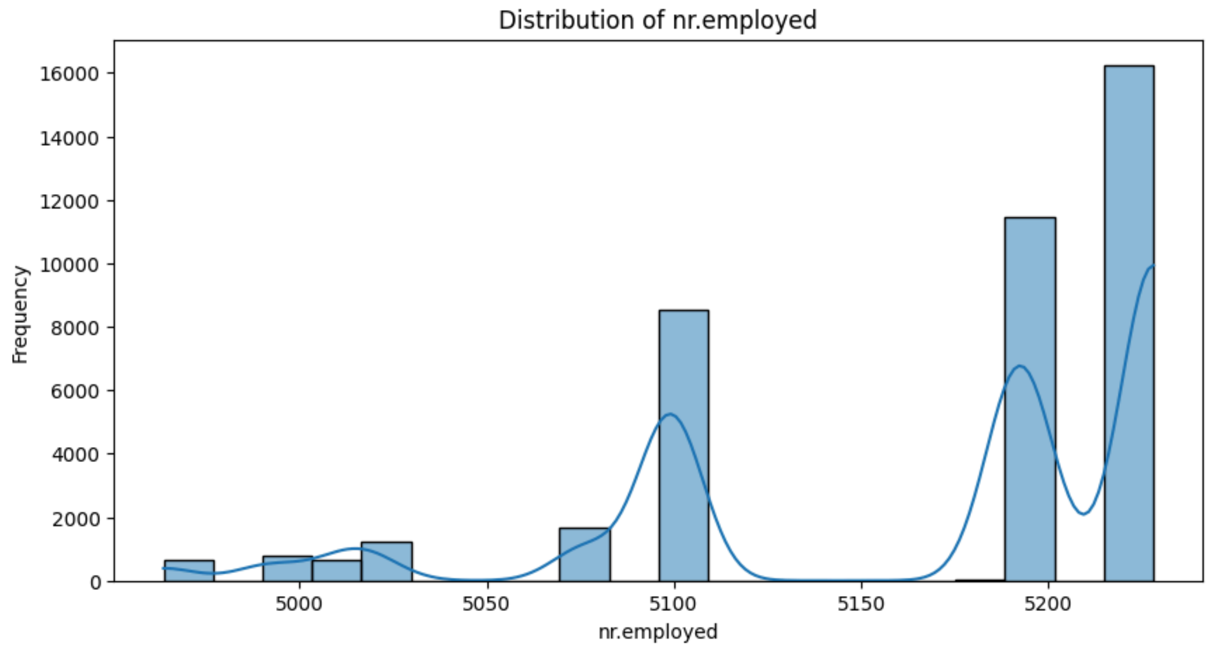



In [173…

```
## lets analyze nr.employed
analyze_column(marketing, 'nr.employed')
```

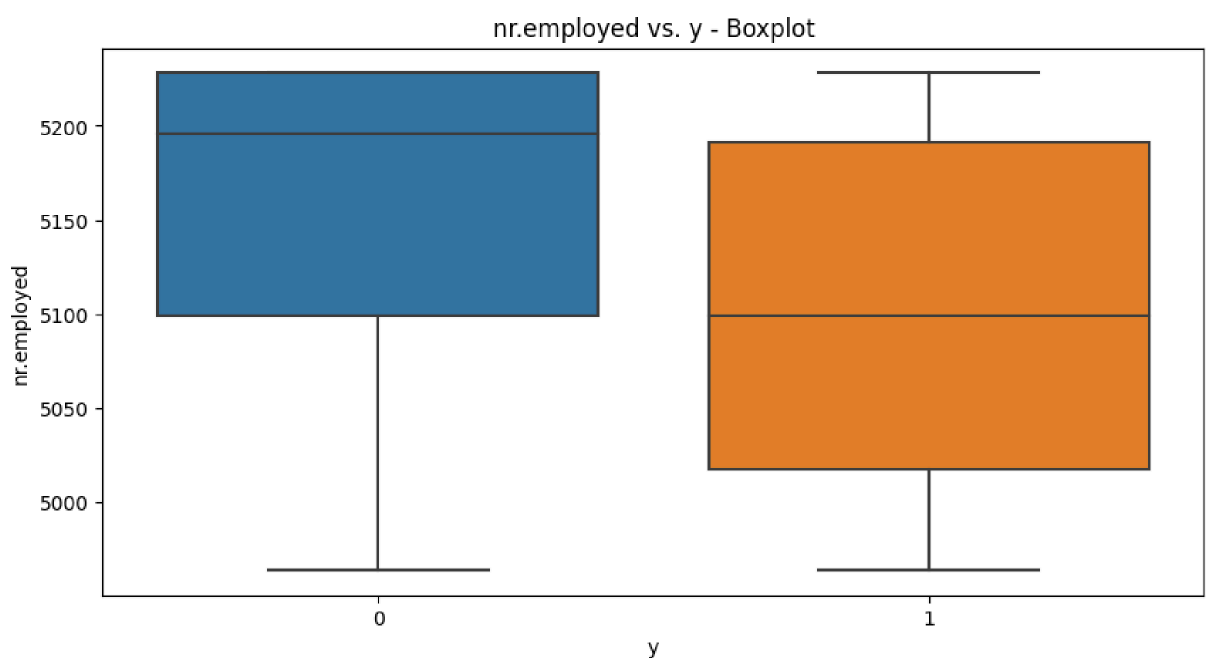
```
Summary of 'nr.employed':
count    41180.000000
mean      5167.053344
std         72.230334
min       4963.600000
25%       5099.100000
50%       5191.000000
75%       5228.100000
max       5228.100000
Name: nr.employed, dtype: float64

Unique values in 'nr.employed':
[5191.  5228.1 5195.8 5176.3 5099.1 5076.2 5017.5 5023.5 5008.7 4991.6
 4963.6]
```

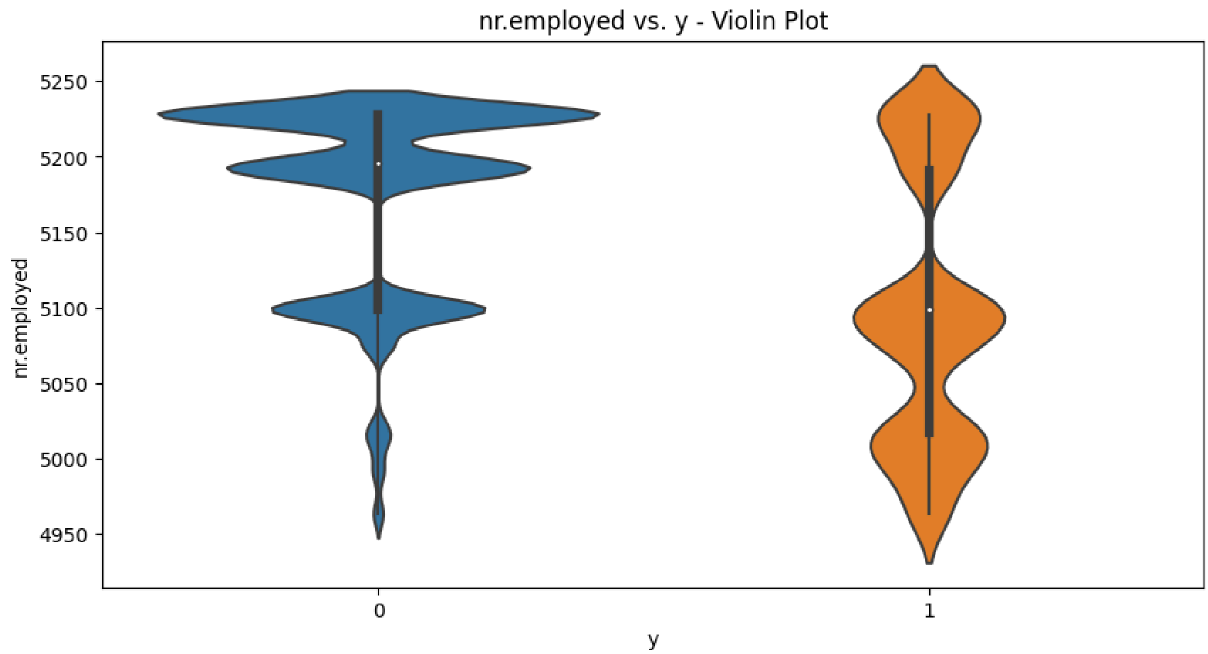


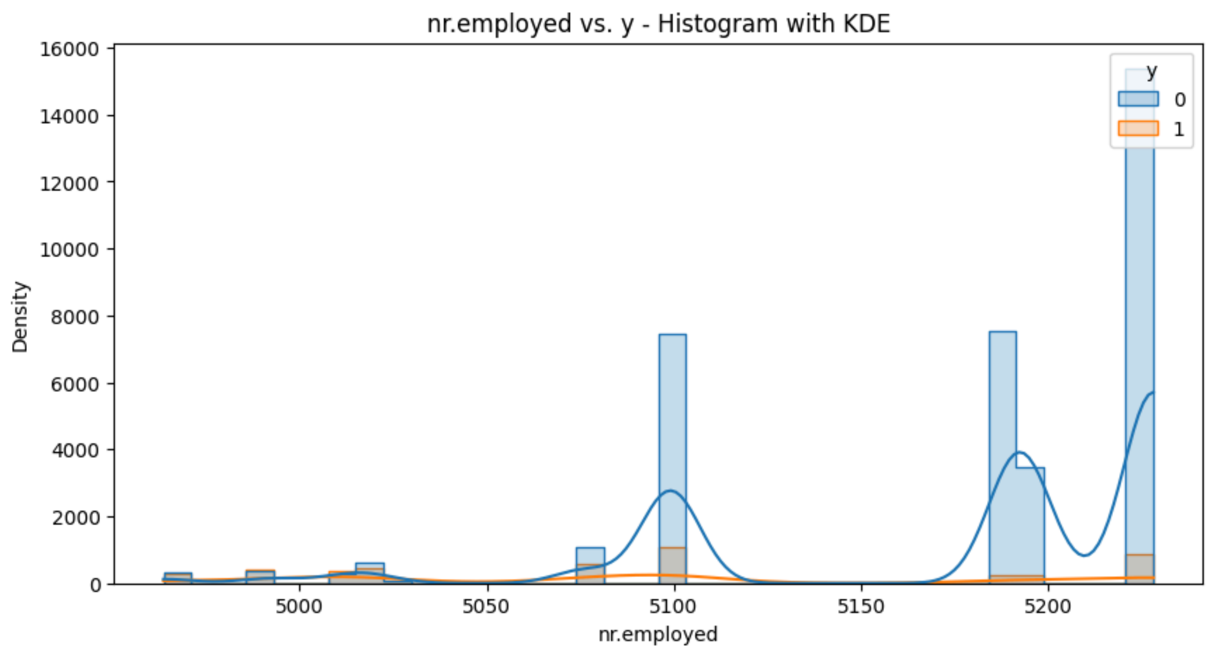
In [174…

```
## bivariate for nr.employed
bivariate_analysis(marketing, 'nr.employed')
```

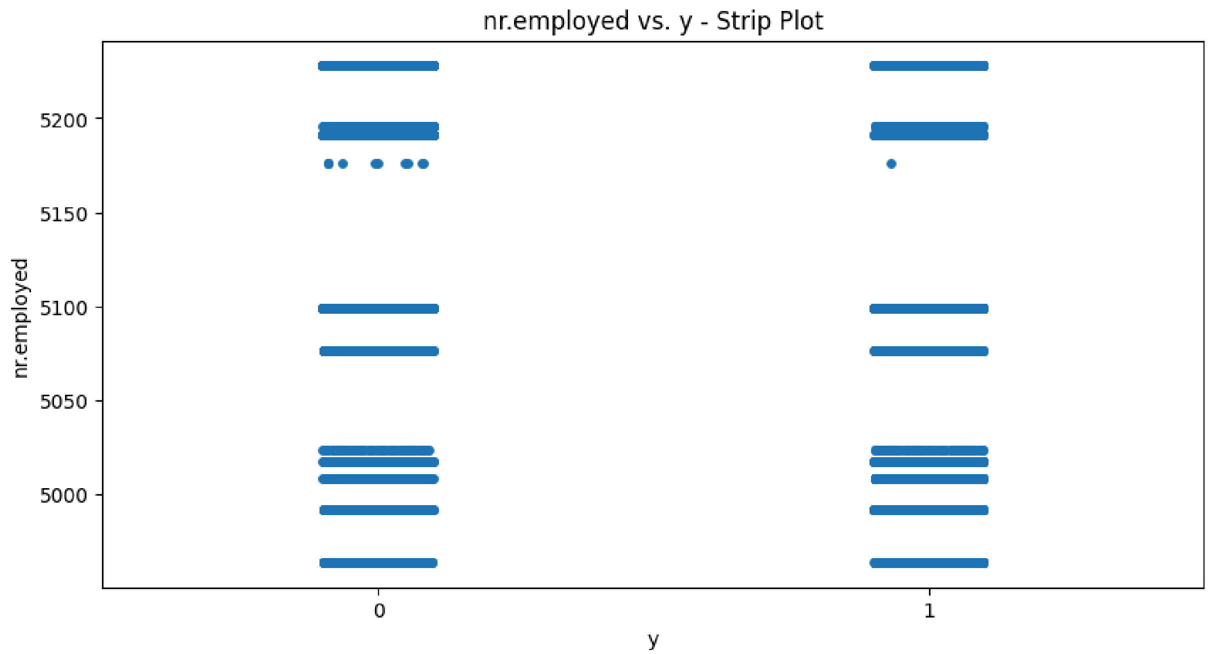
```
Bivariate Analysis of 'nr.employed' and 'y'
```








```
Using categorical units to plot a list of strings that are all parsable as f
loats or dates. If these strings should be plotted as numbers, cast to the a
ppropriate data type before plotting.
Using categorical units to plot a list of strings that are all parsable as f
loats or dates. If these strings should be plotted as numbers, cast to the a
ppropriate data type before plotting.
```



JOB

Univariate

In [175…

```
plot(marketing, 'job')
```

```
 0%|          | 0/76 [00:00<?, ?it/s]
```

```
/usr/local/lib/python3.10/site-packages/dataprep/eda/distribution/render.py:274: FutureWarning: The frame.append method is deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  df = df.append(pd.DataFrame({col: [nrows - npresent]}, index=["Others"]))
```

Out [175… Stats | Bar Chart | Pie Chart | Word Cloud | Word Frequency | Word Length | Value Table

Overview

Approximate Distinct Count	12
Approximate Unique (%)	0.0%
Missing	0
Missing (%)	0.0%
Memory Size	3045478

Sample

1st row	admin.
2nd row	services
3rd row	services
4th row	admin.
5th row	blue-collar

Length

Mean	8.9553
Standard Deviation	2.1644
Median	10
Minimum	6
Maximum	13

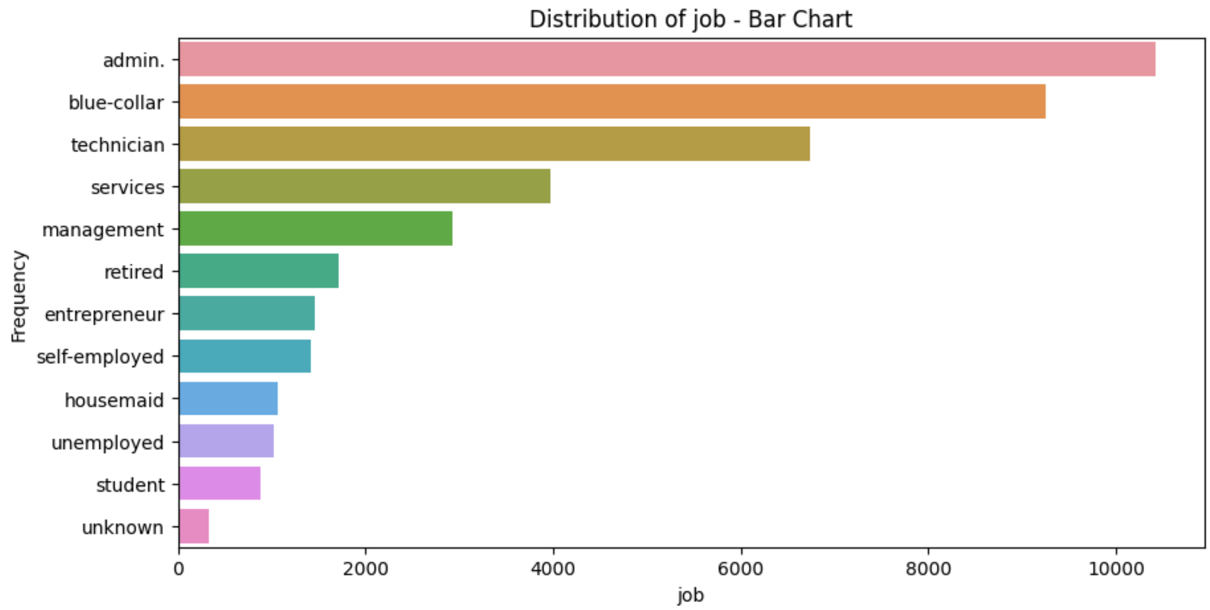
Letter

Count	347682
Lowercase Letter	347682
Space Separator	0
Uppercase Letter	0
Dash Punctuation	10674
Decimal Number	0

In [176…

```python
# Analyze the 'job' variable
analyze_column(marketing, 'job')
```

```
Summary of 'job':
count      41180
unique        12
top       admin.
freq       10422
Name: job, dtype: object

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

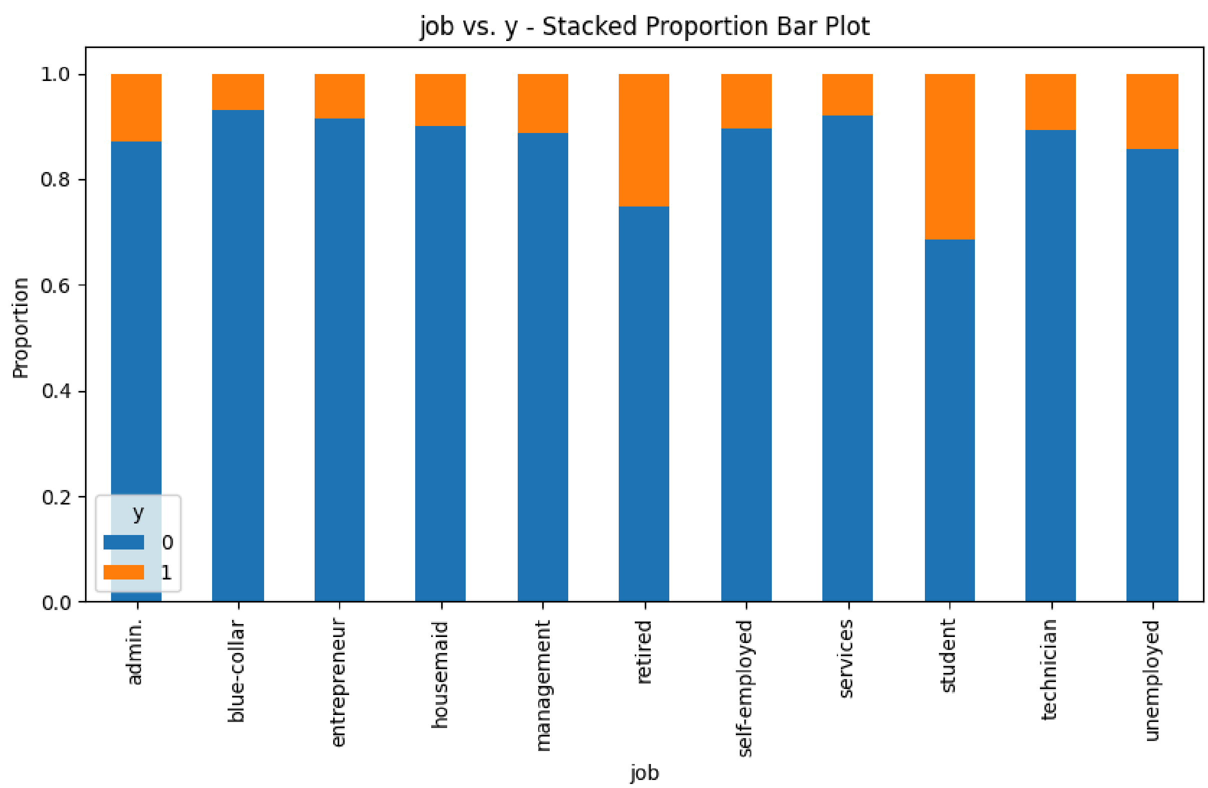


Bivariate

In [210…

```
# Bivariate analysis of 'job' and 'y'
bivariate_analysis(marketing, 'job')
```

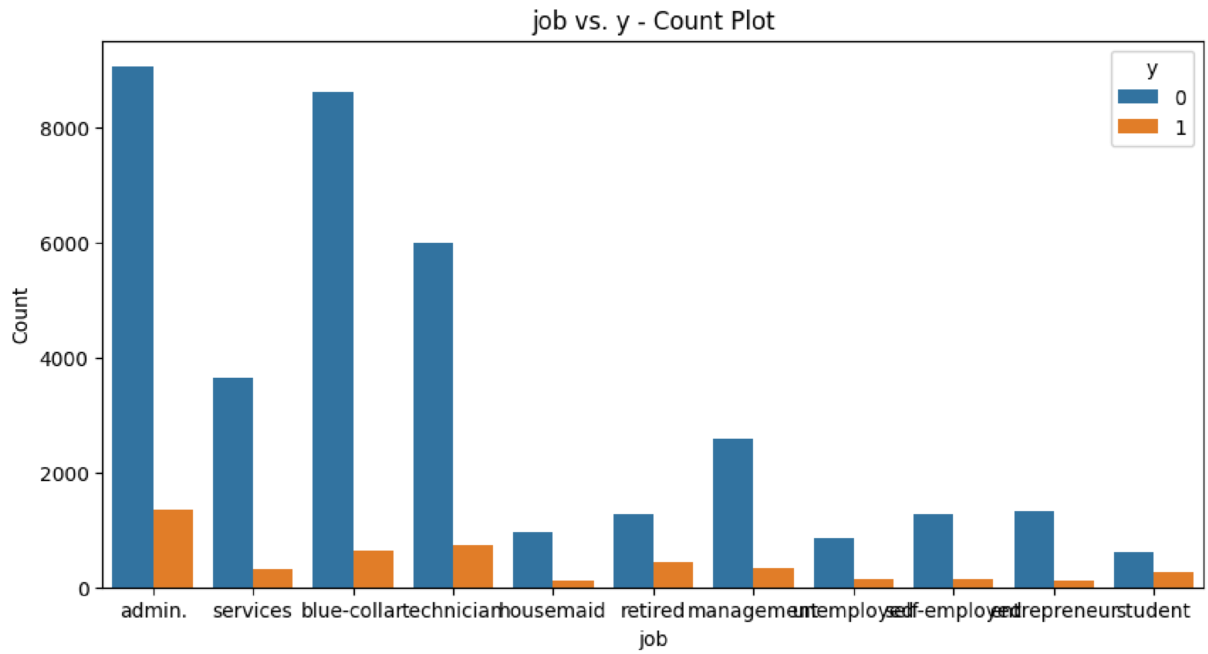
```
Bivariate Analysis of 'job' and 'y'
```



In [178…

```
# Example usage with the 'job' column and a pie chart
bivariate_analysis(marketing, 'job', chart_type='bar')
```

```
Bivariate Analysis of 'job' and 'y'
```



In [179…

```
def generate_summary_table(df, independent_var, target_var='y'):
    """
    Generate a summary table with counts and percentages of the target varia
    of the independent variable, sorted by the 'Yes_percent' in descending c

    Parameters:
    df (pd.DataFrame): The DataFrame containing the data.
    independent_var (str): The name of the independent variable to analyze.
    target_var (str): The name of the target variable (default is 'y').

    Returns:
    pd.DataFrame: A DataFrame with counts and percentages for each category
                  sorted by the 'Yes_percent'.
    """


    # Calculate counts
    count_df = df.groupby([independent_var, target_var]).size().unstack(fill

    # Calculate percentages
    percentage_df = count_df.div(count_df.sum(axis=1), axis=0) * 100

    # Combine counts and percentages
    summary_df = count_df.join(percentage_df, lsuffix='_count', rsuffix='_pe

    # Rename columns for clarity
    summary_df.columns = ['No_count', 'Yes_count', 'No_percent', 'Yes_percer

    # Sort by 'Yes_percent' in descending order
    summary_df = summary_df.sort_values(by='Yes_percent', ascending=False)

    return summary_df
```

```
# Example usage with the 'job' column
job_summary = generate_summary_table(marketing, 'job')

# Display the summary table
job_summary
```

Out[179…

job	No_count	Yes_count	No_percent	Yes_percent
student	600	275	68.571429	31.428571
retired	1285	433	74.796275	25.203725
unemployed	870	144	85.798817	14.201183
admin.	9070	1352	87.027442	12.972558
management	2595	328	88.778652	11.221348
unknown	293	37	88.787879	11.212121
technician	6013	729	89.187185	10.812815
self-employed	1272	149	89.514426	10.485574
housemaid	953	106	89.990557	10.009443
entrepreneur	1332	124	91.483516	8.516484
services	3644	323	91.857827	8.142173
blue-collar	8615	638	93.104939	6.895061

Marital

In [180…

```
plot(marketing, 'marital')
```

```
 0%|          | 0/76 [00:00<?, ?it/s]
```

Out[180… Stats | Bar Chart | Pie Chart | Word Cloud | Word Frequency | Word Length | Value Table

Overview

Approximate Distinct Count	4
Approximate Unique (%)	0.0%
Missing	0
Missing (%)	0.0%
Memory Size	2958003

Sample

1st row	married
2nd row	married
3rd row	married
4th row	married
5th row	married

Length

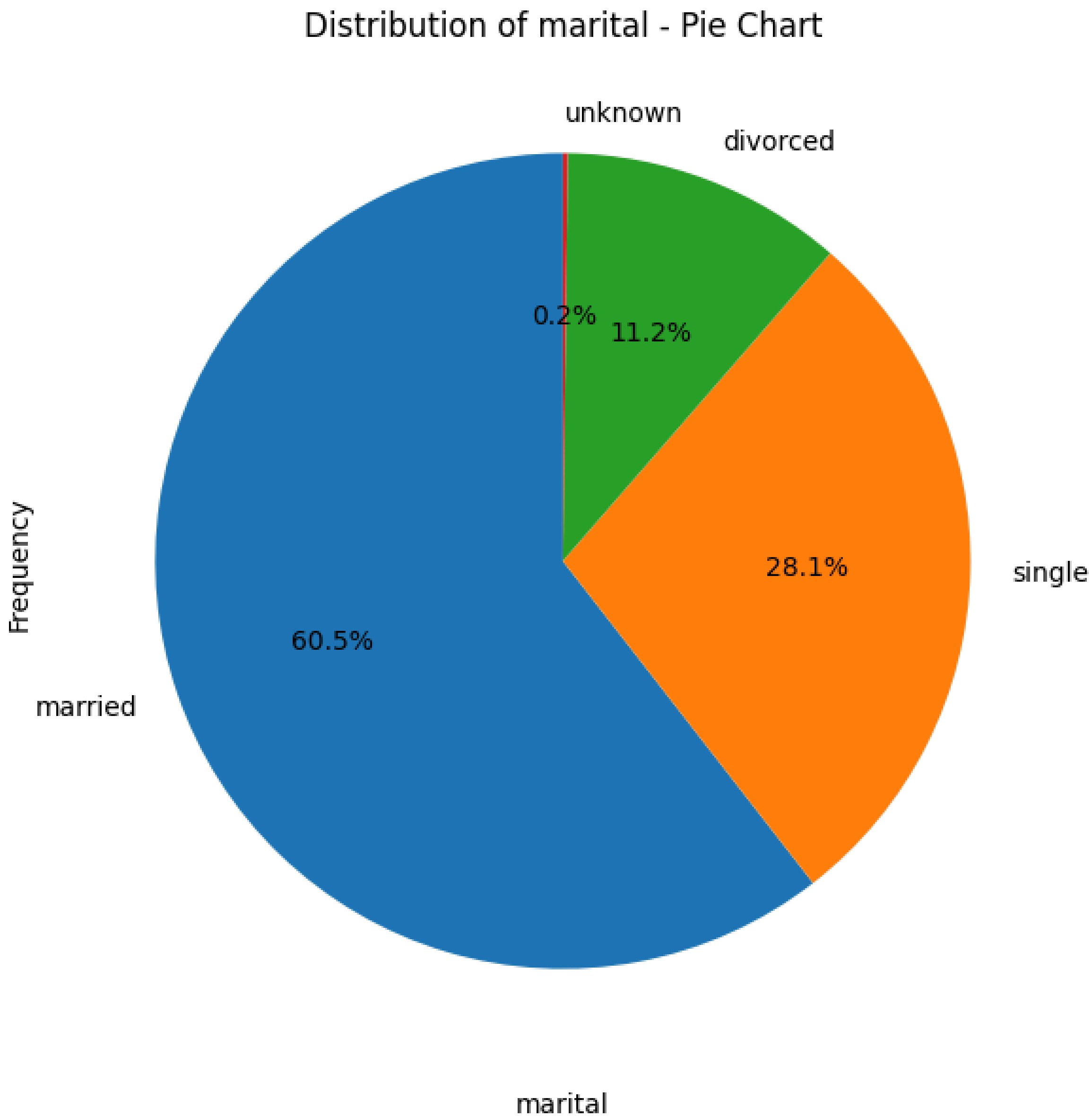
Mean	6.8311
Standard Deviation	0.6036
Median	7
Minimum	6
Maximum	8

Letter

Count	281303
Lowercase Letter	281303
Space Separator	0
Uppercase Letter	0
Dash Punctuation	0
Decimal Number	0

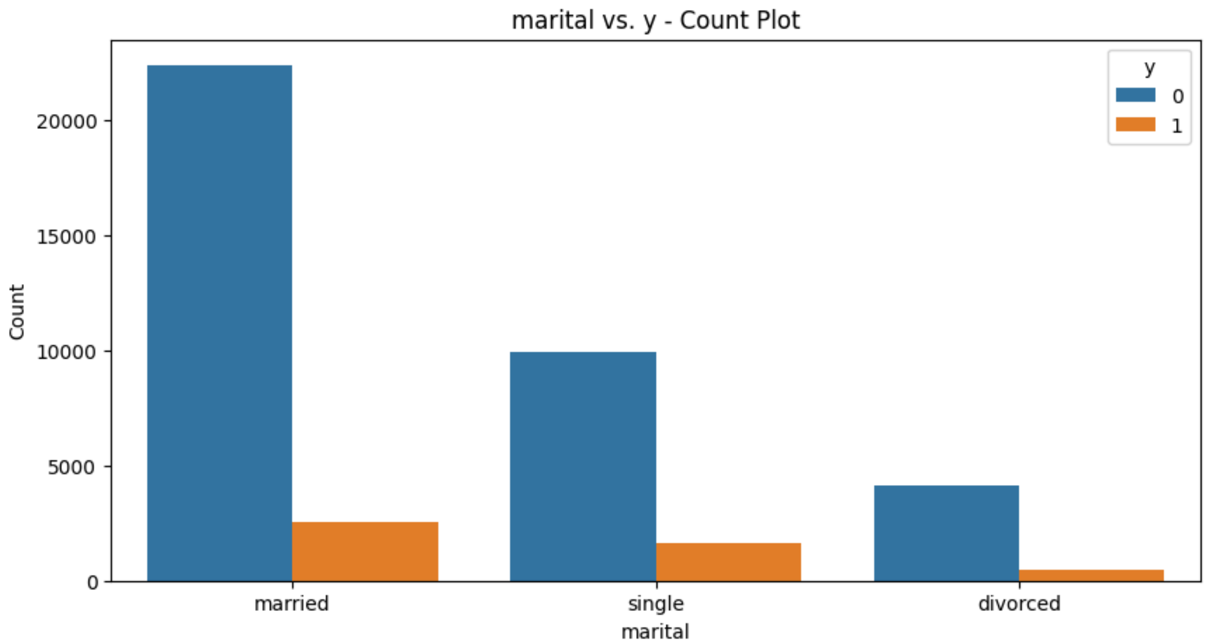
In [181…
```
# Example usage with the 'marital' column and a pie chart
analyze_column(marketing, 'marital', chart_type='pie')
```

```
Summary of 'marital':
count       41180
unique          4
top       married
freq        24921
Name: marital, dtype: object

Unique values in 'marital':
['married' 'single' 'divorced' 'unknown']
```



In [182…
```
# Bivariate analysis of 'marital' and 'y'
bivariate_analysis(marketing, 'marital', chart_type='bar')
```

Bivariate Analysis of 'marital' and 'y'



In [183…

```
# Generate summary table for 'marital' and 'y'
marital_summary = generate_summary_table(marketing, 'marital')

# Display the summary table
marital_summary
```

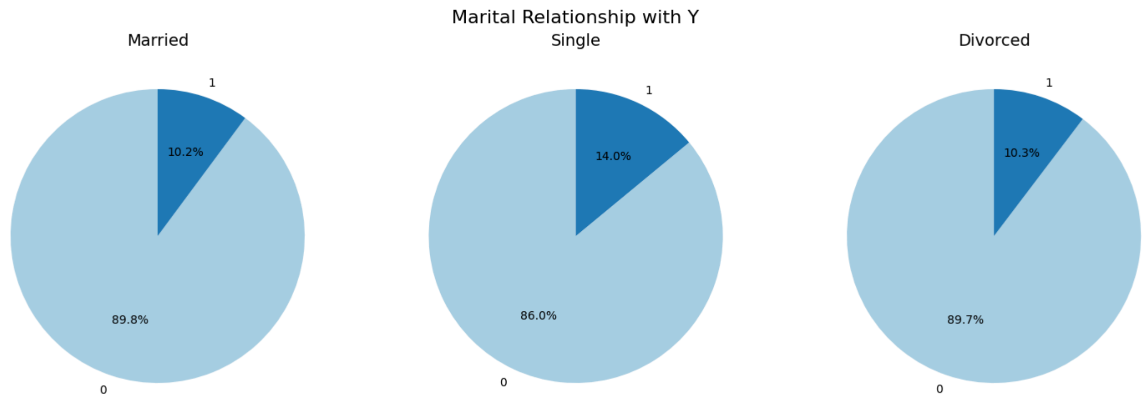
Out[183…

marital	No_count	Yes_count	No_percent	Yes_percent
unknown	68	12	85.000000	15.000000
single	9948	1620	85.995851	14.004149
divorced	4135	476	89.676860	10.323140
married	22391	2530	89.847919	10.152081

In [184…

```
import matplotlib.pyplot as plt

def generate_pie_charts_per_category(df, column, target_var='y', exclude_unk
    """
    Generate pie charts showing the relationship between each category of a

    Parameters:
    df (pd.DataFrame): The DataFrame containing the data.
    column (str): The name of the column to generate pie charts for.
    target_var (str): The target variable, typically 'y'. Default is 'y'.
    exclude_unknown (bool): Whether to exclude 'unknown' categories from the
    colors (list of str): A list of colors to use for the pie chart. Default
    """
    # Filter out 'unknown' values if needed
    if exclude_unknown:
        df = df[df[column] != 'unknown']

    categories = df[column].unique()
```

```
    num_categories = len(categories)

    # Set default colors if none provided
    if colors is None:
        colors = ['#66b3ff', '#99ff99']  # Light blue and light green as def

    fig, axes = plt.subplots(1, num_categories, figsize=(5 * num_categories,
    fig.suptitle(f'{column.capitalize()} Relationship with {target_var.upper

    for i, category in enumerate(categories):
        category_data = df[df[column] == category][target_var]
        category_data.value_counts().plot.pie(autopct='%1.1f%%', startangle=
        axes[i].set_title(f'{category.capitalize()}', fontsize=14)
        axes[i].set_ylabel('')  # Hide the y-label for pie charts

    plt.show()
\
generate_pie_charts_per_category(marketing, 'marital', colors=plt.cm.Paired.
```



Not gigantic but single people are most common to say Yes.

Education

In [185…
```
plot(marketing, 'education')
```

```
 0%|          | 0/76 [00:00<?, ?it/s]
```

Out [185… Stats | Bar Chart | Pie Chart | Word Cloud | Word Frequency | Word Length | Value Table

Overview

Approximate Distinct Count	8
Approximate Unique (%)	0.0%
Missing	0
Missing (%)	0.0%
Memory Size	3200129

Sample

1st row	basic.6y
2nd row	high.school
3rd row	basic.9y
4th row	professional.cours...
5th row	unknown

Length

Mean	12.7108
Standard Deviation	4.3889
Median	11
Minimum	7
Maximum	19

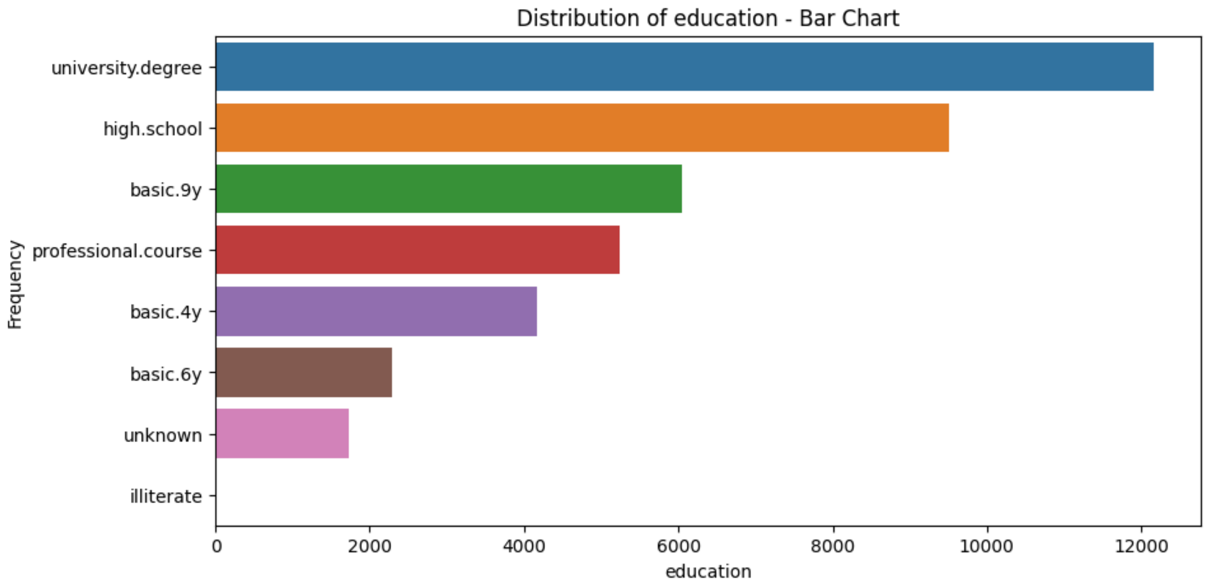
Letter

Count	471487
Lowercase Letter	471487
Space Separator	0
Uppercase Letter	0
Dash Punctuation	0
Decimal Number	12511

In [186…

```
# Analyze the 'education' variable
analyze_column(marketing, 'education', chart_type='bar')
```

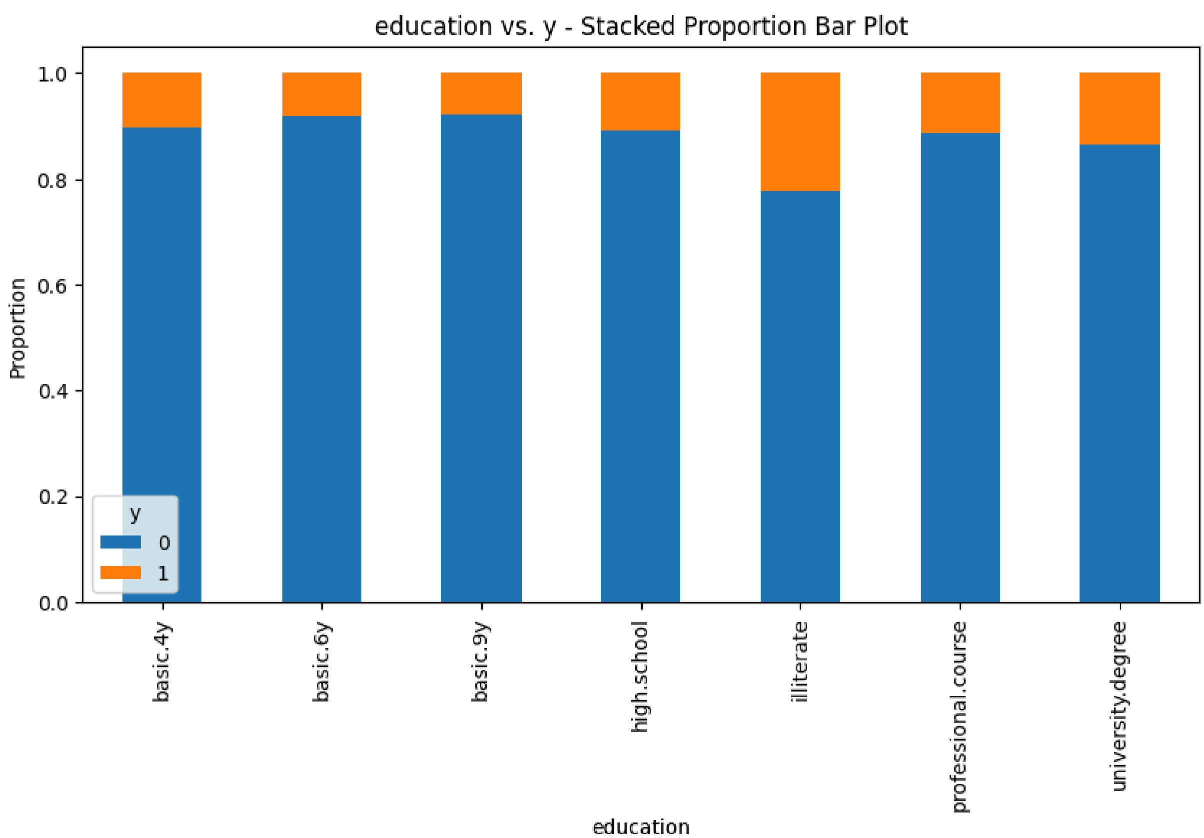
```
Summary of 'education':
count                 41180
unique                    8
top       university.degree
freq                  12166
Name: education, dtype: object

Unique values in 'education':
['basic.6y' 'high.school' 'basic.9y' 'professional.course' 'unknown'
 'basic.4y' 'university.degree' 'illiterate']
```



In [187…

```
# Bivariate analysis of 'education' and 'y'
bivariate_analysis(marketing, 'education', chart_type='stacked_bar')
# Generate summary table for 'education' and 'y'
education_summary = generate_summary_table(marketing, 'education')

# Display the summary table
education_summary
```

Bivariate Analysis of 'education' and 'y'



Out [187…

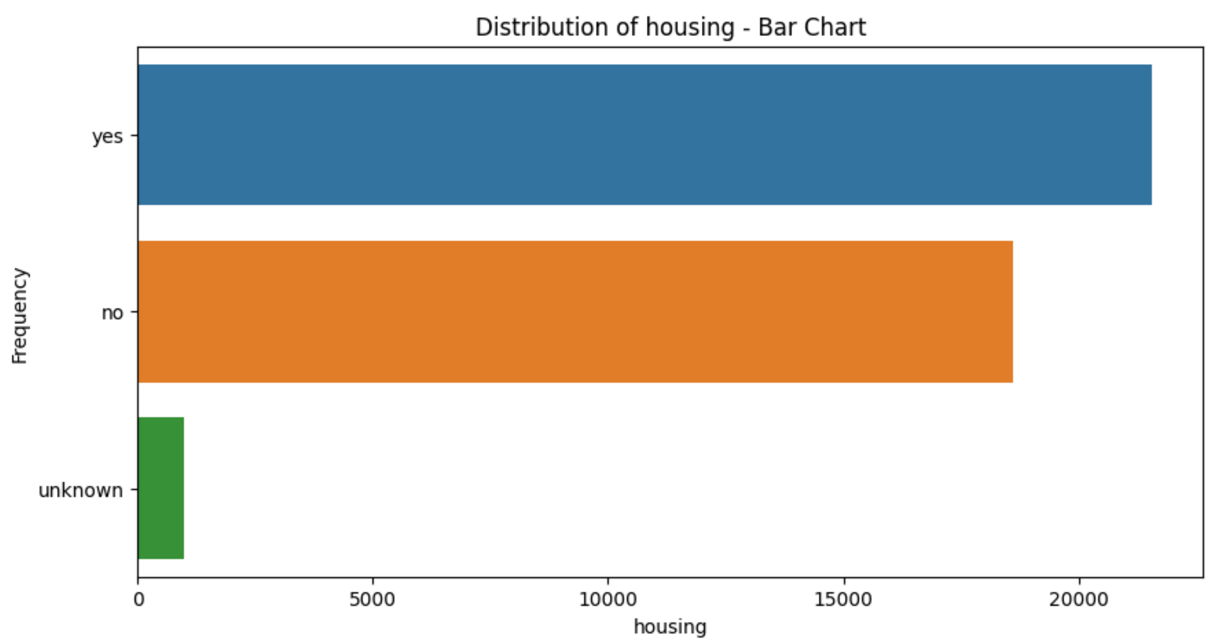
education	No_count	Yes_count	No_percent	Yes_percent
illiterate	14	4	77.777778	22.222222
unknown	1480	251	85.499711	14.500289
university.degree	10497	1669	86.281440	13.718560
professional.course	4647	594	88.666285	11.333715
high.school	8482	1031	89.162199	10.837801
basic.4y	3747	428	89.748503	10.251497
basic.6y	2104	188	91.797557	8.202443
basic.9y	5571	473	92.174057	7.825943

Loan

In [188…

```
# Analyze the 'housing' variable
analyze_column(marketing, 'housing', chart_type='bar')
```

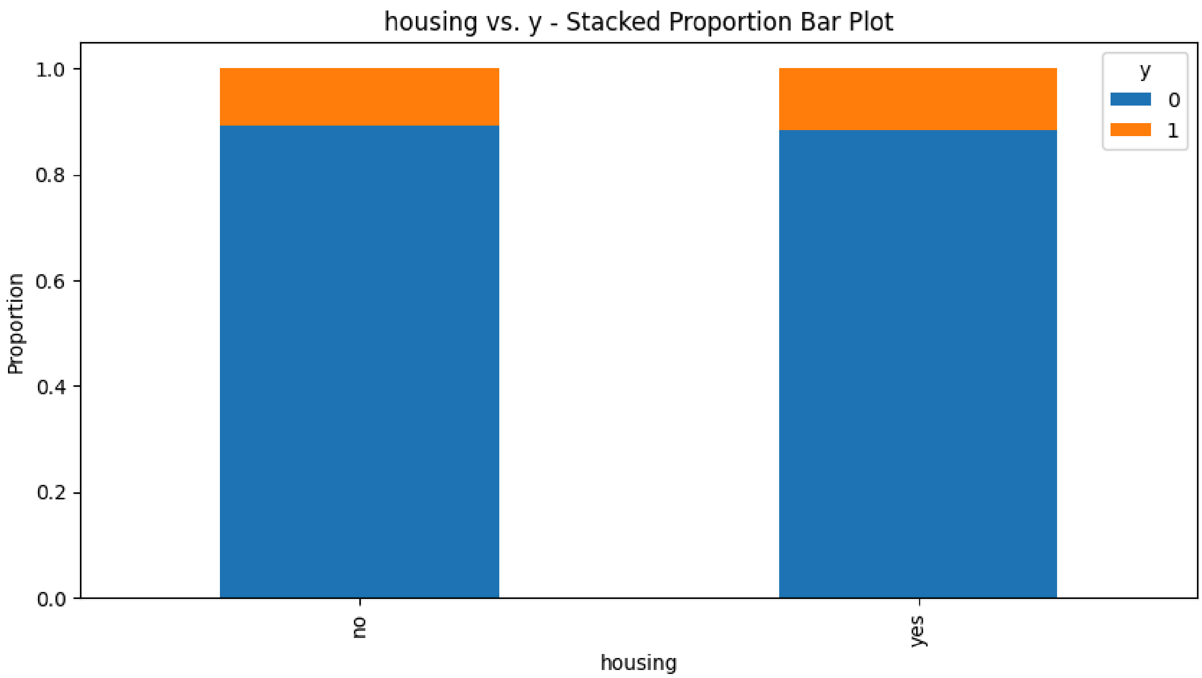
```
Summary of 'housing':
count     41180
unique        3
top         yes
freq      21571
Name: housing, dtype: object

Unique values in 'housing':
['no' 'yes' 'unknown']
```



In [189…

```
# Bivariate analysis of 'housing' and 'y'
bivariate_analysis(marketing, 'housing', chart_type='stacked_bar')

# Generate summary table for 'housing' and 'y'
housing_summary = generate_summary_table(marketing, 'housing')

# Display the summary table
housing_summary
```

Bivariate Analysis of 'housing' and 'y'



Out[189…

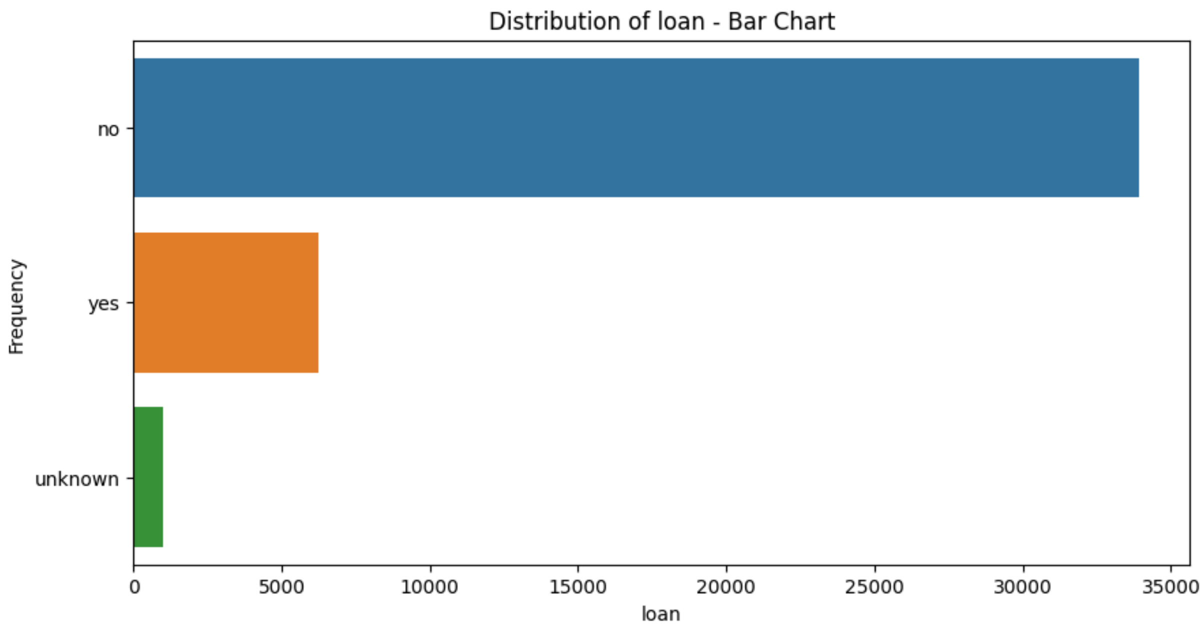
housing	No_count	Yes_count	No_percent	Yes_percent
yes	19065	2506	88.382551	11.617449
no	16594	2025	89.124013	10.875987
unknown	883	107	89.191919	10.808081

Loan

In [190…

```
# Analyze the 'loan' variable
analyze_column(marketing, 'loan', chart_type='bar')
```

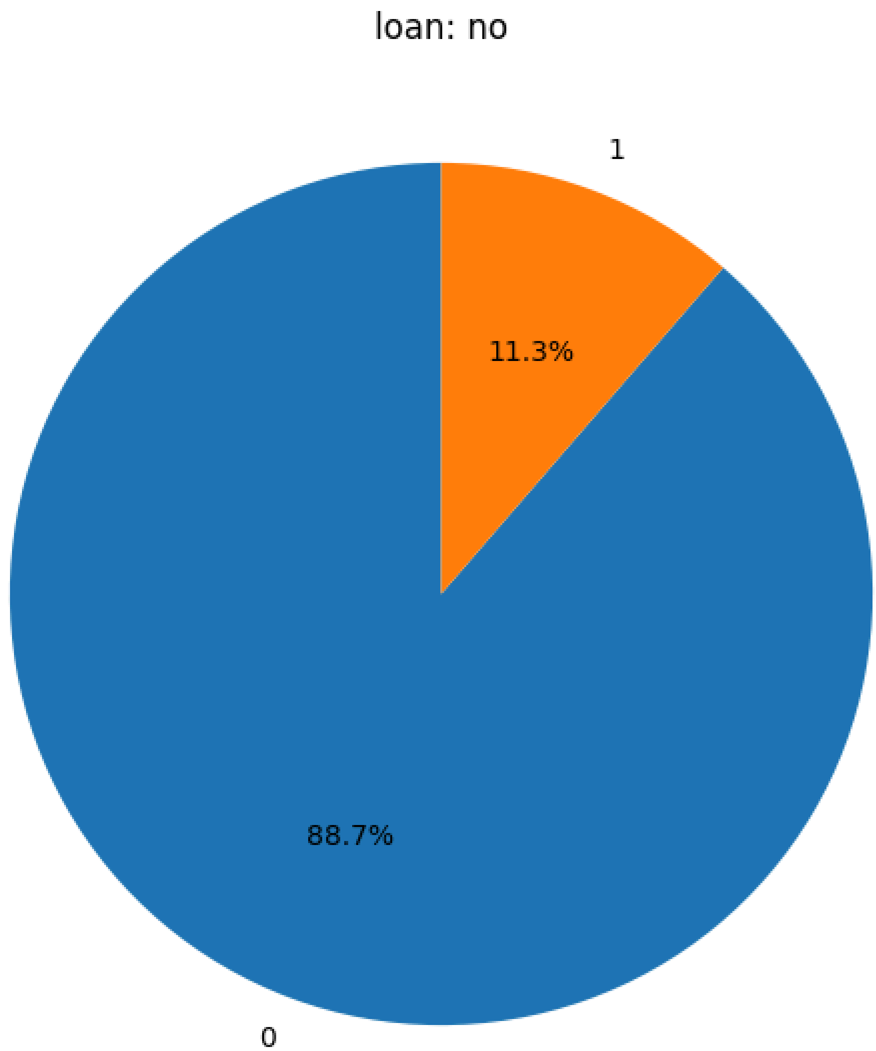
```
Summary of 'loan':
count      41180
unique         3
top           no
freq       33943
Name: loan, dtype: object

Unique values in 'loan':
['no' 'yes' 'unknown']
```

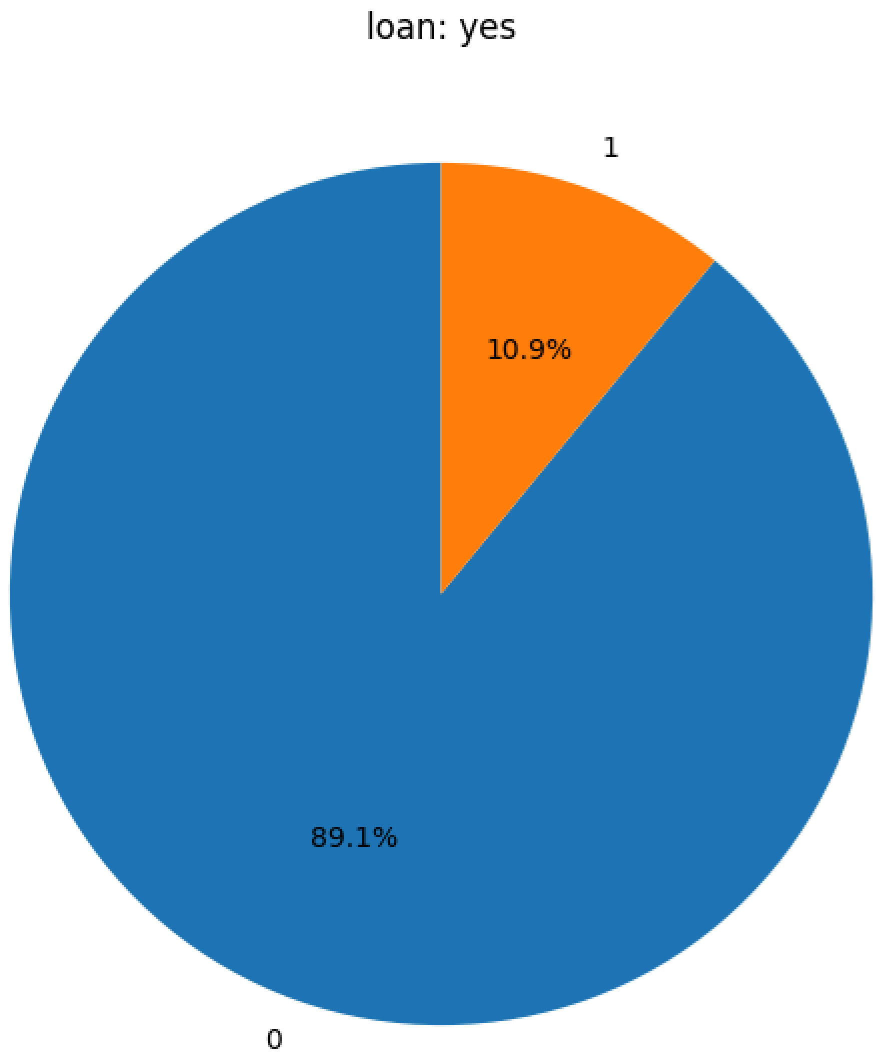


In [191…

```
# Bivariate analysis of 'loan' and 'y'
bivariate_analysis(marketing, 'loan', chart_type='pie')
```

```
Bivariate Analysis of 'loan' and 'y'
```


loan: no
1
11.3%
88.7%
0



No influence in the main variable...

Contact

In [192…
```
plot(marketing, 'contact')
```

```
 0%|          | 0/76 [00:00<?, ?it/s]
```

Out [192... Stats | Bar Chart | Pie Chart | Word Cloud | Word Frequency | Word Length | Value Table

Overview

Approximate Distinct Count	2
Approximate Unique (%)	0.0%
Missing	0
Missing (%)	0.0%
Memory Size	3021180

Sample

1st row	telephone
2nd row	telephone
3rd row	telephone
4th row	telephone
5th row	telephone

Length

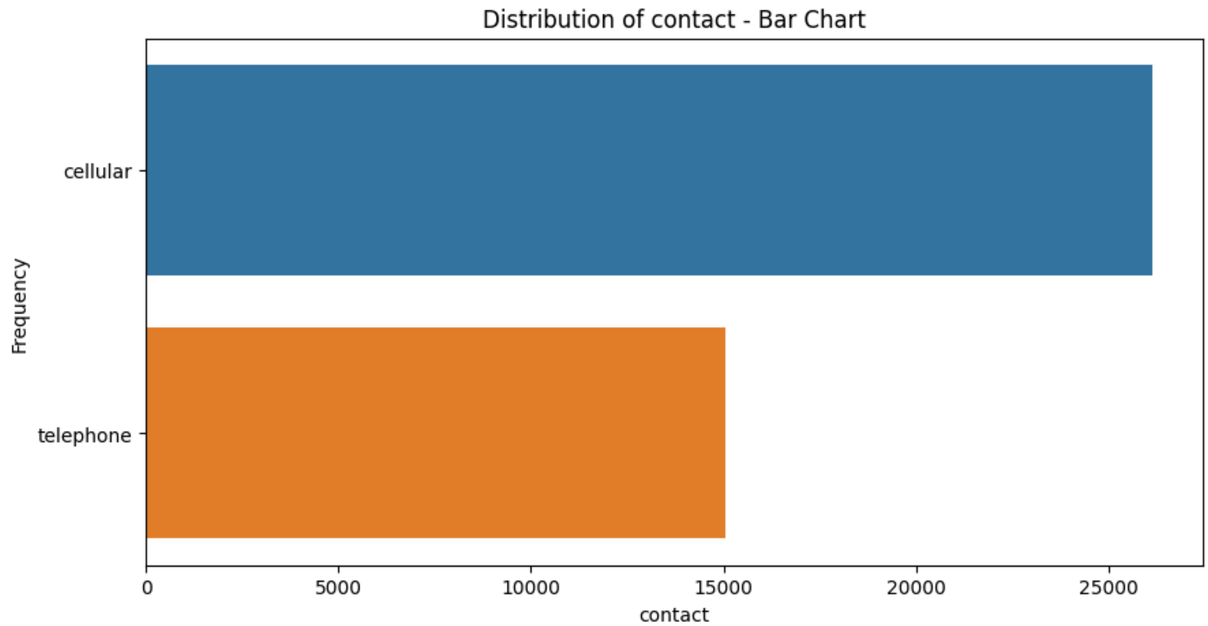
Mean	8.3652
Standard Deviation	0.4815
Median	8
Minimum	8
Maximum	9

Letter

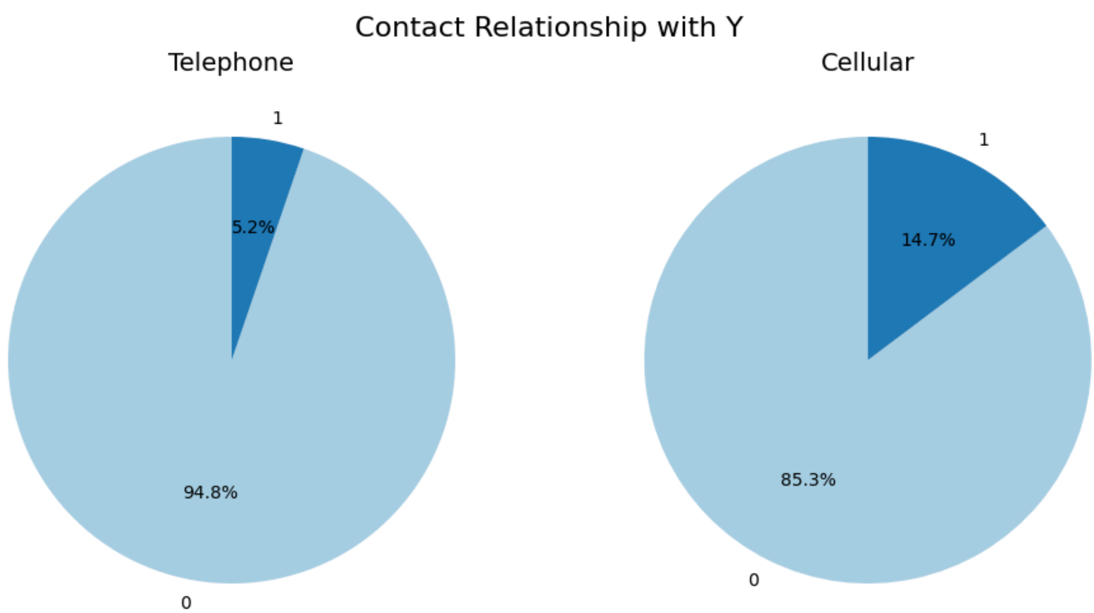
Count	344480
Lowercase Letter	344480
Space Separator	0
Uppercase Letter	0
Dash Punctuation	0
Decimal Number	0

In [193...
```
# Analyze the 'contact' variable
analyze_column(marketing, 'contact', chart_type='bar')
```

```
Summary of 'contact':
count        41180
unique           2
top       cellular
freq         26140
Name: contact, dtype: object

Unique values in 'contact':
['telephone' 'cellular']
```



In [194…
```
# Bivariate analysis of 'contact' and 'y'

generate_pie_charts_per_category(marketing, 'contact', colors=plt.cm.Paired.
```

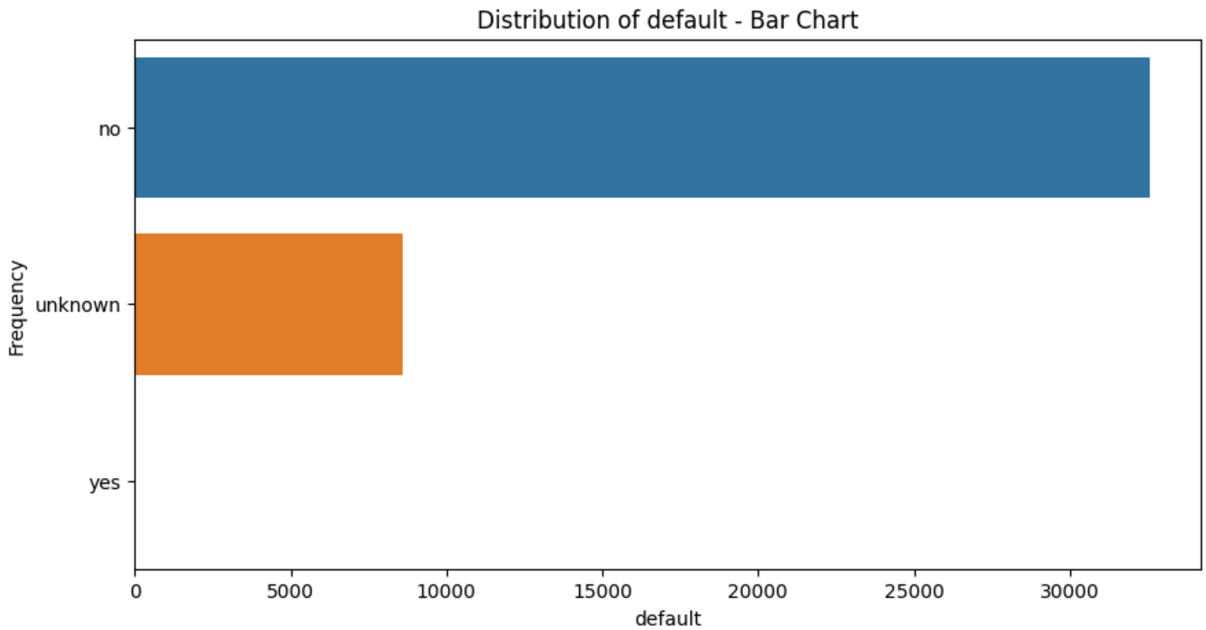


Better to contact them by cellular than telephone definitely.

Default

In [195…
```
# Analyze the 'default' variable
analyze_column(marketing, 'default', chart_type='bar')
```

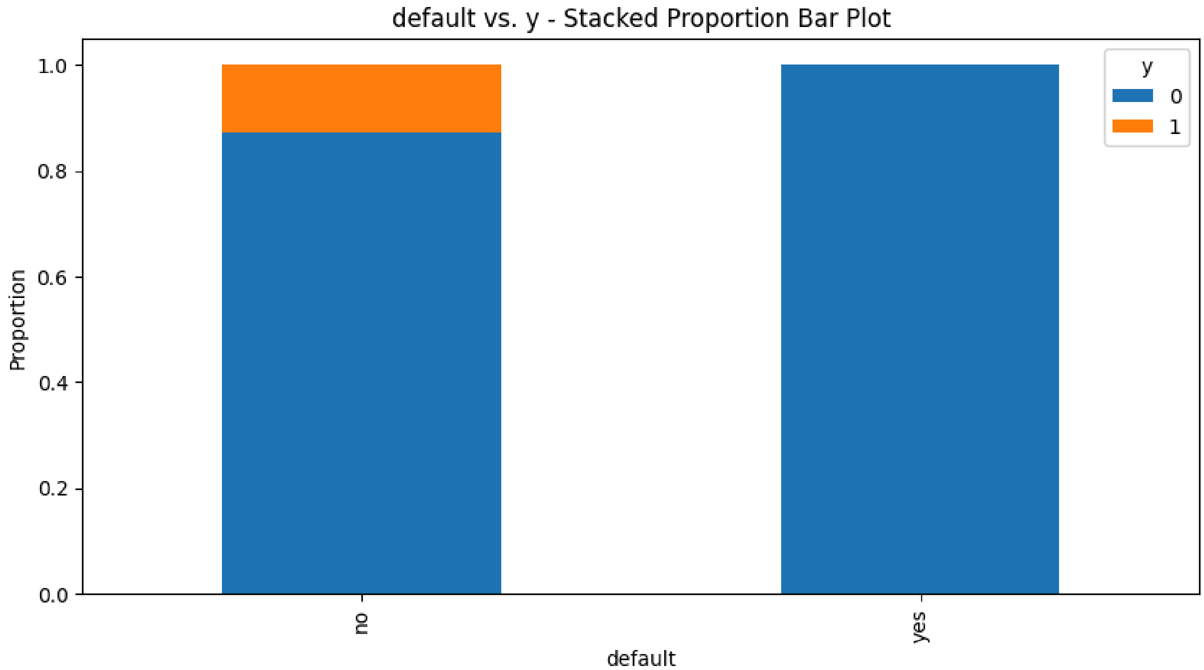
```
Summary of 'default':
count      41180
unique         3
top           no
freq       32581
Name: default, dtype: object

Unique values in 'default':
['no' 'unknown' 'yes']
```



In [196…

```
bivariate_analysis(marketing, 'default')# Generate summary table for 'defaul
default_summary = generate_summary_table(marketing, 'default')

# Display the summary table
print(default_summary)
```

```
Bivariate Analysis of 'default' and 'y'
```




```
         No_count  Yes_count  No_percent  Yes_percent
default
no          28386       4195   87.124398    12.875602
unknown      8153        443   94.846440     5.153560
yes             3          0  100.000000     0.000000
```

Previous Outcome result

In [197…
```
plot(marketing, 'poutcome')
```

```
 0%|          | 0/76 [00:00<?, ?it/s]
```

Out [197… Stats | Bar Chart | Pie Chart | Word Cloud | Word Frequency | Word Length | Value Table

Overview

Approximate Distinct Count	3
Approximate Unique (%)	0.0%
Missing	0
Missing (%)	0.0%
Memory Size	3107196

Sample

1st row	nonexistent
2nd row	nonexistent
3rd row	nonexistent
4th row	nonexistent
5th row	nonexistent

Length

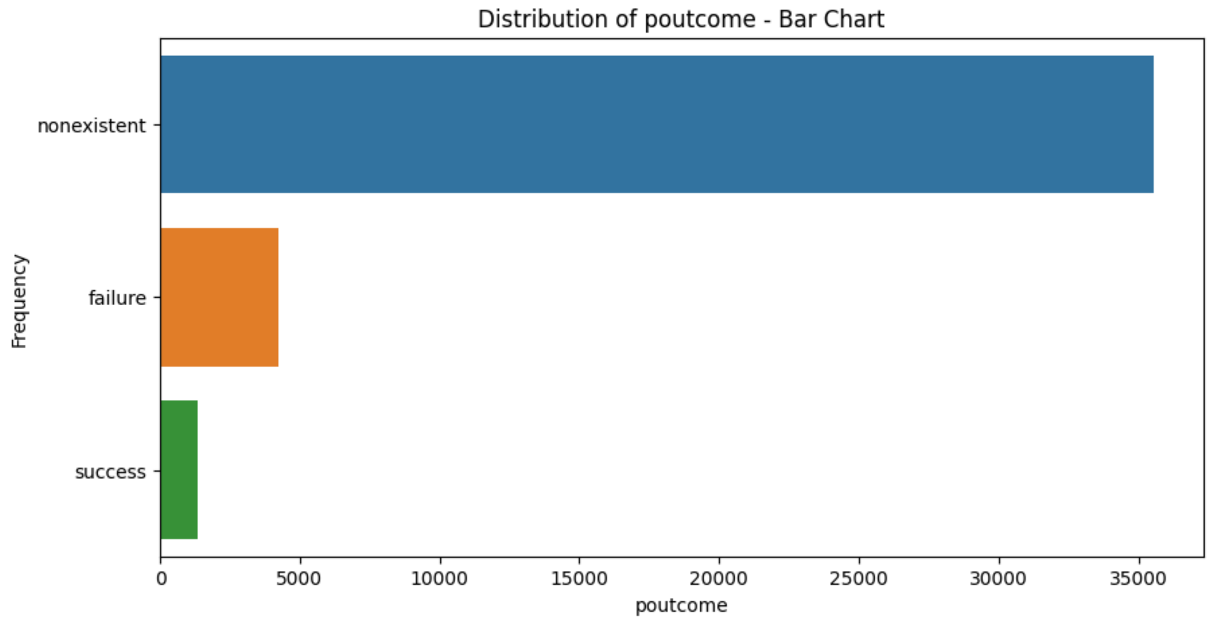
Mean	10.454
Standard Deviation	1.3733
Median	11
Minimum	7
Maximum	11

Letter

Count	430496
Lowercase Letter	430496
Space Separator	0
Uppercase Letter	0
Dash Punctuation	0
Decimal Number	0

In [198…
```
# Analyze the 'poutcome' variable
analyze_column(marketing, 'poutcome', chart_type='bar')
```

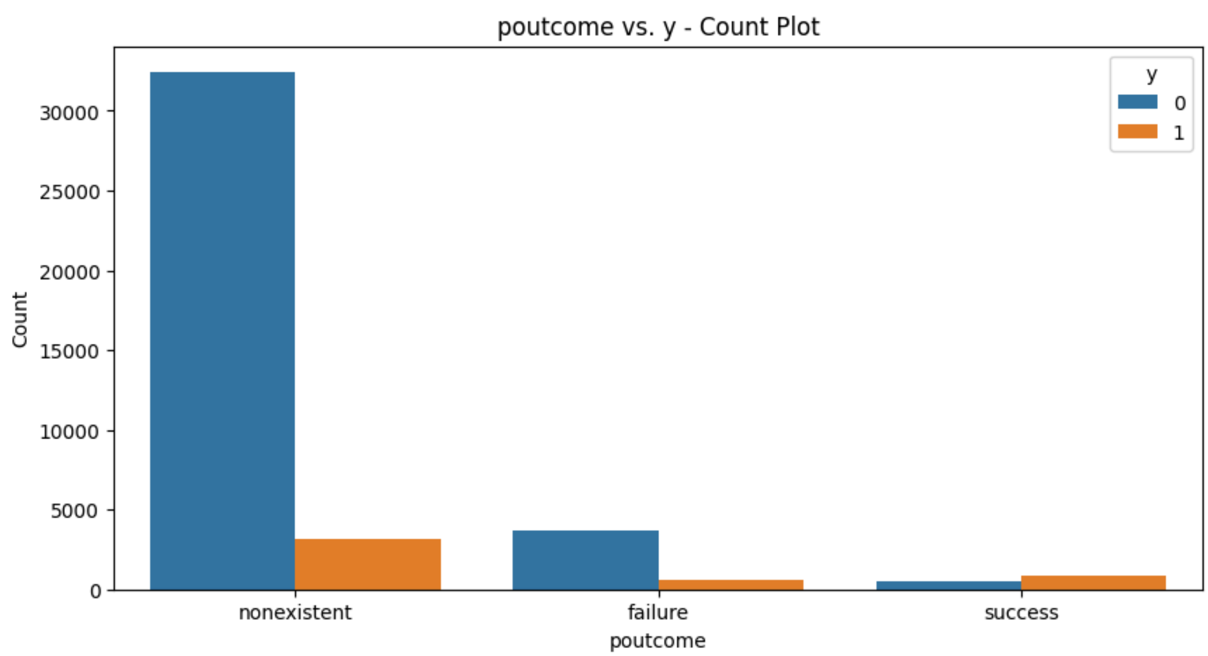
```
Summary of 'poutcome':
count          41180
unique             3
top      nonexistent
freq           35559
Name: poutcome, dtype: object

Unique values in 'poutcome':
['nonexistent' 'failure' 'success']
```



In [199…

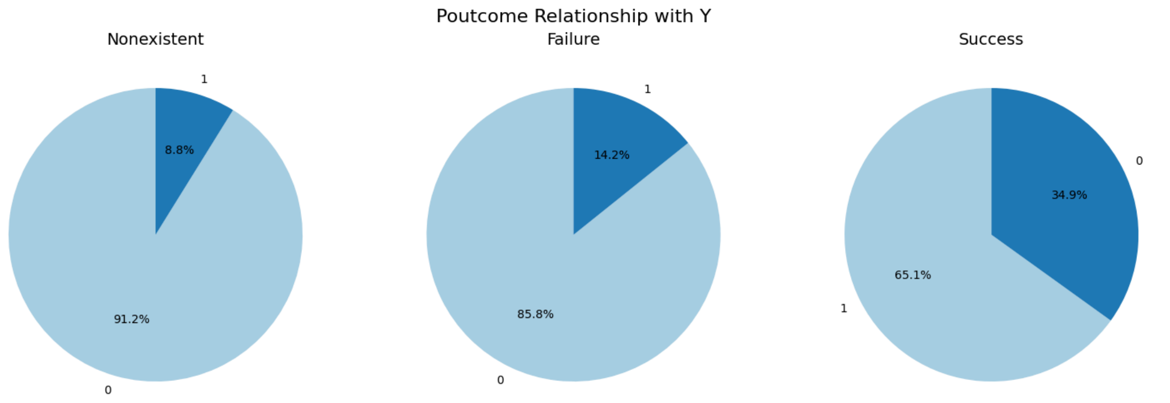
```
# Bivariate analysis of 'poutcome' and 'y'
bivariate_analysis(marketing, 'poutcome', chart_type='bar')
```

```
Bivariate Analysis of 'poutcome' and 'y'
```



In [200…

```
# Bivariate analysis of 'poutcome' and 'y'
generate_pie_charts_per_category(marketing, 'poutcome', colors=plt.cm.Pairec
```



In [201…

```
# Generate summary table for 'poutcome' and 'y'
poutcome_summary = generate_summary_table(marketing, 'poutcome')

# Display the summary table
print(poutcome_summary)
```

```
             No_count  Yes_count  No_percent  Yes_percent
poutcome
success           479        892   34.938001    65.061999
failure          3645        605   85.764706    14.235294
nonexistent     32418       3141   91.166793     8.833207
```

A little check to see if the values are representative

In [202…

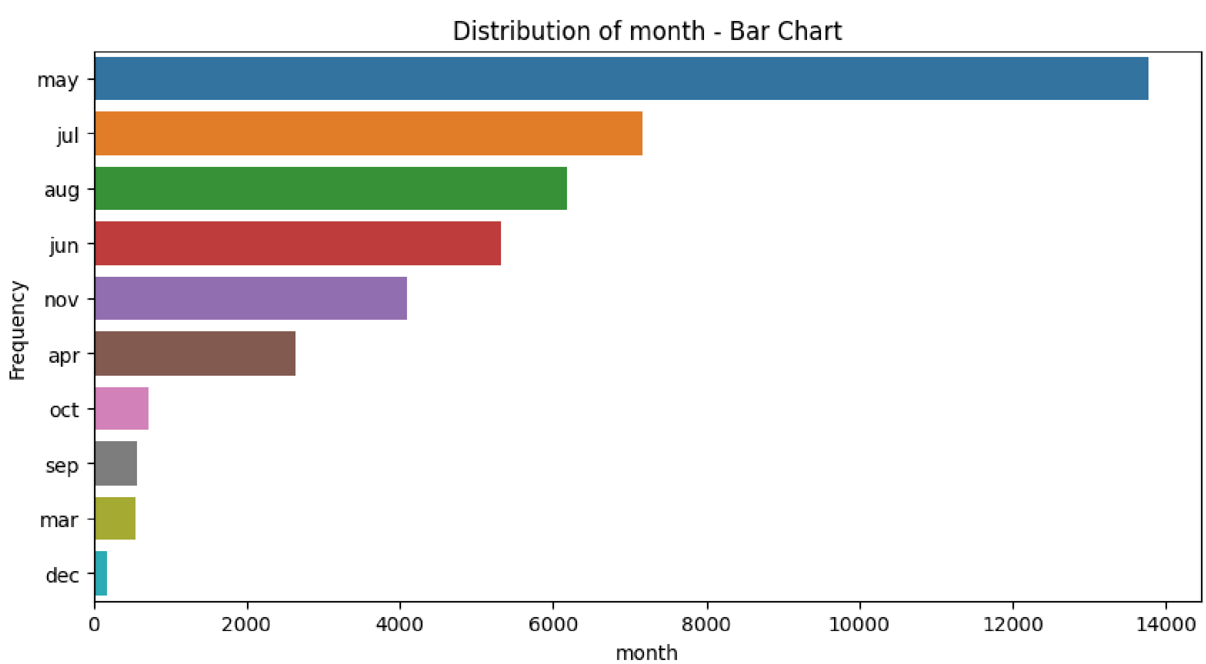
```
df = marketing.copy()
df['y'] = df['y'].map({'yes': 1, 'no': 0})  # Convert 'y' to binary

# Create dummy variables for 'poutcome'
poutcome_dummies = pd.get_dummies(df['poutcome'], drop_first=True)

# Add an intercept column for the regression
X = sm.add_constant(poutcome_dummies)
y = df['y']

# Fit the logistic regression model
model = sm.Logit(y, X).fit()

# Print the summary of the model
print(model.summary())

# Check the p-values of the poutcome categories
print("\nP-values for poutcome categories:\n", model.pvalues)
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
Cell In [202], line 12
      9 y = df['y']
     11 # Fit the logistic regression model
---> 12 model = sm.Logit(y, X).fit()
     14 # Print the summary of the model
     15 print(model.summary())

File /usr/local/lib/python3.10/site-packages/statsmodels/discrete/discrete_model.py:479, in BinaryModel.__init__(self, endog, exog, offset, check_rank, **kwargs)
    477 if not issubclass(self.__class__, MultinomialModel):
    478     if not np.all((self.endog >= 0) & (self.endog <= 1)):
--> 479         raise ValueError("endog must be in the unit interval.")
    481 if offset is None:
    482     delattr(self, 'offset')

ValueError: endog must be in the unit interval.
```

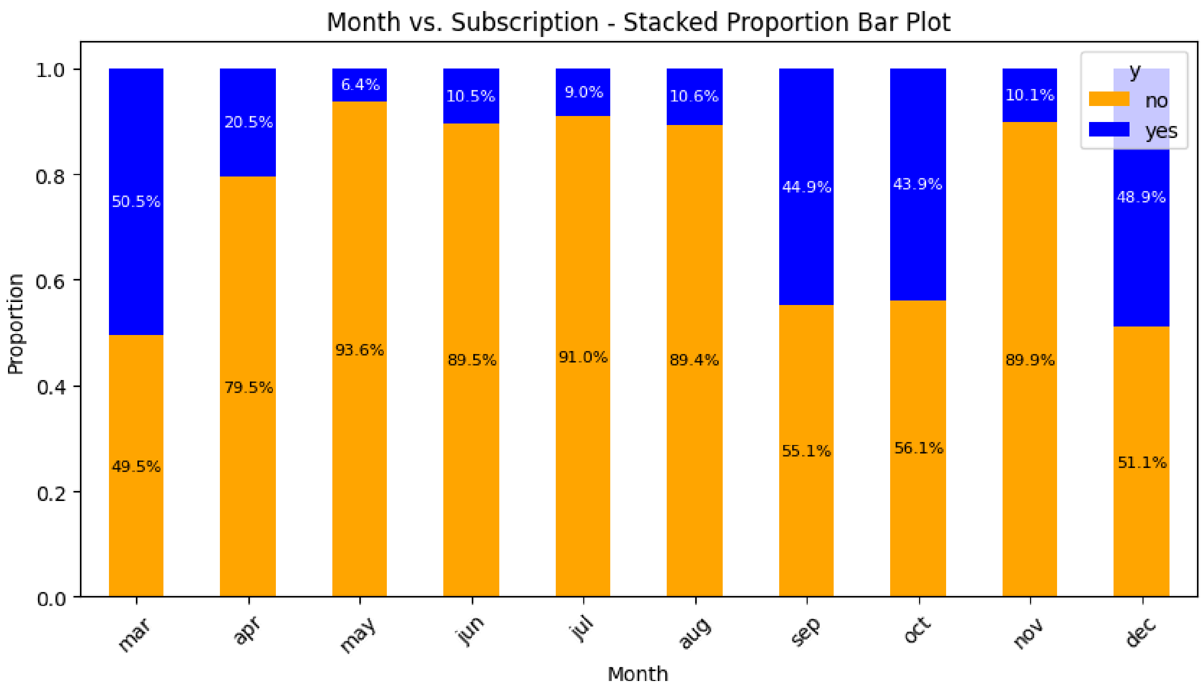
Month

In [48]:
```
# Analyze the 'month' variable
analyze_column(marketing, 'month', chart_type='bar')
```

```
Summary of 'month':
count     41180
unique       10
top         may
freq      13765
Name: month, dtype: object

Unique values in 'month':
['may' 'jun' 'jul' 'aug' 'oct' 'nov' 'dec' 'mar' 'apr' 'sep']
```



In [49]:
```
import matplotlib.pyplot as plt

month_order = ['mar', 'apr', 'may', 'jun', 'jul', 'aug', 'sep', 'oct', 'nov'

# Generate the proportion DataFrame for stacked bar plot
prop_df = (marketing.groupby(['month', 'y']).size() / marketing.groupby(['mo

# Order the DataFrame by the specified month order
prop_df = prop_df.loc[month_order]

# Plot the stacked bar plot
ax = prop_df.plot(kind='bar', stacked=True, figsize=(10, 5), color=['orange'
plt.title('Month vs. Subscription - Stacked Proportion Bar Plot')
plt.xlabel('Month')
plt.ylabel('Proportion')
plt.xticks(rotation=45)

# Annotate the bars with the percentages
for i in range(len(prop_df)):
    for j in range(len(prop_df.columns)):
        value = prop_df.iloc[i, j]
        # Set color based on the section of the bar: white for blue ('no') a
        text_color = 'white' if j == 1 else 'black'
        # Display percentages with respective color
        ax.text(i, value / 2 if j == 0 else 1 - (value / 2),
                f'{value * 100:.1f}%', ha='center', va='center', color=text_

plt.show()

# Generate and display the summary table
month_summary = generate_summary_table(marketing, 'month')
print(month_summary)
```

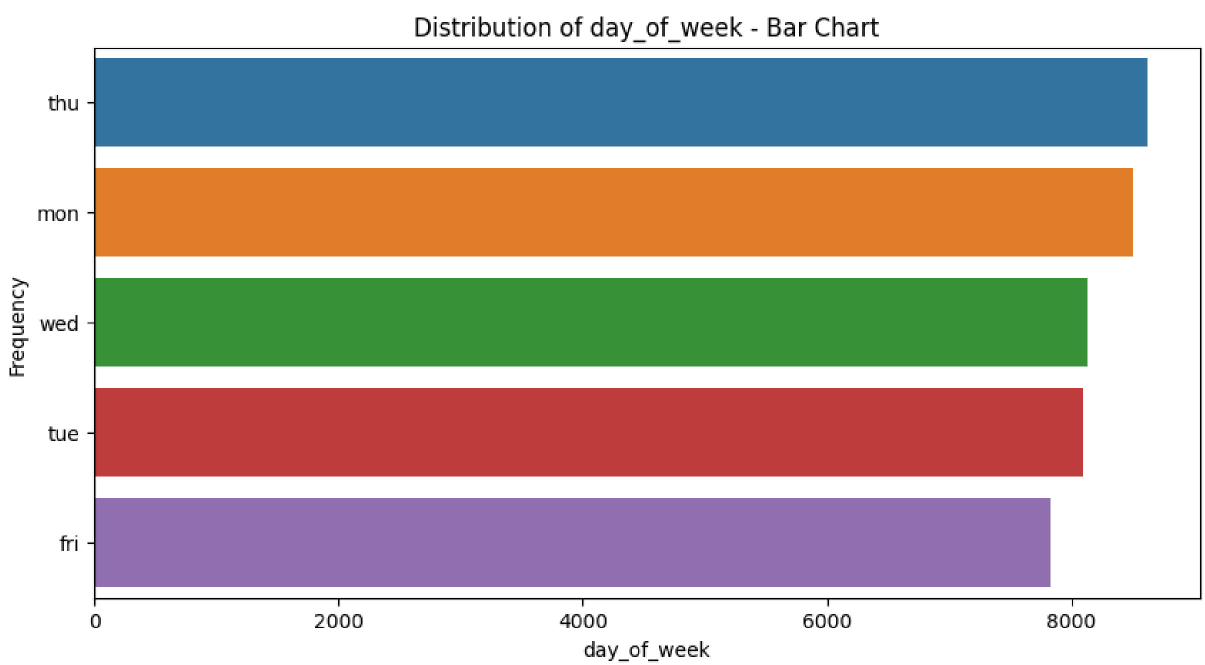


```
       No_count  Yes_count  No_percent  Yes_percent
month
mar         270        276   49.450549    50.549451
dec          93         89   51.098901    48.901099
sep         314        256   55.087719    44.912281
oct         403        315   56.128134    43.871866
apr        2093        539   79.521277    20.478723
aug        5523        655   89.397863    10.602137
jun        4759        559   89.488530    10.511470
nov        3683        414   89.895045    10.104955
jul        6525        649   90.953443     9.046557
may       12879        886   93.563385     6.436615
```

Day of Week

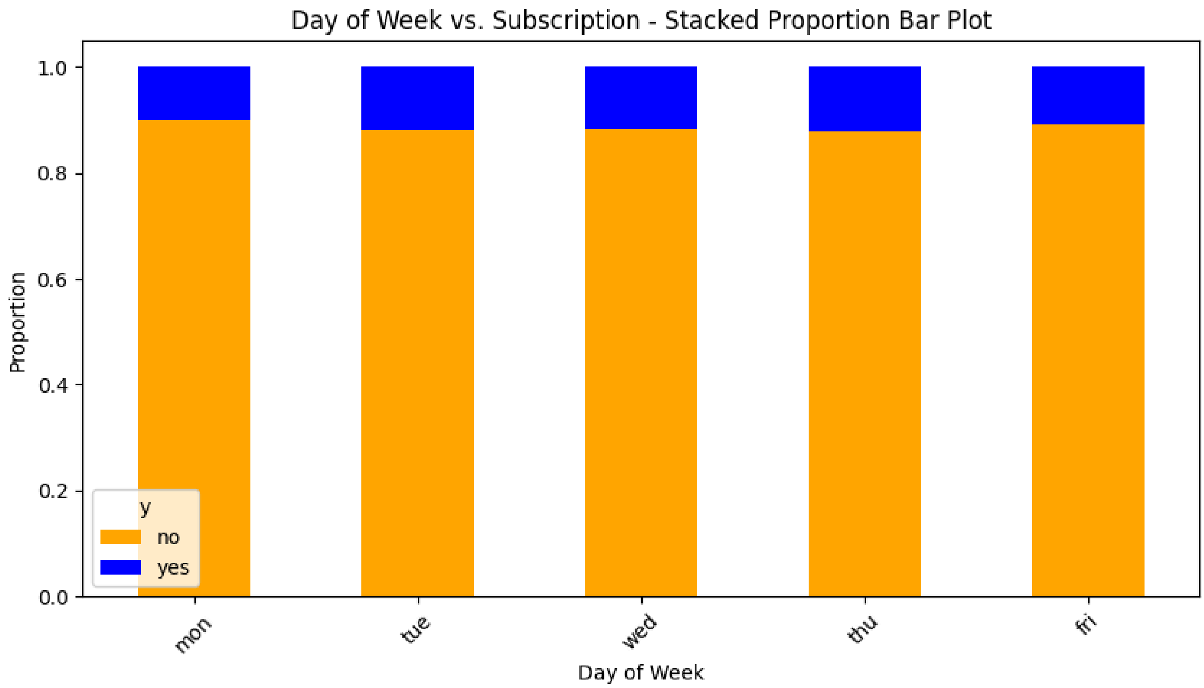
In [50]:
```python
# Analyze the 'day_of_week' variable
analyze_column(marketing, 'day_of_week', chart_type='bar')
```

```
Summary of 'day_of_week':
count     41180
unique        5
top         thu
freq       8622
Name: day_of_week, dtype: object

Unique values in 'day_of_week':
['mon' 'tue' 'wed' 'thu' 'fri']
```



In [51]:
```python
# Define the correct order for the days of the week
day_order = ['mon', 'tue', 'wed', 'thu', 'fri']

# Generate the proportion DataFrame for stacked bar plot
prop_df = (marketing.groupby(['day_of_week', 'y']).size() / marketing.groupb

# Order the DataFrame by the specified day order
```

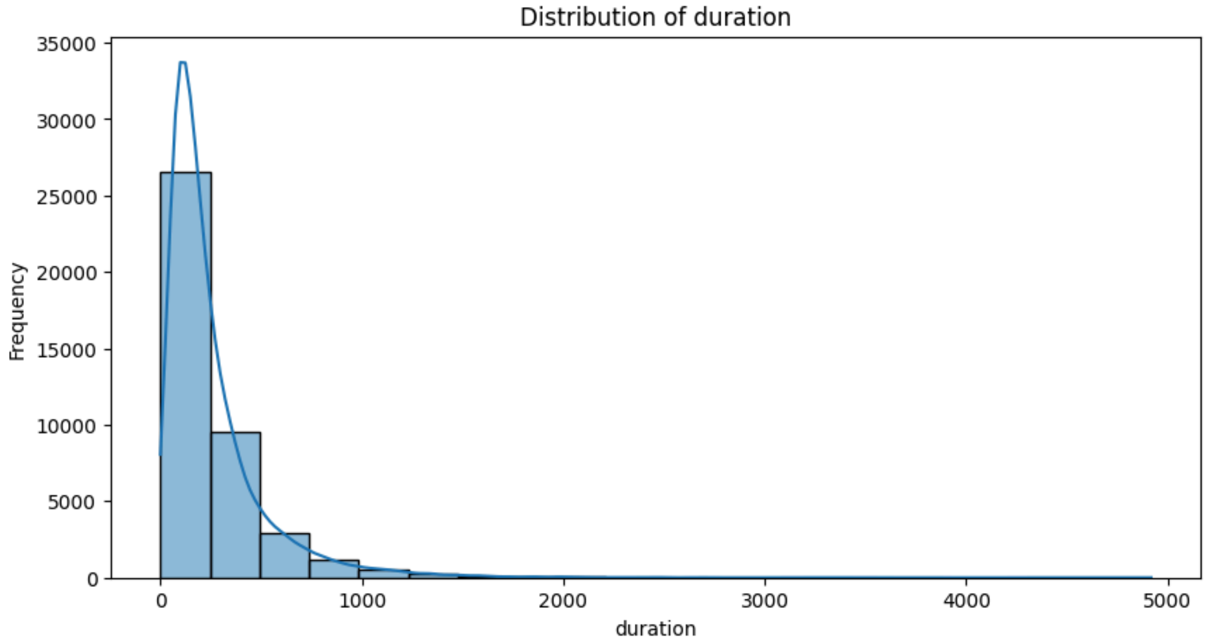
```
prop_df = prop_df.loc[day_order]

# Plot the stacked bar plot
prop_df.plot(kind='bar', stacked=True, figsize=(10, 5), color=['orange', 'bl
plt.title('Day of Week vs. Subscription - Stacked Proportion Bar Plot')
plt.xlabel('Day of Week')
plt.ylabel('Proportion')
plt.xticks(rotation=45)
plt.show()
```



Duration

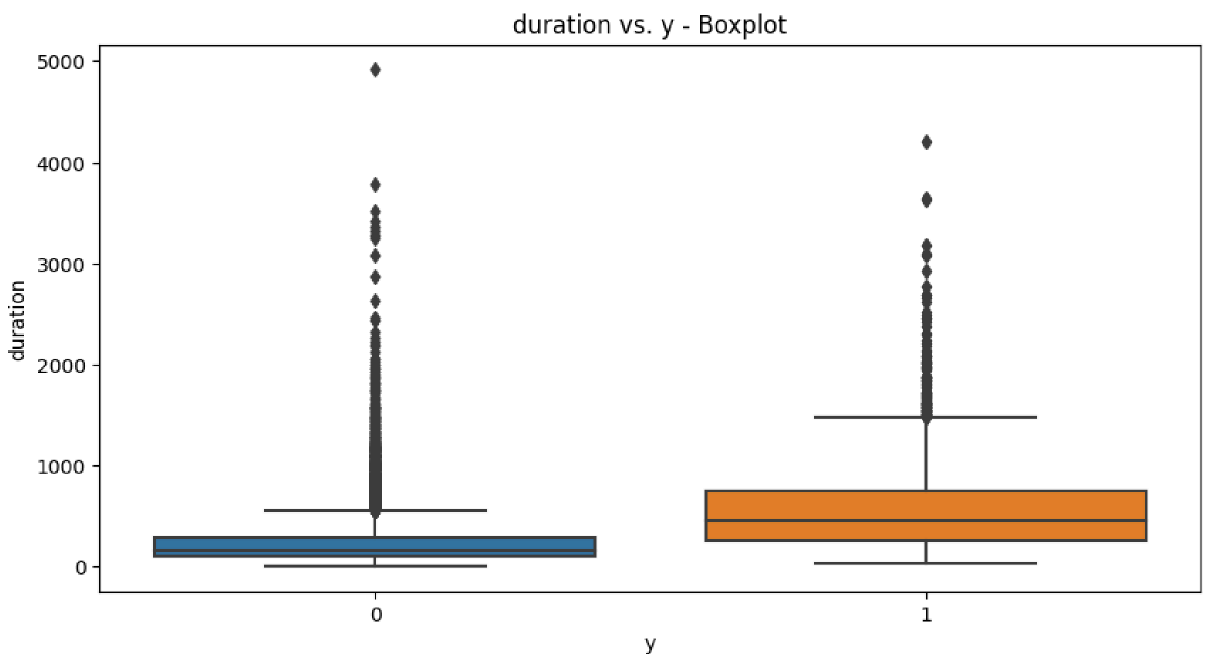
In [52]:
```
# Analyze the 'duration' variable
analyze_column(marketing, 'duration')
```

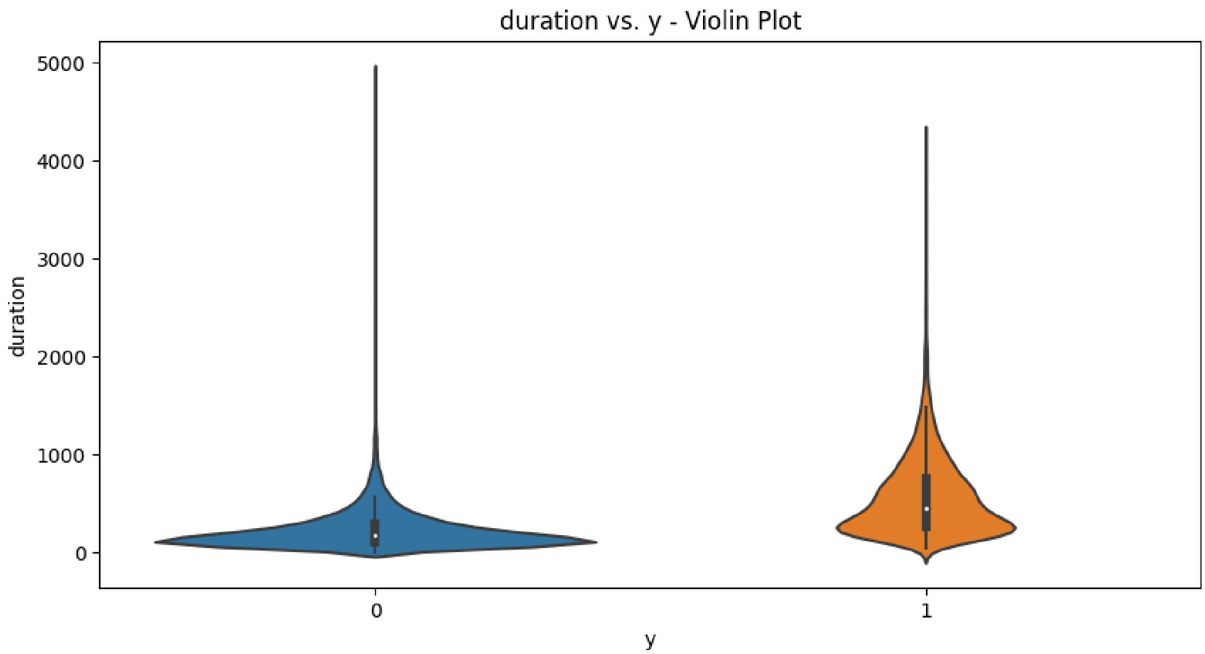
```
Summary of 'duration':
count    41180.000000
mean       258.280427
std        259.299856
min          0.000000
25%        102.000000
50%        180.000000
75%        319.000000
max       4918.000000
Name: duration, dtype: float64

Unique values in 'duration':
[ 151  307  198 ... 1246 1556 1868]
```

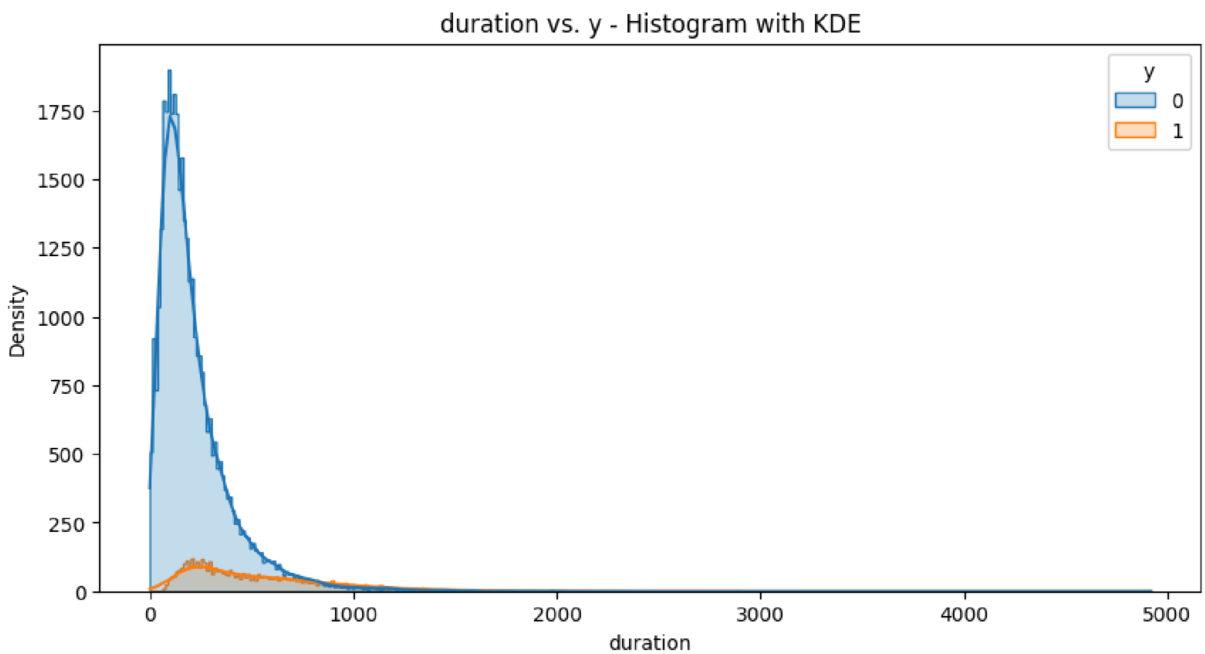


In [203…
```
# Bivariate analysis of 'duration' and 'y'
bivariate_analysis(marketing, 'duration')
```

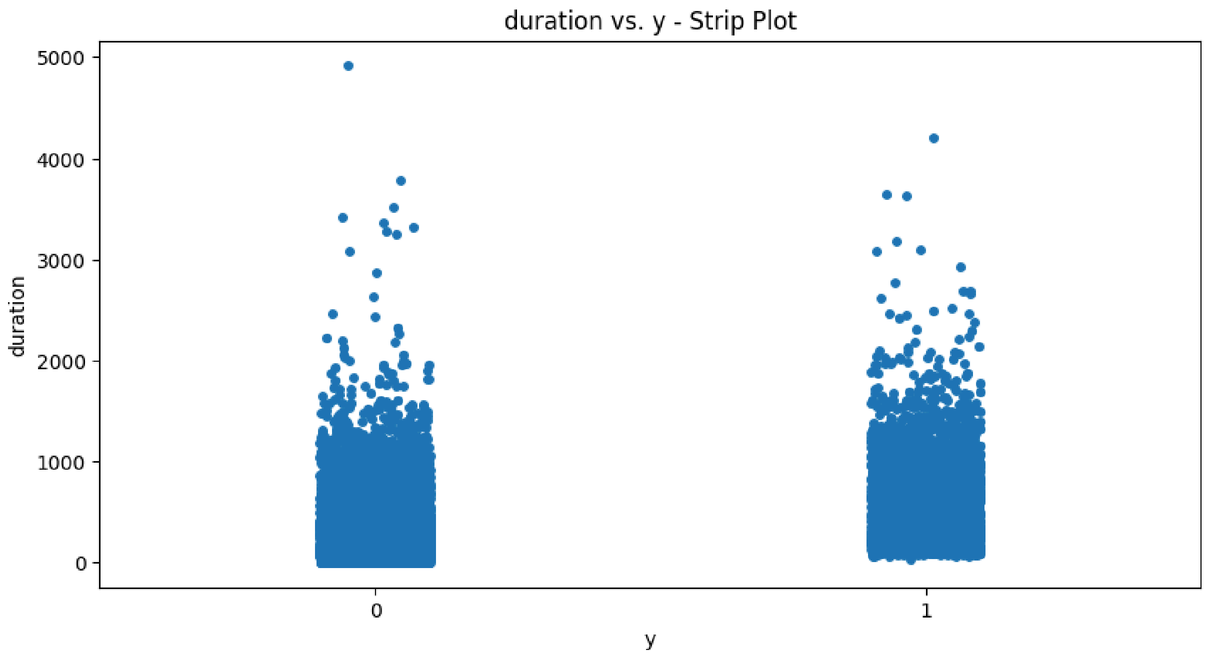
```
Bivariate Analysis of 'duration' and 'y'
```





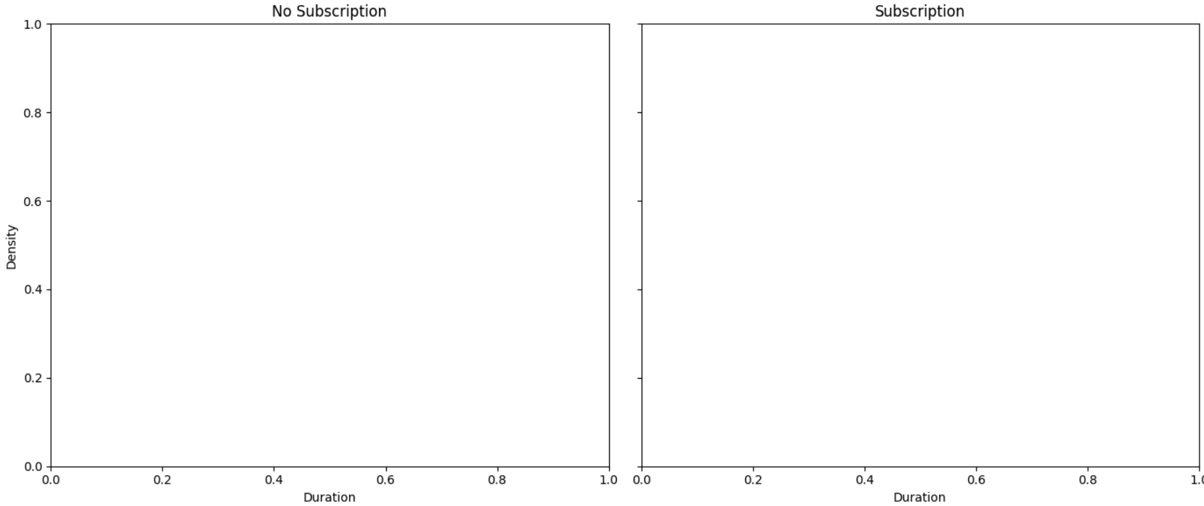


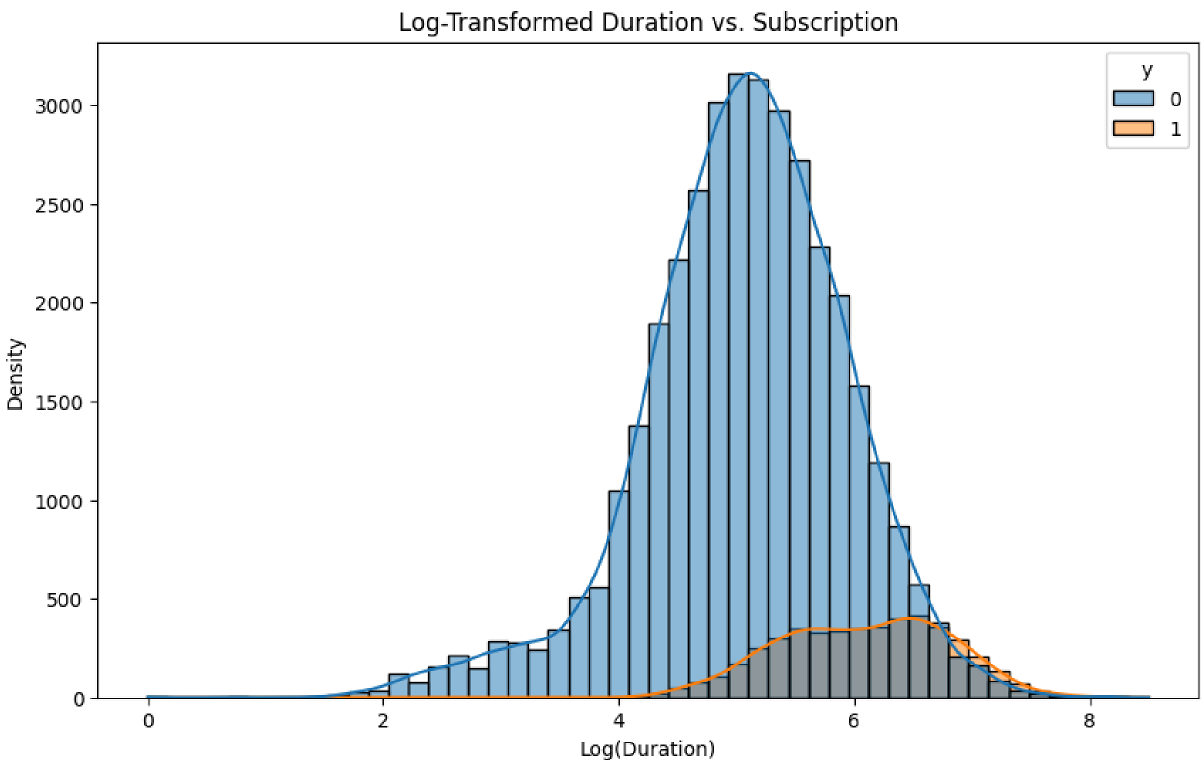

```
Using categorical units to plot a list of strings that are all parsable as f
loats or dates. If these strings should be plotted as numbers, cast to the a
ppropriate data type before plotting.
Using categorical units to plot a list of strings that are all parsable as f
loats or dates. If these strings should be plotted as numbers, cast to the a
ppropriate data type before plotting.
```

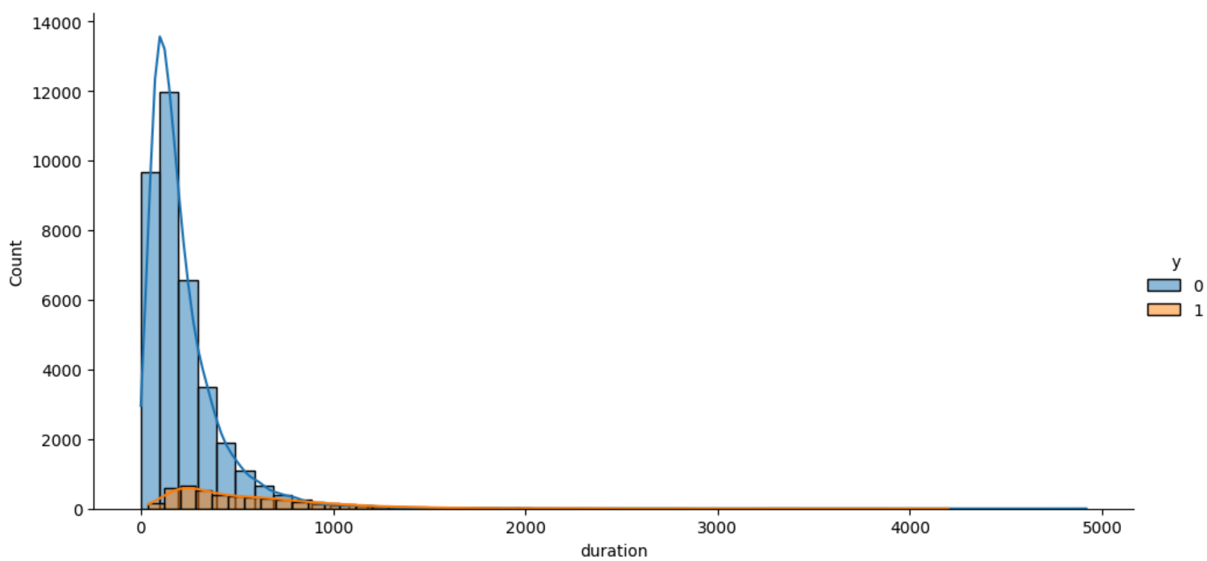


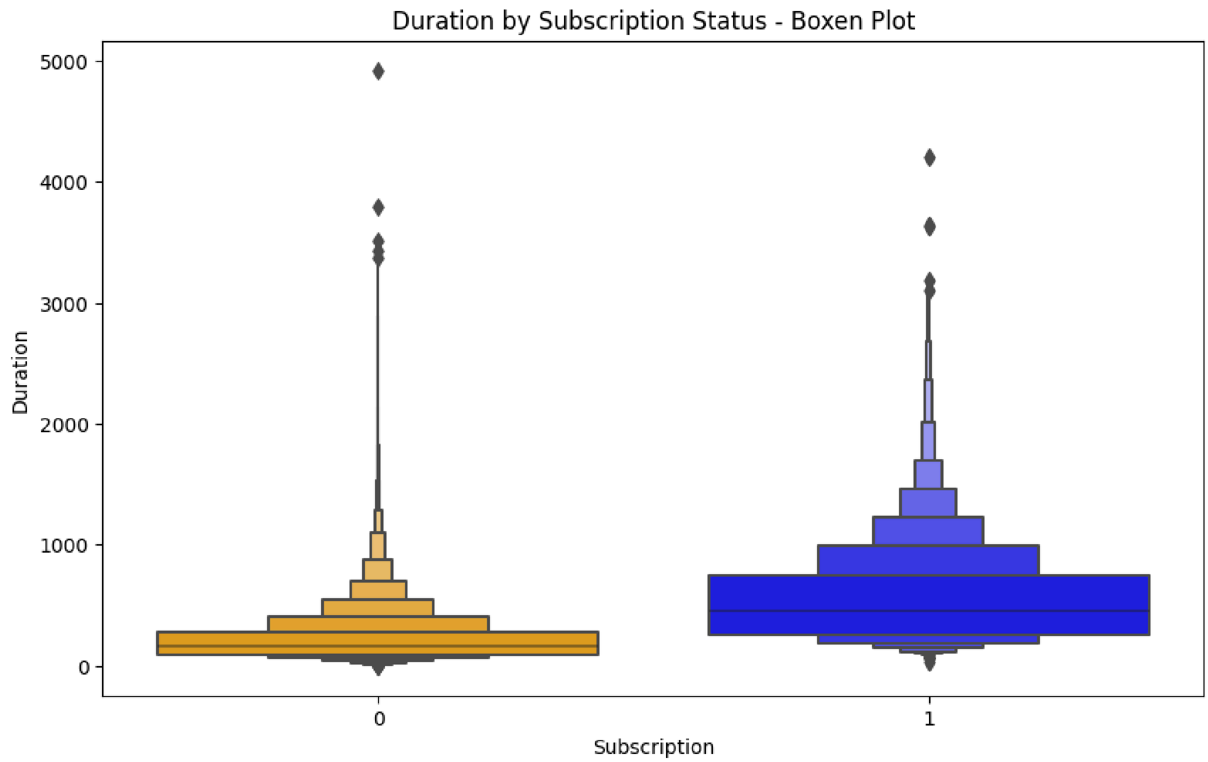
In [204…

```
# Option 1: Separate Histograms for Each Group
fig, axes = plt.subplots(1, 2, figsize=(14, 6), sharey=True)
sns.histplot(marketing[marketing['y'] == 'no']['duration'], kde=True, bins=5
axes[0].set_title('No Subscription')
axes[0].set_xlabel('Duration')
axes[0].set_ylabel('Density')
sns.histplot(marketing[marketing['y'] == 'yes']['duration'], kde=True, bins=
axes[1].set_title('Subscription')
axes[1].set_xlabel('Duration')
plt.tight_layout()
plt.show()

# Option 2: Log Transformation
marketing['log_duration'] = np.log1p(marketing['duration'])  # Log transform
plt.figure(figsize=(10, 6))
sns.histplot(data=marketing, x='log_duration', hue='y', kde=True, bins=50)
plt.title('Log-Transformed Duration vs. Subscription')
plt.xlabel('Log(Duration)')
plt.ylabel('Density')
plt.show()

# Option 3: Faceted Histogram
g = sns.FacetGrid(marketing, hue='y', aspect=2, height=5)
g.map(sns.histplot, 'duration', bins=50, kde=True)
g.add_legend()
plt.show()

# Option 4: Boxen Plot
plt.figure(figsize=(10, 6))
sns.boxenplot(data=marketing, x='y', y='duration', palette=['orange', 'blue'
plt.title('Duration by Subscription Status - Boxen Plot')
plt.xlabel('Subscription')
plt.ylabel('Duration')
plt.show()
```


No Subscription
Subscription
Density
Duration
Duration


Log-Transformed Duration vs. Subscription
y
0
1
Density
Log(Duration)

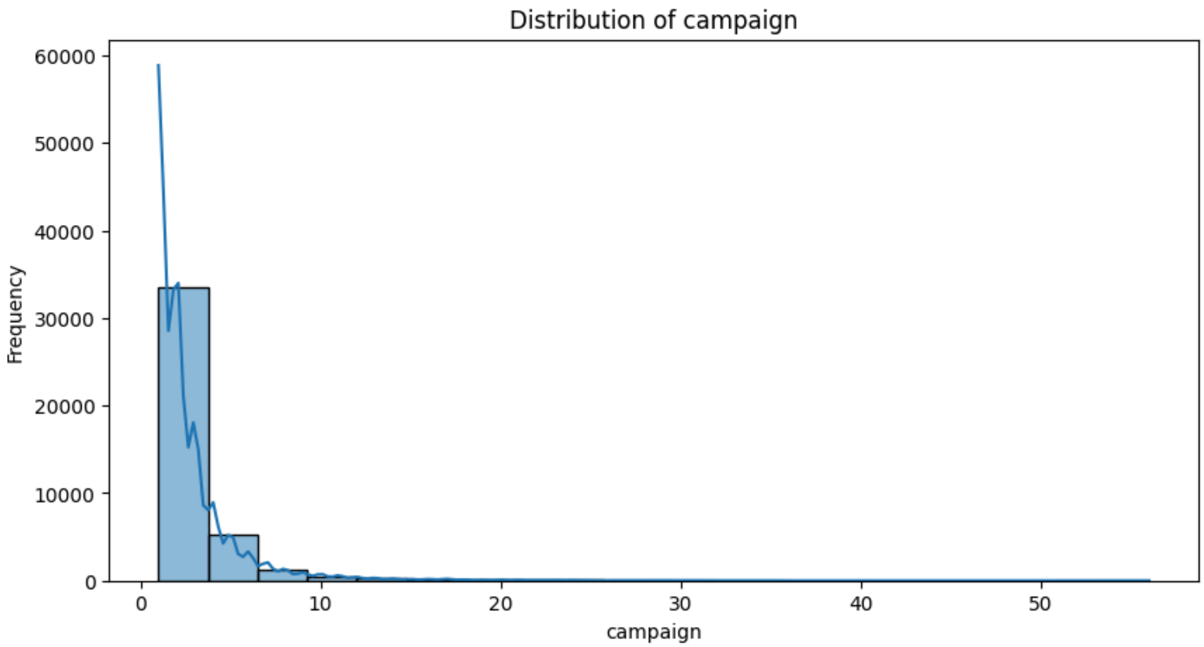

y
0
1
Count
duration



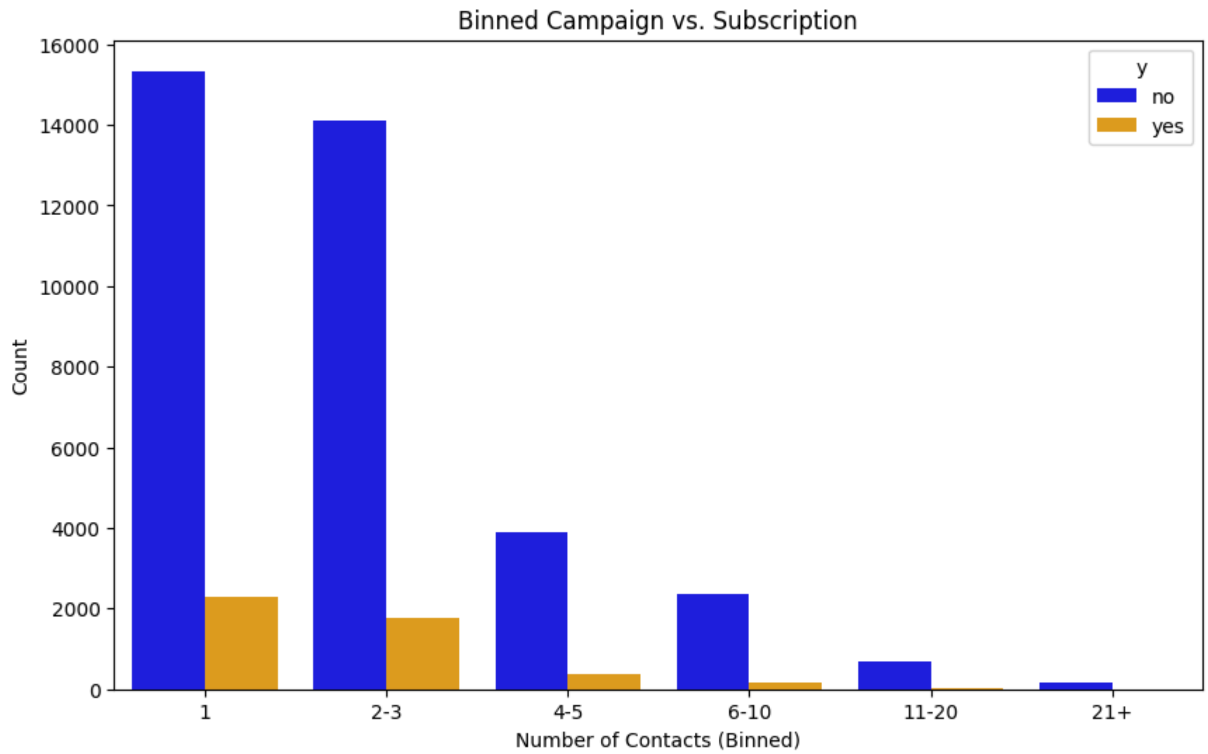
Campaign

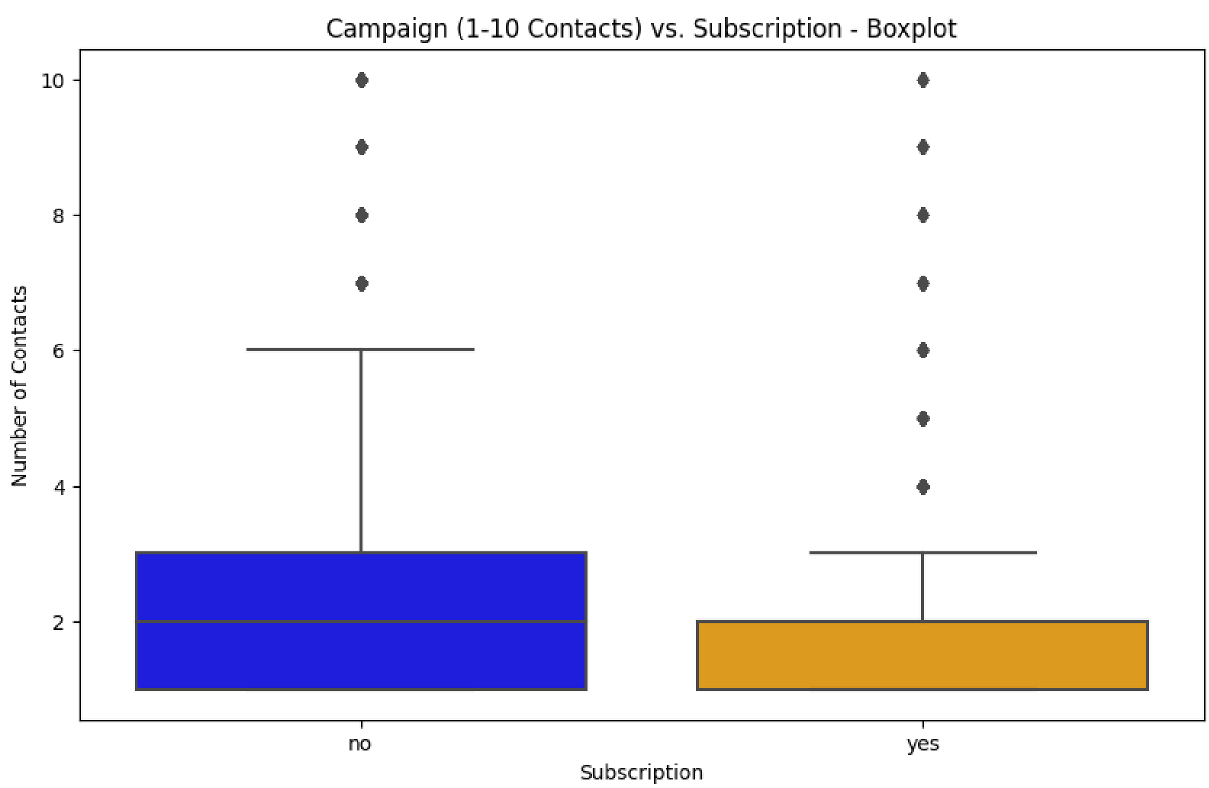
In [55]:
```
# Analyze the 'campaign' variable
analyze_column(marketing, 'campaign')
```

```
Summary of 'campaign':
count    41180.000000
mean         2.567800
std          2.770225
min          1.000000
25%          1.000000
50%          2.000000
75%          3.000000
max         56.000000
Name: campaign, dtype: float64

Unique values in 'campaign':
[ 1  2  3  4  5  6  7  8  9 10 11 12 13 19 18 23 14 22 25 16 17 15 20 56
 39 35 42 28 26 27 32 21 24 29 31 30 41 37 40 33 34 43]
```



In [56]:
```
# Option 2: Binning
bins = [0, 1, 3, 5, 10, 20, np.inf]
labels = ['1', '2-3', '4-5', '6-10', '11-20', '21+']
marketing['campaign_binned'] = pd.cut(marketing['campaign'], bins=bins, labe
plt.figure(figsize=(10, 6))
sns.countplot(x='campaign_binned', hue='y', data=marketing, palette=['blue',
plt.title('Binned Campaign vs. Subscription')
plt.xlabel('Number of Contacts (Binned)')
plt.ylabel('Count')
plt.show()



# Limit the range of 'campaign' to focus on the more typical values (e.g., 1
plt.figure(figsize=(10, 6))
sns.boxplot(data=marketing[marketing['campaign'] <= 10], x='y', y='campaign'
plt.title('Campaign (1-10 Contacts) vs. Subscription - Boxplot')
plt.xlabel('Subscription')
plt.ylabel('Number of Contacts')
plt.show()
```





In [57]:
```
# Generate summary statistics for the 'campaign' variable for each subscript
campaign_summary = marketing.groupby('y')['campaign'].describe()

# Display the summary statistics
print(campaign_summary)
```

```
       count      mean       std  min  25%  50%  75%   max
y
no   36542.0  2.633271  2.873621  1.0  1.0  2.0  3.0  56.0
yes   4638.0  2.051962  1.666532  1.0  1.0  2.0  2.0  23.0
```

P-Days

In [58]:
```
plot(marketing, 'pdays')
```

```
0%|          | 0/122 [00:00<?, ?it/s]
```

Out[58]: Stats Histogram KDE Plot Normal Q-Q Plot Box Plot Value Table

Overview

Approximate Distinct Count	27
Approximate Unique (%)	0.1%
Missing	0
Missing (%)	0.0%
Infinite	0
Infinite (%)	0.0%
Memory Size	658880
Mean	962.5167
Minimum	0
Maximum	999
Zeros	15
Zeros (%)	0.0%
Negatives	0
Negatives (%)	0.0%

Quantile Statistics

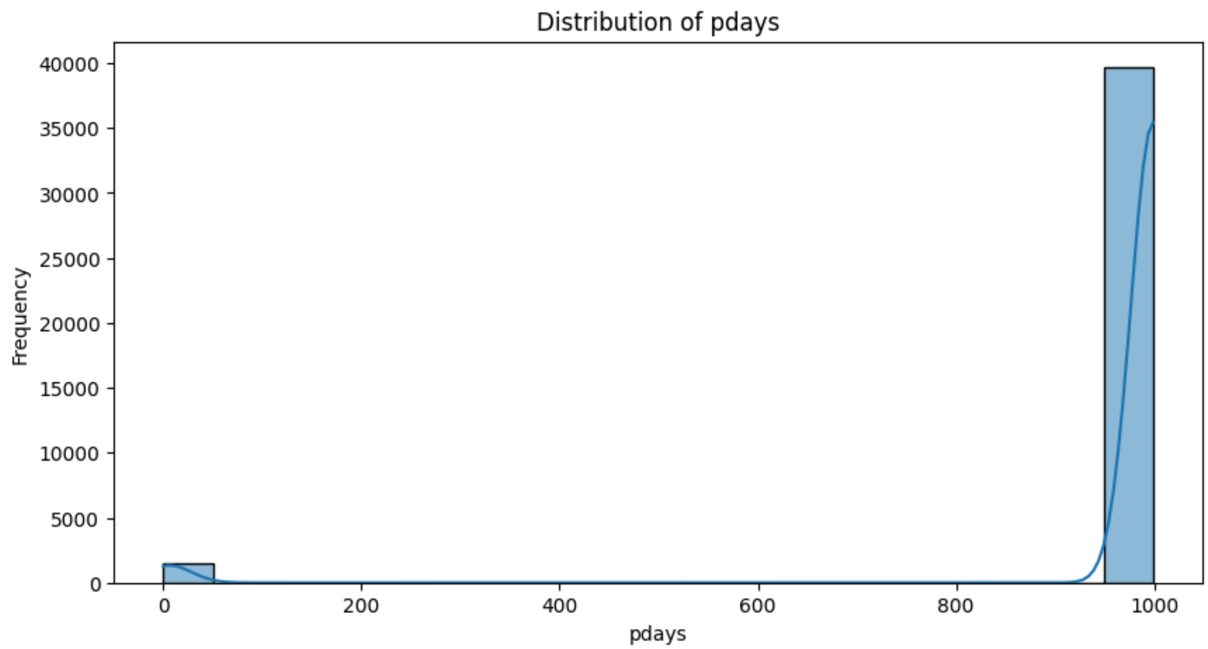
Minimum	0
5-th Percentile	999
Q1	999
Median	999
Q3	999
95-th Percentile	999
Maximum	999
Range	999
IQR	0

Descriptive Statist

Mean	
Standard Deviation	
Variance	3
Sum	3.9
Skewness	
Kurtosis	
Coefficient of Variation	

In [59]:
```
# Analyze the 'campaign' variable
analyze_column(marketing, 'pdays')
```

```
Summary of 'pdays':
count    41180.000000
mean       962.516707
std        186.809028
min          0.000000
25%        999.000000
50%        999.000000
75%        999.000000
max        999.000000
Name: pdays, dtype: float64

Unique values in 'pdays':
[999   6   4   3   5   1   0  10   7   8   9  11   2  12  13  14  15  16
  21  17  18  22  25  26  19  27  20]
```



In [60]:
```
# Create a new column for pdays categories
marketing['pdays_category'] = marketing['pdays'].apply(lambda x: 'Not Contac

# Display the counts of each category
print(marketing['pdays_category'].value_counts())
```

```
Contacted Previously    41180
Name: pdays_category, dtype: int64
```

In [61]:
```
original_data['pdays'].unique()
```

Out[61]:
```
array(['999', '6', '4', '3', '5', '1', '0', '10', '7', '8', '9', '11',
       '2', '12', '13', '14', '15', '16', '21', '17', '18', '22', '25',
       '26', '19', '27', '20'], dtype=object)
```

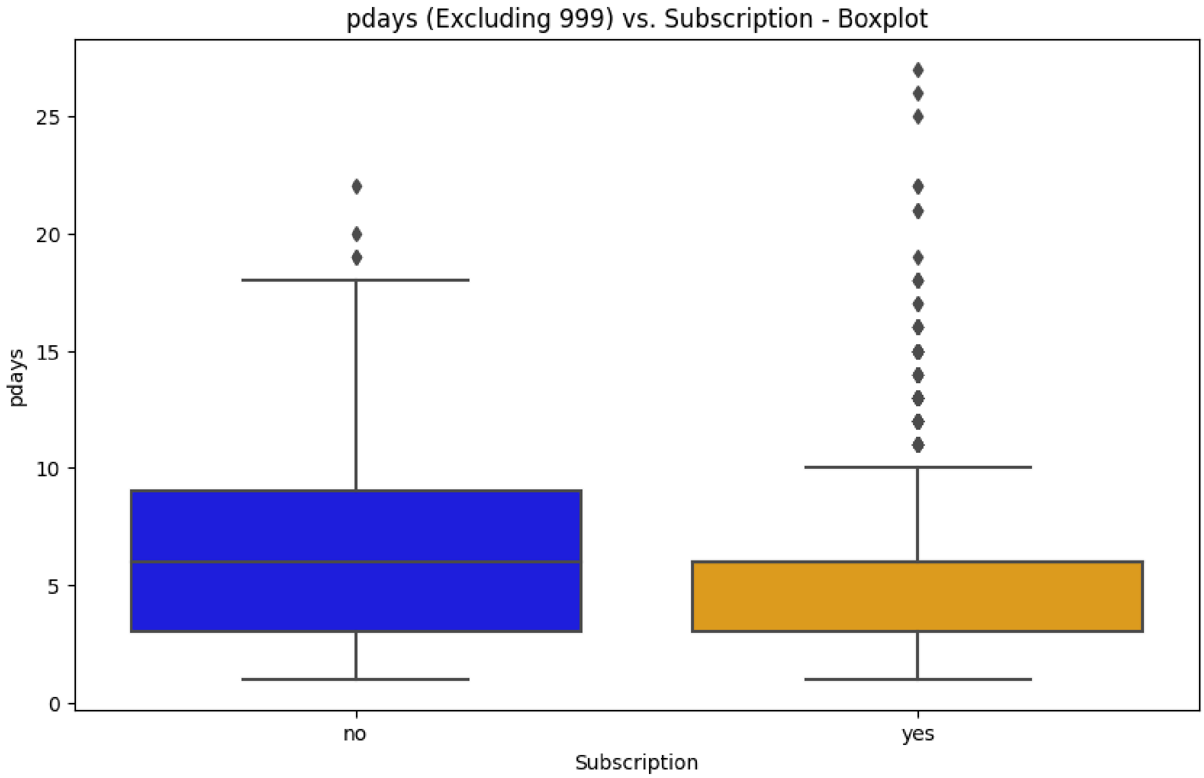
The value for 999 seems to be the -1 which explains when there is no call we should analyze it differently

In [62]:
```
marketing['pdays_category'] = marketing['pdays'].apply(lambda x: 'Not Contac
```

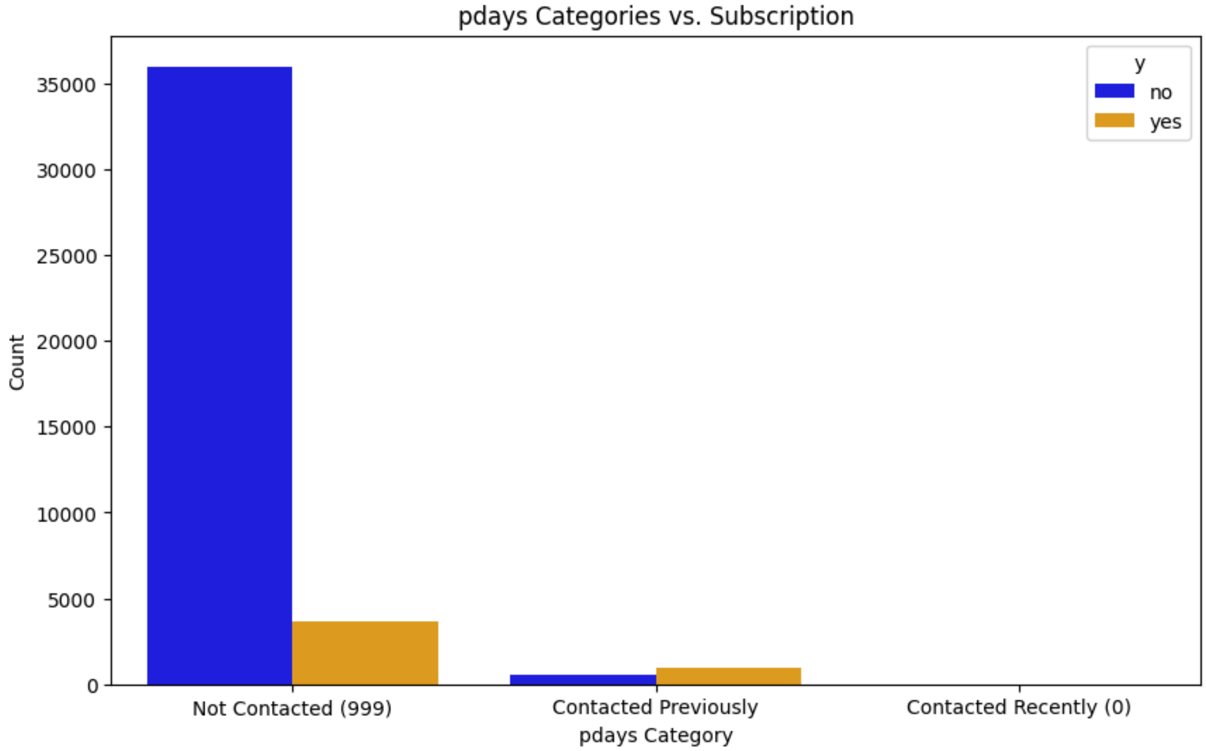
```
# Display the counts of each category
print(marketing['pdays_category'].value_counts())
```

```
Not Contacted (999)       39667
Contacted Previously       1498
Contacted Recently (0)       15
Name: pdays_category, dtype: int64
```

In [63]:
```
# Filter out 'pdays = 999' and possibly 'pdays = 0'
filtered_pdays = marketing[(marketing['pdays'] > 0) & (marketing['pdays'] <

# Re-plot the box plot after filtering out 'pdays = 999'
plt.figure(figsize=(10, 6))
sns.boxplot(data=filtered_pdays, x='y', y='pdays', palette=['blue', 'orange'
plt.title('pdays (Excluding 999) vs. Subscription - Boxplot')
plt.xlabel('Subscription')
plt.ylabel('pdays')
plt.show()
```



In [64]:
```
plt.figure(figsize=(10, 6))
sns.countplot(x='pdays_category', hue='y', data=marketing, palette=['blue',
plt.title('pdays Categories vs. Subscription')
plt.xlabel('pdays Category')
plt.ylabel('Count')
plt.show()
```



In [65]:
```
# Group the data by 'pdays_category' and 'y', and calculate the count
summary_table = marketing.groupby(['pdays_category', 'y']).size().unstack(fi

# Rename the columns for better understanding
summary_table.columns = ['No_count', 'Yes_count']

# Calculate percentages for 'yes' and 'no' in each category
summary_table['No_percent'] = summary_table['No_count'] / (summary_table['No
summary_table['Yes_percent'] = summary_table['Yes_count'] / (summary_table['

# Display the summary table
summary_table.reset_index(inplace=True)
summary_table
```

Out[65]:

	pdays_category	No_count	Yes_count	No_percent	Yes_percent
0	Contacted Previously	543	955	36.248331	63.751669
1	Contacted Recently (0)	5	10	33.333333	66.666667
2	Not Contacted (999)	35994	3673	90.740414	9.259586

Previous

In [66]:
```
plot(marketing, 'previous')
```

```
0%|          | 0/75 [00:00<?, ?it/s]
```

Out[66]: Stats | Bar Chart | Pie Chart | Word Cloud | Word Frequency | Word Length | Value Table

Overview

Approximate Distinct Count	8
Approximate Unique (%)	0.0%
Missing	0
Missing (%)	0.0%
Memory Size	2717880

Sample

1st row	0
2nd row	0
3rd row	0
4th row	0
5th row	0

Length

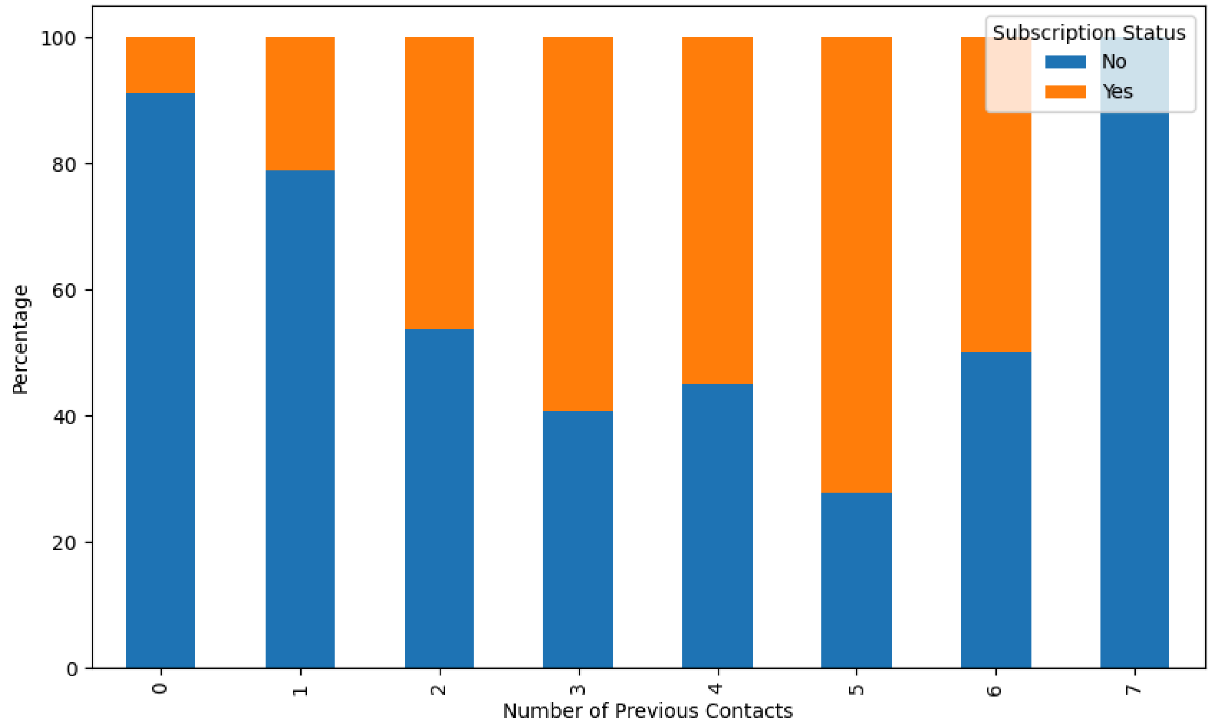
Mean	1
Standard Deviation	0
Median	1
Minimum	1
Maximum	1

Letter

Count	0
Lowercase Letter	0
Space Separator	0
Uppercase Letter	0
Dash Punctuation	0
Decimal Number	41180

In [209…

```
# Group the data by 'previous' and 'y', count the occurrences, and normalize
grouped_data = marketing.groupby(['previous', 'y']).size().unstack(fill_valu

# Calculate percentages
grouped_data_percentage = grouped_data.div(grouped_data.sum(axis=1), axis=0)

# Plot the stacked bar chart with percentages
grouped_data_percentage.plot(kind='bar', stacked=True, figsize=(10, 6), colo
#plt.title('Number of Previous Contacts vs. Subscription Status (Percentage)
plt.xlabel('Number of Previous Contacts')
plt.ylabel('Percentage')
plt.legend(title='Subscription Status', labels=['No', 'Yes'])
plt.show()
```



In [68]:

```
# Group the data by 'previous' and 'y' and calculate counts
previous_summary = marketing.groupby(['previous', 'y']).size().unstack(fill_

# Rename the columns for better understanding
previous_summary.columns = ['No_count', 'Yes_count']

# Calculate percentages for 'yes' and 'no' in each 'previous' category
previous_summary['No_percent'] = previous_summary['No_count'] / (previous_su
previous_summary['Yes_percent'] = previous_summary['Yes_count'] / (previous_

# Reset the index to make it a clean table
previous_summary.reset_index(inplace=True)

# Display the summary table
previous_summary
```

Out[68]:

	previous	No_count	Yes_count	No_percent	Yes_percent
0	0	32418	3141	91.166793	8.833207
1	1	3593	966	78.811143	21.188857
2	2	404	350	53.580902	46.419098
3	3	88	128	40.740741	59.259259
4	4	31	38	44.927536	55.072464
5	5	5	13	27.777778	72.222222
6	6	2	2	50.000000	50.000000
7	7	1	0	100.000000	0.000000

In [69]:
```
marketing['y'].unique()
```

Out[69]:
```
array(['no', 'yes'], dtype=object)
```

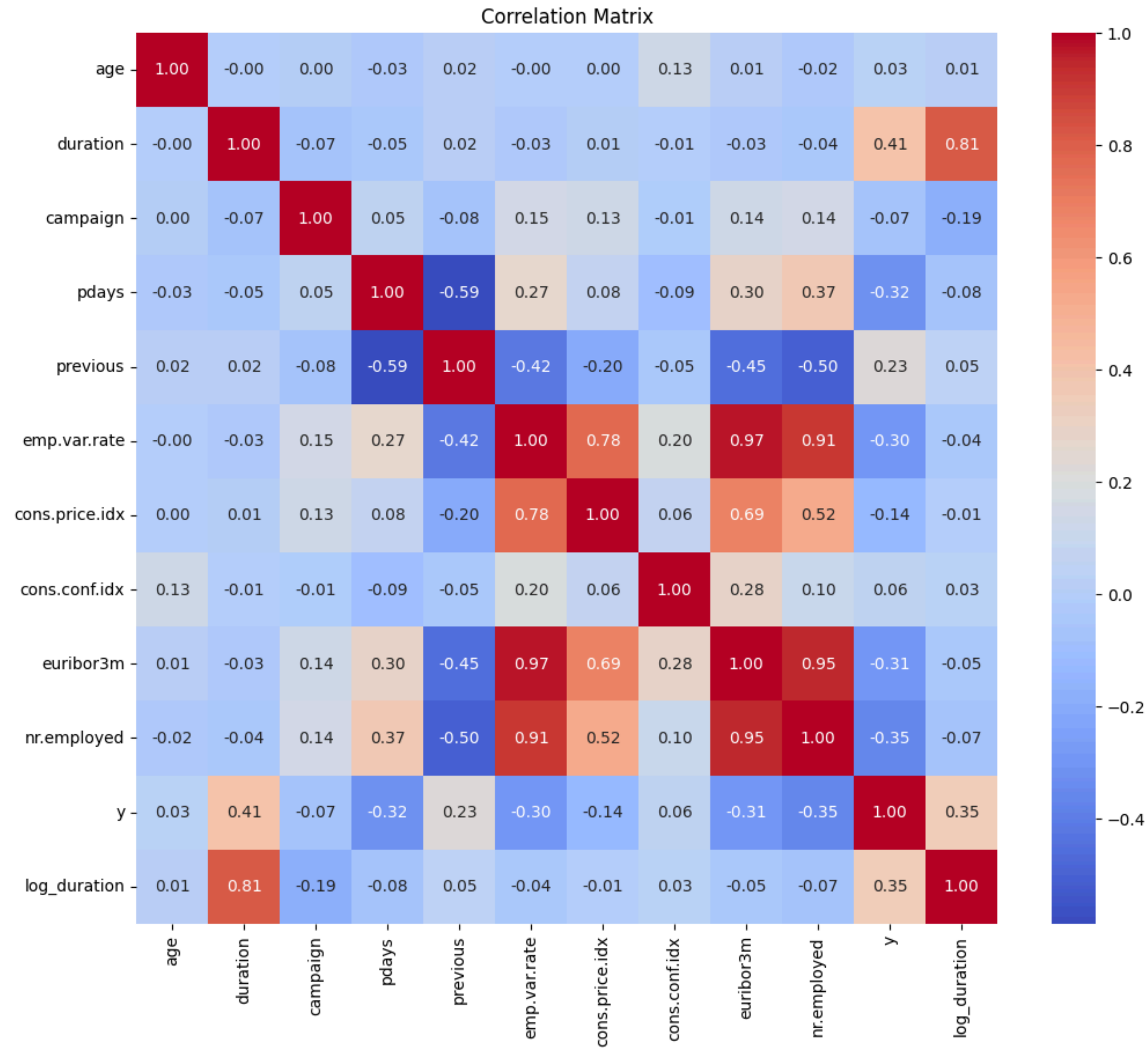
In [69]:
```
## lets drop log duration column
marketing.drop('log_duration', axis=1, inplace=True)
```

In [70]:
```
from sklearn.preprocessing import LabelEncoder
label_encoder = LabelEncoder()
marketing['y'] = label_encoder.fit_transform(marketing['y'])

corr_matrix = marketing.corr()

# lets filter only the target variable correlations and sort it
corr_target = corr_matrix['y'].sort_values(ascending=False)
corr_target
```

Out[70]:
```
y                 1.000000
duration          0.405304
log_duration      0.351018
previous          0.229952
cons.conf.idx     0.055200
age               0.030324
campaign         -0.066340
cons.price.idx   -0.136490
emp.var.rate     -0.298297
euribor3m        -0.307672
pdays            -0.324478
nr.employed      -0.354541
Name: y, dtype: float64
```

In [71]:
```
## generate a heatmap of the correlation matrix
plt.figure(figsize=(12, 10))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Matrix')
```

Out[71]:
```
Text(0.5, 1.0, 'Correlation Matrix')
```


Correlation Matrix
age
duration
campaign
pdays
previous
emp.var.rate
cons.price.idx
cons.conf.idx
euribor3m
nr.employed
y
log_duration

In [ ]: