DATA 622 Assignment 1

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Introduction

This assignment focuses on one of the most important aspects of data science, Exploratory Data Analysis (EDA). Many surveys show that data scientists spend 60-80% of their time on data preparation. EDA allows you to identify data gaps & data imbalances, improve data quality, create better features and gain a deep understanding of your data before doing model training - and that ultimately helps train better models. In machine learning, there is a saying - "better data beats better algorithms" - meaning that it is more productive to spend time improving data quality than improving the code to train the model.

This will be an exploratory exercise, so feel free to show errors and warnings that arise during the analysis.

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

Dataset

A Portuguese bank conducted a marketing campaign (phone calls) to predict if a client will subscribe to a term deposit The records of their efforts are available in the form of a dataset. The objective here is to apply machine learning techniques to analyze the dataset and figure out most effective tactics that will help the bank in next campaign to persuade more customers to subscribe to the bank's term deposit. Download the Bank Marketing Dataset from: https://archive.ics.uci.edu/dataset/222/bank+marketing

```
file_path = "bank-additional-full.csv"
data = pd.read_csv(file_path, sep=';')

data.head()
```

{"type":"dataframe","variable_name":"data"}

Data Cleaning

```
print(list(data.columns))
```

```
['age', 'job', 'marital', 'education', 'default', 'housing', 'loan',
'contact', 'month', 'day_of_week', 'duration', 'campaign', 'pdays',
```

```
'previous', 'poutcome', 'emp.var.rate', 'cons.price.idx',
'cons.conf.idx', 'euribor3m', 'nr.employed', 'y']

data.columns = (
    data.columns
    .str.strip()
    .str.lower()
    .str.replace('.', '_', regex=False)
    .str.replace(' ', '_')
)

print(data.columns.tolist())

['age', 'job', 'marital', 'education', 'default', 'housing', 'loan',
'contact', 'month', 'day_of_week', 'duration', 'campaign', 'pdays',
'previous', 'poutcome', 'emp_var_rate', 'cons_price_idx',
'cons_conf_idx', 'euribor3m', 'nr_employed', 'y']
```

Exploratory Data Analysis

Review the structure and content of the data and answer questions such as:

- Are the features (columns) of your data correlated?
- What is the overall distribution of each variable?
- Are there any outliers present?
- What are the relationships between different variables?
- How are categorical variables distributed?
- Do any patterns or trends emerge in the data?
- What is the central tendency and spread of each variable?
- Are there any missing values and how significant are they?

Are there any missing values and how significant are they?

```
data.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41188 entries, 0 to 41187
Data columns (total 21 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   age             41188 non-null  int64
 1   job             41188 non-null  object
 2   marital         41188 non-null  object
 3   education       41188 non-null  object
 4   default         41188 non-null  object
 5   housing         41188 non-null  object
 6   loan            41188 non-null  object
 7   contact         41188 non-null  object
 8   month           41188 non-null  object
```

```
 9   day_of_week     41188 non-null  object
 10  duration        41188 non-null  int64
 11  campaign        41188 non-null  int64
 12  pdays           41188 non-null  int64
 13  previous        41188 non-null  int64
 14  poutcome        41188 non-null  object
 15  emp_var_rate    41188 non-null  float64
 16  cons_price_idx  41188 non-null  float64
 17  cons_conf_idx   41188 non-null  float64
 18  euribor3m       41188 non-null  float64
 19  nr_employed     41188 non-null  float64
 20  y               41188 non-null  object
dtypes: float64(5), int64(5), object(11)
memory usage: 6.6+ MB
```

```
data.isnull().sum()
```

```
age               0
job               0
marital           0
education         0
default           0
housing           0
loan              0
contact           0
month             0
day_of_week       0
duration          0
campaign          0
pdays             0
previous          0
poutcome          0
emp_var_rate      0
cons_price_idx    0
cons_conf_idx     0
euribor3m         0
nr_employed       0
y                 0
dtype: int64
```

In this dataset there are no missing values. This means that we do not need to fill in missing values.

```
data.replace('unknown', np.nan, inplace=True)

if 'pdays' in data.columns:
    data['pdays'] = data['pdays'].replace(999, np.nan)
```

```
missing_summary = data.isnull().sum()
print(missing_summary[missing_summary >
0].sort_values(ascending=False))
```

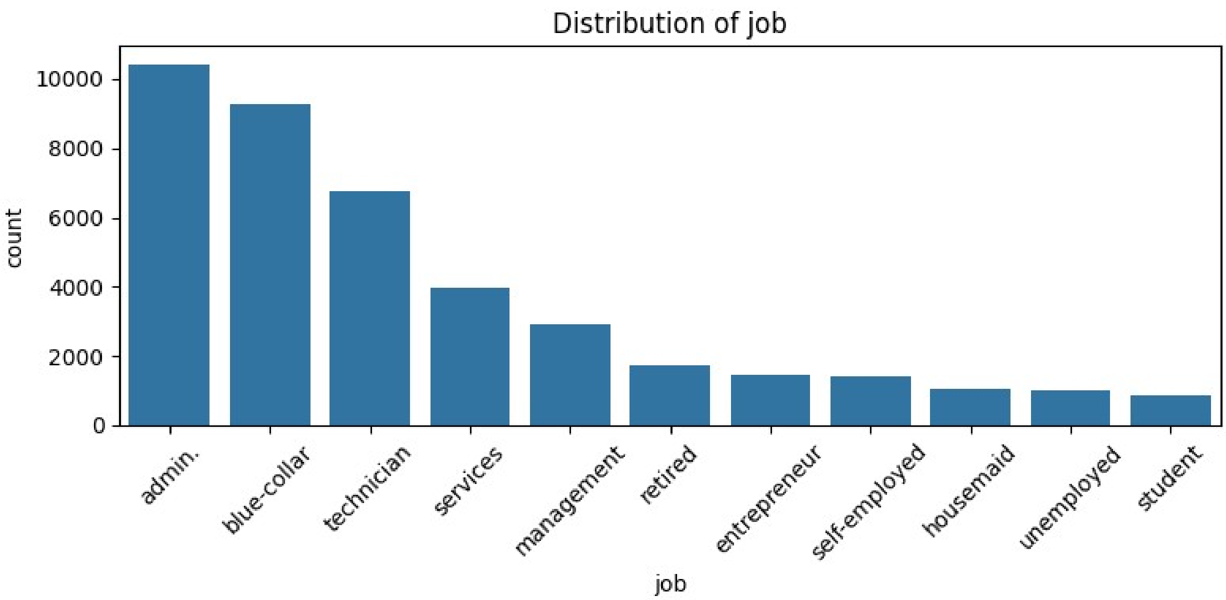
```
pdays        39673
default       8597
education     1731
housing        990
loan           990
job            330
marital         80
dtype: int64
```

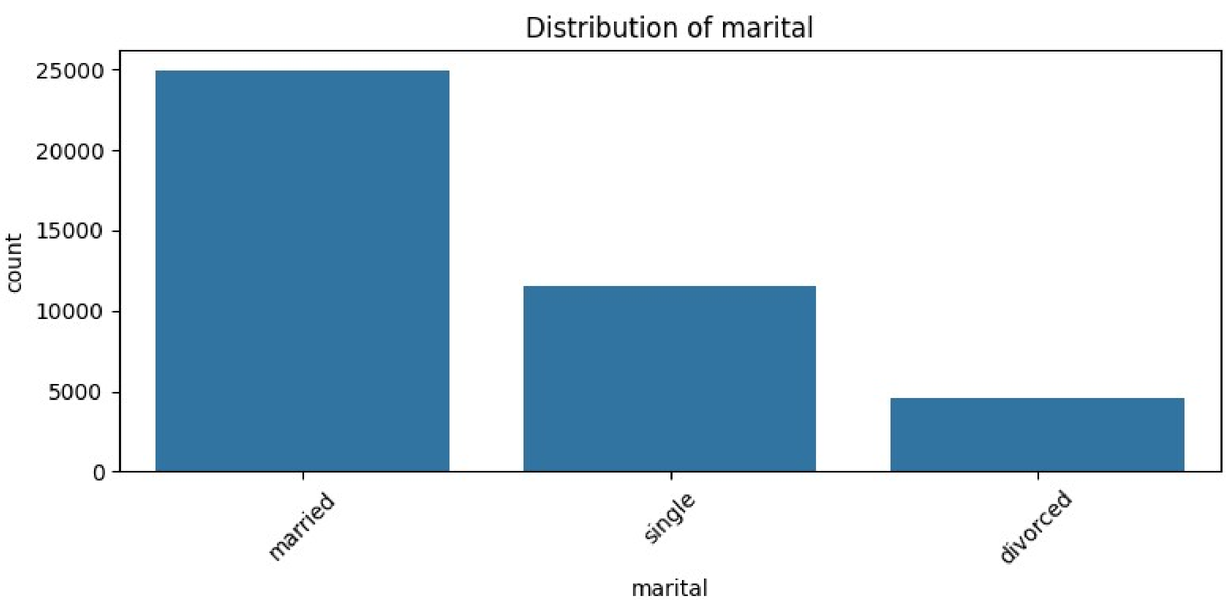
After replacing odd values such as unknown and 999, there maybe a lot of missing values. pdays has about a 91% null rate. In that case dropping those values will make the dataset useless. And so the other options are to impute and fill in that data or even disregard that column compeletely. The latter would be ideal if it had no predictive power.

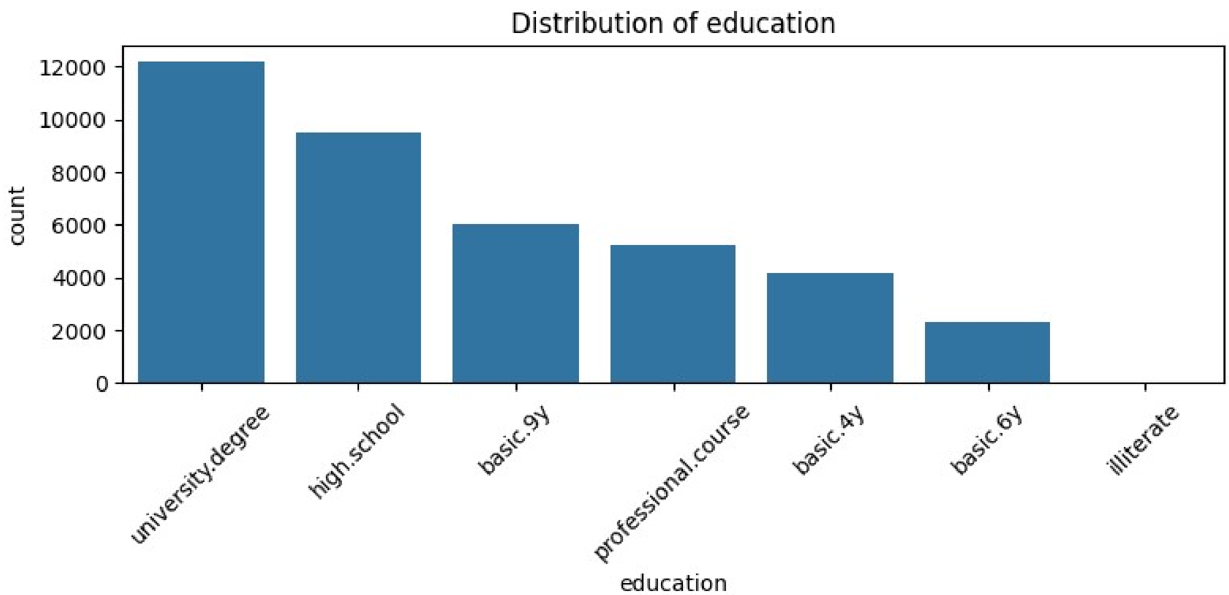
What is the overall distribution of each variable?

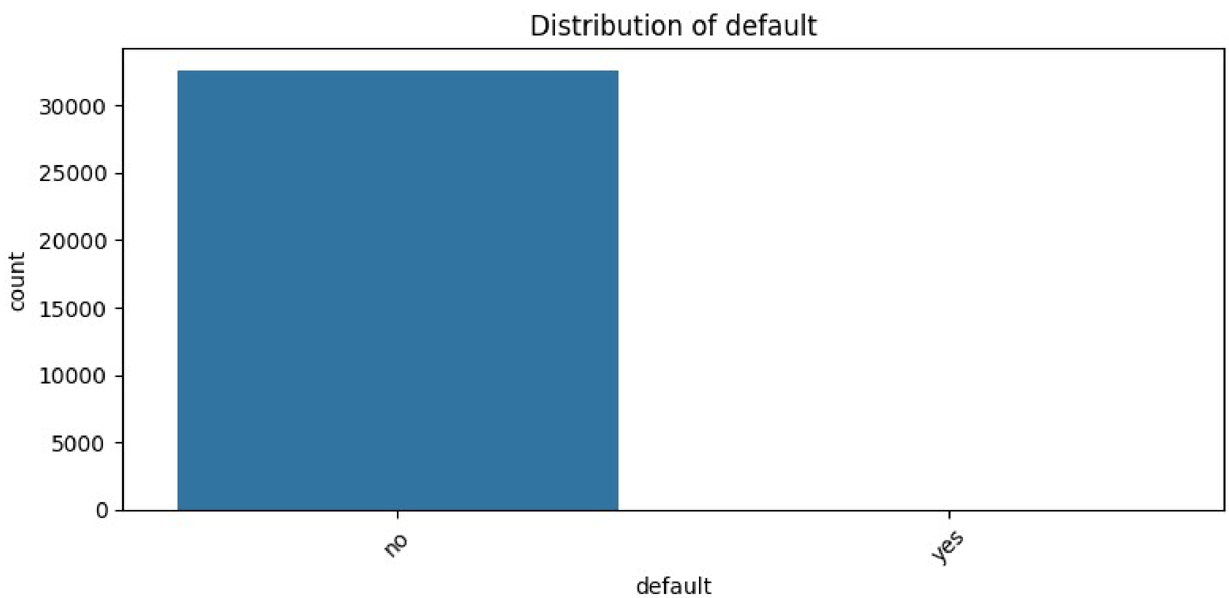
Splitting between categorical and numerical features

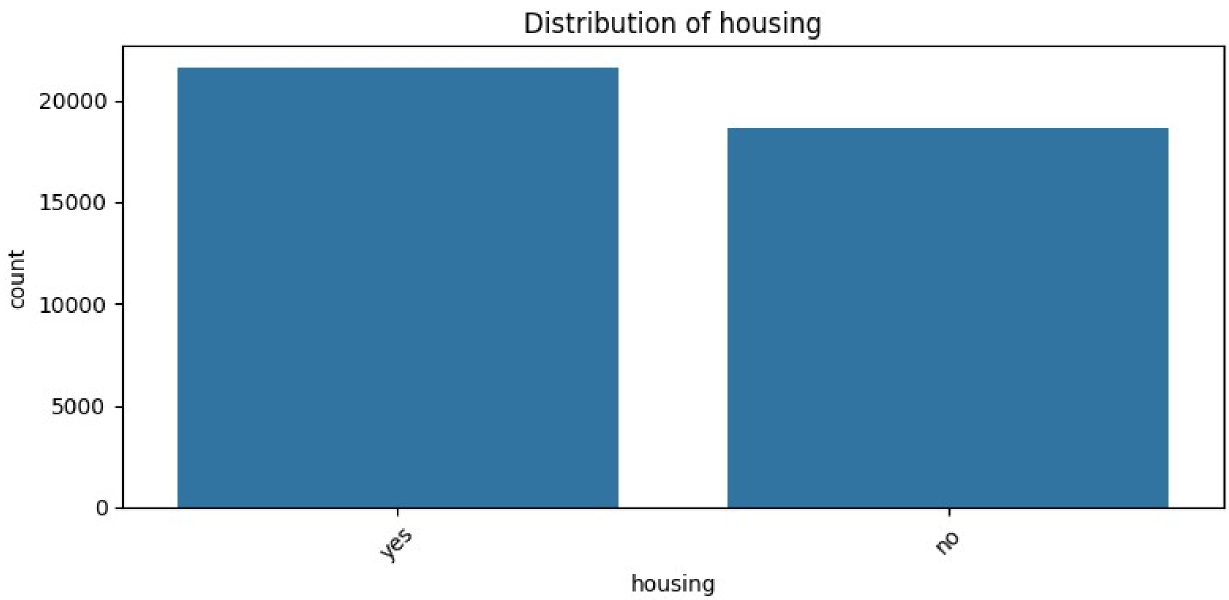
```
categorical_cols = data.select_dtypes(include=['object']).columns
numeric_cols = data.select_dtypes(include=['int64',
'float64']).columns

for col in categorical_cols:
    plt.figure(figsize=(8, 4))
    sns.countplot(data=data, x=col,
order=data[col].value_counts().index)
    plt.title(f'Distribution of {col}')
    plt.xticks(rotation=45)
    plt.tight_layout()
    plt.show()
```

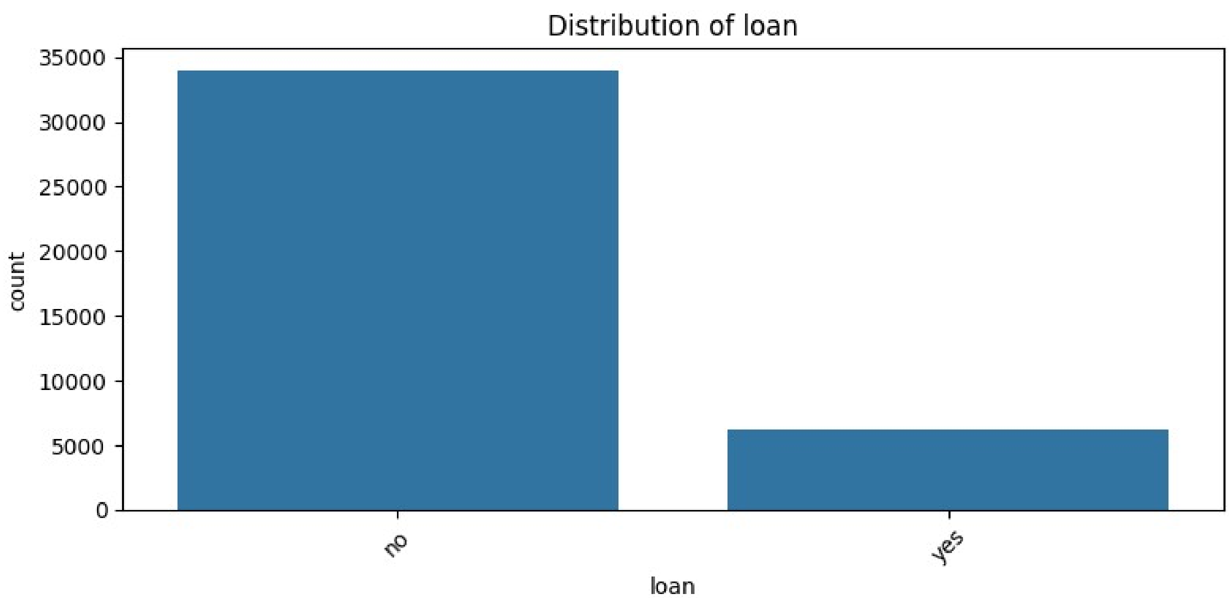

Distribution of job
10000
8000
6000
4000
2000
0
count
admin.
blue-collar
technician
services
management
retired
entrepreneur
self-employed
housemaid
unemployed
student
job

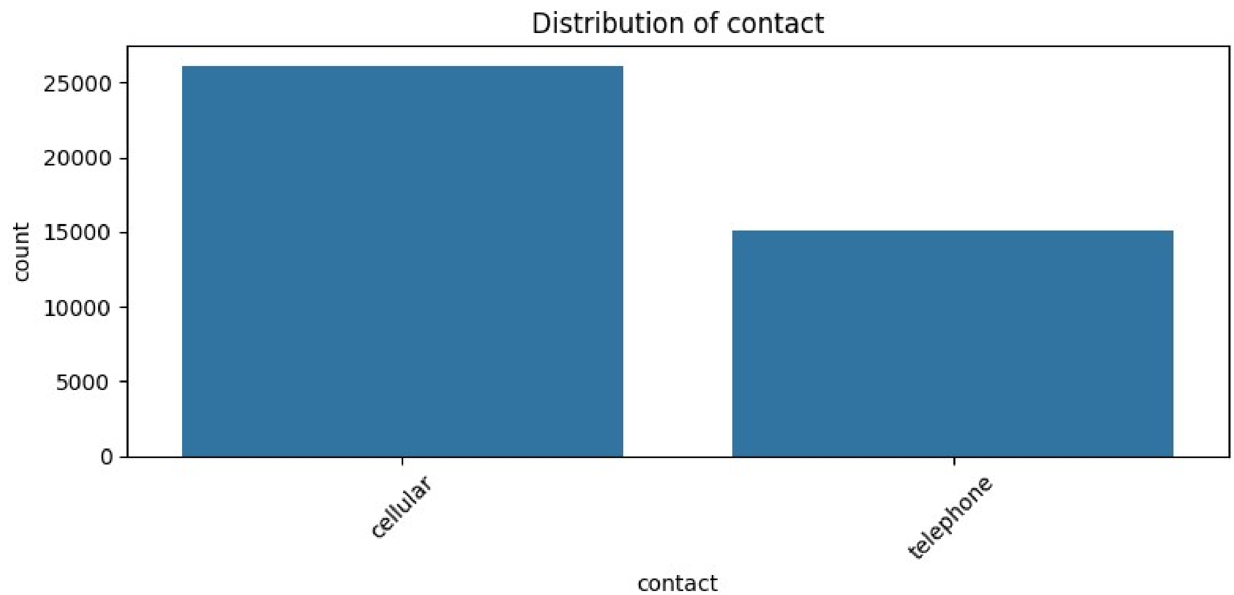

Distribution of marital
25000
20000
15000
10000
5000
0
count
married
single
divorced
marital

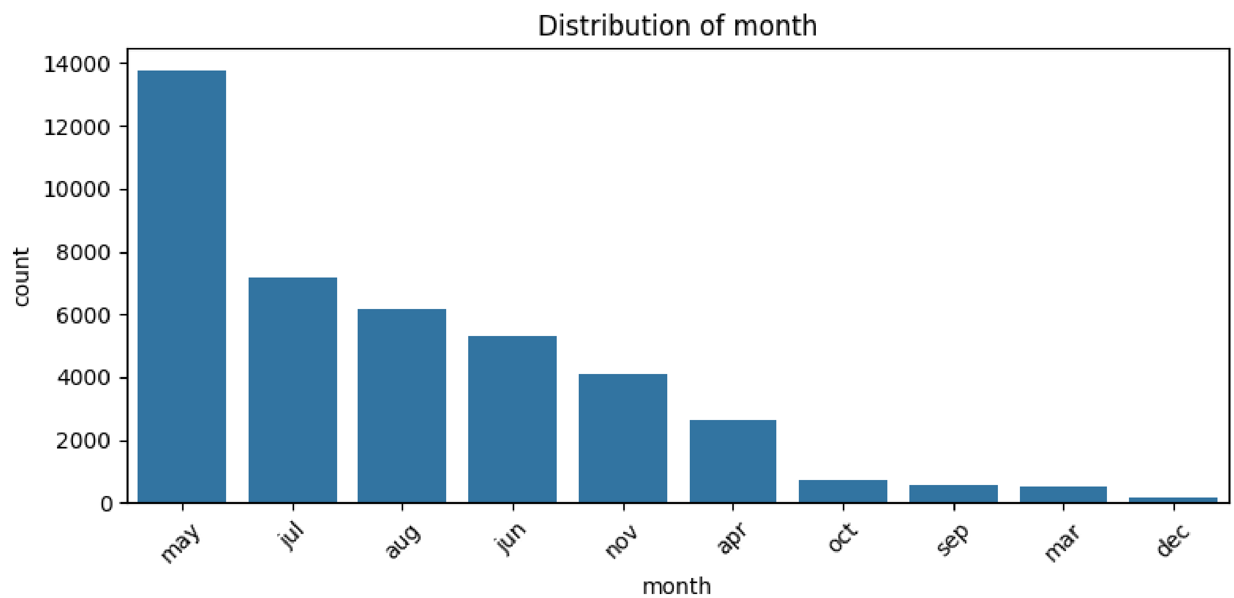

Distribution of education
count
0
2000
4000
6000
8000
10000
12000
university.degree
high.school
basic.9y
professional.course
basic.4y
basic.6y
illiterate
education

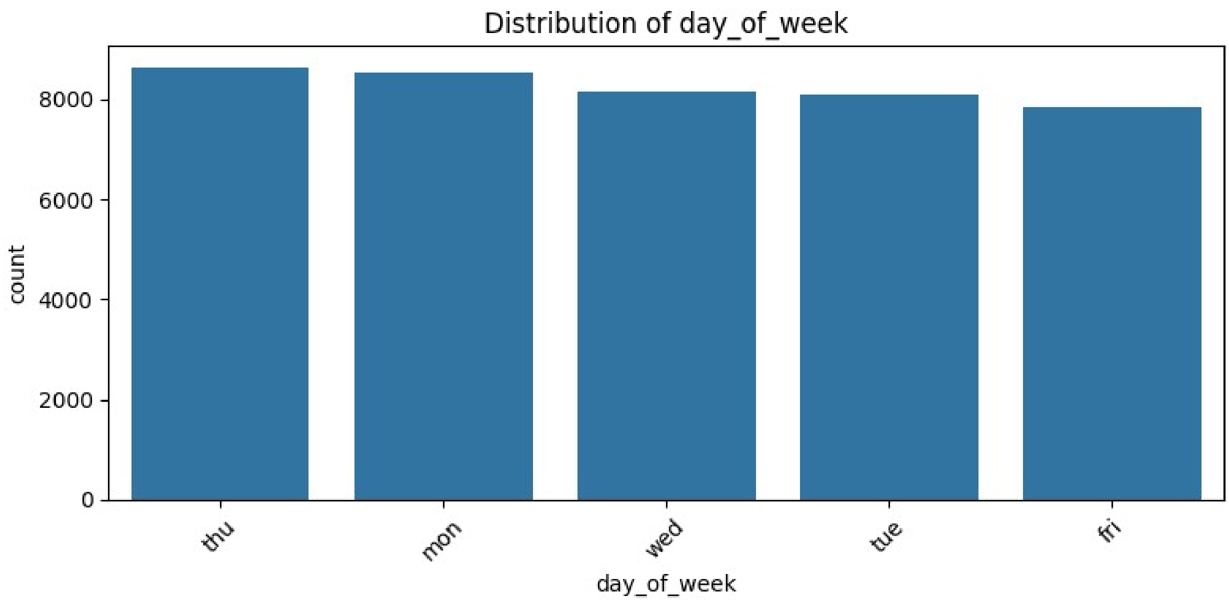

Distribution of default
count
0
5000
10000
15000
20000
25000
30000
no
yes
default

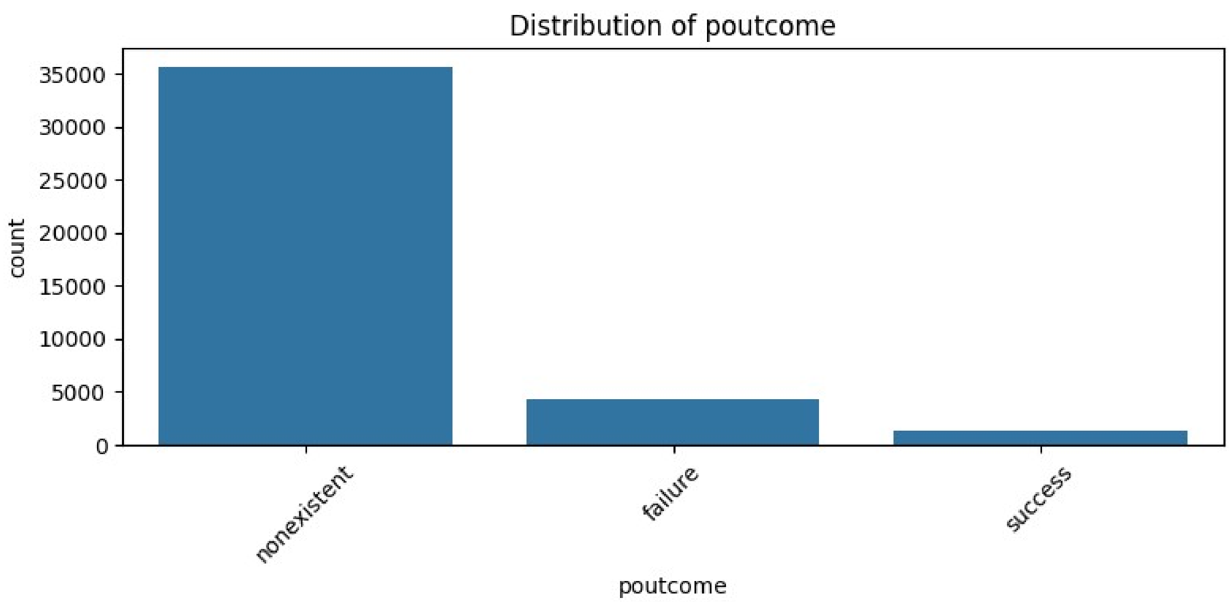

Distribution of housing
20000
15000
10000
5000
0
count
yes
no
housing

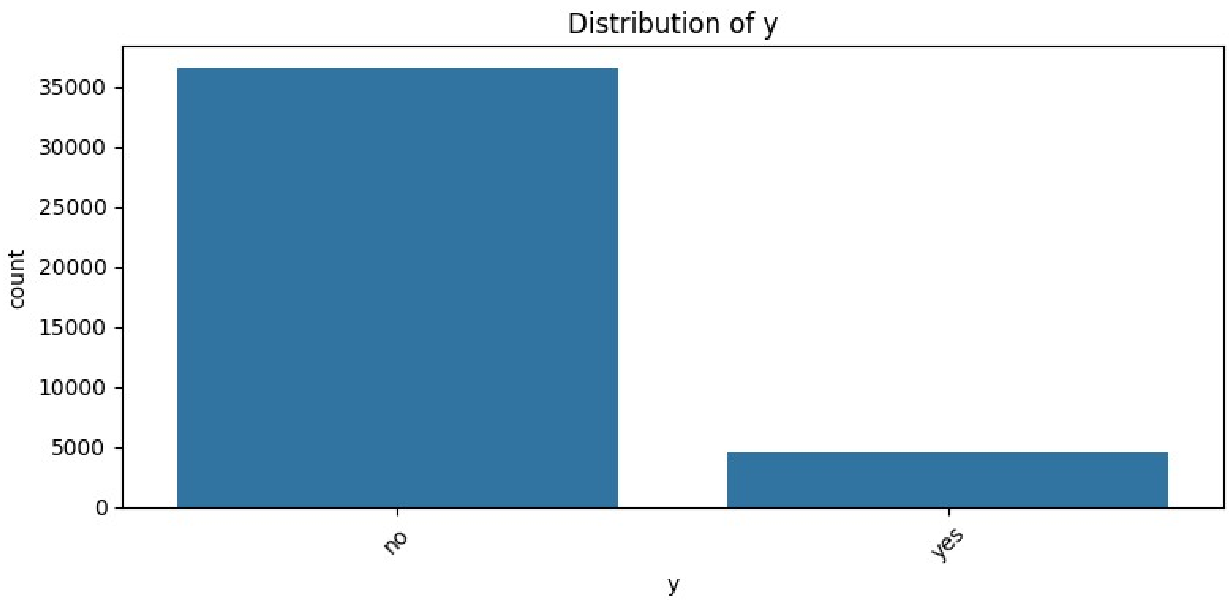

Distribution of loan
35000
30000
25000
20000
15000
10000
5000
0
count
no
yes
loan


Distribution of contact
25000
20000
15000
10000
5000
0
count
cellular
telephone
contact

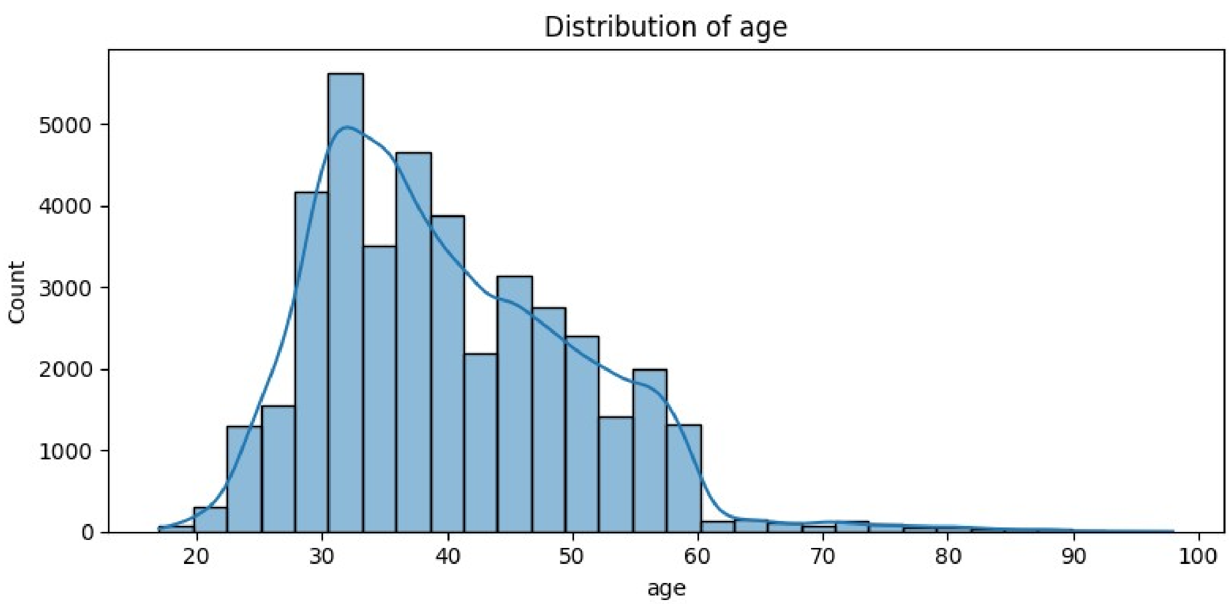

Distribution of month
14000
12000
10000
8000
6000
4000
2000
0
count
may
jul
aug
jun
nov
apr
oct
sep
mar
dec
month

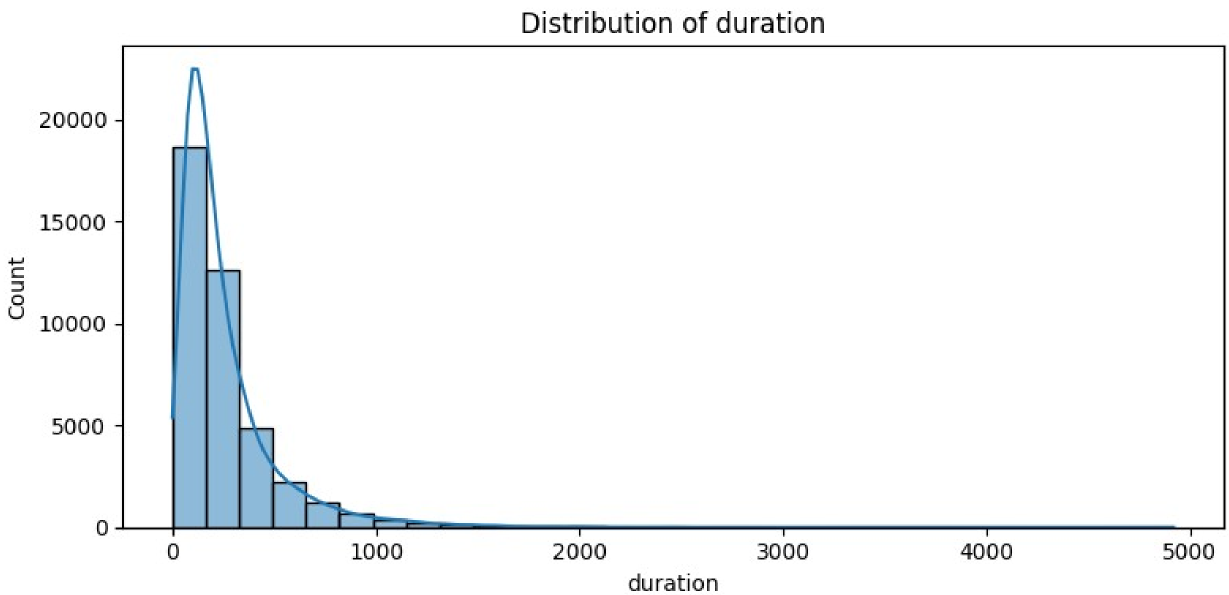

Distribution of day_of_week
count
0
2000
4000
6000
8000
thu
mon
wed
tue
fri
day_of_week

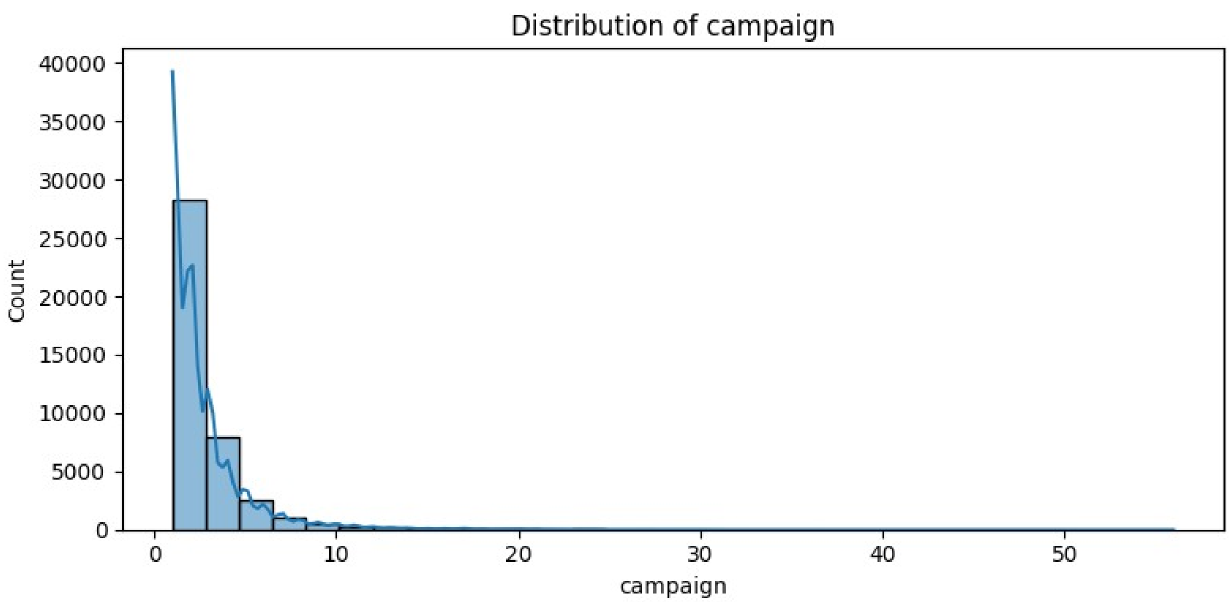

Distribution of poutcome
count
0
5000
10000
15000
20000
25000
30000
35000
nonexistent
failure
success
poutcome

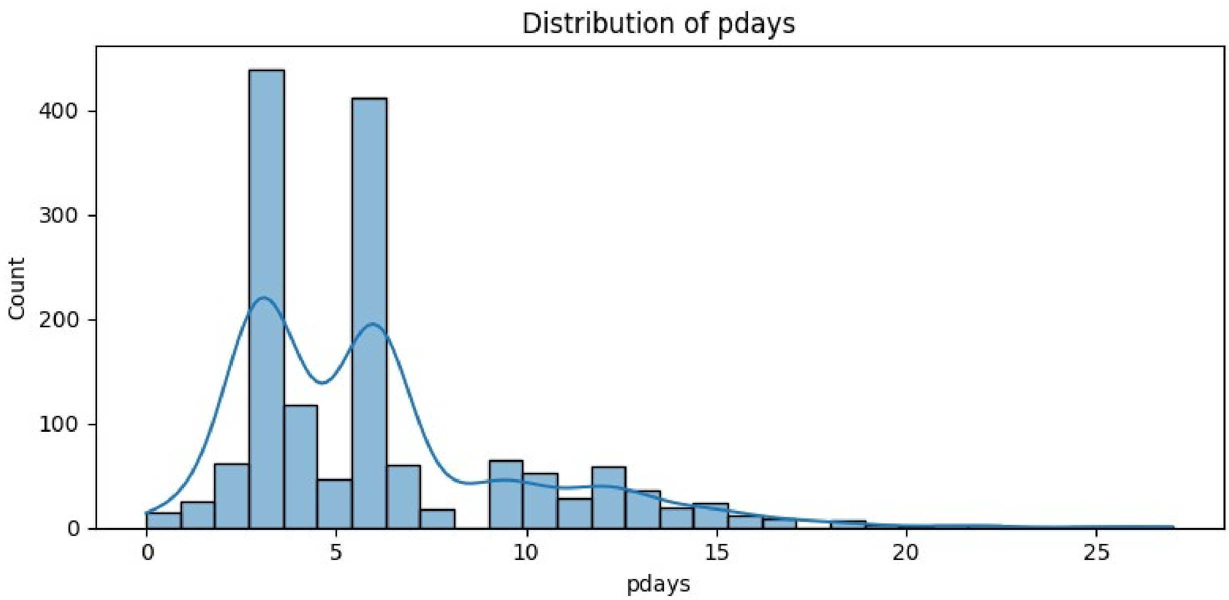



```
for col in numeric_cols:
    plt.figure(figsize=(8, 4))
    sns.histplot(data[col], kde=True, bins=30)
    plt.title(f'Distribution of {col}')
    plt.tight_layout()
    plt.show()
```

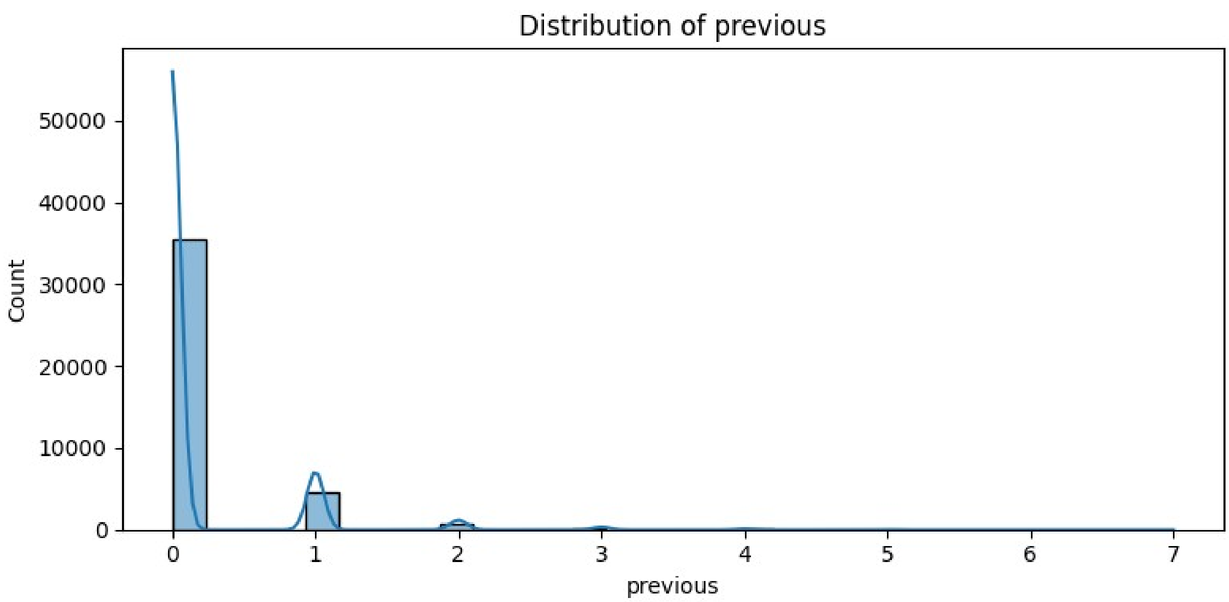



Distribution of duration
Count
20000
15000
10000
5000
0
0
1000
2000
3000
4000
5000
duration

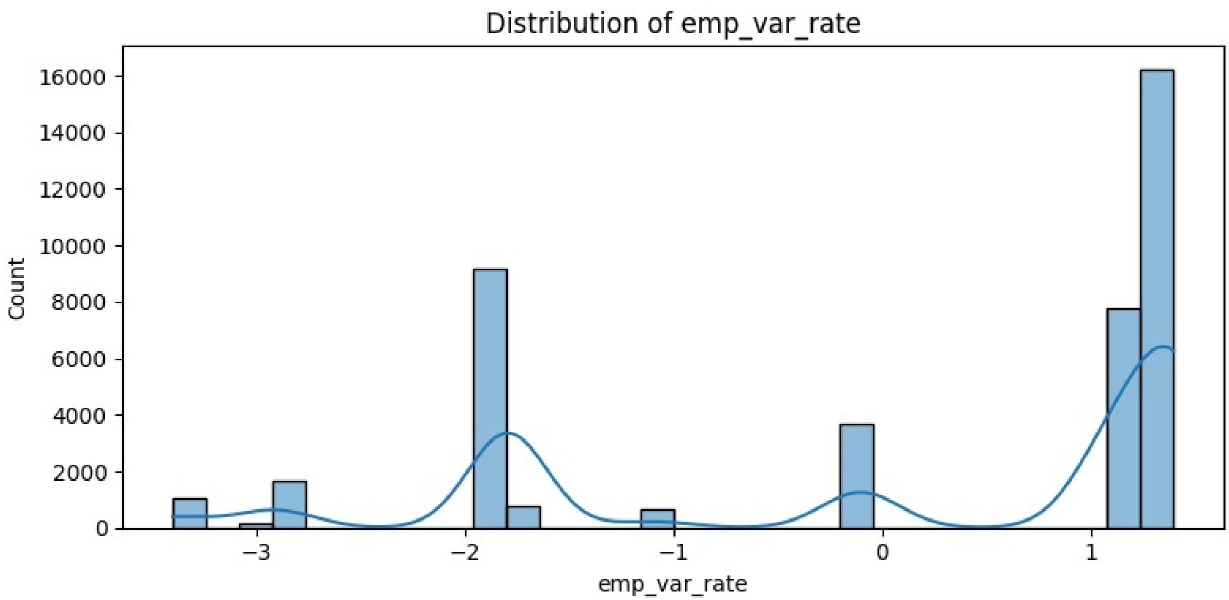

Distribution of campaign
Count
40000
35000
30000
25000
20000
15000
10000
5000
0
0
10
20
30
40
50
campaign

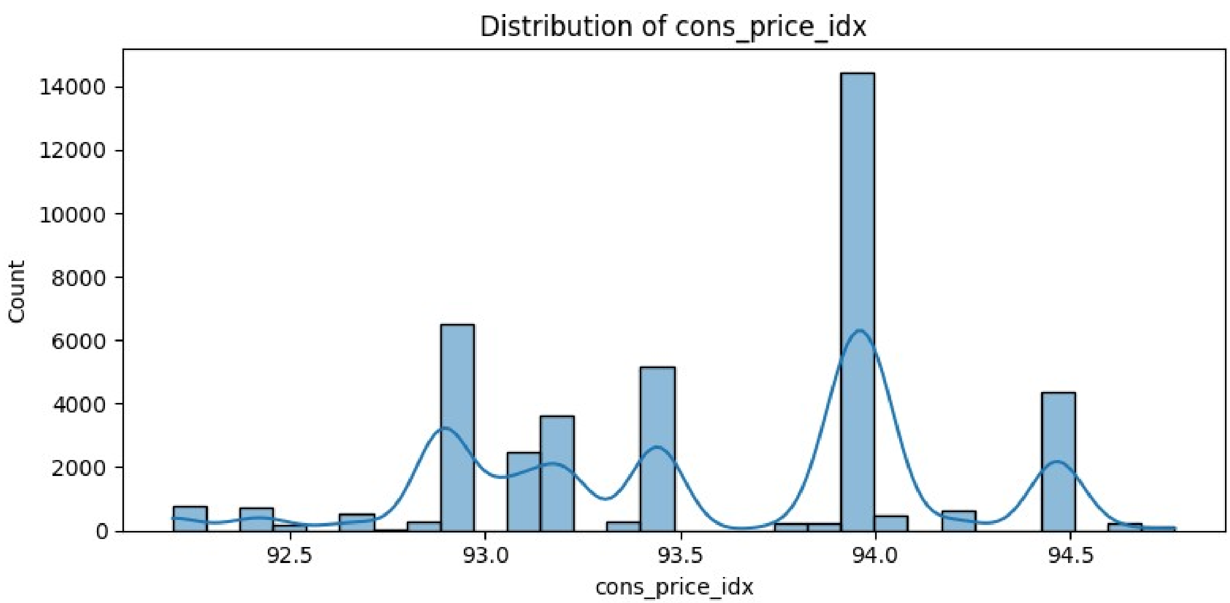


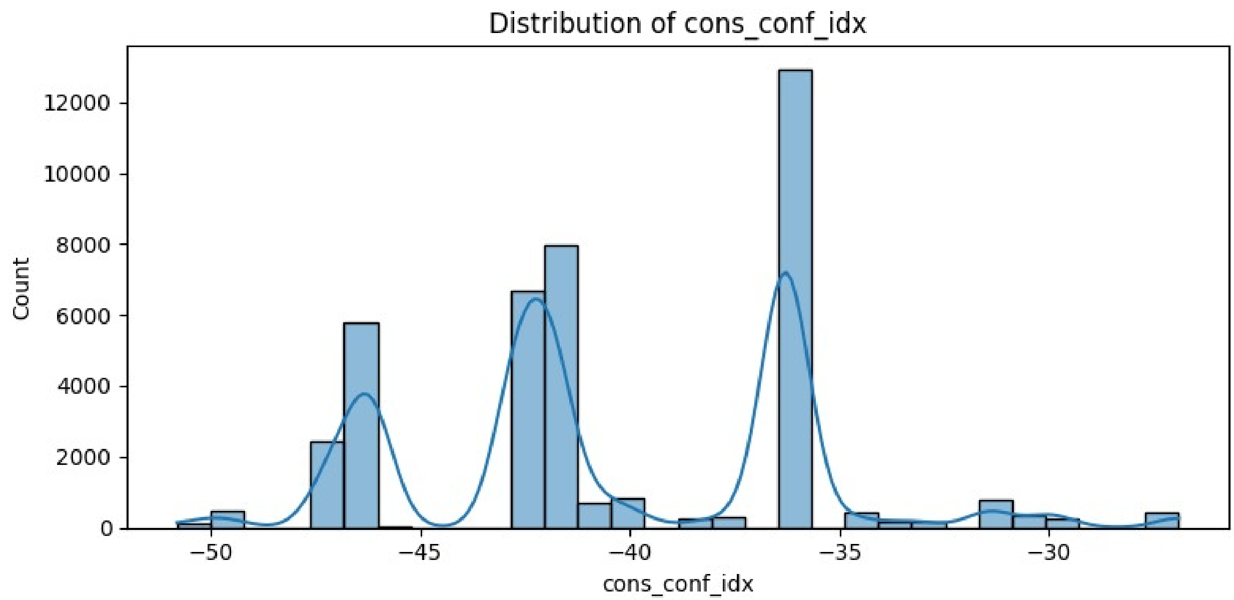
Distribution of pdays
Count
400
300
200
100
0
0
5
10
15
20
25
pdays

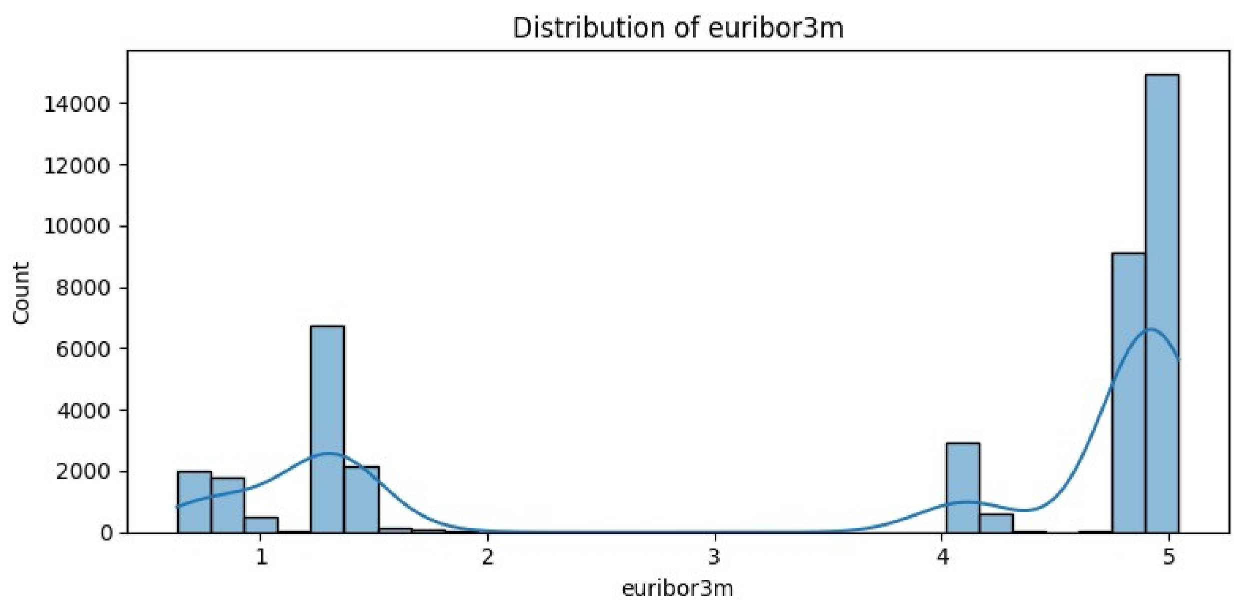


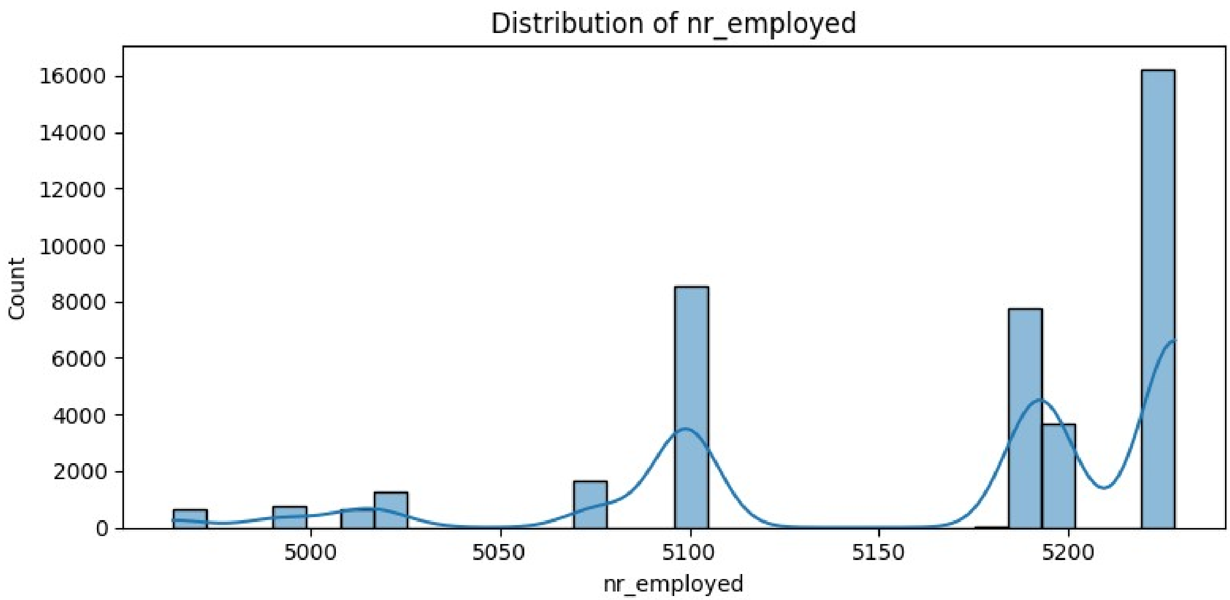
Distribution of previous
Count
50000
40000
30000
20000
10000
0
0
1
2
3
4
5
6
7
previous


Distribution of emp_var_rate
Count
16000
14000
12000
10000
8000
6000
4000
2000
0
−3
−2
−1
0
1
emp_var_rate


Distribution of cons_price_idx
Count
14000
12000
10000
8000
6000
4000
2000
0
92.5
93.0
93.5
94.0
94.5
cons_price_idx


Distribution of cons_conf_idx
Count
12000
10000
8000
6000
4000
2000
0
−50
−45
−40
−35
−30
cons_conf_idx


Distribution of euribor3m
Count
14000
12000
10000
8000
6000
4000
2000
0
1
2
3
4
5
euribor3m

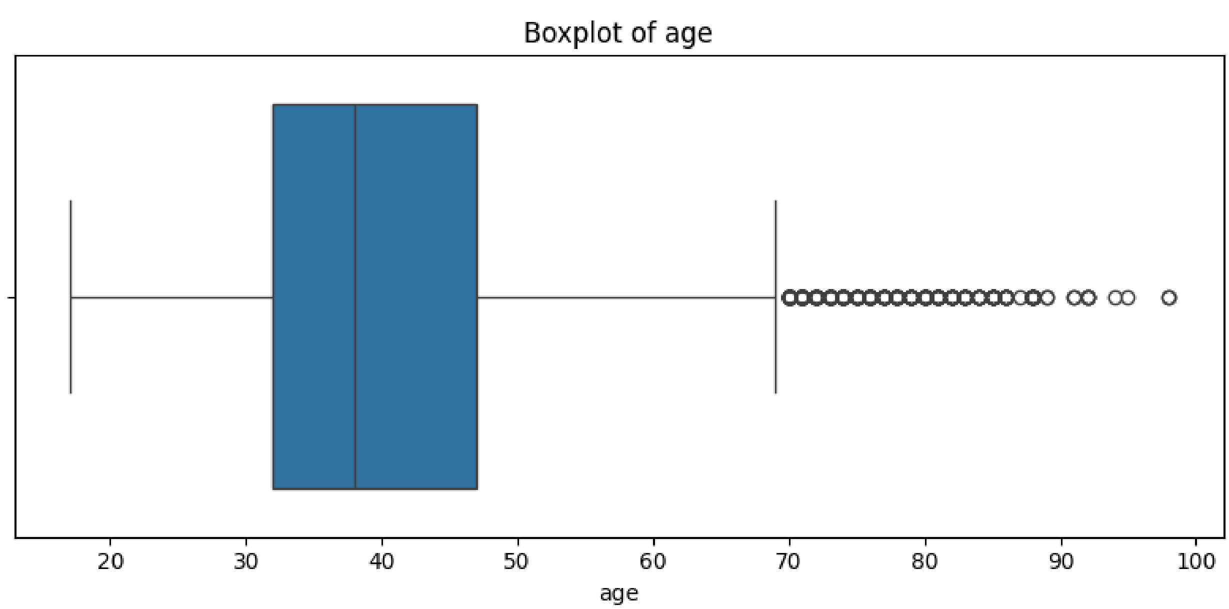


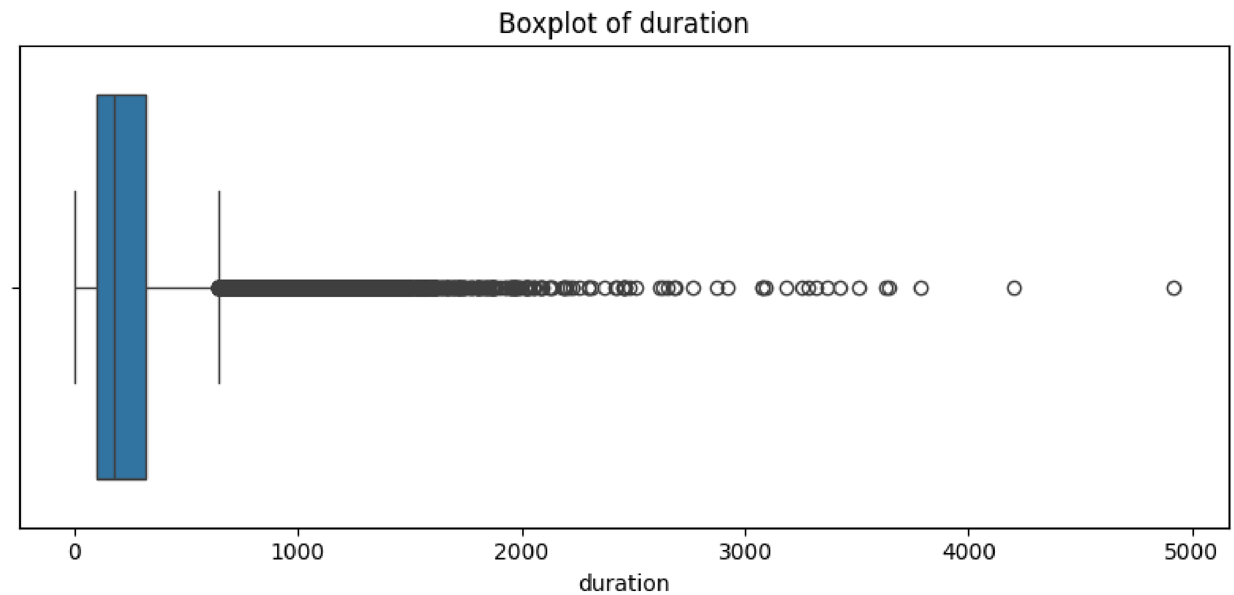
Are the features (columns) correlated?

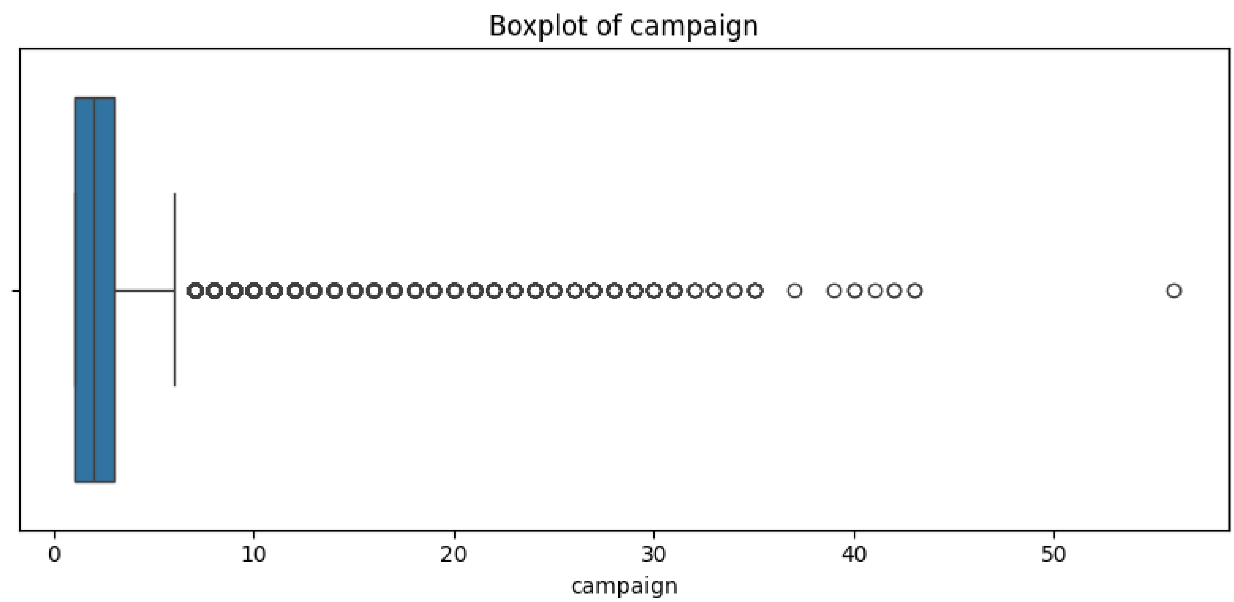
Are there any outliers present?

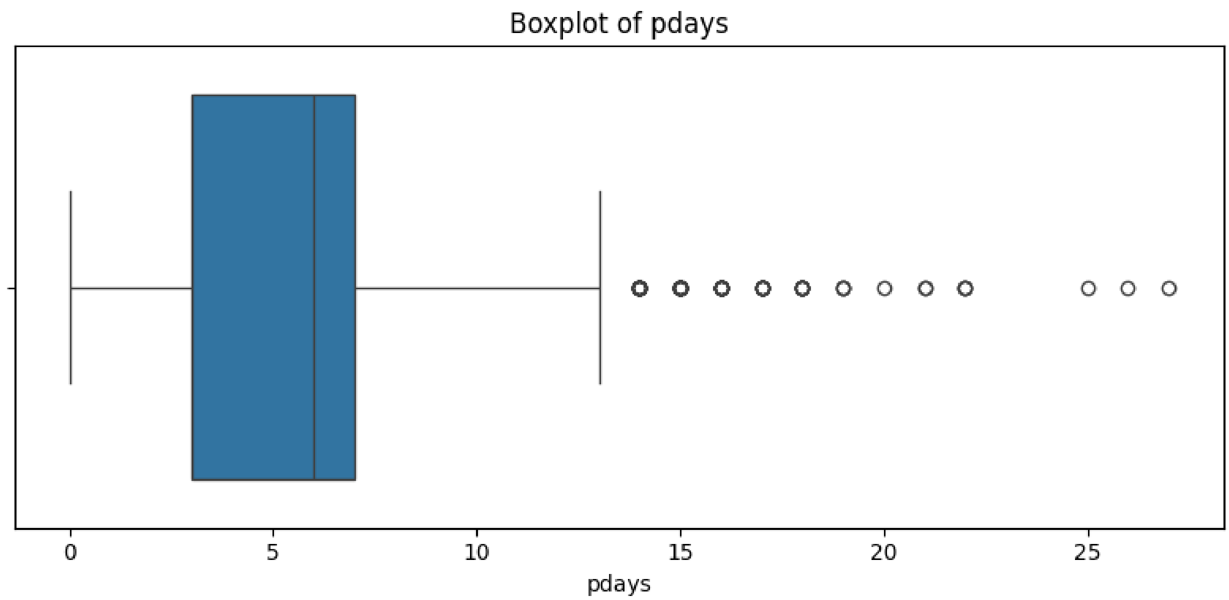
Using Boxplots to visually check for any outliers

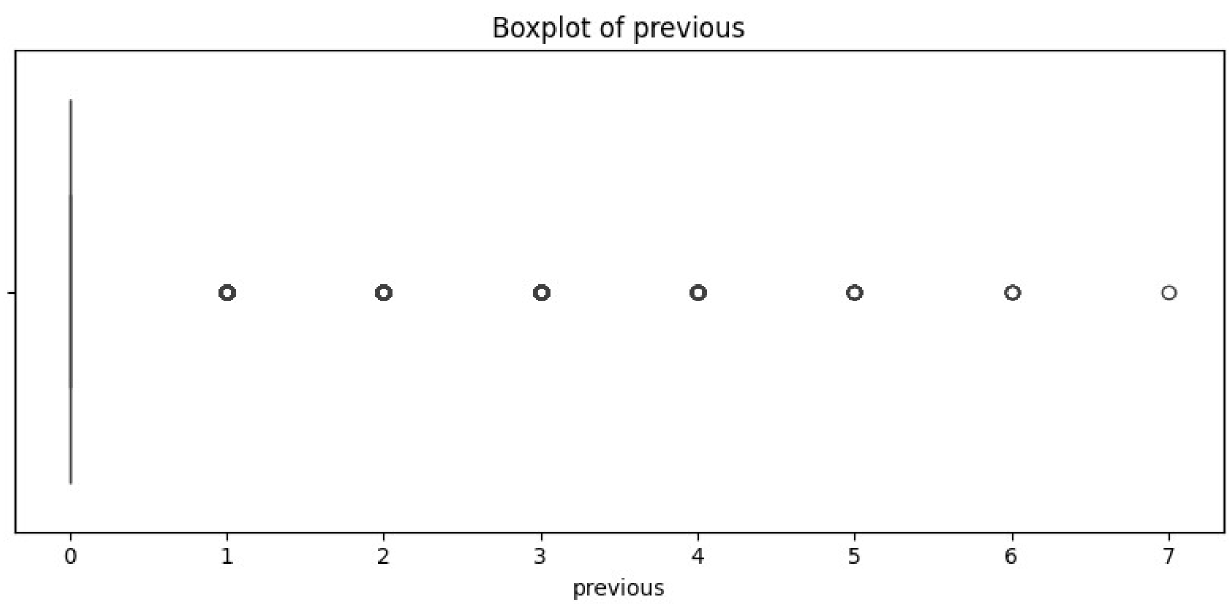
```
for col in numeric_cols:
    plt.figure(figsize=(8, 4))
    sns.boxplot(x=data[col])
    plt.title(f'Boxplot of {col}')
    plt.tight_layout()
    plt.show()
```

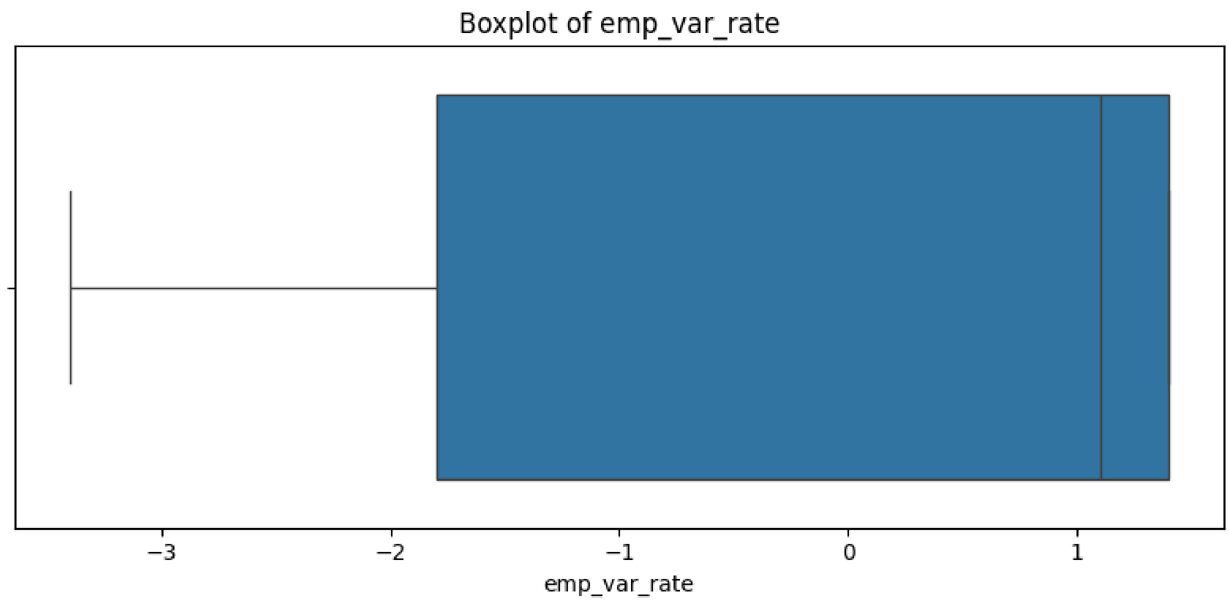


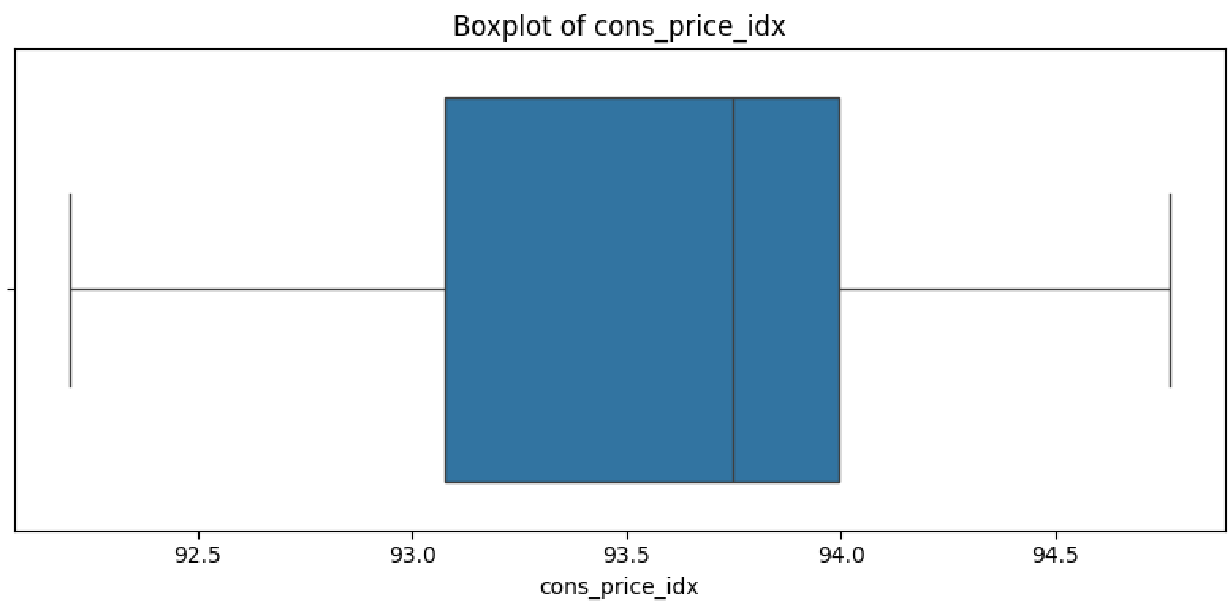

Boxplot of duration
0
1000
2000
3000
4000
5000
duration

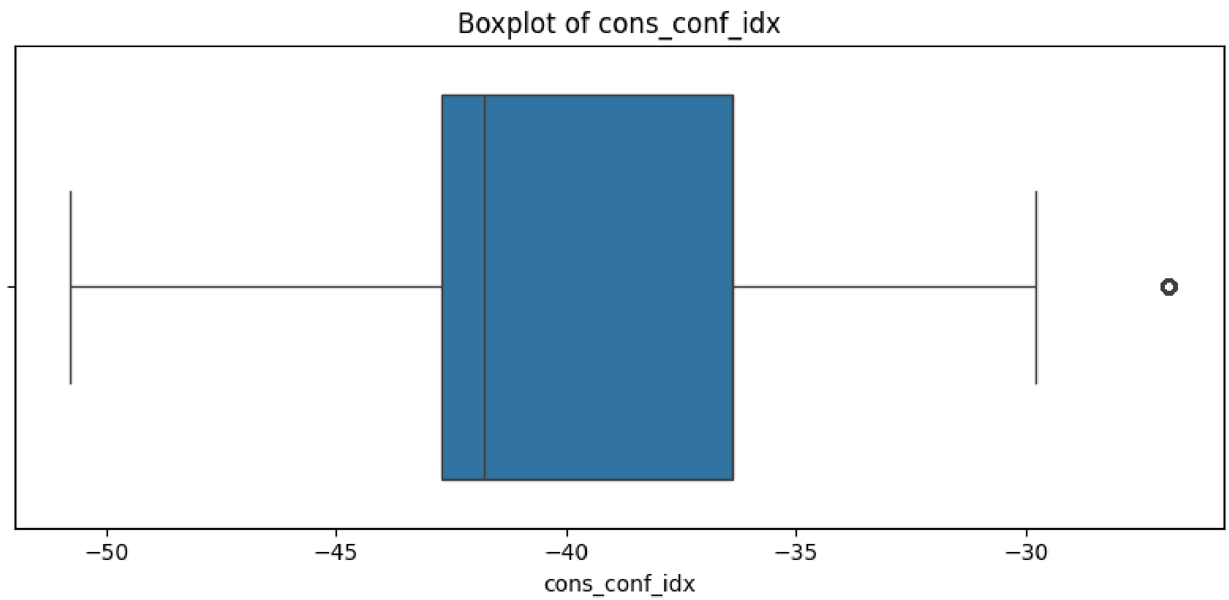

Boxplot of campaign
0
10
20
30
40
50
campaign


Boxplot of pdays
0
5
10
15
20
25
pdays

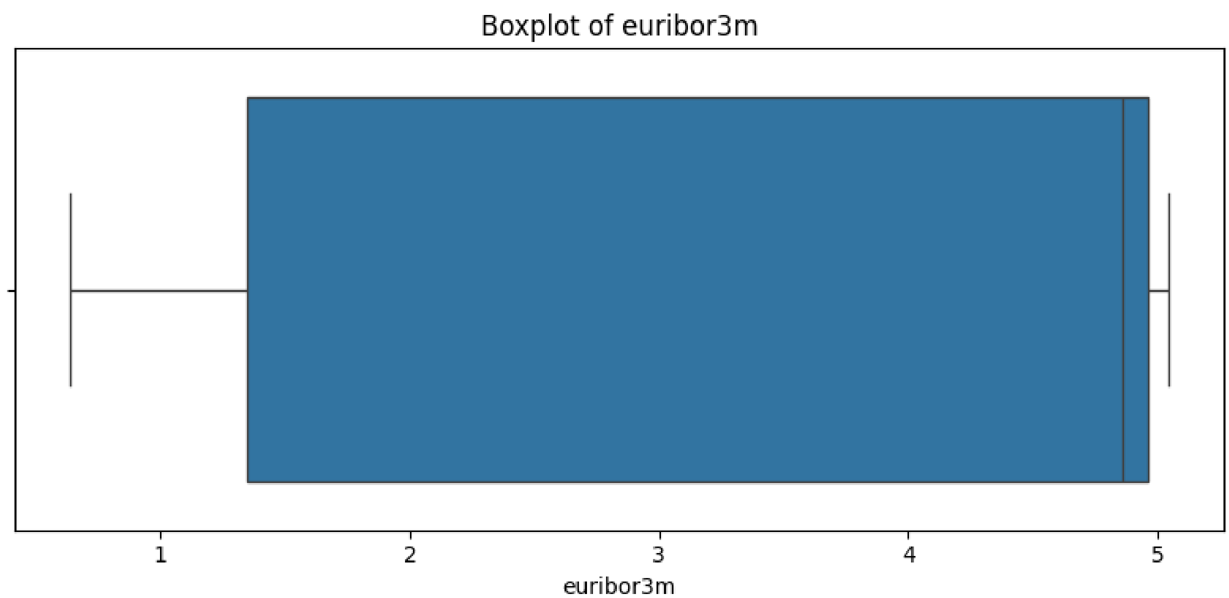

Boxplot of previous
0
1
2
3
4
5
6
7
previous


Boxplot of emp_var_rate
−3
−2
−1
0
1
emp_var_rate

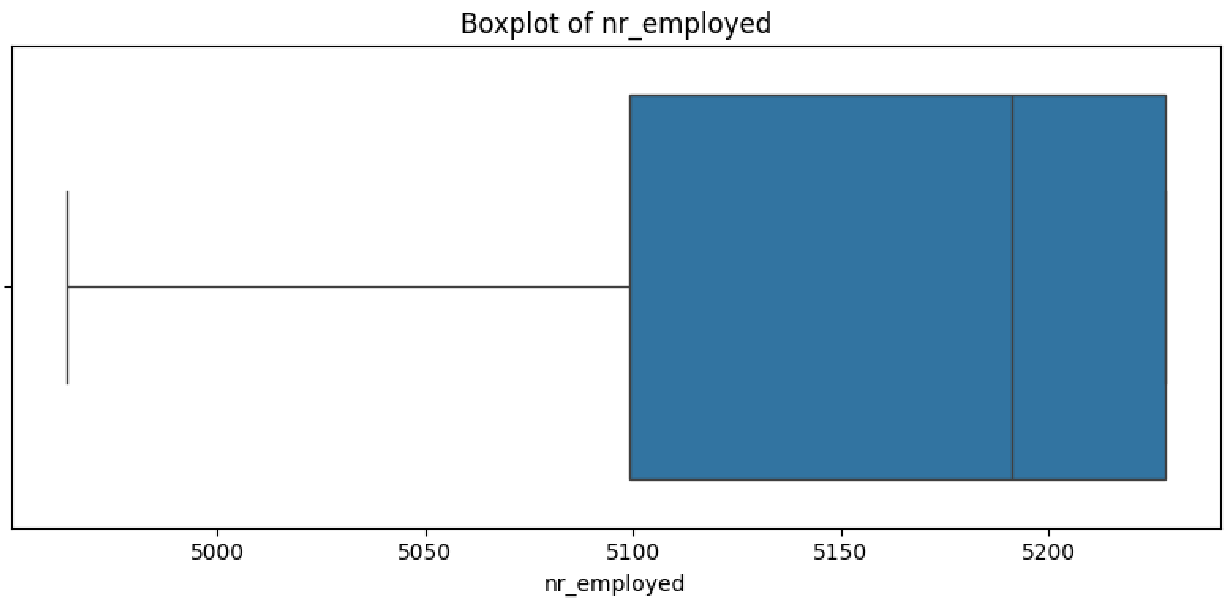

Boxplot of cons_price_idx
92.5
93.0
93.5
94.0
94.5
cons_price_idx



Boxplot of cons_conf_idx
−50
−45
−40
−35
−30
cons_conf_idx



Boxplot of euribor3m
1
2
3
4
5
euribor3m



Using Interquartile rage to determine at outliers

```
for col in numeric_cols:
    Q1 = data[col].quantile(0.25)
    Q3 = data[col].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    outliers = data[(data[col] < lower_bound) | (data[col] >
upper_bound)]

    print(f"{col}: {len(outliers)} outliers")
```

```
age: 469 outliers
duration: 2963 outliers
campaign: 2406 outliers
pdays: 82 outliers
previous: 5625 outliers
emp_var_rate: 0 outliers
cons_price_idx: 0 outliers
cons_conf_idx: 447 outliers
euribor3m: 0 outliers
nr_employed: 0 outliers
```

Using Z-score method to determine outliers, this method assumes normality

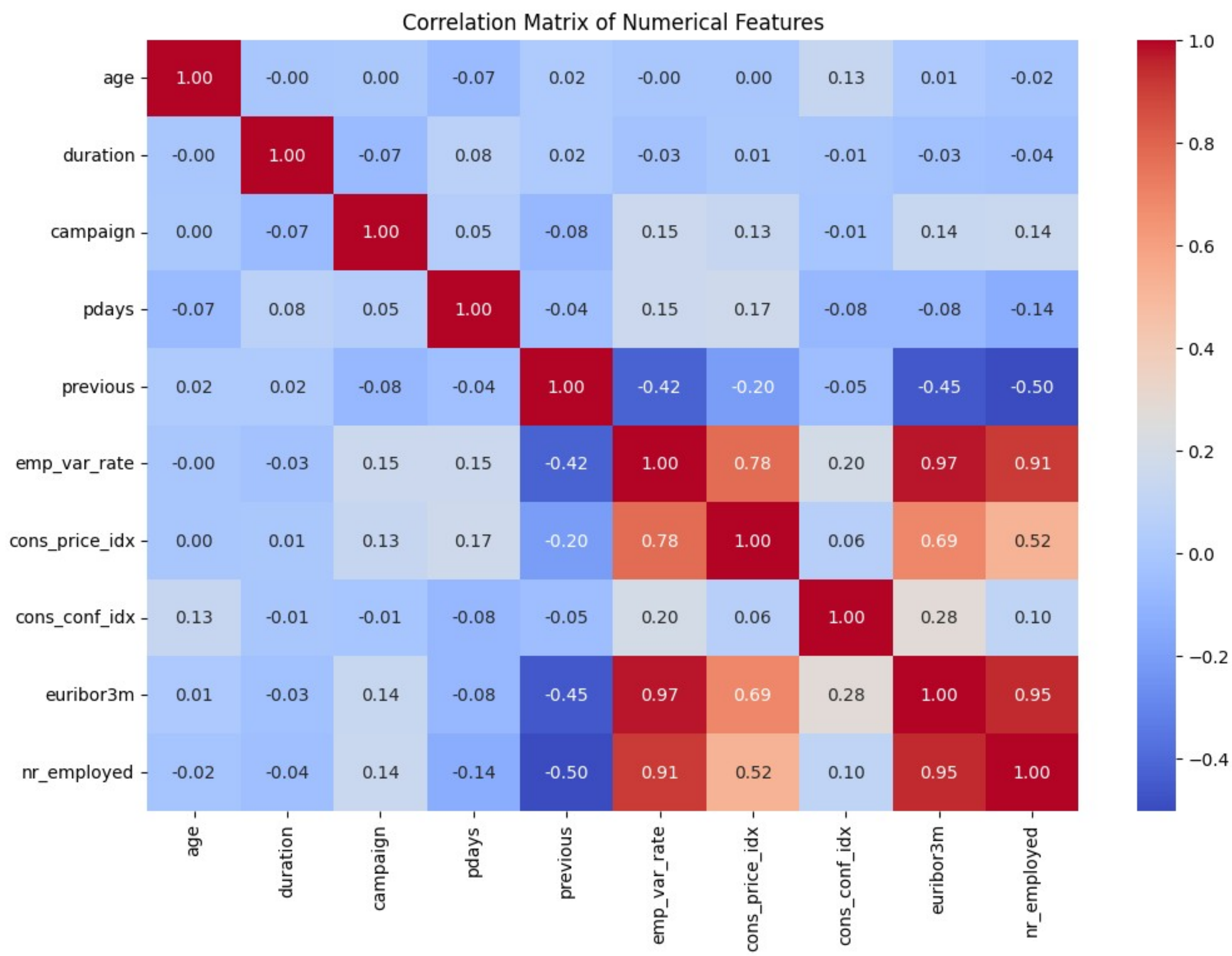
```
from scipy.stats import zscore

z_scores = data[numeric_cols].apply(zscore)
outliers = (z_scores.abs() > 3)
```

```
outlier_counts = outliers.sum()
print(outlier_counts)
```

```
age                  369
duration             861
campaign             869
pdays                  0
previous            1064
emp_var_rate           0
cons_price_idx         0
cons_conf_idx          0
euribor3m              0
nr_employed            0
dtype: int64
```

Are the features (columns) of your data correlated?

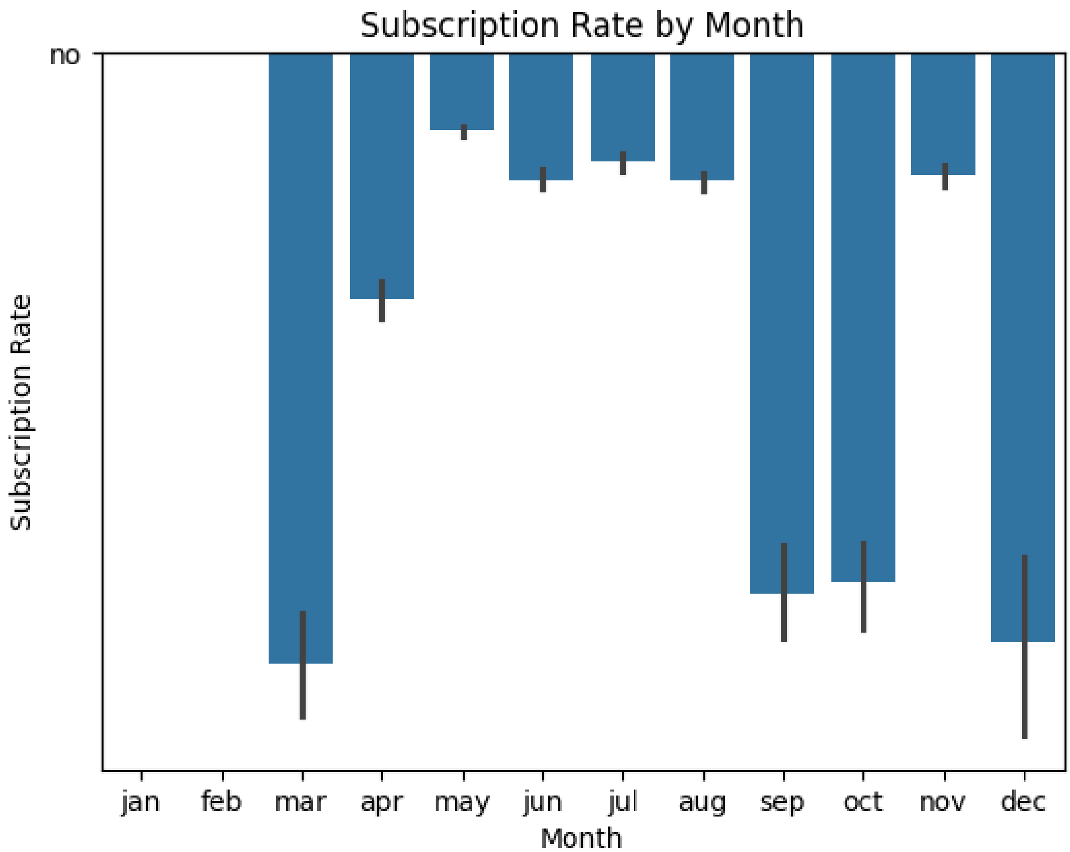
```
correlation_matrix = data[numeric_cols].corr()

plt.figure(figsize=(12, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm',
fmt=".2f")
plt.title('Correlation Matrix of Numerical Features')
plt.show()
```



Do any patterns or trends emerge in the data?

One of the patterns I noticed is that subscipritons are higher in certain months over others.

```
month_order = ['jan', 'feb', 'mar', 'apr', 'may', 'jun',
               'jul', 'aug', 'sep', 'oct', 'nov', 'dec']

sns.barplot(x='month', y='y', data=data, estimator=np.mean,
order=month_order)
plt.title('Subscription Rate by Month')
plt.ylabel('Subscription Rate')
plt.xlabel('Month')
plt.show()
```



What is the central tendency and spread of each variable?

```
data[numeric_cols].describe().T
```

{"summary":"{\n \"name\": \"data[numeric_cols]\",\n \"rows\": 10,\n
\"fields\": [\n   {\n   \"column\": \"count\",\n
\"properties\": {\n   \"dtype\": \"number\",\n   \"std\":
12545.70416118601,\n   \"min\": 1515.0,\n   \"max\":
41188.0,\n   \"num_unique_values\": 2,\n   \"samples\": [\n
1515.0,\n   41188.0\n   ],\n   \"semantic_type\":
\"\",\n   \"description\": \"\"\n   }\n   },\n   {\n
\"column\": \"mean\",\n   \"properties\": {\n   \"dtype\":
\"number\",\n   \"std\": 1623.3698386200358,\n   \"min\": -
40.50260027192386,\n   \"max\": 5167.035910944936,\n
\"num_unique_values\": 10,\n   \"samples\": [\n
3.621290812858114,\n   258.2850101971448\n   ],\n
\"semantic_type\": \"\",\n   \"description\": \"\"\n   }\
n   },\n   {\n   \"column\": \"std\",\n   \"properties\": {\n
\"dtype\": \"number\",\n   \"std\": 81.5270143910843,\n
\"min\": 0.4949010798393183,\n   \"max\": 259.2792488364648,\n
\"num_unique_values\": 10,\n   \"samples\": [\n
1.7344474048511707,\n   259.2792488364648\n   ],\n
\"semantic_type\": \"\",\n   \"description\": \"\"\n   }\

n   },\n   {\n   \"column\": \"min\",\n   \"properties\": {\n
\"dtype\": \"number\",\n   \"std\": 1568.028934002973,\n
\"min\": -50.8,\n   \"max\": 4963.6,\n
\"num_unique_values\": 8,\n   \"samples\": [\n   0.0,\n
-50.8\n   ],\n   \"semantic_type\": \"\",\n
\"description\": \"\"\n   }\n   },\n   {\n   \"column\":
\"25%\",\n   \"properties\": {\n   \"dtype\": \"number\",\n
\"std\": 1606.4969865906967,\n   \"min\": -42.7,\n
\"max\": 5099.1,\n   \"num_unique_values\": 10,\n
\"samples\": [\n   1.344,\n   102.0\n   ],\n
\"semantic_type\": \"\",\n   \"description\": \"\"\n   }\
n   },\n   {\n   \"column\": \"50%\",\n   \"properties\": {\n
\"dtype\": \"number\",\n   \"std\": 1632.7708672535232,\n
\"min\": -41.8,\n   \"max\": 5191.0,\n
\"num_unique_values\": 10,\n   \"samples\": [\n   4.857,\n
180.0\n   ],\n   \"semantic_type\": \"\",\n
\"description\": \"\"\n   }\n   },\n   {\n   \"column\":
\"75%\",\n   \"properties\": {\n   \"dtype\": \"number\",\n
\"std\": 1640.953627391859,\n   \"min\": -36.4,\n   \"max\":
5228.1,\n   \"num_unique_values\": 10,\n   \"samples\": [\n
4.961,\n   319.0\n   ],\n   \"semantic_type\": \"\",\
n   \"description\": \"\"\n   }\n   },\n   {\n
\"column\": \"max\",\n   \"properties\": {\n   \"dtype\":
\"number\",\n   \"std\": 2126.799875142088,\n   \"min\": -
26.9,\n   \"max\": 5228.1,\n   \"num_unique_values\": 10,\n
\"samples\": [\n   5.045,\n   4918.0\n   ],\n
\"semantic_type\": \"\",\n   \"description\": \"\"\n   }\
n   }\n]\n}","type":"dataframe"}


```
for col in categorical_cols:
    print(f"\n{col} distribution:")
    print(data[col].value_counts(normalize=True).round(2))
```

```
job distribution:
job
admin.           0.26
blue-collar      0.23
technician       0.17
services         0.10
management       0.07
retired          0.04
entrepreneur     0.04
self-employed    0.03
housemaid        0.03
unemployed       0.02
student          0.02
Name: proportion, dtype: float64

marital distribution:
```

```
marital
married     0.61
single      0.28
divorced    0.11
Name: proportion, dtype: float64

education distribution:
education
university.degree      0.31
high.school            0.24
basic.9y               0.15
professional.course    0.13
basic.4y               0.11
basic.6y               0.06
illiterate             0.00
Name: proportion, dtype: float64

default distribution:
default
no     1.0
yes    0.0
Name: proportion, dtype: float64

housing distribution:
housing
yes    0.54
no     0.46
Name: proportion, dtype: float64

loan distribution:
loan
no     0.84
yes    0.16
Name: proportion, dtype: float64

contact distribution:
contact
cellular     0.63
telephone    0.37
Name: proportion, dtype: float64

month distribution:
month
may    0.33
jul    0.17
aug    0.15
jun    0.13
nov    0.10
apr    0.06
oct    0.02
```

```
sep    0.01
mar    0.01
dec    0.00
Name: proportion, dtype: float64

day_of_week distribution:
day_of_week
thu    0.21
mon    0.21
wed    0.20
tue    0.20
fri    0.19
Name: proportion, dtype: float64

poutcome distribution:
poutcome
nonexistent    0.86
failure        0.10
success        0.03
Name: proportion, dtype: float64

y distribution:
y
no     0.89
yes    0.11
Name: proportion, dtype: float64
```

Algorithm Selection

Now you have completed the EDA, what Algorithms would suit the business purpose for the dataset. Answer questions such as:

- Select two or more machine learning algorithms presented so far that could be used to train a model (no need to train models - I am only looking for your recommendations).
- What are the pros and cons of each algorithm you selected?
- Which algorithm would you recommend, and why?
- Are there labels in your data? Did that impact your choice of algorithm?
- How does your choice of algorithm relates to the dataset?
- Would your choice of algorithm change if there were fewer than 1,000 data records, and why?

This dataset is used to predict whether a client will subscribe, yes/no. The dataset has labeled outcomes. Which means that it is best suited for supervised learning algorithms.

In this scenario, three algortihms seem to be well fit for the task: Logistic Regression, Random Forest Classifier, and Gradient Boosting.

Logistic Regression is one of the more fundamental algortithms and the baseline for binary classifcation tasks. It is simple and fast to train, has interpretable coefficients which is highly useful for business, it handles categorical and numerical data well if they are encoded, and provides probabilities as well. However, it assumes linearity between features and the log odds of the target and is sensitive to multicollinearity. It also underperforms when trained on complex or non linear patterns.

Random Forest is an ensemble algorithm of decision trees. It handles non linear relationships much better then logistic regression. It performs well when their are outliers and multicollinearity. However, it is less interpretable than logistic regression and much more computationally expensive. Also if not tuned properly may be prone to overfitting.

Lastly Gradient Boosting, is one of the more accurate and advanced algorithms in performing classifications tasks. It has built in handling for missing data and can handle imbalances in the datasets with tuning. It also has very good control over bias variance through hyperparameters. However, it slower to train and harder to interpret. It also has a high risk of overfitting on smaller datasets.

The algorithm that seems best out of the three for this task is Random Forest. Since the dataset has both categorical and numerical features which interact in non linear ways, Random Forest will perform better than logistic regression. Also there is no need for heavy preprocessing and the dataset is not that large. Random Forest robustness to overfitting would put it over gradient boosting.

The size of the dataset effects which algorithm performs better. More advanced algorithms are prone to overfitting on smaller datasets.

Pre-processing

Now you have done an EDA and selected an Algorithm, what pre-processing (if any) would you require for:

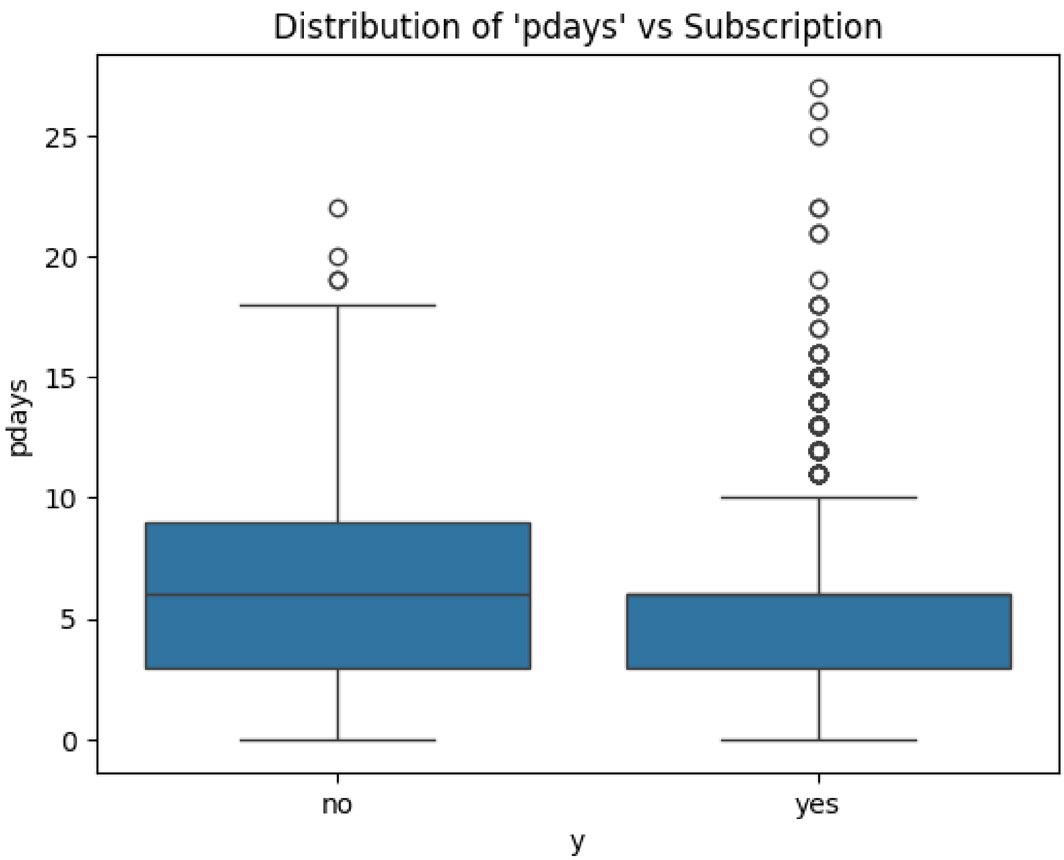
- Data Cleaning - improve data quality, address missing data, etc.
- Dimensionality Reduction - remove correlated/redundant data than will slow down training
- Feature Engineering - use of business knowledge to create new features
- Sampling Data - using sampling to resize datasets
- Data Transformation - regularization, normalization, handling categorical variables
- Imbalanced Data - reducing the imbalance between classes

Data Cleaning - improve data quality, address missing data, etc.

```
data.replace('unknown', np.nan, inplace=True)

if 'pdays' in data.columns:
    data['pdays'] = data['pdays'].replace(999, np.nan)

missing_summary = data.isnull().sum()
print(missing_summary[missing_summary >
0].sort_values(ascending=False))
```

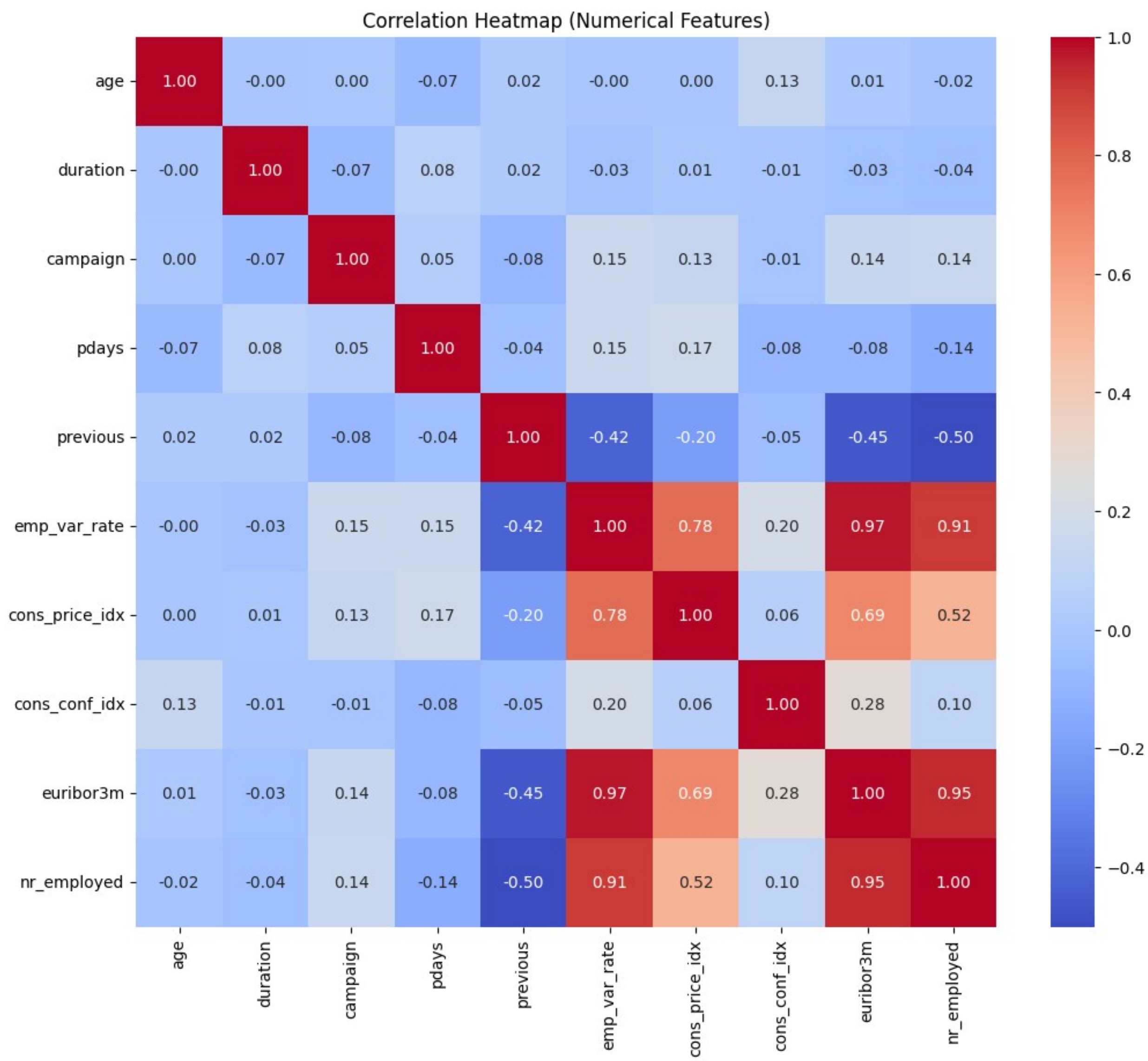
```
pdays        39673
default       8597
education     1731
housing        990
loan           990
job            330
marital         80
dtype: int64
```

```
sns.boxplot(x='y', y='pdays', data=data[data['pdays'] != -1])
plt.title("Distribution of 'pdays' vs Subscription")
plt.show()
```



Dimensionality Reduction - remove correlated/redundant data than will slow down training

```
plt.figure(figsize=(12, 10))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm',
fmt=".2f")
plt.title('Correlation Heatmap (Numerical Features)')
plt.show()
```



emp_var_rate and euribor3m 0.97

euribor3m and nr_employed 0.95

emp.var_rate and nr_employed 0.93

It seems that dropping emp var rate and nr employed would be beneficial since these three are highly correlated.

```
data.drop(columns=['emp_var_rate', 'nr_employed'], inplace=True)
```

Feature Engineering

```
data['contacted_before'] = (data['previous'] > 0).astype(int)
```

```
data['has_credit_risk'] = (
    (data['housing'] == 'yes') |
    (data['loan'] == 'yes') |
    (data['default'] == 'yes')
).astype(int)
```

Sampling and Handling Class Imbalance

```
print(data['y'].value_counts())
print(data['y'].value_counts(normalize=True))

y
no     36548
yes     4640
Name: count, dtype: int64
y
no     0.887346
yes    0.112654
Name: proportion, dtype: float64
```

Splitting dataset

```
y = data['y'].map({'yes': 1, 'no': 0})
X = data.drop(columns=['y'])

X = pd.get_dummies(X, drop_first=True)

from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, stratify=y, random_state=42
)
```

Training and Testing Model

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, confusion_matrix,
roc_auc_score

rf = RandomForestClassifier(
    class_weight='balanced',
    random_state=42,
    n_jobs=-1
)

rf.fit(X_train, y_train)

RandomForestClassifier(class_weight='balanced', n_jobs=-1,
random_state=42)
```

```python
y_pred = rf.predict(X_test)
y_proba = rf.predict_proba(X_test)[:, 1]

print("Confusion Matrix:")
print(confusion_matrix(y_test, y_pred))

print("\nClassification Report:")
print(classification_report(y_test, y_pred))

print("ROC-AUC Score:", roc_auc_score(y_test, y_proba))
```

```
Confusion Matrix:
[[7139  171]
 [ 522  406]]

Classification Report:
              precision    recall  f1-score   support

           0       0.93      0.98      0.95      7310
           1       0.70      0.44      0.54       928

    accuracy                           0.92      8238
   macro avg       0.82      0.71      0.75      8238
weighted avg       0.91      0.92      0.91      8238

ROC-AUC Score: 0.9480187007641869
```