term-deposit-prediction-1

June 3, 2024

1 Term Deposit Prediction by Elma F. Phiri

2 Data collection and Preprocessing

Abstract: This project aims to predict whether a customer will subscribe to a term deposit based on a marketing campaign. By analyzing various customer features and applying predictive analytics, we can identify key factors influencing their decision.

Problem Statement:Predict if a customer subscribes to a term deposits or not, when contacted by a marketing agent, by understanding the different features and performing predictive analytics

3 Importing Libraries

[1]:
```
import pandas as pd
import numpy as np
import ydata_profiling as pp
import matplotlib.pyplot as plt
import seaborn as sns
```

[15]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import classification_report,␣
 ↪confusion_matrix,accuracy_score
from sklearn.model_selection import GridSearchCV
from sklearn.preprocessing import LabelEncoder
from IPython.display import display
```

[2]:
```
#Data loading
bank = pd.read_csv("C:\\Users\\elmaf\\Desktop\\Portfolio projects\\Python\\Term␣
 ↪Deposit Prediction\\bank_data.csv")
print(bank.head())
```

```
   age        job  marital    education  default housing loan    contact  \
0   56  housemaid  married     basic.4y       no      no   no  telephone
1   57   services  married  high.school  unknown      no   no  telephone
2   37   services  married  high.school       no     yes   no  telephone
```

```
3   40     admin.  married     basic.6y       no      no   no  telephone
4   56   services  married  high.school       no      no  yes  telephone

  month day_of_week  …  campaign  pdays  previous     poutcome emp.var.rate  \
0   may         mon  …         1    999         0  nonexistent          1.1
1   may         mon  …         1    999         0  nonexistent          1.1
2   may         mon  …         1    999         0  nonexistent          1.1
3   may         mon  …         1    999         0  nonexistent          1.1
4   may         mon  …         1    999         0  nonexistent          1.1

   cons.price.idx  cons.conf.idx  euribor3m  nr.employed   y
0          93.994          -36.4      4.857       5191.0  no
1          93.994          -36.4      4.857       5191.0  no
2          93.994          -36.4      4.857       5191.0  no
3          93.994          -36.4      4.857       5191.0  no
4          93.994          -36.4      4.857       5191.0  no

[5 rows x 21 columns]
```

4 Data Exploration

[5]:
```
bank.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
```

[10]:
```
bank.shape
```

[10]:
```
(41188, 21)
```

[11]:
```
bank.describe()
```

[11]:

	age	duration	campaign	pdays	previous
count	41188.00000	41188.000000	41188.000000	41188.000000	41188.000000
mean	40.02406	258.285010	2.567593	962.475454	0.172963
std	10.42125	259.279249	2.770014	186.910907	0.494901
min	17.00000	0.000000	1.000000	0.000000	0.000000
25%	32.00000	102.000000	1.000000	999.000000	0.000000
50%	38.00000	180.000000	2.000000	999.000000	0.000000
75%	47.00000	319.000000	3.000000	999.000000	0.000000
max	98.00000	4918.000000	56.000000	999.000000	7.000000

	emp.var.rate	cons.price.idx	cons.conf.idx	euribor3m	nr.employed
count	41188.000000	41188.000000	41188.000000	41188.000000	41188.000000
mean	0.081886	93.575664	-40.502600	3.621291	5167.035911
std	1.570960	0.578840	4.628198	1.734447	72.251528
min	-3.400000	92.201000	-50.800000	0.634000	4963.600000
25%	-1.800000	93.075000	-42.700000	1.344000	5099.100000
50%	1.100000	93.749000	-41.800000	4.857000	5191.000000
75%	1.400000	93.994000	-36.400000	4.961000	5228.100000
max	1.400000	94.767000	-26.900000	5.045000	5228.100000

[12]:
```
bank.values
```

[12]:
```
array([[56, 'housemaid', 'married', …, 4.857, 5191.0, 'no'],
       [57, 'services', 'married', …, 4.857, 5191.0, 'no'],
       [37, 'services', 'married', …, 4.857, 5191.0, 'no'],
       …,
       [56, 'retired', 'married', …, 1.028, 4963.6, 'no'],
       [44, 'technician', 'married', …, 1.028, 4963.6, 'yes'],
       [74, 'retired', 'married', …, 1.028, 4963.6, 'no']], dtype=object)
```

[50]:
```
bank.columns
```

[50]:
```
Index(['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'],
```

```
      dtype='object')
```

[14]:
```
bank.index
```

[14]:
```
RangeIndex(start=0, stop=41188, step=1)
```

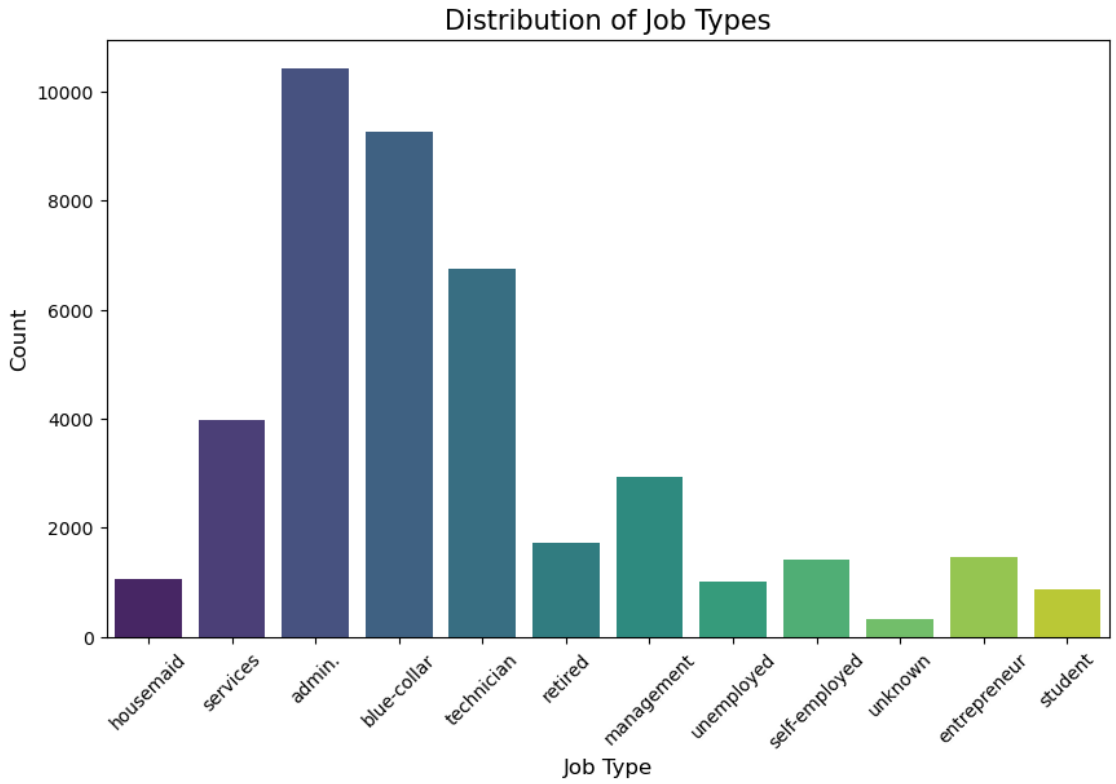
[30]:
```
#Profile report
pp.ProfileReport(bank)
```

```
Summarize dataset:   0%|          | 0/5 [00:00<?, ?it/s]

Generate report structure:   0%|          | 0/1 [00:00<?, ?it/s]

Render HTML:   0%|          | 0/1 [00:00<?, ?it/s]

<IPython.core.display.HTML object>
```

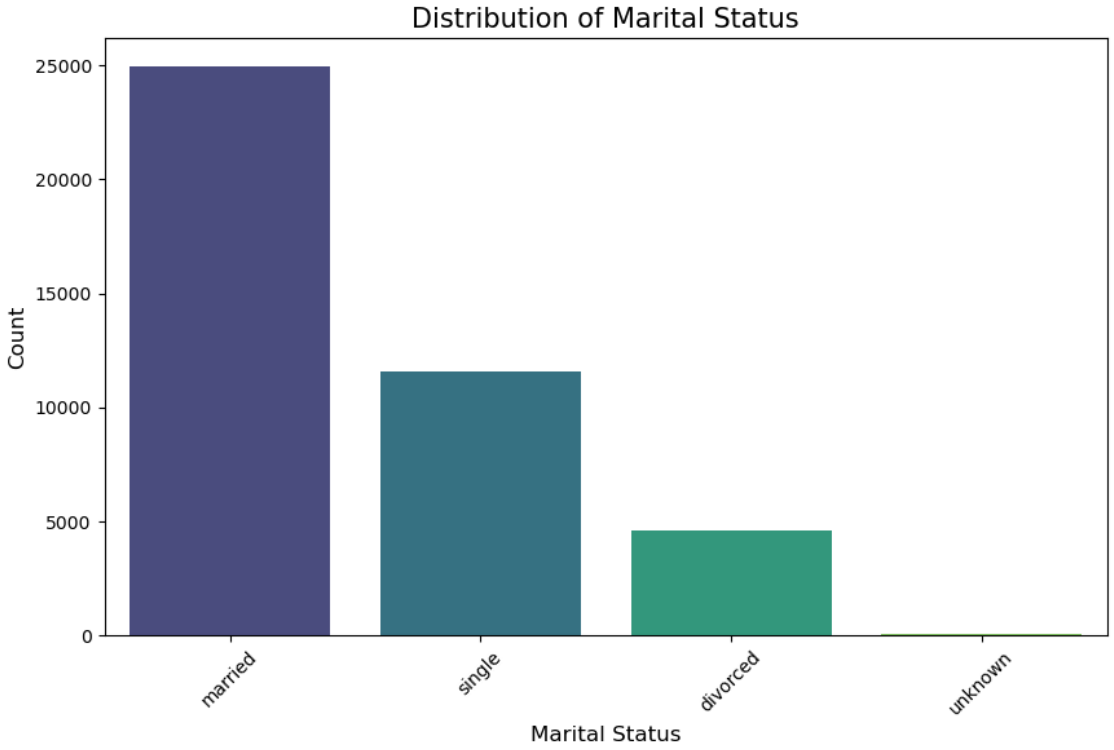
[30]:

From the profile report the following information is observed We have duplicate rows There are no missing values Number of variables 21 Number of observations 41188 Missing cells 0 Missing cells (%) 0.0% Duplicate rows 12

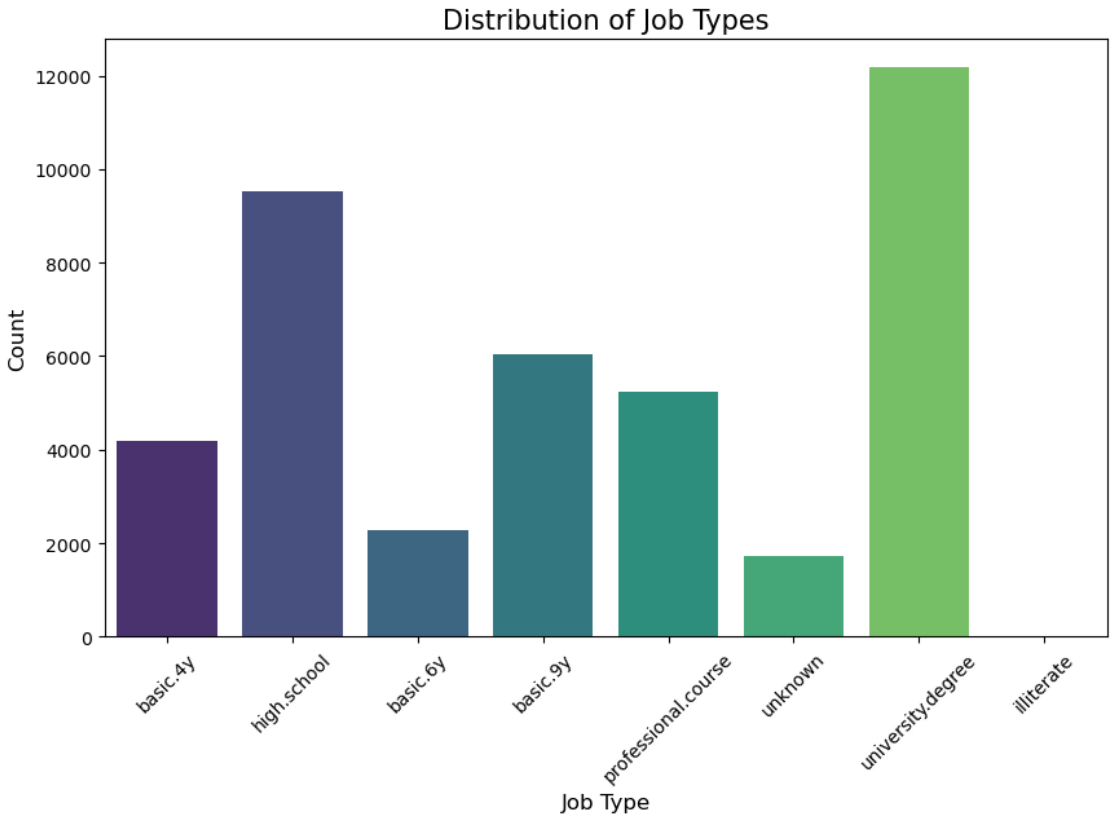
[16]:
```
#Exploring categorical variables
plt.figure(figsize=(10, 6))
sns.countplot(data=bank, x='job', palette='viridis')
plt.xlabel('Job Type', fontsize=12)
plt.ylabel('Count', fontsize=12)
plt.title('Distribution of Job Types', fontsize=15)
plt.xticks(rotation=45)
plt.show()
```



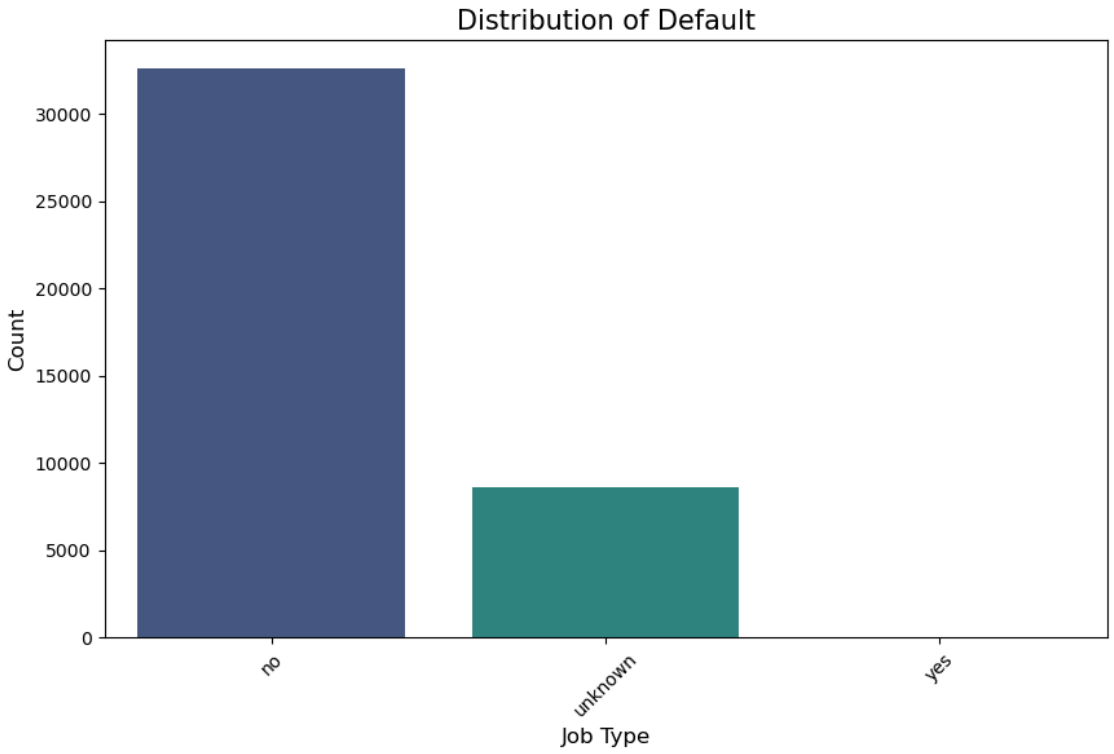
[19]:
```
#Marital Status
plt.figure(figsize=(10, 6))
sns.countplot(data=bank, x='marital', palette='viridis')
plt.xlabel('Marital Status', fontsize=12)
plt.ylabel('Count', fontsize=12)
plt.title('Distribution of Marital Status', fontsize=15)
plt.xticks(rotation=45)
plt.show()
```



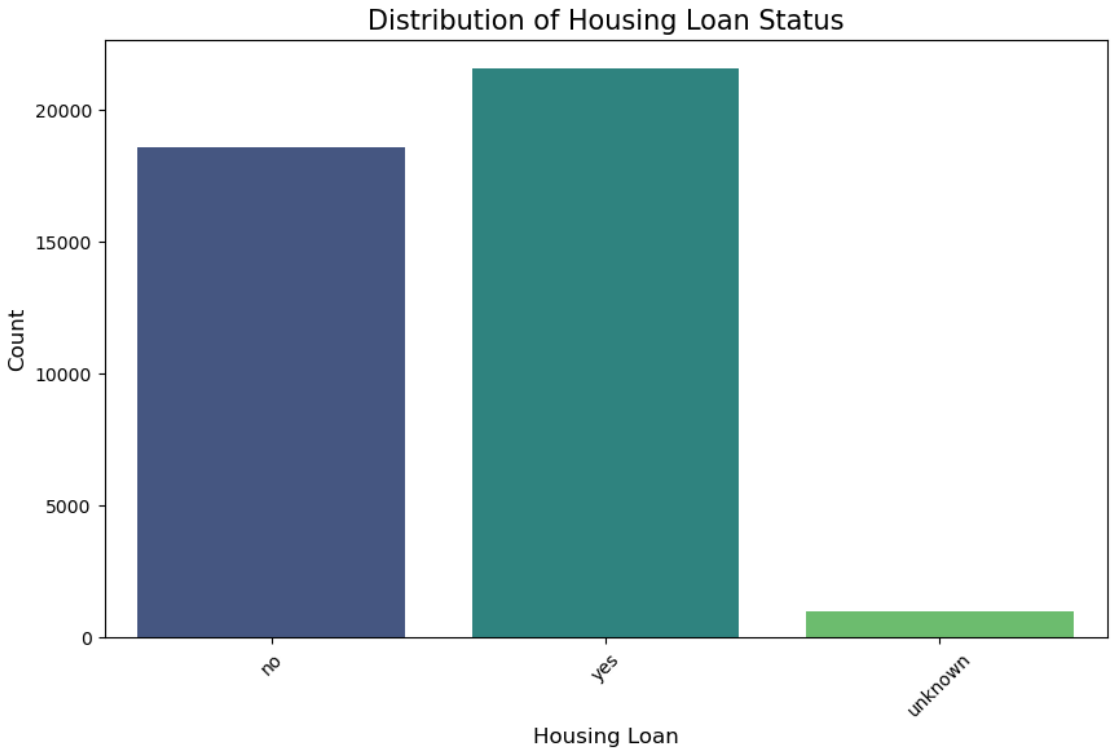
[18]:
```
#education
plt.figure(figsize=(10, 6))
sns.countplot(data=bank, x='education', palette='viridis')
plt.xlabel('Job Type', fontsize=12)
plt.ylabel('Count', fontsize=12)
plt.title('Distribution of Education levels', fontsize=15)
plt.xticks(rotation=45)
plt.show()
```



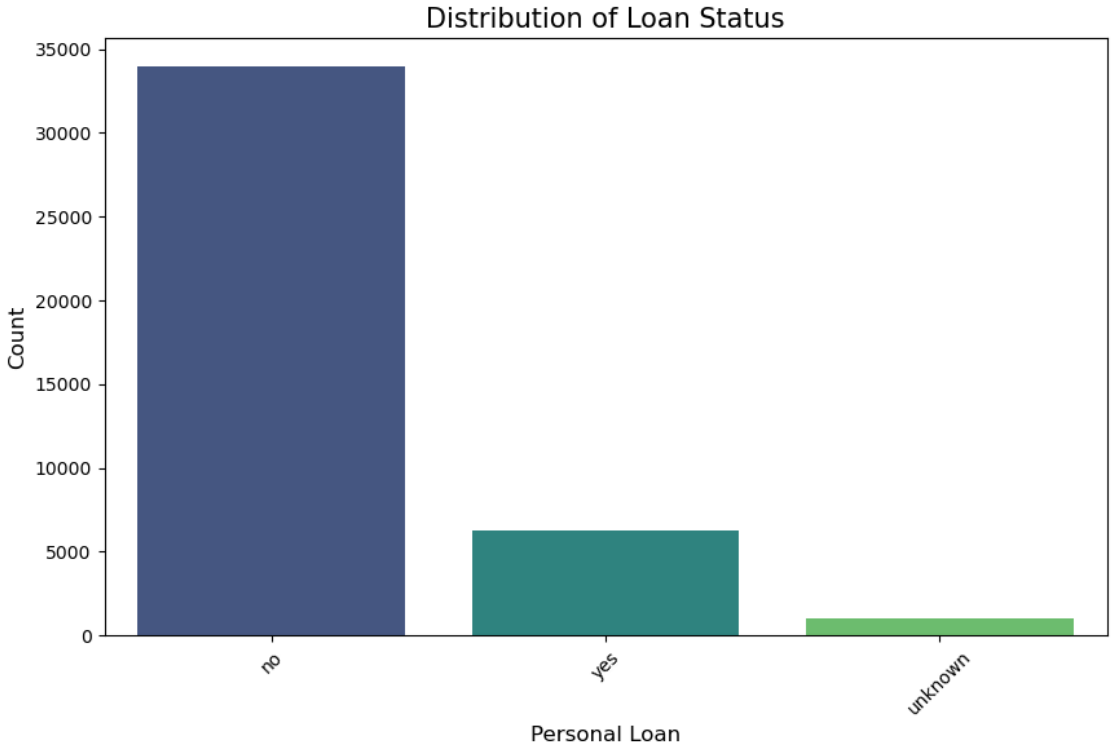
[20]:
```
#default
plt.figure(figsize=(10, 6))
sns.countplot(data=bank, x='default', palette='viridis')
plt.xlabel('Job Type', fontsize=12)
plt.ylabel('Count', fontsize=12)
plt.title('Distribution of Default status', fontsize=15)
plt.xticks(rotation=45)
plt.show()
```



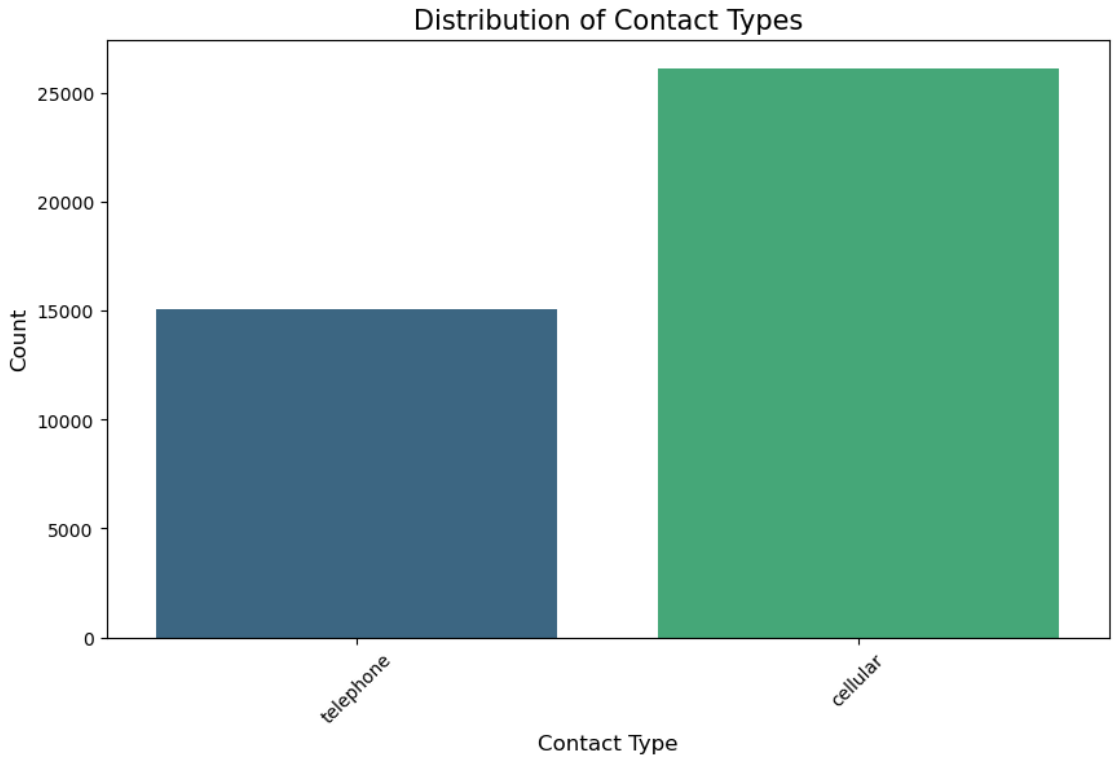
[21]:
```
#Housing loan status distribution
plt.figure(figsize=(10, 6))
sns.countplot(data=bank, x='housing', palette='viridis')
plt.xlabel('Housing Loan', fontsize=12)
plt.ylabel('Count', fontsize=12)
plt.title('Distribution of Housing Loan Status', fontsize=15)
plt.xticks(rotation=45)
plt.show()
```



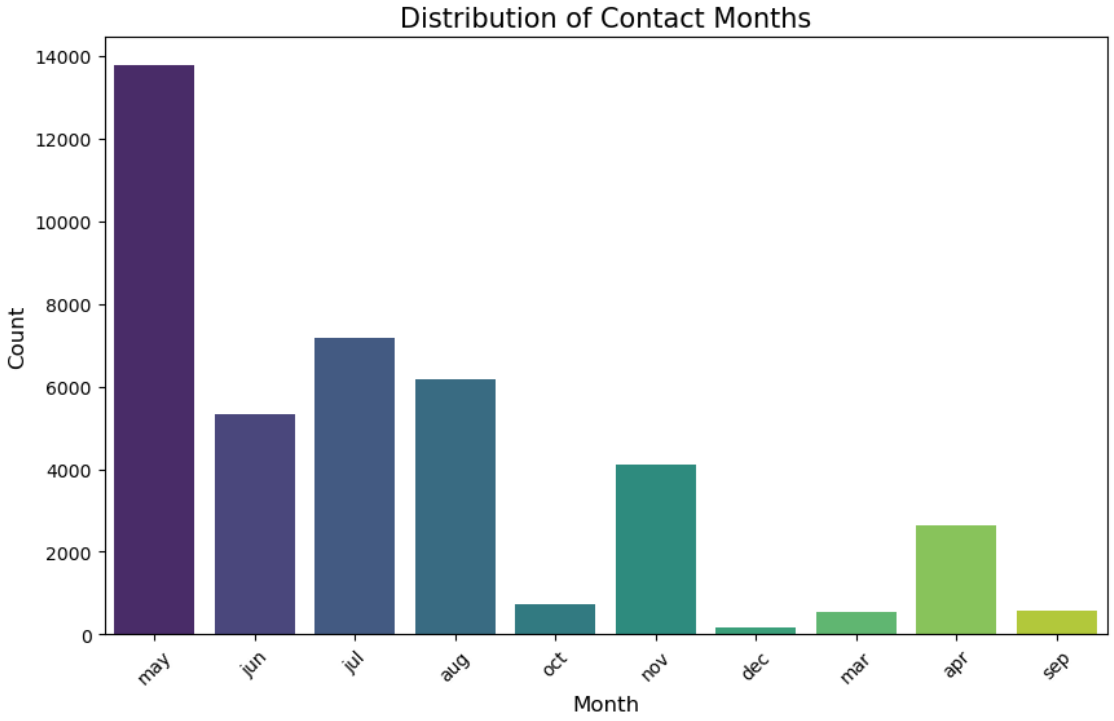
[22]:
```
#Distribution of loan status
plt.figure(figsize=(10, 6))
sns.countplot(data=bank, x='loan', palette='viridis')
plt.xlabel('Personal Loan', fontsize=12)
plt.ylabel('Count', fontsize=12)
plt.title('Distribution of Loan Status', fontsize=15)
plt.xticks(rotation=45)
plt.show()
```



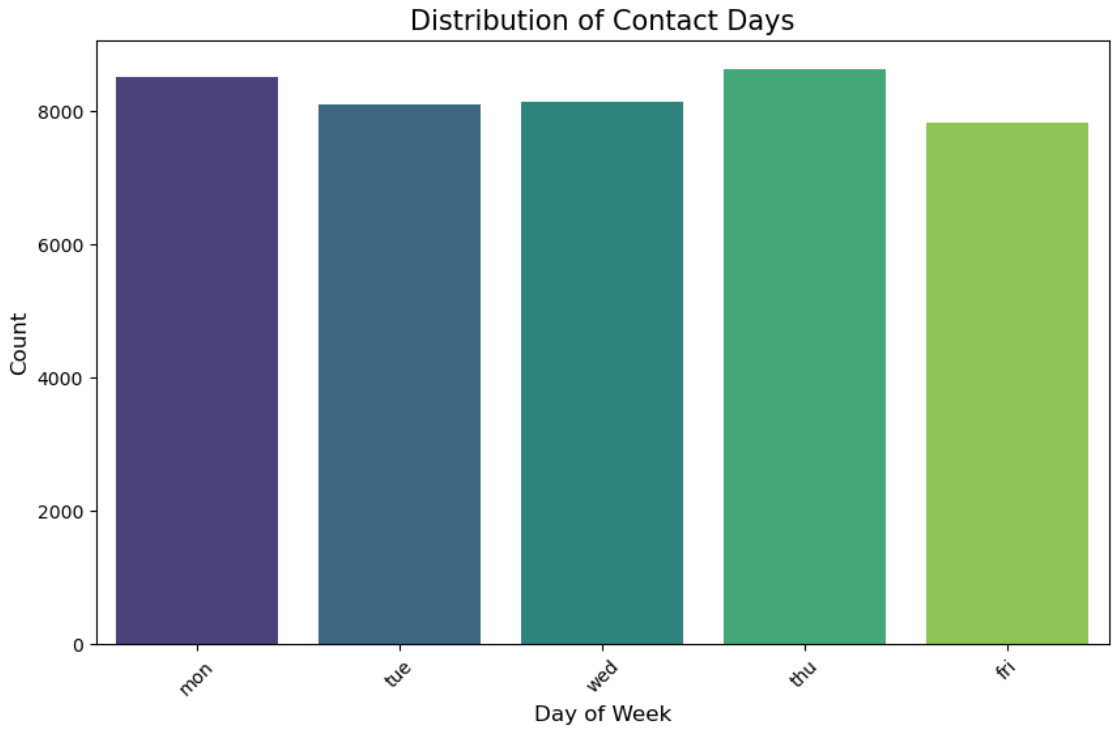
[23]:
```
#Distribution of contact types
plt.figure(figsize=(10, 6))
sns.countplot(data=bank, x='contact', palette='viridis')
plt.xlabel('Contact Type', fontsize=12)
plt.ylabel('Count', fontsize=12)
plt.title('Distribution of Contact Types', fontsize=15)
plt.xticks(rotation=45)
plt.show()
```



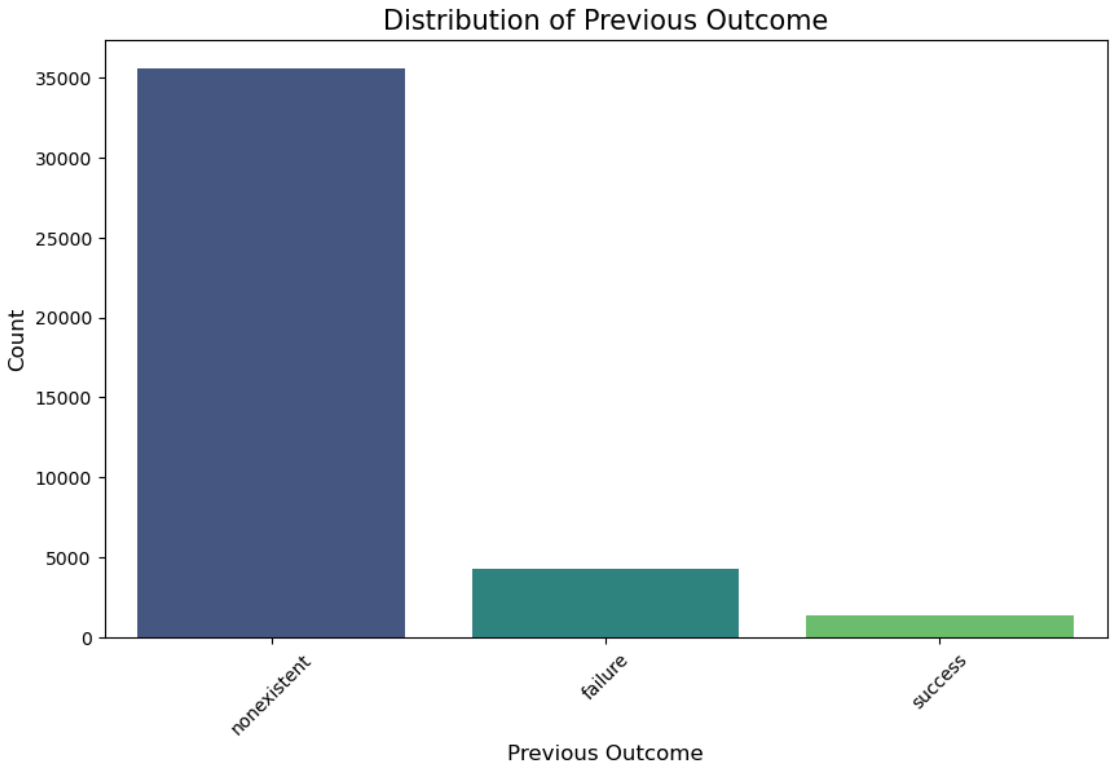
[24]:
```
#Distribution of month contact
plt.figure(figsize=(10, 6))
sns.countplot(data=bank, x='month', palette='viridis')
plt.xlabel('Month', fontsize=12)
plt.ylabel('Count', fontsize=12)
plt.title('Distribution of Contact Months', fontsize=15)
plt.xticks(rotation=45)
plt.show()
```



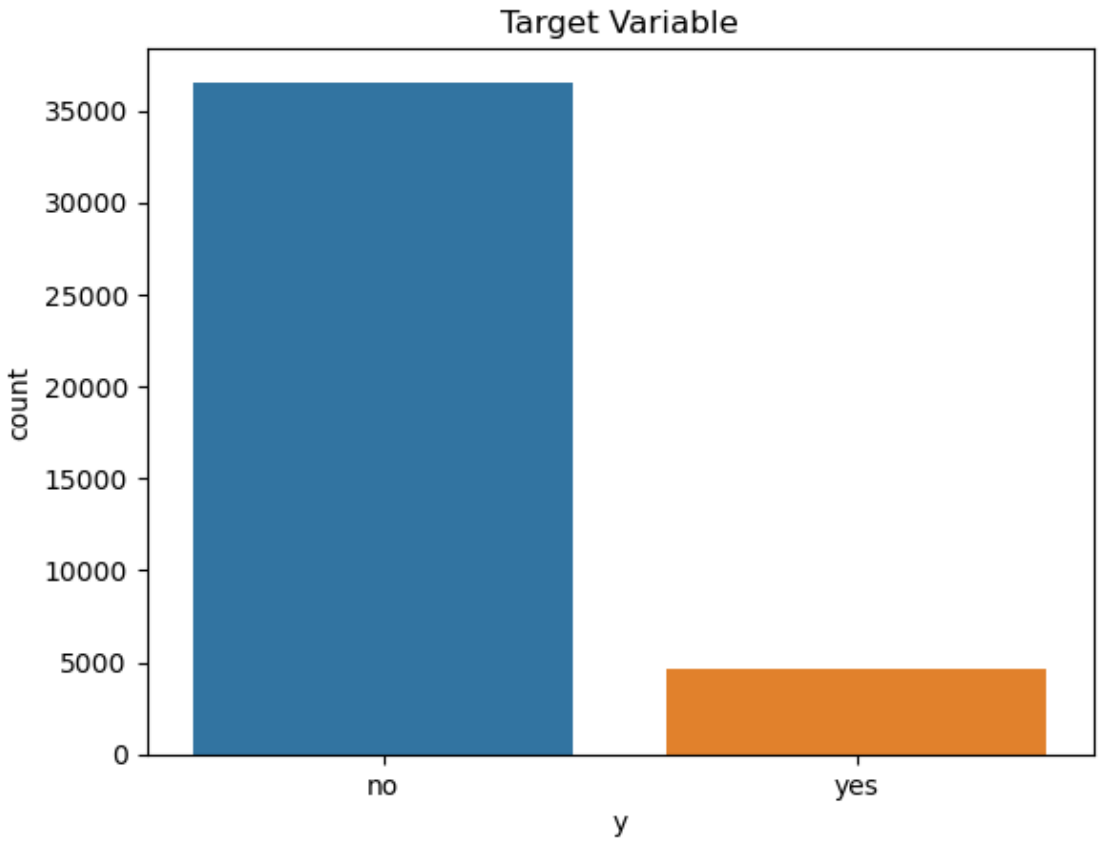
[25]:
```
#Distribution of contact days
plt.figure(figsize=(10, 6))
sns.countplot(data=bank, x='day_of_week', palette='viridis')
plt.xlabel('Day of Week', fontsize=12)
plt.ylabel('Count', fontsize=12)
plt.title('Distribution of Contact Days', fontsize=15)
plt.xticks(rotation=45)
plt.show()
```



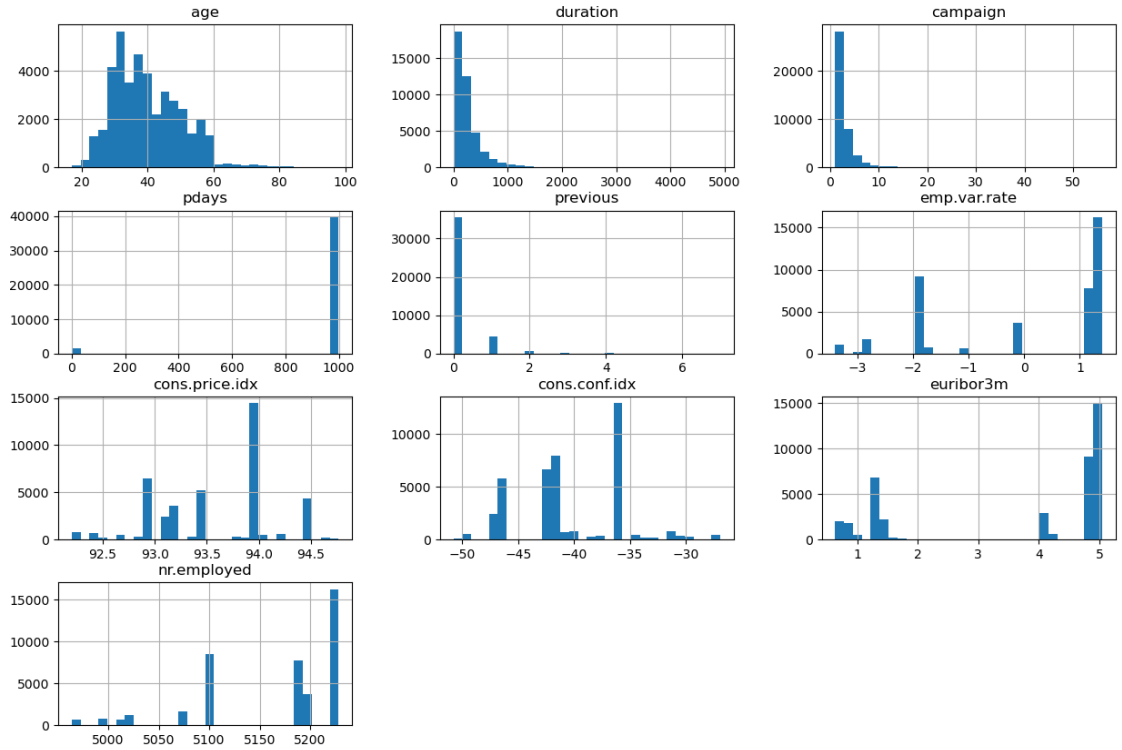
[26]:
```
#Distribution of previous outcome
plt.figure(figsize=(10, 6))
sns.countplot(data=bank, x='poutcome', palette='viridis')
plt.xlabel('Previous Outcome', fontsize=12)
plt.ylabel('Count', fontsize=12)
plt.title('Distribution of Previous Outcome', fontsize=15)
plt.xticks(rotation=45)
plt.show()
```



[16]:
```
# Visualize distribution of target variable
sns.countplot(x='y', data=bank)
plt.title("Target Variable")
plt.show()
```



[29]:
```
#Exploring numerical variables
numerical_features = ['age', 'duration', 'campaign', 'pdays', 'previous', 'emp.
 ↪var.rate', 'cons.price.idx', 'cons.conf.idx', 'euribor3m', 'nr.employed']
bank[numerical_features].hist(bins=30, figsize=(15, 10))
plt.show()
```



[5]:
```
#Identify categorical variables
#categorical_cols = ['job', 'marital','education','default', 'housing',␣
 ↪'loan','contact','month', 'day_of_week', 'poutcome','y']
# Perform one-hot encoding for categorical variables
categorical_cols = [col for col in bank.columns if col in ['job', 'marital',␣
 ↪'education', 'default', 'housing', 'loan', 'contact', 'month',␣
 ↪'day_of_week', 'poutcome', 'y']]
bank_encoded = pd.get_dummies(bank, columns=categorical_cols, drop_first=True)
#bank_encoded.info()
# Extract numerical columns
numerical_cols = [col for col in bank.columns if col not in categorical_cols␣
 ↪and col != 'y']
scaler = StandardScaler()
bank_scaled = bank_encoded.copy()
bank_scaled[numerical_cols] = scaler.fit_transform(bank_encoded[numerical_cols])
# Check if there are any remaining categorical variables
remaining_categorical_cols = [col for col in bank.columns if col not in␣
 ↪numerical_cols and col != 'y']
print("Remaining Categorical Columns:", remaining_categorical_cols)
bank_encoded.info()
```

```
Remaining Categorical Columns: ['job', 'marital', 'education', 'default',
'housing', 'loan', 'contact', 'month', 'day_of_week', 'poutcome']
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41188 entries, 0 to 41187
Data columns (total 54 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   age                             41188 non-null  int64
 1   duration                        41188 non-null  int64
 2   campaign                        41188 non-null  int64
 3   pdays                           41188 non-null  int64
 4   previous                        41188 non-null  int64
 5   emp.var.rate                    41188 non-null  float64
 6   cons.price.idx                  41188 non-null  float64
 7   cons.conf.idx                   41188 non-null  float64
 8   euribor3m                       41188 non-null  float64
 9   nr.employed                     41188 non-null  float64
 10  job_blue-collar                 41188 non-null  uint8
 11  job_entrepreneur                41188 non-null  uint8
 12  job_housemaid                   41188 non-null  uint8
 13  job_management                  41188 non-null  uint8
 14  job_retired                     41188 non-null  uint8
 15  job_self-employed               41188 non-null  uint8
 16  job_services                    41188 non-null  uint8
 17  job_student                     41188 non-null  uint8
 18  job_technician                  41188 non-null  uint8
 19  job_unemployed                  41188 non-null  uint8
 20  job_unknown                     41188 non-null  uint8
 21  marital_married                 41188 non-null  uint8
 22  marital_single                  41188 non-null  uint8
 23  marital_unknown                 41188 non-null  uint8
 24  education_basic.6y              41188 non-null  uint8
 25  education_basic.9y              41188 non-null  uint8
 26  education_high.school           41188 non-null  uint8
 27  education_illiterate            41188 non-null  uint8
 28  education_professional.course   41188 non-null  uint8
 29  education_university.degree     41188 non-null  uint8
 30  education_unknown               41188 non-null  uint8
 31  default_unknown                 41188 non-null  uint8
 32  default_yes                     41188 non-null  uint8
 33  housing_unknown                 41188 non-null  uint8
 34  housing_yes                     41188 non-null  uint8
 35  loan_unknown                    41188 non-null  uint8
 36  loan_yes                        41188 non-null  uint8
 37  contact_telephone               41188 non-null  uint8
 38  month_aug                       41188 non-null  uint8
 39  month_dec                       41188 non-null  uint8
 40  month_jul                       41188 non-null  uint8
 41  month_jun                       41188 non-null  uint8
 42  month_mar                       41188 non-null  uint8
```

```
 43  month_may                       41188 non-null  uint8
 44  month_nov                       41188 non-null  uint8
 45  month_oct                       41188 non-null  uint8
 46  month_sep                       41188 non-null  uint8
 47  day_of_week_mon                 41188 non-null  uint8
 48  day_of_week_thu                 41188 non-null  uint8
 49  day_of_week_tue                 41188 non-null  uint8
 50  day_of_week_wed                 41188 non-null  uint8
 51  poutcome_nonexistent            41188 non-null  uint8
 52  poutcome_success                41188 non-null  uint8
 53  y_yes                           41188 non-null  uint8
dtypes: float64(5), int64(5), uint8(44)
memory usage: 4.9 MB
```

5 DATA PREPROCESSING

[83]:
```
#Missing Values
bank.isnull()
```

[83]:

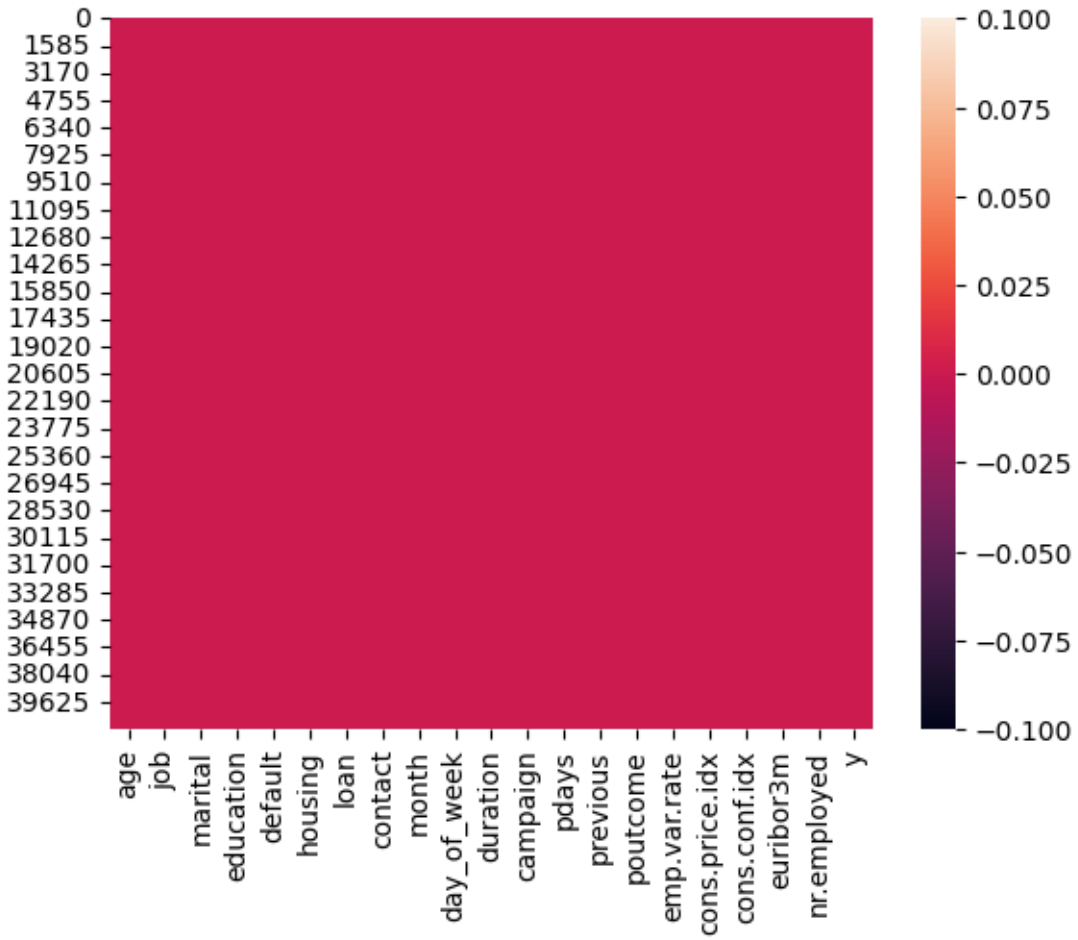
	age	duration	campaign	pdays	previous	emp.var.rate	\
0	False	False	False	False	False	False	
1	False	False	False	False	False	False	
2	False	False	False	False	False	False	
3	False	False	False	False	False	False	
4	False	False	False	False	False	False	
…	…	…	…	…	…	…	
41183	False	False	False	False	False	False	
41184	False	False	False	False	False	False	
41185	False	False	False	False	False	False	
41186	False	False	False	False	False	False	
41187	False	False	False	False	False	False	

	cons.price.idx	cons.conf.idx	euribor3m	nr.employed	…	month_nov	\
0	False	False	False	False	…	False	
1	False	False	False	False	…	False	
2	False	False	False	False	…	False	
3	False	False	False	False	…	False	
4	False	False	False	False	…	False	
…	…	…	…	…	…	…	
41183	False	False	False	False	…	False	
41184	False	False	False	False	…	False	
41185	False	False	False	False	…	False	
41186	False	False	False	False	…	False	
41187	False	False	False	False	…	False	

	month_oct	month_sep	day_of_week_mon	day_of_week_thu	\
0	False	False	False	False	

```
1          False      False            False            False
2          False      False            False            False
3          False      False            False            False
4          False      False            False            False
…          …        …                …              …
41183      False      False            False            False
41184      False      False            False            False
41185      False      False            False            False
41186      False      False            False            False
41187      False      False            False            False

       day_of_week_tue  day_of_week_wed  poutcome_nonexistent  \
0                False            False                 False
1                False            False                 False
2                False            False                 False
3                False            False                 False
4                False            False                 False
…                …              …                     …
41183            False            False                 False
41184            False            False                 False
41185            False            False                 False
41186            False            False                 False
41187            False            False                 False

       poutcome_success  y_yes
0                 False  False
1                 False  False
2                 False  False
3                 False  False
4                 False  False
…                 …    …
41183             False  False
41184             False  False
41185             False  False
41186             False  False
41187             False  False

[41188 rows x 54 columns]
```

[14]:
```
sns.heatmap(bank.isnull())
plt.show()
```



[9]:
```
#Missing values count
bank.isnull().sum().sort_values(ascending = False)
```

[9]:
```
age               0
campaign          0
nr.employed       0
euribor3m         0
cons.conf.idx     0
cons.price.idx    0
emp.var.rate      0
poutcome          0
previous          0
pdays             0
duration          0
job               0
day_of_week       0
month             0
```

```
contact           0
loan              0
housing           0
default           0
education         0
marital           0
y                 0
dtype: int64
```

[10]:
```
#Drop duplicate values
bank.drop_duplicates()
```

[10]:

	age	job	marital	education	default	housing	loan	\
0	56	housemaid	married	basic.4y	no	no	no	
1	57	services	married	high.school	unknown	no	no	
2	37	services	married	high.school	no	yes	no	
3	40	admin.	married	basic.6y	no	no	no	
4	56	services	married	high.school	no	no	yes	
…	…	…	…	…	…	…	…	…
41183	73	retired	married	professional.course	no	yes	no	
41184	46	blue-collar	married	professional.course	no	no	no	
41185	56	retired	married	university.degree	no	yes	no	
41186	44	technician	married	professional.course	no	no	no	
41187	74	retired	married	professional.course	no	yes	no	

	contact	month	day_of_week	…	campaign	pdays	previous	\
0	telephone	may	mon	…	1	999	0	
1	telephone	may	mon	…	1	999	0	
2	telephone	may	mon	…	1	999	0	
3	telephone	may	mon	…	1	999	0	
4	telephone	may	mon	…	1	999	0	
…	…	…	…	…	…	…	…	
41183	cellular	nov	fri	…	1	999	0	
41184	cellular	nov	fri	…	1	999	0	
41185	cellular	nov	fri	…	2	999	0	
41186	cellular	nov	fri	…	1	999	0	
41187	cellular	nov	fri	…	3	999	1	

	poutcome	emp.var.rate	cons.price.idx	cons.conf.idx	euribor3m	\
0	nonexistent	1.1	93.994	-36.4	4.857	
1	nonexistent	1.1	93.994	-36.4	4.857	
2	nonexistent	1.1	93.994	-36.4	4.857	
3	nonexistent	1.1	93.994	-36.4	4.857	
4	nonexistent	1.1	93.994	-36.4	4.857	
…	…	…	…	…	…	
41183	nonexistent	-1.1	94.767	-50.8	1.028	
41184	nonexistent	-1.1	94.767	-50.8	1.028	

```
41185  nonexistent         -1.1          94.767          -50.8      1.028
41186  nonexistent         -1.1          94.767          -50.8      1.028
41187      failure         -1.1          94.767          -50.8      1.028

       nr.employed    y
0           5191.0   no
1           5191.0   no
2           5191.0   no
3           5191.0   no
4           5191.0   no
…              …   …
41183       4963.6  yes
41184       4963.6   no
41185       4963.6   no
41186       4963.6  yes
41187       4963.6   no

[41176 rows x 21 columns]
```

[11]:
```
#correlation matrix
corr_matrix = bank.corr()
corr_matrix
```

```
C:\Users\elmaf\AppData\Local\Temp\ipykernel_14304\303973148.py:2: FutureWarning:
The default value of numeric_only in DataFrame.corr is deprecated. In a future
version, it will default to False. Select only valid columns or specify the
value of numeric_only to silence this warning.
  corr_matrix = bank.corr()
```

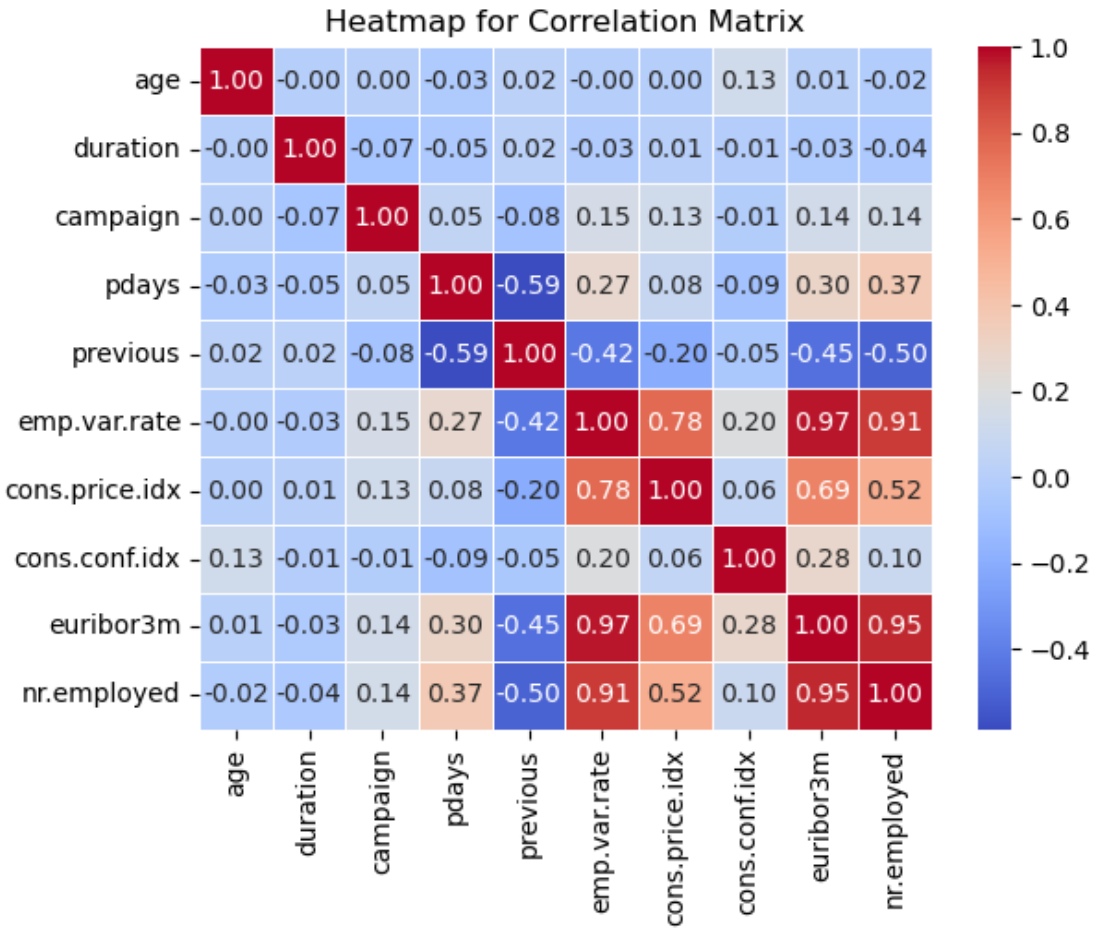
[11]:
```
                      age  duration  campaign     pdays  previous  \
age              1.000000 -0.000866  0.004594 -0.034369  0.024365
duration        -0.000866  1.000000 -0.071699 -0.047577  0.020640
campaign         0.004594 -0.071699  1.000000  0.052584 -0.079141
pdays           -0.034369 -0.047577  0.052584  1.000000 -0.587514
previous         0.024365  0.020640 -0.079141 -0.587514  1.000000
emp.var.rate    -0.000371 -0.027968  0.150754  0.271004 -0.420489
cons.price.idx   0.000857  0.005312  0.127836  0.078889 -0.203130
cons.conf.idx    0.129372 -0.008173 -0.013733 -0.091342 -0.050936
euribor3m        0.010767 -0.032897  0.135133  0.296899 -0.454494
nr.employed     -0.017725 -0.044703  0.144095  0.372605 -0.501333

                 emp.var.rate  cons.price.idx  cons.conf.idx  euribor3m  \
age                 -0.000371        0.000857       0.129372   0.010767
duration            -0.027968        0.005312      -0.008173  -0.032897
campaign             0.150754        0.127836      -0.013733   0.135133
pdays                0.271004        0.078889      -0.091342   0.296899
previous            -0.420489       -0.203130      -0.050936  -0.454494
```

```
emp.var.rate        1.000000        0.775334        0.196041    0.972245
cons.price.idx      0.775334        1.000000        0.058986    0.688230
cons.conf.idx       0.196041        0.058986        1.000000    0.277686
euribor3m           0.972245        0.688230        0.277686    1.000000
nr.employed         0.906970        0.522034        0.100513    0.945154
```

```
                nr.employed
age               -0.017725
duration          -0.044703
campaign           0.144095
pdays              0.372605
previous          -0.501333
emp.var.rate       0.906970
cons.price.idx     0.522034
cons.conf.idx      0.100513
euribor3m          0.945154
nr.employed        1.000000
```

[12]:
```
# Plotting Heatmap for better visualization
corre_matrix = bank.corr()
sns.heatmap(corre_matrix, annot=True, cmap='coolwarm', fmt='.2f', linewidths=.5)
plt.title("Heatmap for Correlation Matrix")
plt.show()
```

```
C:\Users\elmaf\AppData\Local\Temp\ipykernel_14304\2246364141.py:2:
FutureWarning: The default value of numeric_only in DataFrame.corr is
deprecated. In a future version, it will default to False. Select only valid
columns or specify the value of numeric_only to silence this warning.
  corre_matrix = bank.corr()
```



From the correlation matrix the following observations are made nr.employed and euribor3m are highly correlated emp.var.rate and nr.employed are highly correlated emp.var.rate and euribor3m are highly correlated

6 MODEL TRAINING

[6]:
```
# Apply label encoding to categorical columns
le = LabelEncoder()
bank['y'] = le.fit_transform(bank['y'])
bank.tail()
```

[6]:

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

```
        contact month day_of_week  …  campaign  pdays  previous  \
41183  cellular   nov         fri  …         1    999         0
41184  cellular   nov         fri  …         1    999         0
41185  cellular   nov         fri  …         2    999         0
41186  cellular   nov         fri  …         1    999         0
41187  cellular   nov         fri  …         3    999         1

          poutcome emp.var.rate  cons.price.idx  cons.conf.idx  euribor3m  \
41183  nonexistent         -1.1          94.767          -50.8      1.028
41184  nonexistent         -1.1          94.767          -50.8      1.028
41185  nonexistent         -1.1          94.767          -50.8      1.028
41186  nonexistent         -1.1          94.767          -50.8      1.028
41187      failure         -1.1          94.767          -50.8      1.028

       nr.employed  y
41183       4963.6  1
41184       4963.6  0
41185       4963.6  0
41186       4963.6  1
41187       4963.6  0

[5 rows x 21 columns]
```

[7]:
```
# Split data into features and target
X =  bank_encoded.drop( 'y_yes', axis = 1) #Data feeding into the models
Y =  bank_encoded['y_yes']

# Split data into training and test sets
X_train,X_test,Y_train,Y_test = train_test_split(X,Y,test_size = 0.2,␣
 ↪random_state = 0)
```

Model Training

[8]:
```
#Data Scaling
# Normalize the data
#scaler = StandardScaler()
#bank_encoded[numerical_cols] = scaler.
 ↪fit_transform(bank_encoded[numerical_cols])
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
scaler = StandardScaler()
bank_scaled = bank_encoded.copy()
bank_scaled[numerical_cols] = scaler.fit_transform(bank_encoded[numerical_cols])
```

[9]:
```
#Training the model
#initalise the model
```

```python
model = LogisticRegression()

#train the model
model.fit(X_train, Y_train)
```

[9]: LogisticRegression()

Hyperparameter Tuning

[11]:
```python
param_grid = {'C': [0.1, 1, 10], 'solver': ['liblinear', 'saga']}
grid = GridSearchCV(model, param_grid, cv=5)
grid.fit(X_train, Y_train)
best_model = grid.best_estimator_
```

```
C:\Users\elmaf\anaconda3\Lib\site-packages\sklearn\linear_model\_sag.py:350:
ConvergenceWarning: The max_iter was reached which means the coef_ did not
converge
  warnings.warn(
C:\Users\elmaf\anaconda3\Lib\site-packages\sklearn\linear_model\_sag.py:350:
ConvergenceWarning: The max_iter was reached which means the coef_ did not
converge
  warnings.warn(
C:\Users\elmaf\anaconda3\Lib\site-packages\sklearn\linear_model\_sag.py:350:
ConvergenceWarning: The max_iter was reached which means the coef_ did not
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C:\Users\elmaf\anaconda3\Lib\site-packages\sklearn\linear_model\_sag.py:350:
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C:\Users\elmaf\anaconda3\Lib\site-packages\sklearn\linear_model\_sag.py:350:
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C:\Users\elmaf\anaconda3\Lib\site-packages\sklearn\linear_model\_sag.py:350:
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C:\Users\elmaf\anaconda3\Lib\site-packages\sklearn\linear_model\_sag.py:350:
ConvergenceWarning: The max_iter was reached which means the coef_ did not
```

```
converge
  warnings.warn(
C:\Users\elmaf\anaconda3\Lib\site-packages\sklearn\linear_model\_sag.py:350:
ConvergenceWarning: The max_iter was reached which means the coef_ did not
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C:\Users\elmaf\anaconda3\Lib\site-packages\sklearn\linear_model\_sag.py:350:
ConvergenceWarning: The max_iter was reached which means the coef_ did not
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  warnings.warn(
C:\Users\elmaf\anaconda3\Lib\site-packages\sklearn\linear_model\_sag.py:350:
ConvergenceWarning: The max_iter was reached which means the coef_ did not
converge
  warnings.warn(
C:\Users\elmaf\anaconda3\Lib\site-packages\sklearn\linear_model\_sag.py:350:
ConvergenceWarning: The max_iter was reached which means the coef_ did not
converge
  warnings.warn(
C:\Users\elmaf\anaconda3\Lib\site-packages\sklearn\linear_model\_sag.py:350:
ConvergenceWarning: The max_iter was reached which means the coef_ did not
converge
  warnings.warn(
C:\Users\elmaf\anaconda3\Lib\site-packages\sklearn\linear_model\_sag.py:350:
ConvergenceWarning: The max_iter was reached which means the coef_ did not
converge
  warnings.warn(
```

[12]:
```
# Predictions
y_pred = best_model.predict(X_test)
y_pred
```

[12]:
```
array([0, 0, 0, …, 1, 0, 0], dtype=uint8)
```

[127]:
```
#Checking for accuracy
accuracy= accuracy_score(y_pred,Y_test)
accuracy
```

[127]:
```
0.9149065307113377
```

The model is 91% accurate

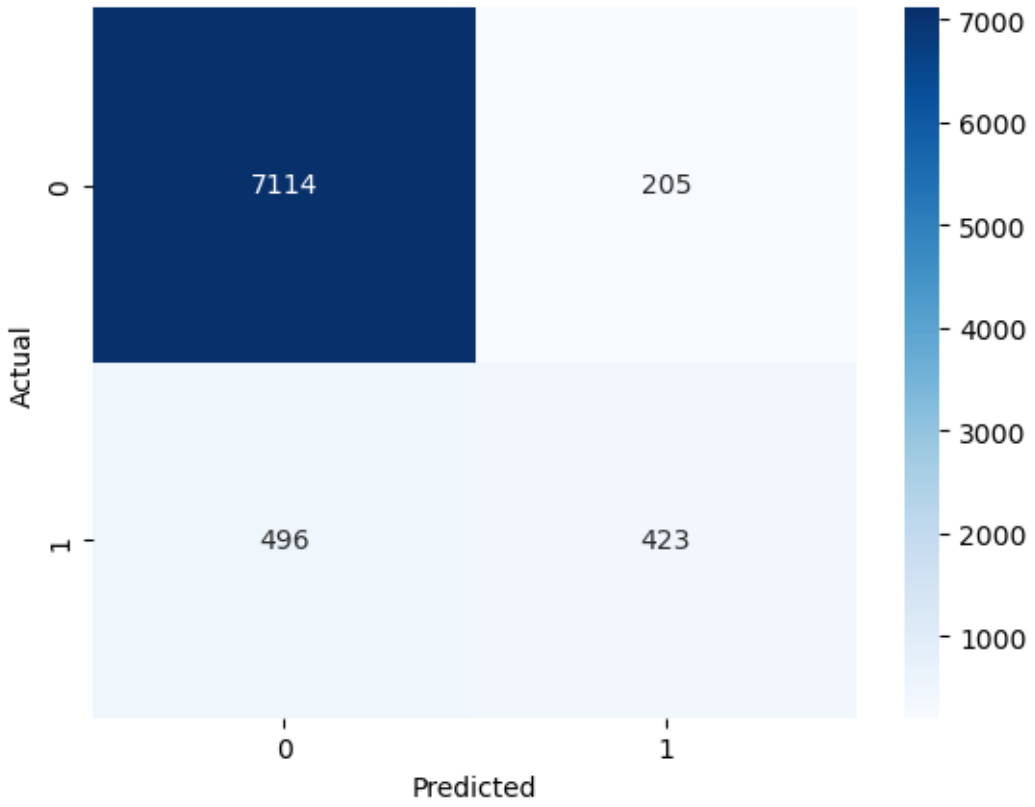
[14]:
```
# Evaluation metrics
print(confusion_matrix(Y_test, y_pred))
print(classification_report(Y_test, y_pred))
sns.heatmap(confusion_matrix(Y_test, y_pred), annot=True, fmt='d', cmap=␣
  ↪'Blues')
plt.xlabel('Predicted')
plt.ylabel('Actual')
```

```
plt.show()
```

```
[[7114  205]
 [ 496  423]]
              precision    recall  f1-score   support

           0       0.93      0.97      0.95      7319
           1       0.67      0.46      0.55       919

    accuracy                           0.91      8238
   macro avg       0.80      0.72      0.75      8238
weighted avg       0.91      0.91      0.91      8238
```

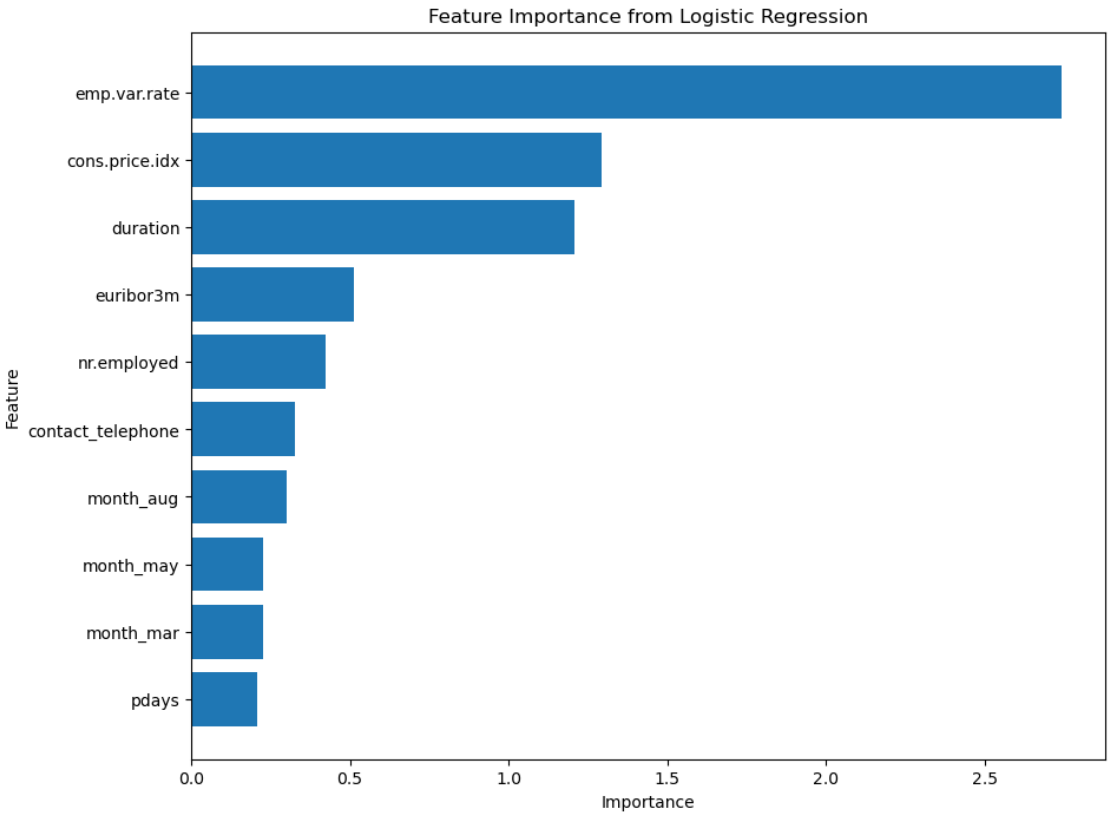


Explanation: True Positives (TP): Correctly predicted positive cases. True Negatives (TN): Correctly predicted negative cases. False Positives (FP): Incorrectly predicted positive cases. False Negatives (FN): Incorrectly predicted negative cases.

[32]:
```
importance = np.abs(model.coef_[0])

#Create a DataFrame for features and their importances
```

```
feature_names = X.columns
feature_importance = pd.DataFrame({'Feature': feature_names, 'Importance':␣
 ↪importance})
feature_importance = feature_importance.sort_values(by='Importance',␣
 ↪ascending=False).head(10)
#Plot the feature importance
plt.figure(figsize=(10, 8))
plt.barh(feature_importance['Feature'], feature_importance['Importance'])
plt.xlabel('Importance')
plt.ylabel('Feature')
plt.title('Feature Importance from Logistic Regression')
plt.gca().invert_yaxis()  # Invert y-axis to show the most important features␣
 ↪on top
plt.show()
```



The bar plot shows the importance of each feature in making predictions. Higher importance indicates a greater influence on the model's predictions.

7 Conclusion

[ ]:

[ ]:

Summary This project successfully predicted customer subscription to term deposits using various features and logistic regression. The model achieved a satisfactory accuracy and highlighted key factors influencing customer decisions.

Future Work Future enhancements could include: - Exploring more complex models like Random Forests or Gradient Boosting. - Performing feature engineering to create new relevant features. - Collecting more data to improve model robustness.

[ ]: