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Task 05: Peronal Loan Acceptance Prediction.

Objective: Predict which customers are likely to accept a personal loan offer.

Dataset: Bank Marketing Dataset (UCI Machine learning Repository). About Dataset: UCI-Bank-Marketing-Dataset. The following information is drawn from the UCI Machine Learning Repository: https://archive.ics.uci.edu/ml/datasets/bank+marketing. Abstract: The data is related with direct marketing campaigns (phone calls) of a Portuguese banking institution. The classification goal is to predict if the client will subscribe a term deposit (variable y). Source: [Moro et al., 2014] S. Moro, P. Cortez and P. Rita. A Data-Driven Approach to Predict the Success of Bank Telemarketing. Decision Support Systems, Elsevier, 62:22-31, June 2014. Data Set Information: The data is related with direct marketing campaigns of a Portuguese banking institution. The marketing campaigns were based on phone calls. Often, more than one contact to the same client was required, in order to access if the product (bank term deposit) would be ('yes') or not ('no') subscribed. There are four datasets: Bank-additional-full.csv with all examples (41188) and 20 inputs, ordered by date (from May 2008 to November 2010), very close to the data analyzed in [Moro et al., 2014] <– this is used 2) bank-additional.csv with 10% of the examples (4119), randomly selected from 1), and 20 inputs. 3) bank-full.csv with all examples and 17 inputs, ordered by date (older version of this dataset with less inputs). 4) bank.csv with 10% of the examples and 17 inputs, randomly selected from 3 (older version of this dataset with less inputs). The classification goal is to predict if the client will subscribe (yes/no) a term deposit (variable y).

Load the Dataset:

[1]:
```
import pandas as pd
```

[2]:
```
Dataset = pd.read_csv("bank-additional-full.csv")
```

[3]:
```
Dataset = pd.read_csv("bank-additional-full.csv", sep=";")
```

Data Exploration:

[4]:
```
Dataset.head()
```

[4]:
```
   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]
```

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

[5]:
```
       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  yes
41184       4963.6   no
41185       4963.6   no
41186       4963.6  yes
41187       4963.6   no
```

[5 rows x 21 columns]

[6]:
```
Dataset.describe()
```

[6]:
```
                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
```

[7]:
```
Dataset.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
```

[8]:
```
Dataset.shape
```

[8]:
```
(41188, 21)
```

[9]:
```
Dataset.columns
```

[9]:
```
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')
```

[10]:
```
Dataset.dtypes
```

[10]:
```
age                 int64
job                object
marital            object
education          object
default            object
housing            object
loan               object
contact            object
month              object
day_of_week        object
duration            int64
campaign            int64
pdays               int64
previous            int64
poutcome           object
emp.var.rate      float64
cons.price.idx    float64
cons.conf.idx     float64
euribor3m         float64
nr.employed       float64
y                  object
dtype: object
```

Perofrm basic data exploration on features such as age, job and martial status.

For job:

[11]:
```
Dataset["job"].value_counts()
```

[11]:
```
job
admin.           10422
blue-collar       9254
technician        6743
services          3969
management        2924
retired           1720
entrepreneur      1456
self-employed     1421
housemaid         1060
unemployed        1014
student            875
unknown            330
Name: count, dtype: int64
```

[12]:
```
Dataset["job"].describe()
```

[12]:
```
count      41188
unique        12
top       admin.
freq       10422
Name: job, dtype: object
```

For age:

[13]:
```
Dataset["age"].value_counts()
```

[13]:
```
age
31    1947
32    1846
33    1833
36    1780
35    1759
      …
89       2
91       2
94       1
87       1
95       1
Name: count, Length: 78, dtype: int64
```

[14]:
```
Dataset["age"].describe()
```

[14]:
```
count    41188.00000
mean        40.02406
```

```
std         10.42125
min         17.00000
25%         32.00000
50%         38.00000
75%         47.00000
max         98.00000
Name: age, dtype: float64
```

For marital status:

[15]:
```
Dataset["marital"].value_counts()
```

[15]:
```
marital
married     24928
single      11568
divorced     4612
unknown        80
Name: count, dtype: int64
```

[16]:
```
Dataset["marital"].describe()
```

[16]:
```
count       41188
unique          4
top       married
freq        24928
Name: marital, dtype: object
```

Basic Data Visulaization:

[17]:
```
import matplotlib as pyplot
from matplotlib import pyplot as plt
import seaborn as sns
```

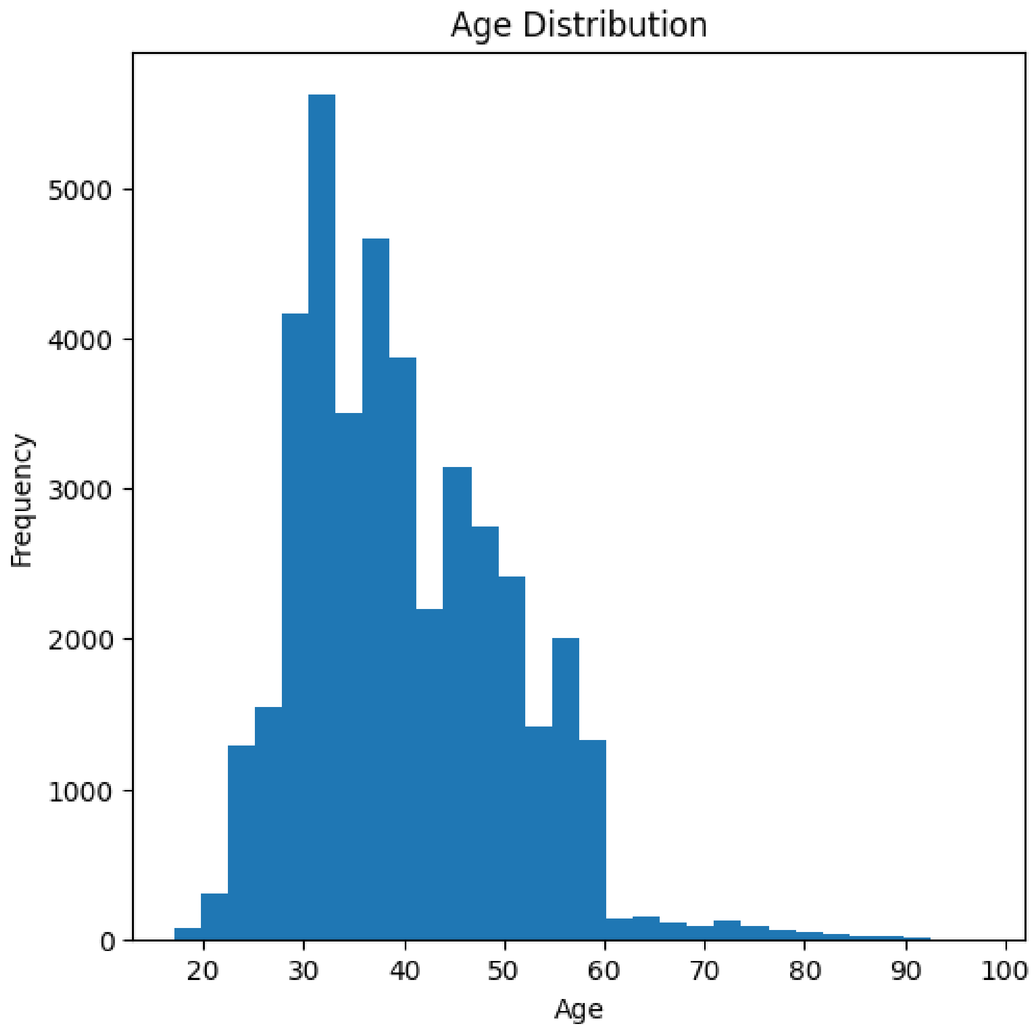
Age Histogram:

[18]:
```
plt.figure(figsize = (6,6))

plt.hist(Dataset["age"], bins = 30)

plt.xlabel("Age")
plt.ylabel("Frequency")
plt.title("Age Distribution")

plt.show()
```



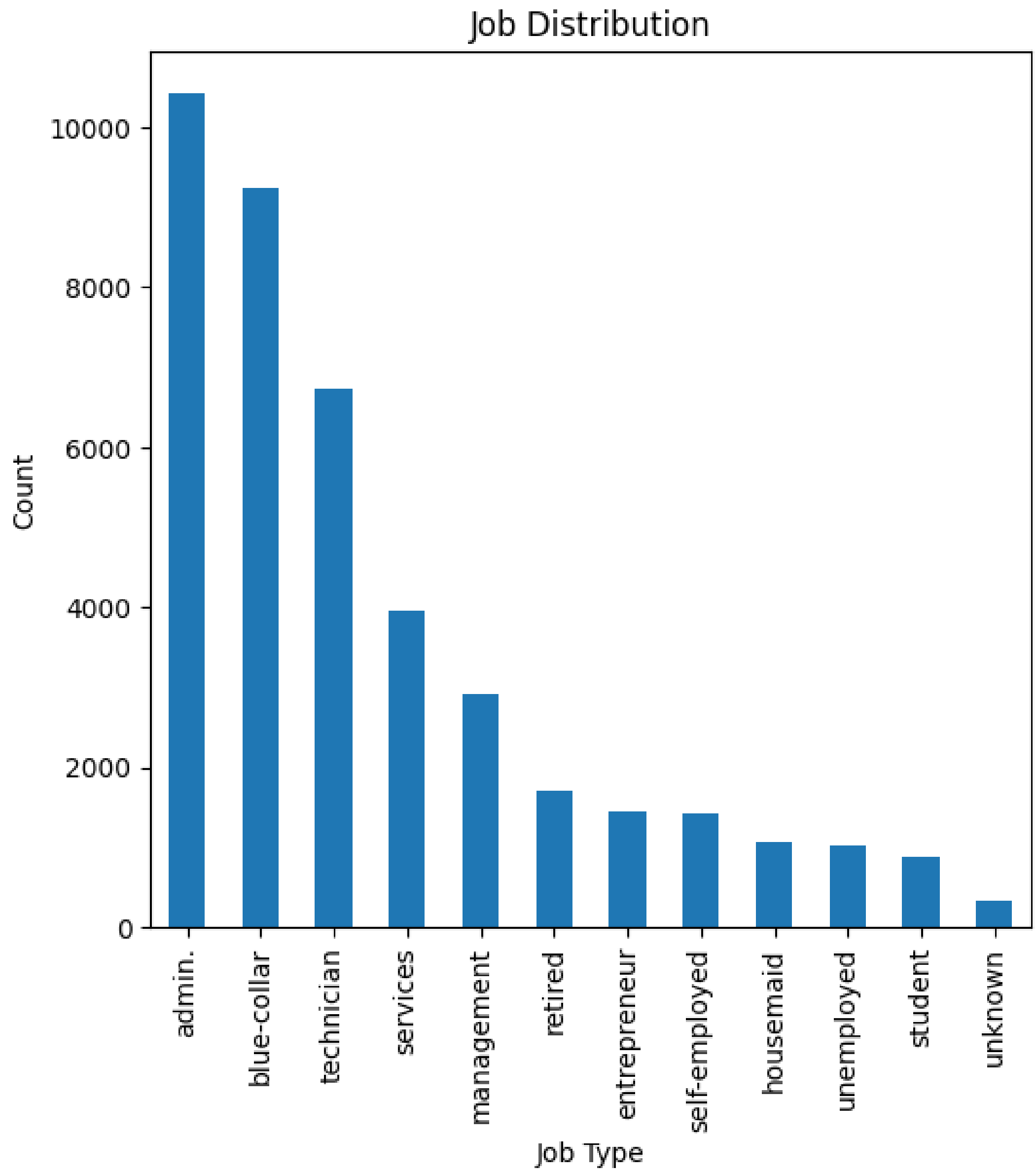
Job Count Plot:

[19]:
```
plt.figure(figsize = (6,6))

Dataset["job"].value_counts().plot(kind="bar")

plt.xlabel("Job Type")
plt.ylabel("Count")
plt.title("Job Distribution")

plt.show()
```



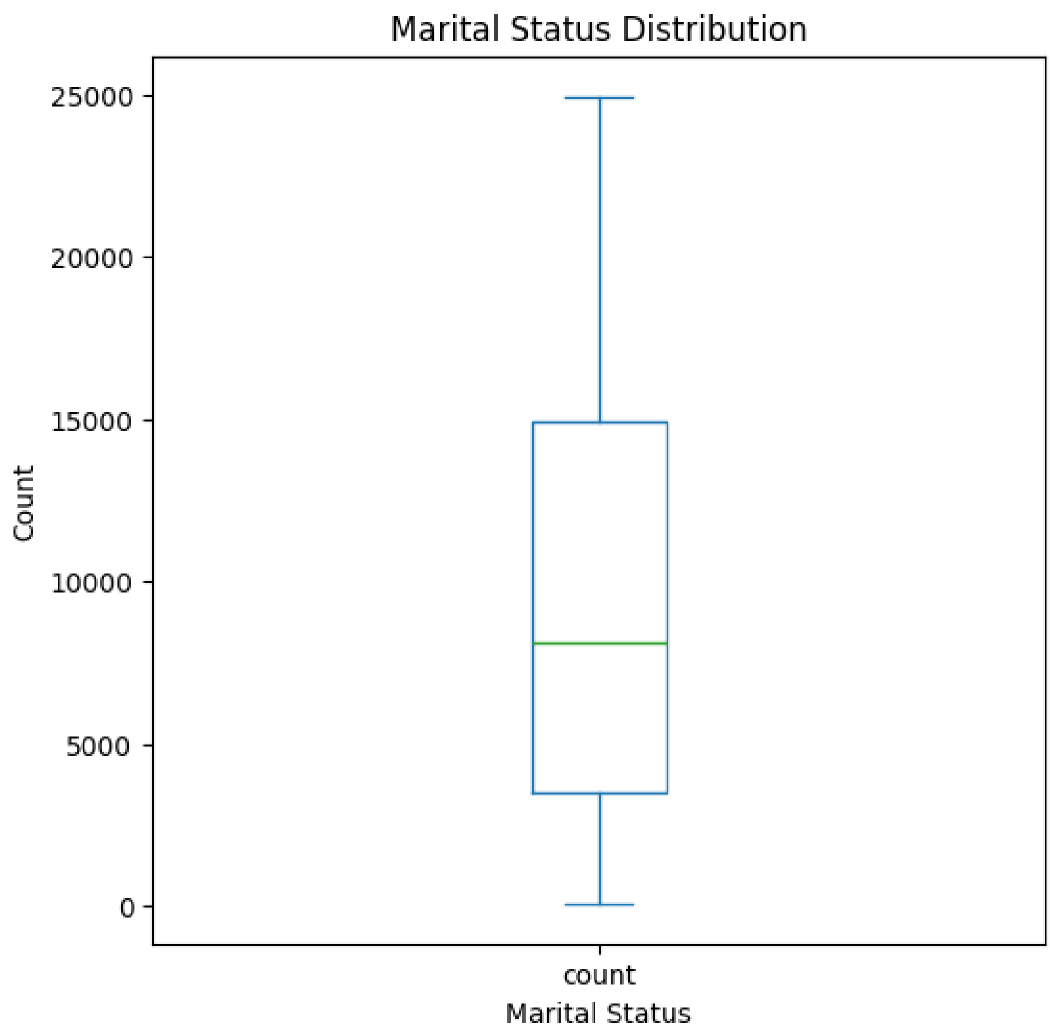
Marital Status Plot:

[20]:
```
plt.figure(figsize = (6,6))

Dataset["marital"].value_counts().plot(kind="box")

plt.xlabel("Marital Status")
plt.ylabel("Count")
plt.title("Marital Status Distribution")

plt.show()
```



Pairplot:

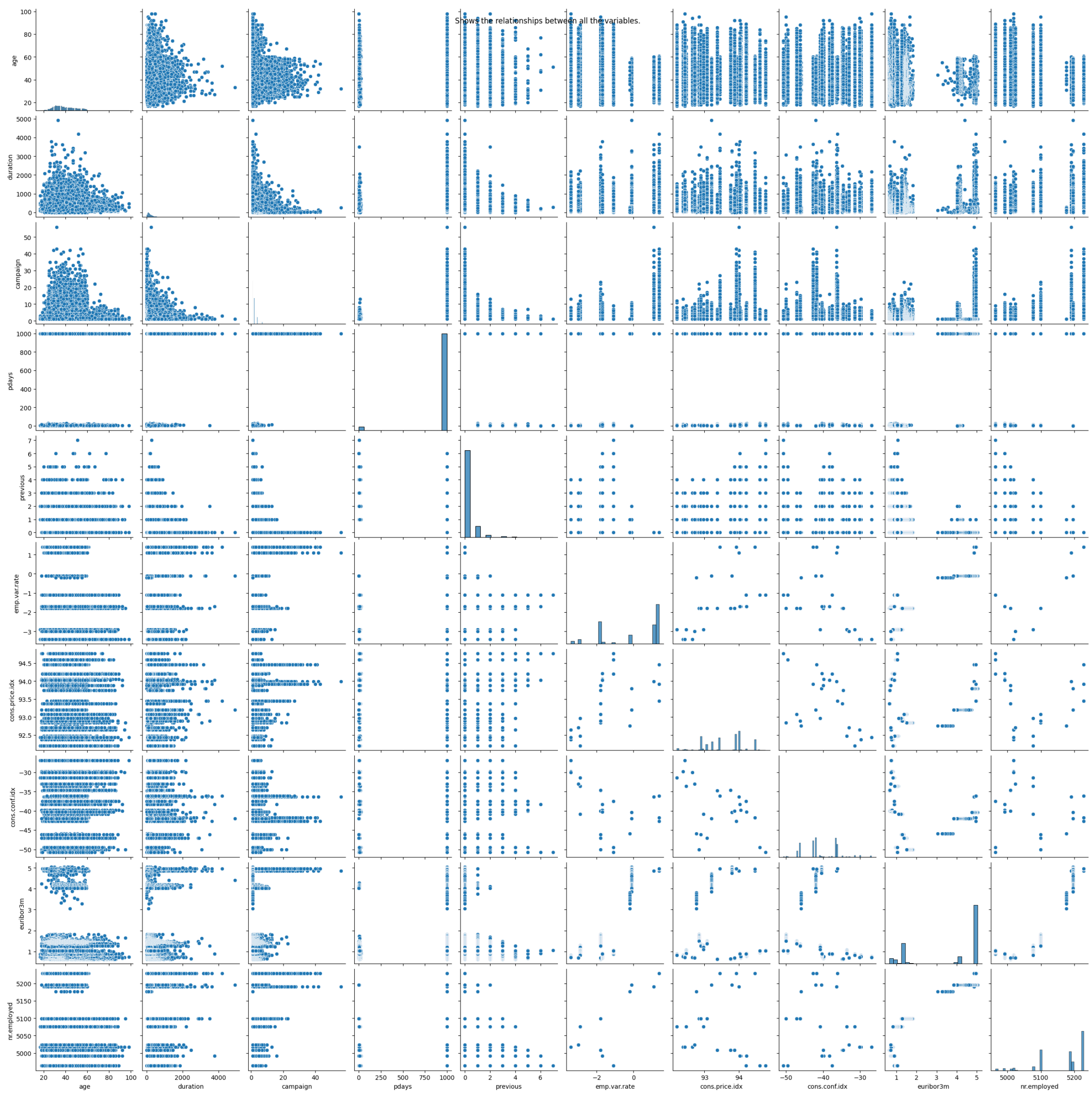
[21]:
```
plt.figure(figsize=(6,6))

sns.pairplot(Dataset)

plt.suptitle("Shows the relationships between all the variables.")

plt.show()
```

```
<Figure size 600x600 with 0 Axes>
```



Analyze the results to identify which customer groups are likely to accept the offer.

Acceptance Rate by Job:

[22]:
```python
pd.crosstab(Dataset["job"], Dataset["y"], normalize="index") * 100
```

[22]:
```
y                    no        yes
job
admin.        87.027442  12.972558
blue-collar   93.105684   6.894316
entrepreneur  91.483516   8.516484
housemaid     90.000000  10.000000
management    88.782490  11.217510
retired       74.767442  25.232558
```

```
self-employed  89.514426  10.485574
services       91.861930   8.138070
student        68.571429  31.428571
technician     89.173958  10.826042
unemployed     85.798817  14.201183
unknown        88.787879  11.212121
```

Acceptance Rate by Marital Status:

[23]:
```
pd.crosstab(Dataset["marital"], Dataset["y"], normalize="index") * 100
```

[23]:
```
y                no        yes
marital
divorced  89.679098  10.320902
married   89.842747  10.157253
single    85.995851  14.004149
unknown   85.000000  15.000000
```

Acceptance Rate by Age Groups:

[24]:
```
Dataset["age_group"] = pd.cut(Dataset["age"], bins=[18,30,40,50,60,100])

pd.crosstab(Dataset["age_group"], Dataset["y"], normalize="index") * 100
```

[24]:
```
y                 no        yes
age_group
(18, 30]   84.897959  15.102041
(30, 40]   90.253280   9.746720
(40, 50]   91.826172   8.173828
(50, 60]   89.346093  10.653907
(60, 100]  54.505495  45.494505
```

Handle Missing Values:

[25]:
```
Dataset.isnull().sum()
```

[25]:
```
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
age_group        33
dtype: int64
```

[26]:
```python
Dataset = pd.get_dummies(Dataset, drop_first=True)
```

[27]:
```python
Dataset.head()
```

[27]:
```
   age  duration  campaign  pdays  previous  emp.var.rate  cons.price.idx  \
0   56       261         1    999         0           1.1          93.994
1   57       149         1    999         0           1.1          93.994
2   37       226         1    999         0           1.1          93.994
3   40       151         1    999         0           1.1          93.994
4   56       307         1    999         0           1.1          93.994

   cons.conf.idx  euribor3m  nr.employed  …  day_of_week_thu  \
0          -36.4      4.857       5191.0  …            False
1          -36.4      4.857       5191.0  …            False
2          -36.4      4.857       5191.0  …            False
3          -36.4      4.857       5191.0  …            False
4          -36.4      4.857       5191.0  …            False

   day_of_week_tue  day_of_week_wed  poutcome_nonexistent  poutcome_success  \
0            False            False                  True             False
1            False            False                  True             False
2            False            False                  True             False
3            False            False                  True             False
4            False            False                  True             False

   y_yes  age_group_(30, 40]  age_group_(40, 50]  age_group_(50, 60]  \
0  False               False               False                True
1  False               False               False                True
2  False                True               False               False
3  False                True               False               False
4  False               False               False                True

   age_group_(60, 100]
0                False
1                False
```

```
2                 False
3                 False
4                 False

[5 rows x 58 columns]
```

Train a Logistic Regression and Decision Tree Classifier.

Logestic Regression:

[28]:
```python
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier

from sklearn.metrics import accuracy_score, confusion_matrix
```

[29]:
```python
x = Dataset.drop("y_yes", axis=1)
y = Dataset["y_yes"]
```

[30]:
```python
x = pd.get_dummies(x, drop_first=True)
```

[31]:
```python
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2,␣
↪random_state=42)
```

[32]:
```python
print("Training Data:", x_train.shape)
print("Testing Data:", x_test.shape)
```

```
Training Data: (32950, 57)
Testing Data: (8238, 57)
```

[33]:
```python
logistic_model = LogisticRegression(max_iter=1000)
logistic_model.fit(x_train, y_train)

y_predict_logistic = logistic_model.predict(x_test)
```

```
c:\Users\zaigh\AppData\Local\Programs\Python\Python313\Lib\site-
packages\sklearn\linear_model\_logistic.py:469: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

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

[34]:
```python
model = LogisticRegression()
model.fit(x_train, y_train)
```

```
c:\Users\zaigh\AppData\Local\Programs\Python\Python313\Lib\site-
packages\sklearn\linear_model\_logistic.py:469: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

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

[34]:
```
LogisticRegression()
```

Evaluate the model using the accuracy and confusion matrix.

[35]:
```python
print("Logistic Regression Accuracy: \n",
      accuracy_score(y_test, y_predict_logistic))

print("Confusion Matrix: \n",
      confusion_matrix(y_test, y_predict_logistic))
```

```
Logistic Regression Accuracy:
 0.9107793153678078
Confusion Matrix:
 [[7106  197]
 [ 538  397]]
```

[36]:
```python
cm = confusion_matrix(y_test, y_predict_logistic)
TN, FP, FN, TP = cm.ravel()

# Create a Structured Table.
metrics_table = pd.DataFrame({
    'Metric': ['TP', 'TN', 'FP', 'FN', 'Accuracy', 'Precision', 'Recall'],
    'Value': [TP, TN, FP, FN,
              (TP+TN)/(TP+TN+FP+FN),
              TP/(TP+FP),
              TP/(TP+FN)]})

print(metrics_table)
```

```
      Metric        Value
0         TP   397.000000
1         TN  7106.000000
2         FP   197.000000
```

```
3          FN   538.000000
4    Accuracy     0.910779
5   Precision     0.668350
6      Recall     0.424599
```

Decision Tree:

[37]:
```python
decisionTree_model = DecisionTreeClassifier(random_state=42)

decisionTree_model.fit(x_train, y_train)

y_predict_decisionTree = decisionTree_model.predict(x_test)
```

Evaluate the model using the accuracy and confusion matrix.

[38]:
```python
print("Decision Tree Accuracy: \n",
      accuracy_score(y_test, y_predict_decisionTree))

print("Confusion Matrix: \n",
      confusion_matrix(y_test, y_predict_decisionTree))
```

```
Decision Tree Accuracy:
 0.8869871327992231
Confusion Matrix:
 [[6816  487]
 [ 444  491]]
```

[39]:
```python
cm = confusion_matrix(y_test, y_predict_decisionTree)
TN, FP, FN, TP = cm.ravel()

# Create a Structured Table.
metrics_table = pd.DataFrame({
    'Metric': ['TP', 'TN', 'FP', 'FN', 'Accuracy', 'Precision', 'Recall'],
    'Value': [TP, TN, FP, FN,
              (TP+TN)/(TP+TN+FP+FN),
              TP/(TP+FP),
              TP/(TP+FN)]})
print(metrics_table)
```

```
      Metric        Value
0          TP   491.000000
1          TN  6816.000000
2          FP   487.000000
3          FN   444.000000
4    Accuracy     0.886987
5   Precision     0.502045
6      Recall     0.525134
```

Skills: Data exploratiion and visulization. Classification modeling. Business insights extraction from the data.

Task Completed. Best Wishes. Zaigham Abbas.