Week 10-11
Final EDA and Model Recommendation

Team Smart Banker (Data Science Specialization)

April 16, 2023

Agenda

01. Meet the Team

02. Problem Description & Business Understanding

03 Data Types and Problems in the Data

04. Approach to Eliminate Problems in the Data

05. Recommended ML Models for the Business Problem

Meet the Team

Group Name: Team Smart Banker

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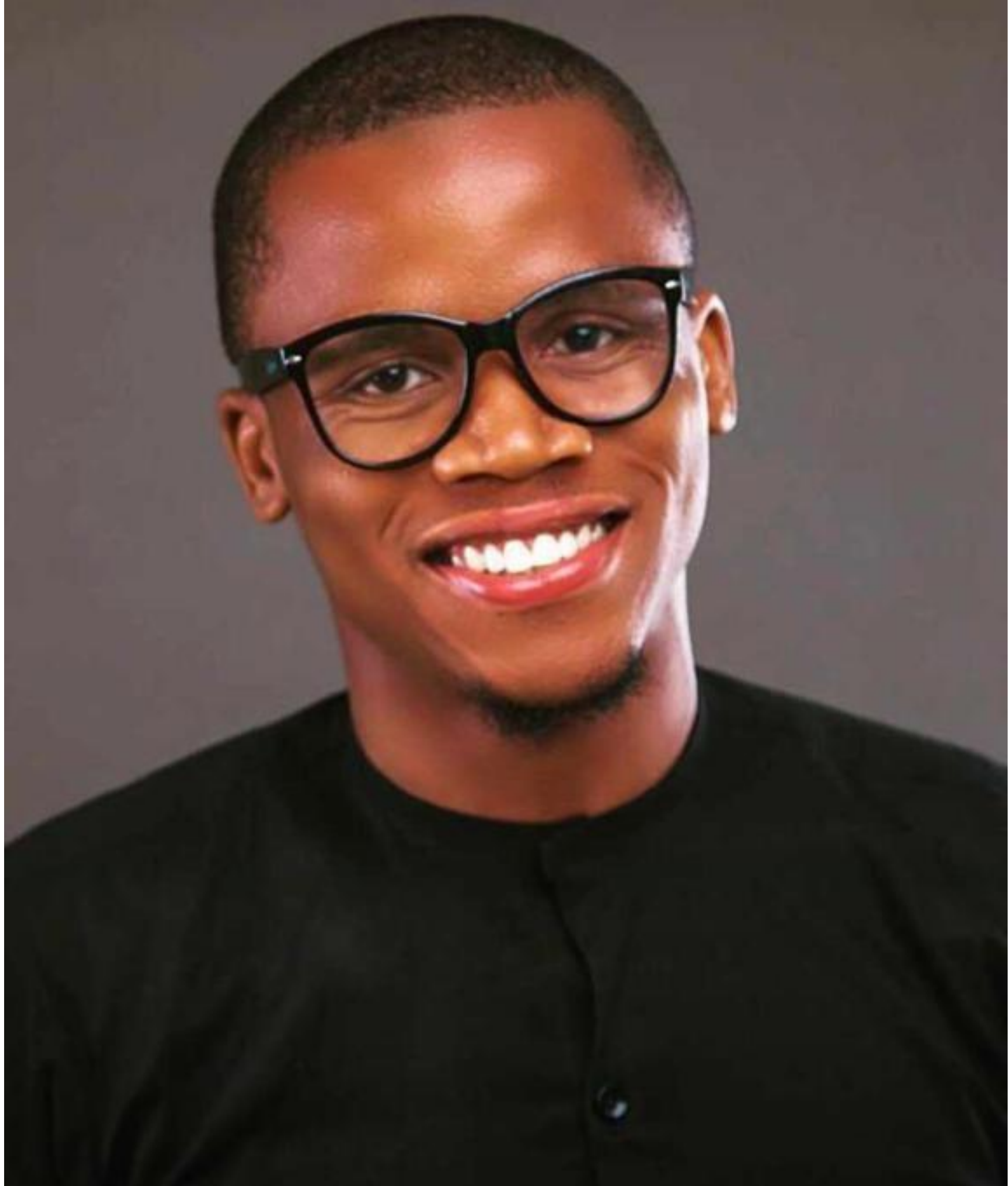
Country: United Kingdom

Specialization: Data Science



Bank Marketing Campaign

A Data Science Project

Problem Description

Objective: Predict if a client will subscribe to a term deposit offered by a bank.

Dataset: Information related to direct marketing campaigns conducted through phone calls by a Portuguese banking institution.

Goal: Build a classification model that predicts whether the client will subscribe to the term deposit or not, based on various input variables such as age, job, marital status, education, etc

Business Understanding

Importance: Success of direct marketing campaigns depends on accuracy of targeting potential customers who are more likely to purchase the offered product..

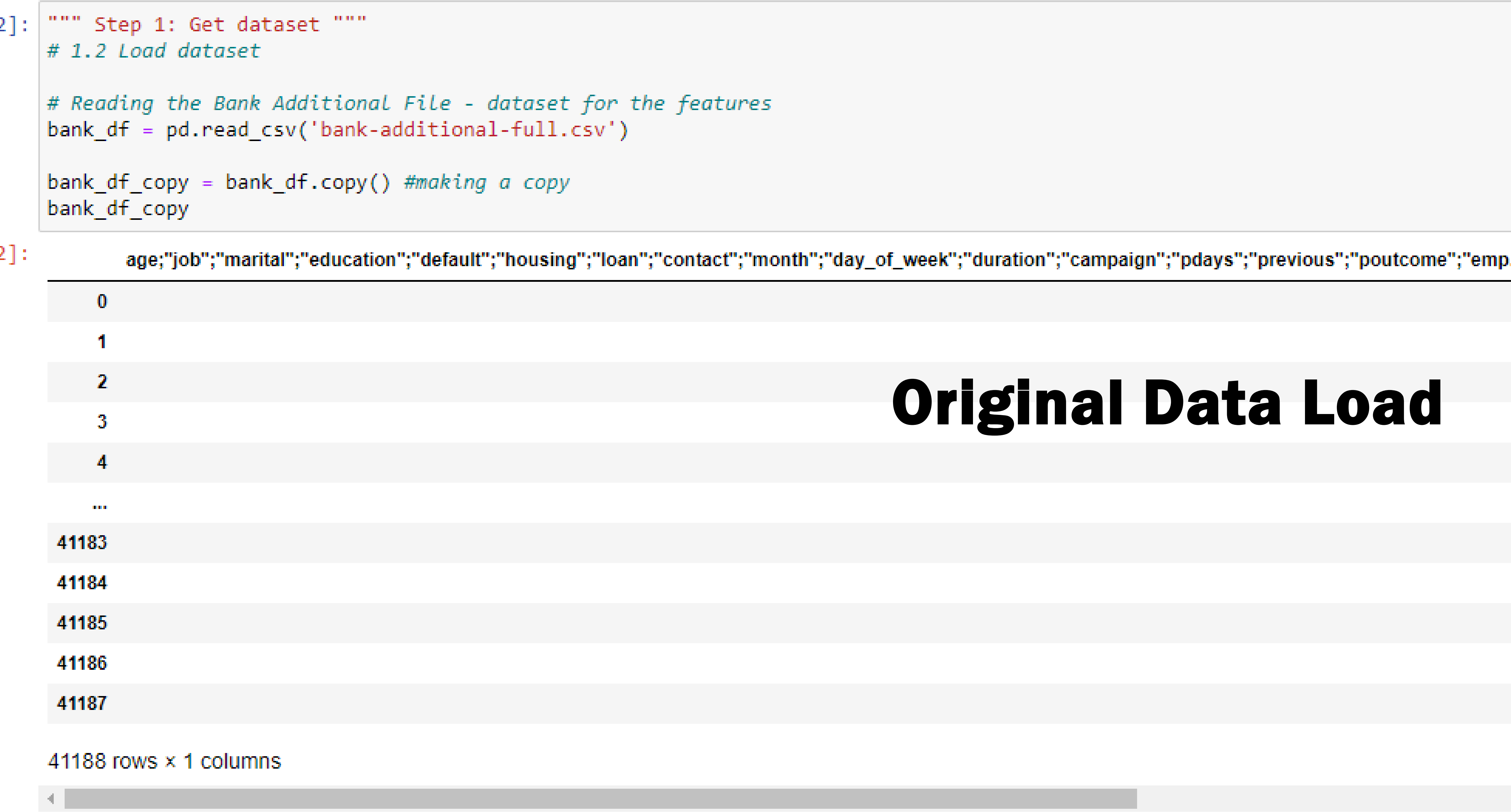
Interest: This is to help a bank identify customers who are more likely to subscribe to a term deposit to optimize their marketing strategy and increase their chances of success while minimizing their costs..

Data Types and Problems in the Data

Data Type: The data was majorly dominated by Categorical Data types – which led to most of the them being converted to viable numeric types for ease of modelling for the Classification problem..

Problem:

1. White spaces in the columns were replaced by ";" thereby making the original data to contain one column instead of 21 columns
2. Some columns were not in their appropriate data types e.g. duration, campaign etc
3. Data contained 0 missing values but 12 duplicated records
4. There were outliers across the numerical columns
5. There is imbalance in the target class, y

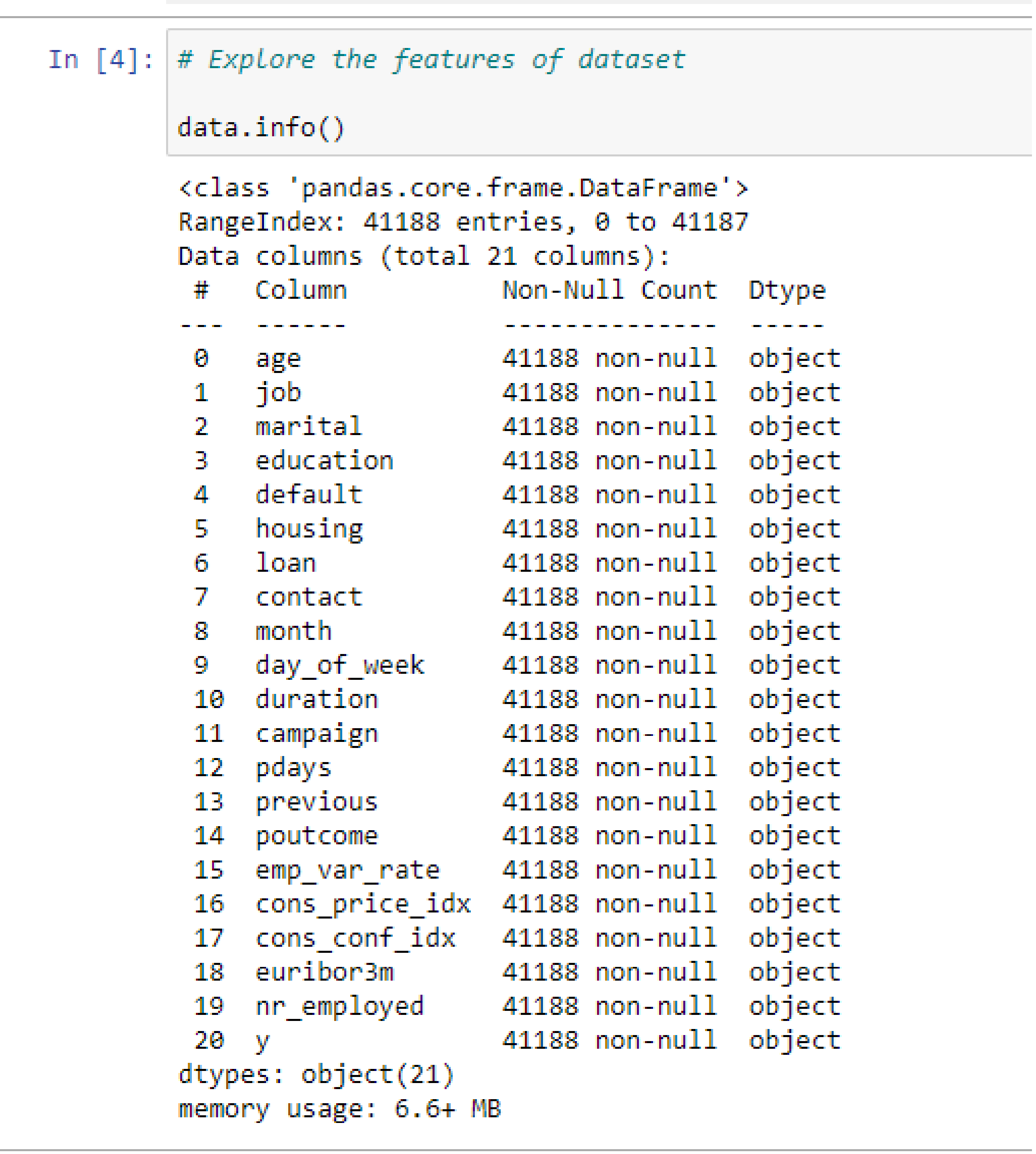


Original Data Load

```
2]: """ Step 1: Get dataset """
    # 1.2 Load dataset

    # Reading the Bank Additional File - dataset for the features
    bank_df = pd.read_csv('bank-additional-full.csv')

    bank_df_copy = bank_df.copy() #making a copy
    bank_df_copy
```

```
2]:        age;"job";"marital";"education";"default";"housing";"loan";"contact";"month";"day_of_week";"duration";"campaign";"pdays";"previous";"poutcome";"emp
        0
        1
        2
        3
        4
      ...
    41183
    41184
    41185
    41186
    41187

41188 rows × 1 columns
```

Inappropriate Datatypes

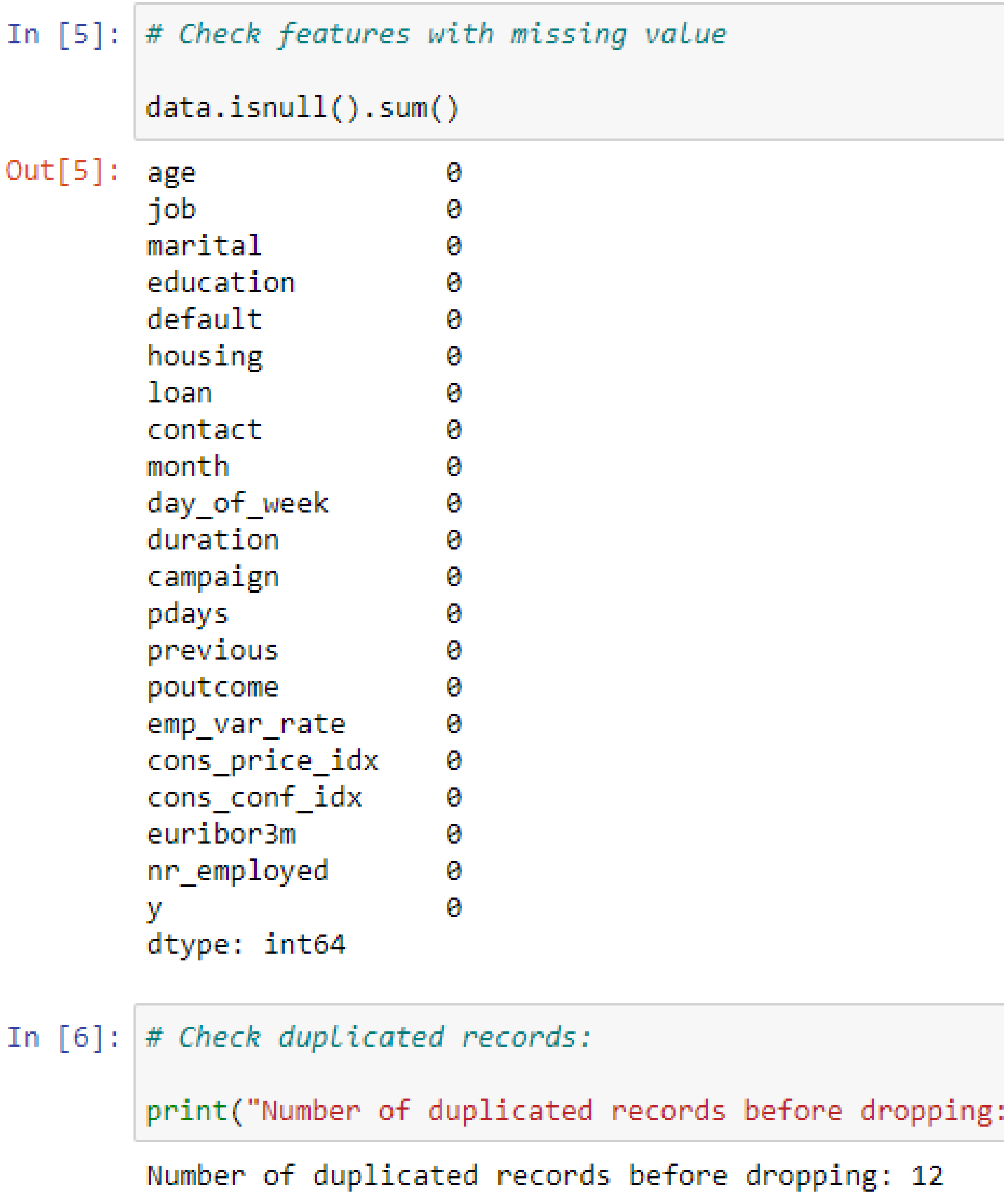


In [4]:

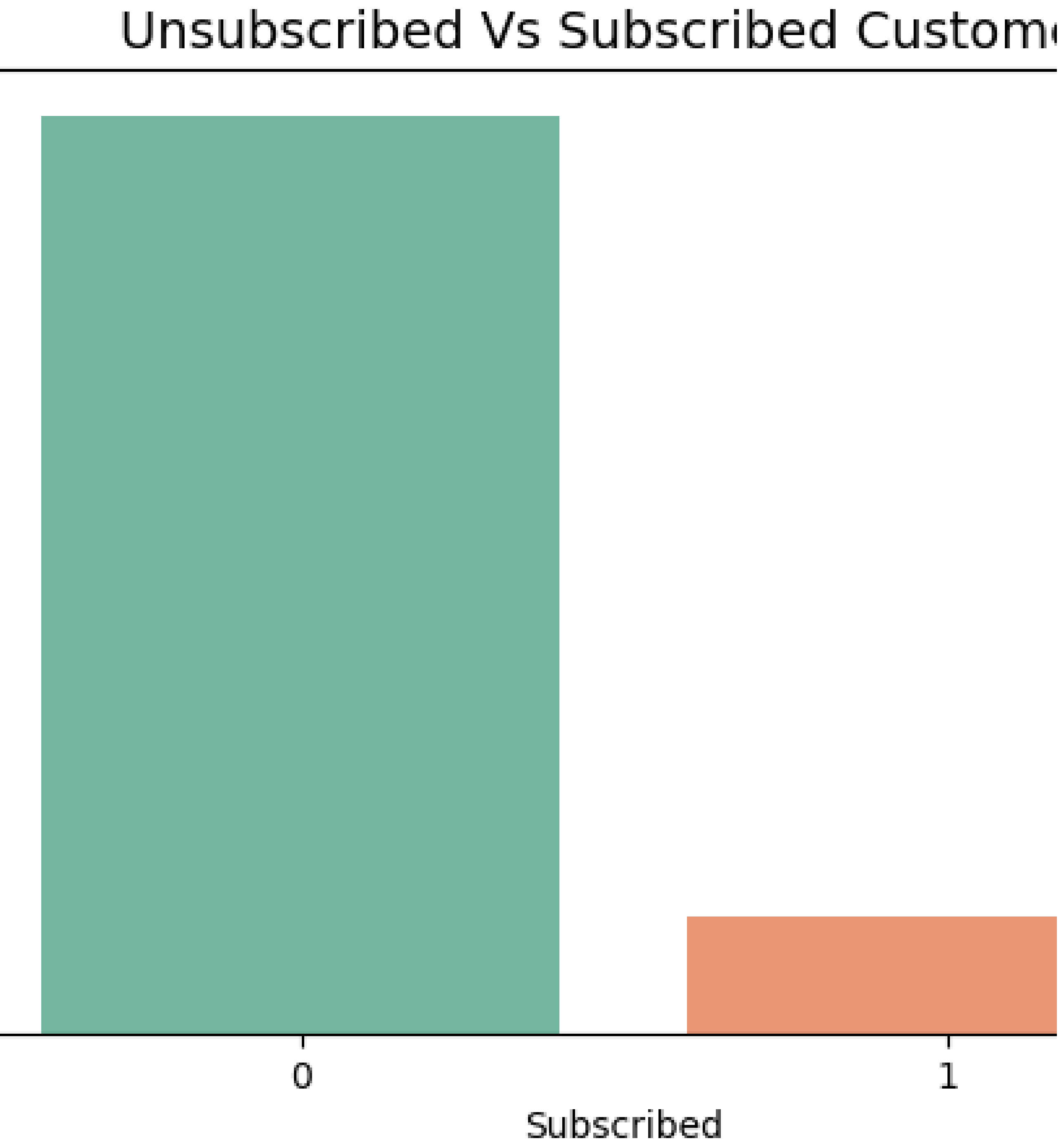
```
# Explore the features of dataset

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  object
 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  object
 11  campaign        41188 non-null  object
 12  pdays           41188 non-null  object
 13  previous        41188 non-null  object
 14  poutcome        41188 non-null  object
 15  emp_var_rate    41188 non-null  object
 16  cons_price_idx  41188 non-null  object
 17  cons_conf_idx   41188 non-null  object
 18  euribor3m       41188 non-null  object
 19  nr_employed     41188 non-null  object
 20  y               41188 non-null  object
dtypes: object(21)
memory usage: 6.6+ MB
```

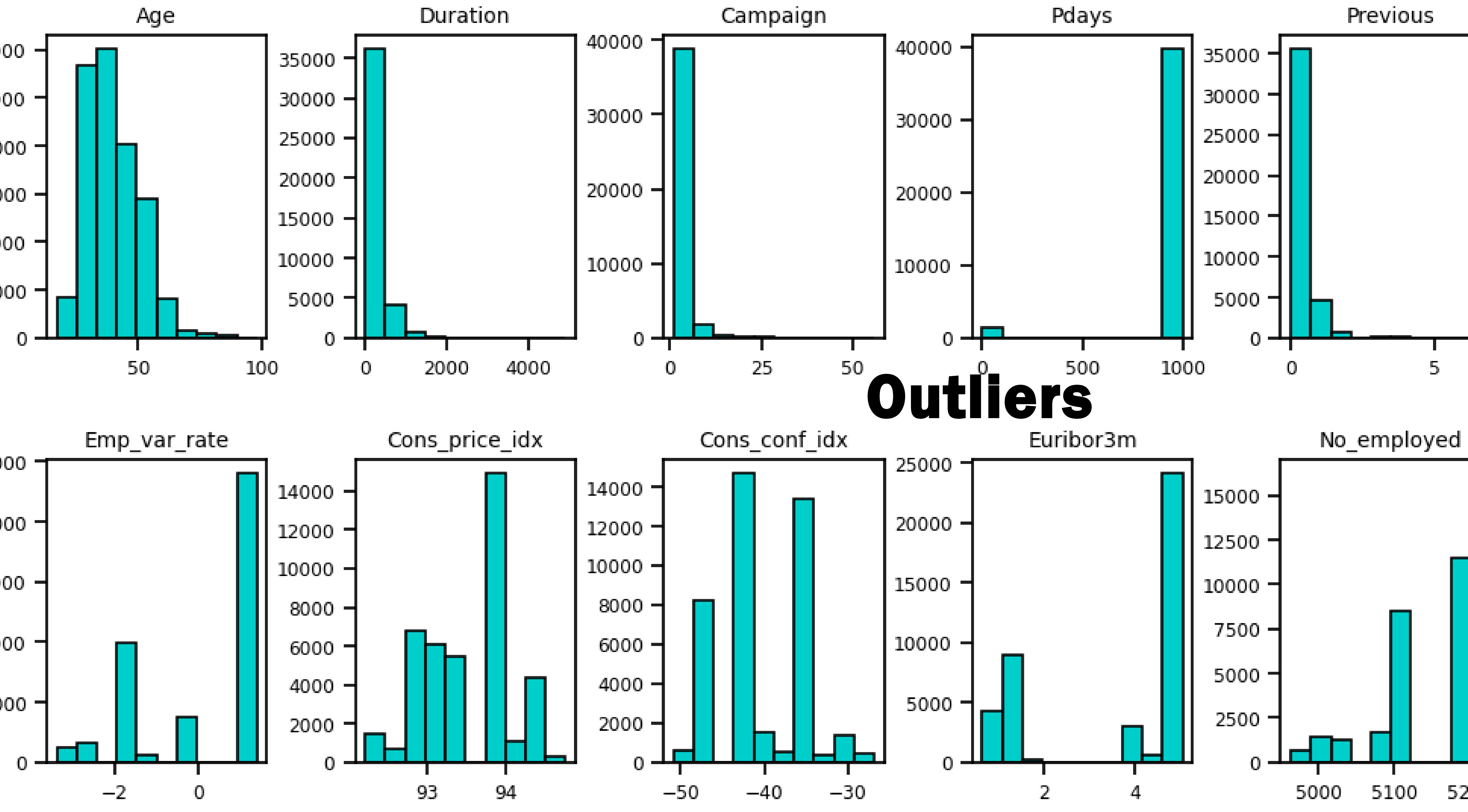
Missing & Duplicated Records



```
In [5]: # Check features with missing value

        data.isnull().sum()

Out[5]: 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 [6]: # Check duplicated records:

        print("Number of duplicated records before dropping:

        Number of duplicated records before dropping: 12
```



Imbalanced Target Class


Age
Duration
Campaign
Pdays
Previous
0
50
100
0
5000
10000
15000
20000
25000
30000
35000
0
2000
4000
0
10000
20000
30000
40000
0
25
50
0
10000
20000
30000
40000
0
500
1000
0
5000
10000
15000
20000
25000
30000
35000
0
5
Emp_var_rate
Cons_price_idx
Cons_conf_idx
Euribor3m
No_employed
0
−2
0
0
2000
4000
6000
8000
10000
12000
14000
93
94
0
2000
4000
6000
8000
10000
12000
14000
−50
−40
−30
0
5000
10000
15000
20000
25000
2
4
0
2500
5000
7500
10000
12500
15000
5000
5100
52

Outliers

Approach to Eliminate Problems in the Data

1. Split the columns using the delimiter, semicolon (;) and removed the double the quotes (“”)

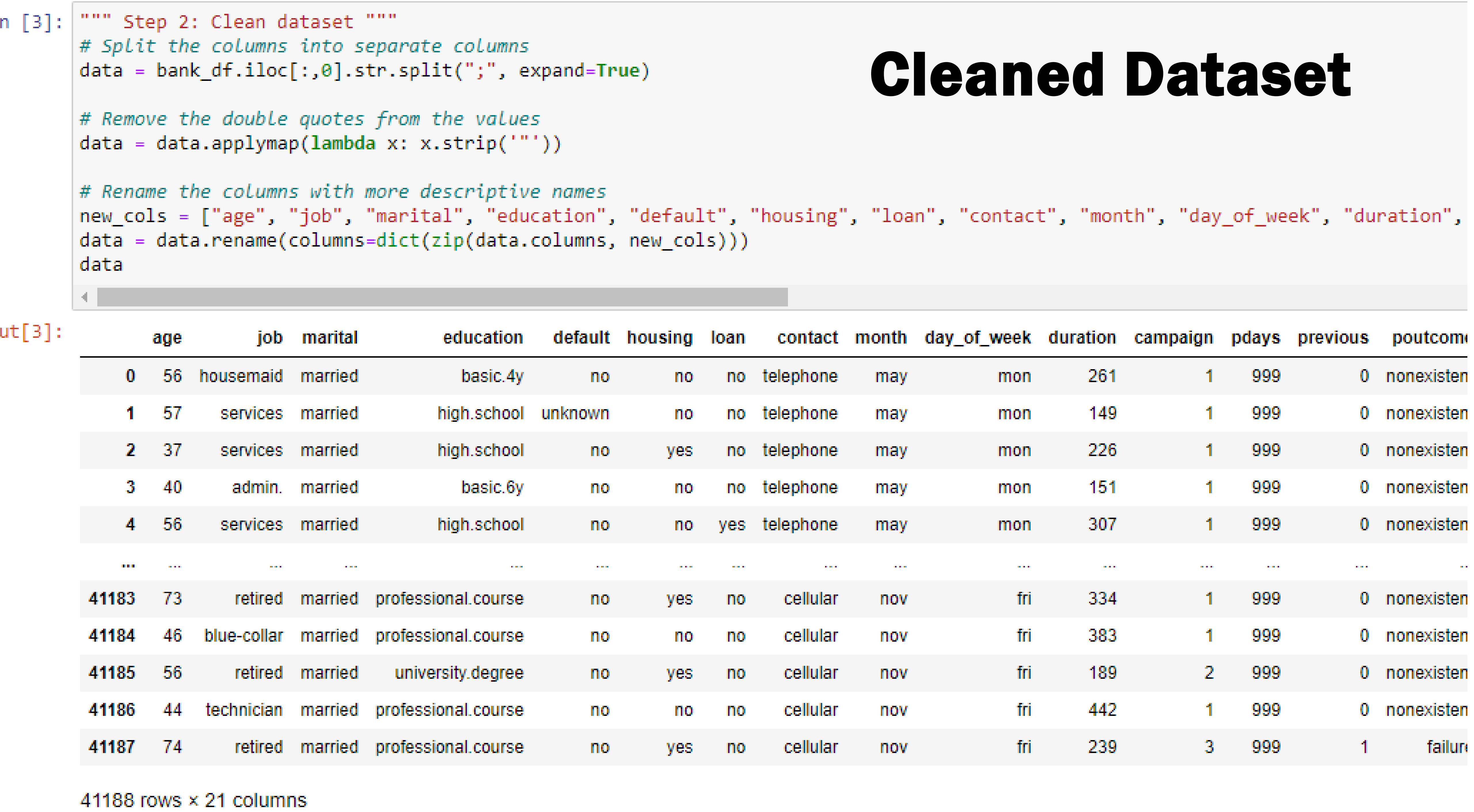
2. Use methods from Pandas library to convert to appropriate datatypes e.g pd.to_numeric()

3. Dropped duplicated rows

4. Use StandardScalar() from sklearn package to limit the effects of the outliers

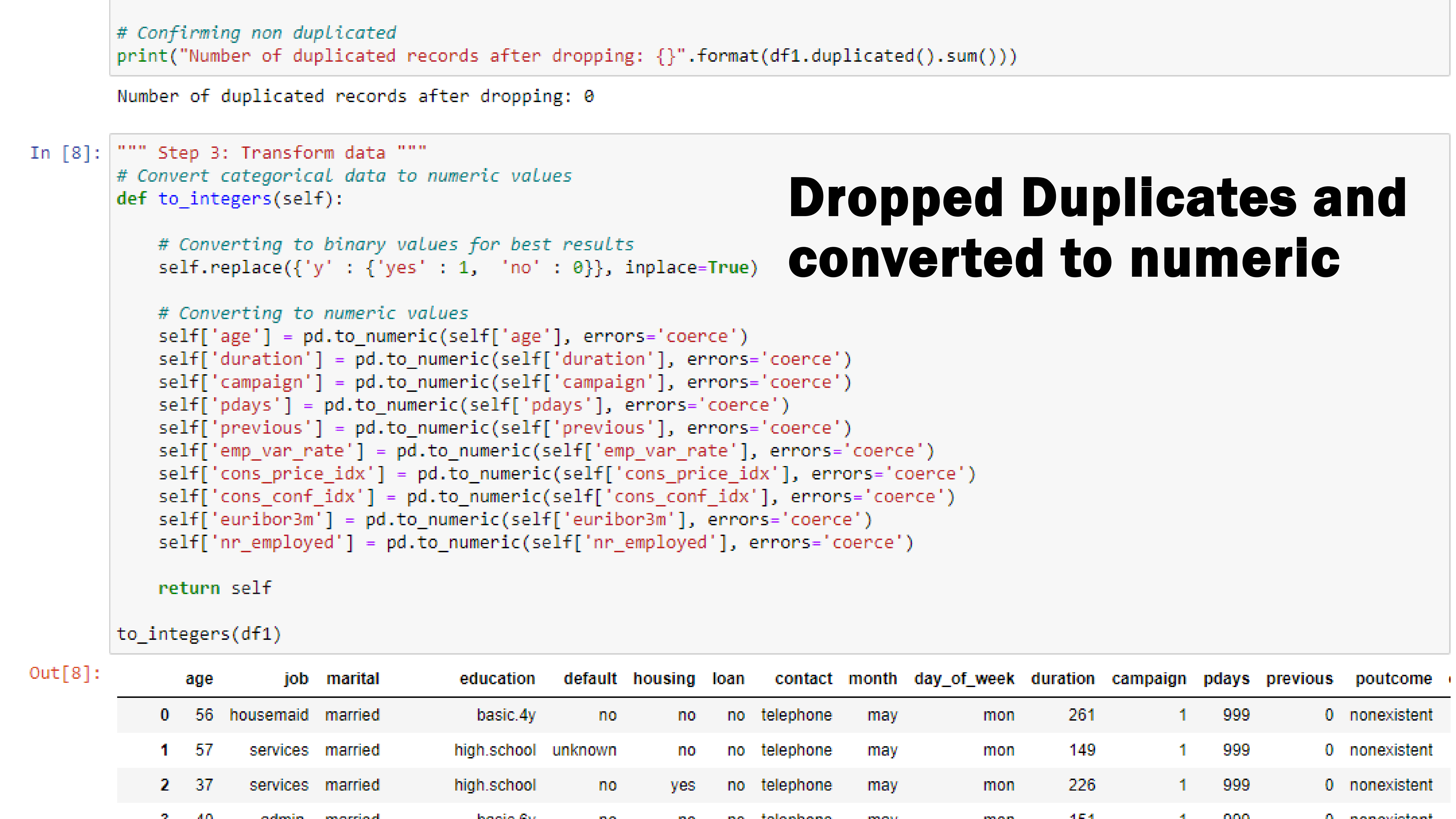
5. Use smote() oversampling technique from imblearn package to handle the imbalance so as not to lose possible data for the training and testing

Cleaned Dataset



```
n [3]:  """ Step 2: Clean dataset """
        # Split the columns into separate columns
        data = bank_df.iloc[:,0].str.split(";", expand=True)

        # Remove the double quotes from the values
        data = data.applymap(lambda x: x.strip('"'))

        # Rename the columns with more descriptive names
        new_cols = ["age", "job", "marital", "education", "default", "housing", "loan", "contact", "month", "day_of_week", "duration",
        data = data.rename(columns=dict(zip(data.columns, new_cols)))
        data
```

```
ut[3]:
         age          job  marital            education  default  housing  loan    contact  month  day_of_week  duration  campaign  pdays  previous    poutcom
     0    56    housemaid  married             basic.4y       no       no    no  telephone    may          mon       261         1    999         0  nonexisten
     1    57     services  married          high.school  unknown       no    no  telephone    may          mon       149         1    999         0  nonexisten
     2    37     services  married          high.school       no      yes    no  telephone    may          mon       226         1    999         0  nonexisten
     3    40       admin.  married             basic.6y       no       no    no  telephone    may          mon       151         1    999         0  nonexisten
     4    56     services  married          high.school       no       no   yes  telephone    may          mon       307         1    999         0  nonexisten
   ...   ...          ...      ...                  ...      ...      ...   ...        ...    ...          ...       ...       ...    ...       ...         ...
 41183    73      retired  married  professional.course       no      yes    no   cellular    nov          fri       334         1    999         0  nonexisten
 41184    46  blue-collar  married  professional.course       no       no    no   cellular    nov          fri       383         1    999         0  nonexisten
 41185    56      retired  married    university.degree       no      yes    no   cellular    nov          fri       189         2    999         0  nonexisten
 41186    44   technician  married  professional.course       no       no    no   cellular    nov          fri       442         1    999         0  nonexisten
 41187    74      retired  married  professional.course       no      yes    no   cellular    nov          fri       239         3    999         1       failur

41188 rows × 21 columns
```



Dropped Duplicates and converted to numeric

```
# Confirming non duplicated
print("Number of duplicated records after dropping: {}".format(df1.duplicated().sum()))
```

```
Number of duplicated records after dropping: 0
```

In [8]:

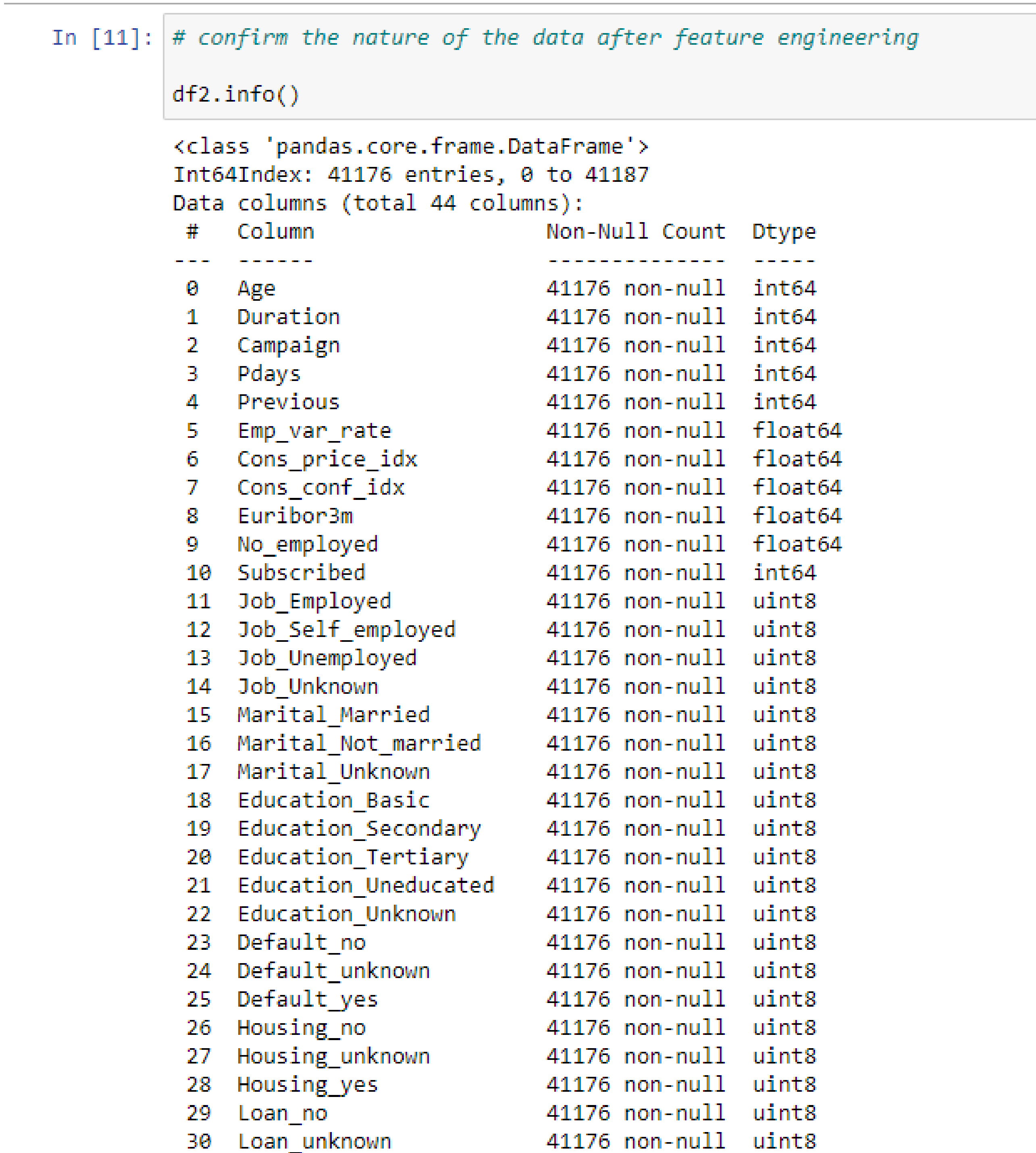
```
""" Step 3: Transform data """
# Convert categorical data to numeric values
def to_integers(self):

    # Converting to binary values for best results
    self.replace({'y' : {'yes' : 1,  'no' : 0}}, inplace=True)

    # Converting to numeric values
    self['age'] = pd.to_numeric(self['age'], errors='coerce')
    self['duration'] = pd.to_numeric(self['duration'], errors='coerce')
    self['campaign'] = pd.to_numeric(self['campaign'], errors='coerce')
    self['pdays'] = pd.to_numeric(self['pdays'], errors='coerce')
    self['previous'] = pd.to_numeric(self['previous'], errors='coerce')
    self['emp_var_rate'] = pd.to_numeric(self['emp_var_rate'], errors='coerce')
    self['cons_price_idx'] = pd.to_numeric(self['cons_price_idx'], errors='coerce')
    self['cons_conf_idx'] = pd.to_numeric(self['cons_conf_idx'], errors='coerce')
    self['euribor3m'] = pd.to_numeric(self['euribor3m'], errors='coerce')
    self['nr_employed'] = pd.to_numeric(self['nr_employed'], errors='coerce')

    return self

to_integers(df1)
```

Out[8]:

	age	job	marital	education	default	housing	loan	contact	month	day_of_week	duration	campaign	pdays	previous	poutcome
0	56	housemaid	married	basic.4y	no	no	no	telephone	may	mon	261	1	999	0	nonexistent
1	57	services	married	high.school	unknown	no	no	telephone	may	mon	149	1	999	0	nonexistent
2	37	services	married	high.school	no	yes	no	telephone	may	mon	226	1	999	0	nonexistent
3	40	admin.	married	basic.6y	no	no	no	telephone	may	mon	151	1	999	0	nonexistent

After Transformation

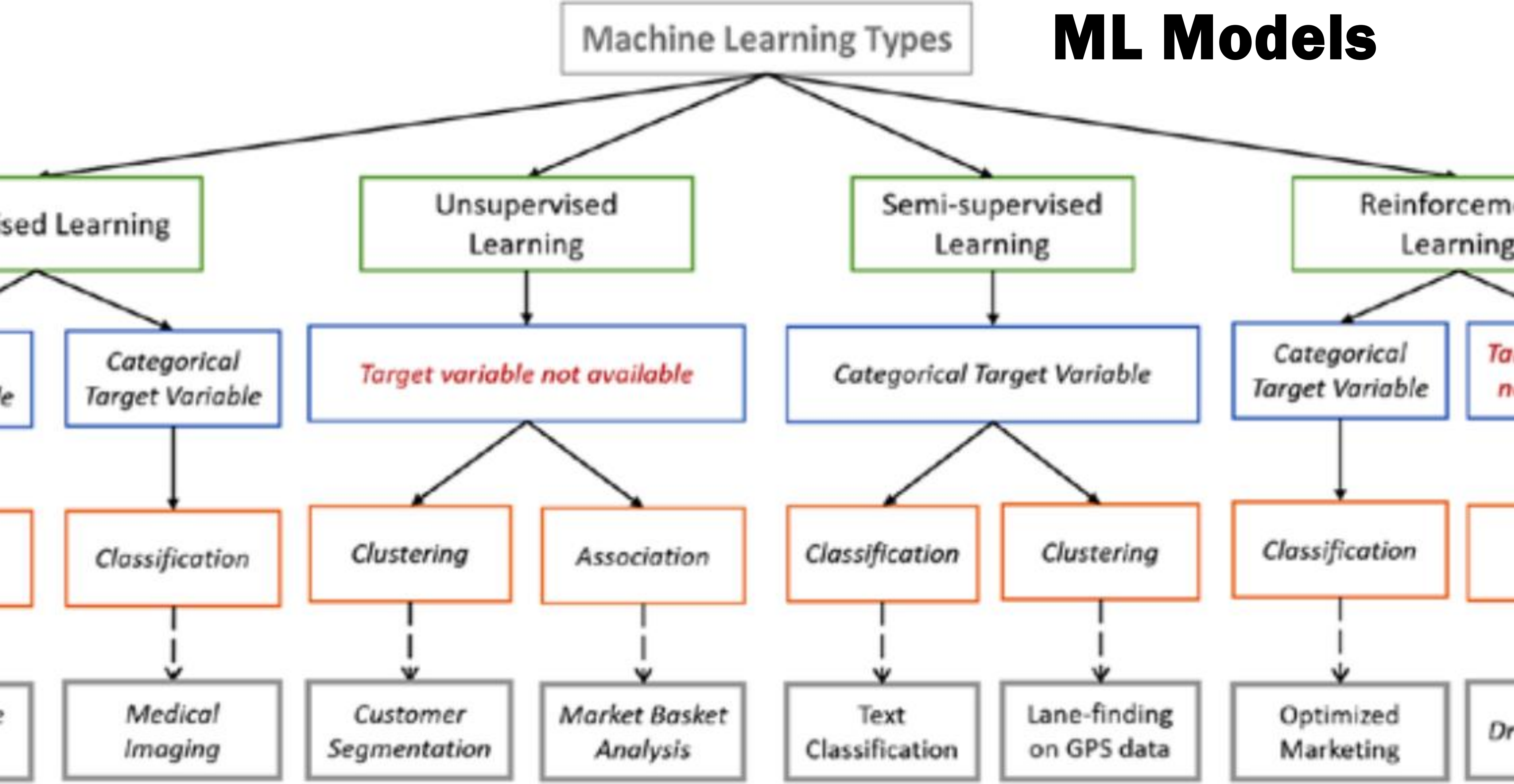
- Cleaned the jam-packed columns into distinct columns
- Removed duplicates
- Converted wrong object datatypes to appropriate numerical types
- Created a function to label encode and further applied one-hot encoding using pd.get_dummies to put the categories into 1's and 0's in order to avoid biases
- Note: The increased number of columns will be tackled with dimensionality reduction strategy like PCA



```
In [11]: # confirm the nature of the data after feature engineering

         df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 41176 entries, 0 to 41187
Data columns (total 44 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   Age                   41176 non-null  int64  
 1   Duration              41176 non-null  int64  
 2   Campaign              41176 non-null  int64  
 3   Pdays                 41176 non-null  int64  
 4   Previous              41176 non-null  int64  
 5   Emp_var_rate          41176 non-null  float64
 6   Cons_price_idx        41176 non-null  float64
 7   Cons_conf_idx         41176 non-null  float64
 8   Euribor3m             41176 non-null  float64
 9   No_employed           41176 non-null  float64
 10  Subscribed            41176 non-null  int64  
 11  Job_Employed          41176 non-null  uint8  
 12  Job_Self_employed     41176 non-null  uint8  
 13  Job_Unemployed        41176 non-null  uint8  
 14  Job_Unknown           41176 non-null  uint8  
 15  Marital_Married       41176 non-null  uint8  
 16  Marital_Not_married   41176 non-null  uint8  
 17  Marital_Unknown       41176 non-null  uint8  
 18  Education_Basic       41176 non-null  uint8  
 19  Education_Secondary   41176 non-null  uint8  
 20  Education_Tertiary    41176 non-null  uint8  
 21  Education_Uneducated  41176 non-null  uint8  
 22  Education_Unknown     41176 non-null  uint8  
 23  Default_no            41176 non-null  uint8  
 24  Default_unknown       41176 non-null  uint8  
 25  Default_yes           41176 non-null  uint8  
 26  Housing_no            41176 non-null  uint8  
 27  Housing_unknown       41176 non-null  uint8  
 28  Housing_yes           41176 non-null  uint8  
 29  Loan_no               41176 non-null  uint8  
 30  Loan_unknown          41176 non-null  uint8  
```

ML Models



Machine Learning Types
sed Learning
Unsupervised Learning
Semi-supervised Learning
Reinforcem
Learning
e
Categorical Target Variable
Target variable not available
Categorical Target Variable
Categorical Target Variable
Ta
n
Classification
Clustering
Association
Classification
Clustering
Classification
e
Medical Imaging
Customer Segmentation
Market Basket Analysis
Text Classification
Lane-finding on GPS data
Optimized Marketing
Dr

ML Model Recommendations for this Dataset

1. Logistics Regression – Linear

2. K-Nearest Neighbour Classifier – Non-parametric

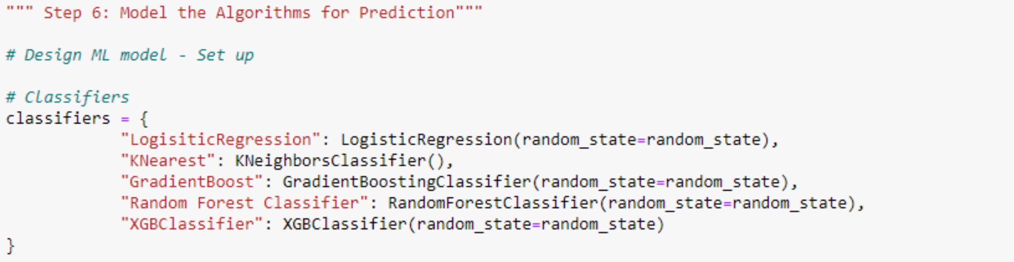
3. Random Forest Classifier - Bagging Ensemble

4. Gradient Boost Classifier - Boosting Ensemble

5. XGBoost Classifier - Boosting Ensemble

6. Neural Networks (Keras) for Deep Learning - Non-linear

Why Choose them?

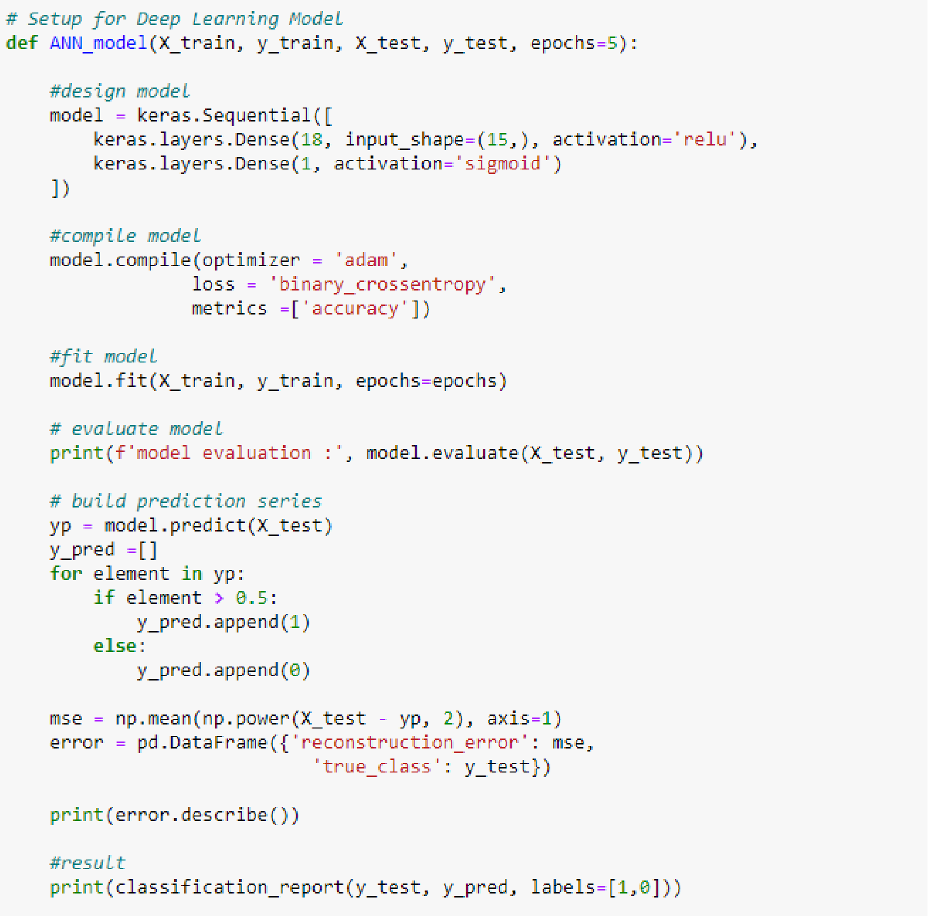


```
""" Step 6: Model the Algorithms for Prediction"""

# Design ML model - Set up

# Classifiers
classifiers = {
            "LogisiticRegression": LogisticRegression(random_state=random_state),
            "KNearest": KNeighborsClassifier(),
            "GradientBoost": GradientBoostingClassifier(random_state=random_state),
            "Random Forest Classifier": RandomForestClassifier(random_state=random_state),
            "XGBClassifier": XGBClassifier(random_state=random_state)
}
```

- Logistics Regression: Linear model. Logistic regression is commonly used in classification problems because it provides a probabilistic interpretation of the outputs, allowing for easy thresholding for binary classification tasks. It can also handle imbalanced classes by adjusting the threshold for classification.

- Gradient Boost Classifier: Ensemble model. Gradient boosting is a technique that combines multiple weak learners to create a strong learner. It can handle imbalanced data because it can assign more weight to the minority class during the boosting process

- Neural Networks (Keras) for Deep Learning: Non-linear model. Neural networks are powerful models that can learn complex patterns in data. They can handle imbalanced data through techniques such as class weighting, oversampling of the minority class, and the use of specialized loss functions



```
# Setup for Deep Learning Model
def ANN_model(X_train, y_train, X_test, y_test, epochs=5):

    #design model
    model = keras.Sequential([
        keras.layers.Dense(18, input_shape=(15,), activation='relu'),
        keras.layers.Dense(1, activation='sigmoid')
    ])

    #compile model
    model.compile(optimizer = 'adam',
                  loss = 'binary_crossentropy',
                  metrics =['accuracy'])

    #fit model
    model.fit(X_train, y_train, epochs=epochs)

    # evaluate model
    print(f'model evaluation :', model.evaluate(X_test, y_test))

    # build prediction series
    yp = model.predict(X_test)
    y_pred =[]
    for element in yp:
        if element > 0.5:
            y_pred.append(1)
        else:
            y_pred.append(0)

    mse = np.mean(np.power(X_test - yp, 2), axis=1)
    error = pd.DataFrame({'reconstruction_error': mse,
                          'true_class': y_test})

    print(error.describe())

    #result
    print(classification_report(y_test, y_pred, labels=[1,0]))
```

Project Timeline

Wk1. 19 Mar – 26 Mar 2023

Data Collection: Download the dataset from the given source and load it into a Jupyter notebook.

Data Exploration: Perform preliminary data exploration to understand the dataset's structure, quality, and potential challenges.

Wk2. 26 Mar – 2 Apr 2023

Data Preparation: Prepare the dataset for modeling by performing data cleaning, feature selection, feature engineering, and data transformation as necessary.

Modeling: Train different classification models on the prepared dataset and evaluate their performance using appropriate metrics.

Wk3. 2 Apr – 9 Apr 2023

Model Tuning: Tune the hyperparameters of the best-performing model to improve its performance further.

Model Interpretation: Interpret the trained model and identify the most significant factors that contribute to the prediction.

Wk4. 9 Apr – 16 Apr 2023

Finalize the project report: Create a comprehensive report documenting the entire project, including problem definition, methodology, results, and interpretation.

Submission: Submit the final report within 2 weeks by April 28, 2023, as per the given deadline..

Thank you

Thanks for going through this interesting journey with us.

We hope we have added value to this work.

GitHub Link

https://github.com/Jeks042/Data-Science-Projects