Responsible AI

Project Description

A large bank has asked us to evaluate the marketing algorithms they use for retail banking. Their sophisticated phone marketing algorithm predicts whether a certain person will subscribe to a term deposit or not. Based on that assessment, the bank then optimises its phone calling strategy. With this algorithm, the bank has been successful in predicting which clients are more likely to subscribe to their term deposits.

Management is now interested in finding out how a classification model can lead to certain decision-making processes.

Data Dictionary

Input variables:

bank client data:

1 - age (numeric)

2 - job : type of job (categorical: 'admin.','blue-collar','entrepreneur','housemaid','management','retired','self-employed','services','student','technician','unemployed','unknown')

3 - marital : marital status (categorical: 'divorced','married','single','unknown'; note: 'divorced' means divorced or widowed)

4 - education (categorical: 'basic.4y','basic.6y','basic.9y','high.school','illiterate','professional.course','university.degree','unknown')

5 - default: has credit in default? (categorical: 'no','yes','unknown')

6 - housing: has housing loan? (categorical: 'no','yes','unknown')

7 - loan: has personal loan? (categorical: 'no','yes','unknown')

related with the last contact of the current campaign:

8 - contact: contact communication type (categorical: 'cellular','telephone')

9 - month: last contact month of year (categorical: 'jan', 'feb', 'mar', ..., 'nov', 'dec')

10 - day_of_week: last contact day of the week (categorical: 'mon','tue','wed','thu','fri')

11 - duration: last contact duration, in seconds (numeric). Important note: this attribute highly affects the output target (e.g., if duration=0 then y='no'). Yet, the duration is not known before a call is performed. Also, after the end of the call y is obviously known. Thus, this input should only be included for benchmark purposes and should be discarded if the intention is to have a realistic predictive model.

other attributes:

12 - campaign: number of contacts performed during this campaign and for this client (numeric, includes last contact)

13 - pdays: number of days that passed by after the client was last contacted from a previous campaign (numeric; 999 means client was not previously contacted)

14 - previous: number of contacts performed before this campaign and for this client (numeric)

15 - poutcome: outcome of the previous marketing campaign (categorical: 'failure','nonexistent','success')

social and economic context attributes

16 - emp.var.rate: employment variation rate - quarterly indicator (numeric)

17 - cons.price.idx: consumer price index - monthly indicator (numeric)

18 - cons.conf.idx: consumer confidence index - monthly indicator (numeric)

19 - euribor3m: euribor 3 month rate - daily indicator (numeric)

20 - nr.employed: number of employees - quarterly indicator (numeric)

Output variable (desired target):

21 - y - has the client subscribed a term deposit? (binary: 'yes','no')

Summary

Number of employees and age has influence on who will subscribe to term deposit

Import Libraries

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

import sklearn

import shap
import statsmodels.api as sm

import datetime
from datetime import datetime, timedelta

import scipy.stats

import pandas_profiling
from pandas_profiling import ProfileReport

#import graphviz

#import xgboost as xgb
#from xgboost import XGBClassifier, XGBRegressor
#from xgboost import to_graphviz, plot_importance

#from sklearn.experimental import enable_hist_gradient_boosting
#from sklearn.linear_model import ElasticNet, Lasso, LinearRegression, LogisticRegression, Ridge
#from sklearn.ensemble import RandomForestClassifier, RandomForestRegressor, ExtraTreesClassifier, ExtraTree
#from sklearn.ensemble import GradientBoostingClassifier, GradientBoostingRegressor, HistGradientBoostingCla


%matplotlib inline
#sets the default autosave frequency in seconds
%autosave 60
sns.set_style('dark')
sns.set(font_scale=1.2)

plt.rc('axes', labelsize=14)
plt.rc('xtick', labelsize=12)
plt.rc('ytick', labelsize=12)


#from sklearn.pipeline import Pipeline
#from sklearn.model_selection import RepeatedStratifiedKFold
#from sklearn.feature_selection import RFE, RFECV, SelectKBest, f_classif, f_regression, chi2

from sklearn.inspection import permutation_importance
from sklearn.model_selection import cross_val_score, train_test_split, GridSearchCV, RandomizedSearchCV
from sklearn.preprocessing import LabelEncoder, StandardScaler, MinMaxScaler, OneHotEncoder
from sklearn.pipeline import Pipeline
from sklearn.tree import export_graphviz, plot_tree
from sklearn.metrics import confusion_matrix, classification_report, mean_absolute_error, mean_squared_error
from sklearn.metrics import plot_confusion_matrix, plot_precision_recall_curve, plot_roc_curve, accuracy_sco
from sklearn.metrics import auc, f1_score, precision_score, recall_score, roc_auc_score


#from tpot import TPOTClassifier, TPOTRegressor
from imblearn.under_sampling import RandomUnderSampler
from imblearn.over_sampling import RandomOverSampler
from imblearn.over_sampling import SMOTE

import warnings
warnings.filterwarnings('ignore')

# import pickle
# from pickle import dump, load

# Use Folium library to plot values on a map.
#import folium

# Use Feature-Engine library

#import feature_engine.missing_data_imputers as mdi
#from feature_engine.outlier_removers import Winsorizer
#from feature_engine import categorical_encoders as ce


from pycaret.classification import *
#from pycaret.clustering import *
#from pycaret.regression import *

pd.set_option('display.max_columns',None)
#pd.set_option('display.max_rows',100)
pd.set_option('display.width', 1000)
pd.set_option('display.float_format','{:.2f}'.format)


random.seed(0)
np.random.seed(0)
np.set_printoptions(suppress=True)
```

```
Autosaving every 60 seconds
```

Exploratory Data Analysis

In [2]:
```
df = pd.read_csv("bank-additional-full.csv", sep=';')
```

In [3]:
```
df
```

Out[3]:

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

41188 rows × 21 columns

In [4]:
```
df.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
```

In [5]:
```
df.describe(include='all')
```

Out[5]:

	age	job	marital	education	default	housing	loan	contact	month	day_of_week	duration	campaign	pdays
count	41188.00	41188	41188	41188	41188	41188	41188	41188	41188	41188	41188.00	41188.00	41188.00
unique	nan	12	4	8	3	3	3	2	10	5	nan	nan	nan
top	nan	admin.	married	university.degree	no	yes	no	cellular	may	thu	nan	nan	nan
freq	nan	10422	24928	12168	32588	21576	33950	26144	13769	8623	nan	nan	nan
mean	40.02	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	258.29	2.57	962.48
std	10.42	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	259.28	2.77	186.91
min	17.00	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	0.00	1.00	0.00
25%	32.00	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	102.00	1.00	999.00
50%	38.00	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	180.00	2.00	999.00
75%	47.00	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	319.00	3.00	999.00
max	98.00	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	4918.00	56.00	999.00

In [6]:
```
df.shape
```

Out[6]:
```
(41188, 21)
```

In [7]:
```
df.columns
```

Out[7]:
```
Index(['age', 'job', 'marital', 'education', 'default', 'housing', 'loan', 'contact', 'month', 'day_of_wee
k', 'duration', 'campaign', 'pdays', 'previous', 'poutcome', 'emp.var.rate', 'cons.price.idx', 'cons.conf.id
x', 'euribor3m', 'nr.employed', 'y'], dtype='object')
```

Groupby Function

In [8]:
```
df.groupby(by='y').mean()
```

Out[8]:

y	age	duration	campaign	pdays	previous	emp.var.rate	cons.price.idx	cons.conf.idx	euribor3m	nr.employed
no	39.91	220.84	2.63	984.11	0.13	0.25	93.60	-40.59	3.81	5176.17
yes	40.91	553.19	2.05	792.04	0.49	-1.23	93.35	-39.79	2.12	5095.12

In [9]:
```
df.groupby(by='y').count()
```

Out[9]:

y	age	job	marital	education	default	housing	loan	contact	month	day_of_week	duration	campaign	pdays	previous	pout
no	36548	36548	36548	36548	36548	36548	36548	36548	36548	36548	36548	36548	36548	36548	
yes	4640	4640	4640	4640	4640	4640	4640	4640	4640	4640	4640	4640	4640	4640	

In [10]:
```
df.y.value_counts()
```

Out[10]:
```
no     36548
yes     4640
Name: y, dtype: int64
```

Pandas-Profiling Reports

In [11]:
```
profile = ProfileReport(df=df, title='Bank Marketing Report', minimal=True)
```

In [12]:
```
profile.to_notebook_iframe()
```

Bank Marketing Report Overview Variables

Overview

Overview Warnings 2 Reproduction

Dataset statistics	
Number of variables	21
Number of observations	41188
Missing cells	0
Missing cells (%)	0.0%
Duplicate rows	12
Duplicate rows (%)	< 0.1%
Total size in memory	6.6 MiB
Average record size in memory	168.0 B

Variable types	
NUM	10
CAT	10
BOOL	1

Variables

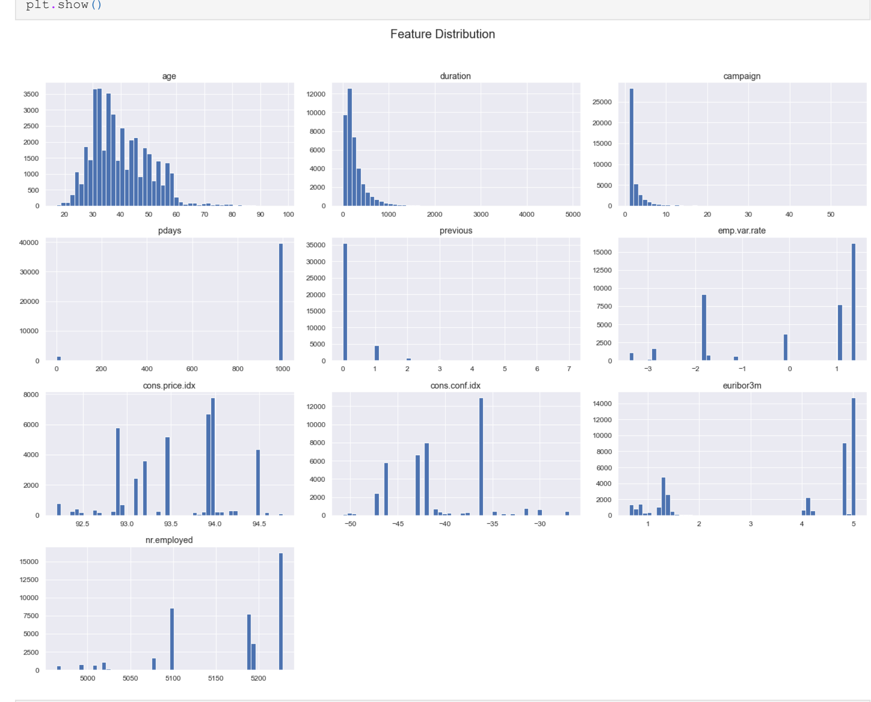
age	Distinct	78	Mean	40.02406041
Real number ($\mathbb{R}_{\geq 0}$)	Distinct (%)	0.2%	Minimum	17

In [13]:
```
profile.to_file("your_report.html")
```

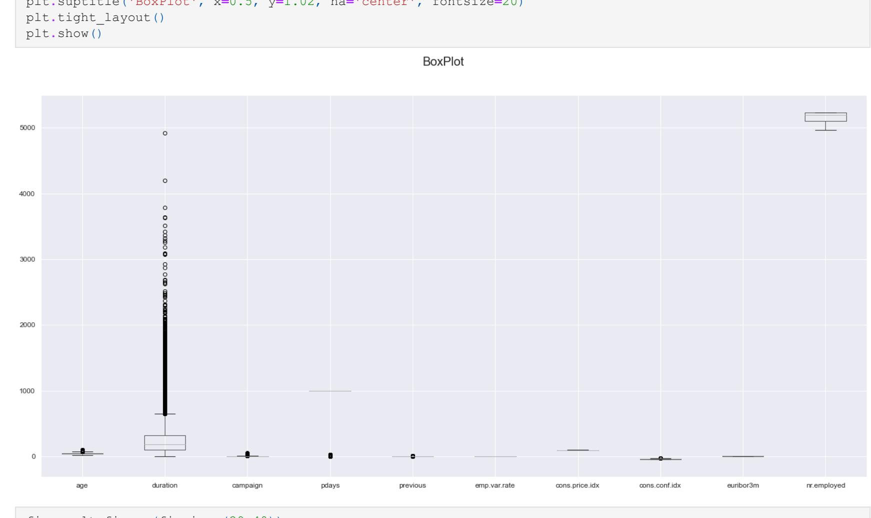
Data Visualization

Univariate Data Exploration

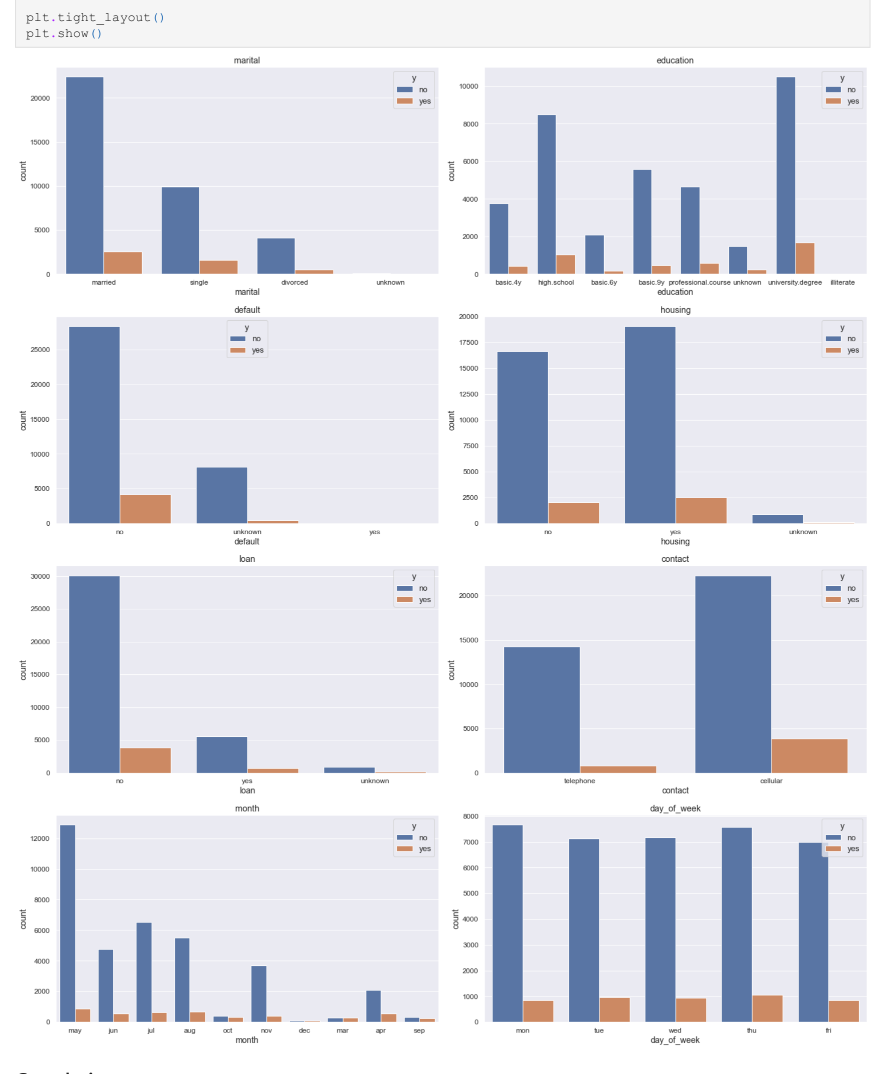
In [14]:
```
df.hist(bins=50, figsize=(20,15))
plt.suptitle('Feature Distribution', x=0.5, y=1.02, ha='center', fontsize=20)
plt.tight_layout()
plt.show()
```



In [15]:
```
df.boxplot(figsize=(20,10))
plt.suptitle('BoxPlot', x=0.5, y=1.02, ha='center', fontsize=20)
plt.tight_layout()
plt.show()
```



In [16]:
```
fig = plt.figure(figsize=(20,40))

plt.subplot(7,2,1)
plt.title("marital")
sns.countplot(df.marital, hue=df.y)

plt.subplot(7,2,2)
plt.title("education")
sns.countplot(df.education, hue=df.y)

plt.subplot(7,2,3)
plt.title("default")
sns.countplot(df.default, hue=df.y)

plt.subplot(7,2,4)
plt.title("housing")
sns.countplot(df.housing, hue=df.y)

plt.subplot(7,2,5)
plt.title("loan")
sns.countplot(df.loan, hue=df.y)

plt.subplot(7,2,6)
plt.title("contact")
sns.countplot(df.contact, hue=df.y)

plt.subplot(7,2,7)
plt.title("month")
sns.countplot(df.month, hue=df.y)

plt.subplot(7,2,8)
plt.title("day_of_week")
sns.countplot(df.day_of_week, hue=df.y)


plt.tight_layout()
plt.show()
```



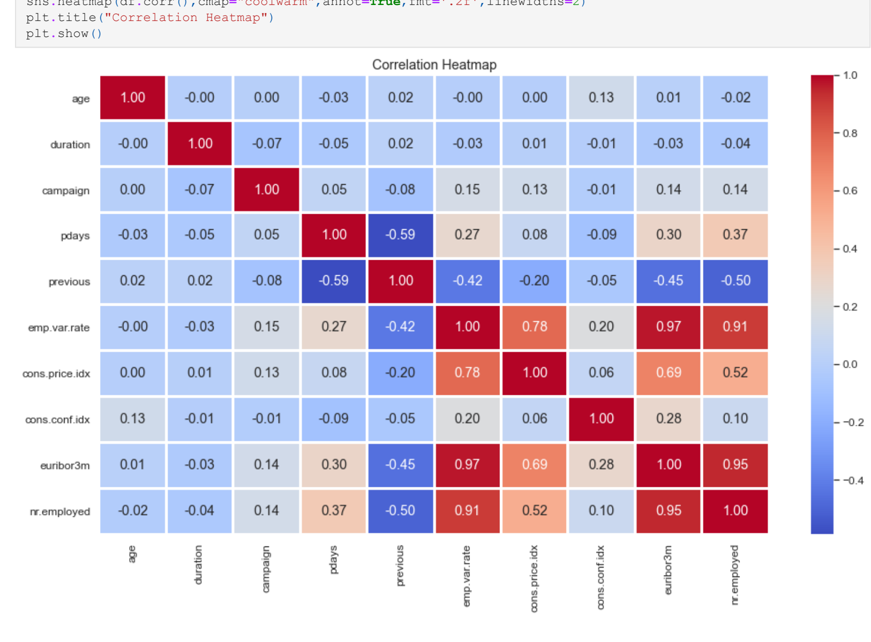
Correlation

In [17]:
```
df.corr()
```

Out[17]:

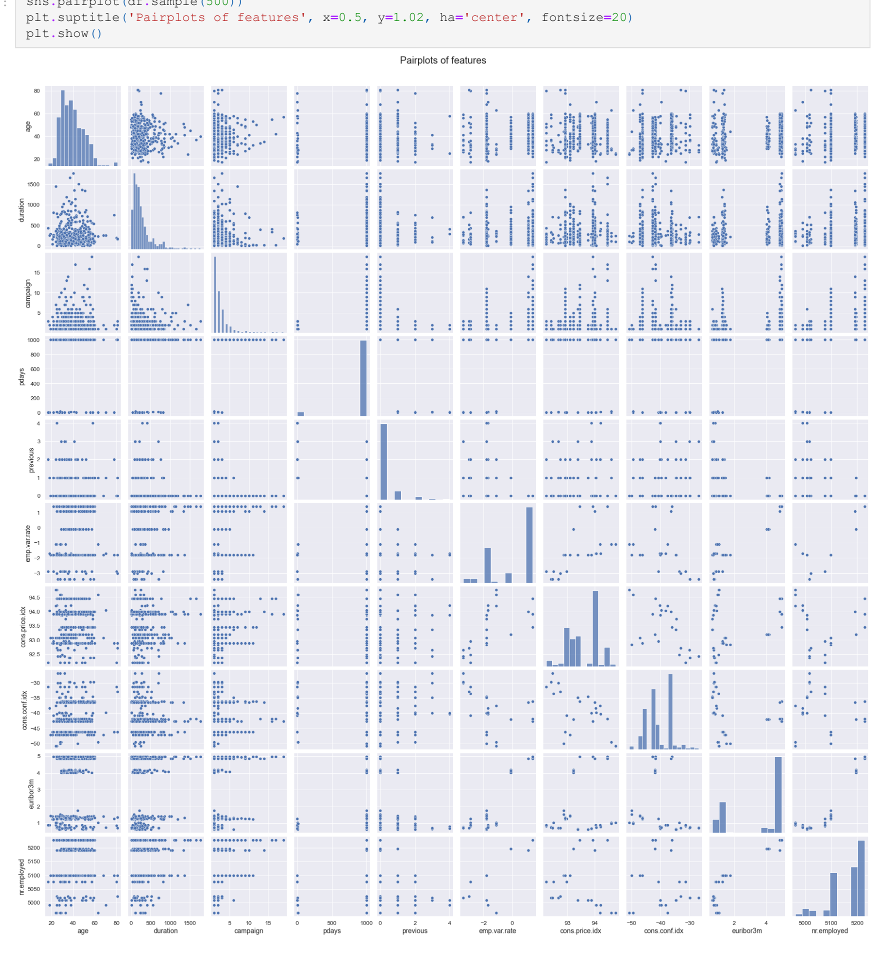
	age	duration	campaign	pdays	previous	emp.var.rate	cons.price.idx	cons.conf.idx	euribor3m	nr.employed
age	1.00	-0.00	0.00	-0.03	0.02	-0.00	0.00	0.13	0.01	-0.02
duration	-0.00	1.00	-0.07	-0.05	0.02	-0.03	0.01	-0.01	-0.03	-0.04
campaign	0.00	-0.07	1.00	0.05	-0.08	0.15	0.13	-0.01	0.14	0.14
pdays	-0.03	-0.05	0.05	1.00	-0.59	0.27	0.08	-0.09	0.30	0.37
previous	0.02	0.02	-0.08	-0.59	1.00	-0.42	-0.20	-0.05	-0.45	-0.50
emp.var.rate	-0.00	-0.03	0.15	0.27	-0.42	1.00	0.78	0.20	0.97	0.91
cons.price.idx	0.00	0.01	0.13	0.08	-0.20	0.78	1.00	0.06	0.69	0.52
cons.conf.idx	0.13	-0.01	-0.01	-0.09	-0.05	0.20	0.06	1.00	0.28	0.10
euribor3m	0.01	-0.03	0.14	0.30	-0.45	0.97	0.69	0.28	1.00	0.95
nr.employed	-0.02	-0.04	0.14	0.37	-0.50	0.91	0.52	0.10	0.95	1.00

In [18]:
```
plt.figure(figsize=(16,9))
sns.heatmap(df.corr(),cmap="coolwarm",annot=True,fmt='.2f',linewidths=2)
plt.title("Correlation Heatmap")
plt.show()
```



Pairplots

In [19]:
```
sns.pairplot(df.sample(500))
plt.suptitle('Pairplots of features', x=0.5, y=1.02, ha='center', fontsize=20)
plt.show()
```



Data Preprocessing

Drop unwanted features

In [20]:
```
df.columns
```

Out[20]:
```
Index(['age', 'job', 'marital', 'education', 'default', 'housing', 'loan', 'contact', 'month', 'day_of_wee
k', 'duration', 'campaign', 'pdays', 'previous', 'poutcome', 'emp.var.rate', 'cons.price.idx', 'cons.conf.id
x', 'euribor3m', 'nr.employed', 'y'], dtype='object')
```

In [21]:
```
df.drop(['contact', 'month', 'day_of_week', 'duration', 'campaign', 'pdays', 'previous', 'poutcome', 'emp.va
```

In [22]:
```
df
```

Out[22]:

	age	job	marital	education	default	housing	loan	nr.employed	y
0	56	housemaid	married	basic.4y	no	no	no	5191.00	no
1	57	services	married	high.school	unknown	no	no	5191.00	no
2	37	services	married	high.school	no	yes	no	5191.00	no
3	40	admin.	married	basic.6y	no	no	no	5191.00	no
4	56	services	married	high.school	no	no	yes	5191.00	no
...	...	...	...	...	...	...	...	...	...
41183	73	retired	married	professional.course	no	yes	no	4963.60	yes
41184	46	blue-collar	married	professional.course	no	no	no	4963.60	no
41185	56	retired	married	university.degree	no	yes	no	4963.60	no
41186	44	technician	married	professional.course	no	no	no	4963.60	yes
41187	74	retired	married	professional.course	no	yes	no	4963.60	no

41188 rows × 9 columns

Treat Missing Values

In [23]:
```
df.isnull().sum()
```

Out[23]:
```
age            0
job            0
marital        0
education      0
default        0
housing        0
loan           0
nr.employed    0
y              0
dtype: int64
```

Treat Duplicate Values

In [24]:
```
df.duplicated(keep='first').sum()
```

Out[24]:
```
17550
```

In [25]:
```
df[df.duplicated(keep=False)] #Check duplicate values
```

Out[25]:

	age	job	marital	education	default	housing	loan	nr.employed	y
0	56	housemaid	married	basic.4y	no	no	no	5191.00	no
2	37	services	married	high.school	no	yes	no	5191.00	no
6	59	admin.	married	professional.course	no	no	no	5191.00	no
7	41	blue-collar	married	unknown	unknown	no	no	5191.00	no
9	25	services	single	high.school	no	yes	no	5191.00	no
...	...	...	...	...	...	...	...	...	...
41163	35	technician	divorced	basic.4y	no	yes	no	4963.60	yes
41172	31	admin.	single	university.degree	no	yes	no	4963.60	yes
41173	62	retired	married	university.degree	no	yes	no	4963.60	yes
41174	62	retired	married	university.degree	no	yes	no	4963.60	yes
41181	37	admin.	married	university.degree	no	yes	no	4963.60	yes

24701 rows × 9 columns

In [26]:
```
df.drop_duplicates(inplace=True)
```

In [27]:
```
df
```

Out[27]:

	age	job	marital	education	default	housing	loan	nr.employed	y
0	56	housemaid	married	basic.4y	no	no	no	5191.00	no
1	57	services	married	high.school	unknown	no	no	5191.00	no
2	37	services	married	high.school	no	yes	no	5191.00	no
3	40	admin.	married	basic.6y	no	no	no	5191.00	no
4	56	services	married	high.school	no	no	yes	5191.00	no
...	...	...	...	...	...	...	...	...	...
41183	73	retired	married	professional.course	no	yes	no	4963.60	yes
41184	46	blue-collar	married	professional.course	no	no	no	4963.60	no
41185	56	retired	married	university.degree	no	yes	no	4963.60	no
41186	44	technician	married	professional.course	no	no	no	4963.60	yes
41187	74	retired	married	professional.course	no	yes	no	4963.60	no

23638 rows × 9 columns

In [28]:
```
df.reset_index(inplace=True, drop=True)
```

In [29]:
```
df
```

Out[29]:

	age	job	marital	education	default	housing	loan	nr.employed	y
0	56	housemaid	married	basic.4y	no	no	no	5191.00	no
1	57	services	married	high.school	unknown	no	no	5191.00	no
2	37	services	married	high.school	no	yes	no	5191.00	no
3	40	admin.	married	basic.6y	no	no	no	5191.00	no
4	56	services	married	high.school	no	no	yes	5191.00	no
...	...	...	...	...	...	...	...	...	...
23633	73	retired	married	professional.course	no	yes	no	4963.60	yes
23634	46	blue-collar	married	professional.course	no	no	no	4963.60	no
23635	56	retired	married	university.degree	no	yes	no	4963.60	no
23636	44	technician	married	professional.course	no	no	no	4963.60	yes
23637	74	retired	married	professional.course	no	yes	no	4963.60	no

23638 rows × 9 columns

Perform One-Hot Encoding

In [30]:
```
df.columns
```

Out[30]:
```
Index(['age', 'job', 'marital', 'education', 'default', 'housing', 'loan', 'nr.employed', 'y'], dtype='objec
t')
```

In [31]:
```
df_cat = df[['job', 'marital', 'education', 'default', 'housing', 'loan']]
```

In [32]:
```
df_num = df[['age','nr.employed', 'y']]
```

In [33]:
```
df_cat2 = pd.get_dummies(df_cat, drop_first=True)
```

In [34]:
```
df_cat2
```

Out[34]:

	job_blue-collar	job_entrepreneur	job_housemaid	job_management	job_retired	job_self-employed	job_services	job_student	job_technician	job_u
0	0	0	1	0	0	0	0	0	0	
1	0	0	0	0	0	0	1	0	0	
2	0	0	0	0	0	0	1	0	0	
3	0	0	0	0	0	0	0	0	0	
4	0	0	0	0	0	0	1	0	0	
...	...	...	...	...	...	...	...	...	...	
23633	0	0	0	0	1	0	0	0	0	
23634	1	0	0	0	0	0	0	0	0	
23635	0	0	0	0	1	0	0	0	0	
23636	0	0	0	0	0	0	0	0	1	
23637	0	0	0	0	1	0	0	0	0	

23638 rows × 27 columns

In [35]:
```
df3 = pd.concat([df_cat2,df_num],axis=1)
```

In [36]:
```
df3
```

Out[36]:

	job_blue-collar	job_entrepreneur	job_housemaid	job_management	job_retired	job_self-employed	job_services	job_student	job_technician	job_u

0	0	0	1	0	0	0	0	0	0
1	0	0	0	0	0	0	1	0	0
2	0	0	0	0	0	0	1	0	0
3	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	1	0	0
...	...	...	...	...	...	...	...	...	...
23633	0	0	0	0	1	0	0	0	0
23634	1	0	0	0	0	0	0	0	0
23635	0	0	0	0	1	0	0	0	0
23636	0	0	0	0	0	0	0	0	1
23637	0	0	0	0	1	0	0	0	0

23638 rows × 30 columns

In [37]:
```
le =  LabelEncoder()
```

In [38]:
```
df3['y'] = le.fit_transform(df3['y'])
```

In [39]:
```
df3
```

Out[39]:

	job_blue-collar	job_entrepreneur	job_housemaid	job_management	job_retired	job_self-employed	job_services	job_student	job_technician
0	0	0	1	0	0	0	0	0	0
1	0	0	0	0	0	0	1	0	0
2	0	0	0	0	0	0	1	0	0
3	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	1	0	0
...	...	...	...	...	...	...	...	...	...
23633	0	0	0	0	1	0	0	0	0
23634	1	0	0	0	0	0	0	0	0
23635	0	0	0	0	1	0	0	0	0
23636	0	0	0	0	0	0	0	0	1
23637	0	0	0	0	1	0	0	0	0

23638 rows × 30 columns

In [40]:
```
df3.y.value_counts()
```

Out[40]:
```
0    19658
1     3980
Name: y, dtype: int64
```

Create and save processed dataset

In [41]:
```
df3.to_csv("bankfinal.csv",index=False)
```

Train Test Split

In [42]:
```
df3.shape
```

Out[42]:
```
(23638, 30)
```

In [43]:
```
X = df3.iloc[:,0:29]
y = df3.iloc[:,29]
```

Treat Imbalance Data

In [44]:
```
y.value_counts()
```

Out[44]:
```
0    19658
1     3980
Name: y, dtype: int64
```

In [45]:
```
ros = RandomUnderSampler(sampling_strategy='auto',random_state=0)
```

In [46]:
```
new_X, new_y = ros.fit_resample(X, y)
```

In [47]:
```
new_y.value_counts()
```

Out[47]:
```
1    3980
0    3980
Name: y, dtype: int64
```

In [48]:
```
new_X
```

Out[48]:

	job_blue-collar	job_entrepreneur	job_housemaid	job_management	job_retired	job_self-employed	job_services	job_student	job_technician
0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	1
2	1	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0
...	...	...	...	...	...	...	...	...	...
7955	0	0	0	0	0	0	0	1	0
7956	0	0	0	0	1	0	0	0	0
7957	0	0	0	0	1	0	0	0	0
7958	0	0	0	0	1	0	0	0	0
7959	0	0	0	0	0	0	0	0	1

7960 rows × 29 columns

Train Test Split Cont'd

In [49]:
```
X.values, y.values
```

Out[49]:
```
(array([[   0. ,    0. ,    1. , ...,    0. ,   56. , 5191. ],
        [   0. ,    0. ,    0. , ...,    0. ,   57. , 5191. ],
        [   0. ,    0. ,    0. , ...,    0. ,   37. , 5191. ],
        ...,
        [   0. ,    0. ,    0. , ...,    0. ,   56. , 4963.6],
        [   0. ,    0. ,    0. , ...,    0. ,   44. , 4963.6],
        [   0. ,    0. ,    0. , ...,    0. ,   74. , 4963.6]]),
 array([0, 0, 0, ..., 0, 1, 0]))
```

In [50]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=0)
```

In [51]:
```
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

Out[51]:
```
((18910, 29), (4728, 29), (18910,), (4728,))
```

Feature Scaling

In [52]:
```
X_train
```

Out[52]:

	job_blue-collar	job_entrepreneur	job_housemaid	job_management	job_retired	job_self-employed	job_services	job_student	job_technician
21286	0	0	0	0	1	0	0	0	0
12223	0	0	0	0	0	0	0	0	1
20584	0	0	0	0	0	0	0	1	0
15965	1	0	0	0	0	0	0	0	0
16454	0	0	0	0	0	0	0	0	0
...	...	...	...	...	...	...	...	...	...
13123	1	0	0	0	0	0	0	0	0
19648	0	0	0	0	0	0	0	0	0
9845	0	0	0	0	0	0	1	0	0
10799	0	0	0	0	0	0	0	0	0
2732	0	0	0	0	0	0	0	0	0

18910 rows × 29 columns

In [53]:
```
scaler = StandardScaler()
```

In [54]:
```
X_train_scaled = scaler.fit_transform(X_train)
```

In [55]:
```
X_test_scaled = scaler.transform(X_test)
```

In [56]:
```
X_train_scaled
```

Out[56]:
```
array([[-0.50222998, -0.22639875, -0.19165713, ..., -0.51318792,
         4.17600905, -1.77687132],
       [-0.50222998, -0.22639875, -0.19165713, ...,  1.94860394,
        -0.91738451,  0.93248166],
       [-0.50222998, -0.22639875, -0.19165713, ..., -0.51318792,
        -1.54288898, -1.02170029],
       ...,
       [-0.50222998, -0.22639875, -0.19165713, ..., -0.51318792,
         1.13784447,  0.93248166],
       [-0.50222998, -0.22639875, -0.19165713, ..., -0.51318792,
         0.60169778,  0.93248166],
       [-0.50222998, -0.22639875, -0.19165713, ..., -0.51318792,
        -0.20252225,  0.45519299]])
```

In [57]:
```
X_test_scaled
```

Out[57]:
```
array([[-0.50222998, -0.22639875, -0.19165713, ...,  1.94860394,
        -0.29188003, -1.69968178],
       [-0.50222998, -0.22639875, -0.19165713, ..., -0.51318792,
        -0.64931116,  0.93248166],
       [-0.50222998, -0.22639875, -0.19165713, ..., -0.51318792,
        -0.20252225,  0.51694462],
       ...,
       [-0.50222998, -0.22639875, -0.19165713, ..., -0.51318792,
         1.67399116,  0.93248166],
       [ 1.99111969, -0.22639875, -0.19165713, ..., -0.51318792,
        -0.11316447,  0.51694462],
       [-0.50222998, -0.22639875, -0.19165713, ..., -0.51318792,
         0.86977113, -2.11007285]])
```

Model Training

Using PyCaret

In [58]:
```
exp_class = setup(data = df3, target = 'y', session_id=0, normalize=True, train_size=0.8)
```

	Description	Value
0	session_id	0
1	Target	y
2	Target Type	Binary
3	Label Encoded	None
4	Original Data	(23638, 30)
5	Missing Values	False
6	Numeric Features	29
7	Categorical Features	0
8	Ordinal Features	False
9	High Cardinality Features	False
10	High Cardinality Method	None
11	Transformed Train Set	(18910, 28)
12	Transformed Test Set	(4728, 28)
13	Shuffle Train-Test	True
14	Stratify Train-Test	False
15	Fold Generator	StratifiedKFold
16	Fold Number	10
17	CPU Jobs	-1
18	Use GPU	False
19	Log Experiment	False
20	Experiment Name	clf-default-name
21	USI	a4f3
22	Imputation Type	simple
23	Iterative Imputation Iteration	None
24	Numeric Imputer	mean
25	Iterative Imputation Numeric Model	None
26	Categorical Imputer	constant
27	Iterative Imputation Categorical Model	None
28	Unknown Categoricals Handling	least_frequent
29	Normalize	True
30	Normalize Method	zscore
31	Transformation	False
32	Transformation Method	None
33	PCA	False
34	PCA Method	None
35	PCA Components	None
36	Ignore Low Variance	False
37	Combine Rare Levels	False
38	Rare Level Threshold	None
39	Numeric Binning	False
40	Remove Outliers	False
41	Outliers Threshold	None
42	Remove Multicollinearity	False
43	Multicollinearity Threshold	None
44	Clustering	False
45	Clustering Iteration	None
46	Polynomial Features	False
47	Polynomial Degree	None
48	Trignometry Features	False
49	Polynomial Threshold	None
50	Group Features	False
51	Feature Selection	False
52	Feature Selection Method	classic
53	Features Selection Threshold	None
54	Feature Interaction	False
55	Feature Ratio	False
56	Interaction Threshold	None
57	Fix Imbalance	False
58	Fix Imbalance Method	SMOTE

In [59]:
```
compare_models(exclude=['catboost','lightgbm','lda','qda','mlp','ada','nb','ridge','rbfsvm','svm'],fold=5) #
```

	Model	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC	TT (Sec)
gbc	Gradient Boosting Classifier	0.8326	0.7616	0.1608	0.5012	0.2429	0.1756	0.2123	0.7300
lr	Logistic Regression	0.8324	0.7430	0.1206	0.4969	0.1938	0.1372	0.1812	1.1580
xgboost	Extreme Gradient Boosting	0.8230	0.7330	0.1817	0.4306	0.2555	0.1734	0.1944	1.4700
knn	K Neighbors Classifier	0.8121	0.6591	0.1906	0.3766	0.2530	0.1586	0.1707	0.8680
rf	Random Forest Classifier	0.7698	0.6337	0.1880	0.2493	0.2143	0.0826	0.0837	0.7620
et	Extra Trees Classifier	0.7524	0.5286	0.2001	0.2267	0.2125	0.0663	0.0665	1.0000
dt	Decision Tree Classifier	0.7298	0.5217	0.2051	0.1996	0.2023	0.0397	0.0397	0.0580

Out[59]:
```
GradientBoostingClassifier(ccp_alpha=0.0, criterion='friedman_mse', init=None,
                           learning_rate=0.1, loss='deviance', max_depth=3,
                           max_features=None, max_leaf_nodes=None,
                           min_impurity_decrease=0.0, min_impurity_split=None,
                           min_samples_leaf=1, min_samples_split=2,
                           min_weight_fraction_leaf=0.0, n_estimators=100,
                           n_iter_no_change=None, presort='deprecated',
                           random_state=0, subsample=1.0, tol=0.0001,
                           validation_fraction=0.1, verbose=0,
                           warm_start=False)
```

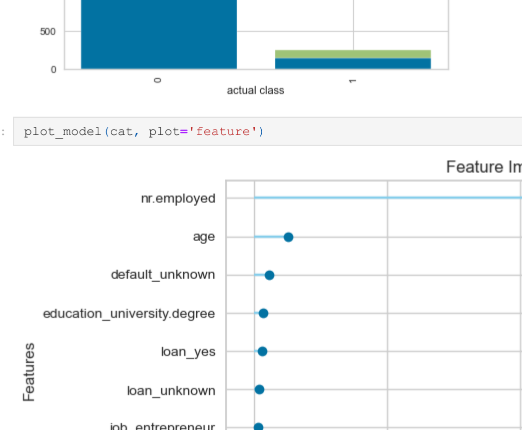
In [60]:
```
cat = create_model('gbc')
```

	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC
0	0.8228	0.7615	0.1424	0.4128	0.2118	0.1379	0.1629
1	0.8355	0.7408	0.1582	0.5263	0.2433	0.1800	0.2214
2	0.8324	0.7430	0.1741	0.4955	0.2576	0.1870	0.2198
3	0.8345	0.7638	0.1709	0.5143	0.2565	0.1889	0.2256
4	0.8419	0.7915	0.1804	0.5876	0.2760	0.2144	0.2621
5	0.8429	0.7765	0.1646	0.6118	0.2594	0.2029	0.2586
6	0.8318	0.7520	0.1614	0.4904	0.2429	0.1745	0.2090
7	0.8355	0.7950	0.1804	0.5229	0.2682	0.1996	0.2359
8	0.8324	0.7584	0.1456	0.4946	0.2249	0.1612	0.1997
9	0.8308	0.7430	0.1619	0.4766	0.2417	0.1717	0.2038
Mean	0.8341	0.7625	0.1640	0.5133	0.2482	0.1818	0.2199
SD	0.0054	0.0186	0.0124	0.0530	0.0185	0.0210	0.0276

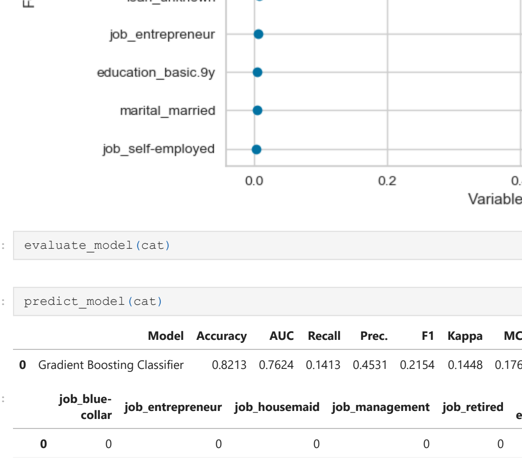
In [61]:
```
print(cat)
```

```
GradientBoostingClassifier(ccp_alpha=0.0, criterion='friedman_mse', init=None,
                           learning_rate=0.1, loss='deviance', max_depth=3,
                           max_features=None, max_leaf_nodes=None,
                           min_impurity_decrease=0.0, min_impurity_split=None,
                           min_samples_leaf=1, min_samples_split=2,
                           min_weight_fraction_leaf=0.0, n_estimators=100,
                           n_iter_no_change=None, presort='deprecated',
                           random_state=0, subsample=1.0, tol=0.0001,
                           validation_fraction=0.1, verbose=0,
                           warm_start=False)
```

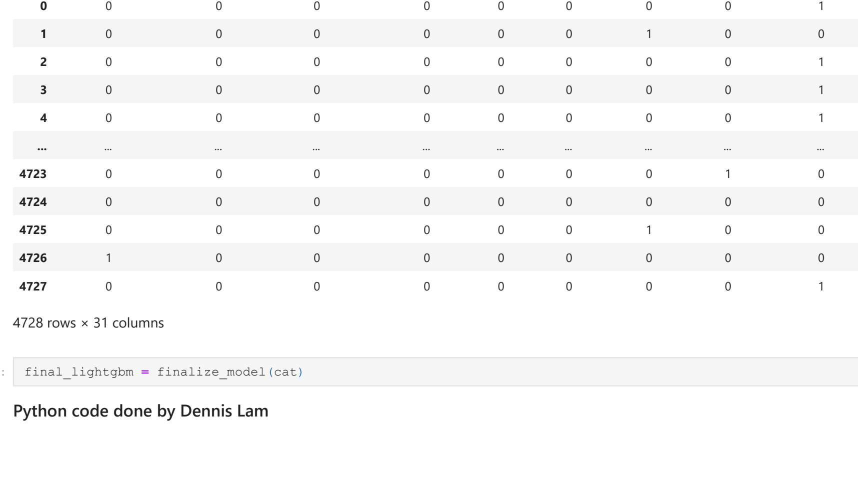
In [62]:
```
plot_model(cat)
```



In [63]:
```
plot_model(cat, plot = 'error')
```



In [64]:
```
plot_model(cat, plot='feature')
```



In [65]:
```
evaluate_model(cat)
```

In [66]:
```
predict_model(cat)
```

	Model	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC
0	Gradient Boosting Classifier	0.8213	0.7624	0.1413	0.4531	0.2154	0.1448	0.1765

Out[66]:

	job_blue-collar	job_entrepreneur	job_housemaid	job_management	job_retired	job_self-employed	job_services	job_student	job_technician
0	0	0	0	0	0	0	0	0	1
1	0	0	0	0	0	0	1	0	0
2	0	0	0	0	0	0	0	0	1
3	0	0	0	0	0	0	0	0	1
4	0	0	0	0	0	0	0	0	1
...	...	...	...	...	...	...	...	...	...
4723	0	0	0	0	0	0	0	1	0
4724	0	0	0	0	0	0	0	0	0
4725	0	0	0	0	0	0	1	0	0
4726	1	0	0	0	0	0	0	0	0
4727	0	0	0	0	0	0	0	0	1

4728 rows × 31 columns

In [67]:
```
final_lightgbm = finalize_model(cat)
```

Python code done by Dennis Lam