Predictive Models

This repository uses the insights we captured from the data to make a predictive model. We use several models and compare the results obtained in each case. The first one displayed below is the **Random Forest** model. Then **SVM** approach is used to compare results

1. Random Forest

This cell contains all the dependencies needed

```
In [25]:
```

```
import numpy as np #Matrix-Maths
import pandas as pd #DataFrame
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
from sklearn.svm import SVC
```

```
In [2]:
```

```
data = pd.read_csv('Data/bank-additional-full.csv', delimiter=';')
```

```
In [3]:
```

```
data.head()
```

Out[3]:

	age	job	marital	education	default	housing	loan	contact	month	day_of_w
0	56	housemaid	married	basic.4y	no	no	no	telephone	may	n
1	57	services	married	high.school	unknown	no	no	telephone	may	n
2	37	services	married	high.school	no	yes	no	telephone	may	n
3	40	admin.	married	basic.6y	no	no	no	telephone	may	n
4	56	services	married	high.school	no	no	yes	telephone	may	n

5 rows × 21 columns

```
In [4]:
```

```
data.shape
```

```
Out[4]:
(41188, 21)
```

```
In [6]:
data['education'] = data['education'].cat.codes
data['job'] = data['job'].cat.codes
data['default'] = data['default'].cat.codes
data['loan'] = data['loan'].cat.codes
data['day of week'] = data['day of week'].cat.codes
data['y'] = data['y'].cat.codes
data['poutcome'] = data['poutcome'].cat.codes
data['contact'] = data['contact'].cat.codes
data['marital'] = data['marital'].cat.codes
data['month'] = data['month'].cat.codes
In [7]:
data.shape
Out[7]:
(41188, 21)
In [8]:
data.head()
```

Out[8]:

In [5]:

for col in data.columns:

if(data[col].dtype == object):

data[col] = data[col].astype('category')

	age	job	marital	education	default	housing	loan	contact	month	day_of_week	•••	ca
0	56	3	1	0	0	no	0	1	6	1		
1	57	7	1	3	1	no	0	1	6	1		
2	37	7	1	3	0	yes	0	1	6	1		
3	40	0	1	1	0	no	0	1	6	1		
4	56	7	1	3	0	no	2	1	6	1		

 $5 \text{ rows} \times 21 \text{ columns}$

```
In [11]:
```

```
cols = list(data.columns)
```

```
features = ['job',
            'education',
            'default',
            'loan',
            'month',
            'day_of_week',
            'pdays',
            'previous',
            'emp.var.rate',
            'cons.price.idx',
            'cons.conf.idx',
            'euribor3m',
            'poutcome',
             'contact',
            'marital',
            'у']
In [16]:
data = data[features]
In [17]:
data.shape
Out[17]:
(41188, 16)
In [19]:
X = data.values[:, :15]
Y = data.values[:, 15]
In [21]:
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.3)
In [22]:
ran_for = RandomForestClassifier()
In [23]:
model = ran_for.fit(X_train, y_train)
In [24]:
model.score(X_test, y_test)
Out[24]:
0.8863801893663511
```

In [15]:

2. Support Vector Machine

```
In [30]:
clf_svm = SVC(kernel='rbf', C=100)

In [31]:
clf_svm.fit(X_train, y_train)
Out[31]:
SVC(C=100, cache_size=200, class_weight=None, coef0=0.0,
    decision_function_shape=None, degree=3, gamma='auto', kernel='rbf'
, max_iter=-1, probability=False, random_state=None, shrinking=True,
    tol=0.001, verbose=False)

In [32]:
clf_svm.score(X_test, y_test)
Out[32]:
0.8896172210083354

In []:
```

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```
In [25]:
```

```
In [3]:
Out[3]:
                              education
                                           default housing loan
                                                                    contact month day_of_wo
   age
                job marital
0
         housemaid
                                basic.4y
     56
                    married
                                                                  telephone
                                               no
                                                        no
                                                              no
                                                                               may
                                                                                             n
                                         unknown
1
     57
           services
                    married
                             high.school
                                                        no
                                                              no
                                                                  telephone
                                                                               may
                                                                                             n
2
     37
           services
                    married
                             high.school
                                                                  telephone
                                               no
                                                       yes
                                                              no
                                                                               may
                                                                                             n
3
     40
            admin.
                    married
                                basic.6y
                                                                  telephone
                                                              no
                                                                               may
                                                                                             n
                                               no
                                                        no
4
           services married high.school
     56
                                                                 telephone
                                                                                             n
                                               no
                                                        no
                                                             yes
                                                                               may
5 \text{ rows} \times 21 \text{ columns}
In [4]:
Out[4]:
(41188, 21)
In [5]:
In [6]:
In [7]:
Out[7]:
(41188, 21)
```

In [2]:

```
In [8]:
Out[8]:
   age job marital education default housing loan contact month day_of_week ... ca
0
    56
         3
                           0
                                  0
                                                0
                                                        1
                 1
                                                               6
                                                                           1 ...
                                          no
    57
                                  1
                                                        1
                                                                            1 ...
                                          no
2
    37
                 1
                           3
                                  0
                                                0
                                                        1
                                         yes
                                                                           1 ...
3
    40
                 1
                           1
                                  0
                                                0
                                                        1
                                                               6
                                          no
                                                                           1 ...
    56
         7
                 1
                           3
                                  0
                                          no
                                                2
                                                        1
                                                               6
                                                                           1 ...
5 rows × 21 columns
In [11]:
In [15]:
In [16]:
In [17]:
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In [24]:
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In [32]:
Out[32]:
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In [ ]:
```