Non-Proctored 2

September 26, 2021

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

[ ]:
```
train=pd.read_csv('bank_train.csv')
test=pd.read_csv('bank_test.csv')

train
```

[ ]:
```
      age         job   marital  education default  balance housing loan  \
0      76     retired   married  secondary      no   2302.0      no   no
1      66     retired  divorced    unknown      no     53.0      no   no
2      51  management   married   tertiary      no   2455.0     yes   no
3      41 blue-collar   married  secondary      no    356.0     yes   no
4      51  technician   married  secondary      no  -1944.0     yes   no
…     …           …         …          …       …        …       …    …
4461   33  management   married   tertiary      no    133.0     yes   no
4462   39    services  divorced  secondary      no    687.0     yes   no
4463   40      admin.    single  secondary      no   2040.0     yes   no
4464   31  technician    single  secondary      no    628.0     yes   no
4465   70     retired  divorced    primary      no    383.0      no   no

        contact  day month  duration  campaign  pdays  previous poutcome  \
0     telephone    5   feb       110         1     87         2  failure
1      cellular   12   jul       562         4     -1         0  unknown
2      cellular   21   jul       553         1     -1         0  unknown
3      cellular   14   may        90         5     -1         0  unknown
4      cellular    7   may       623         1     -1         0  unknown
…           …   …    …         …         …      …        …
4461    unknown   26   may       308         4     -1         0  unknown
4462   cellular    9   jul       869         1     -1         0  unknown
4463   cellular   18   may       906         2    350         2  failure
4464    unknown   12   may      1083         2     -1         0  unknown
4465   cellular   28   apr        50         2     -1         0  unknown

     deposit
0         no
```

```
1        yes
2        yes
3         no
4        yes
…      …
4461      no
4462     yes
4463     yes
4464      no
4465      no

[4466 rows x 17 columns]
```

0.1 Solution 1

```
[ ]: train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4466 entries, 0 to 4465
Data columns (total 17 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   age        4466 non-null   int64
 1   job        4466 non-null   object
 2   marital    4466 non-null   object
 3   education  4466 non-null   object
 4   default    4466 non-null   object
 5   balance    4465 non-null   float64
 6   housing    4466 non-null   object
 7   loan       4466 non-null   object
 8   contact    4466 non-null   object
 9   day        4466 non-null   int64
 10  month      4466 non-null   object
 11  duration   4466 non-null   int64
 12  campaign   4466 non-null   int64
 13  pdays      4466 non-null   int64
 14  previous   4466 non-null   int64
 15  poutcome   4465 non-null   object
 16  deposit    4466 non-null   object
dtypes: float64(1), int64(6), object(10)
memory usage: 593.3+ KB
```

10 columns contain categorical values

0.2 Solution 2

```
[ ]: train[train.isnull().any(axis=1)]
```

[ ]:
```
      age          job  marital  education default  balance housing loan  \
3105   36     services   single  secondary      no      NaN      no   no
3537   44  blue-collar  married  secondary      no    294.0     yes   no

      contact  day month  duration  campaign  pdays  previous poutcome deposit
3105  unknown   17   jun       256         9     -1         0  unknown      no
3537  unknown   19   may        66         2     -1         0      NaN      no
```

[ ]:
```
train2=train.dropna()
```

2 rows have missing values

0.3 Solution 3

[ ]:
```
pd.
 ↪crosstab(index=train2['deposit'],columns=train2['education'],normalize='columns')
```

[ ]:

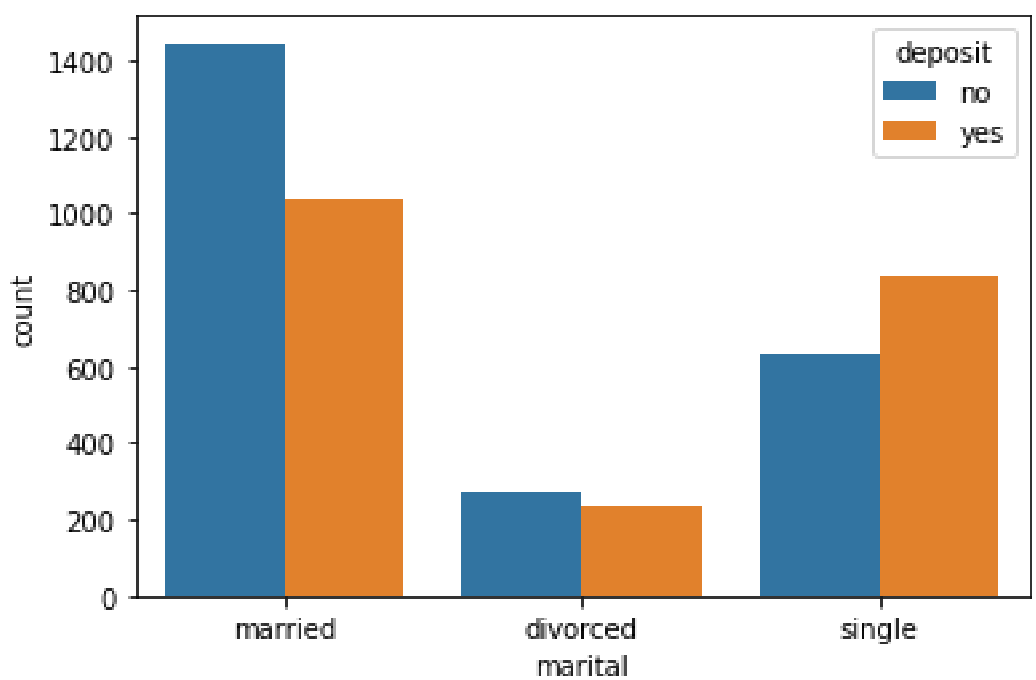
education	primary	secondary	tertiary	unknown
deposit				
no	0.592965	0.565177	0.449535	0.494737
yes	0.407035	0.434823	0.550465	0.505263

56.518 % of clients with secondary education have not subscribed to a deposit

0.4 Solution 4

[ ]:
```
sns.countplot(data=train2,x='marital',hue='deposit')
```

[ ]: <AxesSubplot:xlabel='marital', ylabel='count'>



Single

0.5 Solution 5

[ ]:
```
train3=train2[train2['deposit']=='no']
```

[ ]:
```
train3[(train3['housing']=='yes') | (train3['loan']=='yes')]
```

[ ]:
```
      age          job  marital  education default  balance housing loan  \
3      41  blue-collar  married  secondary      no    356.0     yes   no
7      34  blue-collar  married    primary      no   5299.0     yes   no
9      44  blue-collar  married  secondary      no    879.0     yes   no
10     34     services  married  secondary      no   1637.0     yes   no
12     32   management  married   tertiary      no   9214.0      no  yes
…    …            …        …          …       …        …      …    …
4456   54  blue-collar  married  secondary      no   -102.0     yes   no
4457   43   management  married   tertiary      no   1336.0     yes  yes
4460   54      retired  married  secondary      no    522.0      no  yes
4461   33   management  married   tertiary      no    133.0     yes   no
4464   31   technician   single  secondary      no    628.0     yes   no

       contact  day month  duration  campaign  pdays  previous poutcome  \
3     cellular   14   may        90         5     -1         0  unknown
7      unknown   26   jun        75         5     -1         0  unknown
9     cellular    3   apr       383         1     -1         0  unknown
10    cellular   21   nov       107         4     -1         0  unknown
12     unknown   18   oct        71         1     -1         0  unknown
…          …    …   …         …        …       …         …
4456  cellular   27   aug       164         7     -1         0  unknown
4457  cellular   27   may        82         2    309         1  failure
4460  cellular   14   jul        81         3     -1         0  unknown
4461   unknown   26   may       308         4     -1         0  unknown
4464   unknown   12   may      1083         2     -1         0  unknown

     deposit
3         no
7         no
9         no
10        no
12        no
…        …
4456      no
4457      no
4460      no
4461      no
```

```
4464      no

[1493 rows x 17 columns]
```

1493 clients who have not subscribed to a deposit have a housing or personal loan.

0.6 Solution 6

```
[ ]: train4=train2[train2['poutcome']=='success']
```

```
[ ]: train4
```

```
[ ]:      age            job   marital  education default  balance housing loan  \
19     76  self-employed   married    unknown      no   4984.0      no   no
21     33         admin.   married   tertiary      no     79.0     yes   no
45     71        retired  divorced  secondary      no      0.0      no   no
51     68        retired   married  secondary      no   1146.0      no   no
52     46     management   married   tertiary      no    273.0     yes   no
…    …          …        …        …       …       …        …   …
4408   29      housemaid    single   tertiary      no     19.0      no   no
4413   27     management    single  secondary      no    843.0      no   no
4419   37     management   married   tertiary      no    393.0     yes   no
4448   27    blue-collar    single  secondary      no    535.0      no   no
4455   30     management    single   tertiary      no    265.0      no   no

        contact  day month  duration  campaign  pdays  previous poutcome  \
19    telephone   28   apr       403         1    182         1  success
21     cellular    5   may       389         1    195         4  success
45     cellular   26   feb       771         1    171         1  success
51     cellular   13   may       356         1     71         5  success
52     cellular   18   mar       910         2    184         4  success
…            …  …   …       …       …     …        …       …
4408   cellular    4   may       268         1     88         4  success
4413   cellular   12   jul       123         2    185         1  success
4419   cellular   12   aug        62         2    104         2  success
4448   cellular   16   aug       265         3     95         4  success
4455   cellular   25   nov       295         1     93         3  success

     deposit
19       yes
21       yes
45       yes
51       yes
52       yes
…        …
4408     yes
4413      no
4419      no
```

```
4448     yes
4455      no

[435 rows x 17 columns]
```

[ ]:
```python
train4[train4['deposit']=='yes']
```

[ ]:
```
      age            job   marital  education default  balance housing loan  \
19     76  self-employed   married    unknown      no   4984.0      no   no
21     33         admin.   married   tertiary      no     79.0     yes   no
45     71        retired  divorced  secondary      no      0.0      no   no
51     68        retired   married  secondary      no   1146.0      no   no
52     46     management   married   tertiary      no    273.0     yes   no
…     …              …        …         …       …        …     …   …
4338   38         admin.  divorced  secondary      no     19.0     yes   no
4372   20        student    single  secondary      no    215.0      no   no
4376   42     technician   married  secondary      no    994.0     yes   no
4408   29      housemaid    single   tertiary      no     19.0      no   no
4448   27    blue-collar    single  secondary      no    535.0      no   no

        contact  day month  duration  campaign  pdays  previous poutcome  \
19    telephone   28   apr       403         1    182         1  success
21     cellular    5   may       389         1    195         4  success
45     cellular   26   feb       771         1    171         1  success
51     cellular   13   may       356         1     71         5  success
52     cellular   18   mar       910         2    184         4  success
…           …   …     …         …       …     …        …
4338   cellular    5   feb      1130         3    251         2  success
4372   cellular   24   feb       175         1     92         6  success
4376   cellular   12   nov       227         3     93         6  success
4408   cellular    4   may       268         1     88         4  success
4448   cellular   16   aug       265         3     95         4  success

     deposit
19       yes
21       yes
45       yes
51       yes
52       yes
…        …
4338     yes
4372     yes
4376     yes
4408     yes
4448     yes

[392 rows x 17 columns]
```

```
[ ]: 392/435
```

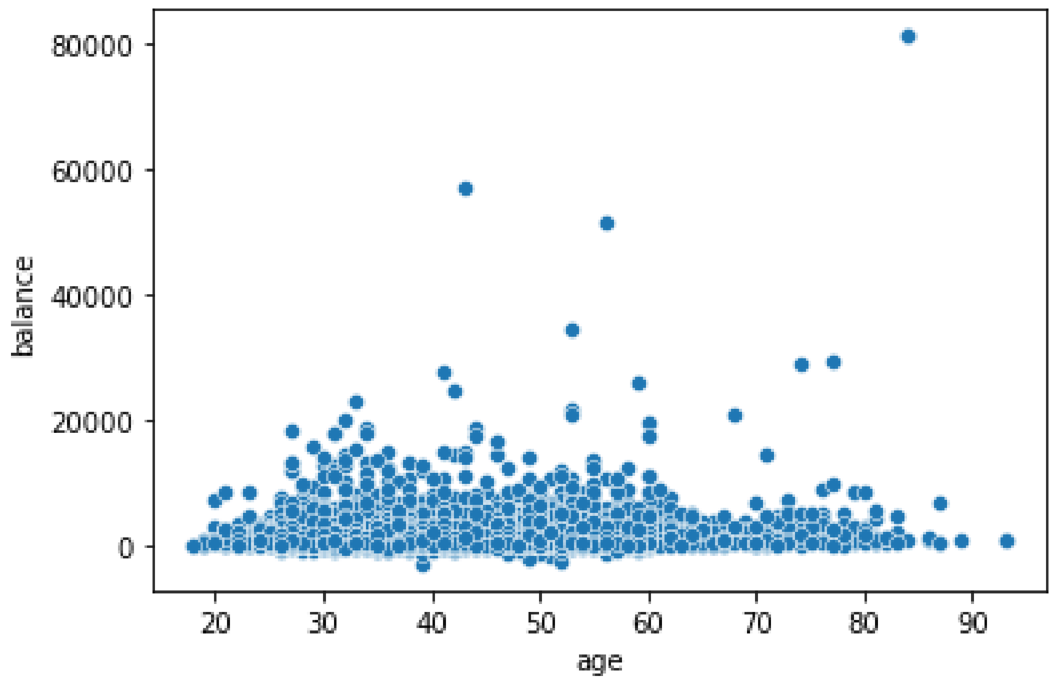
```
[ ]: 0.9011494252873563
```

90.11% of clients have subscribed to a term deposit as an outcome of the successful marketing campaign.

0.7 Solution 7

```
[ ]: sns.scatterplot(data=train2,x='age',y='balance')
```

```
[ ]: <AxesSubplot:xlabel='age', ylabel='balance'>
```



Across all age groups, the average yearly bank balance of most of the clients is less than 20,000 euros

0.8 Solution 8 - 12

0.8.1 Data cleaning

```
[ ]: test[test.isnull().any(axis=1)]
```

```
[ ]:     age         job  marital education default  balance housing loan  \
    44   57  technician  married   primary      no     3376     yes   no

       contact  day month  duration  campaign  pdays  previous poutcome deposit
```

```
44   telephone     2    jun        421          2      -1         NaN  unknown      yes
```

[ ]:
```
test2=test.dropna()
```

[ ]:
```
trainf=pd.get_dummies(data=train2,drop_first=True)
testf=pd.get_dummies(data=test2,drop_first=True)
```

[ ]:
```
X_train=trainf.drop('deposit_yes',axis=1)
y_train=trainf['deposit_yes']

X_test=testf.drop('deposit_yes',axis=1)
y_test=testf['deposit_yes']
```

0.8.2 Model creation (KNN with n=7)

[ ]:
```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import␣
 ↪accuracy_score,classification_report,confusion_matrix
```

[ ]:
```
y_train
```

[ ]:
```
0       0
1       1
2       1
3       0
4       1
       ..
4461    0
4462    1
4463    1
4464    0
4465    0
Name: deposit_yes, Length: 4464, dtype: uint8
```

[ ]:
```
knn=KNeighborsClassifier(n_neighbors=7)
knn.fit(X_train,y_train)
knnpred=knn.predict(X_test)
```

[ ]:
```
accuracy_score(y_test,knnpred)
```

[ ]:
```
0.767921146953405
```

The accuracy of the model is 77%

[ ]:
```
missclassified=y_test!=knnpred
missclassified.value_counts()
```

[ ]:
```
False    857
True     259
Name: deposit_yes, dtype: int64
```

259 samples were misclassified

[ ]:
```
print(confusion_matrix(y_test,knnpred))
```

```
[[490 116]
 [143 367]]
```

[ ]:
```
confusion_metrics(confusion_matrix(y_test,knnpred))
```

```
True Positives: 367
True Negatives: 490
False Positives: 116
False Negatives: 143
--------------------------------------------------
Accuracy: 0.77
Mis-Classification: 0.23
Sensitivity: 0.72
Specificity: 0.81
Precision: 0.81
f_1 Score: 0.76
```

Sensitivity is 0.72

Specificity is 0.81

Prevalence = (TP+FN)/(TP+TN+FP+FN) = 0.46

0.9 Solution 13-15

0.9.1 Model creation (Logistic regression)

[ ]:
```
from sklearn.linear_model import LogisticRegression
```

[ ]:
```
logreg=LogisticRegression(random_state=0,max_iter=3000)
logreg.fit(X_train,y_train)
logpred=logreg.predict(X_test)
```

[ ]:
```
print(confusion_matrix(y_test,logpred))
```

```
[[517  89]
 [105 405]]
```

[ ]:
```
confusion_metrics(confusion_matrix(y_test,logpred))
```

```
True Positives: 405
True Negatives: 517
False Positives: 89
False Negatives: 105
```

```
--------------------------------------------------
Accuracy: 0.83
Mis-Classification: 0.17
Sensitivity: 0.79
Specificity: 0.85
Precision: 0.85
f_1 Score: 0.82
```

Sensitivity is 0.79

Specificity is 0.85

Prevalence = (TP+FN)/(TP+TN+FP+FN) = 0.46

```
[ ]: def confusion_metrics (conf_matrix):
     # save confusion matrix and slice into four pieces
         TP = conf_matrix[1][1]
         TN = conf_matrix[0][0]
         FP = conf_matrix[0][1]
         FN = conf_matrix[1][0]
         print('True Positives:', TP)
         print('True Negatives:', TN)
         print('False Positives:', FP)
         print('False Negatives:', FN)

         # calculate accuracy
         conf_accuracy = (float (TP+TN) / float(TP + TN + FP + FN))

         # calculate mis-classification
         conf_misclassification = 1- conf_accuracy

         # calculate the sensitivity
         conf_sensitivity = (TP / float(TP + FN))
         # calculate the specificity
         conf_specificity = (TN / float(TN + FP))

         # calculate precision
         conf_precision = (TN / float(TN + FP))
         # calculate f_1 score
         conf_f1 = 2 * ((conf_precision * conf_sensitivity) / (conf_precision +␣
      ↪conf_sensitivity))
         print('-'*50)
         print(f'Accuracy: {round(conf_accuracy,2)}')
         print(f'Mis-Classification: {round(conf_misclassification,2)}')
         print(f'Sensitivity: {round(conf_sensitivity,2)}')
         print(f'Specificity: {round(conf_specificity,2)}')
         print(f'Precision: {round(conf_precision,2)}')
```

```python
    print(f'f_1 Score: {round(conf_f1,2)}')
```

[ ]:

```python

```