Non Proctored 1

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.corr()
```

[ ]:

	age	balance	day	duration	campaign	pdays	previous
age	1.000000	0.129043	-0.007330	-0.007839	-0.018284	0.002402	0.029582
balance	0.129043	1.000000	0.009142	0.015043	-0.031025	0.038155	0.044608
day	-0.007330	0.009142	1.000000	-0.013382	0.140019	-0.080303	-0.055446
duration	-0.007839	0.015043	-0.013382	1.000000	-0.040431	-0.040912	-0.032467
campaign	-0.018284	-0.031025	0.140019	-0.040431	1.000000	-0.104013	-0.040107
pdays	0.002402	0.038155	-0.080303	-0.040912	-0.104013	1.000000	0.486493
previous	0.029582	0.044608	-0.055446	-0.032467	-0.040107	0.486493	1.000000

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

[ ]:

	age	balance	day	duration	campaign \
count	4466.000000	4465.000000	4466.000000	4466.000000	4466.000000
mean	41.100090	1484.334378	15.740484	371.089342	2.484774
std	11.905566	3253.910473	8.448066	346.904391	2.633638
min	18.000000	-3058.000000	1.000000	3.000000	1.000000
25%	32.000000	107.000000	8.000000	137.000000	1.000000
50%	38.000000	539.000000	16.000000	256.000000	2.000000
75%	49.000000	1728.000000	22.000000	485.000000	3.000000
max	93.000000	81204.000000	31.000000	3284.000000	43.000000

	pdays	previous
count	4466.000000	4466.000000
mean	52.880878	0.866995
std	111.146726	2.381197
min	-1.000000	0.000000
25%	-1.000000	0.000000
50%	-1.000000	0.000000

```
75%      64.750000    1.000000
max     828.000000   41.000000
```

[ ]:
```
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()
train2
```

[ ]:
```
      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

[4464 rows x 17 columns]
```

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

[ ]:
```
train2[train2['deposit']=='no'].describe()
```

[ ]:
```
               age       balance          day     duration     campaign  \
count  2352.000000   2352.000000  2352.000000  2352.000000  2352.000000
mean     40.908588   1289.947279    16.276786   221.560374     2.778486
std      10.188261   2951.463418     8.323296   208.893123     3.064984
min      18.000000  -2712.000000     1.000000     3.000000     1.000000
25%      33.000000     60.000000     9.000000    93.000000     1.000000
50%      39.000000    396.000000    17.000000   163.000000     2.000000
75%      48.000000   1327.500000    22.000000   275.000000     3.000000
max      89.000000  56831.000000    31.000000  3284.000000    43.000000

             pdays     previous
count  2352.000000  2352.000000
mean     38.459609     0.605867
std     100.381086     2.367334
min      -1.000000     0.000000
25%      -1.000000     0.000000
50%      -1.000000     0.000000
75%      -1.000000     0.000000
max     826.000000    41.000000
```

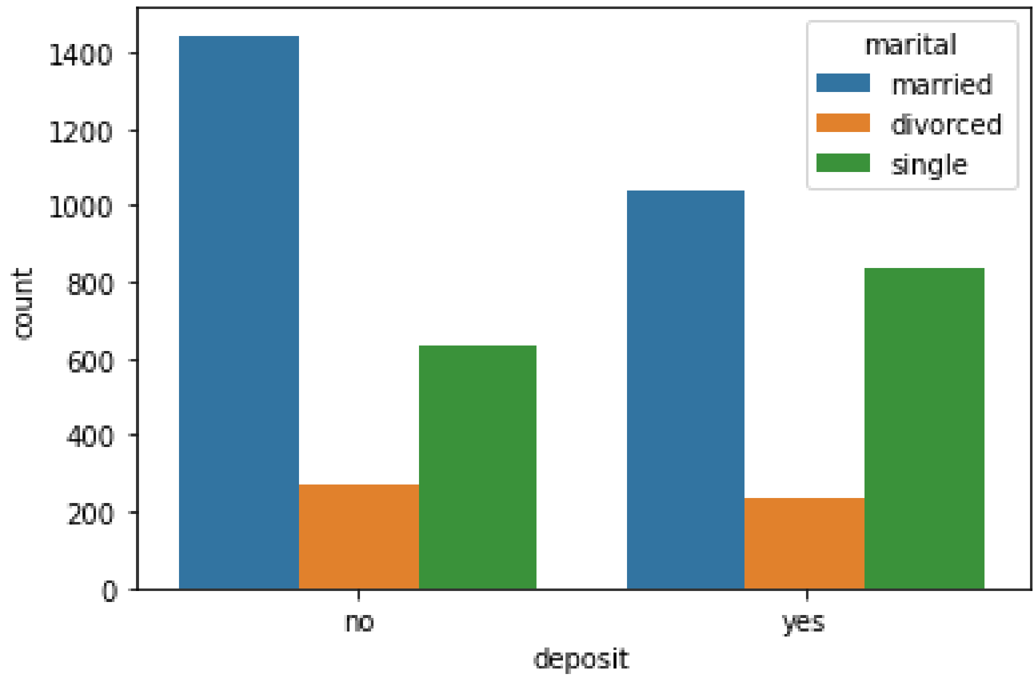
[ ]:
```
train3=train2[train2['deposit']=='yes']
train3[(train3['loan']=='yes') | (train3['housing']=='yes')]
```

[ ]:
```
      age          job  marital  education default  balance housing loan  \
2      51   management  married   tertiary      no   2455.0     yes   no
4      51   technician  married  secondary      no  -1944.0     yes   no
15     37   management   single   tertiary      no    455.0     yes   no
```

```
17      24        admin.    single   tertiary      no      0.0      yes   no
21      33        admin.   married   tertiary      no     79.0      yes   no
…   …          …        …       …       …       …      …   …
4454    30  blue-collar    single  secondary      no    155.0      yes  yes
4458    32  blue-collar   married    primary      no   -454.0      yes  yes
4459    37   technician    single  secondary      no   3326.0      yes   no
4462    39     services  divorced  secondary      no    687.0      yes   no
4463    40        admin.    single  secondary      no   2040.0      yes   no

       contact  day month  duration  campaign  pdays  previous poutcome  \
2     cellular   21   jul       553         1     -1         0  unknown
4     cellular    7   may       623         1     -1         0  unknown
15    cellular   13   aug       904         6     -1         0  unknown
17    cellular   27   may       122         2     -1         0  unknown
21    cellular    5   may       389         1    195         4  success
…         …   …   …       …       …     …       …       …
4454  cellular    9   jul      1426         3     -1         0  unknown
4458  cellular   18   may       801         5    355         2  failure
4459   unknown   21   may       799         1     -1         0  unknown
4462  cellular    9   jul       869         1     -1         0  unknown
4463  cellular   18   may       906         2    350         2  failure

     deposit
2        yes
4        yes
15       yes
17       yes
21       yes
…       …
4454     yes
4458     yes
4459     yes
4462     yes
4463     yes

[893 rows x 17 columns]
```

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

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




```
[ ]: 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()
     test2
```

```
[ ]:       age           job  marital  education default  balance housing loan  \
    0      50    management  married   tertiary      no        0      no   no
    1      50        admin.  married  secondary      no      715      no   no
    2      32      services   single  secondary      no     1168     yes   no
    3      39    technician  married  secondary      no       24     yes   no
    4      35   blue-collar  married  secondary      no      563      no  yes
    …     …             …       …         …       …        …       …    …
    1112   32        admin.   single  secondary      no      -32      no   no
    1113   39   blue-collar  married  secondary      no    11854     yes   no
    1114   54   blue-collar  married    unknown      no     -361     yes   no
    1115   30 self-employed   single   tertiary      no      916      no   no
    1116   42   blue-collar  married    primary      no      201     yes   no

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

```
0     cellular   30   jan       199         1    205        1.0  failure
1     cellular   28   aug       131        13     -1        0.0  unknown
2     cellular   16   nov       411         1     -1        0.0  unknown
3     cellular   28   jan        79         4     -1        0.0  unknown
4     cellular    4   jun       147         1    119        3.0  failure
…          …   …    …      …      …     …       …       …
1112  cellular   29   jan       320         1    185        5.0    other
1113  cellular   15   may        15         9     -1        0.0  unknown
1114   unknown   26   may       227         1     -1        0.0  unknown
1115  cellular   29   dec       449         2     -1        0.0  unknown
1116  cellular   11   aug       265         1    103        3.0  success

     deposit
0         no
1         no
2        yes
3         no
4        yes
…       …
1112      no
1113      no
1114      no
1115     yes
1116     yes

[1116 rows x 17 columns]
```

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

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

[ ]:
```
X=trainf.drop('deposit_yes',axis=1)
y=trainf['deposit_yes']
```

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

[ ]:
```
knn=KNeighborsClassifier(n_neighbors=11)
```

[ ]:
```
knn.fit(X=X,y=y)
```

[ ]:
```
KNeighborsClassifier(n_neighbors=11)
```

[ ]:
```
predictions=knn.predict(testf.drop('deposit_yes',axis=1))
```

[ ]:
```
accuracy_score(testf['deposit_yes'],predictions)
```

[ ]: 0.771505376344086

[ ]:
```
ar=testf['deposit_yes']!=predictions
```

[ ]:
```
ar.value_counts()
```

[ ]:
```
False    861
True     255
Name: deposit_yes, dtype: int64
```

[ ]:
```
print(confusion_matrix(testf['deposit_yes'],predictions))
```

```
[[502 104]
 [151 359]]
```

[ ]:
```
print(classification_report(testf['deposit_yes'],predictions))
```

```
              precision    recall  f1-score   support

           0       0.77      0.83      0.80       606
           1       0.78      0.70      0.74       510

    accuracy                           0.77      1116
   macro avg       0.77      0.77      0.77      1116
weighted avg       0.77      0.77      0.77      1116
```

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

[ ]:
```
confusion_metrics(confusion_matrix(testf['deposit_yes'],predictions))
```

```
True Positives: 359
True Negatives: 502
False Positives: 104
False Negatives: 151
--------------------------------------------------
Accuracy: 0.77
Mis-Classification: 0.23
Sensitivity: 0.7
Specificity: 0.83
Precision: 0.83
f_1 Score: 0.76
```

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

[ ]:
```
log=LogisticRegression(max_iter=9000)
log.fit(X=X,y=y)
logpredictions=log.predict(testf.drop('deposit_yes',axis=1))
```

[ ]:
```
logar=testf['deposit_yes']!=logpredictions
logar.value_counts()
```

[ ]:
```
False    922
True     194
Name: deposit_yes, dtype: int64
```

[ ]:
```
accuracy_score(testf['deposit_yes'],logpredictions)
```

[ ]:
```
0.8261648745519713
```

[ ]:
```
print(classification_report(testf['deposit_yes'],logpredictions))
```

```
              precision    recall  f1-score   support
```

```
           0       0.83      0.85      0.84       606
           1       0.82      0.79      0.81       510

    accuracy                           0.83      1116
   macro avg       0.83      0.82      0.82      1116
weighted avg       0.83      0.83      0.83      1116
```

[ ]:
```
trainf['deposit_yes'].value_counts()
```

[ ]:
```
0    2352
1    2112
Name: deposit_yes, dtype: int64
```

[ ]:
```
testf['deposit_yes'].value_counts()
```

[ ]:
```
0    606
1    510
Name: deposit_yes, dtype: int64
```

[ ]:
```
predictions.value_counts()
```

```
---------------------------------------------------------------------------
AttributeError                            Traceback (most recent call last)
<ipython-input-144-acf40f98e6b6> in <module>
----> 1 predictions.value_counts()

AttributeError: 'numpy.ndarray' object has no attribute 'value_counts'
```

[ ]:
```
print predictions((unique, counts)).
```

```
  File "<ipython-input-146-9850e7bc0d8e>", line 1
    print predictions((unique, counts)).
          ^
SyntaxError: invalid syntax
```

[ ]:
```
import numpy as np

unique, counts = np.unique(predictions, return_counts=True)

print(np.asarray((unique, counts)).T)
```

```
[[  0 653]
 [  1 463]]
```

[ ]:

```

```