DataBase LSAC__Exercise__20200210

February 7, 2020

1 DataBase LSAC | Exercise

2 Install Jupyter Notebook

- Go to ANACONDA PLATFORM https://www.anaconda.com/
- Downoload and install

2.1 1. Check your Pyhton Version & Import Libraries

[1]:
```
# Check your Pyhton Version

from platform import python_version
print(python_version())
```

```
3.7.3
```

[2]:
```
# Import useful libraries
import numpy  as np
import pandas as pd
import sklearn
import os
import math
import matplotlib.pyplot as  plt
from matplotlib.legend_handler import HandlerLine2D
import seaborn as sns

# Machine Leanring libraires
from sklearn.model_selection import KFold, StratifiedKFold, train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC, LinearSVC
from sklearn.neighbors import KNeighborsClassifier


# Import useful Evaluation Metrics
from sklearn import metrics
```

```
from sklearn.metrics import recall_score, roc_auc_score, accuracy_score,␣
↪confusion_matrix, make_scorer, classification_report, roc_curve, auc,␣
↪f1_score
from sklearn.ensemble import RandomForestRegressor, RandomForestClassifier
```

2.2 2. Data Upload & Exploratory Data Analysis

[3]:
```
# Upload data
df = pd.read_excel("data__clean__exercise.xlsx")
```

[4]:
```
# Quick visual check of the head and tail of the uploaed Pandas dataframe
df.head()
#df.tail()
```

[4]:
```
   Unnamed: 0   ID  EZ  D-IN  CRS-R  LCF  TR  RESP  RBI-ST-A  RBI-ST-B  \
0           0  A 1   3     1      0   -4   1   2.0      -500      -100
1           1  A 2   3     3    -18   -6   1   2.0      -500      -100
2           2  A 3   2     1     -1   -3   1   1.0      -500      -100
3           3  A 4   2     2     -7   -2   1   2.0      -500      -100
4           4  A 5   3     3    -15   -6   0   1.0      -450      -100

   PSH-AM-1  N-CRS-1  PSH-AM-2  N-CRS-2  PSH-AM-4M  TARGET
0         4      0.0         3      0.0        3.0       1
1        20      2.0        17      2.0        8.0       0
2         3      0.0         3      0.0        1.0       1
3         2      0.0         4      0.0        2.0       1
4        17      2.0        16      1.0        2.0       1
```

2.2.1 Print dataframe info

[5]:
```
df.info()
print(len(df.columns), 'Number of dataframe columns')
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 156 entries, 0 to 155
Data columns (total 16 columns):
Unnamed: 0    156 non-null int64
ID            156 non-null object
EZ            156 non-null int64
D-IN          156 non-null int64
CRS-R         156 non-null int64
LCF           156 non-null int64
TR            156 non-null int64
RESP          144 non-null float64
RBI-ST-A      156 non-null int64
RBI-ST-B      156 non-null int64
PSH-AM-1      156 non-null int64
```

```
N-CRS-1       144 non-null float64
PSH-AM-2      156 non-null int64
N-CRS-2       144 non-null float64
PSH-AM-4M     142 non-null float64
TARGET        156 non-null int64
dtypes: float64(4), int64(11), object(1)
memory usage: 19.6+ KB
16 Number of dataframe columns
```

2.2.2 Check missing values and decide which strategy to adopt (drop missing values, filling strategy with mean, median.. depending on the data type)

[6]:
```
# check missing values
print(pd.isna(df).sum())
```

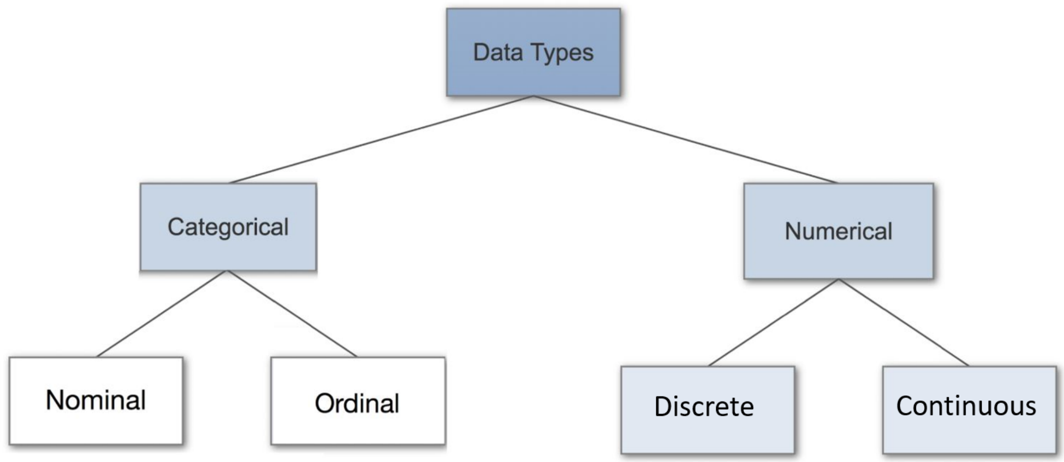
```
Unnamed: 0     0
ID             0
EZ             0
D-IN           0
CRS-R          0
LCF            0
TR             0
RESP          12
RBI-ST-A       0
RBI-ST-B       0
PSH-AM-1       0
N-CRS-1       12
PSH-AM-2       0
N-CRS-2       12
PSH-AM-4M     14
TARGET         0
dtype: int64
```

2.2.3 Data Type is important! | Remeber to check your data type

We will not go into details, but it's always important to know which data type we're using. We have categorical ordinal data in this case, and numerical continuous data.

[7]:
```
from IPython.display import Image
Image(filename='datatype.png', width=600)
```

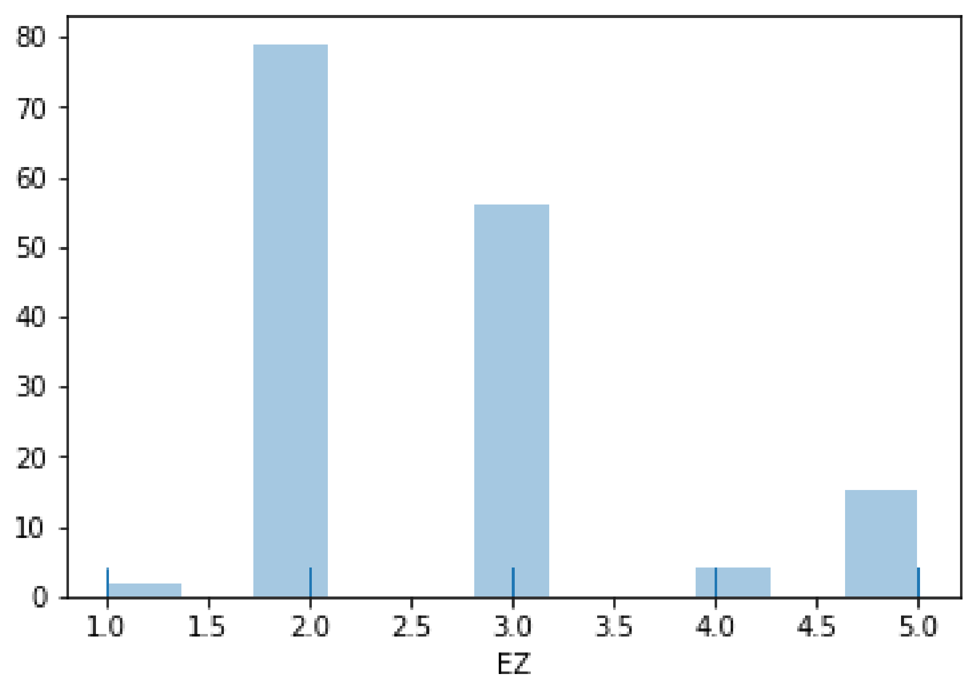
[7]:



2.2.4 Plot variables distributions to look at your data | DISTPLOT

- select other features to see theirdistributions

[8]:
```
# select feature numnber
i = 2
x = df.iloc[:,i]
sns.distplot(x, kde=False, rug=True, axlabel = df.columns[i]);
```



2.3 3. Preprocessing

[9]:
```
# check missing values
print(pd.isna(df).sum())
```

```
Unnamed: 0      0
ID              0
EZ              0
D-IN            0
CRS-R           0
LCF             0
TR              0
RESP           12
RBI-ST-A        0
RBI-ST-B        0
PSH-AM-1        0
N-CRS-1        12
PSH-AM-2        0
N-CRS-2        12
PSH-AM-4M      14
TARGET          0
dtype: int64
```

For this time we decide to drop subject with missing variables

[10]:
```
df.dropna(inplace = True)
```

[11]:
```
pd.isna(df).sum()
```

[11]:
```
Unnamed: 0     0
ID             0
EZ             0
D-IN           0
CRS-R          0
LCF            0
TR             0
RESP           0
RBI-ST-A       0
RBI-ST-B       0
PSH-AM-1       0
N-CRS-1        0
PSH-AM-2       0
N-CRS-2        0
PSH-AM-4M      0
TARGET         0
dtype: int64
```

[12]:
```
print(df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 130 entries, 0 to 155
Data columns (total 16 columns):
Unnamed: 0    130 non-null int64
ID            130 non-null object
EZ            130 non-null int64
D-IN          130 non-null int64
CRS-R         130 non-null int64
LCF           130 non-null int64
TR            130 non-null int64
RESP          130 non-null float64
RBI-ST-A      130 non-null int64
RBI-ST-B      130 non-null int64
PSH-AM-1      130 non-null int64
N-CRS-1       130 non-null float64
PSH-AM-2      130 non-null int64
N-CRS-2       130 non-null float64
PSH-AM-4M     130 non-null float64
TARGET        130 non-null int64
dtypes: float64(4), int64(11), object(1)
memory usage: 17.3+ KB
None
```

2.4 3. Machine Learning

2.4.1 3.1 Select training and target variable

[13]:
```
# Set target variable and
# to begin with, remove first four cols, the target variable and the related␣
↪variables
data = df.copy()

y = data['TARGET'].copy()
X = data.copy()
X.drop(['Unnamed: 0', 'ID', 'TARGET'], axis=1, inplace = True)

# In case you want to selct only some features
# X__input = X[['D-IN', 'CRS-R', 'LCF', 'PSH-AM-1','PSH-AM-2', 'PSH-AM-4M']]
```

[14]:
```
X.head()
#y.head()
```

[14]:
```
   EZ  D-IN  CRS-R  LCF  TR  RESP  RBI-ST-A  RBI-ST-B  PSH-AM-1  N-CRS-1  \
0   3     1      0   -4   1   2.0      -500      -100         4      0.0
1   3     3    -18   -6   1   2.0      -500      -100        20      2.0
2   2     1     -1   -3   1   1.0      -500      -100         3      0.0
```

```
3   2     2     -7   -2   1   2.0       -500       -100          2       0.0
4   3     3    -15   -6   0   1.0       -450       -100         17       2.0

   PSH-AM-2  N-CRS-2  PSH-AM-4M
0         3      0.0        3.0
1        17      2.0        8.0
2         3      0.0        1.0
3         4      0.0        2.0
4        16      1.0        2.0
```

Count responding subjects (TARGET = 1) VS Not-Responding Subjects (TARGET = 0) | Is the sample balanced?

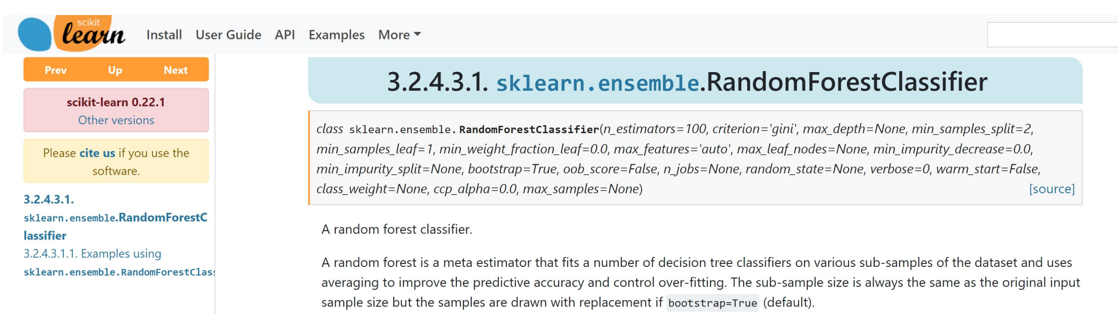
[15]:
```
# Responding
R = df[ df['TARGET'] == 1]['TARGET'].sum()
# Not responding
NR = df[ df['TARGET'] == 0]['TARGET'].value_counts()
print(f'(Responding Subjects, Not responding Subjects): {R, NR[0]}')
```

```
(Responding Subjects, Not responding Subjects): (85, 45)
```

2.4.2 3.2 Model Selection | Random Forest

[16]:
```
from IPython.display import Image
Image(filename='RF__scikitelearn.jpg', width=1020)
```

[16]:



Some main hyperparameters https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomI

- **n_estimators** : # of decision tree classifers
- **criterion / objective function** : function to measure the quality of a split.
- **max_depth** : the maximum depth of the tree. If None, then nodes are expanded until all leaves are pure or until all leaves contain less than min_samples_split samples.
- **min_samples_split**: optional (default=2) The minimum number of samples required to split an internal node

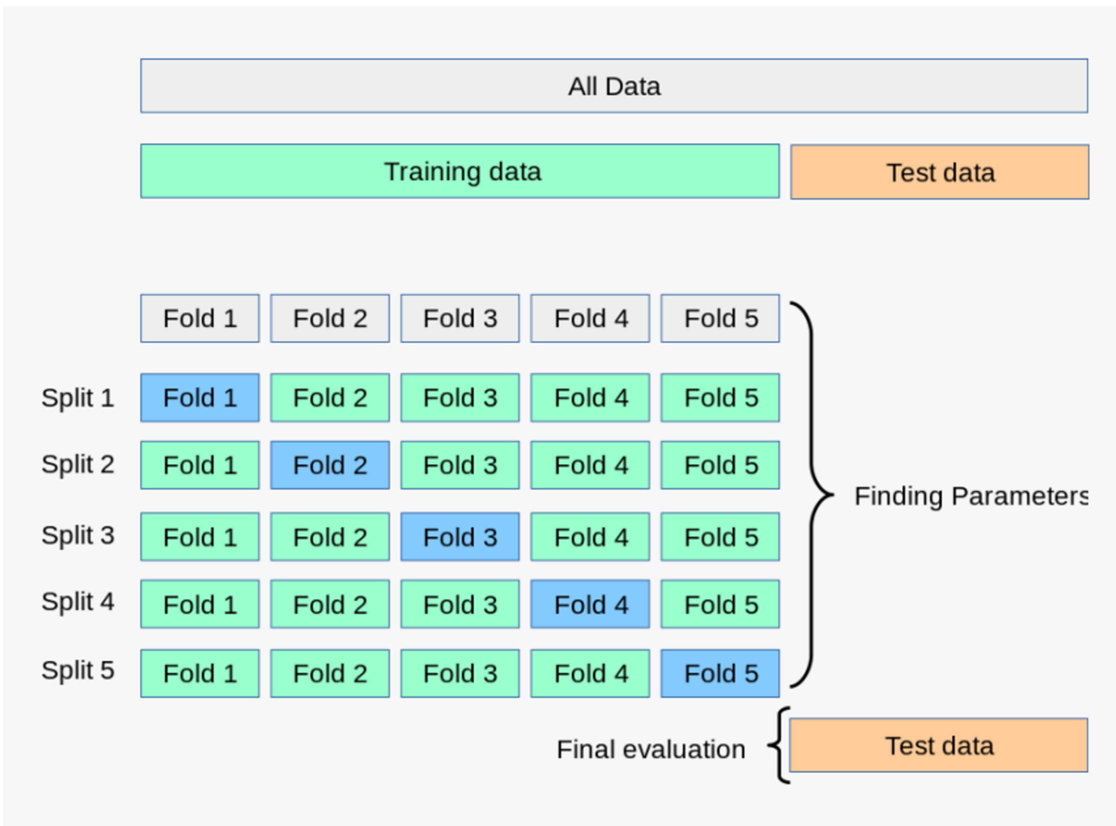
- **class_weight** : The "balanced" mode uses the values of y to automatically adjust weights inversely proportional to class frequencies in the input data. The "balanced_subsample" mode is the same as "balanced" except that weights are computed based on the bootstrap sample for every tree grown.

2.4.3 3.3 Optimization of "N_ESTIMATORS" hyperparam

- Let' use a K-fold Cross-Validation approach

[17]:
```
from IPython.display import Image
Image(filename='cross-validation-k-fold-cross.png', width=600)
```

[17]:



[22]:
```
# Define hyperparameters and storage functions

k_out    = 10      # number of iterations
k_in     = 5      # k-fold cross validation

n_estimators  = [3, 9, 16, 32, 64, 100] # 200 32, 64, 100

train_results = []
test_results  = []
val_results  = []
```

```
train_results_acc = []
test_results_acc  = []
val_results_acc = []

acc = np.zeros(k_in)
sens = np.zeros(k_in)
spec = np.zeros(k_in)
roc = np.zeros(k_in)

acc_avg  = np.zeros(k_out)
sens_avg = np.zeros(k_out)
spec_avg = np.zeros(k_out)
auc_avg = np.zeros(k_out)
```

[23]:
```
i = 0

while i<k_out: # set number of iterations

    # Split training and testing, then use training set for the k-fold cross␣
 ↪validation
    X_train, X_test, Y_train, Y_test = train_test_split(X, y, test_size=0.10,␣
 ↪shuffle=True, stratify = y)

    skf = StratifiedKFold(n_splits=k_in, shuffle = True)
    for train_index, val_index in skf.split(X_train, Y_train):

        # 4-folds for traing
        X_tr = X_train.iloc[train_index]
        y_tr = Y_train.iloc[train_index]

        # 1 fold for validation
        X_val = X_train.iloc[val_index]
        y_val = Y_train.iloc[val_index]

        for estimator in n_estimators:
            rf = RandomForestClassifier(n_estimators=estimator,␣
 ↪class_weight='balanced_subsample', n_jobs=-1)
            rf.fit(X_tr, y_tr)

            train_pred = rf.predict(X_tr)
            false_positive_rate, true_positive_rate, thresholds =␣
 ↪roc_curve(y_tr, train_pred)
            roc_auc = auc(false_positive_rate, true_positive_rate)
            train_acc = accuracy_score(y_tr, train_pred)
            train_results.append(roc_auc)
            train_results_acc.append(train_acc)
```

```
            val_pred = rf.predict(X_val)
            false_positive_rate, true_positive_rate, thresholds =␣
 ↪roc_curve(y_val, val_pred)
            roc_auc = auc(false_positive_rate, true_positive_rate)
            val_acc = accuracy_score(y_val, val_pred)
            val_results.append(roc_auc)
            val_results_acc.append(val_acc)

    i +=1
```

[24]:
```
i
```

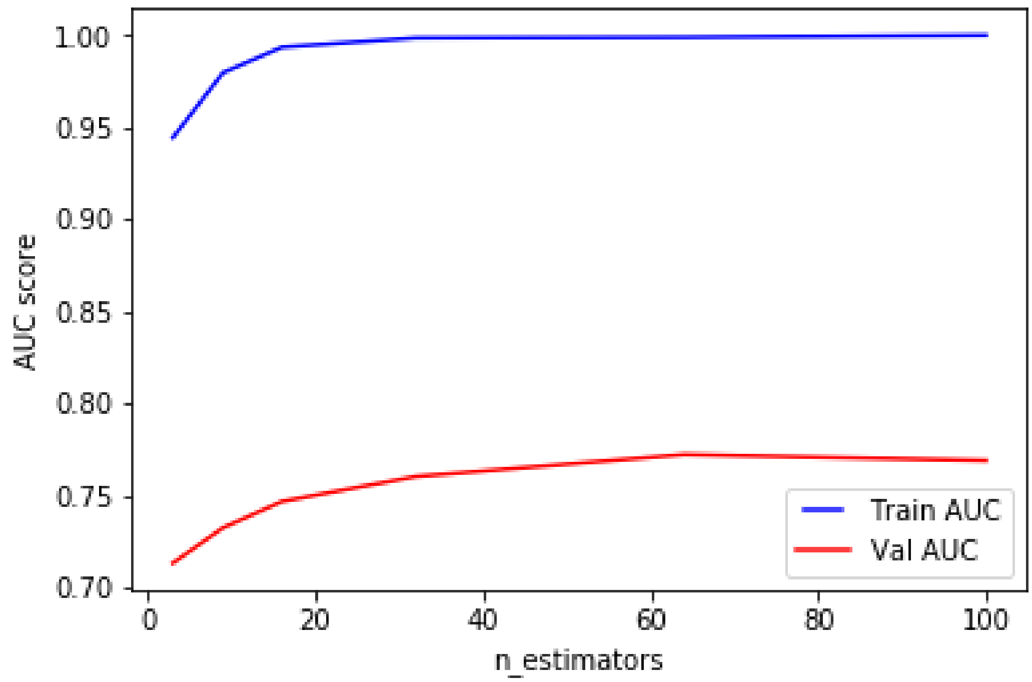
[24]: 10

2.4.4 Plotting AUC vs N_ESTIMATORS

[25]:
```
# N ESTIMATORS | AUC
val_results_avg = np.sum(np.asarray(val_results).reshape((k_in*k_out,␣
 ↪len(n_estimators))), axis = 0)/(k_in*k_out)
train_results_avg = np.sum(np.asarray(train_results).reshape((k_in*k_out,␣
 ↪len(n_estimators))), axis = 0)/(k_in*k_out)

from matplotlib.legend_handler import HandlerLine2D
line1, = plt.plot(n_estimators, train_results_avg, 'b', label='Train AUC')
line2, = plt.plot(n_estimators, val_results_avg, 'r', label='Val AUC')
plt.legend(handler_map={line1: HandlerLine2D(numpoints=2)})
plt.ylabel('AUC score')
plt.xlabel('n_estimators')
plt.show()

print(pd.Series(val_results_avg))
```




```
0    0.713097
1    0.732375
2    0.746625
3    0.760208
4    0.772153
5    0.768931
dtype: float64
```

2.4.5 3.4 DO IT YOURSELF: Plotting ACCURACY vs N_ESTIMATORS

[ ]:

```

```

2.4.6 3.5 DO IT YOURSELF: OPTIMIZE ANOTHER HYPERPARAMETER (e.g max_depth) AND PLOT IT!

[ ]:

```

```

2.4.7 3.6 Random Forest with Optimized Hyperparameters

[26]:

```
# set params

k_out   = 10     # number of splitting repetitions == iterations
n_estim = 64
```

```
acc = np.zeros(k_in)
sens = np.zeros(k_in)
spec = np.zeros(k_in)
roc = np.zeros(k_in)

acc_avg  = np.zeros(k_out)
sens_avg = np.zeros(k_out)
spec_avg = np.zeros(k_out)
auc_avg = np.zeros(k_out)

test_results_acc    = []
test_results_recall = []
test_results_auc    = []
test_results_spec   = []
```

[27]:
```
i = 0
while i<k_out:

    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.10,␣
 ↪shuffle=True, stratify = y)

    # RANDOM FOREST
    model = RandomForestClassifier(n_estimators=n_estim,␣
 ↪class_weight='balanced_subsample')
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)

    # Calculate Evaluation Metrics
    acc = accuracy_score(y_test, y_pred)
    recall = recall_score(y_test, y_pred)
    false_positive_rate, true_positive_rate, thresholds = roc_curve(y_test,␣
 ↪y_pred)
    roc_auc = auc(false_positive_rate, true_positive_rate)
    tn, fp, fn, tp = confusion_matrix(y_test, y_pred).ravel()
    spec = (tn / (tn + fp))

    test_results_acc.append(acc)
    test_results_recall.append(recall)
    test_results_auc.append(roc_auc)
    test_results_spec.append(spec)

    i +=1
```

2.4.8 4. Performances | Evaluation Metrics

[28]:
```
ACC    =  np.asarray(test_results_acc).mean()
RECALL =  np.asarray(test_results_recall).mean()
SPEC   =  np.asarray(test_results_spec).mean()
AUC    =  np.asarray(test_results_auc).mean()

print(ACC, 'Accuracy')
print(RECALL, 'Recall')
print(SPEC, 'Specificity')
print(AUC, 'AUC')
```

```
0.7615384615384615 Accuracy
0.8819444444444444 Recall
0.5299999999999999 Specificity
0.7059722222222222 AUC
```

[ ]:
```
```