CRCLM_ml_0_1_2

May 9, 2023

[1]:
```python
import sys
## import all the packages needed
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import sklearn
import seaborn as sns
```

[2]:
```python
## read NHANES dataset
df = pd.read_csv('/Users/zhiyi/Desktop/for Yupei/CRCLM_ml.csv')
```

[3]:
```python
## find all the distinct values of DIQ170
df.y.value_counts()
```

[3]:
```
0    23100
1     5528
Name: y, dtype: int64
```

[4]:
```python
## data preparation
# exclude null values and NA
df = df[df.y.notnull()]
# check DIQ170
df.y.describe()
```

[4]:
```
count    28628.000000
mean         0.193098
std          0.394736
min          0.000000
25%          0.000000
50%          0.000000
75%          0.000000
max          1.000000
Name: y, dtype: float64
```

[5]:
```python
# exclude non-numeric values
d = df.select_dtypes(['number'])
```

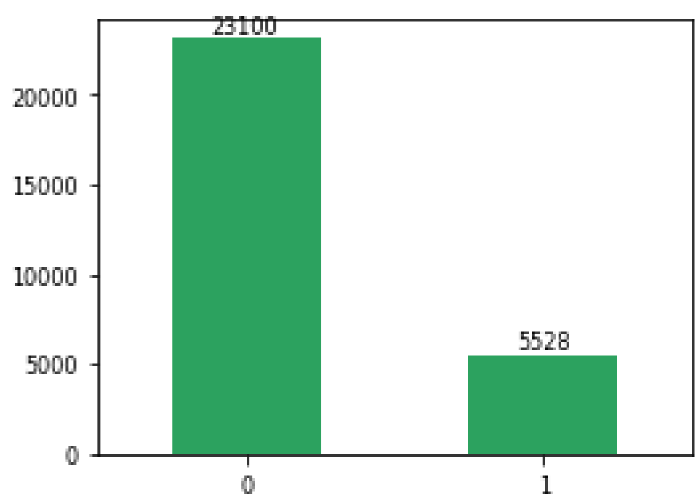
```python
# exclude columns that have over 50% NaN
d = d.dropna(thresh = 0.5*len(d), axis =1)

print(len(d.columns), 'columns are left')
```

```
21 columns are left
```

[6]:
```python
# transform the coding of target variable
d['y']= d.apply(lambda x: 1 if x.y == 1 else 0, axis='columns')
d.y.value_counts()
```

[6]:
```
0    23100
1     5528
Name: y, dtype: int64
```

[7]:
```python
## plot the distribution of values of response variable
vals = d.y.value_counts()

plt.figure(figsize=(4,3))
plt.rc('font', size=8)

ax = vals.plot.bar(rot=0, color='#2ca25f')
for i in range(len(vals)):
    ax.annotate(vals[i], xy=[vals.index[i], vals[i]], ha='center', va='bottom')
```



[8]:
```python
# replace NA with most frequent values
from sklearn.impute import SimpleImputer
sim_imp = SimpleImputer(strategy='most_frequent')

## avoid COD
```

```
d = pd.DataFrame(sim_imp.fit_transform(d), columns=d.columns).
 ↪drop(columns='COD')

## show the complete dataset
d
```

[8]:

```
        y  GENDER  RACE  AGE  SIZE  MARRY  INCOME  SITE  GRADE  KIND  T  N  \
0       1       2     2    3     3      1       3     1      9     1  3  3
1       0       2     1    3     1      2       3     1      2     1  2  1
2       0       1     1    3     1      3       3     2      2     1  2  2
3       0       2     1    3     3      2       3     2      2     1  2  1
4       0       1     3    3     1      3       3     1      9     1  2  1
…     ..     …     …    …     …      …       …     …      …     … .. ..
28623   1       2     2    3     1      3       1     2      2     2  2  1
28624   0       1     1    2     1      1       1     1      9     1  3  3
28625   1       1     2    2     1      2       2     1      9     1  3  1
28626   1       2     1    3     2      3       2     2      2     1  2  1
28627   1       1     2    3     3      2       2     2      9     1  3  3

       SURGERY  RX  RADIATE  CHEM  CEA  BONE  BRAIN  LUNG
0            0   0        0     0    1     0      0     1
1            1   1        0     1    2     0      0     0
2            1   0        0     0    0     0      0     0
3            0   0        0     1    1     0      0     0
4            0   0        0     0    1     0      0     1
…          …  ..       …    …    …    …     …     …
28623        1   0        0     1    2     0      0     0
28624        0   0        0     1    1     0      0     1
28625        0   0        0     1    1     0      0     0
28626        1   0        0     0    1     0      0     1
28627        0   0        0     0    1     0      0     1

[28628 rows x 20 columns]
```

[9]:

```
## separate predictors and responses
X = d.loc[:, d.columns != 'y']
Y = d.y
print('X shape:', X.shape)
print('Y shape:', Y.shape)
```

```
X shape: (28628, 19)
Y shape: (28628,)
```

[10]:

```
## split the data into training dataset and testing dataset (8:2)
from sklearn.model_selection import train_test_split
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.2,␣
 ↪random_state=12)
```

[11]:
```python
## Feature selection: XGBClassifier
from xgboost import XGBClassifier
from sklearn.metrics import classification_report, accuracy_score,␣
 ↪confusion_matrix

model = XGBClassifier()
model.fit(X_train, Y_train)
Y_pred = model.predict(X_test)

accuracy = accuracy_score(Y_test, Y_pred)
print("Accuracy: %.2f%%" % (accuracy * 100.0))

## confusion matrix
def confusion(Y_test, Y_pred):
    conf = pd.DataFrame(confusion_matrix(Y_test, Y_pred), index=['True[0]',␣
 ↪'True[1]'], columns=['Predict[0]', 'Predict[1]'])
    print('Confusion Matrix:')
    print(conf)
    return conf

confusion(Y_test, Y_pred)
```

```
Accuracy: 82.55%
Confusion Matrix:
         Predict[0]  Predict[1]
True[0]        4301         304
True[1]         695         426
```

[11]:

	Predict[0]	Predict[1]
True[0]	4301	304
True[1]	695	426

[12]:
```python
## Oversampling with SMOTE
from imblearn.over_sampling import SMOTE
smote = SMOTE()
X_train_smote, Y_train_smote = smote.fit_resample(X_train, Y_train)
X_test_smote, Y_test_smote = smote.fit_resample(X_test, Y_test)

X_train_smote = pd.DataFrame(X_train_smote, columns=X.columns)
X_test_smote = pd.DataFrame(X_test_smote, columns=X.columns)

## show the dataset after SMOTE
print(Y_train_smote.value_counts())
print(Y_test_smote.value_counts())
```

```
0    18495
1    18495
```

```
Name: y, dtype: int64
0    4605
1    4605
Name: y, dtype: int64
```

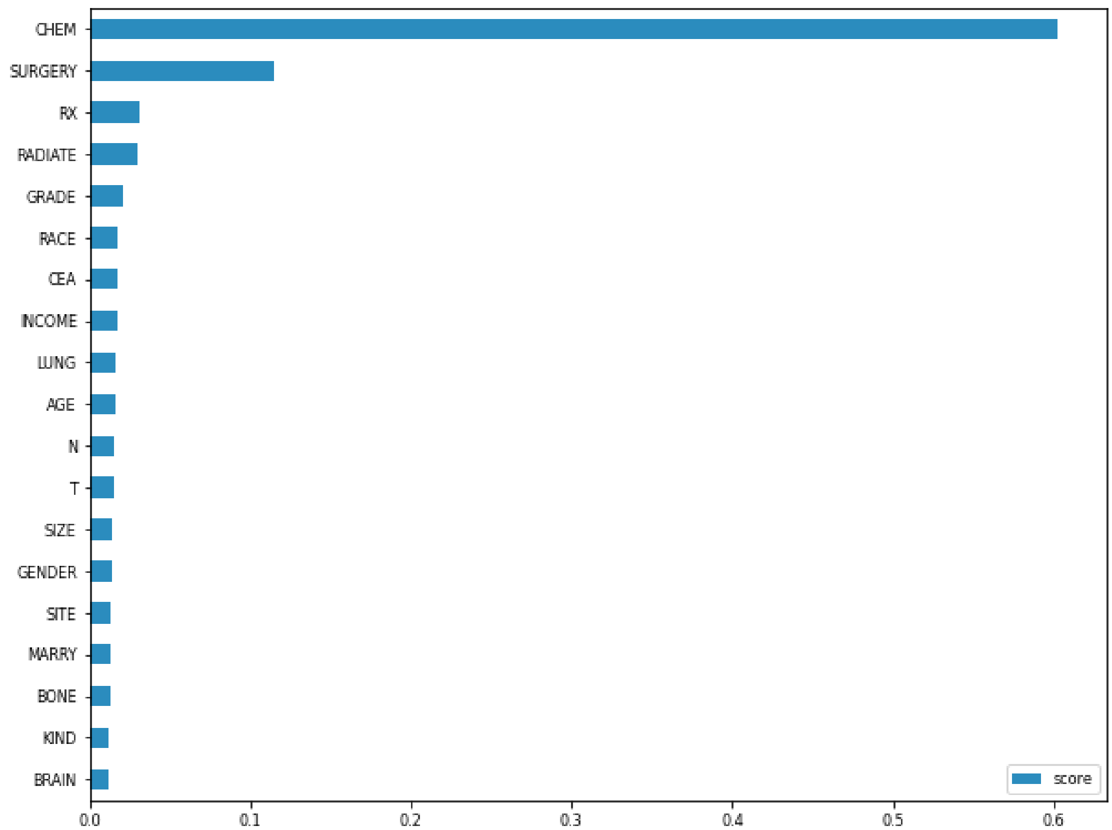
[13]:
```
# The classification result after SMOTE
model = XGBClassifier()
model.fit(X_train_smote, Y_train_smote)
Y_pred_smote = model.predict(X_test_smote)

accuracy = accuracy_score(Y_test_smote, Y_pred_smote)
print("Accuracy: %.2f%%" % (accuracy * 100.0))
conf = pd.DataFrame(confusion_matrix(Y_test_smote, Y_pred_smote),␣
 ↪index=['True[0]', 'True[1]'], columns=['Predict[0]', 'Predict[1]'])
conf
```

```
Accuracy: 75.75%
```

[13]:

	Predict[0]	Predict[1]
True[0]	3616	989
True[1]	1244	3361

[14]:
```
from xgboost import XGBClassifier
from matplotlib import pyplot

# fit model no training data
model = XGBClassifier()
model.fit(X_train_smote, Y_train_smote)

# Features selected by XGBoost
keys = list(model.get_booster().feature_names)
values = list(model.feature_importances_)

data = pd.DataFrame(data=values, index=keys, columns=["score"]).sort_values(by␣
 ↪= "score", ascending=False)

# Top xxx features
xgbfs_ = data[:]

# Plot feature score
xgbfs_.sort_values(by='score').plot(kind='barh', figsize=(10, 8),␣
 ↪color='#2b8cbe')
plt.rc('font', size=8)
```



[15]:

```
xgbfs = xgbfs_.reset_index()
xgbfs.columns=['variable', 'score']

xgbfs['variable'] = xgbfs['variable'].apply(lambda x: x.upper())
```

[16]:

```
## all variables list
var_list = xgbfs.variable.tolist()
var_list.append('y')
print(var_list)
df_final = d.filter(var_list)
df_final
```

```
['CHEM', 'SURGERY', 'RX', 'RADIATE', 'GRADE', 'RACE', 'CEA', 'INCOME', 'LUNG',
'AGE', 'N', 'T', 'SIZE', 'GENDER', 'SITE', 'MARRY', 'BONE', 'KIND', 'BRAIN',
'y']
```

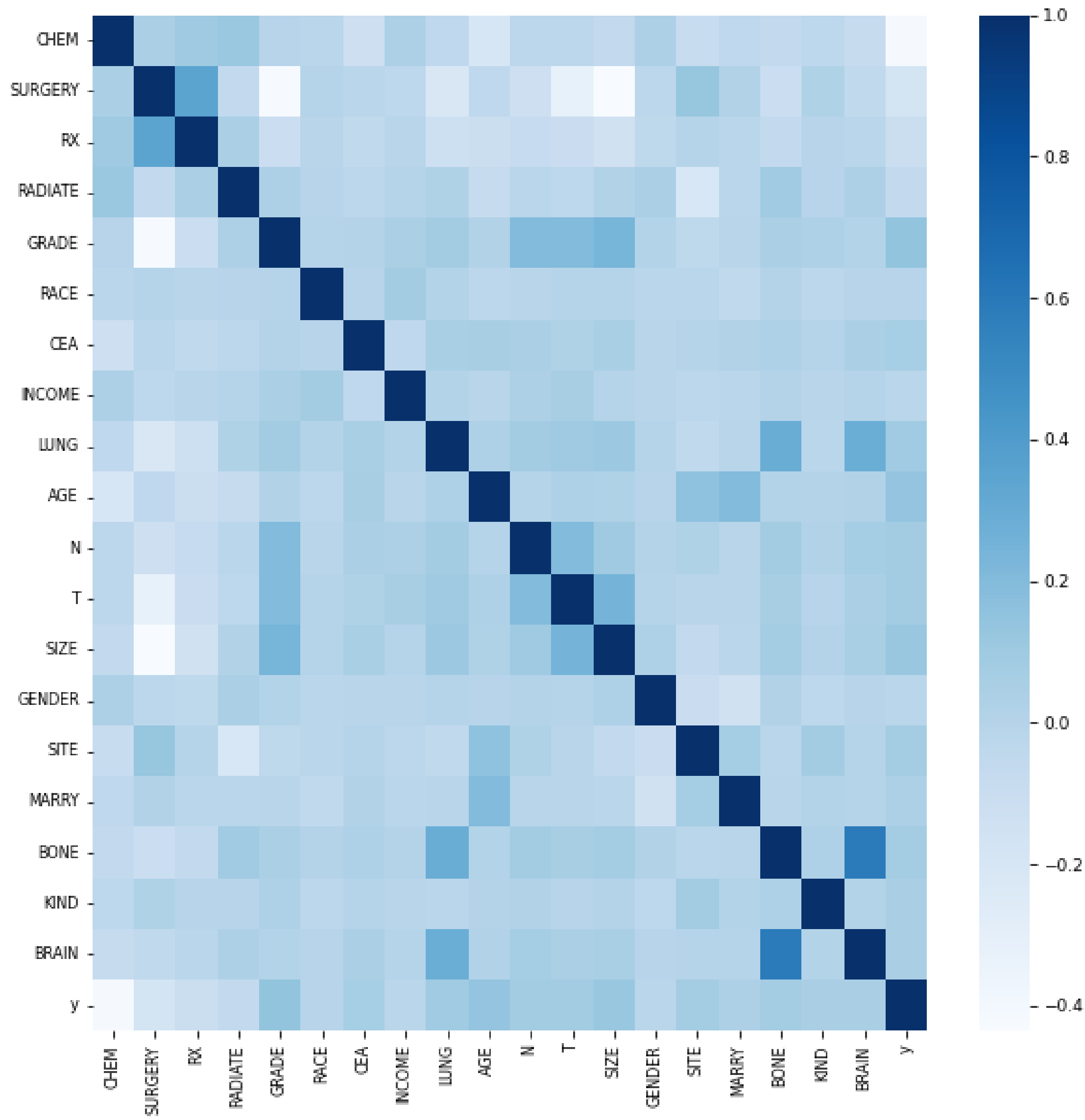
[16]:

	CHEM	SURGERY	RX	RADIATE	GRADE	RACE	CEA	INCOME	LUNG	AGE	N	T	\
0	0	0	0	0	9	2	1	3	1	3	3	3	
1	1	1	1	0	2	1	2	3	0	3	1	2	
2	0	1	0	0	2	1	0	3	0	3	2	2	
3	1	0	0	0	2	1	1	3	0	3	1	2	

```
4          0         0   0         0      9     3    1        3      1    3  1  2
…     …      …  ..      …     …    …   …      …    …   …  ..  ..
28623      1         1   0         0      2     2    2        1      0    3  1  2
28624      1         0   0         0      9     1    1        1      1    2  3  3
28625      1         0   0         0      9     2    1        2      0    2  1  3
28626      0         1   0         0      2     1    1        2      1    3  1  2
28627      0         0   0         0      9     2    1        2      1    3  3  3

       SIZE  GENDER  SITE  MARRY  BONE  KIND  BRAIN  y
0         3       2     1      1     0     1      0  1
1         1       2     1      2     0     1      0  0
2         1       1     2      3     0     1      0  0
3         3       2     2      2     0     1      0  0
4         1       1     1      3     0     1      0  0
…     …     …    …    …    …    …     …  ..
28623     1       2     2      3     0     2      0  1
28624     1       1     1      1     0     1      0  0
28625     1       1     1      2     0     1      0  1
28626     2       2     2      3     0     1      0  1
28627     3       1     2      2     0     1      0  1

[28628 rows x 20 columns]
```

[17]:
```
## draw correlation heatmap
ax = plt.subplots(figsize=(10,10))
plt.rc('font', size=9)

corr = df_final.corr()

sns.heatmap(corr, cmap="Blues")
```

[17]:
```
<AxesSubplot:>
```



[18]:
```
X_scale = df_final.loc[:, df_final.columns != 'y']
Y = df_final.y
```

[19]:
```
## min-max scaling
from sklearn.preprocessing import MinMaxScaler
minmax = MinMaxScaler()
X = pd.DataFrame(minmax.fit_transform(X_scale), columns=X_scale.columns)
X
```

[19]:
```
   CHEM  SURGERY   RX  RADIATE  GRADE  RACE  CEA  INCOME  LUNG  AGE    N  \
0   0.0      0.0  0.0      0.0  1.000   0.5  0.5     1.0   0.5  1.0  1.0
1   1.0      1.0  1.0      0.0  0.125   0.0  1.0     1.0   0.0  1.0  0.0
```

```
2        0.0       1.0   0.0       0.0   0.125   0.0   0.0      1.0    0.0   1.0   0.5
3        1.0       0.0   0.0       0.0   0.125   0.0   0.5      1.0    0.0   1.0   0.0
4        0.0       0.0   0.0       0.0   1.000   1.0   0.5      1.0    0.5   1.0   0.0
…     …      …  …      …     …    …  …      …    …  …  …
28623    1.0       1.0   0.0       0.0   0.125   0.5   1.0      0.0    0.0   1.0   0.0
28624    1.0       0.0   0.0       0.0   1.000   0.0   0.5      0.0    0.5   0.5   1.0
28625    1.0       0.0   0.0       0.0   1.000   0.5   0.5      0.5    0.0   0.5   0.0
28626    0.0       1.0   0.0       0.0   0.125   0.0   0.5      0.5    0.5   1.0   0.0
28627    0.0       0.0   0.0       0.0   1.000   0.5   0.5      0.5    0.5   1.0   1.0

           T  SIZE  GENDER  SITE  MARRY  BONE  KIND  BRAIN
0        1.0   1.0     1.0   0.0    0.0   0.0   0.0    0.0
1        0.5   0.0     1.0   0.0    0.5   0.0   0.0    0.0
2        0.5   0.0     0.0   1.0    1.0   0.0   0.0    0.0
3        0.5   1.0     1.0   1.0    0.5   0.0   0.0    0.0
4        0.5   0.0     0.0   0.0    1.0   0.0   0.0    0.0
…     …    …      …    …     …    …    …     …
28623    0.5   0.0     1.0   1.0    1.0   0.0   1.0    0.0
28624    1.0   0.0     0.0   0.0    0.0   0.0   0.0    0.0
28625    1.0   0.0     0.0   0.0    0.5   0.0   0.0    0.0
28626    0.5   0.5     1.0   1.0    1.0   0.0   0.0    0.0
28627    1.0   1.0     0.0   1.0    0.5   0.0   0.0    0.0

[28628 rows x 19 columns]
```

[20]:
```python
## Create an empty list containing the accuracy scores of the models
mscore=[]
```

[21]:
```python
from sklearn.model_selection import train_test_split
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, random_state=11)

X_train_smote, Y_train_smote = smote.fit_resample(X_train, Y_train)
X_test_smote, Y_test_smote = smote.fit_resample(X_test, Y_test)

X_train_smote = pd.DataFrame(X_train_smote, columns=X.columns)
X_test_smote = pd.DataFrame(X_test_smote, columns=X.columns)
```

[22]:
```python
## Logistic Regression
from sklearn.linear_model import LogisticRegression
import time

clf = LogisticRegression(max_iter=100, solver='lbfgs', class_weight='balanced',␣
 ↪random_state=11)

## time of running
tic = time.time()
clf.fit(X_train_smote, Y_train_smote)
```

```
toc = time.time()
print("Time: " + str(1000*(toc-tic)) + "ms")

clf_prediction_proba = clf.predict_proba(X_test)[:, 1]

## make predictions
Y_pred = clf.predict(X_test)
print('Accuracy Score:', clf.score(X_test, Y_test))
print('Prediction:', Y_pred)

## append the score to the list
mscore.append(['Logistic Regression', clf.score(X_test, Y_test)])

print(classification_report(Y_test, Y_pred))
confusion(Y_test, Y_pred)
```

```
Time: 144.3309783935547ms
Accuracy Score: 0.7510129942713427
Prediction: [0 0 0 … 0 0 1]
              precision    recall  f1-score   support

           0       0.91      0.76      0.83      5739
           1       0.42      0.70      0.53      1418

    accuracy                           0.75      7157
   macro avg       0.67      0.73      0.68      7157
weighted avg       0.82      0.75      0.77      7157

Confusion Matrix:
         Predict[0]  Predict[1]
True[0]        4377        1362
True[1]         420         998
```

[22]:

	Predict[0]	Predict[1]
True[0]	4377	1362
True[1]	420	998

[23]:

```
## random forest model
from sklearn.ensemble import RandomForestClassifier
import time

rnd_clf = RandomForestClassifier(n_estimators=200, criterion='gini',␣
↪max_depth=5,
                                 min_samples_split = 2, min_samples_leaf = 1,␣
↪random_state=11)

## time of running
```

```python
tic = time.time()
rnd_clf.fit(X_train_smote, Y_train_smote)
toc = time.time()
print("Time: " + str(1000*(toc-tic)) + "ms")

rf_prediction_proba = rnd_clf.predict_proba(X_test)[:, 1]

## make predictions
Y_pred = rnd_clf.predict(X_test)
print('Accuracy Score:', rnd_clf.score(X_test, Y_test))
print('Prediction:', Y_pred)

## append the score to the list
mscore.append(['Random Forest', rnd_clf.score(X_test, Y_test)])

print(classification_report(Y_test, Y_pred))
confusion(Y_test, Y_pred)

## print importance tree random forest
print(pd.DataFrame({'Variable':X.columns,
              'Importance':model.feature_importances_}).
 ↪sort_values('Importance', ascending=False))
```

```
Time: 3028.102159500122ms
Accuracy Score: 0.769037306133855
Prediction: [0 0 0 … 0 0 1]
              precision    recall  f1-score   support

           0       0.91      0.80      0.85      5739
           1       0.44      0.66      0.53      1418

    accuracy                           0.77      7157
   macro avg       0.67      0.73      0.69      7157
weighted avg       0.81      0.77      0.78      7157

Confusion Matrix:
         Predict[0]  Predict[1]
True[0]        4563        1176
True[1]         477         941
   Variable  Importance
14     SITE    0.602844
11        T    0.114928
12     SIZE    0.030765
13   GENDER    0.029534
7    INCOME    0.020103
1   SURGERY    0.017172
15    MARRY    0.017033
```

```
5      RACE    0.016895
18    BRAIN    0.016194
2        RX    0.015621
10        N    0.015263
9       AGE    0.014503
3   RADIATE    0.014333
0      CHEM    0.013556
6       CEA    0.013118
4     GRADE    0.012994
16     BONE    0.012251
8      LUNG    0.011788
17     KIND    0.011105
```

[24]:

```
## gradient boosting
from sklearn.ensemble import GradientBoostingClassifier
import time

gbc = GradientBoostingClassifier(learning_rate=0.1, n_estimators=10,␣
 ↪random_state=11)

## time of running
tic = time.time()
gbc.fit(X_train_smote, Y_train_smote)
toc = time.time()
print("Time: " + str(1000*(toc-tic)) + "ms")

gbc_prediction_proba = gbc.predict_proba(X_test)[:, 1]

## make predictions
Y_pred = gbc.predict(X_test)
print('Accuracy Score:', gbc.score(X_test, Y_test))
print('Prediction:', Y_pred)

## append the score to the list
mscore.append(['Gradient Boosting', gbc.score(X_test, Y_test)])

print(classification_report(Y_test, Y_pred))
confusion(Y_test, Y_pred)
```

```
Time: 445.06025314331055ms
Accuracy Score: 0.8006147827301943
Prediction: [0 0 0 … 0 0 0]
              precision    recall  f1-score   support

           0       0.89      0.85      0.87      5739
           1       0.50      0.59      0.54      1418

    accuracy                           0.80      7157
```

```
   macro avg       0.70      0.72      0.71      7157
weighted avg       0.82      0.80      0.81      7157

Confusion Matrix:
         Predict[0]  Predict[1]
True[0]        4888         851
True[1]         576         842
```

[24]:

```
         Predict[0]  Predict[1]
True[0]        4888         851
True[1]         576         842
```

[25]:

```python
## Adaboost Classifier
from sklearn.ensemble import AdaBoostClassifier
import time

ada = AdaBoostClassifier(learning_rate=0.01, n_estimators=30, random_state=11)

tic = time.time()
ada.fit(X_train_smote, Y_train_smote)
toc = time.time()
print("Time: " + str(1000*(toc-tic)) + "ms")

ada_prediction_proba = ada.predict_proba(X_test)[:, 1]

Y_pred = ada.predict(X_test)
print('Accuracy Score:', ada.score(X_test, Y_test))
print('Prediction:', Y_pred)

mscore.append(['Adaptive Boosting', ada.score(X_test, Y_test)])

# from sklearn.metrics import classification_report
print(classification_report(Y_test, Y_pred))
confusion(Y_test, Y_pred)
```

```
Time: 902.2519588470459ms
Accuracy Score: 0.797820315774766
Prediction: [0 0 0 … 0 0 0]
              precision    recall  f1-score   support

           0       0.90      0.85      0.87      5739
           1       0.49      0.60      0.54      1418

    accuracy                           0.80      7157
   macro avg       0.69      0.72      0.71      7157
weighted avg       0.82      0.80      0.80      7157

Confusion Matrix:
```

```
          Predict[0]  Predict[1]
True[0]         4861         878
True[1]          569         849
```

[25]:

```
          Predict[0]  Predict[1]
True[0]         4861         878
True[1]          569         849
```

[26]:

```python
## Extreme Gradient Boosting
from xgboost import XGBClassifier
import time

xgbc = XGBClassifier(eta=0.01, max_depth=3, random_state=11)

tic = time.time()
xgbc.fit(X_train_smote, Y_train_smote)
toc = time.time()
print("Time: " + str(1000*(toc-tic)) + "ms")

xgb_prediction_proba = xgbc.predict_proba(X_test)[:, 1]

Y_pred = xgbc.predict(X_test)
print('Accuracy Score:', xgbc.score(X_test, Y_test))
print('Prediction:', Y_pred)

mscore.append(['XGBoost', xgbc.score(X_test, Y_test)])

# from sklearn.metrics import classification_report
print(classification_report(Y_test, Y_pred))
confusion(Y_test, Y_pred)
```

```
Time: 2475.6009578704834ms
Accuracy Score: 0.7989381025569373
Prediction: [0 0 0 … 0 0 0]
              precision    recall  f1-score   support

           0       0.89      0.85      0.87      5739
           1       0.49      0.60      0.54      1418

    accuracy                           0.80      7157
   macro avg       0.69      0.72      0.71      7157
weighted avg       0.82      0.80      0.81      7157

Confusion Matrix:
          Predict[0]  Predict[1]
True[0]         4872         867
True[1]          572         846
```

[26]:

	Predict[0]	Predict[1]
True[0]	4872	867
True[1]	572	846

[27]:

```
## Support Vector Machine
from sklearn.svm import SVC
import time

svm_clf = SVC(kernel='sigmoid', gamma='auto', random_state=11, probability=True)

## time of running
tic = time.time()
svm_clf.fit(X_train_smote, Y_train_smote)
toc = time.time()
print("Time: " + str(1000*(toc-tic)) + "ms")

svm_prediction_proba = svm_clf.predict_proba(X_test)[:, 1]

Y_pred = svm_clf.predict(X_test)
print('Accuracy Score:', svm_clf.score(X_test, Y_test))
print('Prediction:', Y_pred)

mscore.append(['SVM', svm_clf.score(X_test, Y_test)])

# from sklearn.metrics import classification_report
print(classification_report(Y_test, Y_pred))
confusion(Y_test, Y_pred)
```

```
Time: 725942.412853241ms
Accuracy Score: 0.6797540869079223
Prediction: [0 0 1 … 1 1 0]
              precision    recall  f1-score   support

           0       0.89      0.68      0.77      5739
           1       0.34      0.67      0.45      1418

    accuracy                           0.68      7157
   macro avg       0.62      0.68      0.61      7157
weighted avg       0.78      0.68      0.71      7157

Confusion Matrix:
         Predict[0]  Predict[1]
True[0]        3914        1825
True[1]         467         951
```

[27]:

	Predict[0]	Predict[1]
True[0]	3914	1825

```
True[1]        467        951
```

[28]:
```
## Bagging K-Nearest Neighbors
from sklearn.ensemble import BaggingClassifier
from sklearn.neighbors import KNeighborsClassifier
import time

bagging = BaggingClassifier(base_estimator= KNeighborsClassifier(), max_samples␣
 ↪= 0.5, max_features = 0.5,
                            bootstrap = False, bootstrap_features = False,␣
 ↪random_state=11)

## time of running
tic = time.time()
bagging.fit(X_train_smote, Y_train_smote)
toc = time.time()
print("Time: " + str(1000*(toc-tic)) + "ms")

kn_prediction_proba = bagging.predict_proba(X_test)[:, 1]

## make predictions
Y_pred = bagging.predict(X_test)
print('Accuracy Score:', bagging.score(X_test, Y_test))
print('Prediction:', Y_pred)

bg_score = bagging.score(X_test, Y_test)
bagging.score(X_test, Y_test)

## append the score to the list
mscore.append(['Bagging_KNeighbors', bagging.score(X_test, Y_test)])
```

```
Time: 294.31796073913574ms
Accuracy Score: 0.8043873131200223
Prediction: [0 0 0 … 0 0 1]
```

[29]:
```
## Bagging Decision Tree
from sklearn.tree import DecisionTreeClassifier
import time

bagging = BaggingClassifier(base_estimator= DecisionTreeClassifier(),␣
 ↪max_samples = 0.5, max_features = 0.5,
                            bootstrap = False, bootstrap_features = False,␣
 ↪random_state=11)

## time of running
tic = time.time()
bagging.fit(X_train_smote, Y_train_smote)
```

```
toc = time.time()
print("Time:" + str(1000*(toc-tic)) + "ms")

bdt_prediction_proba = bagging.predict_proba(X_test)[:, 1]

## make predictions
Y_pred = bagging.predict(X_test)
print('Accuracy Score:', bagging.score(X_test, Y_test))
print('Prediction:', Y_pred)

bg_dt_score = bagging.score(X_test, Y_test)
bagging.score(X_test, Y_test)

## append the score to the list
mscore.append(['Bagging_Decision Tree based', bagging.score(X_test, Y_test)])
```

```
Time:373.25477600097656ms
Accuracy Score: 0.8129104373340785
Prediction: [0 0 0 … 0 0 0]
```

[30]:

```
## MLP
from sklearn.neural_network import MLPClassifier
import time

mlp = MLPClassifier(hidden_layer_sizes=(100,100), solver='adam', shuffle=False,␣
 ↪tol = 0.0001, random_state=11)

## time of running
tic = time.time()
mlp.fit(X_train_smote, Y_train_smote)
toc = time.time()
print("Time:" + str(1000*(toc-tic)) + "ms")

mlp_prediction_proba = mlp.predict_proba(X_test)[:, 1]

## make predictions
Y_pred = mlp.predict(X_test)
print('Accuracy Score:', mlp.score(X_test, Y_test))
print('Prediction:', Y_pred)

## see the parameters ready to be adjusted
print("parameter: ", mlp.get_params())

## append the score to the list
mscore.append(['MLP', mlp.score(X_test, Y_test)])
```

```
Time:4644.575834274292ms
```

```
Accuracy Score: 0.4223836803129803
Prediction: [1 1 1 … 1 0 1]
parameter:  {'activation': 'relu', 'alpha': 0.0001, 'batch_size': 'auto',
'beta_1': 0.9, 'beta_2': 0.999, 'early_stopping': False, 'epsilon': 1e-08,
'hidden_layer_sizes': (100, 100), 'learning_rate': 'constant',
'learning_rate_init': 0.001, 'max_fun': 15000, 'max_iter': 200, 'momentum': 0.9,
'n_iter_no_change': 10, 'nesterovs_momentum': True, 'power_t': 0.5,
'random_state': 11, 'shuffle': False, 'solver': 'adam', 'tol': 0.0001,
'validation_fraction': 0.1, 'verbose': False, 'warm_start': False}
```

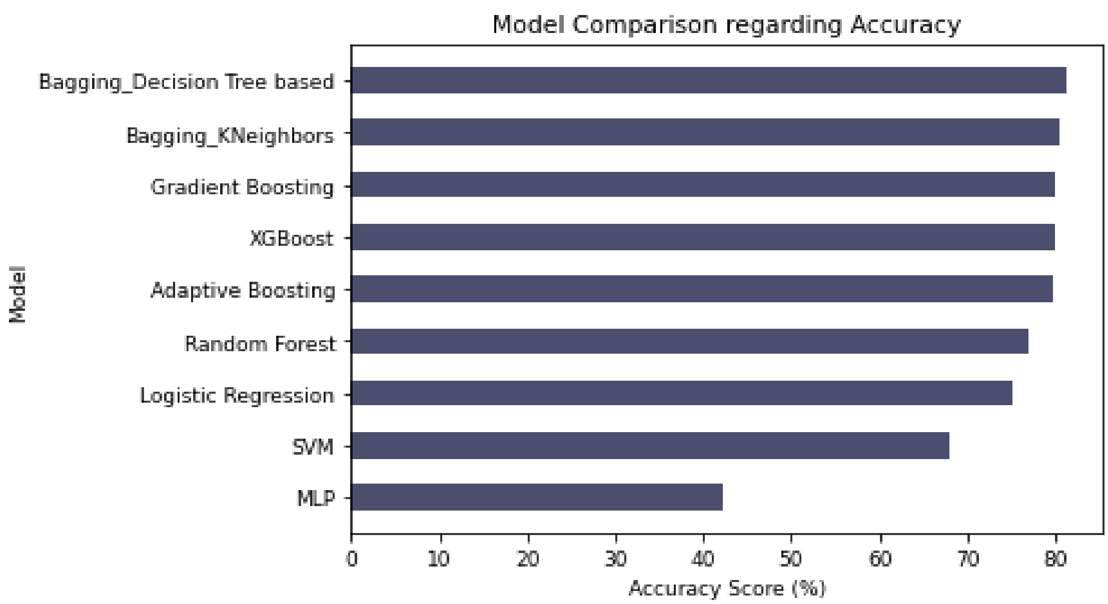
[31]:
```
mscore.sort(key=lambda x: x[1], reverse=True)
mscore
```

[31]:
```
[['Bagging_Decision Tree based', 0.8129104373340785],
 ['Bagging_KNeighbors', 0.8043873131200223],
 ['Gradient Boosting', 0.8006147827301943],
 ['XGBoost', 0.7989381025569373],
 ['Adaptive Boosting', 0.797820315774766],
 ['Random Forest', 0.769037306133855],
 ['Logistic Regression', 0.7510129942713427],
 ['SVM', 0.6797540869079223],
 ['MLP', 0.4223836803129803]]
```

[32]:
```
model = list(i[0] for i in mscore)
score = list(round(i[1]*100,2) for i in mscore)

print('Accuracy Score: \n')
for m,s in zip(model, score):
    print(f'{m}: {s}%')

# creating horizontal bar
plt.barh(model, score, height = 0.5, color='#4B4E6D')

plt.xlabel("Accuracy Score (%)")
plt.ylabel("Model")
plt.title("Model Comparison regarding Accuracy")
plt.gca().invert_yaxis()
plt.rc('font', size=9)
plt.show()
```

```
Accuracy Score:

Bagging_Decision Tree based: 81.29%
Bagging_KNeighbors: 80.44%
Gradient Boosting: 80.06%
XGBoost: 79.89%
Adaptive Boosting: 79.78%
Random Forest: 76.9%
```

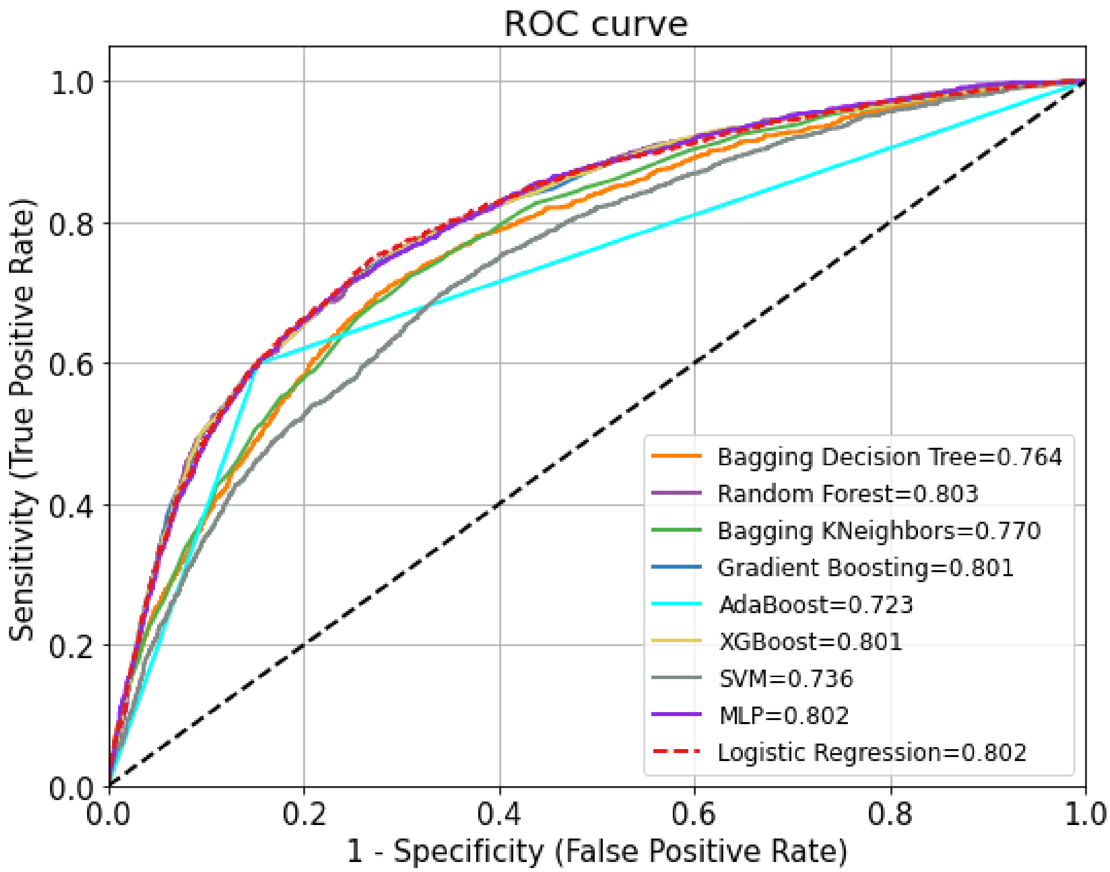
```
Logistic Regression: 75.1%
SVM: 67.98%
MLP: 42.24%
```



[33]:

```
from sklearn.metrics import roc_auc_score, roc_curve
import matplotlib
import matplotlib.pyplot as plt
plt.figure(figsize=(9, 7))
matplotlib.rcParams.update({'font.size': 15})
plt.grid()

def roc_curve_and_score(y_test, pred_proba):
    fpr, tpr, _ = roc_curve(y_test.ravel(), pred_proba.ravel())
    roc_auc = roc_auc_score(y_test.ravel(), pred_proba.ravel())
    return fpr, tpr, roc_auc

## ROC curve
### Bagging Decision Tree
fpr, tpr, roc_auc = roc_curve_and_score(Y_test, bdt_prediction_proba)
plt.plot(fpr, tpr, color='#ff7f00', lw=2,
         label='Bagging Decision Tree={0:.3f}'.format(roc_auc))
### Random Forest
fpr, tpr, roc_auc = roc_curve_and_score(Y_test, rf_prediction_proba)
plt.plot(fpr, tpr, color='#984ea3', lw=2,
         label='Random Forest={0:.3f}'.format(roc_auc))
### Bagging KNeighbors
fpr, tpr, roc_auc = roc_curve_and_score(Y_test, kn_prediction_proba)
```

```python
plt.plot(fpr, tpr, color='#4daf4a', lw=2,
         label='Bagging KNeighbors={0:.3f}'.format(roc_auc))
### Gradient Boosting
fpr, tpr, roc_auc = roc_curve_and_score(Y_test, gbc_prediction_proba)
plt.plot(fpr, tpr, color='#377eb8', lw=2,
         label='Gradient Boosting={0:.3f}'.format(roc_auc))
### AdaBoost
fpr, tpr, roc_auc = roc_curve_and_score(Y_test, ada_prediction_proba)
plt.plot(fpr, tpr, color='#00FFFF', lw=2,
         label='AdaBoost={0:.3f}'.format(roc_auc))
### XGBoost
fpr, tpr, roc_auc = roc_curve_and_score(Y_test, xgb_prediction_proba)
plt.plot(fpr, tpr, color='#E3CF57', lw=2,
         label='XGBoost={0:.3f}'.format(roc_auc))
### SVM
fpr, tpr, roc_auc = roc_curve_and_score(Y_test, svm_prediction_proba)
plt.plot(fpr, tpr, color='#808A87', lw=2,
         label='SVM={0:.3f}'.format(roc_auc))
### MLP
fpr, tpr, roc_auc = roc_curve_and_score(Y_test, mlp_prediction_proba)
plt.plot(fpr, tpr, color='#8A2BE2', lw=2,
         label='MLP={0:.3f}'.format(roc_auc))
### Logistic Regression
fpr, tpr, roc_auc = roc_curve_and_score(Y_test, clf_prediction_proba)
plt.plot(fpr, tpr, color='#e41a1c', lw=2, linestyle='--',
         label='Logistic Regression={0:.3f}'.format(roc_auc))

## reference line (diagonal)
plt.plot([0, 1], [0, 1], color='black', lw=2, linestyle='--')

## add legends, labels, and plot the ROC curves
plt.legend(loc="lower right", fontsize="12")
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('1 - Specificity (False Positive Rate)')
plt.ylabel('Sensitivity (True Positive Rate)')
plt.title("ROC curve")
plt.rc('font', size=9)
plt.show()
```


ROC curve
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
Sensitivity (True Positive Rate)
1 - Specificity (False Positive Rate)
Bagging Decision Tree=0.764
Random Forest=0.803
Bagging KNeighbors=0.770
Gradient Boosting=0.801
AdaBoost=0.723
XGBoost=0.801
SVM=0.736
MLP=0.802
Logistic Regression=0.802

```
[ ]:
```