# OS

## September 12, 2023

```
[1]: 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]: ## read NHANES dataset
     df = pd.read_csv('/Users/zhiyi/Desktop/for Yupei/OS.csv')
[3]: ## find all the distinct values of os
     df.os.value_counts()
[3]: 0
          16745
           4792
     Name: os, dtype: int64
[4]: ## data preparation
     # exclude null values and NA
     df = df[df.os.notnull()]
     # check os
     df.os.describe()
[4]: count
              21537.000000
                  0.222501
    mean
     std
                  0.415935
    min
                  0.000000
    25%
                  0.000000
    50%
                  0.000000
    75%
                  0.000000
    max
                  1.000000
    Name: os, dtype: float64
[5]: # exclude non-numeric values
     d = df.select_dtypes(['number'])
```

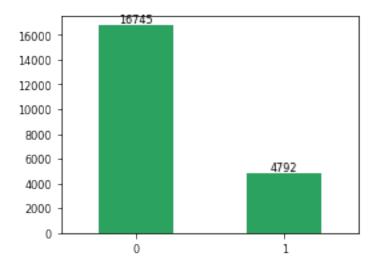
```
# exclude columns that have over 50% NaN
d = d.dropna(thresh = 0.5*len(d), axis =1)
print(len(d.columns), 'columns are left')
```

#### 21 columns are left

```
[6]: ## plot the distribution of values of response variable
vals = d.os.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')
```



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

## show the complete dataset
d = pd.DataFrame(imp_mode.fit_transform(d), columns=d.columns)
d
```

```
[7]:
                                                                        kind ... N
            os
               gender
                        race
                               age
                                    size
                                         marry
                                                  income site grade
             1
                      2
                            2
                                 3
                                        3
                                               1
                                                        3
                                                              1
                                                                     5
                                                                            1
     1
             0
                      1
                            1
                                 3
                                        1
                                               3
                                                              2
                                                                     2
                                                                            1 ... 2
                                                        3
                                               2
     2
             0
                      2
                                 3
                                        3
                                                        3
                                                              2
                                                                     2
                                                                            1 ... 1
                                               3
                                                        3
             0
                      1
                            3
                                 3
                                        1
                                                                     5
```

```
4
                              2
                                                 2
               0
                       1
                                   3
                                          3
                                                          3
                                                                1
                                                                        2
                                                                               1 ... 1
      21532
               0
                       1
                              1
                                   2
                                          1
                                                 2
                                                          1
                                                                        5
                                                                                     3
                                                                                     3
                       2
                                                          2
                                                                        5
      21533
                              1
                                   2
                                          3
                                                 3
                                                                1
      21534
                       2
                              1
                                   3
                                          3
                                                 3
                                                          2
                                                                1
                                                                        5
                                                                               1
                                                                                 ... 1
               1
      21535
                       2
                                          2
                                                 3
                                                          2
                                                                2
                                                                        2
               1
                              1
                                   3
                                                                               1
                                                                                    1
      21536
               1
                       1
                              2
                                   3
                                          3
                                                 2
                                                          2
                                                                2
                                                                        5
                                                                               1
                                                                                     3
              surgery_pri RX_Summ radiate
                                               chem
                                                     CEA
                                                          bone brain
                                                                        lung
      0
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                                            0
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                        0
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                        1
      2
                        0
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                                                                            0
                                                                                    3
      3
                        0
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                                                                            1
                                                                                    3
      4
                        0
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                                                              0
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      21532
                        0
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      21533
                                  0
                                                        2
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                                                                            0
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                        1
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                                                                                    3
                                  0
                                            0
                                                              0
                                                                                    1
      21535
                        1
                                                                                    3
      21536
                                            0
                                                              0
                                                                      0
      [21537 rows x 21 columns]
 [8]: ## separate predictors and responses
      X = d.loc[:, d.columns != 'os']
      y = d.os
      print('X shape:', X.shape)
      print('y shape:', y.shape)
     X shape: (21537, 20)
     y shape: (21537,)
 [9]: 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)
[10]: from xgboost import XGBClassifier
      from sklearn.metrics import classification_report, accuracy_score, u
       ⇔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))
```

```
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: 80.97%
     Confusion Matrix:
             Predict[0] Predict[1]
     True[0]
                   3094
                                278
     True[1]
                    542
                                394
[10]:
             Predict[0] Predict[1]
     True[0]
                    3094
                                 278
     True[1]
                     542
                                 394
[11]: from imblearn.over_sampling import SMOTE
     smote = SMOTE(random_state=12)
     X_train_sm, y_train_sm = smote.fit_resample(X_train, y_train)
     X_test_sm, y_test_sm = smote.fit_resample(X_test, y_test)
     X_train_sm = pd.DataFrame(X_train_sm, columns=X.columns)
     X_test_sm = pd.DataFrame(X_test_sm, columns=X.columns)
     print(y_train_sm.value_counts())
     print(y_test_sm.value_counts())
         13373
     1
     0
          13373
     Name: os, dtype: int64
         3372
     1
          3372
     Name: os, dtype: int64
[12]: # After oversampling, the classification result is more reasonable.
     model = XGBClassifier()
     model.fit(X_train_sm, y_train_sm)
     y_pred_sm = model.predict(X_test_sm)
     accuracy = accuracy_score(y_test_sm, y_pred_sm)
     print("Accuracy: %.2f%%" % (accuracy * 100.0))
     conf = pd.DataFrame(confusion_matrix(y_test_sm, y_pred_sm), index=['True[0]',__
```

```
conf
     Accuracy: 76.90%
[12]:
               Predict[0]
                            Predict[1]
      True[0]
                      2704
                                   668
      True[1]
                       890
                                  2482
[13]: X_scale = d.loc[:, d.columns != 'os']
[14]: ## min-max scaling
      from sklearn.preprocessing import MinMaxScaler
      minmax = MinMaxScaler()
      X = pd.DataFrame(minmax.fit_transform(X_scale), columns=X_scale.columns)
      Х
[14]:
             gender race
                                 size
                                       marry
                                               income
                                                       site
                                                             grade
                                                                     kind
                                                                             Τ
                                                                                  N \
                            age
                                          0.0
      0
                1.0
                       0.5
                            1.0
                                  1.0
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      1
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                       0.0
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                                                    CEA
                                                        bone
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                                                                      lung group
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      21532
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      21535
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                                                                        0.5
                                                                               1.0
      [21537 rows x 20 columns]
```

[15]: 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)
[16]: from imblearn.over sampling import SMOTE
      smote = SMOTE(random_state=12)
      X_train_sm, y_train_sm = smote.fit_resample(X_train, y_train)
      \#X\_test\_sm, y\_test\_sm = smote.fit\_sample(X\_test, y\_test)
      X_train_sm = pd.DataFrame(X_train_sm, columns=X.columns)
      #X_test_sm = pd.DataFrame(X_test_sm, columns=X.columns)
[17]: print('X train shape: ',X_train_sm.shape)
      print('y train values: \n', y_train_sm.value_counts())
      print()
      print('X test shape: ',X_test_sm.shape)
      print('y test values: \n', y_test_sm.value_counts())
     X train shape: (26746, 20)
     y train values:
           13373
      1
          13373
     Name: os, dtype: int64
     X test shape: (6744, 20)
     y test values:
      0
           3372
          3372
     Name: os, dtype: int64
[18]: mscore=[]
[19]: from sklearn.linear_model import LogisticRegression
      from time import process_time
      clf = LogisticRegression(max_iter=100, solver='lbfgs', class_weight='balanced',__
       →random_state=12)
      start = process_time()
      clf.fit(X_train_sm, y_train_sm)
      end = process_time()
      print(end - start)
      clf_prediction_proba = clf.predict_proba(X_test)[:, 1]
      y_pred = clf.predict(X_test)
```

```
print('Accuracy Score:', clf.score(X_test, y_test))
      print('Prediction:', y_pred)
      mscore.append(['Logistic Regression', clf.score(X_test, y_test)])
      print(classification_report(y_test, y_pred))
      confusion(y_test, y_pred)
     0.1834389999999999
     Accuracy Score: 0.7674094707520891
     Prediction: [1 0 0 ... 0 1 0]
                   precision
                                recall f1-score
                                                    support
                                  0.78
                0
                        0.91
                                             0.84
                                                       3372
                1
                        0.48
                                  0.71
                                             0.57
                                                        936
                                             0.77
                                                       4308
         accuracy
        macro avg
                        0.69
                                  0.75
                                             0.71
                                                       4308
     weighted avg
                        0.81
                                  0.77
                                             0.78
                                                       4308
     Confusion Matrix:
              Predict[0] Predict[1]
     True[0]
                    2640
                                  732
     True[1]
                     270
                                  666
[19]:
              Predict[0] Predict[1]
      True[0]
                     2640
                                  732
      True[1]
                      270
                                  666
[20]: from sklearn.ensemble import RandomForestClassifier
      from time import process_time
      rnd_clf = RandomForestClassifier(n_estimators=100, criterion='gini',__
       →random_state=12)
      start = process_time()
      model = rnd_clf.fit(X_train_sm, y_train_sm)
      end = process_time()
      print(end - start)
      rf_prediction_proba = rnd_clf.predict_proba(X_test)[:, 1]
      y_pred = rnd_clf.predict(X_test)
      print('Accuracy Score:', rnd_clf.score(X_test, y_test))
      print('Prediction:', y_pred)
```

## 3.0654910000000015

Accuracy Score: 0.7964252553389044

Prediction: [0 0 0 ... 0 0 0]

	precision	recall	f1-score	support
0	0.85	0.89	0.87	3372
1	0.54	0.45	0.49	936
accuracy			0.80	4308
macro avg	0.70	0.67	0.68	4308
weighted avg	0.79	0.80	0.79	4308

#### Confusion Matrix:

Confusion Macrix.						
	Predict	[0]	Predict[1	[]		
True[	)] 3	009	36	33		
True[	1]	514	42	22		
	Variable	Impo	ortance			
14	chem	0	.200109			
7	grade	0	.091992			
2	age	0	.079690			
4	marry	0	.071066			
5	income	0	.065997			
3	size	0	.060174			
15	CEA	0	.057551			
18	lung	0	.054610			
9	T	0	.050166			
1	race	0.	.042649			
10	N	0.	.036257			
19	group	0	.034877			
0	gender	0 .	.031644			
6	site	0 .	.029710			
16	bone	0	.021557			
11 ຮເ	urgery_pri	0	.016935			
8	kind	0.	.016564			
12	RX_Summ	0.	.015127			
13	radiate	0.	.013905			
17	brain	0	.009419			

```
[21]: from sklearn.ensemble import BaggingClassifier
      from sklearn.tree import DecisionTreeClassifier
      from time import process_time
      bagging = BaggingClassifier(base_estimator=_
       →DecisionTreeClassifier(random_state=12), max_samples = 1.0, max_features = 1.
       ⇔0,
                                  bootstrap = True, bootstrap_features = False,
       →random_state=12)
      start = process_time()
      bagging.fit(X_train_sm, y_train_sm)
      end = process time()
      print(end - start)
      bg_prediction_proba = bagging.predict_proba(X_test)[:, 1]
      y_pred = bagging.predict(X_test)
      print('Accuracy Score:', bagging.score(X_test, y_test))
      print('Prediction:', y_pred)
      mscore.append(['Bagging DecisionTree', bagging.score(X_test, y_test)])
      print(classification_report(y_test, y_pred))
      confusion(y_test, y_pred)
     0.8341029999999989
     Accuracy Score: 0.7748375116063139
     Prediction: [0 0 0 ... 0 1 0]
                   precision
                                recall f1-score
                                                    support
                0
                                                       3372
                        0.84
                                  0.88
                                             0.86
                1
                        0.48
                                   0.40
                                             0.44
                                                        936
                                             0.77
                                                       4308
         accuracy
        macro avg
                        0.66
                                   0.64
                                             0.65
                                                       4308
     weighted avg
                        0.76
                                   0.77
                                             0.77
                                                       4308
     Confusion Matrix:
              Predict[0] Predict[1]
     True[0]
                    2964
                                  408
     True[1]
                     562
                                  374
[21]:
               Predict[0] Predict[1]
```

2964

562

408

374

True[0]

True[1]

```
[22]: from sklearn.neighbors import KNeighborsClassifier
      from time import process_time
      knn = KNeighborsClassifier()
      start = process_time()
      knn.fit(X_train_sm, y_train_sm)
      end = process_time()
      print(end - start)
      knn_prediction_proba = knn.predict_proba(X_test)[:, 1]
      y_pred = knn.predict(X_test)
      print('Accuracy Score:', knn.score(X_test, y_test))
      print('Prediction:', y_pred)
      mscore.append(['KNN', knn.score(X_test, y_test)])
      print(classification_report(y_test, y_pred))
      confusion(y_test, y_pred)
     0.00808999999999264
     Accuracy Score: 0.692200557103064
     Prediction: [1 0 1 ... 0 1 0]
                   precision
                                recall f1-score
                                                    support
                        0.88
                                   0.70
                                             0.78
                0
                                                       3372
                1
                        0.38
                                   0.65
                                             0.48
                                                        936
         accuracy
                                             0.69
                                                       4308
                                             0.63
                                                       4308
        macro avg
                        0.63
                                   0.68
     weighted avg
                        0.77
                                   0.69
                                             0.72
                                                       4308
     Confusion Matrix:
              Predict[0] Predict[1]
     True[0]
                                  999
                    2373
     True[1]
                     327
                                  609
[22]:
               Predict[0] Predict[1]
      True[0]
                     2373
                                  999
      True[1]
                      327
                                  609
[23]: from sklearn.naive_bayes import GaussianNB
      from time import process_time
      gnb = GaussianNB()
```

```
start = process_time()
      gnb.fit(X_train_sm, y_train_sm)
      end = process_time()
      print(end - start)
      gnb_prediction_proba = gnb.predict_proba(X_test)[:, 1]
      y_pred = gnb.predict(X_test)
      print('Accuracy Score:', gnb.score(X_test, y_test))
      print('Prediction:', y_pred)
      mscore.append(['Gaussian Naive Bayes', gnb.score(X_test, y_test)])
      print(classification_report(y_test, y_pred))
      confusion(y_test, y_pred)
     0.0206079999999574
     Accuracy Score: 0.6952181987000928
     Prediction: [1 0 1 ... 1 1 0]
                   precision
                                recall f1-score
                                                    support
                0
                        0.90
                                  0.68
                                             0.78
                                                       3372
                1
                        0.39
                                   0.74
                                             0.51
                                                        936
                                             0.70
                                                       4308
         accuracy
                                  0.71
        macro avg
                        0.65
                                             0.65
                                                       4308
     weighted avg
                        0.79
                                  0.70
                                             0.72
                                                       4308
     Confusion Matrix:
              Predict[0] Predict[1]
     True[0]
                    2304
                                 1068
     True[1]
                     245
                                  691
[23]:
               Predict[0] Predict[1]
      True[0]
                     2304
                                 1068
      True[1]
                      245
                                  691
[24]: from sklearn.ensemble import GradientBoostingClassifier
      from time import process_time
      gbc = GradientBoostingClassifier(learning_rate=0.1, n_estimators=100,__
      →random_state=12)
      start = process_time()
      model = gbc.fit(X_train_sm, y_train_sm)
```

#### 3.0097549999999984

Accuracy Score: 0.8177808727948004

Prediction: [0 0 0 ... 0 1 0]

	precision	recall	f1-score	support
0	0.88	0.89	0.88	3372
1	0.58	0.56	0.57	936
accuracy			0.82	4308
macro avg	0.73	0.72	0.73	4308
weighted avg	0.82	0.82	0.82	4308

#### Confusion Matrix:

Predict[0] Predict[1] True[0] 2999 373 True[1] 412 524 Variable Importance 14 chem 0.433234 7 0.106647 grade 2 0.082341 age 4 0.056565 marry 9 0.048238 Τ 18 lung 0.046718 5 income 0.043684 CEA 0.040733 15 3 size 0.034911 11 surgery\_pri 0.029539 19 0.028804 group 16 0.015489 bone

```
6
                site 0.003307
             radiate 0.003261
     13
                kind 0.002079
     8
     10
                   N
                        0.001972
     0
              gender
                        0.000000
[25]: from sklearn.ensemble import AdaBoostClassifier
      from time import process_time
      ada = AdaBoostClassifier(learning_rate=1.0, n_estimators=50, random_state=12)
      start = process_time()
      model = ada.fit(X_train_sm, y_train_sm)
      end = process_time()
      print(end - start)
      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)
```

'Importance':model.feature\_importances\_}).

#### 0.9511830000000003

1

12

17

0.013821

0.005227

0.003429

race

brain

RX\_Summ

Accuracy Score: 0.8033890436397401

print(pd.DataFrame({'Variable':X.columns,

⇔sort\_values('Importance', ascending=False))

Prediction: [1 0 0 ... 0 1 0]

	precision	recall	f1-score	support
0	0.89	0.86	0.87	3372
1	0.54	0.61	0.58	936
accuracy			0.80	4308
macro avg	0.72	0.74	0.72	4308
weighted avg	0.81	0.80	0.81	4308

Confusion Matrix:

```
True[0]
                     2886
                                  486
     True[1]
                      361
                                  575
            Variable Importance
     4
               marry
                             0.20
                             0.14
     5
              income
                             0.12
     15
                 CEA
                             0.12
     18
                lung
     1
                race
                             0.10
     2
                             0.08
                 age
     3
                             0.06
                size
     7
                             0.04
               grade
     16
                             0.04
                bone
                             0.02
     10
     6
                             0.02
                site
     11
         surgery_pri
                             0.02
     12
             RX_Summ
                             0.02
     14
                             0.02
                chem
     17
               brain
                             0.00
                             0.00
     0
              gender
                             0.00
     13
             radiate
     9
                             0.00
     8
                kind
                             0.00
     19
                             0.00
               group
[26]: from sklearn.svm import SVC
      from time import process_time
      svm_clf = SVC(kernel='rbf', gamma='scale', probability=True, random_state=12)
      start = process_time()
      svm_clf.fit(X_train_sm, y_train_sm)
      end = process_time()
      print(end - start)
      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)
```

Predict[0] Predict[1]

```
316.346303
```

Accuracy Score: 0.7704271123491179

Prediction: [1 0 0 ... 0 1 0]

support	f1-score	recall	precision	
3372	0.84	0.79	0.91	0
936	0.57	0.70	0.48	1
4308	0.77			accuracy
4308	0.71	0.75	0.69	macro avg
4308	0.78	0.77	0.81	weighted avg

#### Confusion Matrix:

Predict[0] Predict[1]
True[0] 2660 712
True[1] 277 659

[26]: Predict[0] Predict[1]
True[0] 2660 712
True[1] 277 659

```
[27]: from xgboost import XGBClassifier
      from time import process_time
      xgbc = XGBClassifier(eta=0.3, max_depth=6, random_state=12)
      start = process_time()
      model = xgbc.fit(X_train_sm, y_train_sm)
      end = process_time()
      print(end - start)
      xgbc_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)
      print(pd.DataFrame({'Variable':X.columns,
                    'Importance':model.feature_importances_}).
       ⇔sort_values('Importance', ascending=False))
```

## 8.831576000000041

Accuracy Score: 0.8161559888579387

Prediction: [0 0 0 ... 0 1 0]

	precision	recall	f1-score	support
0	0.86	0.91	0.89	3372
1	0.60	0.47	0.53	936
accuracy			0.82	4308
macro avg	0.73	0.69	0.71	4308
weighted avg	0.80	0.82	0.81	4308

#### Confusion Matrix:

```
Predict[0] Predict[1]
True[0]
                              296
                3076
True[1]
                 496
                             440
       Variable Importance
14
           chem
                    0.360615
11
    surgery_pri
                    0.078392
2
                    0.067002
            age
18
           lung
                    0.055987
                    0.048411
7
          grade
4
                    0.046379
          marry
5
         income
                    0.045417
15
            CEA
                    0.044645
3
           size
                    0.041301
9
              Т
                    0.040480
19
                    0.035866
          group
1
           race
                    0.023866
16
           bone
                    0.023047
12
        RX_Summ
                    0.019596
17
          brain
                    0.014875
8
           kind
                    0.012955
13
        radiate
                    0.012584
10
              N
                    0.011776
6
                    0.010218
           site
0
         gender
                    0.006586
```

```
mlp_prediction_proba = mlp.predict_proba(X_test)[:, 1]
      mlp_pred_diabetes = mlp.predict(X_test)
      print('Accuracy Score:', mlp.score(X_test, y_test))
      print('Prediction:', mlp_pred_diabetes)
      print("parameter: ", mlp.get_params())
      mscore.append(['MLP', mlp.score(X_test, y_test)])
     52.18636399999997
     Accuracy Score: 0.7432683379758589
     Prediction: [1 0 1 ... 1 1 0]
     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,), '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': 12, 'shuffle':
     True, 'solver': 'adam', 'tol': 0.0001, 'validation_fraction': 0.1, 'verbose':
     False, 'warm_start': False}
     /Users/zhiyi/opt/anaconda3/lib/python3.9/site-
     packages/sklearn/neural_network/_multilayer_perceptron.py:692:
     ConvergenceWarning: Stochastic Optimizer: Maximum iterations (200) reached and
     the optimization hasn't converged yet.
       warnings.warn(
[29]: mscore.sort(key=lambda x: x[1], reverse=True)
      mscore
[29]: [['Gradient Boosting', 0.8177808727948004],
       ['XGBoost', 0.8161559888579387],
       ['Adaptive Boosting', 0.8033890436397401],
       ['Random Forest', 0.7964252553389044],
       ['Bagging DecisionTree', 0.7748375116063139],
       ['SVM', 0.7704271123491179],
       ['Logistic Regression', 0.7674094707520891],
       ['MLP', 0.7432683379758589],
       ['Gaussian Naive Bayes', 0.6952181987000928],
       ['KNN', 0.692200557103064]]
[30]: 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:

Gradient Boosting: 81.78%

XGBoost: 81.62%

Adaptive Boosting: 80.34% Random Forest: 79.64%

Bagging DecisionTree: 77.48%

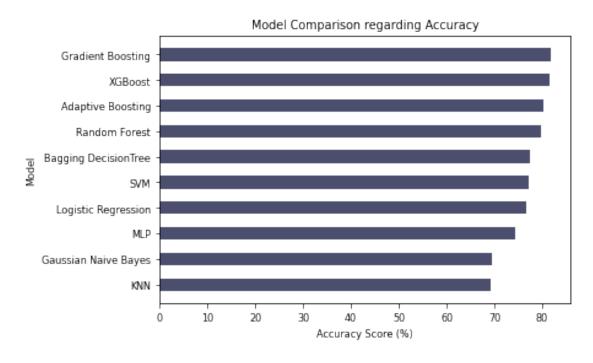
SVM: 77.04%

Logistic Regression: 76.74%

MLP: 74.33%

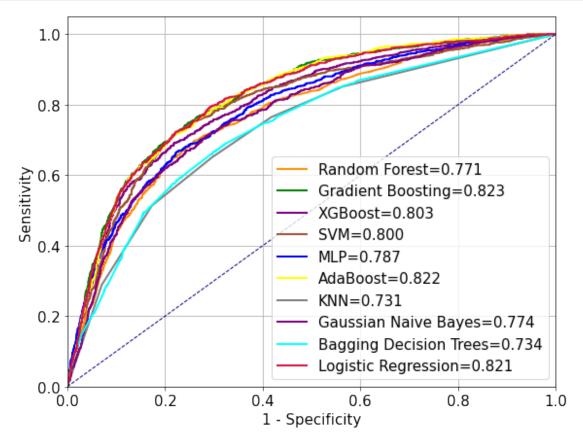
Gaussian Naive Bayes: 69.52%

KNN: 69.22%



```
[31]: rf_prediction_proba = rnd_clf.predict_proba(X_test)[:, 1]
      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
      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()
      fpr, tpr, roc_auc = roc_curve_and_score(y_test, rf_prediction_proba)
      plt.plot(fpr, tpr, color='darkorange', lw=2,
               label='Random Forest={0:.3f}'.format(roc_auc))
      fpr, tpr, roc_auc = roc_curve_and_score(y_test, gbc_prediction_proba)
      plt.plot(fpr, tpr, color='green', lw=2,
               label='Gradient Boosting={0:.3f}'.format(roc_auc))
      fpr, tpr, roc_auc = roc_curve_and_score(y_test, xgbc_prediction_proba)
      plt.plot(fpr, tpr, color='purple', lw=2,
               label='XGBoost={0:.3f}'.format(roc_auc))
      fpr, tpr, roc_auc = roc_curve_and_score(y_test, svm_prediction_proba)
      plt.plot(fpr, tpr, color='sienna', lw=2,
               label='SVM={0:.3f}'.format(roc auc))
      fpr, tpr, roc_auc = roc_curve_and_score(y_test, mlp_prediction_proba)
      plt.plot(fpr, tpr, color='blue', lw=2,
               label='MLP={0:.3f}'.format(roc_auc))
      fpr, tpr, roc_auc = roc_curve_and_score(y_test, ada_prediction_proba)
      plt.plot(fpr, tpr, color='yellow', lw=2,
               label='AdaBoost={0:.3f}'.format(roc_auc))
      fpr, tpr, roc_auc = roc_curve_and_score(y_test, knn_prediction_proba)
      plt.plot(fpr, tpr, color='grey', lw=2,
               label='KNN={0:.3f}'.format(roc_auc))
      fpr, tpr, roc_auc = roc_curve_and_score(y_test, gnb_prediction_proba)
      plt.plot(fpr, tpr, color='purple', lw=2,
               label='Gaussian Naive Bayes={0:.3f}'.format(roc_auc))
      fpr, tpr, roc_auc = roc_curve_and_score(y_test, bg_prediction_proba)
      plt.plot(fpr, tpr, color='cyan', lw=2,
               label='Bagging Decision Trees={0:.3f}'.format(roc_auc))
      fpr, tpr, roc_auc = roc_curve_and_score(y_test, clf_prediction_proba)
      plt.plot(fpr, tpr, color='crimson', lw=2,
               label='Logistic Regression={0:.3f}'.format(roc_auc))
      plt.plot([0, 1], [0, 1], color='navy', lw=1, linestyle='--')
      plt.legend(loc="lower right")
      plt.xlim([0.0, 1.0])
      plt.ylim([0.0, 1.05])
```

```
plt.xlabel('1 - Specificity')
plt.ylabel('Sensitivity')
plt.show()
```



[]: