test

November 2, 2017

1 Deep Learning HW1

1.1 by Won Kim

```
In [23]: import numpy as np
         import pandas as pd
         import matplotlib.pyplot as plt
         %matplotlib inline
         import seaborn as sns; sns.set()
         from sklearn.ensemble import RandomForestClassifier
         from imblearn.over_sampling import *
         from imblearn.under_sampling import *
         from imblearn.combine import *
         from sklearn.metrics import *
In [24]: df = pd.read_csv("train.csv")
         df.tail()
Out [24]:
                               V1
                                                   ٧3
                                                                       ٧5
                                         V2
                                                             V4
                                                                                 ۷6
               172762.0 -0.725459
                                   0.194981 -1.785571 -3.779860
                                                                 2.177420
         29195
                                                                           2.975713
               172764.0 -0.764523 0.588379 -0.907599 -0.418847
         29196
                                                                 0.901528 -0.760802
         29197
               172767.0 -0.268061 2.540315 -1.400915 4.846661
                                                                 0.639105
                                                                           0.186479
         29198
               172785.0 0.120316 0.931005 -0.546012 -0.745097
                                                                 1.130314 -0.235973
                        1.919565 -0.301254 -3.249640 -0.557828
         29199
               172788.0
                                                                 2.630515
                                                                           3.031260
                      V7
                               V8
                                         ۷9
                                                         V21
                                                                   V22
                                                                             V23
         29195 -0.239695
                        0.912303 -3.159994
                                                    29196 0.758545 0.414698 -0.730854
                                                    0.003530 -0.431876 0.141759
                                              . . .
         29197 -0.045911 0.936448 -2.419986
                                             . . .
                                                   -0.263889 -0.857904 0.235172
               0.812722 0.115093 -0.204064
                                                   -0.314205 -0.808520 0.050343
         29198
                                                              0.578229 -0.037501
         29199 -0.296827 0.708417 0.432454
                                                    0.232045
                    V24
                              V25
                                        V26
                                                  V27
                                                            V28
                                                                 Amount
                                                                         Class
               0.717647
                         1.253036
                                                                   7.00
         29195
                                  0.207138 -0.630549 -0.163911
                                                                             0
               0.587119 -0.200998
                                   0.267337 -0.152951 -0.065285
                                                                  80.00
                                                                             0
         29197 -0.681794 -0.668894
                                   0.044657 -0.066751 -0.072447
                                                                  12.82
                                                                             0
         29198
               0.102800 -0.435870 0.124079 0.217940 0.068803
                                                                   2.69
                                                                             0
               0.640134 0.265745 -0.087371 0.004455 -0.026561
         29199
                                                                  67.88
                                                                             0
```

[5 rows x 31 columns] In [25]: df.isnull().sum() Out[25]: Time 0 ۷1 0 ٧2 0 0 ٧3 ۷4 0 ۷5 0 ۷6 0 0 ۷7 V8 0 ۷9 0 V10 0 0 V11 V12 0 V13 0 V140 V15 0 0 V16 0 V17 0 V18 V19 0 V20 0 0 V21 V22 0 V23 0 V24 0 V25 0 V26 0 V27 0 V28 0 Amount 0 Class 0 dtype: int64 In [26]: columns = list(df.columns)[1:30] # except time, class In [50]: plt.figure(figsize = (7, 4*28)) for idx, column in enumerate(columns): plt.subplot(29, 1, idx+1) sns.distplot(df[df["Class"] == 0][column], bins = 50, label = "Normal") sns.distplot(df[df["Class"] == 1][column], bins = 50, label = "Fraud") plt.title(str(column) + "'s Histogram") plt.legend()

plt.tight_layout()
plt.show()





The total counts of each class are 28908 for class 0 and 292 for class 1

1.1.1 Train set preprocessing

```
In [43]: X_train, y_train = preprocessed_df.drop("Class", axis = 1), preprocessed_df.Class
1.1.2 Validation set preprocessing
In [44]: val_df = pd.read_csv("valid.csv")
         preprocessed_val_df = preprocessing(val_df)
In [45]: X_val, y_val = preprocessed_val_df.drop("Class", axis = 1), preprocessed_val_df.Class
1.1.3 Model Learning 1. Random Forest with SMOTE Resampling
In [46]: sm = SMOTE(random_state=0)
         X_train_res, y_train_res = sm.fit_sample(X_train, y_train)
         n_estimators = [10, 20, 30, 40, 50, 60, 70, 80, 90, 100, 110, 120, 130, 140, 150] # 100
         max_depths = list(range(5, 20))
In [47]: def RFClassifier_and_score(n_estimator, max_depth):
             clf_rf = RandomForestClassifier(n_estimators=n_estimator, max_depth = max_depth, ra
             clf_rf.fit(X_train_res, y_train_res)
             predict = clf_rf.predict(X_val)
             print('\nResults with {} estimators and {} max_depth'.format(n_estimator, max_depth
             #print("Train")
             #print("recall: ", recall_score(y_train_res, predict))
             #print("precision: ", precision_score(y_train_res, predict))
             \#print("f1\ measure: ", f1\_score(y\_train\_res, predict))
             print("\nValidation")
             print("recall: ", recall_score(y_val, predict))
             print("precision: ", precision_score(y_val, predict))
             print("f1 measure: ", f1_score(y_val, predict))
In [49]: for n_estimator in n_estimators:
             RFClassifier_and_score(n_estimator, max_depth = None)
Results with 10 estimators and None max_depth
Validation
recall: 0.81
precision: 0.870967741935
f1 measure: 0.839378238342
Results with 20 estimators and None max_depth
Validation
recall: 0.81
precision: 0.910112359551
f1 measure: 0.857142857143
```

Results with 30 estimators and None max_depth

Validation recall: 0.81

precision: 0.920454545455
f1 measure: 0.86170212766

Results with 40 estimators and None max_depth

Validation recall: 0.81

precision: 0.920454545455
f1 measure: 0.86170212766

Results with 50 estimators and None max_depth

Validation recall: 0.81

precision: 0.920454545455
f1 measure: 0.86170212766

Results with 60 estimators and None max_depth

Validation recall: 0.81

precision: 0.920454545455
f1 measure: 0.86170212766

Results with 70 estimators and None max_depth

Validation recall: 0.81

precision: 0.941860465116
f1 measure: 0.870967741935

Results with 80 estimators and None max_depth

Validation recall: 0.81

precision: 0.931034482759
f1 measure: 0.866310160428

Results with 90 estimators and None max_depth

Validation recall: 0.81

precision: 0.931034482759

f1 measure: 0.866310160428

Results with 100 estimators and None max_depth

Validation recall: 0.81

precision: 0.941860465116
f1 measure: 0.870967741935

Results with 110 estimators and None max_depth

Validation recall: 0.81

precision: 0.931034482759
f1 measure: 0.866310160428

Results with 120 estimators and None max_depth

Validation recall: 0.81

precision: 0.941860465116
f1 measure: 0.870967741935

Results with 130 estimators and None max_depth

Validation recall: 0.81

precision: 0.931034482759
f1 measure: 0.866310160428

Results with 140 estimators and None max_depth

Validation recall: 0.81

precision: 0.920454545455
f1 measure: 0.86170212766

Results with 150 estimators and None max_depth

Validation recall: 0.81

precision: 0.920454545455
f1 measure: 0.86170212766

In [48]: RFClassifier_and_score(100, max_depth = None)

Results with 100 estimators and None max_depth

Validation recall: 0.81

precision: 0.941860465116
f1 measure: 0.870967741935

In [20]: for max_depth in max_depths:

RFClassifier_and_score(100, max_depth)

Results with 100 estimators and 5 max_depth

Validation recall: 0.83

precision: 0.691666666667
f1 measure: 0.754545454545

Results with 100 estimators and 6 max_depth

Validation recall: 0.83

precision: 0.721739130435
f1 measure: 0.772093023256

Results with 100 estimators and 7 max_depth

Validation recall: 0.83

precision: 0.7477477478
f1 measure: 0.78672985782

Results with 100 estimators and 8 max_depth

Validation recall: 0.83

precision: 0.775700934579
f1 measure: 0.80193236715

Results with 100 estimators and 9 max_depth

Validation recall: 0.83

precision: 0.805825242718
f1 measure: 0.817733990148

Results with 100 estimators and 10 $\max_{}$ depth

Validation recall: 0.82

precision: 0.803921568627
f1 measure: 0.811881188119

Results with 100 estimators and 11 max_depth

Validation recall: 0.82

precision: 0.836734693878
f1 measure: 0.828282828283

Results with 100 estimators and 12 max_depth

Validation recall: 0.82

precision: 0.854166666667
f1 measure: 0.836734693878

Results with 100 estimators and 13 max_depth

Validation recall: 0.82

precision: 0.881720430108
f1 measure: 0.849740932642

Results with 100 estimators and 14 max_depth

Validation recall: 0.82

precision: 0.91111111111
f1 measure: 0.863157894737

Results with 100 estimators and 15 max_depth

Validation recall: 0.82

precision: 0.863157894737
f1 measure: 0.841025641026

Results with 100 estimators and 16 max_depth

Validation recall: 0.82

precision: 0.901098901099
f1 measure: 0.858638743455

Results with 100 estimators and 17 max_depth

```
Validation
recall: 0.82
precision: 0.911111111111
f1 measure: 0.863157894737

Results with 100 estimators and 18 max_depth

Validation
recall: 0.81
precision: 0.910112359551
f1 measure: 0.857142857143

Results with 100 estimators and 19 max_depth

Validation
recall: 0.81
precision: 0.920454545455
f1 measure: 0.86170212766
```

In [97]: result_df = pd.read_csv('result.csv')

To avoid over-fitting in random forest, the main thing you need to do is optimize a tuning parameter that governs the number of features that are randomly chosen to grow each tree from the bootstrapped data. Typically, you do this via k-fold cross-validation, where k{5,10}, and choose the tuning parameter that minimizes test sample prediction error. In addition, growing a larger forest will improve predictive accuracy, although there are usually diminishing returns once you get up to several hundreds of trees.

new_column = pd.DataFrame({'Class': predicted_labels})

```
result_df = result_df.drop("Class", axis = 1)
result_df["Class"] = new_column
In [100]: result_df.to_csv('result.csv', index=False)
```

2.1 # Another approach

set(labels)

2.1.1 Model Learning 2. Gaussian Mixture Model

In [71]: gmm = GMM(n_components=2, random_state=0)

warnings.warn(msg, category=DeprecationWarning)

warnings.warn(msg, category=DeprecationWarning)

warnings.warn(msg, category=DeprecationWarning)

warnings.warn(msg, category=DeprecationWarning)

warnings.warn(msg, category=DeprecationWarning)

warnings.warn(msg, category=DeprecationWarning)

labels = gmm.fit(X_train_res).predict(X_val)

In [70]: from sklearn.mixture import GMM

```
/home/snu/anaconda3/lib/python3.6/site-packages/sklearn/utils/deprecation.py:75: DeprecationWarr
  warnings.warn(msg, category=DeprecationWarning)
/home/snu/anaconda3/lib/python3.6/site-packages/sklearn/utils/deprecation.py:75: DeprecationWarr
```

/home/snu/anaconda3/lib/python3.6/site-packages/sklearn/utils/deprecation.py:75: DeprecationWarr

/home/snu/anaconda3/lib/python3.6/site-packages/sklearn/utils/deprecation.py:57: DeprecationWarr

/home/snu/anaconda3/lib/python3.6/site-packages/sklearn/utils/deprecation.py:75: DeprecationWarr

/home/snu/anaconda3/lib/python3.6/site-packages/sklearn/utils/deprecation.py:75: DeprecationWarr

/home/snu/anaconda3/lib/python3.6/site-packages/sklearn/utils/deprecation.py:75: DeprecationWarr

```
/home/snu/anaconda3/lib/python3.6/site-packages/sklearn/utils/deprecation.py:75: DeprecationWarr
  warnings.warn(msg, category=DeprecationWarning)
Out[71]: {0, 1}
In [72]: print("recall: ", recall_score(y_val, labels))
         print("precision: ", precision_score(y_val, labels))
         print("f1 measure: ", f1_score(y_val, labels))
```

Gaussian Mixture Model gives me worse result.

recall: 0.81

precision: 0.20822622108
f1 measure: 0.331288343558