Combating Class Imbalance in a Clinical Dataset

Date: December 18, 2019
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Course: ECE414 -- Bayesian Machine Learning
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> **Dataset:** Parkinson's Disease Telemonitoring (from UCI Machine Learning Repository)
> **Application Project:** Pick an interesting application and explore how best to apply machine learning algorithms to solve it.
> **Goal:** data analysis, data-level and algorithm-level class imbalance handling

> ** Class Imbalance Classification, which often occurs with extreme skewness across many real-world domains (along with noise) **

```
import pandas as pd
import numpy as np
import math

# load data
df = pd.read_csv('../parkinsons_data/parkinsons_updrs.data', delimiter=',')
```

```
# suppress warnings
import warnings
# warnings.filterwarnings(action='once')
warnings.filterwarnings(action='ignore')
```

```
# append the library for LIBSVM
import sys
sys.path.append('../libsvm/python')
```

```
# define functions for thresholding, extracting features and target, standardizing and plotting for visualization
df2 = df.copy()

from sklearn import preprocessing
from collections import Counter

# threshold the specified target attribute at the input value
def threshold(df, target_attr='total_UPDRS', value=8):
    update = df.copy()
    update[df[target_attr]<value] = -1 # less than threshold => negative class
    update[df[target_attr]>=value] = 1 # greater than threshold => positive class
    df.update(update[target_attr])

    # imbalance ratio = a proportion of samples in the number of majority class to the number of minority class
    neg = sum(update[target_attr]==-1)
    pos = sum(update[target_attr]==1)
    print(y_attr,"threshold:",value,":: -1's:",neg,"/ +1's",pos)
    if neg > pos:
        print("imbalance ratio (maj:min):", neg,":",pos, round(pos/neg*100,4),"%")
    elif pos > neg:
        print("imbalance ratio (maj:min):",pos,":",neg,"/", round(neg/pos*100,4),"%")

    return df, pos, neg

# extract useful features and target attribute
def X_Y_attr_extract(df, y_attr):
    # separate columns
    ID = df.iloc[:,0]        # ignore patient ID
    times = df.iloc[:,3]     # ignore time
    age_sex = df.iloc[:,1:3] # discrete, categorial (per patient)
    UPDRS = df.iloc[:,4:6]   # target attributes
    attrs = df.iloc[:,6:]    # features

    X = pd.concat([age_sex, attrs], sort=False, axis=1)
    Y = df[y_attr] # total UPDRS

    return X, Y

# standardize the feature values by: z = (x - mean) / std
# using standard scaler --> normalize values to range [-1, 1]
def standardize(df):
```

```
    result = df.copy()
    scaler = preprocessing.StandardScaler().fit(result) # standard scaler: [-1,1]
    standardized = pd.DataFrame(scaler.transform(result), columns=result.columns)

    return standardized

# take unique number from a list
def unique(list1):
    x = np.array(list1)
    unique_list = np.unique(x)
    return unique_list

# for visualization and interpreting the prediction results
def summary(Y_test, y_pred):
    from sklearn.metrics import accuracy_score, balanced_accuracy_score, f1_score, roc_curve, auc
    from imblearn.metrics import geometric_mean_score
    import matplotlib.pyplot as plt
    %matplotlib inline

    # evaluation metrics we are interested in, for imbalanced datasets
    acc = accuracy_score(y_pred, Y_test)
    b_acc = balanced_accuracy_score(y_pred, Y_test)
    f1 = f1_score(y_pred, Y_test)
    gmean = geometric_mean_score(Y_test, y_pred)

    fpr, tpr, _ = roc_curve(Y_test, y_pred)
    roc_auc = auc(fpr, tpr)
    plt.figure()
    lw = 2
    plt.plot(fpr, tpr, color='darkorange',
            lw=lw, label='ROC curve (area = %0.2f)' % roc_auc)
    plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--', label='reference')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('ROC Curve')
    plt.legend(loc='lower right')
    plt.show()

    print('------summary statistics-------')
    print("acc: {:.4f} / balanced acc: {:.4f}, AUC: {:.4f}, F1: {:.4f}, g-mean: {:.4f}".format(acc,b_acc,auc(fpr, tpr),f1,
gmean))
```

```
# apply thresholding and standarization to the data

# y_attr = 'motor_UPDRS'
y_attr = 'total_UPDRS'
thresh = 8
# threshold value ranges
# 7 to 54 for total_UPDRS
# 5 to 39 for motor_UPDRS
list_thresh = np.unique(unique(list(df[y_attr])).astype(np.int))

# threshold, extract attributes and labels, standardize to values between [-1, 1]
df2, npos, nneg = threshold(df2, target_attr=y_attr, value=thresh)
X, Y = X_Y_attr_extract(df2, y_attr)
X = standardize(X)

# print result in a table
result = pd.concat([X,Y], axis=1)
result.head()
```

```
total_UPDRS threshold: 8 :: -1's: 144 / +1's 5731
imbalance ratio (maj:min): 5731 : 144 / 2.5127 %
```

```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	age	sex	Jitter(%)	Jitter(Abs)	Jitter:RAP	Jitter:PPQ5	Jitter:DDP	Shimmer	Shimmer(dB)	Shimmer:APQ3	Shimmer:APQ5
0	0.815695	-0.682509	0.082905	-0.284242	0.327453	-0.028637	0.328505	-0.324594	-0.351642	-0.209709	-0.423356
1	0.815695	-0.682509	-0.560793	-0.756723	-0.533746	-0.476212	-0.534825	-0.534016	-0.573156	-0.545158	-0.565592
2	0.815695	-0.682509	-0.238944	-0.539382	-0.300038	-0.320767	-0.298983	-0.669115	-0.564469	-0.741592	-0.702426
3	0.815695	-0.682509	-0.155370	-0.485186	-0.344859	-0.170682	-0.344871	-0.423692	0.069668	-0.460540	-0.449763
4	0.815695	-0.682509	-0.498557	-0.663894	-0.658604	-0.529814	-0.659682	-0.658276	-0.586186	-0.783145	-0.651413

> Over-sampling

```python
# over-sampilng - random
from imblearn.over_sampling import RandomOverSampler
ros = RandomOverSampler(random_state=42)
X, Y = ros.fit_resample(X, Y)

# check resampled results
print(sorted(Counter(Y).items()))
```

```python
# over-sampling - SMOTE
from imblearn.over_sampling import SMOTE

X, Y = SMOTE(random_state=42).fit_resample(X, Y)
print(sorted(Counter(Y).items()))
```

```python
# over-sampling - ADASYN
from imblearn.over_sampling import ADASYN
X, Y = ADASYN(random_state=42).fit_resample(X, Y)
print(sorted(Counter(Y).items()))
```

```python
# over-sampling - BorderlineSMOTE
from imblearn.over_sampling import BorderlineSMOTE
X, Y = BorderlineSMOTE(random_state=42).fit_resample(X, Y)
print(sorted(Counter(Y).items()))
```

```python
# over-sampling - SVMSMOTE
from imblearn.over_sampling import SVMSMOTE
X, Y = SVMSMOTE(random_state=42).fit_resample(X, Y)
print(sorted(Counter(Y).items()))
```

```python
# over-sampling - KMeansSMOTE
from imblearn.over_sampling import KMeansSMOTE
X, Y = KMeansSMOTE(random_state=42, cluster_balance_threshold=0.05).fit_resample(X, Y)
print(sorted(Counter(Y).items()))
```

```python
# over-sampling - SMOTENC
from imblearn.over_sampling import SMOTENC

def standardize(df):
    result = df.copy()
    scaler = preprocessing.StandardScaler().fit(result.iloc[:,2:]) # standard scaler: [-1,1]
    standardized = pd.DataFrame(scaler.transform(result.iloc[:,2:]), columns=result.iloc[:,2:].columns)
    return standardized

# since SMOTENC takes nominal and continuous data as input, need to treat 'age' and 'sex' as categorial
y_attr = 'total_UPDRS'
thresh = 8
df2, npos, nneg = threshold(df.copy(), target_attr=y_attr, value=thresh)
X, Y = X_Y_attr_extract(df2, y_attr)
X = pd.concat([X.iloc[:,:2], standardize(X)], axis=1)
result = pd.concat([X,Y], axis=1)
result.head()
```

```
X, Y = SMOTENC(random_state=42, categorical_features=[0,1]).fit_resample(X, Y)
print(sorted(Counter(Y).items()))
```

> Under-sampling

```
# under-sampling - RandomUnderSampler
from imblearn.under_sampling import RandomUnderSampler
X, Y = RandomUnderSampler(random_state=42, replacement=True).fit_resample(X, Y) # replacement=True: bootstrapping data
print(sorted(Counter(Y).items()))
```

```
# under-sampling - ClusterCentroids
from imblearn.under_sampling import ClusterCentroids
X, Y = ClusterCentroids(random_state=42).fit_resample(X, Y)
print(sorted(Counter(Y).items()))
```

```
# under-sampling - NearMiss
from imblearn.under_sampling import NearMiss
nm1 = NearMiss(version=1)
X, Y = nm1.fit_resample(X, Y) # selects the (+) samples for which the average distance to the N 'closest' samples of the (-)
class is the smallest
print(sorted(Counter(Y).items()))
```

```
# under-sampling - NearMiss
from imblearn.under_sampling import NearMiss
X, Y = NearMiss(version=2).fit_resample(X, Y) # selects the (+) samples for which the average distance to the N 'farthest'
samples of the (-) class is the smallest
print(sorted(Counter(Y).items()))
```

```
# under-sampling - NearMiss
from imblearn.under_sampling import NearMiss
# 2-step:
# (1) for each (-) sample, their M nearest neighbors will be kept (2) selects the (+) samples for which the average distance to
the N nearest neighbors is the largest
X, Y = NearMiss(version=3).fit_resample(X, Y)
print(sorted(Counter(Y).items()))
```

```
# under-sampling - TomekLinks
from imblearn.under_sampling import TomekLinks
X, Y = TomekLinks().fit_resample(X, Y)
print(sorted(Counter(Y).items()))
```

```
# under-sampling - EditedNearestNeighbours
from imblearn.under_sampling import EditedNearestNeighbours
X, Y = EditedNearestNeighbours().fit_resample(X, Y)
print(sorted(Counter(Y).items()))
```

```
# under-sampling - RepeatedEditedNearestNeighbours
from imblearn.under_sampling import RepeatedEditedNearestNeighbours
X, Y = RepeatedEditedNearestNeighbours().fit_resample(X, Y)
print(sorted(Counter(Y).items()))
```

```
# under-sampling - AllKNN
from imblearn.under_sampling import AllKNN
X, Y = AllKNN().fit_resample(X, Y)
print(sorted(Counter(Y).items()))
```

```
# under-sampling - CondensedNearestNeighbour
from imblearn.under_sampling import CondensedNearestNeighbour
```

```
X, Y = CondensedNearestNeighbour(random_state=42).fit_resample(X, Y)
print(sorted(Counter(Y).items()))
```

```
# under-sampling - OneSidedSelection
from imblearn.under_sampling import OneSidedSelection
X, Y = OneSidedSelection(random_state=42).fit_resample(X, Y)
print(sorted(Counter(Y).items()))
```

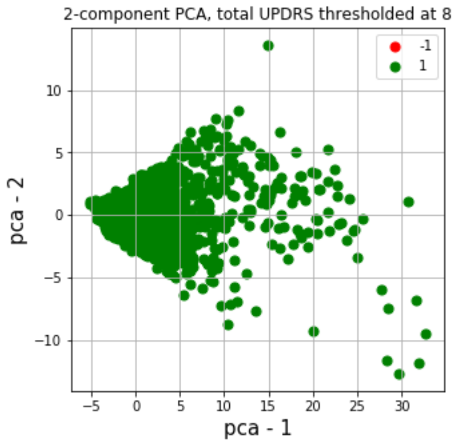
> Combined resampling

```
# combination of over- and under-sampling - SMOTEENN
from imblearn.combine import SMOTEENN
X, Y = SMOTEENN(random_state=42).fit_resample(X, Y)
print(sorted(Counter(Y).items()))
```

```
[(-1.0, 5727), (1.0, 5335)]
```

```
# combination of over- and under-sampling - SMOTETomek
from imblearn.combine import SMOTETomek
X, Y = SMOTETomek(random_state=42).fit_resample(X, Y)
print(sorted(Counter(Y).items()))
```

```
# PCA visualization (2 components)
import matplotlib.pyplot as plt
%matplotlib inline

from sklearn.decomposition import PCA

pca = PCA(n_components=2)
pca_components = pca.fit_transform(X)
pca_df = pd.DataFrame(data=pca_components, columns=['pca1','pca2'])

fig = plt.figure(figsize=(5,5))
ax = fig.add_subplot(1,1,1)
ax.set_xlabel('pca - 1', fontsize=15)
ax.set_ylabel('pca - 2', fontsize=15)
ax.set_title('2-component PCA, total UPDRS thresholded at {}'.format(thresh), fontsize=12)

targets = [-1, 1]
colors = ['r', 'g']
for target, color in zip(targets, colors):
    indices_keep = Y == target
    ax.scatter(pca_df.loc[indices_keep, 'pca1'],
               pca_df.loc[indices_keep, 'pca2'],
               c=color,
               s=50)
ax.legend(targets)
ax.grid()
fig.savefig('')
fig.savefig('log_reg_total_thresh_{}.png'.format(thresh))
```



> Convert to DataFrame before running through a classifier

```
# convert ndarray to dataframes before running through classifiers
X = pd.DataFrame(X)
Y = pd.DataFrame(Y)
```

> Classifiers

```
# 1. (Gaussian) Naive Bayes Classifier

from sklearn.model_selection import StratifiedKFold
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import plot_confusion_matrix
import matplotlib.pyplot as plt
%matplotlib inline

k_fold = StratifiedKFold(n_splits=10, shuffle=True, random_state=42)
for train_index, test_index in k_fold.split(X,Y):
    X_train, X_test = X.iloc[train_index], X.iloc[test_index]
    Y_train, Y_test = Y.iloc[train_index], Y.iloc[test_index]

    gnb = GaussianNB()
    y_pred = gnb.fit(X_train, Y_train).predict(X_test)
    print("Mislabeled %d points out of a total of %d points" % ((Y_test.values != y_pred).sum(), X_test.shape[0]))

    summary(Y_test, y_pred)
    disp = plot_confusion_matrix(gnb, X_test, Y_test,
                                 display_labels=np.unique(Y.values),
                                 cmap=plt.cm.Blues,
                                 normalize='true')
    disp.ax_.set_title('Confusion matrix')
    print("confusion matrix: \n",disp.confusion_matrix)
    plt.show()
```

```
# 2. (Stratified 10-folded) SVM
from sklearn.model_selection import StratifiedKFold
from sklearn.metrics import confusion_matrix
from svmutil import *

k_fold = StratifiedKFold(n_splits=10, shuffle=True, random_state=42)
for train_index, test_index in k_fold.split(X,Y):
    X_train, X_test = X.iloc[train_index], X.iloc[test_index]
    Y_train, Y_test = Y.iloc[train_index], Y.iloc[test_index]

    # define the svm problem
    prob = svm_problem(list(Y_train.values), list(X_train.values))

    param = svm_parameter("-q")
    param.svm_type = 0 # C-SVC
#     param.kernel_type = 0 # 0: Linear
    param.kernel_type = 2 #/ 2: RBF
    param.probability = 0 # disable probabiilty estimation, by default

    # apply grid search
    results = []
    for c in range(-5, 6):
```

```
        for g in range(-5, 6):
            param.C = 2**c
            param.gamma = 2**g
            m = svm_train(prob, param)
            p_label, p_acc, p_val = svm_predict(list(Y_test.values), list(X_test.values), m)
            results.append([2**c, 2**g, p_acc[0]])
    bestIdx = np.argmax(np.array(results)[:,2])
    best_c, best_g, _ = results[bestIdx]
    print("Best C: {}, Best Gamma: {}".format(best_c, best_g))

    # use best hyperparmaters to train
    param.C = best_c
    param.gamma = best_g

    m = svm_train(prob, param)
    y_pred, p_acc, p_val = svm_predict(list(Y_test.values), list(X_test.values), m)

    y_pred = pd.Series(y_pred)
    summary(Y_test, y_pred)
    cm = confusion_matrix(Y_test, y_pred, labels=np.unique(Y.values),normalize='true')
    print("confusion matrix: \n",cm)
```

```
# (Stratified 10-folded) SVM (Different Error Cost (DEC))
from sklearn.model_selection import StratifiedKFold
from sklearn.metrics import confusion_matrix
from svmutil import *
from sklearn.utils.class_weight import compute_class_weight

k_fold = StratifiedKFold(n_splits=10, shuffle=True, random_state=42)
for train_index, test_index in k_fold.split(X,Y):
    X_train, X_test = X.iloc[train_index], X.iloc[test_index]
    Y_train, Y_test = Y.iloc[train_index], Y.iloc[test_index]

    # define the svm problem
    prob = svm_problem(list(Y_train.values), list(X_train.values))

    # apply grid search
    results = []
    for c in range(-5, 6):
        for g in range(-5, 6):
            # adjust class weights by the ratio
            weights = compute_class_weight('balanced', classes=sorted(np.unique(Y_train)), y=Y_train.iloc[:,0])
            w_pos1, w_neg1 = weights
            # -s: svm_type (0 == C-SVC)
            # -b: probability estimate (0 == disabled)
            # -t: type of svm (0 == Linear, 2 == RBF)
            # -c: cost
            # -g: gamma
            # -w0, -w1: weights
            param = svm_parameter('-q -s 0 -b 0 -t 0 -c '+str(2**c)+' -g '+str(2**g)+' -w0 '+str(w_pos1)+' -w1 '+str(w_neg1))
            m = svm_train(prob, param)
            p_label, p_acc, p_val = svm_predict(list(Y_test.values), list(X_test.values), m)
            results.append([2**c, 2**g, p_acc[0]])
    bestIdx = np.argmax(np.array(results)[:,2])
    best_c, best_g, _ = results[bestIdx]
    print("Best C: {}, Best Gamma: {}".format(best_c, best_g))

    # test
    weights = compute_class_weight('balanced', classes=sorted(np.unique(Y_train)), y=Y_train.iloc[:,0])
    w_pos1, w_neg1 = weights
    print(sum(Y_train.values==1), sum(Y_train.values==-1)) # weights are in [1, -1] order
    print("Class weights:",weights)
    param = svm_parameter('-q -s 0 -t 0 -c '+str(best_c)+' -g '+str(best_g)+' -w0 '+str(w_pos1)+' -w1 '+str(w_neg1))

    m = svm_train(prob, param)
    y_pred, p_acc, p_val = svm_predict(list(Y_test.values), list(X_test.values), m)

    y_pred = pd.Series(y_pred)
    summary(Y_test, y_pred)
    cm = confusion_matrix(Y_test, y_pred, labels=np.unique(Y.values),normalize='true')
    print("confusion matrix: \n",cm)
```

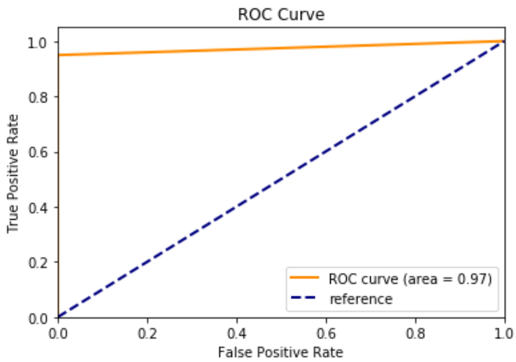
```
# (Stratified 10-folded) SVM (DEC -- one-class learning)
from sklearn.model_selection import StratifiedKFold
from sklearn.metrics import confusion_matrix
from svmutil import *
```

```python
from sklearn.utils.class_weight import compute_class_weight

k_fold = StratifiedKFold(n_splits=10, shuffle=True, random_state=42)
for train_index, test_index in k_fold.split(X,Y):
    X_train, X_test = X.iloc[train_index], X.iloc[test_index]
    Y_train, Y_test = Y.iloc[train_index], Y.iloc[test_index]

    # define the svm problem
    prob = svm_problem(list(Y_train.values), list(X_train.values))

    # apply grid search
    results = []
    for c in range(-5, 6):
        for g in range(-5, 6):
            # adjust class weights by the ratio
            weights = compute_class_weight('balanced', classes=sorted(np.unique(Y_train)), y=Y_train.iloc[:,0])
            w_pos1, w_neg1 = weights
            param = svm_parameter('-q -s 2 -b 0 -t 2 -c '+str(2**c)+' -g '+str(2**g)+' -w0 '+str(0)+' -w1 '+str(w_neg1))
            m = svm_train(prob, param)
            p_label, p_acc, p_val = svm_predict(list(Y_test.values), list(X_test.values), m)
            results.append([2**c, 2**g, p_acc[0]])
    bestIdx = np.argmax(np.array(results)[:,2])
    best_c, best_g, _ = results[bestIdx]
    print("Best C: {}, Best Gamma: {}".format(best_c, best_g))


    # test
    weights = compute_class_weight('balanced', classes=sorted(np.unique(Y_train)), y=Y_train.iloc[:,0])
    w_pos1, w_neg1 = weights
    print(sum(Y_train.values==1), sum(Y_train.values==-1)) # weights are in [1, -1] order
    print("Class weights:",weights)
    param = svm_parameter('-q -s 2 -t 2 -c '+str(best_c)+' -g '+str(best_g)+' -w0 '+str(0)+' -w1 '+str(w_neg1))

    m = svm_train(prob, param)
    y_pred, p_acc, p_val = svm_predict(list(Y_test.values), list(X_test.values), m)

    y_pred = pd.Series(y_pred)
    summary(Y_test, -1*y_pred)
    cm = confusion_matrix(Y_test, y_pred, labels=np.unique(Y.values),normalize='true')
    print("confusion matrix: \n",cm)
```

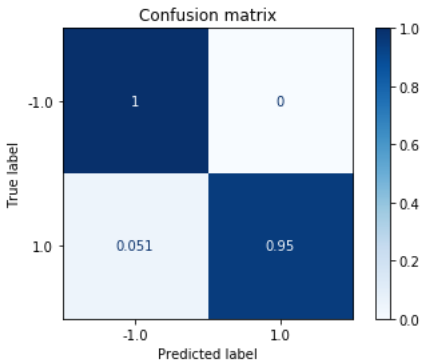
```python
# 3. Logistic Regression
from sklearn.model_selection import cross_val_score, cross_val_predict, train_test_split
from sklearn.linear_model import LogisticRegressionCV
from sklearn.metrics import plot_confusion_matrix
import matplotlib.pyplot as plt
%matplotlib inline

X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, random_state=42)

# initialize model
logreg = LogisticRegressionCV(cv=10, solver='lbfgs',random_state=42)

# cross validated prediction
y_pred = logreg.fit(X_train, Y_train).predict(X_test)
summary(Y_test, y_pred)

disp = plot_confusion_matrix(logreg, X_test, Y_test,
                             display_labels=np.unique(Y.values),
                             cmap=plt.cm.Blues,
                             normalize='true')
disp.ax_.set_title('Confusion matrix')
print("confusion matrix: \n",disp.confusion_matrix)
plt.show()

# plot logistic regression results with PCA
from sklearn.decomposition import PCA

pca = PCA(n_components=2)
pca_components = pca.fit_transform(X)
x_min, x_max = pca_components[:,0].min() - 0.5, pca_components[:,0].max() + 0.5
y_min, y_max = pca_components[:,1].min() - 0.5, pca_components[:,1].max() + 0.5
h = 0.02 # mesh step size
xx, yy = np.meshgrid(np.arange(x_min, x_max, h), np.arange(y_min, y_max, h))

logreg.fit(pca_components, Y)
Z = logreg.predict(np.c_[xx.ravel(), yy.ravel()])
```

```
# put the result into a color plot
Z = Z.reshape(xx.shape)
fig = plt.figure(1, figsize=(8,6))
ax = fig.add_subplot(1,1,1)
ax.pcolormesh(xx, yy, Z, cmap='binary_r') #plt.cm.Paired)

# plot also the training points
ax.scatter(pca_components[:,0], pca_components[:,1], c=Y.iloc[:,0]+1, edgecolors='r', cmap='binary_r') #plt.cm.Paired)
ax.set_xlabel('pca-1')
ax.set_ylabel('pca-2')
ax.set_title('Logistic Regression - total UPDRS thresholded at {}'.format(thresh))
ax.set_xlim(xx.min(), xx.max())
ax.set_ylim(yy.min(), yy.max())
ax.set_xticks(())
ax.set_yticks(())
plt.show()
fig.savefig('log_reg_total_thresh_{}.png'.format(thresh))
```

```
# 4. Ensemble classifier
# -- balanced bagging classifier (EasyEnsemble + BaggingClassifier)
from imblearn.ensemble import BalancedBaggingClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import plot_confusion_matrix

X_train, X_test, Y_train, Y_test = train_test_split(X, Y, random_state=42)
bbc = BalancedBaggingClassifier(random_state=42)
y_pred = bbc.fit(X_train, Y_train).predict(X_test)

summary(Y_test, y_pred)

disp = plot_confusion_matrix(bbc, X_test, Y_test,
                             display_labels=np.unique(Y.values),
                             cmap=plt.cm.Blues,
                             normalize='true')
disp.ax_.set_title('Confusion matrix')
print("confusion matrix: \n",disp.confusion_matrix)
plt.show()
```




```
------summary statistics-------
acc: 0.9503 / balanced acc: 0.6386, AUC: 0.9747, F1: 0.9740, g-mean: 0.9743
confusion matrix:
 [[1.         0.        ]
 [0.05065926 0.94934074]]
```



Ensemble Learning

```
# 4. Ensemble classifier
# -- Boosting - RUSBoostClassifier
from imblearn.ensemble import RUSBoostClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import plot_confusion_matrix

print(X.shape, Y.shape)
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, random_state=42)

rusboost = RUSBoostClassifier(random_state=42)
rusboost.fit(X_train, Y_train)
y_pred = rusboost.predict(X_test)

summary(Y_test, y_pred)

disp = plot_confusion_matrix(rusboost, X_test, Y_test,
                             display_labels=np.unique(Y.values),
                             cmap=plt.cm.Blues,
                             normalize='true')
disp.ax_.set_title('Confusion matrix')
print("confusion matrix: \n",disp.confusion_matrix)
plt.show()
```

```
# 4. Ensemble classifier
# -- Boosting - EasyEnsemblerClassifier (AdaBoost)
from imblearn.ensemble import EasyEnsembleClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import plot_confusion_matrix

print(X.shape, Y.shape)
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, random_state=42)

eec = EasyEnsembleClassifier(random_state=42)
eec.fit(X_train, Y_train)
y_pred = eec.predict(X_test)

summary(Y_test, y_pred)

disp = plot_confusion_matrix(eec, X_test, Y_test,
                             display_labels=np.unique(Y.values),
                             cmap=plt.cm.Blues,
                             normalize='true')
disp.ax_.set_title('Confusion matrix')
print("confusion matrix: \n",disp.confusion_matrix)
plt.show()
```