Fraud_detection

July 3, 2019

```
In [1]: import pandas as pd
        import matplotlib.pyplot as plt
        import numpy as np
        import scipy as sp
        from sklearn.linear_model import LogisticRegression
        from sklearn.model_selection import train_test_split, cross_val_score, cross_validate,
        from sklearn.metrics import roc_curve, auc, precision_recall_curve, roc_auc_score
        import sys
        from sklearn.preprocessing import minmax_scale, MinMaxScaler, StandardScaler
        from sklearn.metrics import recall_score, precision_score
        from sklearn.svm import SVC
        from pandas.plotting import scatter_matrix
        from sklearn.ensemble import GradientBoostingClassifier , RandomForestClassifier
        from xgboost import XGBClassifier
        from scipy import spatial
        from sklearn.neural_network import MLPClassifier
        from sklearn.manifold import TSNE
        from sklearn.dummy import DummyClassifier
```

1 Special Functions

```
In [9]: def smote(X, n = 100):
            """ N, nfeatures = X.shape"""
            XX = np.array(X)
            N, nfeatures = XX.shape
            Xismote = np.zeros([n, nfeatures ])
            np.random.seed(0)
            for k in range(n):
                i = np.random.randint(0,N,1)
                xi  = XX[i]
                XXi = XX #[np.random.randint(0,N,N//4)]
                d = XXi-xi
                d = (d**2).sum(axis = 1)
                dm = d[d>0].min()
                ismote = np.argwhere(d==dm)[0]
                xin = XXi[ismote]
                u = np.random.rand()
```

```
        xis = xi + u*( xin - xi)
        Xismote[k,:] = xis
    return Xismote


def cross_val_method(X,y, model , nsplit = 5):
    """ cross validation with precision recall score"""
    cv = KFold(nsplit, random_state=0)
    X = np.array(X)
    y = np.array(y)
    scoring_ = np.zeros(nsplit)
    i_ = 0
    for train_index, test_index in cv.split(X):
        X_train, X_test, y_train, y_test = X[train_index], X[test_index], y[train_index]
        model.fit(X_train, y_train)
        yh =  model.predict_proba(X_test)[:,1]
        prec, rec, t = precision_recall_curve(y_test,yh)
        scoring_[i_] = auc(rec,prec)
        i_ = i_ + 1
    return scoring_
        #print(roc_auc_score(y_test, yh) )

def cross_val_method_SMOTE(X,y, model , nsplit = 5, nn = 100):
    cv = KFold(nsplit, random_state=0)
    X = np.array(X)
    y = np.array(y)
    scoring_ = np.zeros(nsplit)
    i_ = 0
    for train_index, test_index in cv.split(X):
        X_train, X_test, y_train, y_test = X[train_index], X[test_index], y[train_index]
        Xs = smote(X_train[y_train==1],n = nn)
        ys = np.ones(nnn )
        ys =  np.append(y_train , ys ) # y1_train.append(pd.Series(ys))
        Xs =  np.append(X_train, Xs, axis = 0) # X1_train.append(pd.DataFrame(Xs, columm
        model.fit(Xs, ys)
        yh =  model.predict_proba(X_test)[:,1] # model.decision_function(X1_test)
        #y_pred = model.predict(X_test)
        prec, rec, t = precision_recall_curve(y_test,yh)
        scoring_[i_] = auc(rec,prec)
        i_ = i_ + 1
    return scoring_

def plot_score_C(SC, C, PLOT = 'SEMILOGX'):
    """ N, C.size = SC.shape"""
    SC = np.array(SC)
    CM =SC.mean(axis =1)
    C_min = SC.min(axis =1)
    C_max = SC.max(axis = 1)
```

```
        if PLOT == 'SEMILOGX':
            plt.semilogx(C,CM)
            plt.fill_between(C,C_min, C_max, alpha = 0.4)
        else :
            plt.plot(C,CM)
            plt.fill_between(C,C_min, C_max, alpha = 0.4)
        return
```

2 Reading dataset

Fraud algorithm using data based on this dataset from Kaggle. "The datasets contains transactions made by credit cards in September 2013 by european cardholders. This dataset presents transactions that occurred in two days, where we have 492 frauds out of 284,807 transactions. The dataset is highly unbalanced, the positive class (frauds) account for 0.172% of all transactions."

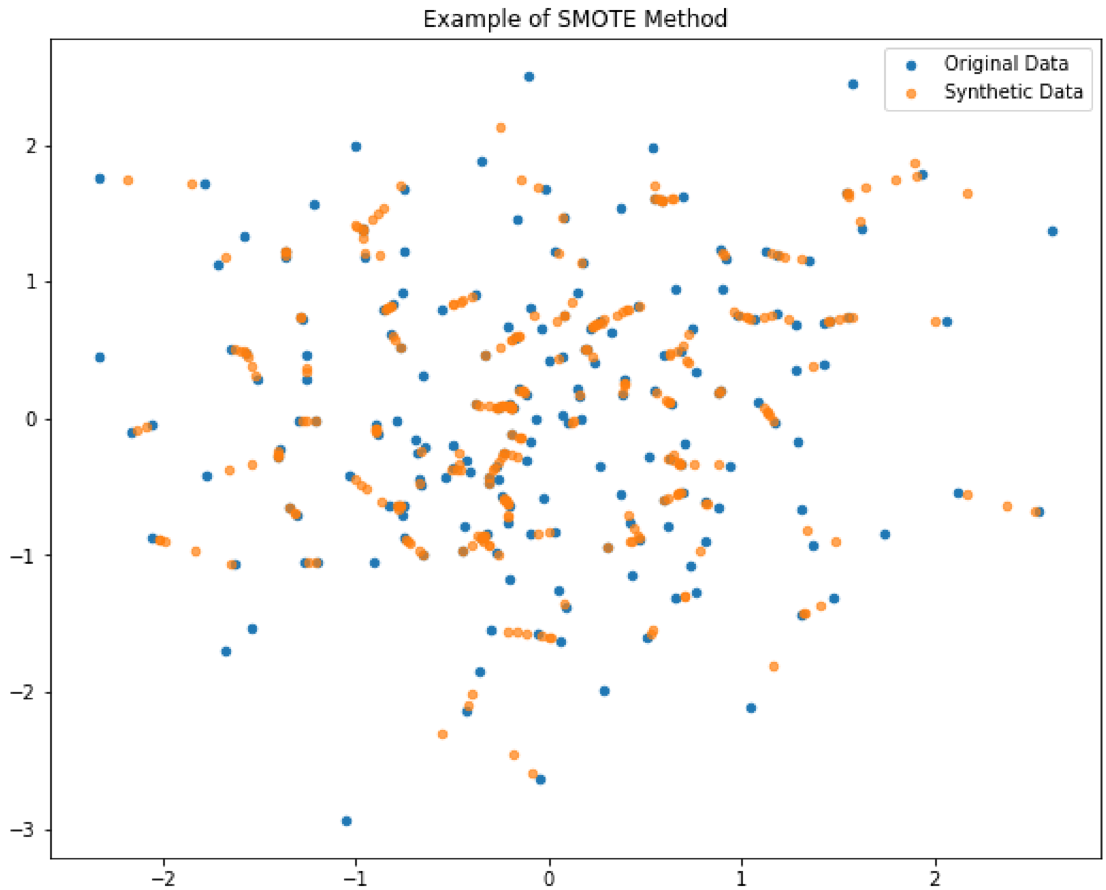
"It contains only numerical input variables which are the result of a PCA transformation. Features V1, V2, ... V28 are the principal components obtained with PCA, the only features which have not been transformed with PCA are 'Time' and 'Amount'. Feature 'Time' contains the seconds elapsed between each transaction and the first transaction in the dataset. The feature 'Amount' is the transaction Amount, this feature can be used for example-dependant cost-senstive learning. Feature 'Class' is the response variable and it takes value 1 in case of fraud and 0 otherwise."

```
In [11]: df = pd.read_csv('creditcard.csv')
         X = df[df.columns[1:-1]]
         y = df[df.columns[-1]]

         # Scalling the dataset
         scaler = StandardScaler()
         X = scaler.fit_transform(X)
```

3 Resampling with SMOTE Method (1)

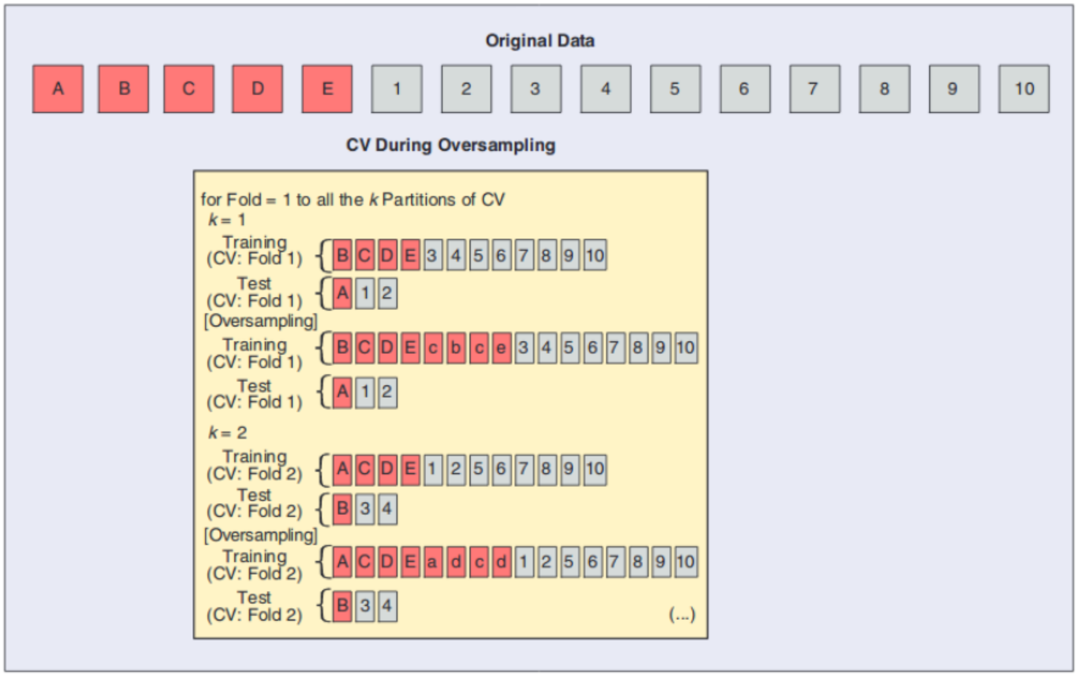
SMOTE (Synthetic Minority Oversampling Technique) is a resampling thecnique where the minority class is over-sampled by taking each minority class sample and introducing synthetic examples along the line segments joining any of the k minority class nearest neighbors. It is common use in case of fraud credit detection, rare diseases diagnosis, Manufacturing defects, etc.

```
In [152]: nnn = 300
          Z = np.random.randn(200,2)
          Zs = smote(Z,n = nnn)
          plt.figure(figsize=(10, 8))
          plt.scatter(Z[:,0],Z[:,1], s= 20, alpha = 1)
          plt.scatter(Zs[:,0],Zs[:,1], s = 20, alpha = .7)
          plt.legend(['Original Data', 'Synthetic Data'])
          plt.title('Example of SMOTE Method')

Out[152]: Text(0.5, 1.0, 'Example of SMOTE Method')
```



4 Cross Validation Approaches Imbalanced Case

Results show in (2) suggest to use this approach in cross-validation in case of imbalanced datasets:



In case of imbalanced datasets (3) recommend to use the area under of curve of precision-recall.

[1] Chawla, N. V., Bowyer, K. W., Hall, L. O., & Kegelmeyer, W. P. (2002). SMOTE: synthetic minority over-sampling technique. Journal of artificial intelligence research, 16, 321-357.

[2] Santos, M. S., Soares, J. P., Abreu, P. H., Araujo, H., & Santos, J. (2018). Cross-Validation for Imbalanced Datasets: Avoiding Overoptimistic and Overfitting Approaches [Research Frontier]. IEEE Computational Intelligence Magazine, 13(4), 59-76.

[3] Fayzrakhmanov, R., Kulikov, A., & Repp, P. (2018, September). The Difference Between Precision-recall and ROC Curves for Evaluating the Performance of Credit Card Fraud Detection Models. In Titel: Proceedings of the 6th International Conference on Applied Innovations in IT. Bibliothek, Hochschule Anhalt.

5 Hyperparameter Optimization

5.1 Logistic Regression

```
In [13]: #with SMOTE
         nnn = 1000
         CC = np.logspace(-1,3, 5)
         AUC_C = []
         for C in CC:
             model = LogisticRegression(C = C, max_iter = 400, penalty = 'l2',   solver = 'newto
             auc_cros = cross_val_method_SMOTE(X,y, model , nsplit = 4, nn = nnn)
             AUC_C.append(auc_cros )
```

```
        print(auc_cros , ', MEAN = ', auc_cros.mean(), ', STD = ' , auc_cros.std() )
```

```
[0.73194954 0.77075856 0.82797988 0.74510748] , MEAN =  0.7689488636227229 , STD =  0.0368283083
[0.72229198 0.76771641 0.82427715 0.74434109] , MEAN =  0.764656657789784 , STD =  0.03798503881
[0.71818834 0.76731271 0.82330984 0.74463735] , MEAN =  0.7633620626278443 , STD =  0.0387318465
[0.71775913 0.7673129  0.8233222  0.7446354 ] , MEAN =  0.7632574090160498 , STD =  0.0388622523
[0.71772929 0.76731288 0.82332212 0.74463536] , MEAN =  0.7632499136834676 , STD =  0.0388709625
```

In [ ]:

In [14]:
```
#without SMOTE
CC = np.logspace(-1,3, 5)
AUC_C_ = []
for C in CC:
    model = LogisticRegression(C = C, max_iter = 400, penalty = 'l2',   solver = 'newto
    auc_cros = cross_val_method(X,y, model , nsplit = 4)
    AUC_C_.append(auc_cros )
    print(auc_cros , ', MEAN = ', auc_cros.mean(), ', STD = ' , auc_cros.std() )
```

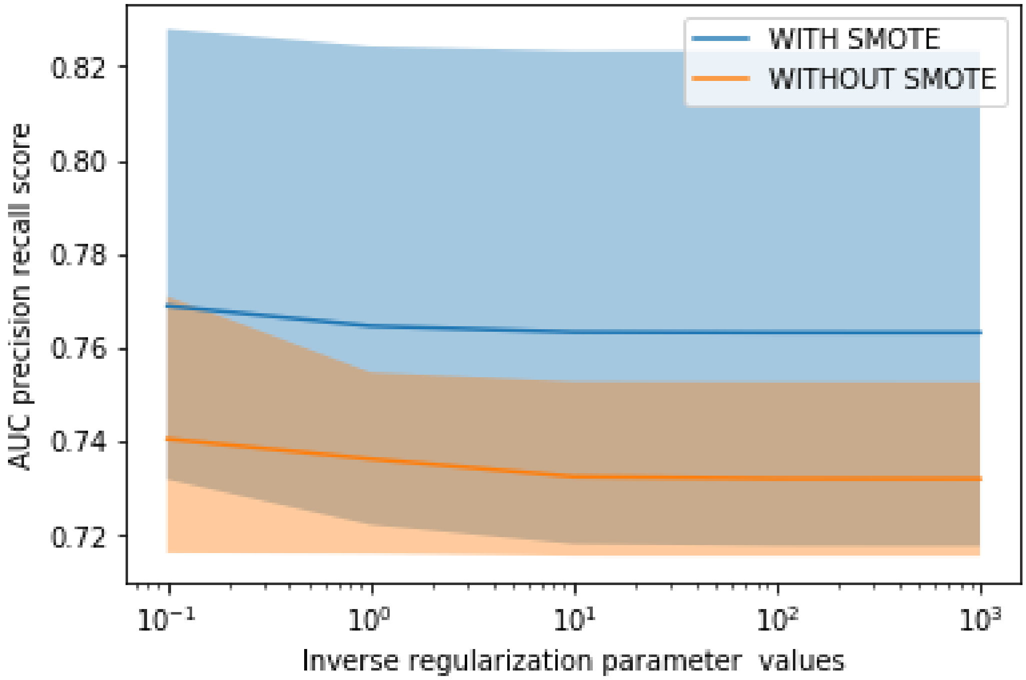
```
[0.73502179 0.74017117 0.77099555 0.71629419] , MEAN =  0.7406206770502821 , STD =  0.0196593495
[0.73844743 0.73600457 0.75480634 0.71614064] , MEAN =  0.7363497437804019 , STD =  0.0137256457
[0.72682566 0.73500703 0.75284106 0.71564254] , MEAN =  0.7325790708972786 , STD =  0.0135682636
[0.72531328 0.73490388 0.75275654 0.71562663] , MEAN =  0.7321500815348294 , STD =  0.0137110889
[0.72516037 0.73490466 0.75274557 0.71562648] , MEAN =  0.7321092695313213 , STD =  0.0137262582
```

In [31]:

5.2 Plotting of Score of Logistic Regression

In [15]:
```
plot_score_C(AUC_C, CC, PLOT = 'SEMILOGX')
plot_score_C(AUC_C_, CC, PLOT = 'SEMILOGX')
plt.xlabel('Inverse regularization parameter  values')
plt.ylabel('AUC precision recall score')
plt.legend(['WITH SMOTE', 'WITHOUT SMOTE'])
```

Out[15]: <matplotlib.legend.Legend at 0x7f888c6c3ef0>



In [ ]:

Results showing that score is better when SMOTE Method is applied

In [ ]:

5.3 Gradient boosting

In [24]:
```
#with SMOTE
nnn = 500
CC = np.arange(3,9)
AUC_C = []
for C in CC:
    model = XGBClassifier(  max_depth = C, learning_rate = .2, n_estimators = 100, n_jo
    auc_cros = cross_val_method_SMOTE(X,y, model , nsplit = 4, nn = nnn)
    AUC_C.append(auc_cros )
    print(auc_cros , ', MEAN = ', auc_cros.mean(), ', STD = ' , auc_cros.std() )
```

```
[0.75596538 0.83070185 0.817419   0.77029585] , MEAN =  0.7935955193845325 , STD =  0.0312383575
[0.79456646 0.82412076 0.82907992 0.77815542] , MEAN =  0.8064806386449062 , STD =  0.0210128949
[0.73141714 0.8211173  0.83765393 0.78234717] , MEAN =  0.7931338857971109 , STD =  0.0408974801
[0.78441631 0.81315904 0.83735086 0.79850898] , MEAN =  0.8083587949032102 , STD =  0.0195821565
[0.79620521 0.81952576 0.84115453 0.79820134] , MEAN =  0.8137717087516372 , STD =  0.0182616161
[0.78844794 0.82455464 0.8352628  0.79550572] , MEAN =  0.8109427740569503 , STD =  0.0195004303
```

In [ ]:

In [ ]:

In [ ]:

In [43]:
```
#without SMOTE
CC = np.arange(3,9)
AUC_C_ = []
for C in CC:
    model = XGBClassifier(  max_depth = C, learning_rate = .2, n_estimators = 100, n_jo
    auc_cros = cross_val_method(X,y, model , nsplit = 4)
    AUC_C_.append(auc_cros )
    print(auc_cros , ', MEAN = ', auc_cros.mean(), ', STD = ' , auc_cros.std() )
```

```
[0.74193754 0.82844531 0.83576805 0.78747072] , MEAN =  0.7984054065834532 , STD =  0.0374384490
[0.80747834 0.82296686 0.83014032 0.77646171] , MEAN =  0.8092618094506567 , STD =  0.0206323045
[0.71383146 0.82306366 0.82676935 0.78195842] , MEAN =  0.7864057222903409 , STD =  0.0454417982
[0.76820683 0.82758158 0.82634623 0.78220785] , MEAN =  0.8010856248783308 , STD =  0.0263510893
[0.77237748 0.81517817 0.84154929 0.78034926] , MEAN =  0.8023635478690991 , STD =  0.0277647696
```

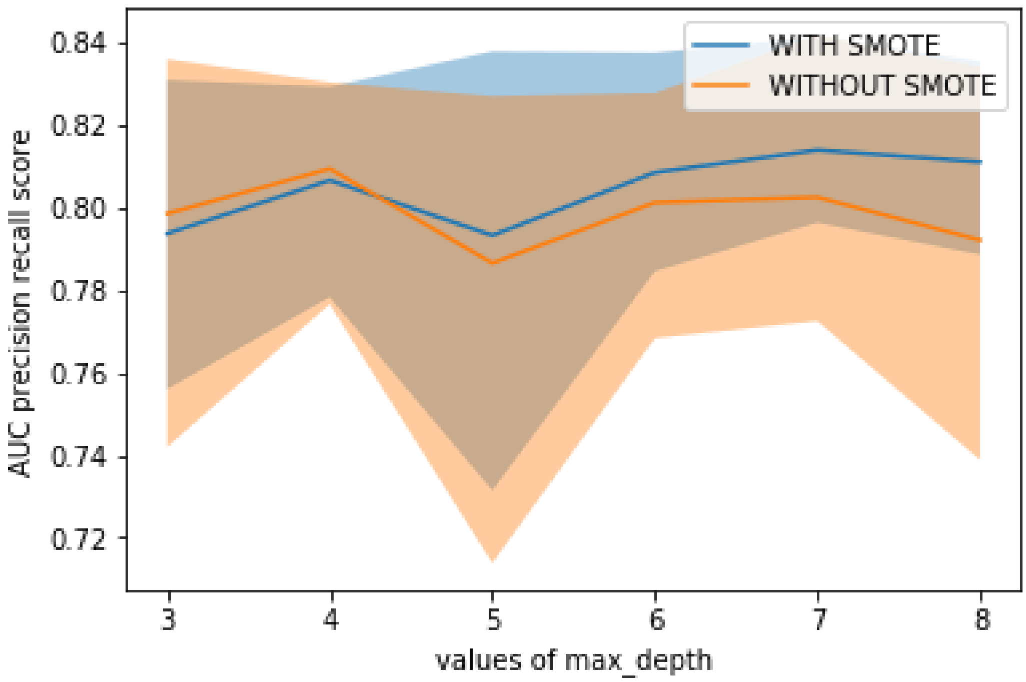
In [ ]:

In [ ]:

5.4 Plotting Score of Gradient boosting

In [25]:
```
plot_score_C(AUC_C, CC, PLOT = 'o')
plot_score_C(AUC_C_, CC, PLOT = 'o')
plt.xlabel('values of max_depth')
plt.ylabel('AUC precision recall score')
plt.legend(['WITH SMOTE', 'WITHOUT SMOTE'])
```

Out[25]:
```
<matplotlib.legend.Legend at 0x7f888bf0a7f0>
```



The best performance is with max_depth = 7 and using SMOTE Method

In [ ]:

5.5 Tuning learning rate with max_depth = 7

In [27]:
```
nnn = 500
CC = np.logspace( np.log10(0.05),  np.log10(0.9), 6)
AUC_C = []
for C in CC:
    model = XGBClassifier(  max_depth = 7, learning_rate = C, n_estimators = 100, n_job
    auc_cros = cross_val_method_SMOTE(X,y, model , nsplit = 4, nn = nnn)
    AUC_C.append(auc_cros )
    print(auc_cros , ', MEAN = ', auc_cros.mean(), ', STD = ' , auc_cros.std() )
```

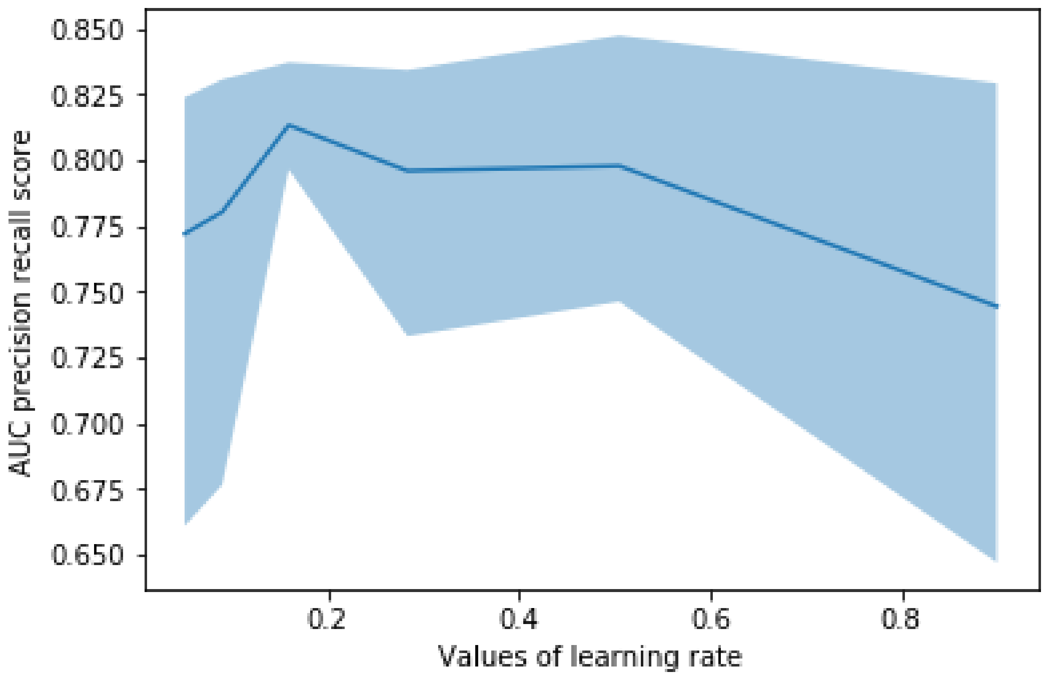
```
[0.66086209 0.82367608 0.81739901 0.78559702] , MEAN =  0.7718835512220693 , STD =  0.0657037820
[0.67643268 0.81883007 0.83050778 0.79474828] , MEAN =  0.7801297021471656 , STD =  0.0612422334
[0.79627743 0.81952996 0.83700407 0.79987581] , MEAN =  0.8131718173752106 , STD =  0.0163600624
[0.73289328 0.8219228  0.83410637 0.79421469] , MEAN =  0.7957842845459305 , STD =  0.0390817926
[0.74607094 0.81445252 0.84724969 0.78297918] , MEAN =  0.7976880830231698 , STD =  0.0374769287
[0.77836162 0.64702471 0.82915417 0.72263666] , MEAN =  0.7442942890293675 , STD =  0.0676243415
```

In [ ]:

In [ ]:

```
In [28]: plot_score_C(AUC_C, CC, PLOT = '')
         plt.xlabel('Values of learning rate')
         plt.ylabel('AUC precision recall score')
```

```
Out[28]: Text(0, 0.5, 'AUC precision recall score')
```



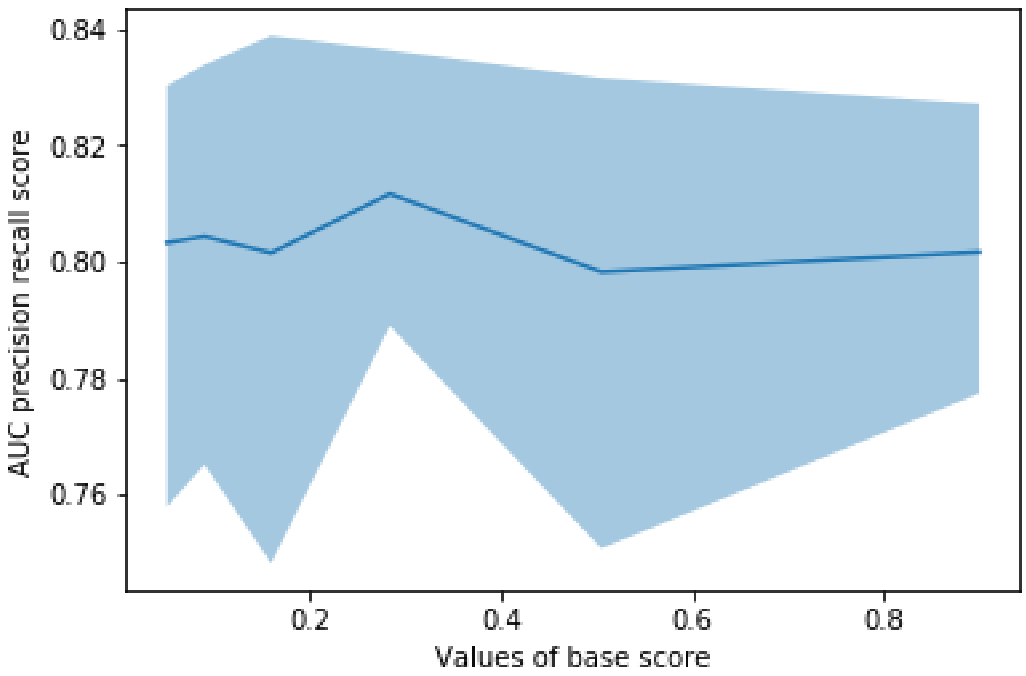
The best performance is with learning rate is between 0.16 and 0.2 approximately

5.6 Tuning base score with learning_rate = 0.16

```
In [35]: nnn = 500
         CC = np.logspace( np.log10(0.05),  np.log10(0.9), 6)
         AUC_C = []
         for C in CC:
             model = XGBClassifier(  max_depth = 7, learning_rate = 0.16, n_estimators = 100, n_
             auc_cros = cross_val_method_SMOTE(X,y, model , nsplit = 4, nn = nnn)
             AUC_C.append(auc_cros )
             print(auc_cros , ', MEAN = ', auc_cros.mean(), ', STD = ' , auc_cros.std() )
```

```
[0.75788773 0.81914589 0.8303415  0.80575652] , MEAN =  0.8032829066588294 , STD =  0.0276163097
[0.76512845 0.82062375 0.83392883 0.79782753] , MEAN =  0.8043771429562057 , STD =  0.0260797442
[0.74815648 0.81842298 0.83893397 0.80057525] , MEAN =  0.8015221710425271 , STD =  0.0336677663
[0.78897899 0.82417139 0.83640427 0.79723156] , MEAN =  0.8116965505036605 , STD =  0.0193094317
[0.75068514 0.82144131 0.83163588 0.78919794] , MEAN =  0.7982400677856509 , STD =  0.0316101599
[0.7773558  0.81519655 0.82720108 0.78687212] , MEAN =  0.8016563879062542 , STD =  0.0202790534
```

```
In [ ]:

In [36]: plot_score_C(AUC_C, CC, PLOT = 'o')
         plt.xlabel('Values of base score')
         plt.ylabel('AUC precision recall score')

Out[36]: Text(0, 0.5, 'AUC precision recall score')
```



The best performance is with learning rate is between 0.25 and 0.3 approximately

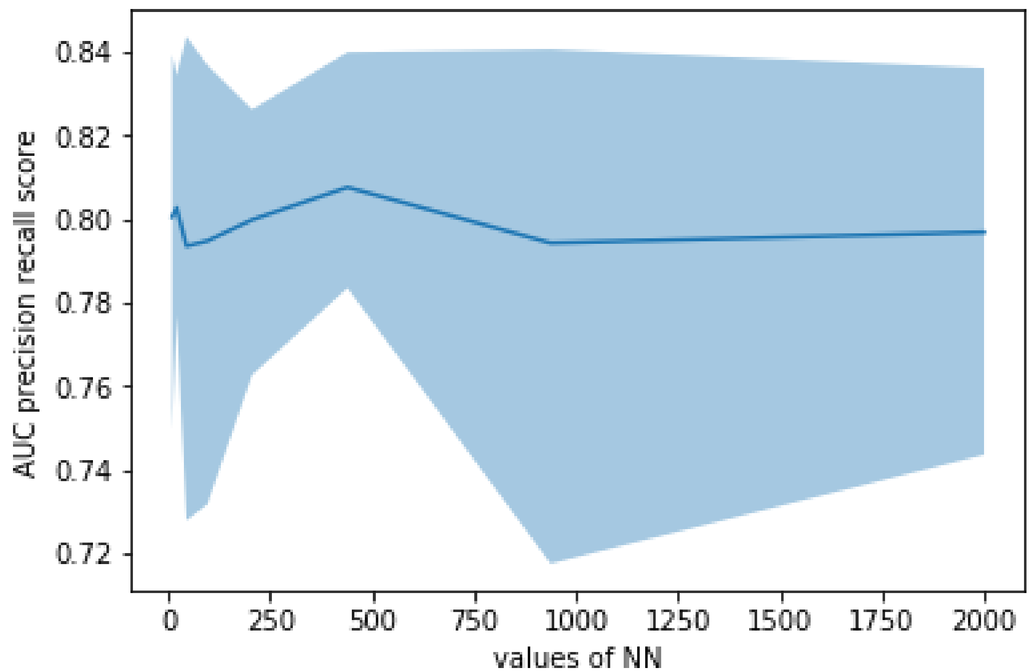
5.7 Tuning Number of resamplong with base_score = 0.28

```
In [ ]:

In [41]: NN = (np.logspace( np.log10(10),  np.log10(2000), 8)).astype(int)
         AUC_C = []
         for nnn in NN:
             model = XGBClassifier(  max_depth = 7, learning_rate = 0.16, n_estimators = 100, n_
             auc_cros = cross_val_method_SMOTE(X,y, model , nsplit = 4, nn = nnn)
             AUC_C.append(auc_cros )
             print(auc_cros , ', MEAN = ', auc_cros.mean(), ', STD = ' , auc_cros.std() )

[0.74961022 0.82722558 0.83920531 0.78557769] , MEAN =  0.800404699098589 , STD =  0.03544279617
[0.77687942 0.81759297 0.83434234 0.78143603] , MEAN =  0.8025626917844741 , STD =  0.0241961841
[0.72781864 0.81775612 0.84357383 0.78455833] , MEAN =  0.7934267292526612 , STD =  0.0432715879
[0.73163105 0.81549596 0.83676843 0.79467136] , MEAN =  0.7946417007582657 , STD =  0.0393061814
```

```
[0.76259266 0.81888681 0.82615482 0.79125987] , MEAN =  0.7997235380328316 , STD =  0.0250807665
[0.78341907 0.81771075 0.83979668 0.78907239] , MEAN =  0.8074997242705808 , STD =  0.0227310530
[0.71745509 0.82412936 0.84048586 0.79458911] , MEAN =  0.7941648548857185 , STD =  0.0472442459
[0.74352009 0.81677074 0.83604063 0.79063314] , MEAN =  0.7967411494439888 , STD =  0.0346966236
```

```
In [42]: plot_score_C(AUC_C, NN, PLOT = 'o')
         plt.xlabel('values of NN')
         plt.ylabel('AUC precision recall score')
```

```
Out[42]: Text(0, 0.5, 'AUC precision recall score')
```




```
In [ ]:
```

The last plot suggests that the best performance is when increasing the number of resampling between 440 and 500, because the variance of the score is lower, for other values the variance increases.

Other hyperameters for the best performance in 'XGBClassifier' are: max_depth = 7, learning_rate = 0.16, and base_score = 0.28 with area under of curve precision recall as metric

```
In [ ]:
```

6 Random Search of Hyperparameters

Results in (4) show that random search experiments are more efficient than grid experiments for hyperparameters on several machine learning techniques.

We search the best hyperparameters for "learning_rate" and "base_score" in $XGBClassifier$ **fixing "max_depth" = 7 and adding 450 synthetic data.**

[4] Bergstra, J., & Bengio, Y. (2012). Random search for hyper-parameter optimization. Journal of Machine Learning Research, 13(Feb), 281-305.

6.1 SMOTE Method

In [78]:
```
nnn = 450
CC = [np.random.rand(15)*.5 , np.random.rand(15)*.5]
CC = np.array(CC).T
AUC_C = []
for C in CC:
    model = XGBClassifier(  max_depth = 7, learning_rate = C[0], n_estimators = 100, n_
    auc_cros = cross_val_method_SMOTE(X,y, model , nsplit = 4, nn = nnn)
    AUC_C.append(auc_cros )
    print('learning_rate = ', C[0], ', base_score = ', C[1])
    print(auc_cros , ', MEAN = ', auc_cros.mean(), ', STD = ' , auc_cros.std() )
```

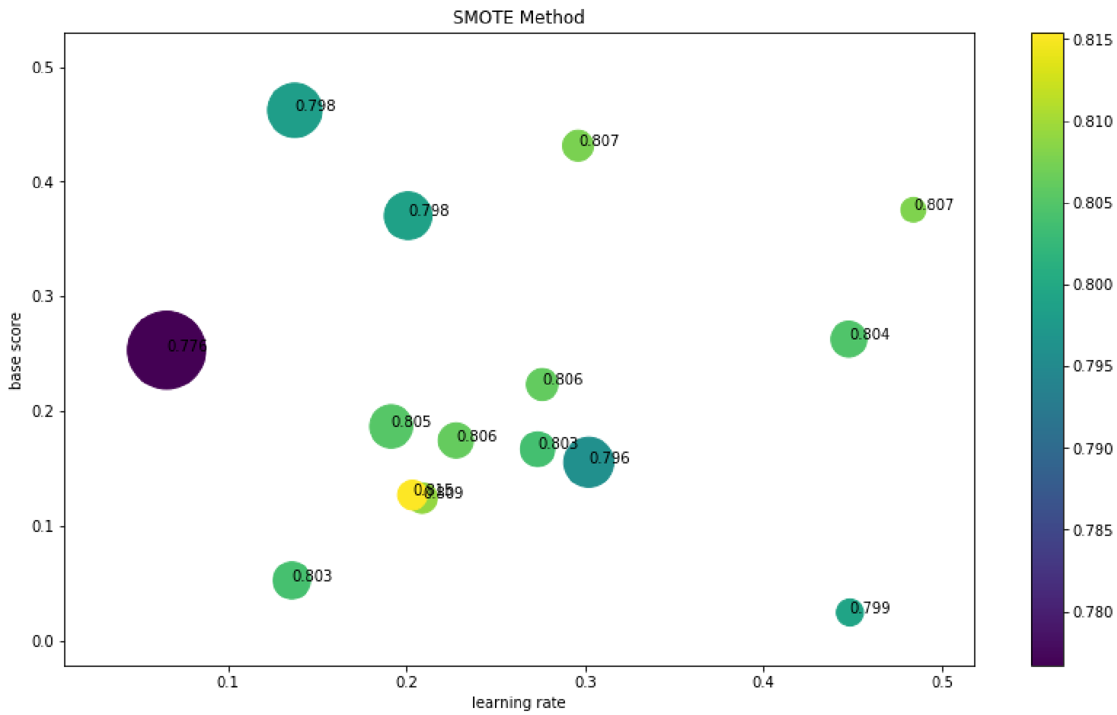
```
learning_rate =  0.2087431873980059 , base_score =  0.12420673254148551
[0.78807728 0.81486556 0.84044808 0.79280576] , MEAN =  0.8090491722961555 , STD =  0.0207568693
learning_rate =  0.06564466423662801 , base_score =  0.2529331919126542
[0.68976606 0.82006211 0.82124868 0.77568303] , MEAN =  0.7766899715082904 , STD =  0.0534401561
learning_rate =  0.302058902010441 , base_score =  0.1551904129899057
[0.74787261 0.81722926 0.83729245 0.78166607] , MEAN =  0.7960150979099325 , STD =  0.0341959588
learning_rate =  0.19140402957892705 , base_score =  0.18651743194037373
[0.76080931 0.82345837 0.83862939 0.7981143 ] , MEAN =  0.8052528422958953 , STD =  0.0294602315
learning_rate =  0.447692942144105 , base_score =  0.26248522112713213
[0.78093828 0.81695693 0.83911416 0.78210921] , MEAN =  0.8047796431844619 , STD =  0.0245433504
learning_rate =  0.48389733589925094 , base_score =  0.37529751146449375
[0.79446905 0.82042613 0.82845833 0.78836185] , MEAN =  0.807928841042211 , STD =  0.01689434451
learning_rate =  0.2734424508347111 , base_score =  0.16675373289563766
[0.77061662 0.8160924  0.83400702 0.79439729] , MEAN =  0.8037783309421309 , STD =  0.0237334836
learning_rate =  0.1374117849337983 , base_score =  0.4620793833103818
[0.73942501 0.82445596 0.83526888 0.79354469] , MEAN =  0.7981736340686516 , STD =  0.0372144001
learning_rate =  0.2961152093809184 , base_score =  0.4311592734179512
[0.77607155 0.82222961 0.8307834  0.8014276 ] , MEAN =  0.807628038954944 , STD =  0.02111654404
learning_rate =  0.4483805791122049 , base_score =  0.02434514798776427
[0.80451753 0.82651618 0.78730242 0.77871154] , MEAN =  0.7992619197727721 , STD =  0.0182740521
learning_rate =  0.20336667291787414 , base_score =  0.12682126212841138
[0.80863262 0.81631737 0.84647218 0.79017094] , MEAN =  0.8153982762880245 , STD =  0.0203016306
learning_rate =  0.2760391383459854 , base_score =  0.22306775632960096
[0.78066759 0.81722596 0.83555644 0.79098174] , MEAN =  0.8061079330780478 , STD =  0.0216034599
learning_rate =  0.13582638380307294 , base_score =  0.05231394437123704
[0.7681454  0.81617632 0.8369469  0.79449163] , MEAN =  0.8039400631164157 , STD =  0.0255426537
learning_rate =  0.2277220747250135 , base_score =  0.17423799451674854
[0.778542   0.81109043 0.84277542 0.79279235] , MEAN =  0.8063000480775826 , STD =  0.0240123272
```

```
learning_rate =  0.20085676768979932 , base_score =  0.37004876280884125
[0.74908576 0.81890199 0.83542975 0.79206446] , MEAN =  0.7988704893921168 , STD =  0.0326446089
```

```
In [155]: Cm = np.mean(AUC_C, axis = 1)
          Cstd = np.std(AUC_C, axis = 1)
          Cmin = np.min(AUC_C, axis = 1)
          Cmax = np.max(AUC_C, axis = 1)
          print('max. score = ' , Cm.max())
          plt.figure(figsize = (14,8))
          plt.scatter(CC[:,0], CC[:,1],s = (Cstd*1000)**2 ,  c = Cm , cmap = 'viridis') , plt.co
          for i, txt in enumerate(Cm):
              plt.annotate(str(txt)[0:5],  ( CC[i,0], CC[i,1]) )

          plt.xlabel('learning rate')
          plt.ylabel('base score')
          plt.title('SMOTE Method')
```

```
max. score =  0.8153982762880245
```

```
Out[155]: Text(0.5, 1.0, 'SMOTE Method')
```



The color bar indicates the mean value of scores and the size of the circle is proportional to the standard deviation of scores in cross-validation.

6.2 Without SMOTE

```
In [93]: AUC_C_ = []
         for C in CC:
             model = XGBClassifier(  max_depth = 7, learning_rate =  C[0], n_estimators = 100, n
             auc_cros = cross_val_method(X,y, model , nsplit = 4)
             AUC_C_.append(auc_cros )
             print('learning_rate = ', C[0], ', base_score = ', C[1])
             print(auc_cros , ', MEAN = ', auc_cros.mean(), ', STD = ' , auc_cros.std() )
```

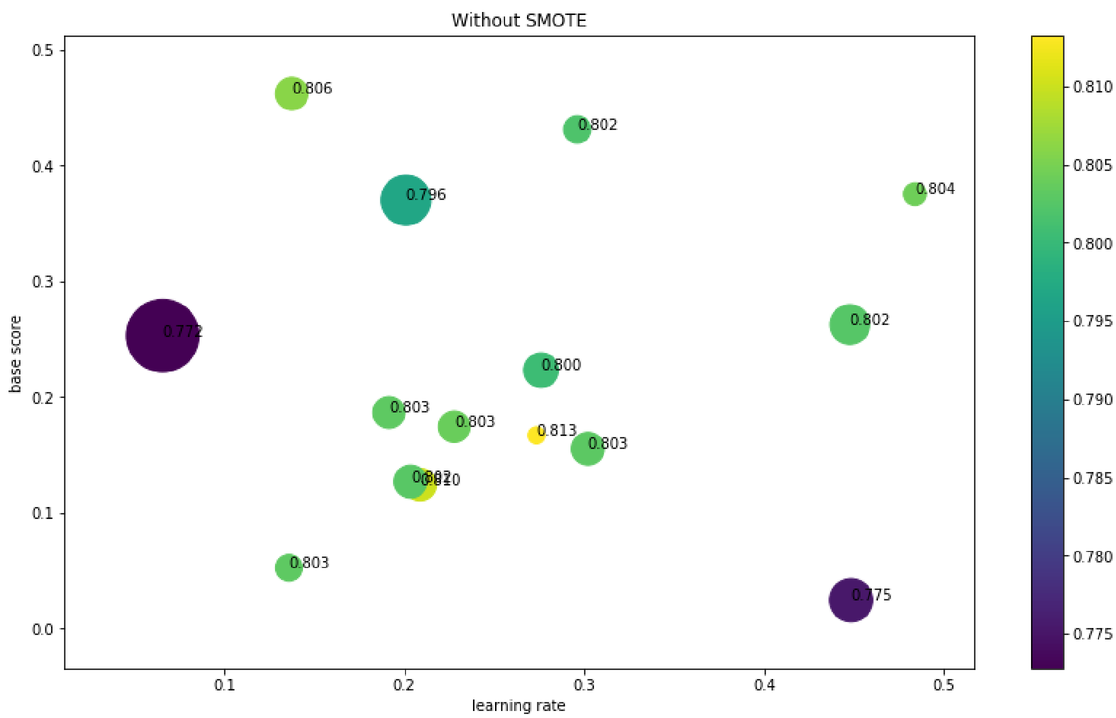
```
learning_rate =  0.2087431873980059 , base_score =  0.12420673254148551
[0.79017914 0.82043579 0.84174647 0.78840733] , MEAN =  0.8101921809763225 , STD =  0.0222244601
learning_rate =  0.06564466423662801 , base_score =  0.2529331919126542
[0.69539519 0.81625018 0.81654533 0.76303185] , MEAN =  0.7728056396467917 , STD =  0.0497204519
learning_rate =  0.302058902010441 , base_score =  0.1551904129899057
[0.77528673 0.80803869 0.83634927 0.79242668] , MEAN =  0.803025343209182 , STD =  0.0224576257
learning_rate =  0.19140402957892705 , base_score =  0.18651743194037373
[0.78160255 0.82279317 0.82716371 0.78127692] , MEAN =  0.8032090904065872 , STD =  0.0218244276
learning_rate =  0.447692942144105 , base_score =  0.26248522112713213
[0.77257465 0.81454745 0.84128931 0.78181639] , MEAN =  0.8025569507061932 , STD =  0.0272629637
learning_rate =  0.48389733589925094 , base_score =  0.37529751146449375
[0.79322713 0.8112933  0.82590355 0.78659404] , MEAN =  0.8042545043504901 , STD =  0.0154249850
learning_rate =  0.2734424508347111 , base_score =  0.16675373289563766
[0.81571485 0.81697143 0.82594643 0.79436907] , MEAN =  0.8132504442296369 , STD =  0.0115932465
learning_rate =  0.1374117849337983 , base_score =  0.4620793833103818
[0.78420403 0.82493397 0.83136935 0.7837551 ] , MEAN =  0.8060656126394867 , STD =  0.0222035006
learning_rate =  0.2961152093809184 , base_score =  0.4311592734179512
[0.7781159  0.82115912 0.81943179 0.78933535] , MEAN =  0.8020105407935613 , STD =  0.0187201941
learning_rate =  0.4483805791122049 , base_score =  0.02434514798776427
[0.77836523 0.81754415 0.7339472  0.77169774] , MEAN =  0.7753885800030389 , STD =  0.0296519930
learning_rate =  0.20336667291787414 , base_score =  0.12682126212841138
[0.78055133 0.81400648 0.83429423 0.7822775 ] , MEAN =  0.8027823867498758 , STD =  0.0225479887
learning_rate =  0.2760391383459854 , base_score =  0.22306775632960096
[0.77295637 0.80600902 0.83619677 0.78704171] , MEAN =  0.8005509657303114 , STD =  0.0236874175
learning_rate =  0.13582638380307294 , base_score =  0.05231394437123704
[0.78156354 0.81428621 0.82682623 0.79023434] , MEAN =  0.8032275813410177 , STD =  0.0181476192
learning_rate =  0.2277220747250135 , base_score =  0.17423799451674854
[0.78261088 0.81510953 0.83357583 0.78443667] , MEAN =  0.8039332291315046 , STD =  0.0214380027
learning_rate =  0.20085676768979932 , base_score =  0.37004876280884125
[0.75234274 0.82452739 0.83489882 0.77498587] , MEAN =  0.7966887079872839 , STD =  0.0341781471
```

```
In [156]: Cm_= np.mean(AUC_C_, axis = 1)
          Cstd_ = np.std(AUC_C_, axis = 1)
          Cmin_ = np.min(AUC_C_, axis = 1)
          Cmax_ = np.max(AUC_C_, axis = 1)
          print('max. score = ' , Cm_.max())
          plt.figure(figsize = (14,8))
```

```
plt.scatter(CC[:,0], CC[:,1],s = (Cstd_*1000)**2 ,  c = Cm_ , cmap = 'viridis') , plt.
for i, txt in enumerate(Cm_):
    plt.annotate(str(txt)[0:5],  ( CC[i,0], CC[i,1]) )

plt.xlabel('learning rate')
plt.ylabel('base score')
plt.title('Without SMOTE')
```

```
max. score =  0.8132504442296369
```

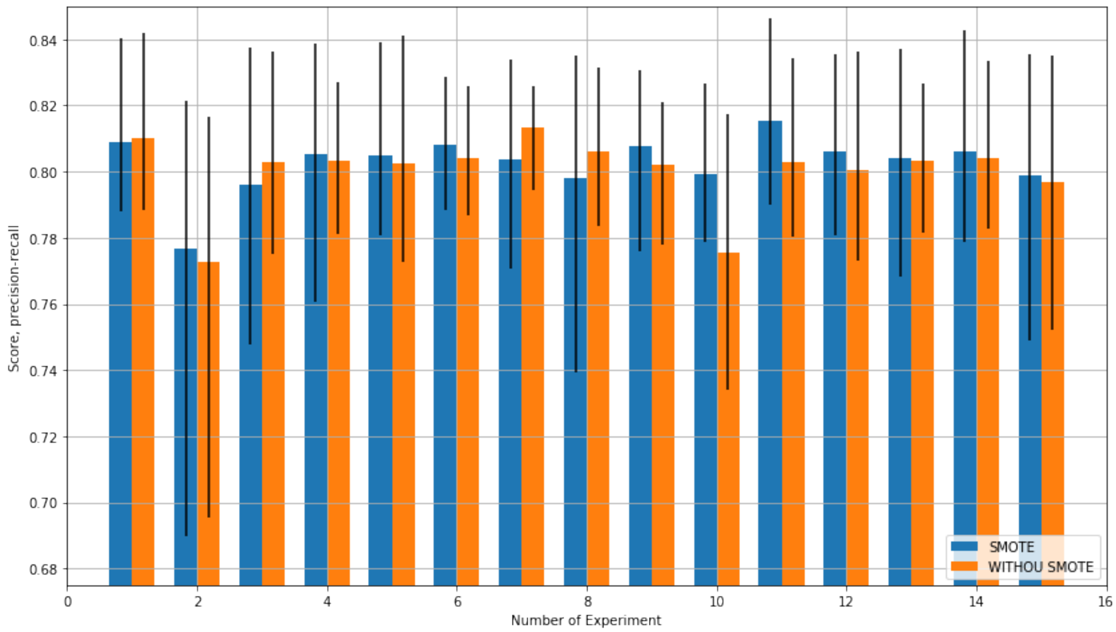
```
Out[156]: Text(0.5, 1.0, 'Without SMOTE')
```



The color bar indicates the mean value of scores and the size of the circle is proportional to the standard deviation of scores in cross-validation.

```
In [161]: ind = np.arange(len(Cm)) +1  # the x locations for the experiments
          width = 0.35  # the width of the bars

          fig, ax = plt.subplots( figsize= (14,8))
          rects1 = ax.bar(ind - width/2, Cm, width, yerr= ([Cm - Cmin,  Cmax-Cm]),
                          label='SMOTE')
          rects2 = ax.bar(ind + width/2, Cm_, width, yerr= ([Cm_ - Cmin_,  Cmax_-Cm_]),
                          label='WITHOU SMOTE')
          plt.axis([ 0, 16, .675 , .85])
          plt.legend(loc = 4)
```

```
plt.xlabel('Number of Experiment')
plt.ylabel('Score, precision-recall')
plt.grid()
```



The last plot shows SMOTE Method in the majority of experiments has better performance, because the means and the maximum values of the score in the cross-validation are greater than not-resampling experiments.

The best parameter are learning_rate = 0.2034 **and base_score =** 0.1268

```
In [ ]:
```