```
In [8]: ### check breast cancer
       import numpy as np
       import pandas as pd
       from sklearn.model_selection import train_test_split
       from xgboost import XGBClassifier
       \textbf{from} \  \, \textbf{sklearn.model\_selection} \  \, \textbf{import} \  \, \textbf{GridSearchCV}
       from sklearn.metrics import r2_score,root_mean_squared_error
In [2]: from sklearn.datasets import load breast cancer
       cancer =load breast cancer()
In [3]: cancer
Out[3]: {'data': array([[1.799e+01, 1.038e+01, 1.228e+02, ..., 2.654e-01, 4.601e-01,
               1.189e-011.
               [2.057e+01, 1.777e+01, 1.329e+02, ..., 1.860e-01, 2.750e-01,
               8.902e-02],
               [1.969e+01, 2.125e+01, 1.300e+02, ..., 2.430e-01, 3.613e-01,
               8.758e-02],
               [1.660e+01, 2.808e+01, 1.083e+02, ..., 1.418e-01, 2.218e-01,
               [2.060e+01, 2.933e+01, 1.401e+02, ..., 2.650e-01, 4.087e-01,
               [7.760e+00, 2.454e+01, 4.792e+01, ..., 0.000e+00, 2.871e-01,
               7.039e-02]]),
        0,\ 0,\ 1,\ 0,\ 1,\ 1,\ 1,\ 1,\ 1,\ 0,\ 0,\ 1,\ 0,\ 0,\ 1,\ 1,\ 1,\ 1,\ 0,\ 1,\ 0,\ 0,
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               1, 1, 1, 0, 1, 1, 0, 0, 1, 1, 1, 0, 0, 1, 1, 1, 1, 0, 1, 1, 0, 1,
               1, 1, 1, 1, 1, 1, 0, 0, 0, 1, 0, 0, 1, 1, 1, 0, 0, 1, 0, 1, 0,
               0,\ 1,\ 0,\ 0,\ 1,\ 1,\ 0,\ 1,\ 1,\ 0,\ 1,\ 1,\ 1,\ 0,\ 1,\ 1,\ 1,\ 1,\ 1,\ 1,\ 1,
               1, 1, 0, 1, 1, 1, 1, 0, 0, 1, 0, 1, 1, 0, 0, 1, 1, 0, 0, 1, 1, 1,
               1, 0, 1, 1, 0, 0, 0, 1, 0, 1, 0, 1, 1, 1, 0, 1, 1, 0, 0, 1, 0, 0,
               0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 1, 1, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0,
               1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 0, 1, 1,
               1, 1, 0, 1, 1, 1, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
               0, 0, 1, 1, 1, 1, 1, 0, 1, 0, 1, 1, 0, 1, 1, 0, 1, 0, 0, 1, 1,
               1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1,
               1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 0,
               0, 1, 1, 1, 1, 0, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0,
               1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 0, 0, 1, 1,
               1,\ 1,\ 1,\ 1,\ 0,\ 1,\ 1,\ 1,\ 1,\ 1,\ 1,\ 0,\ 1,\ 1,\ 1,\ 1,\ 0,\ 1,\ 1,\ 0,
               1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 0, 1, 0, 1, 1, 1, 1,
               1, 0, 1, 1, 0, 1, 0, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0,
               1,\ 1,\ 1,\ 0,\ 1,\ 0,\ 1,\ 1,\ 1,\ 1,\ 1,\ 1,\ 0,\ 0,\ 1,\ 0,\ 1,\ 0,\ 1,\ 1,
               1, 1, 1, 0, 1, 1, 0, 1, 0, 1, 0, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1,
               1, 1, 1, 1, 1, 0, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
               1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 1]),
        'frame': None,
        'target names': array(['malignant', 'benign'], dtype='<U9'),
        'DESCR': '.. _breast_cancer_dataset:\n\nBreast cancer wisconsin (diagnostic) dataset\n-----
        -----\n\n**Data Set Characteristics:**\n\n:Number of Instances: 569\n\n:Number of Attributes: 30
       numeric, predictive attributes and the class\n\n:Attribute Information:\n - radius (mean of distances from c
       enter to points on the perimeter)\n - texture (standard deviation of gray-scale values)\n - perimeter\n
       - area\n - smoothness (local variation in radius lengths)\n - compactness (perimeter\n2 / area - 1.0)\n
        - concavity (severity of concave portions of the contour)\n - concave points (number of concave portions of
       the contour)\n - symmetry\n - fractal dimension ("coastline approximation" - 1)\n\n The mean, standard
       error, and "worst" or largest (mean of the three\n worst/largest values) of these features were computed for
       each image,\n resulting in 30 features. For instance, field 0 is Mean Radius, field\n 10 is Radius SE, f
       ield 20 is Worst Radius.\n\n - class:\n - WDBC-Malignant\n
                                                                                   - WDBC-Benign\n\n:Summary S
       Min
                                                                                              6.981 28.11\nt
       Max\n=======\nradius (mean):
       exture (mean):
                                        9.71 39.28\nperimeter (mean):
                                                                                       43.79 188.5\narea (me
                                                                                  0.053 0.163\ncompactness (m
       an):
                                  143.5 2501.0\nsmoothness (mean):
                             0.019 0.345\nconcavity (mean):
       ean):
                                                                            0.0
                                                                                 0.427\nconcave points (mean)
                      0.0
                                                                     0.106 0.304\nfractal dimension (mean):
                             0.201\nsymmetry (mean):
                                                      0.112 2.873\ntexture (standard error):
       0.05 0.097\nradius (standard error):
                                                                                               6.802 542.2\n
                                                0.757 21.98\narea (standard error):
       4.885\nperimeter (standard error):
                                         0.002 0.031\ncompactness (standard error):
                                                                                        0.002 0.135\nconcavi
       smoothness (standard error):
                                   0.0 0.396\nconcave points (standard error): 0.0 0.053\nsymmetry (stan
       ty (standard error):
                             0.008 0.079\nfractal dimension (standard error): 0.001 0.03\nradius (worst):
       dard error):
       7.93 36.04\ntexture (worst):
                                                      12.02 49.54\nperimeter (worst):
                                                                                                     50.41
                                                185.2 4254.0\nsmoothness (worst):
       251.2\narea (worst):
                                                                                                0.071 0.223\
                                          0.027 1.058\nconcavity (worst):
                                                                                              1.252\nconcav
       ncompactness (worst):
                                                                                         0.0
                                   0.0
                                          0.291\nsymmetry (worst):
                                                                                  0.156 0.664\nfractal dimen
       e points (worst):
                            0.055 0.208\n======\n\n:Missing Attribut
       sion (worst):
```

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e Values: None\n\n:Class Distribution: 212 - Malignant, 357 - Benign\n\creator: Dr. William H. Wolberg, W. N
           ick Street, Olvi L. Mangasarian\n\n:Donor: Nick Street\n\n:Date: November, 1995\n\nThis is a copy of UCI ML Bre
           ast Cancer Wisconsin (Diagnostic) datasets.\nhttps://goo.gl/U2Uwz2\n\nFeatures are computed from a digitized im
           age of a fine needle\naspirate (FNA) of a breast mass. They describe\ncharacteristics of the cell nuclei prese
           nt in the image.\n\nSeparating plane described above was obtained using\nMultisurface Method-Tree (MSM-T) [K. P
            . Bennett, "Decision Tree\nConstruction Via Linear Programming." Proceedings of the 4th\nMidwest Artificial Int
           elligence and Cognitive Science Society,\npp. 97-101, 1992], a classification method which uses linear\nprogram
           ming to construct a decision tree. Relevant features\nwere selected using an exhaustive search in the space of
           1-4\nfeatures and 1-3 separating planes.\n\nThe actual linear program used to obtain the separating plane\nin t
           he 3-dimensional space is that described in:\n[K. P. Bennett and O. L. Mangasarian: "Robust Linear\nProgramming
           Discrimination of Two Linearly Inseparable Sets",\nOptimization Methods and Software 1, 1992, 23-34].\n\nThis d
           a tabase is also available through the UW CS ftp server: \verb|\n\ftp ftp.cs.wisc.edu| ncd math-prog/cpo-dataset/machin| at tabase is also available through the UW CS ftp server: \verb|\n\ftp ftp.cs.wisc.edu| ncd math-prog/cpo-dataset/machin| at tabase is also available through the UW CS ftp server: \verb|\n\ftp ftp.cs.wisc.edu| ncd math-prog/cpo-dataset/machin| at tabase is also available through the UW CS ftp server: \verb|\n\ftp ftp.cs.wisc.edu| ncd math-prog/cpo-dataset/machin| at tabase is also available through the UW CS ftp server: \verb|\n\ftp ftp.cs.wisc.edu| ncd math-prog/cpo-dataset/machin| at tabase is also available through the UW CS ftp server: \verb|\n\ftp ftp.cs.wisc.edu| ncd math-prog/cpo-dataset/machin| at tabase is also available through the UW CS ftp server: \verb|\n\ftp ftp.cs.wisc.edu| ncd math-prog/cpo-dataset/machin| at tabase is also available through the UW CS ftp server: \verb|\n\ftp ftp.cs.wisc.edu| ncd math-prog/cpo-dataset/machin| ncd math-prog
           e-learn/WDBC/\n\n.. dropdown:: References\n\n - W.N. Street, W.H. Wolberg and O.L. Mangasarian. Nuclear featur
                                  for breast tumor diagnosis. IS&T/SPIE 1993 International Symposium on\n Electronic Imaging
           e extraction\n
           : Science and Technology, volume 1905, pages 861-870,\n
                                                                                         San Jose, CA, 1993.\n - O.L. Mangasarian, W.N. Stre
           et and W.H. Wolberg. Breast cancer diagnosis and\n prognosis via linear programming. Operations Research, 43
           (4), pages 570-577,\n July-August 1995.\n - W.H. Wolberg, W.N. Street, and O.L. Mangasarian. Machine learni
           ng techniques\n to diagnose breast cancer from fine-needle aspirates. Cancer Letters 77 (1994)\n
           \n',
             'feature_names': array(['mean radius', 'mean texture', 'mean perimeter', 'mean area',
                      'mean smoothness', 'mean compactness', 'mean concavity', 'mean concave points', 'mean symmetry', 'mean fractal dimension',
                      'radius error', 'texture error', 'perimeter error', 'area error',
                      'smoothness error', 'compactness error', 'concavity error',
                      'concave points error', 'symmetry error',
                      'fractal dimension error', 'worst radius', 'worst texture',
                      'worst perimeter', 'worst area', 'worst smoothness',
                      'worst compactness', 'worst concavity', 'worst concave points',
                      'worst symmetry', 'worst fractal dimension'], dtype='<U23'),
             'filename': 'breast_cancer.csv',
             'data_module': 'sklearn.datasets.data'}
In [4]: x,y =cancer.data ,cancer.target
In [5]: ### input variable
Out[5]: array([[1.799e+01, 1.038e+01, 1.228e+02, ..., 2.654e-01, 4.601e-01,
                      1.189e-01],
                     [2.057e+01, 1.777e+01, 1.329e+02, ..., 1.860e-01, 2.750e-01,
                      8.902e-02],
                     [1.969e+01, 2.125e+01, 1.300e+02, ..., 2.430e-01, 3.613e-01,
                      8.758e-02],
                     [1.660e+01, 2.808e+01, 1.083e+02, ..., 1.418e-01, 2.218e-01,
                      7.820e-02],
                     [2.060e+01, 2.933e+01, 1.401e+02, ..., 2.650e-01, 4.087e-01,
                      1.240e-01],
                     [7.760e+00, 2.454e+01, 4.792e+01, ..., 0.000e+00, 2.871e-01,
                      7.039e-02]])
In [6]: ### output variable
0, 0, 1, 0, 1, 1, 1, 1, 0, 0, 1, 0, 0, 1, 1, 1, 1, 0, 1, 0, 0,
                    1, 1, 1, 1, 0, 1, 0, 0, 1, 0, 1, 0, 0, 1, 1, 1, 0, 0, 1, 0, 0,
                    1,\ 1,\ 1,\ 0,\ 1,\ 1,\ 0,\ 0,\ 1,\ 1,\ 0,\ 0,\ 1,\ 1,\ 1,\ 1,\ 0,\ 1,\ 1,\ 0,\ 1,
                    1, 1, 1, 1, 1, 1, 0, 0, 0, 1, 0, 0, 1, 1, 1, 0, 0, 1, 0, 1, 0,
                    0, 1, 0, 0, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
                    1, 1, 0, 1, 1, 1, 1, 0, 0, 1, 0, 1, 1, 0, 0, 1, 1, 0, 0, 1, 1, 1,
                    1, 0, 1, 1, 0, 0, 0, 1, 0, 1, 0, 1, 1, 1, 0, 1, 1, 0, 0, 1, 0, 0,
                    0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 1, 1, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0,
                    1, 1, 1, 0, 1, 1, 1, 1, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 1,
                     1, 1, 0, 1, 1, 1, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                    0,\ 0,\ 1,\ 1,\ 1,\ 1,\ 1,\ 0,\ 1,\ 0,\ 1,\ 1,\ 0,\ 1,\ 1,\ 0,\ 1,\ 1,
                    1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1,
                    1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 0, 1, 1, 1, 1, 0, 0,
                    0, 1, 1, 1, 1, 0, 1, 0, 1, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 0,
                    1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 0, 0, 1, 1,
                    1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 0,
                    1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 0, 1, 0, 1, 1, 1, 1,
                    1, 0, 1, 1, 0, 1, 0, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0,
                    1, 1, 1, 0, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 0, 0, 1, 0, 1, 0, 1, 1,
                    1, 1, 1, 0, 1, 1, 0, 1, 0, 1, 0, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1,
                    1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 1])
In [9]: X train ,X test ,Y train ,Y test =train test split(x,y ,test size=0.2 ,random state=42)
```

```
In [10]: ### apply model
         param grid = {
             'max_depth': [3, 4, 5],
             'learning_rate': [0.1, 0.01, 0.05],
              'n estimators': [50, 100, 200],
             'subsample': [0.8, 1.0],
             'colsample bytree': [0.8, 1.0]
In [11]: model =XGBClassifier(objective='binary:logistic' ,random state =42)
In [12]: gc=GridSearchCV(estimator=model ,param_grid=param_grid ,cv =4 ,n_jobs=1)
In [13]: gc.fit(X train ,Y train)
Out[13]: -
                    GridSearchCV
          ▶ best_estimator_: XGBClassifier
                    ▶ XGBClassifier
In [14]: pred =gc.predict(X_test)
In [15]: pred
Out[15]: array([1, 0, 0, 1, 1, 0, 0, 0, 0, 1, 1, 0, 1, 0, 1, 0, 1, 1, 1, 0, 1, 1,
                 0,\ 1,\ 1,\ 1,\ 1,\ 1,\ 1,\ 0,\ 1,\ 1,\ 1,\ 1,\ 1,\ 1,\ 0,\ 1,\ 0,\ 1,\ 1,\ 0,\ 1,\ 1,
                 1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 0, 0, 1, 1, 0, 0, 1, 1, 1,
                0, 0, 1, 1, 0, 0, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 0, 0, 0,
                1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 1, 1, 0, 0, 1,
                0, 1, 1, 0])
In [16]: ### check accuracy of model
         print("best score :" ,gc.best_score_)
         print("best estimator :",gc.best_estimator_)
         print("best para_gramid :",gc.best_params_)
        best score: 0.9714136003726129
        best estimator : XGBClassifier(base score=None, booster=None, callbacks=None,
                      colsample_bylevel=None, colsample_bynode=None,
                      colsample bytree=1.0, device=None, early stopping rounds=None,
                      enable_categorical=False, eval metric=None, feature_types=None,
                      gamma=None, grow policy=None, importance type=None,
                      interaction_constraints=None, learning_rate=0.05, max_bin=None,
                      max cat threshold=None, max cat to onehot=None,
                      max_delta_step=None, max_depth=3, max_leaves=None,
                      min_child_weight=None, missing=nan, monotone_constraints=None,
                      multi_strategy=None, n_estimators=100, n_jobs=None,
                      num_parallel_tree=None, random_state=42, ...)
        best para_gramid : {'colsample_bytree': 1.0, 'learning_rate': 0.05, 'max_depth': 3, 'n_estimators': 100, 'subsam
        ple': 0.8}
In [18]: model2=XGBClassifier(n estimators= 100 ,max depth =3 ,learning rate =0.05)
In [19]: model2.fit(X train ,Y train)
Out[19]:
                                           XGBClassifier
         XGBClassifier(base score=None, booster=None, callbacks=None,
                        colsample bylevel=None, colsample bynode=None,
                        colsample bytree=None, device=None, early stopping rounds=Non
         e,
                        enable categorical=False, eval metric=None, feature types=Non
         e,
                        gamma=None, grow policy=None, importance type=None,
                        interaction constraints=None, learning rate=0.05, max bin=Non
         e,
In [20]: ### prediction
         prediction =model2.predict(X_test)
In [21]: #### find out the accuracy
         from sklearn.metrics import accuracy_score ,classification_report ,confusion_matrix
         accuracy score =accuracy score(Y test ,prediction)
```

```
Out[22]: 0.956140350877193
In [23]: ### classification report
        classification_report =classification_report(Y_test ,prediction)
         print(classification_report)
                    precision recall f1-score support
                  0
                       0.95 0.93 0.94
                                                      43
                  1
                        0.96
                                0.97
                                          0.97
                                                      71
                                           0.96
                                                     114
           accuracy
                       0.96 0.95
0.96 0.96
          macro avg
                                          0.95
                                                    114
                                           0.96
       weighted avg
                                                     114
In [24]: ## confusion matrix
         confusion_matrix =confusion_matrix(Y_test ,prediction)
        print(confusion_matrix)
       [[40 3]
        [ 2 69]]
In [25]: x.shape
Out[25]: (569, 30)
In [26]: X_train.shape
Out[26]: (455, 30)
 In [ ]:
```

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In [22]: accuracy\_score