```
Classification of Breast Cancer based on SUPPORT VECTOR MACHINES
        Hanah Chang
        1. Introduction
        In this project, we are going to predict if the cancer diagnosis is benign or malignant. The dataset is from
        (https://archive.ics.uci.edu/ml/datasets/Breast+Cancer+Wisconsin+(Diagnostic) Examples of key variables are:
              - radius (mean of distances from center to points on the perimeter)
              - texture (standard deviation of gray-scale values)
              - perimeter
              - area
              - smoothness (local variation in radius lengths)
              - compactness (perimeter^2 / area - 1.0)

    concavity (severity of concave portions of the contour)

              - concave points (number of concave portions of the contour)
              - symmetry
              - fractal dimension ("coastline approximation" - 1)
        Our target variable is binary, Maliganat or Benign
       2. Data & Libaray
        By looking at types of our data, we know that our dataset 'Cancer' is a Bunch object exposing six keys. The shape of a key'data' tells us there are 569
        observations and 30 independent variables.
 In [1]: import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        import seaborn as sns
        %matplotlib inline
 In [2]: # import dataset
        from sklearn.datasets import load_breast_cancer
        cancer = load_breast_cancer()
 In [3]: print(type(cancer))
        print(cancer.keys())
        print(cancer['data'].shape)
        <class 'sklearn.utils.Bunch'>
        dict_keys(['data', 'target', 'target_names', 'DESCR', 'feature_names', 'filename'])
        (569, 30)
        Now we turn our Bunch object into dataframe
 In [4]: df_cancer = pd.DataFrame(np.c_[cancer['data'], cancer['target']], columns = np.append(cancer['feature_names'], ['tar
        get']))
 In [5]: df_cancer.head()
 Out[5]:
                                                                                     worst worst
          radius texture perimeter
                            area smoothness compactness concavity
                                                                              texture perimeter
                                                                                          area smoothness comp
                                                             symmetry
                                                                                     184.60 2019.0
                      122.80 1001.0
                                  0.11840
                                           0.27760
                                                  0.3001
                                                       0.14710
                                                               0.2419
                                                                      0.07871 ...
                                                                              17.33
                                                                                                  0.1622
          17.99
                      132.90 1326.0
                                  0.08474
                                           0.07864
                                                   0.0869
                                                       0.07017
                                                               0.1812
                                                                      0.05667
                                                                                     158.80 1956.0
                                                                                                  0.1238
                                                                              23.41
                21.25
                      130.00 1203.0
                                  0.10960
                                           0.15990
                                                  0.1974
                                                       0.12790
                                                               0.2069
                                                                      0.05999
                                                                               25.53
                                                                                     152.50 1709.0
                                                                                                  0.1444
          19.69
                      77.58 386.1
                                  0.14250
                                                       0.10520
                                                                      0.09744 ...
                                                                                     98.87 567.7
                                                                                                  0.2098
          11.42
                                           0.28390
                                                  0.2414
                                                               0.2597
                                                                              26.50
                                  0.10030
                                                                                                  0.1374
                      135.10 1297.0
                                           0.13280
                                                       0.10430
                                                               0.1809
                                                                      0.05883 ...
                                                                               16.67
                                                                                     152.20 1575.0
          20.29
                14.34
                                                  0.1980
        5 rows × 31 columns
 In [6]: df cancer.columns
Out[6]: Index(['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='object')
       3. Explanatory Analysis & Data Cleaning
        By looking at scatter plots we can have a sense of whether classes are pretty separable. In most cases, classes are separable, except for mean smoothness.
        Mean/median for both classes(0,1) look similar for mean smoothness
 In [7]: sns.pairplot(df_cancer, hue = 'target', vars = ['mean radius', 'mean texture', 'mean area', 'mean perimeter', 'mean
        smoothness'] )
 Out[7]: <seaborn.axisgrid.PairGrid at 0x160d2da5408>
           25
         듩 20
          E 15
          2500
          2000
        j 1500
                                                                                                   • 0.0
        E 1000
                                                                                                   1.0
          500
          175
          150
          125
          100
           50
          0.16
         g 0.14
          0.12
          0.10
         ₽ 0.08
          0.06
                 mean radius
                                  mean texture
                                                    mean area
                                                                    mean perimeter
                                                                                     mean smoothness
        Out of total 569 patients, 357 (62.7)% diagnosed as malagnant
 In [8]: df_cancer.target.value_counts()
 Out[8]: 1.0
             357
        0.0
             212
        Name: target, dtype: int64
        Prior to training our model, we are going to normalize our data. By looking at range, we know that the data needs to be scaled in a way that it ranges from 0 to
        1 without distorting differences in the ranges of values. Otherwise, attributed 'mean area' for instance, will intrinsically influence the result more due to its larger
        value.
 In [9]: df_range = pd.DataFrame(df_cancer.max() - df_cancer.min())
        df_range
 Out[9]:
                        21.129000
               mean radius
                        29.570000
              mean texture
                       144.710000
             mean perimeter
                       2357.500000
                mean area
                         0.110770
           mean smoothness
           mean compactness
                         0.326020
                         0.426800
             mean concavity
                         0.201200
          mean concave points
             mean symmetry
                         0.198000
        mean fractal dimension
                         0.047480
                         2.761500
               radius error
                         4.524800
               texture error
                        21.223000
             perimeter error
                        535.398000
                area error
           smoothness error
                         0.029417
                         0.133148
           compactness error
                         0.396000
          concave points error
                         0.052790
        fractal dimension error
                         0.028945
                        28.110000
               worst radius
              worst texture
                        37.520000
             worst perimeter
                       200.790000
                       4068.800000
                worst area
           worst smoothness
                         0.151430
                         1.030710
           worst compactness
             worst concavity
                         1.252000
                         0.291000
         worst concave points
             worst symmetry
                         0.507300
        worst fractal dimension
                         0.152460
                         1.000000
In [10]: | df_cancer_scaled = (df_cancer-df_cancer.min())/(df_cancer.max() - df_cancer.min())
        df_cancer_scaled.head()
Out[10]:
                                                                           mean
                                                             mean
                                       mean
                                                mean
                                                       mean
                                                                    mean
                                                                                   worst
                                                                                          worst
                                                                                                worst
                         mean
                               mean
                                                           concave
                                                                           fractal
           radius
                                area smoothness compactness concavity
                                                                 symmetry
                                                                                                 area smoothi
                 texture perimeter
                                                                                   texture
                                                                                        perimeter
        0 0.521037
                0.022658
                       0.545989
                             0.363733
                                     0.593753
                                              0.792037
                                                    0.703140
                                                           0.731113
                                                                  0.686364
                                                                         0.605518
                                                                                  0.141525
                                                                                        0.668310
                                                                                              0.450698
        1 0.643144 0.272574 0.615783 0.501591
                                     0.289880
                                              0.181768
                                                    0.203608
                                                           0.348757
                                                                  0.379798
                                                                         0.141323
                                                                                 0.303571 0.539818 0.435214
        2 0.601496 0.390260
                       0.595743
                             0.449417
                                     0.514309
                                              0.431017  0.462512  0.635686
                                                                  0.509596
                                                                         0.211247
                                                                               ... 0.360075 0.508442 0.374508
                                              0.811361 0.565604 0.522863
        3 0.210090 0.360839 0.233501 0.102906
                                     0.811321
                                                                 0.776263
                                                                         1.000000
                                                                                 4 0.629893 0.156578 0.630986 0.489290
                                     0.430351
                                              0.186816 ... 0.123934 0.506948 0.341575
        5 rows × 31 columns
        4. Support Vector Machine - Training / Optimizing
In [11]: X = df_cancer_scaled.drop(['target'], axis=1)
        y = df_cancer_scaled['target']
In [12]: # random split our data into train/test set
        from sklearn.model_selection import train_test_split
        X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.20, random_state=123)
In [13]: | print("X_train:", X_train.shape, "y_train:", y_train.shape, "X_test:", X_test.shape, "y_test:", y_test.shape, )
        X_train: (455, 30) y_train: (455,) X_test: (114, 30) y_test: (114,)
        Fit our model using training data
In [14]: from sklearn.svm import SVC
        svc_model = SVC()
        svc_model.fit(X_train, y_train)
Out[14]: SVC(C=1.0, break_ties=False, cache_size=200, class_weight=None, coef0=0.0,
           decision_function_shape='ovr', degree=3, gamma='scale', kernel='rbf',
           max_iter=-1, probability=False, random_state=None, shrinking=True,
           tol=0.001, verbose=False)
        The average accuracy of the model is 98% and we accurately predicted 112 cases.
In [15]: from sklearn.metrics import classification_report, confusion_matrix
       y_predict = svc_model.predict(X_test)
        cm = confusion_matrix(y_test, y_predict)
        sns.heatmap(cm, annot=True)
Out[15]: <matplotlib.axes._subplots.AxesSubplot at 0x160d44875c8>
        0
                                        - 10
In [16]: print(classification_report(y_test, y_predict))
                              recall f1-score support
                   precision
               0.0
                       1.00
                                0.95
                                        0.97
                                                  41
               1.0
                       0.97
                                1.00
                                        0.99
                                                  73
                                        0.98
                                                 114
           accuracy
          macro avg
                       0.99
                                0.98
                                        0.98
                                                 114
        weighted avg
                       0.98
                                0.98
                                        0.98
                                                 114
        In order to more generalize our model to prevent overfit, let's iterate algorithm using different values of C and Gamma parameters. We expect by decreasing C
        parameter we less penalize misclassification and by decreasing Gamma, the decision boundary gets smoother.
In [17]: # grids for all possible c, gamma premeters
        grid = {'C': [0.01, 0.1, 1, 10, 100], 'gamma': [1, 0.1, 0.01, 0.001, 0.0001], 'kernel': ['rbf']}
In [18]: from sklearn.model_selection import GridSearchCV
        refit_model = GridSearchCV(SVC(), grid, refit=True, verbose=4) #verbose: num of details we wna to show
        As the algorithm iterates, we can see that scores are changing. The best result were achieved with C parameter 10, and Gamma parameter 0.1
In [19]: refit model.fit(X train, y train)
        Fitting 5 folds for each of 25 candidates, totalling 125 fits
        [CV] C=0.01, gamma=1, kernel=rbf ......
        [CV] ...... C=0.01, gamma=1, kernel=rbf, score=0.615, total= 0.0s
        [CV] C=0.01, gamma=1, kernel=rbf ......
        [CV] ..... C=0.01, gamma=1, kernel=rbf, score=0.626, total= 0.0s
        [CV] C=0.01, gamma=1, kernel=rbf .....
        [CV] ...... C=0.01, gamma=1, kernel=rbf, score=0.626, total= 0.0s
        [CV] C=0.01, gamma=1, kernel=rbf .....
        [CV] ...... C=0.01, gamma=1, kernel=rbf, score=0.626, total= 0.0s
        [CV] C=0.01, gamma=1, kernel=rbf .....
        [CV] ...... C=0.01, gamma=1, kernel=rbf, score=0.626, total= 0.0s
        [CV] C=0.01, gamma=0.1, kernel=rbf .......
        [CV] ..... C=0.01, gamma=0.1, kernel=rbf, score=0.615, total= 0.0s
        [CV] C=0.01, gamma=0.1, kernel=rbf ......
        [CV] ..... C=0.01, gamma=0.1, kernel=rbf, score=0.626, total= 0.0s
        [CV] C=0.01, gamma=0.1, kernel=rbf .......
        [CV] ..... C=0.01, gamma=0.1, kernel=rbf, score=0.626, total= 0.0s
        [CV] C=0.01, gamma=0.1, kernel=rbf ......
        [CV] ..... C=0.01, gamma=0.1, kernel=rbf, score=0.626, total= 0.0s
        [CV] ..... C=0.01, gamma=0.1, kernel=rbf, score=0.626, total= 0.0s
        [CV] ..... C=0.01, gamma=0.01, kernel=rbf, score=0.615, total= 0.1s
        [CV] ..... C=0.01, gamma=0.01, kernel=rbf, score=0.626, total= 0.0s
        [CV] C=0.01, gamma=0.01, kernel=rbf ......
        [CV] ..... C=0.01, gamma=0.01, kernel=rbf, score=0.626, total= 0.0s
        [CV] ..... C=0.01, gamma=0.01, kernel=rbf, score=0.626, total= 0.0s
        [CV] C=0.01, gamma=0.01, kernel=rbf ......
        [Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers
        [Parallel(n_jobs=1)]: Done 1 out of 1 | elapsed:
                                                      0.0s remaining:
        [Parallel(n_jobs=1)]: Done 2 out of 2 | elapsed:
                                                      0.0s remaining:
                                                                      0.0s
        [Parallel(n_jobs=1)]: Done 3 out of 3 | elapsed:
                                                      0.0s remaining:
                                                                      0.0s
        [CV] ..... C=0.01, gamma=0.01, kernel=rbf, score=0.626, total= 0.0s
        [CV] C=0.01, gamma=0.001, kernel=rbf .......
        [CV] ..... C=0.01, gamma=0.001, kernel=rbf, score=0.615, total= 0.0s
        [CV] ..... C=0.01, gamma=0.001, kernel=rbf, score=0.626, total= 0.0s
        [CV] C=0.01, gamma=0.001, kernel=rbf ......
        [CV] ..... C=0.01, gamma=0.001, kernel=rbf, score=0.626, total= 0.0s
        [CV] C=0.01, gamma=0.001, kernel=rbf .....
        [CV] ..... C=0.01, gamma=0.001, kernel=rbf, score=0.626, total= 0.0s
        [CV] C=0.01, gamma=0.001, kernel=rbf ......
        [CV] ..... C=0.01, gamma=0.001, kernel=rbf, score=0.626, total= 0.0s
        [CV] C=0.01, gamma=0.0001, kernel=rbf ......
        [CV] .... C=0.01, gamma=0.0001, kernel=rbf, score=0.615, total= 0.0s
        [CV] C=0.01, gamma=0.0001, kernel=rbf .......
        [CV] .... C=0.01, gamma=0.0001, kernel=rbf, score=0.626, total= 0.0s
        [CV] .... C=0.01, gamma=0.0001, kernel=rbf, score=0.626, total= 0.0s
        [CV] C=0.01, gamma=0.0001, kernel=rbf ......................
        [CV] .... C=0.01, gamma=0.0001, kernel=rbf, score=0.626, total= 0.0s
        [CV] C=0.01, gamma=0.0001, kernel=rbf .......
        [CV] .... C=0.01, gamma=0.0001, kernel=rbf, score=0.626, total= 0.0s
        [CV] C=0.1, qamma=1, kernel=rbf ......
        [CV] ..... C=0.1, gamma=1, kernel=rbf, score=0.978, total= 0.0s
        [CV] C=0.1, gamma=1, kernel=rbf ......
        [CV] \dots C=0.1, gamma=1, kernel=rbf, score=0.934, total= 0.0s
        [CV] C=0.1, gamma=1, kernel=rbf .....
        [CV] ..... C=0.1, gamma=1, kernel=rbf, score=0.923, total= 0.0s
        [CV] C=0.1, gamma=1, kernel=rbf ......
        [CV] ..... C=0.1, gamma=1, kernel=rbf, score=0.956, total= 0.0s
        [CV] ..... C=0.1, gamma=1, kernel=rbf, score=0.934, total= 0.0s
        [CV] C=0.1, gamma=0.1, kernel=rbf ........
        [CV] ...... C=0.1, gamma=0.1, kernel=rbf, score=0.945, total= 0.0s
        [CV] C=0.1, gamma=0.1, kernel=rbf .......
        [CV] ...... C=0.1, gamma=0.1, kernel=rbf, score=0.934, total= 0.0s
        [CV] C=0.1, gamma=0.1, kernel=rbf ......
        [CV] ...... C=0.1, gamma=0.1, kernel=rbf, score=0.890, total= 0.0s
        [CV] ..... C=0.1, gamma=0.1, kernel=rbf, score=0.879, total= 0.0s
        [CV] C=0.1, gamma=0.1, kernel=rbf ......
        [CV] ...... C=0.1, gamma=0.1, kernel=rbf, score=0.890, total= 0.0s
        [CV] C=0.1, gamma=0.01, kernel=rbf ......
        [CV] ..... C=0.1, gamma=0.01, kernel=rbf, score=0.615, total= 0.0s
        [CV] C=0.1, gamma=0.01, kernel=rbf ......
        [CV] ..... C=0.1, gamma=0.01, kernel=rbf, score=0.626, total= 0.0s
        [CV] C=0.1, gamma=0.01, kernel=rbf .......
        [CV] ..... C=0.1, gamma=0.01, kernel=rbf, score=0.626, total= 0.0s
        [CV] C=0.1, gamma=0.01, kernel=rbf .......
        [CV] ..... C=0.1, gamma=0.01, kernel=rbf, score=0.626, total= 0.0s
        [CV] C=0.1, gamma=0.01, kernel=rbf ......
        [CV] ..... C=0.1, gamma=0.01, kernel=rbf, score=0.626, total= 0.0s
        [CV] ..... C=0.1, gamma=0.001, kernel=rbf, score=0.615, total= 0.0s
        [CV] ..... C=0.1, gamma=0.001, kernel=rbf, score=0.626, total= 0.0s
        [CV] C=0.1, gamma=0.001, kernel=rbf ......
        [CV] ..... C=0.1, gamma=0.001, kernel=rbf, score=0.626, total= 0.0s
        [CV] C=0.1, gamma=0.001, kernel=rbf ......
        [CV] ..... C=0.1, gamma=0.001, kernel=rbf, score=0.626, total= 0.0s
        [CV] ..... C=0.1, gamma=0.001, kernel=rbf, score=0.626, total= 0.0s
        [CV] C=0.1, gamma=0.0001, kernel=rbf .......
        [CV] ..... C=0.1, gamma=0.0001, kernel=rbf, score=0.615, total= 0.0s
        [CV] ..... C=0.1, gamma=0.0001, kernel=rbf, score=0.626, total= 0.0s
        [CV] ..... C=0.1, gamma=0.0001, kernel=rbf, score=0.626, total= 0.0s
        [CV] ..... C=0.1, gamma=0.0001, kernel=rbf, score=0.626, total= 0.0s
        [CV] C=0.1, gamma=0.0001, kernel=rbf .......
        [CV] ..... C=0.1, gamma=0.0001, kernel=rbf, score=0.626, total= 0.0s
        [CV] C=1, gamma=1, kernel=rbf ......
        [CV] ..... C=1, gamma=1, kernel=rbf, score=0.989, total= 0.0s
        [CV] C=1, gamma=1, kernel=rbf .....
        [CV] ..... C=1, gamma=1, kernel=rbf, score=0.956, total= 0.0s
        [CV] C=1, gamma=1, kernel=rbf ......
        [CV] ...... C=1, gamma=1, kernel=rbf, score=0.978, total= 0.0s
        [CV] ...... C=1, gamma=1, kernel=rbf, score=0.978, total= 0.0s
        [CV] C=1, gamma=1, kernel=rbf ......
        [CV] ...... C=1, gamma=1, kernel=rbf, score=0.967, total= 0.0s
        [CV] ..... C=1, gamma=0.1, kernel=rbf, score=0.978, total= 0.0s
        [CV] ..... C=1, gamma=0.1, kernel=rbf, score=0.934, total= 0.0s
        [CV] C=1, gamma=0.1, kernel=rbf ......
        [CV] ..... C=1, gamma=0.1, kernel=rbf, score=0.945, total= 0.0s
        [CV] C=1, gamma=0.1, kernel=rbf ......
        [CV] ..... C=1, gamma=0.1, kernel=rbf, score=0.945, total= 0.0s
        [CV] C=1, gamma=0.1, kernel=rbf .....
        [CV] ..... C=1, gamma=0.1, kernel=rbf, score=0.945, total= 0.0s
        [CV] C=1, gamma=0.01, kernel=rbf ......
        [CV] ..... C=1, gamma=0.01, kernel=rbf, score=0.956, total= 0.0s
        [CV] C=1, gamma=0.01, kernel=rbf ......
        [CV] ..... C=1, gamma=0.01, kernel=rbf, score=0.934, total= 0.0s
        [CV] ...... C=1, gamma=0.01, kernel=rbf, score=0.890, total= 0.0s
        [CV] C=1, gamma=0.01, kernel=rbf .....
        [CV] ..... C=1, gamma=0.01, kernel=rbf, score=0.879, total= 0.0s
        [CV] C=1, gamma=0.01, kernel=rbf ......
        [CV] ..... C=1, gamma=0.01, kernel=rbf, score=0.890, total= 0.0s
        [CV] C=1, gamma=0.001, kernel=rbf .......
        [CV] ..... C=1, gamma=0.001, kernel=rbf, score=0.615, total= 0.0s
        [CV] C=1, gamma=0.001, kernel=rbf ......
        [CV] ..... C=1, gamma=0.001, kernel=rbf, score=0.626, total= 0.0s
        [CV] C=1, gamma=0.001, kernel=rbf ......
        [CV] ...... C=1, gamma=0.001, kernel=rbf, score=0.626, total= 0.0s
        [CV] C=1, gamma=0.001, kernel=rbf ......
        [CV] ..... C=1, gamma=0.001, kernel=rbf, score=0.626, total= 0.0s
        [CV] C=1, gamma=0.001, kernel=rbf ......
        [CV] ...... C=1, gamma=0.001, kernel=rbf, score=0.626, total= 0.0s
        [CV] C=1, gamma=0.0001, kernel=rbf ......
        [CV] ..... C=1, gamma=0.0001, kernel=rbf, score=0.615, total= 0.0s
        [CV] C=1, gamma=0.0001, kernel=rbf ......
        [CV] ..... C=1, gamma=0.0001, kernel=rbf, score=0.626, total= 0.0s
        [CV] ..... C=1, gamma=0.0001, kernel=rbf, score=0.626, total= 0.0s
        [CV] ..... C=1, gamma=0.0001, kernel=rbf, score=0.626, total= 0.0s
        [CV] C=1, gamma=0.0001, kernel=rbf ......
        [CV] ...... C=1, gamma=0.0001, kernel=rbf, score=0.626, total= 0.0s
        [CV] C=10, gamma=1, kernel=rbf ......
        [CV] ..... C=10, gamma=1, kernel=rbf, score=0.989, total= 0.0s
        [CV] C=10, gamma=1, kernel=rbf ......
        [CV] ...... C=10, gamma=1, kernel=rbf, score=0.956, total= 0.0s
        [CV] C=10, gamma=1, kernel=rbf ......
        [CV] ..... C=10, gamma=1, kernel=rbf, score=1.000, total= 0.0s
        [CV] C=10, gamma=1, kernel=rbf ..............
        [CV] ..... C=10, gamma=1, kernel=rbf, score=0.956, total= 0.0s
        [CV] C=10, gamma=1, kernel=rbf ......
        [CV] ...... C=10, gamma=1, kernel=rbf, score=0.967, total= 0.0s
        [CV] C=10, gamma=0.1, kernel=rbf .................
        [CV] ...... C=10, gamma=0.1, kernel=rbf, score=1.000, total= 0.0s
        [CV] C=10, gamma=0.1, kernel=rbf .....
        [CV] ...... C=10, gamma=0.1, kernel=rbf, score=0.967, total= 0.0s
        [CV] C=10, gamma=0.1, kernel=rbf ......
        [CV] ...... C=10, gamma=0.1, kernel=rbf, score=0.989, total= 0.0s
        [CV] C=10, gamma=0.1, kernel=rbf .....
        [CV] ..... C=10, gamma=0.1, kernel=rbf, score=0.989, total= 0.0s
        [CV] C=10, gamma=0.1, kernel=rbf ......
        [CV] ...... C=10, gamma=0.1, kernel=rbf, score=0.967, total= 0.0s
        [CV] ..... C=10, gamma=0.01, kernel=rbf, score=0.978, total= 0.0s
        [CV] C=10, gamma=0.01, kernel=rbf .......
        [CV] ...... C=10, qamma=0.01, kernel=rbf, score=0.945, total= 0.0s
        [CV] C=10, gamma=0.01, kernel=rbf .......
        [CV] ...... C=10, gamma=0.01, kernel=rbf, score=0.956, total= 0.0s
        [CV] ...... C=10, gamma=0.01, kernel=rbf, score=0.945, total= 0.0s
        [CV] ...... C=10, gamma=0.01, kernel=rbf, score=0.945, total= 0.0s
        [CV] ..... C=10, gamma=0.001, kernel=rbf, score=0.956, total= 0.0s
        [CV] C=10, gamma=0.001, kernel=rbf ......
        [CV] ..... C=10, gamma=0.001, kernel=rbf, score=0.934, total= 0.0s
        [CV] C=10, gamma=0.001, kernel=rbf ......
        [CV] ..... C=10, gamma=0.001, kernel=rbf, score=0.890, total= 0.0s
        [CV] C=10, gamma=0.001, kernel=rbf ......
        [CV] ..... C=10, gamma=0.001, kernel=rbf, score=0.879, total= 0.0s
        [CV] ..... C=10, gamma=0.001, kernel=rbf, score=0.890, total= 0.0s
        [CV] C=10, gamma=0.0001, kernel=rbf ......
        [CV] ..... C=10, gamma=0.0001, kernel=rbf, score=0.615, total= 0.0s
        [CV] ..... C=10, gamma=0.0001, kernel=rbf, score=0.626, total= 0.0s
        [CV] ..... C=10, gamma=0.0001, kernel=rbf, score=0.626, total= 0.0s
        [CV] C=10, qamma=0.0001, kernel=rbf ......
        [CV] ..... C=10, gamma=0.0001, kernel=rbf, score=0.626, total= 0.0s
        [CV] C=10, gamma=0.0001, kernel=rbf ......
        [CV] ..... C=10, gamma=0.0001, kernel=rbf, score=0.626, total= 0.0s
        [CV] C=100, gamma=1, kernel=rbf .....
        [CV] ...... C=100, gamma=1, kernel=rbf, score=0.978, total= 0.0s
        [CV] C=100, gamma=1, kernel=rbf ......
        [CV] ..... C=100, gamma=1, kernel=rbf, score=0.923, total= 0.0s
        [CV] C=100, gamma=1, kernel=rbf ......
        [CV] ..... C=100, gamma=1, kernel=rbf, score=0.967, total= 0.0s
        [CV] ..... C=100, gamma=1, kernel=rbf, score=0.934, total= 0.0s
        [CV] C=100, gamma=1, kernel=rbf .....
        [CV] ..... C=100, gamma=1, kernel=rbf, score=0.967, total= 0.0s
        [CV] ...... C=100, gamma=0.1, kernel=rbf, score=0.978, total= 0.0s
        [CV] C=100, gamma=0.1, kernel=rbf ......
        [CV] ...... C=100, gamma=0.1, kernel=rbf, score=0.967, total= 0.0s
        [CV] C=100, gamma=0.1, kernel=rbf ......
        [CV] ...... C=100, gamma=0.1, kernel=rbf, score=1.000, total= 0.0s
        [CV] C=100, gamma=0.1, kernel=rbf ......
        [CV] ...... C=100, gamma=0.1, kernel=rbf, score=0.967, total= 0.0s
        [CV] C=100, gamma=0.1, kernel=rbf .......
        [CV] ..... C=100, gamma=0.1, kernel=rbf, score=0.934, total= 0.0s
        [CV] C=100, gamma=0.01, kernel=rbf ......
        [CV] ..... C=100, gamma=0.01, kernel=rbf, score=1.000, total= 0.0s
        [CV] C=100, gamma=0.01, kernel=rbf ......
        [CV] ..... C=100, gamma=0.01, kernel=rbf, score=0.967, total= 0.0s
        [CV] C=100, gamma=0.01, kernel=rbf ......
        [CV] ..... C=100, gamma=0.01, kernel=rbf, score=0.989, total= 0.0s
        [CV] ...... C=100, gamma=0.01, kernel=rbf, score=0.989, total= 0.0s
        [CV] C=100, gamma=0.01, kernel=rbf ......
        [CV] ..... C=100, gamma=0.01, kernel=rbf, score=0.967, total= 0.0s
        [CV] C=100, gamma=0.001, kernel=rbf ......
        [CV] ..... C=100, gamma=0.001, kernel=rbf, score=0.978, total= 0.0s
        [CV] C=100, gamma=0.001, kernel=rbf ......
        [CV] ..... C=100, gamma=0.001, kernel=rbf, score=0.945, total= 0.0s
        [CV] C=100, gamma=0.001, kernel=rbf .....
        [CV] ..... C=100, gamma=0.001, kernel=rbf, score=0.956, total= 0.0s
        [CV] C=100, gamma=0.001, kernel=rbf .....
        [CV] ..... C=100, gamma=0.001, kernel=rbf, score=0.945, total= 0.0s
        [CV] C=100, gamma=0.001, kernel=rbf .....
        [CV] ..... C=100, gamma=0.001, kernel=rbf, score=0.945, total= 0.0s
        [CV] C=100, gamma=0.0001, kernel=rbf ......
        [CV] ..... C=100, gamma=0.0001, kernel=rbf, score=0.956, total= 0.0s
        [CV] C=100, gamma=0.0001, kernel=rbf .....
        [CV] .... C=100, gamma=0.0001, kernel=rbf, score=0.934, total= 0.0s
        [CV] C=100, gamma=0.0001, kernel=rbf .....
        [CV] ..... C=100, gamma=0.0001, kernel=rbf, score=0.890, total= 0.0s
        [CV] C=100, gamma=0.0001, kernel=rbf .....
        [CV] ..... C=100, gamma=0.0001, kernel=rbf, score=0.879, total= 0.0s
        [CV] C=100, gamma=0.0001, kernel=rbf .....
        [CV] ..... C=100, gamma=0.0001, kernel=rbf, score=0.890, total= 0.0s
        [Parallel(n_jobs=1)]: Done 125 out of 125 | elapsed: 0.9s finished
Out[19]: GridSearchCV(cv=None, error_score=nan,
                  estimator=SVC(C=1.0, break_ties=False, cache_size=200,
                              class_weight=None, coef0=0.0,
                              decision_function_shape='ovr', degree=3,
                              gamma='scale', kernel='rbf', max_iter=-1,
                              probability=False, random_state=None, shrinking=True,
                              tol=0.001, verbose=False),
                  iid='deprecated', n_jobs=None,
                  param_grid={'C': [0.01, 0.1, 1, 10, 100],
                             'gamma': [1, 0.1, 0.01, 0.001, 0.0001],
                             'kernel': ['rbf']},
                  pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
                  scoring=None, verbose=4)
In [20]: print(refit_model.best_params_)
        {'C': 10, 'gamma': 0.1, 'kernel': 'rbf'}
        5. Support Vector Machine - Testing / Result
        The accuracy of the model was not increased after optimization. It is likely that the accuracy before model improvement was already very high enough (98%)
In [21]: y_predict2 = refit_model.predict(X_test)
In [22]: cm = confusion_matrix(y_test, y_predict2)
In [23]: sns.heatmap(cm, annot=True)
Out[23]: <matplotlib.axes._subplots.AxesSubplot at 0x160d4344708>
        0
                             73
In [24]: print(classification_report(y_test,y_predict2))
                   precision
                             recall f1-score support
                                0.95
               0.0
                       1.00
                                        0.97
                                                  41
               1.0
                       0.97
                               1.00
                                        0.99
                                                  73
```

0.98

0.98

0.98

accuracy macro avo

weighted avg

0.99

0.98

0.98

0.98

114

114

114

0.602

0.347 0.483

0.91

0.437