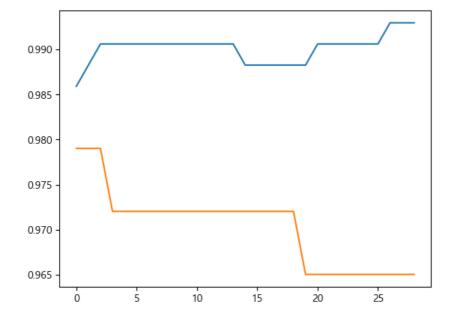
```
Out[204]: {'data': array([[1.799e+01, 1.038e+01, 1.228e+02, ..., 2.654e-01, 4.601e-01,
                  1.189e-011.
                 [2.057e+01, 1.777e+01, 1.329e+02, ..., 1.860e-01, 2.750e-01,
                  8.902e-02],
                 [1.969e+01, 2.125e+01, 1.300e+02, ..., 2.430e-01, 3.613e-01,
                  8.758e-02].
                 [1.660e+01, 2.808e+01, 1.083e+02, ..., 1.418e-01, 2.218e-01,
                  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]]),
          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, 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,
                 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, 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, 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, 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, 0, 1, 1, 0, 1, 0, 1, 1, 1, 1, 0, 0,
                 0, 1, 1, 1, 0, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0,
                0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 0, 0, 1, 0, 0,
                 1, 1, 1, 1, 1, 0, 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, 1, 0, 1, 0, 0, 1, 0, 1, 1, 1, 1,
                 1, 0, 1, 1, 0, 1, 0, 1, 1, 0, 1, 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, 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, 0, 0, 0, 0, 0, 0, 1]),
          'frame': None,
          'target_names': array(['malignant', 'benign'], dtype='<U9'),
          'DESCR': '.. _breast_cancer_dataset:\mm\nBreast cancer wisconsin (diagnostic) dataset\mm
             ------Wn\n**Data Set Characteristics:**\n\n :Number of Instances: 569\n\n :Number of Attributes: 30 n
         umeric, predictive attributes and the class\(\mathbb{W}\)n\(\mathbb{W}\)n :Attribute Information:\(\mathbb{W}\)n - radius (mean of distances from
         center to points on the perimeter)\text{Wn} - texture (standard deviation of gray-scale values)\text{Wn} - perimeter
                              - smoothness (local variation in radius lengths)\mathbb{W}n \qquad - compactness (perimeter^2 / are neavity (severity of concave portions of the contour)\mathbb{W}n \qquad - concave points (number of con
         a - 1.0)₩n - concavity (severity of concave portions of the contour)₩n
         cave 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 threeWn worst/largest values) of these features
         were computed for each image,\( \mathbb{W} \n \) resulting in 30 features. For instance, field \( \tilde{0} \) is Mean Radius, field\( \mathbb{W} \n \)
         10 is Radius SE, field 20 is Worst Radius.₩n₩n - class:₩n
                                                                                  - WDBC-Malignant\n
         WDBC-Benign₩n₩n :Summary Statistics:₩n₩n =======
                                                                                  ===== ====₩n
         6.981
                                                   9.71 39.28₩n perimeter (mean):
         28.11₩n texture (mean):
                                                                                                          43.79 188.
         5₩n area (mean):
                                                  143.5 2501.0₩n smoothness (mean):
                                                                                                       0.053 0.163₩n
                                           0.019 0.345₩n concavity (mean):
                                                                                               0.0 0.427₩n conc
         compactness (mean):
                                        0.0 0.201₩n symmetry (mean):
                                                                                            0.106 0.304₩n fractal
         ave points (mean):
         dimension (mean):
                                    0.05 0.097₩n radius (standard error):
                                                                                        0.112 2.873₩n texture (sta
                                0.36 4.885₩n perimeter (standard error):
                                                                                   0.757 21.98₩n area (standard e
         ndard error):
                                                                               0.002 0.031₩n compactness (standar
         rror):
                             6.802 542.2₩n smoothness (standard error):
                        0.002 0.135₩n concavity (standard error):
                                                                             0.0 0.396\mathbb{W}n concave points (standard
         d error):
                                                                        0.008 0.079\mathbb{W}n fractal dimension (standard e
         error):
                     0.0 0.053₩n symmetry (standard error):
                 0.001 0.03₩n radius (worst):
                                                                    7.93 36.04₩n texture (worst):
         rror):
         12.02 49.54₩n perimeter (worst):
                                                            50.41 251.2₩n area (worst):
         2 4254.0₩n smoothness (worst):
                                                         0.071 0.223₩n compactness (worst):
                                                                                                              0 027
                                            0.0 1.252\mathfracture concave points (worst):
0.156 0.664\mathfractal dimension (worst):
         1.058₩n
                  concavity (worst):
                                                                                                          0.0
                                                                                                                 0.29
         1₩n symmetry (worst):
                                                                                                      0.055 0.208₩n
         n: 212 - Malignant, 357 - Benign\(Wn\)Wn :Creator: Dr. William H. Wolberg, W. Nick Street, Olvi L. Mangasarian\(Wn\)Wn
         :Donor: Nick Street₩n₩n :Date: November, 1995₩n₩nThis is a copy of UCI ML Breast Cancer Wisconsin (Diagnostic) da
         tasets. Whhttps://goo.gl/U2Uwz2WnWnFeatures are computed from a digitized image of a fine needleWnaspirate (FNA) of a
         breast mass. They describeWncharacteristics of the cell nuclei present in the image.WnWnSeparating plane described
         above was obtained using\(WnMultisurface Method-Tree \) (MSM-T) [K. P. Bennett, "Decision Tree\(WnConstruction Via Linear P
         rogramming." Proceedings of the 4thWnMidwest Artificial Intelligence and Cognitive Science Society, Wnpp. 97-101, 199
         2], a classification method which uses linear\u00e4mprogramming to construct a decision tree. Relevant features\u00fcmnwere se
         lected using an exhaustive search in the space of 1-4\minfeatures and 1-3 separating planes.\minfeature prog
         ram used to obtain the separating planeWnin the 3-dimensional space is that described in:Wn[K. P. Bennett and O. L.
         Mangasarian: "Robust Linear₩nProgramming Discrimination of Two Linearly Inseparable Sets",₩nOptimization Methods and
         Software 1, 1992, 23-34]. WnWnThis database is also available through the UW CS ftp server: WnWnftp ftp.cs.wisc.eduWnc
         d math-prog/cpo-dataset/machine-learn/WDBC/\\mathrm{\text{W}}\text{NW}\text{N.} . topic∷ References\\mathrm{\text{W}}\text{NW}\text{N.} Street, W.H. Wolberg and O.L. Mang
         asarian. Nuclear feature extraction \( \mathbb{W} n \) for breast tumor diagnosis. IS&T/SPIE 1993 International Symposium on \( \mathbb{W} n \)
         Electronic Imaging: Science and Technology, volume 1905, pages 861-870,\mathbb{W}n
                                                                                San Jose, CA, 1993.₩n - O.L. Mangasa
```

```
rian, W.N. Street and W.H. Wolberg. Breast cancer diagnosis and ₩n
                                                                                             prognosis via linear programming. Operations
            Research, 43(4), pages 570-577, \( \text{Wn} \) July-August 1995.\( \text{Wn} \) - W.H. Wolberg, W.N. Street, and O.L. Mangasarian. Mach
            ine learning techniques₩n
                                              to diagnose breast cancer from fine-needle aspirates. Cancer Letters 77 (1994) \text{\text{Wn}}
            163-171.',
             '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 [205]: train_input , test_input , train_target , test_target = train_test_split(cancer.data, cancer.target , random_state =
            executed in 15ms, finished 11:57:24 2023-10-25
In [206]: from sklearn.preprocessing import StandardScaler
            ss = StandardScaler()
            ss.fit(train_input)
            executed in 13ms, finished 11:57:24 2023-10-25
Out [206]:
             ▼ StandardScaler
            StandardScaler()
In [207]: | train_scaled = ss.transform(train_input)
            test_scaled = ss.transform(test_input)
            executed in 6ms. finished 11:57:24 2023-10-25
In [208]: decisions = Ir.decision_function(train_scaled[:,:5])
            decisions
            executed in 17ms, finished 11:57:24 2023-10-25
Out[208]: array([[ 0.07042131, 5.29486531, -8.44359052, ..., 6.59081425,
                      1.39492013, -2.67012852],
                    [-3.8751889 , -4.37157959, 11.31746922, ..., 2.58559666, -9.40217833, 4.16025488],
                    [-1.1130764 , 2.08609317, -0.4867963 , ..., 0.13192612,
                      1.92713095, -4.4936687 ],
                    [ 2.45467921, 5.18689785, -7.73469202, ..., 1.55121768,
                      2.43239063, -5.60249733],
                    [-2.31393068,\ -2.85766968,\ \ 7.74188303,\ \ldots,\ \ 3.46854077,
                     -9.03706072, 3.65339436],
                    [-4.079075 , -0.09600672, 7.38259626, ..., -3.22697538, 1.59404047, -4.16571357]])
In [209]: from sklearn.linear_model import LogisticRegression
            Ir = LogisticRegression()
            Ir.fit(train_scaled , train_target)
            executed in 22ms, finished 11:57:24 2023-10-25
Out[209]:
             ▼ LogistidRegression
            LogisticRegression()
In [210]: Ir.score(train_scaled , train_target)
            executed in 7ms, finished 11:57:24 2023-10-25
Out [210]: 0.9859154929577465
In [211]: |Ir.score(test_scaled , test_target)
            executed in 15ms, finished 11:57:24 2023-10-25
Out[211]: 0.9790209790209791
In [212]: Ir.predict(test_scaled[:5])
            executed in 14ms, finished 11:57:24 2023-10-25
Out[212]: array([1, 0, 0, 1, 1])
```

```
In [213]: test_scaled.shape
           executed in 8ms, finished 11:57:24 2023-10-25
Out[213]: (143, 30)
In [214]: proba = Ir.predict_proba(test_scaled[:5])
           np.round(proba , 3)
           executed in 13ms, finished 11:57:24 2023-10-25
Out[214]: array([[0.124, 0.876],
                   [1. , 0. ],
[0.997, 0.003],
                   [0.001, 0.999],
                   [0. , 1. ]])
In [215]: train_score = []
           test_score = []
           for i in range(1,30):
               Ir = LogisticRegression(C = i)
               Ir.fit(train_scaled , train_target)
               train_score.append(Ir.score(train_scaled , train_target))
               test_score.append(Ir.score(test_scaled , test_target))
           executed in 371ms, finished 11:57:24 2023-10-25
In [216]: plt.plot(train_score)
           plt.plot(test_score)
           executed in 263ms, finished 11:57:24 2023-10-25
```

Out[216]: [<matplotlib.lines.Line2D at 0x2bc84bef190>]



```
04. 로지스틱회귀 - Jupyter Notebook
In [217]: pd.DataFrame(cancer.data , columns = cancer.feature_names)
            executed in 35ms, finished 11:57:24 2023-10-25
Out [217]:
                                                                                             mean
                                                                                                                    mean
                  mean
                           mean
                                     mean
                                             mean
                                                           mean
                                                                         mean
                                                                                    mean
                                                                                                        mean
                                                                                                                               worst
                                                                                                                                        worst
                                                                                                                   fractal
                                                                                           concave
                  radius
                         texture
                                  perimeter
                                              area
                                                    smoothness
                                                                  compactness
                                                                                concavity
                                                                                                     symmetry
                                                                                                                               radius
                                                                                                                                       texture
                                                                                             points
                                                                                                                dimension
              0
                  17 99
                           10.38
                                     122 80 1001 0
                                                         0.11840
                                                                       0.27760
                                                                                  0.30010
                                                                                           0 14710
                                                                                                        0.2419
                                                                                                                  0.07871
                                                                                                                               25 380
                                                                                                                                        17 33
              1
                  20.57
                           17.77
                                     132.90 1326.0
                                                         0.08474
                                                                       0.07864
                                                                                  0.08690
                                                                                           0.07017
                                                                                                        0.1812
                                                                                                                  0.05667
                                                                                                                               24.990
                                                                                                                                        23.41
              2
                  19.69
                           21.25
                                     130.00 1203.0
                                                         0.10960
                                                                       0.15990
                                                                                  0.19740
                                                                                           0.12790
                                                                                                        0.2069
                                                                                                                  0.05999
                                                                                                                               23.570
                                                                                                                                        25.53
                                                                                                        0.2597
                   11.42
                           20.38
                                      77.58
                                             386.1
                                                         0.14250
                                                                       0.28390
                                                                                  0.24140
                                                                                           0.10520
                                                                                                                  0.09744 ...
                                                                                                                              14.910
                                                                                                                                        26.50
                           14.34
                                                                                                        0.1809
                  20.29
                                     135.10 1297.0
                                                         0.10030
                                                                       0.13280
                                                                                  0.19800
                                                                                           0.10430
                                                                                                                  0.05883 ... 22.540
                                                                                                                                        16.67
                  21.56
                                     142.00 1479.0
            564
                           22.39
                                                         0.11100
                                                                       0.11590
                                                                                  0.24390
                                                                                           0.13890
                                                                                                        0.1726
                                                                                                                  0.05623 ... 25.450
                                                                                                                                        26.40
             565
                  20.13
                           28.25
                                     131.20 1261.0
                                                         0.09780
                                                                       0.10340
                                                                                  0.14400
                                                                                           0.09791
                                                                                                        0.1752
                                                                                                                  0.05533 ... 23.690
                                                                                                                                        38.25
             566
                   16.60
                           28.08
                                     108.30
                                             858.1
                                                         0.08455
                                                                       0.10230
                                                                                  0.09251
                                                                                           0.05302
                                                                                                        0.1590
                                                                                                                  0.05648 ... 18.980
                                                                                                                                        34.12
            567
                  20.60
                           29.33
                                     140.10 1265.0
                                                         0.11780
                                                                       0.27700
                                                                                  0.35140
                                                                                           0.15200
                                                                                                        0.2397
                                                                                                                  0.07016 ... 25.740
                                                                                                                                        39.42
            568
                    7.76
                           24.54
                                      47.92
                                                         0.05263
                                                                       0.04362
                                                                                  0.00000
                                                                                           0.00000
                                                                                                        0.1587
                                                                                                                  0.05884 ...
                                             181.0
                                                                                                                                9.456
                                                                                                                                        30.37
            569 rows × 30 columns
           4
In [218]: cancer.feature_names[:10]
            executed in 19ms, finished 11:57:24 2023-10-25
Out[218]: array(['mean radius', 'mean texture', 'mean perimeter', 'mean area',
                    'mean smoothness', 'mean compactness', 'mean concavity', 'mean concave points', 'mean symmetry', 'mean fractal dimension'],
                  dtype='<U23')
In [219]: cancer.data[:,:10]
            executed in 13ms, finished 11:57:24 2023-10-25
Out[219]: array([[1.799e+01, 1.038e+01, 1.228e+02, ..., 1.471e-01, 2.419e-01,
                     7.871e-02],
                    [2.057e+01, 1.777e+01, 1.329e+02, ..., 7.017e-02, 1.812e-01,
                    5.667e-02],
                    [1.969e+01, 2.125e+01, 1.300e+02, ..., 1.279e-01, 2.069e-01,
                    5.999e-02],
                    [1.660e+01,\ 2.808e+01,\ 1.083e+02,\ \dots,\ 5.302e-02,\ 1.590e-01,
                     5.648e-02],
                    [2.060e+01, 2.933e+01, 1.401e+02, ..., 1.520e-01, 2.397e-01,
                     7.016e-02],
                    [7.760e+00, 2.454e+01, 4.792e+01, ..., 0.000e+00, 1.587e-01,
                    5.884e-0211)
In [220]: train_input , test_input , train_target , test_target = train_test_split(cancer.data[:,:10], cancer.target , random_sf
            executed in 10ms, finished 11:57:24 2023-10-25
In [221]: from sklearn.preprocessing import StandardScaler
            ss = StandardScaler()
           ss fit(train input)
```

executed in 9ms, finished 11:57:24 2023-10-25

```
Out[221]:
            ▼ StandardScaler
           Standard$caler()
```

```
In [222]:
           train_scaled = ss.transform(train_input)
           test_scaled = ss.transform(test_input)
           executed in 16ms, finished 11:57:24 2023-10-25
```

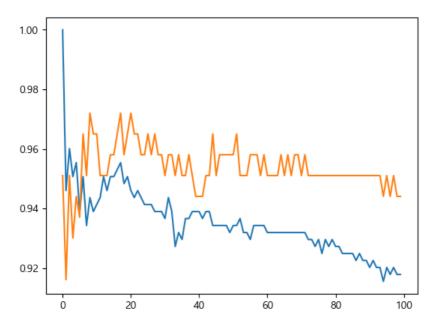
```
In [223]:
          from sklearn.linear_model import LogisticRegression
           Ir = LogisticRegression(C = 6)
           Ir.fit(train_scaled , train_target)
           executed in 27ms, finished 11:57:25 2023-10-25
Out[223]:

    LogisticRegression

           LogisticRegression(C=6)
In [224]: |print(Ir.score(train_scaled , train_target))
           print(Ir.score(test_scaled , test_target))
           executed in 14ms, finished 11:57:25 2023-10-25
           0.9436619718309859
           0.9440559440559441
In [225]: result = Ir.predict(test_scaled)
           from sklearn.metrics import classification_report
           print(classification_report(result , test_target))
           executed in 19ms, finished 11:57:25 2023-10-25
                          precision
                                       recall f1-score
                      0
                               0.94
                                         0.91
                                                    0.93
                                                                 56
                               0.94
                                          0.97
                                                    0.95
                                                                 87
               accur acy
                                                    0.94
                                                                143
                                          0.94
                               0.94
                                                    0.94
                                                                143
              macro ava
           weighted avg
                               0.94
                                         0.94
                                                    0.94
                                                                143
  In [ ]:
In [226]:
          from sklearn.neighbors import KNeighborsClassifier
           kn = KNeighborsClassifier()
           kn.fit(train_scaled , train_target)
           executed in 18ms, finished 11:57:25 2023-10-25
Out[226]:
           ▼ KNeighborsClassifier
           KNeighborsClassifier()
In [227]: len(train_scaled)
           executed in 16ms, finished 11:57:25 2023-10-25
Out[227]: 426
In [228]: train_score = []
           test_score = []
           for i in range(1,101):
               knn = KNeighborsClassifier(n_neighbors = i)
               knn.fit(train_scaled , train_target)
               train_score.append(knn.score(train_scaled , train_target))
               test_score.append(knn.score(test_scaled , test_target))
           executed in 1.80s, finished 11:57:26 2023-10-25
```

```
In [229]: plt.plot(train_score) plt.plot(test_score) executed in 127ms, finished 11:57:27 2023-10-25
```

Out[229]: [<matplotlib.lines.Line2D at 0x2bc830126a0>]



```
In [230]: for i in range(len(train_score)):
    if train_score[i]<test_score[i]:
        print(i)
        break

executed in 4ms, finished 11:57:27 2023-10-25
```

6

```
In [231]: from sklearn.neighbors import KNeighborsClassifier
kn = KNeighborsClassifier(n_neighbors = 5)
kn.fit(train_scaled , train_target)
```

executed in 16ms, finished 11:57:27 2023-10-25

```
Out[231]: 

* KNeighborsClassifier

KNeighborsClassifier()
```

```
In [232]: print(kn.score(train_scaled , train_target)) print(kn.score(test_scaled , test_target))
```

executed in 26ms, finished 11:57:27 2023-10-25

- 0.9553990610328639 0.9440559440559441
- In [233]: from sklearn.datasets import load_iris
 iris = load_iris()

executed in 14ms, finished 11:57:27 2023-10-25

```
In [234]: iris
           executed in 20ms, finished 11:57:27 2023-10-25
Out[234]: {'data': array([[5.1, 3.5, 1.4, 0.2],
                    [4.9, 3., 1.4, 0.2], [4.7, 3.2, 1.3, 0.2],
                    [4.6, 3.1, 1.5, 0.2],
                    [5., 3.6, 1.4, 0.2], [5.4, 3.9, 1.7, 0.4],
                    [4.6, 3.4, 1.4, 0.3],
                    [5., 3.4, 1.5, 0.2],
                    [4.4, 2.9, 1.4, 0.2],
                    [4.9, 3.1, 1.5, 0.1],
                    [5.4, 3.7, 1.5, 0.2],
                     [4.8, 3.4, 1.6, 0.2],
                    [4.8, 3. , 1.4, 0.1],
                    [4.3, 3., 1.1, 0.1],
                    [5.8, 4. , 1.2, 0.2],
[5.7, 4.4, 1.5, 0.4],
                    [5.4, 3.9, 1.3, 0.4],
                    [5.1, 3.5, 1.4, 0.3],
                    [5.7, 3.8, 1.7, 0.3],
In [235]: | train_input , test_input , train_target , test_target = train_test_split(iris.data, iris.target , random_state = 42)
           executed in 11ms, finished 11:57:27 2023-10-25
In [236]: from sklearn.linear_model import LogisticRegression
           Ir = LogisticRegression()
           Ir.fit(train_input , train_target)
           print(Ir.score(train_input , train_target))
           print(Ir.score(test_input , test_target))
           executed in 20ms, finished 11:57:27 2023-10-25
           0.9642857142857143
           1.0
In [237]: train_score = []
           test_score = []
           for i in range(1,30):
                Ir = LogisticRegression(C = i)
                Ir.fit(train_input , train_target)
                train_score.append(Ir.score(train_input , train_target))
                test_score.append(Ir.score(test_input , test_target))
           executed in 344ms, finished 11:57:27 2023-10-25
In [238]: plt.plot(train_score)
           plt.plot(test_score)
           executed in 129ms, finished 11:57:27 2023-10-25
Out[238]: [<matplotlib.lines.Line2D at 0x2bc82b475b0>]
             1.000
             0.995
             0.990
             0.985
             0.980
             0.975
             0.970
             0.965
                                    ż
                                                10
                                                             15
                                                                          20
                                                                                       25
```

```
In [239]: from sklearn.linear_model import LogisticRegression
           Ir = LogisticRegression(C = 10)
           Ir.fit(train_input , train_target)
           print(Ir.score(train_input , train_target))
           print(Ir.score(test_input , test_target))
           executed in 20ms, finished 11:57:27 2023-10-25
           0.9910714285714286
           1.0
In [240]: |np.round(Ir.predict_proba(train_input) , 3)
           executed in 15ms, finished 11:57:27 2023-10-25
Out[240]: array([[0.997, 0.003, 0.
                  [0.998, 0.002, 0.
                         , 0.036, 0.964],
                  [0.
                  [0.001, 0.961, 0.038],
                  [0. , 0.962, 0.038],
                   [0.998, 0.002, 0. ],
                  [0.994, 0.006, 0.
                  [0.004, 0.995, 0.001],
                  [0. , 0.496, 0.504],
                       , 0.054, 0.946],
                  10
                  [0. , 0.992, 0.007],
                        , 0.001, 0.999],
                  [0.
                  [0.001, 0.991, 0.008],
                   [0.
                        , 0.
                               , 1.
                  [0.001, 0.908, 0.092],
                  [0.996, 0.004, 0. ],
                       , 0. , 1.
                  [0.
                  [0.001, 0.998, 0.001],
                  [0.994, 0.006, 0. ],
In [241]: decisions = Ir.decision_function(train_input)
           decisions
           executed in 18ms, finished 11:57:27 2023-10-25
Out[241]: array([[ 12.30534073, 6.49706033, -18.80240106],
                    13.01663648, 6.89327622, -19.9099127],
-7.89444059, 2.30269426, 5.59174633],
                    -3.57225913, 3.40023233, 0.1720268],
                    -5.07740319, 4.15170857, 0.92569462],
                    12.82031872,
                                    6.55558949, -19.37590821],
                                   6.84701483, -18.80055931],
                   11 95354448
                    -1.09875917, 4.33362381, -3.23486465],
                   [ -7.16806645, 3.57625482, 3.59181163],
[ -8.75562338, 2.94667037, 5.80895301],
                   [ -3.84484923, 4.36656271, -0.52171348],
                  [-11.71768411, 2.13449051, 9.58319361],
[-2.72431581, 3.77819383, -1.05387802],
                   [-14.41227508, 3.03730925, 11.37496583],
                    -4.06001417,
                                   3.17599955, 0.88401463],
                   [ 12.06535383,
                                    6.58233002, -18.64768385],
                                    3.26829161, 11.81735749],
                  [-15.0856491 ,
                  [ -2.22926363, 4.48499912, -2.2557355 ],
                  [ 11.82536693,
                                   6.66759971, -18.49296664],
In [242]: from sklearn.neighbors import KNeighborsClassifier
           kn = KNeighborsClassifier(n_neighbors = 3)
           kn.fit(train_input , train_target)
           print(kn.score(train_input , train_target))
           print(kn.score(test_input , test_target))
           executed in 13ms, finished 11:57:27 2023-10-25
           0.9464285714285714
           1.0
In [243]: train_score = []
           test_score = []
           for i in range(1,20):
               knn = KNeighborsClassifier(n_neighbors = i)
               knn.fit(train_input , train_target)
               train_score.append(knn.score(train_input , train_target))
               test_score.append(knn.score(test_input , test_target))
           executed in 112ms, finished 11:57:27 2023-10-25
```

```
In [244]: plt.plot(train_score)
plt.plot(test_score)
executed in 132ms, finished 11:57:27 2023-10-25
```

Out[244]: [<matplotlib.lines.Line2D at 0x2bc83b97550>]

```
In [245]:

from sklearn.neighbors import KNeighborsClassifier
kn = KNeighborsClassifier(n_neighbors = 7)
kn.fit(train_input , train_target)
print(kn.score(train_input , train_target))
print(kn.score(test_input , test_target))
executed in 18ms, finished 11:57:27 2023-10-25
```

0.9732142857142857 1.0

executed in 15ms, finished 11:57:27 2023-10-25

	precision	recall	f1-score	suppor t
0	1.00	1.00	1.00	15 11
2	1.00	1.00	1.00	12
accuracy			1.00	38
macro avg	1.00	1.00	1.00	38
weighted avg	1.00	1.00	1.00	38

```
In [247]: iris.target_names[result] executed in 15ms, finished 11:57:27 2023-10-25
```

```
Out[247]: array(['versicolor', 'setosa', 'virginica', 'versicolor', 'versicolor', 'setosa', 'versicolor', 'virginica', 'versicolor', 'virginica', 'setosa', 'setosa', 'setosa', 'setosa', 'versicolor', 'virginica', 'versicolor', 'virginica', 'setosa', 'virginica', 'setosa', 'virginica', 'virginica', 'virginica', 'virginica', 'virginica', 'virginica', 'virginica', 'setosa', 'setosa', 'setosa', 'setosa', 'setosa', 'setosa', 'setosa', 'setosa', 'setosa', 'dirginica', 'versicolor', 'setosa', 'dirginica', 'versicolor', 'setosa', 'dirginica', 'versicolor', 'setosa'], dtype='<U10')
```

In []: