KNN em python

October 18, 2022

```
[1]: from IPython.display import Image
      %matplotlib inline
 [3]: from sklearn import datasets
      import numpy as np
      iris = datasets.load_iris()
      X = iris.data[:, [2, 3]]
      y = iris.target
 [4]: from sklearn.model_selection import train_test_split
      X_train, X_test, y_train, y_test = train_test_split(
      X, y, test_size=0.3, random_state=1, stratify=y)
 [5]: from sklearn.preprocessing import StandardScaler
      sc = StandardScaler()
      sc.fit(X_train)
 [5]: StandardScaler()
 [6]: X_train_std = sc.transform(X_train)
      X_test_std = sc.transform(X_test)
[12]: X_test_std
[12]: array([[ 0.89820289, 1.44587881],
             [-1.16537974, -1.04507821],
             [-1.33269725, -1.17618121],
             [ 0.39625036, 0.65926081],
             [ 0.34047786, 0.2659518 ],
             [ 0.11738784, 0.1348488 ],
             [ 1.12129291, 0.79036381],
             [ 0.39625036, 0.3970548 ],
             [ 0.84243039, 0.92146681],
             [-1.38846976, -1.04507821],
```

```
[ 0.61934037, 0.79036381],
             [-1.33269725, -1.30728421],
             [-0.27301968, -0.2584602],
             [-1.33269725, -1.30728421],
             [ 0.56356787, 0.2659518 ],
             [ 0.73088538, 1.44587881],
             [ 0.39625036, 0.3970548 ],
             [ 0.28470535, 0.1348488 ],
             [ 0.78665788, 1.05256981],
             [ 1.17706541, 1.18367281],
             [-1.33269725, -1.43838721],
             [ 0.34047786, 0.2659518 ],
             [ 0.61934037, 1.05256981],
             [ 0.22893285, 0.1348488 ],
             [ 0.50779537, 0.5281578 ],
             [-0.4403372, -0.1273572],
             [ 1.0655204 , 1.70808482],
             [-1.22115225, -0.78287221],
             [ 0.67511288, 1.05256981],
             [-1.22115225, -1.30728421],
             [-1.33269725, -1.30728421],
             [0.11738784, -0.2584602],
             [ 0.11738784, 0.1348488 ],
             [ 1.40015543, 0.79036381],
             [ 0.9539754 , 1.18367281],
             [-1.33269725, -1.43838721],
             [-1.22115225, -1.30728421],
             [-1.33269725, -1.30728421],
             [ 0.50779537, 0.2659518 ],
             [ 1.0655204 , 1.44587881],
             [ 0.73088538, 0.79036381],
             [0.45202286, 0.3970548],
             [-1.27692475, -1.30728421],
             [-1.27692475, -1.43838721]])
[14]: X combined std = np.vstack((X train std, X test std))
      y_combined_std = np.hstack((y_train, y_test))
 [8]: from matplotlib.colors import ListedColormap
      import matplotlib.pyplot as plt
      # To check recent matplotlib compatibility
      import matplotlib
      from distutils.version import LooseVersion
```

[-1.27692475, -1.04507821],

```
def plot_decision_regions(X, y, classifier, test_idx=None, resolution=0.02):
    # setup marker generator and color map
    markers = ('s', 'x', 'o', '^', 'v')
    colors = ('red', 'blue', 'lightgreen', 'gray', 'cyan')
    cmap = ListedColormap(colors[:len(np.unique(y))])
    # plot the decision surface
    x1_{min}, x1_{max} = X[:, 0].min() - 1, X[:, 0].max() + 1
    x2_{min}, x2_{max} = X[:, 1].min() - 1, X[:, 1].max() + 1
    xx1, xx2 = np.meshgrid(np.arange(x1_min, x1_max, resolution),
                           np.arange(x2_min, x2_max, resolution))
    Z = classifier.predict(np.array([xx1.ravel(), xx2.ravel()]).T)
    Z = Z.reshape(xx1.shape)
    plt.contourf(xx1, xx2, Z, alpha=0.3, cmap=cmap)
    plt.xlim(xx1.min(), xx1.max())
    plt.ylim(xx2.min(), xx2.max())
    for idx, cl in enumerate(np.unique(y)):
        plt.scatter(x=X[y == cl, 0],
                    y=X[y == c1, 1],
                    alpha=0.8,
                    color=colors[idx],
                    marker=markers[idx],
                    label=cl,
                    edgecolor='black')
    # highlight test examples
    if test_idx:
        # plot all examples
        X_test, y_test = X[test_idx, :], y[test_idx]
        if LooseVersion(matplotlib.__version__) < LooseVersion('0.3.4'):</pre>
            plt.scatter(X_test[:, 0],
                        X_test[:, 1],
                        c=11,
                        edgecolor='black',
                        alpha=1.0,
                        linewidth=1,
                        marker='o',
                        s=100,
                        label='test set')
        else:
            plt.scatter(X_test[:, 0],
                        X_test[:, 1],
                        c='none',
```

```
edgecolor='black',
alpha=1.0,
linewidth=1,
marker='o',
s=100,
label='test set')
```

[9]: from sklearn.neighbors import KNeighborsClassifier

KNN = KNeighborsClassifier(n_neighbors=5, p=2, metric='minkowski')

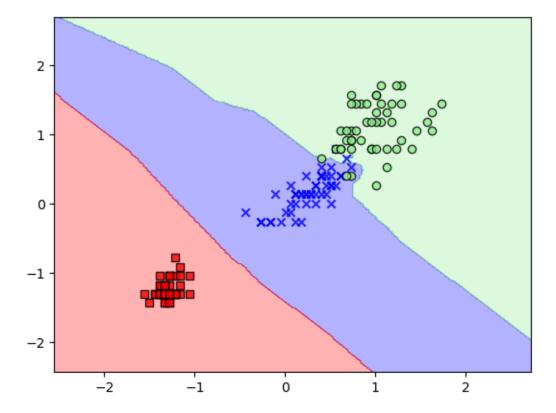
[10]: KNN.fit(X_train_std, y_train)

[10]: KNeighborsClassifier()

[15]: plot_decision_regions(X_combined_std, y_combined_std, classifier=KNN)

/tmp/ipykernel_178950/3366577703.py:28: UserWarning: You passed a edgecolor/edgecolors ('black') for an unfilled marker ('x'). Matplotlib is ignoring the edgecolor in favor of the facecolor. This behavior may change in the future.

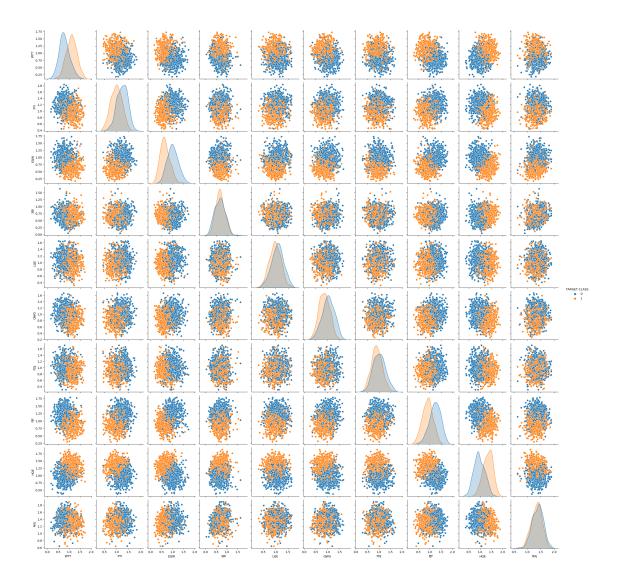
plt.scatter(x=X[y == c1, 0],



```
import pandas as pd
[16]:
      import seaborn as sns
      import matplotlib.pyplot as plt
      import pandas as pd
      import numpy as np
[31]:
     data = pd.read csv('ClassificaDados', index col=0)
[32]:
      data.head(20)
[32]:
               WTT
                          PTI
                                    EQW
                                               SBI
                                                         LQE
                                                                    QWG
                                                                               FDJ
                                                                                    \
      0
          0.913917
                     1.162073
                               0.567946
                                          0.755464
                                                    0.780862
                                                               0.352608
                                                                          0.759697
          0.635632
                     1.003722
                               0.535342
                                          0.825645
                                                    0.924109
                                                               0.648450
      1
                                                                          0.675334
      2
          0.721360
                     1.201493
                               0.921990
                                          0.855595
                                                    1.526629
                                                               0.720781
                                                                          1.626351
      3
          1.234204
                     1.386726
                               0.653046
                                          0.825624
                                                    1.142504
                                                               0.875128
                                                                          1.409708
      4
          1.279491
                     0.949750
                               0.627280
                                          0.668976
                                                    1.232537
                                                               0.703727
                                                                          1.115596
          0.833928
                     1.523302
                               1.104743
                                          1.021139
                                                    1.107377
                                                               1.010930
      5
                                                                          1.279538
      6
          0.944705
                     1.251761
                               1.074885
                                          0.286473
                                                    0.996440
                                                               0.428860
                                                                          0.910805
      7
          0.816174
                     1.088392
                               0.895343
                                          0.243860
                                                    0.943123
                                                               1.045131
                                                                          1.146536
      8
          0.776551
                     1.463812
                               0.783825
                                          0.337278
                                                    0.742215
                                                               1.072756
                                                                          0.880300
      9
          0.772280
                     0.515111
                               0.891596
                                          0.940862
                                                    1.430568
                                                               0.885876
                                                                          1.205231
      10
          1.284999
                     1.331018
                               0.618910
                                          0.657017
                                                    1.037191
                                                               0.717346
                                                                          0.778501
      11
          1.064356
                     1.414885
                               0.896798
                                          0.629088
                                                    1.447704
                                                               0.791923
                                                                          0.921676
      12
          0.682953
                     1.254723
                               0.998870
                                          0.397701
                                                    1.011621
                                                               0.567863
                                                                          1.335120
      13
          0.953318
                     1.318987
                               0.562921
                                          0.905503
                                                    1.248314
                                                               0.677795
                                                                          1.017305
      14
          0.801268
                               0.696960
                                          0.972440
                                                    0.851299
                                                               1.443119
                     0.936390
                                                                          1.194476
          1.061691
                     1.044892
                               0.599729
                                          0.465285
                                                    0.930288
                                                               0.974341
                                                                          1.213450
      15
          0.715645
      16
                     1.378594
                               0.997797
                                          0.674996
                                                    1.228928
                                                               1.223293
                                                                          0.589346
      17
          0.899792
                     1.225875
                               1.330887
                                          0.335989
                                                    1.273570
                                                               1.100361
                                                                          1.019617
          0.883813
                     1.275891
                               0.924066
                                          0.668814
                                                    1.269021
                                                               1.382093
      18
                                                                          0.728286
      19
          0.768311
                     1.394304
                               0.823118
                                          0.612072
                                                    1.267414
                                                               0.881943
                                                                          1.104178
               PJF
                                    NXJ
                                          TARGET CLASS
                          HQE
      0
          0.643798
                    0.879422
                               1.231409
                                                      1
      1
          1.013546
                     0.621552
                               1.492702
                                                     0
                                                     0
      2
          1.154483
                     0.957877
                               1.285597
      3
          1.380003
                     1.522692
                               1.153093
                                                      1
      4
          0.646691
                     1.463812
                               1.419167
                                                     1
      5
          1.280677
                     0.510350
                               1.528044
                                                     0
                                                     0
      6
          0.755305
                     1.111800
                               1.110842
      7
          1.341886
                     1.225324
                                                     0
                               1.425784
                                                     0
      8
          1.312951
                     1.118165
                               1.225922
                     1.542580
      9
                                                     1
          0.596858
                               0.981879
      10
          0.599317
                     1.245676
                               1.441695
                                                     1
          1.237249
                     0.564281
                                                     0
      11
                               1.423668
      12
          1.093735
                     0.847015
                               1.374779
                                                     0
      13
          0.528065
                     1.541712
                               1.118960
                                                      1
```

```
14 1.641496 1.118737
                             1.426573
                                                  0
      15 1.247551 1.217625
                             1.623154
                                                   1
      16 1.559900 0.845324
                             1.248714
                                                  0
      17
         1.223891
                   1.113441
                             1.490151
                                                  0
      18 0.726723 0.975833
                             1.653815
                                                  0
      19
         1.660998 0.742885
                             1.098704
                                                  0
[33]: data.info()
     <class 'pandas.core.frame.DataFrame'>
     Int64Index: 1000 entries, 0 to 999
     Data columns (total 11 columns):
                        Non-Null Count Dtype
      #
          Column
                        _____
                        1000 non-null
      0
          WTT
                                        float64
                        1000 non-null
      1
          PTI
                                        float64
      2
          EQW
                        1000 non-null
                                        float64
      3
          SBI
                        1000 non-null
                                        float64
      4
          LQE
                        1000 non-null
                                        float64
      5
          QWG
                        1000 non-null
                                        float64
      6
                        1000 non-null
                                        float64
          FDJ
      7
          PJF
                        1000 non-null
                                        float64
      8
          HQE
                        1000 non-null
                                        float64
      9
          NXJ
                        1000 non-null
                                        float64
      10 TARGET CLASS 1000 non-null
                                        int64
     dtypes: float64(10), int64(1)
     memory usage: 93.8 KB
[34]: data.columns
[34]: Index(['WTT', 'PTI', 'EQW', 'SBI', 'LQE', 'QWG', 'FDJ', 'PJF', 'HQE', 'NXJ',
             'TARGET CLASS'],
            dtype='object')
[22]: sns.pairplot(data, hue='TARGET CLASS')
```

[22]: <seaborn.axisgrid.PairGrid at 0x7fc4d3712110>



```
[35]: from sklearn.preprocessing import StandardScaler

sc = StandardScaler()

sc.fit(data.drop('TARGET CLASS', axis=1))

[35]: StandardScaler()

[36]: dados=sc.transform(data.drop('TARGET CLASS', axis=1))

[26]: dados

[26]: array([[-0.12354188, 0.18590747, -0.91343069, ..., -1.48236813, -0.9497194, -0.64331425], [-1.08483602, -0.43034845, -1.02531333, ..., -0.20224031,
```

```
-1.82805088, 0.63675862],
            [-0.78870217, 0.33931821, 0.30151137, ..., 0.28570652,
             -0.68249379, -0.37784986],
            [0.64177714, -0.51308341, -0.17920486, ..., -2.36249443,
             -0.81426092, 0.11159651],
            [0.46707241, -0.98278576, -1.46519359, ..., -0.03677699,
              0.40602453, -0.85567 ],
            [-0.38765353, -0.59589427, -1.4313981, ..., -0.56778932,
              0.3369971 , 0.01034996]])
[37]: DF = pd.DataFrame(dados, columns = data.columns[:-1])
[38]: DF.head()
[38]:
             WTT
                      PTI
                                EQW
                                          SBI
                                                   LQE
                                                             QWG
                                                                      FDJ \
     0 \ -0.123542 \quad 0.185907 \ -0.913431 \quad 0.319629 \ -1.033637 \ -2.308375 \ -0.798951
     2 -0.788702 0.339318 0.301511 0.755873 2.031693 -0.870156 2.599818
     3 0.982841 1.060193 -0.621399 0.625299 0.452820 -0.267220 1.750208
     4 1.139275 -0.640392 -0.709819 -0.057175 0.822886 -0.936773 0.596782
             PJF
                      HQE
                                NXJ
     0 -1.482368 -0.949719 -0.643314
     1 -0.202240 -1.828051 0.636759
     2 0.285707 -0.682494 -0.377850
     3 1.066491 1.241325 -1.026987
     4 -1.472352 1.040772 0.276510
     0.1 Divisão Treino e Teste
[39]: from sklearn.model_selection import train_test_split
[41]: X_train, X_test, y_train, y_test = train_test_split(dados, data['TARGET CLASS'],
                                                       test_size=0.3,_
       →random_state=1)
[42]: y_train
[42]: 731
            1
     716
            0
     640
            1
     804
            1
     737
            1
           . .
     767
            1
     72
            1
```

```
235
             1
      37
      Name: TARGET CLASS, Length: 700, dtype: int64
[43]: X train
[43]: array([[ 2.05621551, -0.32655566, 0.2186274 , ..., -0.41322254,
               0.09995974, 1.31436215],
                           1.2943079 , -0.15774655, ..., -0.71699735,
             Γ-0.66162431.
             -1.3585909 , -0.56024653],
             [0.39523395, -2.09199987, -1.38109288, ..., -0.67612905,
               0.21135605, 0.11393259],
                           0.00424662, -1.01972037, ..., -0.34549064,
             [ 0.90344929,
             -0.09885529, 1.19270428],
                           1.24838194, -0.78177643, ..., -1.4002669 ,
             [-0.00962074,
               0.49192358, -0.1189531 ],
             [0.10483098, 1.27975307, -0.13195213, ..., -1.28654429,
               1.13589455, -0.29048815]])
[44]: from sklearn.neighbors import KNeighborsClassifier
[45]: KNN = KNeighborsClassifier(n neighbors=1)
[46]: KNN.fit(X_train, y_train)
[46]: KNeighborsClassifier(n_neighbors=1)
     predicao = KNN.predict(X_test)
[48]: predicao
[48]: array([0, 1, 0, 0, 1, 0, 1, 1, 1, 1, 1, 0, 0, 0, 1, 1, 1, 1, 1, 0, 1,
             1, 1, 0, 0, 1, 1, 1, 1, 1, 0, 1, 0, 0, 1, 1, 0, 0, 1, 0, 1, 0, 1,
             1, 1, 1, 0, 1, 1, 1, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1,
             0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0,
             0, 0, 0, 0, 1, 1, 0, 0, 0, 1, 1, 0, 1, 1, 1, 1, 0, 1, 0, 1, 0, 0,
             1, 1, 0, 1, 0, 1, 0, 0, 1, 1, 1, 0, 1, 0, 0, 1, 1, 0, 0, 1, 0, 1,
             1, 0, 1, 0, 0, 1, 1, 1, 0, 1, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 0,
             0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 1, 0, 0, 1, 1, 1,
             0, 0, 0, 1, 0, 0, 1, 1, 1, 0, 1, 0, 0, 1, 1, 1, 0, 1, 1, 0, 1, 0,
             1, 0, 1, 1, 1, 1, 0, 0, 0, 1, 0, 1, 0, 1, 0, 1, 0, 0, 1, 1, 1, 1, 0,
             0, 1, 1, 1, 1, 0, 1, 0, 1, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 0,
             0, 0, 0, 1, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0,
             1, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 0, 0, 0, 1, 1, 0, 0, 0,
             1, 0, 1, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 1])
```

908

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0.2 Avaliando os resultados

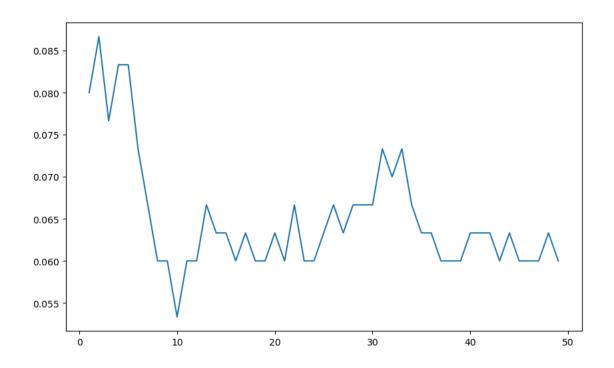
```
[49]: from sklearn.metrics import classification_report, confusion_matrix
[50]: print(confusion_matrix(y_test, predicao))
     [[147 14]
      [ 10 129]]
[51]: prob=(147+129)/(24)
[52]: prob
[52]: 11.5
[53]: print(classification_report(y_test, predicao))
                                 recall f1-score
                   precision
                                                    support
                0
                        0.94
                                   0.91
                                             0.92
                                                        161
                                   0.93
                1
                         0.90
                                             0.91
                                                        139
                                             0.92
                                                        300
         accuracy
                                             0.92
        macro avg
                        0.92
                                   0.92
                                                        300
     weighted avg
                         0.92
                                   0.92
                                             0.92
                                                        300
     0.3 Técnica do Cotovelo
[54]: error_rate = []
      for i in range(1, 50):
          KNN = KNeighborsClassifier(n_neighbors= i)
          KNN.fit(X_train, y_train)
          preditor_i = KNN.predict(X_test)
```

[56]: [<matplotlib.lines.Line2D at 0x7fc4cae473a0>]

plt.plot(range(1, 50), error_rate)

[56]: plt.figure(figsize=(10,6))

error_rate.append(np.mean(preditor_i != Y_test))



```
[63]: KNN = KNeighborsClassifier(n_neighbors=8)
      KNN.fit(X_train, y_train)
      predicao = KNN.predict(X_test)
      print(confusion_matrix(y_test, predicao))
      print(classification_report(y_test, predicao))
     [[151 10]
      [ 8 131]]
                   precision
                                                     support
                                 recall f1-score
                0
                         0.95
                                   0.94
                                             0.94
                                                         161
                         0.93
                                   0.94
                                             0.94
                                                         139
                                             0.94
                                                         300
         accuracy
        macro avg
                         0.94
                                   0.94
                                             0.94
                                                         300
     weighted avg
                         0.94
                                   0.94
                                             0.94
                                                         300
```

0.4 Criando um grid de busca de parametros para KNN

```
[64]: from sklearn.model_selection import GridSearchCV

[65]: k_list = list(range(1,30))
   weight_list = ['uniform', 'distance']
   p_list=[1, 2]
```

```
[66]: parametros = dict(n_neighbors=k_list, weights = weight_list, p = p_list)
     grid = GridSearchCV(KNN, parametros, cv=5, scoring='accuracy')
[67]:
      grid.fit(dados, data['TARGET CLASS'])
[68]:
[68]: GridSearchCV(cv=5, estimator=KNeighborsClassifier(n neighbors=8),
                   param grid={'n neighbors': [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12,
                                               13, 14, 15, 16, 17, 18, 19, 20, 21, 22,
                                               23, 24, 25, 26, 27, 28, 29],
                               'p': [1, 2], 'weights': ['uniform', 'distance']},
                   scoring='accuracy')
[69]:
     grid.cv_results_
[69]: {'mean_fit_time': array([0.00256987, 0.00158482, 0.00161514, 0.00160398,
      0.00153265,
              0.00170612, 0.00157261, 0.00155387, 0.0016531, 0.00157886,
              0.00158052, 0.00151086, 0.00161533, 0.00160589, 0.00166326,
              0.00155201, 0.0018312, 0.00145826, 0.00162272, 0.00158086,
              0.00167294, 0.00145693, 0.00166698, 0.00160575, 0.00153966,
              0.0014771 , 0.00154181, 0.00157194, 0.00149183, 0.00142994,
              0.0014338 , 0.00144963, 0.00152264, 0.00159183, 0.0014524 ,
              0.00150628, 0.001477, 0.00144978, 0.00149322, 0.00151243
              0.00151029, 0.00157022, 0.00164232, 0.00162706, 0.00162735,
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       0.91 , 0.905, 0.905, 0.93 , 0.93 , 0.915, 0.915, 0.92 , 0.91 ,
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       0.92 , 0.92 , 0.94 , 0.93 , 0.93 , 0.92 , 0.935, 0.935, 0.92 ,
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       0.93, 0.935, 0.92, 0.935, 0.93, 0.945, 0.925, 0.93, 0.94,
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       0.935, 0.945, 0.935, 0.94 , 0.935, 0.935, 0.935, 0.935, 0.94 ,
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       0.96, 0.96, 0.965, 0.965, 0.965, 0.96, 0.955, 0.96, 0.97,
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       0.96 , 0.975, 0.97 , 0.97 , 0.96 , 0.96 , 0.965, 0.97 , 0.97 ,
       0.965, 0.965, 0.97, 0.965, 0.97, 0.97, 0.97, 0.96, 0.965,
       0.975, 0.97 , 0.96 , 0.965, 0.97 , 0.97 , 0.955, 0.965, 0.97 ,
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[70]: print("Melhores parametros {} com valor de acuracia {}".format(grid.
       ⇒best_params_, grid.best_score_))
```

Melhores parametros {'n_neighbors': 24, 'p': 1, 'weights': 'uniform'} com valor de acuracia 0.944

Parametros importantes em KNN:

- n neighbors= Numero de vizinhos;
- weights= Peso da amostra dos vizinhos (padrão = uniform);
- metric= Métrica usada para o calculo da distância (padrão = minkowski);

- \mathbf{p} = Parâmetro de poder da métrica (padrão = 2);
- $\mathbf{n}_{\mathbf{jobs}} = \text{Número de threads que podem ser paralelizados durante a busca dos vizinhos (padrão = 1).}$

[]: