Logistic Regression Implementation with IRIS dataset

February 29, 2024

1 Logistic Regression Implementation

```
[1]: from sklearn.datasets import load_iris
[2]: dataset=load_iris()
[4]: print(dataset.DESCR)
    .. _iris_dataset:
   Iris plants dataset
   **Data Set Characteristics:**
       :Number of Instances: 150 (50 in each of three classes)
       :Number of Attributes: 4 numeric, predictive attributes and the class
       :Attribute Information:
           - sepal length in cm
          - sepal width in cm
           - petal length in cm
           - petal width in cm
           - class:
                  - Iris-Setosa
                  - Iris-Versicolour
                  - Iris-Virginica
       :Summary Statistics:
       SD
                     Min Max
                               Mean
                                          Class Correlation
       ____________
       sepal length:
                     4.3 7.9
                               5.84
                                     0.83
                                            0.7826
       sepal width:
                     2.0 4.4
                               3.05
                                     0.43
                                           -0.4194
       petal length:
                     1.0 6.9
                               3.76
                                     1.76
                                            0.9490
                                                   (high!)
       petal width:
                     0.1 2.5
                               1.20
                                     0.76
                                            0.9565
                                                    (high!)
```

:Missing Attribute Values: None

:Class Distribution: 33.3% for each of 3 classes.

:Creator: R.A. Fisher

:Donor: Michael Marshall (MARSHALL%PLU@io.arc.nasa.gov)

:Date: July, 1988

The famous Iris database, first used by Sir R.A. Fisher. The dataset is taken from Fisher's paper. Note that it's the same as in R, but not as in the UCI Machine Learning Repository, which has two wrong data points.

This is perhaps the best known database to be found in the pattern recognition literature. Fisher's paper is a classic in the field and is referenced frequently to this day. (See Duda & Hart, for example.) The data set contains 3 classes of 50 instances each, where each class refers to a type of iris plant. One class is linearly separable from the other 2; the latter are NOT linearly separable from each other.

.. topic:: References

- Fisher, R.A. "The use of multiple measurements in taxonomic problems" Annual Eugenics, 7, Part II, 179-188 (1936); also in "Contributions to Mathematical Statistics" (John Wiley, NY, 1950).
- Duda, R.O., & Hart, P.E. (1973) Pattern Classification and Scene Analysis. (Q327.D83) John Wiley & Sons. ISBN 0-471-22361-1. See page 218.
- Dasarathy, B.V. (1980) "Nosing Around the Neighborhood: A New System Structure and Classification Rule for Recognition in Partially Exposed Environments". IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. PAMI-2, No. 1, 67-71.
- Gates, G.W. (1972) "The Reduced Nearest Neighbor Rule". IEEE Transactions on Information Theory, May 1972, 431-433.
- See also: 1988 MLC Proceedings, 54-64. Cheeseman et al"s AUTOCLASS II conceptual clustering system finds 3 classes in the data.
- Many, many more ...
- [8]: dataset.keys()
- [8]: dict_keys(['data', 'target', 'frame', 'target_names', 'DESCR', 'feature_names', 'filename', 'data_module'])
- [5]: import pandas as pd import numpy as np
- [12]: df=pd.DataFrame(dataset.data,columns=dataset.feature_names)
- [13]: df.head()

```
[13]:
     sepal length (cm) sepal width (cm) petal length (cm) petal width (cm)
                                        1.4
                                                    0.2
   0
               5.1
                           3.5
               4.9
                                        1.4
                                                    0.2
   1
                           3.0
    2
               4.7
                           3.2
                                        1.3
                                                    0.2
    3
                                        1.5
               4.6
                           3.1
                                                    0.2
    4
               5.0
                           3.6
                                        1.4
                                                    0.2
[16]: df['target']=dataset.target
[19]: df.head()
[19]:
     sepal length (cm) sepal width (cm) petal length (cm) petal width (cm) \
               5.1
                           3.5
                                        1.4
                                                    0.2
               4.9
                           3.0
                                        1.4
                                                    0.2
    1
               4.7
    2
                           3.2
                                        1.3
                                                    0.2
    3
               4.6
                           3.1
                                        1.5
                                                    0.2
               5.0
                           3.6
                                        1.4
                                                    0.2
     target
    0
         0
    1
         0
    2
         0
    3
         0
         0
[20]: dataset.target
1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
        [23]: ## binary classification
    df_copy=df[df['target']!=2]
[26]: df_copy.head()
[26]:
     sepal length (cm) sepal width (cm) petal length (cm) petal width (cm)
    0
               5.1
                           3.5
                                        1.4
                                                    0.2
    1
               4.9
                           3.0
                                        1.4
                                                    0.2
    2
               4.7
                           3.2
                                        1.3
                                                    0.2
    3
               4.6
                           3.1
                                        1.5
                                                    0.2
    4
               5.0
                                        1.4
                                                    0.2
                           3.6
```

```
0
              0
              0
      1
      2
              0
      3
              0
              0
     1.1 independent and dependent features
[51]: x=df_copy.iloc[:,:-1]
      y=df_copy.iloc[:,-1]
[52]: from sklearn.linear_model import LogisticRegression
     1.2 train test split
[53]: from sklearn.model_selection import train_test_split
      x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.
       →33, random_state=42)
[54]: classifier=LogisticRegression()
[55]: classifier.fit(x_train,y_train)
[55]: LogisticRegression()
     1.3 prediction
[56]: | y_pred=classifier.predict(x_test)
[57]: y_pred
[57]: array([1, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 1, 1, 0, 0, 1, 1,
             0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 1])
[60]: y_test
[60]: 83
      53
            1
      70
            1
      45
            0
      44
            0
      39
            0
      22
```

target

80

```
10
      0
0
       0
18
      0
30
      0
73
       1
33
      0
90
       1
4
      0
76
       1
77
       1
12
      0
31
      0
55
       1
88
       1
26
      0
42
      0
69
      1
15
      0
40
      0
96
       1
9
      0
72
      1
11
      0
47
      0
85
       1
Name: target, dtype: int64
```

weighted avg

1.00

1.4 confusion matrix, accuracy score, classification report

1.00

```
[58]: from sklearn.metrics import
       Genfusion_matrix,accuracy_score,classification_report
[61]: print(confusion_matrix(y_pred,y_test))
      print(accuracy_score(y_pred,y_test))
      print(classification_report(y_pred,y_test))
     [[19 0]
      [ 0 14]]
     1.0
                   precision
                                recall f1-score
                                                    support
                0
                        1.00
                                   1.00
                                             1.00
                                                         19
                1
                        1.00
                                   1.00
                                             1.00
                                                         14
                                             1.00
         accuracy
                                                         33
        macro avg
                        1.00
                                   1.00
                                             1.00
                                                         33
```

1.00

```
[62]: classifier.predict_proba(x_test)
[62]: array([[0.00144451, 0.99855549],
             [0.01745661, 0.98254339],
             [0.00359664, 0.99640336],
             [0.96427472, 0.03572528],
             [0.93476204, 0.06523796],
             [0.96670676, 0.03329324],
             [0.99197567, 0.00802433],
             [0.03414716, 0.96585284],
             [0.97022597, 0.02977403],
             [0.97501069, 0.02498931],
             [0.94876941, 0.05123059],
             [0.95432911, 0.04567089],
             [0.00502877, 0.99497123],
             [0.98309763, 0.01690237],
             [0.01045624, 0.98954376],
             [0.97788605, 0.02211395],
             [0.00251305, 0.99748695],
             [0.00154296, 0.99845704],
             [0.96995374, 0.03004626],
             [0.95518866, 0.04481134],
             [0.00835685, 0.99164315],
             [0.02378303, 0.97621697],
             [0.95343728, 0.04656272],
             [0.98084327, 0.01915673],
             [0.02881772, 0.97118228],
             [0.97696692, 0.02303308],
             [0.97878312, 0.02121688],
             [0.01706457, 0.98293543],
             [0.96440543, 0.03559457],
             [0.0018048, 0.9981952],
             [0.96391062, 0.03608938],
             [0.97430387, 0.02569613],
             [0.00915764, 0.99084236]])
```

1.5 hyperparameter tuning grid search CV

```
[63]: from sklearn.model_selection import GridSearchCV
import warnings
warnings.filterwarnings('ignore')

[69]: parameter={'penalty':('ll','l2','elasticnet',None),'C':[1,10,20]}
[70]: clf=GridSearchCV(classifier,param_grid=parameter,cv=5)
```

```
[71]: ## splitting of train data to calidation data
      clf.fit(x_train,y_train)
[71]: GridSearchCV(cv=5, estimator=LogisticRegression(),
                   param_grid={'C': [1, 10, 20],
                               'penalty': ('11', '12', 'elasticnet', None)})
[72]: clf.best_params_
[72]: {'C': 1, 'penalty': '12'}
[74]: classifier=LogisticRegression(C=1,penalty='12')
[75]: classifier.fit(x_train,y_train)
[75]: LogisticRegression(C=1)
[76]: y_pred=classifier.predict(x_test)
[77]: print(confusion_matrix(y_pred,y_test))
      print(accuracy_score(y_pred,y_test))
      print(classification_report(y_pred,y_test))
     [[19 0]
      [ 0 14]]
     1.0
                   precision
                                recall f1-score
                                                    support
                0
                                   1.00
                         1.00
                                             1.00
                                                         19
                1
                         1.00
                                   1.00
                                             1.00
                                                         14
                                             1.00
                                                         33
         accuracy
                                             1.00
                                                         33
        macro avg
                         1.00
                                   1.00
     weighted avg
                         1.00
                                   1.00
                                             1.00
                                                         33
     1.6 randomized search cv
[78]: from sklearn.model_selection import RandomizedSearchCV
[79]: random_clf=RandomizedSearchCV(LogisticRegression(),param_distributions=parameter,cv=5)
[80]: random_clf.fit(x_train,y_train)
[80]: RandomizedSearchCV(cv=5, estimator=LogisticRegression(),
                         param_distributions={'C': [1, 10, 20],
```

```
[81]: random_clf.best_params_
[81]: {'penalty': None, 'C': 20}
[87]: random_clf=LogisticRegression(C=20,penalty=None)
[89]: random_clf.fit(x_train,y_train)
[89]: LogisticRegression(C=20, penalty=None)
[90]: y_pred=random_clf.predict(x_test)
[91]: print(confusion_matrix(y_pred,y_test))
      print(accuracy_score(y_pred,y_test))
      print(classification_report(y_pred,y_test))
     [[19 0]
      [ 0 14]]
     1.0
                   precision
                                recall f1-score
                                                    support
                         1.00
                                   1.00
                                             1.00
                0
                                                         19
                         1.00
                                   1.00
                                             1.00
                                                         14
                                             1.00
                                                         33
         accuracy
        macro avg
                         1.00
                                   1.00
                                             1.00
                                                         33
     weighted avg
                         1.00
                                   1.00
                                             1.00
                                                         33
 []:
```

'penalty': ('11', '12', 'elasticnet',

None)})