## RedesNeuronales BreastCancer

July 23, 2022

```
[1]: #Usando un dataset de sklearn
     from sklearn.datasets import load_breast_cancer
     cancer = load_breast_cancer()
[2]: cancer.keys()
[2]: dict_keys(['data', 'target', 'frame', 'target_names', 'DESCR', 'feature_names',
     'filename', 'data_module'])
[3]: print(cancer['DESCR'])
    .. _breast_cancer_dataset:
    Breast cancer wisconsin (diagnostic) dataset
    **Data Set Characteristics:**
        :Number of Instances: 569
        :Number of Attributes: 30 numeric, predictive attributes and the class
        :Attribute Information:
            - 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)
            The mean, standard error, and "worst" or largest (mean of the three
            worst/largest values) of these features were computed for each image,
            resulting in 30 features. For instance, field 0 is Mean Radius, field
            10 is Radius SE, field 20 is Worst Radius.
```

## - class:

- WDBC-Malignant
- WDBC-Benign

## :Summary Statistics:

	=====	=====
	Min =====	Max =====
radius (mean):	6.981	28.11
texture (mean):	9.71	39.28
perimeter (mean):	43.79	188.5
area (mean):	143.5	2501.0
<pre>smoothness (mean):</pre>	0.053	0.163
compactness (mean):	0.019	0.345
concavity (mean):	0.0	0.427
concave points (mean):	0.0	0.201
<pre>symmetry (mean):</pre>	0.106	0.304
fractal dimension (mean):	0.05	0.097
radius (standard error):	0.112	2.873
texture (standard error):	0.36	4.885
perimeter (standard error):	0.757	21.98
area (standard error):	6.802	542.2
<pre>smoothness (standard error):</pre>	0.002	0.031
compactness (standard error):	0.002	0.135
concavity (standard error):	0.0	0.396
concave points (standard error):	0.0	0.053
symmetry (standard error):	0.008	0.079
fractal dimension (standard error):	0.001	0.03
radius (worst):	7.93	36.04
texture (worst):	12.02	49.54
perimeter (worst):	50.41	251.2
area (worst):	185.2	4254.0
<pre>smoothness (worst):</pre>	0.071	0.223
compactness (worst):	0.027	1.058
<pre>concavity (worst):</pre>	0.0	1.252
concave points (worst):	0.0	0.291
symmetry (worst):	0.156	0.664
fractal dimension (worst):	0.055	0.208

:Missing Attribute Values: None

:Class Distribution: 212 - Malignant, 357 - Benign

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:Donor: Nick Street

:Date: November, 1995

This is a copy of UCI ML Breast Cancer Wisconsin (Diagnostic) datasets. https://goo.gl/U2Uwz2

Features are computed from a digitized image of a fine needle aspirate (FNA) of a breast mass. They describe characteristics of the cell nuclei present in the image.

Separating plane described above was obtained using Multisurface Method-Tree (MSM-T) [K. P. Bennett, "Decision Tree Construction Via Linear Programming." Proceedings of the 4th Midwest Artificial Intelligence and Cognitive Science Society, pp. 97-101, 1992], a classification method which uses linear programming to construct a decision tree. Relevant features were selected using an exhaustive search in the space of 1-4 features and 1-3 separating planes.

The actual linear program used to obtain the separating plane in the 3-dimensional space is that described in:
[K. P. Bennett and O. L. Mangasarian: "Robust Linear Programming Discrimination of Two Linearly Inseparable Sets", Optimization Methods and Software 1, 1992, 23-34].

This database is also available through the UW CS ftp server:

ftp ftp.cs.wisc.edu
cd math-prog/cpo-dataset/machine-learn/WDBC/

- .. topic:: References
  - W.N. Street, W.H. Wolberg and O.L. Mangasarian. Nuclear feature extraction for breast tumor diagnosis. IS&T/SPIE 1993 International Symposium on Electronic Imaging: Science and Technology, volume 1905, pages 861-870, San Jose, CA, 1993.
- O.L. Mangasarian, W.N. Street and W.H. Wolberg. Breast cancer diagnosis and prognosis via linear programming. Operations Research, 43(4), pages 570-577,

July-August 1995.

- W.H. Wolberg, W.N. Street, and O.L. Mangasarian. Machine learning techniques
- to diagnose breast cancer from fine-needle aspirates. Cancer Letters 77 (1994)

163-171.

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[4]: cancer['data'].shape
[4]: (569, 30)
     cancer['target']
0, 0, 1, 0, 1, 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, 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, 1, 0, 0, 0, 1, 0, 0, 1, 1, 1, 0, 0, 1, 0, 1, 0,
            0, 1, 0, 0, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1,
            1, 1, 0, 1, 1, 1, 1, 0, 0, 1, 0, 1, 1, 0, 0, 1, 1, 0, 0, 1, 1, 1,
            1, 0, 1, 1, 0, 0, 0, 1, 0, 1, 0, 1, 1, 1, 0, 1, 1, 0, 0, 1, 0, 0,
            0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 1, 1, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0,
            1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 0, 1, 1,
            1, 1, 0, 1, 1, 1, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
            0, 0, 1, 1, 1, 1, 1, 0, 1, 0, 1, 1, 0, 1, 1, 0, 1, 0, 0, 1, 1,
            1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1,
            1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1, 0, 0,
            0, 1, 1, 1, 1, 0, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0,
            0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0,
            1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 0, 0, 1, 1,
            1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 0,
            1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 0, 1, 0, 1, 1, 1, 1,
            1, 0, 1, 1, 0, 1, 0, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0,
            1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1,
            1, 1, 1, 0, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 0, 0, 1, 0, 1, 0, 1, 1,
            1, 1, 1, 0, 1, 1, 0, 1, 0, 1, 0, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1,
            1, 1, 1, 1, 1, 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])
[6]: X = cancer['data']
     y = cancer['target']
[8]: #Dividiendo el dataset en test y train
     from sklearn.model selection import train test split
     X_train, X_test, y_train, y_test = train_test_split(X, y)
[9]: #Escalar o normalizar los datos
     from sklearn.preprocessing import StandardScaler
     scaler = StandardScaler()
[10]:
     scaler.fit(X_train)
[10]: StandardScaler()
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[11]: #Aplico las escalas a mis matrices de prueba y de entrenamiento
      X_train = scaler.transform(X_train)
      X_test = scaler.transform(X_test)
[12]: from sklearn.neural_network import MLPClassifier
[47]: mlp = MLPClassifier(hidden_layer_sizes=(30,30,30))
[48]: mlp.fit(X_train,y_train)
[48]: MLPClassifier(hidden_layer_sizes=(30, 30, 30))
[49]: predictions = mlp.predict(X_test)
[50]: predictions
[50]: array([0, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1,
             1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 0, 1, 0,
             1, 0, 1, 1, 0, 1, 0, 0, 1, 1, 0, 0, 1, 1, 1, 1, 0, 0, 1, 1, 0, 1,
             1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 0, 0, 1, 1, 1,
             1, 1, 1, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 1, 1, 0, 1, 1, 1, 0,
             1, 0, 1, 1, 0, 1, 1, 1, 1, 0, 0, 0, 1, 1, 0, 1, 0, 1, 1, 0, 1, 0,
             1, 1, 0, 1, 1, 1, 1, 1, 1, 1])
[51]: from sklearn.metrics import classification_report,confusion_matrix
      print(confusion_matrix(y_test,predictions))
     [[44 4]
      [ 1 94]]
[52]: print(classification_report(y_test,predictions))
                   precision
                                recall f1-score
                                                    support
                0
                        0.98
                                  0.92
                                             0.95
                                                         48
                        0.96
                                   0.99
                1
                                             0.97
                                                         95
         accuracy
                                             0.97
                                                        143
                                             0.96
                                                        143
        macro avg
                        0.97
                                   0.95
     weighted avg
                        0.97
                                  0.97
                                             0.96
                                                        143
[53]: len(mlp.coefs_)
[53]: 4
[54]: len(mlp.coefs_[0])
```

```
[54]: 30
[55]: mlp.coefs_[2][0]
[55]: array([ 0.02649176,
                          0.07576368, -0.26347864, 0.26009984, 0.16896324,
            -0.00568182,
                          0.38496177, 0.2343002, -0.33853773, -0.03478244,
                          0.19624081, 0.02597124, 0.08651019, -0.12874235,
            -0.39648703,
            -0.16285953, -0.06039748, 0.36268687, -0.26692377, 0.08628026,
             0.10122928, -0.31609615, 0.05091023, 0.30757692, 0.20159838,
            -0.19438663, -0.07167765, 0.17924593, -0.25656975, 0.17404835])
[56]: len(mlp.intercepts_)
[56]: 4
[26]: mlp.intercepts_[0][0]
[26]: 0.1356307959371096
 []:
```