```
# R L B P
# What is Logistic Regression?
# A regression algorithm which does classification
# Calculates probability of belonging to a particular class
# p > 50 % -> 1
# p < 50 % -> 0
# Train a logistic regression classfier
# to predict whether a flower is iris virginica or not
from sklearn import datasets
import numpy as np
from sklearn.linear_model import LogisticRegression
import matplotlib.pyplot as plt
iris = datasets.load_iris()
print(list(iris.keys()))
print(iris['data'])
print(iris['target'])
print(iris['DESCR'])
```

 $\overline{2}$

: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.

.. dropdown:: 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 ...

```
print(iris['data'].shape)
```

→ (150, 4)

```
X = iris["data"][:, 3:]
print(iris["data"])
print(X)
```

 $\overline{2}$

```
[1./]
[1.8]
[1.8]
[2.5]
[2.]
[1.9]
[2.1]
[2.]
[2.4]
[2.3]
[1.8]
[2.2]
[2.3]
[1.5]
[2.3]
[2.]
[2.]
[1.8]
[2.1]
[1.8]
[1.8]
[1.8]
[2.1]
[1.6]
[1.9]
[2.]
[2.2]
[1.5]
[1.4]
[2.3]
[2.4]
[1.8]
[1.8]
[2.1]
[2.4]
[2.3]
[1.9]
[2.3]
[2.5]
[2.3]
[1.9]
[2.]
[2.3]
[1.8]]
```

y = (iris["target"]==2)
print(y)

False False

```
# Train a logistic regression classifier
clf = LogisticRegression()
clf.fit(X,y)
```

```
LogisticRegression ()
```

```
example =clf.predict([[2.6]])
print(example)
```

```
→ [ True]
```

```
# Using matplotlib to plot the visualization
X_new = np.linspace(0,3,1000).reshape(1,-1)
print(X_new)
```

 $\overline{\mathbf{T}}$

```
2.4044040 2.40345345 2.40640640 2.45945940 2.46246246 2.4654654/
2.46846847 2.47147147 2.47447447 2.47747748 2.48048048 2.48348348
2.48648649 2.48948949 2.49249249 2.4954955 2.4984985 2.5015015
2.5045045 2.50750751 2.51051051 2.51351351 2.51651652 2.51951952
2.5225252 2.52552553 2.52852853 2.53153153 2.53453453 2.53753754
2.54054054 2.54354354 2.54654655 2.54954955 2.55255255 2.5555556
2.55855856 2.56156156 2.56456456 2.56756757 2.57057057 2.57357357
2.57657658 2.57957958 2.58258258 2.58558559 2.58858859 2.59159159
2.59459459 2.5975976 2.6006006 2.6036036 2.60660661 2.60960961
2.61261261 2.61561562 2.61861862 2.62162162 2.62462462 2.62762763
2.63063063 2.63363363 2.63663664 2.63963964 2.64264264 2.64564565
2.64864865 2.65165165 2.65465465 2.65765766 2.66066066 2.66366366
2.66666667 2.66966967 2.67267267 2.67567568 2.67867868 2.68168168
2.68468468 2.68768769 2.69069069 2.69369369 2.6966967 2.6996997
2.7027027 2.70570571 2.70870871 2.71171171 2.71471471 2.71771772
2.72072072 2.72372372 2.72672673 2.72972973 2.73273273 2.73573574
2.73873874 2.74174174 2.74474474 2.74774775 2.75075075 2.75375375
2.75675676 2.75975976 2.76276276 2.76576577 2.76876877 2.77177177
2.77477477 2.77777778 2.78078078 2.78378378 2.78678679 2.78978979
2.79279279 2.7957958 2.7987988 2.8018018 2.8048048 2.80780781
2.81081081 2.81381381 2.81681682 2.81981982 2.82282282 2.82582583
2.82882883 2.83183183 2.83483483 2.83783784 2.84084084 2.84384384
2.84684685 2.84984985 2.85285285 2.85585586 2.85885886 2.86186186
2.86486486 2.86786787 2.87087087 2.87387387 2.87687688 2.87987988
2.88288288 2.88588589 2.88888889 2.89189189 2.89489489 2.8978979
2.9009009 2.9039039 2.90690691 2.90990991 2.91291291 2.91591592
2.91891892 2.92192192 2.92492492 2.92792793 2.93093093 2.93393393
2.93693694 2.93993994 2.94294294 2.94594595 2.94894895 2.95195195
2.95495495 2.95795796 2.96096096 2.96396396 2.96696697 2.96996997
2.97297297 2.97597598 2.97897898 2.98198198 2.98498498 2.98798799
2.99099099 2.99399399 2.996997
                                 3.
                                           ]]
```

```
X_new = np.linspace(0,3,1000).reshape(-1,1)
y_prob = clf.predict_proba(X_new)
# print(y_proba)
plt.plot(X_new, y_prob[:,1], "g-",label="virginica")
plt.show()
```

```
\overline{2}
      1.0
      0.8
print(y_prob)
[[9.99249051e-01 7.50949397e-04]
      [9.99239224e-01 7.60776030e-04]
      [9.99229269e-01 7.70731151e-04]
      [3.08499021e-03 9.96915010e-01]
      [3.04523414e-03 9.96954766e-01]
      [3.00598887e-03 9.96994011e-01]]
# clf = LogisticRegression()
# clf.fit(X,y)
# Using matplotlib to plot the visualization
# X_new = np.linspace(0,3,1000).reshape(-1.1)
# print(X_new)
Start coding or generate with AI.
```