

ML.py Documentation

CSC 448 Machine Learning Library

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Contents

Perceptron	2
Linear Regression	3
Linear Regression for Polynomials (WIP)	4
Decision Stumps	5
Other Functions	6
Testing	7

Using ML.py

1. Import ML
2. Create class instances and use functions as described on the following pages

Perceptron

The Perceptron class implements the perceptron method of machine learning that consists of making a guess, checking whether a particular point is classified correctly, and adjusting if it isn't. The details behind the idea of a perceptron are available on Wikipedia: <https://en.wikipedia.org/wiki/Perceptron>

Methods

Perceptron()

Parameter	Default	Description
rate	0.01	How much to adjust the guess when a point is misclassified
niter	10	Number of iterations

Perceptron.fit()

Parameter	Default	Description
X		Training input
y		Outputs associated with training input

Adjusts the class's weights based on the given training data, using the Perceptron algorithm

Perceptron.net_input()

Parameter	Default	Description
X		Input to predict

Returns the raw (not restricted to {-1, 1}) prediction of the given input(s)

Perceptron.predict()

Parameter	Default	Description
X		Input to predict

Returns the predicted label (either -1 or 1) of the given input(s)

Example Usage

```
import pandas as pd, numpy as np
from ML import Perceptron
df = pd.read_csv('https://archive.ics.uci.edu/ml/machine-learning-
                  'databases/iris/iris.data', header=None)
y = df.iloc[0:100, 4].values
y = np.where(y == 'Iris-setosa', -1, 1)

X = df.iloc[0:100, [0, 2]].values

pn = Perceptron(0.1, 10)
pn.fit(X, y)

print(pn.weight)
print(pn.errors)
```

Returns:

```
[-0.4 -0.68 1.82]
[2. 2. 3. 2. 1. 0. 0. 0. 0. 0.]
```

Linear Regression

The `LinearRegression` class implements the linear regression method of machine learning with the least squares algorithm. The theory behind the method involves some linear algebra, but it boils down to the following equation, where X and y are the sample inputs and outputs respectively:

$$\vec{\beta} = (X^T X)^{-1} X^T \vec{y}$$

This gives $\vec{\beta}$, which is the least squares solution to

$$\vec{y} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots$$

Further details behind the idea of least squares are available on Wikipedia:

https://en.wikipedia.org/wiki/Ordinary_least_squares

Methods

`LinearRegression.fit()`

Parameter	Default	Description
X		Training input
y		Outputs associated with training input

Adjusts the class's weights based on the given training data, using the Least Squares algorithm

Example Usage

```
import pandas as pd, numpy as np
from ML import Perceptron
lr = LinearRegression()

X = np.array([0, 1, 2, 3, 4])
y = np.array([4, 6, 8, 10, 12])
lr.fit(X, y)
print(lr.weight)
```

Returns:

```
[4, 2]
```

which represents $y = 4 + 2x$

Linear Regression for Polynomials

<Description for Polynomial Linear Regression will be available by the end of the semester>

Decision Stumps

The `DecisionStumps` class implements an empirical risk minimization for decision stumps. A decision stump is a machine learning model consisting of a one-level decision tree. In other words, it asks if a specific feature of a given datapoint is above or below a certain threshold and classifies into one of two classes based only on that.

Methods

`DecisionStumps.ERM()`

Parameter	Default	Description
X		Training input
y		Outputs associated with training input
D		Probability vector

Adjusts the class's weights based on the given training data, using the Least Squares algorithm

Some notes on the inputs:

$X[i][j]$ = the i 'th coordinate of the j 'th input point.

y should be decreasing – that is, y should be any number of 1's followed by any number of -1's. It is valid for y to be all 1's or all -1's.

$D[i]$ = the probability of the i 'th point in X to appear.

Example Usage

```
import pandas as pd, numpy as np
from ML import DecisionStump

ds = DecisionStump()

# Notice only the second coordinate changes, and y = -1 when X[1] > 2.5
X = np.array([[5, 5, 5, 5, 5], [0, 1, 2, 3, 4], [1, 1, 1, 1, 1]])
y = np.array([1, 1, 1, -1, -1])

resp = ds.ERM(X, y, [0.2]*5)
print(resp)
```

Returns:

```
(1, 2.5)
```

which represents the question “Is $x[1] > 2.5$?”

Other Functions

`plot_decision_regions()`

Parameter	Default	Description
X		Input data, ideally from the same source that training data was taken from
y		Output values associated with the input data
classifier		The class used to classify the data. Requires a “predict” class method
resolution	0.02	How accurate the dividing line will be. Lower number = more accurate

Given a classifier and a training set with two real inputs and one output with five or fewer possible values, this function will display which values will be given to points across the plane.

Testing

See `unittests.py` for tests involving each module. This is also a good source of sample code, to see how each module is used.