

# ML Laboratory 02: Logistic Regression

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## 1 Objective

Students should understand and be able use a logistic regression model in Matlab

## 2 Theoretical aspects

Logistic regression is a widely used model for estimating probabilities (e.g. values between 0 and 1). It is also widely used for **binary classification**.

### 2.1 Logistic regression: the model

We have an input vector  $x$  and a predicted value  $y$ :

$$X = [x_1 \ x_2 \ \dots \ x_N] \rightarrow y$$

The logistic regression model: the output is assumed to be a the **sigmoid function** applied to a **linear combination** of the inputs. The sigmoid function is also known as the **logistic function**, hence the name.

$$y \approx \frac{1}{1 + e^{-w_1x_1 - w_2x_2 - \dots - w_Nx_N - b}}.$$

This can be understood as a **sequence of two steps**:

1. Compute a **linear combination**  $z$  of the inputs:

$$z = w_1x_1 + w_2x_2 + \dots + w_Nx_N + b$$

2. Pass  $z$  through the **sigmoid** function  $\sigma(z)$ :

$$y = \frac{1}{1 + e^{-z}}$$

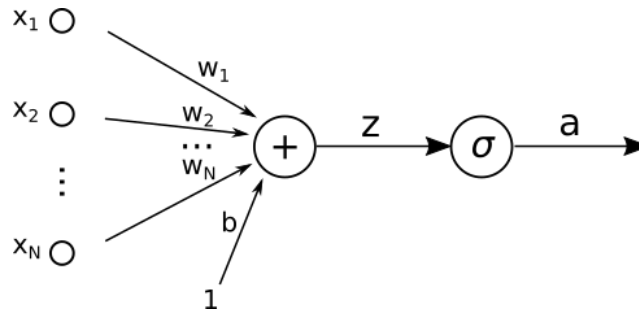


Figure 1: Logistic regression as 1 neuron

Both steps can be represented as one “neuron” like this:

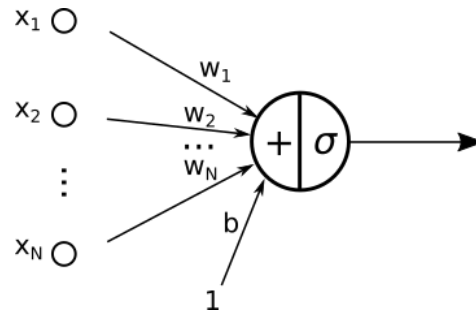


Figure 2: Logistic regression as 1 neuron

## 2.2 The sigmoid function

Let's take a look at the sigmoid function  $\sigma(z)$ :

**Notes:**

- The output value is always between 0 and 1. This makes the result good for modeling **probabilities**, but not good for other types of numeric values.
- The sigmoid can be understood as follows:
  - when  $z$  is much bigger than 0, the result is practically 1
  - when  $z$  is much smaller than 0, the result is practically 0
  - when  $z$  is around 0, there is a “transition zone” from 0 to 1. In particular, when  $z = 0$ , the output is right at the middle,  $\sigma(0) = 0.5$ .

This makes it similar to classification:

- if  $z$  much larger than 0, data belongs almost surely to class 1;
- if  $z$  much smaller than 0, data belongs almost surely to class 0;
- $z = 0$  is the frontier. Around the frontier, we have less confidence in the classification (a sort of “gray area”).

## 2.3 Logistic regression: the parameters

The parameters of the logistic regression model are similar to those of linear regression:

- the **weights**  $w_1, w_2, \dots, w_N$ , and
- the **bias** value  $b$  (also known as the **intercept**).

In a similar way to linear regression, we can consider  $b$  as just another weight  $w_i$  which multiplies a constant input of 1. In this way, we can compute  $z$  as the inner product of two vectors:

$$z = w_1x_1 + w_2x_2 + \dots + w_Nx_N + b = \begin{bmatrix} x_1 & x_2 & \dots & x_N & 1 \end{bmatrix} \cdot \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_N \\ b \end{bmatrix}$$

## 2.4 Cost function (loss function)

In general, any cost function can be chosen for any model. However, because the outputs are typically understood as **probabilities**, we should use a distance function which is appropriate to probabilities: the cross-entropy (also known as the Kullback-Leibler distance).

The **cross-entropy** loss (cost) function, also known as the **Kullback-Leibler distance**, for a single value  $y$ :

$$L(y, \hat{y}) = -y \log \hat{y} - (1 - y) \log (1 - \hat{y})$$

Usually the true value  $y$  is either 0 or 1 (e.g. in a classification: 0 = cat, 1 = dog). In this case the cross-entropy should be understood as:

$$L(y, \hat{y}) = \begin{cases} -\log(\hat{y}) = \log \frac{1}{\hat{y}}, & \text{when true output is } y = 1; \\ -\log(1 - \hat{y}) = \log \frac{1}{1 - \hat{y}}, & \text{when true output is } y = 0; \end{cases}$$

In both cases, the cost is 0 if  $\hat{y} = y$ , and it is  $\infty$  when  $\hat{y}$  is exactly the opposite, as depicted below:

When there are  $N$  input-output pairs, the overall cost is the average for all:

$$J = \frac{1}{N} \sum_i L(y^i, \hat{y}^i) = \frac{1}{N} \sum_i (-y \log \hat{y} - (1 - y) \log 1 - \hat{y})$$

## 2.5 How to train logistic regression?

**Training** = **learning** = finding good values for the unknown parameters.

There is no closed-form solution. The solution is found using numerical algorithms.

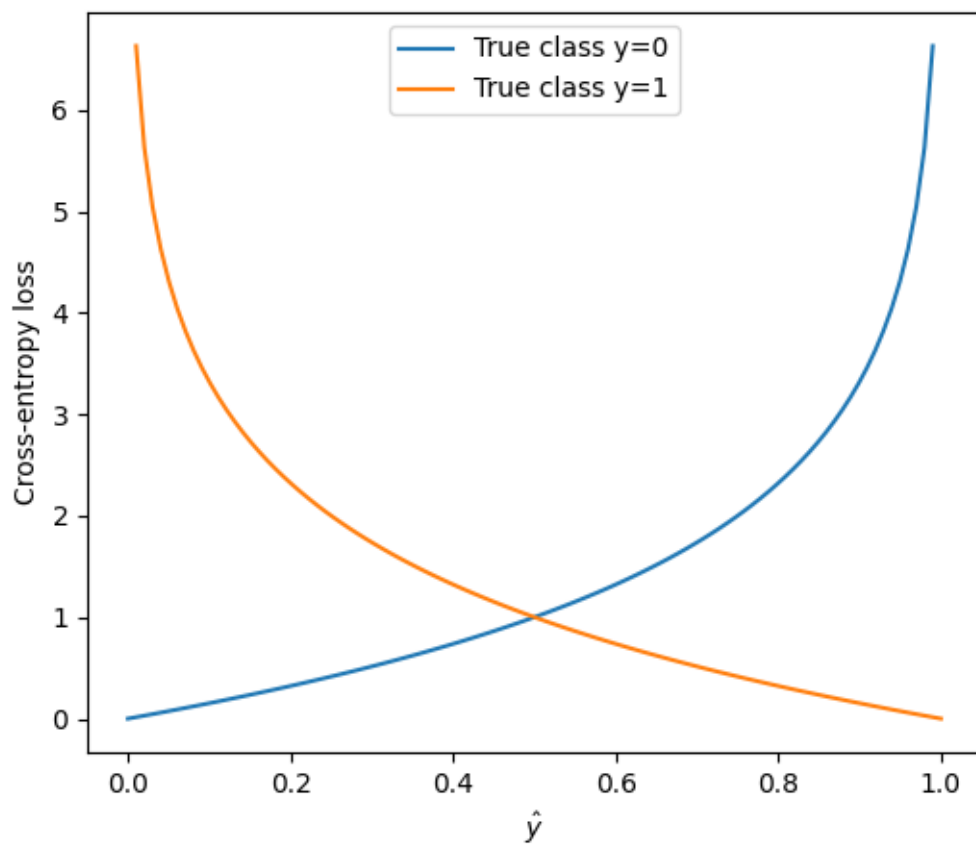


Figure 3: Cross-entropy loss when true class  $y$  is either 0 or 1

## Gradient Descent

We can use the same Gradient Descent approach to train the parameters of the model.

- Initialize parameter vector  $W$  with random values
- Repeat:
  - Compute cost  $J$  (forward pass)
  - Compute the gradient with vector of  $J$  with respect to parameters  $W$ ,  $\frac{dJ}{dW}$
  - Update parameters:  $W = W - \mu \frac{dJ}{dW}$

For the logistic regression with the cross-entropy loss, the gradient is equal to:

$$\frac{dJ}{dW} = X^*(\hat{Y} - Y).$$

(TODO: prove this).

That's right, the gradient of logistic regression with cross-entropy loss is the same as the gradient of linear regression with quadratic loss.

## 3 Logistic Regression in Matlab

### 3.1 Direct implementation example

Below is an example of logistic regression in 2D (there are 2 inputs  $[x_1, x_2]$ ), trained with Gradient Descent.

We have two classes of points:

- one set of points around (0,0)
- another set of points around (2,2)

We want to find the separating line between the two classes.

Each data point has two values  $(x_1, x_2)$ . Since we have two inputs, there will be 3 parameters in the  $W$  vector (including  $b$ ).

**Note:** for a nice graphical animation, please run the code below **directly in Matlab** (file `L2_LogisticRegression_Visualize2D.m`).

```
clear all
close all

% Load some data
```

```

%load('LogisticReg.mat'); % the inputs are X, the outputs are Y
% Generate two clusters of points:
% - one set of points around the point (0,0)
% - second one around the point (2,2)
% - spread of points is 0.5
% - 300 points in each class
[X, Y] = make_data([0,0], [2,2], 0.5, 300)

% Extend X with a column of 1
N = size(X,1);
X = [X, ones(N,1)];

% Initialize the three parameters in W
W = randn(3,1);

% Repeat Gradient Descent iterations
for iter=1:1000
    % Predict
    z = X * W;
    y_pred = 1./(1 + exp(-z));

    % Cost function
    J(iter) = 1/N * sum(-Y .* log(y_pred) - (1-Y) .* log(1-y_pred));

    % Compute gradient (derivatives)
    dW = X' * (y_pred - Y);

    % Update
    mu = 0.0001; % step-size
    W = W - mu*dW; % update rule

    %=====
    % Plotting stuff
    %=====

    % Plot decision boundary
    subplot(1,2,1)
    gscatter(X(:,1),X(:,2),Y)
    title('Data plot');
    hold on

```

```

% Plot decision line on top of points
xx = linspace(-2, 3, 1000);
yy = -W(1)/W(2) * xx - W(3)/W(2);
hold on
plot(xx, yy, 'LineWidth',2);
legend('Class 0', 'Class 1', 'Boundary between classes (output = 0.5)');
hold off
axis([-2, 3, -2, 3])
axis square

% On right side, plot grayscale regions
subplot(1,2,2)
I = zeros(500,500);
x_values = linspace(-2, 3, 500);
y_values = linspace(-2, 3, 500);
for i = 1:length(x_values)
    x = x_values(i);
    for j = 1:length(y_values)
        y = y_values(j);
        % Compute prediction in point (i,j)
        z = [x, y, 1] * W;
        I(501-i,j) = 1 / (1 + exp(-z)); % 0 = black, 1 = white, in-between = gray
    end
end
I = fliplr(flipud(I));
imshow(I);
title('Sigmoid output');
hold on

% Plot line on right side as well
subplot(1,2,2)
xx_rescaled = (xx + 2)*500/5+1;
yy_rescaled = 500 - (yy + 2)*500/5+1;
%plot(xx_rescaled, yy_rescaled, 'LineWidth',2)
plot(xx_rescaled, yy_rescaled, 'LineWidth',2)
hold off
%axis([-2, 3, -2, 3])
axis square

drawnow()

```



```

    %pause(0.1)
    %=====
end

```

## Expected output

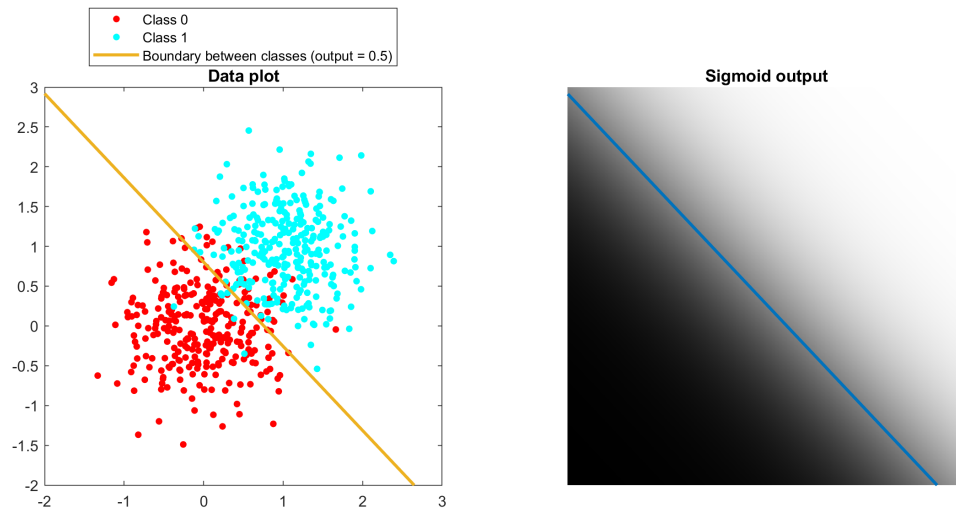


Figure 4: Logistic regression attempts to draw one linear frontier between the classes

## Logistic regression = A separating line

The take-home message from the above example is:

**Logistic regression draws one linear frontier (a “hyperplane”) in the classification space.**

In the following episode we will see how we can combine multiple neurons (multiple hyperplanes) into forming any classification boundary, however complicated.

### 3.2 Matlab's `fitglm()` function'

Logistic regression can be trained in Matlab using the function `fitglm()`, as in the following example:

```
[X, Y] = make_data([0,0], [2,2], 0.5, 300) % points around (0,0) and (2,2), spread=0.5
mdl = fitglm(X, Y, 'Distribution', 'binomial') % X are the inputs, Y is the target vector
```

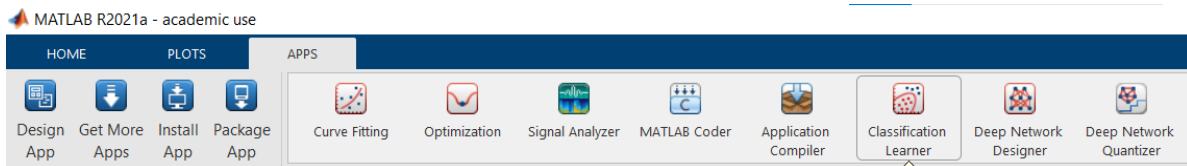
Let's make some predictions with our model:

```
% Predict
mdl.predict([0,0])
mdl.predict([0,0.5])
mdl.predict([3,-1.5])
```

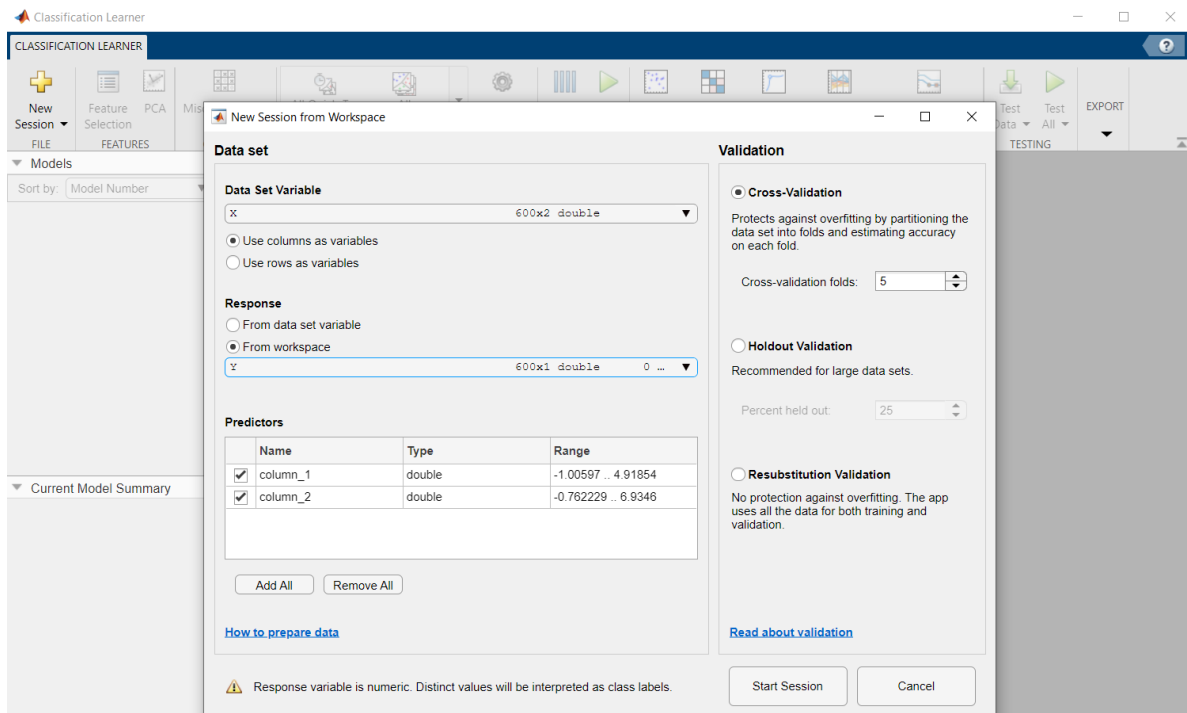
To which class do the previous inputs belong?

### 3.3 Matlab Classification Learner App

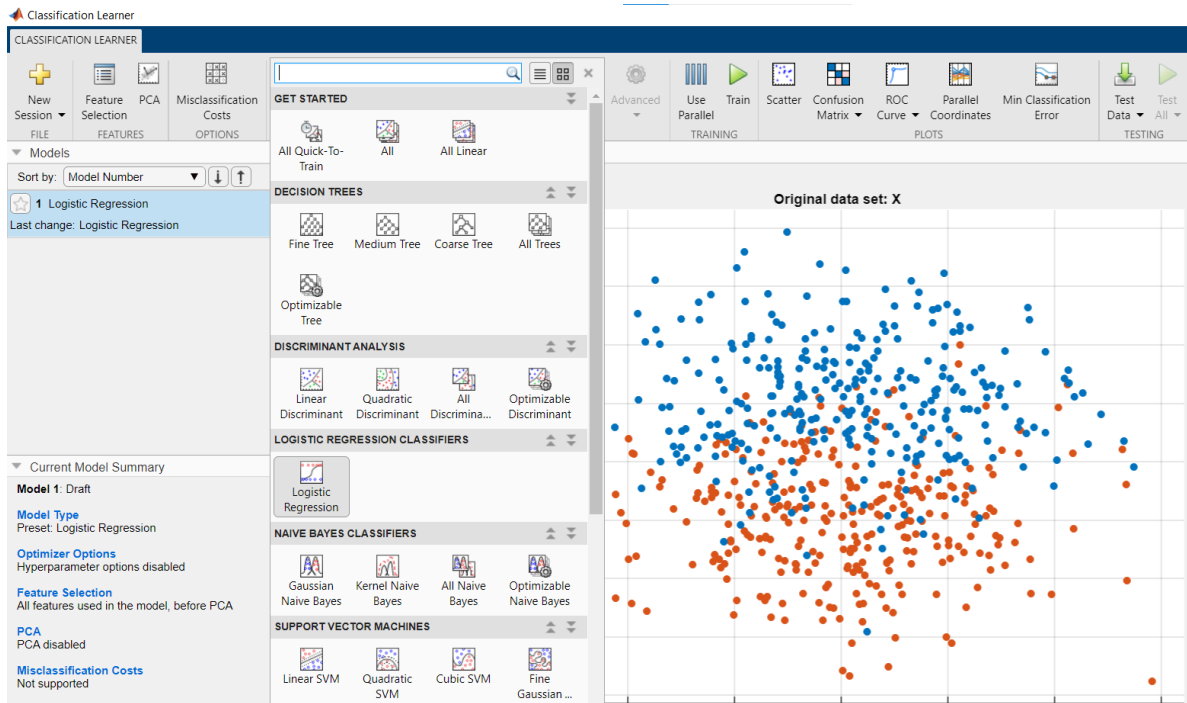
1. Open the GUI tool from the toolbar:



2. Start a new session and specify the input and the output (target) data



3. Click “Start session”
4. From the toolbar select the “Logistic Regression” algorithm



5. Run “Train” to train the model
6. Visualize the outputs: Scatter plot, Confusion matrix, ROC curve
7. Export the model to Matlab’s Workspace, and start using it for predictions

```
% Predict
trainedModel.predictFcn([0,0])
trainedModel.predictFcn([0,0.5])
trainedModel.predictFcn([3,-1.5])
```

You can explore the trained model parameters from the Workspace:

Variables - trainedModel.GeneralizedLinearModel.Coefficients												
	1	2	3	4	5	6	7	8	9	10	11	12
	Estimate	SE	tStat	pValue								
1 (Intercept)	5.6509	0.5088	11.1073	1.1561e-28								
2 column_1	-0.0204	0.1137	-0.1798	0.8573								
3 column_2	-1.8451	0.1459	-12.6459	1.1790e-36								
4												

## 4 Practical work

### 4.1 Exercise 1 - Synthetic data

1. Use the `make_data()` function to generate some data points around  $(-1, 1)$  and  $(1, -1)$ .
2. Train logistic regression with `fitglm()`, as in the example above.
  - a. Predict the class of point  $(0, -0.3)$
  - b. What are the values of the model's coefficients?
3. Train logistic regression with the Classification Learner App, on the same data.
  - a. Show the Confusion Matrix. How many point from Class 0 are mis-classified as Class 1? What is the accuracy of the model?
  - b. Predict the class of point  $(0.4, 0.4)$ ?

### 4.2 Exercise 2 - Titanic survivors

We are using the Titanic Survivors dataset from here: <https://www.kaggle.com/datasets/azeembootwala/titanic>

1. Read about the dataset from here: <https://www.kaggle.com/datasets/azeembootwala/titanic>
2. Load the training file `Titanic/train_data.csv`

The first two columns are useless, the 3rd ("Survived") indicates if the person survived, and the rest of the columns are various info about the passengers.

Use the following code:

```
traindata = readtable('Titanic/train_data.csv');
X = traindata(:, 4:end); % input = columns from 4th onwards
Y = traindata(:, 3);    % output = column 3 ("survived")
X = table2array(X);
Y = table2array(Y);
```

3. Run the Classification Learner App and train a Logistic Regression model on the data.
  - What is the accuracy of the model?

4. Import the testing data `Titanic/test_data.csv` and predict the survival of the those passengers.

You can call `trainedModel.predictFcn( table )` on a full table.

Are the predictions correct (do they match the actual “Survived” value)? Check for the first five persons.

### 4.3 Exercise 3 - Titanic survivors

Repeat the training in Exercise 2, but use only the “Sex”, “Age” and “Fare” columns, not all of them.

What is the accuracy of the model in this case?

### 4.4 Exercise 4 - Spine data

We use the dataset from <https://www.kaggle.com/datasets/sammy123/lower-back-pain-symptoms-dataset>

The file is `Spine/Dataset_spine.csv`

1. Read about the dataset and what the columns specify.  
What is the target column?
2. Run the Classification Learner App and train a Logistic Regression model on the data.
  - a. What is the accuracy of the model?
  - b. How many normal conditions are classified as abnormal by the model?
  - c. How many normal conditions are classified as normal by the model?
3. Predict the result for all the persons in the table.

## 5 Final questions / open discussion

1. What happens if the two classes are **unbalanced** (many more inputs in one class compared to the other)? Do you think this is a problem?
2. Suggest some good termination conditions for Gradient Descent (i.e. when should we stop the iterations)?