	Logistic Regression import library
In [2]:	<pre>import numpy as np import matplotlib.pyplot as plt import matplotlib.colors as colors from matplotlib import ticker, cm</pre>
In [3]:	<pre>load training data fname_data = 'assignment_08_data.csv' data = np.genfromtxt(fname_data, delimiter=',') number_data = data.shape[0]</pre>
	<pre>point_x = data[:, 0] point_y = data[:, 1] label = data[:, 2] print('number of data = ', number_data)</pre>
	<pre>print('data type of point x = ', point_x.dtype) print('data type of point y = ', point_y.dtype) point_x_class_0 = point_x[label == 0] point_y_class_0 = point_y[label == 0] point_x_class_1 = point_x[label == 1] point_y_class_1 = point_y[label == 1]</pre>
	number of data = 600 data type of point x = float64 data type of point y = float64 plot the data
In [4]:	<pre>f = plt.figure(figsize=(8,8)) plt.title('training data') plt.plot(point_x_class_0, point_y_class_0, 'o', color='blue', label='class = 0') plt.plot(point_x_class_1, point_y_class_1, 'o', color='red', label='class = 1') plt.axis('equal') plt.legend()</pre>
	plt.tight_layout() plt.show() training data class = 0 class = 1
	Class – I
	20 -
	10 -
	0 -
	-10 -
In [5]:	define the linear regression function $ \bullet \ \theta = (\theta_0, \theta_1, \theta_2) \\ \bullet \ point = (1, x, y) \in \mathbb{R}^3 $ $ def \ compute_linear_regression(theta, \ \mathsf{point):} $
	<pre># ++++++++++++++++++++++++++++++++++++</pre>
	# ++++++++++++++++++++++++++++++++++++
In [6]:	• $z \in \mathbb{R}$ def sigmoid(z):
	<pre># value = 1/(1 + np.exp(-1 * z)) # # +++++++++++++++++++++++++++++++++</pre>
	define the logistic regression function $ \theta = (\theta_0, \theta_1, \theta_2) \in \mathbb{R}^3 \\ \bullet \ point = (1, x, y) \in \mathbb{R}^3 $
In [7]:	
	<pre>value = sigmoid(compute_linear_regression(theta, point)) # # +++++++++++++++++++++++++++++++++</pre>
	define the residual function $ \bullet \ \theta = (\theta_0,\theta_1,\theta_2) \in \mathbb{R}^3 \\ \bullet \ point = (x,y) \in \mathbb{R}^2 \\ \bullet \ label = l \in \{0,1\} $
In [8]:	
	residual = -1 * label * np.log(compute_logistic_regression(theta, point)) - (1-label) * np.log(1 - compute_logistic_regression(theta, point) # # +++++++++++++++++++++++++++++++++
	define the loss function for the logistic regression $ egin{align*} \bullet & \theta = (\theta_0, \theta_1, \theta_2) \in \mathbb{R}^3 \\ \bullet & point = (1, x, y) \in \mathbb{R}^3 \\ \bullet & label = l \in \{0, 1\} \\ \end{aligned} $
In [34]:	<pre>def compute_loss(theta, point, label): # ++++++++++++++++++++++++++++++++</pre>
	# ++++++++++++++++++++++++++++++++++++
In [50]:	$\begin{array}{l} \bullet \ \theta = (\theta_0,\theta_1,\theta_2) \in \mathbb{R}^3 \\ \bullet \ point = (1,x,y) \in \mathbb{R}^3 \\ \bullet \ label = l \in \{0,1\} \end{array}$ $\begin{array}{l} def \ compute_gradient(theta,\ point,\ label): \end{array}$
	<pre># ++++++++++++++++++++++++++++++++++++</pre>
Tn [51]:	<pre>initialize the gradient descent algorithm num_iteration = 5000 # USE THIS VALUE for the number of gradient descent iterations</pre>
III [31].	<pre>learning_rate = 0.001 # USE THIS VALUE for the learning rate theta = np.array((0, 0, 0)) theta_iteration = np.zeros((num_iteration, theta.size)) loss_iteration = np.zeros(num_iteration) number_point_class_0 = len(point_x_class_0)</pre>
	<pre>number_point_class_1 = len(point_x_class_1) point_class_0 = np.ones((number_point_class_0, 3)) point_class_1 = np.ones((number_point_class_1, 3)) point_class_0[:, 1] = point_x_class_0 point_class_0[:, 2] = point_y_class_0</pre>
	<pre>point_class_1[:, 1] = point_x_class_1 point_class_1[:, 2] = point_y_class_1 label_0 = np.zeros(number_point_class_0) label_1 = np.ones(number_point_class_1) point = np.concatenate((point_class_0, point_class_1), axis=0) label = np.concatenate((label_0, label_1), axis=0)</pre>
	<pre>print('shape of point_class_0 : ', point_class_0.shape) print('shape of point_class_1 : ', point_class_1.shape) print('shape of label_0 : ', label_0.shape) print('shape of label_1 : ', label_1.shape) print('shape of point : ', point.shape) print('shape of label : ', label.shape)</pre>
	<pre>shape of point_class_0 : (300, 3) shape of point_class_1 : (300, 3) shape of label_0 : (300,) shape of label_1 : (300,) shape of point : (600, 3) shape of label : (600,)</pre>
In [52]:	run the gradient descent algorithm to optimize the loss function with respect to the model parameter for i in range(num_iteration): # ***********************************
	<pre>theta = theta - learning_rate * compute_gradient(theta, point, label) loss = compute_loss(theta, point, label) # # ++++++++++++++++++++++++++++++++++</pre>
	theta_optimal = theta
	theta_optimar = theta
Tn [52]:	functions for presenting the results
In [53]:	
In [53]:	<pre>functions for presenting the results def function_result_01(): input1 = np.array([0.1, 0.2, 0.3]) input2 = np.array([[1, 2, 3], [1, -2, -3]]) value = compute_linear_regression(input1, input2) print(value)</pre>
	<pre>functions for presenting the results def function_result_01(): input1 = np.array([0.1, 0.2, 0.3]) input2 = np.array([[1, 2, 3], [1, -2, -3]]) value = compute_linear_regression(input1, input2) print(value) def function_result_02(): input1 = np.array([0.1, 0.2, 0.3]) input2 = np.array([[1, 2, 3], [1, -2, -3]]) value = compute_logistic_regression(input1, input2) print(value)</pre>
In [54]:	<pre>functions for presenting the results def function_result_01(): input1 = np.array([0.1, 0.2, 0.3]) input2 = np.array([[1, 2, 3], [1, -2, -3]]) value = compute_linear_regression(input1, input2) print(value) def function_result_02(): input1 = np.array([0.1, 0.2, 0.3]) input2 = np.array([[1, 2, 3], [1, -2, -3]]) value = compute_logistic_regression(input1, input2) print(value) def function_result_03(): input1 = np.array([0.1, 0.2, 0.3]) input2 = np.array([0.1, 0.2, 0.3]) input3 = np.array([0.1, 0.2, 0.3]) input4 = np.array([0.1, 0.2, 0.3]) input5 = np.array([0.1, 0.2, 0.3]) input6 = np.array([0.1, 0.2, 0.3]) input7 = np.array([0.1, 0.2, 0.3]) input8 = np.array([0.1, 0.2, 0.3]) input9 = np.array([0.1, 0.2, 0.3]) in</pre>
In [54]: In [56]:	<pre>functions for presenting the results def function_result_0[]: inputl = np.array[[0.1, 0.2, 0.3]] inputl = np.array[[1, 2, 3], [1, -2, -3]]) value = computo_linear_regression(inputl, input2) print(value) def function_result_02(): inputl = np.array[[1, 2, 3], [1, -2, -3]]) value = computo_logistic_regression(inputl, input2) print(value) def function_result_03(): inputl = np.array[[0.1, 0.2, 0.3]) input2 = np.array[[0.1, 0.2, 0.3]) input2 = np.array[[0.1, 0.2, 0.3]) input3 = np.array[[0.1, 0.2, 0.3]) input3 = np.array[[0.1, 0.2, 0.3]) input3 = np.array[[0.1, 0.2, 0.3]) input1 = np.array[[0.1, 0.2, 0.3]) input2 = np.array[[0.1, 0.2, 0.3]) input3 = np.array[[0.1, 0.2, 0.3]) input4 = np.array[[0.1, 0.2, 0.3]) input4 = np.array[[0.1, 0.2, 0.3]) input5 = np.array[[0.1, 0.2, 0.3]) input5 = np.array[[0.1, 0.2, 0.3]) input6 = np.array[[0.1, 0.2, 0.3]) input7 = np.array[[0.1, 0.2, 0.3]) input8 = np.array[[0.1, 0.2, 0.3]) input</pre>
In [54]:	<pre>functions for presenting the results def function_result_01(): imput = mp.errey((0.1, 0.2, 0.3)) imput = mp.errey((0.1, 0.2, 0.3)) imput = mp.errey((0.1, 0.2, 0.3)) value = compute_lineer_repression(input, input2) print(value) def function_result_02(): imput = mp.errey((0.1, 0.2, 0.3)) imput = mp.errey((0.1, 0.2, 0.3)) imput = mp.errey((1.1, 0.2, 0.3)) imput = mp.err</pre>
In [54]: In [56]:	<pre>functions for presenting the results def function_result_01(): imput1 = pp_acreyy[(0.1, 0.2, 0.3]) imput2 = pp_acreyy[(1, 2, 3), (1, -2, -3])) value = compute_linear_regression(imput1, imput2) point(vulle) def function_result_02(): imput1 = pp_acreyy[(0.1, 0.2, 0.3]) imput1 = pp_acreyy[(0.1, 0.2, 0.3]); value = compute_linearing_regression(imput1, imput2) print(vulle) def function_result_03(): imput1 = pp_acreyy[(0.1, 0.2, 0.3]); imput2 = pp_acreyy[(1.2, 2, 3), (1, -2, -2])); imput3 = pp_acreyy[(1.2, 2, 3), (1, -2, -2])); imput3 = pp_acreyy[(1.2, 2, 3), (1, -2, -2])); imput3 = pp_acreyy[(0.1, 0.2, 0.3]); imput4 = pp_acreyy[(0.1, 0.2, 0.3]); imput4 = pp_acreyy[(1.2, 2, 3), (1, -2, -3])); imput4 = pp_acreyy[(1.2, 2, 3), (1, -2, -3]); imput5 = pp_acreyy[(1.2, 2, 3), (1, -2, -3]); imput4 = pp_acreyy[(1.2, 2, 3), (1, -2, -3]); imput5 = pp_acreyy[(1.2, 2, 3), (1, -2, -3]); imput6 = pp_acreyy[(1.2, 2, 3), (1, -2, -3]); imput7 = pp_acreyy[(1.2, 2, 3), (1, -2, -3]); imput8 = pp_acreyy[(1.2, 2, 3), (1, -2, -3]); imput8 = pp_acreyy[(1.2, 2, 3), (1, -2, -3]); imput9 = pp_acreyy[(1.2, 2, 3], (1, -2, -3]); imput9 = pp_ac</pre>
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