

Lab assignment 2 – Logistic regression

1. Requirement

- Install logistic regression to predict whether a factory microchip is eligible to be sold on market.
- Raw data has 3 columns: first and second column are features and third column are labels.
- Raw features mapped to new feature domain consists of 28 dimensions. The map_feature function provided in file **map_feature.py** is responsible for this.
- Implement following functions to execute training and prediction:
 - compute_cost: calculate the cost of model of data set (the formula for calculating cost function is provided in “3. The formulas”).
 - compute_gradient: calculate the gradient vector of the cost function (the formula for calculating the gradient vector is provided in “3. The formulas”).
 - gradient_descent: calculate the gradient descent.
 - predict: predict whether a set of microchips are eligible to be sold on market (pass an array of 1 element for prediction of 1 microchip).
 - evaluate: evaluate the performance of model via **Accuracy, Precision, Recall** and **F1-score** metrics.
- Main program:
 - Read the training configuration from file **config.json**.
 - Train with data provided from file **training_data.txt**.
 - Save model to file **model.json**.
 - Evaluate model on training dataset, save result to file **classification_report.json**.

2. Submission rules

- Put all source code and related files to folder named **[student_id]**.
- Compress folder to file **[student_id].zip**.

3. The formulas

- The cost function is calculated by this formula:

$$J(\theta) = \frac{1}{m} \sum_{i=1}^m [-y^{(i)} \log(h_{\theta}(x^{(i)})) - (1 - y^{(i)}) \log(1 - h_{\theta}(x^{(i)}))] + \frac{\lambda}{2m} \sum_{j=1}^n \theta_j^2.$$

- The formula for calculating gradient vector:

$$\frac{\partial J(\theta)}{\partial \theta_0} = \frac{1}{m} \sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)}) x_j^{(i)} \quad \text{for } j = 0$$

$$\frac{\partial J(\theta)}{\partial \theta_j} = \left(\frac{1}{m} \sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)}) x_j^{(i)} \right) + \frac{\lambda}{m} \theta_j \quad \text{for } j \geq 1$$