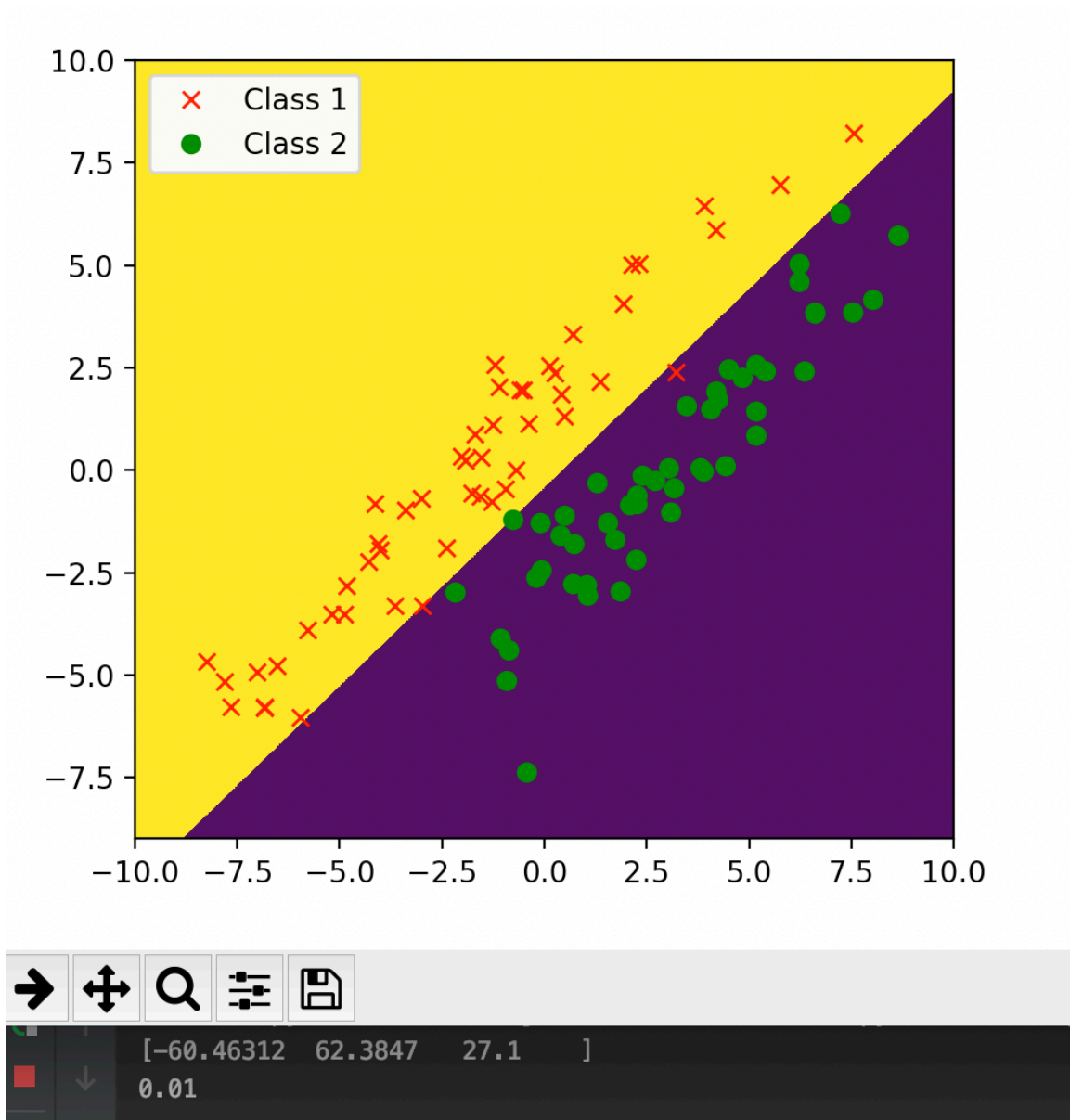


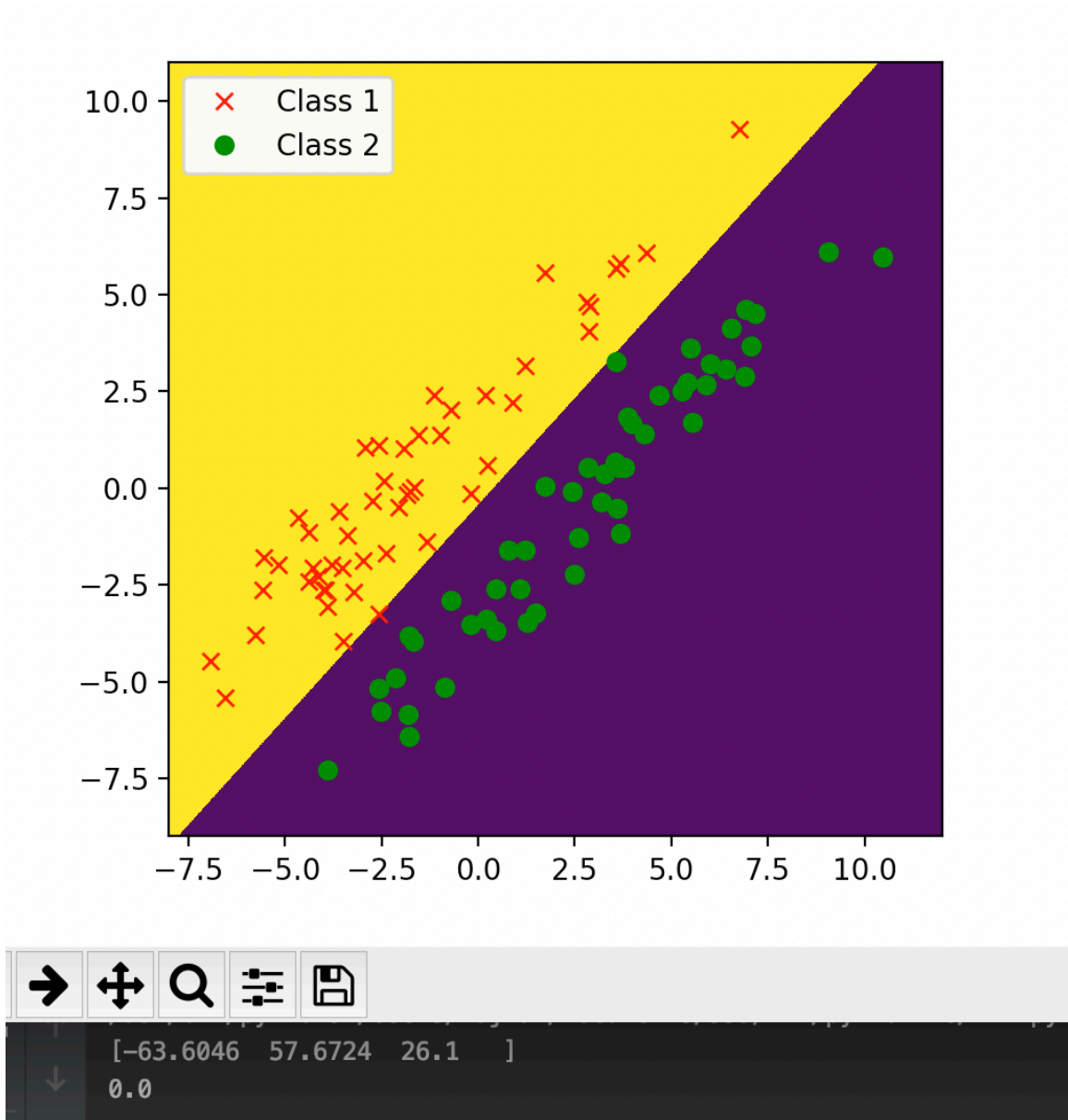
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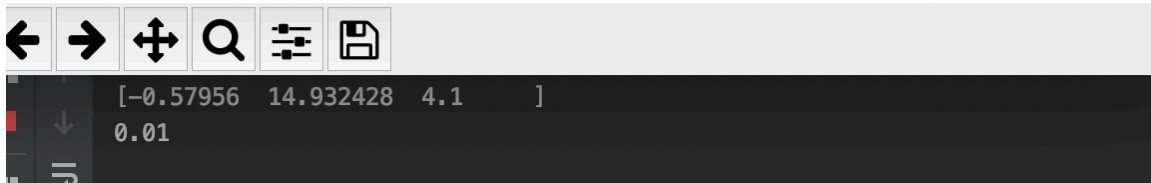
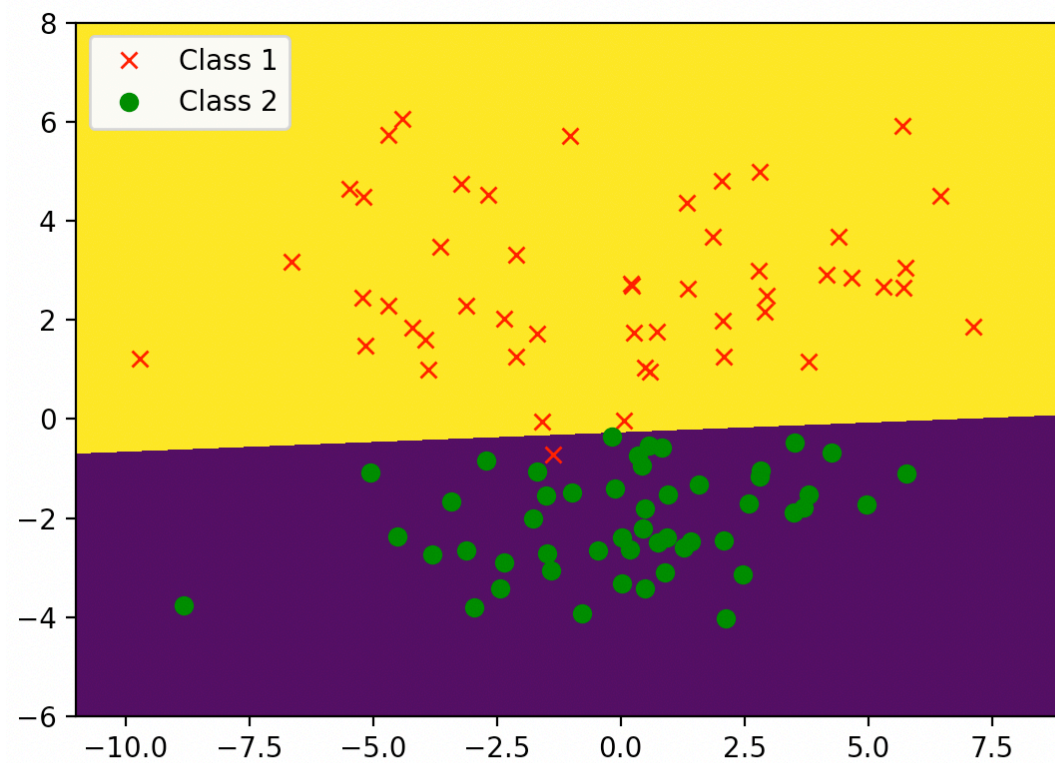
the classification error rate on the training set sythetic1 is 0.01

the weight vector is $[-60.46312 \quad 62.3847 \quad 27.1]$



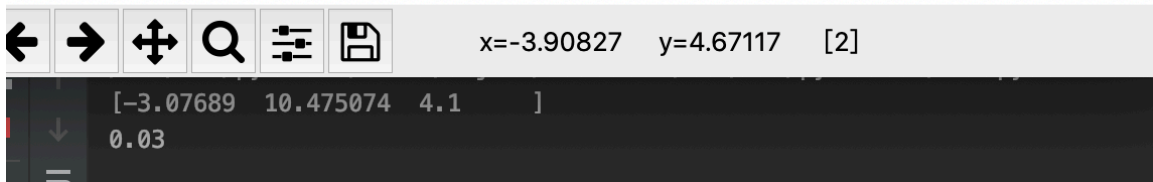
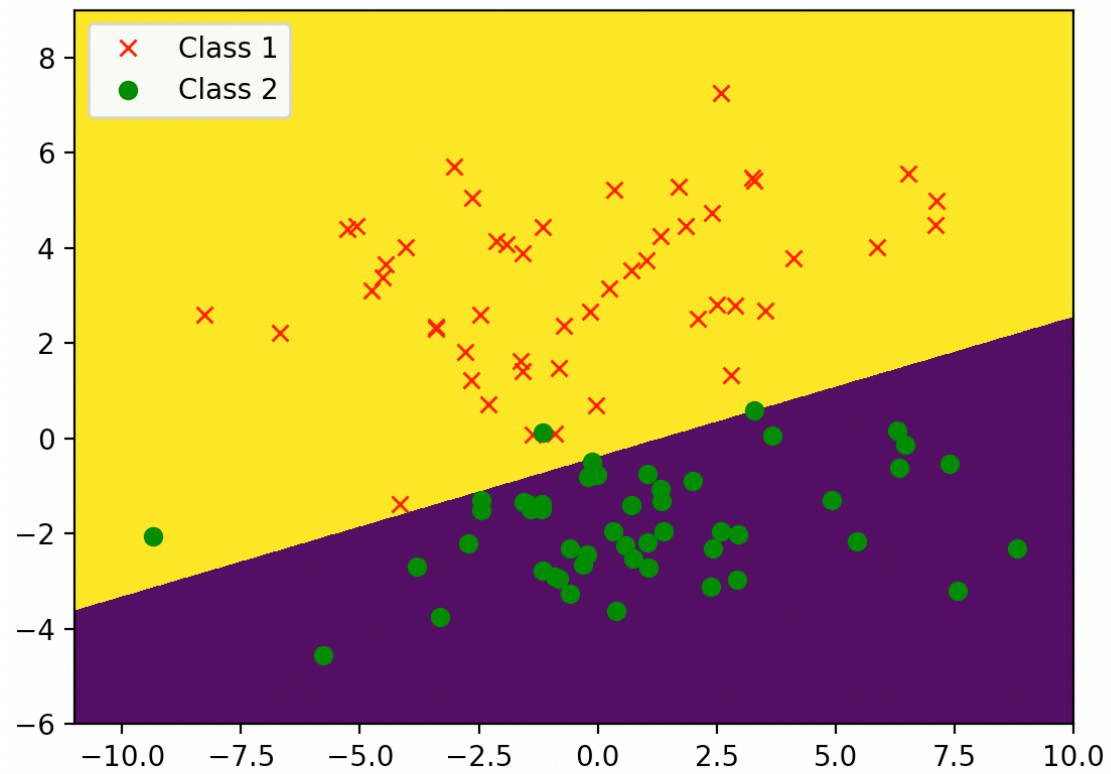
the classification error rate on the test set sythetic1 is 0.0

the weight vector is $[-63.6046 \quad 57.6724 \quad 26.1]$



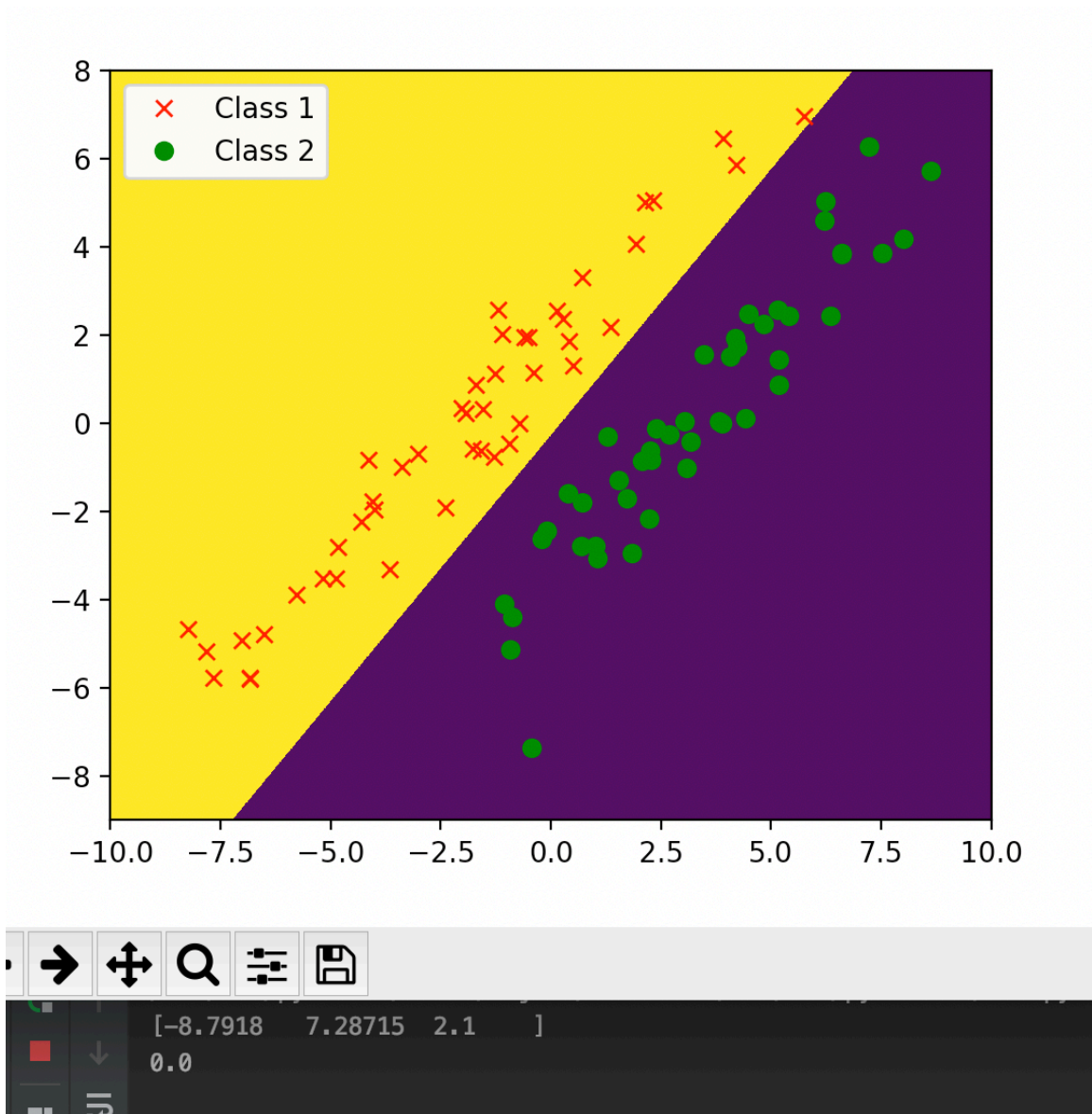
the classification error rate on the training set sythetic2 is 0.01

the weight vector is $[-0.57956 \quad 14.932428 \quad 4.1]$



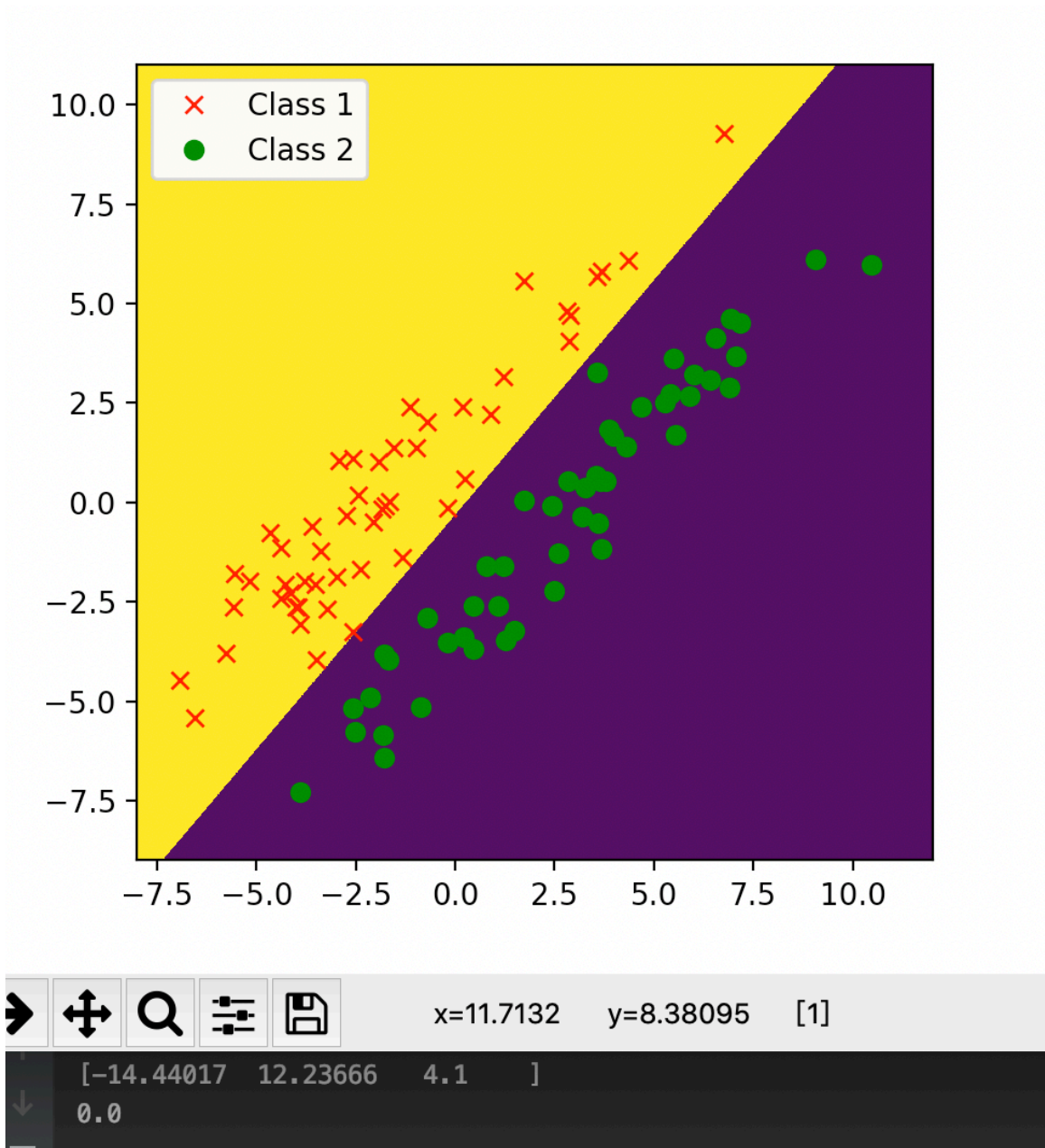
the classification error rate on the test set sythetic2 is 0.03

the weight vector is $[-3.07689 \quad 10.475074 \quad 4.1]$



the classification error rate on the training set sythetic3 is 0

the weight vector is $[-8.7918 \quad 7.28715 \quad 2.1]$



the classification error rate on the test set sythetic3 is 0

the weight vector is $[-14.44017 \quad 12.23666 \quad 4.1]$

(C)

Using nearest means, the error rates of training and test set for synthetic1 are 0.21 and 0.24, for sythetic2 are 0.03 and 0.04.

Using perceptron, the error rates of training and test set for synthetic1 are 0.01 and 0, for sythetic2 are 0.01 and 0.03.

We can find that because the distribution of the datasets is different, sometimes using nearest means can get the results as good as perceptron, but sometimes it cannot.

But in the data sets synthetic1 and synthetic2, perceptron always has a good result.

$$\begin{aligned}
 (a) \quad E[\Delta w(i)] &= E[w(i+1)] - E[w(i)] \\
 w(i+1) &= w(i) - \eta(i) \nabla_w J_w(i) \\
 \therefore E[\Delta w(i)] &= -\eta(i) E[\nabla_w J_w(i)] \\
 E[\Delta w(i)] &= -\eta \cdot \frac{1}{N} \sum_{i=1}^N \nabla_w J_w(w_i)
 \end{aligned}$$

(b) for batch gradient descent

$$\begin{aligned}
 \Delta w(i) &= w(i+1) - w(i) \\
 \Delta w(i) &= -\eta(i) \sum_{i=1}^N \nabla_w J_w(w_i)
 \end{aligned}$$

Because from (a) we have:

$$E[\Delta w(i)] = -\eta \cdot \frac{1}{N} \sum_{i=1}^N \nabla_w J_w(w_i)$$

$$\text{so, we have } \Delta w(i) = N E[\Delta w(i)]$$

so, we know the expected value of SGD equals to $\frac{1}{N}$ batch GD update

explanation: Because batch GD using the whole data set to calculate loss function, so $\frac{1}{N}$ of batch GD means average loss of the whole data set.

SGD means we choose data randomly from the dataset, and expected value of SGD also means "average" of the data we chosen.

so, we can know that the expected value of SGD equals to $\frac{1}{N}$ batch GD update