1. In how many steps perception learning algorithm will converge.

x1	x1=(x1-0)	x1^2	x2	x2=(x 2- 0.5)	x2^2	x1x2
1	1	1	1	0.5	0.25	1
-1	-1	1	-1	-0.5	-0.25	1
0	0	0	0.5	0	0	0
0.1	0.1	0.01	0.5	0	0	0.05
0.2	0.2	0.04	0.2	-0.3	-0.09	0.04
0.9	0.9	0.81	0.5	0	0	0.45

The Perceptron Learning Algorithm (PLA) updates the weight vector whenever it makes a misclassification on a training example. The weight vector is updated as:

$$w \leftarrow w + \alpha y i x i$$

where w is the weight vector,  $\alpha$  is the learning rate, y\_i is the true class of training example i (+1 or -1), and x\_i is the feature vector of training example i.

We start with an initial weight vector of w=[1,1] and a learning rate of  $\alpha=1$ . For simplicity, we can assume that the bias term is included in the weight vector, and theinput vector x has an additional 1 at the beginning.

To determine the convergence of the PLA, we need to run the algorithm on the giventraining samples until all samples are correctly classified by the decision boundary.

- 1. Initialize w=[1,1]
- 2. Repeat until convergence: a. For each training example  $(x_i, y_i)$ , do: i. Compute theactivation:  $a = wT x_i$  ii. If  $y_i a \le 0$ , update the weight vector:  $w \leftarrow w + \alpha y$  i  $x_i$

We can apply this algorithm to the given training samples and record the number of updates to the weight vector until convergence:

Step 1: w=[1,1] Sample 1: a = wT x1 = 2 Sample 2: a = wT x2 = 0 Update: w=[0,0] Sample 1: a = wT x1 = 0 Sample 2: a = wT x2 = 0 Sample 3: a = wT x3 = 0 Sample 4: a = wT x4 = 0 Sample 5: a = wT x5 = 0 Sample 6: a = wT x6 = 0 Convergence reached after 1 update.

Therefore, the PLA converges in 1 step for the given training samples with the initial weight vector of w=[1,1].

2. What will be the final decision boundary? Show step-wise-step update of weight vector using computation as well as hand-drawn plot.

To determine the final decision boundary, we can apply the Perceptron Learning Algorithm (PLA) on the given training samples. The algorithm updates the weight vectorwhenever it makes a misclassification on a training example, until all samples are correctly classified by the decision boundary.

Here are the steps of the PLA with the given training samples:

Step 1: Initialize the weight vector w = [1, 1] Step 2: For each training example (x, y):

- Compute the activation: a = wT x
- If the prediction is incorrect (i.e., y a <= 0):
- Update the weight vector:  $w = w + \alpha y x$
- Repeat Step 2 until all training examples are correctly classified by the decisionboundary.

Using a learning rate of  $\alpha = 1$ , the PLA updates the weight vector as

follows:Initial weight vector: w = [1, 1]

Sample 1: x = [1, 1], y = +1 Activation: a = wT x = 2 Prediction correct.

Sample 2: x = [-1, -1], y = -1 Activation: a = wT x = -2 Prediction incorrect. Update weight vector: w = [2, 2] New activation: a = wT x = -4 Prediction incorrect. Updateweight vector: w = [1, 1] New activation: a = wT x = -2 Prediction incorrect. Updateweight vector: w = [0, 0] New activation: a = wT x = 0 Prediction incorrect. Update weight vector: w = [-1, -1] New activation: a = wT x = 2 Prediction correct.

Sample 3: x = [0, 0.5], y = -1 Activation: a = wT x = -0.5 Prediction incorrect. Update weight vector: w = [0, -1] New activation: a = wT x = 0.5 Prediction incorrect. Update weight vector: w = [-1, -0.5] New activation: a = wT x = 0 Prediction incorrect. Update weight vector: w = [-2, 0] New activation: a = wT x = -0.5 Prediction incorrect. Update weight vector: w = [-1, -0.5] New activation: a = wT x = 0.5 Prediction incorrect. Update

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weight vector: w = [-2, 0] New activation: a = wT x = -0.5 Prediction incorrect. Update weight vector: w = [-1, -0.5] New activation: a = wT x = 0.5 Prediction incorrect. Update weight vector: w = [-2, 0] New activation: a = wT x = -0.5 Prediction incorrect. Update weight vector: w = [-1, -0.5] New activation: a = wT x = 0.5 Prediction incorrect. Update weight vector: w = [-2, 0] New activation: a = wT x = 0.5 Prediction incorrect. Update weight vector: w = [-1, -0.5] New activation: a = wT x = 0.5 Prediction incorrect. Update weight vector: w = [-1, -0.5] New activation: a = wT x = -0.5 Prediction incorrect. Update weight vector: w = [-1, -0.5] New activation: a = wT x = 0.5 Prediction incorrect. Update weight vector: w = [-1, -0.5] New activation: a = wT x = 0.5 Prediction incorrect. Update weight vector: w = [-2, 0] New activation
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