

# Introduction to Machine Learning: Assignment #2

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## 1 Logistic Regression

### Question 1

\_\_\_\_\_ is a widely used discriminative classification model  $p(y|\mathbf{x}; \boldsymbol{\theta})$ , where  $\mathbf{x} \in \mathbb{R}^D$  is a fixed-dimensional input vector,  $y \in \{0, 1\}$  is the class label, and  $\boldsymbol{\theta}$  are the parameters.

- (a) Conditional Probability
- (b) Linear Regression
- (c) Multinomial Logistic Regression
- (d) Binary Logistic Regression

### Question 2

The sigmoid function  $\sigma(a) = \frac{1}{1+e^{-a}}$  is typically used in the logistic regression because (Check all that apply)

- it squeezes the logits  $a$  to a value between 0 and 1
- it is differentiable
- it is a linear function
- it has a value of 0.5 for any  $a > 0$

### Question 3

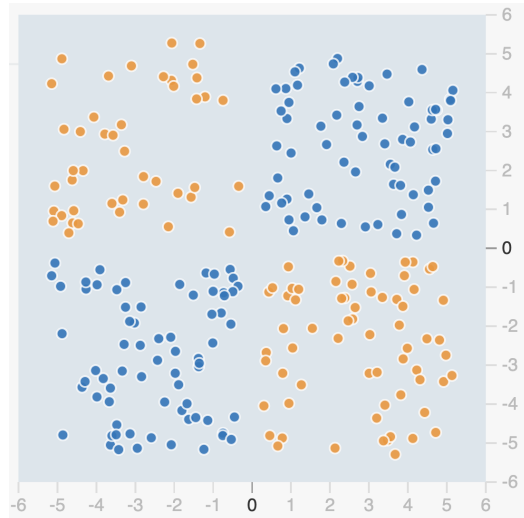
In logistic regression, the plane  $\mathbf{w}^T \mathbf{x} + b = 0$  is often called the \_\_\_\_\_ separating the 3d space into two halves.

- (a) decision boundary
- (b) linearly separable
- (c) perceptron
- (d) prediction

Question 4

In logistic regression, we can often make a problem linearly separable by preprocessing the inputs in a suitable way. Let  $w = [0; 0; 1]$ , which of the following non-linear functions  $\phi(x_1, x_2)$  is the most suitable one for the given data points:

- (a)  $\phi(x_1, x_2) = [1; x_1^2; x_2^2]$
- (b)  $\phi(x_1, x_2) = [1; x_1x_2; x_2]$
- (c)  $\phi(x_1, x_2) = [1; \cos(x_1); \sin(x_2)]$
- (d)  $\phi(x_1, x_2) = [1; x_1; x_1x_2]$



Question 5

A non linearly-separable data can always be made linearly-separable in another feature space

- (a) True
- (b) False

Question 6

To ensure the objective function is convex, we must prove the hessian is negative semi-definite

- (a) True
- (b) False

Question 7

Which of the following solutions/estimates avoids overfitting:

- (a) Maximum Likelihood Estimator (MLE)
- (b) Maximum A Posterior (MAP)
- (c) Iteratively Reweighted Least Squares (IRLS)
- (d) Ordinary Least Squares (OLS)

Question 8

The *Negative Log Likelihood (NLL)* for the multi-label logistic regression  $\prod_{n=1}^N \prod_{c=1}^C \text{Ber}(y_c | \sigma(\mathbf{w}_c^T \mathbf{x}_n))$  with  $\text{Ber}(y|\theta) \triangleq \theta^y(1-\theta)^{1-y}$ :

- (a)  $-\frac{1}{N} \sum_{n=1}^N y_n \log \sigma(\mathbf{w}_c^T \mathbf{x}_n) + (1 - y_n) \log (1 - \sigma(\mathbf{w}_c^T \mathbf{x}_n))$
- (b)  $-\frac{1}{N} \sum_{n=1}^N \sigma(\mathbf{w}_c^T \mathbf{x}_n) \log y_n + (1 - \sigma(\mathbf{w}_c^T \mathbf{x}_n)) \log (1 - y_n)$
- (c)  $-\frac{1}{N} \sum_{n=1}^N \left[ \sum_{c=1}^C y_{nc} \log \sigma(\mathbf{w}_c^T \mathbf{x}_n) + (1 - y_{nc}) \log (1 - \sigma(\mathbf{w}_c^T \mathbf{x}_n)) \right]$
- (d)  $-\frac{1}{N} \sum_{n=1}^N \left[ \sum_{c=1}^C \sigma(\mathbf{w}_c^T \mathbf{x}_n) \log y_{nc} + (1 - \sigma(\mathbf{w}_c^T \mathbf{x}_n)) \log (1 - y_{nc}) \right]$

Question 9

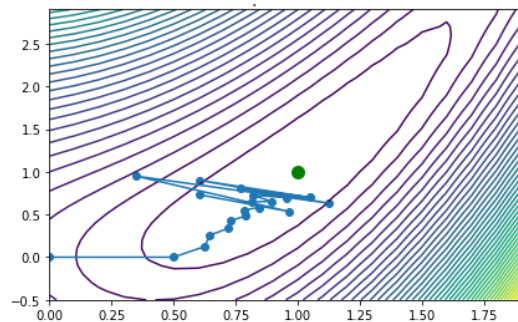
In Multinomial Logistic Regression  $p(y|\mathbf{x}; \boldsymbol{\theta}) = \text{Cat}(y|\psi(W\mathbf{x} + \mathbf{b}))$ , we commonly use the following activation function  $\psi(\cdot)$ :

- (a) Softmax
- (b) Sigmoid
- (c) Heaviside step function
- (d) Rectified Linear Unit

Question 10

The model on the right hand side suffers from convergence. This could be attributed to (Check all that apply)

- low learning rate
- high learning rate
- low weight decay
- high weight decay



Question 11

Consider the following dataset for a binary classification problem with input of  $D = 3$  features and binary output  $y \in \{0, 1\}$ . Then, it is possible to achieve 100% accuracy on this dataset.

- (a) True
- (b) False

$x_1$	$x_2$	$x_2$	$y$
3	4	5	1
2	4	3	1
2	3	1	1
2	4	3	0
1	3	5	0

Question 12

The vector  $w$  defines the \_\_\_\_ of the decision boundary, and its magnitude,  $\|w\|_2 = \sqrt{\sum_{d=1}^D w_d^2}$  controls the \_\_\_\_ of the sigmoid, and hence the confidence of the predictions.

- (a) steepness, orientation
- (b) weights, prediction
- (c) orientation, steepness
- (d) prediction, weights

Question 13

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- (a) steepness, orientation
- (b) weights, prediction
- (c) orientation, steepness
- (d) prediction, weights

Question 14 From ML Course – Andrew Ng

Consider training a logistic regression classifier by stochastic gradient descent. You observe that the average cost over the last 100 examples, plotted as a function of the number of iterations, is slowly increasing. Which of the following changes is likely to have the greatest impact?

- (a) Attempt to reduce the learning rate by half, and see if the cost drops consistently. If not, reduce the learning rate by half again until it does.
- (b) Train with fewer examples.
- (c) Consider averaging the cost over a smaller number of examples.
- (d) Using stochastic gradient descent, this is not possible, because theta converges to the optimum.

Question 15

Consider a classification model with NLL as an objective function. Let  $\theta_0 \triangleq (w, b) = (4, 5)$  with a gradient  $g_0 = (4, 10)$ . What is the suitable learning rate  $\eta$  to reach the optimal parameter  $\theta_{opt} = (1, -1)$  given the gradient at the second iteration is  $g_1 = (2, 2)$ :

- (a) 1
- (b) 0.5
- (c) -1
- (d) -0.5

