

# Linear Regression with Multiple Variables

TOTAL POINTS 5

Suppose  $m=4$  students have taken some class, and the class had a midterm exam and a final exam. You have collected a dataset of their scores on the two exams, which is as follows:

1 point

midterm exam	(midterm exam) <sup>2</sup>	final exam
89	7921	96
72	5184	74
94	8836	87
69	4761	78

You'd like to use polynomial regression to predict a student's final exam score from their midterm exam score. Concretely, suppose you want to fit a model of the form  $h_{\theta}(x) = \theta_0 + \theta_1 x_1 + \theta_2 x_2$ , where  $x_1$  is the midterm score and  $x_2$  is (midterm score)<sup>2</sup>. Further, you plan to use both feature scaling (dividing by the "max-min", or range, of a feature) and mean normalization.

What is the normalized feature  $x_1^{(3)}$ ? (Hint: midterm = 94, final = 87 is training example 3.) Please round off your answer to two decimal places and enter in the text box below.

0.52

# Linear Regression with Multiple Variables

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Suppose  $m=4$  students have taken some class, and the class had a midterm exam and a final exam. You have collected a dataset of their scores on the two exams, which is as follows:

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You'd like to use polynomial regression to predict a student's final exam score from their midterm exam score. Concretely, suppose you want to fit a model of the form  $h_{\theta}(x) = \theta_0 + \theta_1 x_1 + \theta_2 x_2$ , where  $x_1$  is the midterm score and  $x_2$  is (midterm score)<sup>2</sup>. Further, you plan to use both feature scaling (dividing by the "max-min", or range, of a feature) and mean normalization.

What is the normalized feature  $x_2^{(2)}$ ? (Hint: midterm = 72, final = 74 is training example 2.) Please round off your answer to two decimal places and enter in the text box below.

-0.37

**You run gradient descent for 15 iterations**

1 point

**with  $\alpha = 0.3$  and compute**

**$J(\theta)$  after each iteration. You find that the**

**value of  $J(\theta)$  decreases slowly and is still**

**decreasing after 15 iterations. Based on this, which of the**

**following conclusions seems most plausible?**

- ☐ Rather than use the current value of  $\alpha$ , it'd be more promising to try a smaller value of  $\alpha$  (say  $\alpha = 0.1$ ).
- ☐  $\alpha = 0.3$  is an effective choice of learning rate.
- ☒ Rather than use the current value of  $\alpha$ , it'd be more promising to try a larger value of  $\alpha$  (say  $\alpha = 1.0$ ).

**Suppose you have  $m = 14$  training examples with  $n = 3$  features (excluding the additional all-ones feature for the intercept term, which you should add). The normal equation is  $\theta = (X^T X)^{-1} X^T y$ . For the given values of  $m$  and  $n$ , what are the dimensions of  $\theta$ ,  $X$ , and  $y$  in this equation?**

1 point

- ☐  $X$  is  $14 \times 3$ ,  $y$  is  $14 \times 1$ ,  $\theta$  is  $3 \times 1$
- ☐  $X$  is  $14 \times 4$ ,  $y$  is  $14 \times 4$ ,  $\theta$  is  $4 \times 4$
- ☐  $X$  is  $14 \times 3$ ,  $y$  is  $14 \times 1$ ,  $\theta$  is  $3 \times 3$
- ☒  $X$  is  $14 \times 4$ ,  $y$  is  $14 \times 1$ ,  $\theta$  is  $4 \times 1$

1 point

**You run gradient descent for 15 iterations**

**with  $\alpha = 0.3$  and compute  $J(\theta)$  after each**

**iteration. You find that the value of  $J(\theta)$  increases over**

**time. Based on this, which of the following conclusions seems**

**most plausible?**

- ☒ Rather than use the current value of  $\alpha$ , it'd be more promising to try a smaller value of  $\alpha$  (say  $\alpha = 0.1$ ).
  - ☐ Rather than use the current value of  $\alpha$ , it'd be more promising to try a larger value of  $\alpha$  (say  $\alpha = 1.0$ ).
  - ☐  $\alpha = 0.3$  is an effective choice of learning rate.
-

Suppose you have a dataset with  $m = 1000000$  examples and  $n = 200000$  features for each example. You want to use multivariate linear regression to fit the parameters  $\theta$  to our data. Should you prefer gradient descent or the normal equation?

1 point

- ☐ The normal equation, since it provides an efficient way to directly find the solution.
- ☐ Gradient descent, since it will always converge to the optimal  $\theta$ .
- ☒ Gradient descent, since  $(X^T X)^{-1}$  will be very slow to compute in the normal equation.
- ☐ The normal equation, since gradient descent might be unable to find the optimal  $\theta$ .

Which of the following are reasons for using feature scaling?

1 point

- ☐ It is necessary to prevent the normal equation from getting stuck in local optima.
- ☐ It prevents the matrix  $X^T X$  (used in the normal equation) from being non-invertable (singular/degenerate).
- ☒ It speeds up gradient descent by making it require fewer iterations to get to a good solution.
- ☐ It speeds up gradient descent by making each iteration of gradient descent less expensive to compute.