

## Environment Setup Instructions

### Multivariate Linear Regression

- ✓ **Video:** Multiple Features 8 min
- ✓ **Reading:** Multiple Features 3 min
- ✓ **Video:** Gradient Descent for Multiple Variables 5 min
- ✓ **Reading:** Gradient Descent For Multiple Variables 2 min
- ✓ **Video:** Gradient Descent in Practice I - Feature Scaling 8 min
- ✓ **Reading:** Gradient Descent in Practice I - Feature Scaling 3 min
- ✓ **Video:** Gradient Descent in Practice II - Learning Rate 8 min
- ✓ **Reading:** Gradient Descent in Practice II - Learning Rate 4 min
- ✓ **Video:** Features and Polynomial Regression 7 min
- ✓ **Reading:** Features and Polynomial Regression 3 min

### Computing Parameters Analytically

- ✓ **Video:** Normal Equation 16 min
- ✓ **Reading:** Normal Equation 3 min
- ✓ **Video:** Normal Equation Noninvertibility 5 min
- ✓ **Reading:** Normal Equation Noninvertibility 2 min

### Submitting Programming Assignments

#### Review

#### Octave/Matlab Tutorial

#### Review



## Normal Equation

**Note:** [8:00 to 8:44 - The design matrix  $X$  (in the bottom right side of the slide) given in the example should have elements  $x$  with subscript 1 and superscripts varying from 1 to  $m$  because for all  $m$  training sets there are only 2 features  $x_0$  and  $x_1$ . 12:56 - The  $X$  matrix is  $m$  by  $(n+1)$  and NOT  $n$  by  $n$ .]

Gradient descent gives one way of minimizing  $J$ . Let's discuss a second way of doing so, this time performing the minimization explicitly and without resorting to an iterative algorithm. In the "Normal Equation" method, we will minimize  $J$  by explicitly taking its derivatives with respect to the  $\theta_j$ 's, and setting them to zero. This allows us to find the optimum theta without iteration. The normal equation formula is given below:

$$\theta = (X^T X)^{-1} X^T y$$

Examples:  $m = 4$ .

	Size (feet <sup>2</sup> )	Number of bedrooms	Number of floors	Age of home (years)	Price (\$1000)
$x_0$	$x_1$	$x_2$	$x_3$	$x_4$	$y$
1	2104	5	1	45	460
1	1416	3	2	40	232
1	1534	3	2	30	315
1	852	2	1	36	178

  

$$X = \begin{bmatrix} 1 & 2104 & 5 & 1 & 45 \\ 1 & 1416 & 3 & 2 & 40 \\ 1 & 1534 & 3 & 2 & 30 \\ 1 & 852 & 2 & 1 & 36 \end{bmatrix}$$

$m \times (n+1)$

  

$$y = \begin{bmatrix} 460 \\ 232 \\ 315 \\ 178 \end{bmatrix}$$

$m$ -dimensional vector

  

$$\theta = (X^T X)^{-1} X^T y$$

There is **no need** to do feature scaling with the normal equation.

The following is a comparison of gradient descent and the normal equation:

Gradient Descent	Normal Equation
Need to choose alpha	No need to choose alpha
Needs many iterations	No need to iterate
$O(kn^2)$	$O(n^3)$ , need to calculate inverse of $X^T X$
Works well when $n$ is large	Slow if $n$ is very large

With the normal equation, computing the inversion has complexity  $O(n^3)$ . So if we have a very large number of features, the normal equation will be slow. In practice, when  $n$  exceeds 10,000 it might be a good time to go from a normal solution to an iterative process.

✓ Complete

Go to next item