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 θ 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:
$$m = 4$$
.

	J	Size (feet²)	Number of bedrooms	Number of floors	Age of home (years)	Price (\$1000)
$\rightarrow x_0$		x_1	x_2	x_3	x_4	y	_
	1	2104	5	1	45	460	٦
	1	1416	3	2	40	232	- 1
	1	1534	3	2	30	315	- (
	1	852	2	_1	_36	178	٧
$X = \begin{bmatrix} 1 & 2104 \\ 1 & 1416 \\ 1 & 1534 \\ 1 & 852 \\ \hline \theta = (X^T X)^{-1} X^T \end{bmatrix}$				45 2 40 2 30 36	$\underline{y} = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$	460 232 315 178	tedeur

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^TX		
Works well when n is large	Slow if n is very large		

With the normal equation, computing the inversion has complexity $\mathcal{O}(n^3)$. 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.

✓ Completado



