

Multiple Features

Multivariate Linear Regression

Linear Regression with Multiple Variables

Introduction

- Linear regression with multiple variables is also known as "multivariate linear regression".
- We now introduce notation for equations where we can have any number of input variables.

Multiple features (variables).

Size (feet ²)	Price (\$1000)
x	y
2104	460
1416	232
1534	315
852	178
...	...

$$h_{\theta}(x) = \theta_0 + \theta_1 x$$

Multiple features (variables).

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

$$m = 47$$

$$x^{(2)} = \begin{bmatrix} 1416 \\ 3 \\ 2 \\ 40 \end{bmatrix}$$

Notation:

→ n = number of features

$$n = 4$$

→ $x^{(i)}$ = input (features) of i^{th} training example.

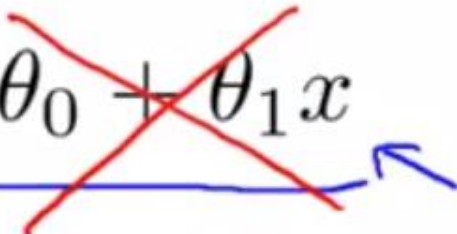
$x_j^{(i)}$ = value of feature j in i^{th} training example.

Hypothesis:

Previously: $h_{\theta}(x) = \theta_0 + \theta_1 x$

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$$h_{\theta}(x) = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \theta_3 x_3 + \theta_4 x_4$$

$$\text{e.g. } h_{\theta}(x) = 80 + 0.1x_1 + 0.01x_2 + 3x_3 - 2x_4$$

$$\rightarrow h_{\theta}(x) = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \cdots + \theta_n x_n$$

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For convenience of notation, define $x_0 = 1$. ($x_0^{(i)} = 1$)

$$x = \begin{bmatrix} x_0 \\ x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} \in \mathbb{R}^{n+1}$$

$$\theta = \begin{bmatrix} \theta_0 \\ \theta_1 \\ \theta_2 \\ \vdots \\ \theta_n \end{bmatrix} \in \mathbb{R}^{n+1}$$

$$h_{\theta}(x) = \theta_0 x_0 + \theta_1 x_1 + \dots + \theta_n x_n$$

$\downarrow = 1$

$$= \boxed{\theta^T x}$$

$\begin{bmatrix} \theta_0 & \theta_1 & \dots & \theta_n \end{bmatrix}$
 θ^T
 $(n+1) \times 1$
 matrix
 $\theta^T x$

$\begin{bmatrix} x_0 \\ x_1 \\ \vdots \\ x_n \end{bmatrix}$
 x

Multivariate linear regression. \leftarrow

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Gradient Descent For MLR

Hypothesis: $\underline{h_{\theta}(x) = \theta^T x = \theta_0 x_0 + \theta_1 x_1 + \theta_2 x_2 + \dots + \theta_n x_n}$

Parameters: $\underline{\theta_0, \theta_1, \dots, \theta_n}$ $\underline{\mathcal{O}}$ $n+1$ -dimensional vector

Cost function:

$$\underline{J(\theta_0, \theta_1, \dots, \theta_n)} = \frac{1}{2m} \sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)})^2$$

$\underline{J(\theta)}$

Gradient descent:

Repeat {

$$\rightarrow \theta_j := \theta_j - \alpha \left[\frac{\partial}{\partial \theta_j} \underline{J(\theta_0, \dots, \theta_n)} \right] \underline{J(\theta)}$$

}

(simultaneously update for every $j = 0, \dots, n$)

Feature Scaling

- We can speed up gradient descent by having each of our input values in roughly the same range.
- This is because θ will descend
 - quickly on small ranges and
 - slowly on large ranges,
- So it will oscillate inefficiently down to the optimum when the variables are very uneven.

Feature Scaling

Idea: Make sure features are on a similar scale.

E.g. x_1 = size (0-2000 feet²)

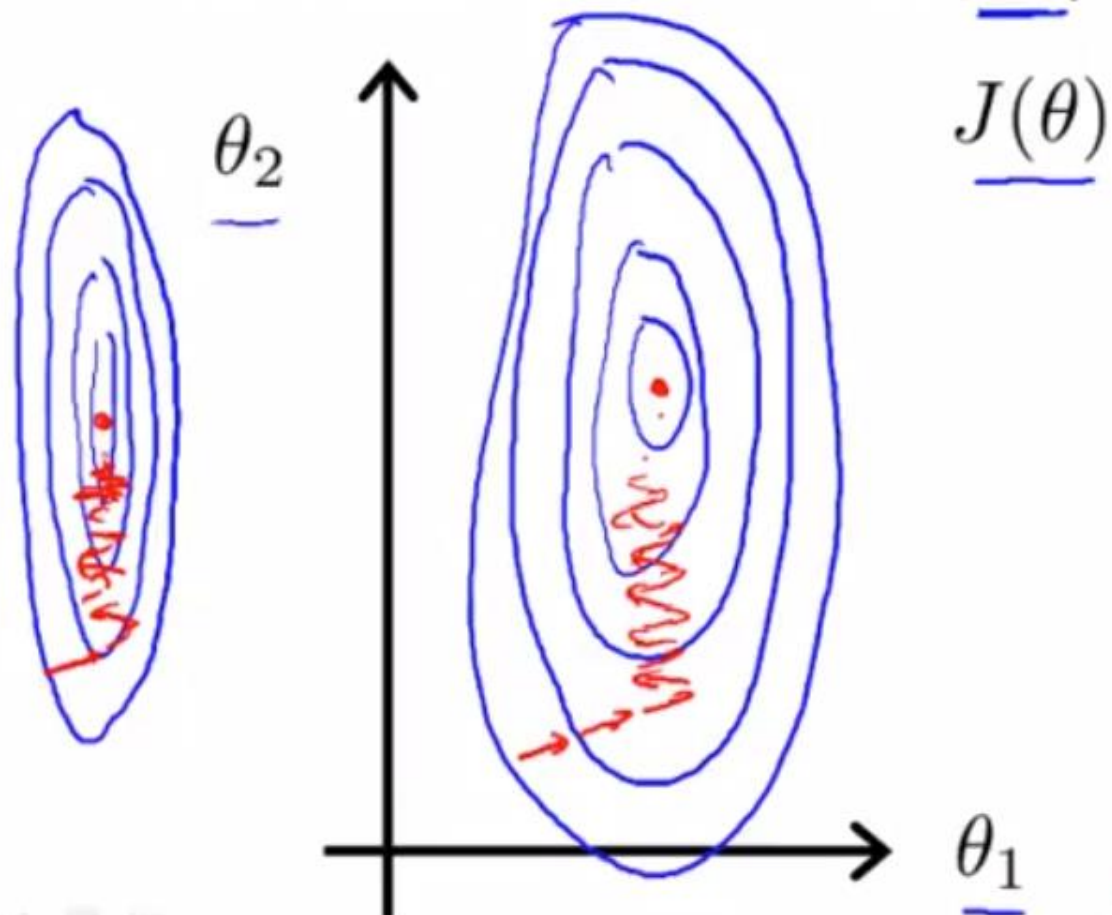
x_2 = number of bedrooms (1-5)

Feature Scaling

Idea: Make sure features are on a similar scale.

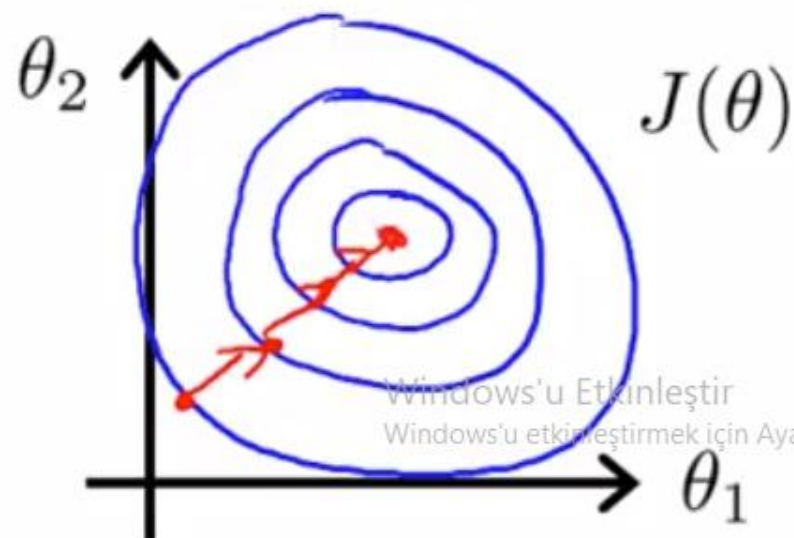
E.g. $x_1 = \text{size (0-2000 feet}^2\text{)}$ \leftarrow

$x_2 = \text{number of bedrooms (1-5)}$ \leftarrow



$$\rightarrow x_1 = \frac{\text{size (feet}^2\text{)}}{2000}$$

$$\rightarrow x_2 = \frac{\text{number of bedrooms}}{5}$$



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Feature Scaling

Get every feature into approximately a $-1 \leq x_i \leq 1$ range.

$$x_0 = 1$$

$$0 \leq x_1 \leq 3 \quad \checkmark$$

$$-2 \leq x_2 \leq 0.5 \quad \checkmark$$

$$-100 \leq x_3 \leq 100 \quad \times$$

$$-0.0001 \leq x_4 \leq 0.0001 \quad \times$$

$$-3 \text{ to } 3 \quad \checkmark$$

$$-\frac{1}{5} \text{ to } \frac{1}{5} \quad \checkmark$$

Feature Scaling

E.g. $\rightarrow x_1 = \frac{\text{size} - 1000}{2000}$

Average size = 1000

$$x_2 = \frac{\# \text{bedrooms} - 2}{5}$$

1-5 bedrooms

$$-0.5 \leq x_1 \leq 0.5, -0.5 \leq x_2 \leq 0.5$$

$$x_1 \leftarrow \frac{x_1 - \mu_1}{s_1}$$

← avg value of x_1 in training set

← range (max-min) (or standard deviation)

$$x_2 \leftarrow \frac{x_2 - \mu_2}{s_2}$$

Exercise

- Suppose you are using a learning algorithm to estimate the price of houses in a city. You want one of your features x_i to capture the age of the house.
- In your training set, all of your houses have an age between 30 and 50 years, with an average age of 38 years.
- How do you normalize your data using mean normalization?

Normal Equation

Computing Parameters Analytically

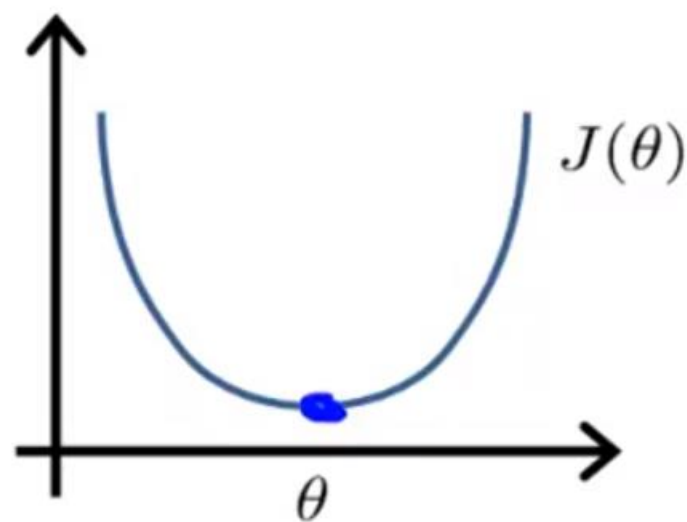
Linear Regression with Multiple Variables

Intuition: If 1D ($\theta \in \mathbb{R}$)

$\rightarrow \underline{J(\theta) = a\theta^2 + b\theta + c}$

$\frac{d}{d\theta} J(\theta) = \dots \stackrel{\text{set}}{=} 0$

Solve for θ



$$\theta \in \mathbb{R}^{n+1} \quad J(\theta_0, \theta_1, \dots, \theta_m) = \frac{1}{2m} \sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)})^2$$

$$\frac{\partial}{\partial \theta_j} J(\theta) = \dots = 0 \quad (\text{for every } j)$$

Solve for $\theta_0, \theta_1, \dots, \theta_n$

Examples: $m = 4$.

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$\underline{X} = \begin{bmatrix} 1 & 2104 & 5 & 1 & 45 \\ 1 & 1416 & 3 & 2 & 40 \\ 1 & 1534 & 3 & 2 & 30 \\ 1 & 852 & 2 & 1 & 36 \end{bmatrix}$
 $m \times (n+1)$

$\underline{y} = \begin{bmatrix} 460 \\ 232 \\ 315 \\ 178 \end{bmatrix}$
 m -dimensional vector

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

Exercise

- Suppose you have the training in the table below:

age (x_1)	height in cm (x_2)	weight in kg (y)
4	89	16
9	124	28
5	103	20

- You would like to predict a child's weight as a function of his age and height with the model
- $weight = \theta_0 + \theta_1 x_1 + \theta_2 x_2$
- What are X and y?

How to choose them?

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