## Lecture 2

# Linear Regression 

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## Outline

## Linear Regression

Gradient Descent?

## Multi Feature Representation

Questions and Answers

## Review of Machine Learning

Input (X)


For each input $x$, output $y=h(x)$

## Linear Regression



Table 1: Training data of housing price in Hanoi
In Supervised Learning, each training data consists of 2 elements: input x (features) and output y (response)

Notation
( $\mathrm{x}, \mathrm{y}$ )
$\left(x^{(i)}, y^{(i)}\right)$
: One training data
: the $\mathrm{i}^{\text {th }}$ training data

## Linear Regression

## Plotting of training data

Price of House in Hanoi


Linear Regression: Assume that the output $\boldsymbol{y}$ is a linear function of input $\boldsymbol{x}$

$$
y=h(x)=a^{*} x+b
$$

## Linear Regression

## Objective:

Learning the function $y=h(x)=a^{*} x+b$, such as it returns the minimize error- cost function for the training data (optimization problem)

Find the coefficient $a, b$ to minimize the cost function

## Linear Regression

## Cost Function:

## The error for training data:

$$
e^{(1)}=\frac{1}{2}\left(h\left(x^{(1)}\right)-y^{(1)}\right)^{2}=\frac{1}{2}(30 a+b-2.5)^{2}
$$

$$
e^{(2)}=\frac{1}{2}\left(h\left(x^{(2)}\right)-y^{(2)}\right)^{2}=\frac{1}{2}(43 a+b-3.4)^{2}
$$

| Size $\left(m^{2}\right)$ | Price (b.VND) |
| :---: | :---: |
| 30 | 2.5 |
| 43 | 3.4 |
| 25 | 1.8 |
| 51 | 4.5 |
| 40 | 3.2 |
| 20 | 1.6 |

$e^{(m)}=\frac{1}{2}\left(h\left(x^{(m)}\right)-y^{(m)}\right)^{2}=\frac{1}{2}\left(x^{(m)} a+b-y^{(m)}\right)^{2}$
The cost function is define as:

$$
\begin{gathered}
E=\frac{1}{m}\left(e^{(1)}+e^{(2)}+\ldots+e^{(m)}\right)=\frac{1}{m} \sum_{i=1}^{m} e^{(i)}=\frac{1}{2 m} \sum_{i=1}^{m}\left(h\left(x^{(i)}\right)-y^{(i)}\right)^{2} \\
E=\frac{1}{2 m} \sum_{i=1}^{m}\left(a x^{(i)}+b-y^{(i)}\right)^{2}
\end{gathered}
$$

## Gradient Descent

## Objective:

Use the gradient function to find a minimum of a function

$$
E=\frac{1}{2 m} \sum_{i=1}^{m}\left(a x^{(i)}+b-y^{(i)}\right)^{2}
$$

Note that E is a function of a and b , we have only 2 variables a and b.

Idea:
Choose random number for $a$ and $b$, the algorithm is implemented in many steps. At each step, modify $a$ and $b$ such $s$ the cost function is reduced

$$
a:=a-\alpha \frac{\partial}{\partial_{a}} E(a) \quad b:=b-\alpha \frac{\partial}{\partial_{b}} E(b)
$$

## Gradient Descent

A demonstration and explanation of Gradient Descent algorithm can be found at the following website:
http://www.onmyphd.com/?p=gradient.descent

## Gradient Descent

Suppose that ( $\mathrm{x} 0, \mathrm{y} 0$ ) is a local minimum of the cost function, what will 1 iteration of gradient descent do?

1. Leave $x 0$ unchanged
2. Change $x 0$ in random direction
3. Move $x 0$ toward the global minimum
4. Decrease x0


## Gradient Descent

Calculate the derivations of the cost function: $\frac{\partial}{\partial_{a}} E(a) \quad \frac{\partial}{\partial_{b}} E(b)$

$$
E=\frac{1}{2 m} \sum_{i=1}^{m}\left(a x^{(i)}+b-y^{(i)}\right)^{2}
$$

Given the following formula:

$$
\frac{\partial}{\partial_{x}}\left(x^{2}\right)=2 x
$$

$$
\frac{\partial}{\partial_{x}}\left(f(x)^{2}\right)=2 f(x) \cdot \frac{\partial}{\partial_{x}} f(x)
$$

## Gradient Descent

$$
\begin{gathered}
\frac{\partial}{\partial_{a}} E(a)=\frac{1}{m} \sum_{i=1}^{m}\left(a x^{(i)}+b-y^{(i)}\right) \cdot x^{(i)} \\
\frac{\partial}{\partial_{b}} E(b)=\frac{1}{m} \sum_{i=1}^{m}\left(a x^{(i)}+b-y^{(i)}\right)
\end{gathered}
$$

## Gradient Descent

## Exercise:

Starting at $a=0$ and $b=0, \alpha=0.01$, what is the cost function?
Calculate the value of $a$ and $b$ after first iteration (first step). Confirm if the cost function is reduced or not?

| Size $\left(m^{2}\right)$ | Price (b.VND) |
| :---: | :---: |
| 30 | 2.5 |
| 43 | 3.4 |
| 25 | 1.8 |
| 51 | 4.5 |
| 40 | 3.2 |
| 20 | 1.6 |

## Gradient Descent

## Batch and Stochastic Gradient Descent

## Batch gradient Descent:

Compute the Gradient Descent using the whole data set

## Stochastic Gradient Descent:

Compute the Gradient Descent using 1 training example at a time

- Randomly reorder the training data
- Use $\left(x^{(1)}, y^{(1)}\right)$ to calculate the gradient descent in order to update a,b
- Use ( $\left.x^{(2)}, y^{(2)}\right)$ to update
......


## Gradient Descent

## Mini-Batch Gradient Descent

Compute the Gradient Descent for $t$ example at a time $(1<t<m)$
Example:
We have 1000 training data.
Step 1: Update the coefficient using 10 data 1-10
Step 2: Update the coefficient using 10 data 11-20

## Gradient Descent



Big value of $\alpha$ may lead to the incensement of cost function and not convergence
$\Rightarrow$ Gradient Descent works if the cost function decrease at each step

## Gradient Descent

## Convergence:

How to know if a function is converged or not?

- Cost function is smaller than a predefined threshold
- After a big enough number of step
- Cost function decreased less than a predefine threshold


## Gradient Descent

Summarization:

1. Calculate the cost function
2. Select random value for coefficient $a, b$
3. Step by step modify $a, b$ such as the cost function is decreased While (not converged)
do

$$
a:=a-\frac{\partial}{\partial_{a}} E(a) \quad b:=b-\frac{\partial}{\partial_{b}} E(b)
$$

## Multiple Input Representation

## Example:

Consider the same example, but with more inputs

| Size $\left(\mathrm{m}^{2}\right)$ | $\mathrm{N}^{0}$ of floors | $N^{0}$ of rooms | Price (billion <br> VND) |
| :---: | :---: | :---: | :---: |
| 30 | 3 | 6 | 2.5 |
| 43 | 4 | 8 | 3.4 |
| 25 | 2 | 3 | 1.8 |
| 51 | 4 | 9 | 4.5 |
| 40 | 3 | 5 | 3.2 |
| 20 | 1 | 2 | 1.6 |

$x^{(i)}$ : the input of $\mathrm{i}^{\text {th }}$ training data
$x_{j}{ }^{(i)}$ : the component j of $\mathrm{i}^{\text {th }}$ training data

## Multiple Input Representation

## Matrix representation:

$$
\begin{gathered}
y=h(x)=\theta_{0}+\theta_{1} x_{1}+\theta_{2} x_{2}+\ldots+\theta_{m} x_{m} \\
x=\left[\begin{array}{c}
1 \\
x_{1} \\
\ldots \\
x_{m}
\end{array}\right] \quad \theta=\left[\begin{array}{c}
\theta_{0} \\
\theta_{1} \\
\ldots \\
\theta_{m}
\end{array}\right]
\end{gathered}
$$



## Multiple Input Representation

## Cost Function:

$$
E(\theta)=\frac{1}{2 m} \sum_{i=1}^{m}\left(h_{\theta}\left(x^{(i)}\right)-y^{(i)}\right)^{2}=\frac{1}{2 m} \sum_{i=1}^{m}\left(\theta^{T} x^{(i)}-y^{(i)}\right)^{2}
$$

## Multiple Input Representation

## Gradient Descent

Start with random value of $\theta$, step by step modify $\theta$ in order to decrease the cost function

$$
\begin{aligned}
\theta_{j} & :=\theta_{j}-\alpha \frac{\partial}{\partial_{\theta_{j}}} E(\theta) \\
\frac{\partial}{\partial_{\theta_{j}}} E(\theta) & =\frac{1}{2 m} \sum_{i=1}^{m} \frac{\partial}{\partial_{\theta_{j}}}\left(\theta^{T} x^{(i)}-y^{(i)}\right)^{2} \\
& =\frac{1}{m} \sum_{i=1}^{m}\left(\theta^{T} x^{(i)}-y^{(i)}\right) x_{j}^{(i)}
\end{aligned}
$$

## Multiple Input Representation

## Gradient Descent

Start with random value of $\theta$, step by step modify $\theta$ in order to decrease the cost function

$$
\begin{aligned}
\theta_{j} & :=\theta_{j}-\alpha \frac{\partial}{\partial_{\theta_{j}}} E(\theta) \\
\frac{\partial}{\partial_{\theta_{j}}} E(\theta) & =\frac{1}{2 m} \sum_{i=1}^{m} \frac{\partial}{\partial_{\theta_{j}}}\left(\theta^{T} x^{(i)}-y^{(i)}\right)^{2} \\
& =\frac{1}{m} \sum_{i=1}^{m}\left(\theta^{T} x^{(i)}-y^{(i)}\right) x_{j}^{(i)}
\end{aligned}
$$

## Normal Equations

## Linear Regression:

Minimize the value of the cost function:

$$
E(\theta)=\frac{1}{2 m} \sum_{i=1}^{m}\left(h_{\theta}\left(x^{(i)}\right)-y^{(i)}\right)^{2}=\frac{1}{2 m} \sum_{i=1}^{m}\left(\theta^{T} x^{(i)}-y^{(i)}\right)^{2}
$$

## Normal Equations:

Solve the following equation to find out the optimized value of $\theta$

$$
\frac{\partial}{\partial_{\theta}} E(\theta)=0
$$

## Normal Equations

## Linear Regression:

Minimize the value of the cost function:

$$
E(\theta)=\frac{1}{2 m} \sum_{i=1}^{m}\left(h_{\theta}\left(x^{(i)}\right)-y^{(i)}\right)^{2}=\frac{1}{2 m} \sum_{i=1}^{m}\left(\theta^{T} x^{(i)}-y^{(i)}\right)^{2}
$$

## Normal Equations:

Solve the following equation to find out the optimized value of $\theta$

$$
\frac{\partial}{\partial_{\theta}} E(\theta)=0 \quad \forall j \in(0,1, \ldots, n), \frac{\partial}{\partial_{\theta_{j}}} E(\theta)=0
$$

## Normal Equations

## Solution:

Given a training set of $m$ training example, each contain $n$ inputs, we have the matrix $X(m, n+1)$ of inputs and vector of output $Y$

$$
X=\left[\begin{array}{cccc}
x_{0}^{(1)} & x_{1}^{(1)} & \ldots & x_{n}^{(1)} \\
x_{0}^{(2)} & x_{1}^{(2)} & \ldots & x_{n}^{(2)} \\
& & & \\
& & \ldots & \\
x_{0}^{(m)} & x_{1}^{(m)} & \ldots & x_{n}^{(m)}
\end{array}\right]=\left[\begin{array}{c}
\left(x^{(1)}\right)^{T} \\
\left(x^{(2)}\right)^{T} \\
\ldots \\
\left(x^{(m)}\right)^{T}
\end{array}\right] \quad Y=\left[\begin{array}{c}
y^{(1)} \\
y^{(2)} \\
\ldots \\
y^{(m)}
\end{array}\right]
$$

Solution of normal equations is:

$$
\theta=\left(X^{T} X\right)^{-1} X^{T} Y
$$

## Homework

Write a program in (Matlab/C++)to implement gradient descent algorithm for the following training data with different learning method: batch learning, stochastic and mini-batch, normal equation. Send your code and report on what do you see from the result to my email before 20 October 2016

| Size $\left(\mathrm{m}^{2}\right)$ | $\mathrm{N}^{0}$ of floors | $N^{0}$ of rooms | Price (billion <br> VND) |
| :---: | :---: | :---: | :---: |
| 30 | 3 | 6 | 2.5 |
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## Polynomial Regression

## Polynomial Regression

Output is an polynomial function of the input
For example

$$
h(x)=\theta_{0}+\theta_{1} x+\theta_{2} x^{2}+\ldots+\theta_{n} x^{n}
$$

Assume $\quad x_{1}=x$

$$
\begin{aligned}
& x_{2}=x^{2} \\
& \ldots \\
& x_{n}=x^{n}
\end{aligned} \quad h(x)=\theta_{0}+\theta_{1} x_{1}+\theta_{2} x_{2}+\ldots+\theta_{n} x_{n}
$$

## References

http://openclassroom.stanford.edu/MainFolder/VideoPage.php?co urse=MachineLearning\&video=02.4-LinearRegressionlGradientDescent\&speed=100

## Feature Rescale

Objective: Scale all features to the same scale, in order to have easier computation
Popular scale : [0,1],[-0.5,0.5]
$x=x / \max (x)$
$c=\operatorname{mean}(x) x=x-c / \max (x)=>$

