Notes

Machine Learning by Andrew Ng on Coursera

Sparsh Jain

September 23, 2020

Contents

Chapter 1

Introduction

Machine learning (task, experience, performance) can be classified into *Supervised* and *Unsupervised* learning.

1.1 Supervised Learning

Supervised learning can be basically classified into *Regression* and *Classification* problems.

1.1.1 Regression Problem

Regression problems work loosely on continuous range of outputs.

1.1.2 Classification Problems

Classification problems work loosely on discrete range of outputs.

1.2 Unsupervised Learning

An example is *Clustering Problem*.

Check Appendix A for more details.

Chapter 2

Linear Regression with One Variable

2.1 Notations

$$
\begin{aligned}
m &= \text{number of training examples} \\
x\text{'s} &= \text{'input' variables / features} \\
y\text{'s} &= \text{'output' variables / 'target' variables} \\
(x, y) &= \text{single training example} \\
(x^{(i)}, y^{(i)}) &= i^{th} \text{ example}
\end{aligned}
$$

2.2 Supervised Learning

We have a data set (*Training Set*).

Training Set $\rightarrow$ Learning Algorithm $\rightarrow$ h (*hypothesis*, a function $X \rightarrow Y$)

To Represent h

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

Cost

$$\underset{\theta_0,\ \theta_1}{\text{minimize}} \frac{1}{2m} \sum_{1}^{m} (h_\theta(x) - y)^2$$

Cost Function

Squared Error Cost Function

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

$$\underset{\theta_0,\ \theta_1}{\text{minimize}}\, J(\theta_0, \theta_1)$$

2.3 Gradient Descent

Finds local optimum:

1. Start with some value
2. Get closer to optimum

Algorithm

$$\theta_j := \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta)\ \forall j$$

where α = learning rate

Important!

Simultaneous Update!

$$temp_j := \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta)\ \forall j$$
$$\theta_j := temp_j\ \forall j$$

2.4 Gradient Descent for Linear Regression

Cost function for linear regression is convex!

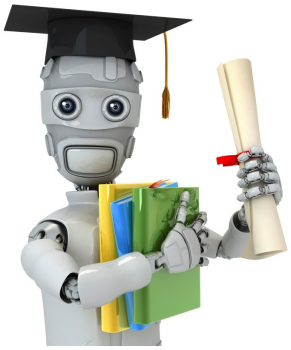
Batch Gradient Descent: Each step of gradient descent uses all training examples.

Check Appendix B for more details.

Appendices

Appendix A

Lecture 1



Machine Learning

Introduction

Welcome

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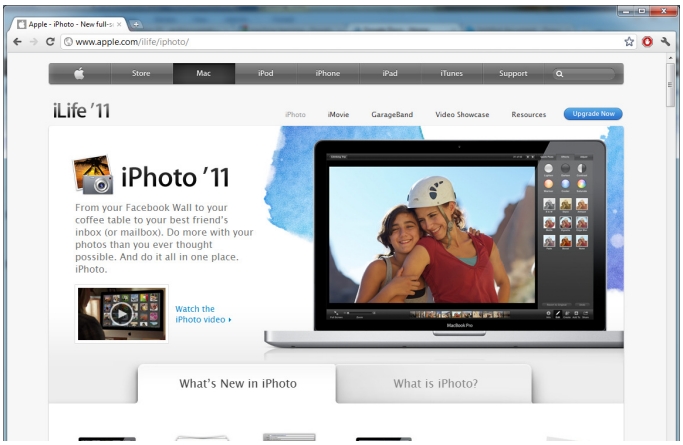
Apple - iPhoto - New full-
www.apple.com/ilife/iphoto/
Store
Mac
iPod
iPhone
iPad
iTunes
Support
iLife '11
iPhoto
iMovie
GarageBand
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Resources
Upgrade Now
iPhoto '11
From your Facebook Wall to your coffee table to your best friend's inbox (or mailbox). Do more with your photos than you ever thought possible. And do it all in one place. iPhoto.
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What is iPhoto?

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Machine Learning

- Grew out of work in AI
- New capability for computers

Examples:

- Database mining
  Large datasets from growth of automation/web.
  E.g., Web click data, medical records, biology, engineering
- Applications can't program by hand.
  E.g., Autonomous helicopter, handwriting recognition, most of Natural Language Processing (NLP), Computer Vision.

Machine Learning

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- Self-customizing programs
  E.g., Amazon, Netflix product recommendations

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- Applications can't program by hand.
  E.g., Autonomous helicopter, handwriting recognition, most of Natural Language Processing (NLP), Computer Vision.
- Self-customizing programs
  E.g., Amazon, Netflix product recommendations
- Understanding human learning (brain, real AI).

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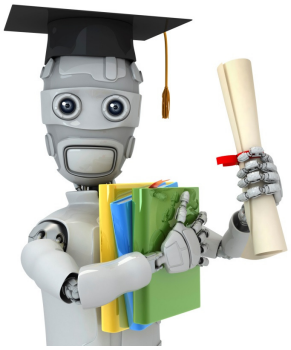

Machine Learning

Introduction

What is machine learning

Machine Learning definition

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- Arthur Samuel (1959). Machine Learning: Field of study that gives computers the ability to learn without being explicitly programmed.

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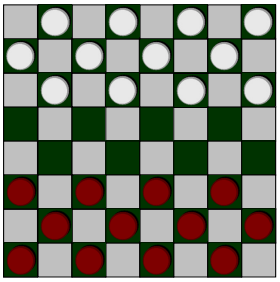

Machine Learning definition

- Arthur Samuel (1959). Machine Learning: Field of study that gives computers the ability to learn without being explicitly programmed.
- Tom Mitchell (1998) Well-posed Learning Problem: A computer program is said to *learn* from experience E with respect to some task T and some performance measure P, if its performance on T, as measured by P, improves with experience E.

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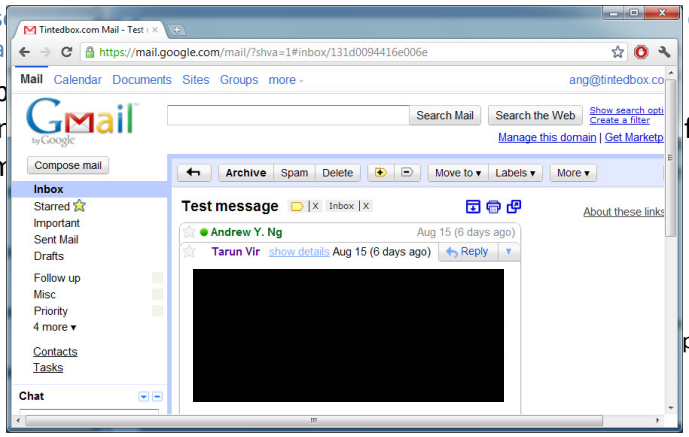
Suppose your email program watches which emails you do or do not mark as spam, and based on that learns how to better filter spam. What is the task T in this setting?

- ◯ Classifying emails as spam or not spam.
- ◯ Watching you label emails as spam or not spam.
- ◯ The number (or fraction) of emails correctly classified as spam/not spam.
- ◯ None of the above—this is not a machine learning problem.

"A computer program is said to *learn* from experience E with respect to s on T, a

Supp or do not r filter spam



pam.

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Machine learning algorithms:

- Supervised learning
- Unsupervised learning

Others: Reinforcement learning, recommender systems.

Also talk about: Practical advice for applying learning algorithms.

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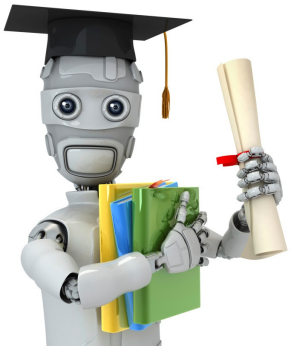
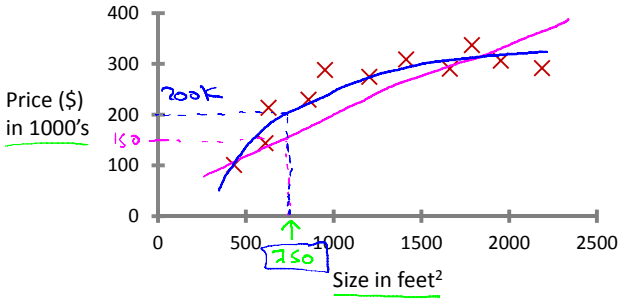


Machine Learning

Introduction

Supervised Learning

Housing price prediction.

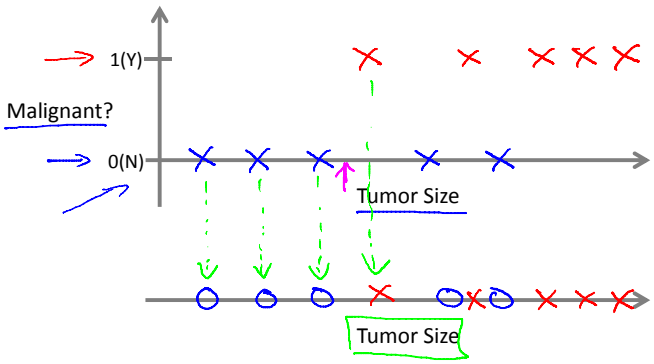


Supervised Learning

"right answers" given

Regression: Predict continuous valued output (price)

Breast cancer (malignant, benign)



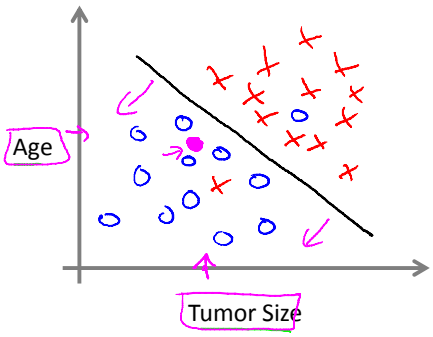
Classification

Discrete valued output (0 or 1)

0, 1, 2, 3

benign

type 1 cancer



- Clump Thickness
- Uniformity of Cell Size
- Uniformity of Cell Shape

...

You're running a company, and you want to develop learning algorithms to address each of two problems.

1000's

Problem 1: You have a large inventory of identical items. You want to predict how many of these items will sell over the next 3 months.

Problem 2: You'd like software to examine individual customer accounts, and for each account decide if it has been hacked/compromised. 0 – not hacked, 1 – hacked

Should you treat these as classification or as regression problems?

- ◯ Treat both as classification problems.
- ◯ Treat problem 1 as a classification problem, problem 2 as a regression problem.
- ◯ Treat problem 1 as a regression problem, problem 2 as a classification problem.
- ◯ Treat both as regression problems.

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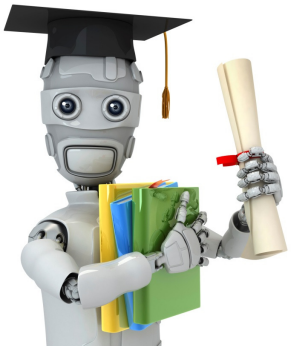
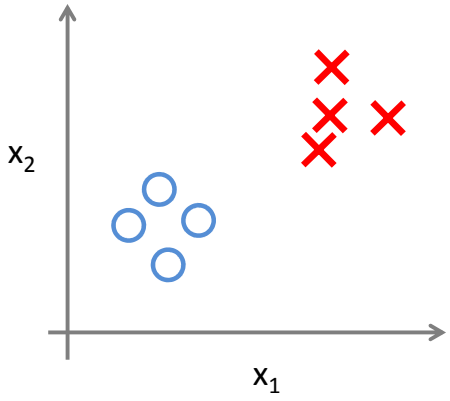


Machine Learning

Introduction

Unsupervised Learning

Supervised Learning



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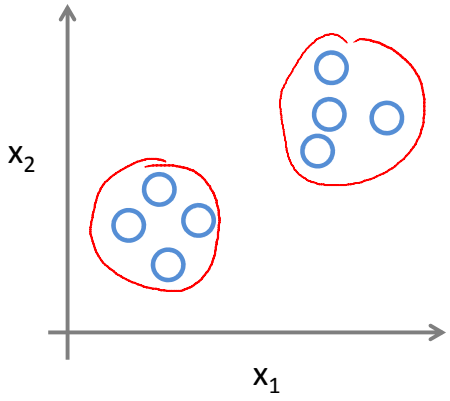
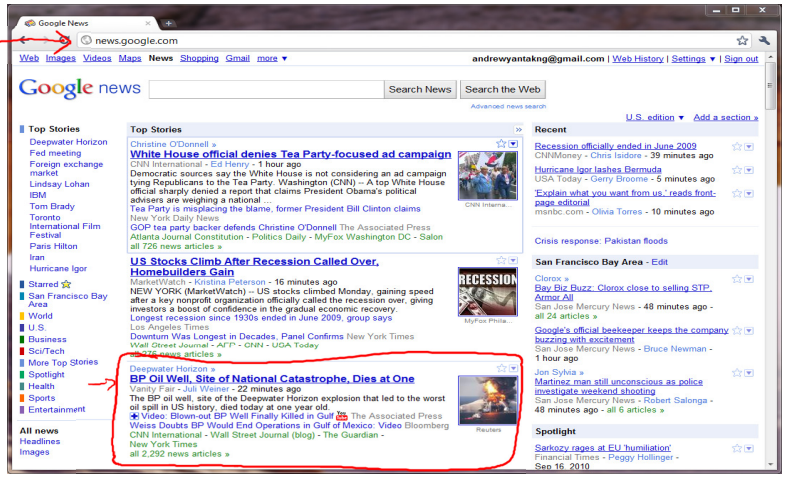
Unsupervised Learning

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Google news
Search News
Search the Web
Advanced news search
U.S. edition ▾
Add a section »
Top Stories
Deepwater Horizon
Fed meeting
Foreign exchange market
Lindsay Lohan
IBM
Tom Brady
Toronto International Film Festival
Paris Hilton
Iran
Hurricane Igor
Starred
San Francisco Bay Area
World
U.S.
Business
Sci/Tech
More Top Stories
Spotlight
Health
Sports
Entertainment
All news
Headlines
Images
Top Stories
Christine O'Donnell »
White House official denies Tea Party-focused ad campaign
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Democratic sources say the White House is not considering an ad campaign tying Republicans to the Tea Party. Washington (CNN) -- A top White House official sharply denied a report that claims President Obama's political advisers are weighing a national ...
Tea Party is misplacing the blame, former President Bill Clinton claims New York Daily News
GOP tea party backer defends Christine O'Donnell The Associated Press
Atlanta Journal Constitution - Politics Daily - MyFox Washington DC - Salon
all 726 news articles »
US Stocks Climb After Recession Called Over, Homebuilders Gain
MarketWatch - Kristina Peterson - 16 minutes ago
NEW YORK (MarketWatch) -- US stocks climbed Monday, gaining speed after a key nonprofit organization officially called the recession over, giving investors a boost of confidence in the gradual economic recovery.
Longest recession since 1930s ended in June 2009, group says Los Angeles Times
Downturn Was Longest in Decades, Panel Confirms New York Times
Wall Street Journal - AFP - CNN - USA Today
4,276 news articles »
RECESSION
MyFox Phila...
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BP Oil Well, Site of National Catastrophe, Dies at One
Vanity Fair - Juli Weiner - 22 minutes ago
The BP oil well, site of the Deepwater Horizon explosion that led to the worst oil spill in US history, died today at one year old.
Video: Blown-out BP Well Finally Killed in Gulf The Associated Press
Weiss Doubts BP Would End Operations in Gulf of Mexico: Video Bloomberg
CNN International - Wall Street Journal (blog) - The Guardian - New York Times
all 2,292 news articles »
Reuters
Recent
Recession officially ended in June 2009
CNNMoney - Chris Isidore - 39 minutes ago
Hurricane Igor lashes Bermuda
USA Today - Gerry Broome - 5 minutes ago
'Explain what you want from us,' reads front-page editorial
msnbc.com - Olivia Torres - 10 minutes ago
Crisis response: Pakistan floods
San Francisco Bay Area - Edit
Clorox »
Bay Biz Buzz: Clorox close to selling STP, Armor All
San Jose Mercury News - 48 minutes ago - all 24 articles »
Google's official beekeeper keeps the company buzzing with excitement
San Jose Mercury News - Bruce Newman - 1 hour ago
Jon Sylvia »
Martinez man still unconscious as police investigate weekend shooting
San Jose Mercury News - Robert Salonga - 48 minutes ago - all 6 articles »
Spotlight
Sarkozy rages at EU 'humiliation'
Financial Times - Peggy Hollinger - Sep 16, 2010

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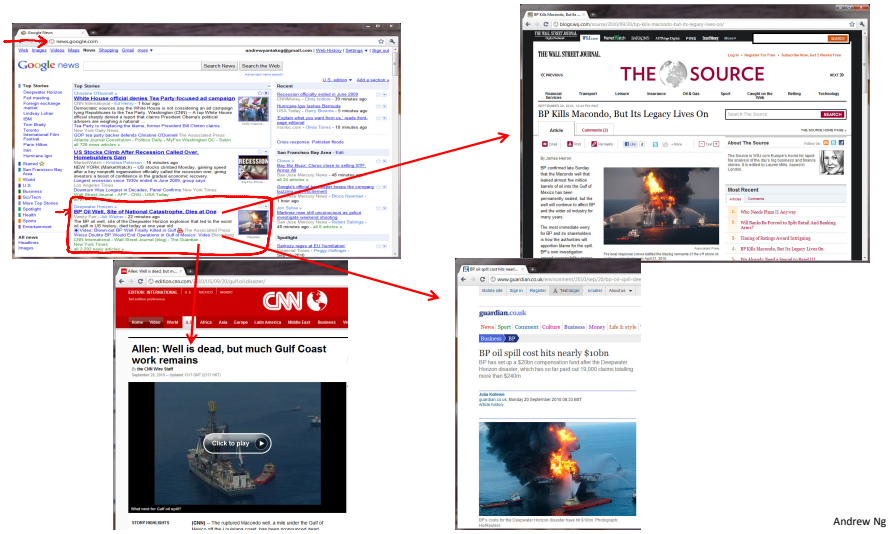
Google news
BP Oil Well, Site of National Catastrophe, Dies at One
THE SOURCE
BP Kills Macondo, But Its Legacy Lives On
CNN
Allen: Well is dead, but much Gulf Coast work remains
Click to play
guardian.co.uk
BP oil spill cost hits nearly $10bn

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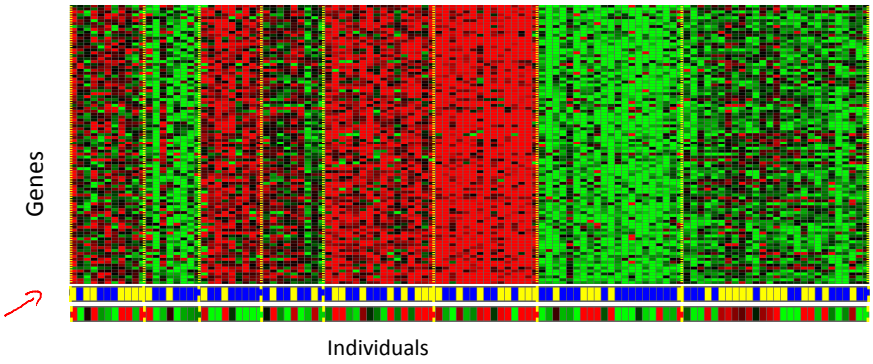
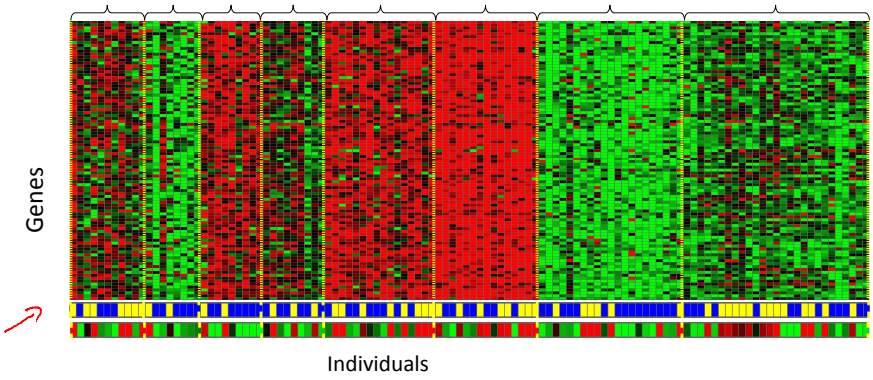
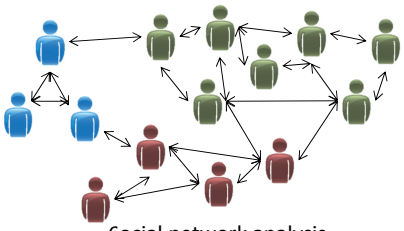


[Source: Daphne Koller]

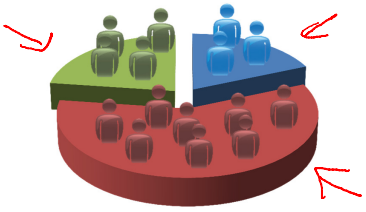


[Source: Daphne Koller]

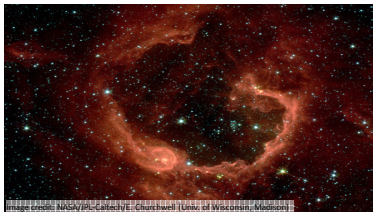
Organize computing clusters



Social network analysis

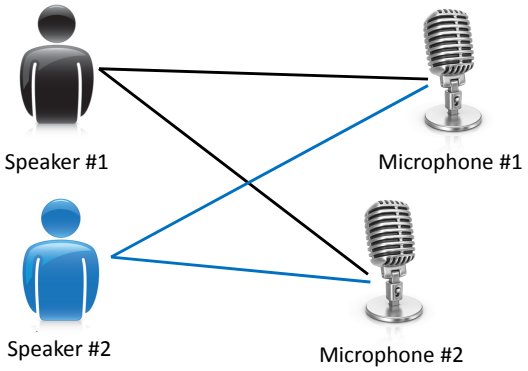


Market segmentation



Astronomical data analysis

Cocktail party problem



Microphone #1: Output #1:

Microphone #2: Output #2:

Microphone #1: Output #1:

Microphone #2: Output #2:

[Audio clips courtesy of Te-Won Lee.]

Cocktail party problem algorithm

```
[W,s,v] = svd((repmat(sum(x.*x,1),size(x,1),1).*x)*x');
```

[Source: Sam Roweis, Yair Weiss & Eero Simoncelli]

Of the following examples, which would you address using an unsupervised learning algorithm? (Check all that apply.)

- [ ] Given email labeled as spam/not spam, learn a spam filter.
- [ ] Given a set of news articles found on the web, group them into set of articles about the same story.
- [ ] Given a database of customer data, automatically discover market segments and group customers into different market segments.
- [ ] Given a dataset of patients diagnosed as either having diabetes or not, learn to classify new patients as having diabetes or not.

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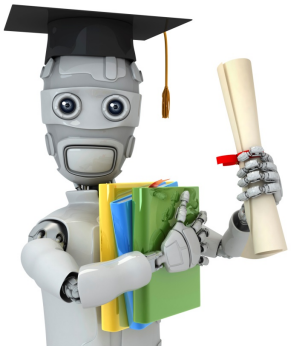
Appendix B

Lecture 2

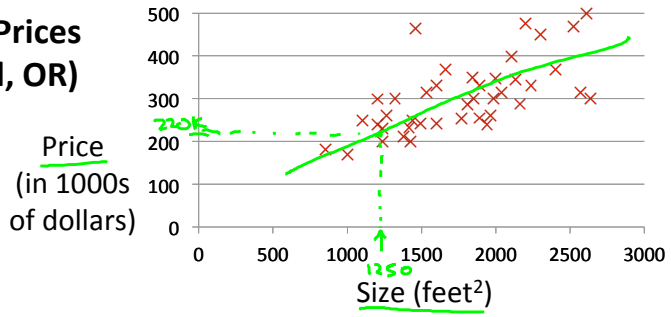


Machine Learning

Linear regression with one variable

Model representation

Housing Prices (Portland, OR)



Supervised Learning

Given the "right answer" for each example in the data.

Regression Problem

Predict real-valued output

Classification: Discrete-valued output

Training set of housing prices (Portland, OR)

Size in feet^2 (x)	Price ($) in 1000's (y)
2104	460
1416	232
1534	315
852	178
…	…

m = 47

Notation:

- **m** = Number of training examples
- **x**'s = "input" variable / features
- **y**'s = "output" variable / "target" variable

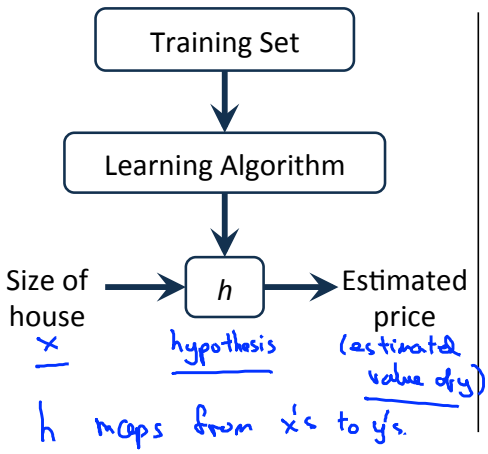
(x, y) - one training example

$(x^{(i)}, y^{(i)})$ - i^{th} training example

$x^{(1)} = 2104$

$x^{(2)} = 1416$

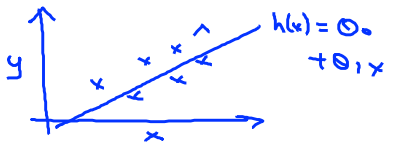
$y^{(1)} = 460$



How do we represent *h* ?

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

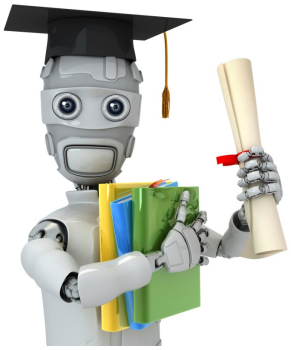
Shorthand: $h(x)$



Linear regression with one variable.

Univariate linear regression.

↳ one variable



Machine Learning

Linear regression with one variable

Cost function

Training Set

Size in feet² (x)	Price ($) in 1000's (y)
2104	460
1416	232
1534	315
852	178
…	…

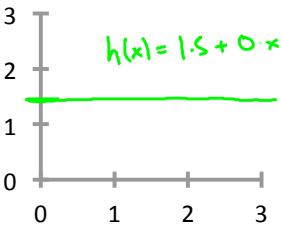
$m = 47$

Hypothesis: $h_\theta(x) = \theta_0 + \theta_1 x$

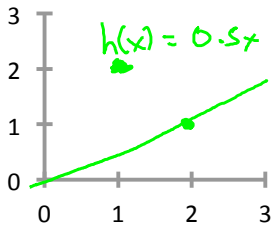
θ_i's: Parameters

How to choose θ_i's ?

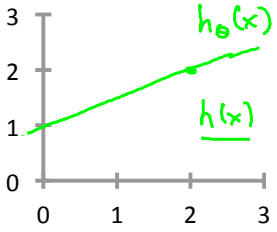
$h_\theta(x) = \theta_0 + \theta_1 x$



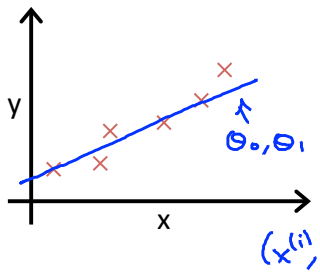
- $\theta_0 = 1.5$
- $\theta_1 = 0$



- $\theta_0 = 0$
- $\theta_1 = 0.5$



- $\theta_0 = 1$
- $\theta_1 = 0.5$



#training examples

$$\underset{\theta_0,\theta_1}{\text{minimize}} \; \frac{1}{2m}\sum_{i=1}^{m}\left(h_\theta(x^{(i)}) - y^{(i)}\right)^2$$

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

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

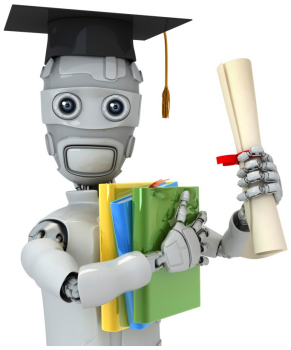
Idea: Choose θ_0, θ_1 so that $h_\theta(x)$ is close to y for our training examples (x, y)

x, y

$$\underset{\theta_0,\theta_1}{\text{minimize}} \; J(\theta_0,\theta_1)$$

Cost function

Squared error function



Machine Learning

Linear regression with one variable

Cost function intuition I

Hypothesis:

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

Parameters:

θ_0, θ_1

Cost Function:

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

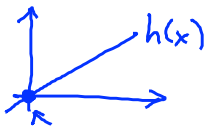
Goal: $\underset{\theta_0, \theta_1}{\text{minimize}}\ J(\theta_0, \theta_1)$

Simplified

$h_\theta(x) = \theta_1 x$

$\theta_0 = 0$

θ_1



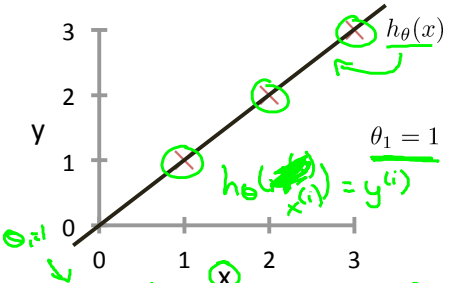
$J(\theta_1) = \frac{1}{2m} \sum_{i=1}^{m} \left(h_\theta(x^{(i)}) - y^{(i)} \right)^2$

$\theta, x^{(i)}$

$\underset{\theta_1}{\text{minimize}}\ J(\theta_1)$

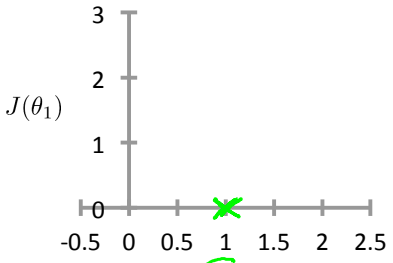
$h_\theta(x)$

(for fixed θ_1, this is a function of x)



$J(\theta_1)$

(function of the parameter θ_1)



$h_\theta(x^{(i)}) = y^{(i)}$

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

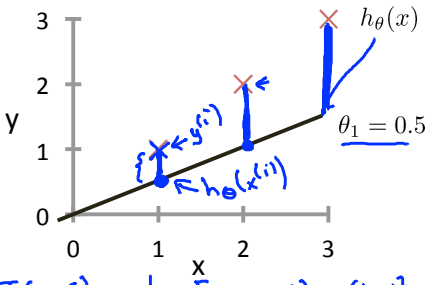
$= \frac{1}{2m} \sum_{i=1}^{m} (\theta_1 x^{(i)} - y^{(i)})^2 = \frac{1}{2m}(0^2 + 0^2 + 0^2) = 0$

$\theta_1 = 0.5$?

$J(1) = 0$

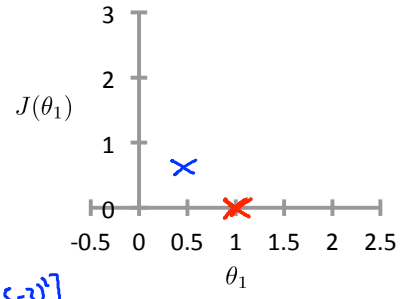
$h_\theta(x)$

(for fixed θ_1, this is a function of x)



$J(\theta_1)$

(function of the parameter θ_1)

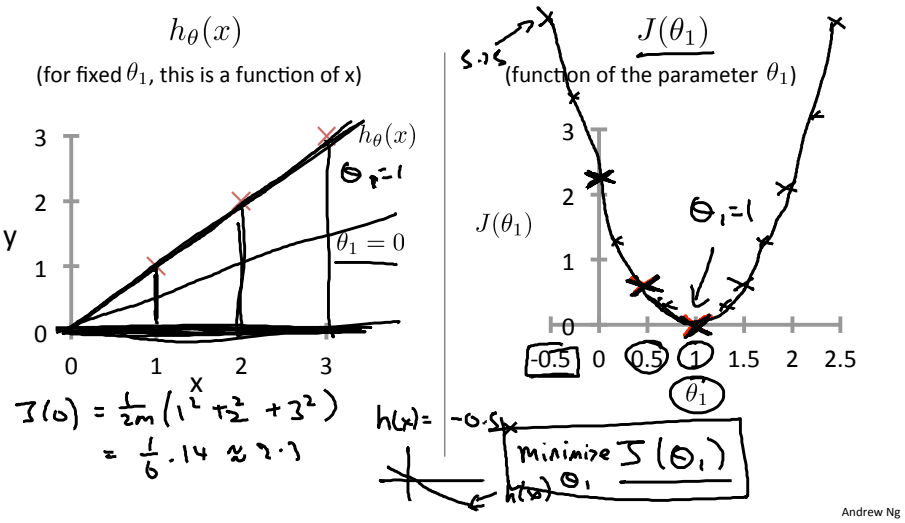


$J(0.5) = \frac{1}{2m}\left[(0.5-1)^2 + (1-2)^2 + (1.5-3)^2\right]$

$= \frac{1}{2\times 3}(3.5) = \frac{3.5}{6} \approx 0.58$

$\theta_1 = 0?$

$J(0) = ?$


$h_\theta(x)$
(for fixed θ_1, this is a function of x)
$h_\theta(x)$
$\theta_1 = 1$
$\theta_1 = 0$
y
x
0
1
2
3
$J(\theta_1)$
(function of the parameter θ_1)
$J(\theta_1)$
θ_1
-0.5
0.5
1
1.5
2
2.5
$\theta_1 = 1$
$J(0) = \frac{1}{2m}(1^2 + 2^2 + 3^2)$
$= \frac{1}{6} \cdot 14 \approx 2.3$
$h(x) = -0.5 \cdot x$
minimize $J(\theta_1)$
θ_1

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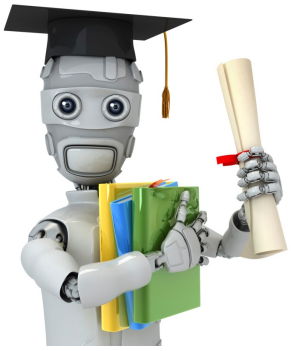


Machine Learning

Linear regression with one variable

Cost function intuition II

Hypothesis: $h_\theta(x) = \theta_0 + \theta_1 x$

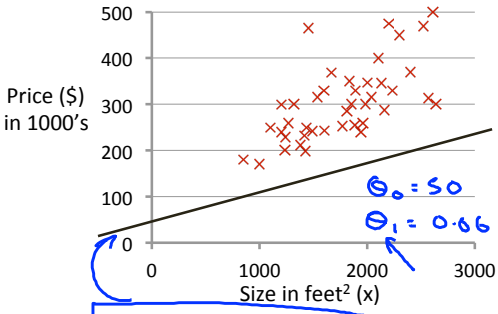
Parameters: θ_0, θ_1

Cost Function: $J(\theta_0, \theta_1) = \frac{1}{2m} \sum_{i=1}^{m} \left(h_\theta(x^{(i)}) - y^{(i)} \right)^2$

Goal: $\underset{\theta_0, \theta_1}{\text{minimize}}\ J(\theta_0, \theta_1)$

$h_\theta(x)$

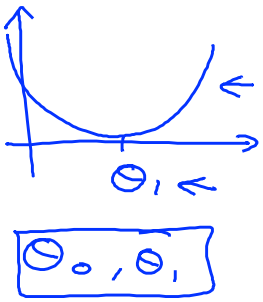
(for fixed θ_0, θ_1, this is a function of x)



$h_\theta(x) = 50 + 0.06x$

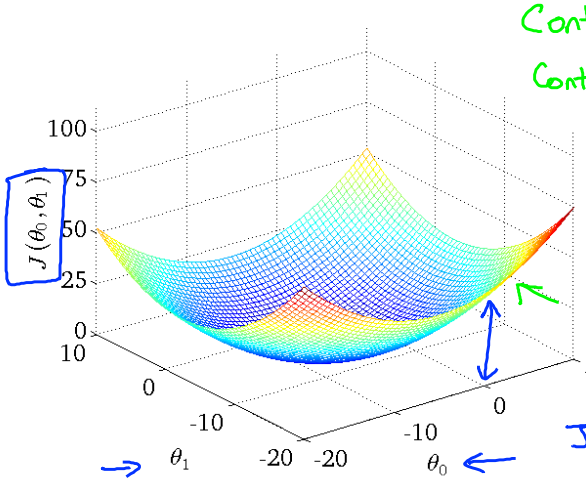
$J(\theta_0, \theta_1)$

(function of the parameters θ_0, θ_1)



Contour plots

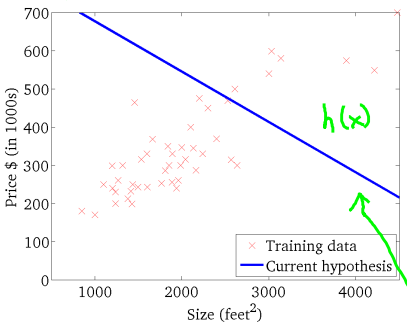
Contour figures -



$J(\theta_0, \theta_1)$

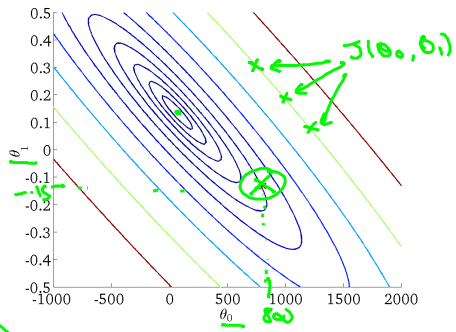
$h_\theta(x)$

(for fixed θ_0, θ_1, this is a function of x)



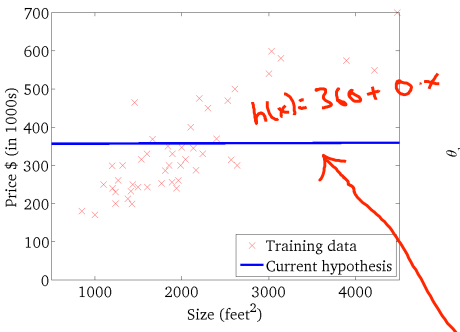
$J(\theta_0, \theta_1)$

(function of the parameters θ_0, θ_1)



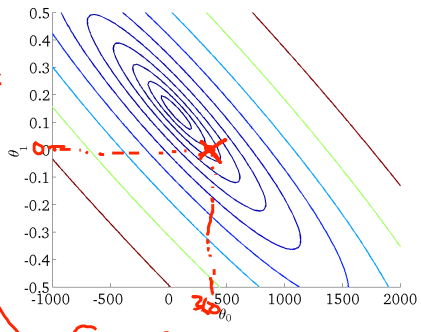
$h_\theta(x)$

(for fixed θ_0, θ_1, this is a function of x)



$J(\theta_0, \theta_1)$

(function of the parameters θ_0, θ_1)

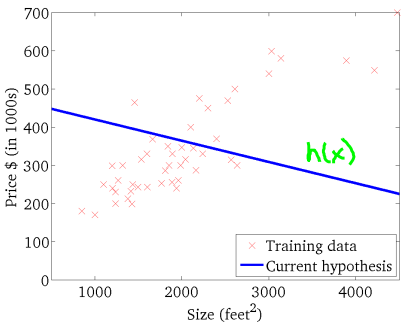


$\theta_0 = 360$

$\theta_1 = 0$

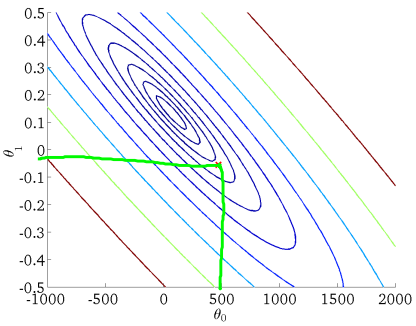
$h_\theta(x)$

(for fixed θ_0, θ_1, this is a function of x)



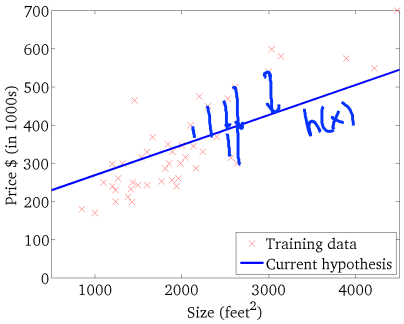
$J(\theta_0, \theta_1)$

(function of the parameters θ_0, θ_1)



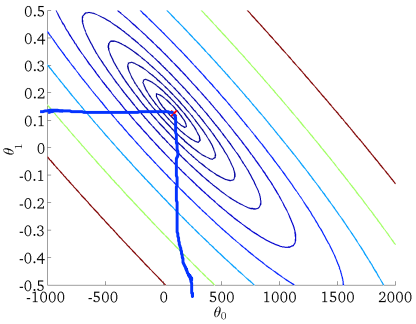
$h_\theta(x)$

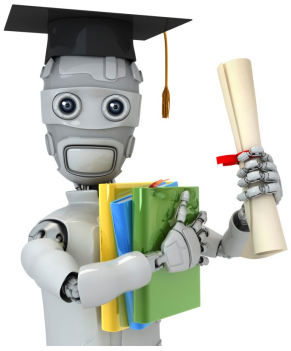
(for fixed θ_0, θ_1, this is a function of x)



$J(\theta_0, \theta_1)$

(function of the parameters θ_0, θ_1)





Machine Learning

Linear regression with one variable

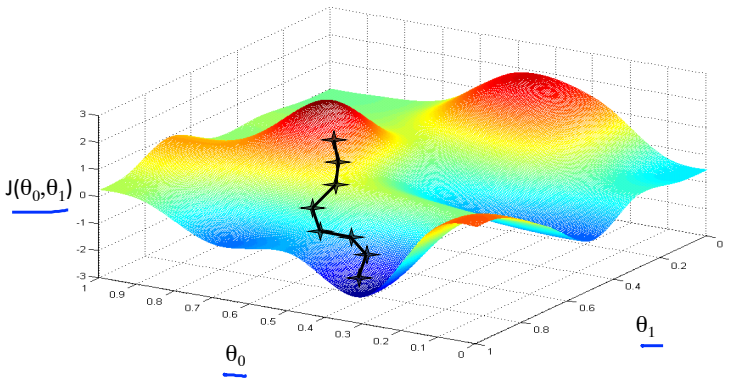
Gradient descent

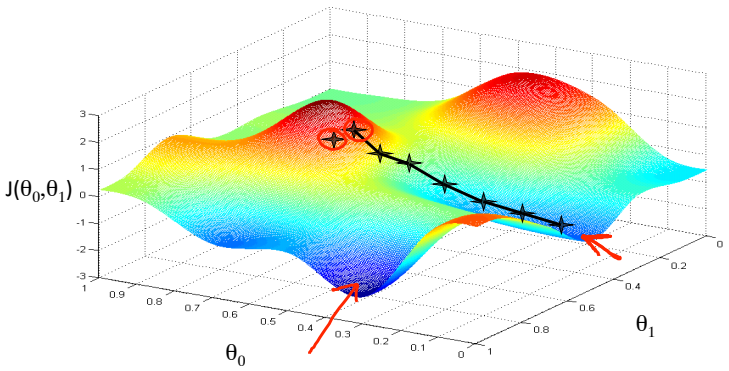
Have some function $J(\theta_0, \theta_1)$

Want $\min_{\theta_0, \theta_1} J(\theta_0, \theta_1)$

Outline:

- Start with some θ_0, θ_1
- Keep changing θ_0, θ_1 to reduce $J(\theta_0, \theta_1)$ until we hopefully end up at a minimum


$J(\theta_0,\theta_1)$
3
2
1
0
-1
-2
-3
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
θ_0
0
0.2
0.4
0.6
0.8
1
θ_1


$J(\theta_0,\theta_1)$
3
2
1
0
-1
-2
-3
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
θ_0
0
0.2
0.4
0.6
0.8
1
θ_1

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Gradient descent algorithm

repeat until convergence {

$$\theta_j := \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta_0, \theta_1) \quad \text{(for } j = 0 \text{ and } j = 1\text{)}$$

}

learning rate

Simultaneously update θ_0 and θ_1

Assignment: $a := b$, $a := a+1$

Truth assertion: $a = b$, $a = a+1$ ✗

Correct: Simultaneous update

$\text{temp0} := \theta_0 - \alpha \frac{\partial}{\partial \theta_0} J(\theta_0, \theta_1)$

$\text{temp1} := \theta_1 - \alpha \frac{\partial}{\partial \theta_1} J(\theta_0, \theta_1)$

$\theta_0 := \text{temp0}$

$\theta_1 := \text{temp1}$

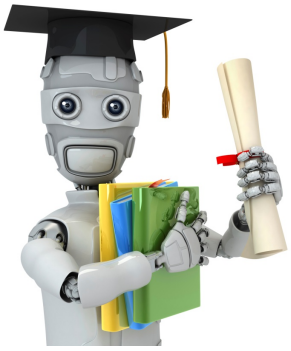
Incorrect:

$\text{temp0} := \theta_0 - \alpha \frac{\partial}{\partial \theta_0} J(\theta_0, \theta_1)$

$\theta_0 := \text{temp0}$

$\text{temp1} := \theta_1 - \alpha \frac{\partial}{\partial \theta_1} J(\theta_0, \theta_1)$

$\theta_1 := \text{temp1}$



Machine Learning

Linear regression with one variable

Gradient descent intuition

Gradient descent algorithm

repeat until convergence {

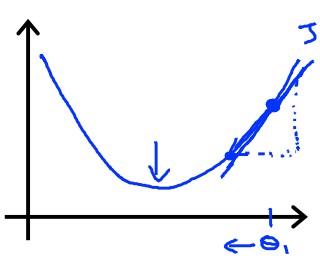
$\theta_j := \theta_j - \alpha \dfrac{\partial}{\partial \theta_j} J(\theta_0, \theta_1)$ (simultaneously update $j = 0$ and $j = 1$)

}

learning rate

derivative

$\min_{\theta_1} J(\theta_1)$ $\theta_1 \in \mathbb{R}$.

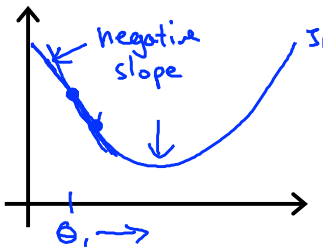


$J(\theta_1)$ $(\theta_1 \in \mathbb{R})$

$\theta_1 := \theta_1 - \alpha \boxed{\frac{d}{d\theta_1} J(\theta_1)}$

$\frac{d}{d\theta_1} J(\theta_1) \geq 0$

$\theta_1 := \theta_1 - \alpha \cdot (\text{positive number})$

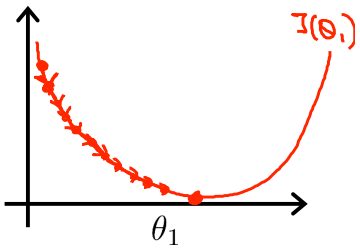


$\frac{d}{d\theta_1} J(\theta_1) \leq 0$

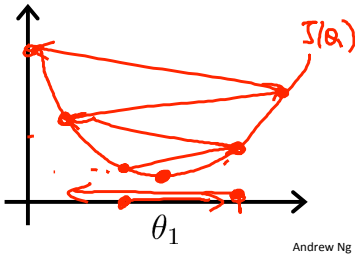
$\theta_1 := \theta_1 - \alpha \, (\text{negative number})$

$$\theta_1 := \theta_1 - \alpha \frac{\partial}{\partial \theta_1} J(\theta_1)$$

If α is too small, gradient descent can be slow.



If α is too large, gradient descent can overshoot the minimum. It may fail to converge, or even diverge.



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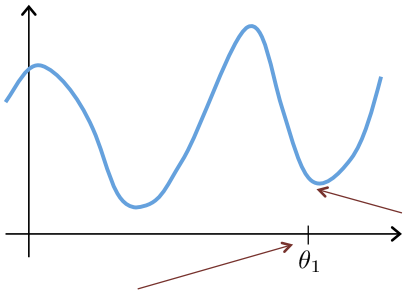
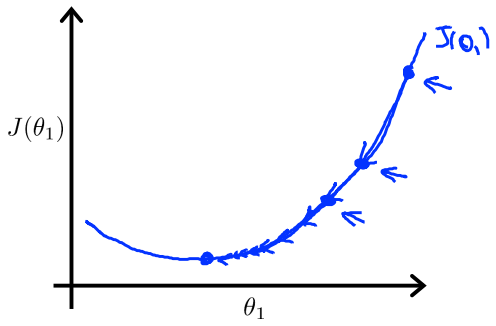


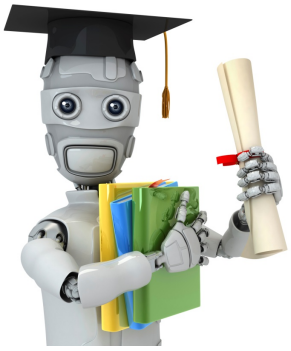
$$\theta_1 := \theta_1 - \alpha \frac{d}{d\theta_1} J(\theta_1)$$

Gradient descent can converge to a local minimum, even with the learning rate α fixed.

$$\theta_1 := \theta_1 - \alpha \frac{d}{d\theta_1} J(\theta_1)$$

As we approach a local minimum, gradient descent will automatically take smaller steps. So, no need to decrease α over time.





Machine Learning

Linear regression with one variable

Gradient descent for linear regression

Gradient descent algorithm

repeat until convergence {

$$\theta_j := \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta_0, \theta_1)$$

(for $j = 1$ and $j = 0$)

}

Linear Regression Model

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

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

$$\frac{\partial}{\partial \theta_j} J(\theta_0, \theta_1) = \frac{\partial}{\partial \theta_j} \frac{1}{2m} \sum_{i=1}^{m} \left(h_\theta(x^{(i)}) - y^{(i)} \right)^2$$

$$= \frac{\partial}{\partial \theta_j} \frac{1}{2m} \sum_{i=1}^{m} \left(\theta_0 + \theta_1 x^{(i)} - y^{(i)} \right)^2$$

$$j = 0 : \frac{\partial}{\partial \theta_0} J(\theta_0, \theta_1) = \frac{1}{m} \sum_{i=1}^{m} \left(h_\theta(x^{(i)}) - y^{(i)} \right)$$

$$j = 1 : \frac{\partial}{\partial \theta_1} J(\theta_0, \theta_1) = \frac{1}{m} \sum_{i=1}^{m} \left(h_\theta(x^{(i)}) - y^{(i)} \right) \cdot x^{(i)}$$

Gradient descent algorithm

repeat until convergence {

$$\theta_0 := \theta_0 - \alpha \frac{1}{m} \sum_{i=1}^{m} \left(h_\theta(x^{(i)}) - y^{(i)} \right)$$

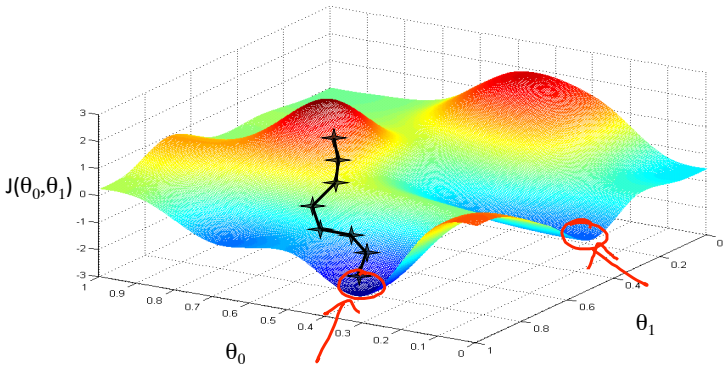
$$\theta_1 := \theta_1 - \alpha \frac{1}{m} \sum_{i=1}^{m} \left(h_\theta(x^{(i)}) - y^{(i)} \right) \cdot x^{(i)}$$

}

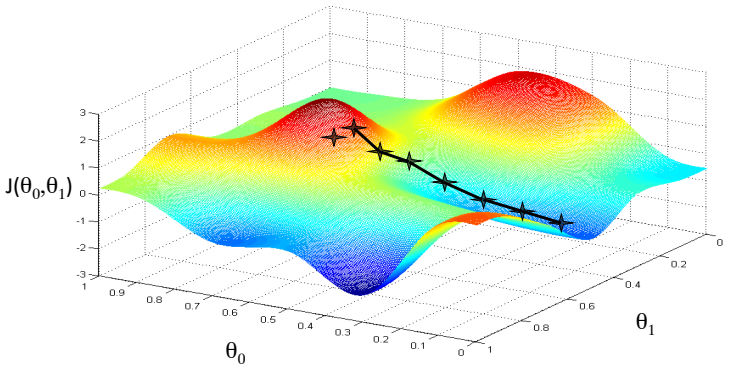
update θ_0 and θ_1 simultaneously

$\frac{\partial}{\partial \theta_0} J(\theta_0, \theta_1)$

$\frac{\partial}{\partial \theta_1} J(\theta_0, \theta_1)$

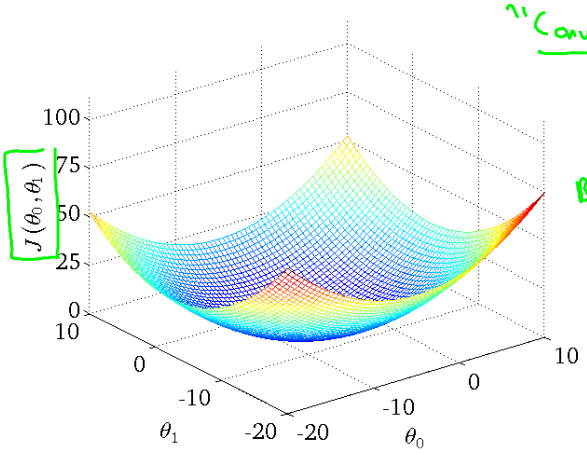

$J(\theta_0,\theta_1)$
3
2
1
0
-1
-2
-3
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
θ_0
0
0.2
0.4
0.6
0.8
1
θ_1

Andrew Ng


$J(\theta_0,\theta_1)$
3
2
1
0
-1
-2
-3
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
θ_0
0
0.2
0.4
0.6
0.8
1
θ_1

Andrew Ng

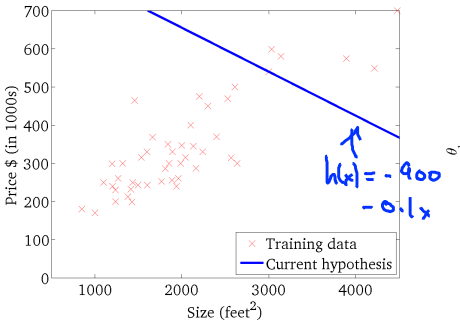
"Convex function"



Bowl-shaped

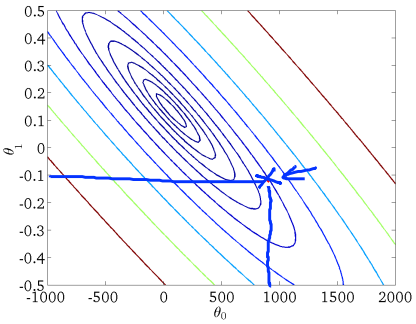
$h_\theta(x)$

(for fixed θ_0, θ_1, this is a function of x)



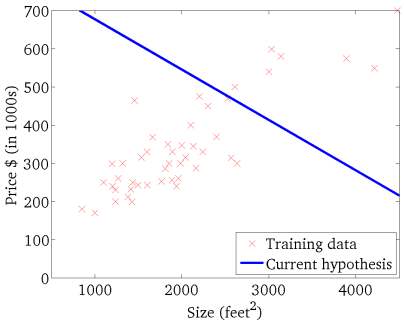
$J(\theta_0, \theta_1)$

(function of the parameters θ_0, θ_1)



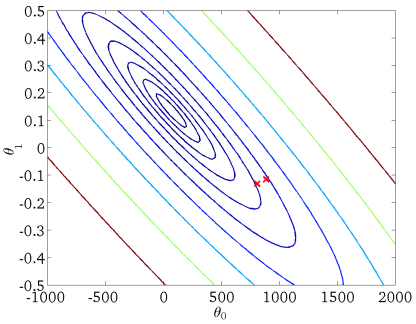
$h_\theta(x)$

(for fixed θ_0, θ_1, this is a function of x)



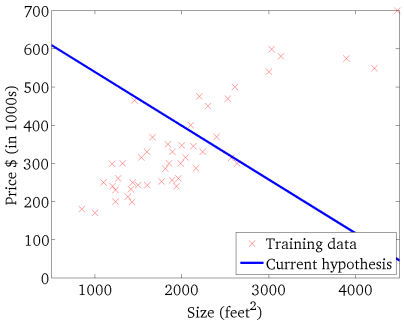
$J(\theta_0, \theta_1)$

(function of the parameters θ_0, θ_1)



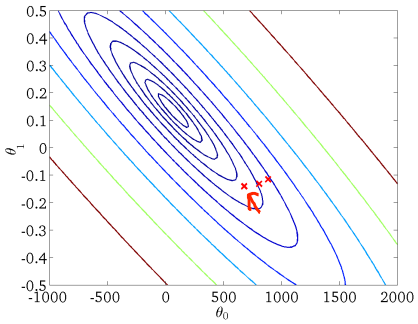
$h_\theta(x)$

(for fixed θ_0, θ_1, this is a function of x)



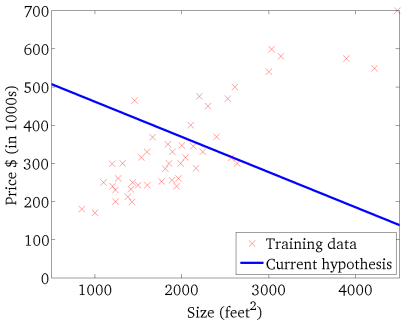
$J(\theta_0, \theta_1)$

(function of the parameters θ_0, θ_1)



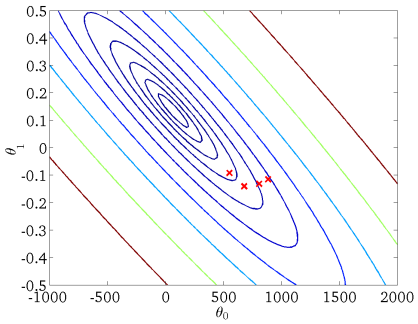
$h_\theta(x)$

(for fixed θ_0, θ_1, this is a function of x)



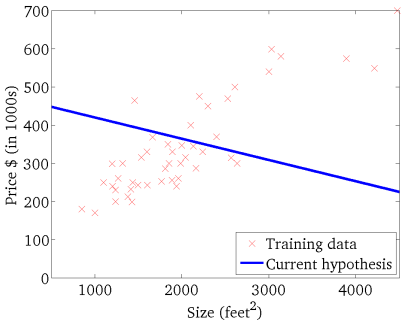
$J(\theta_0, \theta_1)$

(function of the parameters θ_0, θ_1)



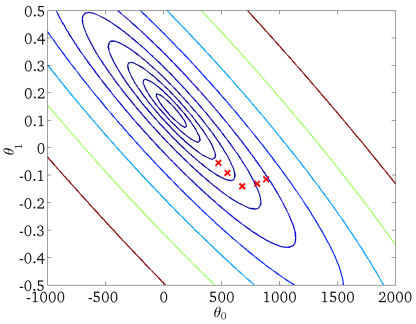
$h_\theta(x)$

(for fixed θ_0, θ_1, this is a function of x)



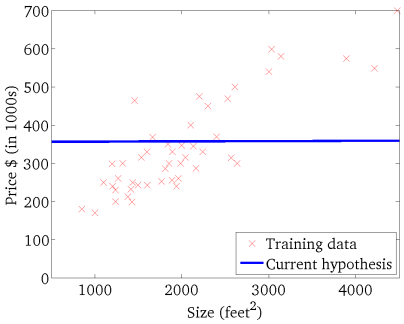
$J(\theta_0, \theta_1)$

(function of the parameters θ_0, θ_1)



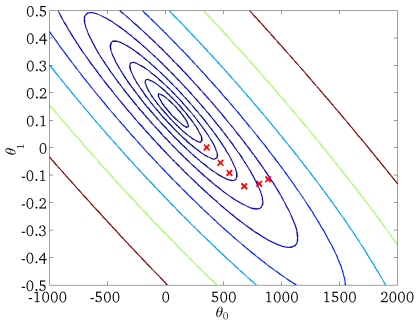
$h_\theta(x)$

(for fixed θ_0, θ_1, this is a function of x)



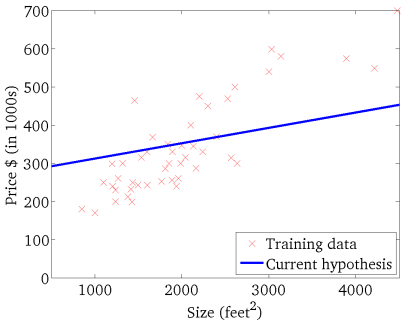
$J(\theta_0, \theta_1)$

(function of the parameters θ_0, θ_1)



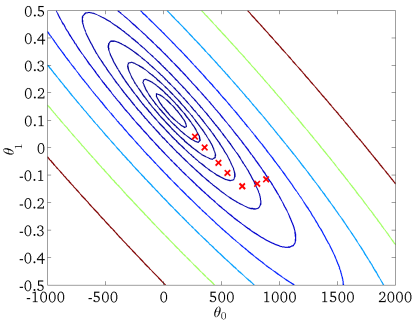
$h_\theta(x)$

(for fixed θ_0, θ_1, this is a function of x)



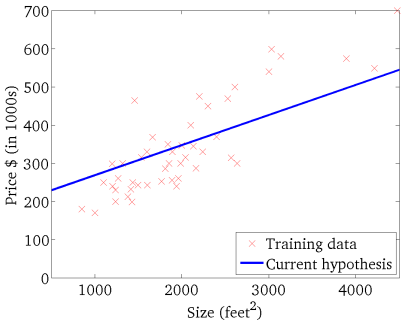
$J(\theta_0, \theta_1)$

(function of the parameters θ_0, θ_1)



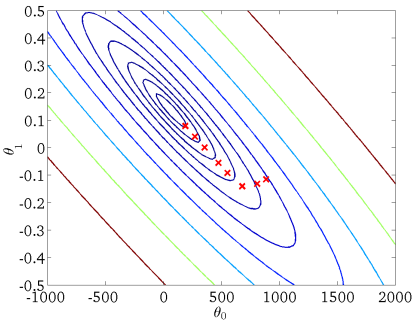
$h_\theta(x)$

(for fixed θ_0, θ_1, this is a function of x)



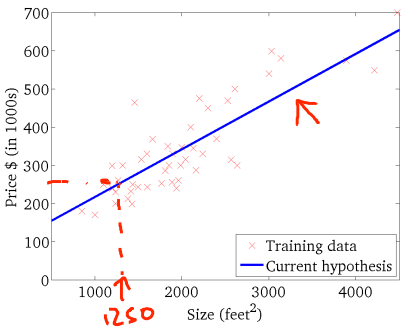
$J(\theta_0, \theta_1)$

(function of the parameters θ_0, θ_1)



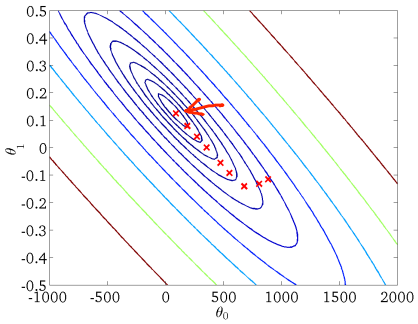
$h_\theta(x)$

(for fixed θ_0, θ_1, this is a function of x)



$J(\theta_0, \theta_1)$

(function of the parameters θ_0, θ_1)



“Batch” Gradient Descent

“Batch”: Each step of gradient descent uses all the training examples.

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