### Introduction to Machine Learning &

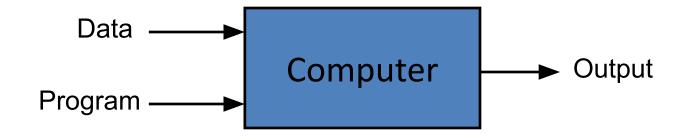
Linear Regression – Model Representation

Acknowledgments: Andrew Ng and Pedro Domingos

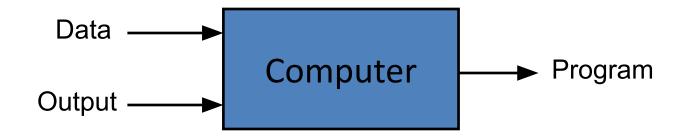
### So What Is Machine Learning?

- ☐ Automating automation
- ☐ Getting computers to program themselves
- ☐ Let the **data** do the work!

### □ Traditional Programming



### ■ Machine Learning



#### **Machine Learning**

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

#### Examples:

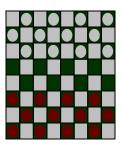
- Database mining
  - Large datasets from growth of automation/web.
  - E.g., Web click data, medical records, biology, engineering
- Applications can't program by hand.
  - E.g., Autonomous helicopter, handwriting recognition, most of Natural Language Processing (NLP), Computer Vision.

### **Practical Applications of Machine Learning**

- Spam filtering
- Speech/handwriting recognition
- Object detection/recognition
- Weather prediction
- Stock market analysis
- Search engines (e.g, Google)
- Ad placement on websites
- Credit-card fraud detection
- Webpage clustering (e.g., Google News)
- Social Network Analysis
- Recommendation systems (e.g., Netflix, Amazon)
- Automatic vehicle navigation

### 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.

"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."

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?

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

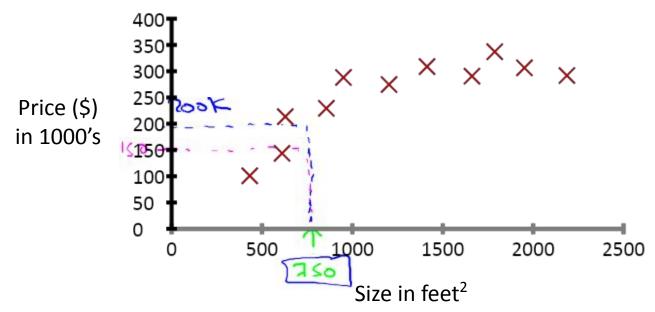
### Machine learning algorithms:

- Supervised learning
- Unsupervised learning

Others: recommender systems.

# Introduction to Supervised Learning

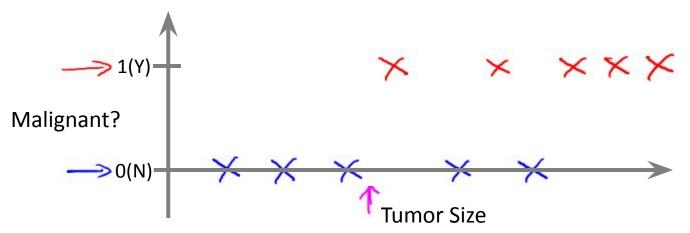
### Housing price prediction.



Supervised Learning "right answers" given

Regression: Predict continuous valued output (price)

### Cancer (malignant, benign)

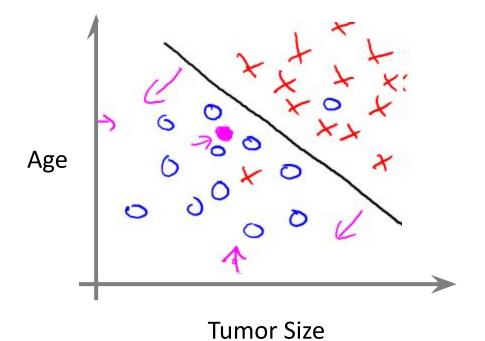


### Classification

Discrete valued output (0 or 1)



**Tumor Size** 



- 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.

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.

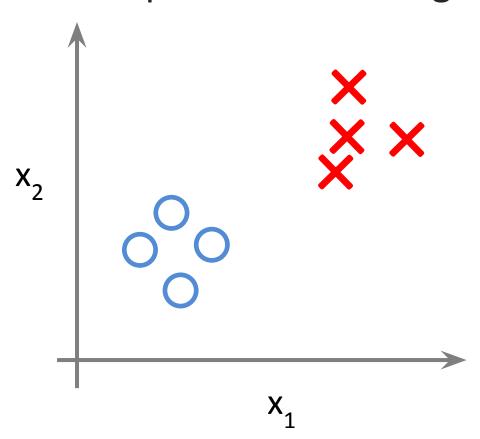
Problem 2: You'd like software to examine individual customer accounts, and for each account decide if it has been hacked/compromised.

Should you treat these as classification or as regression problems?

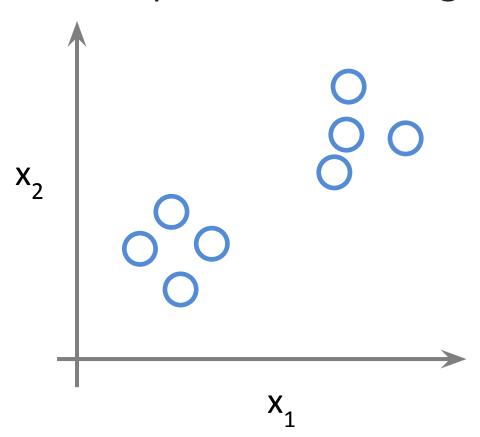
- a) Treat both as classification problems.
- b) Treat problem 1 as a classification problem, problem 2 as a regression problem.
- c) Treat problem 1 as a regression problem, problem 2 as a classification problem.
- d) Treat both as regression problems.

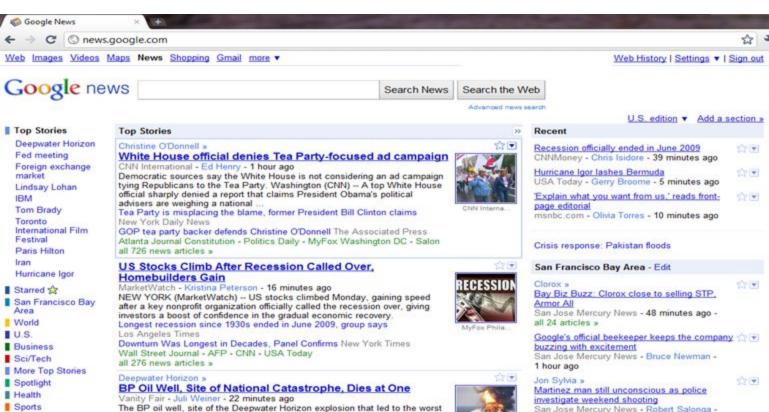
# Introduction to Unsupervised Learning

### **Supervised Learning**



### **Unsupervised Learning**





All news Headlines Images

■ Entertainment

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 a

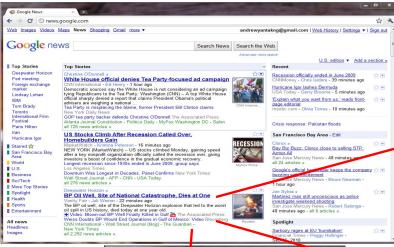


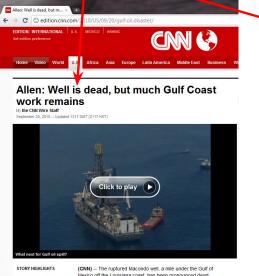
Spotlight

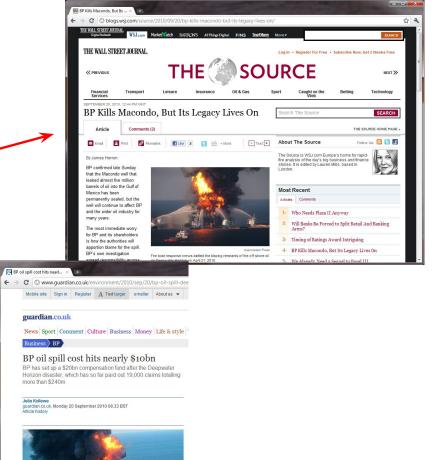
Sarkozy rages at EU 'humiliation' Financial Times - Peggy Hollinger -

48 minutes ago - all 6 articles »



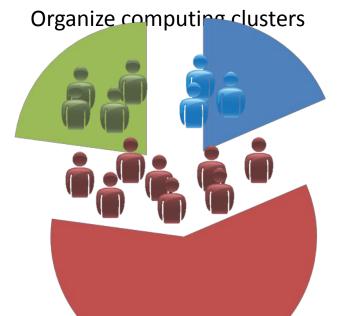


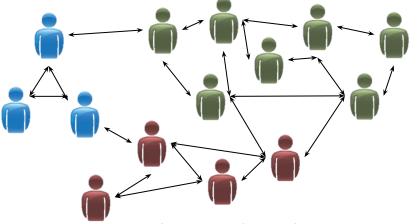




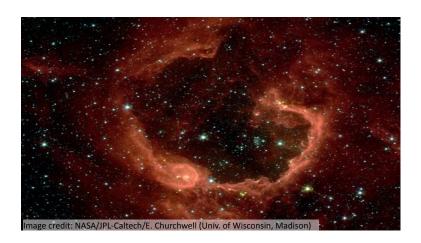
BP's costs for the Deepwater Horizon disaster have hit \$10bn. Photograph:







Social network analysis



Astronomical data analysis

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

Given email labeled as spam/not spam, learn a spam filter.

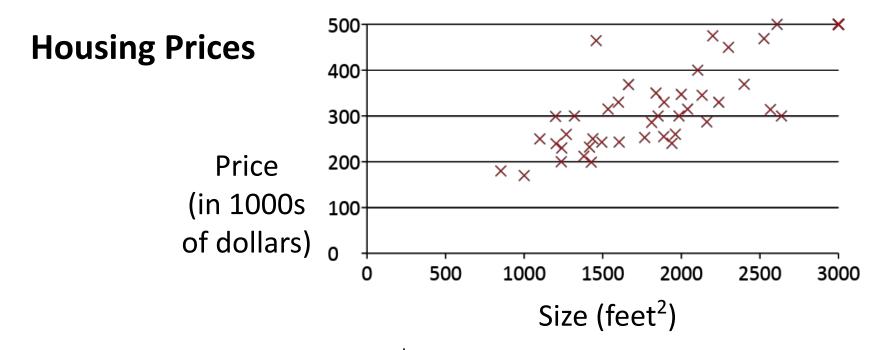
Given a set of news articles found on the web, group them into set of articles about the same story.

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.

### Linear regression with one variable

### Model representation



### Supervised Learning

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

### Regression Problem

Predict real-valued output

<b>Training</b>	set	of
housing	pric	es

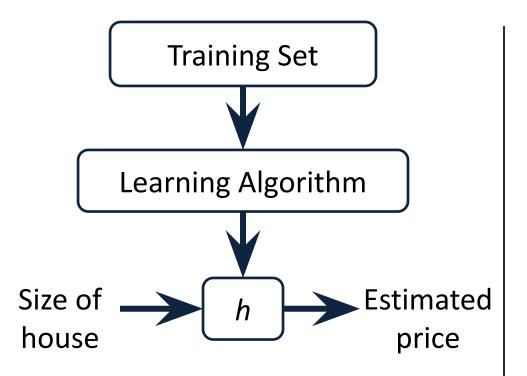
Size in feet <sup>2</sup> (x)	(y) Price (\$) in 1000's (y)	
2104	460	
1416	232	
1534	315	
852	178	

#### Notation:

```
m = Number of training examples
```

x's = "input" variable / features

y's = "output" variable / "target" variable



#### How do we represent h?

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

Linear regression with one variable. Univariate linear regression.

### Linear regression with one variable

### **Cost function**

Training Set

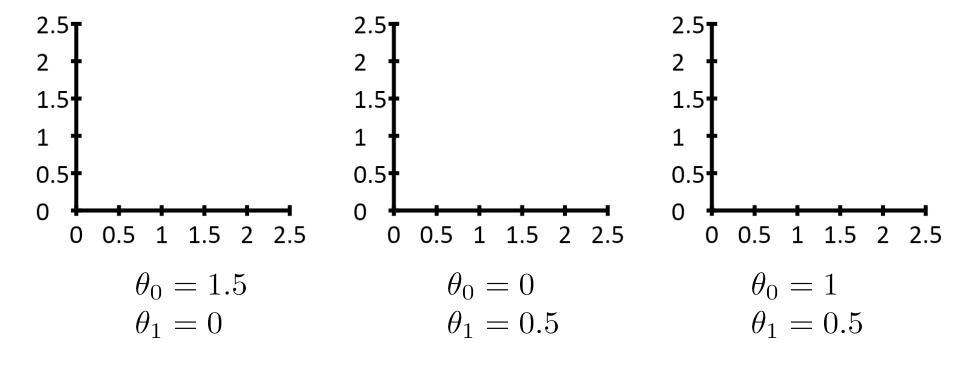
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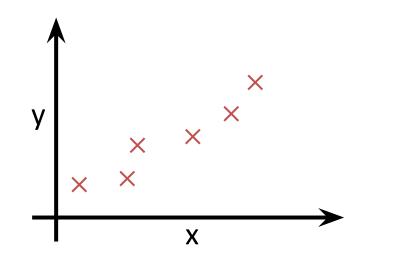
Hypothesis: 
$$h_{\theta}(x) = \theta_0 + \theta_1 x$$

 $\theta_i$ 's: Parameters

How to choose  $\theta_i$ 's ?

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





Cost Function (Squared Errror function):

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

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

Idea: Choose  $\theta_0, \theta_1$  so that  $h_{\theta}(x)$  is close to y for our training examples (x,y)

### Linear regression with one variable

## Cost function intuition I

### Hypothesis:

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

$$heta_0, heta_1$$

### **Cost Function:**

nction: 
$$h_0(\theta_1) = rac{1}{2m} \sum_{i=1}^m \left(h_{ heta}(x_i)\right)$$

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

$$J( heta_0, heta_1)=rac{1}{2m}\sum_{i=1}^{\infty}\left(h_{ heta}(x^{(i)})\right)$$
 Goal: minimize  $J( heta_0, heta_1)$ 

$$\frac{1}{1} = \frac{1}{2m} \sum_{i=1}^{\infty} \left( h_{\theta}(x^i) \right)$$

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

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

Simplified (to understand

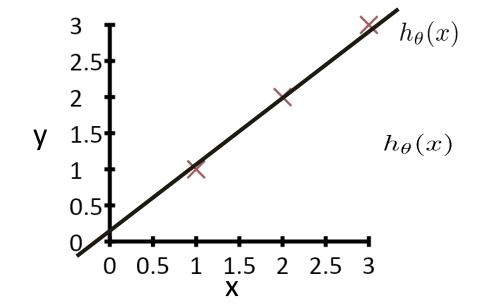
cost function better)

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

$$\theta_1$$

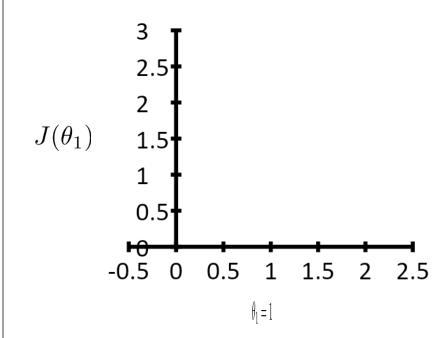
### $h_{\theta}(x)$

(for fixed h=1, this is a function of x)



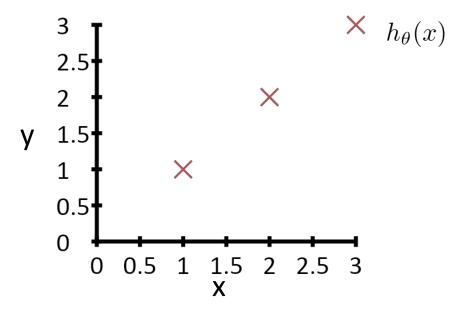


(function of the parameter  $\theta_1$ =1)



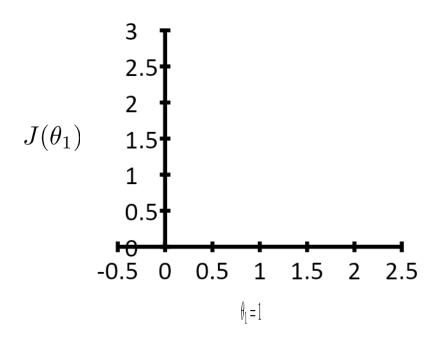
$$h_{\theta}(x)$$

(for fixed h=1, this is a function of x)



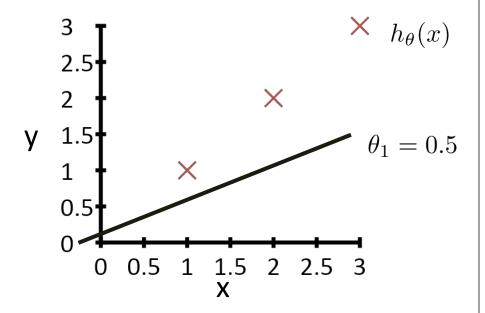
 $J(\theta_1)$ 

(function of the parameter  $f_{i-1}$ )



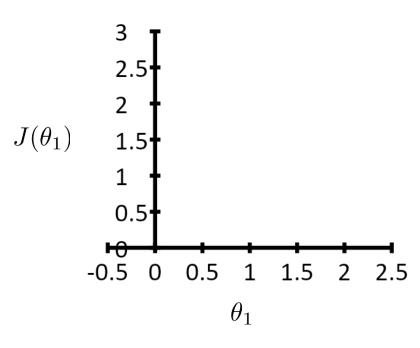
$$h_{\theta}(x)$$

(for fixed  $\theta_1=0.5$ , this is a function of x)



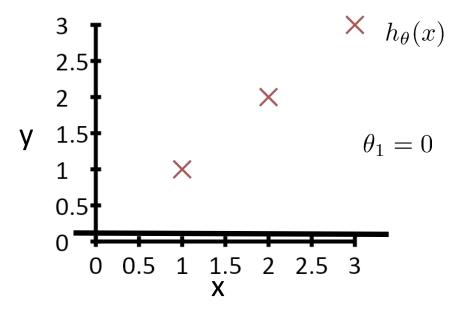
 $f(\theta_1)$ 

(function of the parameter  $\, heta_1$ )



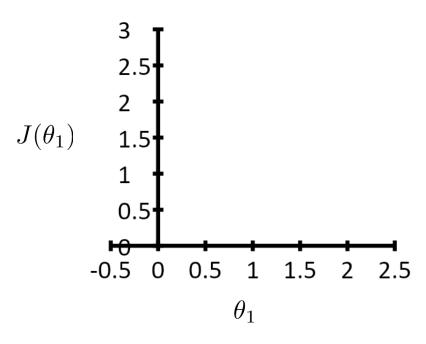
$$h_{\theta}(x)$$

(for fixed  $\theta_1 = 0$ , this is a function of x)



 $(\theta_1)$ 

(function of the parameter  $\theta_1$ )



### Linear regression with one variable

## Cost function intuition II

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

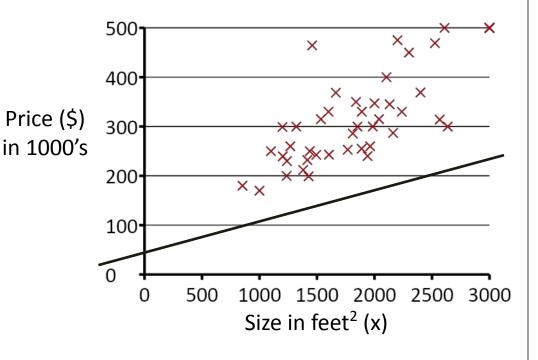
Parameters: 
$$\theta_0, \theta_1$$

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

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

$$h_{\theta}(x)$$

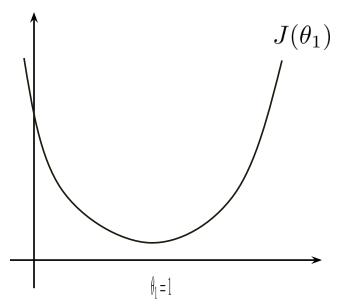
(for fixed  $\theta_0$ ,  $\theta_1$ , this is a function of x)



$$\theta_0 = 50$$
  $\theta_1 = 0.06$ 

$$J(\theta_0, \theta_1)$$

(function of the parameters  $\, heta_0, heta_1\!)$ 



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

