

INTERNATIONAL ORGANISATION OF  
SOFTWARE DEVELOPERS

# MACHINE LEARNING

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I am a 3rd year student at Delhi Technological University. Having tried my hands on Android Development, Web Development using PHP, and now Machine learning, I have a broad scope of knowledge. I have previously interned at CISF(Central Industrial Security Forces), Le Jensoft, Echoes, Coding Ninjas (as a Machine learning content creator). I will be interning at SAP Labs this summer. I love participating in hackathons and since my 1st year I have participated in 19 hackathons and won 4 of them.

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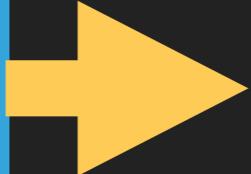
# ABOUT ME

**COMPUTERS ARE ABLE TO  
SEE, HEAR AND LEARN.  
WELCOME TO THE FUTURE.**

Dave Waters

# AI

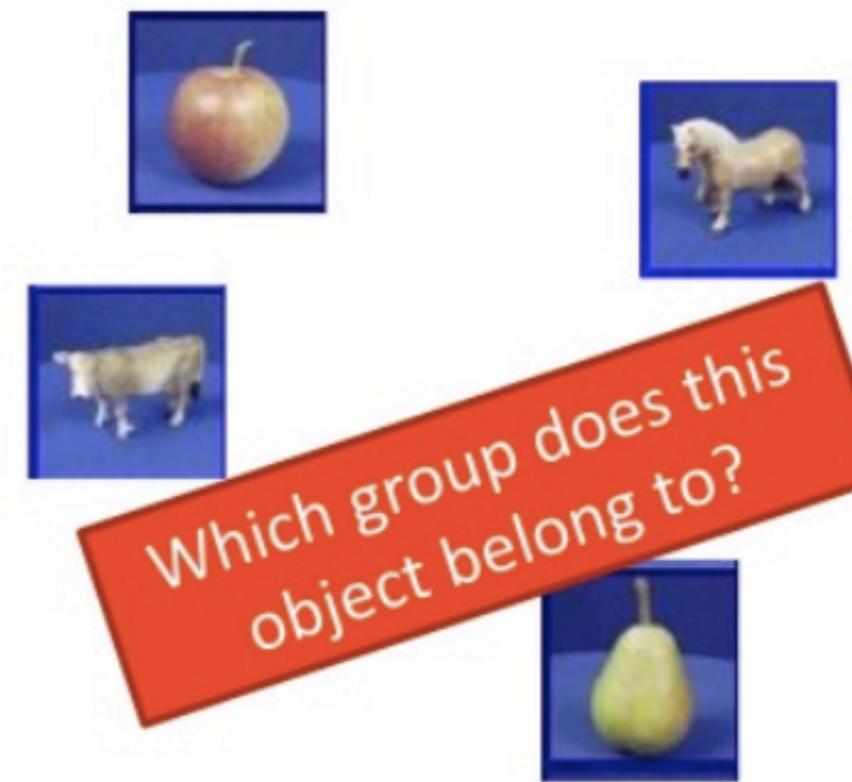
ARTIFICIAL INTELLIGENCE IS THE SCIENCE AND ENGINEERING OF MAKING COMPUTERS BEHAVE IN WAYS THAT, UNTIL RECENTLY, WE THOUGHT REQUIRED HUMAN INTELLIGENCE.



# ML

MACHINE LEARNING IS THE STUDY OF COMPUTER ALGORITHMS THAT IMPROVE AUTOMATICALLY THROUGH EXPERIENCE.

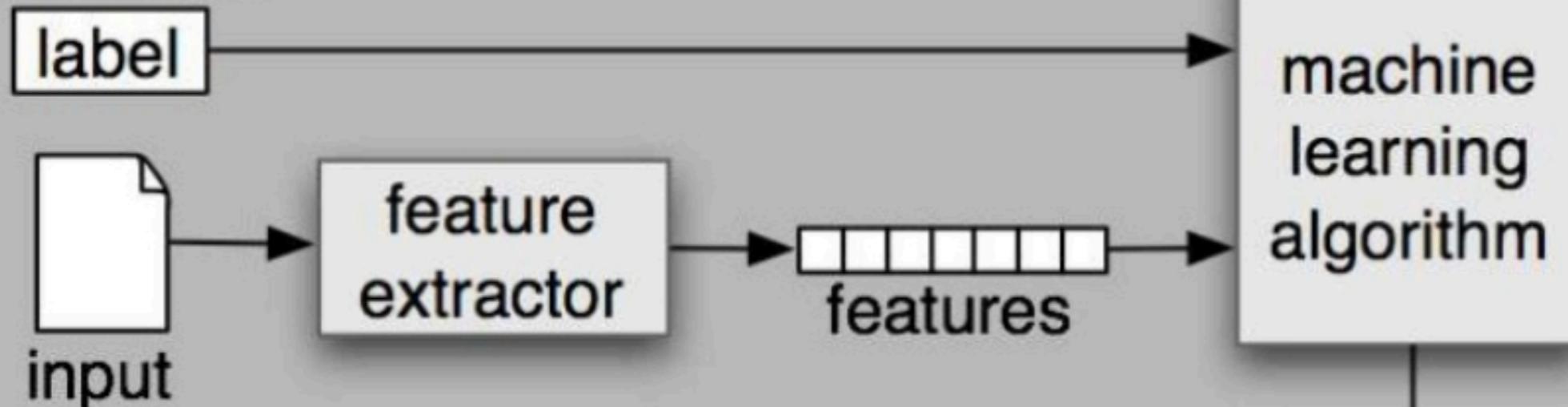
# The Learning



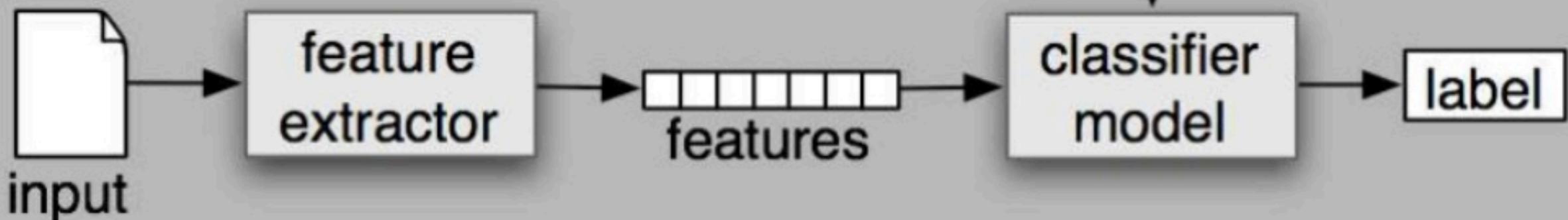
# WHAT IS MACHINE LEARNING?

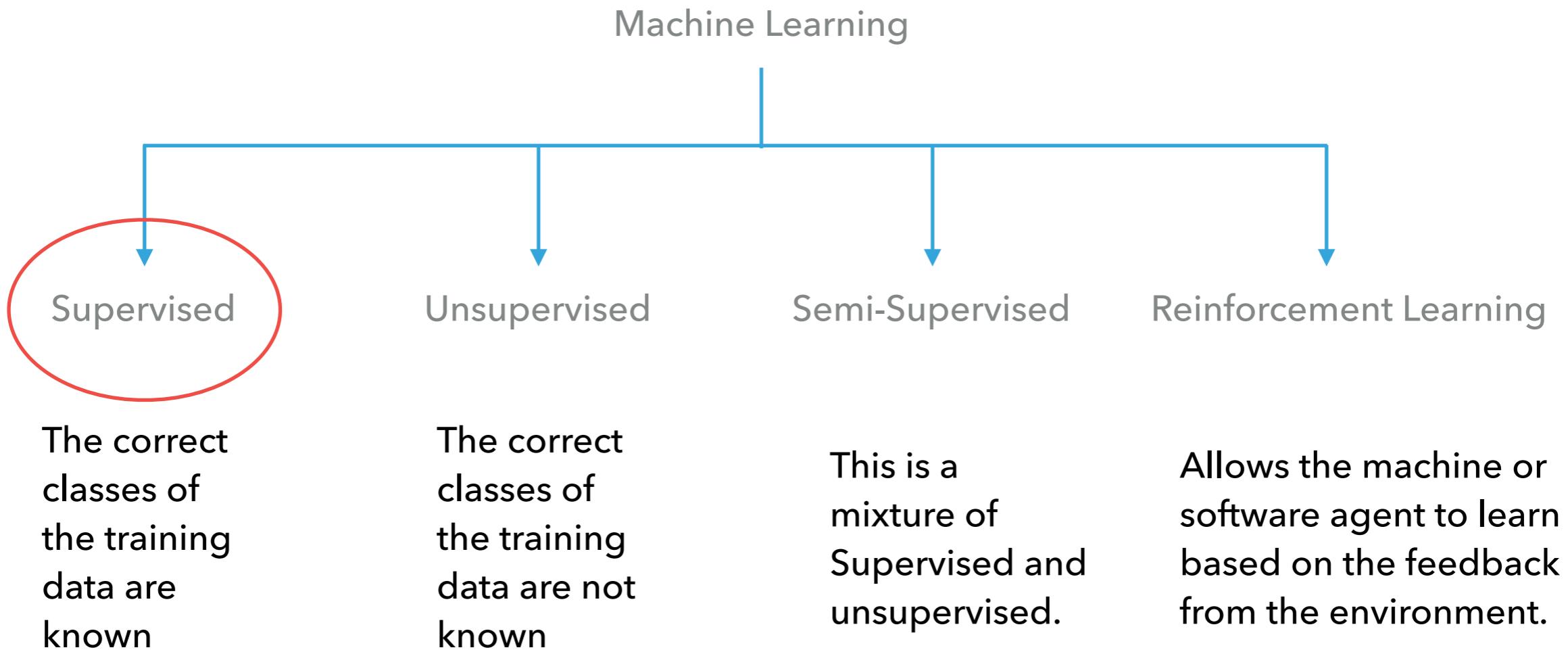
- ▶ How does our brain process an image?
- ▶ How does grouping happen?
- ▶ Human brain processed the given images - learning
- ▶ After learning, the brain simply looked at the new images and compared with the groups classified the image to the closest group - Classification
- ▶ If a machine has to perform the same operation, we use machine learning.
- ▶ We are writing programs for learning and then classification, this is nothing but machine learning.

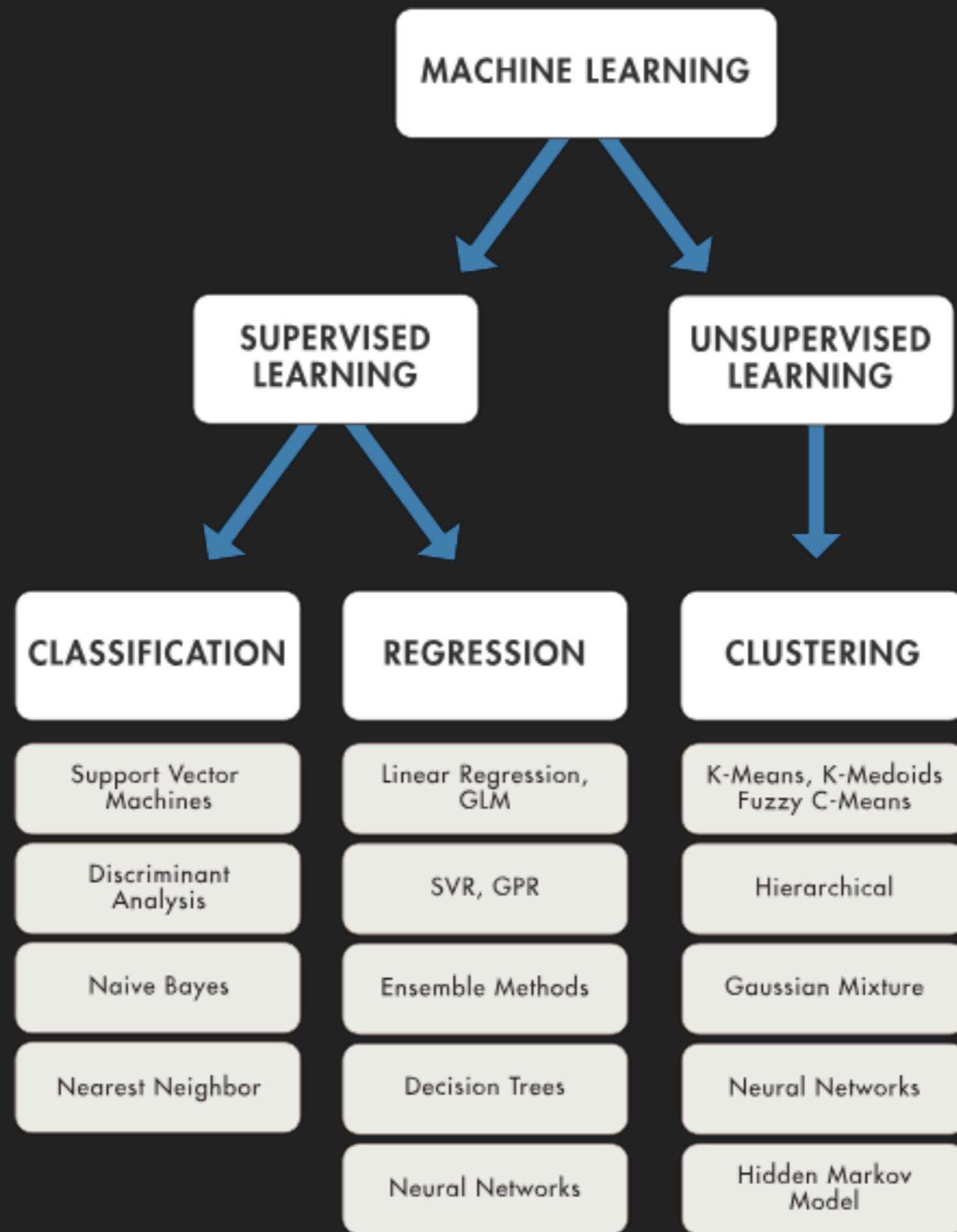
**(a) Training**



**(b) Prediction**

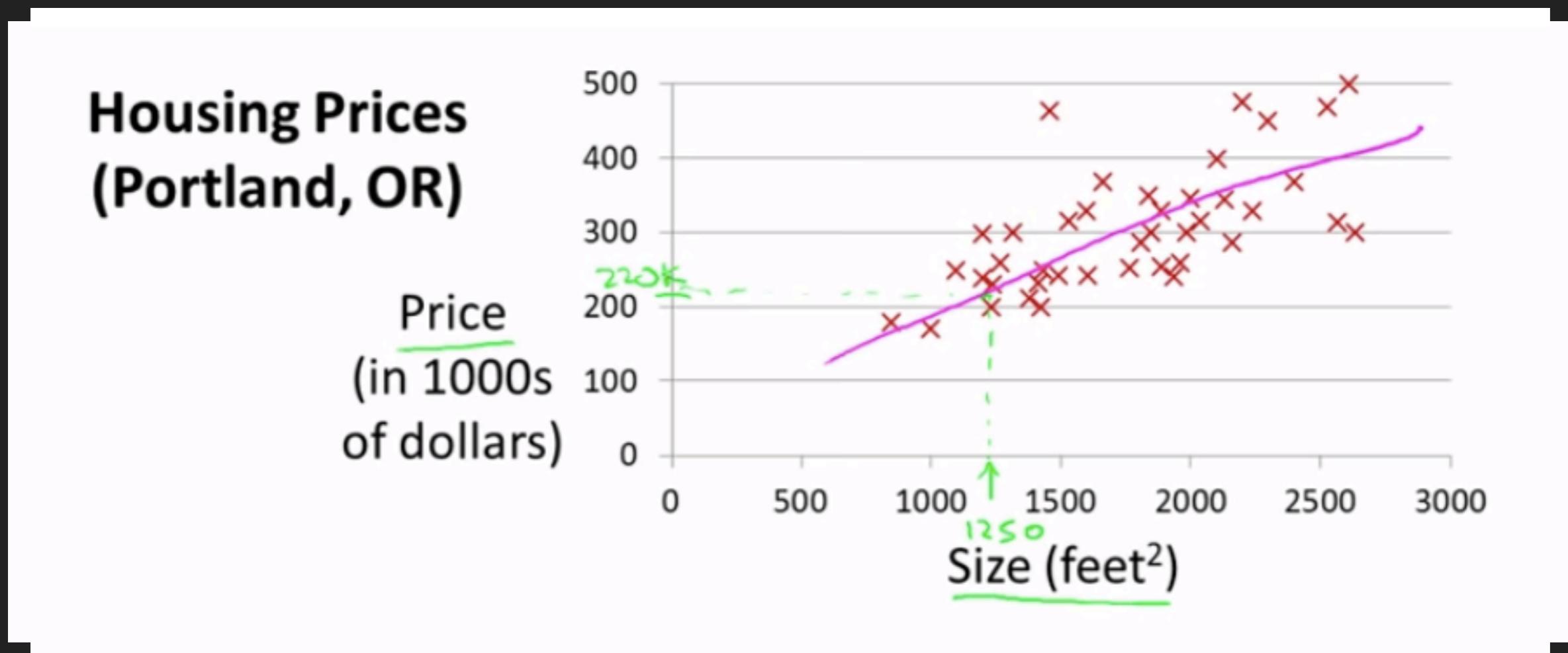






# LINEAR REGRESSION

- ▶ Evaluating trends
- ▶ Finding relationship between two variables.



## **Training set of housing prices (Portland, OR)**

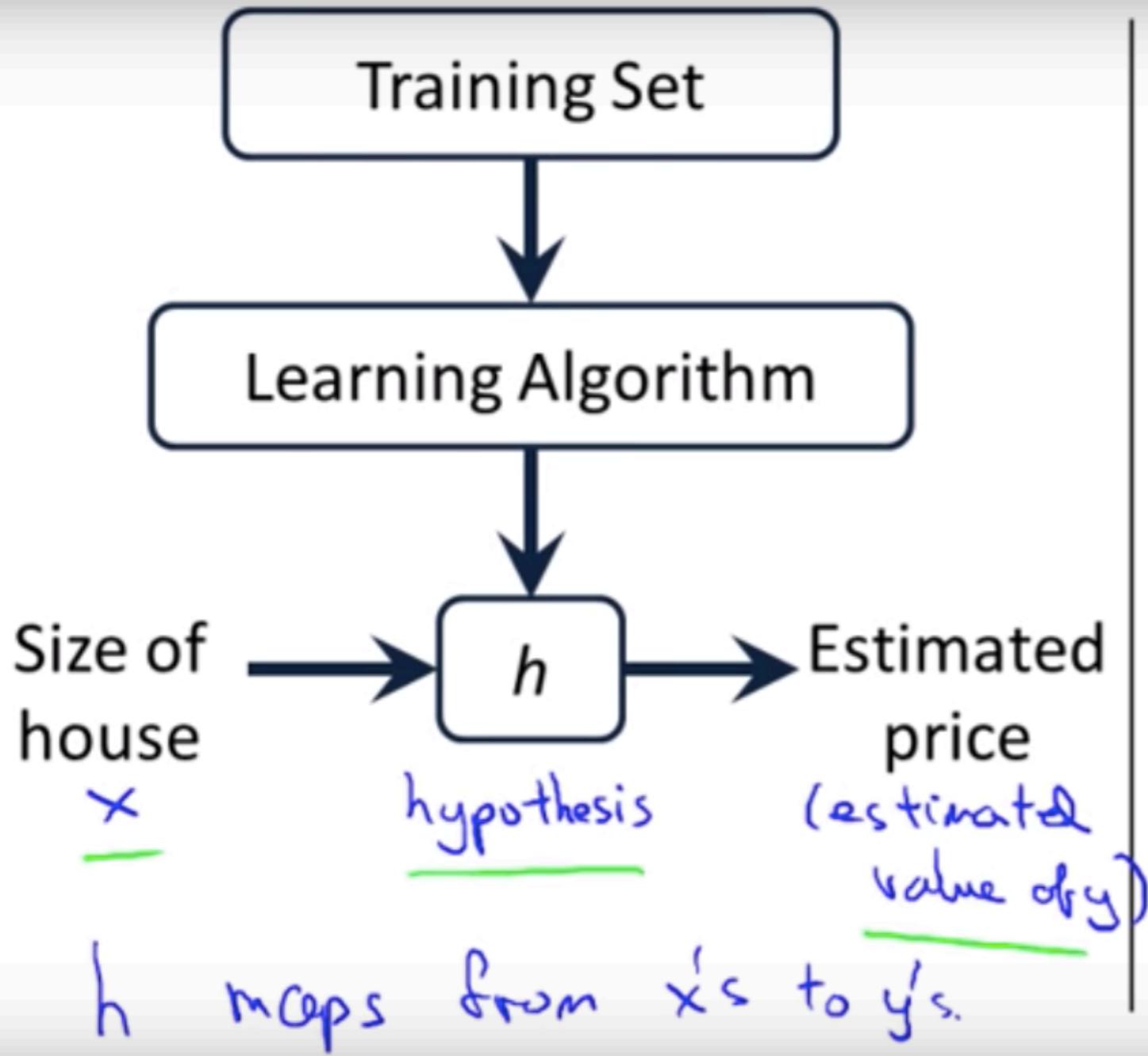
<b>Size in feet<sup>2</sup> (x)</b>	<b>Price (\$) in 1000's (y)</b>
2104	460
1416	232
1534	315
852	178
...	...

**Notation:**

**m** = Number of training examples

**x**'s = “input” variable / features

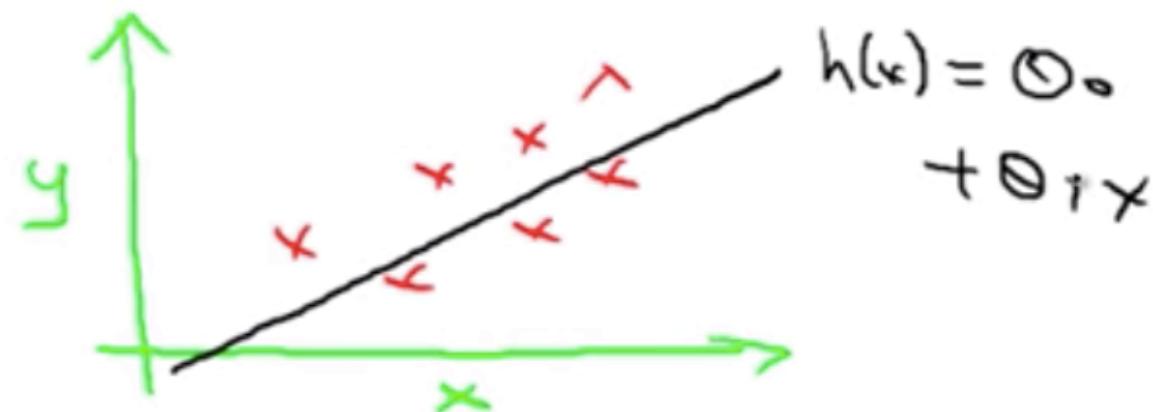
**y**'s = “output” variable / “target” variable



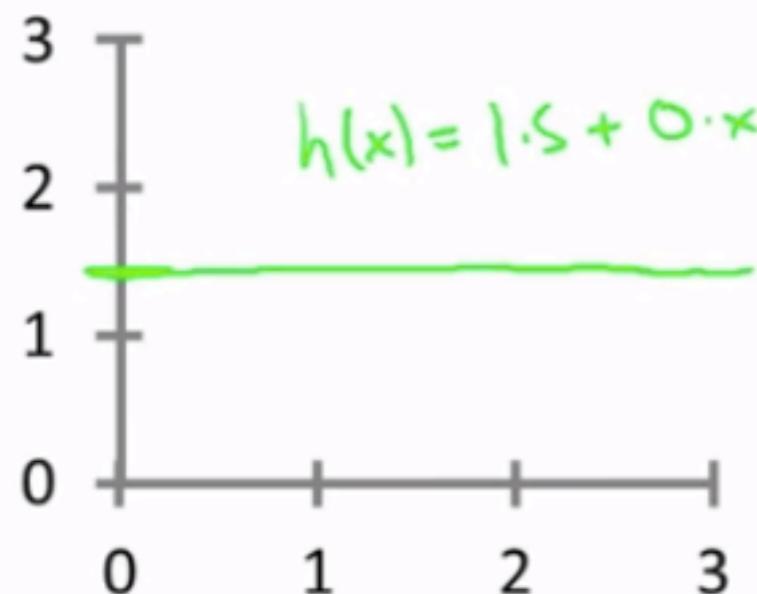
How do we represent  $h$  ?

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

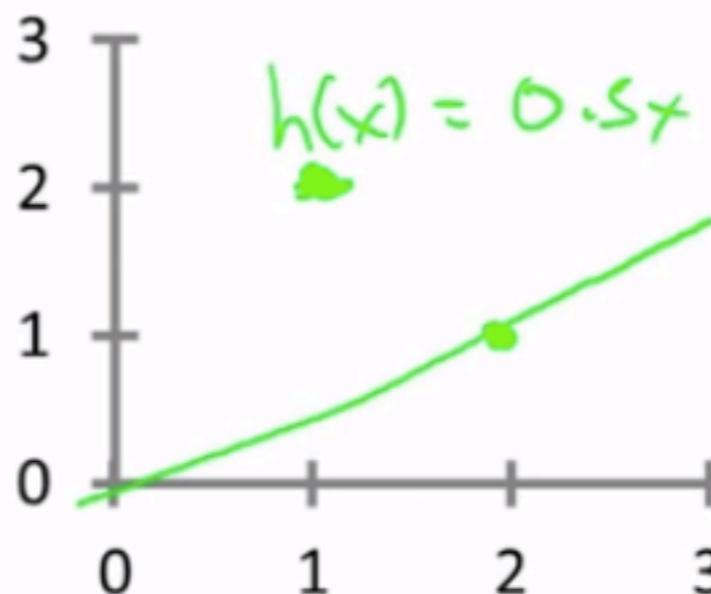
Shorthand:  $h(x)$



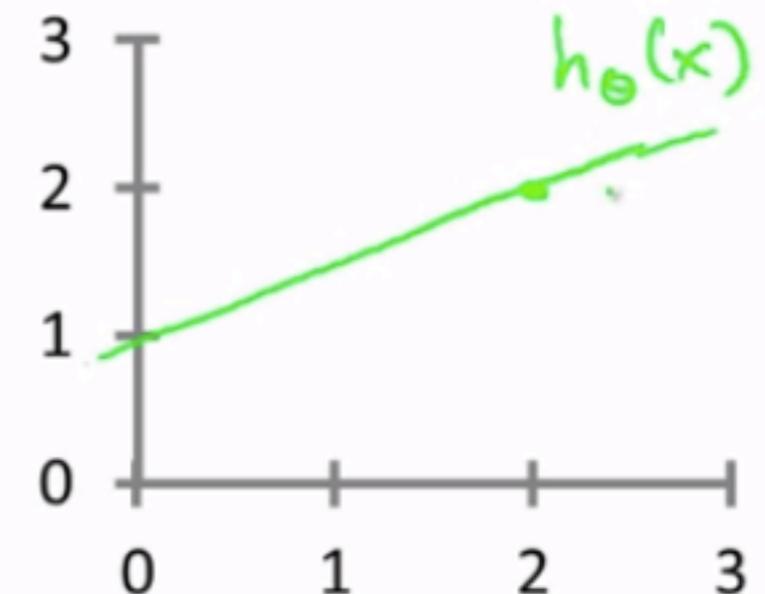
$$\underline{h_{\theta}(x) = \theta_0 + \theta_1 x}$$



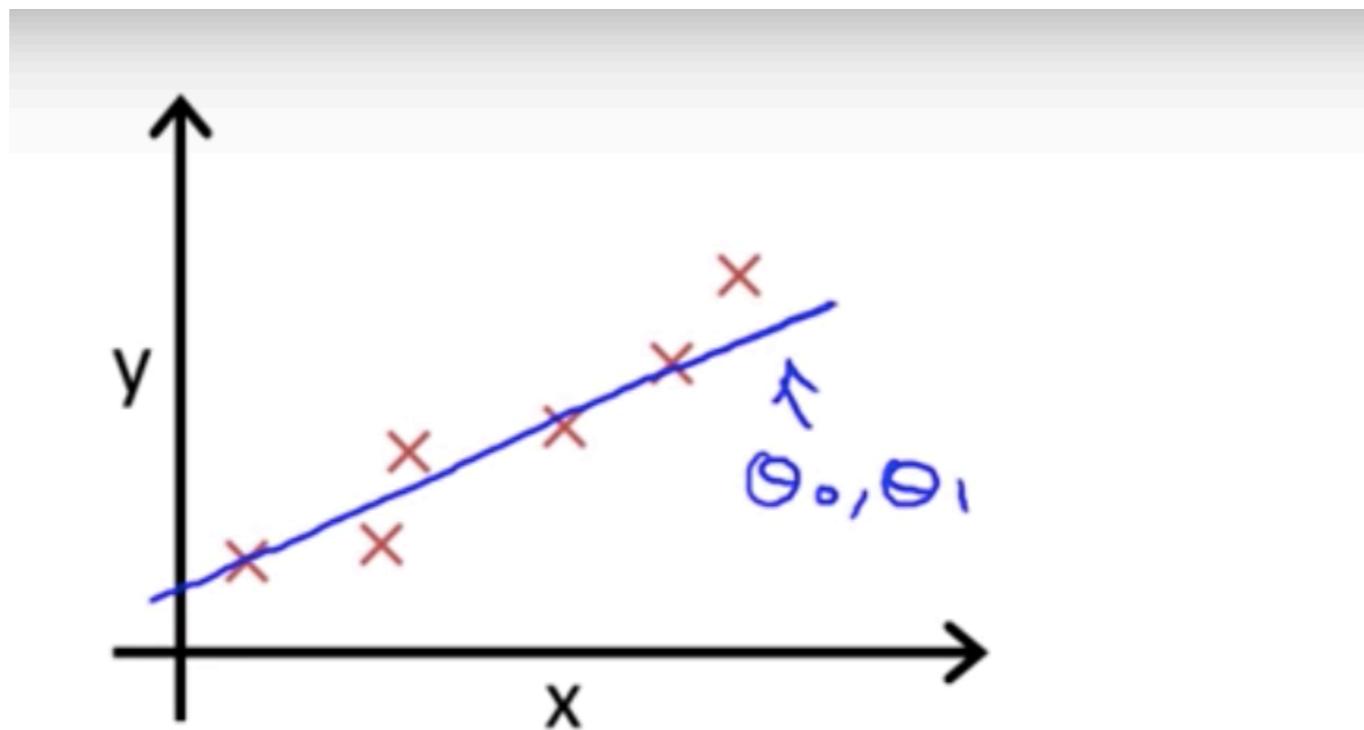
$$\begin{aligned}\rightarrow \theta_0 &= 1.5 \\ \rightarrow \theta_1 &= 0\end{aligned}$$



$$\begin{aligned}\rightarrow \theta_0 &= 0 \\ \rightarrow \theta_1 &= 0.5\end{aligned}$$

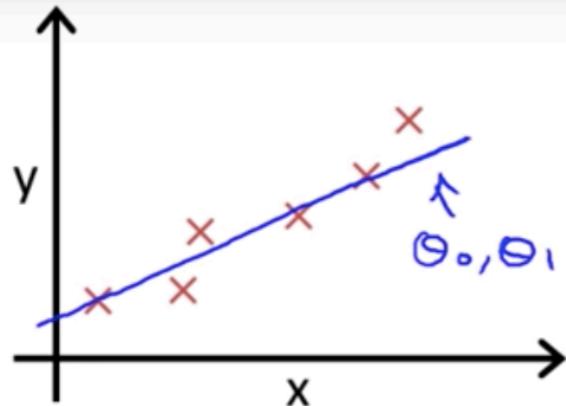


$$\begin{aligned}\rightarrow \theta_0 &= 1 \\ \rightarrow \theta_1 &= 0.5\end{aligned}$$



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

$x, y$



## Squared Error Function

Idea: Choose  $\theta_0, \theta_1$  so that

$h_\theta(x)$  is close to  $y$  for our  
training examples  $(x, y)$

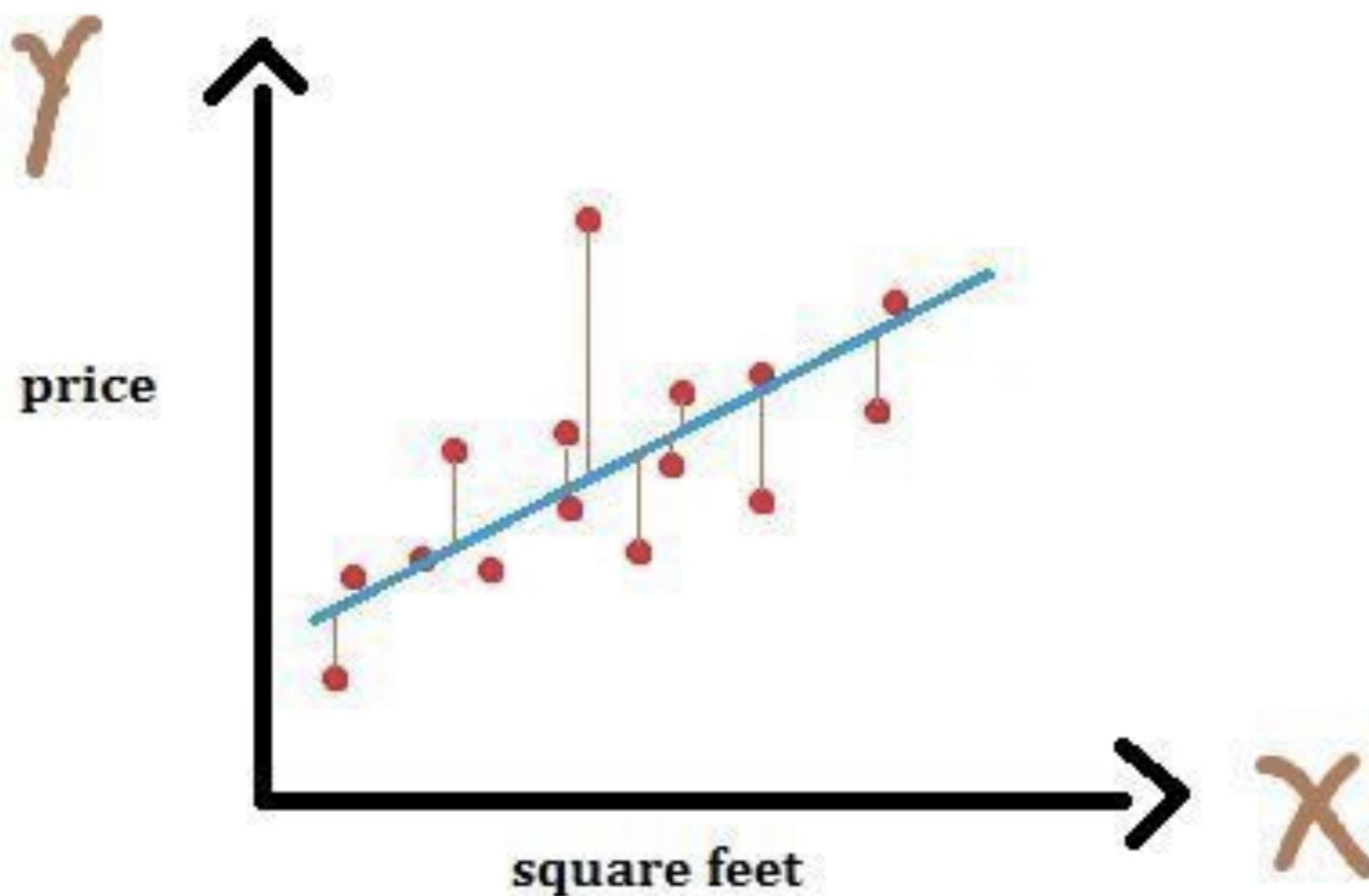
$x, y$

minimize  $\theta_0, \theta_1$

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

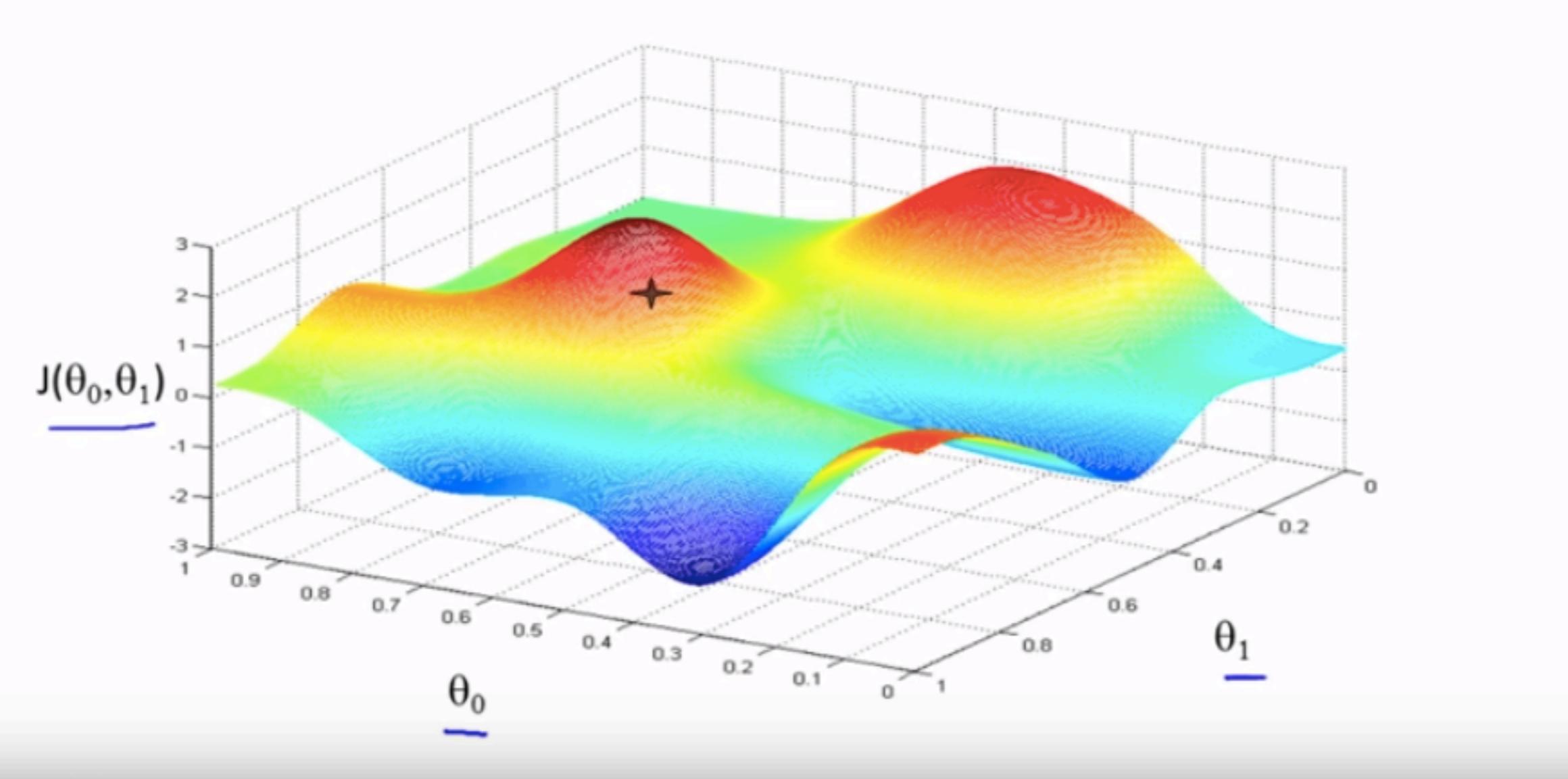
$\underbrace{\qquad\qquad\qquad}_{\# \text{ training examples}}$

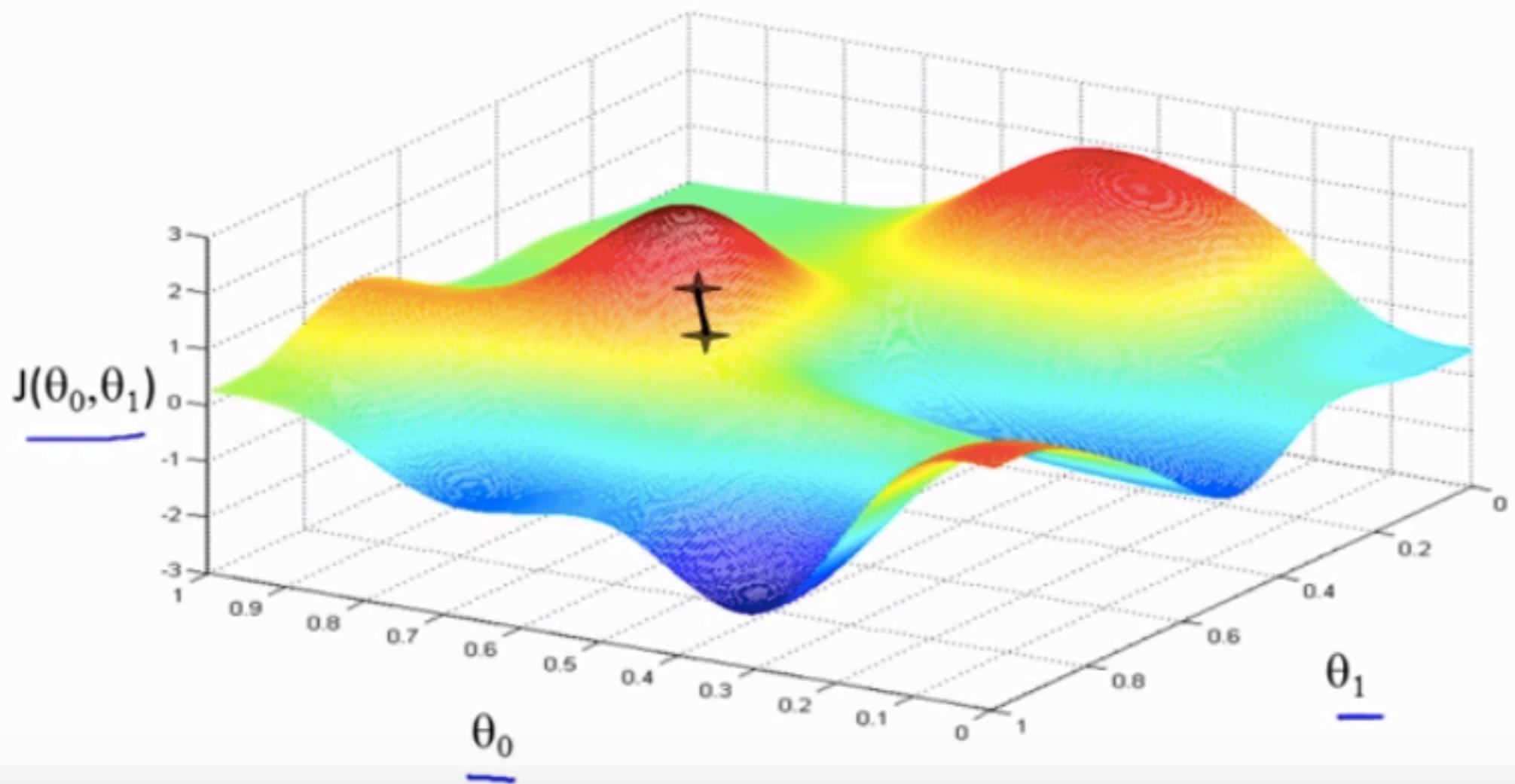
$h_{\theta_0, \theta_1}(x^{(i)}) = \underline{\theta_0} + \underline{\theta_1 x^{(i)}}$

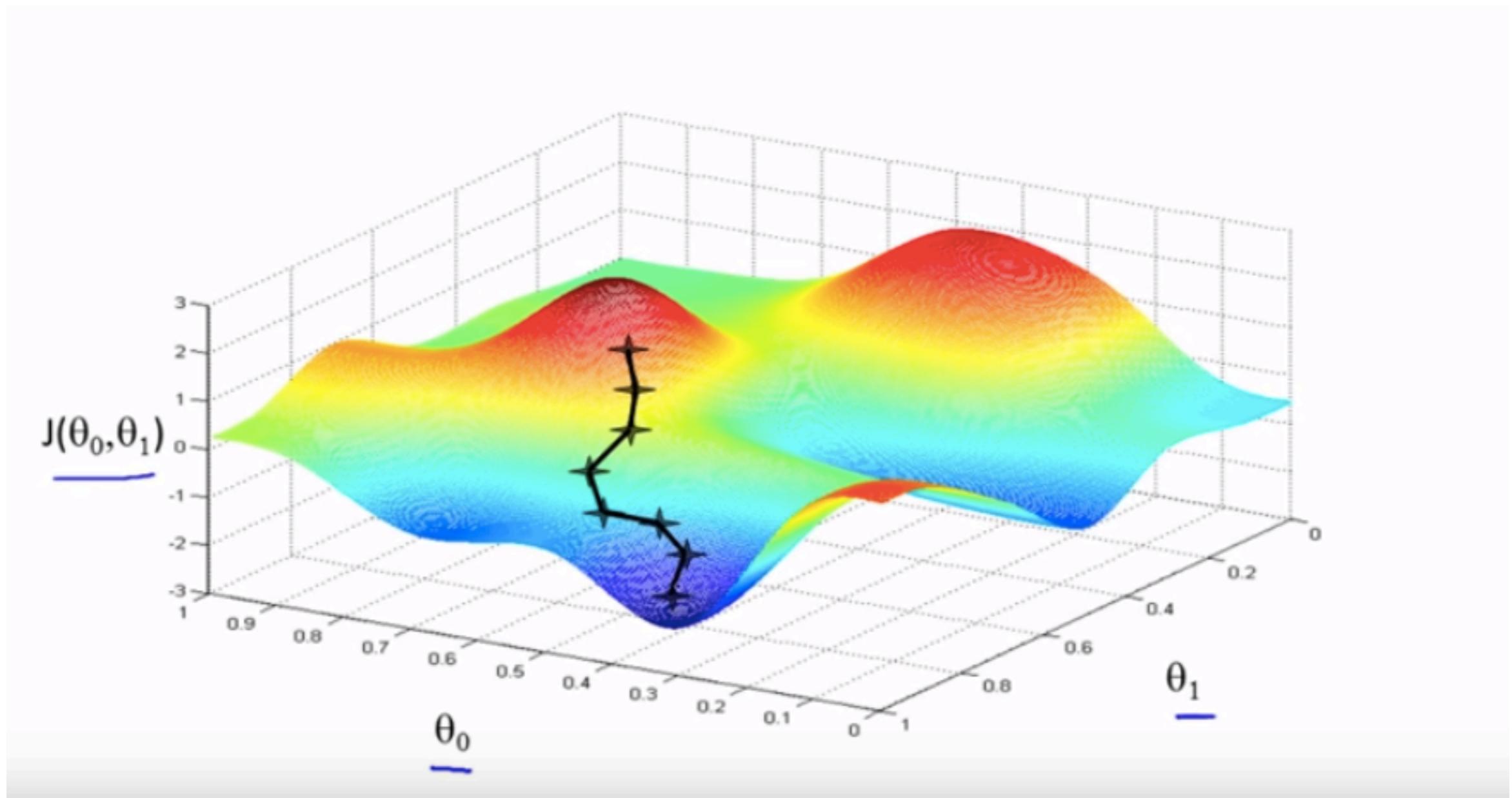


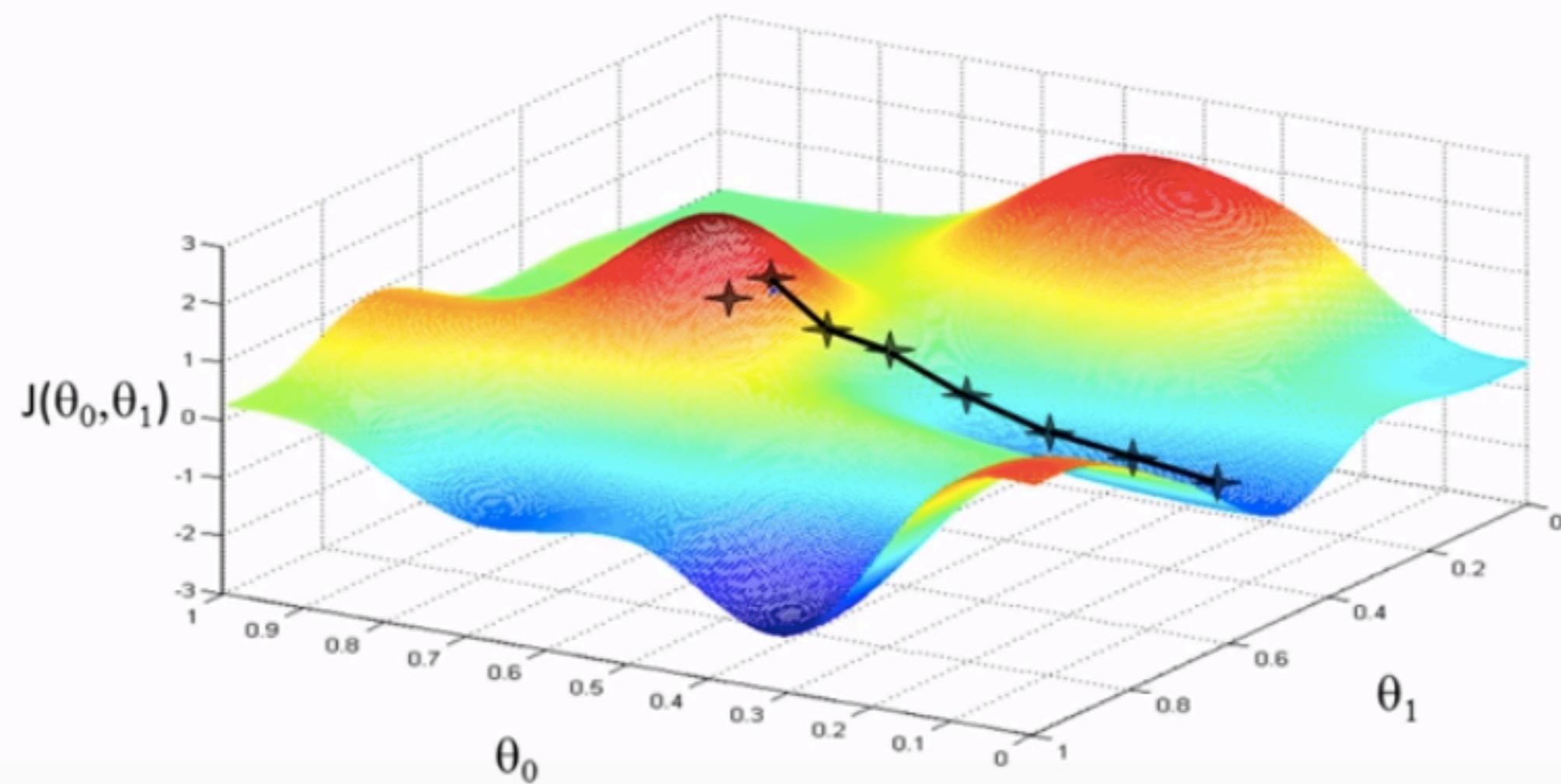
## Cost Function

# HOW TO EFFICIENTLY MINIMIZE COST FUNCTION?









## Gradient descent algorithm

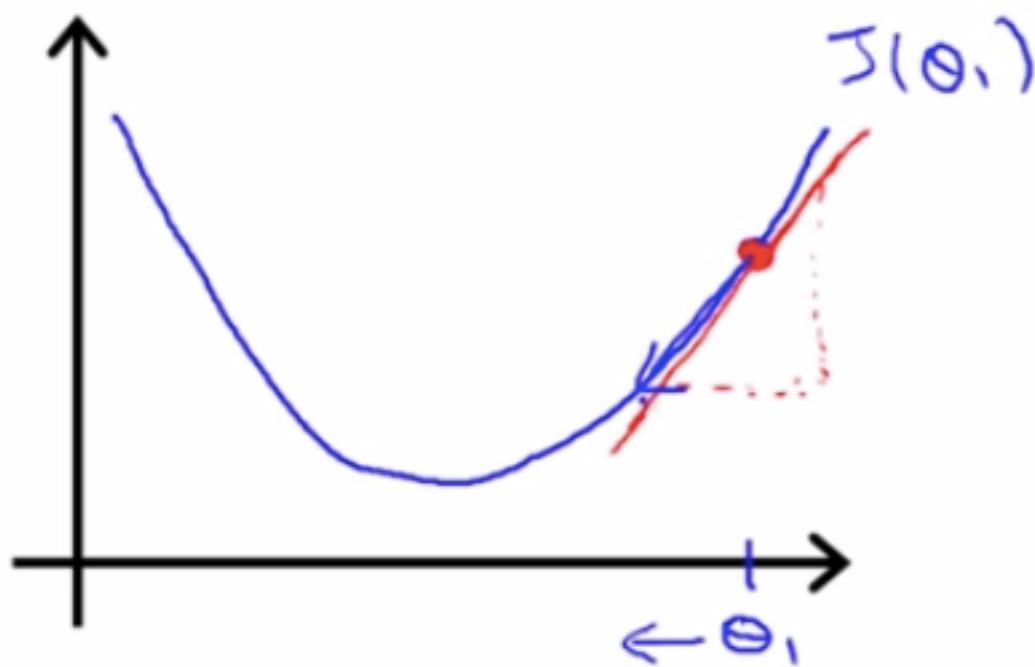
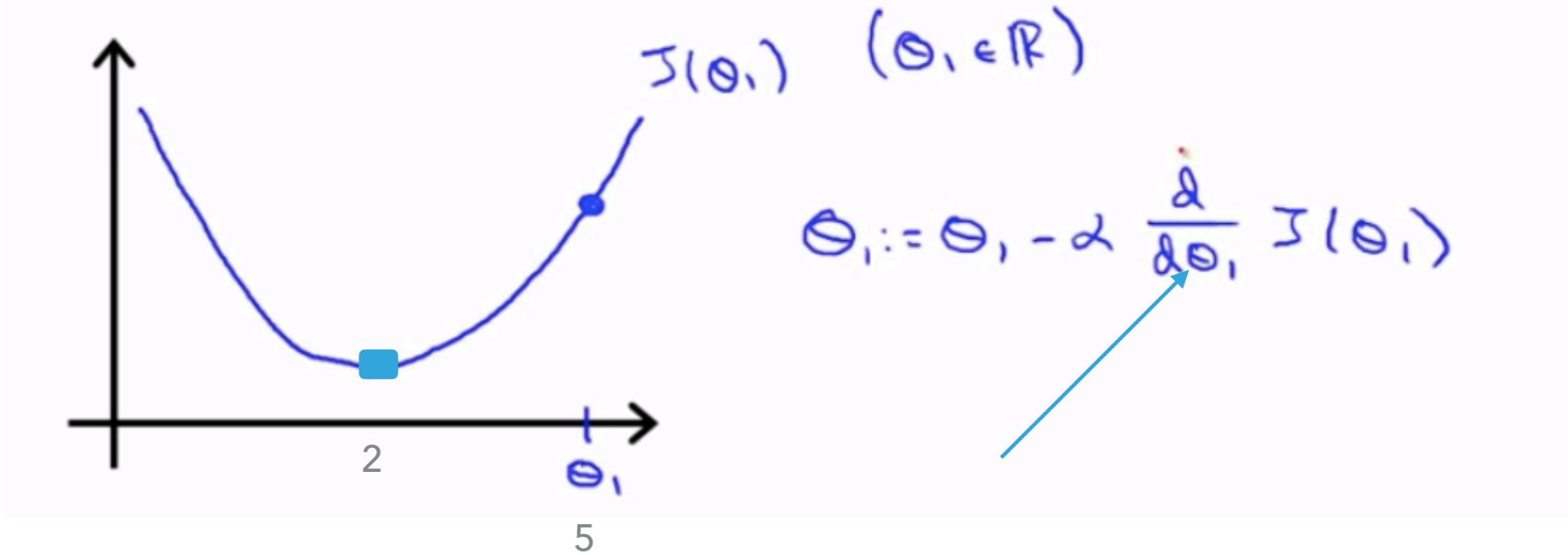
repeat until convergence {

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

}

Learning Rate

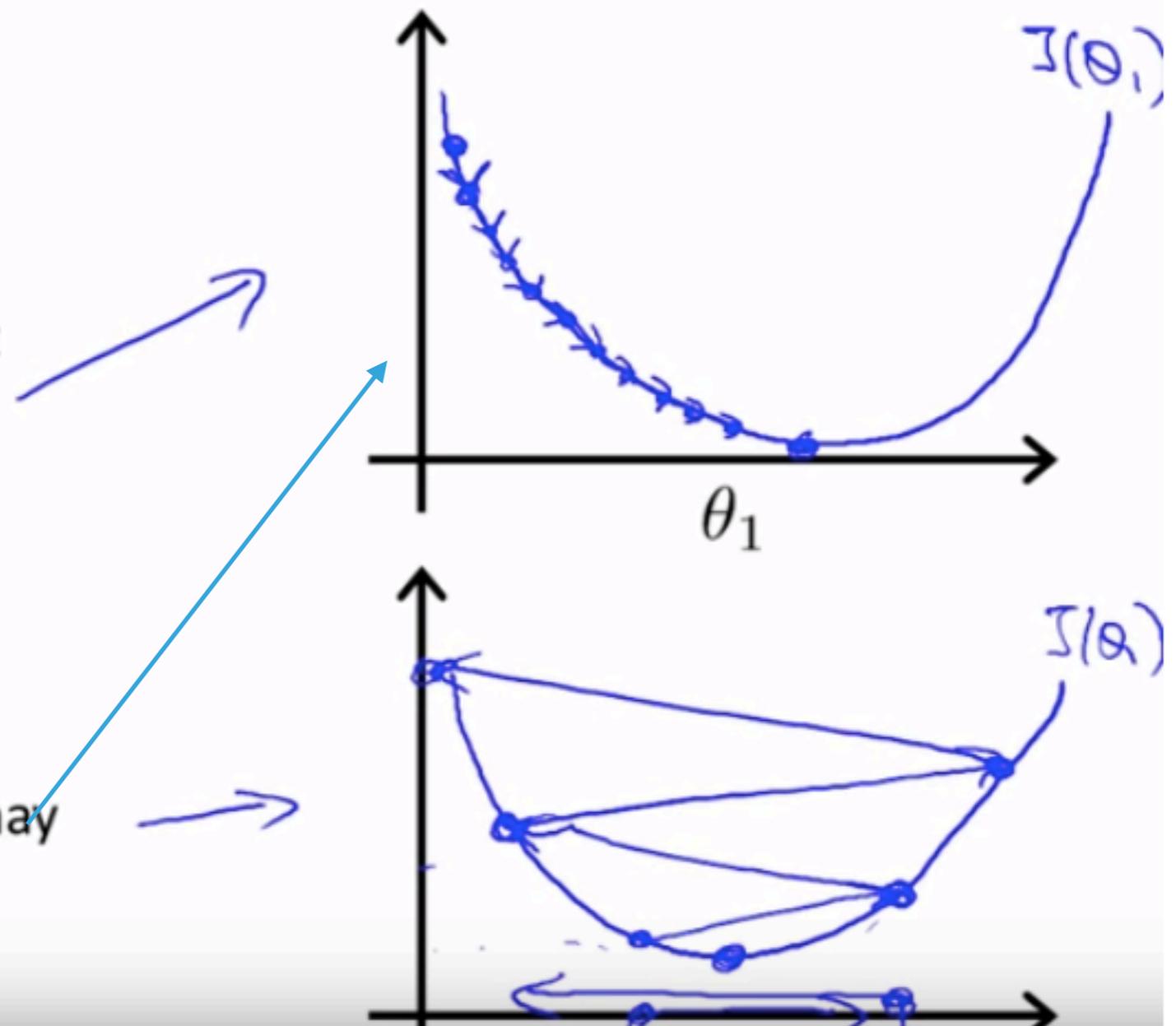
Slope



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

If  $\alpha$  is too small, gradient descent can be slow.

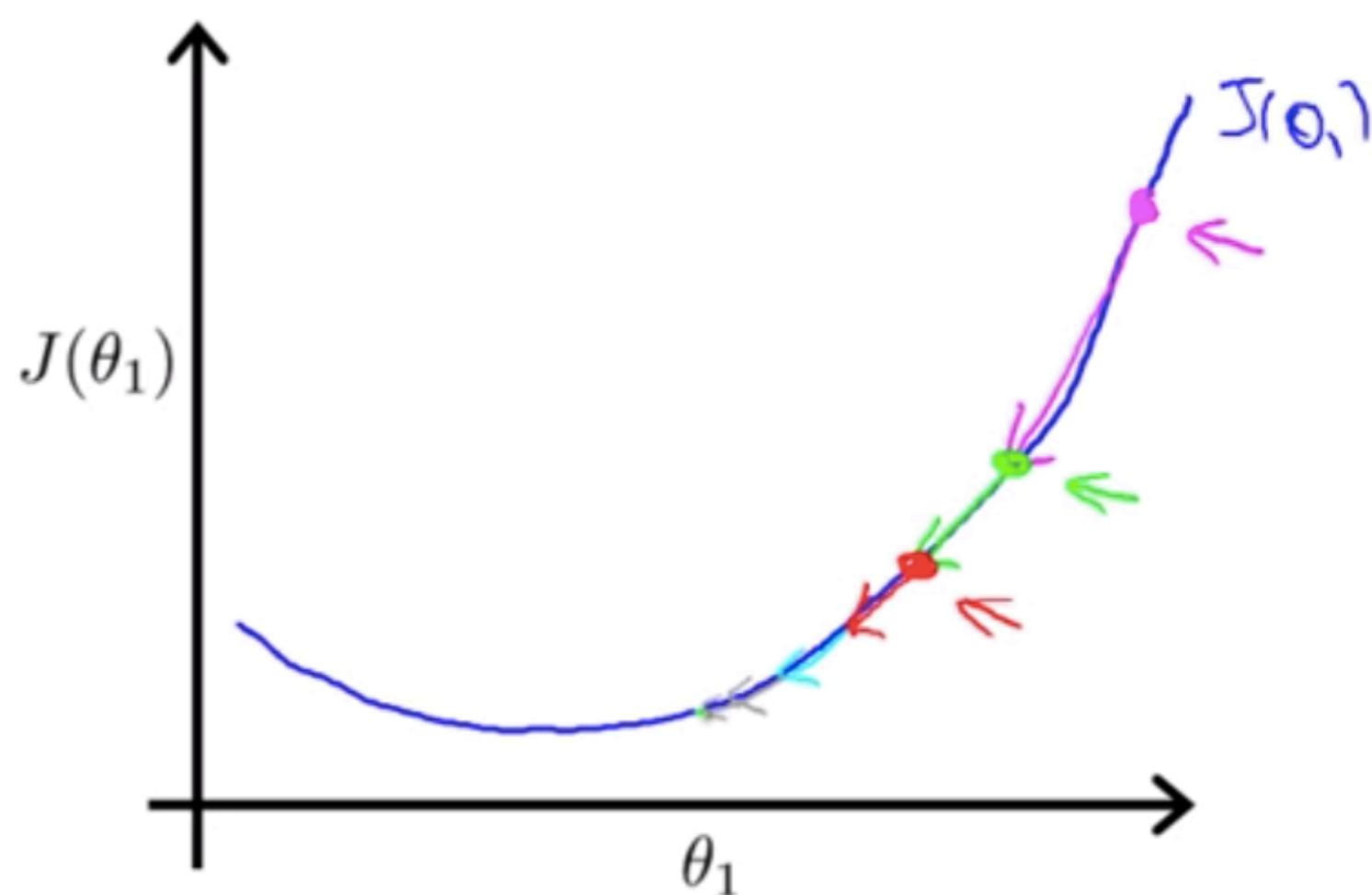
If  $\alpha$  is too large, gradient descent can overshoot the minimum. It may fail to converge, or even diverge.



Gradient descent can converge to a local minimum, even with the learning rate  $\alpha$  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  $\alpha$  over time.



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

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

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

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

## Gradient descent algorithm

repeat until convergence {

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

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

}

# LET'S CODE

<https://colab.research.google.com>