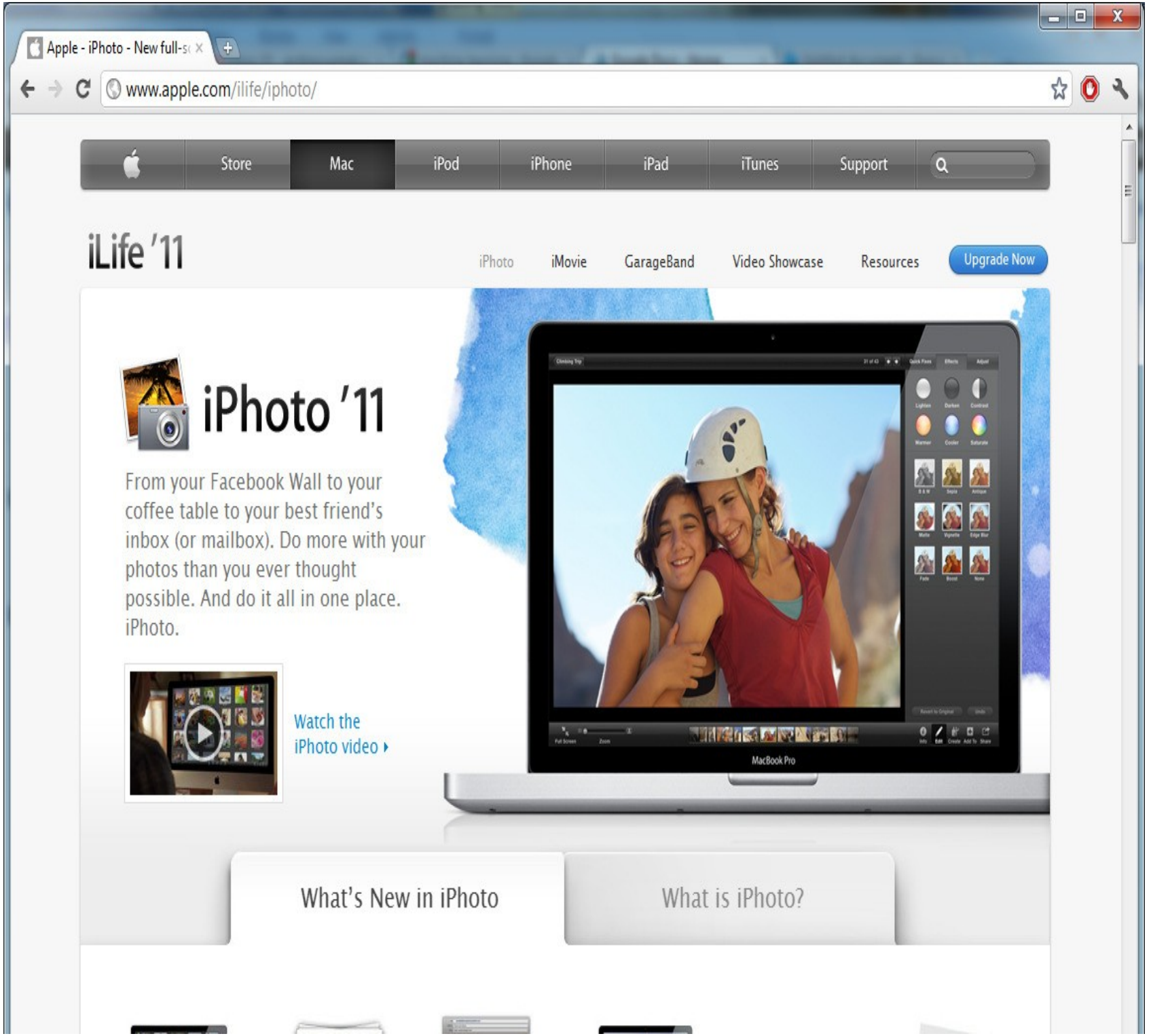
What is AI/MachineLearning?

Introduction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SPAM

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, mos

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- Self-customizing programs

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- Self-customizing programs

  E.g., Amazon, Netflix product recommendations

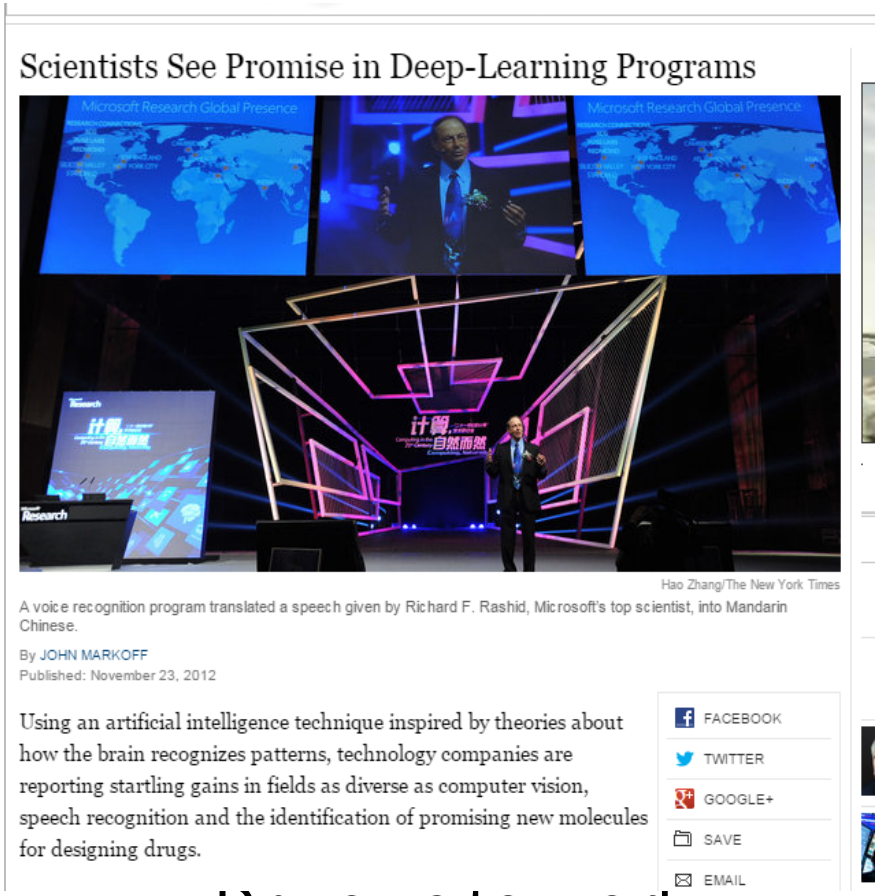
- Understanding human learning (brain, real AI).

What do we want AI to do?

Keep us organized

Guide us to content

Help us find things



Scientists See Promise in Deep-Learning Programs

Hao Zhang/The New York Times

A voice recognition program translated a speech given by Richard F. Rashid, Microsoft's top scientist, into Mandarin Chinese.

By JOHN MARKOFF
Published: November 23, 2012

Using an artificial intelligence technique inspired by theories about how the brain recognizes patterns, technology companies are reporting startling gains in fields as diverse as computer vision, speech recognition and the identification of promising new molecules for designing drugs.

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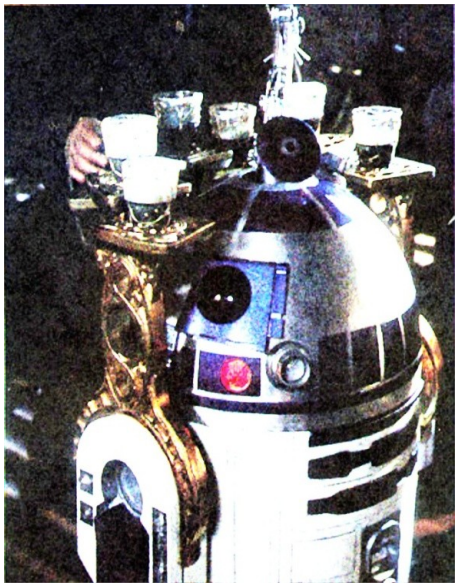
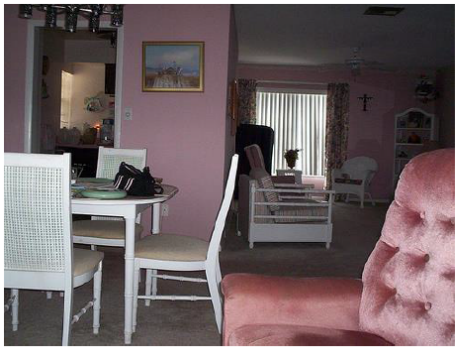
Help us communicate
帮助我们沟通

Drive us to work



Serve drinks?

Two dogs and one person.
A person is playing with a dog.



Six chairs and one table and one person.
The image is taken in a room.

A living room with a carpeting, a cream sofa and chair, and a large door.

The room in the apartment gets some afternoon sun.

Living room with white couch and blue carpeting.

Five bottles and one desk and one person.
A person is sitting on a chair

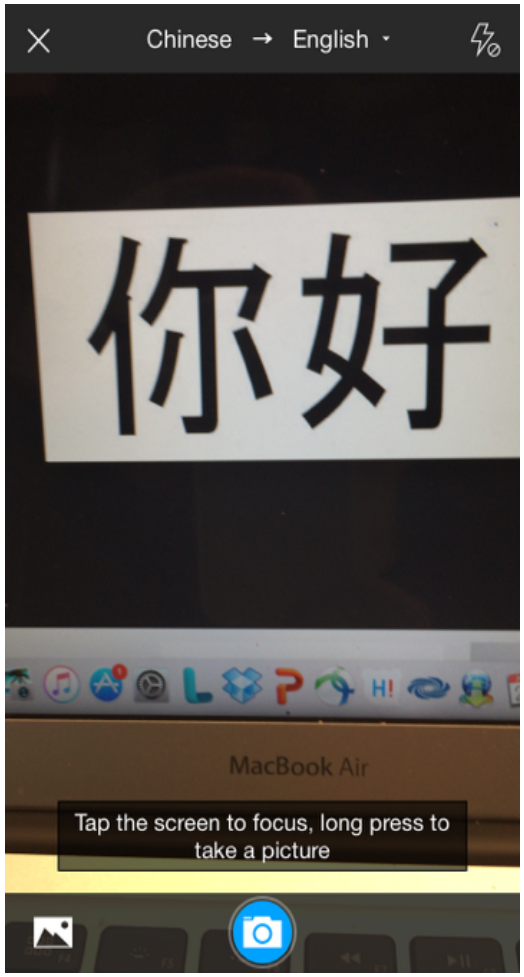
One motorbike and one person.
A person is riding a motorbike.

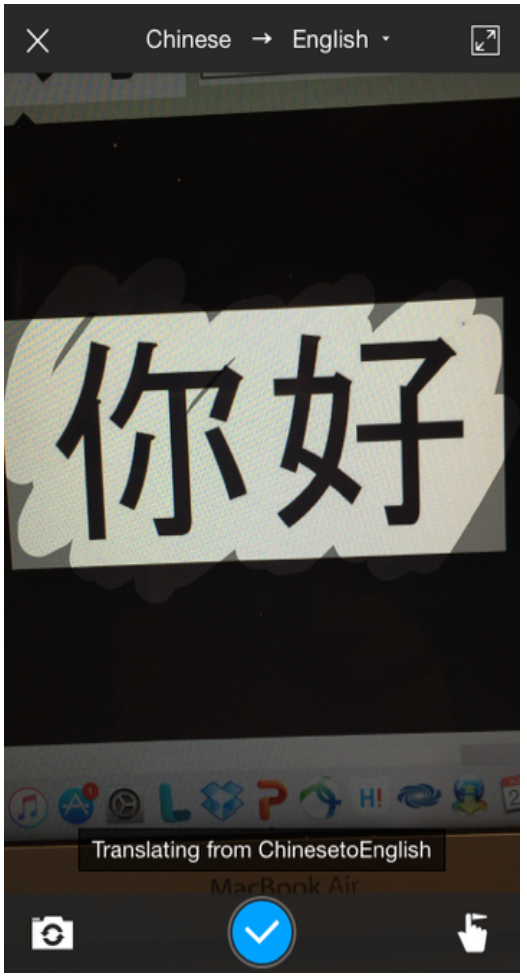
A yellow bus driving down a road with green trees and grass in the background.

School bus on a street.

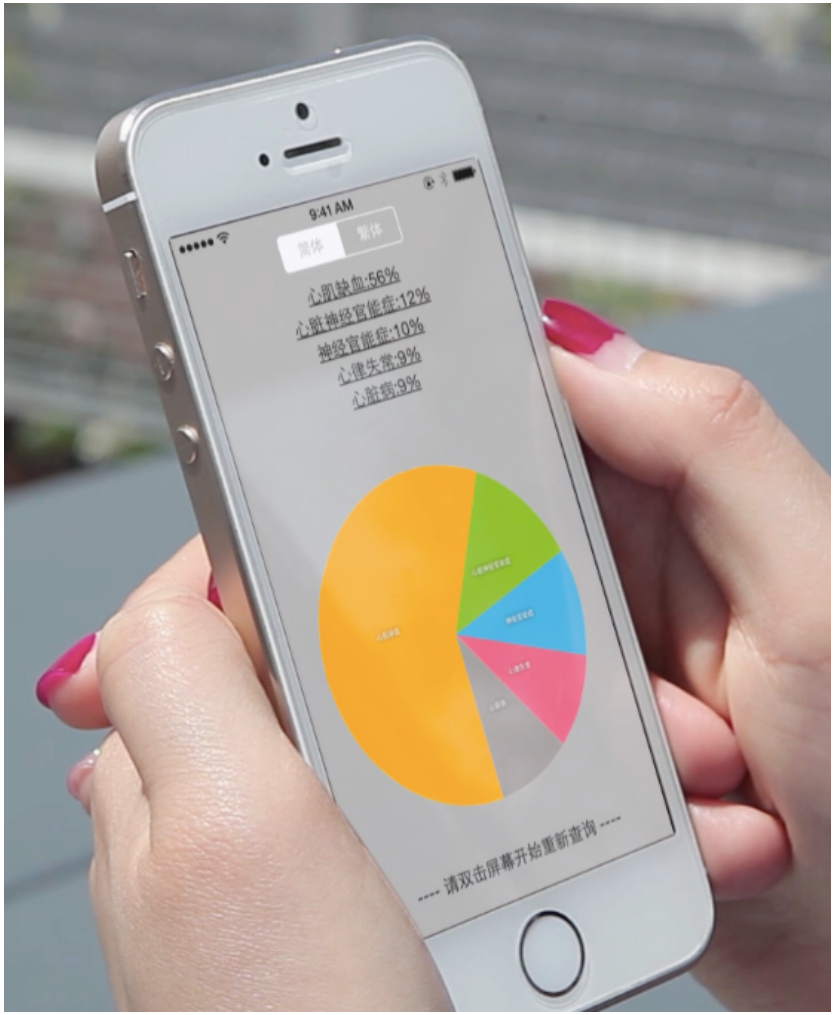
Yellow bus with trees in the background.

OCR-based Translation App



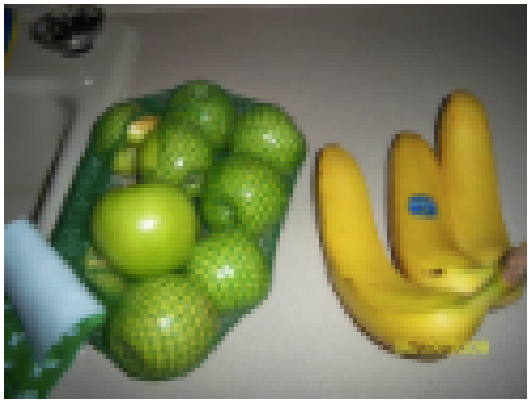
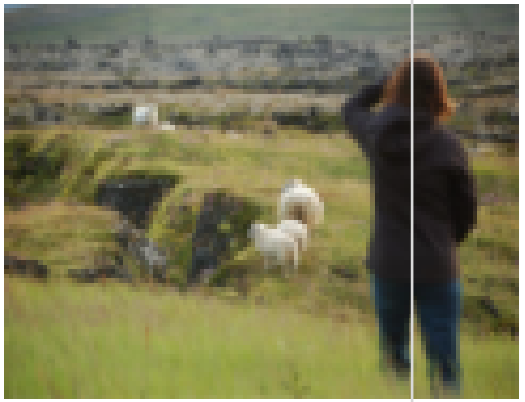


Medical Diagnostics App

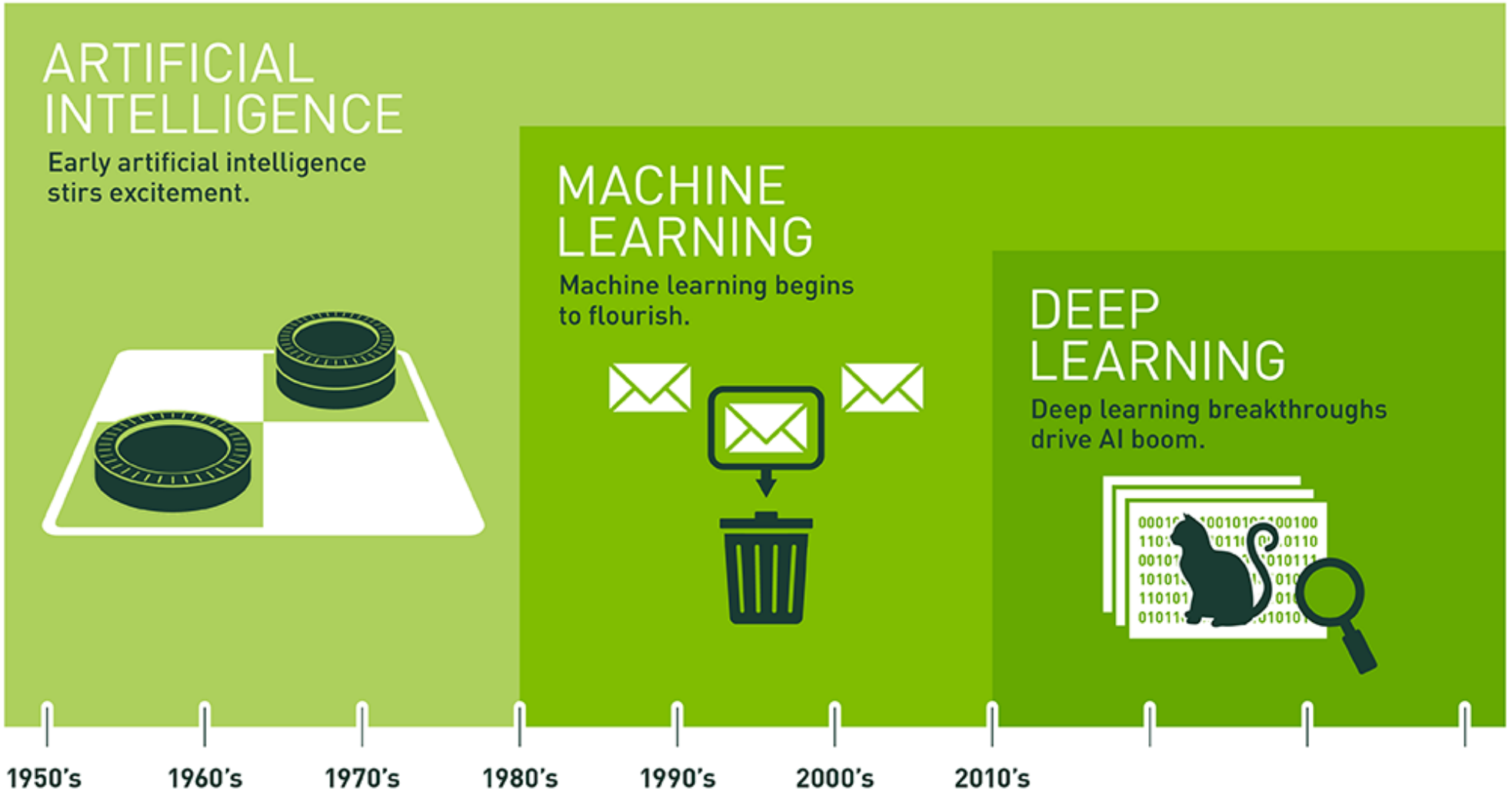


AskADoctor can assess 520 different diseases, representing ~90 percent of the most common medical problems.

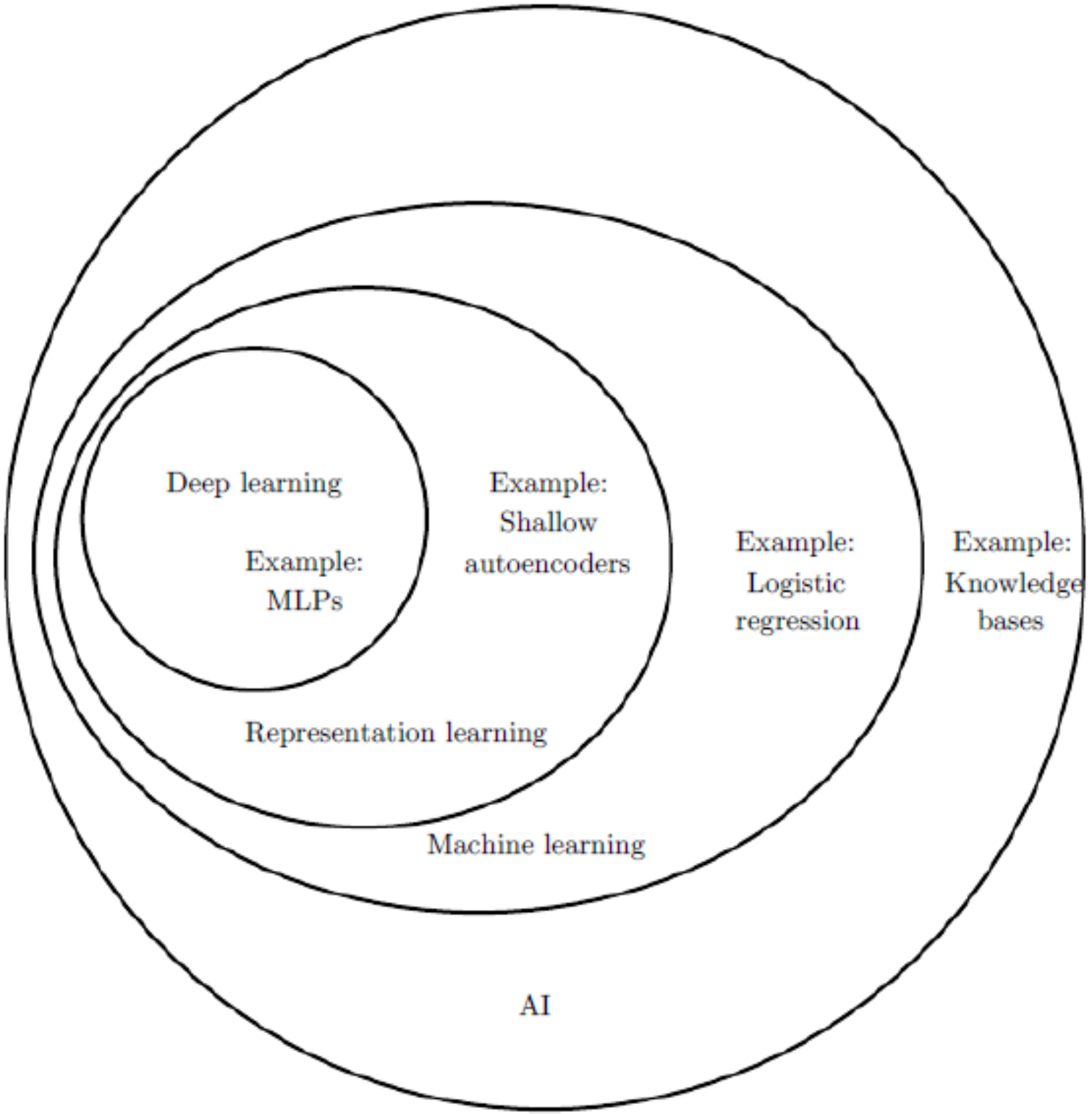
Image Q&A

Image			
Question	公共汽车是什么颜色的？ What is the color of the bus?	黄色的是什么？ What is there in yellow?	草地上除了人以外还有什么动 What is there on the grass, except the person?
Answer	公共汽车是红色的。 The bus is red.	香蕉。 Bananas.	羊。 Sheep.

Sample questions and answers



Since an early flush of optimism in the 1950s, smaller subsets of artificial intelligence – first machine learning, then deep learning, a subset of machine learning – have created ever larger disruptions.


Deep learning
Example:
MLPs
Example:
Shallow
autoencoders
Representation learning
Example:
Logistic
regression
Machine learning
Example:
Knowledge
bases
AI

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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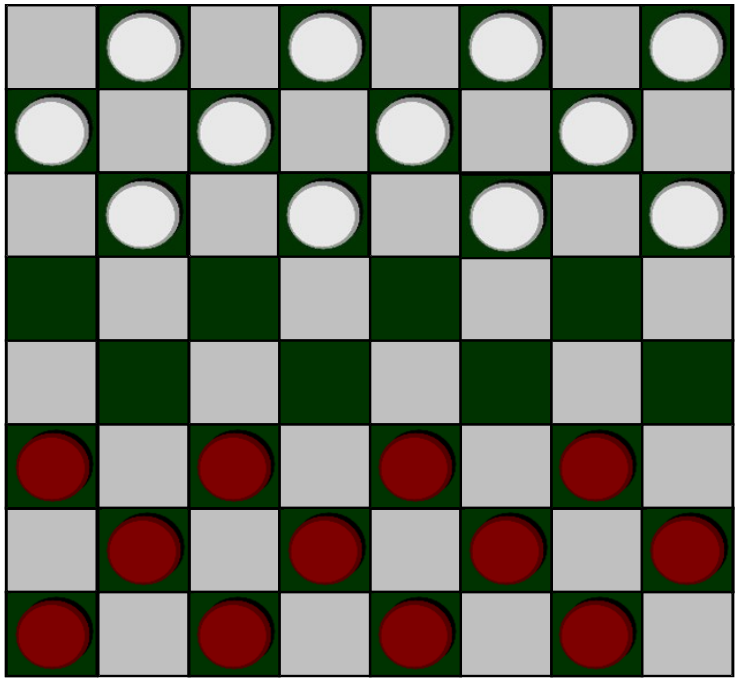


Machine Learning definition

- 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.

Machine learning algorithms:

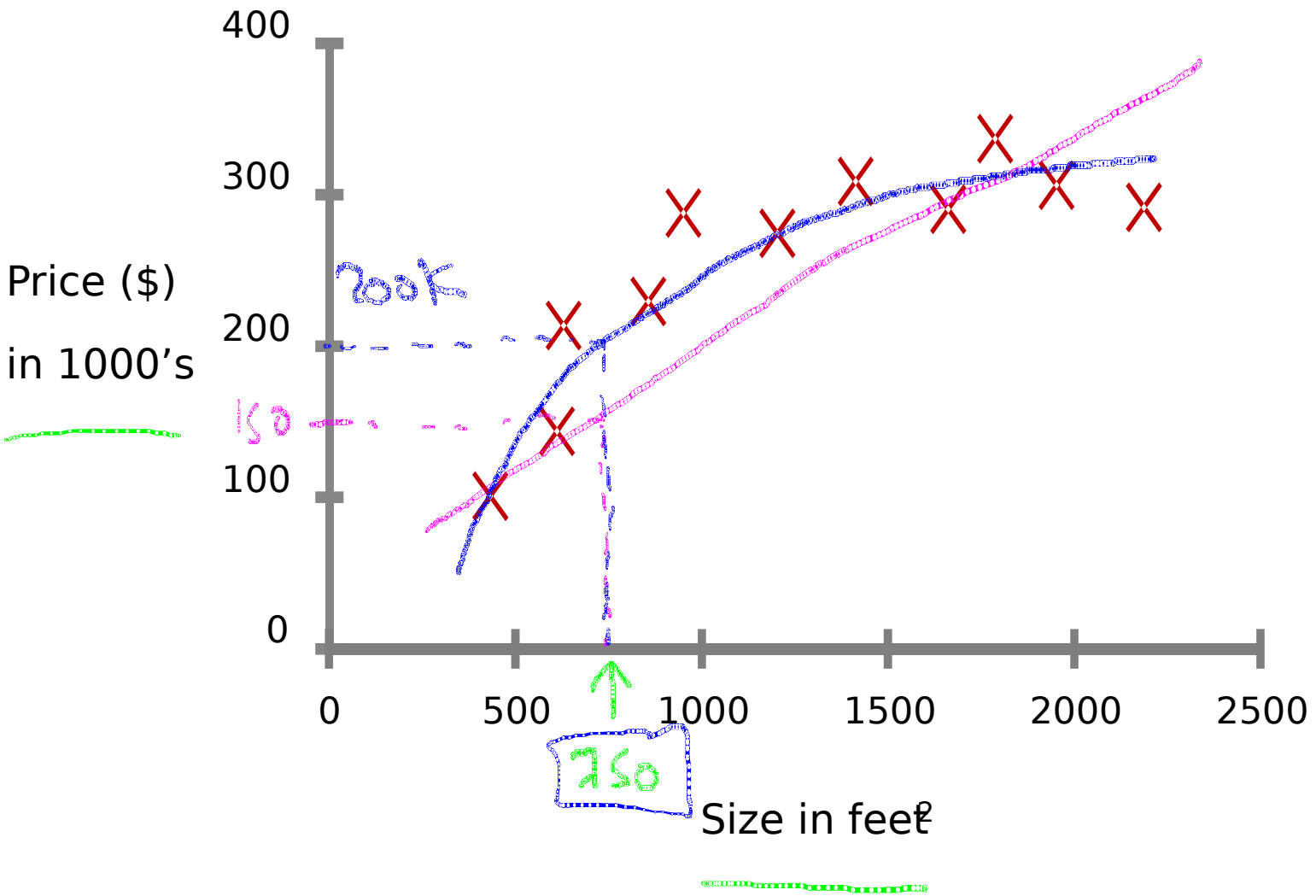
- Supervised learning
- Unsupervised learning

Others: Reinforcement learning, recommender systems.

Also talk about: Practical advice for applying learning algorithms.

Supervised Learning

Housing price prediction.

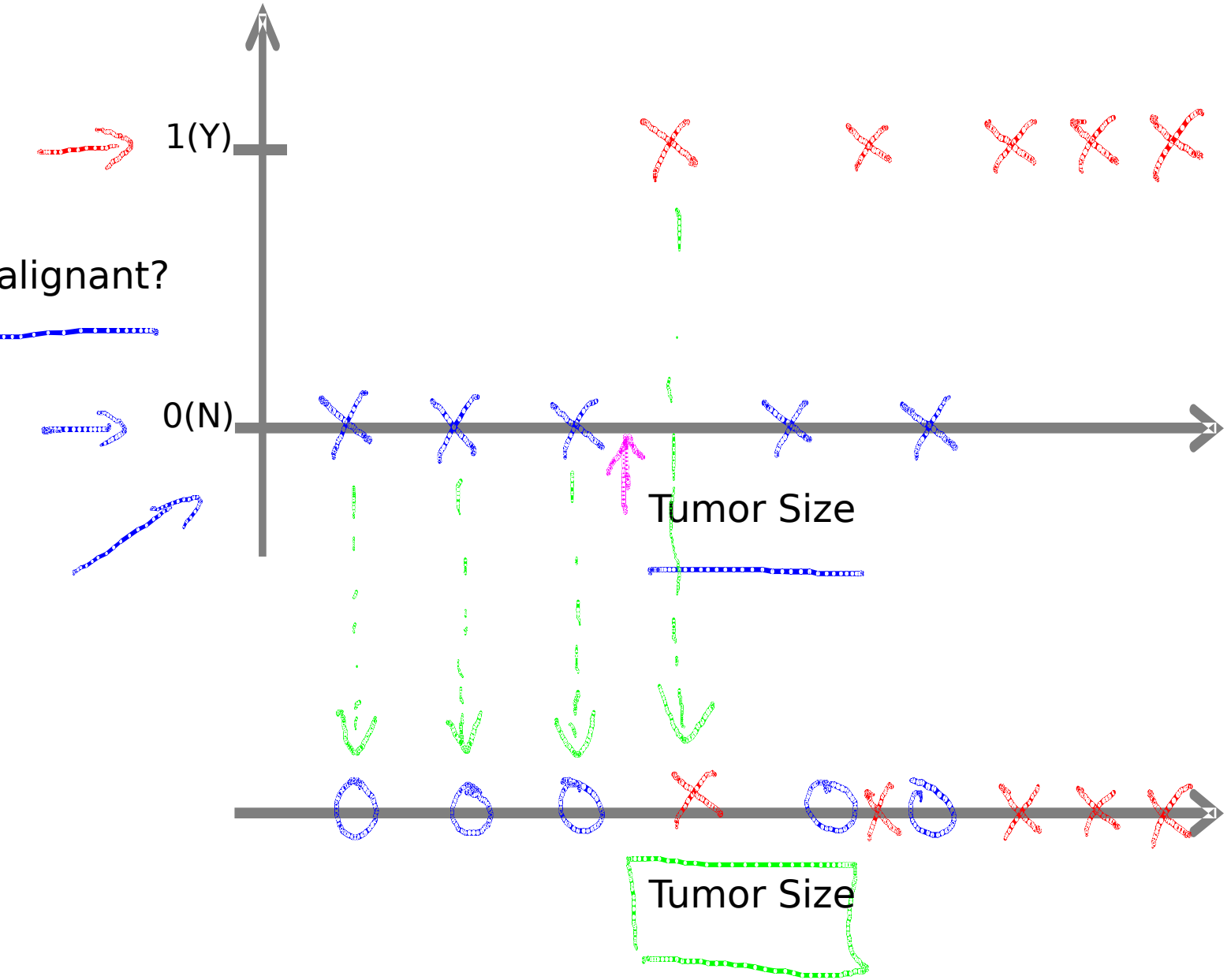


Supervised Learning

"right answers" given

Regression: Predict continuous valued output (price)

Breast cancer (malignant, benign)



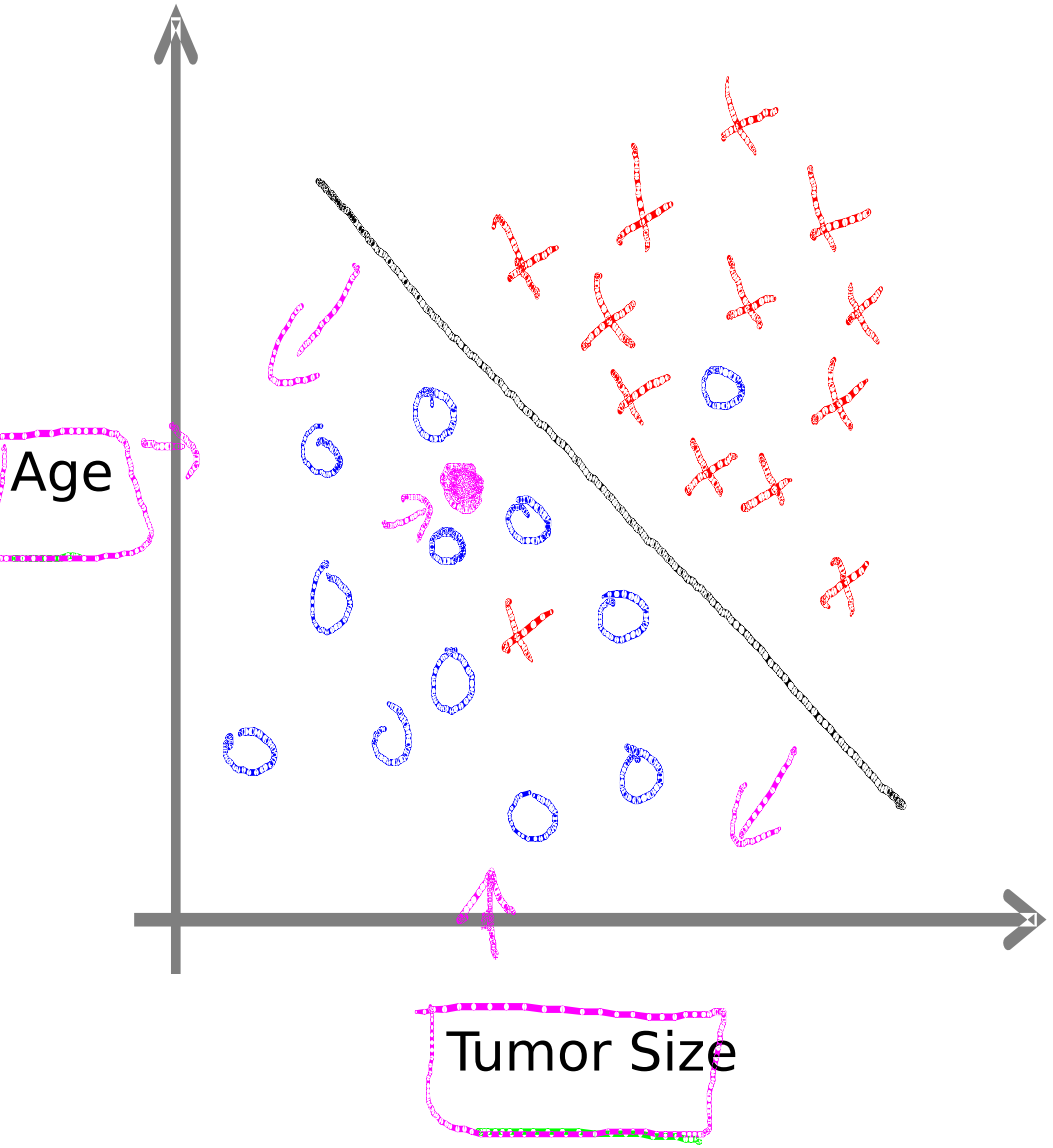
Classification

Discrete value

output (0 or 1)

0, 1, 2, 3, ...

benign, type 1 cancer

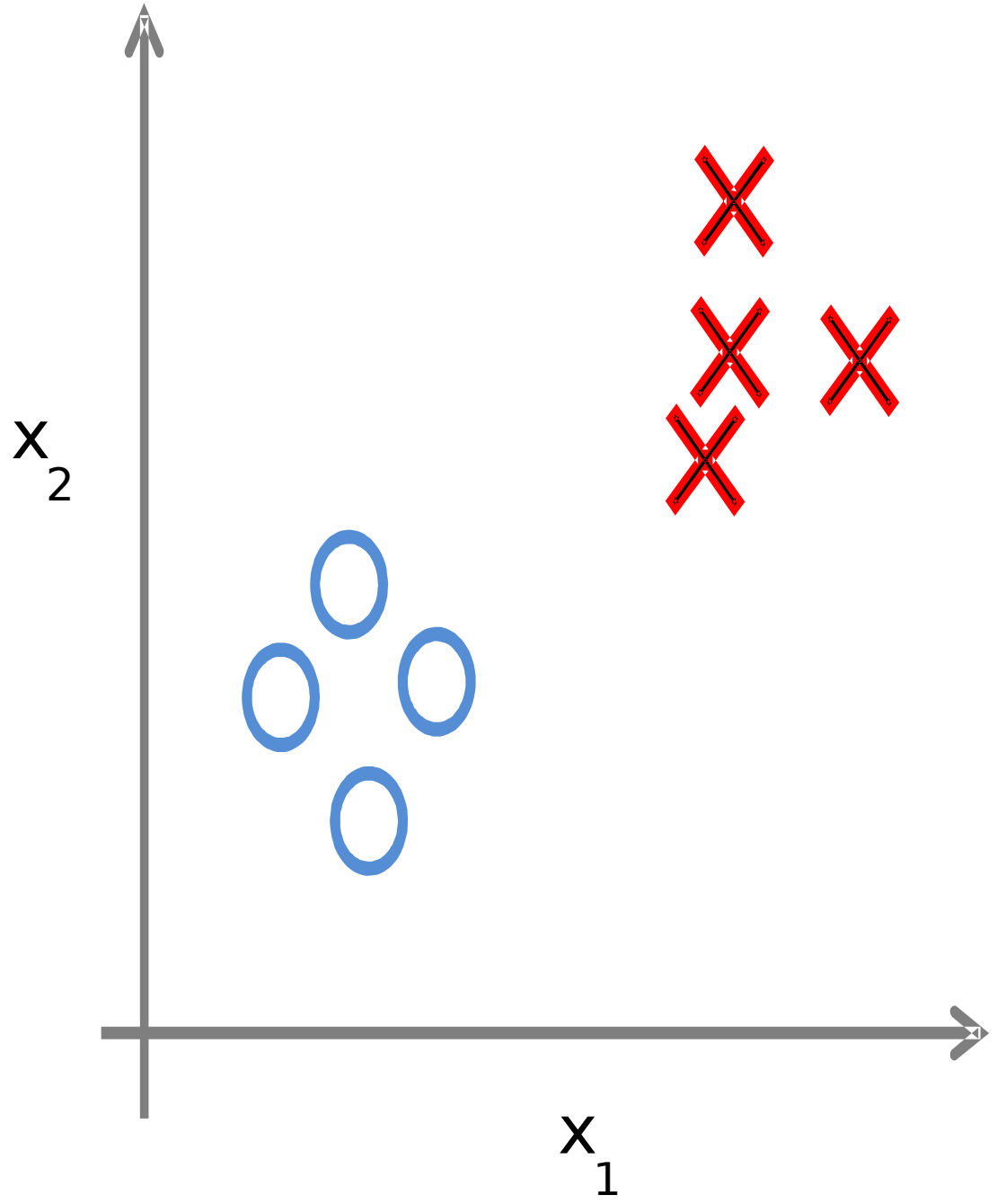


- Clump Thickness
- Uniformity of Cell Size
- Uniformity of Cell Shape

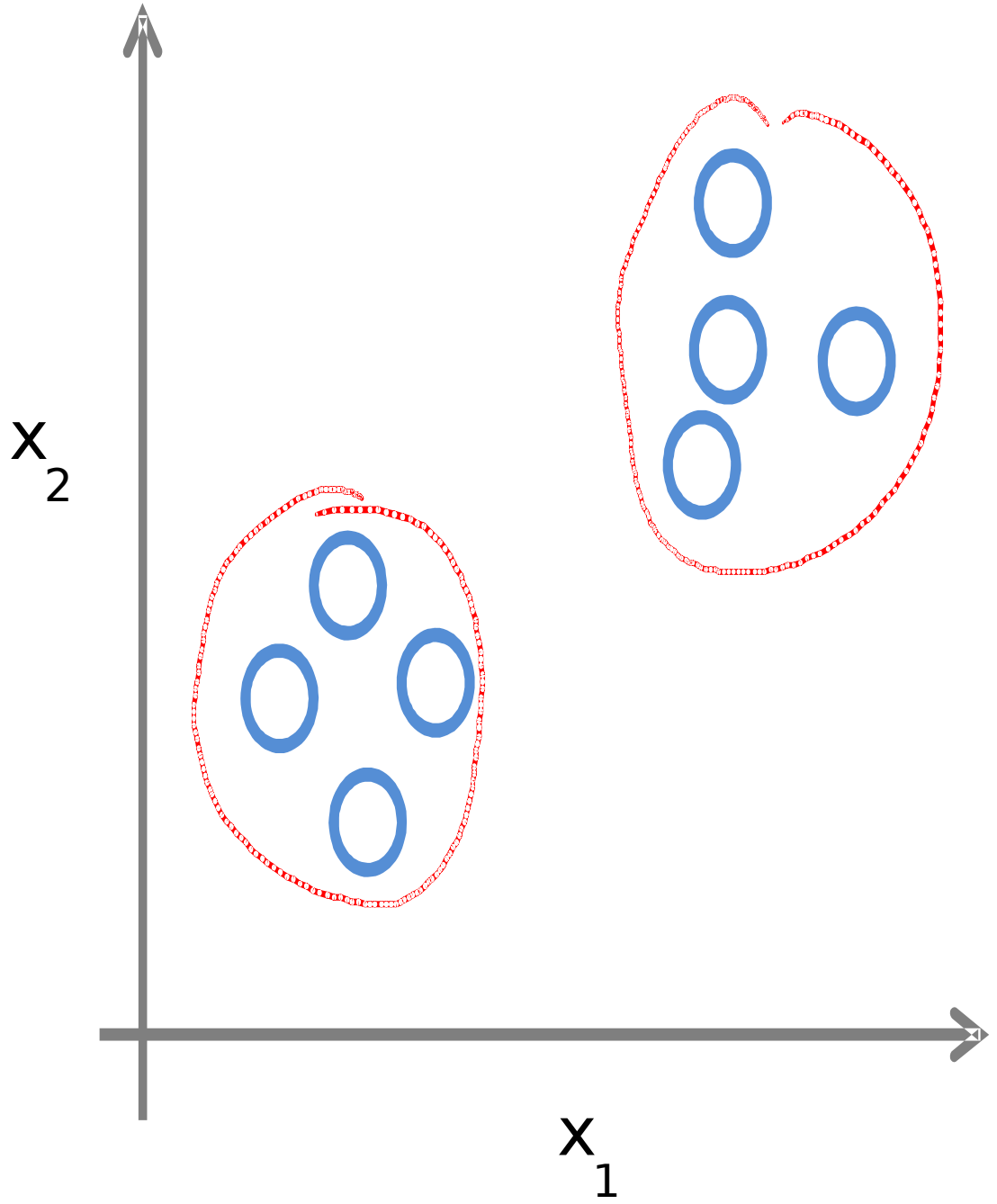
...

Unsupervised Learning

Supervised Learning



Unsupervised Learning



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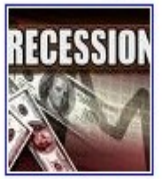

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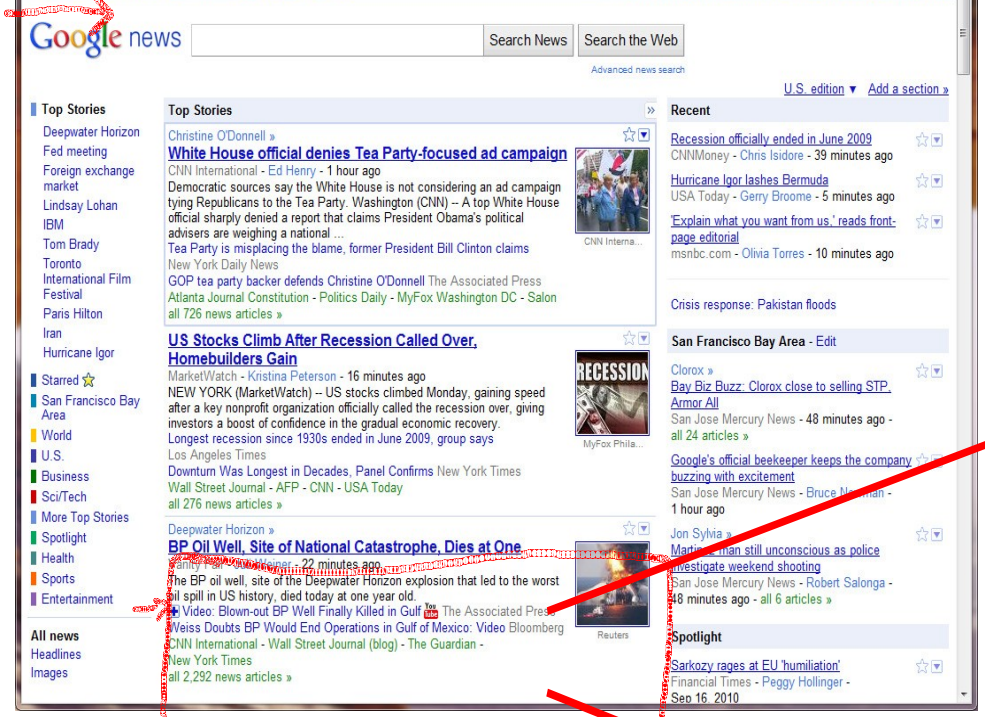
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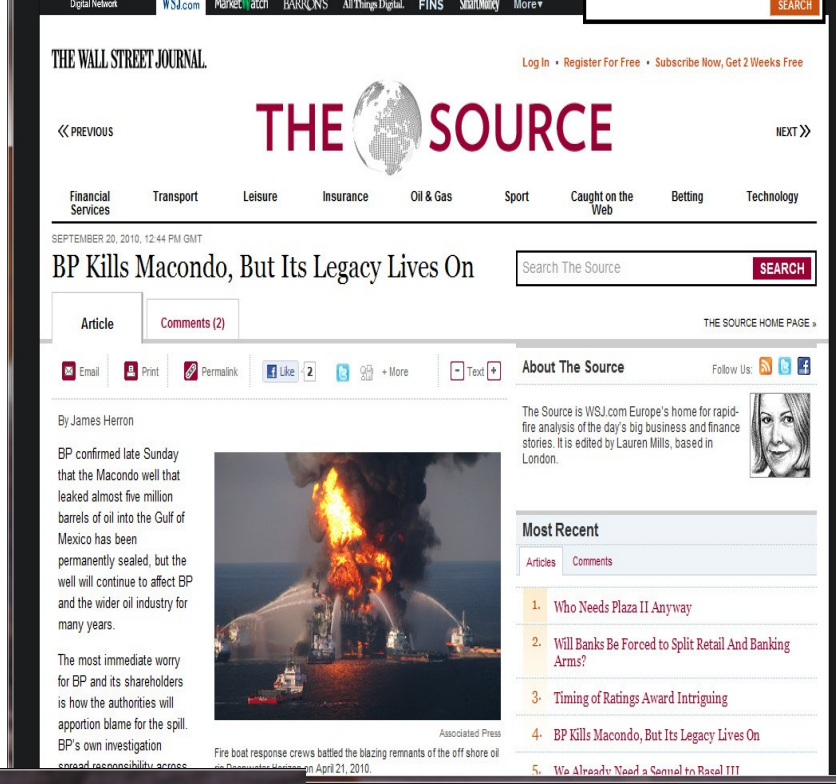
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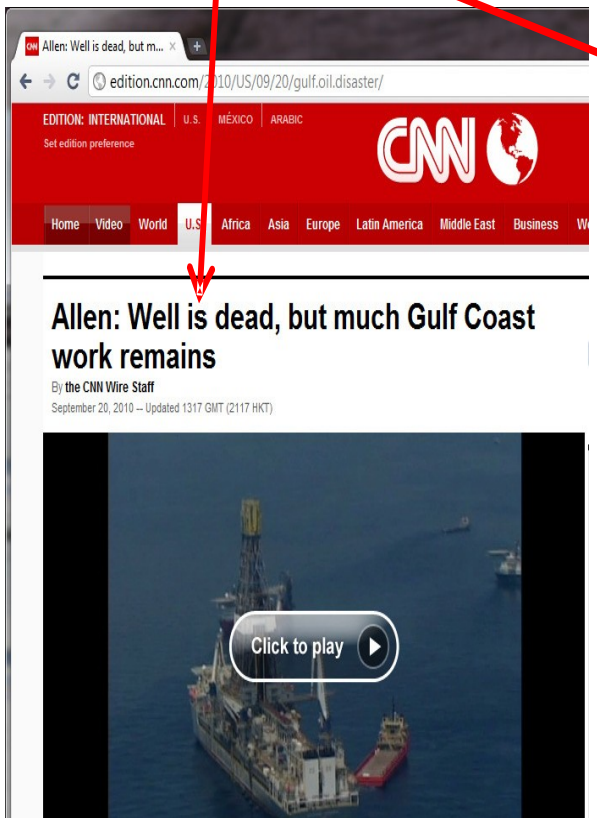
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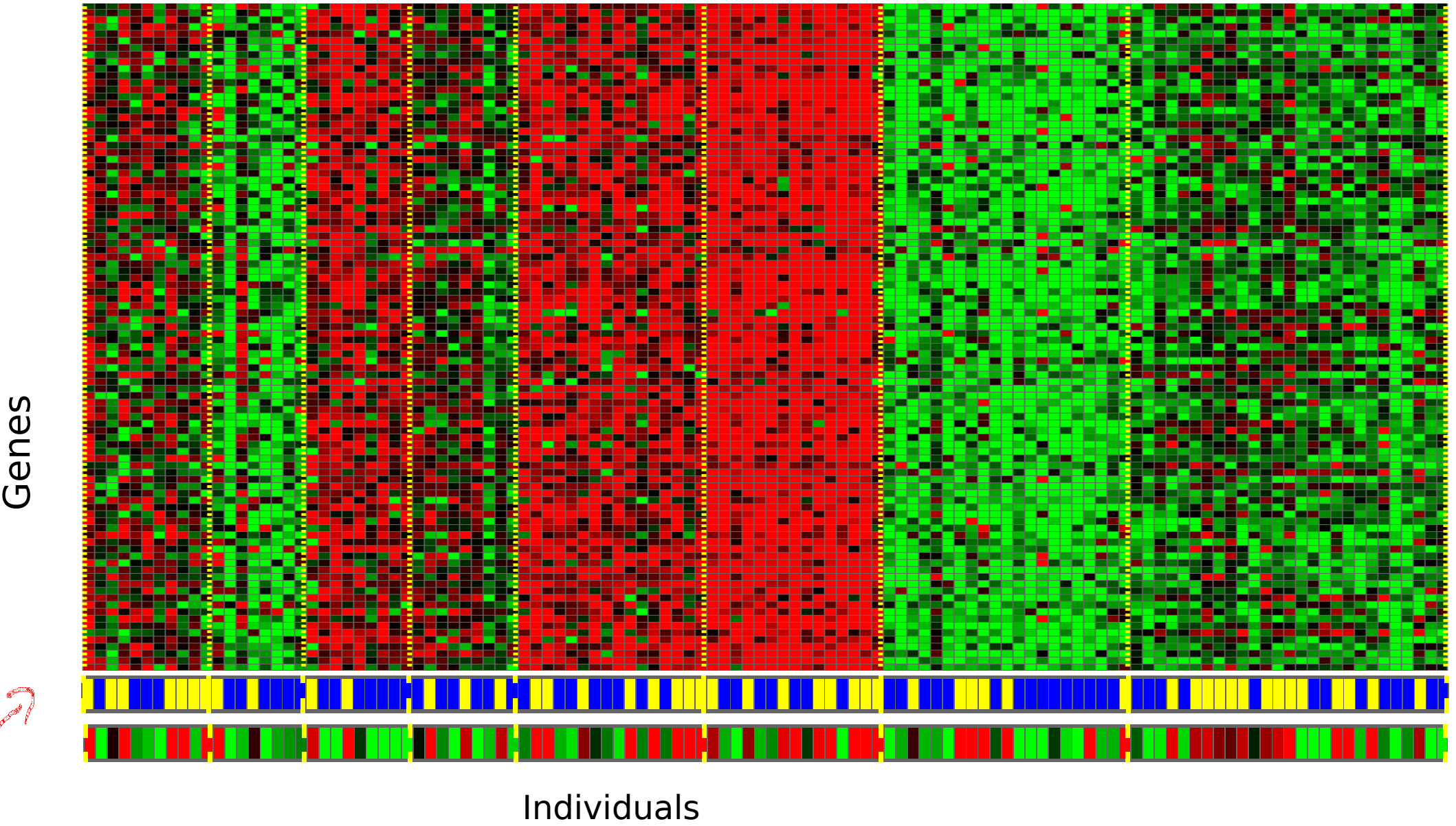
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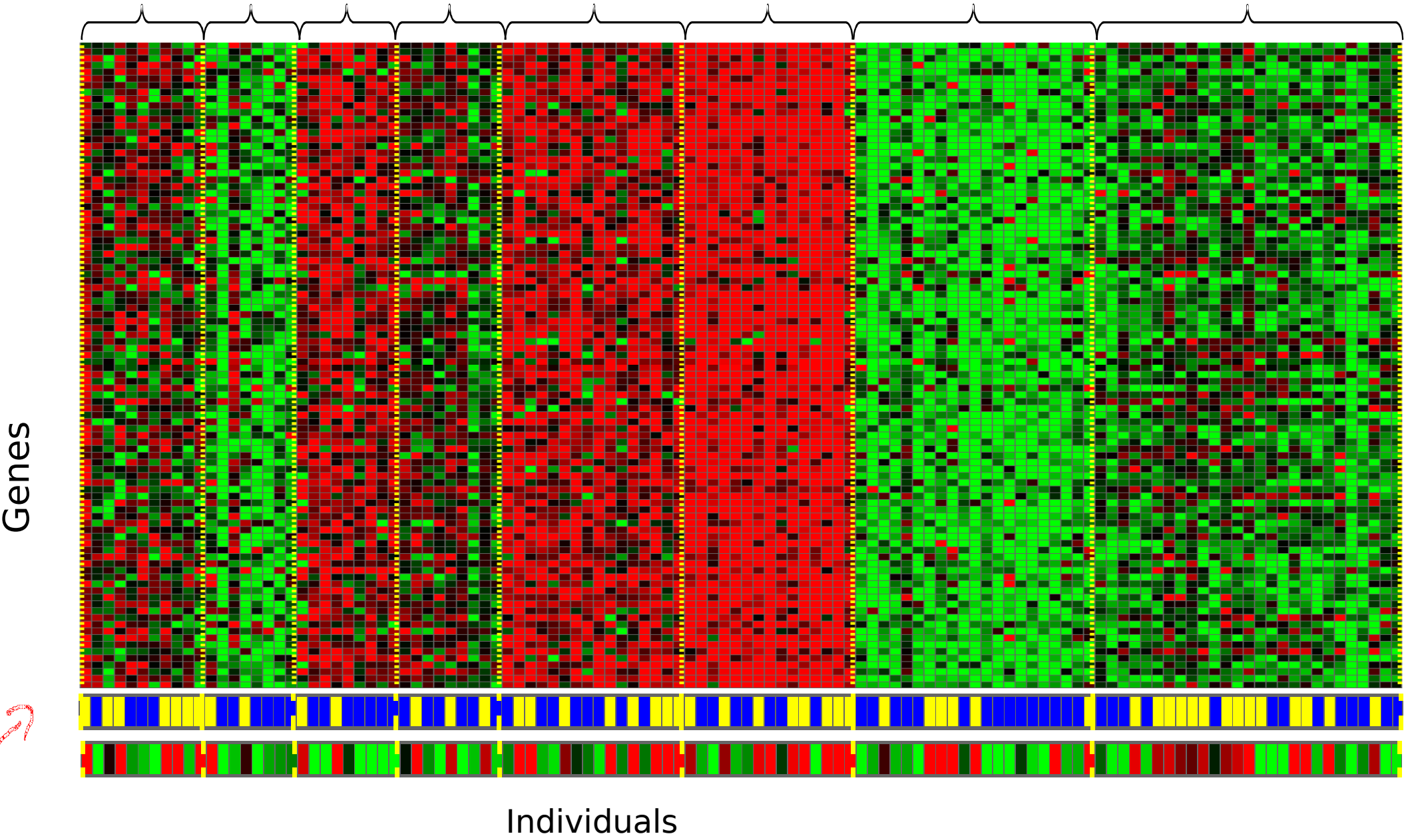
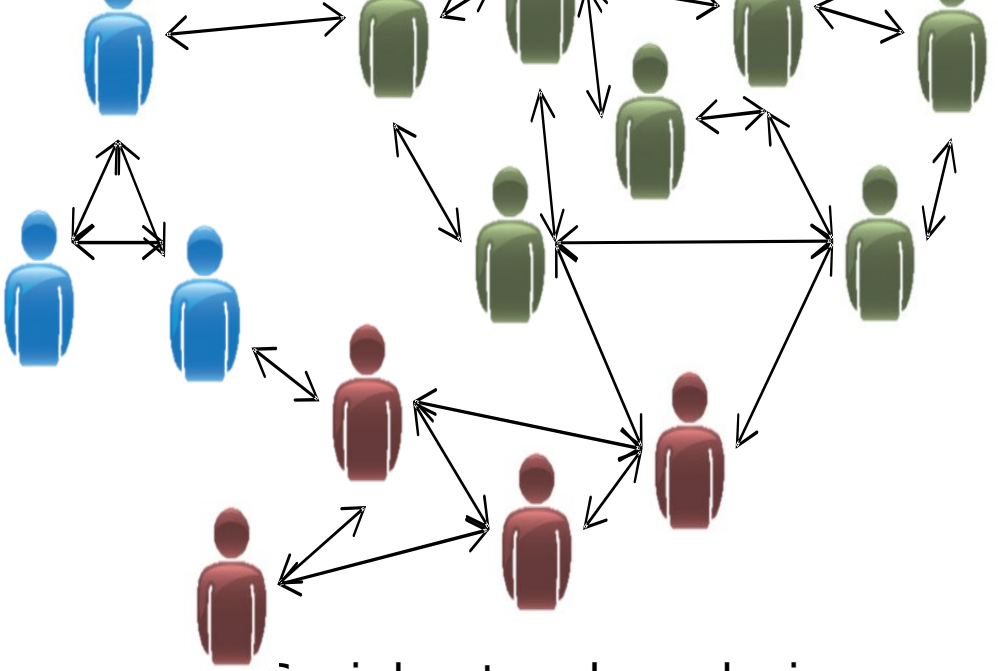
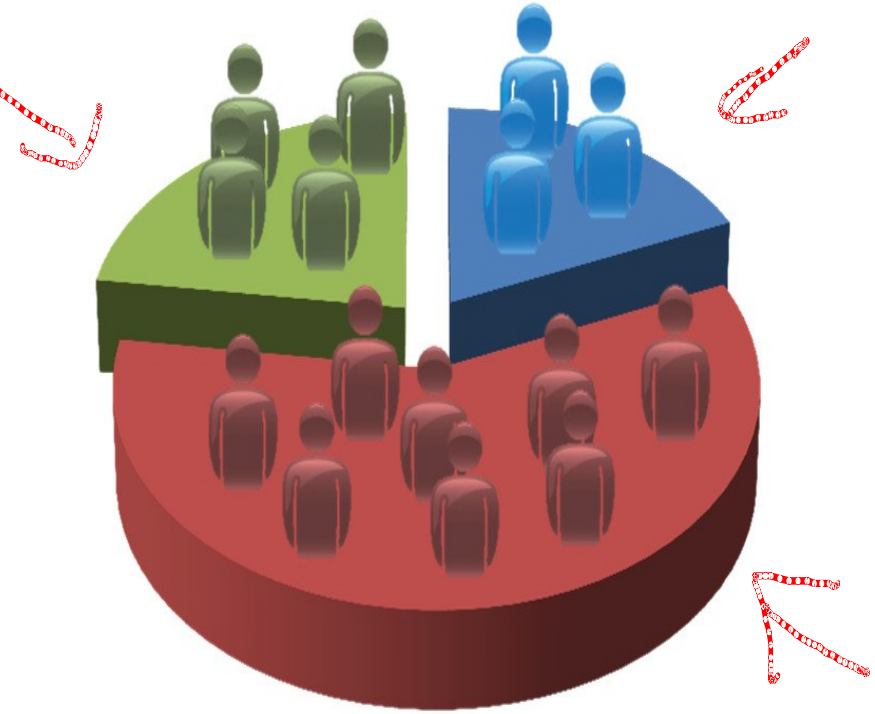
Individuals


Genes
Individuals

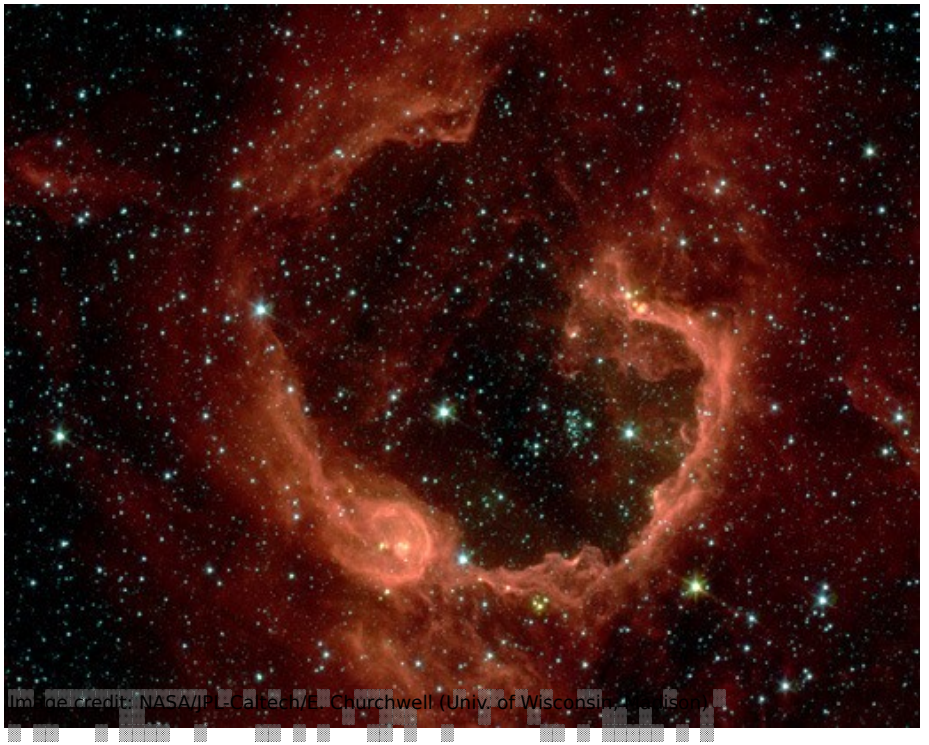
Organize computing clusters



Social network analysis

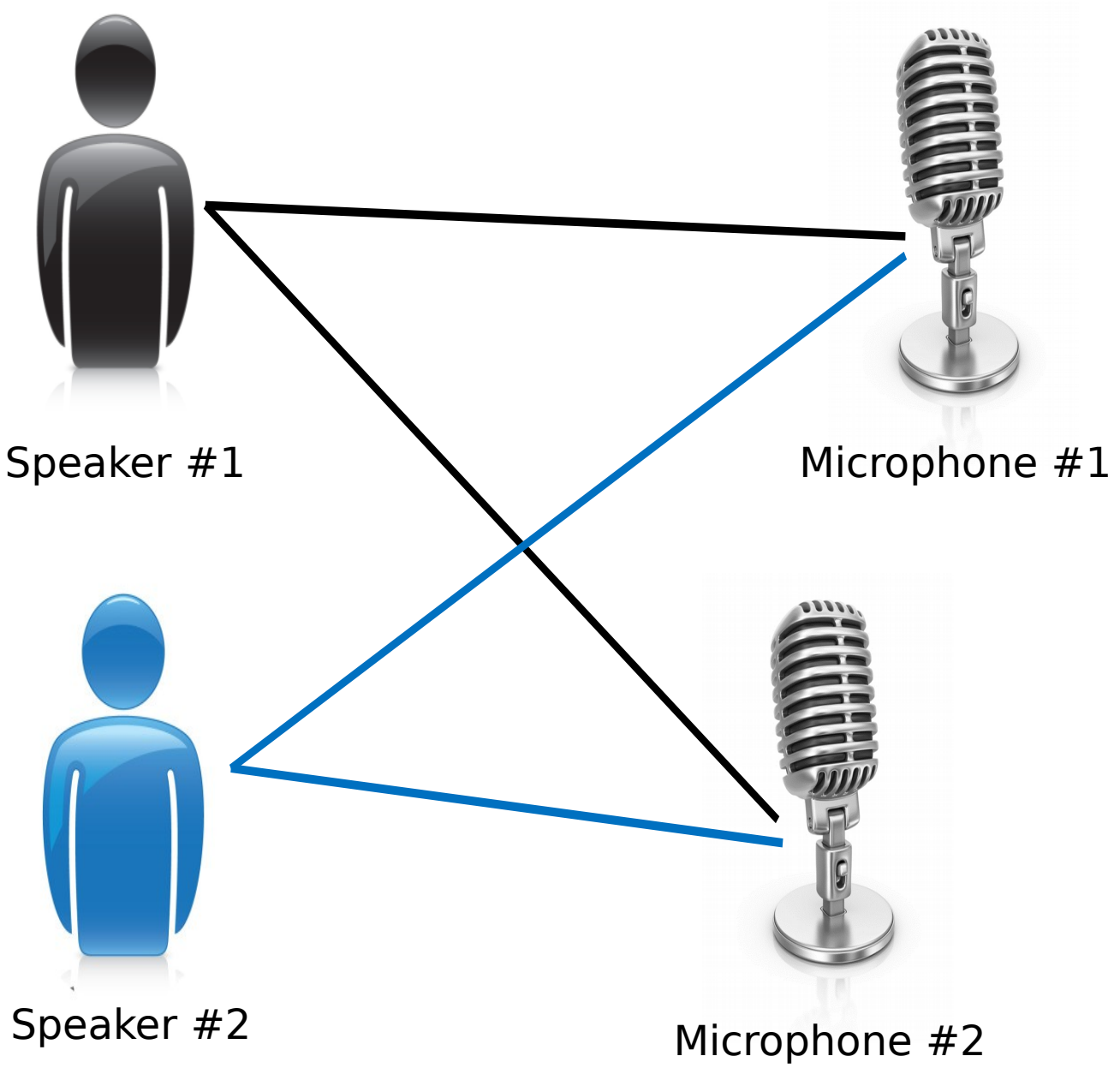


Market segmentation



Astronomical data analysis

Cocktail party problem

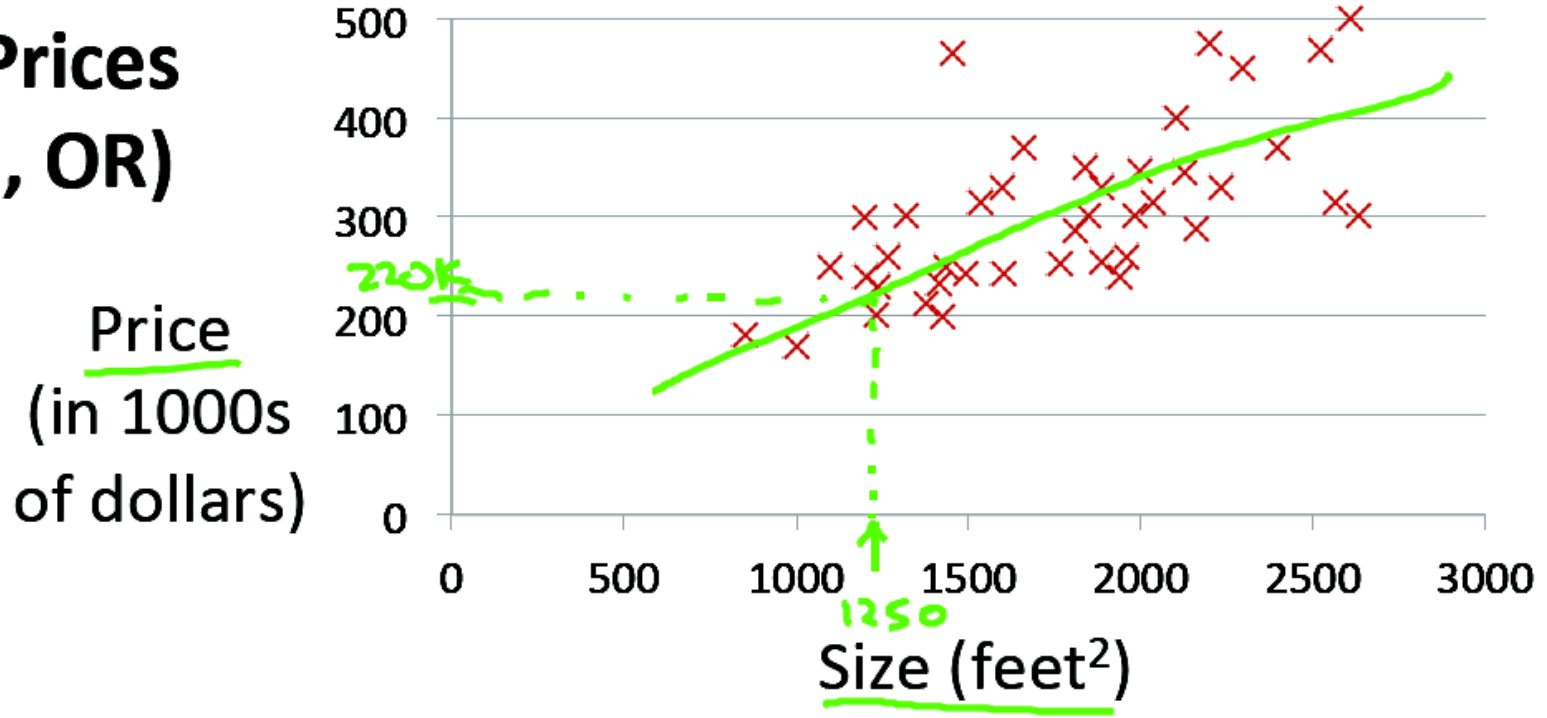


Cocktail party problem algorithm

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

Linear Regression

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

Linear Regression

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

$x^{(1)} = 2104$

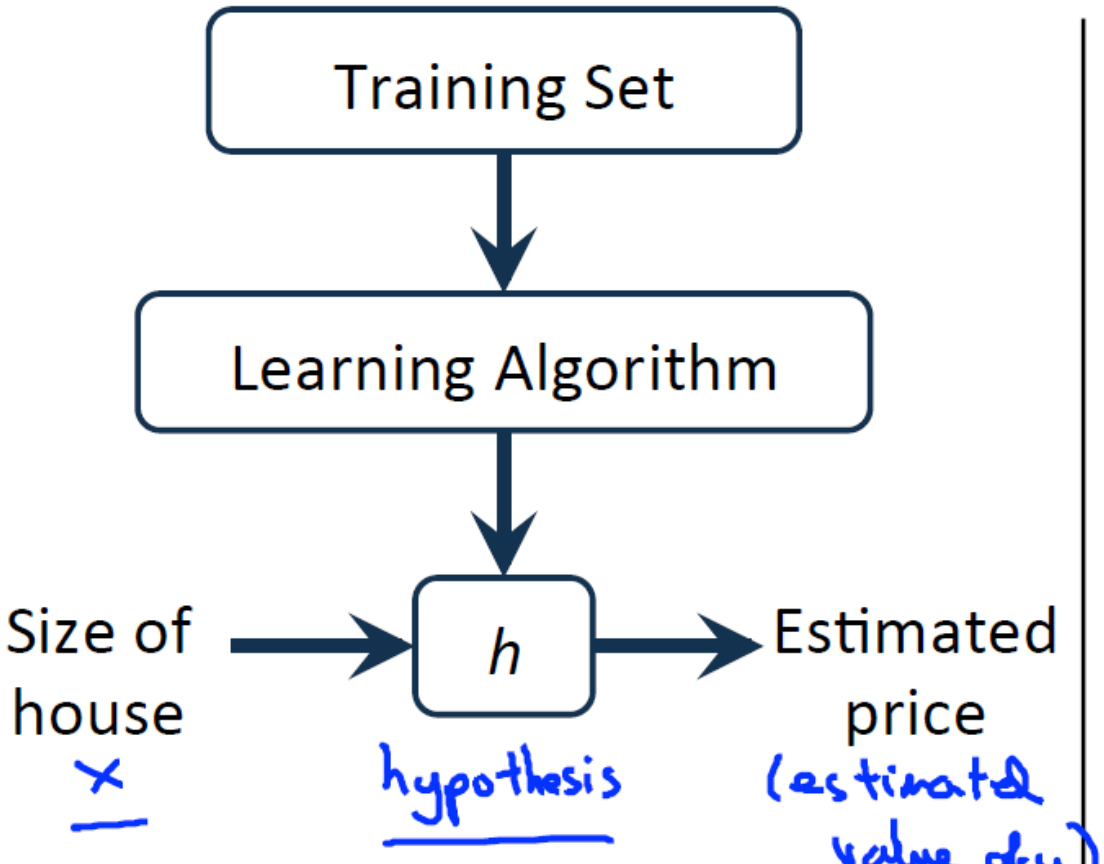
$x^{(2)} = 1416$

$y^{(1)} = 460$

(x, y) - one training example

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

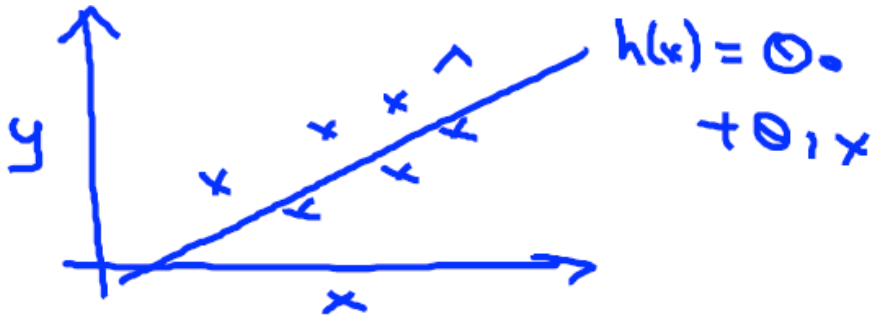
Linear Regression



How do we represent *h* ?

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

Shorthand: $h(x)$



Linear regression with one variable. (x)

Univariate linear regression.

└ one variable

Linear Regression:Cost Function

Training Set

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

m = 47

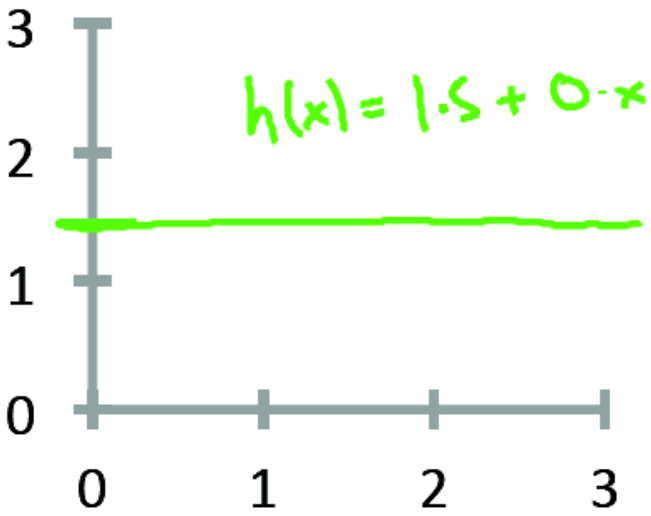
Hypothesis: $h_\theta(x) = \theta_0 + \theta_1 x$

θ_i's: Parameters

How to choose θ_i's ?

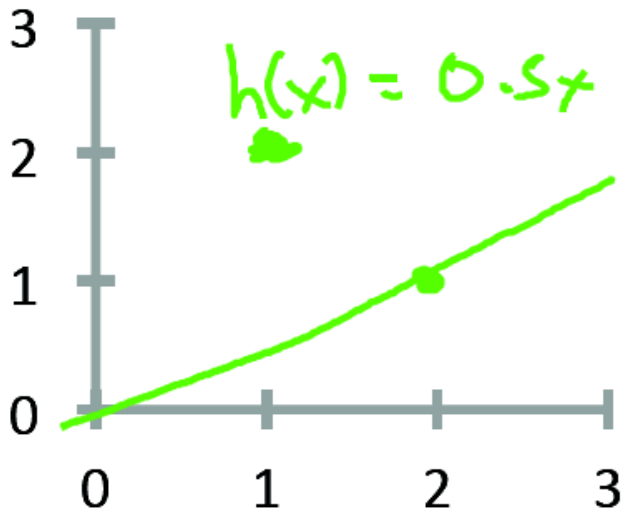
Linear Regression:Cost Function

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



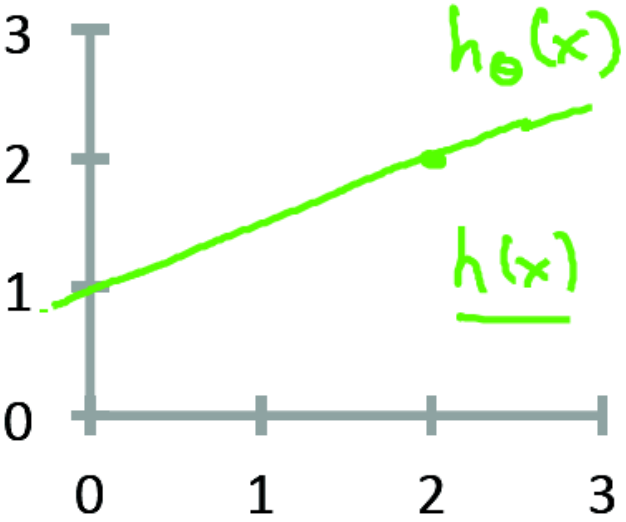
→ $\theta_0 = 1.5$

→ $\theta_1 = 0$



→ $\theta_0 = 0$

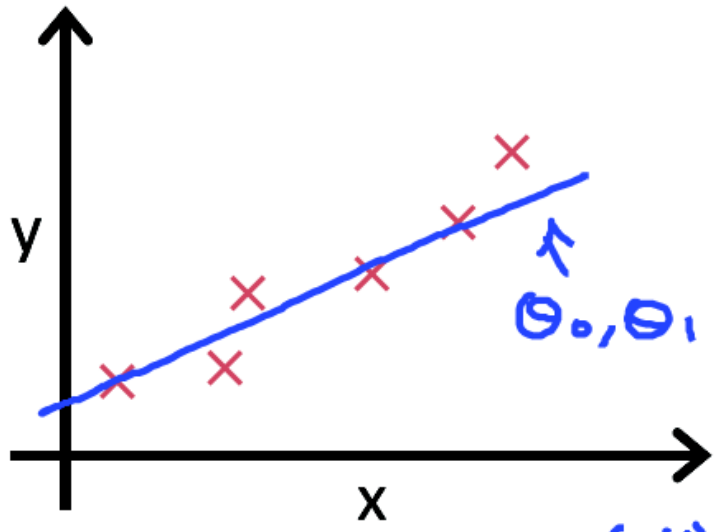
→ $\theta_1 = 0.5$



→ $\theta_0 = 1$

→ $\theta_1 = 0.5$

Linear Regression:Cost Function



#training examples

minimize θ_0, θ_1 $\frac{1}{2m} \sum_{i=1}^{m} \left(h_\theta(x^{(i)}) - y^{(i)} \right)^2$

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

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

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

x, y

Minimize θ_0, θ_1 $J(\theta_0, \theta_1)$

Cost function

Squared error function

Linear Regression:Cost Function:intuitively

Hypothesis:

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

Parameters:

$$\theta_0, \theta_1$$

Cost Function:

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

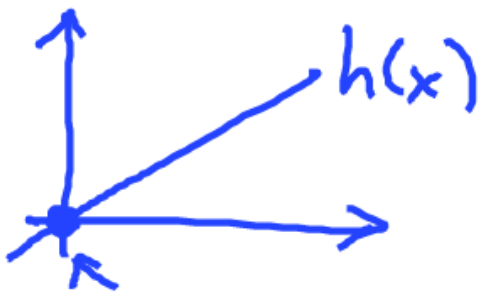
Goal: $\underset{\theta_0, \theta_1}{\text{minimize}}\ J(\theta_0, \theta_1)$

Simplified

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

$\theta_0 = 0$

θ_1



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

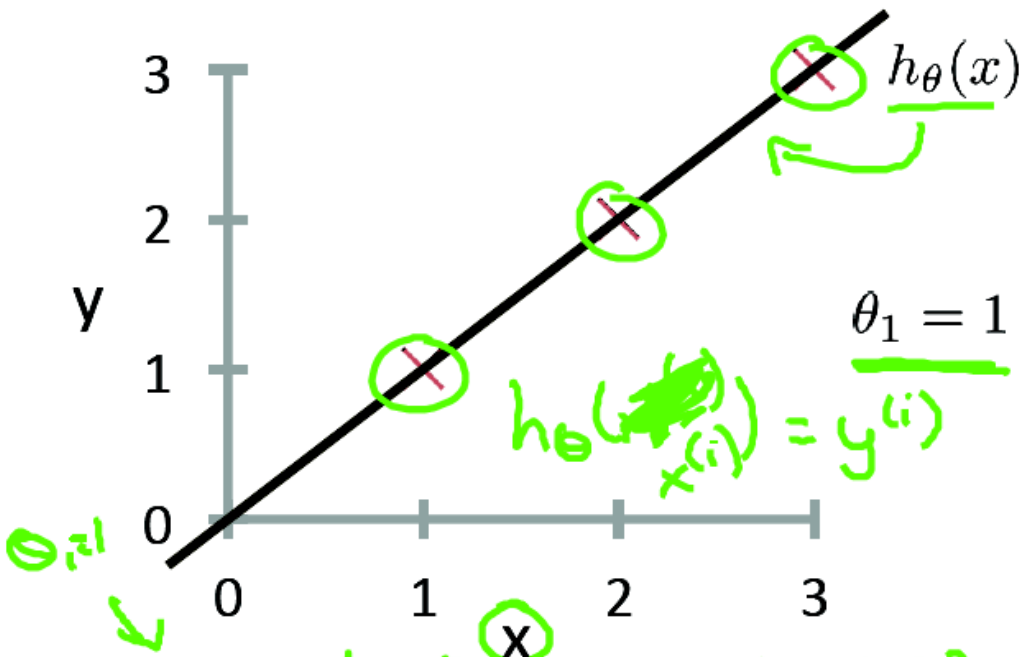
$\theta_1, x^{(i)}$

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

Linear Regression:Cost Function:intuitively

→ $h_\theta(x)$

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



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

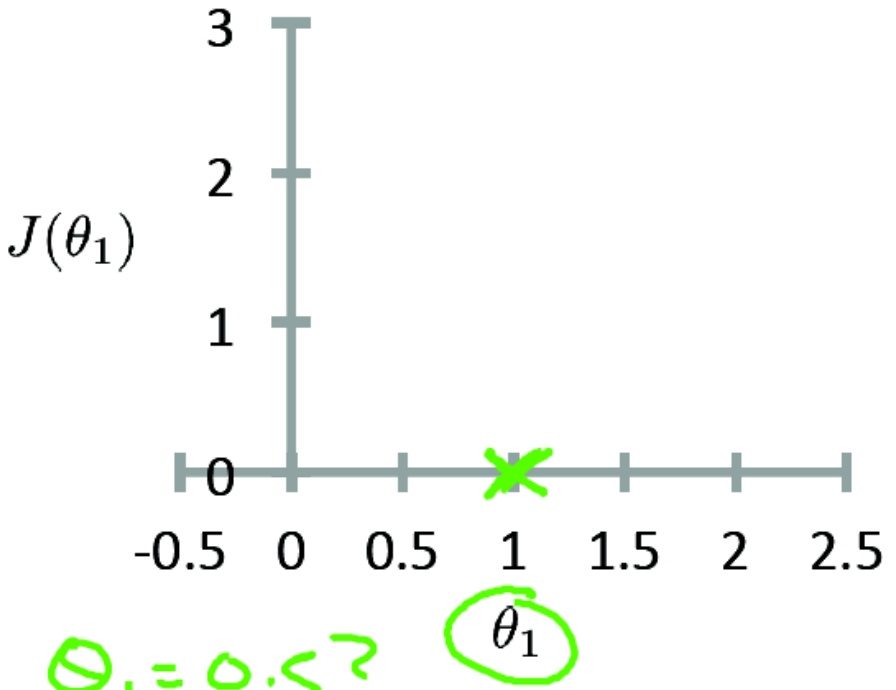
$\theta_1 = 1$

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

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

→ $J(\theta_1)$

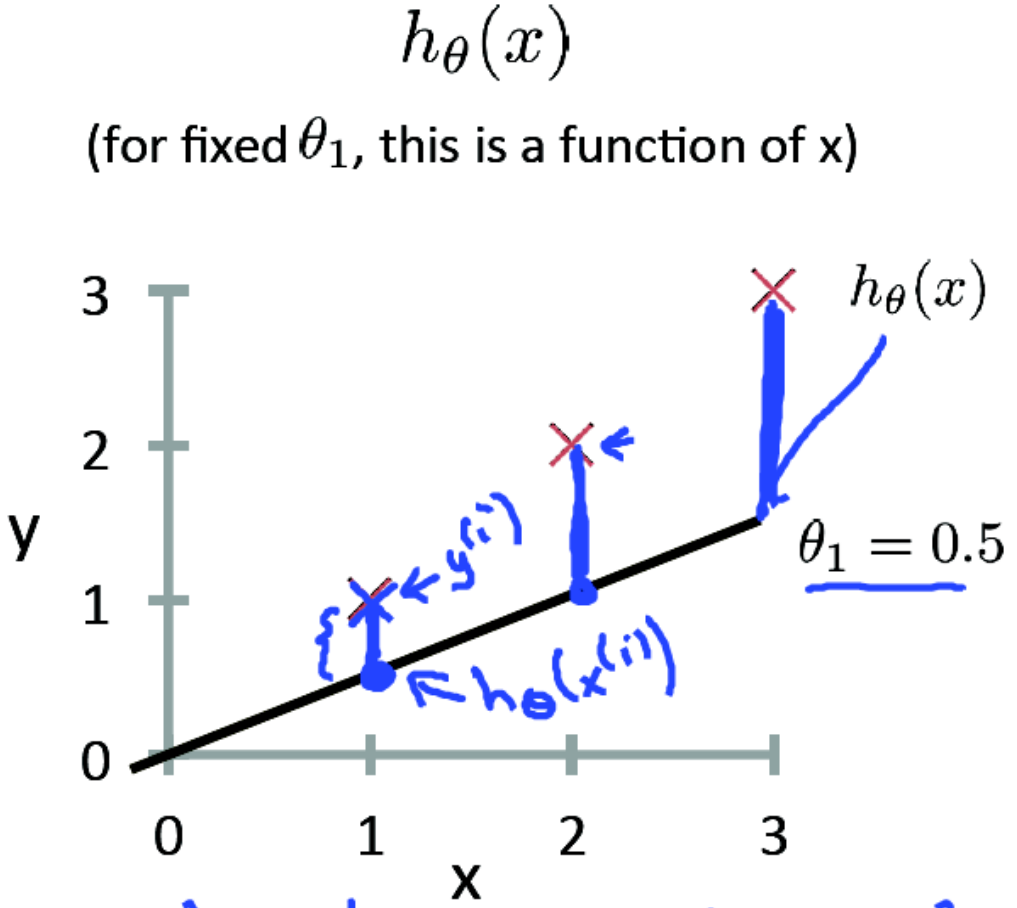
(function of the parameter θ_1)

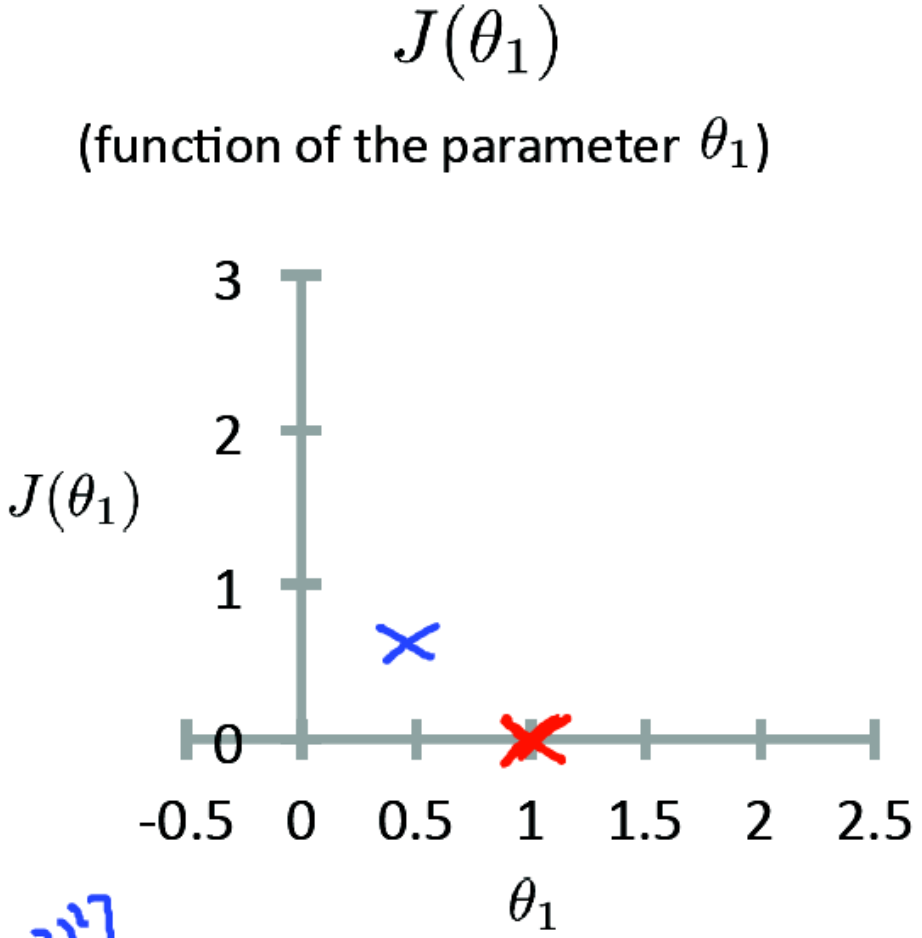


$\theta_1 = 0.5$?

$J(1) = 0$

Linear Regression:Cost Function:intuitively





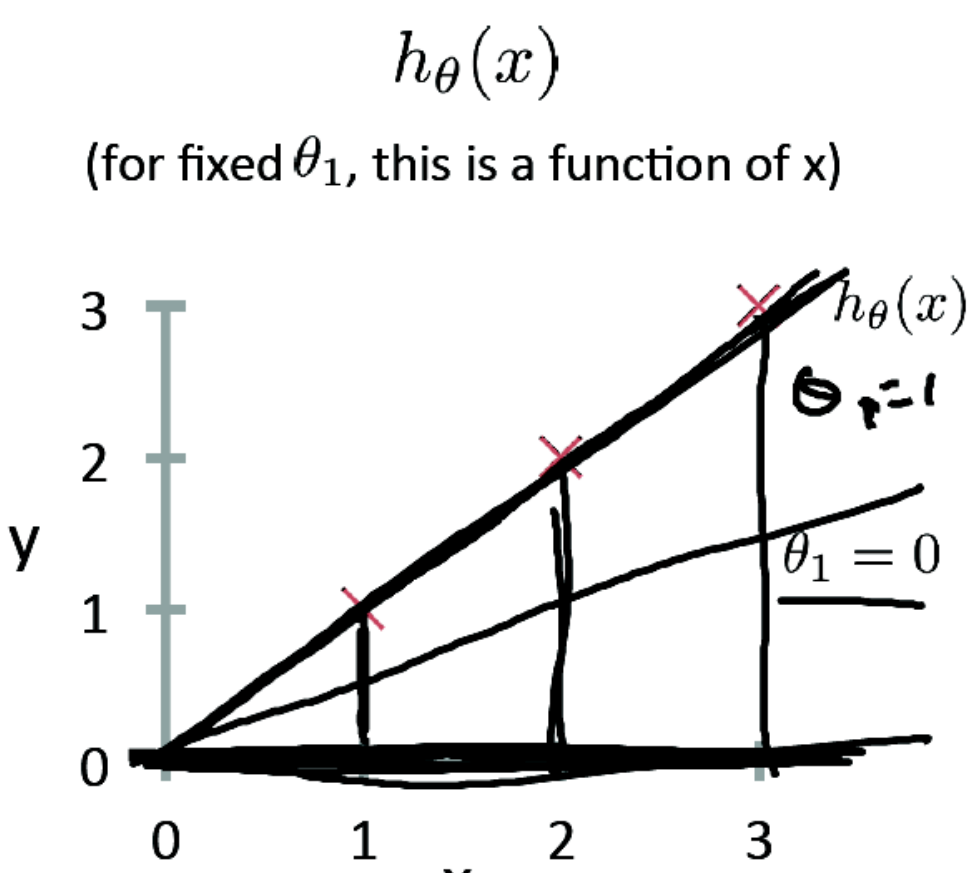
$J(0.5) = \frac{1}{2m}\left[(0.5-1)^2 + (1-2)^2 + (1.5-3)^2\right]$

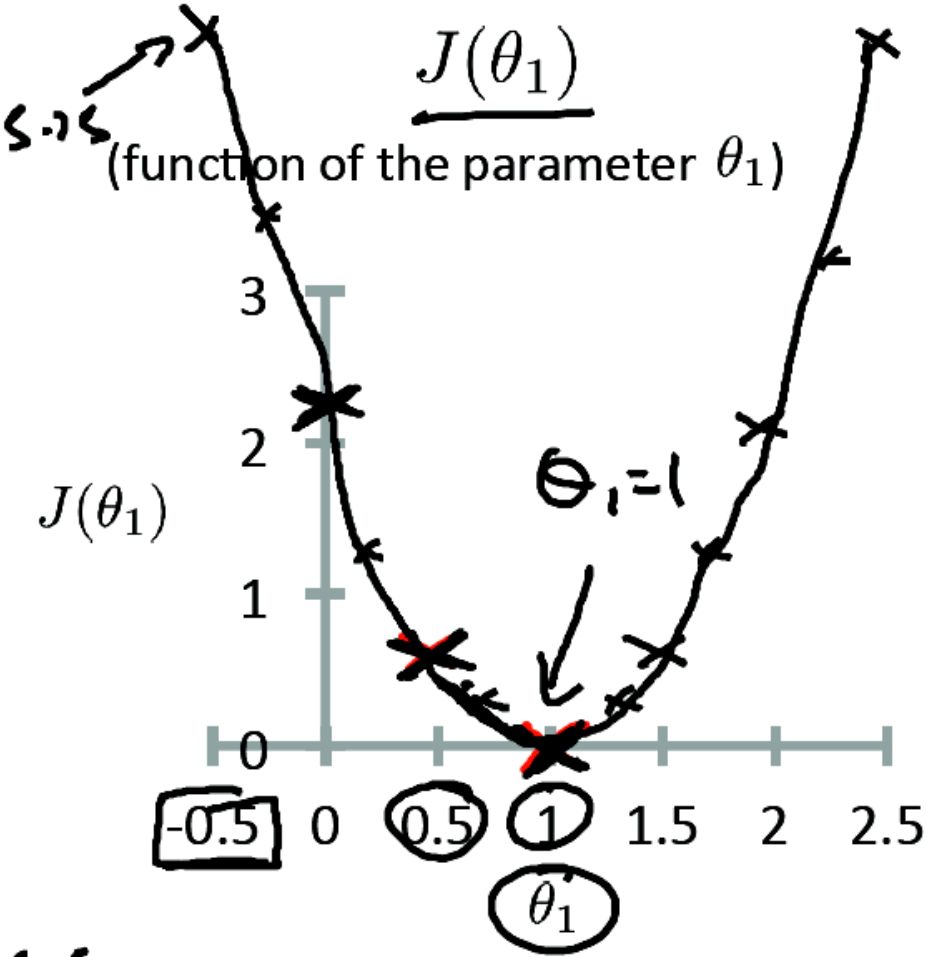
$= \frac{1}{2\times 3}(3.5) = \frac{3.5}{6} \approx 0.58$

$\theta_1 = 0?$

$J(0) = ?$

Linear Regression:Cost Function:intuitively





$$J(0) = \frac{1}{2m}(1^2 + 2^2 + 3^2)$$
$$= \frac{1}{6} \cdot 14 \approx 2.3$$

$h(x) = -0.5x$

Minimize $J(\theta_1)$
θ_1

Linear Regression:Gradient Descent

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

Parameters: θ_0, θ_1

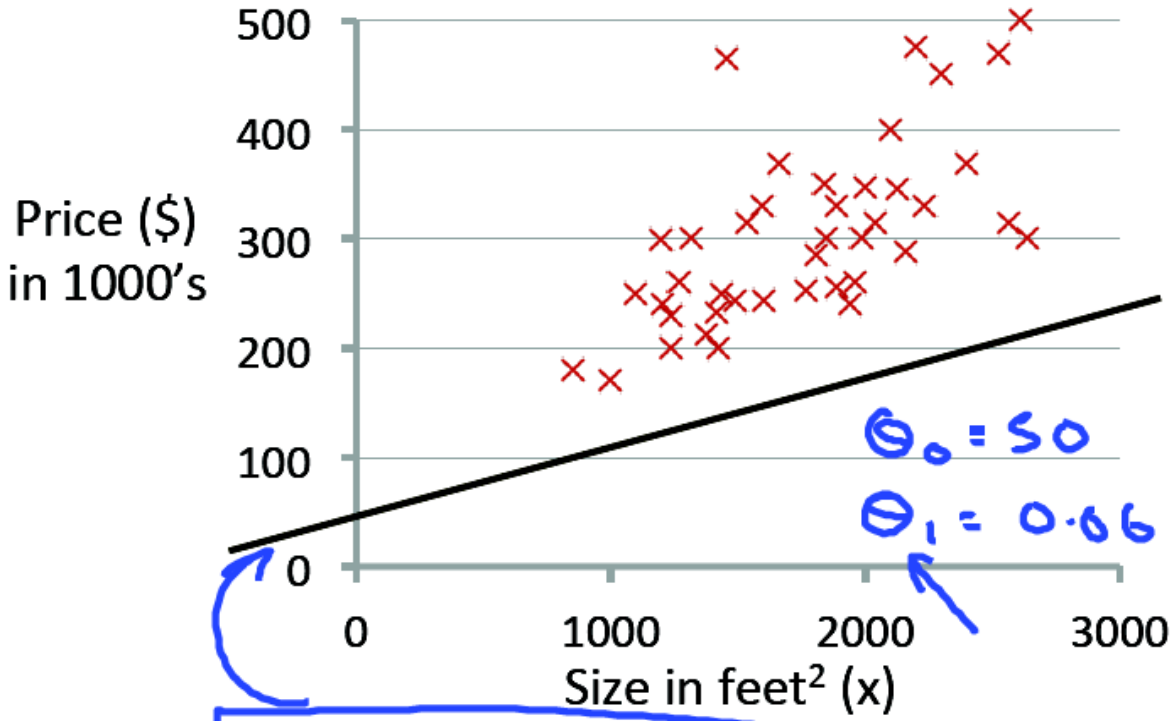
Cost Function: $J(\theta_0, \theta_1) = \frac{1}{2m} \sum_{i=1}^{m} \left(h_\theta(x^{(i)}) - y^{(i)} \right)^2$

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

Linear Regression:Gradient Descent

$h_\theta(x)$

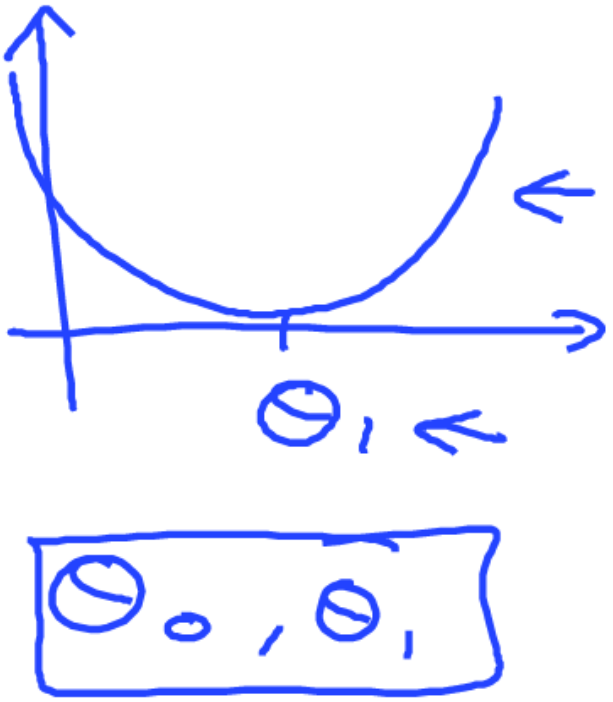
(for fixed θ_0, θ_1, this is a function of x)



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

$J(\theta_0, \theta_1)$

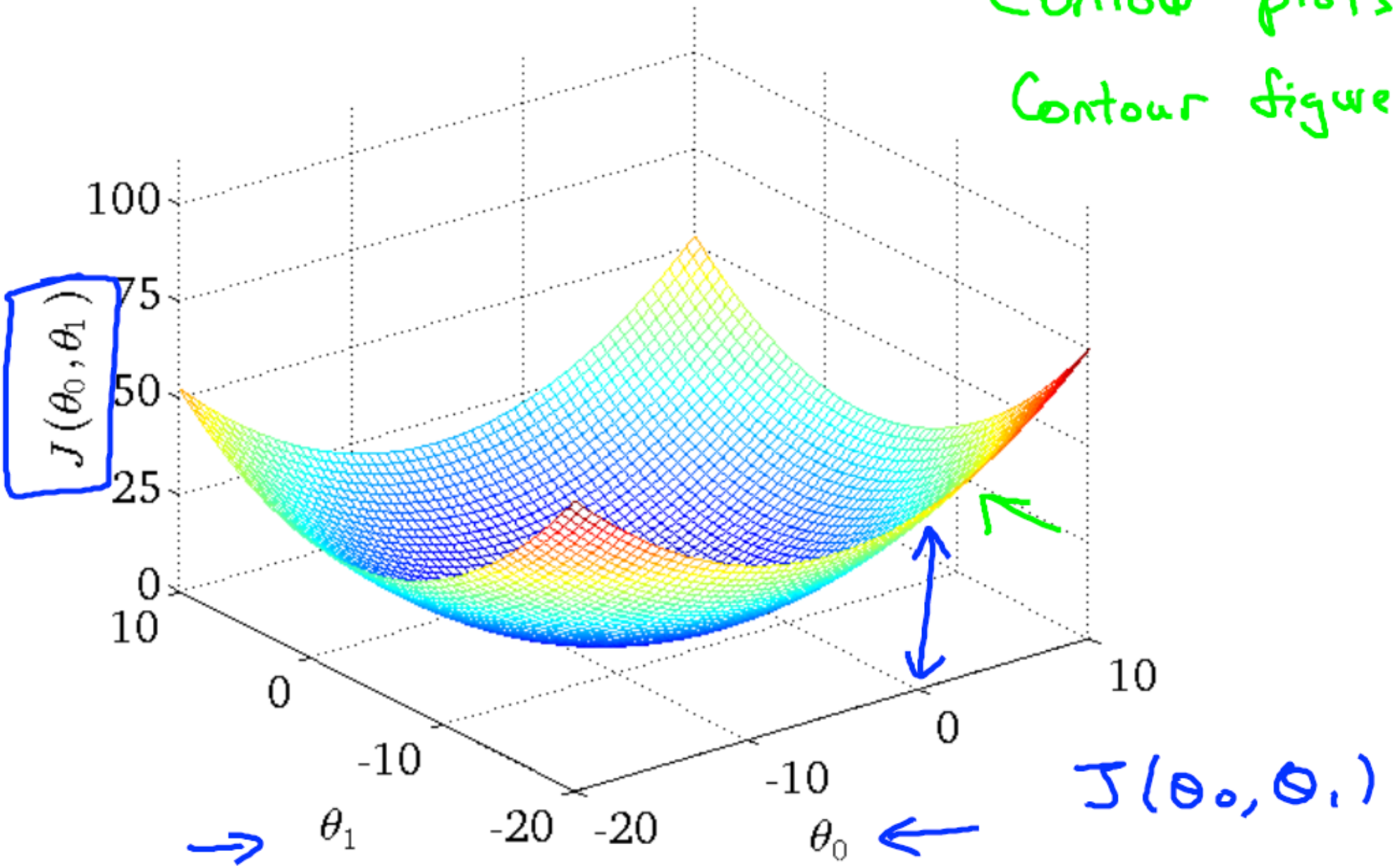
(function of the parameters θ_0, θ_1)



Linear Regression:Gradient Descent

Contour plots

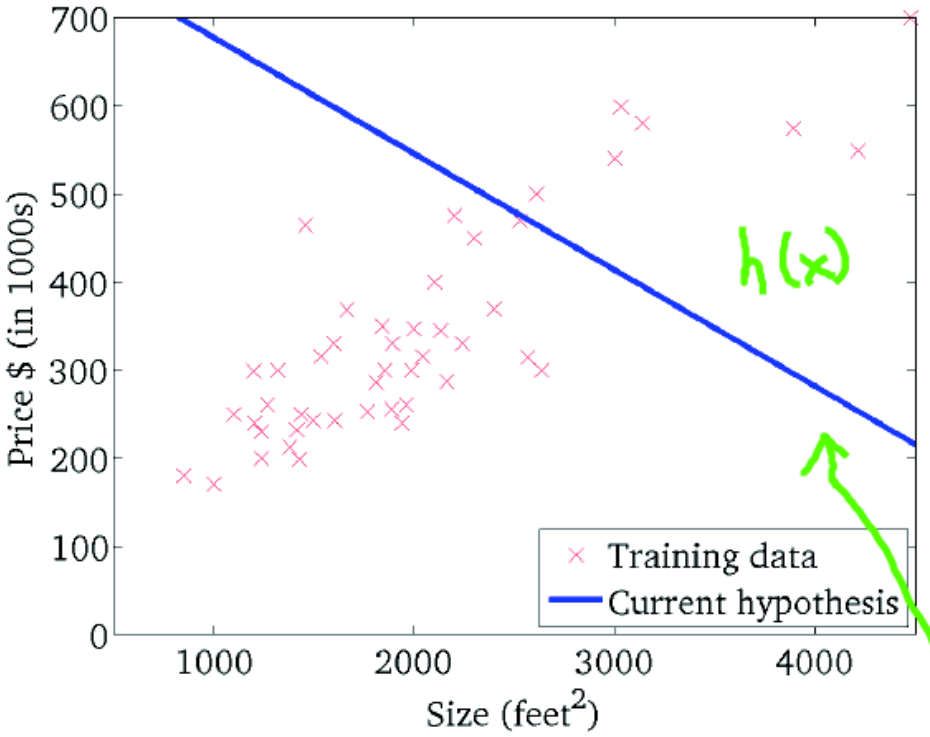
Contour figures -



Linear Regression:Gradient Descent

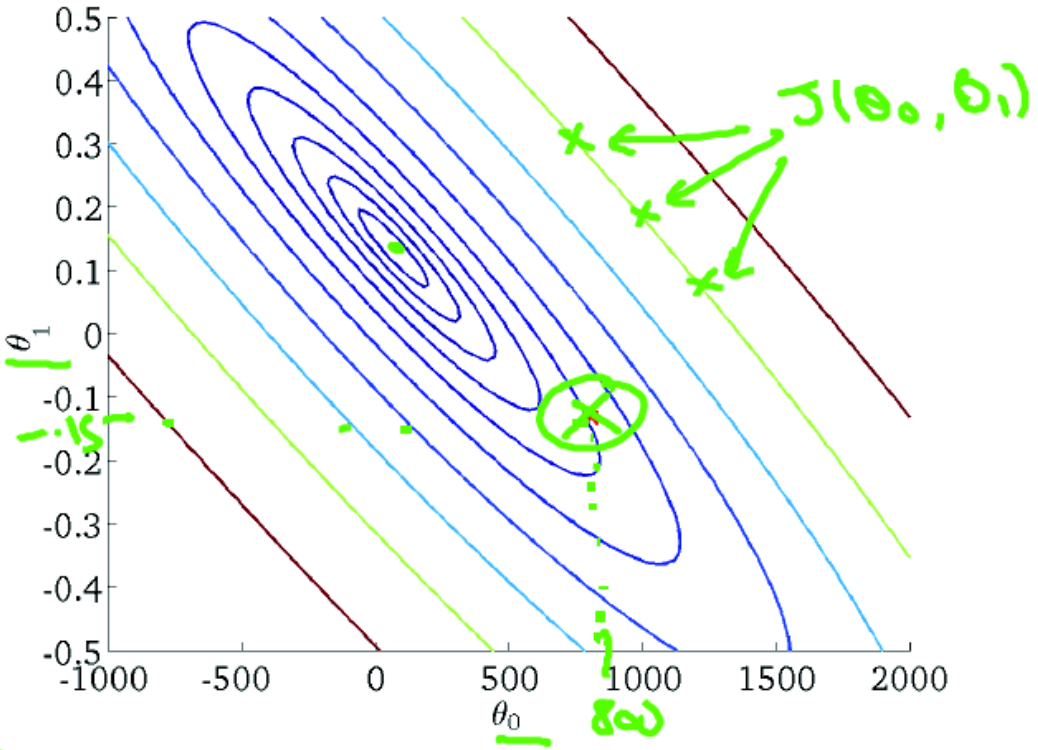
$h_\theta(x)$

(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)



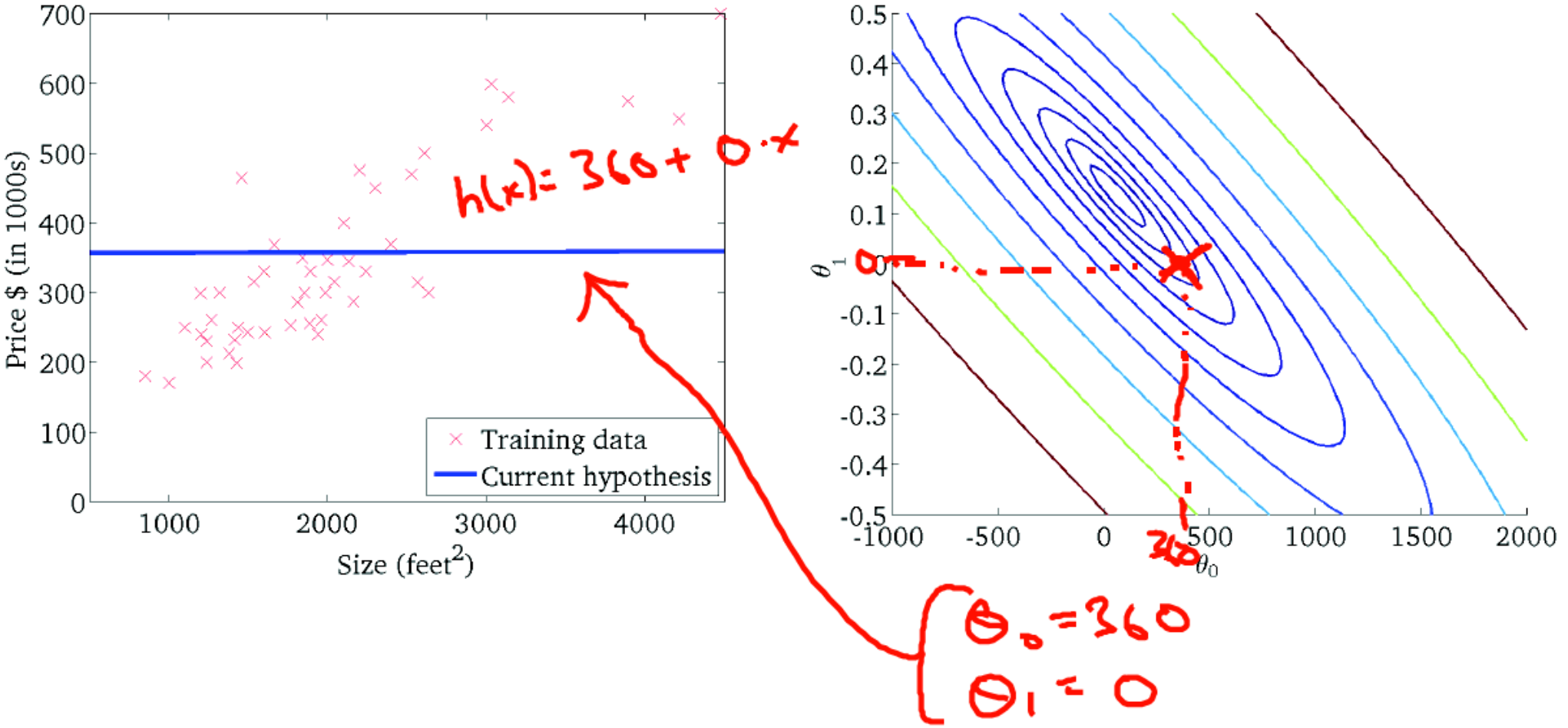
Linear Regression:Gradient Descent

$h_\theta(x)$

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

$J(\theta_0, \theta_1)$

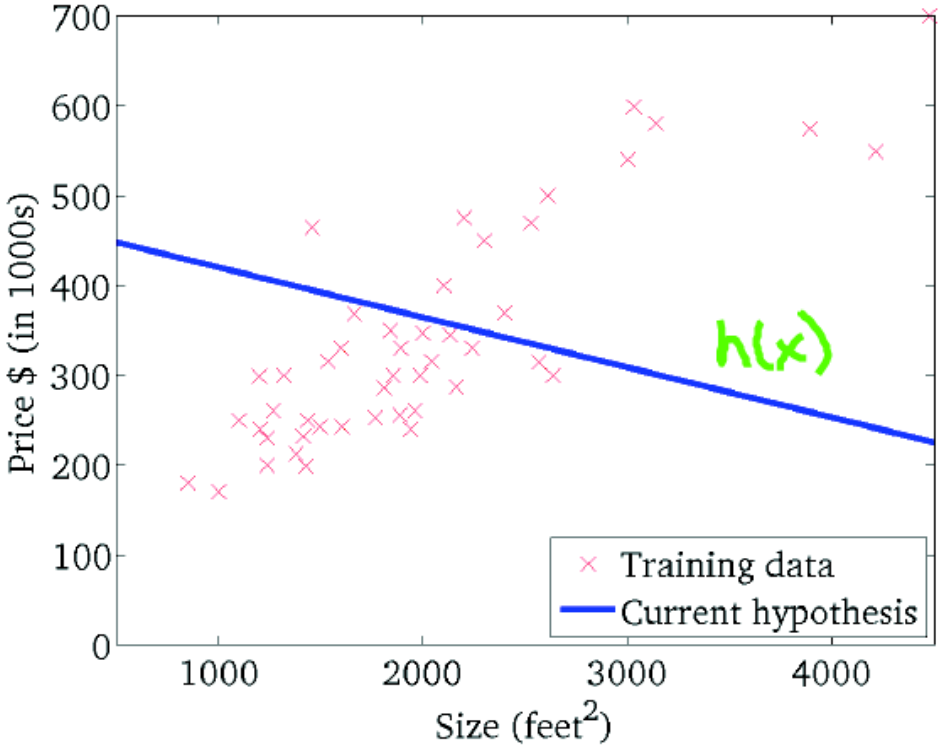
(function of the parameters θ_0, θ_1)



Linear Regression:Gradient Descent

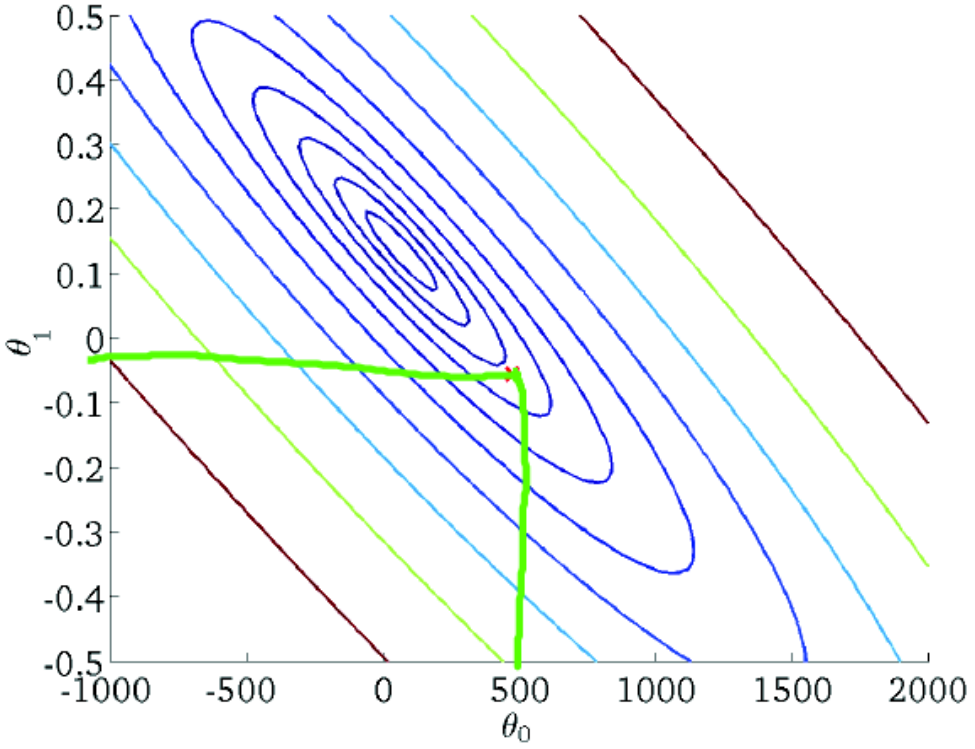
$h_\theta(x)$

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



$J(\theta_0, \theta_1)$

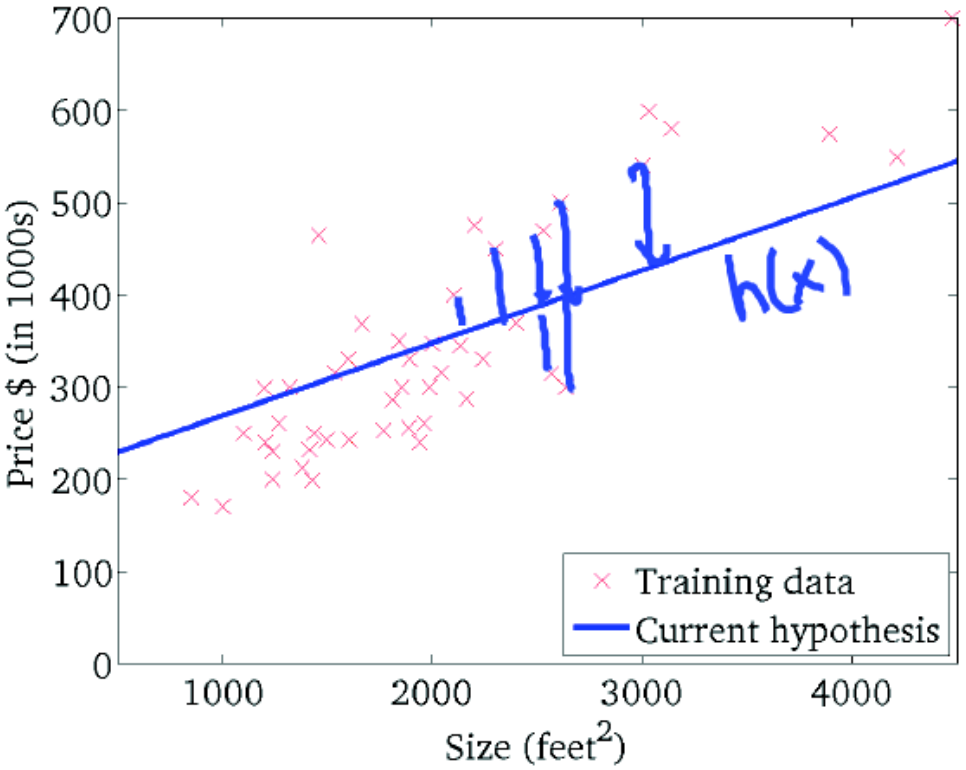
(function of the parameters θ_0, θ_1)



Linear Regression:Gradient Descent

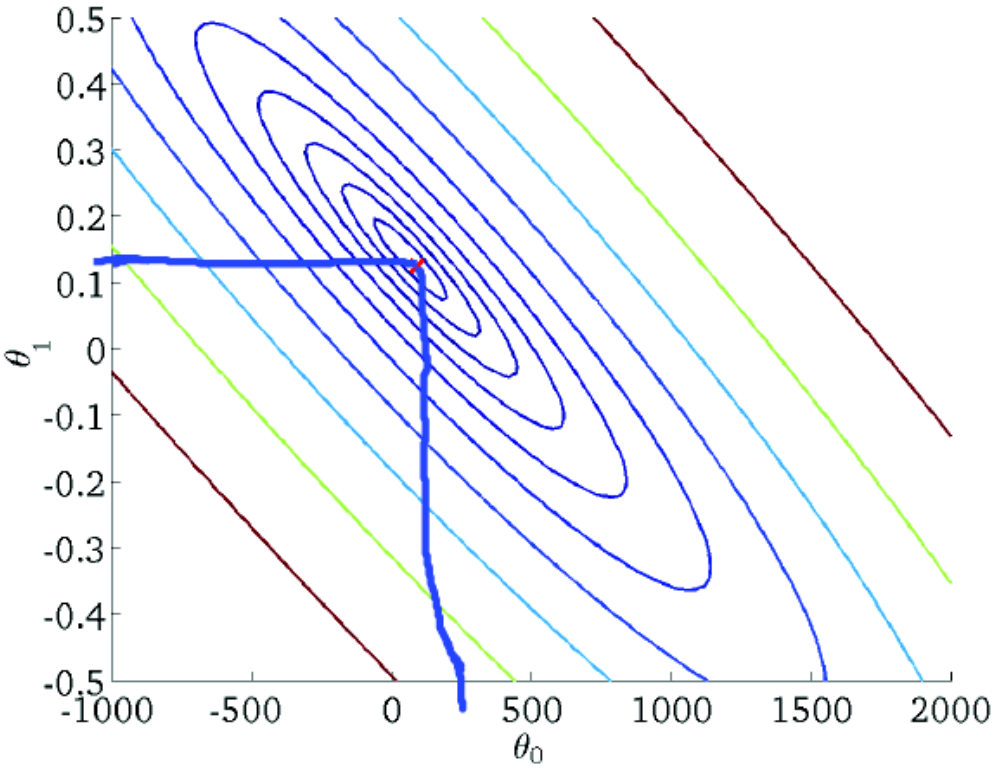
$h_\theta(x)$

(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)



Linear Regression:Gradient Descent

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

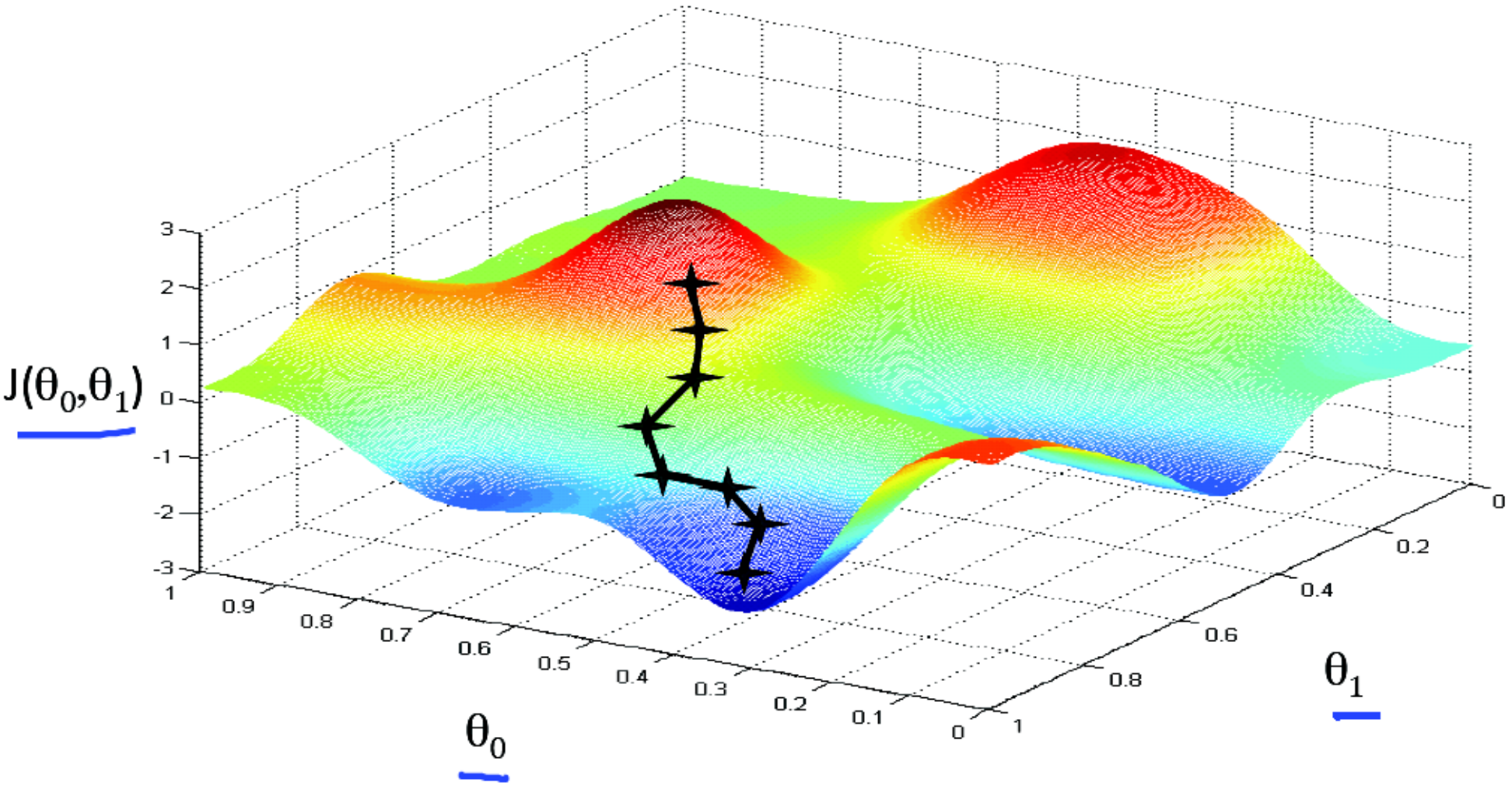
Want $\min_{\theta_0,\theta_1} J(\theta_0, \theta_1)$

Outline:

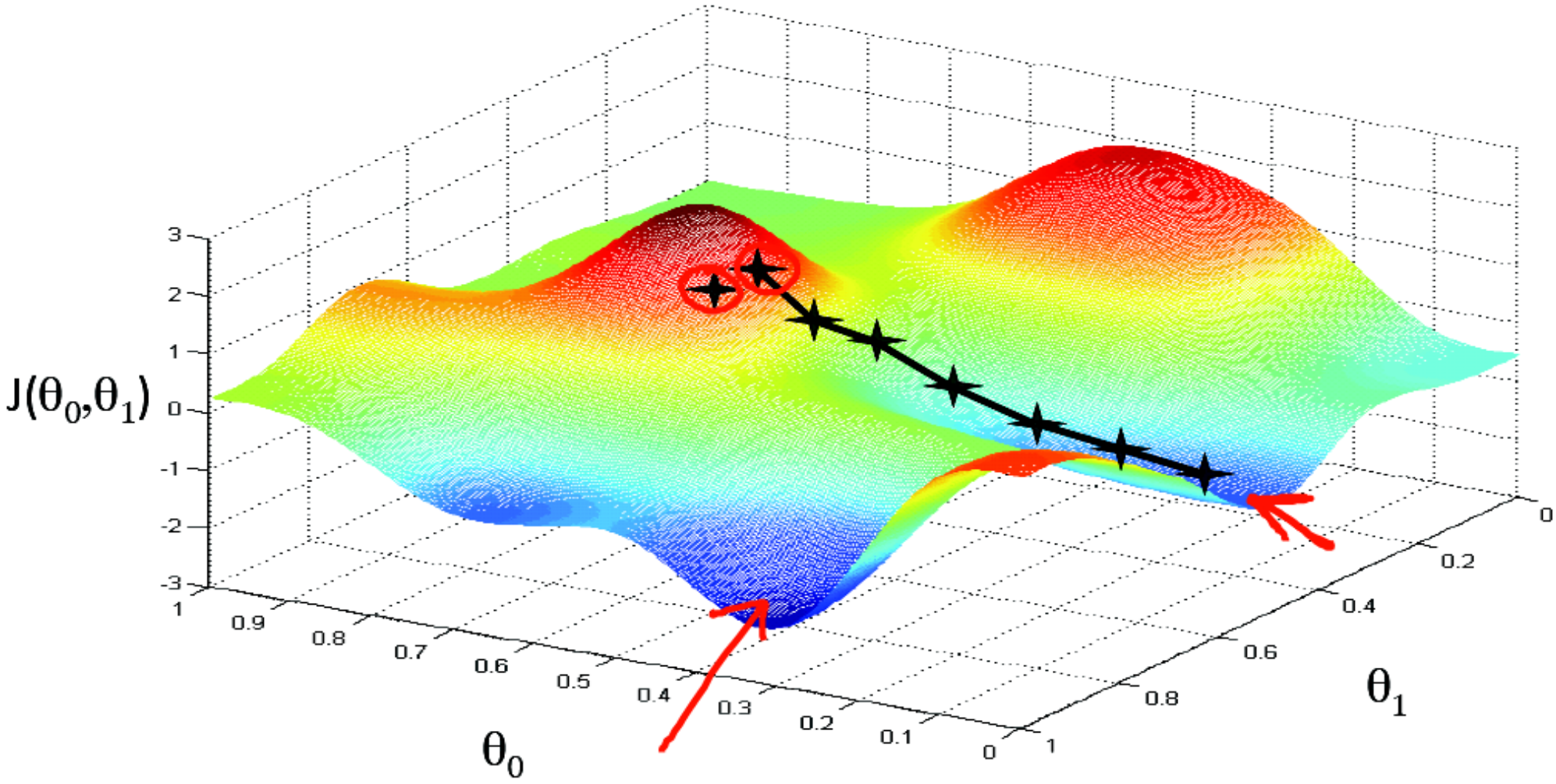
- Start with some θ_0, θ_1
- Keep changing θ_0, θ_1 to reduce $J(\theta_0, \theta_1)$

  until we hopefully end up at a minimum

Linear Regression:Gradient Descent



Linear Regression:Gradient Descent



Linear Regression:Gradient Descent Algorithm

Gradient descent algorithm

repeat until convergence {

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

}

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:

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

$\theta_0 := \text{temp0}$

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

$\theta_1 := \text{temp1}$

Linear Regression:Gradient Descent Algorithm

Gradient descent algorithm

repeat until convergence {

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

(simultaneously update $j = 0$ and $j = 1$)

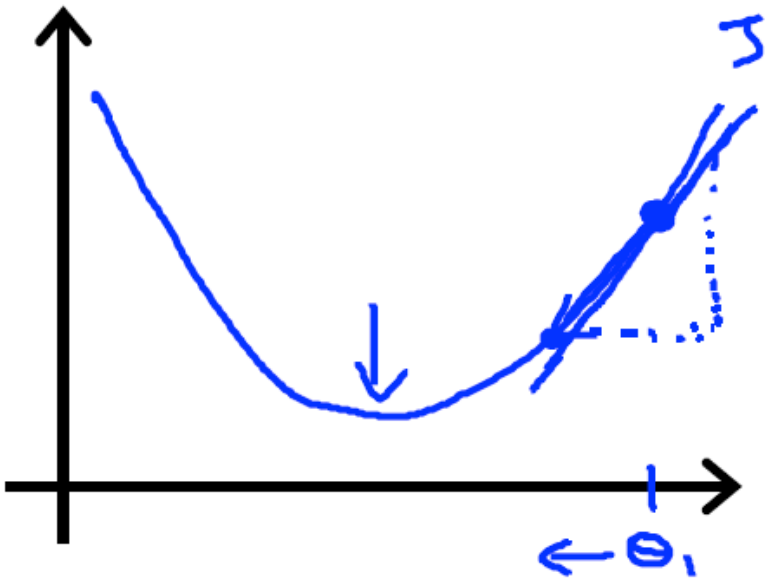
}

learning rate

derivative

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

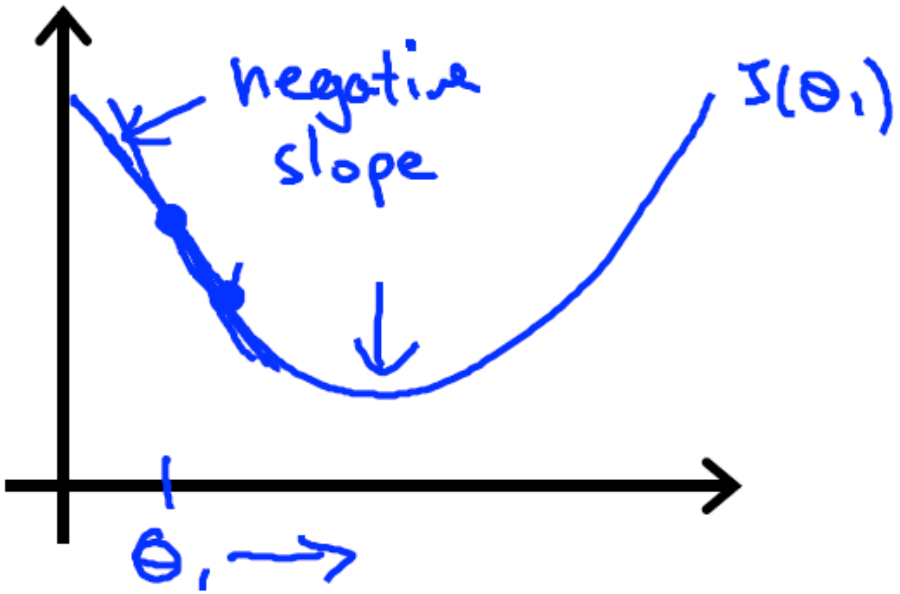
Linear Regression:Gradient Descent Algorithm



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

$$\theta_1 := \theta_1 - \alpha \underbrace{\frac{d}{d\theta_1} J(\theta_1)}_{\geq 0}$$

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



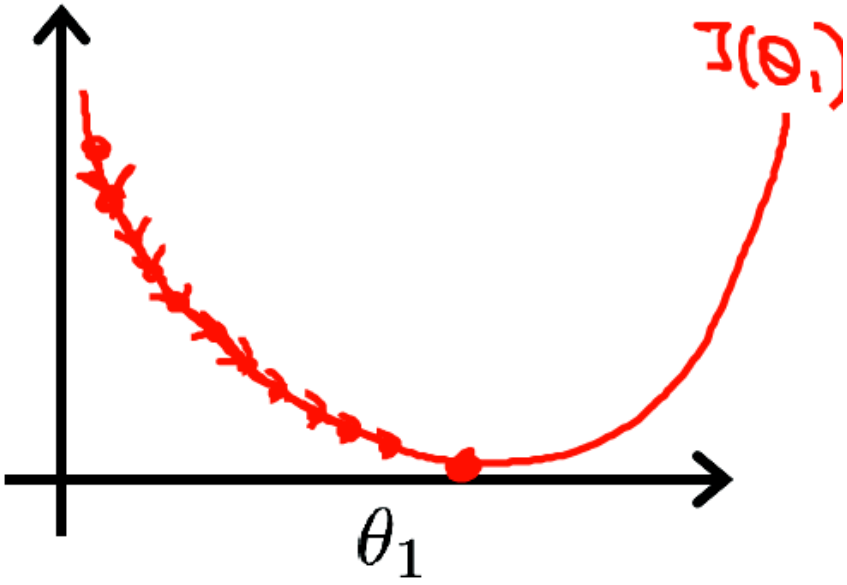
$$\underbrace{\frac{d}{d\theta_1} J(\theta_1)}_{\leq 0}$$

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

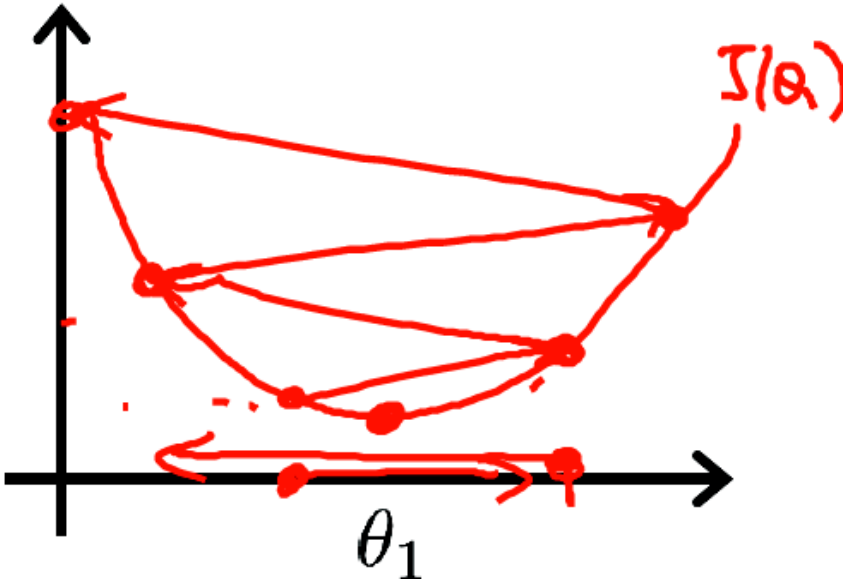
Linear Regression:Gradient Descent Algorithm

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

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



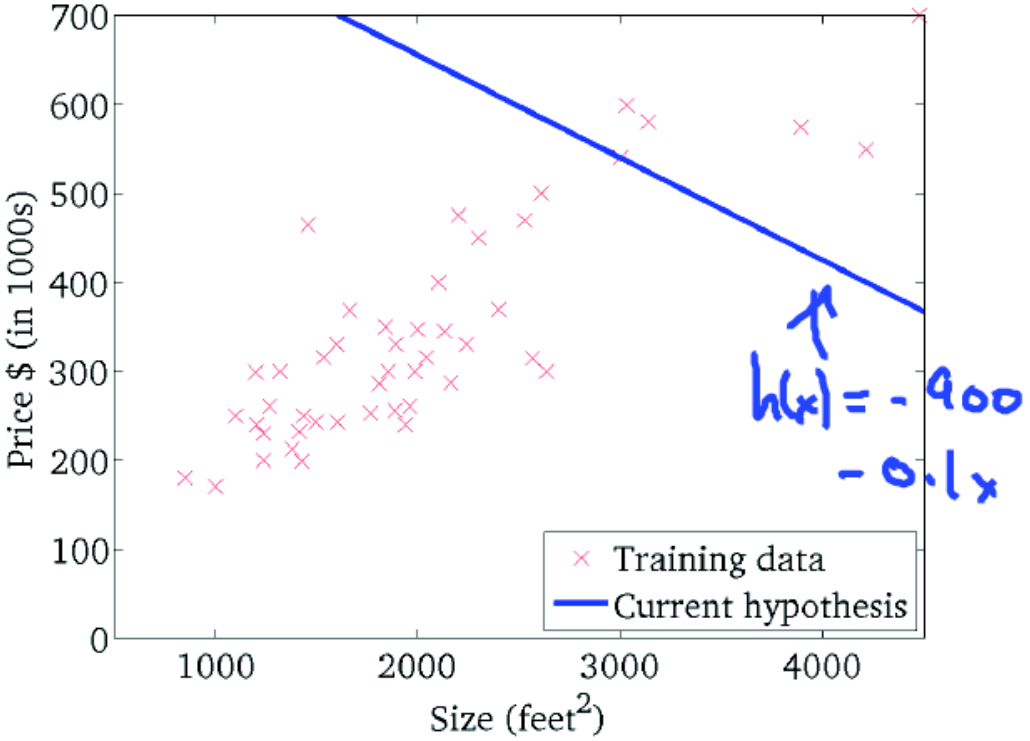
If α is too large, gradient descent can overshoot the minimum. It may fail to converge, or even diverge.



Linear Regression:Gradient Descent Algorithm:intuitively

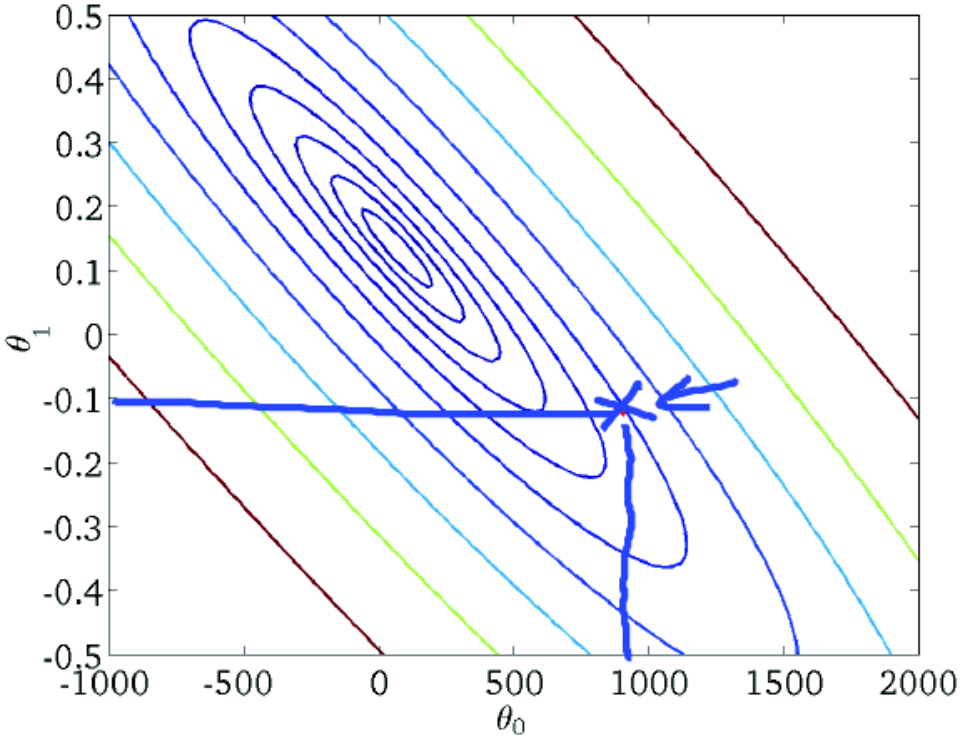
$h_\theta(x)$

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



$J(\theta_0, \theta_1)$

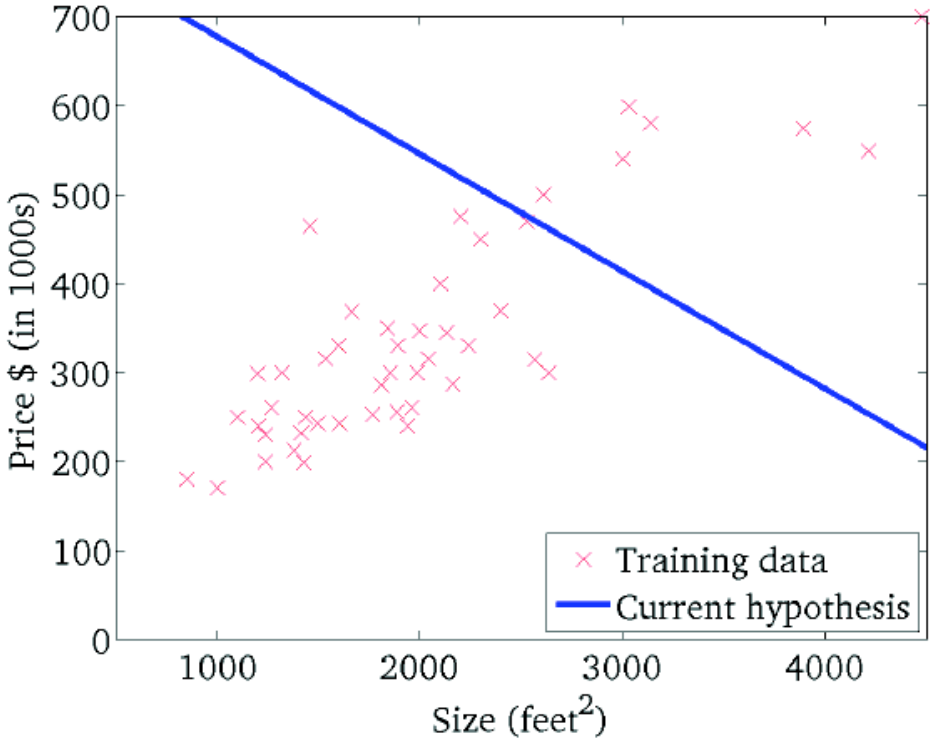
(function of the parameters θ_0, θ_1)



Linear Regression:Gradient Descent Algorithm:intuitively

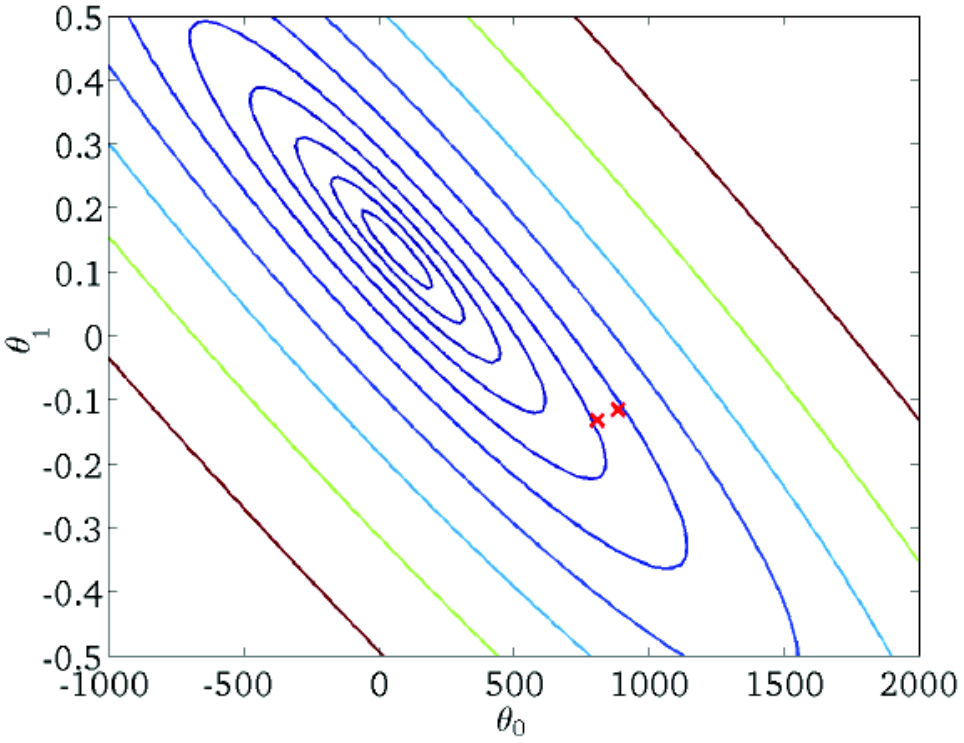
$h_\theta(x)$

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



$J(\theta_0, \theta_1)$

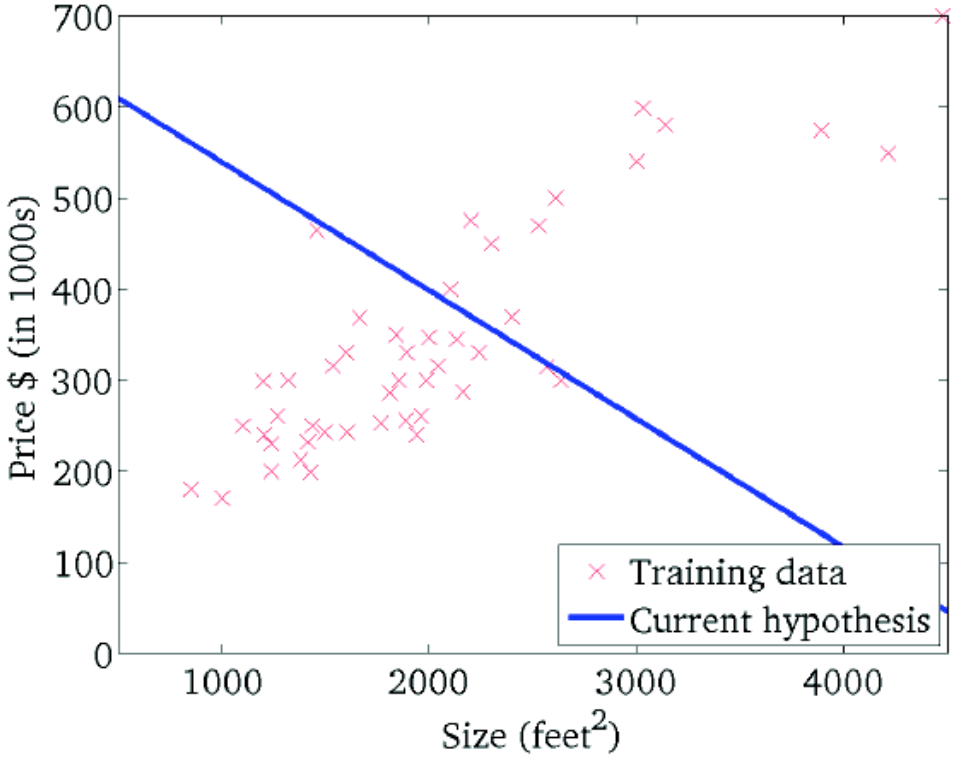
(function of the parameters θ_0, θ_1)



Linear Regression:Gradient Descent Algorithm:intuitively

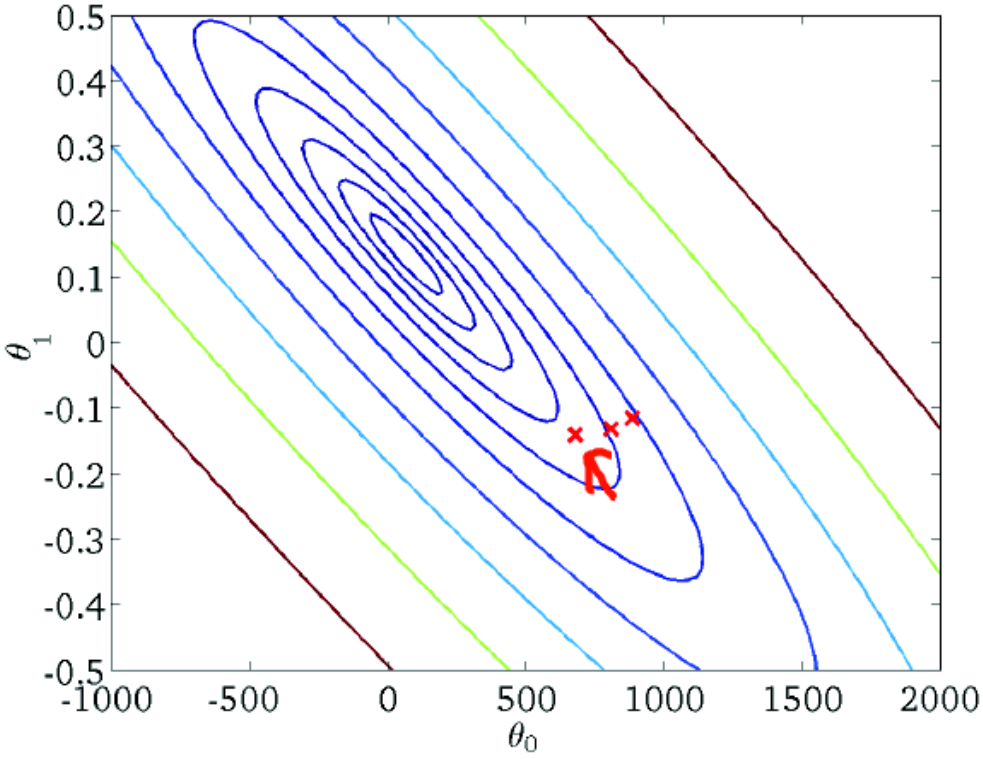
$h_\theta(x)$

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



$J(\theta_0, \theta_1)$

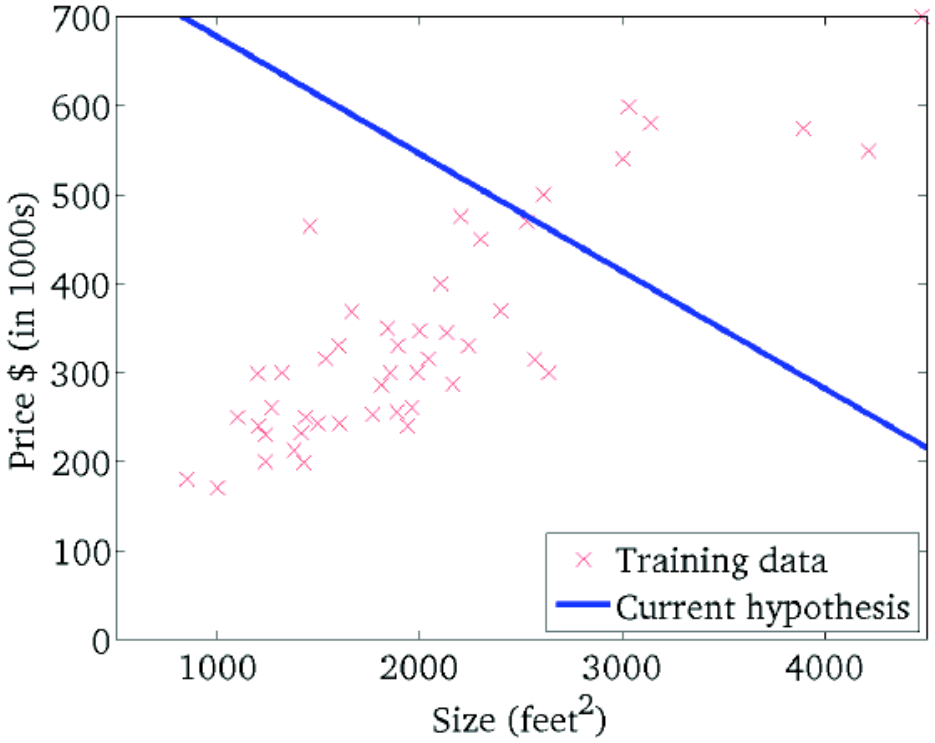
(function of the parameters θ_0, θ_1)



Linear Regression:Gradient Descent Algorithm:intuitively

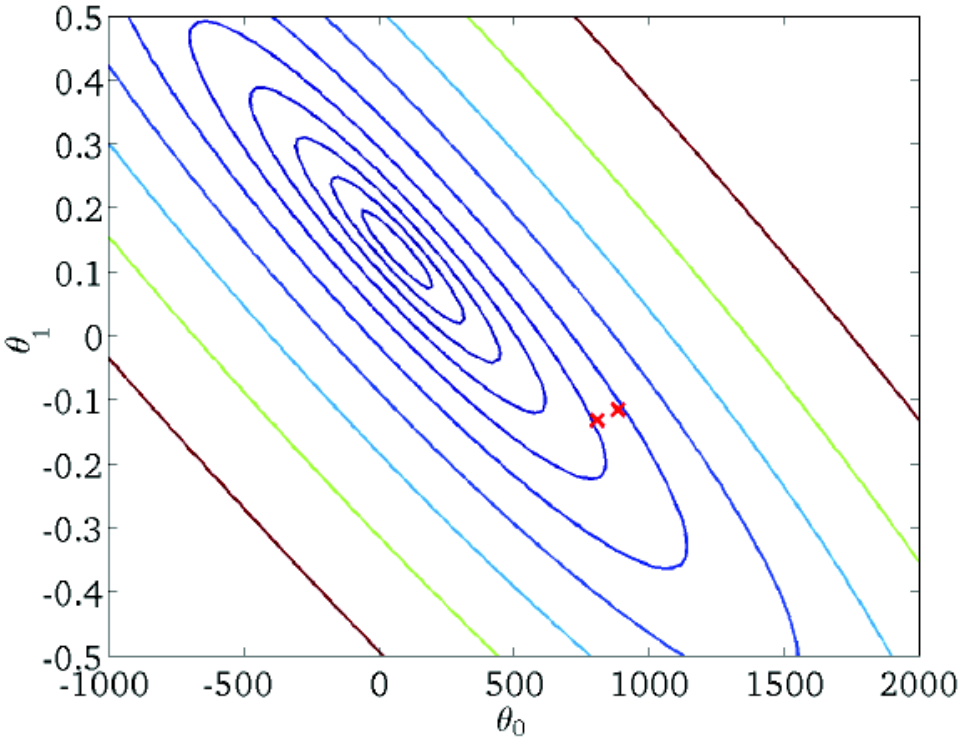
$h_\theta(x)$

(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)



Linear Regression:Gradient Descent Algorithm:intuitively

$h_\theta(x)$

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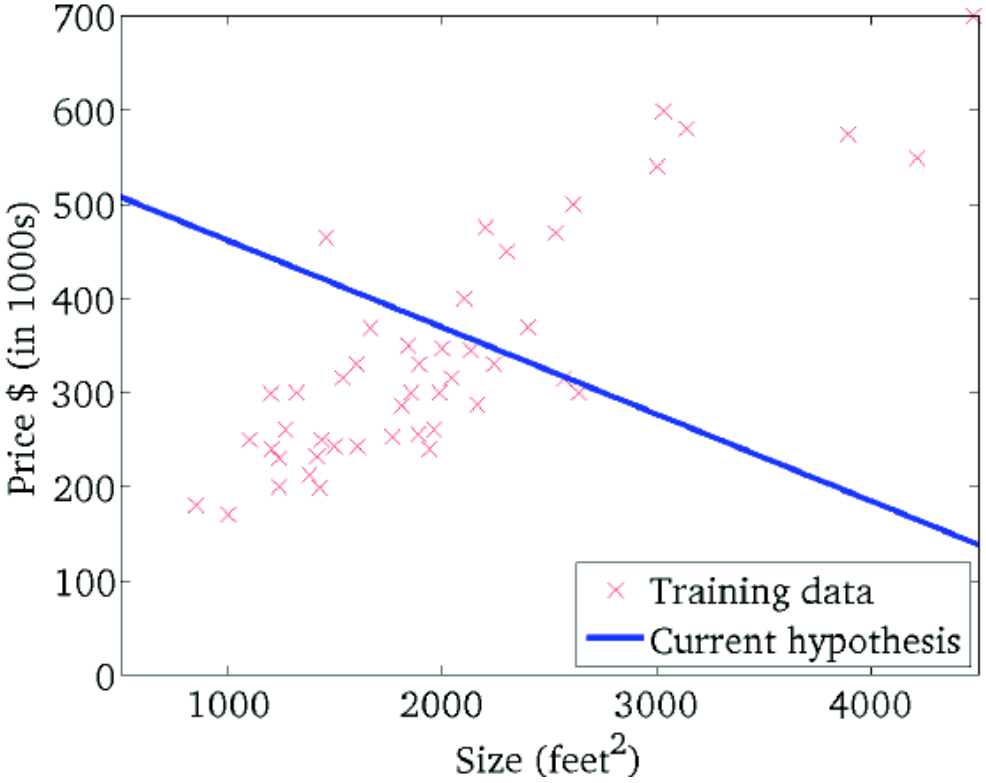

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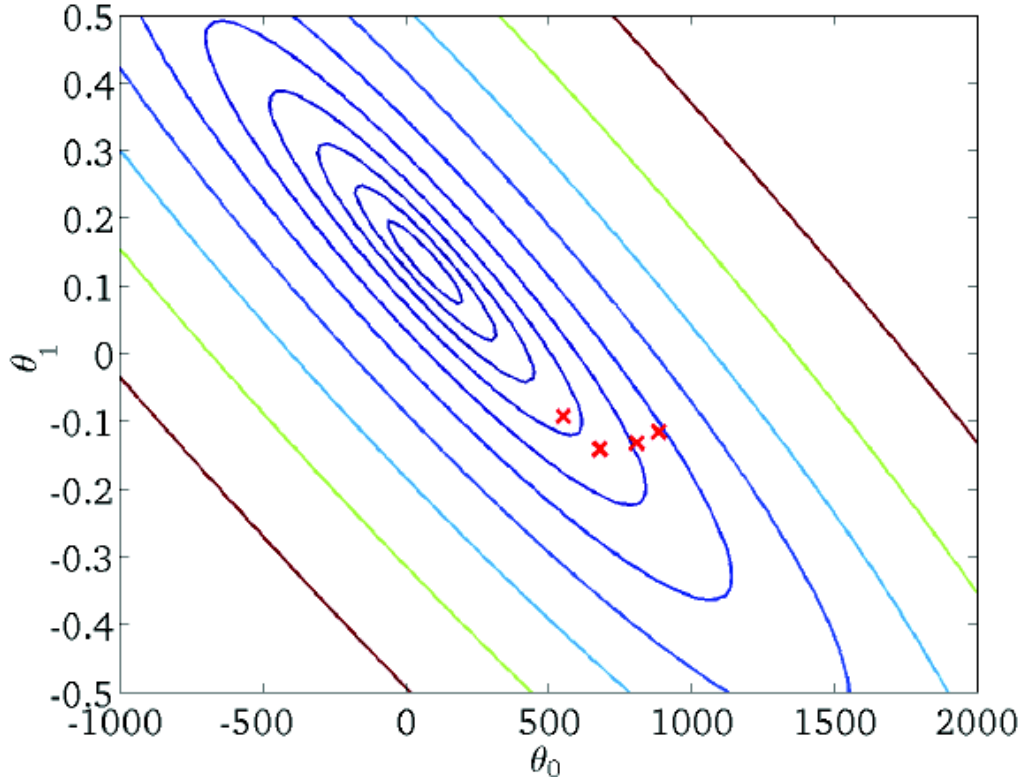

Linear Regression:Gradient Descent Algorithm:intuitively

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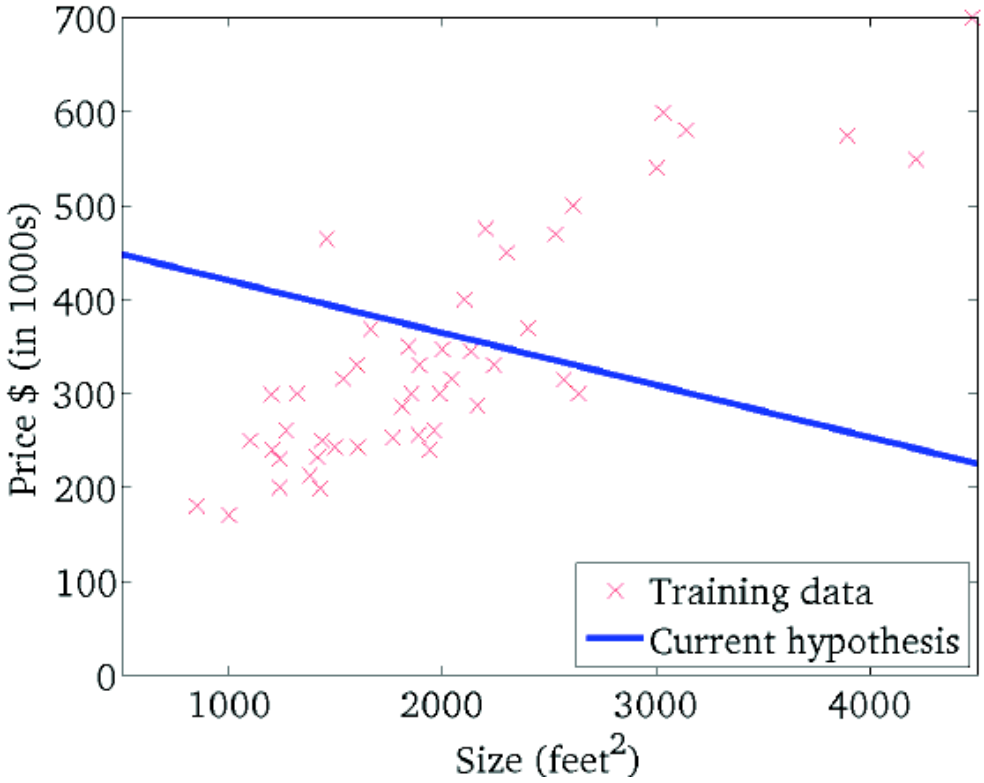

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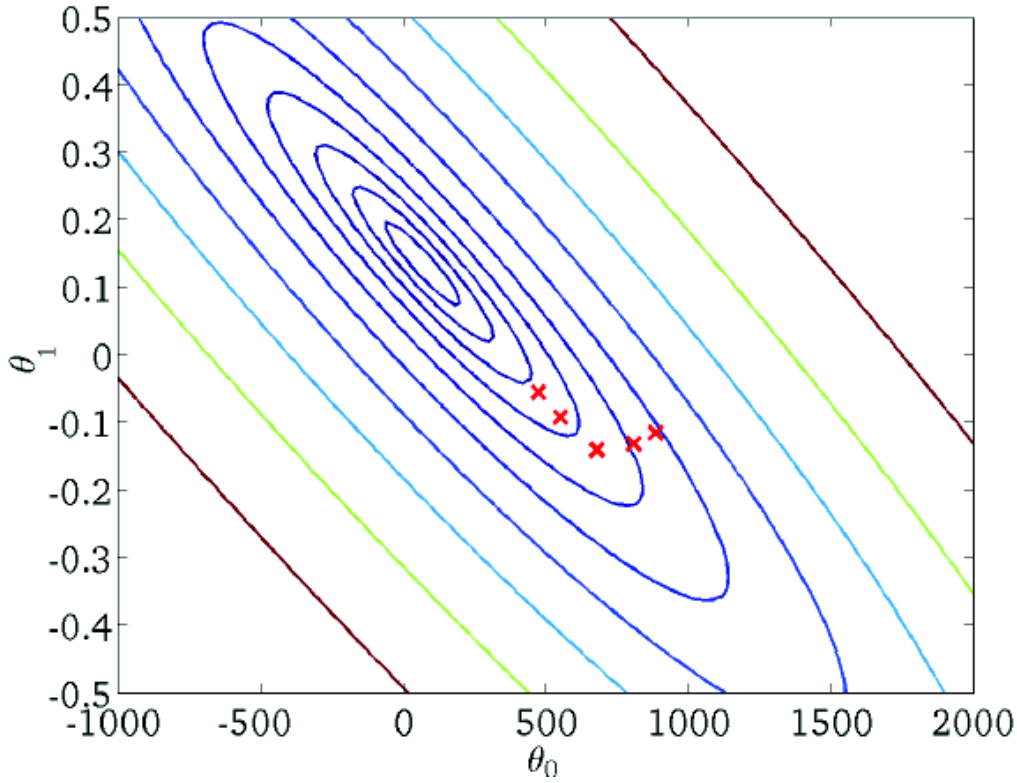

Linear Regression:Gradient Descent Algorithm:intuitively

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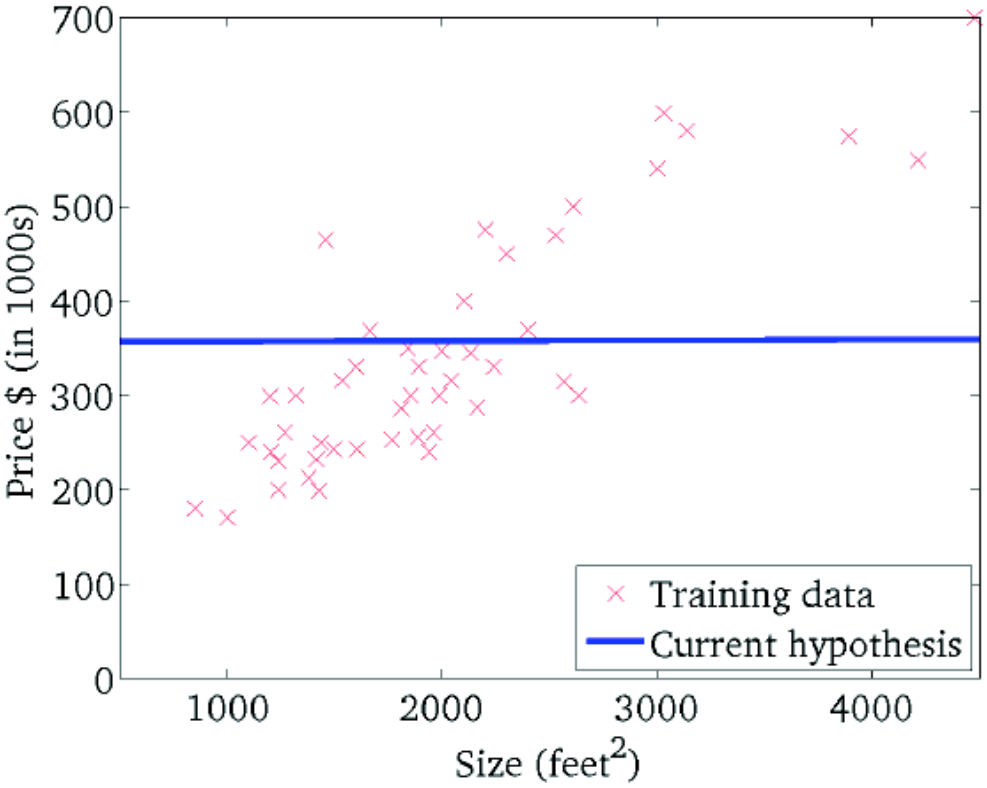

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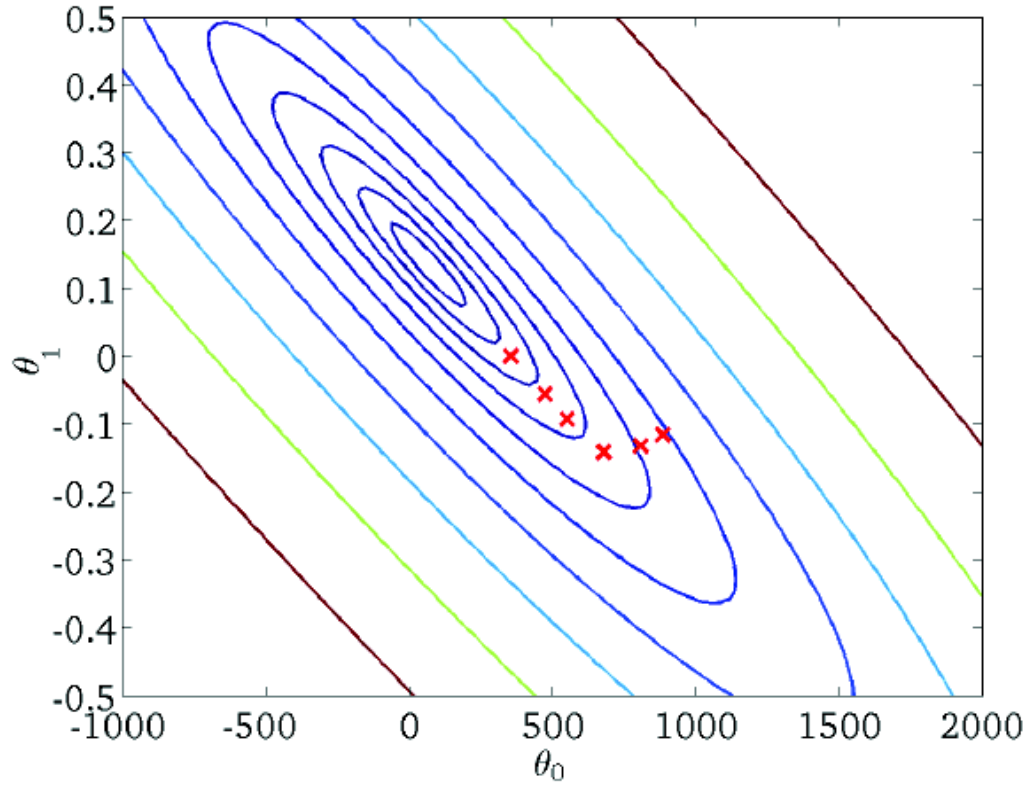

Linear Regression:Gradient Descent Algorithm:intuitively

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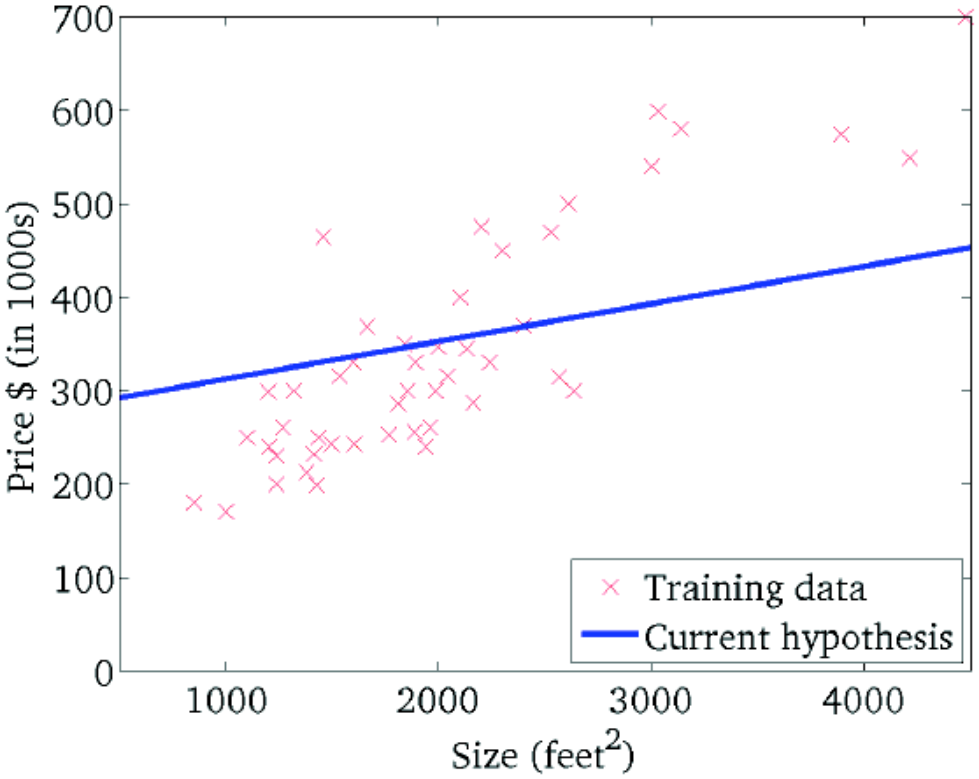

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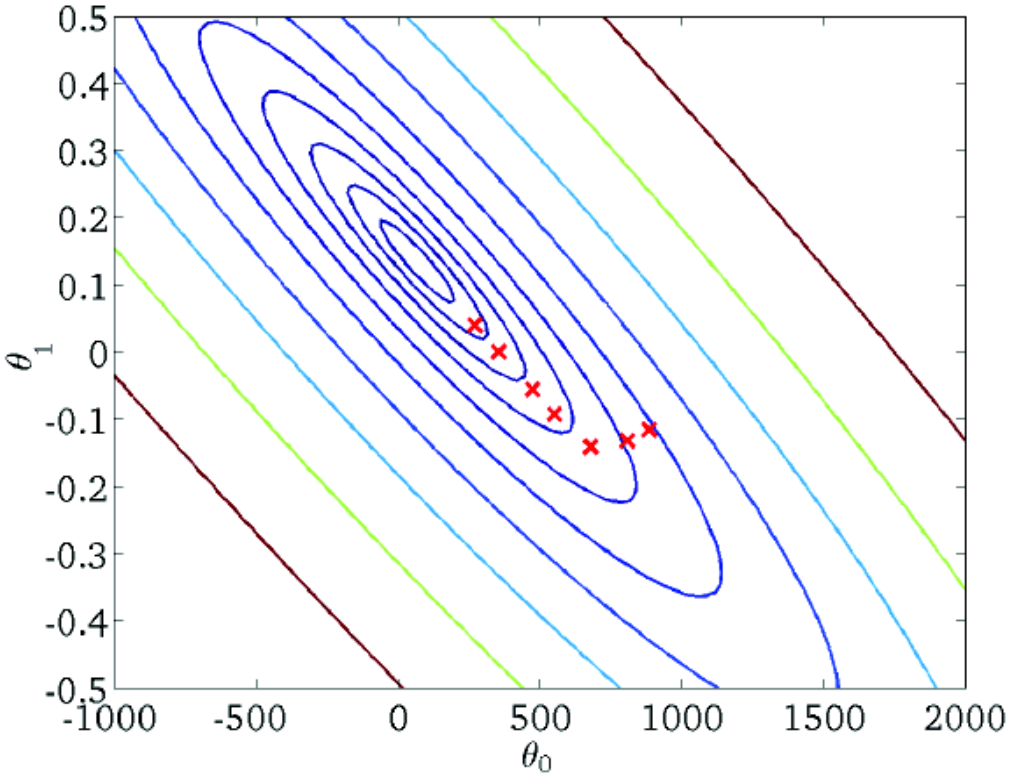

Linear Regression:Gradient Descent Algorithm:intuitively

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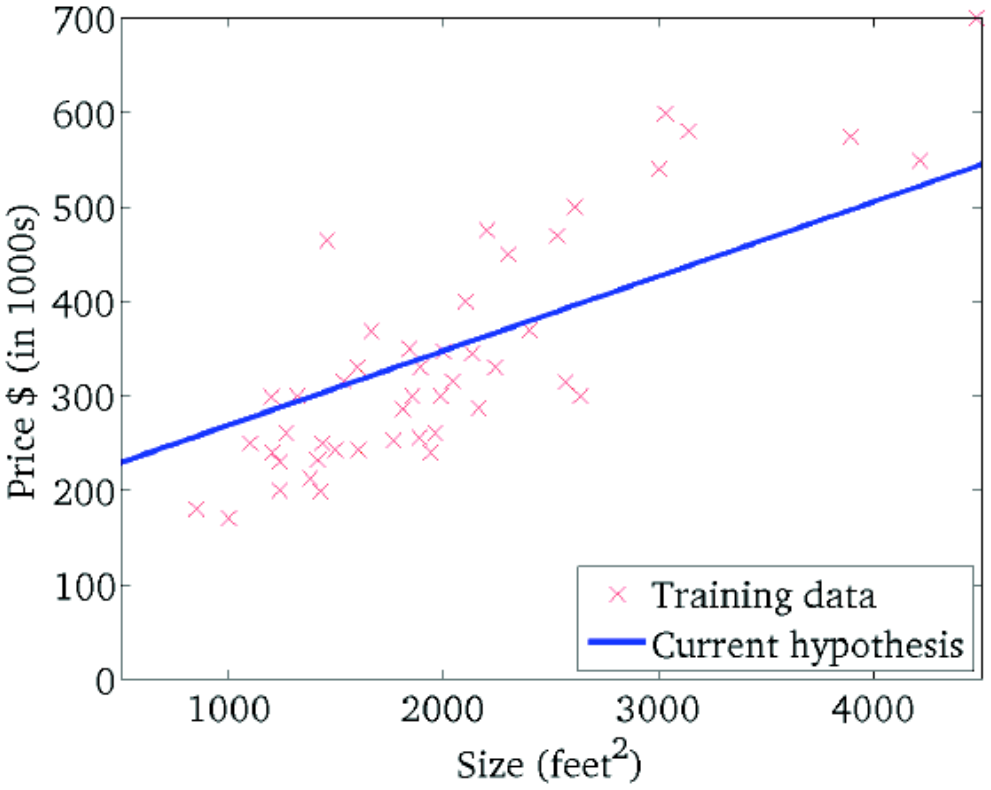

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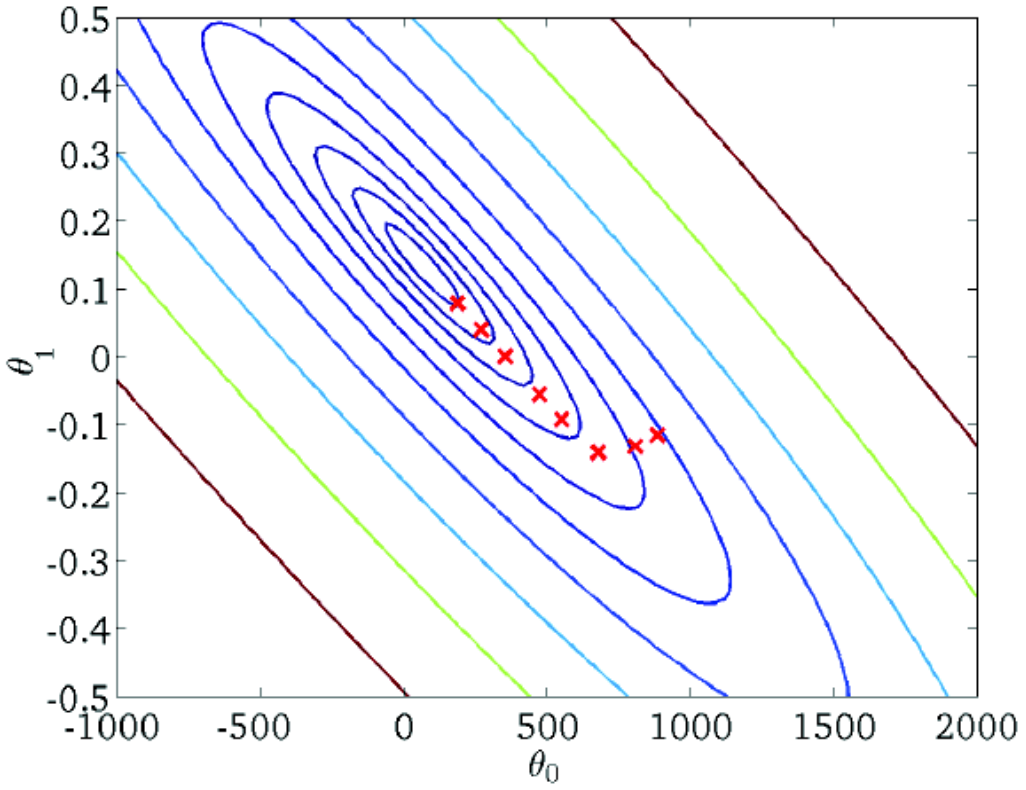

Linear Regression:Gradient Descent Algorithm:intuitively

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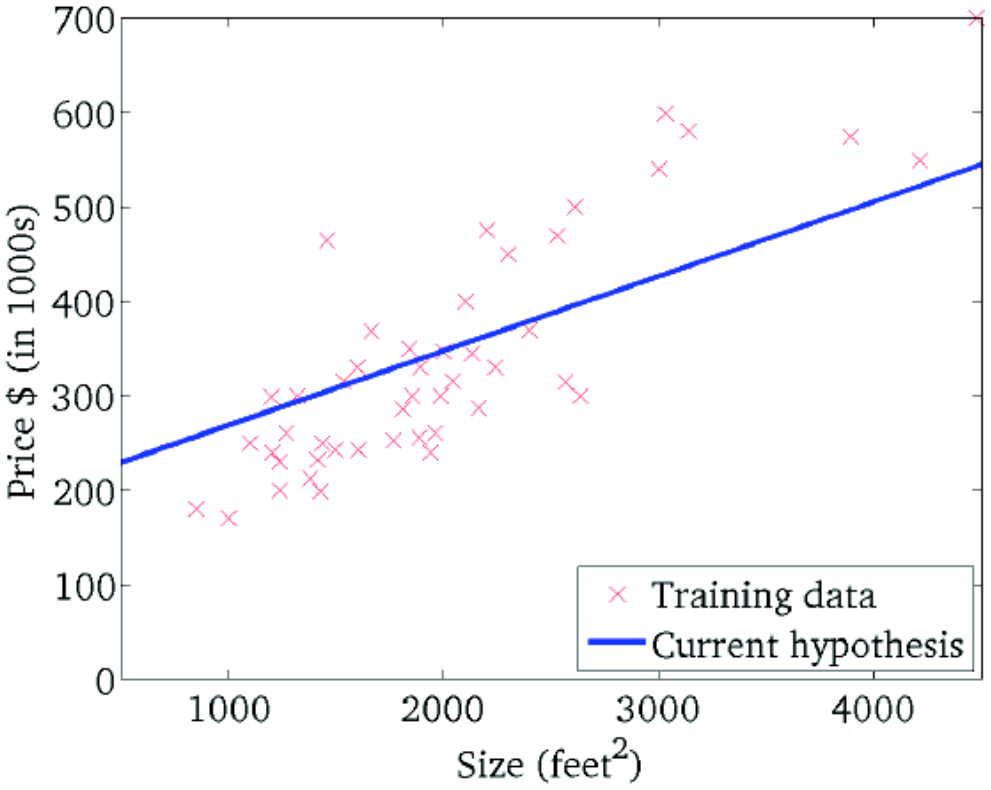

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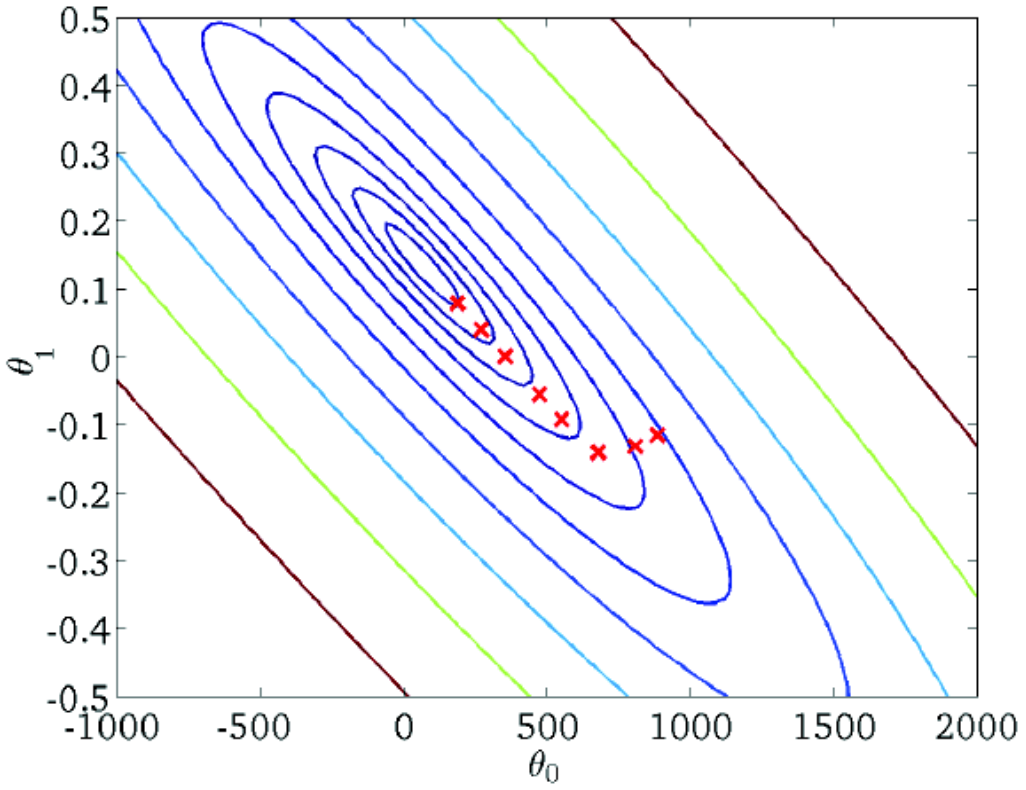

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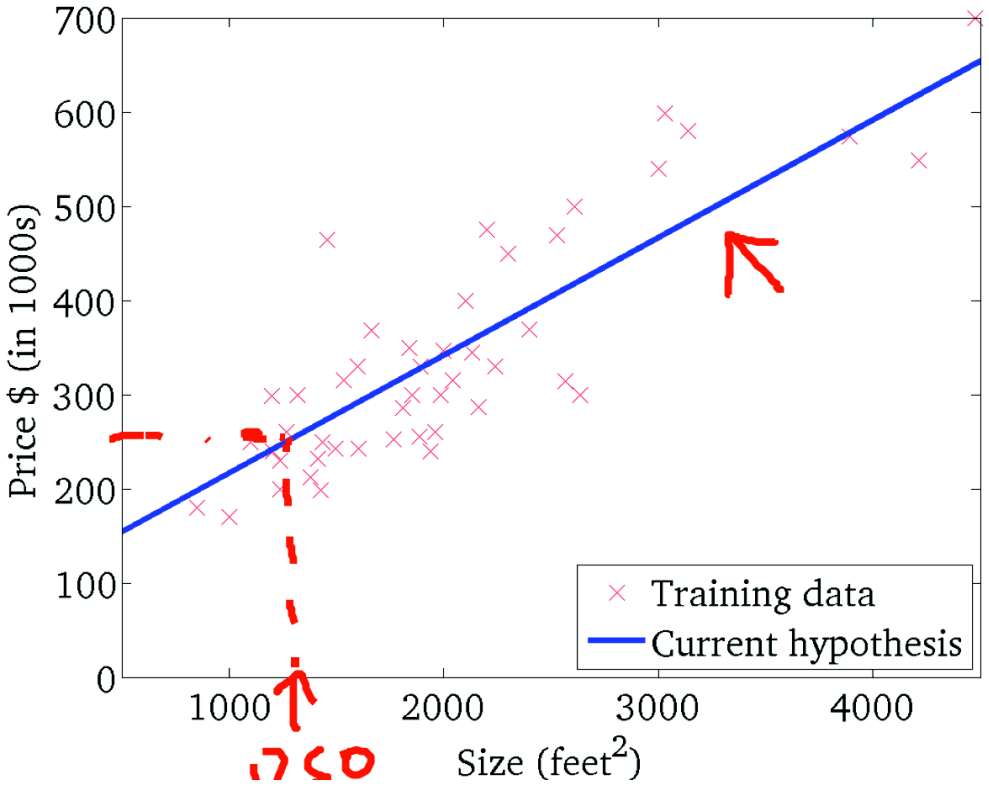

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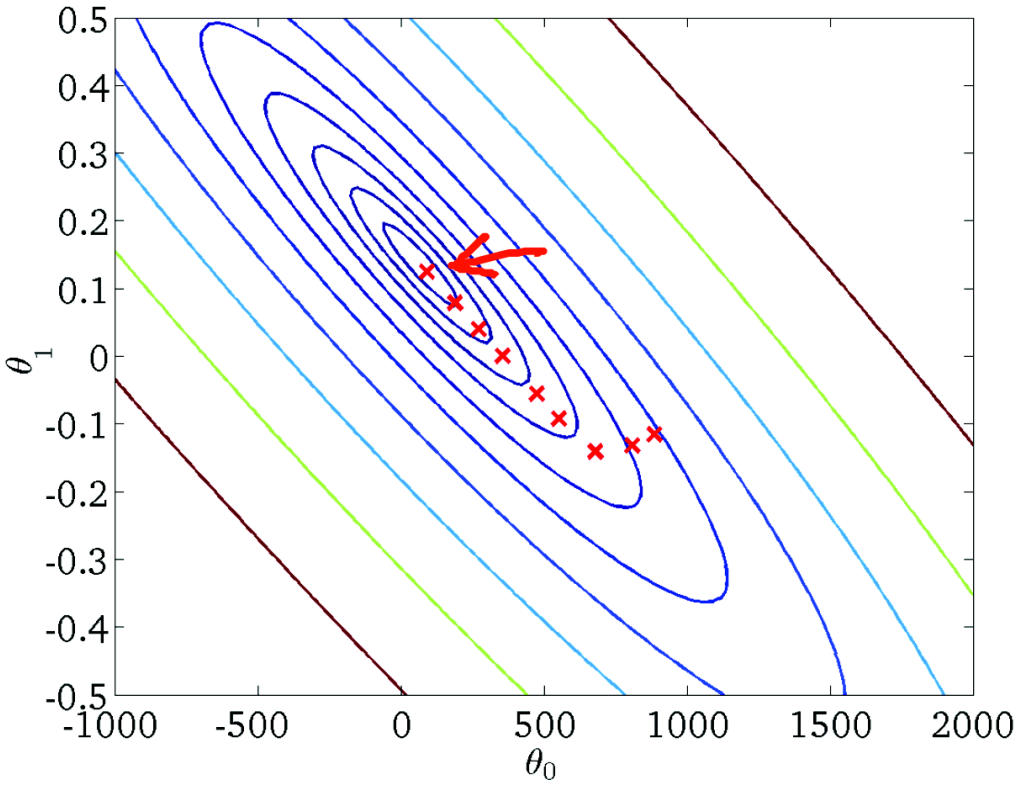


Logistic Regression

- Logistic regression can be seen as a special case of the generalized linear model and thus analogous to linear regression.

Logistic Regression

Classification

- Email: Spam / Not Spam?
- Online Transactions: Fraudulent (Yes / No)?
- Tumor: Malignant / Benign ?

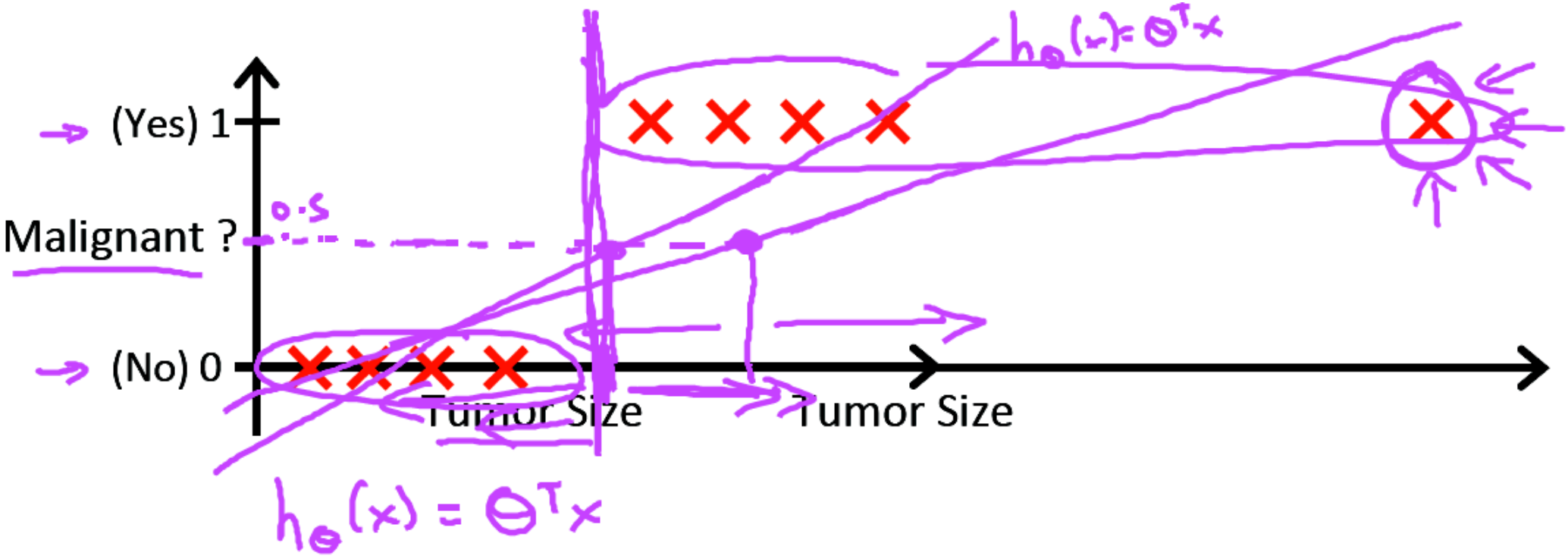
$y \in \{0, 1\}$

0: "Negative Class" (e.g., benign tumor)

1: "Positive Class" (e.g., malignant tumor)

$y \in \{0, 1, 2, 3\}$

Logistic Regression



- Threshold classifier output $h_\theta(x)$ at 0.5:
  - If $h_\theta(x) \geq 0.5$, predict "y = 1"
  - If $h_\theta(x) < 0.5$, predict "y = 0"

Logistic Regression

Classification: $y = 0$ or 1

$h_\theta(x)$ can be > 1 or < 0

Logistic Regression: $0 \leq h_\theta(x) \leq 1$

Classification

Logistic Regression

Logistic Regression Model

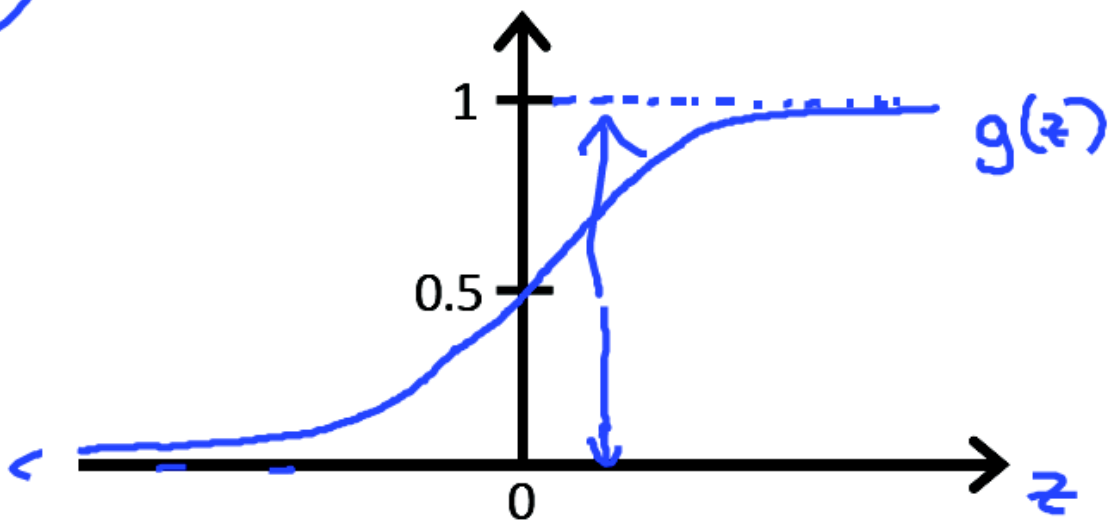
Want $0 \leq h_\theta(x) \leq 1$

$$h_\theta(x) = g(\theta^T x)$$

$$g(z) = \frac{1}{1+e^{-z}}$$

$z = \theta^T x$

$$h_\theta(x) = \frac{1}{1+e^{-\theta^T x}}$$



Parameters θ.

- Sigmoid function
- Logistic function

Logistic Regression

Logistic Regression Model

Want $0 \leq h_\theta(x) \leq 1$

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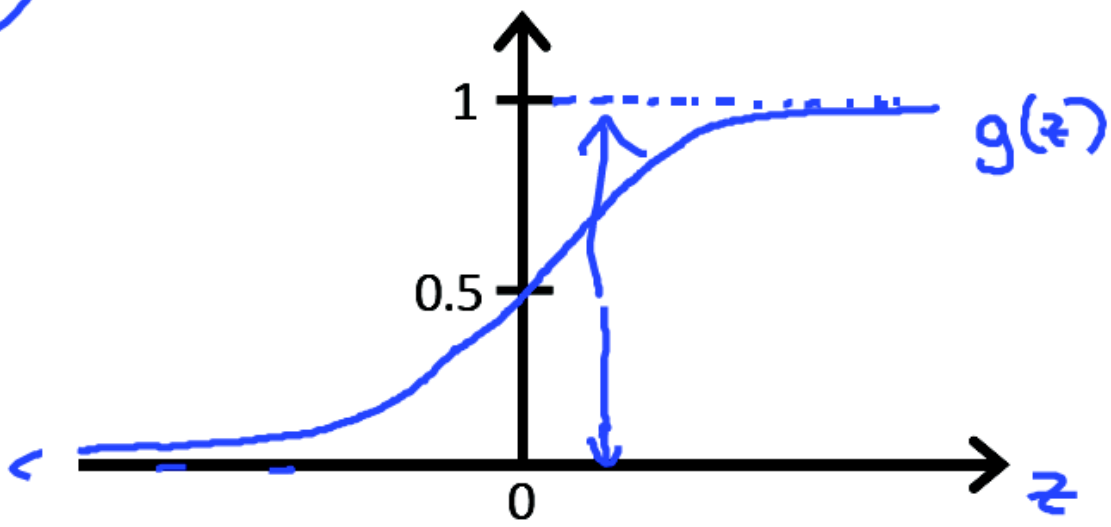
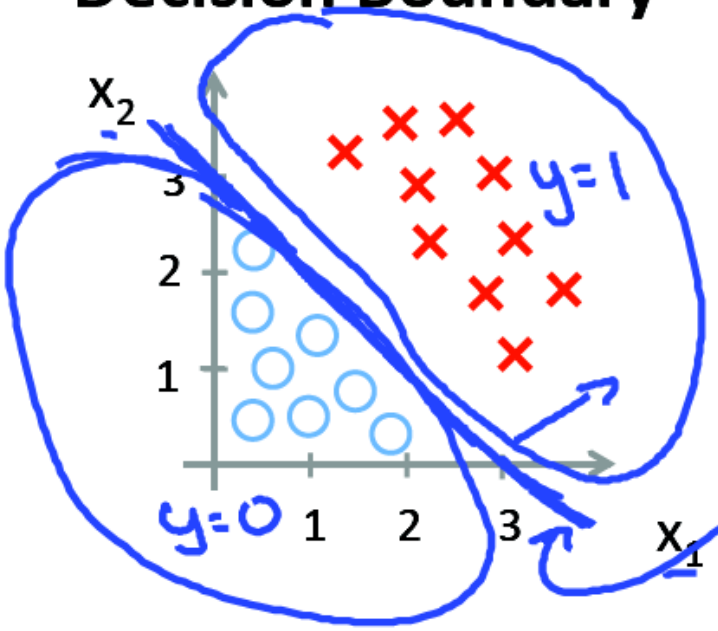


Parameters θ.

- Sigmoid function
- Logistic function

Logistic Regression

Decision Boundary



$\theta = \begin{bmatrix} -3 \\ 1 \\ 1 \end{bmatrix}$

$$h_\theta(x) = g(\theta_0 + \theta_1 x_1 + \theta_2 x_2)$$

$\theta_0 = -3$, $\theta_1 = 1$, $\theta_2 = 1$

Decision boundary

Predict "$y = 1$" if $-3 + x_1 + x_2 \geq 0$

$\theta^T x$

$x_1 + x_2 \geq 3$

x_1, x_2

$h_\theta(x) = 0.5$

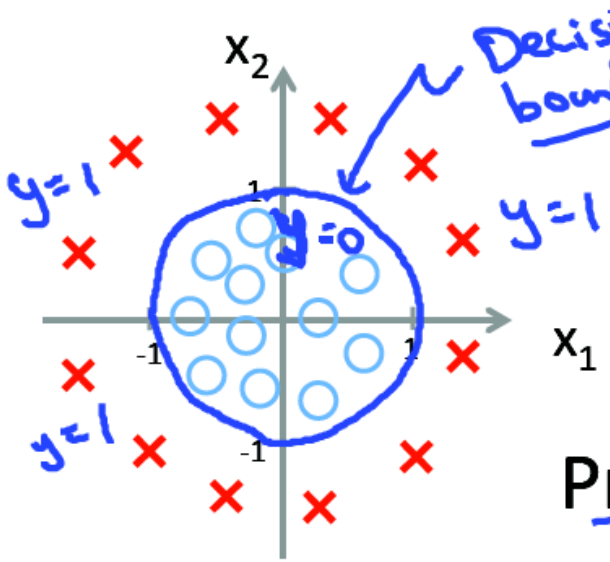
$x_1 + x_2 = 3$

$x_1 + x_2 < 3$

$y = 0$

Logistic Regression

Non-linear decision boundaries



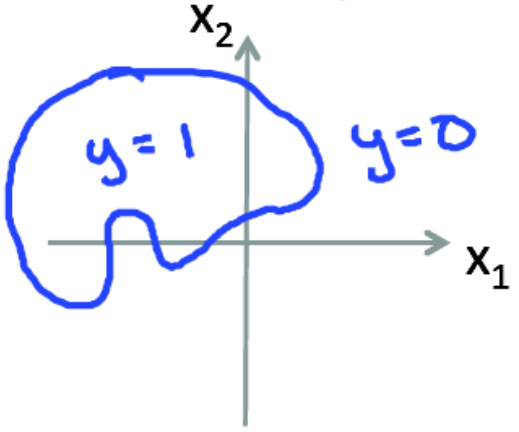
$$h_\theta(x) = g(\theta_0 + \theta_1 x_1 + \theta_2 x_2 + \theta_3 x_1^2 + \theta_4 x_2^2)$$

$$\theta = \begin{bmatrix} -1 \\ 0 \\ 0 \\ 1 \\ 1 \end{bmatrix}$$

Predict "$y = 1$" if $-1 + x_1^2 + x_2^2 \geq 0$

$x_1^2 + x_2^2 = 1$

$x_1^2 + x_2^2 \geq 1$



$$h_\theta(x) = g(\theta_0 + \theta_1 x_1 + \theta_2 x_2 + \theta_3 x_1^2 + \theta_4 x_1^2 x_2 + \theta_5 x_1^2 x_2^2 + \theta_6 x_1^3 x_2 + \ldots)$$

Logistic Regression

Training set: $\{(x^{(1)}, y^{(1)}), (x^{(2)}, y^{(2)}), \cdots, (x^{(m)}, y^{(m)})\}$

m examples $x \in \begin{bmatrix} x_0 \\ x_1 \\ \cdots \\ x_n \end{bmatrix}$ $\mathbb{R}^{n+1}$ $x_0 = 1, y \in \{0, 1\}$

$$h_\theta(x) = \frac{1}{1 + e^{-\theta^T x}}$$

How to choose parameters θ ?

Logistic Regression

Cost function

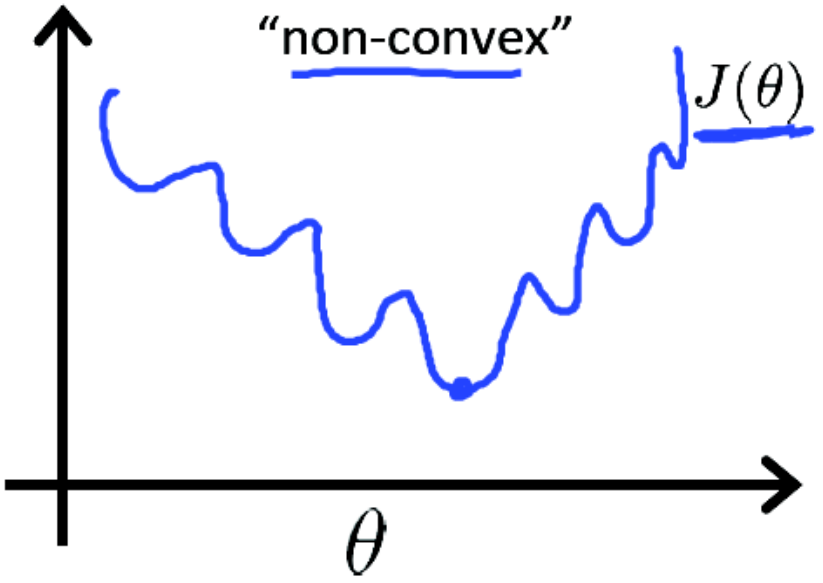
→ ~~Linear~~ regression: $J(\theta) = \frac{1}{m}\sum_{i=1}^{m} \frac{1}{2}\left(h_\theta(x^{(i)}) - y^{(i)}\right)^2$

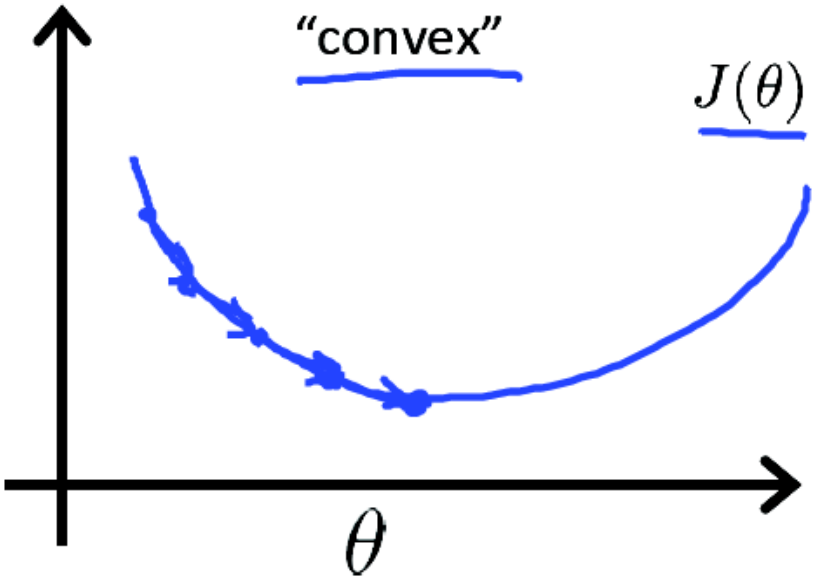
Logistic

$\rightarrow \text{Cost}(h_\theta(x^{(i)}), y^{(i)}) = \frac{1}{2}\left(h_\theta(x^{(i)}) - y^{(i)}\right)^2$

$\text{cost}(h_\theta(x^{(i)}), y)$

$\frac{1}{1 + e^{-\theta^T x}}$

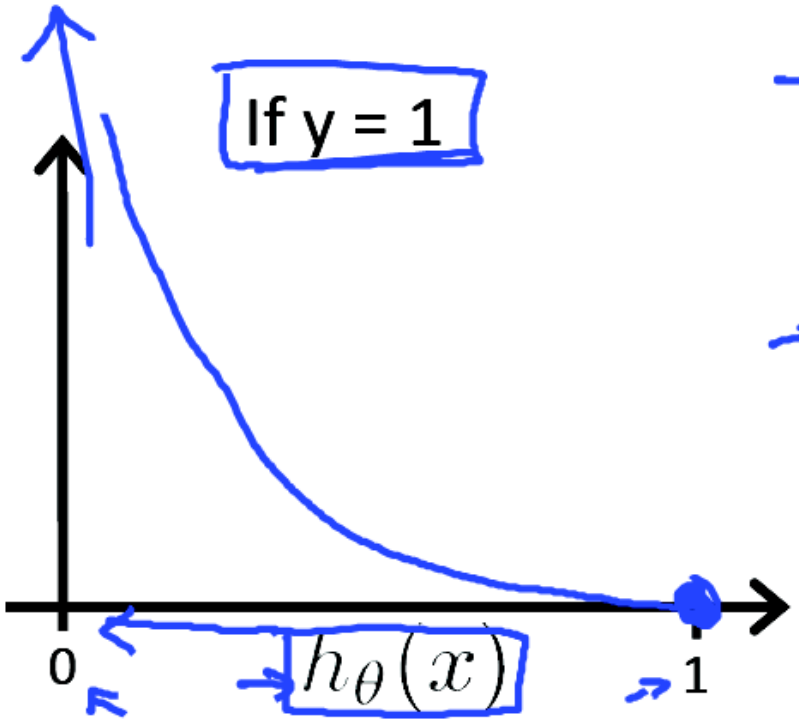




Logistic Regression

Logistic regression cost function

$$\text{Cost}(h_\theta(x), y) = \begin{cases} -\log(h_\theta(x)) & \text{if } y = 1 \\ -\log(1 - h_\theta(x)) & \text{if } y = 0 \end{cases}$$



→ $\text{Cost} = 0$ if $y = 1, h_\theta(x) = 1$

But as $h_\theta(x) \to 0$

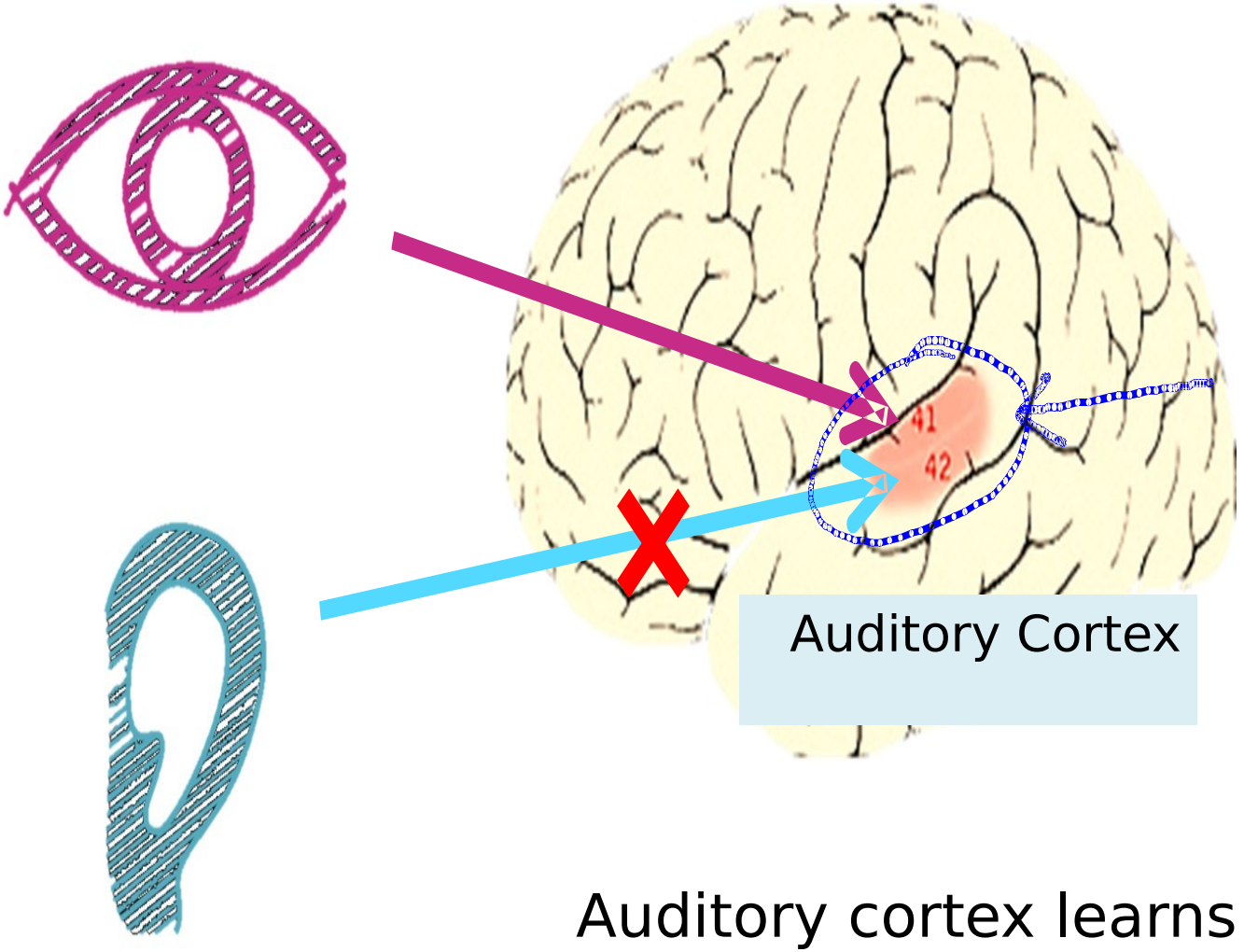
$Cost \to \infty$

→ Captures intuition that if $h_\theta(x) = 0$, (predict $P(y = 1|x; \theta) = 0$), but $y = 1$, we'll penalize learning algorithm by a very large cost.

Neural Networks

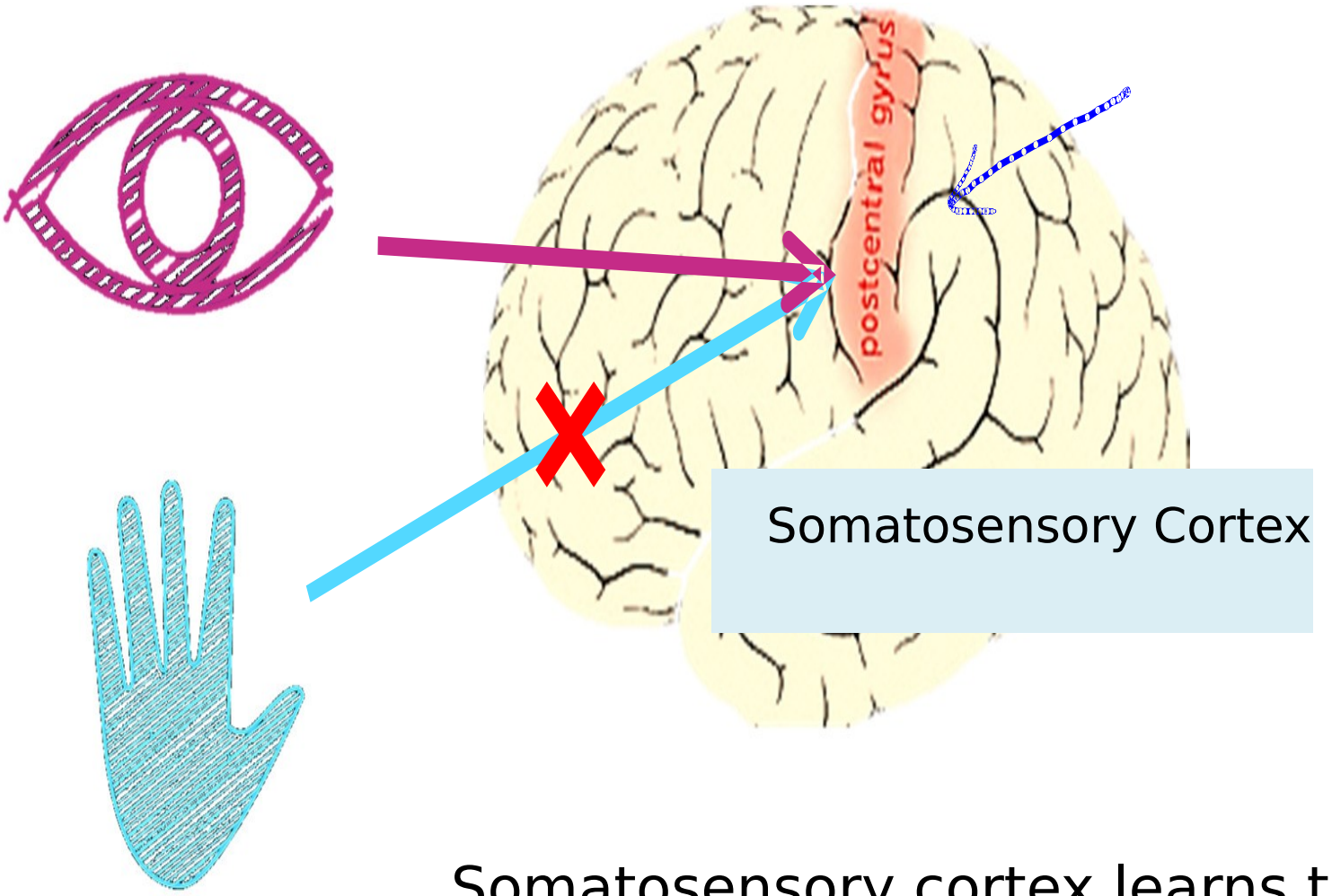
- Origins: Algorithms that try to mimic the brain.
- Was very widely used in 80s and early 90s; popularity diminished in late 90s.
- Recent resurgence: State-of-the-art technique for many applications

The “one learning algorithm” hypothesis



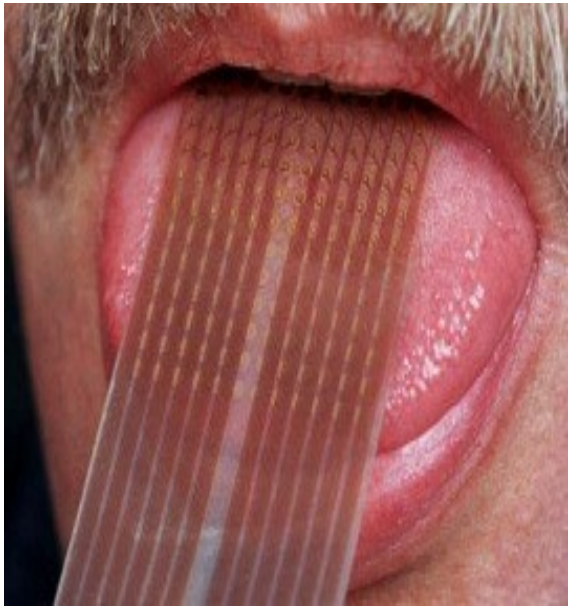
Auditory cortex learns to see

The “one learning algorithm” hypothesis



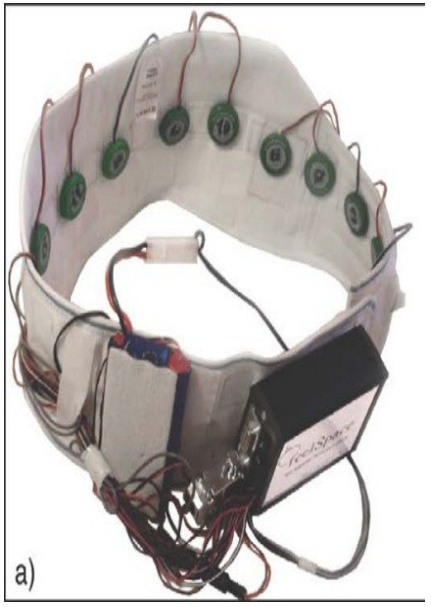
Somatosensory cortex learns to see

Sensor representations in the brain

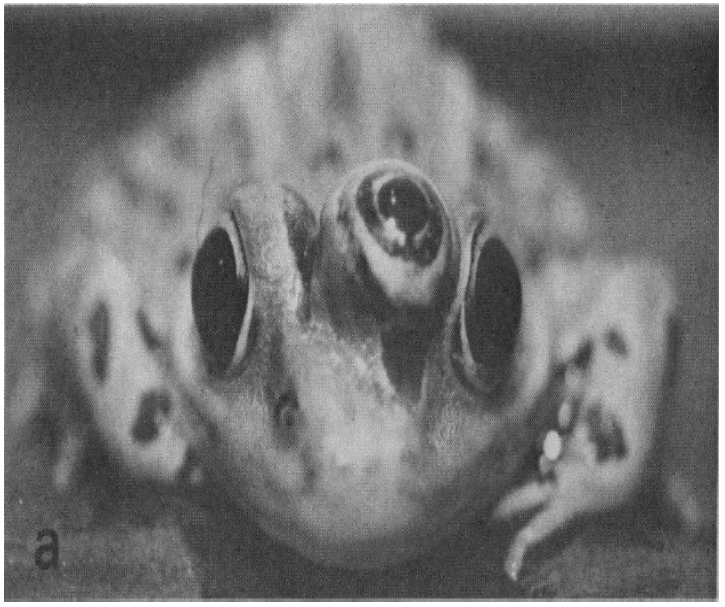


Seeing with your tongue

Human echolocation (sonar)

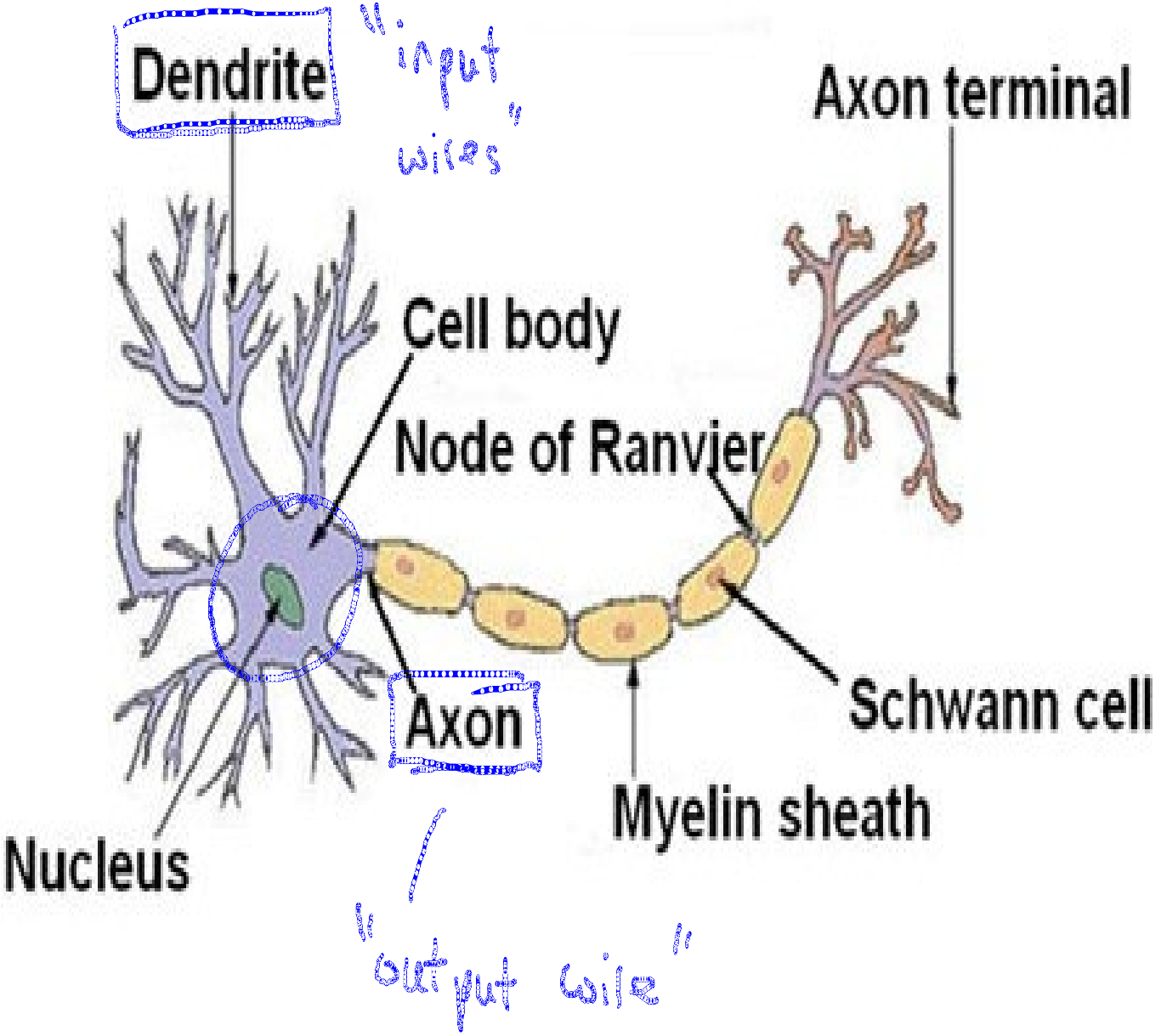


Haptic belt: Direction sense

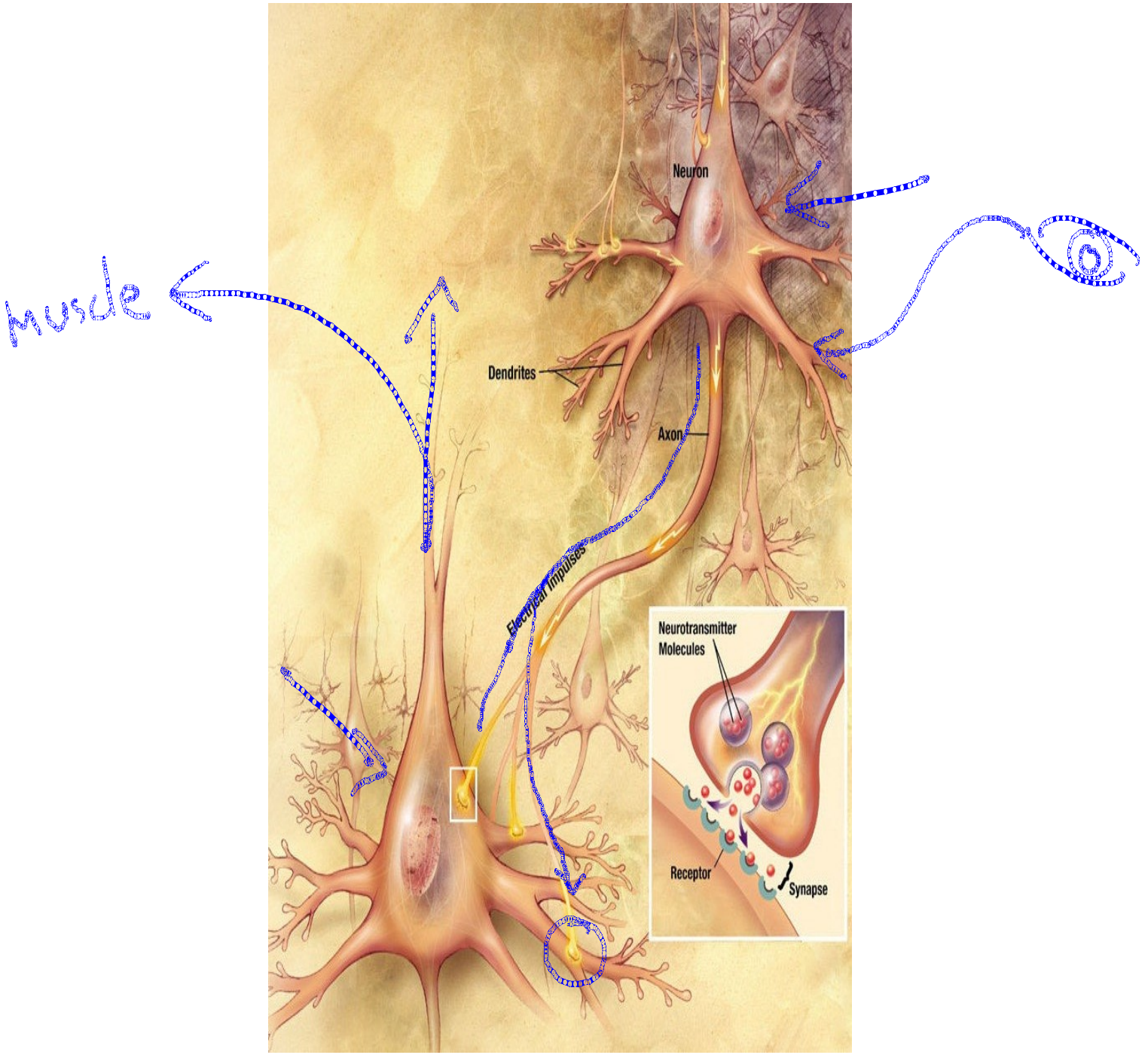


Implanting a 3rd eye

Neuron in the brain



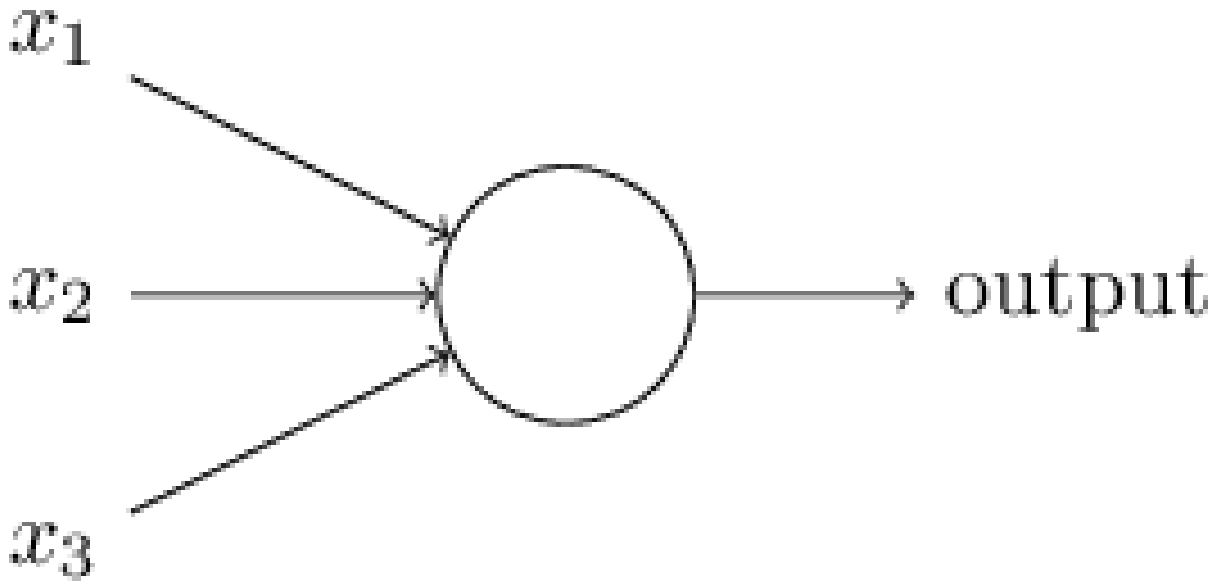
Neurons in the brain



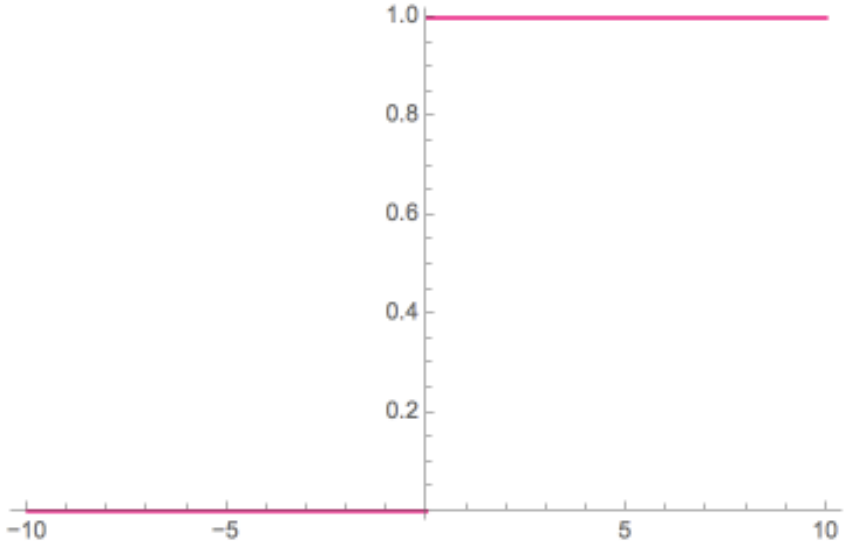
Artificial Neurons:Perceptrons

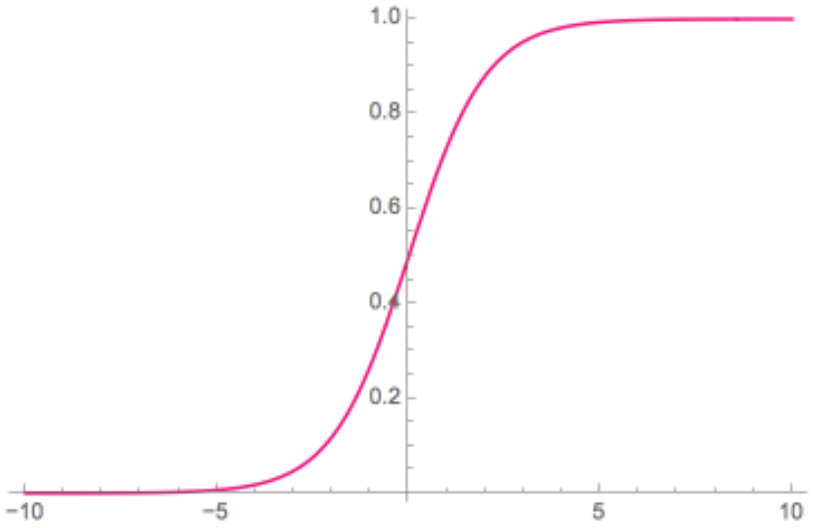
- Suppose the weekend is coming up, and you've heard that there's going to be a food festival in your city.
- You might make your decision by weighing up three factors:
  - Is the weather good?
  - Does your boyfriend or girlfriend want to accompany you?
  - Is the festival near public transit? (You don't own a car).

Artificial Neurons:Perceptrons

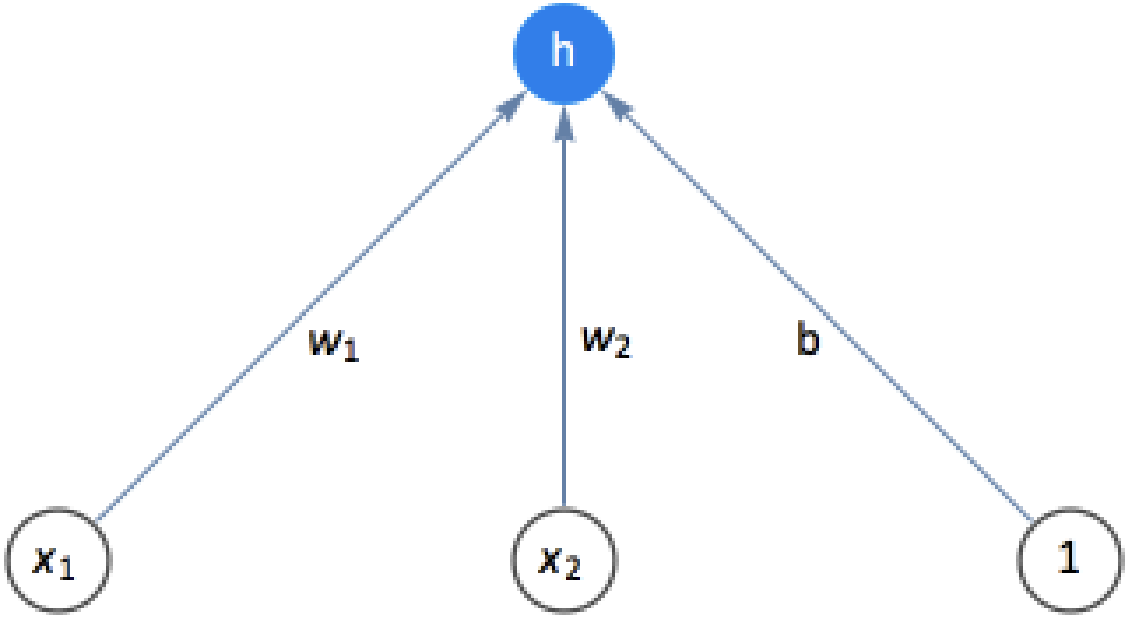


Artificial Neurons:Sigmoid Neuron



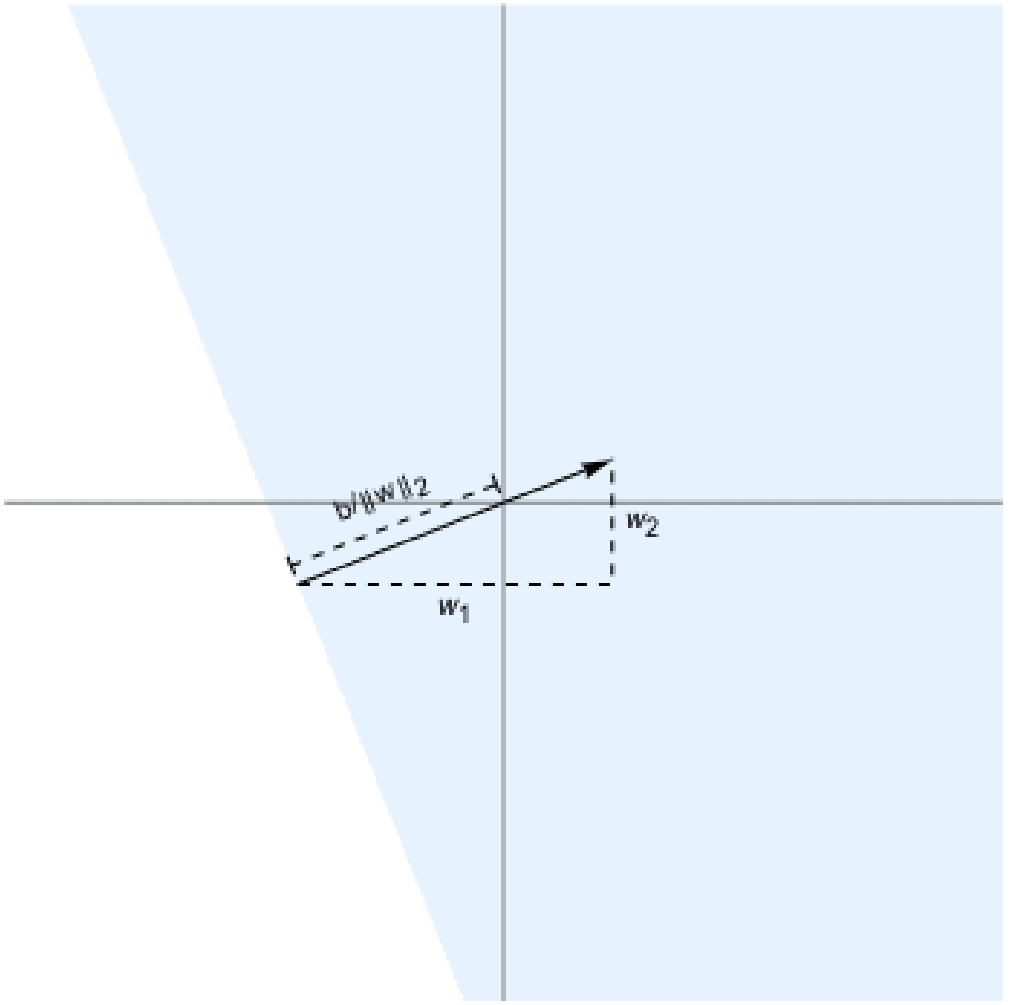


Artificial Neurons:Sigmoid Neuron

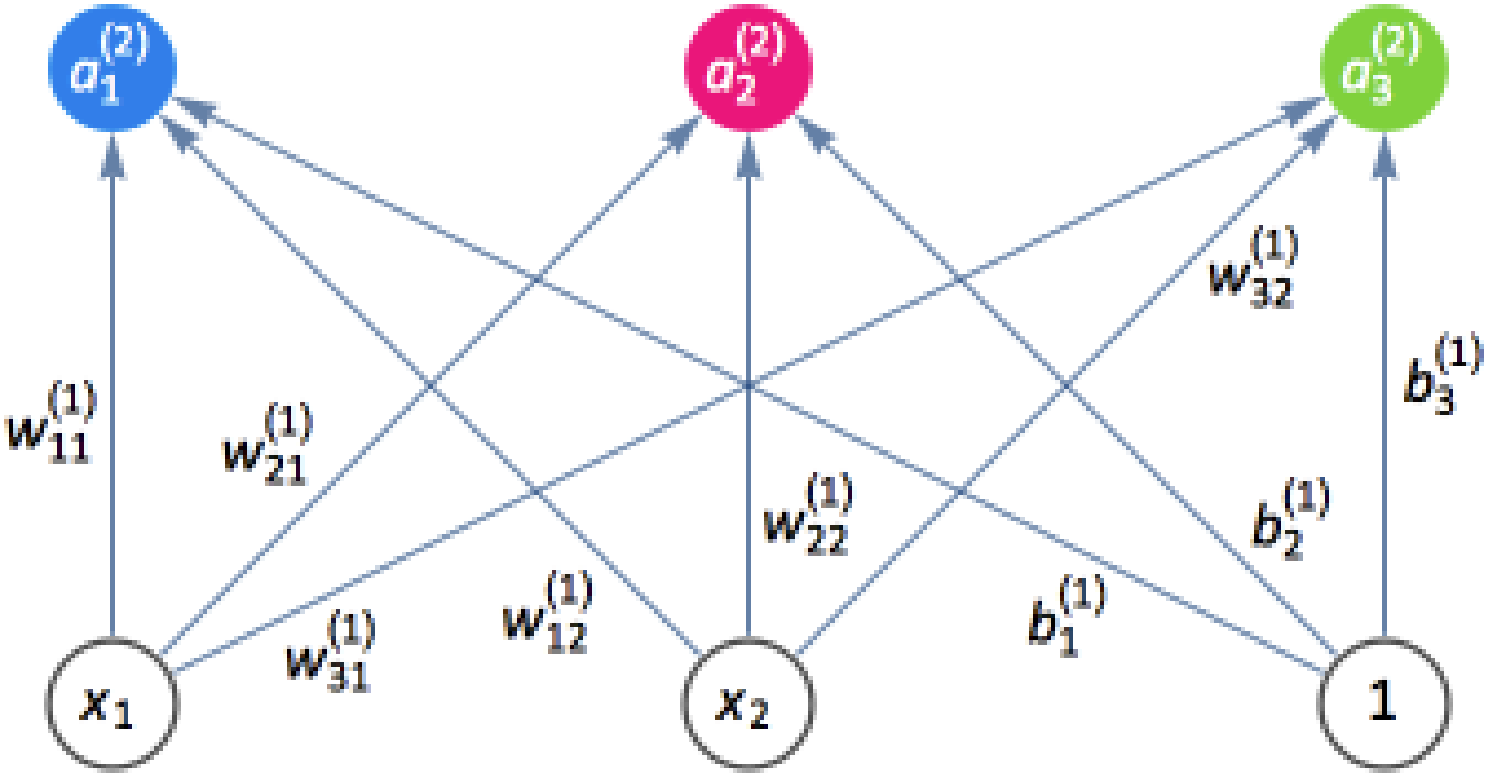


$$h = f\left(w_1 x_1 + w_2 x_2 + b\right)$$

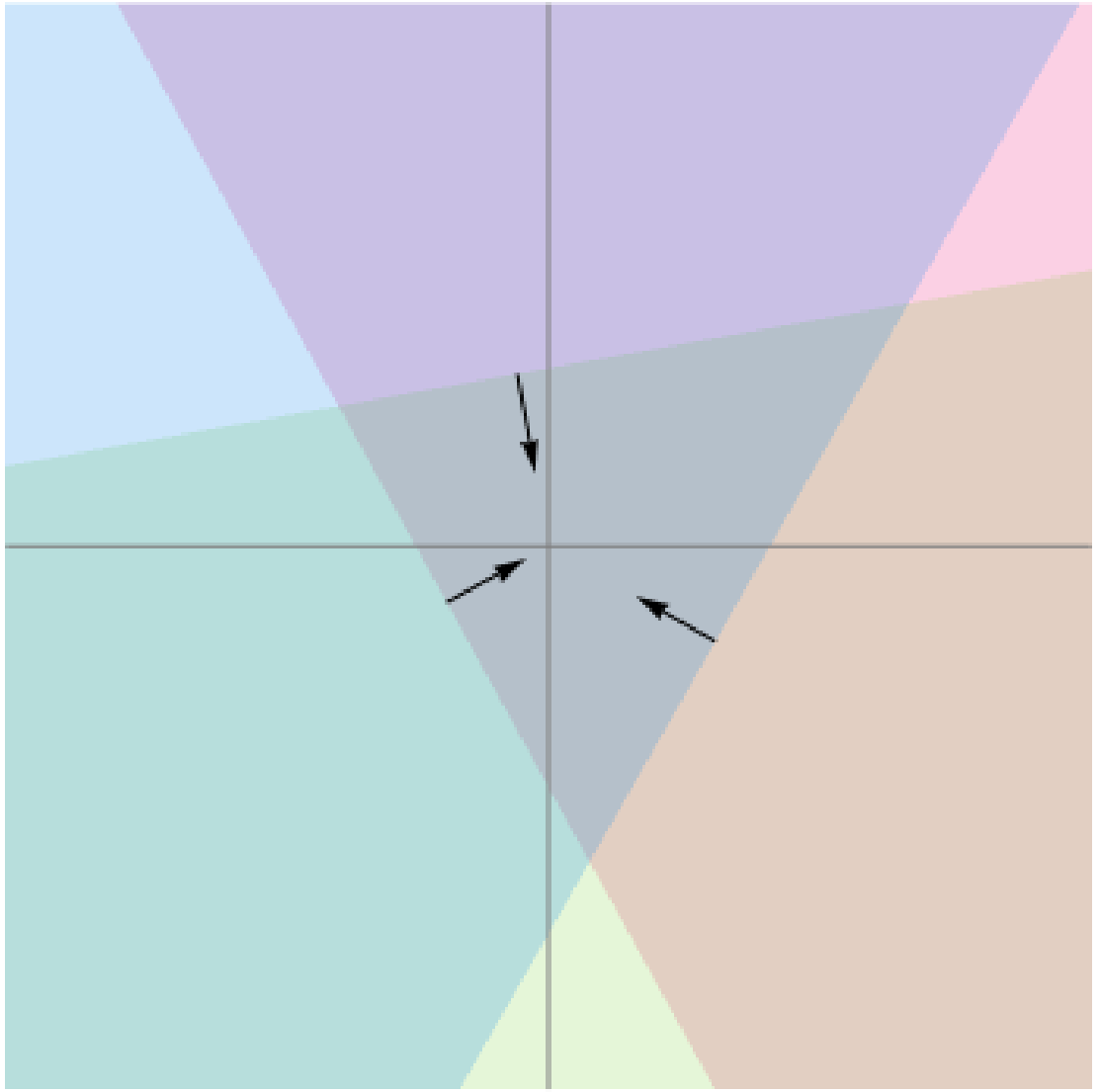
Artificial Neurons:Sigmoid Neuron



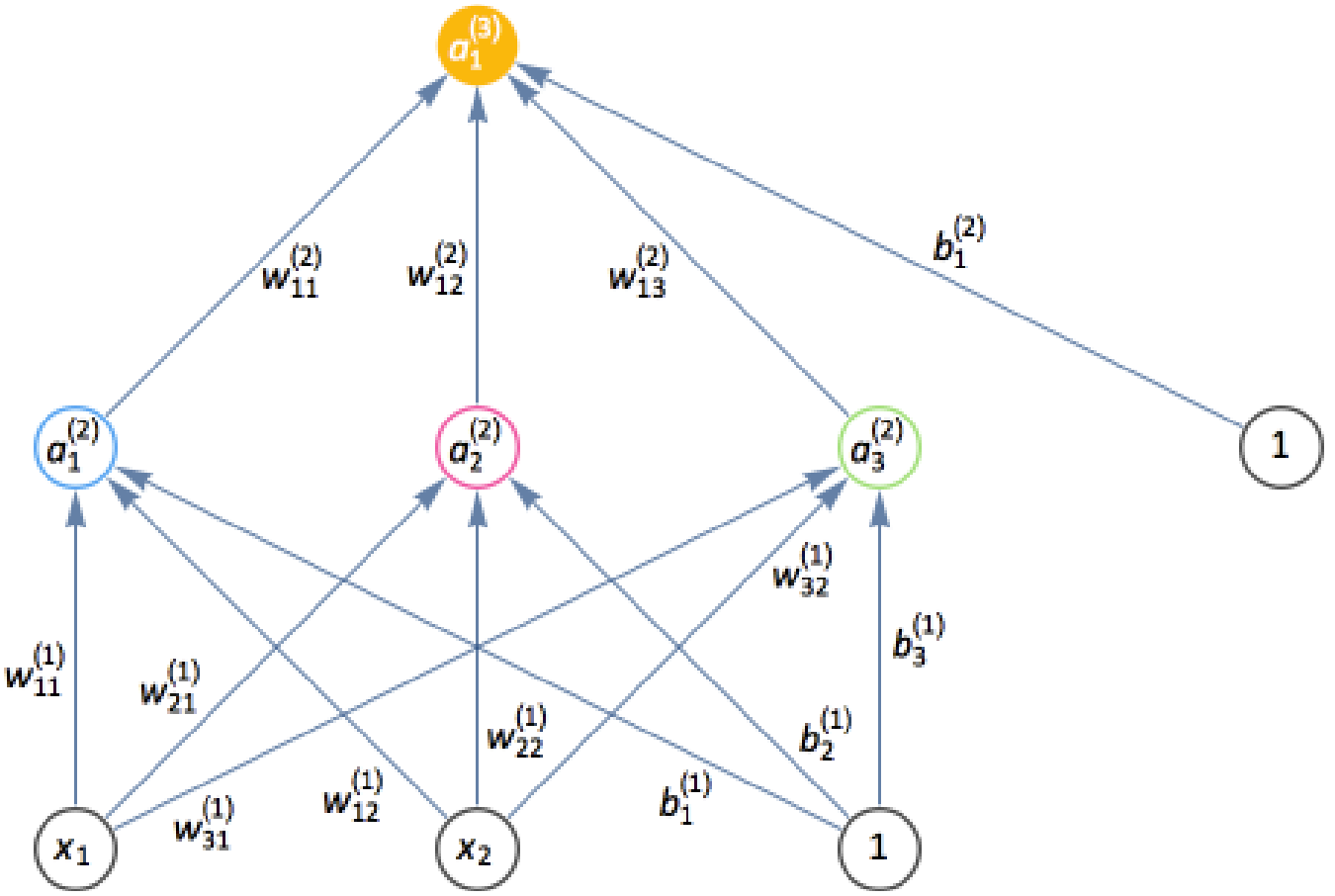
Deep Neural Network



Deep Neural Network

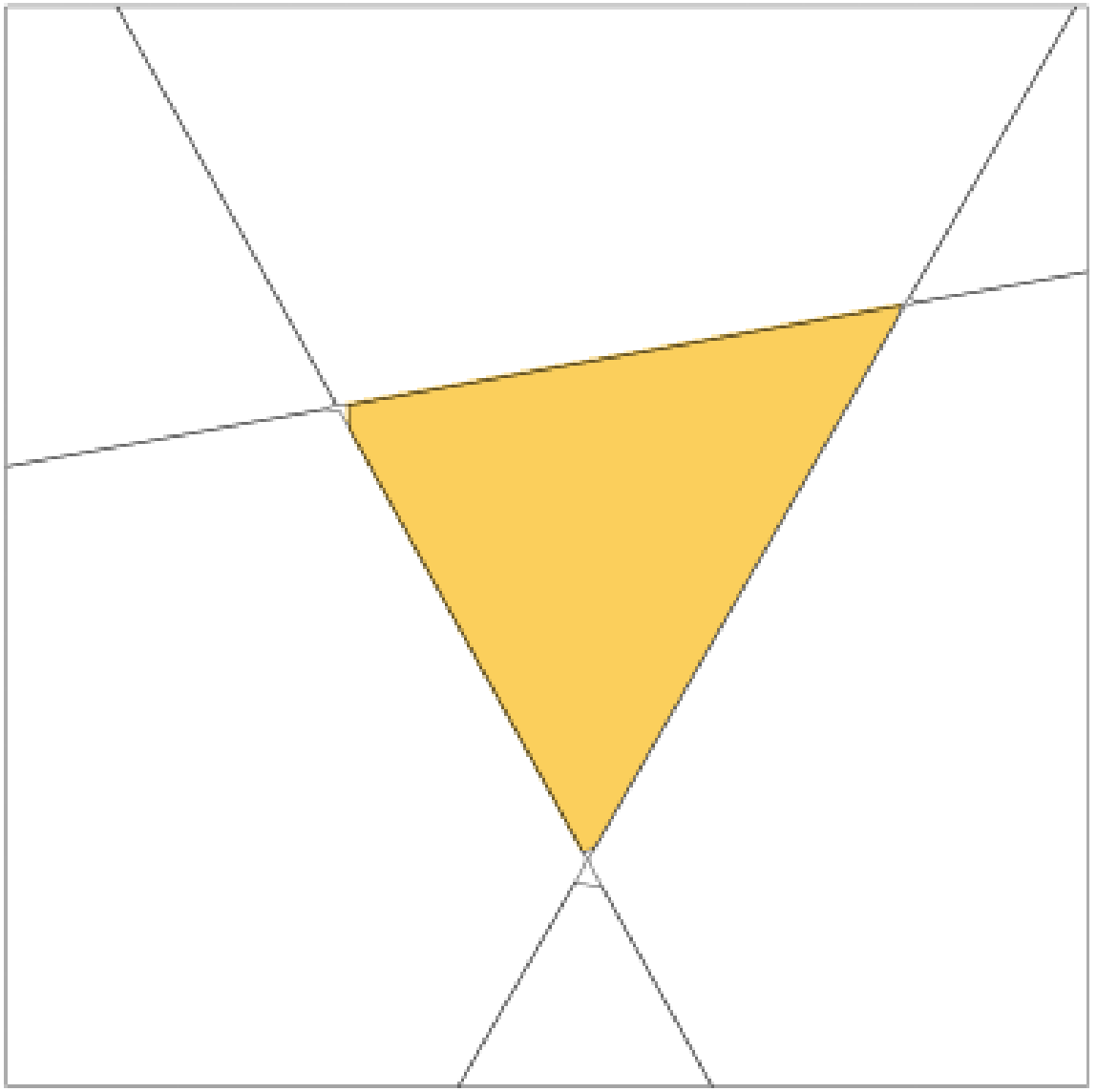


Deep Neural Network



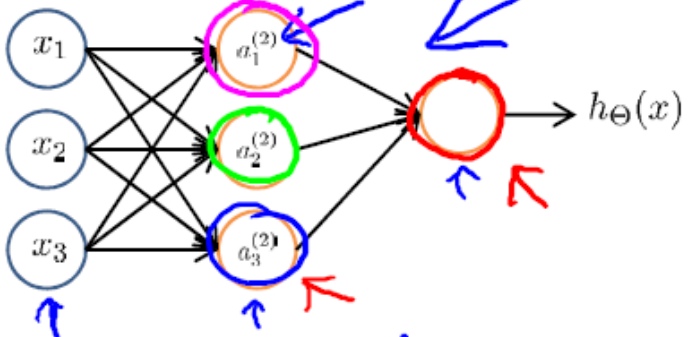
$$a_1^{(3)} = f\left(w_{11}^{(2)} a_1^{(2)} + w_{12}^{(2)} a_2^{(2)} + w_{13}^{(2)} a_3^{(2)} + b_1^{(2)}\right)$$

Deep Neural Network



Deep Neural Network

Neural Network



→ $a_i^{(j)}$ = "activation" of unit i in layer j

→ $\Theta^{(j)}$ = matrix of weights controlling function mapping from layer j to layer $j+1$

$\Theta^{(1)} \in \mathbb{R}^{3\times 4}$

$h_\Theta(x)$

→ $a_1^{(2)} = g(\Theta_{10}^{(1)} x_0 + \Theta_{11}^{(1)} x_1 + \Theta_{12}^{(1)} x_2 + \Theta_{13}^{(1)} x_3)$

→ $a_2^{(2)} = g(\Theta_{20}^{(1)} x_0 + \Theta_{21}^{(1)} x_1 + \Theta_{22}^{(1)} x_2 + \Theta_{23}^{(1)} x_3)$

→ $a_3^{(2)} = g(\Theta_{30}^{(1)} x_0 + \Theta_{31}^{(1)} x_1 + \Theta_{32}^{(1)} x_2 + \Theta_{33}^{(1)} x_3)$

$\Theta^{(2)}$

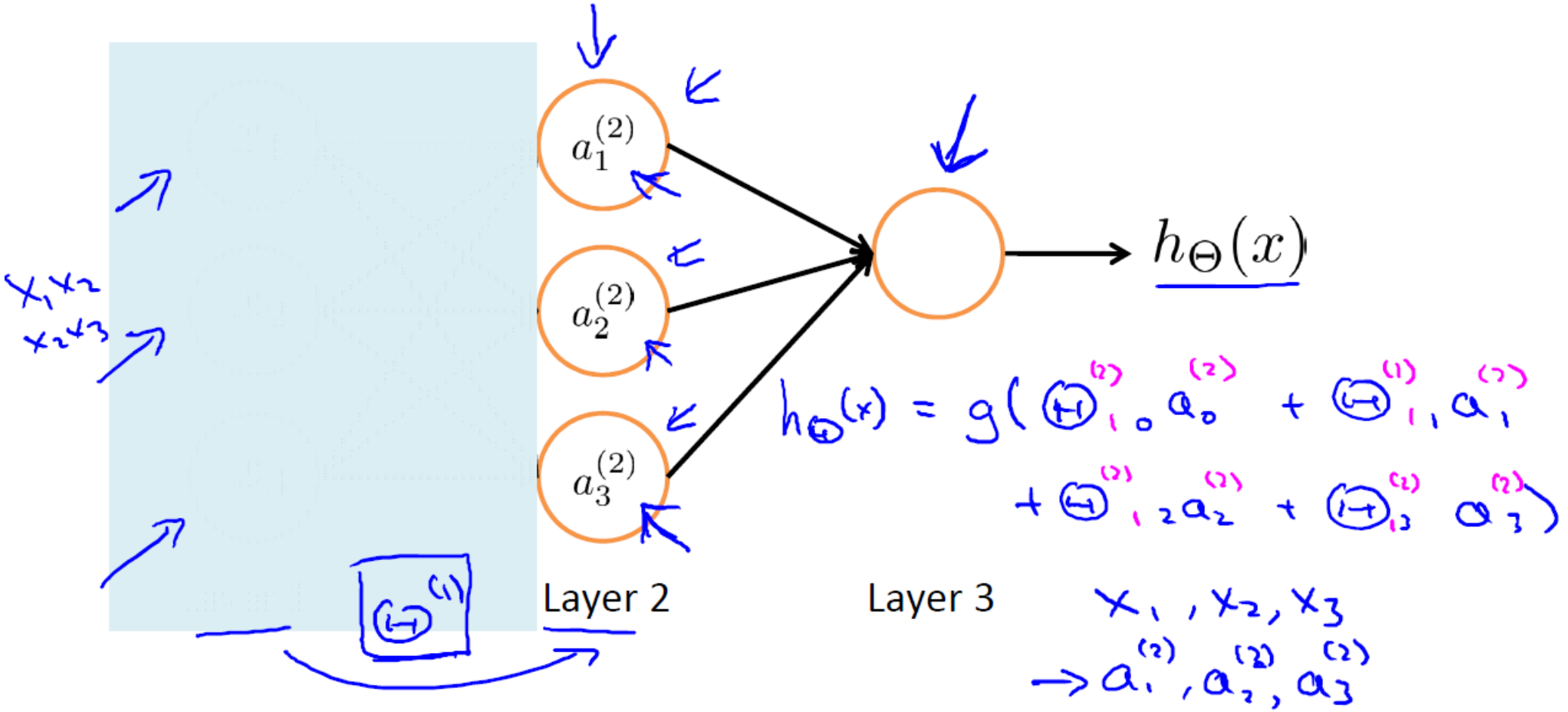
→ $h_\Theta(x) = a_1^{(3)} = g(\Theta_{10}^{(2)} a_0^{(2)} + \Theta_{11}^{(2)} a_1^{(2)} + \Theta_{12}^{(2)} a_2^{(2)} + \Theta_{13}^{(2)} a_3^{(2)})$

→ If network has s_j units in layer j, s_{j+1} units in layer $j+1$, then $\Theta^{(j)}$ will be of dimension $s_{j+1} \times (s_j + 1)$.

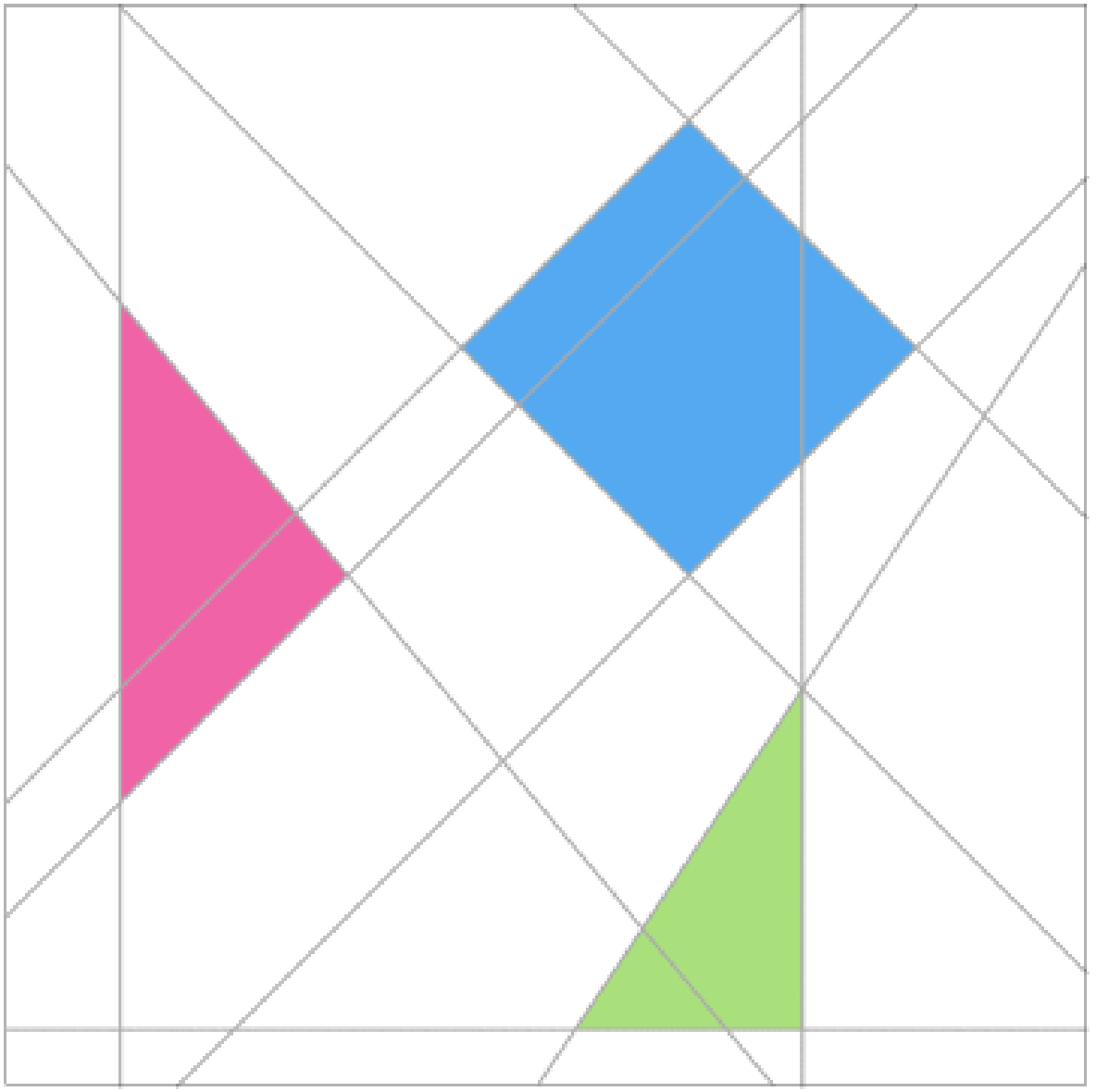
$s_{j+1} \times (s_j + 1)$

Deep Neural Network

Neural Network learning its own features



Deep Neural Network

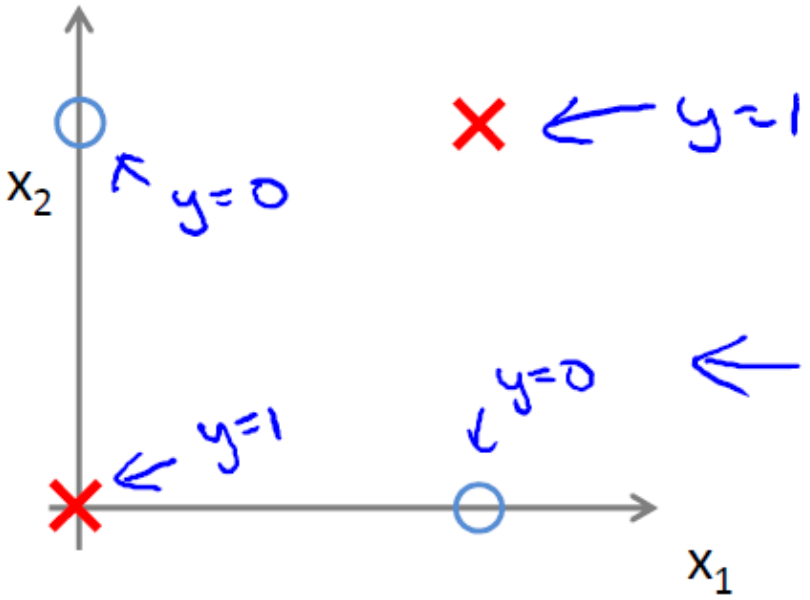


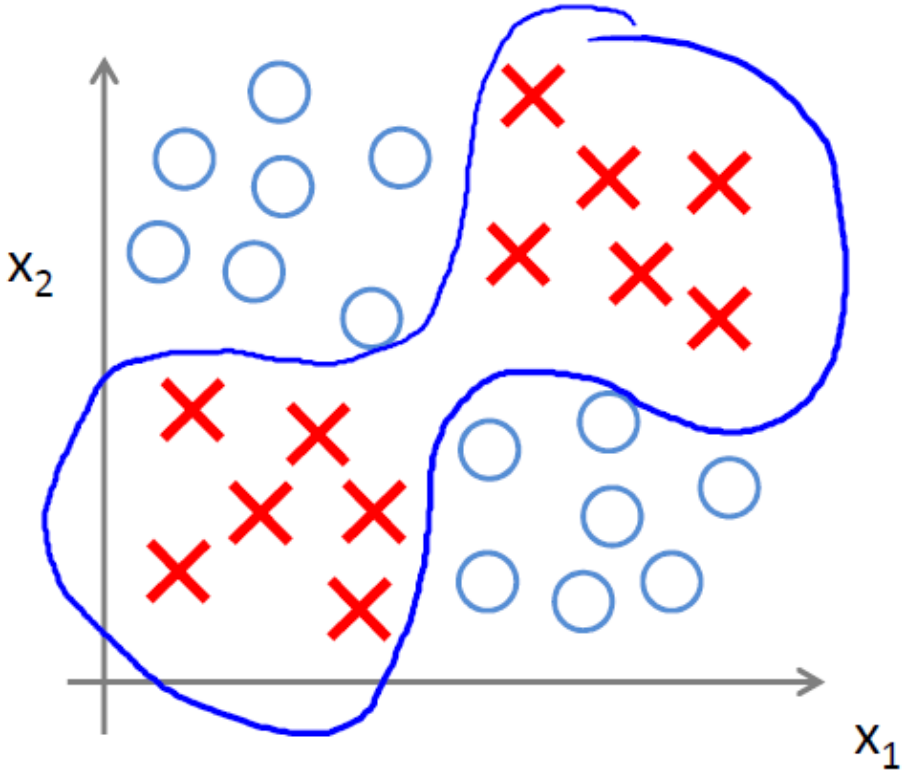
Deep Neural Network

Deep Neural Network

Non-linear classification example: XOR/XNOR

x_1, x_2 are binary (0 or 1).





$y = x_1 \text{ XOR } x_2$

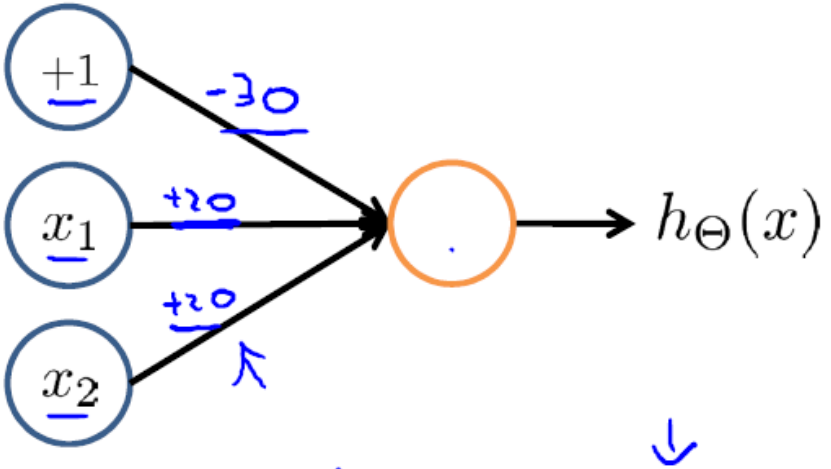
$x_1 \text{ XNOR } x_2$

$\text{NOT } (x_1 \text{ XOR } x_2)$

Deep Neural Network

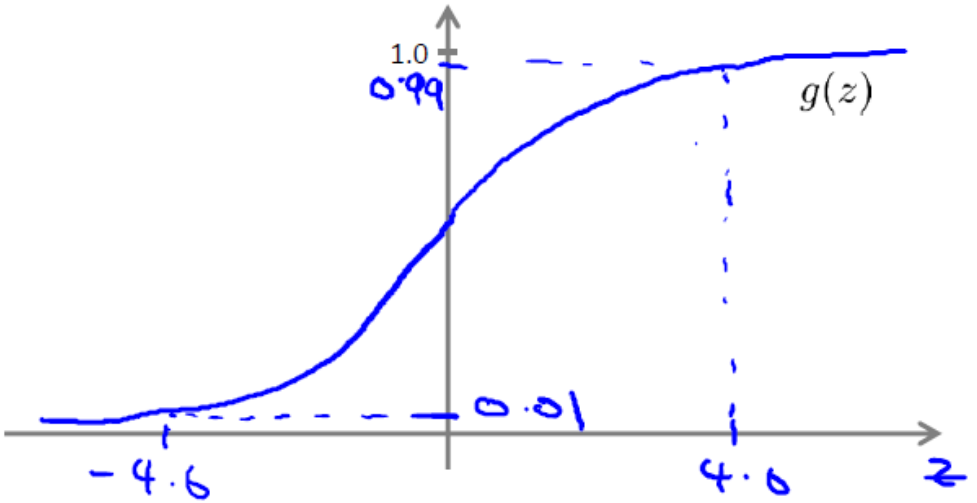
Simple example: AND

- $x_1, x_2 \in \{0, 1\}$
- $y = x_1$ AND x_2



$h_\Theta(x) = g(-30 + 20x_1 + 20x_2)$

$\Theta^{(1)}_{10}$ $\Theta^{(1)}_{11}$ $\Theta^{(1)}_{12}$

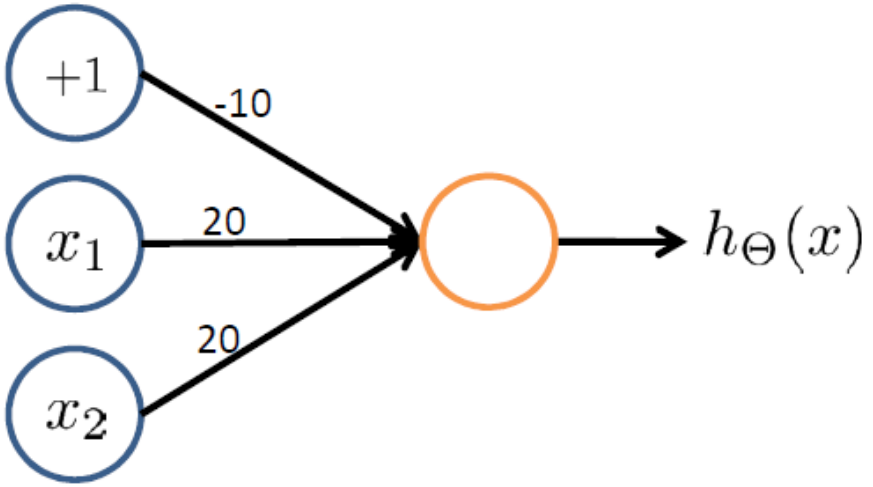


x_1	x_2	$h_\Theta(x)$
0	0	$g(-30) \approx 0$
0	1	$g(-10) \approx 0$
1	0	$g(-10) \approx 0$
1	1	$g(10) \approx 1$

$h_\Theta(x) \approx x_1$ AND x_2

Deep Neural Network

Example: OR function



$g(-10 + 20x_1 + 20x_2)$

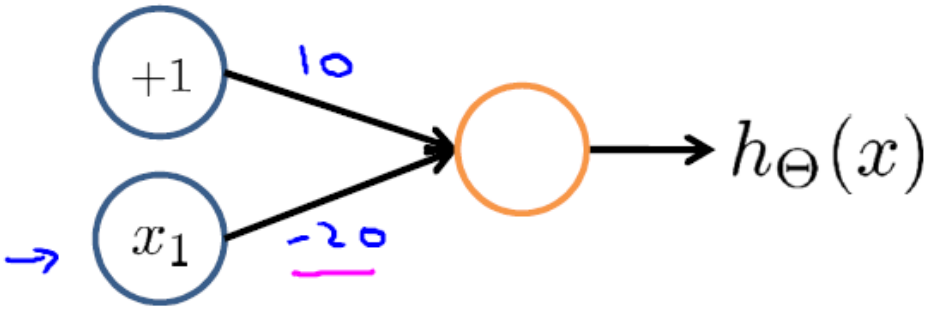
x_1	x_2	$h_\Theta(x)$
0	0	$g(-10) \approx 0$
0	1	$g(10) \approx 1$
1	0	≈ 1
1	1	≈ 1

Deep Neural Network

→ x_1 AND x_2 → x_1 OR x_2 {0,1}.

Negation:

NOT x_1



x_1	$h_\Theta(x)$
0	$g(10) \approx 1$
1	$g(-10) \approx 0$

$h_\Theta(x) = g(10 - 20x_1)$

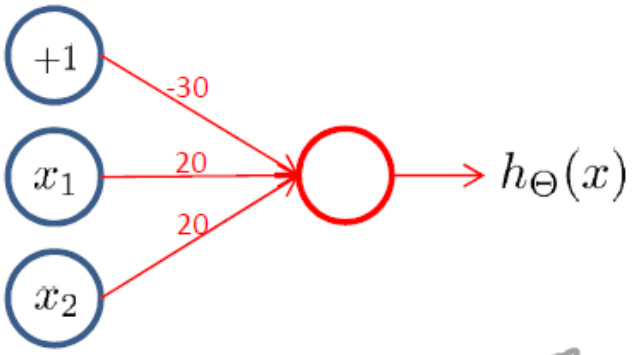
→ (NOT x_1) AND (NOT x_2)

(=1 if and only if

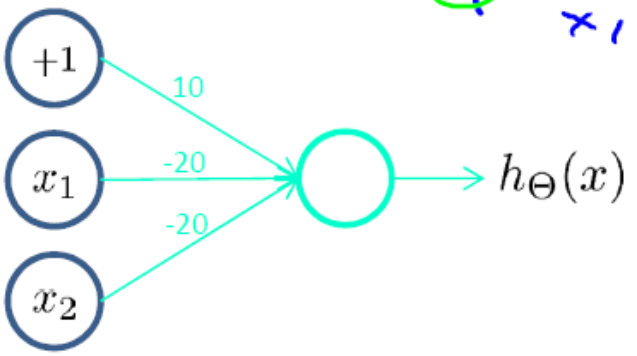
→ $x_1 = x_2 = 0$

Deep Neural Network

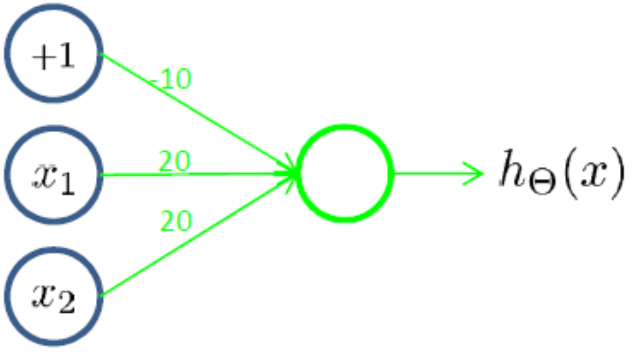
Putting it together: x_1 XNOR x_2



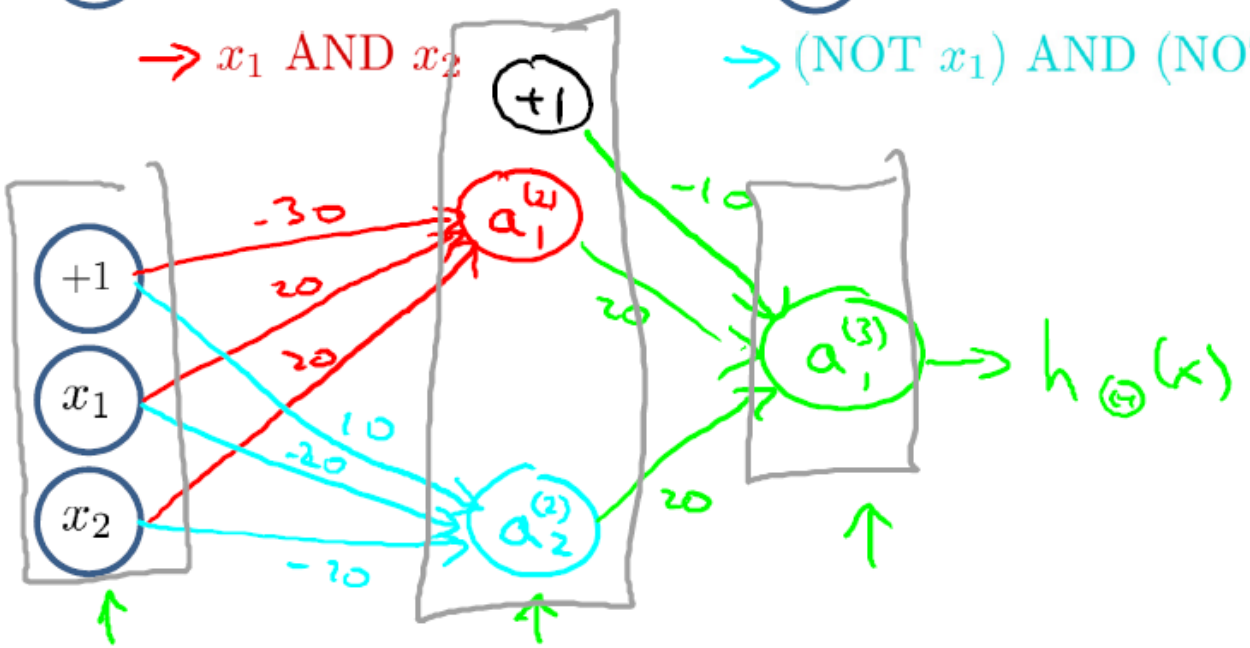
→ x_1 AND x_2



→ (NOT x_1) AND (NOT x_2)

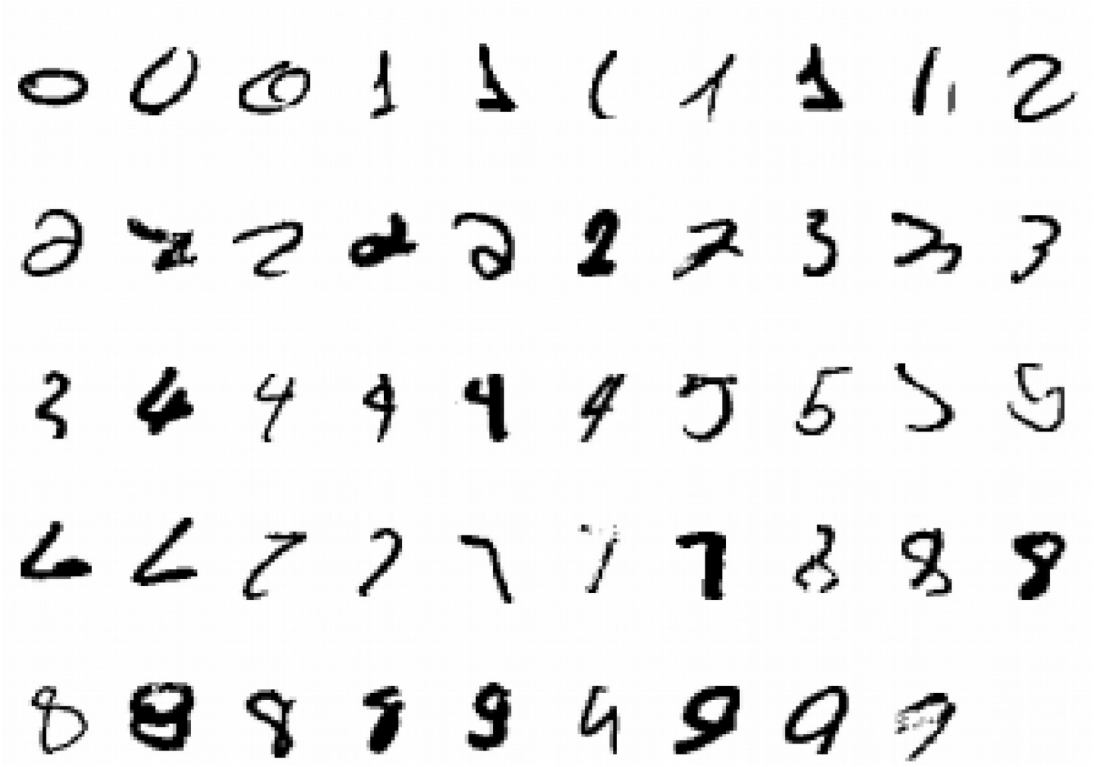


→ x_1 OR x_2



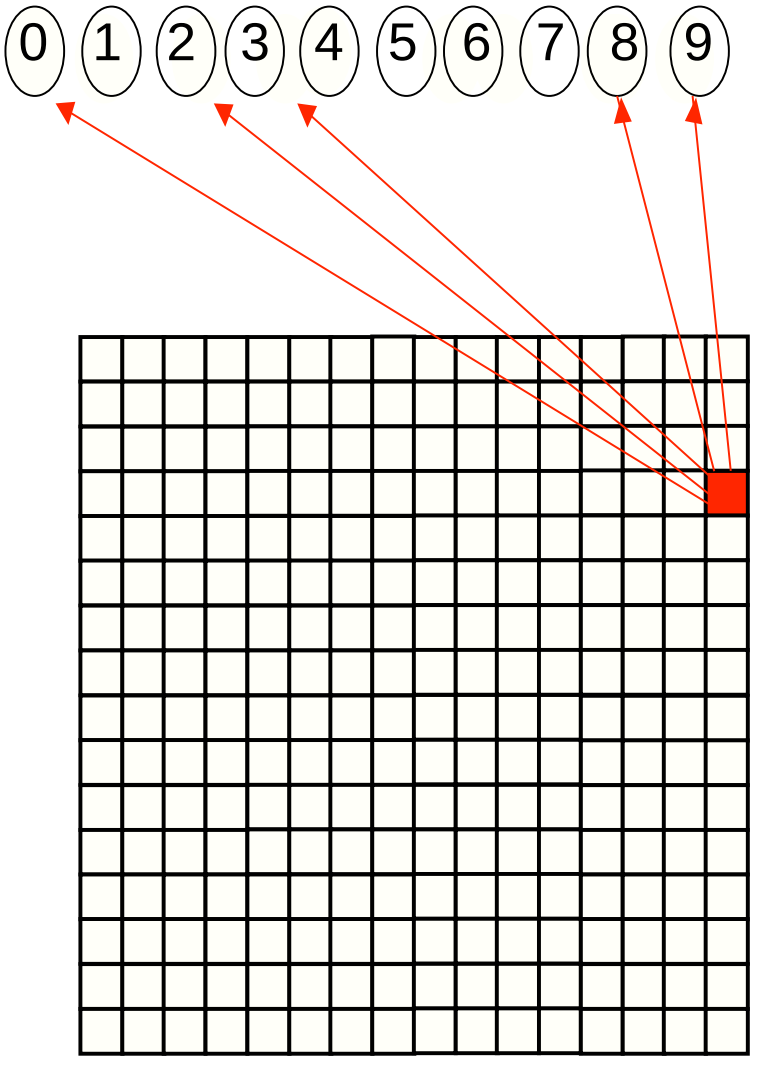
x_1	x_2	$a_1^{(2)}$	$a_2^{(2)}$	$h_\Theta(x)$
0	0	0	1	1
0	1	0	0	0
1	0	0	0	0
1	1	1	0	1

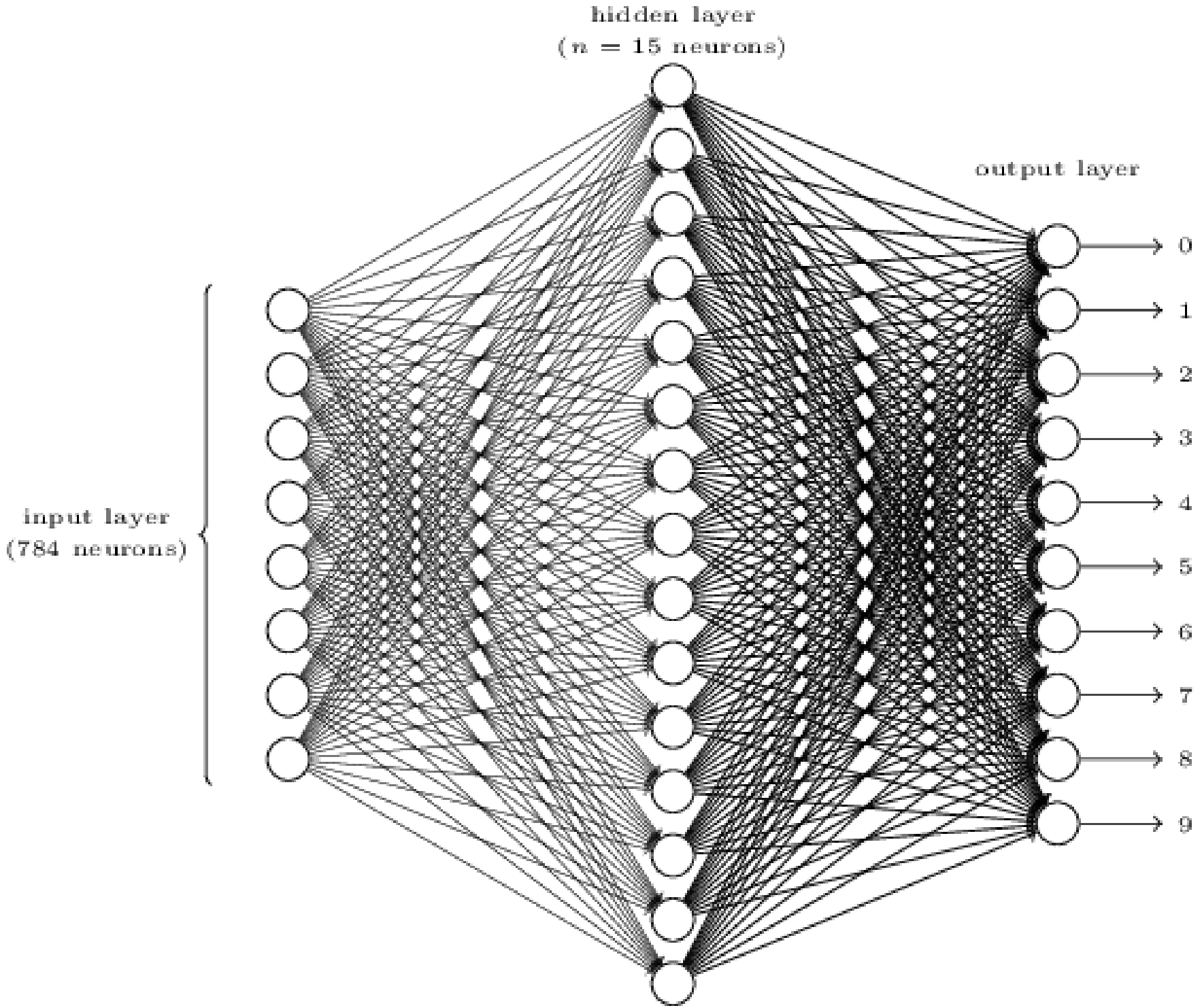
It is very hard to say what makes a 2



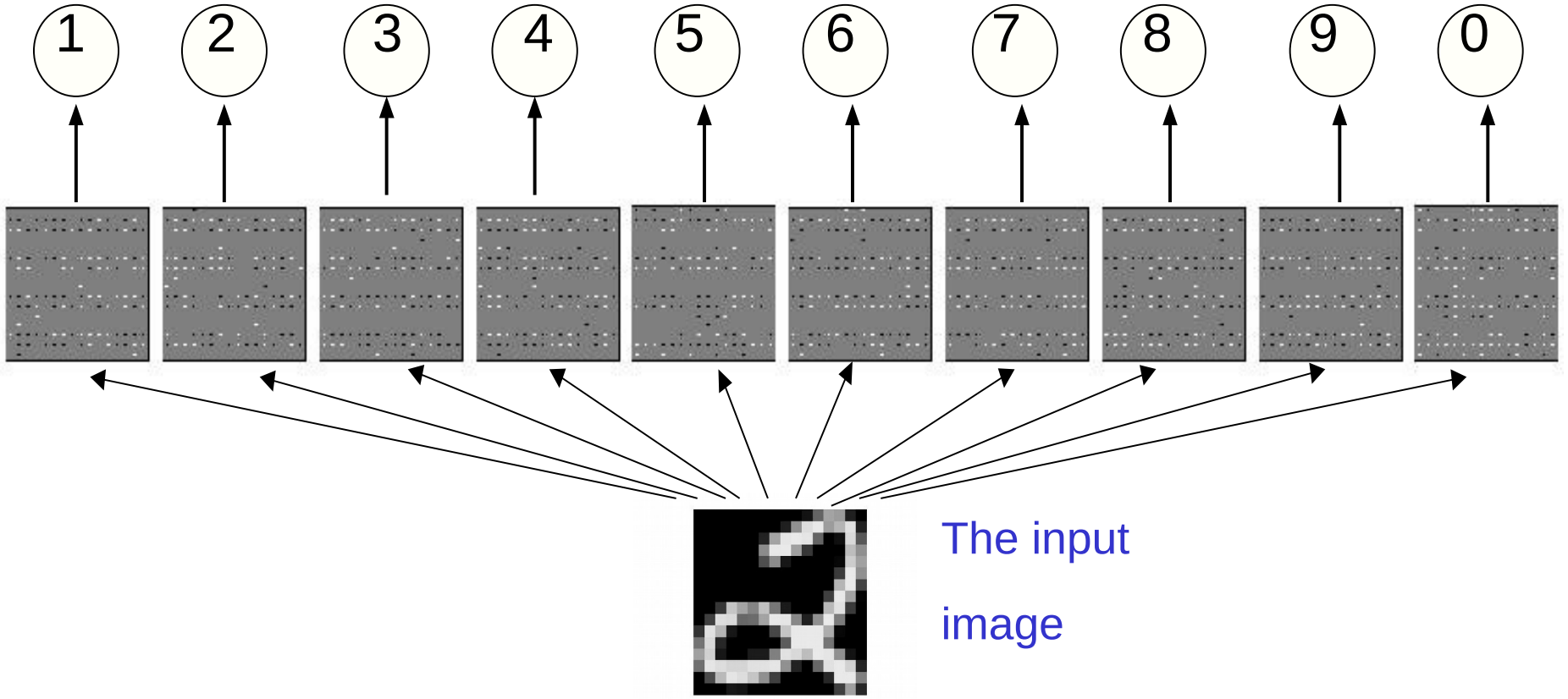
A very simple way to recognize handwritten shapes

- ? Consider a neural network with two layers of neurons.
  - ? neurons in the top layer represent known shapes.
  - ? neurons in the bottom layer represent pixel intensities.
- ? A pixel gets to vote if it has ink on it.
  - ? Each inked pixel can vote for several different shapes.
- ? The shape that gets the most votes wins.




hidden layer
(n = 15 neurons)
output layer
input layer
(784 neurons)
0
1
2
3
4
5
6
7
8
9

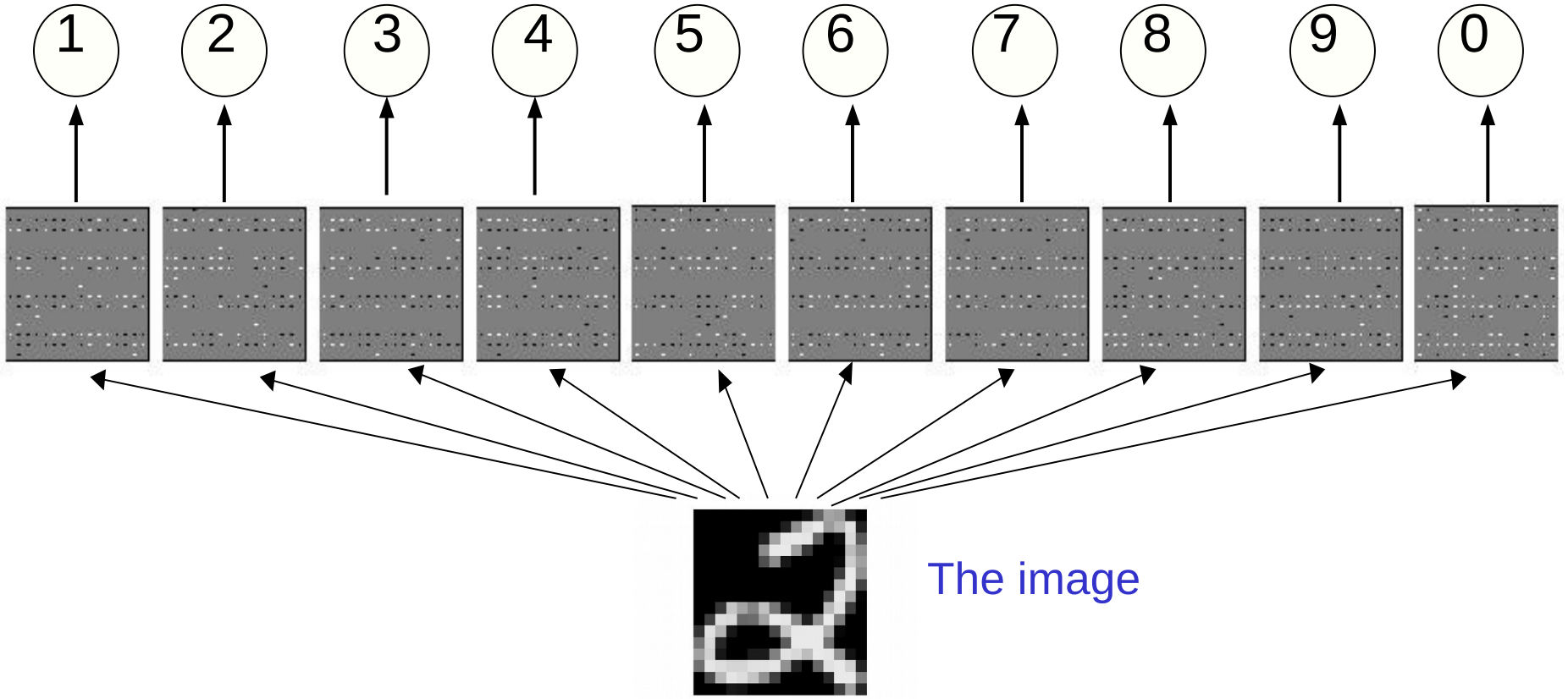
How to display the weights



Give each output unit its own “map” of the input image and display the weight coming from each pixel in the location of that pixel in the map.

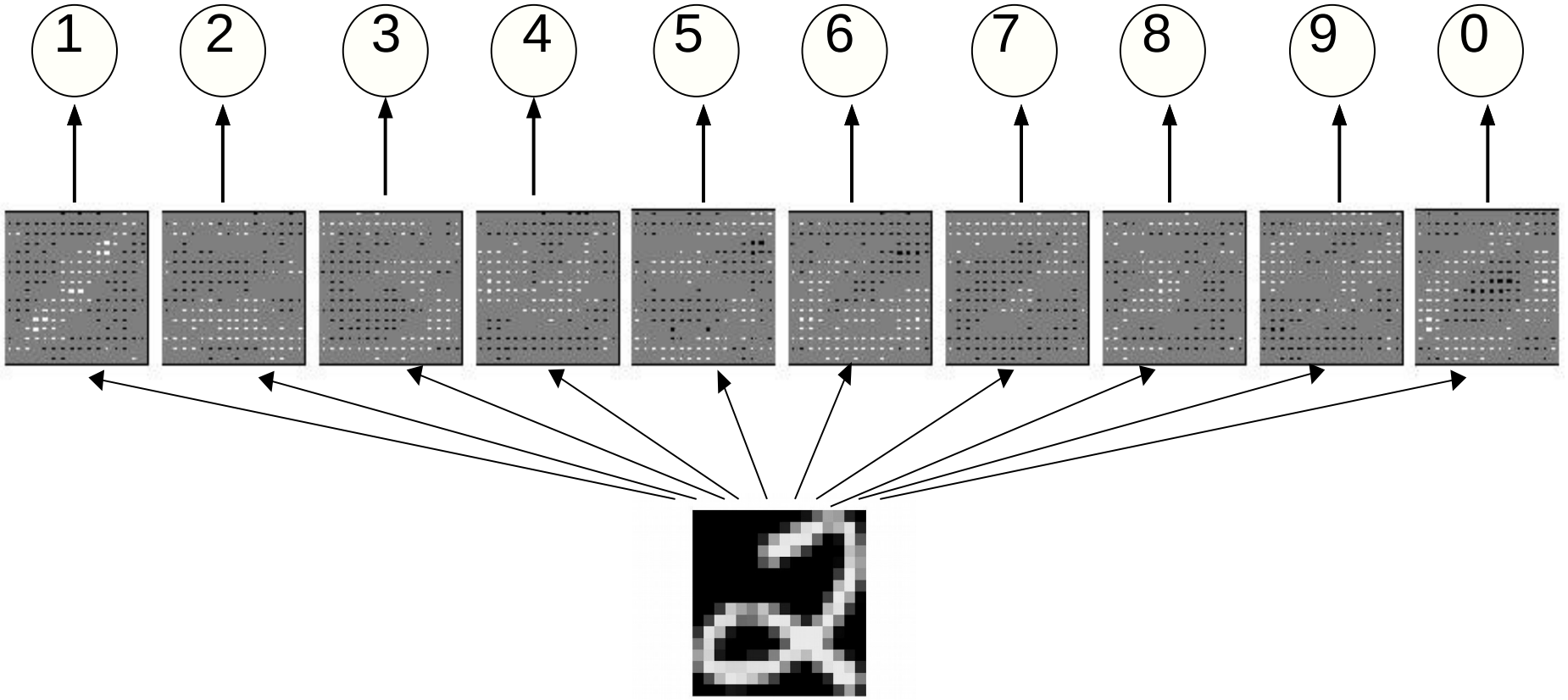
Use a black or white blob with the area representing the magnitude of the weight and the color representing the sign.

How to learn the weights

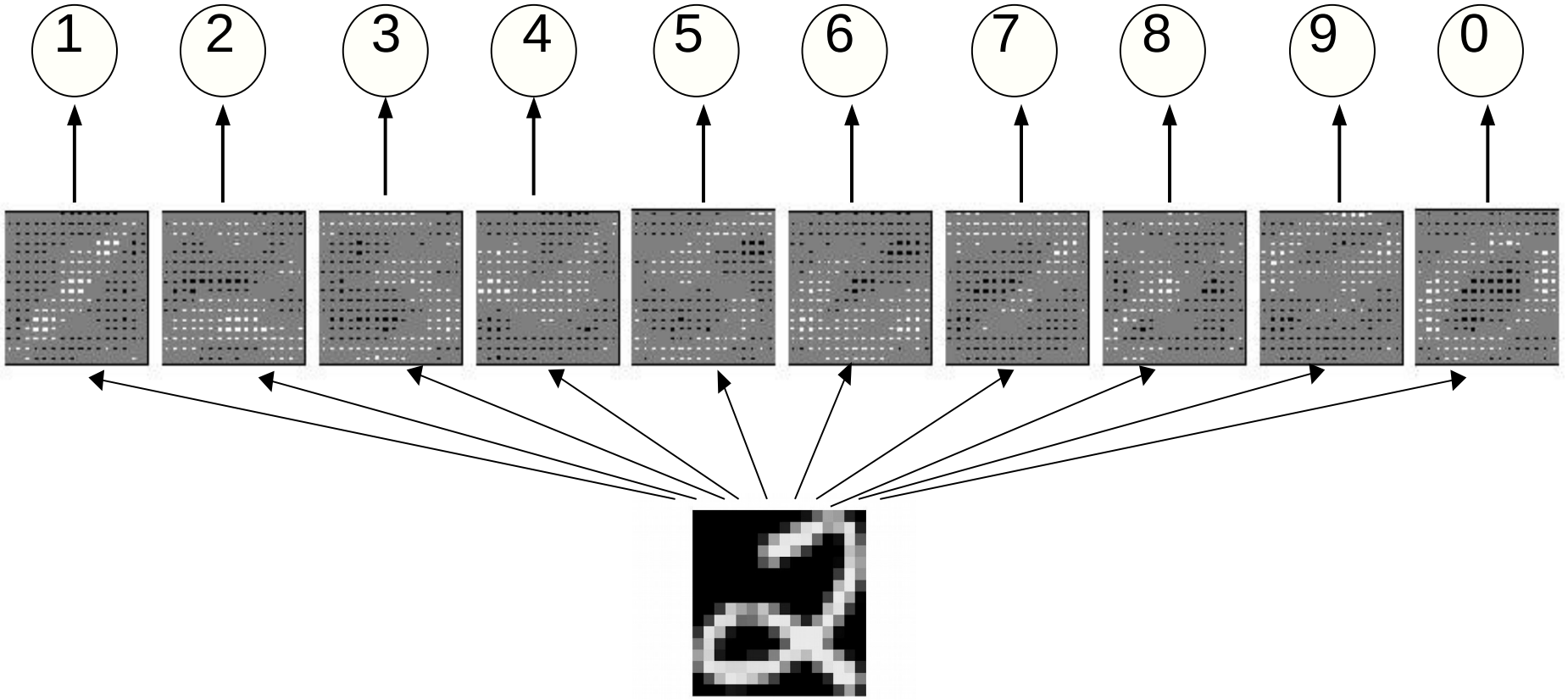


Show the network an image and increment the weights from active pixels to the correct class.

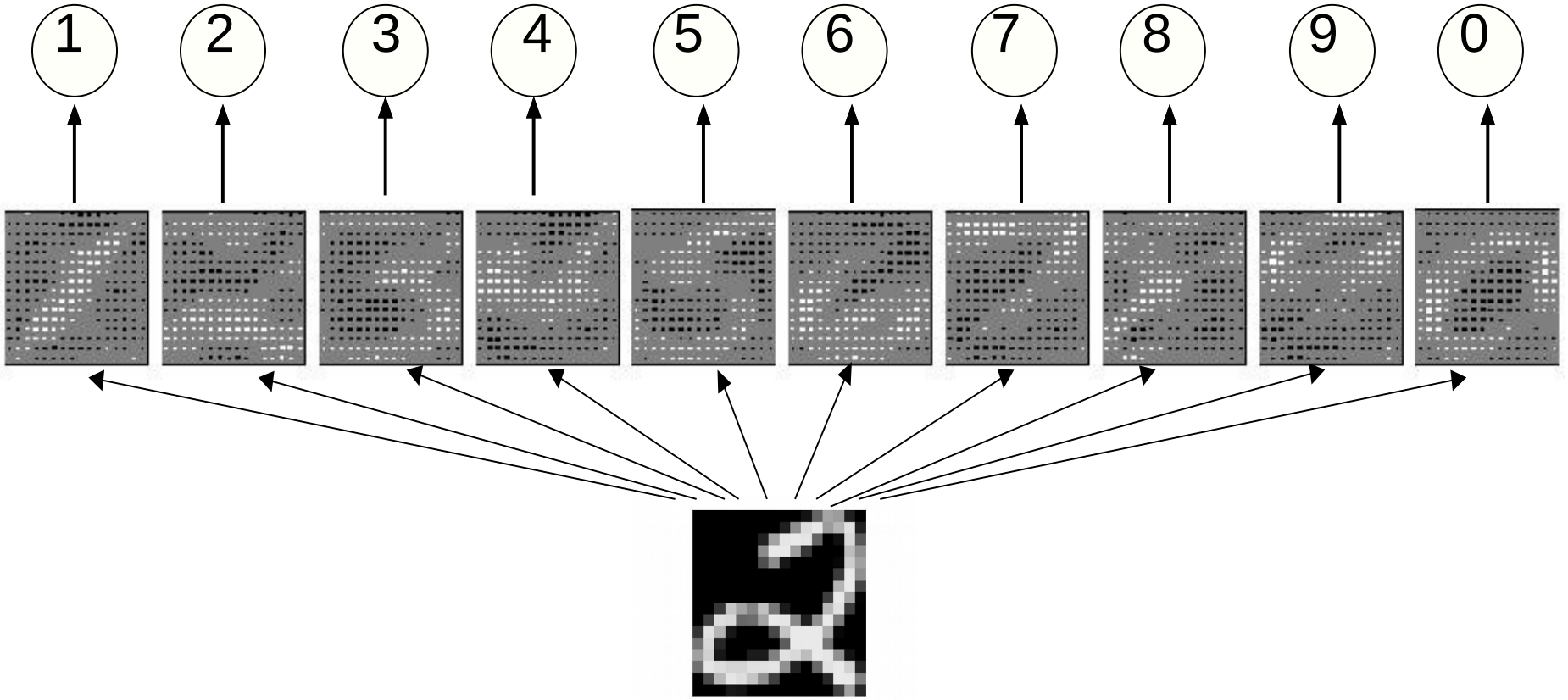
Then decrement the weights from active pixels to whatever class the network guesses.



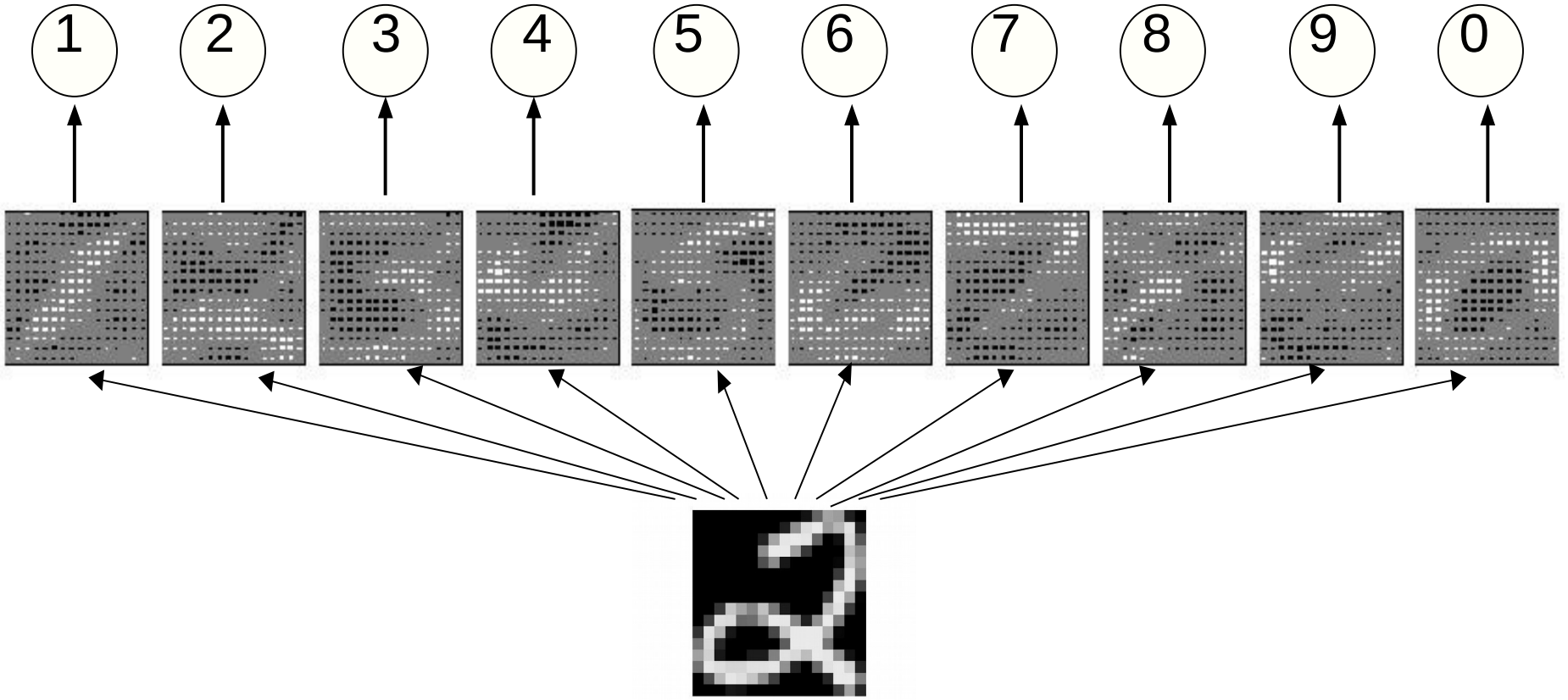
The image



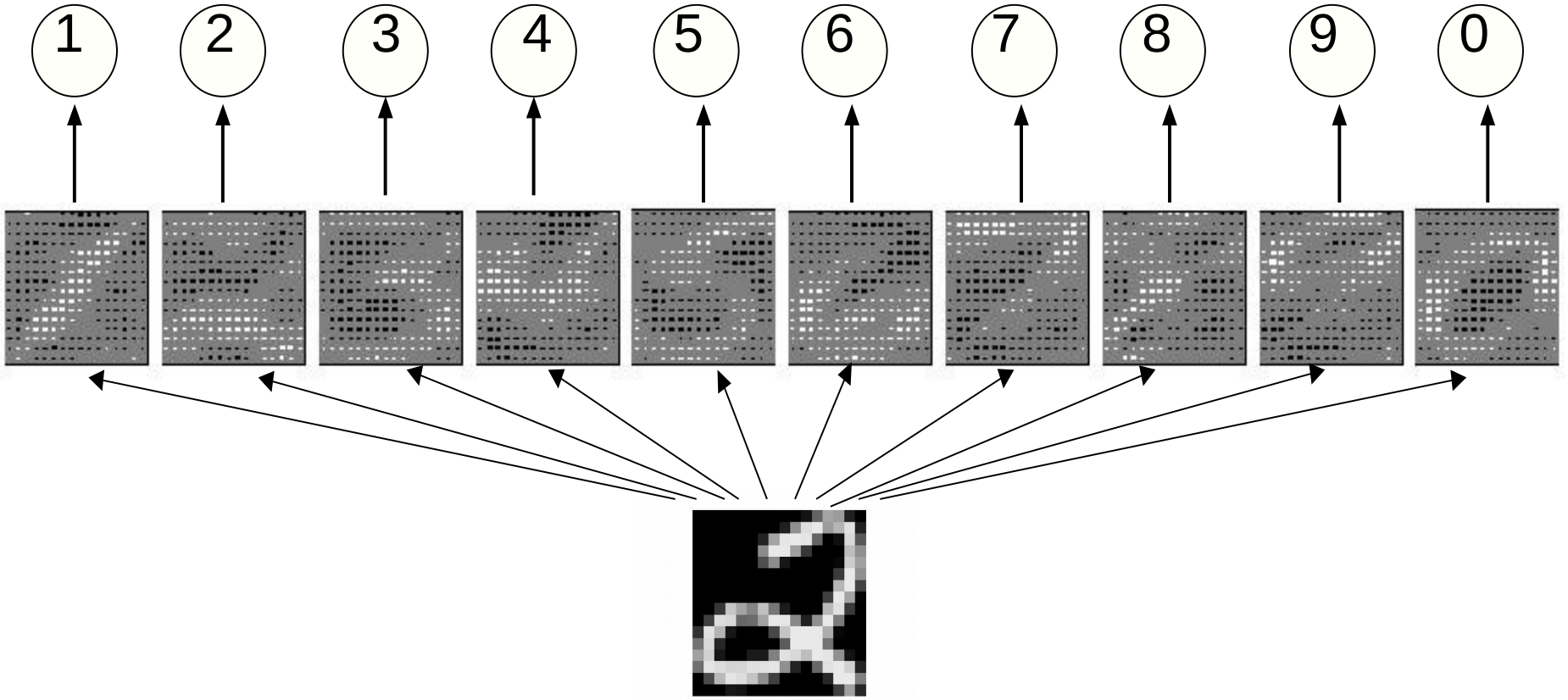
The image



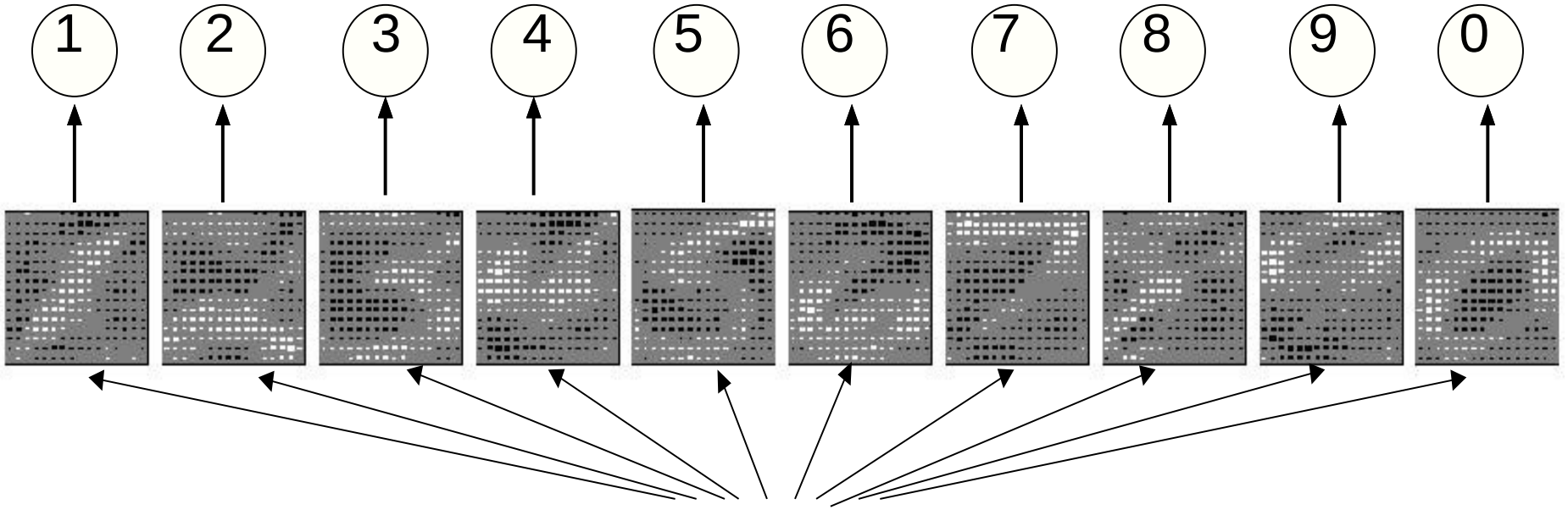
The image



The image

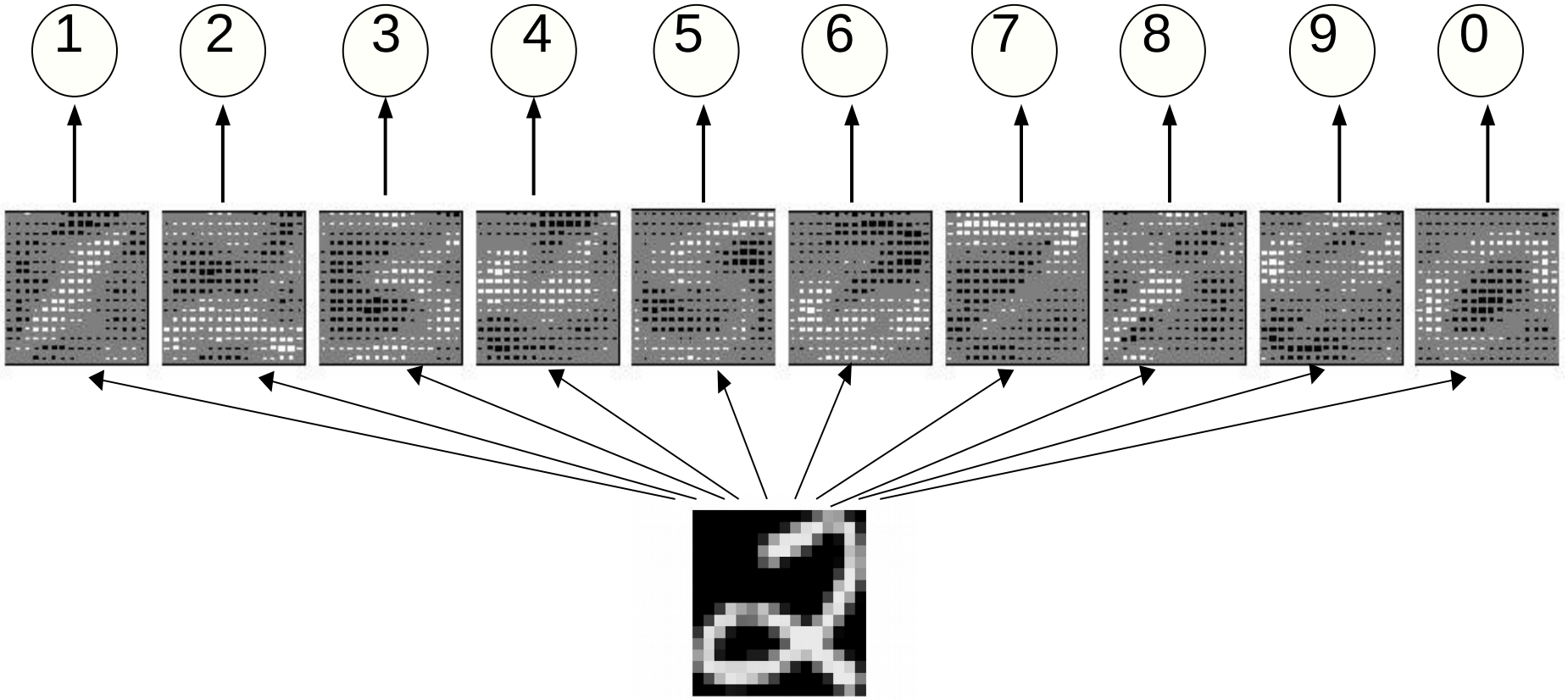


The image

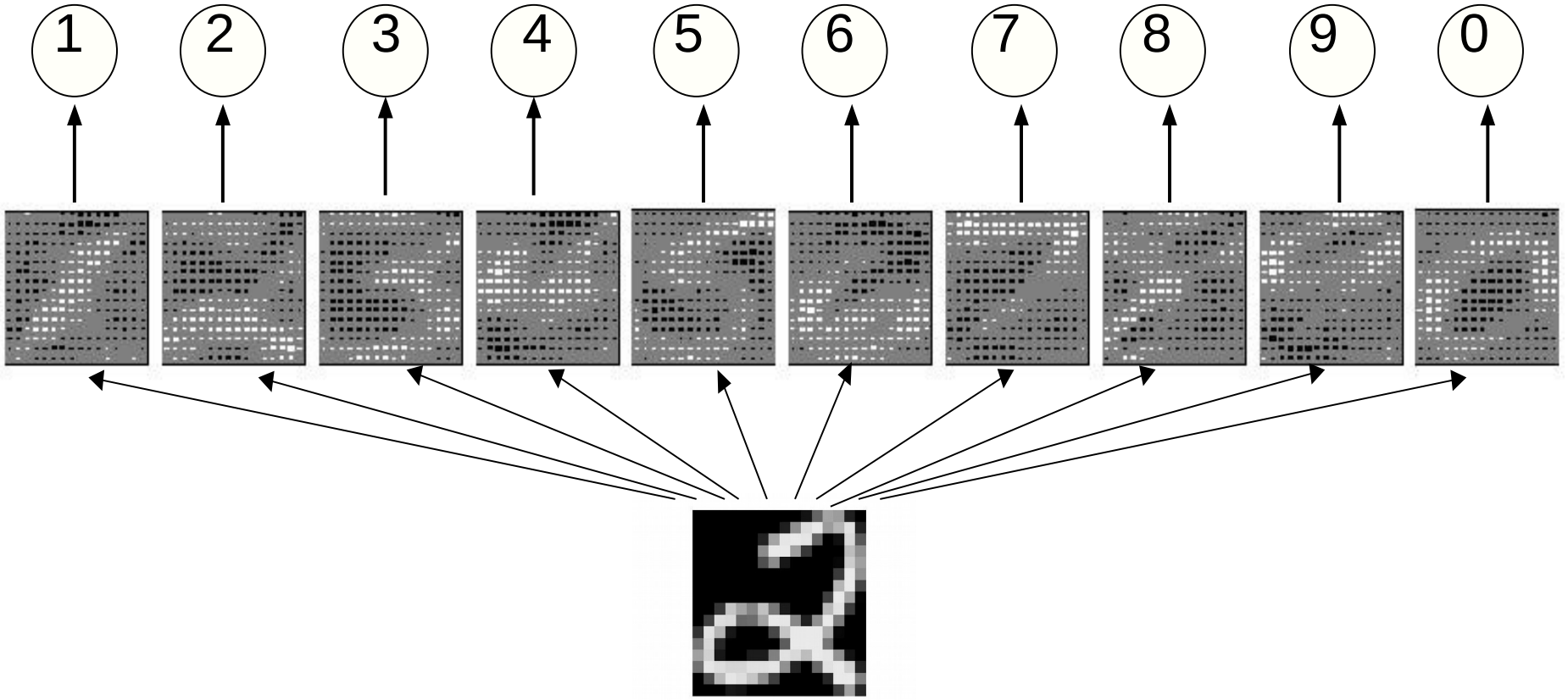


The image

The learned weights



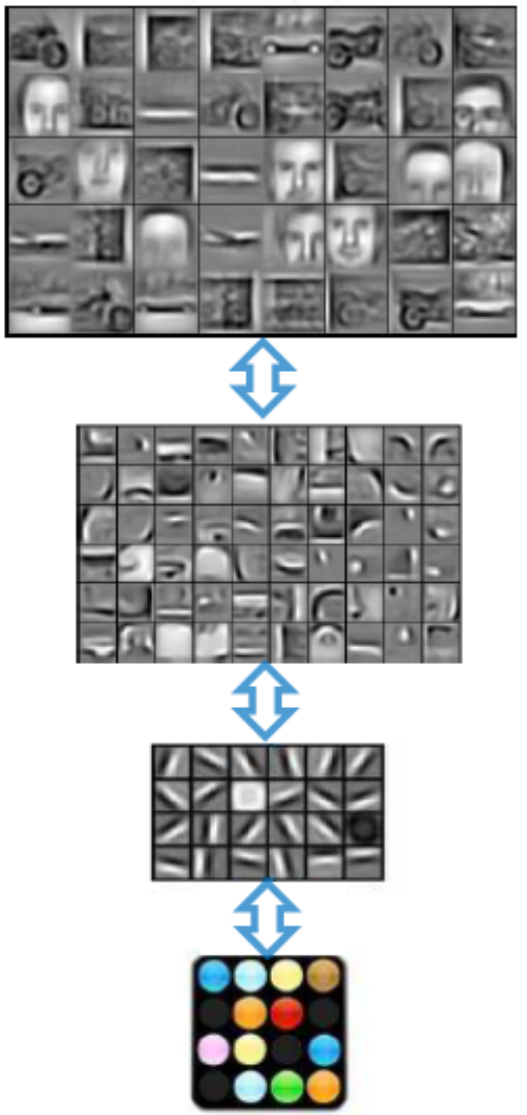
The image

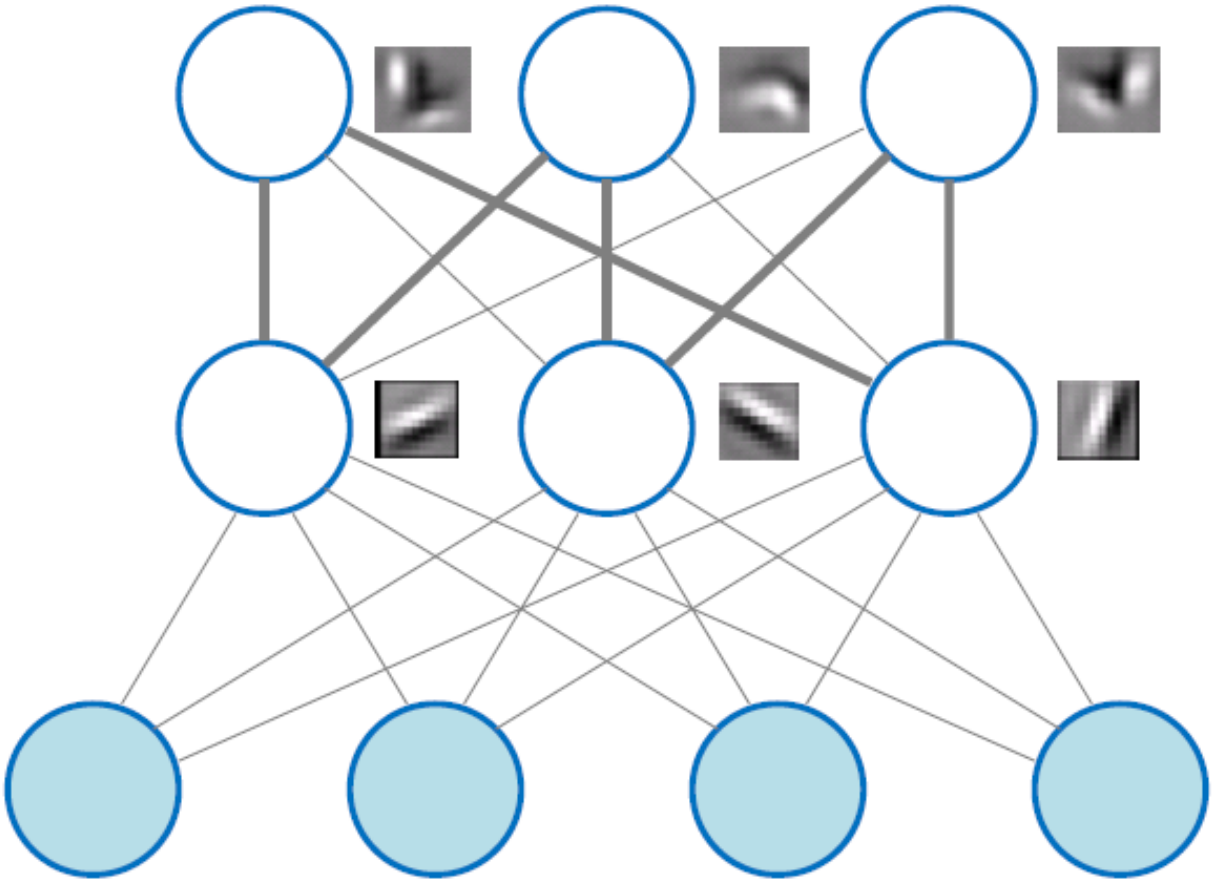


The image

Learning Feature Hierarchy

- Deep Learning
  - Deep architectures can be representationally efficient.
  - Natural progression from low level to high level structures.
  - Can share the lower-level representations for multiple tasks.





Higher layer: DBNs
(Combinations
of edges)

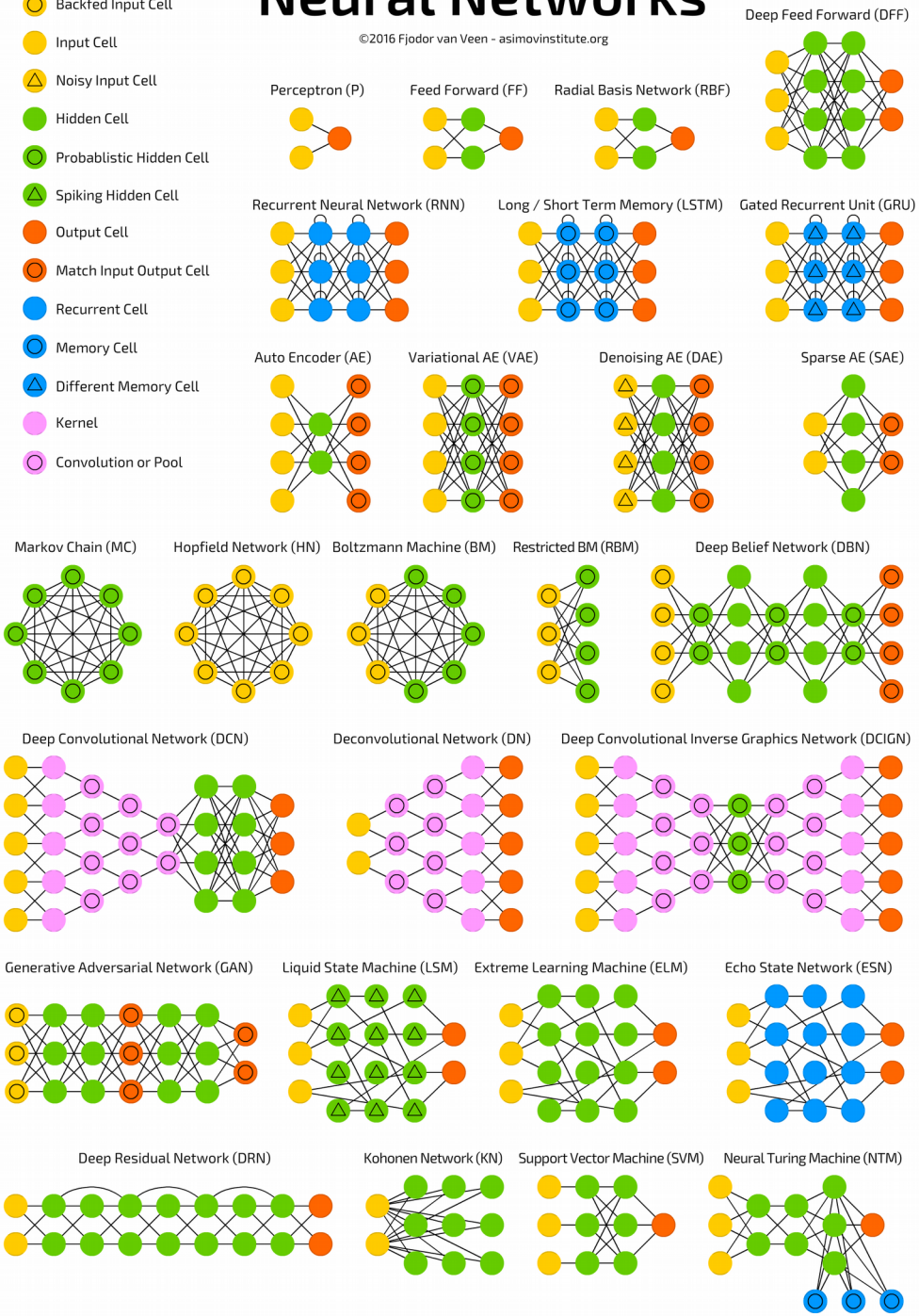
First layer: RBMs
(edges)

Input image patch
(pixels)

A mostly complete chart of

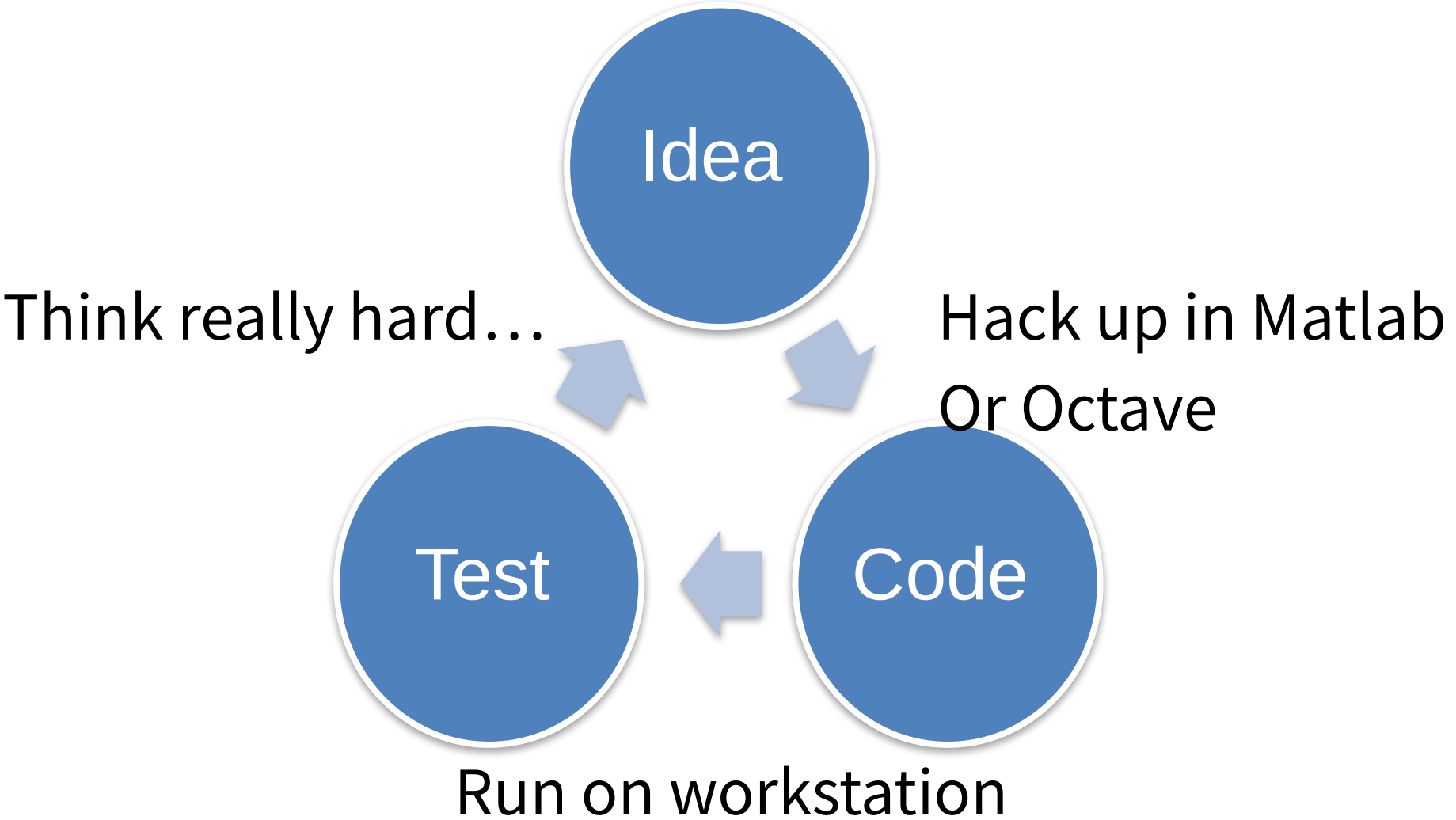
Neural Networks

- Backfed Input Cell
- Input Cell
- Noisy Input Cell
- Hidden Cell
- Probablistic Hidden Cell
- Spiking Hidden Cell
- Output Cell
- Match Input Output Cell
- Recurrent Cell
- Memory Cell
- Different Memory Cell
- Kernel
- Convolution or Pool



AI in practice

- Enormous amounts of research time spent inventing new features.

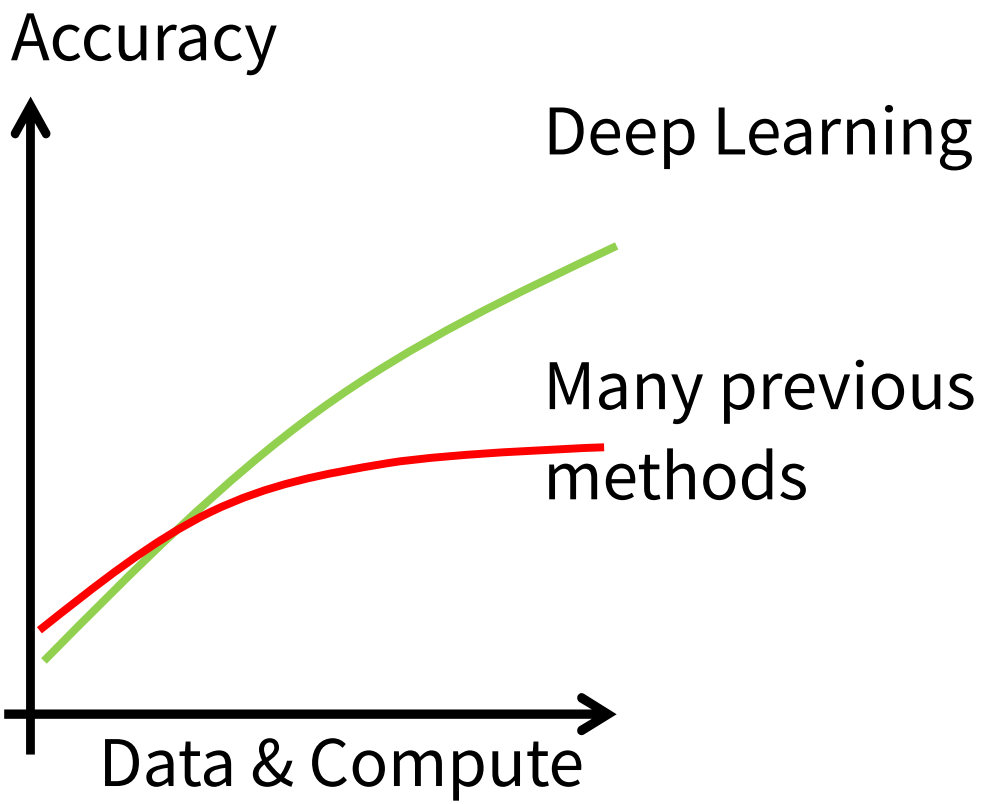


Why Deep Learning?

1. Scale Matters
   - Bigger models usually win

2. Data Matters
   - More data means less cleverness necessary

3. Productivity Matters
   - Teams with better tools can try out more ideas

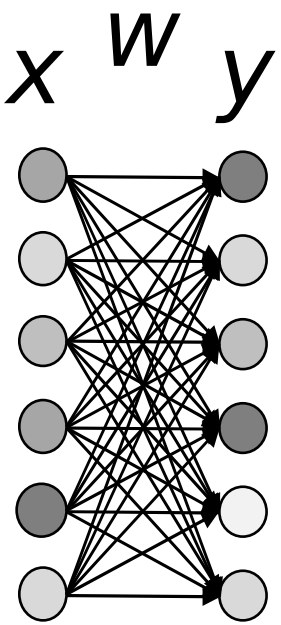


Scaling up

- Make progress on AI by focusing on systems
  - Make models bigger
  - Tackle more data
  - Reduce research cycle time
    - Accelerate large-scale experiments

Training Deep Neural Networks

$$y_j = f\left(\sum_i w_{ij}\, x_i\right)$$



- Computation dominated by dot products
- Multiple inputs, multiple outputs, batch means GEMM
  - Compute bound
- Convolutional layers even more compute bound

Computational Characteristics

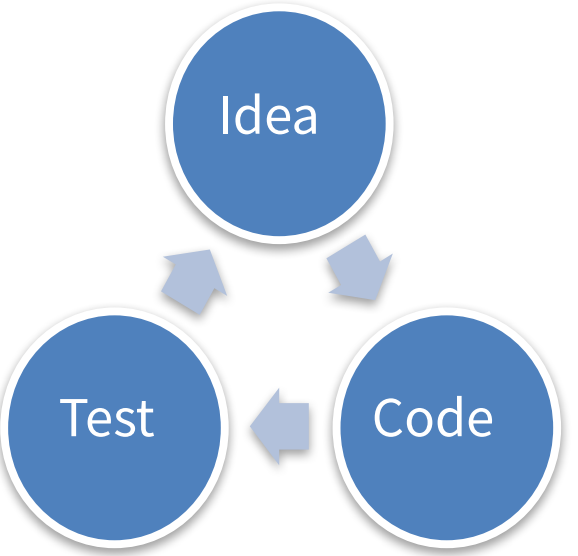
- High arithmetic intensity
  - Arithmetic operations / byte of data
  - O(Exaflops) / O(Terabytes) : 10^6
    - In contrast, some other ML training jobs are O(Petaflops)/O(Petabytes) = 10^0

- Medium size datasets
  - Generally fit on 1 node
  - HDFS, fault tolerance, disk I/O not bottlenecks

Training 1 model: ~20 Exaflops

Deep Neural Network training is HPC

- Turnaround time is key
- Use most efficient hardware
  - Parallel, heterogeneous computing
  - Fast interconnect (PCIe, Infiniband)
- Push strong scalability
  - Models and data have to be of commensurate size



Infrastructure

- Software: CUDA, MPI, Majel (internal library)
- Hardware:

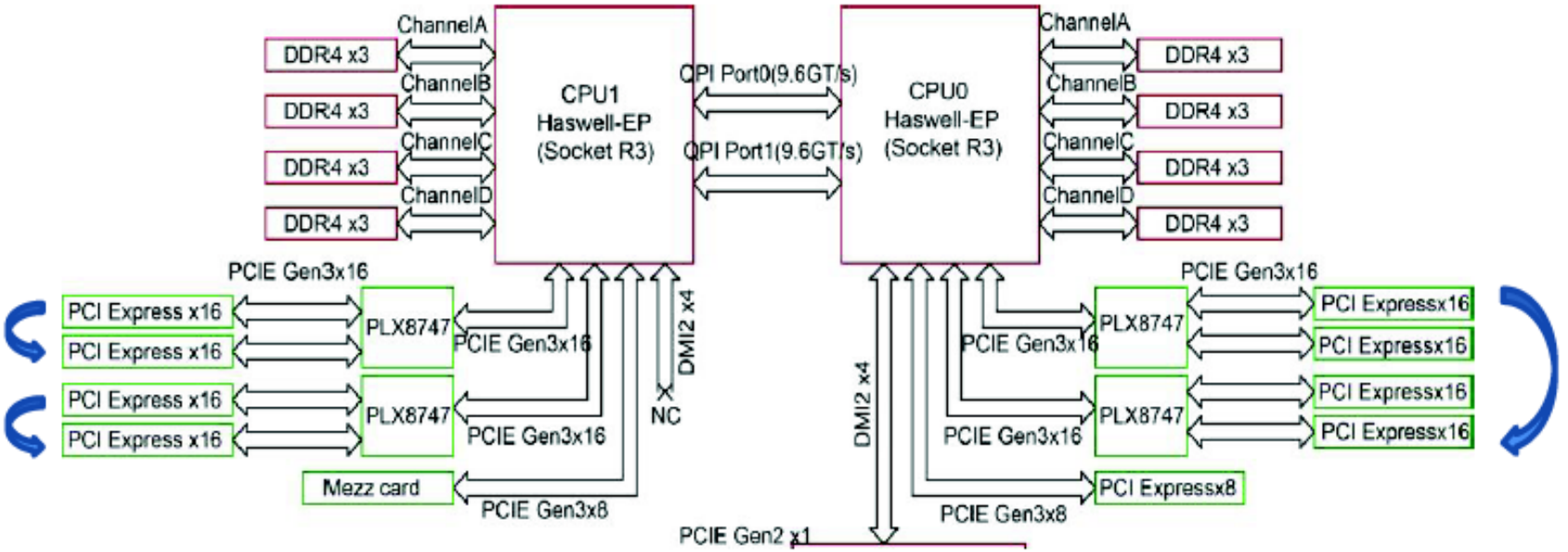
NVIDIA GeForce GTX Titan X

Titan X x8

Mellanox Interconnect

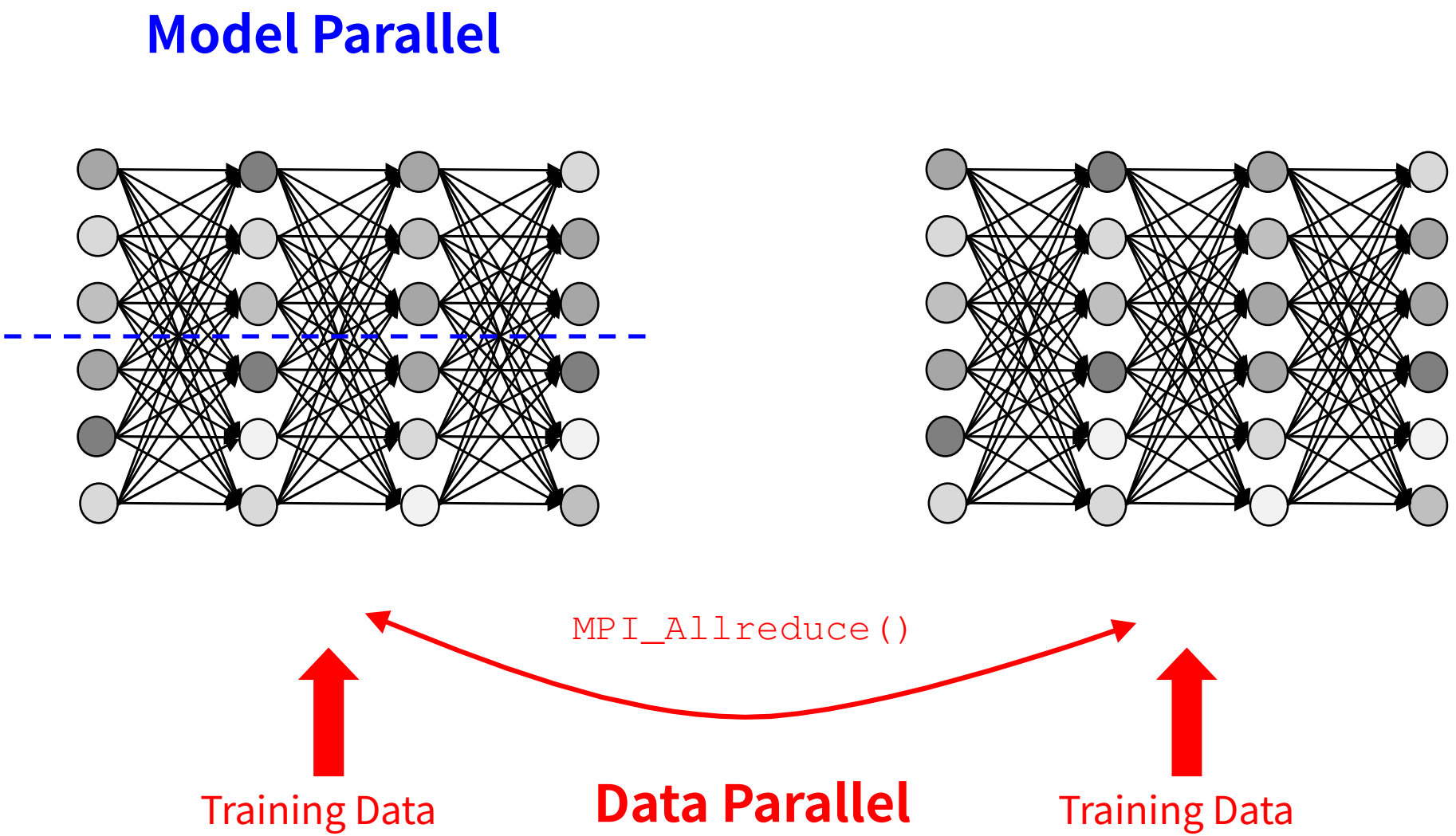
http://www.tyan.com

Node Architecture



- All pairs of GPUs communicate simultaneously over PCIe Gen 3 x16
- Groups of 4 GPUs form Peer to Peer domain
- Avoid moving data to CPUs or across QPI

Parallelism



Determinism

- Determinism very important
- So much randomness,
  hard to tell if you have a bug
- Networks train despite bugs,
  although accuracy impaired
- Reproducibility is important
  - For the usual scientific reasons
  - Progress not possible without reproducibility

Conclusions

- Computationally dense processors (like GPUs) required
- Programmability
  - We don't know the algorithms of the future
- Lower precision
  - But not too low
  - Interesting algorithm/dataset engineering here
- We need better support for multi-GPU
  - E.g. Atomics between GPUs, collectives
  - Looking forward to NVLink

Conclusions

- Deep Learning is solving many hard problems
- Training deep neural networks is an HPC problem
- Scaling brings AI progress!

How can we help fintechs?

- Discover regulatory and compliance issues before violations happen, preventing fines and enforcement investigations.
- Advanced pattern recognition detects activity likely to be high-risk, flagging hidden threats well before disaster strikes.
- Examines profitability, cost drivers, and industry-specific risk factors to incentivize behaviors and improve firm performance.
- Finds outlier events, by understanding historical trends, environmental context and correlation within firm activity.
- We show financial institutions the true power of artificial intelligence by delivering clearly prioritized calls to action. This empowers decision makers to solve challenging business problems.

How can we help fintechs?

- SPOOFING SIMILARITY
- ABUSIVE MESSAGING DETECTION
- MOMENTUM IGNITION DETECTION
- SUSPICIOUS PRICE MOVEMENT DETECTION
- PINGING AND PHISHING DETECTION
- WASH TRADE DETECTION
- CROSS TRADE DETECTION
- CLOSING PERIOD ABUSE DETECTION