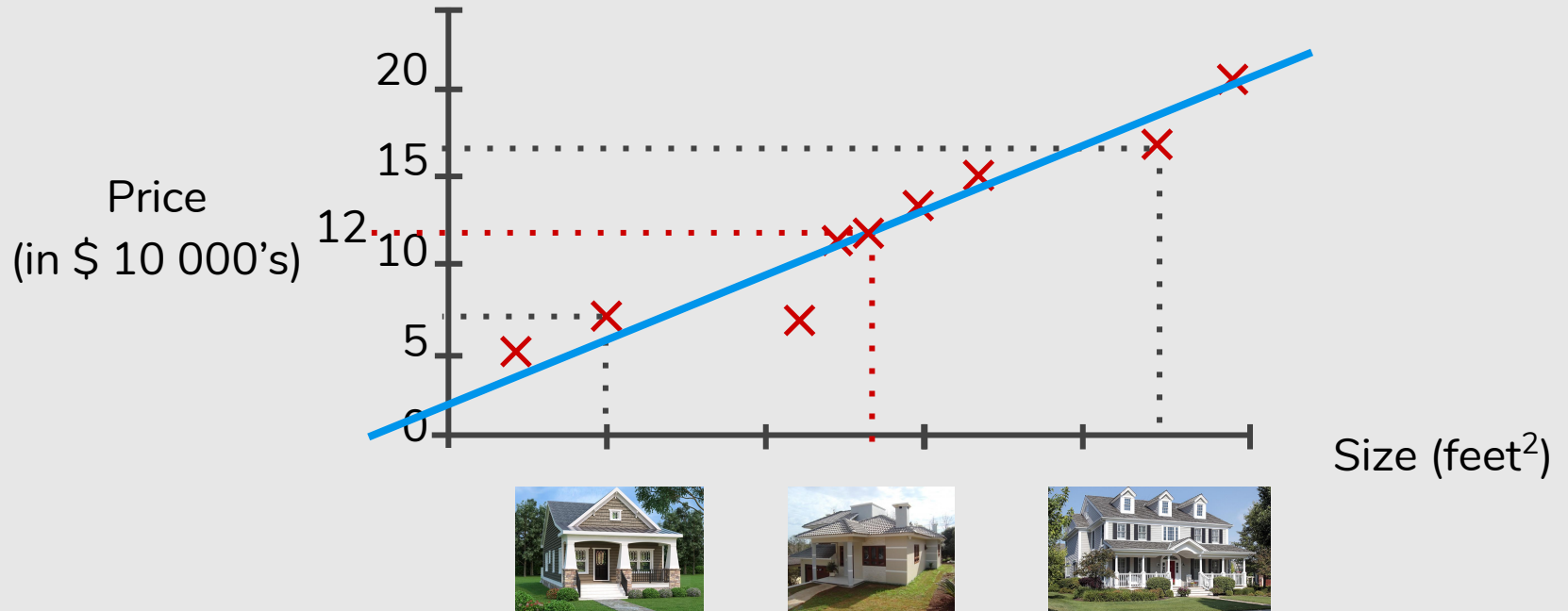


Recall from last time ...

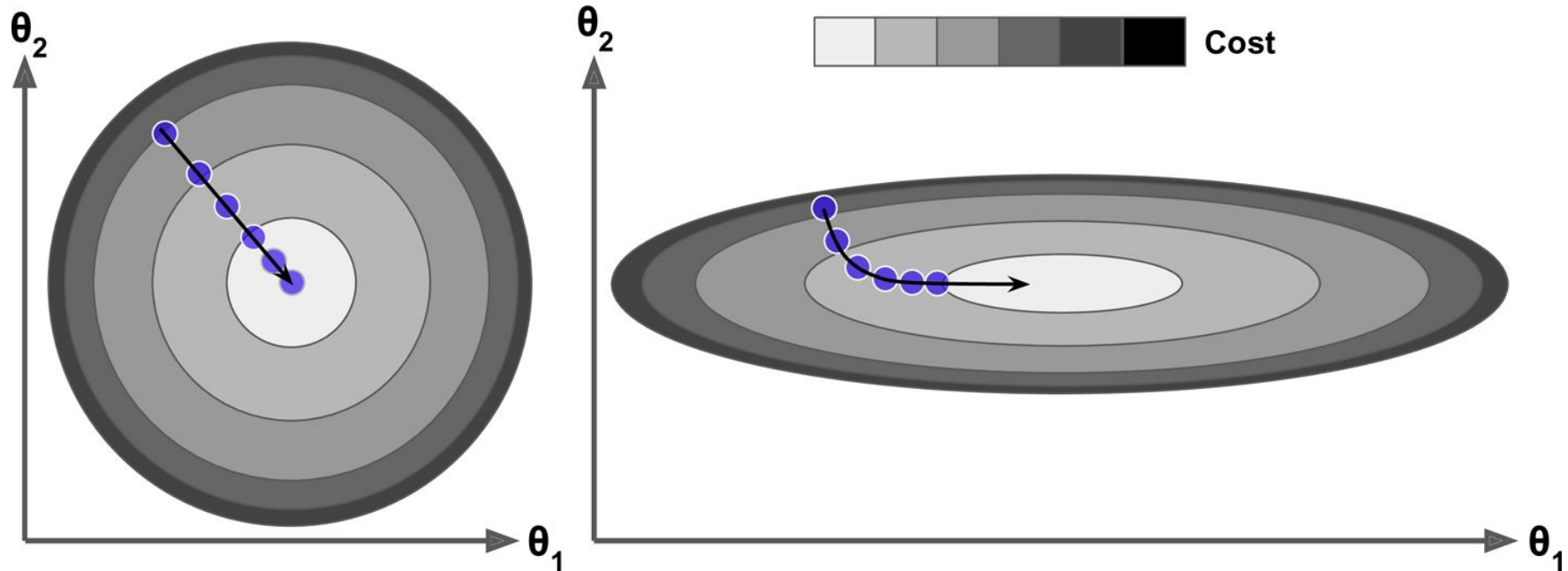
Linear Regression



Feature Scaling

Feature Scaling

Idea: Make sure features are on similar scale.



Features and Polynomial Regression

Housing prices prediction

$$h_{\theta}(x) = \theta_0 + \theta_1 \times \text{frontage} + \theta_2 \times \text{depth}$$



x_1



x_2



Area $x = \text{frontage} \times \text{depth}$

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

Normal Equation

Examples: $m = 4$.

x_0	Size (feet ²) x_1	Number of bedrooms x_2	Number of floors x_3	Age of home (years) x_4	Price (\$) in 1000's y
1	2104	5	1	45	460
1	1416	3	2	40	232
1	1534	3	2	30	315

$X =$ features/variables

$y =$ target

$\theta =$ parameters

$$X = \begin{bmatrix} 1 & 2104 & 5 & 1 & 45 \\ 1 & 1416 & 3 & 2 & 40 \\ 1 & 1534 & 3 & 2 & 30 \\ 1 & 852 & 2 & 1 & 36 \end{bmatrix}_{m \times (n+1)} \quad y = \begin{bmatrix} 460 \\ 232 \\ 315 \\ 178 \end{bmatrix}_m$$

$$\theta = (X^T X)^{-1} X^T y$$



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- Neural Networks ...



Essence of linear algebra

14 videos • 3,671,987 views • Last updated on Aug 1, 2018



3Blue1Brown

A geometric understanding of matrices, determinants, eigen-stuffs and more.

- 10 **Cross products** | Essence of linear algebra, Chapter 10
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- 11 **Cross products as transformations** | Essence of linear algebra
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- 12 **Change of basis** | Essence of linear algebra, chapter 12
3Blue1Brown
- 13 **Eigenvectors and eigenvalues** | Essence of linear algebra, chapter 13
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- 14 **Abstract vector spaces** | Essence of linear algebra, chapter 14

Gradient Descent

- 🙄 Need to choose α .
- 🙄 Needs many iterations.
- 😄 Works well even when n is large.

m examples and n features

Normal Equation

- 😄 No need to choose α .
- 😄 Don't need to iterate.
- 😄 **Don't need to scale.**
- 🙄 Need to compute $(X^T X)^{-1} \rightarrow O(n^3)$.
- 🙄 Slow if n is very large.

Categorical/Nominal Variables

Size (feet ²) x_1	Number of bedrooms x_2	Number of floors x_3	Age of home (years) x_4	Color x_5	Price (\$) in 1000's y
2104	5	1	45	blue	460
1416	3	2	40	white	232
1534	3	2	30	pink	315
852	2	1	36	green	178

Categorical/Nominal Variables

Dummy coding & One-hot encoding

<http://www.statisticssolutions.com/dummy-coding-the-how-and-why/>

[https://en.wikiversity.org/wiki/Dummy_variable_\(statistics\)](https://en.wikiversity.org/wiki/Dummy_variable_(statistics))

Categorical/Nominal Variables

Dummy coding & One-hot encoding

- blue = 1, white = 2, pink = 3, and green = 4.

<http://www.statisticssolutions.com/dummy-coding-the-how-and-why/>

[https://en.wikiversity.org/wiki/Dummy_variable_\(statistics\)](https://en.wikiversity.org/wiki/Dummy_variable_(statistics))

Categorical/Nominal Variables

Dummy coding & **One-hot encoding**

color	blue	white	pink	green
blue	1	0	0	0
white	0	1	0	0
pink	0	0	1	0
green	0	0	0	1

In this simplified data set, if we know that color is not Blue, not White, and not Pink, then it is Green.

So we only need to use three of these four.

Logistic Regression

Machine Learning

(Largely based on slides from Andrew Ng)

Prof. Sandra Avila
Institute of Computing (IC/Unicamp)

MC886, August 21, 2019

Today's Agenda

- Logistic Regression
 - Classification
 - Hypothesis Representation
 - Decision Boundary
 - Cost Function
 - Simplified Cost Function and Gradient Descent
 - Multiclass Classification

Classification

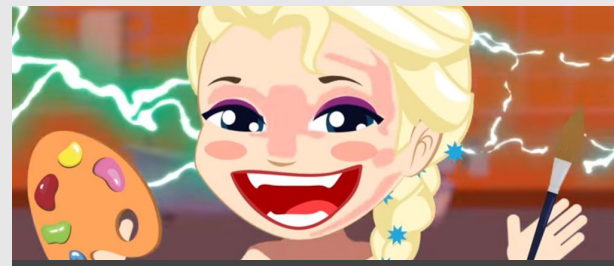
Spam Filtering



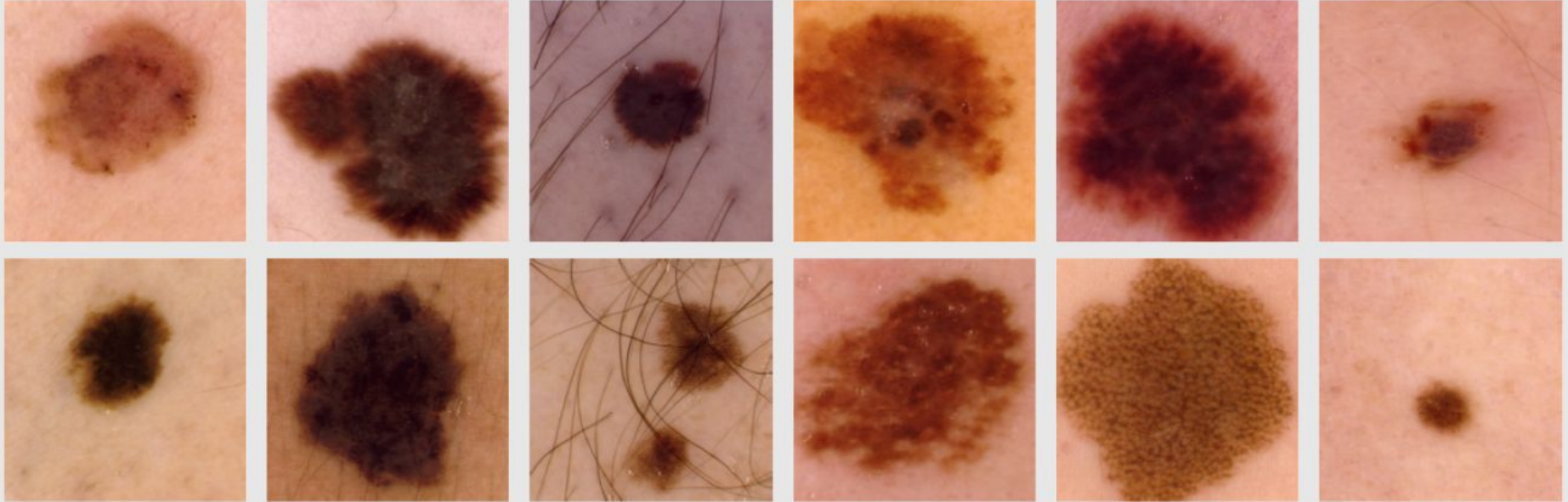
Bad Cures fast and effective! - Canadian *** Pharmacy #1 Internet
Inline Drugstore Viagra Cheap Our price \$1.99 ...

Good Interested in your research on graphical models - Dear Prof., I
have read some of your papers on probabilistic graphical models.
Because I ...

Sensitive Content Classification (Elsagate)



Skin Cancer Classification



Melanomas (top row) and **benign** skin lesions (bottom row)

Classification

Email: **Spam** / **Not Spam**?

Content Video: **Sensitive** / **Non-sensitive**?

Skin Lesion: **Malignant** / **Benign**?

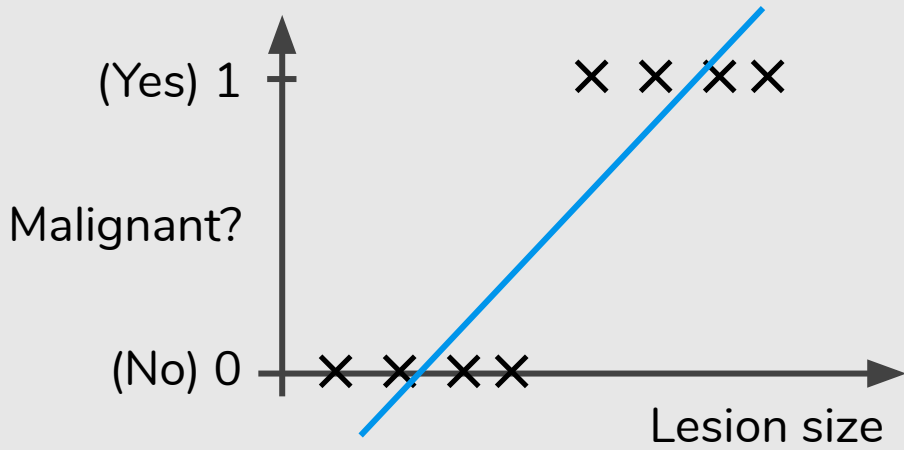
Classification

Email: **Spam** / **Not Spam**?

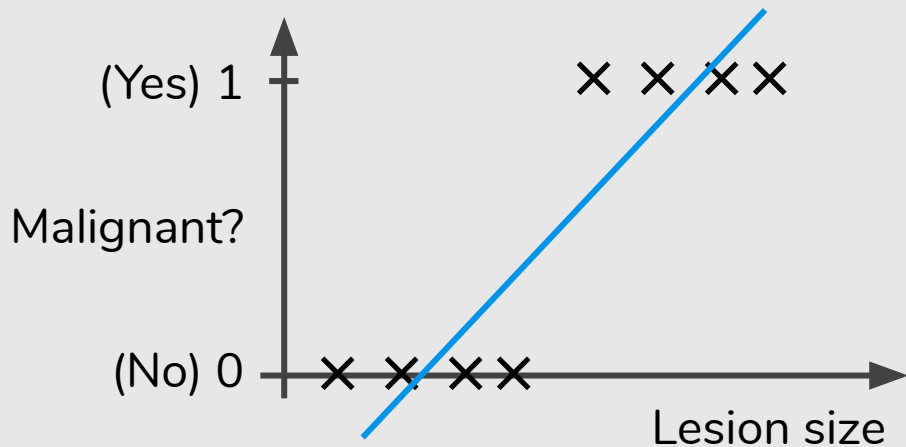
Content Video: **Sensitive** / **Non-sensitive**?

Skin Lesion: **Malignant** / **Benign**?

$y \in \{0,1\}$ 0: “Negative Class” (e.g., Benign skin lesion)
 1: “Positive Class” (e.g., Malignant skin lesion)



$$h_{\theta}(x) = \theta^T x$$

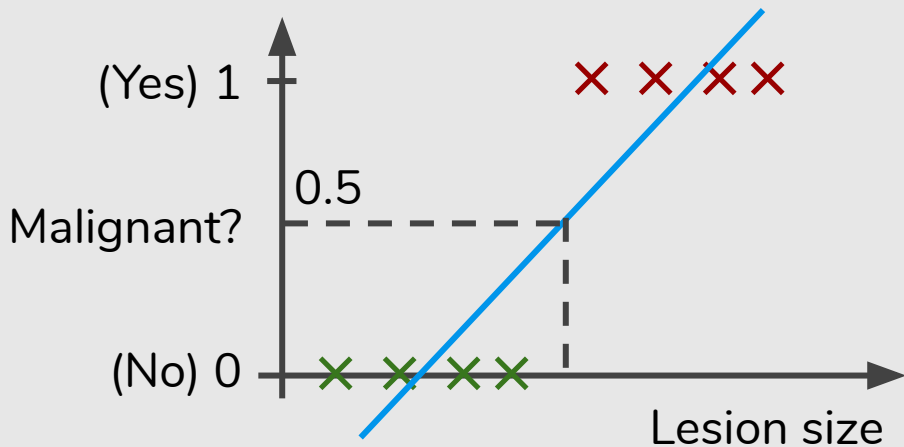


$$h_{\theta}(x) = \theta^T x$$

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 “ $y = 0$ ”



$$h_{\theta}(x) = \theta^T x$$

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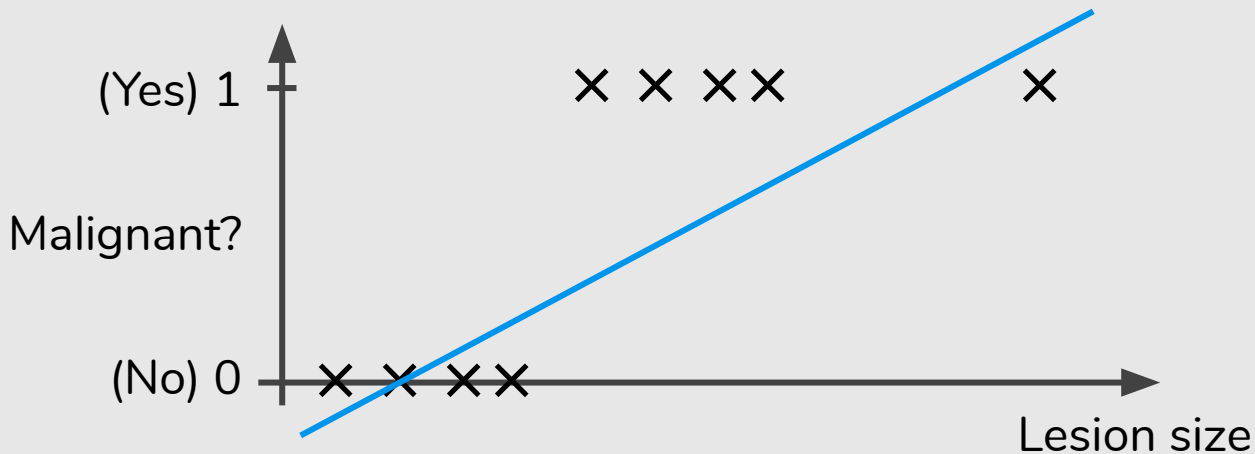


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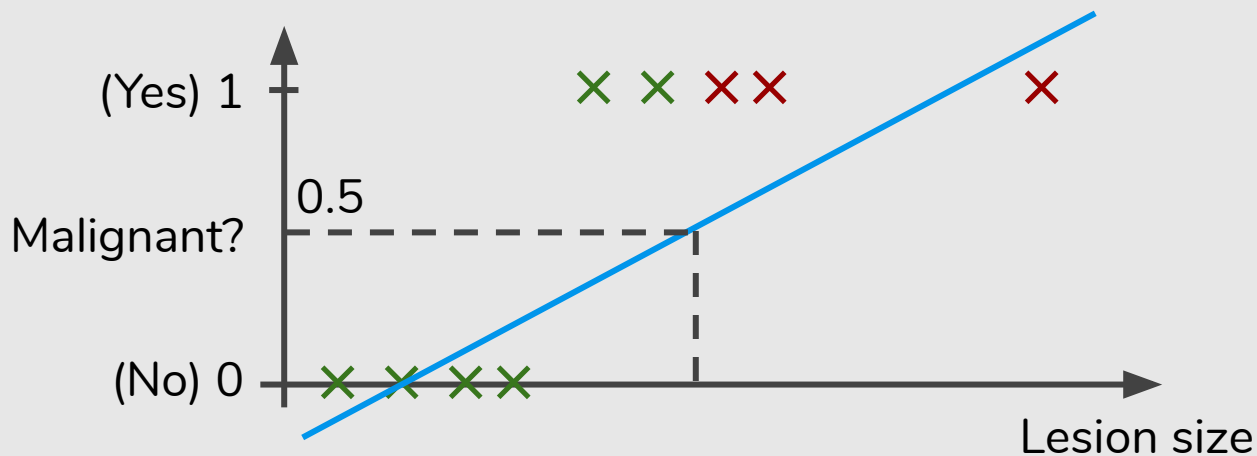


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$$h_{\theta}(x) = \theta^T x$$

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 “ $y = 0$ ”

Classification: $y = 0$ or $y = 1$

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

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

Hypothesis Representation

Logistic Regression Model

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

Logistic Regression Model

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

$$h_{\theta}(x) = \theta^T x$$

Logistic Regression Model


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

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

Logistic Regression Model

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


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


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

Logistic Regression Model

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

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


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

Sigmoid Function


Logistic Function

Logistic Regression Model

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

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

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


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

Sigmoid Function

Logistic Function

Logistic Regression Model

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

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

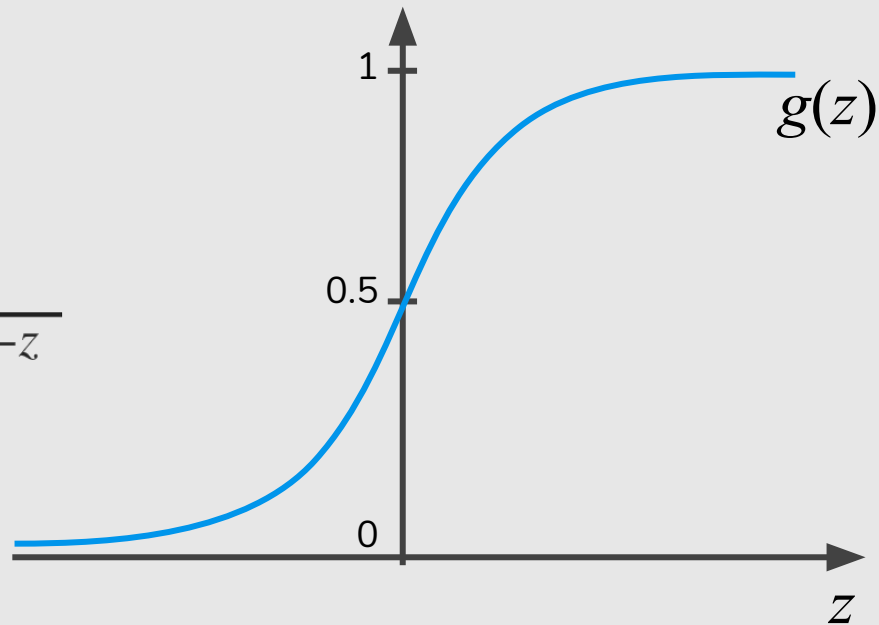
↙

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

Sigmoid Function

Logistic Function

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



Interpretation of Hypothesis Output

$h_{\theta}(x)$ = estimated probability that $y = 1$ on input x

Interpretation of Hypothesis Output

$h_{\theta}(x)$ = estimated probability that $y = 1$ on input x

Example: If $x = \begin{bmatrix} x_0 \\ x_1 \end{bmatrix} = \begin{bmatrix} 1 \\ \text{tumorSize} \end{bmatrix}$

$$h_{\theta}(x) = 0.7$$



Tell patient that 70%
chance of tumor being
malignant

Interpretation of Hypothesis Output

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Example: If $x = \begin{bmatrix} x_0 \\ x_1 \end{bmatrix} = \begin{bmatrix} 1 \\ \text{tumorSize} \end{bmatrix}$

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Tell patient that 70%
chance of tumor being
malignant

$$h_{\theta}(x) = P(y = 1 \mid x; \theta)$$

Interpretation of Hypothesis Output

$h_{\theta}(x)$ = estimated probability that $y = 1$ on input x

Example: If $x = \begin{bmatrix} x_0 \\ x_1 \end{bmatrix} = \begin{bmatrix} 1 \\ \text{tumorSize} \end{bmatrix}$

$$h_{\theta}(x) = 0.7$$



“probability that $y = 1$, given x ,
parameterized by θ ”

Tell patient that 70%
chance of tumor being
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$$h_{\theta}(x) = P(y = 1 \mid x; \theta)$$

Interpretation of Hypothesis Output

$h_{\theta}(x)$ = estimated probability that $y = 1$ on input x

Example: If $x = \begin{bmatrix} x_0 \\ x_1 \end{bmatrix} = \begin{bmatrix} 1 \\ \text{tumorSize} \end{bmatrix}$

$$h_{\theta}(x) = 0.7$$



“probability that $y = 1$, given x ,
parameterized by θ ”

Tell patient that 70%
chance of tumor being
malignant

$$P(y = 0 \mid x; \theta) + P(y = 1 \mid x; \theta) = 1$$

$$P(y = 1 \mid x; \theta) = 1 - P(y = 0 \mid x; \theta)$$

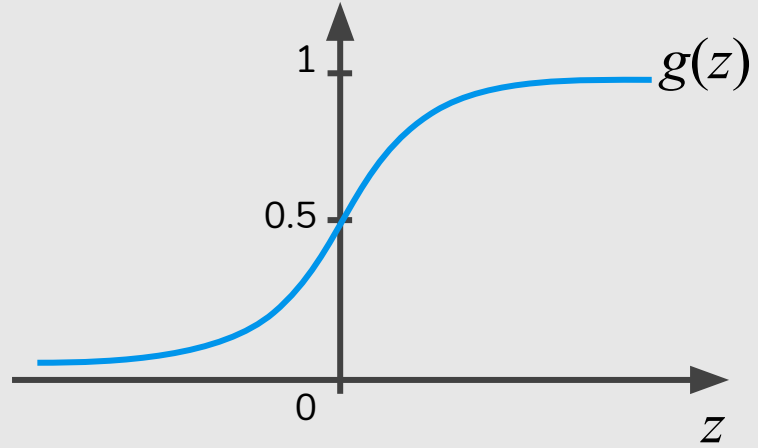
$$h_{\theta}(x) = P(y = 1 \mid x; \theta)$$

Decision Boundary

Logistic Regression

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

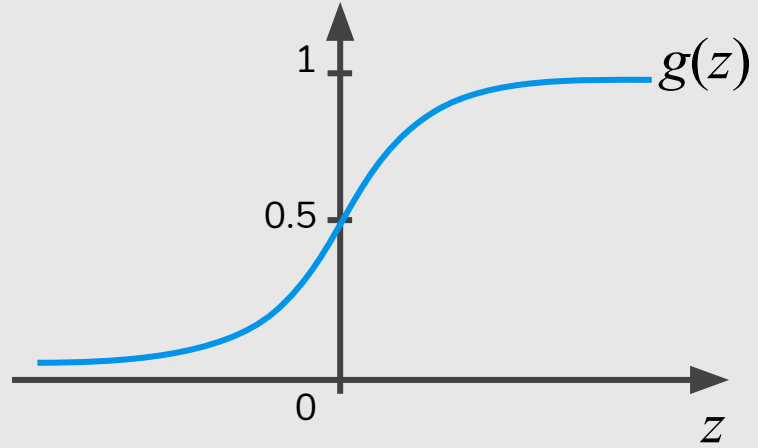
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Logistic Regression

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

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



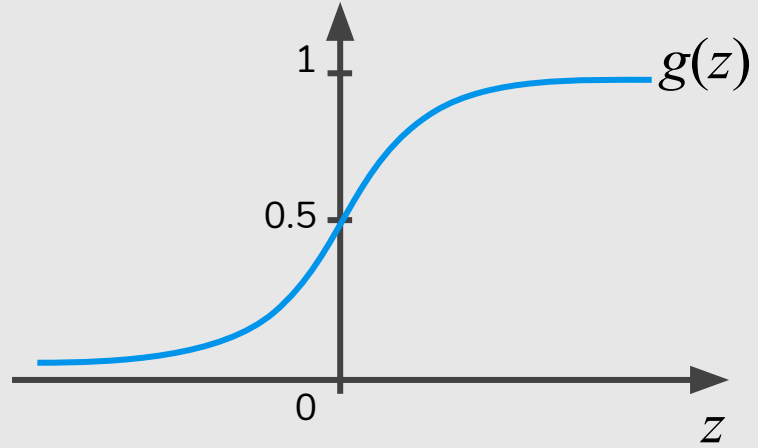
Suppose predict “ $y = 1$ ” if $h_{\theta}(x) \geq 0.5$

predict “ $y = 0$ ” if $h_{\theta}(x) < 0.5$

Logistic Regression

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

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



Suppose predict “ $y = 1$ ” if $h_{\theta}(x) \geq 0.5$

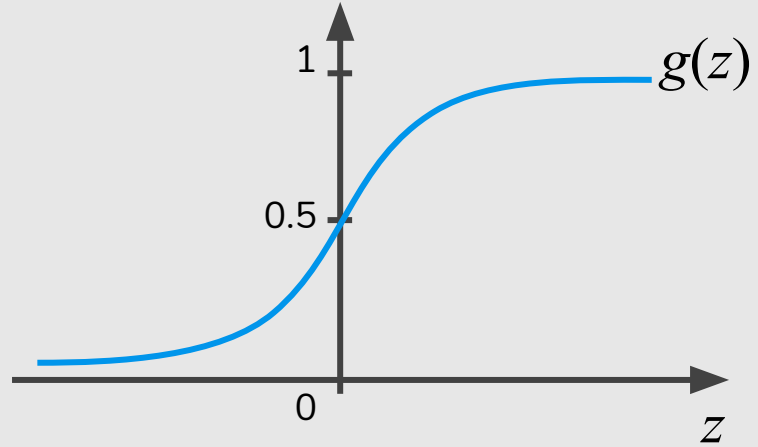
$g(z) \geq 0.5$ when $z \geq 0$

predict “ $y = 0$ ” if $h_{\theta}(x) < 0.5$

Logistic Regression

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

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



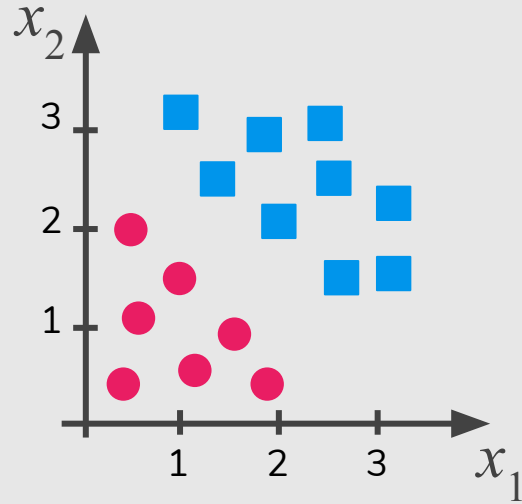
Suppose predict “ $y = 1$ ” if $h_{\theta}(x) \geq 0.5$

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predict “ $y = 0$ ” if $h_{\theta}(x) < 0.5$

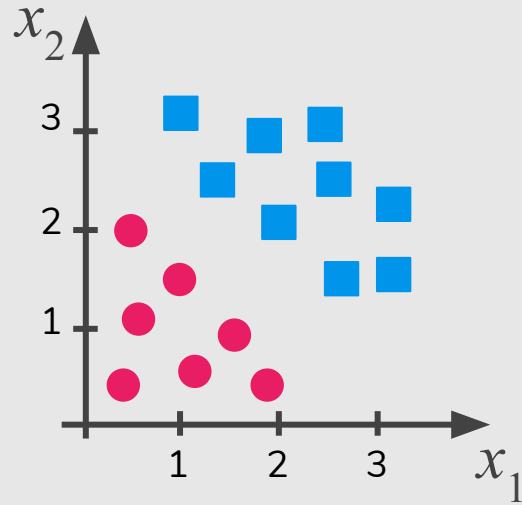
$g(z) < 0.5$ when $z < 0$

Decision Boundary



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

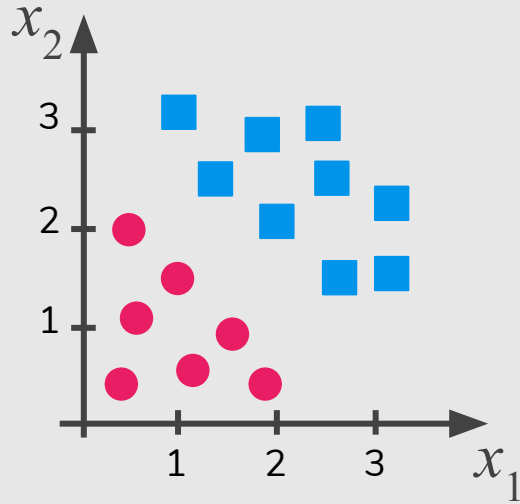
Decision Boundary



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

-3 1 1
↑ ↑ ↑

Decision Boundary

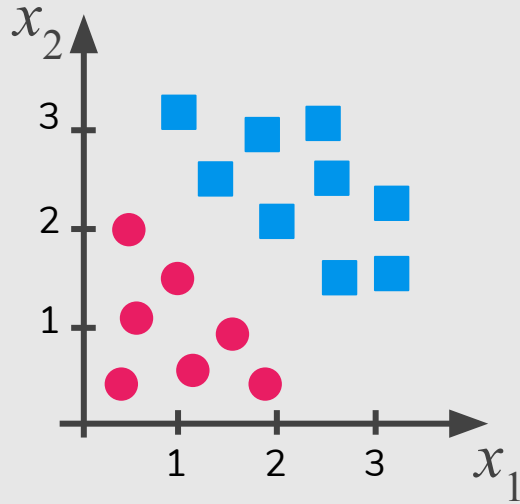


$$h_{\theta}(x) = g(\theta_0 + \theta_1 x_1 + \theta_2 x_2)$$

-3 1 1
↑ ↑ ↑

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

Decision Boundary

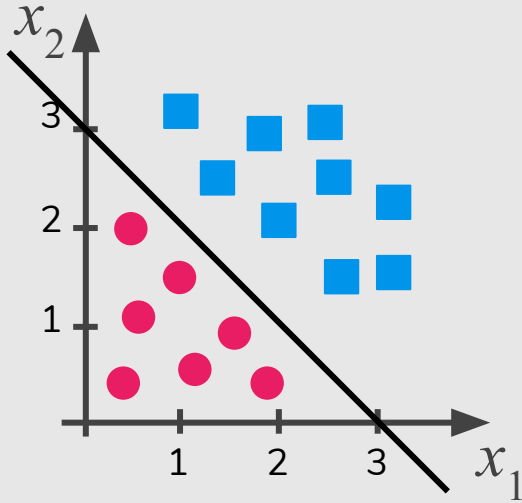


$$h_{\theta}(x) = g(\theta_0 + \theta_1 x_1 + \theta_2 x_2)$$

-3 1 1
↑ ↑ ↑

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

Decision Boundary

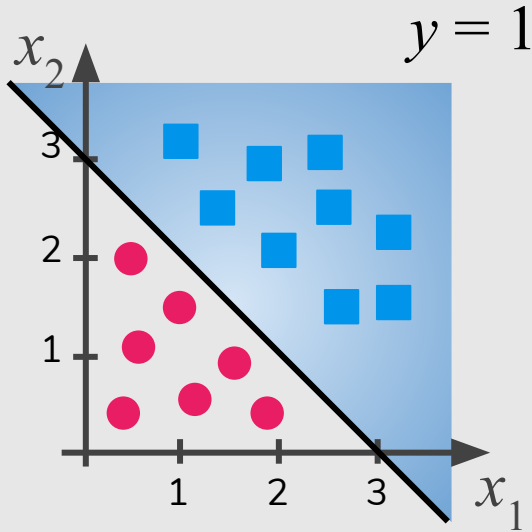


$$h_{\theta}(x) = g(\theta_0 + \theta_1 x_1 + \theta_2 x_2)$$

-3 1 1
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Predict “ $y = 1$ ” if $-3 + x_1 + x_2 \geq 0$
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Decision Boundary

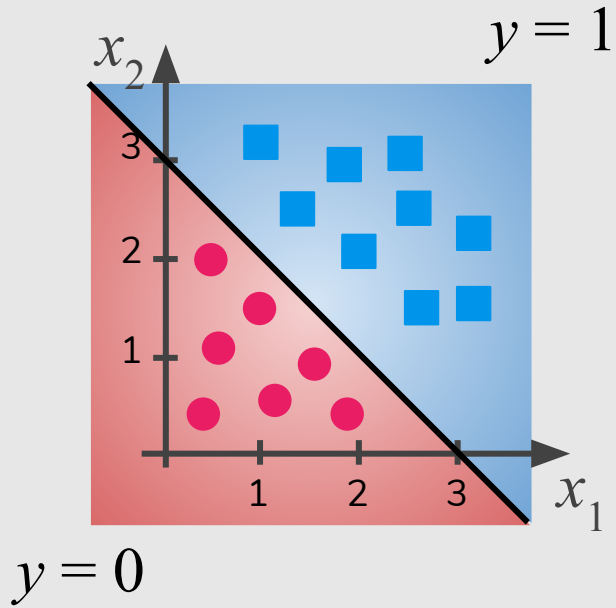


$$h_{\theta}(x) = g(\theta_0 + \theta_1 x_1 + \theta_2 x_2)$$

-3 1 1
↑ ↑ ↑

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

Decision Boundary



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

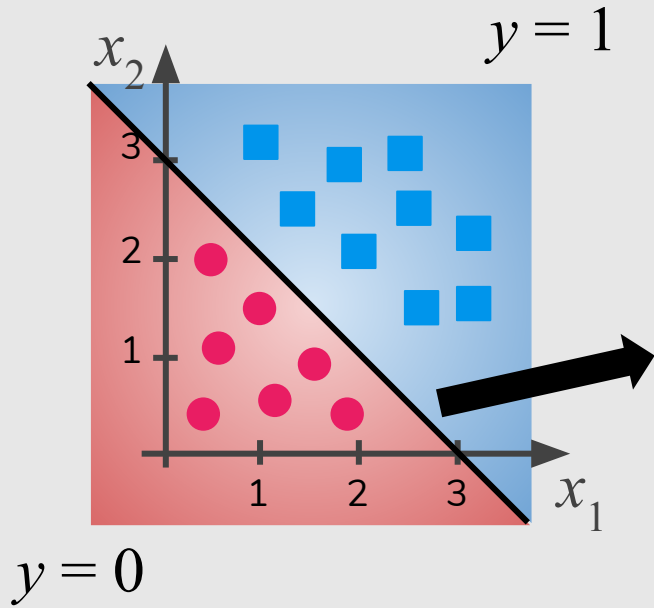
-3 1 1
↑ ↑ ↑

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

$$x_1 + x_2 \geq 3$$

$$y = 0, x_1 + x_2 < 3$$

Decision Boundary



$$\begin{array}{ccc} -3 & 1 & 1 \\ \uparrow & \uparrow & \uparrow \end{array}$$

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

Decision Boundary

$$x_1 + x_2 = 3$$

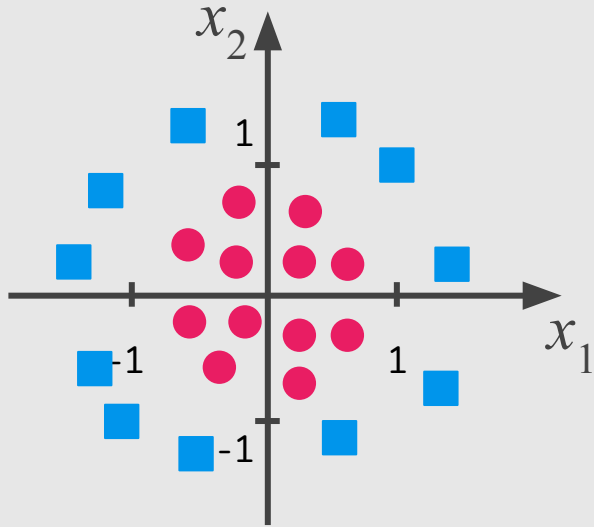
$$h_{\theta}(x) = 0.5$$

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

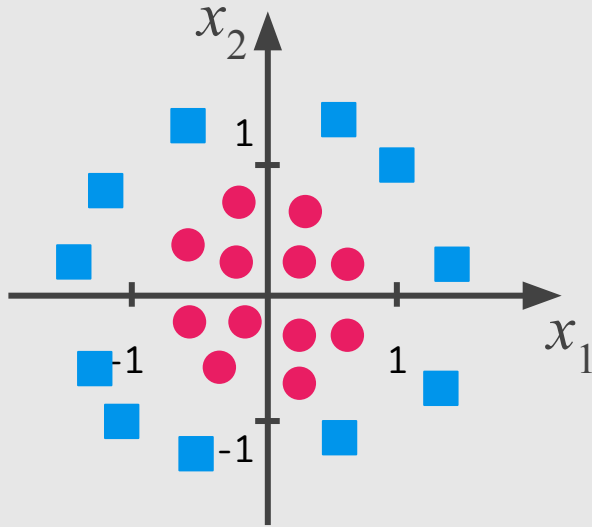
$$x_1 + x_2 \geq 3$$

$$y = 0, x_1 + x_2 < 3$$

Non-linear Decision Boundaries

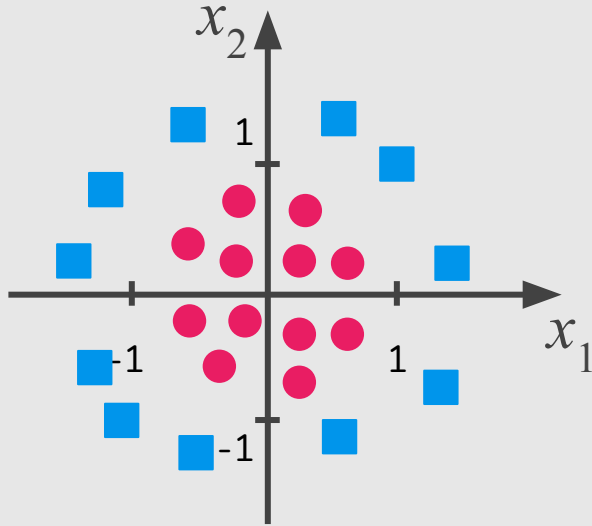


Non-linear Decision Boundaries



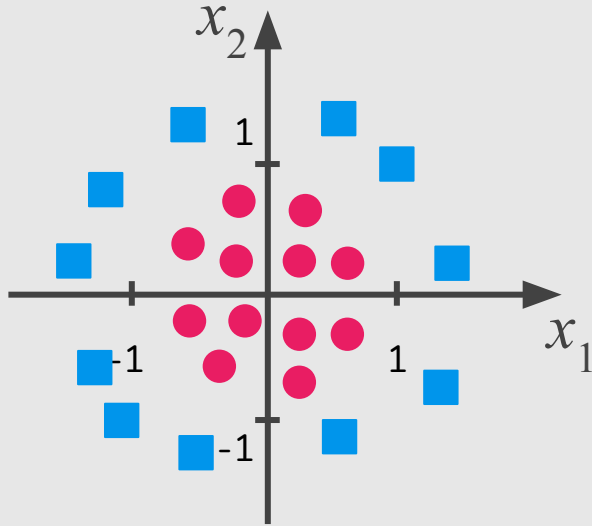
$$h_{\theta}(x) = g(\theta_0 + \theta_1 x_1 + \theta_2 x_2 + \theta_3 x_1^2 + \theta_4 x_2^2)$$

Non-linear Decision Boundaries



$$h_{\theta}(x) = g(\underbrace{\theta_0}_{-1} + \underbrace{\theta_1 x_1}_{0} + \underbrace{\theta_2 x_2}_{0} + \underbrace{\theta_3 x_1^2}_{1} + \underbrace{\theta_4 x_2^2}_{1})$$

Non-linear Decision Boundaries

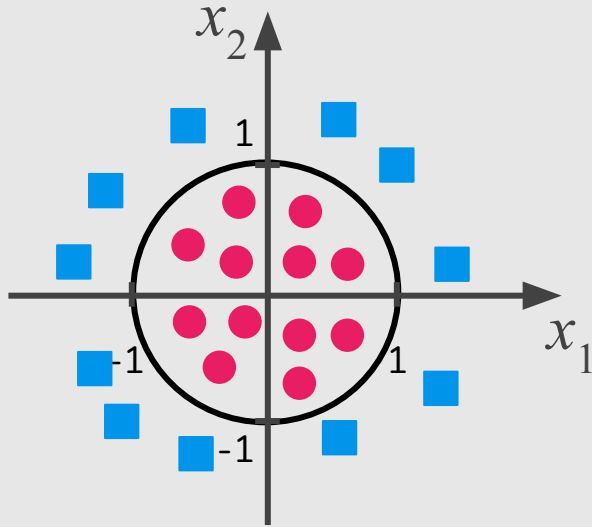


$$h_{\theta}(x) = g(\underbrace{\theta_0}_{-1} + \underbrace{\theta_1}_{0}x_1 + \underbrace{\theta_2}_{0}x_2 + \underbrace{\theta_3}_{1}x_1^2 + \underbrace{\theta_4}_{1}x_2^2)$$

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

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

Non-linear Decision Boundaries

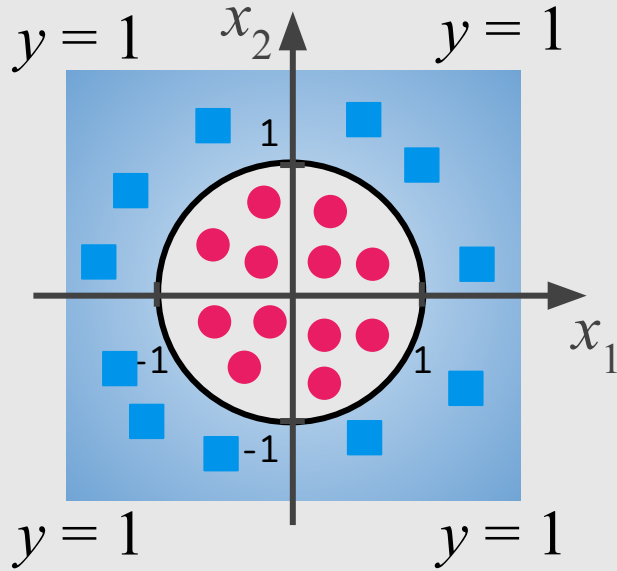


$$h_{\theta}(x) = g(\underbrace{\theta_0}_{-1} + \underbrace{\theta_1}_{0}x_1 + \underbrace{\theta_2}_{0}x_2 + \underbrace{\theta_3}_{1}x_1^2 + \underbrace{\theta_4}_{1}x_2^2)$$

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Non-linear Decision Boundaries

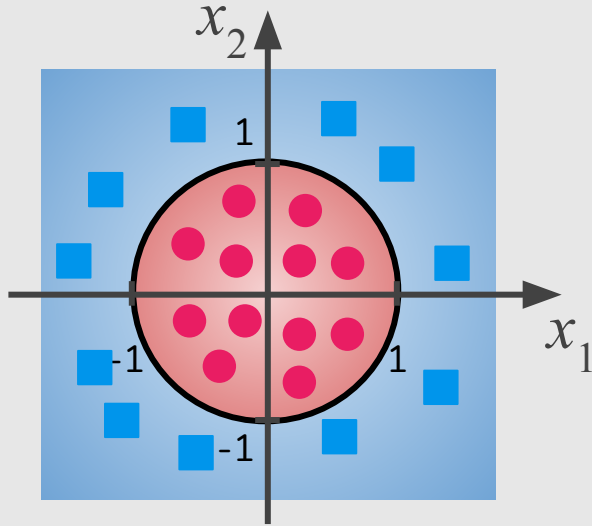


$$h_{\theta}(x) = g(\underbrace{\theta_0}_{-1} + \underbrace{\theta_1}_{0}x_1 + \underbrace{\theta_2}_{0}x_2 + \underbrace{\theta_3}_{1}x_1^2 + \underbrace{\theta_4}_{1}x_2^2)$$

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Non-linear Decision Boundaries



$$h_{\theta}(x) = g(\underbrace{\theta_0}_{-1} + \underbrace{\theta_1}_{0}x_1 + \underbrace{\theta_2}_{0}x_2 + \underbrace{\theta_3}_{1}x_1^2 + \underbrace{\theta_4}_{1}x_2^2)$$

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

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

Today's Agenda

- Logistic Regression
 - Classification
 - Hypothesis Representation
 - Decision Boundary
 - **Cost Function**
 - Simplified Cost Function and Gradient Descent
 - Multiclass Classification

Cost Function

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

$$h_{\theta}(x) = \frac{1}{1 + e^{-\theta^T x}} \quad x \in \begin{bmatrix} x_0 \\ x_1 \\ \vdots \\ x_n \end{bmatrix} \quad x_0 = 1, y \in \{0, 1\}$$

How to choose parameters θ ?

Cost Function

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

Cost Function

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

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

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

Cost Function

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

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

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

Cost Function

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

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

Logistic

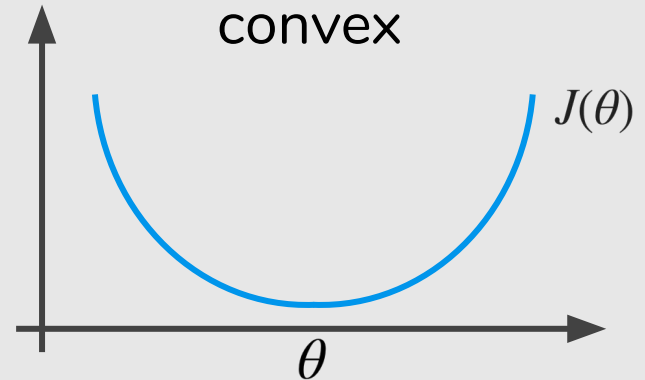
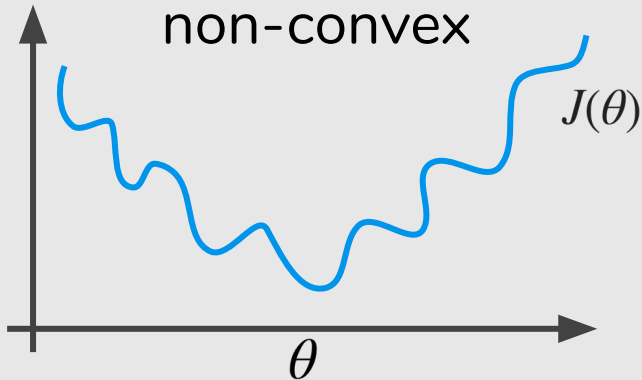
$$\text{Cost}(h_{\theta}(x), y) = \frac{1}{2} (h_{\theta}(x) - y)^2 \quad h_{\theta}(x) = \frac{1}{1 + e^{-\theta^T x}}$$

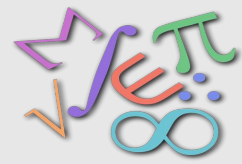
Cost Function

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

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

$$\text{Cost}(h_{\theta}(x), y) = \frac{1}{2} (h_{\theta}(x) - y)^2 \quad h_{\theta}(x) = \frac{1}{1 + e^{-\theta^T x}}$$





Derivative of Logistic Function

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

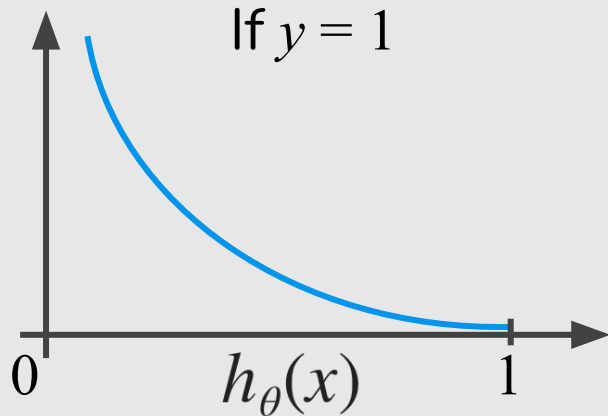
$$\begin{aligned} g'(z) &= \frac{d}{dz} \frac{1}{1 + e^{-z}} \\ &= \frac{0 \cdot (1 + e^{-z}) - 1 \cdot (-e^{-z})}{(1 + e^{-z})^2} \quad (\text{quotient rule}) \\ &= \frac{e^{-z}}{(1 + e^{-z})^2} \\ &= \left(\frac{1}{1 + e^{-z}} \right) \left(1 - \frac{1}{1 + e^{-z}} \right) \\ &= g(z)(1 - g(z)) \end{aligned}$$

Logistic Regression Cost Function

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

Logistic Regression Cost Function

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



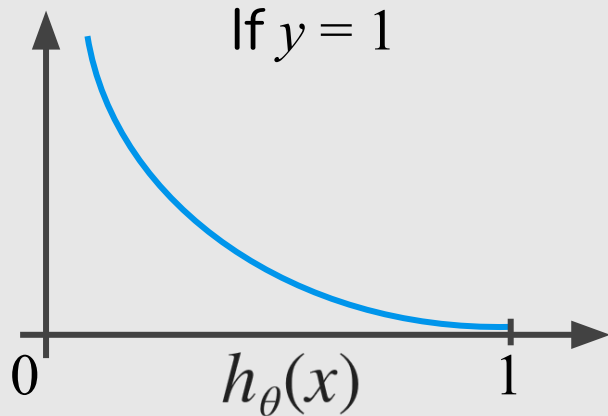
Cost = 0 if $y = 1, h_{\theta}(x) = 1$

But as $h_{\theta}(x) \rightarrow 0$

Cost $\rightarrow \infty$

Logistic Regression Cost Function

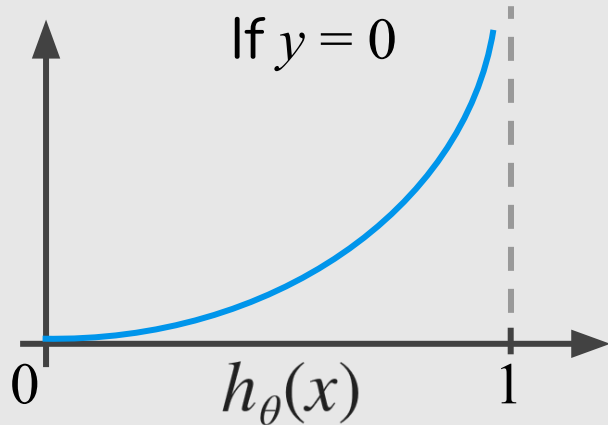
$$\text{Cost}(h_{\theta}(x), y) = \begin{cases} -\log(h_{\theta}(x)) & \text{if } y = 1 \\ -\log(1 - h_{\theta}(x)) & \text{if } y = 0 \end{cases}$$



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.

Logistic Regression Cost Function

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



Simplified Cost Function and Gradient Descent

Logistic Regression Cost Function

$$J(\theta) = \frac{1}{m} \sum_{i=1}^m \text{Cost}(h_{\theta}(x^{(i)}), y^{(i)})$$

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

Logistic Regression Cost Function

$$J(\theta) = \frac{1}{m} \sum_{i=1}^m \text{Cost}(h_{\theta}(x^{(i)}), y^{(i)})$$

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

$$\text{Cost}(h_{\theta}(x), y) = -y \log(h_{\theta}(x)) - (1-y) \log(1 - h_{\theta}(x))$$

Logistic Regression Cost Function

$$J(\theta) = \frac{1}{m} \sum_{i=1}^m \text{Cost}(h_{\theta}(x^{(i)}), y^{(i)})$$

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

$$\text{Cost}(h_{\theta}(x), y) = -y \log(h_{\theta}(x)) - (1-y) \log(1 - h_{\theta}(x))$$

~~$y = 1$~~

Logistic Regression Cost Function

$$J(\theta) = \frac{1}{m} \sum_{i=1}^m \text{Cost}(h_{\theta}(x^{(i)}), y^{(i)})$$

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

$$\text{Cost}(h_{\theta}(x), y) = -y \log(h_{\theta}(x)) - (1-y) \log(1 - h_{\theta}(x))$$

~~$y = 0$~~

Logistic Regression Cost Function

$$\begin{aligned} J(\theta) &= \frac{1}{m} \sum_{i=1}^m \text{Cost}(h_{\theta}(x^{(i)}), y^{(i)}) \\ &= -\frac{1}{m} \left[\sum_{i=1}^m y^{(i)} \log(h_{\theta}(x^{(i)})) + (1-y^{(i)}) \log(1-h_{\theta}(x^{(i)})) \right] \end{aligned}$$

Logistic Regression Cost Function

$$J(\theta) = \frac{1}{m} \sum_{i=1}^m \text{Cost}(h_{\theta}(x^{(i)}), y^{(i)})$$
$$= -\frac{1}{m} \left[\sum_{i=1}^m y^{(i)} \log(h_{\theta}(x^{(i)})) + (1-y^{(i)}) \log(1-h_{\theta}(x^{(i)})) \right]$$

To fit parameters θ : $\min_{\theta} J(\theta)$

Logistic Regression Cost Function

$$J(\theta) = \frac{1}{m} \sum_{i=1}^m \text{Cost}(h_{\theta}(x^{(i)}), y^{(i)})$$
$$= -\frac{1}{m} \left[\sum_{i=1}^m y^{(i)} \log(h_{\theta}(x^{(i)})) + (1 - y^{(i)}) \log(1 - h_{\theta}(x^{(i)})) \right]$$

To fit parameters θ : $\min_{\theta} J(\theta)$

To make a new prediction given new x : Output $h_{\theta}(x) = \frac{1}{1 + e^{-\theta^T x}}$

Gradient Descent

$$J(\theta) = -\frac{1}{m} \left[\sum_{i=1}^m y^{(i)} \log(h_{\theta}(x^{(i)})) + (1-y^{(i)}) \log(1-h_{\theta}(x^{(i)})) \right]$$

Want $\min_{\theta} J(\theta)$:

repeat {

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

} (simultaneously update θ_j for $j = 0, 1, \dots, n$)

Gradient Descent

$$J(\theta) = -\frac{1}{m} \left[\sum_{i=1}^m y^{(i)} \log(h_{\theta}(x^{(i)})) + (1-y^{(i)}) \log(1-h_{\theta}(x^{(i)})) \right]$$

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repeat {

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

} (simultaneously update θ_j for $j=0, 1, \dots, n$)

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





Gradient Descent

<https://math.stackexchange.com/questions/477207/derivative-of-cost-function-for-logistic-regression>

Want $\min_{\theta} J(\theta)$:

repeat {

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

} (simultaneously update θ_j for $j = 0, 1, \dots, n$)



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

Gradient Descent

$$J(\theta) = -\frac{1}{m} \left[\sum_{i=1}^m y^{(i)} \log(h_{\theta}(x^{(i)})) + (1-y^{(i)}) \log(1-h_{\theta}(x^{(i)})) \right]$$

Want $\min_{\theta} J(\theta)$:

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Gradient Descent

$$J(\theta) = -\frac{1}{m} \left[\sum_{i=1}^m y^{(i)} \log(h_{\theta}(x^{(i)})) + (1-y^{(i)}) \log(1-h_{\theta}(x^{(i)})) \right]$$

Want $\min_{\theta} J(\theta)$:

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

} (simultaneously update θ_j for $j = 0, 1, \dots, n$)

**Algorithm looks
identical to linear
regression!**

Gradient Descent

$$J(\theta) = -\frac{1}{m} \left[\sum_{i=1}^m y^{(i)} \log(h_{\theta}(x^{(i)})) + (1-y^{(i)}) \log(1-h_{\theta}(x^{(i)})) \right]$$

Want $\min_{\theta} J(\theta)$: $h_{\theta}(x) = \theta^T x \rightarrow h_{\theta}(x) = \frac{1}{1 + e^{-\theta^T x}}$

repeat {

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

} (simultaneously update θ_j for $j = 0, 1, \dots, n$)

Algorithm looks identical to linear regression!

Multiclass Classification: One-vs-all

Classification

Email tagging: Work, Friends, Family

Skin Lesion: Melanoma, Carcinoma, Nevus, Keratosis

Video: Pornography, Violence, Gore scenes, Child abuse

Classification

Email tagging: Work, Friends, Family

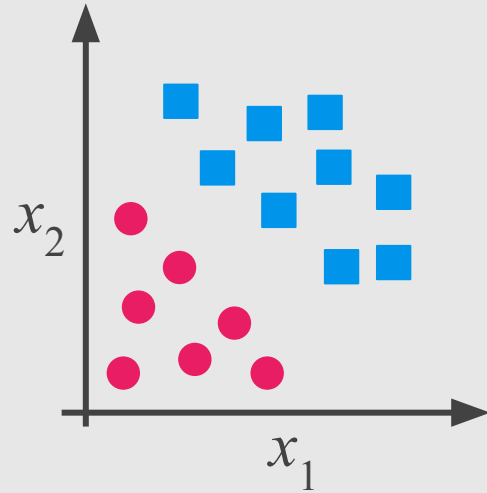
$$y = 1 \quad y = 2 \quad y = 3$$

Skin Lesion: Melanoma, Carcinoma, Nevus, Keratosis

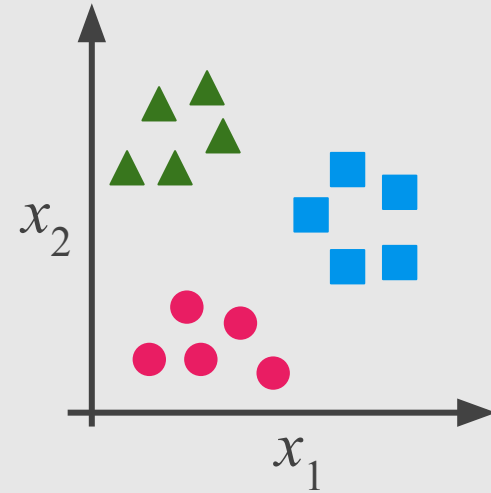
$$y = 1 \quad y = 2 \quad y = 3 \quad y = 4$$

Video: Pornography, Violence, Gore scenes, Child abuse

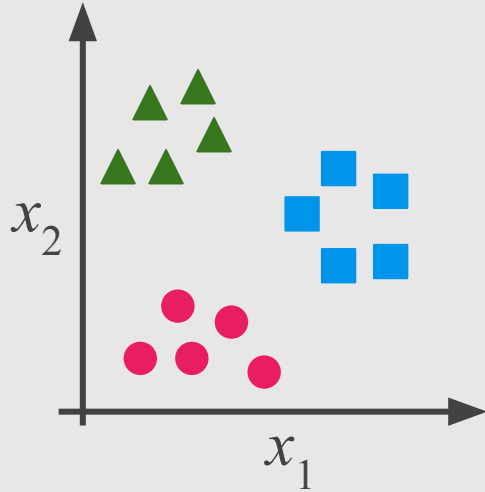
Binary Classification



Multi-class Classification



One-vs-All (One-vs-Rest)

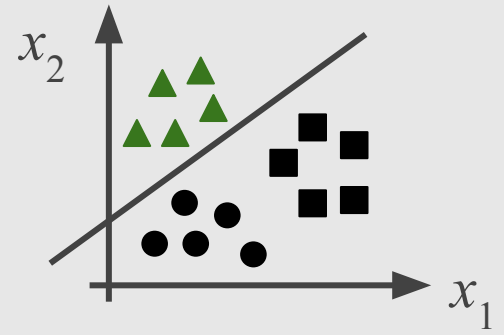
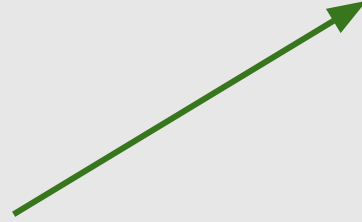
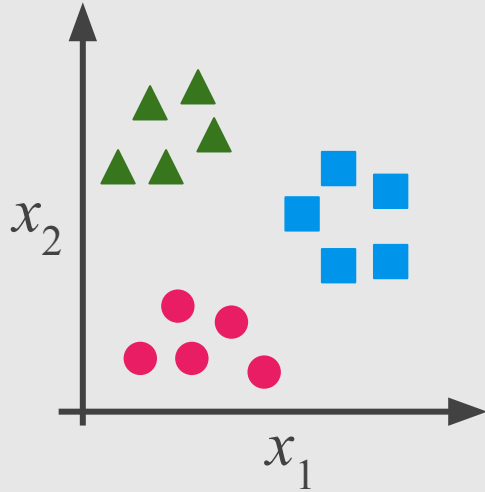


Class 1: ▲

Class 2: ■

Class 3: ●

One-us-All (One-us-Rest)

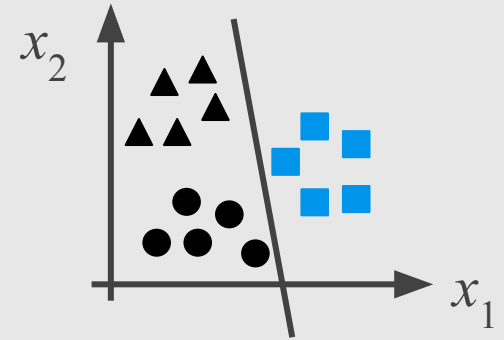
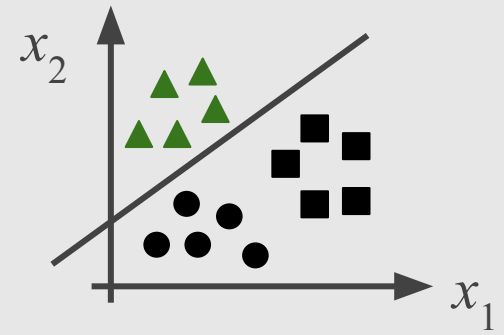
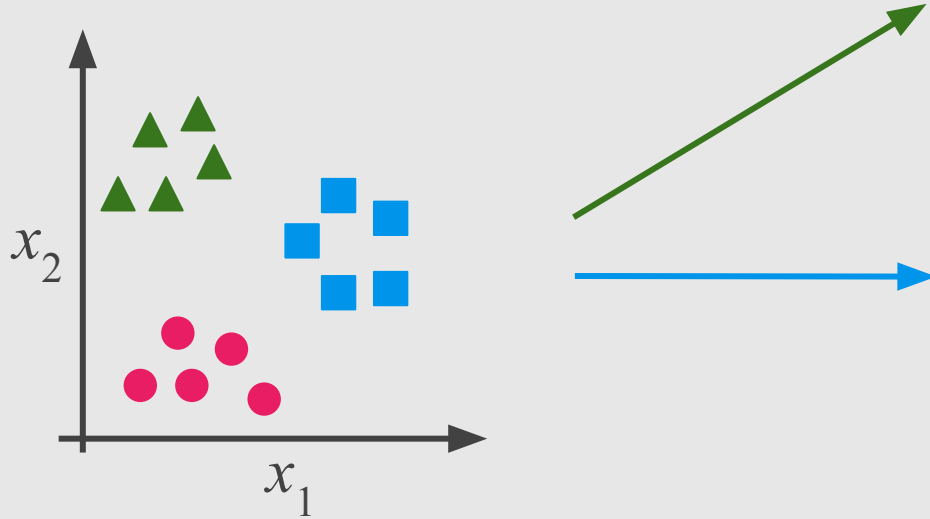


Class 1: ▲

Class 2: ■

Class 3: ●

One-us-All (One-us-Rest)

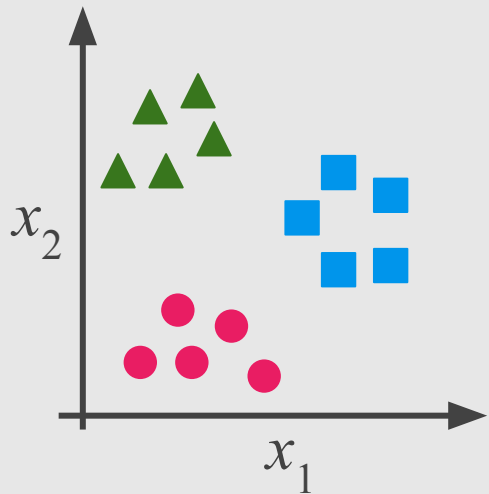


Class 1: ▲

Class 2: ■

Class 3: ●

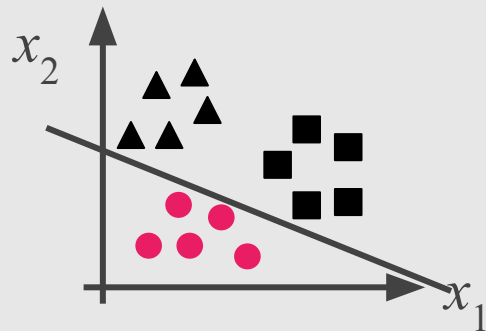
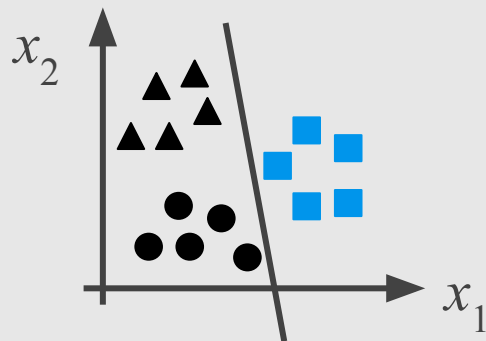
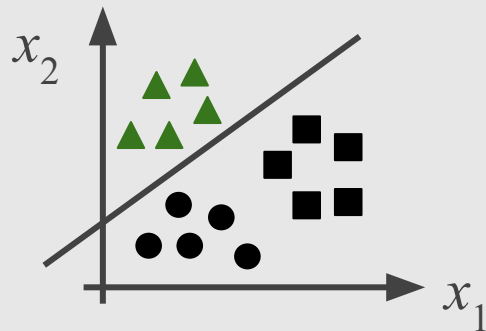
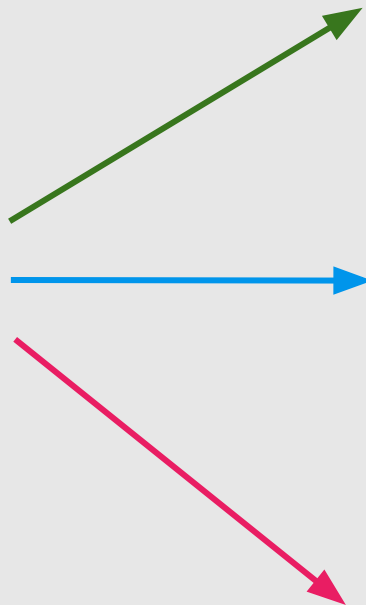
One-us-All (One-us-Rest)



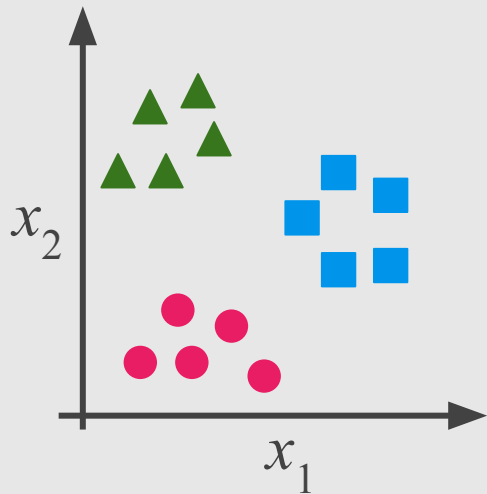
Class 1: ▲

Class 2: ■

Class 3: ●



One-vs-All (One-vs-Rest)

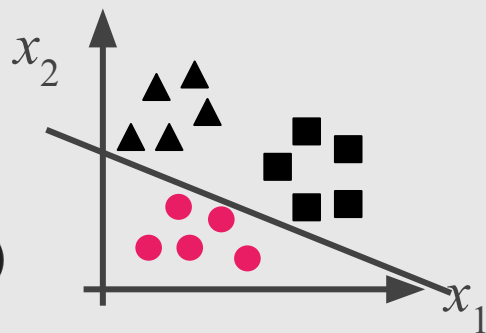
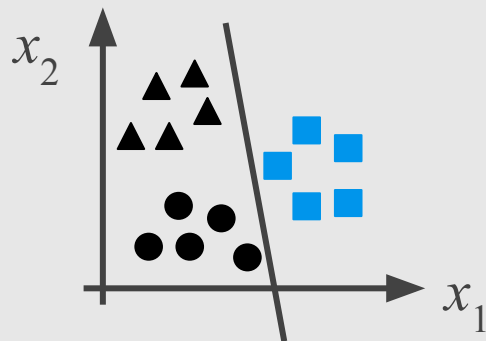
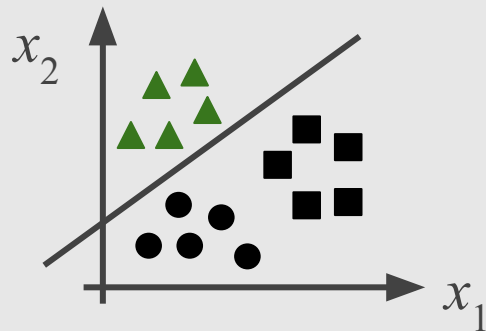
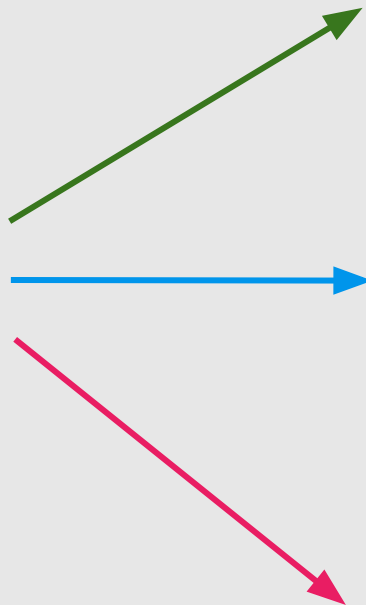


Class 1: ▲

Class 2: ■

Class 3: ●

$$h_{\theta}^{(i)}(x) = P(y=i \mid x; \theta) \quad (i=1,2,3)$$



One-vs-All (One-vs-Rest)

Train a logistic regression classifier $h_{\theta}^{(i)}(x)$ for each class i to predict the probability that $y = i$.

On a new input x , to make a prediction, pick the class i that maximizes

$$\max_i h_{\theta}^{(i)}(x)$$

Logistic Regression — The Math of Intelligence (Week 2) by Siraj Raval <https://youtu.be/D8alok2P468>



YouTube

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What is Logistic regression?

Logistic regression is named for the function used at the core of the method, the logistic function. In linear regression, the outcome (dependent variable) is continuous. It can have any one of an infinite number of possible values. In logistic regression, the outcome (dependent variable) has only a limited number of possible values. Logistic Regression is used when response variable is categorical in nature.

The logistic function, also called the sigmoid function is an S-shaped curve that can take any real-valued number and map it into a value between 0 and 1, but never exactly at those limits.

$$y = \frac{1}{1 + e^{-x}}$$

Where e is the base of the natural logarithms (Euler's number or the EXP() function in your spreadsheet) and value is the actual numerical value that you transform. E is a really convenient number for math, for example Whenever you take the derivative of e^x (that's e to the x), you get e^x back again. It's the only function on Earth that will do that.

Logistic regression uses an equation as the representation, similar to linear regression. The central premise of Logistic Regression is the assumption that the input space can be separated into two nice "regions", one for each class, by a linear (read: straight) boundary. Your data must be linearly separable in n dimensions

The Math of Intelligence

Siraj Raval - 4 / 19



- Logistic Regression - The Math of Intelligence (Week 2)**
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- Vectors - The Math of Intelligence #3**
Siraj Raval 10:59
- K-Means Clustering - The Math of Intelligence (Week 3)**
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- Neural Networks - The Math of Intelligence #4**
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References

Machine Learning Books

- Hands-On Machine Learning with Scikit-Learn and TensorFlow, Chap. 4
- Pattern Recognition and Machine Learning, Chap. 4

Machine Learning Courses

- <https://www.coursera.org/learn/machine-learning>, Week 3
- Logistic Regression — The Math of Intelligence (Week 2):
<https://youtu.be/D8alok2P468>
- <http://cs229.stanford.edu/notes/cs229-notes1.pdf>