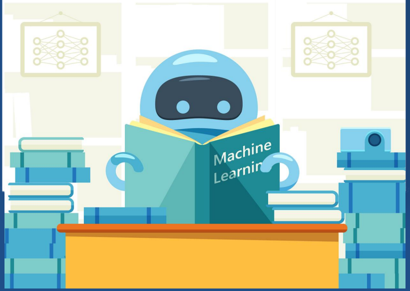
山东大学软件学院
SCHOOL OF SOFTWARE, SHANDONG UNIVERSITY

Machine Learning

机器学习



Chapter 6
Neural Networks

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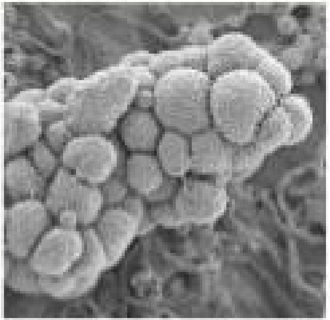
DEEP LEARNING EVERYWHERE

MIMA

INTERNET & CLOUD

Image Classification
Speech Recognition
Language Translation
Sentiment Analysis
Recommendation



MEDICINE & BIOLOGY

Cancer Cell Detection
Diabetic Grading
Drug Discovery

MEDIA & ENTERTAINMENT

Video Captioning
Video Search
Real Time Translation

SECURITY & DEFENSE

Face Detaction
Video Surveilance
Satellite Imagery

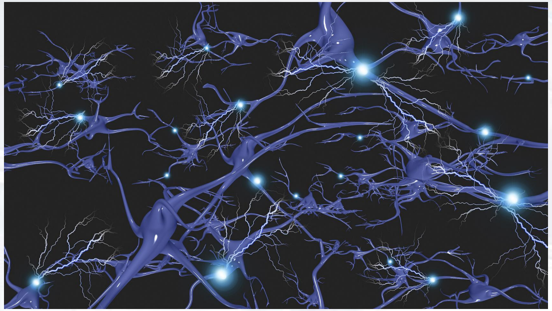
AUTONOMOUS & MACHINES

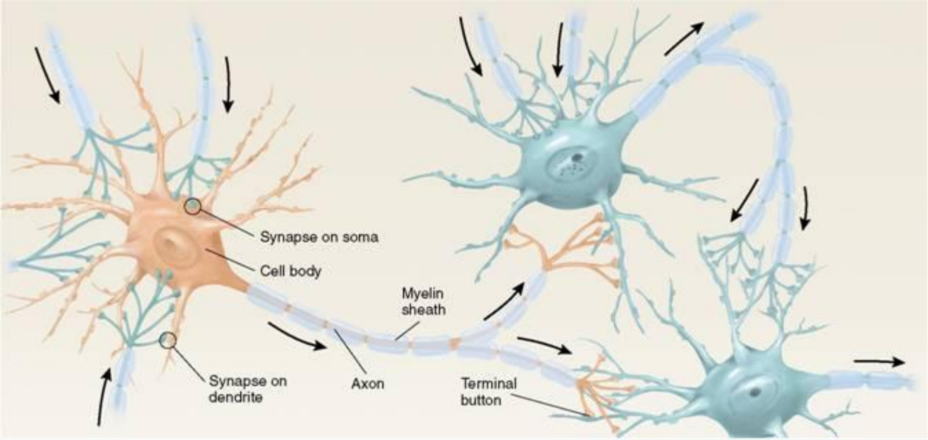
Pedestrian Detection
Lane Tracking
Recognize Traffic Sign

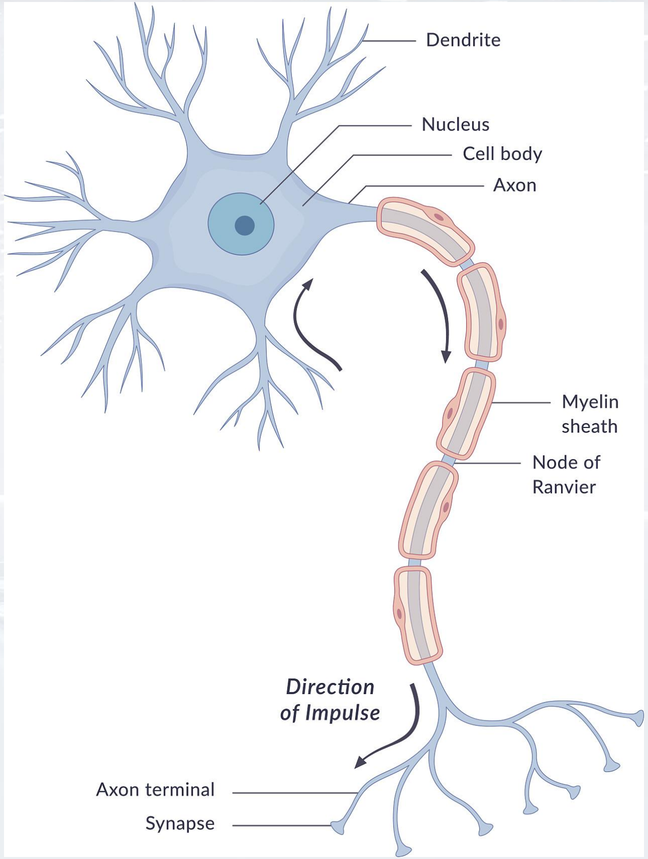
Contents

MIMA

Biological Neural Systems



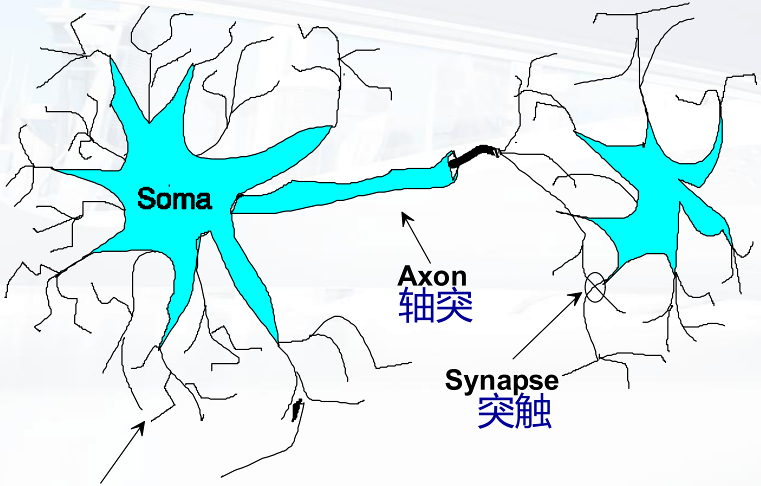




Biological Neural Systems

MIMA

- The brain is composed of approximately 100 billion (10^{11}) neurons

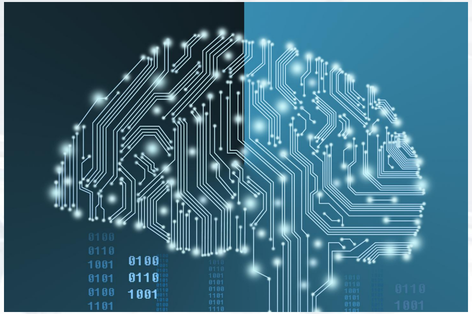


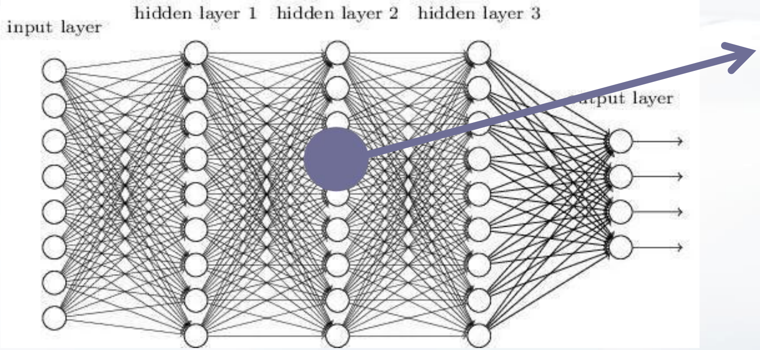
Schematic drawing of two biological neurons connected by synapses

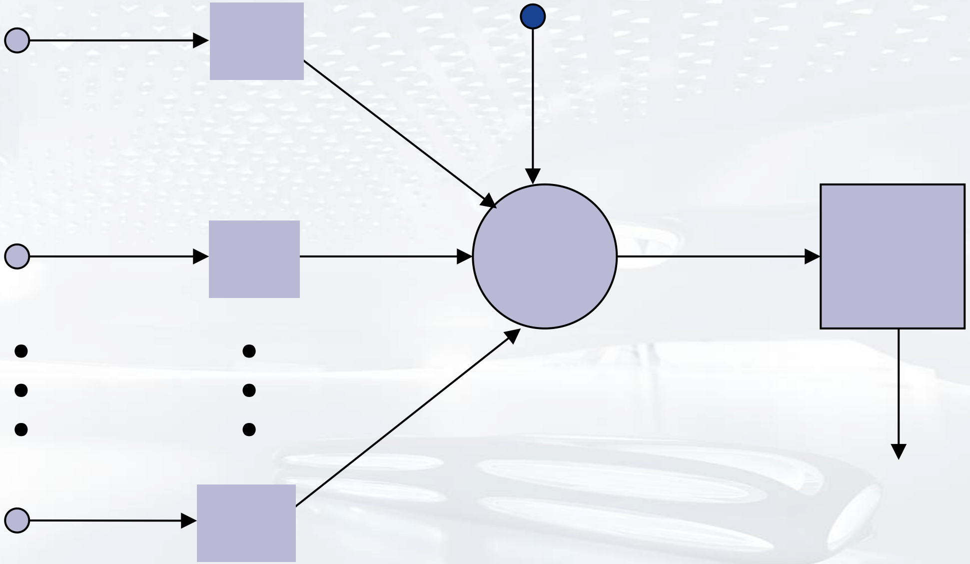
- A typical neuron collects signals from other neurons through a host of fine structures called **dendrites**（树突）.
- The neuron sends out spikes of electrical activity through a long, thin strand known as an **axon**（轴突）, which splits into thousands of branches.
- At the end of the branch, a structure called a **synapse**（突触）converts the activity from the axon into electrical effects that inhibit or excite activity in the connected neurons.
- When a neuron receives excitatory input that is sufficiently large compared with its inhibitory input, it sends a spike of electrical activity down its axon.

Learning occurs by changing the effectiveness of the synapses so that the influence of one neuron on the other changes

人工神经网络







Introduction

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- (Artificial) Neural Networks are
  - Computational models which mimic the brain's learning processes.
  - They have the essential features of neurons and their interconnections as found in the brain.
  - Typically, a computer is programmed to simulate these features.
- Other definitions …
  - A neural network is a massively parallel distributed processor made up of simple processing units, which has a natural propensity for storing experimental knowledge and making it available for use. It resembles the brain in two respects:
    - Knowledge is acquired by the network from its environment through a learning process.
    - Interneuron connection strengths, known as synaptic weights, are used to store the acquired knowledge.

Introduction

MIMA

- A neural network is a machine learning approach inspired by the way in which the brain performs a particular learning task:
  - Knowledge about the learning task is given in the form of examples.
  - Inter neuron connection strengths (weights) are used to store the acquired information (the training examples) .
  - During the learning process the weights are modified in order to model the particular learning task correctly on the training examples.

Neural Networks

- A NN is a machine learning approach inspired by the way in which the brain performs a particular learning task
- Various types of neurons
- Various network architectures
- Various learning algorithms
- Various applications

Characteristics of NN' s

- Characteristics of Neural Networks
  - Large scale and parallel processing
  - Robust
  - Self-adaptive and organizing
  - Good enough to simulate non-linear relations
  - Hardware

Applications

- Combinatorial Optimization
- Pattern Recognition
- Bioinformatics
- Text processing
- Natural language processing
- Data Mining
- …

Types

- Structure
  - Feed-forward
  - Feed-back
- Learning method
  - Supervised
  - Unsupervised
- Signal type
  - Continuous
  - Discrete

Historical Background

- 1943 McCulloch and Pitts proposed the first computational models of neuron.
- 1949 Hebb proposed the first learning rule.
- 1958 Rosenblatt’ s work in perceptrons（感知器）.
- 1969 Minsky and Papert exposed limitation of the theory.
- 1970s Decade of dormancy for neural networks.
- 1980-90s Neural network return (self-organization, back-propagation algorithms, etc)

Historical Background

- 弗兰克·罗森布拉特

(Frank Rosenblatt，康奈尔大学的心理学家)

- 1958年，在《纽约时报 (New York Times)》上发表文章《Electronic ‘Brain’ Teaches Itself.》，正式把算法取名为“**感知器**”

- 它有400个光传感器，它们一起充当视网膜，将信息传递给大约1000个“神经元”，这些神经元进行处理并输出单一信息。

图片来源https://baijiahao.baidu.com/s?id=1713433120837173170&wfr=spider&for=pc

Historical Background

MIMA

- 马文·明斯基

  "人工智能之父" (Marvin Minsky) 1970图灵奖获得者

- 1969年，Minsky 和Papert所著的《Perceptron》一书出版，从数学角度证明了关于单层感知器的计算具有根本的局限性，指出感知器的处理能力有限，甚至连XOR这样的问题也不能解决

- 神经网络进入了萧条期
- 第一个**人工智能冬天**

<u>计算机有限的内存和处理速度不足以解决任何实际的人工智能问题</u>

——《人工智能发展简史》

中共中央网络安全和信息化委员会办公室
中华人民共和国国家互联网信息办公室
http://www.cac.gov.cn/2017-01/23/c_1120366748.htm

图片来源https://baijiahao.baidu.com/s?id=1713433120837173170&wfr=spider&for=pc

Historical Background

- 杰弗里·辛顿

  “神经网络之父”(Geoffrey Hinton) 2019图灵奖获得者

- 多伦多大学的辛顿实现了一种叫做**反向传播**的原理来让神经网络从他们的错误中学习 1986

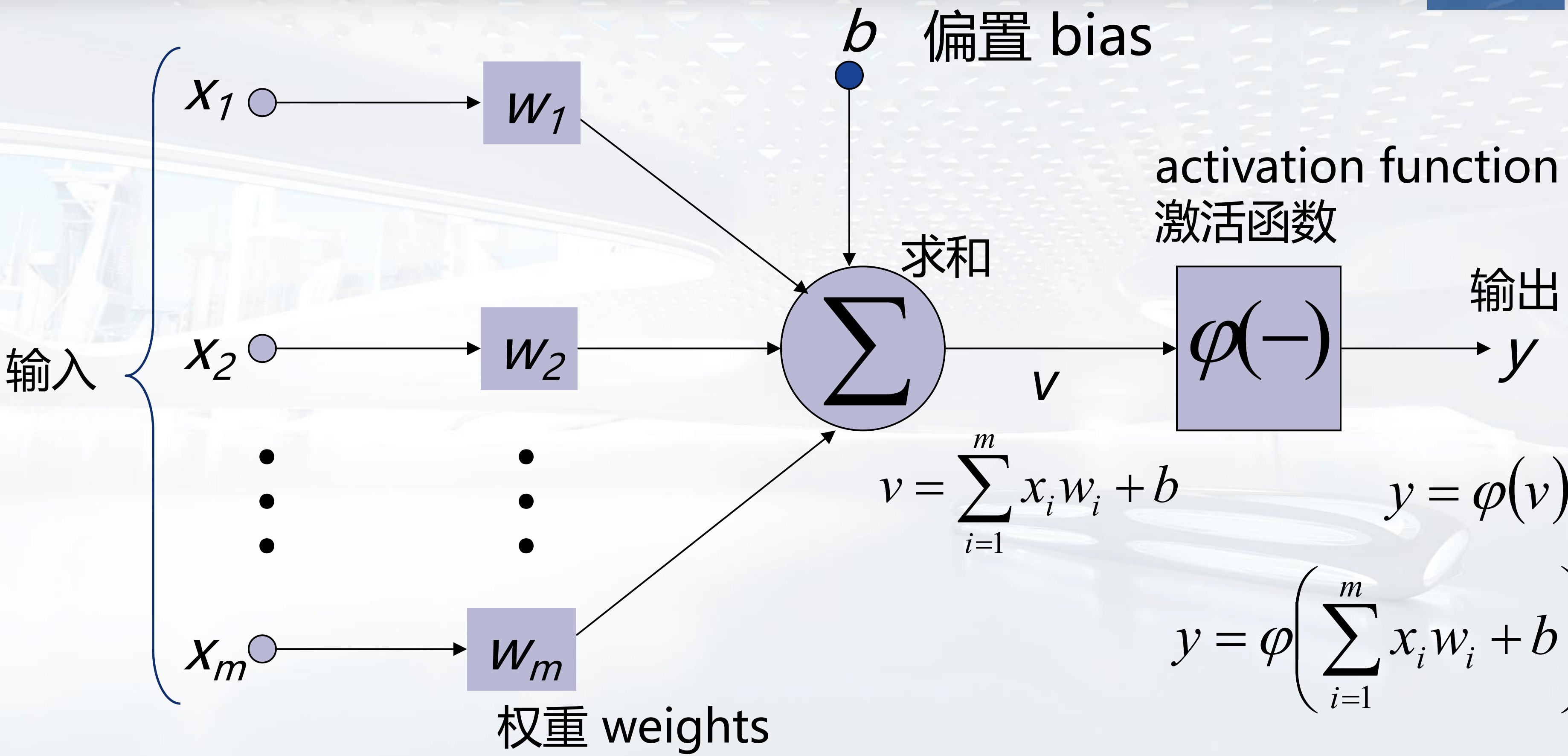
- 为人工智能的发展奠定了基础
- **“数据、算法、算力”**人工智能三要素

- 2004年IEEE Frank Rosenblatt Award成立，Frank Rosenblatt被尊称为神经网络的创立者

图片来源https://baijiahao.baidu.com/s?id=1713433120837173170&wfr=spider&for=pc

Contents

感知机



$$v=\sum_{i=1}^{m} x_i w_i + b$$

$$y=\varphi(v)$$

$$y=\varphi\left(\sum_{i=1}^{m} x_i w_i + b\right)$$

感知机 - Bias of a Neuron

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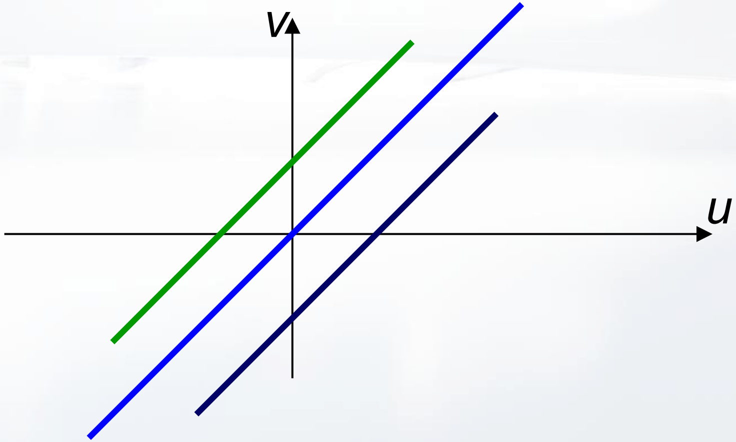
- Bias b has the effect of applying an affine transformation to u

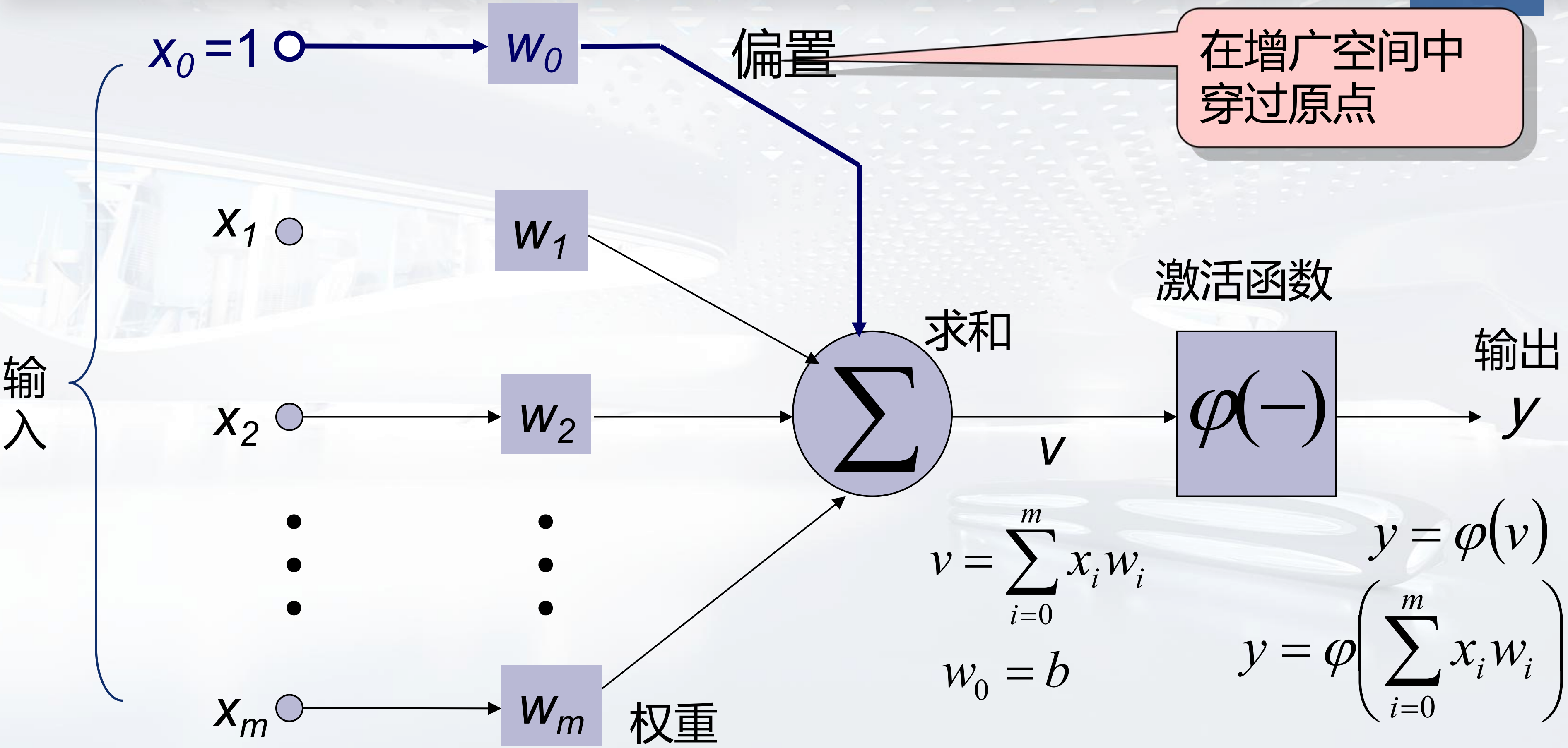
$$v = u + b$$

- v is the **induced field** of the neuron



$$u = \sum_{j=1}^{m} w_j x_j$$

感知机 - Bias as Extra Input



$$v = \sum_{i=0}^{m} x_i w_i$$

$$w_0 = b$$

$$y = \varphi(v)$$

$$y = \varphi\left(\sum_{i=0}^{m} x_i w_i\right)$$

The Neuron

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- The neuron is the basic information processing unit of a NN. It consists of:

  1 A set of synapses or connecting links, each link characterized by a weight:

  $$W_1,\ W_2,\ \ldots,\ W_m$$

  2 An adder function (linear combiner) which computes the weighted sum of the inputs:

  $$v = \sum_{i=1}^{m} x_i w_i + b \qquad\qquad v = \sum_{i=0}^{m} x_i w_i$$

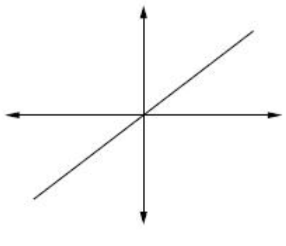
  3 Activation function (squashing function) for limiting the amplitude of the output of the neuron.

  $$y = \varphi(v) \qquad\qquad y = \varphi\left(\sum_{i=0}^{m} x_i w_i\right)$$

感知机 - 激活函数

- 1.线性函数 linear function

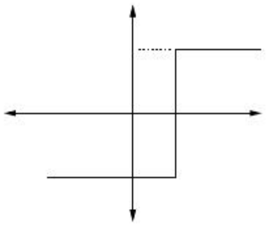
$$f(x) = ax$$



Linear function

- 2. 阶梯函数 step function

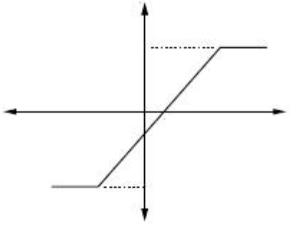
$$f(x) = \begin{cases} a_1 & if\ x \geq \theta \\ a_2 & if\ x < \theta \end{cases}$$



Step function

- 3. 斜坡函数 ramp function

$$f(x) = \begin{cases} \alpha & if\ x \geq \theta \\ x & if\ -\theta < x < \theta \\ -\alpha & if\ x \leq \theta \end{cases}$$



Ramp function

感知机 - 激活函数

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- 4. 逻辑函数 logistic function

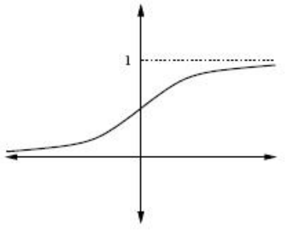
$$f(x) = \frac{1}{1+e^{-\lambda x}}$$

- 5. 双曲正切函数 hyperbolic tangent

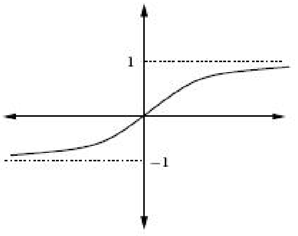
$$f(x) = \frac{e^{\lambda x} - e^{-\lambda x}}{e^{\lambda x} + e^{-\lambda x}}$$

- 6. 高斯函数 Gaussian function

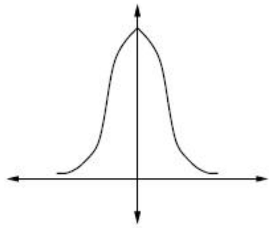
$$f(x) = e^{-x^2/\sigma^2}$$



Sigmoid function



Hyperbolic tangent function



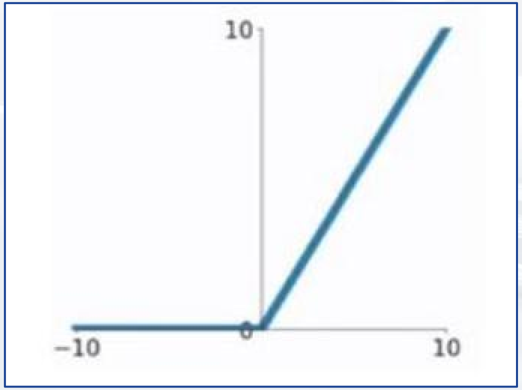
Gaussian function

Activation Function

- 7. ReLU function

修正线性单元 (Rectified Linear Unit)

$$g(z) = \begin{cases} z, & \text{if } z > 0 \\ 0, & \text{if } z < 0 \end{cases}$$



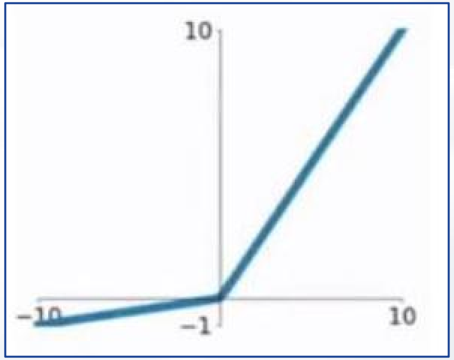
Activation Function

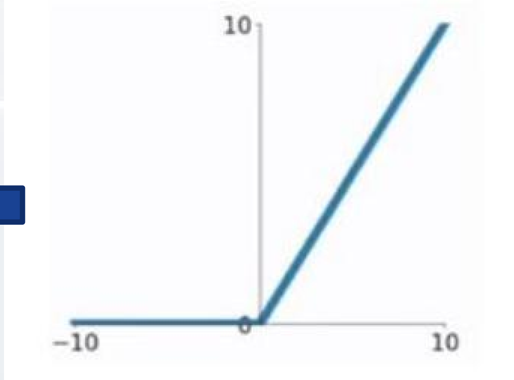
- 8. Leaky ReLU function

又称为PReLU函数

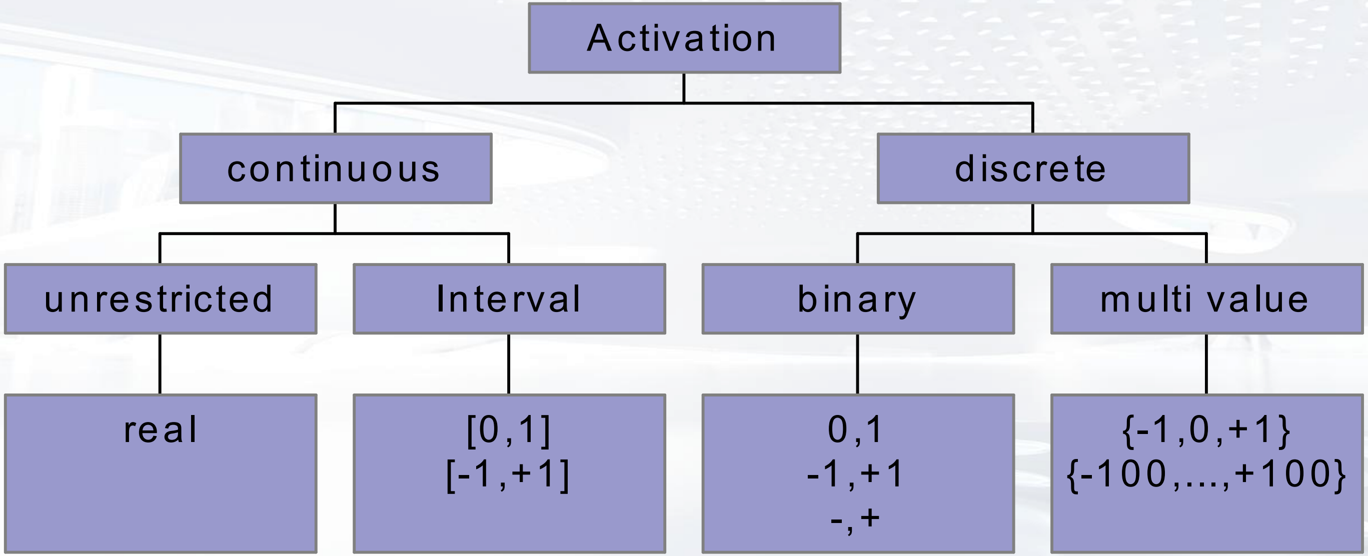
$$g(z) = \begin{cases} z, & \text{if } z > 0 \\ az, & \text{if } z < 0 \end{cases}$$

$$g(z) = \begin{cases} z, & \text{if } z > 0 \\ 0, & \text{if } z < 0 \end{cases}$$





Activation function



Perceptron

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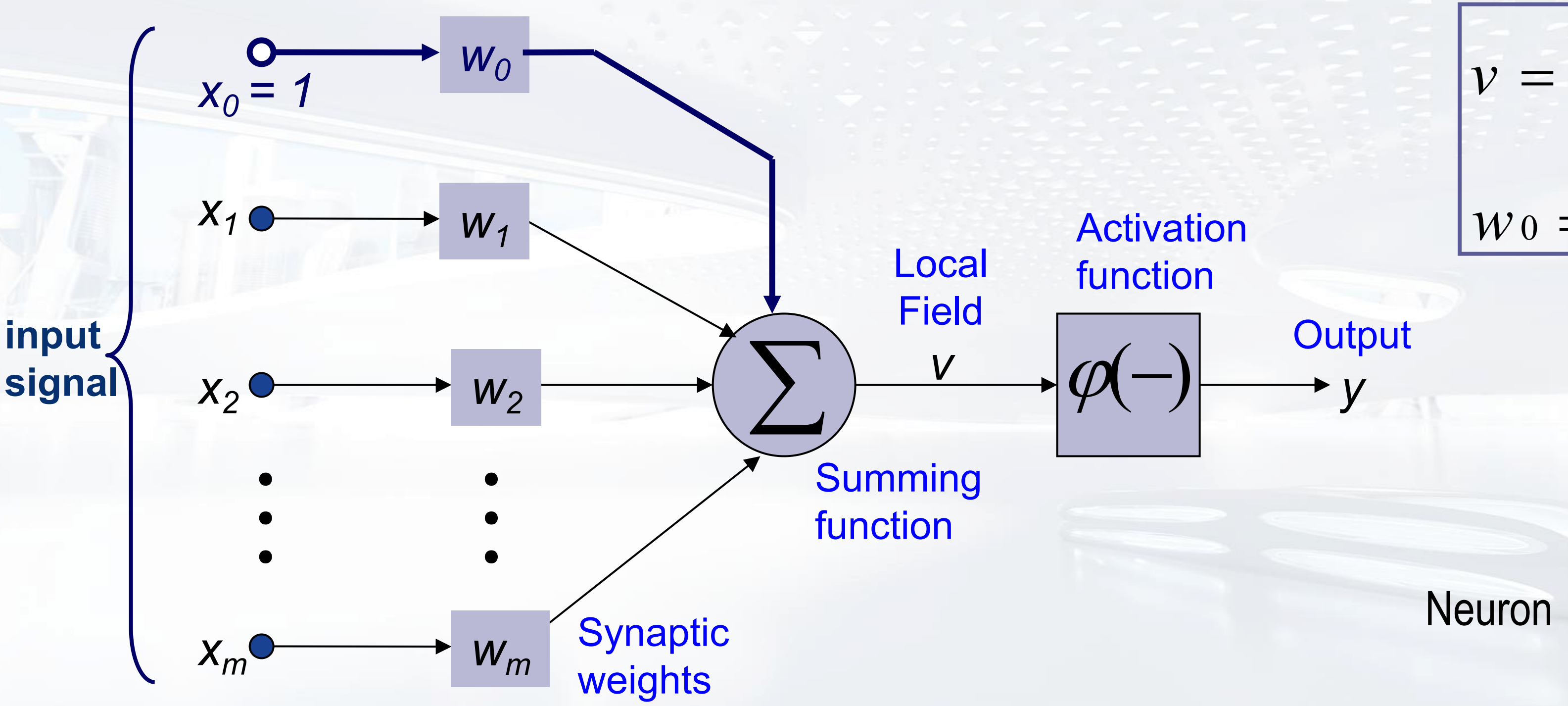
- In 1943, McCulloch and Pitts proposed the first single neuron model.
- Hebb proposed the theory that the learning process is generated from the change of weights between synapses.
- In 1958, Rosenblatt combined them together, and proposed "Perceptron".
- Perceptron is just a single neural model, and is composed of synaptic weights and threshold.
- It is the simplest and earliest neural network model, used for **classification**.

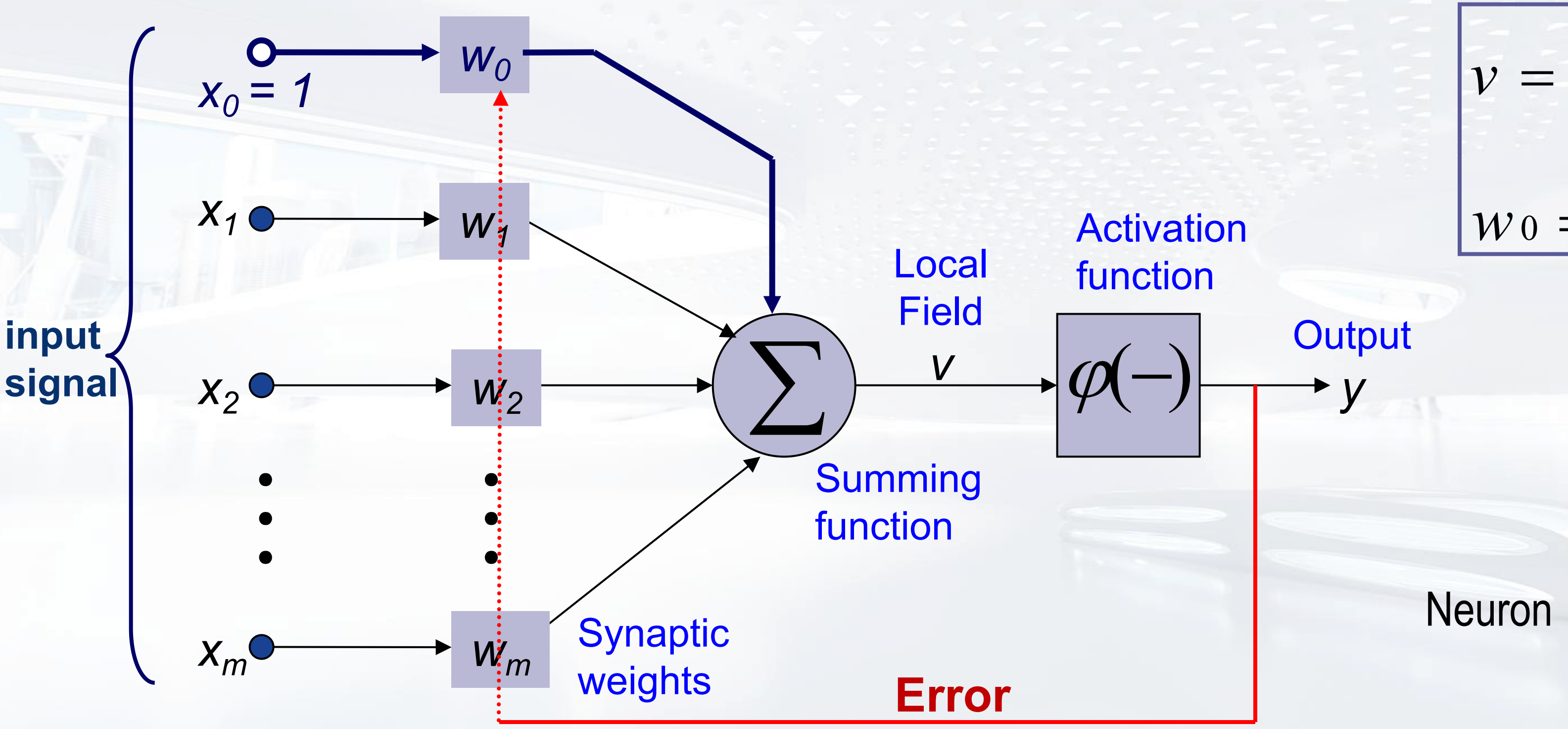
Perceptron



$$v = \sum_{j=0}^{m} w_j x_j$$

$$w_0 = b$$

Perceptron



$$v = \sum_{j=0}^{m} w_j x_j$$

$$w_0 = b$$

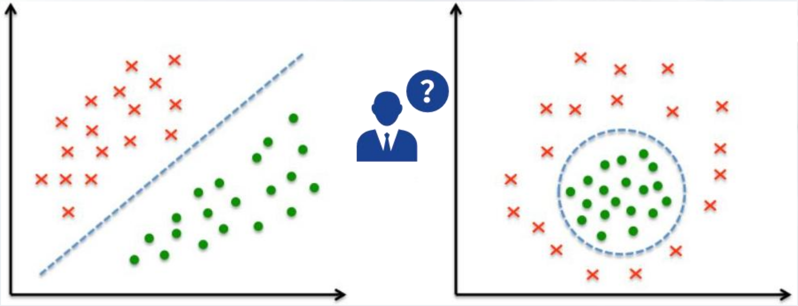
感知机

MIMA

- 我们有训练集 $T_1 \in C_1$ 和 $T_2 \in C_2$ 。其中，样本表示为 $\mathbf{x}=(x_0, x_1, x_2, \dots, x_m)^T$，且 $x_1, x_2, \dots, x_m \in R$ ， $x_0 = 1$。
- 假设 T_1 和 T_2 是 **线性可分的** linearly separable。
- 能否给出一个感知机将数据正确划分？ $\mathbf{w}=(w_0, w_1, w_2, \dots, w_m)^T$

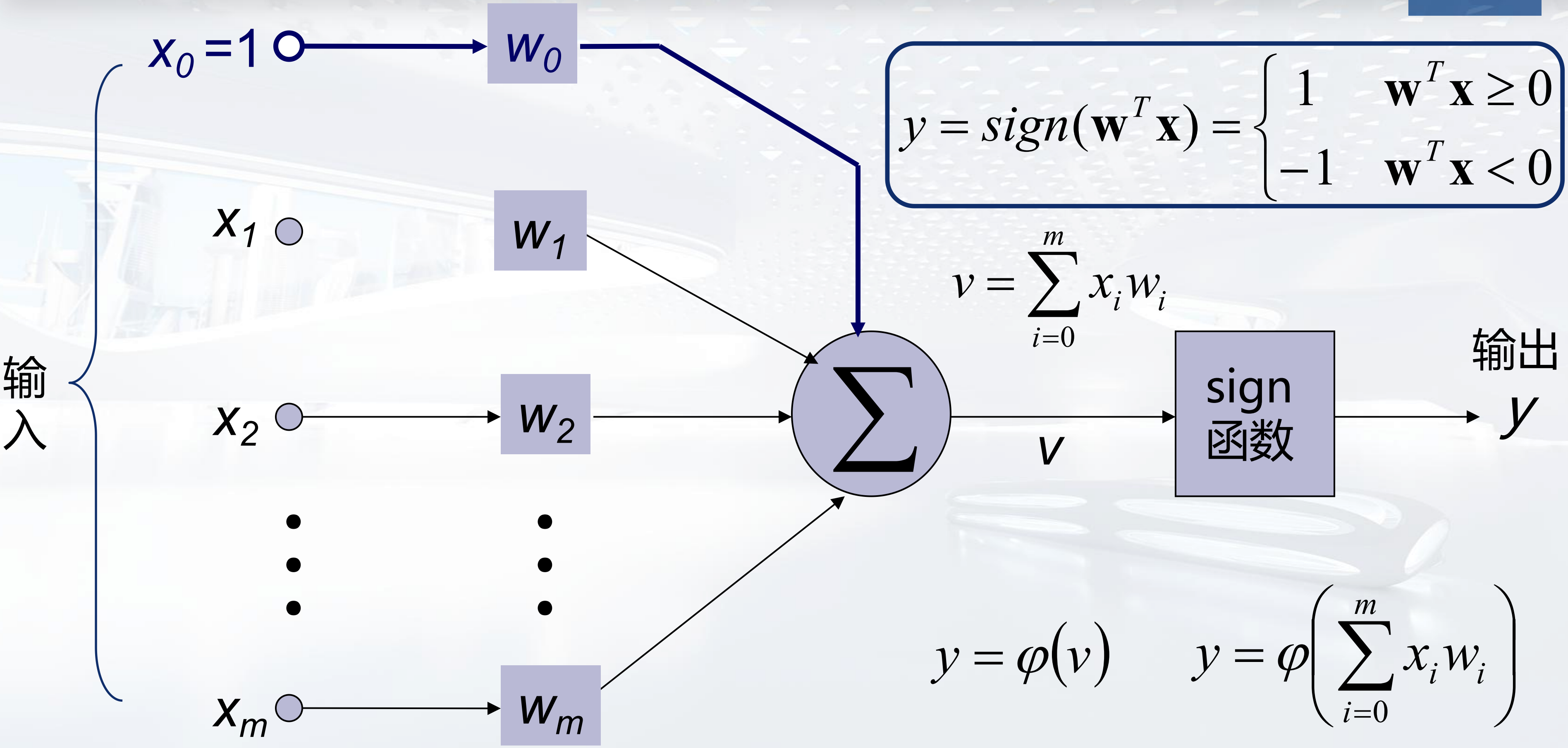
$d = +1$

$d = -1$



图片来源https://blog.csdn.net/pxhdky/article/details/85248575

感知机

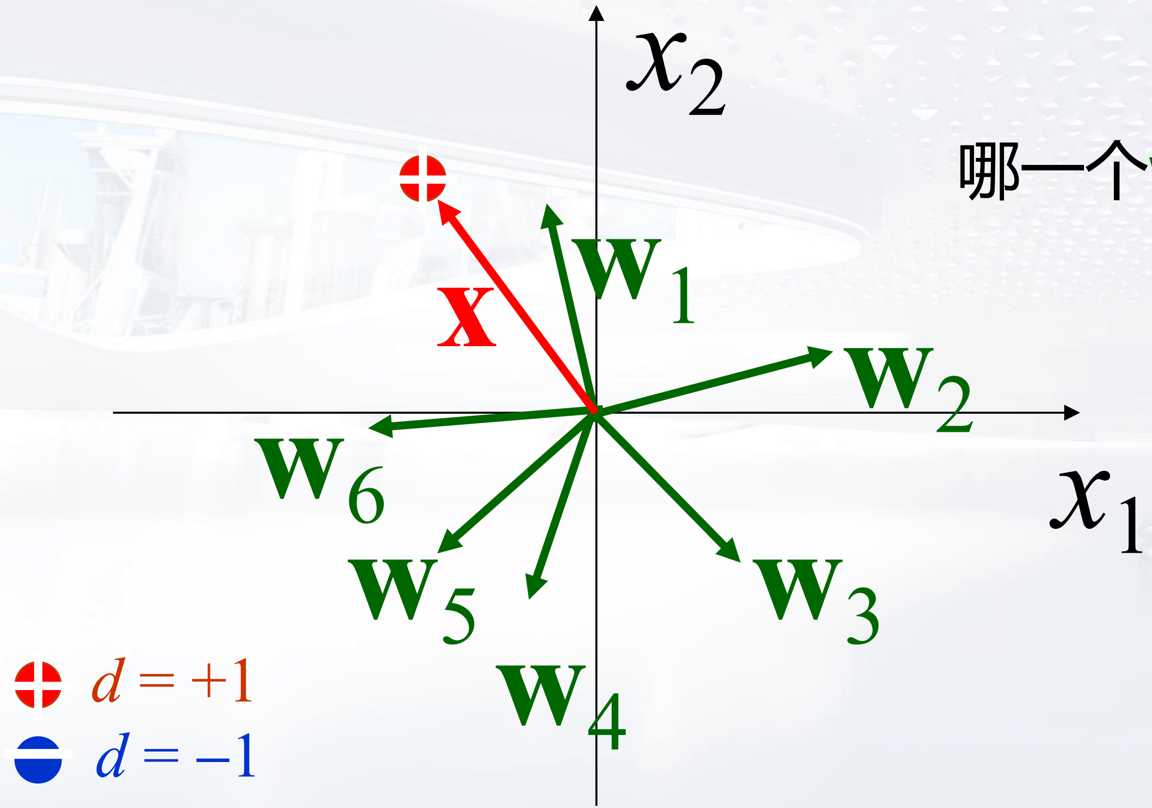


$$y = sign(\mathbf{w}^T\mathbf{x}) = \begin{cases} 1 & \mathbf{w}^T\mathbf{x} \geq 0 \\ -1 & \mathbf{w}^T\mathbf{x} < 0 \end{cases}$$

$$v = \sum_{i=0}^{m} x_i w_i$$

$$y = \varphi(v) \qquad y = \varphi\left(\sum_{i=0}^{m} x_i w_i\right)$$

感知机 - 求解

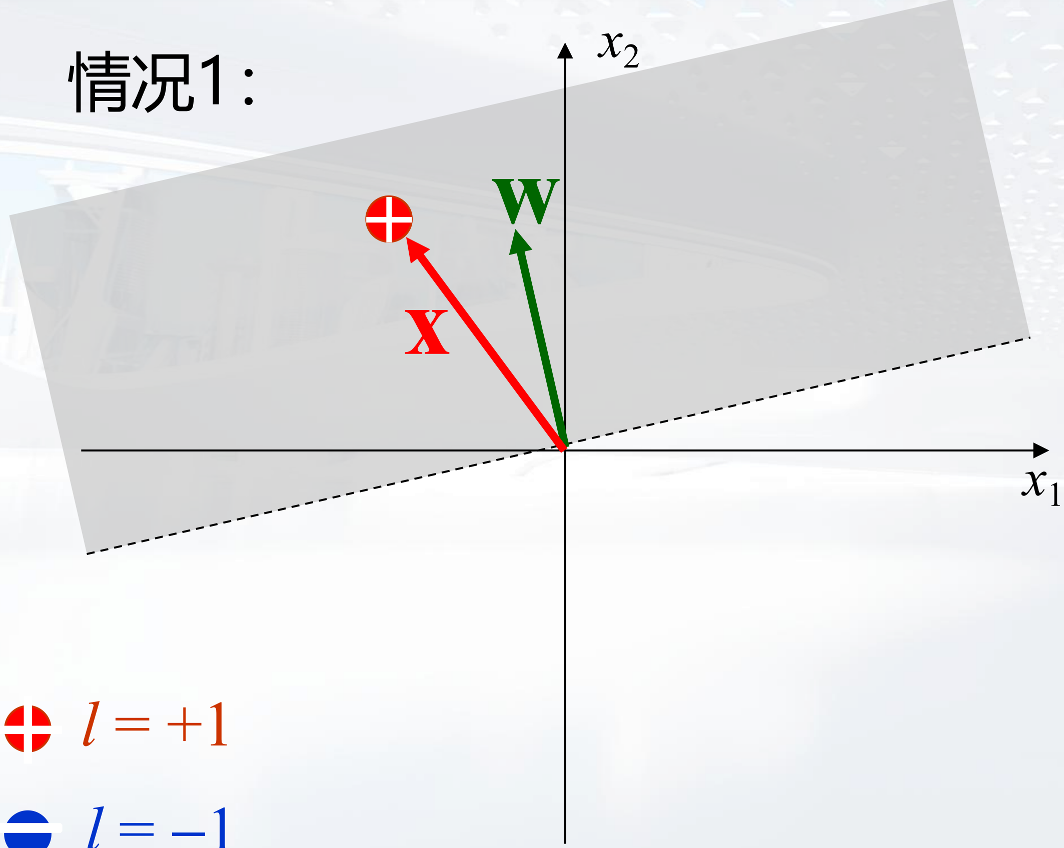


哪一个**w**可以正确的分类**x**?

感知机的学习机制

MIMA

情况1：



这个w代表的感知机可行吗?

可行 不行

$$\mathbf{w}^T\mathbf{x} > 0$$

$$\boxed{y = sign(\mathbf{w}^T\mathbf{x}) = 1}$$

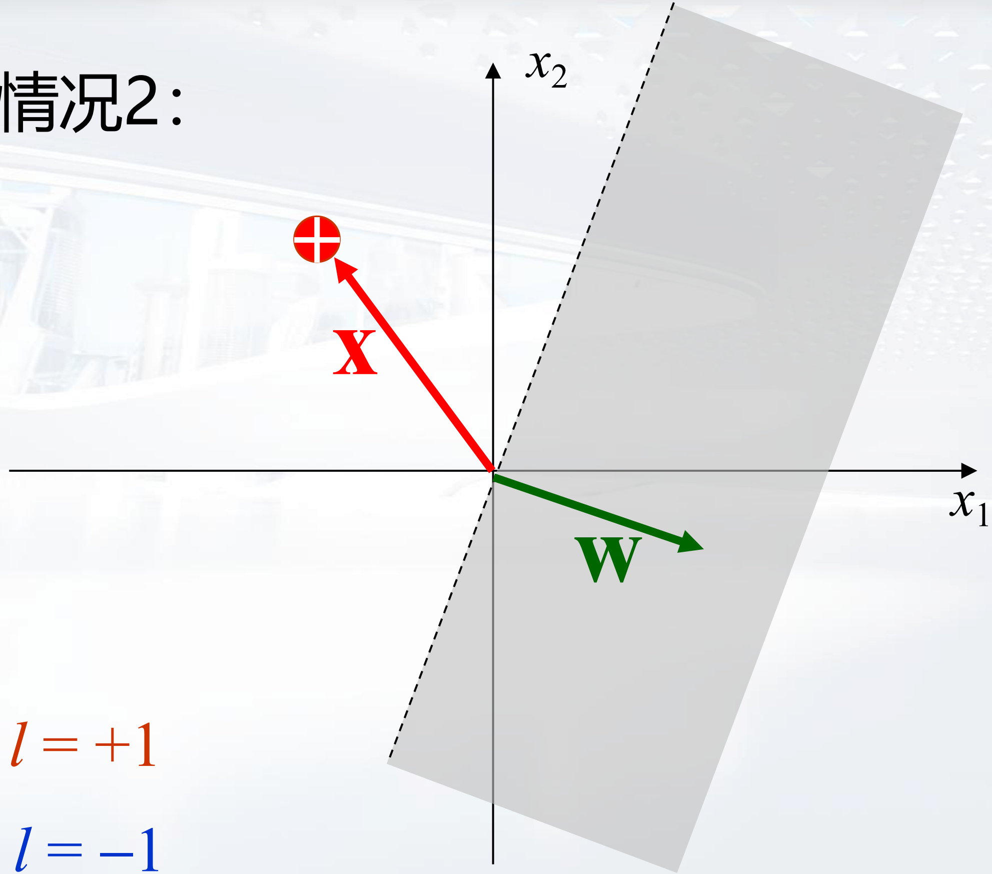
w 不需要更新（学习）

$l = +1$

$l = -1$

感知机的学习机制

情况2：



$l = +1$

$l = -1$

这个w代表的感知机可行吗？

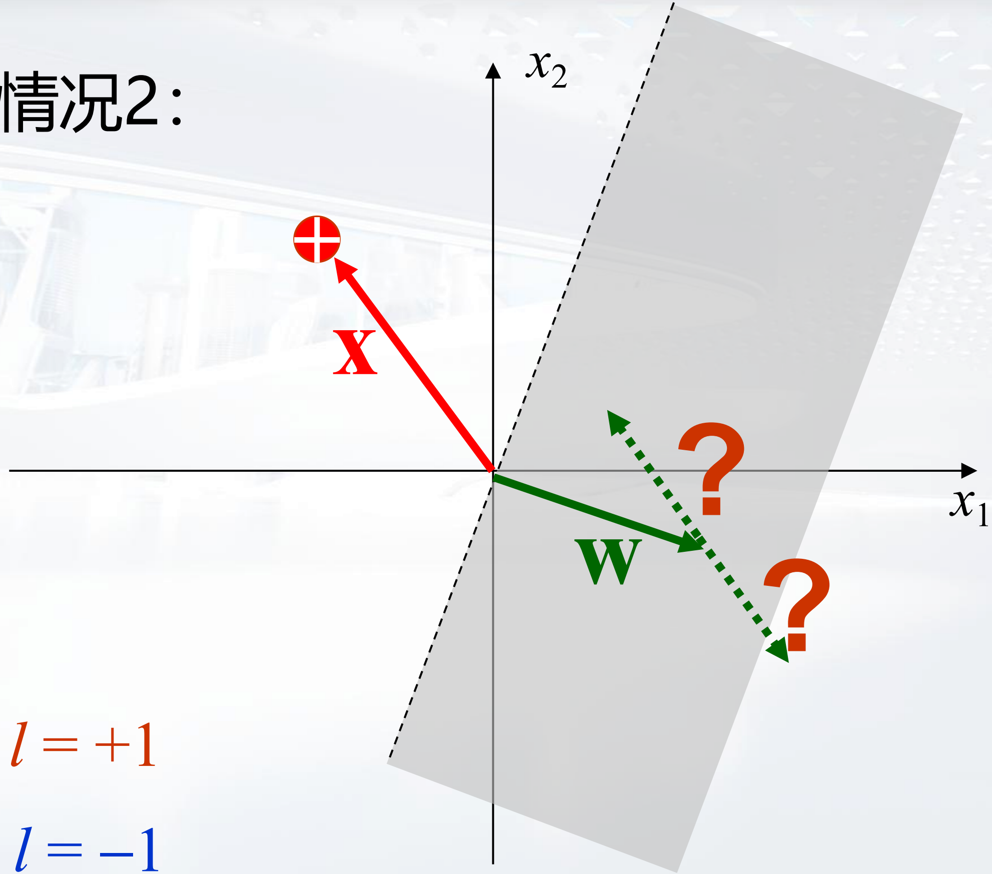
可行 不行

$\mathbf{w}^T\mathbf{x} < 0$ ✖

$$\boxed{y = sign(\mathbf{w}^T\mathbf{x}) = -1}$$

感知机的学习机制

情况2：



如何更新w让感知机变得可行?

$\mathbf{w}^T\mathbf{x} < 0$ 当前

$\mathbf{w}^T\mathbf{x} > 0$ 目标

$\Delta\mathbf{w} = ?$

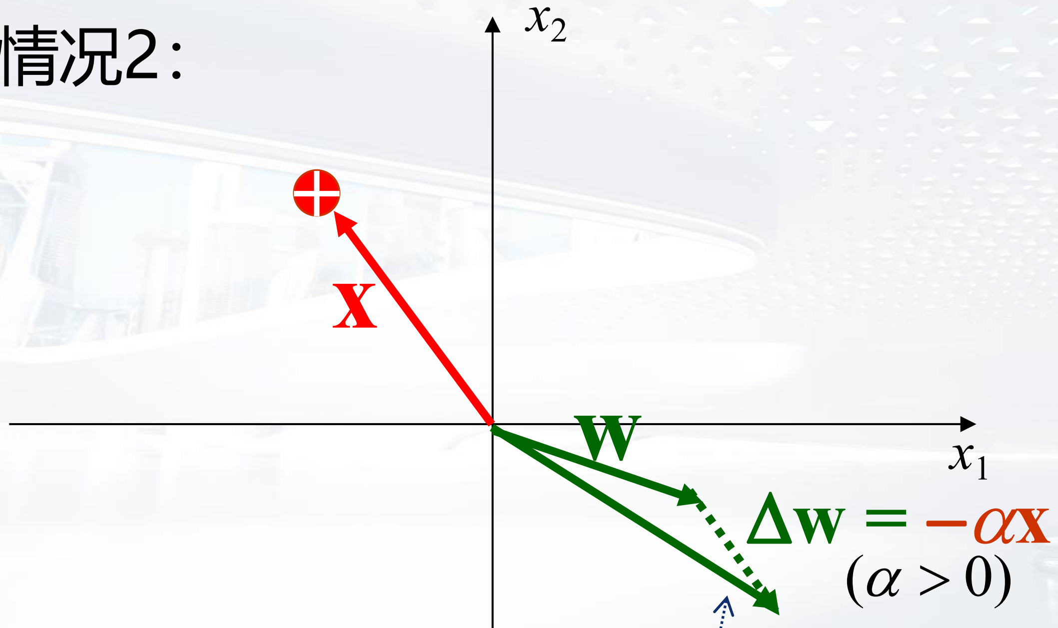
$l = +1$

$l = -1$

感知机的学习机制

MIMA

情况2：



如何更新**w**让感知机变得可行?

$\mathbf{w}^T\mathbf{x} < 0$ 当前

↓

$\mathbf{w}^T\mathbf{x} > 0$ 目标

$$(\mathbf{w}+\Delta\mathbf{w})^T\mathbf{x} = \underbrace{\mathbf{w}^T\mathbf{x}}_{<0} \underbrace{-\,\alpha\mathbf{x}^T\mathbf{x}}_{<0}$$

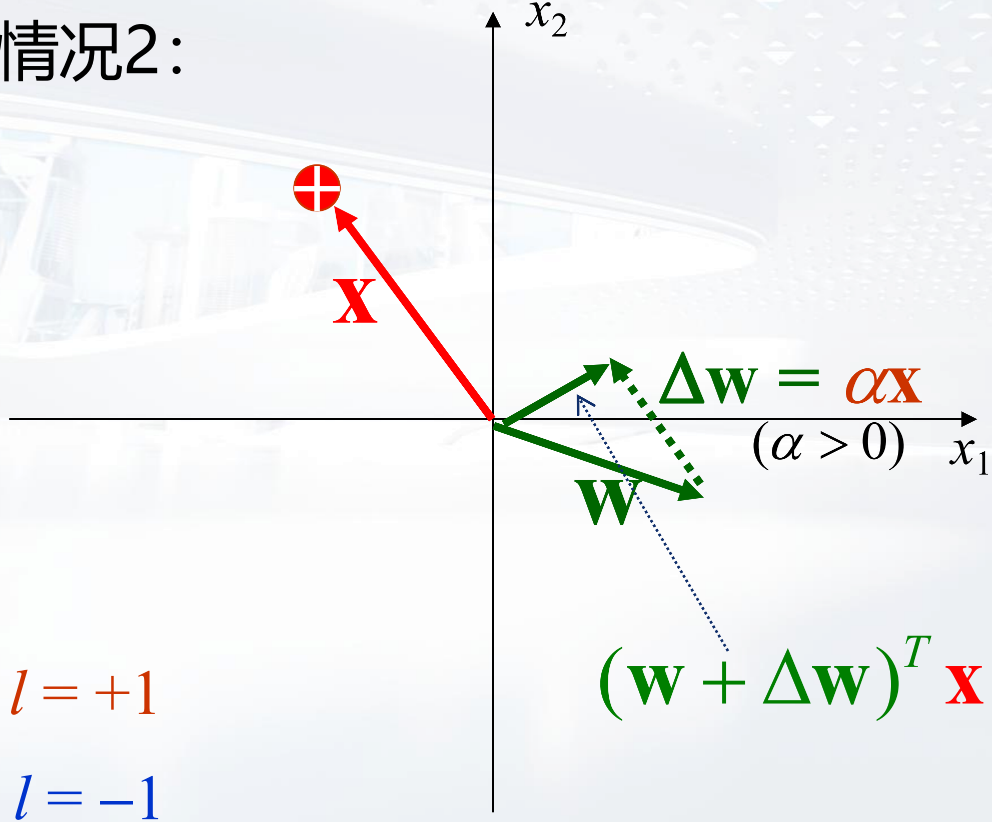
$l = +1$

$l = -1$

感知机的学习机制

MIMA

情况2：



如何更新**w**让感知机变得可行?

$\mathbf{w}^T\mathbf{x} < 0$ 当前

$\mathbf{w}^T\mathbf{x} > 0$ 目标

$$(\mathbf{w}+\Delta\mathbf{w})^T\mathbf{x} = \underbrace{\mathbf{w}^T\mathbf{x}}_{<0} + \underbrace{\alpha\mathbf{x}^T\mathbf{x}}_{>0}$$

$l = +1$

$l = -1$

感知机的学习机制

- 如果分类正确的话（情况1）　$l = y = 1$　$\mathbf{W}$ 不变

- 如果分类错误的话（情况2）
  - $l = +1$　$y = -1$　$\Delta\mathbf{w} = \alpha\mathbf{x}$
  - $l = -1$　$y = +1$　$\Delta\mathbf{w} = -\alpha\mathbf{x}$

给出一种设计：

$$r = l - y = \begin{cases} +2 \\ -2 \\ 0 \end{cases}$$

真实类别 - 预测类别

真实类别-预测类别

$+2$	1 - (-1)	把正的错分成负的，假负例
-2	(-1) - 1	把负的错分成正的，假正例
0 No error	1 - 1 (-1) - (-1)	预测正确

感知机的学习机制

- 如果分类正确的话（情况1） $l = y = 1$ $\mathbf{w}$ 不变
- 如果分类错误的话（情况2）

$l = +1 \quad y = -1 \quad \Delta\mathbf{w} = \alpha\mathbf{x}$

$l = -1 \quad y = +1 \quad \Delta\mathbf{w} = -\alpha\mathbf{x}$

给出一种设计：

真实类别-预测类别

$$r = l - y = \begin{cases} +2 \\ -2 \\ 0 \end{cases}$$

真实类别 - 预测类别

$+2$	⊕ → ⊖	1 - (-1)
-2	⊖ → ⊕	(-1) - 1
0	No error	1 - 1 (-1) - (-1)

$$\Delta\mathbf{w} = \eta r \mathbf{x}$$

学习率 $\eta > 0$

误差

输入

把正的错分成负的，假负例

把负的错分成正的，假正例

预测正确

感知机 - 求解

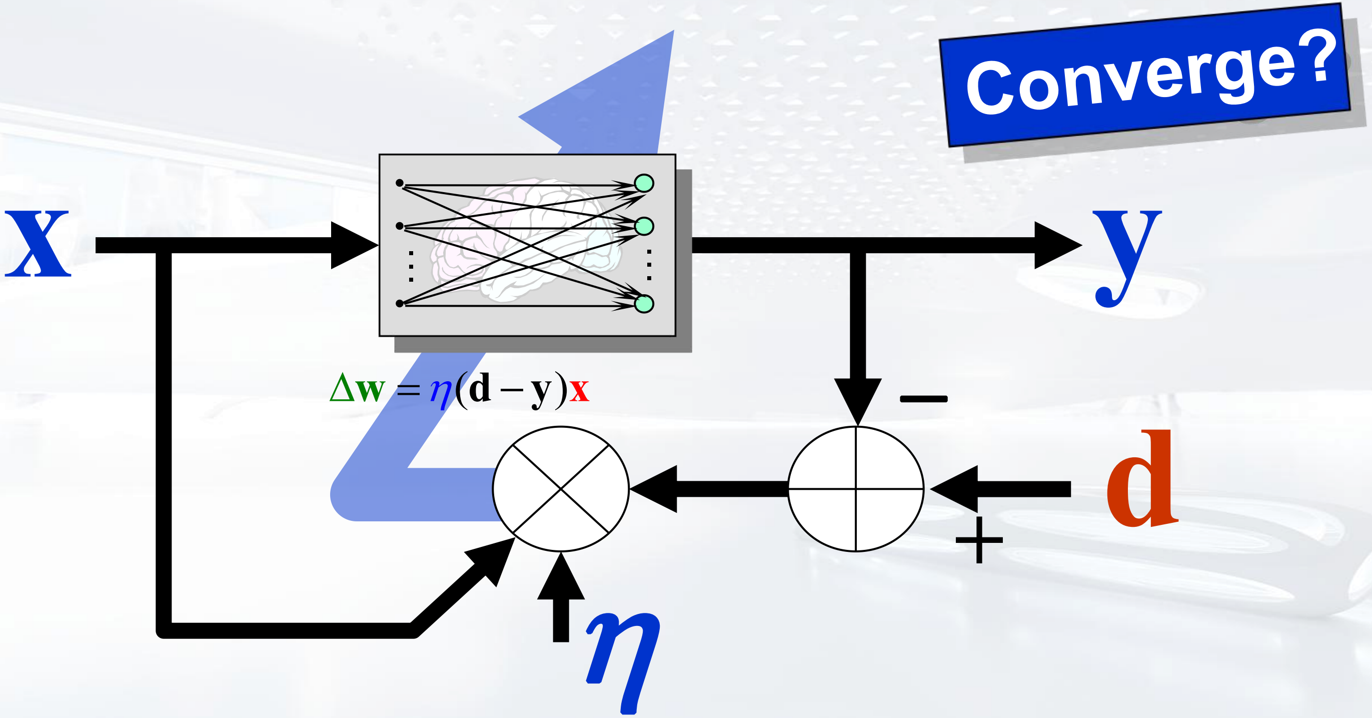
多点 情况如何更新**w**?

$$\Delta w_i(t) = \eta r_i x_i(t)$$

$$r_i = d_i - y_i = \begin{cases} 0 & d_i = y_i \\ +2 & d_i = 1, y_i = -1 \\ -2 & d_i = -1, y_i = 1 \end{cases}$$

$$\Delta w_i(t) = \eta (d_i - y_i) x_i(t)$$

Learning Rule

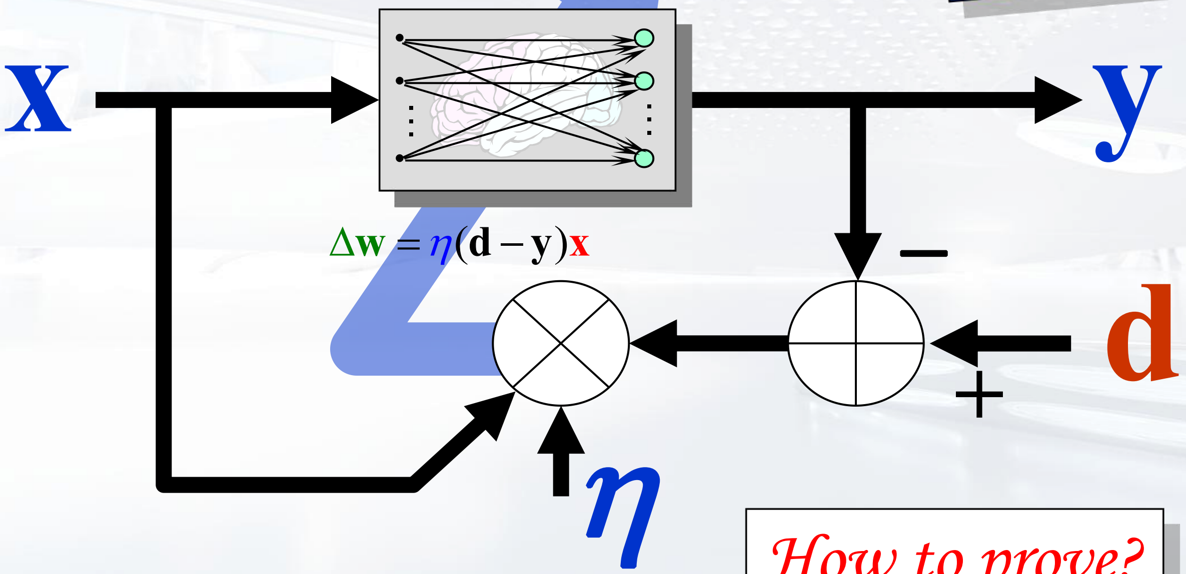


Learning Rule

MIMA

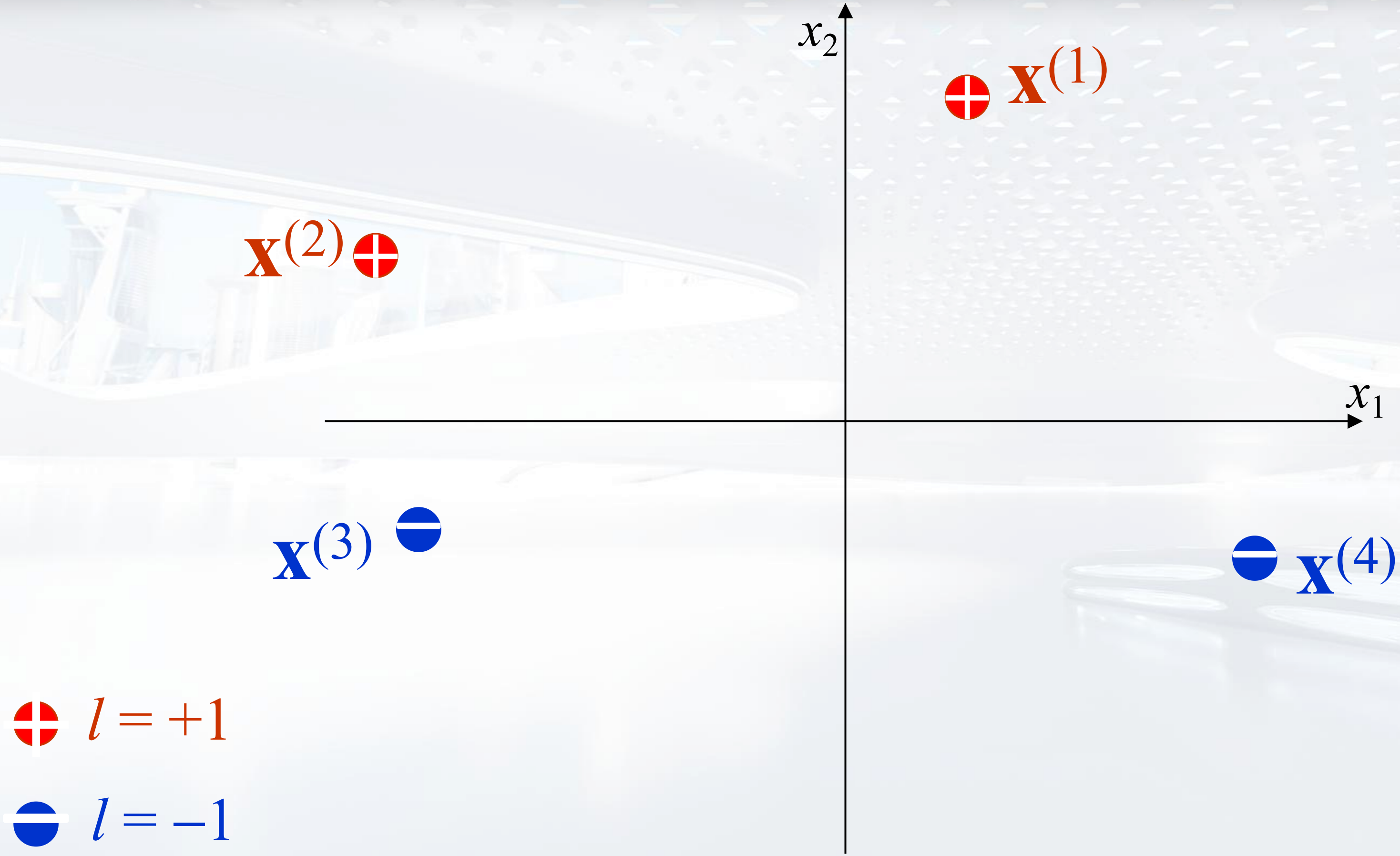
If the given training set is linearly separable, the learning process will converge in a finite number of steps.

Converge?

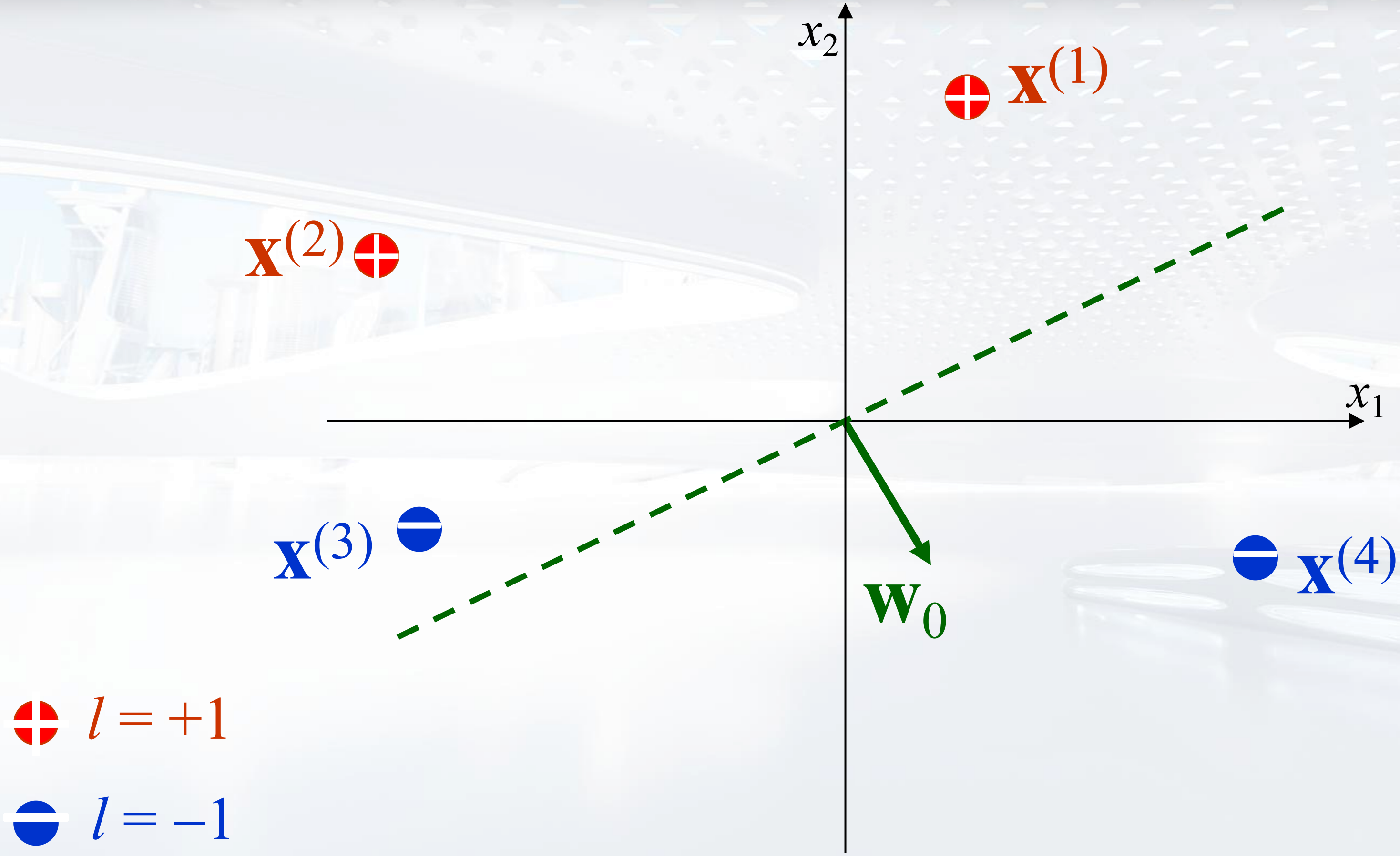


How to prove?

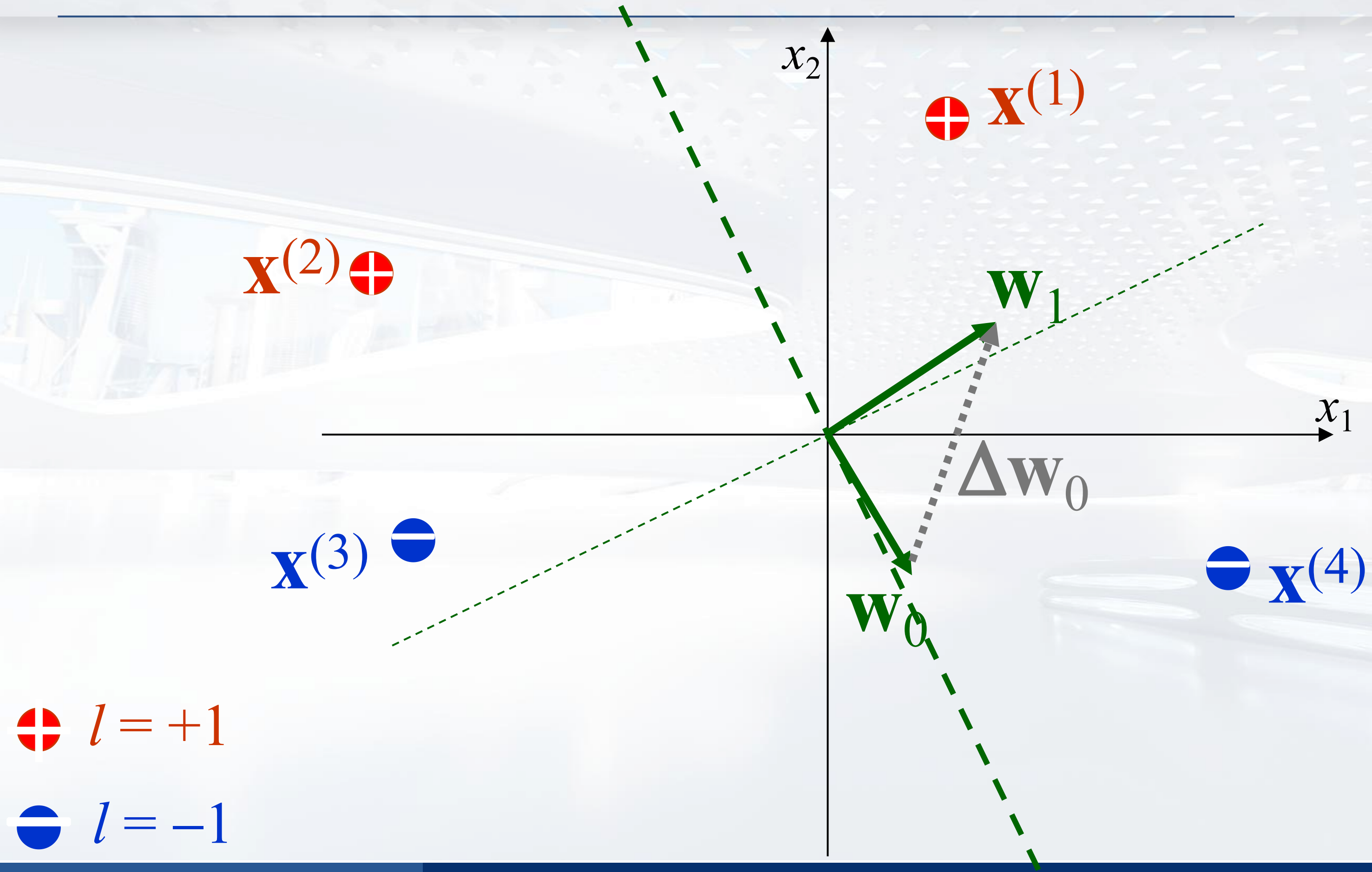
感知机的学习机制



感知机的学习机制

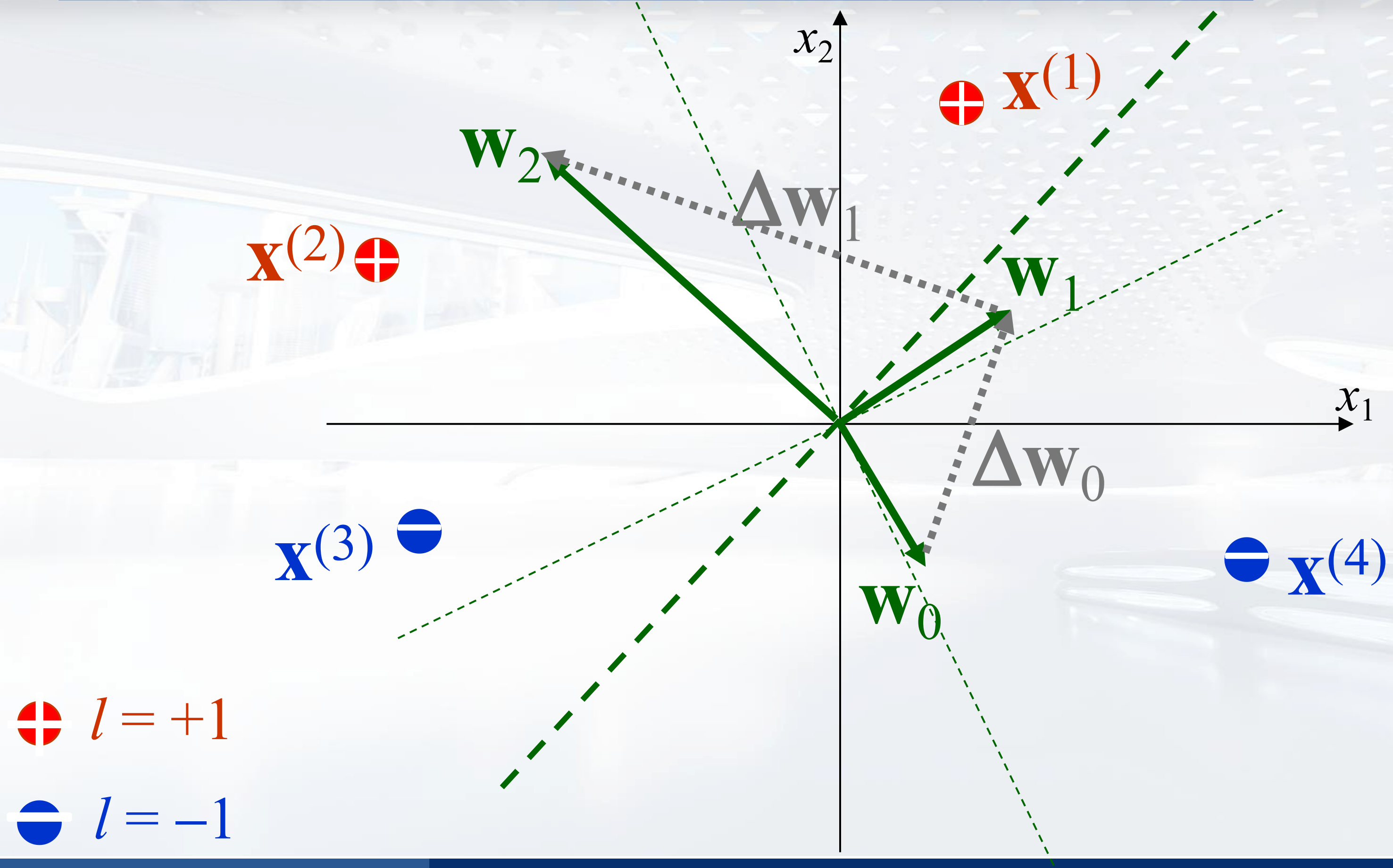


感知机的学习机制



x_2
$\mathbf{x}^{(1)}$
$\mathbf{x}^{(2)}$
$\mathbf{w}_1$
x_1
$\Delta\mathbf{w}_0$
$\mathbf{x}^{(3)}$
$\mathbf{x}^{(4)}$
$\mathbf{w}_0$
$l = +1$
$l = -1$

感知机的学习机制



x_2
x_1
$\mathbf{x}^{(1)}$
$\mathbf{x}^{(2)}$
$\mathbf{x}^{(3)}$
$\mathbf{x}^{(4)}$
$\mathbf{w}_2$
$\Delta\mathbf{w}_1$
$\mathbf{w}_1$
$\Delta\mathbf{w}_0$
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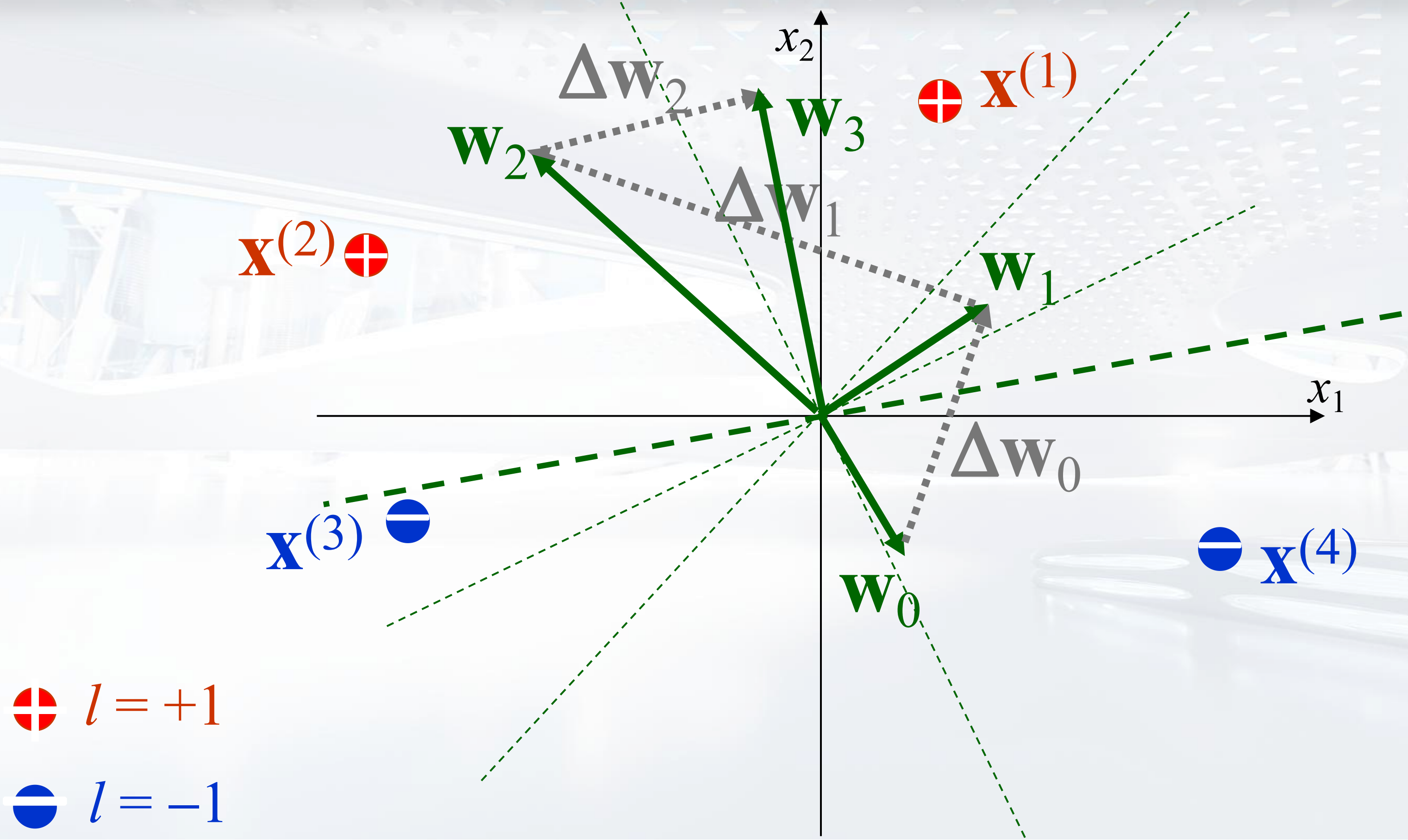
$l = -1$

感知机的学习机制


x_2
x_1
$\Delta\mathbf{w}_2$
$\mathbf{w}_3$
$\mathbf{x}^{(1)}$
$\mathbf{w}_2$
$\Delta\mathbf{w}_1$
$\mathbf{x}^{(2)}$
$\mathbf{w}_1$
$\Delta\mathbf{w}_0$
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$\mathbf{w}_0$
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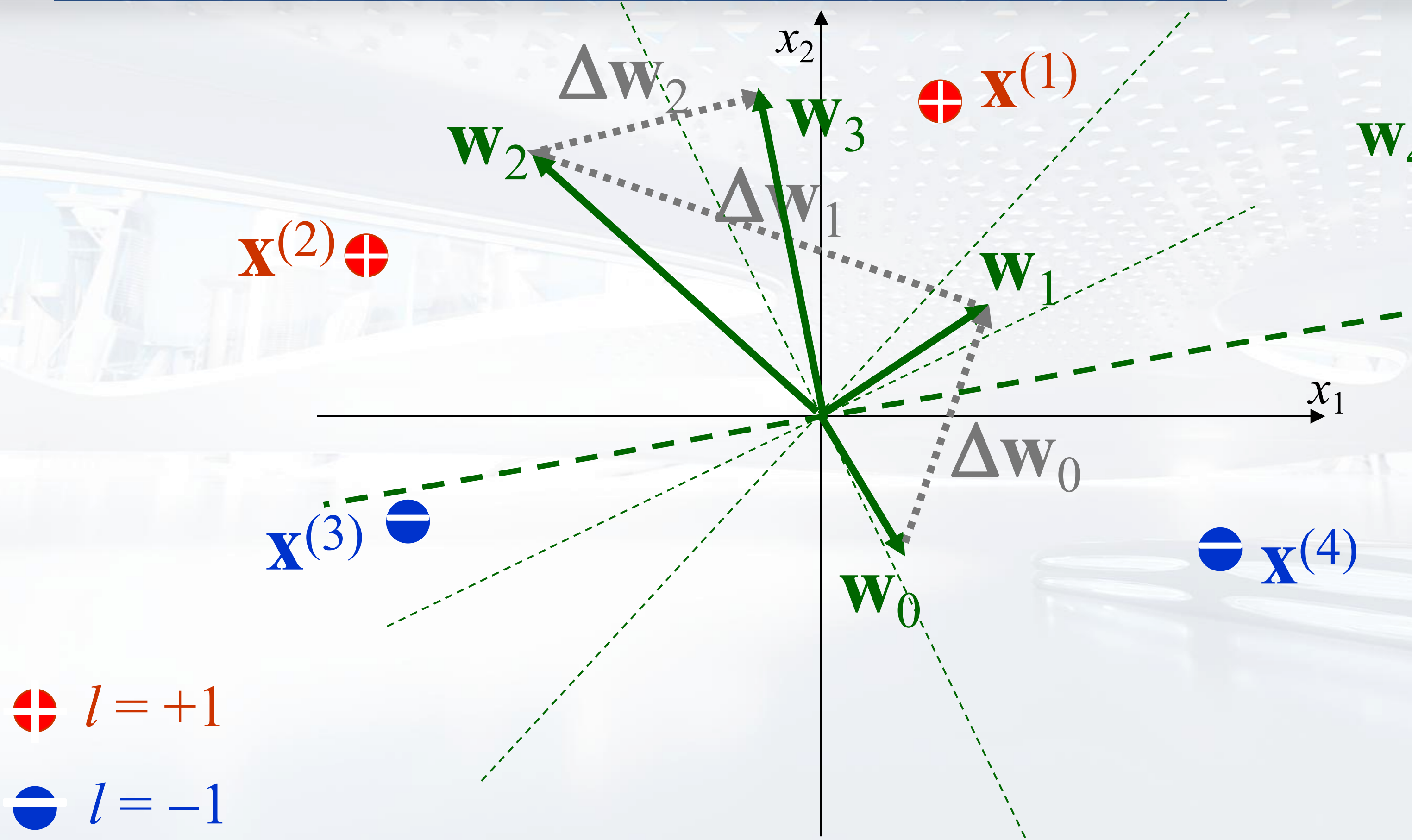
感知机的学习机制


x_2
x_1
$\Delta \mathbf{w}_2$
$\mathbf{w}_3$
$\mathbf{x}^{(1)}$
$\mathbf{w}_4 = \mathbf{w}_3$
$\mathbf{w}_2$
$\Delta \mathbf{w}_1$
$\mathbf{x}^{(2)}$
$\mathbf{w}_1$
$\Delta \mathbf{w}_0$
$\mathbf{x}^{(3)}$
$\mathbf{x}^{(4)}$
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$l = +1$
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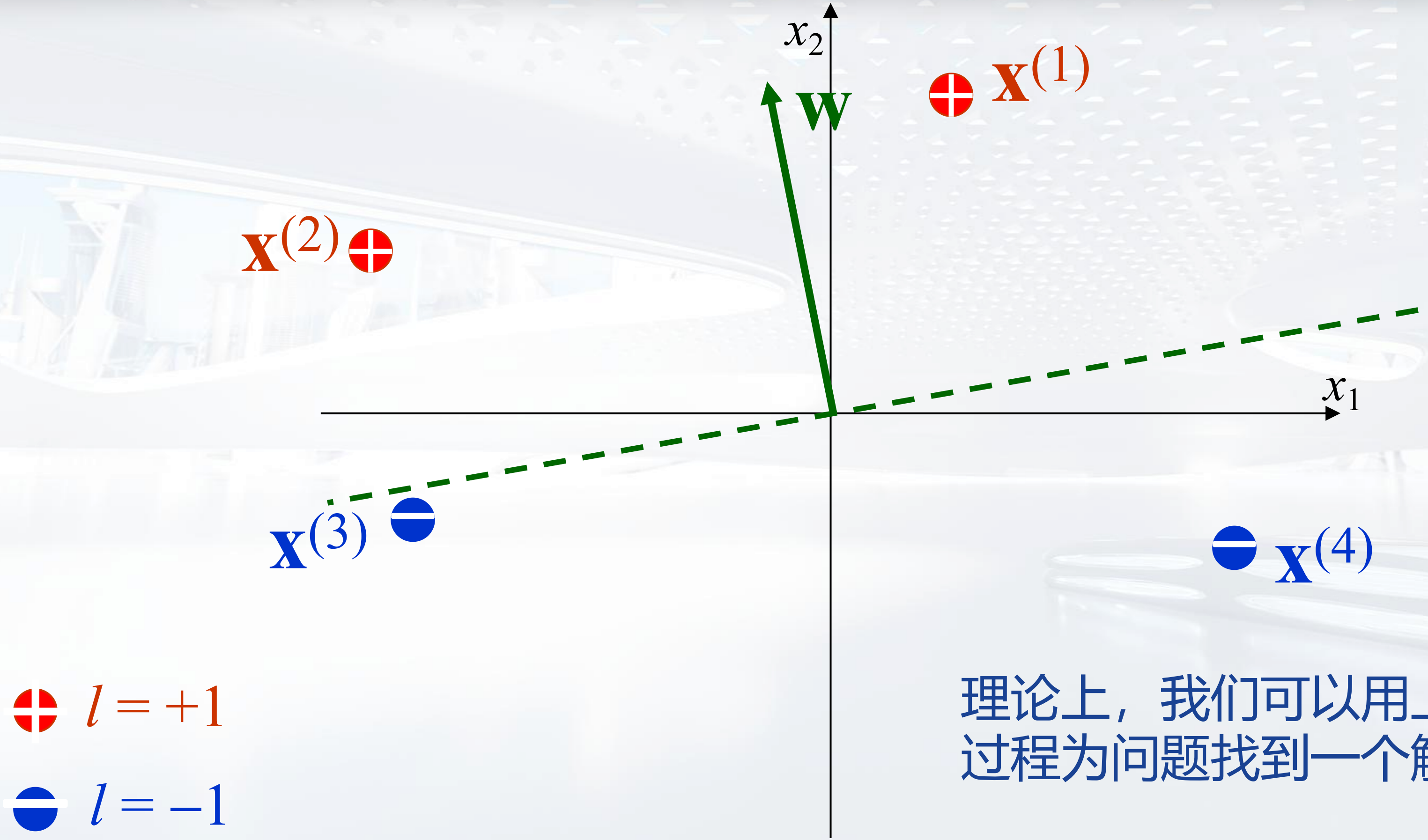
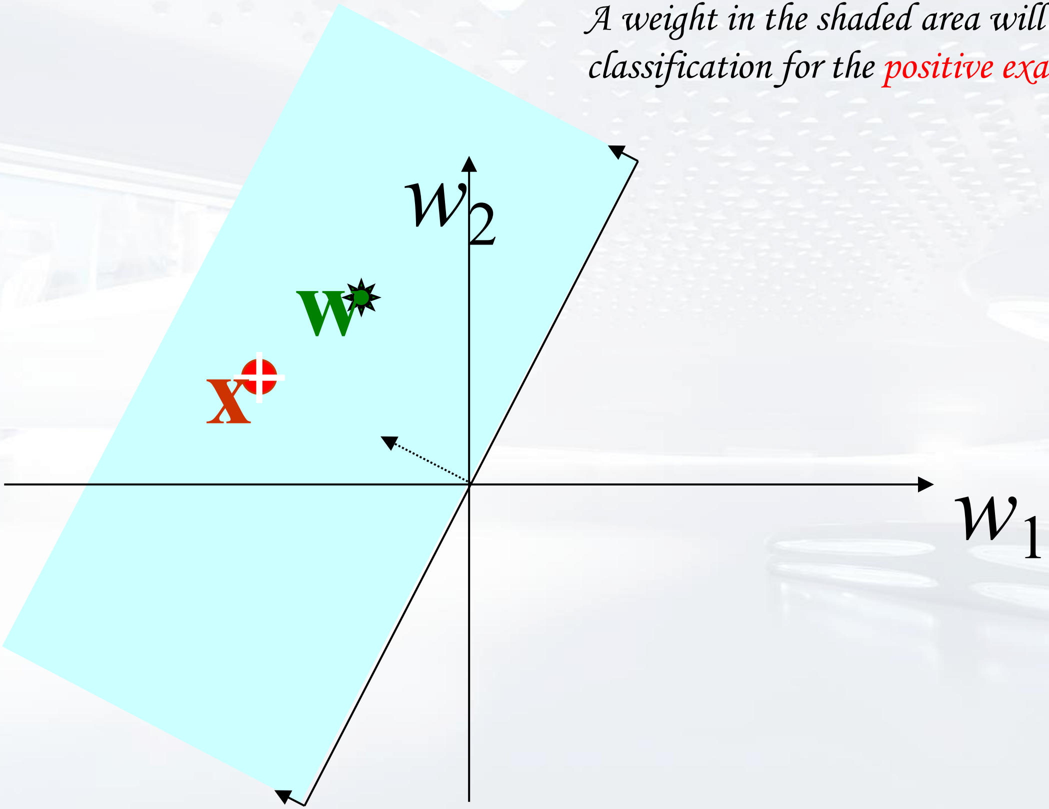
感知机的学习机制



理论上，我们可以用上述过程为问题找到一个解。

Weight Space

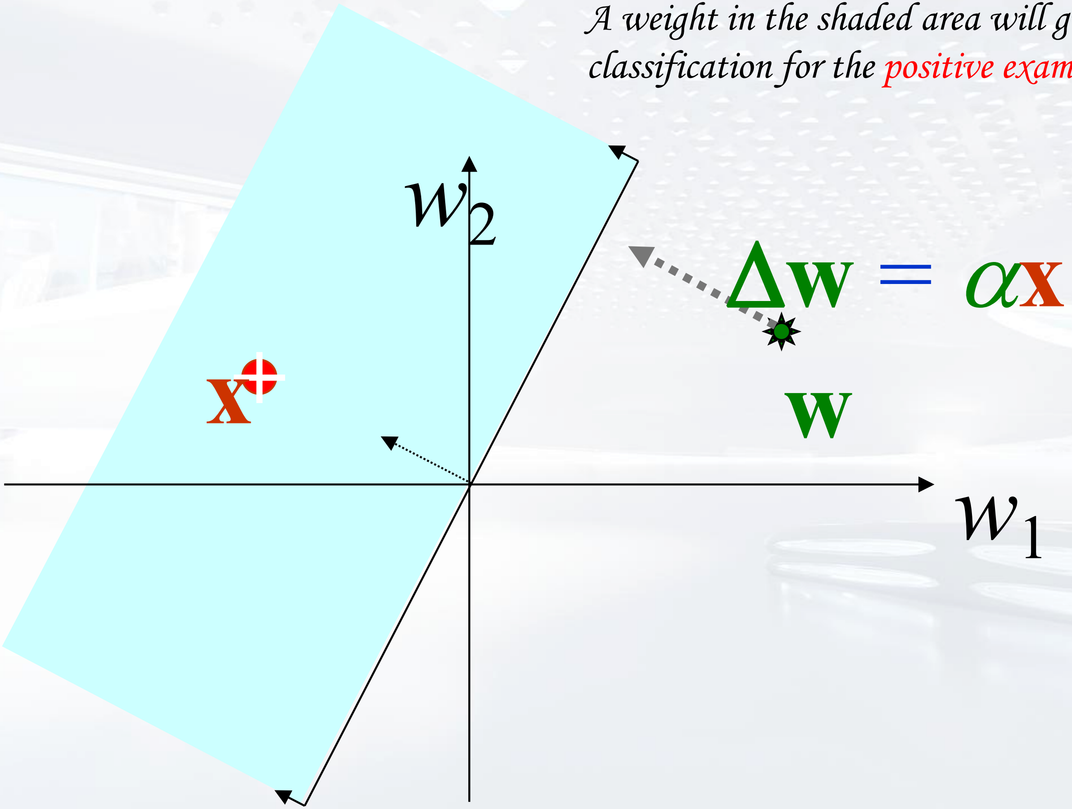
A weight in the shaded area will give correct classification for the positive example.



Weight Space

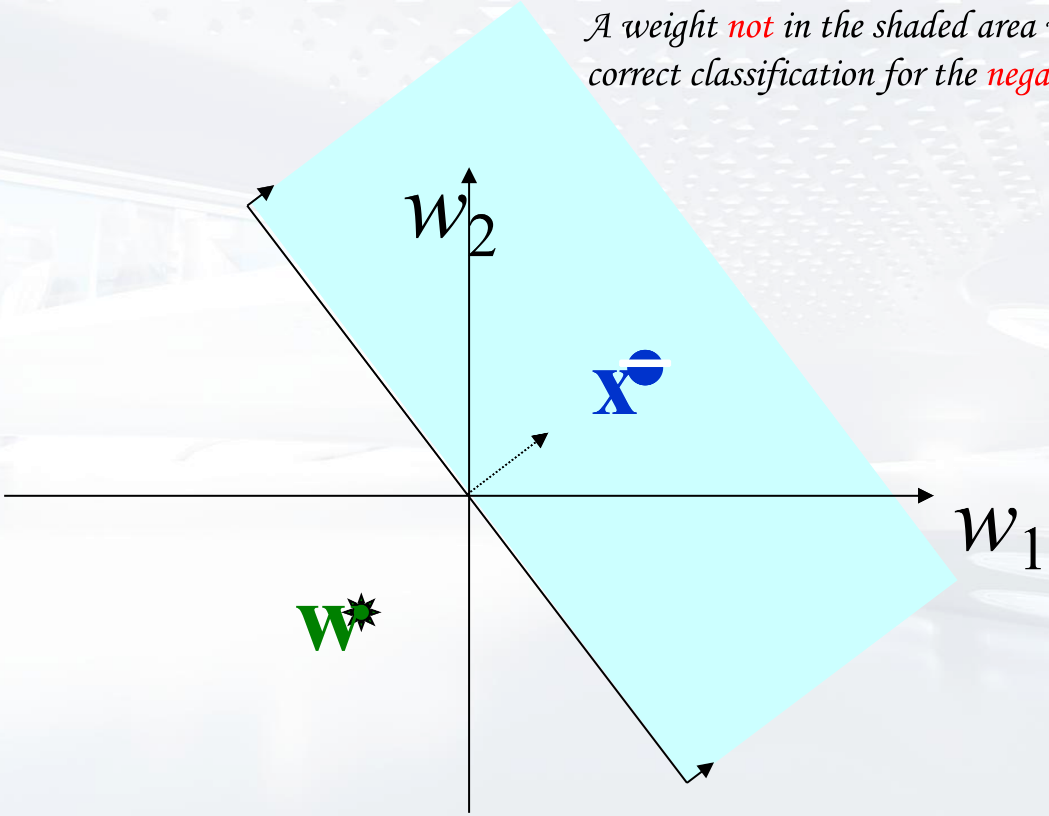
MIMA

A weight in the shaded area will give correct classification for the positive example.



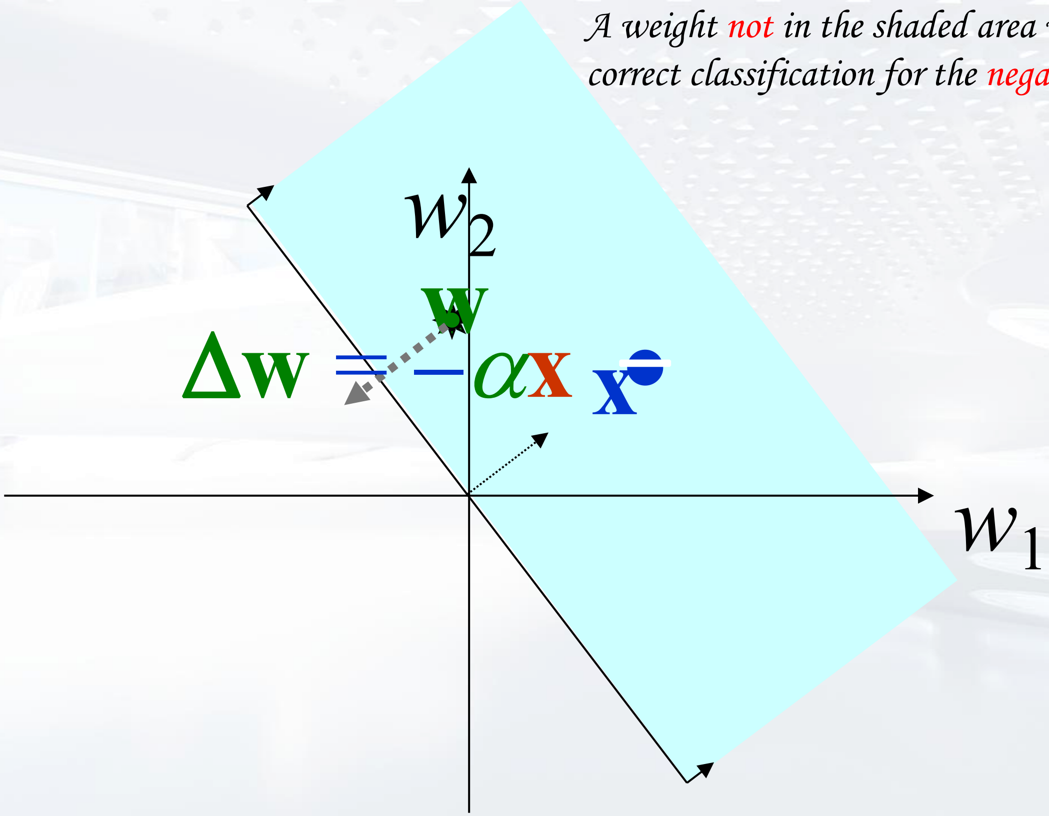
Weight Space

*A weight **not** in the shaded area will give correct classification for the **negative example.***

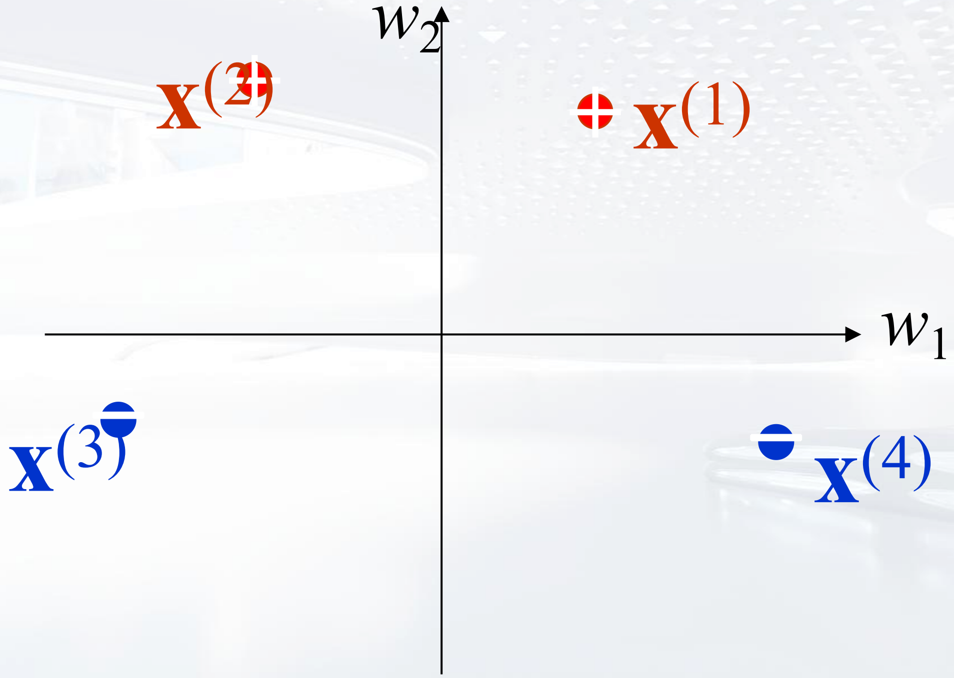


Weight Space

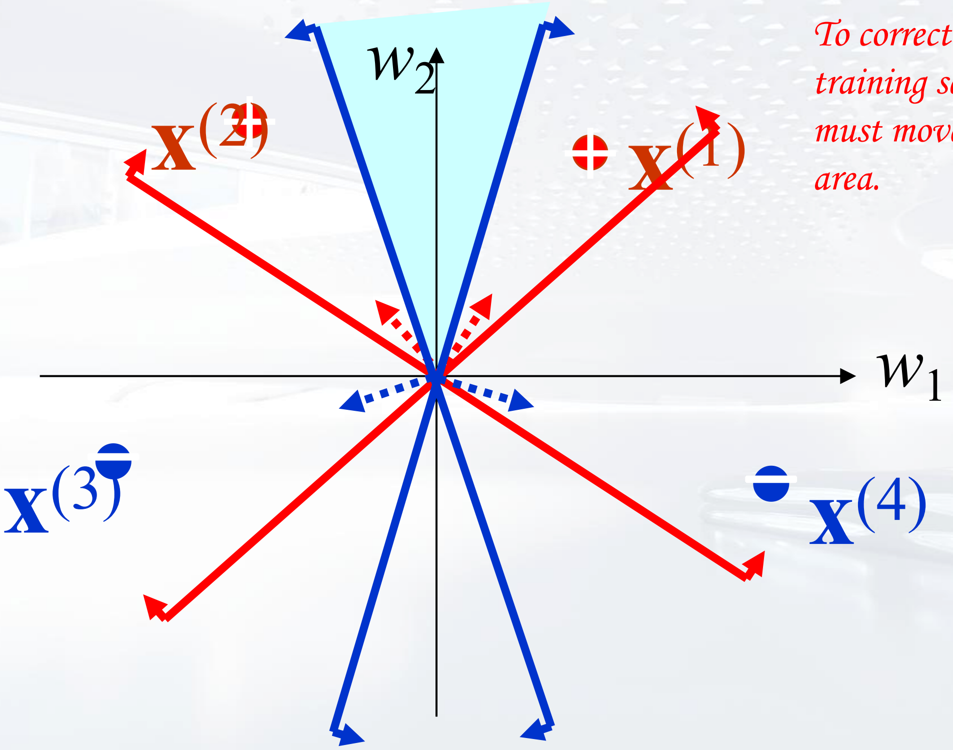
*A weight **not** in the shaded area will give correct classification for the **negative example.***



Learning Scenario in Weight Space

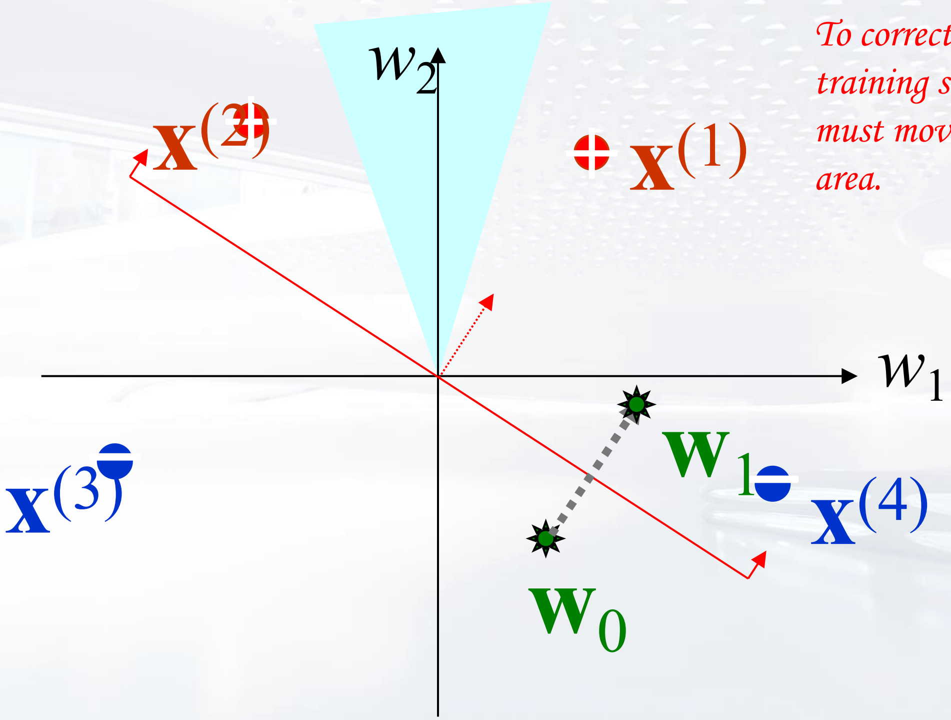


Learning Scenario in Weight Space



To correctly classify the training set, the weight must move into the shaded area.

Learning Scenario in Weight Space



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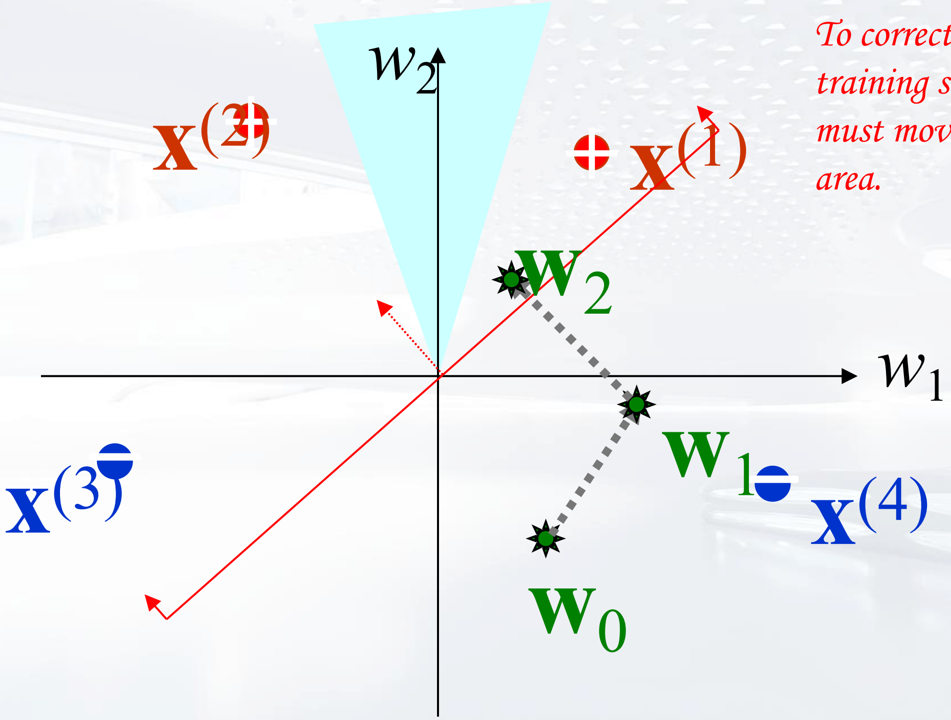
Learning Scenario in Weight Space



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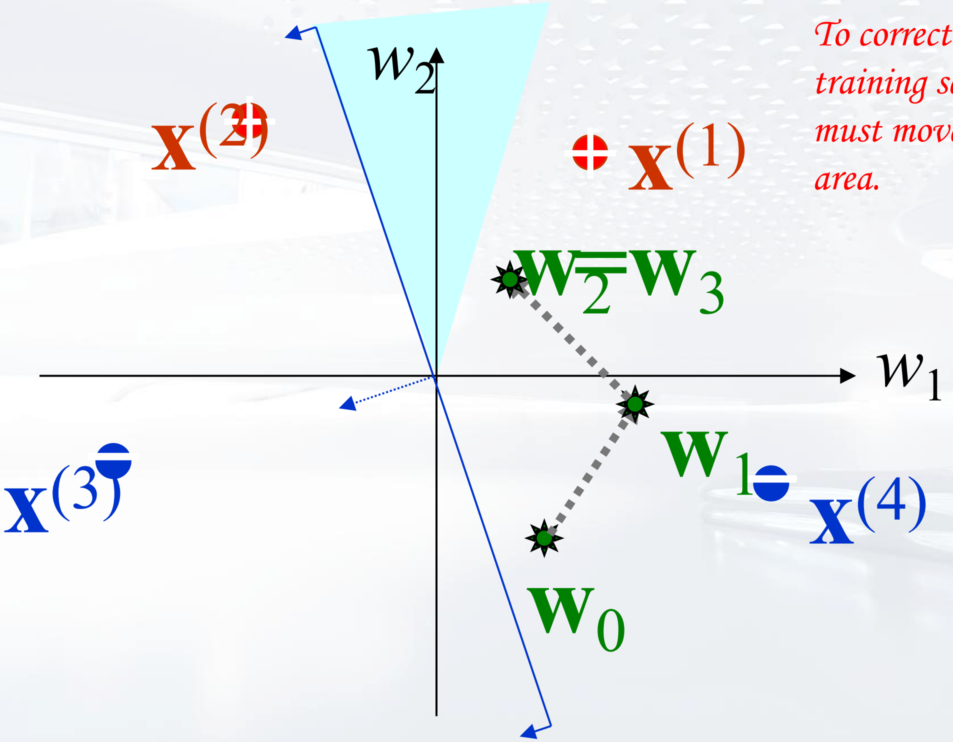
Learning Scenario in Weight Space

MIMA



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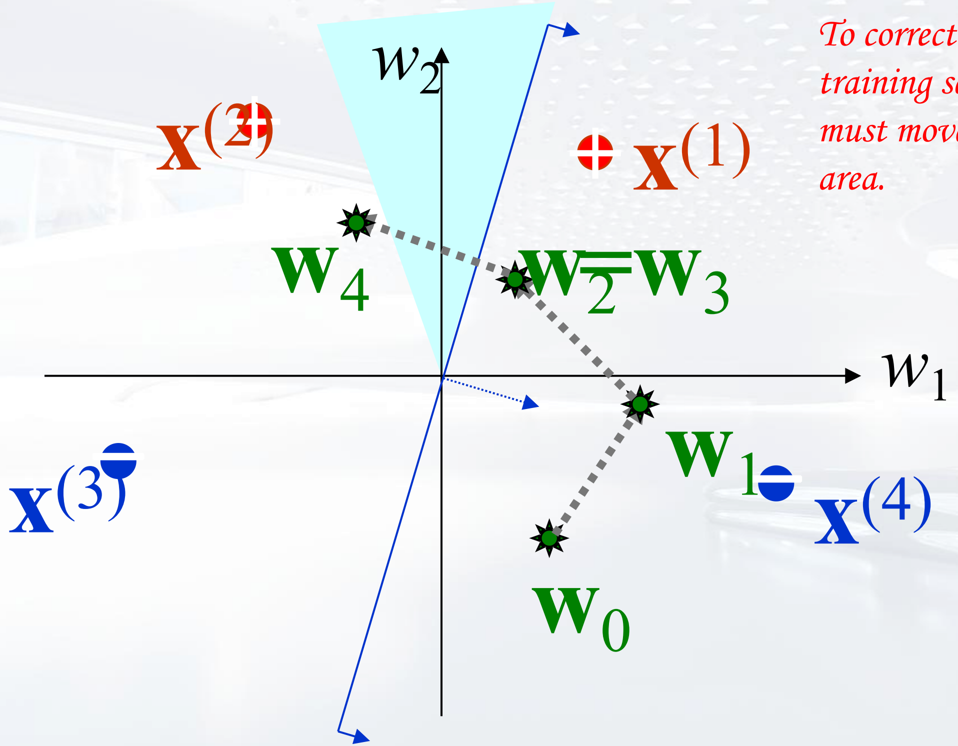
Learning Scenario in Weight Space



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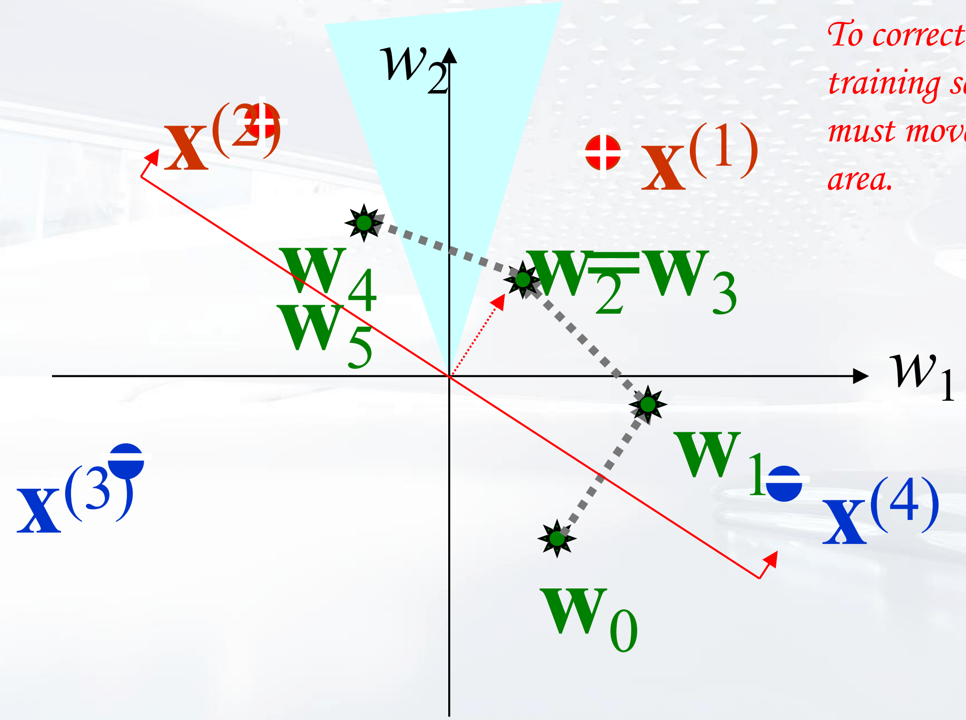
Learning Scenario in Weight Space

MIMA



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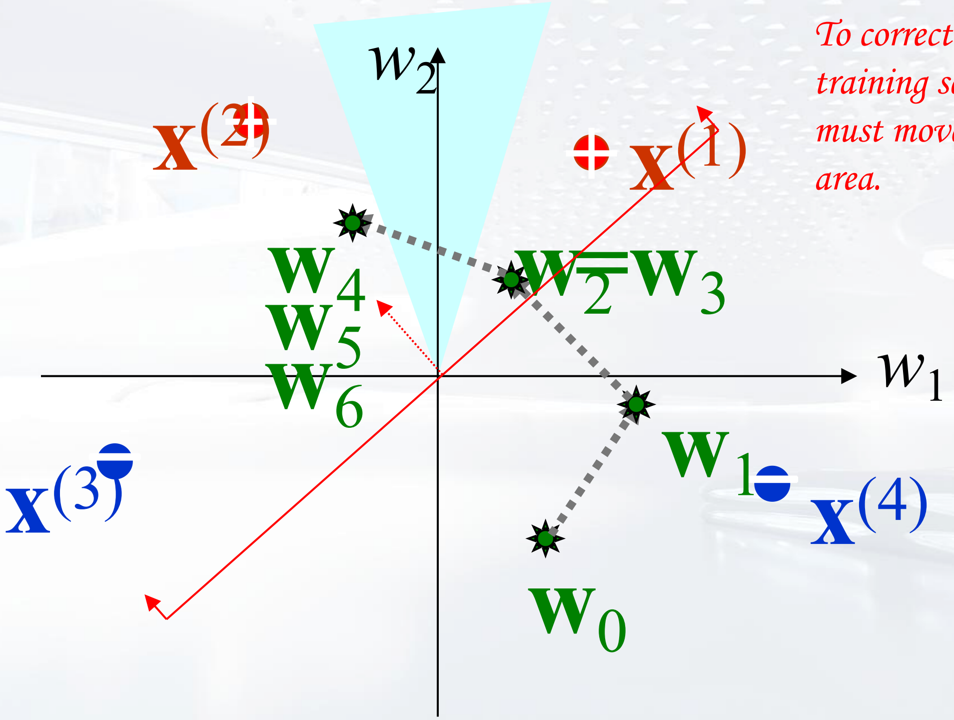
Learning Scenario in Weight Space



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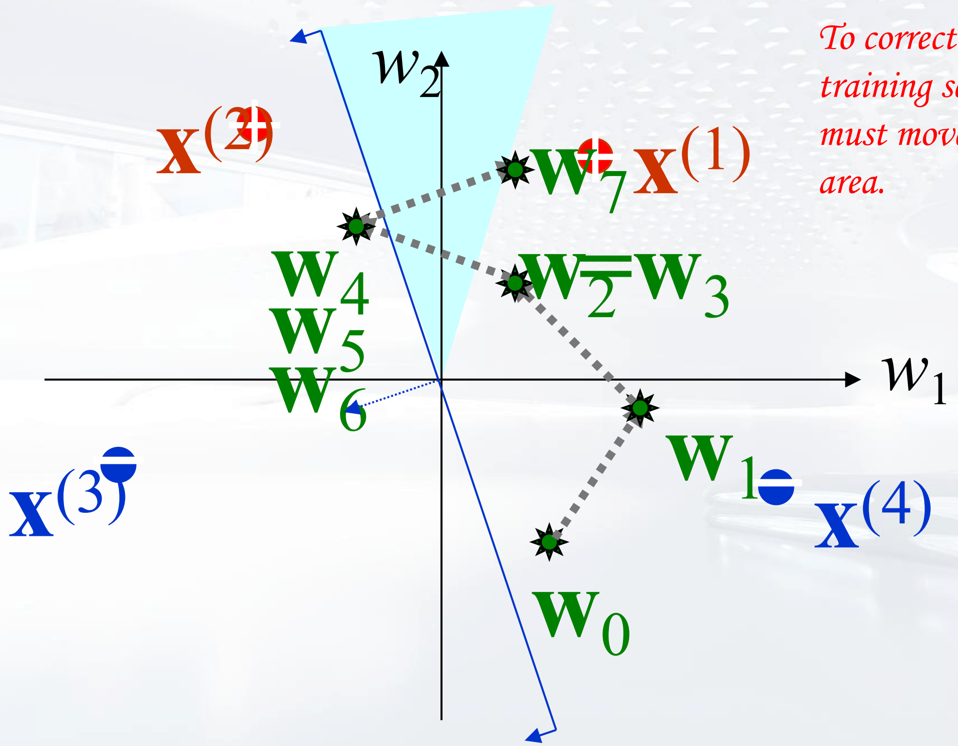
Learning Scenario in Weight Space



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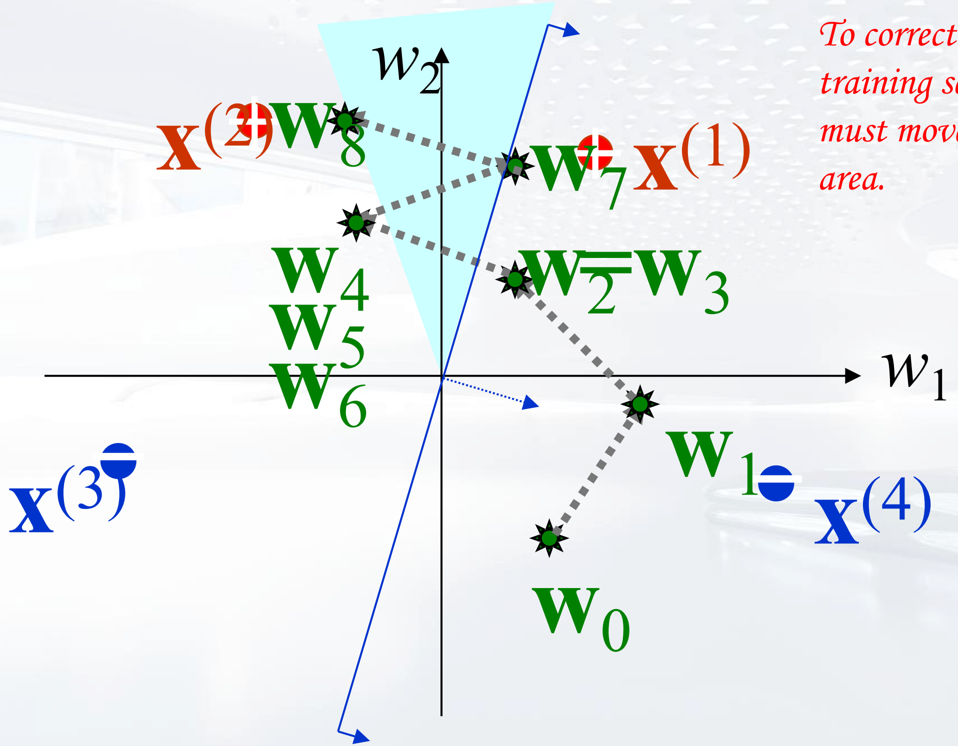
Learning Scenario in Weight Space



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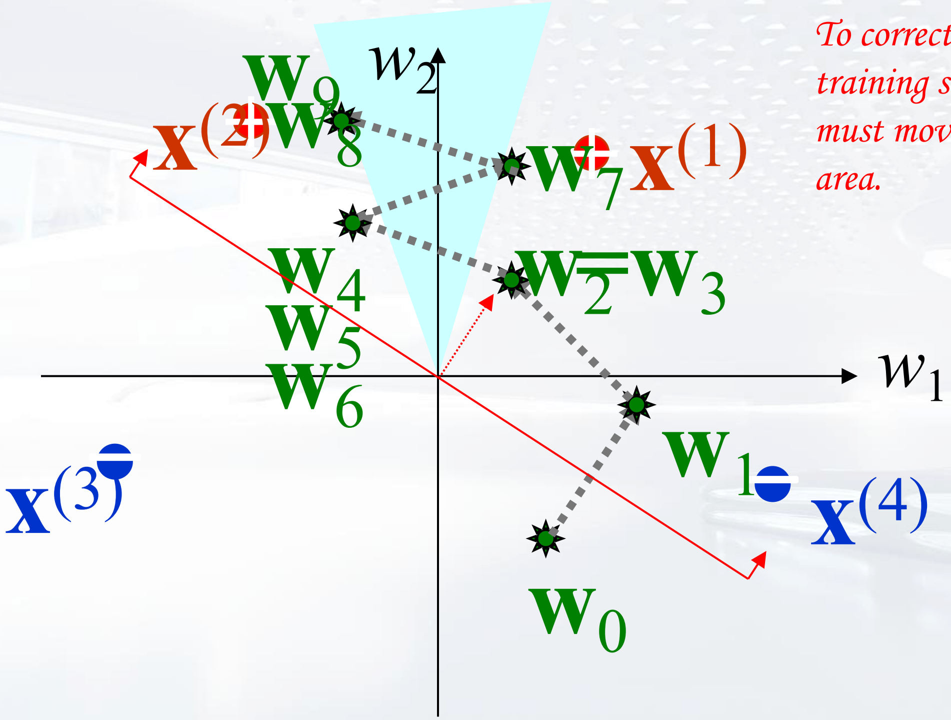
Learning Scenario in Weight Space



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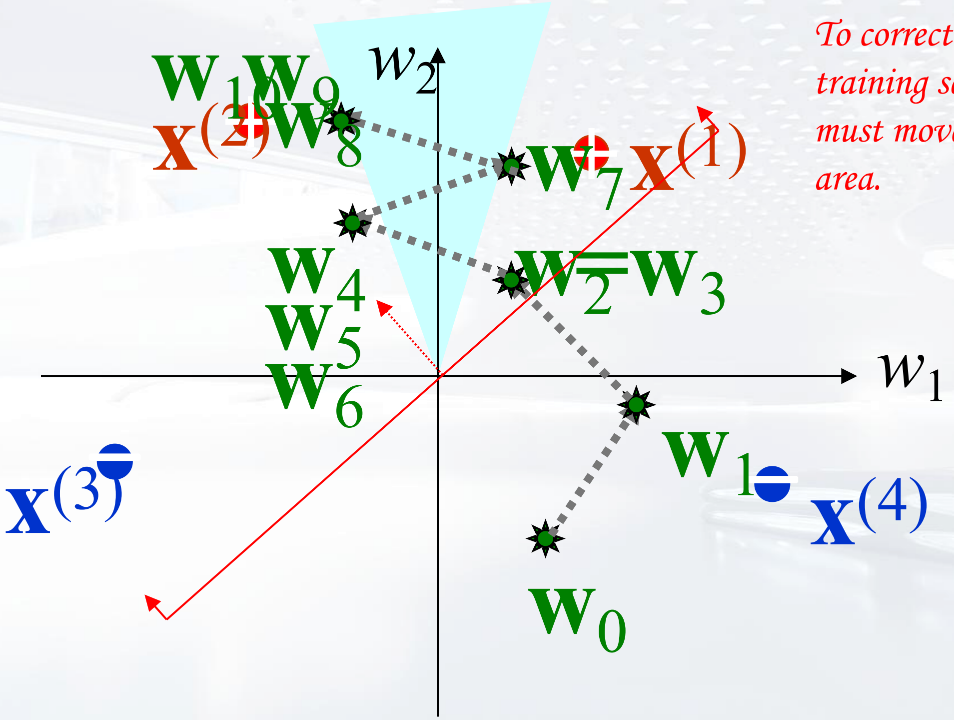
Learning Scenario in Weight Space

MIMA



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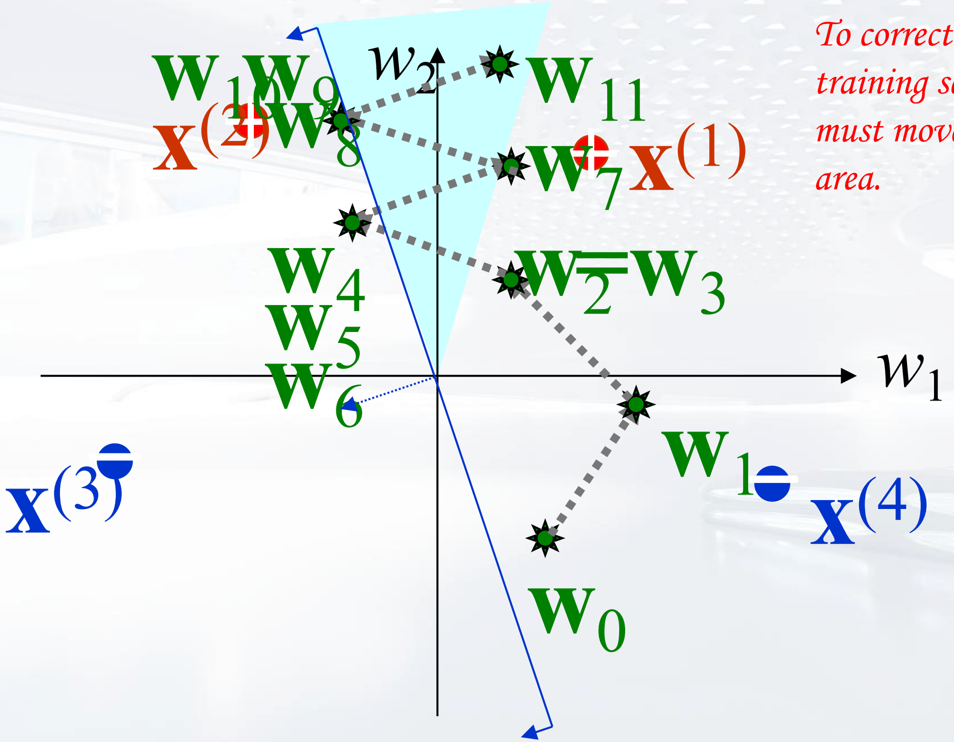

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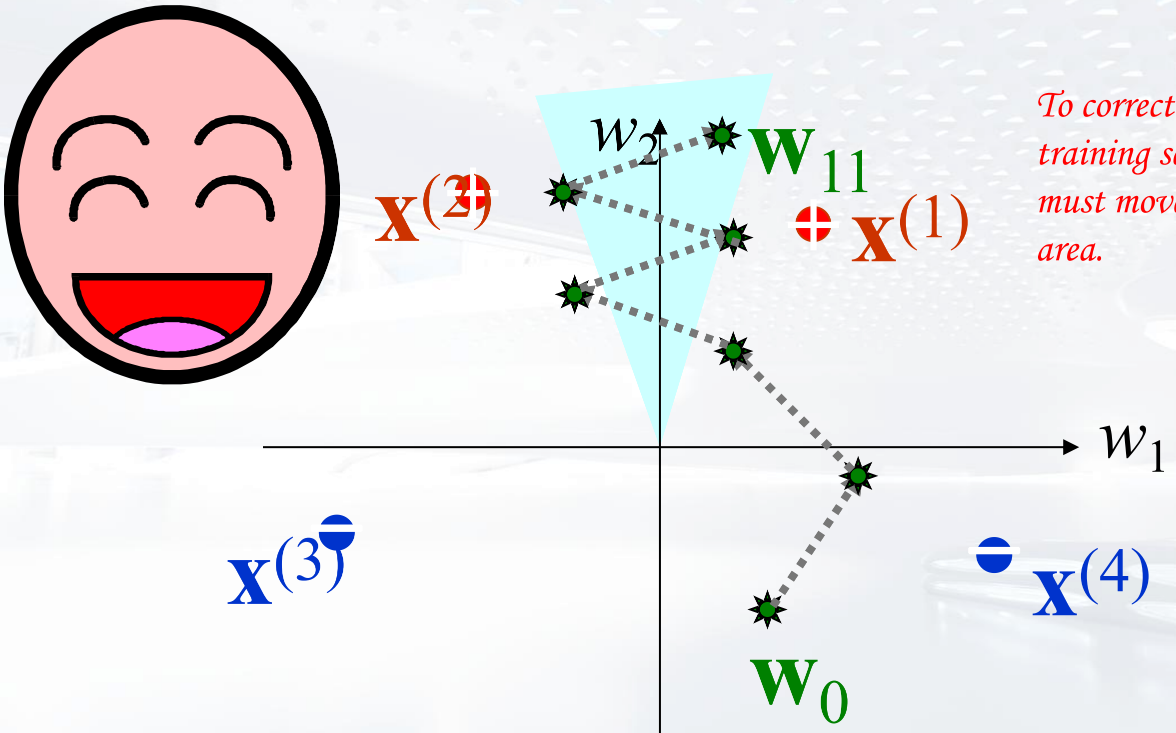


To correctly classify the training set, the weight must move into the shaded area.

Conceptually, in weight space, we move the weight into the feasible region.

Least Mean Square Learning

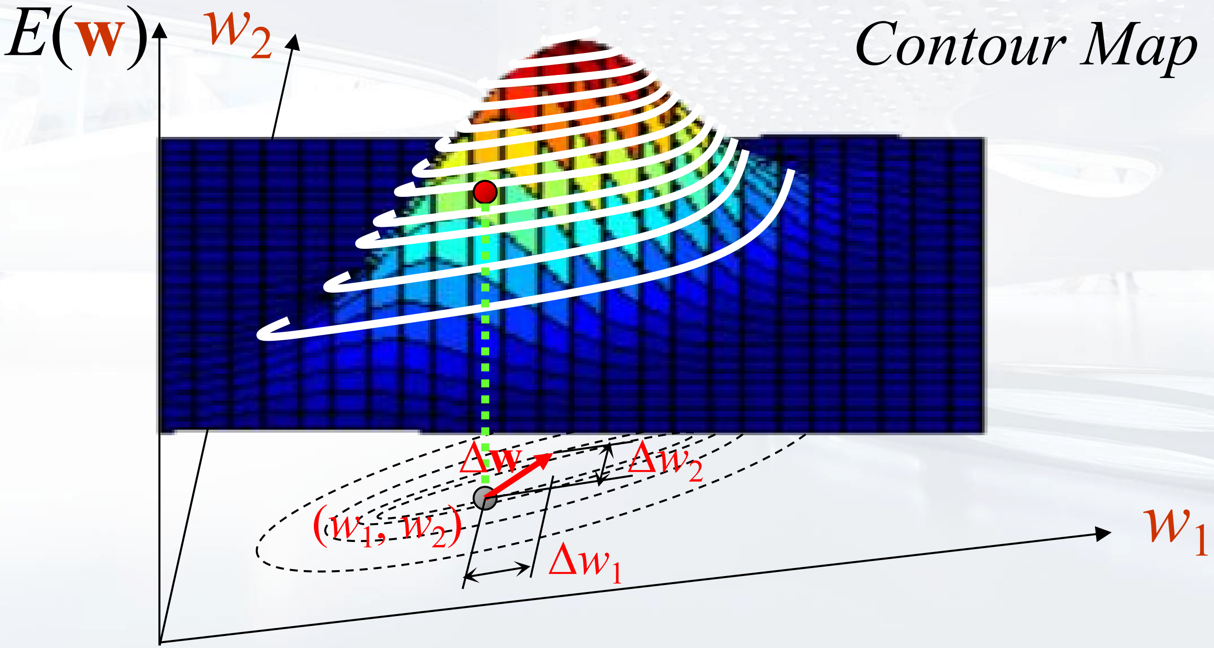
- Minimize the cost function (error function):

$$E(\mathbf{w}) = \frac{1}{2}\sum_{k=1}^{p}(d^{(k)} - y^{(k)})^2$$
$$= \frac{1}{2}\sum_{k=1}^{p}(d^{(k)} - \mathbf{w}^T\mathbf{x}^{(k)})^2$$
$$= \frac{1}{2}\sum_{k=1}^{p}\left(d^{(k)} - \sum_{l=1}^{m} w_l x_l^{(k)}\right)^2$$

d是真实的“正负”
y是预测的结果

Least Mean Square Learning

- Our goal is to go *downhill*.



Least Mean Square Learning

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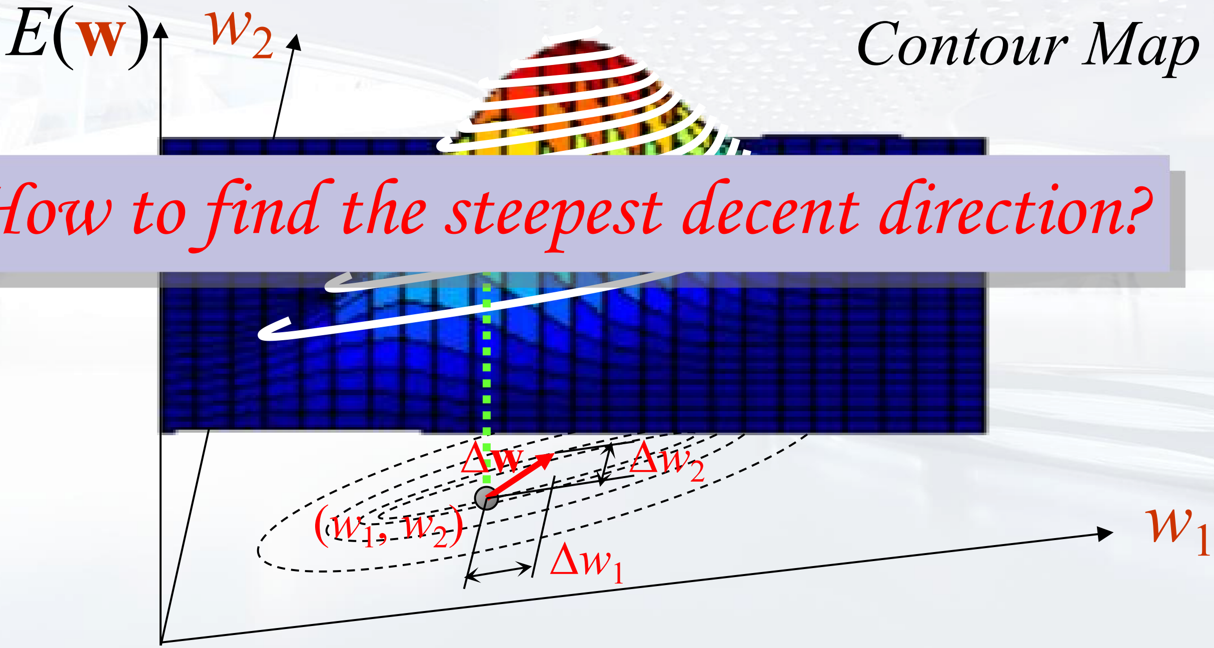


How to find the steepest decent direction?

Least Mean Square Learning

MIMA

- Gradient Operator

Let $f(\mathbf{w}) = f(w_1, w_2, \ldots, w_m)$ be a function over R^m.

$$df = \frac{\partial f}{\partial w_1} dw_1 + \frac{\partial f}{\partial w_2} dw_2 + \cdots + \frac{\partial f}{\partial w_m} dw_m$$

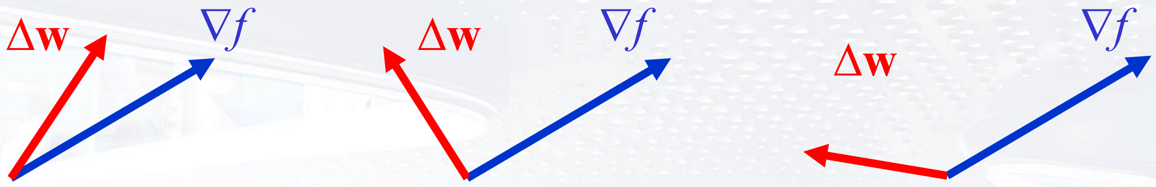
Define

$$\nabla f = \left(\frac{\partial f}{\partial w_1}, \frac{\partial f}{\partial w_2}, \cdots, \frac{\partial f}{\partial w_m} \right)^T$$

$$\Delta \mathbf{w} = \left(dw_1, dw_2, \cdots, dw_m \right)^T$$

$$\Rightarrow \quad df = \langle \nabla f, \Delta \mathbf{w} \rangle = \nabla f \bullet \Delta \mathbf{w}$$

Least Mean Square Learning



df : positive — Go uphill

df : zero — Plain

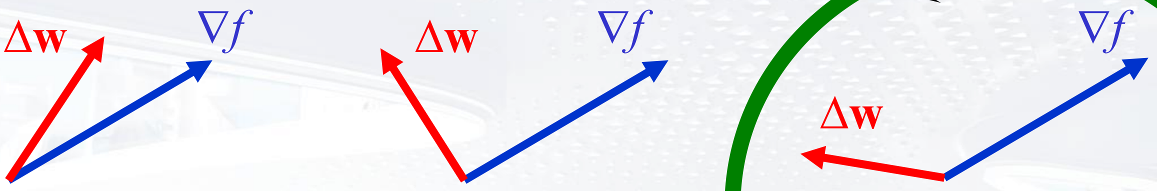
df : negative — Go downhill

$$df = \langle \nabla f, \Delta\mathbf{w} \rangle = \nabla f \bullet \Delta\mathbf{w}$$

Least Mean Square Learning

To minimize f, we choose

$$\Delta \mathbf{w} = -\eta \nabla f$$



df : positive	df : zero	df : negative
Go uphill	Plain	Go downhill

$$df = \langle \nabla f, \Delta \mathbf{w} \rangle = \nabla f \bullet \Delta \mathbf{w}$$

Least Mean Square Learning

- Minimize the cost function (error function):

$$E(\mathbf{w}) = \frac{1}{2}\sum_{k=1}^{p}\left(d^{(k)} - \sum_{l=1}^{m} w_l x_l^{(k)}\right)^2$$

$$\frac{\partial E(\mathbf{w})}{\partial w_j} = -\sum_{k=1}^{p}\left(d^{(k)} - \sum_{l=1}^{m} w_l x_l^{(k)}\right)x_j^{(k)}$$

$$= -\sum_{k=1}^{p}\left(d^{(k)} - \mathbf{w}^T\mathbf{x}^{(k)}\right)x_j^{(k)} = -\sum_{k=1}^{p}\overbrace{\left(d^{(k)} - y^{(k)}\right)}^{\delta^{(k)}}x_j^{(k)}$$

$$\boxed{\frac{\partial E(\mathbf{w})}{\partial w_j} = -\sum_{k=1}^{p}\delta^{(k)}x_j^{(k)} \qquad \delta^{(k)} = d^{(k)} - y^{(k)}}$$

Least Mean Square Learning

MIMA

- Minimize the cost function (error function):

$$E(\mathbf{w}) = \frac{1}{2}\sum_{k=1}^{p}\left(d^{(k)} - \sum_{l=1}^{m} w_l x_l^{(k)}\right)^2$$

$$\nabla_w E(\mathbf{w}) = \left(\frac{\partial E(\mathbf{w})}{\partial w_1}, \frac{\partial E(\mathbf{w})}{\partial w_2}, \ldots, \frac{\partial E(\mathbf{w})}{\partial w_m}\right)^T$$

$$\Delta \mathbf{w} = -\eta \nabla_{\mathbf{w}} E(\mathbf{w})$$ — Weight Modification Rule

$$\boxed{\frac{\partial E(\mathbf{w})}{\partial w_j} = -\sum_{k=1}^{p} \delta^{(k)} x_j^{(k)} \qquad \delta^{(k)} = d^{(k)} - y^{(k)}}$$

Least Mean Square Learning

- Learning Modes
  - Batch Learning Mode

$$\Delta w_j = \eta \sum_{k=1}^{p} \delta^{(k)} x_j^{(k)}$$

  - Incremental Learning Mode

$$\Delta w_j = \eta \delta^{(k)} x_j^{(k)}$$

$$\frac{\partial E(\mathbf{w})}{\partial w_j} = -\sum_{k=1}^{p} \delta^{(k)} x_j^{(k)} \qquad \delta^{(k)} = d^{(k)} - y^{(k)}$$

Perceptron

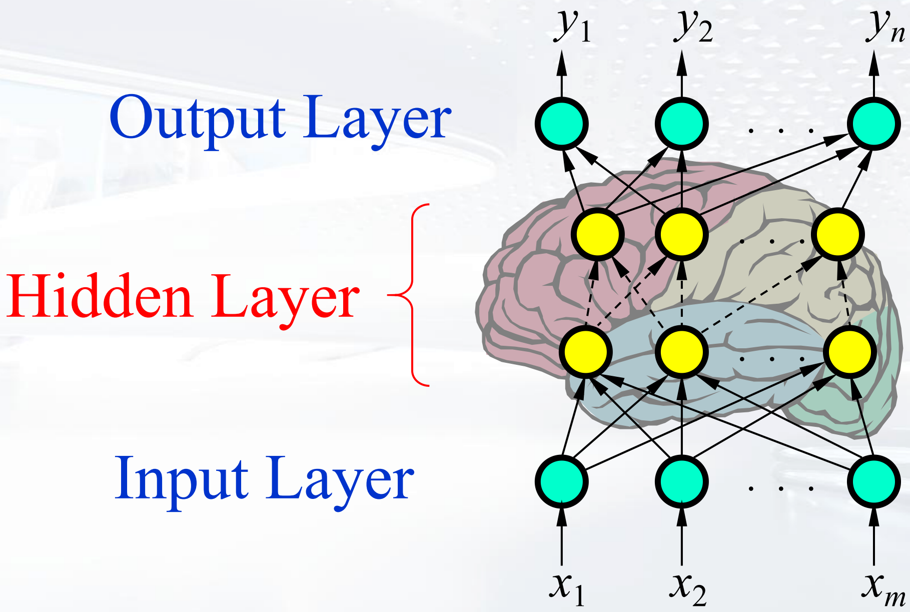
- Summary
  - Separability: some parameters get the training set perfectly correct.
  - Convergence: if the training is separable, perceptron will eventually converge (binary case)?

- The Perceptron convergence theorem

- The relation between perceptron and Bayes classifier

Contents

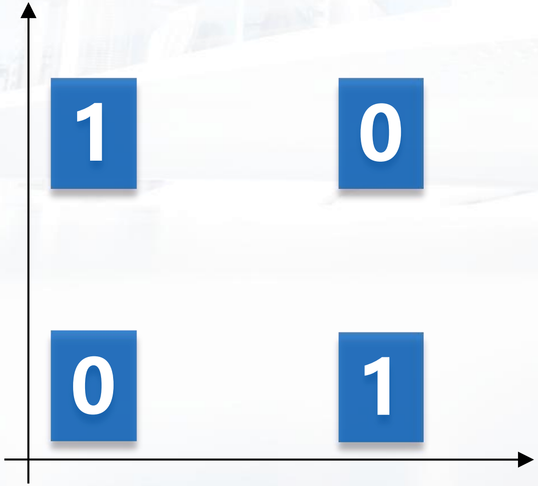
Multilayer Perceptron



How an MLP Works?

Example:

- Not linearly separable.
- Is a single layer perceptron workable?



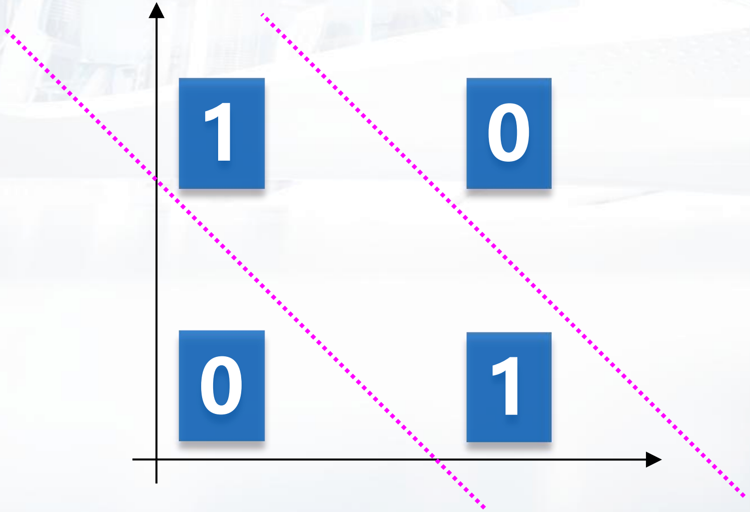
输入		异或 xor
0	0	0
0	1	1
1	0	1
1	1	0

How an MLP Works?

MIMA

Example:

- Not linearly separable.
- Is a single layer perceptron workable?



输入		异或 xor
0	0	0
0	1	1
1	0	1
1	1	0

How an MLP Works?

输入		或 or	与非 nand	与 and
0	0	0		
0	1	1		
1	0	1		
1	1	1		

输入		异或 xor
0	0	0
0	1	1
1	0	1
1	1	0

How an MLP Works?

输入		或 or	与非 nand	与 and
0	0		1	
0	1		1	
1	0		1	
1	1		0	

输入		异或 xor
0	0	0
0	1	1
1	0	1
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How an MLP Works?

输入		或 or	与非 nand	与 and
		0	1	0
		1	1	1
		1	1	1
		1	0	0

输入		异或 xor
0	0	0
0	1	1
1	0	1
1	1	0

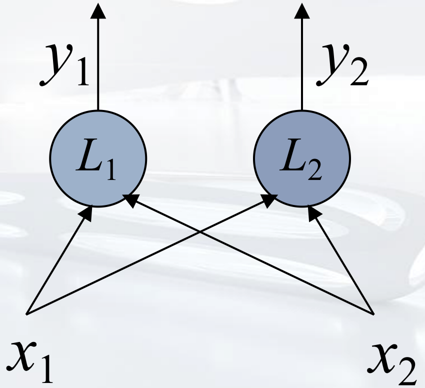
How an MLP Works?

输入		或 or	与非 nand	与 and
input		hidden		output
0	0	0	1	0
0	1	1	1	1
1	0	1	1	1
1	1	1	0	0

输入		异或 xor
0	0	0
0	1	1
1	0	1
1	1	0

How an MLP Works?

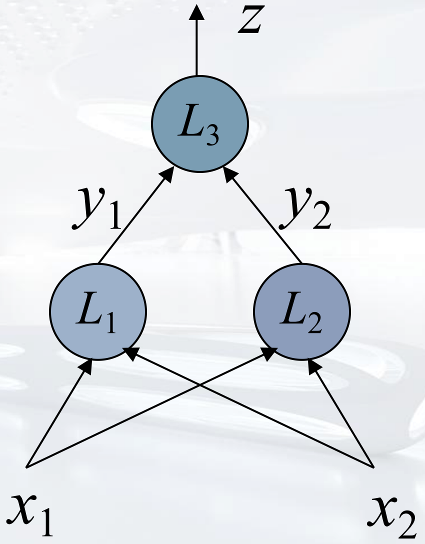
input		hidden		output
输入		或 or	与非 nand	与 and
0	0	0	1	0
0	1	1	1	1
1	0	1	1	1
1	1	1	0	0



How an MLP Works?

MIMA

input		hidden		output
输入		或 or	与非 nand	与 and
0	0	0	1	0
0	1	1	1	1
1	0	1	1	1
1	1	1	0	0



How an MLP Works?

input		hidden		output
输入		或 or	与非 nand	与 and
0	0	0		
0	1	1		
1	0	1		
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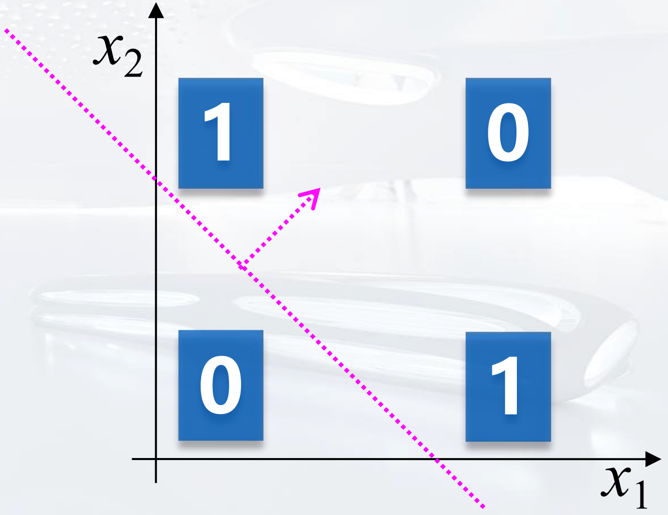

How an MLP Works?

MIMA

input		hidden		output
输入		或 or	与非 nand	与 and
0	0		1	
0	1		1	
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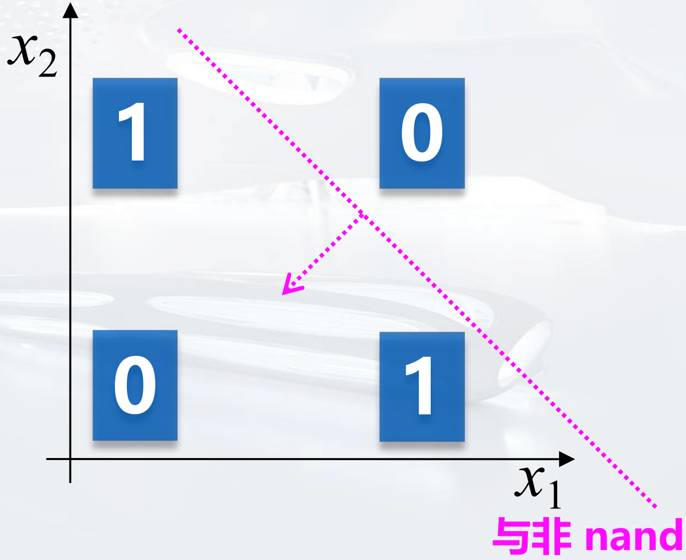
1	1		0	



How an MLP Works?

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input		hidden		output
输入		或 or	与非 nand	与 and
0	0	0	1	
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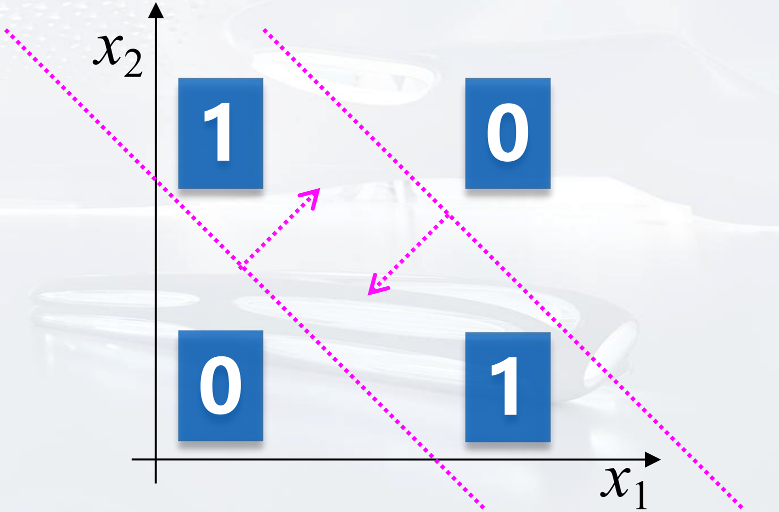
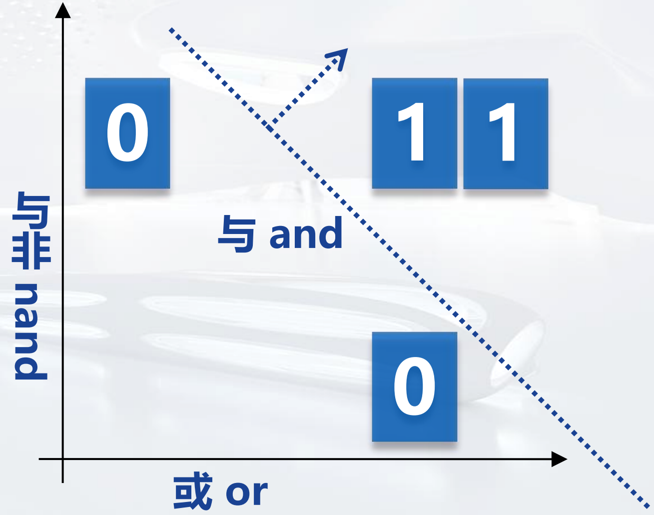


How an MLP Works?

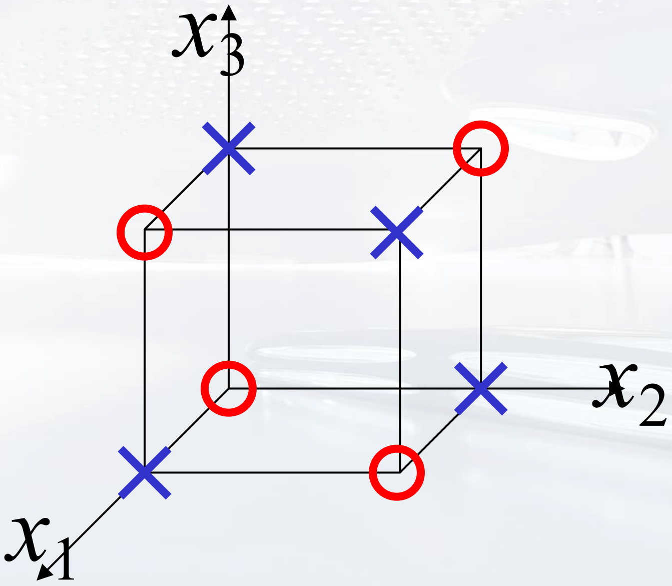
input		hidden		output
输入		或 or	与非 nand	与 and
		0	1	0
		1	1	1
		1	1	1
		1	0	0



Parity Problem

Is the problem linearly separable?

$x_1 x_2 x_3$	
000	0
001	1
010	1
011	0
100	1
101	0
110	0
111	1



Parity Problem

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$x_1 x_2 x_3$	
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001	1
010	1
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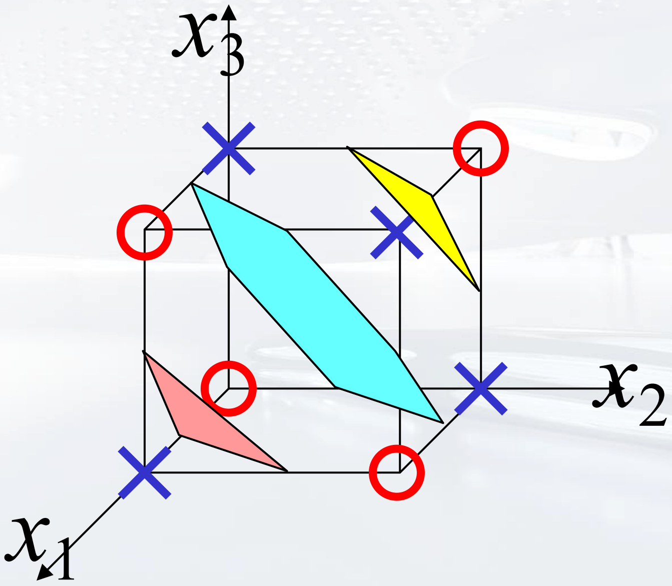

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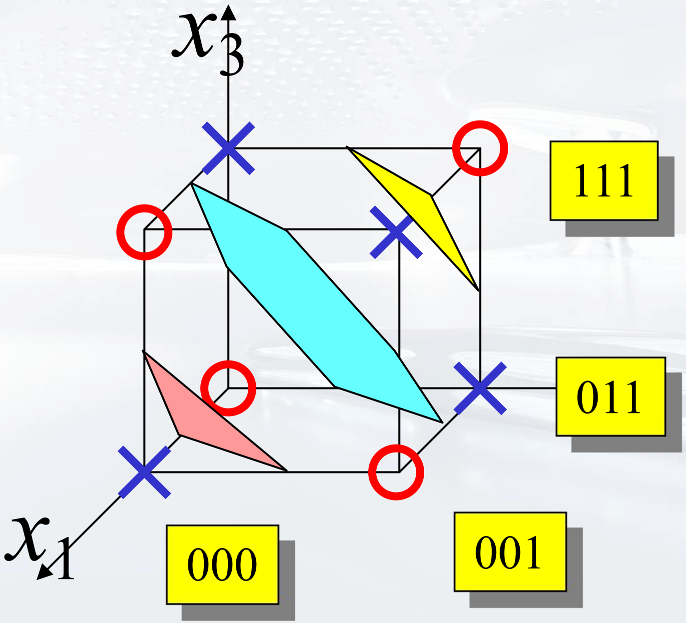
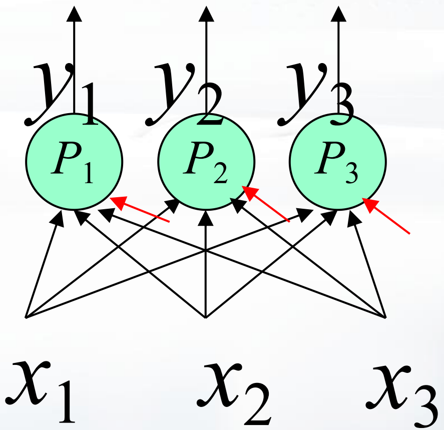
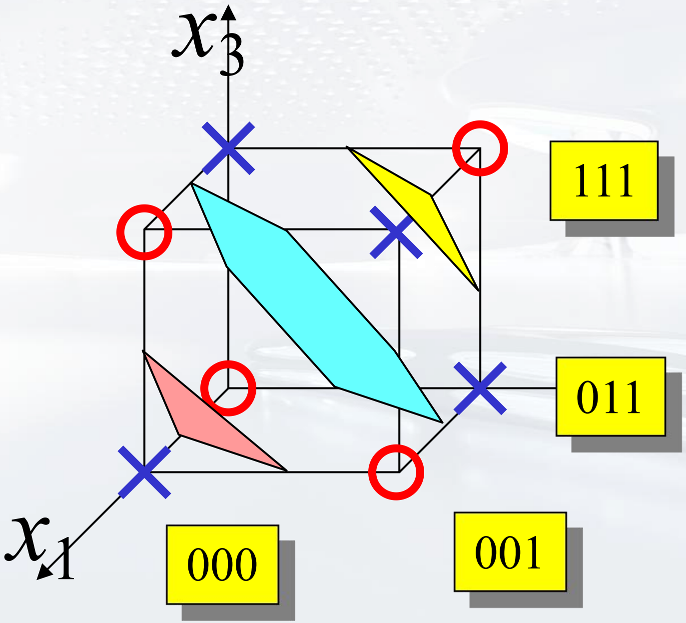
110	0
111	1



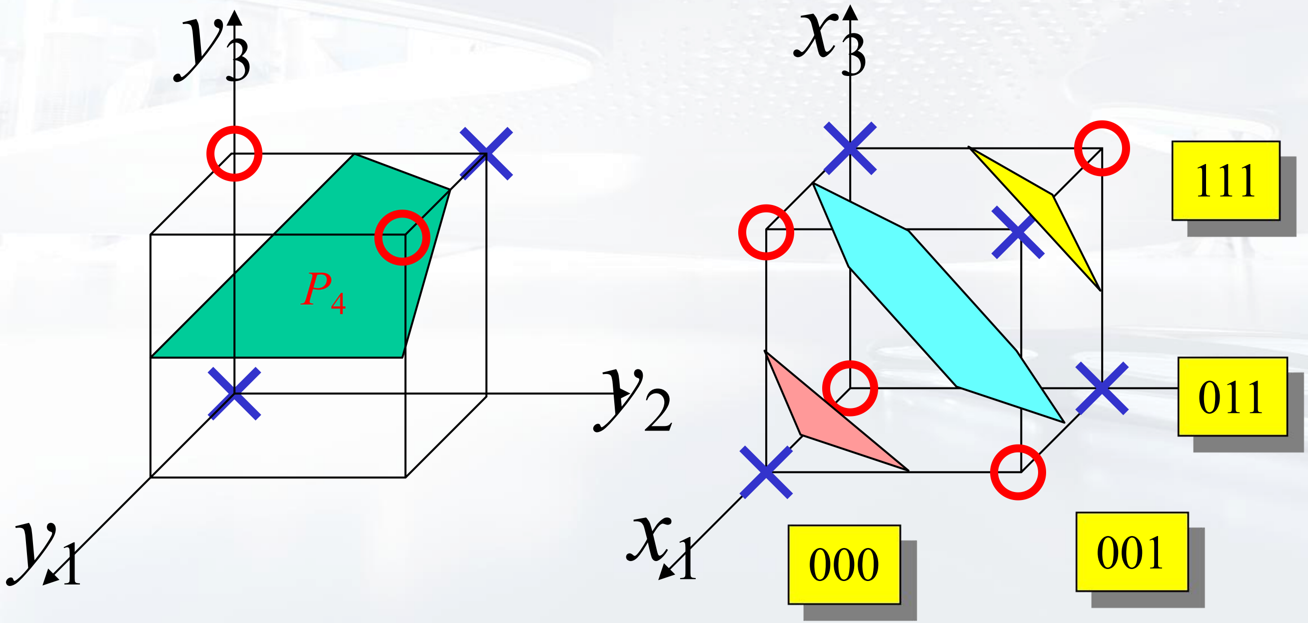
Parity Problem

Is the problem linearly separable?

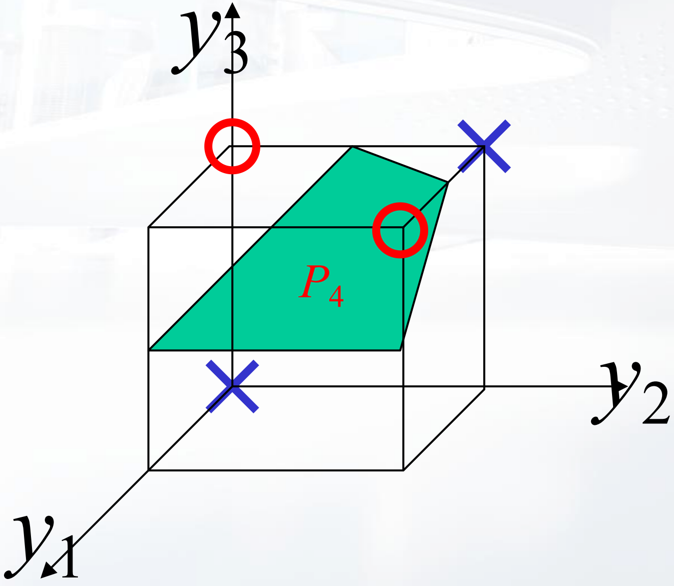


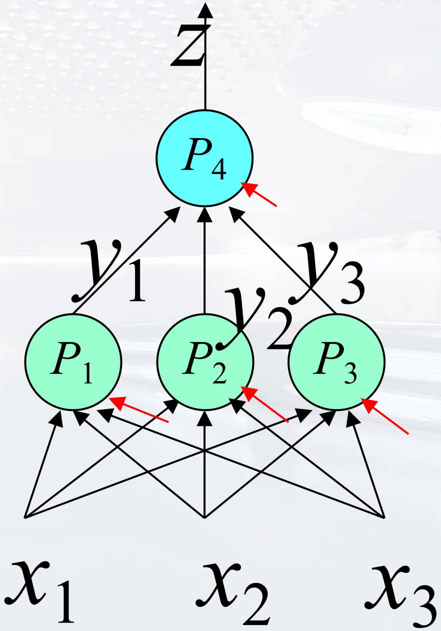


Parity Problem



Parity Problem





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