



# Computational Learning Theory

## 1.3 Hypothesis Space

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# Homogeneous Outputformat

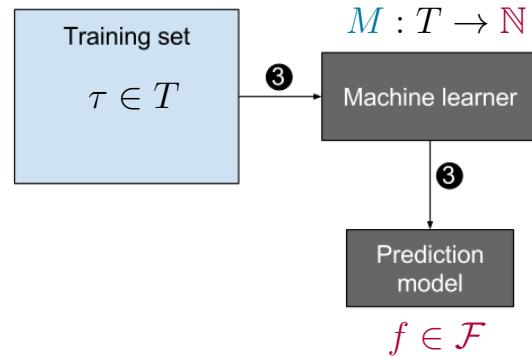


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## Definition (Hypothesis Space, Learner)

A set  $\mathcal{F} = \{f_i \mid i \in \mathbb{N}\}$  of prediction models is called *hypothesis space* if there is a computer program which on an array  $[i, n]$  of non-negative integers returns 1 if  $f_i(n) = 1$  and 0 otherwise.

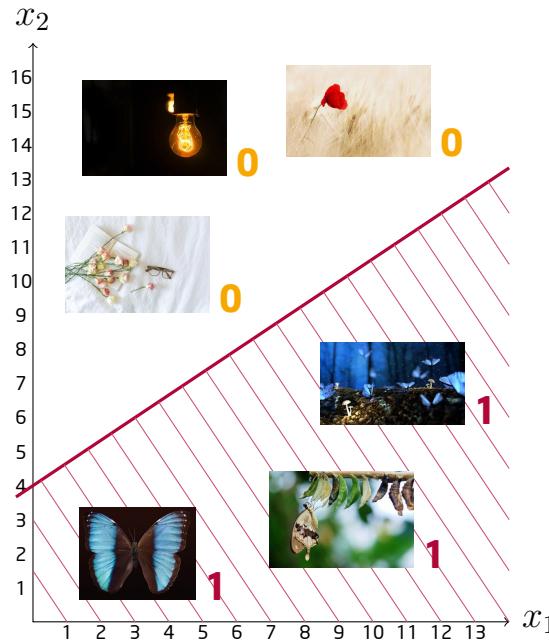
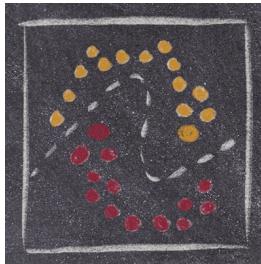
A *machine learner*  $M$  is a computable function  $M : T \rightarrow \mathbb{N}$  with the output interpreted with respect to a prefixed hypothesis space  $\mathcal{F}$ .

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October 8, 2020

# Hypothesis Space of SVMs and Perceptron

- Input: training data  $((\mathbf{x}_1, y_1), \dots, (\mathbf{x}_t, y_t))$ .
- Output: **halfspace**.
- **Realizability** Assumption: data linearly separable.  
(No-Free-Lunch-Theorem)
- Many learning algorithms use halfspaces as prediction models, sometimes combined with a **kernel** function.

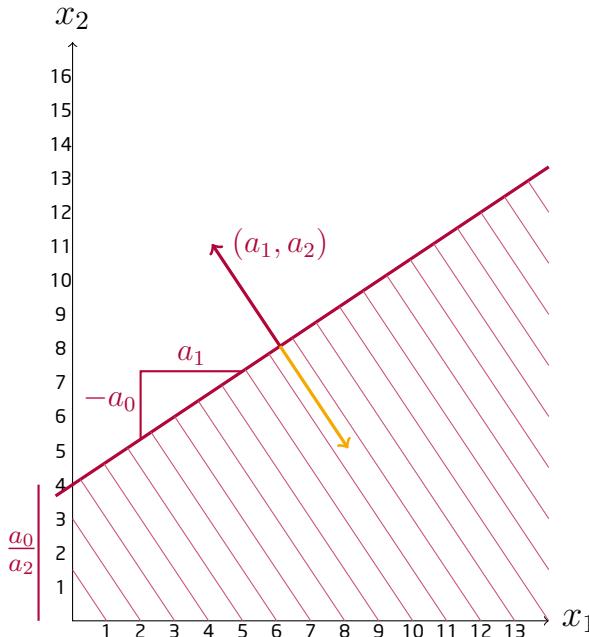


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# The Hypothesis Space of Halfspaces I

- The line is given by the formula  $x_2 = \frac{2}{3}x_1 + 4$  or equivalently  $12 = -2x_1 + 3x_2$ .
- The normal vector  $(-2, 3)$  points outside the halfspace.
- The line  $-12 = 2x_1 - 3x_2$  describes the halfspace on the other side of the same line.

We consider the set of all halfspaces given by a line  $a_0 = a_1x_1 + a_2x_2$  with  $a_0, a_1, a_2 \in \mathbb{Z}$ .



# The Hypothesis Space of Halfspaces II

We consider the set of all halfspaces given by a line  $a_0 = a_1x_1 + a_2x_2$  with  $a_0, a_1, a_2 \in \mathbb{Z}$ .

- Given  $a_0 = 12, a_1 = -2, a_2 = 3$  and vector  $(x_1, x_2) = (-2, 7)$ , a computer can decide whether the vector lies in the halfspace  $L_{12,-2,3} = \{(x_1, x_2) \mid 12 \geq -2x_1 + 3x_2\}$  given by the line  $12 = -2x_1 + 3x_2$ .
- It follows the same method for other values of  $a_0, a_1, a_2$  and  $x_1, x_2$ .
- The decision procedure is in this sense universal in the inputs  $(a_0, a_1, a_2)$  and  $(x_1, x_2)$ .

How is a halfspace represented by a natural number?

# The Hypothesis Space of Halfspaces III

We consider the set of all halfspaces given by a line  $a_0 = a_1x_1 + a_2x_2$  with  $a_0, a_1, a_2 \in \mathbb{Z}$ .

How is a **halfspace** represented by a **natural number**?

- The computer can **identify each integer with a natural number**

$\mathbb{Z}$	0	-1	1	-2	2	-3	3	-4	4	...
$\mathbb{N}$	0	1	2	3	4	5	6	7	8	...

- Applying the **merge method**, the computer can for inputs  $i, n \in \mathbb{N}$  reconstruct  $(i_0, i_1, i_2)$  and  $(n_1, n_2)$  corresponding to  $(a_0, a_1, a_2)$  and  $(x_1, x_2)$ , respectively.
- Then it does **run the uniform decision procedure** to decide whether  $(x_1, x_2) \in L_{a_0, a_1, a_2}$ .
- The computer does **return 1** if the answer is yes and 0 otherwise. This defines  $f_i(n)$ .

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A *machine learner*  $M$  is a computable function  $M : T \rightarrow \mathbb{N}$  with the output interpreted with respect to a prefixed hypothesis space  $\mathcal{F}$ .

The **set of halfspaces** is a **hypothesis space**.

- The **formal definitions cover** the **binary classification** of images with halfspaces.
- There are a lot of other hypothesis spaces, e.g., the **set of weight vectors** for a fixed neural network architecture.

# Combinatorial Analysis of Learning

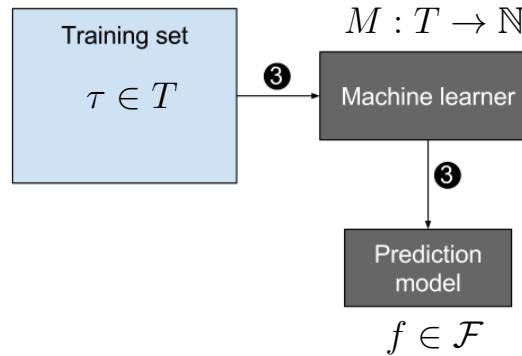


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Is there an  $M$  that *learns* a well performing  $f \in \mathcal{F}$   
from sequences  $\tau \in T$  of increasing length?

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