

# Valiant's theory of the learnable

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# Introduction

L G Valiant *A theory of the learnable*, Comm. ACM **27**, 1134-42 (1984)

We want to learn an unknown Boolean function (predicate)  $F$

- to do this in general would take exponential time - must test  $n$ -ary  $F$  for  $2^n$  input combinations
- so we restrict  $F$ , and then can achieve polynomial time

# Learning protocol

$t$  Boolean variables  $p_1, p_2, \dots, p_t$

vector:  $\{0, 1, *\}^t$  (\*=undetermined). *Total* means no \* in vector

We have available **EXAMPLE()**

- gives us a positive exemplification of  $F$
- that is, an assignment of variables making  $F$  true
- for example,  $F(p) = p_1 p_2 + p_3$ 
  - ▷ **EXAMPLE()**  $\rightarrow$   $(*, *, 1)$
  - ▷ **EXAMPLE()**  $\rightarrow$   $(1, 1, 0)$

and **ORACLE(x)**

- tells us if  $F$  is true for some given assignment  $x$  of variables
- for example:
  - ▷ **ORACLE**(1, 0, 0)  $\rightarrow$  0
  - ▷ **ORACLE**(0, 0, 1)  $\rightarrow$  1

Let  $D$  be a probability distribution on the set of vectors  $v$  such that  $F(v) = 1$

# Learnability

A predicate is *learnable* if  $\exists$  an algorithm such that:

- it runs in polynomial time in  $t$  and in a parameter  $h$
- with probability  $1-1/h$ , the deduced predicate  $g$  never outputs 1 when it should not, but outputs 1 almost always when it should

$L(h, s)$  is defined (for  $\mathbb{R} \ni h > 0, s \in \mathbb{Z}^+$ ) as the smallest integer such that in  $L$  independent Bernoulli trials each with probability  $1/h$  of success, the probability of having fewer than  $s$  successes is less than  $1/h$

- For  $s \geq 1$  and  $h > 1$ ,  $L(h, s) \leq 2h(s + \log h)$

$h$	$s$	$L(h, s)$	bound
10	2	38	86
10	5	78	146
10	10	140	246
100	2	662	1321
100	5	1157	1921
100	10	1874	2921

# Finite CNF expressions

A conjunctive normal form (CNF) is a product of sums

- that is, an *and* of *ors*
- Valiant requires each clause  $c_i$  in a CNF to be a sum of literals, where a literal is either a variable  $p_j$  or a negation of a variable
- For example,  $p_2 + \overline{p_3} + p_6$  is a clause
- In a  $k$ -CNF, each clause contains at most  $k$  literals

**Theorem A:** for each  $k > 0$ , any  $k$ -CNF is learnable via an algorithm that uses  $L(h, (2t)^{k+1})$  calls of EXAMPLE and no call of ORACLE

# Algorithm A

$g =$  product of all possible  $k$ -clauses

For  $n = 1, 2, \dots, L$

- $v = \text{EXAMPLE}()$
- for each  $c_i$  in  $g$ 
  - ▷ if  $v \not\models c_i$ , then delete  $c_i$  from  $g$

# DNF expressions

A disjunctive normal form (DNF) is a sum of products

- that is, an *or* of *ands*
- Valiant requires the DNF to be *monotone*, that is, no variable is notted
- For example,  $p_1p_3p_4 + p_2 + p_3p_6$  is in DNF

Theorem B: any monotone DNF of degree  $d$  is learnable via an algorithm that uses  $L(h, d)$  calls of EXAMPLE and  $dt$  calls of ORACLE, where  $t$  is the number of variables

# Algorithm B

$g = 0$

For  $n = 1, 2, \dots, L$

- $v = \text{EXAMPLE}()$
- if  $v \not\Rightarrow g$ , then for  $i = 1, 2, \dots, t$ 
  - ▷ if  $p_i$  is determined in  $v$  (i.e. is not  $*$ ), then
    - ◇ set  $v$  equal to  $\bar{v}$  but with  $p_i = *$
    - ◇ if  $\text{ORACLE}(\bar{v}) = 1$  then  $v = \bar{v}$
  - ▷  $m = \text{product of all literals } q \text{ such that } v \Rightarrow q$
  - ▷  $g += m$