# Exact VC-Dimension of Boolean Monomials<sup>\*</sup>

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#### Abstract

We show that the Vapnik-Chervonenkis dimension of Boolean monomials over n variables is at most n for all  $n \ge 2$ . It follows that the VC-dimension is determined exactly and is, except for n = 1, equal to the VC-dimension of the proper subclass of monotone monomials.

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### 1 Introduction

The Vapnik-Chervonenkis dimension VC-dim( $\mathcal{C}$ ) of a collection  $\mathcal{C}$  of subsets of a set X is defined as the maximum cardinality of any set  $S \subseteq X$  that is shattered by  $\mathcal{C}$ . A set S is shattered by  $\mathcal{C}$  if for every subset T of S there exists a  $C \in \mathcal{C}$  such that  $T = S \cap C$ .

The VC-dimension of a class  $\mathcal{F}$  of functions  $f: X \to \{0, 1\}$  is defined by identifying each element  $f \in \mathcal{F}$  with the set  $\{x \in X : f(x) = 1\}$ . Thus VC-dim $(\mathcal{F})$ is the maximum cardinality of any set  $S \subseteq X$  for which  $\mathcal{F}$  induces all functions  $g: S \to \{0, 1\}$ .

The Vapnik-Chervonenkis dimension gives almost tight bounds for the number of examples required for learning in Valiant's PAC-model [5]. For a detailed description we refer the reader to the article of Blumer *et al.* [2] and to the books of Anthony and Biggs [1] and Natarajan [4].

In this paper we investigate the VC-dimension of Boolean monomials. The class MONOMIALS<sub>n</sub> is the set of all conjunctions of literals over the variables  $\{x_1, \ldots, x_n\}$ , including the constant functions **0** and **1**. A monomial is called monotone if it does not contain negations. The corresponding class is denoted by MONOTONE-MONOMIALS<sub>n</sub>. We also include the constant functions **0** and **1** in the class MONOTONE-MONOMIALS<sub>n</sub>.

The upper bound  $(\log 3)n$  for VC-dim(MONOMIALS<sub>n</sub>) has been given by Anthony and Biggs [1, p. 76] based on the familiar relationship VC-dim( $\mathcal{F}$ )  $\leq$  $\log |\mathcal{F}|$  for finite  $\mathcal{F}$ .<sup>1</sup> Here, log denotes the logarithm to base 2. A lower bound of n has been known for quite a while [3]. The latter proof in fact uses monotone monomials only, hence VC-dim(MONOTONE-MONOMIALS<sub>n</sub>)  $\geq n$ .

In the following we show that n is also an upper bound even for the class MONOMIALS<sub>n</sub> for  $n \ge 2$ . Thus, the VC-dimension of monomials is determined exactly. Furthermore, it follows that adding negations to monotone monomials does not increase the VC-dimension, except for n = 1. The results are easily transferred to the dual class of Boolean clauses.

#### 2 The upper bound

**Theorem 2.1** *VC-dim*(*MONOMIALS*<sub>n</sub>)  $\leq n$  for all  $n \geq 2$ .

**Proof.** Let  $S \subseteq \{0, 1\}^n$  be an arbitrary set of cardinality n+1 and assume that it can be shattered by MONOMIALS<sub>n</sub>. We fix an enumeration  $u^{(1)}, \ldots, u^{(n+1)}$  of the elements of S and define  $S_i := S \setminus \{u^{(i)}\}$  for  $i = 1, \ldots, n+1$ . The definition of shattering implies in particular that for each  $S_i$  there exists a monomial  $m_i \in$ MONOMIALS<sub>n</sub> such that  $S_i = S \cap m_i$ . Thus, for  $i, j = 1, \ldots, n+1$ 

<sup>&</sup>lt;sup>1</sup>The authors of [1] disregard the function **0** in their definition of monomials (see p. 12). Thus, the bound  $\log(3^n + 1)$  is more advisable in our case.

 $m_i$  is false on  $u^{(j)}$  iff i = j. (1)

Therefore, each  $u^{(i)}$  must contain a component  $u_{h(i)}^{(i)}$  and each  $m_i$  must contain a literal  $l_{k(i)}$  such that  $l_{k(i)}$  is false on  $u_{h(i)}^{(i)}$ . Among the literals  $l_{k(1)}, \ldots, l_{k(n+1)}$  at least one variable occurs twice. Without loss of generality we assume that  $l_{k(1)}$ and  $l_{k(2)}$  both contain the same variable. Then there are two cases:  $l_{k(1)} = l_{k(2)}$ and  $l_{k(1)} = \neg l_{k(2)}$ .

If  $l_{k(1)} = l_{k(2)}$  then  $l_{k(1)}$  is false on both  $u_{h(1)}^{(1)}$  and  $u_{h(2)}^{(2)}$ . But then  $m_1$  is false on both  $u^{(1)}$  and  $u^{(2)}$  in contradiction to (1).

If  $l_{k(1)} = \neg l_{k(2)}$  then consider  $u^{(3)}$ . (Recall that  $n \ge 2$ .) Either  $l_{k(1)}$  or  $l_{k(2)}$  is false on  $u^{(3)}$ . Consequently, either  $m_1$  is false on  $u^{(3)}$  or  $m_2$  is false on  $u^{(3)}$  in contradiction to (1).  $\Box$ 

It is easy to see that the set  $\{0, 1\}$  can be shattened by MONOMIALS<sub>1</sub>. Therefore, we have VC-dim(MONOMIALS<sub>1</sub>) = 2.

#### **3** Conclusions

Together with the lower bound established by Ehrenfeucht  $et \ al. \ [3]$  we obtain precise values for the VC-dimension of monomials:

**Corollary 3.1** *VC-dim*(*MONOMIALS*<sub>n</sub>) =  $\begin{cases} n & if \quad n \ge 2\\ 2 & if \quad n = 1. \end{cases}$ 

The cited lower bound result also holds for monotone monomials. The set  $\{0, 1\}$  cannot be shattered by MONOTONE-MONOMIALS<sub>1</sub> because this class contains only three functions  $\{0,1,x\}$ . Therefore, the VC-dimensions of both classes are equal except for n = 1.

**Corollary 3.2** VC-dim $(MONOTONE-MONOMIALS_n) = n$  for all n.

Finally, we state that the results are transferable to MONOTONE-CLAUSES<sub>n</sub> and CLAUSES<sub>n</sub> by duality. A (monotone) clause is a disjunction of (non-negated) literals.

**Corollary 3.3**  $VC\text{-}dim(CLAUSES_n) = \begin{cases} n & \text{if } n \ge 2\\ 2 & \text{if } n = 1 \end{cases}$ and  $VC\text{-}dim(MONOTONE\text{-}CLAUSES_n) = n \text{ for all } n.$ 

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