

# AN EQUIVALENCE RESULT FOR VC CLASSES OF SETS

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Let  $\mathcal{R}$  and  $\Theta$  be infinite sets and let  $A \subseteq \mathcal{R} \times \Theta$ . We show that the class of projections of  $A$  onto  $\mathcal{R}$  is a Vapnik–Chervonenkis (VC) class of sets if and only if the class of projections of  $A$  onto  $\Theta$  is a VC class. We illustrate the result in the context of semiparametric estimation of a transformation model. In this application, the VC property is hard to establish for the projection class of interest but easy to establish for the other projection class.

## 1. INTRODUCTION

In the course of establishing the uniformity results (uniform laws of large numbers, stochastic equicontinuity) used to establish the limiting behavior of econometric estimators, it is sometimes useful to show that certain classes of sets are Vapnik–Chervonenkis, or VC, classes (see, e.g., Pollard, 1984, 1989; Andrews, 1994; and references therein). This is particularly true for estimators that optimize averages or generalized averages of indicator functions of sets involving finite-dimensional parameters. Examples include the maximum score estimators of Manski (1975, 1985) and the rank estimators of Han (1987a, 1987b), Cavanagh and Sherman (1998), Abrevaya (1999, 2002), Khan (2001), Chen (2002), and Asparouhova, Asparouhov, Golanski, Kasprzyk, and Sherman (2002). This paper establishes an equivalence result for VC classes of sets that can be used in such settings. This equivalence result had been previously established by van den Dries (1998, Ch. 5, Prop. 2.10) and was discovered by a referee and brought to the attention of the authors after this paper had been accepted for publication.

Let  $\mathcal{R}$  and  $\Theta$  be infinite sets and let  $A$  be a subset of the product space  $\mathcal{R} \times \Theta$ . For each  $\theta \in \Theta$ , define  $\Pi_{\mathcal{R}}(A|\theta) = \{r \in \mathcal{R} : (r, \theta) \in A\}$ . We call  $\Pi_{\mathcal{R}}(A|\theta)$  the projection of  $A$  onto  $\mathcal{R}$  given  $\theta$ . Define the class of projections  $\Pi_{\mathcal{R}}(A) = \{\Pi_{\mathcal{R}}(A|\theta) : \theta \in \Theta\}$ . Similarly, for each  $r \in \mathcal{R}$ , define  $\Pi_{\Theta}(A|r) = \{\theta \in \Theta : (r, \theta) \in A\}$  and  $\Pi_{\Theta}(A) = \{\Pi_{\Theta}(A|r) : r \in \mathcal{R}\}$ .

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In a typical econometric application,  $\mathcal{R}$  is the range space of the random variables in the econometric model,  $\Theta$  is a finite-dimensional parameter space, and  $A$  has the form  $\{(r, \theta) \in \mathcal{R} \times \Theta : h(r, \theta) > 0\}$  where  $h$  is a real-valued function on  $\mathcal{R} \times \Theta$ . Then  $\Pi_{\mathcal{R}}(A)$  is the class of positivity sets  $\{r \in \mathcal{R} : h(r, \theta) > 0\} : \theta \in \Theta\}$ . The objective is to show that  $\Pi_{\mathcal{R}}(A)$  is a VC class of sets. If the function  $h$  is linear in the components of  $\theta$ , then the VC property can be immediately deduced from a standard result in the empirical process literature (see, e.g., Pakes and Pollard, 1989, Lemma 2.4). However, if  $h$  is nonlinear in the components of  $\theta$ , then this result does not apply, and one must argue from first principles to show that  $\Pi_{\mathcal{R}}(A)$  is a VC class.

In the next section, we show that no matter what form the set  $A$  has,  $\Pi_{\mathcal{R}}(A)$  is a VC class of sets if and only if  $\Pi_{\Theta}(A)$  is a VC class of sets. We illustrate the usefulness of the result in the context of a semiparametric transformation model involving a function  $h$  that is nonlinear in parameters. In this example, it is difficult to show that  $\Pi_{\mathcal{R}}(A)$  is a VC class but easy to show that  $\Pi_{\Theta}(A)$  is a VC class.

## 2. EQUIVALENCE RESULT

We begin by recalling the definition of a VC class of sets. A class of subsets  $\mathcal{D}$  of a set  $S$  shatters a set  $S_0$  of  $V$  points in  $S$  if  $\{D \cap S_0 : D \in \mathcal{D}\} = \mathcal{P}(S_0)$ , the power set of  $S_0$ . In other words,  $\mathcal{D}$  shatters  $S_0$  if it picks out all  $2^V$  subsets of  $S_0$ . The class  $\mathcal{D}$  is a VC class of sets if there exists a  $V < \infty$  such that  $\mathcal{D}$  can shatter no  $V$  point set  $S_0 \subseteq S$  (see, e.g., Pollard, 1984, Ch. 2). The following result was proved by van den Dries in 1998.

**THEOREM 1.**  *$\Pi_{\mathcal{R}}(A)$  is a VC class of sets if and only if  $\Pi_{\Theta}(A)$  is a VC class of sets.*

*Proof.* By symmetry, it is enough to show that  $\Pi_{\Theta}(A)$  not VC implies  $\Pi_{\mathcal{R}}(A)$  not VC. So, suppose that  $\Pi_{\Theta}(A)$  is not a VC class of sets. We must show that for each  $n \geq 1$ , there exists an  $n$  point set  $\mathcal{R}_0 \subseteq \mathcal{R}$  that  $\Pi_{\mathcal{R}}(A)$  shatters.

Fix  $n \geq 1$ . Since  $\Pi_{\Theta}(A)$  is not VC, it can shatter some  $V$  point set for each  $V \geq 1$ . In particular, there exists a  $2^n$  point set  $\Theta_0 = \{\theta_i : 1 \leq i \leq 2^n\} \subseteq \Theta$  that  $\Pi_{\Theta}(A)$  shatters. This implies that there exists a  $2^{2^n}$  point set  $\mathcal{R}_1 = \{r_j : 1 \leq j \leq 2^{2^n}\} \subseteq \mathcal{R}$  such that  $\{\Pi_{\Theta}(A|r_j) \cap \Theta_0 : r_j \in \mathcal{R}_1\} = \mathcal{P}(\Theta_0)$ . Define a  $2^n \times 2^{2^n}$  matrix  $M_n$  such that for  $i = 1, \dots, 2^n$  and  $j = 1, \dots, 2^{2^n}$ ,

$$M_n^{ij} = \begin{cases} 1 & \text{if } (r_j, \theta_i) \in A \\ 0 & \text{if } (r_j, \theta_i) \notin A. \end{cases}$$

Thus, the  $j$ th column of  $M_n$  corresponds to  $\Pi_{\Theta}(A|r_j) \cap \Theta_0$ , the subset of  $\Theta_0$  that  $\Pi_{\Theta}(A|r_j)$  picks out. For example, take  $n = 2$  and order the  $r_j$ 's so that

$$M_2 = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 1 & 1 & 0 & 1 & 1 \\ 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 1 & 1 & 0 & 1 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 1 & 0 & 1 & 1 & 1 & 1 & 0 & 1 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 1 & 1 & 0 & 1 & 1 & 1 & 1 \end{bmatrix}.$$

The ninth column of  $M_2$  is  $[0, 1, 1, 0]'$ , and so  $\Pi_{\Theta}(A|r_9) \cap \Theta_0 = \{\theta_2, \theta_3\}$ .

The key insight is that the  $i$ th row of  $M_n$  corresponds to  $\Pi_{\mathcal{R}}(A|\theta_i) \cap \mathcal{R}_1$ , the subset of  $\mathcal{R}_1$  that  $\Pi_{\mathcal{R}}(A|\theta_i)$  picks out. We want to select  $\mathcal{R}_0 \subseteq \mathcal{R}_1$  such that  $\mathcal{R}_0$  is an  $n$  point set and  $\{\Pi_{\mathcal{R}}(A|\theta_i) \cap \mathcal{R}_0 : \theta_i \in \Theta_0\} = \mathcal{P}(\mathcal{R}_0)$ . This will prove the result.

For  $n \geq 1$ , define  $P_n$  to be the  $2^n \times n$  matrix of 0's and 1's such that the rows of  $P_n$  correspond to the  $2^n$  subsets of an  $n$  element set. For example,

$$P_2 = \begin{bmatrix} 0 & 0 \\ 0 & 1 \\ 1 & 0 \\ 1 & 1 \end{bmatrix}.$$

Note that the columns of both  $M_n$  and  $P_n$  have  $2^n$  elements. Moreover, by construction,  $M_n$  consists of all possible columns of  $2^n$  elements of 0's and 1's. In particular, the columns of  $P_n$  must appear as columns of  $M_n$ , say, as columns  $j_1, j_2, \dots, j_n$ . Let  $\mathcal{R}_0 = \{r_{j_1}, r_{j_2}, \dots, r_{j_n}\}$ . From the previous discussion,  $\{\Pi_{\mathcal{R}}(A|\theta_i) \cap \mathcal{R}_0 : \theta_i \in \Theta_0\} = \mathcal{P}(\mathcal{R}_0)$ . ■

Remark. The VC dimension of a class of subsets  $\mathcal{D}$  of a set  $S$  is the largest  $V$  for which some set of  $V$  points in  $S$  is shattered by  $\mathcal{D}$ . Fix  $n \geq 1$ . We see from the proof of Theorem 1 that if  $\Pi_{\Theta}(A)$  has VC dimension at least  $2^n$ , then  $\Pi_{\mathcal{R}}(A)$  has VC dimension at least  $n$ . See Wenocur and Dudley (1981) and Stengle and Yukich (1989) for complementary results on VC classes of sets.<sup>1</sup>

We apply Theorem 1 to an example in Asparouhova et al. (2002). These authors state sufficient conditions for  $\sqrt{n}$ -consistency and asymptotic normality of rank estimator of Han (1987a) of the parameter vector characterizing the transformation in a semiparametric transformation model. They also state sufficient conditions for  $\sqrt{n}$ -consistency and asymptotic normality of a new class of rank estimators of this parameter vector.

Their key assumption, A7, is that a certain class of sets is a VC class. In the special case of the Box-Cox (1964) transformation, this class of sets has the form  $\Pi_{\mathcal{R}}(A)$ , where  $\mathcal{R} = \mathbb{R}_+^4$ ,  $\Theta = \mathbb{R}_+$ , and  $A = \{(r, \theta) \in \mathcal{R} \times \Theta : h(r, \theta) > 0\}$  with  $r = (y_1, y_2, y_3, y_4)$  and  $h(r, \theta) = y_1^\theta - y_2^\theta - y_3^\theta + y_4^\theta$ . The nonlinearity of  $h$  as a function of  $\theta$  makes it difficult to prove directly that

$\Pi_{\mathcal{R}}(A)$  is a VC class. Because of this nonlinearity, Lemma 2.4 in Pakes and Pollard (1989) does not apply.

However, showing that  $\Pi_{\Theta}(A)$  is a VC class is easy. Fix  $r \in \mathcal{R}$ . Simple calculus shows that  $h(r, \cdot)$  has at most three zeros. It follows that  $\Pi_{\Theta}(A|r)$  is a union of at most two intervals on  $\Theta$ . Since the set of all intervals on  $\Theta$  is a VC class, and, for each  $k \geq 1$ , the set of all unions of  $k$  sets from a VC class is a VC class (see, e.g., Pollard, 1989), it follows that  $\Pi_{\Theta}(A)$  is a VC class. Deduce from Theorem 1 that  $\Pi_{\mathcal{R}}(A)$  is a VC class.

Finally, we note that Lemma 1 in Asparouhova et al. (2002) is used to establish that  $\Pi_{\mathcal{R}}(A)$  is a VC class of sets for the Box–Cox (1964) example. Though the respective proofs are quite different, their Lemma 1 can be viewed as a special case of Theorem 1. Their Lemma 1 requires that (i) the parameter space  $\Theta$  be a subset of the real line and (ii) the set  $A$  have the form  $\{(r, \theta) \in \mathcal{R} \times \Theta : h(r, \theta) > 0\}$ . Theorem 1, on the other hand, applies to an arbitrary parameter space (e.g., it could be infinite-dimensional) and does not require that the set  $A$  have the form specified in (ii);  $A$  can be any subset of the product space  $\mathcal{R} \times \Theta$ .

#### NOTE

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