HAL
archives-ouvertes.fr

Vapnik-Chervonenkis Dimension of Axis-Parallel Cuts

Servane Gey

To cite this version:

Servane Gey. Vapnik-Chervonenkis Dimension of Axis-Parallel Cuts. MAP5 2012-07. 2012. <hal-00675553v3>

HAL Id: hal-00675553

https://hal.archives-ouvertes.fr/hal-00675553v3

Submitted on 19 Oct 2016

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Vapnik-Chervonenkis Dimension of Axis-Parallel Cuts

Servane Gey[a]

[a] *Laboratoire MAP5 - UMR 8145, Université Paris Descartes, 75270 Paris Cedex 06, France*

Abstract

Algorithms in high dimension uses axis-parallel cuts to partition $\mathbb{R}^d$ in order to reduce the computational time of classifiers or regressors. Evaluating the complexity of such partitions is then crucial to evaluate estimation performance.
In this framework, we show that the Vapnik-Chervonenkis dimension (VC dimension) of the set of half-spaces of $\mathbb{R}^d$ with frontiers parallel to the axes is of the order of $\log_2 d$.

Keywords: Vapnik-Chervonenkis dimension, axis-parallel cuts
2010 MSC: 62G99 62H99

1. Introduction

The VC dimension of a set of subsets has been introduced by Vapnik and Chervonenkis [9, 10] to measure its complexity. The VC dimension of a real-valued function space $\mathcal{F}$ is then the VC dimension of $\{\{x;\ f(x) \geqslant 0\};\ f \in \mathcal{F}\}$. In particular, the VC dimension of sets of classifiers or regressors appears commonly in the statistical learning area when evaluating their performance. For example, Vapnik's theory in the classification framework is now widely known (see [3] for instance): let (X, Y) be a couple of variables taking values in $\mathbb{R}^d \times \{0; 1\}$, and let $\mathcal{L}$ be a sample of n independent replications of (X, Y). If $\hat{f}$ is a classifier minimizing the average misclassification rate of $\mathcal{L}$ on a set of classifiers having finite VC dimension V, then, without further assumption on the distribution P of (X, Y), the performance of $\hat{f}$ is evaluated as follows:

$$\mathbb{E}_{\mathcal{L}}\left[\mathrm{P}\left(\hat{f}(X) \neq Y\right)\right] \leqslant C_1 bias^2(\hat{f}) + C_2\sqrt{\frac{V}{n}}, \tag{1}$$

Email address: `Servane.Gey@parisdescartes.fr` (Servane Gey)

where $\mathbb{E}_{\mathcal{L}}$ denotes the expectation with respect to the sample distribution, $bias(\hat{f})$ denotes the bias of the classifier $\hat{f}$, and C_1 and C_2 are absolute constants.

Functional estimates defined on partitions of $\mathbb{R}^d$ are often used to estimate relationships between two variables $X \in \mathbb{R}^d$ and $Y \in \{0;1\}$ or $Y \in \mathbb{R}$ (such as histograms, piecewise polynomials, or splines for example). In many cases, the VC dimension of the set of subsets used to construct the partition appears inside risk bounds when evaluating the performance of such estimators. For example, if the set used is the set of all half-spaces of $\mathbb{R}^d$, often its VC dimension $d+1$ has to be taken into account.
When d is large, it is often computationally easier to construct partitions using axis-parallel cuts. For example, some theoretical developments on dyadic partitions of $\mathbb{R}^2$ are given in [4, 1], and the VC dimension of axis-parallel cuts appears more particularly in the results obtained on the performance of classification and regression binary decision trees (CART) introduced by Breiman *et. al* [2] in 1984, and theoretically studied in [8, 7, 5, 6]. In particular, it is to be found in the results of [6] that the VC dimension of axis-parallel cuts is of order $\log_2 d$.

2. Reminder about VC Dimension

The VC dimension of a set $\mathcal{A}$ of subsets of some measurable space $\mathcal{X}$ is based on counting the number of intersects of $\mathcal{A}$ with a finite set of fixed points in $\mathcal{X}$.

Definition 1 (Vapnik-Chervonenkis Dimension). *Let $\mathcal{A}$ be a set of subsets of some measurable space $\mathcal{X}$. Then $(x_1, \ldots, x_n) \in \mathcal{X}^n$ will be said to be shattered by $\mathcal{A}$ if all subsets of $\{x_1; \ldots; x_n\}$ are covered by $\mathcal{A}$, that is if $|\{\{x_1, \ldots, x_n\} \cap A \ ; \ A \in \mathcal{A}\}| = 2^n$.*
The Vapnik-Chervonenkis dimension $VC(\mathcal{A})$ of $\mathcal{A}$ is then defined as the maximal integer n such that there exists n points in $\mathcal{X}$ shattered by $\mathcal{A}$, i.e.

$$VC(\mathcal{A}) = \max\left\{n \ ; \ \max_{(x_1,\ldots,x_n)\in\mathcal{X}^n} |\{\{x_1, \ldots, x_n\} \cap A \ ; \ A \in \mathcal{A}\}| = 2^n\right\}.$$

If no such n exists, then $VC(\mathcal{A}) = +\infty$.

Thus, it is easily seen that the larger $VC(\mathcal{A})$, the more complex $\mathcal{A}$.

For example, if $\mathcal{A} = \{]-\infty; x] \ ; \ x \in \mathbb{R}\}$, $VC(\mathcal{A}) = 1$; or if $\mathcal{A}$ is the set of all half-spaces in $\mathbb{R}^d$, then $VC(\mathcal{A}) = d+1$.

Since axis-parallel cuts is a subset of the set of all half-spaces in $\mathbb{R}^d$, it could be natural to think that its VC dimension is of order d. Actually, it is shown in what follows that it is of order $\log_2 d$

3. VC Dimension of axis-parallel cuts

We give a formula to compute the VC dimension of axis-parallel cuts in $\mathbb{R}^d$. Since the obtained formula is not always easy to handle, an approximation is also given.

Lemma 1. *Let*

$$\mathcal{A}_d = \left\{ \{x \in \mathbb{R}^d \ ; \ x^i \leq a\}; \ i = 1, \ldots, d \ , \ a \in \mathbb{R} \right\}.$$

Then

$$VC(\mathcal{A}_d) = \max \left\{ n \ ; \ \binom{n}{\lfloor n/2 \rfloor} \leq d \right\},$$

where $\lfloor n/2 \rfloor$ denotes the integer part of $n/2$.
Furthermore, the following approximation of $VC(\mathcal{A}_d)$ is available for all $d \geqslant 3$:

$$\log_2 d + \frac{\log_2 \pi - 1}{2} \leqslant VC(\mathcal{A}_d) \leqslant \frac{3}{2} \log_2 d + 0.63.$$

Remark: A simple calculation gives $VC(\mathcal{A}_d) = d$ for $d \leqslant 3$.

Figure 1 shows that $VC(\mathcal{A}_d)$ is a piecewise constant function of the space dimension d, which increases at a rate of order $\log_2 d$. It also shows that the lower bound of Lemma 1 is conveniently sharp; the upper bound is sharp for d small, and then grows farther apart from $VC(\mathcal{A}_d)$. The bounds are obtained thanks to the Stirling's formula, which is really sharp. Actually, an approximation factor depending on d has to be calibrated, leading to the observed behavior when d grows.

Proof. Let $n \geqslant 1$ and $(x_1, \ldots, x_n)$ be n points in $\mathbb{R}^d$. The idea is that, if there exists $p \leq n$ such that there is more than $d+1$ subsets of $\{x_1, \ldots, x_n\}$ having p elements, then $\mathcal{A}_d$ will miss at least $\binom{n}{p} - d$ subsets: suppose that n is such that $\binom{n}{\lfloor n/2 \rfloor} > d$. This means that there are at least $d+1$ subsets of $\{x_1, \ldots, x_n\}$ of size $\lfloor n/2 \rfloor$. For each coordinate $i = 1, \ldots, d$, let us denote by $x_{i(.)}$ the ordered statistic computed from the ith coordinate of $(x_1, \ldots, x_n)$, that is, for all $i = 1, \ldots, d$,

$$x^i_{i(1)} \leq x^i_{i(2)} \leq \ldots \leq x^i_{i(n)}.$$

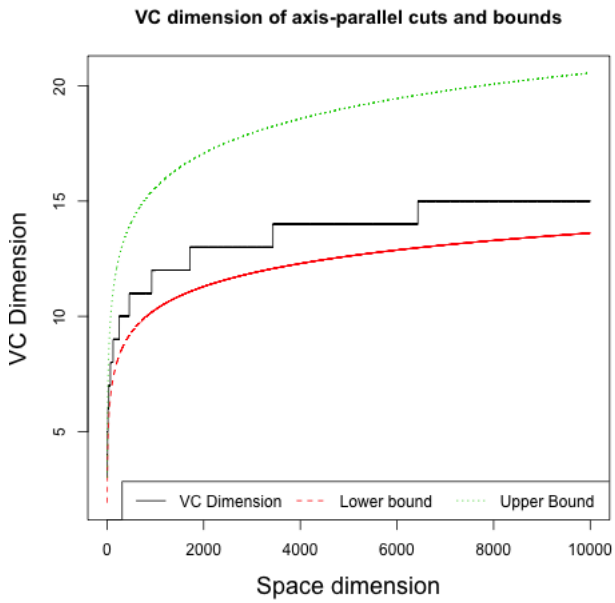

Figure 1: $VC(\mathcal{A}_d)$ and Stirling's bounds with respect to the space dimension d.

Let $p = \lfloor n/2 \rfloor$ and let

$$\begin{aligned} \mathcal{B}_p &= \left\{ \{x_{i(1)}; \ldots ; x_{i(p)}\} \; ; \; i = 1, \ldots, d \text{ and } |\{x_{i(1)}; \ldots ; x_{i(p)}\}| = p \right\}, \\ \mathcal{B}_p^c &= \{B \subset \{x_1, \ldots, x_n\}; |B| = p \text{ and } B \notin \mathcal{B}_p\}. \end{aligned}$$

Hence $\mathcal{B}_p$ is covered by $\mathcal{A}_d$ (by simply taking $A = \{x^i \leq (x^i_{i(p)} + x^i_{i(p+1)})/2\}$ for each coordinate), and we have that:

$$|\mathcal{B}_p| \leq d \quad \text{and} \quad |\mathcal{B}_p^c| \geqslant \binom{n}{p} - d > 0.$$

Let $B \in \mathcal{B}_p^c$ and $A = \{x^i \leq a\} \in \mathcal{A}_d$. If $|\{x_1, \ldots, x_n\} \cap A| \neq p$, then $\{x_1, \ldots, x_n\} \cap A \neq B$. Else, since $\{x_1, \ldots, x_n\} \cap A = \{x_j \; ; \; x^i_j \leq a\}$, we have that $x^i_{i(j)} \leq a$ for all $j = 1, \ldots, p$, and $x^i_{i(j)} > a$ for all $j = p+1, \ldots, n$. So $\{x_1, \ldots, x_n\} \cap A = \{x_{i(1)}; \ldots ; x_{i(p)}\}$ and $|\{x_{i(1)}; \ldots ; x_{i(p)}\}| = p$, leading to $\{x_1, \ldots, x_n\} \cap A \in \mathcal{B}_p$, and then to $\{x_1, \ldots, x_n\} \cap A \neq B$. So, for all $B \in \mathcal{B}_p^c$ and all $A \in \mathcal{A}_d$, $\{x_1, \ldots, x_n\} \cap A \neq B$.

So, if $\binom{n}{\lfloor n/2 \rfloor} > d$, $(x_1, \ldots, x_n)$ can not be shattered by $\mathcal{A}_d$. Thus

$$VC(\mathcal{A}_d) \leq \max \left\{ n \ ; \ \binom{n}{\lfloor n/2 \rfloor} \leq d \right\}.$$

Let $n \geqslant 1$ such that $\binom{n}{\lfloor n/2 \rfloor} \leq d$. Let $(x_1, \ldots, x_n)$ be n points of $\mathbb{R}^d$ defined as follows: for each coordinate $i = 1, \ldots, \binom{n}{\lfloor n/2 \rfloor}$, let $\{i_1; \ldots; i_{\lfloor n/2 \rfloor}\}$ be the ith subset of $\lfloor n/2 \rfloor$ indices in $\{1; \ldots; n\}$, where the indices are denoted in ascending order, i.e.:

$$1 \leq i_1 < \ldots < i_{\lfloor n/2 \rfloor} \leq n.$$

Since $\binom{n}{\lfloor n/2 \rfloor} \leq d$, we obtain $\binom{n}{\lfloor n/2 \rfloor}$ distinct subsets of indices.
Hence we take for each such coordinate

$$x^i_{i_k} = k.$$

Then the remaining values of $(x_1, \ldots, x_n)$ are taken as follows:

- Since $\binom{n}{\lfloor n/2 \rfloor + 1} \leq d$, for each subset $\{i_1; \ldots; i_{\lfloor n/2 \rfloor + 1}\}$ of $\{1; \ldots; n\}$ with $\lfloor n/2 \rfloor + 1$ elements, there exists $i' \in \{1; \ldots; \binom{n}{\lfloor n/2 \rfloor}\}$ such that $\{i_1; \ldots; i_{\lfloor n/2 \rfloor}\} = \{i'_1; \ldots; i'_{\lfloor n/2 \rfloor}\}$. Then take $x^{i'}_{i_{\lfloor n/2 \rfloor + 1}} = \lfloor n/2 \rfloor + 1$. Let us note that, if n is odd, there is a bijection between i and i'.
- Let $\{j_1; \ldots; j_m\} = \{j \notin \{i_1; \ldots; i_{\lfloor n/2 \rfloor + 1}\}\}$, with $j_1 < \ldots < j_m$, and let $j_0 = i_{\lfloor n/2 \rfloor + 1}$. Then take $x^{i'}_{j_k} = x^{i'}_{j_{k-1}} + 1$.

If not filled, the last coordinates are set to be equal to n.
Hence, we obtain that, for all $j \notin \{i_1; \ldots; i_{\lfloor n/2 \rfloor}\}$, $x^i_j \geqslant \lfloor n/2 \rfloor + 1$.
Then $(x_1, \ldots, x_n)$ is shattered by $\mathcal{A}_d$: for $p \in \{0; \ldots; n\}$, let $B = \{x_{i_1}; \ldots; x_{i_p}\} \subset \{x_1, \ldots, x_n\}$, with $1 \leq i_1 < i_2 < \ldots < i_p \leq n$ as soon as $p \neq 0$.
If $p = 0$, let

$$i_0 = \text{argmin}_{1 \leq i \leq d} \min_j x^i_j,$$

and take $A = \{x^{i_0} \leq \min_j x^{i_0}_j - 1\}$. Then $B = \{x_1, \ldots, x_n\} \cap A = \emptyset$.
If $p = n$, let

$$i_n = \text{argmax}_{1 \leq i \leq d} \max_j x^i_j,$$

and take $A = \{x^{i_n} \leq \max_j x_j^{i_n} + 1\}$. Then $B = \{x_1, \ldots, x_n\} \cap A = \{x_1, \ldots, x_n\}$.
If $0 < p \leq \lfloor n/2 \rfloor$, let $A \in \mathcal{A}_d$ be the subset defined by $A = \{x^i \leq p + 1/2\}$, with i the coordinate corresponding to a subset of indices $\{i_1; \ldots; i_{\lfloor n/2 \rfloor}\}$ containing $\{i_1; \ldots; i_p\}$. Then, by definition of $(x_1^i, \ldots, x_n^i)$, $B = \{x_1, \ldots, x_n\} \cap A$.
If $\lfloor n/2 \rfloor + 1 \leq p < n$, let i' be the coordinate corresponding to the configuration $\{i_1; \ldots; i_{\lfloor n/2 \rfloor + 1}\}$ (as defined by $(x_1, \ldots, x_n)$). Let $A \in \mathcal{A}_d$ be the subset defined by $A = \{x^{i'} \leq p + 1/2\}$. Then, by definition of $(x_1^{i'}, \ldots, x_n^{i'})$, $B = \{x_1, \ldots, x_n\} \cap A$.
Thus

$$VC(\mathcal{A}_d) \geqslant \max \left\{ n \ ; \ \binom{n}{\lfloor n/2 \rfloor} \leqslant d \right\}.$$

The bounds are computed thanks to the Stirling's formula: for all $n \geqslant 1$,

$$e^{\frac{1}{12n+1}} \sqrt{2\pi n} \left(\frac{n}{e}\right)^n \leq n! \leq e^{\frac{1}{12n}} \sqrt{2\pi n} \left(\frac{n}{e}\right)^n.$$

It follows by a simple computation that, for all $n \geqslant 1$, $\binom{n}{\lfloor n/2 \rfloor} \leqslant \frac{2^{n+1/2}}{\sqrt{\pi}}$, leading to the lower bound of $VC(\mathcal{A}_d)$.
Since $VC(\mathcal{A}_d) \leqslant d$ is increasing with d, we have $VC(\mathcal{A}_d) \geqslant 3$ for all $d \geqslant 3$. So we will focus only on integers $3 \leqslant n \leqslant d$ to compute the upper bound. We obtain from the Stirling's formula:

- if n is even

$$\binom{n}{n/2} \geqslant e^{-\frac{9n+1}{6n(12n+1}} \frac{2^{n+1/2}}{\sqrt{\pi n}} \geqslant e^{-\frac{14}{333}} \frac{2^{n+1/2}}{\sqrt{\pi d}},$$

- if n is odd

$$\binom{n}{\lfloor n/2 \rfloor} \geqslant \left(1 - \frac{1}{n^2}\right)^{-\frac{n+1}{2}} \sqrt{\frac{n-1}{n+1}} e^{-\frac{2n}{6(n^2-1)} + \frac{1}{12n+1}} \frac{2^{n+1/2}}{\sqrt{\pi n}} \geqslant \frac{81}{64\sqrt{2}} e^{-\frac{29}{396}} \frac{2^{n+1/2}}{\sqrt{\pi d}}.$$

Thus, it follows that, for all $n \geqslant 3$ such that $\binom{n}{\lfloor n/2 \rfloor} \leq d$, $\frac{81}{64\sqrt{2}} e^{-\frac{29}{396}} \frac{2^{n+1/2}}{\sqrt{\pi}} \leq d^{\frac{3}{2}}$, leading to the upper bound.

□

[1] Akakpo, N. (2012). Adaptation to anisotropy and inhomogeneity via dyadic piecewise polynomial selection. *Mathematical Methods of Statistics*, 21(1):1–28.

[2] Breiman, L., Friedman, J. H., Olshen, R. A., and Stone, C. J. (1984). *Classification And Regression Trees*. Chapman & Hall.

[3] Devroye, L., Györfi, L., and Lugosi, G. (1996). *A probabilistic theory of pattern recognition*, volume 31 of *Applications of Mathematics (New York)*. Springer-Verlag, New York.

[4] Donoho, D. L. (1997). CART and best-ortho-basis : A connection. *The Annals of Statistics*, 25(5):1870–1911.

[5] Gey, S. (2012). Risk bounds for cart classifiers under a margin condition. *Pattern Recognition*, 45:3523–3534.

[6] Gey, S. and Mary Huard, T. (2012). Risk bounds for embedded variable selection in classification trees. *IEEE Trans. Inform. Theory*, 60(3):1688–1699.

[7] Gey, S. and Nedelec, E. (2005). Model selection for CART regression trees. *IEEE Trans. Inform. Theory*, 51(2):658–670.

[8] Nobel, A. B. (2002). Analysis of a complexity-based pruning scheme for classification trees. *IEEE Trans. Inform. Theory*, 48(8):2362–2368.

[9] Vapnik, V. N. and Chervonenkis, A. Y. (1971). Theory of uniform convergence of frequencies of events to their probabilities and problems of search for an optimal solution from empirical data. *Avtomat. i Telemeh.*, (2):42–53.

[10] Vapnik, V. N. and Chervonenkis, A. Y. (1974). *Teoriya raspoznavaniya obrazov. Statisticheskie problemy obucheniya*. Izdat. “Nauka”, Moscow.