Machine Learning

VC-Dimension

Fabio Vandin

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Restrictions

Definition (Restriction of \mathcal{H} to \mathcal{C})

Let \mathcal{H} be a class of functions from \mathcal{X} to $\{0,1\}$ and let $C = \{c_1, \dots, c_m\} \subset \mathcal{X}$. The restriction \mathcal{H}_C of \mathcal{H} to C is:

$$\mathcal{H}_{C} = \{ [h(c_1), \ldots, h(c_m)] : h \in \mathcal{H} \}$$

where we represent each function from C to $\{0,1\}$ as a vector in $\{0,1\}^{|C|}$.

Note: \mathcal{H}_C is the set of functions from C to $\{0,1\}$ that can be derived from \mathcal{H} .

VC-dimension and Shattering

Definition (Shattering)

Given $C \subset \mathcal{X}$, \mathcal{H} shatters C if \mathcal{H}_C contains all $2^{|C|}$ functions from C to $\{0,1\}$.

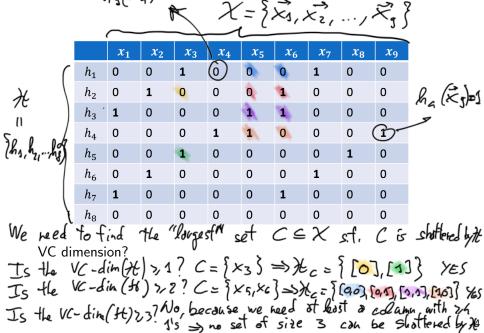
Definition (VC-dimension)

The VC-dimension VCdim (\mathcal{H}) of a hypothesis class \mathcal{H} , is the maximal size of a set $C \subset \mathcal{X}$ that can be shattered by \mathcal{H} .

Notes:

- VC = Vapnik-Chervonenkis, that introduced it in 1971
- if \mathcal{H} can shatter sets of arbitrarily large size then we say that $VCdim(\mathcal{H}) = +\infty$;
- if $|\mathcal{H}| < +\infty \Rightarrow VCdim(\mathcal{H}) \leq \log_2 |\mathcal{H}|$

Intuition: the VC-dimension measures the *complexity* of \mathcal{H} (\approx how large a dataset that is perfectly classified using the functions in \mathcal{H} can be)



Example

Note

To show that $VCdim(\mathcal{H}) = d$ we need to show that:

- 1 $VCdim(\mathcal{H}) \geq d$
- **2** $VCdim(\mathcal{H}) \leq d$

that translates to

- 1 there exists a set C of size d which is shattered by H
- 2 *every* set of size d+1 is not shattered by \mathcal{H}

Question: why don't we need to consider sets of size > d + 1?

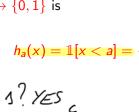
Example: Threshold Functions

where $h_a: \mathbb{R} \to \{0,1\}$ is

instance

$$\rightarrow \{0,1\}$$
 i

 $\mathcal{H} = \{h_a : a \in \mathbb{R}\}$



$$\{0,1\}$$
 is
$$h_a(x) = \mathbb{1}[x < a] = \begin{cases} 1 & \text{if } x < a \\ 0 & \text{if } x \ge a \end{cases}$$

VC-din (H) 7,1? YES c
instance
$$\rightarrow$$
 $\Rightarrow h_{0,1}(c) = 0$
 $h_{0,1}$ $\Rightarrow h_{0,1}(c) = 0$

Example: Threshold Functions

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$$VC\text{-dimension?}$$

OBTAINED

Example: Intervals

$$\mathcal{H} = \{h_{a,b} : a, b \in \mathbb{R}, a < b\}$$

where $h_{a,b}: \mathbb{R} \to \{0,1\}$ is

$$h_{a,b}(x) = \mathbb{I}[x \in (a,b)] = \begin{cases} 1 & \text{if } a < x < b \\ 0 & \text{otherwise} \end{cases}$$

$$VC \dim(\mathcal{H}) \sim \mathbf{2}$$

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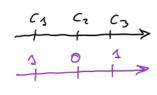
Example: Intervals

$$\mathcal{H} = \{ h_{a,b} : a, b \in \mathbb{R}, a < b \}$$

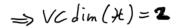
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1 connect be obtained with



Example: Axis Aligned Rectangles

$$\mathcal{H} = \{h_{(a_1, a_2, b_1, b_2)} : a_1, a_2, b_1, b_2 \in \mathbb{R}, a_1 \le a_2, b_1 \le b_2\}$$

$$h_{(a_1, a_2, b_1, b_2)}(x_1, x_2) = \begin{cases} 1 & \text{if } a_1 \le x_1 < a_2, b_1 \le x_2 \le b_2 \\ 0 & \text{otherwise} \end{cases}$$

$$0 & \text{if } x_1 \le x_2 \le b_2$$

$$0 & \text{otherwise}$$

$$0 & \text{if } x_2 \le b_2 \le b_2$$

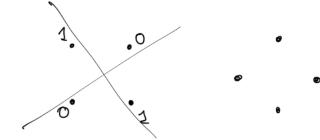
$$0 & \text{otherwise}$$

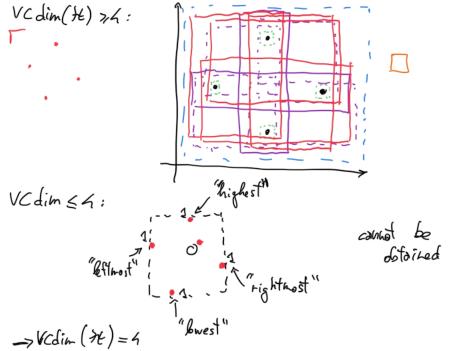
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VC-dimension?





Example: Convex Sets

Model set \mathcal{H} such that for $h \in \mathcal{H}$, $h : \mathbb{R}^2 \to \{0,1\}$ with

$$h(\mathbf{x}) = \begin{cases} 1 & \text{if } \mathbf{x} \in S \\ 0 & \text{otherwise} \end{cases}$$

where S is a convex subset of \mathbb{R}^2



Consider on arbitrary value of ne IN+
(n = size of the set to be shattered)

Consider an orbitrary labeling of C1, C2, ..., Cn:

10 1 5 the hypothesis corresponding to the convex set with vortices given by pairs (Ei, yi)

with y;=1 gives the desired labeling => It can shatter a set of a points for any orsitrorely longe n => Wdin (>t) = +0

Exercise

Consider the classification problem with $\mathcal{X} = \mathbb{R}^2$, $\mathbb{Y} = \{0,1\}$. Consider the hypothesis class $\mathcal{H} = \{h_{(\mathbf{c},a)}, \mathbf{c} \in \mathbb{R}^2, a \in \mathbb{R}\}$ with

$$h_{(\mathbf{c},a)}(\mathbf{x}) = \begin{cases} 1 & \text{if } ||\mathbf{x} - \mathbf{c}|| \le a \\ 0 & \text{otherwise} \end{cases}$$

Find the VC-dimension of \mathcal{H} .

The Fundamental Theorems of Statistical Learning

Theorem

Let \mathcal{H} be a hypothesis class of functions from a domain \mathcal{X} to $\{0,1\}$ and consider the 0-1 loss function. Assume that $VCdim(\mathcal{H}) = d < +\infty$. Then there are absolute constants C_1, C_2 such that

 H has the uniform convergence property with sample complexity

$$C_1 \frac{d + \log(1/\delta)}{\varepsilon^2} \leq m_{\mathcal{H}}^{UC}(\varepsilon, \delta) \leq C_2 \frac{d + \log(1/\delta)}{\varepsilon^2}$$

• H is agnostic PAC learnable with sample complexity

$$C_1 \frac{d + \log(1/\delta)}{\varepsilon^2} \le m_{\mathcal{H}}(\varepsilon, \delta) \le C_2 \frac{d + \log(1/\delta)}{\varepsilon^2}$$

Equivalently:

Theorem

Let H be an hypothesis class with VC-dimension

 $VCdim(\mathcal{H}) < +\infty$. Then, with probability $\geq 1 - \delta$ (over $S \sim \mathcal{D}^m$) we have:

$$\forall h \in \mathcal{H}, L_{\mathcal{D}}(h) \leq L_{\mathcal{S}}(h) + C\sqrt{\frac{VCdim(\mathcal{H}) + \log(1/\delta)}{2m}}$$

where C is a universal constant.

Note: finding $h \in \mathcal{H}$ that minimizes the upper bound (above) to $L_{\mathcal{D}}(h) \Rightarrow \text{ERM rule}$

Theorem

Let \mathcal{H} be a class with $VCdim(\mathcal{H}) = +\infty$. Then \mathcal{H} is not PAC learnable.

Notes:

 the VC-dimension characterizes PAC learnable hypothesis classes

Exercise

Let

$$\mathcal{H}_d = \{ h_{\mathbf{w}}(\mathbf{x}) : h_{\mathbf{w}}(\mathbf{x}) = \operatorname{sign}(\langle \mathbf{w}, \mathbf{x} \rangle) \}$$

where $\mathcal{X} = \mathbb{R}^d$.

Prove that $VCdim(\mathcal{H}_d) = d$.

An Interesting Example...

Note: in previous examples the VC-dimension is equivalent to the number of parameters that define the model... but it is not always the case!

Function of one parameter: $f_{\theta}(x) = \sin^2 \left[2^{8x} \arcsin \sqrt{\theta} \right]$

VC-dimension of $f_{\theta}(x)$ is infinite!

In fact, $f_{\theta}(x)$ can approximate any function $\mathbb{R} \to \mathbb{R}$ by changing the value of θ !

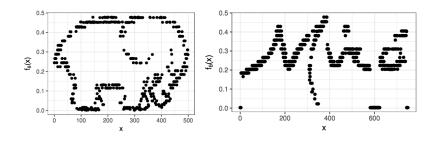


FIG. 1: A scatter plot of f_{θ} for $\theta=0.2446847266734745458227540656\cdots$ plotted at integer x values, showing that a single parameter can fit an elephant (left). The same model run with parameter $\theta=0.0024265418055000401935387620\cdots$ showing a fit of a scatter plot to Joan Miró's signature (right). Both use r=8 and require hundreds to thousands of digits of precision in θ .

["One parameter is always enough", Piantadosi, 2018]

Machine Learning

Clustering

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Unsupervised Learning

In unsupervised learning, the training dataset is $(x_1, x_2, ..., x_m)$ \Rightarrow no target values!

We are interested in finding some interesting *structure* in the data, or, equivalently, to organize it in some meaningful way.

We are going to see the most common unsupervised learning approaches: *clustering*

We are going to focus on the most commonly used techniques:

- k-means
- linkage-based clustering,

There are also other general techniques: dimensionality reduction, association analysis,...

Example



- Data: features (e.g. product bought, demographic info, etc.) for a large number of customers
- Goal: customers
 segmentation = identify
 subgroups of homogeneous
 customers
- useful for: advertizing, product development, ...

Example (2)



Data:

- rows = genes ($\approx 20 \times 10^3$)
- columns = samples, cancer patients ($\approx 10^3 10^4$)
- values = expression of a gene in a patient (∈ ℝ)

Goal: find similar cancer samples

 cluster colunms (samples) to find similar subgroups of patients (e.g., disease subtypes)

Goal: find genes with similar gene expression profiles

 cluster rows (genes) to deduce function of unknown genes from experimentally known genes with similar profiles

Other Applications

- Information Retrieval: clustering is used to find topics/categories of documents that are not explicitly given
- Image Processing: used for several tasks/applications, including: identification of different types of tissues in PET scans; identification of areas of similar land use in satellite pictures;...
- Analysis of Social Networks: detection of communities
- ...