Margin Natarajan dimension of Multi-Layer Perceptrons

Tom Masini

LORIA - UL

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Margin Multi-category Classifiers

- Theoretical Framework
- Guaranteed Risks



(3) γ - Ψ -dimensions

- Definitions
- Structural Results



Agnostic Learning (Kearns et al., 1994) for Pattern Classification

Problem characterization

- **()** Link between descriptions $x \in \mathcal{X}$ and their categories $y \in \mathcal{Y} = \llbracket 1; C \rrbracket$
- Existence of a random pair (X, Y) taking values in Z = X × Y, distributed according to a probability measure P
- The joint distribution of (X, Y) is unknown.

What is available

- Z_m = ((X_i, Y_i))_{1≤i≤m}: m-sample made up of independent copies of (X, Y)
 {G_k : 1 ≤ k ≤ C}: set of classes of functions from X into [-M_G, M_G] with M_G ≥ 1 which are uniform Glivenko-Cantelli (uGC) classes
- G ⊂ ∏^C_{k=1} G_k : margin classifier, with the decision rule dr which maps every function g ∈ G to dr_g ∈ (𝔅 ∪ {*})^𝔅. For every pair (g, x) ∈ G × 𝔅, dr_g (x) is either the index of the component function of g taking the highest value at x, or the dummy category * in case of ex æquo.

Majoration bound theory

Objective

Find a Law of large numbers that uniformly upper bounds the probability of error as a function of the frequency of error and a confidence interval depending on the basic parameters : m, C and γ .

Margin operator

Definition 1 (Margin operator ρ)

Let ${\cal G}$ be a function class defined as above. Define ρ as an operator on ${\cal G}$ such that:

$$\rho: \begin{array}{ccc} \mathcal{G} & \longrightarrow & \rho_{\mathcal{G}} \\ g & \mapsto & \rho_{g} \end{array}$$
$$\forall (x,k) \in \mathcal{Z}, \quad \rho_{g}(x,k) = \frac{1}{2} \left(g_{k}(x) - \max_{l \neq k} g_{l}(x) \right).$$

The function ρ_g is the margin function associated with g.

Risks

Definition 2 (Margin loss functions)

A class of margin loss functions ϕ_{γ} parameterized by $\gamma \in (0, 1]$ is a class of nonincreasing functions from \mathbb{R} into [0, 1] satisfying:

$$\begin{cases} \forall \gamma \in (0,1], \ \phi_{\gamma}(0) = 1 \ \textit{and} \ \phi_{\gamma}(\gamma) = 0 \\ \forall \left(\gamma, \gamma'\right) \in \left(0,1\right]^{2}, \ \gamma < \gamma' \Longrightarrow \phi_{\gamma'} \ \textit{majorizes} \ \phi_{\gamma} \end{cases}$$

Definition 3 (Squashing operator π_{γ})

Let $\mathcal{F} \subset \mathbb{R}^{\mathcal{T}}$. For $\gamma \in (0, 1]$, define the piecewise-linear squashing operator π_{γ} as:

 $\forall t \in \mathbb{R}, \ f_{\gamma}(t) = f(t) \mathbb{1}_{\{f(t) \in (0,\gamma]\}} + \gamma \mathbb{1}_{\{f(t) > \gamma\}}.$

Risks

The function class whose behaviour characterizes the generalization performance is

$$\rho_{\mathcal{G},\gamma} = \{\rho_{g,\gamma} = \pi_{\gamma} \circ \rho_{g} : g \in \mathcal{G}\}.$$

Definition 4 (Risks)

Let \mathcal{G} be a function class defined as above and ϕ_{γ} a margin loss function. Let P_m be the empirical measure supported on \mathbf{Z}_m .

Guaranteed Risks

Starting point

Theorem 1 (Basic supremum inequalities)

Let ${\mathcal G}$ be a function class defined as above. For $\gamma \in (0,1]$ and $\delta \in (0,1)$,

$$P^{m}\left\{\sup_{g\in\mathcal{G}}\left(L_{*}\left(g\right)-L_{\gamma,m}\left(g\right)\right)>F_{i}\left(m,\gamma,\delta,cap\left(\rho_{\mathcal{G},\gamma}\right)\right)\right\}\leqslant\delta,$$

where L_* is either L or L_{γ} and F_i is the confidence interval, with cap $(\rho_{\mathcal{G},\gamma})$ standing for the capacity of $\rho_{\mathcal{G},\gamma}$.

Objective

Theorem 2 (Guaranteed risks)

Let $\mathcal G$ be a function class defined as above. For $\gamma \in (0,1]$ and $\delta \in (0,1)$,

$$P^{m}\left\{\sup_{g\in\mathcal{G}}\left(L_{*}\left(g\right)-L_{\gamma,m}\left(g\right)\right)>F_{f}\left(m,C,\gamma,\delta\right)\right\}\leqslant\delta.$$

Capacity Measures - Combinatorial Dimension

Definition 5 (γ -dimension, Kearns and Schapire, 1994)

Let \mathcal{F} be a class of real-valued functions on \mathcal{T} . For $\gamma \in \mathbb{R}^*_+$, $s_{\mathcal{T}^n} = \{t_i : 1 \leq i \leq n\} \subset \mathcal{T}$ is said to be γ -shattered by \mathcal{F} if there is a vector $\mathbf{b}_n = (b_i)_{1 \leq i \leq n} \in \mathbb{R}^n$ such that, for every vector $\mathbf{s}_n = (s_i)_{1 \leq i \leq n} \in \{-1, 1\}^n$, there is a function $f_{\mathbf{s}_n} \in \mathcal{F}$ satisfying

$$\forall i \in \llbracket 1; n \rrbracket, \ s_i \left(f_{\mathbf{s}_n} \left(t_i \right) - b_i \right) \geqslant \gamma.$$

The γ -dimension of \mathcal{F} , γ -dim (\mathcal{F}) , is the maximal cardinality of a subset of \mathcal{T} γ -shattered by \mathcal{F} , if such maximum exists. Otherwise, \mathcal{F} is said to have infinite γ -dimension.

$$\mathcal{F} \subset \{-1,1\}^{\mathcal{T}} \Longrightarrow 1\text{-dim}\left(\mathcal{F}\right) = \mathsf{VC}\text{-dim}\left(\mathcal{F}\right)$$

Canonical Scheme of Derivation of the Guaranteed Risks

Figure: Graph of the transitions from a function F_i to a function F_f , where $\mathcal{G}_0 = \bigcup_{k=1}^{C} \mathcal{G}_k$.

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2 Structural result for the γ -dimension

$\Im \gamma - \Psi$ -dimensions

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4 Margin Natarajan dimension of MLPs

Structural Result for the γ -dimension

Lemma 1 (After Lemma 6.2 in Duan, 2012)

Let \mathcal{G} be a function class defined as above. For every $\gamma \in (0,1]$ and $\epsilon \in \left(0,\frac{\gamma}{2}\right]$,

$$\begin{aligned} \epsilon - \dim(\rho_{\mathcal{G},\gamma}) \leqslant & \epsilon - \dim(\rho_{\mathcal{G}}) \\ \leqslant & 320 \log_2\left(\frac{24M_{\mathcal{G}}\sqrt{C}}{\epsilon}\right) \sum_{k=1}^C \left(\frac{\epsilon}{96\sqrt{C}}\right) - \dim(\mathcal{G}_k) \\ \leqslant & 320 \log_2\left(\frac{24M_{\mathcal{G}}\sqrt{C}}{\epsilon}\right) C\left(\frac{\epsilon}{96\sqrt{C}}\right) - \dim(\mathcal{G}_0) \,. \end{aligned}$$

Derivation of the Structural Result

Figure: Transitions from ϵ -dim ($\rho_{\mathcal{G},\gamma}$) to ϵ''' -dim (\mathcal{G}_0).

Discussion

- Lemma 1 is useless.
- ② Can a change of combinatorial dimension bring an improvement?

The fat-shattering dimension of $\rho_{\mathcal{G}}$ can be replaced with γ - Ψ -dimensions.

Derivation of Guaranteed Risks Involving γ - Ψ -dimensions

Figure: Paths from F_i to F_f involving γ - Ψ -dimensions of the class $\rho_{\mathcal{G}}$.

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γ - Ψ -dimensions

Definition 6 (γ - Ψ -dimensions, Definition 28 in Guermeur, 2007)

Let $\mathcal{F} \subset \mathbb{R}^{\mathcal{Z}}$ be such that:

$$\forall f \in \mathcal{F}, \ \forall x \in \mathcal{X}, \ \max_{1 \leq k < l \leq C} \left\{ f\left(x,k\right) + f\left(x,l\right) \right\} = 0.$$

Let Ψ be a family of mappings from \mathcal{Y} into $\{-1,0,1\}$. For $\gamma \in \mathbb{R}^*_+$, a subset $s_{\mathcal{Z}^n} = \{z_i = (x_i, y_i) : 1 \le i \le n\}$ of \mathcal{Z} is said to be γ - Ψ -shattered by \mathcal{F} if there is a vector $\psi_n = (\psi^{(i)})_{1 \le i \le n} \in \Psi^n$ satisfying $(\psi^{(i)}(y_i))_{1 \le i \le n} = \mathbf{1}_n$, and a vector $\mathbf{b}_n = (b_i)_{1 \le i \le n} \in \mathbb{R}^n_+$ such that, for every vector $\mathbf{s}_n = (s_i)_{1 \le i \le n} \in \{-1, 1\}^n$, there is a function $f_{\mathbf{s}_n} \in \mathcal{F}$ satisfying

$$\forall i \in \llbracket 1; n \rrbracket, \quad s_i \left(s_i \max_{\{k: \psi^{(i)}(k) = s_i\}} f_{s_n}(x_i, k) - b_i \right) \ge \gamma.$$
(1)

The γ - Ψ -dimension of \mathcal{F} , denoted by γ - Ψ -dim(\mathcal{F}), is the maximal cardinality of a subset of $\mathcal{Z} \gamma$ - Ψ -shattered by \mathcal{F} , if such maximum exists. Otherwise, \mathcal{F} is said to have infinite γ - Ψ -dimension.

Margin Natarajan Dimension

Definition 7 (Margin Natarajan dimension)

Let \mathcal{F} be a function class defined as in Definition 6 and let $\gamma \in \mathbb{R}^*_+$. The Natarajan dimension with margin γ of \mathcal{F} , denoted by γ -N-dim (\mathcal{F}) , is the γ - Ψ -dimension of \mathcal{F} corresponding to the following choice for Ψ :

$$\Psi_{N} = \left\{ \left(\psi_{k,l} : y \mapsto \mathbb{1}_{\{y=k\}} - \mathbb{1}_{\{y=l\}} \right) : \ \{k,l\} \subset \mathcal{Y} \right\}.$$

Remark 1

For the instantiation of (1) associated with the margin Natarajan dimension, choosing ψ_n is equivalent to choosing a vector $\mathbf{c}_n = (c_i)_{1 \leq i \leq n} \in \mathcal{Y}^n$ (satisfying for every $i \in [\![1; n]\!]$, $c_i \neq y_i$). Then, ψ_n is set equal to $(\psi_{y_i, c_i})_{1 \leq i \leq n}$, so that (1) becomes

$$\forall i \in \llbracket 1; n \rrbracket, \begin{cases} \text{if } s_i = 1, \ f_{s_n}(x_i, y_i) - b_i \ge \gamma \\ \text{if } s_i = -1, \ f_{s_n}(x_i, c_i) + b_i \ge \gamma \end{cases}$$

Structural Results - Margin Natarajan Dimension

Lemma 2

Let \mathcal{G} be a function class defined as above and let $\mathcal{D}_{\mathcal{G}}$ be the function class $\{\frac{1}{2}(g_k - g_l) : g \in \mathcal{G}, 1 \leq k < l \leq C\}$. Then for every value of γ in $(0, M_{\mathcal{G}}]$,

$$\gamma$$
-*N*-dim $(\rho_{\mathcal{G}}) \leq \binom{C}{2} \cdot \gamma$ -dim $(\mathcal{D}_{\mathcal{G}})$

and

$$\gamma$$
-*N*-dim $(\rho_{\mathcal{G}}) \leq 384 \binom{C}{2} \log_2 \left(\frac{20M_{\mathcal{G}}}{\gamma}\right) \left(\frac{\gamma}{48}\right)$ -dim (\mathcal{G}_0) .

Many popular classifiers have the closure property $\mathcal{D}_{\mathcal{G}} \subset \mathcal{G}_0$.

Structural Results - Margin Natarajan Dimension

Corollary 1

Let $\mathcal{H}^{(1)}$ be a class of functions from \mathcal{X} into a Hilbert space $(\mathbf{H}, \langle \cdot, \cdot \rangle_{\mathbf{H}})$ and $(\Lambda_1, \Lambda_2) \in (\mathbb{R}^*_+)^2$. Let $\mathcal{H}^{(2)}$ be the class of functions $h^{(2)}$ from \mathcal{X} into $[-\Lambda_1\Lambda_2, \Lambda_1\Lambda_2]^C$ of the form:

$$\forall x \in \mathcal{X}, \ h^{(2)}(x) = \left(\left\langle \mathbf{w}_{k}, h^{(1)}(x) \right\rangle_{\mathbf{H}}\right)_{1 \leqslant k \leqslant C},$$

where $h^{(1)} \in \mathcal{H}^{(1)}$ satisfies $\sup_{x \in \mathcal{X}} \|h^{(1)}(x)\|_{\mathbf{H}} \leq \Lambda_1$ and the vector $(\mathbf{w}_k)_{1 \leq k \leq C} \in \mathbf{H}^C$ satisfies $\max_{1 \leq k \leq C} \|\mathbf{w}_k\|_{\mathbf{H}} \leq \Lambda_2$. Let $\mathcal{H}_0^{(2)}$ be the class of all the component functions of the functions in $\mathcal{H}^{(2)}$. Then,

$$\forall \gamma \in (0, \Lambda_1 \Lambda_2], \ \gamma \text{-N-dim}\left(\rho_{\mathcal{H}^{(2)}}\right) \leqslant \binom{\mathsf{C}}{2} \cdot \gamma \text{-dim}\left(\mathcal{H}_0^{(2)}\right).$$

Corollary 1 applies to both C-category SVMs and C-category MLPs.

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Multi-layer Perceptrons

Definition 8 (MLPs)

Let \mathcal{F} be a function class from \mathbb{R}^{d_0} to [-M/2, M/2], with $d_0 \in \mathbb{N}^*$ and M > 0. For $\Lambda \ge 0$, we define the class \mathcal{H} of vector-valued functions h parameterised by $d_1 \in \mathbb{N}^*$, $(f_j)_{1 \le j \le d_1} \in \mathcal{F}^{d_1}$ and the matrix $A = (a_{kj}) \in \mathcal{M}_{C,d_1}(\mathbb{R})$, such that :

$$\mathcal{H} = \left\{ h = A(f_j)_{1 \leq j \leq d_1} : \|A\|_1 \leq \Lambda \right\}.$$

Multi-layer Perceptrons

Lemma 3

Let \mathcal{H}_0 be the class of binary MLPs and $\gamma \in (0, \Lambda M/2]$. Then,

$$\gamma$$
-dim $(\mathcal{H}_0) \leqslant \frac{KM^2\Lambda^2}{\gamma^2}\log_2\left(\frac{25M\Lambda}{\gamma}\right)\left(\frac{\gamma}{192\Lambda}\right)$ -dim (\mathcal{F}) ,

where K = 2560.

Corollary 2

Let \mathcal{H} be a function class defined as Definition 8 and $\gamma \in (0, \Lambda M/2]$. Then,

$$\gamma$$
-N-dim $(\rho_{\mathcal{H}}) \leq \binom{C}{2} \frac{KM^2\Lambda^2}{\gamma^2} \log_2\left(\frac{25M\Lambda}{\gamma}\right) \left(\frac{\gamma}{192\Lambda}\right)$ -dim (\mathcal{F}) ,

where K = 2560.

Conclusion and Future work

Conclusion

First workable upper bound on a combinatorial dimension of MLPs

Ongoing research Derivation of a sharper bound for a more general model of MLPs

Future work

Include this contribution in the general study on phase transitions

Capacity Measures - Rademacher Complexity

Definition 9 (Rademacher complexity, Bartlett and Mendelson, 2002)

Let $(\mathcal{T}, \mathcal{A}_{\mathcal{T}}, \mathcal{P}_{\mathcal{T}})$ be a probability space and let T be a random variable distributed according to $\mathcal{P}_{\mathcal{T}}$. For $n \in \mathbb{N}^*$, let $\mathbf{T}_n = (T_i)_{1 \leq i \leq n}$ be an n-sample made up of independent copies of T and let $\boldsymbol{\sigma}_n = (\sigma_i)_{1 \leq i \leq n}$ be a Rademacher sequence. Let \mathcal{F} be a class of real-valued functions with domain \mathcal{T} . The empirical Rademacher complexity of \mathcal{F} given \mathbf{T}_n is

$$\hat{R}_{n}(\mathcal{F}) = \mathbb{E}_{\boldsymbol{\sigma}_{n} \sim \{\pm 1\}^{n}} \left[\sup_{f \in \mathcal{F}} \frac{1}{n} \sum_{i=1}^{n} \sigma_{i} f(T_{i}) \middle| \mathbf{T}_{n} \right]$$

The Rademacher complexity of $\mathcal F$ is

$$R_{n}(\mathcal{F}) = \mathbb{E}_{\mathbf{T}_{n} \sim P_{\mathcal{T}}^{n}}\left[\hat{R}_{n}(\mathcal{F})\right].$$

Capacity Measures - Covering and Packing Numbers

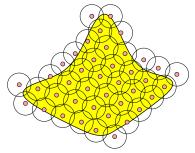


Figure: ϵ -net and ϵ -cover of a set \mathcal{E}' in a pseudo-metric space (\mathcal{E}, ρ)

Definition 10 (Covering numbers, Kolmogorov and Tihomirov, 1961) $\mathcal{N}(\epsilon, \mathcal{E}', \rho)$: minimal number of open balls of radius ϵ needed to cover \mathcal{E}' (or $+\infty$) $\mathcal{N}^{int}(\epsilon, \mathcal{E}', \rho)$: the ϵ -nets considered are included in \mathcal{E}' (proper to \mathcal{E}') Definition 11 (Packing numbers, Kolmogorov and Tihomirov, 1961) $\mathcal{E}' \subset \mathcal{E}$ is ϵ -separated $\iff \forall \{e, e'\} \subset \mathcal{E}', \rho(e, e') \ge \epsilon$ $\mathcal{M}(\epsilon, \mathcal{E}', \rho)$: maximal cardinality of an ϵ -separated subset of \mathcal{E}' (or $+\infty$)

Structural Results - Rademacher Complexity

Lemma 4 (After Theorem 9.2 in Mohri et al., 2018)

Let \mathcal{G} be a function class defined as above. Then,

 $\forall \gamma \in (0,1], \forall n \in \mathbb{N}^*, R_n(\rho_{\mathcal{G},\gamma}) \leq \min \{R_n(\rho_{\mathcal{G}}), CR_n(\mathcal{G}_0)\}.$

Structural Results - Covering Numbers

Lemma 5 (Lemma 1 in Guermeur, 2017)

Let \mathcal{G} be a function class defined as above. For every $\gamma \in (0, 1]$, $\epsilon \in \mathbb{R}^*_+$, $n \in \mathbb{N}^*$, $p \in [1, +\infty]$, and $\mathbf{z}_n = ((x_i, y_i))_{1 \leqslant i \leqslant n} \in \mathbb{Z}^n$,

$$\mathcal{N}^{int}\left(\epsilon,\rho_{\mathcal{G},\gamma},d_{p,\mathbf{z}_{n}}\right) \leqslant \mathcal{N}^{int}\left(\epsilon,\rho_{\mathcal{G}},d_{p,\mathbf{z}_{n}}\right) \leqslant \prod_{k=1}^{C} \mathcal{N}^{int}\left(C^{-\frac{1}{p}}\epsilon,\mathcal{G}_{k},d_{p,\mathbf{x}_{n}}\right)$$
$$\leqslant \left(\mathcal{N}^{int}\left(C^{-\frac{1}{p}}\epsilon,\mathcal{G}_{0},d_{p,\mathbf{x}_{n}}\right)\right)^{C},$$

where $\mathbf{x}_n = (x_i)_{1 \leq i \leq n}$.

Combinatorial Results - Margin Natarajan Dimension

Lemma 6

Let \mathcal{F} be a function class defined as in Definition 6. For $\epsilon \in \mathbb{R}^*_+$, let $d_N(\epsilon) = \epsilon$ -N-dim (\mathcal{F}) . Then for every $\gamma \in (0,1]$, $\epsilon \in (0,\gamma]$ and $n \in \mathbb{N}^*$ such that $n \ge d_N(\frac{\epsilon}{4})$,

$$\mathcal{M}_{\infty}\left(\epsilon, \mathcal{F}_{\gamma}, n\right) \leqslant \left(\frac{6\gamma\sqrt{C-1}n}{\epsilon}\right)^{d_{N}\left(\frac{\epsilon}{4}\right)\log_{2}\left(\frac{2\gamma(C-1)en}{d_{N}\left(\frac{\epsilon}{4}\right)\epsilon}\right)}$$

Lemma 7

Let \mathcal{F} be a function class defined as in Definition 6. For $\epsilon \in \mathbb{R}^*_+$, let $d_N(\epsilon) = \epsilon$ -N-dim (\mathcal{F}) . Then for every $\gamma \in (0, 1]$, $\epsilon \in (0, \gamma]$ and $n \in \mathbb{N}^*$,

$$\mathcal{M}_{2}(\epsilon, \mathcal{F}_{\gamma}, \mathbf{n}) \leqslant \left((C-1) \left(\frac{4\gamma}{\epsilon} \right)^{5} \right)^{\frac{3}{2} \log_{2} \left(2 \left(\frac{14\gamma}{\epsilon} \right)^{2} (C-1) \right) d_{N} \left(\frac{\epsilon}{28} \right)}$$