

Rademacher Complexity of Margin Multi-category Classifiers

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Agnostic Learning (Kearns et al., 1994)

Problem Characterization

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

What is available

- 1 $\mathbf{Z}_m = ((X_i, Y_i))_{1 \leq i \leq m}$: m -sample made up of independent copies of (X, Y)
- 2 For $k \in \llbracket 1, C \rrbracket$, \mathcal{G}_k : class of functions from \mathcal{X} into $[-M_G, M_G]$ with $M_G \geq 1$ which is a uniform Glivenko-Cantelli class

Uniform Glivenko-Cantelli class

Definition 1 (Dudley et al., 1991)

Let $(\mathcal{T}, \mathcal{A}_{\mathcal{T}})$ be a measurable space and let T be a random variable with values in \mathcal{T} , distributed according to a probability measure $P_{\mathcal{T}}$ on $(\mathcal{T}, \mathcal{A}_{\mathcal{T}})$. 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 . Let \mathcal{F} be a class of measurable functions on \mathcal{T} . Then \mathcal{F} is a uniform Glivenko-Cantelli class if for every $\epsilon \in \mathbb{R}_+^*$,

$$\lim_{n \rightarrow +\infty} \sup_{P_{\mathcal{T}}} \mathbb{P} \left(\sup_{n' \geq n} \sup_{f \in \mathcal{F}} \left| \mathbb{E}_{T' \sim P_{\mathbf{T}_{n'}}} [f(T')] - \mathbb{E}_{T \sim P_{\mathcal{T}}} [f(T)] \right| > \epsilon \right) = 0,$$

where \mathbb{P} denotes the infinite product measure $P_{\mathcal{T}}^{\infty}$ and $P_{\mathbf{T}_{n'}}$ denotes the empirical measure supported on $\mathbf{T}_{n'}$.

Margin Classifier

Pattern Classification

- 1 $\mathcal{G} = \prod_{k=1}^C \mathcal{G}_k$: class of functions $g = (g_k)_{1 \leq k \leq C}$, from \mathcal{X} into $[-M_G, M_G]^C$
- 2 Decision rule dr : operator from \mathcal{G} into $(\mathcal{Y} \cup \{*\})^{\mathcal{X}}$ mapping g to dr_g

$$\forall g \in \mathcal{G}, \forall x \in \mathcal{X}, \begin{cases} |\operatorname{argmax}_{1 \leq k \leq C} g_k(x)| = 1 \implies \text{dr}_g(x) = \operatorname{argmax}_{1 \leq k \leq C} g_k(x) \\ |\operatorname{argmax}_{1 \leq k \leq C} g_k(x)| > 1 \implies \text{dr}_g(x) = * \end{cases}$$

where $|\cdot|$ returns the cardinality of its argument and $*$ stands for a dummy category

Function Selection

Minimization over \mathcal{G} of the risk $L(g) = \mathbb{E}_{Z \sim P} [\mathbb{1}_{\{\text{dr}_g(X) \neq Y\}}] = P(\text{dr}_g(X) \neq Y)$

Margin

Definition 2 (Class of functions $\mathcal{F}_{\mathcal{G}}$)

Let \mathcal{G} be the class of functions computed by a margin multi-category classifier. For every $g \in \mathcal{G}$, the function f_g from $\mathcal{X} \times \llbracket 1, C \rrbracket$ into $[-M_{\mathcal{G}}, M_{\mathcal{G}}]$ is defined by:

$$\forall (x, k) \in \mathcal{X} \times \llbracket 1, C \rrbracket, f_g(x, k) = \frac{1}{2} \left(g_k(x) - \max_{l \neq k} g_l(x) \right).$$

Then, the class $\mathcal{F}_{\mathcal{G}}$ is defined as follows: $\mathcal{F}_{\mathcal{G}} = \{f_g : g \in \mathcal{G}\}$.

Definition 3 (Margin)

Let g be a function computed by a margin multi-category classifier. The margin of g on (x, y) is defined as $f_g(x, y)$.

- 1 $L(g) = \mathbb{E}_{Z \sim P} [\mathbb{1}_{\{f_g(Z) \leq 0\}}]$
- 2 The margin bears useful information on the generalization performance.
- 3 Its exploitation calls for the implementation of a scale-sensitive approach.

Margin Risks

Definition 4 (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:

- 1 $\forall \gamma \in (0, 1], \phi_\gamma(0) = 1 \wedge \phi_\gamma(\gamma) = 0;$
- 2 $\forall (\gamma, \gamma') \in (0, 1]^2, \gamma < \gamma' \implies \forall t \in (0, \gamma), \phi_\gamma(t) \leq \phi_{\gamma'}(t).$

Definition 5 (Margin risk)

Let \mathcal{G} be the class of functions computed by a margin multi-category classifier and ϕ_γ a margin loss function. The risk with margin γ of $g \in \mathcal{G}$ is defined as:

$$L_\gamma(g) = \mathbb{E}_{Z \sim P} [\phi_\gamma \circ f_g(Z)].$$

$L_{\gamma,m}(g)$ designates the corresponding empirical risk, measured on \mathbf{Z}_m .

Guaranteed Risks

Definition 6 (Piecewise-linear squashing function π_γ)

For $\gamma \in (0, 1]$, the piecewise-linear squashing function π_γ is defined by:

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

Definition 7 (Class of functions $\mathcal{F}_{\mathcal{G}, \gamma}$)

Let \mathcal{G} be the class of functions computed by a margin multi-category classifier.

$\forall \gamma \in (0, 1]$, the class $\mathcal{F}_{\mathcal{G}, \gamma}$ is defined as follows: $\mathcal{F}_{\mathcal{G}, \gamma} = \{f_{g, \gamma} = \pi_\gamma \circ f_g : g \in \mathcal{G}\}$.

Theorem 1 (Guaranteed risk)

Let \mathcal{G} be the class of functions computed by a margin multi-category classifier.

Let $\gamma \in (0, 1]$ and $\delta \in (0, 1)$. With P^m -probability at least $1 - \delta$,

$$\sup_{g \in \mathcal{G}} (L(g) - L_{\gamma, m}(g)) \leq F(C, m, \gamma, \delta, d(\mathcal{F}_{\mathcal{G}, \gamma}))$$

where $d(\mathcal{F}_{\mathcal{G}, \gamma})$ is a *scale-sensitive measure of the capacity* of $\mathcal{F}_{\mathcal{G}, \gamma}$.

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Rademacher Complexity

Definition 8 (Rademacher complexity)

Let \mathcal{F} be a class of real-valued functions on \mathcal{T} . For $n \in \mathbb{N}^*$, let $\mathbf{T}_n = (T_i)_{1 \leq i \leq n}$ be a sequence of n i.i.d. random variables taking values in \mathcal{T} and let $\sigma_n = (\sigma_i)_{1 \leq i \leq n}$ be a Rademacher sequence. The empirical Rademacher complexity of \mathcal{F} given \mathbf{T}_n is

$$\hat{R}_n(\mathcal{F}) = \mathbb{E}_{\sigma_n} \left[\sup_{f \in \mathcal{F}} \frac{1}{n} \sum_{i=1}^n \sigma_i f(T_i) \mid \mathbf{T}_n \right].$$

The Rademacher complexity of \mathcal{F} is

$$R_n(\mathcal{F}) = \mathbb{E}_{\mathbf{T}_n} \left[\hat{R}_n(\mathcal{F}) \right] = \mathbb{E}_{\mathbf{T}_n \sigma_n} \left[\sup_{f \in \mathcal{F}} \frac{1}{n} \sum_{i=1}^n \sigma_i f(T_i) \right].$$

Covering Numbers

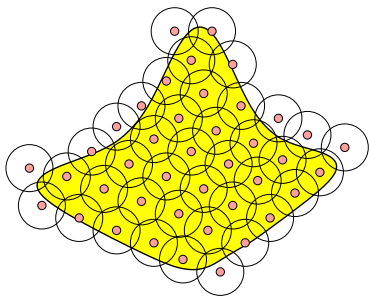


Figure : ϵ -net and ϵ -cover of a set \mathcal{E}' in a pseudo-metric space (\mathcal{E}, ρ)

Definition 9 (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}')

Packing Numbers

Definition 10 (Packing numbers, Kolmogorov and Tihomirov, 1961)

Let (\mathcal{E}, ρ) be a pseudo-metric space and $\epsilon \in \mathbb{R}_+^*$. A set $\mathcal{E}' \subset \mathcal{E}$ is ϵ -separated if, for any distinct points e and e' in \mathcal{E}' , $\rho(e, e') \geq \epsilon$. The ϵ -packing number of $\mathcal{E}'' \subset \mathcal{E}$, $\mathcal{M}(\epsilon, \mathcal{E}'', \rho)$, is the maximal cardinality of an ϵ -separated subset of \mathcal{E}'' , if such maximum exists. Otherwise, the ϵ -packing number of \mathcal{E}'' is defined to be infinite.

Lemma 1 (After Theorem IV in Kolmogorov and Tihomirov, 1961)

Let (\mathcal{E}, ρ) be a pseudo-metric space. For every totally bounded set $\mathcal{E}' \subset \mathcal{E}$ and $\epsilon \in \mathbb{R}_+^*$,

$$\mathcal{N}^{int}(\epsilon, \mathcal{E}', \rho) \leq \mathcal{M}(\epsilon, \mathcal{E}', \rho) \leq \mathcal{N}^{int}\left(\frac{\epsilon}{2}, \mathcal{E}', \rho\right).$$

Fat-Shattering Dimension

Definition 11 (Fat-shattering 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

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

The fat-shattering dimension with margin γ of the class \mathcal{F} , $\gamma\text{-dim}(\mathcal{F})$, 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 fat-shattering dimension with margin γ .

Empirical Pseudo-metrics

Definition 12 (Pseudo-distance d_{p, \mathbf{t}_n})

Let \mathcal{F} be a class of real-valued functions on \mathcal{T} and $\mathbf{t}_n = (t_i)_{1 \leq i \leq n} \in \mathcal{T}^n$. Then,

$$\begin{cases} \forall p \in [1, +\infty), \forall (f, f') \in \mathcal{F}^2, & d_{p, \mathbf{t}_n}(f, f') = \left(\frac{1}{n} \sum_{i=1}^n |f(t_i) - f'(t_i)|^p \right)^{\frac{1}{p}} \\ \forall (f, f') \in \mathcal{F}^2, & d_{\infty, \mathbf{t}_n}(f, f') = \max_{1 \leq i \leq n} |f(t_i) - f'(t_i)| \end{cases}$$

Definition 13 (Uniform covering and packing numbers)

Let \mathcal{F} be a class of real-valued functions on \mathcal{T} and $\bar{\mathcal{F}} \subset \mathcal{F}$. For $p \in [1, +\infty]$, $\epsilon \in \mathbb{R}_+^*$ and $n \in \mathbb{N}^*$, the uniform covering number $\mathcal{N}_p(\epsilon, \bar{\mathcal{F}}, n)$ and the uniform packing number $\mathcal{M}_p(\epsilon, \bar{\mathcal{F}}, n)$ are defined as follows:

$$\begin{cases} \mathcal{N}_p(\epsilon, \bar{\mathcal{F}}, n) = \sup_{\mathbf{t}_n \in \mathcal{T}^n} \mathcal{N}(\epsilon, \bar{\mathcal{F}}, d_{p, \mathbf{t}_n}) \\ \mathcal{M}_p(\epsilon, \bar{\mathcal{F}}, n) = \sup_{\mathbf{t}_n \in \mathcal{T}^n} \mathcal{M}(\epsilon, \bar{\mathcal{F}}, d_{p, \mathbf{t}_n}) \end{cases}$$

Accordingly,

$$\mathcal{N}_p^{int}(\epsilon, \bar{\mathcal{F}}, n) = \sup_{\mathbf{t}_n \in \mathcal{T}^n} \mathcal{N}^{int}(\epsilon, \bar{\mathcal{F}}, d_{p, \mathbf{t}_n})$$

Transitions Between Capacity Measures

”Complete” Pathway

$$R(\mathcal{F}) \xrightarrow{\text{chaining}} \mathcal{N}_p^{\text{int}}(\epsilon, \mathcal{F}, n) \xrightarrow{\leq} \mathcal{M}_p(\epsilon, \mathcal{F}, n) \xrightarrow{\text{Sauer-Shelah lemma}} \gamma\text{-dim}(\mathcal{F})$$

”Partial” Pathways

Depend on the choice of the norm, the classifier. . .

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Guaranteed Risk Based on the L_∞ -norm

Margin Loss Function

$$\forall \gamma \in (0, 1], \forall t \in \mathbb{R}, \phi_{\infty, \gamma}(t) = \mathbb{1}_{\{t < \gamma\}}$$

Basic Supremum Inequality

Theorem 2 (After Theorem 22 in Guermeur, 2007)

Let \mathcal{G} be the class of functions computed by a margin multi-category classifier. Let $\gamma \in (0, 1]$ and $\delta \in (0, 1)$. With P^m -probability at least $1 - \delta$,

$$\sup_{g \in \mathcal{G}} (L(g) - L_{\gamma, m}(g)) \leq \sqrt{\frac{2}{m} \left(\ln \left(\mathcal{N}_\infty^{\text{int}} \left(\frac{\gamma}{2}, \mathcal{F}_{\mathcal{G}, \gamma}, 2m \right) \right) + \ln \left(\frac{2}{\delta} \right) \right)} + \frac{1}{m}.$$

Guaranteed Risk Based on the L_∞ -norm

Decomposition Lemma

Lemma 2 (Lemma 1 in Guermeur, 2017)

Let \mathcal{G} be the class of functions computed by a margin multi-category classifier. Then for $\gamma \in (0, 1]$, $\epsilon \in \mathbb{R}_+^*$, $m \in \mathbb{N}^*$ and $\mathbf{z}_m = ((x_i, y_i))_{1 \leq i \leq m} \in \mathcal{Z}^m$,

$$\forall p \in [1, +\infty], \mathcal{N}^{int}(\epsilon, \mathcal{F}_{\mathcal{G}, \gamma}, d_{p, \mathbf{z}_m}) \leq \prod_{k=1}^C \mathcal{N}^{int}\left(C^{-\frac{1}{p}} \epsilon, \mathcal{G}_k, d_{p, \mathbf{x}_m}\right),$$

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

Generalized Sauer-Shelah Lemma

Lemma 3 (After Lemma 3.5 in Alon et al., 1997)

Let \mathcal{F} be a class of functions from \mathcal{T} into $[-M_{\mathcal{F}}, M_{\mathcal{F}}]$. For $\epsilon \in (0, M_{\mathcal{F}}]$, let $d(\epsilon) = \epsilon\text{-dim}(\mathcal{F})$. Then for $\epsilon \in (0, 2M_{\mathcal{F}}]$ and $n \in \mathbb{N}^*$,

$$\mathcal{M}_\infty(\epsilon, \mathcal{F}, n) < 2 \left(\frac{16M_{\mathcal{F}}^2 n}{\epsilon^2} \right)^{d\left(\frac{\epsilon}{4}\right) \log_2 \left(\frac{4M_{\mathcal{F}} n}{d\left(\frac{\epsilon}{4}\right) \epsilon} \right)}.$$

Guaranteed Risk Based on the L_∞ -norm

Theorem 3 (Theorem 3 in Guermeur, 2017)

Let \mathcal{G} be the class of functions computed by a margin multi-category classifier. For $\epsilon \in (0, M_G]$, let $d(\epsilon) = \max_{1 \leq k \leq C} \epsilon\text{-dim}(\mathcal{G}_k)$. Let $\gamma \in (0, 1]$ and $\delta \in (0, 1)$. With P^m -probability at least $1 - \delta$,

$$\sup_{g \in \mathcal{G}} (L(g) - L_{\gamma, m}(g)) \leq \sqrt{\frac{2}{m} \left(3Cd \left(\frac{\gamma}{8} \right) \ln^2 \left(\frac{128M_G^2 m}{\gamma^2} \right) + \ln \left(\frac{2}{\delta} \right) \right)} + \frac{1}{m}.$$

Guaranteed Risk Based on the L_2 -norm

Margin Loss Function

$$\forall \gamma \in (0, 1], \forall t \in \mathbb{R}, \phi_{2,\gamma}(t) = \mathbb{1}_{\{t \leq 0\}} + \left(1 - \frac{t}{\gamma}\right) \mathbb{1}_{\{t \in (0, \gamma)\}}.$$

Basic Supremum Inequality

Theorem 4 (After Theorem 8.1 in Mohri et al., 2012)

Let \mathcal{G} be the class of functions computed by a margin multi-category classifier. Let $\gamma \in (0, 1]$ and $\delta \in (0, 1)$. With P^m -probability at least $1 - \delta$,

$$\sup_{g \in \mathcal{G}} (L_\gamma(g) - L_{\gamma,m}(g)) \leq \frac{2}{\gamma} R_m(\mathcal{F}_{\mathcal{G},\gamma}) + \sqrt{\frac{\ln\left(\frac{1}{\delta}\right)}{2m}}.$$

Guaranteed Risk Based on the L_2 -norm

Decomposition Lemma

Lemma 4 (Kuznetsov et al., 2014)

Let \mathcal{G} be the class of functions computed by a margin multi-category classifier. For $\gamma \in (0, 1]$,

$$R_m(\mathcal{F}_{\mathcal{G}, \gamma}) \leq CR_m \left(\bigcup_{k=1}^C \mathcal{G}_k \right).$$

Theorem 5 (After Theorem 3 in Kuznetsov et al., 2014)

Let \mathcal{G} be the class of functions computed by a margin multi-category classifier. Let $\gamma \in (0, 1]$ and $\delta \in (0, 1)$. With P^m -probability at least $1 - \delta$,

$$\sup_{g \in \mathcal{G}} (L_\gamma(g) - L_{\gamma, m}(g)) \leq \frac{2C}{\gamma} R_m \left(\bigcup_{k=1}^C \mathcal{G}_k \right) + \sqrt{\frac{\ln \left(\frac{1}{\delta} \right)}{2m}}.$$

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State-of-the-Art L_p -norm Sauer-Shelah Lemma

Theorem 6 (After Theorem 3.2 in Mendelson, 2002)

Let \mathcal{F} be a class of functions from \mathcal{T} into $[-M_{\mathcal{F}}, M_{\mathcal{F}}]$. For $\epsilon \in (0, M_{\mathcal{F}}]$, let $d(\epsilon) = \epsilon\text{-dim}(\mathcal{F})$. Then for $\epsilon \in (0, 2M_{\mathcal{F}}]$ and $n \in \mathbb{N}^*$,

$$\forall p \in [1, +\infty), \quad \ln(\mathcal{M}_p(\epsilon, \mathcal{F}, n)) \leq K_p \cdot d\left(\frac{\epsilon}{8}\right) \ln^2\left(\frac{2 \cdot d\left(\frac{\epsilon}{8}\right)}{\epsilon}\right),$$

where K_p is a constant depending only on p .

Main Lemmas in the Proof

Probabilistic Extraction Result

Lemma 5 (After Lemma 3.1 in Mendelson, 2002)

Let \mathcal{F} be a class of functions from \mathcal{T} into $[M_{\mathcal{F}^-}, M_{\mathcal{F}^+}]$. For $n \in \mathbb{N}^*$, $\mathbf{t}_n = (t_i)_{1 \leq i \leq n} \in \mathcal{T}^n$, $p \in [1, +\infty)$ and $\epsilon \in [0, M_{\mathcal{F}^+} - M_{\mathcal{F}^-}]$, assume that $\mathcal{M}(\epsilon, \mathcal{F}, d_{p, \mathbf{t}_n}) > 1$. Then there exists a subvector \mathbf{t}_q of \mathbf{t}_n of size q satisfying $q \leq K_p \left(\frac{M_{\mathcal{F}^+} - M_{\mathcal{F}^-}}{\epsilon} \right)^p \ln(\mathcal{M}(\epsilon, \mathcal{F}, d_{p, \mathbf{t}_n}))$ such that

$$\mathcal{M}(\epsilon, \mathcal{F}, d_{p, \mathbf{t}_n}) \leq \mathcal{M}\left(\frac{\epsilon}{2}, \mathcal{F}, d_{\infty, \mathbf{t}_q}\right),$$

where K_p is a constant depending only on p .

Sauer-Shelah Lemma of Alon and co-authors (Lemma 3)

State-of-the-Art L_2 -norm Sauer-Shelah Lemma

Lemma 6 (After Theorem 1 in Mendelson and Vershynin, 2003)

Let \mathcal{F} be a class of functions from \mathcal{T} into $[-M_{\mathcal{F}}, M_{\mathcal{F}}]$. For $\epsilon \in (0, M_{\mathcal{F}}]$, let $d(\epsilon) = \epsilon\text{-dim}(\mathcal{F})$. Then for $\epsilon \in (0, 2M_{\mathcal{F}}]$ and $n \in \mathbb{N}^*$,

$$\mathcal{M}_2(\epsilon, \mathcal{F}, n) \leq \left(K \left(\frac{2M_{\mathcal{F}}}{\epsilon} \right)^5 \right)^{4d\left(\frac{\epsilon}{96}\right)}$$

where $K = 3584e$.

Lemma 7

Let \mathcal{G} be the class of functions computed by a margin multi-category classifier. Then, for $\epsilon \in (0, \gamma]$,

$$\ln(\mathcal{N}_2^{\text{int}}(\epsilon, \mathcal{F}_{\mathcal{G}, \gamma}, m)) \leq 20Cd \left(\frac{\epsilon}{96\sqrt{C}} \right) \ln \left(\frac{14M_{\mathcal{G}}\sqrt{C}}{\epsilon} \right)$$

where $d(\epsilon) = \max_{1 \leq k \leq C} \epsilon\text{-dim}(\mathcal{G}_k)$.

Key Lemma in the Proof

Probabilistic Extraction Result

Lemma 8 (After Lemma 13 in Mendelson and Vershynin, 2003)

Let $\mathcal{T} = \{t_i : 1 \leq i \leq n\}$ be a finite set and $\mathbf{t}_n = (t_i)_{1 \leq i \leq n}$. Let \mathcal{F} be a finite class of functions from \mathcal{T} into $[-M_{\mathcal{F}}, M_{\mathcal{F}}]$. Assume that for some $\epsilon \in (0, 2M_{\mathcal{F}}]$, \mathcal{F} is ϵ -separated with respect to the pseudo-metric d_{2, \mathbf{t}_n} . If $r \in [1, n]$ is such that $|\mathcal{F}| \leq \exp(K_e r \epsilon^4)$ with

$$K_e = \frac{3}{112(2M_{\mathcal{F}})^4},$$

then there exists a subvector \mathbf{t}_q of \mathbf{t}_n of size $q \leq r$ such that \mathcal{F} is $\frac{\epsilon}{2}$ -separated with respect to the pseudo-metric d_{2, \mathbf{t}_q} .

L_p -norm Sauer-Shelah Lemma

Lemma 9 (Lemma 2 in Guermeur, 2017)

Let \mathcal{F} be a class of functions from \mathcal{T} into $[-M_{\mathcal{F}}, M_{\mathcal{F}}]$. For $\epsilon \in (0, M_{\mathcal{F}}]$, let $d(\epsilon) = \epsilon\text{-dim}(\mathcal{F})$. Then for $\epsilon \in (0, 2M_{\mathcal{F}}]$ and $n \in \mathbb{N}^*$,

$$\forall p \in [1, +\infty), \mathcal{M}_p(\epsilon, \mathcal{F}, n) \leq 4^{K_{\epsilon}(p)+1} \left(\frac{6272eK_{\epsilon}(p)}{3} \left(\frac{2M_{\mathcal{F}}}{\epsilon} \right)^{2p+1} \right)^{2K_{\epsilon}(p)d\left(\frac{\epsilon}{45}\right)},$$

where $K_{\epsilon}(p) = \log_2 \left(\left\lceil \left\lceil \frac{112M_{\mathcal{F}}}{\epsilon} \right\rceil^{p+2} \right\rceil \right)$.

A logarithmic factor is gained compared to Mendelson's lemma (Theorem 6).

Key Lemmas in the Proof

Main Combinatorial Result

Lemma 10 (L_p -norm extension of Lemma 8 in Bartlett and Long, 1995)

Let $\mathcal{T} = \{t_i : 1 \leq i \leq n\}$ be a finite set and $\mathbf{t}_n = (t_i)_{1 \leq i \leq n}$. Let \mathcal{F} be a class of functions from \mathcal{T} into $\mathcal{S} = \left\{ 2M_{\mathcal{F}} \frac{j}{N} : 0 \leq j \leq N \right\}$ with $M_{\mathcal{F}} \in \mathbb{R}_+^*$ and $N \in \mathbb{N} \setminus \llbracket 0, 3 \rrbracket$. For $\epsilon \in \left(\frac{6M_{\mathcal{F}}}{N}, 2M_{\mathcal{F}} \right]$, let $d = \left(\frac{\epsilon}{2} - \frac{3M_{\mathcal{F}}}{N} \right) \text{-dim}(\mathcal{F})$. Then

$$\forall p \in [1, +\infty), \quad \mathcal{M}(\epsilon, \mathcal{F}, d_{p, \mathbf{t}_n}) < 2 \lceil N^{p+2} \rceil \left(\frac{e(N-1)n}{d} \right)^{\log_2(\lceil N^{p+2} \rceil) d}.$$

Probabilistic Extraction Result

L_p -norm extension of Lemma 13 in Mendelson and Vershynin (2003)

L_2 -norm Sauer-Shelah Lemma

Lemma 11

Let \mathcal{G} be the class of functions computed by a margin multi-category classifier.
Then for $\epsilon \in (0, \gamma]$,

$$\ln(\mathcal{M}_2(\epsilon, \mathcal{F}_{\mathcal{G}, \gamma}, m)) \leq 3Cd \left(\frac{\epsilon}{16}\right) \ln^2 \left(\frac{K (2M_{\mathcal{G}})^3 \gamma^2 C^{\frac{3}{2}} d \left(\frac{\epsilon}{192\sqrt{C}}\right)}{\epsilon^5} \right)$$

where $d(\epsilon) = \max_{1 \leq k \leq C} \epsilon\text{-dim}(\mathcal{G}_k)$ and $K = \frac{143360}{3}$.

Idea: Use the L_2 -norm to get a dimension-free result and the L_∞ -norm to optimize the dependency on C (get the best of two worlds)

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 - State of the Art
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Chaining Method

Theorem 7 (Dudley's metric entropy bound)

Let \mathcal{F} be a class of bounded real-valued functions on \mathcal{T} . For $n \in \mathbb{N}^*$, let $\mathbf{t}_n = (t_i)_{1 \leq i \leq n} \in \mathcal{T}^n$ and let $\text{diam}(\mathcal{F}) = \sup_{(f, f') \in \mathcal{F}^2} d_{2, \mathbf{t}_n}(f, f')$. Let h be a positive and decreasing function on \mathbb{N} such that $h(0) \geq \text{diam}(\mathcal{F})$. Then for $N \in \mathbb{N}^*$,

$$\hat{R}_n(\mathcal{F}) \leq h(N) + 2 \sum_{j=1}^N (h(j) + h(j-1)) \sqrt{\frac{\ln(\mathcal{N}^{\text{int}}(h(j), \mathcal{F}, d_{2, \mathbf{t}_n}))}{n}}$$

and

$$\hat{R}_n(\mathcal{F}) \leq 12 \int_0^{\frac{1}{2} \cdot \text{diam}(\mathcal{F})} \sqrt{\frac{\ln(\mathcal{N}^{\text{int}}(\epsilon, \mathcal{F}, d_{2, \mathbf{t}_n}))}{n}} d\epsilon.$$

Polynomial Growth of the γ -dimension

Hypothesis 1

We consider margin multi-category classifiers for which there exists a pair $(d_G, K_G) \in (\mathbb{R}_+^*)^2$ such that

$$\forall \epsilon \in (0, M_G], \max_{1 \leq k \leq C} \epsilon\text{-dim}(\mathcal{G}_k) \leq K_G \epsilon^{-d_G}.$$

| Classifier | d_G | Reference |
|------------|-------|-----------------------------------|
| MLP | 4 | (Bartlett, 1998) |
| M-SVM | 2 | (Bartlett and Shawe-Taylor, 1999) |
| LVQ | ? | |

Table : Characterization of γ -dimensions

Bound Based on the Lemma of Mendelson and Vershynin

Theorem 8 (Theorem 7 in Guermeur, 2017)

Let \mathcal{G} be a class of functions satisfying Hypothesis 1 and $\gamma \in (0, 1]$.

| $d_{\mathcal{G}}$ | Bound on $R_m(\mathcal{F}_{\mathcal{G}, \gamma})$ |
|-------------------|---|
| < 2 | $8 \frac{1+2^{\frac{2}{2-d_{\mathcal{G}}}}}{\sqrt{2(2-d_{\mathcal{G}})}} \gamma^{1-\frac{d_{\mathcal{G}}}{2}} \sqrt{\frac{5 \cdot 96^{d_{\mathcal{G}}} K_{\mathcal{G}}}{m}} C^{\frac{d_{\mathcal{G}}+2}{4}} \left\{ \sqrt{\ln(F(C))} + \sqrt{\frac{1}{4 \ln(F(C))}} \right\}$ |
| 2 | $\frac{\gamma C^{\frac{3}{4}}}{\sqrt{m}} + 1152 \sqrt{\frac{5 K_{\mathcal{G}}}{m}} C \left[\frac{1}{2} \log_2 \left(\frac{m}{C} \right) \right] \sqrt{\ln \left(\frac{14 M_{\mathcal{G}} \sqrt{m}}{\gamma C^{\frac{1}{4}}} \right)}$ |
| > 2 | $\gamma \sqrt{C} \left(\frac{C}{m} \right)^{\frac{1}{d_{\mathcal{G}}}} \left(1 + 8 \left(1 + 2^{\frac{2}{d_{\mathcal{G}}-2}} \right) \gamma^{-\frac{d_{\mathcal{G}}}{2}} \sqrt{5 \cdot 96^{d_{\mathcal{G}}} K_{\mathcal{G}}} \sqrt{\ln \left(\frac{14 M_{\mathcal{G}}}{\gamma} \left(\frac{m}{C} \right)^{\frac{1}{d_{\mathcal{G}}}} \right)} \right)$ |

where

$$F(C) = 2 \left(\frac{14 M_{\mathcal{G}} \sqrt{C}}{\gamma} \right)^{\frac{2-d_{\mathcal{G}}}{2}}.$$

Bound Based on the New L_2 -norm Lemma

Theorem 9

Let \mathcal{G} be a class of functions satisfying Hypothesis 1 and $\gamma \in (0, 1]$. Then

$$R_m(\mathcal{F}_{\mathcal{G}, \gamma}) \leq K(M_{\mathcal{G}}, \gamma, d_{\mathcal{G}}) F(m, C)$$

with

| $d_{\mathcal{G}}$ | $F(m, C)$ (Guermeur, 2017) | $F(m, C)$ Present study |
|-------------------|--|---|
| < 2 | $\sqrt{\frac{C^{\frac{d_{\mathcal{G}}+2}{2}} \ln(C)}{m}}$ | $\frac{\sqrt{C} \ln(C)}{\sqrt{m}}$ |
| 2 | $\frac{C \ln^{\frac{3}{2}}\left(\frac{m}{C}\right)}{\sqrt{m}}$ | $\frac{\sqrt{C} \ln(Cm) \ln(m)}{\sqrt{m}}$ |
| > 2 | $\sqrt{C} \left(\frac{C}{m}\right)^{\frac{1}{d_{\mathcal{G}}}} \sqrt{\ln\left(\frac{m}{C}\right)}$ | $\frac{\sqrt{C} \ln(Cm)}{m^{\frac{1}{d_{\mathcal{G}}}}$ |

Rademacher Complexity of a Linear Separator

Theorem 10 (Theorem 4.3 in Mohri et al., 2012)

Let $\mathcal{H} = \{x \mapsto w \cdot x\}$ with $\|x\| \leq \Lambda_x$ and $\|w\| \leq \Lambda_w$. Then,

$$R_m(\mathcal{H}) \leq \frac{\Lambda_w \Lambda_x}{\sqrt{m}}.$$

Covering Numbers of a Linear Separator

Theorem 11 (Theorem 4 in Zhang, 2002)

Let $\mathcal{H} = \{x \mapsto w \cdot x\}$ with $\|x\| \leq \Lambda_x$ and $\|w\| \leq \Lambda_w$. Then,

$$\ln(\mathcal{N}_{\infty}^{\text{int}}(\epsilon, \mathcal{H}, m)) \leq 36 \left(\frac{\Lambda_w \Lambda_x}{\epsilon} \right)^2 \ln \left(2 \left\lceil \frac{4\Lambda_w \Lambda_x}{\epsilon} + 2 \right\rceil m + 1 \right).$$

Conclusions and Ongoing Research

Conclusions

- 1 The control terms of our guaranteed risks grow sublinearly with C .
- 2 An optimal trade-off between this dependency and the convergence rate is to be looked for.

Ongoing research

- 1 Application to LVQ
- 2 Derivation of lower bounds
- 3 Characterization of the phase transitions