

Efficient Conversion of Learners to Bounded Sample Compressors

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Abstract

We give an algorithmically efficient version of the learner-to-compression scheme conversion in Moran and Yehudayoff (2016). In extending this technique to real-valued hypotheses, we also obtain an efficient regression-to-bounded sample compression converter. To our knowledge, this is the first general compressed regression result (regardless of efficiency or boundedness) guaranteeing uniform approximate reconstruction. Along the way, we develop a generic procedure for constructing weak real-valued learners out of abstract regressors; this may be of independent interest. In particular, this partially resolves an open question of H. Simon (1997). We show applications to two regression problems: learning Lipschitz and bounded-variation functions.

Keywords: sample compression, regression, boosting, weak learning

1. Introduction

Sample compression is a natural learning strategy, whereby the learner seeks to retain a small subset of the training examples, which (if successful) may then be decoded as a hypothesis with low empirical error. Overfitting is controlled by the size of this learner-selected “compression set”. Part of a more general *Occam learning* paradigm, such results are commonly summarized by “compression implies learning”. A fundamental question, posed by Littlestone and Warmuth (1986), concerns the reverse implication: Can every learner be converted into a sample compression scheme? Or, in a more quantitative formulation: Does every VC class admit a constant-size sample compression scheme? A series of partial results (Floyd, 1989; Helmbold et al., 1992; Floyd and Warmuth, 1995; Ben-David and Litman, 1998; Kuzmin and Warmuth, 2007; Rubinstein et al., 2009; Rubinstein and Rubinstein, 2012; Chernikov and Simon, 2013; Livni and Simon, 2013; Moran et al., 2015) culminated in Moran and Yehudayoff (2016) which resolved the latter question¹.

Moran and Yehudayoff’s solution involved a clever use of von Neumann’s minimax theorem, which allows one to make the leap from the existence of a weak learner uniformly over all *distributions on examples* to the existence of a *distribution on weak hypotheses* under which they achieve a certain performance simultaneously over all of the examples. Although their paper can be understood without any knowledge of boosting, Moran and Yehudayoff note the well-known connection between boosting and compression. Indeed, boosting may be used to obtain a constructive proof of the minimax theorem (Freund and Schapire, 1996, 1999) — and this connection was what motivated

1. The refined conjecture of Littlestone and Warmuth (1986), that any concept class with VC-dimension d admits a compression scheme of size $O(d)$, remains open.

us to seek an efficient algorithm implementing [Moran and Yehudayoff](#)'s existence proof. Having obtained an efficient conversion procedure from consistent PAC learners to bounded-size sample compression schemes, we turned our attention to the case of real-valued hypotheses. It turned out that a virtually identical boosting framework could be made to work for this case as well, although a novel analysis was required.

Our contribution. Our point of departure is the simple but powerful observation ([Schapire and Freund, 2012](#)) that many boosting algorithms (e.g., AdaBoost, α -Boost) are capable of outputting a family of $O(\log(m)/\gamma^2)$ hypotheses such that not only does their (weighted) majority vote yield a sample-consistent classifier, but in fact a $\approx (\frac{1}{2} + \gamma)$ super-majority does as well. This fact implies that after boosting, we can sub-sample a constant (i.e., independent of sample size m) number of classifiers and thereby efficiently recover the sample compression bounds of [Moran and Yehudayoff \(2016\)](#).

Our chief technical contribution, however, is in the real-valued case. As we discuss below, extending the boosting framework from classification to regression presents a host of technical challenges, and there is currently no off-the-shelf general-purpose analogue of AdaBoost for real-valued hypotheses. One of our insights is to impose distinct error metrics on the weak and strong learners: a “stronger” one on the latter and a “weaker” one on the former. This allows us to achieve two goals simultaneously:

- (a) We give apparently the first generic construction for our weak learner, demonstrating that the object is natural and abundantly available. This is in contrast with many previous proposed weak regressors, whose stringent or exotic definitions made them unwieldy to construct or verify as such. The construction is novel and may be of independent interest.
- (b) We show that the output of a certain real-valued boosting algorithm may be sparsified so as to yield a constant size sample compression analogue of the [Moran and Yehudayoff](#) result for classification. This gives the first general constant-size sample compression scheme having uniform approximation guarantees on the data.

2. Definitions and notation

We will write $[k] := \{1, \dots, k\}$. An *instance space* is an abstract set \mathcal{X} . For a concept class $\mathcal{C} \subset \{0, 1\}^{\mathcal{X}}$, if say that \mathcal{C} *shatters* a set $\{x_1, \dots, x_k\} \subset \mathcal{X}$ if

$$\mathcal{C}(S) = \{(f(x_1), f(x_2), \dots, f(x_k)) : f \in \mathcal{C}\} = \{0, 1\}^k.$$

The VC-dimension $d = d_{\mathcal{C}}$ of \mathcal{C} is the size of the largest shattered set (or ∞ if \mathcal{C} shatters sets of arbitrary size) ([Vapnik and Červonenkis, 1971](#)). When the roles of \mathcal{X} and \mathcal{C} are exchanged — that is, an $x \in \mathcal{X}$ acts on $f \in \mathcal{C}$ via $x(f) = f(x)$, — we refer to $\mathcal{X} = \mathcal{C}^*$ as the *dual class* of \mathcal{C} . Its VC-dimension is then $d^* = d_{\mathcal{C}^*} := d_{\mathcal{C}^*}$, and referred to as the *dual VC dimension*. [Assouad \(1983\)](#) showed that $d^* \leq 2^{d+1}$.

For $\mathcal{F} \subset \mathbb{R}^{\mathcal{X}}$ and $t > 0$, we say that \mathcal{F} *t-shatters* a set $\{x_1, \dots, x_k\} \subset \mathcal{X}$ if

$$\mathcal{F}(S) = \{(f(x_1), f(x_2), \dots, f(x_k)) : f \in \mathcal{F}\} \subseteq \mathbb{R}^k$$

contains the translated cube $\{-t, t\}^k + r$ for some $r \in \mathbb{R}^k$. The *t-fat-shattering dimension* $d(t) = d_{\mathcal{F}}(t)$ is the size of the largest *t-shattered* set (possibly ∞) ([Alon et al., 1997](#)). Again, the roles of

\mathcal{X} and \mathcal{F} may be switched, in which case $\mathcal{X} = \mathcal{F}^*$ becomes the dual class of \mathcal{F} . Its t -fat-shattering dimension is then $d^*(t)$, and Assouad's argument shows that $d^*(t) \leq 2^{d(t)+1}$.

A *sample compression scheme* (κ, ρ) for a hypothesis class $\mathcal{F} \subset \mathcal{Y}^{\mathcal{X}}$ is defined as follows. A k -compression function κ maps sequences $((x_1, y_1), \dots, (x_m, y_m)) \in \bigcup_{\ell \geq 1} (\mathcal{X} \times \mathcal{Y})^\ell$ to elements in $\mathcal{K} = \bigcup_{\ell \leq k'} (\mathcal{X} \times \mathcal{Y})^\ell \times \bigcup_{\ell \leq k''} \{0, 1\}^\ell$, where $k' + k'' \leq k$. A *reconstruction* is a function $\rho : \mathcal{K} \rightarrow \mathcal{Y}^{\mathcal{X}}$. We say that (κ, ρ) is a k -size sample compression scheme for \mathcal{F} if κ is a k -compression and for all $h^* \in \mathcal{F}$ and all $S = ((x_1, h^*(x_1)), \dots, (x_m, h^*(y_m)))$, we have $\hat{h} := \rho(\kappa(S))$ satisfies $\hat{h}(x_i) = h^*(x_i)$ for all $i \in [m]$.

For real-valued functions, we say it is a *uniformly ε -approximate* compression scheme if

$$\max_{1 \leq i \leq m} |\hat{h}(x_i) - h^*(x_i)| \leq \varepsilon.$$

3. Main results

Throughout the paper, we implicitly assume that all hypothesis classes are *admissible* in the sense of satisfying mild measure-theoretic conditions, such as those specified in Dudley (1984, Section 10.3.1) or Pollard (1984, Appendix C). We begin with an algorithmically efficient version of the learner-to-compression scheme conversion in Moran and Yehudayoff (2016):

Theorem 1 (Efficient compression for classification) *Let \mathcal{C} be a concept class over some instance space \mathcal{X} with VC-dimension d , dual VC-dimension d^* , and suppose that \mathcal{A} is a (proper, consistent) PAC-learner for \mathcal{C} : For all $0 < \varepsilon, \delta < 1/2$, all $f^* \in \mathcal{C}$, and all distributions D over \mathcal{X} , if \mathcal{A} receives $m \geq m_{\mathcal{C}}(\varepsilon, \delta)$ points $S = \{x_i\}$ drawn iid from D and labeled with $y_i = f^*(x_i)$, then \mathcal{A} outputs an $\hat{f} \in \mathcal{C}$ such that*

$$\mathbb{P}_{S \sim D^m} \left(\mathbb{P}_{X \sim D} \left(\hat{f}(X) \neq f^*(X) \mid S \right) > \varepsilon \right) < \delta.$$

For every such \mathcal{A} , there is a randomized sample compression scheme for \mathcal{C} of size $O(k \log k)$, where $k = O(dd^)$. Furthermore, on a sample of any size m , the compression set may be computed in expected time*

$$O((m + T_{\mathcal{A}}(cd)) \log m + mT_{\mathcal{E}}(cd)(d^* + \log m)),$$

where $T_{\mathcal{A}}(\ell)$ is the runtime of \mathcal{A} to compute \hat{f} on a sample of size ℓ , $T_{\mathcal{E}}(\ell)$ is the runtime required to evaluate \hat{f} on a single $x \in \mathcal{X}$, and c is a universal constant.

Although for our purposes the existence of a distribution-free sample complexity $m_{\mathcal{C}}$ is more important than its concrete form, we may take $m_{\mathcal{C}}(\varepsilon, \delta) = O(\frac{d}{\varepsilon} \log \frac{1}{\varepsilon} + \frac{1}{\varepsilon} \log \frac{1}{\delta})$ (Vapnik and Chervononkis, 1974; Blumer et al., 1989), known to bound the sample complexity of empirical risk minimization; indeed, this loses no generality, as there is a well-known efficient reduction from empirical risk minimization to any proper learner having a polynomial sample complexity (Pitt and Valiant, 1988; Haussler et al., 1991). We allow the evaluation time of \hat{f} to depend on the size of the training sample in order to account for non-parametric learners, such as nearest-neighbor classifiers. A naive implementation of the Moran and Yehudayoff (2016) existence proof yields a runtime of order $m^{cd}T_{\mathcal{A}}(c'd) + m^{cd^*}$ (for some universal constants c, c'), which can be doubly exponential when $d^* = 2^d$; this is without taking into account the cost of computing the minimax distribution on the $m^{cd} \times m$ game matrix.

Next, we extend the result in Theorem 1 from classification to regression:

Theorem 2 (Efficient compression for regression) *Let $\mathcal{F} \subset [0, 1]^{\mathcal{X}}$ be a function class with t -fat-shattering dimension $d(t)$, dual t -fat-shattering dimension $d^*(t)$, and suppose that \mathcal{A} is a (proper, consistent) learner for \mathcal{F} : For all $f^* \in \mathcal{C}$, and all distributions D over \mathcal{X} , if \mathcal{A} receives m points $S = \{x_i\}$ drawn iid from D and labeled with $y_i = f^*(x_i)$, then \mathcal{A} outputs an $\hat{f} \in \mathcal{F}$ such that $\max_{i \in [m]} |\hat{f}(x_i) - f^*(x_i)| = 0$. For every such \mathcal{A} , there is a randomized uniformly ε -approximate sample compression scheme for \mathcal{F} of size $O(k\tilde{m} \log(k\tilde{m}))$, where $\tilde{m} = O(d(c\varepsilon) \log(1/\varepsilon))$ and $k = O(d^*(c\varepsilon) \log(d^*(c\varepsilon)/\varepsilon))$. Furthermore, on a sample of any size m , the compression set may be computed in expected time*

$$O(mT_{\mathcal{E}}(\tilde{m})(k + \log m) + T_{\mathcal{A}}(\tilde{m}) \log(m)),$$

where $T_{\mathcal{A}}(\ell)$ is the runtime of \mathcal{A} to compute \hat{f} on a sample of size ℓ , $T_{\mathcal{E}}(\ell)$ is the runtime required to evaluate \hat{f} on a single $x \in \mathcal{X}$, and c is a universal constant.

A key component in the above result is our construction of a generic (η, γ) -weak learner.

Definition 3 *For $\eta \in [0, 1]$ and $\gamma \in [0, 1/2]$, we say that $f : \mathcal{X} \rightarrow \mathbb{R}$ is an (η, γ) -weak hypothesis (with respect to distribution D and target $f^* \in \mathcal{F}$) if*

$$\mathbb{P}_{X \sim D}(|f(X) - f^*(X)| > \eta) \leq \frac{1}{2} - \gamma.$$

Theorem 4 (Generic weak learner) *Let $\mathcal{F} \subset [0, 1]^{\mathcal{X}}$ be a function class with t -fat-shattering dimension $d(t)$. For some universal numerical constants $c_1, c_2, c_3 \in (0, \infty)$, for any $\eta, \delta \in (0, 1)$ and $\gamma \in (0, 1/11)$, any $f^* \in \mathcal{F}$, and any distribution D , letting X_1, \dots, X_m be drawn iid from D , where*

$$m = \left\lceil c_1 \left(d(c_2 \eta \gamma) \ln \left(\frac{c_3}{\eta \gamma} \right) + \ln \left(\frac{1}{\delta} \right) \right) \right\rceil,$$

with probability at least $1 - \delta$, every $f \in \mathcal{F}$ with $\max_{i \in [m]} |f(X_i) - f^*(X_i)| = 0$ is an (η, γ) -weak hypothesis with respect to D and f^* .

In the Appendix, we give applications to sample compression for nearest-neighbor and bounded-variation regression.

4. Related work

It appears that generalization bounds based on sample compression were independently discovered by Littlestone and Warmuth (1986) and Devroye et al. (1996) and further elaborated upon by Graepel et al. (2005); see Floyd and Warmuth (1995) for background and discussion. A more general kind of Occam learning was discussed in Blumer et al. (1989). Computational lower bounds on sample compression were obtained in Gottlieb et al. (2014), and some communication-based lower bounds were given in Kane et al. (2017).

Beginning with Freund and Schapire (1997)'s AdaBoost.R algorithm, there have been numerous attempts to extend AdaBoost to the real-valued case (Bertoni et al., 1997; Drucker, 1997; Avnimelech and Intrator, 1999; Karakoulas and Shawe-Taylor, 2000; Duffy and Helmbold, 2002; Kégl, 2003; Nock and Nielsen, 2007) along with various theoretical and heuristic constructions of particular weak regressors (Mason et al., 1999; Friedman, 2001; Mannor and Meir, 2002); see also the survey Mendes-Moreira et al. (2012).

Duffy and Helmbold (2002, Remark 2.1) spell out a central technical challenge: no boosting algorithm can “always force the base regressor to output a useful function by simply modifying the distribution over the sample”. This is because unlike a binary classifier, which localizes errors on specific examples, a real-valued hypothesis can spread its error evenly over the entire sample, and it will not be affected by reweighting. The (η, γ) -weak learner, which has appeared, among other works, in Anthony et al. (1996); Simon (1997); Avnimelech and Intrator (1999); Kégl (2003), gets around this difficulty — but provable general constructions of such learners have been lacking. Likewise, the heart of our sample compression engine, MedBoost, has been widely in use since Freund and Schapire (1997) in various guises. Our Theorem 4 supplies the remaining piece of the puzzle: *any* sample-consistent regressor applied to some random sample of bounded size yields an (η, γ) -weak hypothesis. The closest analogue we were able to find was Anthony et al. (1996, Theorem 3), which is non-trivial only for function classes with finite pseudo-dimension, and is inapplicable, e.g., to classes of 1-Lipschitz or bounded variation functions.

The literature on general sample compression schemes for real-valued functions is quite sparse. There are well-known narrowly tailored results on specifying functions or approximate versions of functions using a finite number of points, such as the classical fact that a polynomial of degree p can be perfectly recovered from $p + 1$ points. To our knowledge, the only *general* results on sample compression for real-valued functions (applicable to *all* learnable function classes) is Theorem 4.3 of David, Moran, and Yehudayoff (2016). They propose a general technique to convert any learning algorithm achieving an arbitrary sample complexity $M(\varepsilon, \delta)$ into a compression scheme of size $O(M(\varepsilon, \delta) \log(M(\varepsilon, \delta)))$, where δ may approach 1. However, their notion of compression scheme is significantly weaker than ours: namely, they allow $\hat{h} = \rho(\kappa(S))$ to satisfy merely $\frac{1}{m} \sum_{i=1}^m |\hat{h}(x_i) - h^*(x_i)| \leq \varepsilon$, rather than our *uniform* ε -approximation requirement $\max_{1 \leq i \leq m} |\hat{h}(x_i) - h^*(x_i)| \leq \varepsilon$. In particular, in the special case of \mathcal{F} a family of *binary*-valued functions, their notion of sample compression does *not* recover the usual notion of sample compression schemes for classification, whereas our uniform ε -approximate compression notion *does* recover it as a special case. We therefore consider our notion to be a more fitting generalization of the definition of sample compression to the real-valued case.

5. Boosting Real-Valued Functions

As mentioned above, the notion of a *weak learner* for learning real-valued functions must be formulated carefully. The naïve thought that we could take any learner guaranteeing, say, absolute loss at most $\frac{1}{2} - \gamma$ is known to not be strong enough to enable boosting to ε loss. However, if we make the requirement too strong, such as in Freund and Schapire (1997) for AdaBoost.R, then the sample complexity of weak learning will be so high that weak learners cannot be expected to exist for large classes of functions. However, our Definition 3, which has been proposed independently by Simon (1997) and Kégl (2003), appears to yield the appropriate notion of *weak learner* for boosting real-valued functions.

In the context of boosting for real-valued functions, the notion of an (η, γ) -weak hypothesis plays a role analogous to the usual notion of a weak hypothesis in boosting for classification. Specifically, the following boosting algorithm was proposed by Kégl (2003). As it will be convenient for our later results, we express its output as a sequence of functions and weights; the boosting guarantee from Kégl (2003) applies to the weighted quantiles (and in particular, the weighted median) of these function values.

Algorithm 1: $\text{MedBoost}(\{(x_i, y_i)\}_{i \in [m]}, T, \gamma, \eta)$

- 1: Define P_0 as the uniform distribution over $\{1, \dots, n\}$
- 2: **for** $t = 0, \dots, T$ **do**
- 3: Call weak learner to get h_t and $(\eta/2, \gamma)$ -weak hypothesis wrt $(x_i, y_i) : i \sim P_t$
 (repeat until it succeeds)
- 4: **for** $i = 1, \dots, m$ **do**
- 5: $\theta_i^{(t)} \leftarrow 1 - 2\mathbb{I}[|h_t(x_i) - y_i| > \eta/2]$
- 6: **end for**
- 7: $\alpha_t \leftarrow \frac{1}{2} \ln \left(\frac{(1-\gamma) \sum_{i=1}^m P_t(i) \mathbb{I}[\theta_i^{(t)}=1]}{(1+\gamma) \sum_{i=1}^m P_t(i) \mathbb{I}[\theta_i^{(t)}=-1]} \right)$
- 8: **if** $\alpha_t = \infty$ **then**
- 9: Return T copies of h_t , and $(1, \dots, 1)$
- 10: **end if**
- 11: **for** $i = 1, \dots, m$ **do**
- 12: $P_{t+1}(i) \leftarrow P_t(i) \frac{\exp\{-\alpha_t \theta_i^{(t)}\}}{\sum_{j=1}^m P_t(j) \exp\{-\alpha_t \theta_j^{(t)}\}}$
- 13: **end for**
- 14: **end for**
- 15: Return (h_1, \dots, h_T) and $(\alpha_1, \dots, \alpha_T)$

Here we define the weighted median as

$$\text{Median}(y_1, \dots, y_T; \alpha_1, \dots, \alpha_T) = \min \left\{ y_j : \frac{\sum_{t=1}^T \alpha_t \mathbb{I}[y_j < y_t]}{\sum_{t=1}^T \alpha_t} < \frac{1}{2} \right\}.$$

Also define the weighted *quantiles*, for $\gamma \in [0, 1/2]$, as

$$Q_\gamma^+(y_1, \dots, y_T; \alpha_1, \dots, \alpha_T) = \min \left\{ y_j : \frac{\sum_{t=1}^T \alpha_t \mathbb{I}[y_j < y_t]}{\sum_{t=1}^T \alpha_t} < \frac{1}{2} - \gamma \right\}$$

$$Q_\gamma^-(y_1, \dots, y_T; \alpha_1, \dots, \alpha_T) = \max \left\{ y_j : \frac{\sum_{t=1}^T \alpha_t \mathbb{I}[y_j > y_t]}{\sum_{t=1}^T \alpha_t} < \frac{1}{2} - \gamma \right\},$$

and abbreviate $Q_\gamma^+(x) = Q_\gamma^+(h_1(x), \dots, h_T(x); \alpha_1, \dots, \alpha_T)$ and $Q_\gamma^-(x) = Q_\gamma^-(h_1(x), \dots, h_T(x); \alpha_1, \dots, \alpha_T)$ for h_1, \dots, h_T and $\alpha_1, \dots, \alpha_T$ the values returned by MedBoost .

Then [Kégl \(2003\)](#) proves the following result.

Lemma 5 ([Kégl \(2003\)](#)) *For a training set $Z = \{(x_1, y_1), \dots, (x_m, y_m)\}$ of size m , the return values of MedBoost satisfy*

$$\frac{1}{m} \sum_{i=1}^m \mathbb{I} \left[\max \left\{ \left| Q_{\gamma/2}^+(x_i) - y_i \right|, \left| Q_{\gamma/2}^-(x_i) - y_i \right| \right\} > \eta/2 \right] \leq \prod_{t=1}^T e^{\gamma \alpha_t} \sum_{i=1}^m P_t(i) e^{-\alpha_t \theta_i^{(t)}}.$$

We note that, in the special case of binary classification, MedBoost is closely related to the well-known AdaBoost algorithm ([Freund and Schapire, 1997](#)), and the above results correspond

to a standard margin-based analysis of [Schapire et al. \(1998\)](#). For our purposes, we will need the following immediate corollary of this, which follows from plugging in the values of α_t and using the weak learning assumption, which implies $\sum_{i=1}^m P_t(i) \mathbb{I}[\theta_i^{(t)} = 1] \geq \frac{1}{2} + \gamma$ for all t .

Corollary 6 For $T = \Theta\left(\frac{1}{\gamma^2} \ln(m)\right)$, every $i \in \{1, \dots, m\}$ has

$$\max\left\{\left|Q_{\gamma/2}^+(x_i) - y_i\right|, \left|Q_{\gamma/2}^-(x_i) - y_i\right|\right\} \leq \eta/2.$$

6. The Sample Complexity of Weak Learning

This section reveals our intention in choosing this notion of weak hypothesis, rather than using, say, an ε -good strong learner under absolute loss. In addition to being a strong enough notion for boosting to work, we show here that it is also a weak enough notion for the sample complexity of weak learning to be of reasonable size: namely, a size quantified by the fat-shattering dimension, which is an unavoidable complexity for learning real-valued functions. This result also addresses an open question posed by [Simon \(1997\)](#), who proved a lower bound for the sample complexity of finding an (η, γ) -weak hypothesis, also expressed in terms of the fat-shattering dimension, and asked whether a near-matching upper bound might also hold. We establish a general upper bound here, witnessing the same dependence on the fat-shattering dimension as observed in Simon's lower bound. However, we have a slightly worse dependence on the other leading factor.

Define $\rho_{\eta/2}(f, g) = P_{2m}(x : |f(x) - g(x)| > \eta/2)$, where P_{2m} is the empirical measure on the m data points and m ghost points. Define $N_{\eta/2}(\gamma)$ as the γ -covering numbers of \mathcal{F} under the $\rho_{\eta/2}$ pseudo-metric.

Theorem 7 Fix any $\eta \in (0, 1)$, $\gamma \in (0, 1/10)$, and $m \geq 1/(2\gamma^2)$. For some numerical constant $c > 0$, for X_1, \dots, X_m iid P , with probability at least $1 - \mathbb{E}[N_{\eta/2}(\gamma)] \exp\{-cm(1 - 10\gamma)^2\}$, every $f \in \mathcal{F}$ with $\sum_{i=1}^m |f(X_i) - f^*(X_i)| = 0$ is an (η, γ) -weak hypothesis.

Proof This proof roughly follows the usual symmetrization argument for uniform convergence [Vapnik and Červonenkis \(1971\)](#); [Haussler \(1992\)](#), with a few important modifications to account for this definition of weak hypothesis, and to use the metric $\rho_{\eta/2}$. If $\mathbb{E}[N_{\eta/2}(\gamma)]$ is infinite, then the result is trivial, so let us suppose it is finite for the remainder of the proof. Without loss of generality, suppose $f^*(x) = 0$ everywhere and every $f \in \mathcal{F}$ is non-negative (otherwise subtract f^* from every $f \in \mathcal{F}$ and redefine \mathcal{F} as the absolute values of the differences).

Let X_1, \dots, X_{2m} be iid P . Denote by P_m the empirical measure induced by X_1, \dots, X_m , and by P'_m the empirical measure induced by X_{m+1}, \dots, X_{2m} . We have

$$\begin{aligned} & \mathbb{P}\left(\exists f \in \mathcal{F} : P'_m(x : f(x) > \eta) > \frac{1}{2} - 2\gamma \text{ and } P_m(x : f(x) = 0) = 1\right) \\ & \geq \mathbb{P}\left(\exists f \in \mathcal{F} : P(x : f(x) > \eta) > \frac{1}{2} - \gamma \text{ and } P_m(x : f(x) = 0) = 1 \right. \\ & \quad \left. \text{and } P(x : f(x) > \eta) - P'_m(x : f(x) > \eta) \leq \gamma\right). \end{aligned}$$

Denote by A_m the event that there exists $f \in \mathcal{F}$ satisfying $P(x : f(x) > \eta) > \frac{1}{2} - \gamma$ and $P_m(x : f(x) = 0) = 1$, and on this event let \tilde{f} denote such an $f \in \mathcal{F}$ (chosen solely based on

X_1, \dots, X_m); when A_m fails to hold, take \tilde{f} to be some arbitrary fixed element of \mathcal{F} . Then the expression on the right hand side above is at least as large as

$$\mathbb{P}\left(A_m \text{ and } P(x : \tilde{f}(x) > \eta) - P'_m(x : \tilde{f}(x) > \eta) \leq \gamma\right),$$

and noting that the event A_m is independent of X_{m+1}, \dots, X_{2m} , this equals

$$\mathbb{E}\left[\mathbb{I}_{A_m} \cdot \mathbb{P}\left(P(x : \tilde{f}(x) > \eta) - P'_m(x : \tilde{f}(x) > \eta) \leq \gamma \mid X_1, \dots, X_m\right)\right]. \quad (1)$$

Then note that for any $f \in \mathcal{F}$, Hoeffding's inequality implies

$$\begin{aligned} & \mathbb{P}\left(P(x : f(x) > \eta) - P'_m(x : f(x) > \eta) \leq \gamma\right) \\ &= 1 - \mathbb{P}\left(P(x : f(x) > \eta) - P'_m(x : f(x) > \eta) > \gamma\right) \geq 1 - \exp\{-2m\gamma^2\} \geq \frac{1}{2}, \end{aligned}$$

where we have used the assumption that $m \geq \frac{1}{2\gamma^2}$ here. In particular, this implies that the expression in (1) is no smaller than $\frac{1}{2}\mathbb{P}(A_m)$. Altogether, we have established that

$$\begin{aligned} & \mathbb{P}\left(\exists f \in \mathcal{F} : P(x : f(x) > \eta) > \frac{1}{2} - \gamma \text{ and } P_m(x : f(x) = 0) = 1\right) \\ & \leq 2\mathbb{P}\left(\exists f \in \mathcal{F} : P'_m(x : f(x) > \eta) > \frac{1}{2} - 2\gamma \text{ and } P_m(x : f(x) = 0) = 1\right). \quad (2) \end{aligned}$$

Now let $\sigma(1), \dots, \sigma(m)$ be independent random variables, with $\sigma(i) \sim \text{Uniform}(\{i, m+i\})$, denote $\sigma(m+i)$ as the sole element of $\{i, m+i\} \setminus \{\sigma(i)\}$ for each $i \leq m$. Also denote by $P_{m,\sigma}$ the empirical measure induced by $X_{\sigma(1)}, \dots, X_{\sigma(m)}$, and by $P'_{m,\sigma}$ the empirical measure induced by $X_{\sigma(m+1)}, \dots, X_{\sigma(2m)}$. By exchangeability of (X_1, \dots, X_{2m}) , the right hand side of (2) is equal

$$\mathbb{P}\left(\exists f \in \mathcal{F} : P'_{m,\sigma}(x : f(x) > \eta) > \frac{1}{2} - 2\gamma \text{ and } P_{m,\sigma}(x : f(x) = 0) = 1\right).$$

Now let $\hat{\mathcal{F}} \subseteq \mathcal{F}$ be a minimal subset of \mathcal{F} such that $\max_{f \in \mathcal{F}} \min_{\hat{f} \in \hat{\mathcal{F}}} \rho_{\eta/2}(\hat{f}, f) \leq \gamma$. The size of $\hat{\mathcal{F}}$ is at most $N_{\eta/2}(\gamma)$, which is finite almost surely (since we have assumed above that its expectation is finite). Then note that (denoting by $X_{[2m]} = (X_1, \dots, X_{2m})$) the above expression is at most

$$\begin{aligned} & \mathbb{P}\left(\exists f \in \hat{\mathcal{F}} : P'_{m,\sigma}(x : f(x) > \eta/2) > \frac{1}{2} - 3\gamma \text{ and } P_{m,\sigma}(x : f(x) > \eta/2) \leq 2\gamma\right) \\ & \leq \mathbb{E}\left[N_{\eta/2}(\gamma) \max_{f \in \hat{\mathcal{F}}} \mathbb{P}\left(P'_{m,\sigma}(x : f(x) > \eta/2) > \frac{1}{2} - 3\gamma \text{ and } P_{m,\sigma}(x : f(x) > \eta/2) \leq 2\gamma \mid X_{[2m]}\right)\right]. \quad (3) \end{aligned}$$

Then note that for any $f \in \mathcal{F}$, we have almost surely

$$\begin{aligned} & \mathbb{P}\left(P'_{m,\sigma}(x : f(x) > \eta/2) > \frac{1}{2} - 3\gamma \text{ and } P_{m,\sigma}(x : f(x) > \eta/2) \leq 2\gamma \mid X_{[2m]}\right) \\ & \leq \mathbb{P}\left(P'_{m,\sigma}(x : f(x) > \eta/2) - P_{m,\sigma}(x : f(x) > \eta/2) > \frac{1}{2} - 5\gamma \mid X_{[2m]}\right). \end{aligned}$$

Denoting by ξ_1, \dots, ξ_m iid $\text{Uniform}(\{-1, 1\})$ random variables (also independent from $X_{[2m]}$), the expression on the right hand side of this inequality is equal to

$$\begin{aligned}
 & \mathbb{P}\left(\frac{1}{m} \sum_{i=1}^m \xi_i (\mathbb{I}[f(X_i) > \eta/2] - \mathbb{I}[f(X_{m+i}) > \eta/2]) > \frac{1}{2} - 5\gamma \middle| X_{[2m]}\right) \\
 & \leq \mathbb{P}\left(\frac{1}{m} \left| \sum_{i=1}^m \xi_i \mathbb{I}[f(X_i) > \eta/2] \right| > \frac{1}{4} - \frac{5}{2}\gamma \middle| X_{[2m]}\right) \\
 & \quad + \mathbb{P}\left(\frac{1}{m} \left| \sum_{i=1}^m \xi_i \mathbb{I}[f(X_{m+i}) > \eta/2] \right| > \frac{1}{4} - \frac{5}{2}\gamma \middle| X_{[2m]}\right) \\
 & = 2\mathbb{P}\left(\frac{1}{m} \left| \sum_{i=1}^m \xi_i \mathbb{I}[f(X_i) > \eta/2] \right| > \frac{1}{4} - \frac{5}{2}\gamma \middle| X_1, \dots, X_m\right) \\
 & \leq 4 \exp\left\{-m \left(\frac{1}{4} - \frac{5}{2}\gamma\right)^2 / 2\right\},
 \end{aligned}$$

where the last line is by Hoeffding's inequality. Together with (2) and (3), we conclude that

$$\begin{aligned}
 & \mathbb{P}\left(\exists f \in \mathcal{F} : P(x : f(x) > \eta) > \frac{1}{2} - \gamma \text{ and } P_m(x : f(x) = 0) = 1\right) \\
 & \leq \mathbb{E}[N_{\eta/2}(\gamma)] 8 \exp\left\{-m \left(\frac{1}{4} - \frac{5}{2}\gamma\right)^2 / 2\right\}.
 \end{aligned}$$

Simplifying the constants in this expression yields the result. ■

Lemma 8 *There exist universal numerical constants $c, c' \in (0, \infty)$ such that $\forall \eta, \gamma \in (0, 1)$,*

$$N_\eta(\gamma) \leq \left(\frac{2}{\eta\gamma}\right)^{cd(c'\eta\gamma)},$$

where $d(\cdot)$ is the fat-shattering dimension.

Proof [Mendelson and Vershynin \(2003, Theorem 1\)](#) establishes that the $\eta\gamma$ -covering number of \mathcal{F} under the $L_2(P_{2m})$ pseudo-metric is at most

$$\left(\frac{2}{\eta\gamma}\right)^{cd(c'\eta\gamma)} \tag{4}$$

for some universal numerical constants $c, c' \in (0, \infty)$. Then note that for any $f, g \in \mathcal{F}$, Markov's and Jensen's inequalities imply $\rho_\eta(f, g) \leq \frac{1}{\eta} \|f - g\|_{L_1(P_{2m})} \leq \frac{1}{\eta} \|f - g\|_{L_2(P_{2m})}$. Thus, any $\eta\gamma$ -cover of \mathcal{F} under $L_2(P_{2m})$ is also a γ -cover of \mathcal{F} under ρ_η , and therefore (4) is also a bound on $N_\eta(\gamma)$. ■

It is not clear (to the authors) whether the bound on $N_\eta(\gamma)$ in the above lemma can generally be improved. Combining the above two results yields the following theorem.

Theorem 4 (restated) For some universal numerical constants $c_1, c_2, c_3 \in (0, \infty)$, for any $\eta, \delta \in (0, 1)$ and $\gamma \in (0, 1/11)$, letting X_1, \dots, X_m be iid P , where

$$m = \left\lceil c_1 \left(d(c_2\eta\gamma) \ln\left(\frac{c_3}{\eta\gamma}\right) + \ln\left(\frac{1}{\delta}\right) \right) \right\rceil,$$

with probability at least $1 - \delta$, every $f \in \mathcal{F}$ with $\sum_{i=1}^m |f(X_i) - f^*(X_i)| = 0$ is an (η, γ) -weak hypothesis.

Proof The result follows immediately from combining Theorem 7 and Lemma 8. \blacksquare

To discuss tightness of the above result, we note that Simon (1997) proved the following lower bound on the sample complexity of finding an $(\eta, 1/2 - \beta)$ -weak hypothesis with probability at least $1 - \delta$:

$$\Omega\left(\frac{d(\eta)}{\beta} + \frac{1}{\beta} \log \frac{1}{\delta}\right).$$

In our case, because we are considering these learners to be “weak”, we are concerned with the case of β bounded away from 0 (corresponding to γ bounded away from $1/2$), in which case the above lower bound simplifies to $\Omega(d(\eta) + \log(1/\delta))$. In comparison, the upper bound established in our Theorem 4 implies an upper bound $O(d(c_2\eta\gamma) \log(1/\eta\gamma) + \log(1/\delta))$. In the case of γ also bounded away from 0, this simplifies to $O(d(c\eta) \log(1/\eta) + \log(1/\delta))$, so that there is essentially only a logarithmic gap between our weak learning sample complexity bound and the lower bound on the optimal sample complexity established by Simon (1997). Determining whether this logarithmic factor can be removed is a very interesting question. In the special case of binary classification, we can effectively consider η to itself be bounded away from 0, so that the upper bound simplifies to $O(d + \log(1/\delta))$, where d denotes the VC dimension in that case.

7. From Boosting to Compression

Generally, our strategy for converting the boosting algorithm `MedBoost` into a sample compression scheme of smaller size follows a strategy of Moran and Yehudayoff for binary classification, based on arguing that because the ensemble makes its predictions with a *margin* (corresponding to the results on *quantiles* in Corollary 6), it is possible to recover the same proximity guarantees for the predictions while using only a smaller *subset* of the functions from the original ensemble. Specifically, we use the following general *sparsification* strategy.

For $\alpha_1, \dots, \alpha_T \in [0, 1]$ with $\sum_{t=1}^T \alpha_t = 1$, denote by $\text{Cat}(\alpha_1, \dots, \alpha_T)$ the *categorical distribution*: i.e., the discrete probability distribution on $\{1, \dots, T\}$ with probability mass α_t on t .

For any values a_1, \dots, a_n , denote the (unweighted) median

$$\text{Med}(a_1, \dots, a_n) = \text{Median}(a_1, \dots, a_n; 1, \dots, 1).$$

Our intention in discussing the above algorithm is to argue that, for a sufficiently large choice of n , the above procedure returns a set $\{f_1, \dots, f_n\}$ such that

$$\forall i \in [m], |\text{Med}(f_1(x_i), \dots, f_n(x_i)) - y_i| \leq \eta.$$

We analyze this strategy separately for binary classification and real-valued functions, since the argument in the binary case is much simpler (and demonstrates more directly the connection to the original argument of Moran and Yehudayoff), and also because we arrive at a tighter result for binary functions than for real-valued functions.

Algorithm 2: $\text{Sparsify}(\{(x_i, y_i)\}_{i \in [m]}, \gamma, T, n)$

- 1: Run $\text{MedBoost}(\{(x_i, y_i)\}_{i \in [m]}, T, \gamma, \eta)$
- 2: Let h_1, \dots, h_T and $\alpha_1, \dots, \alpha_T$ be its return values
- 3: Denote $\alpha'_t = \alpha_t / \sum_{t'=1}^T \alpha_{t'}$ for each $t \in [T]$
- 4: **repeat**
- 5: Sample $(J_1, \dots, J_n) \sim \text{Cat}(\alpha'_1, \dots, \alpha'_T)^n$
- 6: Let $F = \{h_{J_1}, \dots, h_{J_n}\}$
- 7: **until** $\max_{1 \leq i \leq m} |\{f \in F : |f(x_i) - y_i| > \eta\}| < n/2$
- 8: Return F

7.1. Binary Classification

We begin with the simple observation about binary classification (i.e., where the functions in \mathcal{F} all map into $\{0, 1\}$). The technique here is quite simple, and follows a similar line of reasoning to the original argument of Moran and Yehudayoff. The argument for real-valued functions below will diverge from this argument in several important ways, but the high level ideas remain the same.

The compression function is essentially the one introduced by Moran and Yehudayoff, except applied to the classifiers produced by the above Sparsify procedure, rather than a set of functions selected by a minimax distribution over all classifiers produced by $O(d)$ samples each. The weak hypotheses in MedBoost for binary classification can be obtained using samples of size $O(d)$. Thus, if the Sparsify procedure is successful in finding n such classifiers whose median predictions are within η of the target y_i values for all i , then we may encode these n classifiers as a compression set, consisting of the set of $k = O(nd)$ samples used to train these classifiers, together with $k \log k$ extra bits to encode the order of the samples.² To obtain Theorem 1, it then suffices to argue that $n = \Theta(d^*)$ is a sufficient value. The proof follows.

Proof [Proof of Theorem 1] Recall that d^* bounds the VC dimension of the class of sets $\{\{h_t : t \leq T, h_t(x_i) = 1\} : 1 \leq i \leq m\}$. Thus for the iid samples h_{J_1}, \dots, h_{J_n} obtained in Sparsify , for $n = 64(2309 + 16d^*) > \frac{2304 + 16d^* + \log(2)}{1/8}$, by the VC uniform convergence inequality of Vapnik and Červonenkis (1971), with probability at least $1/2$ we get that

$$\max_{1 \leq i \leq m} \left| \left(\frac{1}{n} \sum_{j=1}^n h_{J_j}(x_i) \right) - \left(\sum_{t=1}^T \alpha'_t h_t(x_i) \right) \right| < 1/8.$$

In particular, if we choose $\gamma = 1/8$, $\eta = 1$, and $T = \Theta(\log(m))$ appropriately, then Corollary 6 implies that every $y_i = \mathbb{I}\left[\sum_{t=1}^T \alpha'_t h_t(x_i) \geq 1/2\right]$ and $\left|\frac{1}{2} - \sum_{t=1}^T \alpha'_t h_t(x_i)\right| \geq 1/8$ so that the above event would imply every $y_i = \mathbb{I}\left[\frac{1}{n} \sum_{j=1}^n h_{J_j}(x_i) \geq 1/2\right] = \text{Med}(h_{J_1}(x_i), \dots, h_{J_n}(x_i))$. Note that the Sparsify algorithm need only try this sampling $\log_2(1/\delta)$ times to find such a set of n functions. Combined with the description above (from Moran and Yehudayoff, 2016) of how to encode this collection of h_{J_i} functions as a sample compression set plus side information, this completes the construction of the sample compression scheme. \blacksquare

2. In fact, $k \log n$ bits would suffice if the weak learner is permutation-invariant in its data set.

7.2. Real-Valued Functions

Next we turn to the general case of real-valued functions (where the functions in \mathcal{F} may generally map into $[0, 1]$). We have the following result, which says that the `Sparsify` procedure can reduce the ensemble of functions from one with $T = O(\log(m)/\gamma^2)$ functions in it, down to one with a number of functions *independent of* m .

Theorem 9 *Choosing $n = \Theta\left(\frac{1}{\gamma^2}d^*(c\eta)\log^2(d^*(c\eta)/\eta)\right)$ suffices for the `Sparsify` procedure to return $\{f_1, \dots, f_n\}$ with $\max_{1 \leq i \leq m} |\text{Med}(f_1(x_i), \dots, f_n(x_i)) - y_i| \leq \eta$.*

Proof Recall from Corollary 6 that `MedBoost` returns functions $h_1, \dots, h_T \in \mathcal{F}$ and $\alpha_1, \dots, \alpha_T \geq 0$ such that $\forall i \in \{1, \dots, m\}$,

$$\max\left\{\left|Q_{\gamma/2}^+(x_i) - y_i\right|, \left|Q_{\gamma/2}^-(x_i) - y_i\right|\right\} \leq \eta/2,$$

where $\{(x_i, y_i)\}_{i=1}^m$ is the training data set.

We use this property to sparsify h_1, \dots, h_T from $T = O(\log(m)/\gamma^2)$ down to k elements, where k will depend on η, γ , and the dual fat-shattering dimension of \mathcal{F} (actually, just of $H = \{h_1, \dots, h_T\} \subseteq \mathcal{F}$) — but **not** sample size m .

Letting $\alpha'_j = \alpha_j / \sum_{t=1}^T \alpha_t$ for each $j \leq T$, we will sample k hypotheses $\{\tilde{h}_1, \dots, \tilde{h}_k\} =: \tilde{H} \subseteq H$ with each $\tilde{h}_i = h_{J_i}$, where $(J_1, \dots, J_k) \sim \text{Cat}(\alpha'_1, \dots, \alpha'_T)^k$ as in `Sparsify`. Define a function $\hat{h}(x) = \text{Med}(\tilde{h}_1(x), \dots, \tilde{h}_k(x))$. We claim that for any fixed $i \in [m]$, with high probability

$$|\hat{h}(x_i) - f^*(x_i)| \leq \eta/2. \quad (5)$$

Indeed, partition the indices $[T]$ into the disjoint sets

$$\begin{aligned} L(x) &= \{j \in [T] : h_j(x) < Q_{\gamma}^-(h_1(x), \dots, h_T(x); \alpha_1, \dots, \alpha_T)\}, \\ M(x) &= \{j \in [T] : Q_{\gamma}^-(h_1(x), \dots, h_T(x); \alpha_1, \dots, \alpha_T) \leq h_j(x) \leq Q_{\gamma}^+(h_1(x), \dots, h_T(x); \alpha_1, \dots, \alpha_T)\}, \\ R(x) &= \{j \in [T] : h_j(x) > Q_{\gamma}^+(h_1(x), \dots, h_T(x); \alpha_1, \dots, \alpha_T)\}. \end{aligned}$$

Then the only way (5) can fail is if half or more indices J_1, \dots, J_k sampled fall into $R(x_i)$ — or if half or more fall into $L(x_i)$. Since the sampling distribution puts mass less than $1/2 - \gamma$ on each of $R(x_i)$ and $L(x_i)$, Chernoff's bound puts an upper estimate of $\exp(-2k\gamma^2)$ on either event. Hence,

$$\mathbb{P}\left(|\hat{h}(x_i) - f^*(x_i)| > \eta/2\right) \leq 2\exp(-2k\gamma^2). \quad (6)$$

Next, our goal is to ensure that with high probability, (5) holds simultaneously for all $i \in [m]$. Define the map $\xi : [m] \rightarrow \mathbb{R}^k$ by $\xi(i) = (\tilde{h}_1(x_i), \dots, \tilde{h}_k(x_i))$. Let $G \subseteq [m]$ be a minimal subset of $[m]$ such that $\max_{i \in [m]} \min_{j \in G} \|\xi(i) - \xi(j)\|_{\infty} \leq \eta/2$. This is just a minimal ℓ_{∞} covering of $[m]$. Then

$$\begin{aligned} \mathbb{P}(\exists i \in [m] : |\text{Med}(\xi(i)) - f^*(x_i)| > \eta) &\leq \\ \sum_{j \in G} \mathbb{P}(\exists i : |\text{Med}(\xi(i)) - f^*(x_i)| > \eta, \|\xi(i) - \xi(j)\|_{\infty} \leq \eta/2) &\leq \\ \sum_{j \in G} \mathbb{P}(|\text{Med}(\xi(j)) - f^*(x_j)| > \eta/2) &\leq 2N_{\infty}([m], \eta/2) \exp(-2k\gamma^2), \end{aligned}$$

where $N_\infty([m], \eta/2)$ is the $\eta/2$ -covering number (under ℓ_∞) of $[m]$, and we used the fact that $|\text{Med}(\boldsymbol{\xi}(i)) - \text{Med}(\boldsymbol{\xi}(j))| \leq \|\boldsymbol{\xi}(i) - \boldsymbol{\xi}(j)\|_\infty$. Finally, to bound $N_\infty([m], \eta/2)$, note that $\boldsymbol{\xi}$ embeds $[m]$ into the dual class \mathcal{F}^* . Thus, we may apply the bound in (Rudelson and Vershynin, 2006, Display (1.4)):

$$\log N_\infty([m], \eta/2) \leq Cd^*(c\eta) \log^2(k/\eta),$$

where C, c are universal constants and $d^*(\cdot)$ is the dual fat-shattering dimension of \mathcal{F} . It now only remains to choose a k that makes $\exp(Cd^*(c\eta) \log^2(k/\eta) - 2k\gamma^2)$ as small as desired. ■

To establish Theorem 2, we use the weak learner from above, with the booster `MedBoost` from Kégl, and then apply the `Sparsify` procedure. Combining the corresponding theorems, together with the same technique for converting to a compression scheme discussed above for classification (i.e., encoding the functions with the set of training examples they were obtained from, plus extra bits to record the order and which examples which weak hypothesis was obtained by training on), this immediately yields the result claimed in Theorem 2, which represents our main new result for sample compression of general families of real-valued functions.

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Appendix A. Sample compression for BV functions

The function class $BV(v)$ consists of all $f : [0, 1] \rightarrow \mathbb{R}$ for which

$$V(f) := \sup_{n \in \mathbb{N}} \sup_{0=x_0 < x_1 < \dots < x_n=1} \sum_{i=1}^{n-1} |f(x_{i+1}) - f(x_i)| \leq v.$$

It is known (Anthony and Bartlett, 1999, Theorem 11.12) that $d_{BV(v)}(t) = 1 + \lfloor v/(2t) \rfloor$. In Theorem 11 below, we show that the dual class has $d_{BV(v)}^*(t) = \Theta(\log(v/t))$. Long (2004) presented an efficient, proper, consistent learner for the class $\mathcal{F} = BV(1)$ with range restricted to $[0, 1]$, with sample complexity $m_{\mathcal{F}}(\varepsilon, \delta) = O(\frac{1}{\varepsilon} \log \frac{1}{\delta})$. Combined with Theorem 2, this yields

Corollary 10 *Let $\mathcal{F} = BV(1) \cap [0, 1]^{[0,1]}$ be the class $f : [0, 1] \rightarrow [0, 1]$ with $V(f) \leq 1$. Then the proper, consistent learner \mathcal{L} of Long (2004), with target generalization error ε , admits a sample compression scheme of size $O(k \log k)$, where*

$$k = O\left(\frac{1}{\varepsilon} \log^2 \frac{1}{\varepsilon} \cdot \log\left(\frac{1}{\varepsilon} \log \frac{1}{\varepsilon}\right)\right).$$

The compression set is computable in expected runtime

$$O\left(n \frac{1}{\varepsilon^{3.38}} \log^{3.38} \frac{1}{\varepsilon} \left(\log n + \log \frac{1}{\varepsilon} \log \left(\frac{1}{\varepsilon} \log \frac{1}{\varepsilon}\right)\right)\right).$$

The remainder of this section is devoted to proving

Theorem 11 For $\mathcal{F} = \text{BV}(v)$ and $t < v$, we have $d_{\mathcal{F}}^*(t) = \Theta(\log(v/t))$.

First, we define some preliminary notions:

Definition 12 For a binary $m \times n$ matrix M , define

$$\begin{aligned} V(M, i) &:= \sum_{j=1}^m \mathbb{I}[M_{j,i} \neq M_{j+1,i}], \\ G(M) &:= \sum_{i=1}^n V(M, i), \\ V(M) &:= \max_{i \in [n]} V(M, i). \end{aligned}$$

Lemma 13 Let M be a binary $2^n \times n$ matrix. If for each $b \in \{0, 1\}^n$ there is a row j in M equal to b , then

$$V(M) \geq \frac{2^n}{n}.$$

In particular, for at least one row i , we have $V(M, i) \geq 2^n/n$.

Proof Let M be a $2^n \times n$ binary such that for each $b \in \{0, 1\}^n$ there is a row j in M equal to b . Given M 's dimensions, every $b \in \{0, 1\}^n$ appears exactly in one row of M , and hence the minimal Hamming distance between two rows is 1. Summing over the $2^n - 1$ adjacent row pairs, we have

$$G(M) = \sum_{i=1}^n V(M, i) = \sum_{i=1}^n \sum_{j=1}^m \mathbb{I}[M_{j,i} \neq M_{j+1,i}] \geq 2^n - 1,$$

which averages to

$$\frac{1}{n} \sum_{i=1}^n V(M, i) = \frac{G(M)}{n} \geq \frac{2^n - 1}{n}.$$

By the pigeon-hole principle, there must be a row $j \in [n]$ for which $V(M, i) \geq \frac{2^n - 1}{n}$, which implies $V(M) \geq \frac{2^n - 1}{n}$. ■

We split the proof of Theorem 11 into two estimates:

Lemma 14 For $\mathcal{F} = \text{BV}(v)$ and $t < v$, $d_{\mathcal{F}}^*(t) \leq 2 \log_2(v/t)$.

Lemma 15 For $\mathcal{F} = \text{BV}(v)$ and $4t < v$, $d_{\mathcal{F}}^*(t) \geq \lfloor \log_2(v/t) \rfloor$.

Proof [Proof of Lemma 14] Let $\{f_1, \dots, f_n\} \subset \mathcal{F}$ be a set of functions that are t -shattered by \mathcal{F}^* . In other words, there is an $r \in \mathbb{R}^n$ such that for each $b \in \{0, 1\}^n$ there is an $x_b \in \mathcal{F}^*$ such that

$$\forall i \in [n], x_b(f_i) \begin{cases} \geq r_i + t, & b_i = 1 \\ \leq r_i - t, & b_i = 0 \end{cases}.$$

Let us order the x_b s by magnitude $x_1 < x_2 < \dots < x_{2^n}$, denoting this sequence by $(x_i)_{i=1}^{2^n}$. Let $M \in \{0, 1\}^{2^n \times n}$ be a matrix whose i th row is b_j , the latter ordered arbitrarily.

By Lemma 13, there is $i \in [n]$ s.t.

$$\sum_{j=1}^{2^n} \mathbb{I}[M(j, i) \neq M(j+1, i)] \geq \frac{2^n}{n}.$$

Note that if $M(j, i) \neq M(j+1, i)$ shattering implies that

$$x_j(f_i) \geq r_i + t \text{ and } x_{j+1}(f_i) \leq r_i - t$$

or

$$x_j(f_i) \leq r_i - t \text{ and } x_{j+1}(f_i) \geq r_i + t;$$

either way,

$$|f_i(x_j) - f_i(x_{j+1})| = |x_j(f_i) - x_{j+1}(f_i)| \geq 2t.$$

So for the function f_i , we have

$$\sum_{j=1}^{2^n} |f_i(x_j) - f_i(x_{j+1})| = \sum_{j=1}^{2^n} |x_j(f_i) - x_{j+1}(f_i)| \geq \sum_{j=1}^{2^n} \mathbb{I}[b_{j_i} \neq b_{j+1_i}] \cdot 2t \geq \frac{2^n}{n} \cdot 2t.$$

As $\{x_j\}_{j=1}^{2^n}$ is a partition of $[0, 1]$ we get

$$v \geq \sum_{j=1}^{2^n} |f_i(x_j) - f_i(x_{j+1})| \geq \frac{t2^{n+1}}{n} \geq t2^{n/2}$$

and hence

$$\begin{aligned} v/t &\geq 2^{n/2} \\ \Rightarrow 2 \log_2(v/t) &\geq n. \end{aligned}$$

■

Proof [Proof of Lemma 16] We construct a set of $n = \lfloor \log_2(v/t) \rfloor$ functions that are t -shattered by \mathcal{F}^* . First, we build a balanced Gray code (Flahive and Bose, 2007) with n bits, which we arrange into the rows of M . Divide the unit interval into 2^n segments and define, for each $j \in [2^n]$,

$$x_j := \frac{j}{2^n}.$$

Define the functions $f_1, \dots, f_{\lfloor \log_2(v/t) \rfloor}$ as follows:

$$f_i(x_j) = \begin{cases} t, & M(j, i) = 1 \\ -t, & M(j, i) = 0 \end{cases}.$$

We claim that each $f_i \in \mathcal{F}$. Since M is balanced Gray code,

$$V(M) = \frac{2^n}{n} \leq \frac{v}{t \log_2(v/t)} \leq \frac{v}{2t}.$$

Hence, for each f_i , we have

$$V(f_i) \leq 2tV(M, i) \leq 2t \frac{v}{2t} = v.$$

Next, we show that this set is shattered by \mathcal{F}^* . Fix the trivial offset $r_1 = \dots = r_n = 0$. For every $b \in \{0, 1\}^n$ there is a $j \in [2^n]$ s.t. $b = b_j$. By construction, for every $i \in [n]$, we have

$$x_j(f_i) = f_i(x_j) = \begin{cases} t \geq r_i + t, & M(j, i) = 1 \\ -t \leq r_i - t, & M(j, i) = 0 \end{cases}.$$

■

Appendix B. Sample compression for nearest-neighbor regression

Let (\mathcal{X}, ρ) be a metric space and define, for $L \geq 0$, the collection \mathcal{F}_L of all $f : \mathcal{X} \rightarrow [0, 1]$ satisfying

$$|f(x) - f(x')| \leq L\rho(x, x');$$

these are the L -Lipschitz functions. [Gottlieb et al. \(2017b\)](#) showed that

$$d_{\mathcal{F}_L}(t) = O\left(\lceil L \text{diam}(\mathcal{X})/t \rceil^{\text{ddim}(\mathcal{X})}\right),$$

where $\text{diam}(\mathcal{X})$ is the diameter and ddim is the *doubling dimension*, defined therein. The proof is achieved via a packing argument, which also shows that the estimate is tight. Below we show that $d_{\mathcal{F}_L}^*(t) = \Theta(\log(M(\mathcal{X}, 2t/L)))$, where $M(\mathcal{X}, \cdot)$ is the packing number of (\mathcal{X}, ρ) . Applying this to the efficient nearest-neighbor regressor³ of [Gottlieb et al. \(2017a\)](#), we obtain

Corollary 16 *Let (\mathcal{X}, ρ) be a metric space with hypothesis class \mathcal{F}_L , and let \mathcal{L} be a consistent, proper learner for \mathcal{F}_L with target generalization error ε . Then \mathcal{L} admits a compression scheme of size $O(k \log k)$, where*

$$k = O\left(D(\varepsilon) \log \frac{1}{\varepsilon} \cdot \log D(\varepsilon) \log \left(\frac{1}{\varepsilon} \log D(\varepsilon)\right)\right)$$

and

$$D(\varepsilon) = \left\lceil \frac{L \text{diam}(\mathcal{X})}{\varepsilon} \right\rceil^{\text{ddim}(\mathcal{X})}.$$

3. In fact, the technical machinery in [Gottlieb et al. \(2017a\)](#) was aimed at achieving *approximate* Lipschitz-extension, so as to gain a considerable runtime speedup. An *exact* Lipschitz extension is much simpler to achieve. It is more computationally costly but still polynomial-time in sample size.

We now prove our estimate on the dual fat-shattering dimension of \mathcal{F} :

Lemma 17 For $\mathcal{F} = \mathcal{F}_L$, $d_{\mathcal{F}}^*(t) \leq \log_2(\mathcal{M}(\mathcal{X}, 2t/L))$.

Proof Let $\{f_1, \dots, f_n\} \subset \mathcal{F}_L$ a set that is t -shattered by \mathcal{F}_L^* . For $b \neq b' \in \{0, 1\}^n$, let i be the first index for which $b_i \neq b'_i$, say, $b_i = 1 \neq 0 = b'_i$. By shattering, there are points $x_b, x_{b'} \in \mathcal{F}_L^*$ such that $x_b(f_i) \geq r_i + t$ and $x_{b'}(f_i) \leq r_i - t$, whence

$$f_i(x_b) - f_i(x_{b'}) \geq 2t$$

and

$$L\rho(x_b, x_{b'}) \geq f_i(x_b) - f_i(x_{b'}) \geq 2t.$$

It follows that for $b \neq b' \in \{0, 1\}^n$, we have $\rho(x_b, x_{b'}) \geq 2t/L$. Denoting by $M(\mathcal{X}, \varepsilon)$ the ε -packing number of \mathcal{X} , we get

$$2^n = |\{x_b \mid b \in \{0, 1\}^n\}| \leq \mathcal{M}(\mathcal{X}, 2t/L).$$

■

Lemma 18 For $\mathcal{F} = \mathcal{F}_L$ and $t < L$, $d_{\mathcal{F}}^*(t) \geq \log_2(\mathcal{M}(\mathcal{X}, 2t/L))$.

Proof Let $S = \{x_1, \dots, x_m\} \subseteq \mathcal{X}$ be a maximal $2t/L$ -packing of \mathcal{X} . Suppose that $c : S \rightarrow \{0, 1\}^{\lfloor \log_2 m \rfloor}$ is one-to-one. Define the set of function $F = \{f_1, \dots, f_{\lfloor \log_2(m) \rfloor}\} \subseteq \mathcal{F}_L$ by

$$f_i(x_j) = \begin{cases} t, & c(x_j)_i = 1 \\ -t, & c(x_j)_i = 0 \end{cases}.$$

For every $f \in F$ and every two points $x, x' \in S$ it holds that

$$|f(x) - f(x')| \leq 2t = L \cdot 2t/L \leq L\rho(x, x').$$

This set of functions is t -shattered by S and is of size $\lfloor \log_2 m \rfloor = \lfloor \log_2(\mathcal{M}(\mathcal{X}, 2t/L)) \rfloor$.

■