

Research Article

ε -Coverings of Hölder-Zygmund Type Spaces on Data-Defined Manifolds

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We first determine the asymptotes of the ε -covering numbers of Hölder-Zygmund type spaces on data-defined manifolds. Secondly, a fully discrete and finite algorithmic scheme is developed providing explicit ε -coverings whose cardinality is asymptotically near the ε -covering number. Given an arbitrary Hölder-Zygmund type function, the nearby center of a ball in the ε -covering can also be computed in a discrete finite fashion.

1. Introduction

Data processing in the digital era often deals with finitely many high-dimensional data chunks stemming from measurements that obey some continuous physical model. The implementation and numerical evaluation require estimates on the accuracy of the discretization with respect to the underlying model. As an elementary tool providing accuracy guarantees, we will address ε -coverings of some function spaces related to information theory and machine learning.

As a standard concept in discrete mathematics, the ε -covering number $n_\varepsilon(Y)$ is the minimal number of balls of radius ε that cover a compact metric space Y . An arbitrary element in Y can be represented by a nearby center preserving precision up to ε . As such, ε -coverings are also an integral part of approximation theory, especially if Y is some function space. Covering numbers capture the complexity of Y and the approximation aspects are used in many fields such as information theory, statistics, nonparametric density estimation, and machine learning. There are estimates on the asymptotics of the ε -covering numbers of the standard function spaces (cf. [1, 2]), but some fields such as machine learning involve data lying on some manifold, so that target functions are naturally defined on this manifold. To clarify the terminology, we consider smoothness spaces on manifolds as somewhat

the number of bits needed to enumerate the ε -covering (cf. [1]). Moreover, we compute an explicit ε -covering, such that

$$\frac{\log_2(\hat{n}_\varepsilon)}{\log_2(n_\varepsilon)} \leq \left(1 + \log_2\left(\frac{1}{\varepsilon}\right)\right), \quad (1)$$

where $\hat{n}_\varepsilon$ is the cardinality of the constructed covering and $\leq$ means that the left-hand side can be bounded by a generic constant times the right-hand side. Hence, our covering is optimal up to a logarithmic factor by means of the metric entropy. We allow the underlying manifold to be unknown in our scheme and, instead, to be represented through a finite sampling. This sampling must be chosen carefully and is the key to obtaining a finite scheme. The centers of our ε -covering can then be determined through a finite process, and we can measure any function's distance to these centers in a finite manner.

For constructions of ε -coverings on periodic smoothness spaces, for instance, we refer to [4, 5]. The concept of ε -entropy is also closely related to entropy numbers; see [6–8].

The outline of this paper is as follows. In Section 2 we introduce the setting, define the Hölder-Zygmund type space $\mathcal{E}^s(\mathbb{X})$, and determine the metric entropy for its unit ball. An explicit covering is computed in Section 3.

2. Covering Numbers for Hölder-Zygmund Type Spaces

We first fix the setting and list some technical assumptions used throughout the paper. Let $\mathbb{X} \subset \mathbb{R}^d$ be an α -dimensional compact and connected Riemannian manifold without boundary and with nonnegative Ricci curvature, geodesic distance ρ , and μ being the normalized Riemannian volume measure on $\mathbb{X}$; $\{\varphi_k\}_{k=0}^\infty$ are the eigenfunctions of the Laplacian on $\mathbb{X}$, and $\{-\lambda_k^2\}_{k=0}^\infty$ are the corresponding eigenvalues arranged in nonincreasing order, so that $0 = \lambda_0 \leq \lambda_1 \leq \dots$. Readers who are not familiar with some terms from differential geometry that are used here may simply think of a “nice” manifold without boundary, such as the sphere, the real projective space, the (real) Grassmann manifold, or more generally compact homogeneous spaces. The above properties ensure certain estimates on the heat kernel on $\mathbb{X}$ (see [9, 10]), which were used in a series of papers [9, 11–13] to develop approximation schemes for smooth functions on the manifold. Here, we will make use of those approximation schemes, but we will keep the technical details at a minimum level.

Let N be a positive integer and most of the time we will restrict ourselves to $N = 2^j$, where j is some nonnegative integer. The space of *diffusion polynomials* up to degree N is

$$\Pi_N := \text{span}\{\varphi_k : \lambda_k \leq N\}. \quad (2)$$

Later, we will use the fact that the above conditions imply the following estimate on the Christoffel function:

$$\sum_{\lambda_k \leq N} |\varphi_k(x)|^2 \asymp N^\alpha, \quad x \in \mathbb{X}, \quad N >$$

Therefore, $(g_N)_{N=1}^\infty$ is a Cauchy sequence and, hence, converges towards some $g \in L_\infty(\mathbb{X})$. Standard calculations reveal that g is an accumulation point of $(f_j)_{j=1}^\infty$ and is contained in $\overline{\mathcal{E}^s}(\mathbb{X})$, which concludes the proof. $\square$

We can now derive the asymptotes of the ε -covering number of $\overline{\mathcal{E}^s}(\mathbb{X})$ in $L_\infty(\mathbb{X})$.

Theorem 2. *If $s > 0$ is fixed and $0 < \varepsilon \leq 1$, then*

$$\log_2(n_\varepsilon(\overline{\mathcal{E}^s}(\mathbb{X}))) \asymp \varepsilon^{-\alpha/s} \quad (7)$$

holds, where the generic constants do not depend on ε .

Analogous results can be derived for similar concepts such as different types of n -widths of functions spaces (cf. [14–16]). Theorem 2 and its proof are rather classical and can be derived from [17]. To guide the interested reader, we will provide the outline of the proof that is based on a general Banach space result and is also used in [18, Theorem 4.1]. Let X be a Banach space and let $\{\phi_k\}_{k=1}^\infty \subset X$ be a sequence of linearly independent elements whose linear span is dense in X , and define $X_k := \text{span}\{\phi_1, \dots, \phi_k\}$ with $X_0 = \{0\}$. Let $\{\delta_k\}_{k=0}^\infty$ be a nonincreasing sequence of positive numbers with $\lim_{k \rightarrow \infty} \delta_k = 0$. The full approximation space is

$$\begin{aligned} \mathcal{A}(X; \{\delta_k\}_{k=0}^\infty, \{\phi_k\}_{k=1}^\infty) \\ := \{f \in X : E(f, X_k, X) \leq \delta_k, \text{ for } k = 0, 1, \dots\}. \end{aligned} \quad (8)$$

A proof similar to Lemma 1 yields that this space is compact, and we can formulate the result from Banach space theory that goes back to Lorentz in [17].

Theorem 3 (see [19, Theorem 3.3]). *Let $\{\delta_k\}_{k=0}^\infty$ be a nonincreasing sequence of positive numbers such that $\delta_{2k} \leq c\delta_k$, for $k = 1, 2, \dots$ and some constant $c \in (0, 1)$. For $\ell \geq 0$, let $M_\ell := \min\{k : \delta_k \leq e^{-\ell}\}$. If n_ε denotes the ε -covering number of $\mathcal{A}(X; \{\delta_k\}_{k=0}^\infty, \{\phi_k\}_{k=1}^\infty)$ in X , then one has, for $0 < \varepsilon \leq 1$,*

$$\log_2(n_\varepsilon) \asymp \sum_{\ell=1}^L M_\ell, \quad (9)$$

where $L := 2 + \lfloor \log(1/\varepsilon) \rfloor$.

where $h : \mathbb{R}_{\geq 0} \rightarrow \mathbb{R}$ is an infinitely often differentiable and nonincreasing function with $h(t) = 1$ for $t \leq 1/2$ and $h(t) = 0$ for $t \geq 1$. Although we will not explicitly use it in the present paper, we want to point out that many advantageous properties of σ_N are steered by the so-called localization of the kernel K_N ; that is, for fixed $S > \alpha$ and all $x \neq y$ with $N = 1, 2, \dots$,

$$|K_N(x, y)| \leq \frac{N^{\alpha-S}}{\rho(x, y)^S}. \quad (15)$$

See [12, 13]. Later, we will apply

$$\sup_{x \in \mathbb{X}} \int_{\mathbb{X}} |K_N(x, y)| d|\nu_N|(y) \leq 1 \quad (16)$$

(cf. [11]). Those estimates are used in [12, 13] to characterize the Hölder-Zygmund type smoothness by means of σ_N .

Theorem 5. Assume that $(\nu_N)_{N=1}^\infty$ is a family of quadrature measures of order N , respectively. Then, for all $f \in \mathcal{C}^s(\mathbb{X})$, one has

$$\|f - \sigma_N(f)\|_{L_\infty(\mathbb{X})} \leq N^{-s} \|f\|_{\mathcal{C}^s(\mathbb{X})}, \quad (17)$$

where the generic constants do not depend on N or f . On the other hand, if, for $f \in L_p(\mathbb{X})$, there are generic constants not depending on N such that $\|f - \sigma_N(f)\|_{L_\infty(\mathbb{X})} \leq N^{-s}$ holds, then $f \in \mathcal{C}^s(\mathbb{X})$.

Next, by using $h(\lambda_k/N)h(\lambda_k/2N) = h(\lambda_k/N)$ and applying the quadrature property of ν_N , a straightforward calculation yields

$$\sigma_N(f, x) = \int_{\mathbb{X}} \sigma_N(f, y) K_{2N}(x, y) d\nu_N(y). \quad (18)$$

For some fixed $S > 1$, we define the actual approximation by

$$\begin{aligned} \sigma_N^\circ(f, x) &:= \int_{\mathbb{X}} I_N(f, y) K_{2N}(x, y) d\nu_N(y), \\ \text{where } I_N(f, y) &= N^{-S} \lfloor N^S \sigma_N(f, y) \rfloor. \end{aligned} \quad (19)$$

In other words, we replace $\sigma_N(f, y)$ in (18) with a number on the grid $(1/N^S)\mathbb{Z}$. We define the following collection:

$$\mathcal{M}_{S,N} := \{\sigma_N^\circ(f$$

Therefore, our scheme is optimal up to a logarithmic factor by means of the metric entropy.

Our results are also related to the field of manifold learning, in which a function must be reconstructed from finite training data (cf. [22–25]). When actually applying our scheme, we first acquire a set of samples $\{x_\ell\}_{\ell=1}^m$ sufficiently well covering $\mathbb{X}$ and we also need the function values $\{f(x_\ell)\}_{\ell=1}^m$, which altogether build the training data. Next, we compute a quadrature measure ν_N for some maximal N such that $\text{supp}(\nu_N) \subset \{x_\ell\}_{\ell=1}^m$; see [11, 21] for an algorithm. Here, we need that the sample points $\{x_\ell\}_{\ell=1}^m$ are well distributed and larger N require more samples. An element in $\mathcal{M}_{S,N}$ that is ε -close to f is simply given by $\sigma_N^\circ(f)$, whose computation only requires knowledge of f and $\{\varphi_k : \lambda_k \leq N\}$ on the finite set $\text{supp}(\nu_N)$; see (14) and (19). In other words, we do not need to know the entire manifold but only the finite sampling of the training data $\{x_\ell\}_{\ell=1}^m$, the sampling of the target function $\{f(x_\ell)\}_{\ell=1}^m$, and, more delicately, the sampling of the eigenfunctions $\{\varphi_k(x_\ell) : \lambda_k \leq N, \ell = 1, \dots, m\}$ of the Laplacian. Those eigenfunctions, however, are not explicitly known except for few special cases, such as the sphere, projective space, the Grassmann manifold, and few more. Fortunately, approximation of those eigenfunctions is a common procedure in manifold learning. Computational schemes are based on the graph Laplacian to be built from the training data and, at least under suitable assumptions, converging towards the Laplacian on the manifold when the cardinality of the data increases (cf. [26–28] and references therein). Those schemes approximately sample the first few eigenfunctions on the training data. Thus, our proposed approach is indeed fully discrete and computationally feasible even if the eigenfunctions $\{\varphi_k\}_{k=0}^\infty$ are not explicitly known. In fact, the manifold itself can be unknown. As long as $\mathbb{X}$ satisfies the theoretical assumptions, it is simply represented by means of a finite sample.

Remark 7. The technical assumptions on the manifold $\mathbb{X}$ and the function system $\{\varphi_k\}_{k=0}^\infty$ imply certain estimates on the heat kernel on $\mathbb{X}$ (see [9, 10]), mainly used to ensure that the localization property (15) holds (cf. [12, 13]). Our assumptions also imply the existence of quadrature measures ν_N and that $f \cdot g \in \Pi_{a,N}$ for all $f, g \in \Pi_N$ and some constant $a > 0$. These items lead to the characterization of the Hölder-Zygmund type space by means of σ_N in Theorem 5. Moreover, the family $(\nu_N)_{N=1}^\infty$ can be chosen with finite support, in fact with $\#\text{supp}(\nu_N) \leq N^\alpha$ (cf. [11]). Theorem 5 and $\#\text{supp}(\nu_N) \leq N^\alpha$ are indeed the two main ingredients of the proof of our results in Theorem 6.

Remark 8. The reader familiar with the approximation scheme developed in [9, 11–13] may expect that the presented results can be generalized to a wider class of Besov spaces on metric spaces. This is indeed true but requires more technical details and does not lead to a fully discrete scheme in the end. Here, we intended to emphasize the main ideas by keeping technical details at a minimum level and to focus on the development of a fully discrete covering algorithm. The more general approach will be described elsewhere.

Conflict of Interests

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