Research Article

Consistency Analysis of Spectral Regularization Algorithms

Yukui Zhu and Hongwei Sun

Shandong Provincial Key Laboratory of Network based Intelligent Computing, School of Mathematic Science, University of Jinan, Jinan 250022, China

Correspondence should be addressed to Hongwei Sun, ss_sunhw@ujn.edu.cn

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We investigate the consistency of spectral regularization algorithms. We generalize the usual definition of regularization function to enrich the content of spectral regularization algorithms. Under a more general prior condition, using refined error decompositions and techniques of operator norm estimation, satisfactory error bounds and learning rates are proved.

1. Introduction

In this paper, we study the consistency analysis of spectral regularization algorithms in regression learning.

Let \((X, d)\) be a compact metric space and \(\rho\) a probability distribution on \(Z = X \times Y\) with \(Y = \mathbb{R}\). The regression learning aims at estimating or approximating the regression function

\[
f_\rho(x) = \int_y y d\rho(y | x)
\]

through a set of samples \(z = \{(x_i, y_i)\}_{i=1}^m \in Z^m\) drawn independently and identically according to \(\rho\) from \(Z\).

In learning theory, a reproducing kernel Hilbert space (RKHS) associated with a Mercer kernel \(K(x, y)\) is usually taken as the hypothesis space. Recall that a function \(K : X \times X \to \mathbb{R}\) is called a Mercer kernel if it is continuous, symmetric, and positive semidefinite. The reproducing kernel Hilbert space \(\mathcal{H}_K\) is defined to be the closure of the linear span of \(K_x := K(\cdot, x), x \in X\). The reproducing property takes the form

\[
f(x) = \langle f, K_x \rangle_K, \quad \forall f \in \mathcal{H}_K, \forall x \in X.
\]
For the Mercer kernel $K(x, y)$, we denote that
\[
\kappa = \max_{x \in X} \sqrt{K(x, x)}.
\] (1.3)

Our first contribution is to generalize the definition of regularization in [1] such that many more learning algorithms can be included in the scope of spectral algorithms.

Definition 1.1. We say that a family of continuous functions $g_\lambda : [0, \kappa^2] \to R$, $\lambda \in (0, 1]$ is regularization, if the following conditions hold.

(i) There exists a constant $D$ such that
\[
\sup_{0<\sigma \leq \kappa^2} |\sigma g_\lambda(\sigma)| \leq D.
\] (1.4)

(ii) There exists a constant $B > 0$, $0 < \alpha \leq 1$ such that
\[
\sup_{0<\sigma \leq \kappa^2} |g_\lambda(\sigma)| \leq \frac{B}{\lambda^\alpha}.
\] (1.5)

(iii) There exists a constant $\gamma$ such that
\[
\sup_{0<\sigma \leq \kappa^2} |1 - g_\lambda(\sigma)\sigma| \leq \gamma.
\] (1.6)

(iv) The qualification $\nu_0$ of the regularization $g_\lambda$ is the maximal $\nu$ such that
\[
\sup_{0<\sigma \leq \kappa^2} |1 - g_\lambda(\sigma)\sigma|^{\nu} \leq \gamma_\lambda^{\nu},
\] (1.7)

where $\gamma_\nu$ does not depend on $\lambda$.

Our definition for regularization is different from that in [1]. In fact, the definition given by [1] is the special case when taking $\alpha = 1$ in (1.5) and (1.7). So from this viewpoint, our assumption is more mild and it is fit for more general situations, for example, coefficient regularization algorithms correspond to spectral algorithms with $\alpha = 1/2$, the relation between coefficient regularization algorithms and spectral algorithms had been explored in [2].

Let $x = \{x_i\}_{i=1}^m$ and $y = \{y_i\}_{i=1}^m$. The sample operator $S_x : \mathcal{H}_K \to \mathbb{R}^m$ is defined as $S_x f = \{f(x_i)\}_{i=1}^m$. The adjoint of $S_x$ under $1/m$ times the Euclidean norm is $S_x^*c = (1/m) \sum_{i=1}^m c_i K_{x_i}$. For simplicity, we use $T_x$ to stand for $S_x^*S_x$.

The spectral regularization algorithm considered here is given by
\[
f^\lambda_x = g_\lambda(T_x) S_x^* y.
\] (1.8)

The regularization $g_\lambda$, $\lambda \in (0, 1]$ in (1.8) was proposed originally to solve ill-posed inverse problems. The relation between learning theory and regularization of linear ill-posed problems has been well discussed in a series of articles, see [1, 3] and the references therein.
The analysis made in previous literatures provides us with a deep understanding of the connection between learning theory and regularization. A large class of learning algorithms can be considered as spectral regularization algorithms in accordance with different regularizations.

**Example 1.2.** The regularized least square algorithm is given as

\[ f_\lambda^z = \arg \min_{f \in \mathcal{H}} \frac{1}{m} \sum_{i=1}^{m} (y_i - f(x_i))^2 + \lambda \|f\|_K^2. \] (1.9)

It has been well understood due to a lot of literatures [4–11], and so forth. It is proved in [7] that

\[ f_\lambda^z = (T_x + \lambda I)^{-1} S_x^T y, \] (1.10)

which corresponds to algorithm (1.8) with the regularization

\[ g_\lambda(\sigma) = (\sigma + \lambda)^{-1}. \] (1.11)

In this case, we have \( B = D = \gamma = \gamma_0 = \alpha = 1 \), the qualification \( \nu_0 = 1 \).

**Example 1.3.** In regression learning, the coefficient regularization with \( \ell^2 \) norm becomes

\[ f_\lambda^z = f_{\alpha^*}, \quad \alpha^* = \arg \min_{\alpha \in \mathbb{R}^m} \frac{1}{m} \sum_{i=1}^{m} (y_i - f_{\alpha}(x_i))^2 + \lambda m \sum_{i=1}^{m} \alpha_i^2, \] (1.12)

where

\[ f_{\alpha} = \sum_{i=1}^{m} \alpha_i K_{x_i}, \quad \forall \alpha \in \mathbb{R}^m. \] (1.13)

The coefficient regularization was first introduced by Vapnik [12] to design linear programming support vector machines. The consistency of this algorithm has been studied in literatures [2, 13, 14]. In [2], it is proved that the sample error has \( O(1/\sqrt{m}) \) decay, even for nonpositive semidefinite kernels, and

\[ f_\lambda^z = \left( \lambda I + T_x^2 \right)^{-1} T_x S_x^T y. \] (1.14)

Thus, it corresponds to algorithm (1.8) with the regularization

\[ g_\lambda(\sigma) = \left( \sigma^2 + \lambda \right)^{-1}. \] (1.15)

In this case, we have \( B = D = \gamma = \gamma_0 = 1 \), the qualification \( \nu_0 = 2 \) and \( \alpha = 1/2 \).
Example 1.4. Landweber iteration is defined by \( g_\lambda(x) = \sum_{i=0}^{[1/\lambda] - 1} (1 - \lambda)^i \) where \( |a| = \max\{m : m \in \mathbb{Z}, m \leq a\} \). This corresponds to the gradient descent algorithm in Yao et al. [15] with constant step-size. In this case, we have that any \( \nu \in [0, +\infty) \) can be considered as qualification of this method and \( \gamma_{\nu} = 1 \) if \( 0 < \nu \leq 1 \) and \( \gamma_{\nu} = \nu' \) otherwise.

Let \( f_{\lambda}^\perp \) be the projection of \( f_\rho \) onto \( \mathcal{R}_K \), here \( \mathcal{R}_K \) denotes the closure of \( \mathcal{R}_K \) in \( L^2_{\rho_X}(X) \). The generalization error of \( f_\lambda^\perp \) is

\[
\mathcal{E}(f_{\lambda}^\perp) = \int_Z \left( f_{\lambda}^\perp(x) - \nu \right)^2 d\rho = \int_X \left( f_{\lambda}^\perp(x) - f^*_{\mathcal{R}_K}(x) \right)^2 d\rho_X + \int_X \left( f^*_{\mathcal{R}_K}(x) - f_\rho(x) \right)^2 d\rho_X + \sigma^2,
\]

where \( \rho_X \) is the marginal distribution of \( \rho \) on \( X \), \( \sigma^2 \) is the variance of random variable \( \nu - f_\rho(x) \). So the goodness of the approximation \( f_{\lambda}^\perp \) is measured by \( \|f_{\lambda}^\perp - f^*_{\mathcal{R}_K}\|_{\rho_X} \), where we take the \( L^2 \) norm defined as

\[
\|f\|_{\rho_X} = \left( \int_X |f(x)|^2 d\rho_X \right)^{1/2}, \quad \forall f \in L^2_{\rho_X}(X).
\]

The integral operator \( L_K \) associated with kernel \( K \) from \( L^2_{\rho_X}(X) \) to \( L^2_{\rho_X}(X) \) is defined by

\[
L_K f(x) = \int_X K(x, t) f(t) d\rho_X(t), \quad \forall f \in L^2_{\rho_X}(X).
\]

\( L_K \) is a nonnegative self-adjoint compact operator [4]. If the domain of \( L_K \) is restricted to \( \mathcal{R}_K \), it also is a nonnegative self-adjoint compact operator from \( \mathcal{R}_K \) to \( \mathcal{R}_K \), with norm \( \|L_K\|_{\mathcal{R}_K \to \mathcal{R}_K} \leq \kappa^2 \) [16]. In the sequel, we simply write \( \|L_K\| \) instead of \( \|L_K\|_{\mathcal{R}_K \to \mathcal{R}_K} \) and assume that \( |\nu| \leq M \) almost surely.

As usual, we use the following error decomposition:

\[
\|f_{\lambda}^\perp - f^*_{\mathcal{R}_K}\|_{\rho_X} \leq \|f_{\lambda}^\perp - f_\lambda\|_{\rho_X} + \|f_\lambda - f^*_{\mathcal{R}_K}\|_{\rho_X},
\]

where

\[
f_\lambda = g_\lambda(L_K) L_K f^*_{\mathcal{R}_K}.
\]

The first term on the right-hand side of (1.19) is called sample error, and the second one is approximation error. Sample error depends on the sampling, and the law of large numbers would lead to its estimation; approximation error is independent of the sampling, and its estimation is mainly through the method of operator approximation.

In order to deduce the error bounds and learning rates, we have to set restriction on the class of possible probability measures that is usually called prior condition. In previous
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Prior conditions are usually described through the smoothness of regression function $f_\rho$. We suppose the following prior condition:

$$f^\rho_x = \varphi(L_K)h_0, \quad h_0 \in L^2_{p\rho}(X), \quad \|h_0\|_{p\rho} \leq R. \quad (1.21)$$

Here, $\varphi$ called the index function is some continuous nondecreasing function defined on $[0, \kappa^2]$ with $\varphi(0) = 0$. In the sequel, we request the qualification $\nu_0 > 1/2$, and there exists $\mu_0 > 0$ covering $\varphi$, which means that there is $c > 0$ such that

$$c \frac{\lambda^{\mu_0}}{\varphi(\lambda)} \leq \inf_{\lambda \leq \sigma \leq \kappa^2} \frac{\sigma^{\mu_0}}{\varphi(\sigma)}, \quad 0 < \lambda \leq \kappa^2. \quad (1.22)$$

It is easy to see that, for any $\mu \geq \mu_0$, $\mu$ covers $\varphi$.

Furthermore, we request that $\varphi(t)$ is operator monotone on $[0, \kappa^2]$, that is, there is a constant $c_\varphi < \infty$, such that for any pair $U, V$ of nonnegative self-adjoint operators on some Hilbert space with norm less than $\kappa^2$, it holds

$$\|\varphi(U) - \varphi(V)\| \leq c_\varphi \varphi(\|U - V\|), \quad (1.23)$$

and, there is $d_\varphi > 0$ such that

$$d_\varphi \frac{\lambda}{\varphi(\lambda)} \leq \frac{\sigma}{\varphi(\sigma)}, \quad 0 < \lambda < \sigma \leq \kappa^2. \quad (1.24)$$

It is proved that $\varphi(t) = t^\alpha$ for $0 \leq \alpha \leq 1$ is operator monotone [8].

In [1], Bauer et al. consider the following prior condition:

$$f^\rho_x \in \Omega_{\varphi,R}, \quad \Omega_{\varphi,R} = \{ f \in \mathcal{H}_K : f = \varphi(L_K)v, \|v\|_K \leq R \}. \quad (1.25)$$

This condition is somewhat restrictive, since it asks that $f^\rho_x$ must belong to $\mathcal{H}_K$.

Our result shows that satisfactory error bound is available with a more general prior condition, this is our second main contribution. So from this viewpoint, our work is meaningful. The main result of this paper is the following theorem.

**Theorem 1.5.** Suppose the index function $\varphi$ with covering number $\mu_0 > 0$ is operator monotone on $[0, \kappa^2]$. The qualification $\nu_0$ satisfies $\nu_0 > \max\{1/2, \mu_0\}$ and that $m \geq 2 \log(4/\delta)$ for $0 < \delta < 1$. Then, with confidence $1 - \delta$, there holds

$$\left\| f^\lambda_x - f^\rho_x \right\|_{p\rho} \leq C_1 \left\{ \left( 1 + 1^{-\alpha/2} \zeta^{1/2} \right) \left( \varphi(\lambda) \lambda^{(\alpha-1)\mu_0} + \varphi(\zeta) + \lambda^{-\alpha/2} \eta \right) \right.$$  

$$\left. + \lambda^{(\alpha-1)} \left( \varphi(\lambda) \right)^{1/\mu_0} \min[\mu_0, \nu_0^{-1/2}] \right\}, \quad (1.26)$$
where

\[
\zeta = 2\kappa^2 \sqrt{\frac{2\log(4/\delta)}{m}},
\]

\[
\eta = \varphi(\lambda)\lambda^{-\mu_0+\min\{\alpha(\mu_0-1)/2, 0\}} m^{-1} \log \frac{4}{\delta} + \left(1 + \varphi(\lambda)\lambda^{(\alpha-1)\mu_0}\right) m^{-1/2} \sqrt{\log \frac{4}{\delta}}
\]

(1.27)

and \( C_1 \) is a constant independent of \( \lambda, m, \delta \).

This theorem shows the consistency of the spectral algorithms, gives the error bound, and also can lead to satisfactory learning rates by the explicit expression of \( \varphi \).

This paper is prepared as follows. In Section 2, we will prove a basic lemma about estimation of operator norms related to the regularization and two concentration inequalities with vector value random variables. In Section 3, we give the proof of Theorem 1.5. In Section 4, we derive learning rate under the setting of several specific regularization.

### 2. Some Lemmas

We simply write \( y_0 \) instead of \( y_{v_0} \) in (1.7) for qualification \( v_0 \). To estimate the error \( \|f_\hat{z}^1 - f_{\hat{w}}^1\|_{\rho_X} \), we need the following lemma to bound the norms of some operators.

**Lemma 2.1.** Let \( \varphi \) be an index function and \( v_0 > \max\{1/2, \mu_0\} \). Then, the following inequalities hold true:

\[
\sup_{0 < \sigma \leq \sigma^*} \left| 1 - g_1(\sigma) \right| \sigma^s \leq \sqrt{1-s/v_0} \frac{\sigma^{s/v_0} \lambda^{a s}}{v_0}, \quad \forall 0 < s \leq v_0,
\]

(2.1)

\[
\sup_{0 < \sigma \leq \sigma^*} \left| 1 - g_1(\sigma) \right| \varphi^*(\sigma) \leq \alpha_s \varphi^*(\lambda) \lambda^{(a-1)\mu_0 s}, \quad \forall 0 < s \leq \frac{v_0}{\mu_0},
\]

(2.2)

\[
\sup_{0 < \sigma \leq \sigma^*} \left| 1 - g_1(\sigma) \right| \varphi(\sigma) \sqrt{\sigma} \leq \beta_1 \lambda^{\min\{\mu_0, \mu_0-1/2\}(\alpha-1)+a/2} \left(\varphi(\lambda)\right)^{\min\{2v_0-1)/2\mu_0, 1\}},
\]

(2.3)

\[
\sup_{0 < \sigma \leq \sigma^*} \left| g_1(\sigma) \sigma^{1/2} \varphi(\sigma) \right| \leq \beta_2 \varphi(\lambda) \lambda^{\min\{\alpha(\mu_0-1/2), 0\}-\mu_0}.
\]

(2.4)

Here, \( \alpha_s, \beta_1, \beta_2 \) are constants only dependent on \( v_0, \mu_0, \gamma, y_0, c, \varphi(\kappa^2) \).

**Proof.** By (1.6) and (1.7), for any \( 0 < s \leq v_0 \), we have

\[
\sup_{0 < \sigma \leq \sigma^*} \left| 1 - g_1(\sigma) \right| \sigma^s \leq \sup_{0 < \sigma \leq \sigma^*} \left[ \left| 1 - g_1(\sigma) \right| \sigma^{\min\{s/v_0, \gamma\}} \times \left| 1 - g_1(\sigma) \right|^{1-s/v_0} \right] \sqrt{1-s/v_0} \lambda^{a s}.
\]

(2.5)
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Since \( \mu_0 s \leq \nu_0 \) and \( \varphi \) is covered by \( \mu_0 \), by (2.1) and (1.6), we get

\[
\sup_{0 < \sigma \leq \infty} |1 - g_\lambda(\sigma)| |\varphi^*(\sigma)| = \max\left\{ \sup_{0 < \sigma < 1} |1 - g_\lambda(\sigma)| |\varphi^*(\sigma)|, \sup_{\lambda \leq \sigma \leq \infty} |1 - g_\lambda(\sigma)| |\varphi^*(\sigma)| \right\} \\
\leq \max\left\{ \gamma |\varphi^*(\lambda)|, \frac{1}{c_s^2} |\varphi^*(\lambda)| \lambda^{1 - \mu_0 s / \nu_0} \lambda^{(a - 1)\mu_0 s} \right\} \\
= \max\left\{ \gamma, \frac{1}{c_s^2} \right\} |\varphi^*(\lambda)| \lambda^{1 - \mu_0 s / \nu_0} \lambda^{(a - 1)\mu_0 s}.
\] (2.6)

In order to prove the third inequality, let \( \tau = \min\{2\nu_0/(2\nu_0 - 1), \nu_0 / \mu_0 \} \) and \( \tau(1 - 1/2\nu_0) = (1/\mu_0) \min\{\mu_0, \nu_0 - 1/2\} \), by (2.2), we have

\[
\sup_{0 < \sigma \leq \infty} |1 - g_\lambda(\sigma)| |\varphi(\sigma)|^{1-2\nu_0} = \sup_{0 < \sigma \leq \infty} \left[ |1 - g_\lambda(\sigma)| |\varphi^*(\sigma)| \right]^{1-2\nu_0} \left( \varphi(\sigma) \right)^{\tau(1-1/2\nu_0)} \\
\leq \left( \varphi(\kappa^2) \right)^{1-\tau(1-1/2\nu_0)} \alpha_\tau^{1-2\nu_0} \lambda^{\min\{\mu_0, \nu_0 - 1/2\}(a-1)} \\
\times \left( \varphi(\lambda) \right)^{\min\{2\nu_0-1/2\mu_0, 1\}}.
\] (2.7)

Thus,

\[
\sup_{0 < \sigma \leq \infty} |1 - g_\lambda(\sigma)| |\varphi(\sigma)| = \sup_{0 < \sigma \leq \infty} \left[ |1 - g_\lambda(\sigma)| |\varphi^*(\sigma)| \right]^{1/2 \nu_0} \times |1 - g_\lambda(\sigma)| |\varphi(\sigma)| \\
\leq \beta_1 \lambda^{\min\{\mu_0, \nu_0 - 1/2\}(a-1) + a/2} \left( \varphi(\lambda) \right)^{\min\{2\nu_0-1/2\mu_0, 1\}}
\] (2.8)

where \( \beta_1 \) is a constant only dependent on \( \nu_0, \mu_0, \gamma, y_0, c, \varphi(\kappa^2) \).

If \( 0 < \mu_0 \leq 1/2 \), we have

\[
\sup_{0 < \sigma \leq \infty} |g_\lambda(\sigma)|^{1/2} |\varphi(\sigma)| = \max\left\{ \sup_{0 < \sigma < 1} |g_\lambda(\sigma)|^{1/2} |\varphi(\sigma)|, \sup_{\lambda \geq \sigma \leq \infty} |g_\lambda(\sigma)|^{1/2} |\varphi(\sigma)| \right\} \\
\leq \max\left\{ \sup_{0 < \sigma < 1} |g_\lambda(\sigma)|^{1/2} |g_\lambda(\sigma)|^{1/2} |\varphi(\sigma)|, \frac{\varphi(\lambda)}{c_\lambda y_0} \lambda^{\mu_0 + 1/2} B^{1/2 - \mu_0} \lambda^{(1/2 - \mu_0)\alpha} \right\} \\
\leq \max\left\{ \sqrt{BD}, c^{-1} \lambda^{\mu_0 + 1/2} B^{1/2 - \mu_0} \right\} \varphi(\lambda) \lambda^{\alpha(\mu_0 - 1/2) - \mu_0}.
\] (2.9)

Similarly computation shows that, for \( \mu_0 \geq 1/2 \),

\[
\sup_{0 < \sigma \leq \infty} |g_\lambda(\sigma)|^{1/2} |\varphi(\sigma)| \leq \max\left\{ \sqrt{BD}, c^{-1} \lambda^{2\mu_0 - 1} \right\} \varphi(\lambda) \lambda^{-\mu_0}.
\] (2.10)

Thus, the last inequality holds, and we complete the proof. \( \square \)
By taking $s = 1/2$ in (2.1), we have

$$\sup_{0 < \sigma \leq 2} |1 - g_1(\sigma)| \sigma^{1/2} \leq \gamma^{1-1/2n_0} \lambda_0^{1/2} \lambda^{1/2}. \quad (2.11)$$

The estimates of operator norm mainly adopt the following classical argument in operator theory. Argument: let $A$ be a positive operator in a Hilbert space, for $f \in C[0, \|A\|]$, then $f(A)$ is self-adjoint by [17, Proposition 4.4.7] and $\sigma(f(A)) = \{f(t) : t \in \sigma(A)\}$ by [17, Theorem 4.4.8] where $\sigma(A)$ is the spectral set of $A$. Consequently, $\|f(A)\| \leq \|f\|_\infty$.

The following probability inequality concerning random variables with values in a Hilbert space is proved in [18].

**Lemma 2.2.** Let $H$ be a Hilbert space and $\xi$ a random variable on $(\mathbb{Z}, \rho)$ with values in $H$. Assume $\|\xi\| \leq M < \infty$ almost surely. Denote $\sigma^2(\xi) = E(\|\xi\|^2)$, Let $\{z_i\}_{i=1}^m$ be independent random drawers of $\rho$. For any $0 < \delta < 1$, with confidence $1 - \delta$, there holds

$$\left\| \frac{1}{m} \sum_{i=1}^m [\xi(z_i) - E(\xi)] \right\| \leq \frac{2M \log(2/\delta)}{m} + \sqrt{\frac{2\sigma^2(\xi) \log(2/\delta)}{m}}. \quad (2.12)$$

Let $\text{HS}(\mathcal{H}_K)$ be the class of all the Hilbert Schmidt operators on $\mathcal{H}_K$. It forms a Hilbert space with inner product

$$\langle T, S \rangle_{\text{HS}} := \sum_{i=1}^\infty \langle T\varphi_i, S\varphi_i \rangle_K, \quad (2.13)$$

where $\varphi_i$ is an orthonormal basis of $\mathcal{H}_K$ and this definition does not depend on the choice of the basis. The integral operator $L_K$, as an operator on $\mathcal{H}_K$, belongs to $\text{HS}(\mathcal{H}_K)$ and $\|L_K\|_{\text{HS}} \leq \kappa^2$ (see [9]). By Lemma 2.2, we can estimate the following operator norms.

**Lemma 2.3.** Let $x = \{x_i\}_{i=1}^m$ be a sample set i.i.d drawn from $(X, \rho_X)$. With confidence $1 - \delta$, we have

$$\|L_K - S_x^T S_x\| \leq \kappa^2 \left( \frac{2\log(2/\delta)}{m} + \sqrt{\frac{2\log(2/\delta)}{m}} \right). \quad (2.14)$$

**Proof.** Observe that $S_x^T S_x = (1/m) \sum_{i=1}^m K(x_i, \cdot)_K$. Denote $S_x^T S_x = (1/m) \sum_{i=1}^m \xi(x_i)$. Here $\xi$ is the random variable on $(X, \rho_X)$ given by $\xi(x) = K_x(\cdot, K_x)_K$.

Consider

$$\langle \xi(x), \xi(x) \rangle_{\text{HS}} = \sum_{i=1}^\infty \langle K_x(\varphi_i, K_x)_K, K_x(\varphi_i, K_x)_K \rangle_K = \sum_{i=1}^\infty \|\varphi_i, K_x\|_K^2 \kappa(x, x) \leq \kappa^4. \quad (2.15)$$

For $x \in X$ and $f \in \mathcal{H}_K$, the reproducing property insures that

$$\xi(x)(f) = K_x(f, K_x)_K = f(x)K_x. \quad (2.16)$$
Lemma 2.4. Under the assumption of Lemma 2.1. Let

\[ (L_K - S_x^T S_x) = E \xi - \frac{1}{m} \sum_{i=1}^{m} \xi(x_i). \]  

(2.17)

According to (2.15), there holds \( \sigma^2(\xi) = E \| \xi \|_{\text{HS}}^2 \leq \kappa^4 \). Inequality (2.14) then follows from (2.12) and the fact that \( \| L_K - S_x^T S_x \| \leq \| L_K - S_x^T S_x \|_{\text{HS}} \). \qed

**Lemma 2.4.** Under the assumption of Lemma 2.1. Let \( z = \{ z_i \}_{i=1}^{m} \) be a sample i.i.d drawn from \((Z, \rho)\). With confidence \( 1 - \delta \), we have

\[ \| S_x^T y - T_x f_1 \|_K \leq 2\kappa \left( M + \kappa \beta_2 R \varphi(\lambda) \lambda^{-\mu_0 + \min \{ \alpha(\mu_0 - 1/2), 0 \}} \right) \log \frac{2/\delta}{m} + \beta_1 \min \{ \mu_0, \nu_0 - 1/2 \} (\alpha - 1) + \alpha/2 \]

\[ \times \left( \varphi(\lambda) \min \{ 2\nu_0 - 1, 2\nu_0 - 1 \} \right) + \kappa \left( \alpha_1 \lambda^{(\alpha - 1)\mu_0} \varphi(\lambda) R + c_\rho \right) \sqrt{\frac{2 \log(2/\delta)}{m}}. \]

(2.18)

**Proof.** Define \( \zeta = (f_1(x) - y)K_x \), so \( \zeta \) is a random variable from \( Z \) to \( \mathcal{K} \). Combing the reproducing property with Cauchy-Schwartz inequality, we get

\[ \| f_1 \|_\infty = \sup_{x \in X} | \langle f_1, K_x \rangle | \leq \kappa \| f_1 \|_K. \]  

(2.19)

Since \( L_K^{-1/2} \) is an isometric isomorphism from \((\mathcal{K}, \| \cdot \|_K)\) onto \((\mathcal{K}, \| \cdot \|_K)\) (see [16]), we obtain

\[ \| f_1 \|_K = \left\| G_1(L_K) L_K^{-1/2} \varphi(L_K) L_K^{1/2} h_0 \right\|_K \]

\[ \leq \left\| G_1(L_K) L_K^{-1/2} \varphi(L_K) \right\|_K \times \| h_0 \|_{\rho x} \]

\[ \leq \sup_{0 \leq t \leq x^2} \left| G_1(t) t^{1/2} \varphi(t) \right| \times R \]

\[ \leq \beta_2 \varphi(\lambda) \lambda^{\min \{ \alpha(\mu_0 - 1/2), 0 \} - \mu_0} R, \]  

(2.20)

where the last inequality follows from (2.4).

By \( |y| \leq M \) almost surely, there holds

\[ \| \zeta \|_K = \left\langle (f_1(x) - y)K_x, (f_1(x) - y)K_x \right\rangle \leq \kappa^2 \left( M + \kappa \beta_2 \varphi(\lambda) \lambda^{\min \{ \alpha(\mu_0 - 1/2), 0 \} - \mu_0} R \right)^2. \]  

(2.21)
By (2.3) and $L_K f_\rho = L_K f_{\rho}^+$, we get

$$E\|\epsilon\|_K = \|L_K (f_\rho - f_\lambda)\|_K = \|L_K (f_{\rho}^+ - f_\lambda)\|_K = \|L_K \varphi(L_K)(I - g_1(L_K)h_0)\|_K$$

$$\leq \left\| (I - g_1(L_K)h_0) \right\|_K \right\| L_K^{1/2} \left\| \left\| \varphi(L_K) \right\|_K$$

$$\leq \beta_1 R \lambda^{\min\{\mu_0, \nu_0 - 1/2\} (\alpha - 1/2) \varphi(\lambda)}_{(2n - 1)/2 \nu_0, 1}\right\|_K.$$

$$E\|\epsilon\|^2 = E(y - f_\lambda(x))^2 K(x, x)$$

$$\leq \kappa^2 \left( \int_Z (y - f_\rho(x))^2 \right) + \int_X (f_\rho(x) - f_{\rho}^+(x))^2 d\rho x + \int_X (f_{\rho}^+(x) - f_\lambda(x))^2 d\rho x$$

$$\leq \kappa^2 \left( \alpha_1 \lambda^{2(\alpha - 1) \mu_0} \varphi(\lambda) R^2 + \int_Z (y - f_\rho(x))^2 + \|f_\rho - f_{\rho}^+\|\rho x|^2$$

(2.22)

where, in the last step, we used the result of Proposition 3.1 in Section 3. For simplicity, we write $c_\rho^2$ for $\int_Z (y - f_\rho(x))^2 d\rho + \|f_\rho - f_{\rho}^+\|\rho x|^2$. Applying Lemma 2.2, there holds

$$\left\| \frac{1}{m} \sum_{i=1}^m [\epsilon(z_i) - E\epsilon] \right\|_K \leq 2 \kappa \left( M + \kappa \beta_2 R \lambda^{\mu_0 + \min\{\alpha(\mu_0 - 1/2), 0\}} \right) \frac{\log(2/\delta)}{m}$$

$$+ \kappa \left( \alpha_1 \lambda^{(\alpha - 1) \mu_0} \varphi(\lambda) R + c_\rho \right) \sqrt{\frac{2 \log(2/\delta)}{m}}.$$  

Then, we can use the following inequality to get the desired error bound,

$$\left\| S_k y - T_k f_\lambda \right\|_K \leq \left\| \frac{1}{m} \sum_{i=1}^m [\epsilon(z_i) - E\epsilon] \right\|_K + \left\| E\epsilon \right\|_K.$$  

(2.24)

This completes the proof of Lemma 2.4.

\[ \square \]

3. Error Analysis

**Proposition 3.1.** Let $\varphi$ be an index function with $\mu_0 > 0$ covering $\varphi$ and $\nu_0 > \max\{1/2, \mu_0\}$, so under the assumptions of (1.21), there holds $\|f_\lambda - f_{\rho}^+\|\rho x \leq \alpha_1 \lambda^{(\alpha - 1) \mu_0} \varphi(\lambda) R$.

**Proof.** From the definition of $f_\lambda$ and $f_{\rho}^+$, we have

$$f_\lambda - f_{\rho}^+ = g_1(L_K)h_0 - (g_1(L_K)L_K - I)\varphi(L_K)h_0.$$

(3.1)
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So the following error estimation holds

\[ \| f_1 - f_\cdot^+ \|_{px} \leq \| (g_\lambda (L_K) L_K - I) \varphi(L_K) \| \times \| h_0 \|_{px} \]

\[ \leq \sup_{0 < \sigma \leq K^2} \left| (g_\lambda(\sigma) \sigma - 1) \varphi(\sigma) \right| \times \| h_0 \|_{px} \]

\[ \leq \alpha_1 \lambda^{(a-1)/2} \varphi(\lambda) R, \]

where the last inequality follows from (2.2).

Let us focus on the estimation of sample error. Consider

\[ \| f_\lambda^1 - f_\cdot^1 \|_{px} = \left\| T^{1/2}_K (f_\lambda^1 - f_\cdot^1) \right\|_K \leq \left\| T^{1/2}_K (g_\lambda(T_x)T_x - I) f_\lambda^1 - (g_\lambda(T_x)T_x - I) L^{1/2}_K f_\cdot^1 \right\|_K \]

\[ + \left\| (g_\lambda(T_x)T_x - I) g_\lambda(L_K) L_K \varphi(L_K) L^{1/2}_K h_0 \right\|_K + \left\| L^{1/2}_K g_\lambda(T_x) \left( S_T y - T_x f_\cdot \right) \right\|_K \]

\[ := \| I_1 \|_K + \| I_2 \|_K + \| I_3 \|_K. \] (3.3)

The idea is to separately bound each term in \( \mathcal{R}_K \). We start dealing with the first term of (3.3). Consider

\[ I_1 = \left( L^{1/2}_K - T^{1/2}_x \right) \left( g_\lambda(T_x)T_x - I \right) (\varphi(L_K) - \varphi(T_x)) g_\lambda(L_K) L^{1/2}_K L^{1/2}_K h_0 \]

\[ + \left( L^{1/2}_K - T^{1/2}_x \right) \left( g_\lambda(T_x)T_x - I \right) \varphi(T_x) g_\lambda(L_K) L^{1/2}_K L^{1/2}_K h_0 \]

\[ + \left( g_\lambda(T_x)T_x - I \right) \left( T^{1/2}_x - L^{1/2}_K \right) \varphi(L_K) g_\lambda(L_K) L^{1/2}_K L^{1/2}_K h_0 \]

\[ = I_1 + I_2 + I_3. \] (3.4)

According to (1.4) and (1.5), we derive the following bound:

\[ \left\| g_\lambda(L_K) L^{1/2}_K \right\| \leq \sup_{0 < \sigma \leq K^2} \left| g_\lambda(\sigma) \sigma^{1/2} \right| \leq \sup_{0 < \sigma \leq K^2} \sqrt{|g_\lambda(\sigma)|} \times \sqrt{|g_\lambda(\sigma)|} \]

\[ \leq \lambda^{-a/2} \sqrt{D \bar{B}}. \] (3.5)

Now, we are in the position to bound (3.4).
Suppose that $m \geq 2 \log(4/\delta)$, then

\[
\kappa^2 \left( \frac{2 \log(4/\delta)}{m} + \sqrt{\frac{2 \log(4/\delta)}{m}} \right) \leq 2 \kappa \sqrt{\frac{2 \log(4/\delta)}{m}} := \zeta.
\]

\[
2\kappa \left( M + \kappa \beta^2 R \varphi(\lambda) \lambda^{-\mu_0 + \min[\alpha(\mu_0 - 1/2), 0]} \right) \frac{\log(4/\delta)}{m} + \kappa \left( M + \alpha_1 \lambda^{(a-1)\mu_0} R + c_\rho \right) \sqrt{\frac{2 \log(4/\delta)}{m}}
\]

\[
+ \beta_1 R \lambda^{\min[\alpha(\mu_0 - 1/2), 0]} (\varphi(\lambda))^{\min(2\nu_0 - 1/2\mu_0, 1)}
\]

\[
\leq C_0 \left( \varphi(\lambda) \lambda^{-\mu_0 + \min[\alpha(\mu_0 - 1/2), 0]} \right) m^{-1} \log \frac{4}{\delta} + \left( 1 + \varphi(\lambda) \lambda^{(a-1)\mu_0} \right) m^{-1/2} \sqrt{\log \frac{4}{\delta}}
\]

\[
+ \lambda^{\min[\mu_0, \nu_0 - 1/2](a-1)\mu_0}(\varphi(\lambda))^{\min(2\nu_0 - 1/2\mu_0, 1)}
\]

\[
:= C_0 \eta.
\]

(3.6)

By Lemmas 2.3 and 2.4, with confidence $1 - \delta$, the following inequalities hold simultaneously:

\[
\left\| L_K - S_x^T S_x \right\| \leq \zeta, \quad \left\| S_x^T y - T_x f_\lambda \right\|_{K} \leq C_0 \eta.
\]

(3.7)

Combining (1.6), (3.5) together with the operator monotonicity property of $\varphi(t)$ and $t^{1/2}$, we obtain

\[
\| J_1 \|_K \leq \left\| L_K^{1/2} - T_x^{1/2} \right\| \times \left\| g_1(T_x) T_x - I \right\| \times \left\| \varphi(L_K) - \varphi(T_x) \right\|
\]

\[
\times \left\| g_1(L_K) L_K^{1/2} \right\| \times \left\| L_K^{1/2} h_0 \right\|_K
\]

\[
\leq c_{\varphi} \gamma \sqrt{DB} \lambda^{-\mu_0/2} \left\| L_K - T_x \right\|^{1/2} \times \varphi(\left\| L_K - T_x \right\|)
\]

\[
\leq c_{\varphi} \gamma \sqrt{DB} \lambda^{-\mu_0/2} \eta^{1/2} \varphi(\zeta).
\]

(3.8)

By Lemma 2.1 and (3.5),

\[
\| J_2 \|_K \leq \left\| L_K^{1/2} - T_x^{1/2} \right\| \times \left\| (g_1(T_x) T_x - I) \varphi(T_x) \right\| \times \left\| g_1(L_K) L_K^{1/2} \right\| \times \left\| L_K^{1/2} h_0 \right\|_K
\]

\[
\leq R \sqrt{DB} \left\| L_K - T_x \right\|^{1/2} \times \alpha_1 \lambda^{(a-1)\mu_0 - \alpha/2} \varphi(\lambda)
\]

\[
\leq \alpha_1 R \sqrt{DB} \eta^{1/2} \varphi(\lambda) \lambda^{(a-1)\mu_0 - \alpha/2}.
\]

(3.9)
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For the purpose of bounding $\|J_3\|_K$, we rewritten $J_3$ as the following form:

$$J_3 = (g_\lambda(T_x)T_x - I)T_x^{1/2}(\varphi(L_K) - \varphi(T_x))g_\lambda(L_K)L_K^{1/2}h_0$$

$$+ (g_\lambda(T_x)T_x - I)T_x^{1/2}\varphi(T_x)g_\lambda(L_K)L_K^{1/2}h_0$$

$$- (g_\lambda(T_x)T_x - I)(\varphi(L_K) - \varphi(T_x))g_\lambda(L_K)L_K^{1/2}h_0$$

$$- (g_\lambda(T_x)T_x - I)\varphi(T_x)g_\lambda(L_K)L_K^{1/2}h_0.$$  \(3.10\)

In the same way, we have that

$$\|J_3\|_K \leq \gamma^{1-1/2\nu_0} \gamma^{1/2\nu_0} R\sqrt{DB}\varphi(\xi) + \beta_1\lambda^{\min(\mu_0,\nu_0-1/2)(\alpha-1)}(\varphi(\lambda))^{\min(2\nu_0-1)/2\mu_0,1}\sqrt{DBR}$$

$$+ \gamma R\varphi(\xi) + \alpha_1\lambda^{(\alpha-1)\mu_0}.$$ \(3.11\)

Thus, we can get the bound for $\|I_1\|_K$ by combining (3.8), (3.9), and (3.11). What left is to estimate $\|I_2\|_K$ and $\|I_3\|_K$, we can employ the same way used in the estimation of $\|I_1\|_K$.

Consider

$$\|I_2\|_K \leq \left\|(g_\lambda(T_x)T_x - I)(\varphi(L_K) - \varphi(T_x))g_\lambda(L_K)L_K^{1/2}h_0\right\|_K$$

$$+ \left\|(g_\lambda(T_x)T_x - I)\varphi(T_x)g_\lambda(L_K)L_K^{1/2}h_0\right\|_K$$

$$\leq \gamma R\varphi(\xi) + \alpha_1 R\varphi(\lambda)\lambda^{(\alpha-1)\mu_0},$$ \(3.12\)

$$\|I_3\|_K \leq \left\|(L_K^{1/2} - T_x^{1/2})g_\lambda(T_x)(S_x^Ty - T_xf_\lambda)\right\|_K$$

$$+ \left\|T_x^{1/2}g_\lambda(T_x)S_x^Ty - T_xf_\lambda\right\|_K$$

$$\leq C_0\lambda^{-\delta}\alpha_2^{1/2}\eta + C_0\sqrt{DB}\eta\lambda^{(\alpha-1)\mu_0}.$$ \(3.13\)

Lastly, combining (3.8) to (3.13) with Proposition 3.1, we have Theorem 1.5 holds.

4. Learning Rates

Significance of this paper lies in two facts; firstly, we generalize the definition of regularization and enrich the content of spectral regularization algorithms; secondly, analysis of this paper is able to undertake on the very general prior condition (1.21). Thus, our results can be applied to many different kinds of regularization, such as regularized least square learning, coefficient regularization learning, and (accelerate) landweber iteration and spectral cutoff. In this section, we will choose a suitable index function and apply Theorem 1.5 to some specific algorithms mentioned in Section 1.

4.1. Least Square Regularization

In this case, the regularization is $g_\lambda(\sigma) = 1/(\sigma + \lambda), \lambda \in (0,1]$ with $B = D = \gamma = \gamma_0 = \alpha = 1$. The qualification of this algorithm is $\nu_0 = 1$. Suppose $\varphi(t) = t^\sigma$ with $0 < \sigma \leq 1$, that means $f_\lambda = L_K^{1/2}h_0, h_0 \in L^{2,1}(X)$. Thus, we have that $\mu_0 = r$ covering $\varphi(t)$.
Using the result of Theorem 1.5, we obtain the following corollary.

**Corollary 4.1.** Under the assumptions of Theorem 1.5, we have the following.

(i) For $0 < r \leq 1/2$, with confidence $1 - \delta$, there holds

$$\| f^1_z - f^+_{\tilde{\varphi}} \|_{\rho_X} \leq O\left( \left( \lambda^r + m^{-r/2} + \lambda^{-1/2} m^{-3/4} \right) \left( 1 + \lambda^{-1/2} m^{-1/4} \right) \left( \log \frac{4}{\delta} \right)^{5/4} \right).$$

(4.1)

By taking $\lambda = m^{-1/2}$, we have the following learning rate:

$$\| f^1_z - f^+_{\tilde{\varphi}} \|_{\rho_X} \leq O\left( \left( m^{-r/2} \left( \log \frac{4}{\delta} \right)^{5/4} \right) \right).$$

(4.2)

(ii) For $1/2 \leq r < 1$, with confidence $1 - \delta$, there holds

$$\| f^1_z - f^+_{\tilde{\varphi}} \|_{\rho_X} \leq O\left( \left( \lambda^{1/2} + \lambda^{-1/2} m^{-1/2} + \lambda^{-1/2} m^{-3/4} + m^{-1/4} \right) \left( \log \frac{4}{\delta} \right)^{5/4} \right).$$

(4.3)

By taking $\lambda = m^{-1/2}$, we have the following learning rate:

$$\| f^1_z - f^+_{\tilde{\varphi}} \|_{\rho_X} \leq O\left( \left( m^{-1/4} \left( \log \frac{4}{\delta} \right)^{5/4} \right) \right).$$

(4.4)

### 4.2. Coefficient Regularization with the $L^2$ Norm

In this case, the regularization is $g_1(\gamma) = \sigma/(\sigma^2 + \lambda)$, $\lambda \in (0,1]$ with $B = D = \gamma = \gamma_0 = 1$, $\alpha = 1/2$. The qualification is $\nu = 2$. We also consider the index function $\varphi(t) = t^r$ with $0 < r \leq 1$ and $\mu_0 = r$.

**Corollary 4.2.** Under the assumptions of Theorem 1.5, we have the following.

(i) For $0 < r \leq 1/2$, with confidence $1 - \delta$, there holds

$$\| f^1_z - f^+_{\tilde{\varphi}} \|_{\rho_X} \leq O\left( \left( 1 + \lambda^{-1/4} m^{-1/4} \right) \left( \lambda^{r/2} + m^{-r/2} + m^{-1/2} \lambda^{-1/4} + m^{-1/4} \lambda^{1/2} \right) \left( \log \frac{4}{\delta} \right)^{5/4} \right).$$

(4.5)

By taking $\lambda = m^{-1}$, we have the following learning rate:

$$\| f^1_z - f^+_{\tilde{\varphi}} \|_{\rho_X} \leq O\left( m^{-r/2} \left( \log \frac{4}{\delta} \right)^{5/4} \right).$$

(4.6)
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(ii) For \( 1/2 \leq r \leq 1 \), with confidence \( 1 - \delta \), there holds

\[
\| f_z^1 - f_{\mathcal{X}}^1 \|_{\rho_X} \leq O \left( \left( 1 + \lambda^{-1/4} m^{-1/4} \right) \left( 1^{r/2} + m^{-r/2} + m^{-1/2} \lambda^{-1/4} \right) \left( \log \frac{4}{\delta} \right)^{5/4} \right). \tag{4.7}
\]

By taking \( \lambda = m^{2/(2r+1)} \), we have the following learning rate:

\[
\| f_z^1 - f_{\mathcal{X}}^1 \|_{\rho_X} \leq O \left( m^{-r/(2r+1)} \left( \log \frac{4}{\delta} \right)^{5/4} \right). \tag{4.8}
\]

For coefficient regularization, the learning rates derived by Theorem 1.5 are almost the same, see Corollary 5.2 in [2]. For least square regularization, the learning rates in Corollary 4.1 are weak, the analysis in [8] by integral operator method gives learning rate \( O(m^{-3r/(4(1+r))}) \) for \( 0 < r \leq 1/2 \); leave one out analysis in [11] gives the rate \( O(m^{-r/(1+2r)}) \).

Our analysis is influenced by both the prior condition and the regularization. Under the weaker prior condition (1.21), some techniques for error analysis in [1] are inapplicable; we take more complicated error decomposition and refined analysis to estimate error bounds and learning rates.

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