A Unifying Framework for Vector-valued Manifold Regularization and Multi-view Learning - Supplementary Material

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Abstract

The Supplementary Material contains three elements. First, in Section 1, we give the proofs for all the main mathematical results in the paper. Second, in Section 2, we provide a natural generalization of our framework to the case the point evaluation operator $f(x)$ is replaced by a general bounded linear operator. Last, in Section 3, we provide an exact description of Algorithm 1 with the Gaussian or similar kernels in the degenerate case, when the kernel width $\sigma \to \infty$.

1. Proofs of Main Results

For clarity, we restate all the results in the main paper that we prove here.

Notation: the definition of $\mathbf{f}$ as given by

$$\mathbf{f} = (f(x_1), \ldots, f(x_{u+l})) \in \mathcal{W}^{u+l}, \tag{1}$$

is adopted because it is also applicable when $\mathcal{W}$ is an infinite-dimensional Hilbert space. For $\mathcal{W} = \mathbb{R}^m$,

$$\mathbf{f} = (f^1(x_1), \ldots, f^m(x_1), \ldots, f^1(x_{u+l}), \ldots, f^m(x_{u+l})).$$

This is different from (Rosenberg et al., 2009), where

$$\mathbf{f} = (f^1(x_1), \ldots, f^1(x_{u+l}), \ldots, f^m(x_1), \ldots, f^m(x_{u+l})).$$

This means that our matrix M is necessarily a permutation of the matrix M in (Rosenberg et al., 2009) when they give rise to the same semi-norm.

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1.1. Proof of the Representer Theorem

Recall our general minimization problem

$$f_{\mathbf{z},\gamma} = \text{argmin}_{f \in \mathcal{H}_K} \frac{1}{l} \sum_{i=1}^{l} V(y_i, Cf(x_i)) + \gamma_A ||f||^2_{\mathcal{H}_K} + \gamma_I \langle \mathbf{f}, M\mathbf{f} \rangle_{\mathcal{W}^{u+l}}, \tag{2}$$

and its least square version

$$f_{\mathbf{z},\gamma} = \text{argmin}_{f \in \mathcal{H}_K} \frac{1}{l} \sum_{i=1}^{l} ||y_i - Cf(x_i)||^2_{\mathcal{Y}} + \gamma_A ||f||^2_{\mathcal{H}_K} + \gamma_I \langle \mathbf{f}, M\mathbf{f} \rangle_{\mathcal{W}^{u+l}}. \tag{3}$$

Theorem 1. *The minimization problem (2) has a unique solution, given by $f_{\mathbf{z},\gamma} = \sum_{i=1}^{u+l} K_{x_i} a_i$ for some vectors $a_i \in \mathcal{W}$, $1 \leq i \leq u+l$.*

The following is a generalization of the proof for the Representer Theorem in (Minh & Sindhwani, 2011). Since $f(x) = K_x^* f$, the minimization problem (2) is

$$f_{\mathbf{z},\gamma} = \text{argmin}_{f \in \mathcal{H}_K} \frac{1}{l} \sum_{i=1}^{l} V(y_i, CK_{x_i}^* f) + \gamma_A ||f||^2_{\mathcal{H}_K} + \gamma_I \langle \mathbf{f}, M\mathbf{f} \rangle_{\mathcal{W}^{u+l}}. \tag{4}$$

Consider the operator $E_{C,\mathbf{x}} : \mathcal{H}_K \to \mathcal{Y}^l$, defined by

$$E_{C,\mathbf{x}} f = (CK_{x_1}^* f, \ldots, CK_{x_l}^* f), \tag{5}$$

with $CK_{x_i}^* : \mathcal{H}_K \to \mathcal{Y}$ and $K_{x_i} C^* : \mathcal{Y} \to \mathcal{H}_K$. For $\mathbf{b} = (b_1, \ldots, b_l) \in \mathcal{Y}^l$, we have

$$\langle \mathbf{b}, E_{C,\mathbf{x}} f \rangle_{\mathcal{Y}^l} = \sum_{i=1}^{l} \langle b_i, CK_{x_i}^* f \rangle_{\mathcal{Y}}$$

$$= \sum_{i=1}^{l} \langle K_{x_i} C^* b_i, f \rangle_{\mathcal{H}_K} = \langle \sum_{i=1}^{l} K_{x_i} C^* b_i, f \rangle_{\mathcal{H}_K}.$$

The adjoint operator $E^*_{C,\mathbf{x}} : \mathcal{Y}^l \to \mathcal{H}_K$ is thus

$$E^*_{C,\mathbf{x}} : (b_1, \ldots, b_l) \to \sum_{i=1}^{l} K_{x_i} C^* b_i. \tag{6}$$

The operator $E^*_{C,\mathbf{x}} E_{C,\mathbf{x}} : \mathcal{H}_K \to \mathcal{H}_K$ is then

$$E^*_{C,\mathbf{x}} E_{C,\mathbf{x}} f \to \sum_{i=1}^{l} K_{x_i} C^* C K^*_{x_i} f, \tag{7}$$

with $C^*C : \mathcal{W} \to \mathcal{W}$.

Proof of Theorem 1. Denote the right handside of (2) by $I_l(f)$. Then $I_l(f)$ is coercive and strictly convex in f, and thus has a unique minimizer. Let $\mathcal{H}_{K,\mathbf{x}} = \{\sum_{i=1}^{u+l} K_{x_i} w_i : \mathbf{w} \in \mathcal{W}^{u+l}\}$. For $f \in \mathcal{H}^{\perp}_{K,\mathbf{x}}$, by the reproducing property, $E_{C,\mathbf{x}}$ satisfies

$$\langle \mathbf{b}, E_{C,\mathbf{x}} f \rangle_{\mathcal{Y}^l} = \langle f, \sum_{i=1}^{l} K_{x_i} C^* b_i \rangle_{\mathcal{H}_K} = 0,$$

for all $\mathbf{b} \in \mathcal{Y}^l$, since $C^* b_i \in \mathcal{W}$. Thus

$$E_{C,\mathbf{x}} f = (C K^*_{x_1} f, \ldots, C K^*_{x_l} f) = 0.$$

Similarly, by the reproducing property, the sampling operator $S_{\mathbf{x}}$ satisfies

$$\langle S_{\mathbf{x}} f, \mathbf{w} \rangle_{\mathcal{W}^{u+l}} = \langle f, \sum_{i=1}^{u+l} K_{x_i} w_i \rangle_{\mathcal{H}_K} = 0,$$

for all $\mathbf{w} \in \mathcal{W}^{u+l}$. Thus

$$\mathbf{f} = S_{\mathbf{x}} f = (f(x_1), \ldots, f(x_{u+l})) = 0.$$

For an arbitrary $f \in \mathcal{H}_K$, consider the orthogonal decomposition $f = f_0 + f_1$, with $f_0 \in \mathcal{H}_{K,\mathbf{x}}$, $f_1 \in \mathcal{H}^{\perp}_{K,\mathbf{x}}$. Then, because $||f_0 + f_1||^2_{\mathcal{H}_K} = ||f_0||^2_{\mathcal{H}_K} + ||f_1||^2_{\mathcal{H}_K}$, the result just obtained shows that

$$I_l(f) = I_l(f_0 + f_1) \geq I_l(f_0)$$

with equality if and only if $||f_1||_{\mathcal{H}_K} = 0$, that is $f_1 = 0$. Thus the minimizer of (2) must lie in $\mathcal{H}_{K,\mathbf{x}}$. □

1.2. Proofs for the Least Square Case

Proposition 1. *The minimization problem (3) has a unique solution $f_{\mathbf{z},\gamma} = \sum_{i=1}^{u+l} K_{x_i} a_i$, where the vectors $a_i \in \mathcal{W}$ are given by*

$$l\gamma_I \sum_{j,k=1}^{u+l} M_{ik} K(x_k, x_j) a_j + C^*C(\sum_{j=1}^{u+l} K(x_i, x_j) a_j) + l\gamma_A a_i = C^* y_i, \tag{8}$$

for $1 \leq i \leq l$, and

$$\gamma_I \sum_{j,k=1}^{u+l} M_{ik} K(x_k, x_j) a_j + \gamma_A a_i = 0, \tag{9}$$

for $l+1 \leq i \leq u+l$.

The following is a generalization of the proof for Proposition 1 in (Minh & Sindhwani, 2011). We have

$$f_{\mathbf{z},\gamma} = \operatorname{argmin}_{f \in \mathcal{H}_K} \frac{1}{l} \sum_{i=1}^{l} ||y_i - C K^*_{x_i} f||^2_{\mathcal{Y}} + \gamma_A ||f||^2_K + \gamma_I \langle \mathbf{f}, M\mathbf{f} \rangle_{\mathcal{W}(u+l)}. \tag{10}$$

With the operator $E_{C,\mathbf{x}}$, (10) is transformed into the minimization problem

$$f_{\mathbf{z},\gamma} = \operatorname{argmin}_{f \in \mathcal{H}_K} \frac{1}{l} ||E_{C,\mathbf{x}} f - \mathbf{y}||^2_{\mathcal{Y}^l} + \gamma_A ||f||^2_K + \gamma_I \langle \mathbf{f}, M\mathbf{f} \rangle_{\mathcal{W}^{u+l}}. \tag{11}$$

Proof of Proposition 1. By the Representer Theorem, (3) has a unique solution. Differentiating (11) and setting the derivative to zero gives

$$(E^*_{C,\mathbf{x}} E_{C,\mathbf{x}} + l\gamma_A I + l\gamma_I S^*_{\mathbf{x},u+l} M S_{\mathbf{x},u+l}) f_{\mathbf{z},\gamma} = E^*_{C,\mathbf{x}} \mathbf{y}.$$

By definition of the operators $E_{C,\mathbf{x}}$ and $S_{\mathbf{x}}$, this is

$$\sum_{i=1}^{l} K_{x_i} C^* C K^*_{x_i} f_{\mathbf{z},\gamma} + l\gamma_A f_{\mathbf{z},\gamma} + l\gamma_I \sum_{i=1}^{u+l} K_{x_i} (M\mathbf{f}_{\mathbf{z},\gamma})_i = \sum_{i=1}^{l} K_{x_i} C^* y_i,$$

which we rewrite as

$$f_{\mathbf{z},\gamma} = -\frac{\gamma_I}{\gamma_A} \sum_{i=1}^{u+l} K_{x_i} (M\mathbf{f}_{\mathbf{z},\gamma})_i + \sum_{i=1}^{l} K_{x_i} \frac{C^* y_i - C^* C K^*_{x_i} f_{\mathbf{z},\gamma}}{l\gamma_A}.$$

This shows that there are vectors a_i's in $\mathcal{W}$ such that

$$f_{\mathbf{z},\gamma} = \sum_{i=1}^{u+l} K_{x_i} a_i.$$

We have $f_{\mathbf{z},\gamma}(x_i) = \sum_{j=1}^{u+l} K(x_i, x_j) a_j$, and

$$(M\mathbf{f}_{\mathbf{z},\gamma})_i = \sum_{k=1}^{u+l} M_{ik} \sum_{j=1}^{u+l} K(x_k, x_j) a_j = \sum_{j,k=1}^{u+l} M_{ik} K(x_k, x_j) a_j.$$

Also $K_{x_i}^* f_{\mathbf{z},\gamma} = f_{\mathbf{z},\gamma}(x_i) = \sum_{j=1}^{u+l} K(x_i, x_j)a_j$. Thus for $1 \leq i \leq l$:

$$a_i = -\frac{\gamma_I}{\gamma_A} \sum_{j,k=1}^{u+l} M_{ik} K(x_k, x_j) a_j + \frac{C^* y_i - C^* C(\sum_{j=1}^{u+l} K(x_i, x_j) a_j)}{l\gamma_A},$$

which gives the formula

$$l\gamma_I \sum_{j,k=1}^{u+l} M_{ik} K(x_k, x_j) a_j + C^* C(\sum_{j=1}^{u+l} K(x_i, x_j) a_j) + l\gamma_A a_i = C^* y_i.$$

Similarly, for $l+1 \leq i \leq u+l$,

$$a_i = -\frac{\gamma_I}{\gamma_A} \sum_{j,k=1}^{u+l} M_{ik} K(x_k, x_j) a_j,$$

which is equivalent to

$$\gamma_I \sum_{j,k=1}^{u+l} M_{ik} K(x_k, x_j) a_j + \gamma_A a_i = 0.$$

This completes the proof. □

Proposition 2.

$$(\mathbf{C}^* \mathbf{C} J_l^{\mathcal{W},u+l} K[\mathbf{x}] + l\gamma_I M K[\mathbf{x}] + l\gamma_A I)\mathbf{a} = \mathbf{C}^* \mathbf{y}, \quad (12)$$

where $\mathbf{a} = (a_1, \ldots, a_{u+l})$, $\mathbf{y} = (y_1, \ldots, y_{u+l})$ are considered as column vectors in $\mathcal{W}^{u+l}$ and $\mathcal{Y}^{u+l}$, respectively, and $y_{l+1} = \cdots = y_{u+l} = 0$.

Proof of Proposition 2. This is straightforward to obtain from Proposition 1 using the operator-valued matrix formulation described in the main paper. □

Proposition 3. *For $C = \mathbf{c}^T \otimes I_P$, $\mathbf{c} \in \mathbb{R}^m$, $M_W = L \otimes I_P$, $M_B = I_{u+l} \otimes (M_m \otimes I_P)$, the system of linear equations (12) in Proposition 2 is equivalent to*

$$BA = Y_C, \quad (13)$$

where

$$B = \left((J_l^{u+l} \otimes \mathbf{c}\mathbf{c}^T) + l\gamma_B (I_{u+l} \otimes M_m) + l\gamma_W L\right) G[\mathbf{x}] + l\gamma_A I_{(u+l)m}, \quad (14)$$

which is of size $(u+l)m \times (u+l)m$, A is the matrix of size $(u+l)m \times P$ such that $\mathbf{a} = \mathrm{vec}(A^T)$, and Y_C is the matrix of size $(u+l)m \times P$ such that $\mathbf{C}^* \mathbf{y} = \mathrm{vec}(Y_C^T)$. $J_l^{u+l} : \mathbb{R}^{u+l} \to \mathbb{R}^{u+l}$ is a diagonal matrix of size $(u+l) \times (u+l)$, with the first l entries on the main diagonal being 1 and the rest being 0.

Proof of Proposition 3. Recall some properties of the Kronecker tensor product:

$$(A \otimes B)(C \otimes D) = AC \otimes BD, \quad (15)$$

$$(A \otimes B)^T = A^T \otimes B^T, \quad (16)$$

and

$$\mathrm{vec}(ABC) = (C^T \otimes A)\mathrm{vec}(B). \quad (17)$$

Thus the equation

$$AXB = C \quad (18)$$

is equivalent to

$$(B^T \otimes A)\mathrm{vec}(X) = \mathrm{vec}(C). \quad (19)$$

In our context,$\gamma_I M = \gamma_B M_B + \gamma_W M_W$, which is

$$\gamma_I M = \gamma_B I_{u+l} \otimes M_m \otimes I_P + \gamma_W L \otimes I_P.$$

$$\mathbf{C}^* = I_{u+l} \otimes C^*.$$

Using the property stated in Equation (16), we have for $C = \mathbf{c}^T \otimes I_P$,

$$\mathbf{C}^* = I_{u+l} \otimes \mathbf{c} \otimes I_P \in \mathbb{R}^{Pm(u+l) \times P(u+l)}, \quad (20)$$

$$C^* C = (\mathbf{c} \otimes I_P)(\mathbf{c}^T \otimes I_P) = (\mathbf{c}\mathbf{c}^T \otimes I_P).$$

So then

$$\mathbf{C}^* \mathbf{C} = (I_{u+l} \otimes \mathbf{c}\mathbf{c}^T \otimes I_P). \quad (21)$$

$$J_l^{\mathcal{W},u+l} = J_l^{u+l} \otimes I_m \otimes I_P. \quad (22)$$

It follows that

$$\mathbf{C}^* \mathbf{C} J_l^{\mathcal{W},u+l} = (J_l^{u+l} \otimes \mathbf{c}\mathbf{c}^T \otimes I_P). \quad (23)$$

Then

$$\mathbf{C}^* \mathbf{C} J_l^{\mathcal{W},u+l} K[\mathbf{x}] = (J_l^{u+l} \otimes \mathbf{c}\mathbf{c}^T) G[\mathbf{x}] \otimes I_P.$$

$$\gamma_I M K[\mathbf{x}] = (\gamma_B I_{u+l} \otimes M_m + \gamma_W L) G[\mathbf{x}] \otimes I_P.$$

Consider again now the system

$$(\mathbf{C}^* \mathbf{C} J_l^{\mathcal{W},u+l} K[\mathbf{x}] + l\gamma_I M K[\mathbf{x}] + l\gamma_A I)\mathbf{a} = \mathbf{C}^* \mathbf{y}.$$

The left hand side is

$$(B \otimes I_P)\mathrm{vec}(A^T),$$

where $\mathbf{a} = \mathrm{vec}(A^T)$, A is of size $(u+l)m \times P$ and

$$B = \left((J_l^{u+l} \otimes \mathbf{c}\mathbf{c}^T) + l\gamma_B (I_{u+l} \otimes M_m) + l\gamma_W L\right) G[\mathbf{x}] + l\gamma_A I_{(u+l)m}.$$

Then we have the linear system

$$(B \otimes I_P)\mathrm{vec}(A^T) = \mathrm{vec}(Y_C^T),$$

which, by properties (18) and (19), is equivalent to

$$A^T B^T = Y_C^T \Longleftrightarrow BA = Y_C.$$

This completes the proof. □

Remark 1. The vec operator is implemented by the flattening operation (:) in MATLAB. To compute the matrix Y_C^T, note that by definition

$$\text{vec}(Y_C^T) = \mathbf{C}^*\mathbf{y} = (I_{u+l} \otimes C^*)\mathbf{y} = \text{vec}(C^*Y),$$

where Y is the $P \times (u+l)$ matrix with the ith column being y_i, with

$$\mathbf{y} = \text{vec}(Y).$$

Note that Y_C^T and C^*Y in general are not the same: Y_C^T is of size $P \times (u+l)m$, whereas C^*Y is of size $Pm \times (u+l)$.

2. Learning with General Bounded Linear Operators

The present framework generalizes naturally beyond the point evaluation operator

$$f(x) = K_x^* f.$$

Let $\mathcal{H}$ be a separable Hilbert space of functions on $\mathcal{X}$. We are *not* assuming that the functions in $\mathcal{H}$ are defined pointwise or with values in $\mathcal{W}$, rather we assume that $\forall x \in \mathcal{X}$, there is a bounded linear operator

$$E_x : \mathcal{H} \to \mathcal{W}, \quad ||E_x|| < \infty, \tag{24}$$

with adjoint $E_x^* : \mathcal{W} \to \mathcal{H}$. Consider the minimization

$$f_{\mathbf{z},\gamma} = \text{argmin}_{\mathcal{H}_K} \frac{1}{l}\sum_{i=1}^{l} V(y_i, CE_{x_i}f) + \gamma_A ||f||^2_{\mathcal{H}} + \gamma_I \langle \mathbf{f}, M\mathbf{f}\rangle_{\mathcal{W}^{u+l}}, \quad \text{where} \quad \mathbf{f} = (E_{x_i}f)_{i=1}^{u+l}, \tag{25}$$

and its least square version

$$f_{\mathbf{z},\gamma} = \text{argmin}_{\mathcal{H}_K} \frac{1}{l}\sum_{i=1}^{l} ||y_i - CE_{x_i}f||^2_{\mathcal{Y}} + \gamma_A ||f||^2_{\mathcal{H}} + \gamma_I \langle \mathbf{f}, M\mathbf{f}\rangle_{\mathcal{W}^{u+l}}. \tag{26}$$

Following are the corresponding Representer Theorem and Proposition stating the explicit solution for the least square case. When $\mathcal{H} = \mathcal{H}_K$, $E_x = K_x^*$, we recover Theorem 1 and Proposition 1, respectively.

Theorem 2. *The minimization problem (25) has a unique solution, given by $f_{\mathbf{z},\gamma} = \sum_{i=1}^{u+l} E_{x_i}^* a_i$ for some vectors $a_i \in \mathcal{W}$, $1 \leq i \leq u+l$.*

Proposition 4. *The minimization problem (26) has a unique solution $f_{\mathbf{z},\gamma} = \sum_{i=1}^{u+l} E_{x_i}^* a_i$, where the vectors $a_i \in \mathcal{W}$ are given by*

$$l\gamma_I \sum_{j,k=1}^{u+l} M_{ik} E_{x_k} E_{x_j}^* a_j + C^*C(\sum_{j=1}^{u+l} E_{x_i} E_{x_j}^* a_j) + l\gamma_A a_i = C^* y_i, \tag{27}$$

for $1 \leq i \leq l$, and

$$\gamma_I \sum_{j,k=1}^{u+l} M_{ik} E_{x_k} E_{x_j}^* a_j + \gamma_A a_i = 0, \tag{28}$$

for $l+1 \leq i \leq u+l$.

The reproducing kernel structures come into play through the following.

Lemma 1. *Let $E : \mathcal{X} \times \mathcal{X} \to \mathcal{L}(\mathcal{W})$ be defined by*

$$E(x,t) = E_x E_t^*. \tag{29}$$

Then E is a positive definite operator-valued kernel.

Proof of Lemma 1. For each pair $(x,t) \in \mathcal{X} \times \mathcal{X}$, the operator $E(x,t)$ satisfies

$$E(t,x)^* = (E_t E_x^*)^* = E_x E_t^* = E(x,t).$$

For every set $\{x_i\}_{i=1}^N$ in $\mathcal{X}$ and $\{w_i\}_{i=1}^N$ in $\mathcal{W}$,

$$\sum_{i,j=1}^{N} \langle w_i, E(x_i,x_j)w_j\rangle_{\mathcal{W}} = \sum_{i,j=1}^{N} \langle w_i, E_{x_i}E_{x_j}^* w_j\rangle_{\mathcal{W}}$$

$$= \sum_{i,j=1}^{N} \langle E_{x_i}^* w_i, E_{x_j}^* w_j\rangle_{\mathcal{H}} = ||\sum_{i=1}^{N} E_{x_i}^* w_i||^2_{\mathcal{H}} \geq 0.$$

Thus E is an $\mathcal{L}(\mathcal{W})$-valued positive definite kernel. □

Proofs of Theorem 2 and Proposition 4. These are entirely analogous to those of Theorem 1 and Proposition 1, respectively. Instead of the sampling operator $S_{\mathbf{x}}$, we consider the operator $E_{\mathbf{x}} : \mathcal{H} \to \mathcal{W}^l$, with

$$E_{\mathbf{x}} f = (E_{x_i} f)_{i=1}^{l}, \tag{30}$$

with the adjoint $E_{\mathbf{x}}^* : \mathcal{W}^l \to \mathcal{H}$ given by

$$E_{\mathbf{x}}^* \mathbf{b} = \sum_{i=1}^{l} E_{x_i}^* b_i. \tag{31}$$

for all $\mathbf{b} = (b_i)_{i=1}^l \in \mathcal{W}^l$. The operator $E_{C,\mathbf{x}} : \mathcal{H} \to \mathcal{Y}^l$ is now defined by

$$E_{C,\mathbf{x}} f = (CE_{x_1}f, \ldots, CE_{x_l}f). \tag{32}$$

The adjoint $E_{C,\mathbf{x}}^* : \mathcal{Y}^l \to \mathcal{H}$ is

$$E_{C,\mathbf{x}}^* \mathbf{b} = \sum_{i=1}^{l} E_{x_i}^* C^* b_i, \tag{33}$$

for all $\mathbf{b} \in \mathcal{Y}^l$, and $E_{C,\mathbf{x}}^* E_{C,\mathbf{x}} : \mathcal{H} \to \mathcal{H}$ is

$$E_{C,\mathbf{x}}^* E_{C,\mathbf{x}} f = \sum_{i=1}^{l} E_{x_i}^* C^* C E_{x_i} f. \tag{34}$$

We then apply all the steps in the proofs of Theorem 1 and Proposition 1 to get the desired results. □

Remark 2. We stress that in general, the function $f_{\mathbf{z},\gamma}$ is *not* defined pointwise, which is the case in the following example. Thus one cannot make a statement about $f_{\mathbf{z},\gamma}(x)$ for all $x \in \mathcal{X}$ without additional assumptions.

Example 1. (Wahba, 1977) $\mathcal{X} = [0,1]$, $\mathcal{H} = L^2(\mathcal{X})$, $\mathcal{W} = \mathbb{R}$. Let $G : \mathcal{X} \times \mathcal{X} \to \mathbb{R}$ be continuous and

$$E_x f = \int_0^1 G(x,t) f(t) dt. \tag{35}$$

for $f \in \mathcal{H}$. One has the reproducing kernel

$$E_x E_t^* = E(x,t) = \int_0^1 G(x,u) G(t,u) du. \tag{36}$$

3. The Degenerate Case

This section deals with the Gaussian kernel $k(x,t) = \exp\left(-\frac{||x-t||^2}{\sigma^2}\right)$ when $\sigma \to \infty$ and other kernels with similar behavior. We show that the matrix A in Proposition 3 has an analytic expression. This can be used to verify the correctness of an implementation of our algorithm. At $\sigma = \infty$, for each pair (x,t), we have

$$K(x,t) = I_{Pm}, \tag{37}$$

and

$$f_{\mathbf{z},\gamma}(x) = \sum_{i=1}^{u+l} K(x_i, x) a_i = \sum_{i=1}^{u+l} a_i. \tag{38}$$

Thus $f_{\mathbf{z},\gamma}$ is a constant function. Let us examine the form of the coefficients a_i's for the case

$$C = \frac{1}{m} \mathbf{e}_m^T \otimes I_P.$$

We have

$$G[\mathbf{x}] = \mathbf{e}_{u+l} \mathbf{e}_{u+l}^T \otimes I_m.$$

For $\gamma_I = 0$, we have

$$B = \frac{1}{m^2} (J_l^{u+l} \otimes \mathbf{e}_m \mathbf{e}_m^T)(\mathbf{e}_{u+l} \mathbf{e}_{u+l}^T \otimes I_m) + l\gamma_A I_{(u+l)m},$$

which is

$$B = \frac{1}{m^2} (J_l^{u+l} \mathbf{e}_{u+l} \mathbf{e}_{u+l}^T \otimes \mathbf{e}_m \mathbf{e}_m^T) + l\gamma_A I_{(u+l)m}.$$

Equivalently,

$$B = \frac{1}{m^2} (J_{ml}^{(u+l)m} \mathbf{e}_{(u+l)m} \mathbf{e}_{(u+l)m}^T) + l\gamma_A I_{(u+l)m}.$$

The inverse of B in this case has a closed form:

$$B^{-1} = \frac{I_{(u+l)m}}{l\gamma_A} - \frac{J_{ml}^{(u+l)m} \mathbf{e}_{(u+l)m} \mathbf{e}_{(u+l)m}^T}{l^2 m\gamma_A (m\gamma_A + 1)}, \tag{39}$$

where we have used the identity

$$\mathbf{e}_{(u+l)m} \mathbf{e}_{(u+l)m}^T J_{ml}^{(u+l)m} \mathbf{e}_{(u+l)m} \mathbf{e}_{(u+l)m}^T = ml \mathbf{e}_{(u+l)m} \mathbf{e}_{(u+l)m}^T. \tag{40}$$

We have thus

$$A = B^{-1} Y_C = \left(\frac{I_{(u+l)m}}{l\gamma_A} - \frac{J_{ml}^{(u+l)m} \mathbf{e}_{(u+l)m} \mathbf{e}_{(u+l)m}^T}{l^2 m\gamma_A (m\gamma_A + 1)} \right) Y_C. \tag{41}$$

Thus in this case we have an analytic expression for the coefficient matrix A, as we claimed.

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