

Supplementary Material for Density Ratio-Free Doubly Robust Proxy Causal Learning

Section (A) reviews our doubly robust identification result and proves Theorem (2.7). Section (B) outlines semiparametric theory and derives the efficient influence function for discrete treatments. In Section (C), we present derivations for our proposed algorithms: Doubly Robust Kernel Proxy Variable (DRKPV) and Doubly Robust Proxy Maximum Moment Restriction (DRPMMR). Section (D) discusses conditions for the existence of outcome and treatment bridge functions. Section (E) proves consistency of our methods. Section (F) details the experimental setup, including hyperparameter tuning and additional results.

A Doubly robust identification

Here, we prove Theorem (2.7). For completeness, we restate the theorem below.

Theorem A.1 (Doubly robust causal identification; Replica of Theorem (2.7)). *The dose-response can be identified with*

$$\theta_{ATE}^{(DR)}(a; h, \varphi) |_{(h=h_0, \varphi=\varphi_0)} = \mathbb{E}[\varphi_0(Z, a)(Y - h_0(W, a)) | A = a] + \mathbb{E}[h_0(W, a)],$$

where h_0 and φ_0 are the outcome and treatment bridge functions that satisfy Equations (1) and (2), respectively. Furthermore, $\theta_{ATE}^{(DR)}(a; h, \varphi)$ admits double robustness such that $\theta_{ATE}^{(DR)}$ identifies the dose-response curve if **either** h solves Equation (1) **or** φ solves Equation (2)—but not necessarily both.

Proof. To understand why $\theta_{ATE}^{(DR)}(a)$ exhibits double robustness, we consider the following two cases:

Case i: Suppose that h is correctly specified, i.e. $h = h_0$. Then,

$$\begin{aligned} \theta_{ATE}^{(DR)}(a; h_0, \varphi) &= \mathbb{E}[\varphi(Z, a)(Y - h_0(W, a)) | A = a] + \mathbb{E}[h_0(W, a)] \\ &= \int \varphi(z, a) \underbrace{\left(\int (y - h_0(w, a)) p(y, w|z, a) dy dw \right)}_{=0 \text{ due to Equation (1)}} p(z|a) dz + \mathbb{E}[h_0(W, a)] = \theta_{ATE}(a) \end{aligned}$$

where the final equality is due to Theorem (2.4).

Case ii: Now, suppose that φ is correctly specified, i.e., $\varphi = \varphi_0$. Then, we note that

$$\theta_{ATE}^{(DR)}(a; h, \varphi_0) = \mathbb{E}[Y \varphi_0(Z, a) | A = a] - \mathbb{E}[\varphi_0(Z, a) h(W, a) | A = a] + \mathbb{E}[h(W, a)]$$

First off, note that the first component $\mathbb{E}[Y \varphi_0(Z, a) | A = a]$ identifies the dose-response due to Theorem (2.6). Next, we consider the remaining two terms

$$\begin{aligned} & - \mathbb{E}[\varphi_0(Z, a) h(W, a) | A = a] + \mathbb{E}[h(W, a)] \\ &= - \int \int \varphi_0(z, a) h(w, a) p(z, w|a) dz dw + \mathbb{E}[h(W, a)] \\ &= - \int \int \varphi_0(z, a) h(w, a) p(z|w, a) p(w|a) dz dw + \mathbb{E}[h_0(W, a)] \\ &= - \int \left(\int \varphi_0(z, a) p(z|w, a) dz \right) h(w, a) p(w|a) dw + \mathbb{E}[h(W, a)] \\ &= - \int (\mathbb{E}[\varphi_0(Z, a) | w, a]) h(w, a) p(w|a) dw + \mathbb{E}[h_0(W, a)] \\ &= - \int \frac{p(w)}{p(w|a)} h(w, a) p(w|a) dw + \mathbb{E}[h(W, a)] = -\mathbb{E}[h(W, a)] + \mathbb{E}[h(W, a)] = 0, \end{aligned}$$

where the first equality in the last line above is due to Equation (2). \square

The following lemma is the direct implication of Theorem (2.7), which shows that the dose-response curve can also be identified with the conditional expectation of the multiplication of bridge functions.

Lemma A.2. Let h_0 and φ_0 be outcome and treatment bridge functions satisfying Equation (1) and (2), respectively. Then, the dose-response can be identified by the following slack function $\theta_{ATE}(a) = \mathbb{E}[\varphi_0(Z, a)h_0(W, a) \mid A = a]$.

Proof. As we observe in the second case of the proof of Theorem (2.7)

$$\mathbb{E}[\varphi_0(Z, a)h_0(W, a) \mid A = a] = \int \frac{p(w)}{p(w|a)} h_0(w, a) p(w|a) dw = \mathbb{E}[h_0(W, a)] = \theta_{ATE}(a).$$

□

B Derivation of efficient influence function in discrete treatment setting

B.1 Background on efficient influence functions

Let \mathcal{P} denote a nonparametric statistical model, and let $\psi : \mathcal{P} \rightarrow \mathbb{R}$ be a target functional of interest—such as the dose-response curve $\theta_{ATE}(a)$. In semiparametric efficiency theory, a statistical parameter such as the average treatment effect is viewed as a functional mapping the underlying data-generating law $p \in \mathcal{P}$ to a real number. In this section, we denote by \mathbb{P} the true distribution with $\mathbb{P}\ell = \mathbb{E}[\ell]$, \mathbb{P}_n the empirical distribution with $\mathbb{P}_n(\ell) := \frac{1}{n} \sum_{i=1}^n \ell(Z_i)$. The $\mathcal{L}_2(\mathbb{P})$ norm is written $\|\ell\|^2 := \int \ell^2 d\mathbb{P}$. We are interested in how the functional θ changes as the data-generating distribution $p \in \mathcal{P}$ varies. When θ is sufficiently smooth, it admits a *Gâteaux derivative*, defined as:

$$\theta'(p; H) := \left. \frac{d}{d\epsilon} \theta(p + \epsilon H) \right|_{\epsilon=0}$$

for H in the tangent space of \mathcal{P} . The functional is said to be Gâteaux differentiable at P if $\theta'(p; H)$ exists and is linear and continuous in H . The Gâteaux derivative formalizes the local sensitivity of the functional to infinitesimal perturbations of the distribution. It extends the notion of a directional derivative to the space of probability laws and provides a linear approximation of how $\theta(p)$ varies when p is displaced along an admissible direction H within the tangent space.

This gives rise to the *von Mises expansion* [56, 28]:

$$\theta(q) = \theta(p) + \theta'(p; q - p) + R_2(p, q)$$

where $R_2(p, q)$ is a second-order remainder depending on products or squares of differences between q and p . The von Mises expansion plays an analogous role to a first-order Taylor expansion in finite dimensions, expressing the change in the functional as a linear term—captured by the influence function—plus a higher-order remainder. This expansion enables the definition of the *influence function*.

Definition B.1 (Influence function [29, 28, 31]). A measurable function $\psi(\cdot; p) \in \mathcal{L}_2(p)$ is the influence function of θ at p if

$$\theta'(p; q - p) = \int \psi(z; p) d(q - p)(z), \quad \text{for all } q \in \mathcal{P}$$

with $\int \psi(z; p) dp(z) = 0$ and $\mathbb{E}_p[\psi(Z; p)^2] < \infty$.

The influence function ψ is the *Riesz representer* of the derivative $\theta'(p; \cdot)$, as $\mathcal{L}_2(p)$ is a Hilbert space. It is also referred to as the *pathwise derivative gradient* [57] or *Neyman orthogonal score* [30, 33]. Intuitively, the influence function measures how sensitive the parameter of interest is to infinitesimal changes in the data-generating distribution. It can be seen as the “directional derivative” of the functional with respect to perturbations of the underlying distribution—much like a gradient in function space. This makes it a key tool for constructing estimators that correct first-order bias and achieve minimal asymptotic variance.

To compute influence functions, we analyze *parametric submodels* $\{p_\epsilon\} \subset \mathcal{P}$ such that $p_{\epsilon=0} = p$ and $\epsilon \mapsto p_\epsilon$ is smooth. A canonical choice is the *tilted model*:

$$\frac{dp_\epsilon}{dp}(z) = 1 + \epsilon s(z), \quad \text{where } \|s\|_\infty \leq M, \quad \epsilon < 1/M$$

The associated *score function* is $s_\epsilon(z) = s(z) = \frac{\partial}{\partial \epsilon} \log p_\epsilon(z) \Big|_{\epsilon=0}$ [58, 31].

Applying the von Mises expansion to p_ϵ , we obtain:

$$\theta(p_\epsilon) = \theta(p) + \epsilon \int \psi(z; p) s(z) dp(z) + R_2(p, p_\epsilon)$$

Since $R_2(p, p_\epsilon)$ is second-order, it satisfies $\frac{d}{d\epsilon} R_2(p, p_\epsilon) \Big|_{\epsilon=0} = 0$, a condition known as *Neyman orthogonality* [33]. Thus,

$$\frac{d}{d\epsilon} \theta(p_\epsilon) \Big|_{\epsilon=0} = \int \psi(z; p) s(z) dp(z)$$

This defines *pathwise differentiability*, and the function ψ satisfying this identity is the efficient influence function.

Definition B.2 (Pathwise differentiability [29, 28]). *A functional θ is pathwise differentiable at p if for every smooth parametric submodel $\{p_\epsilon\} \subset \mathcal{P}$ with score $s_\epsilon(z)$, we have:*

$$\frac{d}{d\epsilon} \theta(p_\epsilon) \Big|_{\epsilon=0} = \int \psi(z; p) s_\epsilon(z) dp(z)$$

Once ψ is known, it can be used to construct an *efficient estimator*. Suppose \hat{p} estimates p , and let \mathbb{P}_n denote the empirical measure. The *plug-in estimator* $\hat{\theta}_{\text{pi}} := \theta(\hat{p})$ admits the expansion:

$$\theta(\hat{p}) - \theta(p) = -\mathbb{E}_p[\psi(Z; \hat{p})] + R_2(\hat{p}, p)$$

This motivates the *one-step estimator*, which corrects the plug-in estimator with an estimation of the first-order bias $\mathbb{E}_P[\psi(Z; \hat{p})]$:

$$\hat{\theta}^{\text{os}} := \theta(\hat{p}) + \mathbb{P}_n[\psi(Z; \hat{p})]$$

When analyzing one-step estimators, it is common to write the following decomposition [28]:

$$\hat{\theta}^{\text{os}} - \theta(p) = (\mathbb{P}_n - \mathbb{P})[\psi(Z; p)] + \underbrace{(\mathbb{P}_n - \mathbb{P})[\psi(Z; \hat{p}) - \psi(Z; p)]}_{\text{empirical process}} + \underbrace{R_2(\hat{p}, p)}_{\text{second-order remainder}}.$$

The first term is a sample average and converges by the central limit theorem. The second term, known as the *empirical process*, vanishes at rate $o_{\mathbb{P}}(n^{-1/2})$ if the estimated influence function $\hat{\psi}$ is \mathcal{L}_2 -consistent (i.e. $\|\hat{\psi}(Z) - \psi(Z)\|_2 \rightarrow_{\mathbb{P}} 0$, where $\|\ell\|_2^2 = \int \ell^2 dp$.) which is the case if it lies in a Donsker class or is estimated via cross-fitting (see [28]).

The third term, $R_2(\hat{p}, p)$, is the *second-order remainder*, which captures nonlinear errors. This term often exhibits a rate which depends on product of nuisance error rates. Therefore, under standard product-rate conditions, such as nuisance errors converging at rate $n^{-1/4}$, we obtain $R_2 = o_{\mathbb{P}}(n^{-1/2})$.

Together, these results imply that $\hat{\theta}^{\text{os}}$ is asymptotically linear and efficient. Specifically, in nonparametric models, the best achievable precision for estimating a target parameter θ is governed by a *local asymptotic minimax bound* which is attained by this estimator.

This bound extends the classical Cramér–Rao inequality using pathwise differentiability and parametric submodels. For any smooth submodel $\{p_\epsilon\}$ with score $s(z)$, the Cramér–Rao lower bound is:

$$\frac{(\mathbb{E}[\psi(Z; p) s(z)])^2}{\mathbb{E}[s(z)^2]} \leq \mathbb{E}[\psi(Z; p)^2],$$

where ψ is the influence function. Equality is achieved when $s = \psi$, yielding the *nonparametric efficiency bound*:

$$\text{var}\{\psi(Z; p)\}$$

Since the one-step estimator satisfies

$$\sqrt{n}(\hat{\theta}^{\text{os}} - \theta) \rightsquigarrow N(0, \text{var}\{\psi(Z; p)\}),$$

it achieves this bound and is thus locally efficient.

Eventually, note that the efficient influence function (EIF) is defined relative to the model's *tangent space*, which formalizes the allowable directions of perturbation around the true distribution. The tangent space is the set of valid perturbations around the true law and thus determines which directions contribute to efficiency.

In *nonparametric models*, the tangent space is the entire Hilbert space of square-integrable, mean-zero functions:

$$\mathcal{T} = \{\ell \in \mathcal{L}_2(\mathbb{P}) : \mathbb{E}_{\mathbb{P}}[\ell(Z)] = 0\}.$$

This ensures that any regular, pathwise differentiable functional admits a *unique* influence function ψ that also serves as the EIF.

In contrast, a *semiparametric model* imposes structural constraints on the distribution (e.g., conditional independence, smoothness, or dimension reduction). These constraints reduce the tangent space to a strict subspace of $\mathcal{L}_2(\mathbb{P})$. In this case, there may exist multiple functions ψ satisfying the von Mises expansion, but only those that lie within the tangent space correspond to valid perturbations. Among them, the EIF is defined as the unique ψ that also lies in the tangent space and minimizes variance. Therefore, careful attention must be paid to ensure that the candidate ψ lies in the tangent space, as only then does it correspond to the efficiency bound [28].

B.2 Derivation of the efficient influence function

In this section, we consider discrete treatment setting, i.e., $A \in \{0, 1, \dots, d_A\}$. We define the conditional expectation operator $T : \mathcal{L}_2(p_{W,A}) \rightarrow \mathcal{L}_2(p_{Z,A})$ by $T(\ell) = \mathbb{E}[\ell(W, A) | Z, A]$, and its adjoint $T^* : \mathcal{L}_2(p_{Z,A}) \rightarrow \mathcal{L}_2(p_{W,A})$ by $T^*(\ell) = \mathbb{E}[\ell(Z, A) | W, A]$, where $p_{Z,A}$ and $p_{W,A}$ denote the joint distributions of the random variables (Z, A) and (W, A) , respectively. Here, $\mathcal{L}_2(\mathcal{F}, p)$ denotes the space of square-integrable functions on domain \mathcal{F} with respect to the measure p . We impose the following regularity condition on the conditional mean operators following the setup in Cui et al. [21]:

Assumption B.3. T and T^* are surjective.

Under this setting, we derive the efficient influence function (EIF) of the dose-response curve, following the framework of [21, Theorem 3.1].

Theorem B.4. (*Efficient influence function*) *The efficient influence function of $\theta_{ATE}(a)$ where Assumption (B.3) holds, and Equation (1) holds at the true data generating law, is given by*

$$\psi_{ATE}(\mathcal{O}; a) = \varphi_0(Z, A)(Y - h_0(W, A)) \frac{1}{p(A)} \mathbf{1}[A = a] + h_0(W, a) - \theta_{ATE}(a)$$

where \mathcal{O} is the collection of the variables (Y, A, W, Z) , and $\mathbf{1}[\cdot]$ is the indicator function. Therefore, the corresponding semiparametric local efficiency bound of $\theta_{ATE}(a)$ equals to $\mathbb{E}[\psi_{ATE}(\mathcal{O}; a)^2]$.

Remark B.5. We note that our identification result for the dose-response curve in the continuous treatment setting can be viewed as a generalization of the identification result implied by the efficient influence function in Theorem (B.4). Specifically, observe that, since the expectation of the influence function is zero, we have:

$$\begin{aligned} 0 &= \mathbb{E}[\varphi_0(Z, a)(Y - h_0(W, a)) \frac{1}{p(a)} \mathbf{1}[A = a] + h_0(W, a) - \theta_{ATE}(a)] \\ &= \mathbb{E}[\varphi_0(Z, a)(Y - h_0(W, a)) | A = a] + \mathbb{E}[h(W, a)] - \theta_{ATE}(a) \end{aligned}$$

Therefore, in the discrete treatment case, the dose-response curve can be identified by

$$\theta_{ATE}(a) = \mathbb{E}[\varphi_0(Z, a)(Y - h_0(W, a)) | A = a] + \mathbb{E}[h(W, a)] \quad (7)$$

In Theorem (2.7), we show that the same representation identifies the dose-response curve in the continuous treatment case, while also exhibiting the double robustness property.

Remark B.6. We note that the formulation of our efficient influence function (EIF) differs from that of Cui et al. [21] particularly in the treatment bridge function term. In their framework, the treatment bridge function $q_0 : \mathcal{Z} \times \mathcal{A} \rightarrow \mathbb{R}$ is defined as the solution to

$$\mathbb{E}[q_0(Z, a) | W, A = a] = \frac{1}{p(A = a | W)} = \frac{p(W)}{p(W, a)}, \quad \forall a \in \mathcal{A}, \quad (8)$$

and the outcome bridge function solves (1). Under the Assumption (B.3) and assuming that Equation (1) holds under the true data generating law, Cui et al. [21] shows that the EIF of the dose-response is given by

$$\psi_{ATE}^q(\mathcal{O}; a) = q_0(Z, A)(Y - h_0(W, A))\mathbf{1}[A = a] + h_0(W, a) - \theta_{ATE}(a),$$

which leads to the identification formula

$$\theta_{ATE}(a) = \mathbb{E}[q_0(Z, A)(Y - h_0(W, A))\mathbf{1}[A = a]] + \mathbb{E}[h(W, a)]. \quad (9)$$

Instead, our identification result in Equation (7) differs from Equation (9) in two key ways: (i) We use a treatment bridge function φ_0 that solves Equation (2), which includes an additional factor of $p(a)$ in the numerator compared to Equation (8); (ii) As a result, the first term in our identification formula involves the conditional expectation $\mathbb{E}[\varphi_0(Z, a)(Y - h_0(W, a)) \mid A = a]$ over the distribution $p(Y, Z, W \mid A = a)$, whereas in Equation (9), the expectation is taken over the joint distribution $p(Y, Z, W, A)$ with an indicator function enforcing the treatment level. Because of this difference, our framework extends naturally to continuous treatments without the kernel smoothing step of Wu et al. [22], whose technique has been extensively used in the doubly-robust literature to handle continuous treatments [59, 60, 61]. Furthermore, this structural difference extends the applicability of our methods to high-dimensional treatments, where kernel-smoothing-based DR approaches are ineffective as we demonstrated with dSprite experiment in Section (5).

Proof of Theorem (B.4). We consider the following [28, 31, 57] parametric sub-model for nonparametric \mathcal{P} indexed by ϵ which includes the true data generating law at $\epsilon = 0$ for some mean-zero function $\ell : \mathcal{O} \rightarrow \mathbb{R}$,

$$p_\epsilon(\mathcal{O}) = p(\mathcal{O})\{1 + \epsilon\ell(\mathcal{O})\} \quad (10)$$

where $\mathcal{O} = (Y, Z, W, A)$ is the collection of variables of interest, $\|\ell\|_\infty \leq M < \infty$, and $\epsilon < 1/M$ so that $p_\epsilon(\mathcal{O}) \geq 0$. We have the score function $s_\epsilon(\mathcal{O})|_{\epsilon=0} = \frac{\partial}{\partial \epsilon} \log p_\epsilon(\mathcal{O})|_{\epsilon=0}$. To find the efficient influence function for $\theta_{ATE}(a)$, we need to find the curve ψ_{ATE} that satisfies

$$\frac{\partial}{\partial \epsilon} \theta_{ATE}(a; p_\epsilon) \Big|_{\epsilon=0} = \int \psi_{ATE}(\mathcal{O}; p) s_\epsilon(\mathcal{O}) dp(\mathcal{O}) \Big|_{\epsilon=0} \quad (11)$$

First of all, we recall that

$$\mathbb{E}[Y \mid Z, A] = \int h(w, A) dp(w \mid Z, A)$$

and define the bridge function h_ϵ so that:

$$\mathbb{E}_{p_\epsilon}[Y \mid Z, A] = \int h_\epsilon(w, A) p_\epsilon(w \mid Z, A) dw.$$

Therefore, we have

$$\int (y - h_\epsilon(w, a)) p_\epsilon(w, y \mid z, a) |_{\epsilon=0} dw dy = 0,$$

which implies that

$$\int \frac{\partial h_\epsilon(w, a)}{\partial \epsilon} \Big|_{\epsilon=0} p(w \mid z, a) dw = \int (y - h(w, a)) \frac{\partial \log p_\epsilon(w, y \mid z, a)}{\partial \epsilon} p_\epsilon(w, y \mid z, a) \Big|_{\epsilon=0} dw dy \quad (12)$$

Now, we recall that

$$\theta_{ATE}(a; p_\epsilon) = \int h_\epsilon(w, a) p_\epsilon(w) dw.$$

Hence,

$$\begin{aligned} \frac{\partial \theta_{ATE}(a; p_\epsilon)}{\partial \epsilon} \Big|_{\epsilon=0} &= \int \frac{\partial h_\epsilon(w, a)}{\partial \epsilon} \Big|_{\epsilon=0} p(w) dw + \int h(w, a) \frac{\partial p_\epsilon(w)}{\partial \epsilon} \Big|_{\epsilon=0} dw \\ &= \int \frac{\partial h_\epsilon(w, a)}{\partial \epsilon} \Big|_{\epsilon=0} p(w) dw + \int h(w, a) \frac{\partial \log p_\epsilon(w)}{\partial \epsilon} \Big|_{\epsilon=0} p(w) dw \end{aligned} \quad (13)$$

We notice that

$$\int h(w, a) \frac{\partial \log p_\epsilon(w)}{\partial \epsilon} \Big|_{\epsilon=0} p(w) dw = \mathbb{E} \left[(h(W, a) - \theta_{ATE}(a)) \frac{\partial \log p_\epsilon(Z, Y, A, W)}{\partial \epsilon} \Big|_{\epsilon=0} \right]. \quad (14)$$

One can show this as follows:

$$\begin{aligned} & \mathbb{E} \left[(h(W, a) - \theta_{ATE}(a)) \frac{\partial \log p_\epsilon(Z, Y, A, W)}{\partial \epsilon} \Big|_{\epsilon=0} \right] \\ &= \int h(w, a) \frac{\partial p_\epsilon(z, y, a', w)}{\partial \epsilon} \Big|_{\epsilon=0} dp(z, y, a', w) - \theta_{ATE}(a) \int \frac{\partial \log p_\epsilon(z, y, a', w)}{\partial \epsilon} \Big|_{\epsilon=0} dp(z, y, a', w) \\ &= \int h(w, a) \frac{\partial \log p_\epsilon(w)}{\partial \epsilon} \Big|_{\epsilon=0} dp(z, y, a', w) + \int h(w, a) \frac{\partial \log p_\epsilon(z, y, a' | w)}{\partial \epsilon} \Big|_{\epsilon=0} dp(z, y, a', w) \\ &\quad - \theta_{ATE}(a) \underbrace{\int \frac{\partial \log p_\epsilon(w)}{\partial \epsilon} \Big|_{\epsilon=0} dp(z, y, a', w)}_{=0} - \theta_{ATE}(a) \int \frac{\partial \log p_\epsilon(z, y, a' | w)}{\partial \epsilon} \Big|_{\epsilon=0} dp(z, y, a', w) \\ &= \int h(w, a) \frac{\partial \log p_\epsilon(w)}{\partial \epsilon} \Big|_{\epsilon=0} dp(z, y, a', w) + \int (h(w, a) - \theta_{ATE}(a)) \frac{\partial \log p_\epsilon(z, y, a' | w)}{\partial \epsilon} \Big|_{\epsilon=0} dp(z, y, a', w) \\ &= \int h(w, a) \frac{\partial \log p_\epsilon(w)}{\partial \epsilon} \Big|_{\epsilon=0} dp(z, y, a', w) \\ &\quad + \int (h(w, a) - \theta_{ATE}(a)) \underbrace{\left(\int \frac{\partial \log p_\epsilon(z, y, a' | w)}{\partial \epsilon} \Big|_{\epsilon=0} dp(z, y, a' | w) \right)}_{=0} dp(w) \\ &= \int h(w, a) \frac{\partial \log p_\epsilon(w)}{\partial \epsilon} \Big|_{\epsilon=0} dp(w). \end{aligned}$$

Next, we consider the first component in Equation (13):

$$\begin{aligned} & \int \frac{\partial h_\epsilon(w, a)}{\partial \epsilon} \Big|_{\epsilon=0} p(w) dw = \int \frac{\partial h_\epsilon(w, a)}{\partial \epsilon} \Big|_{\epsilon=0} \frac{p(w)}{p(w, a)} p(w, a) dw \\ &= \int \frac{\partial h_\epsilon(w, a')}{\partial \epsilon} \Big|_{\epsilon=0} \mathbf{1}[a = a'] \frac{p(w)}{p(w, a')} p(w, a') dw da' \\ &= \int \frac{\partial h_\epsilon(w, a')}{\partial \epsilon} \Big|_{\epsilon=0} \mathbf{1}[a = a'] \frac{1}{p(a')} \mathbb{E}[\varphi_0(Z, a') \mid W = w, A = a'] p(w, a') dw da' \\ &= \int \frac{\partial h_\epsilon(w, a')}{\partial \epsilon} \Big|_{\epsilon=0} \mathbf{1}[a = a'] \frac{1}{p(a')} \varphi_0(z, a') p(z, w, a') dw da' \\ &= \int \mathbf{1}[a = a'] \frac{1}{p(a')} \varphi_0(z, a') \left(\int \frac{\partial h_\epsilon(w, a')}{\partial \epsilon} \Big|_{\epsilon=0} p(w | z, a') dw \right) p(z, a') dz da' \\ &= \int \mathbf{1}[a = a'] \frac{1}{p(a')} \varphi_0(z, a') \left(\int (y - h(w, a)) \frac{\partial \log p_\epsilon(w, y | z, a)}{\partial \epsilon} \Big|_{\epsilon=0} p(w, y | z, a') dw dy \right) p(z, a') dz da' \end{aligned} \quad (15)$$

$$\begin{aligned} &= \int \mathbf{1}[a = a'] \frac{1}{p(a')} \varphi_0(z, a') (y - h(w, a)) \frac{\partial \log p_\epsilon(w, y | z, a')}{\partial \epsilon} \Big|_{\epsilon=0} p(w, y, z, a') dw dy dz da' \\ &\quad + \underbrace{\int \mathbf{1}[a = a'] \frac{1}{p(a')} \varphi_0(z, a') (y - h(w, a)) \frac{\partial \log p_\epsilon(z, a')}{\partial \epsilon} \Big|_{\epsilon=0} p(w, y, z, a') dw dy dz da'}_{=0} \\ &= \mathbb{E} \left[\mathbf{1}[A = a] \frac{1}{p(A)} \varphi_0(Z, A) (Y - h(W, A)) \frac{\partial \log p_\epsilon(W, Y, Z, A)}{\partial \epsilon} \Big|_{\epsilon=0} \right], \end{aligned} \quad (16)$$

where equality in Equation (15) is due to Equation (12). Now, combining the results in Equations (14) and (16), we obtain

$$\frac{\partial \theta_{ATE}(a; p_\epsilon)}{\partial \epsilon} \Big|_{\epsilon=0} =$$

$$\mathbb{E} \left[\left(\mathbf{1}[A = a] \frac{1}{p(A)} \varphi_0(Z, A)(Y - h(W, A)) + h(W, a) - \theta_{ATE}(a) \right) \frac{\partial \log p_\epsilon(W, Y, Z, A)}{\partial \epsilon} \Big|_{\epsilon=0} \right],$$

which shows that the efficient influence function for $\theta_{ATE}(a)$ is given by

$$\psi_{ATE}(\mathcal{O}; a) = \varphi_0(Z, A)(Y - h(W, A)) \frac{1}{p(A)} \mathbf{1}[A = a] + h_0(W, a) - \theta_{ATE}(a) \quad (17)$$

Next, we show that $\psi_{ATE}(a)$ belongs to a tangent space $\mathcal{T}_1 + \mathcal{T}_2$ using Assumption (B.3), where

$$\mathcal{T}_1 := \{s(Z, A) \in \mathcal{L}_2(\mathcal{Z} \times \mathcal{A}, p_{Z,A}) \mid \mathbb{E}[s(Z, A)] = 0\}$$

$$\mathcal{T}_2 := \{s(Y, W \mid Z, A) \in \mathcal{L}_2(\mathcal{Z} \times \mathcal{A}, p_{Z,A})^\perp \mid \mathbb{E}[(Y - h(W, A))s(Y, W \mid Z, A) \mid Z, A] \in cl(\mathcal{R}(T))\}.$$

Here, $\mathcal{L}_2(\mathcal{Z} \times \mathcal{A}, p_{Z,A})^\perp$ is the orthogonal complement of $\mathcal{L}_2(\mathcal{Z} \times \mathcal{A}, p_{Z,A})$, $\mathcal{R}(T)$ is the range space of the conditional mean operator T , and $cl(\cdot)$ denotes the closure. We decompose Equation (17) as follows:

$$\begin{aligned} & \mathbb{E}[h(W, a) - \theta_{ATE}(a) \mid Z, A] \\ & + h(W, a) - \theta_{ATE}(a) - \mathbb{E}[h(W, a) - \theta_{ATE}(a) \mid Z, A] \\ & + \frac{1}{p(A)} \mathbf{1}[A = a] \varphi_0(Z, A)(Y - h(W, A)). \end{aligned}$$

Notice that $\mathbb{E}[h(W, a) - \theta_{ATE}(a) \mid Z, A] \in \mathcal{T}_1$ due to Equation (1). For the remaining two terms, notice that

$$\mathbb{E}[h(W, a) - \theta_{ATE}(a) - \mathbb{E}[h(W, a) - \theta_{ATE}(a) \mid Z, A] \mid Z, A] = 0 \quad (18)$$

$$\mathbb{E} \left[\frac{1}{p(A)} \mathbf{1}[A = a] \varphi_0(Z, A)(Y - h(W, A)) \mid Z, A \right] = 0. \quad (19)$$

Hence, using Equations (18) and (19) and Assumption (B.3), we observe that

$$\begin{aligned} & \mathbb{E}[(Y - h_0(W, A))(h(W, a) - \theta_{ATE}(a) - \mathbb{E}[h(W, a) - \theta_{ATE}(a) \mid Z, A]) \mid Z, A] \in cl(\mathcal{R}(T)), \\ & \mathbb{E} \left[\frac{1}{p(A)} \mathbf{1}[A = a] \varphi_0(Z, A)(Y - h(W, A))^2 \mid Z, A \right] \in cl(\mathcal{R}(T)). \end{aligned}$$

□

C Algorithm derivations

In this section, we derive the doubly robust PCL algorithms, called doubly robust kernel proxy variable (DRKPV) and doubly robust proxy maximum moment restriction (DRPMMR). We begin by reviewing the results from Mastouri et al. [11] and Bozkurt et al. [23], which establish estimation procedures for the outcome and treatment bridge functions: namely, the Kernel Proxy Variable (KPV), Proxy Maximum Moment Restriction (PMMR), and Kernel Alternative Proxy (KAP) methods. Building on these, we introduce fully kernelized doubly robust algorithms for estimating the dose-response curve from observational data, without requiring an explicit density ratio estimation step. This property makes our methods particularly suitable for continuous and high-dimensional treatment settings.

C.1 Outcome bridge function-based approaches

Two kernel-based methods KPV and PMMR have been proposed in [11] to estimate the outcome bridge function $h : \mathcal{W} \times \mathcal{A} \rightarrow \mathbb{R}$, which satisfies

$$\mathbb{E}[Y \mid Z, A] = \int h_0(w, A) p(w \mid Z, A) dw.$$

Once h_0 satisfies this equation, the dose-response curve can be identified by $\mathbb{E}[h_0(W, a)]$ [5, 11, 13], as stated in Theorem (2.4). In both approaches proposed by Mastouri et al. [11], h_0 is assumed to lie in the RKHS $\mathcal{H}_{\mathcal{W}} \otimes \mathcal{H}_{\mathcal{A}}$. Therefore, we note that

$$\theta_{ATE}(a) = \mathbb{E}[h_0(W, a)] = \mathbb{E}[\langle h_0, \phi_{\mathcal{W}}(W) \otimes \phi_{\mathcal{A}}(a) \rangle_{\mathcal{H}_{\mathcal{W}} \otimes \mathcal{H}_{\mathcal{A}}}]$$

$$= \langle h_0, \mathbb{E}[\phi_{\mathcal{W}}(W)] \otimes \phi_{\mathcal{A}}(a) \rangle_{\mathcal{H}_{\mathcal{W}} \otimes \mathcal{H}_{\mathcal{A}}} \approx \langle h_0, \hat{\mu}_W \otimes \phi_{\mathcal{A}}(a) \rangle_{\mathcal{H}_{\mathcal{W}} \otimes \mathcal{H}_{\mathcal{A}}},$$

where $\hat{\mu}_W = \frac{1}{t_h} \sum_{i=1}^n \phi_{\mathcal{W}}(\bar{w}_i)$ is the sample-based estimate of the mean embedding $\mathbb{E}[\phi_{\mathcal{W}}(W)]$. As a result, by replacing h_0 with its approximation \hat{h} in the above expression, the dose-response can be estimated using the inner product:

$$\theta_{ATE}(a) \approx \left\langle \hat{h}, \hat{\mu}_W \otimes \phi_{\mathcal{A}}(a) \right\rangle_{\mathcal{H}_{\mathcal{W}} \otimes \mathcal{H}_{\mathcal{A}}}.$$

In the following, we review the estimation procedures of both KPV and PMMR proposed by Mastouri et al. [11]. Both methods yield closed-form solutions for the estimation of the bridge function and the causal function, which we present in the subsequent subsections.

C.1.1 Kernel proxy variable algorithm

To solve the outcome bridge function equation in Equation (1), the KPV method aims to minimize the following regularized population loss function, assuming that $h \in \mathcal{H}_{\mathcal{W}\mathcal{A}}$:

$$\mathcal{L}_{KPV}(h) = \mathbb{E} \left[(Y - \mathbb{E}[h(W, A) \mid Z, A])^2 \right] + \lambda_{h,2} \|h\|_{\mathcal{H}_{\mathcal{W}} \otimes \mathcal{H}_{\mathcal{A}}},$$

where $\lambda_{h,2}$ is the regularization constant for the second stage regression of KPV. Since this loss function involves the conditional expectation $\mathbb{E}[h(W, A) \mid Z, A]$, it cannot be directly minimized. To address this, the KPV algorithm decomposes the problem into two-stage regressions. Note that, under Assumption (3.1), the conditional expectation can be rewritten as

$$\begin{aligned} \mathbb{E}[h(W, A) \mid Z, A] &= \mathbb{E}[\langle h, \phi_{\mathcal{W}}(W) \otimes \phi_{\mathcal{A}}(A) \rangle \mid Z, A] \\ &= \langle h, \mathbb{E}[\phi_{\mathcal{W}}(W) \mid Z, A] \otimes \phi_{\mathcal{A}}(A) \rangle. \end{aligned}$$

Thus, the first step in KPV is to approximate the conditional mean embedding $\mu_{W|Z,A}(z, a) = \mathbb{E}[\phi_{\mathcal{W}}(W) \mid Z = z, A = a]$ using vector-valued kernel ridge regression. In particular, under the regularity condition that $\mathbb{E}[g(W) \mid Z = \cdot, A = \cdot]$ lies in $\mathcal{H}_{\mathcal{Z}\mathcal{A}}$ for all $g \in \mathcal{H}_{\mathcal{W}}$, there exists an operator $C_{W|Z,A} \in \mathcal{S}_2(\mathcal{H}_{\mathcal{Z}\mathcal{A}}, \mathcal{H}_{\mathcal{W}})$ such that $\mu_{W|Z,A}(z, a) = C_{W|Z,A}(\phi_{\mathcal{Z}}(z) \otimes \phi_{\mathcal{A}}(a))$.

Let $\{\bar{w}_i, \bar{z}_i, \bar{a}_i\}_{i=1}^{n_h}$ be i.i.d. samples from the distribution $p(W, Z, A)$, representing the first-stage regression samples, where n_h is the number of first-stage samples for KPV algorithm. The conditional expectation operator is estimated by minimizing the following regularized least-squares objective:

$$\hat{\mathcal{L}}_{KPV}^c(C) = \frac{1}{n_h} \sum_{i=1}^{n_h} \|\phi_{\mathcal{W}}(\bar{w}_i) - C(\phi_{\mathcal{Z}}(\bar{z}_i) \otimes \phi_{\mathcal{A}}(\bar{a}_i))\|^2 + \lambda_{h,1} \|C\|_{\mathcal{S}_2(\mathcal{H}_{\mathcal{W}}, \mathcal{H}_{\mathcal{Z}\mathcal{A}})}^2,$$

where $\lambda_{h,1}$ is the regularization constant for the first stage regression of KPV. The minimizer $\hat{C}_{W|Z,A}$ has a closed form solution and is given by [11]:

$$\hat{C}_{W|Z,A}(\phi_{\mathcal{Z}}(z) \otimes \phi_{\mathcal{A}}(a)) = \hat{\mu}_{W|Z,A}(z, a) = \sum_{i=1}^{n_h} \beta_i(z, a) \phi_{\mathcal{W}}(\bar{w}_i),$$

where

$$\beta(z, a) = (\mathbf{K}_{\bar{Z}\bar{Z}} \odot \mathbf{K}_{\bar{A}\bar{A}} + n\lambda_1 \mathbf{I})^{-1} (\mathbf{K}_{\bar{Z}z} \odot \mathbf{K}_{\bar{A}a}).$$

By substituting this approximation into the sample-based version of the loss function $\mathcal{L}_{KPV}(h)$, the KPV algorithm estimates the bridge function h_0 . Specifically, let $\{\tilde{y}_i, \tilde{z}_i, \tilde{a}_i\}_{i=1}^{m_h}$ be i.i.d. samples from the distribution $p(Y, Z, A)$, denoting the second-stage data, where m_h is the number of second-stage samples for the KPV algorithm. The sample-based KPV objective is then given by

$$\hat{\mathcal{L}}_{KPV}(h) = \frac{1}{m_h} \sum_{i=1}^{m_h} (\tilde{y}_i - \langle h, \hat{\mu}_{W|Z,A}(\tilde{z}_i, \tilde{a}_i) \otimes \phi_{\mathcal{A}}(\tilde{a}_i) \rangle)^2 + \lambda_{h,2} \|h\|_{\mathcal{H}_{\mathcal{W}\mathcal{A}}}^2. \quad (20)$$

By the representer theorem [44], h admits the representation

$$h = \sum_{i=1}^{n_h} \sum_{j=1}^{m_h} \alpha_{ij} \phi_{\mathcal{W}}(\bar{w}_i) \otimes \phi_{\mathcal{A}}(\tilde{a}_j), \quad (21)$$

for some coefficients α_{ij} . Substituting this representation into the sample loss in Equation (20), KPV finds a closed-form solution for the bridge function by minimizing for the coefficients α_{ij} . For further details, we refer the reader to [11].

Below, we summarize the pseudo-code for the KPV algorithm. Unlike the original implementation in [11], we use a more numerically stable version that optimizes fewer parameters, as presented in [62] (see Appendix F in [62]). This version of the KPV algorithm optimizes m_h parameters rather than $n_h \times m_h$ parameters.

Algorithm 2 Kernel Proxy Variable Algorithm [11, 62]

Input: First-stage samples $\{\bar{w}_i, \bar{z}_i, \bar{a}_i\}_{i=1}^{n_h}$, Second-stage samples $\{\tilde{y}_i, \tilde{z}_i, \tilde{a}_i\}_{i=1}^{m_h}$,

Parameters: Regularization parameters $\lambda_{h,1}$ and $\lambda_{h,2}$, and kernel functions $k_{\mathcal{F}}(\cdot, \cdot)$ for each $\mathcal{F} \in \{\mathcal{A}, \mathcal{Z}, \mathcal{W}\}$.

Output: Bridge function estimation \hat{h} .

- 1: For variables $F \in \{W, Z, A\}$ with domain \mathcal{F} , define the (required) first and second-stage kernel matrices/vectors as follows:

$$\begin{aligned} \mathbf{K}_{\bar{F}\bar{F}} &= [k_{\mathcal{F}}(\bar{f}_i, \bar{f}_j)]_{ij} \in \mathbb{R}^{n_h \times n_h}, \quad \mathbf{K}_{\bar{F}\tilde{F}} = [k_{\mathcal{F}}(\bar{f}_i, \tilde{f}_j)]_{ij} \in \mathbb{R}^{n_h \times m_h}, \\ \mathbf{K}_{\tilde{F}\tilde{F}} &= [k_{\mathcal{F}}(\tilde{f}_i, \tilde{f}_j)]_{ij} \in \mathbb{R}^{m_h \times m_h}, \quad \mathbf{K}_{\bar{F}f} = [k_{\mathcal{F}}(\bar{f}_i, f)]_i \in \mathbb{R}^{n_h}, \\ \mathbf{K}_{\tilde{F}f} &= [k_{\mathcal{F}}(\tilde{f}_j, f)]_j \in \mathbb{R}^{m_h}. \end{aligned}$$

- 2: Define the following matrices and coefficient vector:

$$\begin{aligned} \mathbf{B} &= (\mathbf{K}_{\bar{A}\bar{A}} \odot \mathbf{K}_{\bar{Z}\bar{Z}} + n_h \lambda_{h,1} \mathbf{I})^{-1} (\mathbf{K}_{\bar{A}\bar{A}} \odot \mathbf{K}_{\bar{Z}\bar{Z}}), \\ \mathbf{M} &= \mathbf{K}_{\bar{A}\bar{A}} \odot (\mathbf{B}^\top \mathbf{K}_{\bar{W}\bar{W}} \mathbf{B}), \\ \boldsymbol{\alpha} &= (\mathbf{M} + m_h \lambda_{h,2} \mathbf{I})^{-1} \tilde{\mathbf{Y}}. \end{aligned}$$

- 3: The bridge function estimation is given by $\hat{h}(w, a) = \boldsymbol{\alpha}^\top (\mathbf{K}_{\bar{A}a} \odot (\mathbf{B}^\top \mathbf{K}_{\bar{W}w}))$.
- 4: The dose-response estimation is given by

$$\hat{\theta}_{ATE}(a) = \sum_{i=1}^t \hat{h}(\dot{w}_i, a) = \sum_{i=1}^t \boldsymbol{\alpha}^\top (\mathbf{K}_{\bar{A}a} \odot (\mathbf{B}^\top \mathbf{K}_{\bar{W}\dot{w}_i}))$$

where we take $\{\dot{w}_i\}_{i=1}^t = \{\bar{w}_i\}_{i=1}^{n_h} \cup \{\tilde{w}_i\}_{i=1}^{m_h}$

C.1.2 Proximal maximum moment restriction algorithm

The PMMR algorithm relies on the following conditional moment restriction result:

Lemma C.1 (Lemma (1) in [11]). *A measurable function h on the domain $\mathcal{W} \times \mathcal{A}$ solves*

$$\mathbb{E}[Y|Z = z, A = a] = \int_{\mathcal{W}} h(w, a) p(w|z, a) dw$$

if and only if it satisfies the conditional moment restriction (CMR): $\mathbb{E}[Y - h(W, A)|Z, A] = 0$.

Lemma (C.1) implies that $\mathbb{E}[(Y - h(W, A))g(Z, A)] = 0$ for all measurable g defined on the domain $\mathcal{Z} \times \mathcal{A}$. Thus, to solve the CMR, the PMMR algorithm solves the CMR by minimizing the regularized maximum moment restriction (MMR) objective to find the function $h \in \mathcal{H}_{\mathcal{W}\mathcal{A}}$:

$$\mathcal{L}_{\text{MMR}}(h) = \sup_{\substack{g \in \mathcal{H}_{\mathcal{Z}\mathcal{A}} \\ \|g\| \leq 1}} \mathbb{E}[(Y - h(W, A))g(Z, A)]^2 + \lambda_{\text{MMR}} \|h\|_{\mathcal{H}_{\mathcal{W}\mathcal{A}}}. \quad (22)$$

Under the integrability condition $\mathbb{E}[(Y - h(W, A))^2 \langle \phi_{\mathcal{Z}\mathcal{A}}(Z, A), \phi_{\mathcal{Z}\mathcal{A}}(Z, A) \rangle_{\mathcal{H}_{\mathcal{Z}\mathcal{A}}}] < \infty$, Mastouri et al. [11, Lemma (2)] shows that the regularized MMR objective admits the equivalent form:

$$\mathcal{L}_{\text{MMR}}(h) = \mathbb{E}[(Y - h(W, A))(Y' - h(W', A')) \langle \phi_{\mathcal{Z}\mathcal{A}}(Z, A), \phi_{\mathcal{Z}\mathcal{A}}(Z', A') \rangle_{\mathcal{H}_{\mathcal{Z}\mathcal{A}}}] + \lambda_{\text{MMR}} \|h\|_{\mathcal{H}_{\mathcal{W}\mathcal{A}}}, \quad (23)$$

where V' denotes an independent copy of $V \in A, Z, W$, and $\phi_{\mathcal{Z}\mathcal{A}}$ is the canonical feature map of $\mathcal{H}_{\mathcal{Z}\mathcal{A}}$. In this paper, we adopt the tensor product structure for the feature map and RKHS by defining

$\phi_{\mathcal{Z}\mathcal{A}}(z, a) = \phi_{\mathcal{Z}}(z) \otimes \phi_{\mathcal{A}}(a)$ and $\mathcal{H}_{\mathcal{Z}\mathcal{A}} = \mathcal{H}_{\mathcal{Z}} \otimes \mathcal{H}_{\mathcal{A}}$. This choice allows us to construct $\mathcal{H}_{\mathcal{Z}\mathcal{A}}$ from separate kernels over \mathcal{Z} and \mathcal{A} . However, it is also possible to define a kernel directly on the joint domain $\mathcal{Z} \times \mathcal{A}$ for PMMR algorithm, in which case the feature map and RKHS do not need to take the form of a tensor product.

As a result, given training samples $\{y_i, w_i, z_i, a_i\}_{i=1}^t$, the empirical objective for PMMR is defined as

$$\hat{\mathcal{L}}_{\text{MMR}}(h) = \frac{1}{t^2} \sum_{i=1}^t \sum_{j=1}^t (y_i - h_i)(y_j - h_j) k_{ij} + \lambda_{\text{MMR}} \|h\|_{\mathcal{H}_{\mathcal{W}\mathcal{A}}}, \quad (24)$$

where $h_i = h(w_i, a_i)$ and $k_{ij} = \langle \phi_{\mathcal{Z}\mathcal{A}}(z_i, a_i), \phi_{\mathcal{Z}\mathcal{A}}(z_j, a_j) \rangle_{\mathcal{H}_{\mathcal{Z}\mathcal{A}}}$. Recall that we assume $h \in \mathcal{H}_{\mathcal{W}} \otimes \mathcal{H}_{\mathcal{A}}$. By the representer theorem [44], the solution to Equation (24) admits the following representation:

$$h = \sum_{i=1}^t \alpha_i \phi_{\mathcal{W}}(w_i) \otimes \phi_{\mathcal{A}}(a_i).$$

Substituting this representation into the sample loss in Equation (24), the empirical objective becomes

$$\hat{\alpha} = \arg \min_{\alpha} \frac{1}{t^2} (\mathbf{Y} - \mathbf{L}\alpha)^\top \mathbf{W} (\mathbf{Y} - \mathbf{L}\alpha) + \lambda_{\text{MMR}} \alpha^\top \mathbf{L}\alpha,$$

where $\mathbf{Y} = [y_1 \ y_2 \ \dots \ y_t]^\top$, $\alpha = [\alpha_1 \ \alpha_2 \ \dots \ \alpha_t]^\top$, $[\mathbf{L}]_{ij} = k_{\mathcal{W}}(w_i, w_j) k_{\mathcal{A}}(a_i, a_j)$, and $[\mathbf{W}]_{ij} = k_{\mathcal{Z}}(z_i, z_j) k_{\mathcal{Z}}(a_i, a_j)$. The PMMR algorithm solves for the coefficient vector α . We summarize the procedure in Algorithm (3), following the variant presented by Xu and Gretton [62].

Algorithm 3 Proximal Maximum Moment Restriction Algorithm [11, 62]

Input: Training samples $\{w_i, z_i, a_i, y_i\}_{i=1}^t$,

Parameters: Regularization parameter λ_{MMR} , and kernel functions $k_{\mathcal{F}}(\cdot, \cdot)$ for each $\mathcal{F} \in \{\mathcal{A}, \mathcal{Z}, \mathcal{W}\}$.

Output: Bridge function estimation \hat{h} .

- 1: For variables $F \in \{W, Z, A\}$ with domain \mathcal{F} , define the (required) kernel matrices/vectors as follows:

$$\mathbf{K}_{FF} = [k_{\mathcal{F}}(f_i, f_j)]_{ij} \in \mathbb{R}^{t \times t}, \quad \mathbf{K}_{Ff} = [k_{\mathcal{F}}(f_i, f)]_i \in \mathbb{R}^t.$$

- 2: Construct the following kernel matrices and the coefficient vector:

$$\mathbf{L} = \mathbf{K}_{AA} \odot \mathbf{K}_{WW}, \quad \mathbf{G} = \mathbf{K}_{AA} \odot \mathbf{K}_{ZZ}, \quad \alpha = \sqrt{\mathbf{G}} \left(\sqrt{\mathbf{G}} \mathbf{L} \sqrt{\mathbf{G}} + t \lambda_{\text{MMR}} \mathbf{I} \right)^{-1} \sqrt{\mathbf{G}} \mathbf{Y},$$

where $\sqrt{\mathbf{G}}$ is the square root of the matrix \mathbf{G} .

- 3: The bridge function estimation is given by $\hat{h}(w, a) = \alpha^\top (\mathbf{K}_{Aa} \odot \mathbf{K}_{Ww})$.

- 4: The dose-response estimation is given by $\hat{\theta}_{ATE}(a) \approx \sum_{i=1}^t \hat{h}(w_i, a) = \sum_{i=1}^t \alpha^\top (\mathbf{K}_{Aa} \odot \mathbf{K}_{Ww_i})$.
-

C.2 Treatment bridge function-based algorithm

An alternative identification result in the proxy causal learning setting, based on density ratios, is presented in [23]. Unlike previous works [21, 22], this approach bypasses the explicit density ratio estimation step by leveraging a novel bridge function definition. Specifically, [23] proposes Kernel Alternative Proxy (KAP) algorithm, a two-stage regression method to estimate the treatment bridge function φ_0 satisfying

$$\mathbb{E}[\varphi_0(Z, a) \mid W, A = a] = \frac{p(W)p(a)}{p(W, a)}.$$

This new approach aims to minimize the following regularized population loss function, assuming that $\varphi \in \mathcal{H}_{\mathcal{Z}\mathcal{A}}$

$$\mathcal{L}_{\text{KAP}}(\varphi) = \mathbb{E} \left[(r(W, A) - \mathbb{E}[\varphi(Z, A) \mid W, A])^2 \right] + \lambda_{\varphi, 2} \|\varphi\|_{\mathcal{H}_{\mathcal{Z}\mathcal{A}}}$$

$$= \mathbb{E} [\mathbb{E} [\varphi(Z, A) \mid W, A]^2] - 2\mathbb{E}_W \mathbb{E}_A [\mathbb{E} [\varphi(Z, A) \mid W, A]] + \lambda_{\varphi,2} \|\varphi\|_{\mathcal{H}_{Z,A}} + \text{const.}, \quad (25)$$

where $\lambda_{\varphi,2}$ is the regularization parameter for the second stage regression, the notation $\mathbb{E}_W \mathbb{E}_A[\cdot]$ denotes the decoupled expectation taken over W and A , i.e., for any function ℓ , $\mathbb{E}_W \mathbb{E}_A[\ell(W, A)] = \int \ell(w, a) p(w) p(a) dw da$, and 'const.' represents the terms independent of φ . As in the outcome bridge function estimation, this loss function cannot be directly minimized due to the presence of the conditional expectation term $\mathbb{E} [\varphi(Z, A) \mid W, A]$. Notably, appealing to Assumption (3.1), this expectation can be rewritten as

$$\begin{aligned} \mathbb{E} [\varphi(Z, A) \mid W, A] &= \mathbb{E} [\langle \varphi, \phi_Z(Z) \otimes \phi_A(A) \rangle_{\mathcal{H}_{Z,A}} \mid W, A] \\ &= \langle \varphi, \mathbb{E} [\phi_Z(Z) \mid W, A] \otimes \phi_A(A) \rangle_{\mathcal{H}_{Z,A}} \end{aligned}$$

Thus, the first step in KAP method is to estimate the conditional mean embedding $\mu_{Z|W,A}(w, a) = \mathbb{E} [\phi_Z(Z) \mid W = w, A = a]$ using vector valued kernel ridge regression. Specifically, under the regularity condition that $\mathbb{E} [g(Z) \mid W = \cdot, A = \cdot]$ lies in $\mathcal{H}_{W,A}$ for all $g \in \mathcal{H}_Z$, there exists an operator $C_{Z|W,A} \in \mathcal{S}_2(\mathcal{H}_{W,A}, \mathcal{Z})$ such that $\mu_{Z|W,A}(w, a) = C_{Z|W,A}(\phi_W(w) \otimes \phi_A(a))$. Let $\{\bar{w}_i, \bar{z}_i, \bar{a}_i\}_{i=1}^{n_\varphi}$ be i.i.d. samples from the distribution $p(W, Z, A)$, denoting the first-stage samples, where n_φ is the number of first-stage samples for KAP algorithm. The conditional expectation operator is learned by minimizing the regularized least-squares function:

$$\hat{\mathcal{L}}^c(C)_{\text{KAP}} = \frac{1}{n} \sum_{i=1}^n \|\phi_Z(\bar{z}_i) - C(\phi_W(\bar{w}_i) \otimes \phi_A(\bar{a}_i))\|^2 + \lambda_{\varphi,1} \|C\|_{\mathcal{S}_2(\mathcal{H}_{W,A}, \mathcal{H}_Z)}^2,$$

where $\lambda_{\varphi,1}$ is the regularization parameter for first-stage regression of KAP method. The minimizer $\hat{C}_{Z|W,A}$ admits a closed form solution and is given by [23]:

$$\hat{\mu}_{Z|W,A}(w, a) = \hat{C}_{Z|W,A}(\phi_Z(z) \otimes \phi_A(a)) = \sum_{i=1}^{n_\varphi} \beta_i(w, a) \phi_Z(\bar{z}_i),$$

where

$$\beta(w, a) = (K_{\bar{W}\bar{W}} \odot K_{\bar{A}\bar{A}} + n_\varphi \lambda_{\varphi,1} \mathbf{I})^{-1} (K_{\bar{W}w} \odot K_{\bar{A}a}).$$

By substituting this approximation into the sample-based version of the loss function $\mathcal{L}_{\text{KAP}}(\varphi)$, Bozkurt et al. [23] derives an algorithm to estimate the bridge function φ_0 . Let $\{\tilde{w}_i, \tilde{a}_i\}_{i=1}^{m_\varphi}$ be i.i.d. samples from the distribution $p(W, A)$, denoting the second-stage samples, where m_φ is the number of samples for the second-stage regression of KAP algorithm. The sample-based version of the loss function in Equation (25) can be written as

$$\begin{aligned} \hat{\mathcal{L}}(\varphi)_{\text{KAP}} &= \frac{1}{m_\varphi} \sum_{i=1}^{m_\varphi} \langle \varphi, \hat{\mu}_{Z|W,A}(\tilde{w}_i, \tilde{a}_i) \otimes \phi_A(\tilde{a}_i) \rangle_{\mathcal{H}_{Z,A}}^2 \\ &\quad - 2 \frac{1}{m_\varphi(m_\varphi - 1)} \sum_{i=1}^{m_\varphi} \sum_{\substack{j=1 \\ j \neq i}}^{m_\varphi} \left\langle \varphi, \hat{\mu}_{Z|W,A}(\tilde{w}_j, \tilde{a}_j) \otimes \phi_A(\tilde{a}_j) \right\rangle_{\mathcal{H}_{Z,A}} + \lambda_{\varphi,2} \|\varphi\|_{\mathcal{H}_{Z,A}}^2 \quad (26) \end{aligned}$$

The representer theorem [44] ensures that φ admits the representation

$$\varphi = \sum_{i=1}^{m_\varphi} \gamma_i \hat{\mu}_{Z|W,A}(\tilde{w}_i, \tilde{a}_i) \otimes \phi_A(\tilde{a}_i) + \frac{\gamma_{m_\varphi+1}}{m_\varphi(m_\varphi - 1)} \sum_{j=1}^{m_\varphi} \sum_{\substack{l=1 \\ l \neq j}}^{m_\varphi} \hat{\mu}_{Z|W,A}(\tilde{w}_l, \tilde{a}_j) \otimes \phi_A(\tilde{a}_j)$$

for some coefficients $\{\gamma_i\}_{i=1}^{m_\varphi+1}$. By substituting this representation into the sample loss in Equation (26), the minimizer $\hat{\varphi}$ admits a closed-form solution, as given in Bozkurt et al. [23], which we outline in Algorithm (4). Furthermore, the dose-response curve can be estimated via $\theta_{ATE}(a) \approx \mathbb{E}[Y \hat{\varphi}(Z, a) \mid A = a]$. Noting that

$$\begin{aligned} \mathbb{E}[Y \hat{\varphi}(Z, a) \mid A = a] &= \mathbb{E} [Y \langle \hat{\varphi}, \phi_Z(Z) \otimes \phi_A(a) \rangle_{\mathcal{H}_{Z,A}} \mid A = a] \\ &= \langle \hat{\varphi}, \mathbb{E}[Y \phi_Z(Z) \mid A = a] \otimes \phi_A(a) \rangle_{\mathcal{H}_{Z,A}}. \quad (27) \end{aligned}$$

evaluating the above inner product requires estimating the conditional mean embedding $\mu_{Y|Z|A}(a) = \mathbb{E}[Y\phi_Z(Z) \mid A = a]$, which can be obtained via vector-valued kernel ridge regression, similar to the first-stage regression. In particular, let $\{\dot{y}_i, \dot{z}_i, \dot{a}_i\}_{i=1}^{t_\varphi}$ denote i.i.d. samples from the distribution $p(Y, Z, A)$, denoting the third-stage samples for KAP algorithm which we take to be $\{\dot{y}_i, \dot{z}_i, \dot{a}_i\}_{i=1}^{t_\varphi} = \{\bar{y}_i, \bar{z}_i, \bar{a}_i\}_{i=1}^{n_\varphi} \cup \{\tilde{y}_i, \tilde{z}_i, \tilde{a}_i\}_{i=1}^{m_\varphi}$. Then, the conditional mean embedding $\mu_{Y|Z|A}(a) = C_{YZ|A}\phi_A(a)$ is learned by minimizing the regularized least squares objective:

$$\mathcal{L}_{\text{KAP}}^{C_{YZ|A}}(C) = \frac{1}{t} \sum_{i=1}^t \|\dot{y}_i \phi_Z(\dot{z}_i) - C \phi_A(\dot{a}_i)\|_{\mathcal{H}_Z}^2 + \lambda_{\varphi,3} \|C\|_{S_2(\mathcal{H}_A, \mathcal{H}_Z)}^2,$$

where $\lambda_{\varphi,3}$ denotes the regularization parameter for the third-stage regression of KAP method. The minimizer is given by

$$\hat{\mu}_{YZ|A}(a) = \hat{C}_{YZ|A}\phi_A(a) = \dot{\Phi}_Z \text{diag}(\dot{\mathbf{Y}}) [\mathbf{K}_{\dot{A}\dot{A}} + n\lambda_{\varphi,3}\mathbf{I}]^{-1} \mathbf{K}_{\dot{A}a},$$

where $\dot{\Phi}_Z = [\phi_Z(\dot{z}_1) \ \dots \ \phi_Z(\dot{z}_t)]$, $\dot{\mathbf{Y}} = [\dot{y}_1 \ \dots \ \dot{y}_t]^T$, $\mathbf{K}_{\dot{A}\dot{A}} \in \mathbb{R}^{t_\varphi \times t_\varphi}$ is the kernel matrix over $\{\dot{a}_i\}_{i=1}^{t_\varphi}$, and $\mathbf{K}_{\dot{A}a}$'s the kernel vector between the training points $\{\dot{a}_i\}_{i=1}^{t_\varphi}$ and the target treatment a . As a result, by substituting the estimation $\hat{\mu}_{YZ|A}(a)$ in Equation (27), the dose-response curve can be estimated with a closed-form solution that is efficiently implemented via matrix operations [23], as summarized below in Algorithm (4). For further details of this algorithm, we refer the reader to [23].

Algorithm 4 Alternative Kernel Proxy Variable Algorithm [23]

Input: First-stage, second-stage, and third-stage: $\{\bar{w}_i, \bar{z}_i, \bar{a}_i\}_{i=1}^{n_\varphi}, \{\bar{y}_i, \bar{z}_i, \bar{a}_i\}_{i=1}^{m_\varphi}, \{\dot{y}_i, \dot{z}_i, \dot{a}_i\}_{i=1}^{t_\varphi}$,

Parameters: Regularization parameters $\lambda_{\varphi,1}, \lambda_{\varphi,2}$, and $\lambda_{\varphi,3}$, and kernel functions $k_{\mathcal{F}}(\cdot, \cdot)$ for each $\mathcal{F} \in \{\mathcal{A}, \mathcal{Z}, \mathcal{W}\}$.

Output: Bridge function and dose response estimations: $\hat{\varphi}(\cdot, \cdot), \hat{\theta}_{ATE}(\cdot)$.

- 1: For variables $F \in \{W, Z, A\}$ with domain \mathcal{F} , define the (required) first- and second- and third-stage kernel matrices/vectors as follows:

$$\begin{aligned} \mathbf{K}_{\bar{F}\bar{F}} &= [k_{\mathcal{F}}(\bar{f}_i, \bar{f}_j)]_{ij} \in \mathbb{R}^{n_\varphi \times n_\varphi}, & \mathbf{K}_{\bar{F}\tilde{F}} &= [k_{\mathcal{F}}(\bar{f}_i, \tilde{f}_j)]_{ij} \in \mathbb{R}^{n_\varphi \times m_\varphi}, \\ \mathbf{K}_{\tilde{F}\tilde{F}} &= [k_{\mathcal{F}}(\tilde{f}_i, \tilde{f}_j)]_{ij} \in \mathbb{R}^{m_\varphi \times m_\varphi}, & \mathbf{K}_{\bar{F}f} &= [k_{\mathcal{F}}(\bar{f}_i, f)]_i \in \mathbb{R}^{n_\varphi}, \\ \mathbf{K}_{\tilde{F}f} &= [k_{\mathcal{F}}(\tilde{f}_j, f)]_j \in \mathbb{R}^{m_\varphi}, & \mathbf{K}_{\dot{F}\dot{F}} &= [k_{\mathcal{F}}(\dot{f}_i, \dot{f}_j)]_{ij} \in \mathbb{R}^{t_\varphi \times t_\varphi}, \\ \mathbf{K}_{\bar{F}\dot{F}} &= [k_{\mathcal{F}}(\bar{f}_i, \dot{f}_j)]_{ij} \in \mathbb{R}^{n_\varphi \times t_\varphi}, & \mathbf{K}_{\dot{F}f} &= [k_{\mathcal{F}}(\dot{f}_i, f)] \in \mathbb{R}^{t_\varphi} \end{aligned}$$

- 2: Define the following matrices:

$$\begin{aligned} \mathbf{B} &= (\mathbf{K}_{\bar{W}\bar{W}} \odot \mathbf{K}_{\bar{A}\bar{A}} + n_\varphi \lambda_{\varphi,1} \mathbf{I})^{-1} (\mathbf{K}_{\bar{W}\bar{W}} \odot \mathbf{K}_{\bar{A}\bar{A}}), \\ \tilde{\mathbf{B}} &\in \mathbb{R}^{m_\varphi \times n_\varphi} \text{ where } \tilde{\mathbf{B}}_{:,j} = \frac{1}{m-1} \sum_{\substack{l=1 \\ l \neq j}}^m (\mathbf{K}_{\bar{W}\bar{W}} \odot \mathbf{K}_{\bar{A}\bar{A}} + n_\varphi \lambda_{\varphi,1} \mathbf{I})^{-1} (\mathbf{K}_{\bar{W}\bar{w}_l} \odot \mathbf{K}_{\bar{A}\bar{a}_l}) \\ \mathbf{L} &= \left[\begin{array}{c} \mathbf{B}^T \mathbf{K}_{\bar{Z}\bar{Z}} \mathbf{B} \odot \mathbf{K}_{\bar{A}\bar{A}} \\ (\frac{1}{m_\varphi})^T [\mathbf{B}^T \mathbf{K}_{\bar{Z}\bar{Z}} \tilde{\mathbf{B}} \odot \mathbf{K}_{\bar{A}\bar{A}}]^T \end{array} \right]^T \in \mathbb{R}^{m_\varphi \times (m_\varphi + 1)}, \\ \mathbf{M} &= \left[\begin{array}{c} [\mathbf{B}^T \mathbf{K}_{\bar{Z}\bar{Z}} \tilde{\mathbf{B}} \odot \mathbf{K}_{\bar{A}\bar{A}}] \frac{1}{m_\varphi} \\ (\frac{1}{m_\varphi})^T [\tilde{\mathbf{B}}^T \mathbf{K}_{\bar{Z}\bar{Z}} \tilde{\mathbf{B}} \odot \mathbf{K}_{\bar{A}\bar{A}}] \frac{1}{m_\varphi} \end{array} \right] \in \mathbb{R}^{(m_\varphi + 1)}, \\ \mathbf{N} &= [\mathbf{L} \quad \mathbf{M}] \in \mathbb{R}^{(m_\varphi + 1) \times (m_\varphi + 1)}, \\ \boldsymbol{\gamma} &= \left(\frac{1}{m_\varphi} \mathbf{L}^T \mathbf{L} + \lambda_{\varphi,2} \mathbf{N} \right)^{-1} \mathbf{M} \in \mathbb{R}^{m_\varphi + 1} \end{aligned}$$

- 3: The bridge function estimation is given by $\hat{\varphi}(z, a) = \boldsymbol{\gamma}_{1:m_\varphi}^T [(\mathbf{B}^T \mathbf{K}_{\bar{Z}z}) \odot \mathbf{K}_{\bar{A}a}] + \boldsymbol{\gamma}_{m_\varphi+1}^T \left(\frac{1}{m_\varphi} \right)^T [(\tilde{\mathbf{B}}^T \mathbf{K}_{\bar{Z}z}) \odot \mathbf{K}_{\bar{A}a}]$

- 4: The dose response estimation is given by

$$\begin{aligned} \hat{\theta}_{ATE}(a) &= \boldsymbol{\gamma}_{1:m}^T \left(\mathbf{B}^T (\mathbf{K}_{\bar{Z}\bar{Z}} \text{diag}(\dot{\mathbf{Y}}) [\mathbf{K}_{\bar{A}\dot{A}} + t_\varphi \lambda_{\varphi,3} \mathbf{I}]^{-1} \mathbf{K}_{\bar{A}a}) \odot \mathbf{K}_{\bar{A}a} \right) \\ &\quad + \boldsymbol{\gamma}_{m+1}^T \left(\tilde{\mathbf{B}}^T (\mathbf{K}_{\bar{Z}\bar{Z}} \text{diag}(\dot{\mathbf{Y}}) [\mathbf{K}_{\bar{A}\dot{A}} + t_\varphi \lambda_{\varphi,3} \mathbf{I}]^{-1} \mathbf{K}_{\bar{A}a}) \odot \mathbf{K}_{\bar{A}a} \right) \frac{1}{m_\varphi} \end{aligned}$$

C.3 Doubly robust kernel proxy variable algorithm

Armed with the estimation procedures for the outcome and treatment bridge functions, we now present the doubly robust estimation algorithm for the dose-response curve. As discussed in Section (3.2), we need to derive an algorithm to estimate the term $\mathbb{E}[\varphi_0(Z, a) h_0(W, a) \mid A = a]$. Let $\{z_i, w_i, a_i\}_i^t \subset \mathcal{D}$ denote i.i.d. observations from the distribution $\mathbb{P}(Z, W, A)$. We observe the following

$$\begin{aligned} \mathbb{E}[\varphi_0(Z, a) h_0(W, a) \mid A = a] &\approx \mathbb{E}[\hat{\varphi}(Z, a) \hat{h}(W, a) \mid A = a] \\ &= \mathbb{E} \left[\left\langle \hat{\varphi}, \phi_{\mathcal{Z}}(Z) \otimes \phi_{\mathcal{A}}(a) \right\rangle_{\mathcal{H}_{\mathcal{Z}} \otimes \mathcal{H}_{\mathcal{A}}} \left\langle \hat{h}, \phi_{\mathcal{W}}(W) \otimes \phi_{\mathcal{A}}(a) \right\rangle_{\mathcal{H}_{\mathcal{W}} \otimes \mathcal{H}_{\mathcal{A}}} \right] \\ &= \mathbb{E} \left[\left\langle \hat{\varphi} \otimes \hat{h}, (\phi_{\mathcal{Z}}(Z) \otimes \phi_{\mathcal{A}}(a)) \otimes (\phi_{\mathcal{W}}(W) \otimes \phi_{\mathcal{A}}(a)) \right\rangle_{\mathcal{H}_{\mathcal{Z}} \otimes \mathcal{H}_{\mathcal{A}} \otimes \mathcal{H}_{\mathcal{W}} \otimes \mathcal{H}_{\mathcal{A}}} \right]. \end{aligned}$$

As detailed in Section (S.M. C.1.1), the outcome bridge function in the KPV algorithm has the following representation (see Appendix B.3 in [11]):

$$\hat{h} = \sum_i^{n_h} \sum_j^{m_h} \beta_{ij} \phi_{\mathcal{W}}(\bar{w}_i) \otimes \phi_{\mathcal{A}}(\bar{a}_j)$$

where the set of variables \tilde{w}_i and \tilde{a}_j denote the samples from first and second stage regressions of KPV algorithm, respectively. Furthermore, as detailed in Appendix (C.2), the treatment bridge function admits the representation

$$\hat{\varphi} = \sum_{i=1}^{m_\varphi} \gamma_i \hat{\mu}_{Z|W,A}(\tilde{w}_i, \tilde{a}_i) \otimes \phi_{\mathcal{A}}(\tilde{a}_i) + \frac{\gamma_{m_\varphi+1}}{m_\varphi(m_\varphi-1)} \sum_{j=1}^{m_\varphi} \sum_{\substack{l=1 \\ l \neq j}}^{m_\varphi} \hat{\mu}_{Z|W,A}(\tilde{w}_l, \tilde{a}_j) \otimes \phi_{\mathcal{A}}(\tilde{a}_j),$$

which we can write without loss of generality as

$$\hat{\varphi} = \sum_{l=1}^{m_\varphi} \sum_{t=1}^{m_\varphi} \gamma_{lt} \hat{\mu}_{Z|W,A}(\tilde{w}_t, \tilde{a}_l) \otimes \phi_{\mathcal{A}}(\tilde{a}_l)$$

by appropriately choosing the coefficients γ_{lt} from the set $\{\alpha_i\}_{i=1}^{m+1} \cup \{0\}$. Next, we notice the following

$$\begin{aligned} & \mathbb{E}[\hat{\varphi}(Z, a) \hat{h}(W, a) \mid A = a] = \\ &= \mathbb{E} \left[\left\langle \left(\sum_l \sum_t \gamma_{lt} \hat{\mu}_{Z|W,A}(\tilde{w}_t, \tilde{a}_l) \otimes \phi_{\mathcal{A}}(\tilde{a}_l) \right) \otimes \left(\sum_i \sum_j \beta_{ij} \phi_{\mathcal{W}}(\tilde{w}_i) \otimes \phi_{\mathcal{A}}(\tilde{a}_j) \right) \right. \right. \\ & \quad \left. \left. , (\phi_{\mathcal{Z}}(Z) \otimes \phi_{\mathcal{A}}(a)) \otimes (\phi_{\mathcal{W}}(W) \otimes \phi_{\mathcal{A}}(a)) \right\rangle_{\mathcal{H}_{\mathcal{Z}, \mathcal{A}} \otimes \mathcal{H}_{\mathcal{W}, \mathcal{A}}} \middle| A = a \right] \\ &= \sum_{i,j} \sum_{l,t} \alpha_{ij} \gamma_{lt} \mathbb{E} \left[\left\langle \hat{\mu}_{Z|W,A}(\tilde{w}_t, \tilde{a}_l) \otimes \phi_{\mathcal{A}}(\tilde{a}_l) \otimes \phi_{\mathcal{W}}(\tilde{w}_i) \otimes \phi_{\mathcal{A}}(\tilde{a}_j) \right. \right. \\ & \quad \left. \left. , \phi_{\mathcal{Z}}(Z) \otimes \phi_{\mathcal{A}}(a) \otimes \phi_{\mathcal{W}}(W) \otimes \phi_{\mathcal{A}}(a) \right\rangle_{\mathcal{H}_{\mathcal{Z}, \mathcal{A}} \otimes \mathcal{H}_{\mathcal{W}, \mathcal{A}}} \middle| A = a \right] \\ &= \sum_{i,j} \sum_{l,t} \alpha_{ij} \gamma_{lt} \mathbb{E} \left[\left\langle \hat{\mu}_{Z|W,A}(\tilde{w}_t, \tilde{a}_l), \phi_{\mathcal{Z}}(Z) \right\rangle_{\mathcal{H}_{\mathcal{Z}}} \left\langle \phi_{\mathcal{A}}(\tilde{a}_l), \phi_{\mathcal{A}}(a) \right\rangle_{\mathcal{H}_{\mathcal{A}}} \right. \\ & \quad \left. \left\langle \phi_{\mathcal{W}}(\tilde{w}_i), \phi_{\mathcal{W}}(W) \right\rangle_{\mathcal{H}_{\mathcal{W}}} \left\langle \phi_{\mathcal{A}}(\tilde{a}_j), \phi_{\mathcal{A}}(a) \right\rangle_{\mathcal{H}_{\mathcal{A}}} \middle| A = a \right] \\ &= \sum_{i,j} \sum_{l,t} \alpha_{ij} \gamma_{lt} \mathbb{E} \left[\left\langle \hat{\mu}_{Z|W,A}(\tilde{w}_t, \tilde{a}_l) \otimes \phi_{\mathcal{W}}(\tilde{w}_i), \phi_{\mathcal{Z}}(Z) \otimes \phi_{\mathcal{W}}(W) \right\rangle_{\mathcal{H}_{\mathcal{Z}, \mathcal{W}}} \right. \\ & \quad \left. \left\langle \phi_{\mathcal{A}}(\tilde{a}_l) \otimes \phi_{\mathcal{A}}(\tilde{a}_j), \phi_{\mathcal{A}}(a) \otimes \phi_{\mathcal{A}}(a) \right\rangle_{\mathcal{H}_{\mathcal{A}, \mathcal{A}}} \middle| A = a \right] \\ &= \sum_{i,j} \sum_{l,t} \alpha_{ij} \gamma_{lt} \left\langle \hat{\mu}_{Z|W,A}(\tilde{w}_t, \tilde{a}_l) \otimes \phi_{\mathcal{W}}(\tilde{w}_i), \mathbb{E}[\phi_{\mathcal{Z}}(Z) \otimes \phi_{\mathcal{W}}(W) \mid A = a] \right\rangle_{\mathcal{H}_{\mathcal{Z}, \mathcal{W}}} \\ & \quad \left\langle \phi_{\mathcal{A}}(\tilde{a}_l) \otimes \phi_{\mathcal{A}}(\tilde{a}_j), \phi_{\mathcal{A}}(a) \otimes \phi_{\mathcal{A}}(a) \right\rangle_{\mathcal{H}_{\mathcal{A}, \mathcal{A}}}. \end{aligned} \tag{28}$$

In order to evaluate the sum of inner products above, we need the conditional mean embedding $\mu_{Z,W|A}(a) = \mathbb{E}[\phi_{\mathcal{Z}}(Z) \otimes \phi_{\mathcal{W}}(W) \mid A = a]$. We approximate this term with vector-valued kernel ridge regression. In particular, under the regularity condition $\mathbb{E}[g(Z, W) \mid A = \cdot] \in \mathcal{H}_{\mathcal{A}}$ for all $g \in \mathcal{H}_{\mathcal{Z}, \mathcal{W}}$, there exists an operator $C_{Z,W|A} \in \mathcal{S}_2(\mathcal{H}_{\mathcal{A}}, \mathcal{H}_{\mathcal{Z}, \mathcal{W}})$ such that $\mathbb{E}[\phi_{\mathcal{Z}}(Z) \otimes \phi_{\mathcal{W}}(W) \mid A = a] = C_{Z,W|A} \phi_{\mathcal{A}}(a)$. This operator can be learned by minimizing the regularized least-squares function:

$$\hat{\mathcal{L}}_{DR}^c(C) = \frac{1}{t} \sum_{i=1}^t \|\phi_{\mathcal{Z}}(z_i) \otimes \phi_{\mathcal{W}}(w_i) - C \phi_{\mathcal{A}}(a_i)\|_{\mathcal{H}_{\mathcal{Z}, \mathcal{W}}}^2 + \lambda_{DR} \|C\|_{\mathcal{S}_2(\mathcal{H}_{\mathcal{A}}, \mathcal{H}_{\mathcal{Z}, \mathcal{W}})}^2.$$

The minimizer is given by

$$\hat{\mu}_{Z,W|A}(a) = \hat{C}_{Z,W|A} \phi_{\mathcal{A}}(a) = \sum_i \xi_i \phi_{\mathcal{Z}}(z_i) \otimes \phi_{\mathcal{W}}(w_i) = \Phi_{\mathcal{Z}, \mathcal{W}} (\mathbf{K}_{AA} + t \lambda_{DR} \mathbf{I})^{-1} \mathbf{K}_{Aa}, \tag{29}$$

where $\xi_i = \left[(\mathbf{K}_{AA} + t \lambda_{DR} \mathbf{I})^{-1} \mathbf{K}_{Aa} \right]_i$ and $\Phi_{\mathcal{Z}, \mathcal{W}} = [\phi_{\mathcal{Z}}(z_1) \otimes \phi_{\mathcal{W}}(w_1) \ \dots \ \phi_{\mathcal{Z}}(z_t) \otimes \phi_{\mathcal{W}}(w_t)]$. By plugging this approximation to conditional

mean embedding in Equation (28), we observe that

$$\begin{aligned}
& \sum_{i,j} \sum_{l,t} \alpha_{ij} \gamma_{lt} \left\langle \hat{\mu}_{Z|W,A}(\tilde{w}_t, \tilde{a}_l) \otimes \phi_{\mathcal{W}}(\bar{w}_i), \sum_s \xi_s \phi_{\mathcal{Z}}(z_s) \otimes \phi_{\mathcal{W}}(w_s) \right\rangle_{\mathcal{H}_{\mathcal{ZW}}} \\
& \left\langle \phi_{\mathcal{A}}(\tilde{a}_l) \otimes \phi_{\mathcal{A}}(\tilde{a}_j), \phi_{\mathcal{A}}(a) \otimes \phi_{\mathcal{A}}(a) \right\rangle_{\mathcal{H}_{\mathcal{AA}}} \\
& = \sum_{i,j} \sum_{l,t} \sum_s \alpha_{ij} \gamma_{lt} \xi_s \left\langle \hat{\mu}_{Z|W,A}(\tilde{w}_t, \tilde{a}_l) \otimes \phi_{\mathcal{W}}(\bar{w}_i), \phi_{\mathcal{Z}}(z_s) \otimes \phi_{\mathcal{W}}(w_s) \right\rangle_{\mathcal{H}_{\mathcal{ZW}}} \\
& \left\langle \phi_{\mathcal{A}}(\tilde{a}_l) \otimes \phi_{\mathcal{A}}(\tilde{a}_j), \phi_{\mathcal{A}}(a) \otimes \phi_{\mathcal{A}}(a) \right\rangle_{\mathcal{H}_{\mathcal{AA}}} \\
& = \sum_s \xi_s \left\langle \sum_{l,t} \gamma_{lt} \hat{\mu}_{Z|W,A}(\tilde{w}_t, \tilde{a}_l) \otimes \phi_{\mathcal{A}}(\tilde{a}_l), \phi_{\mathcal{Z}}(z_s) \otimes \phi_{\mathcal{A}}(a) \right\rangle_{\mathcal{H}_{\mathcal{ZA}}} \\
& \left\langle \sum_{i,j} \alpha_{ij} \phi_{\mathcal{W}}(\bar{w}_i) \otimes \phi_{\mathcal{A}}(\tilde{a}_j), \phi_{\mathcal{W}}(w_s) \otimes \phi_{\mathcal{A}}(a) \right\rangle_{\mathcal{H}_{\mathcal{WA}}} \\
& = \sum_s \xi_s \hat{\varphi}(z_s, a) \hat{h}(w_s, a).
\end{aligned}$$

In conclusion, we estimate the term $\mathbb{E}[\varphi_0(Z, a) h_0(W, a) \mid A = a]$ with the following expression:

$$\mathbb{E}[\varphi_0(Z, a) h_0(W, a) \mid A = a] \approx \sum_s \xi_s(a) \hat{\varphi}(z_s, a) \hat{h}(w_s, a), \quad (30)$$

where $\xi_s(a) = \left[(\mathbf{K}_{AA} + t\lambda_{DR}\mathbf{I})^{-1} \mathbf{K}_{Aa} \right]_s$. The same procedure can be applied with the PMMR representation of the outcome-bridge function \hat{h} that will lead to the same form of estimation in Equation (30). For completeness of this section, we repeat the pseudo-code of doubly robust dose-response estimation algorithms that we give in Section (3.2) below. Note that DRKPV uses the KPV algorithm (summarized in Algorithm (2)), whereas DRPMMR employs the PMMR method (summarized in Algorithm (3)).

Algorithm 5 Doubly Robust Kernel Proxy Variable Algorithm (Replication of Algorithm (1) in Section (3.2)).

Input: Training samples $\{y_i, w_i, z_i, a_i\}_{i=1}^t \subset \mathcal{D}$.

Parameters: Regularization parameter λ_{DR} and the parameters of Algorithms (4) and (2) or (3).

Output: Doubly robust dose-response estimation $\hat{\theta}_{ATE}^{(DR)}(a)$ for all $a \in \mathcal{A}$.

- 1: Compute the estimated outcome bridge function \hat{h} and dose-response curve $\hat{\theta}_1(\cdot) = \hat{E}[\hat{h}(W, \cdot)]$ with either Algorithm (2) or (3).
- 2: Compute the estimated treatment bridge function $\hat{\varphi}$ and the dose-response curve $\hat{\theta}_2(\cdot) = \hat{E}[Y\hat{\varphi}(Z, \cdot) \mid A = \cdot]$ with Algorithm (4).
- 3: Let $\hat{\theta}_3(\cdot)$ be given by $\hat{\theta}_3(\cdot) = \sum_i \xi_i(\cdot) \hat{\varphi}(z_i, \cdot) \hat{h}(w_i, \cdot)$, where $\xi_i(a) = [(\mathbf{K}_{AA} + t\lambda_{DR}\mathbf{I})^{-1} \mathbf{K}_{Aa}]_i$ for all $a \in \mathcal{A}$.
- 4: For each $a \in \mathcal{A}$, return the doubly robust dose-response estimation as

$$\hat{\theta}_{ATE}^{(DR)}(a) = \hat{\theta}_1(a) + \hat{\theta}_2(a) - \hat{\theta}_3(a).$$

D Discussion on the existence of bridge functions

In this section, we present the conditions under which the outcome and treatment bridge functions exist in their respective RKHSs, following the formulations in Miao et al. [5], Deaner [10], Xu et al. [13], and Bozkurt et al. [23]. To this end, we consider the conditional expectation operators defined by

$$\begin{aligned}
E_a : \mathcal{L}_2(\mathcal{W}, p_{W|A=a}) &\rightarrow \mathcal{L}_2(\mathcal{Z}, p_{Z|A=a}), \\
F_a : \mathcal{L}_2(\mathcal{Z}, p_{Z|A=a}) &\rightarrow \mathcal{L}_2(\mathcal{W}, p_{W|A=a}),
\end{aligned}$$

such that

$$\begin{aligned} E_a \ell(z) &= \mathbb{E}[\ell(W)|Z = z, A = a], & z \in \mathcal{Z} \\ F_a \ell(w) &= \mathbb{E}[\ell(Z)|W = w, A = a], & w \in \mathcal{W}. \end{aligned}$$

Here, $p_{W|A=a}$ and $p_{Z|A=a}$ denote the conditional distributions of W and Z given $A = a$, respectively.

To ensure the existence of the bridge functions, we impose the following assumptions on the conditional expectation operators.

Assumption D.1 (Assumption (4) in [13]). *For each $a \in \mathcal{A}$, the operator E_a is compact operator with singular value decomposition $\{\eta_{E_a,i}, \phi_{E_a,i}, \psi_{E_a,i}\}_{i=1}^\infty$.*

Assumption D.2 (Assumption (10.3) in [23]). *For each $a \in \mathcal{A}$, the operator F_a is compact operator with singular value decomposition $\{\eta_{F_a,i}, \phi_{F_a,i}, \psi_{F_a,i}\}_{i=1}^\infty$.*

To apply Picard's Theorem [63, Theorem 15.8]—as used in Lemma (2) of Xu et al. [13] and Theorem (10.6) of Bozkurt et al. [23]—to establish the existence of bridge functions, we make the following additional assumptions.

Assumption D.3 (Assumption (5) in [13]). *For each $a \in \mathcal{A}$, the conditional expectation $\ell_{Y|a} := \mathbb{E}[Y | Z = \cdot, A = a]$ satisfies*

$$\sum_{i=1}^{\infty} \frac{1}{\eta_{E_a,i}^2} \left| \langle \ell_{Y|a}, \psi_{E_a,i} \rangle_{\mathcal{L}_2(\mathcal{Z}, p_{Z|A=a})} \right|^2 < \infty,$$

where the singular system $\{\eta_{E_a,i}, \phi_{E_a,i}, \psi_{E_a,i}\}_{i=1}^\infty$ is given in Assumption (D.1).

Assumption D.4 (Assumption (10.4) in [23]). *For each $a \in \mathcal{A}$, the density ratio $r_a(W) := \frac{p(W)p(a)}{p(W,a)}$ satisfies*

$$\sum_{i=1}^{\infty} \frac{1}{\eta_{F_a,i}^2} \left| \langle r_a, \psi_{F_a,i} \rangle_{\mathcal{L}_2(\mathcal{W}, p_{W|A=a})} \right|^2 < \infty,$$

where the singular system $\{\eta_{F_a,i}, \phi_{F_a,i}, \psi_{F_a,i}\}_{i=1}^\infty$ is given in Assumption (D.2).

We are now ready to state the results on the existence of bridge functions. The following lemma establishes the existence of the outcome bridge function.

Lemma D.5 (Lemma (2) in [13]). *Suppose that Assumptions (2.2), (2.5), (D.1), and (D.3) hold. Then, for each $a \in \mathcal{A}$, there exists a solution to the functional equation*

$$\mathbb{E}[Y | Z, A] = \int h_0(w, A) p(w | Z, A) dw.$$

The next lemma establishes the existence of the treatment bridge function.

Lemma D.6 (Theorem (10.6) in [23]). *Suppose that Assumptions (2.2), (2.3), (D.2), and (D.4) hold. Then, for each $a \in \mathcal{A}$, there exists a solution to the functional equation*

$$\mathbb{E}[\varphi_0(Z, a) | W, A = a] = \frac{p(W)p(a)}{p(W, a)}, \quad a \in \mathcal{A}.$$

Note that the existence of the **outcome bridge function** hinges on Assumption (2.5), which also ensures the identifiability of the dose-response curve when using the **treatment bridge function** (see Theorem (2.6)). Conversely, the existence of the **treatment bridge function** hinges on Assumption (2.3), which guarantees identifiability of the dose-response curve through the **outcome bridge function** (see Theorem (2.4)). Therefore, these completeness assumptions play distinct yet complementary roles in establishing both existence and identifiability for the respective bridge functions.

E Consistency results

In this section, we provide the convergence results of the algorithms that we proposed. First, the following two sections respectively review the consistency results for outcome bridge function- and treatment bridge function-based methods from [11, 12, 23].

E.1 Consistency results for treatment bridge function-based method

Here, we overview the consistency result of the treatment bridge function based on the results in [23]. For expositional clarity, we first review the results from [23], as we leverage similar developments in presenting the consistency results for the outcome bridge function in the next section. We begin by introducing the assumptions regarding the noise between the treatment and the outcome.

Assumption E.1 (Assumption (12.1-iv) in [23]). *We assume that there exists $R, \sigma > 0$ such that for all $q \geq 2$, P_A -almost surely,*

$$\mathbb{E}[(Y - \mathbb{E}[Y | A])^q | A] \leq \frac{1}{2} q! \sigma^2 R^{q-2}. \quad (31)$$

Next, we assume that the problem is well-specified, as stated in the following assumption:

Assumption E.2 (Assumption (5.1) in [23]). *(1) There exists $C_{Z|W,A} \in S_2(\mathcal{H}_{W,A}, \mathcal{H}_Z)$ such that $\mu_{Z|W,A}(W, A) = C_{Z|W,A} \phi_{W,A}(W, A)$; (2) There exists a solution $\varphi_0 \in \mathcal{H}_{Z,A}$ of Equation (2); (3) There exists $C_{Y|Z,A} \in S_2(\mathcal{H}_A, \mathcal{H}_Z)$ such that $\mathbb{E}[Y \phi_Z(Z) | A] = C_{Y|Z,A} \phi_A(A)$.*

Following proof techniques from [64], Bozkurt et al. [23] show that convergence to the minimum RKHS norm solution of the treatment bridge equation—characterized in the following definition—is sufficient for consistency in estimating the dose-response curve using the Kernel Alternative Proxy (KAP) method. We follow the same setting here.

Definition E.3 (Treatment bridge function solution with minimum RKHS norm, Definition (12.2) in [23]). *Under Assumption (E.1-2)), the minimum RKHS solution to Equation (2) is defined as*

$$\bar{\varphi}_0 = \arg \min_{\varphi \in \mathcal{H}_{Z,A}} \|\varphi\|_{\mathcal{H}_{Z,A}} \quad \text{s.t.} \quad \mathbb{E}[\varphi(Z, A) | W, A] = r(W, A),$$

$$\text{with } r(W, A) = \frac{p(W)p(A)}{p(W, A)}.$$

Next, we define the (uncentered) covariance operators corresponding to the three-stages of the KAP method:

Definition E.4 (Definition (12.4) in [23]). *The covariance operators are defined as*

- (Stage 1) $\Sigma_{\varphi,1} = \mathbb{E}[\phi_{W,A}(W, A) \otimes \phi_{W,A}(W, A)]$, $\phi_{W,A}(W, A) = \phi_W(W) \otimes \phi_A(A)$;
- (Stage 2) $\Sigma_{\varphi,2} = \mathbb{E}[(\mu_{Z|W,A}(W, A) \otimes \phi_A(A)) \otimes (\mu_{Z|W,A}(W, A) \otimes \phi_A(A))]$;
- (Stage 3) $\Sigma_{\varphi,3} = \mathbb{E}[\phi_A(A) \otimes \phi_A(A)]$.

The operators $\Sigma_{\varphi,1}$, $\Sigma_{\varphi,2}$, and $\Sigma_{\varphi,3}$ are self-adjoint and positive semi-definite. With Assumption (3.1), they belong to the trace class, which ensures their compactness and implies that they have a countable spectrum [65].

Furthermore, we state the source condition (SRC) and eigenvalue decay (EVD) assumptions [66, 67]:

Assumption E.5 (Assumption (12.6) in [23]). *We assume that the following conditions hold:*

- There exists a constant $B_{\varphi,1} < \infty$ such that for a given $\beta_{\varphi,1} \in (1, 3]$,

$$\|C_{Z|W,A} \Sigma_{\varphi,1}^{-\frac{\beta_{\varphi,1}-1}{2}}\|_{S_2(\mathcal{H}_{W,A}, \mathcal{H}_Z)} \leq B_{\varphi,1}$$

- There exists a constant $B_{\varphi,2} < \infty$ such that for a given $\beta_{\varphi,2} \in (1, 3]$,

$$\|\Sigma_{\varphi,2}^{-\frac{\beta_{\varphi,2}-1}{2}} \bar{\varphi}_0\|_{\mathcal{H}_{Z,A}} \leq B_{\varphi,2}.$$

- There exists a constant $B_{\varphi,3} < \infty$ such that for a given $\beta_{\varphi,3} \in (1, 3]$,

$$\|C_{Y|Z,A} \Sigma_{\varphi,3}^{-\frac{\beta_{\varphi,3}-1}{2}}\|_{S_2(\mathcal{H}_A, \mathcal{H}_Z)} \leq B_{\varphi,3}.$$

Assumption E.6 (Assumption (12.9) in [23]). *We assume the following conditions hold*

- Let $(\lambda_{\varphi,1,i})_{i \geq 1}$ be the eigenvalues of $\Sigma_{\varphi,1}$. For some constant $c_{\varphi,1} > 0$ and parameter $p_{\varphi,1} \in (0, 1]$ and for all $i \geq 1$,

$$\lambda_{\varphi,1,i} \leq c_{\varphi,1} i^{-1/p_{\varphi,1}}.$$

- Let $(\lambda_{\varphi,2,i})_{i \geq 1}$ be the eigenvalues of $\Sigma_{\varphi,2}$. For some constant $c_{\varphi,2} > 0$ and parameter $p_{\varphi,2} \in (0, 1]$ and for all $i \geq 1$,

$$\lambda_{\varphi,2,i} \leq c_{\varphi,2} i^{-1/p_{\varphi,2}}.$$

- Let $(\lambda_{\varphi,3,i})_{i \geq 1}$ be the eigenvalues of $\Sigma_{\varphi,3}$. For some constant $c_{\varphi,3} > 0$ and parameter $p_{\varphi,3} \in (0, 1]$ and for all $i \geq 1$,

$$\lambda_{\varphi,3,i} \leq c_{\varphi,3} i^{-1/p_{\varphi,3}}.$$

Now, we are ready to state the convergence result of the treatment bridge function. We note that Assumptions (E.2-3), (E.5-3) and (E.6-3) are not required for the bridge function consistency. However, the consistency of our proposed double robust estimators rely on these assumptions as we show in Section (S.M. E.3).

Theorem E.7 (Theorem 12.21 in [23]). *Suppose Assumptions (3.1), (E.1), (E.2-1 & 2), (E.5-1 & 2) and (E.6-1 & 2) hold and set $\lambda_{\varphi,1} = \Theta \left(n_{\varphi}^{-\frac{1}{\beta_{\varphi,1}+p_{\varphi,1}}} \right)$ and $n_{\varphi} = m_{\varphi}^{\frac{\iota_{\varphi} \beta_{\varphi,1}+p_{\varphi,1}}{\beta_{\varphi,1}-1}}$ where $\iota_{\varphi} > 0$. Then,*

- i. *If $\iota_{\varphi} \leq \frac{\beta_{\varphi,2}+1}{\beta_{\varphi,2}+p_{\varphi,2}}$ then $\|\hat{\varphi} - \bar{\varphi}_0\|_{\mathcal{H}_{\mathcal{Z}\mathcal{A}}} = O_p \left(m_{\varphi}^{-\frac{\iota_{\varphi} \beta_{\varphi,2}-1}{2 \beta_{\varphi,2}+1}} \right)$ with $\lambda_{\varphi,2} = \Theta \left(m_{\varphi}^{-\frac{\iota_{\varphi}}{\beta_{\varphi,2}+1}} \right)$;*
- ii. *If $\iota_{\varphi} \geq \frac{\beta_{\varphi,2}+1}{\beta_{\varphi,2}+p_{\varphi,2}}$ then $\|\hat{\varphi} - \bar{\varphi}_0\|_{\mathcal{H}_{\mathcal{Z}\mathcal{A}}} = O_p \left(m_{\varphi}^{-\frac{1}{2} \frac{\beta_{\varphi,2}-1}{\beta_{\varphi,2}+p_{\varphi,2}}} \right)$ with $\lambda_{\varphi,2} = \Theta \left(m_{\varphi}^{-\frac{1}{\beta_{\varphi,2}+p_{\varphi,2}}} \right)$.*

ι_{φ} controls the ratio of stage 1 to stage 2 samples. In Theorem E.7-(ii), when $\iota_{\varphi} \geq \frac{\beta_{\varphi,2}+1}{\beta_{\varphi,2}+p_{\varphi,2}}$, i.e. when we have enough stage 1 samples relatively to stage 2 samples, the convergence rate is optimal in m_{φ} under the assumptions of the theorem (see Section 5 [23]).

E.2 Consistency results for outcome bridge function-based methods

In the following subsections, we review the consistency results for the outcome bridge functions of both the KPV and PMMR methods.

E.2.1 Consistency result for kernel proxy variable

We first review the consistency result of the outcome bridge function with the Kernel Proxy Variable (KPV) algorithm that have been obtained concurrently by [11, 12]. We assume that the problem is well-specified as stated in the following assumption:

Assumption E.8 (Assumption (2.1) and (8.1) in [12]). *(1) There exists $C_{W|Z,A} \in S_2(\mathcal{H}_{\mathcal{Z}\mathcal{A}}, \mathcal{H}_{\mathcal{W}})$ such that $\mu_{W|Z,A}(Z, A) = C_{W|Z,A} \phi_{\mathcal{Z}\mathcal{A}}(Z, A)$; (2) There exists a solution $h_0 \in \mathcal{H}_{\mathcal{W}\mathcal{A}}$ of Equation (1).*

Following a similar convention to [23], we define the minimum RKHS norm solution to the outcome bridge function equation:

Definition E.9 (Outcome bridge function solution with minimum RKHS norm). *Under Assumption (E.8-(2)), the minimum RKHS solution to Equation (1) is defined as*

$$\bar{h}_0 = \arg \min_{h \in \mathcal{H}_{\mathcal{W}\mathcal{A}}} \|h\|_{\mathcal{H}_{\mathcal{W}\mathcal{A}}} \quad \text{s.t.} \quad \mathbb{E}[h(W, A)|Z, A] = \int yp(y | z, a) dy,$$

Similar to [23], we establish the convergence to the minimum norm RKHS solution for the outcome bridge function. Now, we define the covariance operators corresponding to different stages of regression of KPV.

Definition E.10 (Covariance Operators). *The covariance operators are defined as*

- (Stage 1) $\Sigma_{h,1} = \mathbb{E} [\phi_{\mathcal{Z}\mathcal{A}}(Z, A) \otimes \phi_{\mathcal{Z}\mathcal{A}}(Z, A)]$, $\phi_{\mathcal{Z}\mathcal{A}}(Z, A) = \phi_{\mathcal{Z}}(Z) \otimes \phi_{\mathcal{A}}(A)$;
- (Stage 2) $\Sigma_{h,2} = \mathbb{E} [(\mu_{W|Z,A}(Z, A) \otimes \phi_{\mathcal{A}}(A)) \otimes (\mu_{W|Z,A}(Z, A) \otimes \phi_{\mathcal{A}}(A))]$;

Similarly to the previous section $\Sigma_{h,1}$ and $\Sigma_{h,2}$ are self-adjoint, positive semi-definite and trace class under Assumption (3.1). We state the source condition (SRC) and eigenvalue decay (EVD) assumptions [66, 67] :

Assumption E.11 (SRC for KPV). *We assume that the following conditions hold:*

- *There exists a constant $B_{h,1} < \infty$ such that for a given $\beta_{h,1} \in (1, 3]$,*

$$\|C_{W|Z,A} \Sigma_{h,1}^{-\frac{\beta_{h,1}-1}{2}}\|_{S_2(\mathcal{H}_{Z,A}, \mathcal{H}_W)} \leq B_{h,1}$$

- *There exists a constant $B_{h,2} < \infty$ such that for a given $\beta_{h,2} \in (1, 3]$,*

$$\|\Sigma_{h,2}^{-\frac{\beta_{h,2}-1}{2}} \bar{h}_0\|_{\mathcal{H}_{W,A}} \leq B_{h,2}.$$

Assumption E.12 (EVD for KPV). *We assume the following conditions hold*

- *Let $(\lambda_{h,1,i})_{i \geq 1}$ be the eigenvalues of $\Sigma_{h,1}$. For some constant $c_{h,1} > 0$ and parameter $p_{h,1} \in (0, 1]$ and for all $i \geq 1$,*

$$\lambda_{h,1,i} \leq c_{h,1} i^{-1/p_{h,1}}.$$

- *Let $(\lambda_{h,2,i})_{i \geq 1}$ be the eigenvalues of $\Sigma_{h,2}$. For some constant $c_{h,2} > 0$ and parameter $p_{h,2} \in (0, 1]$ and for all $i \geq 1$,*

$$\lambda_{h,2,i} \leq c_{h,2} i^{-1/p_{h,2}}.$$

Theorem E.13 (Theorem (7) [11]). *Suppose Assumptions (3.1), (E.1), (E.8), (E.11), and (E.12) hold*

and set $\lambda_{h,1} = \Theta\left(n_h^{-\frac{1}{\beta_{h,1}+p_{h,1}}}\right)$ and $n_h = m_h^{\frac{\beta_{h,1}+p_{h,1}}{\beta_{h,1}-1} \iota_h}$ where $\iota_h > 0$. Then,

- If $\iota_h \leq \frac{\beta_{h,2}+1}{\beta_{h,2}+p_{h,2}}$, then $\|\hat{h} - \bar{h}_0\|_{\mathcal{H}_{W,A}} = O_p\left(m_h^{-\frac{\iota_h}{2} \frac{\beta_{h,2}-1}{\beta_{h,2}+1}}\right)$ with $\lambda_{h,2} = \Theta\left(m_h^{-\frac{\iota_h}{\beta_{h,2}+1}}\right)$,*
- If $\iota_h \geq \frac{\beta_{h,2}+1}{\beta_{h,2}+p_{h,2}}$, then $\|\hat{h} - \bar{h}_0\|_{\mathcal{H}_{W,A}} = O_p\left(m_h^{-\frac{1}{2} \frac{\beta_{h,2}-1}{\beta_{h,2}+p_{h,2}}}\right)$ with $\lambda_{h,2} = \Theta\left(m_h^{-\frac{1}{\beta_{h,2}+p_{h,2}}}\right)$.*

Similarly to Theorem (E.7), ι_h controls the ratio of stage 1 to stage 2 samples. In Theorem (E.13-(ii)), when we have enough stage 1 samples relatively to stage 2 samples, the convergence rate is optimal in m_h under the assumptions of the theorem. A similar result is obtained by Singh [12, Theorem (3)] with a slightly worse requirement on stage 1 samples in order to achieve the optimal rate in m_h .

Technically, Mastouri et al. [11] require Y to be almost surely bounded. However, we can resort to the weaker assumption of sub-exponential noise, Assumption (E.1), by using the concentration inequality of [67, Theorem (26)] as done in [64, 23].

E.2.2 Consistency result for proximal maximum moment restriction

Here, we state the convergence result of the outcome bridge function for the PMMR algorithm, originally established by Mastouri et al. [11]. This result plays a key role in our consistency analysis of the DRPMMR algorithm. Similarly to KPV, we assume that the problem is well-specified but we only require Assumption (E.8-(2)).

Definition E.14 (Outcome bridge function solution with minimum RKHS norm - PMMR). *Under Assumption (E.8-(2)), we define*

$$\check{h}_0 = \arg \min_{h \in \mathcal{H}_{W,A}} \|h\|_{\mathcal{H}_{W,A}} \quad s.t. \quad \mathbb{E}[h(W, A)\phi(Z, A)] = \mathbb{E}[Y\phi(Z, A)].$$

Note that under Assumption (E.8-(2)) there is always a solution to $\mathbb{E}[h(W, A)\phi(Z, A)] = \mathbb{E}[Y\phi(Z, A)]$. Next, we introduce the cross-covariance operator associated to PMMR.

Definition E.15 (Cross-covariance Operator). $T = \mathbb{E}[\phi_{Z,A}(Z, A) \otimes \phi_{W,A}(W, A)]$.

To ensure the consistency of the PMMR outcome bridge function estimator, we require the following assumption.

Assumption E.16 (Assumption 6 in [11]). *We assume that there exist C_Y such that $|Y| < C_Y$ almost surely and $\mathbb{E}[Y] < C_Y$.*

Assumption E.17 (SRC for PMMR - Assumption 16 in [11]). *There exists a constant $B'_{h,2} < \infty$ such that for a given $\gamma \in (1, 3]$,*

$$\|(T^*T)^{-\frac{\gamma-1}{2}} \check{h}_0\|_{\mathcal{H}_{\mathcal{W}\mathcal{A}}} \leq B'_{h,2}.$$

Theorem E.18 (Theorem 3 in [11]). *Suppose Assumptions (3.1), (E.16), (E.8-(2)), and (E.17) hold and set $\lambda_{\text{PMMR}} = \Theta\left(t^{-\frac{1}{\gamma+1}}\right)$, then*

$$\|\hat{h} - \check{h}_0\|_{\mathcal{H}_{\mathcal{A}\mathcal{W}}} = O_p\left(t^{-\frac{1}{2} \frac{\gamma-1}{\gamma+1}}\right)$$

Using a refined analysis as done in [64, 23] it should be possible to improve their result with a rate depending on the eigenvalue decay of the operator T as well as relaxing Assumption (E.16) to Assumption (E.1).

Remark E.19. *Notice that the convergence rate given in Mastouri et al. [11, Theorem 3] is $\|\hat{h} - \check{h}_0\|_{\mathcal{H}_{\mathcal{A}\mathcal{W}}} = O_p\left(t^{-\frac{1}{2} \min(\frac{1}{2}, \frac{\gamma-1}{\gamma+1})}\right)$. However, since $\gamma \in (1, 3]$, we have $\frac{\gamma-1}{\gamma+1} \leq \frac{1}{2}$. Therefore, the $\min(\cdot)$ operation in this consistency result is not necessary.*

E.3 Consistency results for doubly robust kernel methods

In this section, we provide the consistency results of our proposed methods DRKPV and DRPMMR. Our results will rely on the consistency results of the outcome bridge function- and treatment bridge function-based methods that we discussed in Section (S.M. E.2) and (S.M. E.1). Furthermore, we have seen that our doubly robust estimation procedures require learning the conditional mean embedding $\mu_{Z,W|A}(a) = C_{Z,W|A}\phi_{\mathcal{A}}(a) = \mathbb{E}[\phi_{\mathcal{Z}}(Z) \otimes \phi_{\mathcal{W}}(W) \mid A = a]$. Recall that we approximate this CME via kernel ridge regression. We assume the following conditions:

Assumption E.20. *There exists $C_{Z,W|A} \in S_2(\mathcal{H}_{\mathcal{A}}, \mathcal{H}_{\mathcal{Z}\mathcal{W}})$ such that $\mu_{Z,W|A}(a) = C_{Z,W|A}\phi_{\mathcal{A}}(a)$.*

Assumption E.21. *There exists a constant $B_{DR} < \infty$ such that for a given $\beta_{DR} \in (1, 3]$,*

$$\|C_{Z,W|A} \Sigma_{\varphi,3}^{-\frac{\beta_{DR}-1}{2}}\|_{S_2(\mathcal{H}_{\mathcal{A}}, \mathcal{H}_{\mathcal{Z}\mathcal{W}})} \leq B_{DR}.$$

First, recall that we showed in Theorem (2.7) that the dose-response can be identified with

$$\theta_{ATE}(a) = \mathbb{E}[\varphi_0(Z, a)(Y - h_0(W, a)) \mid A = a] + \mathbb{E}[h_0(W, a)].$$

We define an intermediate quantity $\bar{\theta}_{ATE}(a)$ that is given by

$$\bar{\theta}_{ATE}(a) = \mathbb{E}\left[\hat{\varphi}(Z, a) \left(Y - \hat{h}(W, a)\right) \mid A = a\right] + \mathbb{E}[\hat{h}(W, a)].$$

Noticing, by triangle inequality, that

$$|\theta_{ATE}(a) - \hat{\theta}_{ATE}(a)| \leq |\theta_{ATE}(a) - \bar{\theta}_{ATE}(a)| + |\bar{\theta}_{ATE}(a) - \hat{\theta}_{ATE}(a)|,$$

we will subsequently derive bounds for the two terms above in order to achieve the consistency result of our proposed methods.

Lemma E.22. *Let h_0 and φ_0 be outcome and treatment bridge functions that satisfy Equations (1) and (2), respectively. Then,*

$$\theta_{ATE}(a) - \bar{\theta}_{ATE}(a) = \mathbb{E}\left[(\varphi_0(Z, a) - \hat{\varphi}(Z, a)) \left(h_0(W, a) - \hat{h}(W, a)\right) \mid A = a\right].$$

Proof.

$$\theta_{ATE}(a) - \bar{\theta}_{ATE}(a) = \mathbb{E}[\varphi_0(Z, a)(Y - h_0(W, a)) \mid A = a] + \mathbb{E}[h_0(W, a)]$$

$$\begin{aligned}
& -\mathbb{E} \left[\hat{\varphi}(Z, a) \left(Y - \hat{h}(W, a) \right) \middle| A = a \right] - \mathbb{E}[\hat{h}(W, a)] \\
& = \mathbb{E}[\varphi_0(Z, a)Y \mid A = a] - \mathbb{E}[\hat{\varphi}(Z, a)Y \mid A = a] \\
& - \mathbb{E}[\varphi_0(Z, a)h_0(W, a) \mid A = a] + \mathbb{E}[\hat{\varphi}(Z, a)\hat{h}(W, a) \mid A = a] + \mathbb{E}[h_0(W, a) - \hat{h}(W, a)] \\
& - \mathbb{E}[\hat{\varphi}(Z, a)h_0(W, a) \mid A = a] + \mathbb{E}[\hat{\varphi}(Z, a)\hat{h}(W, a) \mid A = a] \\
& = \mathbb{E}[(\varphi_0(Z, a) - \hat{\varphi}(Z, a))Y \mid A = a] - \mathbb{E}[(\varphi_0(Z, a) - \hat{\varphi}(Z, a))h_0(W, a) \mid A = a] \\
& - \mathbb{E}[\hat{\varphi}(Z, a)(h_0(W, a) - \hat{h}(W, a)) \mid A = a] + \mathbb{E}[h_0(W, a) - \hat{h}(W, a)] \\
& + \mathbb{E}[\varphi_0(Z, a)(h_0(W, a) - \hat{h}(W, a)) \mid A = a] - \mathbb{E}[\hat{\varphi}(Z, a)(h_0(W, a) - \hat{h}(W, a)) \mid A = a] \\
& = \mathbb{E}[(\varphi_0(Z, a) - \hat{\varphi}(Z, a))(Y - h_0(W, a)) \mid A = a] \\
& + \mathbb{E}[(\varphi_0(Z, a) - \hat{\varphi}(Z, a))(h_0(W, a) - \hat{h}(W, a)) \mid A = a] + \mathbb{E}[h_0(W, a) - \hat{h}(W, a)] \\
& - \mathbb{E}[\varphi_0(Z, a)(h_0(W, a) - \hat{h}(W, a)) \mid A = a] \\
& = \mathbb{E}[\mathbb{E}[Y - h_0(W, a) \mid Z, A = a] (\varphi_0(Z, a) - \hat{\varphi}(Z, a)) \mid A = a] \\
& + \mathbb{E}[(\varphi_0(Z, a) - \hat{\varphi}(Z, a))(h_0(W, a) - \hat{h}(W, a)) \mid A = a] + \mathbb{E}[h_0(W, a) - \hat{h}(W, a)] \\
& - \mathbb{E}[\varphi_0(Z, a)(h_0(W, a) - \hat{h}(W, a)) \mid A = a] \\
& = \mathbb{E}[(\varphi_0(Z, a) - \hat{\varphi}(Z, a)) (h_0(W, a) - \hat{h}(W, a)) \mid A = a] \\
& + \mathbb{E}[\varphi_0(Z, a) (h_0(W, a) - \hat{h}(W, a)) \mid A = a] + \mathbb{E}[h_0(W, a) - \hat{h}(W, a)] \\
& = \mathbb{E}[(\varphi_0(Z, a) - \hat{\varphi}(Z, a)) (h_0(W, a) - \hat{h}(W, a)) \mid A = a] \\
& + \underbrace{\int \left(\int \varphi_0(z, a) p(z \mid w, a) dz \right) (h_0(w, a) - \hat{h}(w, a)) p(w \mid a) dw}_{p(w)/p(w \mid a)} \\
& + \mathbb{E}[h_0(W, a) - \hat{h}(W, a)] \\
& = \mathbb{E}[(\varphi_0(Z, a) - \hat{\varphi}(Z, a)) (h_0(W, a) - \hat{h}(W, a)) \mid A = a] \\
& + \int (h_0(w, a) - \hat{h}(w, a)) p(w) dw + \mathbb{E}[h_0(W, a) - \hat{h}(W, a)] \\
& = \mathbb{E}[(\varphi_0(Z, a) - \hat{\varphi}(Z, a)) (h_0(W, a) - \hat{h}(W, a)) \mid A = a]
\end{aligned}$$

□

Lemma E.23. Suppose Assumption (3.1) hold and let h_0, φ_0 be as in Lemma (E.22), with $h_0 \in \mathcal{H}_{\mathcal{W}\mathcal{A}}$ and $\varphi_0 \in \mathcal{H}_{\mathcal{Z}\mathcal{A}}$. Then,

$$|\theta_{ATE}(a) - \bar{\theta}_{ATE}(a)| \leq \kappa^4 \|\varphi_0 - \hat{\varphi}\| \|h_0 - \hat{h}\|.$$

Proof. By Lemma (E.22),

$$\begin{aligned}
|\theta_{ATE}(a) - \bar{\theta}_{ATE}(a)| & = \left| \mathbb{E} \left[(\varphi_0(Z, a) - \hat{\varphi}(Z, a)) (h_0(W, a) - \hat{h}(W, a)) \middle| A = a \right] \right| \\
& \leq \mathbb{E} \left[|\varphi_0(Z, a) - \hat{\varphi}(Z, a)| |h_0(W, a) - \hat{h}(W, a)| \middle| A = a \right] \\
& = \mathbb{E} \left[|\langle \varphi_0 - \hat{\varphi}, \phi_{\mathcal{Z}}(Z) \otimes \phi_{\mathcal{A}}(a) \rangle| |\langle h_0 - \hat{h}, \phi_{\mathcal{W}}(W) \otimes \phi_{\mathcal{A}}(a) \rangle| \middle| A = a \right] \\
& \leq \mathbb{E} \left[\|\varphi_0 - \hat{\varphi}\| \|\phi_{\mathcal{Z}}(Z) \otimes \phi_{\mathcal{A}}(a)\| \|h_0 - \hat{h}\| \|\phi_{\mathcal{W}}(W) \otimes \phi_{\mathcal{A}}(a)\| \middle| A = a \right] \\
& \leq \kappa^4 \|\varphi_0 - \hat{\varphi}\| \|h_0 - \hat{h}\|.
\end{aligned}$$

□

Next, we need to derive a bound for $|\bar{\theta}_{ATE}(a) - \hat{\theta}_{ATE}(a)|$.

Lemma E.24. *Suppose Assumptions (3.1), and (E.20) hold and let h_0, φ_0 be as in Lemma E.23. Then,*

$$\begin{aligned} & |\bar{\theta}_{ATE}(a) - \hat{\theta}_{ATE}(a)| \\ & \leq \kappa^2 (\|\hat{\varphi} - \varphi_0\| + \|\varphi_0\|) \|C_{YZ|A} - \hat{C}_{YZ|A}\| + \kappa \left(\|\hat{h} - h_0\| + \|h_0\| \right) \|\hat{\mu}_{\mathcal{W}} - \mu_{\mathcal{W}}\| \\ & + \kappa^3 \left(\|\varphi_0\| \|h_0\| + \|\hat{\varphi} - \varphi_0\| \|h_0\| + \|\hat{h} - h_0\| \|\varphi_0\| + \|\hat{\varphi} - \varphi_0\| \|\hat{h} - h_0\| \right) \|C_{ZW|A} - \hat{C}_{ZW|A}\|. \end{aligned}$$

Proof. We start by noting that we can write

$$\begin{aligned} \bar{\theta}_{ATE}(a) &= \mathbb{E} \left[\hat{\varphi}(Z, a)(Y - \hat{h}(W, a)) \mid A = a \right] + \mathbb{E}[\hat{h}(W, a)] \\ &= \mathbb{E}[Y \hat{\varphi}(Z, a) \mid A = a] + \mathbb{E}[\hat{h}(W, a)] - \mathbb{E}[\hat{\varphi}(Z, a) \hat{h}(W, a) \mid A = a] \\ &= \mathbb{E}[\langle \hat{\varphi}, Y \phi_{\mathcal{Z}}(Z) \otimes \phi_{\mathcal{A}}(a) \rangle \mid A = a] + \mathbb{E}[\langle \hat{h}, \phi_{\mathcal{W}}(W) \otimes \phi_{\mathcal{A}}(a) \rangle] \\ &\quad - \mathbb{E}[\langle \hat{\varphi} \otimes \hat{h}, (\phi_{\mathcal{Z}}(Z) \otimes \phi_{\mathcal{A}}(a)) \otimes (\phi_{\mathcal{W}}(W) \otimes \phi_{\mathcal{A}}(a)) \rangle \mid A = a] \\ &= \langle \hat{\varphi}, C_{YZ|A} \phi_{\mathcal{A}}(a) \otimes \phi_{\mathcal{A}}(a) \rangle + \langle \hat{h}, \mu_{\mathcal{W}} \otimes \phi_{\mathcal{A}}(a) \rangle - \left\langle \hat{\varphi} \otimes \hat{h}, C_{ZW|A}^{(a)} \phi_{\mathcal{A}}(a) \right\rangle, \end{aligned}$$

where we define

$$C_{ZW|A}^{(a)} \phi_{\mathcal{A}}(a) = \mathbb{E}[(\phi_{\mathcal{Z}}(Z) \otimes \phi_{\mathcal{A}}(a)) \otimes (\phi_{\mathcal{W}}(W) \otimes \phi_{\mathcal{A}}(a)) \mid A = a]. \quad (32)$$

Similarly, we observe that we can write our doubly robust estimate as

$$\hat{\theta}_{ATE}(a) = \langle \hat{\varphi}, \hat{C}_{YZ|A} \phi_{\mathcal{A}}(a) \otimes \phi_{\mathcal{A}}(a) \rangle + \langle \hat{h}, \hat{\mu}_{\mathcal{W}} \otimes \phi_{\mathcal{A}}(a) \rangle - \left\langle \hat{\varphi} \otimes \hat{h}, \hat{C}_{ZW|A}^{(a)} \phi_{\mathcal{A}}(a) \right\rangle,$$

and define $\hat{C}_{ZW|A}^{(a)}$ to be the augmented version of the conditional mean operator estimate in Equation (29), that is given by

$$\hat{C}_{Z,W|A}^{(a)} \phi_{\mathcal{A}}(a) = \sum_i \xi_i \phi_{\mathcal{Z}}(z_i) \otimes \phi_{\mathcal{A}}(a) \otimes \phi_{\mathcal{W}}(w_i) \otimes \phi_{\mathcal{A}}(a)$$

where $\xi_i(a) = \left[(\mathbf{K}_{AA} + t\lambda_{DR} \mathbf{I})^{-1} \mathbf{K}_{Aa} \right]_i$. Therefore, we have that

$$\begin{aligned} \bar{\theta}_{ATE}(a) - \hat{\theta}_{ATE}(a) &= \langle \hat{\varphi}, C_{YZ|A} \phi_{\mathcal{A}}(a) \otimes \phi_{\mathcal{A}}(a) \rangle + \langle \hat{h}, \mu_{\mathcal{W}} \otimes \phi_{\mathcal{A}}(a) \rangle - \left\langle \hat{\varphi} \otimes \hat{h}, C_{ZW|A}^{(a)} \phi_{\mathcal{A}}(a) \right\rangle \\ &\quad - \langle \hat{\varphi}, \hat{C}_{YZ|A} \phi_{\mathcal{A}}(a) \otimes \phi_{\mathcal{A}}(a) \rangle - \langle \hat{h}, \hat{\mu}_{\mathcal{W}} \otimes \phi_{\mathcal{A}}(a) \rangle + \left\langle \hat{\varphi} \otimes \hat{h}, \hat{C}_{ZW|A}^{(a)} \phi_{\mathcal{A}}(a) \right\rangle \\ &= \left\langle \hat{\varphi}, \left(C_{YZ|A} - \hat{C}_{YZ|A} \right) \phi_{\mathcal{A}}(a) \otimes \phi_{\mathcal{A}}(a) \right\rangle \\ &\quad + \left\langle \hat{h}, (\mu_{\mathcal{W}} - \hat{\mu}_{\mathcal{W}}) \otimes \phi_{\mathcal{A}}(a) \right\rangle - \left\langle \hat{\varphi} \otimes \hat{h}, \left(C_{ZW|A}^{(a)} - \hat{C}_{ZW|A}^{(a)} \right) \phi_{\mathcal{A}}(a) \right\rangle \\ &= \left\langle \hat{\varphi} - \varphi_0, \left(C_{YZ|A} - \hat{C}_{YZ|A} \right) \phi_{\mathcal{A}}(a) \otimes \phi_{\mathcal{A}}(a) \right\rangle \\ &\quad + \left\langle \varphi_0, \left(C_{YZ|A} - \hat{C}_{YZ|A} \right) \phi_{\mathcal{A}}(a) \otimes \phi_{\mathcal{A}}(a) \right\rangle \\ &\quad + \left\langle \hat{h} - h_0, (\mu_{\mathcal{W}} - \hat{\mu}_{\mathcal{W}}) \otimes \phi_{\mathcal{A}}(a) \right\rangle + \langle h_0, (\mu_{\mathcal{W}} - \hat{\mu}_{\mathcal{W}}) \otimes \phi_{\mathcal{A}}(a) \rangle \\ &\quad - \left\langle \hat{\varphi} \otimes \hat{h}, \left(C_{ZW|A}^{(a)} - \hat{C}_{ZW|A}^{(a)} \right) \phi_{\mathcal{A}}(a) \right\rangle \end{aligned}$$

As a result,

$$|\bar{\theta}_{ATE}(a) - \hat{\theta}_{ATE}(a)|$$

$$\begin{aligned} &\leq \kappa^2 (\|\hat{\varphi} - \varphi_0\| + \|\varphi_0\|) \|C_{YZ|A} - \hat{C}_{YZ|A}\| + \kappa (\|\hat{h} - h_0\| + \|h_0\|) \|\hat{\mu}_{\mathcal{W}} - \mu_{\mathcal{W}}\| \\ &+ \left(\|\varphi_0\| \|h_0\| + \|\hat{\varphi} - \varphi_0\| \|h_0\| + \|\hat{h} - h_0\| \|\varphi_0\| + \|\hat{\varphi} - \varphi_0\| \|\hat{h} - h_0\| \right) \left\| \left(C_{ZW|A}^{(a)} - \hat{C}_{ZW|A}^{(a)} \right) \phi_{\mathcal{A}}(a) \right\| \end{aligned}$$

Note that $\mathcal{H}_{\mathcal{ZAWA}}$ and $\mathcal{H}_{\mathcal{ZWAA}}$ are isometric Hilbert spaces. Let Ψ be the canonical isomorphism,

$$\Psi : \mathcal{H}_{\mathcal{Z}} \otimes \mathcal{H}_{\mathcal{W}} \otimes \mathcal{H}_{\mathcal{A}} \otimes \mathcal{H}_{\mathcal{A}} \rightarrow \mathcal{H}_{\mathcal{Z}} \otimes \mathcal{H}_{\mathcal{A}} \otimes \mathcal{H}_{\mathcal{W}} \otimes \mathcal{H}_{\mathcal{A}}$$

such that it acts on the elementary tensors as $\Psi(u \otimes v \otimes a_1 \otimes a_2) = u \otimes a_1 \otimes v \otimes a_2$. Ψ is a unitary isomorphism, hence,

$$\begin{aligned} &\left\| C_{ZW|A}^{(a)} \phi_{\mathcal{A}}(a) - \hat{C}_{ZW|A}^{(a)} \phi_{\mathcal{A}}(a) \right\|_{\mathcal{H}_{\mathcal{ZAWA}}} \\ &= \left\| \Psi \left((C_{ZW|A} \phi_{\mathcal{A}}(a)) \otimes \phi_{\mathcal{A}}(a) \otimes \phi_{\mathcal{A}}(a) \right) - P \left(\left(\hat{C}_{ZW|A} \phi_{\mathcal{A}}(a) \right) \otimes \phi_{\mathcal{A}}(a) \otimes \phi_{\mathcal{A}}(a) \right) \right\|_{\mathcal{H}_{\mathcal{ZAWA}}} \\ &= \left\| (C_{ZW|A} \phi_{\mathcal{A}}(a)) \otimes \phi_{\mathcal{A}}(a) \otimes \phi_{\mathcal{A}}(a) - \left(\hat{C}_{ZW|A} \phi_{\mathcal{A}}(a) \right) \otimes \phi_{\mathcal{A}}(a) \otimes \phi_{\mathcal{A}}(a) \right\|_{\mathcal{H}_{\mathcal{ZWAA}}} \\ &\leq \kappa^2 \left\| C_{ZW|A} \phi_{\mathcal{A}}(a) - \hat{C}_{ZW|A} \phi_{\mathcal{A}}(a) \right\|_{\mathcal{H}_{\mathcal{ZW}}} \leq \kappa^3 \left\| C_{ZW|A} - \hat{C}_{ZW|A} \right\|_{S_2(\mathcal{H}_{\mathcal{A}}, \mathcal{H}_{\mathcal{ZW}})} \end{aligned}$$

Using this inequality, we obtain the desired bound as

$$\begin{aligned} &|\bar{\theta}_{ATE}(a) - \hat{\theta}_{ATE}(a)| \\ &\leq \kappa^2 (\|\hat{\varphi} - \varphi_0\| + \|\varphi_0\|) \|C_{YZ|A} - \hat{C}_{YZ|A}\| + \kappa (\|\hat{h} - h_0\| + \|h_0\|) \|\hat{\mu}_{\mathcal{W}} - \mu_{\mathcal{W}}\| \\ &+ \kappa^3 \left(\|\varphi_0\| \|h_0\| + \|\hat{\varphi} - \varphi_0\| \|h_0\| + \|\hat{h} - h_0\| \|\varphi_0\| + \|\hat{\varphi} - \varphi_0\| \|\hat{h} - h_0\| \right) \|C_{ZW|A} - \hat{C}_{ZW|A}\| \end{aligned}$$

□

Combining the bounds from Lemma (E.23) and (E.24), we observe that

$$\begin{aligned} &|\theta_{ATE}(a) - \hat{\theta}_{ATE}(a)| \leq \kappa^4 \|\varphi_0 - \hat{\varphi}\| \|h_0 - \hat{h}\| \\ &+ \kappa^2 (\|\hat{\varphi} - \varphi_0\| + \|\varphi_0\|) \|C_{YZ|A} - \hat{C}_{YZ|A}\| + \kappa (\|\hat{h} - h_0\| + \|h_0\|) \|\hat{\mu}_{\mathcal{W}} - \mu_{\mathcal{W}}\| \\ &+ \kappa^3 \left(\|\varphi_0\| \|h_0\| + \|\hat{\varphi} - \varphi_0\| \|h_0\| + \|\hat{h} - h_0\| \|\varphi_0\| + \|\hat{\varphi} - \varphi_0\| \|\hat{h} - h_0\| \right) \|C_{ZW|A} - \hat{C}_{ZW|A}\| \end{aligned} \tag{33}$$

Hence, the convergence of our methods will depend on the factors $\|\hat{h} - h_0\|$, $\|\hat{\varphi} - \varphi_0\|$, $\|\hat{\mu}_{\mathcal{W}} - \mu_{\mathcal{W}}\|$, $\|C_{YZ|A} - \hat{C}_{YZ|A}\|$, and $\|C_{ZW|A} - \hat{C}_{ZW|A}\|$. We have already established the consistency results for $\|\hat{h} - h_0\|$ and $\|\hat{\varphi} - \varphi_0\|$, and $\|\hat{\mu}_{\mathcal{W}} - \mu_{\mathcal{W}}\|$ converges with $O_p(t^{-1/2})$ [11]. Hence, we need to establish the converge results for $\|C_{YZ|A} - \hat{C}_{YZ|A}\|$, and $\|C_{ZW|A} - \hat{C}_{ZW|A}\|$.

Theorem E.25 (Theorem (12.22) [23], Theorem (3) [45]). *Suppose Assumptions (E.1), (E.2-3), (3.1) (E.5-3) and (E.6-3) hold and take $\lambda_{\varphi,3} = \Theta \left(t_{\varphi}^{-\frac{1}{\beta_{\varphi,3} + p_{\varphi,3}}} \right)$. There is a constant $J_3 > 0$ independent of $t_{\varphi} \geq 1$ and $\delta \in (0, 1)$ such that*

$$\left\| \hat{C}_{YZ|A} - C_{YZ|A} \right\|_{S_2(\mathcal{H}_{\mathcal{A}}, \mathcal{H}_{\mathcal{Z}})} \leq J_3 \log(5/\delta) \left(\frac{1}{\sqrt{t_{\varphi}}} \right)^{\frac{\beta_{\varphi,3}-1}{\beta_{\varphi,3}+p_{\varphi,3}}} =: r_{\varphi,3}(\delta, t_{\varphi}, \beta_{\varphi,3}, p_{\varphi,3}),$$

is satisfied for sufficiently large $t_{\varphi} \geq 1$ with probability at least $1 - \delta$.

Theorem E.26 (Theorem (3) [45]). *Suppose Assumptions (E.20), (3.1), (E.21) and (E.6-3), hold and take $\lambda_{DR} = \Theta \left(t^{-\frac{1}{\beta_{DR} + p_{\varphi,3}}} \right)$. There is a constant $J_{DR} > 0$ independent of $t \geq 1$ and $\delta \in (0, 1)$ such that*

$$\left\| \hat{C}_{ZW|A} - C_{ZW|A} \right\|_{S_2(\mathcal{H}_{\mathcal{A}}, \mathcal{H}_{\mathcal{ZW}})} \leq J_{DR} \log(5/\delta) \left(\frac{1}{\sqrt{t}} \right)^{\frac{\beta_{DR}-1}{\beta_{DR}+p_{\varphi,3}}} =: r_{DR}(\delta, t, \beta_{DR}, p_{\varphi,3}),$$

is satisfied for sufficiently large $t \geq 1$ with probability at least $1 - \delta$.

Recall that KPV and KAP use the number of samples $\{n_h, m_h, t_h\}$ and $\{n_\varphi, m_\varphi, t_\varphi\}$ in their first, second, and third stage of regression, respectively. Following the original implementations from Mastouri et al. [11] and Bozkurt et al. [23], we will reuse the data in their third-stage, i.e., $t_h = t_\varphi = t$, as pointed out in Algorithms (2) and (4).

Theorem E.27. *Suppose the assumptions in Theorems (E.7), (E.13), (E.25), and (E.26) hold. For a given training dataset $\mathcal{D} = \{y_i, w_i, z_i, a_i\}_{i=1}^t$, let $\{n_h, m_h, t_h\}$ and $\{n_\varphi, m_\varphi, t_\varphi\}$ denote the number of samples used in first-, second-, and third-stage regressions for KPV and KAP, respectively, with $t_h = t_\varphi = t$. Then, for DRKPV algorithm with high probability,*

i. If $\iota_h \leq \frac{\beta_{h,2}+1}{\beta_{h,2}+p_{h,2}}$ and $\iota_\varphi \leq \frac{\beta_{\varphi,2}+1}{\beta_{\varphi,2}+p_{\varphi,2}}$. Set $\lambda_{h,2} = \Theta\left(m_h^{-\frac{\iota_h}{\beta_{h,2}+1}}\right)$ and $\lambda_{\varphi,2} = \Theta\left(m_\varphi^{-\frac{\iota_\varphi}{\beta_{\varphi,2}+1}}\right)$. Then,

$$|\theta_{ATE}(a) - \hat{\theta}_{ATE}(a)| = O_p\left(t^{-\frac{1}{2}\frac{\beta_{\varphi,3}-1}{\beta_{\varphi,3}+p_{\varphi,3}}} + m_h^{-\frac{\iota_h}{2}\frac{\beta_{h,2}-1}{\beta_{h,2}+1}} m_\varphi^{-\frac{\iota_\varphi}{2}\frac{\beta_{\varphi,2}-1}{\beta_{\varphi,2}+1}}\right)$$

ii. If $\iota_h \leq \frac{\beta_{h,2}+1}{\beta_{h,2}+p_{h,2}}$ and $\iota_\varphi \geq \frac{\beta_{\varphi,2}+1}{\beta_{\varphi,2}+p_{\varphi,2}}$. Set $\lambda_{h,2} = \Theta\left(m_h^{-\frac{\iota_h}{\beta_{h,2}+1}}\right)$ and $\lambda_{\varphi,2} = \Theta\left(m_\varphi^{-\frac{1}{\beta_{\varphi,2}+p_{\varphi,2}}}\right)$. Then,

$$|\theta_{ATE}(a) - \hat{\theta}_{ATE}(a)| = O_p\left(t^{-\frac{1}{2}\frac{\beta_{\varphi,3}-1}{\beta_{\varphi,3}+p_{\varphi,3}}} + m_h^{-\frac{\iota_h}{2}\frac{\beta_{h,2}-1}{\beta_{h,2}+1}} m_\varphi^{-\frac{1}{2}\frac{\beta_{\varphi,2}-1}{\beta_{\varphi,2}+p_{\varphi,2}}}\right)$$

iii. If $\iota_h \geq \frac{\beta_{h,2}+1}{\beta_{h,2}+p_{h,2}}$ and $\iota_\varphi \leq \frac{\beta_{\varphi,2}+1}{\beta_{\varphi,2}+p_{\varphi,2}}$. Set $\lambda_{h,2} = \Theta\left(m_h^{-\frac{1}{\beta_{h,2}+p_{h,2}}}\right)$ and $\lambda_{\varphi,2} = \Theta\left(m_\varphi^{-\frac{\iota_\varphi}{\beta_{\varphi,2}+1}}\right)$. Then,

$$|\theta_{ATE}(a) - \hat{\theta}_{ATE}(a)| = O_p\left(t^{-\frac{1}{2}\frac{\beta_{\varphi,3}-1}{\beta_{\varphi,3}+p_{\varphi,3}}} + m_h^{-\frac{1}{2}\frac{\beta_{h,2}-1}{\beta_{h,2}+p_{h,2}}} m_\varphi^{-\frac{\iota_\varphi}{2}\frac{\beta_{\varphi,2}-1}{\beta_{\varphi,2}+1}}\right)$$

iv. If $\iota_h \geq \frac{\beta_{h,2}+1}{\beta_{h,2}+p_{h,2}}$ and $\iota_\varphi \geq \frac{\beta_{\varphi,2}+1}{\beta_{\varphi,2}+p_{\varphi,2}}$. Set $\lambda_{h,2} = \Theta\left(m_h^{-\frac{1}{\beta_{h,2}+p_{h,2}}}\right)$ and $\lambda_{\varphi,2} = \Theta\left(m_\varphi^{-\frac{1}{\beta_{\varphi,2}+p_{\varphi,2}}}\right)$. Then,

$$|\theta_{ATE}(a) - \hat{\theta}_{ATE}(a)| = O_p\left(t^{-\frac{1}{2}\frac{\beta_{\varphi,3}-1}{\beta_{\varphi,3}+p_{\varphi,3}}} + m_h^{-\frac{1}{2}\frac{\beta_{h,2}-1}{\beta_{h,2}+p_{h,2}}} m_\varphi^{-\frac{1}{2}\frac{\beta_{\varphi,2}-1}{\beta_{\varphi,2}+p_{\varphi,2}}}\right)$$

Proof. We combine the bounds in Lemmas (E.23) and (E.24), by using the convergence to the minimum norm RKHS norm bridge function solutions and discarding the faster terms, to obtain

$$\begin{aligned} |\theta_{ATE}(a) - \hat{\theta}_{ATE}(a)| &\lesssim \|\bar{\varphi}_0 - \hat{\varphi}\| \|\bar{h}_0 - \hat{h}\| + \|C_{YZ|A} - \hat{C}_{YZ|A}\| \\ &\quad + \|\hat{\mu}_{\mathcal{W}} - \mu_{\mathcal{W}}\| + \|C_{ZW|A} - \hat{C}_{ZW|A}\|. \end{aligned}$$

Note that the term $\|\hat{\mu}_{\mathcal{W}} - \mu_{\mathcal{W}}\|$ converges with $t^{-1/2}$ rate [11] hence can be discarded as well. The terms $\|C_{YZ|A} - \hat{C}_{YZ|A}\|$ and $\|C_{ZW|A} - \hat{C}_{ZW|A}\|$ converges with $O_p\left(t^{-\frac{1}{2}\frac{\beta_{\varphi,3}-1}{\beta_{\varphi,3}+p_{\varphi,3}}}\right)$ with the given regularizer parameters $\lambda_{\varphi,3}$ and λ_{DR} in Theorems (E.25) and (E.26). Hence, the convergence will be governed by

$$|\theta_{ATE}(a) - \hat{\theta}_{ATE}(a)| \lesssim \|\bar{\varphi}_0 - \hat{\varphi}\| \|\bar{h}_0 - \hat{h}\| + t^{-\frac{1}{2}\frac{\beta_{\varphi,3}-1}{\beta_{\varphi,3}+p_{\varphi,3}}}.$$

Appealing to the conditions in Theorems (E.7) and (E.13), we will have four conditions depending on the first and second stage data splitting conditions of KPV and KAP algorithms:

- i. Suppose $\iota_h \leq \frac{\beta_{h,2}+1}{\beta_{h,2}+p_{h,2}}$ and $\iota_\varphi \leq \frac{\beta_{\varphi,2}+1}{\beta_{\varphi,2}+p_{\varphi,2}}$. Then, condition [i] in Theorem (E.13) and condition [i] in Theorem (E.7) apply. Combining these bound gives

$$|\theta_{\text{ATE}}(a) - \hat{\theta}_{\text{ATE}}(a)| = O_p \left(t^{-\frac{1}{2} \frac{\beta_{\varphi,3}-1}{\beta_{\varphi,3}+p_{\varphi,3}}} + m_h^{-\frac{\iota_h}{2} \frac{\beta_{h,2}-1}{\beta_{h,2}+1}} m_\varphi^{-\frac{\iota_\varphi}{2} \frac{\beta_{\varphi,2}-1}{\beta_{\varphi,2}+1}} \right),$$

$$\text{with } \lambda_{h,2} = \Theta \left(m^{-\frac{\iota_h}{\beta_{h,2}+1}} \right) \text{ and } \lambda_{\varphi,2} = \Theta \left(m_\varphi^{-\frac{\iota_\varphi}{\beta_{\varphi,2}+1}} \right).$$

- ii. Suppose $\iota_h \leq \frac{\beta_{h,2}+1}{\beta_{h,2}+p_{h,2}}$ and $\iota_\varphi \geq \frac{\beta_{\varphi,2}+1}{\beta_{\varphi,2}+p_{\varphi,2}}$. Then, condition [i] in Theorem (E.13) and condition [ii] in Theorem (E.7) apply. Combining these bound gives

$$|\theta_{\text{ATE}}(a) - \hat{\theta}_{\text{ATE}}(a)| = O_p \left(t^{-\frac{1}{2} \frac{\beta_{\varphi,3}-1}{\beta_{\varphi,3}+p_{\varphi,3}}} + m_h^{-\frac{\iota_h}{2} \frac{\beta_{h,2}-1}{\beta_{h,2}+1}} m_\varphi^{-\frac{1}{2} \frac{\beta_{\varphi,2}-1}{\beta_{\varphi,2}+p_{\varphi,2}}} \right).$$

$$\text{with } \lambda_{h,2} = \Theta \left(m^{-\frac{\iota_h}{\beta_{h,2}+1}} \right) \text{ and } \lambda_{\varphi,2} = \Theta \left(m_\varphi^{-\frac{1}{\beta_{\varphi,2}+p_{\varphi,2}}} \right).$$

- iii. Suppose $\iota_h \geq \frac{\beta_{h,2}+1}{\beta_{h,2}+p_{h,2}}$ and $\iota_\varphi \leq \frac{\beta_{\varphi,2}+1}{\beta_{\varphi,2}+p_{\varphi,2}}$. Then, condition [ii] in Theorem (E.13) and condition [i] in Theorem (E.7) apply. Combining these bound gives

$$|\theta_{\text{ATE}}(a) - \hat{\theta}_{\text{ATE}}(a)| = O_p \left(t^{-\frac{1}{2} \frac{\beta_{\varphi,3}-1}{\beta_{\varphi,3}+p_{\varphi,3}}} + m_h^{-\frac{1}{2} \frac{\beta_{h,2}-1}{\beta_{h,2}+p_{h,2}}} m_\varphi^{-\frac{\iota_\varphi}{2} \frac{\beta_{\varphi,2}-1}{\beta_{\varphi,2}+1}} \right),$$

$$\text{with } \lambda_{h,2} = \Theta \left(m_h^{-\frac{1}{\beta_{h,2}+p_{h,2}}} \right) \text{ and } \lambda_{\varphi,2} = \Theta \left(m_\varphi^{-\frac{\iota_\varphi}{\beta_{\varphi,2}+1}} \right).$$

- iv. Suppose $\iota_h \geq \frac{\beta_{h,2}+1}{\beta_{h,2}+p_{h,2}}$ and $\iota_\varphi \geq \frac{\beta_{\varphi,2}+1}{\beta_{\varphi,2}+p_{\varphi,2}}$. Then, condition [ii] in Theorem (E.13) and condition [ii] in Theorem (E.7) apply. Combining these bound gives

$$|\theta_{\text{ATE}}(a) - \hat{\theta}_{\text{ATE}}(a)| = O_p \left(t^{-\frac{1}{2} \frac{\beta_{\varphi,3}-1}{\beta_{\varphi,3}+p_{\varphi,3}}} + m_h^{-\frac{1}{2} \frac{\beta_{h,2}-1}{\beta_{h,2}+p_{h,2}}} m_\varphi^{-\frac{1}{2} \frac{\beta_{\varphi,2}-1}{\beta_{\varphi,2}+p_{\varphi,2}}} \right).$$

$$\text{with } \lambda_{h,2} = \Theta \left(m_h^{-\frac{1}{\beta_{h,2}+p_{h,2}}} \right) \text{ and } \lambda_{\varphi,2} = \Theta \left(m_\varphi^{-\frac{1}{\beta_{\varphi,2}+p_{\varphi,2}}} \right).$$

□

Theorem E.28. Suppose the assumptions in Theorems (E.7), (E.17), (E.25), and (E.26) hold. For a given training dataset $\mathcal{D} = \{y_i, w_i, z_i, a_i\}_{i=1}^t$, let $\{n_\varphi, m_\varphi, t_\varphi\}$ denote the number of samples used in first-, second-, and third-stage regressions of KAP algorithm with $t_\varphi = t$. Then, for DRPMMR algorithm with high probability

- i. If $\iota_\varphi \leq \frac{\beta_{\varphi,2}+1}{\beta_{\varphi,2}+p_{\varphi,2}}$, set $\lambda_{\varphi,2} = \Theta \left(m_\varphi^{-\frac{\iota_\varphi}{\beta_{\varphi,2}+1}} \right)$. Then,

$$|\theta_{\text{ATE}}(a) - \hat{\theta}_{\text{ATE}}(a)| = O_p \left(t^{-\frac{1}{2} \frac{\beta_{\varphi,3}-1}{\beta_{\varphi,3}+p_{\varphi,3}}} + t^{-\frac{1}{2} \frac{\gamma-1}{\gamma+1}} m_\varphi^{-\frac{\iota_\varphi}{2} \frac{\beta_{\varphi,2}-1}{\beta_{\varphi,2}+p_{\varphi,2}}} \right),$$

ii. If $\iota_\varphi \geq \frac{\beta_{\varphi,2}+1}{\beta_{\varphi,2}+p_{\varphi,2}}$, set $\lambda_{\varphi,2} = \Theta\left(m_\varphi^{-\frac{1}{\beta_{\varphi,2}+p_{\varphi,2}}}\right)$. Then,

$$|\theta_{\text{ATE}}(a) - \hat{\theta}_{\text{ATE}}(a)| = O_p\left(t^{-\frac{1}{2}\frac{\beta_{\varphi,3}-1}{\beta_{\varphi,3}+p_{\varphi,3}}} + t^{-\frac{1}{2}\frac{\gamma-1}{\gamma+1}}m_\varphi^{-\frac{1}{2}\frac{\beta_{\varphi,2}-1}{\beta_{\varphi,2}+p_{\varphi,2}}}\right),$$

Proof. Combining the bounds from Lemmas (E.23) and (E.24), and using the convergence of the estimators to the minimum-norm RKHS bridge function solutions, we obtain the following by discarding higher-order terms:

Similar to the proof of Theorem (E.27), the bound will be governed by

$$|\theta_{\text{ATE}}(a) - \hat{\theta}_{\text{ATE}}(a)| \lesssim \|\tilde{\varphi}_0 - \hat{\varphi}\| \|\check{h}_0 - \hat{h}\| + t^{-\frac{1}{2}\frac{\beta_{\varphi,3}-1}{\beta_{\varphi,3}+p_{\varphi,3}}}.$$

Now, using the conditions in Theorem (E.7) and the rate in Theorem (E.17), we will have two conditions:

i. Suppose $\iota_\varphi \leq \frac{\beta_{\varphi,2}+1}{\beta_{\varphi,2}+p_{\varphi,2}}$, then condition [i] in Theorem (E.13) applies. Hence,

$$|\theta_{\text{ATE}}(a) - \hat{\theta}_{\text{ATE}}(a)| = O_p\left(t^{-\frac{1}{2}\frac{\beta_{\varphi,3}-1}{\beta_{\varphi,3}+p_{\varphi,3}}} + t^{-\frac{1}{2}\frac{\gamma-1}{\gamma+1}}m_\varphi^{-\frac{\iota_\varphi}{2}\frac{\beta_{\varphi,2}-1}{\beta_{\varphi,2}+p_{\varphi,2}}}\right),$$

$$\text{with } \lambda_{\varphi,2} = \Theta\left(m_\varphi^{-\frac{\iota_\varphi}{\beta_{\varphi,2}+1}}\right).$$

ii. Suppose $\iota_\varphi \geq \frac{\beta_{\varphi,2}+1}{\beta_{\varphi,2}+p_{\varphi,2}}$, then condition [ii] in Theorem (E.13) applies. Hence,

$$|\theta_{\text{ATE}}(a) - \hat{\theta}_{\text{ATE}}(a)| = O_p\left(t^{-\frac{1}{2}\frac{\beta_{\varphi,3}-1}{\beta_{\varphi,3}+p_{\varphi,3}}} + t^{-\frac{1}{2}\frac{\gamma-1}{\gamma+1}}m_\varphi^{-\frac{1}{2}\frac{\beta_{\varphi,2}-1}{\beta_{\varphi,2}+p_{\varphi,2}}}\right),$$

$$\text{with } \lambda_{\varphi,2} = \Theta\left(m_\varphi^{-\frac{1}{\beta_{\varphi,2}+p_{\varphi,2}}}\right).$$

□

Remark E.29 (Curse of Dimensionality). *Our proposed algorithms (DRKPV and DRPMMR), along with KPV and KAP methods, rely on multi-stage kernel ridge regressions. Kernel Ridge Regression is known to achieve minimax-optimal rates in moderate dimension, but in very high-dimensional regimes, particularly when the input dimension d grows with the sample size t (i.e., $d/t^\beta \rightarrow c$ for some $\beta \in (0, 1)$), the situation becomes more subtle [46, 45].*

Specifically, the effectiveness of KRR suffers from two primary issues in high dimensions:

- *When functions lie in Sobolev classes, the achievable rate explicitly depends on both smoothness and dimension. Intuitively, the regression function must be smooth enough relative to the ambient dimension d for KRR to remain consistent. More specifically, Fischer and Steinwart [67, Corollary 5 & 6] (for standard scalar KRR) and Li et al. [45, Corollary 1 & 2] (for vector-valued KRR) show that if the target function has smoothness parameter s (in Sobolev sense), the optimal rate of convergence in L_2 norm is $O(t^{-\frac{s}{s+d/2}})$. This rate clearly demonstrates the curse of dimensionality, as for a fixed s , the bound becomes vacuous as $d \rightarrow \infty$.*
- *Donhauser et al. [46] show that for rotationally invariant kernels (such as RBF or Matérn), a polynomial approximation barrier arises: the learned function is effectively restricted to low-degree polynomials as d grows, regardless of eigenvalue decay. This implies that consistency in high dimensions is limited unless additional structural assumptions are imposed.*

In our work, we do not address the curse of dimensionality. Instead, our contribution is to show that doubly robust PCL estimators can be constructed without density ratio estimation and kernel-smoothing, thereby extending practical applicability to continuous and high-dimensional treatments

where prior DR methods [21, 22] fail. Our theorems remain valid in high-dimensional settings provided the smoothness and effective RKHS dimension assumptions hold. However, we acknowledge that when input dimension grows with sample size, methods based on standard RBF or Matérn kernels may indeed fail. Addressing this deeper theoretical limitation is left as a future work.

Remark E.30 (Asymptotic Efficiency and Normality). While our identification formula in Theorem (2.7) is derived from the Efficient Influence Function (EIF), our resulting estimator is not a classical one-step estimator [47, 48] and does not automatically inherit local efficiency or asymptotic normality [28]. Unlike standard EIF-based estimators that leverage first-order orthogonality [30] between two coupled nuisance components (e.g., outcome regression and propensity score), our method involves three components—the outcome bridge, treatment bridge, and a correction term—each estimated separately. As a result, the bias terms accumulate additively, rather than canceling multiplicatively, as in traditional doubly robust estimators. Establishing local efficiency would thus require further analysis, including proving asymptotic linearity, implementing cross-fitting, and verifying attainment of the semiparametric variance bound—steps we leave for future work. Similarly, asymptotic normality is not guaranteed; although the estimator is consistent and derived from an EIF, a central limit theorem would require controlling higher-order remainder terms across all three nuisance components—particularly challenging in our framework. We therefore refrain from claiming asymptotic normality in the present version. Given the nonregularity typical of continuous treatment settings [59, 60, 61], a slower-than- \sqrt{n} convergence rate is generally expected for the parameter, a point supported by both theory and our convergence results.

F Supplementary on numerical experiments

Here, we provide additional details on the numerical experiments presented in Section (5), including hyperparameter optimization procedures and supplementary experimental results.

F.1 Kernel

We utilize the Gaussian (RBF) kernel for our experiments, defined as

$$k_{\mathcal{F}}(f_i, f_j) = \exp\left(\frac{-\|f_i - f_j\|_2^2}{2l^2}\right) \quad (34)$$

for $f_i, f_j \in \mathbb{R}^{d_{\mathcal{F}}}$. This kernel is widely used due to its boundedness, continuity, and characteristic property [68]. The parameter $l > 0$, known as the length scale, controls the smoothness of the kernel. We set l using the commonly adopted *median heuristic*, which sets l^2 to half the median of the pairwise squared Euclidean distances in the dataset $\{f_i\}_{i=1}^n$, that is:

$$l^2 = \frac{1}{2} \text{median}(\{\|f_i - f_j\|_2^2 : 1 \leq i < j \leq n\}).$$

This approach has been frequently used in causal inference applications, including Singh et al. [69], Mastouri et al. [11], Singh [12], Xu and Gretton [62], Bozkurt et al. [23].

In addition, we consider a dimension-wise variant of the Gaussian kernel, defined as the product of one-dimensional Gaussian kernels applied to each coordinate:

$$k_{\mathcal{F}}(f_i, f_j) = \prod_{k=1}^{d_{\mathcal{F}}} \exp\left(\frac{-\|f_i^{(k)} - f_j^{(k)}\|_2^2}{2l^{(k)2}}\right) \quad (35)$$

where $f_i^{(k)}$ denotes the k -th coordinate of vector f_i . Each length scale $l^{(k)}$ can be set independently using the median heuristic applied to that specific dimension. We refer to the kernel in Equation (35) as the *columnwise Gaussian kernel*.

Following the setup in Bozkurt et al. [23], we apply the columnwise Gaussian kernel to the outcome proxy variable W within the KAP algorithm for the synthetic low-dimensional experiment in Section (5). For all other experiments and for all variables used in both outcome and treatment bridge-based methods, we use the standard Gaussian kernel defined in Equation (34).

We also consider the Matérn kernel which provides a flexible alternative to the Gaussian kernel by introducing a smoothness parameter. The Matérn kernel between two points f_i and f_j is given by [70]

$$k_{\mathcal{F},\nu}(f_i, f_j) = \frac{2^{1-\nu}}{\Gamma(\nu)} \left(\frac{\sqrt{2\nu}}{l} \|f_i - f_j\|_2 \right)^\nu \mathcal{K}_\nu \left(\frac{\sqrt{2\nu}}{l} \|f_i - f_j\|_2 \right). \quad (36)$$

Here, the parameters ν and l are positive variables, $\Gamma(\cdot)$ is the gamma function, and $\mathcal{K}_\nu(\cdot)$ is modified Bessel function of the second kind [71]. The Matérn family of kernels satisfies the assumptions on kernels, including those in Assumption (3.1) [72]. The parameter ν directly controls the differentiability of the kernel function; as $\nu \rightarrow \infty$, the kernel converges to the Gaussian kernel in Equation (34).

For practical implementation and to explore varying levels of smoothness, we use cases where ν is a half integer in the form $\nu = p + 1/2$, which yield simplified, closed-form polynomial expressions [70]:

$$k_{\mathcal{F},\nu=p+1/2}(f_i, f_j) = \exp \left(-\frac{\sqrt{2\nu}}{l} \|f_i - f_j\| \right) \frac{\Gamma(p+1)}{\Gamma(2p+1)} \sum_{k=0}^p \frac{(p+k)!}{k!(p-k)!} \left(\frac{\sqrt{8\nu}}{l} \|f_i - f_j\| \right)^{p-k}. \quad (37)$$

In our ablation studies in Section (S.M. (F.7)), we test the performance of our method across Matérn kernels corresponding to different integer values of p .

F.2 Discussion on the data splitting of KPV and KAP

We detail the data splitting strategy employed for the multi-stage KPV and KAP algorithms, which derive their samples from the full training observations $\{y_i, w_i, z_i, a_i\}_{i=1}^t$.

Algorithm Stage	Samples Used	Implementation Details
KPV (Stage 1)	$\{\bar{w}_i, \bar{z}_i, \bar{a}_i\}_{i=1}^{n_h}$	Uses $n_h = \lfloor t/2 \rfloor$ random samples.
KPV (Stage 2)	$\{\tilde{y}_i, \tilde{z}_i, \tilde{a}_i\}_{i=1}^{m_h}$	Uses $m_h = t - n_h$. Samples are disjoint from Stage 1.
KPV (Stage 3)	$\{\dot{w}_i\}_{i=1}^{t_h}$	Uses the full set: $t_h = t$.
KAP (Stage 1)	$\{\bar{w}_i, \bar{z}_i, \bar{a}_i\}_{i=1}^{n_\varphi}$	Uses $n_\varphi = \lfloor t/2 \rfloor$ random samples.
KAP (Stage 2)	$\{\tilde{w}_i, \tilde{a}_i\}_{i=1}^{m_\varphi}$	Uses $m_\varphi = t - n_\varphi$. Samples are disjoint from Stage 1.
KAP (Stage 3)	$\{\dot{y}_i, \dot{z}_i, \dot{a}_i\}_{i=1}^{t_\varphi}$	Uses the full set: $t_\varphi = t$.

While we use this structured splitting in our implementation, our consistency proofs in Section (E) do not assume disjoint splits, similar to [11, 12, 23]. Indeed, using the full dataset per stage still retains theoretical consistency (e.g., Corollary 1 in [12] for outcome bridge-based methods).

However, structured data splitting is useful in practice for two main reasons:

1. **Hyperparameter Tuning:** For regression stages lacking a closed-form LOOCV solution (such as the second stage of both KPV and KAP), using the first-stage data as a held-out set provides a clean and non-overlapping validation loss for regularizer tuning. See Section (S.M. F.3) for the corresponding discussion.
2. **Observation Types:** Splitting naturally accommodates the structure of the different marginal distributions required across stages. For instance, the KAP first-stage utilizes the marginal distribution of (W, Z, A) , whereas the third-stage requires data from the distribution of (Y, Z, A) , facilitating estimation when only partial marginals are available.

F.3 Hyperparameter optimization procedures

We describe the procedures used to tune the regularization parameters $\lambda_{h,1}, \lambda_{h,2}, \lambda_{\varphi,1}, \lambda_{\varphi,2}, \lambda_{\varphi,3}, \lambda_{\text{MMR}}$, and λ_{DR} . Specifically, $\lambda_{h,1}, \lambda_{\varphi,1}, \lambda_{\varphi,3}$, and λ_{DR} are selected using leave-one-out cross-validation (LOOCV), which admits a closed-form solution in the case of kernel ridge regression. In

contrast, $\lambda_{h,2}$, $\lambda_{\varphi,2}$ and λ_{MMR} are tuned using validation loss on a held-out set. To avoid repetition, we first review the LOOCV procedure in the general kernel ridge regression setting, followed by the closed-form expressions for the relevant regression stages of the KPV and KAP algorithms. We then present the validation loss formulas used to tune $\lambda_{\varphi,2}$ and λ_{MMR} .

Leave one out cross validation in kernel ridge regression: We consider the problem of estimating the conditional mean function $f_0(x) = \mathbb{E}[Y | X = x]$ from an observational data $\{x_i, y_i\}_{i=1}^t \subset \mathbb{R}^{d_X} \times \mathbb{R}^{d_Y}$, denote the dimensions of inputs and outputs, respectively. The kernel ridge regression (KRR) estimator for f_0 is given by

$$\hat{f} = \arg \min_{f \in \mathcal{H}_X} \frac{1}{t} \sum_{i=1}^t \|y_i - \langle f, \phi_X(x_i) \rangle_{\mathcal{H}_X}\|_{\mathcal{Y}}^2 + \lambda \|f\|_{\mathcal{H}_X}, \quad (38)$$

where \mathcal{H}_X is a reproducing kernel Hilbert space (RKHS) on domain \mathcal{X} with the associated canonical feature map $\phi_X(\cdot) : \mathcal{X} \rightarrow \mathcal{H}_X$, and $\lambda > 0$ is the regularization parameter. The closed-form solution to Equation (38) is

$$\hat{f} = \mathbf{Y}^\top (\mathbf{K}_{XX} + t\lambda \mathbf{I})^{-1} \Phi_X, \quad (39)$$

where $\mathbf{Y} = [y_1 \ \dots \ y_t]^\top$, $\Phi_X = [\phi_X(x_1) \ \dots \ \phi_X(x_t)]$, and \mathbf{K}_{XX} is the kernel matrix computed from the inputs $\{x_i\}_{i=1}^t$. To select an appropriate value for λ , we employ leave-one-out cross-validation (LOOCV), which assesses generalization by sequentially excluding each data point and evaluating prediction error. The LOOCV objective is defined as

$$\text{LOOCV}(\lambda) = \frac{1}{t} \sum_{j=1}^t \left\| y_j - \hat{f}_{-j}(x_j) \right\|_{\mathcal{Y}}^2, \quad (40)$$

where \hat{f}_{-j} KRR estimator trained on all data except the j -th observation. In the KRR setting, the LOOCV loss admits a closed-form expression, as given by the following result:

Theorem F.1 (Algorithm (F.1) in [69]). *Consider the kernel ridge regression setup introduced in Equation (38) where $\{x_i\}_{i=1}^t$ denotes the input data and $\{y_i\}_{i=1}^t$ denotes the corresponding outputs. Then, the LOOCV loss is given by*

$$\text{LOOCV}(\lambda) = \frac{1}{t} \left\| \tilde{\mathbf{H}}_\lambda^{-1} \mathbf{H}_\lambda \mathbf{Y} \right\|_{\mathcal{Y}}^2 = \frac{1}{t} \text{Tr} \left(\tilde{\mathbf{H}}_\lambda^{-1} \mathbf{H}_\lambda \mathbf{Y} \mathbf{Y}^\top \mathbf{H}_\lambda^\top \tilde{\mathbf{H}}_\lambda^{-\top} \right), \quad (41)$$

where

$$\mathbf{H}_\lambda = \mathbf{I} - \mathbf{K}_{XX} (\mathbf{K}_{XX} + n\lambda \mathbf{I})^{-1} \in \mathbb{R}^{t \times t}, \quad \tilde{\mathbf{H}}_\lambda = \text{diag}(\mathbf{H}_\lambda) \in \mathbb{R}^{t \times t}.$$

The regularization parameter λ can then be selected by minimizing the LOOCV loss over a predefined grid $\Lambda \subset \mathbb{R}$:

$$\lambda^* = \arg \min_{\Lambda \subset \mathbb{R}} \frac{1}{t} \left\| \tilde{\mathbf{H}}_\lambda^{-1} \mathbf{H}_\lambda \mathbf{Y} \right\|_{\mathcal{Y}}^2.$$

The proof of Theorem (F.1) can be found in Singh et al. [69] (see Algorithm (F.1)). We apply Theorem (F.1) to tune the regularization parameters $\lambda_{h,1}$, $\lambda_{\varphi,1}$, $\lambda_{\varphi,3}$, and λ_{DR} .

F.3.1 Hyperparameter selection for $\lambda_{h,1}$, $\lambda_{\varphi,1}$, $\lambda_{\varphi,3}$, and λ_{DR}

Below, we present the application of the LOOCV tuning procedure to the regularization parameters $\lambda_{h,1}$, $\lambda_{\varphi,1}$, $\lambda_{\varphi,3}$, and λ_{DR} .

- **KPV first-stage regression:** The first-stage regression in the KPV algorithm, given samples $\{\bar{w}_i, \bar{z}_i, \bar{a}_i\}_{i=1}^{n_h}$, is a kernel ridge regression from inputs $\{\phi_{\mathcal{Z}}(\bar{z}_i) \otimes \phi_{\mathcal{A}}(\bar{a}_i)\}_{i=1}^{n_h}$ to the outcomes $\{\phi_{\mathcal{W}}(\bar{w}_i)\}_{i=1}^{n_h}$. Therefore, the LOOCV loss for $\lambda_{h,1}$ is given by

$$\text{LOOCV}(\lambda_{h,1}) = \frac{1}{n_h} \text{Tr} \left(\tilde{\mathbf{H}}_{\lambda_{h,1}}^{-1} \mathbf{H}_{\lambda_{h,1}} \mathbf{K}_{\bar{W}\bar{W}} \mathbf{H}_{\lambda_{h,1}}^\top \tilde{\mathbf{H}}_{\lambda_{h,1}}^{-\top} \right),$$

where

$$\begin{aligned} \mathbf{H}_{\lambda_{h,1}} &= \mathbf{I} - (\mathbf{K}_{\bar{Z}\bar{Z}} \odot \mathbf{K}_{\bar{A}\bar{A}}) (\mathbf{K}_{\bar{Z}\bar{Z}} \odot \mathbf{K}_{\bar{A}\bar{A}} + n_h \lambda_{h,1} \mathbf{I})^{-1} \in \mathbb{R}^{n_h \times n_h}, \\ \tilde{\mathbf{H}}_{\lambda_{h,1}} &= \text{diag}(\mathbf{H}_{\lambda_{h,1}}) \in \mathbb{R}^{n_h \times n_h}. \end{aligned}$$

We use a logarithmically spaced grid of 25 values in the range $[5 \times 10^{-5}, 1]$ and select the value of $\lambda_{h,1}$ that minimizes the LOOCV loss.

- **KAP first-stage regression:** The first-stage regression in the KAP algorithm, using samples $\{\bar{w}_i, \bar{z}_i, \bar{a}_i\}_{i=1}^{n_\varphi}$, is a kernel ridge regression from inputs $\{\phi_{\mathcal{W}}(\bar{w}_i) \otimes \phi_{\mathcal{A}}(\bar{a}_i)\}_{i=1}^{n_\varphi}$ to the outcomes $\{\phi_{\mathcal{Z}}(\bar{z}_i)\}_{i=1}^{n_\varphi}$. Hence, the LOOCV loss for $\lambda_{\varphi,1}$ is given by

$$\text{LOOCV}(\lambda_{\varphi,1}) = \frac{1}{n_\varphi} \text{Tr} \left(\tilde{\mathbf{H}}_{\lambda_{\varphi,1}}^{-1} \mathbf{H}_{\lambda_{\varphi,1}} \mathbf{K}_{\bar{Z}\bar{Z}} \mathbf{H}_{\lambda_{\varphi,1}}^\top \tilde{\mathbf{H}}_{\lambda_{\varphi,1}}^{-\top} \right),$$

where

$$\begin{aligned} \mathbf{H}_{\lambda_{\varphi,1}} &= \mathbf{I} - (\mathbf{K}_{\bar{W}\bar{W}} \odot \mathbf{K}_{\bar{A}\bar{A}}) (\mathbf{K}_{\bar{W}\bar{W}} \odot \mathbf{K}_{\bar{A}\bar{A}} + n_\varphi \lambda_{\varphi,1} \mathbf{I})^{-1} \in \mathbb{R}^{n_\varphi \times n_\varphi}, \\ \tilde{\mathbf{H}}_{\lambda_{\varphi,1}} &= \text{diag}(\mathbf{H}_{\lambda_{\varphi,1}}) \in \mathbb{R}^{n_\varphi \times n_\varphi}. \end{aligned}$$

We perform a grid search over 25 logarithmically spaced values in the range $[5 \times 10^{-5}, 1]$ and select the value of $\lambda_{\varphi,1}$ that minimizes the LOOCV loss.

- **KAP third-stage regression:** With the third-stage data $\{\dot{y}_i, \dot{z}_i, \dot{a}_i\}_{i=1}^{t_\varphi}$, the KAP algorithm performs kernel ridge regression from the inputs $\{\phi_{\mathcal{A}}(\dot{a}_i)\}_{i=1}^{t_\varphi}$ to the outcomes $\{\dot{y}_i \phi_{\mathcal{Z}}(\dot{z}_i)\}_{i=1}^{t_\varphi}$. Thus, the LOOCV loss for $\lambda_{\varphi,3}$ is given by

$$\text{LOOCV}(\lambda_{\varphi,3}) = \frac{1}{t_\varphi} \text{Tr} \left(\tilde{\mathbf{H}}_{\lambda_{\varphi,3}}^{-1} \mathbf{H}_{\lambda_{\varphi,3}} \left(\mathbf{K}_{\dot{Z}\dot{Z}} \odot \dot{\mathbf{Y}} \dot{\mathbf{Y}}^\top \right) \mathbf{H}_{\lambda_{\varphi,3}}^\top \tilde{\mathbf{H}}_{\lambda_{\varphi,3}}^{-\top} \right),$$

where

$$\begin{aligned} \mathbf{H}_{\lambda_{\varphi,3}} &= \mathbf{I} - \mathbf{K}_{\dot{A}\dot{A}} (\mathbf{K}_{\dot{A}\dot{A}} + t_\varphi \lambda_{\varphi,3} \mathbf{I})^{-1} \in \mathbb{R}^{t_\varphi \times t_\varphi}, \\ \tilde{\mathbf{H}}_{\lambda_{\varphi,3}} &= \text{diag}(\mathbf{H}_{\lambda_{\varphi,3}}) \in \mathbb{R}^{t_\varphi \times t_\varphi}. \end{aligned}$$

We perform a grid search over 25 logarithmically spaced values in the range $[5 \times 10^{-5}, 1]$ and select the value of $\lambda_{\varphi,3}$ that minimizes the LOOCV loss.

- **Slack term estimation:** Our doubly robust estimator includes a term of the form $\mathbb{E}[\varphi_0(Z, a) h_0(W, a) \mid A = a]$, which requires estimating the conditional mean embedding $E[\phi_{\mathcal{Z}}(Z) \otimes \phi_{\mathcal{W}}(W) \mid A = a]$ as we derive in Section (S.M. C.3). Using training data $\{z_i, w_i, a_i\}_{i=1}^t$, we fit a kernel ridge regression from the inputs $\{\phi_{\mathcal{A}}(a_i)\}_{i=1}^t$ to the outputs $\{\phi_{\mathcal{Z}}(z_i) \otimes \phi_{\mathcal{W}}(w_i)\}_{i=1}^t$ with the regularization parameter λ_{DR} . As a result, the LOOCV for λ_{DR} is given by

$$\text{LOOCV}(\lambda_{\text{DR}}) = \frac{1}{t} \text{Tr} \left(\tilde{\mathbf{H}}_{\lambda_{\text{DR}}}^{-1} \mathbf{H}_{\lambda_{\text{DR}}} (\mathbf{K}_{\mathcal{Z}\mathcal{Z}} \odot \mathbf{K}_{\mathcal{W}\mathcal{W}}) \mathbf{H}_{\lambda_{\text{DR}}}^\top \tilde{\mathbf{H}}_{\lambda_{\text{DR}}}^{-\top} \right),$$

where

$$\begin{aligned} \mathbf{H}_{\lambda_{\text{DR}}} &= \mathbf{I} - \mathbf{K}_{\mathcal{A}\mathcal{A}} (\mathbf{K}_{\mathcal{A}\mathcal{A}} + t \lambda_{\text{DR}} \mathbf{I})^{-1} \in \mathbb{R}^{t \times t}, \\ \tilde{\mathbf{H}}_{\lambda_{\text{DR}}} &= \text{diag}(\mathbf{H}_{\lambda_{\text{DR}}}) \in \mathbb{R}^{t \times t}. \end{aligned}$$

For λ_{DR} , we use a grid search over 25 logarithmically spaced values in the range $[5 \times 10^{-5}, 1]$ to minimize the LOOCV loss.

F.3.2 Hyperparameter selection for $\lambda_{h,2}$, $\lambda_{\varphi,2}$, and λ_{MMR}

In this section, we provide details of the tuning procedures of the other regularization parameters $\lambda_{h,2}$, $\lambda_{\varphi,2}$, and λ_{MMR} . Specifically, we leverage the validation loss on a held-out set to tune these parameters.

- **KPV second-stage regression:** The second-stage regression in KPV approximates the outcome bridge function via optimizing the objective given in Equation (20) To tune the regularization

parameter $\lambda_{h,2}$, we treat the first-stage samples $\{\bar{w}_i, \bar{z}_i, \bar{a}_i\}_{i=1}^{n_h}$ as a held-out validation set and minimize the validation loss:

$$\lambda_{h,2}^* = \arg \min \frac{1}{n_h} \sum_{i=1}^{n_h} \left(\bar{y}_i - \langle \hat{h}, \hat{\mu}_{W|Z,A}(\bar{z}_i, \bar{a}_i) \otimes \phi_{\mathcal{A}}(\bar{a}_i) \rangle \right)^2,$$

where \hat{h} is the solution to the optimization problem in Equation (20), as described in Algorithm (2), and $\hat{\mu}_{W|Z,A}$ denotes the estimated conditional mean embedding from the first stage.

In our experiments, we used a grid of 25 logarithmically spaced values in the range $[5 \times 10^{-5}, 1]$.

- **KAP second-stage regression:** The second-stage regression of KAP estimates the treatment bridge function via optimizing the objective given in Equation (26). To tune the regularization parameter $\lambda_{\varphi,2}$, we treat the first-stage samples $\{\bar{w}_i, \bar{z}_i, \bar{a}_i\}_{i=1}^{n_{\varphi}}$ as a held-out validation set and minimize the validation loss:

$$\begin{aligned} \hat{\mathcal{L}}(\varphi)_{\text{KAP}}^{\text{Val}} &= \frac{1}{n_{\varphi}} \sum_{i=1}^{n_{\varphi}} \langle \varphi, \hat{\mu}_{Z|W,A}(\bar{w}_i, \bar{a}_i) \otimes \phi_{\mathcal{A}}(\bar{a}_i) \rangle_{\mathcal{H}_{Z\mathcal{A}}}^2 \\ &\quad - 2 \frac{1}{m_{\varphi}(n_{\varphi} - 1)} \sum_{i=1}^{n_{\varphi}} \sum_{\substack{j=1 \\ j \neq i}}^{m_{\varphi}} \left\langle \varphi, \hat{\mu}_{Z|W,A}(\bar{w}_j, \bar{a}_i) \otimes \phi_{\mathcal{A}}(\bar{a}_i) \right\rangle_{\mathcal{H}_{Z\mathcal{A}}}. \end{aligned}$$

This objective admits a closed-form expression:

$$\begin{aligned} \hat{\mathcal{L}}_{\text{KAP}}^{\text{Val}}(\varphi) &= \frac{1}{n} \begin{bmatrix} \alpha_{1:m_{\varphi}} \\ \alpha_{m_{\varphi}+1} \end{bmatrix} \begin{bmatrix} B^T K_{ZZ} C \odot K_{\bar{A}\bar{A}} \\ (\frac{1}{m_{\varphi}})^T (\tilde{B}^T K_{ZZ} C \odot K_{\bar{A}\bar{A}}) \end{bmatrix} \begin{bmatrix} C^T K_{ZZ} B \odot K_{\bar{A}\bar{A}} \\ (C^T K_{ZZ} \tilde{B} \odot K_{\bar{A}\bar{A}}) \frac{1}{m_{\varphi}} \end{bmatrix}^T \begin{bmatrix} \alpha_{1:m_{\varphi}} \\ \alpha_{m_{\varphi}+1} \end{bmatrix} \\ &\quad - 2 \begin{bmatrix} \alpha_{1:m_{\varphi}} \\ \alpha_{m_{\varphi}+1} \end{bmatrix}^T \begin{bmatrix} (B^T K_{ZZ} \bar{C} \odot K_{\bar{A}\bar{A}}) \frac{1}{n_{\varphi}} \\ (\frac{1}{m_{\varphi}})^T (\tilde{B}^T K_{ZZ} \bar{C} \odot K_{\bar{A}\bar{A}}) \frac{1}{n_{\varphi}} \end{bmatrix}. \end{aligned}$$

Here, the matrices C and \bar{C} are defined as:

$$\begin{aligned} C &= \left(K_{\bar{W}\bar{W}} \odot K_{\bar{A}\bar{A}} + n_{\varphi} \lambda_{\varphi,1} I \right)^{-1} (K_{\bar{W}\bar{W}} \odot K_{\bar{A}\bar{A}}), \\ \bar{C}_{:,j} &= \frac{1}{n_{\varphi}} \sum_{\substack{l=1 \\ l \neq j}}^{n_{\varphi}} \left(K_{\bar{W}\bar{W}} \odot K_{\bar{A}\bar{A}} + n_{\varphi} \lambda_{\varphi,1} I \right)^{-1} (K_{\bar{W}\bar{w}_l} \odot K_{\bar{A}\bar{a}_j}), \quad \forall j. \end{aligned}$$

For full derivation, see Bozkurt et al. [23, Section (13.2.2)]. To avoid overfitting, Bozkurt et al. [23] additionally propose minimizing the validation loss augmented by a model complexity penalty:

$$\lambda_{\varphi,2}^* = \arg \min \hat{\mathcal{L}}_{\text{KAP}}^{\text{Val}}(\varphi) + \frac{2\sigma_{\varphi}^2}{m_{\varphi}} \text{Tr} \left((L^T L + m \lambda_{\varphi,2} I)^{-1} L^T L \right).$$

for some fixed $\sigma_{\varphi} > 0$.

In our experiments, we used a grid of 25 logarithmically spaced values in the range $[5 \times 10^{-5}, 1]$ to tune $\lambda_{\varphi,2}$. Following the complexity regularization parameters in Bozkurt et al. [23], we set $\sigma_{\varphi} = 1$ for the synthetic low-dimensional setting as well as the legalized abortion and crime dataset, and $\sigma_{\varphi} = 3$ for dSprite and grade retention datasets.

- **PMMR regularization parameter tuning:** To tune the regularization parameter λ_{MMR} , we follow a procedure similar to that used in the second-stage regression of the KPV algorithm. Specifically, we set aside a small validation subset from the training data $\{y_i, w_i, z_i, a_i\}_{i=1}^t$ and evaluate the validation loss based on the bridge function predictions. We use a grid of 25 logarithmically spaced values in the range $[5 \times 10^{-5}, 10^{-3}]$ to tune λ_{MMR} , with 10% of the training set held out as a validation set.

F.4 Additional numerical experiments with misspecified bridge functions

A higher-resolution version of the misspecification analysis presented in Section (5) (Figure (3)) is provided below in Figure (4) for enhanced legibility.

Here, we conduct an additional ablation study to evaluate the robustness of our methods under misspecification of bridge functions, building on the experimental setup from Section (5). In this experiment, we introduce higher levels of noise into the bridge function coefficients. Recall that, by the representer theorem, the bridge functions admit the following forms:

- KPV: $\hat{h} = \sum_{i=1}^{n_h} \sum_{j=1}^{m_h} \alpha_{ij} \phi_{\mathcal{W}}(w_i) \otimes \phi_{\mathcal{A}}(\tilde{a}_j)$,
- PMMR: $\hat{h} = \sum_{i=1}^t \alpha_i \phi_{\mathcal{W}}(w_i) \otimes \phi_{\mathcal{A}}(a_i)$,
- KAP: $\hat{\varphi} = \sum_{l=1}^{m_\varphi} \sum_{t=1}^{m_\varphi} \gamma_{lt} \hat{\mu}_{Z|W,A}(\tilde{w}_t, \tilde{a}_l) \otimes \phi_{\mathcal{A}}(\tilde{a}_l)$

To simulate misspecification, we first train DRKPV (or DRPMMR) in the synthetic low-dimensional setting and then perturb either the outcome (KPV/PMMR) or treatment (KAP) bridge coefficients by injecting Gaussian noise.

Figures (5a) and (5b) display DRKPV results, averaged over five independent runs with standard deviation bands. In Figure (5a), outcome bridge coefficients are perturbed via $\alpha_{ij} \leftarrow \alpha_{ij} + \varepsilon_{ij}$, where $\varepsilon_{ij} \sim \mathcal{N}(0, 0.5)$. Similarly, in Figure (5b), treatment bridge coefficients are jittered as $\gamma_{ij} \leftarrow \gamma_{ij} + \varepsilon_{ij}$ with $\varepsilon_{ij} \sim \mathcal{N}(0, 0.5)$. Despite the misspecification, DRKPV successfully recovers the true causal function, with the slack term compensating for the introduced error.

Figures (5c) and (5d) present analogous results for DRPMMR, where Gaussian noise $\mathcal{N}(0, 0.5)$ is added to one of the learned bridge functions. As with DRKPV, DRPMMR remains robust, accurately recovering the true causal effect even under significant misspecification.

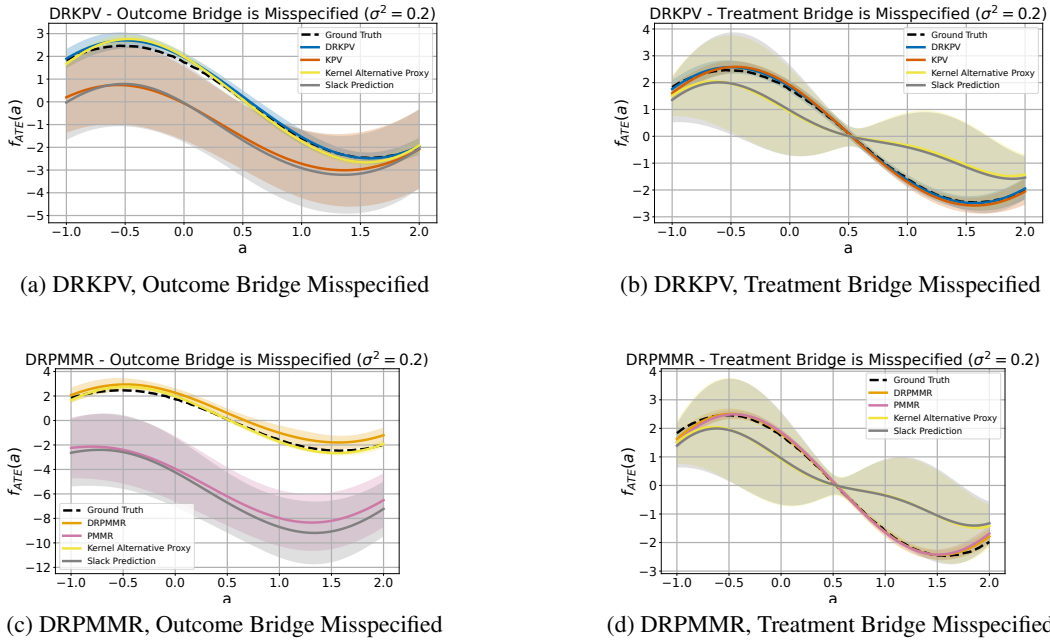
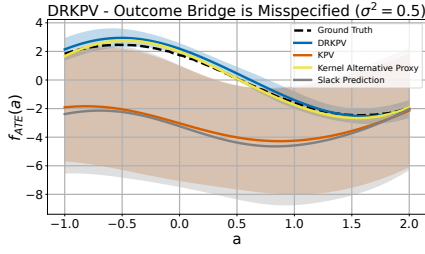
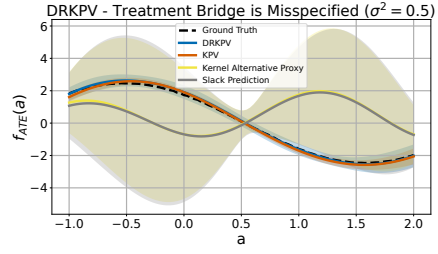


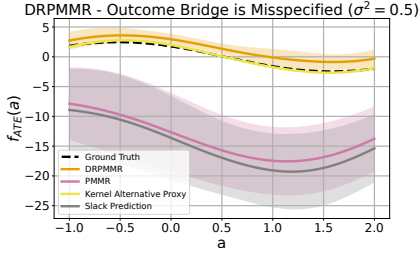
Figure 4: (Duplicate of Figure (3)) Experimental results in bridge function misspecifications with the synthetic low-dimensional data with jittering noise sampled from $\mathcal{N}(0, 0.2)$: (a) DRKPV estimates under outcome bridge misspecification; (b) DRKPV estimates under treatment bridge misspecification; (c) DRPMMR estimates under outcome bridge misspecification; and (d) DRPMMR estimates under treatment bridge misspecification.



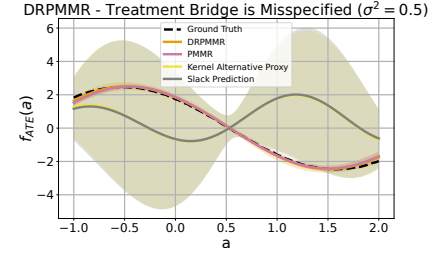
(a) DRKPV, Outcome Bridge Misspecified



(b) DRKPV, Treatment Bridge Misspecified



(c) DRPMMR, Outcome Bridge Misspecified



(d) DRPMMR, Treatment Bridge Misspecified

Figure 5: Experimental results under bridge function misspecifications with the synthetic low dimensional data with jittering noise sampled from $\mathcal{N}(0, 0.5)$: (a) DRKPV estimation when the outcome bridge is misspecified, (b) DRKPV estimation when the treatment bridge function is misspecified, (c) DRPMMR estimation when the outcome bridge function is misspecified, (d) DRPMMR estimation when the treatment bridge is misspecified.

F.5 Numerical experiments with Job Corps dataset

In this section, we present numerical experiments with the Job Corps dataset [54, 55], which we accessed through the public repository provided by Singh et al. [69] (<https://github.com/liyuan9988/KernelCausalFunction/tree/master>). The U.S. Job Corps Program is an educational initiative designed to support disadvantaged youth. In the corresponding observational dataset, the treatment variable A captures the total number of hours participants spent in academic or vocational training, whereas the outcome variable Y measures the proportion of weeks the participant was employed during the program's second year. The covariate vector $U \in \mathbb{R}^{65}$ includes demographic and socioeconomic features such as gender, ethnicity, age, language proficiency, education level, marital status, household size, among others.

To adapt this dataset to the proximal causal learning (PCL) framework, Bozkurt et al. [23] proposed synthetic proxy generation schemes specifically crafted to test the limits of the completeness conditions stated in Assumptions (2.3) and (2.5). We adopt the six experimental settings introduced in their work to evaluate the performance of our proposed doubly robust estimators.

Setting 1: Let $W = U + \epsilon_w$ and $Z = g(U^{(1:20)} / \max(U^{(1:20)})) + \epsilon_z$ where $g(x) = 0.8 \frac{\exp(x)}{1 + \exp(x)} + 0.1$ is applied elementwise, and both the division and maximum operations are performed elementwise. Here, the notation $U^{(1:20)}$ refers to the first 20 components of the vector U . Noise terms are sampled as $\epsilon_w^{(i)} \sim \mathcal{N}(0, 1) \forall i = 1, \dots, 65$, $\epsilon_z^{(i)} \sim \mathcal{U}[-1, 1] \forall i = 1, \dots, 20$.

Setting 2: Let $Z = U + \epsilon_z$ and $W = g(U^{(1:20)} / \max(U^{(1:20)})) + \epsilon_w$ with $\epsilon_z^{(i)} \sim \mathcal{N}(0, 1) \forall i$, $\epsilon_w^{(i)} \sim \mathcal{U}[-1, 1] \forall i$.

Setting 3: Let $W = U + \epsilon_w$ and $Z = g(U^{(20:40)} / \max(U^{(20:40)})) + \epsilon_z$ with $\epsilon_w^{(i)} \sim \mathcal{N}(0, 1) \forall i$, $\epsilon_z^{(i)} \sim \mathcal{U}[-1, 1] \forall i$.

Setting 4: Let $Z = U + \epsilon_z$ and $W = g(U^{(20:40)} / \max(U^{(20:40)})) + \epsilon_w$ with $\epsilon_z^{(i)} \sim \mathcal{N}(0, 1) \forall i$, $\epsilon_w^{(i)} \sim \mathcal{U}[-1, 1] \forall i$.

Setting 5: Let $W = U + \epsilon_w$ and $Z = g(U^{(40:60)} / \max(U^{(40:60)})) + \epsilon_z$ with $\epsilon_w^{(i)} \sim \mathcal{N}(0, 1) \forall i$, $\epsilon_z^{(i)} \sim \mathcal{U}[-1, 1] \forall i$.

Setting 6: Let $Z = U + \epsilon_z$ and $W = g(U^{(40:60)} / \max(U^{(40:60)})) + \epsilon_w$ with $\epsilon_z^{(i)} \sim \mathcal{N}(0, 1) \forall i$, $\epsilon_w^{(i)} \sim \mathcal{U}[-1, 1] \forall i$.

Notice that the odd numbered settings are constructed to introduce an incomplete link between the treatment proxy Z and the confounder U , combined with a nonlinear transformation. These configurations are prone to violating Assumption (2.3) that hinges the identifiability of dose-response with outcome bridge function (see Theorem (2.4)). On the other hand, even numbered settings are constructed to introduce an incomplete link between the outcome proxy W and the confounder U , combined with a nonlinear transformation. These setups are likely to violate Assumption (2.5), which underpins the identifiability guarantees of dose response with treatment bridge function (see Theorem (2.6)).

Bozkurt et al. [23] showed that their treatment bridge-based method, KAP, produces estimates that are more closely aligned with those of the oracle method *Kernel-ATE* [69], which assumes access to the true confounder U , compared to outcome bridge-based approaches such as KPV and KNC. They attribute this to KAP’s robustness when the existence of the bridge function is violated, rather than when the assumption underlying the identifiability of the causal function is compromised. Conversely, their results suggest that KPV and KNC tend to yield estimates closer to the oracle method in scenarios where the existence of the bridge function is violated but the assumption ensuring the causal function’s identifiability remains potentially valid—highlighting their strength under different failure modes. While these findings emphasize the complementary robustness of the two classes of methods under varying conditions, determining which condition holds in practice is often difficult. In this work, we demonstrate that our proposed doubly robust estimators effectively unify the strengths of both approaches, yielding consistently strong performance across diverse scenarios.

Figure (6) presents the estimated dose-response curves produced by our proposed methods across all six experimental settings averaged over 5 different realizations with standard deviation envelopes. For comparison, we include estimates from methods based solely on outcome or treatment bridge functions, along with the oracle method *Kernel-ATE* from Singh et al. [69], which has access to the true confounder U . For numerical comparison, Table (1) reports the mean squared distance between each algorithm’s estimate and that of the oracle method. Across all settings, DRKPV consistently outperforms its non-doubly robust counterpart KPV, as well as the baselines KNC and KAP. In Settings 1, 3, 4, and 5, DRPMMR also outperforms its non-doubly robust variant PMMR and the other baselines. The only exceptions are Settings 2 and 6, where PMMR performs better than DRPMMR, based on the oracle method’s dose-response estimates as the ground truth.

Table 1: Mean squared distance between each algorithm’s estimated dose-response curve and that of the oracle method across the six experimental settings for the Job Corps dataset described in Section (S.M. F.5).

	DRKPV	DRPMMR	KPV	PMMR	KNC	KAP
Set. 1	0.87 ± 0.30	1.17 ± 0.49	15.58 ± 2.38	1.55 ± 0.44	4.45 ± 1.37	1.95 ± 0.21
Set. 2	1.78 ± 0.83	2.02 ± 0.50	4.30 ± 2.05	0.84 ± 0.21	2.74 ± 1.12	9.67 ± 2.95
Set. 3	2.58 ± 0.65	1.17 ± 0.20	8.92 ± 3.33	1.63 ± 0.35	6.49 ± 1.59	3.15 ± 0.96
Set. 4	2.29 ± 0.43	1.87 ± 0.31	5.25 ± 4.01	1.96 ± 0.14	2.86 ± 2.11	4.12 ± 1.21
Set. 5	1.07 ± 0.43	0.89 ± 0.34	10.20 ± 5.32	1.26 ± 0.30	4.45 ± 2.29	1.83 ± 0.71
Set. 6	0.99 ± 0.42	1.03 ± 0.13	4.99 ± 2.59	0.62 ± 0.19	2.87 ± 1.02	2.70 ± 1.48

F.6 Ablation study: hyperparameter sensitivity on the length scale

Here, we investigate the sensitivity of our methods to the selection of the kernel length-scale hyperparameter, l , for the Gaussian kernel used throughout our experiments. In the main paper (and detailed in Section (S.M. F.1)), we employed the median heuristic to set the length scale. This process

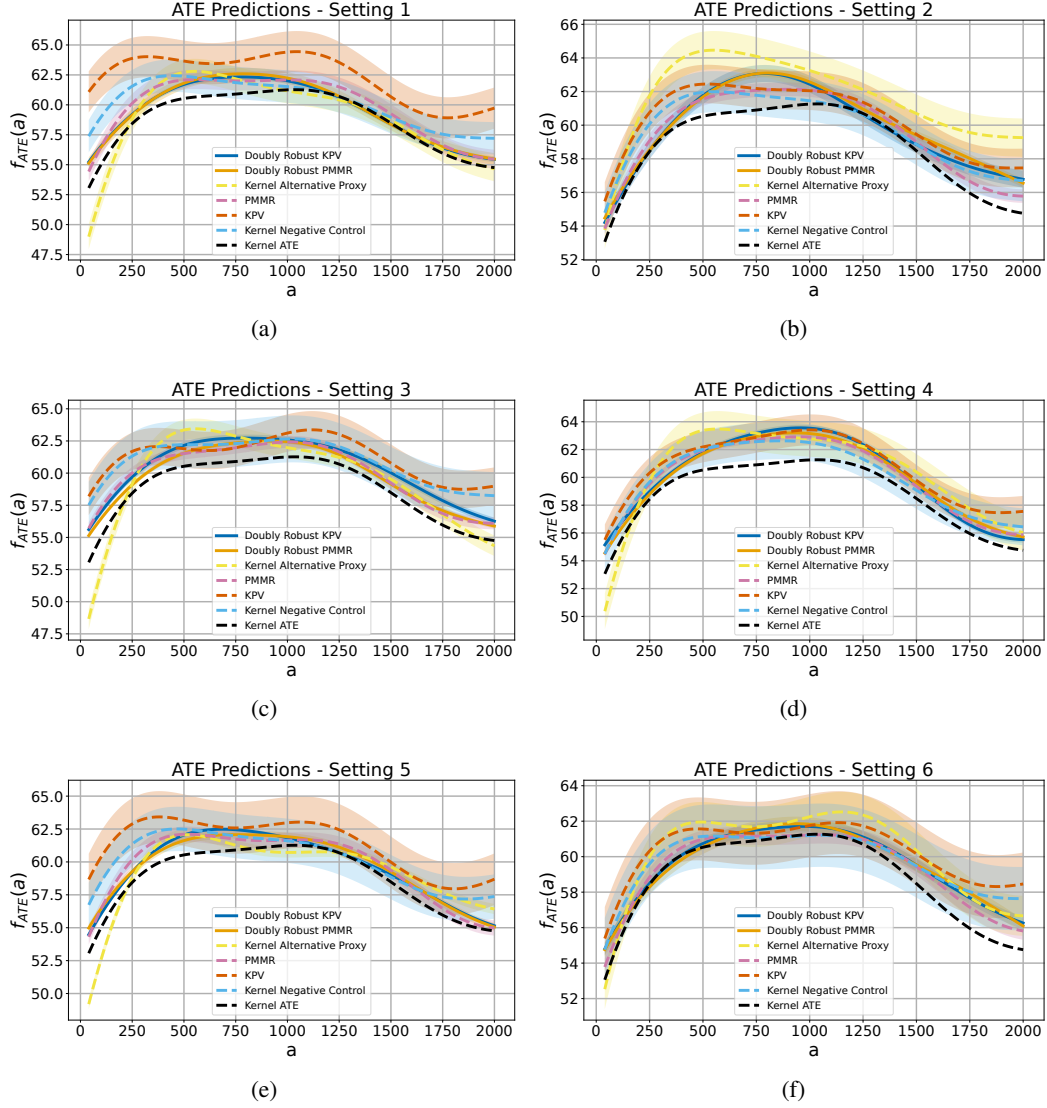


Figure 6: Dose-response estimation curves for the Job Corps experimental settings described in Section (S.M. F.5). Figures (6a)-(6f) display the dose-response estimates from our proposed methods, DRKPV and DRPMMR, compared against KPV, PMMR, KNC, KAP, and the oracle method, Kernel-ATE.

involves setting l equal to the 0.5-quantile of the computed pairwise distances across all training data. To demonstrate the robustness of our proposed DRKPV and DRPMMR methods, we vary the quantile value used for setting l for each of the involved kernels. Specifically, we test the algorithms on the synthetic low-dimensional setting (with $t = 2000$) and the Legalized Abortion & Crime dataset by varying the quantile within the set $\{0.25, 0.4, 0.5, 0.6, 0.75, 0.9\}$. The corresponding results are presented in Table (2). The table demonstrates that the performance of both DRKPV and DRPMMR is stable across a broad range of length-scale quantile selections, and confirms that the 0.50-quantile (median heuristic) is a robust choice. Degradation in performance is only significant at the extreme high end of the scale (e.g., the 0.90-quantile in the synthetic dataset), indicating that our methods are generally robust to the specific selection of l .

Table 2: Ablation study on hyperparameter sensitivity: Mean Squared Error (MSE) across different length-scale (ℓ) selections for the RBF kernel. The length scale is set to the specified quantile of pairwise distances.

Algorithm	Quantile	MSE (mean \pm std)	
		Synthetic Low-Dim	Abortion & Crime
DRKPV	0.25	0.055 ± 0.035	0.024 ± 0.007
	0.40	0.028 ± 0.016	0.020 ± 0.014
	0.50 (Median)	0.026 ± 0.015	0.018 ± 0.010
	0.60	0.027 ± 0.018	0.019 ± 0.012
	0.75	0.034 ± 0.019	0.023 ± 0.016
	0.90	0.22 ± 0.096	0.021 ± 0.018
DRPMMR	0.25	0.026 ± 0.011	0.016 ± 0.005
	0.40	0.020 ± 0.011	0.015 ± 0.008
	0.50 (Median)	0.019 ± 0.012	0.016 ± 0.009
	0.60	0.024 ± 0.018	0.018 ± 0.009
	0.75	0.034 ± 0.033	0.025 ± 0.013
	0.90	0.22 ± 0.130	0.022 ± 0.015

F.7 Ablation study: performance with the Matérn kernel class

We now demonstrate the performance of our proposed methods across different kernel choices by conducting an experiment with the Matérn kernel class in the synthetic low-dimensional setting (with $t = 2000$) and the Legalized Abortion & Crime dataset.

As detailed in Section (S.M. F.1), the Matérn kernel is controlled by the smoothness parameter ν . In this study, we focus on cases where ν is a half-integer, i.e., $\nu = p + 1/2$ where p is an integer. The closed form polynomial expression is given in Equation (37).

We report the performance of our proposed methods, DRKPV and DRPMMR, for varying values of the integer p within the set $\{0, 1, 2, 3, 10\}$. This range allows us to explore kernel smoothness from the least smooth Exponential kernel ($\nu = 1/2, p = 0$) up to an approximation of the highly smooth Gaussian kernel ($\nu = 10.5, p = 10$).

Table 3: Ablation Study: Mean Squared Error (MSE) for various Matérn kernel selections, controlled by the smoothness parameter $\alpha = p + 1/2$.

Algorithm	Smoothness Parameter (p)	MSE (mean \pm std)	
		Synthetic Low-Dim	Abortion & Crime
DRKPV	0 ($\nu = 0.5$)	0.032 ± 0.016	0.019 ± 0.007
	1 ($\nu = 1.5$)	0.022 ± 0.013	0.022 ± 0.015
	2 ($\nu = 2.5$)	0.022 ± 0.013	0.020 ± 0.012
	3 ($\nu = 3.5$)	0.022 ± 0.013	0.023 ± 0.017
	10 ($\nu = 10.5$)	0.024 ± 0.015	0.023 ± 0.014
DRPMMR	0 ($\nu = 0.5$)	0.029 ± 0.011	0.016 ± 0.003
	1 ($\nu = 1.5$)	0.019 ± 0.013	0.019 ± 0.009
	2 ($\nu = 2.5$)	0.019 ± 0.013	0.018 ± 0.010
	3 ($\nu = 3.5$)	0.018 ± 0.013	0.018 ± 0.010
	10 ($\nu = 10.5$)	0.022 ± 0.016	0.021 ± 0.011

F.8 Scalability analysis: impact of Nyström approximation on performance

We now analyze the computational complexity of our proposed DRKPV method and introduce the Nyström approximation as a technique to enhance its scalability for large datasets. While we focus on DRKPV for simplicity, this discussion extends directly to DRPMMR.

The DRKPV framework comprises three primary computational components: 1) the KPV algorithm (Algorithm (2)), 2) the KAP algorithm (Algorithm (4)), and 3) the estimation of the slack correction term (step 3 in Algorithm (1)). We break down the complexity analysis as follows:

- **KPV Algorithm (Stage 1):** Utilizes n_h data samples and involves the inversion of an $n_h \times n_h$ Gram matrix, yielding a complexity dominated by the matrix inversion, $O(n_h^3)$.
- **KPV Algorithm (Stage 2):** Uses m_h data samples and requires the inversion of $m_h \times m_h$ Gram matrix. Its complexity is therefore $O(m_h^3)$.
- **KAP Algorithm (Stage 1):** Uses n_φ data samples and involves the inverting an $n_\varphi \times n_\varphi$ Gram matrix, with a complexity of $O(n_\varphi^3)$.
- **KAP Algorithm (Stage 2):** The complexity is dominated by the inversion of $(m_\varphi + 1) \times (m_\varphi + 1)$ matrix, scaling with $O(m_\varphi^3)$, where m_φ is the number of samples in the second stage.
- **KAP Algorithm (Stage 3):** Leverages t_φ data samples, and its complexity is governed by inversion of $t_\varphi \times t_\varphi$ Gram matrix, scaling with $O(t_\varphi^3)$.
- **DRKPV - Slack correction term:** As outlined in Equation (6), this step requires inverting a $t \times t$ Gram matrix, where t is the total number of data samples. Hence, the computational complexity is $O(t^3)$.

In conclusion, the overall computational complexity of our method, DRKPV, is dominated by the inversion of the largest matrix, scaling as $O(t^3)$. This is similar to the complexity of standard kernel methods like kernel ridge regression.

In general, the $O(t^3)$ computational complexity is a significant bottleneck for applications involving large datasets. To address this, we propose the Nyström approximation as a concrete step towards making our method more scalable.

Nyström approximation: Recall from Equations (38)-(39), the kernel ridge regression (KRR) estimator for the conditional mean function $f_0 = \mathbb{E}[Y | X = x]$ uses observational data $\{x_i, y_i\}_{i=1}^t$ and is given by:

$$\hat{f}(x) = \mathbf{Y}^\top (\mathbf{K}_{XX} + t\lambda \mathbf{I})^{-1} \mathbf{K}_{Xx}.$$

As detailed in the complexity breakdown above, the required matrix inversion of the $t \times t$ matrix $(\mathbf{K}_{XX} + t\lambda \mathbf{I})$ makes this solution expensive to compute, as the complexity scales cubically with the number of data points. The Nyström approximation technique [73] tackles this bottleneck by relying on a low-rank approximation to the Gram matrix \mathbf{K}_{XX} . This approximation is constructed by using a smaller subset of landmark points $\{s_i\}_{i=1}^p \subset \{x_i\}_{i=1}^t$, where $p \ll t$. These landmarks are typically selected using various sampling schemes [74]. The closed form expression with this approximation is given by (See Equation (2) in [75]):

$$\hat{f}(x) = \mathbf{Y}^\top \mathbf{K}_{XS} (\mathbf{K}_{XS}^\top \mathbf{K}_{XS} + t\lambda \mathbf{K}_{SS})^{-1} \mathbf{K}_{Sx} \quad (42)$$

where $[\mathbf{K}_{XS}]_{i,j} = k_X(x_i, s_j)$, $[\mathbf{K}_{SS}]_{ij} = k_X(s_i, s_j)$, and $[\mathbf{K}_{Sx}]_i = k_X(s_i, x)$. The primary computational advantage of this Nyström form is that the matrix requiring inversion, $(\mathbf{K}_{XS}^\top \mathbf{K}_{XS} + t\lambda \mathbf{K}_{SS})^{-1}$, is now only $p \times p$. Assuming that the number of landmarks p is substantially smaller than the total number of samples ($p \ll t$), the computational cost of kernel ridge regression solution is reduced from $O(t^3)$ to $O(p^2 t)$.

We apply this low-rank approximation to the computationally intensive kernel regression stages in our DRKPV algorithm:

- KPV (Stage 1): Kernel ridge regression from the input features $\{\phi_Z(\bar{z}_i \otimes \phi_A(\bar{a}_i))\}_{i=1}^{n_h}$ to the observations $\{\phi_W(\bar{w}_i)\}_{i=1}^{n_h}$.
- KPV (Stage 2): Kernel ridge regression from the input features $\{\hat{\mu}_{W|Z,A}(\tilde{z}_i, \tilde{a}_i) \otimes \phi_A(\tilde{a}_i)\}_{i=1}^{m_h}$ to the observations $\{\tilde{y}_i\}_{i=1}^{m_h}$.
- KAP (Stage 1): Kernel ridge regression from the input features $\{\phi_W(\bar{w}_i \otimes \phi_A(\bar{a}_i))\}_{i=1}^{n_\varphi}$ to the observations $\{\phi_Z(\bar{z}_i)\}_{i=1}^{n_\varphi}$.
- KAP (Stage 3): Kernel ridge regression from the input features $\{\phi_A(\hat{a}_i)\}_{i=1}^{t_\varphi}$ to the observations $\{\hat{y}_i \phi_Z(\hat{z}_i)\}_{i=1}^{t_\varphi}$.
- Doubly robust correction term (Equation 29): Kernel ridge regression from the input features $\{\phi_A(a_i)\}_{i=1}^t$ to the observations $\{\phi_Z(z_i) \otimes \phi_W(w_i)\}_{i=1}^t$.

The second-stage regression of KAP involves a more specialized setup that deviates from standard KRR, but it is equally amenable to approximation techniques. Table 4 presents synthetic low-dimensional experiments comparing the full-kernel DRKPV to its Nyström-approximated version ($p = 500$ and $p = 1000$), where all regularization parameters are uniformly set to 10^{-3} . Results clearly demonstrate that the Nyström approximation effectively reduces the algorithm’s runtime while maintaining or even improving prediction accuracy. Future work will also explore stronger scalable alternatives such as scalable kernel ridge regression [75] and the neural network approaches [13, 35], including for the second-stage regression of KAP.

Table 4: Performance and scalability comparison of DRKPV with Nyström approximation in synthetic low-dimensional experiments.

Algorithm	Data Size (t)	MSE (mean \pm std)	Algo Run Time (s)
DRKPV (Original)	5000	0.0097 ± 0.0046	61.1 ± 0.21
DRKPV (Nyström, $p = 500$)	5000	0.0082 ± 0.0033	42.5 ± 0.19
DRKPV (Nyström, $p = 100$)	5000	0.0071 ± 0.0028	39.2 ± 0.22
DRKPV (Original)	7500	0.0070 ± 0.0033	194.5 ± 0.35
DRKPV (Nyström, $p = 500$)	7500	0.0085 ± 0.0044	132.7 ± 0.04
DRKPV (Nyström, $p = 100$)	7500	0.0091 ± 0.0046	127.6 ± 0.00
DRKPV (Original)	10000	0.0065 ± 0.0026	453.9 ± 0.51
DRKPV (Nyström, $p = 500$)	10000	0.0059 ± 0.0014	306.7 ± 0.02
DRKPV (Nyström, $p = 100$)	10000	0.0062 ± 0.0022	299.5 ± 0.00

NeurIPS Paper Checklist

1. Claims

Question: Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope?

Answer: [\[Yes\]](#)

Justification: The abstract and introduction clearly state the paper's contributions and scope, namely the development of doubly robust estimators for proxy causal learning using kernel mean embeddings.

Guidelines:

- The answer NA means that the abstract and introduction do not include the claims made in the paper.
- The abstract and/or introduction should clearly state the claims made, including the contributions made in the paper and important assumptions and limitations. A No or NA answer to this question will not be perceived well by the reviewers.
- The claims made should match theoretical and experimental results, and reflect how much the results can be expected to generalize to other settings.
- It is fine to include aspirational goals as motivation as long as it is clear that these goals are not attained by the paper.

2. Limitations

Question: Does the paper discuss the limitations of the work performed by the authors?

Answer: [\[Yes\]](#)

Justification: Section (6) discusses the limitations of our work and outlines future directions.

Guidelines:

- The answer NA means that the paper has no limitation while the answer No means that the paper has limitations, but those are not discussed in the paper.
- The authors are encouraged to create a separate "Limitations" section in their paper.
- The paper should point out any strong assumptions and how robust the results are to violations of these assumptions (e.g., independence assumptions, noiseless settings, model well-specification, asymptotic approximations only holding locally). The authors should reflect on how these assumptions might be violated in practice and what the implications would be.
- The authors should reflect on the scope of the claims made, e.g., if the approach was only tested on a few datasets or with a few runs. In general, empirical results often depend on implicit assumptions, which should be articulated.
- The authors should reflect on the factors that influence the performance of the approach. For example, a facial recognition algorithm may perform poorly when image resolution is low or images are taken in low lighting. Or a speech-to-text system might not be used reliably to provide closed captions for online lectures because it fails to handle technical jargon.
- The authors should discuss the computational efficiency of the proposed algorithms and how they scale with dataset size.
- If applicable, the authors should discuss possible limitations of their approach to address problems of privacy and fairness.
- While the authors might fear that complete honesty about limitations might be used by reviewers as grounds for rejection, a worse outcome might be that reviewers discover limitations that aren't acknowledged in the paper. The authors should use their best judgment and recognize that individual actions in favor of transparency play an important role in developing norms that preserve the integrity of the community. Reviewers will be specifically instructed to not penalize honesty concerning limitations.

3. Theory assumptions and proofs

Question: For each theoretical result, does the paper provide the full set of assumptions and a complete (and correct) proof?

Answer: [\[Yes\]](#)

Justification: We provide complete proofs and all necessary assumptions for our novel results, referencing the Supplementary Material when needed. Assumptions and results from prior work are properly cited and referenced.

Guidelines:

- The answer NA means that the paper does not include theoretical results.
- All the theorems, formulas, and proofs in the paper should be numbered and cross-referenced.
- All assumptions should be clearly stated or referenced in the statement of any theorems.
- The proofs can either appear in the main paper or the supplemental material, but if they appear in the supplemental material, the authors are encouraged to provide a short proof sketch to provide intuition.
- Inversely, any informal proof provided in the core of the paper should be complemented by formal proofs provided in appendix or supplemental material.
- Theorems and Lemmas that the proof relies upon should be properly referenced.

4. **Experimental result reproducibility**

Question: Does the paper fully disclose all the information needed to reproduce the main experimental results of the paper to the extent that it affects the main claims and/or conclusions of the paper (regardless of whether the code and data are provided or not)?

Answer: [\[Yes\]](#)

Justification: We include our Python code with instructions and dependencies in the supplementary zip. Experimental setups, hyperparameters, and implementation details are provided in Sections (5) and S.M.(F), with derivations and pseudocode in S.M. (C).

Guidelines:

- The answer NA means that the paper does not include experiments.
- If the paper includes experiments, a No answer to this question will not be perceived well by the reviewers: Making the paper reproducible is important, regardless of whether the code and data are provided or not.
- If the contribution is a dataset and/or model, the authors should describe the steps taken to make their results reproducible or verifiable.
- Depending on the contribution, reproducibility can be accomplished in various ways. For example, if the contribution is a novel architecture, describing the architecture fully might suffice, or if the contribution is a specific model and empirical evaluation, it may be necessary to either make it possible for others to replicate the model with the same dataset, or provide access to the model. In general, releasing code and data is often one good way to accomplish this, but reproducibility can also be provided via detailed instructions for how to replicate the results, access to a hosted model (e.g., in the case of a large language model), releasing of a model checkpoint, or other means that are appropriate to the research performed.
- While NeurIPS does not require releasing code, the conference does require all submissions to provide some reasonable avenue for reproducibility, which may depend on the nature of the contribution. For example
 - (a) If the contribution is primarily a new algorithm, the paper should make it clear how to reproduce that algorithm.
 - (b) If the contribution is primarily a new model architecture, the paper should describe the architecture clearly and fully.
 - (c) If the contribution is a new model (e.g., a large language model), then there should either be a way to access this model for reproducing the results or a way to reproduce the model (e.g., with an open-source dataset or instructions for how to construct the dataset).
 - (d) We recognize that reproducibility may be tricky in some cases, in which case authors are welcome to describe the particular way they provide for reproducibility. In the case of closed-source models, it may be that access to the model is limited in some way (e.g., to registered users), but it should be possible for other researchers to have some path to reproducing or verifying the results.

5. Open access to data and code

Question: Does the paper provide open access to the data and code, with sufficient instructions to faithfully reproduce the main experimental results, as described in supplemental material?

Answer: [Yes]

Justification: We include our Python code with the supplementary zip file, along with instructions to reproduce and required packages. Dataset sources and URLs are cited in Sections (5) and S.M. (F). The synthetic data can be reproduced using our code or the descriptions provided in the paper.

Guidelines:

- The answer NA means that paper does not include experiments requiring code.
- Please see the NeurIPS code and data submission guidelines (<https://nips.cc/public/guides/CodeSubmissionPolicy>) for more details.
- While we encourage the release of code and data, we understand that this might not be possible, so “No” is an acceptable answer. Papers cannot be rejected simply for not including code, unless this is central to the contribution (e.g., for a new open-source benchmark).
- The instructions should contain the exact command and environment needed to run to reproduce the results. See the NeurIPS code and data submission guidelines (<https://nips.cc/public/guides/CodeSubmissionPolicy>) for more details.
- The authors should provide instructions on data access and preparation, including how to access the raw data, preprocessed data, intermediate data, and generated data, etc.
- The authors should provide scripts to reproduce all experimental results for the new proposed method and baselines. If only a subset of experiments are reproducible, they should state which ones are omitted from the script and why.
- At submission time, to preserve anonymity, the authors should release anonymized versions (if applicable).
- Providing as much information as possible in supplemental material (appended to the paper) is recommended, but including URLs to data and code is permitted.

6. Experimental setting/details

Question: Does the paper specify all the training and test details (e.g., data splits, hyperparameters, how they were chosen, type of optimizer, etc.) necessary to understand the results?

Answer: [Yes]

Justification: We provide full details of our experimental setup in the main text (Section (5)) and additional training details, including hyperparameter selection procedures, in the supplementary material (S.M. (F)).

Guidelines:

- The answer NA means that the paper does not include experiments.
- The experimental setting should be presented in the core of the paper to a level of detail that is necessary to appreciate the results and make sense of them.
- The full details can be provided either with the code, in appendix, or as supplemental material.

7. Experiment statistical significance

Question: Does the paper report error bars suitably and correctly defined or other appropriate information about the statistical significance of the experiments?

Answer: [Yes]

Justification: We report results over multiple realizations and include boxplots or standard deviation bars to illustrate the variability and statistical significance of our methods.

Guidelines:

- The answer NA means that the paper does not include experiments.

- The authors should answer "Yes" if the results are accompanied by error bars, confidence intervals, or statistical significance tests, at least for the experiments that support the main claims of the paper.
- The factors of variability that the error bars are capturing should be clearly stated (for example, train/test split, initialization, random drawing of some parameter, or overall run with given experimental conditions).
- The method for calculating the error bars should be explained (closed form formula, call to a library function, bootstrap, etc.)
- The assumptions made should be given (e.g., Normally distributed errors).
- It should be clear whether the error bar is the standard deviation or the standard error of the mean.
- It is OK to report 1-sigma error bars, but one should state it. The authors should preferably report a 2-sigma error bar than state that they have a 96% CI, if the hypothesis of Normality of errors is not verified.
- For asymmetric distributions, the authors should be careful not to show in tables or figures symmetric error bars that would yield results that are out of range (e.g. negative error rates).
- If error bars are reported in tables or plots, The authors should explain in the text how they were calculated and reference the corresponding figures or tables in the text.

8. Experiments compute resources

Question: For each experiment, does the paper provide sufficient information on the computer resources (type of compute workers, memory, time of execution) needed to reproduce the experiments?

Answer: [No]

Justification: We did not report compute resources, as our methods are lightweight and all experiments can be run on a standard personal computer with Python on it.

Guidelines:

- The answer NA means that the paper does not include experiments.
- The paper should indicate the type of compute workers CPU or GPU, internal cluster, or cloud provider, including relevant memory and storage.
- The paper should provide the amount of compute required for each of the individual experimental runs as well as estimate the total compute.
- The paper should disclose whether the full research project required more compute than the experiments reported in the paper (e.g., preliminary or failed experiments that didn't make it into the paper).

9. Code of ethics

Question: Does the research conducted in the paper conform, in every respect, with the NeurIPS Code of Ethics <https://neurips.cc/public/EthicsGuidelines>?

Answer: [Yes]

Justification: Our research fully complies with the NeurIPS Code of Ethics.

Guidelines:

- The answer NA means that the authors have not reviewed the NeurIPS Code of Ethics.
- If the authors answer No, they should explain the special circumstances that require a deviation from the Code of Ethics.
- The authors should make sure to preserve anonymity (e.g., if there is a special consideration due to laws or regulations in their jurisdiction).

10. Broader impacts

Question: Does the paper discuss both potential positive societal impacts and negative societal impacts of the work performed?

Answer: [No]

Justification: Our paper focuses on methodological and theoretical contributions and does not include a discussion of broader societal impacts. We do not foresee any negative societal impacts from the research presented.

Guidelines:

- The answer NA means that there is no societal impact of the work performed.
- If the authors answer NA or No, they should explain why their work has no societal impact or why the paper does not address societal impact.
- Examples of negative societal impacts include potential malicious or unintended uses (e.g., disinformation, generating fake profiles, surveillance), fairness considerations (e.g., deployment of technologies that could make decisions that unfairly impact specific groups), privacy considerations, and security considerations.
- The conference expects that many papers will be foundational research and not tied to particular applications, let alone deployments. However, if there is a direct path to any negative applications, the authors should point it out. For example, it is legitimate to point out that an improvement in the quality of generative models could be used to generate deepfakes for disinformation. On the other hand, it is not needed to point out that a generic algorithm for optimizing neural networks could enable people to train models that generate Deepfakes faster.
- The authors should consider possible harms that could arise when the technology is being used as intended and functioning correctly, harms that could arise when the technology is being used as intended but gives incorrect results, and harms following from (intentional or unintentional) misuse of the technology.
- If there are negative societal impacts, the authors could also discuss possible mitigation strategies (e.g., gated release of models, providing defenses in addition to attacks, mechanisms for monitoring misuse, mechanisms to monitor how a system learns from feedback over time, improving the efficiency and accessibility of ML).

11. Safeguards

Question: Does the paper describe safeguards that have been put in place for responsible release of data or models that have a high risk for misuse (e.g., pretrained language models, image generators, or scraped datasets)?

Answer: [NA]

Justification: Not applicable to the research presented in this paper.

Guidelines:

- The answer NA means that the paper poses no such risks.
- Released models that have a high risk for misuse or dual-use should be released with necessary safeguards to allow for controlled use of the model, for example by requiring that users adhere to usage guidelines or restrictions to access the model or implementing safety filters.
- Datasets that have been scraped from the Internet could pose safety risks. The authors should describe how they avoided releasing unsafe images.
- We recognize that providing effective safeguards is challenging, and many papers do not require this, but we encourage authors to take this into account and make a best faith effort.

12. Licenses for existing assets

Question: Are the creators or original owners of assets (e.g., code, data, models), used in the paper, properly credited and are the license and terms of use explicitly mentioned and properly respected?

Answer: [Yes]

Justification: We properly credit all datasets used: Legalized Abortion and Crime [51, 52], Grade Retention [53, 10], and Job Corps [54, 55]. We also cite the GitHub repository from Mastouri et al. [11] where some datasets were sourced.

Guidelines:

- The answer NA means that the paper does not use existing assets.

- The authors should cite the original paper that produced the code package or dataset.
- The authors should state which version of the asset is used and, if possible, include a URL.
- The name of the license (e.g., CC-BY 4.0) should be included for each asset.
- For scraped data from a particular source (e.g., website), the copyright and terms of service of that source should be provided.
- If assets are released, the license, copyright information, and terms of use in the package should be provided. For popular datasets, paperswithcode.com/datasets has curated licenses for some datasets. Their licensing guide can help determine the license of a dataset.
- For existing datasets that are re-packaged, both the original license and the license of the derived asset (if it has changed) should be provided.
- If this information is not available online, the authors are encouraged to reach out to the asset's creators.

13. **New assets**

Question: Are new assets introduced in the paper well documented and is the documentation provided alongside the assets?

Answer: [\[Yes\]](#)

Justification: We provide well-structured code for our methods in the supplementary material zip file, including a README with instructions to reproduce the experiments.

Guidelines:

- The answer NA means that the paper does not release new assets.
- Researchers should communicate the details of the dataset/code/model as part of their submissions via structured templates. This includes details about training, license, limitations, etc.
- The paper should discuss whether and how consent was obtained from people whose asset is used.
- At submission time, remember to anonymize your assets (if applicable). You can either create an anonymized URL or include an anonymized zip file.

14. **Crowdsourcing and research with human subjects**

Question: For crowdsourcing experiments and research with human subjects, does the paper include the full text of instructions given to participants and screenshots, if applicable, as well as details about compensation (if any)?

Answer: [\[NA\]](#)

Justification: Our work does not involve crowdsourcing or research with human subjects.

Guidelines:

- The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
- Including this information in the supplemental material is fine, but if the main contribution of the paper involves human subjects, then as much detail as possible should be included in the main paper.
- According to the NeurIPS Code of Ethics, workers involved in data collection, curation, or other labor should be paid at least the minimum wage in the country of the data collector.

15. **Institutional review board (IRB) approvals or equivalent for research with human subjects**

Question: Does the paper describe potential risks incurred by study participants, whether such risks were disclosed to the subjects, and whether Institutional Review Board (IRB) approvals (or an equivalent approval/review based on the requirements of your country or institution) were obtained?

Answer: [\[NA\]](#)

Justification: This paper does not involve research with human subjects or crowdsourcing.

Guidelines:

- The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
- Depending on the country in which research is conducted, IRB approval (or equivalent) may be required for any human subjects research. If you obtained IRB approval, you should clearly state this in the paper.
- We recognize that the procedures for this may vary significantly between institutions and locations, and we expect authors to adhere to the NeurIPS Code of Ethics and the guidelines for their institution.
- For initial submissions, do not include any information that would break anonymity (if applicable), such as the institution conducting the review.

16. **Declaration of LLM usage**

Question: Does the paper describe the usage of LLMs if it is an important, original, or non-standard component of the core methods in this research? Note that if the LLM is used only for writing, editing, or formatting purposes and does not impact the core methodology, scientific rigorousness, or originality of the research, declaration is not required.

Answer: [NA]

Justification: LLMs were only used for grammar and writing assistance, not for core methodology or scientific content.

Guidelines:

- The answer NA means that the core method development in this research does not involve LLMs as any important, original, or non-standard components.
- Please refer to our LLM policy (<https://neurips.cc/Conferences/2025/LLM>) for what should or should not be described.