Optimally tackling covariate shift in RKHS-based nonparametric regression

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Success of machine learning

Core assumption: $P_{\text{train}} = Q_{\text{test}}$
Our focus: covariate shift

\[ P_{\text{train}}(X) \neq Q_{\text{test}}(X), \quad \text{while} \quad P_{\text{train}}(Y \mid X) = Q_{\text{test}}(Y \mid X) \]

due to variability in medical equipment, scanning protocols, subject populations
Key questions

• What is the statistical limit of estimation in the presence of covariate shift? And how does this limit depend on the “amount” of covariate shift?

• Is nonparametric least-squares estimation still optimal under covariate shift? If not, what is the optimal way of tackling covariate shift?
Problem setup
Nonparametric regression under covariate shift

• In standard nonparametric regression, one observes \( n \) random pairs \( \{x_i, y_i\}_{i=1}^n \), where \( x_i \sim P \), and

\[
y_i = f^*(x_i) + w_i \quad \text{with} \quad w_i \sim \mathcal{N}(0, \sigma^2)
\]

We measure performance of estimator \( \hat{f} \) by its \( L^2(P) \)-error:

\[
\|\hat{f} - f^*\|_P^2 := \int_X (\hat{f}(x) - f^*(x))^2 p(x) dx
\]

• Under covariate shift, however, our goal is to find an estimator \( \hat{f} \) whose \( L^2(Q) \)-error is small, where target distribution \( Q \) is different from source distribution \( P \)
Reproducing kernel Hilbert spaces (RKHSs)

- We assume throughout that \( f^* \) lies in some RKHS \( \mathcal{H} \) in \( L^2(Q) \)

- Eigen-decomposition of kernel \( \mathcal{K} : \mathcal{X} \times \mathcal{X} \to \mathbb{R} \):

\[
\mathcal{K}(x, x') := \sum_{j=1}^{\infty} \mu_j \phi_j(x) \phi_j(x')
\]

with \( \{\mu_j\}_{j \geq 1} \) sequence of non-negative eigenvalues, and \( \{\phi_j\}_{j \geq 1} \) orthonormal basis of \( L^2(Q) \)

- Hilbert norm (measure of smoothness):

\[
\|f\|_{\mathcal{H}}^2 = \sum_{j=1}^{\infty} \frac{\theta_j^2}{\mu_j}, \quad \text{where } \theta_j := \int_{\mathcal{X}} f(x) \phi_j(x) q(x) dx
\]

- Parametrization of \( \mathcal{H} \):

\[
\mathcal{H} := \left\{ f = \sum_{j=1}^{\infty} \theta_j \phi_j \mid \sum_{j=1}^{\infty} \frac{\theta_j^2}{\mu_j} < \infty \right\}
\]

We assume throughout that \( \sup_{x \in \mathcal{X}} \mathcal{K}(x, x) \leq \kappa^2 \)
Examples of RKHSs

- Linear kernels: \( \mathcal{K}(x, x') = \langle x, x' \rangle \) with \( \mathcal{X} = \mathbb{R}^d \), and \( \mathcal{H} \) all linear functions

- Polynomial kernels: \( \mathcal{K}(x, x') = (1 + \langle x, x' \rangle)^m \) with \( \mathcal{X} = \mathbb{R}^d \), and \( \mathcal{H} \) being polynomials of degree \( m \) or less

- First-order Sobolev space: \( \mathcal{K}(x, x') = \min\{x, x'\} \) with \( \mathcal{X} = [0, 1] \), and

\[
\mathcal{H} = \left\{ f : [0, 1] \to \mathbb{R} \mid f(0) = 0, \int_0^1 |f'(x)|^2 dx < \infty \right\}
\]
Family of source-target pairs

Discrepancy between $L_2(P)$ and $L_2(Q)$ norms are controlled by likelihood ratios (LRs)

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We focus on two broad families of covariate shift pairs $(P, Q)$:

- **Uniformly $B$-bounded families**: $\sup_{x \in \mathcal{X}} \rho(x) \leq B$, where $B \geq 1$
  
  $B = 1$ recovers no-covariate-shift case

- **$\chi^2$-bounded families**: $\mathbb{E}_{X \sim P} [\rho^2(X)] \leq V^2$ for some $V^2 \geq 1$
  
  more general than (1), and related to $\chi^2(Q||P) := \mathbb{E}_{X \sim P} [\rho^2(X)] - 1$
Uniformly $B$-bounded likelihood ratios
Upper bounds

A naive kernel ridge regression estimator (KRR):

$$\hat{f}_\lambda := \arg \min_{f \in \mathcal{H}} \left\{ \frac{1}{n} \sum_{i=1}^{n} (f(x_i) - y_i)^2 + \lambda \|f\|_{\mathcal{H}}^2 \right\}$$

**Theorem 1 (Ma, Pathak, Wainwright, 2022)**

Assume $B$-bounded likelihood ratios and $\kappa$-uniformly bounded kernel. For any $\lambda \geq 10\kappa^2/n$, w.h.p. KRR $\hat{f}_\lambda$ satisfies the bound

$$\|\hat{f}_\lambda - f^*\|_Q^2 \lesssim \lambda B \|f^*\|_{\mathcal{H}}^2 + \frac{\sigma^2 B \log n}{n} \sum_{j=1}^{\infty} \frac{\mu_j}{\mu_j + \lambda B}$$

$$+ b_\lambda^2(B)$$

$$- v_\lambda(B)$$
Bias-variance trade-off

Upper bound of KRR:

\[
\| \hat{f}_\lambda - f^* \|_Q^2 \lesssim \lambda B \| f^* \|_H^2 \quad + \quad \underbrace{b_\lambda^2(B)}_{\text{Bias} \lambda B \| f^* \|_H^2} + \underbrace{\frac{\sigma^2 B \log n}{n} \sum_{j=1}^{\infty} \frac{\mu_j}{\mu_j + \lambda B}}_{\text{Variance} \cdot \lambda B} \log n \sum_{j=1}^{\infty} \mu_j
\]

- **Bias** \( \lambda B \| f^* \|_H^2 \): increase as \( \lambda \) increases
- **Variance**:
  \[
  \frac{\sigma^2 B \log n}{n} \sum_{j=1}^{\infty} \frac{\mu_j}{\mu_j + \lambda B} \] : decrease as \( \lambda \) increases
Bias-variance trade-off

Upper bound of KRR:

$$\| \hat{f}_\lambda - f^* \|_Q^2 \lesssim \lambda B \| f^* \|_H^2 + \left\{ \begin{array}{c} \underbrace{b_\lambda^2(B)}_{\text{Bias } \lambda B \| f^* \|_H^2} \end{array} \right\} + \left\{ \begin{array}{c} \underbrace{\frac{\sigma^2 B \log n}{n} \sum_{j=1}^{\infty} \frac{\mu_j}{\mu_j + \lambda B}}_{\text{Variance } \sigma^2 B \log n \sum_{j=1}^{\infty} \frac{\mu_j}{\mu_j + \lambda B}} \end{array} \right\}$$

- Bias $\lambda B \| f^* \|_H^2$: increase as $\lambda$ increases
- Variance: $\frac{\sigma^2 B \log n}{n} \sum_{j=1}^{\infty} \frac{\mu_j}{\mu_j + \lambda B}$: decrease as $\lambda$ increases

Familiar! What’s new?
Bias-variance trade-off

Bias/variance trade-off under covariate shift

\[ \mu_j = j^{-2}, \text{ sample size } n = 8000, \text{ and noise variance } \sigma^2 = 1 \]

Optimal \( \lambda^*(B) \) shifts leftwards to smaller values as \( B \) is increased
Upper bounds for specific kernels

- Finite-rank kernels (i.e., $\mu_j = 0$ for $j > D$) with optimal rate $\sigma^2 B \frac{D}{n}$

- Kernels with $\alpha$-decaying eigenvalues (i.e., $\mu_j \lesssim j^{-2\alpha}$) with optimal rate $(\sigma^2 B/n)^{\frac{2\alpha}{2\alpha+1}}$

Unweighted KRR is minimax optimal for these RKHSs
Sub-optimality of constrained estimator

Suppose that $\|f^*\|_{\mathcal{H}} \leq 1$. A seemingly “equivalent” estimator:

$$\hat{f}_{\text{erm}} := \arg \min_{f \in \mathcal{B}_H(1)} \frac{1}{n} \sum_{i=1}^{n} (f(x_i) - y_i)^2$$

with $\mathcal{B}_H(1)$ denoting the ball with unit Hilbert norm
Suppose that $\|f^*\|_H \leq 1$. A seemingly “equivalent” estimator:

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with $B_H(1)$ denoting the ball with unit Hilbert norm

- Without covariate shift, constrained least-squares estimator is also rate-optimal

- However, under covariate shift, $\hat{f}_{\text{erm}}$ is provably sub-optimal. One can construct $B$-bounded pair $(P, Q)$ and RKHS such that optimal rate is $(B/n)^{2/3}$, while $\mathbb{E}\left[\|\hat{f}_{\text{erm}} - f^*\|_Q^2\right] \gtrsim B^3/n^2$
Key observation: $\|f_{\lambda}\|_{H^2}^2$ increases as $B$ increases, where $\lambda = \lambda^*(B)$
$\chi^2$-bounded likelihood ratios
— going beyond uniform boundedness
A simple example

- Source distribution $P = \mathcal{N}(0, 0.9)$
- Target distribution $Q = \mathcal{N}(0, 1)$
- Unbounded likelihood ratio as $\lim_{|x| \to \infty} \rho(x) \to \infty$
- However, second moment of LRs is bounded
Unweighted KRR?

In the bounded likelihood ratio case, the key to the success of *unweighted* KRR:

\[
\hat{f}_\lambda := \arg \min_{f \in \mathcal{H}} \left\{ \frac{1}{n} \sum_{i=1}^{n} (f(x_i) - y_i)^2 + \lambda \|f\|_\mathcal{H}^2 \right\}
\]

is the following nice relation

\[
\Sigma_P \succeq \frac{1}{B} I
\]

\[
\Sigma_P := \mathbb{E}_{X \sim P}[\phi(X)\phi(X)^\top], \text{ and } I = \Sigma_Q := \mathbb{E}_{X \sim Q}[\phi(X)\phi(X)^\top]
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Unweighted KRR?

In the bounded likelihood ratio case, the key to the success of *unweighted* KRR:

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\[ \Sigma_P \succeq \frac{1}{B} I \]

\[ \Sigma_P := \mathbb{E}_{X \sim P}[\phi(X)\phi(X)^\top], \text{ and } I = \Sigma_Q := \mathbb{E}_{X \sim Q}[\phi(X)\phi(X)^\top] \]

In contrast, such a nice relationship (with \( B \) replaced by \( V^2 \)) does NOT appear to hold with unbounded likelihood ratios.
Likelihood-reweighted estimator

It is therefore natural to consider the likelihood-reweighted estimate

$$\arg\min_{f \in \mathcal{H}} \frac{1}{n} \sum_{i=1}^{n} \rho(x_i)(f(x_i) - y_i)^2 + \lambda \|f\|_{\mathcal{H}}^2$$

- The first term is an unbiased estimate of $\mathbb{E}_Q[(Y - f(X))^2]$
- However, the variability could be huge due to multiplication by potentially *unbounded* $\rho(x)$

Therefore we consider truncated estimator

$$\hat{f}_{\lambda}^{rw} := \arg\min_{f \in \mathcal{H}} \frac{1}{n} \sum_{i=1}^{n} \rho_{\tau_i}(x_i)(f(x_i) - y_i)^2 + \lambda \|f\|_{\mathcal{H}}^2$$
Importance-reweighted estimator is near-optimal

With properly chosen $\lambda$ and $\tau_n$, $\hat{f}^{\text{TW}}_{\lambda}$ is optimal for a range of kernel classes including:

- Finite-rank kernels with optimal rate $\frac{DV^2\sigma^2}{n}$

- Kernels with $\alpha$-decaying eigenvalues with optimal rate $\left(\frac{\sigma^2 V^2}{n}\right)^{\frac{2\alpha}{2\alpha+1}}$ as long as the kernel eigenfunctions are bounded $\sup_{x \in \mathcal{X}} |\phi_j(x)| \leq 1$
Conclusions and open questions

- When LRs are uniformly bounded, unweighted KRR is optimal while constrained estimator is sub-optimal
- When LRs are unbounded, likelihood reweighted KRR is optimal

Future directions:
- Prove theoretically unweighted KRR (fails to) achieve optimality
- Remove extra condition on uniformly-bounded eigen-functions
Paper:

“Optimally tackling covariate shift in RKHS-based nonparametric regression,”