A. Theoretical analysis

Appendix A.2 proves the main results under some assumptions about the kernel parameterization, using intermediate results about uniform convergence of our estimators in Appendix A.3. Appendix A.4 then shows that these assumptions hold for different settings of kernel learning.

A.1. Preliminaries

Given a kernel $k_\omega$ and sample sets $\{X_i\}_{i=1}^n \sim P^n$, $\{Y_i\}_{i=1}^n \sim Q^n$, define the $n \times n$ matrix

$$H_{ij}^{(\omega)} = k_\omega(X_i, X_j) + k_\omega(Y_i, Y_j) - k_\omega(X_i, Y_j) - k_\omega(X_j, Y_i);$$

we will often omit $\omega$ when it is clear from context. The $U$-statistic estimator of the squared MMD (2) is

$$\hat{\eta}_\omega = \frac{1}{n(n-1)} \sum_{i \neq j} H_{ij}. $$

The squared MMD is $\eta_\omega = E[H_{12}]$. The variance of $\hat{\eta}_\omega$ is given by Lemma 10.

**Lemma 10.** For a fixed kernel $k_\omega$ and random sample sets $\{X_i\}_{i=1}^n$, $\{Y_i\}_{i=1}^n$, we have

$$\text{Var}[\hat{\eta}_\omega] = \frac{4(n-2)}{n(n-1)} \xi_1^{(\omega)} + \frac{2}{n(n-1)} \xi_2^{(\omega)} = \frac{4}{n} \xi_1^{(\omega)} + \frac{2 \xi_2^{(\omega)} - 4 \xi_1^{(\omega)}}{n(n-1)},$$

where

$$\xi_1^{(\omega)} = \mathbb{E} \left[ H_{12}^{(\omega)} H_{13}^{(\omega)} \right] - \mathbb{E} \left[ H_{12}^{(\omega)} \right]^2, \quad \xi_2^{(\omega)} = \mathbb{E} \left[ \left( H_{12}^{(\omega)} \right)^2 \right] - \mathbb{E} \left[ H_{12}^{(\omega)} \right]^2.$$

Thus as $n \to \infty$,

$$n \text{Var}[\hat{\eta}_\omega] \to 4 \xi_1^{(\omega)} =: \sigma_\omega^2.$$

**Proof.** Let $U$ denote the pair $(X, Y)$, and $h_\omega(U, U') = k_\omega(X, X') + k_\omega(Y, Y') - k_\omega(X, Y') - k_\omega(X', Y)$, so that $H_{ij}^{(\omega)} = h_\omega(U_i, U_j)$. Via Lemma A in Section 5.2.1 of Serfling (1980), we know that (8) holds with

$$\xi_1^{(\omega)} = \text{Var}_U \left[ \mathbb{E}_{U'} [h_\omega(U, U')] \right]$$

$$= \mathbb{E}_U \mathbb{E}_{U'} [h_\omega(U, U')] \mathbb{E}_{U'} [h_\omega(U, U')] - \mathbb{E}_U [\mathbb{E}_{U'} [h_\omega(U, U')]]^2 = \mathbb{E}[H_{12}^{(\omega)} H_{13}^{(\omega)}] - \mathbb{E}[H_{12}^{(\omega)}]^2$$

and

$$\xi_2^{(\omega)} = \text{Var}_{U,U'} [h_\omega(U, U')] = \mathbb{E} \left[ \left( H_{12}^{(\omega)} \right)^2 \right] - \mathbb{E} \left[ H_{12}^{(\omega)} \right]^2. \quad \square$$

We use a $V$-statistic estimator (5) for $\sigma_\omega^2$:

$$\hat{\sigma}_\omega^2 = 4 \left( \frac{1}{n} \sum_{i=1}^n \frac{1}{n} \sum_{j=1}^n H_{ij}^{(\omega)} \right) - \left( \frac{1}{n^2} \sum_{i=1}^n \sum_{j=1}^n H_{ij}^{(\omega)} \right)^2.$$

As a $V$-statistic, $\hat{\sigma}_\omega^2$ is biased. In fact, Sutherland et al. (2017) and Sutherland (2019) provide an unbiased estimator of $\text{Var}[\hat{\eta}_\omega]$—including the terms of order $\frac{1}{n(n-1)}$. Although this estimator takes the same quadratic time to compute as (5), it contains many more terms, which are cumbersome both for implementation and for analysis. (5) is also marginally more convenient in that it is always at least nonnegative. As we show in Lemma 18, the amount of bias is negligible as $n$ increases. In practice, we expect the difference to be unimportant— or the $V$-statistic may in fact be beneficial, since underestimating $\sigma^2$ harms the estimate of $\eta/\sigma^2$ more than overestimating it does.

Similarly, although we use the $U$-statistic estimator (2), it would be very similar to use the biased estimator $n^{-2} \sum_{ij} H_{ij}$, or the minimum variance unbiased estimator $n^{-1} (n-1)^{-1} \sum_{i \neq j} (k(X_i, X_j) + k(Y_i, Y_j)) - 2n^{-2} \sum_{ij} k(X_i, Y_j)$. Showing comparable concentration behavior to Proposition 15 is trivially different, and in fact it is also not difficult to show $\sigma_\omega^2$ is the same for all three estimators (up to lower-order terms).
A.2. Main results

We will require the following assumptions. These are fairly agnostic as to the kernel form; Appendix A.4.2 shows that these assumptions hold (and gives the constants) for the kernels (1) we use in the paper.

(A) The kernels \( k_\omega \) are uniformly bounded:

\[
\sup_{\omega \in \Omega} \sup_{x \in \mathcal{X}} k_\omega(x, x) \leq \nu.
\]

For the kernels we use in practice, \( \nu = 1 \).

(B) The possible kernel parameters \( \omega \) lie in a Banach space of dimension \( D \). Furthermore, the set of possible kernel parameters \( \Omega \) is bounded by \( R_\omega, \Omega \subseteq \{ \omega \mid \| \omega \| \leq R_\Omega \} \).

Appendix A.4.2 builds this space and its norm for the kernels we use in the paper.

(C) The kernel parameterization is Lipschitz: for all \( x, y \in \mathcal{X} \) and \( \omega, \omega' \in \Omega \),

\[
|k_\omega(x, y) - k_{\omega'}(x, y)| \leq L_k\|\omega - \omega'\|.
\]

Proposition 23 in Appendix A.4.2 gives an expression for \( L_k \) for the kernels we use in the paper.

We will first show the main results under these general assumptions, using uniform convergence results shown in Appendix A.3, then show Assumptions (B) and (C) for particular kernels in Appendix A.4.2.

Theorem 11. Under Assumptions (A) to (C), let \( \bar{\Omega}_\omega \subseteq \Omega \) be the set of kernel parameters for which \( \sigma^2_\omega \geq s^2 \), and assume \( \nu \geq 1 \). Take \( \lambda = n^{-1/3} \). Then, with probability at least \( 1 - \delta \),

\[
\sup_{\omega \in \bar{\Omega}_\omega} \left| \frac{\hat{\eta}_\omega}{\sigma_{\omega, \lambda}} - \frac{\eta_\omega}{\sigma_\omega} \right| \leq \frac{2\nu}{s^2 n^{1/3}} \left( \frac{1}{s + 2304^2} + \left[ \frac{4s}{n^{1/6}} + 1024\nu \right] \left[ L_k + \sqrt{2 \log \frac{2}{\delta} + 2D \log (4R_\Omega \sqrt{n})} \right] \right),
\]

and thus, treating \( \nu \) as a constant,

\[
\sup_{\omega \in \bar{\Omega}_\omega} \left| \frac{\hat{\eta}_\omega}{\sigma_{\omega, \lambda}} - \frac{\eta_\omega}{\sigma_\omega} \right| = O_P \left( \frac{1}{s^2 n^{1/3}} \left[ \frac{1}{s} + L_k + \sqrt{D} \right] \right).
\]

Proof. Let \( \sigma^2_{\omega, \lambda} := \sigma^2_\omega + \lambda \). Using \( |\hat{\eta}_\omega| \leq 4\nu \), we begin by decomposing

\[
\sup_{\omega \in \bar{\Omega}_\omega} \left| \frac{\hat{\eta}_\omega}{\sigma_{\omega, \lambda}} - \frac{\eta_\omega}{\sigma_\omega} \right| \leq \sup_{\omega \in \bar{\Omega}_\omega} \left| \frac{\hat{\eta}_\omega}{\sigma_{\omega, \lambda}} - \frac{\hat{\eta}_\omega}{\sigma_{\omega, \lambda}} \right| + \sup_{\omega \in \bar{\Omega}_\omega} \left| \frac{\hat{\eta}_\omega}{\sigma_{\omega, \lambda}} - \frac{\eta_\omega}{\sigma_\omega} \right| + \sup_{\omega \in \bar{\Omega}_\omega} \left| \frac{\eta_\omega}{\sigma_\omega} - \frac{\eta_\omega}{\sigma_\omega} \right|
\]

\[
= \sup_{\omega \in \bar{\Omega}_\omega} \left| \frac{\hat{\eta}_\omega}{\sigma_{\omega, \lambda}} - \frac{\hat{\eta}_\omega}{\sigma_{\omega, \lambda}} \right| + \sup_{\omega \in \bar{\Omega}_\omega} \left| \frac{\hat{\eta}_\omega}{\sigma_{\omega, \lambda}} - \frac{\eta_\omega}{\sigma_{\omega, \lambda}} \right| + \sup_{\omega \in \bar{\Omega}_\omega} \left| \frac{\eta_\omega}{\sigma_{\omega, \lambda}} - \frac{\eta_\omega}{\sigma_{\omega, \lambda}} \right|
\]

\[
\leq \sup_{\omega \in \bar{\Omega}_\omega} \frac{4\nu}{\sqrt{\lambda}} \frac{1}{s + \sqrt{\lambda}} \left| \sigma^2_{\omega, \lambda} - \sigma^2_\omega \right| + \sup_{\omega \in \bar{\Omega}_\omega} \frac{1}{s^2} \left| \sigma^2_{\omega, \lambda} - \sigma^2_\omega \right| + \sup_{\omega \in \bar{\Omega}_\omega} \frac{1}{s^2} \left| \sigma^2_\omega - \sigma^2_\omega \right|
\]

\[
\leq \frac{4\nu}{s^2 \sqrt{\lambda}} \sup_{\omega \in \Omega} \left| \sigma^2_{\omega, \lambda} - \sigma^2_\omega \right| + \frac{2\nu}{s^3} \lambda + \frac{1}{s} \sup_{\omega \in \Omega} \left| \eta_\omega - \eta_\omega \right|.
\]

Propositions 15 and 16 show uniform convergence of \( \hat{\eta}_\omega \) and \( \hat{\sigma}^2_\omega \), respectively. Thus, with probability at least \( 1 - \delta \), the error is at most

\[
\frac{2\nu}{s^3} \lambda + \frac{8\nu}{s^3 n^{1/3}} + \frac{1792\nu}{s^3 n^{1/3}} \sqrt{2 \log \frac{2}{\delta} + 2D \log (4R_\Omega \sqrt{n})} + \frac{8}{s^3 n^{1/3}} + \frac{2048\nu^2}{s^3 n^{1/3}} L_k + \frac{4608\nu^3}{s^3 n^{1/3}}.
\]

Taking \( \lambda = n^{-1/3} \) gives

\[
\frac{2\nu}{s^3 n^{1/3}} + \frac{8\nu}{s^3 n^{1/3}} + \frac{1792\nu}{s^3 n^{1/3}} \sqrt{2 \log \frac{2}{\delta} + 2D \log (4R_\Omega \sqrt{n})} + \frac{8}{s^3 n^{1/3}} + \frac{2048\nu^2}{s^3 n^{1/3}} L_k + \frac{4608\nu^3}{s^3 n^{1/3}}.
\]
Using $1 \leq \nu$, $1792 < 2048$, we can get the slightly simpler upper bound
\[
\frac{2\nu}{s^2 n^{1/3}} + \left[ \frac{8\nu}{s^2 n^{1/3}} + \frac{2048\nu^2}{s^2 n^{1/3}} \right] \left[ L_k + \sqrt{2 \log \frac{2}{\delta} + 2D \log (4R_{\Omega}\sqrt{n})} \right] + \frac{4608\nu^3}{s^2 n^{5/6}}.
\]

It is worth noting that, if we are particularly concerned about the $s$ dependence, we can make some slightly different choices in the decomposition to improve the dependence on $s$ while worsening the rate with $n$.

**Corollary 12.** In the setup of Theorem 11, additionally assume that there is a unique population maximizer $\omega^*$ of $J$ from (3), i.e. for each $t > 0$ we have
\[
\sup_{\omega \in \Omega_\delta : \|\omega - \omega^*\| \geq t} J(P, Q; k_\omega) < J(P, Q; k_{\omega^*}).
\]

For each $n$, let $S_p^{(n)}$ and $S_Q^{(n)}$ be sequences of sample sets of size $n$, let $\hat{J}_n(\omega)$ denote $J_{\lambda=n^{-1/3}}(S_p^{(n)}, S_Q^{(n)}; k_\omega)$, and take $\hat{\omega}_n$ to be a maximizer of $\hat{J}_n(\omega)$. Then $\hat{\omega}_n^*$ converges in probability to $\omega^*$.

**Proof.** By Theorem 11, $\sup_{\omega \in \Omega_\delta} |J(\omega) - J(\omega)| \to P$. Then the result follows by Theorem 5.7 of Van der Vaart (2000).

**Corollary 13.** In the setup of Theorem 11, suppose we use $n$ sample points to select a kernel $\hat{\omega}_n \in \arg\max_{\omega \in \Omega_\delta} \hat{J}_\lambda(\omega)$ and $m$ sample points to run a test of level $\alpha$. Let $r_{\hat{\omega}_n}^{(m)}$ denote the rejection threshold for a test with that kernel of size $m$. Define $J^* := \sup_{\omega \in \Omega_\delta} J(\omega)$, and constants $C, C', C''$, $N_0$ depending on $\nu, L_k, D, R_\Omega$ and $s$. For any $n \geq N_0$, with probability at least $1 - \delta$, this test procedure has power
\[
\Pr \left( m \hat{\eta}_{\hat{\omega}_n} > r_{\hat{\omega}_n}^{(m)} \right) \geq \Phi \left( \sqrt{m} J^* - C \frac{\sqrt{m}}{n^{1/3}} \sqrt{\log \frac{n}{\delta}} - C' \sqrt{\log \frac{1}{\alpha}} \right) - \frac{C''}{\sqrt{m}}.
\]

**Proof.** Let $\hat{\omega}_n \in \arg\max_{\omega \in \Omega_\delta} \hat{J}_\lambda(\omega)$. By Theorem 11, there are some $N_0, C$ depending on $\nu, L_k, D, R_\Omega$, and $s$ such that as long as $n \geq N_0$, with probability at least $1 - \delta$ it holds that
\[
\sup_{\omega \in \Omega_\delta} |J_\lambda(\omega) - J(\omega)| \leq \frac{1}{2} C n^{-1/3} \sqrt{\log \frac{n}{\delta}} =: \epsilon_n.
\]

Assume for the remainder of this proof that this event holds. Letting $\omega^* \in \arg\max J(\omega)$, we know because $\hat{\omega}_n$ maximizes $\hat{J}_\lambda$ that $\hat{J}_\lambda(\hat{\omega}_n) \geq \hat{J}_\lambda(\omega^*)$. Using uniform convergence twice,
\[
J(\hat{\omega}_n) \geq J(\hat{\omega}_n) - \epsilon_n \geq \hat{J}_\lambda(\omega^*) - \epsilon_n \geq (J(\omega^*) - \epsilon_n) - \epsilon_n = J^* - 2\epsilon_n.
\]

Now, although Proposition 2 establishes that $r_{\omega}^{(m)} \to r_{\omega}$ and it is even known (Korolyuk & Borovskikh, 1988, Theorem 5) that $|r_{\omega}^{(m)} - r_{\omega}|$ is $o(1/\sqrt{m})$, the constant in that convergence will depend on the choice of $\omega$ in an unknown way. It’s thus simpler to use the very loose but uniform (McDiarmid-based) bound given by Corollary 11 of Gretton et al. (2012a), which implies $r_{\omega}^{(m)} \leq 4\nu \sqrt{\log(\alpha^{-1})}m$ no matter the choice of $\omega$.

We will now need a more precise characterization of the power than that provided by the central limit theorem of Proposition 2. Callaert & Janssen (1978) provide such a result, a Berry-Esseen bound on $U$-statistic convergence: there is some absolute constant $C_{BS} = 2^{1/4} C_{BS}$ such that
\[
\sup_t |\Pr_{\hat{H}_1} \left( \sqrt{m} \hat{\eta}_\omega - \eta_\omega \sigma_\omega^{-2} \leq t \right) - \Phi(t)\rangle \leq \frac{C_{BS} \mathbb{E}|H_{12}|^3}{(\sigma_\omega/2)^3 \sqrt{m}} \leq \frac{C_{BS} \nu^3}{\sigma_\omega \sqrt{m}}.
\]

\(^3\)In fact, it suffices for the $\hat{\omega}_n^*$ to only approximately maximize $\hat{J}_n$, as long as their suboptimality is $o_P(1)$.
Letting $r_{\omega}^{(m)}$ be the appropriate rejection threshold for $k_{\omega}$ with $m$ samples, the power of a test with kernel $k_{\omega}$ is

$$\Pr \left( \sqrt{m} \hat{\eta}_{\omega} > r_{\omega}^{(m)} \right) = \Pr \left( \frac{\sqrt{m} \hat{\eta}_{\omega} - \eta_{\omega}}{\sqrt{m} \sigma_{\omega}} > \frac{r_{\omega}^{(m)} - \eta_{\omega}}{\sqrt{m} \sigma_{\omega}} \right)$$

$$\geq \Phi \left( \sqrt{m} J(\omega) - \frac{r_{\omega}^{(m)}}{\sqrt{m} \sigma_{\omega}} \right) - C_{BS} \nu^3$$

$$\geq \Phi \left( \sqrt{m} J(\omega) - \frac{r_{\omega}^{(m)}}{s \sqrt{m}} \right) - C''$$

using a new constant $C'' := C_{BS} \nu^3 / s^3$. Combining the previous results on $J(\hat{\omega}_n)$ and $\hat{r}_{\omega}^{(m)}$ yields the claim.

**Corollary 14.** In the setup of Corollary 13, suppose we are given $N$ data points to divide between $n$ training points and $m = N - n$ testing points, and $\delta < 0.22$ is fixed. Ignoring the Berry-Esseen convergence term outside of $\Phi$, the asymptotic power upper bound

$$\Phi \left( \sqrt{m} J^* - C' \sqrt{\frac{n}{n^*}} \sqrt{\log \frac{n}{\delta}} - C' \sqrt{\log \frac{1}{\alpha}} \right)$$

is maximized only when, as other quantities remain constant,

$$\lim_{N \to \infty} \left( \frac{C' \sqrt{n \log N}}{\sqrt{3 J^*}} \right)^{\frac{3}{2}} = 1.$$

**Proof.** Because the $C'$ term is constant, we wish to choose

$$\arg \max_{0 < n < N} \frac{J^*}{C} \sqrt{\frac{n + 2N}{n^*}} \sqrt{\frac{n}{n} \delta} - \frac{\sqrt{N - n}}{n^{3/2}} \sqrt{\log \frac{n}{\delta}}.$$

Clearly neither endpoint is optimal. Relaxing $n$ to be real-valued, the optimum must be achieved at a stationary point, where

$$\frac{-J^*}{2C \sqrt{N - n}} + \frac{\sqrt{\log \frac{n}{\delta}}}{2 \sqrt{N - n} \delta} + \frac{1}{3} \sqrt{N - n} \frac{n^{3/2} \sqrt{\log \frac{n}{\delta}} - \frac{1}{2}} {2 \sqrt{N - n} \frac{n^{3/2} \sqrt{\log \frac{n}{\delta}} - \frac{1}{2}}} = 0.$$

Multiplying by $2 \sqrt{N - n} \frac{n^{3/2} \sqrt{\log \frac{n}{\delta}}}$ and rearranging, we get that a stationary point is achieved exactly when

$$\frac{1}{3} \left[ n + 2N \right] \log \frac{n}{\delta} + n = J^* \sqrt{N \log N} \log \frac{n}{\delta} + n.$$

Now write, without loss of generality, $n = (A_N \sqrt{N \log N})^{\frac{3}{2}}$, and so

$$D = \frac{1}{3} \left[ A_N^{\frac{3}{2}} N^{\frac{3}{2} (\log N)^{\frac{3}{2}}} + 2N \right] \left[ \frac{3}{4} \log A_N + \frac{3}{4} \log N + \frac{3}{8} \log \log N + \log \frac{1}{\delta} \right] + A_N^{\frac{3}{2}} N^{\frac{3}{2} (\log N)^{\frac{3}{2}}}$$

$$E = \frac{J^*}{C} A_N N \sqrt{\log N} \left[ \frac{3}{4} \log A_N + \frac{3}{4} \log N + \frac{3}{8} \log \log N + \log \frac{1}{\delta} + N. \right]$$

We will show that $D - E \to 0$ requires $A_N \to C/(\sqrt{3} J^*)$, implying the result.
We first suppose $A_N = \omega(1)$, further breaking into cases which result in different terms inside $D$ and $E$ becoming dominant:

If $A_N = \Omega(N)$, $D = \Theta\left(\frac{N^\frac{3}{2}}{\sqrt{\log N}}N^\frac{3}{2}\log N\right)$, $E = \Theta\left(A_N \sqrt{\log(N) \log(A_N)}\right)$.

If $A_N = \Omega\left(\frac{N^\frac{3}{2}}{\sqrt{\log N}}\right)$, $A_N = o(N)$, $D = \Theta\left(A_N^3 N^\frac{3}{2}(\log N)^{\frac{3}{2}} \log N\right)$, $E = \Theta\left(A_N N \log N\right)$.

If $A_N = \omega(1)$, $A_N = o\left(\frac{N^\frac{3}{2}}{\sqrt{\log N}}\right)$, $D = \Theta(N \log N)$, $E = \Theta\left(A_N N \log n\right)$.

In each case, $E = \omega(D)$ and so $D - E \to -\infty$, contradicting that $D = E$. Thus a stationary point requires $A_N = O(1)$ for a stationary point.

We now do the same for $A_N = o(1)$. First, clearly $n \geq 1$; suppose that in fact $n = \Theta(1)$, i.e. $A_N = \Theta\left(1/(N \sqrt{\log N})\right)$. In this case, we would have $D = \frac{2}{3}N \log \frac{n}{8} + \Theta(1)$ and $E = N + \Theta(1)$, so that $D = E$ requires $\frac{2}{3} \log \frac{n}{8} \to 1$, i.e. $n \to \delta \exp \frac{3}{2} \approx 4.5 \delta$. For $\delta < 0.22$, this contradicts $n \geq 1$. So we know that $\log n = \omega(1)$. Now, the remaining options for $A_N$ all yield $D - E \to \infty$:

If $A_N = o(1)$, $A_N = \Omega\left(\frac{1}{\log N}\right)$, $D = \Theta(N \log n)$, $E = \Theta\left(A_N N \log n\right)$.

If $A_N = o\left(\frac{1}{\log N}\right)$, $A_N = \omega\left(\frac{1}{N \sqrt{\log N}}\right)$, $D = \Theta(N \log n)$, $E = \Theta(N)$.

Thus we have established that $A_N = \Theta(1)$. Thus, we obtain that

$$D = \frac{1}{2}N \log N + O(N) \quad E = \frac{\sqrt{3}J^*}{2C} A_N N \log N + O\left(N \sqrt{\log N}\right).$$

Asymptotic equality hence requires $A_N \to C/(\sqrt{3}J^*)$.

\[\square\]

A.3. Uniform convergence results

These results, on the uniform convergence of $\hat{\eta}$ and $\hat{\sigma}^2$, were used in the proof of Theorem 11.

**Proposition 15.** Under Assumptions (A) to (C), we have that with probability at least $1 - \delta$,

$$\sup_{\omega} |\hat{\eta}_\omega - \eta_\omega| \leq \frac{8}{\sqrt{n}} \left[ \nu \frac{2 \log 2}{\delta} + \frac{2D}{\delta} \log \left(4R_D\sqrt{n}\right) + L_k \right].$$

**Proof.** Theorem 7 of Sriperumbudur et al. (2009) gives a similar bound in terms of Rademacher chaos complexity, but for ease of combination with our bound on convergence of the variance estimator, we use a simple $\epsilon$-net argument instead.

We study the random error function

$$\Delta(\omega) := \hat{\eta}_\omega - \eta_\omega.$$

First, we place $T$ points $\{\omega_i\}_{i=1}^T$ such that for any point $\omega \in \Omega$, $\min_i \|\omega - \omega_i\| \leq q$; Assumption (B) ensures this is possible with at most $T = (4R_D/q)^D$ points (Cucker & Smale, 2001, Proposition 5).

Now, $E \Delta = 0$, because $\hat{\eta}$ is unbiased. Recall that $\hat{\eta} = \frac{1}{n(n-1)} \sum_{i \neq j} H_{ij}$, and via Assumption (A) we know $|H_{ij}| \leq 4\nu$. This $\hat{\eta}$, and hence $\Delta$, satisfies bounded differences: if we replace $(X_1, Y_1)$ with $(X_1', Y_1')$, obtaining $\hat{\eta}' = \frac{1}{n(n-1)} \sum_{i \neq j} F_{ij}$ where $F$ agrees with $H$ except when $i$ or $j$ is 1, then

$$|\hat{\eta} - \hat{\eta}'| \leq \frac{1}{n(n-1)} \sum_{i \neq j} |H_{ij} - F_{ij}| = \frac{1}{n(n-1)} \sum_{i > 1} |H_{i1} - F_{i1}| + \frac{1}{n(n-1)} \sum_{j > 1} |H_{1j} - F_{1j}| \leq \frac{2}{n(n-1)} \sum_{i > 1} 8\nu = \frac{16\nu}{n}.$$
We also have via Assumption (C), for any two \( \omega, \omega' \in \Omega \),
\[
|\hat{\eta}_\omega - \hat{\eta}_{\omega'}| \leq \frac{1}{n(n-1)} \sum_{i \neq j} |H_{ij}^{(\omega)} - H_{ij}^{(\omega')}| \leq \frac{1}{n(n-1)} \sum_{i \neq j} 4L_k \|\omega - \omega\| = 4L_k \|\omega - \omega\|
\]
\[
|\eta_\omega - \eta_{\omega'}| = \|E[H_{12}^{(\omega)}] - E[H_{12}^{(\omega')}]\| \leq E|H_{12}^{(\omega)} - H_{12}^{(\omega')}| \leq 4L_k \|\omega - \omega\|
\]
so that \( \|\Delta\|_L \leq 8L_k \). Combining these two results, we know that with probability at least \( 1 - \delta \)
\[
\sup_\omega |\Delta(\omega)| \leq \max_{i \in \{1, \ldots, T\}} |\Delta(\omega_i)| + 8L_k q \leq \frac{8\nu}{\sqrt{n}} \sqrt{2 \log \frac{2T}{\delta} + 2D \log \frac{4R\Omega}{q} + 8L_k q};
\]
setting \( q = 1/\sqrt{n} \) yields the desired result.

**Proposition 16.** Under Assumptions (A) to (C), with probability at least \( 1 - \delta \),
\[
\sup_{\omega \in \Omega} |\hat{\sigma}_\omega^2 - \sigma_\omega^2| \leq \frac{64}{\sqrt{n}} \left[ 7 \sqrt{2 \log \frac{2T}{\delta} + 2D \log \frac{4R\Omega}{q} + \frac{18\nu^2}{\sqrt{n}} + 8L_k \nu} \right] .
\]

**Proof.** We again use an \( \varepsilon \)-net argument on the (random) error function
\[
\Delta(\omega) := \hat{\sigma}_\omega^2 - \sigma_\omega^2.
\]
First, choose \( T \) points \( \{\omega_t\}_{t=1}^T \) such that for any point \( \omega \in \Omega \), \( \min_\omega \|\omega - \omega_t\| \leq q \); again, via Assumption (B) and Proposition 5 of Cucker & Smale (2001) we have \( T \leq (4R\Omega/q)^D \). By Lemmas 17 and 18 and a union bound, with probability at least \( 1 - \delta \),
\[
\max_{i \in \{1, \ldots, T\}} |\Delta(\omega)| \leq 448 \sqrt{\frac{2T}{n} \log \frac{2T}{\delta} + \frac{1152\nu^2}{n}} \leq 448 \sqrt{\frac{2}{n} \log \frac{2T}{\delta} + \frac{2}{n} D \log \frac{4R\Omega}{q} + \frac{1152\nu^2}{n}}.
\]
Lemma 19 shows that \( \|\Delta\|_L \leq 512L_k \nu \), which means that with probability at least \( 1 - \delta \),
\[
\sup_{\omega \in \Omega} |\Delta(\omega)| \leq 448 \sqrt{\frac{2}{n} \log \frac{2T}{\delta} + \frac{2}{n} D \log \frac{4R\Omega}{q} + \frac{1152\nu^2}{n} + 512L_k \nu q}.
\]
Taking \( q = 1/\sqrt{n} \) gives the desired result.

**Lemma 17.** For any kernel \( k \) bounded by \( \nu \) (Assumption (A)), with probability at least \( 1 - \delta \),
\[
|\hat{\sigma}_k^2 - E[\hat{\sigma}_k^2]| \leq 448 \sqrt{\frac{2}{n} \log \frac{2}{\delta}}.
\]

**Proof.** We simply apply McDiarmid’s inequality to \( \hat{\sigma}_k^2 \). Suppose we change \( (X_1, Y_1) \) to \( (X_1', Y_1') \), giving a new \( H \) matrix \( F \) which agrees with \( H \) on all but the first row and column. Note that \( |H_{ij}| \leq 4\nu \), and recall
\[
\hat{\sigma}_k^2 = 4 \left( \frac{1}{n^2} \sum_i \left( \sum_j H_{ij} \right)^2 - \left( \frac{1}{n^2} \sum_{ij} H_{ij} \right)^2 \right),
\]
The first term in the parentheses of $\hat{\sigma}_k^2$ changes by

$$\left|\frac{1}{n^3} \sum_i \left( \sum_j H_{ij} \right)^2 - \frac{1}{n^2} \sum_i \left( \sum_j F_{ij} \right)^2 \right| \leq \frac{1}{n^2} \sum_{i,j} |H_{ij} H_{i\ell} - F_{ij} F_{i\ell}|.$$  

In this sum, if none of $i$, $j$, or $\ell$ are one, the term is zero. The $n^2$ terms for which $i = 1$ are each upper-bounded by $32\nu^2$, simply bounding each $H$ or $F$ by $4\nu$. Of the remainder, there are $(n - 1)$ terms where $j = \ell = 1$, each $|H_{11}^2 - F_{11}^2| \leq 16\nu^2$. We are left with $2(n - 1)^2$ terms which have exactly one of $j$ or $\ell$ equal to 1; the $j = 1$ terms $|H_{1i} H_{i\ell} - F_{1i} H_{i\ell} | \leq |H_{1i} - F_{1i}| |H_{i\ell}| \leq (8\nu)(4\nu)$, so each of these terms is at most $32\nu^2$. The total sum is thus at most

$$\frac{1}{n^3} (n^2 32\nu^2 + (n-1)16\nu^2 + 2(n-1)^232\nu^2) = \left(\frac{6}{n} - \frac{7}{n^2} + \frac{3}{n^3}\right) 16\nu^2.$$  

The remainder of the change in $\hat{\sigma}_k^2$ can be determined by bounding

$$\left|\sum_{ij} H_{ij} - \sum_{ij} F_{ij}\right| \leq \sum_{ij} |H_{ij} - F_{ij}| = \sum_j |H_{1j} - F_{1j}| + \sum_{i>1} H_{i1} - F_{i1}|$$

which then gives us

$$\left|\left(\frac{1}{n^3} \sum_{ij} H_{ij} \right)^2 - \left(\frac{1}{n^2} \sum_{ij} F_{ij} \right)^2 \right| = \left|\frac{1}{n^2} \sum_{ij} H_{ij} + \frac{1}{n^2} \sum_{ij} F_{ij} |\sum_{ij} H_{ij} - \frac{1}{n^2} \sum_{ij} F_{ij}\right|$$

$$\leq (2 \cdot 4\nu) \frac{2n-1}{n^2} (8\nu) = 64\nu^2 \left(\frac{2}{n} - \frac{1}{n^2}\right).$$  

Thus

$$|\hat{\sigma}_k^2 - (\hat{\sigma}_k')^2| \leq 4 \left[ \left(\frac{6}{n} - \frac{7}{n^2} + \frac{3}{n^3}\right) 16\nu^2 + \left(\frac{2}{n} - \frac{1}{n^2}\right) 64\nu^2 \right] = \frac{64\nu^2}{n^3} \left[14n^2 - 11n + 3\right] \leq \frac{896\nu^2}{n}.$$  

Because the same holds for changing any of the $(X_i, Y_i)$ pairs, the result follows by McDiarmid’s inequality. □

**Lemma 18.** For any kernel $k$ bounded by $\nu$ (Assumption (A)), the estimator $\hat{\sigma}_k^2$ satisfies

$$|E \hat{\sigma}_k^2 - \sigma_k^2| \leq \frac{1152\nu^2}{n}.$$  

**Proof.** We have that

$$E \hat{\sigma}_k^2 = 4 \left(\frac{1}{n^3} \sum_{ij\ell} E[H_{ij} H_{j\ell}] - \frac{1}{n^4} \sum_{ijab} E[H_{ij} H_{ab}] \right).$$  

Most terms in these sums have their indices distinct; these are the ones that we care about. (We could evaluate the expectations of the other terms exactly, but it would be tedious.) We can thus break down the first term as

$$\frac{1}{n^3} \sum_{ij\ell} E[H_{ij} H_{j\ell}] = \frac{1}{n^3} \sum_{ij\ell: |\{i,j,\ell\}|=3} E[H_{ij} H_{j\ell}] + \frac{1}{n^3} \sum_{ij\ell: |\{i,j,\ell\}|<3} E[H_{ij} H_{j\ell}]$$

$$= \frac{n(n-1)(n-2)}{n^3} E[H_{12} H_{13}] + \left(1 - \frac{n(n-1)(n-2)}{n^3}\right) q,$$
where \( q \) is the appropriately-weighted mean of the various \( \mathbb{E}[H_{ij}H_{j\ell}] \) terms for which \( i, j, \ell \) are not mutually distinct. Since \( |H_{ij}| \leq 4\nu \), \( \mathbb{E}[H_{ij}H_{j\ell}] < 16\nu^2 \) and so \( |q| \leq 16\nu^2 \) as well. Noting that

\[
\frac{n(n-1)(n-2)}{n^3} = 1 - \frac{3}{n} + \frac{2}{n^2}
\]

we obtain

\[
\left| \frac{1}{n^4} \sum_{ij\ell} \mathbb{E}[H_{i\ell}H_{j\ell}] - \mathbb{E}[H_{12}H_{13}] \right| = \left( \frac{3}{n} - \frac{2}{n^2} \right) | - \mathbb{E}[H_{12}H_{13}] + q | \leq \left( \frac{3}{n} - \frac{2}{n^2} \right) 32\nu^2.
\]

The second term can be handled similarly:

\[
\frac{1}{n^4} \sum_{ijab} \mathbb{E}[H_{ij}H_{ab}] = \frac{1}{n^4} \sum_{ijab: \{i,j,a,b\} = \{1,2\}} \mathbb{E}[H_{ij}H_{ab}] + \frac{1}{n^4} \sum_{ijab: \{i,j,a,b\} < \{1,2\}} \mathbb{E}[H_{ij}H_{ab}]
\]

\[
= \frac{n(n-1)(n-2)(n-3)}{n^4} \mathbb{E}[H_{ij}H_{ab}] + \left( 1 - \frac{n(n-1)(n-2)(n-3)}{n^4} \right) r,
\]

where \( r \) is the appropriately-weighted mean of the non-distinct terms, \( |r| \leq 16\nu^2 \). For \( i, j, a, b \) all distinct, \( \mathbb{E}[H_{ij}H_{ab}] = \mathbb{E}[H_{12}]^2 \). Here

\[
\frac{n(n-1)(n-2)(n-3)}{n^4} = \frac{(n-1)(n^2 - 5n + 6)}{n^4} = 1 - \frac{6}{n} + \frac{11}{n^2} - \frac{6}{n^3}
\]

and so

\[
\left| \frac{1}{n^4} \sum_{ijab} \mathbb{E}[H_{ij}H_{ab}] - \mathbb{E}[H_{12}]^2 \right| \leq \left( \frac{6}{n} - \frac{11}{n^2} + \frac{6}{n^3} \right) 32\nu^2.
\]

Recalling \( \sigma_k^2 = 4(\mathbb{E}[H_{12}H_{13}] - \mathbb{E}[H_{12}]^2) \),

\[
|\mathbb{E}[\hat{\sigma}_k^2 - \sigma_k^2] | \leq 128\nu^2 \left( \frac{9}{n} - \frac{13}{n^2} + \frac{6}{n^3} \right),
\]

and since \( n \geq 1 \), we have \( 13/n^2 > 6/n^3 \), yielding the result.

\[\square\]

Lemma 19. Under Assumptions (A) and (C), we have

\[
\sup_{\omega, \omega' \in \Omega} \frac{|\hat{\sigma}_k^2 - \sigma_k^2|}{\|\omega - \omega'\|} \leq 256L_k\nu \quad \text{and} \quad \sup_{\omega, \omega' \in \Omega} \frac{|\sigma_k^2 - \sigma_k^2|}{\|\omega - \omega'\|} \leq 256L_k\nu.
\]

Proof. We first handle the change in \( \hat{\sigma}_k \):

\[
|\hat{\sigma}_k^2 - \sigma_k^2| = 4 \frac{n}{n^3} \sum_{ij\ell} H_{i\ell}^{(w)} H_{j\ell}^{(w)} - \frac{n}{n^3} \sum_{ij\ell} H_{i\ell}^{(w')} H_{j\ell}^{(w')} - \frac{n}{n^3} \sum_{ijab} H_{ij}^{(w)} H_{ab}^{(w)} + \frac{n}{n^3} \sum_{ijab} H_{ij}^{(w')} H_{ab}^{(w')} |
\]

\[
\leq 4 \frac{n}{n^3} \sum_{ij\ell} |H_{i\ell}^{(w)} H_{j\ell}^{(w)} - H_{i\ell}^{(w')} H_{j\ell}^{(w')} | + \frac{n}{n^3} \sum_{ijab} |H_{ij}^{(w)} H_{ab}^{(w)} - H_{ij}^{(w')} H_{ab}^{(w')} |.
\]

We can handle both terms by bounding

\[
|H_{ij}^{(w)} H_{ab}^{(w)} - H_{ij}^{(w')} H_{ab}^{(w')} | \leq |H_{ij}^{(w)} H_{ab}^{(w)} - H_{ij}^{(w)} H_{ab}^{(w')} | + |H_{ij}^{(w)} H_{ab}^{(w')} - H_{ij}^{(w')} H_{ab}^{(w')} |
\]

\[
= |H_{ij}^{(w)} ||H_{ab}^{(w)} - H_{ab}^{(w')} | + |H_{ij}^{(w)} - H_{ij}^{(w')} ||H_{ab}^{(w')} |
\]

\[
\leq 4\nu \left( |H_{ab}^{(w)} - H_{ab}^{(w')} | + |H_{ij}^{(w)} - H_{ij}^{(w')} | \right).
\]

Using Assumption (C) and the definition of \( H \),

\[
|H_{ij}^{(w)} - H_{ij}^{(w')} | \leq 4L_k \|\omega - \omega'\|
\]
so
\[ |H_{ij}^{(\omega)} H_{ab}^{(\omega)} - H_{ij}^{(\omega')} H_{ab}^{(\omega')}| \leq 32\nu L_k \|\omega - \omega'\| \]  
and hence
\[ |\hat{\sigma}_\omega^2 - \hat{\sigma}_{\omega'}^2| \leq 256\nu L_k \|\omega - \omega'\|. \]

Again using (12), we also have
\[
|\sigma_\omega^2 - \sigma_{\omega'}^2| \leq 4E\left[H_{12}^{(\omega)} H_{13}^{(\omega)} - E\left[H_{12}^{(\omega)} H_{13}^{(\omega)}\right]\right] + 4E\left[H_{12}^{(\omega)}\right]^2 - E\left[H_{12}^{(\omega')}\right]^2 \leq 4E|H_{12}^{(\omega)} H_{13}^{(\omega)} - H_{12}^{(\omega')} H_{13}^{(\omega')}| + 4E|H_{12}^{(\omega)} H_{13}^{(\omega)} - H_{12}^{(\omega')} H_{13}^{(\omega')}| \leq 256\nu L_k \|\omega - \omega'\|. \]

\[\]

A.4. Constructing appropriate kernels

We now show Propositions 7 to 9, which each state that Assumption (C) is satisfied by various choices of kernel. The following assumption will be useful for different kernel schemes.

(I) The domain \(\mathcal{X}\) is Euclidean and bounded, \(\mathcal{X} \subseteq \{x \in \mathbb{R}^d : \|x\| \leq R_X\}\) for some constant \(R_X < \infty\).

We begin by recalling a well-known property of the Gaussian kernel, useful for both Gaussian bandwidth selection and deep kernels. A proof is in Appendix A.5.

**Lemma 20.** The Gaussian kernel \(\kappa(a, b) = \exp\left(-\frac{|a-b|^2}{2\sigma^2}\right)\) satisfies
\[
|\kappa(a, b) - \kappa(a', b')| \leq \frac{1}{\sigma\sqrt{e}} (\|a-b\| + \|a'-b'\|) \leq \frac{1}{\sigma\sqrt{e}} (\|a-a'\| + \|b-b'\|). 
\]

A.4.1. Gaussian bandwidth selection (Proposition 7)

Lemma 20 immediately gives us Assumption (C) when we chose among Gaussian kernels:

**Proposition 21.** Define a one-dimensional Banach space for inverse lengthscales of Gaussian kernels \(\gamma > 0\), so that \(k_\gamma(x, y) = \kappa_1/\gamma(x, y)\), with standard addition and multiplication and norms defined by the absolute value, and \(k_0\) taken to be the constant 1 function. Let \(\Omega\) be any subset of this space. Under Assumption (I), Assumption (C) holds: for any \(x, y \in \mathcal{X}\) and \(\gamma, \gamma' \in \Gamma\),
\[
|k_\gamma(x, y) - k_{\gamma'}(x, y)| \leq \frac{2R_X}{\sqrt{e}} |\gamma - \gamma'|. 
\]

**Proof:**
\[
|k_\gamma(x, y) - k_{\gamma'}(x, y)| = |\kappa_1(\gamma x, \gamma y) - \kappa_1(\gamma' x, \gamma y)| \leq \frac{1}{\sqrt{e}} \|\gamma\| \|x - y\| - \gamma' \|x - y\| = \frac{\|x - y\|}{\sqrt{e}} |\gamma - \gamma'|. \]

A.4.2. Deep kernels (Proposition 9)

To handle the deep kernel case, we will need some more assumptions on the form of the kernel.

(II) \(\phi_\omega(x) = \phi_\omega^{(A)}\) is a feedforward neural network with \(A\) layers given by
\[
\phi_\omega^{(0)}(x) = x \quad \phi_\omega^{(A)}(x) = \sigma^{(A)}(W_\omega^{(A)} \phi_\omega^{(A-1)}(x) + b_\omega^{(A)}) ,
\]
where the network parameter \(\omega\) consists of all the weight matrices \(W_\omega^{(A)}\) and biases \(b_\omega^{(A)}\), and the activation functions \(\sigma^{(A)}\) are each 1-Lipschitz, \(\|\sigma^{(A)}(x) - \sigma^{(A)}(y)\| \leq \|x - y\|\), with \(\sigma^{(A)}(0) = 0\) so that \(\|\sigma^{(A)}(x)\| \leq \|x\|\). Define a Banach space on \(\omega\), with addition and scalar multiplication componentwise, and
\[
\|\omega\| = \max_{\ell \in \{1, \ldots, A\}} \max \left(\|W_\omega^{(\ell)}\|, \|b_\omega^{(\ell)}\|\right),
\]
where the matrix norm denotes operator norm \(\|W\| = \sup_{x} \|Wx\|/\|x\|\). (For convolutional networks, see Remark 25.)
(III) \( k_\omega \) is a kernel of the form (1),
\[
  k_\omega(x, y) = [(1 - \epsilon)\kappa(\phi_\omega(x), \phi_\omega(y)) + \epsilon] q(x, y),
\]
with \( 0 \leq \epsilon \leq 1 \), \( \kappa \) a kernel function, and \( q(x, y) \) a kernel with \( \sup_x q(x, x) \leq Q \).

Note that this includes kernels of the form \( k_\omega(x, y) = \kappa(\phi_\omega(x), \phi_\omega(y)) \); take \( \epsilon = 0 \) and \( q(x, y) = 1 \).

(IV) \( \kappa \) in Assumption (III) is a kernel function satisfying
\[
|\kappa(a, b) - \kappa(a', b')| \leq L_\kappa (\|a - a'\| + \|b - b'\|).
\]
This holds for a Gaussian \( \kappa \) via Lemma 20.

We now turn to proving Assumption (C) for deep kernels. First, we will need some smoothness properties of the network \( \phi \).

**Lemma 22.** Under Assumption (II), suppose \( \omega, \omega' \) have \( \|\omega\| \leq R, \|\omega'\| \leq R, \) with \( R \neq 1 \). Then, for any \( x \),
\[
\|\phi_\omega(x)\| \leq R^\Lambda \|x\| + \frac{R}{R - 1} (R^\Lambda - 1)  
\]
(13)
\[
\|\phi_\omega(x) - \phi_{\omega'}(x)\| \leq \left( \Lambda R^{\Lambda - 1} \left( \|x\| + \frac{R}{R - 1} \right) - \frac{R^\Lambda - 1}{(R - 1)^2} \right) \|\omega - \omega'\|.
\]
(14)

If \( R \geq 2 \), we furthermore have
\[
\|\phi_\omega(x)\| \leq R^\Lambda (\|x\| + 2)  
\]
(15)
\[
\|\phi_\omega(x) - \phi_{\omega'}(x)\| \leq \Lambda R^{\Lambda - 1} (\|x\| + 2) \|\omega - \omega'\|.
\]
(16)

The proof, by recursion, is given in Appendix A.5. We are now ready to prove Assumption (C) for deep kernels.

**Proposition 23.** Make Assumptions (I) to (IV) and Assumption (B), with \( R_\Omega \geq 2 \). Then Assumption (C) holds: for any \( x, y \in X \) and \( \omega, \omega' \in \Omega \),
\[
|k_\omega(x, y) - k_{\omega'}(x, y)| \leq 2Q(1 - \epsilon)L_\kappa \Lambda R_\Omega^{\Lambda - 1} (R_X + 2) \|\omega - \omega'\|.
\]

**Proof.**
\[
|k_\omega(x, y) - k_{\omega'}(x, y)| = (1 - \epsilon) |\kappa(\phi_\omega(x), \phi_\omega(y)) - \kappa(\phi_{\omega'}(x), \phi_{\omega'}(y))| q(x, y)
\]
\[
\leq Q(1 - \epsilon)L_\kappa (|\phi_\omega(x) - \phi_{\omega'}(x)| + |\phi_\omega(y) - \phi_{\omega'}(y)|)
\]
\[
\leq Q(1 - \epsilon)L_\kappa \Lambda R_{\Omega}^{\Lambda - 1} (\|x\| + \|y\| + 4) \|\omega - \omega'\|
\]
\[
\leq Q(1 - \epsilon)L_\kappa \Lambda R_{\Omega}^{\Lambda - 1} (2R_X + 4) \|\omega - \omega'\|.
\]

**Remark 24.** For the deep kernels we use in the paper (Assumptions (II) to (IV)) on bounded domains (Assumption (I)), we know \( L_\kappa \) via Proposition 23; Theorem 6 combines Theorem 11, Corollary 12, and Proposition 23. If we further use a Gaussian kernel \( q \) of bandwidth \( \sigma_\phi \), the last bracketed term in the error bound of Theorem 11 becomes
\[
\frac{2(1 - \epsilon)}{\sigma_\phi \sqrt{\epsilon}} \Lambda R_{\Omega}^{\Lambda - 1} (R_X + 2) + \sqrt{2 \log \frac{2}{\delta} + 2D \log (4R_\Omega \sqrt{n})}.
\]
The component \( R_{\Omega}^{\Lambda - 1} (R_X + 2) \), from (15), is approximately the largest that \( \phi_\omega \) could make its outputs’ norms; \( \sigma_\phi \) will generally be on a comparable scale to the norm of the actual outputs of the network, so their ratio is something like the “unused capacity” of the network to blow up its inputs. This term is weighted about equally in the convergence bound with the square root of the total number of parameters in the network.

**Remark 25.** We can handle convolutional networks as follows. We define \( \Omega \) in essentially the same way, letting \( W^{(t)}_\omega \) denote the convolutional kernel (the set of parameters being optimized), but define \( \|\omega\| \) in terms of the operator norm of the linear transform corresponding to the convolution operator. This is given in terms of the operator norm of various discrete Fourier transforms of the kernel matrix by Lemma 2 of Bibi et al. (2019); see also Theorem 6 of Sedghi et al. (2019). The number of parameters \( D \) is then the actual number of parameters optimized in gradient descent, but the radius \( R_\Omega \) is computed differently.

\(^8\)Of course, if we know a bound of \( R_\Omega < 2 \), the result will still hold using \( R_\Omega = 2 \). It is also possible to show a tighter result, via (13) and (14) or their analogue for \( R = 1 \); the expression is simply less compact.
A.4.3. Multiple kernel learning (Proposition 8)

Multiple kernel learning (Gönen & Alpaydın, 2011) also falls into our setting. A special case of this family of kernels was studied for the (easier to analyze) “streaming” MMD estimator by Gretton et al. (2012b).

(V) Let \( \{k_i\}_{i=1}^D \) be a set of base kernels, each satisfying \( \sup_{x \in \mathcal{X}} k_i(x, x) \leq K \) for some finite \( K \). Define \( k_\omega \) as

\[
  k_\omega(x, y) = \sum_{i=1}^D \omega_i k_i(x, y).
\]

Define the norm of a kernel parameter by the norm of the corresponding vector \( \omega \in \mathbb{R}^D \). Let \( \Omega \) be a set of possible parameters such that for each \( \omega \in \Omega \), \( k_\omega \) is positive semi-definite, and \( \|\omega\| \leq R_\Omega \) for some \( R_\Omega < \infty \).

Not only does learning in this setting work (Proposition 26), it is also – unlike the deep setting – efficient to find an exact maximizer of \( \tilde{J}_\lambda \) (Proposition 27).

**Proposition 26.** Assumption (V) implies Assumptions (A) to (C). In particular,

\[
  \sup_{\omega \in \Omega} \sup_{x \in \mathcal{X}} k_\omega(x, x) \leq KR_\Omega \sqrt{D}
\]

\[
  |k_\omega(x, y) - k_\omega(x, y)| \leq K \sqrt{D} \|\omega - \omega'\|.
\]

**Proof.** Assumption (B) is immediate from Assumption (V), since \( \Omega \subset \mathbb{R}^D \). Let \( k(x, y) \in \mathbb{R}^D \) denote the vector whose \( i \)th entry is \( k_i(x, y) \), so that \( k_\omega(x, y) = \omega^T k(x, y) \). As \( \|k(x, y)\| \leq K \), we know \( \|k(x, y)\| \leq K \sqrt{D} \). Assumptions (A) and (C) follow by Cauchy-Schwartz.

**Proposition 27.** Take Assumption (V), and additionally assume that \( \Omega = \{\omega \mid \forall i, \omega_i \geq 0, \sum_i \omega_i = Q\} \) for some \( Q < \infty \). A maximizer of \( \tilde{J}_\lambda(\omega) \) can then be found by scaling the solution to a convex quadratic program,

\[
  \hat{\omega} = \arg\min_{\omega \in [0, \infty)^D : \omega^T b = 1} \omega^T (\mathbf{A} + \lambda I) \omega, \quad \hat{\omega} = \frac{Q}{\sum_i \omega_i} \hat{\omega} \in \arg\max_{\omega \in \Omega} \tilde{J}_\lambda(\omega),
\]

where

\[
  (\mathbf{H}_{ij})_k = k_\ell(X_i, X_j) + k_\ell(Y_i, Y_j) - k_\ell(X_i, Y_j) - k_\ell(X_j, Y_i)
\]

\[
  b = \frac{1}{n(n-1)} \sum_{i \neq j} \mathbf{H}_{ij} \in \mathbb{R}^D
\]

\[
  \mathbf{A} = \frac{4}{n^3} \sum_i \left( \sum_j \mathbf{H}_{ij} \right)^T \left( \sum_j \mathbf{H}_{ij} \right) - \frac{4}{n^4} \left( \sum_{ij} \mathbf{H}_{ij} \right)^T \left( \sum_{ij} \mathbf{H}_{ij} \right) \in \mathbb{R}^{D \times D}
\]

as long as \( \mathbf{b} \) has at least one positive entry.

**Proof.** The \( H \) matrix used by \( \hat{\eta}_\omega \) and \( \hat{\sigma}_\omega \) takes a simple form:

\[
  H_{ij}^{(\omega)} = k_\omega(X_i, X_j) + k_\omega(Y_i, Y_j) - k_\omega(X_i, Y_j) - k_\omega(X_j, Y_i) = \omega^T \mathbf{H}_{ij}.
\]

Thus

\[
  \hat{\eta}_\omega = \omega^T \left( \frac{1}{n(n-1)} \sum_{i \neq j} \mathbf{H}_{ij} \right) = \omega^T \mathbf{b}
\]

\[
  \hat{\sigma}_\omega^2 = \frac{4}{n^3} \sum_i \left( \omega^T \mathbf{H}_{ij} \right)^2 - \frac{4}{n^4} \left( \omega^T \sum_{ij} \mathbf{H}_{ij} \right)^2
\]

\[
  = \omega^T \left( \frac{4}{n^3} \sum_i \left( \sum_j \mathbf{H}_{ij} \right)^T \left( \sum_j \mathbf{H}_{ij} \right) - \frac{4}{n^4} \left( \sum_{ij} \mathbf{H}_{ij} \right)^T \left( \sum_{ij} \mathbf{H}_{ij} \right) \right) \omega = \omega^T \mathbf{A} \omega.
\]
Note that because $\hat{\sigma}_\omega^2 \geq 0$ for any $\omega$, we have $A \geq 0$. We have now obtained a problem equivalent to the one in Section 4 of Gretton et al. (2012b); the argument proceeds as there.

### A.5. Miscellaneous Proofs

The following lemma was used for Propositions 21 and 23.

**Lemma 20.** The Gaussian kernel $\kappa(a, b) = \exp \left( -\frac{\|a-b\|^2}{2\sigma^2} \right)$ satisfies

$$|\kappa(a, b) - \kappa(a', b')| \leq \frac{1}{\sigma \sqrt{e}} (\|a - b\| + \|a' - b'\|) \leq \frac{1}{\sigma \sqrt{e}} (\|a - a'\| + \|b - b'\|).$$

**Proof.** We have that

$$|\kappa(a, b) - \kappa(a', b')| = |\exp \left( -\frac{\|a-b\|^2}{2\sigma^2} \right) - \exp \left( -\frac{\|a'-b'\|^2}{2\sigma^2} \right)|$$

$$\leq \|x \mapsto \exp \left( -\frac{x^2}{2\sigma^2} \right)\|_L \|a - b\| - \|a' - b'\|.$$ 

We can bound the Lipschitz constant as its maximal derivative norm,

$$\sup_x \frac{|x|}{\sigma^2} \exp \left( -\frac{x^2}{2\sigma^2} \right).$$

Noting that

$$\frac{d}{dx} \log \left( \frac{|x|}{\sigma^2} \right) \exp \left( -\frac{x^2}{2\sigma^2} \right) = \frac{1}{x} - \frac{x}{\sigma^2}$$

vanishes only at $x = \pm \sigma$, the supremum is achieved by using that value, giving

$$\|x \mapsto \exp \left( -\frac{x^2}{2\sigma^2} \right)\|_L = \frac{1}{\sigma \sqrt{e}}.$$

The result follows from

$$\|a - b\| - \|a' - b'\| \leq \|a - b - a' + b'\| \leq \|a - a'\| + \|b - b'\|.$$ 

This next lemma was used in Proposition 23.

**Lemma 22.** Under Assumption (II), suppose $\omega, \omega'$ have $\|\omega\| \leq R$, $\|\omega'\| \leq R$, with $R \neq 1$. Then, for any $x$,

$$\|\phi_\omega(x)\| \leq R^\lambda \|x\| + \frac{R}{R - 1} (R^\lambda - 1) \quad (13)$$

$$\|\phi_\omega(x) - \phi_{\omega'}(x)\| \leq \left( \lambda R^{\lambda - 1} \left( \|x\| + \frac{R}{R - 1} \right) - \frac{R^\lambda - 1}{(R - 1)^2} \right) \|\omega - \omega'\|. \quad (14)$$

If $R \geq 2$, we furthermore have

$$\|\phi_\omega(x)\| \leq R^\lambda (\|x\| + 2) \quad (15)$$

$$\|\phi_\omega(x) - \phi_{\omega'}(x)\| \leq \lambda R^{\lambda - 1} (\|x\| + 2) \|\omega - \omega'\|. \quad (16)$$

**Proof.** First, $\|\phi_0^\omega(x)\| = \|x\|$, showing (13) when $\lambda = 0$. In general,

$$\|\phi_\omega^{(\ell)}(x)\| = \|\sigma^{(\ell)} \left( W^{(\ell)} \phi_\omega^{(\ell-1)}(x) + b_\omega^{(\ell)} \right)\|$$

$$\leq \|W^{(\ell)} \phi_\omega^{(\ell-1)}(x) + b_\omega^{(\ell)}\|$$

$$\leq \|W^{(\ell)}\| \|\phi_\omega^{(\ell-1)}(x)\| + \|b^{(\ell)}\|$$

$$\leq R\|\phi_\omega^{(\ell-1)}(x)\| + R,$$
and expanding this recursion gives
\[ \| \phi_{\omega'}^{(\ell)}(x) \| \leq R^{\ell} \| x \| + \sum_{m=1}^{\ell} R^m = R^\ell \| x \| + \frac{R}{R-1} (R^\ell - 1). \]

Now, we have (14) for \( \Delta = 0 \) because \( \phi_{\omega}^{(0)}(x) - \phi_{\omega'}^{(0)}(x) = 0 \). For \( \ell \geq 1 \), we have
\[ \| \phi_{\omega}^{(\ell)}(x) - \phi_{\omega'}^{(\ell)}(x) \| \leq \| W_{\omega} \phi_{\omega}^{(\ell-1)}(x) - W_{\omega'} \phi_{\omega'}^{(\ell-1)}(x) \| + \| W_{\omega} \phi_{\omega'}^{(\ell-1)}(x) - W_{\omega'} \phi_{\omega'}^{(\ell-1)}(x) \| + \| \omega - \omega' \|. \]

Expanding the recursion yields
\[ \| \phi_{\omega}^{(\ell)}(x) - \phi_{\omega'}^{(\ell)}(x) \| \leq \sum_{m=0}^{\ell-1} R^m \left( R^{\ell-m} \| x \| + \frac{R}{R-1} (R^{\ell-m-1} - 1) + 1 \right) \| \omega - \omega' \|. \]
\[ = \sum_{m=0}^{\ell-1} \left( R^{\ell-1} \| x \| + \frac{R^\ell}{R-1} - \frac{R^{m+1}}{R-1} + R^m \right) \| \omega - \omega' \|. \]
\[ = \left( \ell R^{\ell-1} \| x \| + \frac{\ell R^\ell}{R-1} - \left( \frac{R}{R-1} - 1 \right) \sum_{m=0}^{\ell-1} R^m \right) \| \omega - \omega' \|. \]
\[ = \left( \ell R^{\ell-1} \left( \| x \| + \frac{R}{R-1} \right) - \frac{1}{R-1} R^\ell - 1 \right) \| \omega - \omega' \|. \]

When \( R \geq 2 \), we have that \( R/(R-1) \leq 2 \) and \( R^\ell > 1 \), giving (15) and (16).

\[ \square \]

**B. Experimental Details**

**B.1. Details of synthetic datasets**

Table 6 shows details of four synthetic datasets. *Blob* datasets are often used to validate two-sample test methods (Gretton et al., 2012b; Jitkrittum et al., 2016; Sutherland et al., 2017), although we rotate each blob to show the benefits of non-homogeneous kernels. *HDGM* datasets are first proposed in this paper. *HDGM-D* can be regarded as high-dimension Blob-D which contains two modes with the same variance and different covariance.

<table>
<thead>
<tr>
<th>Datasets</th>
<th>( \mathbb{P} )</th>
<th>( \mathbb{Q} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Blob-S</td>
<td>( \sum_{i=1}^{9} \frac{1}{9} \mathcal{N}(\mu_i, 0.03 \times I_d) )</td>
<td>( \sum_{i=1}^{9} \frac{1}{9} \mathcal{N}(\mu_i, 0.03 \times I_d) )</td>
</tr>
<tr>
<td>Blob-D</td>
<td>( \sum_{i=1}^{9} \frac{1}{9} \mathcal{N}(\mu_i, 0.03 \times I_d) )</td>
<td>( \sum_{i=1}^{9} \frac{1}{9} \mathcal{N}(\mu_i, \Delta_b) )</td>
</tr>
<tr>
<td>HDGM-S</td>
<td>( \sum_{i=1}^{2} \frac{1}{2} \mathcal{N}(\mu_i, I_d) )</td>
<td>( \sum_{i=1}^{2} \frac{1}{2} \mathcal{N}(\mu_i, I_d) )</td>
</tr>
<tr>
<td>HDGM-D</td>
<td>( \sum_{i=1}^{2} \frac{1}{2} \mathcal{N}(\mu_i, I_d) )</td>
<td>( \sum_{i=1}^{2} \frac{1}{2} \mathcal{N}(\mu_i, \Delta_b, 0_d, 0_d, 0_d, \Delta_b, 0_d, I_d) )</td>
</tr>
</tbody>
</table>
Learning Deep Kernels for Non-Parametric Two-Sample Tests

B.2. Dataset visualization

Figure 4 shows images from real-MNIST and “fake”-MNIST, while Figure 5 shows samples from CIFAR-10 and CIFAR-10.1.

![Figure 4](image)

(a) Real-MNIST  (b) “Fake”-MNIST

*Figure 4.* Images from real-MNIST and “fake”-MNIST. “Fake”-MNIST is generated by DCGAN (Radford et al., 2016).

B.3. Configurations

We implement all methods on Python 3.7 (Pytorch 1.1) with a NVIDIA Titan V GPU. We run ME and SCF using the official code (Jitkrittum et al., 2016), and implement C2ST-S, C2ST-L, MMD-D and MMD-O by ourselves. We use permutation test to compute p-values of C2ST-S and C2ST-L, MMD-D, MMD-O and tests in Table 4. We set $\alpha = 0.05$ for all experiments. Following Lopez-Paz & Oquab (2017), we use a deep neural network $F$ as the classifier in C2ST-S and C2ST-L, and train the $F$ by minimizing cross entropy. To fairly compare MMD-D with C2ST-S and C2ST-L, the network $\phi_\omega$ in MMD-D has the same architecture with feature extractor in $F$. Namely, $F = g \circ \phi_\omega$, where $g$ is a two-layer fully-connected network.

The network $g$ is a simple binary classifier that takes extracted features (through $\phi_\omega$) as input. For test methods shown in Table 4, the network $\phi_\omega$ in them also has the same architecture with that in MMD-D.

For Blob, HDGM and Higgs, $\phi_\omega$ is a five-layer fully-connected neural network. The number of neurons in hidden and output layers of $\phi_\omega$ are set to 50 for Blob, $3 \times d$ for HDGM and 20 for Higgs, where $d$ is the dimension of samples. These neurons are with softplus activation function, i.e., $\log(1 + \exp(x))$. For MNIST and CIFAR, $\phi_\omega$ is a convolutional neural network (CNN) that contains four convolutional layers and one fully-connected layer. The structure of the CNN follows the structure of the feature extractor in the discriminator of DCGAN (Radford et al., 2016) (see Figures 6 and 8 for the structure of $\phi_\omega$ in MMD-D, and Figures 7 and 9 for the structure of classifier $F$ in C2ST-S and C2ST-L). The link of DCGAN code is [https://github.com/eriklindernoren/PyTorch-GAN/blob/master/implementations/dcgan/dcgan.py](https://github.com/eriklindernoren/PyTorch-GAN/blob/master/implementations/dcgan/dcgan.py).

We use Adam optimizer (Kingma & Ba, 2015) to optimize 1) parameters of $F$ in C2ST-S and C2ST-L, 2) parameters of $\phi_\omega$ in MMD-D and 3) kernel lengthscale in MMD-O. We set drop-out rate to zero when training C2ST-S, C2ST-L and MMD-D on all datasets.

B.4. Detailed parameters of all test methods

In this subsection, we demonstrate detailed parameters of all test methods. Except for learning rate of Adam optimizer, we use default parameters of Adam optimizer provided by Pytorch. We use one validation set (with the same size of training set) to roughly search these parameters. Using these parameters, we compute test power of each test method on 100 test sets (with the same size of training set).

For ME and SCF, we follow Chwialkowski et al. (2015) and set $J = 10$ for Higgs. For other datasets, we set $J = 5$. 

In this subsection, we demonstrate detailed parameters of all test methods. Except for learning rate of Adam optimizer, we use default parameters of Adam optimizer provided by Pytorch. We use one validation set (with the same size of training set) to roughly search these parameters. Using these parameters, we compute test power of each test method on 100 test sets (with the same size of training set).
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Figure 5. Images from CIFAR-10 test set and the new CIFAR-10.1 test set (Recht et al., 2019).

(a) CIFAR-10 test set
(b) CIFAR-10.1 test set

Figure 6. The structure of $\phi_{\omega}$ in MMD-D on MNIST. The kernel size of each convolutional layer is 3; stride (S) is set to 2; padding (P) is set to 1. We do not use dropout. Best viewed zoomed in.

Figure 7. The structure of classifier $F$ in C2ST-S and C2ST-L on MNIST. The kernel size of each convolutional layer is 3; stride (S) is set to 2; padding (P) is set to 1. We do not use dropout. In the first layer, we will convert the CIFAR images from $32 \times 32 \times 3$ to $64 \times 64 \times 3$. Best viewed zoomed in.

Figure 8. The structure of $\phi_{\omega}$ in MMD-D on CIFAR. The kernel size of each convolutional layer is 3; stride (S) is set to 2; padding (P) is set to 1. We do not use dropout in all layers. In the first layer, we will convert the CIFAR images from $32 \times 32 \times 3$ to $64 \times 64 \times 3$. Best viewed zoomed in.

Figure 9. The structure of classifier $F$ in C2ST-S and C2ST-L on CIFAR. The kernel size of each convolutional layer is 3; stride (S) is set to 2; padding (P) is set to 1. We do not use dropout. Best viewed zoomed in.

For C2ST-S and C2ST-L, we set batchsize to $\min\{2 \times n_b, 128\}$ for Blob, 128 for HDGM and Higgs, and 100 for MNIST and CIFAR. We set the number of epochs to 500 for Blob, 1,000 for HDGM, Higgs and CIFAR, and 2,000 for MNIST. We set learning rate to 0.001 for Blob, HDGM and Higgs, and 0.0002 for MNIST and CIFAR (following Radford et al. (2016)).

For MMD-O, we use full batch (i.e., all samples) to train MMD-O. We set the number of epochs to 1,000 for Blob, HDGM, Higgs and CIFAR, and 2,000 for MNIST. We set learning rate to 0.0005 for Blob, MNIST and CIFAR, and 0.001 for HDGM.
Table 7. Results on Higgs (α = 0.05). We report average Type I error on Higgs dataset when increasing number of samples (N). Note that, in Higgs, we have two types of Type I errors: 1) Type I error when two samples drawn from P (no Higgs bosons) and 2) Type I error when two samples drawn from Q (having Higgs bosons). Type I reported here is the average value of 1) and 2). Since Type I error reported here is the average value of two Type I errors, we do not report standard errors of the average Type I error in this table.

<table>
<thead>
<tr>
<th>N</th>
<th>ME</th>
<th>SCF</th>
<th>C2ST-S</th>
<th>C2ST-L</th>
<th>MMD-O</th>
<th>MMD-D</th>
</tr>
</thead>
<tbody>
<tr>
<td>1000</td>
<td>0.048</td>
<td>0.040</td>
<td>0.043</td>
<td>0.048</td>
<td>0.059</td>
<td>0.037</td>
</tr>
<tr>
<td>2000</td>
<td>0.043</td>
<td>0.032</td>
<td>0.060</td>
<td>0.056</td>
<td>0.055</td>
<td>0.053</td>
</tr>
<tr>
<td>3000</td>
<td>0.049</td>
<td>0.043</td>
<td>0.046</td>
<td>0.053</td>
<td>0.051</td>
<td>0.069</td>
</tr>
<tr>
<td>5000</td>
<td>0.056</td>
<td>0.035</td>
<td>0.052</td>
<td>0.065</td>
<td>0.049</td>
<td>0.062</td>
</tr>
<tr>
<td>8000</td>
<td>0.050</td>
<td>0.034</td>
<td>0.065</td>
<td>0.056</td>
<td>0.056</td>
<td>0.037</td>
</tr>
<tr>
<td>10000</td>
<td>0.059</td>
<td>0.032</td>
<td>0.057</td>
<td>0.058</td>
<td>0.045</td>
<td>0.048</td>
</tr>
<tr>
<td>Avg.</td>
<td>0.051</td>
<td>0.036</td>
<td>0.054</td>
<td>0.058</td>
<td>0.050</td>
<td>0.051</td>
</tr>
</tbody>
</table>

Table 8. Results on MNIST given α = 0.05. We report average Type I error±standard errors on real-MNIST vs. real-MNIST when increasing number of samples (N).

<table>
<thead>
<tr>
<th>N</th>
<th>ME</th>
<th>SCF</th>
<th>C2ST-S</th>
<th>C2ST-L</th>
<th>MMD-O</th>
<th>MMD-D</th>
</tr>
</thead>
<tbody>
<tr>
<td>200</td>
<td>0.076 ±0.011</td>
<td>0.073±0.010</td>
<td>0.035±0.006</td>
<td>0.045±0.005</td>
<td>0.068±0.004</td>
<td>0.056±0.003</td>
</tr>
<tr>
<td>400</td>
<td>0.062 ±0.010</td>
<td>0.056±0.007</td>
<td>0.044±0.006</td>
<td>0.040±0.004</td>
<td>0.053±0.005</td>
<td>0.056±0.005</td>
</tr>
<tr>
<td>600</td>
<td>0.051 ±0.003</td>
<td>0.049±0.009</td>
<td>0.039±0.005</td>
<td>0.054±0.007</td>
<td>0.066±0.008</td>
<td>0.056±0.008</td>
</tr>
<tr>
<td>800</td>
<td>0.054 ±0.006</td>
<td>0.046±0.006</td>
<td>0.043±0.005</td>
<td>0.042±0.007</td>
<td>0.051±0.005</td>
<td>0.054±0.007</td>
</tr>
<tr>
<td>1000</td>
<td>0.047 ±0.006</td>
<td>0.045±0.010</td>
<td>0.038±0.006</td>
<td>0.046±0.005</td>
<td>0.041±0.007</td>
<td>0.062±0.006</td>
</tr>
<tr>
<td>Avg.</td>
<td>0.058</td>
<td>0.054</td>
<td>0.040</td>
<td>0.045</td>
<td>0.056</td>
<td>0.057</td>
</tr>
</tbody>
</table>

For MMD-D, we use full batch (i.e., all samples) to train MMD-D with samples from Blob, HDGM and Higgs. We use mini-batch (batchsize is 100) to train MMD-D with samples from MNIST and CIFAR. We set the number of epochs to 1,000 for Blob, HDGM, Higgs and CIFAR, and 2,000 for MNIST. We set learning rate to 0.0005 for Blob and Higgs, 10−5 for HDGM, 0.001 for MNIST and 0.0002 for and CIFAR (following Radford et al. (2016)).

B.5. Links to datasets

Higgs dataset can be downloaded from UCI Machine Learning Repository. The link is https://archive.ics.uci.edu/ml/datasets/HIGGS.

MNIST dataset can be downloaded via Pytorch. See the code in https://github.com/eriklindernoren/PyTorch-GAN/blob/master/implementations/dcgan/dcgan.py.

CIFAR-10.1 is available from https://github.com/modestyachts/CIFAR-10.1/tree/master/data.npy. This new test set contains 2,031 images from TinyImages (Torralba et al., 2008).

B.6. Type I errors on Higgs and MNIST

Table 7 shows average Type I error on Higgs dataset when increasing number of samples (N). Table 8 shows average Type I error on real-MNIST vs. real-MNIST when increasing number of samples (N).

C. Interpretability on CIFAR-10 vs CIFAR-10.1

In Section 7.1, we have shown that images in CIFAR-10 and CIFAR-10.1 are not from the same distribution. Thus, it is interesting to try to understand the major difference between the datasets. Mean Embedding tests (Chwialkowski et al., 2015) compare the mean embeddings \( \mu_P \) and \( \mu_Q \) at test locations \( v_1, \ldots, v_L \), rather than through their overall norm. The test statistic is

\[
\hat{\lambda} = n z_n^T S^{-1} \bar{z}_n, \quad z_i = (k(x_i, y_j) - k(y_i, y_j))_{j=1}^L \in \mathbb{R}^L, \quad \bar{z}_n = \frac{1}{n} \sum_{i=1}^n z_i, \quad S_n = \frac{1}{n-1} \sum_{i=1}^n (z_i - \bar{z}_n)(z_i - \bar{z}_n)^T;
\]
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the asymptotic null distribution of \( \hat{\Lambda} \) is \( \chi^2_L \), and the estimator is computable in linear time rather than \( \hat{\text{MMD}}_U \)'s quadratic time.

Jitkrittum et al. (2017) jointly learn the parameters \( v_j \) and kernel parameters to optimize test power. The best such test locations (\( L = 1 \)) for a Gaussian kernel (with learned bandwidth) are shown in Figure 10. We could also try optimizing a deep kernel (1) and the test locations together; this procedure, however, failed to find a useful test. We can find a better test, though, with a two-stage scheme: first, learn a deep kernel to maximize \( \hat{J}_\Lambda \), then choose \( v_i \) to maximize \( \hat{\Lambda} \) with that kernel fixed. Results are shown in Figure 11.

Although these approaches give nontrivial test power, it is hard to interpret either set of images, as the test locations have moved far outside the set of natural images. We can instead constrain \( v_1 \in S_p \cup S_Q \), simply picking the single point from the dataset which maximizes \( \hat{\Lambda} \) (shown in Figure 12). This achieves similar test power, but lets us see that the difference might lie in images with smaller objects of interest than the mean for CIFAR-10.
Figure 10. The best test locations (learned by an ME test with $L = 1$) from 10 experiments on CIFAR-10 vs CIFAR-10.1. Average rejection rate is 0.415.

Figure 11. The best test locations (learned by an ME test, $L = 1$, with a deep kernel optimized for an MMD test) from 10 experiments on CIFAR-10 vs CIFAR-10.1. Average rejection rate is 0.637.

Figure 12. The best test locations (selected among existing images with our learned deep kernel, $L = 1$) from 10 experiments on CIFAR-10 vs CIFAR-10.1. Average rejection rate is 0.653.