Distributional Convergence of the Sliced Wasserstein Process

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Abstract

Motivated by the statistical and computational challenges of computing Wasserstein distances in high-dimensional contexts, machine learning researchers have defined modified Wasserstein distances based on computing distances between one-dimensional projections of the measures. Different choices of how to aggregate these projected distances (averaging, random sampling, maximizing) give rise to different distances, requiring different statistical analyses. We define the *Sliced Wasserstein Process*, a stochastic process defined by the empirical Wasserstein distance between projections of empirical probability measures to all one-dimensional subspaces, and prove a uniform distributional limit theorem for this process. As a result, we obtain a unified framework in which to prove sample complexity and distributional limit results for all Wasserstein distances based on one-dimensional projections. We illustrate these results on a number of examples where no distributional limits were previously known.

1 Introduction

The Wasserstein distances have become useful tools in machine learning and data science, with applications in transfer learning [5, 32], generative modeling [3, 17], statistics [7, 18], and various scientific domains [35, 43]. Despite the popularity of these distances, they suffer from serious drawbacks in high dimensions. From a statistical standpoint, estimating the Wasserstein distances from data suffers from the *curse of dimensionality*, with convergence rates degrading sharply as the dimension increases [14, 27, 36, 42]. From a computational standpoint, despite recent algorithmic advances [1, 6], the best algorithms for approximately computing general Wasserstein distances between distributions supported on n points in $\mathbb{R}^d$ for $d \geq 2$ have running times scaling quadratically in n, which is prohibitive on very large data sets. These deficiencies have motivated the development of modifications of the Wasserstein distances which reduce the high-dimensional case to a series of one-dimensional problems.

Explicitly, given two compactly supported probability distributions P and Q in $\mathbb{R}^d$, we write P_u and Q_u for the projections of P and Q onto the one-dimensional subspace spanned by u, for any $u \in \mathbb{S}^{d-1}$. Explicitly, if $X \sim P$, we let P_u denote the law of $u^\top X$. The measures P_u and Q_u are probability distributions on $\mathbb{R}$ obtained by collapsing P and Q to the one-dimensional "slice" in the direction of u. Crucially, no matter how large d is, the Wasserstein distance $W_p^p(P_u, Q_u)$ between the one dimensional measures is always easy to work with: it can be estimated from data at the rate that is independent of the dimension, and if P_u and Q_u are supported on n points, then $W_p^p(P_u, Q_u)$ can be computed in *nearly linear* time by a simple sorting procedure.

This observation has given rise to a number of different proposals for defining a distance between P and Q by aggregating the one-dimensional distances, the most prominent of which is the sliced

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Wasserstein distance [2, 31]:

$$SW_p^p(P,Q) := \int W_p^p(P_u, Q_u)\,\mathrm{d}\sigma(u)\,, \tag{1}$$ {sw}

where σ denotes the uniform measure on $\mathbb{S}^{d-1}$. Other options include:

- Discrete Sliced Wasserstein distance: $\widehat{SW}_p^p(P,Q) := \frac{1}{L}\sum_{i=1}^L W_p^p(P_{u_i}, Q_{u_i})$, $\{u_i\} \subseteq \mathbb{S}^{d-1}$ [2].
- Max-Sliced Wasserstein distance: $MSW_p^p(P,Q) := \max_{u\in\mathbb{S}^{d-1}} W_p^p(P_u, Q_u)$ [13, 27, 30].
- Distributional Sliced Wasserstein distance: $DSW_p^p(P,Q) := \sup_{\tau\in\mathcal{P}_C} \int W_p^p(P_u, Q_u)\,\mathrm{d}\tau(u)$, where $\mathcal{P}_C$ is a subset of probability measures on $\mathbb{S}^{d-1}$ [26].

Though the details of these techniques differ, they can be put on a common footing: if we view the function $W : u \mapsto W_p^p(P_u, Q_u)$ as a bounded function on $\mathbb{S}^{d-1}$, then each of these sliced distances takes the form $F(W)$ for some function $F : \ell^\infty(\mathbb{S}^{d-1}) \to \mathbb{R}$.

Since these distances are all based on one-dimensional projections, it is natural to conjecture that they enjoy improved statistical performance. This conjecture has been verified in certain special cases [23, 25, 27] However, the analysis of these distances has largely been conducted separately, with different arguments tailored to each distance. This raises the following fundamental question: is there a *unified* approach to the analysis of these distances, which provides statistical guarantees for all of them simultaneously?

In this work, we develop such a unified approach. In addition to generalizing prior works, our techniques allow us to prove new distributional convergence results for the sliced Wasserstein distance and its many variants. These results make it possible to construct asymptotically valid confidence intervals for variants of the sliced Wasserstein distances and to guarantee the validity of the bootstrap. Prior to our work, such results were only known for the standard sliced Wasserstein distance (1) [23] or for the sliced and max-sliced Wasserstein distances between discrete distributions [29].[1]

Obtaining distributional limits for empirical Wasserstein distances is an active area of research. In the one-dimensional case, fundamental contributions were made by [9, 10], and further progress has been made in the case where one or both of the measures are discrete [12, 37, 39]. Multi-dimensional limits were recently obtained by [8, 11], but these are not centered at the population-level quantities, making them of limited utility for inference. However, when the distributions are very smooth, there exist estimators with distributional limits with good centering [24]. In this work, we draw on techniques recently proposed in [20] to obtain central limit theorems by exploiting duality.

We consider compactly supported probability measures P and Q in $\mathbb{R}^d$ with connected support, and the Wasserstein distances W_p^p for $p > 1$. To analyze the empirical behavior of the sliced Wasserstein distance and its variants, we define a stochastic process

$$\mathbb{G}_n(u) := \sqrt{n}(W_p^p(P_{nu}, Q_{nu}) - W_p^p(P_u, Q_u)) \qquad u \in \mathbb{S}^{d-1}\,. \tag{2}$$ {swp}

where P_n and Q_n consist of i.i.d. samples. We may view $\mathbb{G}_n$ as a random element of $\ell^\infty(\mathbb{S}^{d-1})$, which records the deviation of the Wasserstein distance from its population counterpart along every direction simultaneously. We call $\mathbb{G}_n$ the *Sliced Wasserstein Process*.

Our main result shows that

$$\mathbb{G}_n \rightsquigarrow \mathbb{G} \quad \in \ell^\infty(\mathbb{S}^{d-1})\,, \tag{3}$$ {swp}

where $\mathbb{G}$ is a tight Gaussian process on $\mathbb{S}^{d-1}$. That is, the collection of random variables $\sqrt{n}(W_p^p(P_{nu}, Q_{nu}) - W_p^p(P_u, Q_u))$ indexed by elements of $\mathbb{S}^{d-1}$ enjoys a *uniform* central limit theorem. As is well known in the statistics literature [40], uniform central limit theorems of this type give rise to distributional limits for any sufficiently regular functional on $\ell^\infty(\mathbb{S}^{d-1})$ via the functional delta method—in particular, we directly obtain distributional limit theorems for the sliced Wasserstein distance and its many variants as a special case. Our results likewise give techniques for proving the consistency of the bootstrap for any of the mentioned functionals as a consequence of general results for uniform central limit theorems.

[1] Concurrently and independently of our work, [19] proved distributional limits for the sliced and max-sliced Wasserstein, but not for other variants, as a byproduct of general results for distributional limits for Wasserstein distances.

result

2 Main Result

Throughout, P and Q denote two probability distributions in $\mathbb{R}^d$ with compact support, contained in a closed ball $\overline{B(0,R)}$ around the origin. We fix a $p > 1$, and consider the Wasserstein distance of order p:

$$W_p^p(P,Q) = \inf_{\pi \in \Pi(P,Q)} \int \|x-y\|^p \, \mathrm{d}\pi(x,y)\,, \tag{4}$$

{primal}

where the infimum is taken over all couplings between P and Q. It is well known (see [41]) that this problem possesses a dual formulation:

$$W_p^p(P,Q) = \sup_{f:\overline{B(0,R)} \to \mathbb{R}} \int f \, \mathrm{d}P + \int f^c \, \mathrm{d}Q\,, \tag{5}$$

{dual}

where f^c denotes the c-transform: $f^c(y) = \inf_{x \in \overline{B(0,R)}} \|x-y\|^p - f(x)$. It can be shown (e.g.,[22, Lemma 1 & 5]) that the supremum in this dual formulation is achieved, and that without loss of generality we may assume that f satisfies $f(0) = 0$ and $\|f\|_{\mathrm{Lip}} \le pR^{p-1}$. We denote the class of such functions by $\mathcal{C}$, and call any maximizer a *Kantorovich potential*. In order to obtain Gaussian limits,we adopt the following crucial assumption:

CC

(**CC**) For all $u \in \mathbb{S}^{d-1}$, the support of P_u or Q_u is an interval.

Assumption (**CC**) guarantees that the supremum in (5) is achieved at a *unique* Kantorovich potential in $\mathcal{C}$ [34, Proposition 7.18]. In fact, it is known that the conclusion can still hold under weaker conditions, but we do not pursue this refinement here [38, 44]. In the absence of this uniquness, Gaussian limits fail to hold for the optimal transport problem, even for discrete measures [37].

We now state our main result.

thm:1

Theorem 2.1. *Suppose that P and Q are two probability distributions in $\mathbb{R}^d$ whose supports are contained in the closed d-ball $\overline{B(0,R)}$ for some $R > 0$. Assume that P and Q satisfy (**CC**). Let P_n and Q_m denote empirical measures consisting of n and m i.i.d. samples from P and Q, respectively. If $n/(n+m) \to \lambda \in (0,1)$ as $n, m \to \infty$, then*

$$\sqrt{\frac{nm}{n+m}} \left(W_p^p(P_{n\cdot}, Q_{m\cdot}) - W_p^p(P_\cdot, Q_\cdot) \right) \rightsquigarrow \mathbb{G} \quad \text{in } \ell^\infty(\mathbb{S}^{d-1})\,, \tag{6}$$

{eq:5}

where $\mathbb{G}$ is a tight zero-mean Gaussian process on $\mathbb{S}^{d-1}$ with covariance function

$$\begin{aligned} \mathbb{E}\mathbb{G}(u)\mathbb{G}(v) =& (1-\lambda) \int f_u(u^\top x) f_v(v^\top x) \, \mathrm{d}P(x) + \lambda \int f_u^c(u^\top y) f_v^c(v^\top y) \, \mathrm{d}Q(y) \\ & - (1-\lambda) \int f_u(u^\top x) \, \mathrm{d}P(x) \int f_v(v^\top x) \, \mathrm{d}P(x) \\ & - \lambda \int f_u^c(u^\top y) \, \mathrm{d}Q(x) \int f_v^c(v^\top Y) \, \mathrm{d}Q(x), \end{aligned} \tag{7}$$

{eq:6}

where $f_u, f_v \in \mathcal{C}$ are the unique Kantorovich potentials for (P_u, Q_u) and (P_v, Q_v), respectively.

Theorem 2.1 formally includes the one-sample case as well, by taking $\lambda = 0, 1$.

As alluded to above, Theorem 2.1 gives rise to a wealth of statistical theorems as easy corollaries. To describe these implications, we return to the abstract setting described above: denote by $W : \mathbb{S}^{d-1} \to \mathbb{R}$ the function $W(u) = W_p^p(P_u, Q_u)$, and consider any functional $F : \ell^\infty(\mathbb{S}^{d-1}) \to \mathbb{R}$. Then the distances we consider take the form $F(W)$. By different choices of F, we obtain the sliced Wasserstein distance, the max-sliced Wasserstein distance, and the other variants described above. Theorem 2.1 will allow us to compare $F(W)$ to its empirical counterpart $F(W_{nm})$, where $W_{nm}(u) = W_p^p(P_{nu}, Q_{mu})$.

We recall the definition of directional Hadamard differentiability [33]: we say that F is directionally Hadamard differentiable at Φ if for all sequences $h_n \searrow 0$ and $\Psi_n \to \Psi \in \ell^\infty(\mathbb{S}^{d-1})$, the limit

$$\lim_{n\to\infty} \frac{F(\Phi + h_n \Psi_n) - F(\Phi)}{h_n} =: F'_\Phi(\Psi)$$

exists. We verify in Section 3 the directional Hadamard differentiability of several examples. Under this assumption, we have the following.

Corollary 2.2. *Assume F is directionally Hadamard differentiable. Under the assumptions of Theorem 2.1,*

$$\sqrt{\frac{nm}{n+m}}(F(W_{nm}) - F(W)) \rightsquigarrow F'_W(\mathbb{G})\,.$$

Proof. See [33]. □

We also obtain a consistency result for the bootstrap, which we state for simplicity in the $n = m$ case.

Corollary 2.3. *Assume that F is directionally Hadamard differentiable, and adopt the assumptions of Theorem 2.1. For $k \ll n$ denote by P^* and Q^* bootstrap empirical measures consisting of k i.i.d. draws from P_n and Q_m, respectively, and set $W^* = W_p^p(P_u^*, Q_u^*)$. If $k \to \infty$ and $k/n \to 0$, then*

$$\sup_{h \in BL(1)} \mathbb{E}[h(\sqrt{k}(F(W^*)) - F(W_n))|X_1, \ldots, X_n, Y_1, \ldots, Y_n] \\ - \mathbb{E}[h(\sqrt{n}(F(W_n) - F(W)))] \xrightarrow{p} 0\,,$$

where $BL(1)$ is the set of functions with bounded Lipschitz norm 1.

Proof. See [15]. □

Finally, when the functional $F : \ell^\infty(\mathbb{S}^{d-1}) \to \mathbb{R}$ has a *linear* Hadamard derivative, the resulting statistic will again be asymptotically Gaussian. The following uniform convergence result shows that we can consistently estimate the covariance function of $\mathbb{G}$ from data, which can be used to obtain asymptotic confidence intervals in this setting.

thm:2.4 **Theorem 2.4.** *Under the same assumptions as Theorem 2.1, there exists an estimator $\{\hat{\Sigma}_{u,v}\}_{u,v \in \mathbb{S}^{d-1}}$ for the covariance functions $\{\Sigma_{u,v}\}_{u,v \in \mathbb{S}^{d-1}}$ of the limiting process $\mathbb{G}$ in the sense that*

$$\mathbb{E}_{P,Q} \sup_{u,v \in \mathbb{S}^{d-1}} \|\hat{\Sigma}_{u,v} - \Sigma_{u,v}\|_\infty \to 0 \quad \text{as } n \to 0. \tag{8}$$ {eq:21}

3 Applications

applications

In this section, we focus on the two most popular of the variants we discussed—the sliced and max-sliced Wasserstein distances—and show how our main results obtained in the previous section can be used to obtain accurate asymptotic inference for these quantities. For notational simplicity, we focus on the case where $n = m$, and rescale the resuling Gaussian process by a factor of $\sqrt{2}$.

3.1 Sliced Wasserstein Distance

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Asymptotic and finite-sample inference for the sliced Wasserstein distance (SW) has already been thoroughly studied by [23]. We show that we can recover some of their results from our techniques. Their main focus was on a robustification of the SW distance, the trimmed SW distance, defined as

$$SW_{p,\delta}(P, Q) := \left(\int_{\mathbb{S}^{d-1}} \int_\delta^{1-\delta} |F_\theta^{-1}(t) - G_\theta^{-1}(t)|^p \, dt \, d\sigma^d(\theta) \right)^{\frac{1}{p}},$$

where σ^d denotes the uniform probability measure on $\mathbb{S}^{d-1}$ and F_θ^{-1}, G_θ^{-1} are the (pseudo-)inverse of the CDFs of P_θ, Q_θ respectively. When $\delta = 0$, $SW_{p,\delta}$ reduces to the original sliced Wasserstein distance SW_p. This robustification is necessary when P and Q are no longer assumed to have compact support. [23] derive Gaussian limits and boostrap consistency for this functional.

To see how these results (under our stricter assumptions) can also be obtained from Theorem 2.1, we denote by $F : \ell^\infty(\mathbb{S}^{d-1}) \to \mathbb{R}$ the integration functional:

$$F(\Phi) = \int \Phi(u) \, \mathrm{d}\sigma(u)\,.$$

The dominated convergence theorem immediately implies that F is Hadamard differentiable, with derivative

$$F'_\Phi(\Psi) = \int \Psi(u)\,\mathrm{d}\sigma(u)\,.$$

We obtain the following.

thm:3 **Theorem 3.1.** *Suppose that two compactly supported probability distributions P and Q in $\mathbb{R}^d$ satisfy (**CC**). Then*

$$\sqrt{n}(SW_p^p(P_n, Q_n) - SW_p^p(P, Q)) \xrightarrow{d} S := \int_{\mathbb{S}^{d-1}} \mathbb{G}(\theta)\, d\sigma^d(\theta). \tag{9}$$ {eq:29}

The random variable S is Gaussian, and by integrating (7) it can be shown that its limiting variance agrees with the expression in [23].

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3.2 Max-sliced Wasserstein distance

Unlike integration, the supremum functional is not smooth and does not possess a linear Hadamard derivative. Write $MSW_p^p(P, Q) = \sup_{u\in\mathbb{S}^{d-1}} W_p^p(P_u, Q_u)$, and note that $MSW_p^p(P, Q) = \omega(W)$, where $\omega : \ell^\infty(\mathbb{S}^{d-1}) \to \mathbb{R}$ is the supremum functional. It is shown in Theorem 2.1 of [4] that ω is Hadamard directionally differentiable with the derivative

$$\omega'_f(g) = \lim_{\epsilon\downarrow 0} \sup_{x\in A_\epsilon(f)} g(x),$$

where $A_\epsilon(f) := \{x : f(x) \geq \sup f - \epsilon\}$. Moreover, if f and g are continuous on $\mathbb{S}^{d-1}$ with respect to the standard Euclidean distance, then $\lim_{\epsilon\downarrow 0} \sup_{A_\epsilon(f)} g(x) = \sup_{x\in A_0(f)} g(x)$ where $A_0(f) = \{x : f(x) = \sup f\}$. (See Corollary 2.3 of [4])

Applying the functional delta method to ω and the uniform weak convergence (6), we note that the limiting process $\mathbb{G}$ has continuous samples paths a.s. so the limiting distribution of WPP can be written as

$$\omega'_{W_p^p(W)}(\mathbb{G}) = \sup_{u\in A_0(W_p^p(W))} \mathbb{G}(u). \tag{10}$$ {eq:31}

In the spiked transport model (STM), this expression can be further simplified. The STM was introduced by [27] to formalize the situation where two distributions differ only in a low dimensional subspace of $\mathbb{R}^d$. We describe the special case of one-dimensional spike here fix some $v \in \mathbb{S}^{d-1}$ and let $X, Y \in L := \mathrm{span}(v)$ be two random variables. Let Z be another random variable independent of (X, Y) and supported on the orthogonal complement $L^\perp$ of L. Then we define two distributions in $\mathbb{R}^d$ by $P := \mathrm{law}(X + Z)$, $Q := \mathrm{law}(Y + Z)$. It is shown there that $MSW_p^p(P, Q) = W_p(\mathrm{law}(X), \mathrm{law}(Y)) = W_2(P, Q)$. In addition, in this model the set $A_\epsilon(W_p^p(P_\cdot, Q_\cdot))$ shrinks to the singleton set $\{v\}$ as ϵ goes down to 0. In fact, the Hadamard derivative can be reduced to the random variable $\mathbb{G}(u)$, i.e. the marginal of limiting Gaussian process $\mathbb{G}$ along v. We summarize the result in the following theorem.

thm:4 **Theorem 3.2.** *Suppose that two compactly supported probability distributions P and Q in $\mathbb{R}^d$ fit the spiked transport model with spike $v \in \mathbb{S}^{d-1}$. Assume furthermore P and Q also satisfy (**CC**). Then,*

$$\sqrt{n}\left(\tilde{W}_{p,1}^p(P_n, Q_n) - \tilde{W}_{p,1}^p(P, Q)\right) \xrightarrow{d} \mathbb{G}(v). \tag{11}$$ {eq:32}

rmk:4 **Remark 3.3.** *Note that it is not necessary for P and Q to satisfy the spiked transport model in order to deduce the CLT of max-sliced Wasserstein. Namely, even if the set $\{u \in \mathbb{S}^{d-1} : W_p^p(P_u, Q_u) = MSW(P, Q)\}$ is not a singleton, the same proof still works but the limiting distribution is the supremum of the Gaussian process $\mathbb{G}$ over the set $\{u \in \mathbb{S}^{d-1} : W_p^p(P_u, Q_u) = MSW(P, Q)\}$ which is not necessarily Gaussian. This example shows that certain functionals give rise to non-Gaussian limits, even though the limit in* (6) *is Gaussian.*

simulation

4 Simulation Studies

We illustrate our distributional limit results in Monte Carlo simulations. Specifically, we investigate the speed of convergence for the empirical sliced Wasserstein distance and the empirical projection

robust Wasserstein distance, i.e. Wasserstein project pursuit to their limit distributions. We also illustrate the accuracy of the approximation using the re-scaled bootstrap. All simulations were performed using Python. The Wasserstein distances as well as the sliced Wasserstein distances were calculated using the Python package *POT* [16] and the max-sliced Wasserstein distances were approximated by the Riemannian optimization method proposed in [21].

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4.1 Sliced Wasserstein Distance

We present an example that concerns two different distributions with connected projections along all directions.

Consider a simple model of transport where source and target distributions P, Q are uniform on unit sphere $\mathbb{S}^2$ and the unit sphere $\mathbb{S}^2_{(1,1,1)}$ centered at $(1,1,1)$ respectively.

We first give an explicit representation of the theoretical limit of the example given in section 4.1. Fix any point $\theta \in \mathbb{S}^2$, the projections of P and Q along θ are uniform over $(-1,1)$ and $(-1+a_\theta, 1+a_\theta)$ respectively where $a_\theta := \theta_1 + \theta_2 + \theta_3$. Then the unique 1-Lipschitz function that achieves the 1-Wasserstein distance between P_θ and Q_θ is $\phi_0^\theta(x) = -\text{sign}(a_\theta)x$. Hence, we have

$$\sqrt{n}\left(W_2^2(P_{n\cdot}, Q_{n\cdot} - W_2^2(P_\cdot, Q_\cdot)\right) \rightsquigarrow \mathbb{G},$$

where $\mathbb{G}$ is the mean-zero Gaussian process indexed by $\mathbb{S}^2$ with covariance functions

$$\mathbb{E}\mathbb{G}(u)\mathbb{G}(v) = \frac{8}{3} a_u a_v \langle u, v\rangle.$$

It follows from Theorem 3.1 that the limiting distribution of the empirical 2-Wasserstein distance is the centered Gaussian S with variance

$$\text{Var}(S) = \frac{8}{3}\int_{\mathbb{S}^2}\int_{\mathbb{S}^2} a_u a_v \langle u, v\rangle \, d\sigma(u) d\sigma(v) \approx 0.832.$$

We sample i.i.d. observations $X_1, \ldots, X_n \sim P$ and $Y_1, \ldots, Y_n \sim Q$ with size $n = 50, 100, 500$. This process is repeated 500 times. We then compare the finite distributions of 1-Wasserstein distance with the theoretical limit given in section 3.1. We demonstrate the results using kernel density estimators in Figure 1 along with the corresponding Q-Q plots. We see that the finite-sample empirical distribution gets closer to the limiting Gaussian distribution in 9 as the sample size n increases.

In addition, we simulate the re-scaled plug-in bootstrap approximations by sampling $n = 1000$ observations of P and Q. Fix some empirical SW $\sqrt{n}SW_2^2(P_n, Q_n)$, we generate $B = 500$ replications of $\sqrt{l}(SW_2^2(\hat{P}_n^*, \hat{Q}_n^*) - SW_2^2(P_n, Q_n))$. The distributions of the replications with various replacement numbers l, compared with the finite-sample empirical distribution and the theoretical limit, are shown in Figure 2. We observe that the naive bootstrap ($l = n$) better approximates the finite sample distribution compared to fewer replacements ($l = n^{1/2}, n^{3/4}$). This is consistent with the observation of inference on finite spaces. [28]

simuwpp

4.2 Wasserstein Project Pursuit

We present an example that simulate different behavior of empirical WPP when $p = 2$.

We take P to be the uniform distribution on the unit sphere $\mathbb{S}^2$ and Q to be uniform on the surface of ellipsoid $x^2/a^2 + y^2 + z^2 = 1$ where $a = 8.5$. We sample i.i.d. observations with size $n = 50, 100, 500$ and this process is repeated 2000 times. The estimation plotted in the top part of Figure 3 indicates that the finite sample distributions approximate the limiting Gaussian distribution derived in Theorem 3.2 very well even when the sample size is small.

In terms of the re-scaled bootstrap, the accuracy of the bootstrap approximation seems to be good for all replacement numbers in this case, which is again consistent with the observation of the case when the underlying distributions are supported in finite sets. [28] See Figure 4 for the simulation.

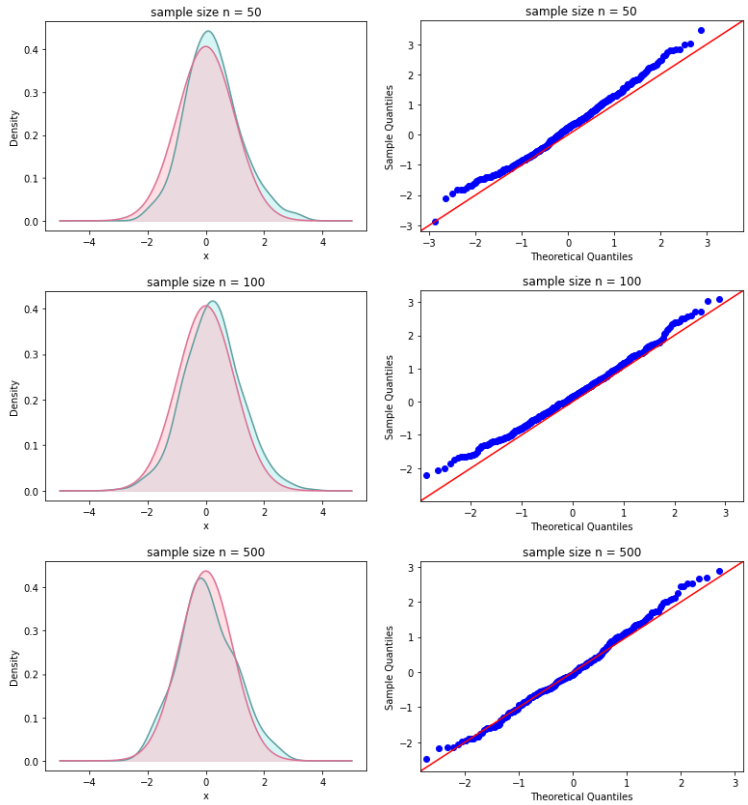

Figure 1: Left: Comparison of the finite sample density (pale turquoise) and the limit distribution of the empirical sliced distance (pink).
Right: The corresponding Q-Q plots where the red solid line indicates perfect fit.

fig:1

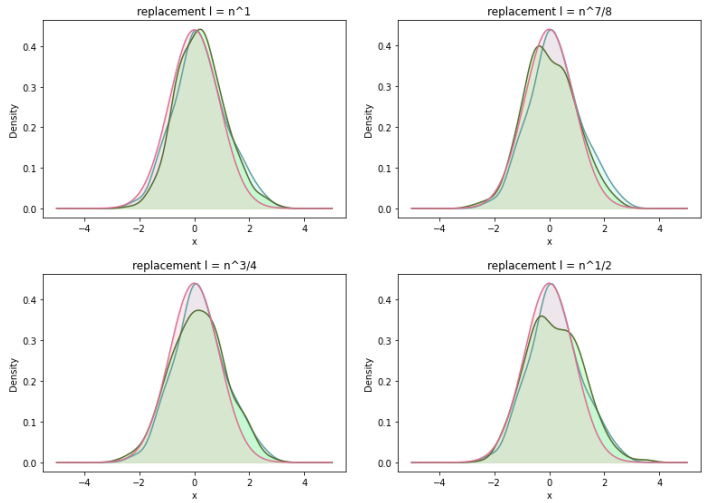

Figure 2: Bootstrap for the empirical sliced distance. Illustration of the re-scaled plug-in bootstrap approximation ($n = 1000$) with replacement $l \in \{n, n^{7/8}, n^{4/5}, n^{1/2}\}$. Finite bootstrap densities (pale green) are compared to the corresponding finite sample density (pale turquoise) and the limit distribution (pink).

fig:2

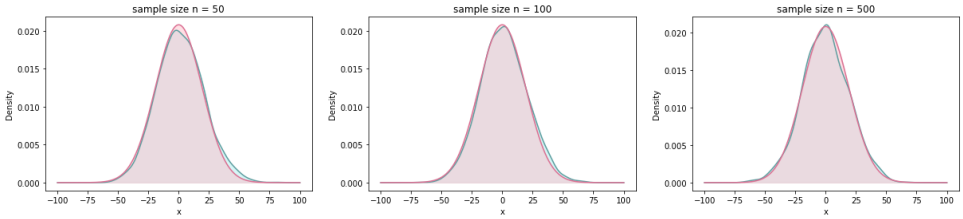

Figure 3: Comparison of the finite sample density (pale turquoise) and the limit distribution of the empirical one-dimensional WPP (pink).

fig:3

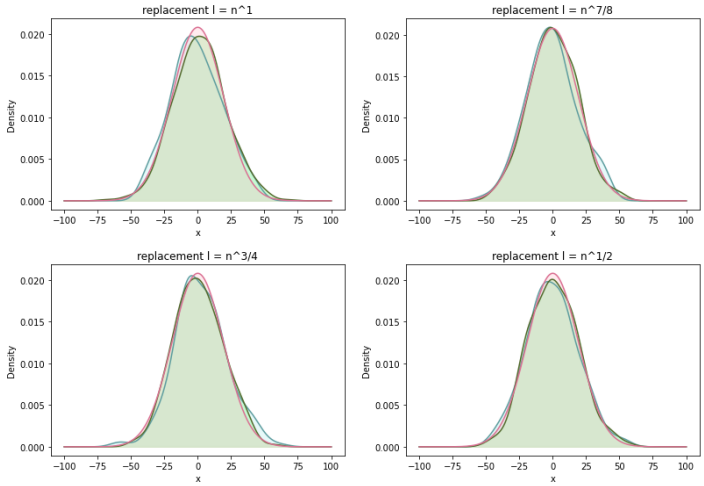

Figure 4: Bootstrap for the empirical one-dimensional WPP. Illustration of the re-scaled plug-in bootstrap approximation ($n = 1000$) with replacement $l \in \{n, n^{7/8}, n^{4/5}, n^{1/2}\}$. Finite bootstrap densities (pale green) are compared to the corresponding finite sample density (pale turquoise) and the limit distribution (pink).

fig:4

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5 Checklist

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes]
   (b) Did you describe the limitations of your work? [Yes] See the discussion at the beginning of section 2.
   (c) Did you discuss any potential negative societal impacts of your work? [N/A]
   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes]
2. If you are including theoretical results...
   (a) Did you state the full set of assumptions of all theoretical results? [Yes] See the statements of theorems along with discussions and remarks before or after the results.
   (b) Did you include complete proofs of all theoretical results? [Yes] See appendix.
3. If you ran experiments...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [Yes] See the url given in the footnote on page 6.
   (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes] See section 4.
   (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [Yes] See section 4.
   (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [Yes] See section 4 and the related reference.
4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...
   (a) If your work uses existing assets, did you cite the creators? [Yes]
   (b) Did you mention the license of the assets? [Yes]
   (c) Did you include any new assets either in the supplemental material or as a URL? [Yes] See the reference.
   (d) Did you discuss whether and how consent was obtained from people whose data you're using/curating? [N/A]
   (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? [N/A]
5. If you used crowdsourcing or conducted research with human subjects...
   (a) Did you include the full text of instructions given to participants and screenshots, if applicable? [N/A]
   (b) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable? [N/A]
   (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [N/A]