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On Low-Dimensional Projections of High-Dimensional Distributions

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Abstract: Let P be a probability distribution on q-dimensional space. The so-called Diaconis-Freedman effect means that for a fixed dimension $d << q$, most d-dimensional projections of P look like a scale mixture of spherically symmetric Gaussian distributions. The present paper provides necessary and sufficient conditions for this phenomenon in a suitable asymptotic framework with increasing dimension q. It turns out that the conditions formulated by Diaconis and Freedman (1984) are not only sufficient but necessary as well. Moreover, letting $\widehat{P}$ be the empirical distribution of n independent random vectors with distribution P, we investigate the behavior of the empirical process $\sqrt{n}(\widehat{P} - P)$ under random projections, conditional on $\widehat{P}$.

1. Introduction

A standard method of exploring high-dimensional datasets is to examine various low-dimensional projections thereof. In fact, many statistical procedures are based explicitly or implicitly on a "projection pursuit", cf. [8]. As shown by Diaconis and Freedman [4], under weak regularity conditions on a distribution $P = P^{(q)}$ on $\mathbb{R}^q$, "most" d-dimensional orthonormal projections of P are similar (in the weak topology) to a mixture of centered, spherically symmetric Gaussian distribution on $\mathbb{R}^d$ if q tends to infinity while d is fixed. A graphical demonstration of this disconcerting phenomenon is given by [3]. Precise quantitative analyses are provided by [9, 10] for situations where most projections are approximately Gaussian. The present paper provides further insight into the general phenomenon. We extend the results of [4] in two directions.

Section 2 gives necessary and sufficient conditions on the sequence $(P^{(q)})_{q \ge d}$ such that "most" d-dimensional projections of P are similar to some distribution Q on $\mathbb{R}^d$. It turns out that these conditions are essentially the conditions of [4]. The novelty here is necessity. The limit distribution Q is automatically a mixture of centered, spherically symmetric Gaussian distributions. The family of such measures arises in [5] in a somewhat different context.

More precisely, let $\Gamma = \Gamma^{(q)}$ be uniformly distributed on the set of column-wise orthonormal matrices in $\mathbb{R}^{q \times d}$ (cf. Section 4.2). Defining

$$\gamma^\top P \ := \ \mathcal{L}_{X \sim P}(\gamma^\top X)$$

for $\gamma \in \mathbb{R}^{d \times q}$, we investigate under what conditions the random distribution $\Gamma^\top P$ converges weakly in probability to an arbitrary fixed distribution Q as $q \to \infty$, while d is fixed.

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In Section 3 we study the relationship between $P = P^{(q)}$ and the empirical distribution $\widehat{P} = \widehat{P}^{(q,n)}$ of n independent random vectors with distribution P, also independent from the projection matrix $\Gamma = \Gamma^{(q)}$. Suppose that the distributions $P^{(q)}$ satisfy the conditions of Section 2. Then the random distributions $\widehat{P}^{(q,n)}$ satisfy these conditions, too, as q and n tend to infinity. Furthermore, the standardized empirical measure $n^{1/2}\big(\Gamma^\top \widehat{P} - \Gamma^\top P\big)$ satisfies a conditional Central Limit Theorem *given the data* $\widehat{P}$.

Proofs are deferred to Section 4. The main ingredients are Poincaré's [11] Lemma and a method invented by Hoeffding [7] in order to prove weak convergence of conditional distributions. Further we utilize standard results from weak convergence and empirical process theory.

2. The Diaconis-Freedman Effect

Let us first settle some terminology. A random distribution $\widehat{Q}$ on a separable metric space $(\mathbb{M}, \rho)$ is a mapping from some probability space into the set of Borel probability measures on $\mathbb{M}$ such that $\int f \, d\widehat{Q}$ is measurable for any function $f \in \mathcal{C}_b(\mathbb{M})$, the space of bounded, continuous functions on $\mathbb{M}$. We say that a sequence $(\widehat{Q}_k)_k$ of random distributions on $\mathbb{M}$ converges weakly in probability to some fixed distribution Q if for each $f \in \mathcal{C}_b(\mathbb{M})$,

$$\int f \, d\widehat{Q}_k \ \to_p \ \int f \, dQ \quad \text{as } k \to \infty.$$

In symbols, $\widehat{Q}_k \to_{w,p} Q$ as $k \to \infty$. Standard approximation arguments (e.g. as in [14], Section 1.12) show that $(\widehat{Q}_k)_k$ converges in probability to Q if, and only if,

$$D_{\mathrm{BL}}(\widehat{Q}_k, Q) := \sup_{f \in \mathcal{F}_{\mathrm{BL}}} \Big| \int f \, d\widehat{Q}_k - \int f \, dQ \Big| \ \to_p \ 0 \quad (k \to \infty),$$

where $\mathcal{F}_{\mathrm{BL}}$ stands for the class of functions $f : \mathbb{M} \to [-1, 1]$ such that $|f(x) - f(y)| \le \rho(x, y)$ for all $x, y \in \mathbb{M}$.

Now we can state the first result. Here and throughout, $\|\cdot\|$ denotes Euclidean norm and $\mathcal{N}_{d,v}$ stands for the Gaussian distribution on $\mathbb{R}^d$ with mean vector 0 and covariance matrix vI_d.

Theorem 2.1. *The following two assertions on the sequence $(P^{(q)})_{q \ge d}$ are equivalent:*

(A1) *There exists a probability measure Q on $\mathbb{R}^d$ such that*

$$\Gamma^\top P \ \to_{w,p} \ Q \quad \text{as } q \to \infty.$$

(A2) *If $X = X^{(q)}, \tilde{X} = \tilde{X}^{(q)}$ are independent random vectors with distribution P, then*

$$\mathcal{L}(\|X\|^2/q) \ \to_w \ R \quad \text{and} \quad X^\top \tilde{X}/q \ \to_p \ 0 \quad \text{as } q \to \infty$$

for some probability measure R on $[0, \infty)$.

The limit distribution Q in (A1) is a normal mixture, precisely,

$$Q \ = \ \int \mathcal{N}_{d,v} \, R(dv)$$

with the limiting distribution R in (A2).

Corollary 2.2. *The random probability measure $\Gamma^\top P$ converges weakly in probability to the standard Gaussian distribution $\mathcal{N}_{d,1}$ if, and only if, the following condition is satisfied:*

(B) *For independent random vectors $X = X^{(q)}, \tilde{X} = \tilde{X}^{(q)}$ with distribution P,*

$$\|X\|^2/q \ \to_p \ 1 \quad \text{and} \quad X^\top \tilde{X}/q \ \to_p \ 0 \quad \text{as } q \to \infty. \qquad \square$$

The implication "(A2) $\Longrightarrow$ (A1)" in Theorem 2.1 as well as sufficiency of condition (B) in Corollary 2.2 are due to [4] (see their Theorem 1.1 and Proposition 4.2). They considered only (deterministic) empirical distributions P, but the extension to arbitrary distributions P is straightforward; see also Section 3.

It should be pointed out here that neither Theorem 2.1 nor Corollary 2.2 are just a consequence of Poincaré's [11] Lemma, although the latter is somehow at the heart of the proof. Poincaré showed that if $U_q = (U_{q,i})_{i=1}^q$ is uniformly distributed on the unit sphere in $\mathbb{R}^q$, then the Lebesgue density of $q^{1/2}U_{q,1}$ converges uniformly to the standard Gaussian density on $\mathbb{R}$. Translated into the present setting, one can show that for a fixed vector $x = x^{(q)} \in \mathbb{R}^q \setminus \{0\}$, the Lebesgue density of the random vector $\Gamma^\top x$ converges uniformly to the Lebesgue density of $\mathcal{N}_{d,v}$ as $q \to \infty$ and $\|x\|^2/q \to v > 0$.

Example 2.3. Condition (A2) is not a very restrictive requirement. For instance, suppose that $X = U(\mu_k + \sigma_k Z_k)_{k=1}^q$, where $(Z_k)_{k\geq 1}$ is a sequence of independent, identically distributed random variables with mean zero and variance one, while $U = U^{(q)}$ is an orthogonal matrix in $\mathbb{R}^{q\times q}$ and $\mu = \mu^{(q)} \in \mathbb{R}^q$, $\sigma = \sigma^{(q)} \in [0,\infty)^q$. Then condition (A2) is satisfied if, and only if,

$$(\mathbf{A3}) \qquad \|\mu\|^2/q \ \to \ 0, \quad \|\sigma\|^2/q \ \to \ v \geq 0 \quad \text{and} \quad \max_{1\leq k\leq q} \sigma_k^2/q \ \to \ 0$$

as $q \to \infty$; see Section 4. Here $R = \delta_v$ and $Q = \mathcal{N}_{d,v}$.

Example 2.4. Suppose that $X \sim P^{(q)}$ has independent, identically distributed components such that

$$\mathbb{P}(X_i = \sqrt{q}) \ = \ 1 - \mathbb{P}(X_i = 0) \ = \ \pi_q,$$

where

$$\lim_{q\to\infty} q\pi_q \ = \ \lambda > 0.$$

Then $\mathcal{L}(\|X\|^2/q) = \mathrm{Bin}(q, \pi_q) \to_w \mathrm{Poiss}(\lambda)$ and $\mathcal{L}(X^\top \tilde{X}/q) = \mathrm{Bin}(q, \pi_q^2) \to_w \delta_0$ as $q \to \infty$. Hence (A2) is satisfied with $R = \mathrm{Poiss}(\lambda)$.

3. Empirical Distributions

From P to $\widehat{P}$. If the distributions $P = P^{(q)}$ satisfy conditions (A1-2), then the empirical distributions $\widehat{P} = \widehat{P}^{(q,n)}$ satisfy these conditions with high probability as $\min(q,n) \to \infty$. Precisely, one can easily deduce from condition (A2) that

$$D_{\mathrm{BL}}\Big(\frac{1}{n}\sum_{i=1}^n \delta_{\|X_i\|^2/q}, R\Big) \ \to_p \ 0$$

and

$$\frac{1}{n^2}\sum_{i,j=1}^n \min\big\{|X_i^\top X_j/q|, 1\big\} \ \to_p \ 0$$

as $\min(q,n) \to \infty$. Thus Theorem 2.1 implies that

$$\Gamma^\top \widehat{P} = \frac{1}{n}\sum_{i=1}^n \delta_{\Gamma^\top X_i} \ \to_{w,p} \ \int \mathcal{N}_{d,v}\, R(dv)$$

as both q and n tend to infinity, where the random projector Γ and the empirical distribution $\widehat{P}$ are assumed to be stochastically independent.

Comparing P and $\widehat{P}$, part 1. In some sense Theorem 2.1 is a negative, though mathematically elegant result. It warns us against hasty conclusions about high-dimensional data sets after examining a couple of low-dimensional projections. In particular, one should not believe in multivariate normality only because several projections of the data "look normal". On the other hand, even small differences between different low-dimensional projections of $\widehat{P}$ may be intriguing. Therefore we study the relationship between projections of the empirical distribution $\widehat{P}$ and corresponding projections of P in more detail.

In particular, we are interested in the halfspace norm

$$\|\Gamma^\top \widehat{P} - \Gamma^\top P\|_{\mathrm{KS}} \ := \sup_{\text{closed halfspaces } H\subset\mathbb{R}^d} |\Gamma^\top \widehat{P}(H) - \Gamma^\top P(H)|$$

of $\Gamma^\top \widehat{P} - \Gamma^\top P$. In case of $d = 1$ this is the usual Kolmogorov-Smirnov norm of $\Gamma^\top \widehat{P} - \Gamma^\top P$. In what follows we use several well-known results from empirical process theory. Instead of citing original papers in various places we simply refer to the excellent monographs of [12] and [14]. It is known that

$$\mathbb{E} \sup_{\gamma\in\mathbb{R}^{q\times d}} \|\gamma^\top \widehat{P} - \gamma^\top P\|_{\mathrm{KS}} \ \le \ C\sqrt{q/n} \tag{1}$$

for some universal constant C. For the latter supremum is just the halfspace norm of $\widehat{P} - P$, and generally the set of closed halfspaces in $\mathbb{R}^k$ is a Vapnik-Cervonenkis class with Vapnik-Cervonenkis index $k+1$. Inequality (1) does not capture the *typical* deviation between d-dimensional projections of $\widehat{P}$ and P. In fact,

$$\sup_{\gamma\in\mathbb{R}^{q\times d}} \mathbb{E}\, \|\gamma^\top \widehat{P} - \gamma^\top P\|_{\mathrm{KS}} \ \le \ C\sqrt{d/n},$$

which implies that

$$\mathbb{E}\, \|\Gamma^\top \widehat{P} - \Gamma^\top P\|_{\mathrm{KS}} \ \le \ C\sqrt{d/n}. \tag{2}$$

Our next result implies the limiting distribution of $\sqrt{n}\|\Gamma^\top \widehat{P} - \Gamma^\top P\|_{\mathrm{KS}}$ under conditions (A1-2). More generally, let $\mathcal{H}$ be a class of measurable functions from $\mathbb{R}^d$ into $[-1,1]$. Any finite signed measure M on $\mathbb{R}^d$ defines an element $h \mapsto M(h) := \int h\, dM$ of the space $\ell_\infty(\mathcal{H})$ of all bounded functions on $\mathcal{H}$ equipped with supremum norm $\|z\|_{\mathcal{H}} := \sup_{h\in\mathcal{H}} |z(h)|$. We shall impose the following three conditions on the class $\mathcal{H}$ and the distribution $Q = \int \mathcal{N}_{d,v}\, R(dv)$:

(C1) There exists a countable subset $\mathcal{H}_o$ of $\mathcal{H}$ auch that each $h \in \mathcal{H}$ can be represented as pointwise limit of some sequence in $\mathcal{H}_o$.

(C2) The set $\mathcal{H}$ satisfies the uniform entropy condition

$$\int_0^1 \sqrt{\log N(u,\mathcal{H})}\, du \ < \ \infty.$$

Here $N(u,\mathcal{H})$ is the supremum of $N(u,\mathcal{H},\tilde{Q})$ over all probability measures $\tilde{Q}$ on $\mathbb{R}^d$, and $N(u,\mathcal{H},\tilde{Q})$ is the smallest number m such that $\mathcal{H}$ can be covered with m balls having radius u with respect to the pseudodistance

$$\rho_{\tilde{Q}}(g,h) \ := \ \sqrt{\tilde{Q}((g-h)^2)}.$$

(C3) For any sequence $(Q_k)_k$ of probability measures converging weakly to Q,

$$\|Q_k - Q\|_{\mathcal{H}} \ \to \ 0 \quad \text{as } k \to \infty.$$

Condition (C1) ensures that random elements such as $\|\Gamma^\top \widehat{P} - \Gamma^\top P\|_{\mathcal{H}}$ are measurable. An example for conditions (C1-2) is the set $\mathcal{H}$ of (indicators of) closed halfspaces in $\mathbb{R}^d$. Then condition (C3) is a consequence of general results by [2], provided that $Q(\{0\}) = 0$, i.e. $R(\{0\}) = 0$.

A particular consequence of (C2) is existence of a centered Gaussian process B_Q, a so-called Q-bridge, having uniformly continuous sample paths with respect to ρ_Q and covariances

$$\mathbb{E}\big(B_Q(g)B_Q(h)\big) \ = \ Q(gh) - Q(g)Q(h),$$

which can be proved via a Chaining argument.

Theorem 3.1. *Suppose that the sequence $(P^{(q)})_{q \ge d}$ satisfies conditions (A1-2) of Theorem 2.1, and suppose that $\mathcal{H}$ fulfills conditions (C1-3). Then*

$$B^{(q,n)} \ := \ \Big(n^{1/2}\big(\Gamma^\top \widehat{P} - \Gamma^\top P\big)(h)\Big)_{h \in \mathcal{H}}$$

converges in distribution in $\ell_\infty(\mathcal{H})$ to B_Q as $\min(q,n) \to \infty$.

Comparing P and $\widehat{P}$, part 2. Theorem 3.1 takes into account the randomness in both the data (i.e. $\widehat{P}$) and the projection matrix Γ. However, exploratory projection pursuit means considering *several* projections of *one* data set. Thus we consider independent copies $\Gamma_\ell = \Gamma_\ell^{(q)}$, $\ell \ge 1$, of Γ which are also independent from $\widehat{P}$. With these projection matrices we define

$$B_\ell^{(q,n)} \ := \ \Big(n^{1/2}\big(\Gamma_\ell^\top \widehat{P} - \Gamma_\ell^\top P\big)(h)\Big)_{h \in \mathcal{H}}$$

and study the distribution of

$$\boldsymbol{B}^{(q,n)} \ := \ \big(B_\ell^{(q,n)}(h)\big)_{(\ell,h) \in \Lambda \times \mathcal{H}}$$

for $\Lambda := \{1, \ldots, L\}$ with an arbitrary fixed integer $L \ge 1$.

Subsequently a particular decomposition of the Q-Brigde B_Q will be used:

$$B_Q \ = \ B_Q' + B_Q''$$

with stochastically independent and centered Gaussian processes B_Q', B_Q'' on $\mathcal{H}$, where

$$\begin{aligned}
\mathbb{E}\big(B_Q'(g)B_Q'(h)\big) \ &= \ Q(gh) - \int \mathcal{N}_{d,v}(g)\,\mathcal{N}_{d,v}(h)\,R(dv) \\
&= \ \int \big(\mathcal{N}_{d,v}(gh) - \mathcal{N}_{d,v}(g)\mathcal{N}_{d,v}(h)\big)\,R(dv) \\
\mathbb{E}\big(B_Q''(g)B_Q''(h)\big) \ &= \ \int \mathcal{N}_{d,v}(g)\mathcal{N}_{d,v}(h)\,R(dv) - Q(g)Q(h).
\end{aligned}$$

By means of Anderson's Lemma (cf. [1]) or a further application of Chaining one can show that both B'_Q and B''_Q admit versions with uniformly continuous sample paths.

Theorem 3.2. *Suppose that the conditions of Theorem 3.1 are satisfied. Further, let* $B'_{Q,1}, B'_{Q,2}, B'_{Q,3}, \ldots$ *be independent copies of* B'_Q *and independent from* B''_Q. *Then for any fixed integer* $L \ge 1$, *the process* $\boldsymbol{B}^{(q,n)} = \big(B_\ell^{(q,n)}(h)\big)_{(\ell,h)\in\Lambda\times\mathcal{H}}$ *converges in distribution in* $\ell_\infty(\Lambda\times\mathcal{H})$ *to*

$$\boldsymbol{B} \ := \ \big(B'_{Q,\ell}(h) + B''_Q(h)\big)_{(\ell,h)\in\Lambda\times\mathcal{H}}$$

as $\min(q,n)\to\infty$.

Remark 3.3 (Understanding the decomposition $B_Q = B'_Q + B''_Q$ heuristically). Note that $B^{(q,n)}(h) = \sqrt{n}\int h(\Gamma^\top x)\,(\widehat{P}-P)(dx)$. Thus

$$\begin{aligned} \mathbb{E}\big(B^{(q,n)}(h)\,\big|\,\widehat{P}\big) &= \sqrt{n}\int \mathbb{E}\, h(\Gamma^\top x)\,(\widehat{P}-P)(dx) \\ &= \sqrt{n}\int \tilde{\mathcal{N}}_{d,q,\|x\|}(h)\,(\widehat{P}-P)(dx) \end{aligned}$$

with $\tilde{\mathcal{N}}_{d,q,\|x\|} := \mathcal{L}(\Gamma^\top x)$. Here we utilize orthogonal invariance of $\mathcal{L}(\Gamma)$. Consequently, $\mathbb{E}(B^{(q,n)}\,|\,\widehat{P})$ is a standardized empirical process indexed by the special functions $x \mapsto \tilde{\mathcal{N}}_{d,q,\|x\|}(h)$, $h\in\mathcal{H}$, and

$$\begin{aligned} &\mathbb{E}\Big(\mathbb{E}\big(B^{(q,n)}(g)\,\big|\,\widehat{P}\big)\,\mathbb{E}\big(B^{(q,n)}(h)\,\big|\,\widehat{P}\big)\Big) \\ &\quad = \int \tilde{\mathcal{N}}_{d,q,\|x\|}(g)\tilde{\mathcal{N}}_{d,q,\|x\|}(h)\,P(dx) - \int \tilde{\mathcal{N}}_{d,q,\|x\|}(g)\,P(dx)\int \tilde{\mathcal{N}}_{d,q,\|x\|}(h)\,P(dx). \end{aligned}$$

Since $\tilde{\mathcal{N}}_{d,q,\|x\|}$ is close to $\mathcal{N}_{d,\|x\|^2/q}$ and $\mathcal{L}(\|X\|^2/q)$ is close to R for large q, the latter covariance is close to

$$\int \mathcal{N}_{d,v}(g)\mathcal{N}_{d,v}(h)\,R(dv) - \int \mathcal{N}_{d,v}(g)\,R(dv)\int \mathcal{N}_{d,v}(h)\,R(dv) \ = \ \mathbb{E}\big(B''_Q(g)B''_Q(h)\big).$$

Example 3.4. Suppose that $d = 1$, and let $\mathcal{H}$ consist of all indicator functions $1_{(-\infty,t]}$, $t\in\mathbb{R}$. Then Theorems 3.1 and 3.2 are applicable whenever $R(\{0\}) = 0$. Writing $M(t)$ instead of $M(1_{(-\infty,t]})$, the covariance functions of B_Q, B'_Q and B''_Q are given by

$$\begin{aligned} \mathbb{E}\big(B_Q(s)B_Q(t)\big) &= Q(\min\{s,t\}) - Q(s)Q(t), \\ \mathbb{E}\big(B'_Q(s)B'_Q(t)\big) &= Q(\min\{s,t\}) - \int \Phi(v^{-1/2}s)\Phi(v^{-1/2}t)\,R(dv), \\ \mathbb{E}\big(B''_Q(s)B''_Q(t)\big) &= \int \Phi(v^{-1/2}s)\Phi(v^{-1/2}t)\,R(dv) - Q(s)Q(t) \end{aligned}$$

for $s,t\in\mathbb{R}$, where $Q(u) = \int \Phi(v^{-1/2}u)\,R(dv)$, and Φ denotes the standard Gaussian distribution function.

Remark 3.5 (Conservative inference). Under conditions (A1-2) and (C1-3), *pretending* the empirical processes $B_\ell^{(q,n)}$, $1\le\ell\le L$, to be independent and identically distributed leads typically to conservative procedures. Precisely, let U be an open subset of $\ell_\infty(\mathcal{H})$. For instance let $U = \{b \in \ell_\infty(\mathcal{H}) : \|b\|_{\mathcal{H}} < \kappa\}$ for some constant $\kappa > 0$. Then it follows from Theorem 3.2 that

$$\liminf_{\min(q,n)\to\infty} \mathbb{P}\big(B_\ell^{(q,n)} \in U \text{ for } 1 \le \ell \le L\big) \ \ge \ \mathbb{P}(B_Q \in U)^L.$$

This may be verified as follows: By Theorem 3.2 and the Portmanteau Theorem, the limes inferior on the left hand side is not smaller than

$$\begin{aligned} \mathbb{P}\big(B'_{Q,\ell} + B''_Q \in U \text{ for } 1 \le \ell \le L\big) &= \mathbb{E}\,\mathbb{P}\big(B'_{Q,\ell} + B''_Q \in U \text{ for } 1 \le \ell \le L \,\big|\, B''_Q\big) \\ &= \mathbb{E}\Big(\mathbb{P}\big(B'_Q + B''_Q \in U \,\big|\, B''_Q\big)^L\Big), \end{aligned}$$

and by Jensen's inequality the latter expression is not smaller than

$$\Big(\mathbb{E}\,\mathbb{P}\big(B'_Q + B''_Q \in U \,\big|\, B''_Q\big)\Big)^L \ = \ \mathbb{P}(B'_Q + B''_Q \in U)^L \ = \ \mathbb{P}(B_Q \in U)^L.$$

If (A.1-2) is strengthened to (B) and $\mathbb{P}(B_Q \in \partial U) = 0$, then the previous arguments lead to

$$\left.\begin{aligned} \lim_{\min(q,n)\to\infty} \mathbb{P}\big(B_\ell^{(q,n)} \in U \text{ for } 1 \le \ell \le L\big) \\ \lim_{\min(q,n)\to\infty} \mathbb{P}\big(B_\ell^{(q,n)} \in \overline{U} \text{ for } 1 \le \ell \le L\big) \end{aligned}\right\} \ = \ \mathbb{P}(B_Q \in U)^L,$$

because $B''_Q \equiv 0$ almost surely.

Remark 3.6 (The conditional point of view). Considering several projections of one data set means that we are interested in the *conditional* distribution of $n^{1/2}(\Gamma^\top \widehat{P} - \Gamma^\top P)$, *given* $\widehat{P}$. Indeed one may interpret Theorem 3.2 in the sense that for large q and n,

$$\mathcal{L}\big(B^{(q,n)} \,\big|\, \widehat{P}\big) \ \approx \ \mathcal{L}\big(B'_Q + B''_Q \,\big|\, B''_Q\big).$$

In case of the stronger condition (B) in Corollary 2.2, $B''_Q \equiv 0$, and

$$\mathcal{L}\big(B^{(q,n)} \,\big|\, \widehat{P}\big) \ \approx \ \mathcal{L}(B_Q).$$

Here are precise statements:

Corollary 3.7. *Suppose that the conditions of Theorem 3.1 are satisified. Let F be any bounded and continuous functional on $\ell_\infty(\mathcal{H})$ such that $F(B^{(q,n)})$ is measurable for all $q \ge d$ and $n \ge 1$. Then*

$$\mathbb{E}\big(F(B^{(q,n)}) \,\big|\, \widehat{P}\big) \ \to_{\mathcal{L}} \ \mathbb{E}\big(F(B'_Q + B''_Q) \,\big|\, B''_Q\big)$$

as $\min(q,n) \to \infty$. *In case of a degenerate distribution R,*

$$\mathbb{E}\big(F(B^{(q,n)}) \,\big|\, \widehat{P}\big) \ \to_p \ \mathbb{E}\, F(B_Q)$$

as $\min(q,n) \to \infty$.

4. Proofs

4.1. Hoeffding's (1952) trick

In connection with randomization tests, [7] observed that weak convergence of conditional distributions of test statistics is equivalent to the weak convergence of the *unconditional* distribution of suitable statistics in $\mathbb{R}^2$. His result can be extended straightforwardly as follows.

Lemma 4.1 (Hoeffding)**.** *For $k \ge 1$ let $X_k, \tilde{X}_k \in \mathbb{X}_k$ and $G_k \in \mathbb{G}_k$ be independent random variables, where $X_k, \tilde{X}_k$ are identically distributed. Further let m_k be some measurable mapping from $\mathbb{X}_k \times \mathbb{G}_k$ into the separable metric space $(\mathbb{M}, \rho)$, and let Q be a fixed Borel probability measure on $\mathbb{M}$. Then, as $k \to \infty$, the following two assertions are equivalent:*

(D1)
$$\mathcal{L}\big(m_k(X_k, G_k) \,\big|\, G_k\big) \ \to_{w,p} \ Q.$$

(D2)
$$\mathcal{L}\big(m_k(X_k, G_k), m_k(\tilde{X}_k, G_k)\big) \ \to_w \ Q \otimes Q.$$

Applications of this equivalence with non-Euclidean spaces $\mathbb{M}$ are presented by [13]. We shall utilize Lemma 4.1 in order to prove Theorem 2.1.

Proof of Lemma 4.1. Define $Y_k := m_k(X_k, G_k)$ and $\tilde{Y}_k := m_k(\tilde{X}_k, G_k)$. Suppose first that (D2) ist true, i.e. $\mathcal{L}(Y_k, \tilde{Y}_k) \to_w Q \otimes Q$. Then for any $f \in \mathcal{C}_b(\mathbb{M})$,

$$\begin{aligned}
&\mathbb{E}\Big(\big(\mathbb{E}(f(Y_k) \,|\, G_k) - Q(f)\big)^2\Big) \\
&\quad = \ \mathbb{E}\big(\mathbb{E}(f(Y_k) \,|\, G_k)^2\big) - 2Q(f)\ \mathbb{E}\,\mathbb{E}(f(Y_k) \,|\, G_k) + Q(f)^2 \\
&\quad = \ \mathbb{E}\,\mathbb{E}\big(f(Y_k)f(\tilde{Y}_k) \,\big|\, G_k\big) - 2Q(f)\ \mathbb{E}\,\mathbb{E}(f(Y_k) \,|\, G_k) + Q(f)^2 \\
&\quad = \ \mathbb{E}\big(f(Y_k)f(\tilde{Y}_k)\big) - 2Q(f)\,\mathbb{E}\,f(Y_k) + Q(f)^2 \\
&\quad \to \ \int f(y)f(\tilde{y})\,Q(dy)Q(d\tilde{y}) - Q(f)^2 \\
&\quad = \ 0.
\end{aligned}$$

Thus $\mathcal{L}(Y_k \,|\, G_k) \to_{w,p} Q$.

On the other hand, suppose that (D1) is satisfied, i.e. $\mathcal{L}(Y_k \,|\, G_k) \to_{w,p} Q$. Then for arbitrary $f, g \in \mathcal{C}_b(\mathbb{M})$,

$$\begin{aligned}
\mathbb{E}\big(f(Y_k)g(\tilde{Y}_k)\big) \ &= \ \mathbb{E}\,\mathbb{E}\big(f(Y_k)g(\tilde{Y}_k) \,\big|\, G_k\big) \\
&= \ \mathbb{E}\big(\mathbb{E}(f(Y_k) \,|\, G_k)\ \mathbb{E}(f(\tilde{Y}_k) \,|\, G_k)\big) \\
&\to \ Q(f)Q(g),
\end{aligned}$$

because $\mathbb{E}(h(Y_k) \,|\, G_k) \ \to_p \ \int h\,dQ$ and $\big|\mathbb{E}(h(Y_k) \,|\, G_k)\big| \ \le \ \|h\|_\infty \ < \ \infty$ for each $h \in \mathcal{C}_b(\mathbb{M})$. Thus we know that $\mathbb{E}\,F(Y_k, \tilde{Y}_k) \to \int F\,dQ \otimes Q$ for arbitrary functions $F(y, \tilde{y}) = f(y)g(\tilde{y})$ with $f, g \in \mathcal{C}_b(\mathbb{M})$. But this is known to be equivalent to weak convergence of $\mathcal{L}(Y_k, \tilde{Y}_k)$ to $Q \otimes Q$; see Chapter 1.4 of [14].

Here is an alternative argument: With $\widehat{Q}_k := \mathcal{L}(Y_k \,|\, G_k)$, Assumption (D1) is equivalent to $D_{\mathrm{BL}}(\widehat{Q}_k, Q) \to_p 0$. To prove that $\mathcal{L}(Y_k, \tilde{Y}_k) \to Q \otimes Q$, it suffices to show that $\mathbb{E}\big(F(Y_k, \tilde{Y}_k) \,\big|\, G_k\big) \to_p \int F\,dQ \otimes Q$ for any function $F : \mathbb{M} \times \mathbb{M} \to [-1, 1]$ such that $\big|F(y, \tilde{y}) - F(z, \tilde{z})\big| \le \rho(y, z) + \rho(\tilde{y}, \tilde{z})$ for arbitrary $y, \tilde{y}, z, \tilde{z} \in \mathbb{M}$. But this entails that $F(y, \cdot), F(\cdot, \tilde{y}) \in \mathcal{F}_{\mathrm{BL}}$ for arbitrary $y, \tilde{y} \in \mathbb{M}$. Consequently,

$$\begin{aligned}
&\Big|\mathbb{E}\big(F(Y_k, \tilde{Y}_k) \,\big|\, G_k\big) - \int F\,dQ \otimes Q\Big| \\
&\quad = \ \Big|\int F\,d\big(\widehat{Q}_k \otimes \widehat{Q}_k - Q \otimes Q\big)\Big| \\
&\quad \le \ \int \Big|\int F(\cdot, \tilde{y})\,d\big(\widehat{Q}_k - Q\big)\Big|\,\widehat{Q}_k(d\tilde{y}) + \int \Big|\int F(y, \cdot)\,d\big(\widehat{Q}_k - Q\big)\Big|\,Q(dy) \\
&\quad \le \ 2D_{\mathrm{BL}}(\widehat{Q}_k, Q).
\end{aligned}$$

□

4.2. Proofs for Section 2

That $\Gamma = \Gamma^{(q)}$ is "uniformly" distributed on the set of column-wise orthonormal matrices in $\mathbb{R}^{q\times d}$ means that $\mathcal{L}(U\Gamma) = \mathcal{L}(\Gamma)$ for any fixed orthonormal matrix $U \in \mathbb{R}^{q\times q}$. For existence and uniqueness of the latter distribution we refer to Chapters 1-2 of [6]. For the present purposes the following explicit construction of Γ described in Chapter 7 of [6] is sufficient. Let $Z = Z^{(q)} := (Z_1, Z_2, \ldots, Z_d)$ be a random matrix in $\mathbb{R}^{q\times d}$ with independent, standard Gaussian column vectors $Z_j \in \mathbb{R}^q$. Then

$$\Gamma \ := \ Z(Z^\top Z)^{-1/2}$$

has the desired distribution, and

$$\Gamma \ = \ q^{-1/2} Z\,(I + O_p(q^{-1/2})) \quad \text{as } q \to \infty. \tag{3}$$

This equality can be viewed as an extension of Poincaré's [11] Lemma.

Proof of Theorem 2.1. Let $\Gamma = \Gamma(Z)$ as above. Suppose that $Z = Z^{(q)}$, $X = X^{(q)}$ and $\tilde{X} = \tilde{X}^{(q)}$ are independent with $\mathcal{L}(X) = \mathcal{L}(\tilde{X}) = P$, and let $Y, \tilde{Y}$ be two independent random vectors in $\mathbb{R}^d$ with distribution Q. According to Lemma 4.1, condition (A1) is equivalent to

$$(\mathbf{A1'}) \qquad \begin{pmatrix} \Gamma^\top X \\ \Gamma^\top \tilde{X} \end{pmatrix} \ \to_{\mathcal{L}} \ \begin{pmatrix} Y \\ \tilde{Y} \end{pmatrix}.$$

Because of equation (3) this can be rephrased as

$$(\mathbf{A1''}) \qquad \begin{pmatrix} Y^{(q)} \\ \tilde{Y}^{(q)} \end{pmatrix} := \begin{pmatrix} q^{-1/2} Z^\top X \\ q^{-1/2} Z^\top \tilde{X} \end{pmatrix} \ \to_{\mathcal{L}} \ \begin{pmatrix} Y \\ \tilde{Y} \end{pmatrix}.$$

Now we prove equivalence of (A1") and (A2) starting from the observation that

$$\mathcal{L}\left(\begin{pmatrix} Y^{(q)} \\ \tilde{Y}^{(q)} \end{pmatrix}\right) \ = \ \mathbb{E}\, \mathcal{L}\left(\begin{pmatrix} Y^{(q)} \\ \tilde{Y}^{(q)} \end{pmatrix} \,\Big|\, X, \tilde{X}\right) \ = \ \mathbb{E}\, \mathcal{N}_{2d}(0, \Sigma^{(q)}),$$

where

$$\Sigma^{(q)} \ := \ \begin{pmatrix} q^{-1}\|X\|^2\, I_d & q^{-1} X^\top \tilde{X}\, I_d \\ q^{-1} X^\top \tilde{X}\, I_d & q^{-1}\|\tilde{X}\|^2\, I_d \end{pmatrix} \ \in \ \mathbb{R}^{2d\times 2d}.$$

Suppose that condition (A2) holds. Then $\Sigma^{(q)}$ converges in distribution to a random diagonal matrix

$$\Sigma \ := \ \begin{pmatrix} S^2\, I_d & 0 \\ 0 & \tilde{S}^2\, I_d \end{pmatrix}$$

with independent random variables $S^2, \tilde{S}^2$ having distribution R. Clearly this implies that

$$\mathbb{E}\, \mathcal{N}_{2d}(0, \Sigma^{(q)}) \ \to_w \ \mathbb{E}\, \mathcal{N}_{2d}(0, \Sigma) \ = \ \mathcal{L}\left(\begin{pmatrix} Y \\ \tilde{Y} \end{pmatrix}\right)$$

with $Q = \mathbb{E}\, \mathcal{N}_d(0, S^2 I_d)$. Hence (A1") holds.

On the other hand, suppose that (A1") holds. For any $t = (t_1^\top, t_2^\top)^\top \in \mathbb{R}^{2d}$, the Fourier transform of $\mathcal{L}\big((Y^{(q)\top}, \tilde{Y}^{(q)\top})^\top\big)$ at t equals

$$\mathbb{E}\, \exp\big(\boldsymbol{i}\,(t_1^\top Y^{(q)} + t_2^\top \tilde{Y}^{(q)})\big) \ = \ \mathbb{E}\, \exp(-t^\top \Sigma^{(q)} t/2) \ = \ H^{(q)}(a(t)),$$

where $\boldsymbol{i}$ stands for $\sqrt{-1}$, $a(t) := \big(\|t_1\|^2/2, \|t_2\|^2/2, t_1^\top t_2\big)^\top \in \mathbb{R}^3$, and

$$H^{(q)}(a) \ := \ \mathbb{E} \exp\big(-a_1\|X\|^2/q - a_2\|\tilde{X}\|^2/q - a_3 X^\top \tilde{X}/q\big)$$

denotes the Laplace transform of $\mathcal{L}\big(\big(\|X\|^2/q, \|\tilde{X}\|^2/q, X^\top\tilde{X}/q\big)^\top\big)$ at $a \in \mathbb{R}^3$. By assumption, the Fourier transform at t converges to

$$\mathbb{E}\exp(\boldsymbol{i}\, t_1^\top Y)\ \mathbb{E}\exp(\boldsymbol{i}\, t_2^\top Y).$$

Setting $t_2 = 0$ and varying t_1 shows that the Laplace transform of $\mathcal{L}(\|X\|^2/q)$ converges pointwise on $[0,\infty)$ to a continuous function. Hence $\|X\|^2/q$ converges in distribution to some random variable $S^2 \ge 0$, and $Q = \mathbb{E}\mathcal{N}_{d,S^2}$. Therefore, if $\tilde{S}^2$ denotes an independent copy of S^2, we know that $H^{(q)}(a(t))$ converges to

$$\mathbb{E}\exp(-a_1(t)S^2)\,\mathbb{E}\exp(-a_2(t)S^2) \ = \ \mathbb{E}\exp\big(-a_1(t)S^2 - a_2(t)\tilde{S}^2 - a_3(t)\cdot 0\big).$$

A problem at this point is that for dimension $d = 1$ the set $\{a(t) : t \in \mathbb{R}^{2d}\} \subset \mathbb{R}^3$ has empty interior. Thus we cannot apply the standard argument about weak convergence and convergence of Laplace transforms. However, letting $t_2 = \pm t_1$ with $\|t_1\|^2/2 = 1$, one may conclude that

$$\begin{aligned}
0 \ &= \ \lim_{q\to\infty} \big(H^{(q)}(1,1,2) + H^{(q)}(1,1,-2) - 2H^{(q)}(1,0,0)^2\big) \\
&= \ \lim_{q\to\infty} \big(H^{(q)}(1,1,2) + H^{(q)}(1,1,-2) - 2\ \mathbb{E}\exp(-\|X\|^2/q - \|\tilde{X}\|^2/q)\big) \\
&= \ 2\lim_{q\to\infty} \mathbb{E}\Big(\exp\big(-\|X\|^2/q - \|\tilde{X}\|^2/q\big)\big(\cosh(2X^\top\tilde{X}/q) - 1\big)\Big).
\end{aligned}$$

But for arbitrary small $\epsilon > 0$ and large $r > 0$,

$$\begin{aligned}
&\mathbb{E}\Big(\exp\big(-\|X\|^2/q - \|\tilde{X}\|^2/q\big)\big(\cosh(2X^\top\tilde{X}/q) - 1\big)\Big) \\
&\quad \ge \ \exp(-2r)(\cosh(2\epsilon) - 1)\ \mathbb{P}\big(\|X\|^2/q < r, \|\tilde{X}\|^2/q < r, |X^\top\tilde{X}/q| \ge \epsilon\big) \\
&\quad \ge \ \exp(-2r)(\cosh(2\epsilon) - 1)\ \Big(\mathbb{P}\big(|X^\top\tilde{X}/q| \ge \epsilon\big) - 2\,\mathbb{P}(\|X\|^2/q \ge r)\Big) \\
&\quad \ge \ \exp(-2r)(\cosh(2\epsilon) - 1)\ \Big(\mathbb{P}\big(|X^\top\tilde{X}/q| \ge \epsilon\big) - 2\,\mathbb{P}(S^2 \ge r) + o(1)\Big).
\end{aligned}$$

Hence

$$\limsup_{q\to\infty} \mathbb{P}\big(|X^\top\tilde{X}/q| \ge \epsilon\big) \ \le \ 2\,\mathbb{P}(S^2 \ge r).$$

Letting $r \to \infty$ shows that $X^\top\tilde{X}/q \to_p 0$. □

Proof of equivalence of (A2) and (A3). Proving that (A3) implies (A2) is elementary. In order to show that (A2) implies (A3) note first that conditions (A2) for the distributions $P^{(q)}$ imply the same conditions for the symmetrized distributions

$$P_o = P_o^{(q)} \ := \ \mathcal{L}(X - \tilde{X}) \ = \ \mathcal{L}\Big(\big(\sigma_k(Z_k - Z_{q+k})\big)_{1\le k\le q}\Big).$$

Condition (A2) for these distributions reads as follows.

$$\mathcal{L}\Big(\sum_{k=1}^q (Z_k - Z_{q+k})^2\sigma_k^2/q\Big) \ \to_w \ R_o = R \star R \quad \text{and} \tag{4}$$

$$\sum_{k=1}^q (Z_k - Z_{q+k})(Z_{2q+k} - Z_{3q+k})\sigma_k^2/q \ \to_p \ 0. \tag{5}$$

The factors $(Z_k - Z_{q+k})(Z_{2q+k} - Z_{3q+k})$, $1 \le k \le q$, in (5) are independent, identically and symmetrically distributed. By conditioning on any one of these factors one can deduce from (5) that $\max_{1\le k\le q} \sigma_k^2/q \to 0$. But then

$$\sum_{k=1}^{q} \sigma_k^2 (Z_k - Z_{q+k})^2/q \;=\; 2\|\sigma\|^2/q + o_p(1 + \|\sigma\|^2/q),$$

and one can deduce from (4) that $\|\sigma\|^2/q$ converges to some fixed number v; in particular, $R = \delta_v$. Now we return to the original distributions P. Here the second half of (A2) means that

$$\begin{aligned}
&\sum_{k=1}^{k} (\mu_k + \sigma_k Z_k)(\mu_k + \sigma_k Z_{q+k})/q \\
&= \|\mu\|^2/q + \sum_{k=1}^{q} \mu_k \sigma_k (Z_k + Z_{q+k})/q + \sum_{k=1}^{q} \sigma_k^2 Z_k Z_{q+k}/q \\
&= o_p(1).
\end{aligned}$$

Since

$$\begin{aligned}
\mathbb{E}\Big(\Big(\sum_{k=1}^{q} \mu_k \sigma_k (Z_k + Z_{q+k})/q \Big)^2 \Big) &= \sum_{k=1}^{q} \mu_k^2 \sigma_k^2 / q^2 \;=\; o(\|\mu\|^2/q), \\
\mathbb{E}\Big(\Big(\sum_{k=1}^{q} \sigma_k^2 Z_k Z_{q+k}/q \Big)^2 \Big) &= \sum_{k=1}^{q} \sigma_k^4/q^2 \;\to\; 0,
\end{aligned}$$

it follows that $\|\mu\|^2/q \to 0$. □

4.3. Proofs for Section 3

Since Theorem 3.1 is just Theorem 3.2 with $L = 1$, it suffices to verify the latter.

Proof of Theorem 3.2. It suffices to verify the following two claims:

(F1) As $q \to \infty$ and $n \to \infty$, the finite-dimensional marginal distributions of the process $\boldsymbol{B}^{(q,n)}$ converge to the corresponding finite-dimensional distributions of $\boldsymbol{B}$.
(F2) As $q \to \infty$, $n \to \infty$ and $\delta \downarrow 0$,

$$\max_{\ell \in \Lambda} \sup_{g,h \in \mathcal{H}: \rho_Q(g,h) < \delta} \Big| B_\ell^{(q,n)}(g) - B_\ell^{(q,n)}(h) \Big| \;\to_p\; 0.$$

The second condition, (F2), means that the processes $\boldsymbol{B}^{(q,n)}$ are asymptotically equicontinuous with respect to the pseudodistance

$$\boldsymbol{\rho}_Q\big((\ell, g), (m, h)\big) \;:=\; 1\{\ell \ne m\} + \rho_Q(g,h)$$

on $\Lambda \times \mathcal{H}$.

In order to verify assertions (F1-2) we consider the conditional distribution of $\boldsymbol{B}^{(q,n)}$ given the random matrix

$$\boldsymbol{\Gamma} = \boldsymbol{\Gamma}^{(q)} \;:=\; (\Gamma_1, \Gamma_2, \ldots, \Gamma_L) \;\in\; \mathbb{R}^{q \times Ld}.$$

In fact, if we define

$$f_{\ell,h}(\boldsymbol{v}) \ := \ h(v_\ell) \quad \text{for } \boldsymbol{v} = (v_1^\top, \ldots, v_L^\top)^\top \in \mathbb{R}^{Ld},$$

then

$$B_\ell^{(q,n)}(h) \ = \ n^{1/2}(\boldsymbol{\Gamma}^\top \widehat{P} - \boldsymbol{\Gamma}^\top P)(f_{\ell,h}).$$

Thus $\mathcal{L}(\boldsymbol{B}^{(q,n)} \,|\, \boldsymbol{\Gamma})$ is essentially the distribution of an empirical process based on n independent random vectors with distribution $\boldsymbol{\Gamma}^\top P$ on $\mathbb{R}^{Ld}$ and indexed by the family $\tilde{\mathcal{H}} := \{f_{\ell,h} : \ell \in \Lambda, h \in \mathcal{H}\}$.

The multivariate version of Lindeberg's Central Limit Theorem entails that for large q and n, the finite-dimensional marginal distributions of $\boldsymbol{B}^{(q,n)}$, conditional on $\boldsymbol{\Gamma}$, can be approximated by the corresponding finite-dimensional distributions of a centered Gaussian process on $\Lambda \times \mathcal{H}$ with the same covariance function, namely,

$$\begin{aligned} \Sigma^{(q)}\big((\ell,g),(m,h)\big) \ &:= \ \mathrm{Cov}\big(B_\ell^{(q,n)}(g), B_m^{(q,n)}(h) \,\big|\, \boldsymbol{\Gamma}\big) \\ &= \ \boldsymbol{\Gamma}^\top P(f_{\ell,g} f_{m,h}) - \boldsymbol{\Gamma}^\top P(f_{\ell,g}) \boldsymbol{\Gamma}^\top P(f_{m,h}). \end{aligned}$$

It follows from equality (3) and the proof of Theorem 2.1 that

$$\boldsymbol{\Gamma}^\top P \ \to_{w,p} \ \boldsymbol{Q} \ := \ \int \mathcal{N}_{Ld,v}\, R(dv) \quad \text{as } q \to \infty,$$

and this should imply convergence of $\Sigma^{(q)}$ to some limiting function as well. It was shown by [2] that condition (C3) is equivalent to

$$\lim_{\delta \downarrow 0} \sup_{h \in \mathcal{H}} Q\Big\{ y \in \mathbb{R}^d : \sup_{z : \|z-y\| < \delta} |h(z) - h(y)| > \epsilon \Big\} \ = \ 0 \quad \text{for any } \epsilon > 0. \tag{6}$$

Note that the d-dimensional marginal distributions of $\boldsymbol{Q}$ are just Q. Therefore one can easily deduce from (6) that for any fixed $\epsilon > 0$,

$$\lim_{\delta \downarrow 0} \sup_{f', f'' \in \tilde{\mathcal{H}} \cup \{1\}} \boldsymbol{Q}\Big\{ \boldsymbol{v} \in \mathbb{R}^{Ld} : \sup_{\boldsymbol{w} : \|\boldsymbol{w} - \boldsymbol{v}\| < \delta} |f'f''(\boldsymbol{w}) - f'f''(\boldsymbol{v})| > \epsilon \Big\} \ = \ 0.$$

Hence a second application of [2] shows that

$$\sup_{f', f'' \in \tilde{\mathcal{H}} \cup \{1\}} |\boldsymbol{\Gamma}^\top P(f'f'') - \boldsymbol{Q}(f'f'')| \ \to \ 0 \quad \text{as } q \to \infty, \tag{7}$$

because $\boldsymbol{\Gamma}^\top P \to_{w,p} \boldsymbol{Q}$. In particular, the conditional covariance function $\Sigma^{(q)}$ converges uniformly in probability to the covariance function Σ, where

$$\begin{aligned} \Sigma\big((\ell,g),(m,h)\big) \ &:= \ \boldsymbol{Q}(f_{\ell,g} f_{m,h}) - \boldsymbol{Q}(f_{\ell,g}) \boldsymbol{Q}(f_{m,h}) \\ &= \ \int \mathcal{N}_{Ld,v}(f_{\ell,g} f_{m,h})\, R(dv) - Q(g)Q(h) \\ &= \ \begin{cases} \int \mathcal{N}_{d,v}(gh)\, R(dv) - Q(g)Q(h) & \text{if } \ell = m, \\ \int \mathcal{N}_{d,v}(g) \mathcal{N}_{d,v}(h)\, R(dv) - Q(g)Q(h) & \text{if } \ell \neq m, \end{cases} \\ &= \ \mathrm{Cov}\big(B'_{Q,\ell}(g) + B''_Q(g), B'_{Q,m}(h) + B''_Q(h)\big) \end{aligned}$$

as $q \to \infty$. This proves assertion (F1).

As for assertion (F2), it is well-known from empirical process theory that conditions (C1-2) imply that for arbitrary fixed $\epsilon > 0$,

$$\max_{\ell\in\Lambda} \mathbb{P}\Big(\sup_{g,h\in\mathcal{H}:\rho_\ell^{(q)}(g,h)<\delta} \Big|B_\ell^{(q,n)}(g) - B_\ell^{(q,n)}(h)\Big| \geq \epsilon \,\Big|\, \mathbf{\Gamma}\Big) \ \to_p \ 0 \tag{8}$$

as $\min(q, n) \to \infty$ and $\delta \downarrow 0$. Here

$$\rho_\ell^{(q)}(g,h) \ := \ \sqrt{\mathbf{\Gamma}^\top P((f_{\ell,g} - f_{\ell,h})^2)} \ = \ \sqrt{\Gamma_\ell^\top P((g-h)^2)}.$$

But it follows from (7) that

$$\max_{\ell\in\Lambda} \sup_{g,h\in\mathcal{H}} |\rho_\ell^{(q)}(g,h)^2 - \rho_Q(g,h)^2| \ \to_p \ 0$$

as $q \to \infty$. Hence one may replace $\rho_\ell^{(q)}$ in (8) with ρ_Q and obtain assertion (F2). □

Proof of Corollary 3.7. The main trick is to replace conditional expectations with suitable sample means. Note that conditional on $\widehat{P}$, the processes $B_1^{(q,n)}$, $B_2^{(q,n)}$, $B_3^{(q,n)}$, ... are independent copies of $B^{(q,n)}$. Likewise, conditional on B_Q'', the processes $B_{Q,1}' + B_Q'', B_{Q,2}' + B_Q'', B_{Q,3}' + B_Q'', \ldots$ are independent copies of $B_Q' + B_Q''$. Hence

$$\left.\begin{array}{r} \mathbb{E}\Big|\mathbb{E}\big(F(B^{(q,n)}) \,\big|\, \widehat{P}\big) - L^{-1}\sum_{\ell=1}^L F(B_\ell^{(q,n)})\Big| \\ \mathbb{E}\Big|\mathbb{E}\big(F(B_Q' + B_Q'') \,\big|\, B_Q''\big) - L^{-1}\sum_{\ell=1}^L F(B_{Q,\ell}' + B_Q'')\Big| \end{array}\right\} \ \leq \ L^{-1/2}\|F\|_\infty$$

for any integer $L \geq 1$. Consequently it suffices to show that for any fixed $L \geq 1$, the random variable $L^{-1}\sum_{\ell=1}^L F(B_\ell^{(q,n)})$ converges in distribution to the random variable $L^{-1}\sum_{\ell=1}^L F(B_{Q,\ell}' + B_Q'')$ as $\min(q, n) \to \infty$. But this is a consequence of Theorem 3.2 and the Continuous Mapping Theorem, because

$$\boldsymbol{b} = \big(b_\ell(h)\big)_{(\ell,h)\in\Lambda\times\mathcal{H}} \ \mapsto \ L^{-1}\sum_{\ell=1}^L F(b_\ell)$$

defines a continuous mapping from $\ell_\infty(\Lambda \times \mathcal{H})$ to $\mathbb{R}$. □

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