Abstract

We develop a general approach to Stein’s method for approximating a random process in the path space $\mathbb{D}([0, T] \to \mathbb{R}^d)$ by a real continuous Gaussian process. We then use the approach in the context of processes that have a representation as integrals with respect to an underlying point process, deriving a general quantitative Gaussian approximation. The error bound is expressed in terms of couplings of the original process to processes generated from the reduced Palm measures associated with the point process. As applications, we study certain GI/GI/$\infty$ queues in the “heavy traffic” regime.

Keywords: Stein’s method; Gaussian processes; Palm measure; GI/GI/$\infty$ queues.

1 INTRODUCTION

Gaussian processes arise as approximations to real processes in a wide variety of applications. Often, the approximation is taken as read, and Gaussian processes become part of the model, as in stochastic integrals in finance. In other circumstances, as in queuing systems, they arise as approximations in the limit; see, for example, [Robert, 2003] and [Pang, Talreja, and Whitt, 2007]. The fundamental example, which forms the basis of many other limiting results, is Donsker’s theorem, which states that random walk, after proper normalization, converges weakly in path space to Brownian motion. Then probabilities for systems that converge to a Gaussian process may be approximated by the analogous limiting probabilities, which are typically more tractable, due to the many beautiful and useful properties of Gaussians. A key task in this setting is to estimate the error made in the approximation. For Donsker’s theorem, this is well understood, but for more general processes there are few results.

In this paper, we establish a Stein equation, together with properties of its solutions, suitable for use in quantifying the error in approximating a multi-dimensional càdlàg process by a general Gaussian process. The approach generalizes and improves the theory for approximation by Brownian motion presented in [Barbour, 1990], and dovetails with [Barbour, Ross, and Zheng, 2021] to give bounds on the error in terms of the Lévy–Prokhorov distance, which metrizes weak convergence with respect to the Skorokhod topology. As a concrete application of the method, we prove a general result, Theorem 1.10, that gives such
bounds when the process being approximated can be expressed as an integral with respect to a point process. Theorem 1.10 is then applied to $M/GI/\infty$ and $GI/GI/\infty$ queues in the heavy traffic regime, obtaining the first rates of convergence in some settings that are closely related to limiting approximations given in [Iglehart, 1965; Borovkov, 1967; Whitt, 1982; Krichagina and Puhalskii, 1997] and [Puhalskii and Reed, 2010], where the limiting processes are typically not Brownian motion.

### 1.1 Setup

Let $N$ be a simple point process on $\mathbb{R}^d$ with mean measure $\lambda$. Let the collection of functions

$$\{J_u : [0, T] \to \mathbb{R}^p\}_{u \in \mathbb{R}^d},$$

be such that $J(s) \in L^2(\mathbb{R}^d \to \mathbb{R}^p, \lambda)$ for all $s \in [0, T]$, and $(u, s) \mapsto J_u(s)$ is jointly measurable. We study the random process $X : [0, T] \to \mathbb{R}^p$ defined by

$$X(s) := \int_{\mathbb{R}^d} J_u(s)N(du).$$

It is shown in Sections 1.3 and 1.4 that many queueing processes can be written in this form. Before going into specific detail, we first need to establish the general framework.

Define the centered and scaled random measure $\widetilde{N} := \sigma^{-1}(N - \lambda)$, where $\sigma > 0$ is a scaling parameter, and define the process $\widetilde{X}$ by

$$\widetilde{X}(s) := \int_{\mathbb{R}^d} J_u(s)\widetilde{N}(du). \quad (1.1)$$

We are interested in the distribution of $\widetilde{X}$ when $\lambda$ is at “high intensity”, meaning that the mass of $\lambda$ is large, and the choice of $\sigma$ stabilizes $\widetilde{N}$; and, in particular, we want to approximate the distribution of $\widetilde{X}$ by that of a Gaussian process $(Z(t), t \in [0, T])$. Informally, we think of $\widetilde{N}$ as close in distribution to a centered Gaussian random measure $N$ with intensity measure $\Lambda \approx \sigma^{-2}\lambda$, and then in turn $Z(s) = \int_{\mathbb{R}^d} \widetilde{J}_u(s)N(du)$, for some possibly different family of functions $\{\widetilde{J}_u\}_{u \in \mathbb{R}^d}$. Formally, $Z$ is a centered Gaussian process with covariance function

$$\mathbb{E}[Z(s)Z(t)\top] = \int_{\mathbb{R}^d} \widetilde{J}_u(s)\widetilde{J}_u(t)\top \Lambda(du), \quad t, s \in [0, T],$$

where $Z$ and $\widetilde{J}$ are column vectors, and $\top$ denotes transpose. If $N$ is a Poisson process, then the natural approximating Gaussian process has $\Lambda = \sigma^{-2}\lambda$ and $\widetilde{J}_u = J_u$, but this is not necessarily the case for other point processes.

The corresponding approximation result, Theorem 1.10 below, gives a bound on

$$|\mathbb{E}[g(\widetilde{X})] - \mathbb{E}[g(Z)]|$$

for a certain set $\mathcal{M}$ of “test” functions $g$. The bound in the approximation result is completely general for $X$ of the form above, but requires the construction of close couplings $(N, N^{(u)})_{u \in \mathbb{R}^d}$ of $N$ with its “reduced Palm measures” at $u \in \mathbb{R}^d$. In the case where $N$ is a Poisson process,
we can set \( N^{(u)} = N \), and our bound becomes very simple; see (1.16). The test functions are described in detail in Section 1.2, but are essentially those introduced in [Barbour, 1990], and include smooth functions of the process at a fixed number of times. Such test functions are now commonly used for Gaussian process approximation in the Stein’s method literature; see, for example [Kasprzak, 2017, 2020b]. For a sequence of processes \((\tilde{X}_n)_{n \geq 1}\), the fact that \( \mathbb{E}[g(\tilde{X}_n)] - \mathbb{E}[g(Z)] \to 0 \) for all test functions \( g \) in \( \mathcal{M} \) does not alone imply weak convergence of the processes with respect to either the supremum or the Skorokhod topologies, but with the results of [Barbour et al., 2021] and a little extra work, it is not too difficult in our applications to obtain bounds on the Lévy–Prokhorov distance (with respect to the Skorokhod topology) that tend to zero, and hence imply weak convergence.

We next discuss the test functions in detail.

### 1.2 Test functions

Let \( \mathbb{D}^p := \mathbb{D}([0, T] \to \mathbb{R}^p) \) be the set of functions from \([0, T]\) to \(\mathbb{R}^p\) that are right continuous with left limits. Endowed with the sup norm, \( \mathbb{D}^p \) is a Banach space (though not separable), and so for functions \( g: \mathbb{D}^p \to \mathbb{R} \), we denote their Fréchet derivatives by \( D, D^2, \ldots \). Following [Barbour, 1990] (see also [Kasprzak, Duncan, and Vollmer, 2017]), for \( g: \mathbb{D}^p \to \mathbb{R} \), we define

\[
\|g\|_L := \sup_{w \in \mathbb{D}^p} \frac{|g(w)|}{1 + \|w\|^2},
\]

where \( \|w\| = \sup_{0 \leq t \leq T} |w(t)| \) denotes the sup-norm, and then define the Banach space

\[
L := \left\{ g: \mathbb{D}^p \to \mathbb{R}: g \text{ is continuous and } \|g\|_L < \infty \right\}.
\]

For \( g \) twice Fréchet differentiable, we define

\[
\|g\|_M := \|g\|_L + \sup_{w \in \mathbb{D}^p} \frac{\|Dg(w)\|_1}{1 + \|w\|^2} + \sup_{w \in \mathbb{D}^p} \frac{\|D^2g(w)\|}{1 + \|w\|} + \sup_{w, h \in \mathbb{D}^p} \frac{\|D^2g(w + h) - D^2g(w)\|}{\|h\|},
\]

where \( \|A\| := \sup_{\|w\| = 1} |A[w^{(k)}]| \) for \( A \) a \( k \)-linear form, and \( A[w^{(k)}] := A[w, w, \ldots, w] \). This leads to the space

\[
M := \left\{ g: \mathbb{D}^p \to \mathbb{R}: g \text{ is twice Fréchet differentiable and } \|g\|_M < \infty \right\}.
\]

We also work on its subspace

\[
M' := \left\{ g \in M: \sup_{w \in \mathbb{D}^p} \|D^2g(w)\| < \infty \right\},
\]

and for \( g \in M' \), we define the norm

\[
\|g\|_{M'} := \sup_{w \in \mathbb{D}^p} \frac{|g(w)|}{1 + \|w\|^2} + \sup_{w \in \mathbb{D}^p} \frac{\|Dg(w)\|_1}{1 + \|w\|} + \sup_{w \in \mathbb{D}^p} \|D^2g(w)\| + \sup_{w, h : \mathbb{D}^p} \frac{\|D^2g(w + h) - D^2f(w)\|}{\|h\|}.
\]

Note that for \( g \in M' \), \( \|g\|_M \leq \|g\|_{M'} \). Defining \( I_t(s) := 1[s \geq t] \), we also typically assume that a test function \( g \) satisfies the smoothness condition that, for any \( r, s, t \) in \([0, T]\) and \( x_1, x_2 \in \mathbb{R}^p \),

\[
\sup_{w \in \mathbb{D}^p} \left| D^2g(w)[x_1I_r, x_2(I_s - I_t)] \right| \leq S_g |x_1||x_2||s - t|^{1/2}, \tag{1.2}
\]

where \( S_g \) is some constant depending on \( g \) and \( |\cdot| \) denotes Euclidean norm.
1.3 M/GI/∞ queue

Let $M_n$ be a Poisson process on $S := [0, T] \times \mathbb{R}_+$ with intensity measure

$$\ell_n(dt, dy) := n\alpha(dt)G(dy),$$

where $\alpha$ is a finite measure on $[0, T]$ and $G$ is a distribution function supported on $\mathbb{R}_+$. Viewing $M_n$ as a measure, let $(Y_i, i \geq 1)$ be i.i.d. with distribution function $\tilde{G}$ supported on $\mathbb{R}_+$, and set

$$N_n := M_n + \sum_{i=1}^{x_n} \delta_{(0,Y_i)},$$

where $x_n \geq 0$ is an integer. Then $N_n$ is a point process with mean measure

$$\lambda_n := \ell_n + x_n(\delta_0 \times \tilde{G}).$$

For $(t, y) \in S$, we define

$$J_{t,y}(s) := 1\{t \leq s < t + y\}$$

and the process $X_n : [0, T] \to \mathbb{R}_+$ by

$$X_n(s) := \int_S J_{t,y}(s)N_n(dt, dy).$$

The process $X_n$ can be regarded as the number of customers in an M/GI/∞ queue: A point $(t, y) \in N_n$ represents a customer arriving at time $t$ with service time $y$, and such a customer will be in the system at any instant $s$ satisfying $t \leq s < t + y$. We allow the customers initially in the system to have a different service distribution, to model the situation where the process is first observed at a typical time; in such a case, the residual service times would have a distribution derived from $G$, but not necessarily the same as $G$. We consider the “heavy traffic” regime in which $n$ is large, so that the total rate of arrivals $n\alpha(dt)$ is large.

Define the centered and scaled random measure

$$\tilde{N}_n := \sigma_n^{-1}(N_n - \lambda_n) \quad \text{with} \quad \sigma_n^2 = n,$$

and the process $\tilde{X}_n$ by

$$\tilde{X}_n(s) := \int_S J_{t,y}(s)\tilde{N}_n(dt, dy). \quad (1.3)$$

Our main result in this setting is the following.

**Theorem 1.1.** Assume that the convolution $G*\alpha$ defined by $(G*\alpha)(s) := \int_0^s G(s-u)\alpha(du)$, the cumulative intensity $A$ defined by $A(s) := \int_0^s \alpha(du)$, and the distribution function $\tilde{G}$ are all Hölder continuous with exponent $\beta \in (1/2, 1]$ and constants $c_{G,\alpha}$, $c_\alpha$ and $c_{\tilde{G}}$, respectively. Define the measure on $S := [0, T] \times \mathbb{R}_+$ by

$$\Lambda := (\alpha \times G) + x(\delta_0 \times \tilde{G}),$$
where \( x \geq 0 \) is fixed. Now set \( \tilde{J}_{(t,y)} := J_{t,y} \) for \( t > 0 \) and \( \tilde{J}_{(0,y)} := J_{0,y} - (1 - \tilde{G}) \), and let \( Z \) be a real centred Gaussian process with covariance function, for \( 0 \leq s_1 \leq s_2 \leq T \),

\[
\mathbb{E}[Z(s_1)Z(s_2)] = \int_{s} \tilde{J}_{(t,y)}(s_1)\tilde{J}_{(t,y)}(s_2)\Lambda(dt,dy)
= \int_{0}^{s_1} (1 - G(s_2 - t))\alpha(dt) + x\tilde{G}(s_1)(1 - \tilde{G}(s_2)). \tag{1.4}
\]

Then, for any \( g \in M' \) either satisfying (1.2), or of the form \( g(w) = F(w(t_1), \ldots, w(t_k)) \) for some (twice differentiable) \( F: \mathbb{R}^k \to \mathbb{R} \) and distinct instants \( t_1, \ldots, t_k \in [0, T] \), defining

\[
\Psi_n(x, x_n, \alpha, T) := 3\sqrt{\frac{\pi x_n/2 + |x_n - nx|}{2n}} + \frac{\alpha([0,T]) + n^{-1}x_n}{2\sqrt{n}}, \tag{1.5}
\]

we have

\[
\left| \mathbb{E}[g(\tilde{X}_n)] - \mathbb{E}[g(Z)] \right| \leq 2^{3/2}\|g\|_{M'}\Psi_n(x, x_n, \alpha, T). \tag{1.6}
\]

If \( \beta = 1 \) and \( 1 \leq \alpha([0,T]) \leq \alpha_*T \), for some \( \alpha_* < \infty \), and if \( T \geq n^{1/2}|x_n^{-1} - x| \), then, for any \( \chi > 0 \), there is a constant \( K_\chi \) such that

\[
d_{LP}(\mathcal{L}(\tilde{X}_n), \mathcal{L}(Z)) \leq K_\chi n^{\chi}T^{2/5}n^{-1/20}.
\]

where \( d_{LP} \) denotes the Lévy–Prokhorov distance (with respect to Skorokhod topology).

**Remark 1.2.** (1) The constant \( S_g \) from the smoothness condition (1.2) does not appear in the bound, since the condition is only used to apply a technical result; see Lemma 5.3 below.

(2) As we only consider time intervals \([0, T]\), we only require the Hölder continuity on \([0, T]\).

(3) Bounds can also be derived under more general assumptions on \( \alpha \) and \( \beta \). These can be deduced from the proof of the theorem.

**Remark 1.3.** That \( \mathcal{L}(\tilde{X}_n) \to \mathcal{L}(Z) \) with respect to Skorokhod topology for \( x_n = 0 \) is due to [Borovkov, 1967] — see the discussion in [Whitt, 1982] — and, for general \( x_n \), follows from the results of [Krichagina and Puhalskii, 1997]. The only rates of convergence we are aware of are those of [Besanson, Decreusefond, and Moyal, 2020] and [Besançon, Coutin, Decreusefond, and Moyal, 2021], which give Wasserstein bounds (with respect to the supremum metric) in the special case of the \( M/M/\infty \) queue. Using [Barbour et al., 2021, Theorem 1.1] with the bounds of this paper would lead to rates in the Wasserstein distance that would be worse than those derived in [Besançon et al., 2021] in this case. However, our results apply more generally to \( M/GI/\infty \) queues, which do not appear to be within the scope of their methods.

In the best possible case, where \( \beta = 1 \), our rate of convergence for the Lévy–Prokhorov metric, of \( O(T^{2/5}n^{-1/20+\chi}) \) for any \( \chi > 0 \), is, to the best of our knowledge, the first rate of convergence in this metric. A further advantage of our bounds is that the dependence on \( T \) is explicit, and that \( T \) could grow like a small power of \( n \) while still yielding a small bound; this would cover transient approximation almost to stationarity.
Remark 1.4. We can represent $Z$ as a sum of three independent centred Gaussian processes $Z = Z_1 + Z_2 + Z_3$, where

1. $Z_1$ represents the randomness from the services and has covariance structure

$$E[Z_1(s_1)Z_1(s_2)] = \int_0^{s_1} G(s_1 - t)(1 - G(s_2 - t))\alpha(dt),$$

for $0 \leq s_1 \leq s_2 \leq T$.

2. The second process $Z_2$ represents the randomness from the arrival process (a kind of weighted renewal functional CLT) and is given by the stochastic integral

$$Z_2(s) = \int_0^{s} (1 - G(s - t))B(dt),$$

where $B(\cdot)$ is a Gaussian random measure with intensity measure $\alpha(dt)$, that is,

$$E[Z_2(s_1)Z_2(s_2)] = \int_0^{s_1} (1 - G(s_1 - t))(1 - G(s_2 - t))\alpha(dt);$$

for $0 \leq s_1 \leq s_2 \leq T$.

3. The third process $Z_3$ is a time-changed Brownian bridge: $Z_3(t) = \sqrt{t}B^{br}(\tilde{G}(t))$, where $B^{br}$ is a Brownian bridge with $B^{br}(0) = B^{br}(1) = 0$.

For $x = 0$, this decomposition is identified in [Borovkov, 1967]; see also [Whitt, 1982, (2.5) and (2.6)] and the discussion there. The addition of $Z_3$ is due to the presence of customers initially in the system. The number of those remaining in the system at time $t$ is just the number with service time greater than $t$, the empirical complementary cumulative distribution function at $t$. This, after scaling, converges as a function of $t$ to a time–changed Brownian bridge.

Remark 1.5. If $g(w) = F(w(t_1), \ldots, w(t_k))$, and $F$ is bounded with bounded partial derivatives of order up to three, then $\|g\|_{M} \leq c k^3$, where $c$ is an upper bound for $F$ and its first three partial derivatives. Assuming that $|x_n - nx| = O(n^{1/2})$, the bound (1.6) is of order $O(k^3 n^{-1/2})$, and standard smoothing arguments, as in [Götze, Naumov, Spokoiny, and Ulyanov, 2019, Section 1.1.4], imply that for any convex $K \subseteq \mathbb{R}^k$ and $\varepsilon > 0$,

$$\left| \mathbb{P}\left( (\tilde{X}_n(t_i))_{i=1}^k \in K \right) - \mathbb{P}\left( (Z(t_i))_{i=1}^k \in K \right) \right| \leq C\{\varepsilon^{-3}k^3 n^{-1/2} + k^{1/4}\varepsilon\}.$$

Choosing $\varepsilon = k^{11/16} n^{-1/8}$, leads to a uniform upper bound of order $k^{15/16} n^{-1/8}$ on the difference of convex set probabilities for any $k$-dimensional distributions of $\tilde{X}_n$ and $Z$. The power of $k$ in the bound is likely not optimal, but still leads to meaningful results for $k$ growing like a small power of $n$. 

6
1.4 GI/GI/∞ queue

Consider a stationary renewal process $V_n$ on $[0, T]$, whose renewal distribution $\nu_n$ is that of $R/n$, where $R$ is a positive integer valued random variable with aperiodic support having mean $m$, variance $v^2$ and $\mathbb{E}[R^r] < \infty$ for some fixed $r \geq 5$. Let $G$ be a distribution function supported on $\mathbb{R}_+$ and let $(Y_i, i \geq 1)$ be an i.i.d. sequence with distribution $G$ that is also independent of the renewal process $V_n$. Now define the random measure $N_n$ on $S := [0, T] \times \mathbb{R}_+$ by

$$N_n := \sum_{i=1}^{\lfloor nT \rfloor} M_n(i/n) \delta_{(i/n, Y_i)},$$

where now

$$M_n(s) := V_n(s) - V_n(s-) := 1[\text{a renewal occurs at time } s], \quad s \in [0, T],$$

and $Y_i$ represents the service time of a customer arriving at time $i/n$. Due to the stationarity, the mean measure of $N_n$ is

$$\lambda_n := \frac{1}{m} \sum_{i=1}^{\lfloor nT \rfloor} (\delta_{i/n} \times G).$$

For $(t, y) \in S$, we define $J_{t,y}(s) := 1[t \leq s < t + y]$ and

$$X_n(s) := \int_S J_{t,y}(s) N_n(dt, dy).$$

As for the M/GI/∞ queue, the process $X_n$ can be regarded as the number of customers in a GI/GI/∞ queue with arrival times given by a stationary renewal process driven by $\nu_n$ and service times distributed according to $G$. Note that because $\nu_n$ (the law of $R/n$) is discrete, the results of the previous section are not a special case of those derived here.

Define the centered and scaled random measure

$$\tilde{N}_n := \sigma_n^{-1}(N_n - \lambda_n),$$

where

$$\sigma^2_n := nv^2/m^3,$$

and define the process $\tilde{X}_n$ by

$$\tilde{X}_n(s) := \int_S J_{t,y}(s) \tilde{N}_n(dt, dy).$$

Writing $I_t(\cdot) := 1\{\cdot \geq t\}$ and $\overline{G} := 1 - G$, our main result of the section is the following.

**Theorem 1.6.** Recall the notation just above. Assume that $\mathbb{E}R^5 < \infty$ and that, for some $\beta \in (0, 1]$ and $0 < \eta < 1$, the distribution function $G$ satisfies

$$G(t) - G(s) \leq g_G(s)(t - s)^\beta, \quad 0 < s < t \leq T,$$

(1.8)
where \( g_G : \mathbb{R}_+ \to \mathbb{R}_+ \) is bounded and non-increasing and such that \( \int_0^{\infty} g_G^n(s) \, ds < \infty \). Define the measure on \( S := [0,T] \times \mathbb{R}_+ \) by

\[
\Lambda(dt,dy) := dt \, G(dy),
\]

set

\[
\tilde{J}_{t,y}(s) := \frac{m}{v} J_{t,y}(s) - \frac{m + v}{v} G(s - t) I_1(s),
\]

and let \( Z \) be a Gaussian process with covariance function, for \( 0 \leq s_1 < s_2 \leq T \),

\[
\mathbb{E}[Z(s_1)Z(s_2)] = \int_S \tilde{J}_{t,y}(s_1) \tilde{J}_{t,y}(s_2) \Lambda(dt,dy)
\]

\[
= \frac{m^2}{v^2} \int_0^{s_1} G(s_2 - t) G(s_1 - t) dt + \int_0^{s_1} G(s_1 - t) G(s_2 - t) dt. \quad (1.9)
\]

Then, for any \( g \in M' \) satisfying the smoothness condition (1.2) for some \( S_g \), there is a constant \( C \) depending on \( L(R) \) and \( g_G(0) \) such that, with \( \beta := \min\{\beta, 1/2\} \), we have

\[
|\mathbb{E}[g(\tilde{X}_n)] - \mathbb{E}[g(Z)]| \leq C T \left( S_g n^{-1/2} + \|g\|_{\mathcal{M}} n^{-\beta} \right). \quad (1.10)
\]

If \( g \in M' \) is of the form \( g(w) = F(w(t_1), \ldots, w(t_k)) \) for some (twice differentiable) \( F : \mathbb{R}^k \to \mathbb{R} \) and distinct instants \( t_1, \ldots, t_k \in [0,1] \), then the same bound holds, but with \( S_g n^{-1/2} \) replaced by \( \|g\|_{\mathcal{M}} k^3 n^{-1} \).

Moreover, assuming that \( T \geq 1 \), taking \( l_r := \lceil (r - \eta (r - 1)) / 2 \rceil - 1 \), \( \beta_r := \beta (r - 2) / (r - 1) \), we have

\[
\text{d}_{\mathcal{L}}(\mathcal{L}(\tilde{X}_n), \mathcal{L}(Z)) \leq C \sqrt{\log n} \left\{ (T^4 n^{-\beta})^{(l_r \beta_r - 1)} T^3 \right\}^{1/(6l_r + 4l_r \beta_r - 1)}, \quad (1.11)
\]

where \( \text{d}_{\mathcal{L}} \) denotes the Lévy–Prokhorov distance (with respect to the Skorokhod topology). For instance, if the distribution of \( R \) has all positive moments, and if \( G \) has a finite moment and a bounded and ultimately monotone density, and if \( T \leq n^\psi \) for some \( \psi < 1/8 \), then, for any \( \chi > 0 \), there is a constant \( K_\chi \) such that

\[
\text{d}_{\mathcal{L}}(\mathcal{L}(\tilde{X}_n), \mathcal{L}(Z)) \leq K_\chi n^\chi T^{2/5} n^{-1/20}.
\]

**Remark 1.7.** The expression (1.9) for the covariance agrees (up to scaling) with [Whitt, 1982, (2.5) and (2.7)]. Note also that choosing \( G \) supported on \( (T, \infty) \) corresponds to the renewal CLT, where the limiting Gaussian process is the standard Brownian motion. The decomposition in Remark 1.4 still applies here with \( Z = (m^2 / \nu^2) Z_1 + Z_2 \) and \( \alpha(dt) = dt \). The addition of initial customers would contribute to the limit in the same way as in Theorem 1.1; that is, it would add a Brownian bridge component as described in Remark 1.4, but we omit this for the sake of clarity. Weaker convergence with respect to the Skorokhod topology was (essentially) shown in [Borovkov, 1967], and here we can view (1.11) as a rate of convergence. We are not aware of previous results with rates of convergence. The same considerations as in Remark 1.5 lead to a uniform upper bound of order \( k^{15/16} n^{-\beta/4} \) on the difference of convex set probabilities for any \( k \)-dimensional distributions of \( \tilde{X}_n \) and \( Z \). Again, we remark that an appealing aspect of our bound is the explicit incorporation of \( T \).
Theorem 1.10. Recall the notation and definitions of Section 1.1 leading up to reduced Palm measures, see [Daley and Vere-Jones, 2008, Chapter 13].

Definition 1.9. For a process $X_n'$ defined analogously to $X_n$, but driven by $V_n'$ defined to be a delayed (rather than stationary) renewal process with inter-renewal distribution $\mathcal{L}(R/n)$, it is easy to see that $X_n$ and $X_n'$ can be constructed on the same space so that $\|X_n - X_n'\|$ is stochastically dominated by the coupling time

$$T_c := \inf\{i \geq 1: M_n(i/n) = M'_n(i/n) = 1\},$$

where $M'_n(s) = V'_n(s) - V'_n(s-)\) is defined in analogy with $M_n$ (here, we view $V_n$ and $V'_n$ as renewal processes on $[0, \infty)$, and so $T_c$ does not depend on $n$). Defining the scaled process

$$\tilde{X}'_n := \frac{X'_n - \int S J_y \kappa(dV,y)}{\sigma_n},$$

we thus easily find that $\|\tilde{X}_n - \tilde{X}'_n\|$ is stochastically dominated by $(m^{3/2}T_c/v)n^{-1/2}$. Under the hypotheses of the theorem, [Pitman, 1974, Proposition (6.10)] implies that $T_c$ is finite with probability one, and if the delay distribution has finite $(r+1)$-moment, that $E[T_c] < \infty$. Under this moment condition, for any function $g \in M'$ with $\|Dg(w)\| < \infty$, we then easily have that

$$\left|E[g(\tilde{X}'_n)] - E[g(\tilde{X}_n)]\right| \leq \|Dg(w)\| \frac{m^{3/2}E[T_c]}{v\sqrt{n}}.$$

Combining this with the bounds of the theorem and the triangle inequality gives bounds on $|E[g(\tilde{X}'_n)] - E[g(\tilde{Z})]|$ for $g \in M'$ with $\|Dg(w)\| < \infty$, and subsequent bounds of the same order on $d_{LP}$ (the restriction that $\|Dg(w)\| < \infty$ is no problem, since the key result Theorem 5.1 only requires bounds on a smaller class of test functions with bounded derivatives).

1.5 General approximation theorem

Here we state the general approximation theorem used to prove Theorems 1.1 and 1.6. We first need a definition.

Definition 1.9. For a point process $\Xi \subseteq \mathbb{R}^d$ with mean measure $\kappa$, we say $\Xi^{(u)}$ is distributed as the reduced Palm measure of $\Xi$, if

$$E\left[\int g(\Xi, u)\Xi(du)\right] = E\left[\int g(\Xi^{(u)} + \delta_u, u)\kappa(du)\right]$$

for all functions $g$ such that the integral on the left hand side exists.

For simple point processes (meaning there is at most one point at any location), we think of $\Xi^{(u)} + \delta_u$ as having the distribution of $\Xi$ conditional on there being a point at $u$, which explains why we can take $\Xi^{(u)} = \Xi$ if $\Xi$ is a Poisson process. For rigorous background on reduced Palm measures, see [Daley and Vere-Jones, 2008, Chapter 13].

Theorem 1.10. Recall the notation and definitions of Section 1.1 leading up to (1.1). Let $(N, N^{(u)})_{u \in \mathbb{R}^d}$ be a collection of couplings of $N$ with its reduced Palm measures and define

$$X^{(u)}(s) := \int_{\mathbb{R}^d} J_v(s)N^{(u)}(dv), \ s \in [0, T].$$
Let $Z$ be a centered Gaussian process with almost surely continuous sample paths with
\[
\mathbb{E}[Z(s)Z(t)\top] = \int_{u \in \mathbb{R}^d} \widetilde{J}_u(s)\widetilde{J}_u(t)\top\Lambda(du),
\tag{1.12}
\]
where the function $(u, s) \mapsto \widetilde{J}_u(s) \in \mathbb{R}^p$ is measurable such that
\[
\widetilde{J}_u(\cdot) \in L^2([0, T] \to \mathbb{R}^p) \text{ and } \widetilde{J}(s) \in L^2(\mathbb{R}^d \to \mathbb{R}^p, \Lambda), \text{ for all } s \in [0, T] \text{ and all } u \in \mathbb{R}^d.
\]

Now suppose that $g \in M$, and define $f := f_g$ to be the Stein solution given in Theorem 2.2. Then we have
\[
|\mathbb{E}[g(\widetilde{X})] - \mathbb{E}[g(Z)]| \leq \left| \int_{\mathbb{R}^d} D^2 f(\widetilde{X})[\widetilde{J}_u^2]\Lambda(du) - \int_{\mathbb{R}^d} D^2 f(\widetilde{X}) [J_u, \mathbb{E}[X^{(u)} - X + J_u]](\sigma^{-2}\lambda(du)) \right| \tag{1.13}
\]
\[
+ \left| \mathbb{E} \left[ \int_{\mathbb{R}^d} D^2 f(\widetilde{X}) [J_u, (X^{(u)} - X) - \mathbb{E}[X^{(u)} - X]](\sigma^{-2}\lambda(du)) \right] \right| \tag{1.14}
\]
\[
+ \frac{\|g\|_M^2}{2\sigma^2} \mathbb{E} \left[ \int_{\mathbb{R}^d} \|J_u\|^2 \|X^{(u)} - X + J_u\|^2(\sigma^{-2}\lambda(du)) \right]. \tag{1.15}
\]

If $N$ is a Poisson point process, $\Lambda = \sigma^{-2}\lambda$ and $\widetilde{J}_u = J_u$, then for any $g \in M$,
\[
|\mathbb{E}[g(\widetilde{X})] - \mathbb{E}[g(Z)]| \leq \frac{\|g\|_M^2}{2\sigma^2} \left[ \int_{\mathbb{R}^d} \|J_u\|^3(\sigma^{-2}\lambda(du)) \right]. \tag{1.16}
\]

**Remark 1.11.** (1) Although our focus in this work is about real Gaussian process approximation, there is no essential extra difficulty in establishing the above multivariate Gaussian approximation result. See Section 3 for an illustration in the multivariate setting.

(2) To check the hypothesis that $Z$ has continuous sample paths, it is enough to establish that, for some positive constants $C, b$, we have
\[
\mathbb{E}\left[|Z(s) - Z(t)|^2\right] \leq C|s - t|^b,
\tag{1.17}
\]
which, using Gaussianity, implies the Kolmogorov continuity criterion.

(3) In general, the terms in (1.15) and (1.16) are not automatically finite. In our applications, the integrand $J_u$ is uniformly bounded, $\mathbb{E}[\|X\|^2]$ is finite and $N$ is a simple point process over a subset $S$ of $\mathbb{R}^d$ with finite intensity measure such that $N(S)$ has finite second moment. Under these extra assumptions, the aforementioned terms are finite.

**Remark 1.12.** In practice, the choice of $\Lambda$ and $\{\widetilde{J}_u\}_{u \in \mathbb{R}^d}$ arises from computing the quantity $\mathbb{E}[X^{(u)} - X + J_u]$, plugging the resulting expression into the second term of the difference of (1.13), and then discarding the asymptotically negligible terms. This is an appealing aspect of the theorem, as it suggests a candidate limit, while also providing an intuitive expression for the covariance of the limit in the form (1.12).
Remark 1.13. Bounding (1.13) and (1.14) in applications requires using the structure of $(X^{(u)} - X)$ and its mean, along with the bounds and “smoothness” properties of $f$ given in Theorem 2.2 below. Bounding (1.14) is the main difficulty in applying the theorem, and typically requires constructing intermediate couplings that exploit local or weak global dependence.

To apply the theorem for the $M/GI/\infty$ queue, we need to define the reduced Palm couplings of the arrival/service point process. Away from time zero, the arrivals/services are a Poisson point process, and so we can take the reduced Palm measure to be the original process. For the customers in the system at time zero, the Palm measure corresponds to removing a point at random, which is only a small perturbation of the original process. For the $GI/GI/\infty$ queue, the arrival/service point process is no longer Poisson. However, because the service times are i.i.d., constructing the reduced Palm measure coupling at a point $(s, y)$ comes down to constructing a close coupling of a stationary renewal process to one conditioned to have a renewal at $s$, which in turn is similar to coupling a stationary renewal sequence to a zero-delayed renewal process, and this is well-understood. The details are in Sections 3 and 4.

Theorem 1.10 follows from a new development of Stein’s method [Stein, 1972, 1986], formulated as Theorem 2.2. Stein’s method provides a general framework for bounding the error when approximating a complicated distribution of interest by a well-understood target distribution; see [Ross, 2011] for a basic introduction. By now, Stein’s method has been developed for a large number of univariate distributions, as in the monographs [Chen, Goldstein, and Shao, 2011] for the normal and [Barbour, Holst, and Janson, 1992] for the Poisson. Stein’s method for multivariate distributions other than the normal is not so well developed, and even less is known for random processes. Poisson process approximation is a notable exception, with a succession of papers going back to [Barbour, 1988] and [Arratia, Goldstein, and Gordon, 1989]. There is also work on approximation by Brownian motion, which began with [Barbour, 1990], and on some closely related Gaussian processes, such as time changes of Brownian motion [Kasprzak, 2017, 2020b] and multivariate correlated Brownian motions [Kasprzak, 2020a; Döbler and Kasprzak, 2021]; there has also been recent work for Dirichlet Process approximation [Gan and Ross, 2021].

All of the Gaussian process approximation results just cited are derived using Barbour’s generator approach [Barbour, 1990], which identifies a “characterizing” operator of a Gaussian process as the generator of the Ornstein–Uhlenbeck semigroup. To avoid working with the generator in the continuum, these papers first approximate the process of interest by a discretized version of the Gaussian process, which has an Ornstein–Uhlenbeck generator of a simple form. After this is achieved, the problem is reduced to showing that the discretized Gaussian process is close to the true Gaussian process. Here we avoid this two step procedure, by developing the relevant properties of the “Stein solution” for any Gaussian process with continuous sample paths; see Theorem 2.2 below. This theorem can be used to prove approximation bounds in quite general settings, in which the dependency structures are amenable to Stein’s method, such as those exhibiting an exchangeable pair. The formulation is particularly useful in our applications, where the jumps of the processes that we study occur at random times. A final remark on this point is that any discretization error between the process and the target Gaussian process is captured by (1.13) from Theorem 1.10, and
bounding this term typically relies on the smoothness property (1.2).

The recent papers [Coutin and Decreusefond, 2020] and [Besançon et al., 2021] use Stein’s method to obtain bounds in the bounded Wasserstein distance for Donsker’s theorem, and for Lipschitz functionals of Poisson measures. As discussed in [Barbour et al., 2021], they obtain rates of convergence in this restricted setting of better order than those that our method typically yields, though less good than those obtainable using strong approximation. However, in their approach, they make use of the independence structure within the process being approximated, and of the fact that the limiting process is Brownian motion; we need neither of these simplifications.

There is also an approach to Stein’s method on Hilbert and abstract Wiener spaces, initiated in [Shih, 2011] and developed further in [Coutin and Decreusefond, 2013; Besançon et al., 2020; Bourguin and Campese, 2020] and [Bourguin, Campese and Dang, 2021]. These approximations are not sufficient to directly imply weak convergence with respect to the Skorokhod topology, and hence do not imply rates for such convergence, either; see the nice discussion of some of these approaches in [Döbler and Kasprzak, 2021, Section 1.5].

The remainder of the paper is organised as follows. In Section 2, we develop Stein’s method in the general context of Gaussian process approximation, establishing Theorem 2.2, together with some ancillary results. We then prove Theorem 1.10. In Sections 3 and 4 we apply Theorem 1.10 to the M/GI/∞ and GI/GI/∞ queue examples given above, proving Theorems 1.1 and 1.6.

2 STEIN’S METHOD FOR GAUSSIAN PROCESSES

Our first step in developing Stein’s method for Gaussian processes is to establish a useful form for the characterizing operator.

**Proposition 2.1.** Let $Z$ be a real centred continuous $\mathbb{R}^p$-valued Gaussian process on $[0, T]$ with

$$K(s_1, s_2) := \mathbb{E}[Z(s_1)Z(s_2)^\top] = \int_{\mathbb{R}^d} J_u(s_1)J_u(s_2)^\top \Lambda(du),$$  \hspace{1cm} (2.1)

where $\Lambda$ is a measure on $\mathbb{R}^d$ and the function $(u, s) \mapsto J_u(s) \in \mathbb{R}^p$ is measurable such that $J_u(\cdot) \in L^2([0, T] \to \mathbb{R}^p)$ and $J(\cdot) \in L^2(\mathbb{R}^d \to \mathbb{R}^p, \Lambda)$, for all $s \in [0, T]$ and all $u \in \mathbb{R}^d$.

Then for any function $f \in M$,

$$\mathbb{E} \left( D^2 f(w)[Z]^2 \right) = \int_{\mathbb{R}^d} D^2 f(w)[J_u^2] \Lambda(du),$$  \hspace{1cm} (2.2)

and

$$\mathbb{E} \left( \int_{\mathbb{R}^d} D^2 f(Z)[J_u^2] \Lambda(du) - D f(Z)[Z] \right) = 0.$$  \hspace{1cm} (2.3)

**Proof.** First we show that all the expectations exist. Since $f \in M$, we have

$$|D^2 f(w)[Z]^2| \leq \|D^2 f\|(1 + \|w\|)\|Z\|^2$$ and

$$|D f(Z)[Z]| \leq \|D f\|(1 + \|Z\|^2)\|Z\|,$$
so that we need to show that \( \|Z\| \) has finite third moment, which is guaranteed by Fernique’s theorem. To establish the expressions for the moments, we use the multivariate Karhunen–Loève expansion of \( Z \); see [Happ and Greven, 2018, Section 2.2]. Define the linear operator \( T \) on the Hilbert space \( L^2([0,T] \rightarrow \mathbb{R}^p) \) by setting
\[
(Tf)(s) := \int_0^T K(s,t)f(t)dt.
\]
It is easy to see that \( T \) is a positive and compact self-adjoint operator on \( L^2([0,T] \rightarrow \mathbb{R}^p) \), so that by the spectral theorem, we can find \( \{h_k, k \in \mathbb{N}\} \) that is an orthonormal basis of \( L^2([0,T] \rightarrow \mathbb{R}^p) \) formed by the eigenvectors of \( T \) with respective eigenvalues \( \{\ell_k, k \in \mathbb{N}\} \subset \mathbb{R}_+ \).

As a result, \( Z(t) \) admits the following representation
\[
Z(t) = \sum_{k \in \mathbb{N}} X_k h_k(t),
\]
where
\[
X_k := \int_0^T Z(t)^\top h_k(t) \, dt = \int_0^T h_k(t)^\top Z(t) \, dt,
\]
and the convergence in (2.4) can be taken in \( L^2(\Omega) \), uniformly in \( t \in [0,T] \), and, because of the assumption of continuity of sample paths, can also be taken with respect to sup norm; see [Adler and Taylor, 2007, Theorem 3.1.2].

For \( k, j \in \mathbb{N} \), we have
\[
\mathbb{E}[X_k X_j] = \mathbb{E} \left[ \int_0^T \int_0^T h_j(s)^\top Z(s) Z(t)^\top h_k(t) \, ds \, dt \right] = \int_0^T \int_0^T h_j(s)^\top K(s,t) h_k(t) \, ds \, dt
\]
\[
= \int_0^T h_j(s)^\top (Th_k)(s) \, ds = \ell_k 1[k = j],
\]
and so the variables \( \{X_k\}_{k \in \mathbb{N}} \) are independent centred Gaussian random variables.

Using the representation (2.4), we have, for the symmetric bilinear form \( A = D^2 f(w) \),
\[
A[Z, Z] = A \left[ \sum_{k \in \mathbb{N}} X_k h_k, \sum_{j \in \mathbb{N}} X_j h_j \right] = \sum_{k,j \in \mathbb{N}} X_k X_j A[h_k, h_j],
\]
so that
\[
\mathbb{E}[A[Z, Z]] = \mathbb{E} \left[ \sum_{k,j \in \mathbb{N}} X_k X_j A[h_k, h_j] \right] = \sum_{k \in \mathbb{N}} \ell_k A[h_k, h_k].
\]
(2.5)

On the other hand, expanding \( J_u \) in the orthonormal basis \( \{h_k\} \) implies
\[
J_u = \sum_{k \in \mathbb{N}} h_k J_u^{(k)},
\]
where \( J_u^{(k)} := \int_0^T J_u(s)^\top h_k(s) \, ds \in \mathbb{R} \) for each \( k \in \mathbb{N} \). It follows that
\[
\int_{\mathbb{R}^d} A[J_u, J_u] \Lambda(du) = \int_{\mathbb{R}^d} A \left[ \sum_{k \in \mathbb{N}} h_k J_u^{(k)}, \sum_{j \in \mathbb{N}} h_j J_u^{(j)} \right] \Lambda(du)
\]
\[
= \sum_{k,j \in \mathbb{N}} A[h_k, h_j] \int_{\mathbb{R}^d} J_u^{(k)} J_u^{(j)} \Lambda(du).
\]
(2.6)
For (2.3), the first equality in (2.7) implies that it is enough to establish that

\[ Df \] is independent of \( k \) is independent of \( x \).

Continuing with straightforward calculations, we have

\[
\int_{\mathbb{R}^d} J_u^{(k)} J_u^{(j)} \Lambda(du) = \int_{\mathbb{R}^d} \left( \int_0^T h_k(s)^T J_u(s) \, ds \right) \left( \int_0^T J_u(t)^T h_j(t) \, dt \right) \Lambda(du) \\
= \int_0^T \int_0^T h_k(s)^T \left\{ \int_{\mathbb{R}^d} J_u(s) J_u(t)^T \Lambda(du) \right\} h_j(t) \, ds \, dt \\
= \int_0^T \int_0^T h_k(s)^T K(s,t) h_j(t) \, ds \, dt = \int_0^T h_k(s)^T (Th_j)(s) \, ds \\
= \ell_j \int_0^T h_k(s)^T h_j(s) \, ds = \ell_j [k = j].
\]

Plugging this into (2.6), and noting (2.5) gives (2.2):

\[
\int_{\mathbb{R}^d} A[J_u, J_u] \Lambda(du) = \sum_{k \in \mathbb{N}} \ell_k A[h_k, h_k] = \mathbb{E}[A[Z, Z]]. \tag{2.7}
\]

For (2.3), the first equality in (2.7) implies that it is enough to establish that

\[
\mathbb{E}[Df(Z)[Z]] = \sum_{k \in \mathbb{N}} \ell_k \mathbb{E}[D^2 f(Z)[h_k, h_k]]. \tag{2.8}
\]

Writing \( Z_k := Z - X_k h_k \), we have

\[
\mathbb{E}[Df(Z)[Z]] = \sum_{k \in \mathbb{N}} \mathbb{E}[X_k Df(Z_k + X_k h_k)[h_k]] = \sum_{k \in \mathbb{N}} \mathbb{E}\left[ \mathbb{E} \left( X_k Df(Z_k + X_k h_k)[h_k] \mid Z_k \right) \right].
\]

Since \( Z_k \) is independent of \( X_k \), we can apply the one dimensional Stein identity

\[
\mathbb{E}[X_k g(X_k) \mid Z_k] = \ell_k \mathbb{E}[g'(X_k) \mid Z_k]
\]

with \( g(x) = Df(Z_k + x h_k)[h_k] \) to each term in this sum. Then (2.8) easily follows by noting that \( g'(x) = D^2 f(Z_k + x h_k)[h_k, h_k] \) and thus \( g'(X_k) = D^2 f(Z)[h_k, h_k] \).

The next result represents the foundation of Stein’s method for continuous Gaussian processes.

**Theorem 2.2.** Let \( Z \) be a centred continuous Gaussian process with covariance function given by (2.1). Given \( g \in M \), we define \( f_g : \mathbb{D}^p \to \mathbb{R} \) by

\[
f_g(w) := -\int_0^\infty \left( \mathbb{E}[g(we^{-s} + \sqrt{1 - e^{-2s}}Z)] - \mathbb{E}[g(Z)] \right) ds. \tag{2.9}
\]

Then \( f_g \in M \) and for \( k \in \{1, 2\},

\[
D^k f_g(w) = -\mathbb{E} \int_0^\infty e^{-ks} D^k g(we^{-s} + \sqrt{1 - e^{-2s}}Z) ds. \tag{2.10}
\]

Furthermore, for \( w, w', w_1, w_2 \in \mathbb{D}^p \), we have

\[
|D^2 f_g(w + w')[w_1, w_2] - D^2 f_g(w)[w_1, w_2]| \leq \|g\|_M \|w_1\| \|w_2\| \|w'\|. \tag{2.11}
\]

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and if \( g \in M' \), then
\[
|D^2 f_g(w)[w_1, w_2]| \leq (3/2)\|g\|_{M'}\|w_1\|\|w_2\|,
\] (2.12)

Finally, \( f_g \) satisfies the Stein’s equation
\[
A f_g(w) := \int_{\mathbb{R}^d} D^2 f_g(w)[J_0^{[2]}] \Lambda(du) - D f_g(w)[w] = g(w) - \mathbb{E}[g(Z)].
\] (2.13)

Proof. That \( f_g \in M \) and that (2.10) holds follow from the arguments of [Kasprzak et al., 2017, Lemma 4.1] (see also [Barbour, 1990]) for the special case of Brownian motion. Their argument only relies on the supremum of the Gaussian process having finite third moment, which is also valid in our setting.

The bounds on the derivatives also more or less follow along the same lines as existing work, see [Kasprzak, 2020b, Proposition 3.2] or [Kasprzak, 2020a, Proposition 5.5], but our setting is different enough that we include a proof. To show (2.12), we use equation (2.10) and Lemma 2.4 below, which relates the absolute value of a bilinear form at a given argument to its norm, to find that
\[
|D^2 f_g(w)[w_1, w_2]| \leq \int_0^{\infty} e^{-2s} \mathbb{E}\left[|D^2 g(we^{-s} + \sqrt{1 - e^{-2s}}Z)[w_1, w_2]|\right] ds
\leq 3\|w_1\|\|w_2\| \int_0^{\infty} e^{-2s} \mathbb{E}\left[\|D^2 g(we^{-s} + \sqrt{1 - e^{-2s}}Z)\|\right] ds
\leq 3\|g\|_{M'}\|w_1\|\|w_2\| \int_0^{\infty} e^{-2s} ds = (3/2)\|g\|_{M'}\|w_1\|\|w_2\|,
\]
where the third inequality uses that \( g \in M' \). The proof of (2.11) follows from similar arguments using equation (2.10), Lemma 2.4 and the Lipschitz continuity of \( D^2 g \).

The usual path to show (2.13) is to view the family of operators \( P_s: g \mapsto g(we^{-s} + \sqrt{1 - e^{-2s}}Z) \) as an Ornstein–Uhlenbeck semigroup with generator equal to the characterizing operator \( A \), and then the result follows essentially from strong continuity of the semigroup. However, the semigroup is not strongly continuous, even for \( Z \) a Brownian motion, and so an alternative approach is to follow the proof of the relevant result for strongly continuous semigroups; see [Kasprzak et al., 2017]. While such a strategy could work in our setting, we provide a direct proof that is simpler than existing approaches, using Gaussian calculations and (2.10).

Putting \( W_s = we^{-s} + \sqrt{1 - e^{-2s}}Z \) and using (2.2), (2.10), we can rewrite the left hand side of (2.13) as
\[
\mathbb{E} \int_0^{\infty} e^{-s} Dg(W_s)[w] ds - \mathbb{E} \int_0^{\infty} e^{-2s} D^2 g(W_s)[Z', Z'] ds,
\] (2.14)
where \( Z' \) is an independent copy of \( Z \). The right hand side of (2.13) can be written as
\[
\mathbb{E}[g(w) - g(Z)] = -\mathbb{E} \int_0^{\infty} \frac{d}{ds} g(W_s) ds,
\]
and, since $g \in M$,
\[
\frac{d}{ds} g(W_s) = Dg(W_s) \left[ -e^{-s}w + \frac{e^{-2s}}{\sqrt{1 - e^{-2s}}} Z \right].
\]

Thus, using linearity of the derivative,
\[
g(w) - \mathbb{E}[g(Z)] = -\mathbb{E} \int_0^\infty Dg(W_s) \left[ -e^{-s}w + \frac{e^{-2s}}{\sqrt{1 - e^{-2s}}} Z \right] ds
\]
\[
= \mathbb{E} \int_0^\infty e^{-s} Dg(W_s)[w] ds - \mathbb{E} \int_0^\infty \frac{e^{-2s}}{\sqrt{1 - e^{-2s}}} Dg(W_s)[Z] ds.
\]

Comparing with (2.14), it only remains to show
\[
\mathbb{E} \int_0^\infty \frac{e^{-2s}}{\sqrt{1 - e^{-2s}}} Dg(W_s)[Z] ds = \mathbb{E} \int_0^\infty e^{-2s} D^2 g(W_s)[Z', Z'] ds. \tag{2.15}
\]

We claim that, after swapping the order of integration, the integrands are equal. To see this, for fixed $w \in D^p$, and $s \in [0, \infty)$, we write
\[
h(\hat{w}) = g(e^{-s}w + \sqrt{1 - e^{-2s}} \hat{w}).
\]

Then for any $x, y \in D^p$,
\[
Dh(\hat{w})[x] = \sqrt{1 - e^{-2s}} Dg(e^{-s}w + \sqrt{1 - e^{-2s}} \hat{w})[x],
\]
\[
D^2 h(\hat{w})[x, y] = (1 - e^{-2s}) D^2 g(e^{-s}w + \sqrt{1 - e^{-2s}} \hat{w})[x, y].
\]

Now, the Stein equation (2.3) with (2.2) implies
\[
\mathbb{E}[Dh(Z)[Z]] = \mathbb{E}[D^2 h(Z)[Z', Z']],
\]
which, using the definition of $h$, is the same as
\[
\mathbb{E}[Dg(W_s)[Z]] = \sqrt{1 - e^{-2s}} \mathbb{E}[D^2 g(W_s)[Z', Z']].
\]

This implies (2.15), and thus (2.13). \qed

**Remark 2.3.** Theorem 2.2 can be used to establish quantitative approximation of a process $W \in D^p$ by a continuous Gaussian process $Z$ in ways typical of Stein’s method. Taking any test function $g \in M$, the difference $\mathbb{E}[g(W)] - \mathbb{E}[g(Z)]$ can be bounded by
\[
\left| \mathbb{E} \left\{ \int_{\mathbb{R}^d} D^2 f_g(W)[J_u^{(2)}] \Lambda(du) - Df_g(W)[W] \right\} \right|,
\]
where the functions $J_u$ and the measure $\Lambda$ are as in the representation (2.1) of the covariance function of $Z$. The quantity $\mathbb{E}\{Df_g(W)[W]\}$ can then be treated in one of a number of standard ways, depending on the context. For Theorem 1.10, $W$ is an integral with respect to a point process, the expectation is evaluated using Palm theory, and $\Lambda$ and the functions $J_u$ emerge naturally in the resulting calculations.
For making estimates when exploiting the above approach, the following two lemmas are often useful. They are needed, for example, in proving Theorem 1.10.

**Lemma 2.4.** If \( f \in M \) and \( w, w', w_1, w_2 \in \mathbb{D}^p \), then
\[
|D^2f(w)[w_1, w_2]| \leq 3\|w_1\||w_2\||D^2f(w)|,
\]
and
\[
|D^2f(w + w')[w_1, w_2] - D^2f(w)[w_1, w_2]| \leq 3\|w_1\||w_2\||D^2f(w + w') - D^2f(w)|
\]

**Proof.** Using bilinearity, we have
\[
D^2f(w)[w_1, w_2] = \frac{1}{2}(D^2f(w)[w_1 + w_2, w_1 + w_2] - D^2f(w)[w_1, w_1] - D^2f(w)[w_2, w_2]).
\]
Taking the absolute value and using the triangle inequality implies
\[
|D^2f(w)[w_1, w_2]| \leq \frac{1}{2}|D^2f(w)||(|w_1|^2 + |w_2|^2 + |w_1 + w_2|^2)
\]
\[
\leq \frac{3}{2}|D^2f(w)||(|w_1|^2 + |w_2|^2),
\]
and we deduce from the bilinearity that for any \( t > 0 \)
\[
|D^2f(w)[w_1, w_2]| = |D^2f(w)[tw_1, t^{-1}w_2]| \leq \frac{3}{2}|D^2f(w)||t^2|w_1|^2 + t^{-2}|w_2|^2).
\]
Taking \( t^2 = ||w_2||/||w_1|| \) yields the first inequality. The second inequality follows from the same arguments, with \( D^2f(w) \) replaced by \( D^2f(w + w') - D^2f(w) \).

**Lemma 2.5.** If \( f \in M \) and \( w_1, w_2, J \in \mathbb{D}^p \), then
\[
Df(w_2)[J] - Df(w_1)[J] = D^2f(w_1)[J, w_2 - w_1]
\]
\[
+ \int_0^1 (D^2f(w_1 + t(w_2 - w_1))[J, w_2 - w_1] - D^2f(w_1)[J, w_2 - w_1])dt.
\]

**Proof.** Set \( h(t) = Df(w_1 + t(w_2 - w_1))[J] \), and note that
\[
h'(t) = D^2f(w_1 + t(w_2 - w_1))[J, w_2 - w_1]
\]
is continuous on \([0, 1]\). Therefore,
\[
h(1) - h(0) = h'(0) + \int_0^1 (h'(t) - h'(0))dt,
\]
which is the lemma.

We now turn to proving our second main result.
Proof of Theorem 1.10. Recall that
\[
\tilde{X}(s) = \int_{\mathbb{R}^d} J_u(s) \frac{(N - \lambda)(dv)}{\sigma},
\]
and let \( f = f_g \) be the Stein solution in Theorem 2.2. In view of (2.13), it suffices to show the bound for
\[
|\mathbb{E} Af(\tilde{X})| = \left| \mathbb{E} \int_{\mathbb{R}^d} D^2 f(\tilde{X})[\tilde{J}_u] \lambda(du) - \mathbb{E} [Df(\tilde{X})[\tilde{X}]] \right|. \tag{2.16}
\]
Using the definition of \( \tilde{X} \), we first write
\[
\mathbb{E} Df(\tilde{X})[\tilde{X}] = \mathbb{E} \int_{\mathbb{R}^d} Df(\tilde{X})[J_u] \tilde{N}(du)
= \sigma^{-1} \mathbb{E} \left[ \int_{\mathbb{R}^d} Df(\tilde{X})[J_u] N(du) - \int_{\mathbb{R}^d} Df(\tilde{X})[J_u] \lambda(du) \right]. \tag{2.17}
\]
Now, with \( g(N, u) := Df(\tilde{X})[J_u] \), we can write
\[
\mathbb{E} \int_{\mathbb{R}^d} g(N, u) N(du) = \mathbb{E} \int_{\mathbb{R}^d} g(N^{(u)} + \delta_u, u) \lambda(du)
= \mathbb{E} \int_{\mathbb{R}^d} Df(\sigma^{-1}(X^{(u)} + J_u - \mathbb{E}[X]))[J_u] \lambda(du).
\]
Combining this with (2.17), we find that
\[
\mathbb{E} [Df(\tilde{X})[\tilde{X}]] = \sigma^{-1} \mathbb{E} \left[ \int_{\mathbb{R}^d} \left( Df(\sigma^{-1}(X^{(u)} + J_u - \mathbb{E}[X]))[J_u] - Df(\tilde{X})[J_u] \right) \lambda(du) \right].
\]
Applying Lemma 2.5 with \( w_1 = \tilde{X}, w_2 = \sigma^{-1}(X^{(u)} + J_u - \mathbb{E}[X]) \) and \( J = J_u \) yields
\[
\mathbb{E} Df(\tilde{X})[\tilde{X}] = \frac{1}{\sigma^2} \mathbb{E} \left[ \int_{\mathbb{R}^d} D^2 f(\tilde{X})[J_u, X^{(u)} - X + J_u] \lambda(du) \right] \tag{2.18}
+ \frac{1}{\sigma^2} \mathbb{E} \left[ \int_{\mathbb{R}^d} \int_0^1 \left( D^2 f(\tilde{X} + t\sigma^{-1}(X^{(u)} + J_u - X)) \right)[J_u, X^{(u)} + J_u - X]
- D^2 f(\tilde{X})[J_u, X^{(u)} + J_u - X] \right] dt \lambda(du) \right].
\]
Now the first bound of the theorem easily follows by adding and subtracting
\[
\frac{1}{\sigma^2} \mathbb{E} \left[ \int_{\mathbb{R}^d} D^2 f(\tilde{X})(J_u, \mathbb{E}[X^{(u)} - X + J_u]) \lambda(du) \right]
\]
to the right hand side of (2.18), plugging the resulting expression for \( \mathbb{E} Df(\tilde{X})[\tilde{X}] \) into (2.16), and then applying (2.11) to arrive at (1.15).

The second assertion (1.16) follows from the first, after observing that we can set \( N^{(u)} = N \), and hence \( X^{(u)} = X \). \( \square \)
3 M/GI/∞ QUEUE: PROOF OF THEOREM 1.1

Let us first recall some notation: $\mathcal{S} := [0, T] \times \mathbb{R}_+$, $\alpha$ is a finite measure on $[0, T]$ with $\alpha([0, T]) \geq 1$, and $G$ and $\tilde{G}$ are distribution functions on $\mathbb{R}_+$. The point process $N_n$ that we consider has the following form: (1.14),

$$N_n = M^{(1)}_n + M^{(2)}_n,$$

where $x_n \geq 1$ is an integer, $(Y_i, i \geq 1)$ is a sequence of i.i.d. random variables with distribution $\tilde{G}$, and $M^{(1)}_n$ is a Poisson point process on $\mathcal{S}$ with intensity measure $\ell_n(dt, dy) := n\alpha(dt)G(dy)$ that is independent of $(Y_i, i \geq 1)$. $\Lambda$ denotes the measure $(\alpha \times G) + x(\delta_0 \times \tilde{G})$.

In order to illustrate the use of Theorem 1.10 in a multivariate context, we define

$$J_{t,y}(s) := \begin{cases} 
1[t \leq s < t + y]e^{(1)}, & \text{if } t > 0; \\
1[0 \leq s < y]e^{(2)}, & \text{if } t = 0,
\end{cases}$$

where $e^{(i)}$, $i = 1, 2$, denotes the coordinate vectors in $\mathbb{R}^2$, and then define

$$U^{(i)}_n(s) := \int_S J_{t,y}(s)M^{(i)}_n(dt, dy), \quad i = 1, 2; \quad U_n := U^{(1)}_n + U^{(2)}_n.$$

Then $X_n := (1, 1)^\top U_n$ models the number of customers in an M/G/∞ queue, and $U_n$ distinguishes those who were in the queue at time 0 and those who arrived afterwards. We quantify the convergence of $\bar{U}_n := n^{-1/2}(U_n - \mathbb{E}U_n)$ to the bivariate centred Gaussian process $\tilde{Z}$ with covariance matrix

$$\mathbb{E}\{\tilde{Z}(s_1)\tilde{Z}(s_2)^\top\} := \int_0^{s_1} (1 - G(s_2 - t))\alpha(dt)e^{(1)}(e^{(1)})^\top + x\tilde{G}(s_1)(1 - \tilde{G}(s_2))e^{(2)}(e^{(2)})^\top,$$

and use this to deduce Theorem 1.1; in particular, see (3.4).

We start with the following proposition, which states the well known families of reduced Palm couplings $(M^{(1),+}_n, M^{(1)}_n)_{(t,y) \in \mathcal{S}}$ and $(M^{(2),+}_n, M^{(2)}_n)_{y \in \mathbb{R}_+}$.

**Proposition 3.1.** Let $M^{(i)}_n$, $i = 1, 2$, be defined as above. For $(t, y) \in \mathcal{S}$, and given $M^{(1)}_n$, let $M^{(1),+}_n := M^{(1)}_n$, $t > 0$. Then $M^{(1),+}_n$ has the reduced Palm distribution of $M^{(1)}_n$ at $(t, y)$. Similarly, given $M^{(2)}_n$, let $Y$ be a point uniformly and independently chosen from $\{Y_1, \ldots, Y_{n_2}\}$. Then $M^{(2),+}_n := M^{(2)}_n - \delta_{(0,Y)}$ has the reduced Palm distribution of $M^{(2)}_n$ at $(0, y)$.

Because $M^{(1)}_n$ and $M^{(2)}_n$ are independent, it follows that the reduced Palm distributions of $N_n$ are given by $N^{(t,y)}_n = N_n - \delta_{(0,Y)}1\{t = 0\}$, and hence that $U^{(t,y)}_n := \int_S J_{t,y}N^{(t,y)}_n(dt, dy)$ satisfies

$$U^{(t,y)}_n - U_n = -J_{0,Y}1\{t = 0\}.$$  \hfill (3.1)
**Proof of Theorem 1.1.** We start by computing the bounds in Theorem 1.10 on the difference $|\mathbb{E}g(\tilde{U}_n) - \mathbb{E}g(\tilde{Z})|$. We first show that the process $\tilde{Z}$ has a continuous modification. Since, by assumption, neither $G \ast \alpha$ nor $\tilde{G}$ have atoms in $[0, T]$, it is clear from (1.4) that the covariance function is continuous. Moreover, for any $s \geq 0$ and $0 \leq h \leq (T - s) \wedge 1$, (1.4) and the Hölder continuity of $G \ast \alpha$ easily imply that

$$
\left| \mathbb{E}\left[ (s + h)\mathbb{E}\left[ s + h \right] \right] - \mathbb{E}\left[ (s + h)\mathbb{E}\left[ s + h \right] \right] \right|
= \int_{s}^{s+h} (1 - G(s + h - t))\alpha(dt) + x(1 - \tilde{G}(s + h)) [\tilde{G}(s + h) - \tilde{G}(s)]
\leq (c_{G, \alpha} + xc_{\tilde{G}})h^\beta,
$$

and, similarly, that

$$
\left| \mathbb{E}\left[ (s)\mathbb{E}\left[ s \right] - \mathbb{E}\left[ (s)\mathbb{E}\left[ s \right] \right] \right] \right|
\leq (c_{G, \alpha} + xc_{\tilde{G}})h^\beta,
$$

so that (1.17) is satisfied. Therefore, in view of Remark 1.11, the Gaussian process $\tilde{Z}$ has a continuous modification. In what follows, we will work with this continuous Gaussian process, that we still denote by $\tilde{Z}$.

The contributions to the integrals in (1.13)–(1.15) from $\{0\} \times \mathbb{R}_+$ and $\{(0, T] \times \mathbb{R}_+\}$ can be separately bounded, and the results added for the overall bounds. First, on $\{(0, T] \times \mathbb{R}_+\}$, $U_n^{((t,y))} - U_n = 0$, in view of (3.1), so that there is no contribution from (1.14), or from (1.13) either, since $\Lambda = \alpha \times G = n^{-1}\ell_n$ on $\{0, T] \times \mathbb{R}_+$; and (1.15) contributes at most

$$
\|g\|_M \int_{S} \|J_{t,y}\|^3\alpha(dt)G(dy) \leq \frac{\|g\|_M\alpha([0, T])}{2\sqrt{n}}.
$$

Next, on $\{0\} \times \mathbb{R}_+$, $U_n^{((t,y))} - U_n = -J_{0,Y}$, and so

$$
\mathbb{E}[U_n^{((t,y))} - U_n] = -\int J_{0,Y} \tilde{G}(dy) = -(1 - \tilde{G})e^{(2)}.
$$

Now consider the contribution to (1.13), with $\Lambda = x(\delta_0 \times \tilde{G})$ and $\lambda = x_n(\delta_0 \times \tilde{G})$ on $\{0\} \times \mathbb{R}_+$, taking $\tilde{J}_{(0,y)} := J_{(0,y)} - (1 - \tilde{G})e^{(2)}$. The contribution can be written as

$$
x \int_{\mathbb{R}_+} D^2 f(\tilde{U}_n)[(J_{0,y} - (1 - \tilde{G})e^{(2)})^2] \tilde{G}(dy) - \frac{x_n}{n} \int_{\mathbb{R}_+} D^2 f(\tilde{U}_n)[J_{0,y}, J_{0,y} - (1 - \tilde{G})e^{(2)}] \tilde{G}(dy)
= \frac{nx - x_n}{n} \int_{\mathbb{R}_+} D^2 f(\tilde{U}_n)[(J_{0,y} - (1 - \tilde{G})e^{(2)})^2] \tilde{G}(dy)
- \frac{x_n}{n} \int_{\mathbb{R}_+} D^2 f(\tilde{U}_n)[(1 - \tilde{G})e^{(2)}, J_{0,y} - (1 - \tilde{G})e^{(2)}] \tilde{G}(dy)
= \frac{nx - x_n}{n} \int_{\mathbb{R}_+} D^2 f(\tilde{U}_n)[(J_{0,y} - (1 - \tilde{G})e^{(2)})^2] \tilde{G}(dy),
$$

where the last line uses (3.3), as well as Lemma 5.3 below (noting in particular that $J_{0,y}(s) = (1\{s \geq 0\} - 1\{s \geq y\})e^{(2)}$ and that $f$ inherits from $g$ either its smoothness property (1.2) or its being a function of a finite number of values of its argument, using (2.10).
of Theorem 2.2). Therefore, using (2.12) of Theorem 2.2, the contribution to (1.13) on \( \{0\} \times \mathbb{R}_+ \) is bounded by

\[
(3/2)\|g\|_{M'} |n^{-1}x_n - x|.
\]

For the contribution to (1.14) on \( \{0\} \times \mathbb{R}_+ \), we use (2.12) and (3.1), giving

\[
\mathbb{E} \left[ \int_{\mathbb{R}_+} \left| D^2 f(\tilde{U}_n) \right| \left| J_{0,Y_n} - U_n - \mathbb{E}[U_{n}^{0,y}] - U_n \right| \right] |n^{-1}x_n\tilde{G}(dy)|
\]

\[
\leq (3/2)\|g\|_{M'} \int_{\mathbb{R}_+} \left| J_{0,Y_n} \right| \| \mathbb{E} \left[ \frac{1}{x_n} \sum_{i=1}^{x_n} (J_{0,Y_i} - \mathbb{E}[J_{0,Y}] ) \right] \| |n^{-1}x_n\tilde{G}(dy)|.
\]

Then (3.3) implies that

\[
\int_{\mathbb{R}_+} \left| J_{0,Y_n} \right| \mathbb{E} \left[ \left| \frac{1}{x_n} \sum_{i=1}^{x_n} (J_{0,Y_i} - \mathbb{E}[J_{0,Y}] ) \right| \right] |n^{-1}x_n\tilde{G}(dy)|
\]

\[
= \frac{x_n}{n} \int_{\mathbb{R}_+} \mathbb{E} \left[ \left| \frac{1}{x_n} \sum_{i=1}^{x_n} J_{0,Y_i} - (1 - \tilde{G})\mathbb{E}(2) \right| \right] \tilde{G}(dy) = \frac{x_n}{n} \mathbb{E} \left[ \left| \frac{1}{x_n} \sum_{i=1}^{x_n} 1[Y_i > \cdot] - (1 - \tilde{G}) \right| \right]
\]

\[
= \frac{x_n}{n} \mathbb{E} \left[ \left| \frac{1}{x_n} \sum_{i=1}^{x_n} 1[Y_i \leq \cdot] - \tilde{G} \right| \right].
\]

Thus we must bound the mean of the sup-norm of the difference between an empirical CDF and its limit. According to [Massart, 1990, Corollary 1] (improving on [Dvoretzky, Kiefer, and Wolfowitz, 1956]), for any \( y > 0 \),

\[
\mathbb{P} \left( \left| \frac{1}{x_n} \sum_{i=1}^{x_n} 1[Y_i \leq \cdot] - \tilde{G} \right| > y \right) \leq 2e^{-2xy^2},
\]

so that

\[
\mathbb{E} \left[ \left| \frac{1}{x_n} \sum_{i=1}^{x_n} 1[Y_i \leq \cdot] - \tilde{G} \right| \right] \leq 2 \int_0^\infty e^{-2xy^2} dy = \sqrt{\frac{\pi}{2x_n}},
\]

giving a contribution to (1.14) on \( \{0\} \times \mathbb{R}_+ \) of at most \((3/2)\|g\|_{M'}\sqrt{\pi/(2x_n)}\).

For the contribution to (1.15) on \( \{0\} \times \mathbb{R}_+ \), we use (3.3) and (3.1) to easily find that

\[
\int_{\mathbb{R}_+} \| J_{0,y} \| \| U_n^{0,y} - U_n + J_{0,y} \| n^{-1}x_n\tilde{G}(dy) = \int_{\mathbb{R}_+} \| J_{0,y} \| \| J_{0,y} - J_{0,Y} \| n^{-1}x_n\tilde{G}(dy) \leq n^{-1}x_n,
\]

giving a contribution to (1.15) on \( \{0\} \times \mathbb{R}_+ \) of at most \((1/2)\|g\|_{M'}n^{-3/2}x_n\). Collecting these bounds, we deduce that, for any \( g \in M' \),

\[
|\mathbb{E}[g(\tilde{U})] - \mathbb{E}[g(\tilde{Z})]| \leq \|g\|_{M'} \Psi_n(x_n, \alpha, T), \tag{3.4}
\]

where \( \Psi_n(x_n, \alpha, T) \) is as given in (1.5). Noting that, for \( \tilde{g} : \mathbb{D}^1 \to \mathbb{R} \) and \( g : \mathbb{D}^2 \to \mathbb{R} \) defined by \( g(w_1, w_2) := \tilde{g}(w_1 + w_2) \), we have \( \|\tilde{g}\|_{M'} \leq 2^{3/2}\|g\|_{M'} \), the bound (1.6) in Theorem 1.1 follows.
To prove the bound on the Lévy–Prokhorov distance, we use the main results of [Barbour et al., 2021], as stated in Theorem 5.1 below. The first hypothesis of the theorem is satisfied with \( \kappa_2 = 0 \), and with \( \kappa_1 \) upper bounded by a quantity of order \( O(\|n^{-1}x_n-x\| + \alpha([0, T])n^{-1/2}) \), read from the bound (1.6) just established (noting that \( \|g\|_{M^9} \leq \|g\|_{M^9} \)).

To bound the modulus of continuity terms, we use Lemma 5.2, treating the components \( \tilde{X}_n^{(1)} \) and \( \tilde{X}_n^{(2)} \) of \( \tilde{U}_n \) separately (so that \( \tilde{U}_n^{(i)} = \tilde{X}_n^{(i)}e^{(i)} \)). To verify (5.1) for \( \tilde{X}_n^{(1)} \), let

\[
\mathcal{R}_s := \left\{(u, y) : 0 \leq u \leq s, \ 0 < y < s - u \right\}, \quad \mathcal{R}_1(s_1, s_2) := \mathcal{R}_{s_2} \setminus \mathcal{R}_{s_1},
\]

and \( \mathcal{R}_2(s_1, s_2) := (s_1, s_2] \times \mathbb{R}_+ \), \( s_1 < s_2 \).

Fix \( 0 \leq s < t \leq T \) with \( 1/(2n) \leq (t - s) \leq 1/2 \). Recalling the definition of the random measure \( M_n^{(1)} \), we have

\[
\tilde{X}_n^{(1)}(t) - \tilde{X}_n^{(1)}(s) = \tilde{Y}_n(2; s, t) - \tilde{Y}_n(1; s, t),
\]

where

\[
\tilde{Y}_n(i; s, t) := n^{-1/2}\left\{ M_n^{(1)}(\mathcal{R}_i(s, t)) - \ell_n(\mathcal{R}_i(s, t)) \right\}, \quad i = 1, 2,
\]

are (dependent) centred and normalized Poisson random variables with means

\[
\ell_n(\mathcal{R}_1(s, t)) \leq n c_{G, \alpha}(t - s) \beta \quad \text{and} \quad \ell_n(\mathcal{R}_2(s, t)) \leq n c_\alpha(t - s) \beta,
\]

by the Hölder continuity of \( G \ast \alpha \) and \( A \). Now, for \( W_n \) a sum of \( n \) independent Bernoulli random variables with success probability \( \tilde{p} \leq \mu \), it follows from Rosenthal’s inequality that, for any \( l \geq 1 \),

\[
n^{-l}\mathbb{E}|W_n - \mathbb{E}[W_n]|^{2l} \leq C_2n^{-l}\max\{(n\mu)^l, n\mu\} \leq C_2l\max\{\mu^l, n^{-l+1}\mu\},
\]

where \( C_r \) is the Rosenthal constant for exponent \( r \). A limiting argument shows that the inequality (3.8) holds also for \( W_n \sim \text{Po}(n\mu) \). Thus it follows that, for any \( l \geq 1 \) and \( |t - s| \geq (1/2)n^{-1/\beta} \),

\[
\mathbb{P}\left[|\tilde{Y}_n(i; s, t)| \geq \theta/2 \right] \leq C_22^{2l}\theta^{-2l}\max\left\{(c_{G, \alpha} \vee c_\alpha)t - s|^{\beta}, (c_{G, \alpha} \vee c_\alpha)n^{-l+1}|t - s|^{\beta} \right\} \leq K_1^{(i)}\theta^{-2l}|t - s|^\beta, \quad i = 1, 2,
\]

which implies (5.1) for \( \tilde{X}_n^{(1)} \) with \( M = n^{1/\beta} \), \( K = 2K_1^{(1)} \), \( a = l\beta - 1 \) and \( b = 2l \), for any \( l \geq 1 \).

To establish (5.2) for \( \tilde{X}_n^{(1)} \), with \( M = n^{1/\beta} \), observe that, for all \( s \) such that \( (k - 1)/M \leq s \leq k/M \),

\[
\left| \tilde{X}_n^{(1)}(s) - \tilde{X}_n^{(1)}((k - 1)/M) \right| 
\leq n^{-1/2}\sum_{i=1}^{2} \left\{ M_n^{(1)}\left(\mathcal{R}_i\left(\frac{k - 1}{M}, \frac{k}{M}\right)\right) + \ell_n\left(\mathcal{R}_i\left(\frac{k - 1}{M}, \frac{k}{M}\right)\right) \right\} 
\leq \sum_{i=1}^{2} \tilde{Y}_n(i; \frac{k - 1}{M}, \frac{k}{M}) + 2n^{-1/2}\sum_{i=1}^{2} \ell_n\left(\mathcal{R}_i\left(\frac{k - 1}{M}, \frac{k}{M}\right)\right),
\]

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and that \( \ell_n(\mathcal{R}_i(k^n/M, k^n/M)) \leq c_{G,\alpha} \vee c_\alpha \), see (3.7) and (3.6). Hence, if \( \theta \geq 4(c_{G,\alpha} \vee c_\alpha)n^{-1/2} \), then

\[
\mathbb{P} \left[ \sup_{k^n/M \leq s \leq k^n/M} |\tilde{X}_n^{(1)}(s) - \bar{X}_n^{(1)}((k - 1)/M)| \geq \theta \right] \leq \mathbb{P} \left( \sum_{i=1}^{2} \left| \bar{Y}_n(i; k - 1/M, k/M) \right| \geq \theta/2 \right) \leq \sum_{i=1}^{2} \mathbb{P} \left[ \left| \bar{Y}_n(i; k - 1/M, k/M) \right| \geq \theta/4 \right],
\]

and this probability is bounded by \( 2^{2l'+1}K_{l'}\theta^{-2l'}n^{-l'} \), for any \( l' \geq 1 \), in view of (3.9) as established above. Hence, for \( \theta \geq 4(c_{G,\alpha} \vee c_\alpha)n^{-1/2} \), we can take

\[
\varphi^{(1)}_M(\theta) := n^{1/2}2^{2l'+1}K_{l'}\theta^{-2l'} \leq 2^{2l'+1}K_{l'}\theta^{-2l'}\epsilon^\beta - 1
\]

in (5.2), for any \( l' \geq 1/\beta \) and \( \epsilon \geq n^{-1/\beta} \), to be compared with the bound in (5.1). In particular, taking \( \theta \geq 4(c_{G,\alpha} \vee c_\alpha)n^{-1/2} \) and \( l' = l \), for any \( l > 1/\beta \), and applying Lemma 5.2 with \( M = n^{1/\beta} \), it follows that, for any \( \epsilon \in (n^{-1/\beta}, 1] \) and for any \( \theta > 4(c_{G,\alpha} \vee c_\alpha)n^{-1/2} \), we have

\[
\mathbb{P}[\omega_{\tilde{X}_n^{(1)}}(\epsilon) \geq \theta/2] \leq TC\theta^{-2l}\epsilon^\beta - 1,
\]

for a suitable constant \( C \) that does not depend on \((\epsilon, n, \theta)\). By observing that, for \( \epsilon \geq n^{-1/\beta} \) and \( \theta \leq 4(c_{G,\alpha} \vee c_\alpha)n^{-1/2} \), the bound (3.11) is comparable to or larger than 1, the constant \( C \) can be chosen in such a way that the bound is valid for all \( \theta > 0 \).

Turning to \( \tilde{X}_n^{(0)} \), we can first assume that \( x_n/n \leq 2x \) without loss of generality, because \( T \geq n^{1/2}|x_n/n - x| \) and the final bound is only meaningful for \( T \ll n^{1/3} \). Note that, for \( s < t \),

\[
\tilde{X}_n^{(0)}(t) - \tilde{X}_n^{(0)}(s) = n^{-1/2} \sum_{i=1}^{x_n} \{1[s < Y_i \leq t] - (\tilde{G}(t) - \tilde{G}(s))\}
\]

is a normalized sum of independent centred Bernoulli random variables, and that, by assumption, \( x_n(\tilde{G}(t) - \tilde{G}(s)) \leq 2nx \sigma_G(t - s) \beta \). Arguing exactly as for \( \tilde{X}^{(1)} \) now yields (5.1) for \( \tilde{X}_n^{(0)} \), for any \( l \geq 1 \), with \( 1 + a = l\beta \) and \( b = 2l \), and with \( K = K_i^{(0)} = 2^{l+1}x\sigma_G \max\{x\sigma_G, 1\}^{l-1} \).

For (5.2), the argument is again as for \( \tilde{X}_n^{(1)} \). We first write

\[
\sup \left\{ \left| \tilde{X}_n^{(0)}(s) - \bar{X}_n^{(0)}((k - 1)/M) \right| : \frac{k - 1}{M} \leq s \leq \frac{k}{M} \right\} \leq n^{-1/2} \sum_{i=1}^{x_n} \left\{1\left[ \frac{k - 1}{M} < Y_i \leq \frac{k}{M} \right] + \left[ \tilde{G}\left( \frac{k}{M} \right) - \tilde{G}\left( \frac{k - 1}{M} \right) \right] \right\} \leq n^{-1/2}\left| W_n - \mathbb{E}[W_n] \right| + 4x n^{1/2}\left[ \tilde{G}(k/M) - \tilde{G}((k - 1)/M) \right],
\]

where \( W_n \) is a sum of \( x_n \) i.i.d. Bernoulli random variables with success probability \( \tilde{p} \leq c_{\sigma_G}M^{-\beta} \). Therefore, with \( M = n^{1/\beta} \), it follows from (3.8) and by first considering \( \theta > 8x c_{\sigma_G}n^{-1/2} \) that we can take

\[
\varphi^{(0)}_M(\theta) := n^{-l'}\epsilon^{l'}2^{2l'}K^{(0)}_{l'}\theta^{-2l'} - 1
\]

(3.12)
for $\varphi_M(\theta)$ in (5.2) for any $l' \geq 1$. Hence, from Lemma 5.2, for any $\epsilon \in (n^{-1/\beta}, 1]$ and any $\theta > 0$, we have
\[
P[\omega_{X_n}(\epsilon) \geq \theta/2] \leq TC\theta^{-2l' \epsilon^{l' \beta - 1}},
\]for any $l \geq 1/\beta$, for a suitable constant $C$.

For the analogous inequality for $\hat{Z}$, an easy calculation shows that, for any $0 \leq u < s \leq T$,
\[
E[|\hat{Z}(s) - \hat{Z}(u)|^2] \leq 2(1 + x)c(s - u)^\beta,
\]
and so [Barbour et al., 2021, Remark 1.6] implies there is a constant $C$ depending on $x, c, \beta$ such that, for each component $\hat{Z}(i)$ of $\hat{Z}$,
\[
P[\omega_{\hat{Z}(i)}(\epsilon) \geq \theta] \leq CT\theta^{-2l' \epsilon^{l' \beta - 1}}, \quad i = 1, 2,
\]
for any $l \geq 1$.

A bound on the Lévy–Prokhorov distance between $L(\tilde{U}_n)$ and $L(\hat{Z})$ now follows by using (3.11), (3.13) and (3.14) in Theorem 5.1 below, with $\kappa_1 = O(|x_n n^{-1} - x| + \alpha([0, T]) n^{-1/2})$ (from (3.4)) and $\kappa_2 = 0$, giving a bound of order
\[
O\left(\theta + \delta \sqrt{T \log n} + (\epsilon \delta)^{-3} \kappa_1 T^{3/2} + T \theta^{-2l' \epsilon^{l' \beta - 1}}\right)
\]
for the Lévy–Prokhorov distance, for any $\delta, \theta > 0$ and $\epsilon \in (n^{-1/\beta}, 1)$. Taking $\delta \sqrt{T} = \theta$ and matching $(\epsilon \delta)^{-3} \kappa_1 T^{3/2} = T \theta^{-2l' \epsilon^{l' \beta - 1}}$ reduces the bound (3.15) to
\[
O\left(\theta \sqrt{\log n} + \kappa_1 T^3 (\epsilon \theta)^{-3}\right) \quad \text{with} \quad \epsilon = (\kappa_1 T^2 \theta^{2l-3})^{2/3l\beta} > n^{-1/\beta}
\]
and then balancing $\theta$ with $\kappa_1 T^3 (\epsilon \theta)^{-3}$ yields the bound $O(\theta \sqrt{\log n})$ with
\[
\theta = (\kappa_1 T^3)^{(l\beta - 1)/(6l + 4l\beta - 1)} T^{3/(6l + 4l\beta - 1)}.
\]
That is, we have a bound of order
\[
O\left(\sqrt{\log n} (T^4 n^{-\varphi})^{(l\beta - 1)/(6l + 4l\beta - 1)} T^{3/(6l + 4l\beta - 1)}\right),
\]
for any $l \geq 1/\beta$, where
\[
\varphi := \min \left\{ \frac{1}{2} + \log \left( \frac{T}{\alpha([0, T])} \right), \log \left( \frac{T}{|x_n n^{-1} - x|} \right) \right\}.
\]
The simplified bound given in the statement of Theorem 1.1, for $\beta = 1$ and $n^{1/2} |x_n/n - x| \leq \alpha([0, T]) = O(T)$, follows, for any $\chi > 0$, by taking $l$ large enough.
Let us first recall some notation from Section 1.4. The stationary renewal process $V_n$ is driven by $R/n$, and the point process $N_n$ that we consider has the form

$$N_n := \sum_{i=1}^{\lfloor nT \rfloor} M_n(i/n)\delta(i/n, Y_i),$$

where

(i) $M_n(i/n)$ marks the arrival of a customer at time $i/n$, and can be represented as

$$M_n(i/n) := \sum_{j=1}^{\infty} 1[R_0 + R_1 + ... + R_j = i],$$

where $(R_j, j \geq 1)$ are independent copies of $R$, and $R_0$ has the delay distribution $\mathbb{P}(R_0 = k) = m^{-1}\mathbb{P}(R \geq k), k \in \mathbb{N}$;

(ii) the service times $Y := (Y_i, i \geq 1)$ are i.i.d. with distribution $G$,

(iii) $M_n$ and $Y$ are independent.

As in the previous section, we begin with a coupling lemma.

**Lemma 4.1.** With the above notation, let $(R_{ik}, 1 \leq i, k < \infty)$ and $(R'_{ik}, 1 \leq i, k < \infty)$ be independent i.i.d. sequences with the same distribution as $R$ that are also independent of $V_n$ and $Y$. Define

$$S_{ij} := \sum_{k=1}^{j} R_{ik}, \quad S'_{ij} := \sum_{k=1}^{j} R'_{ik}, \quad i,j \in \{1,2,\ldots\};$$

$$\hat{M}_{n}^{(ij/n)} := \sum_{j=1}^{\infty}(\delta(i+S_{ij})/n + \delta(i-S'_{ij})/n), \quad i \in \{0,1,...,n\};$$

then set

$$T_i := \min\{\lfloor nT \rfloor - i + 1, \inf\{j \geq 1: M_n((i + j)/n) = \hat{M}_{n}^{(ij/n)}((i + j)/n) = 1\}\};$$

$$T'_i := \min\{i, \inf\{j \geq 1: M_n((i - j)/n) = \hat{M}_{n}^{(ij/n)}((i - j)/n) = 1\}\};$$

and finally define

$$M_{n}^{(ij/n)}(j/n) := \begin{cases} \hat{M}_{n}^{(ij/n)}(j/n), & i - T'_i < j < i + T_i \\ M_n(j/n), & \text{otherwise}. \end{cases}$$

Then

$$N_{n}^{(ij/n)} := \sum_{j=1}^{\lfloor nT \rfloor} M_{n}^{(ij/n)}(j/n)\delta(j/n, Y_j)$$

has the reduced Palm distribution of $N_n$ at $(i/n, y) \in S$. 

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Proof. It is well known that \( \hat{M}_{n}^{(i/n)} \) has the reduced Palm measure of \( M_{n} \) at \( (i/n) \); see for example [Daley and Vere-Jones, 2008, Chapter 13]. Then note that \( M_{n}^{(i/n)} \overset{d}{=} \hat{M}_{n}^{(i/n)} \), since \( T_{i} \) is the first time there is a renewal in both the zero delayed renewal process started from \( i: (i + S_{ij})_{j \geq 1} \) appearing in the definition of \( \hat{M}_{n}^{(i/n)} \), and the analogous stationary process induced by \( M_{n} \), at which point we can continue using either process without changing the distribution. A similar statement holds for \( T_{i}' \) but now moving backwards in time. From this observation, it is clear that \( N_{n}^{(i/n)} \) is distributed as claimed. \( \Box \)

Remark 4.2. We write \( N_{n}^{(i/n)} \) for the reduced Palm distribution at \( (i/n, y) \), for all \( y \).

The next result gives an expression for \( \mathbb{E}[X_{n}^{(i/n)} - X_{n}] \), to be used in (1.13) of Theorem 1.10.

Lemma 4.3. With the notation above, let

\[
X_{n}^{(i/n)} := \int_{S} J_{t,y}(s)N_{n}^{(i/n)}(dt, dy).
\]

If \( \mathbb{E}[R^{r}] < \infty \) for some \( r > 3 \), and if \( G \) satisfies the assumptions (1.8), then there is a constant \( C \), depending only on \( \mathcal{L}(R) \), \( \beta \) and \( g_{\gamma}(0) \), such that

\[
A_{n,i}(s) := \mathbb{E}[X_{n}^{(i/n)}(s)] - \mathbb{E}[X_{n}(s)] - 1\{s \geq in^{-1}\}G(s - in^{-1}) \left( \frac{v^{2} - m^{2}}{m^{2}} \right)
\]

satisfies

\[
|A_{n,i}(s)| \leq C \left\{ n^{-\beta} + (|i - |ns|| + 1)^{-r-2} + i^{-r-2} \right\}.
\]

Proof. First note that

\[
X_{n}^{(i/n)}(s) - X_{n}(s) = \sum_{j=1}^{\lfloor nT \rfloor} (M_{n}^{(i/n)}(j/n) - M_{n}(j/n))1[j/n \leq s < Y_{j} + j/n],
\]

so that, using the independence of \( Y \) and \( (M_{n}, M_{n}^{(i/n)}) \), we have

\[
\mathbb{E}[X_{n}^{(i/n)}(s)] - \mathbb{E}[X_{n}(s)] = \sum_{j=1}^{\lfloor ns \rfloor} \left( \mathbb{E}[M_{n}^{(i/n)}(j/n)] - \mathbb{E}[M_{n}(j/n)] \right)G(s - jn^{-1}). \tag{4.1}
\]

By stationarity, \( \mathbb{E}[M_{n}(j/n)] = 1/m \); and by Lemma 4.1,

\[
\mathbb{E}[M_{n}^{(i/n)}(j/n)] = u_{0}^{0}_{j} := u_{j-i}^{0}1\{j \neq i\},
\]

where \( u_{t} \) is the probability that there is a renewal at time \( l \) in a renewal process with inter-arrival distribution \( \mathcal{L}(R) \), started from zero. Hence we can write (4.1) in the form

\[
\mathbb{E}[X_{n}^{(i/n)}(s)] - \mathbb{E}[X_{n}(s)] = \sum_{j=1}^{\lfloor ns \rfloor} (u_{0}^{0}_{j} - m^{-1})G(s - jn^{-1})
\]

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The remainder of the proof consists of showing that the first term in (4.2) is close to $1\{s \geq i/n\}|G(s - in^{-1})/(v^2 - m^2)/m^2|$, and that the second term is small. The main tool is the inequality
\[
|\mathbb{E}[M_{n}(j/n)] - 1/m| \leq C_R(|j - i| + 1)^{-(r-1)},
\] (4.3)
for a suitable constant $C_R$, which follows from [Pitman, 1974, Corollary (6.21)], together with the observation that
\[
\sum_{j=-\infty}^{\infty} (u_{j,i}^0 - m^{-1}) = \frac{v^2 - m^2}{m^2}.
\] (4.4)

For the first term in (4.2), using (4.3) and (4.4), for $s \geq i/n$, we have
\[
\left|\sum_{j=1}^{[ns]} (u_{j-i}^0 - m^{-1}) - \frac{v^2 - m^2}{m^2}\right| \leq C_R\left\{\sum_{j=1}^{0} (|j - i| + 1)^{-(r-1)} + \sum_{j=[ns]+1}^{\infty} (|j - i| + 1)^{-(r-1)}\right\}
\leq C_R \frac{r}{r-2} \left\{i^{-(r-2)} + ||ns| - i + 1|^{-(r-2)}\right\}.
\] (4.5)
for $s < i/n$, the term is zero because of the factor $1\{s \geq in^{-1}\}$. For the second term in (4.2), for $s \geq i/n$, using (1.8),
\[
|G(s - i/n) - G(s - j/n)| \leq g_G(0)|n^{-1}(i - j)|^\beta, \quad 1 \leq j \leq [ns],
\]
so that
\[
\left|\sum_{j=1}^{[ns]} (u_{j-i}^0 - m^{-1}) \left(G(s - jn^{-1}) - G(s - in^{-1})1\{s \geq in^{-1}\}\right)\right|
\leq \sum_{j=1}^{[ns]} C_R(|j - i| + 1)^{-(r-1)} g_G(0)n^{-\beta}|i - j|^\beta \leq n^{-\beta} C_R g_G(0)\left(\frac{2}{r - 2 - \beta}\right).
\] (4.6)

Finally, for $s < i/n$, we have
\[
\sum_{j=1}^{[ns]} |u_{j-i}^0 - m^{-1}| G(s - jn^{-1}) \leq C_R \sum_{j=1}^{[ns]} (|j - i| + 1)^{-(r-1)}
\leq C_R \left\{\frac{r-1}{r-2}\right\} ||ns| - i + 1|^{-(r-2)}.
\] (4.7)

Combining (4.5)–(4.7) with (4.2) proves the lemma. □
We now use the coupling of Lemma 4.1 and Theorem 1.10 to prove Theorem 1.6.

**Proof of Theorem 1.6.** Following the notation in Theorem 1.10, we set

\[
\Lambda(dt, dy) := dt G(dy) \quad \text{and} \quad \hat{J}_{t,y} := \frac{m}{v} J_{t,y} - \frac{m + v}{v} G_t I_t,
\]

where \( \overline{\Lambda}(s) := \overline{G}(s - t) \) and \( I_t(s) := 1\{s \geq t\} \).

From the assumptions (1.8) on \( G \), it is clear from (1.9) that the covariance function is continuous. Moreover, for any \( s \geq 0 \) and \( 0 \leq h \leq (T - s) \wedge 1 \), they easily imply, with (1.9), that there is a constant \( c' \) such that

\[
\mathbb{E}[(Z(s + h) - Z(s))^2] \leq c'h^2,
\]

so that (1.17) is satisfied. Therefore, in view of Remark 1.11, we can assume that \( Z \) has continuous sample paths.

To bound the term corresponding to (1.13), there are two issues. The first is that we need to compare integration against the atom-less \( \Lambda \) to the atoms of \( \lambda_n/\sigma_n^2 \) corresponding to the renewals of \( X_n \) occurring on a discrete lattice. The second is that there are error terms in the differences of the means of \( X_n^{(i/n)} \) and \( X_n \), as given in Lemma 4.3. To handle the first issue, we introduce \( \Lambda_n := \frac{1}{n} \sum_{i=1}^{[nT]} (\delta_{i/n} \times G) \) as a discretized version of \( \Lambda \). Then we can compute

\[
\mathbb{E}\left[ \int D^2 f(\tilde{X}_n)[\tilde{\Lambda}^2_{t,y}, \Lambda(dt, dy)] - \int D^2 f(\tilde{X}_n)[\tilde{\Lambda}^2_{t,y}, \Lambda_n(dt, dy)] \right] \tag{4.8}
\]

\[
= \sum_{i=1}^{[nT]} \int_{\mathbb{R}^+} \mathbb{E}\left[ \int_{(i-1)/n}^{i/n} (D^2 f(\tilde{X}_n)[\tilde{\Lambda}^2_{t,y}] - D^2 f(\tilde{X}_n)[\tilde{\Lambda}^2_{i/n,y}]) dt \right] G(dy)
\]

\[
= \sum_{i=1}^{[nT]} \int_{\mathbb{R}^+} \mathbb{E}\left[ \int_{(i-1)/n}^{i/n} (D^2 f(\tilde{X}_n)[\tilde{J}_{t,y} - \tilde{J}_{i/n,y}, \tilde{J}_{t,y} + D^2 f(\tilde{X}_n)[\tilde{J}_{i/n,y}, \tilde{J}_{t,y} - \tilde{J}_{i/n,y}] dt \right] G(dy).
\]

We work on

\[
|D^2 f(\tilde{X}_n)[\tilde{J}_{t,y} - \tilde{J}_{i/n,y}, \tilde{J}_{s,y}]|, \tag{4.9}
\]

where \( t \in ((i - 1)/n, i/n) \), and \( s \geq 0 \). First, note that we can write

\[
\tilde{J}_{r,y} = \frac{m}{v} (I_r - I_{r+y}) - \frac{m + v}{v} (I_r - G_r), \tag{4.10}
\]

so that

\[
\tilde{J}_{t,y} - \tilde{J}_{i/n,y} = \frac{m}{v} ((I_t - I_{i/n}) - (I_{t+y} - I_{i/n+y})) - \frac{m + v}{v} ((I_t - I_{i/n}) - (G_t - G_{i/n})),
\]

and thus bilinearity implies that (4.9) is bounded by

\[
C\left\{ |D^2 f(\tilde{X}_n)[I_t - I_{i/n}, \tilde{J}_{s,y}]| + |D^2 f(\tilde{X}_n)[I_{t+y} - I_{i/n+y}, \tilde{J}_{s,y}]| + |D^2 f(\tilde{X}_n)[G_t - G_{i/n}, \tilde{J}_{s,y}]| \right\}; \tag{4.11}
\]

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here and below we allow $C$ to change from line to line, but only depending on $\mathcal{L}(R)$ and $g_C(0)$.

To bound the last term of (4.11), Equation (2.12) of Theorem 2.2 and the assumption (1.8) on $G$ (noting that $|t - i/n| \leq 1/n$) imply that

$$
\left| D^2 f(\tilde{X}_n)[G_t - G_{i/n}, \tilde{J}_{s,y}] \right| \leq C\|g\|_{M'} n^{-\beta}. \quad (4.12)
$$

To bound the first two terms, we apply (2.10) and, noting that $J_{s,y} = I_s - I_{s+y}$, we have

$$
\left| D^2f_g(w)[I_t - I_{i/n}, J_{s,y}] \right| \leq \int_0^{\infty} e^{-2z} E\left[ D^2 g(we^{-z} + \sqrt{1 - e^{-2z}}Z)[I_t - I_{i/n}, J_{s,y}] \right] dz
$$

\[
\leq \begin{cases} 
S_g n^{-1/2}, & \text{if } g \text{ satisfies (1.2),} \\
\sum_{j=1}^{k} 1\{t_j \in ((i-1)/n, i/n]\}, & \text{if } g(w) = F(w(t_1), \ldots, w(t_k)),
\end{cases}
\]

where, in the first case, we use the smoothness condition (1.2), and in the second the explicit expression

$$
D^2 g(w)[w_1, w_2] = \sum_{j, \ell=1}^k F_{j\ell}(w(t_1), \ldots, w(t_k)) w_1(t_j) w_2(t_\ell),
$$

where we write $F_{j\ell}$ for the mixed partial derivative of $F$ in the coordinates $j$ and $\ell$. Similarly, using Lemma 5.3, we can write

$$
\left| D^2 f(\tilde{X}_n)[I_t - I_{i/n}, G_s] \right| = \left| \int D^2f(\tilde{X}_n)[I_t - I_{i/n}, I_{s+y}] G(dy') \right|
$$

\[
\leq \begin{cases} 
S_g n^{-1/2}, & \text{if } g \text{ satisfies (1.2),} \\
\sum_{j=1}^{k} 1\{t_j \in ((i-1)/n, i/n]\}, & \text{if } g(w) = F(w(t_1), \ldots, w(t_k)),
\end{cases}
\]

and there are analogous bounds for the last two displays, when replacing $t$ by $t+y$ and $i/n$ by $i/n+y$. Noting that $\sum_{i=1}^{[nT]} \sum_{j=1}^{k} 1\{t_j \in ((i-1)/n, i/n]\} = k$, we can apply these last inequalities with the representation (4.10) for $\tilde{J}_{s,y}$ to see that the absolute value of (4.8) is bounded by

$$
\left| \mathbb{E} \left[ \int D^2f(\tilde{X}_n)[\tilde{J}_{s,y}^{[2]}] \Lambda(dt, dy) - \int D^2f(\tilde{X}_n)[\tilde{J}_{s,y}^{[2]}] \Lambda_n(dt, dy) \right] \right|
$$

\[
\leq CT \begin{cases} 
\|g\|_{M'} n^{-\beta} + S_g n^{-1/2}, & \text{if } g \text{ satisfies (1.2),} \\
\|g\|_{M'} (n^{-\beta} + k^3 n^{-1}), & \text{if } g(w) = F(w(t_1), \ldots, w(t_k)).
\end{cases}
\]

(4.13)

To finish bounding (1.13), we can apply Lemma 5.3 (after rewriting $\tilde{J}$ as per (4.10)) to find

$$
\mathbb{E} \left[ \int D^2f(\tilde{X}_n)[\tilde{J}_{s,y}^{[2]}] \Lambda_n(dt, dy) \right] = \frac{m^2}{u^2 n} \sum_{i=1}^{[nT]} \mathbb{E} \left[ D^2f(\tilde{X}_n)[J_{i/n,y}^{[2]}] \right] G(dy)
$$

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\[ + \frac{v^2 - m^2}{v^2 n} \sum_{i=1}^{[nT]} \mathbb{E} \left[ D^2 f(\tilde{X}_n) \left( (l_{i/n} G_{i/n})^2 \right) \right]. \]  

Since \( \lambda_n/\sigma^2_n = (m^2/v^2) \frac{1}{n} \sum_{i=1}^{[nT]} (\delta_{i/n} \times G) \), we have

\[
\mathbb{E} \left[ \int D^2 f(\tilde{X}_n) [J_{t,y}, \mathbb{E}[X_n^{(t,y)} - X_n + J_{t,y}]] (\sigma_n^{-2} \lambda_n(dt, dy)) \right]
\]

\[= \frac{m^2}{v^2 n} \sum_{i=1}^{[nT]} \int_{R_+} \mathbb{E} \left[ D^2 f(\tilde{X}_n) [J_{i/n,y}, \mathbb{E}[X_n^{(i/n)} - X_n + J_{i/n,y}]] \right] G(dy). \quad (4.15)\]

From Lemma 4.3 (and using the notation there), we have

\[
\mathbb{E} \left[ X_n^{(i/n)} - X_n + J_{i/n,y} \right] = J_{i/n,y} + \frac{v^2 - m^2}{m^2} I_{i/n} G_{i/n} + A_{n,i}. \quad (4.16)\]

Hence (4.14) – (4.16) imply that the contribution from Equation (1.13) is bounded by

\[
\left| \mathbb{E} \left[ \int D^2 f_y(\tilde{X}_n)[\tilde{J}_{i,y}^{(2)}] A_n(dt, dy) - \int D^2 f_y(\tilde{X}_n)[J_{t,y}, \mathbb{E}[X_n^{(t,y)} - X_n + J_{t,y}]] \frac{\lambda_n(dt, dy)}{\sigma^2_n} \right] \right|
\]

\[\leq \frac{C}{n} \sum_{i=1}^{[nT]} \int_{R_+} \left| \mathbb{E} \left[ D^2 f_y(\tilde{X}_n)[J_{i/n,y}, A_n] \right] \right| G(dy) \quad (4.17)\]

\[\leq CT \begin{cases} 
\|g\|_{M'} n^{-\beta} + S g n^{-1/2}, & \text{if } g \text{ satisfies (1.2),} \\
\|g\|_{M'} (n^{-\beta} + k^3 n^{-1}), & \text{if } g(w) = F(w(t_1), \ldots, w(t_k)),
\end{cases} \quad (4.18)\]

where we have used the bounds of Lemma 4.3, writing

\[
(|i - [ns]| + 1)^{-(r-2)} = \sum_{j=0}^{[nT]-1} \left( s \in [j/n, (j+1)/n] \right) (|i - j| + 1)^{-(r-2)},
\]

and using the same smoothness/finite number of instants arguments leading to (4.13).

To bound (1.14), we first construct processes \( \tilde{X}_n^{[i/n]} \) and \( X_n^{[i/n]} \) such that \( \tilde{X}_n^{[i/n]} \) is independent of \( X_n^{(i/n)} - X_n \), the pair of processes \( X_n^{[i/n]} \) and \( \tilde{X}_n^{[i/n]} \) are close to one another, and \( \mathcal{L}(X_n^{(i/n)} - X_n, X_n^{[i/n]}) = \mathcal{L}(X_n^{(i/n)} - X_n, X_n) \). To do so, recalling the notation of Lemma 4.1, let \( M^* \) be a copy of \( M_n \) that is independent of both \( M_n \) and \( M_n^{(i/n)} \). Define

\[
\hat{T}_i := \min \left\{ n - i + 1, \inf \{ j > T_i : M_n((i + j)/n) = M^*((i + j)/n) = 1 \} \right\}, \\
\hat{T}_i' := \min \left\{ i, \inf \{ j > T_i' : M_n((i - j)/n) = M^*((i - j)/n) = 1 \} \right\}.
\]

Now set

\[
M_n^{[i/n]}(j/n) := \begin{cases} 
M_n(j/n), & i - \hat{T}_i' < j < i + \hat{T}_i \\
M_n^*(j/n), & \text{otherwise}
\end{cases}
\]

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and, for \((Y'_j, j \geq 1)\) i.i.d. with distribution function \(G\) and independent of the previous variables, set

\[
N_{n}^{[i/n]} := \sum_{j=\tilde{T}_i}^{i+\tilde{T}_i} M_{n}^{[i/n]}(j/n)\delta(j/n, Y'_j) + \sum_{j \notin [i-\tilde{T}_i, i+\tilde{T}_i]} M_{n}^{[i/n]}(j/n)\delta(j/n, Y'_j);
\]

\[
N_{n}^* := \sum_{j=1}^{[nT]} M_{n}^*(j/n)\delta(j/n, Y'_j),
\]

and then set

\[
X_{n}^{[i/n]} := \int_S J_{t,y} N_{n}^{[i/n]}(dt, dy); \quad X_{n}^* := \int_S J_{t,y} N_{n}^*(dt, dy).
\]

It is clear that \(L(N_{n}^{[i/n]}, N_{n}^{[i/n]} - N_n) = L(N_n, N_{n}^{[i/n]} - N_n)\), because \(N_n\) and \(N_{n}^{[i/n]}\) differ only by having different choices of independent and identically distributed zero–delayed renewal processes defining their continuations outside the interval \([i - \tilde{T}_i, i + \tilde{T}_i]\), and these are independent of \(N_{n}^{[i/n]} - N_n\), which is determined by events defined only on \([i - \tilde{T}_i, i + \tilde{T}_i]\).

Now, defining

\[
\tilde{X}_{n}^{[i/n]} := \sigma_n^{-1}(X_{n}^{[i/n]} - \lambda_n); \quad \tilde{X}_{n}^* := \sigma_n^{-1}(X_{n}^* - \lambda_n),
\]

we observe that

\[
\mathbb{E}\left[\int D^2 f(\tilde{X}_n^*) [J_{i/n, y}, (X_{n}^{[i/n]} - X_n) - \mathbb{E}[X_{n}^{[i/n]} - X_n]] G(dy)\right] = 0. \quad (4.19)
\]

This follows primarily because \(M_{n}^*\) is independent of both \(M_n\) and \(M_{n}^{[i/n]}\), and hence \(\tilde{X}_{n}^*\) and \(X_{n}^{[i/n]} - X_n\) are independent. In more detail, because \(M_{n}^{[i/n]}(j/n) = M_n(j/n)\) for \(j \notin (i - T'_i, i + T'_i)\), and because of the independence of \((M_{n}^{[i/n]} - M_n), (Y_j, j \geq 1)\) and \(\tilde{X}_{n}^*\), we can use Lemma 5.3 to show that

\[
\mathbb{E}\left[D^2 f(\tilde{X}_n^*) [J_{i/n, y}, (X_{n}^{[i/n]} - X_n)]\right]
\]

\[
= \mathbb{E}\left[\sum_{j=i-\tilde{T}_i+1}^{i+\tilde{T}_i-1} (M_{n}^{[i/n]}(j/n) - M_n(j/n)) \mathbb{E}\{D^2 f(\tilde{X}_n^*) [J_{i/n, y}, I_{j/n} - I_{j-1+n+y_j}]\}\right]
\]

\[
= \mathbb{E}\left[\sum_{j=i-\tilde{T}_i+1}^{i+\tilde{T}_i-1} (M_{n}^{[i/n]}(j/n) - M_n(j/n)) \int_{\mathbb{R}_+} D^2 f(\tilde{X}_n^*) [J_{i/n, y}, I_{j/n} - I_{j-1+n+y_j}] G(dy)\right]
\]

\[
= \mathbb{E}\left[\sum_{j=i-\tilde{T}_i+1}^{i+\tilde{T}_i-1} (M_{n}^{[i/n]}(j/n) - M_n(j/n)) D^2 f(\tilde{X}_n^*) [J_{i/n, y}, I_{j/n} \overline{G}_{j/n}]\right]
\]

\[
= \sum_{j=1}^{[nT]} \mathbb{E}[M_{n}^{[i/n]}(j/n) - M_n(j/n)] \mathbb{E}[D^2 f(\tilde{X}_n^*) [J_{i/n, y}, I_{j/n} \overline{G}_{j/n}]]
\]
= \mathbb{E}\left[D^2 f(\bar{X}_n)\left[J_{i/n,y}, \sum_{j=1}^{[nT]} \mathbb{E}[M_n^{(i/n)}(j/n) - M_n(j/n)] I_{j/n} \bar{G}_{j/n}\right]\right]
= \mathbb{E}\left[D^2 f(\bar{X}_n^*)\left[J_{i/n,y}, \mathbb{E}[X_n^{(i/n)} - X_n]\right]\right],

and integrating with respect to \(y\) gives (4.19). Thus, we can bound the term corresponding to (1.14) as follows. First observe that, because \(\mathcal{L}(N_n^{[i/n]}, N_n^{(i/n)} - N_n) = \mathcal{L}(N_n, N_n^{(i/n)} - N_n),\)

\[\left|\frac{m^2}{v^2 n} \sum_{i=1}^{[nT]} \int_{\mathbb{R}^+} \mathbb{E}\left[D^2 f(\bar{X}_n)[J_{i/n,y}, (X_n^{(i/n)} - X_n) - \mathbb{E}[X_n^{(i/n)} - X_n]]\right] G(dy)\right| \leq \frac{C\|g\|_M n}{\sqrt{n}} \sum_{i=1}^{[nT]} \mathbb{E}\left[\left|\bar{X}_n^{[i/n]} - \bar{X}_n^*\right|^2 \left|\left(X_n^{(i/n)} - X_n\right) - \mathbb{E}\left[X_n^{(i/n)} - X_n\right]\right|^2\right],\]

where the second inequality follows from (2.11), the third is because \(N_n^{[i/n]}(j/n) = N_n^{(i/n)}(j/n)\) for \(j \notin [i - \hat{T}_i, i + \hat{T}_i]\) and \(N_n^{(i/n)}(j/n) = N_n(j/n)\) for \(j \notin [i - T_i', i + T_i]\), and the final inequality is obtained by using Cauchy-Schwarz and then noting that, by [Pitman, 1974, Proposition (6.10)], under the assumption \(\mathbb{E}[R^3] < \infty\), \(T_i, T_i', \hat{T}_i\) and \(\hat{T}_i'\) all have finite second moments, whose values depend only on \(\mathcal{L}(R)\).

Similarly, to bound (1.15), note that

\[\mathbb{E}\left[\left|X_n^{(i/n)} - X_n + J_{i/n,y}\right|^2\right] \leq \mathbb{E}\left[(1 + T_i + T_i')^2\right] \leq C,\]

again if \(\mathbb{E}[R^3] < \infty\). Thus

\[\left|\frac{C\|g\|_M n}{2\sigma_n} \int_{\mathbb{R}^+} \|J_{t,y}\|\left|X_n^{(t,y)} - X_n + J_{t,y}\right|^2 (\sigma_n^{-2} \lambda_n(dt, dy))\right| \leq \frac{C\|g\|_M n}{\sqrt{n}}.\]

Combining (4.13), (4.18), (4.21) and (4.22) yields the bound given in (1.10).

To prove the bound on the Lévy–Prokhorov distance, we follow the template for the M/GI/∞ queue, and use the main results of [Barbour et al., 2021], as stated in Theorem 5.1.
below. The first hypothesis of Theorem 5.1 is satisfied, with \( \kappa_1 \) and \( \kappa_2 \) read from the bound (1.10) (noting that \( \|g\| \leq \|g\| \leq \|g\|_p \)).

To bound the modulus of continuity terms, we again use Lemma 5.2. To verify (5.1), for any \( 0 \leq s_1 < s_2 \leq T \), define the regions

\[
\mathcal{R}_1(s_1, s_2) := \mathcal{R}_{s_2} \setminus \mathcal{R}_{s_1} \quad \text{and} \quad \mathcal{R}_2(s_1, s_2) := (s_1, s_2] \times \mathbb{R}_+,
\]

as before at (3.5), so that

\[
\bar{X}_n(t) - \bar{X}_n(s) = \bar{Y}_n(2; s, t) - \bar{Y}_n(1; s, t),
\]

where \( \bar{Y}_n(i; s_1, s_2) := \sigma_n^{-1/2}\{N_n(\mathcal{R}_i(s_1, s_2)) - \lambda_n(\mathcal{R}_i(s_1, s_2))\} \), \( i = 1, 2 \). We now use Markov’s inequality to bound each term in

\[
\mathbb{P}(|\bar{X}_n(t) - \bar{X}_n(s)| \geq \theta) \leq \mathbb{P}(|\bar{Y}_n(1; s, t)| \geq \theta/2) + \mathbb{P}(|\bar{Y}_n(2; s, t)| \geq \theta/2).
\]

First, \( \sigma_n \bar{Y}_n(2; s, t) = \sum_{ns < i \leq nt}[M_n(i/n) - m^{-1}] \) is the centred number of renewals in the interval \((ns, nt)\). By the usual renewal theory coupling arguments, as in [Glynn, 1982, Proposition 6.10], writing \( \tilde{M}_i := M_n(i/n) \), the sequence \((\tilde{M}_i, 1 \leq i \leq nt)\) is strong mixing as introduced in [Rosenblatt, 1956] with coefficients \( \alpha_j \leq k_R j^{-(r - 1)} \), \( j = 1, 2, \ldots \), for a constant \( k_R < \infty \), depending only on \( \mathcal{L}(R) \), that we can choose to be at least 1, and \( \alpha_0 := 1/2 \). Thus, for \( 0 < u < 1 \), as in [Rio, 2013, (1.21)],

\[
\alpha^{-1}(u) := \sum_{j \geq 0} 1\{u < \alpha_j\} \leq (k_R/u)^{1/(r - 1)} + 1\{u < 1/2\} \leq 2(k_R/u)^{1/(r - 1)}.
\]

Applying [Rio, 2013, Theorem 2.2], it follows that, for any \( l \in \mathbb{N} \), there is a constant \( C_{l,R} \) depending only on \( \mathcal{L}(R) \) and \( l \) such that

\[
\mathbb{E}\left[ (\bar{Y}_n(2; s, t))^2 \right] \leq C_{l,R} \sigma_n^{-2l} \left\{ \left( \sum_{ns < i \leq nt} \int_0^1 \alpha^{-1}(u) Q_i^2(u) \, du \right)^l + \sum_{ns < i \leq nt} \int_0^1 [\alpha^{-1}(u)]^{2l - 1} Q_i^2(u) \, du \right\},
\]

where \( Q_i := q_{1/m} \) and, for \( w \in [0, 1] \) and \( u \in (0, 1] \),

\[
q_w(u) = \begin{cases} 
  w1_{(0, 1-w]}(u) + (1-w)1_{(1-w, 1]}(u), & w \geq 1/2, \\
  (1-w)1_{[0,w]}(u) + w1_{(w, 1]}(u), & w < 1/2.
\end{cases} \quad (4.23)
\]

Straightforward computing now shows that, for \( l < r/2 \),

\[
\mathbb{E}\left[ (\bar{Y}_n(2; s, t))^2 \right] \leq K_{l,R} \sigma_n^{-2l} \left[ (\lfloor nt \rfloor - \lfloor ns \rfloor)^l + (\lfloor nt \rfloor - \lfloor ns \rfloor) \right],
\]

for a constant \( K_{l,R} < \infty \). Markov’s inequality and (1.7) thus imply that, if \( n(t-s) \geq 1/2 \) and for \( l < r/2 \),

\[
\mathbb{P}(|\bar{Y}_n(2; s, t)| \geq \sigma_n \theta/2) \leq K_{l,R} \left( \frac{m^3}{v^2} \right)^l 2^{2l+1} \theta^{-2l} 3^l (t-s)^l =: C_l^{(1)} \theta^{-2l} (t-s)^l. \quad (4.24)
\]
For \( \widetilde{Y}_n(1; s, t) \), we observe that
\[
N_n(\mathcal{R}_1(s, t)) - \lambda_n(\mathcal{R}_1(s, t)) = \sum_{1 \leq i \leq nt} [M_n(i/n)B_{i,n} - m^{-1}p_{i,n}],
\]
where
\[
B_{i,n} := 1[(s-in^{-1})_+ < Y_i \leq t-in^{-1}] \sim \text{Be}(p_{i,n}); \quad p_{i,n} := G(t-i/n) - G((s-i/n)_+).
\]
The fact that the random variables \( (B_{i,n}, 1 \leq i \leq nT) \) are independent of \( N_n \) implies that the mixing properties of the sequence \( (\widetilde{M}_i, 1 \leq i \leq nT) \) are inherited by the sequence \( (\widetilde{M}_iB_{i,n}, 1 \leq i \leq nT) \), so that [Rio, 2013, Theorem 2.2] can be applied with the same function \( \alpha^{-1} \), giving
\[
\mathbb{E}\left[ (\widetilde{Y}_n(1; s, t))^{2l} \right] \leq C_{l,R}\sigma_n^{2l} \left\{ \sum_{1 \leq i \leq nt} \int_0^{1} \alpha^{-1}(u)Q_i^2(u)du \right\}^l + \sum_{1 \leq i \leq nt} \int_0^{1} \left[ \alpha^{-1}(u) \right]^{2l-1}Q_i^2(u)du, \tag{4.25}
\]
where now \( Q_i := q_{p_{i,n}/m} \). Using (4.23), we have that for \( 1 \leq l < r/2 \),
\[
\int_0^{1} (\alpha^{-1}(u))^{2l-1}q_w^2(u)du \leq c_1(r, R, l)w^{(r-2l)/(r-1)}. \tag{4.26}
\]
From the assumptions on \( G \), by comparing sums and integrals, it follows that, for \( 1/(2n) \leq (t-s) \leq 1 \),
\[
n^{-1} \sum_{1 \leq i \leq nt} p_{i,n} \leq \int_s^t G(v)dv + 2n^{-1} \leq 5(t-s), \tag{4.27}
\]
and, using (4.26), for \( 1 \leq l < r/2 \) such that \( (r-2l)/(r-1) \geq \eta \), we have
\[
n^{-1} \sum_{1 \leq i \leq nt} p_{i,n}^{(r-2l)/(r-1)} \leq (t-s)^{\beta(r-2l)/(r-1)} \left\{ \int_0^{\infty} (g_G(v))^{(r-2l)/(r-1)}dv + 2(g_G(0))^{(r-2l)/(r-1)} \right\} \leq c_3(r, R, l)(t-s)^{\beta(r-2l)/(r-1)}. \tag{4.28}
\]
Hence, from (4.25), if \( r(1-\beta) \geq 1 \), writing \( \beta_r := \beta(r-2)/(r-1) \), we find that, for \( 0 \leq s < t \leq T \) and for \( n(t-s) \geq 1/2 \),
\[
\mathbb{E}\left[ (\widetilde{Y}_n(1; s, t))^{2l} \right] \leq C_{l,R}(n/\sigma_n^2)^l(t-s)^{l\beta_r},
\]
for any \( l < (r-\eta(r-1))/2 \). The assumption \( r(1-\beta) \geq 1 \) ensures the exponent \( l\beta_r \) is no larger than those appearing when applying (4.25), (4.26) and (4.28). It now follows, by Markov’s inequality and (1.7), that, for such \( l \), and if \( r(1-\beta) \geq 1 \),
\[
\mathbb{P}(|\widetilde{Y}_n(1; s, t)| \geq \theta/2) \leq C_l^{(1)}\theta^{-2l}(t-s)^{l\beta_r}, \quad n(t-s) \geq 1/2. \tag{4.29}
\]
If $r(1 - \beta) < 1$, the inequality (4.29) holds only for $0 \leq s < t \leq T$ such that $(t - s)n^{(r-1)/r}\beta \geq 1/2$.

To verify (5.2) for $\tilde{X}_n$, we note that, for $(k-1)/M \leq u \leq k/M$,

$$|\tilde{Y}_n(i; (k-1)/M, u)| \leq |\tilde{Y}_n(i, (k-1)/M, k/M)| + 2\sigma_i^{-1}\lambda_n(\mathcal{R}_1((k-1)/M, k/M)),$$

$i = 1, 2$, where $\lambda_n(\mathcal{R}_2((k-1)/M, k/M)) = m^{-1}n/M$ and, because of (4.27), $\lambda_n(\mathcal{R}_1((k-1)/M, k/M)) \leq 5m^{-1}n/M$. Writing $\rho := \rho(r, \beta) := \min\{1, (r-1)/r\beta\}$, and taking $M := n^\rho$, it follows from (4.24) and (4.29) that we can take

$$\varphi_M(\theta) := M^{1-l\beta}C_l^{(3)}\theta^{-2l}$$

in (5.2), for a suitable constant $C_l^{(3)}$, if $\theta > 48m^{-1}n^{1-\rho}/\sigma_n$. We can now apply Lemma 5.2 with $b = 2l$ and $a = l\beta - 1$, for $l = l_r := \lceil (r - \eta)/(r - 1) \rceil - 1$, and with $M := n^\rho$, to find that, for $\theta > 48(1 - 2^{-(l_r\beta - 1)/4l_r})^{-1}m^{-1}n^{1-\rho}/\sigma_n$ and $\epsilon \in (n^{-\rho}, 1)$,

$$\mathbb{P}(\omega_{\tilde{X}_n}(\epsilon) \geq \theta/2) \leq C\theta^{-2l_r}e^{l\beta - 1},$$

(4.31)

for some suitable constant $C$.

For the modulus of continuity of $Z$, an easy calculation shows that for any $0 \leq r < s \leq T$,

$$\mathbb{E}\left[\left(Z(s) - Z(r)\right)^2\right] \leq C(s - r)^\beta.$$

and so [Barbour et al., 2021, Remark 1.6] implies that for any $l \geq 1$,

$$\mathbb{P}(\omega_Z(\epsilon) \geq \theta) \leq C\theta^{-2l}e^{l\beta - 1}.$$  

(4.32)

From (4.13), (4.18), (4.21) and (4.22), and for $T \geq 1$, we can now apply Theorem 5.1 with

$$\kappa_1 = O(Tn^{-\bar{\beta}}), \quad \text{where } \bar{\beta} := \min\{\beta, 1/2\}; \quad \kappa_2 = O(Tn^{-1/2}).$$

This, using (4.31) and (4.32), for any choice of $\epsilon, \delta > 0$ and $\theta > cn^{1/2-\rho(r, \beta)}$, and for any $l \geq 1$, implies a bound of

$$C(\delta \sqrt{T \log n} + \theta + T^{5/2}n^{-\beta}(\epsilon \delta)^{-3} + T^{3/2}n^{-1/2}(\epsilon \delta)^{-2} + T^{l_r\beta - 1}\theta^{-2l_r} + T^{l\beta - 1}\theta^{-2l}),$$

for a suitable constant $C$, where we recall that $\beta_r := \beta(r - 2)/(r - 1)$ and that $\rho(r, \beta) := \min\{1, (r-1)/r\beta\}$. Taking

$$\theta = \sqrt{T \delta} = \left\{(T^4n^{-\bar{\beta}}l_{r\beta_r - 1}T^3\right)^{1/(6l_r + 4l_r\beta_r - 1)}; \quad \epsilon = \left\{(T^4n^{-\bar{\beta}})^{2l_r + 1}T^{-4}\right\}^{1/(6l_r + 4l_r\beta_r - 1)},$$

gives a bound of order

$$O\left(\sqrt{\log n} \left\{(T^{5/2}n^{-\bar{\beta}}l_{r\beta_r - 1}T^3\right)^{1/(6l_r + 4l_r\beta_r - 1)}\right).$$

Here, we note that if $\epsilon \leq 1$, for example if $T \leq n^{\psi'}$ for $\psi' < \bar{\beta}(2l_r + 1)/(8l_r)$, then the term $Te^{l\beta - 1}\theta^{-2l}$ can be made smaller order than the others by choosing $l = l_r$, noting $\beta_r < \beta$. A calculation also shows that this choice of $\theta$ indeed satisfies $\theta > 48(1 - 2^{-(l_r\beta_r - 1)/4l_r})^{-1}m^{-1}n^{1-\rho}/\sigma_n$ for all $n$ sufficiently large. 

\[\square\]
5 SMOOTHING RESULT

We state a specific consequence of the main results of [Barbour et al., 2021], which we use above to prove weak convergence. Let \( M^0 \subset M' \) be the set of functions \( h : \mathbb{D}^p \to \mathbb{R} \) such that

\[
\|h\|_{M^0} := \sup_{w \in \mathbb{D}^p} |h(w)| + \sup_{w \in \mathbb{D}^p} \|Dh(w)\| + \sup_{w \in \mathbb{D}^p} \|D^2h(w)\| + \sup_{w,v \in \mathbb{D}^p} \frac{\|D^2h(w + v) - D^2h(w)\|}{\|v\|}
\]

is finite. Note that \( \|h\|_{M'} \leq \|h\|_{M^0} \). For \( x \in \mathbb{D}^p \), let \( \omega_x(\varepsilon) := \sup_{0 \leq s,t \leq T; |s-t| < \varepsilon} |x(t) - x(s)| \) denote the modulus of continuity of \( x \).

**Theorem 5.1** (Theorem 1.1 of [Barbour et al., 2021]). Let \( Y,Z \) be random elements of \( \mathbb{D}^p := \mathbb{D}([0,T], \mathbb{R}^p) \), with \( T \geq 1 \), such that \( Z \) has almost surely continuous sample paths. Suppose that there are \( \kappa_1,\kappa_2 \geq 0 \) such that for any \( g \in M^0 \) satisfying the smoothness condition (1.2), we have

\[
|\mathbb{E}g(Y) - \mathbb{E}g(Z)| \leq \kappa_1 \|h\|_{M^0} + S_g \kappa_2.
\]

Letting \( d_{LP} \) denote the Lévy-Prokhorov metric, we have that for any positive \( \delta,\epsilon,\theta,\gamma \) with \( \epsilon,\delta \in (0,1) \),

\[
d_{LP}(\mathcal{L}(X),\mathcal{L}(Z)) \leq \widehat{C} \max\left\{ \theta + \gamma, \frac{\kappa_1 T^{3/2}}{(\epsilon \delta)^3} + \frac{\kappa_2 T^{1/2}}{(\epsilon \delta)^2} + \mathbb{P}(\omega_Y(\epsilon) \geq \theta) + \mathbb{P}(\omega_Z(\epsilon) \geq \theta) + e^{-\frac{a^2}{2p^2\theta^2}} \right\},
\]

where \( \widehat{C} \) is a universal constant.

To bound the modulus of continuity terms appearing in the previous theorem, we use the following lemma, also noted in [Barbour et al., 2021, Lemma 1.3 and Remark 1.4(1)], applied to each component.

**Lemma 5.2.** Let \( X \in \mathbb{D} \) be such that there are positive constants \( a, b \) and \( K \) such that

\[
\mathbb{P}(|X(s) - X(t)| \geq \theta) \leq K \theta^{-b} |s-t|^{1+a} \quad \text{for} \quad \frac{1}{2} M^{-1} \leq |s-t| \leq 1/2,
\]

and that

\[
M \mathbb{P}\left( \sup_{(k-1)/M \leq s \leq k/M} |X(s) - X((k-1)/M)| \geq \theta \right) \leq \varphi_M(\theta) \quad \text{for} \quad 1 \leq k \leq \lceil MT \rceil.
\]

Then, for any \( \epsilon \in (M^{-1}, 1) \),

\[
\mathbb{P}(\omega_X(\epsilon) \geq \theta) \leq 2T \left\{ \varphi_M(\theta(1 - 2^{-a/(2b)})/18) + C'(K,a,b)\theta^{-b} \epsilon^a \right\},
\]

for a constant \( C'(K,a,b) < \infty \).

We have also used the following, technical lemma.
Lemma 5.3. Assume $f \in M'$ either satisfies the smoothness condition (1.2), or is a function of the form $f(w) = F(w(t_1), \ldots, w(t_k))$ for some $F: (\mathbb{R}^p)^k \to \mathbb{R}$ and $\{t_1, \ldots, t_k\} \subseteq [0, T]$. Letting $I_r(s) := 1\{s \geq r\}$ and $G_t(s) := G(s - t)$ for a distribution function $G$, then for any $w, x_1, x_2 \in \mathbb{D}^p$ and $r, t \geq 0$, we have

$$\int_{\mathbb{R}^+} D^2 f(w)[x_1 I_r, x_2 I_{t+y}] G(dy) = D^2 f(w)[x_1 I_r, \int_{\mathbb{R}^+} x_2 I_{t+y} G(dy)] = D^2 f(w)[x_1 I_r, x_2 G_t].$$

and

$$\int_{\mathbb{R}^+} D^2 f(w)[x_1 G_r, x_2 I_{t+y}] G(dy) = D^2 f(w)[x_1 G_r, \int_{\mathbb{R}^+} x_2 I_{t+y} G(dy)] = D^2 f(w)[x_1 G_r, x_2 G_t].$$

Proof. If $f(w) = F(w(t_1), \ldots, w(t_k))$, then a simple calculation shows that

$$D^2 f(w)[w_1, w_2] = \sum_{i,j=1}^k w_1(t_i)^\top F_{ij}(w(t_1), \ldots, w(t_k)) w_2(t_j),$$

where we write $F_{ij}$ for the $p \times p$ matrix corresponding to the mixed partial of $F$ in coordinates $i$ and $j$. The result now follows directly after noting that $\int I_{t+y} G(dy) = G_t$.

Now assume that $f$ satisfies the smoothness condition (1.2). Both results are obviously true from bilinearity if $G$ is a discrete distribution function. By considering the atoms separately, we can without loss of generality assume $G$ is continuous. We show the result by approximating $G$ by a discretised version. Let $Y \sim G$ and define $Y_m := [mY]/m$, noting that $Y_m$ converges almost surely (so in distribution) to $Y$, as $m \to \infty$. For the first assertion, the function

$$y \mapsto D^2 f(w)[x_1 I_r, x_2 I_{t+y}]$$

is continuous for $y \geq 0$, since

$$D^2 f(w)[x_1 I_r, x_2 I_{t+y+\varepsilon}] - D^2 f(w)[x_1 I_r, x_2 I_{t+y}] = D^2 f(w)[x_1 I_r, x_2 (I_{t+y+\varepsilon} - I_{t+y})] \to 0,$$

by (1.2). By applying Lemma 2.4 and noting that $f \in M'$, it is also easy to see the function is bounded. Thus, because of weak convergence, as $m \to \infty$,

$$\mathbb{E}[D^2 f(w)[x_1 I_r, x_2 I_{t+Y_m}]] \to \mathbb{E}[D^2 f(w)[x_1 I_r, x_2 I_{t+Y}]] = \int_{\mathbb{R}^+} D^2 f(w)[x_1 I_r, x_2 I_{t+y}] G(dy).$$

On the other hand, because $Y_m$ is discrete, we have

$$\mathbb{E}[D^2 f(w)[x_1 I_r, x_2 I_{t+Y_m}]] = D^2 f(w)[x_1 I_r, x_2 \mathbb{E}[I_{t+Y_m}]],$$

and, again because of Lemma 2.4 and because $f \in M'$, we have

$$|D^2 f(w)[x_1 I_r, x_2 \mathbb{E}[I_{t+Y_m}]] - D^2 f(w)[x_1 I_r, x_2 \mathbb{E}[I_{t+Y}]]| \leq 3\|f\|_{M'} \|x_1\| \|x_2\| \|\mathbb{E}[I_{t+Y_m}] - \mathbb{E}[I_{t+Y}]\|.$$
which converges to zero, since
\[ \left\| \mathbb{E}[I_{t+Y_m}] - \mathbb{E}[I_{t+Y}] \right\| = \sup_{y \in [0,T]} \left| \mathbb{P}(Y \leq y - t) - \mathbb{P}(Y_m \leq y - t) \right| \]
\[ \leq \sup_{y \in [0,T]} \left| \mathbb{P}\left(Y \in \left(y, \frac{my + 1}{m}\right)\right) \right| \to 0, \text{ by the continuity of } G. \]

For the second assertion, the function \( y \mapsto D^2 f(w)[x_1 I_r, x_2 I_{t+y}] \) is bounded continuous on \( \mathbb{R}_+ \), since, using the first assertion as well as the condition (1.2),
\[ D^2 f(w)[x_1 I_r, x_2 I_{t+y+\varepsilon}] - D^2 f(w)[x_1 I_r, x_2 I_{t+y}] \]
\[ = \int_{\mathbb{R}_+} D^2 f(w)[x_1 I_{r+y'}, x_2 (I_{t+y+\varepsilon} - I_{t+y})]G(dy') \xrightarrow{\varepsilon \downarrow 0} 0. \]

The rest of the proof follows in exactly the same way as for the first assertion, replacing \( I_r \) by \( G_r \).

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