Poisson process approximation for dependent superposition of point processes

Louis H. Y. Chen* and Aihua Xia†
National University of Singapore and University of Melbourne

8 April, 2010
(First version: 16 January, 2009)

Abstract

Although the study of weak convergence of superposition of point processes to the Poisson process dates back to the work of Grigelionis in 1963, it was only recently that Schuhmacher (2005a) obtained error bounds for the weak convergence. Schuhmacher considered dependent superposition, truncated the individual point processes to 0–1 point processes and then applied Stein’s method to the latter. In this paper we take a different approach to the problem by using Palm theory and Stein’s method, thereby expressing the error bounds in terms of the mean measures of the individual point processes, which is not possible by Schuhmacher’s approach. We consider locally dependent superposition as a generalization of the locally dependent point process introduced in Chen and Xia (2004) and apply the main theorem to the superposition of thinned point processes and of renewal processes.

Key words and phrases. Stein’s method, Poisson process approximation, dependent superposition of point processes, sparse point processes, thinned point processes, renewal processes.

AMS 2000 subject classifications. Primary 60G55; secondary 60F05, 60E15, 60K05.

1 Introduction

The study of weak convergence of superposition of point processes dates back to Grigelionis (1963) who proved that the superposition of independent sparse point processes converges weakly to a Poisson process on the carrier space $\mathbb{R}_+$. His result was subsequently extended

*Postal address: Department of Mathematics, National University of Singapore, 2, Science Drive 2, Singapore 117543, Republic of Singapore. Email address: matchyl@nus.edu.sg
†Postal address: Department of Mathematics and Statistics, the University of Melbourne, VIC 3010, Australia. Email address: xia@ms.unimelb.edu.au
to more general carrier spaces by Goldman (1967) and Jagers (1972) [see Činlar (1973) and Brown (1978) for further discussions]. It was further extended to superposition of dependent sparse point processes by Banis (1975, 1985), Kallenberg (1975), Brown (1979) and Banys (1980). For a systematic account of these developments, see Kallenberg (1983).

Surprisingly, it was only recently that error bounds for such convergence of point processes were studied. Using Stein’s method for Poisson process approximation as developed by Barbour (1988) and Barbour and Brown (1992), Schuhmacher (2005a) obtained an error bound on the $d_2$ Wasserstein distance between a sum of weakly dependent sparse point processes $\{\xi_{ni}, 1 \leq i \leq k_n\}_{n \in \mathbb{N}}$ and an approximating Poisson process. As he truncated the sparse point processes to 0–1 point processes as in the proof of the Grigelionis theorem, his error bound contains the term $\sum_{i=1}^{k_n} \mathbb{P}[\xi_{ni}(B) \geq 2]$, whose convergence to 0 for every bounded Borel subset $B$ of the carrier space is a condition for the Grigelionis theorem to hold. A consequence of such truncation is that the mean measure of the approximating Poisson process is not equal to the sum of the mean measures of the individual point processes.

In this paper we take a different approach to the Poisson process approximation in which we do not use the truncation, but apply the Palm theory and express the error bounds in terms of the mean measures of the individual sparse point processes. Such an approach also ensures that the mean measure of the approximating Poisson process is equal to the sum of the mean measures of the sparse point processes.

As in Schuhmacher (2005a), we study the dependent superposition of sparse point processes. But we consider only locally dependent superposition which is a natural extension of the point processes $\sum I_i \delta_{U_i}$ studied in Section 4 of Chen and Xia (2004), where $\delta_x$ is the point mass at $x$, $U_i$’s are $S$-valued independent random elements with $S$ a locally compact metric space, the indicators $I_i$’s are locally dependent and the $I_i$’s are independent of the $U_i$’s.

In our main theorem (Theorem 2.1), with the help of Lemma 3.1 in Brown, Weinberg and Xia (2000), it is possible to recover a factor of order $1/\lambda$ from the term $1/(|\Xi^{(i)}| + 1)$. Hence the error bound on the $d_2$ Wasserstein distance yields the so-called Stein factor $1/\lambda$, by which approximation remains good for large $\lambda$, a feature always sought after for Poisson-type approximations. In the error bound obtained by Schuhmacher (2005a), a leading term does not have the Stein factor [see Remark 4.4 for further details].

Our main theorem and some corollaries are presented in Section 2. Applications to thinned point processes and renewal processes are given in Sections 3 and 4 respectively.

## 2 The main theorem

Throughout this paper, we assume that $\Gamma$ is a locally compact metric space with metric $d_0$ bounded by 1. In estimating the error of Poisson process approximation to the superposition of dependent point processes $\{\Xi_i, i \in I\}$ on the carrier space $\Gamma$ with $I$ a finite or countably infinite index set, one natural approach is to partition the index set $I$ into $\{\{i\}, I^s_i, I^w_i\}$, where $I^s_i$ is the set of the indices of the point processes which are strongly dependent of $\Xi_i$ and $I^w_i$ the set of the indices of the point processes which are weakly dependent of $\Xi_i$.
Parallel to the local dependence structures defined in Chen and Shao (2004), we introduce:

**[LD1]** For each \( i \in I \), there exists a neighbourhood \( A_i \) such that \( i \in A_i \) and \( \Xi_i \) is independent of \( \{\Xi_j, \ j \in A_i^c\} \).

**[LD2]** Condition [LD1] and for each \( i \in I \), there exists a neighbourhood \( B_i \) such that \( A_i \subset B_i \) and \( \{\Xi_j, \ j \in A_i^c\} \) is independent of \( \{\Xi_j, \ i \in B_i^c\} \).

The index set \( I \) in [LD1] and [LD2] will be assumed to be finite or countably infinite in this paper, although it may be as general as that considered in Barbour and Xia (2006). The superposition of \( \{\Xi_i : i \in I\} \) which satisfies the condition [LD1] is more general than point processes of the form \( \sum I_i \delta_{U_i} \) where the \( I_i \)'s are locally dependent indicators with one level of dependent neighborhoods in \( I \) (that is, the \( I_i \)'s satisfy [LD1] in Chen and Shao (2004, p. 1986)). Such a point process is a typical example of locally dependent point processes defined in Chen and Xia (2004, p. 2548). Likewise, the superposition of \( \{\Xi_i : i \in I\} \) which satisfies the condition [LD2] is more general than point processes of the form \( \sum I_i \delta_{U_i} \) where the \( I_i \)'s are locally dependent indicators with two levels of dependent neighborhoods in \( I \) (that is, the \( I_i \)'s satisfy [LD2] in Chen and Shao (2004, p. 1986)).

Three metrics will be used to describe the accuracy of Poisson process approximation: the total variation metric for Poisson random variable approximation \( d_{TV} \), the total variation metric for Poisson process approximation \( d_{TV} \) and a Wasserstein metric \( d_2 \) [see Barbour, Holst and Janson (1992) or Xia (2005)].

To briefly define these metrics, let \( \mathcal{H} \) be the space of all finite point process configurations on \( \Gamma \), i.e., each \( \xi \in \mathcal{H} \) is a non-negative integer-valued finite measure on \( \Gamma \). Let \( \mathcal{K} \) stand for the set of \( d_0 \)-Lipschitz functions \( k : \Gamma \to [-1, 1] \) such that \( |k(\alpha) - k(\beta)| \leq d_0(\alpha, \beta) \) for all \( \alpha, \beta \in \Gamma \). The first Wasserstein metric \( d_1 \) on \( \mathcal{H} \) is defined by

\[
d_1(\xi_1, \xi_2) = \begin{cases} 
0, & \text{if } |\xi_1| = |\xi_2| = 0, \\
1, & \text{if } |\xi_1| \neq |\xi_2|, \\
|\xi_1|^{-1} \sup_{k \in \mathcal{K}} \left| \int k d\xi_1 - \int k d\xi_2 \right|, & \text{if } |\xi_1| = |\xi_2| > 0,
\end{cases}
\]

where \( |\xi_i| \) is the total mass of \( \xi_i \). A metric \( d_1' \) equivalent to \( d_1 \) can be defined as follows [see Brown and Xia (1995)]: for two configurations \( \xi_1 = \sum_{i=1}^n \delta_{y_i} \) and \( \xi_2 = \sum_{i=1}^m \delta_{z_i} \) with \( m \geq n \),

\[
d_1'(\xi_1, \xi_2) = \min_{\pi} \sum_{i=1}^n d_0(y_i, z_{\pi(i)}) + (m - n),
\]

where \( \pi \) ranges over all permutations of \((1, \ldots, m)\). Both \( d_1 \) and \( d_1' \) generate the weak topology on \( \mathcal{H} \) [see Xia (2005, Proposition 4.2)] and we use \( B(\mathcal{H}) \) to stand for the Borel \( \sigma \)-algebra generated by the weak topology. Define three subsets of real valued functions on \( \mathcal{H} \).
as $\mathcal{F}_{tv} = \{A(\xi) : A \subset \mathbb{Z}_+\}$, $\mathcal{F}_{d_1} = \{f : |f(\xi_1) - f(\xi_2)| \leq d_1(\xi_1, \xi_2) \text{ for all } \xi_1, \xi_2 \in \mathcal{H}\}$ and $\mathcal{F}_{TV} = \{A(\xi) : A \in \mathcal{B}(\mathcal{H})\}$. Then the pseudometric $d_{tv}$ and the metrics $d_2$ and $d_{TV}$ are defined on probability measures on $\mathcal{H}$ by

\[
\begin{align*}
d_{tv}(Q_1, Q_2) &= \inf_{(X_1, X_2)} P(|X_1| \neq |X_2|) = \sup_{f \in \mathcal{F}_{tv}} \left| \int f dQ_1 - \int f dQ_2 \right|, \\
d_2(Q_1, Q_2) &= \inf_{(X_1, X_2)} E[d_1(X_1, X_2)] = \sup_{f \in \mathcal{F}_{d_1}} \left| \int f dQ_1 - \int f dQ_2 \right|, \\
d_{TV}(Q_1, Q_2) &= \inf_{(X_1, X_2)} P(X_1 \neq X_2) = \sup_{f \in \mathcal{F}_{TV}} \left| \int f dQ_1 - \int f dQ_2 \right|,
\end{align*}
\]

where the infima are taken over all couplings of $(X_1, X_2)$ such that $\mathcal{L}(X_i) = Q_i$, $i = 1, 2$ and the second equations are due to the duality theorem [see Rachev (1991, p. 168)].

To bound the error of Poisson process approximation, we need the Palm distributions $Q_\alpha$ of a point process $X_2$ with respect to a point process $X_1$ with finite mean measure $\nu$ at $\alpha$. When $X_1$ is a simple point process, i.e., it has at most one point at each location, the Palm distribution $Q_\alpha$ may be intuitively interpreted as the conditional distribution of $X_2$ given that $X_1$ has a point at $\alpha$. More precisely, let $\mathcal{B}(\Gamma)$ denote the Borel $\sigma$-algebra in $\Gamma$ generated by the metric $d_0$ and define the Campbell measure $C$ of $(X_1, X_2)$ on $\mathcal{B}(\Gamma) \times \mathcal{B}(\mathcal{H})$:

\[
C(B \times M) = E[X_1(B)1_{X_2 \in M}], \quad B \in \mathcal{B}(\Gamma), \quad M \in \mathcal{B}(\mathcal{H}).
\]

Since the mean measure $\nu$ of $X_1$ is finite, by [Kallenberg (1983, 15.3.3)], there exist probability measures $Q_\alpha$ on $\mathcal{B}(\mathcal{H})$ such that

\[
E[X_1(B)1_{X_2 \in M}] = \int_B Q_\alpha(M)\nu(d\alpha), \quad \forall \ B \in \mathcal{B}(\Gamma), \ M \in \mathcal{B}(\mathcal{H}), \quad (2.1)
\]

which is equivalent to

\[
Q_\alpha(M) = \frac{E[1_{X_2 \in M}X_1(d\alpha)]}{\nu(d\alpha)}, \quad \forall \ M \in \mathcal{B}(\mathcal{H}), \ \alpha \in \Gamma \ \nu - \text{a.s.}
\]

[see Kallenberg (1983, section 10.1)]. It is possible to realize a family of point processes $Y_\alpha$ on some probability space such that $Y_\alpha \sim Q_\alpha$, and we say that $Y_\alpha$ is a Palm process of $X_2$ with respect to $X_1$ at $\alpha$. Moreover, when $X_1 = X_2$, we call the point process $Y_\alpha - \delta_\alpha$ the reduced Palm process of $X_2$ at $\alpha$ [see Kallenberg (1983, Lemma 10.2)].

As noted in Goldstein and Xia (2006), when $\Gamma$ is reduced to one point only, the Palm distribution of $X_2$ (with respect to itself) is the same as the size-biased distribution and general guidelines for the construction of size-biased variables are investigated in Goldstein and Rinott (1996).

**Theorem 2.1** Let $\{\Xi_i, i \in I\}$ be a collection of point processes on $\Gamma$ with mean measures $\lambda_i$, $i \in I$ respectively. Set $\Xi = \sum_{i \in I} \Xi_i$ with mean measure denoted by $\lambda$ and assume that
\( \lambda := \lambda(\Gamma) < \infty. \) If [LD1] holds, then
\[
d_{tv}(L(\Xi), \text{Po}(\lambda)) \leq \frac{1}{\lambda} \mathbb{E} \sum_{i \in I} \int_{\Gamma} \{||V_i| - |V_{i,\alpha}| + ||\Xi_i| - |\Xi_{i,\alpha}|\} \lambda_i(d\alpha), \tag{2.2}
\]
\[
d_2(L(\Xi), \text{Po}(\lambda)) \leq \mathbb{E} \sum_{i \in I} \left( \frac{3.5}{\lambda} + \frac{2.5}{|\Xi^{(i)}|+1} \right) \int_{\Gamma} d'_1(V_i, V_{i,\alpha}) \lambda_i(d\alpha)
+ \sum_{i \in I} \left( \frac{3.5}{\lambda} + \frac{2.5}{|\Xi^{(i)}|+1} \right) \mathbb{E} \int_{\Gamma} d'_1(\Xi_i, \Xi_{i,\alpha}) \lambda_i(d\alpha), \tag{2.3}
\]
\[
d_{TV}(L(\Xi), \text{Po}(\lambda)) \leq \mathbb{E} \sum_{i \in I} \int_{\Gamma} \{||V_i - V_{i,\alpha}| + ||\Xi_i - \Xi_{i,\alpha}|\} \lambda_i(d\alpha), \tag{2.4}
\]
where \( \Xi^{(i)} = \sum_{j \in A_i \setminus i} \Xi_j, \) \( V_i = \sum_{j \in A_i \setminus \{i\}} \Xi_j; \) \( \Xi_{i,\alpha} \) is the reduced Palm process of \( \Xi_i \) at \( \alpha, \) \( V_{i,\alpha} \) is the Palm process of \( V_i \) with respect to \( \Xi_i \) at \( \alpha \) such that \( \Xi^{(i)} + V_{i,\alpha} + \Xi_{i,\alpha} + \delta_\alpha \) is the Palm process of \( \Xi \) with respect to \( \Xi_i \) at \( \alpha, \) and \( || \cdot || \) denotes the variation norm of signed measure. Under the condition of [LD2], (2.2) and (2.4) remain the same but (2.3) can be further reduced to
\[
d_2(L(\Xi), \text{Po}(\lambda)) \leq \sum_{i \in I} \left( \frac{3.5}{\lambda} + \mathbb{E} \frac{2.5}{|\Xi^{(i)}|+1} \right) \mathbb{E} \int_{\Gamma} d'_1(V_i, V_{i,\alpha}) \lambda_i(d\alpha)
+ \sum_{i \in I} \left( \frac{3.5}{\lambda} + \mathbb{E} \frac{2.5}{|\Xi^{(i)}|+1} \right) \mathbb{E} \int_{\Gamma} d'_1(\Xi_i, \Xi_{i,\alpha}) \lambda_i(d\alpha) \tag{2.5}
\]
\[
\leq \sum_{i \in I} \left( \frac{3.5}{\lambda} + 2.5 \cdot \sqrt{\kappa_i(1 + \kappa_i/4) + 1 + \kappa_i/2} \right) \frac{\lambda_i \mathbb{E}|V_i|}{\sum_{j \in B_i} \lambda_j + 1}
+ \mathbb{E}(|V_i| \cdot |\Xi_i|) + |\Xi_i|^2 + \mathbb{E} \left( |\Xi_i|^2 - \lambda_i \right), \tag{2.6}
\]
where \( \lambda_i = \lambda_i(\Gamma) \) and
\[
\kappa_i = \frac{\sum_{j \in B_i} \sum_{j_2 \in B_i \cap A_{i,j_1}} \text{cov}(|\Xi_{j_1}|, |\Xi_{j_2}|)}{\sum_{j \in B_i} \lambda_j + 1}.
\]

**Proof.** We employ Stein’s method for Poisson process approximation established in Barbour (1988) and Barbour and Brown (1992) to prove the theorem. To this end, for suitable measurable function \( h \) on \( \mathcal{H}, \) let
\[
\mathcal{A}h(\xi) = \int_{\Gamma} [h(\xi + \delta_\alpha) - h(\xi)] \lambda(d\alpha) + \int_{\Gamma} [h(\xi - \delta_x) - h(\xi)] \xi(dx).
\]
Then \( \mathcal{A} \) defines a generator of the spatial immigration-death process with immigration intensity \( \lambda \) and with unit per capita death rate, and the equilibrium distribution of the spatial immigration-death process is \( \text{Po}(\lambda) \) [see Xia (2005, section 3.2) for more details]. The Stein equation based on \( \mathcal{A} \) is
\[
\mathcal{A}h(\xi) = f(\xi) - \text{Po}(\lambda)(f) \tag{2.7}
\]
with solution
\[ h_f(\xi) = -\int_0^\infty [E f(Z_\xi(t)) - Po(\lambda)(f)] dt, \]
where \( \{Z_\xi(t), t \geq 0\} \) is the spatial immigration-death process with generator \( A \) and initial configuration \( Z_\xi(0) = \xi \). To obtain bounds on the errors in the approximation, we need to define

\[
\begin{align*}
\Delta h_f(\xi; x) &:= h_f(\xi + \delta_x) - h_f(\xi), \\
\Delta^2 h_f(\xi; x, y) &:= \Delta h_f(\xi + \delta_x; y) - \Delta h_f(\xi; y), \\
\Delta^2 h_f(\xi, \eta; x) &:= \Delta h_f(\xi; x) - \Delta h_f(\eta; x),
\end{align*}
\]
for corresponding test functions \( f \). Xia (2005, Propositions 5.6 and 5.12) [see also Barbour and Eagleson (1983), Barbour and Brown (1992)] and Xia (2005, Lemma 5.26) state that, for all \( x, y \in \Gamma \),

\[
\begin{align*}
|\Delta^2 h_f(\xi; x, y)| &\leq \frac{1 - e^{-\lambda}}{\lambda}, \forall f \in \mathcal{F}_{TV}; \\
|\Delta^2 h_f(\xi; x, y)| &\leq 1, \forall f \in \mathcal{F}_{TV}; \\
|\Delta^2 h_f(\xi, \eta; x)| &\leq \left( \frac{3.5}{\lambda} + \frac{2.5}{|\eta| \wedge |\xi| + 1} \right) d^*_i(\xi, \eta), \forall f \in \mathcal{F}_{dt}.
\end{align*}
\] (2.8) (2.9) (2.10)

Now, since \( \Xi^{(i)} + V_{i,\alpha} + \Xi_{i,\alpha} + \delta_\alpha \) is the Palm process of \( \Xi \) with respect to \( \Xi_i \) at \( \alpha \), it follows from (2.1) that

\[
\begin{align*}
\mathbb{E} \int_\Gamma [h(\Xi) - h(\Xi - \delta_\alpha)] \Xi(d\alpha) \\
= \sum_{i \in I} \mathbb{E} \int_\Gamma [h(\Xi) - h(\Xi - \delta_\alpha)] \Xi_i(d\alpha) \\
= \sum_{i \in I} \mathbb{E} \int_\Gamma \Delta h(\Xi^{(i)} + V_{i,\alpha} + \Xi_{i,\alpha}; \alpha) \lambda_i(d\alpha).
\end{align*}
\]

On the other hand, by the Stein equation (2.7), we have

\[
\begin{align*}
|\mathbb{E} f(\Xi) - Po(\lambda)(f)| \\
= |\mathbb{E} \int_\Gamma [h_f(\Xi + \delta_\alpha) - h_f(\Xi)] \lambda(d\alpha) + \mathbb{E} \int_\Gamma [h_f(\Xi - \delta_x) - h_f(\Xi)] \Xi(d\alpha)| \\
= \sum_{i \in I} \mathbb{E} \int_\Gamma \{\Delta h_f(\Xi; \alpha) - \Delta h_f(\Xi^{(i)} + V_{i,\alpha} + \Xi_{i,\alpha}; \alpha)\} \lambda_i(d\alpha) | \\
\leq \sum_{i \in I} \mathbb{E} \int_\Gamma \{|\Delta h_f(\Xi^{(i)} + V_i + \Xi_i; \alpha) - \Delta h_f(\Xi^{(i)} + V_{i,\alpha} + \Xi_{i,\alpha}; \alpha)| \\
+ |\Delta h_f(\Xi^{(i)} + V_{i,\alpha} + \Xi_{i,\alpha}; \alpha) - \Delta h_f(\Xi^{(i)} + V_{i,\alpha} + \Xi_{i,\alpha}; \alpha)|\} \lambda_i(d\alpha). \tag{2.12}
\end{align*}
\]
To prove (2.2), we note that the test functions \( f \in \mathcal{F}_{d_{1}} \) satisfy \( f(\xi) = f(|\xi|\delta) \) for a fixed point \( z \in \Gamma \), and so we have \( h_{f}(\xi) = h_{f}(|\xi|\delta) \). Hence, for all \( \eta, \xi_{1}, \xi_{2} \in \mathcal{H} \),

\[
\sum_{j=1}^{\lfloor |\xi_{1}| - |\xi_{2}| \rfloor} |\Delta h_{f}(\eta + (|\xi_{1}| \lor |\xi_{2}|)\delta; \alpha) - \Delta h_{f}(\eta + |\xi_{1}| \lor |\xi_{2}|\delta; \alpha)| \\
\leq \sum_{j=1}^{\lfloor |\xi_{1}| - |\xi_{2}| \rfloor} |\Delta^{2} h_{f}(\eta + (|\xi_{1}| \lor |\xi_{2}| + j)\delta; z, \alpha)| \\
\leq \|\xi_{1} - |\xi_{2}|\| \frac{1 - e^{-\lambda}}{\lambda},
\]

where the last inequality is due to (2.8). Combining (2.13) with (2.12) yields (2.2).

Next, (2.10) and (2.11) imply that for \( f \in \mathcal{F}_{d_{1}} \),

\[
|\mathbb{E} f(\Xi) - \text{Po}(\lambda)(f)| \\
\leq \sum_{i \in \mathcal{I}} \mathbb{E} \int_{\Gamma} \left( \frac{3.5}{\lambda} + \frac{2.5}{|\Xi(0)| + 1} \right) d'_{i}(V_{i} + \Xi_{i}, V_{i,\alpha} + \Xi_{i,\alpha}) \lambda_{i}(d\alpha).
\]

Because \( d'_{i}(V_{i} + \Xi_{i}, V_{i,\alpha} + \Xi_{i,\alpha}) \leq d'_{i}(V_{i}, V_{i,\alpha}) + d'_{i}(\Xi_{i}, \Xi_{i,\alpha}) \) and, for each \( i \in \mathcal{I} \), \( \Xi_{i} \) is independent of \( \Xi^{(i)} \), (2.3) follows. On the other hand, due to the independence between \{\( V_{i}, \Xi_{i} \)\} and \{\( \Xi_{j}, j \in B_{n_{i}}^{c} \)\} implied by [LD2], (2.5) is immediate. To prove (2.6), one can verify that

\[
\text{Var} \left( \sum_{j \in B_{n_{i}}^{c}} |\Xi_{j}| \right) = \sum_{j_{1} \in B_{n_{i}}^{c}} \sum_{j_{2} \in B_{n_{i}}^{c} \cap A_{j_{1}}} \text{cov}(\{|\Xi_{j_{1}}|, |\Xi_{j_{2}}|\})
\]

and that \( \mathbb{E} \sum_{j \in B_{n_{i}}^{c}} |\Xi_{j}| = \sum_{j \in B_{n_{i}}^{c}} \lambda_{j} \). Hence (2.6) follows from Lemma 3.1 in Brown, Weinberg and Xia (2000) and the fact that \( d'_{i}(V_{i}, V_{i,\alpha}) \leq |V_{i}| + |V_{i,\alpha}| \) and \( d'_{i}(\Xi_{i}, \Xi_{i,\alpha}) \leq |\Xi_{i}| + |\Xi_{i,\alpha}| \).

Finally, we show (2.4). For \( \xi_{1}, \xi_{2} \in \mathcal{H} \), we define

\[
\xi_{1} \land \xi_{2} = \sum_{j=1}^{k} (a_{1j} \land a_{2j}) \delta_{x_{j}},
\]

where \( \{x_{1}, \ldots, x_{k}\} \) is the support of the point measure \( \xi_{1} + \xi_{2} \) so that \( \xi_{i} = \sum_{j=1}^{k} a_{ij} \delta_{x_{j}} \) for \( i = 1, 2 \) with \( a_{ij} \)'s being nonnegative integers. Then, for all \( f \in \mathcal{F}_{TV}, \eta, \xi_{1}, \xi_{2} \in \mathcal{H} \),

\[
|\Delta h_{f}(\eta + \xi_{1}; \alpha) - \Delta h_{f}(\eta + \xi_{2}; \alpha)| \\
\leq |\Delta h_{f}(\eta + \xi_{1}; \alpha) - \Delta h_{f}(\eta + \xi_{1} \land \xi_{2}; \alpha)| + |\Delta h_{f}(\eta + \xi_{2}; \alpha) - \Delta h_{f}(\eta + \xi_{1} \land \xi_{2}; \alpha)| \\
\leq (|\xi_{1} - |\xi_{1} \land \xi_{2}|| + |\xi_{2} - |\xi_{1} \land \xi_{2}||) \\
= \|\xi_{1} - \xi_{2}\|,
\]

where the last inequality is due to (2.9). Applying (2.14) in (2.12), we obtain (2.4).
Corollary 2.2 With the notation in Theorem 2.1, if \( \{\Xi_i, i \in I\} \) are all independent, then

\[
d_{tv}(\mathcal{L}(\Xi), \text{Po}(\lambda)) \leq \frac{1 - e^{-\lambda}}{\lambda} E \sum_{i \in I} \int \left| |\Xi_i| - |\Xi_{i,\alpha}| \right| \lambda_i(d\alpha),
\]

(2.15)

\[
d_2(\mathcal{L}(\Xi), \text{Po}(\lambda)) \leq \sum_{i \in I} \left( \frac{3.5}{\lambda} + E \frac{2.5}{\sum_{j \neq i} |\Xi_j| + 1} \right) E \int_{\Gamma} d_{1}(\Xi_i, \Xi_{i,\alpha}) \lambda_i(d\alpha)
\]

\[
\leq \left( \frac{3.5}{\lambda} + 2.5 \cdot \sqrt{\kappa(1 + \kappa/4) + 1 + \kappa/2} \right) \lambda \max_{j \in I} \lambda_j + \frac{1}{1 + \kappa/2} \lambda \max_{j \in I} \lambda_j \lambda_i \sum_{i \in I} \lambda_i^2 + E \left( |\Xi_i|^2 - \lambda_i \right),
\]

(2.16)

\[
d_{TV}(\mathcal{L}(\Xi), \text{Po}(\lambda)) \leq E \sum_{i \in I} \int |\Xi_i - |\Xi_{i,\alpha}| \lambda_i(d\alpha),
\]

(2.17)

where \( \kappa = \frac{\sum_{i \in I} \text{Var}(\Xi_i)}{\lambda \max_{j \in I} \lambda_j + 1} \).

**Proof.** Let \( A_i = B_i = \{i\} \), then (2.15), (2.16), (2.17) and (2.18) follow from (2.2), (2.5), (2.6) and (2.4) respectively. □

Corollary 2.3 [cf Chen and Xia (2004, Theorem 4.1)] Let \( \{\Xi_i, i \in I\} \) be dependent indicators with \( I \) a finite or countably infinite index set and let \( \{\mathcal{U}_i, i \in I\} \) be \( \Gamma \)-valued independent random elements independent of \( \{\Xi_i, i \in I\} \). Define \( \Xi = \sum_{i \in I} \Xi_i \mathcal{U}_i \) with mean measure \( \lambda \), let \( \mathbb{E} \mathcal{U}_i = p_i \), and assume that \( \lambda = \sum_{i \in I} p_i < \infty \). For each \( i \in I \), let \( A_i \) be the set of indices of those \( \Xi_j \)'s which are dependent on \( \Xi_i \), that is, \( \Xi_i \) is independent of \( \{\Xi_j : j \in A_i^c\} \). Then

\[
d_{tv}(\mathcal{L}(\Xi), \text{Po}(\lambda)) \leq \frac{1 - e^{-\lambda}}{\lambda} \sum_{i \in I} \left\{ \sum_{j \in A_i \setminus \{i\}} \mathbb{E} I_j I_j + \sum_{j \in A_i} p_i p_j \right\},
\]

(2.19)

\[
d_2(\mathcal{L}(\Xi), \text{Po}(\lambda)) \leq \mathbb{E} \sum_{i \in I} \sum_{j \in A_i \setminus \{i\}} \left( \frac{3.5}{\lambda} + \frac{2.5}{S_i + 1} \right) I_j I_j
\]

\[
+ \sum_{i \in I} \sum_{j \in A_i} \left( \frac{3.5}{\lambda} + \mathbb{E} \left[ \frac{2.5}{S_i + 1} \bigg| I_j = 1 \right] \right) p_i p_j,
\]

(2.20)

\[
d_{TV}(\mathcal{L}(\Xi), \text{Po}(\lambda)) \leq \sum_{i \in I} \left\{ \sum_{j \in A_i \setminus \{i\}} \mathbb{E} I_j I_j + \sum_{j \in A_i} p_i p_j \right\},
\]

(2.21)

where \( S_i = \sum_{j \in A_i} I_j \). For each \( i \in I \), let \( B_i \) be the set of indices of those \( I_i \)'s which are dependent on \( \{I_j : j \in A_i\} \) so that \( \{I_j : j \in A_i\} \) is independent of \( \{I_l : l \in B_i^c\} \). Then
(2.19) and (2.21) remain the same but (2.20) can be further reduced to

\[
d_2(\mathcal{L}(\Xi), \text{Po}(\lambda)) \leq \sum_{i \in \mathcal{I}} \sum_{j \in A_i \setminus \{i\}} \left( \frac{3.5}{\lambda} + \mathbb{E} \frac{2.5}{W_i + 1} \right) \mathbb{E}(I_i I_j) \\
+ \sum_{i \in \mathcal{I}} \sum_{j \in A_i} \left( \frac{3.5}{\lambda} + \mathbb{E} \frac{2.5}{W_i + 1} \right) p_i p_j \\
\leq \sum_{i \in \mathcal{I}} \left( \frac{3.5}{\lambda} + 2.5 \cdot \frac{\sqrt{\kappa_i(1 + \kappa_i/4) + 1 + \kappa_i/2}}{\sum_{j \in B_i^c} p_j + 1} \right) \left( \sum_{j \in B_i^c} \mathbb{E} I_j + \sum_{j \in A_i} p_i p_j \right) 
\]  

(2.22)

where \( W_i = \sum_{j \notin B_i} I_j \) and

\[
\kappa_i = \frac{\sum_{j_1 \in B_i^c} \sum_{j_2 \in B_i^c \cap A_i} \text{cov}(I_{j_1}, I_{j_2})}{\sum_{j \in B_i^c} p_j + 1}.
\]

**Proof.** Set \( \Xi_i = I_i \delta_{1/n}, i \in \mathcal{I} \), then \( \Xi_i \) is independent of \( \{ \Xi_j : j \notin A_i \} \), so [LD1] holds, \( \Xi_{i,\alpha} = 0 \), and the claims (2.19), (2.20) and (2.21) follow from (2.2), (2.3) and (2.4) respectively. On the other hand, \( \{ \Xi_j : j \in A_i \} \) is independent of \( \{ \Xi_j : j \notin B_i \} \), so [LD2] holds and (2.22) and (2.23) are direct consequences of (2.5) and (2.6).

A typical example of Poisson process approximation is that of the Bernoulli process defined as follows [see Xia (2005, section 6.1) for further discussion]. Let \( I_1, \ldots, I_n \) be independent indicators with

\[
\mathbb{P}(I_i = 1) = 1 - \mathbb{P}(I_i = 0) = p_i, \ i = 1, \ldots, n.
\]

Let \( \Gamma = [0, 1] \), \( \Xi = \sum_{i=1}^{n} I_i \delta_{i/n} \) and \( \lambda = \sum_{i=1}^{n} p_i \delta_{i/n} \) be the mean measure of \( \Xi \). We set \( \Xi_i = I_i \delta_{1/n}, i = 1, \ldots, n \), then the reduced Palm process of \( \Xi_i \) at \( \alpha \in \Gamma \) is \( \Xi_{i,\alpha} = 0 \) and the Palm distribution of \( \Xi_j \) with respect to point process \( X_i \) at \( \alpha \) for \( j \neq i \) is the same that of \( \Xi_j \). Hence, Corollary 2.2 together with (2.16) and Chen and Xia (2004, Proposition 4.5) can be used to obtain immediately the following (known) result.

**Example 2.4** [Xia (2005, section 6.1)] For the Bernoulli process \( \Xi \) on \( \Gamma = [0, 1] \) with mean measure \( \lambda \),

\[
d_{tv}(\mathcal{L}(\Xi), \text{Po}(\lambda)) \leq \frac{1 - e^{-\lambda}}{\lambda} \sum_{i=1}^{n} p_i^2, \\
d_{TV}(\mathcal{L}(\Xi), \text{Po}(\lambda)) \leq \sum_{i=1}^{n} p_i^2, \\
d_2(\mathcal{L}(\Xi), \text{Po}(\lambda)) \leq \frac{6}{\lambda - \max_{1 \leq i \leq n} p_i} \sum_{i=1}^{n} p_i^2.
\]

9
Example 2.5 Throw $n$ points uniformly and independently onto the interval $[0, n]$ and let $\Xi$ be the configuration of the points on $[0, T] := \Gamma$ with $n \gg T$ and $\lambda$ be the mean measure of $\Xi$, then
\[ d_2(\mathcal{L}(\Xi), \text{Po}(\lambda)) \leq \frac{6T}{n-1}. \]

**Proof.** Let $I_i = 1$ if the $i$th point is in $\Gamma$ and 0 if it is not in $\Gamma$. Then the configuration of the $i$th point on $\Gamma$ can be written as $\Xi_i = I_i \delta_{U_i}$ and $\Xi = \sum_{i=1}^n \Xi_i$, where $U_i$'s are independent and identically distributed uniform random variables on $\Gamma$ and are independent of the $I_i$'s.

Noting that the reduced Palm process $\Xi_{\cdot, \alpha} = 0$, we obtain the bound by applying (2.22) with $p_i = \mathbb{P}(I_i = 1) = T/n$ and Chen and Xia (2004, Proposition 4.5).

3 Superposition of thinned dependent point processes

Assume that $q$ is a measurable retention function on $\Gamma$ and $X$ is a point process on $\Gamma$. For a realization $X(\omega)$ of $X$, we thin its points as follows. For each point of $X(\omega)$ at $\alpha$, it is retained with probability $q(\alpha)$ and discarded with probability $1 - q(\alpha)$, independently of the other points [see Daley and Vere-Jones (1988), p. 554, for dependent thinning and Schuhmacher (2005b) for discussions of more thinning strategies]. The thinned configuration is denoted as $X_q(\omega)$. For retention functions $q_1, q_2, \ldots, q_n$, let $\sum_{i=1}^n X_q^i$ be the process arising from the superposition of independent realizations of $X_{q_1}, X_{q_2}, \ldots, X_{q_n}$, that is, $X_q^1, X_q^2, \ldots, X_q^n$ are independent and $\mathcal{L}(X_q^i) = \mathcal{L}(X_q^i)$ for $i = 1, \ldots, n$. Fichtner (1977) showed that a sequence of such superpositions, obtained from the rows of an infinitesimal array of retention functions, converges to a Poisson process under standard conditions [see also Kallenberg (1983, Exercise 8.8)]. Serfozo (1984) presented convergence theorems for sums of dependent point processes that are randomly thinned by a two-step procedure which deletes each entire point process with a probability and for each retained point process, its points are deleted or retained according to another thinning strategy. Necessary and sufficient conditions are given for a sum of two-step thinned point processes to converge in distribution and the limit is shown to be a Cox process [see also Fichtner (1975) and Liese (1980)].

For simplicity, we assume that $\{\Xi_i, \ i \in I\}$ is a locally dependent collection of point processes (satisfying [LD1]) on a locally compact metric space $\Gamma$ with metric $d_0$ bounded by 1. For each point of $\Xi_i$, we delete the point with probability $1 - p$ and retain it with probability $p$, independent of the others. The thinned point process is denoted by $\Xi^p_i, \ i \in I$, and in general, for each point process $X$, we use $X^p$ to stand for its thinned process. Let $\Xi^p = \sum_{i \in I} \Xi^p_i$. As before, we define $A_i$ as the collection of indices $j$ of the point processes $\Xi_j$ which are dependent on $\Xi_i$, i.e., $\Xi_i$ is independent of $\{\Xi_j, \ j \in A_i^c\}$.

**Theorem 3.1** Let $\mu_i$ be the mean measure of $\Xi_i$, $\mu_i = \mu_i(\Gamma) = \mathbb{E}(|\Xi_i|), \ i \in I$ and assume
that λ = \sum_{i \in I} \mu_i < \infty. Then the mean measure of Ξ^p is \( \lambda^p = p \sum_{i \in I} \mu_i \) and

\[
d_{tv}(\mathcal{L}(\Xi^p), \text{Po}(\lambda^p)) \leq p \left( 1 + \frac{1}{\lambda} \right) \mathbb{E} \sum_{i \in I} \{([V_i] + |\Xi_i|)\lambda_i + [V_i] + |\Xi_i| - 1)\Xi_i]\}, \tag{3.1}
\]

\[
d_2(\mathcal{L}(\Xi^p), \text{Po}(\lambda^p)) \leq p \mathbb{E} \sum_{i \in I} \left( \frac{3.5}{p\lambda} + \frac{2.5}{\sum_{j \in A_i^{\mathcal{I}}} \Xi_j + 1} \right) \{([V_i] + |\Xi_i|)\lambda_i + [V_i] + |\Xi_i| - 1)\Xi_i]\}. \tag{3.2}
\]

\[
d_{TV}(\mathcal{L}(\Xi^p), \text{Po}(\lambda^p)) \leq p \mathbb{E} \sum_{i \in I} \{([V_i] + |\Xi_i|)\lambda_i + [V_i] + |\Xi_i| - 1)\Xi_i]\}. \tag{3.3}
\]

**Proof.** We prove (3.2) only, as the proofs of (3.1) and (3.3) are similar to that of (3.2). By conditioning on the configurations, we have, for each Borel set \( B \subset \Gamma \),

\[
\mathbb{E}[\Xi_i^p(B)] = \mathbb{E}\{\mathbb{E}[\Xi_i^p(B)|\Xi_i]\} = \mathbb{E}[\xi_i(B)p],
\]

which implies that the mean measure of Ξ^p is \( \lambda^p = p \mu_i \) and hence \( \lambda^p = p \sum_{i \in I} \mu_i \). By (2.3) and the fact that \( d'(\xi_1, \xi_2) \leq |\xi_1| + |\xi_2| \), we obtain

\[
d_2(\mathcal{L}(\Xi^p), \text{Po}(\lambda^p)) \leq \mathbb{E} \sum_{i \in I} \left( \frac{3.5}{p\lambda} + \frac{2.5}{\sum_{j \in A_i^{\mathcal{I}}} \Xi_j + 1} \right) \int_\Gamma ([V_i^p] + |\Xi_i^p\|\lambda_i + [V_i] + |\Xi_i^p| - 1)\Xi_i^p(d\alpha)
\]

\[
\leq \mathbb{E} \sum_{i \in I} \left( \frac{3.5}{p\lambda} + \frac{2.5}{\sum_{j \in A_i^{\mathcal{I}}} \Xi_j + 1} \right) \int_\Gamma \{([V_i^p] + |\Xi_i^p|)\lambda_i + [V_i] + |\Xi_i| - 1)\Xi_i^p(d\alpha)\}
\]

\[
\leq \mathbb{E} \sum_{i \in I} \left( \frac{3.5}{p\lambda} + \frac{2.5}{\sum_{j \in A_i^{\mathcal{I}}} \Xi_j + 1} \right) \{([V_i^p] + |\Xi_i|)\lambda_i + [V_i] + |\Xi_i| - 1)\Xi_i\}_{p^2}.
\]

Since the points are thinned independently, we can condition on the configuration of \{\Xi_i, i \in I\}. Noting that for \( Z \sim \text{Binomial}(n, p) \), \( \mathbb{E}[\frac{1}{Z+1}] \leq \frac{1}{(n+1)p} \) and \( \mathbb{E}[\sqrt{(X - 1)X}] = n(n - 1)p^2 \), we obtain

\[
d_2(\mathcal{L}(\Xi^p), \text{Po}(\lambda^p)) \leq \mathbb{E} \sum_{i \in I} \left( \frac{3.5}{p\lambda} + \frac{2.5}{\sum_{j \in A_i^{\mathcal{I}}} \Xi_j + 1} \right) \{([V_i] + |\Xi_i|)\lambda_i + [V_i] + |\Xi_i| - 1)\Xi_i\}_{p^2}.
\]

This completes the proof of (3.2). \( \blacksquare \)

**Remark 3.2** Serfozo (1984, Example 3.6) obtained the rate \( p \) for the convergence of a sum of thinned point processes to a Poisson process. Theorem 3.1 shows that the rate \( p \) is valid for all of the three metrics used.
4 Superposition of renewal processes

Viswanathan (1992, page 290) states that if \( \{ \Xi_i, 1 \leq i \leq n \} \) are independent renewal processes on \([0, T]\), each representing the process of calls generated by a subscriber, then the total number of calls can be modeled by a Poisson process. In this section, we quantify the statement by giving an error bound for Poisson process approximation to the sum of independent sparse renewal processes. We begin with a technical lemma.

**Lemma 4.1** Let \( \eta \sim G, \xi_i \sim F, i \geq 1 \) be independent nonnegative random variables and define

\[
N_t = \max\{ n : \eta + \xi_1 + \cdots + \xi_{n-1} \leq t \}, \quad t \geq 0.
\]

Then

\[
G(t) \leq \mathbb{E}(N_t) \leq \frac{G(t)}{1 - F(t)}, \tag{4.1}
\]

\[
\mathbb{E}(N_t^2) - \mathbb{E}(N_t) \leq 2F(t)\mathbb{E}(N_t) \leq \frac{2F(t)G(t)}{(1 - F(t))^2}. \tag{4.2}
\]

**Proof.** Let \( V(t) = \mathbb{E}(N_t) \). The renewal equation gives

\[
V(t) = G(t) + \int_0^t V(t - s)dF(s) \leq G(t) + V(t)F(t), \tag{4.3}
\]

which implies (4.1). For (4.2), define \( V_2(t) = \mathbb{E}[N_t(N_t + 1)] \). Then using the same arguments as for proving the renewal equation,

\[
V_2(t) = 2V(t) + \int_0^t V_2(t - s)dF(s).
\]

This implies \( V_2(t) \leq 2V(t) + V_2(t)F(t) \), which in turn implies

\[
V_2(t) \leq \frac{2V(t)}{1 - F(t)}.
\]

Since

\[
\mathbb{E}(N_t^2) - \mathbb{E}(N_t) = V_2(t) - 2V(t) = \int_0^t V_2(t - s)dF(s) \leq V_2(t)F(t) \leq \frac{2F(t)V(t)}{1 - F(t)},
\]

(4.2) follows from (4.1). \( \blacksquare \)

**Theorem 4.2** Suppose that \( \{ \Xi_i, 1 \leq i \leq n \} \) are independent renewal processes on \([0, T]\) with the first arrival time of \( \Xi_i \) having distribution \( G_i \) and its inter-arrival time having distribution \( F_i \). Let \( \Xi = \sum_{i=1}^n \Xi_i \) and \( \lambda \) be its mean measure. Then

\[
d_2(\mathcal{L}(\Xi), \text{Po}(\lambda)) \leq \frac{6 \sum_{i=1}^n [2F_i(T) + G_i(T)]G_i(T)}{(\sum_{i=1}^n G_i(T) - \max_j G_j(T))(1 - F_i(T))^2}. \tag{4.4}
\]
Proposition 4.5 of Chen and Xia (2004) gives

\[ G \]

Remark 4.4

However, applying Proposition 4.5 of Chen and Xia (2004) gives

\[
\mathbb{E} \left[ \sum_{j \neq i} \frac{1}{|\Xi_j' + 1|} \right] \leq \mathbb{E} \left[ \sum_{j \neq i} |\Xi_j'| \right] = \mathbb{E} \left[ \sum_{j \neq i} G_j(T) \right]
\]

and using (4.1), we obtain

\[
\lambda \geq \sum_{i=1}^{n} G_i(T).
\]

Remark 4.3 If \{\Xi_i, 1 \leq i \leq n\} are independent and identically distributed stationary renewal processes on \([0,T]\) with the successive inter-arrival time distribution \(F\), then

\[
d_2(\mathcal{L}(\Xi), \text{Po}(\lambda)) \leq \frac{6n[2F(T) + G(T)]}{(n-1)(1-F(T))^2},
\]

where \(G(t) = \int_{0}^{t} (1 - F(s))ds / \int_{0}^{\infty} (1 - F(s))ds\) [see Daley and Vere-Jones (1988), p. 71].

Remark 4.4 An application of Theorem 2.1 of Schuhmacher (2005a) to the sum of the renewal processes \{\Xi_i, 1 \leq i \leq n\} in Remark 4.3 with the natural partition \(\{\{i\}, \emptyset, \{1, \ldots, i-1, i+1, \ldots, n\}\}\) for each \(1 \leq i \leq n\) will give an error bound

\[
n[F(T) + G(T)] + \theta G(T)(1 + \ln^+ n),
\]

where \(\theta\) is a constant. The first term of the bound increases linearly in \(n\) and the bound is clearly not as sharp as the bound in Remark 4.3.

Since the thinned process \(X^p\) of a renewal process \(X\) with mean measure \(\mu\) is still a renewal process [see Daley and Vere-Jones (1988, pp. 75-76)] with mean measure \(\mu^p = p\mu\) [see the proof of Theorem 3.1], a repetition of the proof of Theorem 4.2 yields the following proposition.

Proposition 4.5 Suppose that \{\Xi_i, 1 \leq i \leq n\} are independent renewal processes on \([0,T]\) with the first arrival time of \(\Xi_i\) having distribution \(G_i\) and its inter-arrival time having distribution \(F_i\). Let \(\Xi^p_i\) be the thinned point process obtained from \(\Xi_i\) by deleting each point with probability \(1 - p\) and retaining it with probability \(p\), independently of the other points. Let \(\Xi^p = \sum_{i=1}^{n} \Xi^p_i\) and \(\lambda^p\) be its mean measure. Then

\[
d_2(\mathcal{L}(\Xi^p), \text{Po}(\lambda^p)) \leq \frac{6p \sum_{i=1}^{n} [2F_i(T) + G_i(T)]G_i(T)}{(\sum_{i=1}^{n} G_i(T) - \max_j G_j(T))(1 - F_i(T))^2}.
\]
Acknowledgements

This research was partially supported by Grant C-389-000-010-101 at the National University of Singapore (LC), the ARC Centre of Excellence for Mathematics and Statistics of Complex Systems (AX) and the Belz Fund of the University of Melbourne (LC).

References

[1] Banis, R. (1975). The convergence of sums of dependent point processes to Poisson processes. (Russian. Lithuanian, English summary) Litovsk. Mat. Sb. 15, 11–23, 223.

[2] Banis, R. (1985). A Poisson limit theorem for rare events of a discrete random field. (Russian. English, Lithuanian summary) Litovsk. Mat. Sb. 25, 3–8.

[3] Banys, R. (1980). On superpositions of random measures and point processes. Mathematical statistics and probability theory (Proc. Sixth Internat. Conf., Wisla, 1978), 26–37, Lecture Notes in Statist., 2, Springer, New York-Berlin.

[4] Barbour, A. D. (1988). Stein’s method and Poisson process convergence. J. Appl. Probab. 25 (A), 175–184.

[5] Barbour, A. D. and Brown, T. C. (1992). Stein’s method and point process approximation. Stochastic Processes and their Applications 43, 9–31.

[6] Barbour, A. D. and Eagleson, G. K. (1983). Poisson approximation for some statistics based on exchangeable trials. Adv. Appl. Prob. 15, 585–600.

[7] Barbour, A. D., Holst, L. and Janson, S. (1992). Poisson Approximation. Oxford Univ. Press.

[8] Barbour, A. D. and Xia, A. (2006). Normal approximation for random sums. Adv. Appl. Prob. 38, 693–728.

[9] Brown, T. C. (1978). A martingale approach to the Poisson convergence of simple point processes. Ann. Probab. 6, 615–628.

[10] Brown, T. C. (1979). Position dependent and stochastic thinning of point processes. Stochastic Processes and their Applications 9, 189–193.

[11] Brown, T. C., Weinberg, G. V. and Xia, A. (2000). Removing logarithms from Poisson process error bounds. Stochastic Processes and their Applications 87, 149–165.

[12] Brown, T. C. and Xia, A. (1995). On Metrics in Point Process Approximation. Stochastics and Stochastics Reports 52, 247–263.

[13] Chen, L. H. Y. and Shao, Q. M. (2004). Normal approximation under local dependence. Ann. Probab. 32, 1985–2028.
[14] Chen, L. H. Y. and Xia, A. (2004). Stein’s method, Palm theory and Poisson process approximation. Ann. Probab. 32, 2545–2569.

[15] Çinlar, E. (1972). Superposition of point processes. Stochastic point processes: statistical analysis, theory, and applications (Conf., IBM Res. Center, Yorktown Heights, N.Y., 1971), 549–606. Wiley-Interscience, New York.

[16] Daley, D. J. and Vere-Jones, D. (1988). An Introduction to the Theory of Point Processes. Springer-Verlag.

[17] Fichtner, K. (1975). Schwache Konvergenz von unabhängigen Überlagerungen verdünnte zufälliger Punkfolgen. Math. Nachr. 66, 333–341.

[18] Fichtner, K. (1977). Poissonsche zufällige Punktfolgen und ortsabhängige Verdünnungen. (German) Transactions of the Seventh Prague Conference on Information Theory, Statistical Decision Functions, Random Processes and of the Eighth European Meeting of Statisticians (Tech. Univ. Prague, Prague, 1974), Vol. A, pp. 123–133.

[19] Goldman, J. R. (1967). Stochastic point processes: limit theorems. Ann. Math. Statist. 38, 771–779.

[20] Goldstein, L. and Rinott, Y. (1996). Multivariate normal approximations by Stein’s method and size bias couplings. J. Appl. Probab. 33, 1–17.

[21] Goldstein, L. and Xia, A. (2006). Zero Biasing and a Discrete Central Limit Theorem. Ann. Probab. 34, 1782–1806.

[22] Grigelionis, B. (1963). On the convergence of sums of random step processes to a Poisson process. Theory Probab. Appl. 8, 177–182.

[23] Jagers, P. (1972). On the weak convergence of superpositions of point processes. Z. Wahrsch. Verw. Gebiete 22, 1–7.

[24] Kallenberg, O. (1975). Limits of compound and thinned point processes. J. Appl. Probab. 12, 269–278.

[25] Kallenberg, O. (1983). Random Measures. Academic Press, London.

[26] Liese, F. (1980). Überlagerung verdünnter und schwach abhängiger Punktprozesse. (German) Math. Nachr. 95, 177–186.

[27] Rachev, S. T. (1991). Probability metrics and the Stability of Stochastic Models. John Wiley & Sons.

[28] Serfozo, R. (1984). Thinning of cluster processes: convergence of sums of thinned point processes. Math. Oper. Res. 9, 522–533.

[29] Schuhmacher, D. (2005a). Distance estimates for dependent superpositions of point processes. Stochastic Processes and their Applications 115, 1819–1837.
[30] Schuhmacher, D. (2005b). Distance estimates for Poisson process approximations of dependent thinnings. Electron. J. Probab. 10, 165–201 (electronic).

[31] Viswanathan, T. (1992). Telecommunication switching systems and networks. Prentice-Hall of India.

[32] Xia, A. (2005). Stein’s method and Poisson process approximation. In: An Introduction to Stein’s Method, Eds. A. D. Barbour and L. H. Y. Chen, World Scientific Press, Singapore, 115–181.