Weak convergence proof (in progress)

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Theorem 1. *Let $\nu_t^{(1:N)}$ denote the offspring numbers in an interacting particle system satisfying the standing assumption and such that, for any N sufficiently large, for all finite t, $\mathbb{P}\{\tau_N(t) = \infty\} = 0$. Suppose that there exists a deterministic sequence $(b_N)_{N\geq 1}$ such that $\lim_{N\to\infty} b_N = 0$ and*

$$\frac{1}{(N)_3} \sum_{i=1}^{N} \mathbb{E}_t\{(\nu_t^{(i)})_3\} \leq b_N \frac{1}{(N)_2} \sum_{i=1}^{N} \mathbb{E}_t\{(\nu_t^{(i)})_2\} \tag{1}$$

for all N, uniformly in $t \geq 1$. Then the rescaled genealogical process $(G_{\tau_N(t)}^{(n,N)})_{t\geq 0}$ converges weakly to Kingman's n-coalescent as $N \to \infty$.

Proof. Define $p_t := \max_{\xi\in E}\{1 - p_{\xi\xi}(t)\} = 1 - p_{\Delta\Delta}(t)$, where Δ denotes the trivial partition of $\{1,\dots,n\}$ into singletons. For a proof that the maximum is attained at $\xi = \Delta$, see Lemma 1. Following Möhle (1999), we now construct the two-dimensional Markov process $(Z_t, S_t)_{t\in\mathbb{N}}$ with transition probabilities

$$\mathbb{P}(Z_t = j, S_t = \eta \mid Z_{t-1} = i, S_{t-1} = \xi) = \begin{cases} 1 - p_t & \text{if } j = i \text{ and } \xi = \eta \\ p_{\xi\xi}(t) + p_t - 1 & \text{if } j = i+1 \text{ and } \xi = \eta \\ p_{\xi\eta}(t) & \text{if } j = i+1 \text{ and } \xi \neq \eta \\ 0 & \text{otherwise.} \end{cases} \tag{2}$$

The construction is such that the marginal (S_t) has the same distribution as the genealogical process of interest, and (Z_t) has jumps at all the times (S_t) does plus some extra jumps. (The definition of p_t ensures that the probability in the second case is non-negative, attaining the value zero when $\xi = \Delta$.)

Denote by $0 = T_0^{(N)} < T_1^{(N)} < \dots$ the jump times of the rescaled process $(Z_{\tau_N(t)})_{t\geq 0}$, and $\omega_i^{(N)} := T_i^{(N)} - T_{i-1}^{(N)}$ the corresponding holding times ($i \in \mathbb{N}$).

... □

Lemma 1. $\max_{\xi\in E}(1 - p_{\xi\xi}(t)) = 1 - p_{\Delta\Delta}(t)$.

Proof. Consider any $\xi \in E$ consisting of k blocks ($1 \leq k \leq n-1$), and any $\xi' \in E$ consisting of $k+1$ blocks. From the definition of $p_{\xi\eta}(t)$ (Koskela et al., 2018, Equation (1)),

$$p_{\xi\xi}(t) = \frac{1}{(N)_k} \sum_{\substack{i_1,\dots,i_k \\ \text{all distinct}}} \nu_t^{(i_1)} \cdots \nu_t^{(i_k)}. \tag{3}$$

Similarly,

$$\begin{aligned} p_{\xi'\xi'}(t) &= \frac{1}{(N)_{k+1}} \sum_{\substack{i_1,\dots,i_k,i_{k+1} \\ \text{all distinct}}} \nu_t^{(i_1)} \cdots \nu_t^{(i_k)} \nu_t^{(i_{k+1})} \\ &= \frac{1}{(N)_k (N-k)} \sum_{\substack{i_1,\dots,i_k \\ \text{all distinct}}} \left\{ \nu_t^{(i_1)} \cdots \nu_t^{(i_k)} \sum_{\substack{i_{k+1}=1 \\ \text{also distinct}}}^{N} \nu_t^{(i_{k+1})} \right\}. \end{aligned} \tag{4}$$

Discarding the zero summands,

$$p_{\xi'\xi'}(t) = \frac{1}{(N)_k (N-k)} \sum_{\substack{i_1,\dots,i_k \\ \text{all distinct:} \\ \nu_t^{(i_1)},\dots,\nu_t^{(i_k)}>0}} \left\{ \nu_t^{(i_1)} \cdots \nu_t^{(i_k)} \sum_{\substack{i_{k+1}=1 \\ \text{also distinct}}}^{N} \nu_t^{(i_{k+1})} \right\}. \tag{5}$$

The inner sum is

$$\sum_{\substack{i_{k+1}=1 \\ \text{also distinct}}}^{N} \nu_t^{(i_{k+1})} = \left\{ \sum_{i=1}^{N} \nu_t^{(i)} - \sum_{i \in \{i_1,\dots,i_k\}} \nu_t^{(i)} \right\} \leq N-k \tag{6}$$

since $\nu_t^{(i_1)}, \dots, \nu_t^{(i_k)}$ are all at least 1. Hence

$$p_{\xi'\xi'}(t) \leq \frac{N-k}{(N)_k (N-k)} \sum_{\substack{i_1,\dots,i_k \\ \text{all distinct:} \\ \nu_t^{(i_1)},\dots,\nu_t^{(i_k)}>0}} \nu_t^{(i_1)} \cdots \nu_t^{(i_k)} = p_{\xi\xi}(t). \tag{7}$$

Thus $p_{\xi\xi}(t)$ is decreasing in the number of blocks of ξ, and is therefore minimised by taking $\xi = \Delta$, which achieves the maximum n blocks. This choice in turn maximises $1 - p_{\xi\xi}(t)$, as required. □

Lemma 2. *For any* $t > 0$,

$$\lim_{N\to\infty} \mathbb{E}\left[\prod_{r=1}^{\tau_N(t)} (1 - p_r) \right] = e^{-\alpha t} \tag{8}$$

where $\alpha := n(n-1)/2$.

Proof. The strategy is to find upper and lower bounds on $\mathbb{E}\left[\prod_{r=1}^{\tau_N(t)}(1-p_r)\right]$, both of which converge to $e^{-\alpha t}$.

Lower Bound

From Brown et al. (2020, Equation (14)), taking $\xi = \Delta$, we have

$$1 - p_t = p_{\Delta\Delta}(t) \geq 1 - \alpha(1 + O(N^{-1}))\left[c_N(t) + B_n D_N(t)\right] \tag{9}$$

where $B_n > 0$ and the $O(N^{-1})$ term does not depend on t. In particular,

$$1 - p_t = p_{\Delta\Delta}(t) \geq 1 - \frac{N^{n-2}}{(N-2)_{n-2}} \alpha c_N(t) - \frac{N^{n-3}}{(N-3)_{n-3}} B_n D_N(t). \tag{10}$$

Since $D_N(t) \leq c_N(t)$, a sufficient condition for the bound to be positive is

$$E_t := \left\{ c_N(t) < \frac{(N-3)_{n-3}}{N^{n-3}} \left(\alpha \left(1 + \frac{2}{N-2} \right) + B_n \right)^{-1} \right\}. \tag{11}$$

Hence, by a multinomial expansion,

$$\begin{aligned}
\prod_{r=1}^{\tau_N(t)} (1 - p_r) &\geq \prod_{r=1}^{\tau_N(t)} \left\{ 1 - \alpha(1 + O(N^{-1}))\left[c_N(r) + B_n D_N(r)\right] \right\} \times \prod_{r=1}^{\tau_N(t)} \mathbb{1}_{E_r} \\
&= \left(1 + \sum_{k=1}^{\tau_N(t)} \sum_{\substack{r_1<\dots<r_k \\ =1}}^{\tau_N(t)} \prod_{j=1}^{k} \left\{ -\alpha(1 + O(N^{-1}))\left[c_N(r_j) + B_n D_N(r_j)\right] \right\} \right) \times \prod_{r=1}^{\tau_N(t)} \mathbb{1}_{E_r} \\
&= \prod_{r=1}^{\tau_N(t)} \mathbb{1}_{E_r} + \sum_{k=1}^{\tau_N(t)} \left\{ -\alpha(1 + O(N^{-1})) \right\}^k \left(\prod_{r=1}^{\tau_N(t)} \mathbb{1}_{E_r} \right) \sum_{\substack{r_1<\dots<r_k \\ =1}}^{\tau_N(t)} \prod_{j=1}^{k} \left\{ c_N(r_j) + B_n D_N(r_j) \right\}.
\end{aligned} \tag{12}$$

Taking expectations,

$$
\begin{aligned}
\mathbb{E}\left[\prod_{r=1}^{\tau_N(t)}(1-p_r)\right] \geq \mathbb{E}\left[\prod_{r=1}^{\tau_N(t)}\mathbb{1}_{E_r}\right] \\
&+\mathbb{E}\left[\sum_{k=1}^{\infty}\left\{-\alpha(1+O(N^{-1}))\right\}^k \mathbb{1}_{\{k\leq\tau_N(t)\}}\mathbb{1}_{\bigcap E_r}\sum_{\substack{r_1<\cdots<r_k\\=1}}^{\tau_N(t)}\prod_{j=1}^{k}\{c_N(r_j)+B_nD_N(r_j)\}\right] \\
&=\mathbb{P}\left[\bigcap_{r=1}^{\tau_N(t)}E_r\right] \\
&+\sum_{k=1}^{\infty}\left\{-\alpha(1+O(N^{-1}))\right\}^k\mathbb{E}\left[\sum_{\substack{r_1<\cdots<r_k\\=1}}^{\tau_N(t)}\prod_{j=1}^{k}\{c_N(r_j)+B_nD_N(r_j)\}\middle| k\leq\tau_N(t),\bigcap_{r=1}^{\tau_N(t)}E_r\right] \\
&\times\mathbb{P}\left[k\leq\tau_N(t),\bigcap_{r=1}^{\tau_N(t)}E_r\right]. \qquad (13)
\end{aligned}
$$

We want to show that the conditional expectation on the right converges to $t^k/k!$, for reasons that will become clear. The strategy is to upper and lower bound this expectation by quantities that converge to $t^k/k!$.

First the lower bound. Assume that $k\leq\tau_N(t)$, ensuring that the sum is non-empty. From Koskela et al. (2018, Equation (8)),

$$
\begin{aligned}
\sum_{\substack{r_1<\cdots<r_k\\=1}}^{\tau_N(t)}\prod_{j=1}^{k}\{c_N(r_j)+B_nD_N(r_j)\} &\geq \sum_{\substack{r_1<\cdots<r_k\\=1}}^{\tau_N(t)}\prod_{j=1}^{k}c_N(r_j) \\
&\geq\frac{1}{k!}\left(\sum_{s=1}^{\tau_N(t)}c_N(s)\right)^k-\frac{1}{k!}\binom{k}{2}\left(\sum_{s=1}^{\tau_N(t)}c_N(s)^2\right)\left(\sum_{s=1}^{\tau_N(t)}c_N(s)\right)^{k-2} \\
&\geq\frac{1}{k!}t^k-\frac{1}{k!}\binom{k}{2}(t+1)^{k-2}\left(\sum_{s=1}^{\tau_N(t)}c_N(s)^2\right) \qquad (14)
\end{aligned}
$$

by the definition of τ_N. Then, since the conditioning can only decrease the values of $c_N(s)$,

$$
\begin{aligned}
&\mathbb{E}\left[\sum_{\substack{r_1<\cdots<r_k\\=1}}^{\tau_N(t)}\prod_{j=1}^{k}\{c_N(r_j)+B_nD_N(r_j)\}\middle| k\leq\tau_N(t),\bigcap_{r=1}^{\tau_N(t)}E_r\right] \\
&\quad\geq\frac{1}{k!}t^k-\frac{1}{k!}\binom{k}{2}(t+1)^{k-2}\mathbb{E}\left[\sum_{s=1}^{\tau_N(t)}c_N(s)^2\middle| k\leq\tau_N(t),\bigcap_{r=1}^{\tau_N(t)}E_r\right] \\
&\quad\geq\frac{1}{k!}t^k-\frac{1}{k!}\binom{k}{2}(t+1)^{k-2}\mathbb{E}\left[\sum_{s=1}^{\tau_N(t)}c_N(s)^2\right]\longrightarrow\frac{1}{k!}t^k \qquad (15)
\end{aligned}
$$

as $N\to\infty$ using Brown et al. (2020, Equation (5)).

Now for the upper bound. We start with a multinomial expansion and some manipulations of the sums:

$$
\begin{aligned}
\sum_{\substack{r_1<\cdots<r_k\\=1}}^{\tau_N(t)} \prod_{j=1}^{k} \{c_N(r_j)+B_n D_N(r_j)\} &= \frac{1}{k!} \sum_{\substack{r_1\neq\cdots\neq r_k\\ \text{all distinct}}}^{\tau_N(t)} \prod_{j=1}^{k} \{c_N(r_j)+B_n D_N(r_j)\} \\
&= \frac{1}{k!} \sum_{\substack{r_1\neq\cdots\neq r_k\\ \text{all distinct}}}^{\tau_N(t)} \sum_{\mathcal{I}\subseteq\{1,\dots,k\}} (B_n)^{k-|\mathcal{I}|} \left\{\prod_{i\in\mathcal{I}} c_N(r_i)\right\} \left\{\prod_{j\notin\mathcal{I}} D_N(r_j)\right\} \\
&= \frac{1}{k!} \sum_{\mathcal{I}\subseteq\{1,\dots,k\}} (B_n)^{k-|\mathcal{I}|} \sum_{\substack{r_1\neq\cdots\neq r_k\\ \text{all distinct}}}^{\tau_N(t)} \left\{\prod_{i\in\mathcal{I}} c_N(r_i)\right\} \left\{\prod_{j\notin\mathcal{I}} D_N(r_j)\right\} \\
&= \frac{1}{k!} \sum_{I=0}^{k} \binom{k}{I} (B_n)^{k-I} \sum_{\substack{r_1\neq\cdots\neq r_k\\ \text{all distinct}}}^{\tau_N(t)} \left\{\prod_{i=1}^{I} c_N(r_i)\right\} \left\{\prod_{j=I+1}^{k} D_N(r_j)\right\} \\
&= \frac{1}{k!} \sum_{\substack{r_1\neq\cdots\neq r_k\\ \text{all distinct}}}^{\tau_N(t)} \left\{\prod_{i=1}^{k} c_N(r_i)\right\} \\
&\quad + \frac{1}{k!} \sum_{I=0}^{k-1} \binom{k}{I} (B_n)^{k-I} \sum_{\substack{r_1\neq\cdots\neq r_k\\ \text{all distinct}}}^{\tau_N(t)} \left\{\prod_{i=1}^{I} c_N(r_i)\right\} \left\{\prod_{j=I+1}^{k} D_N(r_j)\right\}. \qquad (16)
\end{aligned}
$$

Then, using that $D_N(s) \leq c_N(s)$ for all s (Koskela et al., 2018, p.9), along with the definition of τ_N,

$$
\begin{aligned}
&\frac{1}{k!} \sum_{\substack{r_1\neq\cdots\neq r_k\\ \text{all distinct}}}^{\tau_N(t)} \left\{\prod_{i=1}^{k} c_N(r_i)\right\} + \frac{1}{k!} \sum_{I=0}^{k-1} \binom{k}{I} (B_n)^{k-I} \sum_{\substack{r_1\neq\cdots\neq r_k\\ \text{all distinct}}}^{\tau_N(t)} \left\{\prod_{i=1}^{I} c_N(r_i)\right\} \left\{\prod_{j=I+1}^{k} D_N(r_j)\right\} \\
&\leq \frac{1}{k!} \left(\sum_{r=1}^{\tau_N(t)} c_N(r)\right)^{k} + \frac{1}{k!} \sum_{I=0}^{k-1} \binom{k}{I} (B_n)^{k-I} \sum_{\substack{r_1\neq\cdots\neq r_k\\ \text{all distinct}}}^{\tau_N(t)} \left\{\prod_{i=1}^{k-1} c_N(r_i)\right\} D_N(r_k) \\
&\leq \frac{1}{k!} \{t + c_N(\tau_N(t))\}^k + \frac{1}{k!} \sum_{I=0}^{k-1} \binom{k}{I} (B_n)^{k-I} \left\{\sum_{\substack{r_1\neq\cdots\neq r_{k-1}\\ \text{all distinct}}}^{\tau_N(t)} \prod_{i=1}^{k-1} c_N(r_i)\right\} \left(\sum_{r_k=1}^{\tau_N(t)} D_N(r_k)\right) \\
&\leq \frac{1}{k!} \{t + c_N(\tau_N(t))\}^k + \frac{1}{k!} \sum_{I=0}^{k-1} \binom{k}{I} (B_n)^{k-I} \left(\sum_{r=1}^{\tau_N(t)} c_N(r)\right)^{k-1} \left(\sum_{r=1}^{\tau_N(t)} D_N(r)\right) \\
&\leq \frac{1}{k!} \{t + c_N(\tau_N(t))\}^k + \frac{1}{k!} \sum_{I=0}^{k-1} \binom{k}{I} (B_n)^{k-I} (t+1)^{k-1} \left(\sum_{r=1}^{\tau_N(t)} D_N(r)\right). \qquad (17)
\end{aligned}
$$

Taking expectations,

$$
\begin{aligned}
&\lim_{N\to\infty} \mathbb{E}\left[\sum_{\substack{r_1<\dots<r_k\\=1}}^{\tau_N(t)} \prod_{j=1}^{k} \{c_N(r_j) + B_n D_N(r_j)\} \middle| k \le \tau_N(t), \bigcap_{r=1}^{\tau_N(t)} E_r \right] \\
&\quad \le \frac{1}{k!} \lim_{N\to\infty} \mathbb{E}\left[\{t + c_N(\tau_N(t))\}^k \middle| k \le \tau_N(t), \bigcap_{r=1}^{\tau_N(t)} E_r \right] \\
&\qquad + \frac{1}{k!} \sum_{I=0}^{k-1} \binom{k}{I} (B_n)^{k-I} (t+1)^{k-1} \lim_{N\to\infty} \mathbb{E}\left[\sum_{r=1}^{\tau_N(t)} D_N(r) \middle| k \le \tau_N(t), \bigcap_{r=1}^{\tau_N(t)} E_r \right] \\
&\quad \le \frac{1}{k!} \lim_{N\to\infty} \mathbb{E}\left[\{t + c_N(\tau_N(t))\}^k \right] + \frac{1}{k!} \sum_{I=0}^{k-1} \binom{k}{I} (B_n)^{k-I} (t+1)^{k-1} \lim_{N\to\infty} \mathbb{E}\left[\sum_{r=1}^{\tau_N(t)} D_N(r) \right] \\
&\quad = \frac{1}{k!} t^k \qquad (18)
\end{aligned}
$$

again using that the conditioning can only decrease the expectations. The limit follows from Brown et al. (2020, Equations (3),(4)) along with the fact that, since $c_N(s) \in [0,1]$ for all s, $\mathbb{E}[c_N(s)^k] \le \mathbb{E}[c_N(s)]$ for all $k \ge 1$, and the expansion

$$
\mathbb{E}\left[\{t + c_N(\tau_N(t))\}^k \right] = \sum_{i=0}^{k} \binom{k}{i} t^i \, \mathbb{E}\left[c_N(\tau_N(t))^{k-i} \right] \longrightarrow t^k. \qquad (19)
$$

Combining these upper and lower limits, we conclude that

$$
\lim_{N\to\infty} \mathbb{E}\left[\sum_{\substack{r_1<\dots<r_k\\=1}}^{\tau_N(t)} \prod_{j=1}^{k} \{c_N(r_j) + B_n D_N(r_j)\} \middle| k \le \tau_N(t), \bigcap_{r=1}^{\tau_N(t)} E_r \right] = \frac{1}{k!} t^k \qquad (20)
$$

and thus

$$
\begin{aligned}
&\lim_{N\to\infty} \mathbb{E}\left[\prod_{r=1}^{\tau_N(t)} \mathbb{1}_{E_r} + \sum_{k=1}^{\tau_N(t)} \left\{ -\alpha(1+O(N^{-1})) \right\}^k \left(\prod_{r=1}^{\tau_N(t)} \mathbb{1}_{E_r} \right) \sum_{\substack{r_1<\dots<r_k\\=1}}^{\tau_N(t)} \prod_{j=1}^{k} \{c_N(r_j) + B_n D_N(r_j)\} \right] \\
&= \lim_{N\to\infty} \mathbb{P}\left[\bigcap_{r=1}^{\tau_N(t)} E_r \right] \\
&\quad + \lim_{N\to\infty} \sum_{k=1}^{\infty} \left\{ -\alpha(1+O(N^{-1})) \right\}^k \mathbb{E}\left[\mathbb{1}_{\{k \le \tau_N(t)\}} \left(\prod_{r=1}^{\tau_N(t)} \mathbb{1}_{E_r} \right) \sum_{\substack{r_1<\dots<r_k\\=1}}^{\tau_N(t)} \prod_{j=1}^{k} \{c_N(r_j) + B_n D_N(r_j)\} \right] \\
&= \lim_{N\to\infty} \mathbb{P}\left[\bigcap_{r=1}^{\tau_N(t)} E_r \right] \\
&\quad + \sum_{k=1}^{\infty} (-\alpha)^k \lim_{N\to\infty} \mathbb{E}\left[\sum_{\substack{r_1<\dots<r_k\\=1}}^{\tau_N(t)} \prod_{j=1}^{k} \{c_N(r_j) + B_n D_N(r_j)\} \middle| k \le \tau_N(t), \bigcap_{r=1}^{\tau_N(t)} E_r \right] \times \lim_{N\to\infty} \mathbb{P}\left[k \le \tau_N(t), \bigcap_{r=1}^{\tau_N(t)} E_r \right] \\
&= 1 + \sum_{k=1}^{\infty} (-\alpha)^k \frac{t^k}{k!} \times 1 = e^{-\alpha t} \qquad (21)
\end{aligned}
$$

as $N \to \infty$, where the last line follows from (20) and Lemma 3.

Upper Bound

From Koskela et al. (2018, Lemma 1 Case 1), taking $\xi = \Delta$, we have

$$
1 - p_t = p_{\Delta\Delta}(t) \le 1 - \alpha(1+O(N^{-1})) \left[c_N(t) - B'_n D_N(t) \right]. \qquad (22)
$$

A multinomial expansion as before yields

$$\prod_{r=1}^{\tau_N(t)} (1-p_r) \leq 1 + \sum_{k=1}^{\tau_N(t)} \left\{-\alpha(1+O(N^{-1}))\right\}^k \sum_{\substack{r_1<\cdots<r_k\\=1}}^{\tau_N(t)} \prod_{j=1}^{k} \{c_N(r_j) - B_n' D_N(r_j)\}. \tag{23}$$

Analogously to (16), assuming $k \leq \tau_N(t)$ we can write

$$\begin{aligned}\sum_{\substack{r_1<\cdots<r_k\\=1}}^{\tau_N(t)} \prod_{j=1}^{k} \{c_N(r_j) - B_n' D_N(r_j)\} = \frac{1}{k!} \sum_{\substack{r_1\neq\cdots\neq r_k\\ \text{all distinct}}}^{\tau_N(t)} \left\{\prod_{i=1}^{k} c_N(r_i)\right\} \\ + \frac{1}{k!}\sum_{I=0}^{k-1}\binom{k}{I}(-B_n')^{k-I} \sum_{\substack{r_1\neq\cdots\neq r_k\\ \text{all distinct}}} \left\{\prod_{i=1}^{I} c_N(r_i)\right\}\left\{\prod_{j=I+1}^{k} D_N(r_j)\right\}.\end{aligned} \tag{24}$$

We start by dealing with the second term:

$$\begin{aligned}\frac{1}{k!}\sum_{I=0}^{k-1}\binom{k}{I}(-B_n')^{k-I} \sum_{\substack{r_1\neq\cdots\neq r_k\\ \text{all distinct}}} \left\{\prod_{i=1}^{I} c_N(r_i)\right\}\left\{\prod_{j=I+1}^{k} D_N(r_j)\right\} \\ = \frac{1}{k!}\sum_{\substack{I=0:\\ k-I \text{ even}}}^{k-1}\binom{k}{I}(B_n')^{k-I} \sum_{\substack{r_1\neq\cdots\neq r_k\\ \text{all distinct}}} \left\{\prod_{i=1}^{I} c_N(r_i)\right\}\left\{\prod_{j=I+1}^{k} D_N(r_j)\right\} \\ - \frac{1}{k!}\sum_{\substack{I=0:\\ k-I \text{ odd}}}^{k-1}\binom{k}{I}(B_n')^{k-I} \sum_{\substack{r_1\neq\cdots\neq r_k\\ \text{all distinct}}} \left\{\prod_{i=1}^{I} c_N(r_i)\right\}\left\{\prod_{j=I+1}^{k} D_N(r_j)\right\}.\end{aligned} \tag{25}$$

This is lower bounded by

$$0 - \frac{1}{k!}\sum_{\substack{I=0\\ k-I \text{ odd}}}^{k-1}\binom{k}{I}(B_n')^{k-I}(t+1)^{k-1}\left(\sum_{s=1}^{\tau_N(t)} D_N(s)\right) \tag{26}$$

using that $c_N(r), D_N(r) \geq 0$ for all r to bound the even terms below, and arguments from (17) to bound the odd terms above. The same arguments lead to the upper bound

$$\frac{1}{k!}\sum_{\substack{I=0\\ k-I \text{ even}}}^{k-1}\binom{k}{I}(B_n')^{k-I}(t+1)^{k-1}\left(\sum_{s=1}^{\tau_N(t)} D_N(s)\right) - 0. \tag{27}$$

By Brown et al. (2020, Equation (4)), both bounds have vanishing expectation as $N \to \infty$. We are left with the first term in (24), which is upper bounded by

$$\frac{1}{k!} \sum_{\substack{r_1\neq\cdots\neq r_k\\ \text{all distinct}}}^{\tau_N(t)} \left\{\prod_{i=1}^{k} c_N(r_i)\right\} \leq \frac{1}{k!}\left(\sum_{s=1}^{\tau_N(t)} c_N(s)\right)^k \leq \frac{1}{k!}\{t + c_N(\tau_N(t))\}^k \tag{28}$$

the expectation of which converges to $t^k/k!$ as in (19). We use Koskela et al. (2018, Equation (8)) to construct a lower bound:

$$\begin{aligned}\frac{1}{k!} \sum_{\substack{r_1\neq\cdots\neq r_k\\ \text{all distinct}}}^{\tau_N(t)} \left\{\prod_{i=1}^{k} c_N(r_i)\right\} \geq \frac{1}{k!}\left(\sum_{s=1}^{\tau_N(t)} c_N(s)\right)^k - \frac{1}{k!}\binom{k}{2}\left(\sum_{s=1}^{\tau_N(t)} c_N(s)^2\right)\left(\sum_{s=1}^{\tau_N(t)} c_N(s)\right)^{k-2} \\ \geq \frac{1}{k!}t^k - \frac{1}{k!}\binom{k}{2}(t+1)^{k-2}\left(\sum_{s=1}^{\tau_N(t)} c_N(s)^2\right)\end{aligned} \tag{29}$$

The expectation of this bound also converges to $t^k/k!$, using Brown et al. (2020, Equation (5)). We can now conclude that

$$\lim_{N\to\infty} \mathbb{E}\left[\sum_{\substack{r_1<\cdots<r_k\\=1}}^{\tau_N(t)} \prod_{j=1}^{k} \{c_N(r_j) - B_n' D_N(r_j)\}\right] = \frac{1}{k!}t^k \tag{30}$$

and thus, by calculations analogous to (21),

$$\lim_{N\to\infty} \mathbb{E}\left[1 + \sum_{k=1}^{\tau_N(t)} \left\{-\alpha(1+O(N^{-1}))\right\}^k \sum_{\substack{r_1<\cdots<r_k\\=1}}^{\tau_N(t)} \prod_{j=1}^{k} \{c_N(r_j) - B_n' D_N(r_j)\}\right] = 1 + \sum_{k=1}^{\infty}(-\alpha)^k \frac{1}{k!}t^k = e^{-\alpha t} \tag{31}$$

as $N \to \infty$.

We now have upper and lower bounds on $\lim_{N\to\infty} \mathbb{E}\left[\prod_{r=1}^{\tau_N(t)}(1-p_r)\right]$, both of which are equal to $e^{-\alpha t}$, and the result follows. □

Lemma 3. *For any $n \le N \in \mathbb{N}$, for all $t > 0$, define*

$$E_t := \left\{ c_N(t) < \frac{(N-3)_{n-3}}{N^{n-3}} \left(\alpha\left(1 + \frac{2}{N-2}\right) + B_n\right)^{-1}\right\} \tag{32}$$

where α and B_n are positive constants as in (9)*. Then, for all $t > 0$,*

$$\lim_{N\to\infty} \mathbb{P}\left[\bigcap_{r=1}^{\tau_N(t)} E_r\right] = 1. \tag{33}$$

Proof.

$$\mathbb{P}\left[\bigcap_{r=1}^{\tau_N(t)} E_r\right] = 1 - \mathbb{P}\left[\bigcup_{r=1}^{\tau_N(t)} E_r^c\right] \ge 1 - \mathbb{E}\left[\sum_{r=1}^{\tau_N(t)} \mathbb{P}[E_r^c]\right]. \tag{34}$$

Using the generalised Markov inequality,

$$\begin{aligned}\mathbb{P}[E_r^c] &= \mathbb{P}\left[c_N(t) \ge \frac{(N-3)_{n-3}}{N^{n-3}} \left(\alpha\left(1+\frac{2}{N-2}\right)+B_n\right)^{-1}\right] \\ &\le \mathbb{E}[c_N(r)^2] \frac{N^{2(n-3)}}{(N-3)_{n-3}^2} \left(\alpha\left(1+\frac{2}{N-2}\right)+B_n\right)^2.\end{aligned} \tag{35}$$

Now

$$\begin{aligned}\mathbb{P}\left[\bigcap_{r=1}^{\tau_N(t)} E_r\right] &\ge 1 - \mathbb{E}\left[\sum_{r=1}^{\tau_N(t)} \mathbb{E}[c_N(r)^2] \frac{N^{2(n-3)}}{(N-3)_{n-3}^2} \left(\alpha\left(1+\frac{2}{N-2}\right)+B_n\right)^2\right] \\ &= 1 - \frac{N^{2(n-3)}}{(N-3)_{n-3}^2} \left(\alpha\left(1+\frac{2}{N-2}\right)+B_n\right)^2 \mathbb{E}\left[\sum_{r=1}^{\tau_N(t)} c_N(r)^2\right] \\ &\overset{N\to\infty}{\longrightarrow} 1 - (\alpha+B_n)^2 \times 0 = 1.\end{aligned} \tag{36}$$

□

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