

# Non-triviality condition

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## Multinomial resampling: neutral case

**Lemma 1.** *For all  $N \geq 2$ , for all  $t$ ,*

$$\mathbb{E} \left[ c_N(t) \middle| \mathbf{w} = \left( \frac{1}{N}, \dots, \frac{1}{N} \right) \right] = \frac{1}{N}.$$

*Proof.*

$$\begin{aligned} \mathbb{E} [c_N(t) | \mathbf{w} = (1/N, \dots, 1/N)] &= \frac{1}{(N)_2} \sum_{i=1}^N \mathbb{E} \left[ (\nu_t^{(i)})_2 \mid \mathbf{w} = (1/N, \dots, 1/N) \right] \\ &= \frac{1}{(N)_2} \sum_{i=1}^N (N)_2 \left( \frac{1}{N} \right)^2 = \sum_{i=1}^N \frac{1}{N^2} = \frac{1}{N} \end{aligned}$$

□

**Lemma 2.** *For all  $N \geq 4$ , for all  $t$ ,*

$$\mathbb{E} \left[ (c_N(t))^2 \middle| \mathbf{w} = \left( \frac{1}{N}, \dots, \frac{1}{N} \right) \right] = \frac{N+2}{N^3}.$$

*Proof.*

$$\begin{aligned} \mathbb{E} [(c_N(t))^2 | \mathbf{w} = (1/N, \dots, 1/N)] &= \frac{1}{(N)_2^2} \sum_{i=1}^N \sum_{j=1}^N \mathbb{E} \left[ (\nu_t^{(i)})_2 (\nu_t^{(j)})_2 \middle| \mathbf{w} = (1/N, \dots, 1/N) \right] \\ &= \frac{1}{(N)_2^2} \left\{ \sum_{i=1}^N \sum_{j \neq i}^N \mathbb{E} \left[ (\nu_t^{(i)})_2 (\nu_t^{(j)})_2 \middle| \mathbf{w} = (1/N, \dots, 1/N) \right] + \sum_{i=1}^N \mathbb{E} \left[ (\nu_t^{(i)})_2^2 \middle| \mathbf{w} = (1/N, \dots, 1/N) \right] \right\} \\ &= \frac{1}{(N)_2^2} \left\{ \sum_{i=1}^N \sum_{j \neq i}^N \mathbb{E} \left[ (\nu_t^{(i)})_2 (\nu_t^{(j)})_2 \middle| \mathbf{w} = (1/N, \dots, 1/N) \right] + \sum_{i=1}^N \mathbb{E} \left[ (\nu_t^{(i)})_4 + 4(\nu_t^{(i)})_3 + 2(\nu_t^{(i)})_2 \middle| \mathbf{w} = (1/N, \dots, 1/N) \right] \right\} \\ &= \frac{1}{(N)_2^2} \left\{ \sum_{i=1}^N \sum_{j \neq i}^N (N)_4 \left( \frac{1}{N} \right)^2 \left( \frac{1}{N} \right)^2 + \sum_{i=1}^N \left( (N)_4 \left( \frac{1}{N} \right)^4 + 4(N)_3 \left( \frac{1}{N} \right)^3 + 2(N)_2 \left( \frac{1}{N} \right)^2 \right) \right\} \\ &= \frac{1}{(N)_2^2} \left\{ N(N-1)(N)_4 \frac{1}{N^4} + N(N)_4 \frac{1}{N^4} + 4N(N)_3 \frac{1}{N^3} + 2N(N)_2 \frac{1}{N^2} \right\} \\ &= \frac{(N-2)(N-3)}{N^4} + \frac{(N-2)(N-3)}{N^4(N-1)} + \frac{4(N-2)}{N^3(N-1)} + \frac{2}{N^2(N-1)} \\ &= \frac{1}{N^4(N-1)} [(N-2)(N-3)(N-1+1) + 4N(N-2) + 2N^2] \\ &= \frac{1}{N^3(N-1)} [N^2 - 5N + 6 + 4N - 8 + 2N] = \frac{N^2 + N - 2}{N^3(N-1)} = \frac{(N+2)(N-1)}{N^3(N-1)} = \frac{N+2}{N^3}. \end{aligned}$$

□

**Lemma 3.** For all  $N \geq 4$ , for all  $t$ ,

$$\mathbb{P} \left[ c_N(t) > \frac{2}{N^2} \middle| \mathbf{w} = \left( \frac{1}{N}, \dots, \frac{1}{N} \right) \right] \geq \left( 1 - \frac{2}{N} \right)^2 \frac{N}{N+2}.$$

*Proof.* We apply the Paley-Zygmund inequality,

$$\mathbb{P} [c_N(t) > \theta \mathbb{E}[c_N(t) | \mathbf{w} = (1/N, \dots, 1/N)] | \mathbf{w} = (1/N, \dots, 1/N)] \geq (1 - \theta)^2 \frac{\mathbb{E}[c_N(t) | \mathbf{w} = (1/N, \dots, 1/N)]^2}{\mathbb{E}[(c_N(t))^2 | \mathbf{w} = (1/N, \dots, 1/N)]}.$$

Setting  $\theta = 2/N$  and using Lemmata 1–2,

$$\mathbb{P} \left[ c_N(t) > \frac{2}{N^2} \middle| \mathbf{w} = (1/N, \dots, 1/N) \right] \geq \left( 1 - \frac{2}{N} \right)^2 \frac{(1/N)^2}{(N+2)/N^3} = \left( 1 - \frac{2}{N} \right)^2 \frac{N}{N+2}.$$

□

**NB:** We actually have an exact expression for the above probability, which is  $1 - N!N^{-N}$  (see for example the proof of Lemma 4 below). Perhaps it would be better to use that... although the asymptotics seem a bit more obscure then? This could save a page of workings though so probably a good idea in the end.

**Theorem 1.** In the neutral case (i.e. when all weights are equal at every time step) with multinomial resampling, there exists  $N_0$  such that for all  $N > N_0$ , for all finite  $t$ ,  $\mathbb{P}[\tau_N(t) = \infty] = 0$ .

*Proof.* Let us rewrite the event of interest in a different way.

$$\begin{aligned} \mathbb{P}[\tau_N(t) = \infty] = 0 &\Leftrightarrow \mathbb{P}[\tau_N(t) < \infty] = 1 \\ &\Leftrightarrow \mathbb{P} \left[ \min \left\{ s > 1 : \sum_{r=1}^s c_N(r) < t \right\} < \infty \right] = 1 \\ &\Leftrightarrow \mathbb{P} \left[ \exists s < \infty : \sum_{r=1}^s c_N(r) < t \right] = 1 \end{aligned}$$

It is sufficient to show that, for all  $N > N_0$ ,  $c_N(r)$  is bounded away from zero infinitely often in  $r$ . We consider the sequence of events  $E_r := \{c_N(r) > 2/N^2\}$  for  $r \in \mathbb{N}$ . In the neutral case, the resampled family sizes at each generation are independent, hence the events  $E_r$  are independent. By the second Borel-Cantelli lemma,  $E_r$  occurs infinitely often if  $\sum_{r=1}^{\infty} \mathbb{P}(E_r) = \infty$ . A lower bound on  $\mathbb{P}(E_r)$  is given in Lemma 3. For any fixed  $N \geq 4$ , the bound is strictly positive and constant in  $r$ , so the Borel-Cantelli condition is satisfied, thus we conclude that  $E_r$  occurs infinitely often. Hence, taking  $N_0 = 3$ , we have that  $\mathbb{P}[\tau_N(t) = \infty] = 0$  for all  $N > N_0$  and all finite  $t$ , as required. □

## Multinomial resampling: non-neutral case

**Lemma 4.** For all  $N \geq 2$ , for all  $t$ , for any weight vector  $(w_1, \dots, w_N)$ ,

$$\mathbb{P} \left[ c_N(t) > \frac{2}{N^2} \middle| \mathbf{w} = (w_1, \dots, w_N) \right] \geq \mathbb{P} \left[ c_N(t) > \frac{2}{N^2} \middle| \mathbf{w} = \left( \frac{1}{N}, \dots, \frac{1}{N} \right) \right].$$

That is, the probability of having at least one merger is minimised by the vector of equal weights.

*Proof.* Fix arbitrary  $t$  and  $N \geq 2$ . Firstly notice that

$$\begin{aligned} \mathbb{P} \left[ c_N(t) > \frac{2}{N^2} \middle| \mathbf{w} = (w_1, \dots, w_N) \right] &= 1 - \mathbb{P}[c_N(t) = 0 \mid \mathbf{w} = (w_1, \dots, w_N)] \\ &= 1 - \mathbb{P}[\nu_t^{(1:N)} = (1, \dots, 1) \mid \mathbf{w} = (w_1, \dots, w_N)]. \end{aligned}$$

Since, conditional on the weights,  $\nu_t^{(1:N)} \sim \text{Multinomial}(N, (w_1, \dots, w_N))$ , the probability of interest is

$$\mathbb{P}[\nu_t^{(1:N)} = (1, \dots, 1) \mid \mathbf{w} = (w_1, \dots, w_N)] = N! \prod_{i=1}^N w_i. \quad (1)$$

We will show that the global maximum of this function on the simplex  $\mathcal{S}_{N-1}$  is attained at  $\mathbf{w} = (1/N, \dots, 1/N)$ . This weight vector will therefore minimise the probability of the complementary event, implying the desired result.

First, since we are working on the simplex, we encode the constraint  $\sum w_i = 1$  by rewriting the function to optimise as

$$f(\mathbf{w}) := \prod_{i=1}^N w_i = \left(1 - \sum_{j=1}^{N-1} w_j\right) \prod_{i=1}^{N-1} w_i$$

where we have also dropped the constant positive factor  $N!$ . Now, for every  $k \in \{1, \dots, N-1\}$ , we solve

$$\frac{\partial f(\mathbf{w})}{\partial w_k} = \left(1 - w_k - \sum_{j=1}^{N-1} w_j\right) \prod_{i \neq k}^{N-1} w_i = 0.$$

The product over  $i \neq k$  is constant for each  $k$ , so this reduces to solving

$$w_k = 1 - \sum_{j=1}^{N-1} w_j = w_N$$

for all  $k$ . The unique solution is  $w_1 = w_2 = \dots = w_N = 1/N$ .

To verify that this critical point is a maximum, we calculate the Hessian  $H$ :

$$H_{kl}(\mathbf{w}) = \begin{cases} -2 \prod_{i \neq k}^{N-1} w_i & k = l \\ \left(1 - w_k - w_l - \sum_{j=1}^{N-1} w_j\right) \prod_{i \neq k, l}^{N-1} w_i & k \neq l \end{cases}$$

$$H_{kl}((1/N, \dots, 1/N)) = \begin{cases} -2 \left(\frac{1}{N}\right)^{N-2} & k = l \\ -\left(\frac{1}{N}\right)^{N-2} & k \neq l \end{cases}$$

and show that  $H$  is negative semi-definite: for any  $\mathbf{x} \in \mathbb{R}^{N-1}$ ,

$$\begin{aligned} \mathbf{x}^T H \mathbf{x} &= \sum_{k=1}^{N-1} \left[ -2 \left(\frac{1}{N}\right)^{N-2} x_k^2 - \sum_{l \neq k}^{N-1} \left(\frac{1}{N}\right)^{N-2} x_k x_l \right] = \left(\frac{1}{N}\right)^{N-2} \left[ -\sum_{k=1}^{N-1} 2x_k^2 - \sum_{k=1}^{N-1} \sum_{l \neq k}^{N-1} x_k x_l \right] \\ &= \left(\frac{1}{N}\right)^{N-2} \left[ -\sum_{k=1}^{N-1} x_k^2 - \sum_{k=1}^{N-1} \sum_{l=1}^{N-1} x_k x_l \right] = \left(\frac{1}{N}\right)^{N-2} \left[ -\sum_{k=1}^{N-1} x_k^2 - \left(\sum_{k=1}^{N-1} x_k\right)^2 \right] \leq 0. \end{aligned}$$

□

**Theorem 2.** *With multinomial resampling, conditional on any sequence of weight vectors  $\mathbf{w}_r^{(1:N)} \in \mathcal{S}_{N-1}; r \in \mathbb{N}$ , there exists  $N_0$  such that for all  $N > N_0$ , for all finite  $t$ ,  $\mathbb{P}[\tau_N(t) = \infty] = 0$ .*

*Proof.* As in Theorem 1, denote the sequence of events  $E_r := \{c_N(r) > 2/N^2\}$  for  $r \in \mathbb{N}$ . We know from Theorem 1 that, in the neutral case,  $E_r$  occurs infinitely often. Lemma 4 tells us that  $\mathbb{P}[E_r \mid \mathbf{w} = (w_1, \dots, w_N)] \geq \mathbb{P}[E_r \mid \mathbf{w} = (1/N, \dots, 1/N)]$  for all  $r$ . Therefore, by a coupling argument, we conclude that  $E_r$  occurs infinitely often in the non-neutral case as well. □

## Conditional SMC with multinomial resampling: optimal weights

**NB:** The exposition below is more explicit than necessary, in order to reduce dependencies between sections. The expectations under CSMC-mn do not really need to be calculated directly, as they are equal to the expectations under standard-mn, where  $(N-1)$  replaces  $N$  everywhere except in the leading  $(N)_2$  factors. It is probably also possible to infer Theorem 3 by a direct modification of Theorem 1, without the need to calculate moments and apply the PZ inequality again.

Define  $\mathbf{w}^* := \frac{1}{N-1} [(1, \dots, 1) - \mathbf{e}_{i^*}]$ , where  $i^*$  is the immortal index at generation  $t$ , and  $\mathbf{e}_i$  denotes a 1-hot vector.

**Lemma 5.** For all  $N \geq 2$ , for all  $t$ ,

$$\mathbb{E}[c_N(t) \mid \mathbf{w} = \mathbf{w}^*] = \frac{N-2}{N(N-1)}.$$

*Proof.* Since the immortal particle has weight zero, the remaining offspring counts are distributed as Multinomial( $N-1, (1/(N-1), \dots, 1/(N-1))$ ). We can apply the usual formula for factorial moments of the Multinomial distribution:

$$\mathbb{E}[c_N(t) \mid \mathbf{w} = \mathbf{w}^*] = \frac{1}{(N)_2} \sum_{i=1}^N \mathbb{E}[(\nu_t^{(i)})_2 \mid \mathbf{w} = \mathbf{w}^*] = \frac{1}{(N)_2} \sum_{i \neq i^*}^N (N-1)_2 \left(\frac{1}{N-1}\right)^2 = \frac{N-2}{N(N-1)}.$$

□

**Lemma 6.** For all  $N \geq 4$ , for all  $t$ ,

$$\mathbb{E}[(c_N(t))^2 \mid \mathbf{w} = \mathbf{w}^*] = \frac{(N+1)(N-2)^2}{N^2(N-1)^3}.$$

*Proof.*

$$\begin{aligned} \mathbb{E}[(c_N(t))^2 \mid \mathbf{w} = \mathbf{w}^*] &= \frac{1}{(N)_2^2} \sum_{i=1}^N \sum_{j=1}^N \mathbb{E}[(\nu_t^{(i)})_2 (\nu_t^{(j)})_2 \mid \mathbf{w} = \mathbf{w}^*] \\ &= \frac{1}{(N)_2^2} \sum_{i \neq i^*}^N \sum_{j \neq i^*}^N \mathbb{E}[(\nu_t^{(i)})_2 (\nu_t^{(j)})_2 \mid \mathbf{w} = \mathbf{w}^*] \\ &= \frac{1}{(N)_2^2} \left\{ \sum_{i \neq i^*}^N \sum_{j \neq i, i^*}^N \mathbb{E}[(\nu_t^{(i)})_2 (\nu_t^{(j)})_2 \mid \mathbf{w} = \mathbf{w}^*] + \sum_{i \neq i^*}^N \mathbb{E}[(\nu_t^{(i)})_2^2 \mid \mathbf{w} = \mathbf{w}^*] \right\} \\ &= \frac{1}{(N)_2^2} \left\{ \sum_{i \neq i^*}^N \sum_{j \neq i, i^*}^N \mathbb{E}[(\nu_t^{(i)})_2 (\nu_t^{(j)})_2 \mid \mathbf{w} = \mathbf{w}^*] + \sum_{i \neq i^*}^N \mathbb{E}[(\nu_t^{(i)})_4 + 4(\nu_t^{(i)})_3 + 2(\nu_t^{(i)})_2 \mid \mathbf{w} = \mathbf{w}^*] \right\} \\ &= \frac{1}{(N)_2^2} \left\{ \sum_{i \neq i^*}^N \sum_{j \neq i, i^*}^N (N-1)_4 \left(\frac{1}{N-1}\right)^4 + \sum_{i \neq i^*}^N \left( (N-1)_4 \left(\frac{1}{N-1}\right)^4 + 4(N-1)_3 \left(\frac{1}{N-1}\right)^3 + 2(N-1)_2 \left(\frac{1}{N-1}\right)^2 \right) \right\} \\ &= \frac{1}{(N)_2^2} \left\{ \frac{(N-1)_2(N-1)_4}{(N-1)^4} + \frac{(N-1)(N-1)_4}{(N-1)^4} + \frac{4(N-1)(N-1)_3}{(N-1)^3} + \frac{2(N-1)(N-1)_2}{(N-1)^2} \right\} \\ &= \frac{(N+1)(N-2)^2}{N^2(N-1)^3}. \end{aligned}$$

□

**Lemma 7.** For all  $N \geq 4$ , for all  $t$ ,

$$\mathbb{P}\left[c_N(t) > \frac{2}{N^2} \mid \mathbf{w} = \mathbf{w}^*\right] \geq \left(1 - \frac{2(N-1)}{N(N-2)}\right)^2 \frac{N-1}{N+1}.$$

*Proof.* We apply the Paley-Zygmund inequality, with  $\theta = \frac{2(N-1)}{N(N-2)}$ :

$$\begin{aligned} \mathbb{P}[c_N(t) > \theta \mathbb{E}[c_N(t) \mid \mathbf{w} = \mathbf{w}^*] \mid \mathbf{w} = \mathbf{w}^*] &\geq (1-\theta)^2 \frac{\mathbb{E}[c_N(t) \mid \mathbf{w} = \mathbf{w}^*]^2}{\mathbb{E}[(c_N(t))^2 \mid \mathbf{w} = \mathbf{w}^*]} \\ &= \left(1 - \frac{2(N-1)}{N(N-2)}\right)^2 \frac{(N-2)^2}{N^2(N-1)^2} \frac{N^2(N-1)^3}{(N+1)(N-2)^2} = \left(1 - \frac{2(N-1)}{N(N-2)}\right)^2 \frac{N-1}{N+1}. \end{aligned}$$

□

**Theorem 3.** In conditional SMC with multinomial resampling, in the optimal case where the weight vector is equal to  $\mathbf{w}^*$  at every time step, there exists  $N_0$  such that for all  $N > N_0$ , for all finite  $t$ ,  $\mathbb{P}[\tau_N(t) = \infty] = 0$ .

*Proof.* The proof is exactly the same as for Theorem 1; Lemma 7 provides the bound on  $P(E_r)$  which is strictly positive and constant in  $r$ . □

## Conditional SMC with multinomial resampling: general weights

**Lemma 8.** *For all  $N \geq 2$ , for all  $t$ , for any weight vector  $(w_1, \dots, w_N)$ ,*

$$\mathbb{P} \left[ c_N(t) > \frac{2}{N^2} \mid \mathbf{w} = (w_1, \dots, w_N) \right] \geq \mathbb{P} \left[ c_N(t) > \frac{2}{N^2} \mid \mathbf{w} = \mathbf{w}^* \right].$$

*Proof.*

$$\mathbb{P} \left[ c_N(t) > \frac{2}{N^2} \mid \mathbf{w} = (w_1, \dots, w_N) \right] = 1 - \mathbb{P}[\nu_t^{(1:N)} = (1, \dots, 1) \mid \mathbf{w} = (w_1, \dots, w_N)] = (N-1)! \prod_{i \neq i^*}^N w_i$$

since the immortal particle  $i^*$  is automatically assigned one offspring. This is equivalent to the expression we had in the standard case (1), except with  $N-1$  particles rather than  $N$ . As we saw in Lemma 4, this function is maximised at the vector of equal weights, in this case  $\mathbf{w}_{-i^*} = \frac{1}{N-1}(1, \dots, 1)$ . This leaves zero weight for the immortal particle, so overall the maximum is attained at  $\mathbf{w}^* = \frac{1}{N-1} \{(1, \dots, 1) - \mathbf{e}_{i^*}\}$  as required.  $\square$

**Theorem 4.** *In conditional SMC with multinomial resampling, conditional on any sequence of weight vectors  $\mathbf{w}_r^{(1:N)} \in \mathcal{S}_{N-1}; r \in \mathbb{N}$ , there exists  $N_0$  such that for all  $N > N_0$ , for all finite  $t$ ,  $\mathbb{P}[\tau_N(t) = \infty] = 0$ .*

*Proof.* As in Theorem 1, denote the sequence of events  $E_r := \{c_N(r) > 2/N^2\}$  for  $r \in \mathbb{N}$ . We know from the argument behind Theorem 3 (which is completely analogous to Theorem 1) that, in the neutral case,  $E_r$  occurs infinitely often. Lemma 8 tells us that  $\mathbb{P}[E_r \mid \mathbf{w} = (w_1, \dots, w_N)] \geq \mathbb{P}[E_r \mid \mathbf{w} = \mathbf{w}^*]$  for all  $r$ . Therefore, by a coupling argument, we conclude that  $E_r$  occurs infinitely often in the general case as well.  $\square$