

## Additional file 1: TinT probabilistic model

The following derivation is based on a series of  $N$  independent tests. Each test can have  $N+1$  results. The number of results can be from 0 up to  $N$ . However, if any of the results at special time points are impossible, we consider their probabilities equal to 0.

We designate  $p_{i,j}(t)$  as the probability of the results  $j$  for experiments of the  $i$ -th series at time point  $t$  ( $i$  and  $j \in \{1,2\dots N\}$ ,  $t \in T_i = \{\tau_1^i, \tau_2^i, \dots, \tau_{n_j}^i\}$ ).  $T_i$  is the set of time points in which the tests are performed.

We consider, that for any  $t \in T_i$   $\sum_{j=0}^N p_{i,j}(t) = 1$ .

We assume then that  $p_{i,j}(t) \ll 1/N$  (accordingly,  $p_{i,i}(t)$  is close to 1).

In the experiment, values  $m_{i,j}$  of the random variables  $\mu_{i,j}$  are the numbers of approaches of results  $j$  in the  $i$ -th series under the condition that all combinations  $i$  and  $j \in \{1,2\dots N\}$ .

We consider  $n_i = \sum_{j=0}^N m_{i,j}$  as the number of tests in the  $i$ -th series.

We define  $\eta^j(t)$  as the number of elements of the subtype  $j$  (potential hosts) that are present at the time point  $t$ . By including the biological fact that elements of a subtype  $j$  «appear» (first evolve and than distribute) at time points  $\tau_1^j, \tau_2^j, \dots, \tau_{n_j}^j$ , we define  $\eta^j(t)$ :

$$\eta^j(t) = \begin{cases} 0, & t \leq \tau_1^j \\ \dots \\ k, & \tau_k^j < t \leq \tau_{k+1}^j \\ \dots \\ n_j, & \tau_{n_j}^j < t \end{cases} \quad (1)$$

Thus the ratio:

$$F^j(t) = \frac{\eta^j(t)}{n_j}, \quad (2)$$

can be considered as an empirical function of a random variable  $\tau^j$ .

The probability  $p_{i,j}(t)$  is considered to be proportional to  $\eta^j(t)$ :

$$p_{i,j}(t) = \alpha \cdot \eta^j(t) \text{ under the condition } t \in T_i. \quad (3)$$

Further, we assume that  $\alpha \cdot n_j \ll 1$ . For the  $i$ -th series at  $n_i \rightarrow \infty$  the Poisson distribution take place:

$$P\left(\bigcap_{j=1}^N \{\mu_{i,j} = x_j\}\right) = \prod_{j=1}^N \frac{a_{i,j}^{x_j}}{x_j!} \cdot e^{-a_{i,j}}, \quad (4)$$

where

$$a_{i,j} = \sum_{t \in T_i} p_{i,j}(t) = \sum_{k=1}^{n_i} p_{i,j}(\tau_k^i). \quad (5)$$

Accordingly, for all N series

$$P\left(\bigcap_{i=1}^N \bigcap_{i,j} \{\mu_{i,j} = x_{i,j}\}\right) = \prod_{i=1}^N \prod_{i,j} \frac{a_{i,j}^{x_{i,j}}}{x_{i,j}!} \cdot e^{-a_{i,j}}. \quad (6)$$

According to equations (5) and (3) we define  $\alpha_{\square ij}$  as

$$a_{i,j} = \alpha \cdot \sum_{k=1}^{n_i} \eta^j(\tau_k^i). \quad (7)$$

The last sum can be written as the Stieltjes integral:

$$a_{i,j} = \alpha \cdot \int_{-\infty}^{\infty} \eta^j(t) \cdot d\eta^i(t), \quad (8)$$

If we insert this in equation (2), we get the following:

$$a_{i,j} = \alpha \cdot n_i \cdot n_j \cdot \int_{-\infty}^{\infty} F^j(t) \cdot dF^i(t) . \quad (9)$$

As an approximation for  $F^j(t)$  we chose the normal distribution with the parameters  $t_j, \sigma_j$

$$F^j(t) = F\left(\frac{t-t_j}{\sigma_j}\right), \quad (10)$$

where  $F(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^x e^{-\frac{y^2}{2}} dy$  - is the standard function of the normal distribution.

Then, within (9), we receive

$$a_{i,j} = \alpha \cdot n_i \cdot n_j \cdot F_{i,j}, \quad (11)$$

where

$$F_{i,j} = F\left(\frac{t_i - t_j}{\sqrt{\sigma_i^2 + \sigma_j^2}}\right). \quad (12)$$

Thus, the problem is reduced to the search for estimations of the unknown parameters  $\alpha, t_1 \dots t_N, \sigma_1 \dots \sigma_N$ .

To estimate these parameters we use a maximal likelihood method. Replacing in (6)  $x_{i,j}$  with  $m_{i,j}$  and lowering the multipliers not dependent on estimated parameters, and in view of (11), we receive the function of likelihood

$$l = l(\alpha, t_1 \dots t_N, \sigma_1 \dots \sigma_N) = \prod_{i=1}^N \prod_{j=1}^N (\alpha \cdot F_{i,j})^{m_{i,j}} \cdot e^{-\alpha \cdot n_i \cdot n_j \cdot F_{i,j}} . \quad (13)$$

Accordingly, the logarithm of function of likelihood is equal to

$$\ln(l) = \sum_{i=1}^N \sum_j (m_{i,j} \cdot \ln(\alpha \cdot F_{i,j}) - \alpha \cdot n_i \cdot n_j \cdot F_{i,j}). \quad (14)$$

Combining  $F(-x) = 1 - F(x)$  and (12) we get  $F_{i,j} + F_{j,i} = 1$  and  $F_{i,i} = 1/2$ .

So the sum:

$$n_0 = \sum_{i=1}^N \sum_{j=1}^N n_i \cdot n_j \cdot F_{i,j} + \sum_{i=1}^N n_i \cdot n_i \cdot F_{i,i} = \sum_{i=1}^{N-1} \sum_{j=i+1}^N n_i \cdot n_j + 1/2 \sum_{i=1}^N n_i^2, \quad (15)$$

does not depend on any of the parameters. We also suppose:

$$m_0 = \sum_{i=1}^N \sum_{j=1}^N m_{i,j}, \quad (16)$$

It is then possible to describe (14) in the form of

$$\ln(l) = \sum_{i=1}^N \sum_{j=1}^N m_{i,j} \cdot \ln(F_{i,j}) + m_0 \cdot \ln(\alpha) - n_0 \cdot \alpha. \quad (17)$$

Equating zero to a partial derivative

$$\frac{\partial \ln(l)}{\partial \alpha} = \frac{m_0}{\alpha} - n_0,$$

we receive an estimation for  $\alpha$ :

$$\tilde{\alpha} = \frac{m_0}{n_0} \quad (18)$$

$F_{i,j}$  do not change under the replacement:

$$\begin{aligned} \sigma_i &\rightarrow h \cdot \sigma_i \\ t_i &\rightarrow h \cdot t_i + t_0 \end{aligned}$$

Therefore, it is possible to limit  $t_i$  to the condition  $\sum_{i=1}^N t_i = 0$ .

Concerning parameter  $\sigma_i$  we have accepted they are proportional (in particular  $\sigma_i = n_i$ ).