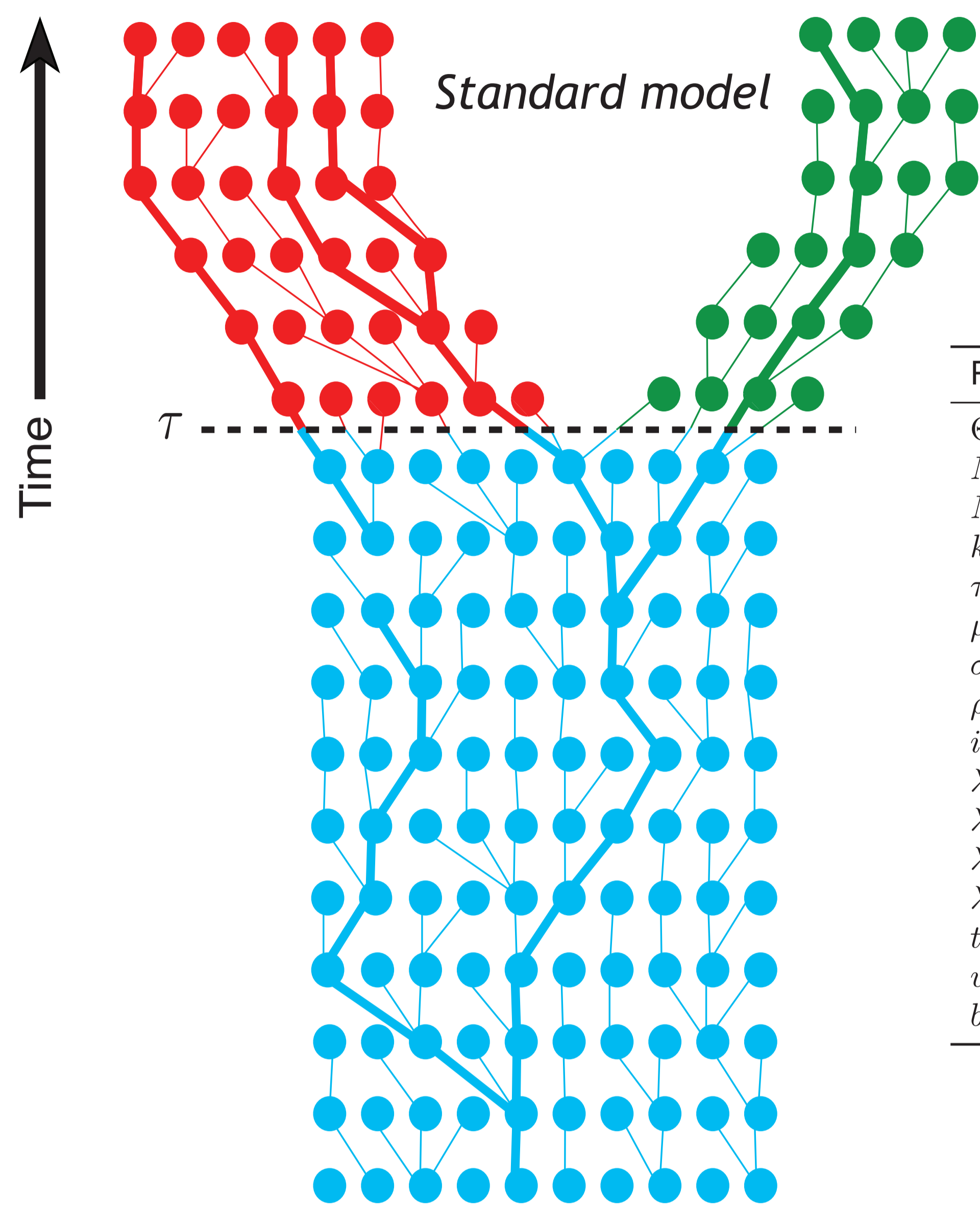


# Population divergence estimation using lineage-label switching

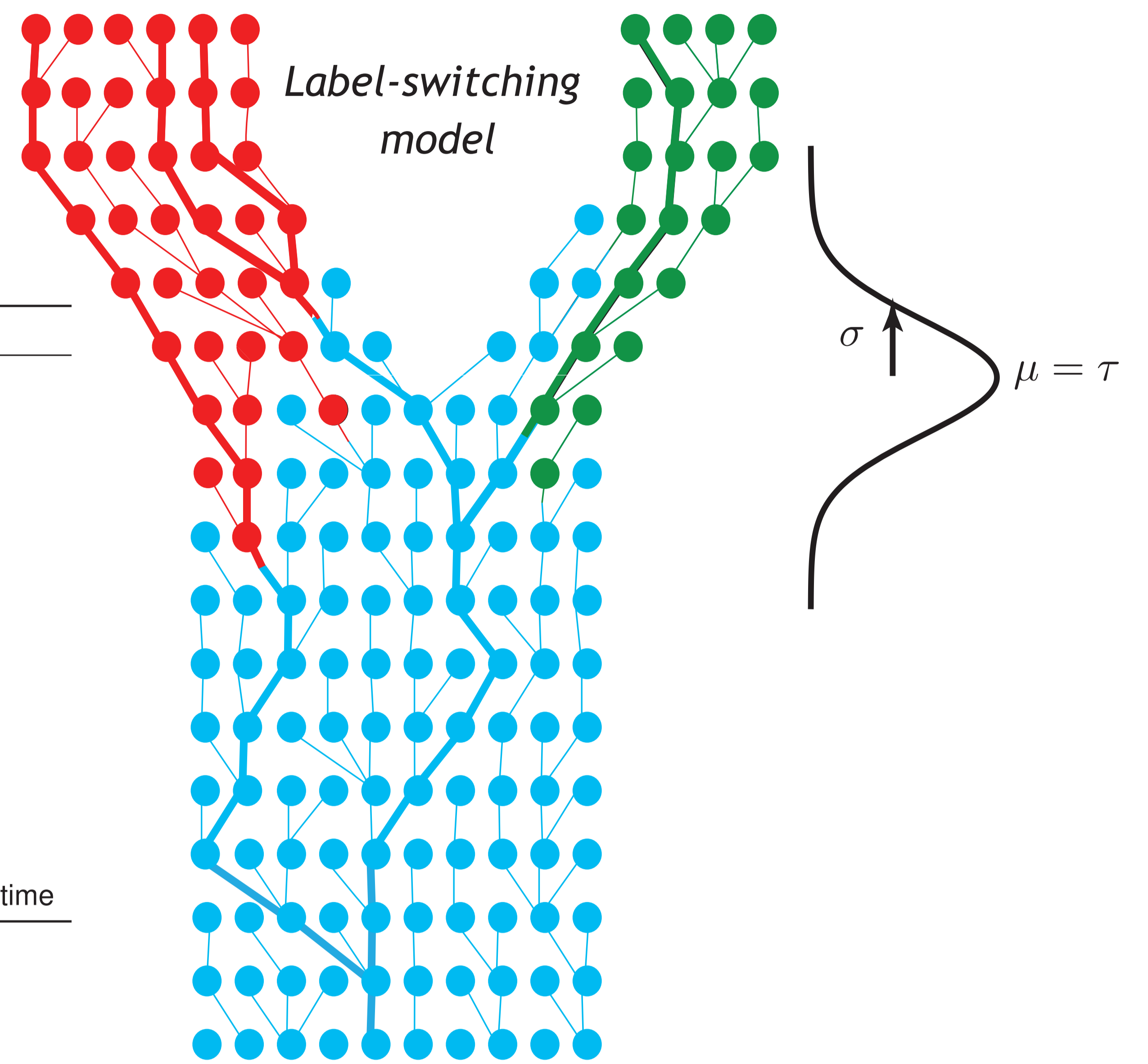


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| Parameter    | Legend                          |
|--------------|---------------------------------|
| $\Theta$     | Scaled Population size          |
| $N_e$        | Effective Population size       |
| $M$          | Scaled immigration rate         |
| $k$          | sample lineages                 |
| $\tau$       | Scaled divergence time          |
| $\mu$        | Divergence time parameter       |
| $\sigma$     | Standard deviation              |
| $\rho$       | All parameters                  |
| $i$          | Subscript for population $i$    |
| $\lambda_c$  | Coalescent rate                 |
| $\lambda_m$  | Migration rate                  |
| $\lambda'_s$ | Divergence rate                 |
| $\lambda_s$  | Integrated Divergence rate      |
| $t_0$        | start time                      |
| $u$          | time interval                   |
| $b_1$        | upper bound for divergence time |



In the standard model the divergence time is a fixed parameter; in inferences this parameter is changed using an arbitrary prior distribution. In contrast, the label-switching model treats the divergence time as a random variable with a truncated normal distribution with parameter  $\mu$  and  $\sigma$

$$\lambda_{c_i} = \frac{k_i(k_i - 1)}{\Theta_i},$$

$$\lambda_{M_i} = \sum_{j=1}^{n_p} k_i M_{ji};$$

We use a hazard function to evaluate the risk of switching the label looking backwards in time; this leads to a mixture of waiting times, in the simplest case we consider coalescent and divergence events, in more complex cases we can add immigration events.

$$\lambda'_s(t) = \lambda_{\mathcal{N}(\mu, \sigma)}(t) = \frac{\sqrt{\frac{2}{\pi}} e^{-\frac{(\mu-t)^2}{2\sigma^2}}}{\sigma \left( \operatorname{erf}\left(\frac{\mu-t}{\sqrt{2}\sigma}\right) - \operatorname{erf}\left(\frac{\mu-b_1}{\sqrt{2}\sigma}\right) \right)}, \lambda_s(t_0, t_0 + u) = \log \left( \frac{\operatorname{erf}\left(\frac{\mu-t_0}{\sqrt{2}\sigma}\right) - \operatorname{erf}\left(\frac{\mu-b_1}{\sqrt{2}\sigma}\right)}{\operatorname{erf}\left(\frac{\mu-(t_0+u)}{\sqrt{2}\sigma}\right) - \operatorname{erf}\left(\frac{\mu-b_1}{\sqrt{2}\sigma}\right)} \right).$$

$$p_d(u|G, t_0, \rho) = \frac{1}{k} e^{-u(\lambda_c + \lambda_m) + \lambda_s(t_0+u)} [\lambda_c + \lambda_m + \lambda'_s(t_0+u)] \int_0^\infty e^{-u\lambda_c} e^{-u\lambda_m} \lambda'_s(t) e^{\lambda_s(t_0, t_0+u)} du.$$

Unfortunately, the integral needs to be solved numerically. This makes the above calculation very slow. Instead of solving the integral numerically, we approximate using the midpoint rule, this approximation leads to a simpler, approximate, solution:

$$p_s(u|G, t_0, \rho) = e^{-u\left(\frac{k(k-1)}{\Theta} + kM + \lambda'_s(t_0+\epsilon)\right)} \frac{\lambda'_s(t_0+\epsilon)}{k}$$

We implemented this method in the program MIGRATE version 4, which is available from the MIGRATE website (in the preview section): <http://peterbeerli.com/migrate-html5> or <http://pop-gen.sc.fsu.edu>

