Online Appendix to **When Being Hot is Not Cool: Monitoring Hot Lists for Information Security**

Proof of Proposition 1

By closely examining the differential equation (3) and the boundary condition (6), we can propose the following separable solution form

$$f(x_1, ..., x_n) = \prod_{i=1}^{n-1} g(x_i) g_1(x_n). \tag{52}$$

Such a form is symmetric in $x_i, i = 1, ..., n-1$, but not in x_n as we can see from Equation (6). Then plugging (52) into (3) and (6), we can get the differential equations that g and g_1 should satisfy:

$$\frac{\partial g(x)}{\partial x} = -\theta(x) g(x) \tag{53}$$

$$\frac{\partial g_1(x)}{\partial x} = -(\lambda + \theta(x)) g_1(x) \tag{54}$$

and the boundary conditions:

$$g(0) g_1(x_n) = \int_0^{x_n} \theta(x_i) g(x_i) g_1(x_n) dx_i + \int_{x_n}^{\infty} (\lambda + \theta(x)) g(x_n) g_1(x) dx \tag{55}$$

It is easy to verify that the following proposed solutions

$$g(x) = c_1 e^{-\phi(x)}, \quad g_1(x) = c_2 e^{-(\lambda x + \phi(x))} \tag{56}$$

with $\phi(x) = \int_0^x \theta(y) dy$ satisfies the differential equations (53) and (54). Furthermore, the right-hand side of the boundary condition (55) is

$$c_1(1 - e^{-\phi(x_n)}) c_2 e^{-(\lambda x_n + \phi(x_n))} + c_1 e^{-\phi(x_n)} c_2 e^{-(\lambda x_n + \phi(x_n))} = c_1 c_2 e^{-(\lambda x_n + \phi(x_n))} \tag{57}$$

which equals the left-hand side of (55). Therefore, (56) satisfy (53) and (54) and the boundary condition (55) and are the solution we are looking for. Then (52) can be rewritten as

$$f(x_1, x_2, ..., x_n) = e^{-\left[\lambda x_n + \sum_{i=1}^{n} \phi(x_i)\right]} / \omega \tag{58}$$

where ω is the normalization factor:

$$\omega = \int_0^{\infty} dx_n e^{-(\lambda x_n + \phi(x_n))} \left[\int_0^{x_n} dx e^{-\phi(x)}\right]^{n-1} \tag{59}$$

□

Proof of Lemma 1:
First from (11), we can get

$$\begin{aligned}\int_0^{x_n} \theta(x)dx e^{-\phi(x)} &= \int_0^{x_n} d\phi(x) e^{-\phi(x)} \\ &= 1 - e^{-\phi(x_n)} = 1 - \left(\frac{\alpha x_n + \beta}{\beta}\right)^{-\frac{1}{\alpha}} \end{aligned} \tag{60}$$

Plugging (7) into (15), we get:

$$\begin{aligned} H &= \int_0^{\infty} dx_n \int_0^{x_n} dx_{n-1} ... \int_0^{x_n} dx_1 f(x_1, x_2, ..., x_n) \sum_{i=1}^{n} \theta(x_i) \\ &= \int_0^{\infty} dx_n \int_0^{x_n} dx_{n-1} ... \int_0^{x_n} dx_1 e^{-\left[\lambda x_n + \sum\limits_{i=1}^{n} \phi(x_i)\right]} / \omega \sum_{i=1}^{n} \theta(x_i) \\ &= \int_0^{\infty} dx_n \int_0^{x_n} dx_{n-1} ... \int_0^{x_n} dx_1 e^{-\sum\limits_{i=1}^{n-1} \phi(x_i)} \left[\sum_{i=1}^{n-1} \theta(x_i) + \theta(x_n)\right] e^{-(\lambda x_n + \phi(x_n))} / \omega \\ &= \int_0^{\infty} dx_n \left[(n-1)\left(\int_0^{x_n} \theta(x) e^{-\phi(x)} dx\right)\left(\int_0^{x_n} e^{-\phi(x)} dx\right)^{n-2} + \theta(x_n)\left(\int_0^{x_n} e^{-\phi(x)} dx\right)^{n-1}\right] e^{-(\phi(x_n) + \lambda x_n)} / \omega \\ &= \int_0^{\infty} dx_n \left(\int_0^{x_n} e^{-\phi(x)} dx\right)^{n-2} \left[(n-1) \int_0^{x_n} \theta(x) e^{-\phi(x)} dx + \theta(x_n) \int_0^{x_n} e^{-\phi(x)} dx\right] e^{-(\phi(x_n) + \lambda x_n)} / \omega \end{aligned} \tag{61}$$

Plugging (10), (11) and (60) into the above equation (61), we can get

$$\begin{aligned} H &= \int_0^{\infty} dx_n \left\{\frac{\beta}{1-\alpha}\left[1 - \left(\frac{\alpha x_n + \beta}{\beta}\right)^{1-\frac{1}{\alpha}}\right]\right\}^{n-2} \\ &\times \left\{(n-1)\left[1 - \left(\frac{\alpha x_n + \beta}{\beta}\right)^{-\frac{1}{\alpha}}\right] + \theta(x_n) \frac{\beta}{1-\alpha}\left[1 - \left(\frac{\alpha x_n + \beta}{\beta}\right)^{1-\frac{1}{\alpha}}\right]\right\} \\ &\times e^{-\lambda x_n} \left(\frac{\alpha x_n + \beta}{\beta}\right)^{-\frac{1}{\alpha}} / \omega \end{aligned} \tag{62}$$

where ω is given in (13).

By transformation of variable $y = \dfrac{\alpha x_n + \beta}{\beta}$, we can get the final expression of H in (16). $\square$

Proof of Proposition 2:
Let Y be the value of y that yields the peak of $g_n(y)$. By using the peak approximation, we can approximate the integrations in (16) by simply evaluating the integrands at $y = Y$:

$$
\begin{aligned}
H &= \frac{1-\alpha}{\beta}\frac{\int_1^\infty dy g_{n-1}(y)\left[(n-1)\left(1-y^{-\frac{1}{\alpha}}\right)+\frac{1}{1-\alpha}\frac{1}{y}\left(1-y^{1-\frac{1}{\alpha}}\right)\right]}{\int_1^\infty dy g_n(y)} \\
&= \frac{1-\alpha}{\beta}\frac{g_{n-1}(y)\left[(n-1)\left(1-y^{-\frac{1}{\alpha}}\right)+\frac{1}{1-\alpha}\frac{1}{y}\left(1-y^{1-\frac{1}{\alpha}}\right)\right]}{g_n(y)}|_{y=Y} \\
&= \frac{1-\alpha}{\beta}\frac{1}{1-Y^{1-\frac{1}{\alpha}}}\left[(n-1)\left(1-Y^{-\frac{1}{\alpha}}\right)+\frac{1}{1-\alpha}\frac{1}{Y}\left(1-Y^{1-\frac{1}{\alpha}}\right)\right]
\end{aligned} \tag{63}
$$

where we have used the expression of $g_n(y)$ in (19) in the last step.

The value of Y satisfies the first-order condition of $dg_n(y)/dy = 0|_{y=Y} = dLn[g_n(y)]/dy = 0|_{y=Y}$. From (19), we can have

$$
\begin{aligned}
0 &= \frac{d}{dy}\left(-\frac{\beta\lambda}{\alpha}y - \frac{1}{\alpha}Ln[y] + (n-1)Ln[Y^{1-\frac{1}{\alpha}}-1]\right)|_{y=Y} \\
&= -\frac{\beta\lambda}{\alpha} - \frac{1}{\alpha Y} + (n-1)\frac{(1-\frac{1}{\alpha})Y^{-\frac{1}{\alpha}}}{Y^{1-\frac{1}{\alpha}}-1} \\
&= -\frac{\beta}{\alpha}\left(\lambda + \frac{1}{\beta Y}\right) + \frac{(n-1)(\alpha-1)/\alpha}{Y - Y^{\frac{1}{\alpha}}}
\end{aligned} \tag{64}
$$

Rearranging the above equation, we can get Equation (21).

Then we can use Equation (21) to further simplify the expression of H in Equation (63):

$$
\begin{aligned}
H &= \frac{(1-\alpha)(n-1)}{\beta(Y^{\frac{1}{\alpha}}-Y)}(Y^{\frac{1}{\alpha}}-1) + \frac{1}{\beta Y} \\
&= (\lambda + \frac{1}{\beta Y})(Y^{\frac{1}{\alpha}}-1) + \frac{1}{\beta Y} \\
&= -\lambda + (\lambda + \frac{1}{\beta Y})Y^{\frac{1}{\alpha}}
\end{aligned} \tag{65}
$$

which is Equation (20). We shall have $Y > 1$ for H in (65) to be positive. □

Proof of Lemma 2:

First, under the high traffic assumption, we shall have $\lambda \gg 1/(\beta Y)$ since $Y > 1$. Then (21) can be simplified as (22). We can get the expression of $\frac{\partial Y}{\partial n}$ from (22):

$$
\frac{\partial Y}{\partial n} = \frac{1}{\frac{1}{\alpha}Y^{\frac{1}{\alpha}-1} - 1}\frac{1-\alpha}{\beta\lambda} \tag{66}
$$

and we have $\frac{\partial Y}{\partial n} > 0$ since $Y > 1$.

Plugging (66) into (25), the first-order condition (FOC) $\dfrac{\partial J}{\partial n} = 0$, we can obtain:

$$\frac{\partial J}{\partial n} = c_a P \frac{1}{\alpha} Y^{\frac{1}{\alpha}-1} \frac{1}{\frac{1}{\alpha} Y^{\frac{1}{\alpha}-1} - 1} \frac{1-\alpha}{\beta} - c_0 = 0. \tag{67}$$

which can be rewritten as:

$$\frac{\partial J}{\partial n} = c_a P \frac{1-\alpha}{\beta} \left(1 + \frac{1}{\frac{1}{\alpha} Y^{\frac{1}{\alpha}-1} - 1}\right) - c_0 = 0.$$

Then,

$$\begin{aligned}
\frac{\partial^2 J}{\partial n^2} &= c_a P \frac{1-\alpha}{\beta} (-1) \frac{\frac{1}{\alpha}(\frac{1}{\alpha}-1) Y^{\frac{1}{\alpha}-2}}{(\frac{1}{\alpha} Y^{\frac{1}{\alpha}-1} - 1)^2} \frac{\partial Y}{\partial n} \\
&= (-1) c_a P \frac{1}{\beta} \frac{(\frac{1}{\alpha}-1)^2 Y^{\frac{1}{\alpha}-2}}{(\frac{1}{\alpha} Y^{\frac{1}{\alpha}-1} - 1)^2} \frac{\partial Y}{\partial n} \\
&< 0
\end{aligned} \tag{68}$$

□

Proof of Proposition 3:

Solving for Y from (67) derived in Lemma 2, we can get:

$$Y = A^{\alpha}, \quad A \equiv \left[\frac{c_0 \alpha \beta}{c_0 \beta - c_a P (1-\alpha)}\right]^{1/(1-\alpha)}. \tag{69}$$

Then we can get n from (22):

$$n = 1 + \frac{\beta \lambda}{1-\alpha} (A - A^{\alpha}). \tag{70}$$

□

Proof of Corollary 1:

From the expression of n given in Equation (27), we can get:

$$\frac{\partial n}{\partial c_0} = \frac{\beta \lambda}{1-\alpha} (1 - \alpha A^{\alpha-1}) \frac{\partial A}{\partial c_0} \tag{71}$$

The first two terms on the right-hand side of the above equation (71) are positive since $\alpha < 1$

and $A > 1$. From (69) we can get the expression of $\dfrac{\partial A}{\partial c_0}$:

$$\begin{aligned}
\frac{\partial A}{\partial c_0} &= A\frac{\partial Ln[A]}{\partial c_0} \\
&= A\left(-\frac{1}{1-\alpha}\frac{1}{\beta - \frac{c_a P(1-\alpha)}{c_0}}\frac{c_a P(1-\alpha)}{c_0^2}\right) \\
&= -A\frac{1}{1-\alpha}\frac{1}{c_0\beta - c_a P(1-\alpha)}\frac{c_a P(1-\alpha)}{c_0} < 0
\end{aligned}$$

since $c_0\beta - c_a P(1-\alpha) > 0$ and $\alpha < 1$. Therefore, we have:

$$\frac{\partial n}{\partial c_0} < 0 \tag{72}$$

Furthermore, from Equation (22) and the FOC (67), we can see that n and λ affect $\dfrac{\partial J}{\partial n}$ only through Y by a combination of $(n-1)/\lambda$, i.e., the FOC (67) can be expressed as $\dfrac{\partial J}{\partial n}(n,\lambda) = \dfrac{\partial J}{\partial n}(Y(\dfrac{n-1}{\lambda}))$. Then, we have

$$\frac{\partial^2 J}{\partial n \partial \lambda}(Y(\frac{n-1}{\lambda})) = \frac{\partial^2 J}{\partial n \partial Y}Y'\frac{-(n-1)}{\lambda^2} = \frac{-(n-1)}{\lambda}\frac{\partial^2 J}{\partial n^2}. \tag{73}$$

By using the Envelope Theorem (Korn and Korn 2000), we can determine the sign of $\dfrac{\partial n}{\partial \lambda}$:

$$\frac{\partial n}{\partial \lambda} = -\frac{\partial^2 J}{\partial n \partial \lambda}/\frac{\partial^2 J}{\partial n^2} = \frac{n-1}{\lambda} > 0. \tag{74}$$

□

Derivation of FOC $\dfrac{\partial J}{\partial P_f} = 0$ in Equation (33):

First, using the high traffic assumption $\lambda \gg 1/\beta$, we can simplify H in Equation (20) as

$$H = \lambda(Y^{\frac{1}{\alpha}} - 1) \tag{75}$$

Then, from the expressions of λ and P given in Equations (28) and (29), we can rewrite the objective function of (30) as

$$\max_{n,P_f} J = \max_{n,P_f}(c_a\lambda_0 P_0 P_d(Y^{\frac{1}{\alpha}} - 1) - c_0 n) \tag{76}$$

Now we can write the FOC $\dfrac{\partial J}{\partial P_f} = 0$ as

$$\frac{\partial J}{\partial P_f} = c_a\lambda_0 P_0\left[qP_f^{q-1}(Y^{\frac{1}{\alpha}} - 1) + P_d\frac{\partial}{\partial P_f}Y^{\frac{1}{\alpha}}\right] = 0 \tag{77}$$

Also under the high traffic assumption, we can rewrite Equation (21) as:

$$\lambda(Y^{\frac{1}{\alpha}} - Y) = \lambda\left(Y^{\frac{1}{\alpha}} - (Y^{\frac{1}{\alpha}})^{\alpha}\right) = \frac{(n-1)(1-\alpha)}{\beta} \tag{78}$$

Taking the derivative of the above equation (78) with respect to P_f, we can get:

$$\left(1 - \alpha Y^{\frac{\alpha-1}{\alpha}}\right)\frac{\partial}{\partial P_f}Y^{\frac{1}{\alpha}} - YLn[Y^{\frac{1}{\alpha}}]\frac{\partial\alpha}{\partial P_f} = (n-1)\frac{\partial}{\partial P_f}\frac{(1-\alpha)}{\beta\lambda} \tag{79}$$

from which we can get the expression of $\frac{\partial}{\partial P_f}Y^{\frac{1}{\alpha}}$:

$$\frac{\partial}{\partial P_f}Y^{\frac{1}{\alpha}} = \frac{1}{1-\alpha Y^{\frac{\alpha-1}{\alpha}}}\left[(n-1)\frac{\partial}{\partial P_f}\frac{1-\alpha}{\beta\lambda} + YLn[Y^{\frac{1}{\alpha}}]\frac{\partial\alpha}{\partial P_f}\right]. \tag{80}$$

Plugging it into (77), we get Equation (33). □

Proof of Lemma 3:

Optimal decision variables of n^* and P_f^* are determined by two FOCs in (25) and (33) respectively with Y defined in Equation (22). By transformation of variable $m = (n-1)/\lambda_0$, we have two new decision variables satisfying the following modified FOCs:

$$c_a P_d P_0 \frac{1}{\alpha} Y^{\frac{1}{\alpha}-1}\frac{\partial Y}{\partial m} - c_0 = 0. \tag{81}$$

$$qP_f^{q-1}(Y^{\frac{1}{\alpha}} - 1) + P_d\frac{1}{1-\alpha Y^{\frac{\alpha-1}{\alpha}}}\left[m\frac{\partial}{\partial P_f}\frac{1-\alpha}{\beta(P_dP_0 + P_f(1-P_0))} + YLn[Y^{\frac{1}{\alpha}}]\frac{\partial\alpha}{\partial P_f}\right] = 0. \tag{82}$$

and Y is now given by:

$$(Y^{\frac{1}{\alpha}} - Y) = \frac{m(1-\alpha)}{(P_dP_0 + P_f(1-P_0))\beta} \tag{83}$$

Since none of the three equations (81) – (83) contains parameter λ_0, we conclude that $\partial P_f^*/\partial\lambda_0 = 0$ and $\partial m^*/\partial\lambda_0 = 0$ that is equivalent to $(n^*-1)/\lambda_0 = constant$. □

Proof of Proposition 4:

To perform comparative static analysis, we start with the FOCs $\frac{\partial J}{\partial n} = 0$ and $\frac{\partial J}{\partial P_f} = 0$ which are given in (25) and (33) respectively. We can derive the following set of equations:

$$\frac{\partial}{\partial c_0}\frac{\partial J}{\partial P_f} = \frac{\partial^2 J}{\partial P_f^2}\frac{\partial P_f}{\partial c_0} + \frac{\partial^2 J}{\partial P_f \partial n}\frac{\partial n}{\partial c_0} + \frac{\partial^2 J}{\partial P_f \partial c_0} = 0 \tag{84}$$

$$\frac{\partial}{\partial c_0}\frac{\partial J}{\partial n} = \frac{\partial^2 J}{\partial P_f \partial n}\frac{\partial P_f}{\partial c_0} + \frac{\partial^2 J}{\partial^2 n}\frac{\partial n}{\partial c_0} + \frac{\partial^2 J}{\partial n \partial c_0} = 0 \tag{85}$$

Then from (84) and (85) we can solve for $\frac{\partial P_f}{\partial c_0}$ and $\frac{\partial n}{\partial c_0}$ and get:

$$\frac{\partial P_f^*}{\partial c_0} = -\begin{vmatrix} \frac{\partial^2 J}{\partial P_f \partial c_0} & \frac{\partial^2 J}{\partial P_f \partial n} \\ \frac{\partial^2 J}{\partial n \partial c_0} & \frac{\partial^2 J}{\partial n^2} \end{vmatrix} /D, \quad \frac{\partial n^*}{\partial c_0} = -\begin{vmatrix} \frac{\partial^2 J}{\partial P_f^2} & \frac{\partial^2 J}{\partial P_f \partial c_0} \\ \frac{\partial^2 J}{\partial P_f \partial n} & \frac{\partial^2 J}{\partial n \partial c_0} \end{vmatrix} /D. \tag{86}$$

where the determinant of the Hessian matrix is given by

$$D = \begin{vmatrix} \frac{\partial^2 J}{\partial P_f^2} & \frac{\partial^2 J}{\partial P_f \partial n} \\ \frac{\partial^2 J}{\partial P_f \partial n} & \frac{\partial^2 J}{\partial n^2} \end{vmatrix}.$$

For n^* and P_f^* to maximize the objective function J, the related Hessian matrix at this point should be negative definite (Korn and Korn 2000), i.e., $\frac{\partial^2 J}{\partial n^2} < 0$, $\frac{\partial^2 J}{\partial P_f^2} < 0$, and $D > 0$.

From the first order conditions (25) and (33), we can get

$$\frac{\partial^2 J}{\partial P_f \partial c_0} = 0, \frac{\partial^2 J}{\partial n \partial c_0} = -1. \tag{87}$$

Then plugging the above equation (87) in to (86) we can get the expression of $\frac{\partial n^*}{\partial c_0}$:

$$\frac{\partial n^*}{\partial c_0} = \frac{\partial^2 J}{\partial P_f^2}/D < 0 \tag{88}$$

since the related Hessian matrix is negative definite.

Similarly, we can get the expression of $\frac{\partial P_f^*}{\partial c_0}$ from (86):

$$\frac{\partial P_f^*}{\partial c_0} = -\frac{\partial^2 J}{\partial P_f \partial n}/D. \tag{89}$$

Using (25), we can get:

$$\begin{aligned} \frac{1}{c_a \lambda_0 P_0} \frac{\partial^2 J}{\partial P_f \partial n} &= \frac{\partial}{\partial P_f}\left(P_d \frac{\partial Y^{1/\alpha}}{\partial n} \right) \\ &= q P_f^{q-1} \frac{\partial Y^{1/\alpha}}{\partial n} + P_d \frac{\partial}{\partial P_f} \frac{\partial Y^{1/\alpha}}{\partial n} \\ &= q P_f^{q-1} \frac{\partial Y^{1/\alpha}}{\partial n} + P_d \frac{\partial}{\partial P_f} \left(\frac{1-\alpha}{\beta \lambda} \frac{1}{1 - \alpha Y^{\frac{\alpha - 1}{\alpha}}} \right) \end{aligned} \tag{90}$$

where we have used (22) to derive the expression of $\partial Y^{1/\alpha}/\partial n$ and plug it in the last step.

Given the complexity of (90), we have to make some approximation in order to derive analytical results. Assume that a is small and we can ignore the terms of $\partial\alpha/\partial P_f$ and $\partial\beta/\partial P_f$ in (90). Then the last term in (90) can be shown as:

$$\frac{\partial}{\partial P_f}\left(\frac{1-\alpha}{\beta\lambda}\frac{1}{1-\alpha Y^{\frac{\alpha-1}{\alpha}}}\right) = \frac{1}{1-\alpha Y^{\frac{\alpha-1}{\alpha}}}\frac{-(1-\alpha)}{\beta\lambda^2}\frac{d\lambda}{dP_f}\left[1+\frac{(1-\alpha)}{\beta\lambda}\frac{\alpha(\alpha-1)}{(1-\alpha Y^{\frac{\alpha-1}{\alpha}})^2}Y^{\frac{\alpha-2}{\alpha}}(n-1)\right] \tag{91}$$

after we have used (80) and ignored the terms of $\partial\alpha/\partial P_f$ and $\partial\beta/\partial P_f$. The right-hand side of Equation (91) is negative since $d\lambda/dP_f$ is positive from (29).

Using the FOC in (25), we can get the expression of $\frac{\partial Y^{1/\alpha}}{\partial n}$. Plugging $\frac{\partial Y^{1/\alpha}}{\partial n}$ and (91) into (90), we can get

$$\begin{aligned}\frac{1}{c_a\lambda_0 P_0}\frac{\partial^2 J}{\partial P_f\partial n} &= qP_f^{q-1}\frac{c_0}{c_a\lambda_0 P_0 P_d}\\ &- P_d\frac{1}{1-\alpha Y^{\frac{\alpha-1}{\alpha}}}\frac{1-\alpha}{\beta\lambda^2}\frac{d\lambda}{dP_f}\left[1+\frac{(1-\alpha)}{\beta\lambda}\frac{\alpha(\alpha-1)}{(1-\alpha Y^{\frac{\alpha-1}{\alpha}})^2}Y^{\frac{\alpha-2}{\alpha}}(n-1)\right]\end{aligned} \tag{92}$$

If c_0 is sufficiently small, then the right-hand side of (92) is negative. Otherwise, it is positive. Let the switching point to be $\bar{c}_0$. Then $\frac{\partial P_f^*}{\partial c_0}$ in (89) is positive if $c_0 < \bar{c}_0$ and negative otherwise. □

Pseudo Code for Simulation:

The following is the pseudo code:

1. Initialization
   (a) Define a *HotList* (of type SortedList) that stores sessions (of type Class) sorted by time a session is added to this list.
   (b) Add a session to *HotList*
2. Run the Simulation

   While *NumSuspiciousEvents* detected < *MaxNumEvents* to detect:

   (a) If *NumSuspiciousEvents* detected = *NumEvents_WarmUp*
   Record statistics such as *ClockTime_WarmUp*.
   (b) Record *minimumTime* of the following times and the corresponding *actionType*:
   - Time to switch to a different state of MMPP process
   - Time for a new session to arrive
   - Earliest time for a suspicious event to happen in HotList
   - Earliest death time for sessions in HotList

- Time to drop the oldest session in HotList (for an (n, τ) policy)

(c) Advance the system by time increment *minimumTime*:

- Adjust all the relevant times
- Take action according to *actionType*
  - State switching: set a new session arrival rate and *time_to_switch*
  - Session arrival: add a random number of new sessions to HotList and drop the same number of oldest sessions from HotList
  - New suspicious event from a session: Reset this session's age to be zero and increment *NumSuspiciousEvents*
  - Session death: Remove this session from HotList
  - Session age passing τ: Remove this session from HotList (for an (n, τ) policy)

3. Calculate and output statistics such as $H_{sim} = \dfrac{MaxNumEvents - NumEvents\_WarmUp}{TotalClockTime - ClockTime\_WarmUp}$.

In the pseudo code, variable *MaxNumEvents* holds the total number of events to be detected. Therefore, numbers of suspicious events in warm-up and data collection periods are represented by *NumEvents_WarmUp* and $(MaxNumEvents - NumEvents\_WarmUp)$. To minimize the impact of warm-up period and statistical error, we make these two numbers sufficiently large (in the order of 10^6) so that a large change in either number does not change the final statistics noticeably. $\square$

References

Korn, G.A. and Korn, T.M.. 2000. *Mathematical Handbook for Scientists and Engineers*. Dover Publications Inc., Mineola, NY.