





A Mathematical Model of Manual and Digital Contact Tracing

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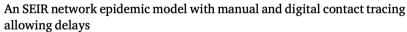
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Original Research Article





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This work was included in my PhD thesis, defended in June 2024.

Introduction: Contact Tracing

Contact tracing (CT) interrupts chains of transmission - aims at identifying infected individuals early and preventing further transmission. It was widely used during Covid-19.

Manual CT

- Interviews conducted by public health agencies or self-reporting (in Sweden).
- Identified cases are asked to report their contacts and advise them to test (and self-quarantine).
- Mainly among close contacts (family, workplace, friends)

Digital CT

- Contact tracing apps were introduced during Covid-19 in certain countries.
- Smartphone-based proximity notifications
- Instantaneous alerts between app-users



Start with an SEIR network epidemic model with random contacts

- Initially, the number of infectious individuals I(0) = 1 and the number of susceptibles S(0) = n 1. (size of population n)
- Infectious individuals make two types of contacts:
 - **local contacts** with each neighbour in G (represented by a configuration model having degree distribution $D \sim \{p_k = \mathbb{P}(D=k), k=0,1,2,...\}$ with finite mean μ) at rate β_L ;
 - random (global) contacts with individuals chosen uniformly from the entire population (neighbors or not) at rate β_G ;
- If a contacted individual is susceptible then they are infected and become exposed for a random period T_L , otherwise nothing happens.
- Once T_L ends, they become infectious for a period $T_I \equiv \tau_I$, after which they are recovered (becomes immune).
- All random quantities above are mutually independent. The epidemic goes on until first time T when I(T) = 0.



Network SEIR epidemic: early epidemic approximation

- **If population size** *n* **is large**, then all infectious contacts at the beginning will be with susceptibles (with large probability); local and global infections behave independently.
- So for large *n*, during the **early stage** of the epidemic, the epidemic behaves like a **two-type branching process**, with
 - **type-L**: infected through the network (by a local contact) **type-G**: infected by a global contact
- Then we can compute the **basic reproduction number** R_0 , which is the largest eigenvalue of the corresponding **next-generation matrix** $M=(m_{ij})$ with m_{ij} of type-j offsprings produced by a type-i individual, for i,j=L,G [1]. When $D\sim Poi(\mu)$, it has a "simple" expression: $R_0=\beta_G\tau_I+\mu(1-e^{-\beta_L\tau_I})$

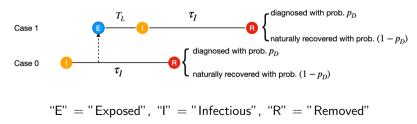
Important threshold property:

A major outbreak can occur with positive probability if and only if $R_0 > 1$, while a minor outbreak occurs with probability 1 when $R_0 < 1$.



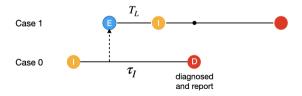
Introducing diagnosis

- We assume that diagnosis is the only trigger for CT.
- After infectious period τ_I , an infective is
 - diagnosed with probability pD
 - otherwise we say the infective is naturally recovered.



Manual CT on network with delay

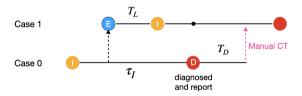
- Forward, only for network contacts: upon diagnosis, the infective is interviewed and reports each of their *infectee neighbours* with probability p_M independently.
- Tracing delay: If such reported neighbours are infectious/latent after a delay period of time T_D , they are isolated (stop spreading) and said to be traced. (No assumption about the form of T_D , suppose the distribution is known.)
- Non-iterative: Only diagnosed person can perform manual CT.
- The random delays of all infectees with the same infector are mutually independent.



"E" = "Exposed", "I" = "Infectious", "D" = "Diagnosed"

Manual CT on network with delay

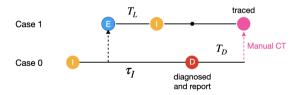
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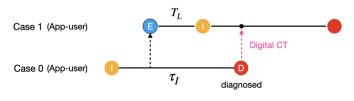
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Instantaneous Digital CT on network and global contacts

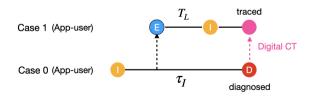
- A fraction π_A of individuals use the tracing app (and follow the recommendations); and we assume random mixing between app-users and non-app-users.
- Forward, instantaneous: Once infectious app-users are diagnosed, all app-users they infected (neighbours or not, including those who are latent) will be *immediately* notified and self-isolated (hence stop spreading).
- **Non-iterative:** As for manual CT, we also assume that only the diagnosed app-users could trigger digital CT.



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Instantaneous Digital CT on network and global contacts

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Introducing both Manual and Digital CT

- There is an app-using fraction π_A .
- Upon removal, **if the non-app-users are diagnosed**, each of the neighbours infected by them is reported with probability p_M . Among the reported infectees, those who are infectious or latent after a delay period of time T_D are isolated and stop spreading.
- If an app-user is diagnosed, all of their app-using infectees (neighbours or not) will be traced immediately; meanwhile each of non-app-using infectee neighbours is reported with probability p_M.
- Only the diagnosed individuals could trigger CT (manual and/or digital CT).

Next slides: approximation of the early epidemic with CT - multi-type branching processes

Key assumptions enabling the branching process approximation

- Challenge: With CT, infected individuals usually do not behave independently ⇒ branching process approximation typically breaks down.
- Our key modelling assumptions restore independence:
 - The infectious period is **deterministic**: $T_I \equiv \tau_I$
 - CT is triggered only when an individual is diagnosed
- **Consequence:** For a diagnosed infector with k infectees that have a CT link (manual or digital), the infection times of these infectees are independent and uniformly distributed over the infectious period:

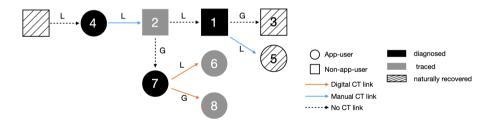
$$U_1, \ldots, U_k \stackrel{i.i.d}{\sim} \text{Uniform}(0, \tau_I)$$

• Why this matters: If T_I were random, then the U_i 's would become dependent \Rightarrow loss of independence between offspring \Rightarrow branching process approximation fails.

Early epidemic approximation: epidemic with combined CT

Assuming large population, we can approximate the initial phase of epidemic by a **eight-type branching process**.

Example of an infection tree containing the eight types ("L" = "local contact", "G" = "global contact"):



Reproduction number R_{MD} is the largest eigenvalue of the corresponding next-generation (8-by-8) matrix.

Reproduction numbers for manual/digital CT only

One straightforward approach: setting $R_M = R_{MD}(\pi_A = 0)$ and $R_D = R_{MD}(p_M = 0)$.

Alternatively, we can have the similar branching process approximation for each:

Manual CT only:

Assuming large population, we can approximate the initial phase of epidemic by a **three-type branching process**. Reproduction number R_M is the largest eigenvalue of the corresponding next-generation (3-by-3) matrix.

Digital CT only:

Approximated by a **six-type branching process**. Reproduction number R_D is the largest eigenvalue of the corresponding next-generation (6-by-6) matrix.

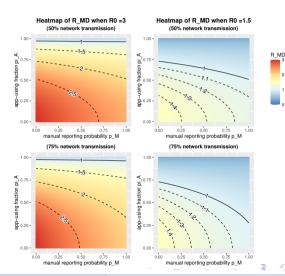
Numerical Illustrations

We quantify the effectiveness of CT numerically through the reduction of the reproduction number.

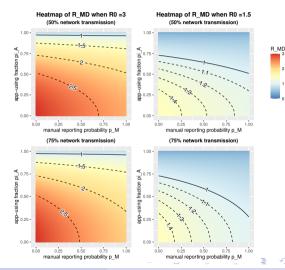
Parameter	Values
Degree distribution	$D \sim extit{Poi}(\mu)$ with mean degree $\mu = 5$ [6]
	(average household size in EU (2019) was 2.3;
	one meets 3 more at work etc.)
Latent period	$T_L \equiv 4$ days [3, 4]
Infectious period	$ au_I=$ 5 days [4]
Tracing delay	$T_D \equiv 3 \text{ day } [5]$

Contact rates β_L , β_G are chosen so that there are $\alpha=50\%$ and 75% transmissions on the network when $R_0=3$ and $R_0=1.5$. We also fix the probability of diagnosis $p_D=0.8$, if not specified.

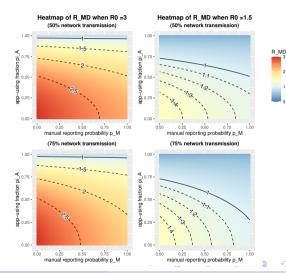
• As expected, the reproduction number for combined CT R_{MD} is monotonically decreasing in both manual reporting probability p_M and app-using fraction π_A .



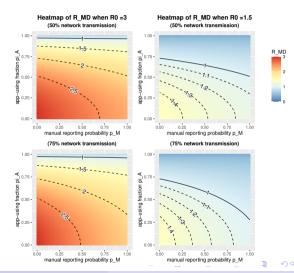
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- When $R_0 = 3$, realistic values of p_M and π_A cannot bring R_{MD} below 1.
- Even if $R_0 = 1.5$, a fairly large app-using fraction is still required to prevent a major outbreak
- With 75% of infections occurring through the network, $R_{MD} < 1$ is achievable with strong manual CT and moderate app usage.



Combined effect in comparison with the two separate effects

Let r_M , r_D and r_{MD} be the **relative reductions in** R_0 attributed to manual, digital and both types of CT, respectively:

$$R_M = R_0(1 - r_M), R_D = R_0(1 - r_D), R_{MD} = R_0(1 - r_{MD}).$$

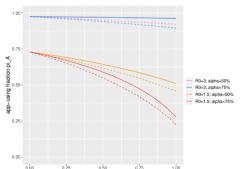
If manual and digital CT would have acted independently, then $R_{MD} \stackrel{?}{=} R_0 (1 - r_M) (1 - r_D)$

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manual reporting probability p. M.

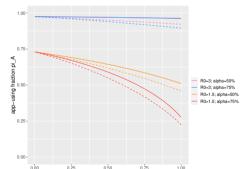
Critical
$$(p_M, \pi_A)$$
 - curves: $R_{MD} = 1$ (solid), $R_0(1 - r_M)(1 - r_D) = 1$ (dashed)

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The effect of combining manual and digital CT is actually smaller than the product of their separate effect!

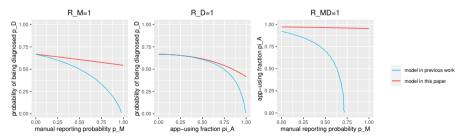
Comparison with other CT models

- Earlier CT models [7, 2]: both manual and digital CT are forward, backward, and iterative without delay (highly optimistic scenario).
- This CT model [8]: forward, non-iterative CT, manual CT with delay (more conservative assumptions)

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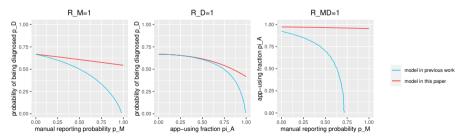
Plots of critical combinations of (p_D, p_M) , (p_D, π_A) and (p_M, π_A) such that R_M, R_D and R_{MD} equal 1:



Comparison with other CT models

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Plots of critical combinations of (p_D, p_M) , (p_D, π_A) and (p_M, π_A) such that R_M, R_D and R_{MD} equal 1:



Real-world outcomes may lie somewhere in between!

Conclusion and possible extensions

Main conclusion:

- The models for manual, digital and combined CT could be approximated by different multi-type branching processes.
- The corresponding effective reproduction numbers could be derived.
- App-using fraction plays an essential role in the overall effectiveness of CT.
- The combined CT model would achieve a better effect if manual and digital CT acted independently.

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Interesting extensions:

- Incorporating CT within household structures, where manual tracing may be more effective.
- Allowing for assortative mixing in app adoption, reflecting that app-users tend to cluster within social networks.



Thanks for your attention!

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