



COVID-19 RISK ESTIMATION FROM CONTACT TRACING DATA

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https://github.com/sphinxteam/sir_inference

CONTACT TRACING DATA



- ▶ Information about individuals (stored on the phone of the individual):
Age, syndromes, health related-risks, etc.
- ▶ Information about contacts (stored on the phone of the two individuals):
Time, duration, distance during the contact, barrier-measures used (mask etc.).

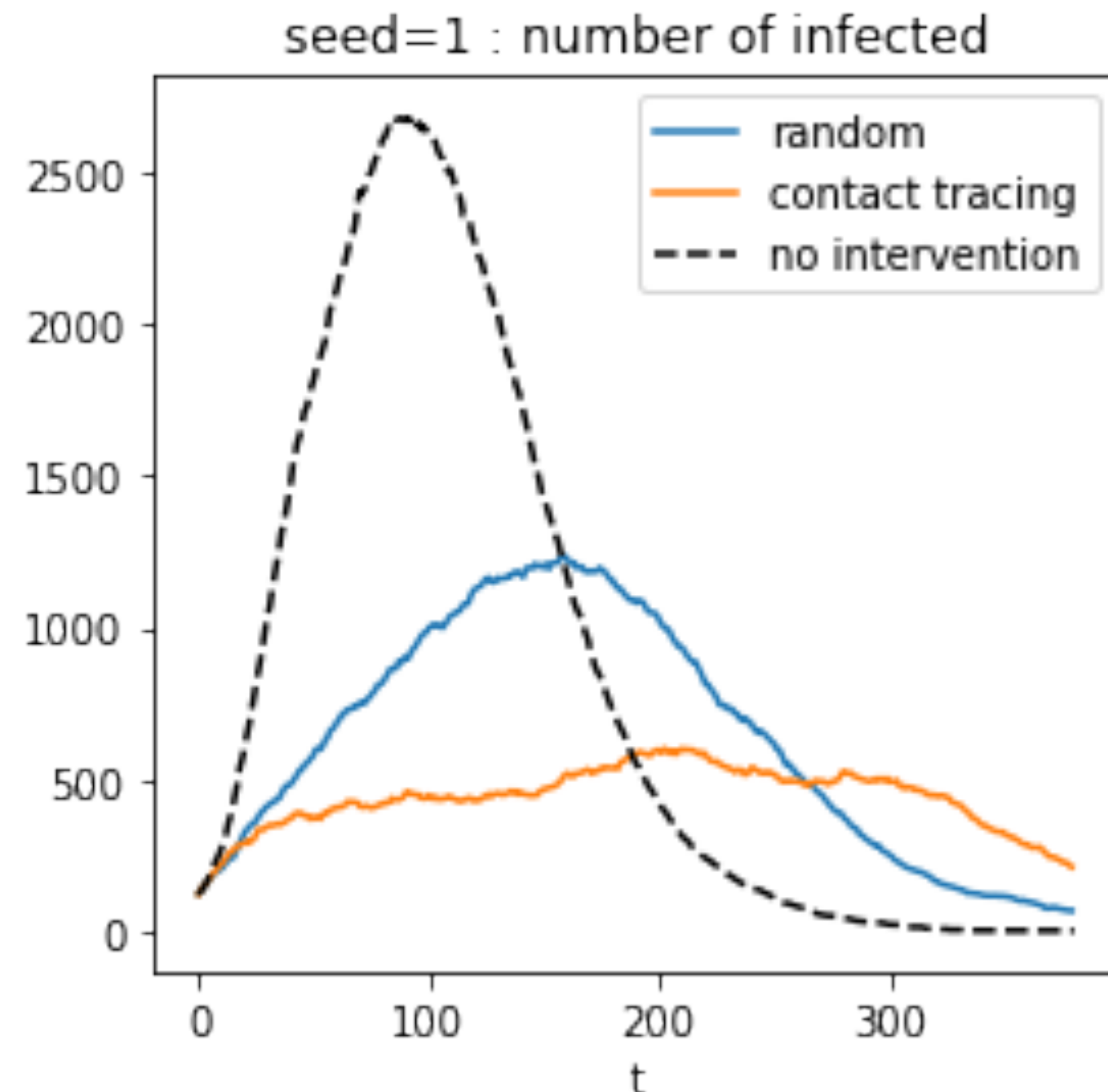
CONTACT TRACING: STATE-OF-THE-ART



- ▶ Contact tracing as implemented currently (Google & Apple, DP3T, etc.):
Upon a positive test of an individual, his/her recent, sufficiently close, and long contacts are contacted and advised to be tested or to self-isolate.
- ▶ Effective Configurations of a Digital Contact Tracing App: A report to NHSX.
Hinch,, **Ferretti**, et al. (**talk at 2nd Ellis-Covid**), et. al. https://cdn.theconversation.com/static_files/files/1009/Report_-_Effective_App_Configurations.pdf?1587531217

HOW TRACING INFLUENCES EPIDEMIC SPREAD

- Uncontrolled epidemic **vs.** Random Tests & isolation **vs.** Tracing & isolation.



Random geometric contact graph in 2D, scale 1.1,
daily on average 7.4 contacts. Population size= 10000,
 $\lambda=0.02$, $\mu=0.03$, Initially 20 infected + 10 time steps of uncontrolled evolution.
Tests: 1 random, 7 infected, and 21 from ranking, 1/2 of all infected, quarantine = 50 steps.



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https://colab.research.google.com/drive/1pRq13j8o6Y8GRWa_IDb_Erj-jqyjWDnM#scrollTo=bVi7bEAGgijX

BETTER THAN TRACING: SMART INFERENCE OF PEOPLE AT RISK (SIPAR)

- ▶ Risk can be estimated more accurately than the mere list of contacts.
Individual should account for increased risks of their neighbours and spread the information to their neighbours.
- ▶ **What is needed from the app?** Communication between individuals who have been in contact (through a server, in an encrypted manner, only small bandwidth needed). Exchange of simple messages (probabilities) when in contact.
- ▶ Apps (we know of) that do estimate (or plan to) a more refined risk level:
 - Covi app, by Bengio & MILA (**talk at 1st Ellis-Covid**), implemented in Canada:
<https://docs.google.com/presentation/d/1uZ1-oiaE6LO7O0mxD34MTBD2xP68ED3wV9ed2Yi8fyQ/edit?usp=sharing>.
 - ViraTrace, by Bestvina, implemented in India: <https://github.com/ViraTrace/InfectionModel>.

OUR WORK: DEVELOPMENT OF ALGORITHMS FOR SIPAR

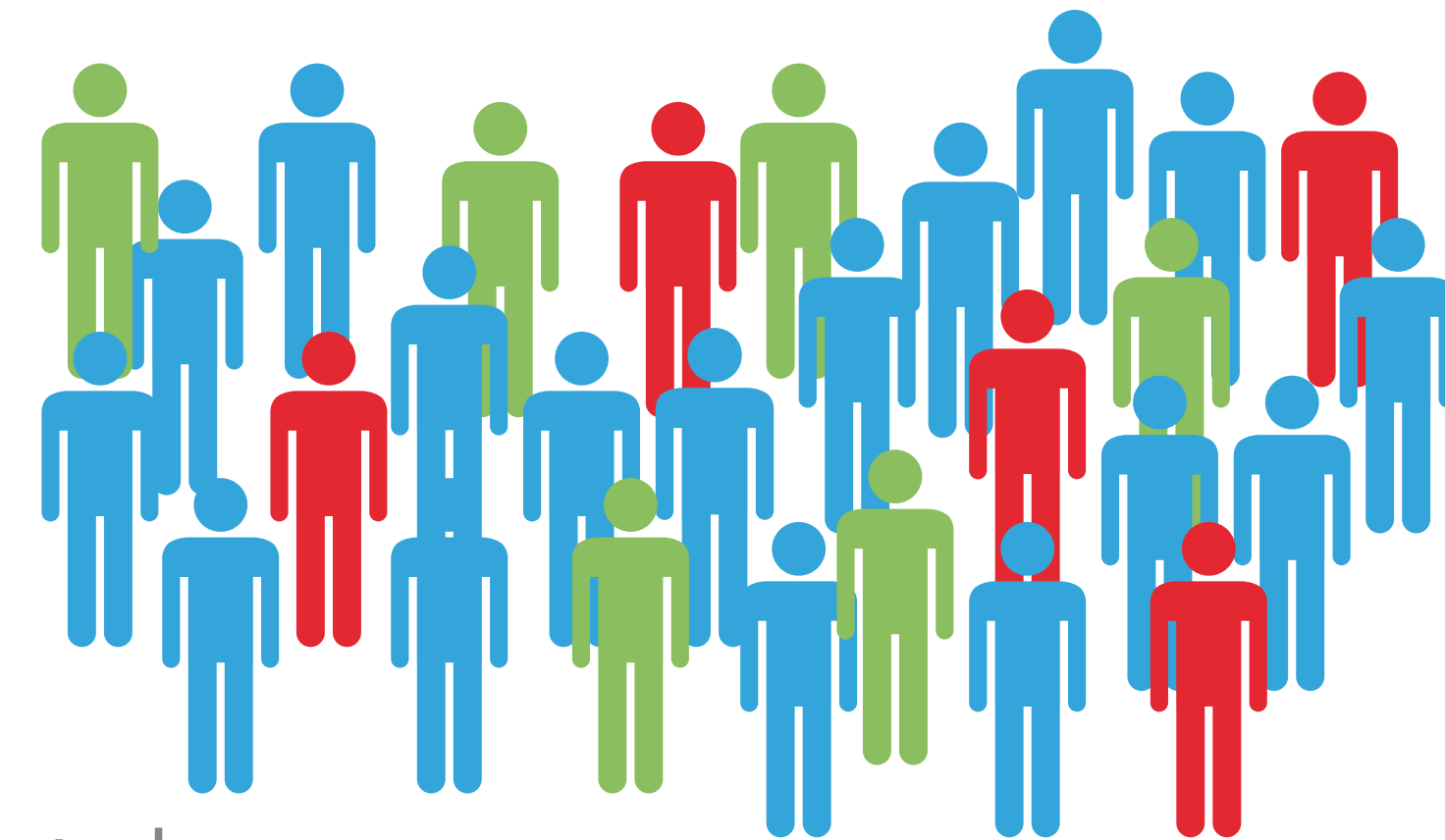
- ▶ Mean-field risk estimation (basics in next slides): <https://www.overleaf.com/read/tfhcpbvhmwcwq>
- ▶ Dynamical message passing approach (Lokhov, Mézard, Ohta, LZ, [PRE '14](#) & [PRE '15](#))
In the present context: <https://www.overleaf.com/read/tfhcpbvhmwcwq>
- ▶ Belief propagation on trajectories and the probabilistic model that conditions the SIR dynamics to the observations. Github repo: <https://github.com/sibyl-team/epibench>
(Altarelli, Braunstein, Dall'Asta et al, [PRL'14](#), Braunstein, Ingrosso [Sci. Rep.'16](#))

SUSCEPTIBLE-INFECTED-RECOVERED (SIR) MODEL

► Population of N individuals

► Spreading of a virus

- Susceptible individuals (S) → Can be infected
- Infected individuals (I) → Can infect others
- Removed individuals (R) → Cannot spread or be infected



Parameters:

- $\lambda_{ij}(t)$ **attack rate** = probability that if susceptible i meets infected j , j **infects** i . Depends on the duration and distance of contact, the barrier measures etc
- μ_i : **Recovery rate** = probability of person i becoming removed in one time-step. Depends on the individual (age, health, etc)

► What is the probability of person i to be in state S, I or R at time t ? $P_S^i(t)$, $P_I^i(t)$, $P_R^i(t)$

MEAN-FIELD MESSAGE PASSING (MF)

- ▶ **time evolution** equations for $P_S^i(t)$, $P_I^i(t)$, and $P_R^i(t)$

$$P_S^i(t+1) = P_S^i(t) \left(1 - \sum_{j \in \partial i(t)} P_I^j(t) \lambda_{ij}(t) \right)$$

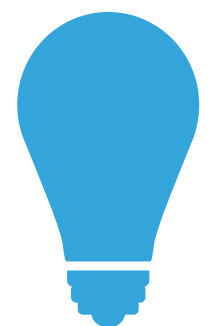
$$P_R^i(t+1) = P_R^i(t) + \mu_i P_I^i(t)$$

$$P_I^i(t+1) = P_I^i(t) + P_S^i(t) \sum_{j \in \partial i(t)} P_I^j(t) \lambda_{ij}(t) - \mu_i P_I^i(t)$$

Parameters:

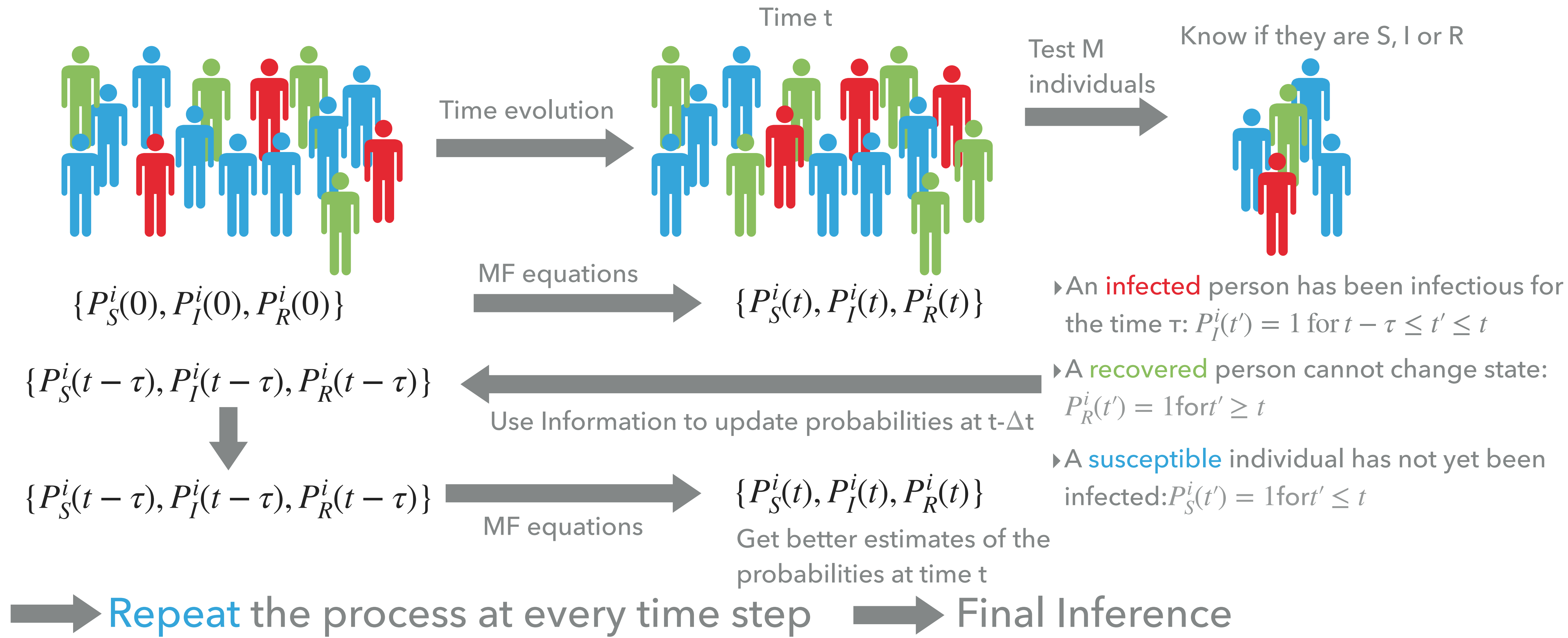
- $\lambda_{ij}(t)$: Probability that if susceptible i meets infected j , j **infects** i :
 - ▶ depends on the individuals: barrier measures etc
 - ▶ depends on time: duration and distance of contact
- μ_i : **Recovery** probability of person i :
 - ▶ depends on the individual (age, health, etc)
- $\partial i(t)$: Sum over **ALL** the individuals i was in contact with at time t :
 - ▶ Tracked with **App**

- ▶ Given an initial conditions $\{P_S^i(0), P_I^i(0), P_R^i(0)\} + \text{Parameters} \rightarrow \{P_S^i(t), P_I^i(t), P_R^i(t)\}$



Needed: Use test results + symptoms to better estimate the probabilities

FEED BACK LOOP: USE TEST RESULTS



➡ NB: Symptoms can be incorporated in this feedback loop analogously

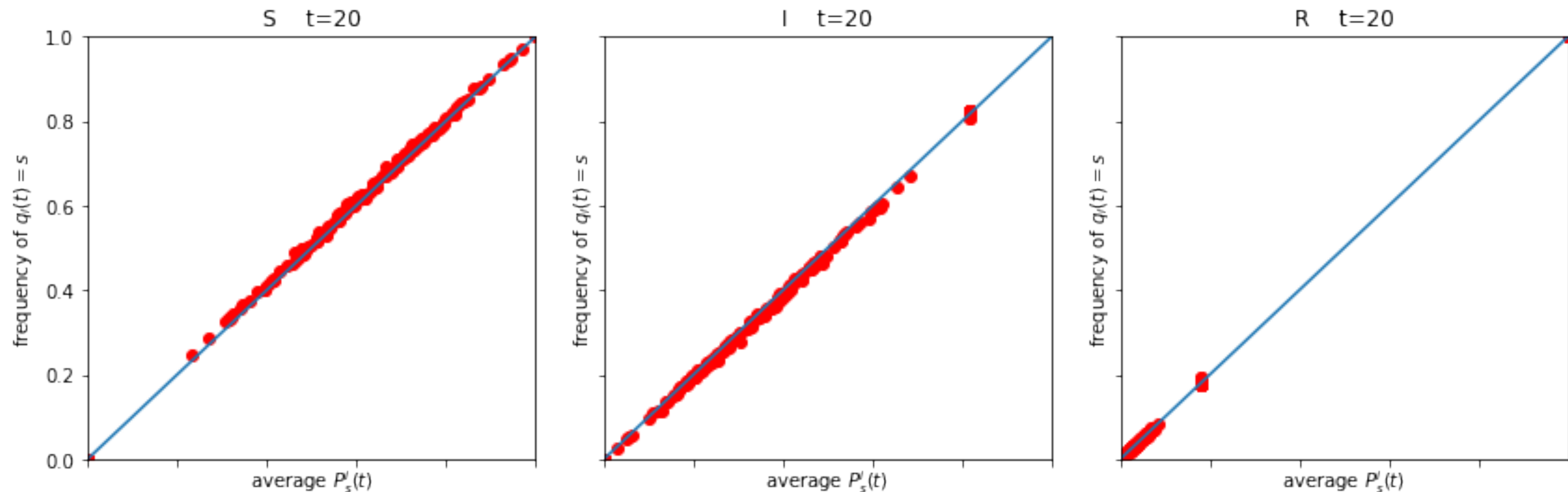
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PROBABILITY ESTIMATION WORKS

- Validation of the tree-like approximation: Inference (without feed-back) correlates well with ground truth

Scatter plot: Y-axes average over 10000 simulations, X-axes MF risks.



Random geometric graph. Population size= 500, $\lambda=0.02$, $\mu=0.01$, 2% Infected Individuals at $t=0$



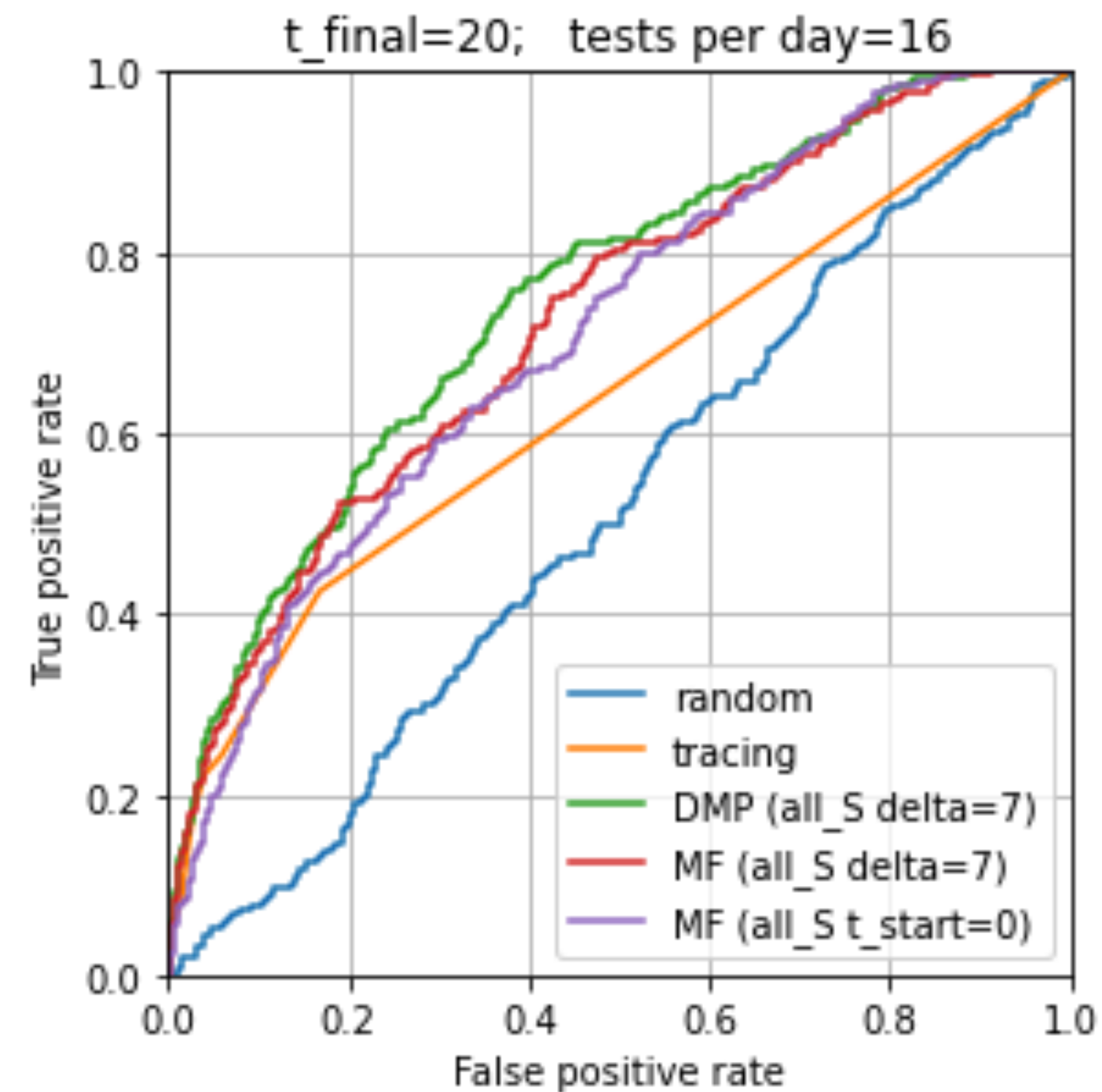
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ROC CURVES (UNCONTROLLED EPIDEMIC, NO INTERVENTIONS)

Contact graph provided by L. Ferretti & R. Hinch, Population size= 10000; 12.7 contacts on average a day,



Epidemic spread and inference with: $\lambda=0.02$, $\mu=0.07$, 10 Infected Individuals at $t=0$, $\tau=7$



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https://colab.research.google.com/drive/15qCIUFJl_mWTVL6e2VG9mgsAgRQ9Armb

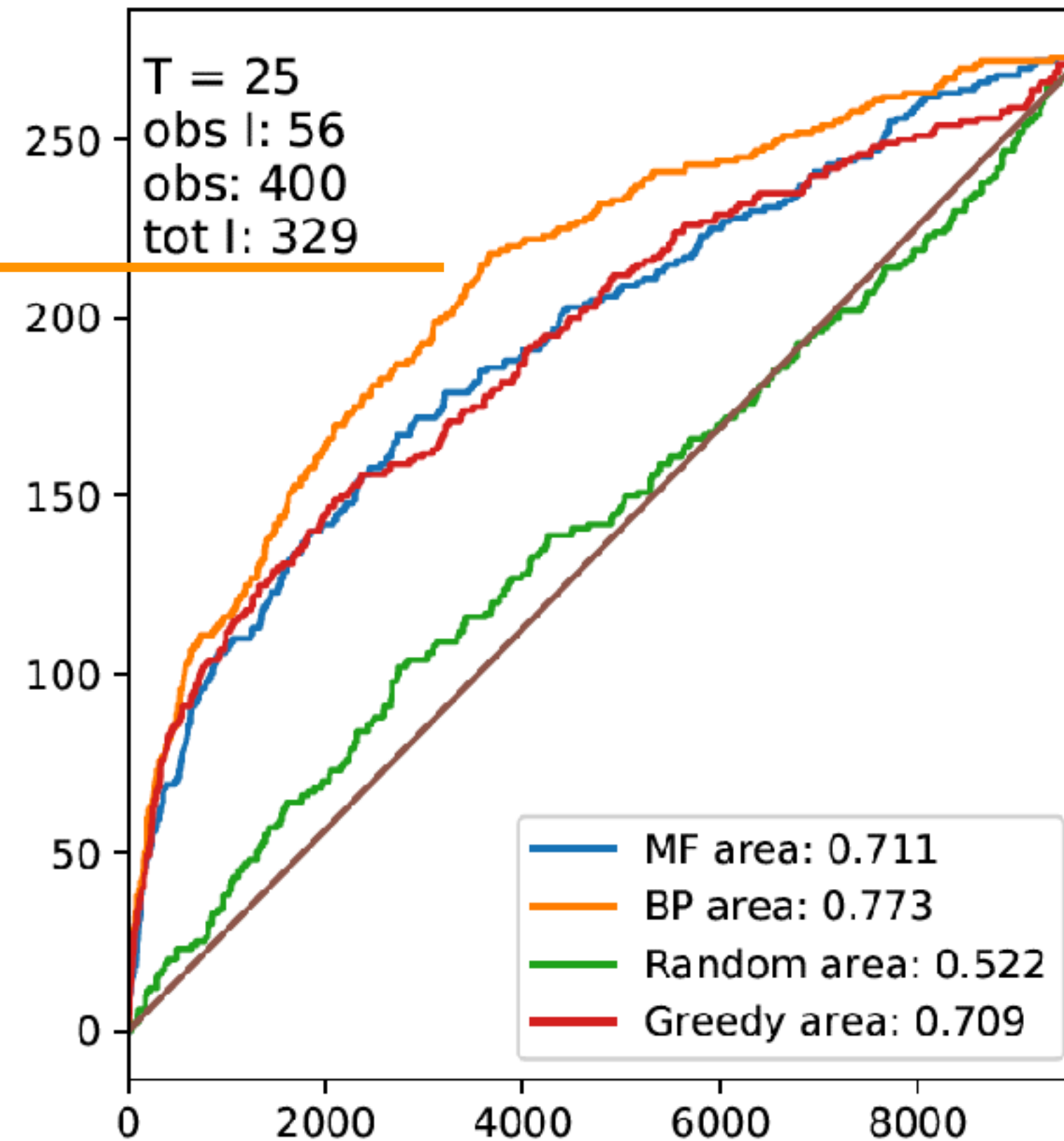
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Epidemic: Realistic uncontrolled epidemic spread from Hinch et al. report ($\lambda \sim 0.04$, $\mu \sim 1/12$)

BP on trajectories, Braunstein et al.

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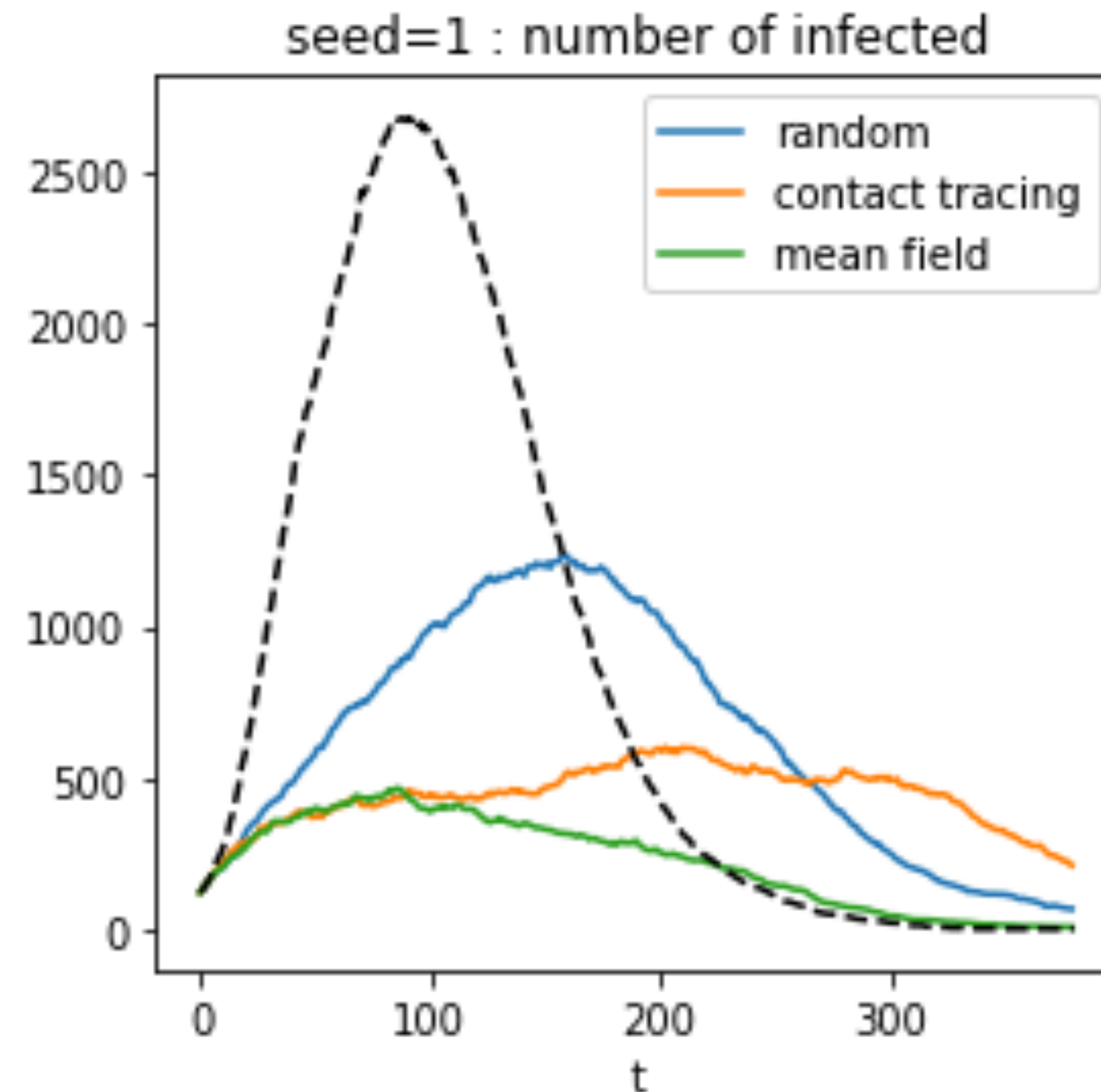


MF inference with: $\lambda=0.02$, $\mu=0.01$, $\tau=5$, $\delta=8$ (note the mismatch in λ, μ after cross-validation)



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EXPERIMENTS ON CONTROL OF EPIDEMIC



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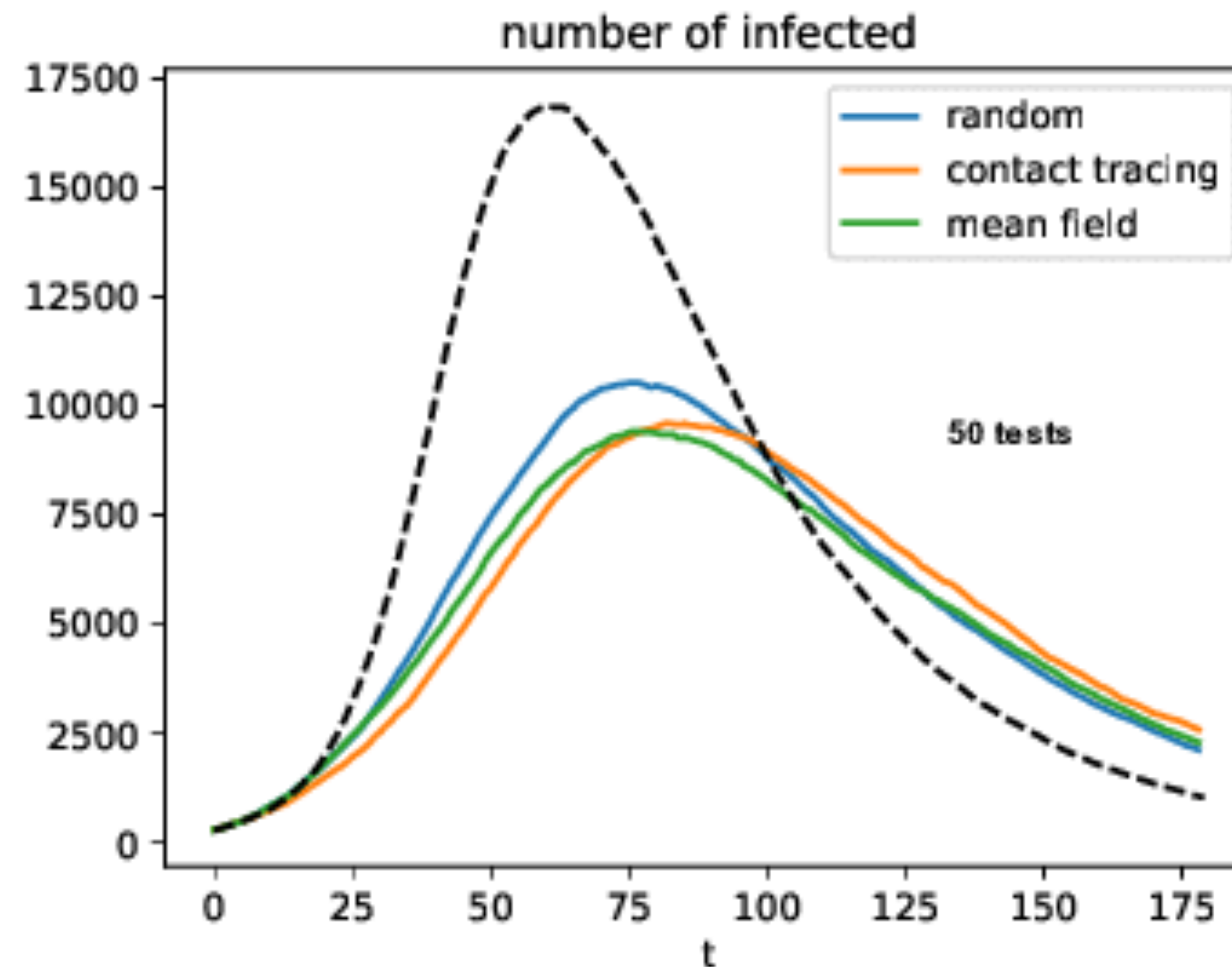


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EXPERIMENTS ON CONTROL OF EPIDEMIC



X tests a day + symptomatic

Contact graph from R. Hinch, . . . L. Ferretti, et al model. Population size= 50000; 11.3 contacts on average a day,
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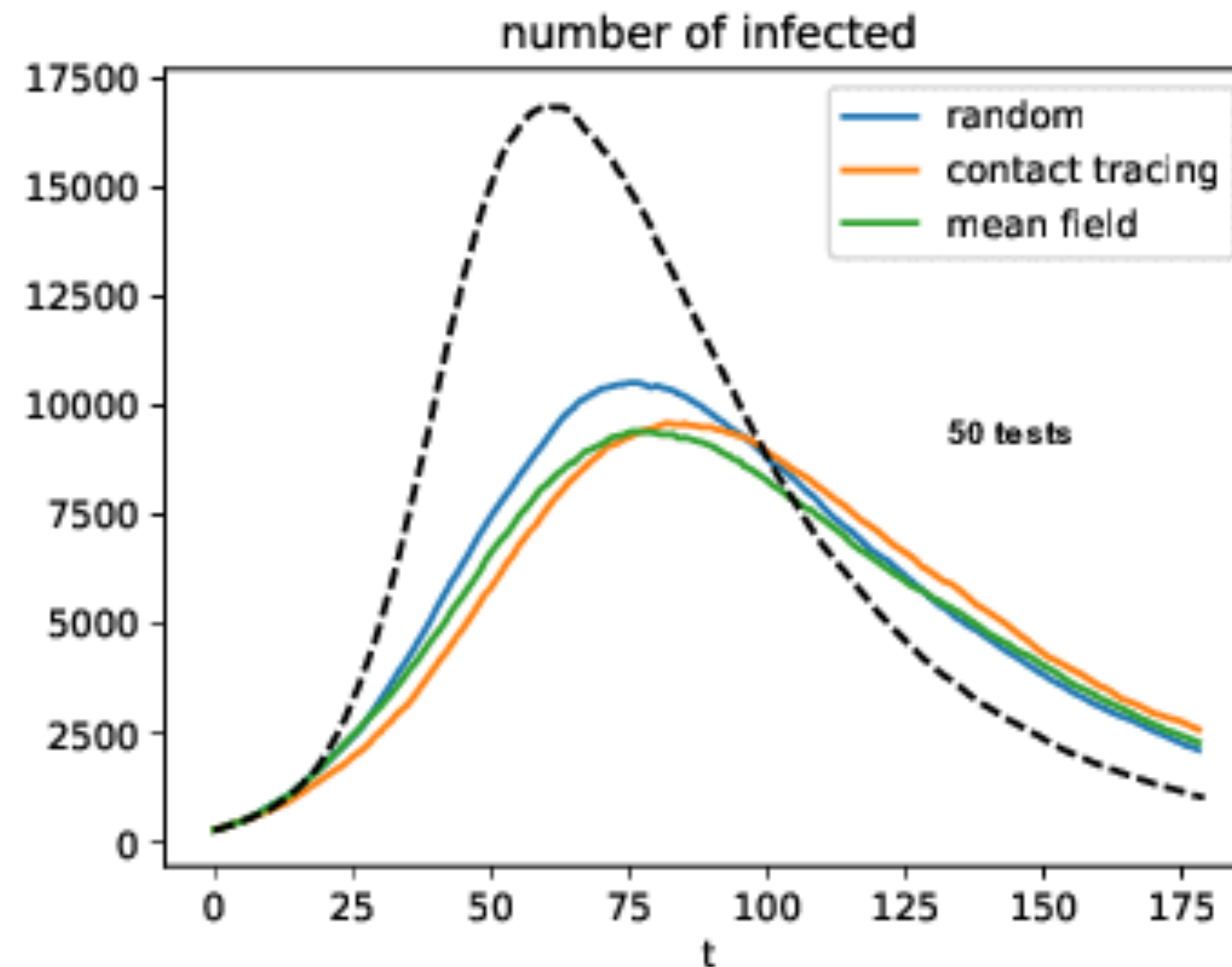


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ONGOING WORK:

- ▶ Epidemic control with BP SIPAR strategy of Braunstein et al.
- ▶ Explore the role of the various parameters.
- ▶ Larger networks, realistic epidemic spread ($<1\%$ infected, millions of nodes),
- ▶ Include more info from the simulator (age groups, households, details about syndromes, ...)
- ▶ Learn parameters with expectation maximisation from observed data.

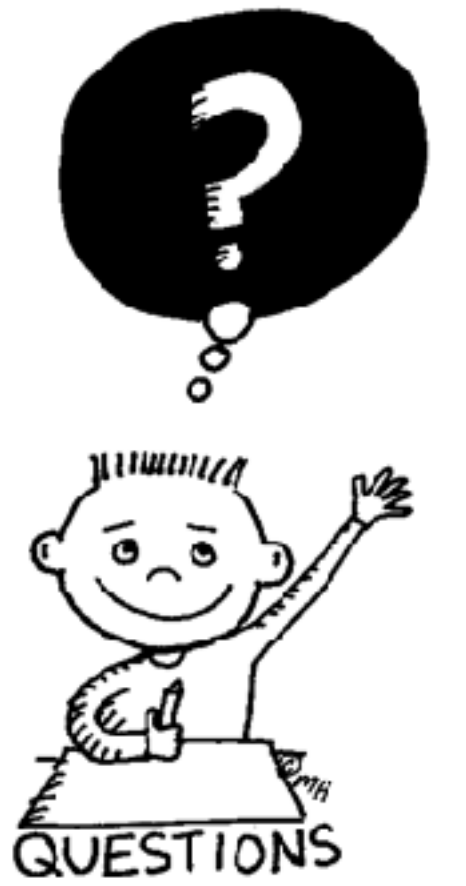
WHAT'S NEXT?

- ▶ Implementation respecting privacy constraints (limited bandwidth of communication, privacy consistent user identification, etc.)
- ▶ Learn a generative model with graph neural networks? In progress in MILA group. Max Welling's call-for-interest on Facebook.

Our progress can be followed at: https://github.com/sphinxteam/sir_inference/
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We are interested to collaborate.

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