



COVID-19 RISK ESTIMATION FROM CONTACT TRACING DATA

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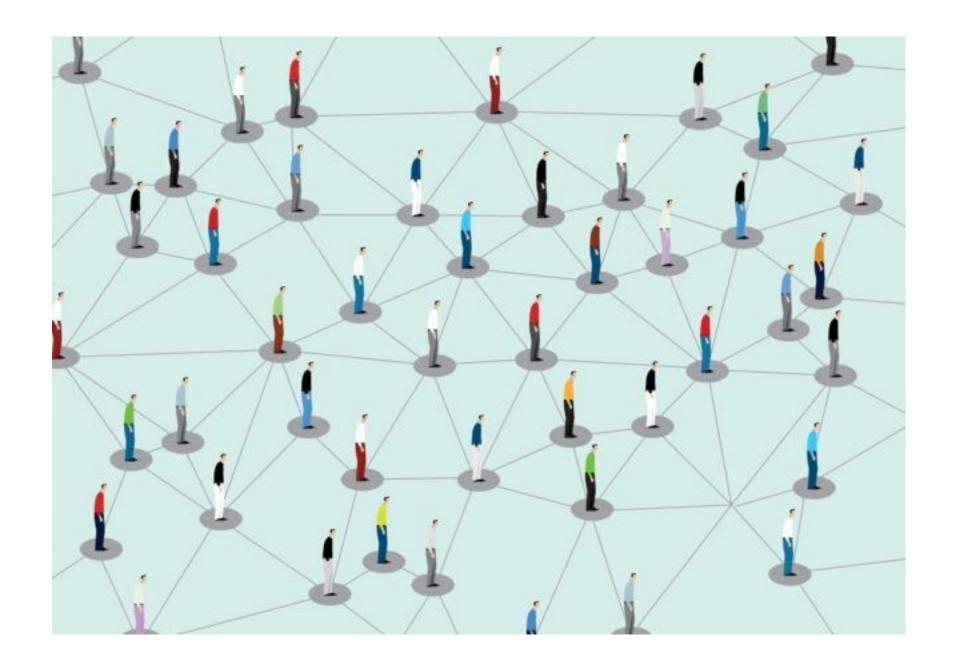
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HELP AND DISCUSSIONS FROM: YOSHUA BENGIO, IRINA RISH, OTHERS AT MILA, LUCA FERRETTI, IVAN BESTVINA



https://github.com/sphinxteam/sir_inference

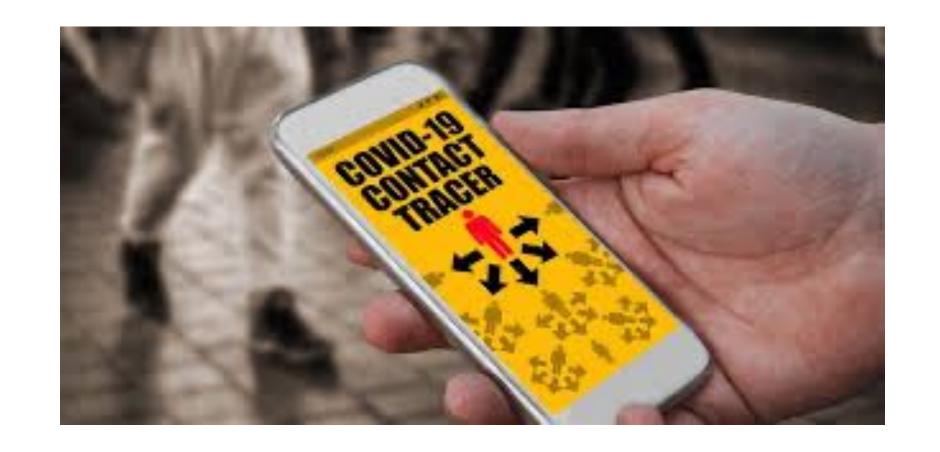
CONTACT TRACING DATA



- 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

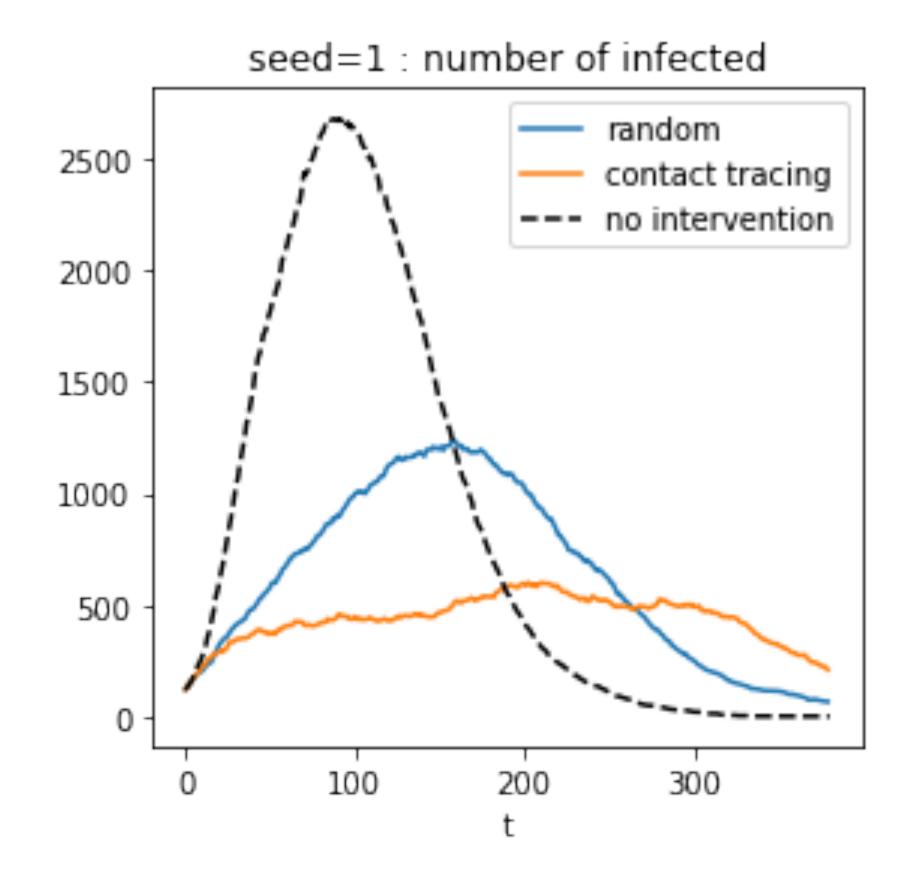


Contact tracing as implemented currently (Google & Apple, DP3T, etc.): Upon a positive test of an individual, his/her recent, sufficiently close, and long contacts are contacted and advised to be tested or to self-isolate.

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, λ =0.02, μ =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.





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/tfhcpbvhmcwq
- Dynamical message passing approach (Lokhov, Mézard, Ohta, LZ, PRE '14 & PRE '15)
 In the present context: https://www.overleaf.com/read/tfhcpbvhmcwq
- ▶ 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)
 - duals (S) Can be infected
 - Infected individuals (I)

- Can infect others
- Removed individuals (R)



Cannot spread or be infected



- $\lambda_{ij}(t)$ 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 $P_R^i(t)$

$$\begin{split} P_{S}^{i}(t+1) &= P_{S}^{i}(t) \left(1 - \sum_{j \in \partial i(t)} P_{I}^{j}(t) \lambda_{ij}(t)\right) \\ P_{R}^{i}(t+1) &= P_{R}^{i}(t) + \mu_{i} P_{I}^{i}(t) \\ P_{I}^{i}(t+1) &= P_{I}^{i}(t) + P_{S}^{i}(t) \sum_{j \in \partial i(t)} P_{I}^{j}(t) \lambda_{ij}(t) - \mu_{i} P_{I}^{i}(t) \end{split}$$

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 $\{P_S^i(0), P_I^i(0), P_R^i(0)\}$ + Parameters \longrightarrow $\{P_S^i(t), P_I^i(t), P_R^i(t)\}$

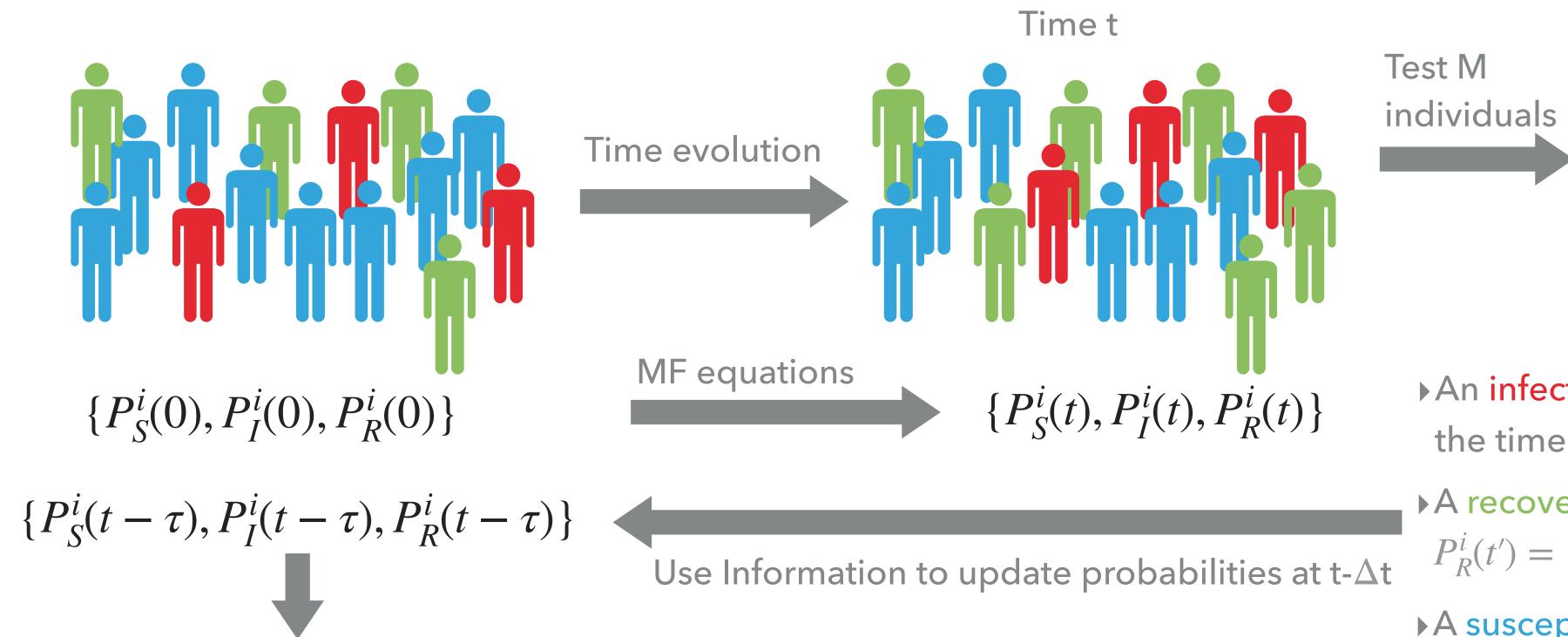


Needed: Use test results + symptoms to better estimate the probabilities





FEED BACK LOOP: USE TEST RESULTS



MF equations

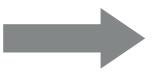
Test M individuals

Know if they are S, I or R

- An infected person has been infectious for the time τ : $P_I^i(t') = 1$ for $t \tau \le t' \le t$
- A recovered person cannot change state: $P_R^i(t') = 1 \text{for} t' \ge t$
- A susceptible individual has not yet been infected: $P_S^i(t') = 1$ for $t' \le t$

Repeat the process at every time step

 $\{P_S^i(t-\tau), P_I^i(t-\tau), P_R^i(t-\tau)\}$



Get better estimates of the

 $\{P_{S}^{i}(t), P_{I}^{i}(t), P_{R}^{i}(t)\}$

probabilities at time t

Final Inference

NB: Symptoms can be incorporated in this feedback loop analogously



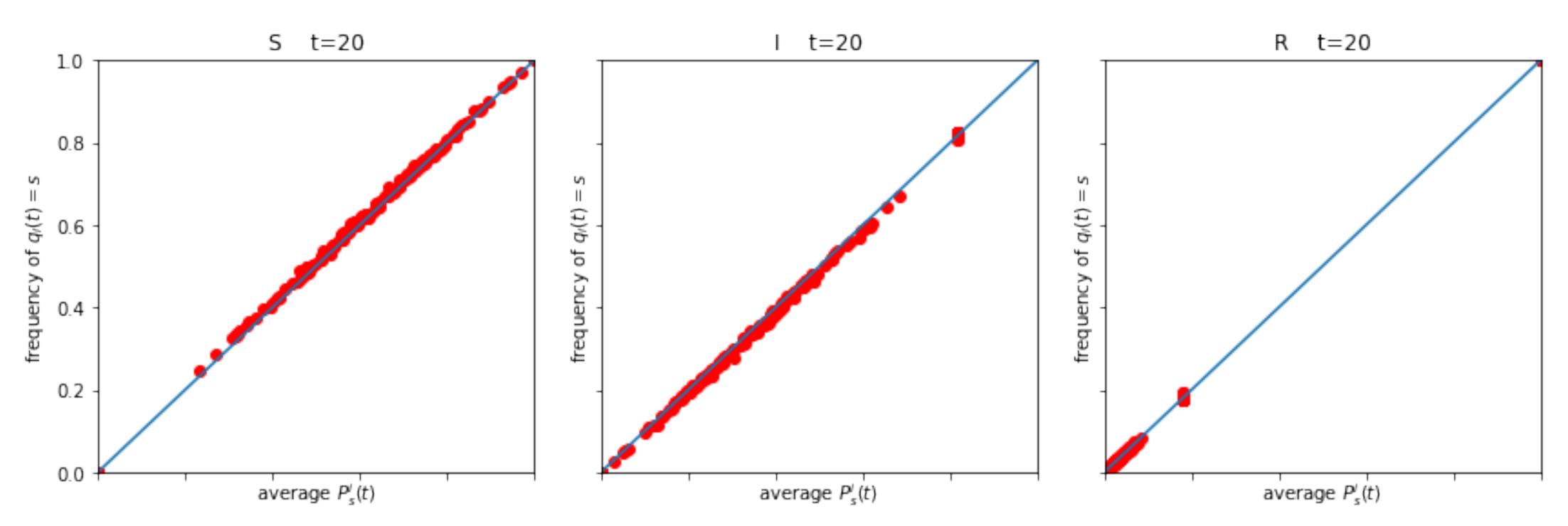
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PROBABILITY ESTIMATION WORKS

> 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.



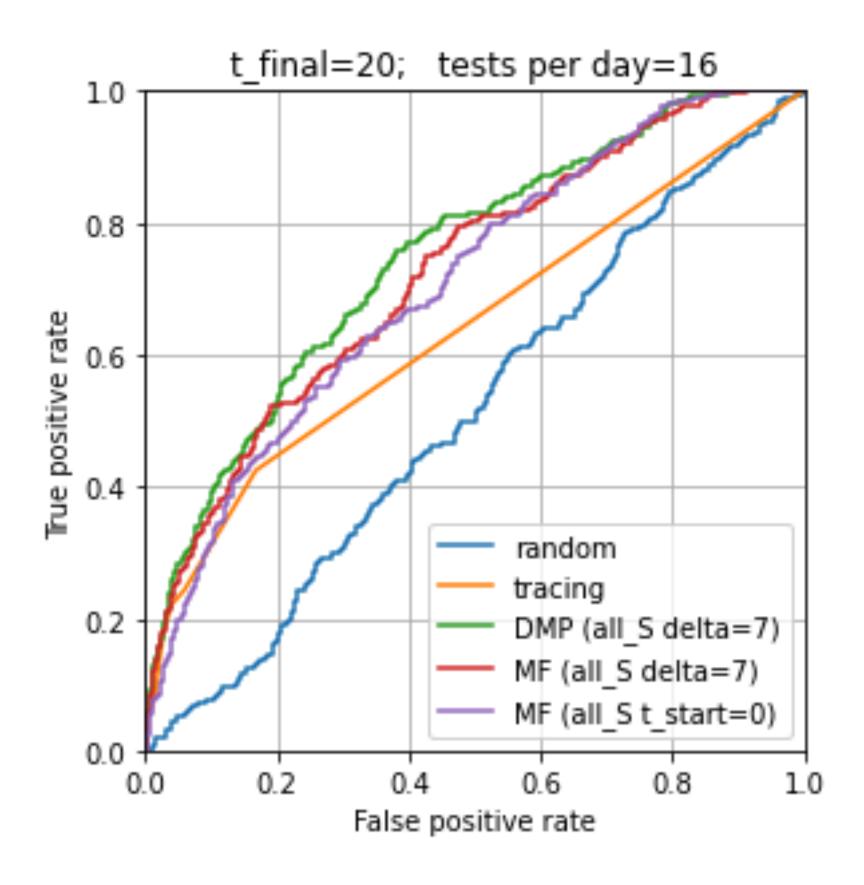
Random geometric graph. Population size= 500, λ =0.02 , μ =0.01 , 2% Infected Individuals at t=0





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: λ =0.02 , μ =0.07 , 10 Infected Individuals at t=0, τ =7

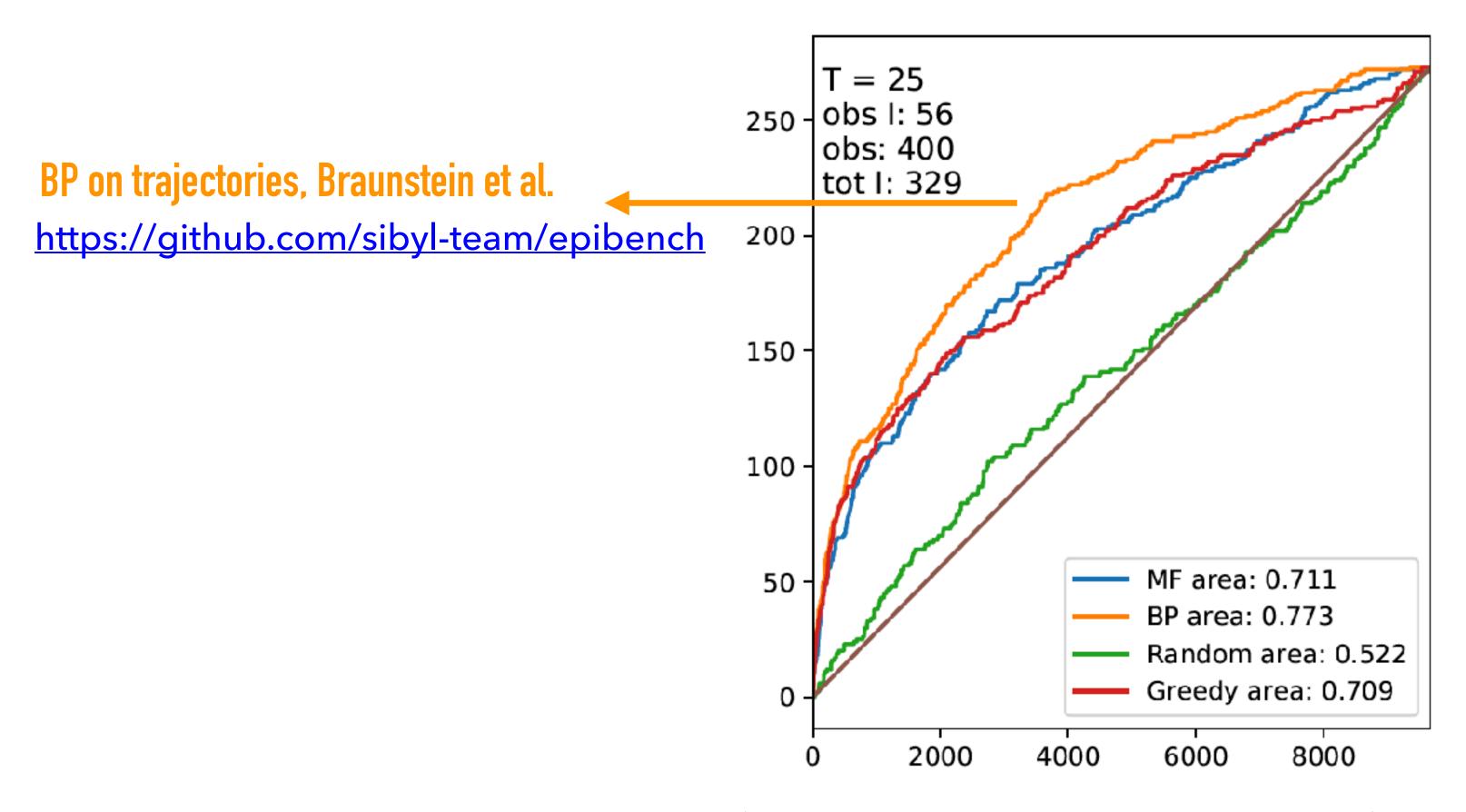




ROC CURVES (UNCONTROLLED EPIDEMIC, NO INTERVENTIONS)

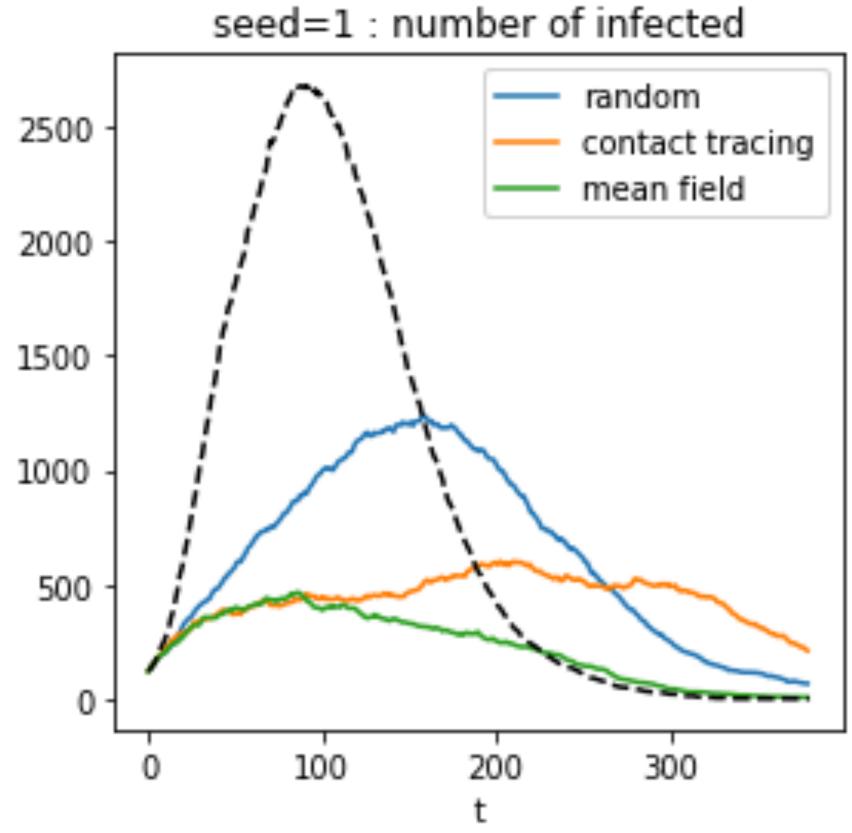
Contact graph provided by L. Ferretti & R. Hinch, Population size= 10000; 12.7 contacts on average a day,

Epidemic: Realistic uncontrolled epidemic spread from Hinch et al. report (λ ~ 0.04 , μ ~ 1/12)



MF inference with: λ =0.02 , μ =0.01 , τ =5, δ = 8 (note the mismatch in λ , μ after cross-validation)

EXPERIMENTS ON CONTROL OF EPIDEMIC

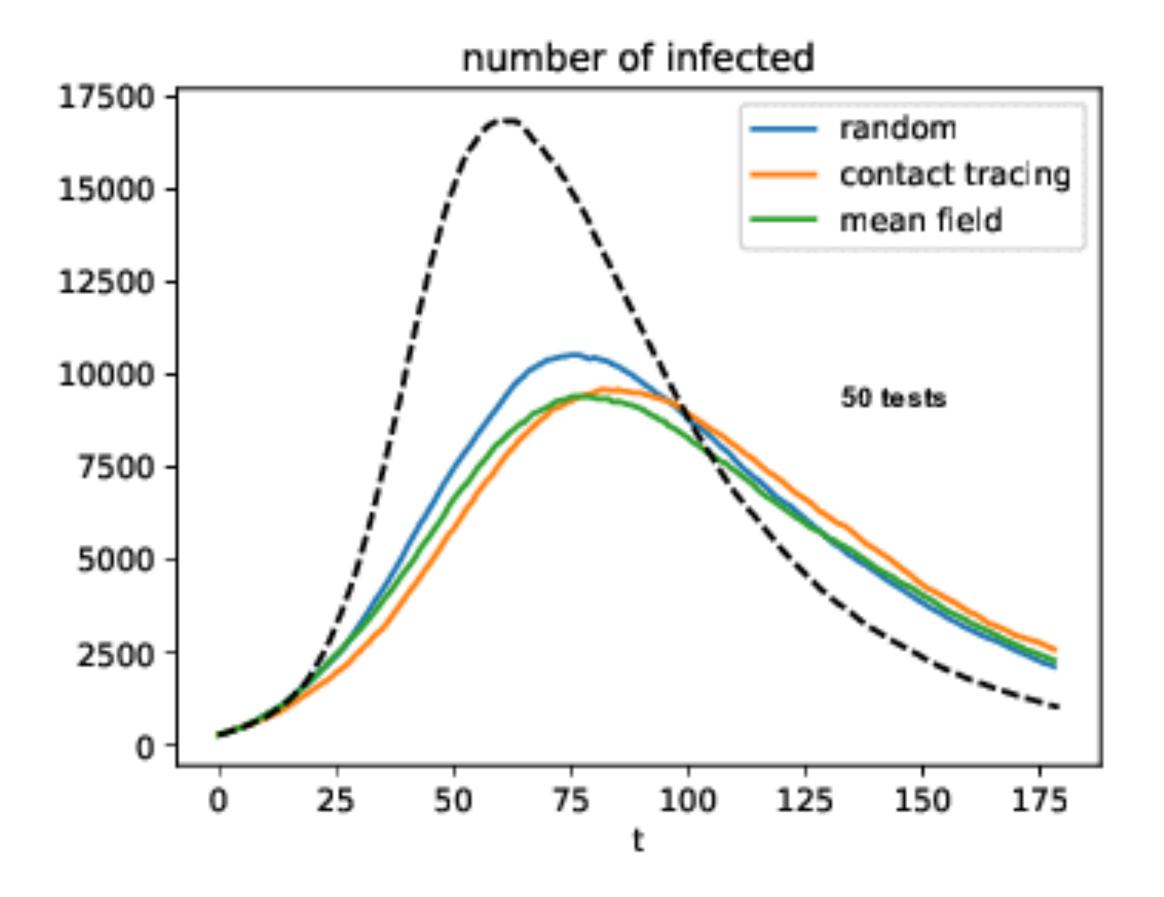


Random geometric contact graph in 2D, scale 1.1, daily on average 7.4 contacts. Population size= 10000, λ =0.02, μ =0.03. Initially 20 infected + 10 time steps of uncontrolled evolution, τ =5, δ =15. Tests: symptomatic = 1/2 of all infected, 1 at random, 7 among infected, and 21 from ranking, quarantine = 50 time steps,





EXPERIMENTS ON CONTROL OF EPIDEMIC



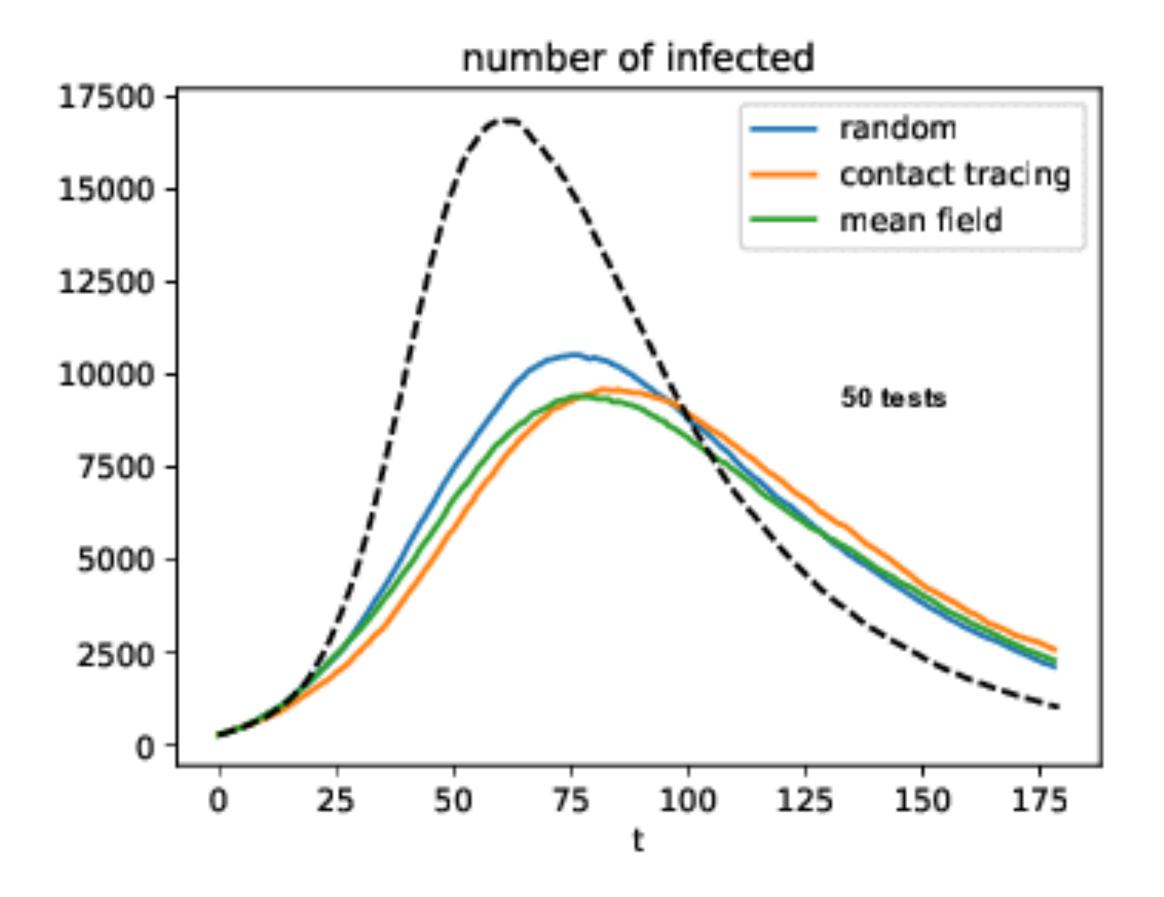
X tests a day + symptomatic

Contact graph from R. Hinch, ... L. Ferretti, et al model. Population size= 50000; 11.3 contacts on average a day, λ =0.01, μ =0.033. Initially 50 infected + 20 time steps of uncontrolled evolution, τ =5, δ =15. Tests: symptomatic = 1/2 of all infected, and X from ranking, quarantine = 50 time steps,





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, λ =0.01, μ =0.033. Initially 50 infected + 20 time steps of uncontrolled evolution, τ =5, δ =15. Tests: symptomatic = 1/2 of all infected, and X from ranking, quarantine = 50 time steps,





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/ with notes on the methods: https://www.overleaf.com/read/tfhcpbvhmcwq

We are interested to collaborate.

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