



Early-Warning Signals of COVID-19 using Proactive Contact Tracing (PCT)

CIFAR/ELLIS Workshop

Yoshua Bengio (Mila, Université de Montréal)

Prateek Gupta (Mila, University of Oxford, The Alan Turing Institute)

Nasim Rahaman (Mila, Max-Planck-Institute for Intelligent Systems Tübingen)

October 15th, 2020

Outline



- Motivation
- Comparison with existing methods
- Proactive Contact Tracing (PCT) framework
- Heuristic PCT - Rule based implementation of PCT
- Machine Learning enabled PCT

COVI (Source code coming soon...)

COVI White Paper - Version 1.0

Hannah Alsdurf¹, Yoshua Bengio^{2,3}, Tristan Deleu^{2,3}, Prateek Gupta^{2,4,5},
Daphne Ippolito⁶, Richard Janda⁷, Max Jarvie⁸, Tyler Kolody⁷,
Sekoul Krastev⁹, Tegan Maharaj^{2,3}, Robert Obryk, Dan Pilat⁹,
Valérie Pisano², Benjamin Prud'homme², Meng Qu,^{2,10} Nasim Rahaman^{2,11},
Irina Rish^{2,3}, Jean-François Rousseau¹², Abhinav Sharma⁷, Brooke Struck⁹,
Jian Tang^{2,10}, Martin Weiss^{2,3}, Yun William Yu¹³

Nanor Minoyan
Harnois-Leblanc Sören
Akshay Patel
Joanna Merckx
Andrew Williams

We would like to thank Sumukh Aithal, Behrouz Babaki, Henri Barbeau, Edmond Belliveau, Vincent Berenz, Olexa Bilaniuk, Amélie Bissonnette-Montminy, Pierre Boivin, Emélie Brunet, Joé Bussière, Gaétan Marceau Caron, René Cadieux, Pierre Luc Carrier, Hyunghoon Cho, Anthony Courchesne, Linda Dupuis, Justine Gauthier, Joumana Ghosn, Gauthier Gidel, Marc-Henri Gires, Simon Guist, Deborah Hinton, Bogdan Hlveca, Bernd Holznagel, Samuel Huberman, Shrey Jain, Jameson Jones-Doyle, Dilshan Kathiriarachchi, Giancarlo Kerg, Soundarya Krishnan, David Lazar, Frédéric Laurin, Sacha Leprêtre, Stéphane Létourneau, Libeo team, Alexandre Limoges, Danielle Langlois, Frédéric Laurin, Vincent Martineau, Lucas Mathieu, Philippe Matte, Rim Mohsen, Eilif Muller, Ermanno Napolitano, David Noreau, Ivan Oreshnikov, Satya Ortiz-Gagné, Jean-Claude Passy, Marie Pellat, Dan Popovici, Daniel Powell, Brad Rabin, Catherine Saine, Victor Schmidt, Shanya Sharma, Kareem Shehata, Pierre-Luc St-Charles, Marie-Claude Surprenant, Mélisande Teng, Julien Tremblay-Gravel, David Wu, and Lenka Zdeborova for their help.



<https://arxiv.org/abs/2005.08502>

ML/Epi/Econ Team



Yoshua Bengio



Hannah Alsdurf



Tristan Deleu



Abhinav Sharma



Prateek Gupta



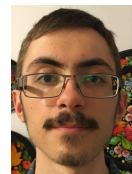
Soren
Harnois-Leblanc



Akshay Patel



Bernhard Schölkopf



Olexa Bilanuik



Tegan Maharaj



Joanna Merckx



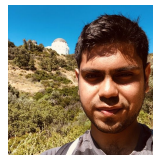
Nanoy Minoyan



Irina Rish



Meng Qu



Nasim Rahaman



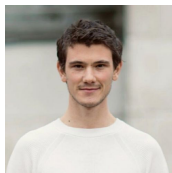
Christopher Pal



Pierre-Luc Carrier



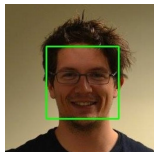
David Buckeridge



Victor Schmidt



Pierre-Luc St
Charles



Martin Weiss



Andrew Williams



Yang Zhang



Eilif B. Muller



Joumana Ghosn



Jian Tang



Gaétan Marceau Caron

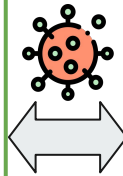
COVID -19 has posed a novel social planning problem

Health policy experts:

Min COVID-19 transmission (R_t)

S.t

- Keep society functioning
- Minimize deaths



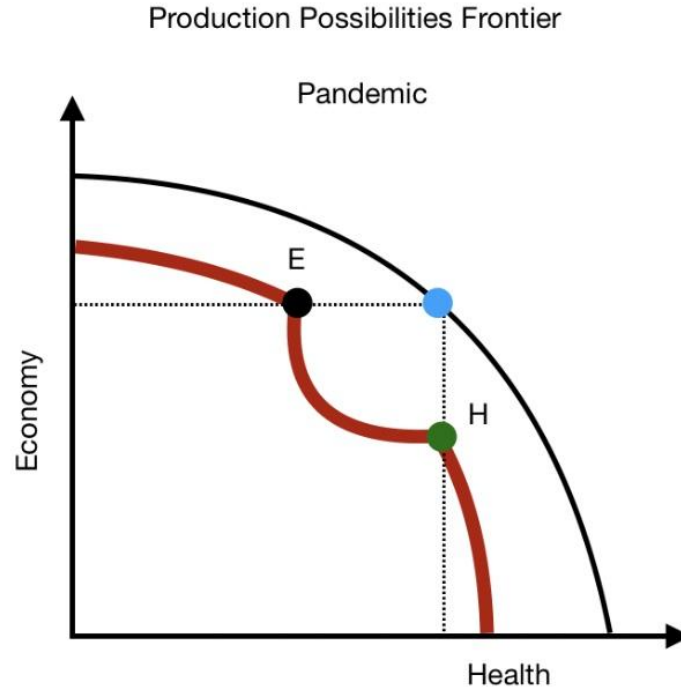
Economists:

Max Social Welfare

S.t

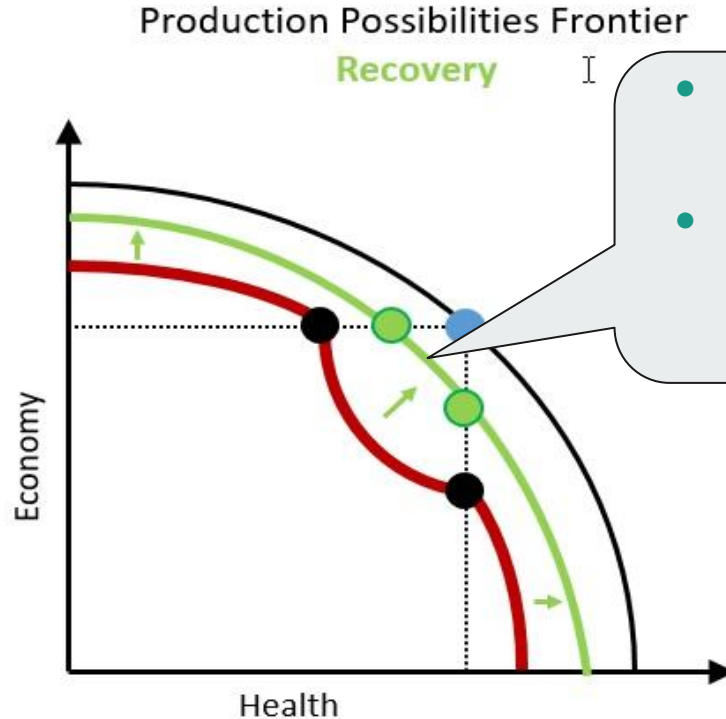
- Technological constraints
- Incentive constraints

Inefficient economic and health outcome following COVID



Source: Gans(2020), "Health Before Wealth: the Economic Logic", March 25, 2020
<https://blog.usejournal.com/health-before-wealth-the-economic-logic-9c5414ae259c>

How could we expand the frontier during the pandemic?



- **Public policies**
 - Public health policy
 - Monetary and fiscal policies
- **Health and technology advancement**
 - Vaccine development and health research
 - **Tracing and testing**



Optimizing policy coordination calls for advanced technology

What we observe...

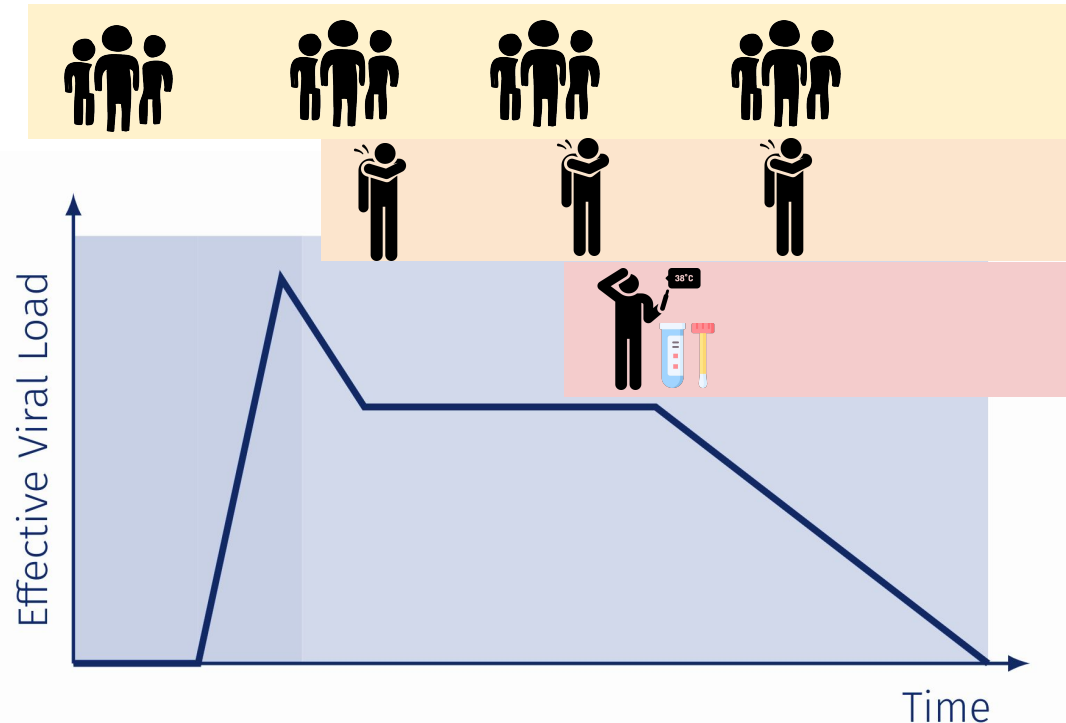
Contacts

Symptoms

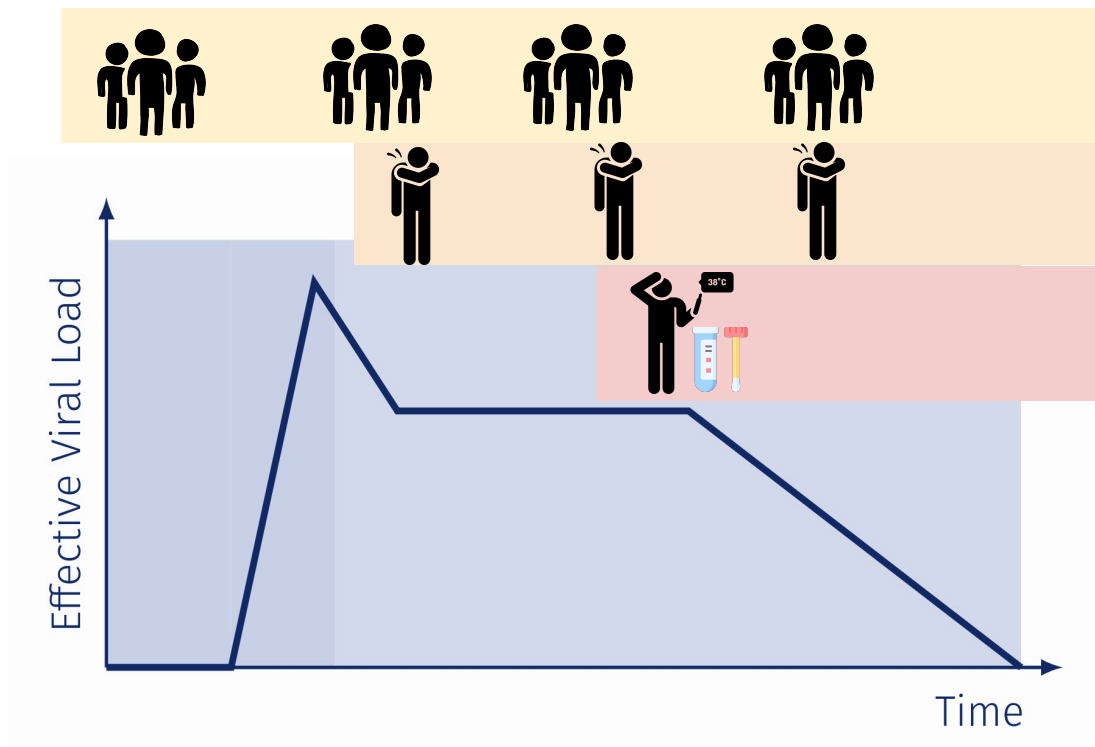
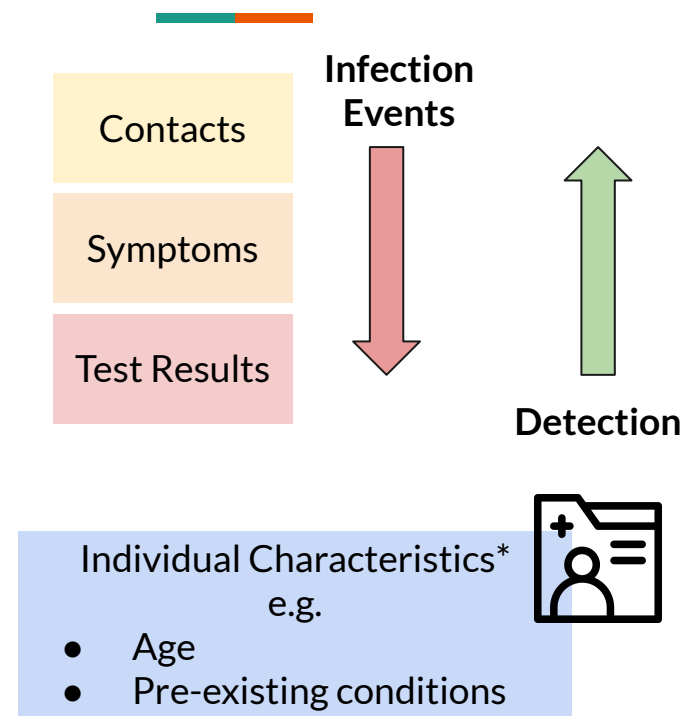
Test Results

Individual Characteristics*
e.g.

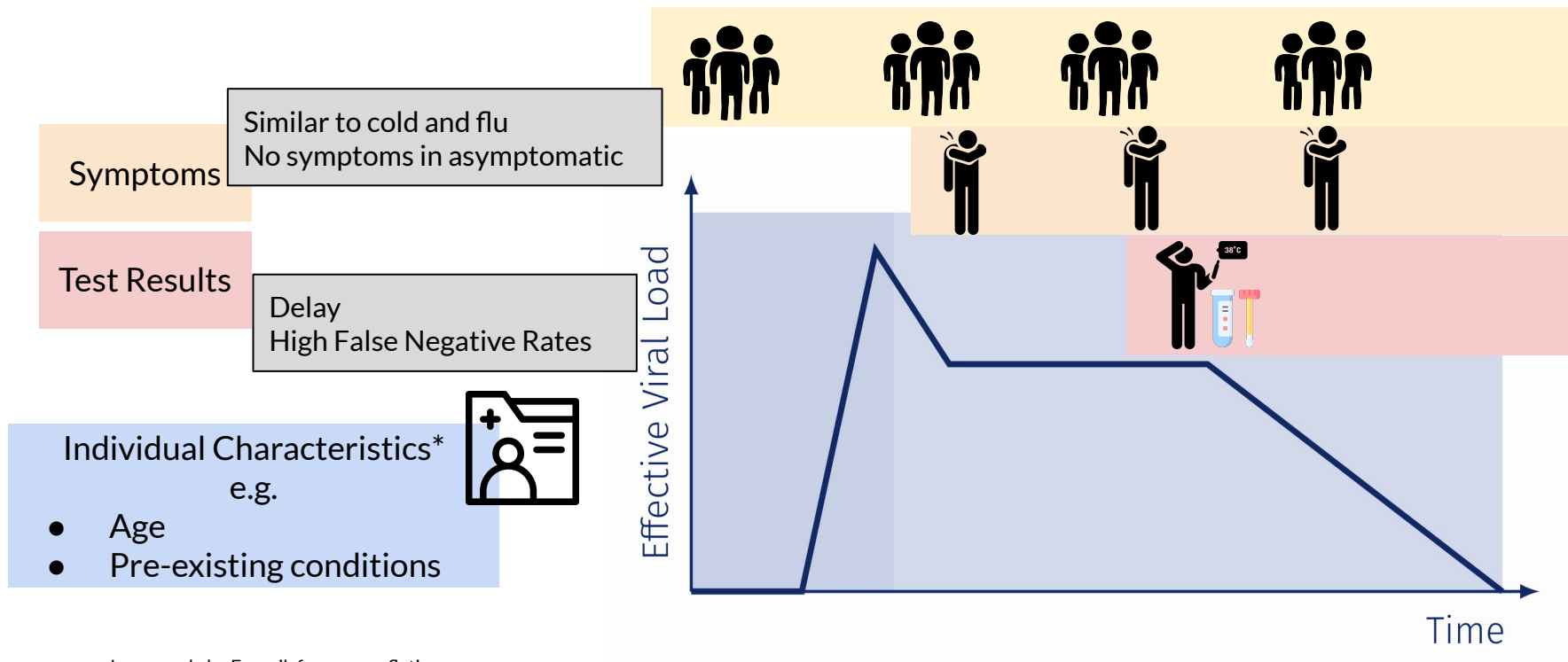
- Age
- Pre-existing conditions






Contact Tracing













Many noisy signals...









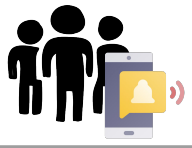








Landscape of tracing methods

	 Manual Tracing	Binary Contact Tracing (BCT) 	Proactive Contact Tracing (PCT) 
Potential Contacts			
Clues Used			
Recommendations			







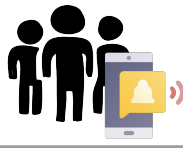

















Manual Tracing is subject to memory challenges

	 Manual Tracing	Binary Contact Tracing (BCT) 	Proactive Contact Tracing (PCT) 
Potential Contacts	 		
Clues Used	  		
Recommendations	 		

BDT provides precise contacts info, yet lacking some individual clues

	 Manual Tracing	Binary Contact Tracing (BCT) 	Proactive Contact Tracing (PCT) 
Potential Contacts	 	 	
Clues Used	  		
Recommendations	 	 	

COVI encompasses BDT and profits from richer info

	 Manual Tracing	Binary Contact Tracing (BCT) 	Proactive Contact Tracing (PCT) 
Potential Contacts	 	 	 
Clues Used	  		   
Recommendations	 	 	  

Example Scenario: Better Early Warning Signals



	M	T	W	T	F	S	S	M	T	W	T	F	S	S
Manual tracing only			Jim has a contact with high-risk stranger at the grocery store		Stranger starts showing symptoms		Stranger's symptoms grow worse	Jim GOES to work	Stranger sees doctor, gets tested	Test result comes back positive			Jim is contacted directly by public health	
Binary contact tracing	Jim installs the app		Jim has a contact with high-risk stranger at the grocery store		Stranger starts showing symptoms		Stranger's symptoms grow worse	Jim GOES to work	Stranger sees doctor, gets tested	Test result comes back positive			Jim is contacted directly by public health	
Our approach	Jim installs the app		Jim has a contact with high-risk stranger at the grocery store		Stranger starts showing symptoms		Stranger's symptoms grow worse	Jim DOES NOT go to work	Stranger sees doctor, gets tested	Test result comes back positive			Jim is contacted directly by public health	

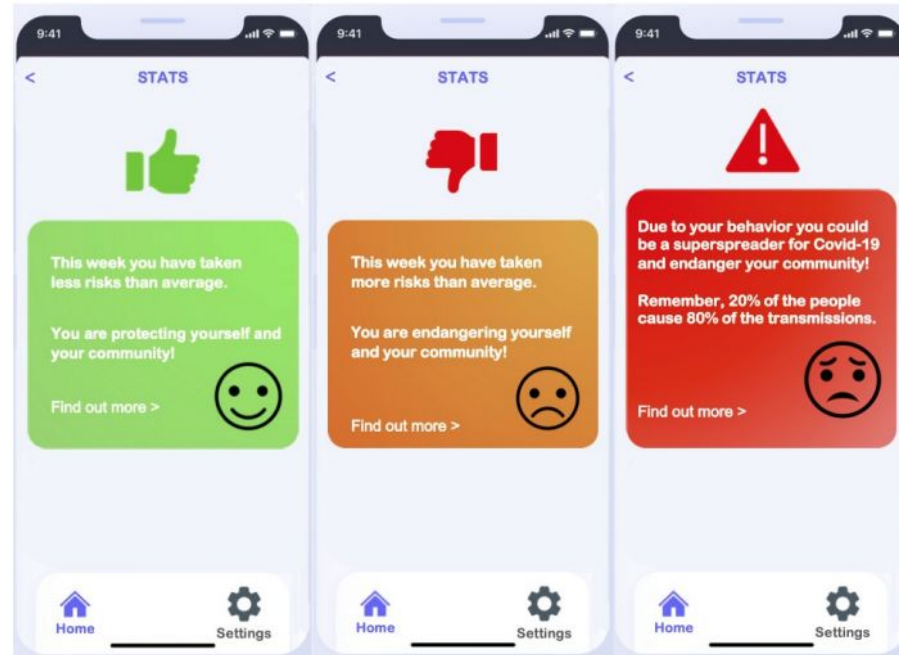
Effectiveness of In-app notifications

How to Make COVID-19 Contact Tracing Apps work: Insights
From Behavioral Economics

Ian Ayres,¹ Alessandro Romano^{1, 2}, Chiara Sotis,³

¹ Yale Law School, ² Bocconi Law School, ³ London School of Economics and Political Science

A recent user-behavior research
(Ayres, Ian, et al. 2020) suggests that
**users respond positively to the
notifications from CT apps.**



Proactive Contact Tracing (PCT): Framework



Predict **today's and past contagiousness** using all the clues

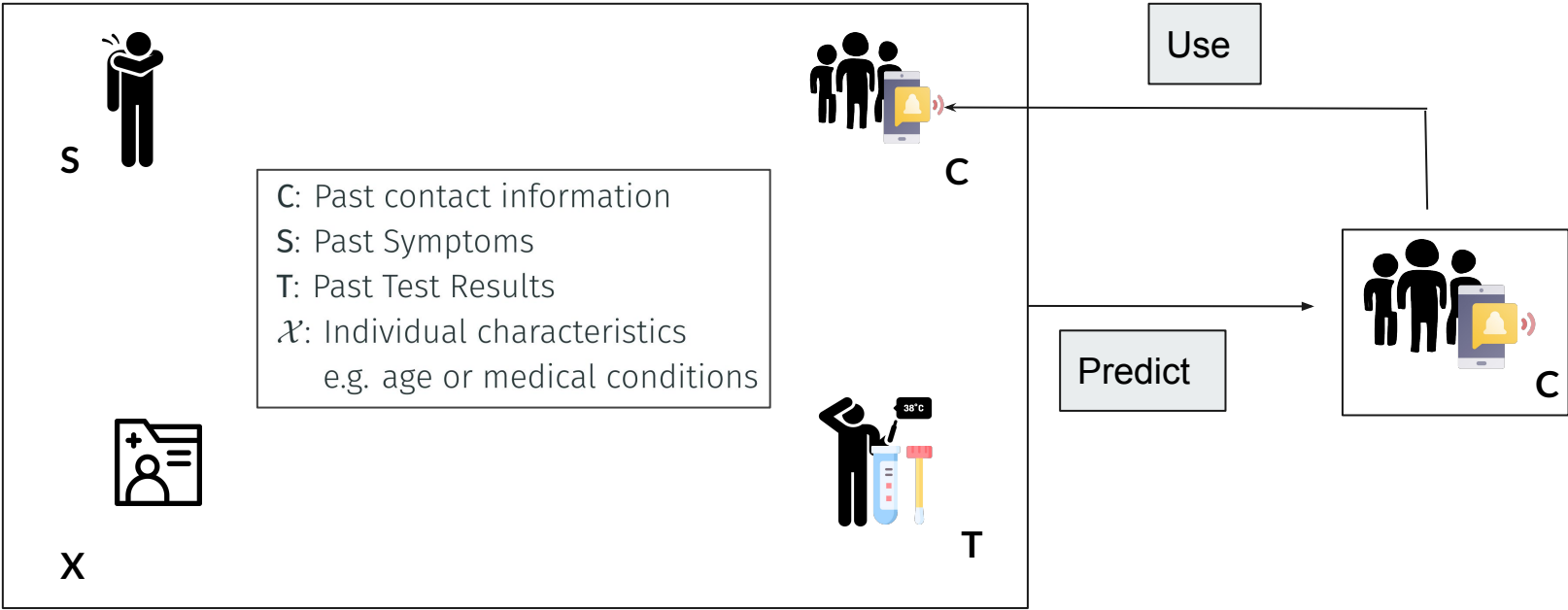


Send **secure messages** to previous contacts



Recommend **user behavior** based on **assessed risk levels**
E.g. normal (green), wear mask/self-isolate (blue), quarantine (red)

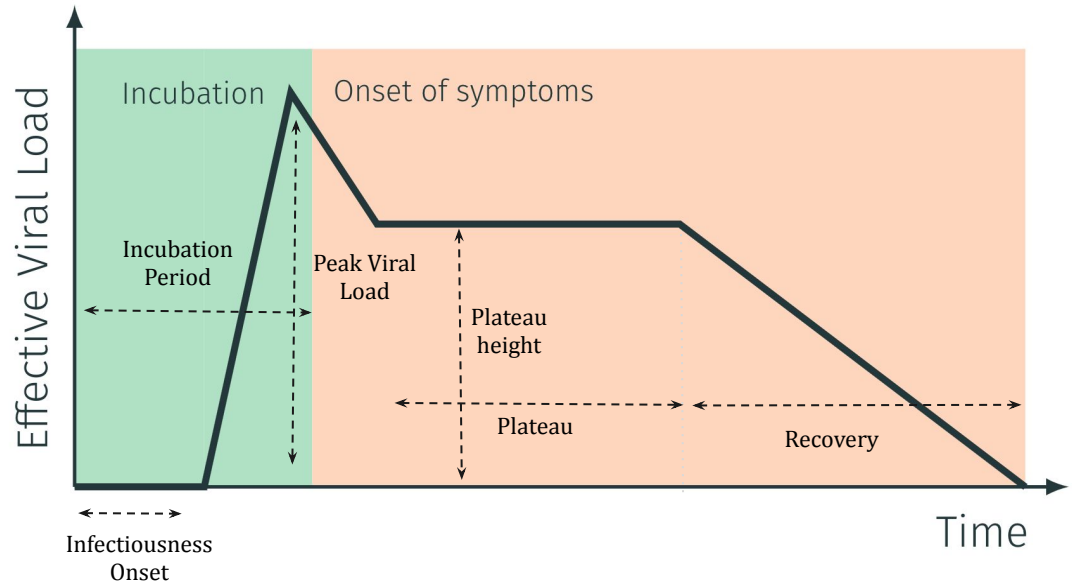
Clues used by PCT



Viral Load Curve

χ Individual Characteristics

$\nu(t)$ Functional form of Effective Viral Load (Contagiousness)
(To, Kelvin Kai-Wang, et al., 2020)



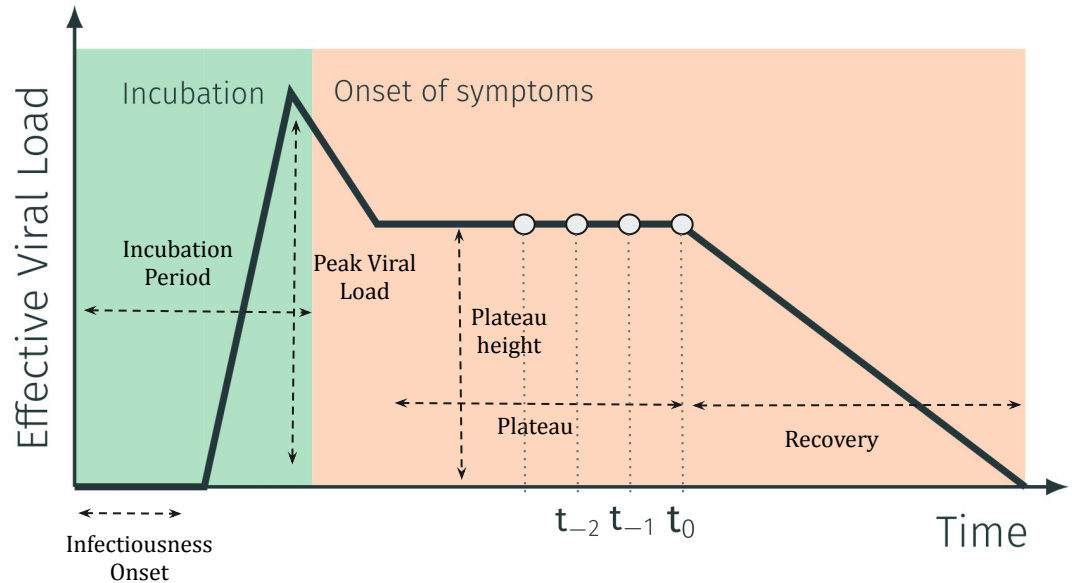
Viral Load Curve

χ Individual Characteristics

$\nu(t)$ Functional form of Effective Viral Load (Contagiousness)

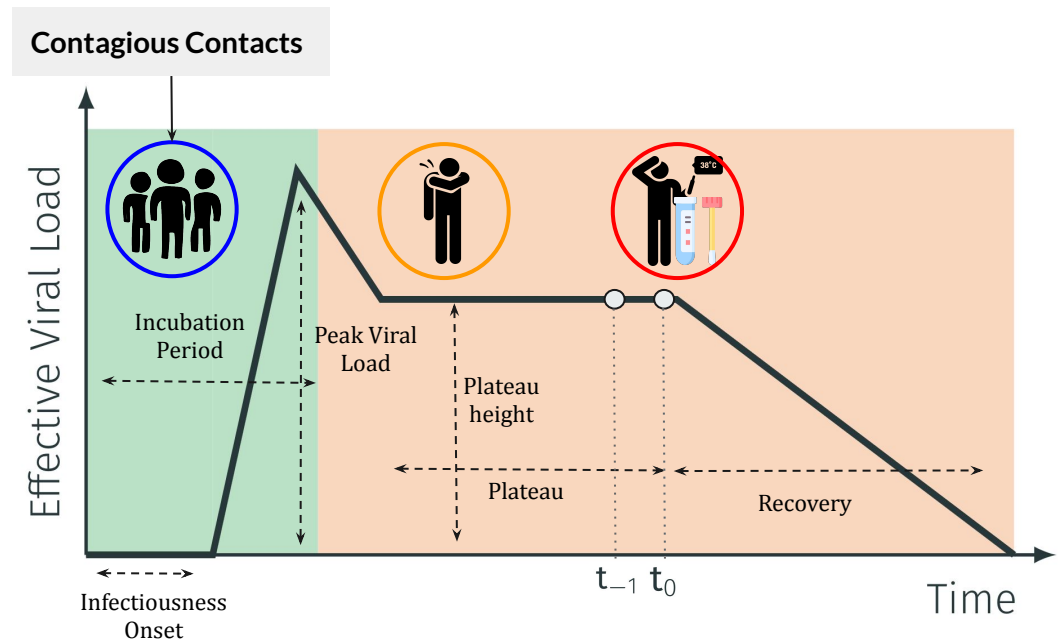
For simplicity, we consider Effective Viral Load for each day in the past 14 days -

$\nu(t_{-14}, t_{-13}, \dots, t_0)$



How simulated Viral Load Curve produces observables

$$\mathcal{V}(t) = f(\text{Contacts}, \mathcal{X})$$
$$\text{Symptoms}(t) = f(\mathcal{V}(t), \mathcal{X})$$
$$\text{TestResults} = f(\mathcal{V}, \text{Symptoms}, \mathcal{X})$$
$$\text{Contacts} = f(\mathcal{V}, \text{Symptoms}, \text{TestResults}, \mathcal{X})$$



What to predict?

$$\mathcal{V}(t) = f(\text{Contacts}, \mathcal{X})$$

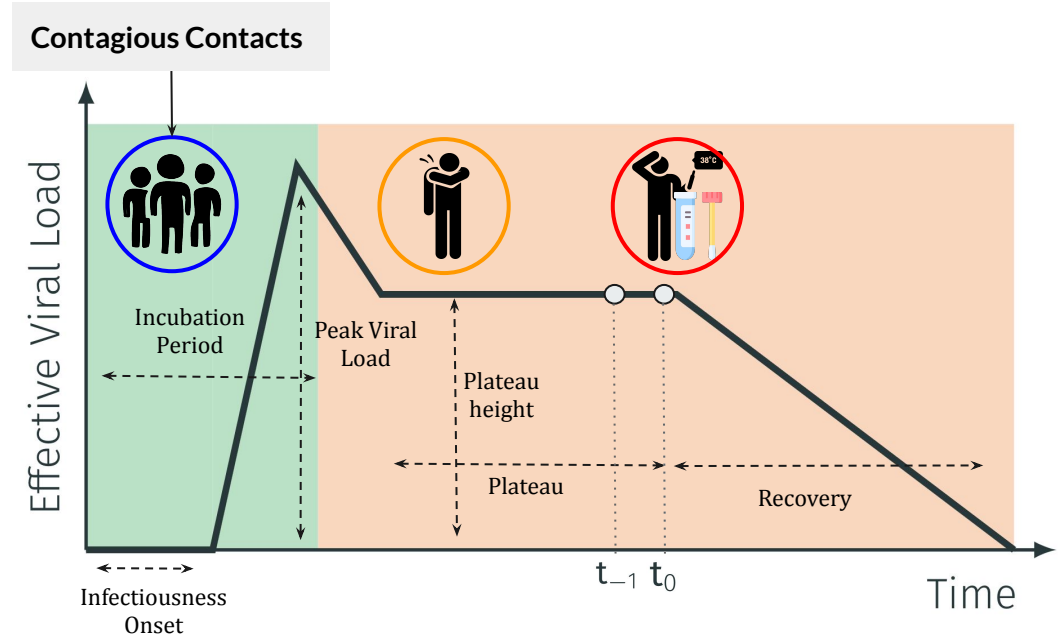
$$\text{Symptoms}(t) = f(\mathcal{V}(t), \mathcal{X})$$

$$\text{TestResults} = f(\mathcal{V}, \text{Symptoms}, \mathcal{X})$$

$$\text{Contacts} = f(\mathcal{V}, \text{Symptoms}, \text{TestResults}, \mathcal{X})$$

Predict Effective Viral Load as the clues are observed

$$\hat{\mathcal{V}}(t_{-14}, t_{-13}, \dots, t_0) = g(\mathcal{C}, \mathcal{S}, \mathcal{T}, \mathcal{X})$$



PCT: Predict - Inform - Advice

C: Past contact information

S: Past Symptoms

T: Past Test Results

\mathcal{X} : Individual characteristics
e.g. age or medical conditions



Predict **today's and past contagiousness** using all the clues i.e.

$$\hat{v}(t_{-14}, t_{-13}, \dots, t_0) = g(C, S, T, \mathcal{X})$$



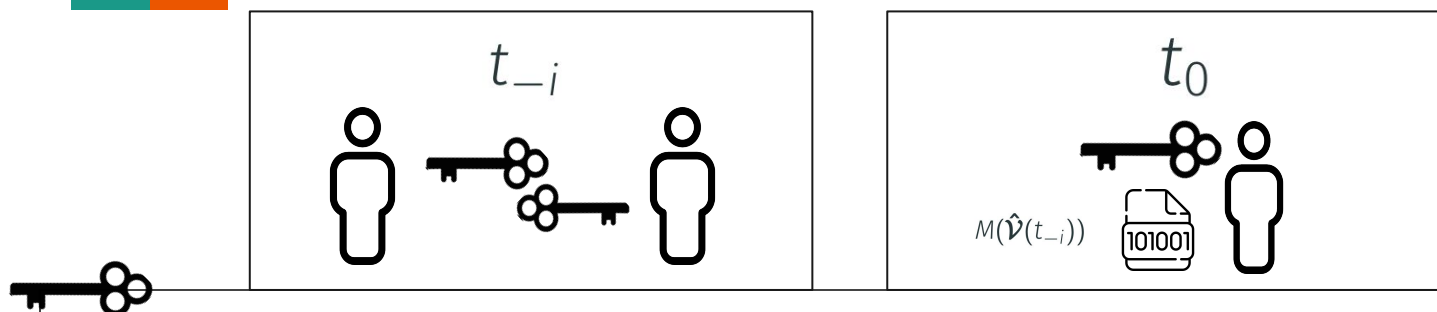
Send $\hat{v}(t_{-i})$ to the contacts on day t_{-i}

Add it to C of the **contact** and repeat



Use \hat{v} to **recommend user behavior**
e.g. quarantine, wear mask, self-isolate, etc.

Privacy-Preserving PCT



- A **unique key** is exchanged for every 15 minutes two apps are in proximity of 2 meters
- **Only N bits** can be sent via any key
 - **Risk Levels (R):** Quantize $\hat{v}(t_{-i})$ to an integer using the map **M**
 $M : \mathcal{R} \rightarrow \{1, 2, 3, \dots, 2^N\}$ $R(t_{-i}) = M(\hat{v}(t_{-i}))$
 - Simulation uses **N = 4**
 - Digital Binary Tracing (GoC), $N=1$ i.e only 0 or 1 is sent.
- **Send $R(t_{-i})$ only when it's different from the previously predicted risk level on t_{-i}**

- ❖ Detailed discussion of privacy considerations in Alsdurf, Hannah, et al 2020.
- ❖ WIP - Sensitivity analysis on N bits

Privacy-Preserving PCT

C: Past contact information
S: Past Symptoms
T: Past Test Results
 \mathcal{X} : Individual characteristics
e.g. age or medical conditions



Predict **today's and past contagiousness** using all the clues i.e.

$$\hat{v}(t_{-14}, t_{-13}, \dots, t_0) = g(C, S, T, \mathcal{X})$$



Send $R(t_{-i})$ to the contacts on day t_{-i}

Add it to C of the **contact** and repeat



Use \hat{v} to **recommend user behavior**
e.g. quarantine, wear mask, self-isolate, etc.

Heuristic PCT Supports Mobility of Individuals

Set Risk Levels

$$R(t_{-14}, t_{-13}, \dots, t_0) = g_{Heuristic}(C, S, T)$$

T - If the user reports a **positive test result** set **R = 4** for the past 14 days



S - Depending on the **severity of reported symptom**, set **R** as

- 1. Severe** symptoms: Set **R=3** for the past 7 days
- 2. Moderate** symptoms: Set **R = 2** for the past 7 days
- 3. Mild** symptoms: Set **R = 1** for the past 7 days



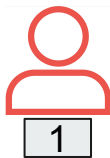
C - Break down all **received risk levels R'** into three categories

- 1. High** ($R' = 4$) : Set **R =3** until the day of receipt of R'
- 2. Medium** ($R' = 3$): Set **R = 2** until the day of receipt of R'
- 3. Mild** ($R' \leq 2$) : Set **R = 1** until the day of receipt of R'



T + C1.
yields **BCT**

User Recommendations

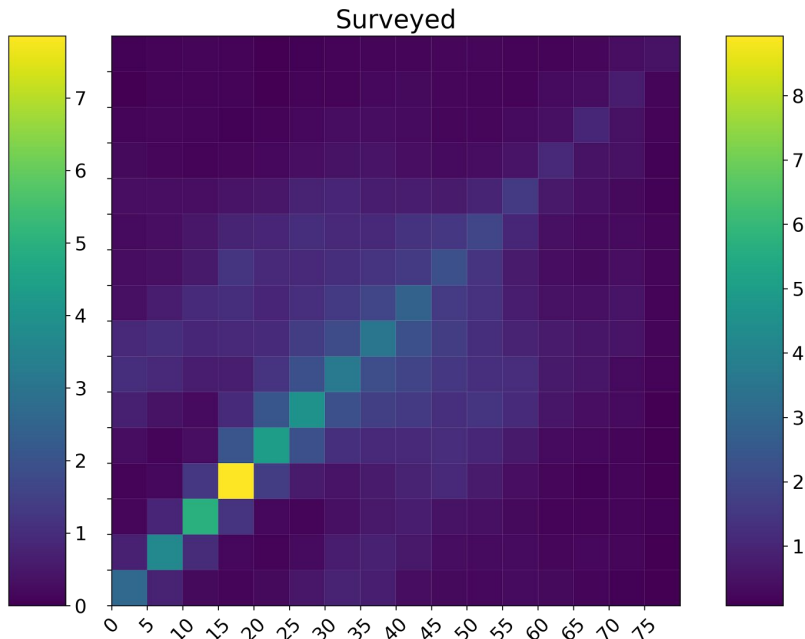
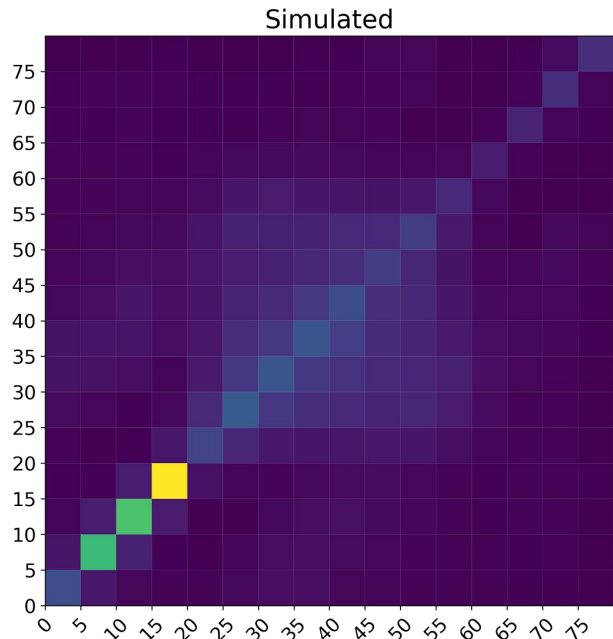


Finally, take the max of risk levels on each day obtained from above computation

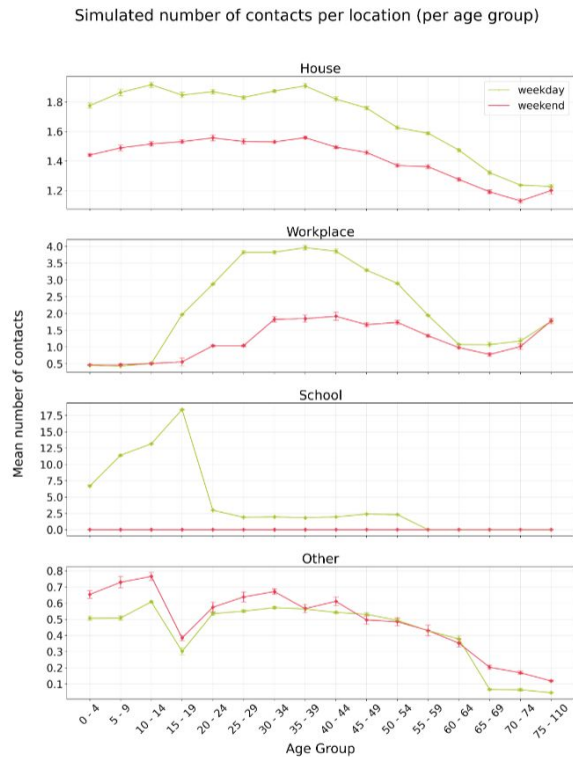
Simulator: Age-stratified contact patterns



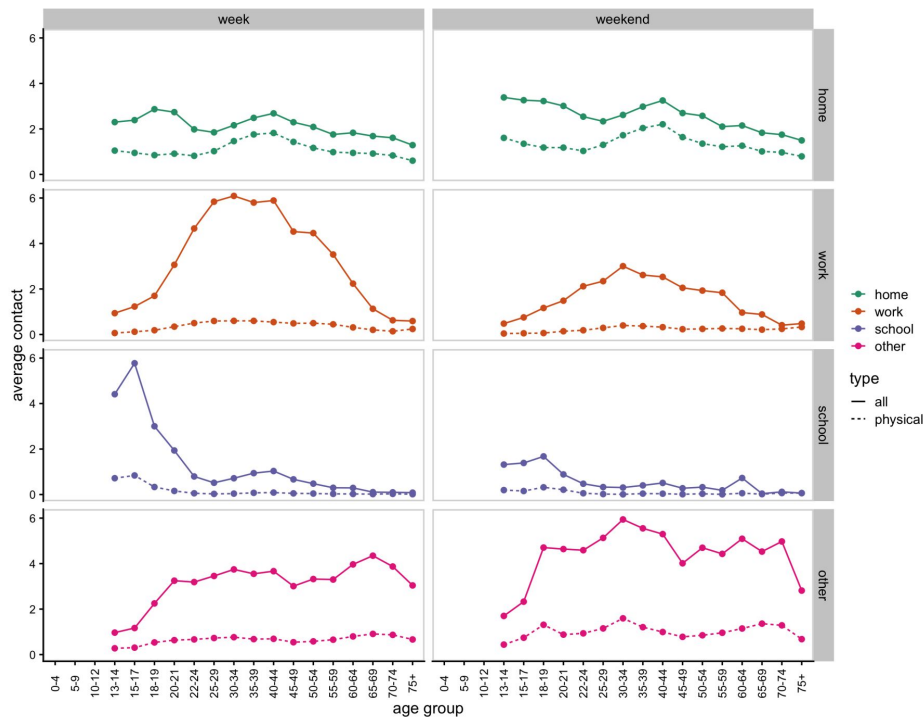
Contact Matrices for All



Simulator: Location dependent contact patterns



Surveyed contacts (UK)

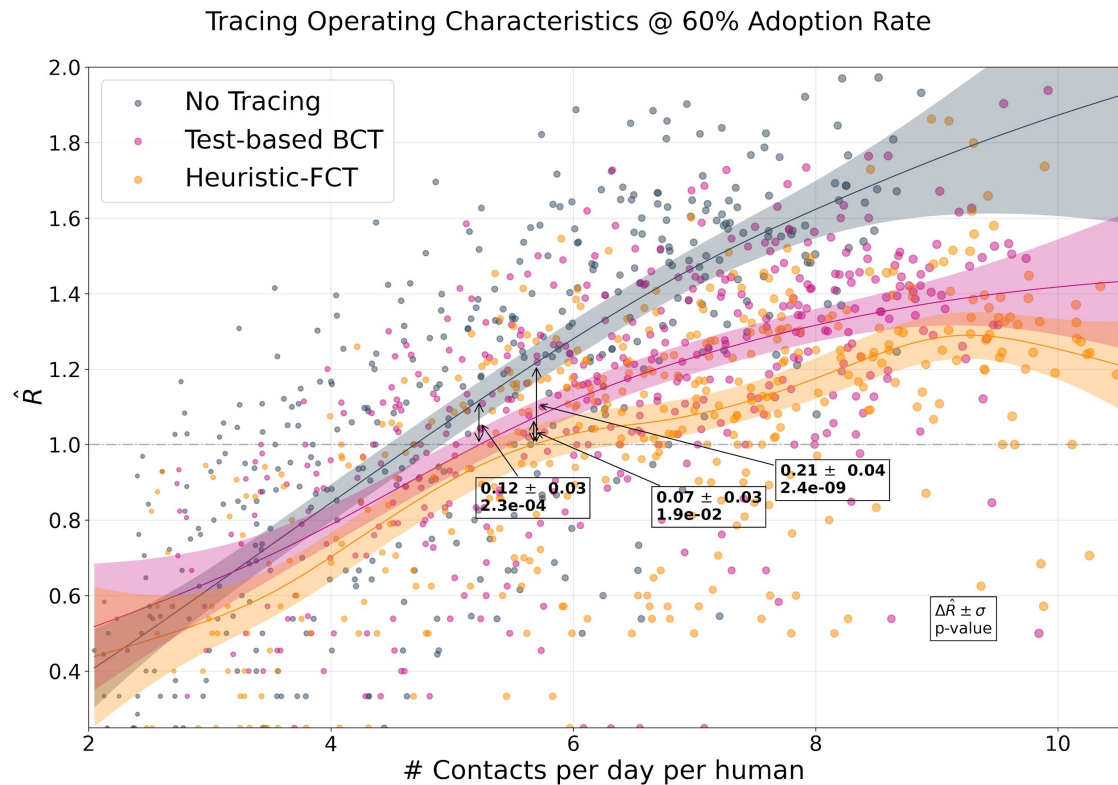


Simulations



- **Population size:** 3000
- Initial number of infected individuals: 6 (0.2% of the population)
- **25% Asymptomatic population**
- **Number of tests per day** = 3 (0.1% of the population)
- Behavior Modifications -
 - **High Risk Agents** have 0 contacts (Quarantine)
 - **Medium-High Risk Agents** have contacts according to post-lockdown (Brisson et al. 2020)
 - **Medium Risk Agents** have half the contacts as Medium-High Risk Agents
 - **Low Risk Agents** have half the contacts as Medium Risk Agents
- **Adherence to recommendations** is modeled via dropout of 0.02 probability of following the recommendations
- **Quality of self-diagnosis** is modeled via dropout on symptoms of 0.2 i.e a user is 20% likely to not report their specific symptoms
- More details about the simulator and heuristic algorithm in Gupta et al. (2020)

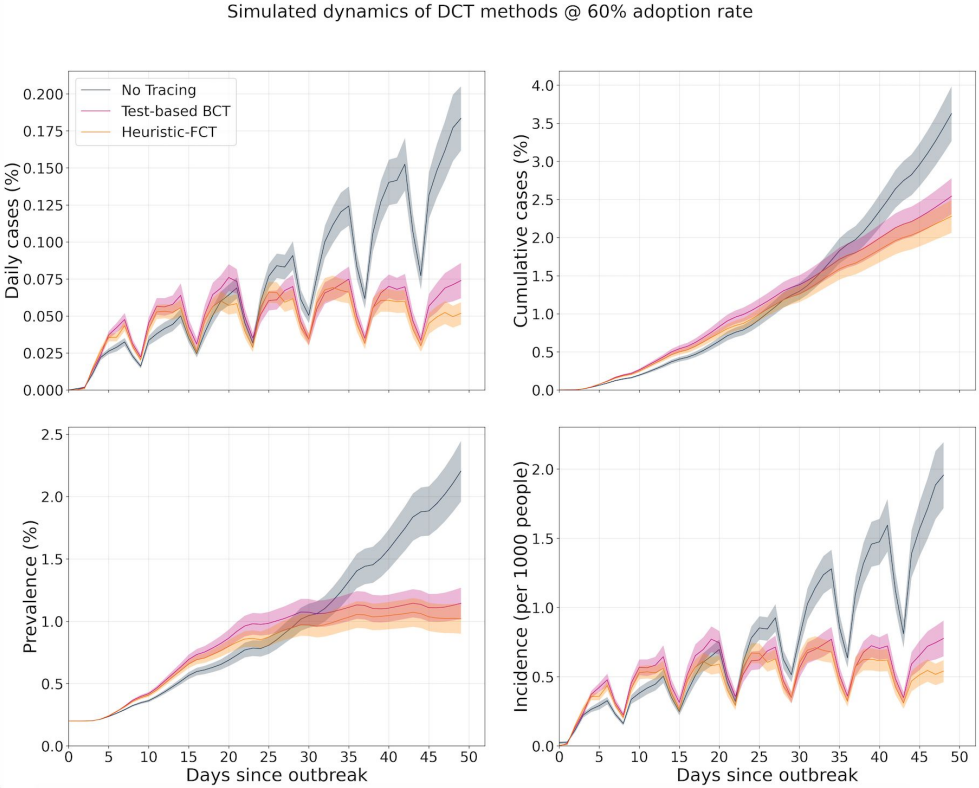
Simulation Results: Mobility vs Virus Transmission (R)



Simulation Results: Improved Case Curves Under Heuristic-PCT



Daily cases

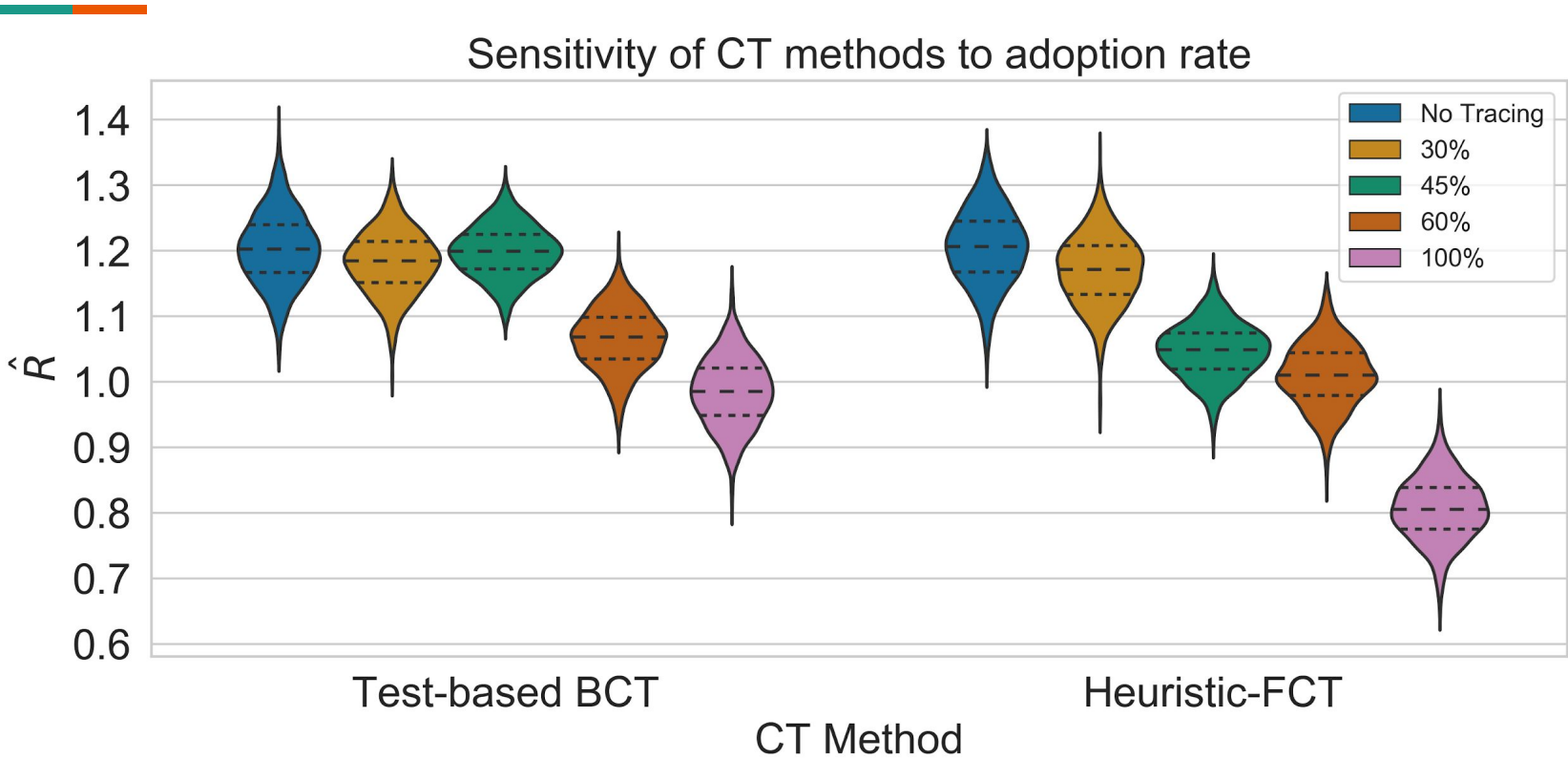


Fraction of infected population up to date

Fraction of population infected at any point in time

Average risk of infection

Simulation Results: Adoption rate sensitivity

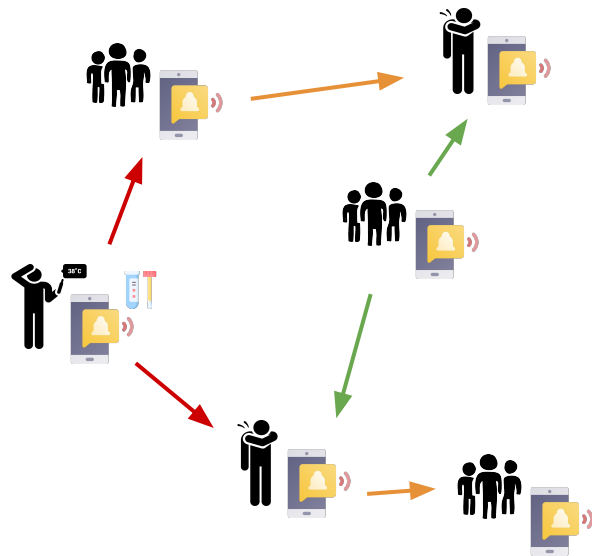


Why Machine Learning?

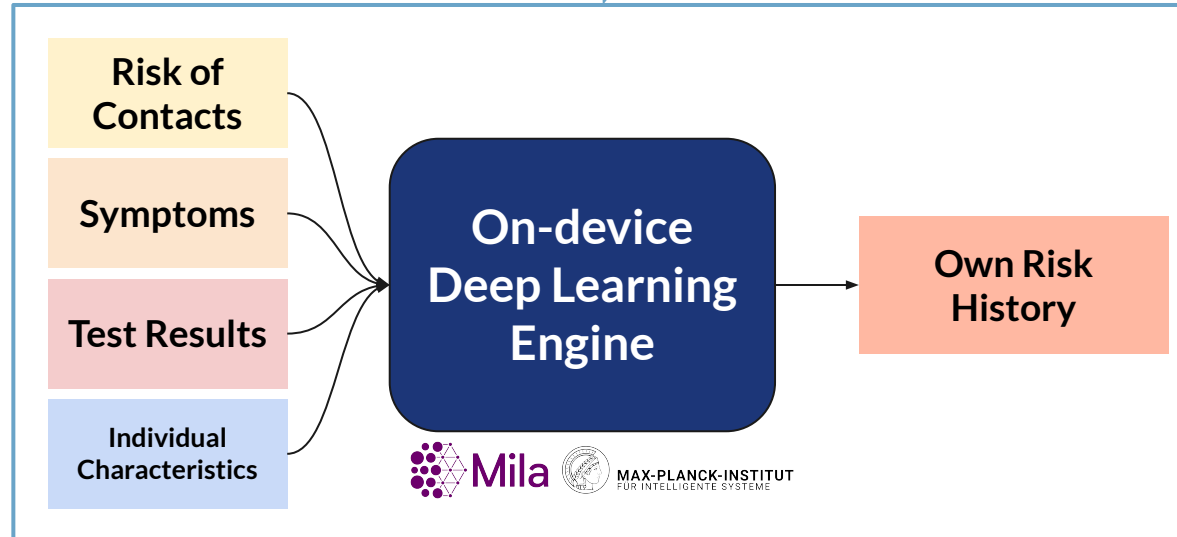
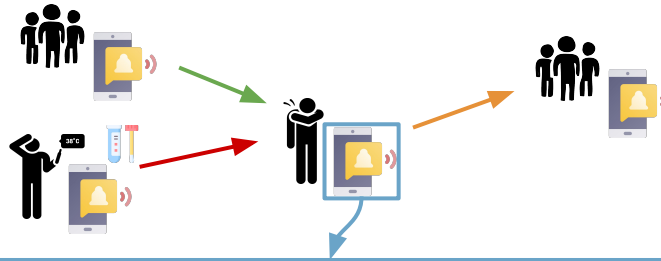
Why Machine / Deep Learning?



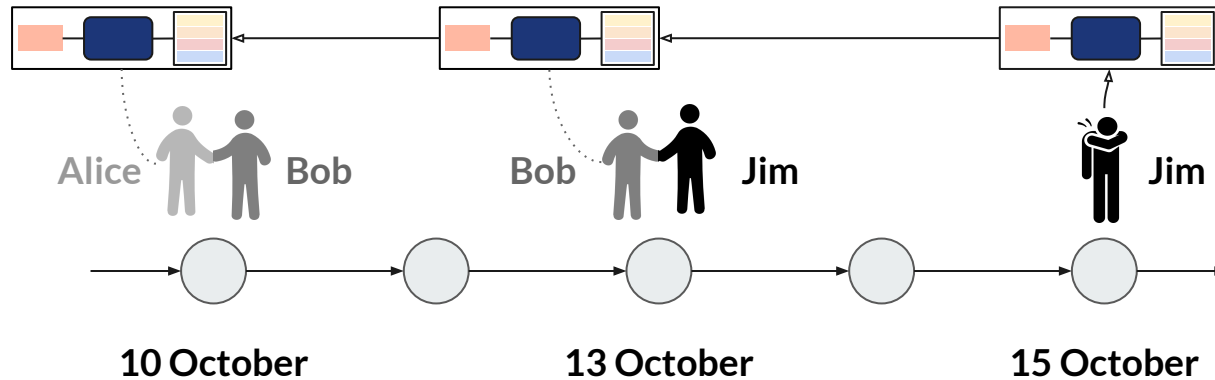
- It's tricky to decide what messages one user should send to the other about its risk.
 - In Binary Contact Tracing (BCT), the decision is based on the test results.
 - But can we do better at sending early warning signals?
- Machine learning enables us to **learn** to decide what messages to send using real and simulation data in an automated and scalable way.



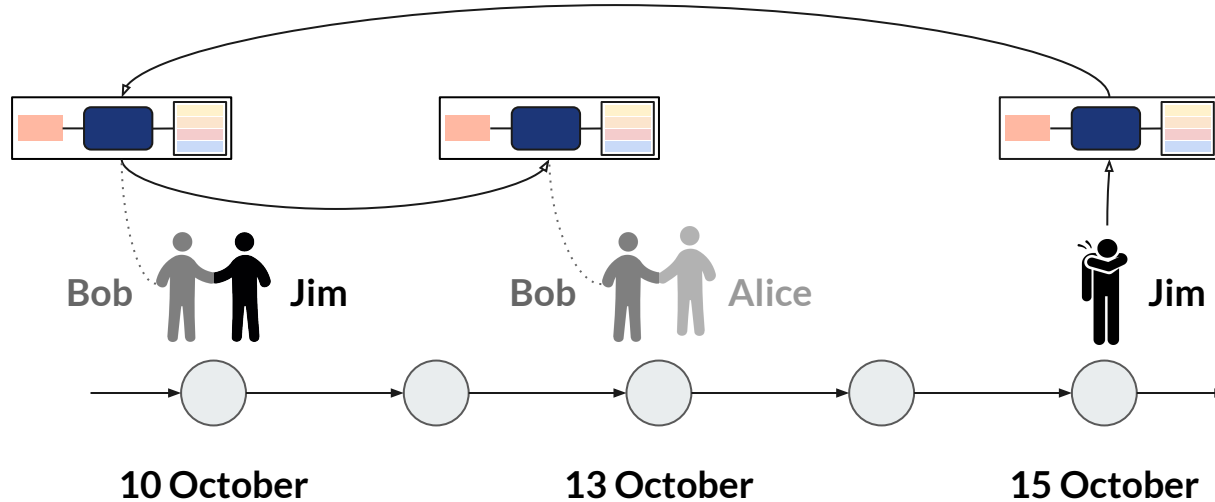
What happens on the phone?



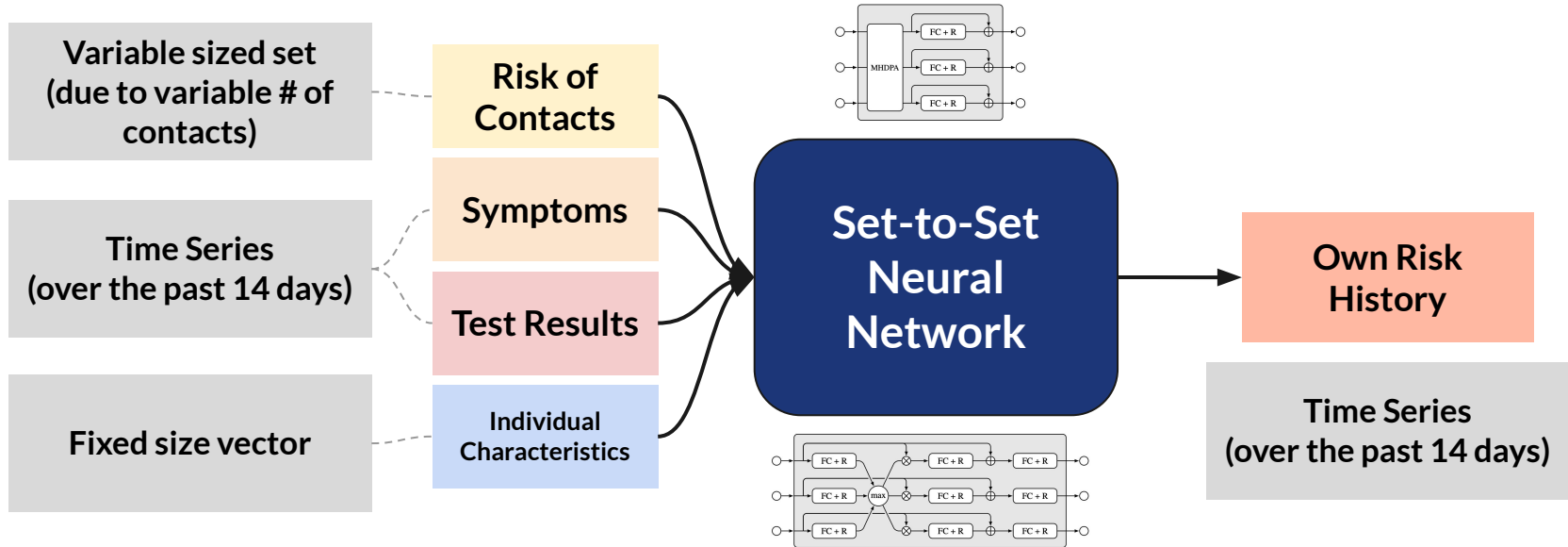
How risk messages cascade in time



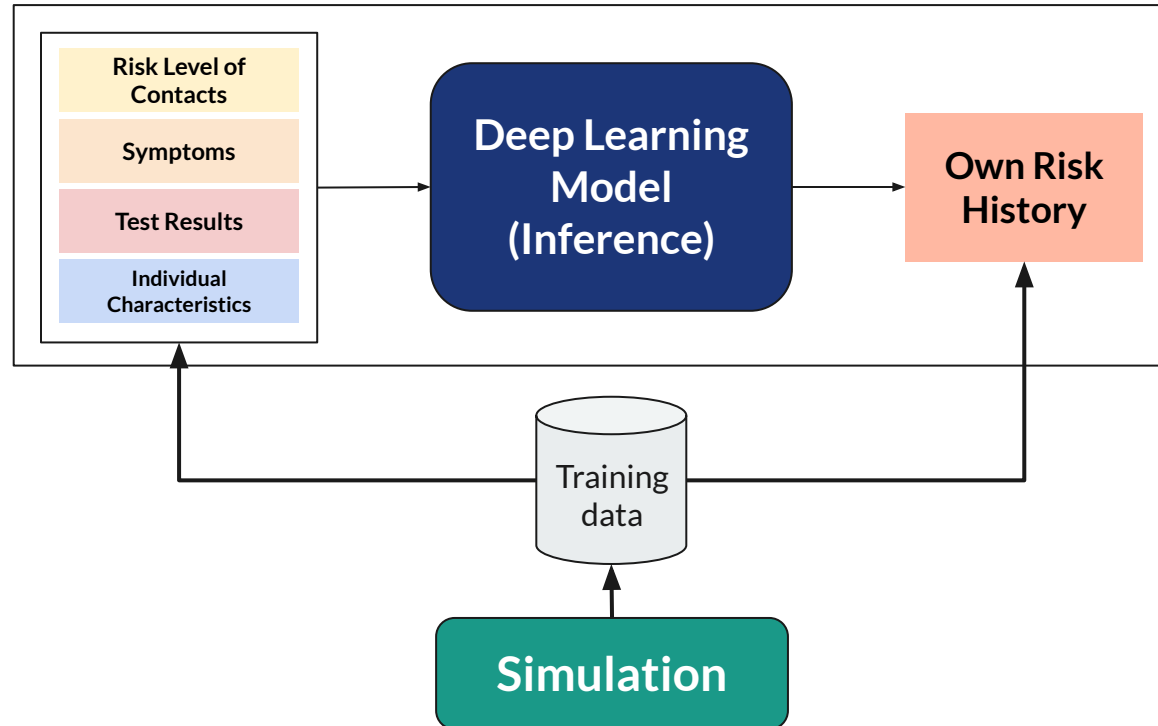
How risk messages cascade in time



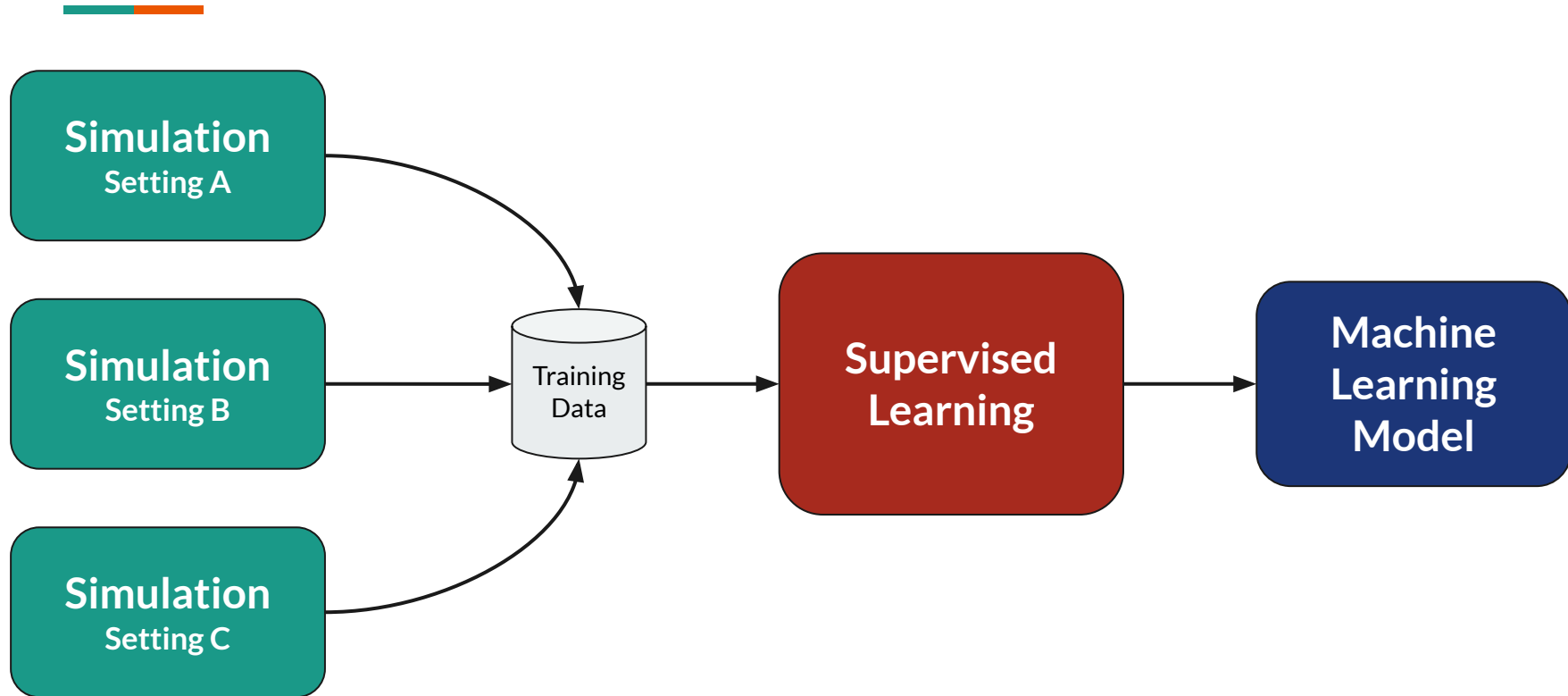
The Deep Learning Engine Unboxed



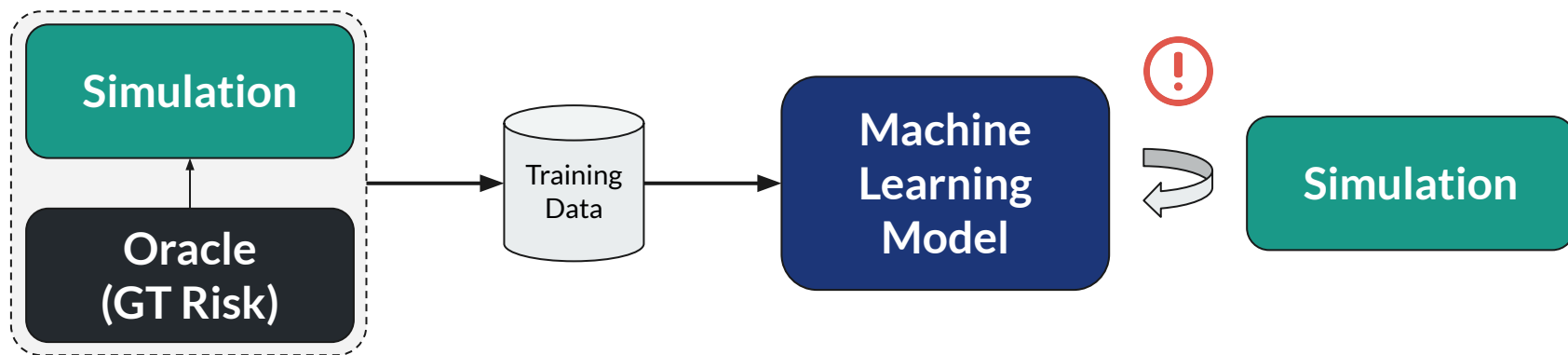
First Step: Learning from Simulations



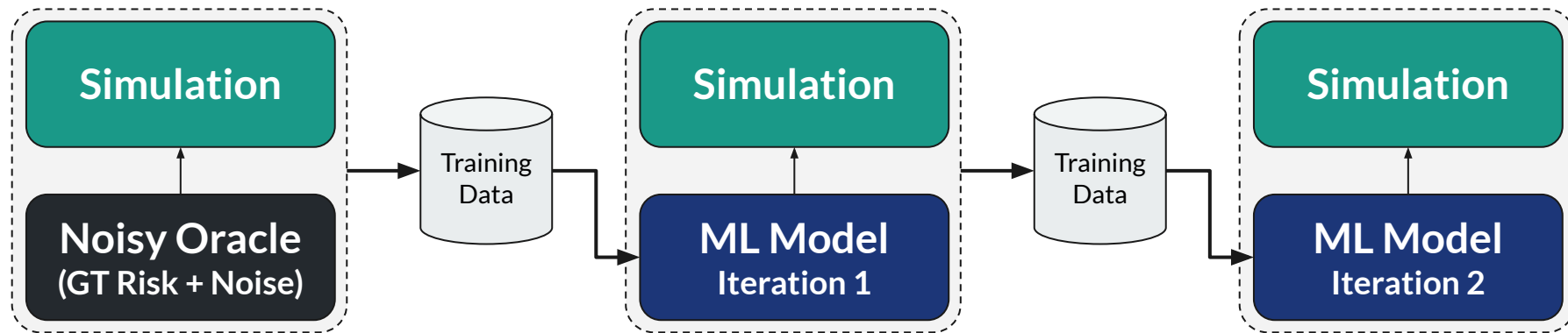
Learning from *Domain Randomized* Data



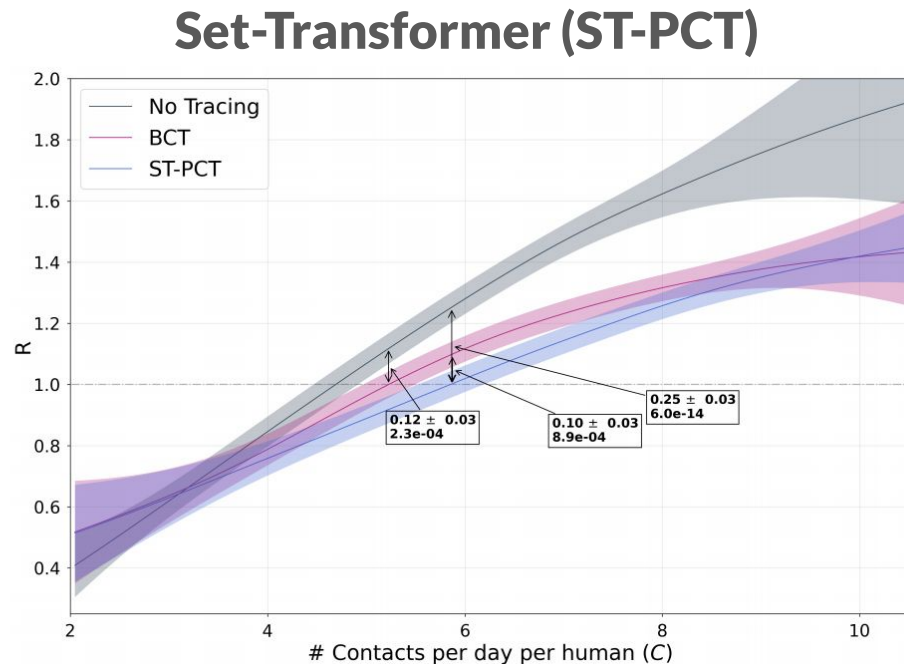
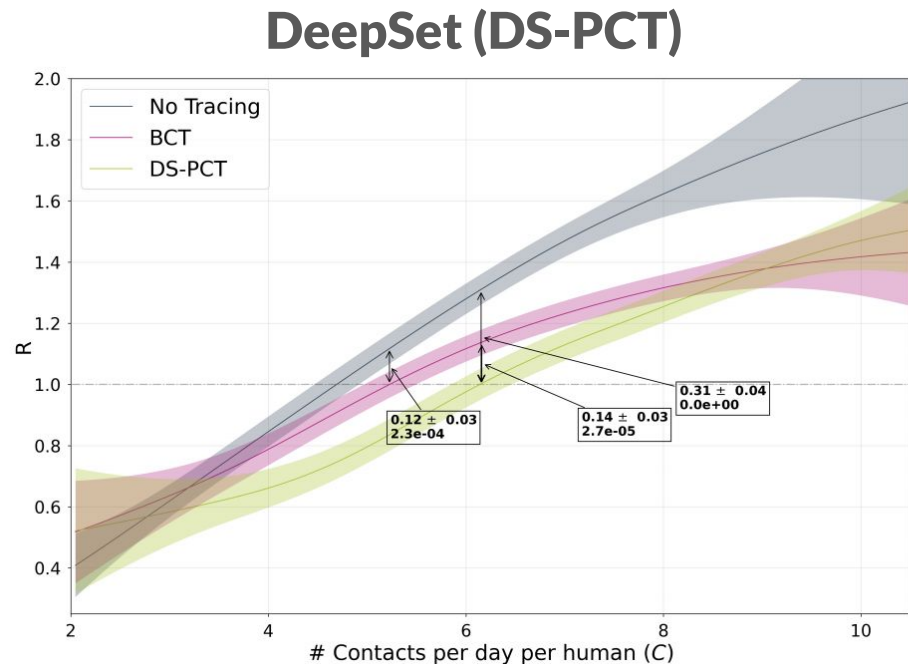
The Out-of-Distribution Problem



Solution: Multiple iterations of training



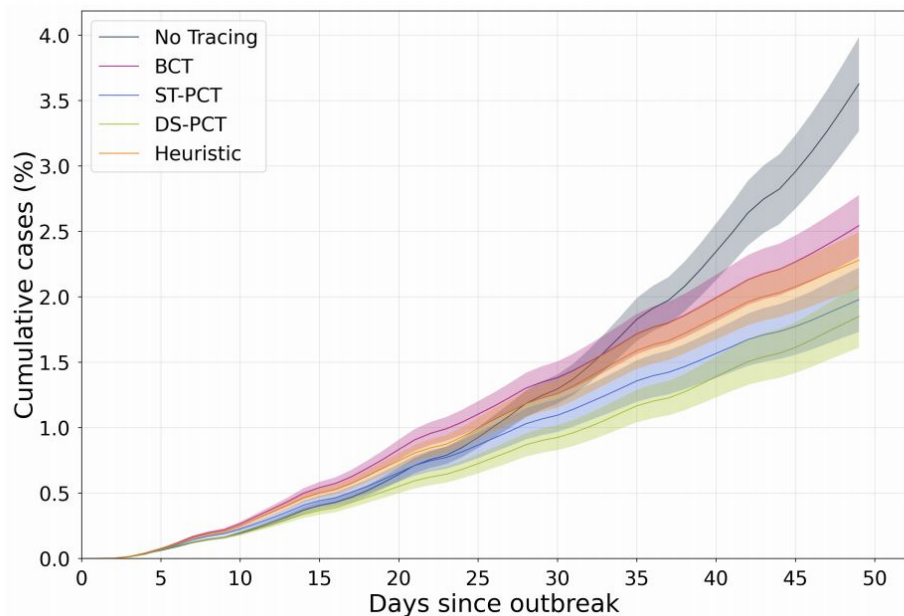
Pareto Frontier between Mobility and Spread of Disease



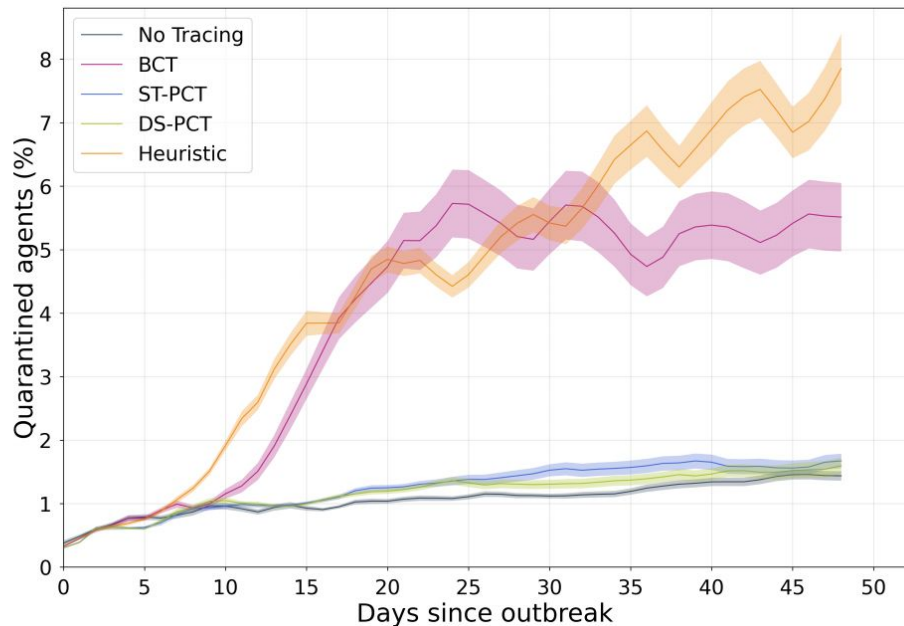
We find a better trade-off between mobility and spread of disease (R).

Case Curves and the Fraction of Quarantined Agents

Case Curves

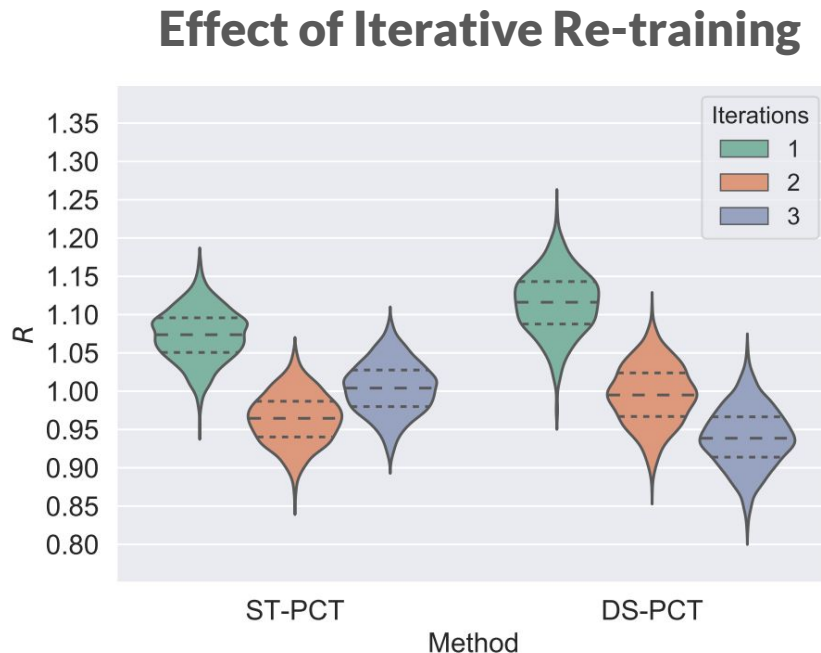
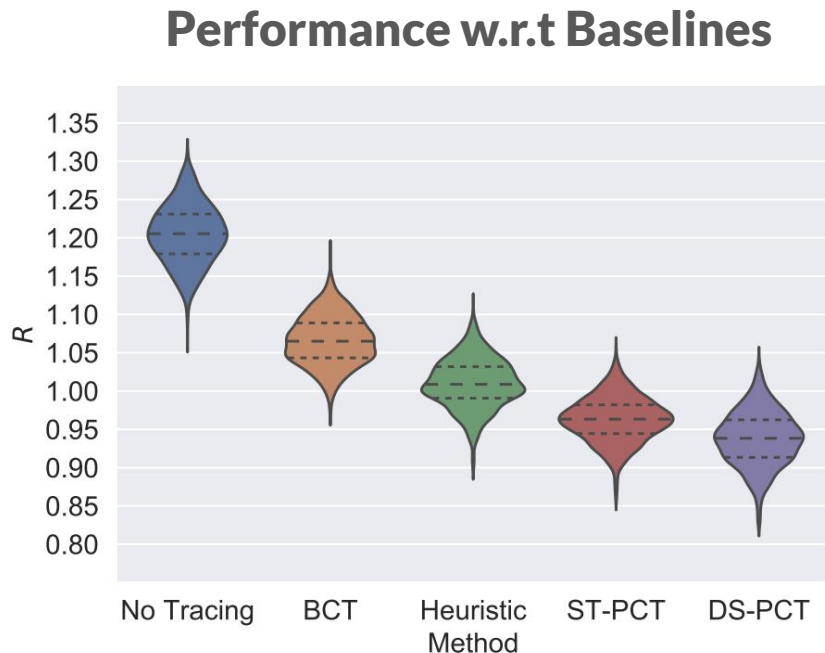


% Agents Recommended Quarantine



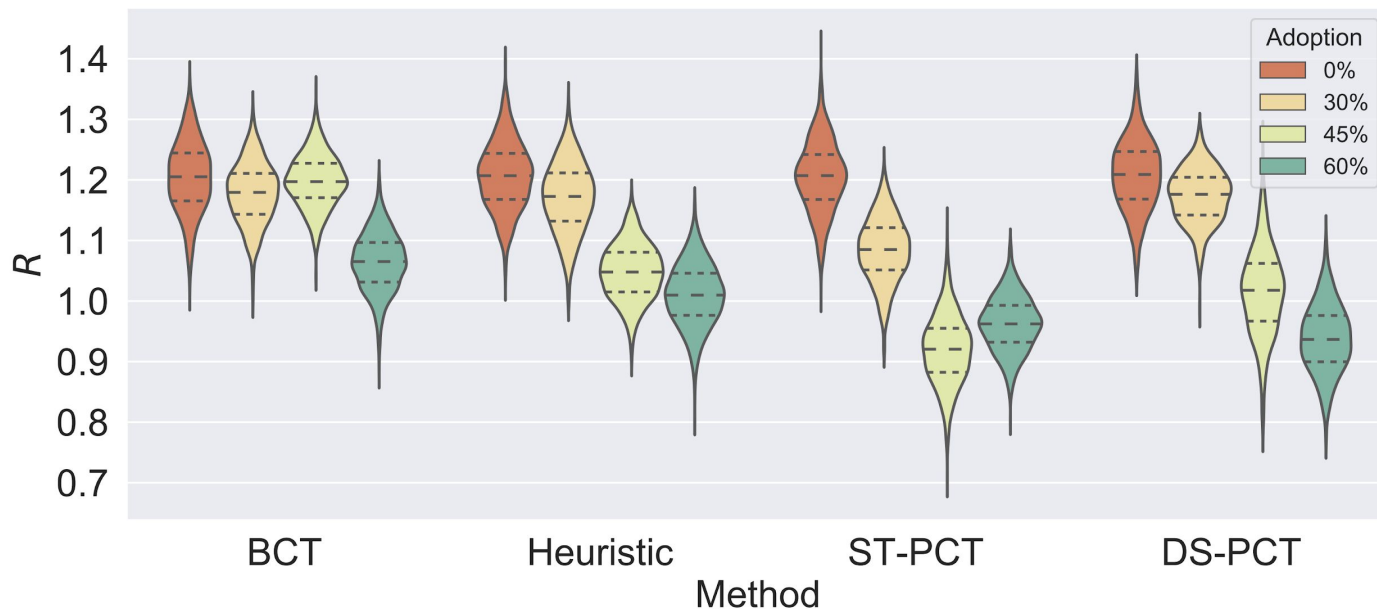
At $R = 1.2$ for no-tracing baseline, we recommend quarantine to the “right” agents.

Comparison with Baseline Methods



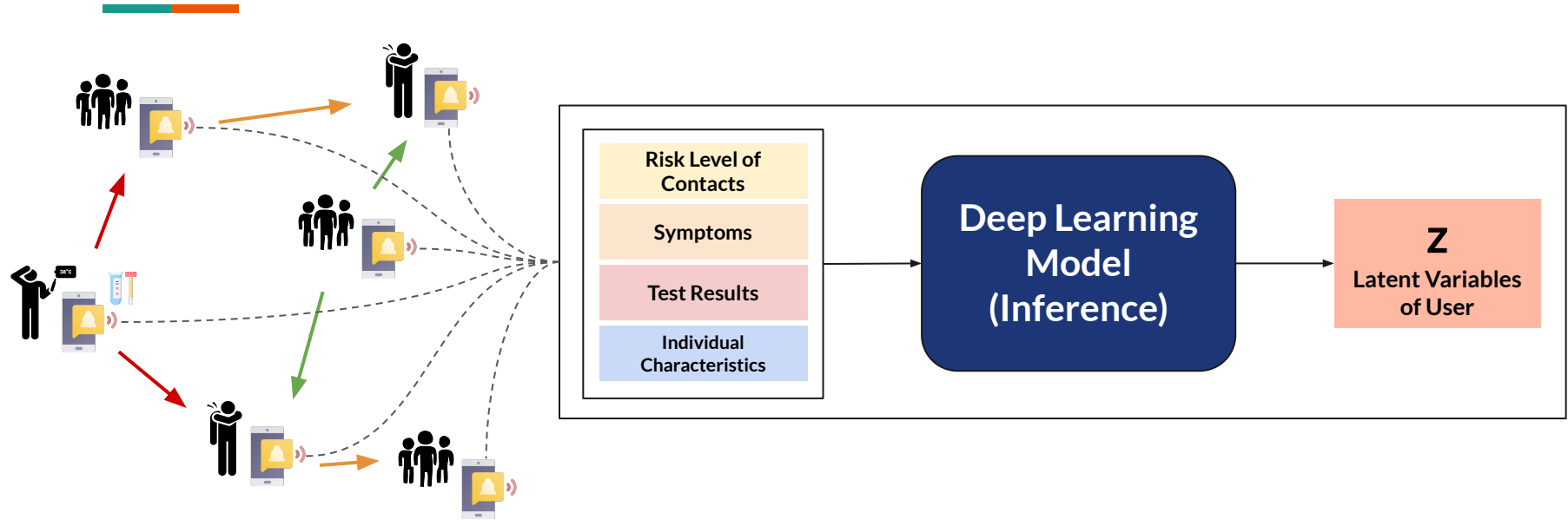
All methods work better than no-tracing, and DS-PCT works best in this setting.
Also, iterative retraining helps!

What happens when fewer people use the app?



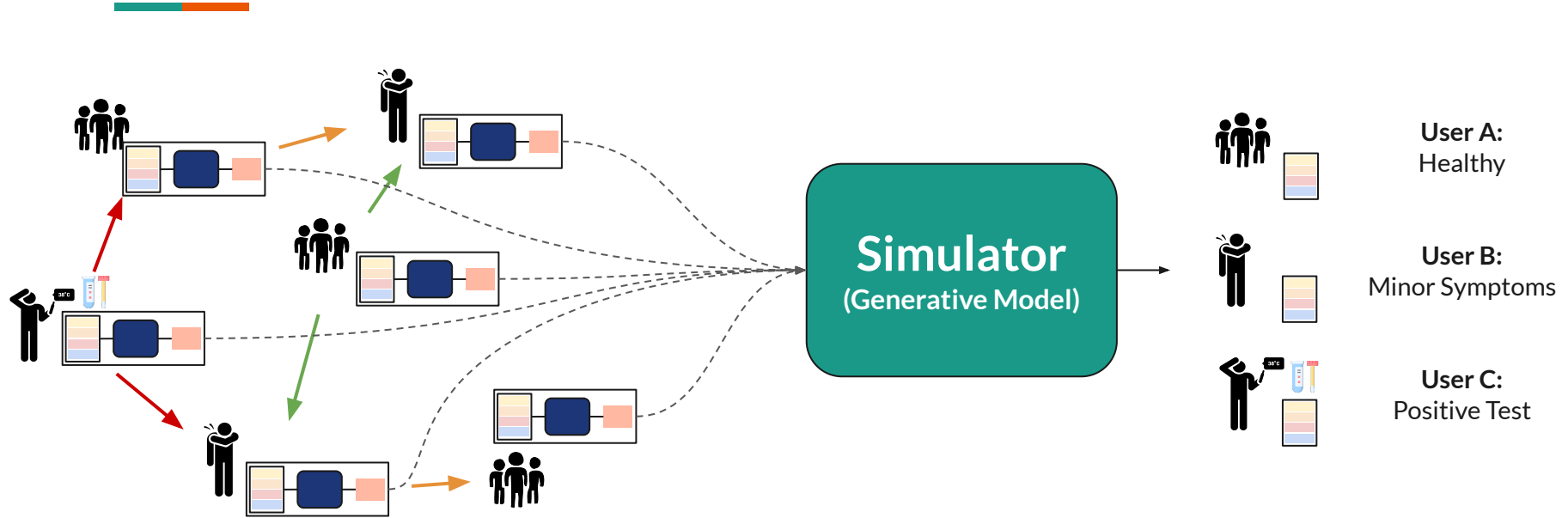
All methods work better than no-tracing, even at lower adoption rates. ST-PCT works best at 30% and 45%, whereas DS-PCT works best at 60%.

Learning from Real World Data (Work in Progress!)



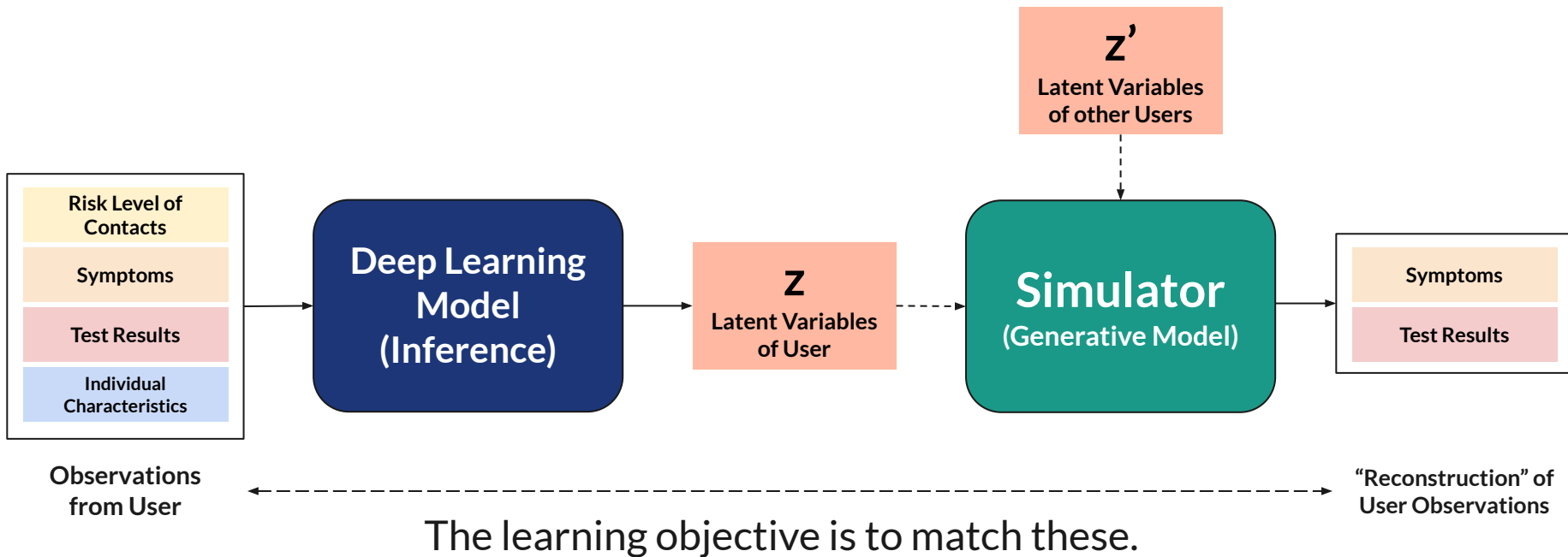
The “inference model” runs on every app-users’ phone.

Learning from Real World Data (Work in Progress!)



The “generative model” receives latent variables from every app user (who has consented), and predicts their respective states.

Learning from Real World Data (Work in Progress!)



References



Ayres, Ian, Alessandro Romano, and Chiara Sotis. "How to Make COVID-19 Contact Tracing Apps work: Insights From Behavioral Economics." *Available at SSRN 3689805* (2020).

To, Kelvin Kai-Wang, et al. "Temporal profiles of viral load in posterior oropharyngeal saliva samples and serum antibody responses during infection by SARS-CoV-2: an observational cohort study." *The Lancet Infectious Diseases* (2020).

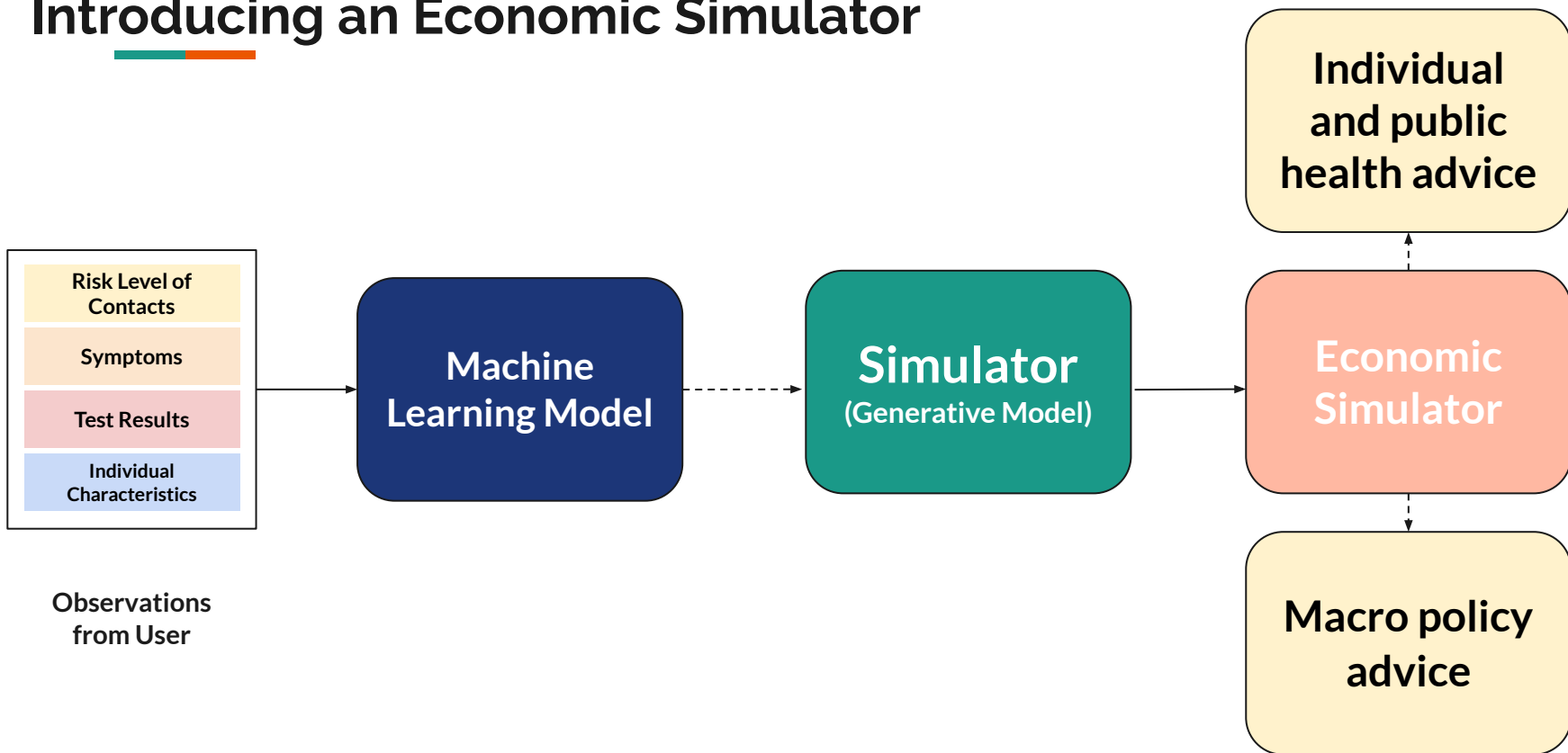
Brisson et al. "Épidémiologie et modélisation de l'évolution de la COVID-19 au Québec".
<https://www.inspq.qc.ca/covid-19/donnees/projections/29-juin> (2020)

Alsdurf, Hannah, et al. "COVI White Paper." *arXiv preprint arXiv:2005.08502* (2020).

Gupta et al. "COVIsim: an Agent-based Model for Evaluating Methods of Digital Contact Tracing". OpenReview Preprint (2020)

The Health and Economic Impacts of Tracing

Introducing an Economic Simulator

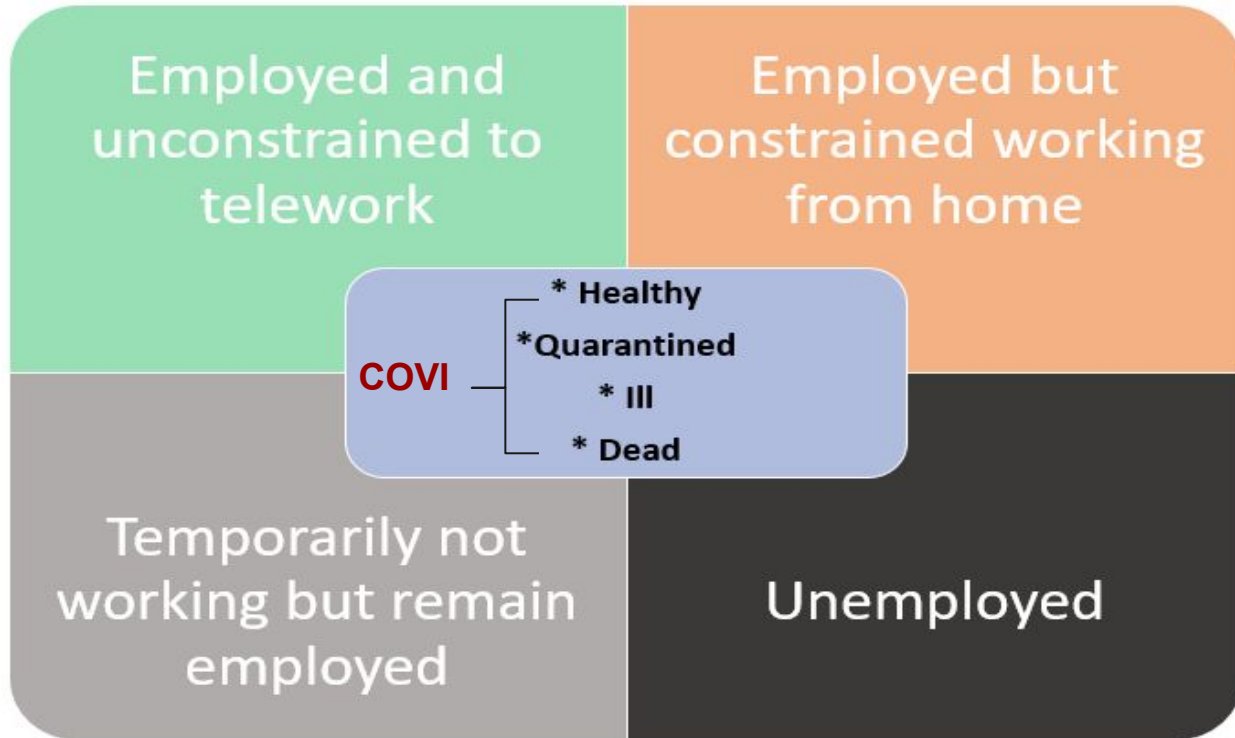


adaptER-COVID19: an application to national data

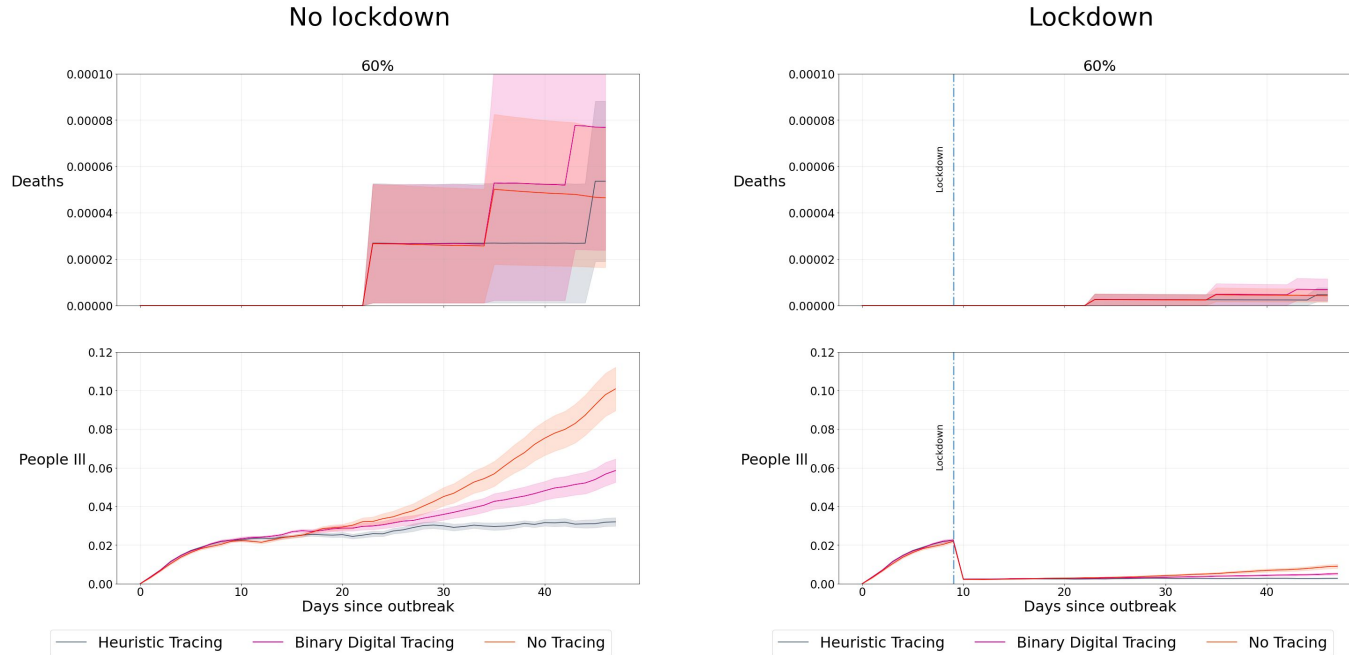
01	Input-output Model	<ul style="list-style-type: none">• Labour, capital, imports as inputs for production• Consumption, investment and export sectors
02	Corporate Bankruptcy Model	<ul style="list-style-type: none">• Agent-based corporate defaults• Connected to IO-Model through net operating surplus of companies
03	Individual Insolvency Model	<ul style="list-style-type: none">• Model household earnings• Behavior (fear factor) determining risk of insolvency

Source: <https://github.com/BDI-pathogens/OpenABM-Covid19>
<https://www.coronavirus-fraser-group.org/>

Mapping COVI into a matrix of employment & health status

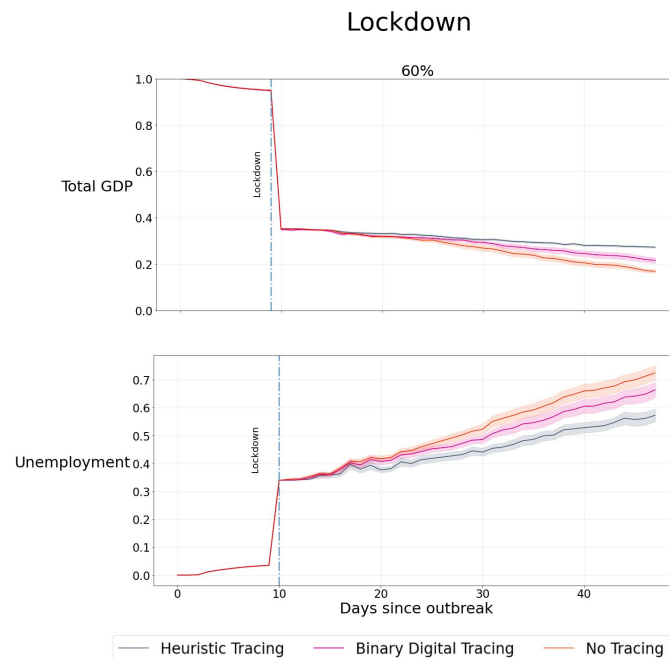
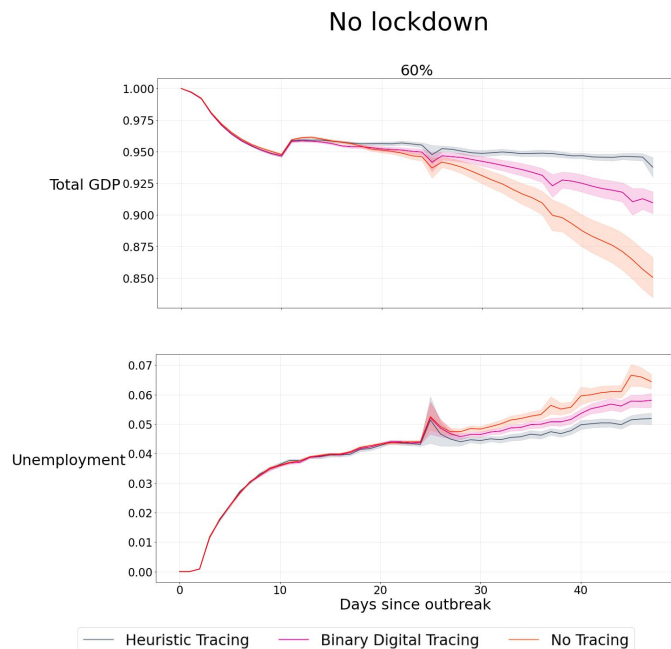


COVI improves health outcome (lower # of ill and deaths)...



Source: “The Daily - Study: Willingness of Canadians to use a contact tracing application”, Statistics Canada. July 31, 2020.
<https://www150.statcan.gc.ca/n1/daily-quotidien/200731/dq200731d-eng.htm>

... while incurring smaller economic cost (higher GDP & lower U rate)







Some limitations in adapterER - COVID19



- **I-O model uses accounting identity, no pricing optimization**
 - Switching to realistic production function considering input substitutability
- **Modelling labour and capital market may benefit from general equilibrium models**
 - Workers don't have the ability to switch jobs
 - No part-time, self-employment
- **Don't account for interest payments and leverage of firms**

ACTION: Expand the Health-Economic Frontier with Technology!

	 No Tracing	Digital Binary Tracing 	PRA (COVI) 
Individual mobility (social wellbeing)	High, but at risk of forced lockdown	Low	Intermediate
Infection Transmission rate (R0)	High	Intermediate	Low
Economic impact (GDP, jobs)	Poor	Intermediate	 Improved

Appendix

Future Work & Limitations & Challenges



- Scalability of simulations
- Sensitivity Analysis on privacy parameters / economical scenarios / (WIP)
- Pilot cohort study
- Deployment in developing countries
- Evaluation of risk of getting infected
- Running AdaptER-Covid19 on Canadian Datasets with support mechanisms

Ethical considerations



- Ensured privacy based on decentralized approach to data
- Cryptographic technology for risk information notification
- Pseudonymized nature of optional volunteered data
- Governance and inclusivity

Preliminary Simulations



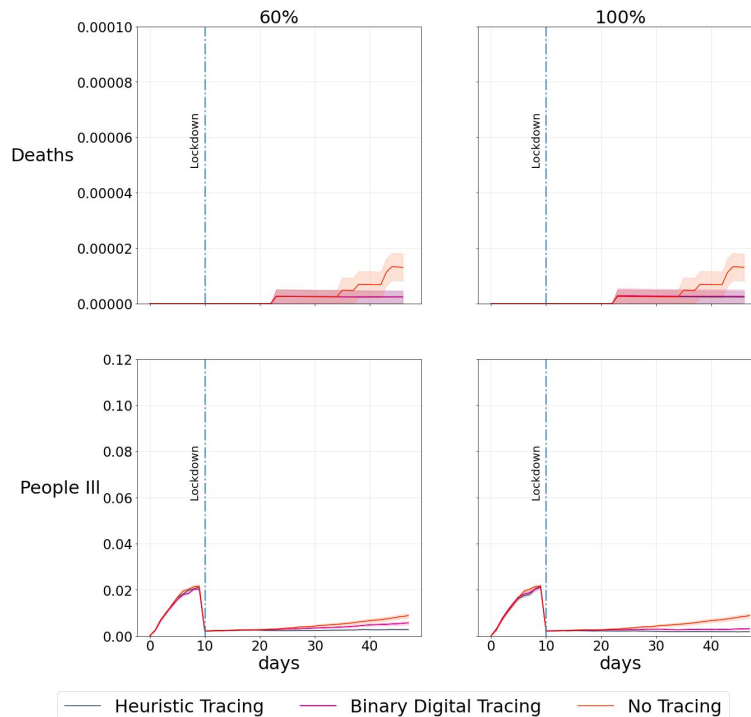
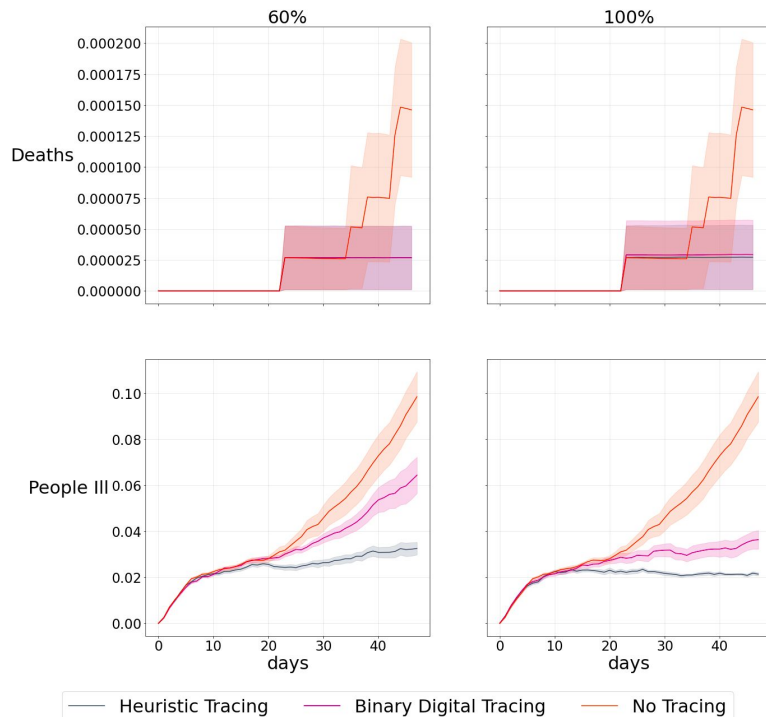
- Population size: 3000
- Initial number of infected individuals: 6 (0.2% of the population)
- 25% Asymptomatic population
- Number of tests per day = 3 (0.1% of the population)
- Behavior Modifications -
 - Low Risk Agents have 1/8th of the contacts as compared to pre COVID-19 contacts
 - Medium Risk Agents have 1/4th of the contacts as compared to pre-COVID-19 contacts
 - High Risk Agents have 0 contacts (Quarantine)
- Adherence to recommendations is modeled via dropout of 0.02 probability of following the recommendations
- Quality of self-diagnosis is modeled via dropout on symptoms of 0.2 i.e a user is 20% likely to not report their specific symptoms

100% adoption rate comparison



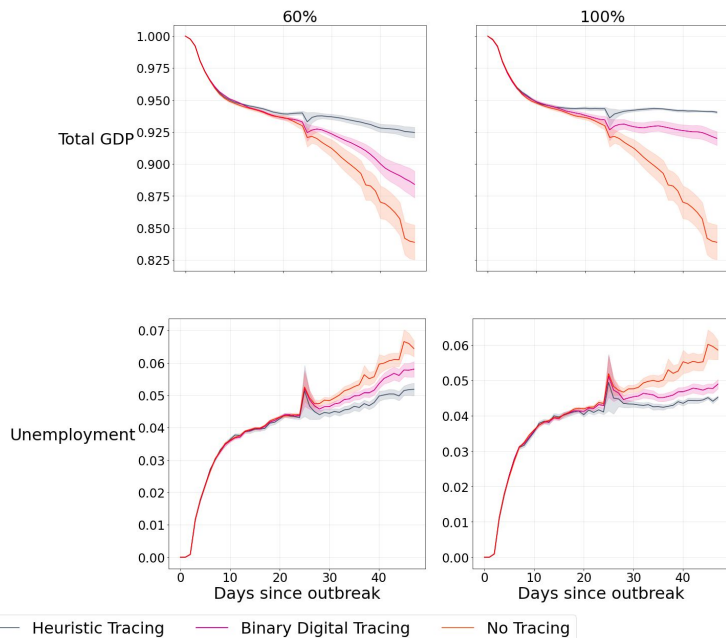
No lockdown

Lockdown



100% adoption rate comparison

No lockdown



Lockdown

