Probabilistic Risk Awareness (PRA) Framework to Generate Early-Warning Signals of COVID-19

Bank of Canada COVID-19 Webinar

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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

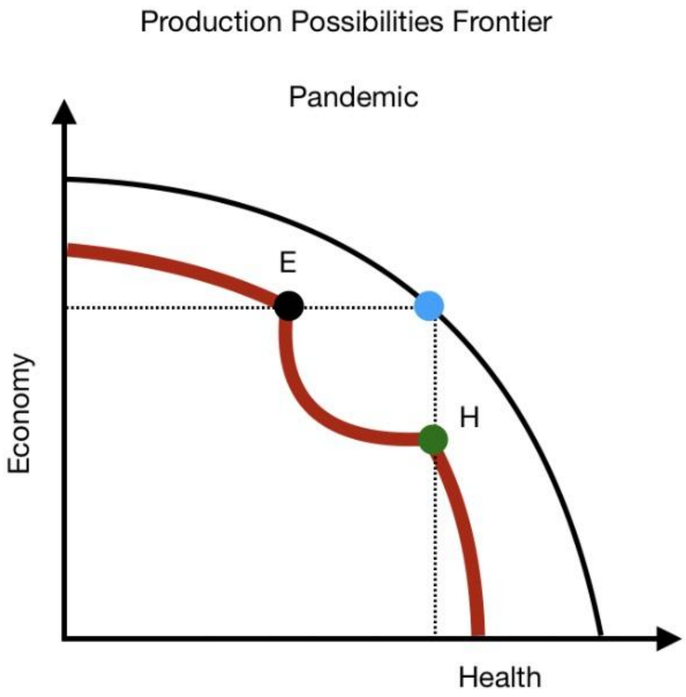
Economists:

Max Social Welfare

S.t

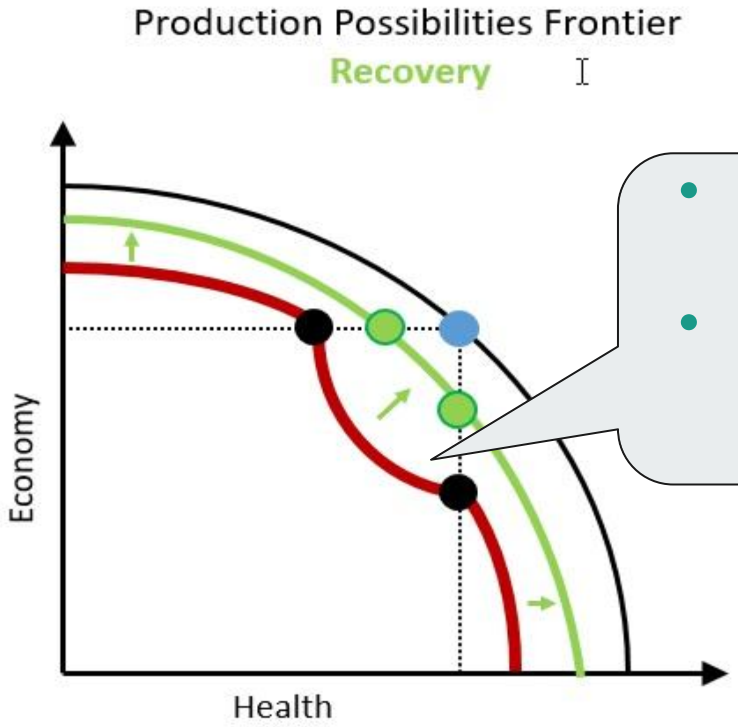
- Technological constraints
- Incentive constraints

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

Roadmap of the talk

- Probabilistic Risk Assessment (PRA) Framework for Tracing
- A Machine / Deep Learning approach to PRA
- An Application of PRA to Economic and Health Assessment
- Conclusion and ongoing research

COVI (Source code coming soon...)

COVI White Paper - Version 1.0

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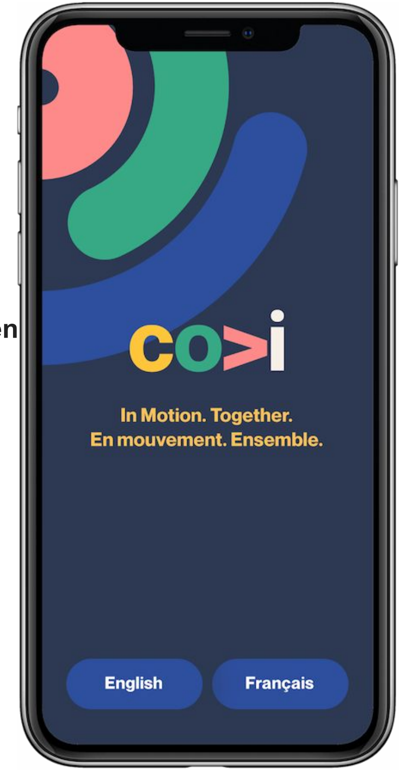

https://arxiv.org/abs/2005.08502

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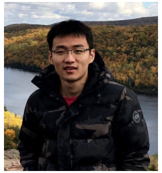
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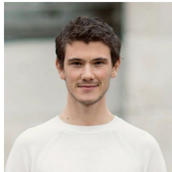
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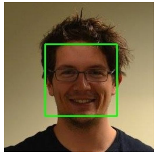
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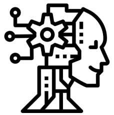
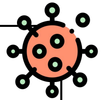
Built Upon An Agent-Based Epidemiological Model

Agents

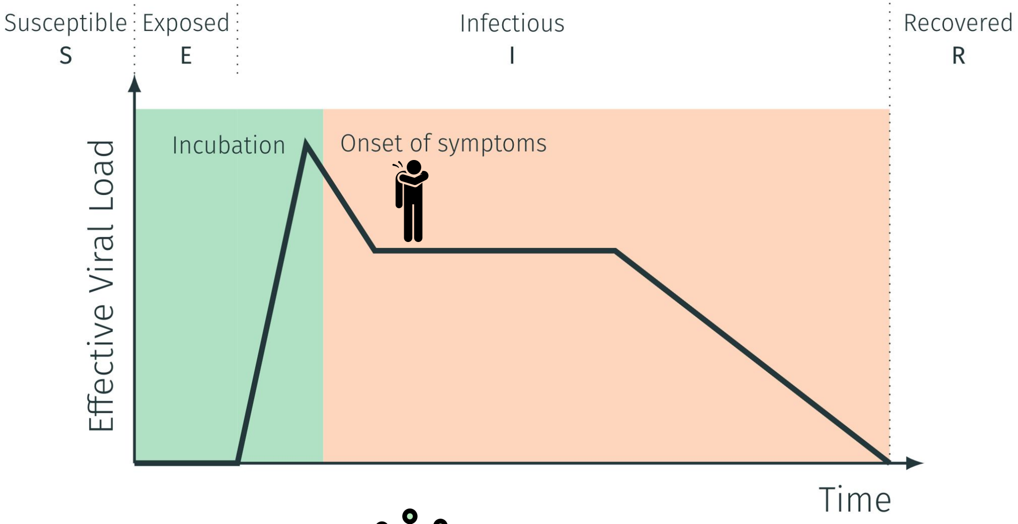


Contagiousness
or
Effective Viral Load

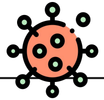


Susceptible
Exposed
Infectious
Recovered

Incubation
(Avg: 5 days)



Index Case



Secondary Case

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What we observe...

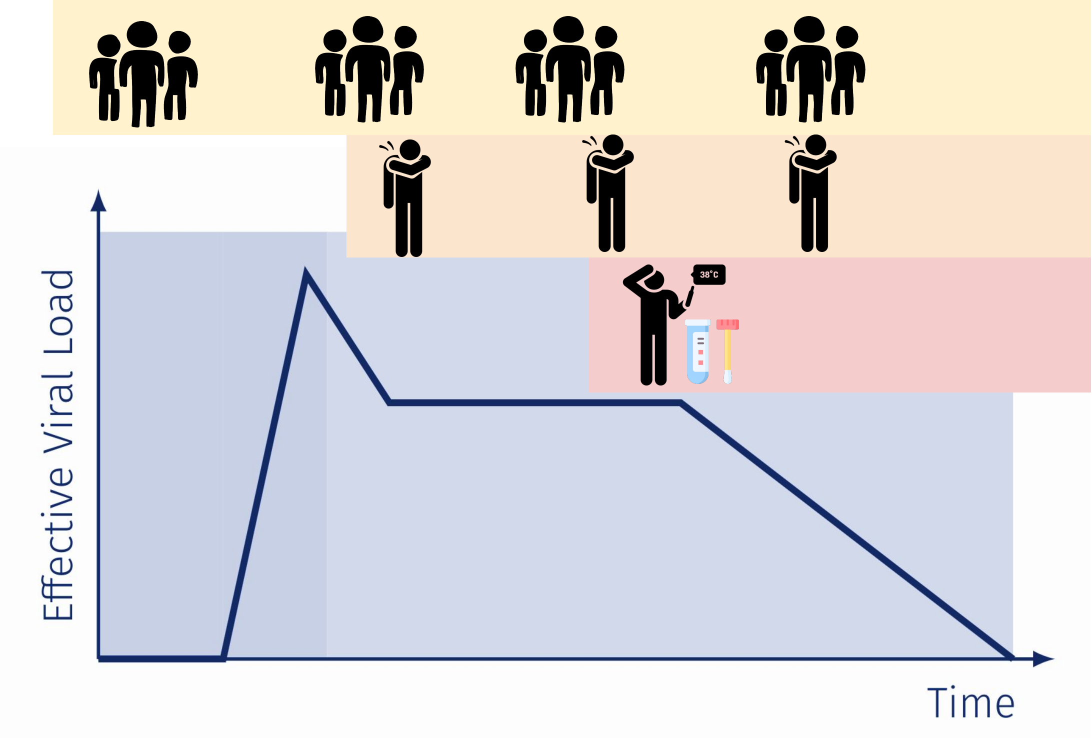
Contacts

Symptoms

Test Results

Individual Characteristics*
e.g.

- **Age**
- **Pre-existing conditions**



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Noise in observations...

Symptoms

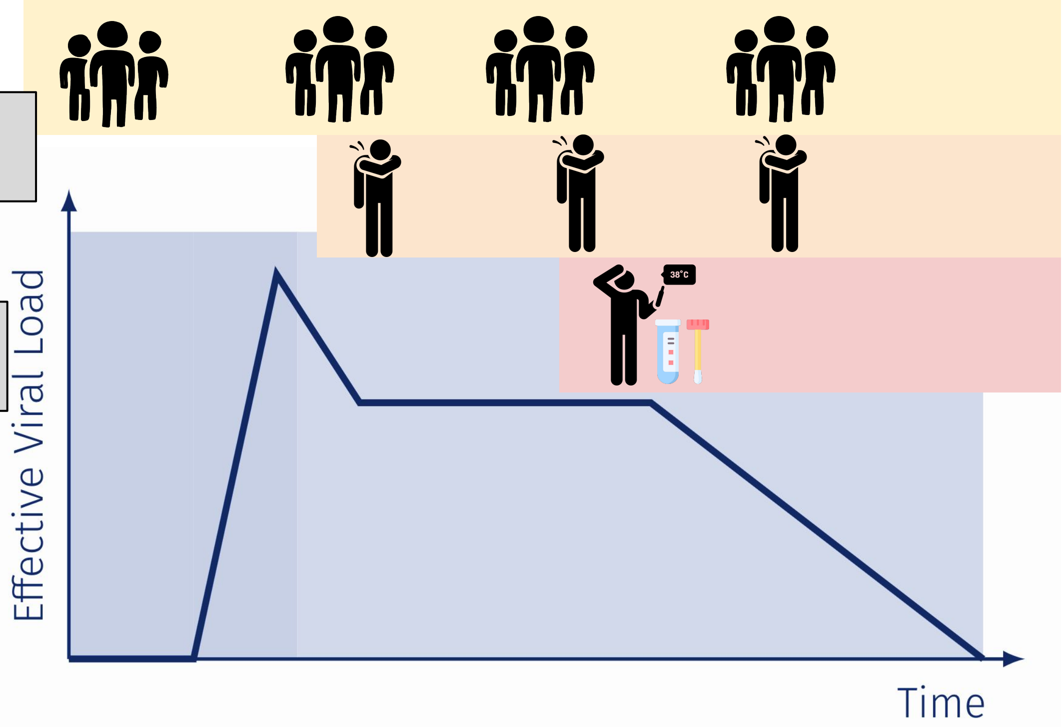
Similar to cold and flu
No symptoms in asymptomatic

Test Results

Delay
High False Negative Rates

Individual Characteristics*
e.g.

- Age
- Pre-existing conditions



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Contact Tracing

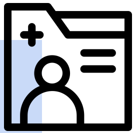
Contacts

Symptoms

Test Results

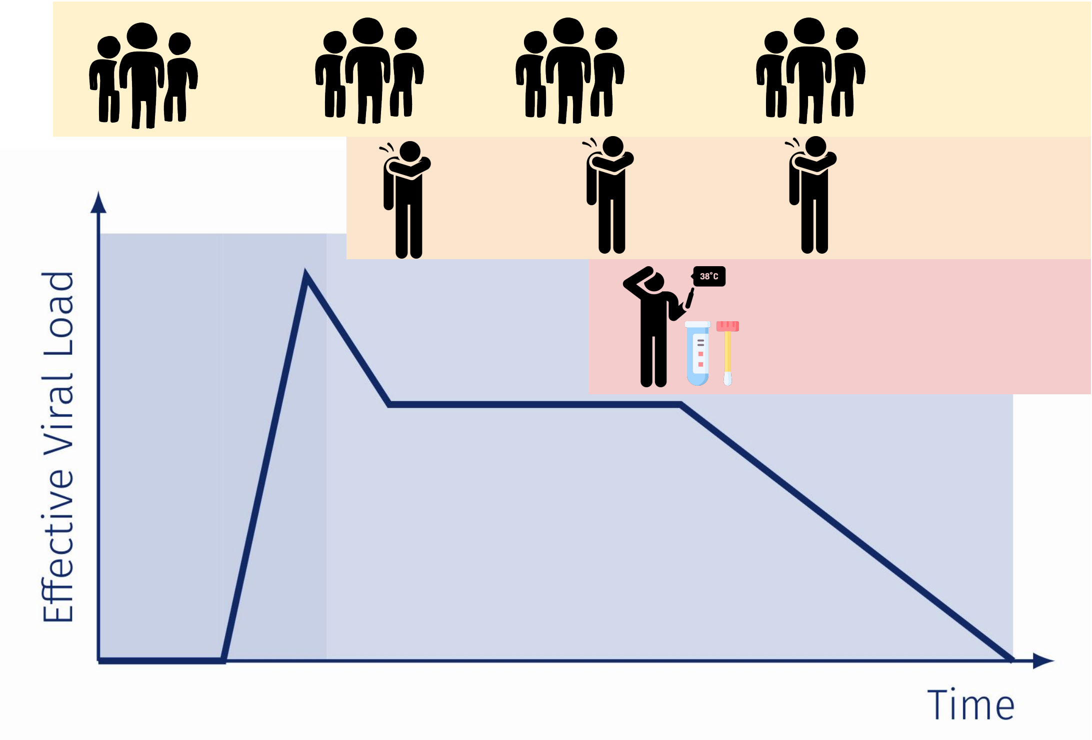
Infection Events

Detection



Individual Characteristics*
e.g.

- Age
- Pre-existing conditions



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Landscape of tracing methods

	Manual Tracing	Digital Binary Tracing (BDT)	PRA (COVI)
Potential Contacts			
Clues Used			
Recommendations			

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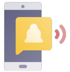
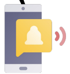
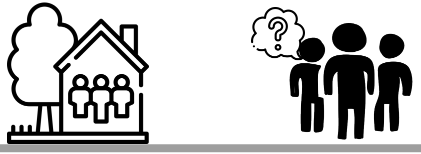
Manual Tracing is subject to memory challenges

	 Manual Tracing	Digital Binary Tracing (BDT) 	PRA (COVI) 
Potential Contacts			
Clues Used			
Recommendations			

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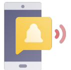
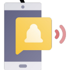
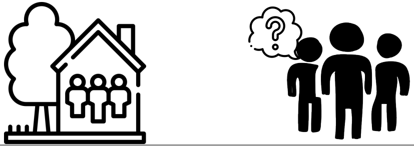
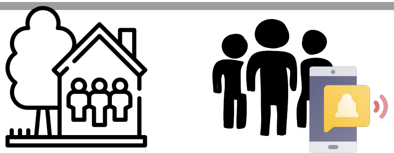
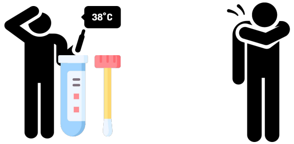
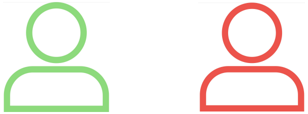
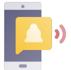
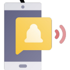
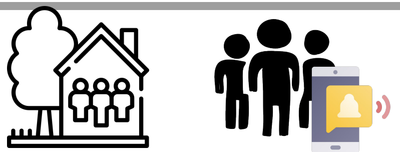
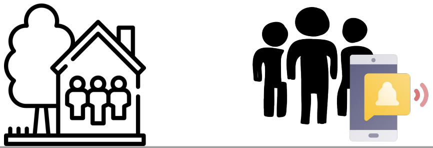
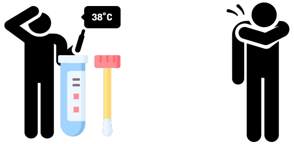
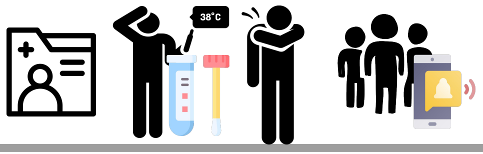
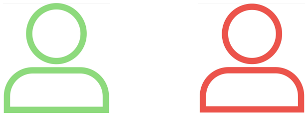
BDT provides precise contacts info, yet lacking some individual clues

	 Manual Tracing	Digital Binary Tracing (BDT) 	PRA (COVI) 
Potential Contacts			
Clues Used			
Recommendations			

COVI encompasses BDT and profits from richer info from ABM

	 Manual Tracing	Digital Binary Tracing (BDT) 	PRA (COVI) 
Potential Contacts			
Clues Used			
Recommendations			

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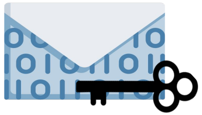
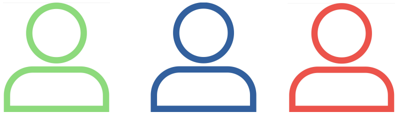
Probabilistic Risk Awareness (PRA): Framework

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

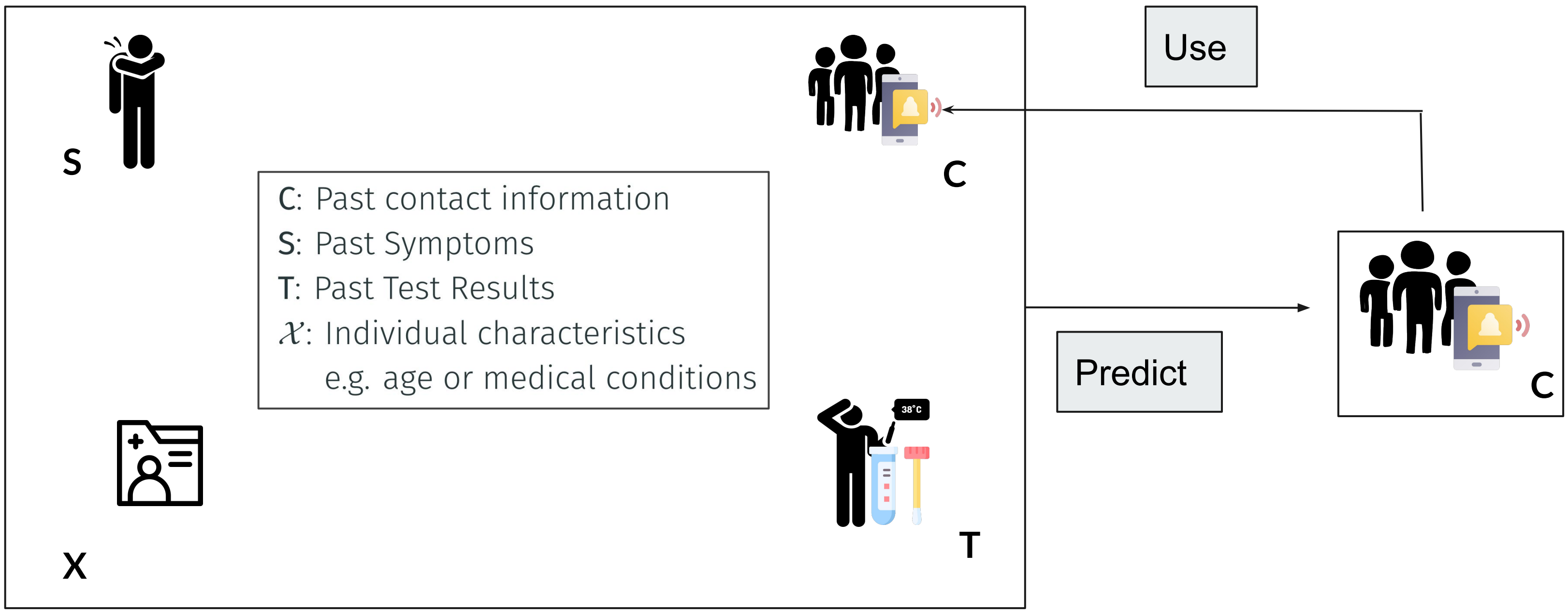


Send secure messages to previous contacts



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

Clues used by PRA



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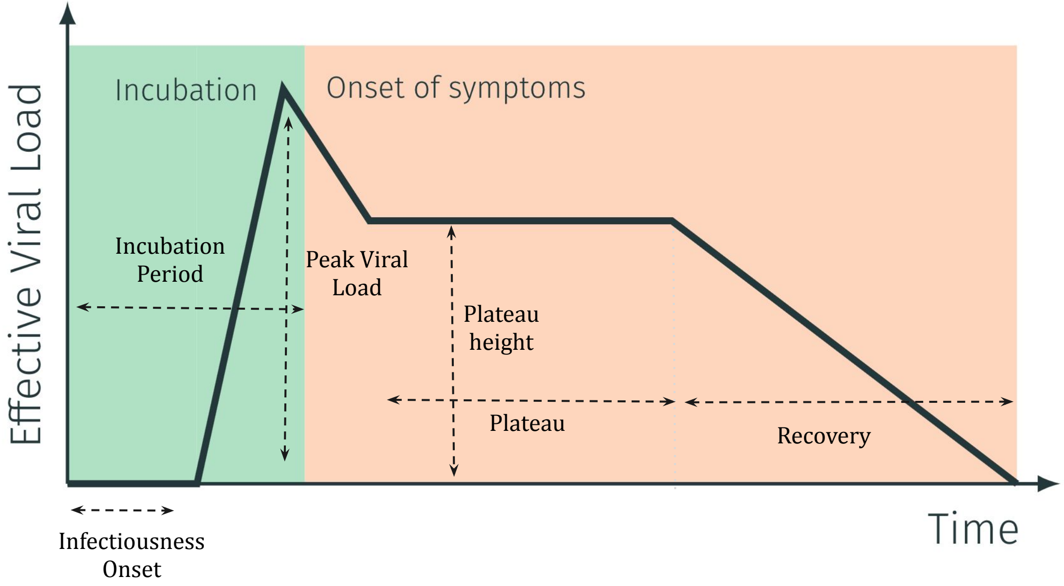
Viral Load Curve

x Individual Characteristics

$v(t)$ Functional form of Effective Viral Load (Contagiousness)



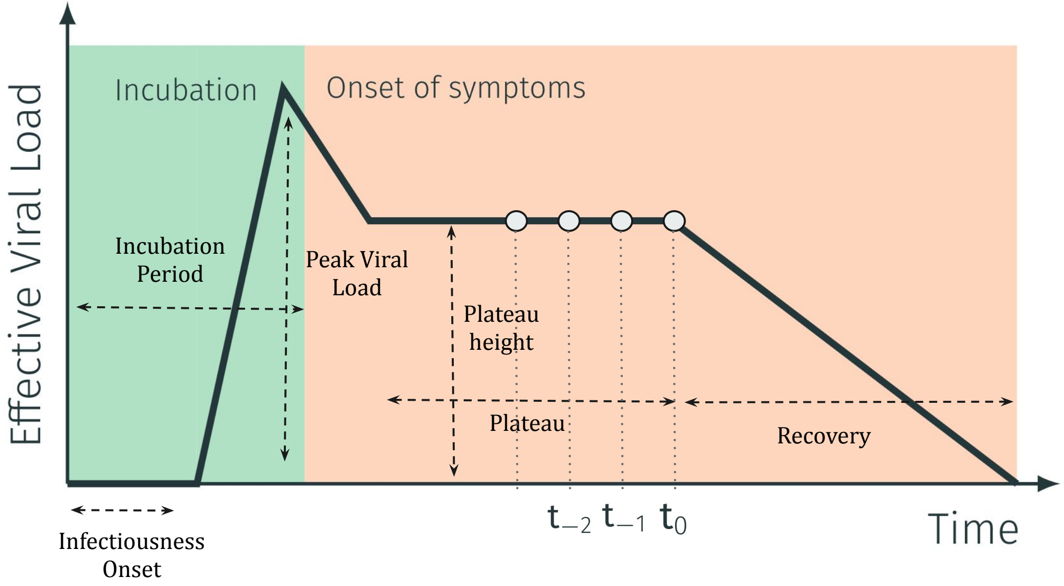
Viral Load Curve

$\mathcal{X}$ Individual Characteristics

$\mathcal{V}(t)$ Functional form of Effective Viral Load (Contagiousness)

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

$$\mathcal{V}(t_{-14}, t_{-13}, \ldots, t_0)$$



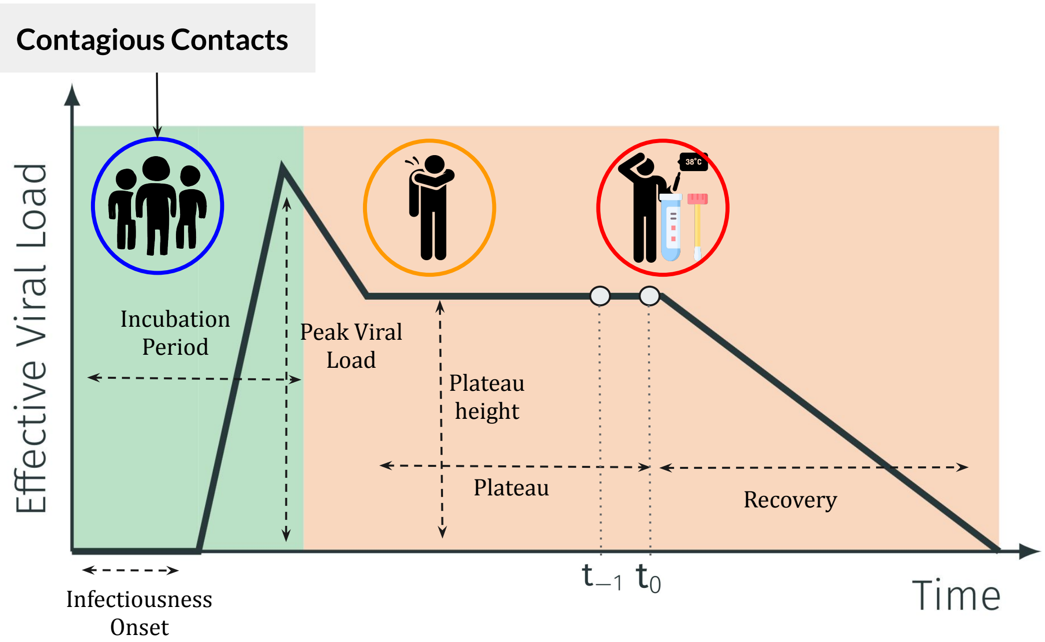
How simulated Viral Load Curve produces observables

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

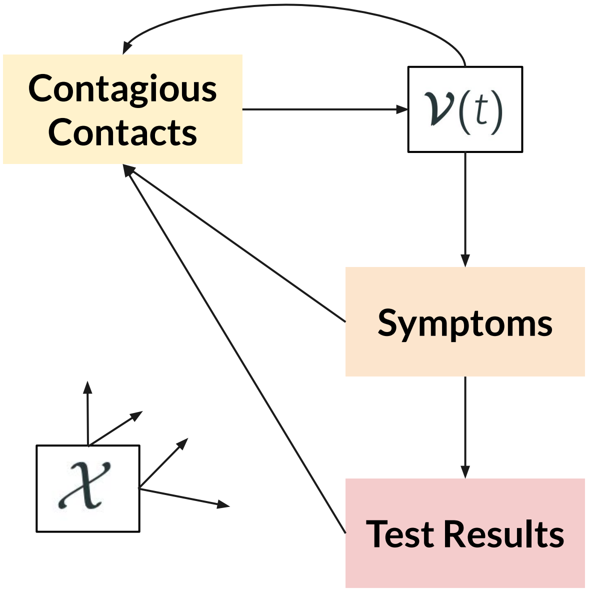
$$\boxed{Symptoms}(t) = f(\mathcal{V}(t), \mathcal{X})$$

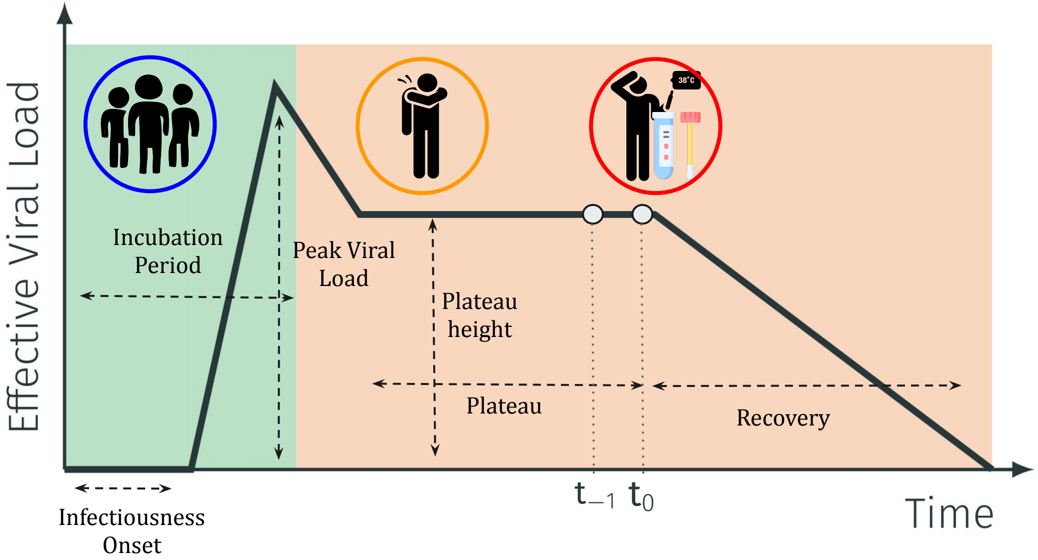
$$\boxed{TestResults} = f(\mathcal{V}, Symptoms, \mathcal{X})$$

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



Vicious Circle





What to predict?

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

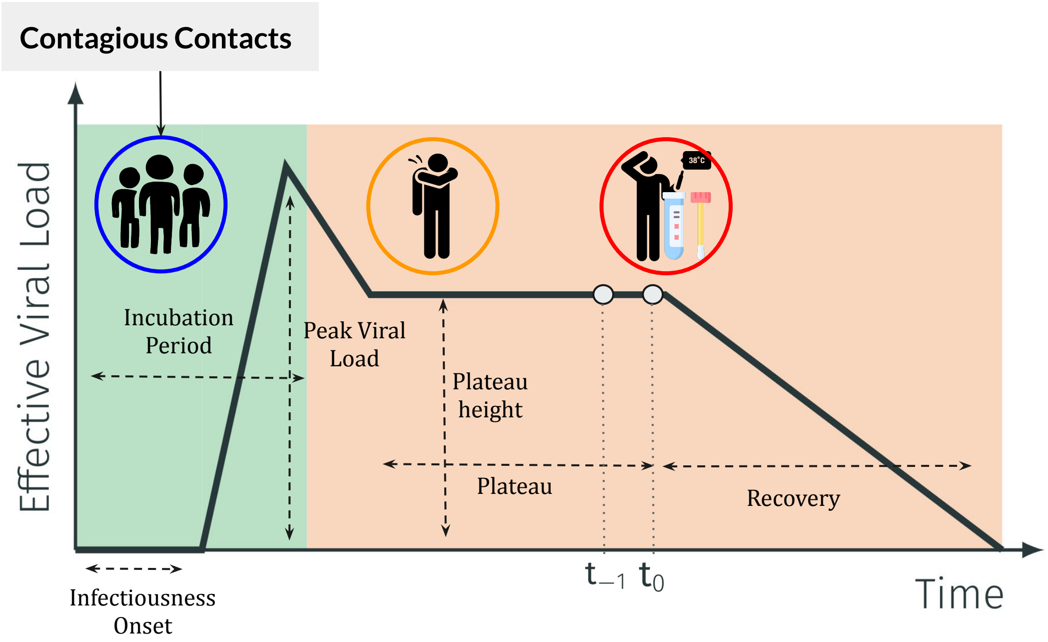
$$\boxed{Symptoms}(t) = f(\mathcal{V}(t), \mathcal{X})$$

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

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

Predict Effective Viral Load as the clues are observed

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



PRA: 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.

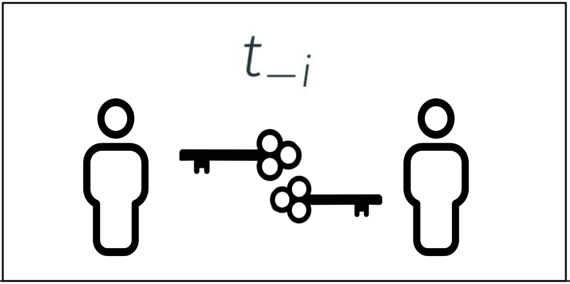
$$\hat{\mathcal{V}}(t_{-14}, t_{-13}, \ldots, t_0) = g(\mathsf{C}, \mathsf{S}, \mathsf{T}, \mathcal{X})$$

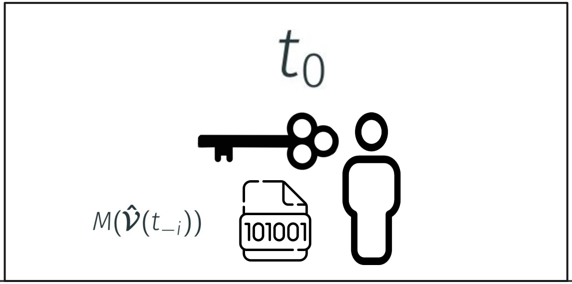
Send $\boxed{\hat{\mathcal{V}}(t_{-i})}$ to the contacts on day $\boxed{t_{-i}}$

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

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

Privacy Preserving PRA





- 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 $\hat{\mathcal{V}}(t_{-i})$ to an integer using the map **M**

    $\boxed{M : \mathcal{R} \rightarrow \{1, 2, 3, ..., 2^N\}}$ $\boxed{R(t_{-i}) = M(\hat{\mathcal{V}}(t_{-i}))}$

  - 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}

❖ For detailed discussion of privacy considerations in COVI, please refer to the white paper.
❖ WIP - Sensitivity analysis on N bits

PRA: Predict - Inform - Advice

C: Past contact information
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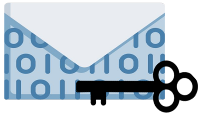
$\mathcal{X}$: Individual characteristics
e.g. age or medical conditions

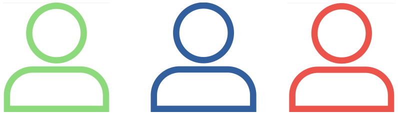
Predict **today's and past contagiousness** using all the clues i.e.

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



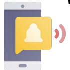
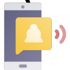
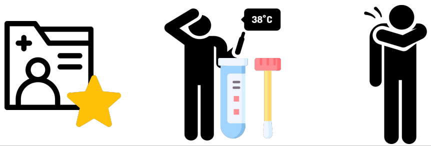
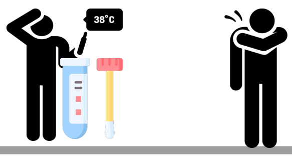
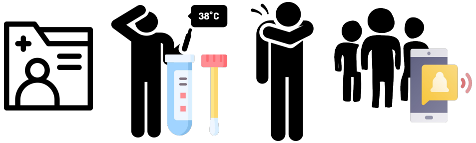
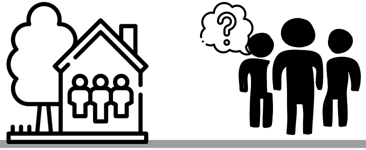
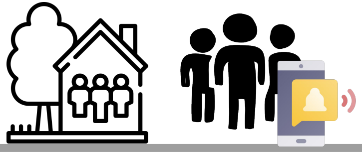
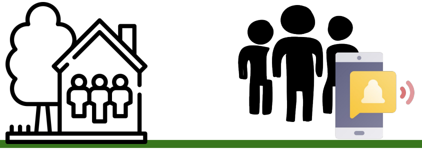
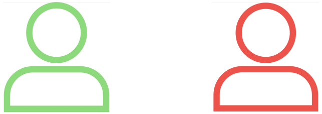
Send $\boxed{R(t_{-i})}$ to the contacts on day $\boxed{t_{-i}}$

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



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

PRA provides multi-level recommendation thanks to richer clues

	 Manual Tracing	Digital Binary Tracing 	PRA (COVI) 
Clues Used			
Potential Contacts			
Recommendations			

Icons made by Freepik, fjstudio, Pixel Perfect , photo3idea_studio, Gregor Cresnar, Vitaly Gorbachev from www.flaticon.com

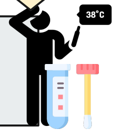
Heuristic PRA Supports Mobility of Individuals

T + C1. Gives Digital Binary Tracing (GoC)

Set Risk Levels

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

T - If the user **reports** a **positive test result** set **R = 15 for the past 14 days**

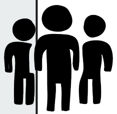


S - Depending on the **severity of reported symptom** severity, set R as

1. **Severe** symptoms: Set **R=12 for the past 7 days**
2. **Moderate** symptoms: Set **R = 10 for the past 7 days**
3. **Mild** symptoms: Set **R = 7 for the past 7 days**

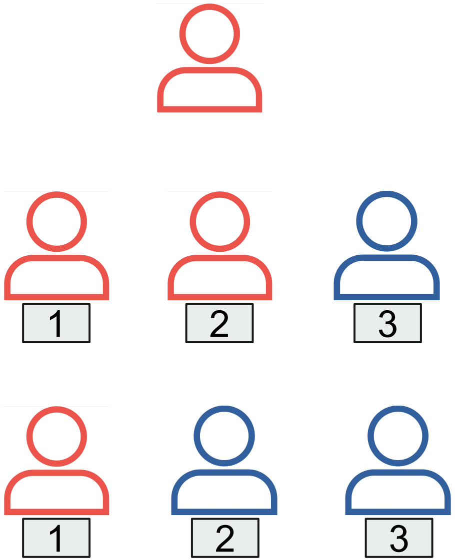
C - Break down all **received risk levels R`** into three categories

1. High (R` >=12) : Set **R = R` - 5 until the day of receipt of R`**
2. Medium (10 <= R` < 12 ): Set **R = R` - 5 until the day of receipt of R`**
3. Mild (R` < 10) : Set **R = R` - 5 until the day of receipt of R`**

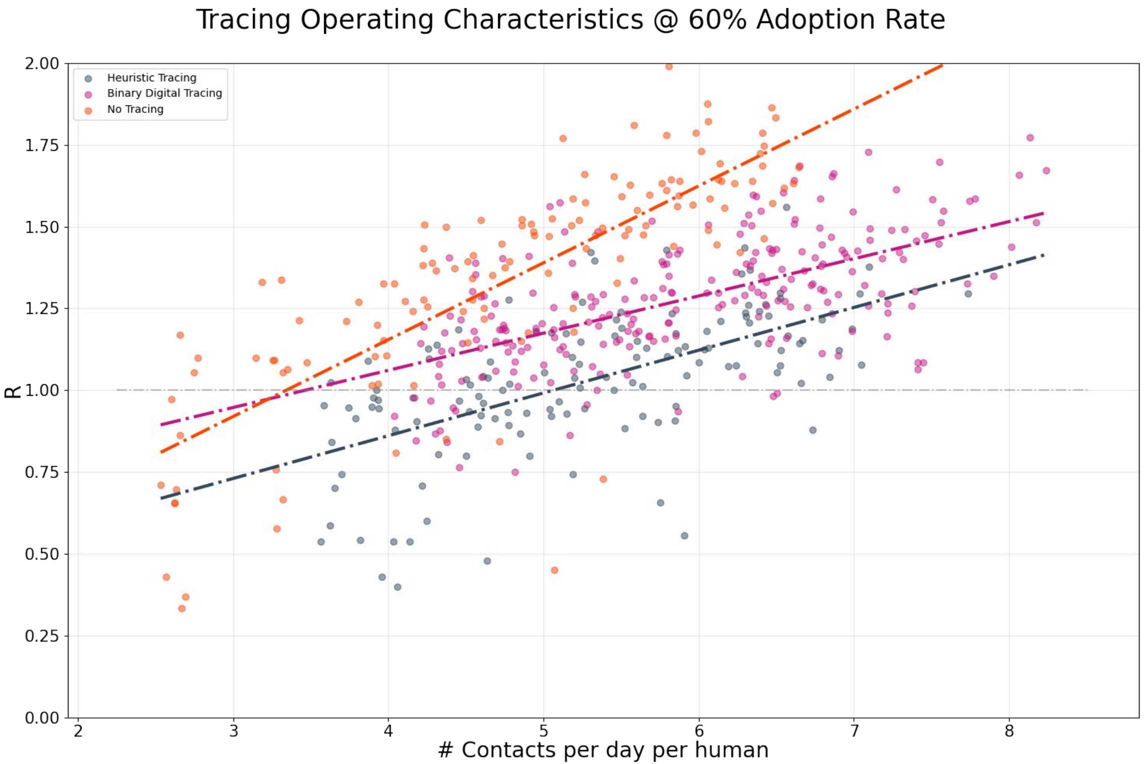


Finally, take the max of risk levels on each day obtained from above computation

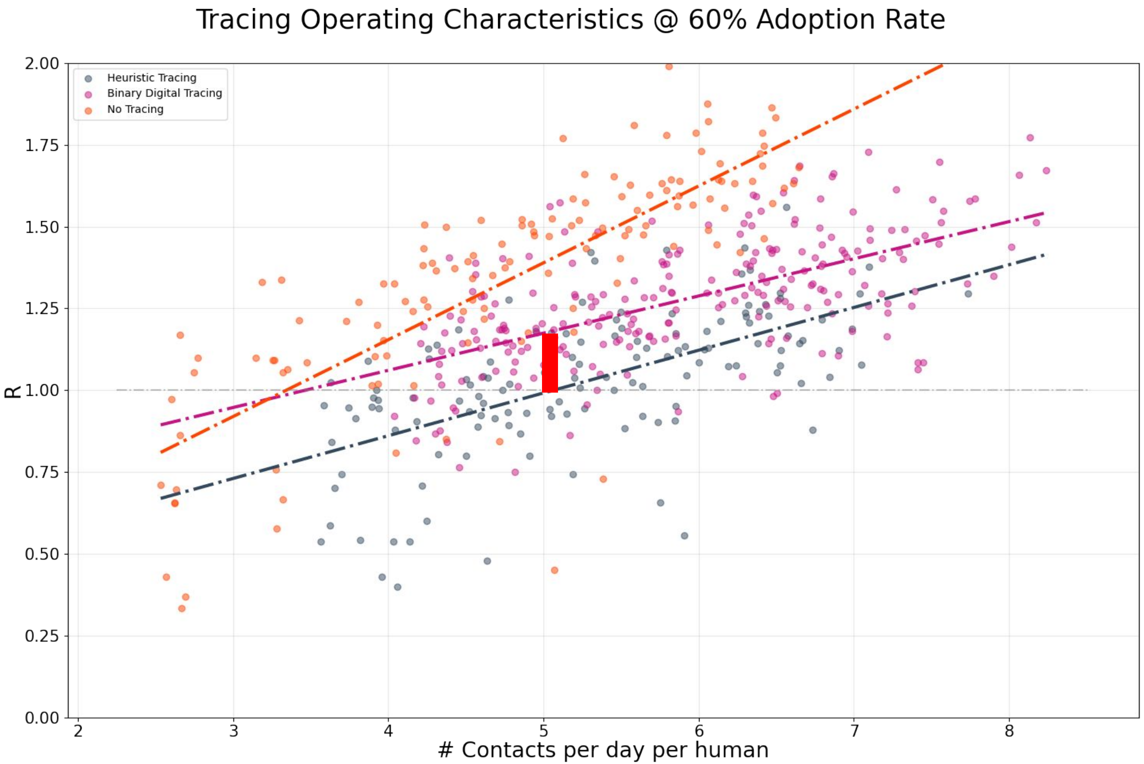
User Recommendations



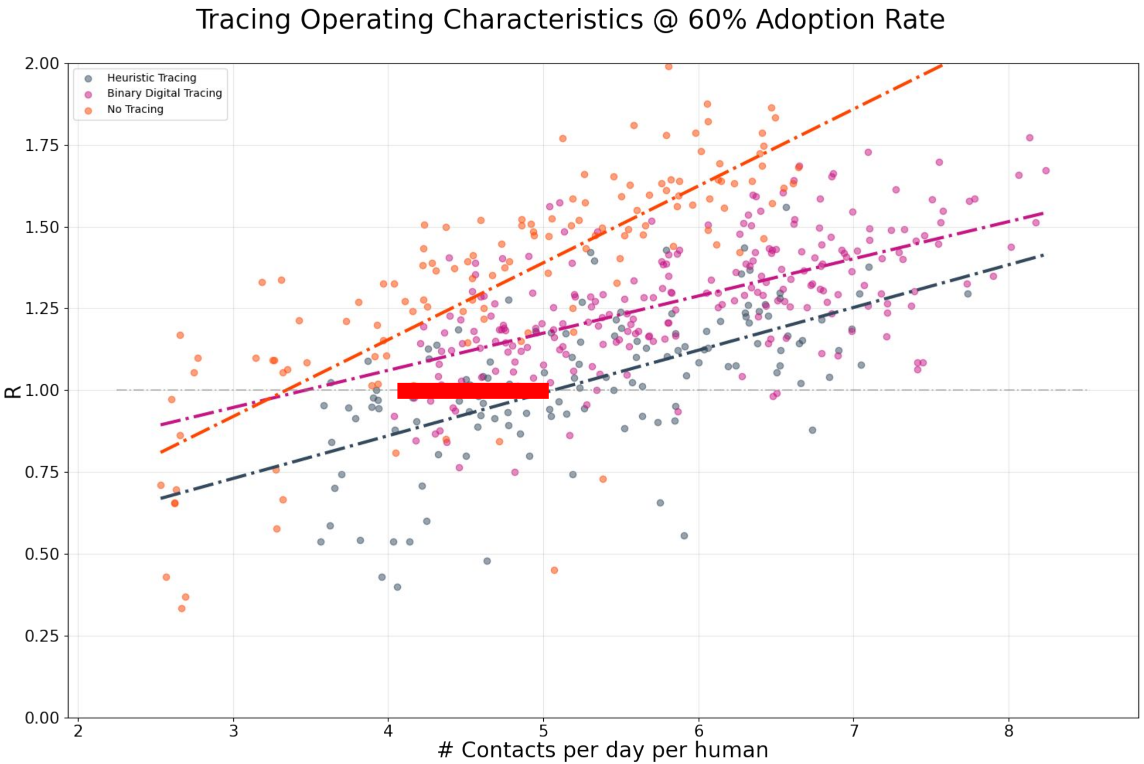
Simulation Results: COVI Balances Mobility and Virus Transmission (R)



Simulation Results: COVI Balances Mobility and Virus Transmission (R)



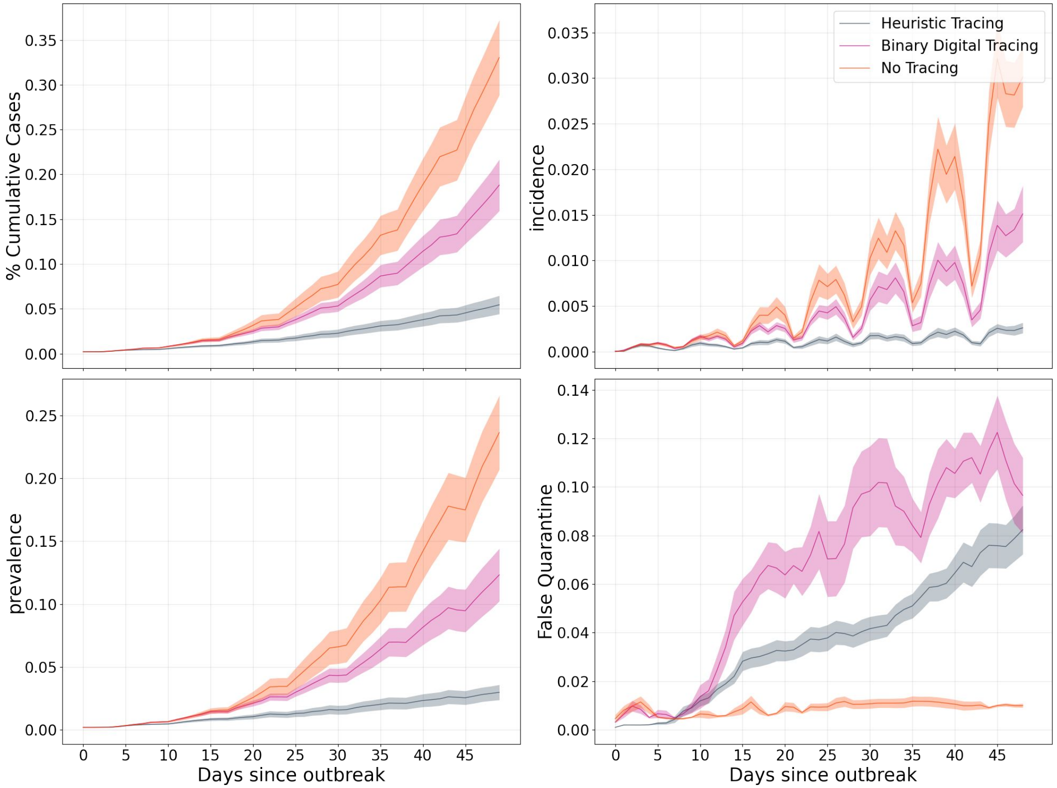
Simulation Results: COVI Balances Mobility and Virus Transmission (R)



Simulation Results: Improved Case Curves Under COVI

Fraction of infected population up to date

Fraction of population infected at any point in time



Average risk of infection

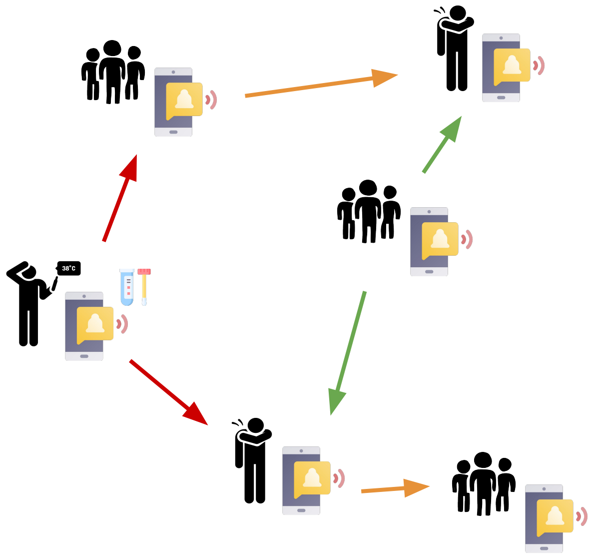
Average % population not infected but quarantined

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 Digital Tracing (BDT, GoC App), the decision is based on the test results.
  - But can we do better at sending early warning signals?

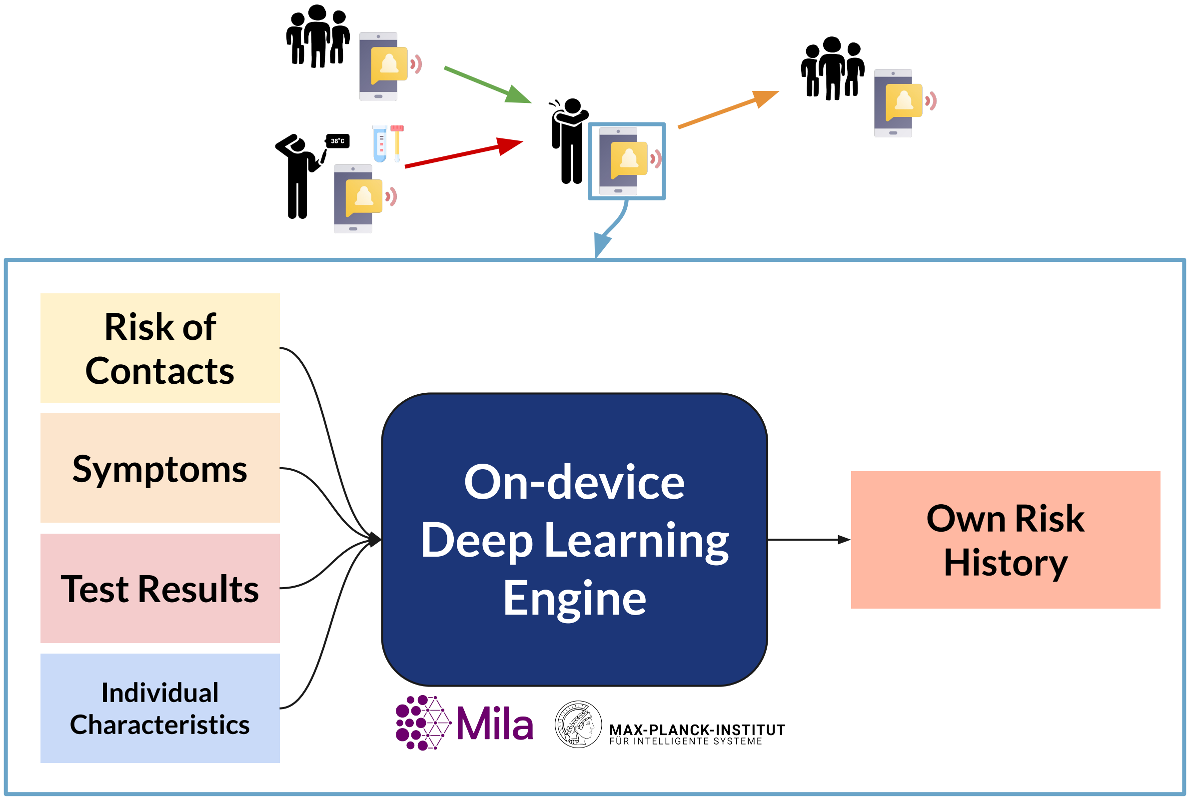
- Machine learning enables us to **learn** to decide what messages to send using real and simulation data in an automated and scalable way.



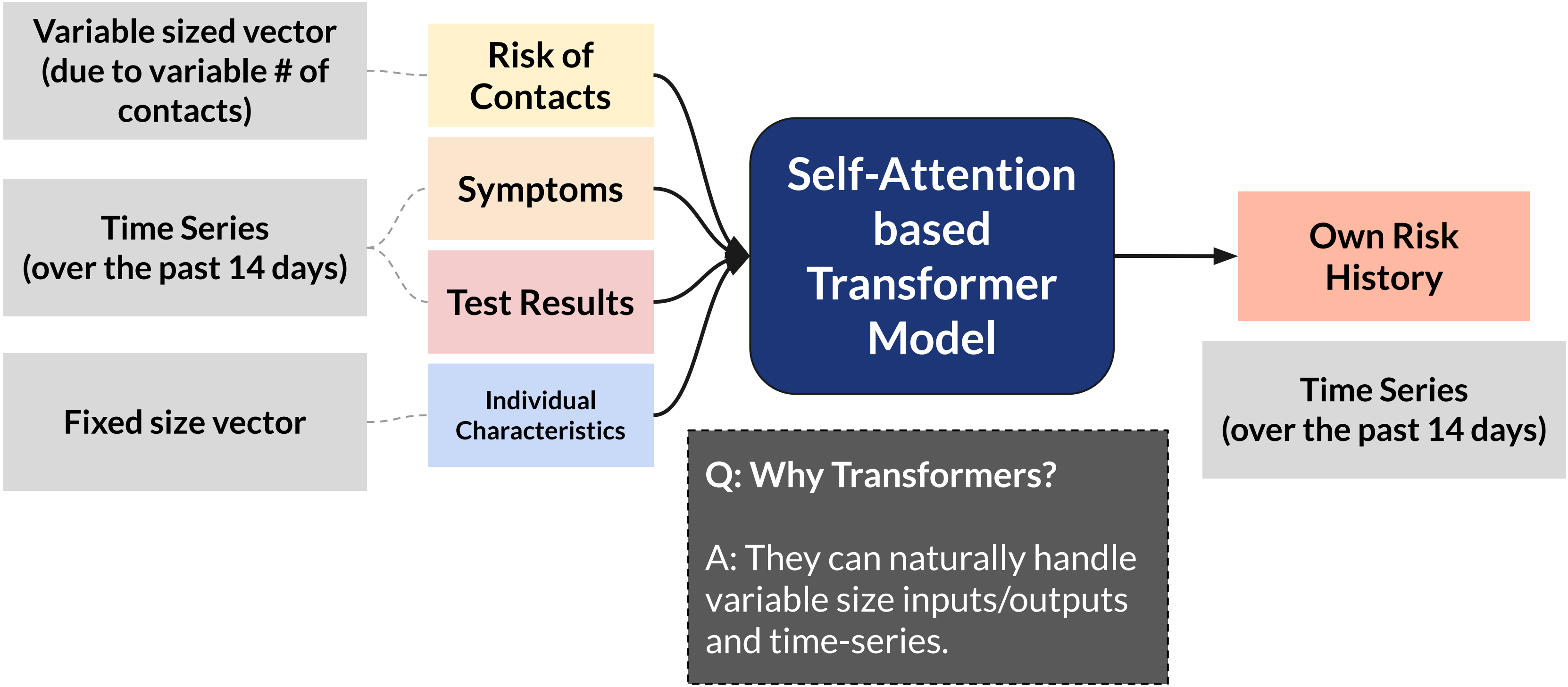
Example Scenario: Better Early Warning Signals

	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	

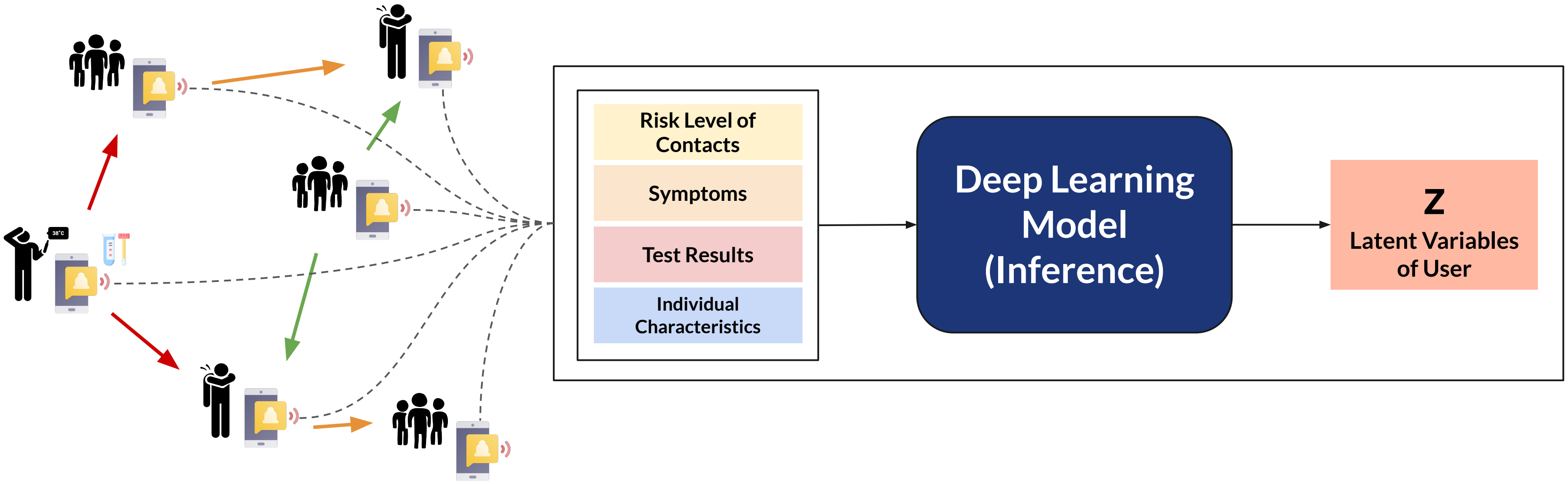
What happens on the phone?



The Deep Learning Engine Unboxed

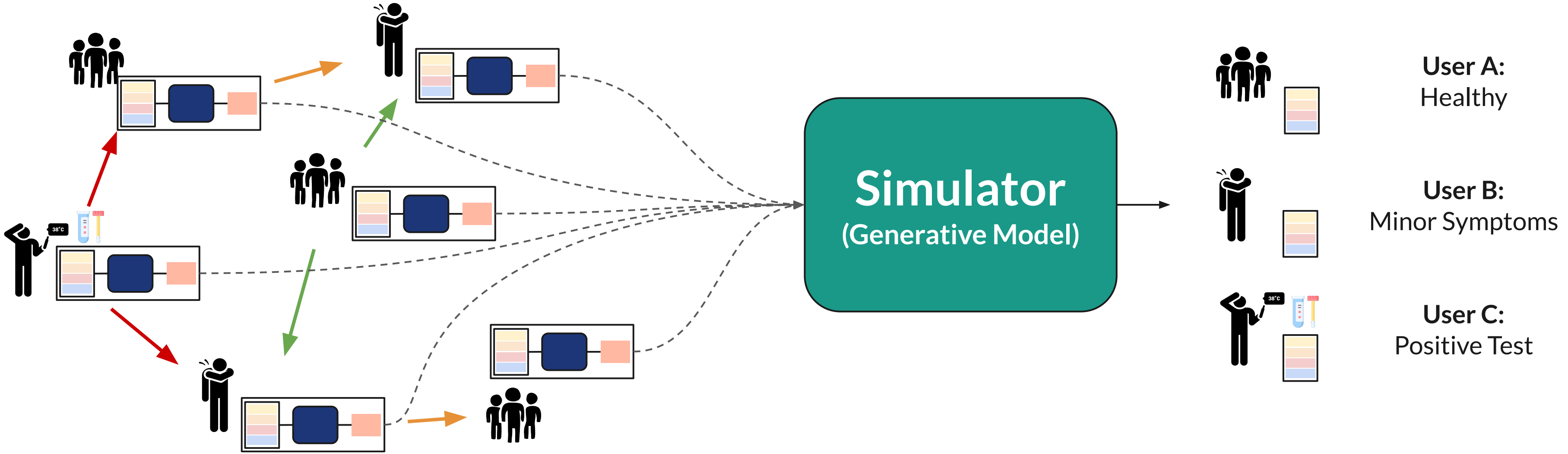


Learning from Real World Data (Work in Progress!)



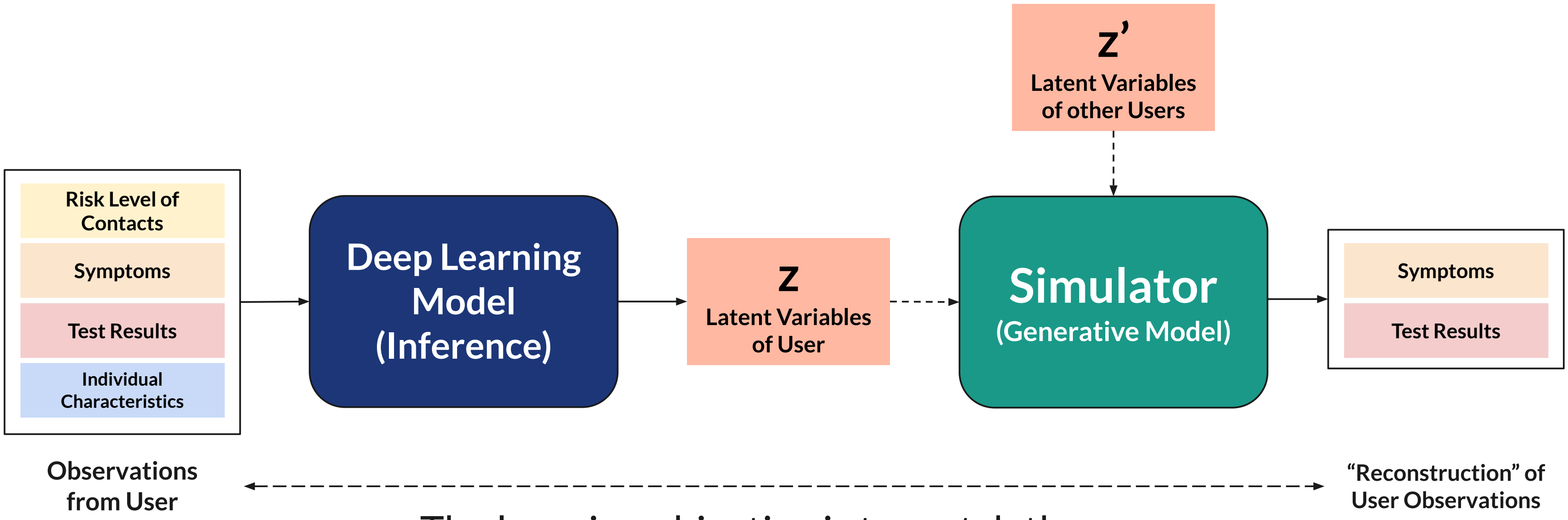
The "inference model" runs on every app-users' phone.

Learning from Real World Data (Work in Progress!)



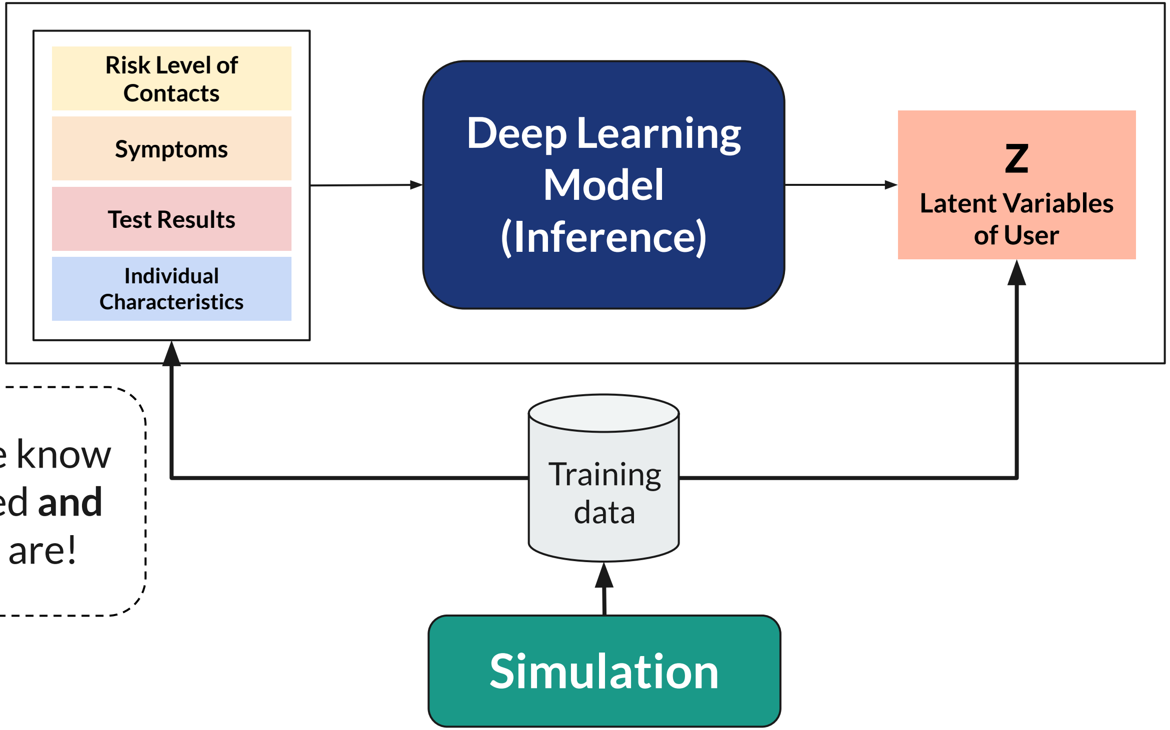
The “generative model” receives latent variables from every app user (who has consented), and predicts their respective states.

Learning from Real World Data (Work in Progress!)



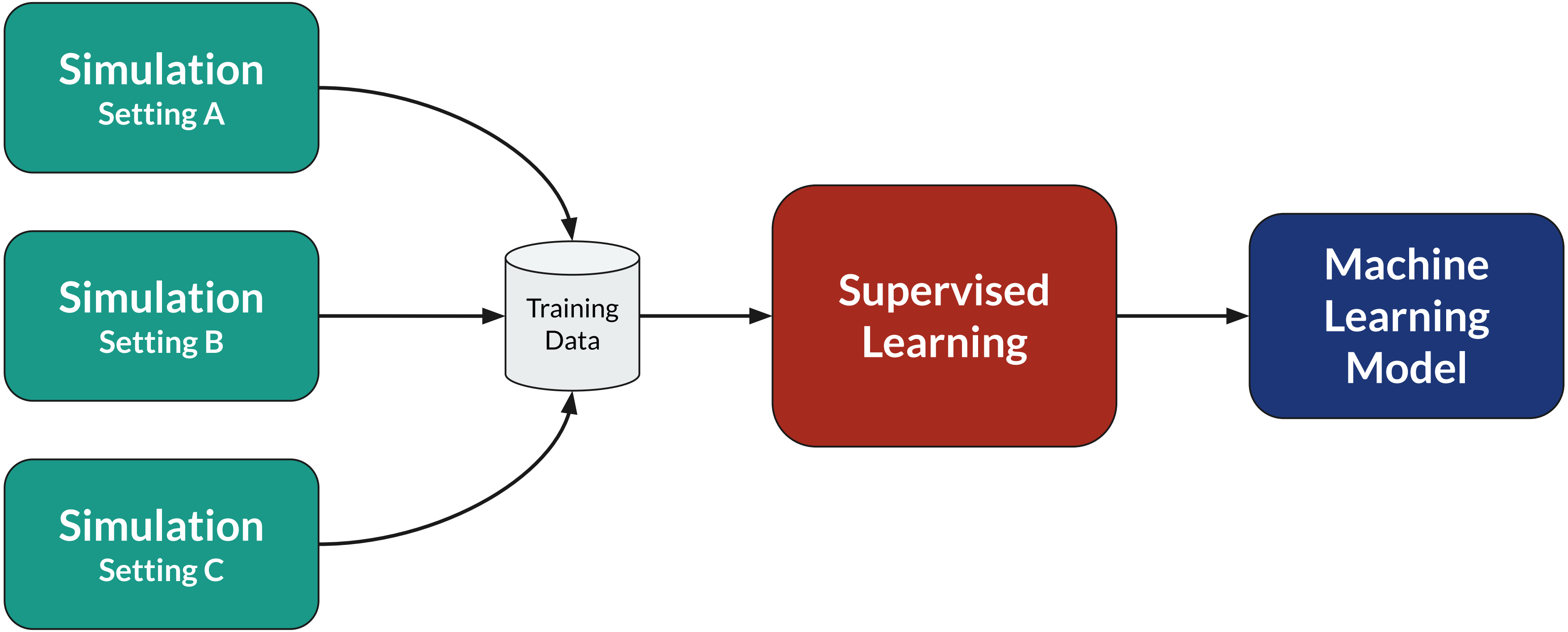
The learning objective is to match these.

Milestone: Learning from Simulations

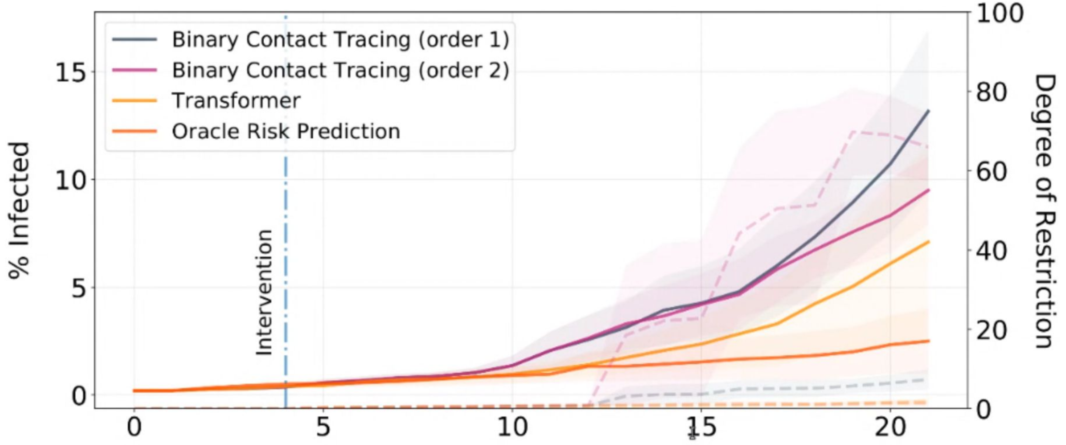


In simulations, we know what the observed **and** latent variables are!

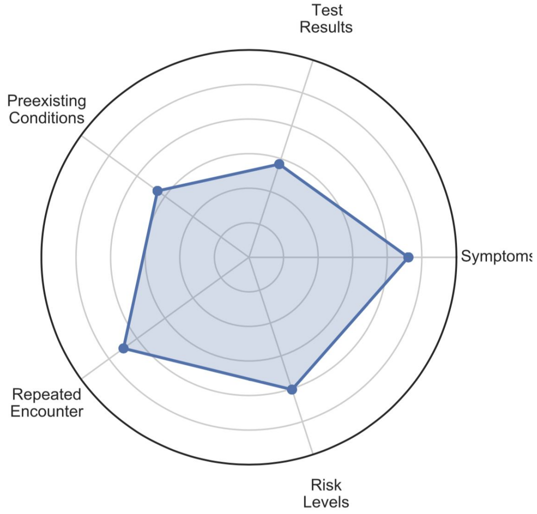
Learning from *Domain Randomized* Data



First Results



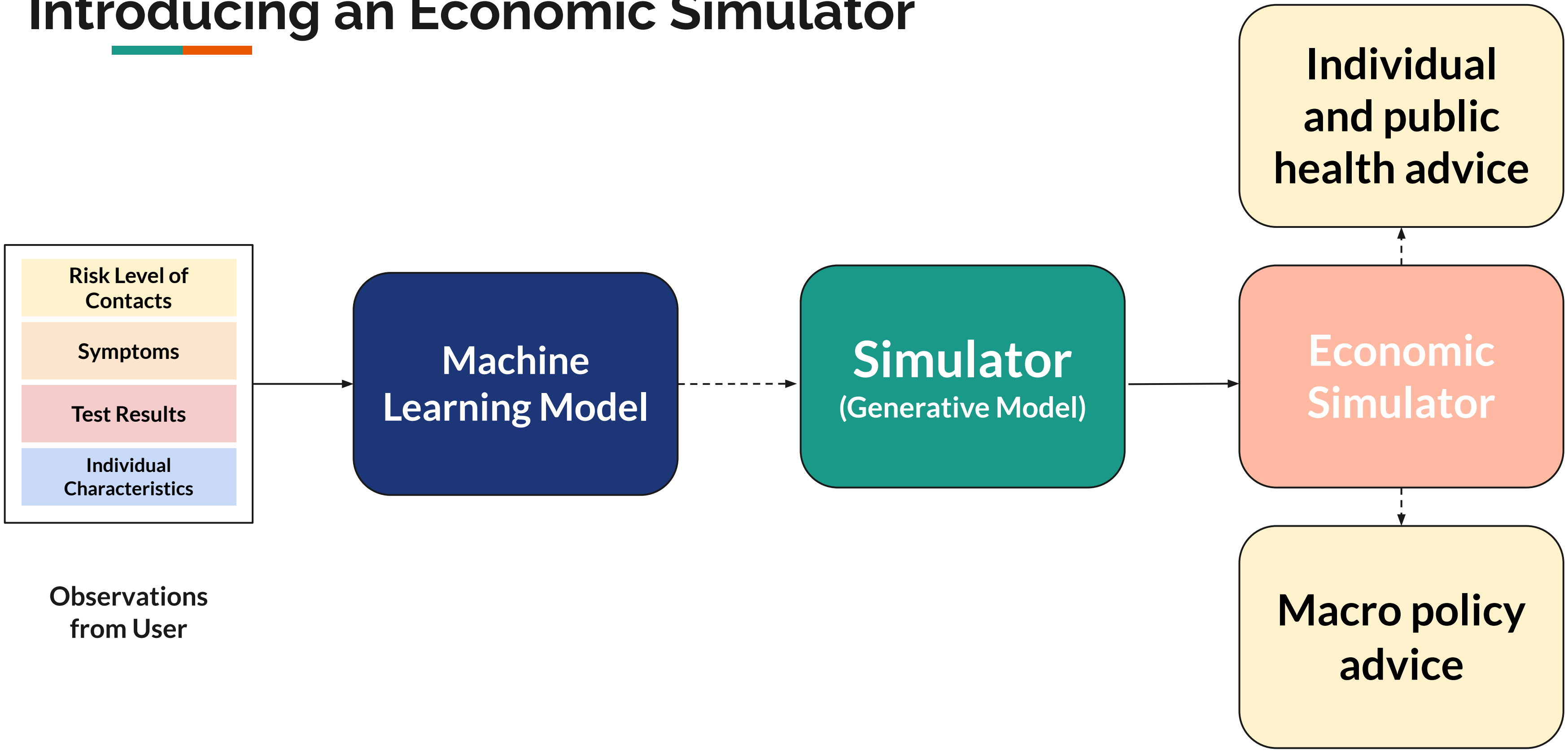
The transformer controls the infection better than BDT (while being less constraining)



Importance of input features for the transformer

The Health and Economic Impacts of Tracing

Introducing an Economic Simulator

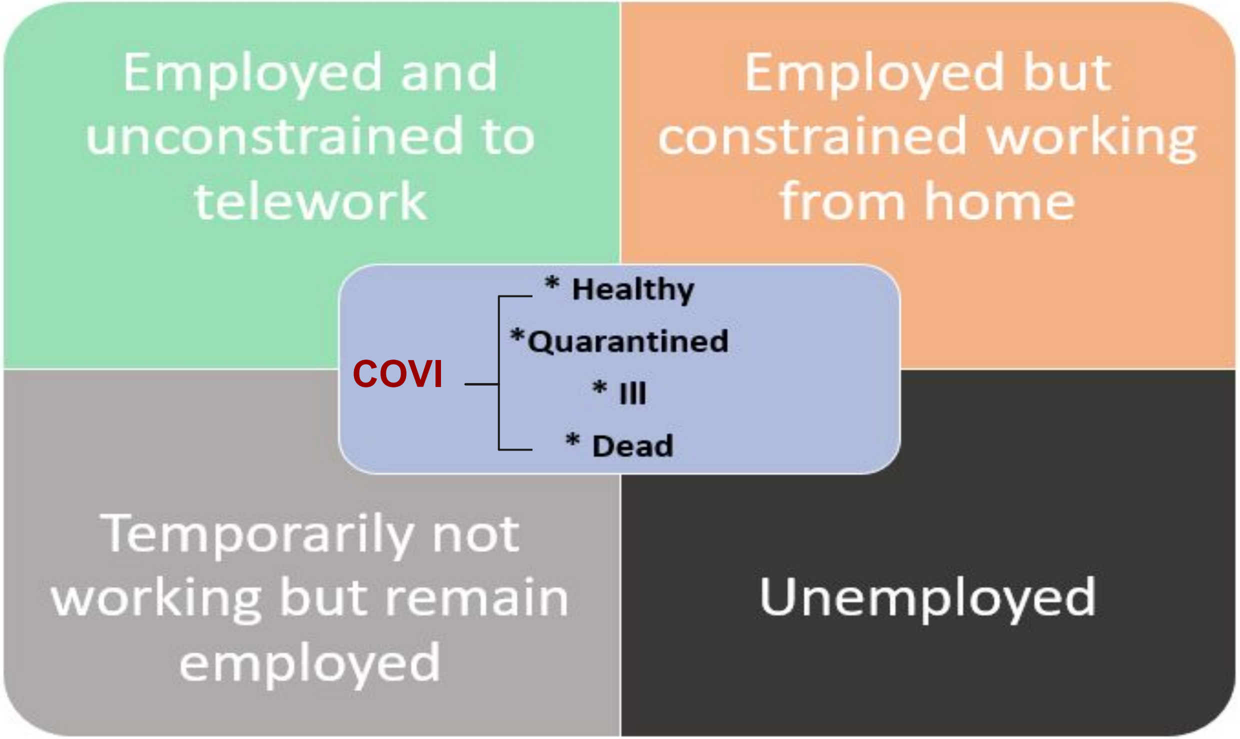


adaptER-COVID19: an application to national data

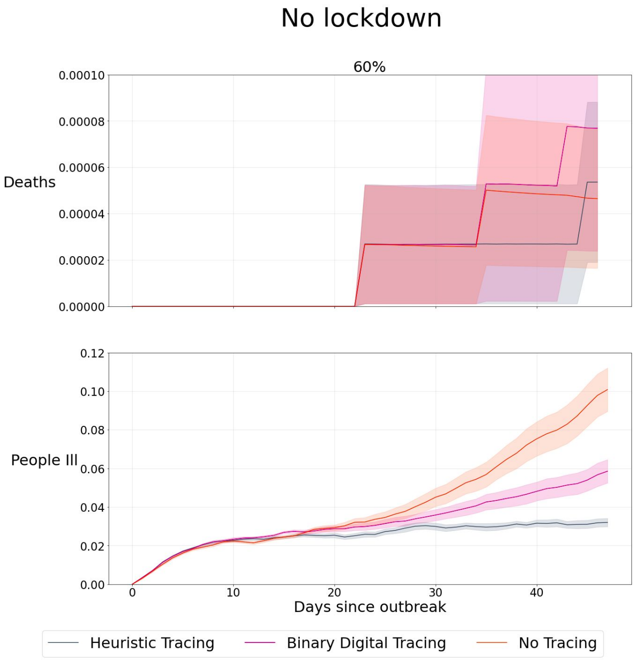
01	Input-output Model	• Labour, capital, imports as inputs for production • Consumption, investment and export sectors
02	Corporate Bankruptcy Model	• Agent-based corporate defaults • Connected to IO-Model through net operating surplus of companies
03	Individual Insolvency Model	• Model household earnings • Behavior (fear factor) determining risk of insolvency

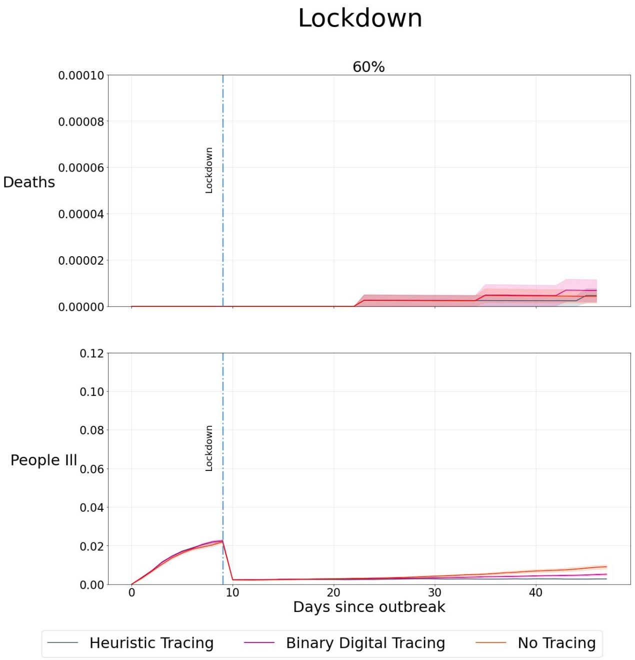
Source: https://github.com/BDI-pathogens/OpenABM-Covid19
https://www.coronavirus-fraser-group.org/

Mapping COVI into a matrix of employment & health status



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

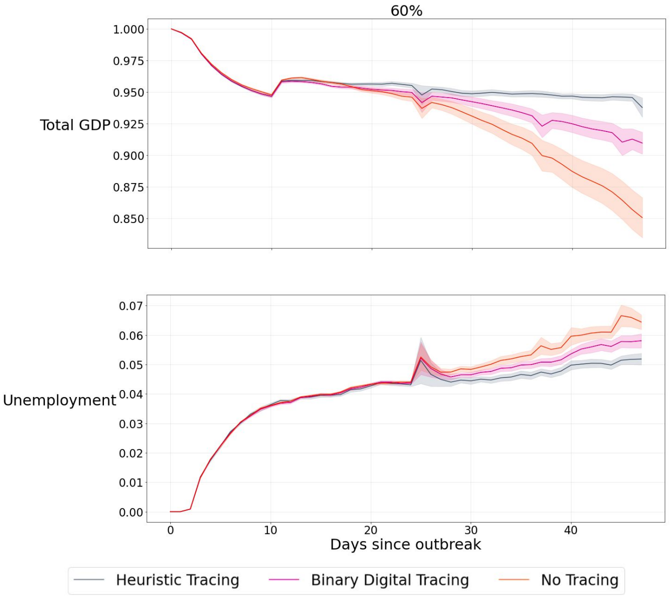




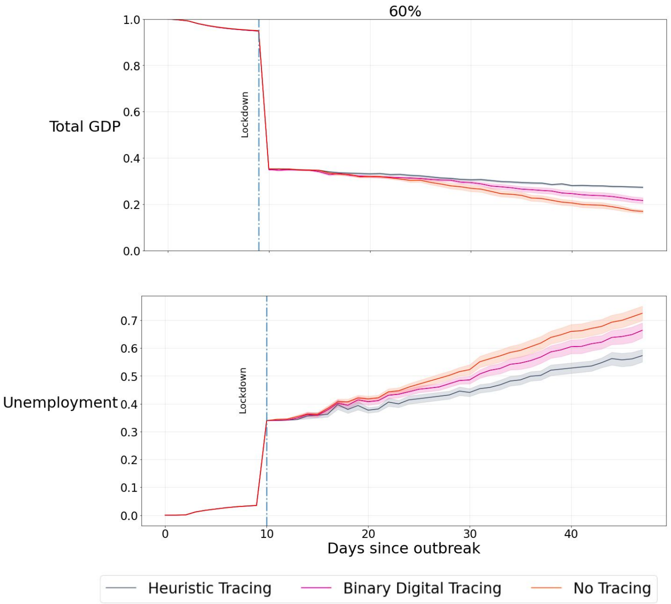
Source: “The Daily - Study: Willingness of Canadians to use a contact tracing application”, Statistics Canada. July 31, 2020.
https://www150.statcan.gc.ca/n1/daily-quotidien/200731/dq200731d-eng.htm

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

No lockdown



Lockdown



Data source: Pathogen Dynamics group, University of Oxford, IBM UK. Data collection for Canada is underway.

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

Icons made by Freepik, fjstudio, Pixel Perfect , photo3idea_studio, Gregor Cresnar, Vitaly Gorbachev from www.flaticon.com

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

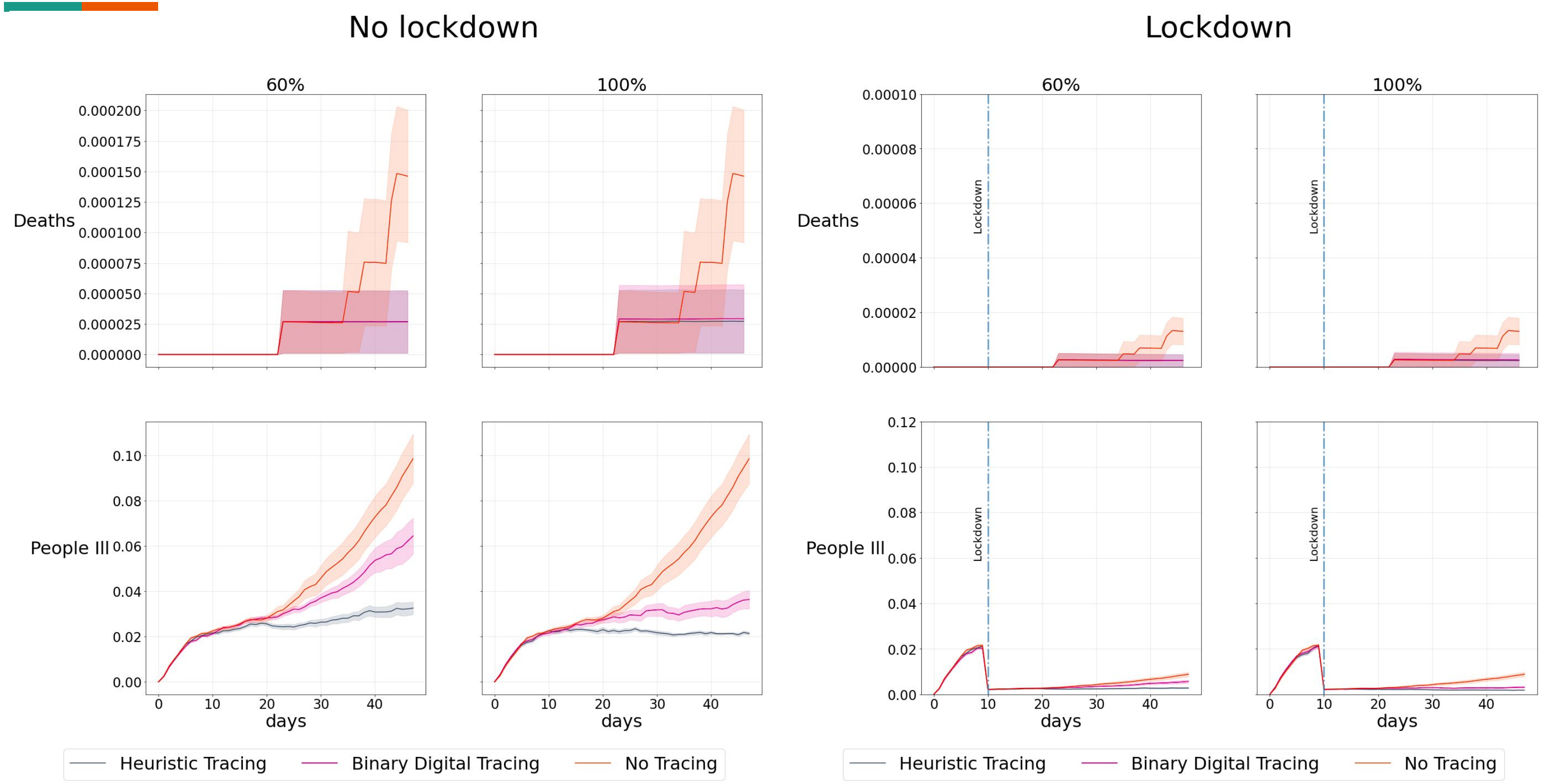
Ethical considerations

- 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

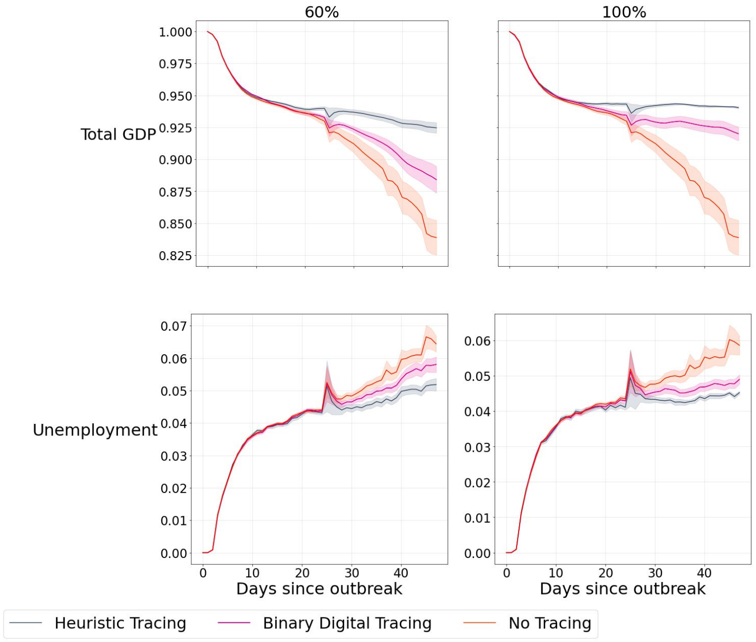
- Population size: 3000
- Initial number of infected individuals: 6 (0.2% of the population)
- 25% Asymptomatic population
- Number of tests per day = 3 (0.1% of the population)
- Behavior Modifications -
    - Low Risk Agents have 1/8th of the contacts as compared to pre COVID-19 contacts
    - Medium 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



100% adoption rate comparison

No lockdown



Lockdown