What can we learn from a **billion** agents?

Ayush Chopra
MIT

github.com/AgentTorch/AgentTorch

AI economist with 4 agents

Zheng et al (2021)

AI economist with 4 agents

Zheng et al (2021)

Smallville with 25 agents

Park et al (2023)

AI economist with 4 agents

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Minecraft with 1000 agents

Yang et al (2024)

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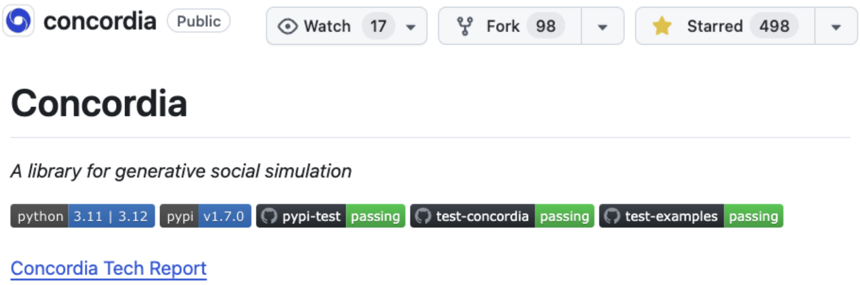
Minecraft with 1000 agents

Yang et al (2024)

Deepmind framework for generative social simulations



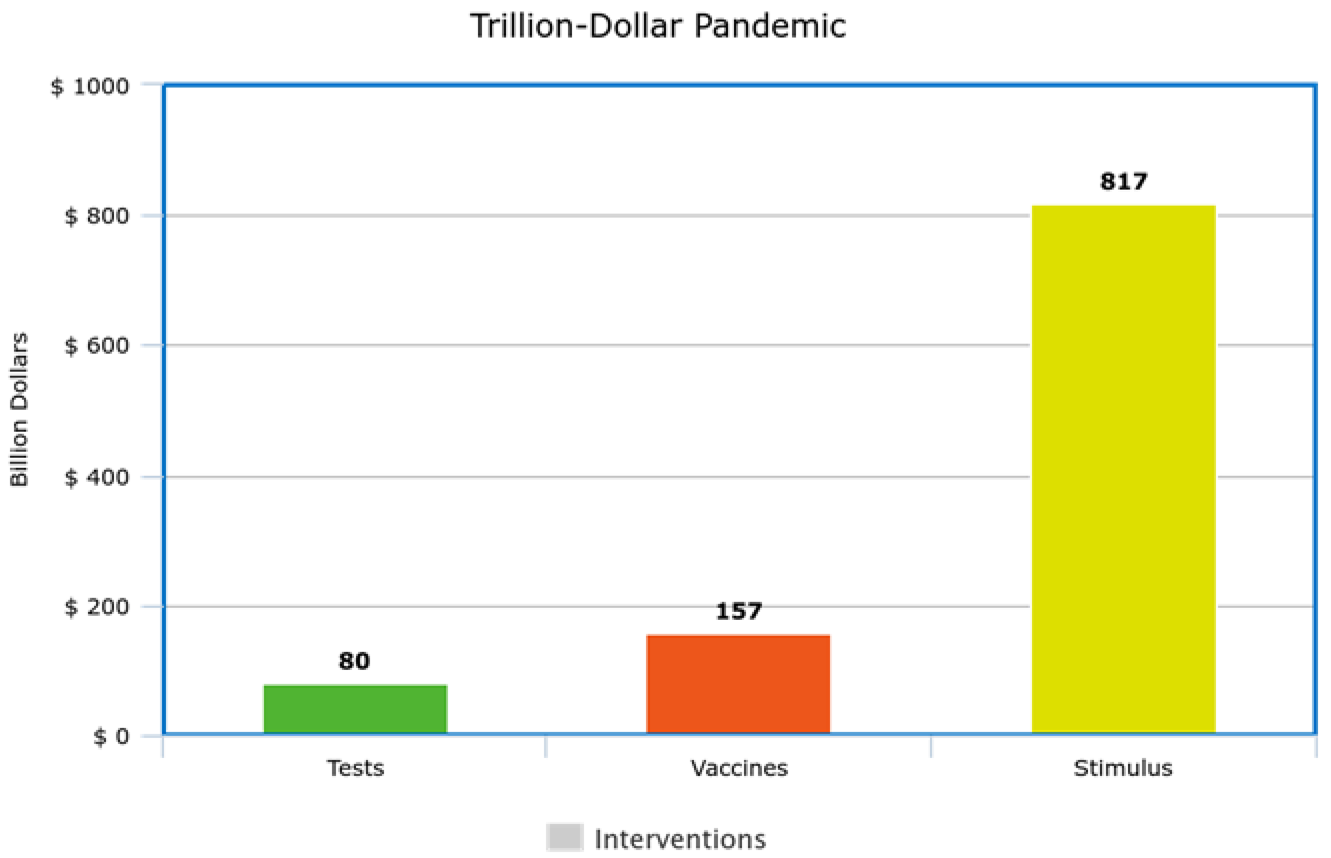
Vezhnevets et al (2023)

Imagine millions of autonomous agents

mimic global demographics + calibrated to reality

high-resolution agents + population-scale interactions

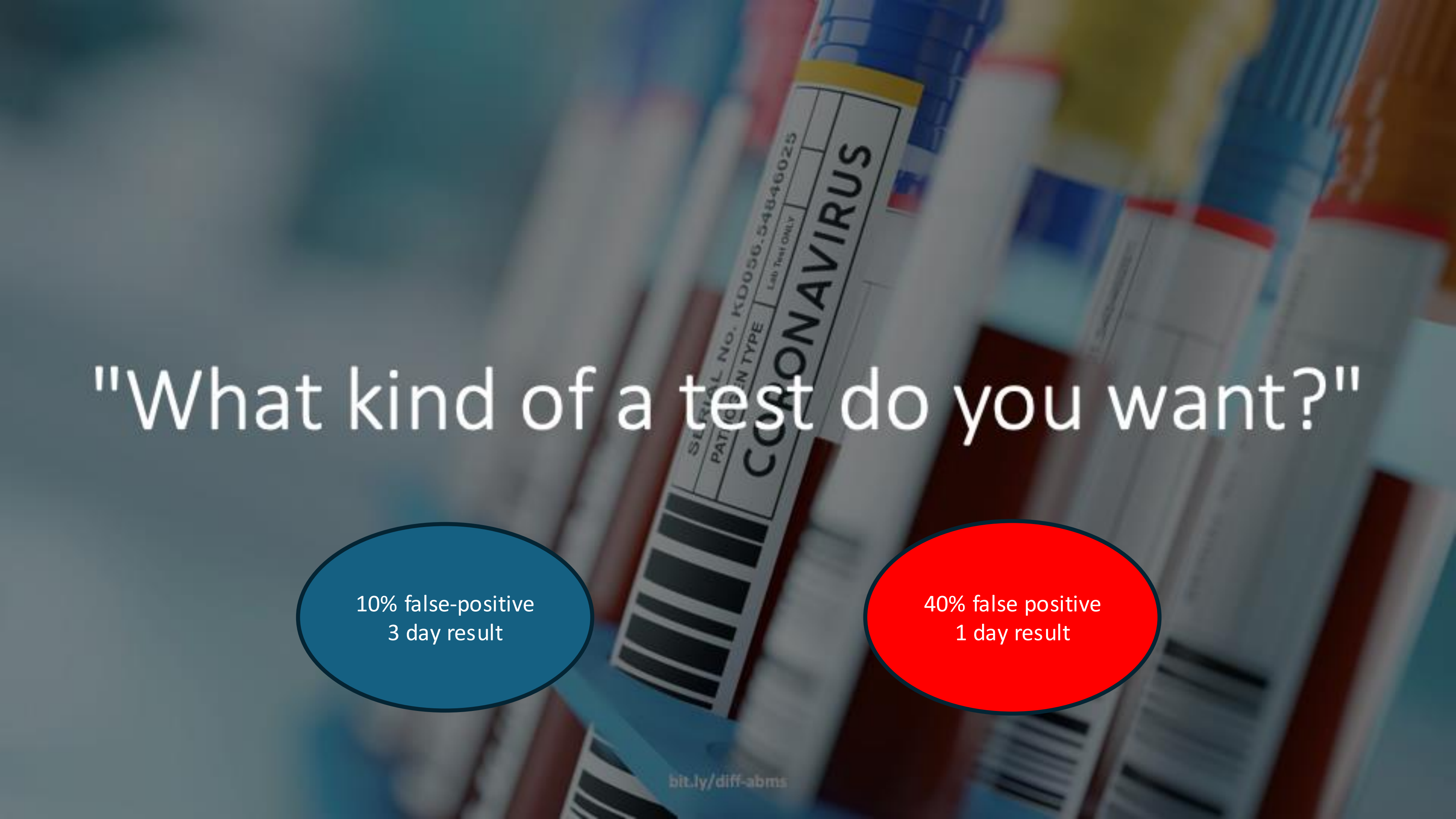

END THE LOCKDOWN
VACCINATE HIMSELF!
COVID = SCAM
THIS SIGN TESTED POSITIVE FOR COVID 19
SAVE CALIFORNIA
SIGN HERE


Trillion-Dollar Pandemic
$ 1000
$ 800
$ 600
$ 400
$ 200
$ 0
Billion Dollars
80
157
817
Tests
Vaccines
Stimulus
Interventions

"What kind of a test do you want?"

10% false-positive
3 day result

40% false positive
1 day result



Large Population Models

lpm.media.mit.edu/platform

model millions of interacting agents to capture collective dynamics

5 million citizens

30 million households

$ billion supply chains

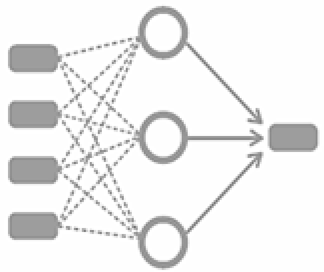
Outline: What can we learn from a billion agents?

- Motivation and Impact
- Introduction
    - Large Population Models (LPMs)
    - The AgentTorch framework
- Case Study
    - Modeling disease spread over 8.4 million agents
- Conclusion

Challenges with agent-based simulations

Expressive agents

Adaptive
Heterogeneous



Dynamic interactions

Multi-scale
Stochastic

Synchronized analysis

Decentralized
Sensitive

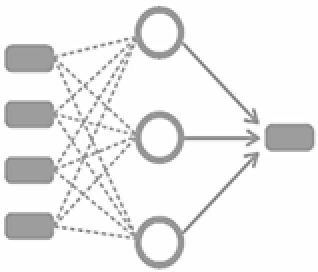
Large Population Models

Expressive agents

Adaptive
Heterogeneous

LLM Archetypes

AAMAS'23; arxiv'24



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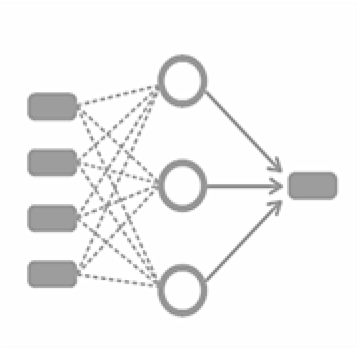
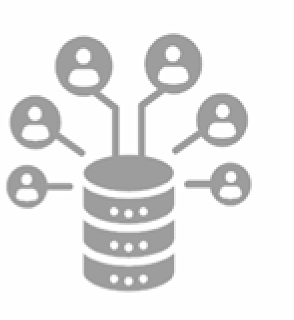


Dynamic interactions

Multi-scale
Stochastic

Differentiability

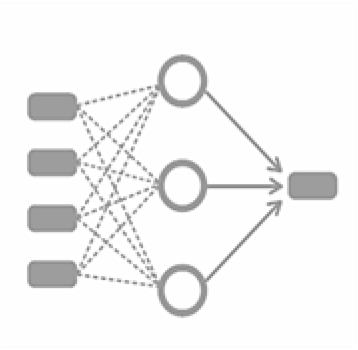
BMJ'21; AAMAS'23;
AAMAS'24 (Best paper runner-up)



Synchronized analysis

Decentralized
Sensitive

Large Population Models



Expressive agents	Dynamic interactions	Synchronized analysis
Adaptive Heterogeneous	Multi-scale Stochastic	Decentralized Sensitive
LLM Archetypes	**Differentiability**	**Secure MPC**
AAMAS’23; arxiv’24	BMJ’21; AAMAS’23; AAMAS’24 (Best paper runner-up)	ICML-W’22 (Best paper); AAMAS’24; Nature Medicine’25

Simulate an entire country on commodity hardware

Execute upto 300,000 interactions/sec and scale to 60 million agents/GPU

Method	Simulation	Calibration	Analysis
Conventional ABM*	50 hours	100,000 hours	5,000 hours
LPM	5 minutes	12 hours	10 seconds

*Mesa, JUNE, Simudyne

8 million london agents

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Method	Simulation	Calibration	Analysis
Conventional ABM*	50 hours	100,000 hours	5,000 hours
LPM	5 minutes	12 hours	10 seconds
	+ 600x	**+ 8300x**	**+ 5000x**

*Mesa, JUNE, Simudyne

8 million london agents

github.com/AgentTorch/AgentTorch

pip install agent-torch

SCAN ME

Build end-to-end workflows in 3 lines of code

```python
from agent_torch.core import env
from agent_torch.core import models, populations

# create
simulation = env.create_from_template(
                models.epidemiology,
                populations.new_zealand
             )

# execute
simulation.execute()

# visualize
simulation.visualize(
        geo_index='agent/positions')
```

Expressive templates   Custom populations   High-res visualizations

Build end-to-end workflows in 3 lines of code

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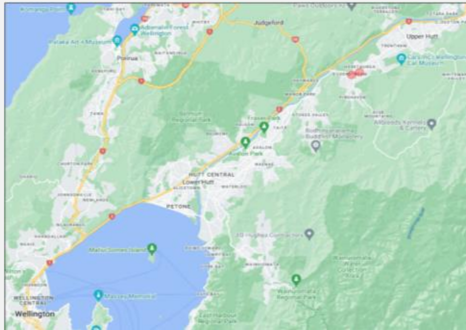
Expressive templates   Custom populations   High-res visualizations



Comparison with other frameworks

Feature	AgentTorch	Concordia	Flame	Mesa
GPU Execution	✅	✅	✅	❌
Million-agent Populations	✅	❌	✅	⚠️
Differentiable Environments	✅	❌	❌	❌
Mechanistic Environments	✅	❌	✅	✅
LLM Integration	✅	✅	❌	❌
Neural Composition	✅	⚠️	❌	❌

Outline: What can we learn from a billion agents?

- Motivation and Impact
- Introduction
- Case Study:
  - Problem Formulation: modeling disease spread over 8.4 million agents
  - Part 1: Population Prompting via Archetypes
  - Part 2: Gradient-assisted simulation via Differentiable Environments
  - Part 3: Decentralized analysis via Secret Sharing
- Conclusion

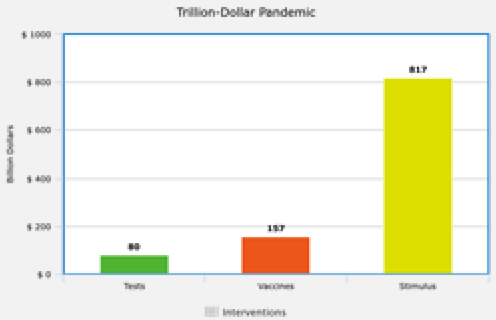
END THE LOCKDOWN
VACCINATE HIMSELF!
LOCKDOW
DON'T BE A LAB RA
COVID = SCAM
THIS SIGN TESTED POSITIVE FOR COVID-19
SAVE CALIFORNIA
SIGN HERE

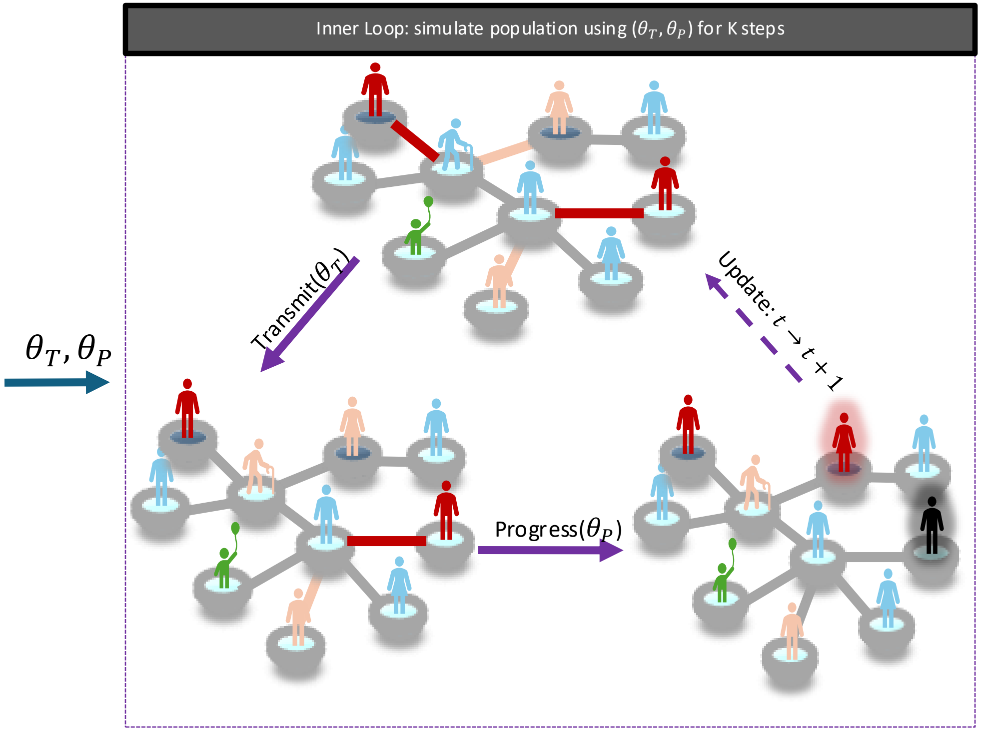
New York City

- 5 boroughs
- 8.4 million people
- 3.3 million households
- 200,000 small businesses

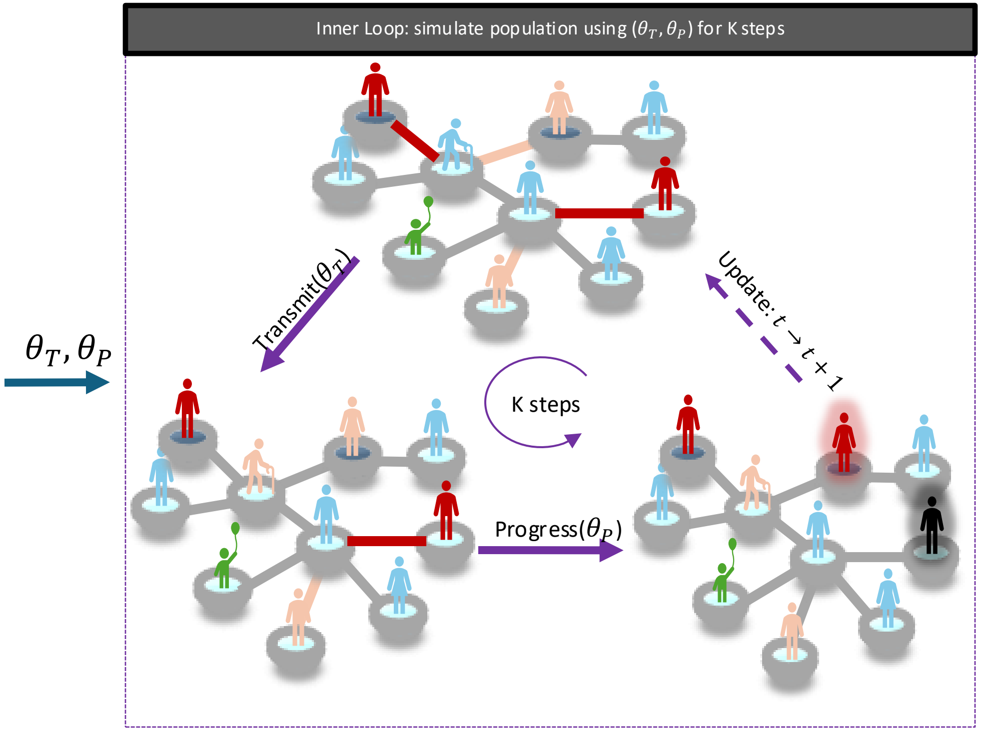
2020-2022

What if we give $500 stimulus payments?





Inner Loop: simulate population using (θ_T, θ_P) for K steps
θ_T, θ_P
Transmit(θ_T)
Progress(θ_P)
Update: $t \to t+1$



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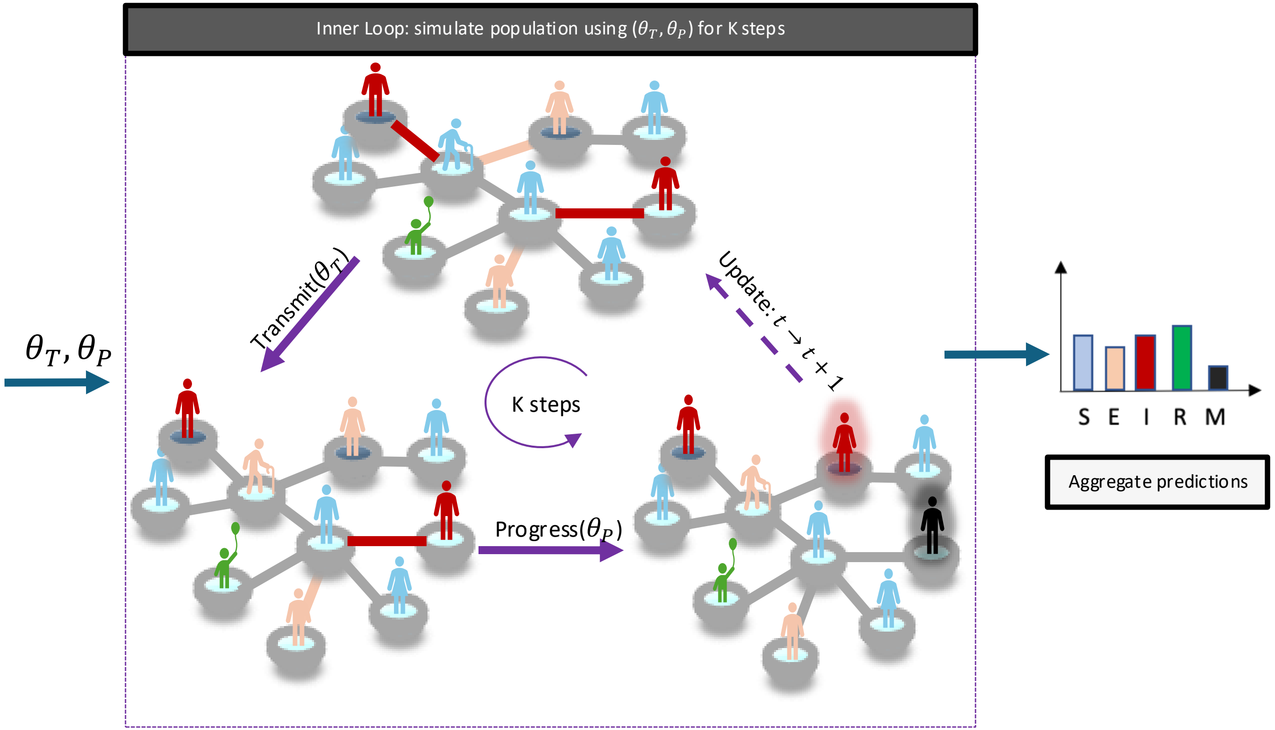
K steps
Progress(θ_P)



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θ_T, θ_P
Transmit(θ_T)
Update: $t \rightarrow t+1$
K steps
Progress(θ_P)
S E I R M
Aggregate predictions

$$\mathbf{z}_i(t+1) = f\left(\mathbf{z}_i(t),\ \bigoplus_{j \in \mathcal{N}_i(t)} M_{ij}(t),\ \boldsymbol{\theta},\ \ell(\cdot|\mathbf{z}_i(t))\right)$$

environmental influence

Current state of agent

$$\mathbf{z}_i(t+1) = f\left(\mathbf{z}_i(t),\ \bigoplus_{j \in \mathcal{N}_i(t)} M_{ij}(t),\ \boldsymbol{\theta},\ \ell(\cdot|\mathbf{z}_i(t))\right)$$

New state of agent

neighborhood influence

Individual agency

- Disease status
- Age, Income, Occupation

Current state of agent

“Spread factor” of the variant

environmental influence

$$\mathbf{z}_i(t+1) = f\left(\mathbf{z}_i(t),\ \bigoplus_{j \in \mathcal{N}_i(t)} M_{ij}(t),\ \boldsymbol{\theta},\ \ell(\cdot|\mathbf{z}_i(t))\right)$$

New state of agent

- New disease status
- Age, Income, Occupation

neighborhood influence

- Time since infection
- Vaccination status

Individual agency

Willingness to interact

Q1: model individual agency?

- Varies with agent state
- Need to be sampled online

$$\mathbf{z}_i(t+1) = f\left(\mathbf{z}_i(t), \bigoplus_{j \in \mathcal{N}_i(t)} M_{ij}(t), \boldsymbol{\theta}, \ell(\cdot|\mathbf{z}_i(t))\right)$$

LLMs to prompt 8.4 millions agents in NYC?

Chopra et al. “On the limits of agency in agent-based models" (In review, arxiv’24)

Large Population Models

Expressive agents

Adaptive
Heterogeneous

LLM Archetypes

AAMAS'23; arxiv'24

Dynamic interactions

Multi-scale
Stochastic

Differentiability

BMJ'21; AAMAS'23;
AAMAS'24 (Best paper runner-up)

Data-driven analysis

Decentralized
Sensitive

Secure MPC

ICML-W'22 (Best paper);
AAMAS'24; Nature Medicine'25

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LLM Archetypes

Scale LLMs to prompt millions of agents

```
from agent_torch.core import Archetype, Behavior
from agent_torch.populations import NYC

# Create an object of Archetype class
# n_arch estimates a predictive posterior over outcomes
archetype = Archetype(n_arch=7)

# Create an object of Behavior class
work_behavior = Behavior(archetype=archetype.llm(prompt),
                         region=NYC)

will_work = work_behavior.sample()
```

Agent Prompt

User Prompt

You are a {gender} of age {age}, living in the {location} region. You work in {occupation } industry with monthly income of {income }.

The number of new cases in your neighborhood is {cases}, which is a {change}% change from the previous month. It has been {duration} months since the start of the pandemic.

This month, you have received a stimulus payment of {payment} to support your living expenses.

Given these factors, do you choose to isolate at home? (isolation behavior)

"There isn't enough information" and "It is unclear" are not acceptable answers. Give a "Yes" or "No" answer, followed by a period. Give one sentence explaining your choice.

#archetypes = *age* x *gender* x *regions* x *occupation* x *income-levels*

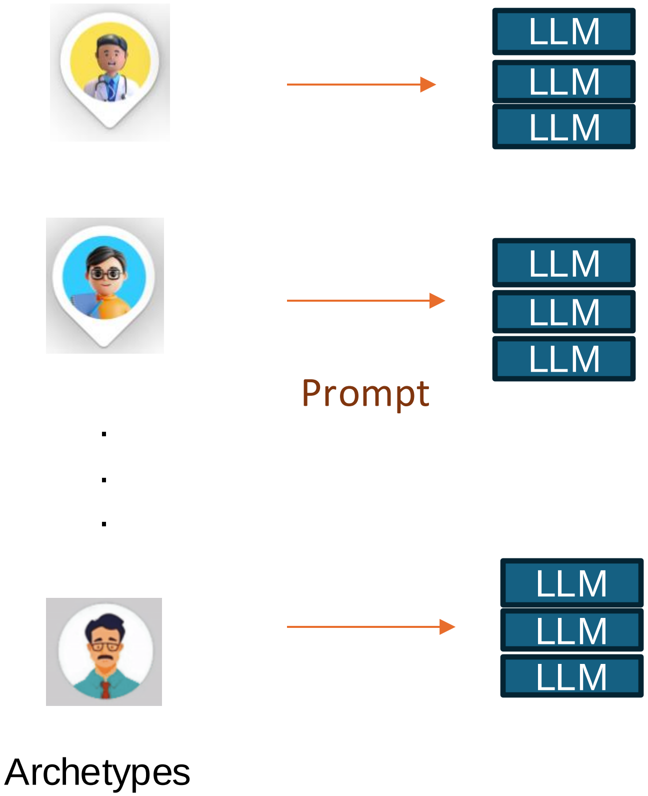
Specify prompt-specific archetypes

8.4 million agents in NYC

~2000 representative archetypes

prompt dimensions
data resolution (e.g. census)

Population Prompting via Archetypes



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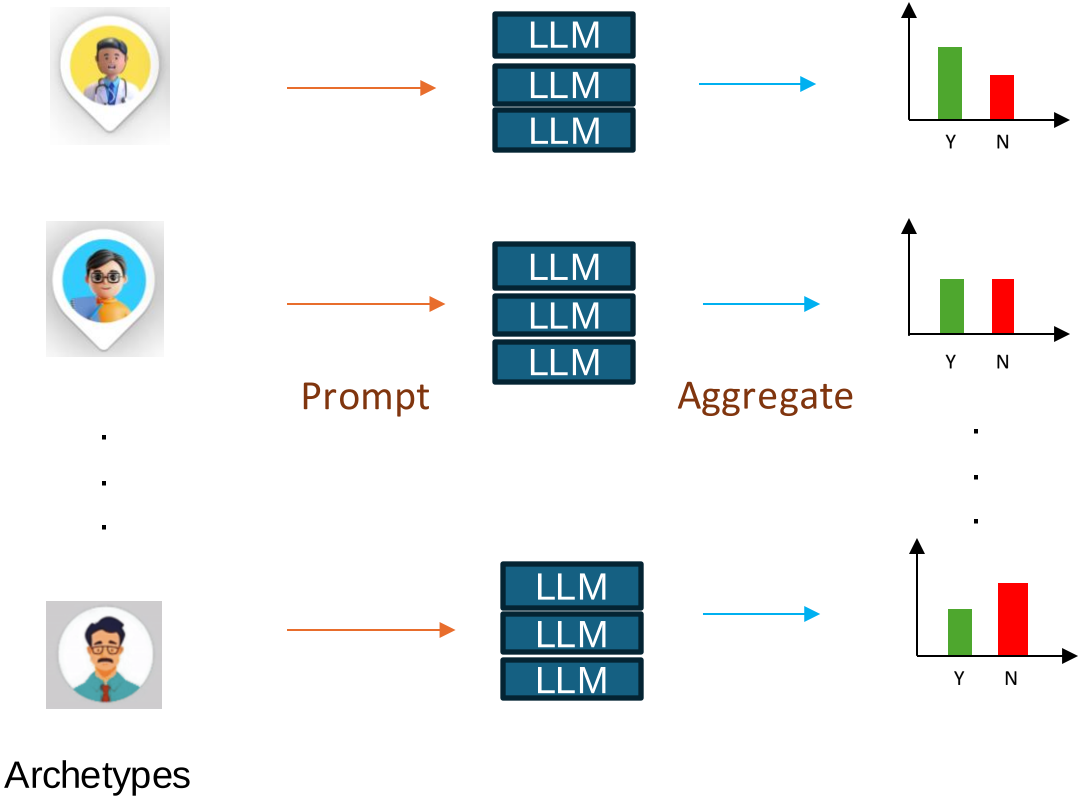
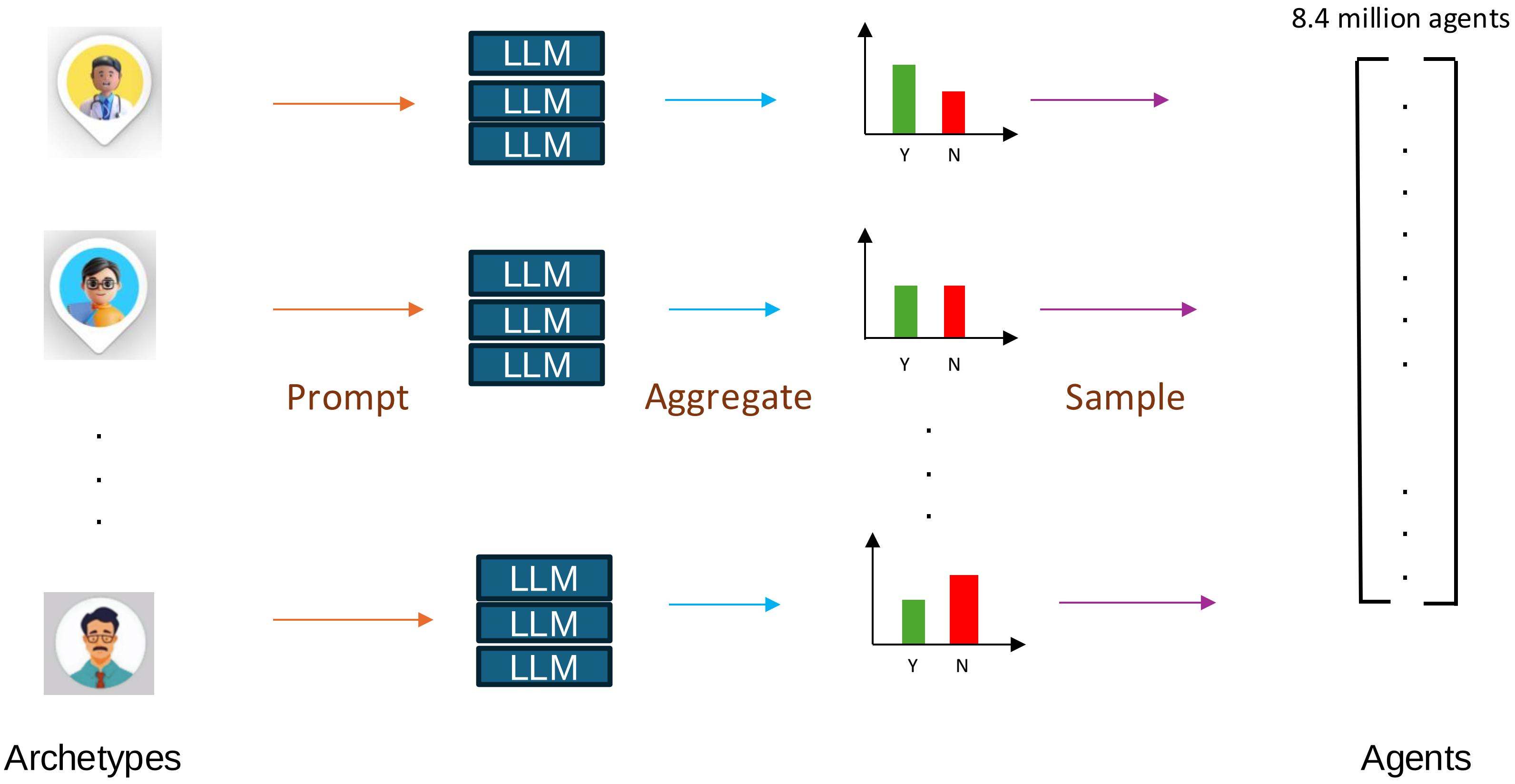


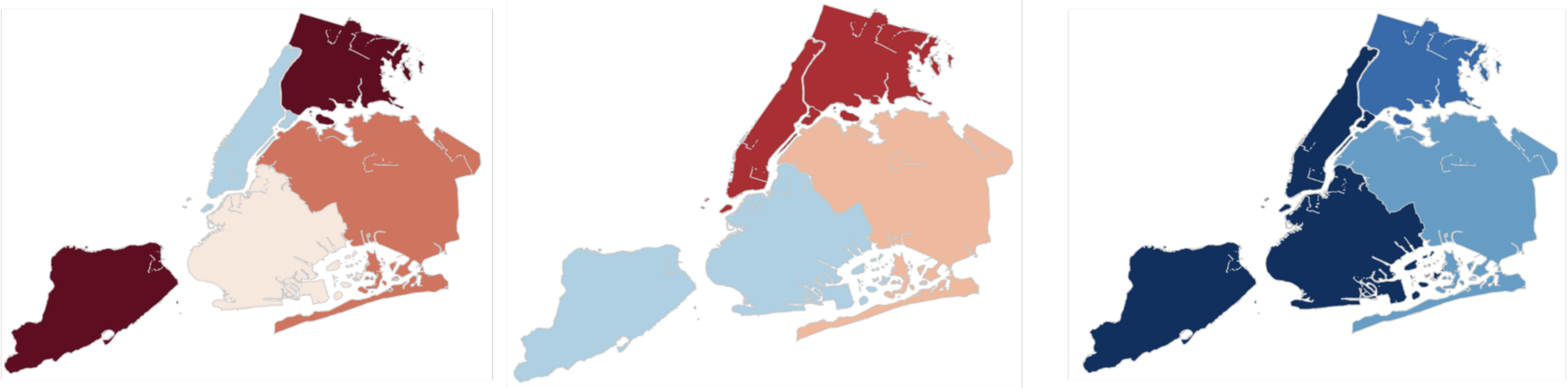
Population Prompting via Archetypes



High variance individual agents produce reliable census-level estimates

Prompt virtual population of 8.4 million agents

Measure correlation with labor force participation census



Prompt axes: demographics | demographics + disease | demographics + disease + stimulus

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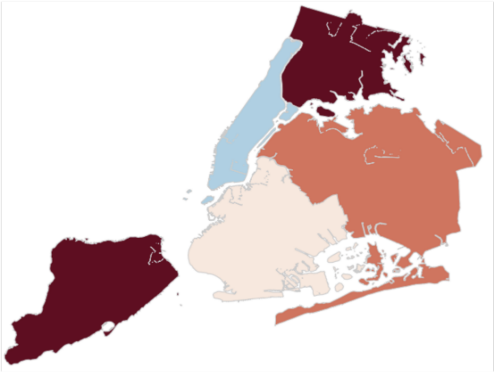

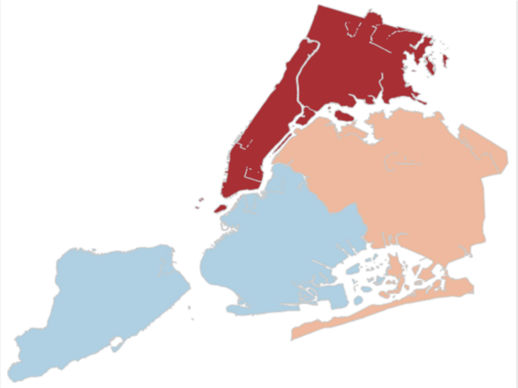

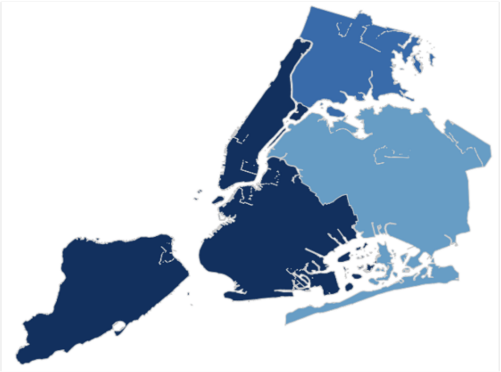

Prompt axes: demographics | demographics + disease | demographics + disease + stimulus

Rebuild the census, in simulation!?

$$\mathbf{z}_i(t+1) = f\left(\mathbf{z}_i(t),\ \bigoplus_{j\in\mathcal{N}_i(t)} M_{ij}(t),\ \boldsymbol{\theta},\ \ell(\cdot|\mathbf{z}_i(t))\right)$$

Q2: simulate and calibrate efficiently?

Simulation involves repeated execution of $\boldsymbol{f}$

Calibration involves estimating $\boldsymbol{\theta}$

$$\mathbf{z}_i(t+1) = f\left(\mathbf{z}_i(t),\ \bigoplus_{j \in \mathcal{N}_i(t)} M_{ij}(t),\ \boldsymbol{\theta},\ \ell(\cdot|\mathbf{z}_i(t))\right)$$

Chopra et al. "differentiable agent-based epidemiology" (AAMAS 2023, Oral)

Chopra et al. "a framework for learning in agent-based models" (AAMAS 2024, Oral)

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- neural or mechanistic
- Stochastic and multiple “sub-steps”

f vectorized and differentiable?

Chopra et al. “differentiable agent-based epidemiology” (AAMAS 2023, Oral)

Chopra et al. “a framework for learning in agent-based models” (AAMAS 2024, Oral)

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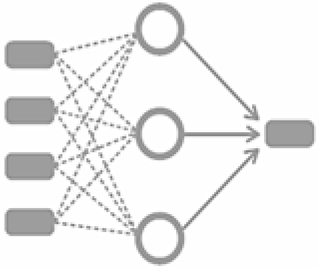

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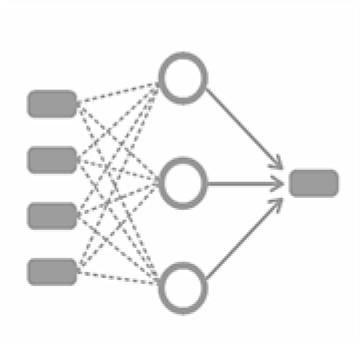

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Stochastic

Differentiability

Compose end-to-end with NNs

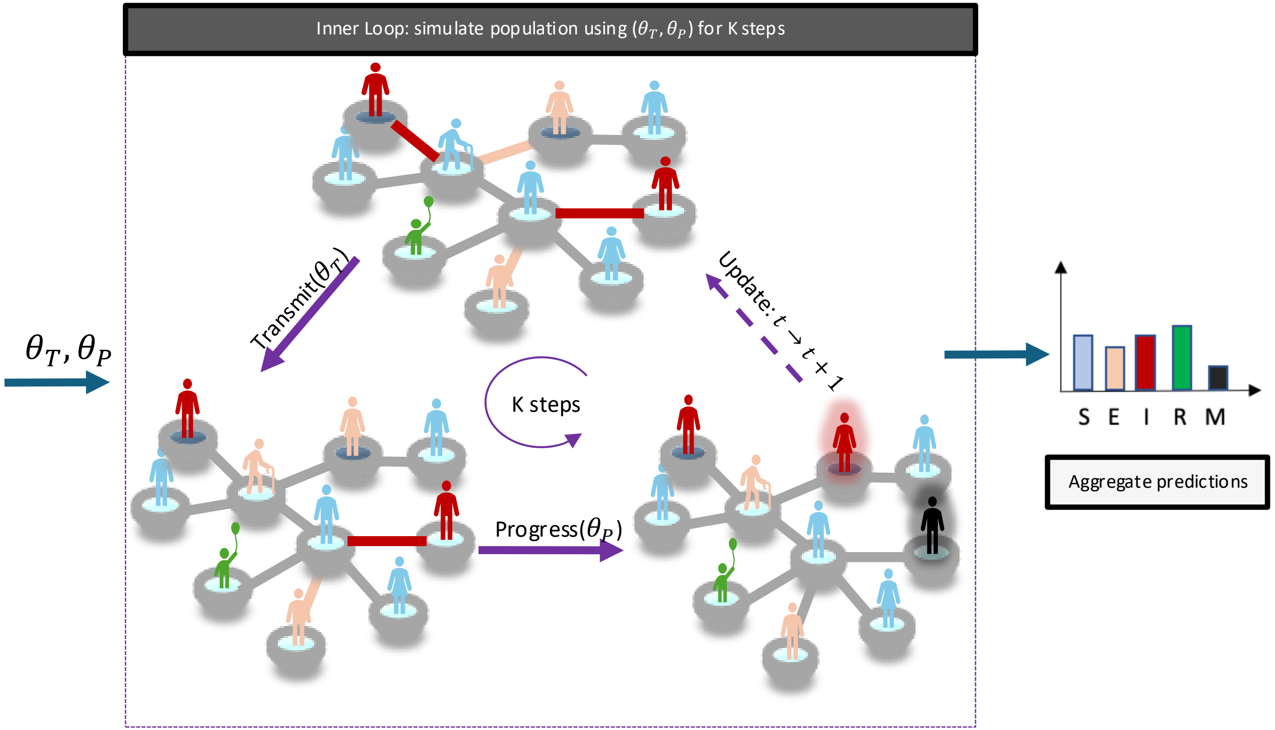
```
# agent_"torch" works seamlessly with the pytorch API
from torch.optim import SGD

nn = compose_nn()

for i in range(n_epochs):
  parameters = compose_nn.forward()

  simulation.step(params=parameters)
  cases, employment = simulation.predict()

  simulation.optimize(SGD)
  simulation.reset()
```



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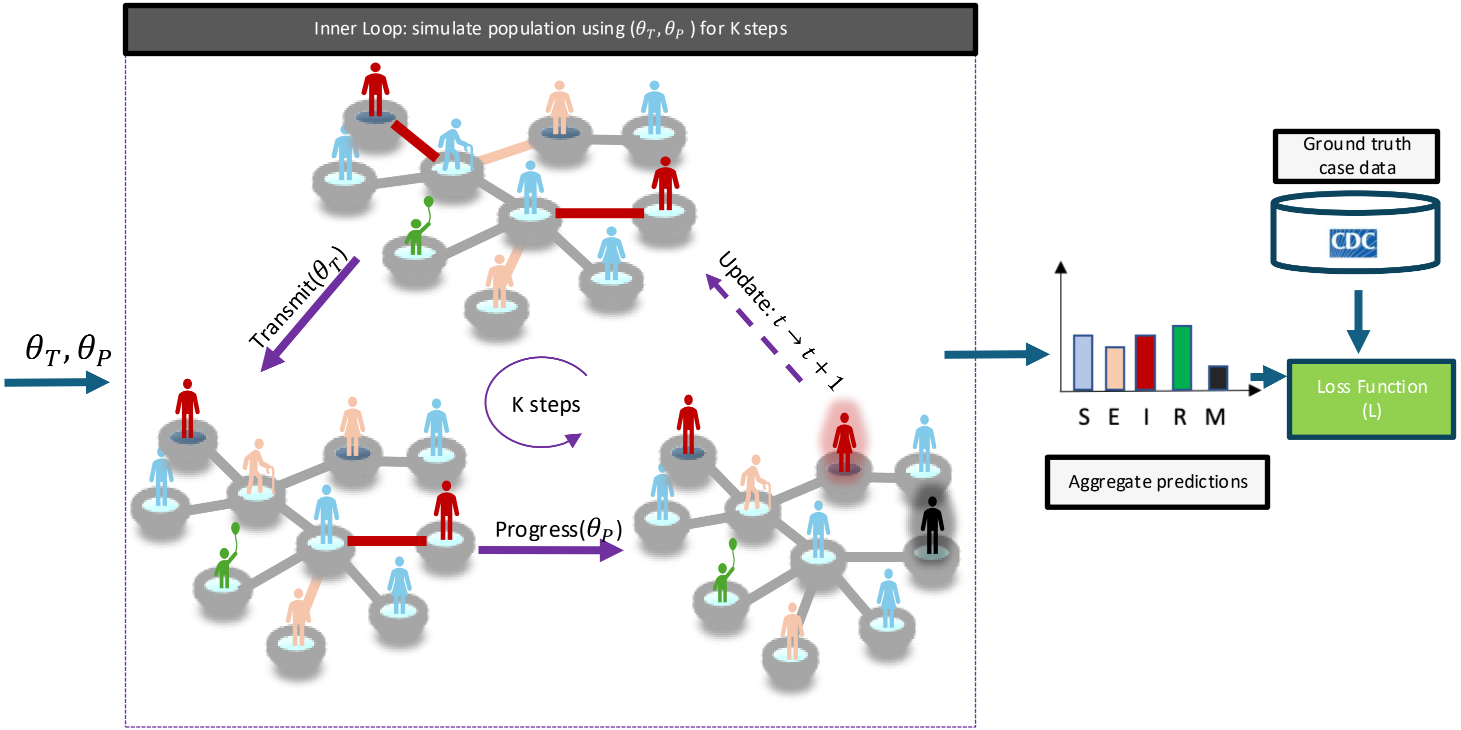
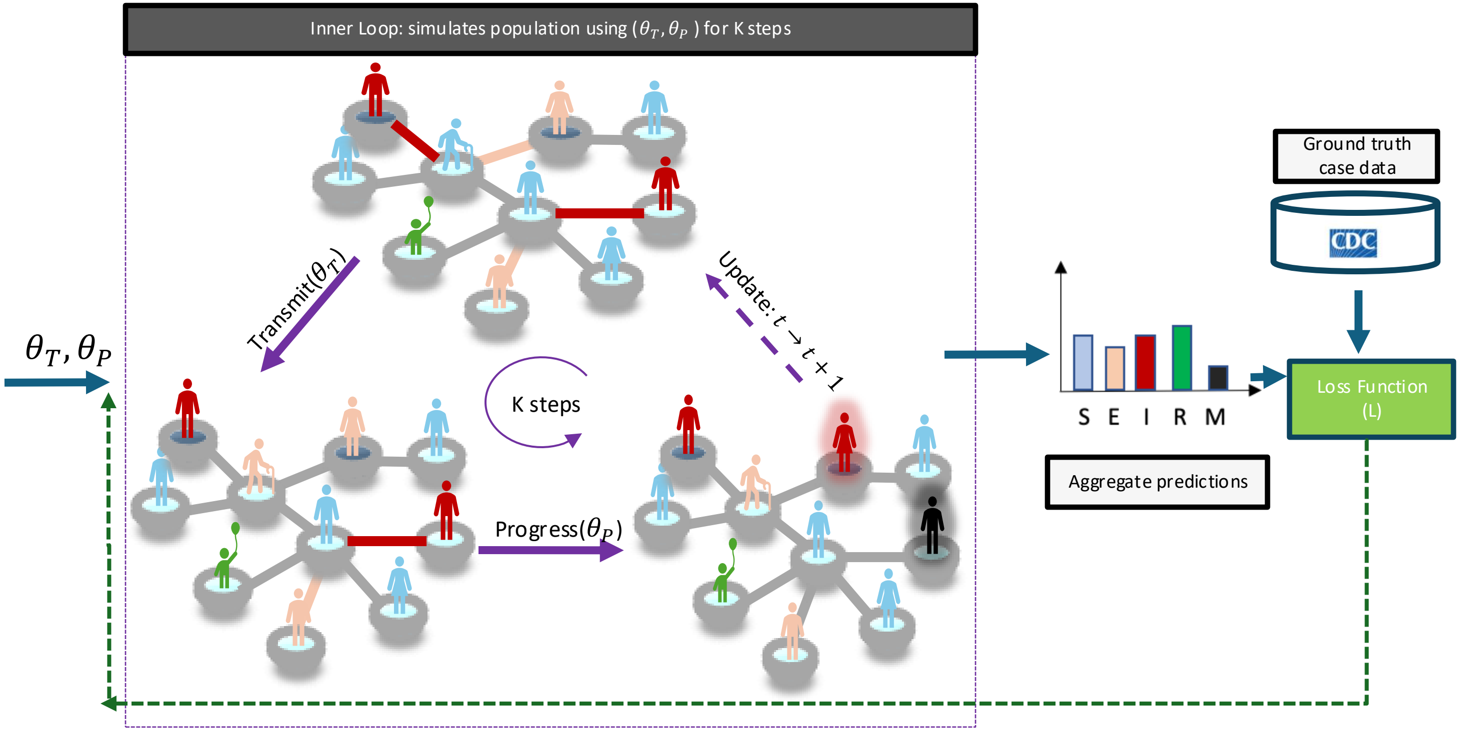
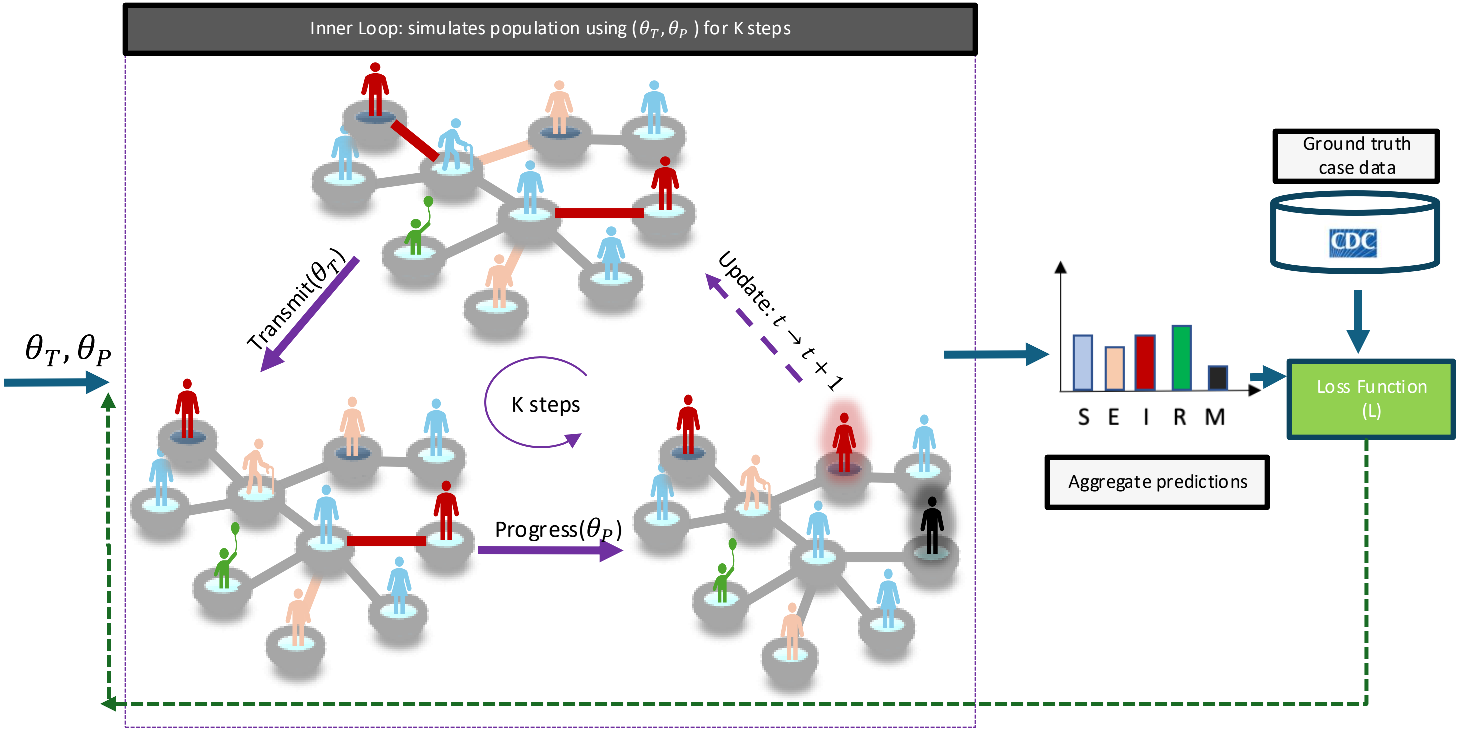
θ_T, θ_P
Transmit(θ_T)
Update: $t \rightarrow t+1$
K steps
Progress(θ_P)
S
E
I
R
M
Aggregate predictions



Inner Loop: simulate population using (θ_T, θ_P) for K steps
θ_T, θ_P
Transmit(θ_T)
Update: $t \rightarrow t+1$
K steps
Progress(θ_P)
Ground truth case data
CDC
S E I R M
Aggregate predictions
Loss Function (L)



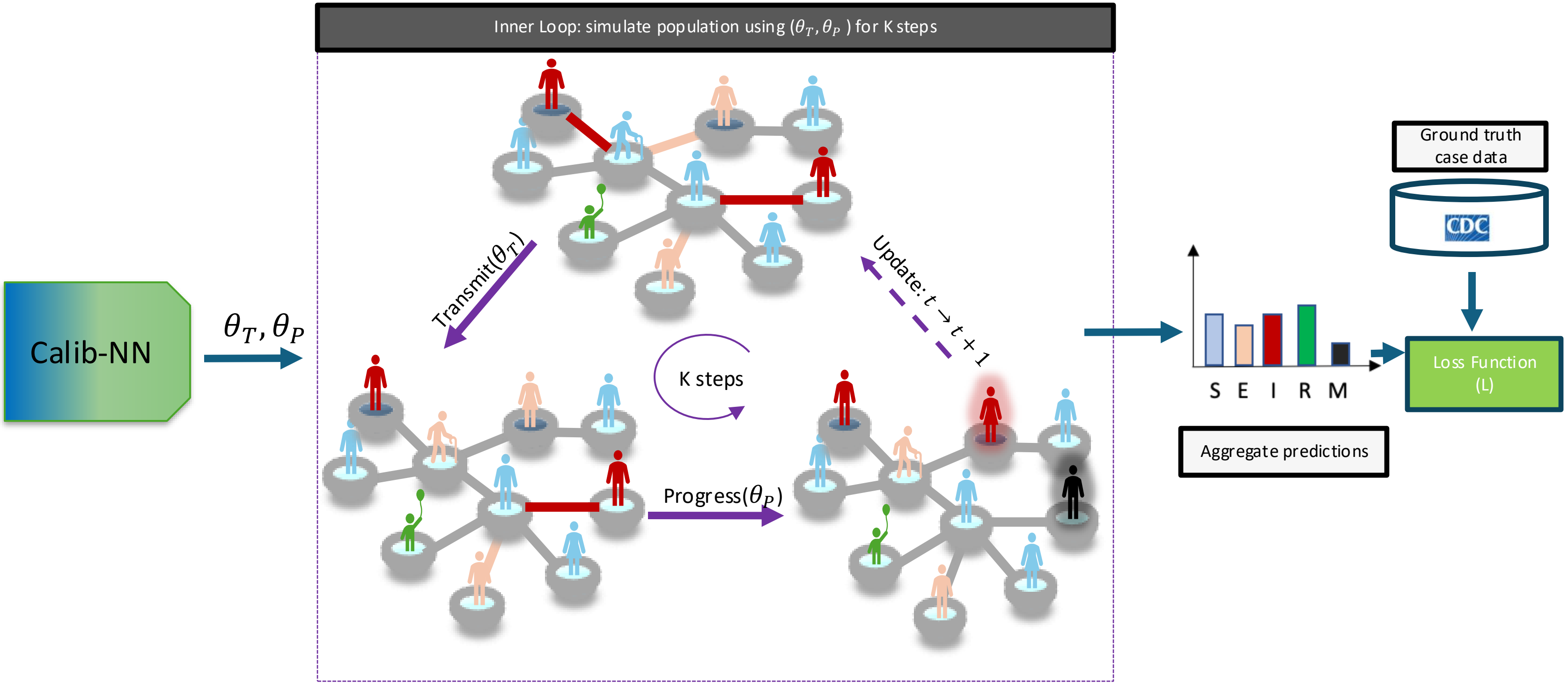
$$\theta_T = \theta_T - \alpha \frac{\partial \mathcal{L}(\hat{y}, y)}{\partial \theta_T} \qquad \theta_P = \theta_P - \alpha \frac{\partial \mathcal{L}(\hat{y}, y)}{\partial \theta_P}$$



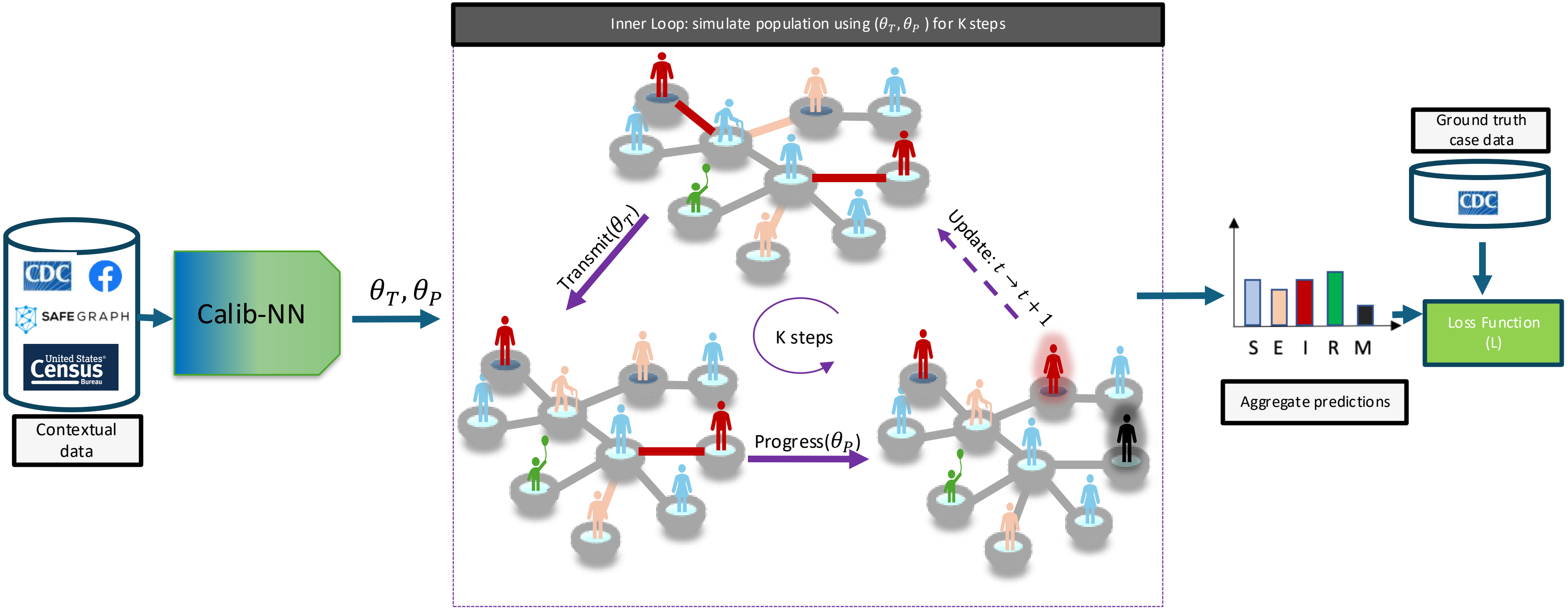
$$\theta_T = \theta_T - \alpha \frac{\partial \mathcal{L}(\hat{y}, y)}{\partial \theta_T}$$

$$\theta_P = \theta_P - \alpha \frac{\partial \mathcal{L}(\hat{y}, y)}{\partial \theta_P}$$

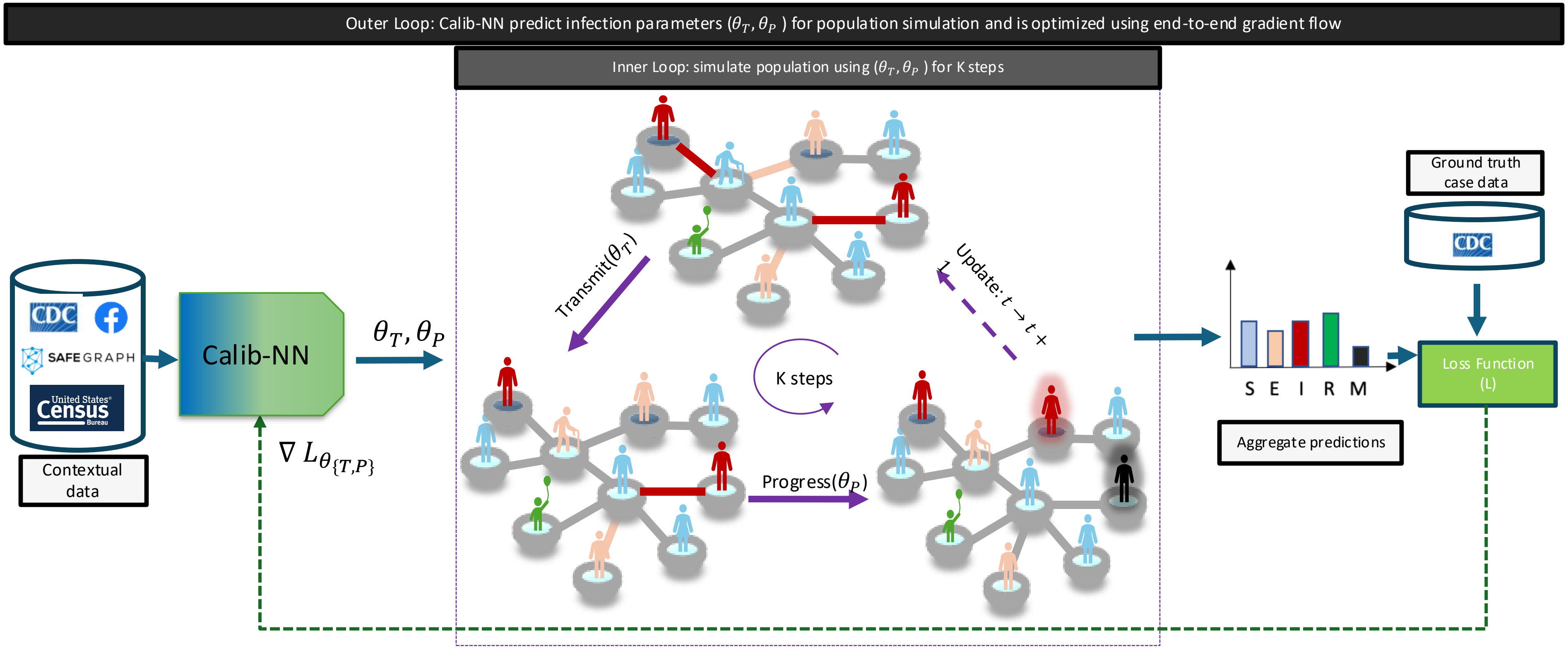
<u>Mode 1</u>: Calibrate **parameters** with gradient descent (c-GRADABM)



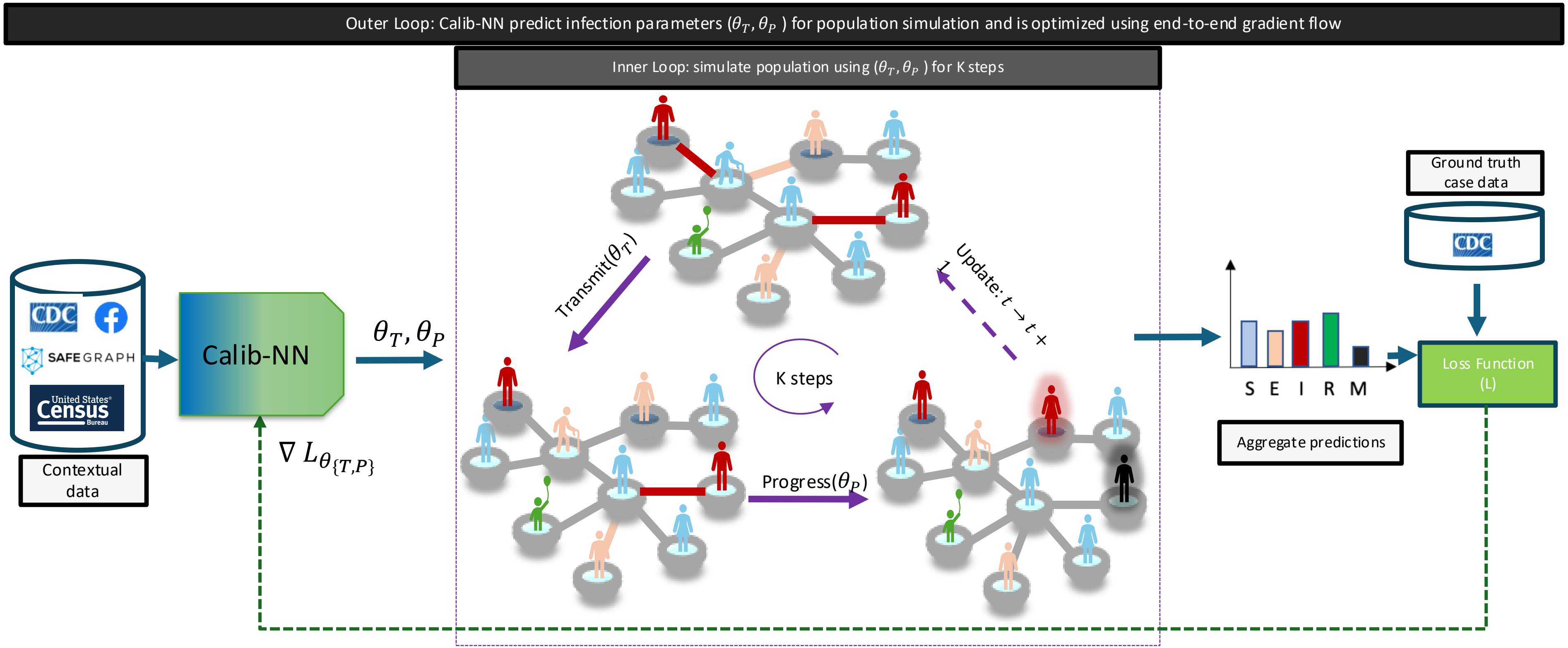
Calib-NN
θ_T, θ_P
Inner Loop: simulate population using (θ_T, θ_P) for K steps
Transmit(θ_T)
Update: $t \to t+1$
K steps
Progress(θ_P)
S E I R M
Aggregate predictions
Ground truth case data
CDC
Loss Function (L)



Inner Loop: simulate population using (θ_T, θ_P) for K steps
Contextual data
Calib-NN
θ_T, θ_P
Transmit(θ_T)
Update: $t \to t+1$
K steps
Progress(θ_P)
S E I R M
Aggregate predictions
Ground truth case data
Loss Function (L)



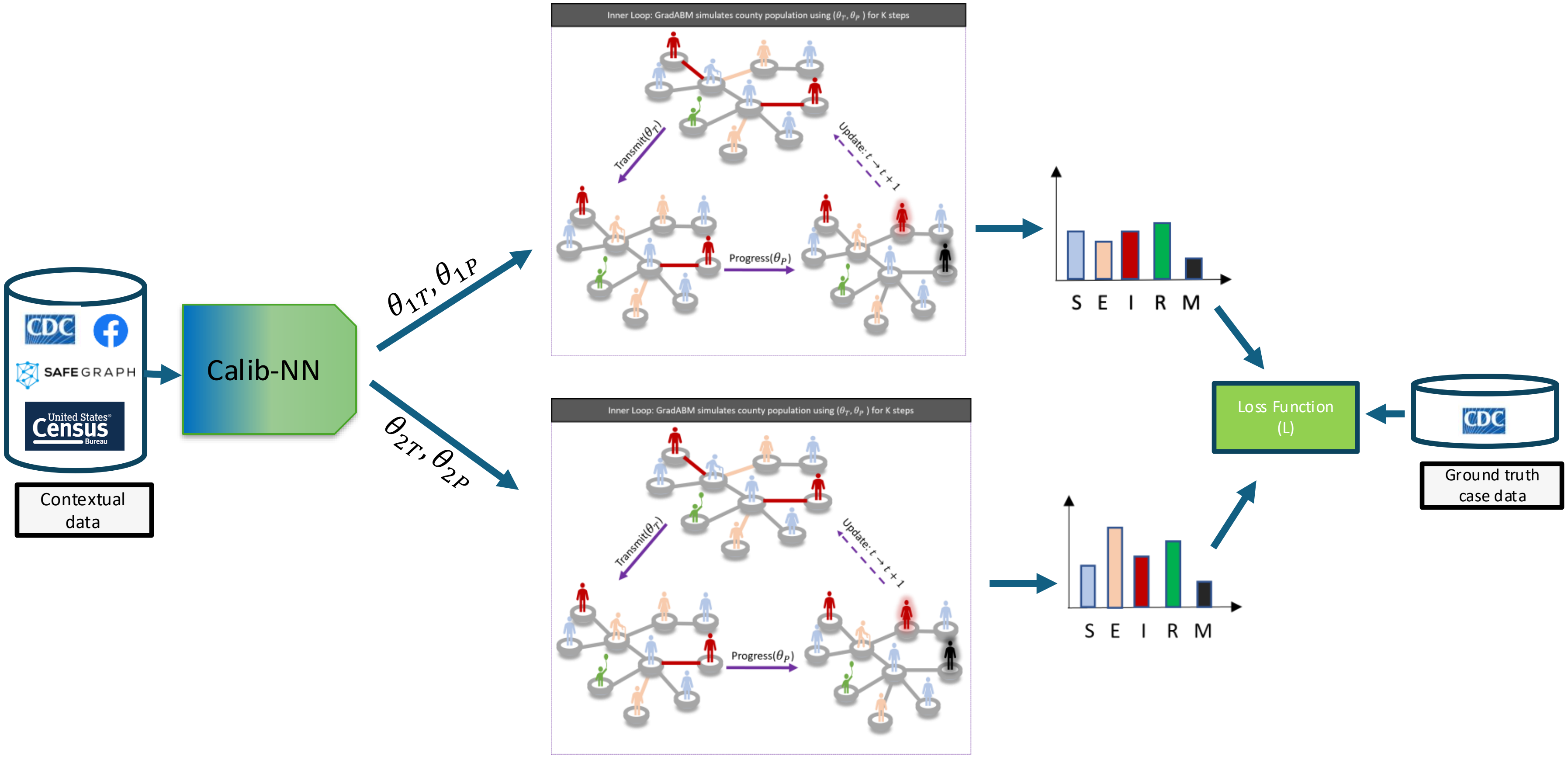
$$\phi = \phi - \alpha \frac{\partial \mathcal{L}(\hat{y}, y; (\theta_T^t, \theta_P^t))}{\partial \phi},$$



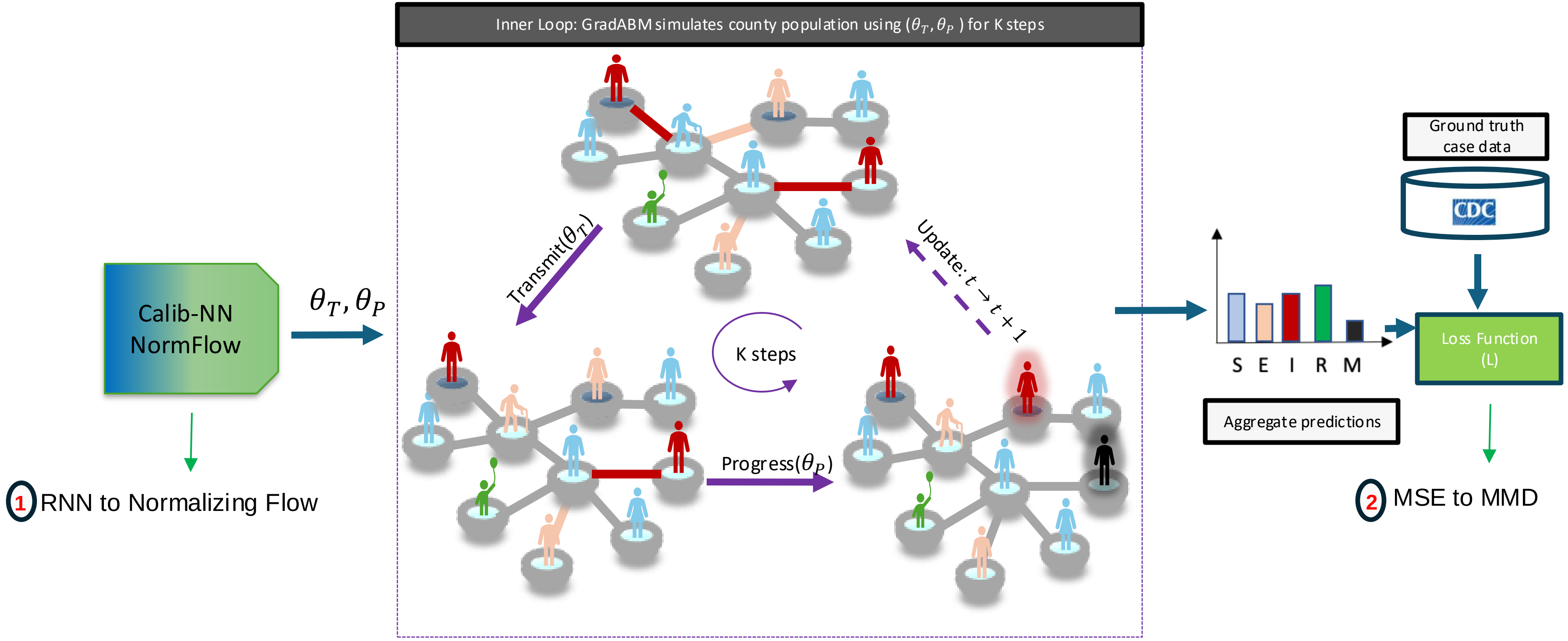
Mode 2: Calibrate **generator function** with gradient descent (dc-GRADABM)

$$\phi = \phi - \alpha \frac{\partial \mathcal{L}(\hat{y}, y; (\theta_T^t, \theta_P^t))}{\partial \phi},$$

Multi-task learning over simulation environments, reduce overfitting



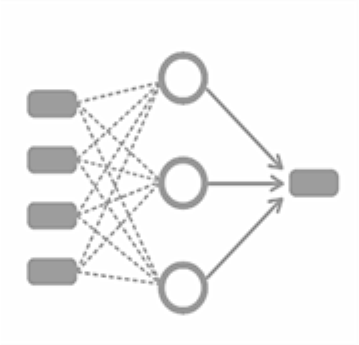
Estimate posteriors over simulation parameters



github.com/AgentTorch/AgentTorch

pip install agent-torch

SCAN ME



Dynamic interactions

Multi-scale
Stochastic

Differentiability

Compose with ODEs

```
from chirho.dynamical.handlers.solver import TorchDiffEq
from chirho.dynamical.ops import simulate


simulation = envs.create(
            model=epidemiology,
            populations=NYC,
            archetype={'immune_dynamics':
                        archetype.ode(chiro_ode, eval_times)
            })

simulation.execute()
```

$$\mathbf{z}_i(t+1) = f\left(\mathbf{z}_i(t),\ \bigoplus_{j \in \mathcal{N}_i(t)} M_{ij}(t),\ \boldsymbol{\theta},\ \ell(\cdot|\mathbf{z}_i(t))\right)$$

Q3: what about the data?

coarse-grained, noisy and stale data
limited granularity from privacy not scarcity?

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- Interaction traces
- Vaccination, disease status

Chopra et al. “private agent-based modeling” (AAMAS 2024, Oral)

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coarse-grained, noisy and stale data
limited granularity from privacy not scarcity?

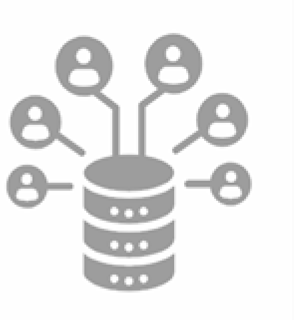
$$\mathbf{z}_i(t+1) = f\left(\mathbf{z}_i(t),\ \bigoplus_{j \in \mathcal{N}_i(t)} M_{ij}(t),\ \boldsymbol{\theta},\ \ell(\cdot|\mathbf{z}_i(t))\right)$$

- Interaction traces
- Vaccination, disease status

decentralize the simulation?

Chopra et al. “private agent-based modeling” (AAMAS 2024, Oral)

Large Population Models



Expressive agents	Dynamic interactions	Data-driven analysis
Adaptive Heterogeneous	Multi-scale Stochastic	Decentralized Sensitive
LLM Archetypes	Differentiability	Secure MPC
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Data-driven analysis

Decentralized
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```python
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```
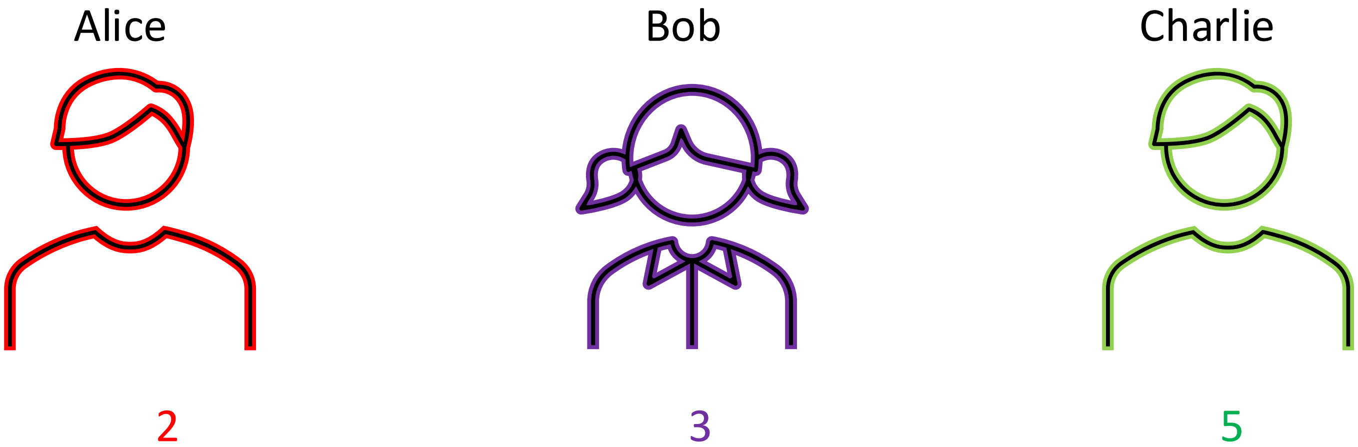

Compose with Physical protocols

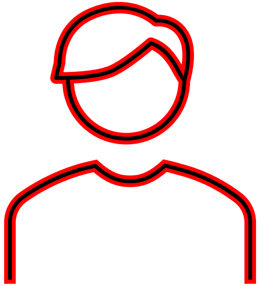
Estimate simulation gradients via MPC

aside: what is secure multi-party computation?


Alice
Bob
Charlie
2
3
5

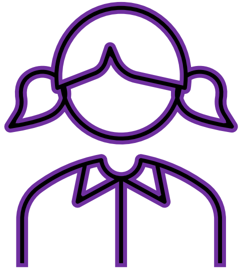
n=11

Alice



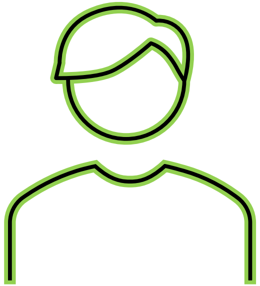
2

Bob



3

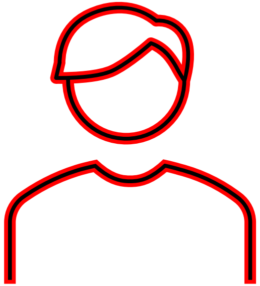
Charlie



5

n=11

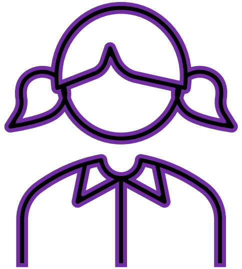
Alice



2

7 + 5 + 1

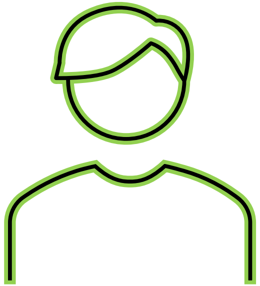
Bob



3

2 + 0 + 1

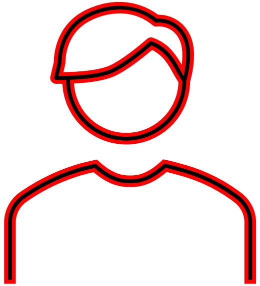
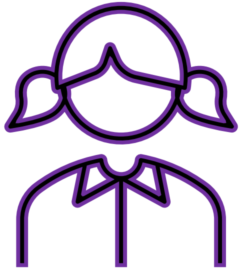
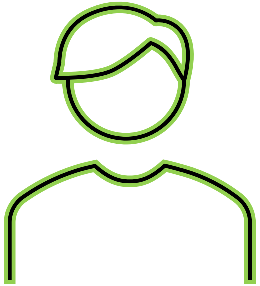
Charlie

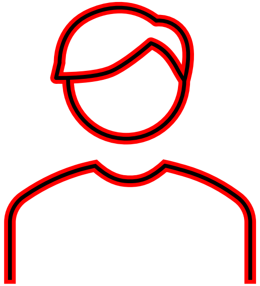
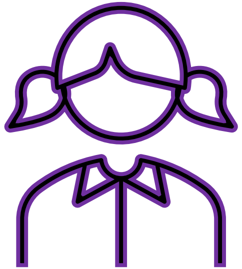
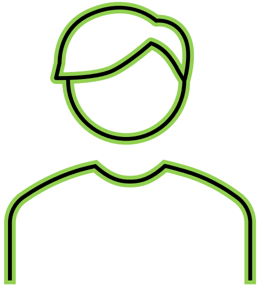


5

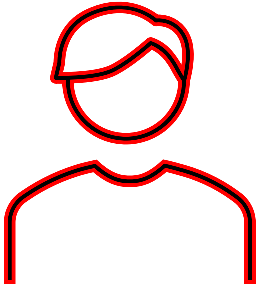
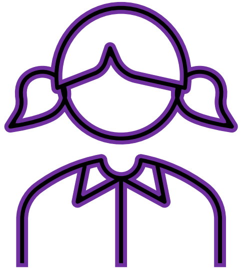
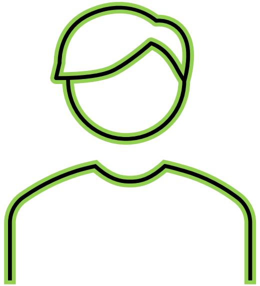
3 + 1 + 1

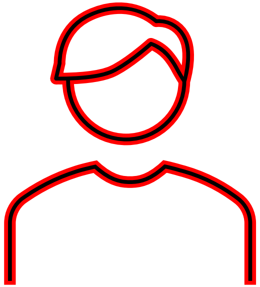
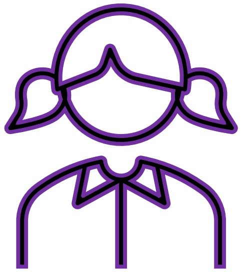
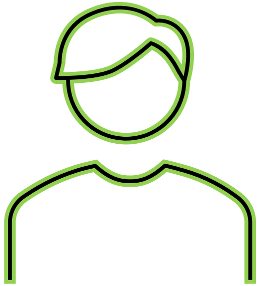
n=11

Alice	Bob	Charlie
		
2	3	5
7 + 5 + 1	2 + 0 + 1	3 + 1 + 1
7 + 2 + 3	5 + 0 + 1	1 + 1 + 1

n=11	Alice	Bob	Charlie
			
	2	3	5
	7 + 5 + 1	2 + 0 + 1	3 + 1 + 1
	7 + 2 + 3	5 + 0 + 1	1 + 1 + 1
	1	6	3

n=11

Alice	Bob	Charlie
		
2	3	5
7 + 5 + 1	2 + 0 + 1	3 + 1 + 1
7 + 2 + 3	5 + 0 + 1	1 + 1 + 1
1	6	3
1 + 6 + 3	1 + 6 + 3	1 + 6 + 3

n=11	Alice	Bob	Charlie
			
	2	3	5
	7 + 5 + 1	2 + 0 + 1	3 + 1 + 1
	7 + 2 + 3	5 + 0 + 1	1 + 1 + 1
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answer	10	10	10

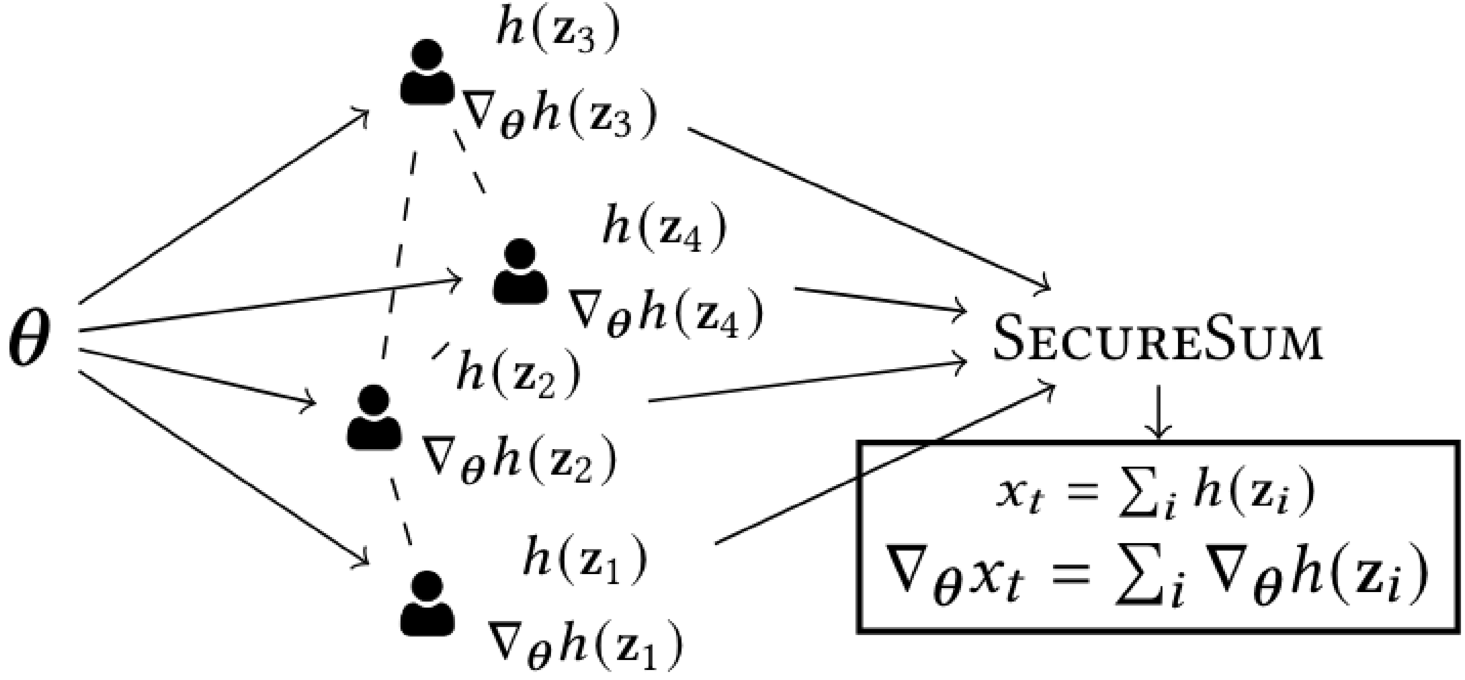
additive secret sharing

$$\mathbf{z}_i(t+1) = f\left(\mathbf{z}_i(t),\ \bigoplus_{j \in \mathcal{N}_i(t)} M_{ij}(t),\ \boldsymbol{\theta},\ \ell(\cdot|\mathbf{z}_i(t))\right)$$

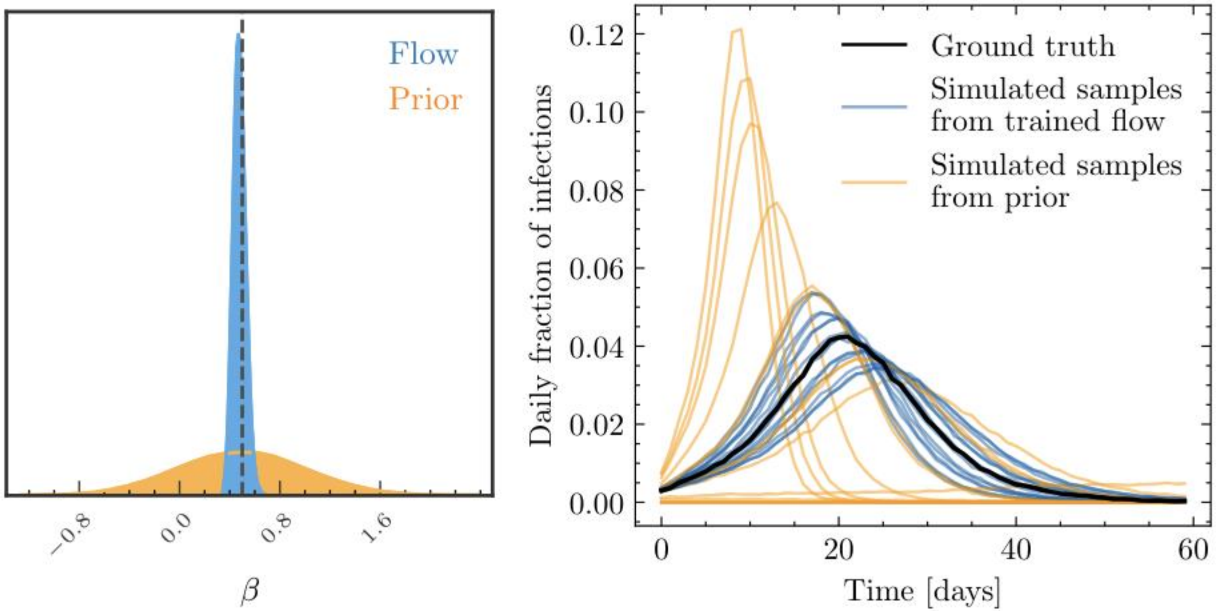
securely estimate $z_i(t+1)$ and $dz/d\theta$ on agent device

Chopra et al. "private agent-based modeling" (AAMAS 2024, Oral)

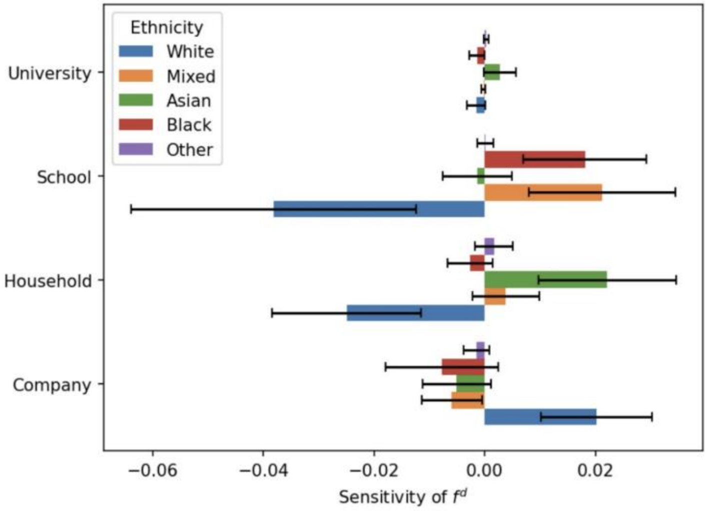
Aggregate Message and Calibration Gradient

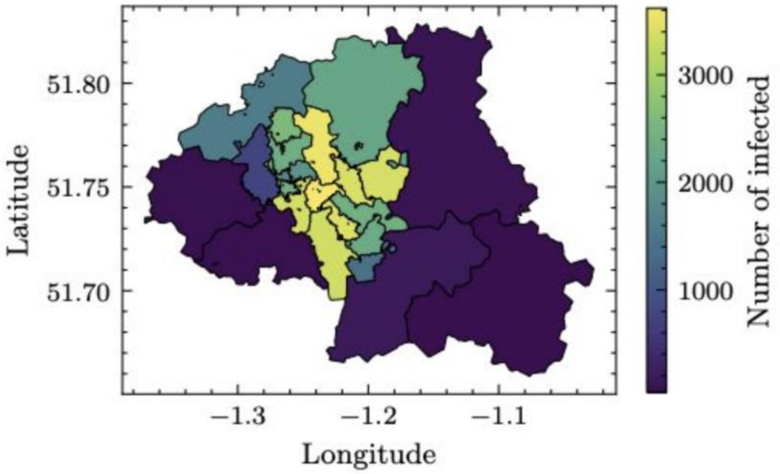


Calibrate disease parameters without leaking an agent's state or interaction trace



Analyze dynamics without leaking individual disease, demographic or geo-location





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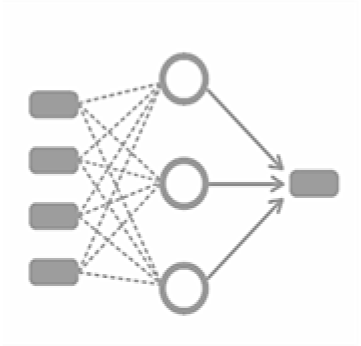
Large Population Models

lpm.media.mit.edu/research.pdf



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Conclusion: Power of Large Population Models

- Scale and Speed: LPMs simulate millions of agents in seconds on standard hardware, enabling unprecedented insights into complex systems.
- Expressive Agents: By leveraging LLMs as behavioral archetypes, LPMs capture nuanced individual behaviors at scale.
- Closing Sim2Real Gap: Secure multi-party computation allows LPMs to incorporate real-world data without compromising privacy.
- Diverse Applications: From pandemic response to energy adoption and supply chain management, LPMs are already making global impact.
- Open-Source Accessibility: AgentTorch democratizes LPM technology, making it available to researchers and policymakers worldwide.

github.com/AgentTorch/AgentTorch

lpm.media.mit.edu/join

github.com/AgentTorch/AgentTorch

pip install agent-torch

SCAN ME

Demo