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Incorporating Adaptive Human Behavior into Epidemiological Models using Equation Learning

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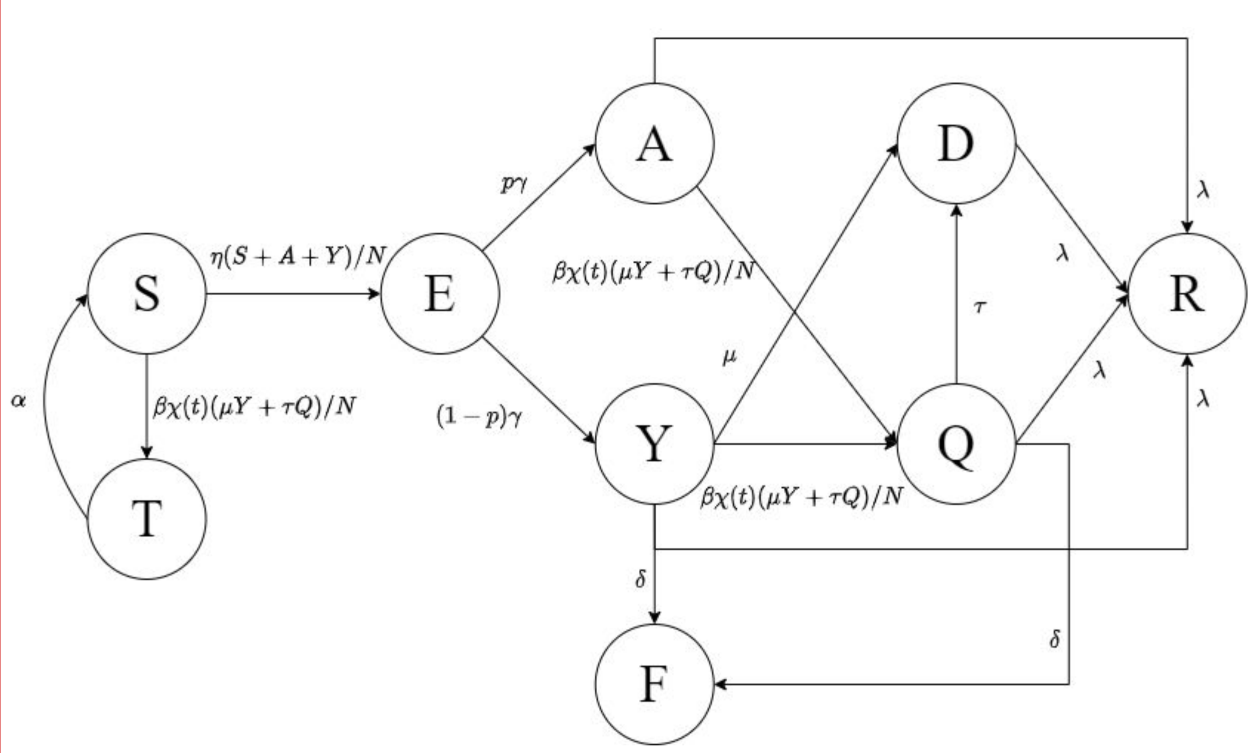
Introduction

Mathematical models have been shown to be valuable tools for forecasting and evaluating public health interventions during epidemics. However, what current mathematical models tend to lack is a representation of how humans genuinely behave during epidemics. In our research, we implemented adaptive human behaviors that represent how humans respond to fluctuating infection spread in an agent-based model (ABM) of COVID-19 called Covasim. We then demonstrate a computational pipeline for estimating parameters, inferring equations, and obtaining an ODE approximation.

Background

- Covasim[1] is a COVID-19 ABM with realistic complexities
  - Model parameters calibrated to real world data
  - Individual level interactions and heterogeneity
- We use an existing compartmental mode as a basel



Compartments:
S: Susceptible, T: Susceptible Quarantined, E: Exposed, A: Asymptomatic, Y: Symptomatic, D: Diagnosed, Q: Quarantined, R: Recovered, F: Fatal/Dead

Fig 1. Compartmental model made with data from Covasim simulations

Adaptive Behaviors

In order to accurately model an epidemic, it is important to be able to model behaviors of agents that are adaptive to the current state of the system they reside. One such adaptive behavior is masking, which may strongly affect the dynamics of the epidemic itself. However, effectively modeling disease spread with adaptive behaviors is difficult.

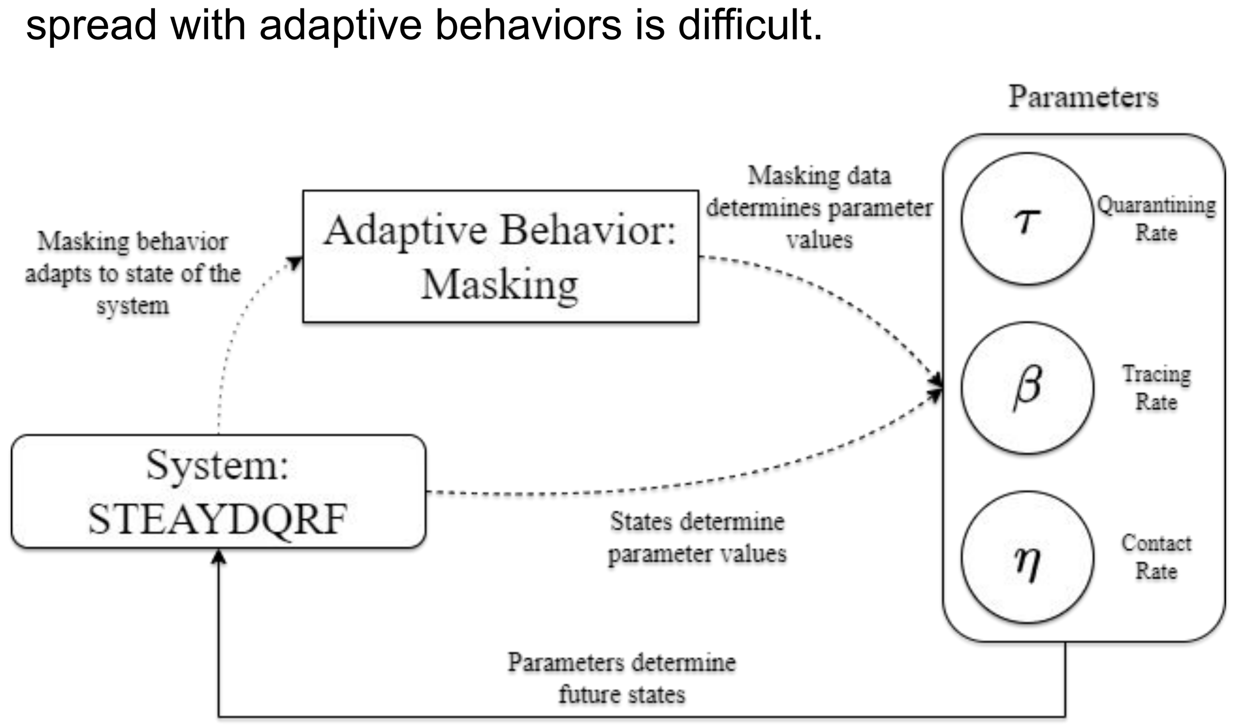


Fig 2. System feedback loop flowchart.

Adaptive Masking Behavior

$$\mathbb{P}(M) = \frac{e^{\xi_0 c + \xi_1 \frac{D(t)+F(t)}{N}} + \xi_2 t}{1 + e^{\xi_0 c + \xi_1 \frac{D(t)+F(t)}{N} + \xi_2 t}}$$

N : population size
c : number of contacts
$D(t)$: diagnosed agents
$F(t)$: dead agents
t : time in days
$\xi_0 = 0.0001$
$\xi_1 = N(\mu, \sigma^2)$
$\xi_2 = -0.001$

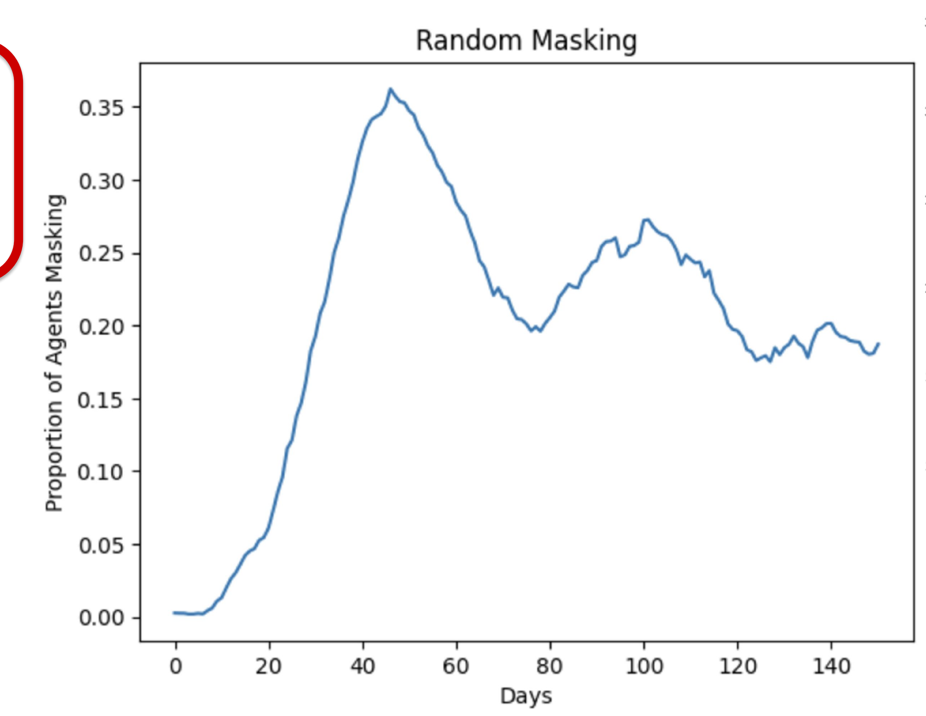


Fig 3. Proportion of agents masking with masking adaptive behavior

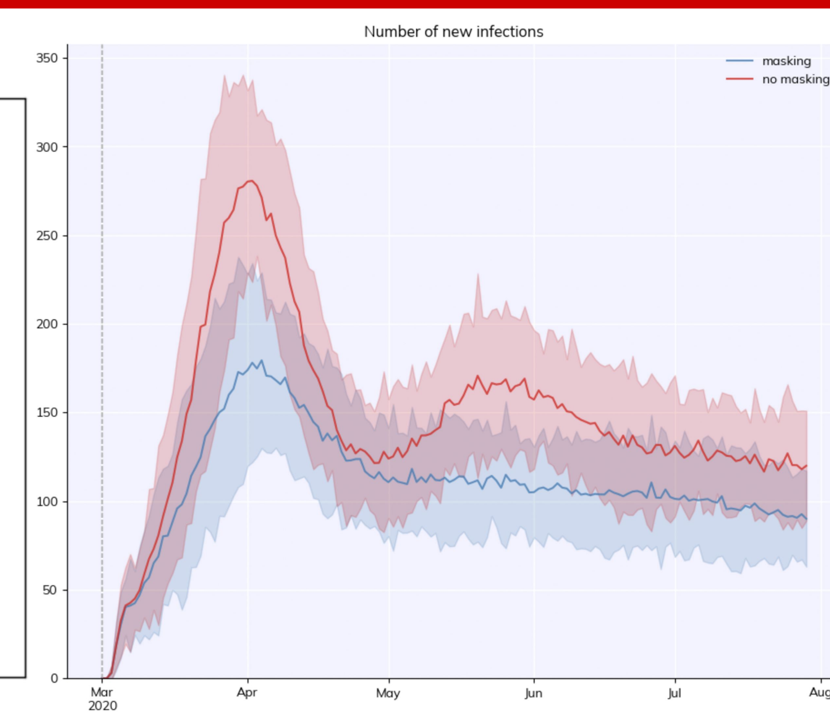


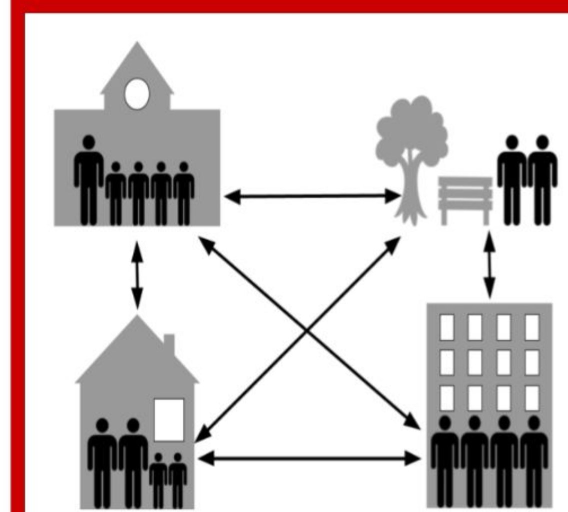
Fig 4. Random Masking (~16.2k infections) over 150 days

Computational Pipeline

- We simulate data with an ABM and then utilize novel equation learning methods to obtain an ODE approximation.
- Leverages advantages of both computational and mathematical models.
- Our approach utilize Biologically-Informed Neural Networks and sparse regression techniques.
- Allows us to minimize *a priori* assumptions about certain nonlinear parameters and enables us to make expert guided inferences about the underlying equations of the learned components.

Data Collection

Agent-Based Model Covasim



Mathematical Modeling

S : Susceptible
T : Susceptible Quarantined
E : Exposed
A : Asymptomatic
Y : Symptomatic
D : Diagnosed
Q : Quarantined
R : Recovered
F : Fatal/Dead
p : $\mathbb{P}$(Asymptomatic)
η : Contact Rate
β : Tracing Rate
τ : Diagnosing Rate

$$\frac{dS}{dt} = -\eta(A+Y)\frac{S}{N} - \beta\chi(\mu Y+\tau Q)\frac{S}{N} + \alpha T$$
$$\frac{dT}{dt} = \beta\chi(\mu Y+\tau Q)\frac{S}{N} - \alpha T$$
$$\frac{dE}{dt} = \eta(A+Y)\frac{S}{N} - \gamma E$$
$$\frac{dA}{dt} = p\gamma E - \lambda A - \beta\chi(\mu Y+\tau Q)\frac{A}{N}$$
$$\frac{dY}{dt} = (1-p)\gamma E - (\mu+\lambda+\delta)Y - \beta\chi(\mu Y+\tau Q)\frac{Y}{N}$$
$$\frac{dD}{dt} = \mu Y + \tau Q - (\lambda+\delta)D$$
$$\frac{dQ}{dt} = \beta\chi(\mu Y+\tau Q)\frac{(A+Y)}{N} - (\tau+\lambda+\delta)Q$$
$$\frac{dR}{dt} = \lambda(A+Y+D+Q)$$
$$\frac{dF}{dt} = \delta(D+Q+Y)$$

Implementing Adaptive Behavior

Masking

$$\mathbb{P}(M) = \frac{e^{\xi_0 c + \xi_1 \frac{D(t)+F(t)}{N}} + \xi_2 t}{1 + e^{\xi_0 c + \xi_1 \frac{D(t)+F(t)}{N} + \xi_2 t}}$$

N : population size
c : number of contacts
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t : time in days
$\xi_0 = 0.0001$
$\xi_1 = N(\mu, \sigma^2)$
$\xi_2 = -0.001$

Learning Parameters

η, β, τ

Biologically-Informed Neural Networks

$\eta = \eta(S, A, Y, M)$
$\beta = \beta(S + A + Y, \chi)$
$\tau = \tau$

Learned Equations

$$\eta = 1.45485(S) + 98.99333(A) + 1.20158(M) + 0.32821(S^2) - 23.32296(SY) + 0.49780(SM) - 7.28284(M^2) + 0.1252$$
$$\beta = 2.4963(S+A+Y) + 0.6779(\chi) - 1.3366(S+A+Y)^2 + 0.1524(\chi)(S+A+Y) + 0.2945(\chi^2) - 0.9994$$
$$\tau = 0.1007$$

Fig 5. The end-to-end computational pipeline.

Equation Learning Steps

Simulate Data | Train BINN on Data | Evaluate Parameter Networks | Sparse Regression | Evaluate Equations

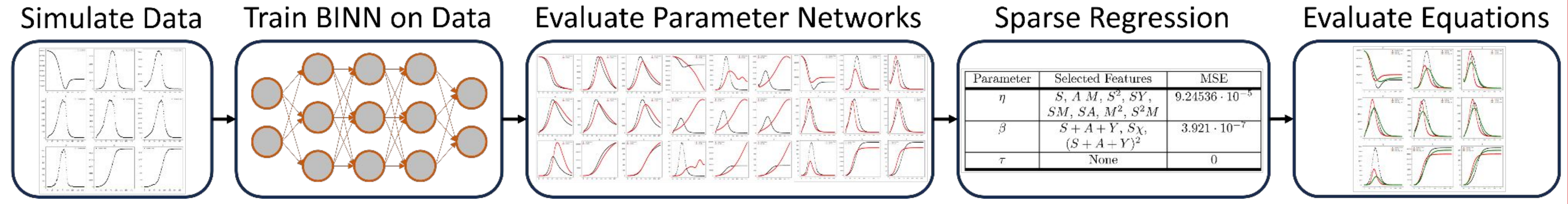


Fig 6. The primary steps of the equation learning pipeline from left to right.

Results

- Learned parameters from trained BINNs are plugged into the right-hand side of the system of differential equations and solved.

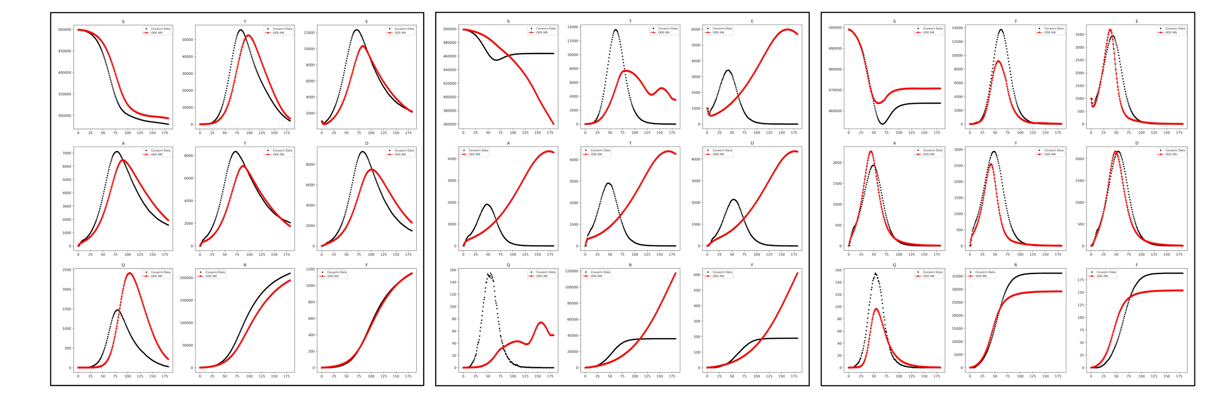
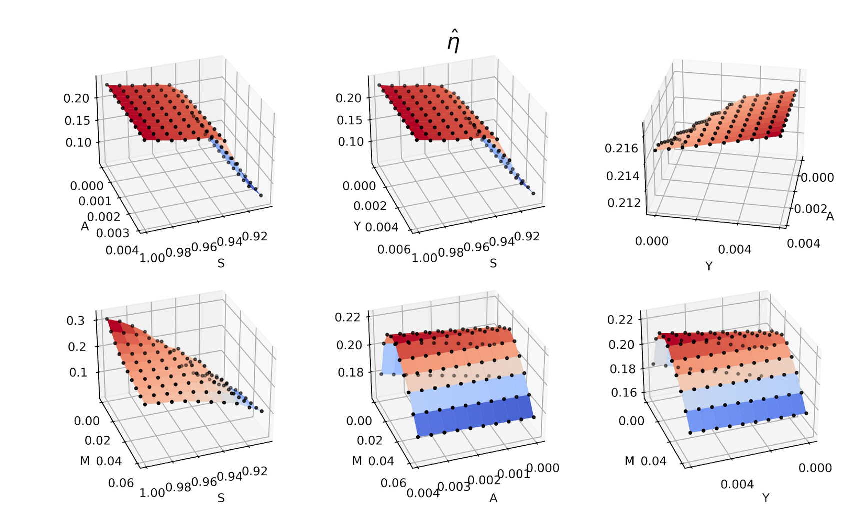


Fig 6. Evaluation curves of learned parameters (below) for data with no masking and no masking included the model (left), data with masking and no masking included in the model (center), and data with masking and masking included in the model as observed input (right)



Equation Inferencing

- We use learned parameters to guide inference on interpretable and physically meaningful characteristics of the components.
- We utilize LASSO regression to obtain parsimonious equations of the parameters and prune them based MSE sensitivity to features.
- Evaluation is done again with the inferred equations for each parameter and compared to ABM data and solutions with parameter networks.

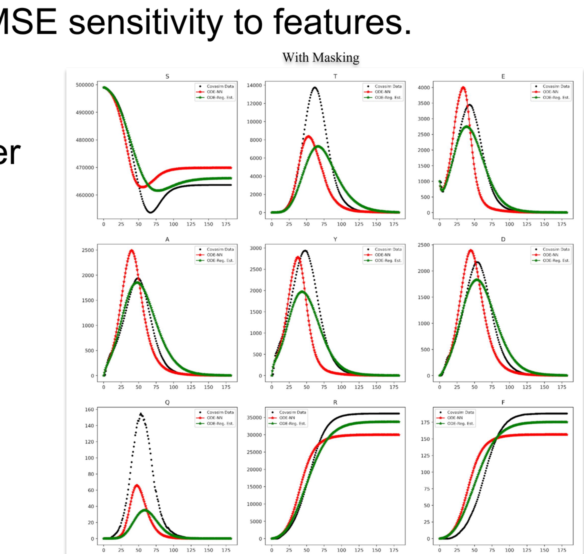


Fig 7. Evaluation curves of inferred parameter equations for data with adaptive masking behavior. ABM data is in black, ODE solution with parameter network is red, and solutions with equations are in green.

Conclusion

- Utilizing flexible computational models and equation learning methods allow us to gain deeper insights into more complex phenomena.
- We demonstrate the ability to infer mathematical models on complex systems with adaptive behavior.

Acknowledgements

References:

1. Kerr, C. C., Stuart, R. M., Mistry, D., Abeysuriya, R. G., Rosenfeld, K., Hart, G. R., Núñez, R. C., Cohen, J. A., Selvaraj, P., Hagedorn, B., George, L., Jastrzębski, M., Izzo, A., Fowler, G., Palmer, A., Delport, D., Scott, N., Kelly, S., Bennette, C. S., … Klein, D. J. (2020). Covasim: An Agent-Based Model of COVID-19 Dynamics and Interventions. https://doi.org/10.1101/2020.05.10.20097469
2. Galasso, V., Pons, V., Profeta, P., Becher, M., Brouard, S., & Foucault, M. (2020, October 15). Gender differences in covid-19 attitudes and behavior: Panel ... - PNAS. https://www.pnas.org/doi/full/10.1073/pnas.2012520117
3. Trevas, S., Manuel, K., Malkani, R., & Hoelscher, D. (2023, February 3). *Mask adherence and social distancing in Houston, TX from January to April 2021*. MDPI. https://www.mdpi.com/1660-4601/20/3/2723
4. Lagergren, J. H., Nardini, J. T., Baker, R. E., Simpson, M. J., & Flores, K. B. (2020). Biologically-informed neural networks guide mechanistic modeling from sparse experimental data. PLOS Computational Biology, 16(12). https://doi.org/10.1371/journal.pcbi.1008462

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