NC STATE UNIVERSITY

Dr. Kevin Flores, Department of Mathematics
Pat Haughey, Graduate Student of Applied Mathematics

Incorporating Adaptive Human Behavior into Epidemiological Models using Equation Learning

Link to GitHub

Austin Barton[1], Jon Greer[2], Jordan Klein[3], Michala Gradner[4]

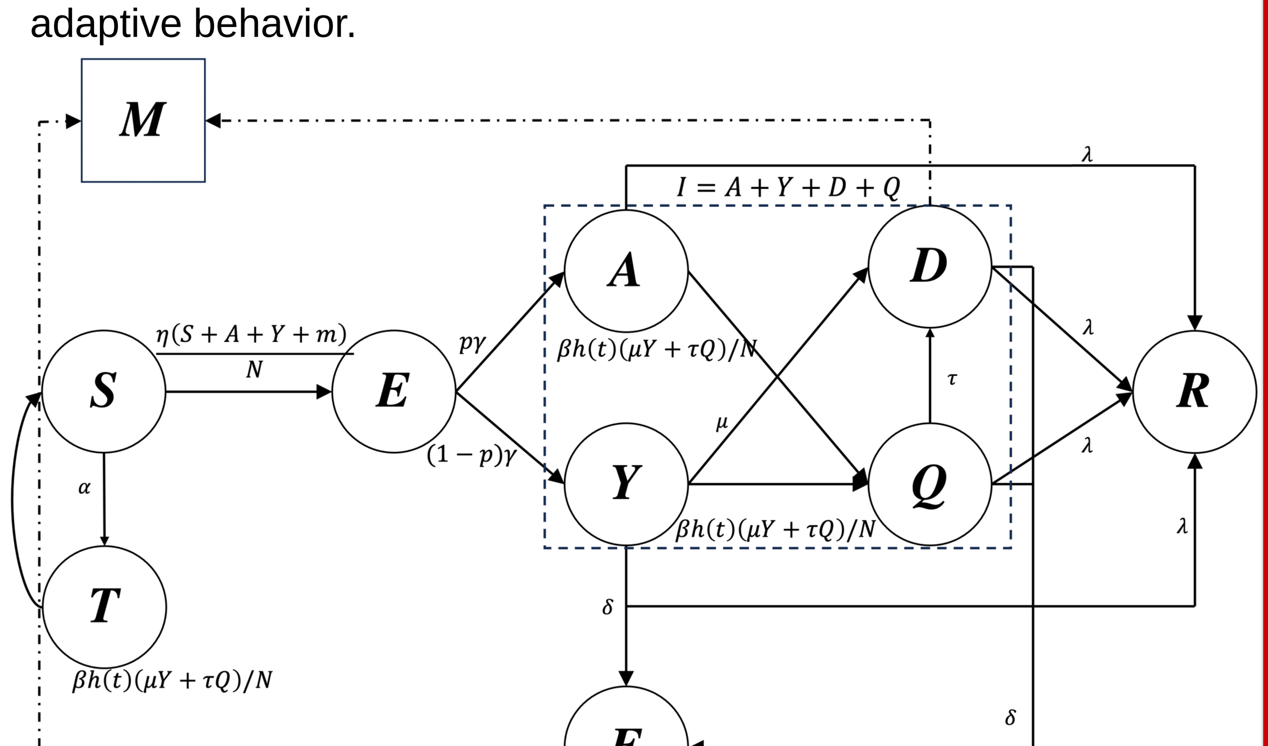
[1]Georgia Institute of Technology
[2]Howard University
[3]Appalachian State University
[4]Texas State University

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 a pre-existing agent-based model (ABM) of COVID-19 called Covasim. We then used biologically-informed neural networks (BINNs) to process data generated from the ABM to learn an ordinary differential equation (ODE) approximation of this model. Our extended ABM and BINNs computational pipeline is open-sourced to provide a quantitative framework for incorporating adaptive human behavior into forecasting future epidemics.

Background

- Covasim[1] is a COVID-19 ABM with realistic complexities and user-flexibility
  - Model parameters calibrated to real world data
  - Age dependent infection susceptibility and disease progression
  - Infectiousness varies with individuals over time
  - Ability to program individual decisions and feedback based on state of the model
- We augment an existing compartmental model in order to mathematically model Covasim with masking as an added adaptive behavior.



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

Other:
M: Masking Average, τ: Diagnosing Rate, η: Contact Rate, β: Tracing Rate

Fig 1. Compartmental model made with data from Covasim simulations

Adaptive Behaviors

The recent spread of COVID-19 illustrated how the behavior of humans is not independent of the state of the epidemic. To accurately model an epidemic, it is important to model behaviors of agents that are adaptive to the current state of the system. One such adaptive behavior is masking, which may strongly affect the dynamics of the epidemic itself. Masking varies from person to person depending on certain unique static and dynamic characteristics. Some research has shown that attributes such as age, gender, and ethnicity can be telling of who is more likely to mask, e.g., research consistently shows that women generally mask more than men due to their appraisal of the disease and willingness to follow guidelines.[1] We use findings from literature to implement numerical values for who will mask.[2]

Adaptive Behavior: Masking

Masking Probability Function

$$\mathbb{P}(M) = \frac{e^{\beta_0 c + \beta_1 \frac{(D(t)+F(t))}{N} - \beta_2 t}}{1 + e^{\beta_0 c + \beta_1 \frac{(D(t)+F(t))}{N} - \beta_2 t}}$$

$N =$ population size,
$c =$ number of contacts,
$D(t) =$ diagnosed agents,
$F(t) =$ dead agents,
$t =$ time (days),
$\beta_0 = 0.0001$,
$\beta_1 = N(\mu, \sigma^2)$,
$\beta_2 = 0.001$

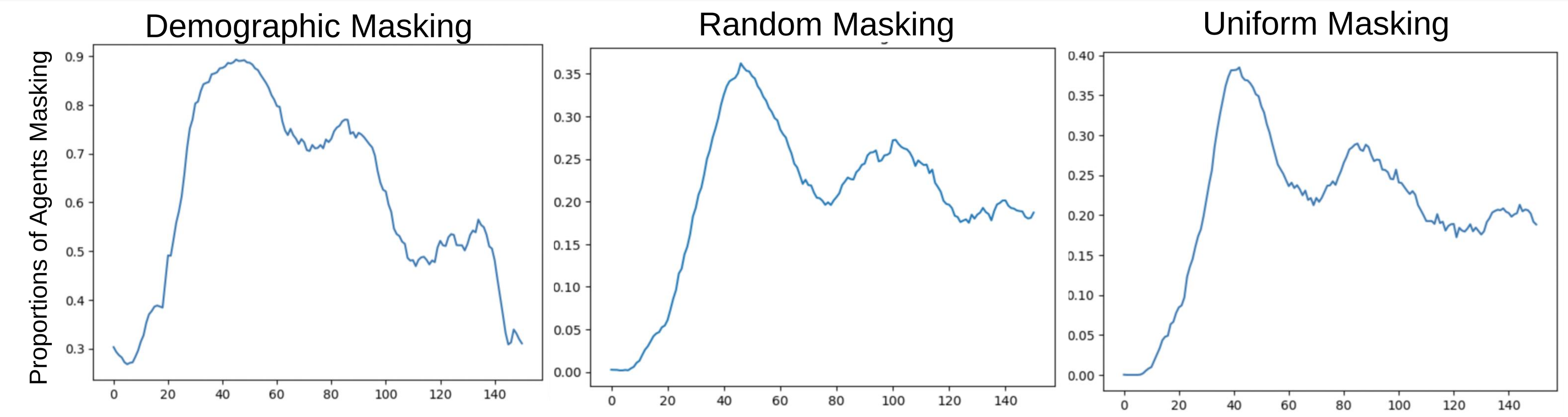


Fig 2. Comparison of the proportion of agents masking between Demographic, Random, and Uniform masking adaptive behaviors over time (in days)

Number of New Infections over 150 days

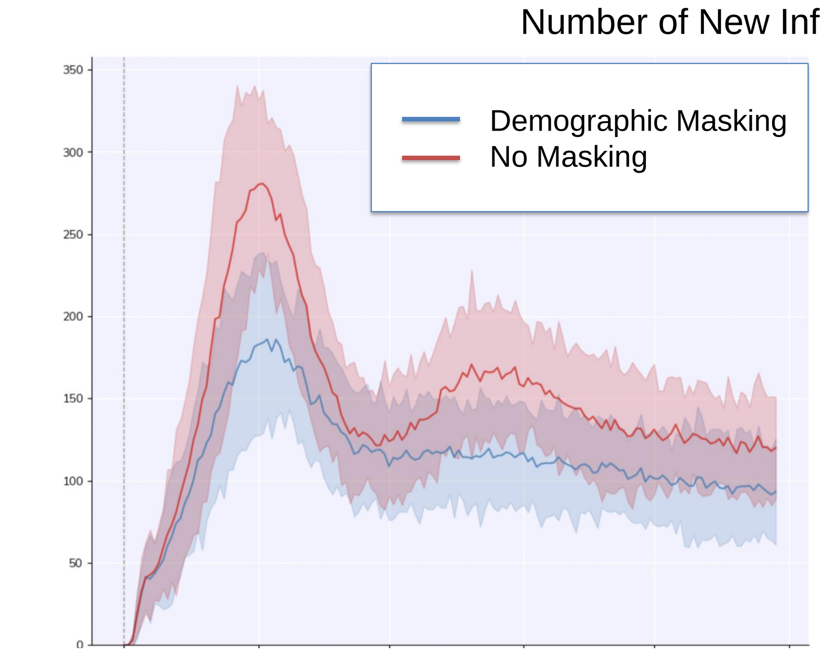


Fig 3. Demographic Masking (~15.1 total infections) vs. No Masking (~22.3k total infections) on 50k agents over 150 days

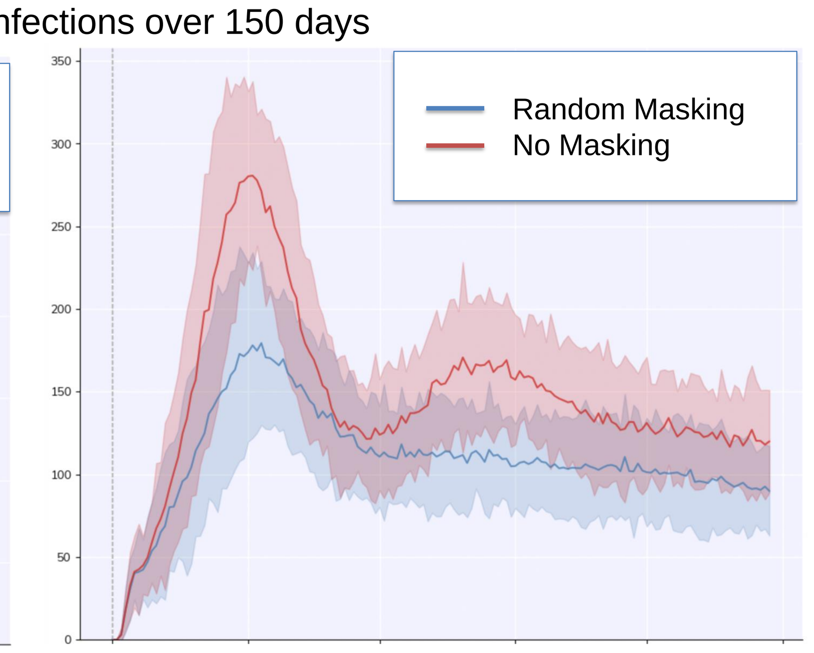


Fig 4. Random Masking (~16.2k total infections) vs. No Masking (~22.3k total infections) on 50k agents over 150 days

Biologically-Informed Neural Networks

- Biologically-Informed Neural Networks (BINNs)[4] are a method of equation learning that learn the components of a governing dynamical system while simultaneously converging to an approximate solution.
- They provide insight into the underlying mechanisms of a natural system by leveraging the universal approximator property of neural networks to estimate nonlinear components and minimize *a priori* assumptions about their form.
- Allow us to make expert guided inferences about the underlying equations of the learned components *a posterior*.
- Leverage automatic differentiation to get the analytic derivatives of the estimated solutions and components for the loss function.
- Denoises data by estimating solutions and uses those estimates as inputs to the parameter networks which are constrained to a governing dynamical system.

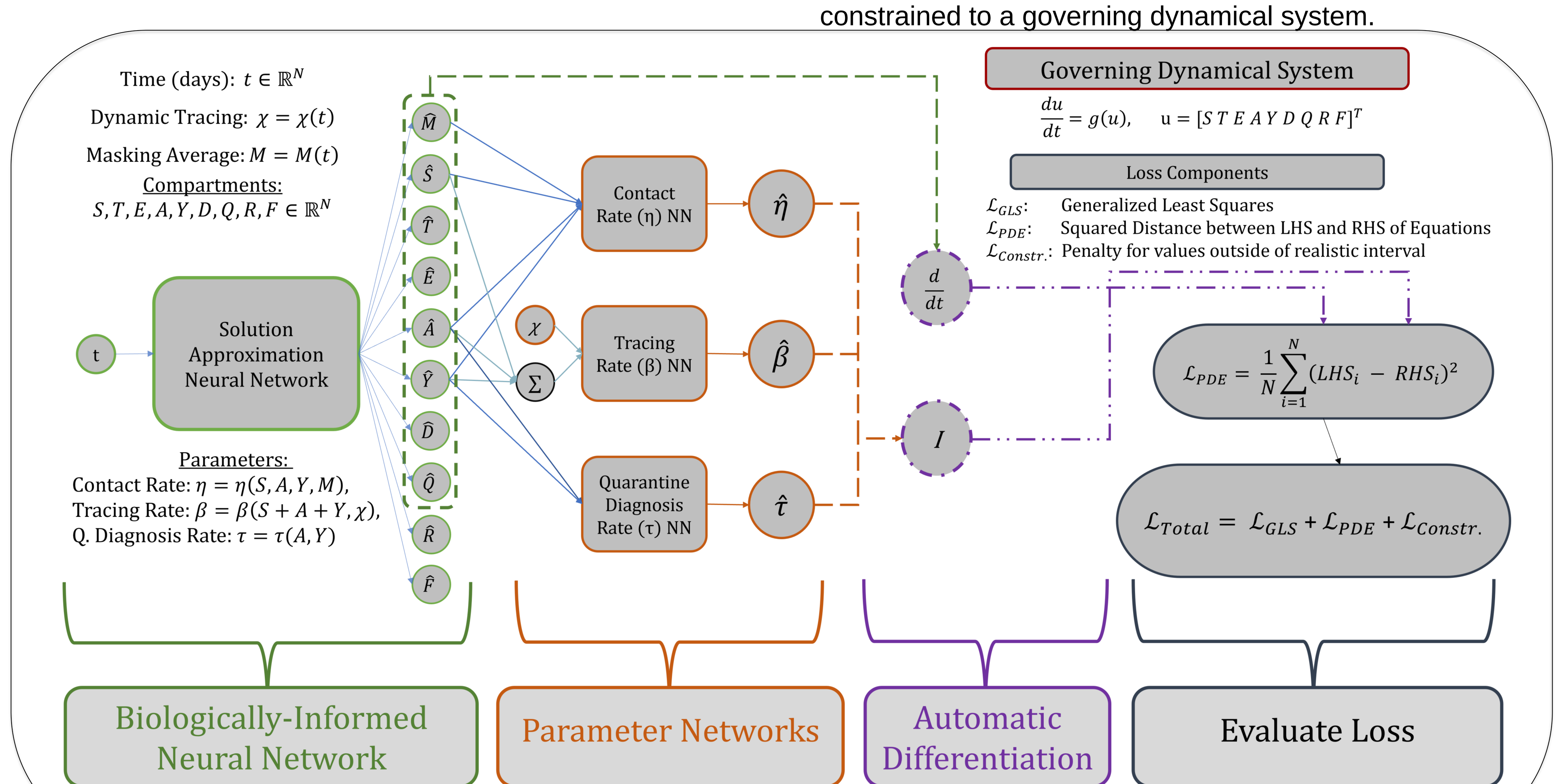


Fig 5. The BINN model for Covasim with added adaptive behavior (masking).

BINNs Results

- Learned parameters from trained BINNs are then plugged into the right-hand side of the system of differential equations and solved numerically.
- Shown below are evaluation curves comparing the observed data (black) with the approximated solutions (red).
- Two datasets, with and without masking, are generated and two models, with and without average masking, are trained on them.

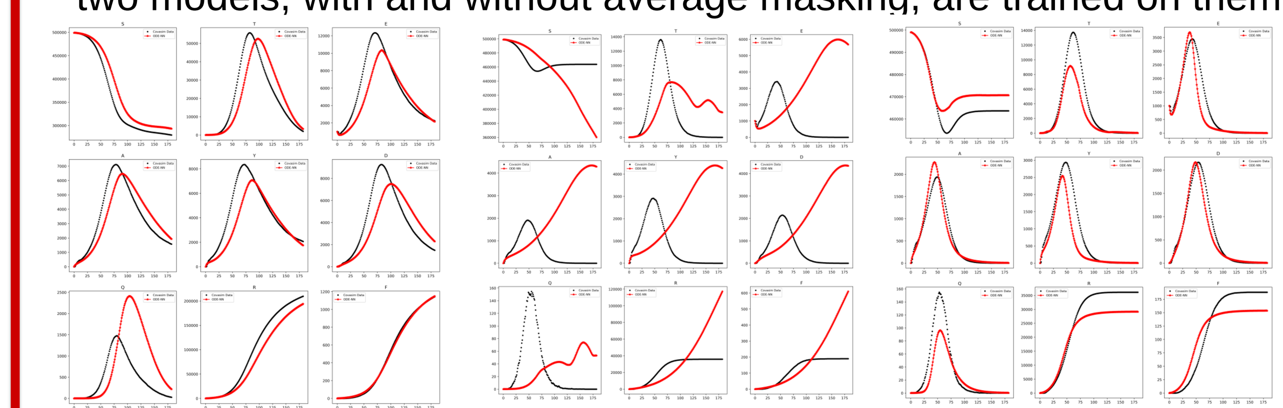


Fig 6. Evaluation curves of learned parameters for data with no masking and no masking included the model (left), data with masking and no masking included in the model (center), and data with masking and masking included in the model as observed input (right)

Equation Inferencing

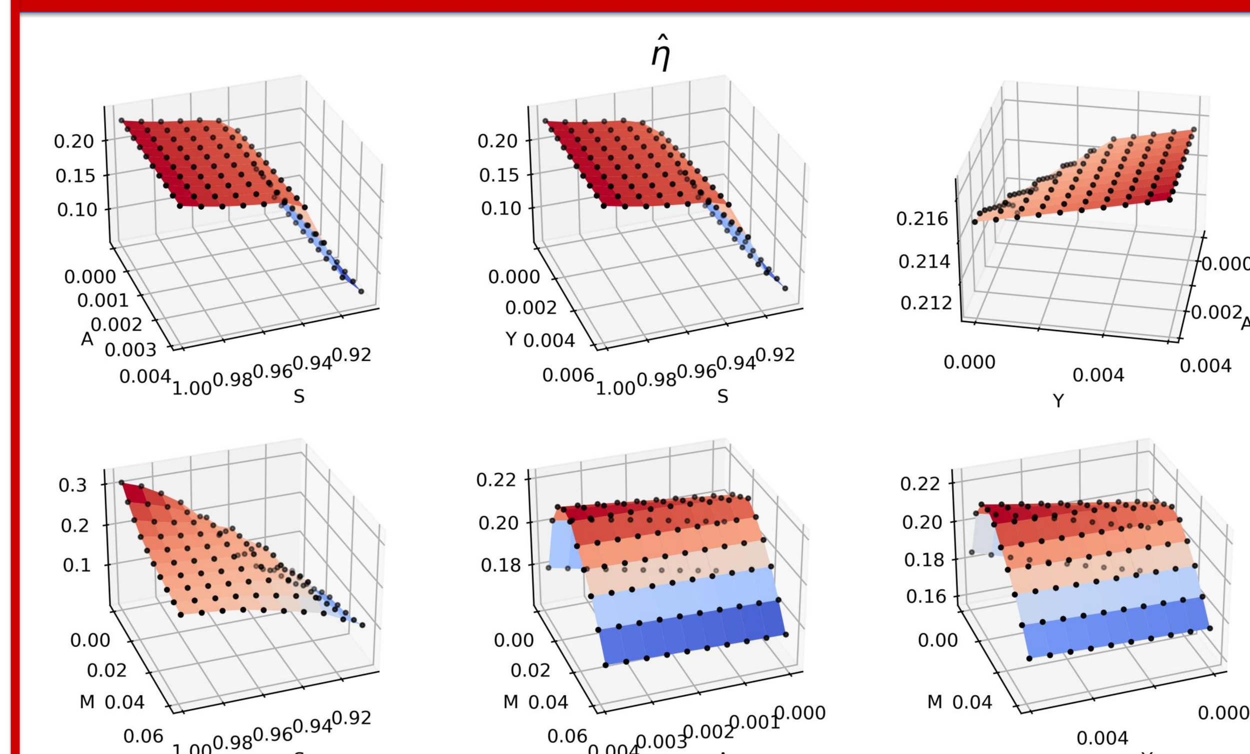


Fig 7. Plot of the trained contact rate parameter network $\hat{\eta}$. Note that $\hat{\eta}_{LASSO}$ estimates this surface.

- We utilize cross validated LASSO regression to generate equations that estimate the surface of the learned parameter networks.

Example of a Learned Equation:

$$\hat{\eta}_{LASSO} = c_0 + c_1 S + c_2 T + c_3 M + c_4 S^2 + c_5 ST + c_6 M^2$$

Conclusion and Discussion

- Utilizing flexible simulation software and equation learning methods allows us to gain insights into more complex phenomena and how to accurately quantify such systems.
- We demonstrate the ability to infer mathematical models on complex systems using neural networks and sparse regression techniques.
- Training BINNs that learn masking averages, finishing equation learning process, and sensitivity analysis of the learned models with adaptive behavior remain to be done.

Acknowledgments

References:

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As part of North Carolina State University's Directed Research for Undergraduates in Mathematics and Statistics (DRUMS) program, our research is supported by the **National Security Agency** (H98230-23-1-0009) and the **National Science Foundation** (DMS#2051010).