Adaptive Prevalence Testing for Epidemic State Estimation Using Particle Filter Recurrent Neural Networks

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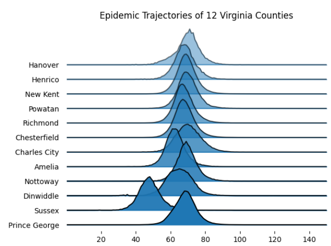
Introduction

Estimation of epidemic prevalence using minimal testing

- In the early stages of novel epidemics, accurate infection rates may be impossible to determine without stockpiles of a large number of accurate tests.



- Spread and infection rates vary in different areas (Figure 1).
- Without current and accurate prevalence information, interventions are nearly impossible.
- Dynamic test assignment conserves tests at times of low infection rates, increases certainty when cases begin to rise.

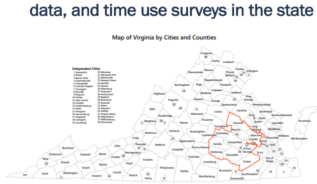
Purpose

- To evaluate the impact of machine and deep learning strategies have on epidemic interventions; we utilize these systems to create optimal testing strategy and epidemic prevalence estimation on simulated epidemic trajectories.

Methods

Agent Based Modeling (ABM) for Epidemic Simulation

- EpiHiper, an NSSAC developed ABM for disease transmission simulations was utilized to generate 100+ epidemic trajectories based on census data, and time use surveys in the state of Virginia.



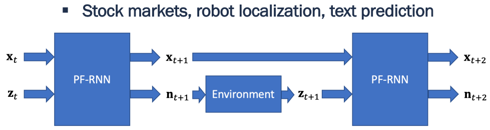
- 12 counties were selected for central location, proximity, and population (Figure 2) as the focus of this study.
- Each county has large amounts of intercounty and health district travel

- For each simulated day of a pandemic, prevalence testing is conducted based on a number of tests returning the current positivity rate on a county basis

Particle Filter Recurrent Neural Networks (PF-RNN)

PF-RNN is a method of state estimation for time series data.

- Combines Recurrent Neural Networks (RNN) and Particle filtering (PF)
  - PF for state estimation, RNN for time series prediction
- Utilized in estimation of data with non-parametric updates or high uncertainty
  - Stock markets, robot localization, text prediction



- PF-RNN interacts with the epidemic trajectories assigning tests and estimating current infection rates for the duration of the simulation (Figure 3)

Loss functions:

- To train the PF-RNN model Mean Squared Error and Evidence Lower Bound (ELBO) loss were utilized

$$a(t) := -(\eta \sum_{n=1}^{N} (\mathbf{x}_t - \mathbf{z}_t) + \eta \sum_{n=1}^{N} (\mathbf{p}_t))$$

$$b(t) := -(\eta \sum_{n=1}^{N} (\mathbf{x}_t - \mathbf{z}_t)^2 + \eta \sum_{n=1}^{N} (\mathbf{p}_t)^2)$$

$$\hat{a}(t) := -(\eta \sum_{n=1}^{N} (\hat{\mathbf{x}}_t - \mathbf{z}_t) + \eta \sum_{n=1}^{N} (\hat{\mathbf{p}}_t))$$

$$\hat{b}(t) := -(\eta \sum_{n=1}^{N} (\hat{\mathbf{x}}_t - \mathbf{z}_t) + \eta \sum_{n=1}^{N} (\hat{\mathbf{p}}_t))$$

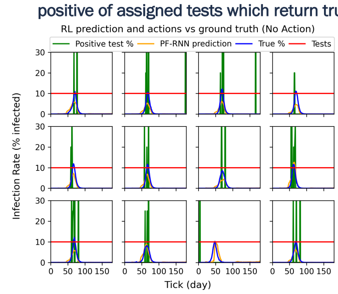
$$r(t) := -(\alpha a(t) + \beta b(t) + \gamma(\log \hat{a}(t) + \hat{b}(t)))$$

Experiments

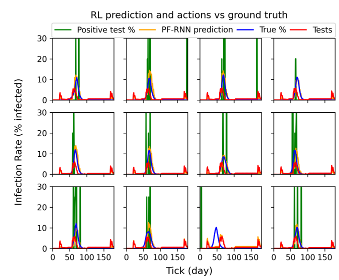
- Using a fixed number of tests, can PF-RNN estimate current infection rates?
- Using dynamic test assignment, can PF-RNN minimize the number of tests used while estimating current infection rates?

Results

- For each experiment, the true trajectory of the epidemic in the 12 counties were plotted along with the models prediction, tests assigned, and percent positive of assigned tests which return true.

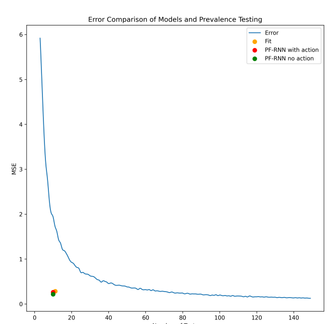


- In the case where a fixed number of tests were assigned, 10 per county per day, the PF-RNN approach is semi accurately able to predict the true curve of the epidemic even with very sparse test information from the environment (green) (Figure 4).



- In the case where testing is dynamic, there is slightly more noise in the prediction and tests assigned, however far fewer tests are used when there are few cases. Additionally, in all but one notable case, the 11th county, it is able to catch peaking infections. One explanation to this miss is almost no tests return positive (Figure 5).

- To evaluate the performance of our PF-RNN implementations, two baselines were established, and performance was compared using Mean Squared Error (MSE) versus the number of tests used.



- The first baseline utilizes a fixed number of tests for each day and the prediction is the percent positive of assigned tests. This was used to create a curve representing the performance of no modeling for different number of assigned tests.
- The second baseline was an Long Short Term Memory (LSTM) model which predicted future prevalence based on the percentage of a small number of tests which were assigned; ten tests per county in this example.

- In this case all three attempted models greatly outperform fixed assignment, with an error associated with 8x as many tests with no prediction.

Future Work

To extend the work done in this research, we hope to explore:

- Different reward functions
- Training on one epidemic trajectory and evaluating on a novel trajectory
- Evaluate the performance on real COVID-19 data

References

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