Modeling and Optimization of Public Health Policy-Making for Epidemics

Dr. Khalil Al Handawi

2023 INFORMS Healthcare Conference

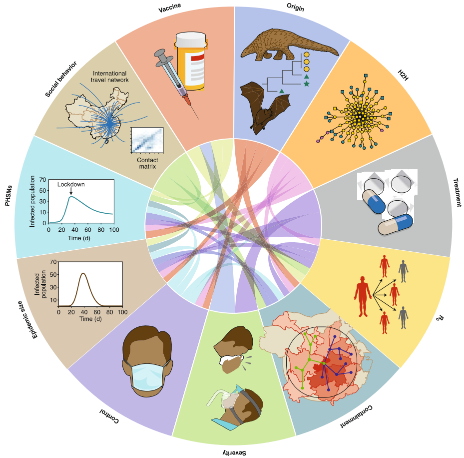
July 26, 2023

Research displinces in epidemiology

Forecasting novel epidemics is a multidisciplinary field involving multiple *targets*[1]

In the early stages of epidemics, we have access to:

Simulation models can be developed based on this information and used in public health and social measures (PHSMs) policy-making.



[1] J. T. Wu, K. Leung, L. T.Y. Lam, M. Y. Ni, C. K.H. Wong, J. S. Peiris, and G. M. Leung, 2021 , *Nature Medicine*

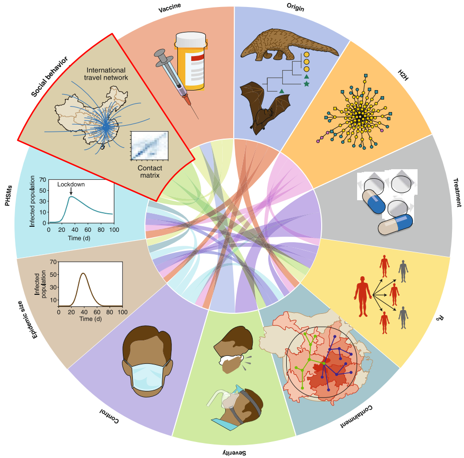
Research displinces in epidemiology

Forecasting novel epidemics is a multidisciplinary field involving multiple *targets*[1]

In the early stages of epidemics, we have access to:

- **Social behaviour and demographics**

Simulation models can be developed based on this information and used in public health and social measures (PHSMs) policy-making.



[1] J. T. Wu, K. Leung, L. T.Y. Lam, M. Y. Ni, C. K.H. Wong, J. S. Peiris, and G. M. Leung, 2021 , *Nature Medicine*

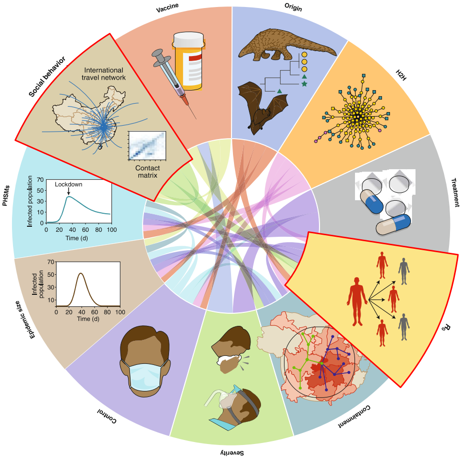
Research displinces in epidemiology

Forecasting novel epidemics is a multidisciplinary field involving multiple *targets*[1]

In the early stages of epidemics, we have access to:

- Social behaviour and demographics
- **Incidence rate data**

Simulation models can be developed based on this information and used in public health and social measures (PHSMs) policy-making.



[1] J. T. Wu, K. Leung, L. T.Y. Lam, M. Y. Ni, C. K.H. Wong, J. S. Peiris, and G. M. Leung, 2021 , *Nature Medicine*

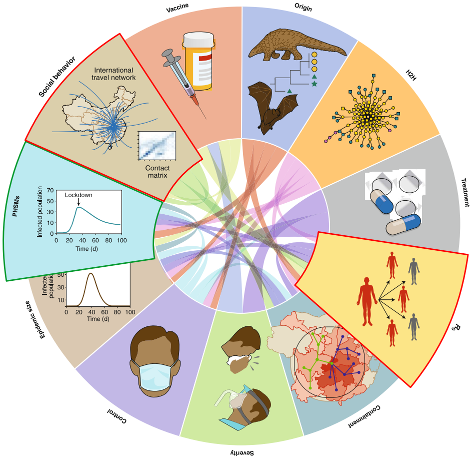
Research displinces in epidemiology

Forecasting novel epidemics is a multidisciplinary field involving multiple *targets*[1]

In the early stages of epidemics, we have access to:

- Social behaviour and demographics
- Incidence rate data

Simulation models can be developed based on this information and used in **public health and social measures (PHSMs)** policy-making.



[1] J. T. Wu, K. Leung, L. T.Y. Lam, M. Y. Ni, C. K.H. Wong, J. S. Peiris, and G. M. Leung, 2021 , *Nature Medicine*

Simulation and modeling of pandemics in early stages[1]

Joint work with: Prof. Michael Kokkolaras

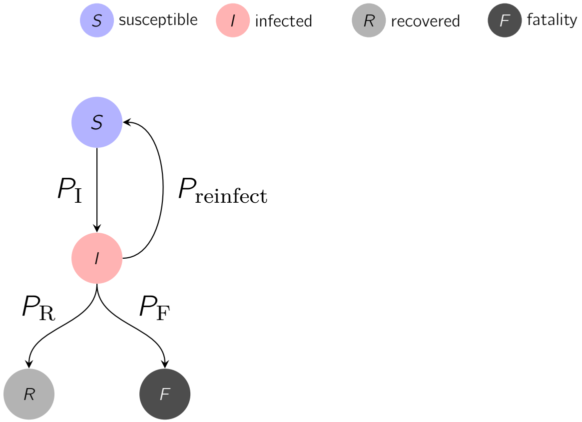
[1] K. Al Handawi and M. Kokkolaras, 2021 , *IEEE Transactions on Emerging Topics in Computational Intelligence*

What are compartmental epidemiological models?

Background: epidemiological models

What are compartmental epidemiological models?

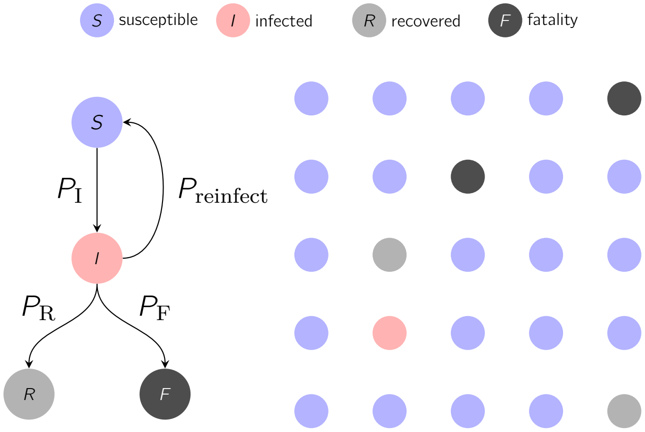
- Described by a *stochastic* process



Background: epidemiological models

What are compartmental epidemiological models?

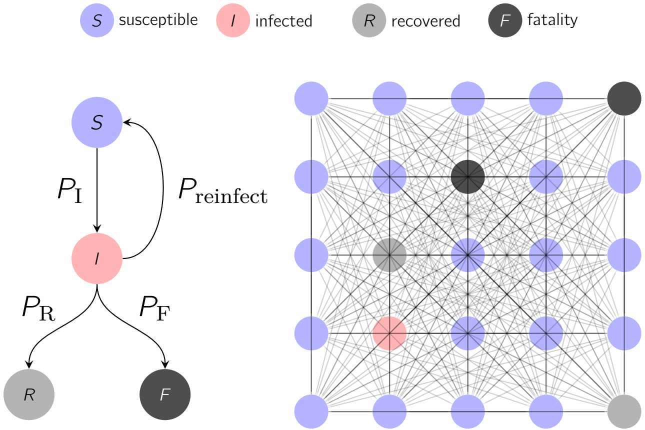
- Described by a *stochastic* process



Background: epidemiological models

What are compartmental epidemiological models?

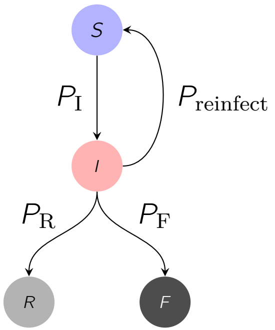
- Described by a *stochastic* process
- Assumes *homogenous* interaction

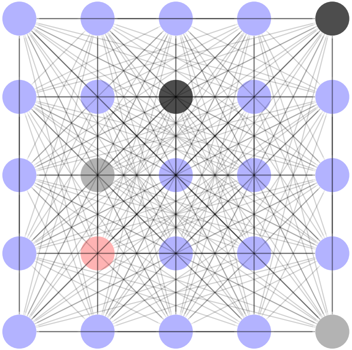


What are compartmental epidemiological models?

S susceptible I infected R recovered F fatality

- Described by a *stochastic* process
- Assumes *homogenous* interaction
- Deterministic response for large N





What are compartmental epidemiological models?

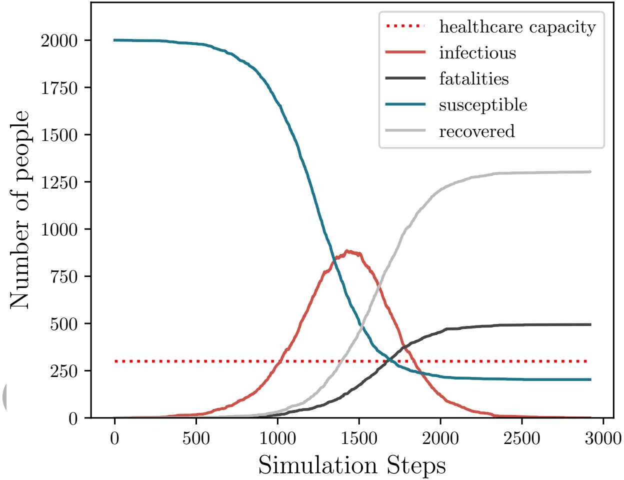
- Described by a *stochastic* process
- Assumes *homogenous* interaction
- Deterministic response for large N

$$\frac{dS}{dt} = -\frac{\beta IS}{N},$$

$$\frac{dI}{dt} = \frac{\beta IS}{N} - \gamma I,$$

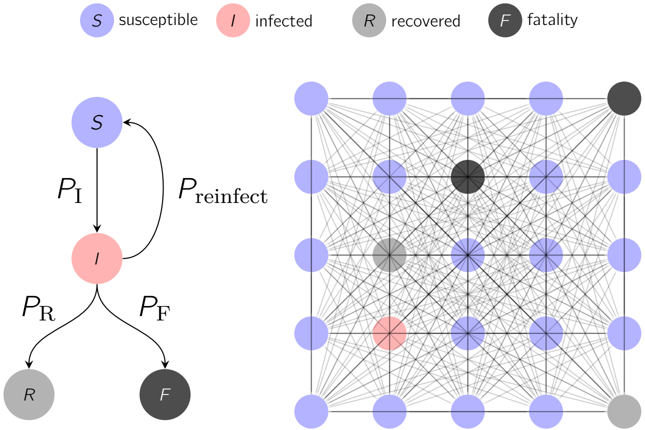
$$\frac{dR}{dt} = \gamma I,$$

where $N = S + I + R$, β controls infection spread, and γ controls recovery rate



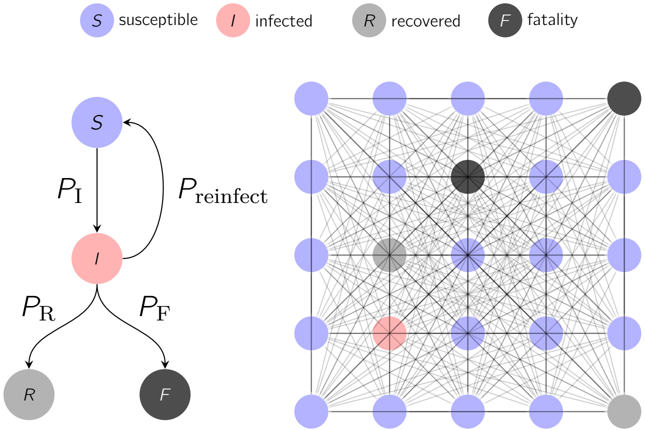
What are compartmental epidemiological models?

✓ Analytical solutions are available



What are compartmental epidemiological models?

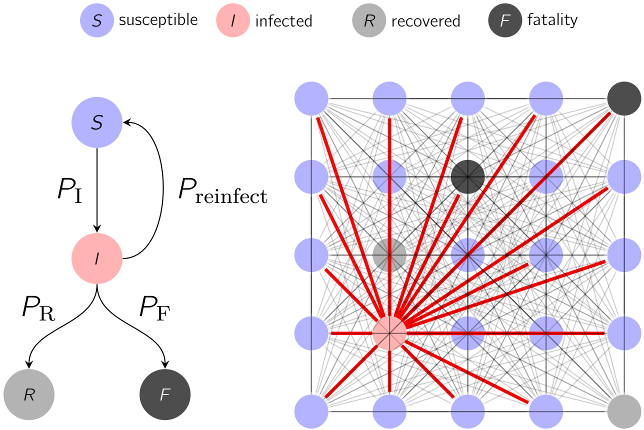
- ✓ Analytical solutions are available
- ✓ Captures large-scale population dynamics



Background: epidemiological models

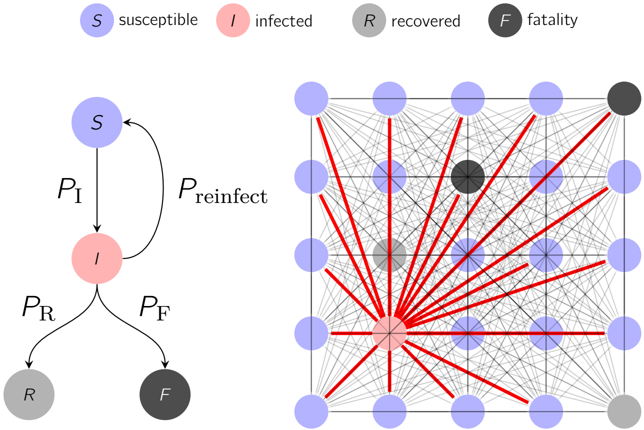
What are compartmental epidemiological models?

- ✓ Analytical solutions are available
- ✓ Captures large-scale population dynamics
- ✗ Does not account for *geography*

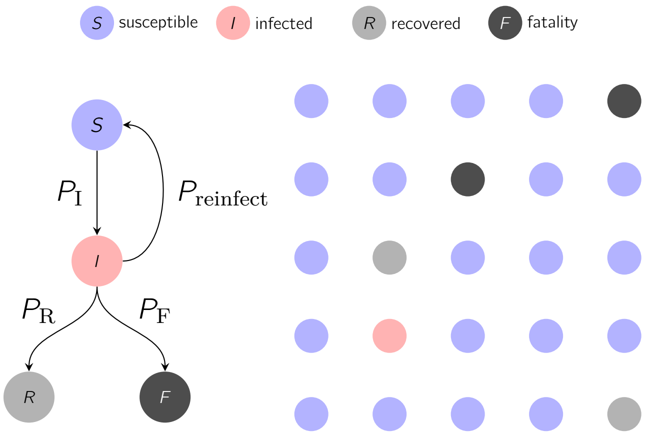


What are compartmental epidemiological models?

- ✓ Analytical solutions are available
- ✓ Captures large-scale population dynamics
- ✘ Does not account for *geography*
- ✘ Cannot model effect of intervention policies

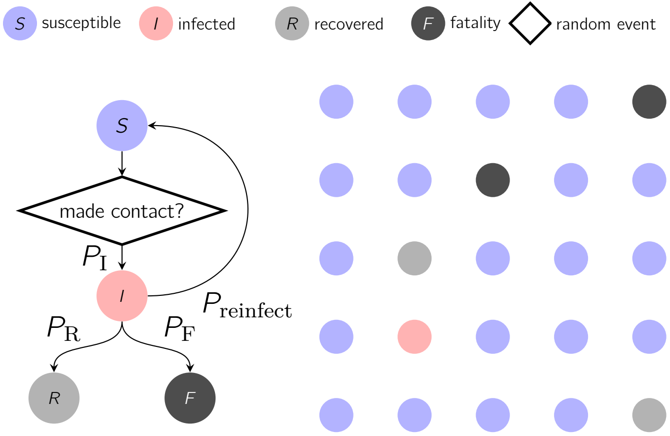


What are agent-based epidemiological models?



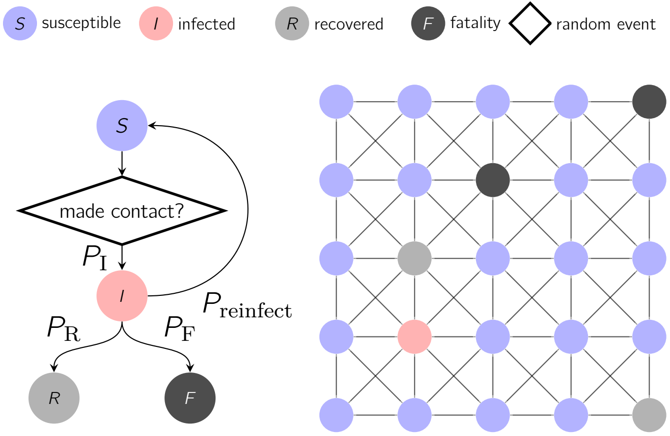
What are agent-based epidemiological models?

- *Stochastic* process



What are agent-based epidemiological models?

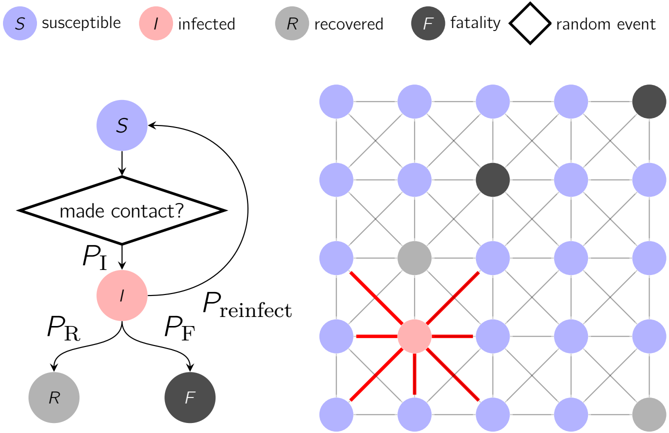
- *Stochastic* process
- Assume *heterogenous* interaction



Background: epidemiological models

What are agent-based epidemiological models?

- *Stochastic* process
- Assume *heterogenous* interaction

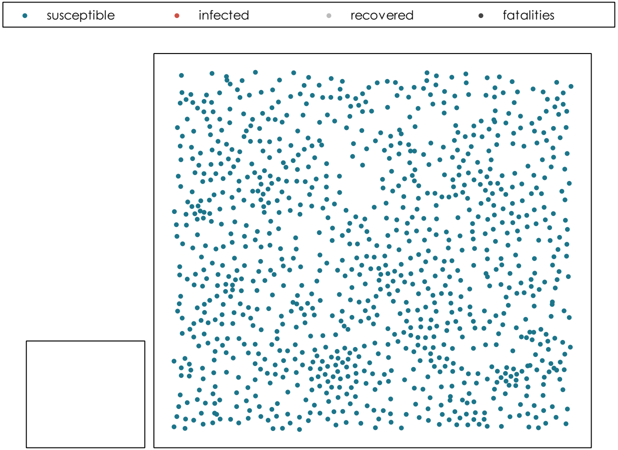


Background: epidemiological models

What are agent-based epidemiological models?

- *Stochastic* process
- Assume *heterogenous* interaction
- Stochastic response

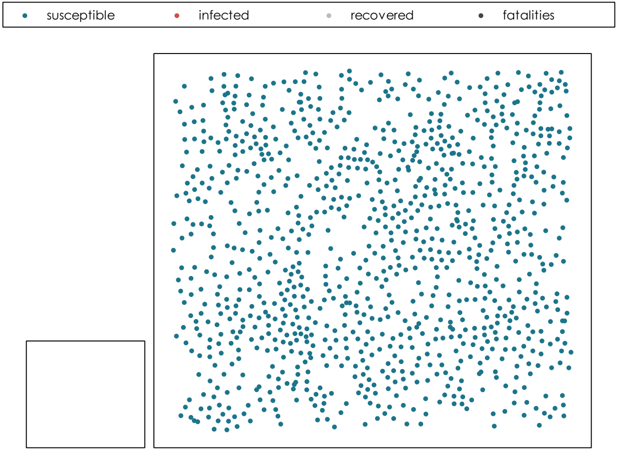
Realization 1



What are agent-based epidemiological models?

- *Stochastic* process
- Assume *heterogenous* interaction
- Stochastic response

Realization 2

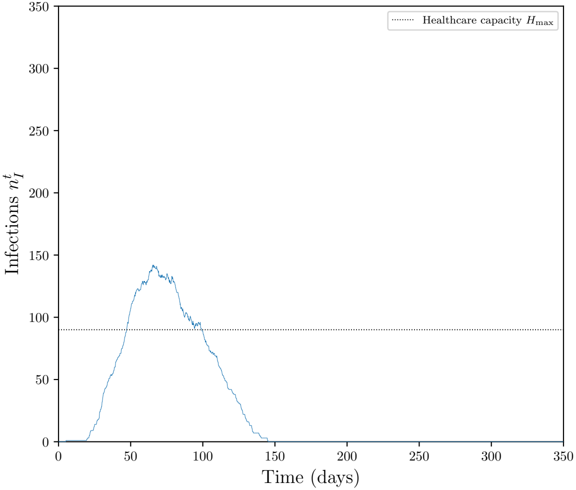


Background: epidemiological models

What are agent-based epidemiological models?

- *Stochastic* process
- Assume *heterogenous* interaction
- Stochastic response

Realization 1

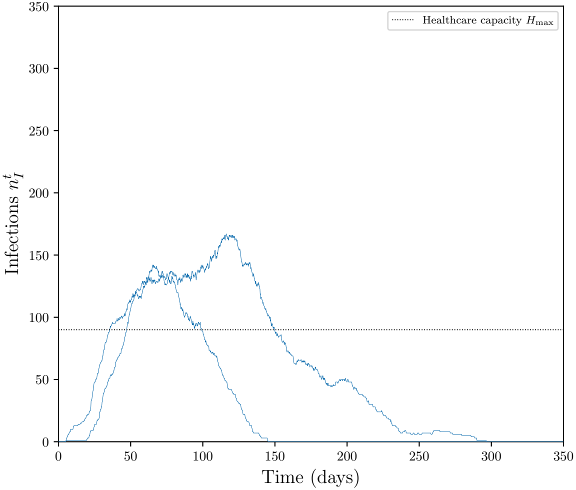


Background: epidemiological models

What are agent-based epidemiological models?

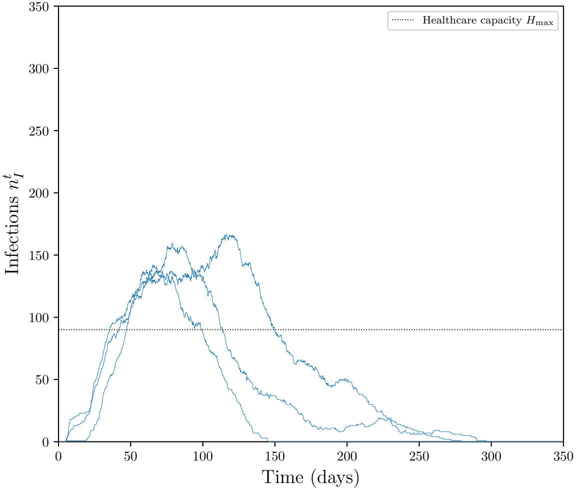
- *Stochastic* process
- Assume *heterogenous* interaction
- Stochastic response

Realization 2



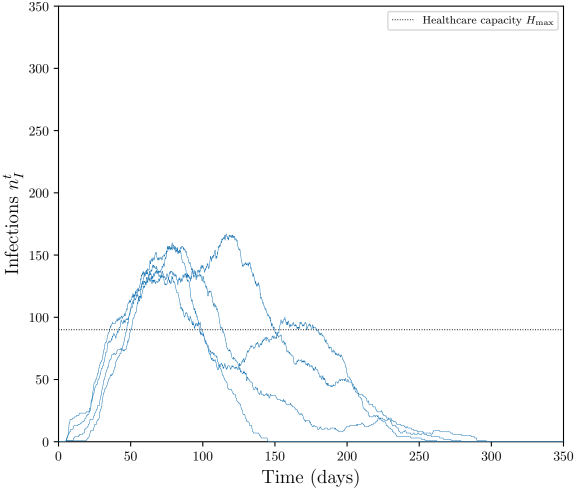
What are agent-based epidemiological models?

- *Stochastic* process
- Assume *heterogenous* interaction
- Stochastic response



What are agent-based epidemiological models?

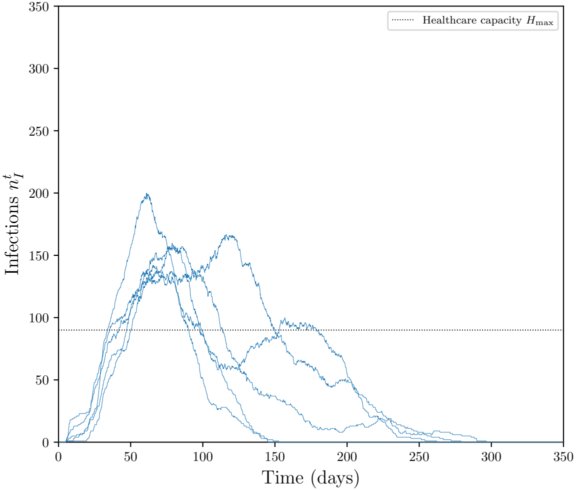
- *Stochastic* process
- Assume *heterogenous* interaction
- Stochastic response



Background: epidemiological models

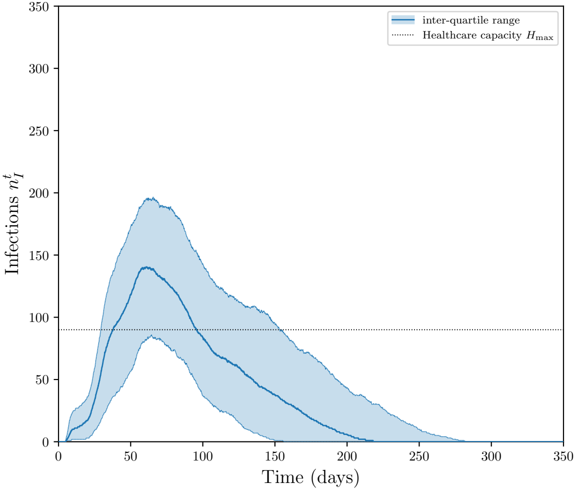
What are agent-based epidemiological models?

- *Stochastic* process
- Assume *heterogenous* interaction
- Stochastic response



What are agent-based epidemiological models?

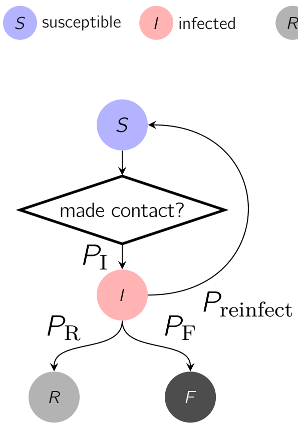
- *Stochastic* process
- Assume *heterogenous* interaction
- Stochastic response

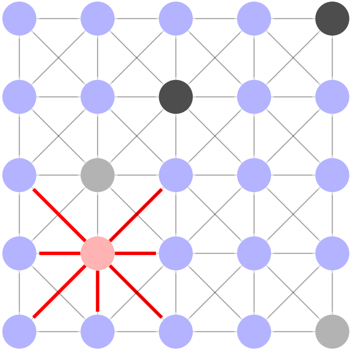


Background: epidemiological models

What are agent-based epidemiological models?

✓ Account for *geography* and *demographics*



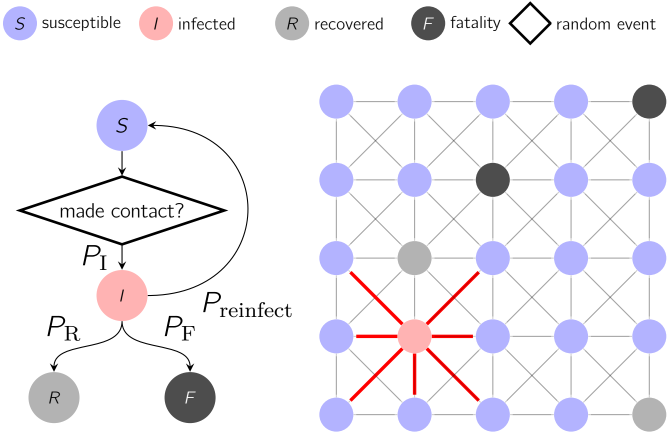


Background: epidemiological models

What are agent-based epidemiological models?

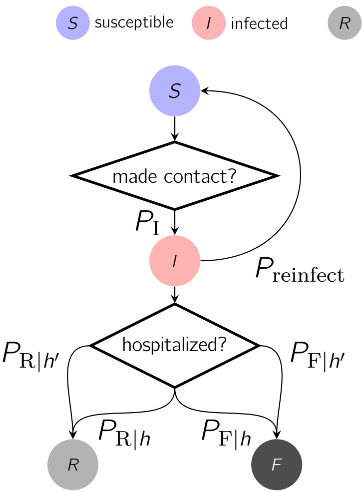
✓ Account for *geography* and *demographics*

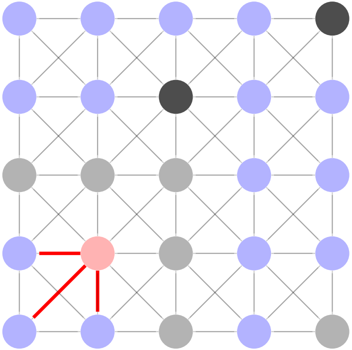
✓ Describe local phenomena



What are agent-based epidemiological models?

- ✓ Account for *geography* and *demographics*
- ✓ Describe local phenomena
- ✓ Can be used to model intervention policies

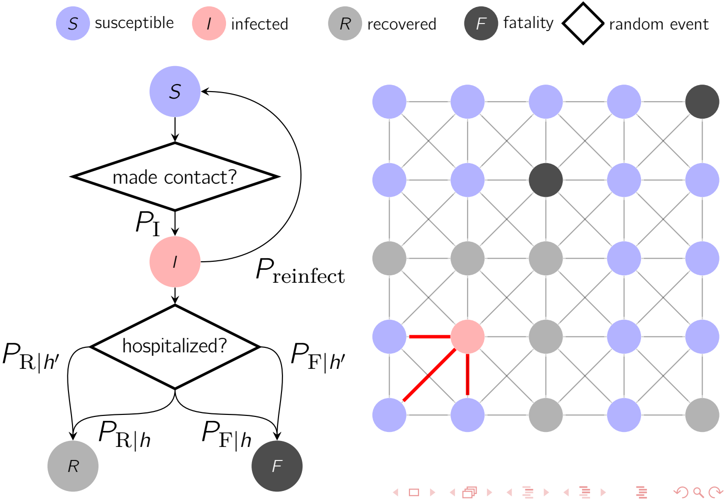




Background: epidemiological models

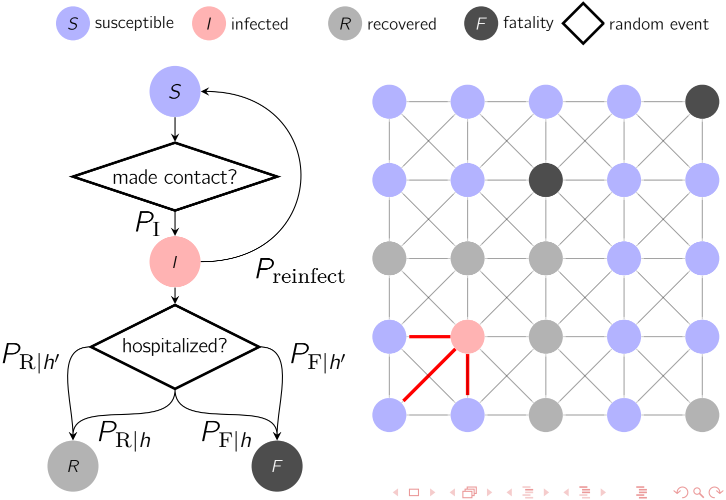
What are agent-based epidemiological models?

- ✓ Account for *geography* and *demographics*
- ✓ Describe local phenomena
- ✓ Can be used to model intervention policies
- ✗ Stochastic response makes decision making challenging



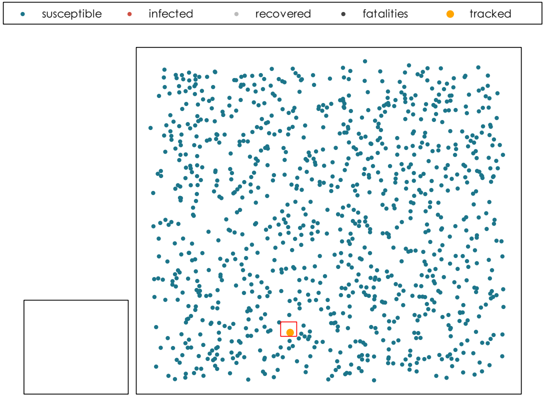
What are agent-based epidemiological models?

- ✓ Account for *geography* and *demographics*
- ✓ Describe local phenomena
- ✓ Can be used to model intervention policies
- ✘ Stochastic response makes decision making challenging
- ✘ Computationally expensive



What is the **cost** of public health interventions?

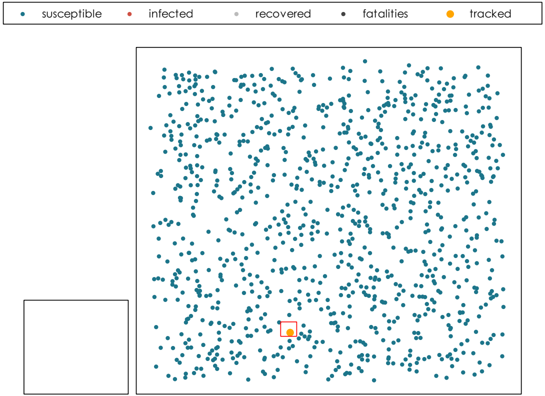
No interventions applied

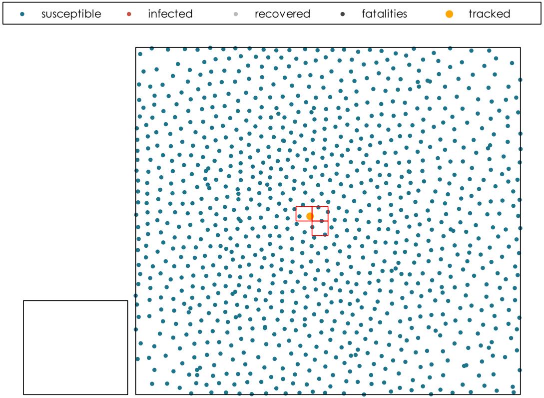


Public health policy-making problem formulation

What is the **cost** of public health interventions?

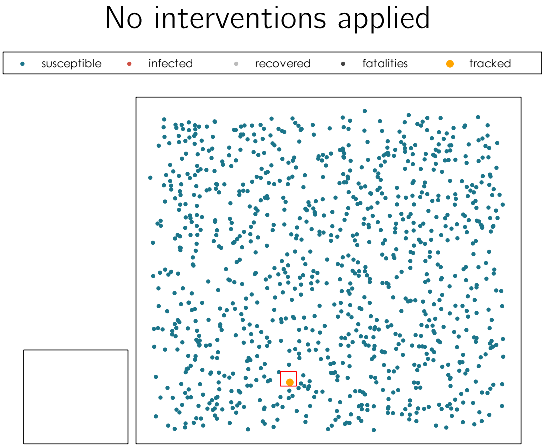
No interventions applied

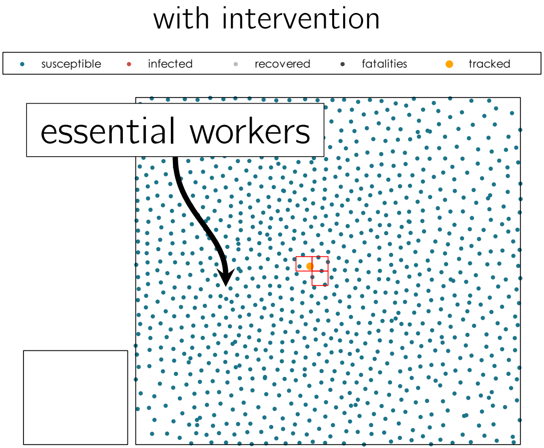




Public health policy-making problem formulation

What is the **cost** of public health interventions?

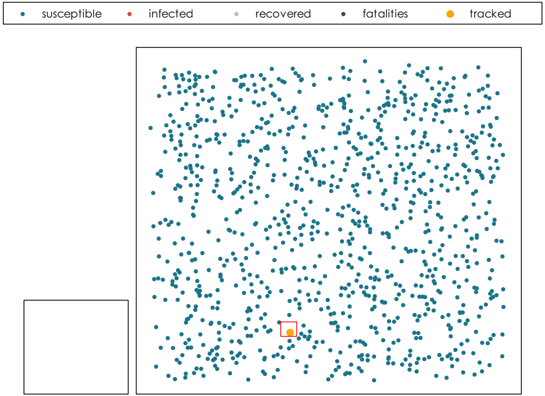




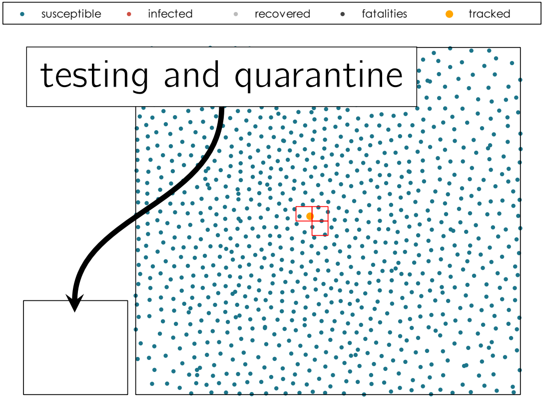
Public health policy-making problem formulation

What is the **cost** of public health interventions?

No interventions applied



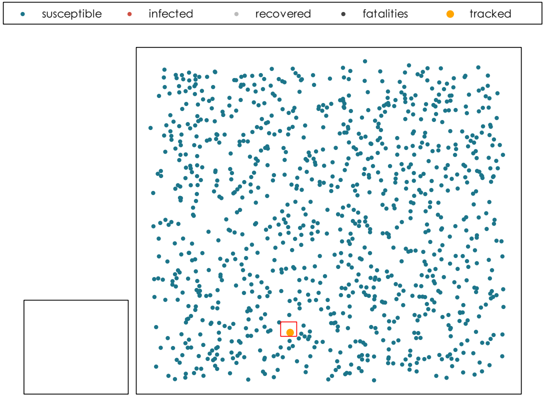
with intervention



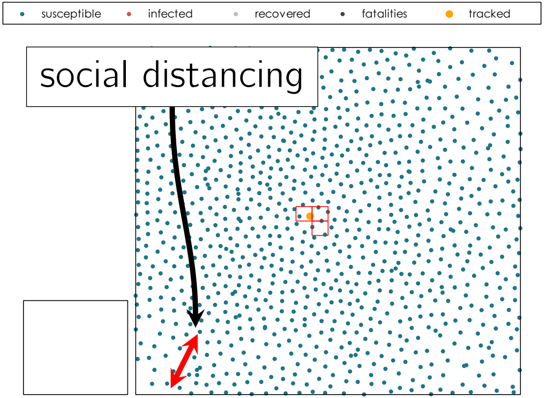
Public health policy-making problem formulation

What is the **cost** of public health interventions?

No interventions applied



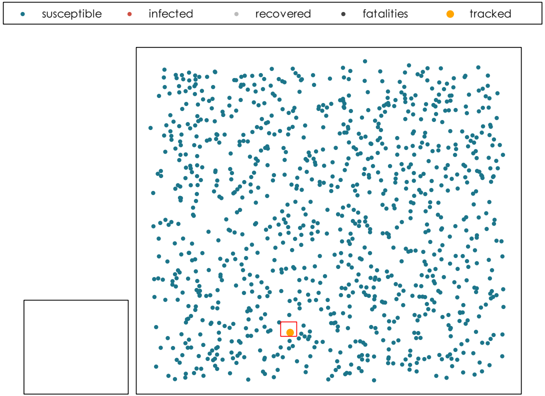
with intervention



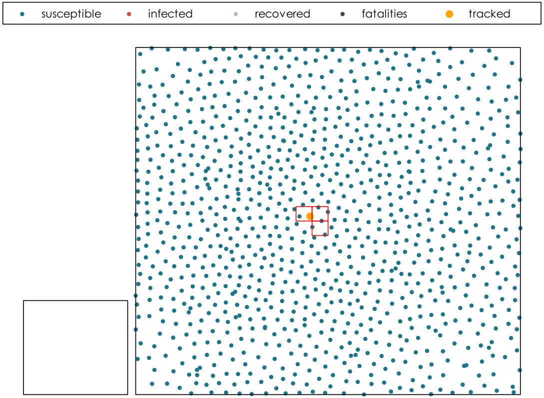
Public health policy-making problem formulation

What is the **cost** of public health interventions?

No interventions applied



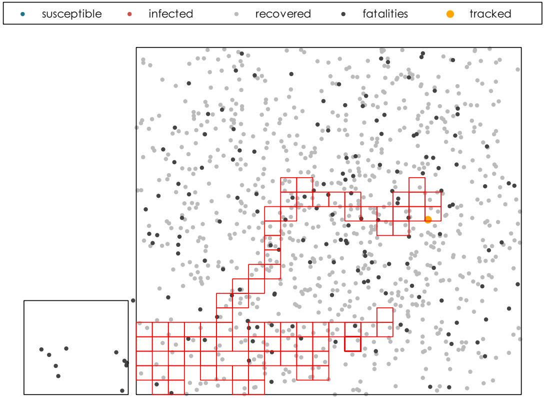
with intervention



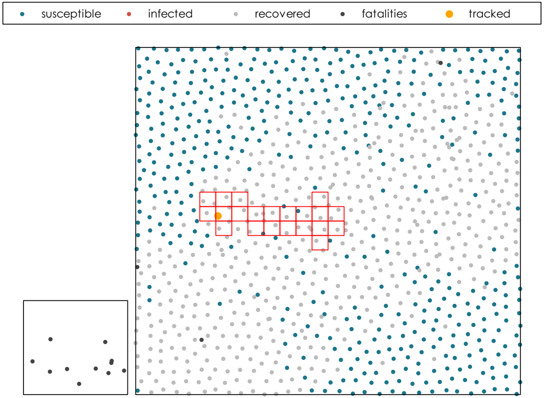
Public health policy-making problem formulation

What is the **cost** of public health interventions?

No interventions applied

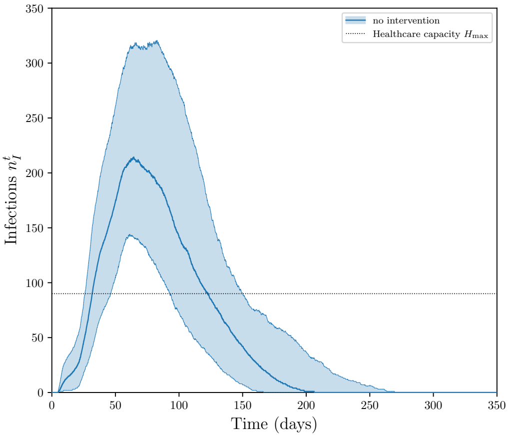


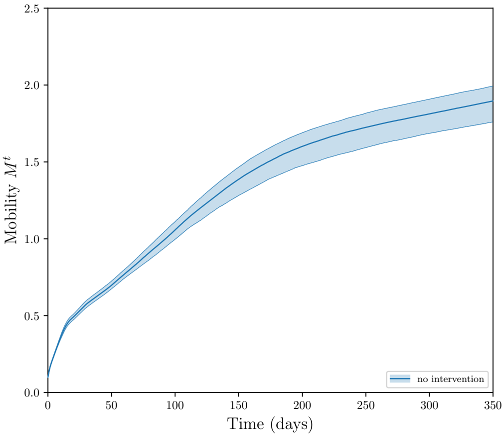
with intervention



Public health policy-making problem formulation

What is the **cost** of public health interventions?

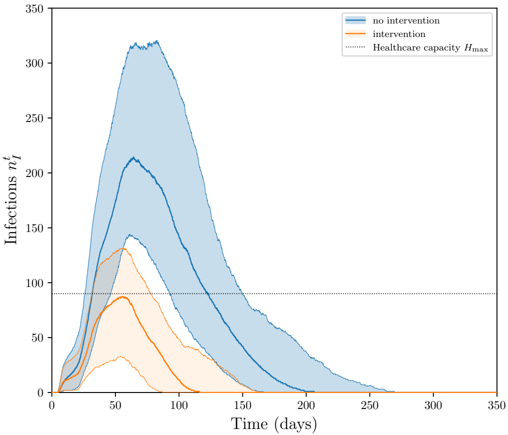




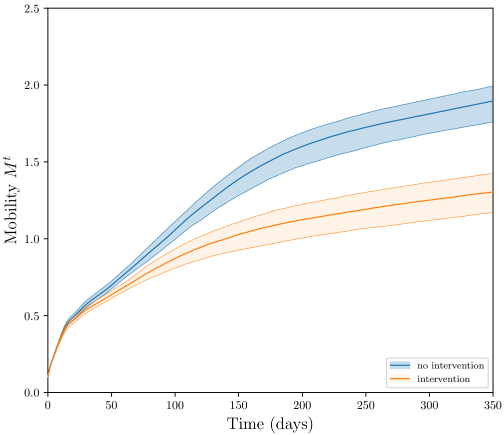
Public health policy-making problem formulation

What is the **cost** of public health interventions?

infections ↓



mobility ↓



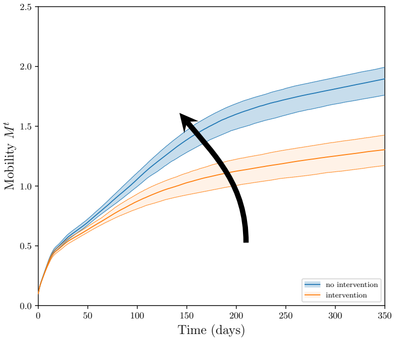
Optimization problem

Objective and constraints

$$\begin{aligned} \min_{\mathrm{x}} \quad & f(\mathrm{x}) = -M^T \\ \text{subject to} \quad & \\ \text{where} \quad & \mathrm{x} = [n_E, S_D, n_T]^T \end{aligned}$$

Design variables

- n_E : Number of essential workers
- S_D : Social distancing factor
- n_T : Number of tests daily



Optimization problem

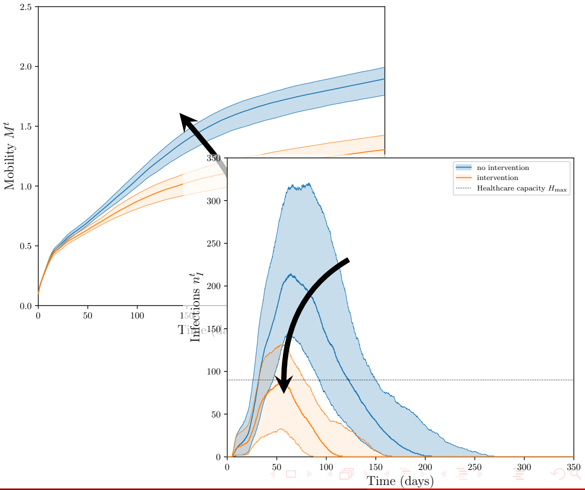
No gradient information available, blackbox is expensive and noisy

Objective and constraints

$$\begin{aligned} \min_{\mathrm{x}} \quad & f(\mathrm{x}) = -M^T \\ \text{subject to} \quad & c(\mathrm{x}) \equiv n_{I,\max} - H_{\max} \leq 0 \\ \text{where} \quad & \mathrm{x} = [n_E, S_D, n_T]^T \end{aligned}$$

Design variables

- n_E : Number of essential workers
- S_D : Social distancing factor
- n_T : Number of tests daily



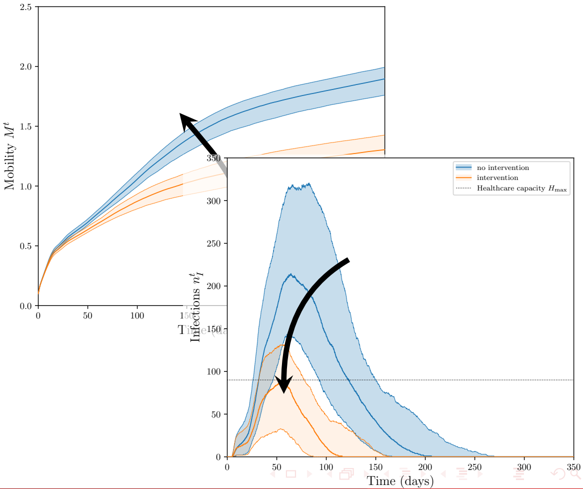
No gradient information available, blackbox is expensive and **noisy**

Objective and constraints

$$\min_{x} \quad f(x) = -M^T$$
$$\text{subject to} \quad c(x) \equiv n_{I,\max} - H_{\max} \leq 0$$
$$\text{where} \quad x = [n_E, S_D, n_T]^T$$

Design variables

- n_E : Number of essential workers
- S_D : Social distancing factor
- n_T : Number of tests daily



Optimization problem

No gradient information available, blackbox is expensive and **noisy**

Objective and constraints

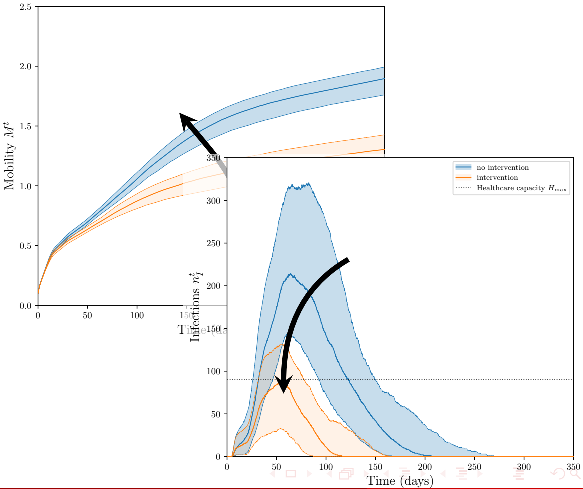
$$\min_{\mathbf{x}} \quad f(\mathbf{x}) = \mathbb{E}_{\Theta}\left[f_{\Theta}(\mathbf{x}) = -M^T\right]$$

$$\text{subject to} \quad c(\mathbf{x}) = \mathbb{E}_{\Theta}\left[c_{\Theta}(\mathbf{x}) \equiv n_{I,\max} - H_{\max}\right] \leq 0$$

$$\text{where} \quad \mathbf{x} = [n_E, S_D, n_T]^T, \ \Theta\text{: realizations}$$

Design variables

- n_E : Number of essential workers
- S_D : Social distancing factor
- n_T : Number of tests daily



Optimization problem

No gradient information available, blackbox is expensive and **noisy**

Objective and constraints

$$\min_{x} \quad f(x) = \mathbb{E}_{\Theta}\left[f_{\Theta}(x) = -M^{T}\right]$$

$$\text{subject to} \quad c(x) = \mathbb{E}_{\Theta}\left[c_{\Theta}(x) \equiv n_{I,\max} - H_{\max}\right] \leq 0$$

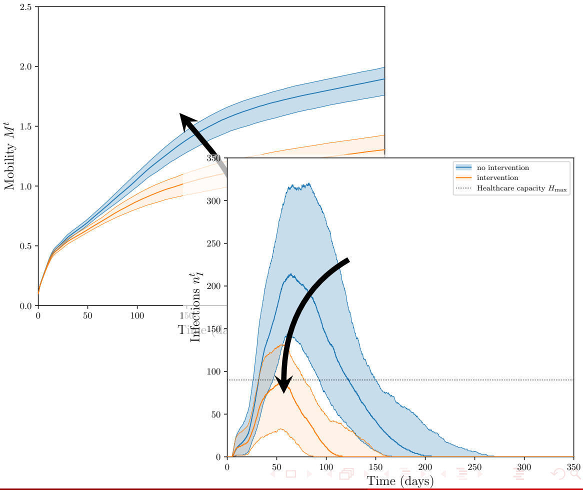
$$\text{where} \quad x = [n_E, S_D, n_T]^T, \ \Theta\text{: realizations}$$

Design variables

- n_E : Number of essential workers
- S_D : Social distancing factor
- n_T : Number of tests daily

Randomly seeded parameters

- Initial conditions
- Interactions, demographics



Optimization results

StoMADS, `NOMAD`[1], and genetic algorithms were used to solve the problem[2]

Objective and constraints

$$\begin{aligned}
&\min_{x} && f(x) = \mathbb{E}_{\Theta}\left[f_{\Theta}(x) = -M^{T}\right] \\
&\text{subject to} && c(x) = \mathbb{E}_{\Theta}\left[c_{\Theta}(x) \equiv n_{I,\max} - H_{\max}\right] \leq 0 \\
&\text{where} && x = [n_E, S_D, n_T]^{T}, \Theta\text{: realizations}
\end{aligned}$$

Design variables

- n_E : Number of essential workers
- S_D : Social distancing factor
- n_T : Number of tests daily

Randomly seeded parameters

- Initial conditions
- Interactions, demographics

[1] S. Le Digabel, C. Tribes, V. Rochon Montplaisir, and C. Audet, 2018 , *https://www.gerad.ca/nomad/Downloads/user_guide.pdf*
[2] K. Al Handawi and M. Kokkolaras, 2021 , *IEEE Transactions on Emerging Topics in Computational Intelligence*

Optimization results

StoMADS, NOMAD[1], and genetic algorithms were used to solve the problem[2]

Objective and constraints

$$\min_{x} \quad f(x) = \mathbb{E}_\Theta\left[f_\Theta(x) = -M^T\right]$$

$$\text{subject to} \quad c(x) = \mathbb{E}_\Theta\left[c_\Theta(x) \equiv n_{I,\max} - H_{\max}\right] \le 0$$

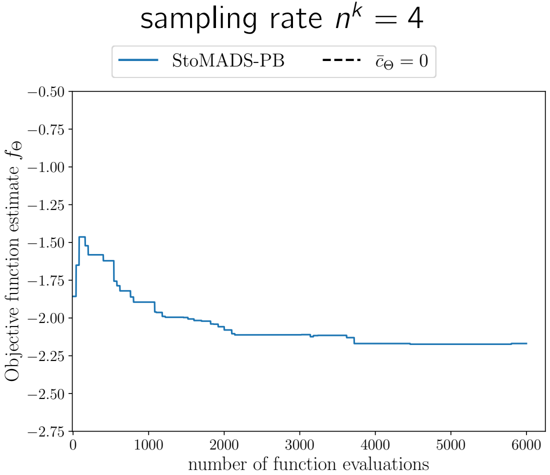
$$\text{where} \quad x = [n_E, S_D, n_T]^T, \Theta\text{: realizations}$$

Design variables

- n_E : Number of essential workers
- S_D : Social distancing factor
- n_T : Number of tests daily

Randomly seeded parameters

- Initial conditions
- Interactions, demographics



[1] S. Le Digabel, C. Tribes, V. Rochon Montplaisir, and C. Audet, 2018 , *https://www.gerad.ca/nomad/Downloads/user_guide.pdf*
[2] K. Al Handawi and M. Kokkolaras, 2021 , *IEEE Transactions on Emerging Topics in Computational Intelligence*

Optimization results

StoMADS, `NOMAD`[1], and genetic algorithms were used to solve the problem[2]

Objective and constraints

$$\min_{x} \quad f(x) = \mathbb{E}_\Theta\left[f_\Theta(x) = -M^T\right]$$

$$\text{subject to} \quad c(x) = \mathbb{E}_\Theta\left[c_\Theta(x) \equiv n_{I,\max} - H_{\max}\right] \leq 0$$

$$\text{where} \quad x = [n_E, S_D, n_T]^T, \Theta\text{: realizations}$$

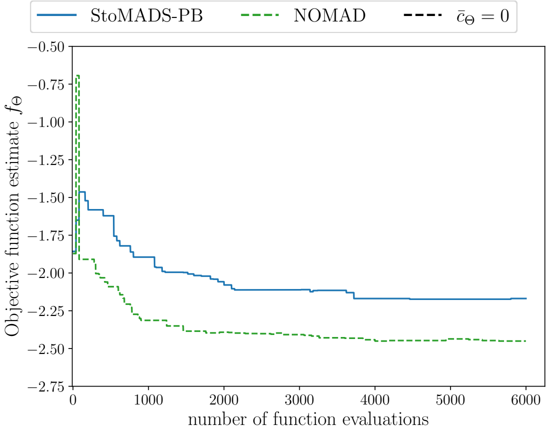
Design variables

- n_E : Number of essential workers
- S_D : Social distancing factor
- n_T : Number of tests daily

Randomly seeded parameters

- Initial conditions
- Interactions, demographics

sampling rate $n^k = 4$



[1] S. Le Digabel, C. Tribes, V. Rochon Montplaisir, and C. Audet, 2018 , *https://www.gerad.ca/nomad/Downloads/user_guide.pdf*
[2] K. Al Handawi and M. Kokkolaras, 2021 , *IEEE Transactions on Emerging Topics in Computational Intelligence*

StoMADS, NOMAD[1], and genetic algorithms were used to solve the problem[2]

Objective and constraints

$\min_{x}$	$f(x) = \mathbb{E}_\Theta\left[f_\Theta(x) = -M^T\right]$
subject to	$c(x) = \mathbb{E}_\Theta\left[c_\Theta(x) \equiv n_{I,\max} - H_{\max}\right] \leq 0$
where	$x = [n_E, S_D, n_T]^T$, Θ: realizations

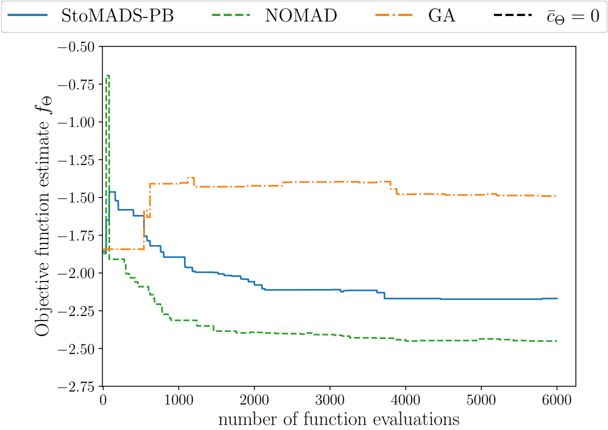
Design variables

- n_E : Number of essential workers
- S_D : Social distancing factor
- n_T : Number of tests daily

Randomly seeded parameters

- Initial conditions
- Interactions, demographics

sampling rate $n^k = 4$



[1] S. Le Digabel, C. Tribes, V. Rochon Montplaisir, and C. Audet, 2018 , *https://www.gerad.ca/nomad/Downloads/user_guide.pdf*
[2] K. Al Handawi and M. Kokkolaras, 2021 , *IEEE Transactions on Emerging Topics in Computational Intelligence*

Optimization results

StoMADS, `NOMAD`[1], and genetic algorithms were used to solve the problem[2]

Objective and constraints

$\min_{x}$	$f(x) = \mathbb{E}_\Theta\left[f_\Theta(x) = -M^T\right]$
subject to	$c(x) = \mathbb{E}_\Theta\left[c_\Theta(x) \equiv n_{I,\max} - H_{\max}\right] \leq 0$
where	$x = [n_E, S_D, n_T]^T$, Θ: realizations

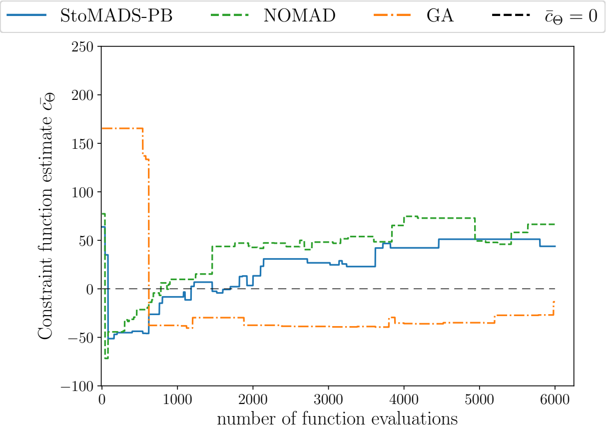
Design variables

- n_E : Number of essential workers
- S_D : Social distancing factor
- n_T : Number of tests daily

Randomly seeded parameters

- Initial conditions
- Interactions, demographics

sampling rate $n^k = 4$



[1] S. Le Digabel, C. Tribes, V. Rochon Montplaisir, and C. Audet, 2018 , *https://www.gerad.ca/nomad/Downloads/user_guide.pdf*
[2] K. Al Handawi and M. Kokkolaras, 2021 , *IEEE Transactions on Emerging Topics in Computational Intelligence*

StoMADS, NOMAD[1], and genetic algorithms were used to solve the problem[2]
best known solution

Objective and constraints

$$\min_{x} \quad f(x) = \mathbb{E}_\Theta\left[f_\Theta(x) = -M^T\right]$$

$$\text{subject to} \quad c(x) = \mathbb{E}_\Theta\left[c_\Theta(x) \equiv n_{I,\max} - H_{\max}\right] \leq 0$$

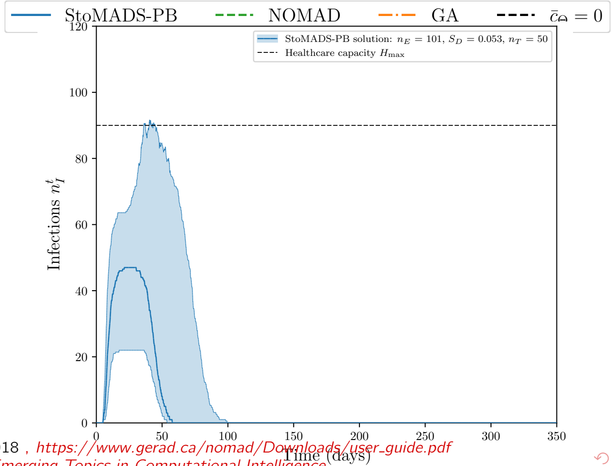
$$\text{where} \quad x = [n_E, S_D, n_T]^T, \Theta\text{: realizations}$$

Design variables

- n_E : Number of essential workers
- S_D : Social distancing factor
- n_T : Number of tests daily

Randomly seeded parameters

- Initial conditions
- Interactions, demographics



[1] S. Le Digabel, C. Tribes, V. Rochon Montplaisir, and C. Audet, 2018 , *https://www.gerad.ca/nomad/Downloads/user_guide.pdf*
[2] K. Al Handawi and M. Kokkolaras, 2021 , *IEEE Transactions on Emerging Topics in Computational Intelligence*

Optimization results

StoMADS, NOMAD[1], and genetic algorithms were used to solve the problem[2]

best known solution

Objective and constraints

$$\min_{x} \quad f(x) = \mathbb{E}_{\Theta}\left[f_{\Theta}(x) = -M^T\right]$$

$$\text{subject to} \quad c(x) = \mathbb{E}_{\Theta}\left[c_{\Theta}(x) \equiv n_{I,\max} - H_{\max}\right] \leq 0$$

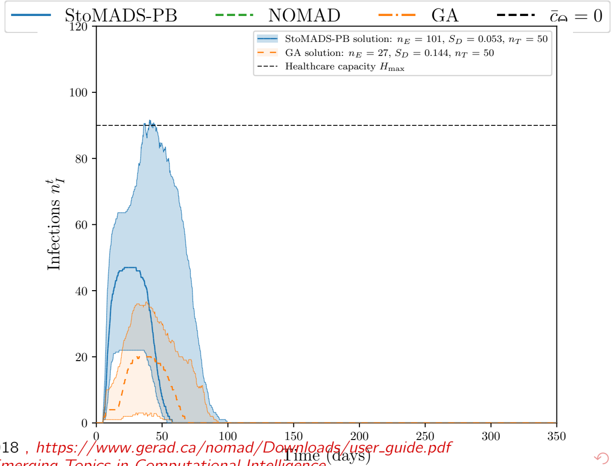
$$\text{where} \quad x = [n_E, S_D, n_T]^T, \Theta\text{: realizations}$$

Design variables

- n_E : Number of essential workers
- S_D : Social distancing factor
- n_T : Number of tests daily

Randomly seeded parameters

- Initial conditions
- Interactions, demographics



[1] S. Le Digabel, C. Tribes, V. Rochon Montplaisir, and C. Audet, 2018 , *https://www.gerad.ca/nomad/Downloads/user_guide.pdf*

[2] K. Al Handawi and M. Kokkolaras, 2021 , *IEEE Transactions on Emerging Topics in Computational Intelligence*

StoMADS, NOMAD[1], and genetic algorithms were used to solve the problem[2]

best known solution

Objective and constraints

$$\min_{x} \quad f(x) = \mathbb{E}_{\Theta}\left[f_{\Theta}(x) = -M^{T}\right]$$

$$\text{subject to} \quad c(x) = \mathbb{E}_{\Theta}\left[c_{\Theta}(x) \equiv n_{I,\max} - H_{\max}\right] \leq 0$$

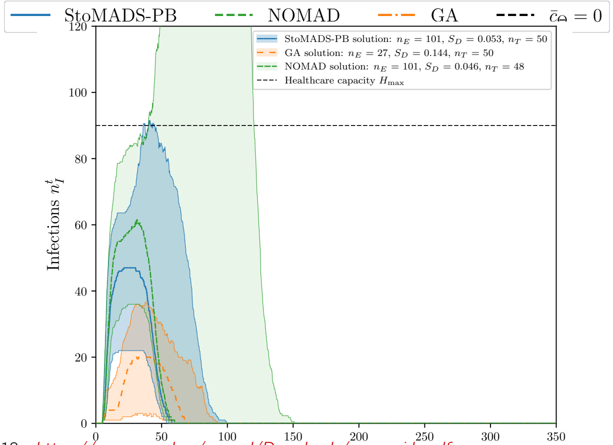
$$\text{where} \quad x = [n_E, S_D, n_T]^{T}, \Theta\text{: realizations}$$

Design variables

- n_E : Number of essential workers
- S_D : Social distancing factor
- n_T : Number of tests daily

Randomly seeded parameters

- Initial conditions
- Interactions, demographics



[1] S. Le Digabel, C. Tribes, V. Rochon Montplaisir, and C. Audet, 2018, *https://www.gerad.ca/nomad/Downloads/user_guide.pdf*
[2] K. Al Handawi and M. Kokkolaras, 2021, *IEEE Transactions on Emerging Topics in Computational Intelligence*

StoMADS, NOMAD[1], and genetic algorithms were used to solve the problem[2]
best known solution

Objective and constraints

$$\min_{x} \quad f(x) = \mathbb{E}_{\Theta}\left[f_{\Theta}(x) = -M^{T}\right]$$

$$\text{subject to} \quad c(x) = \mathbb{E}_{\Theta}\left[c_{\Theta}(x) \equiv n_{I,\max} - H_{\max}\right] \leq 0$$

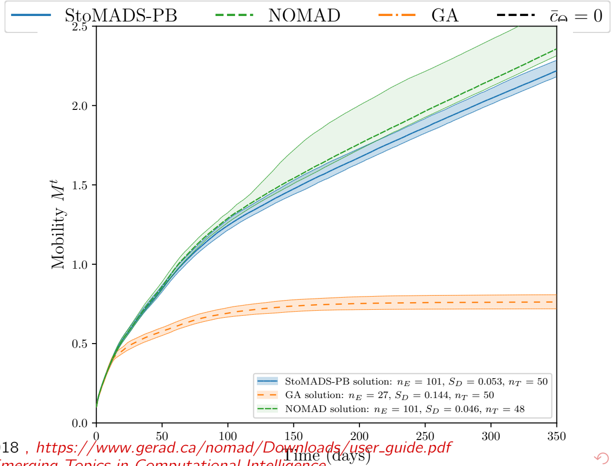
$$\text{where} \quad x = \left[n_E, S_D, n_T\right]^T, \Theta\text{: realizations}$$

Design variables

- n_E : Number of essential workers
- S_D : Social distancing factor
- n_T : Number of tests daily

Randomly seeded parameters

- Initial conditions
- Interactions, demographics



[1] S. Le Digabel, C. Tribes, V. Rochon Montplaisir, and C. Audet, 2018 , *https://www.gerad.ca/nomad/Downloads/user_guide.pdf*

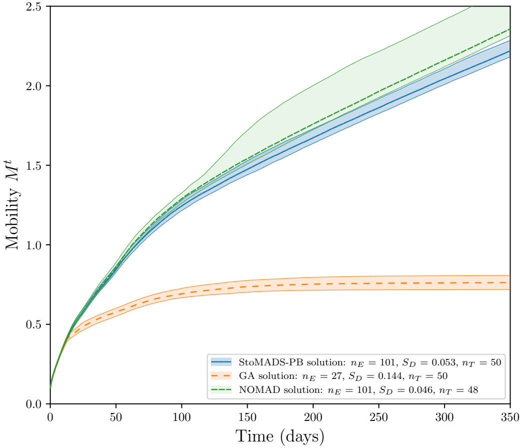
[2] K. Al Handawi and M. Kokkolaras, 2021 , *IEEE Transactions on Emerging Topics in Computational Intelligence*

Conclusion

Formulated and solved public health policy-making problems

- Identified a public health policy that favored

best known solution

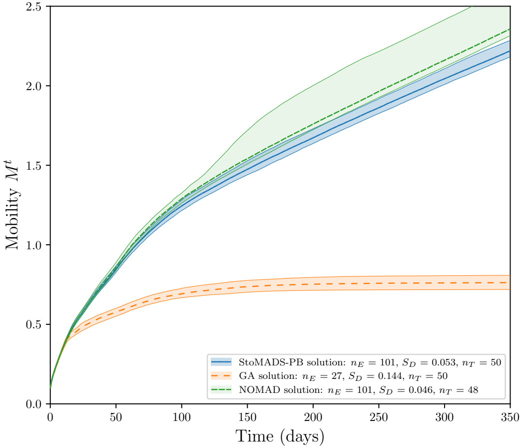


Conclusion

Formulated and solved public health policy-making problems

- Identified a public health policy that favored
  - High testing capacity n_T

best known solution

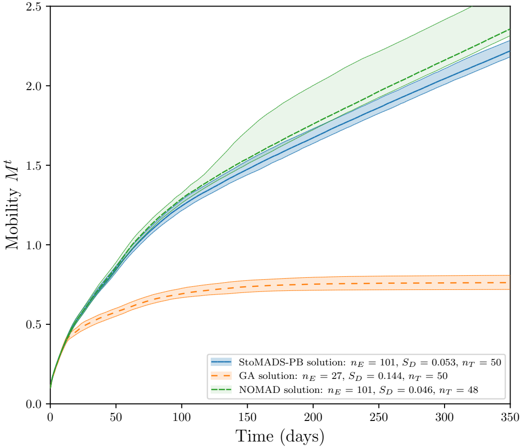


Conclusion

Formulated and solved public health policy-making problems

- Identified a public health policy that favored
  - High testing capacity n_T
  - Large number of essential workers n_E

best known solution

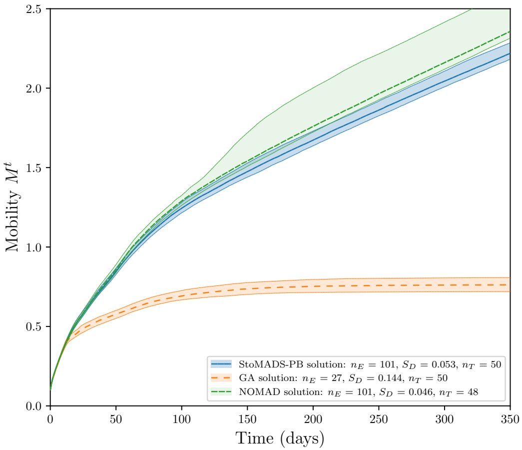


Conclusion

Formulated and solved public health policy-making problems

- Identified a public health policy that favored
  - High testing capacity n_T
  - Large number of essential workers n_E
  - Modest social distancing S_D

best known solution

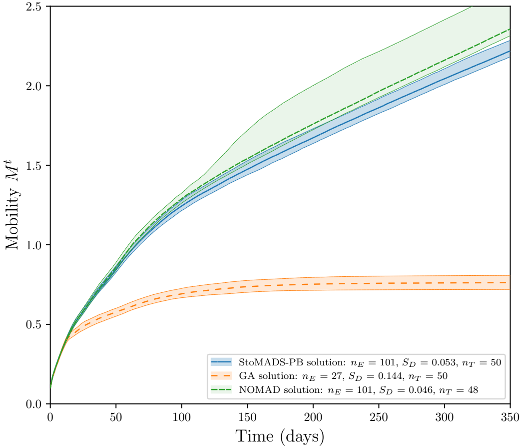


Conclusion

Formulated and solved public health policy-making problems

- Identified a public health policy that favored
  - High testing capacity n_T
  - Large number of essential workers n_E
  - Modest social distancing S_D
- StoMADS outperformed GAs and NOMAD on active constraints

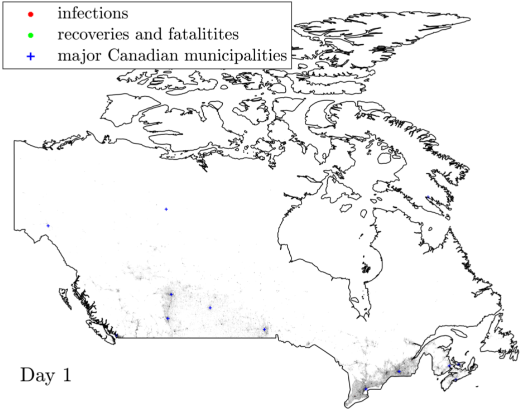
best known solution



Conclusion

Formulated and solved public health policy-making problems

- Identified a public health policy that favored
  - High testing capacity n_T
  - Large number of essential workers n_E
  - Modest social distancing S_D
- StoMADS outperformed GAs and NOMAD on active constraints
- Applicable to other large-scale agent-based models[1]

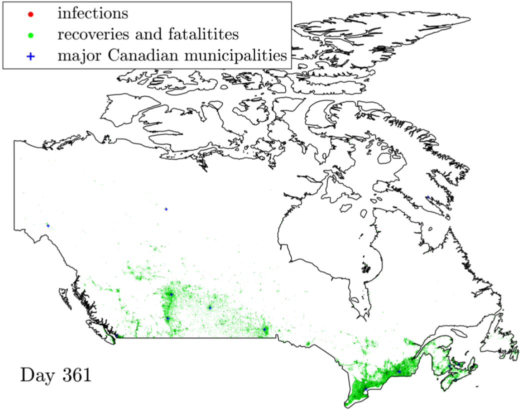


[1] N. Ferguson et al., 2020 , *Imperial College COVID-19 Response Team*

Conclusion

Formulated and solved public health policy-making problems

- Identified a public health policy that favored
  - High testing capacity n_T
  - Large number of essential workers n_E
  - Modest social distancing S_D
- StoMADS outperformed GAs and NOMAD on active constraints
- Applicable to other large-scale agent-based models[1]

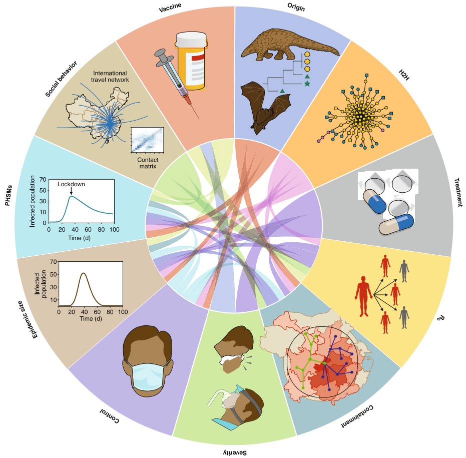


[1] N. Ferguson et al., 2020 , *Imperial College COVID-19 Response Team*

Research displinces in epidemiology

Forecasting novel epidemics is a multidisciplinary field involving multiple *targets*[1]

Inputs for forecasting **epidemic size:**



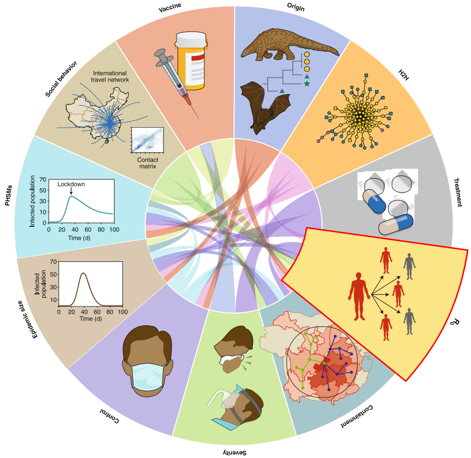
[1] J. T. Wu, K. Leung, L. T.Y. Lam, M. Y. Ni, C. K.H. Wong, J. S. Peiris, and G. M. Leung, 2021 , *Nature Medicine*

Research displinces in epidemiology

Forecasting novel epidemics is a multidisciplinary field involving multiple *targets*[1]

Inputs for forecasting **epidemic size:**

- Growth rate indicators



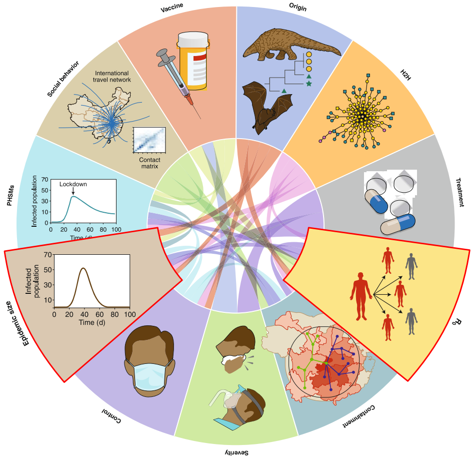
[1] J. T. Wu, K. Leung, L. T.Y. Lam, M. Y. Ni, C. K.H. Wong, J. S. Peiris, and G. M. Leung, 2021 , *Nature Medicine*

Research displinces in epidemiology

Forecasting novel epidemics is a multidisciplinary field involving multiple *targets*[1]

Inputs for forecasting **epidemic size:**

- Growth rate indicators
- Historical incidence rate data



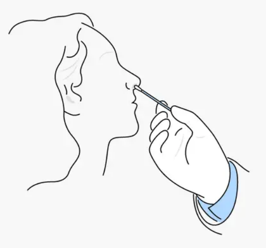
[1] J. T. Wu, K. Leung, L. T.Y. Lam, M. Y. Ni, C. K.H. Wong, J. S. Peiris, and G. M. Leung, 2021 , *Nature Medicine*

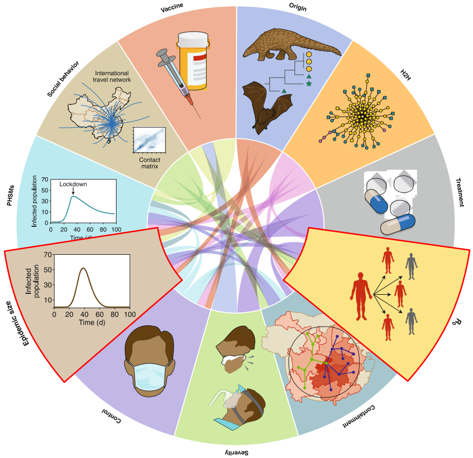
Research displinces in epidemiology

Forecasting novel epidemics is a multidisciplinary field involving multiple *targets*[1]

Inputs for forecasting **epidemic size:**

- Growth rate indicators
- Historical incidence rate data
- Serologic assays





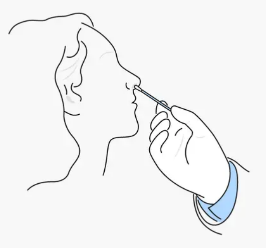
[1] J. T. Wu, K. Leung, L. T.Y. Lam, M. Y. Ni, C. K.H. Wong, J. S. Peiris, and G. M. Leung, 2021 , *Nature Medicine*

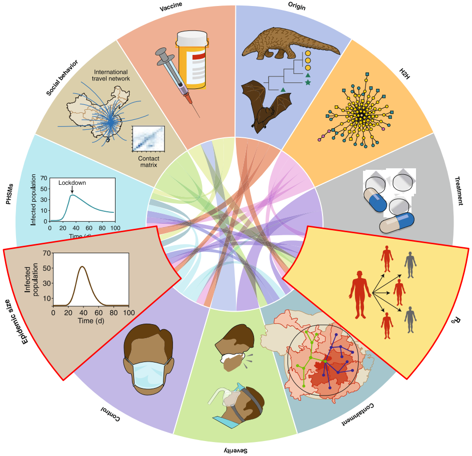
Research displinces in epidemiology

Forecasting novel epidemics is a multidisciplinary field involving multiple *targets*[1]

Inputs for forecasting **epidemic size:**

- Growth rate indicators
- **Historical incidence rate data**
- **Serologic assays**





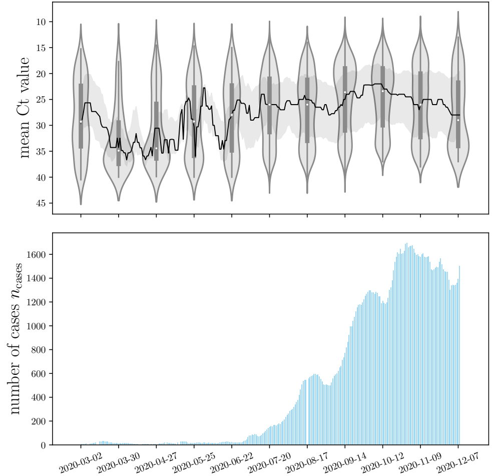
[1] J. T. Wu, K. Leung, L. T.Y. Lam, M. Y. Ni, C. K.H. Wong, J. S. Peiris, and G. M. Leung, 2021 , *Nature Medicine*

Nowcasting epidemic trajectory using statistical models[1]

Joint work with: Dr. Ibrahim Chamseddine, Dr. Athar Khalil, and Prof. Michael Kokkolaras

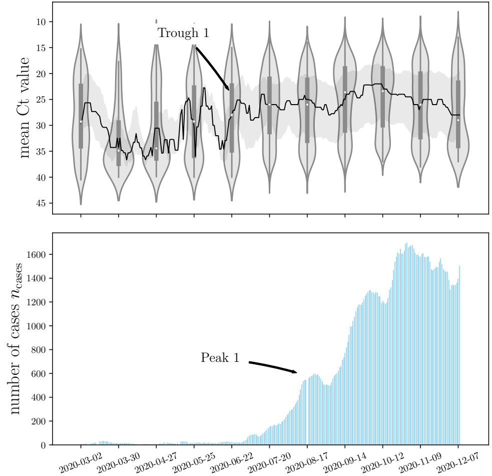
[1] A. Khalil, K. Al Handawi, Z. Mohsen, A. Abdel Nour, R. Feghali, I. Chamseddine, and M. Kokkolaras, 2022 , *Viruses*

How to *design* a machine learning model for forecasting a time-series?

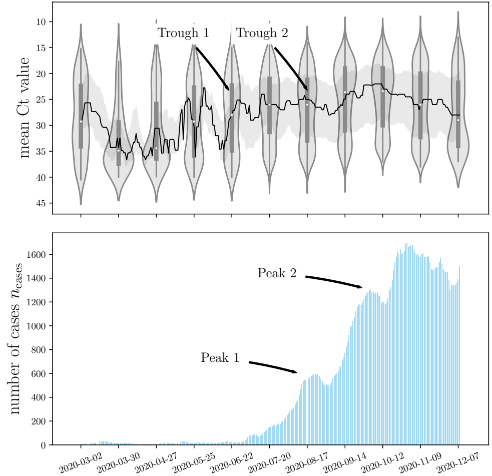


COVID-19 incidence forecasting

How to *design* a machine learning model for forecasting a time-series?

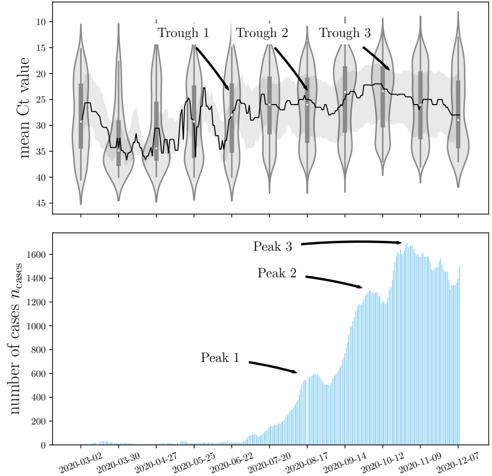


How to *design* a machine learning model for forecasting a time-series?

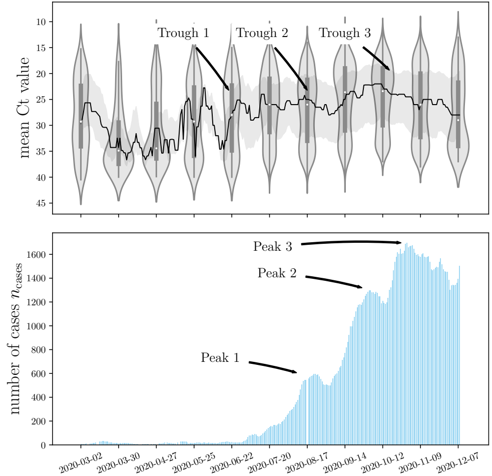


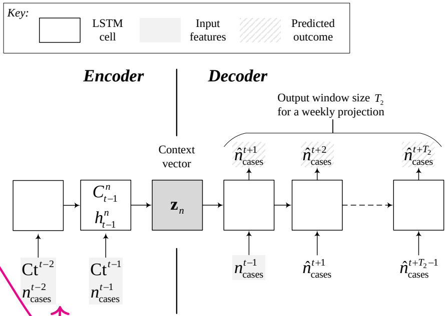
COVID-19 incidence forecasting

How to *design* a machine learning model for forecasting a time-series?



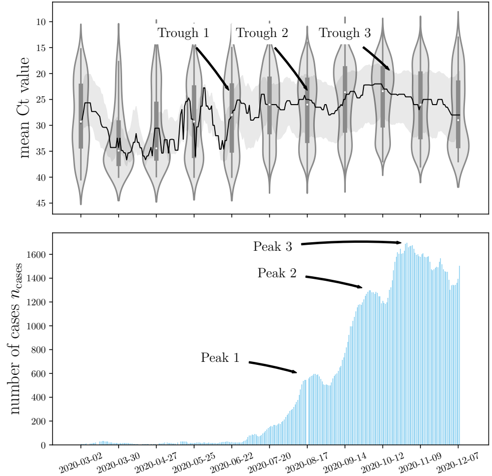
How to *design* a machine learning model for forecasting a time-series?

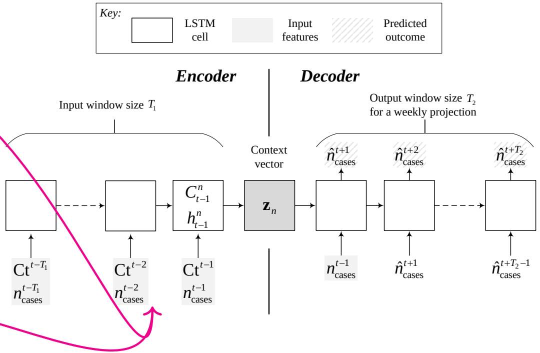




COVID-19 incidence forecasting

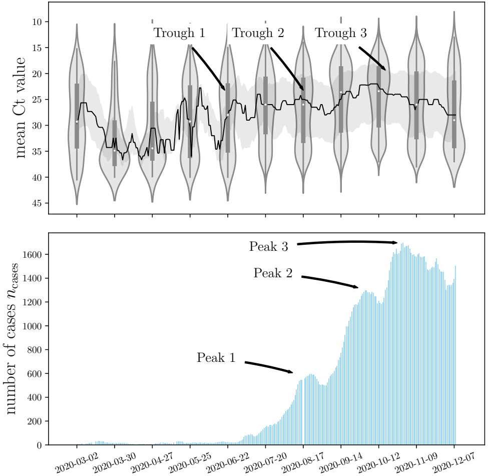
How to *design* a machine learning model for forecasting a time-series?

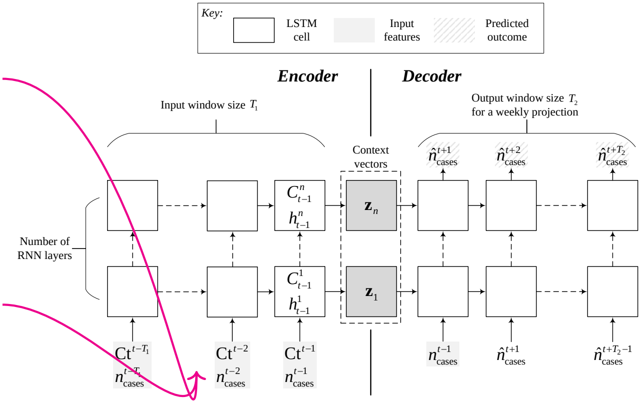




COVID-19 incidence forecasting

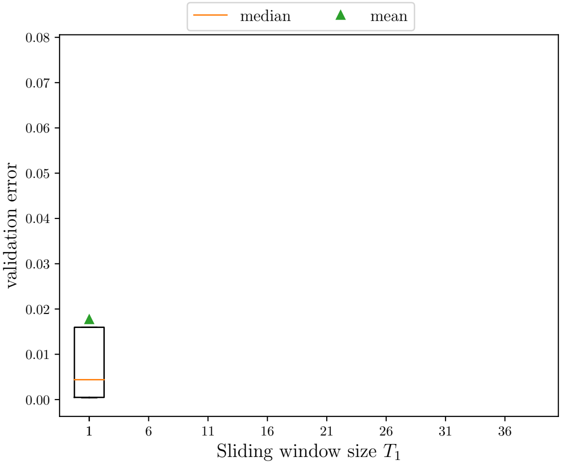
How to *design* a machine learning model for forecasting a time-series?

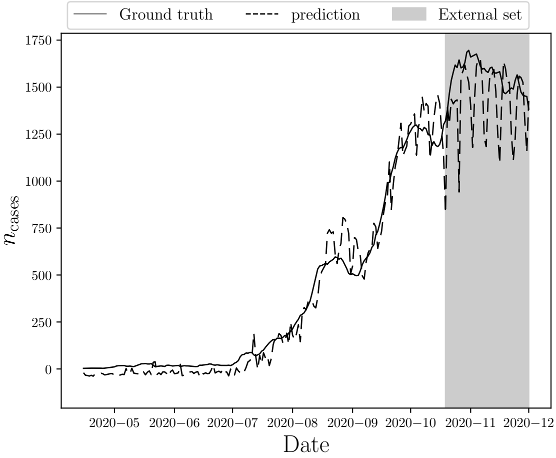




Hyperparameter tuning

We can use StoMADS to tune the hyperparameters[1]

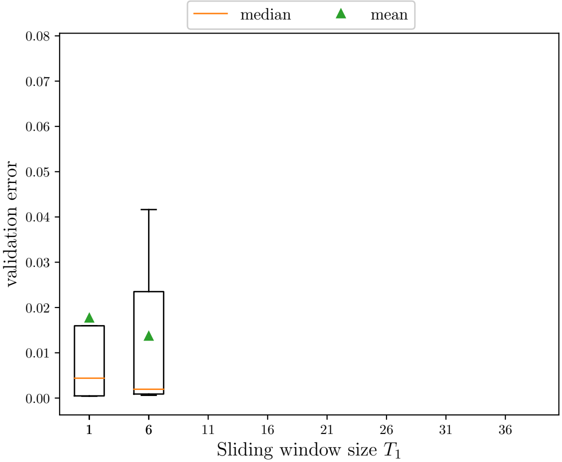


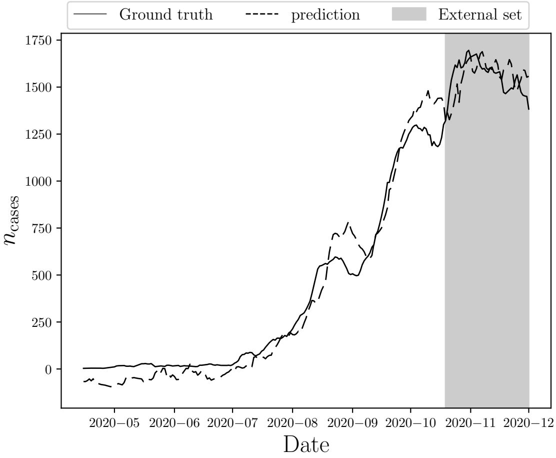


[1] A. Khalil, K. Al Handawi, I. Chamseddine, Z. Mohsen, A. Abdel Nour, R. Feghali, and M. Kokkolaras, 2021 , *medRxiv*

Hyperparameter tuning

We can use StoMADS to tune the hyperparameters[1]

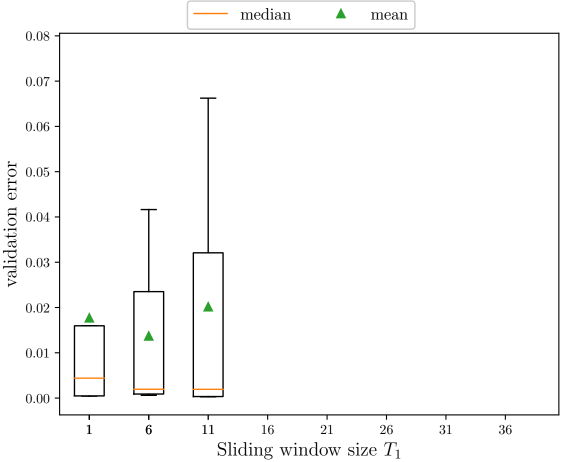


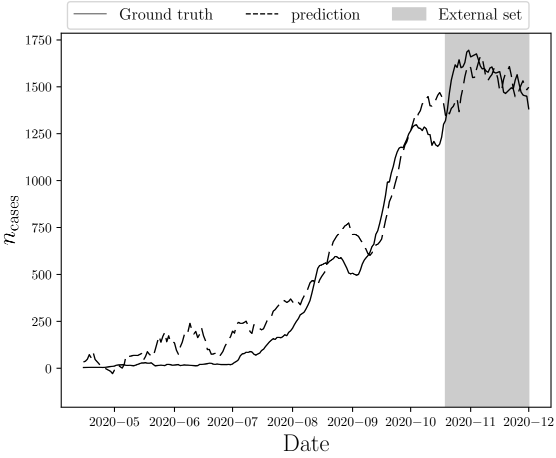


[1] A. Khalil, K. Al Handawi, I. Chamseddine, Z. Mohsen, A. Abdel Nour, R. Feghali, and M. Kokkolaras, 2021 , *medRxiv*

Hyperparameter tuning

We can use StoMADS to tune the hyperparameters[1]

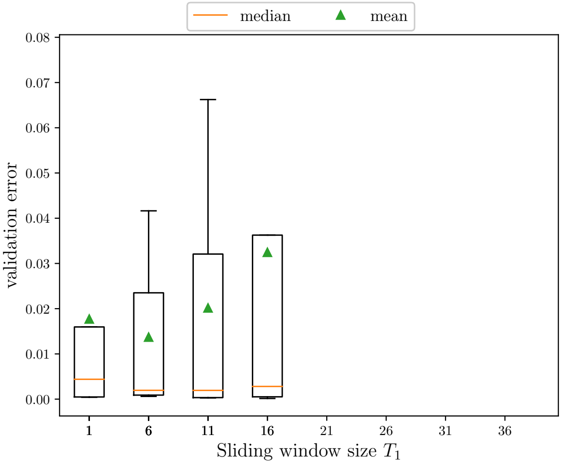


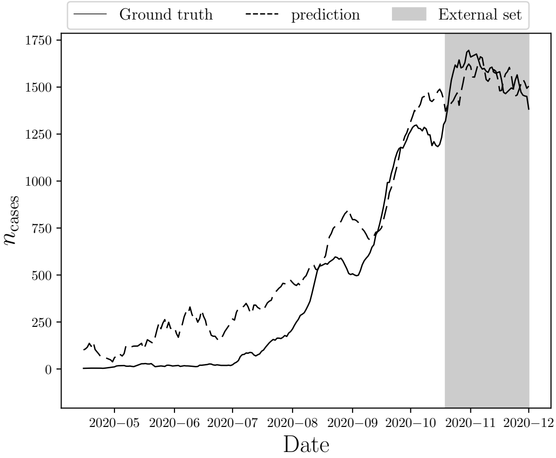


[1] A. Khalil, K. Al Handawi, I. Chamseddine, Z. Mohsen, A. Abdel Nour, R. Feghali, and M. Kokkolaras, 2021 , *medRxiv*

Hyperparameter tuning

We can use StoMADS to tune the hyperparameters[1]

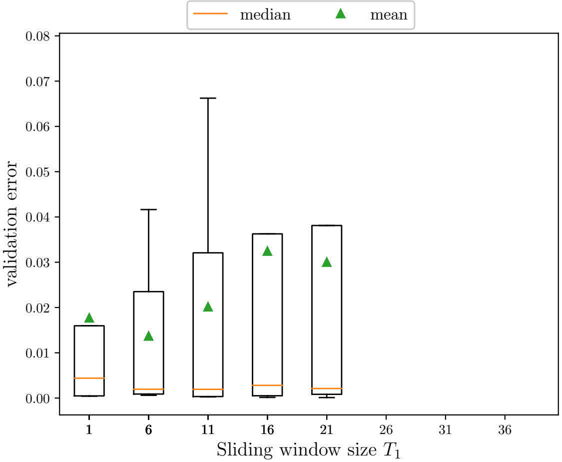


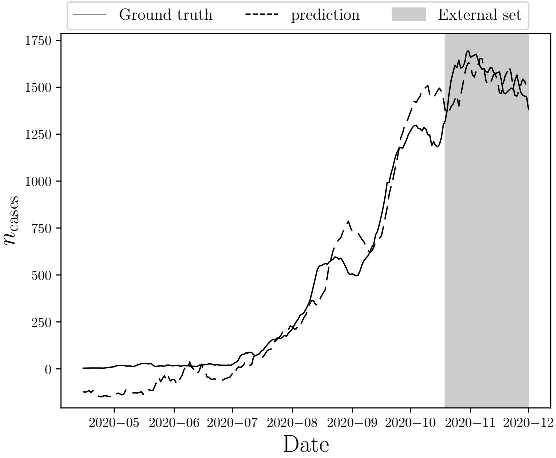


[1] A. Khalil, K. Al Handawi, I. Chamseddine, Z. Mohsen, A. Abdel Nour, R. Feghali, and M. Kokkolaras, 2021 , *medRxiv*

Hyperparameter tuning

We can use StoMADS to tune the hyperparameters[1]

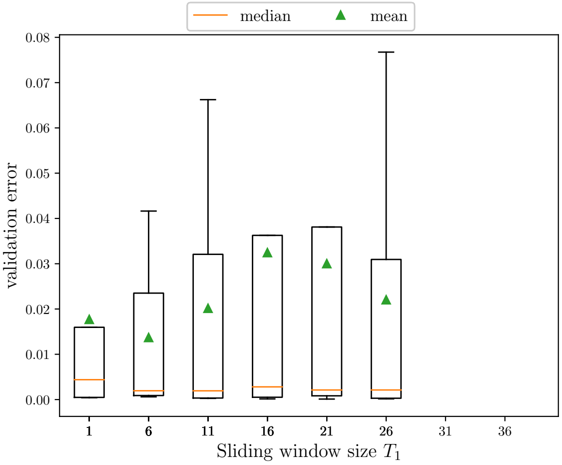


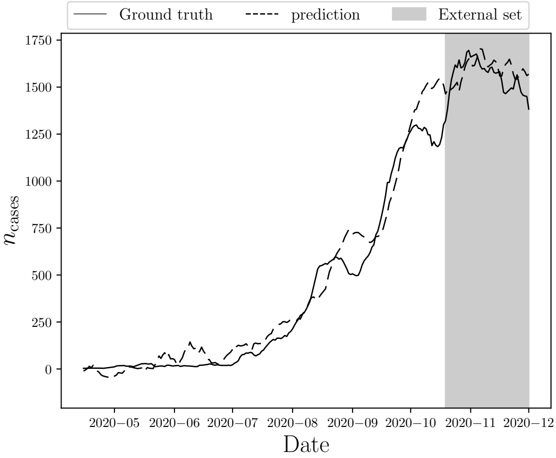


[1] A. Khalil, K. Al Handawi, I. Chamseddine, Z. Mohsen, A. Abdel Nour, R. Feghali, and M. Kokkolaras, 2021 , *medRxiv*

Hyperparameter tuning

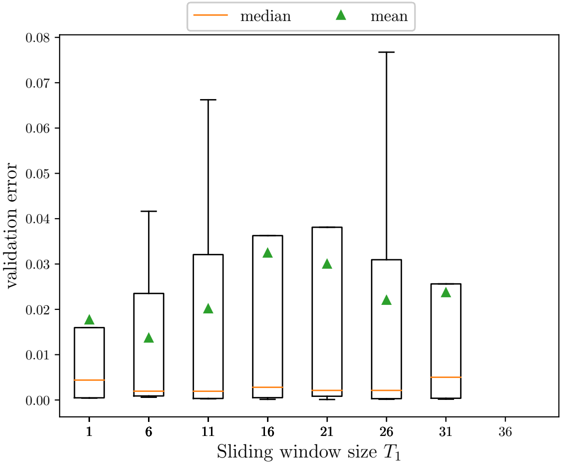
We can use StoMADS to tune the hyperparameters[1]

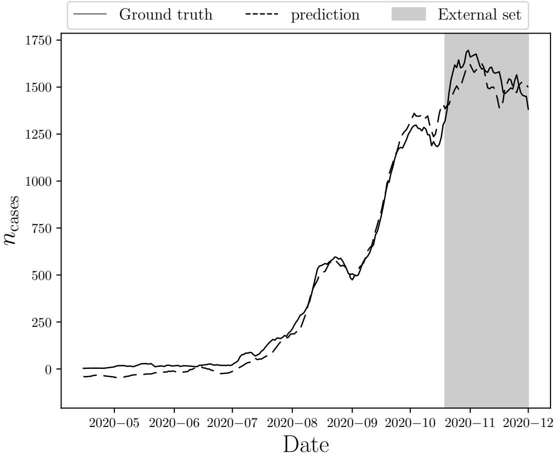




[1] A. Khalil, K. Al Handawi, I. Chamseddine, Z. Mohsen, A. Abdel Nour, R. Feghali, and M. Kokkolaras, 2021 , *medRxiv*

We can use StoMADS to tune the hyperparameters[1]

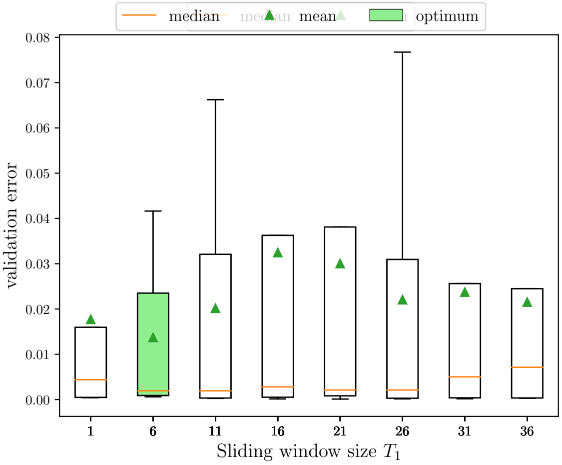


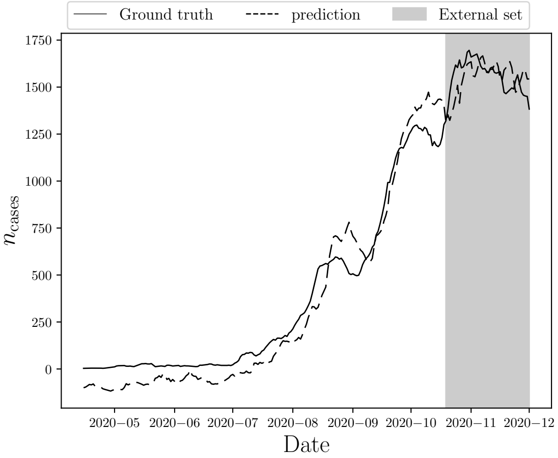


[1] A. Khalil, K. Al Handawi, I. Chamseddine, Z. Mohsen, A. Abdel Nour, R. Feghali, and M. Kokkolaras, 2021 , *medRxiv*

Hyperparameter tuning

We can use StoMADS to tune the hyperparameters[1]

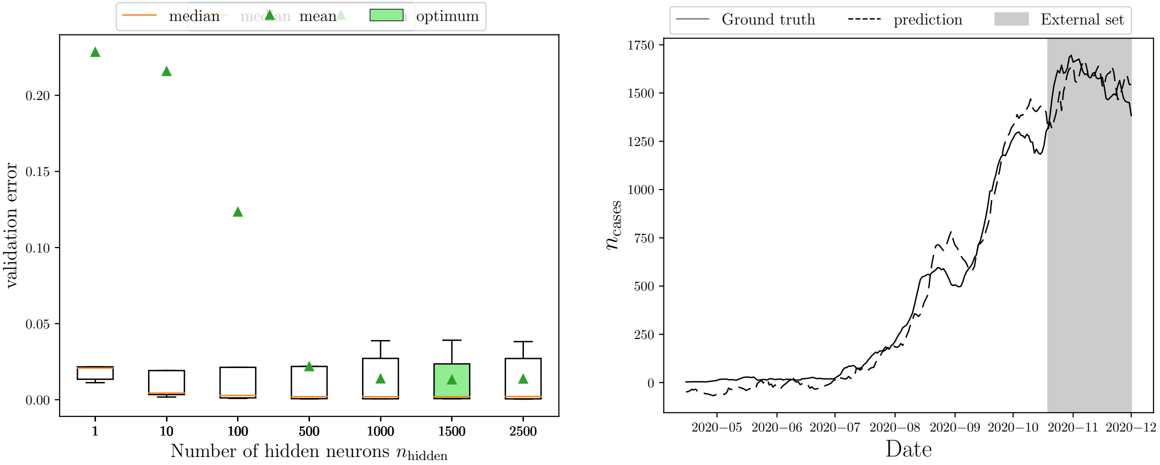




[1] A. Khalil, K. Al Handawi, I. Chamseddine, Z. Mohsen, A. Abdel Nour, R. Feghali, and M. Kokkolaras, 2021 , *medRxiv*

Hyperparameter tuning

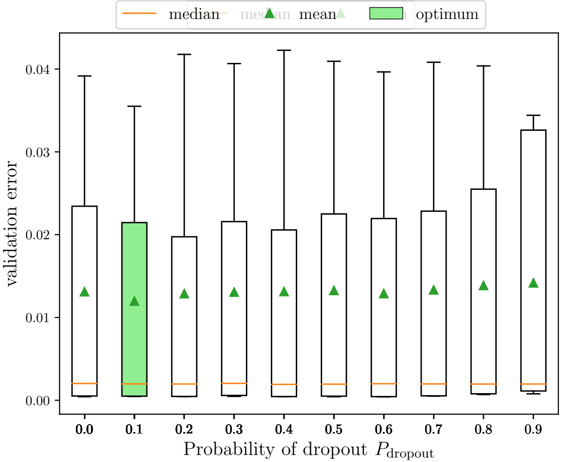
We can use StoMADS to tune the hyperparameters[1]

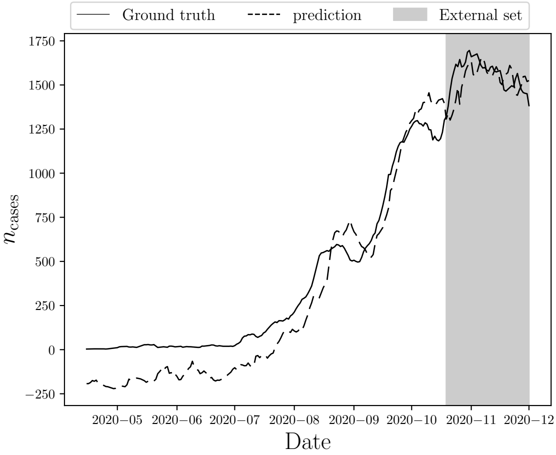


[1] A. Khalil, K. Al Handawi, I. Chamseddine, Z. Mohsen, A. Abdel Nour, R. Feghali, and M. Kokkolaras, 2021 , *medRxiv*

Hyperparameter tuning

We can use StoMADS to tune the hyperparameters[1]





[1] A. Khalil, K. Al Handawi, I. Chamseddine, Z. Mohsen, A. Abdel Nour, R. Feghali, and M. Kokkolaras, 2021 , *medRxiv*

Hyperparameter tuning

We can use StoMADS to tune the hyperparameters[1]

Objective and constraints

$$\min_{x} \quad f(x) = \mathbb{E}_{\Theta}\left[f_{\Theta}(x) = \mathrm{error}_{\mathrm{CV}}\right]$$

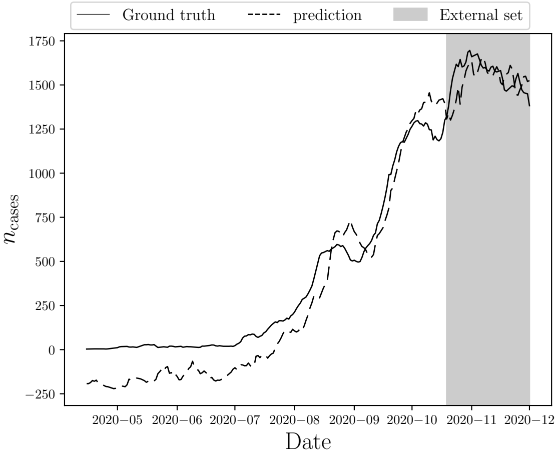
where Θ: realizations

Design variables (x)

- T_1 : Input dimension
- n_{hidden} : Number of hidden neurons
- P_{dropout} : Probability of dropout, etc.

Randomly seeded parameters

- Initial weights
- Gradient descent steps

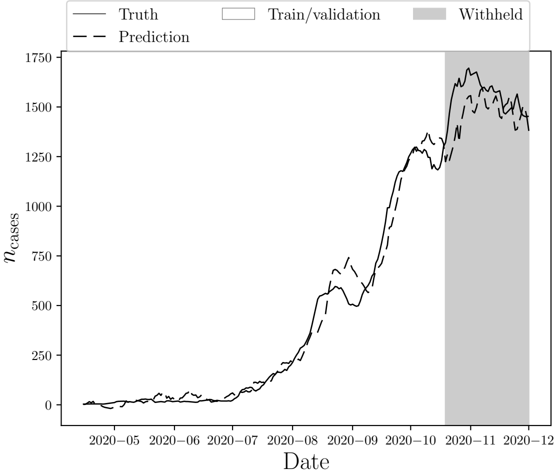


[1] A. Khalil, K. Al Handawi, I. Chamseddine, Z. Mohsen, A. Abdel Nour, R. Feghali, and M. Kokkolaras, 2021 , *medRxiv*

Results: Optimal hyperparameters

Optimal hyperparameters for the *Seq2Seq* model:

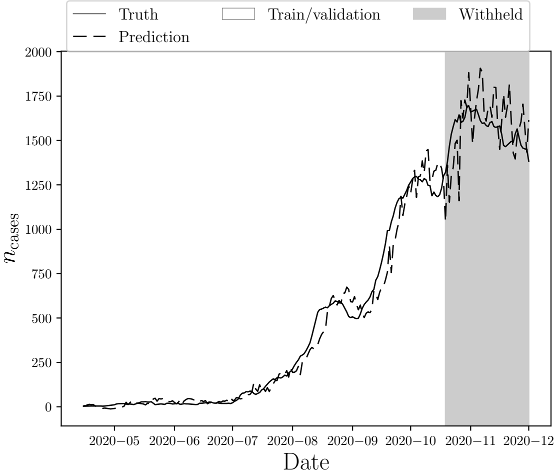
Hyperparameter		**Value**
Sliding window size	T_1	6
Number of hidden neurons	n_{hidden}	1500
Probability of dropout	P_{dropout}	0.8
Number of hidden layers	n_{hidden}	2
Teacher forcing probability	P_{teacher}	0.3
Learning rate	l_{rate}	1×10^{-4}
batch size	b_{size}	32



Results: Optimal hyperparameters

Optimal hyperparameters for the *support vector machine regression (SVR)* model:

Hyperparameter		**Value**
Sliding window size	T_1	6
Ridge factor	λ	1×10^{-4}
Margin of tolerance	ϵ	1×10^{-2}
Stopping criteria tolerance	ϵ_{tol}	0.1
Learning rate	l_{rate}	1×10^{-5}

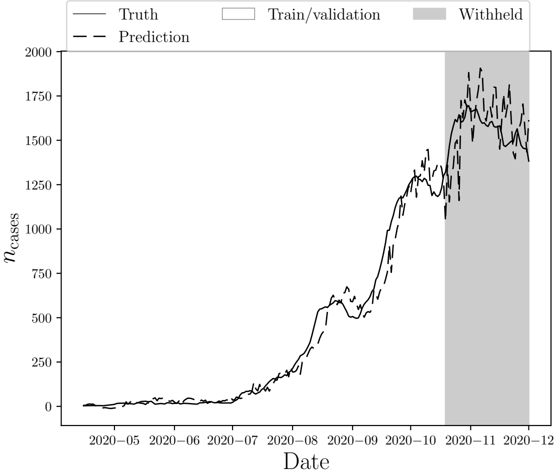


Results: Optimal hyperparameters

Optimal hyperparameters for the *support vector machine regression (SVR)* model:

Hyperparameter		Value
Sliding window size	T_1	6
Ridge factor	λ	1×10^{-4}
Margin of tolerance	ϵ	1×10^{-2}
Stopping criteria tolerance	ϵ_{tol}	0.1
Learning rate	l_{rate}	1×10^{-5}

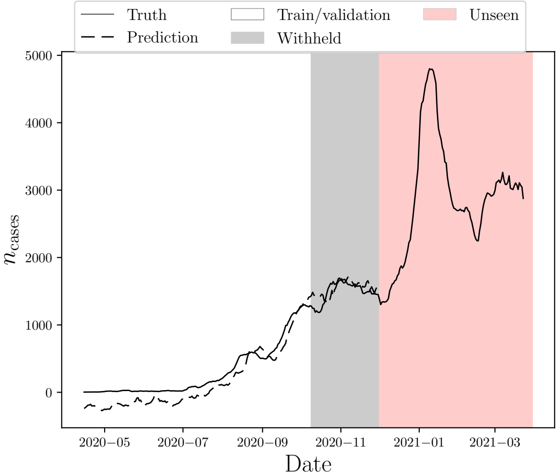
Support vector machine models have **deterministic** performance



Results: Prospective validation

Performance of models on **unseen** data (first 4 months of 2021):

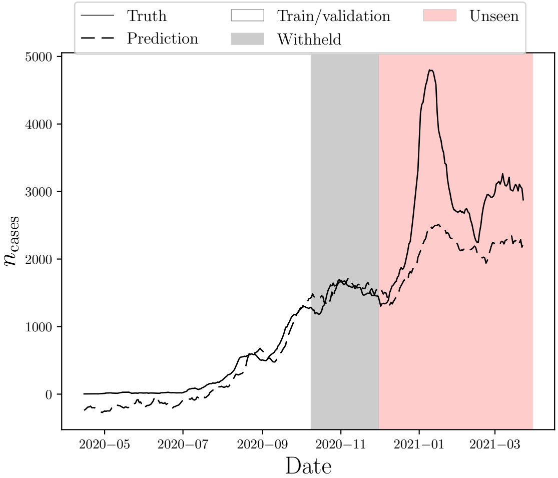
Model	Test error
Seq2Seq	0.571
Long short term memory (LSTM) cell	0.326
feedforward neural network	0.255
Support vector machine	0.168
Gradient boosting	1.444
Linear regression	0.160



Results: Prospective validation

Performance of models on **unseen** data (first 4 months of 2021):

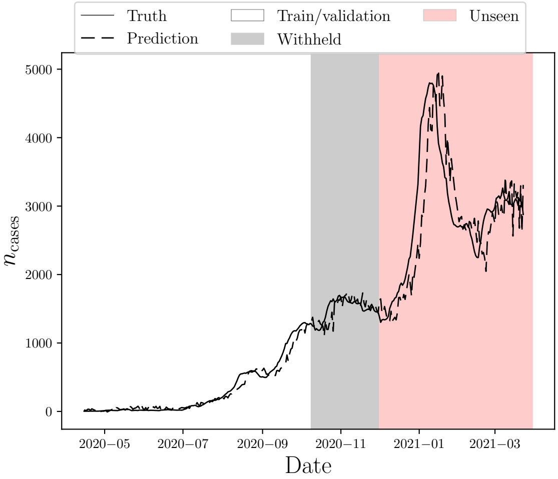
Model	Test error
Seq2Seq	**0.571**
Long short term memory (LSTM) cell	0.326
feedforward neural network	0.255
Support vector machine	0.168
Gradient boosting	1.444
Linear regression	0.160



Results: Prospective validation

Performance of models on **unseen** data (first 4 months of 2021):

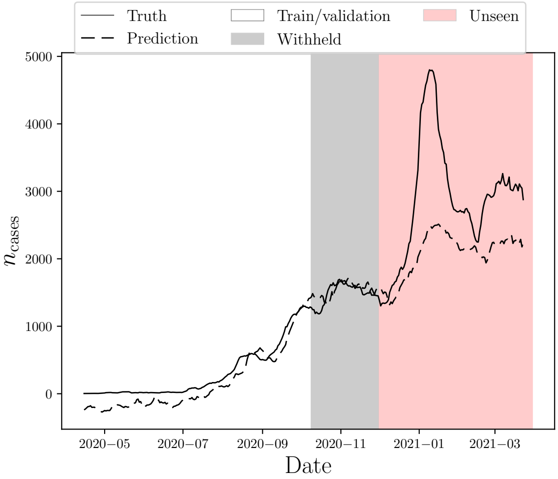
Model	Test error
Seq2Seq	0.571
Long short term memory (LSTM) cell	0.326
feedforward neural network	0.255
Support vector machine	**0.168**
Gradient boosting	1.444
Linear regression	0.160



Results: Prospective validation

Effect of increasing number of training days (Adding 1 month of data):

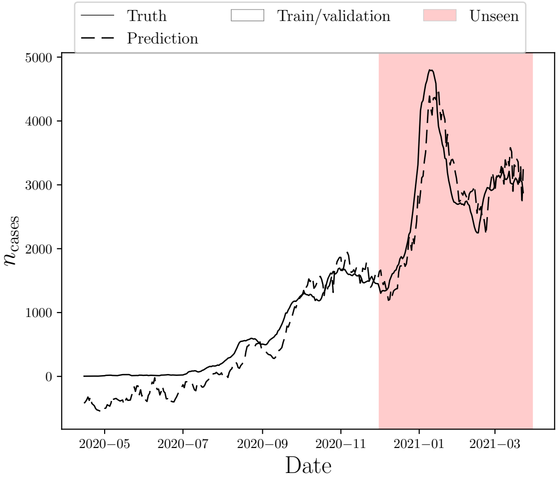
Model	Test error
Seq2Seq	**0.571**
Long short term memory (LSTM) cell	0.326
feedforward neural network	0.255
Support vector machine	0.168
Gradient boosting	1.444
Linear regression	0.160



Results: Prospective validation

Effect of increasing number of training days (Adding 1 month of data):

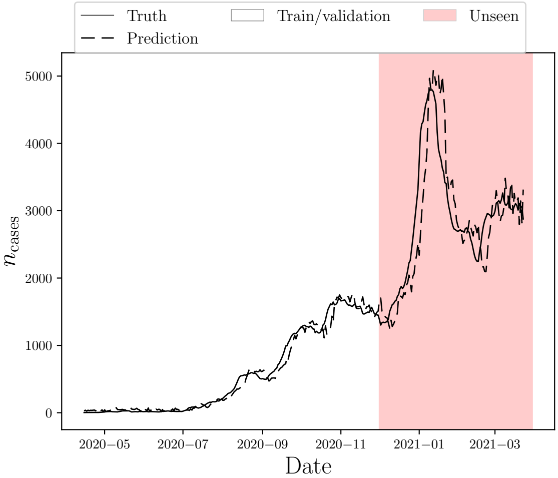
Model	Test error
Seq2Seq	**0.106**
Long short term memory (LSTM) cell	0.326
feedforward neural network	0.255
Support vector machine	0.168
Gradient boosting	1.444
Linear regression	0.160



Results: Prospective validation

Effect of increasing number of training days (Adding 1 month of data):

Model	Test error
Seq2Seq	**0.106**
Long short term memory (LSTM) cell	0.326
feedforward neural network	0.255
Support vector machine	**0.140**
Gradient boosting	1.444
Linear regression	0.160



Conclusion and future directions

Model discovery and development facilitated by hyperparameter optimization

Conclusion and future directions

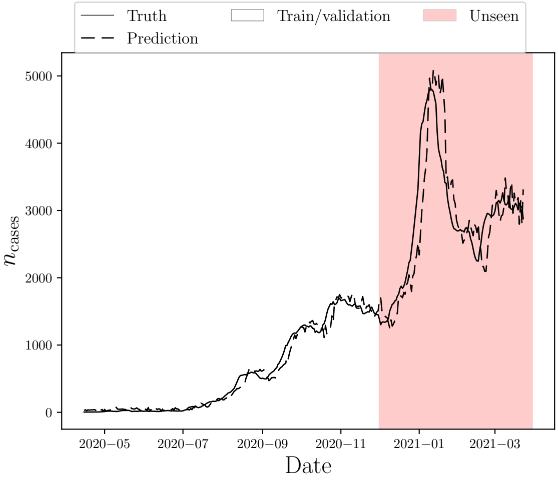
Model discovery and development facilitated by hyperparameter optimization

- Cycle Threshold (Ct) is a useful feature for incidence projection

Conclusion and future directions

Model discovery and development facilitated by hyperparameter optimization

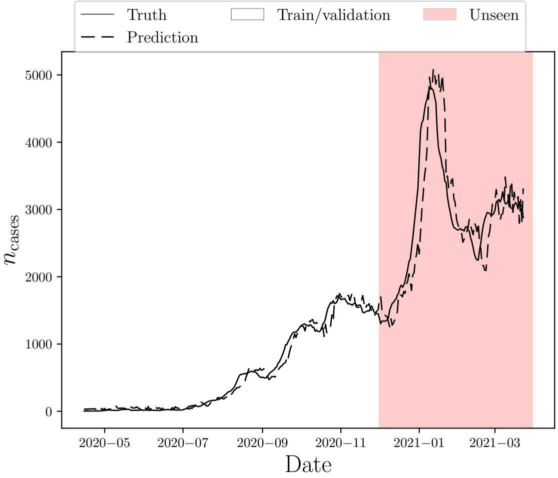
- Cycle Threshold (Ct) is a useful feature for incidence projection
- Model that generalizes well on unseen data



Conclusion and future directions

Model discovery and development facilitated by hyperparameter optimization

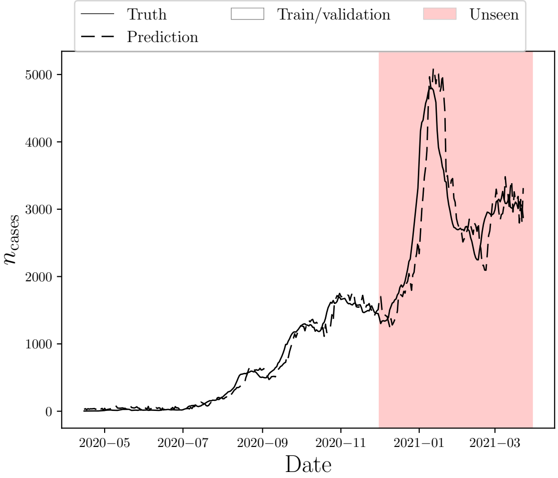
- Cycle Threshold (Ct) is a useful feature for incidence projection
- Model that generalizes well on unseen data
- Simpler models perform well when historical data is limited



Conclusion and future directions

Model discovery and development facilitated by hyperparameter optimization

- Cycle Threshold (Ct) is a useful feature for incidence projection
- Model that generalizes well on unseen data
- Simpler models perform well when historical data is limited
- Works well on other datasets[1]



[1] J. A. Hay, L. Kennedy-Shaffer, S. Kanjilal, H. J. Lennon, S. B. Gabriel, M. Lipsitch, and M. J. Mina, 2021 , *Science*

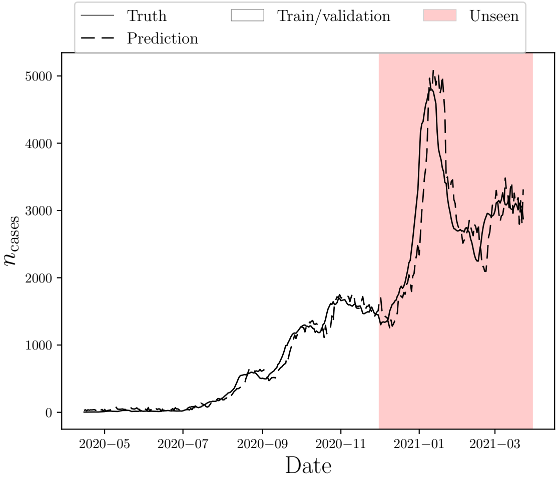
Conclusion and future directions

StoMADS can be improved to solve a wide variety of HPO problems

- Can be used to meet deployment targets

Objective and constraints

$$\begin{aligned} \min_{x} \quad & f(x) = \mathbb{E}_{\Theta}\left[f_{\Theta}(x) = \text{error}_{\text{CV}}\right] \\ \text{subject to} \quad & c(x) = \text{inference time} - \text{threshold} \leq 0 \\ \text{where} \quad & \Theta\text{: realizations} \end{aligned}$$



Conclusion and future directions

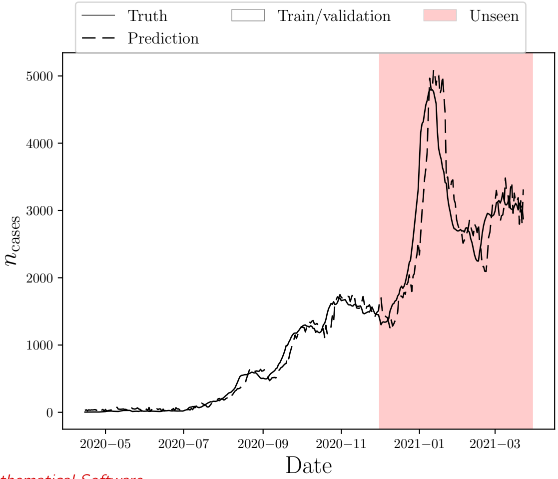
StoMADS can be improved to solve a wide variety of HPO problems

- Can be used to meet deployment targets

Objective and constraints

$$\begin{aligned} \min_{x} \quad & f(x) = \mathbb{E}_{\Theta}\left[f_{\Theta}(x) = \mathrm{error}_{\mathrm{CV}}\right] \\ \text{subject to} \quad & c(x) = \text{inference time} - \text{threshold} \leq 0 \\ \text{where} \quad & \Theta\text{: realizations} \end{aligned}$$

- Should be benchmarked against HyperNOMAD[1], Bayesian optimization[2]



[1] D. Lakhmiri, S. Le Digabel, and C. Tribes, 2019 , *ACM Transactions on Mathematical Software*
[2] J. Bergstra, R. Bardenet, Y. Bengio, and B. Kégl, 2011 , *International conference on neural information processing systems*

Conclusion and future directions

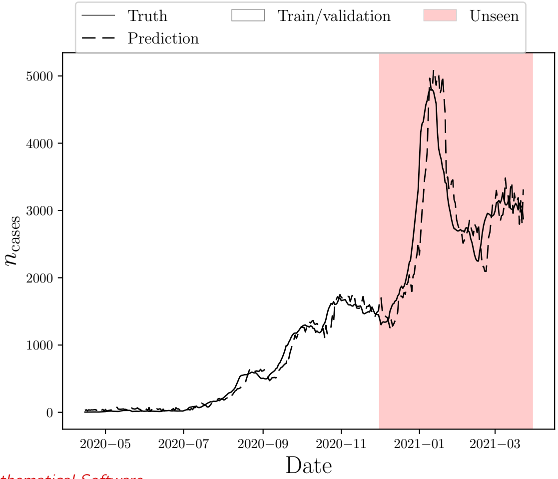
StoMADS can be improved to solve a wide variety of HPO problems

- Can be used to meet deployment targets

Objective and constraints

$$\begin{aligned} \min_{x} \quad & f(x) = \mathbb{E}_{\Theta}\left[f_{\Theta}(x) = \mathrm{error}_{\mathrm{CV}}\right] \\ \text{subject to} \quad & c(x) = \text{inference time} - \text{threshold} \leq 0 \\ \text{where} \quad & \Theta\text{: realizations} \end{aligned}$$

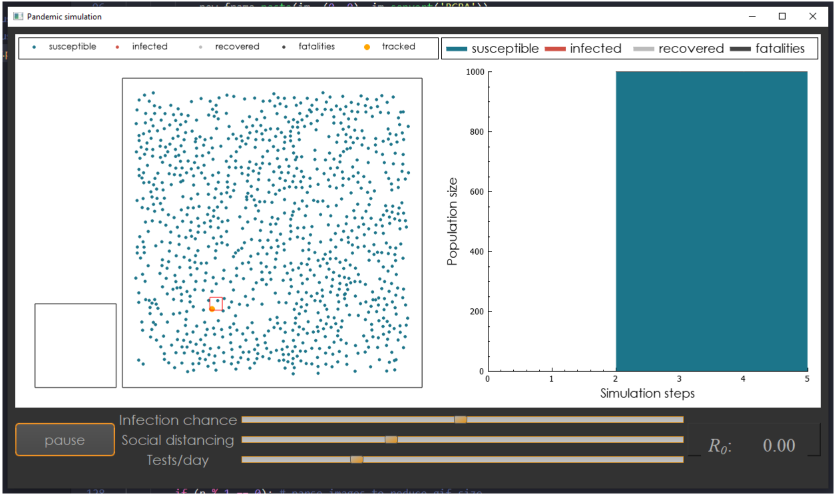
- Should be benchmarked against HyperNOMAD[1], Bayesian optimization[2]
- Mixed variable version is needed



[1] D. Lakhmiri, S. Le Digabel, and C. Tribes, 2019 , *ACM Transactions on Mathematical Software*
[2] J. Bergstra, R. Bardenet, Y. Bengio, and B. Kégl, 2011 , *International conference on neural information processing systems*

Thank you for your time

Open source GPU implementation of agent-based modeling[1]



[1] Khalil Al Handawi, 2021 , *https://github.com/khbalhandawi/COVID_SIM_GPU*

Overview of stochastic mesh adaptive direct search

No gradient information available, blackbox is expensive and **noisy**[1]

Objective and constraints

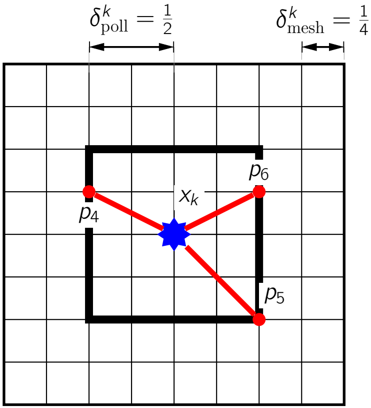
$$\min_{x} \quad f(x) = \mathbb{E}_{\Theta}\left[f_{\Theta}(x)\right]$$
$$\text{subject to} \quad c(x) = \mathbb{E}_{\Theta}\left[c_{\Theta}(x)\right] \leq 0$$
$$\text{where} \quad x: \text{ variables } \Theta: \text{realizations}$$

- Constructs estimates of objective:

$$f^k = \frac{1}{n^k} \sum_{i=1}^{n^k} f_{\Theta_{0,i}}(x_k)$$

- n^k is the sampling rate

Poll **failure**



[1] C. Audet, K. J. Dzahini, M. Kokkolaras, and S. Le Digabel, 2021 , *Computational Optimization and Applications*

No gradient information available, blackbox is expensive and **noisy**[1]

Objective and constraints

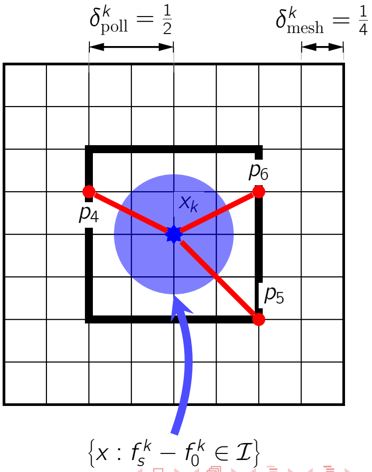
$$\begin{array}{lll} \min\limits_{x} & f(x) = \mathbb{E}_{\Theta}\left[f_{\Theta}(x)\right] \\ \text{subject to} & c(x) = \mathbb{E}_{\Theta}\left[c_{\Theta}(x)\right] \leq 0 \\ \text{where} & x: \text{ variables } \Theta\text{: realizations} \end{array}$$

- Constructs estimates of objective:

$$f^k = \frac{1}{n^k}\sum_{i=1}^{n^k} f_{\Theta_{0,i}}(x_k)$$

- n^k is the sampling rate
- Tracks uncertainty interval $\mathcal{I}(\delta^k_{\text{poll}})$ in the estimate

Poll **certain failure**



[1] C. Audet, K. J. Dzahini, M. Kokkolaras, and S. Le Digabel, 2021 , *Computational Optimization and Applications*

Overview of stochastic mesh adaptive direct search

No gradient information available, blackbox is expensive and **noisy**[1]

Objective and constraints

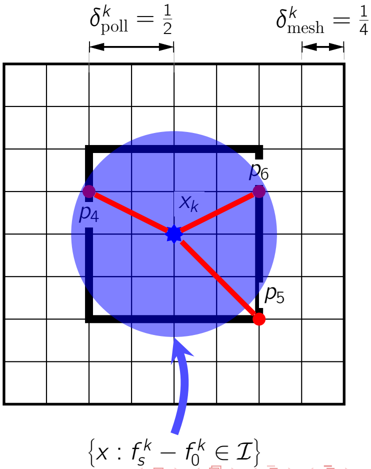
$$\begin{array}{ll} \min_{x} & f(x) = \mathbb{E}_{\Theta}[f_{\Theta}(x)] \\ \text{subject to} & c(x) = \mathbb{E}_{\Theta}[c_{\Theta}(x)] \leq 0 \\ \text{where} & x: \text{ variables } \Theta\text{: realizations} \end{array}$$

- Constructs estimates of objective:

$$f^k = \frac{1}{n^k} \sum_{i=1}^{n^k} f_{\Theta_{0,i}}(x_k)$$

- n^k is the sampling rate
- Tracks uncertainty interval $\mathcal{I}(\delta^k_{\text{poll}})$ in the estimate

Poll **uncertain failure**



[1] C. Audet, K. J. Dzahini, M. Kokkolaras, and S. Le Digabel, 2021 , *Computational Optimization and Applications*

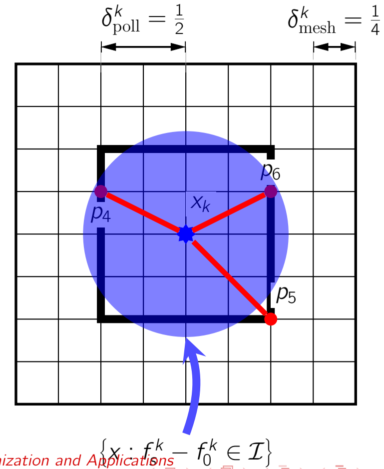
No gradient information available, blackbox is expensive and **noisy**[1]

Objective and constraints

$\min_{x}$	$f(x) = \mathbb{E}_\Theta\left[f_\Theta(x)\right]$
subject to	$c(x) = \mathbb{E}_\Theta\left[c_\Theta(x)\right] \leq 0$
where	$x:$ variables Θ: realizations

Constraint handling using the *progressive barrier* approach [2]

Poll **uncertain failure**



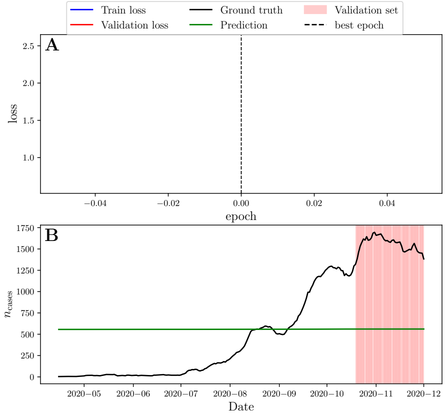
[1] C. Audet, K. J. Dzahini, M. Kokkolaras, and S. Le Digabel, 2021 , *Computational Optimization and Applications*

[2] K. J. Dzahini, M. Kokkolaras, and S. Le Digabel, 2022 , *Mathematical Programming*

Training the model

There are several challenges associated with hyperparameter optimization

- The number of epochs can be tuned using *early stopping*
- This is a form of *regularization* to reduce over-fitting

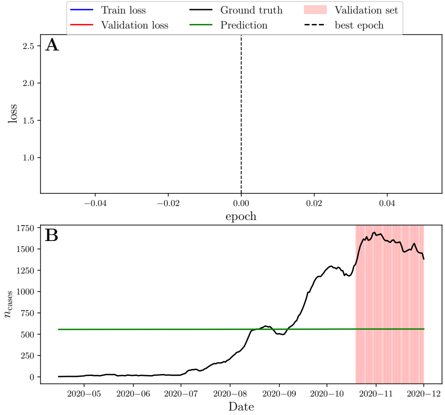


Effect of number of epochs on testing loss

Training the model

There are several challenges associated with hyperparameter optimization

- The number of epochs can be tuned using *early stopping*
- This is a form of *regularization* to reduce over-fitting



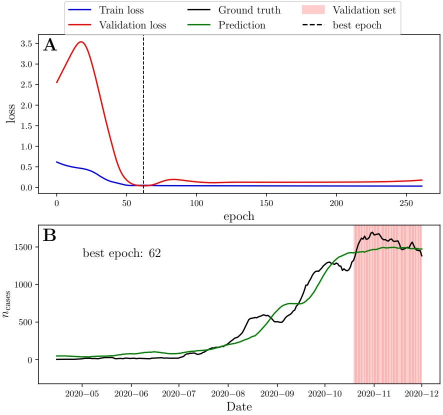
Effect of number of epochs on testing loss

Training the model

There are several challenges associated with hyperparameter optimization

- The number of epochs can be tuned using *early stopping*
- This is a form of *regularization* to reduce over-fitting

However,



Effect of number of epochs on testing loss

Training the model

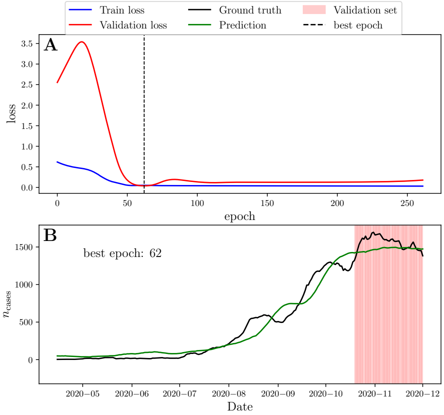
There are several challenges associated with hyperparameter optimization

- The number of epochs can be tuned using *early stopping*
- This is a form of *regularization* to reduce over-fitting

However,

1) Other hyperparameters to tune

- Dropout
- Training batch size
- Activation function(s)



Effect of number of epochs on testing loss

Training the model

There are several challenges associated with hyperparameter optimization

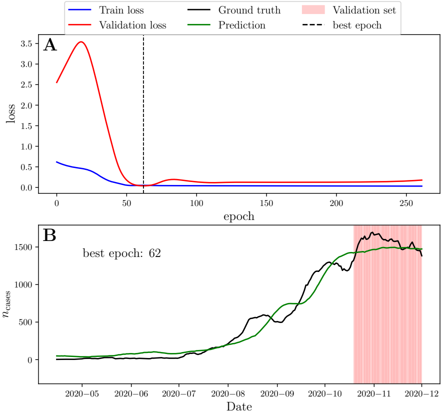
- The number of epochs can be tuned using *early stopping*
- This is a form of *regularization* to reduce over-fitting

However,

1) Other hyperparameters to tune

- Dropout
- Training batch size
- Activation function(s)

2) Training can be **expensive**



Effect of number of epochs on testing loss

Training the model

There are several challenges associated with hyperparameter optimization

- The number of epochs can be tuned using *early stopping*
- This is a form of *regularization* to reduce over-fitting

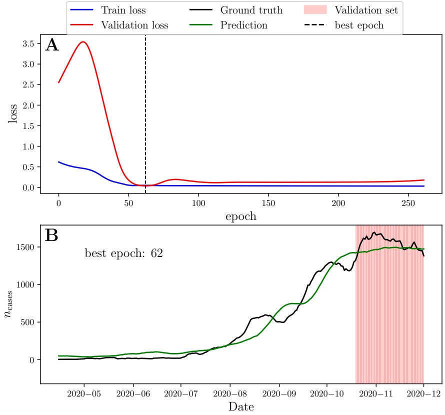
However,

1) Other hyperparameters to tune

- Dropout
- Training batch size
- Activation function(s)

2) Training can be **expensive**

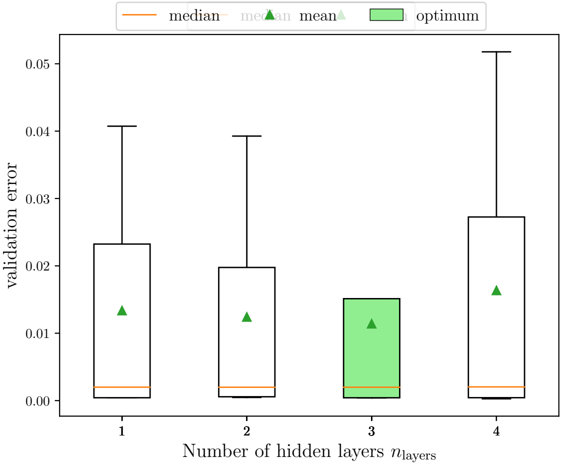
3) Backpropagation is **stochastic**

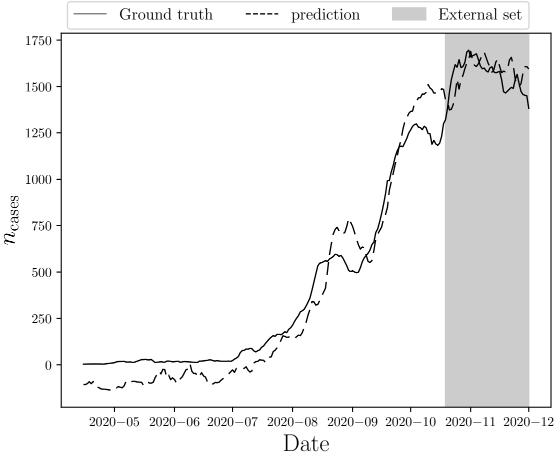


Effect of number of epochs on testing loss

Hyperparameter tuning: other hyperparamters

We can use StoMADS to solve such hyperparameter optimization problems[1]

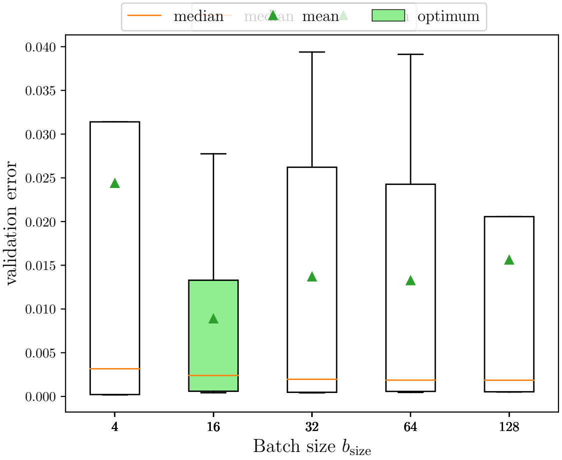


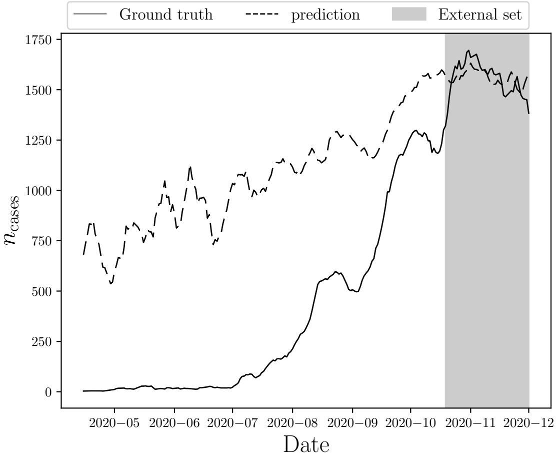


[1] A. Khalil, K. Al Handawi, I. Chamseddine, Z. Mohsen, A. Abdel Nour, R. Feghali, and M. Kokkolaras, 2021 , *medRxiv*

Hyperparameter tuning: other hyperparamters

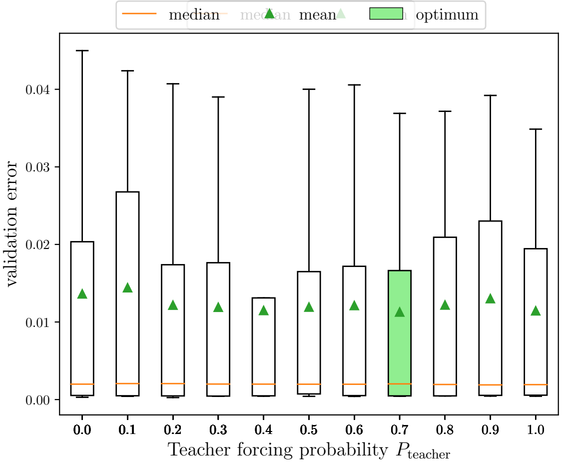
We can use StoMADS to solve such hyperparameter optimization problems[1]

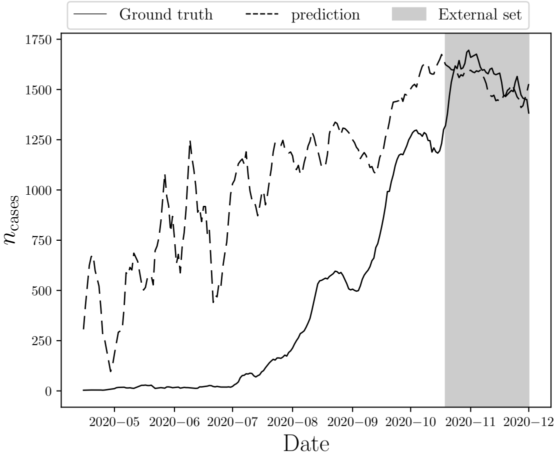




[1] A. Khalil, K. Al Handawi, I. Chamseddine, Z. Mohsen, A. Abdel Nour, R. Feghali, and M. Kokkolaras, 2021 , *medRxiv*

We can use StoMADS to solve such hyperparameter optimization problems[1]

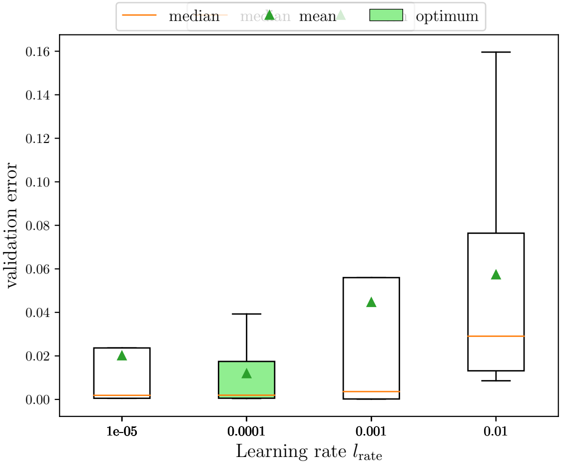


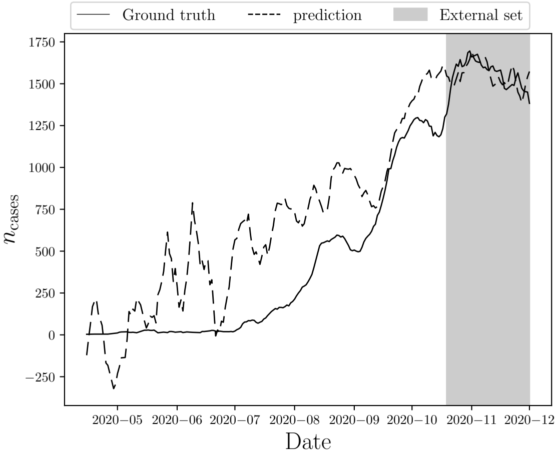


[1] A. Khalil, K. Al Handawi, I. Chamseddine, Z. Mohsen, A. Abdel Nour, R. Feghali, and M. Kokkolaras, 2021 , *medRxiv*

Hyperparameter tuning: other hyperparamters

We can use StoMADS to solve such hyperparameter optimization problems[1]





[1] A. Khalil, K. Al Handawi, I. Chamseddine, Z. Mohsen, A. Abdel Nour, R. Feghali, and M. Kokkolaras, 2021 , *medRxiv*