Age-dependent behavioral changes in SIR model on a network

Physics of Life, Data and Epidemiology project presentation

A.Y. 2025-26

Brocco Luca, Cafagno Samuele

Università degli Studi di Padova

Project introduction

Behavioral changes represent a key aspect in modeling the spread of a disease through a population [1]. They allow for:

Project introduction

Behavioral changes represent a key aspect in modeling the spread of a disease through a population [1]. They allow for:

- modeling how information spreads across the population

Project introduction

Behavioral changes represent a key aspect in modeling the spread of a disease through a population [1]. They allow for:

- modeling how information spreads across the population
- understanding how individual choices affect epidemic dynamics

Project introduction

Behavioral changes represent a key aspect in modeling the spread of a disease through a population [1]. They allow for:

- modeling how information spreads across the population
- understanding how individual choices affect epidemic dynamics

Moreover, heterogeneity in contact patterns, mortality rates and transmissibility among and between **age classes** can have significant effects on epidemic outputs [2].

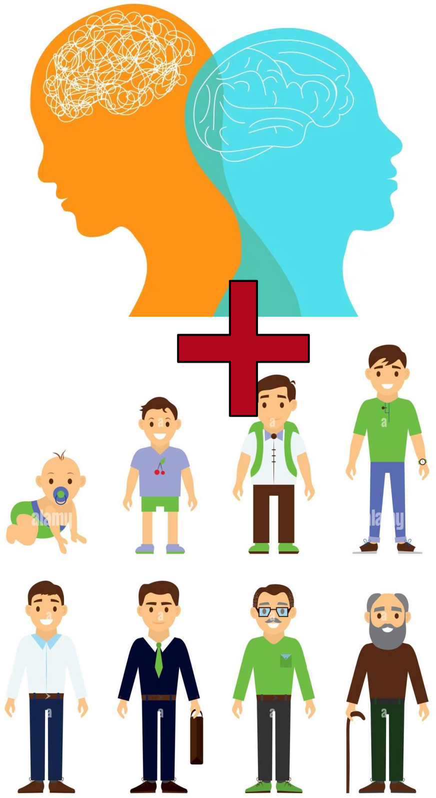
Project introduction

Behavioral changes represent a key aspect in modeling the spread of a disease through a population [1]. They allow for:

- modeling how information spreads across the population
- understanding how individual choices affect epidemic dynamics

Moreover, heterogeneity in contact patterns, mortality rates and transmissibility among and between **age classes** can have significant effects on epidemic outputs [2].

Our project aims to account for both features and aims to unveil dynamics underlying a SIR model with them



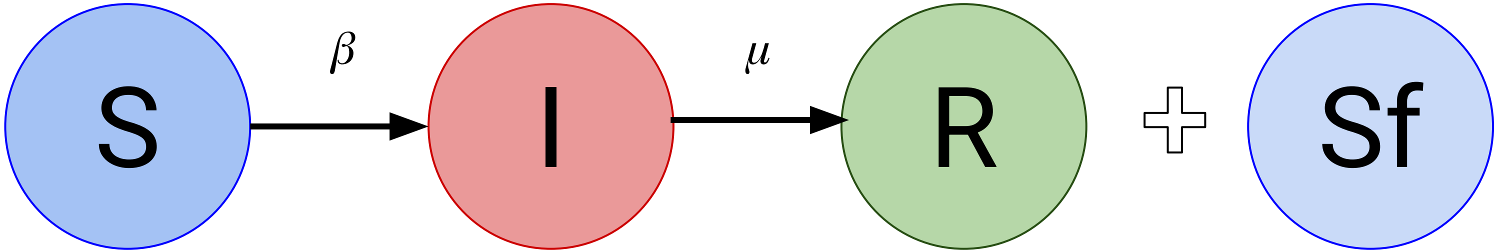
Background

In work of Vespignani et al. [1] behavioral changes are defined as a **change of mobility** or contact patterns and a general framework to model the spread of information about the epidemic is proposed:

Background

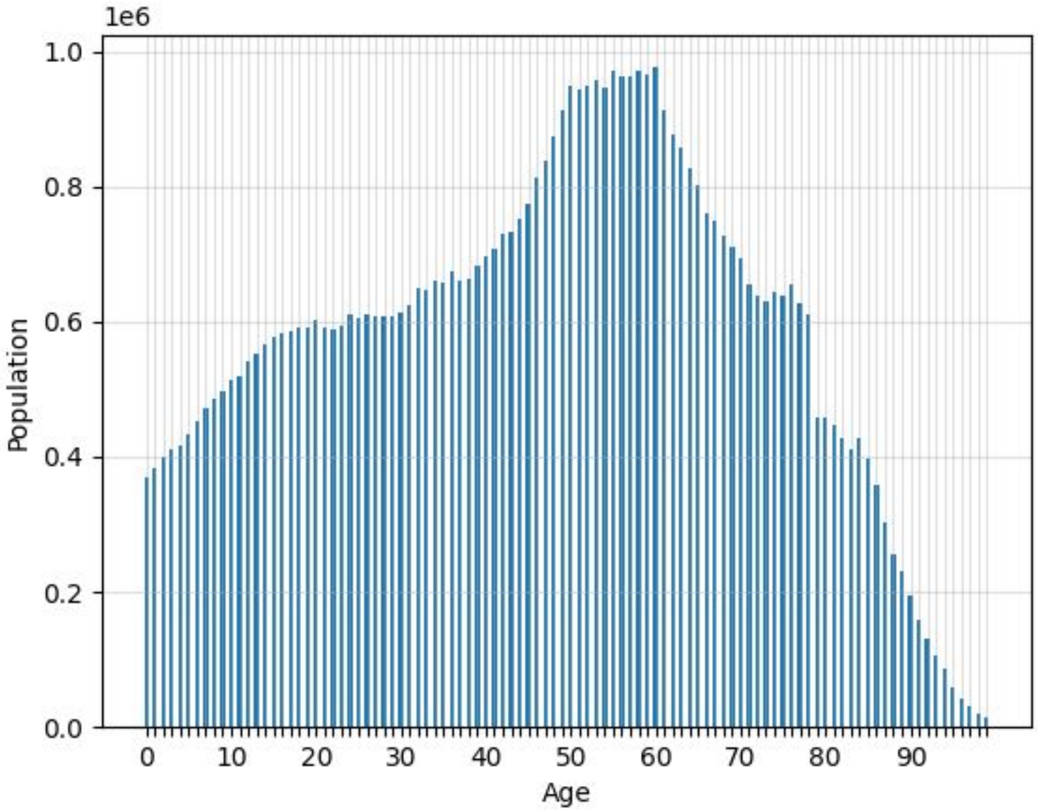
In work of Vespignani et al. [1] behavioral changes are defined as a **change of mobility** or contact patterns and a general framework to model the spread of information about the epidemic is proposed:

we introduce **Sf**, a new class to the SIR model that includes individuals that self-initiate behavioral changes that lead to a transmissibility reduction



Background

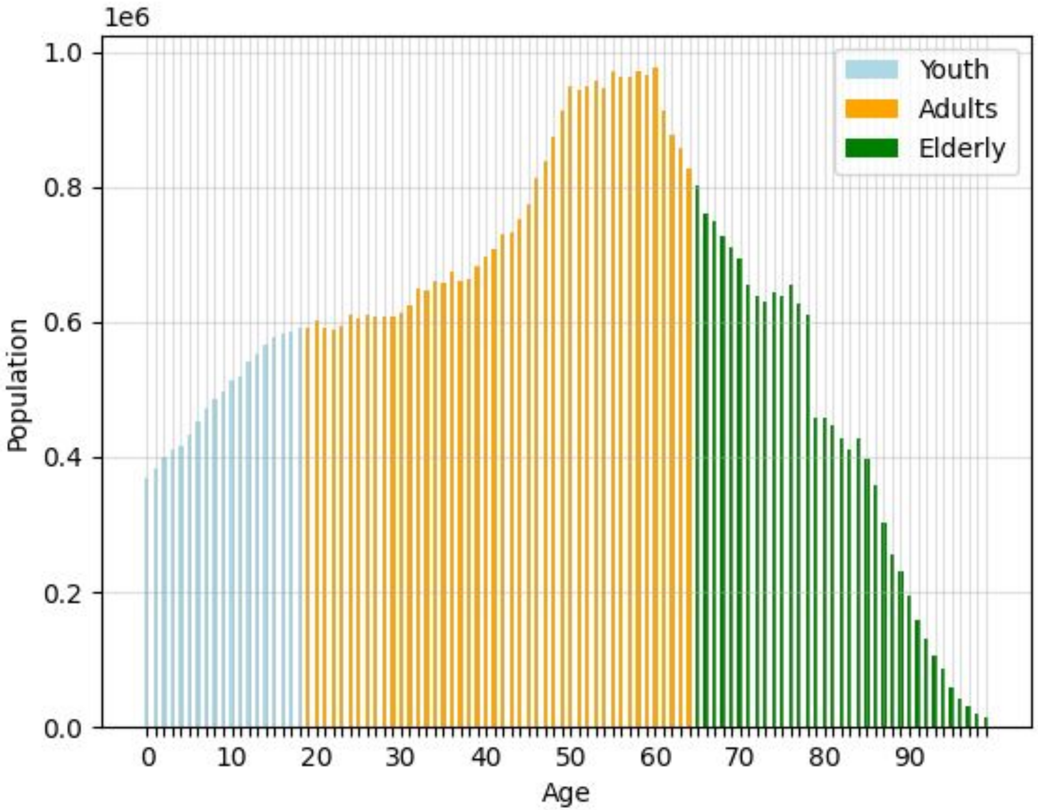
In works such as [2], [3], [4] the population is subdivided into different age classes.
We wish to model a population distributed as the Italian's, that according to Istat [5] is distributed as shown in the graph (2020).



Background

In works such as [2], [3], [4] the population is subdivided into different age classes.
We wish to model a population distributed as the Italian's, that according to Istat [5] is distributed as shown in the graph (2020).

We then propose a subdivision into 3 age classes, for whose the interaction with the disease will be slightly different:



Goal of the study

Our study mainly focuses on answering the following questions:

Goal of the study

Our study mainly focuses on answering the following questions:

- what is the relationship between behavioral changes and the spread of the epidemic?

Goal of the study

Our study mainly focuses on answering the following questions:

- what is the relationship between behavioral changes and the spread of the epidemic?
- how do behavioral changes and age classes interact?

Goal of the study

Our study mainly focuses on answering the following questions:

- what is the relationship between behavioral changes and the spread of the epidemic?
- how do behavioral changes and age classes interact?
- is there any sensible difference in the population before and after the epidemic has occurred?

Goal of the study

Our study mainly focuses on answering the following questions:

- what is the relationship between behavioral changes and the spread of the epidemic?
- how do behavioral changes and age classes interact?
- is there any sensible difference in the population before and after the epidemic has occurred?
- can we use our model to fit real COVID-19 data?

Methods: the idea

We want to construct a SIR model with behavioral changes and age class differentiation

If we want to study a population of relatively small N (3000 $\gtrsim$N) we can rely on a network topology for the system definition

This brings some inherent advantages:

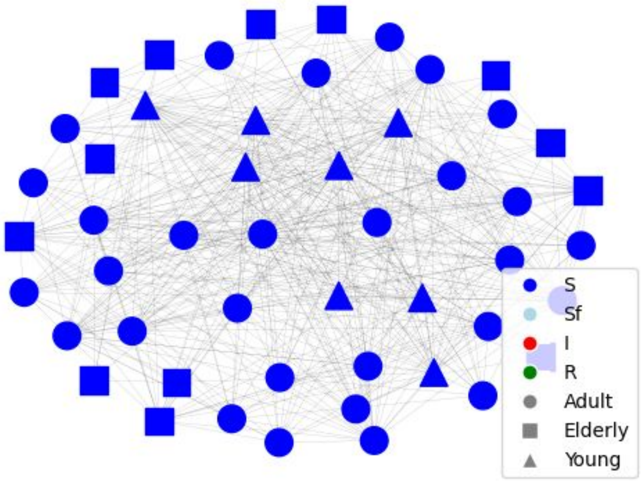
Methods: the idea

We want to construct a SIR model with behavioral changes and age class differentiation

If we want to study a population of relatively small N ($3000 \gtrsim N$) we can rely on a network topology for the system definition

This brings some inherent advantages:

- each node represents an **individual** and its connection its **contacts**



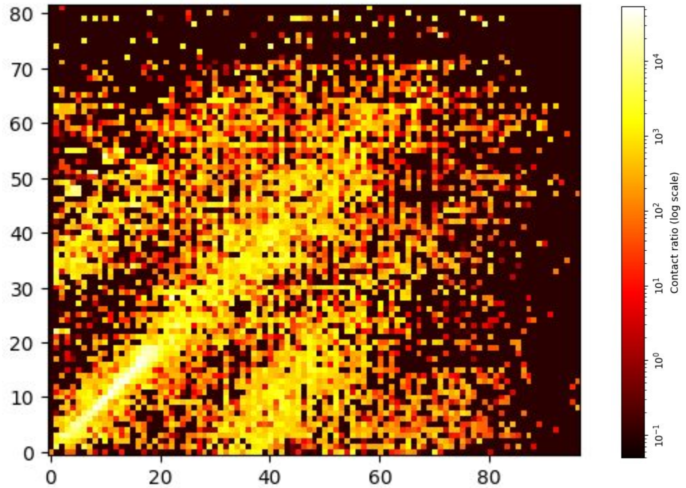
Methods: the idea

We want to construct a SIR model with behavioral changes and age class differentiation

If we want to study a population of relatively small N (3000 $\gtrsim$ N) we can rely on a network topology for the system definition

This brings some inherent advantages:

- each node represents an individual and its connection its contacts
- we can build the network according to **real contact data** [6]



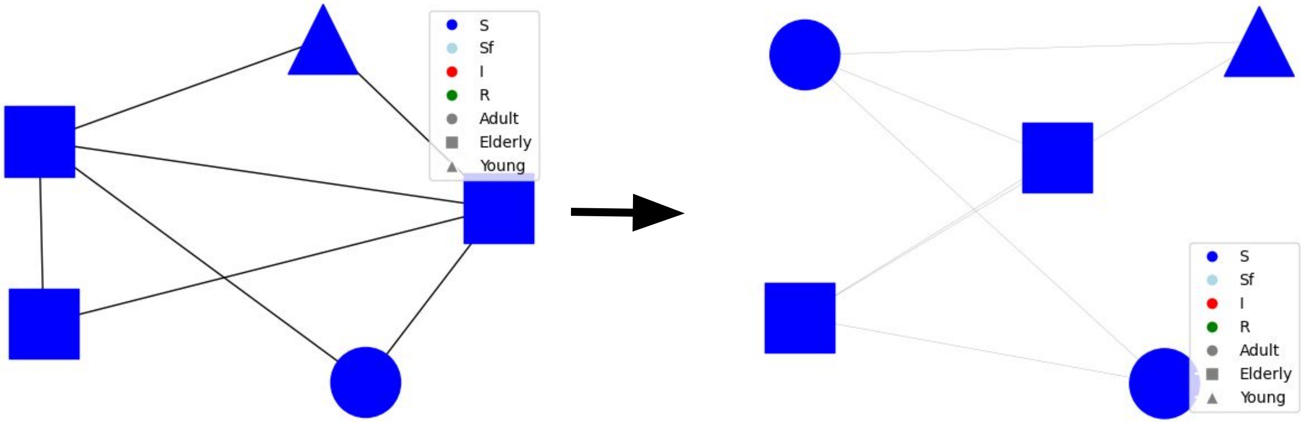
Methods: the idea

We want to construct a SIR model with behavioral changes and age class differentiation

If we want to study a population of relatively small N (3000 $\gtrsim$N) we can rely on a network topology for the system definition

This brings some inherent advantages:

- each node represents an individual and its connection its contacts
- we can build the network according to real contact data [6]
- behavioral changes are represented by **rescaling** of contact weights



Methods: the idea

We want to construct a SIR model with behavioral changes and age class differentiation

If we want to study a population of relatively small N (3000 $\gtrsim$ N) we can rely on a network topology for the system definition

This brings some inherent advantages:

- each node represents an individual and its connection its contacts
- we can build the network according to real contact data [6]
- behavioral changes are represented by **rescaling** of contact weights

… but still, how do we model these behavioral changes?

Methods: the idea

We build a network according to data:

- age data from Istat, to achieve a faithful distribution
- contact data from Italian section of Mossong et al. [6]

Then we iterate Barabasi-Albert algorithm according to data until we reach a network with N nodes

Methods: the idea

We build a network according to data:

- age data from Istat, to achieve a faithful distribution
- contact data from Italian section of Mossong et al. [6]

Then we iterate Barabasi-Albert algorithm according to data until we reach a network with N nodes

Behavioral changes will be represented by a scalar value: **fear**

Methods: the idea

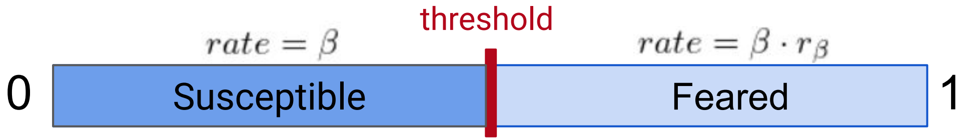
We build a network according to data:

- age data from Istat, to achieve a faithful distribution
- contact data from Italian section of Mossong et al. [6]

Then we iterate Barabasi-Albert algorithm according to data until we reach a network with N nodes

Behavioral changes will be represented by a scalar value: **fear**

In a similar fashion of Scatà et al. [8], we set the occurrence of behavioral changes to be related with the **perceived fear**: if a node's fear goes above a threshold, it becomes feared and rescales its contact weights by a constant $r_\beta < 1$



Methods: the model

In the model several interactions are available [1]:

$S + I \rightarrow I + I$ with rate β

$I \rightarrow R$ with rate μ

standard SIR

Methods: the model

In the model several interactions are available [1]:

$S + I \rightarrow I + I$ with rate β

$I \rightarrow R$ with rate μ

$\boxed{S^F + I \rightarrow 2I \text{ with rate } r_\beta \beta}$ feared individual gets infected

Methods: the model

In the model several interactions are available [1]:

$$S + I \to I + I \text{ with rate } \beta$$
$$I \to R \text{ with rate } \mu$$

$$S^F + I \to 2I \text{ with rate } r_\beta \beta$$
$$\boxed{S + I \to S^F + I \text{ with rate } \beta_F}$$

S individual gets a fear dose from I

Methods: the model

In the model several interactions are available [1]:

$S + I \rightarrow I + I$ with rate β

$I \rightarrow R$ with rate μ

$S^F + I \rightarrow 2I$ with rate $r_\beta \beta$

$S + I \rightarrow S^F + I$ with rate β_F

$\boxed{\lambda = \beta_F(1 - e^{-\delta I(t)}) \text{ (transition is } S \rightarrow S^F)}$

fear transmission through media leads to spontaneous S to Sf transition

Methods: the model

In the model several interactions are available [1]:

$S + I \to I + I$ with rate β

$I \to R$ with rate μ

$S^F + I \to 2I$ with rate $r_\beta \beta$

$S + I \to S^F + I$ with rate β_F

$\lambda = \beta_F(1 - e^{-\delta I(t)})$ (transition is $S \to S^F$)

$\boxed{S + S^F \to 2S^F \text{ with rate } \alpha\beta}$ fear transmission Sf to S

Methods: the model

In the model several interactions are available [1]:

$S + I \to I + I$ with rate β

$I \to R$ with rate μ

$S^F + I \to 2I$ with rate $r_\beta \beta$

$S + I \to S^F + I$ with rate β_F

$\lambda = \beta_F(1 - e^{-\delta I(t)})$ (transition is $S \to S^F$)

$S + S^F \to 2S^F$ with rate $\alpha\beta$

$\boxed{S^F + R \to S + R}$ **fear vanishing due to contact with R (rate μ_f)**

Methods: the model

In the model several interactions are available [1]:

$S + I \to I + I$ with rate β

$I \to R$ with rate μ

$S^F + I \to 2I$ with rate $r_\beta \beta$

$S + I \to S^F + I$ with rate β_F

$\lambda = \beta_F(1 - e^{-\delta I(t)})$ (transition is $S \to S^F$)

$S + S^F \to 2S^F$ with rate $\alpha\beta$

$S^F + R \to S + R$

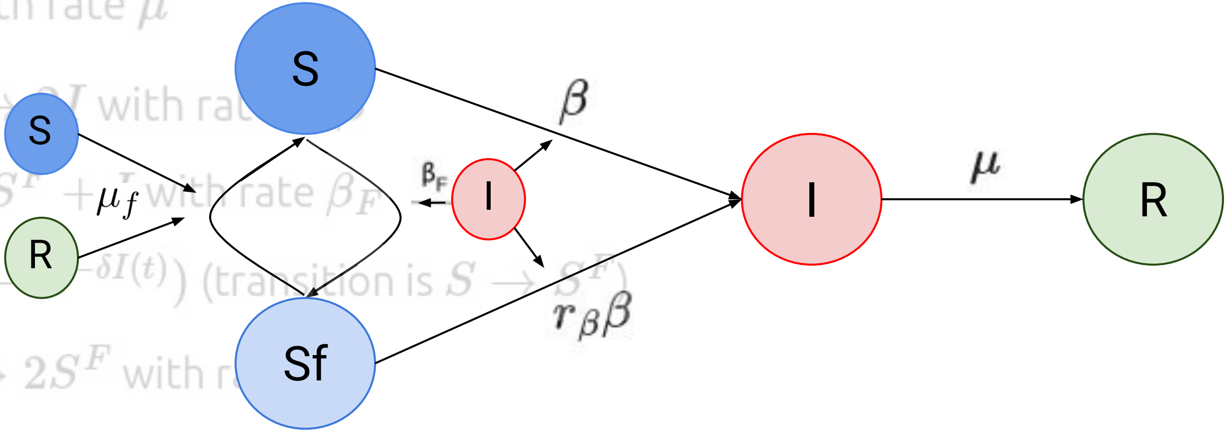
$\boxed{S^F + S \to 2S}$ fear vanishing due to contact with S (rate μ_f)

Methods: the model

In the model several interactions are available [1]:

$S + I \to I + I$ with rate β

$I \to R$ with rate μ



$S^F + R \to S + R$

$S^F + S \to 2S$

Methods: the model

Age class differentiation is provided in terms of parameters: each parameter is a dictionary that contains the parameter relative to the category

```
beta = {'A':0.004,
        'E':0.002,
        'Y':0.006}
```

Methods: the model

Age class differentiation is provided in terms of parameters: each parameter is a dictionary that contains the parameter relative to the category

```
beta = {'A':0.004,
        'E':0.002,
        'Y':0.006}
```

We computed the epidemic threshold and ensured that parameters allow for an epidemic on an equivalent network

Methods: the model

Age class differentiation is provided in terms of parameters: each parameter is a dictionary that contains the parameter relative to the category

```
beta = {'A':0.004,
        'E':0.002,
        'Y':0.006}
```

We computed the epidemic threshold and ensured that parameters allow for an epidemic on an equivalent network

We defined a custom algorithm exploiting Gillespie’s algorithm [9] to run the simulations

Methods: the model

Age class differentiation is provided in terms of parameters: each parameter is a dictionary that contains the parameter relative to the category

```
beta = {'A':0.004,
        'E':0.002,
        'Y':0.006}
```

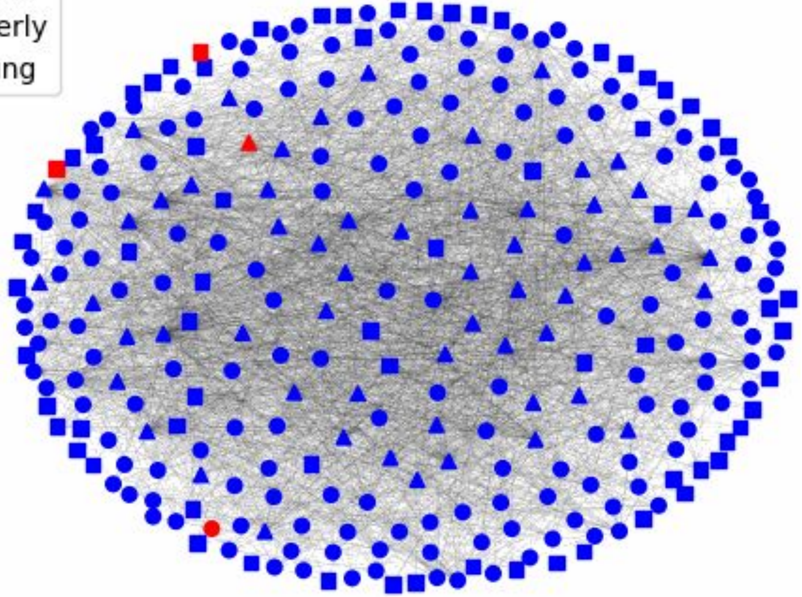
We computed the epidemic threshold and ensured that parameters allow for an epidemic on an equivalent network

We defined a custom algorithm exploiting Gillespie's algorithm [9] to run the simulations

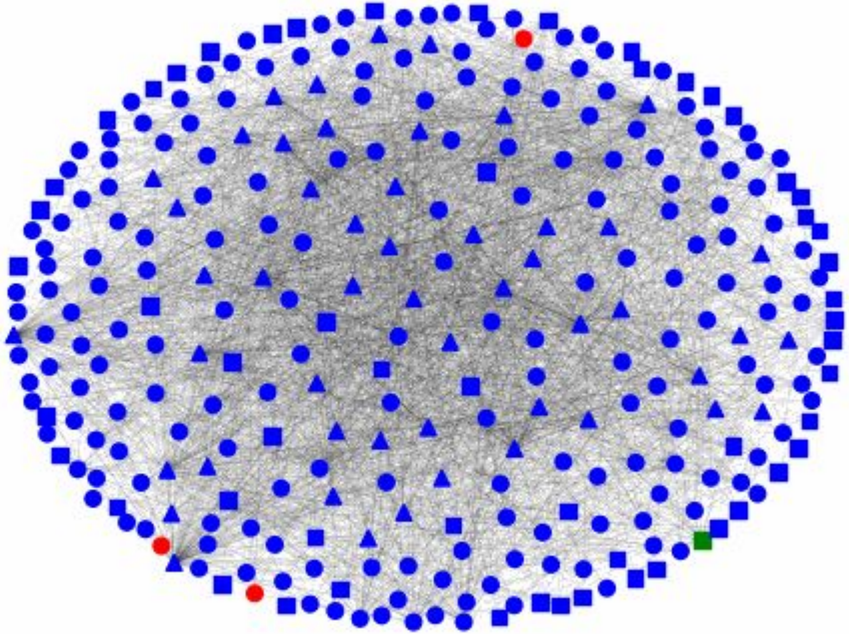
We tried several parameter combinations and network configurations, keeping the distribution of the population and contacts proportional to the starting data

Methods: run example

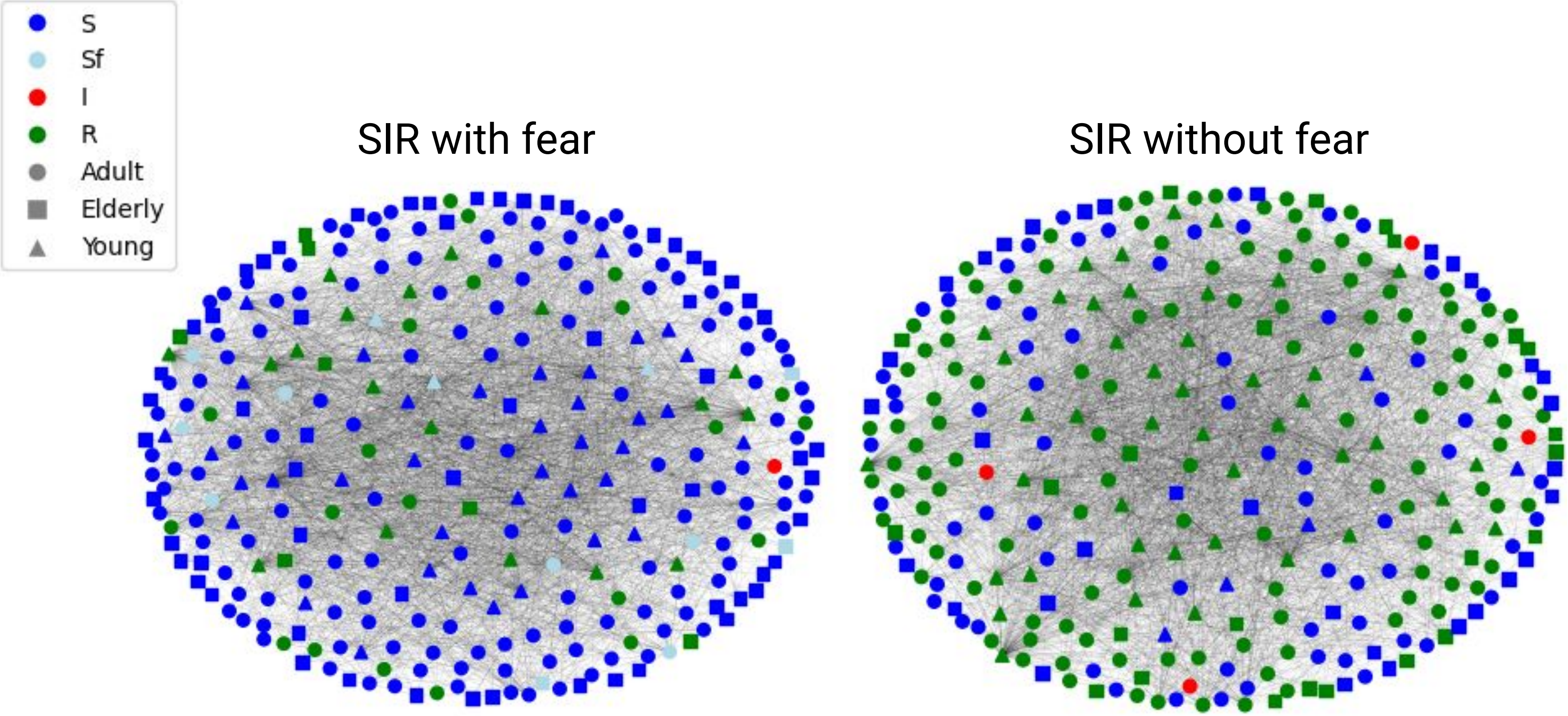
SIR with fear



SIR without fear

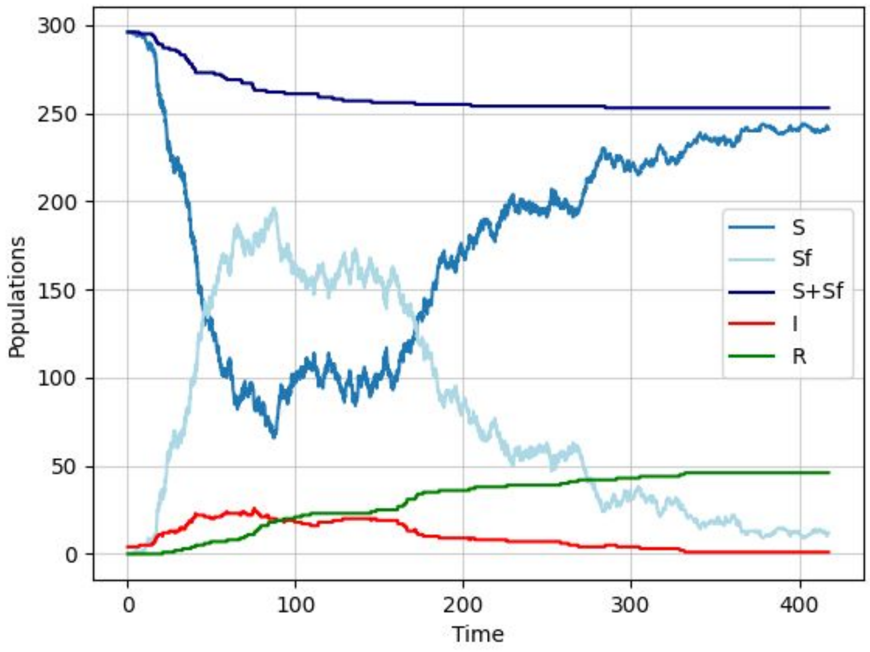


Methods: final snapshot

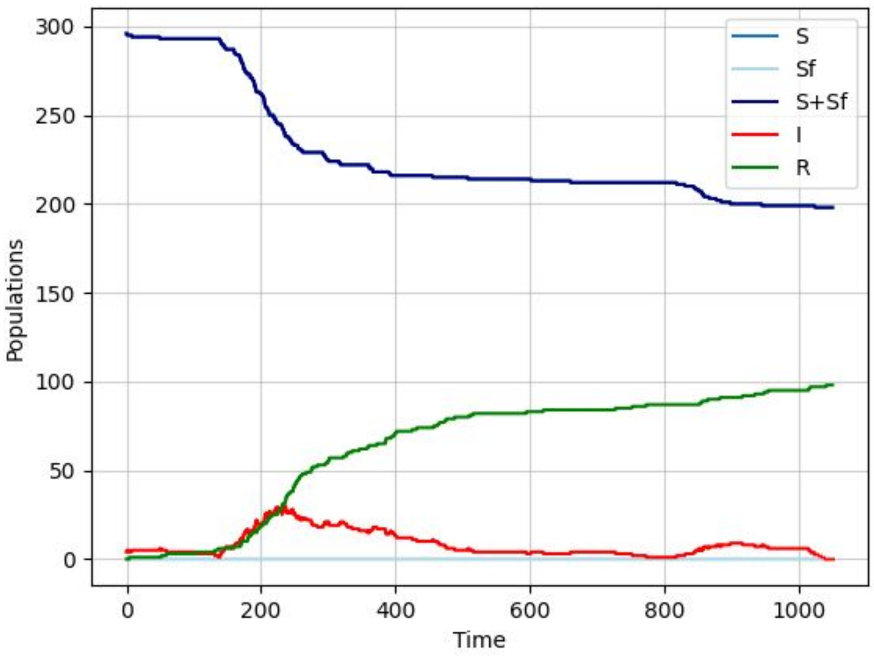


Results: SIR curves

SIR with fear



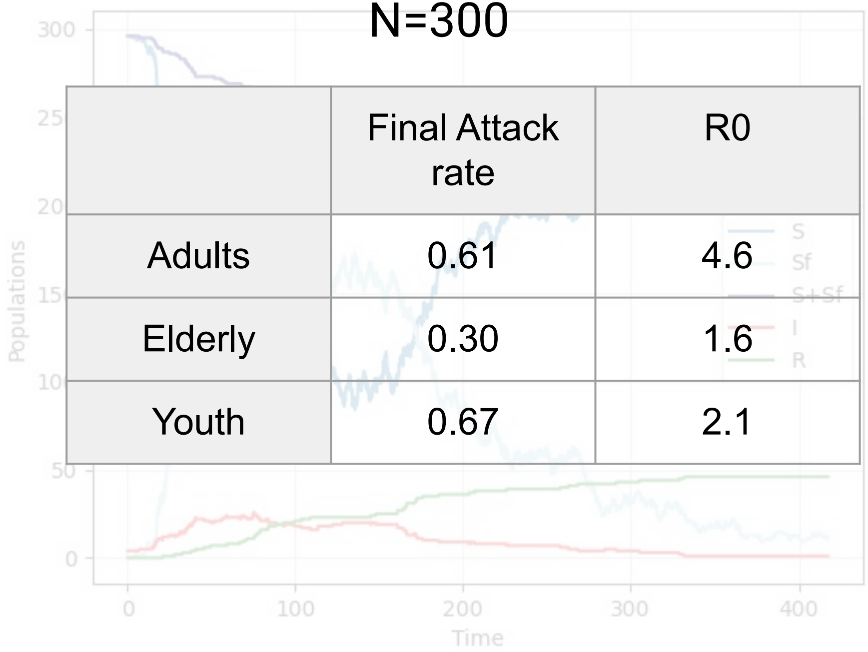
SIR without fear



Università degli Studi di Padova

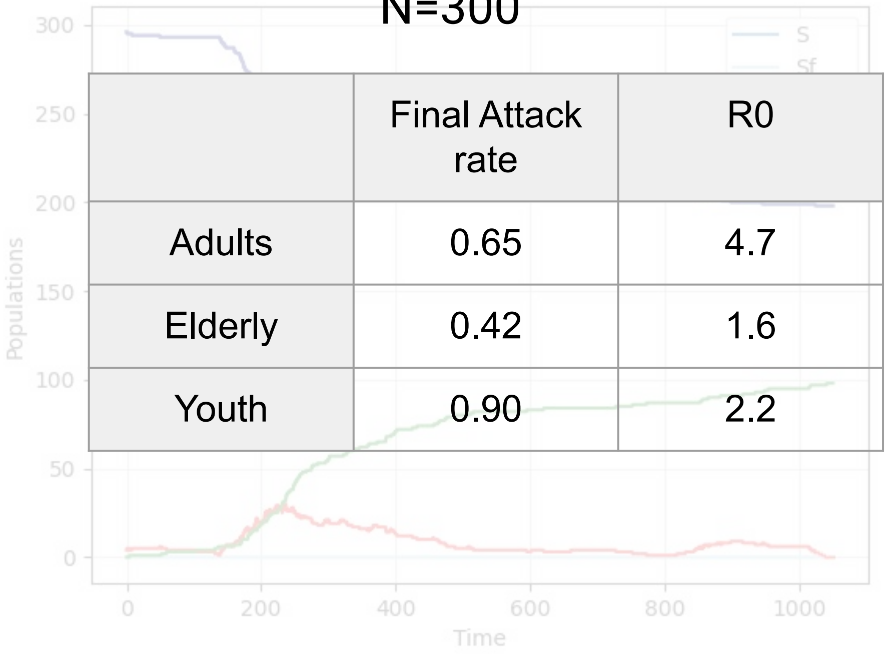
Results: SIR curves

SIR with fear
N=300



	Final Attack rate	R0
Adults	0.61	4.6
Elderly	0.30	1.6
Youth	0.67	2.1

SIR without fear
N=300



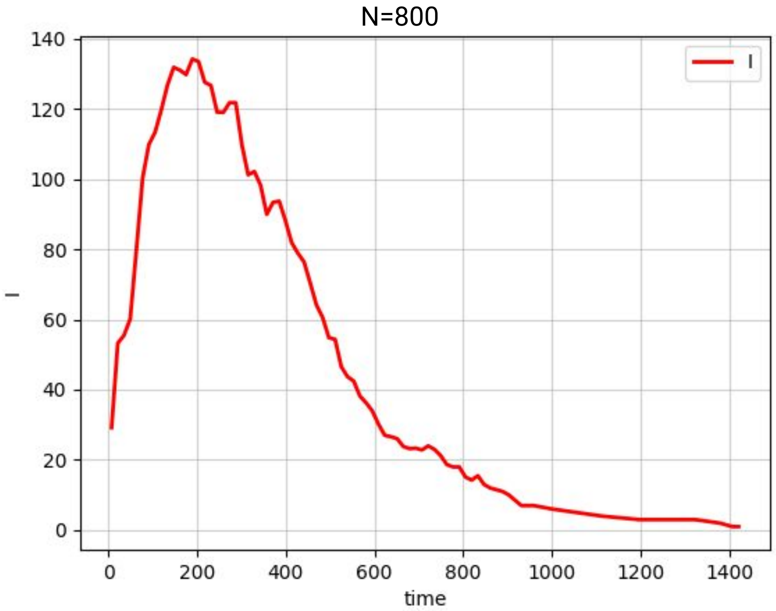
	Final Attack rate	R0
Adults	0.65	4.7
Elderly	0.42	1.6
Youth	0.90	2.2

Results: I curve

We observed that FOI and general shape of the I curve are really dependent on network structure and parameters (and initial conditions, as the initial infected are selected randomly)

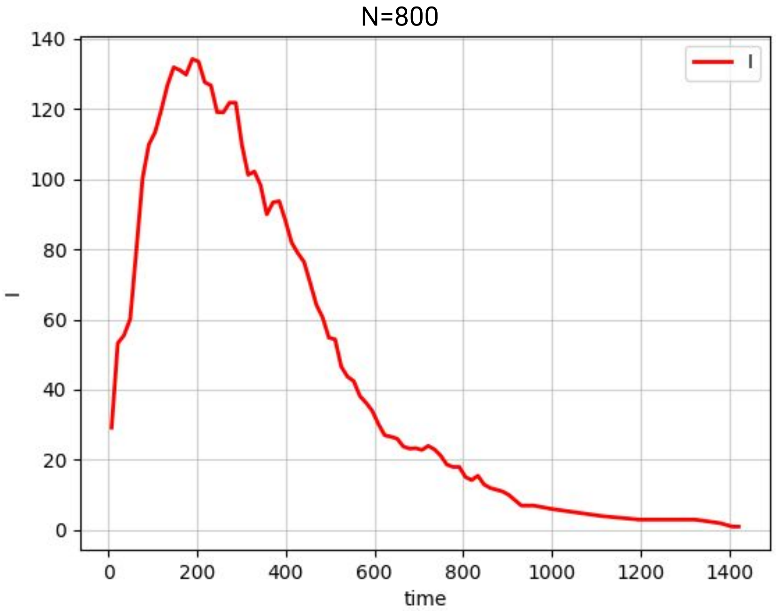
Results: I curve

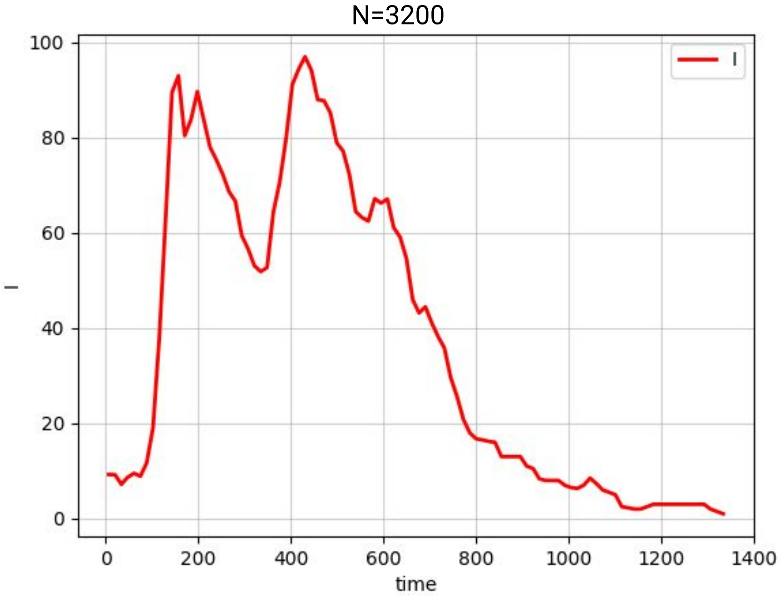
We observed that FOI and general shape of the I curve are really dependent on network structure and parameters (and initial conditions, as the initial infected are selected randomly)



Results: I curve

We observed that FOI and general shape of the I curve are really dependent on network structure and parameters (and initial conditions, as the initial infected are selected randomly)

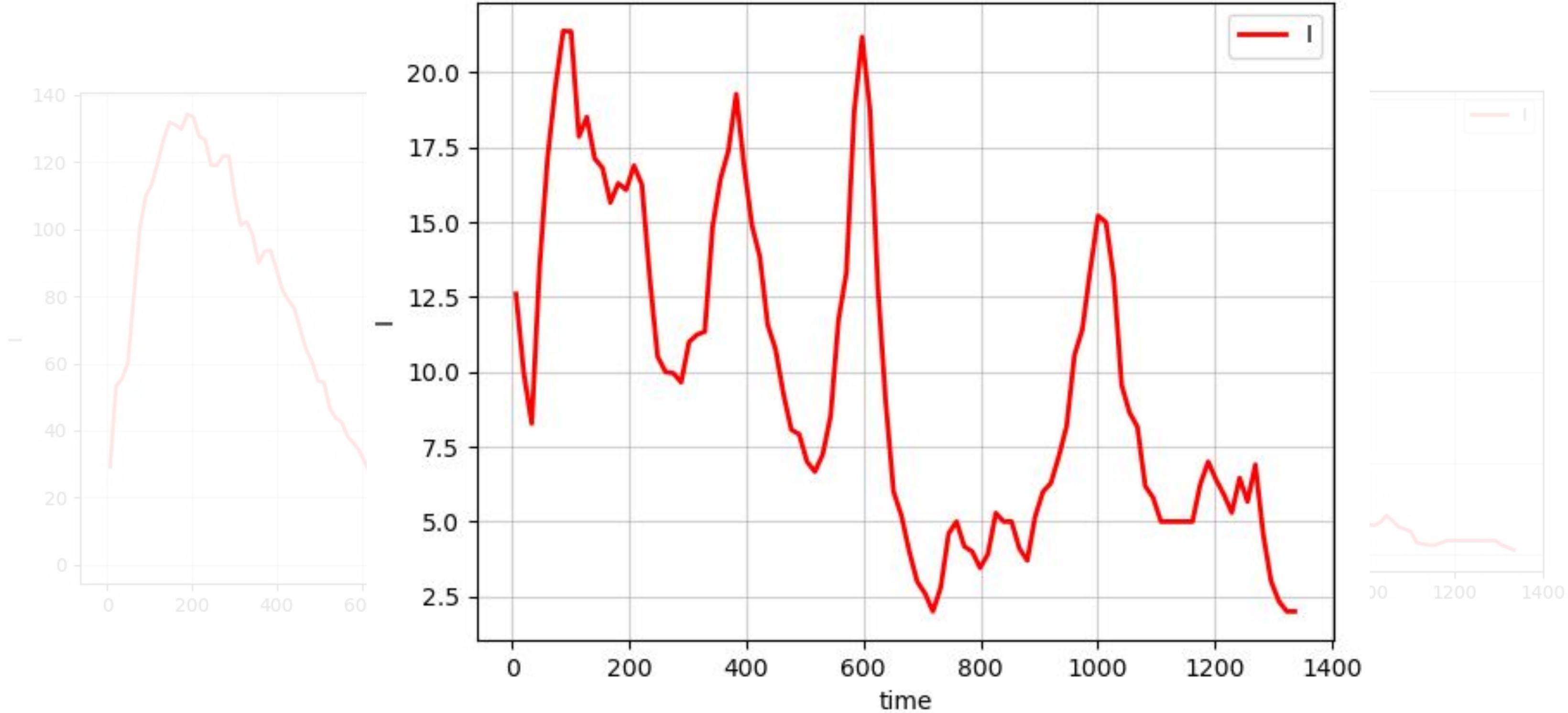




Results: I curve

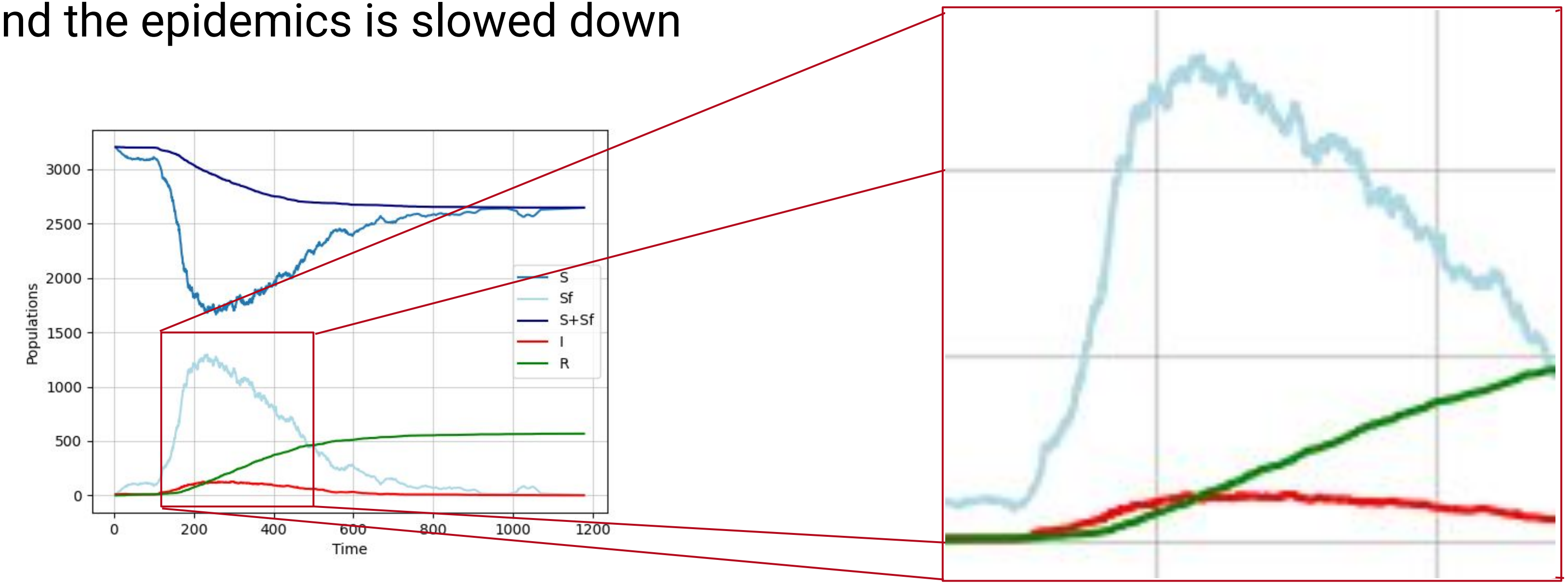
We were able to obtain multiple peaks for very specific parameter choices, in sort of a oscillatory behavior [2]

N=1000



Results: fear vs incidence

“Fear” spreading is way faster than the disease in spreading
As the population gets more and more feared, it gets “virtually” immune (or partially) and the epidemics is slowed down

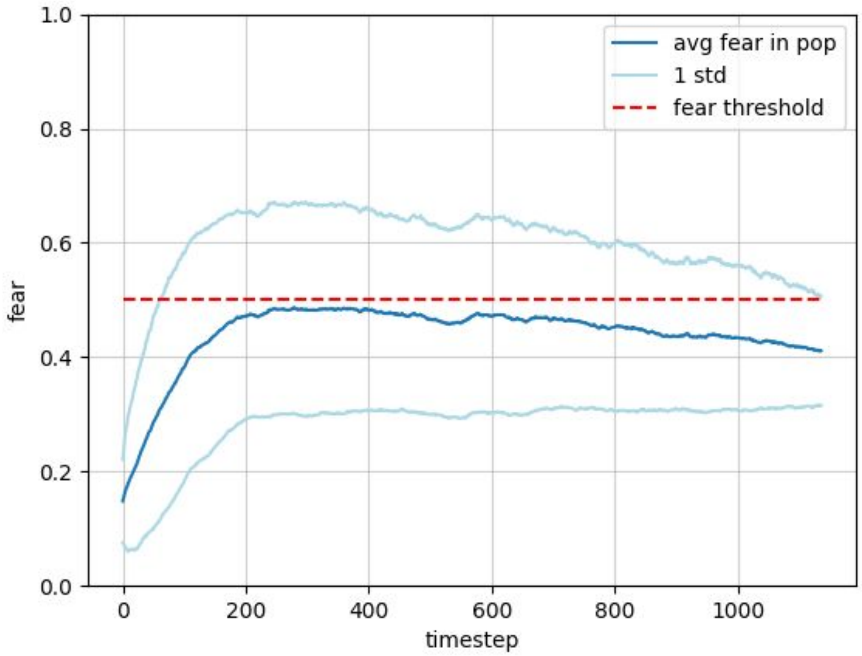


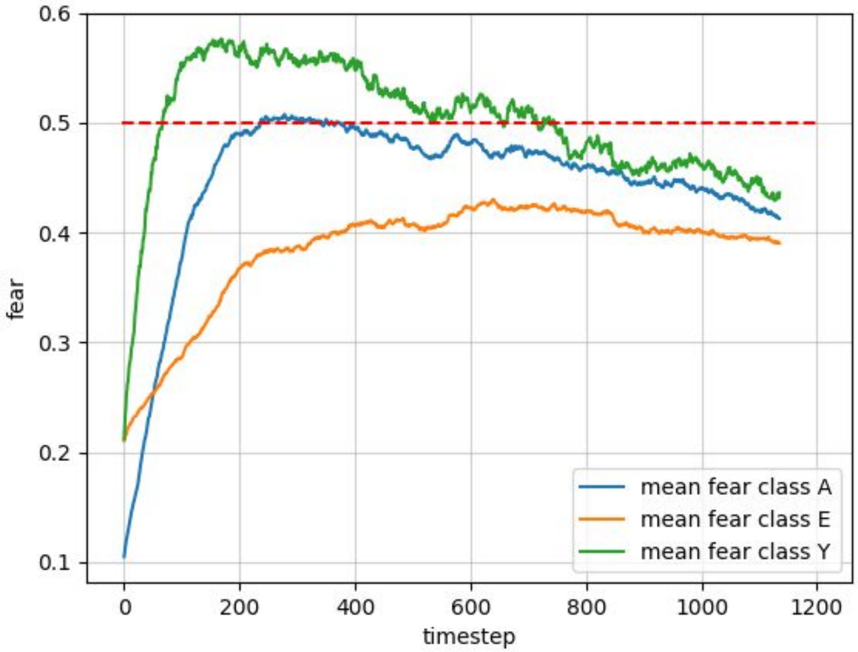
Results: fear by age class

Fear distribution changes depending on the age class

Results: fear by age class

Fear distribution changes depending on the age class

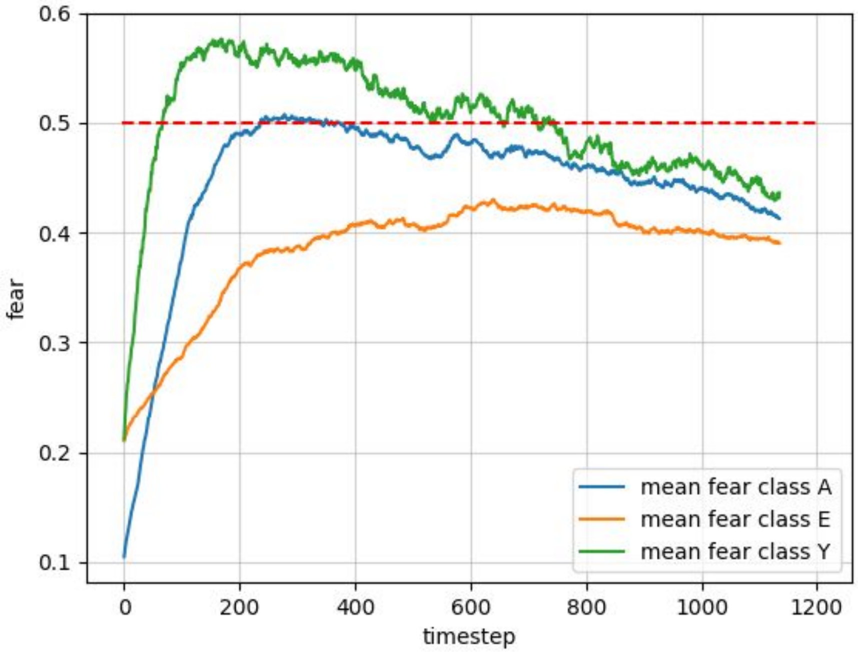




Results: fear by age class

Fear distribution changes depending on the age class

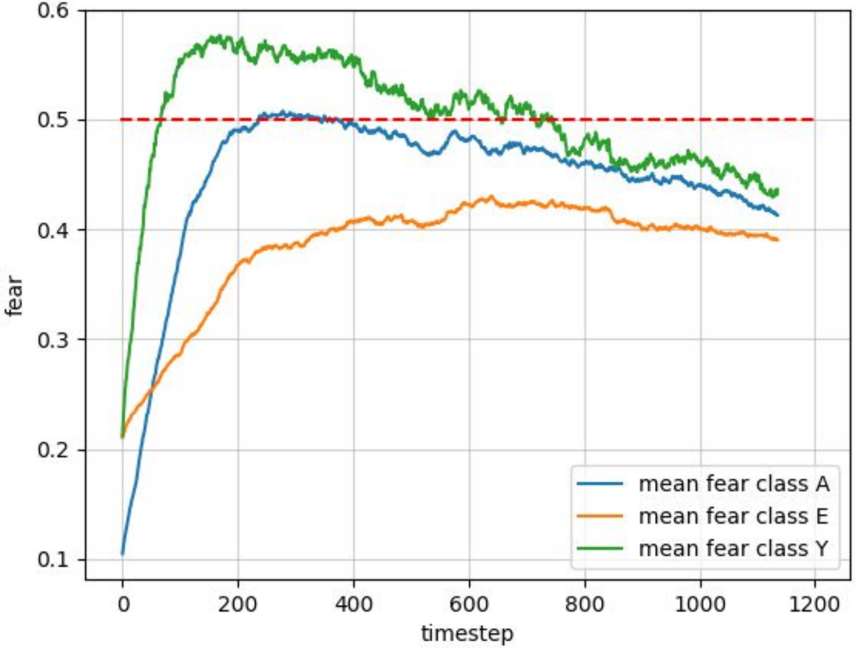
- Fear level is often below the threshold on average, the Youth age class reaches fear level systematically higher than the others. The Youngs end up being the driving force of the suppression of the infection due to fear.



Results: fear by age class

Fear distribution changes depending on the age class

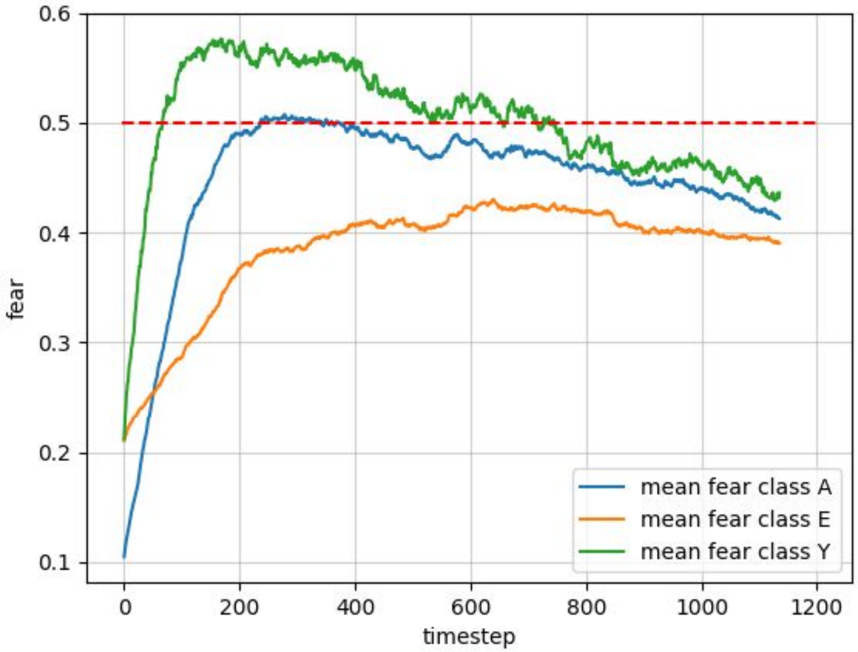
- Fear level is often below the threshold on average, the Youth age class reaches fear level systematically higher than the others. The Youngs end up being the driving force of the suppression of the infection due to fear.
- Elders have much lower fear level, despite being more and initialized with an higher base value.



Results: fear by age class

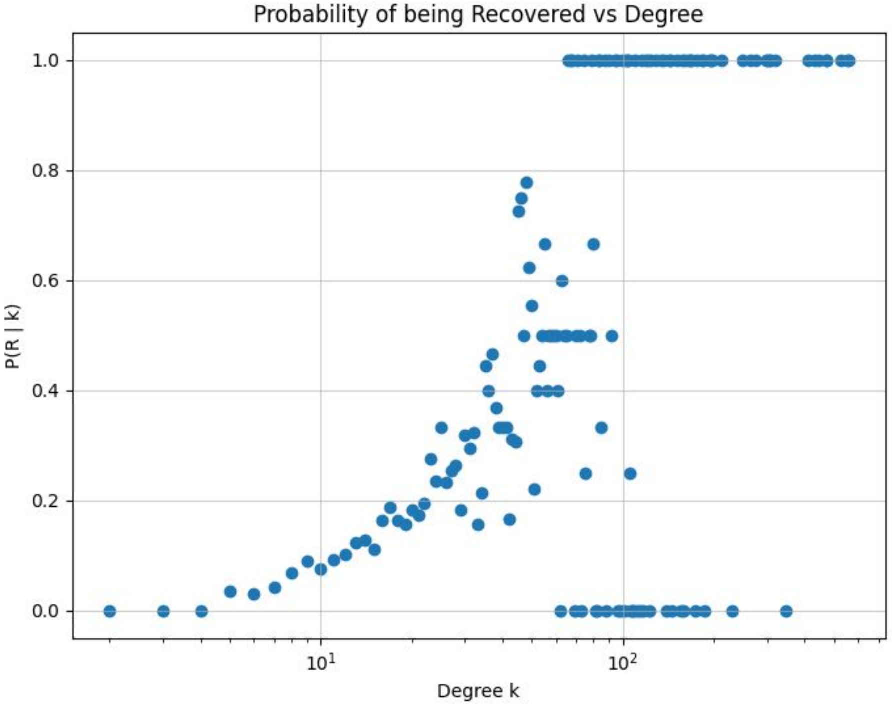
Fear distribution changes depending on the age class

- Fear level is often below the threshold on average, the Youth age class reaches fear level systematically higher than the others. The Youngs end up being the driving force of the suppression of the infection due to fear.
- Elders have much lower fear level, despite being more and initialized with an higher base value.
- The average degree impacting much more on fear spreading than number of individuals or other fixed parameters.



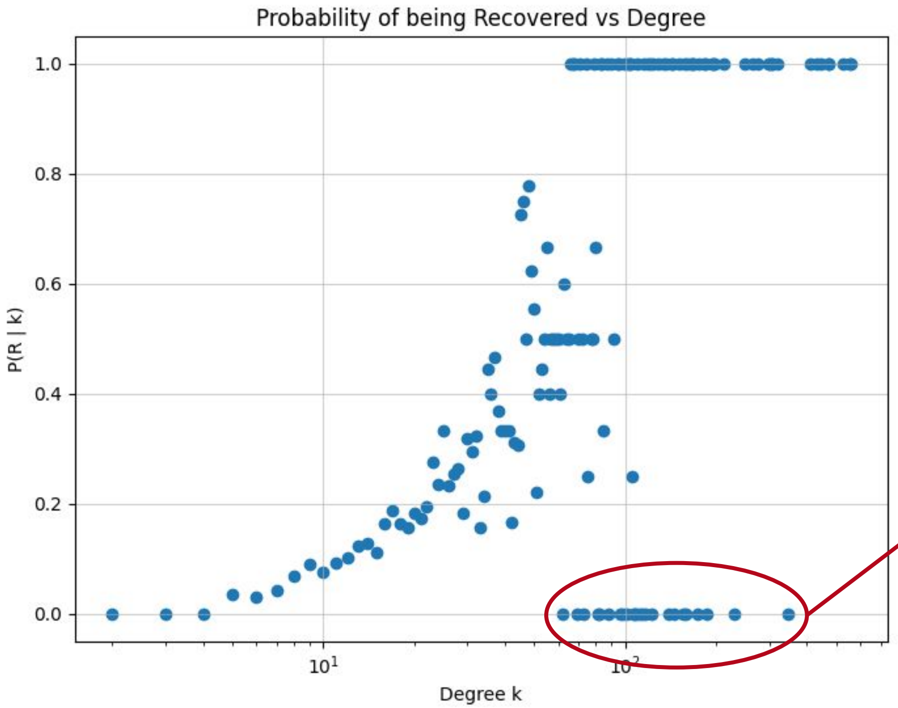
Results: events frequencies

There is a close relationship between degree and probability of getting infected



Results: events frequencies

There is a close relationship between degree and probability of getting infected



having a high degree also implies a high probability of getting feared by contact

Results: events frequencies

The interactions have different frequencies. Here we report results for a run with N=3200

	frequencies
$S + I \rightarrow I + I$ with rate β	0.0027
$I \rightarrow R$ with rate μ	0.0031
$S^F + I \rightarrow 2I$ with rate $r_\beta \beta$	0.00003
$S + I \rightarrow S^F + I$ with rate β_F	0.3611
$\lambda = \beta_F(1 - e^{-\delta I(t)})$ (transition is $S \rightarrow S^F$)	0.0025
$S + S^F \rightarrow 2S^F$ with rate $\alpha\beta$	0.1614
$S^F + R \rightarrow S + R$	0.1206
$S^F + S \rightarrow 2S$	0.3467

Results: events frequencies

The interactions have different frequencies. Here we report results for a run with N=3200

	frequencies
$S + I \to I + I$ with rate β	0.0027
$I \to R$ with rate μ	0.0031
$S^F + I \to 2I$ with rate $r_\beta \beta$	0.00003
$S + I \to S^F + I$ with rate β_F	0.3611
$\lambda = \beta_F(1 - e^{-\delta I(t)})$ (transition is $S \to S^F$)	0.0025
$S + S^F \to 2S^F$ with rate $\alpha\beta$	0.1614
$S^F + R \to S + R$	0.1206
$S^F + S \to 2S$	0.3467

standard SIR events have low occurrence rates

Results: events frequencies

The interactions have different frequencies. Here we report results for a run with N=3200

	frequencies
$S + I \rightarrow I + I$ with rate β	0.0027
$I \rightarrow R$ with rate μ	0.0031
$S^F + I \rightarrow 2I$ with rate $r_\beta \beta$	0.00003
$S + I \rightarrow S^F + I$ with rate β_F	0.3611
$\lambda = \beta_F(1 - e^{-\delta I(t)})$ (transition is $S \rightarrow S^F$)	0.0025
$S + S^F \rightarrow 2S^F$ with rate $\alpha\beta$	0.1614
$S^F + R \rightarrow S + R$	0.1206
$S^F + S \rightarrow 2S$	0.3467

Sf individuals get infected ~100 less times than S
(r_β ~0.005 - 0.01)

Results: events frequencies

The interactions have different frequencies. Here we report results for a run with N=3200

Event	frequencies
$S + I \to I + I$ with rate β	0.0027
$I \to R$ with rate μ	0.0031
$S^F + I \to 2I$ with rate $r_\beta \beta$	0.00003
$S + I \to S^F + I$ with rate β_F	0.3611
$\lambda = \beta_F(1 - e^{-\delta I(t)})$ (transition is $S \to S^F$)	0.0025
$S + S^F \to 2S^F$ with rate $\alpha\beta$	0.1614
$S^F + R \to S + R$	0.1206
$S^F + S \to 2S$	0.3467

fear events occur far more than disease-relative ones

Results: events frequencies

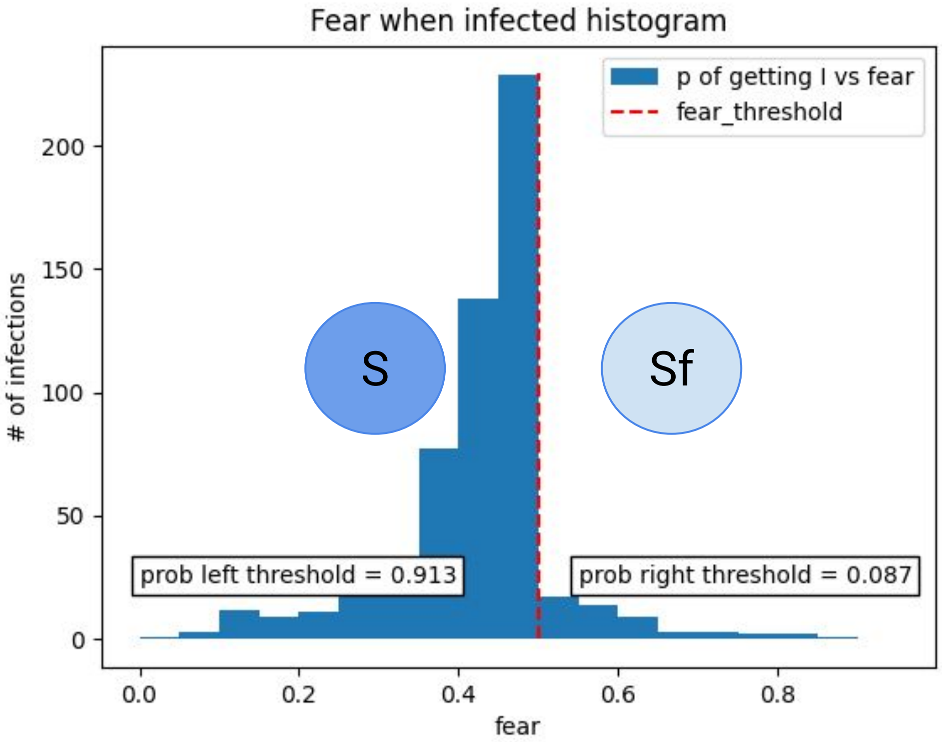
The interactions have different frequencies. Here we report results for a run with N=3200

	frequencies
$S + I \to I + I$ with rate β	0.0027
$I \to R$ with rate μ	0.0031
$S^F + I \to 2I$ with rate $r_\beta \beta$	0.00003
$S + I \to S^F + I$ with rate β_F	0.3611
$\lambda = \beta_F(1 - e^{-\delta I(t)})$ (transition is $S \to S^F$)	0.0025
$S + S^F \to 2S^F$ with rate $\alpha\beta$	0.1614
$S^F + R \to S + R$	0.1206
$S^F + S \to 2S$	0.3467

spontaneous fear transitions are less likely than contact ones

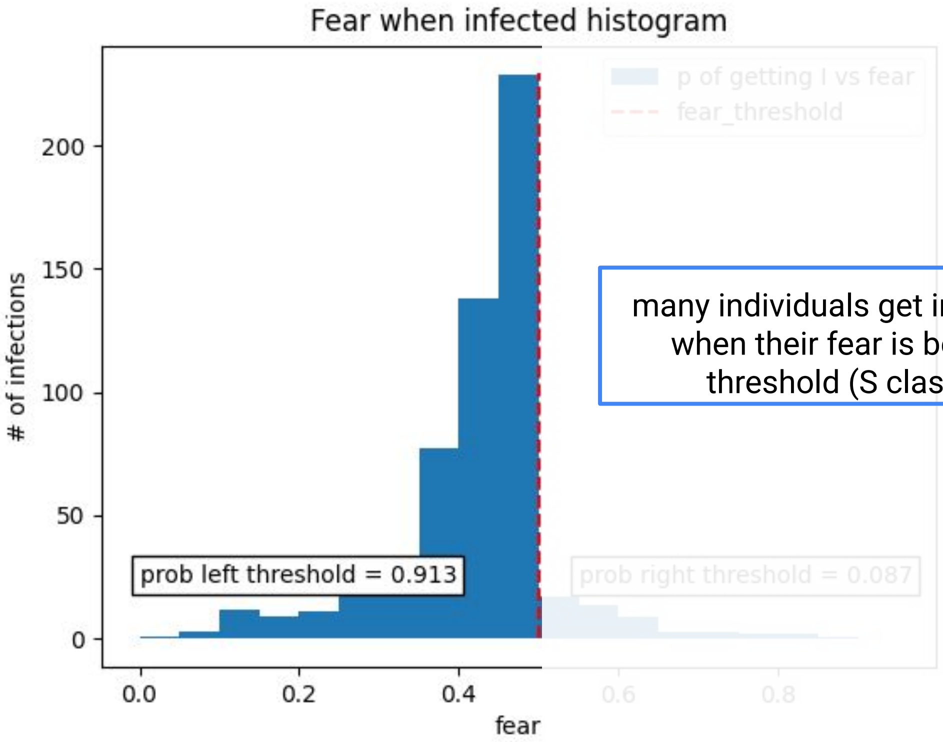
Results: fear vs p. of infection

Behavioral changes should be correlated with the probability of getting the infection. For our choice of behavioral change (framework of [1]) we observe the following tendency:



Results: fear vs p. of infection

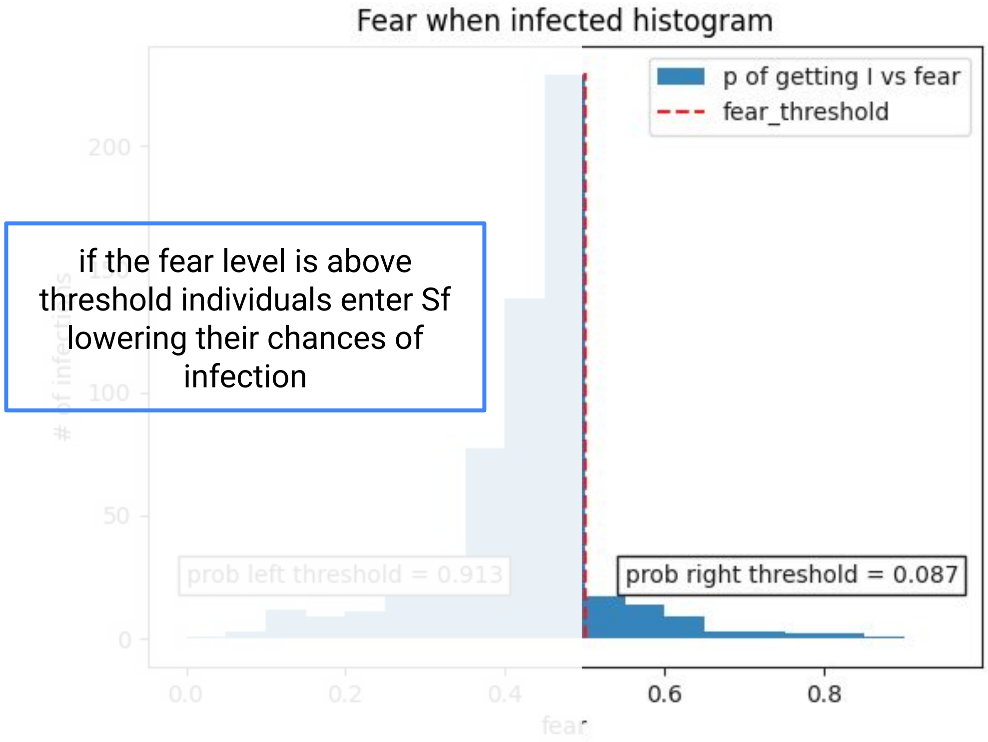
Behavioral changes should be correlated with the probability of getting the infection. For our choice of behavioral change (framework of [1]) we observe the following tendency:



many individuals get infected when their fear is below threshold (S class)

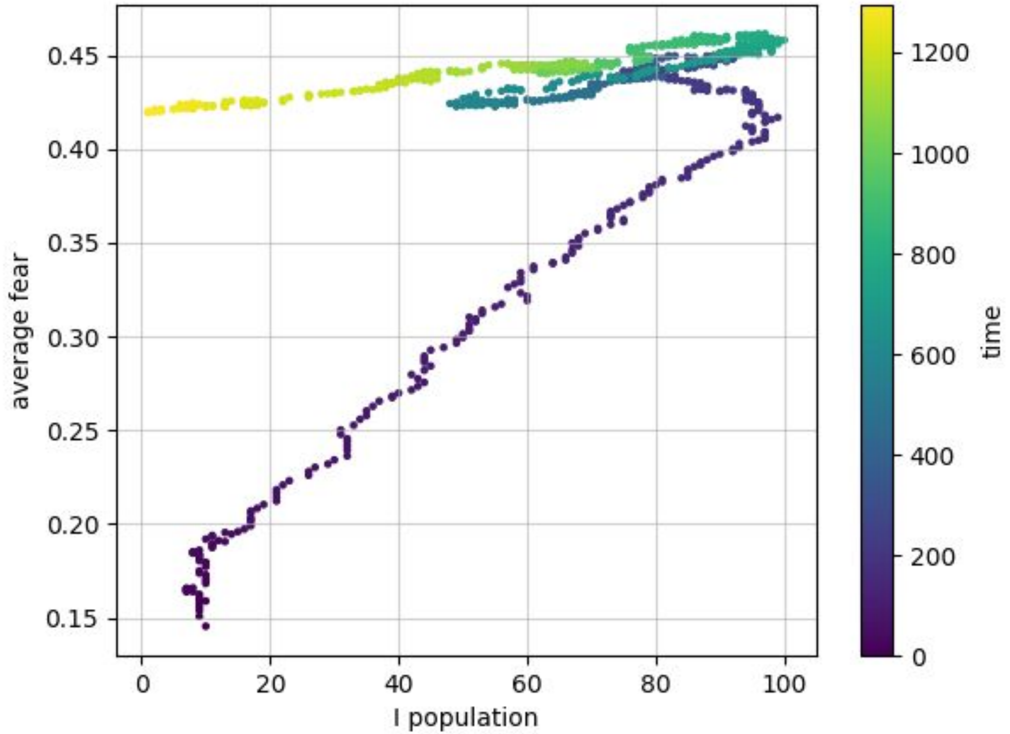
Results: fear vs p. of infection

Behavioral changes should be correlated with the probability of getting the infection. For our choice of behavioral change (framework of [1]) we observe the following tendency:



Results: fear vs time

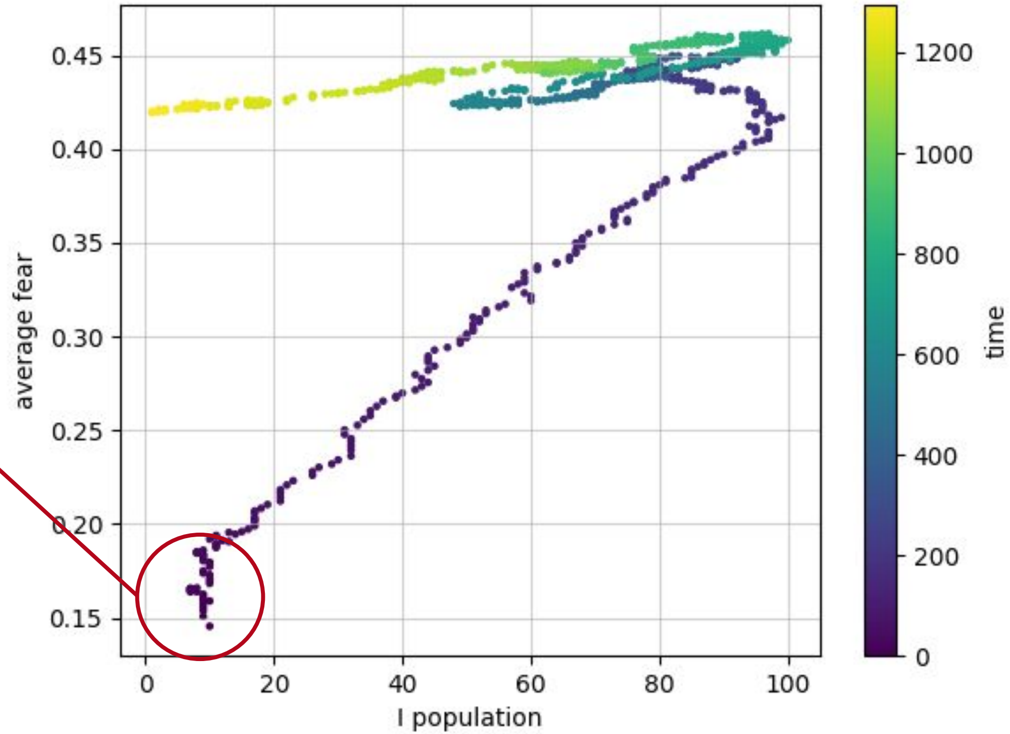
We were also interested in observing changes in fear distribution between the start and the end of the epidemic



Results: fear vs time

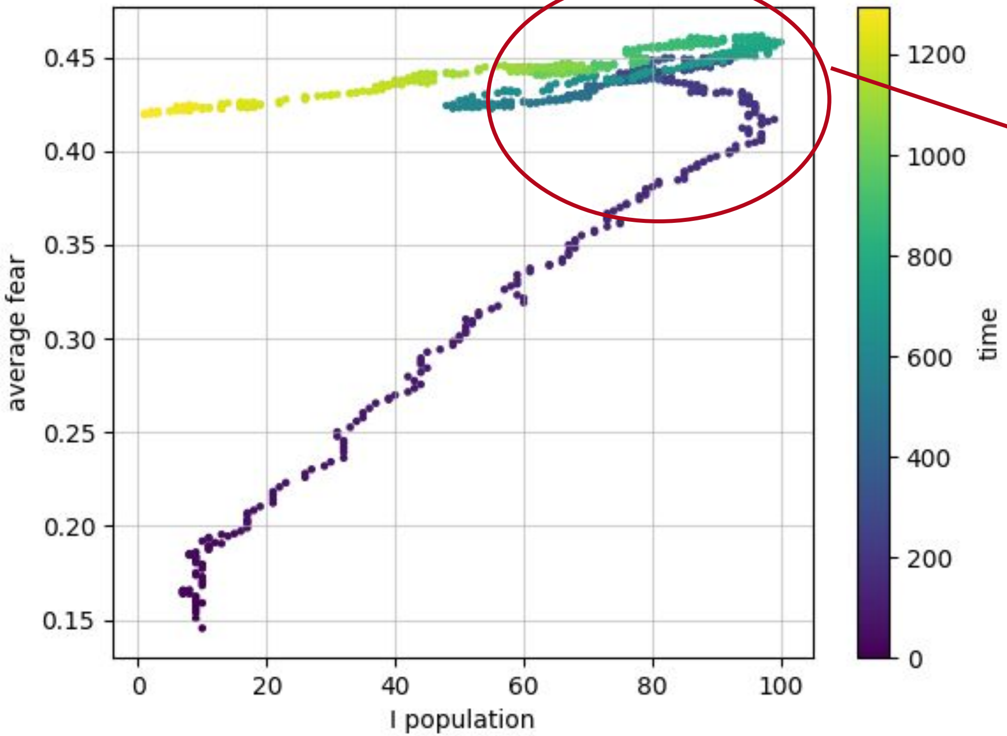
We were also interested in observing changes in fear distribution between the start and the end of the epidemic

we set an arbitrary low average fear level as initial condition



Results: fear vs time

We were also interested in observing changes in fear distribution between the start and the end of the epidemic

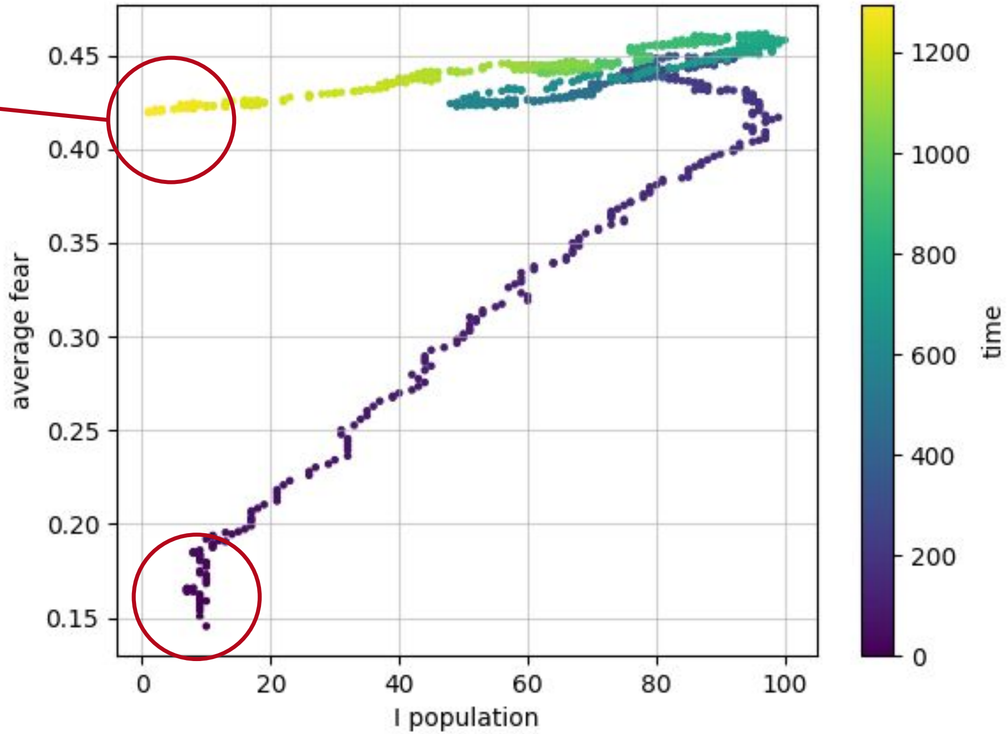


as the I population grows, the average fear gets around threshold

Results: fear vs time

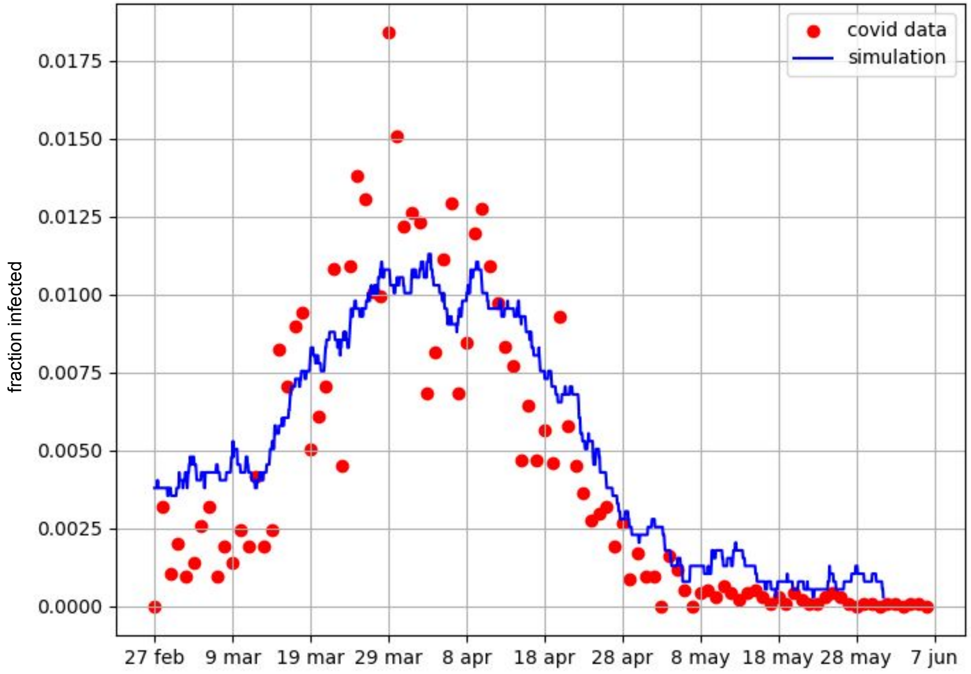
We were also interested in observing changes in fear distribution between the start and the end of the epidemic

at the end of the epidemic the fear level is high



Results: fitting Covid-19 data

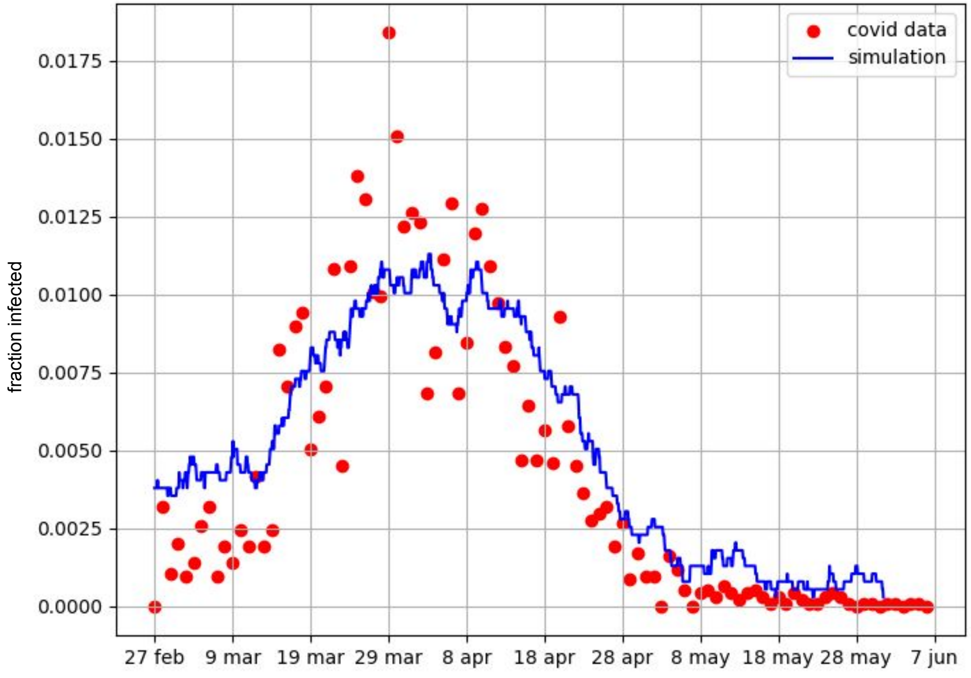
Lastly we tried to fit our model to achieve real Covid data. We took infection data from Padua province in the first infection wave



Results: fitting Covid-19 data

Lastly we tried to fit our model to achieve real Covid data. We took infection data from Padua province in the first infection wave

Our model is capable of simulating small communities (N~3000) so we rescaled the data accordingly

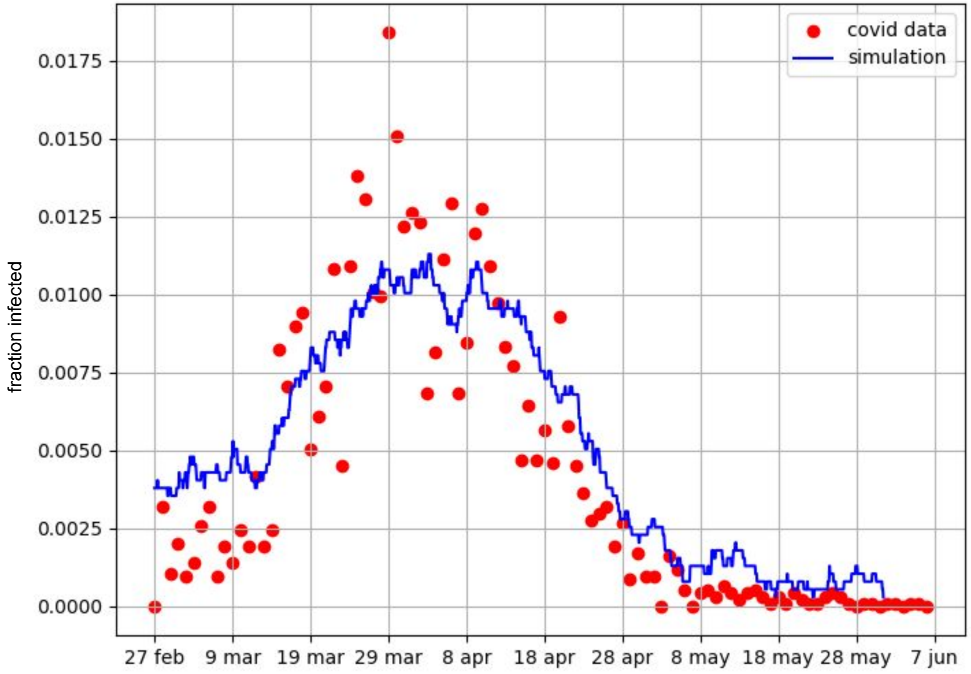


Results: fitting Covid-19 data

Lastly we tried to fit our model to achieve real Covid data. We took infection data from Padua province in the first infection wave

Our model is capable of simulating small communities (N~3000) so we rescaled the data accordingly

After june 2020 Covid epidemic changes significantly:



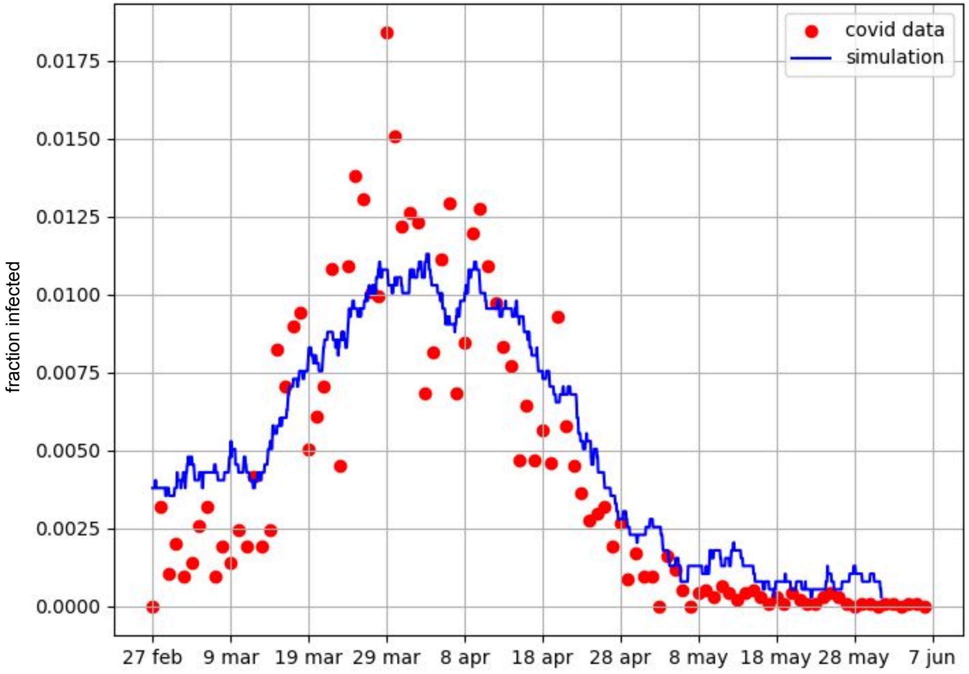
Results: fitting Covid-19 data

Lastly we tried to fit our model to achieve real Covid data. We took infection data from Padua province in the first infection wave

Our model is capable of simulating small communities (N~3000) so we rescaled the data accordingly

After june 2020 Covid epidemic changes significantly:

- regional variants



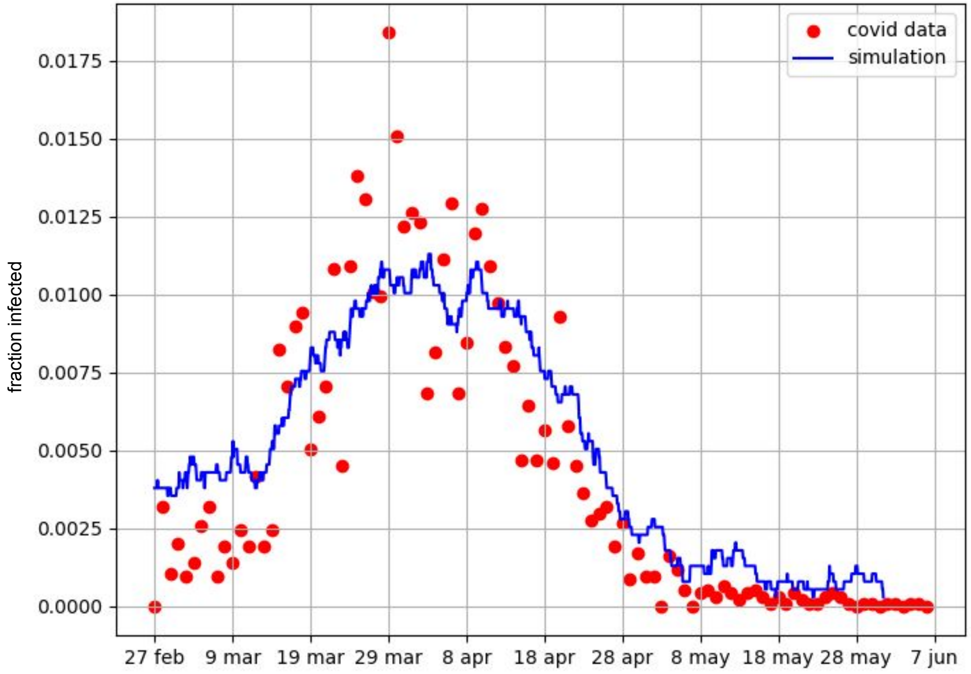
Results: fitting Covid-19 data

Lastly we tried to fit our model to achieve real Covid data. We took infection data from Padua province in the first infection wave

Our model is capable of simulating small communities (N~3000) so we rescaled the data accordingly

After june 2020 Covid epidemic changes significantly:

- regional variants
- political and social constraints



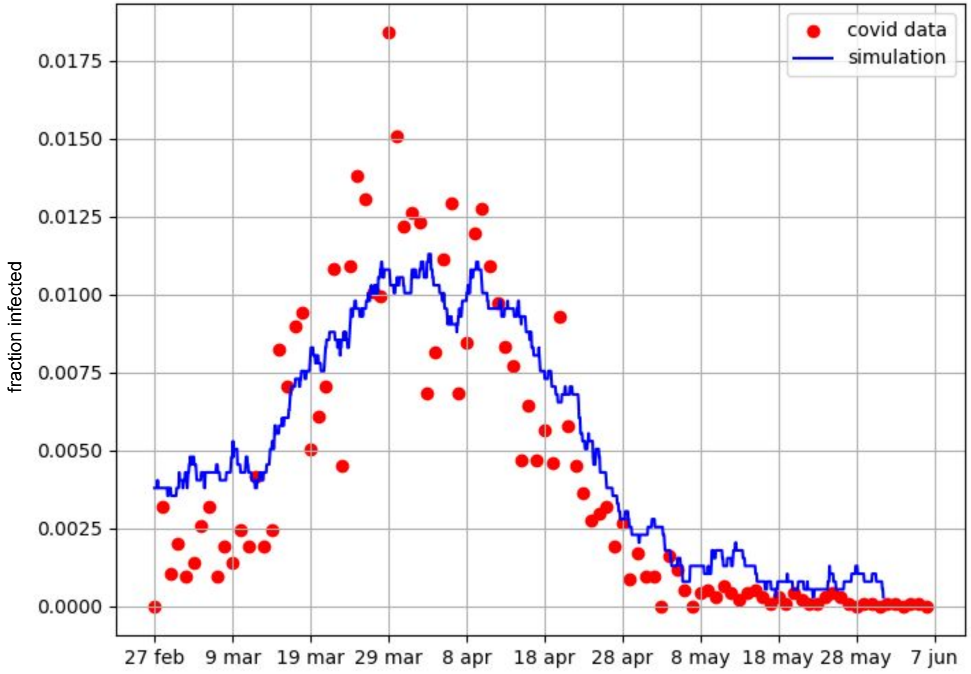
Results: fitting Covid-19 data

Lastly we tried to fit our model to achieve real Covid data. We took infection data from Padua province in the first infection wave

Our model is capable of simulating small communities (N~3000) so we rescaled the data accordingly

After june 2020 Covid epidemic changes significantly:

- regional variants
- political and social constraints
- different individual approach



Results: fitting Covid-19 data

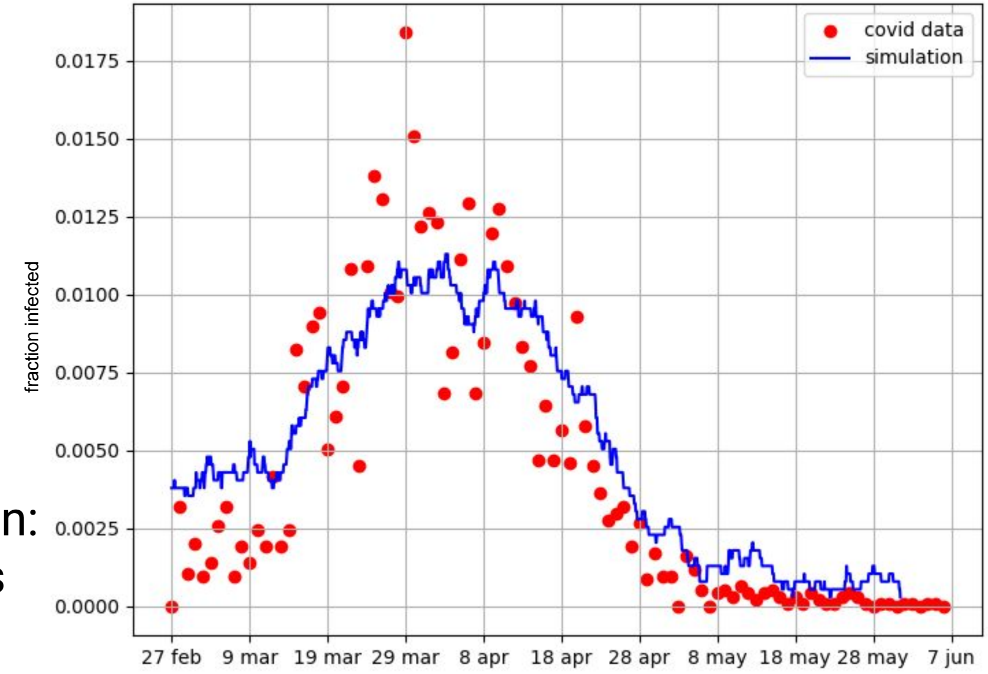
Lastly we tried to fit our model to real Covid data. We took infection data from Padua province in the first infection wave

Our model is capable of simulating small communities (N~3000) so we rescaled the data accordingly

After june 2020 Covid epidemic changes significantly:

- regional variants
- political and social constraints
- different individual approach

We cannot use the same model again: we shall fit with different parameters



Discussion and conclusion

- We have seen that self-initiating behavioral changes have a relevant effect on the spread of the epidemic. In particular, in the framework proposed by [1], fear acts as a stopping force inducing a reduction in FOI.

Discussion and conclusion

- We have seen that self-initiating behavioral changes have a relevant effect on the spread of the epidemic. In particular, in the framework proposed by [1], fear acts as a stopping force inducing a reduction in FOI.
- Age class has an influence on effect of behavioral changes. The Y class is the one with highest average connections, hence being both the driving force of the epidemic and the stopping one once fear has spread enough. Moreover, the Y class is the most hit by the disease proportionally [4].

Discussion and conclusion

- We have seen that self-initiating behavioral changes have a relevant effect on the spread of the epidemic. In particular, in the framework proposed by [1], fear acts as a stopping force inducing a reduction in FOI.
- Age class has an influence on effect of behavioral changes. The Y class is the one with highest average connections, hence being both the driving force of the epidemic and the stopping one once fear has spread enough. Moreover, the Y class is the most hit by the disease proportionally [4].
- The fear distribution has significantly changed between the start and the end of the epidemics: its prevalence manifests as a change in the population behavior that kills the epidemic in shorter times than standard SIR.

Discussion and conclusion

- We have seen that self-initiating behavioral changes have a relevant effect on the spread of the epidemic. In particular, in the framework proposed by [1], fear acts as a stopping force inducing a reduction in FOI.
- Age class has an influence on effect of behavioral changes. The Y class is the one with highest average connections, hence being both the driving force of the epidemic and the stopping one once fear has spread enough. Moreover, the Y class is the most hit by the disease proportionally [4].
- The fear distribution has significantly changed between the start and the end of the epidemics: its prevalence manifests as a change in the population behavior that kills the epidemic in shorter times than standard SIR.
- We were able to reproduce the I(t) trend of the first Covid wave in Padua, although the model shall be adjusted to reproduce more complex trends such as ones of latter Covid waves.

Discussion and conclusion

Strengths:

- allows for inclusion of a variety of behavioral changes (vaccination, lockdown…)
- accurate approximation at the beginning of the epidemic given the constraints
- predicts how each population class interacts with the given behavioral change

Limits:

- computational capabilities (computational time scales badly with N)
- availability of accurate data (contact)

Possible improvements:

- extension of the model to larger populations (needs more resources) or other behavioral changes [11]
- accounting for a more effective global fear trend (threshold global model [10])
- possibility to perform repeated runs and provide expectations
- more accurate parameters fine tuning based on real-life data

References

[1] N. Perra, D. Balcan, B. Goncalves, A. Vespignani, Towards a Characterization of Behavior-Disease Models, Plos One, 2011

[2] R.F. Arthur et al., Age-differentiated incentives for adaptive behavior during epidemics produce oscillatory and chaotic dynamics, Plos Computational Biology, 2023

[3] D. Acemoglu et al., Optimal Targeted Lockdowns in a Multigroup SIR Model, AER Insights, 2021

[4] V. Ram, L. Schaposnik, A modified age-structured SIR model for COVID-19 type viruses, Nature, 2021

[5] Istituto Nazionale di Statistica (ISTAT)

[6] J. Mossong et al., Social Contacts and Mixing Patterns Relevant to the Spread of Infectious Diseases, Plos Medicine, 2008

[7] Epstein et al. Coupled Contagion Dynamics of Fear and Disease: Mathematical and Computational Explorations, Plos One, 2008

[8] M. Scatà et al., The Impact of Heterogeneity and Awareness in Modeling Epidemic Spreading on Multiplex Networks, Nature, 2016

[9] D.T. Gillespie, A general method for numerically simulating the stochastic time evolution of coupled chemical reactions, Journal of Computational Physics, 1976

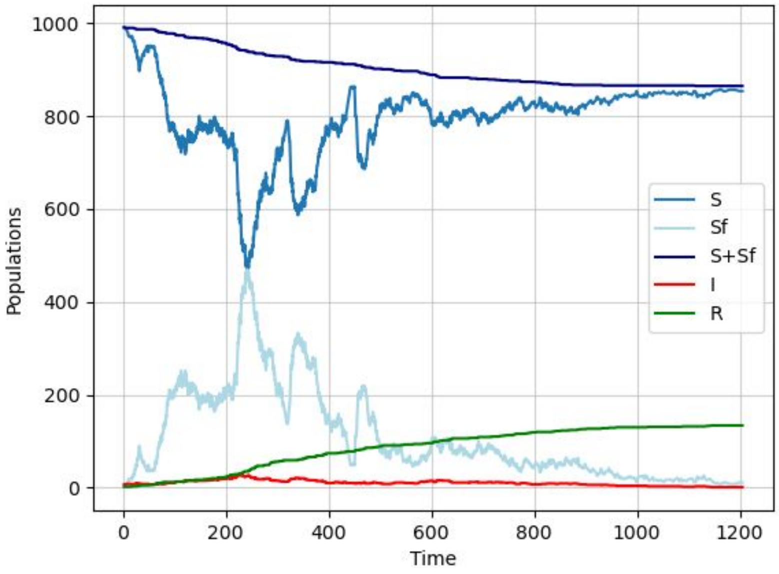
[10] A. A general method for numerically simulating the stochastic time evolution of coupled chemical reactions, T. Kuniya, Global threshold dynamics of an infection age-structured SIR epidemic model with diffusion under the Dirichlet boundary condition, Journal of Differential Equations, 2020

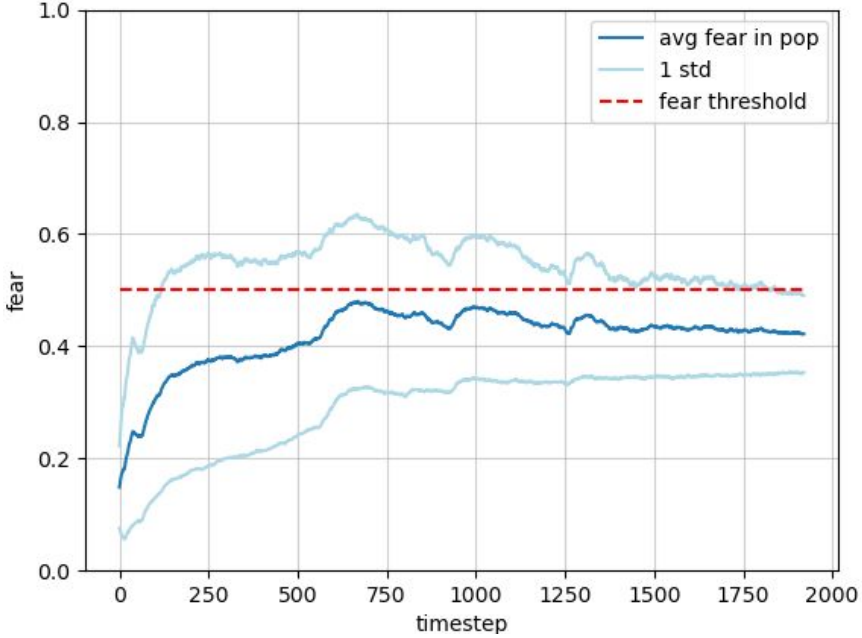
[11] T. Yabe et al., Behavioral changes during the COVID-19 pandemic decreased income diversity of urban encounters, Nature, 2023

[12] M.Tizzani et al., Impact of tiered measures on social contact and mixing patterns of in Italy during the second wave of COVID-19

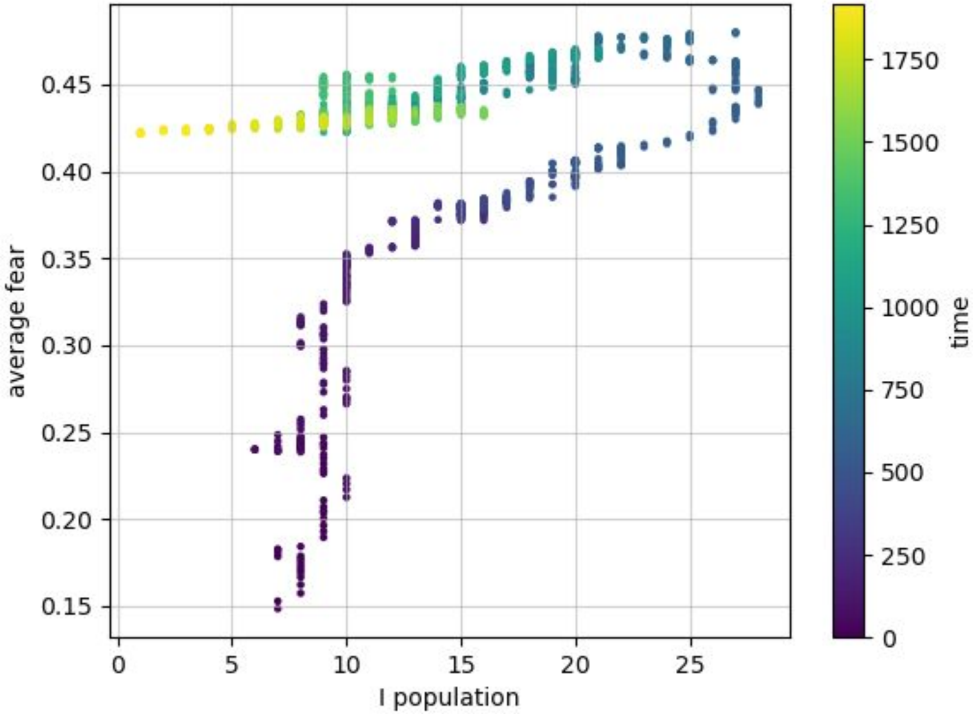
Thank you for your attention!

No age class


Populations
Time
S
Sf
S+Sf
I
R


fear
timestep
avg fear in pop
1 std
fear threshold

No age class


average fear
0.15
0.20
0.25
0.30
0.35
0.40
0.45
I population
0
5
10
15
20
25
time
0
250
500
750
1000
1250
1500
1750

Second COVID wave