

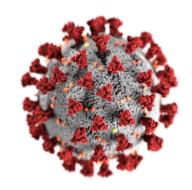
# A multi-age structured SIRVSD model

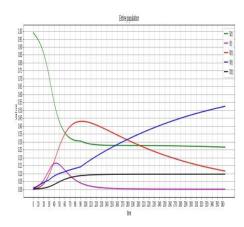
Implementation of a SIRVSD model with different age groups and heterogeneous contacs in Python

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## Introduction to the problem

- Covid-19 has focused on forecasting models to be able to monitor and control the number of infections and deaths within a country
- Need to evaluate different vaccination strategies to defeat the infection
- Need to predict the effect of vaccinations to organize a plan to ease restrictions, especially for the country's economy
- Compartmental models are often applied to the mathematical modelling of infectious disease using ODEs
- Population partitioned into different age groups, considering the impact of heterogeneity in susceptibility, mortality and infectivity within the population on the disease trasmission



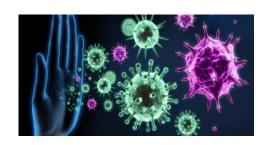


# Model Assumptions

- S+I+R+V+D=1
- Some coefficients are the same for all age group (only trasmission, vaccination and mortality coefficients are different)
- We don't consider vital dynamics (reproduction, 'natural' death, migration)
- Heterogeneous contacts and symmetric contact matrix

- Just one injection of the vaccine is considered
- Both recovery and vaccination immunity are not forever, but they ensure 100% protection from infection
- Contacts between individuals are random, the number of infections is proportional to both I and S
- Horizontal transmission







## Model and Parameters

$$\begin{cases} \frac{dS_j}{dt} = \phi R_j - \eta_j(t) S_j + \rho V_j - S_j \sum_{k=1}^M \beta_{j,k} I_k \\ \frac{dI_j}{dt} = -\gamma I_j - \mu_j I_j + S_j \sum_{k=1}^M \beta_{j,k} I_k \\ \frac{dR_j}{dt} = \gamma I_j - \phi R_j \\ \frac{dV_j}{dt} = \eta_j(t) S_j - \rho V_j \\ \frac{dD_j}{dt} = \mu_j I_j \end{cases}$$

$$\forall j \in (0, M]$$

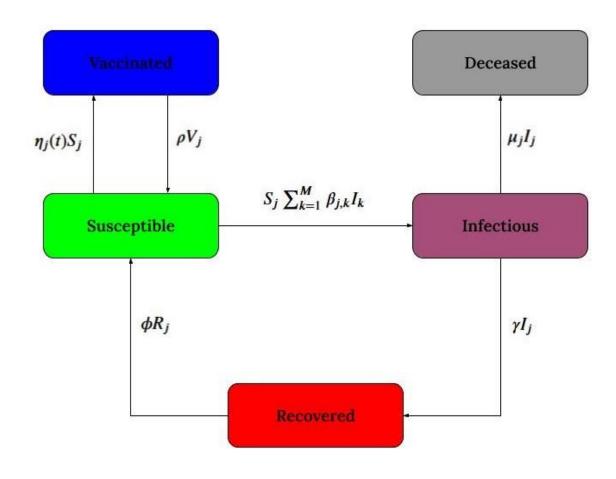
with M = 4 age groups:

- Children (0-9 years)
- Teenagers (10-19 years)
- Adults (20-69 years)
- Senior Citizens (70+ years)
- $\phi$  is the *transfer coefficient* for loss of immunity from Recovered
- is the transfer coefficient for loss of immunity from Vaccinated
- $\rho$  is the *transfer coefficient* for loss of immunity from Vaccinated  $\beta_{j,k}$  is the *infection coefficient*. We define also the entire *contact matrix*:  $\beta = \begin{bmatrix} \beta_{1,1} & \cdots & \beta_{1,M} \\ \vdots & \ddots & \vdots \\ \beta_{M,1} & \cdots & \beta_{M,M} \end{bmatrix}$
- $\gamma$  is the *recovery coefficient* of each infected subject
- $\mu_j$  is the *mortality coefficient*, different for each age group
- $\eta_i(t)$  is a time-dependent vaccination coefficient, defined as follows:

$$\eta_j(t) = \begin{cases} 0 & \text{if } t < t_{vacc_j} \\ \eta_j & \text{otherwise} \end{cases}$$

where  $t_{vacc_j}$  defines the starting day of the vaccination period

## Transition schema



# Qualitative Analysis

- Case Study: COVID-19 pandemic with different vaccination strategies
  - Initial Configuration

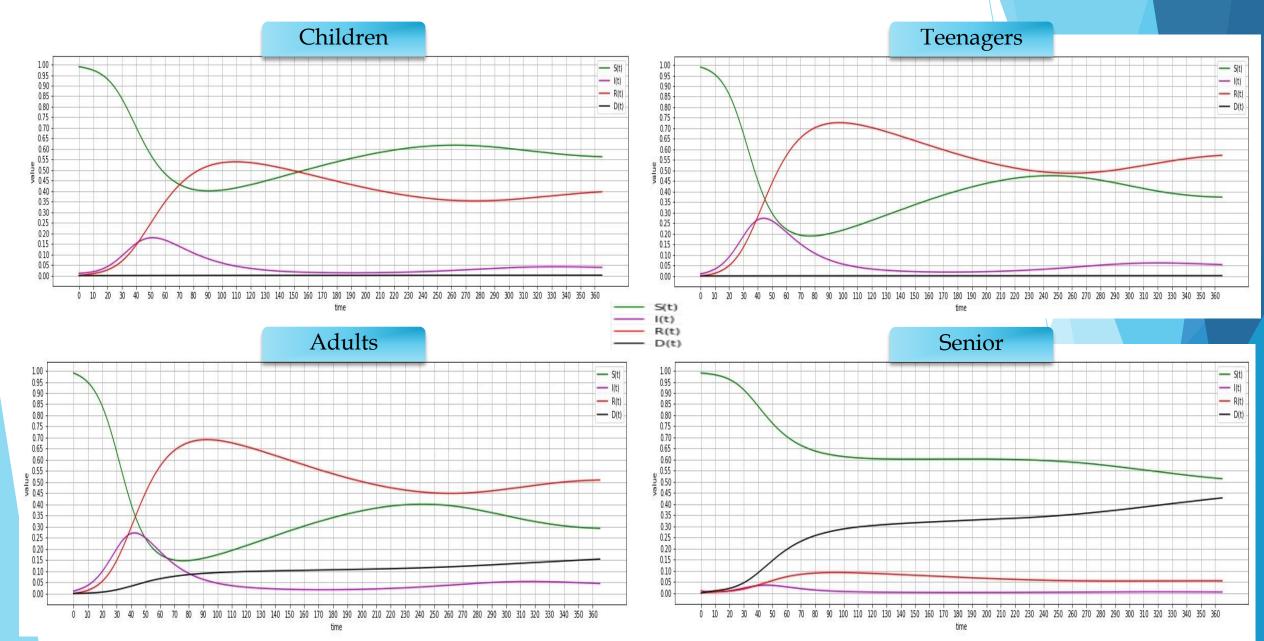
#### Some clarifications

- fifteen days for recovering
- six months of immunity for recovered
- nine months of immunity for vaccinated
- mortality coefficient computed from ISS covid-19 report

	Children	Teenagers	Adults	Senior
S(0)	99%	99%	99%	99%
I(0)	1%	1%	1%	1%
R(0)	0%	0%	0%	0%
V(0)	0%	0%	0%	0%
D(0)	0%	0%	0%	0%
$\gamma$	1/15	1/15	1/15	1/15
$\mu$	0.00009	0.00005	0.00688	0.15987
$\phi$	1/180	1/180	1/180	1/180
ρ	1/270	1/270	1/270	1/270

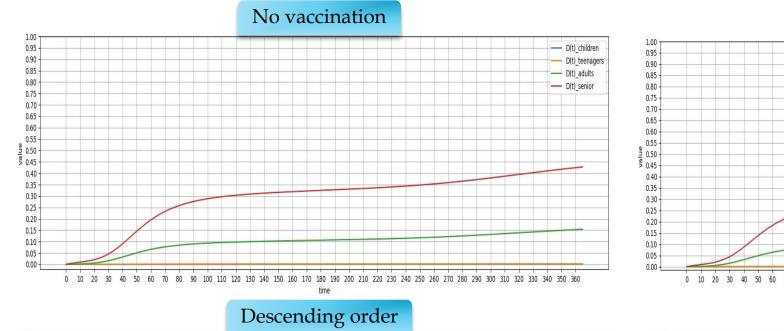
β	Children	Teenagers	Adults	Senior
Children	0.05	0.01	0.04	0.008
Teenagers	0.01	0.09	0.08	0.008
Adults	0.04	0.08	0.1	0.02
Senior	0.008	0.008	0.02	0.03

## No Vaccination

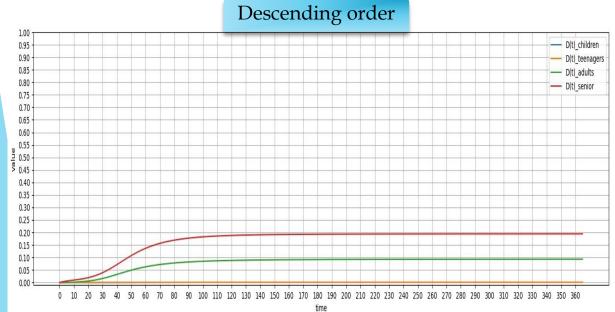


#### Fine-grained analysis

## Mortality comparison for each vaccination strategy

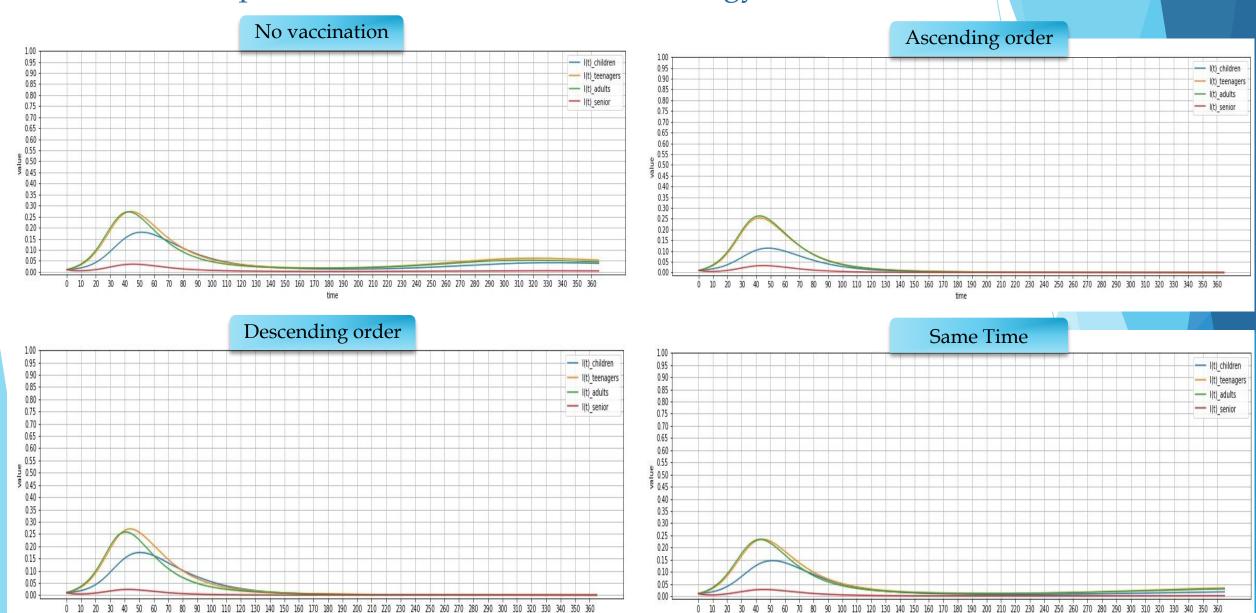








## Infections comparison for each vaccination strategy

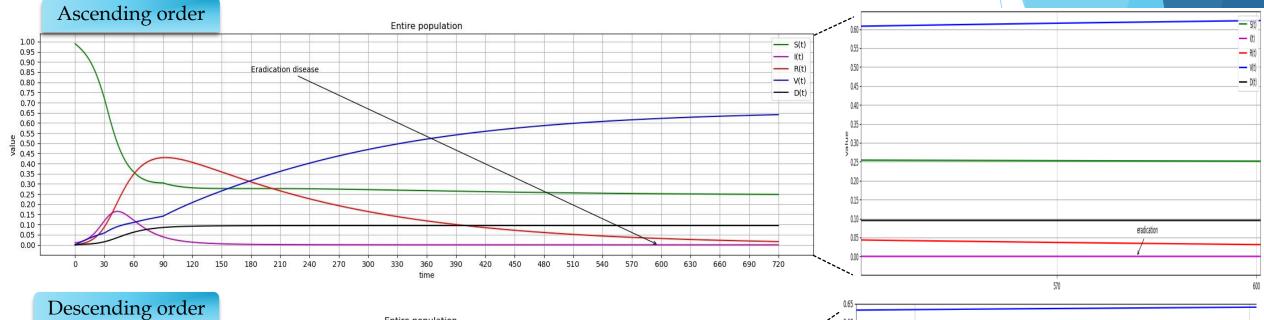


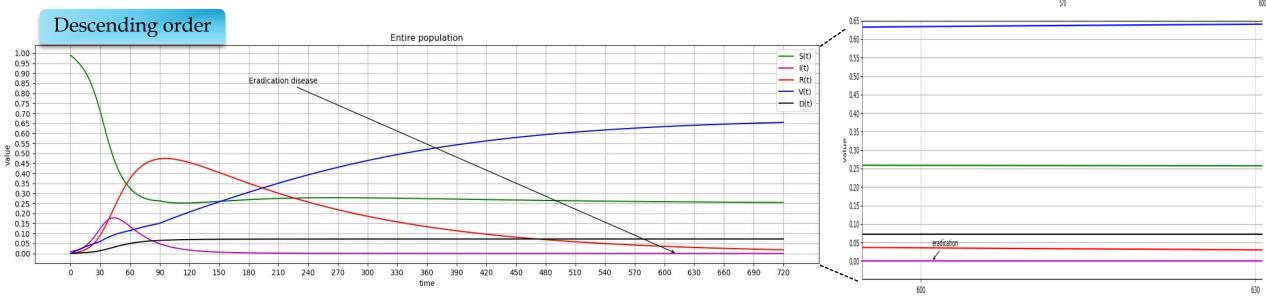
Coarse-grained analysis

## Eradication disease

Ascending	Children	Teenagers	Adults	Senior
$\eta$	0.01	0.01	0.01	0.01
VACC-DAY	0	30	60	90

Descending equal only with reverse order for VACC\_DAY



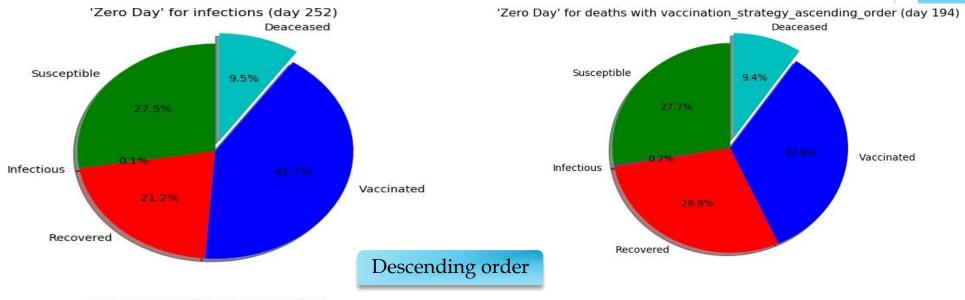


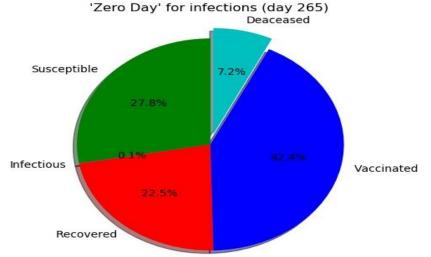
#### Coarse-grained analysis

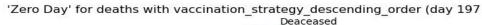
# 'Zero Days'

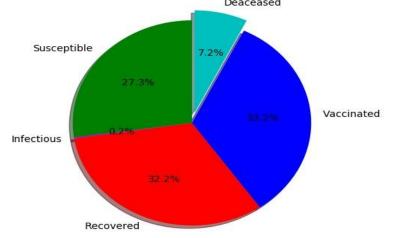
i.e. first day without new infections (or deaths)

#### Ascending order







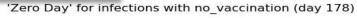


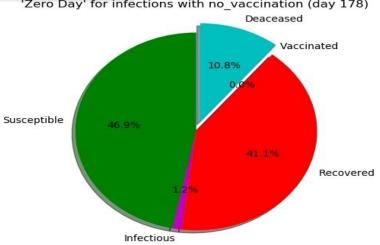
#### Coarse-grained analysis

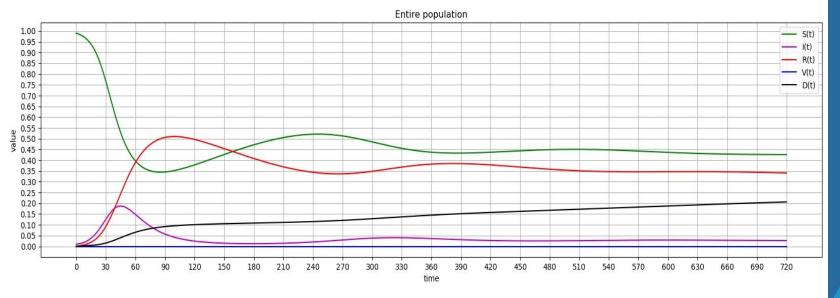
Same Time	Children	Teenagers	Adults	Senior
$\eta$	0.0025	0.0025	0.0025	0.0025
VACC-DAY	0	0	0	0

## **Endemic** infection

#### No vaccination

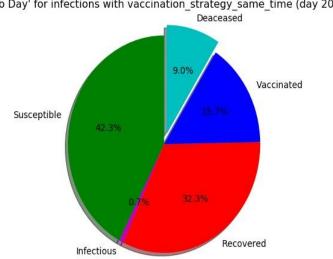


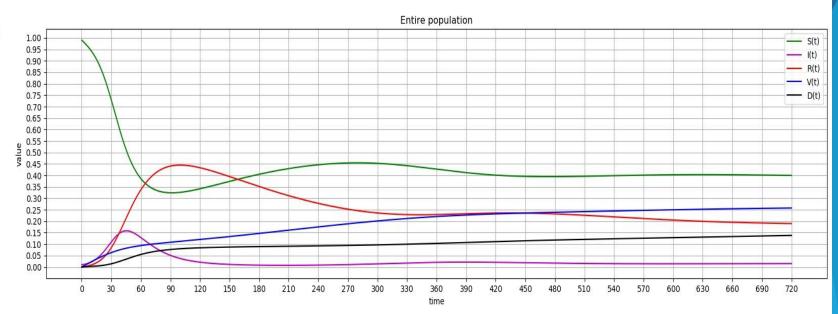




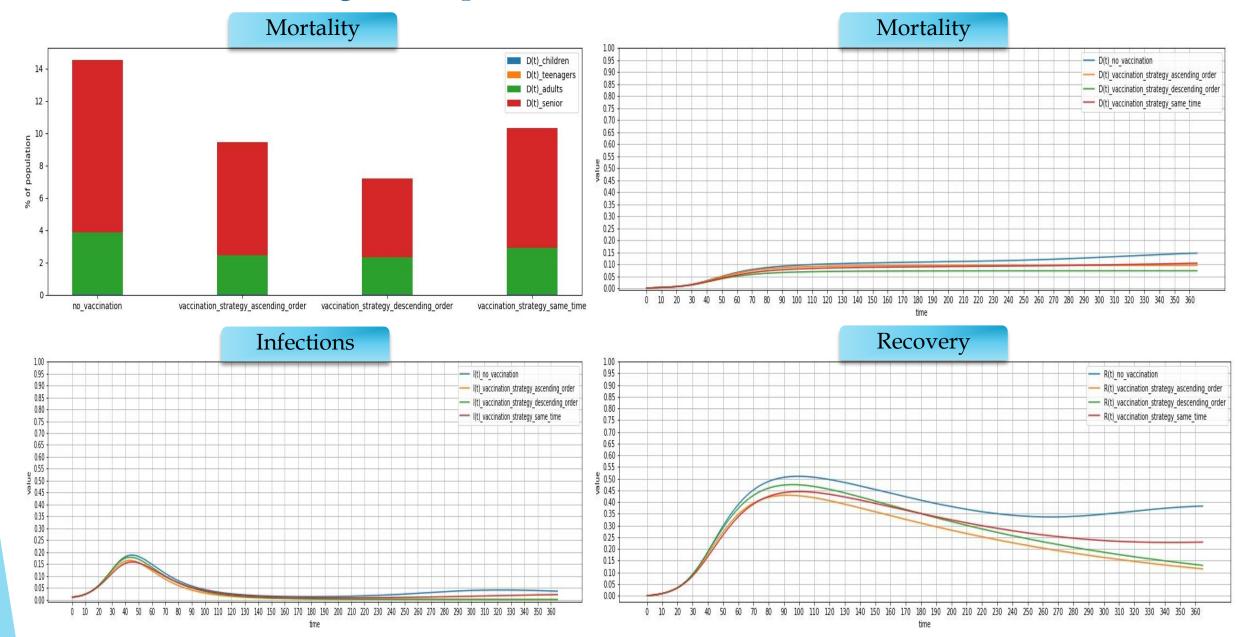
#### Same Time

'Zero Day' for infections with vaccination\_strategy\_same\_time (day 201)





### Final vaccination strategies comparison

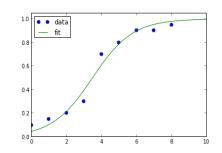


# Final Considerations and Improvements

- This model with ODEs is simple and intuitive and we obtain some expected experimental results
- The model could include compartments like quarantine, intensive care occupation and could take into account the preventive measures used
- Vaccination rate could be described by a logistic function
- Probabilities could be included in the model
- Implement an interactive dashboard with daily measurements
- Parameters estimation and fitting with a real (and accurate) dataset









## References

- Compartmental models in epidemiology Wikipedia, the free encyclopedia
- Modeling Infectious Diseases in Humans and Animals
- <u>Influence of nonlinear incidence rates upon the behavior of SIRS epidemiological models</u>
- Analysis of COVID-19 Data with PRISM: Parameter Estimation and SIR Modelling
- Use of a Modified SIRD Model to Analyze COVID-19 Data
- Global results for an SIRS model with vaccination and isolation
- Mathematical models of contact patterns between age groups for predicting the spread of infectious diseases
- A statistical methodology for data-driven partitioning of infectious disease incidence into age-groups
- <u>Lab24 Coronavirus in Italia, i dati e la mappa</u>
- SIR Modelling with data fitting in Python
- Matplotlib Documentation