# Optimization of Mitigation Strategies during Epidemics using Reinforcement Learning

The rapid spread of infectious diseases such as Covid-19 has devastating societal, economic and political impact. When reacting to events occurring in real-time, approaches based on human decision-making systems usually encounter difficulties in sorting out the most efficient mitigation strategies. We propose a framework for a real-time data-driven decision support tool for policymakers. Our framework is based on a reinforcement learning algorithm meant to optimize governmental responses to the state of the epidemic at each time-step.

## 1 Data Collection

The data are obtained from the following sources:

**Cases and Outcomes:**
Data on Covid-19 cases and their outcomes was collected from Worldometer which pre-processes and collects the data from Centers for Disease Control and Prevention and State governments.
Covid-19 Cases and Outcomes Source

**Vaccinations:**
Vaccination data was collected from Centers for Disease Control and Prevention
Vaccination Data Source

**Hospitalizations:**
Hospitalization data was collected from U.S. Department of Health and Human Services
Hospitalization Data Source

**Testing:**
Testing data was collected from U.S. Department of Health and Human Services
Testing Data Source

**Mobility:**
Mobility was collected from the following sources:

1. Google - Source
   The reports chart movement trends over time by geography, across different categories of places such as retail and recreation, groceries and pharmacies, parks, transit stations, workplaces, and residential.

2. Meta Data for Good - Source
   There are two metrics, Change in Movement and Stay Put, that provide a slightly different perspective on movement trends. Change in Movement looks at how much people are moving around and compares it with a baseline period that predates most social distancing measures, while Stay Put looks at the fraction of the population that appear to stay within a small area during an entire day.

**Economic Effects:**
The data on economic effects of the pandemic and government responses was collected from the PREMISE - Source
The data contains people's responses about:

- Closure of non-essential businesses
- Concern of short-term (30 days) and long term negative impacts of the pandemic
- Change in income because of the pandemic
- Impact of sudden increase in prices of goods and services because of the pandemic

**Behavioral:**
Behavioral Indicator data was collected from "The Delphi Group at Carnegie Mellon University and University of Maryland COVID-19 Trends and Impact Surveys, in partnership with Facebook; Kaiser Family Foundation; YouGov COVID-19 Behaviour Tracker survey."

This data includes the following:

1. **Mask use:** estimated percentage of the population who say they always wear a mask in public.
   Source
2. **Vaccine Acceptance:** estimated percentage of the population who have received a vaccine, have a vaccination appointment or are willing to get vaccinated.
   Source
3. **Social Distancing:**
   Source
   - **In-person School Full-time:** estimated percentage of people whose oldest child is attending in-person school on a full-time basis.
   - **Shop Indoors:** estimated percentage of people who went to an indoor market, grocery store, or pharmacy in the last 24 hours.
   - **Public Transit:** estimated percentage of people who used public transit in the last 24 hours.
   - **Work outside Home:** estimated percentage of people who worked or went to school outside their home in an indoor setting in the last 24 hours.
   - **Spent Time Indoors:** estimated percentage of people who spent time indoors with someone who is not living with them in the last 24 hours.
   - **Indoor dining:** estimated percentage of people who went to an indoor restaurant, bar or cafe in the last 24 hours.
   - **Large Event Indoors:** estimated percentage of people who attended an indoor event with more than 10 people in the last 24 hours.
   - **Travel Outside State:** estimated percentage of people who traveled out of their state in the last 7 days.
4. **Government Handling:** estimated percentage of people who think the government is handling the issue of coronavirus "very" or "somewhat" well.
   Source
5. **Confidence in Health Authorities:** estimated percentage of people who have "a lot" or "a fair amount" of confidence in the health authorities to respond to coronavirus.
   Source
6. **Personal Measures:**
   Source

   Data includes the percentage of people:

   - Avoiding crowded public places
   - Avoiding in-person work
   - Stopping sending children to child care or school
   - Improving personal hygiene
   - Refraining from Touching Objects in Public
   - Avoiding physical contact with tourists

7. **Support for government policies:**
   [Source]
   Data includes the percentage of people who say they would support their government:
   - Quarantining anyone who has been in contact with a contaminated patient
   - Quarantining any location in country that a contaminated patient has been in
   - Encouraging companies to allow people to work from home
   - Temporarily closing schools
   - Cancelling large sporting events
   - Cancelling routine hospital appointments and operations
   - Stopping all inbound flights into country/region
   - Quarantining all passengers on all flights coming into country/region

# 2 SEIHRD Epidemiological Model

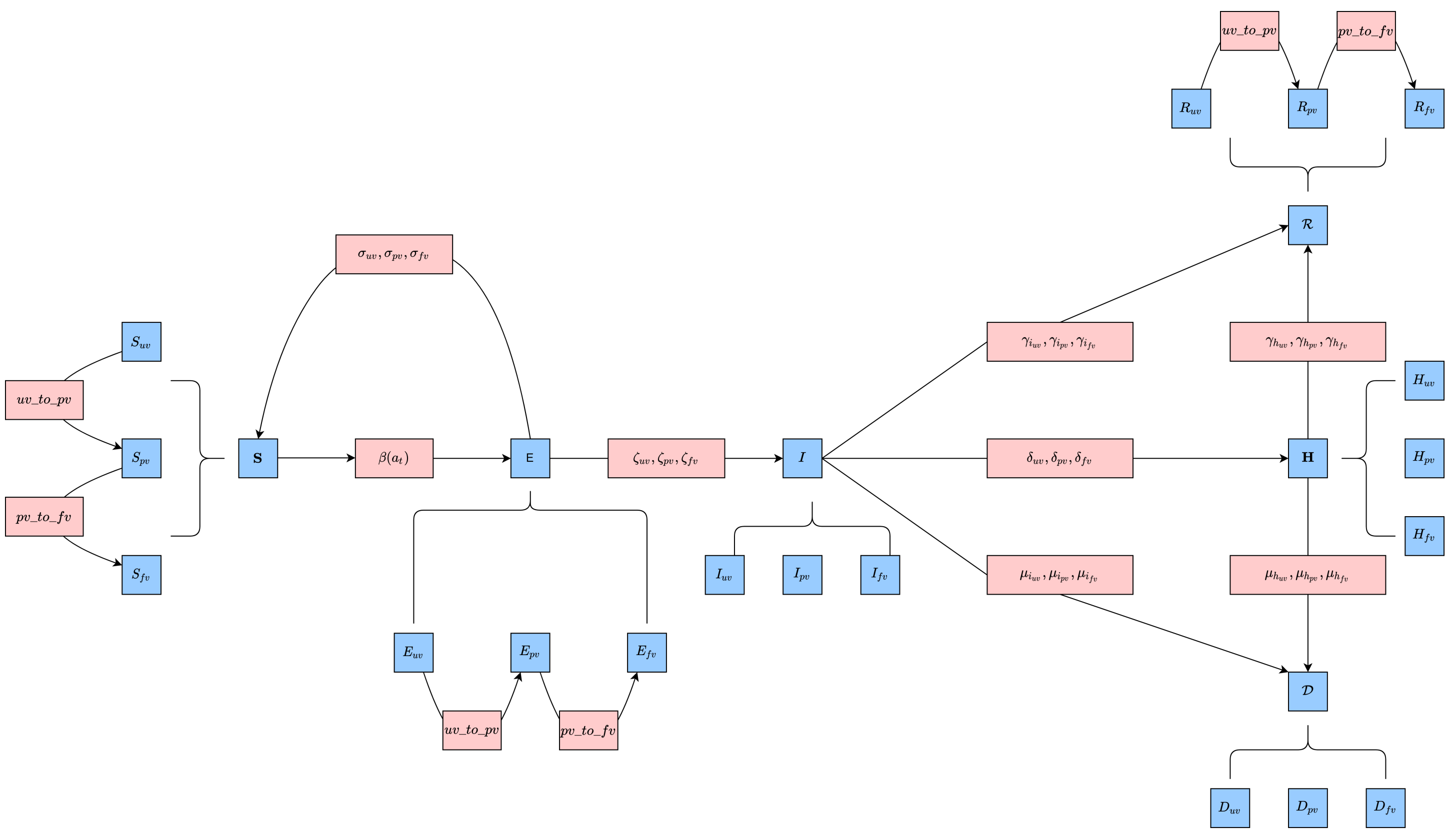


Figure 1: SEIHRD Epidemiological Model

The SEIHRD epidemiological model is a compartmentalized model with the following compartments:

1. **Susceptible:** Individuals who are healthy and susceptible to getting infected
2. **Exposed:** Individuals who are exposed to the virus
3. **Infected:** Individuals who have been infected
4. **Hospitalized:** Individuals who have been hospitalized as a result of being infected
5. **Recovered:** Individuals who have recovered from the infection
6. **Deceased:** Individuals who have died from the infection

At any time individuals can belong to only a single compartment and can move from one compartment to another as per the above figure.

Subscript **uv** denotes individuals who are unvaccinated.
Subscript **pv** denotes individuals who are partially vaccinated.
Subscript **fv** denotes individuals who are fully vaccinated.

**uv_to_pv**: Rate at which unvaccinated individuals get partially vaccinated.
**pv_to_fv**: Rate at which partially vaccinated individuals get fully vaccinated.

**S**: Susceptible individuals.
$\sigma_{\mathbf{uv}}$: Rate at which exposed unvaccinated individuals become susceptible.
$\sigma_{\mathbf{pv}}$: Rate at which exposed partially unvaccinated individuals become susceptible.
$\sigma_{\mathbf{fv}}$: Rate at which exposed fully unvaccinated individuals become susceptible.

**E**: Exposed individuals.
$\beta_{\mathbf{a_t}}$: Rate at which individuals get exposed. This depends on a lot of factors including but not limited to Social Distancing Mandates, Number of active infections, changes in mobility, population mask use.

**I**: Infected individuals.
$\zeta_{\mathbf{uv}}$: Rate at which exposed unvaccinated individuals become infected.
$\zeta_{\mathbf{pv}}$: Rate at which exposed partially unvaccinated individuals become infected.
$\zeta_{\mathbf{fv}}$: Rate at which exposed fully unvaccinated individuals become infected.

**H**: Hospitalized individuals.
$\delta_{\mathbf{uv}}$: Rate at which infected unvaccinated individuals get hospitalized.
$\delta_{\mathbf{pv}}$: Rate at which infected partially unvaccinated individuals get hospitalized.
$\delta_{\mathbf{fv}}$: Rate at which infected fully unvaccinated individuals get hospitalized.

**R**: Recovered individuals.
$\gamma_{\mathbf{i_{uv}}}$: Rate at which infected unvaccinated individuals recover.
$\gamma_{\mathbf{i_{pv}}}$: Rate at which infected partially vaccinated individuals recover.
$\gamma_{\mathbf{i_{fv}}}$: Rate at which infected fully vaccinated individuals recover.
$\gamma_{\mathbf{h_{uv}}}$: Rate at which hospitalized unvaccinated individuals recover.
$\gamma_{\mathbf{h_{pv}}}$: Rate at which hospitalized partially vaccinated individuals recover.
$\gamma_{\mathbf{h_{fv}}}$: Rate at which hospitalized fully vaccinated individuals recover.

**D**: Deceased individuals.
$\mu_{\mathbf{i_{uv}}}$: Rate at which infected unvaccinated individuals die.
$\mu_{\mathbf{i_{pv}}}$: Rate at which infected partially unvaccinated individuals die.
$\mu_{\mathbf{i_{fv}}}$: Rate at which infected fully unvaccinated individuals die.
$\mu_{\mathbf{h_{uv}}}$: Rate at which hospitalized unvaccinated individuals die.
$\mu_{\mathbf{h_{pv}}}$: Rate at which hospitalized partially vaccinated individuals die.
$\mu_{\mathbf{h_{fv}}}$: Rate at which hospitalized fully vaccinated individuals die.

**N**: Total Population.

**Differential Equations for the SEIHRD Epidemiological Model:**

$\frac{dS_{uv}}{dt} = -\beta_{a_t}\frac{S_{uv}(I)^{\alpha}}{N} + \sigma_{uv}E_{uv} - uv\_to\_pv * S_{uv}$ ($\alpha$ is the mixing coefficient to account for imperfect mixing in the population)
$\frac{dS_{pv}}{dt} = -\beta_{a_t}\frac{S_{pv}(I)^{\alpha}}{N} + \sigma_{pv}E_{uv} + uv\_to\_pv * S_{uv} - pv\_to\_fv * S_{pv}$
$\frac{dS_{fv}}{dt} = -\beta_{a_t}\frac{S_{fv}(I)^{\alpha}}{N} + \sigma_{fv}E_{fv} + pv\_to\_fv * S_{pv}$

$\frac{dE_{uv}}{dt} = \beta_{a_t}\frac{S_{uv}(I)^{\alpha}}{N} - \zeta_{uv}E_{fv} - \sigma_{uv}E_{uv} - uv\_to\_pv * E_{uv}$
$\frac{dE_{pv}}{dt} = \beta_{a_t}\frac{S_{pv}(I)^{\alpha}}{N} - \zeta_{pv}E_{fv} - \sigma_{pv}E_{pv} + uv\_to\_pv * E_{uv} - pv\_to\_fv * E_{pv}$
$\frac{dE_{fv}}{dt} = \beta_{a_t}\frac{S_{fv}(I)^{\alpha}}{N} - \zeta_{fv}E_{fv} - \sigma_{fv}E_{fv} + pv\_to\_fv * E_{pv}$

$\frac{dI_{uv}}{dt} = \zeta_{uv}I_{uv} - \gamma_{i_{uv}}I_{uv} - \delta_{uv}I_{uv} - \mu_{i_{uv}}I_{uv}$
$\frac{dI_{pv}}{dt} = \zeta_{pv}I_{pv} - \gamma_{i_{pv}}I_{pv} - \delta_{pv}I_{pv} - \mu_{i_{pv}}I_{pv}$
$\frac{dI_{fv}}{dt} = \zeta_{fv}I_{fv} - \gamma_{i_{fv}}I_{fv} - \delta_{fv}I_{fv} - \mu_{i_{fv}}I_{fv}$

$\frac{dH_{uv}}{dt} = \delta_{uv}I_{uv} - \gamma_{h_{uv}}H_{uv} - \mu_{h_{uv}}H_{uv}$
$\frac{dH_{pv}}{dt} = \delta_{pv}I_{pv} - \gamma_{h_{pv}}H_{pv} - \mu_{h_{pv}}H_{pv}$
$\frac{dH_{fv}}{dt} = \delta_{fv}I_{fv} - \gamma_{h_{fv}}H_{fv} - \mu_{h_{fv}}H_{fv}$

$\frac{dR_{uv}}{dt} = \gamma_{i_{uv}}I_{uv} + \gamma_{h_{uv}}H_{uv} - uv\_to\_pv * R_{uv}$
$\frac{dR_{pv}}{dt} = \gamma_{i_{pv}}I_{pv} + \gamma_{h_{pv}}H_{pv} + uv\_to\_pv * R_{uv} - pv\_to\_fv * R_{pv}$
$\frac{dR_{fv}}{dt} = \gamma_{i_{fv}}I_{fv} + \gamma_{h_{fv}}H_{fv} + pv\_to\_fv * R_{pv}$

$\frac{dD_{uv}}{dt} = \mu_{uv}I_{uv} + \mu_{h_{uv}}H_{uv}$
$\frac{dD_{pv}}{dt} = \mu_{pv}I_{pv} + \mu_{h_{pv}}H_{pv}$
$\frac{dD_{fv}}{dt} = \mu_{fv}I_{fv} + \mu_{h_{fv}}H_{fv}$

## 3 Epidemiological Model Data Pre-processing

While we have the data for number of infected, hospitalized, recovered, deceased individuals, and we can infer the number of susceptible individuals, we do not have the data for number of people who were possibly exposed to the virus and we do not have data on the level of detail specifying how many individuals in the various epidemiological compartments were unvaccinated, partially vaccinated, or fully vaccinated.

**Exposed Compartment:**
We use a heavily cited study published in the The Journal of the American Medical Association to approximate the number of exposed individuals. In this case-ascertained study of 100 cases of confirmed COVID-19 and 2761 close contacts, the overall secondary clinical attack rate (the ratio of confirmed cases among the close contacts) was 0.7%. Thus, we can now use this information to estimate the number of exposed individuals based on the number of new cases we get each day.
To do this we simply multiply the number of new cases each day by $\frac{100}{0.7}$. This gives us the estimated total number of exposed individuals on any given day.

Exposed = New Cases * $\frac{100}{0.7}$

We then split this into groups by their vaccination status. To do this we simply divide the total number of exposed individuals into the different vaccination groups by the ratio of the vaccination groups to the total population. Here we make the assumption that all vaccination groups have equal probability to get exposed to the virus.

Exposed$_{uv}$ = Exposed * $\frac{number\_of\_unvaccinated\_individuals}{population}$

Exposed$_{pv}$ = Exposed * $\frac{number\_of\_partially\_vaccinated\_individuals}{population}$

Exposed$_{fv}$ = Exposed * $\frac{number\_of\_fully\_vaccinated\_individuals}{population}$

**Susceptible Compartment:**
To get the number of susceptible individuals we simply subtract from the total population the number of exposed, infected, hospitalized, recovered and deceased individuals.

Susceptible = Population - Exposed - Infected - Hospitalized - Recovered - Deceased

We then split this into groups by their vaccination status in the same way as we did for the exposed compartment.

**Infected, Hospitalized, and Recovered Compartments:**
We have the data on the number of infected, hospitalized, and recovered individuals on any given day but we do not have the data on how they are split among the different vaccination groups. We cannot just split them by the proportion of the individuals by vaccination status to the total population as we did for the Exposed and Susceptible compartments as this would mean that vaccination does not have an effect on the probabilities of getting infected, being hospitalized or dying. Thus, it is important for us to skew the data as per the official statistics.

We use a study from the Washington State Department of Health which gives us the statistics of infections, hospitalizations, and deaths by vaccination status. We use these results to then skew our data as follows:

We compute the number of individuals in each compartment according to their vaccination status by both the government skew and the proportional skew (ratio of individuals by vaccination status to the total population). We then choose from the two the value which is lower for every day.

E.g., for calculating the number of Infected individuals who are unvaccinated:
Government Skew = Infected * 0.601 ...(According to the study 60.1% of all Covid-19 cases are from individuals who are unvaccinated)
Proportional Skew = Infected * $\frac{number\_\_of\_\_unvaccinated\_\_individuals}{population}$

Infected$_{uv}$ = Government Skew if Government Skew <= Proportional Skew else Proportional Skew

Now, the reason we do not simply multiply the number of infected individuals by the government skew and use that is because the Government data is averaged based on infections from February 2021 to April 2022. In the beginning when unvaccinated individuals comprised majority of the population almost all cases belonged to unvaccinated individuals. If we would have not considered the proportion of people in the population by vaccination status we would have gotten incorrect results e.g., in the initial stages of the pandemic we would get more people who are infected and fully vaccinated than the total number of fully vaccinated individuals in the population which is not possible.

But by doing this we are have "missing" individuals (this occurs when the government skew is less than the proportional skew) and we have to correct for it.

The way we do that is we account for the total number of "missing" individuals in each compartment.
E.g., for Infected Compartment:
Missing Infected Individuals = Infected - (Infected$_{uv}$ + Infected$_{pv}$ + Infected$_{fv}$)

We also account for the total number of "missing" individuals by their vaccination status:
E.g., for unvaccinated individuals:
Missing Unvaccinated Individuals = Unvaccinated Individuals - (Susceptible$_{uv}$ + Exposed$_{uv}$ + Infected$_{uv}$ + Hospitalized$_{uv}$ + Recovered$_{uv}$ + Deceased$_{uv}$)

We distribute the missing individuals into the various groups based on vaccination status as follows:
E.g., for the Infected and Unvaccinated compartment:
Infected Unvaccinated = Infected Unvaccinated + Missing Infected Individuals * Missing Unvaccinated Individuals / Total Missing Individuals

**Deceased Compartment:**
We have to skew the deceased individuals by the government statistics as well but we cannot do that in the same way we did for Infected, Hospitalized and Recovered compartments because it results in situations where the number of deceased unvaccinated individuals can decrease over time as people get vaccinated (as we incorporate the proportion of individuals by their vaccination status in the total population when skewing the data).

We skew the Deceased compartment for each vaccination status simply by the Government's statistics:
E.g., for Deceased and Unvaccinated Individuals:
Deceased$_{uv}$ = Deceased * 0.672 ...(According to the study 67.2% of all Covid-19 related deaths are from individuals who are unvaccinated)
The approach for skewing the Deceased compartment isn't perfect and I am working on an improvement.

We solve the Ordinary Differential Equations as an initial value problem using the "DOP853" algorithm for the parameters $\sigma_{uv}, \sigma_{pv}, \sigma_{fv}, \zeta_{uv}, \zeta_{pv}, \zeta_{fv}, \delta_{uv}, \delta_{pv}, \delta_{fv}, \gamma_{i_{uv}}, \gamma_{i_{pv}}, \gamma_{i_{fv}}, \gamma_{h_{uv}}, \gamma_{h_{pv}}, \gamma_{h_{fv}}, \mu_{i_{uv}}, \mu_{i_{pv}}, \mu_{i_{fv}}, \mu_{h_{uv}}, \mu_{h_{pv}}, \mu_{h_{fv}}$.

The following figure shows the comparision of our model with the data collected for NY State.

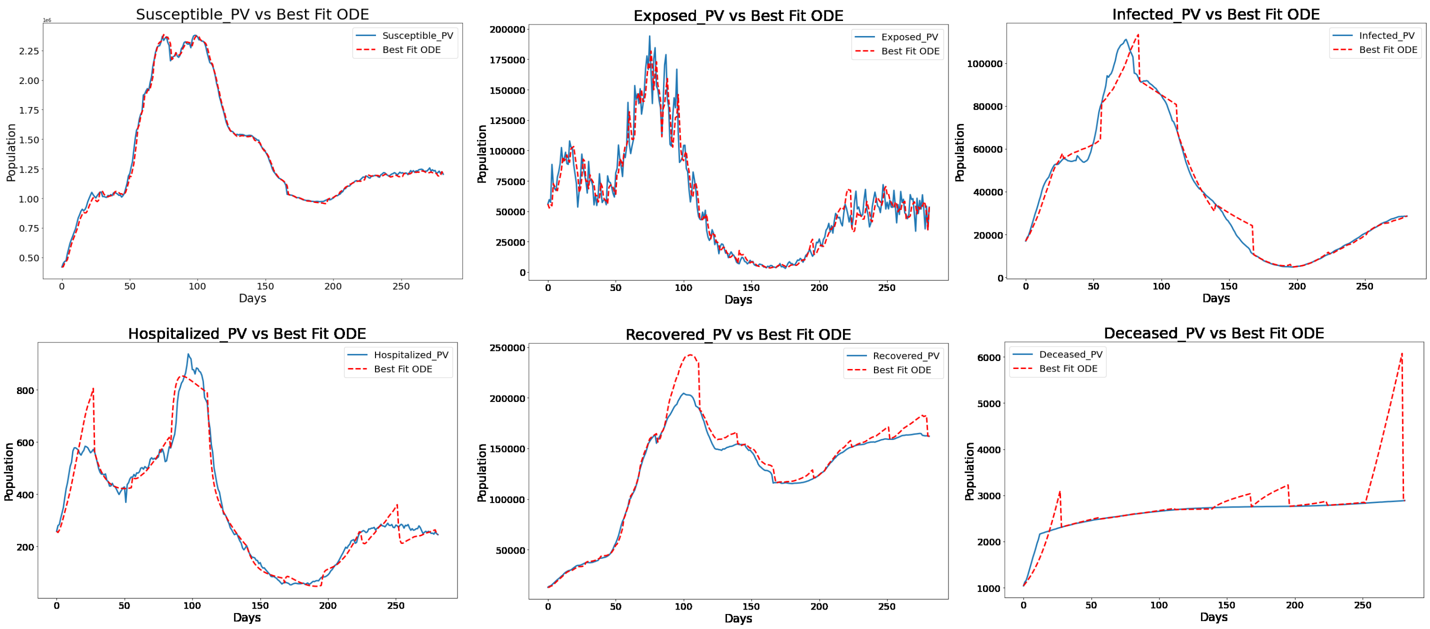


Figure 2: SEIHRD Epidemiological Model vs NY Data

# 4 Reinforcement Learning Environment

This is currently in progress. Here, we aim to set up the SEIHRD epidemiological model in a reinforcement learning environment, setup the different actions the policy makers can take and also incorporating the data on economic effects and people's support of government policies into weighing the rewards.

# 5 Solving the Optimization Problem

This is currently in progress. Here, we aim to solve the task of optimizing the mitigation strategy using a Reinforcement Learning algorithm.

# 6 Paper Writing

This hasn't started yet. I will be writing the paper simultaneously as we work on Part 3 and 4.