Assessing Covid-19 Situation in Vietnam Using a Data-Driven Epidemiological Compartmental Model

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Outline

1. Introduction
2. Literature review
3. Methodologies
4. Results
5. Discussion
6. Conclusion

Outline for Introduction

1 Introduction

The Covid-19 disease

- 230 million infections
- 4.7 deaths
- Economic impacts
- Mental impacts

Why do we need a model?

- Lack of research on the impacts of Non-Pharmaceutical Intervention (NPI) in Vietnam
- Need of a simple tool for assessing the disease current and future progression

Goals

- A model that works with the data availability in Vietnam
- An explainable model that can be used by experts
- Assessment of the effectiveness of mobility data in predicting future cases

Outline for Literature review

2. Literature review
   - Related works
   - Artificial Neural Network

Mathematical models I

Compartmental models [1]

Susceptible-Exposed-Infective-Removed (SEIR) model

$$
\begin{aligned}
S' &= -\beta(N)SI \\
E' &= \beta(N)SI - \kappa E \\
I' &= \kappa E - \alpha I \\
R' &= f\alpha I \\
N' &= -(1-f)\alpha I
\end{aligned}
$$

Mathematical models II

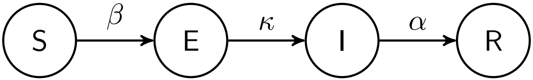

Figure: Graph of transitions between each compartment in the SEIR model

Mathematical models III

Changes made to classical compartmental model for Covid-19 [2]–[6]:

- Inclusion of compartments that represent government interventions
- Inclusion of compartments that specifically represent the behavior of SARS-NCOV-2
- Separation of the infectious compartment into multiple compartments representing the severity of the patients

Mathematical models IV

Agent-based models [7]–[9]

- Model of individualistic behaviors
- Based on population size, age structure, transmission networks

Mathematical models V

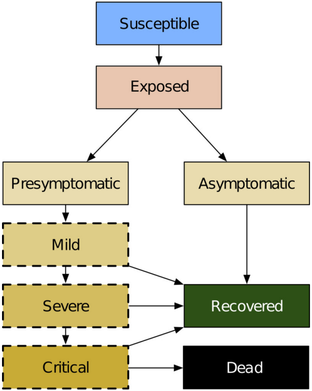

Figure: Agent states used in Covasim [7]

Mathematical models VI

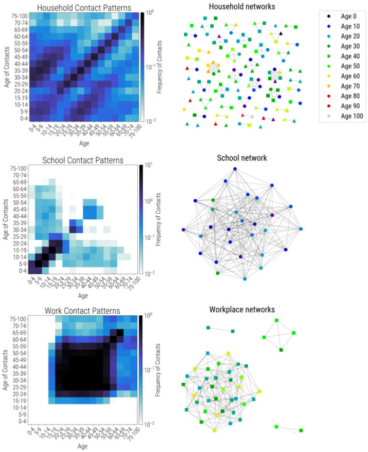

Figure: Transmission networks used in Covasim [7]

Mathematical models VII

Pros

- Explainable
- Based on many years of research
- Easy to understand and implement

Cons

- Low representational capabilities
- The represented dynamics are stationary
- Unrealistic assumptions about real-world scenarios

Data-driven models I

ARIMA models [10]–[12]

- Suitable for modeling changing trends, periodic changes, and random noises
- Suitable for different types of data
- Can capture temporal dependency of time series

Data-driven models II

Deep-learning models [13]–[15]

- Long Short Term Memory (LSTM)
- Bidirectional Long Short Term Memory (Bi-LSTM)
- Gated Recurrent Unit (GRU)

Data-driven models III

Pros

- High prediction accuracy
- Allow for modeling without needing domain knowledge

Cons

- Unexplainable
- Relied on large amount of data
- Inability to capture the true disease dynamics

Novel compartmental models I

Mitigate the disadvantages of compartmental models by incorporating covariates

- using predefined functions based on domain knowledge
- using neural networks

Novel compartmental models II

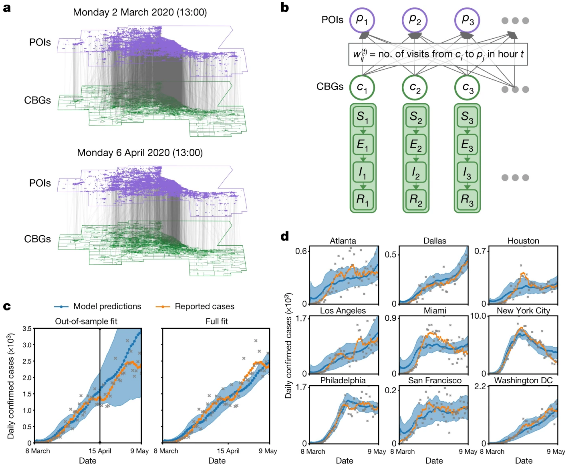

Figure: SEIR model weighted using complex mappings of point-to-point mobility data [16]

Novel compartmental models III

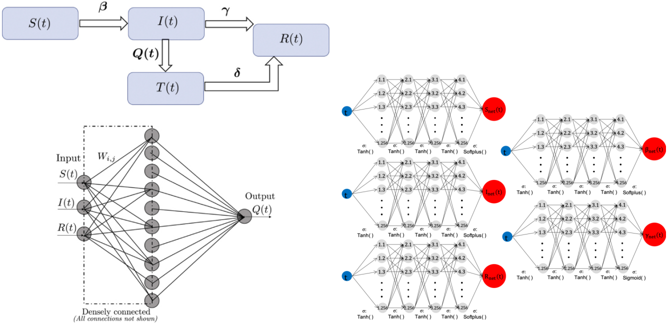

Figure: Using neural networks to predicts the parameters for compartmental models. On the left is the schematic for the QSIR model [17], on the right is the schematic for the time-dependent SIR model [18].

Multi-layer perceptron I

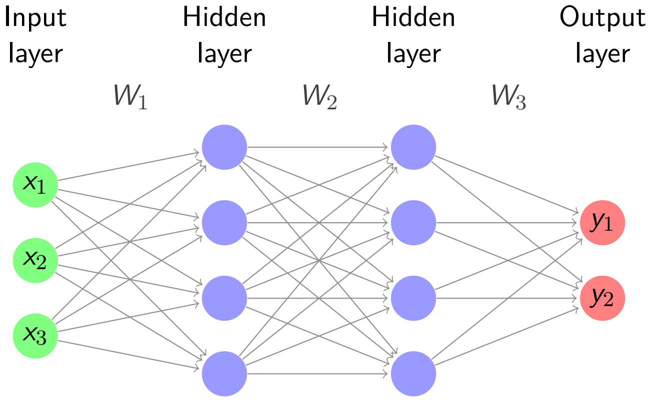

Figure: Graph representation of a multi-layer perceptron with four layers

Multi-layer perceptron II

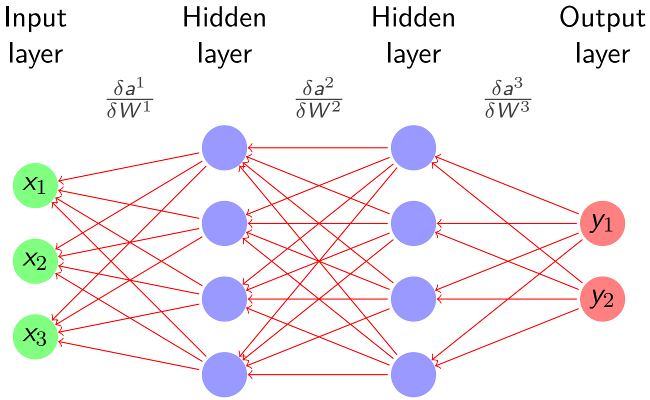

Figure: Graph representation of the back-propagation algorithm on a multi-layer perceptron with four layers

Outline for Methodologies

3 Methodologies

Methodologies

Outline for Results

4 Results

Results

Outline for Discussion

5 Discussion

Discussion

Outline for Conclusion

6 Conclusion

Conclusion

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