Using Machine Learning to drive social learning in a Covid-19 Agent-Based Model

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Abstract.

Disease transmission and governmental interventions influence the spread of Covid-19. Models can be essential tools to optimise these governmental interventions. This requires the exploration of various ways to implement government agent behaviour. In Agent-Based Models (ABMs), government agent behaviour can be rule-based or data-driven, and the agent can be an isolated learner (using only its own data) or a social learner. We explore the creation of a data-driven social approach in which behaviour is based on a Machine Learning (ML) algorithm, and the government considers data from other European countries as input for their decision-making. Governmental actions start with risk perception, based on several parameters, e.g. the number of disease cases, deaths, and hospitalisation rate. The interventions are measured via the stringency index, measuring the simultaneous number of interventions (working from home, wearing a facemask, closing schools, etc.) taken. We test four machine learning algorithms (Bayesian Network (BN), c4.5, Naïve Bayes (NB) and Random Forest (RF)), using a 5-class and a 3-class classification of the stringency level. The algorithms are trained on disease data from many European countries. The best-performing algorithms were c4.5 and RF. The next step is to implement these algorithms into the ABM and evaluate the outcomes compared to the original model.

Keywords. Agent-Based Modelling, Machine Learning, Covid-19

1 Introduction

During the Covid pandemic, we learned that governments play an important role in disease interventions. They can enforce lockdowns, make wearing face masks mandatory and implement vaccination campaigns. Governmental decision-making is based on a strategy of risk perception and coping appraisal. Governments decide on the risk level based on disease incidence, the number of available hospital beds etc. To understand the impact of governmental decisions on disease diffusion, we need to integrate disease models with policy models (Hadley et al., 2021).

Agent-Based Models (ABMs) are good tools for modelling bottom-up disease diffusion and personal decision-making. In many cases, governments are not modelled as agents. When included, governments are modelled as isolated entities that apply rule-based behaviour to decide what interventions to use (Augustijn et al., 2022). However, decision-making might be a more social activity in which governments of various countries collaborate and share experiences.

Social agents are interactive; they communicate with their neighbours (in this case, other European governments) to learn effectively within their groups (Abdulkareem et al., 2020). A complicating factor is that at the pandemic's beginning, nobody had much experience with policies for effective disease control of Covid-19. To simulate this learning process, the intelligence of the government agent should increase during the simulation. This type of learning is best achieved by replacing the rule-based agent decision-making in the ABM with a Machine Learning (ML) algorithm that learns directly from data.

When implementing agent learning via ML, many decisions have to be made concerning the type of ML algorithm, the data used to train the ML algorithm, and the architecture of linking the ML and ABM.

In this research, we take the first step in replacing an isolated government agent that uses rule-based decision-

making with a model where an ML algorithm drives the government agent's decisions for a situation where the exchange of information with other European governments takes place. We do this by testing out several algorithms to depict governmental risk perception.
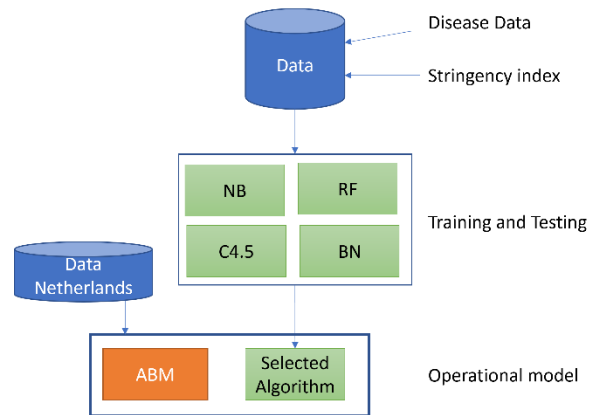
2 Methods

2.1 Agent-Based Model

The ABM is a hybrid compartmental ABM simulating Covid-19 diffusion in the Netherlands (Augustijn et al., 2022). The model contains three sub-models: a population and interaction model, a disease model and a mobility model. The simulated population is divided into nine age categories and split into commuters and non-commuters. The disease diffusion is modelled using a Susceptible, Infected, Recovered (SIR) model using age-dependent transmission rates. Four types of mobility are implemented for different age groups: school commuting, job commuting, gathering and event commuting (GAET) and Visit Travelling (VT). These commuting types match different Covid intervention strategies.

The model contains a government agent that performs risk perception and coping strategies based on the theories of Rogers et al. (1983). Risk is based on two variables: the number of positive tests per 100000 inhabitants per week and the number of hospitalised individuals per day. It recognises five risk levels based on the Road Map used by the Dutch government (Ministerie van Volksgezondheid, 2020). The model was implemented for the Netherlands and predicts the daily number of disease cases for all Dutch municipalities.

2.2 Data

We combined two open-source datasets, one on government interventions (Hale et al., 2021) and one on the number of disease cases in European countries (Edouard Mathieu, 2020). The data provided by Hale et al. (2021) provides a stringency index. This stringency index is based on nine metrics, including school closures, workplace closures and restrictions on all kinds of movements. On a scale of zero to 100, the stringency index expresses the severity of the restricting measures governments apply. We assume that the stricter the measures, the more risk. The stringency index is calculated daily.

Figure 1. The overview of the methods

Risk perception in our ML model is based on three aspects: The number of disease cases per 100000 inhabitants (1), the number of ICUs per 100000 inhabitants (2), and the number of deaths per 100000 inhabitants (3). This does not precisely match the rule-based implementation in the ABM (based on the number of tests and hospitalised individuals). These deviations were made to ensure that the data of the various countries in Europe are as comparable as possible.

To test the ML algorithms, we included daily data from the following countries: Austria, Belgium, Denmark, France, Germany, Italy, Luxembourg, Sweden, Switzerland and the United Kingdom from 1-1-2020 to 9-10-2021.

2.3 Risk Perception

We want to predict based on a limited number of variables (number of disease cases, number of deaths, hospitalisation rate, Intensive care Units (ICUs)) with stringency as the target variable. We classified the stringency in two ways, one set using five stringency classes and the other using three. We used natural breaks for this classification. Although we eventually want to couple this ML model with our ABM, we will perform the test separately to evaluate which algorithm will perform best.

Four algorithms have been selected: Bayesian networks (BNs), decision trees (c4.5), naïve Bayes (NB), and Random Forest (RF). The algorithms have been trained in both 10-fold validation and are split into training and testing datasets (70% and 30%, respectively). With 10-fold cross-validation, the data is split into ten random parts, and the model is trained ten times, using nine parts to train the model and one part to test it. For a 70% - 30% split, 70% of the data will go to the training set and 30% to testing (Xu & Goodacre, 2018).

For all models, we evaluated the accuracy (correctly predicted stringency classes compared to the actual class).

We also evaluate the importance of the features to determine which feature has the highest impact.

2.4 Data and Software Availability

The analyses done for this paper were conducted using the WEKA tool: https://www.cs.waikato.ac.nz/ml/weka/ and the Python Sklearn library. Data and code used in this paper are available and can be accessed via the following DOI: https://doi.org/0.5281/zenodo.7844611.

3 Results

3.1 Data

When we compare the number of cases in the Netherlands to those in other European countries (Figure 1), we see that The Netherlands is somewhere halfway in the graph. Some countries included in our training set have more, and other countries have fewer disease cases.
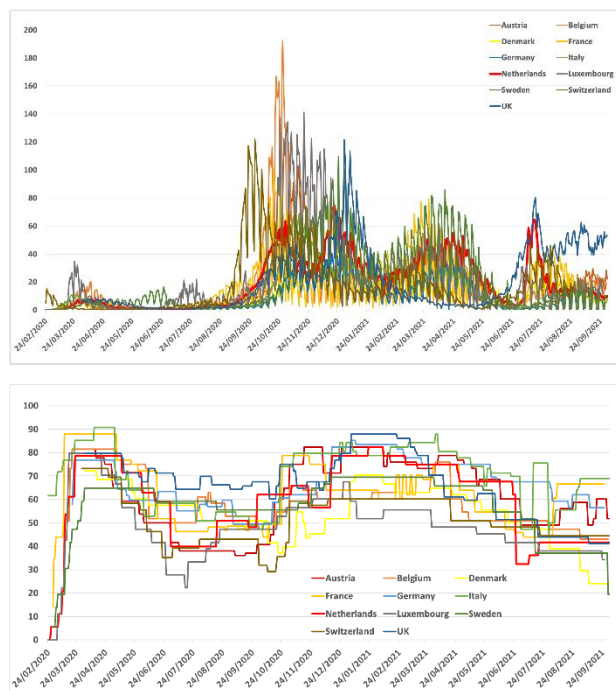
Figure 2. Top: normalized number of infections per country (red is the Netherlands). Bottom: stringency index (red is the Netherlands)

3.2 Results stringency prediction.

Table 1. shows the accuracy of each algorithm per training type. When the algorithms were trained with all five features, the decision trees (c4.5) had higher accuracy when the data was split into 70% for training and 30% for testing. The accuracy was 76%. BNs showed the second-highest accuracy. However, BNs gave a higher accuracy when the algorithm was trained using 10-fold cross-validation (54%).

Table 1. Results.

Stringency classes	Algorithm	Accuracy	
		10-fold cross-validation	Split 70% - 30%
5	BNs	54%	53%
	c4.5	48%	76%
	Naïve Bayes	47%	42%
	RF	49%	44%
3	BNs	52%	50%
	c4.5	60%	49%
	Naïve Bayes	32%	32%
	RF	67%	55%

When three instead of five features were used, RF showed the highest accuracy, followed by decision trees (trained with 10-fold cross-validation) or BNs (trained with splitting data). In all training processes, Naïve Bayes showed the least accuracy (Table 1). This is explainable as Naïve Bayes are effective when there are many features, and their interactions are minimal. The Naïve Bayes algorithm is also sensitive to irrelevant or associated features.

When we evaluate the importance of the features for RF with three stringency classes, this resulted in 0.21 for Disease cases per 100000 inhabitants, 0.41 for Deaths per 100000 inhabitants and 0.38 for ICU per 100000.

4. Discussion

Based on the results in section 3.2, we can conclude that either c4.5 or RF would be the best algorithms. RF outperforms c4.5 when we use three classes, and c4.5 has the best scores for five classes.

The current results are based on models trained on only three features (number of disease cases, number of deaths, and ICUs). The limited number of features was selected due to the original ABM that evaluates risk based on the number of positive tests per 100000 inhabitants and the number of hospitalised individuals. When we look at the importance of the features (RF), we see that the number of disease cases has the smallest impact. We used the daily number of disease cases in our test. A possibility would be to calculate weekly disease cases to come closer to the original model.

We also note that the number of deaths is not included in the original model, yet, it has the highest impact on our model. A re-evaluation of the rule-based model needs to occur, and other indicators besides the number of positive tests and hospitalised individuals should be considered.

Our ultimate aim is to integrate ML into our ABMs to create learning. In our case, the government agent should gradually learn how much risk there is and how to best cope with this risk (select interventions). Our aim is not to create the most intelligent model, as this would ignore the learning aspect.

When we link the ML with the ABM to steer the government agent decisions, we will use a partly trained ML algorithm or add data gradually to improve the model's intelligence. Stopping the algorithm to retrain with new data and then resuming the simulation is possible with Random Forest. It should also be noted that the ultimate aim is to simulate disease cases and not stringency. This can only be achieved by linking the two models, and the impact of risk perception on disease diffusion still has to be evaluated.

In conclusion, RFs can be the best candidate to be integrated with the government agent for steering behaviour. This is because the relation between the features is well-defined and straightforward. In addition, RFs can avoid overfitting because it creates multiple decision trees and then averages their predictions. This usually gives stable and accurate results. Moreover, by assessing each feature's significance based on the decrease in prediction error when it is present, RFs can offer better feature selection.

The next step is to implement the trained algorithm into our ABM model. As we already have a model without social learning (government as an isolated agent), we can compare the new output (number of disease cases) with our previous results. This new output will represent a hypothetical situation in which the Dutch Government would have taken decisions on intervention measures in a completely transparent European setting, taking the experience of all other European governments into account. These results will help to find the optimal decision-making strategy for future pandemics.

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