Exercise 06

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Simulating epidemic evolution through the use of parameter estimation with machine learning

Simulations of epidemiological development can be used to plan interventional actions in the course of a disease outbreak.
These simulations require knowledge about the disease to properly predict its behavior. Unfortunately these properties may not be known initially (as is the case with the COVID-19 pandemic) and thus need to be estimated. ~~There are several papers addressing this question, in particular a paper by Radev et al. [] that uses a machine learning algorithm to estimate the prior distribution of model parameters. Other papers such as [] or [] also model epidemiological dynamics, however using simpler statistical methods for parameter estimation.~~ Radev et al. [4] use a Bayesian inference model in combination with a epidemiological simulation to estimate disease characteristics and their prior distributions. Other papers by Annan et al [1], Antonini et al [2] or He et al [3] propose different models for simulation and more classical approaches to parameter estimation.

A more precise description of the papers

~~We would attempt to create a suitable model for simulating the COVID-19 pandemic starting from the cited papers.~~
~~To achieve this we would need to create a pandemic model [11], [1], [6] and then estimate its parameters.~~
~~We plan to do this estimation through the use of the a *BayesFlow* network architecture [13], the pandemic model itself would be a system of linear differential equations. We could make a comparison between the machine learning approach [11] and 'classical' approaches [1], [6].~~

We would attempt to recreate the work of Radev et al. and apply it to the latest data from different countries. Additionally we would like to modify the epidemiological simulation by adding new parameters, for example parameters that have become relevant only recently such as vaccination

rate.
We would orientate ourselves heavily on [4] for parameter estimation via the *BayesFlow* network architecture (Szegedy et al. [5]). All the papers cited above can be used to create modifications of the epidemiological simulation used by Radev et al.

More precise goals

The data required for this project is widely available to the public provided usually by governmental agencies.
Most European governments publicise infection numbers daily and time series for Germany (as a possible target for simulation) are available at https://bit.ly/3qVDvP0.
~~Data quality can be of concern as reporting, testing and other standards changed in the course of the pandemic.~~

This is taken into account by the simulations

As with the other project we could use Google Collab or other cloud GPU services, this might not be necessary however, because the *BayesFlow* model is not terribly big and can be trained on a regular machine within reasonable times.

~~Possible difficulties we expect are the adaptation of the learning model to changes in the simulation model and inconsistencies in data acquisition, as stated above.~~ It will be interesting to see how the models react to new parameters and data from different countries. How well the estimates for the new parameters will be is to be seen.
One possible difficulty is the emergence of new COVID-19 strains that may significantly change disease characteristics and lead to less precise parameter estimates.

References

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[3] Shaobo He, Yuexi Peng, and Kehui Sun. Seir modeling of the covid-19 and its dynamics. *Springer Nature*, 2020.

[4] Stefan T. Radev, Frederik Graw, Simiao Chen, Nico T. Mutters, Vanessa M. Eichel, Till Bärnighausen, and Ullrich Köthe. Model-based bayesian inference of disease outbreak dynamics with invertible neural networks. Oct, 2020.

[5] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich. Going deeper with convolutions. *IEEE conference*, 2015.