CSE 8803 EPI: Data Science for Epidemiology, Fall 2022

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Lecture 18 : Forecasting IV

1 Introduction

Forecasting plays an important role during the course of an epidemic. It prepares hospitals to scale up their resources for an impending spike in cases, allows governments to set guidelines to reduce the impact of these spikes, and prepares people to take extra precautionary measures to reduce the spread of disease. This makes epidemic forecasting an important area of research.

In this lecture, we first look at the benefits of combining the results of multiple forecasting models to receive results of higher accuracy compared to just using the models by themselves, known as ensemble models. We then proceed to take a closer look at epidemic forecasting in practice, as well as open challenges in the field of epidemic forecasting.

2 Ensembles

2.1 Wisdom of Crowds

The Wisdom of Crowds phenomenon leverages information from multiple groups of people to make better predictions, and has shown to be better than depending on a few experts to make the same predictions.

This phenomenon is used widely in predicting elections and even sports betting, where making correct predictions can be awarding. It basically works by taking a vote of the crowd, and the most highly voted prediction is considered to be the final prediction.

WoC is used in other fields like Prediction markets (ex: elections, stock market). With prediction markets, if we can aggregate the predictions made by people (either laymen or healthcare workers), we will get good prediction accuracy. In the paper (Polgreen+, Clinical Infect. Diseases 2007), participants are not necessarily laymen and they will bet into 5 bins. In a larger study with 562 participants, over +15 months (Sell+, BMC Public Health 2021), we can see the crowd's predictions is better than the chance predictions. If we ask the crowd for sufficiently near predictions, they will be able to predict well when compared to the predictions much farther into the future.

2.2 Epidemic Forecasting

Combining the predictions of several models has been shown to provide better forecasts than a single model. Ensemble models have been shown to be effectively forecast epidemics in various disease like the flu [3], dengue [1] and ebola [4]. In a field as important as epidemic forecasting, which has a wide audience of people depending on these forecasts, high-quality forecasting increases the confidence of the public to depend on them. It is important to note that the ensemble may not perform better than its components at every step of the

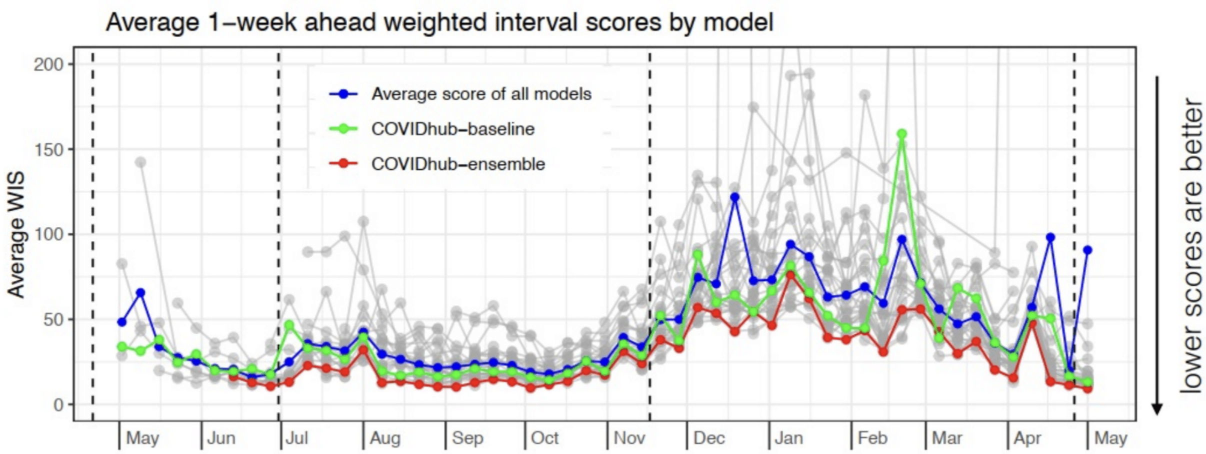

Figure 1: WIS scores of ensemble vs. other models [2]

epidemic, but they have been shown to perform better on average.

There are certain pros and cons when using hybrid models. Some pros include the extension in the capabilities of modeling paradigms, and being able to seamlessly incorporate multimodal data. Some cons include the fact that expert knowledge in mechanistic models and/or predictions can be very wrong and that What-if forecasting from features may be misleading. This introduces us to a few open research question associated with this model, like when should the expert knowledge be trusted and why can we not ensure parameters will change in the right direction.

2.3 Optimality

The optimal ensemble has its component forecasts weighted, and is robust, which means that it doesn't "explode" based of a component's bad prediction. The ensemble which has variations on a weighted median is found to satisfy both of these qualities. The table below depicts the same.

3 Epidemic Forecasting in Practice

3.1 Collaborative Initiatives

Collaborative forecasting initiatives involve several countries working together to forecast diseases in different countries, with the CDC taking initiative to conduct these collaborations.

Another form of collaboration is through forecast hubs, where multiple groups of researchers develop these forecasts and submit them to a common hub, where people can access these forecasts to make decisions.

The FluSight challenge was well known as the goal was on how to make the best visualization. The COVID-19 ForecastHub is also well-known and is where the US started

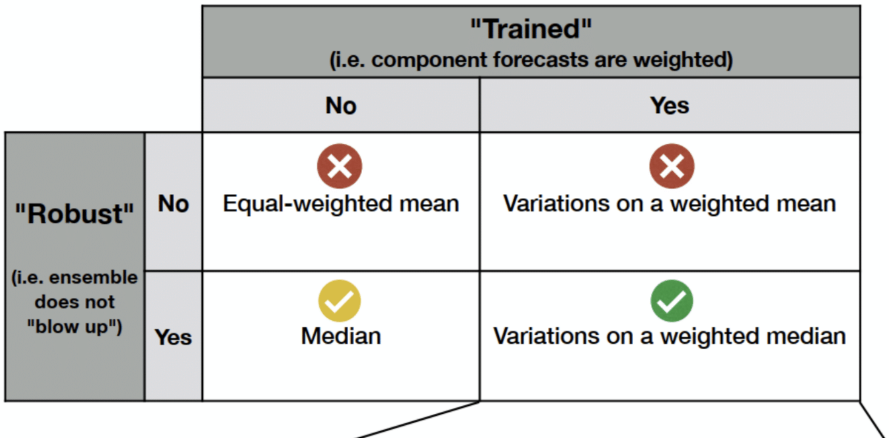

Figure 2: The qualities of an optimal ensemble [2]

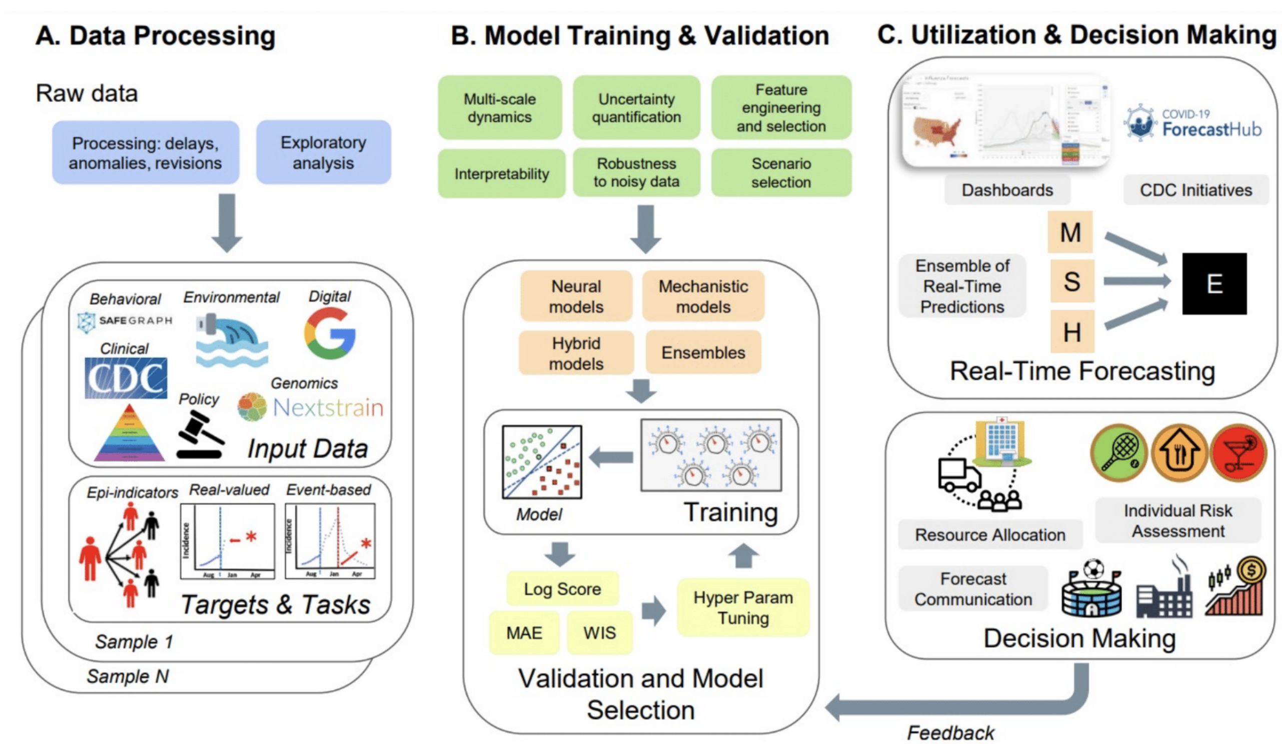

Figure 3: Epidemic Forecasting Pipeline [2]

scenario forecasting and aggregating/ensembling long term projections. But, with scenarios, how do you measure accuracy and pick the best performing model? There has been lots of efforts to standardize real-time forecast submissions so that these can be adapted to other diseases.

3.2 Experiences of Individual Forecasters

With the FluSight challenge, since this was a real-time mechanistic model, it was not ideal for short-term forecasts because there were too many factors associated with ILI as ILI is a composite figure (statistic amalgamation of different factors).

The cons of these competitions include that post-processing can be used to get better scores and that there are data quality issues. Other data challenges include the fact that pipelines need to be constantly and consistently checked and temporal/spacial misalignment (delays and difference in granularity). Dealing with collection/reporting errors, adapting to revisions and anomalies, data privacy, unrealistic longer-term and what-if predictions of ML models, scientific AI, and causal ML and reinforcement learning (RL) are also other data-related challenges. Reinforcement learning is hard to actually implement, and we struggle to figure out how to actually impart knowledge to your ML models

3.3 Bridging Forecasting with Decision Making

Epidemic forecasting is only useful when critical decisions are made by leveraging the knowledge we gain from them. Short-term forecasts can help hospitals prepare for tactical supplies like hospital beds and healthcare worker resources. They also help the government to make decisions on whether to heighten public restrictions to reduce the spread of disease.

The decision making problem is an interesting area of research, where we can make decisions based on the forecast. Using what-if scenarios combined with forecasting data, decisions can be outputted based on the scenario which occurs. Reinforcement learning can be leveraged to make these decisions. They can also optimally allocate resources based on the forecast. Ideally, we'd create an end-end pipeline which is able to generate forecasts, and finally output decisions. However, this is an extremely hard problem to solve.

3.4 Open Challenges

- In reality, the data we get from multiple sources for forecasting is often fraught with errors, so we need to accordingly adapt our models to handle such data.
- Data which has been modified to respect privacy laws can often introduce flaws, so handling such data needs to be further researched.
- Data from rural areas is often fraught with errors, so correcting this data is important.
- In the wake of privacy laws, accessibility to data has diminished. It must be made easier to access this data while respecting the laws.
- While statistical/machine learning models achieve good results in the short-term, the long-term results are not as good, especially compared to mechanistic models. These need to be improved.

- While mechanistic models perform well, we need to find ways to improve their performance by finding ways to incorporate exogenous variables, hopefully increasing their effectiveness.
- Being able to combine statistical and mechanistic models could improve results, by improving short-term and long-term predictions.
- Although it is extremely hard, incorporating reinforcement learning to make decisions would be extremely beneficial.
- We need to find ways to better deal with different temporal and spatial scales, which come from the diverse set of data available.
- There is still room for improvement in the field of ensembles, and feeding useful data to them can improve their effectiveness.
- Determining the source of uncertainty, whether it be from the model or the data, can improve our forecasting.
- While statistical forecasts make good predictions, they are not explainable. Being able to make them explainable would increase the trust of these models amongst the public.

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