CSE 8803 EPI: Data Science for Epidemiology, Fall 2023

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Lecture 15 : FORECASTING I

1 Summary

So far we have looked at methods of modeling diseases, detecting outbreaks, and surveilling their spread. The next step here is to use our modeling of the network and surveillance techniques to try to predict the future of the disease spread. Predicting disease spread is essential for making informed public policy decisions and taking action to minimize the impact of the disease on the population. While the influx of large data collection sources has accelerated research into real-time epidemic forecasting, it is imperative to incorporate the different causal factors while forecasting to ensure accurate predictions.

Epidemic Forecasting can be split into different categories based on the tasks in hand, indicators of interest, and the spatial/temporal scale. These categories also dictate how we evaluate our model's forecasts. We further look into hybrid models which combine the previously discussed mechanistic models with machine learning methods. These models are able to efficiently utilize the variety of datasets available while incorporating the domain-based prior knowledge of mechanistic models.

2 Why Forecasting?

Forecasting diseases is very similar to weather forecasting in the sense that it gives people a sense of what to expect. Additionally, it allows governments to prepare medical resources and make informed public policy decisions, such as allocating budget for ventilators or placing mandates. Not just the government, at some level an individual is a stakeholder too. We make many decisions based on weather forecasts and similarly having insights about public health we would be able to take that into consideration when making a decision. The importance of forecasting makes it crucial that it is accurate and incorporates the different causal factors.

The causal factors mainly are -

- Current Number of Infections
- Interventions in place
- Contact patterns
- Exposure to disease

The advent of social media and communication technologies has brought along vast amounts of data which at first sight might seem unrelated to epidemics but, in fact, are very useful. Google Search Trends, Facebook's Covid Impact Survey, and Safe Graph's mobility data are just some of the examples of different types of data available and are an *indirect* measure of the causal factors. Advancements in machine learning have also made models capable of ingesting such data readily available. Example citation [1]. There are non-linearities in data that traditional methods like ODE model and agent-based methods can't handle.

3 Epidemic Forecasting

The epidemic forecasting pipeline typically consists of data processing, model training & validation, and utilization & decision-making components, as shown in Fig. 1. This section focuses on the objectives of model training & validation. Specifically, we will discuss the following four aspects sequentially: Forecasting Tasks, Targets of Interest, Spatial and Temporal Scale, and Model Evaluation.

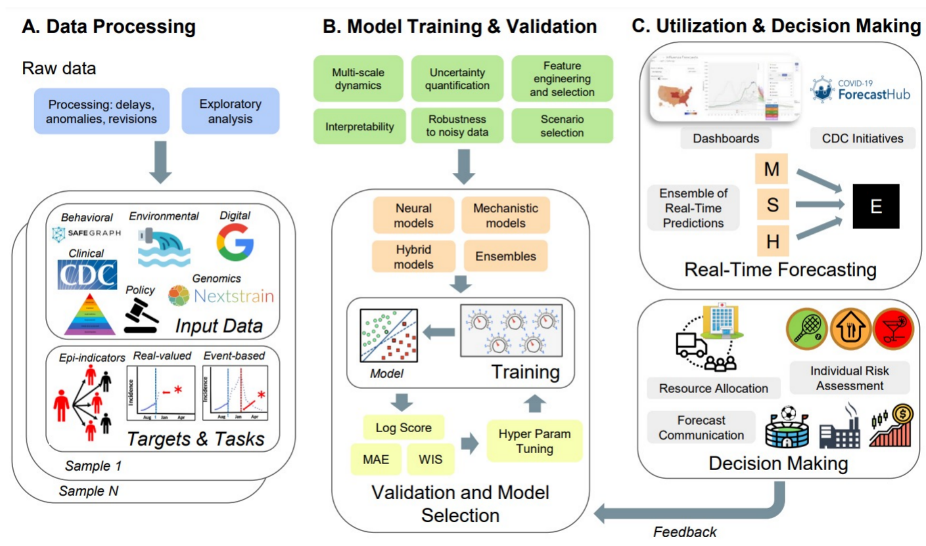

Figure 1: The illustration of epidemic forecasting pipeline

3.1 Forecasting Tasks

Forecasting tasks can be broadly separated into three categories:

- **Real Valued Predictions** - look at epidemic indicators like mortality rate and cases to try and understand the trend of the disease. These can be predicting the future values or the peak intensity of the epidemic. For example, during the COVID-19 pandemic, real-valued predictions were used to estimate the number of infections and deaths in different countries. This information was crucial for governments and health organizations to allocate resources and implement containment measures.

  Since much of the dataset is updated 1–3 weeks in the past, such delays in data make now casting useful. Short-term forecasting helps increase preparedness, while long-term forecasting, although challenging, can help us understand how the epidemic is going to pan out. However, long-term predictions may not be useful, since there may be some policies implemented or interventions that might take place that would change the curve completely. They have some silent assumptions that kind of make them a projection itself.

- **Event-based Predictions** - look into events such as peak-time and onset time, which are indicators of the intensity of the epidemic [4]. These events are used as signals for interventions like shutting off schools and vaccination drives. For instance, during the H1N1 influenza pandemic in 2009, event-based predictions were employed to determine the best time to close schools and initiate vaccination campaigns.

- **Epidemiological indicator Predictions** - look into the composite indicators that characterize the behavior of the epidemic, like the reproduction number and the final infected size [2]. These indicators help in understanding the potential spread and severity of an epidemic. For example, during the Ebola outbreak in 2014, epidemiological indicator predictions were used to estimate the basic reproduction number (R0) and the final infected size. This information was valuable in guiding public health response and intervention strategies.

3.2 Targets of Interest

The epidemic growth can be analyzed by looking at indicators such as number of cases, mortality, and hospitalizations. These indicators, although might not always be accurate because during the COVID season, Influenza %ILI might get mixed with symptomatic COVID outpatients, so additional indicators like lab-tested hospitalizations would be needed as shown in Fig. 2.

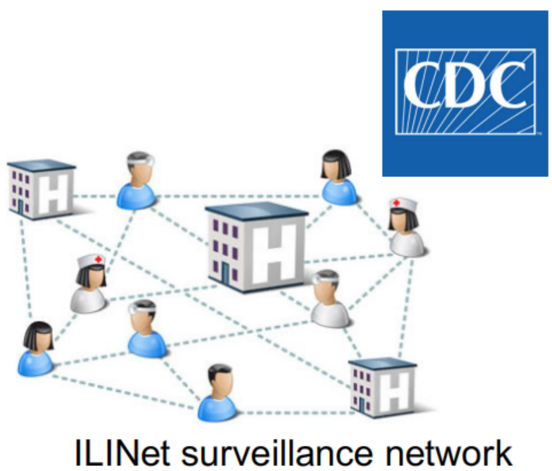

Figure 2: The illustration of an influenza-like illness surveillance network.

3.3 Spatial and Temporal Scales

Forecasting of epidemics is done on different spatial granularity [3]. Regions are grouped together to make monitoring and reporting easier. For example, during the COVID-19 pandemic, forecasts were made at various spatial levels, such as global, national, and even regional or city levels. This allowed authorities to identify hotspots, allocate resources effectively, and implement targeted interventions.

Additionally, forecasts are made for different time scales like weekly and daily. For instance, the Centers for Disease Control and Prevention (CDC) in the United States provides weekly forecasts of COVID-19 cases, hospitalizations, and deaths. On a daily basis, the World Health Organization (WHO) updates its COVID-19 dashboard with the latest data on cases and deaths worldwide. These varying time scales help policymakers and public health officials assess the current state of the epidemic, monitor trends, and evaluate the effectiveness of interventions. Generally, the more you aggregate data either spatially or temporally, the more your model becomes robust.

3.4 Model Evaluation

The next most important step after training models is to evaluate them. We want to measure the success of our predictions, and the success might be different in various forecasting scenarios. Forecasting outcomes can be split into two categories:

- Point Forecasts
- Probabilistic Forecasts

Point Forecasts have single-valued results like the number of infections or deaths. Metrics used for point forecasting include RMSE (Root Mean Squared Error), MAE (Mean Absolute Error), and MAPE (Mean Absolute Percentage Error). RMSE and MAE measure the error in L2 and L1 norms, respectively, whereas MAPE allows us to get the ballpark of our prediction using the prediction error. For example, if a model is predicting the number of daily new cases for COVID-19, RMSE would penalize larger errors more severely, while MAE would give equal weight to all errors. MAPE, on the other hand, would provide a relative measure of the error, making it easier to compare the model's performance across different magnitudes of cases.

Since these forecasts are of great social and economic significance, it becomes essential that we are certain about our predictions. Point forecasts, however, are not able to capture the confidence of the model, and this is why probabilistic forecasts are preferred. Probabilistic forecasts [7] capture the uncertainty of model predictions by using confidence intervals while also considering the accuracy of the model, as shown in Fig. 3. For example, a probabilistic forecast might predict a range of possible cases (e.g., 1000-2000) rather than a single number (e.g., 1500). This approach provides a better understanding of the uncertainty in the model's predictions.

Figure 3: The illustration of point and probabilistic forecasts

The Log Score calculates the binned log probability of the ground truth, while Interval scores are used to penalize how far the model's predictions are from the ground truth.

Additionally, we want to penalize flat distributions because that means the model is not confident in predicting and assigns equal probability to all outcomes. We also want to penalize if the ground truth is lower than the lower bound and greater than the upper bound. Coverage score is another metric that measures the fraction of times the ground truth actually lies in the confidence interval or, in simple words, penalizes an overconfident model. For example, a model with a high coverage score would have a higher percentage of its predictions containing the actual number of cases within its confidence interval, indicating its ability to account for uncertainty more accurately.

More recently, researchers have adopted the Weighted Interval Score (WIS), which aggregates interval scores for multiple intervals and aggregates them. WIS also builds upon log score in the sense that it is unbounded, and especially for forecasting diseases like COVID-19, it is a more suitable metric. WIS combines the advantages of both interval scores and log scores, making it a comprehensive metric for evaluating probabilistic forecasts. It helps assess a model's ability to accurately predict the range of possible outcomes while considering the uncertainty inherent in the data.

Researchers are still trying to find better ways of measuring success and incorporating qualitative metrics. Just giving the number isn't enough. It still needs to be useful for epidemiologists to make decisions.

4 Modeling Paradigms

[6] talks about different types of paradigms, datasets used by them, the type of task, and features used.

4.1 Mechanistic Models

These models have been thoroughly discussed in the previous lectures. Mechanistic models are the workhorses in epidemiology. The population is divided into different compartments based on the disease state, and they move between compartments based on the disease progression. ODEs, Metapopulation models, and Agent-based models are the primary examples. These models require domain knowledge and their parameters require intensive testing for sensitivity.

4.2 Statistical/ML Models

Advancements in machine learning methods have led to a large-scale collection and maintenance of publicly available datasets. Newer architectures have been successful in finding patterns even in complex data forms. Due to their success, numerous optimization algorithms are also available. Some approaches are regression-based, language and/or vision models, neural networks, and density estimation models. ML models [5] are useful as they can handle different types of datasets like Languages, Images, time series, etc.
The idea here is to find a function that can forecast the target based on the input data, however, do note that this would generate an approximate forecast. This is achieved by minimizing the comparison between the prediction from the function and the ground truth. The comparison is called Loss, and the function that generates the comparison is known as a loss function. The goal is to minimize the loss generated by the loss function.

4.3 Hybrid Models

Given the widespread use of ML models, an ML engineer doesn't need to have the domain knowledge to apply a model on an epidemic data set - this might work in certain scenarios, but in most scenarios, domain knowledge combined with an ML model would produce better and more reliable results. Hybrid Models combine the advantages of both Mechanistic Models and ML Models. They use domain-based priors and expert knowledge from mechanistic models and a flexible data-driven approach from statistical/ML methods. A model could use statistics to estimate mechanistic parameters or wisdom of the crowd with ensemble models.

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