Online algorithms with learned predictions for epidemic interventions in healthcare facilities

1 Overview

Unbeknownst to them, the patients admitted in inpatient healthcare facilities are constantly being exposed to a number of potentially hazardous health risks including exposure to pathogens such as *Clostridioides difficile* and *Clostridium sordellii*, antimicrobial-resistant organism (AMROs) including *Methicillin-resistant Staphylococcus aureus*, *Escherichia coli*, *Klebsiella pneumoniae*, and other infectious diseases such as COVID-19 and Influenza. The resulting infections, which fall in the broad category of healthcare-associated infections (HAIs), are a major health and economic burden. The CDC estimates that there are 4.5 HAIs for every 100 hospital admissions and and the annual cost of battling these infections are between 28 and 45 billion USD.

The inevitable contacts between healthcare professionals (HCPs) and patients in the course of care delivery serve as pathways for HAI transmission, as do pathogen-contaminated environmental surfaces. Hence, the mobility logs - detailing movement and contacts between HCPs, patients, and hospital locations - essentially act as a collection of potential infection transmission. While the contacts among individuals and those between individuals and surfaces lead to pathogen exposure, the risk of getting infected and developing symptoms are predominantly determined by the demographic characteristics and medical history of the individual being exposed. Here, I propose to leverage the detailed temporal mobility logs and individual risk factors along with auxiliary real world hospital operations data, to devise online algorithmic solutions for intervention against HAI spread in realtime.

The primary goal of intervention is to change the underlying contact network patterns (e.g. remove nodes by vaccination/quarantining, rewire edges by changing mobility patterns e.t.c.) to make it less vulnerable to future outbreaks. However, this is challenging due to uncertainty in both *past* and *future* events. Past events such as asymptomatic infection, latent transmission of pathogens, and contamination of surfaces with bacterial loads are difficult to observe. Similarly, due to the probabilistic nature of infection spread there is uncertainty on future events. Here, we propose to overcome these by designing online algorithms for *intervention* augmented by *inference* of past events and *forecasts* of future events.

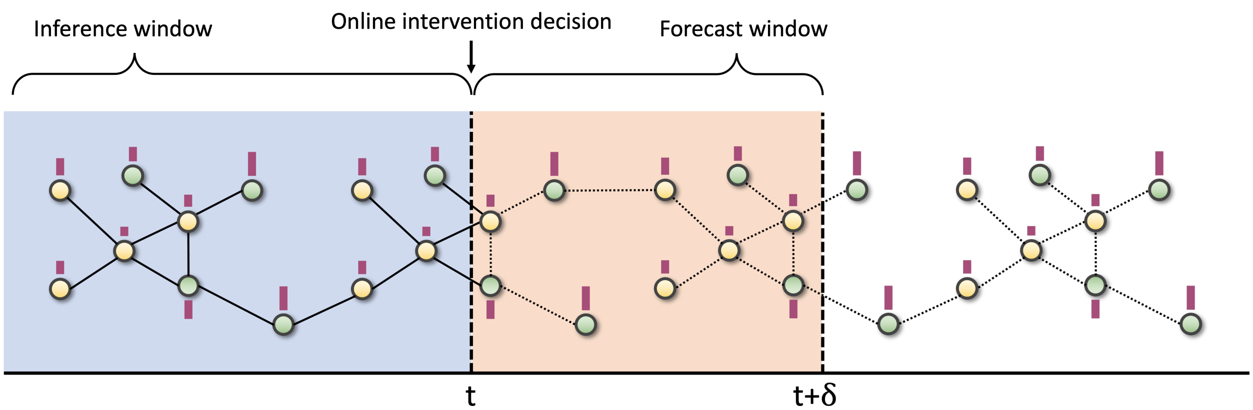

Figure 1: The three thrusts - inference, forecast, and intervention - of the proposal are chronologically ordered. Realtime intervention decisions are augmented by intervention of past events and forecast of future events.

The proposed work diverges from previous work in the following three substantive ways.

1. **Online Setting.** I consider the problems mentioned above in online settings where interactions are occurring and diseases are spreading simultaneously. In online settings, the decisions made in the

current time-stamp will have an impact on both future interactions and infection events. As a result of the problems being posed, and solved, in online settings, I expect the developed approaches to readily lend themselves to real-time applications. Most prior works either focus on a preemptive setting (before disease spread has started) or in a retrospective setting.

2. **Contact patterns and individual risks.** The proposed work takes both contact patterns and individual risk factors, as defined by their demographic features and medical history, into account. Model driven prior works primarily focus only on contact networks, while recent data driven approaches primarily only take individual risk factors into account.

3. **Sophisticated models.** We take sophisticated models whcih capture all aspects of HAI spread into account including load-based models, two-mode models, and popular respiratory infectious diseases based models such as SI, SIR, and SEIR. Most prior works only take the latter into account.