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Demography Laced Surrogate Social Contact Networks for Epidemic Dynamics

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Abstract: ***Progression of infectious diseases is considerably influenced by the patterns of social contacts hidden in the underlying social network of the human population. Network-based approach for studying epidemic dynamics empowers epidemiologists to capture demography-based heterogeneity in social contacts.***

In this paper, we propose to integrate demographic information in the synthetic network for the given geography to abstract interactions in family, social, and work spaces. Desireable result is achieved by considering subdivisions (zones) of the geography and using population statistics to generate the corresponding social network. Each zone is represented by a small-world network module parameterized by the local population density. Each module abstracts local interactions based on the data for the zone. The modules are interlinked in a principled manner using the size of the working population. The resulting network is used for simulating an extended version (SEIHR) of the standard SEIR model for COVID-19. Using Delhi as a case study, we show that demography laced modular network for a geography is an effective surrogate for studying epidemic dynamics.

Key Words: Progression, infectious, patterns, social contacts, hidden, network, human population.

1. Introduction- During the spread of epidemics, accurate predictions of its size and course overtime are of prime concern for governments to prepare and mobilize public health care infrastructure, take administrative decisions for managing and formulating preventive steps. The current COVID-19 pandemic has led to sudden spurt in research for quality models for infectious disease dynamics [1,2,3,4,5,6,7,8,9,10]. Differential equation-based compartmental models, with an ambient assumption of the well-mixed and homogeneous population, are competent to model COVID-19. Fast spreading contagious navigate through social contacts inducing an epidemic/ The spread of infection is governed by the local patterns of contacts arising out of social behavior, which in turn is determined by spatial population structure and demography. Crating network models to reflect population structure accurately is challenging [11,12,13,14,15,16,17,21]. The challenge is exacerbated for highly infectious respiratory disease because the spreading process is a complex and unknown function of public behavior. Modeling interrelationship between the spread of infectious disease and public behavior influenced by dynamic social feedbacks is known challenge [7].

Though the creation and annihilation of edges models dynamic patterns of con- tact arising due to public behavior, it is the underlying topology of the network that implicitly models the interaction patterns. Consequently, its impact on the dynamics of epidemic spread has been a subject of intense interest [18,19,20,21,22,23,31,32]. Small-world topology, which interpolates between regular and random networks and aptly models real-world population, is accepted to be pragmatic for modeling the spread of epidemics [24,25,26]. However, since small-world networks are incapable of reflecting the social structure, they do not accommodate local heterogeneity in social contact patterns. A recent inquiry by Pinto et. al. demonstrates that the dynamics of an infectious disease are highly sensitive to the underlying network model and modular network models facilitate effective simulation of the spread [18].

1.1 Modeling Epidemics on Surrogate Networks

It is well recognized that human populations are never distributed uniformly and

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social interactions among individuals are nuanced and structured [4,21].Since demography and population density are the key determinants of the social structure of the population, we conjecture that the classical small-world network model fortified with demographic information of a geographic region is a good and reasonable approximation of the underlying social contact network. The ingenious network is envisaged to be an effective surrogate to study the spreading dynamics of infection. Inspired by the observations made by Pinto et.al.[18], and recent COVID-19 study [10], we build a modular network of small geographical units, impregnating each module with the regional demographic details. The approach realizes the surrogate social contact network of the geography understudy and provides the wire-frame for simulating the spread of an epidemic.

In this paper, we delineate the methodology for creating a modular social contact network (M-SCN) for the population of the given geography. Frugal with respect to parameters, the methodology is generic in the sense that the network can be created at chosen granularity (e.g. district/state/country).

1. propose a parsimonious epidemic model (SEIHR) for COVID-19 (Sec. 3).
2. delineate method to create surrogate social contact network (M-SCN) of geography while taking into account population demography (Sec. 4).

2. Related Work- In this section, we discuss the works that study the spread of epidemics in small- world networks and are close to our work.

Watts and Strogatz [31] in their seminal article showed that infectious dis- eases spread much more easily and quickly in the small-world network. Therefore, epidemiologists have extensively used SW networks to simulate epidemic process [27,28,29]. Studies suggest that epidemic models need to incorporate social structure and contact patterns that vary across age and locations, in order to improve the effectiveness of the model [19,21,26]. Since the risk of infectious disease trans- mission varies in different social settings, Prem et al. [20] use social contact matrices to model population characteristics and predict the COVID-19 epidemic under different intervention scenarios in Wuhan, China the effectiveness of the model [19].

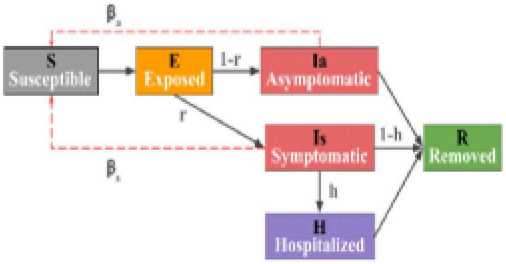

Fig. 1 SEIHR Model: State transition pathways of COVID-19 infected individual.

Since the risk of infectious disease trans- mission varies in different social settings, social contact matrices to model population characteristics and predict the COVID-19 epidemic under different intervention scenarios in Wuhan, China.

Among India specific COVID-19 studies, our proposal is closest to the work- ing paper by TIFR [10]. The paper proposes an agent-based city-scale simulator using demographic and interaction spaces to study the impact of different post lockdown interventions. The simulator is demanding and uses ten parameters for creating the network and eleven for simulating epidemic spread. The elaborate model theoretically captures the real world social network highly realistically, with the caveat that accurate data or their estimates are not available. Bhattacharyya et al. [30,31,32] introduce a multi-lattice small world network, where each ward in a city is modeled as a 2D lattice. The number of zones is the only real-world data used by the authors.

3. Modelling Spreading Process for COVID-19- We extend the classical SEIR epidemic process by introducing ancillary states to model the spread of COVID-19. The model, named SEIHR, considers disease dynamics in six compartments, namely susceptible individuals (S), exposed individuals (E), infected asymptomatic individuals (Ia), infected symptomatic / clinically ill (Is), hospitalized

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individuals (H), and the recovered / deceased individuals (R) as shown in Fig. 1. All infected individuals may not exhibit symptoms. Ex- posed individuals, showing no symptoms within 3-5 days (latent period (l)), are assigned to Asymptomatic infected (Ia) compartment. Unaware of their own infected status, they intermix freely in the population infecting susceptible contacts with high transmission probability ?a . Individuals in compartment Ia recover naturally within time span ra and transit to Removed (R) compartment. Susceptible individuals (S) exposed to pathogen in compartment E, may develop symptoms within 2-3 days (symptom development period (t)) with probability r. Such individuals move to Symptomatic infected (Is) compartment as in [10,15,30]. As these individuals are highly infectious, they are quarantined either at home or in the quarantine zone to curb the spread of pathogen through direct contacts.

However, there is a small finite probability ?s that a susceptible caregiver may contract the disease from a symptomatic individual. Note that ?s ? ?a.

Due to different responses to infection, some symptomatic individuals may recover after a mild illness, while others get very sick requiring hospitalization for proper medical care. Symptomatic individuals for whom the health worsen within time t s, move to Hospital compartment (H) with probability h. Others transit to compartment R after recovery within period rs. Individuals in compartment H, who recover from the illness (recovery period (rh)) or unfortunately die, also move to compartment R.

Symptomatic and hospitalized individuals are isolated, implicitly implying a quarantine state. Thus we eliminate the quarantine state, commonly used in several similar studies [17,25]. It isimportant to mention here that we do not consider the effect of deaths and new birth due to a short epidemic time scale.

4. Modeling of Social Contact Network- High population density induces more social contacts in a typically non-linear fashion. Further, since individuals forge local contacts more often than remote contacts, density and locality are appealing ingredients for modeling the social contact network of the population. Hence, the demography is a strong determinant of the patterns of social contacts within geography. We elucidate the method by considering zones of a city as local geographies corresponding to which network modules are created in Phase I.

4.1 Demography Data for Social Contact Network- Consider city C with Z zones. For zone zi , let pi denote the population, hi denote the number of households, si denote the mean household (family) size, di denote the population density and wi denote the size of working population.

Since geographies are not necessarily homogeneously structured, interactions between individuals are not random [3]. Accordingly, we forge three types of social contacts in the population, viz. (i) family contacts, (ii) work contacts, and (iii) other social contacts. Families are clusters of the smallest granularity with mean household size (s). Work contacts are characteristic of the working population (w), and interactions by individuals outside the household to meet day-to-day shopping needs, medical assistance, etc. generate other social contacts.

4.2 Modular Social Contact Network- In line with the findings of Pinto et. al. [18], we create a modular network for a city by considering each zone as a module, appropriately linked with other modules. Variation in the demography of the modules (zones) creates heterogeneity in contact patterns in the city population. We designate this surrogate as modular social contact network (M-SCN).

Phase II - Link modules: This phase delivers M-SCN by adding inter-zones interactions between modules. Work contacts bridge the modules created in Phase I and effectuate the surrogate social contact network for the city. Shortcut edges are

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added based on the size of the working population to model work contacts. We add wi additional edges for a zone (module) zi such that the other end of the edge may fall randomly in any module. Edges added within z i represent intra-zone work contacts, and those in another module represent inter-zone work interactions. Contact patterns of non-working population (infants, children, old/sick people) are implicitly captured by family and other social contacts.

4.3 Modelling Non-Pharmaceutical Interventions in M-SCN- Governments of most nations implemented non-pharmaceutical interventions to control the COVID-19 infection outbreak and combat the lack of preparedness of healthcare systems. Starting with shutting down education institutes, the hospitality industry, etc., the national lockdown was forced into action in many countries. Modeling of NPIs on the network is straightforward. Lockdown and unlocking forced in multiple phases is simulated by simply adding and annihilating edges from the network. Compliance, which is a function of population behaviour, can also be easily monitored by retaining an appropriate number of edges in the network. Such actions can be employed to simulate both local interventions within the module or uniform impact on spread.

5. Conclusions- In this paper, we propose an approach to create a modular social contact network for a geography by exploiting its demographic details. Three types of interactions viz. family, social and work spaces are modelled using population data to cap- ture interaction between individuals. We use an extended version (SEIHR) of the standard compartmental model (SEIR) for simulating infection spread.

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