Constructing an Optimal Prediction System for Infectious Disease

WELCOME to the fourth issue of IEEE TRANSACTIONS ON COMPUTATIONAL SOCIAL SYSTEMS (TCSS) for the year 2024. We are delighted to announce that TCSS has achieved an impressive impact factor of 4.5, according to the latest Journal Citation Reports (JCR) released by Clarivate's Web of Science in late June. We would like to take this opportunity to express our heartfelt appreciation and extend our congratulations to all contributors for their exceptional dedication and unwavering support.

In this issue, we present 14 regular articles followed by two special issues. The Special Issue on Generating Human Readable Explanations in NLP addresses the challenge of interpretability in natural language processing (NLP) models, particularly in the context of deep learning. As state-of-the-art models have become more advanced, their complexity has led to reduced transparency, making it difficult to understand and trust their predictions. This special issue emphasizes the importance of developing explainable systems that produce human-comprehensible solutions, enhancing prediction accuracy, decision-making understanding, and traceability. It showcases recent advancements in creating interpretable models and techniques in NLP, highlighting their applications in various domains such as legal decision-making, fake news detection, and sentiment analysis. The special issue features 19 accepted articles representing the latest research on generating explanations that are understandable to humans.

Then, the Special Issue on the Dark Side of the Socio-Cyber World: Media Manipulation, Fake News, and Misinformation delves into the negative aspects of the socio-cyber world, focusing on media manipulation, fake news, and misinformation. The widespread use of the internet has transformed the world into a connected village, where platforms such as Google, Facebook, YouTube, Twitter, and Instagram facilitate rapid information dissemination. However, the lack of control over the authenticity of shared news presents significant challenges. Misinformation on these platforms can profoundly affect societal norms and disrupt peace, as demonstrated by events such as the misuse of 87 million Facebook profiles by Cambridge Analytica and the alleged Russian interference in the 2016 U.S. election. These cases underscore serious concerns about online privacy and the potential of misinformation to undermine democracy, the legitimacy of the press, and expert authority. This special issue invites original interdisciplinary research that addresses these issues using AI and deep-learning strategies, aiming to bridge knowledge gaps and set new standards in the field. The special issue features 53 accepted articles.

Finally, we discuss the development of an optimal prediction system for infectious diseases, particularly COVID-19, by integrating dynamical methods and data-driven artificial intelligence (AI) approaches. The proposed system, named DAI, combines the strengths of both approaches: dynamical methods for their interpretability and data-driven methods for their adaptability and flexibility. The DAI system aims to enhance the accuracy and robustness of infectious disease predictions by leveraging deep learning for pattern recognition, parameter estimation, and predictive calculations within a dynamic framework. The article emphasizes the importance of combining physical system principles with AI to achieve comprehensive and reliable epidemic forecasting.

I. Scanning the Issue

Nadeem et al. [A1] explore determinants of tobacco smoking in Pakistan. This study uses Pakistan demographic and health survey data. The analysis comprises of theoretical reasoning, association tests, and logistic regression. In analysis, tobacco use has been used as dependent variable, while age, occupation, region, place of residence, household wealth status, and education level have been used as independent variables. Based upon results of study, it is conferred that to control tobacco use targeted interventions are needed and there is a need to focus on: urban areas, less educated people, poor households, people of age 40 years and above, and people who are self-employed or engaged in agricultural activities.

In [A2], Fang et al. focus on a realistic attack operation via injecting fake nodes. The proposed global attack strategy via node injection is designed under the comprehensive consideration of an unnoticeable perturbation setting from both structure and feature domains. Specifically, to make the node injections as imperceptible and effective as possible, the authors propose a sampling operation to determine the degree of the newly injected nodes and then generate features and select neighbors for these injected nodes based on the statistical information of features and evolutionary perturbations obtained from a genetic algorithm, respectively. In particular, the proposed feature generation mechanism is suitable for both binary and continuous node features.

In [A3], Khelloufi et al. propose a service recommendation system for the Social Internet of Things that uses graph structure learning to discover latent item relationships that underlie multimodal features. The proposed system learns how different aspects of a service are related to each other, based on all the different features that can make up a service, it develops a modality-aware graph structure learning layer that is able to effectively learn item graph structures from multimodal features and then combine them into a single graph. This allowed it to identify complex relationships between different kind of features, such as how a particular service attribute might affect customer satisfaction levels.

Shu et al. [A4] propose a key nodes evaluation method for social networks, which is based on the analytic hierarchy process (AHP) and improved Vise Kriterijumska Optimizacija I Kompromisno Resenje (VIKOR), termed AE-VIKOR. Three evaluation metrics are constructed. The subjective and objective weights are computed by AHP and entropy weight method, respectively. The comprehensive weights of metrics are determined by a combination weighting method based on square sums of distance. Due to the excessive weight of specific metrics and excessive differences in data distribution, the computation of individual regret value depends too much on a single metric in VIKOR method, individual regret value is optimized by weighted sum of closeness between the scheme to be evaluated and the negative ideal scheme.

In [A5], Zhao et al. propose a new unsupervised domain adaptation method called layer-adapted implicit distribution alignment networks (LIDANs) to address the challenge of cross-corpus speech emotion recognition (SER). The key contribution lies in the introduction of a novel regularization term called implicit distribution alignment (IDA). To further enhance this method, they extend IDA to layer-adapted IDA (LIDA), resulting in LIDAN. This layer-adapted extension consists of three modified IDA terms that consider emotion labels at different levels of granularity. To evaluate LIDAN, they conducted extensive cross-corpus SER experiments on EmoDB, eNTERFACE, and CASIA corpora.

The work [A6] proposes a triggerless targeted model poisoning attack (TriMPA) against deep neural network without requiring any change in input to trigger the backdoor. TriMPA identifies active neurons that highly contribute to the prediction of the victim output label and replaces those neurons with that corresponding to the target output label. The performance of the proposed mechanism is evaluated through experiments as well as analyzed theoretically. It is shown that TriMPA achieves a higher attack success rate.

In [A7], based on simple graph and motif-based graph, Zhang et al. propose a multilevel graph convolution framework for extracting higher order topological semantics of graphs. First, they design convolution kernels on both motif-based and simple graphs. Second, they introduce a multilevel graph convolution framework for extracting higher order topological semantics of graphs. Their approach overcomes the limitations of prior methods, demonstrating state-of-the-art performance in downstream tasks with excellent scalability.

In [A8], Lai et al. propose a similarity computation module for implicitly learning a metric matrix to characterize the similarity between prior knowledge and consumer reviews in vector space. Through this process, the model is able to learn and understand the relationship between prior knowledge and corresponding samples during training, thereby improving its ability to identify unforeseen fraudulent behaviors. Additionally, they propose a channel biattention CNN module to adaptively emphasize the importance of relevant prior knowledge to enhance the model's ability to accurately classify boundary samples. To ensure effective model training, they expand and organize a real-world dataset, reducing noise and increasing the number of fraud samples available for analysis.

In [A9], Jia et al. propose an adaptive density subgraph clustering algorithm (ADSC). ADSC follows a systematic three-step procedure. First, the high-density regions in the dataset are recognized as density subgraphs based on k-nearest neighbor density. Second, the initial clustering is carried out by utilizing an automated mechanism to identify the important density subgraphs and allocate outliers. Last, the obtained initial clustering results are further refined in an adaptive manner using the cluster self-ensemble technique, ultimately yielding the final clustering outcomes. The clustering performance of the proposed ADSC algorithm is evaluated on nineteen benchmark datasets.

In [A10], Sharma et al. present an approach named conteNXT for detecting events from Twitter posts (also known as Tweets). To handle large amounts of data, the proposed method divides tweets into bins and uses postprocessing methods to extract burst key phrases. These key phrases are then used to generate a weighted key phrase graph using the Word2Vec model. Finally, Markov clustering is employed to cluster and detect events in the burst key phrase graph. The proposed approach outperforms state-of-the-art methods, including SEDTWik, Twevent, Sentence-BERT, MABED, EDED, Community INDICATOR, and EventX. Additionally, the proposed approach is capable of detecting vital events that are not identified by the aforementioned state-of-the-art methods.

Wang et al. [A11] propose a novel architecture named multichannel hypergraph convolutional neural network (CNN) to achieve a multistep prediction of origin-destination (OD) demand matrices. Inflows and outflows are combined with OD flows to improve the prediction performances of OD matrices. Two types of hypergraphs, i.e., adjacency hypergraph and semantic hypergraph, are particularly adapted to portray hidden patterns from inflows, outflows, and OD flows, which are further modeled by hypergraph convolutional networks and gated recurrent units (GRUs) to learn their hidden spatial–temporal correlations in node levels and edge levels. A multichannel feature fusion module is finally designed to capture spatial–temporal dependencies among them.

Qiao et al. [A12] propose a robust synthetic-to-real dehazing framework with the construction of an intermediate domain. First, the bidirectional match strategy with adversarial training and the constraint of intermediated results is proposed to suppress the rich domain-specific information, which can facilitate the adaptation and perform image dehazing simultaneously. Furthermore, an ensemble dehazing algorithm based on the intermediate domain is proposed in a semisupervised manner. The reconstruction constraint and the enhanced ground truths are employed to maintain the visual fidelity and remove the dim artifacts of unsupervised dehazing results. Finally, they propose the domain-aware residual groups to deal with the distribution discrepancy between synthetic and real hazy images.

In [A13], an approach for analyzing and predicting public opinion on protests based on large language model (LLM) is proposed. Zhang et al. demonstrated that protests generate public opinion on social media with some lag, but that comment sentiment and expression are consistent with protest trends. They analyzed the evolution of public sentiment. They constructed the prompt based on historical data to predict the protests using the p-tuning and Lora approach to fine-tune LLM. In addition, they discuss how to use blockchain technology to optimize distributed, self-organizing protests and reduce the potential for disinformation and violent conflict.

The study [A14] centers on blockchain extractable value (BEV), unveiling a real-time discovery and mining system (RDMS) tailored for arbitrage-based decentralized finance (DeFi) activities. The system employs innovative methodologies for localized computation and execution. It establishes a comprehensive monitoring system for arbitrage and liquidation activities, contributing positively to the DeFi ecosystem. Leveraging round-the-clock on-chain data indexing and event-driven parsing methods, the RDMS enables automated and periodic analysis of BEV activities. This system provides valuable insights for BEV research, particularly in the context of arbitrage and liquidation activities. They are also able to consistently extract value using arbitrage strategies on blockchains, using RDMS that monitors the chain in real time and applies gas cost reduction mechanisms.

II. Constructing an Optimal Prediction System for Infectious Disease

A. Introduction

The COVID-19 pandemic has exerted a profound impact on society, disrupting the economy and causing substantial morbidity and deaths on a global scale [1]. It is necessary to develop an accurate prediction model for the spread of the COVID-19 pandemic. However, the difficulty of precisely identifying complex influential factors and the reality of inadequate and delayed data reported by many countries pose challenges to constructing such a model. So far, the two main technical approaches commonly used to construct predictive models for pandemics are dynamical system methods (i.e., PDEs) and data-driven approaches. The former includes compartmental models such as SIR and SEIRS, and the latter includes statistical methods such as the autoregression moving average model (ARMA) and deep-learning methods such as CNNs and recurrent neural network (RNN). Given that the predictions of regression methods do not rely on the model description of the epidemic dynamics, we herein classify ARMA and other regression models as data-driven methods. Each approach possesses distinct advantages and disadvantages. In this article, we aim to elucidate the distinctions among these main methods and explore the construction of an optimal prediction system for infectious diseases. Our goal is to integrate the strengths of both approaches to develop a comprehensive prediction system that effectively combines dynamical system approaches with data-driven approaches.

B. Traditional Dynamical Approaches

The dynamical approaches focus on the state evolving with time and are commonly utilized in physical areas, including numerical weather prediction and fluid dynamics [2], [3]. The compartmental model and the network model are two classical types of traditional dynamical approaches to describe and predict the pandemic condition, i.e., [4] and [5]. In the compartmental model, a set of partial differential equations (PDEs) is constructed to depict the variation in numbers among the different compartments, such as susceptible (S), exposed (E), infected (I), and recovered (R). The network model focuses on the topological nexus between each discrete object. The connection patterns of the network based on the compartments can be analyzed using graph theory.

Nowadays, more sophisticated models have been derived from the basic SIR model to predict the COVID-19 pandemic. There are two derived paths on the compartmental model, and one approach is centered on latent factors via modeling more complicated relationships between compartments or incorporating the stochastic PDEs [5], [6], [7], [8], [9], [10]. The other approach emphasizes time by constructing time-delayed PDEs or introducing time-dependent parameters [11], [12], [13], [14]. In addition, the data assimilation method, commonly used in numerical weather prediction, has been applied to infer these parameters accurately since the substantial parameter fluctuation in compartmental models [9], [10], [11], [12], [13], [14], [15].

Giordano et al. derived a SIDARTHE model from the basic SEIR [7]. By distinguishing between infected individuals based on diagnosis and symptom severity, the model revealed that diagnosis campaigns can reduce the infection peak and expedite epidemic cessation. In the study of Chang et al., the derived model ACEMod with AMTraC-19 was developed and calibrated specifically for COVID-19 via reported invariants such as the growth rate [8]. In the study of Engbert et al., a stochastic SEIR model with data assimilation was applied to address the spatial heterogeneity of modeling epidemic outbreaks in Germany [9]. A time-delayed SEIR model was constructed by Al-Tuwairqi and Al-Harbi to investigate the impact of time delay in vaccine production on COVID-19 spread [11]. Qualitative analysis indicated that the system variables are biologically meaningful. It demonstrated that the control reproduction number is greater than unity by discussing the equilibrium points of the model. Otunuga established a time-dependent SIS model to study changes in disease transmission and recovery rates [14]. In the study of Chen et al., a contact small world network based on the SIR model was deployed to demonstrate the underlying cause of a linear increase in confirmed cases over extended periods, identifying critical social contact thresholds and proving the effectiveness of nonpharmaceutical interventions (NPIs) such as national lockdowns [16].

Although many new approaches have been derived from traditional dynamical methods of prediction, there are still some disadvantages to these methods. The approximation of the model to reality is the first and foremost. An epidemic is a complex process, with many factors exerting a significant impact on the transmission process, including unobstructed human behavior in response to government control strategies. It is challenging to establish a reliable model to describe the epidemic process. As a result, prior knowledge plays a decisive role in the outcome. Second, whether using PDEs or graph theory, the parameters of the dynamic model must be established in real time, with predetermined environmental conditions, viral variation, and social contact. Consequently, data assimilation becomes essential for accurate prediction. Third, predictability is a sensitive dependence on the initial conditions of the dynamical system, which is another key factor for successful prediction. The necessary conditions for obtaining reliable results also include the selection of suitable seeds for simulation and the correct observation to inverse initial parameters.

C. New-Merged Data-Driven (AI) Approaches

Deep-learning approaches are increasingly applied across various research domains, including pattern recognition, signal processing, autonomous driving, NLP, earth system science, geophysical fluid dynamics, environmental science, and so on [17], [18], [19], [20]. Different from dynamical approaches, it is a significant amount of data for deep-learning approaches to train the model rather than relying on a precise model to characterize physical processes. The deep-learning methods consist of multiple layers of perceptron and can efficiently abstract the hierarchy of multidimensional data while overcoming challenges arising from excessive architectures [21]. There are many specific architectures in deep learning if distinguished by the direction of information flow in the structure, the kernel algorithm, and the training type (i.e., supervised or unsupervised). At present, various deep-learning architectures have been utilized to predict infections including RNNs, GRUs, long short-term memory networks (LSTMs), bidirectional LSTM (BiLSTM), convolutional LSTM (ConvLSTM) [22], graph neural networks (GNNs), variational autoencoder (VAE), and others [23]. It has been demonstrated that these approaches possess the potential to improve infections prediction in terms of time series.

Gao et al. established an Ising dynamics-based LSTM model for spatiotemporal prediction of COVID-19 hospitalization [23]. The model utilizes spatial relationships at different locations to analyze the complex effects of particle information from real-world clinical evidence. The finding suggests that future COVID-19 vaccination efforts may be most impactful in rural areas. Zeroual et al. compared five simple deep-learning methods to predict new cases and recovered cases with limited data [24]. The results demonstrated the superior performance of the VAE compared to other algorithms. Devaraj et al. compared the prediction of cumulative confirmed, death, and recovered global cases of COVID-19 by using ARIMA, LSTM, stacked long short-term memory (SLSTM), and prophet approaches [25]. The results presented that the stacked LSTM achieved higher accuracy with an error of less than 2% compared to other approaches. Meanwhile, many statistical and machine learning classifiers were trained to characterize the propagation of situational information about COVID-19 [26]. The findings emphasized the necessity of adopting various information publishing strategies for different types of situational information. In another study, RNN and LSTM were utilized to develop prediction models [27]. A vanishing gradient point error was discovered in the RNN method when predicting new cases, while the proposed LSTM prediction model exhibited a greater accuracy. In the study of Murphy et al., a GNN for contagion dynamics was proposed [28]. This approach made it possible to explore the properties of the learned dynamics beyond the training data by allowing simulations on arbitrary network structures. Using real data from the COVID-19 outbreak in Spain demonstrated the applicability of this approach.

Deep-learning methods render accurate predictions by learning from massive amounts of data, but there are still some drawbacks that need to be overcome. First, the interpretability is crucial in deep learning, while the lack of interpretability leads to a “black box” in the model learning process. Therefore, interpretability must be enhanced to achieve broader application, especially in early warning of infectious diseases. Second, the causal mechanism is influenced by correlation in many deep-learning methods, leading to challenges in extrapolation. Hence, the physical process should be included to express the causal mechanism in the model. Third, training the deep-learning model requires a large amount of data, but real-world conditions often present a scarcity of adequate data. Finally, evidence [29], [30] demonstrated that the width of the network may result in diverse learning mechanisms, with qualitative differences regarding classification errors and predictive uncertainties. The predictability of the deep-learning methods may be influenced by the network layout.

D. Constructing an Optimal Prediction System

So far, we have discussed two types of prediction models, the dynamical model and the data-driven deep-learning (AI) model, as well as their application in COVID-19 pandemic prediction and their associated disadvantages.

The accuracy of dynamical models depends on the precision of parameters, which are often difficult to obtain. In contrast, data-driven methods can directly learn the disease transmission patterns from historical epidemic data, especially AI models such as deep learning. Regarding adaptability and flexibility, dynamical methods have improved explanatory power based on the inherent physical principles, while data-driven methods are usually more adaptable to linearity prediction at the cost of overfitting and lack of interpretability. Finally, for long-term predictivity, dynamical methods perform better than data-driven

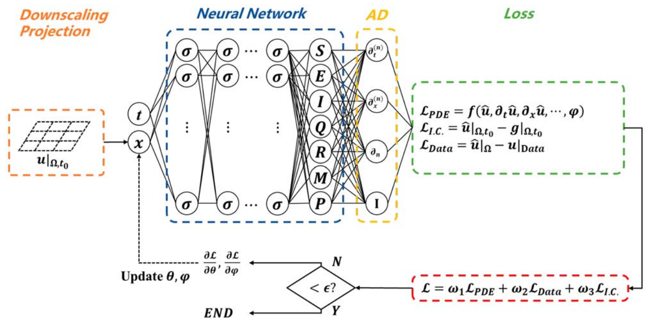

Fig. 1. Scheme of the DAI. $\hat{u} = (S, E, I, Q, R, M, P)'$ is the model evaluation. AD means "auto differentiation." θ is the model weights parameter, and φ is unknown PDE parameters in neural network.

methods, because the former is based on the basic mechanism simulation, while the latter may struggle to predict accurately without sufficient historical data support.

The optimal prediction system remains to be explored. Herein, we propose the dynamical-AI (DAI) as an optimal prediction system for infectious diseases, which combines both the dynamical and data-driven approaches, preserves the structure of dynamical models for better interpretability, and introduces data-driven components to enhance the model's robustness in the face of data changes.

In this DAI prediction system, we combine the deep-learning method in the dynamical framework on the following five conditions: pattern recognition, initial and boundary conditions, parameter estimation, prediction calculation, and result evaluation. In terms of pattern recognition, the deep-learning method can reveal hidden patterns in complex systems [31]. On the aspect of initial and boundary conditions, given that the observations to a certain location may not be fine enough, the initial value and boundary value are first downscaling-projected using a deep-learning method. In parameter estimation, especially for the infectious disease prediction, infection rate, latent time, recovery rate, and other parameters are affected by spatiotemporal varying meteorological and environmental factors. These parameters can be estimated by deep-learning subgrid parameterization [32], [33]. The high-resolution data are coarse-grained to the low-resolution grid by training the neural networks through physical observation. Deep-learning methods can be applied in the calculation process, such as physics-informed neural networks (PINN) [34], [35], [36], ConvLSTM [22], and DeepONet [37]. On the evaluation, deep-learning methods can accelerate assessment when multiple results are evaluated simultaneously.

We draw the seven-parameter epidemic model as an example, which is described by (1)–(8) [38], where S, E, I, Q, R, M, P, and N represent the system variables denoting susceptible, potentially infected, infected, quarantine, recovered, mortality, protected and total cases, respectively. The coefficients $\alpha, \beta, \gamma, \delta, \lambda$, and κ represent the protection rate, infection rate, inverse of the average latent time, the rate at which infected people enter quarantine, time-dependent recovery rate, and time-dependent mortality rate, respectively. As we illustrate for DAI in Fig. 1, the initial value and the priori parameters are first downscaling-projected using a deep-learning method. Subsequently, leveraging these priori values, a physical-informed neural network is used to solve (1)–(8). Inspired by the model evaluation in [39], the systematic accuracy and reliability of this model can be evaluated comprehensively by the standard variance of the time to infection period peak (9), the standard variance of accumulated infected cases (10), and the model spread (11) [40] in a certain area, compared with other infectious disease prediction method.

In the framework of the dynamical method, the DAI can simulate the nonlinear transition point, which is impossible in the deep-learning method. With the assistance of the deep-learning method, subgrid parameters can be accurate and downscaling can be predicted with high precision. As a result, the expectation outcome of DAI system should surpass either the deep learning or the traditional dynamical method alone [38]

$$\frac{dS(t)}{dt} = -\frac{\beta I(t)S(t)}{N} - \alpha S(t) \tag{1}$$

$$\frac{dE(t)}{dt} = \frac{\beta I(t)S(t)}{N} - \gamma E(t) \tag{2}$$

$$\frac{dI(t)}{dt} = \gamma E(t) - \delta I(t) \tag{3}$$

$$\frac{dQ(x,y,t)}{dt} = \delta I(t) - \lambda(t)Q(t) - \kappa(t)Q(t) \tag{4}$$

$$\frac{dR(x,y,t)}{dt} = \lambda(t)Q(t) \tag{5}$$

$$\frac{dM(x,y,t)}{dt} = \kappa(t)Q(t) \tag{6}$$

$$\frac{dP(t)}{dt} = \alpha S(t) \tag{7}$$

$$S + P + E + I + Q + R + M = N \tag{8}$$

$$\text{Index}_{\text{I.P.P.}} = \text{std}\{t_{\text{mod,peak}}(x_i, y_i) - t_{\text{obs,peak}}(x_i, y_i)\} \tag{9}$$

$$\text{Index}_{\text{A.I.C.}} = \text{std}\{I_{\text{mod,accu}}(x_i, y_i) - I_{\text{obs,accu}}(x_i, y_i)\} \tag{10}$$

$$\Delta\text{Mod} = \Sigma_i\Big(\max\big\{\rho(x_i, y_i), \forall_j(x_i, y_i)\big\} - \min\big\{\rho(x_i, y_i), \forall_j(x_i, y_i)\big\}\Big). \tag{11}$$

E. Conclusion and Discussion

From the analysis above, we can conclude that the DAI method represents the optimal prediction system for infectious diseases by integrating both the constraint and implant approaches. With the combination of the strengths of dynamic and data-driven models, DAI ensures the comprehensive consideration of the physical system, accurate parameter fitting, and optimized computational processes.

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APPENDIX
RELATED ARTICLES

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