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Fuzzy cognitive maps and cellular automata: An evolutionary approach for social systems modelling

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ABSTRACT

One of the first decisions to be made when modelling a phenomenon is that of scale: at which level is the phenomenon most appropriately modelled? For some phenomena the answer may seem too obvious to warrant even asking the question, but other phenomena cover the gamut, from high to low levels of abstraction. This paper explores how two modelling approaches that are ‘at home’ at opposite ends of the abstraction spectrum can be combined to yield an evolutionary modelling approach that is especially apt for phenomena that cover a wide range in this spectrum.

We employ fuzzy cognitive maps (FCMs) to model the interplay between high-level concepts, and cellular automata (CA) to model the low-level interactions between individual actors. The combination of these models carries both beyond their respective limitations: the FCM concept is extended beyond the derivation of equilibrium outcomes from static initial conditions, to time-evolving systems where conditions may vary; CA are extended beyond the emergence of patterns from local interactions, to systems where global patterns have local repercussions.

The applicability of the methodology is demonstrated by modelling the spread of human immunodeficiency virus (HIV) in an environment in which injection drug users share paraphernalia.

1. Introduction

Many systems in the real world are characterized as complex systems—non-linear, time-varying systems with feedback loops that make their behaviour hard to predict. Some of the complexity of such real-world systems lies in the different levels of abstraction (scales) at which mechanisms operate in them. Each level of abstraction is characterized with its own concepts or variables, and consequently has different interactions between these concepts. Thus, a model that is appropriate at one level may fall short at another to the point that even applying the same modelling technique at different levels may be inappropriate. This paper explores how modelling techniques that are ‘at home’ at different levels of abstraction can be coupled to reap the benefits of both techniques while cancelling some of their limitations.

We propose a modelling technique that combines a macro-level approach with a micro-level approach to yield an especially apt evolutionary modelling technique, using the macro-level outcomes to parameterize the micro-level model, and feeding statistics from the micro-level model back into the macro-level one to recalculate parameters. The macro-level model of choice is a fuzzy cognitive map (FCM), which aggregates the model domain into concepts and the global interactions between those concepts. The micro-level model of choice is a cellular automaton (CA; plural: cellular automata), which disaggregates the model domain into individual actors that interact locally. In our approach we allow for multiple CA and FCMs to interact (see Fig. 1).

The applicability of the proposed technique is demonstrated by modelling and simulating human immunodeficiency virus (HIV) spread in an environment in which injection drug users (IDUs) share needles or paraphernalia, a key mode of HIV transmission among IDUs [47,67]. The complicating factor in this dynamic is that drug use and needle sharing are individual behaviours [41,42] that are nevertheless influenced by the behaviour of other individuals as well as law enforcement and health care agencies. An FCM is a natural choice for modelling the influence of such macro-level actors (agencies) on behaviour, but it is unable to capture the interpersonal interactions in a heterogeneous population. A micro-level model like a CA, on the other hand, is especially apt to model interactions at the level of the individual, but often incorporates macro-level actors only as a single ‘environment’ variable [10,11], if at all. The combination of (multiple) FCMs and CA allows us not

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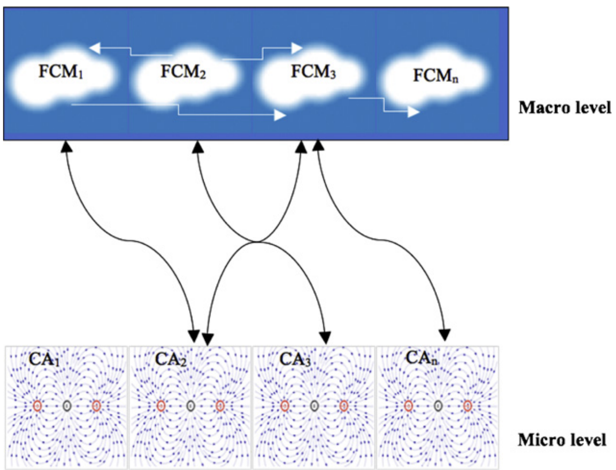

Fig. 1. The structure of an evolutionary model coupling multiple FCMs and CA.

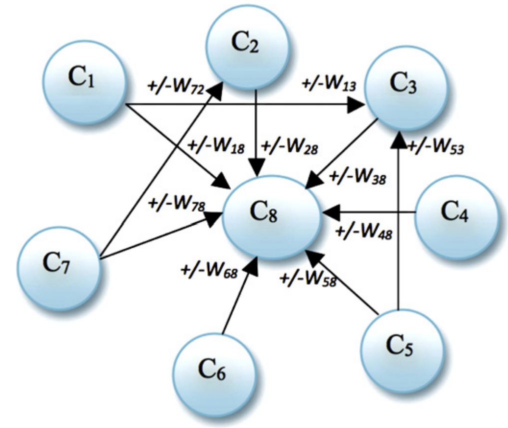

Fig. 2. Basic structure of FCM.

only to incorporate both the macro and micro levels, but also to model the feedback loop that exists between the micro level (e.g., the prevalence of needle sharing) and the macro-level (e.g., government policies), and vice versa.

The remainder of this paper is organized as follows. Section 2 describes the basics of FCM and CA based modelling. Section 3 gives formal definitions for FCMs and CA, which are then used to further define the proposed FCM-CA based evolutionary approach. In Section 4, we apply the approach to our sample scenario of HIV spread when IDUs share needles. There again, we first introduce the FCMs and CA individually, before weaving them together. Finally, in Section 5, we report on the simulations we conducted on the resulting evolutionary system.

2. Fuzzy cognitive map and cellular automata

Before defining our approach more thoroughly in Section 3 and combining FCMs and CA, we present FCM and CA modelling individually to give the reader some intuition of each of these models.

2.1. Preliminaries of FCM based modelling

FCM methodology is a symbolic representation for the description and modelling of complex systems at a high level. An FCM describes different aspects in the behaviour of a complex system in terms of concepts; each concept represents a characteristic of the system and these concepts interact with each other, showing the dynamics of the system.

Kosko introduced FCM [31,32] as a signed directed graph for representing causal reasoning and computational inference processing, exploiting a symbolic representation for the description and modelling of a system. Concepts are utilized to represent different aspects of the system. The construction of an FCM usually requires the input of human experience and knowledge on the system under consideration (both qualitative and quantitative data) but can also be derived from data [59]. Thus, an FCM integrates the accumulated experience and knowledge concerning the underlying causal relationships among factors, characteristics, and components that constitute a system.

An FCM consists of concept nodes, C_i, $i = 1, \ldots, n$, where n is the total number of concepts. Each concept node C_i represents one of the key factors that play a role in the system, and it is characterized by a value $A_i \in [0, 1]$ that is proportional to its activity or presence in the system. The concepts are connected by weighted arcs, which encode the relations among them. An example FCM with eight nodes and ten weighted arcs is illustrated in Fig. 2. Each connection between two concepts C_i and C_j has a weight w_{ij}, which is proportional to the strength of the causal link from C_i to C_j. If $w_{ij} > 0$ then there is a postive causality between concepts, if $w_{ij} < 0$, the causality is negative, and if $w_{ij} = 0$ then there is no causality.

Human knowledge and experience on the system determine the type and the number of nodes, as well as the weights (w_{ij}) of the FCM. This knowledge in the form of fuzzy values, assigned by experts or mined from the literature, is transformed into numeric values, *activation degrees* A_i for each concept C_i and weights w_{ij} for the causal links between them.

The goal of formalizing domain knowledge in this way is to infer the activation degrees of concepts that are at the end of causal chains. This is done by iteratively simulating causation until the FCM converges to a steady state. At each iteration, the value A_i of a concept is influenced by the values of concepts-nodes connected to it, and is updated according to Eq. (1) [62]:

$$A_i^{(\tau+1)} = f\left(A_i^{(\tau)} + \sum_{j \neq i}^{n} A_j^{(\tau)} \times w_{ji}\right) \tag{1}$$

where $A_i^{(\tau)}$ and $A_j^{(\tau)}$ are the activation degree of concepts C_i and C_j at iteration τ, w_{ji} is the weight of the interconnection from concept C_j to concept C_i and f is a *threshold function* that squeezes the result into the interval [0, 1].

The threshold function is used to reduce the unbounded weighted sum to a certain range, which allows for qualitative comparisons between concepts, at the cost of amenability to quantitative analysis. The most popular functions are continuous; however, some research works also utilize binary functions. The most commonly used ones are: binary, trivalent and sigmoidal. For a comparison of different threshold functions for FCMs, please refer to Tsadiras's recent review paper [65].

Example FCM. To make the above more concrete, let us explore an example FCM for needle sharing among IDUs, illustrated in Fig. 3. It is distilled from one of the FCMs used in Section 4.1.

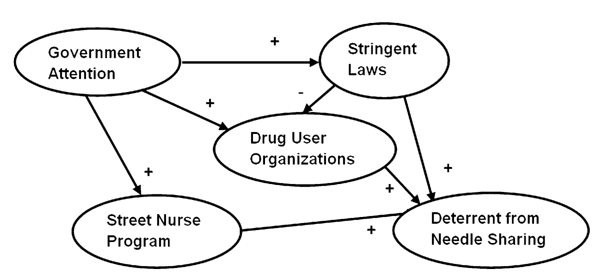

Fig. 3. An example FCM of factors that reduce needle sharing.