Structurally Evolving System Dynamics Models Using Genetic Algorithms

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Abstract

In this paper we discuss how to automatically generate system dynamics models using a kind of genetic algorithm known as a genetic program. This allows both the structure and the parameters of the system dynamics models under study to be evolved. This paper builds on previous work that introduced the use of genetic programs to automatically generate system dynamics models. The paper's contribution is that it discusses how to automatically generate anticipatory system dynamics in weakly constrained, data-sparse domains. The paper also describes how this technique might be applied to an example domain, namely that of transnational organized crime. This paper reports the status of work in progress. At the time of submission, the designs described in this paper were partially, but not fully, implemented.

Background

John Holland's (1992) genetic algorithms are a category of biologically inspired search methods that implement some of the central features of natural selection. Genetic algorithms (Goldberg 1989, Mitchel 1996) evolve a population of individuals, each of which represents a candidate solution to a user-selected problem. Genetic algorithms use a fitness function to rank each individual's effectiveness as a solution to the chosen problem. Genetic algorithms modify their populations over a series of generations using events patterned after natural selection. The events include the deaths of uncompetitive members of the population, the reproduction of competitive individuals, and random mutations among survivors. Reproduction, in particular, can include crossover events where children gain a mixture of the traits of their two parents.

Genetic algorithms have been widely used for a wide range of search and optimization tasks with substantial success (Goldberg 1989, Mitchel 1996). In the case of search, the fitness function quantitatively estimates how well each individual candidate meets the search criteria. For optimization, the fitness function is usually the objective function to be approximately minimized or maximized. It should be noted that for nontrivial problems and achievable run times, genetic algorithms are usually heuristics that do not guarantee optimal results. In practice, genetic algorithms often do quite well despite the caveats. Here we use genetic algorithms for a special kind of optimization to be detailed later.

Related Work

Genetic algorithms have been used in three main ways in the published system dynamics literature. First, genetic algorithms have been used in constrained

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domains to construct system dynamics models that match selected times series data. Second, genetic algorithms have been used to calibrate existing system dynamics models. Third, genetic algorithms have been used to optimize the parameters of existing system dynamics models relative to an objective function. We will now review each of these uses.

System Dynamics Model Creation

Several papers have been published on the use of genetic algorithms to generate system dynamics models or parts of system dynamics models such as stock equations. These papers are reviewed in this section.

Abdelbari, Elsawah, and Shafi (2015) use a genetic algorithm to evolve the stock equations for system dynamics models with one, two, and three stocks with the goal of fitting the resulting equations to known formulas for demonstration purposes. This work is similar to ours, but it does not seek to evolve the overall network structure, it does not take dimensional analysis into account, and it attempts to fit the results to a comparatively dense data set rather than discover new possible formulations.

Chen, Tu, and Jeng (2011) combine recurrent neural network (RNN) encodings of system dynamics models with a genetic algorithm to approximately optimize the models for the purpose of policy design. They use the RNN's to learn system dynamics model parameter settings and apply a genetic algorithm to evolve RNN-encoded system dynamics model structures. They attempt to find system dynamics models that fit a desired policy outcome and, separately, attempt to maximize desired policy outcomes for a given class of models. Chen, Tu, and Jeng (2011)'s work is closely related to ours, but they do not take dimensional analysis into account and seem to generate new models with only incremental changes from the original models.

Koza et al. (2001) and Pawlas and Zall (2012) use a variant of genetic algorithms called genetic programming (Koza 1990) to evolve system dynamics models. Genetic programming can be understood as a special class of genetic algorithm where each individual is a small computer program. These programs are often represented as branching trees of appropriate instructions. Pawlas and Zall (2012) used genetic programming to determine the equations and parameters in selected nodes of a system dynamics model of economic activity designed by subject matter experts. Koza et al. (2001) "reverse engineered both the topology and sizing…of a network of chemical reactions." Koza et al. (2001)'s pioneering work is the closest to that presented in this paper, particularly the molecular approach. Nonetheless, there are significant differences between our paper and those of Koza et al. (2001) and Pawlas and Zall (2012). First, we are modeling a less constrained domain so the search space of potential models is much larger. Second, we have less data and therefore must use techniques appropriate to a data-sparse domain. Third, we are not necessarily attempting to reproduce a known network but rather anticipate networks that might emerge in the future. Fourth, we use a nested two-stage optimization that considers dimensional analysis then system performance rather than a single stage.

System Dynamics Model Calibration
Calibration of an existing system dynamics model using a genetic algorithm usually involves evolutionary tuning of the model's parameters. Typically, each individual in the population represents one candidate set of model parameters. The fitness function result for each candidate is found by running the system dynamics model for a fixed period of time using the associated input parameters and recording either the cumulative or final value of a chosen model output. The calibration may be run once or it may be executed repeatedly to match varying entries in a target time series. Example papers that apply variations of this method are those by Jeng, Chen, and Jeng, Chen, and Liang (2006), Shuhong (2008) and Yu and Wei (2012). The work presented in this paper includes calibration, but goes beyond this by also evolving model structure.

System Dynamics Model Optimization
Optimization of existing models involves using a genetic algorithm to find system dynamics model parameters that approximately minimize or maximize an objective function. The objective function in turn is either the cumulative or final value of a chosen model output as generated by executing the system dynamics model for a fixed period of time using the selected candidate parameters. Examples papers that use this kind of approach include those by Linard (2000), Alborazi (2008), and Eksin (2008) as well as the aforementioned parameter-fitting element of Chen, Tu, and Jeng (2011)'s work. Our work preforms optimization on both the model's input parameters and the model's structure.

There is some debate as to how effective genetic algorithms are for calibration and optimization of system dynamics model parameters. Ventana Systems Inc., the makers of Vensim, have stated that "we have experimented extensively with genetic algorithm optimization and found that the results are very poor" (2015). Other system dynamics tools are reported to have included genetic algorithms for optimization (Linard 2000), at least at one time. Other researchers such as Linard (2000), Alborazi (2008), Eksin (2008), and Chen, Tu, and Jeng (2011) have reported successful results using genetic algorithms to optimize system dynamics model parameters.

Model Design
Two fundamental approaches are being pursued for this paper[4]. Both approaches use the genetic algorithm technique known as genetic programming to dynamically create a series of candidate system dynamics models to be evaluated by subject matter experts.

Each individual in the genetic program consists of a set of assignments to a fixed list of system-level output variables. Each output variable includes a time series of values and an associated unit. The domain-specific output variables are chosen by subject matter experts to represent the system's critical measures of interest. The

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genetic program determines the assignments to these output variables using either molecules or atoms as discussed later.

The fitness function uses rising values to represent increasingly preferred candidates. We use a nested two-stage fitness function that considers dimensional analysis then system performance. The dimensional analysis evaluation adds up any dimensional arithmetic or assignment errors and assigns an undesirable value to the fitness function that is inversely proportional to the total number of errors. The system performance evaluation only occurs when there are no dimensional analysis errors. System performance evaluation involves running the model for a specific period of time and then collecting the output results. Then, the system performance is assigned a desirable function of the output variables selected by the subject matter experts (e.g., maximizing profit). A candidate with the minimal system performance is arranged to have a higher fitness value than a candidate with even a single dimensional analysis error.

Either the molecular or the atomic approaches discussed next will produce generations of models with increasing fitness levels. Once the fitness levels become high enough the resulting models will be considered as possible future networks. Of course, having a high fitness level does not necessarily mean that a given transnational organized crime (TOC) network is a realistic possibility now or in the future. It is possible for networks with high fitness levels to contain subtle problems or to simply be unreachable by transformations from the current state. Nonetheless, novel networks with high fitness values may offer interesting anticipatory windows into possible futures. These candidate networks will be shown to subject matter experts to determine if the networks contain useful insights.

The Molecular Approach

The molecular approach uses Eberlein and Hines' (1996) concept of system dynamics "molecules" to build candidate models. Molecules are small to medium-sized sets of system dynamic components that represent common themes or motifs in a domain of interest. For example, Eberlein and Hines (1996) identify the simple stock and flow structure called a "decay process" as a common example molecule.

The molecular approach to dynamically generating system dynamics models involves subject matter experts identifying common behavioral patterns in their domain that are candidates to become molecules. These molecules are then given standardized interfaces that minimize the chances of dimensional analysis errors and maximize the opportunities for interoperability with other molecules. For example, common units are chosen when possible (e.g., all currency values in are U.S. dollars). It is intended that this will reduce the time spent in finding dimensionally-consistent candidate models.

The Atomic Approach

The atomic approach allows equations to be built up from raw terms rather than molecules. This approach allows greater flexibility than the molecular approach, but also substantially increases the range of possible models. In particular, it is expected that this will increase the optimization time spent on dimensionally-inconsistent models.

Example Application Discussion

Governments are increasingly faced with challenges that present themselves as "wicked problems" (Rittel and Webber, 1973). These problems are complex systems that have many interdependent elements. They are typically not "owned" by one organization, but instead have a myriad of stakeholders with different and sometimes conflicting perspectives on the system. Finally, these problems become especially challenging for areas related to security, where the complex systems being addressed are highly adaptive and covert.

The U.S. government typically addresses these types of complex wicked problems by dissecting them and parsing out the pieces to individual agencies and organizations. It is unreasonable to expect congressionally mandated agencies to reorganize themselves for every wicked problem. Therefore, interagency coordination is often accomplished through committees and task forces. Unfortunately, these approaches have not always been effective against wicked problems.

Collaborative interagency groups need to act like a meta-organization, with a trans-agency structure. To tackle complex adaptive systems, the 'trans-agency' itself needs to become a complex adaptive system. Methods must be developed that can design these trans-agency meta-organizations to be systemically aligned to the wicked problem they are charged with tackling.

Our case study looks at U.S. strategies for addressing the convergence of transnational organized crime with domestic local gang crime. Transnational criminal organizations engage in many kinds of trafficking including that of people, drugs, arms, dangerous chemicals, biological materials, nuclear materials, and funds. Even the illicit transfer of information over the Internet can be categorized as transnational crime. Today, TOC has shocking scale and tragic sophistication that creates enormous costs for both the global economy and the human community (United Nations 2004). For example, one estimate sets the financial cost of TOC at $870 billion annually (United Nations Office on Drugs and Crime 2012).

Criminal networks are not only expanding their operations, but they are also diversifying their activities, resulting in a convergence of transnational threats that has evolved to become increasingly complex, volatile, and destabilizing. These networks threaten U.S. interests in many ways including the forging and feeding of TOC alliances with corrupt elements of governments worldwide.

Several global trends—including dramatically increased trade volumes and velocity, the growth of cyberspace, and population growth—have facilitated an explosion of violent non-state actors, strengthened TOC, supported the emergence of a new set of transcontinental supply chains, and driven the expansion of existing illicit markets. The resourcefulness, adaptability, innovativeness, and ability of illicit networks to circumvent countermeasures make them formidable foes for national governments and international organizations alike (Miklaucic and Brewer 2013).

The complexity of the challenge requires attention to all levels of the illicit trafficking supply chain. The United States government has traditionally sought to address these challenges vertically, with agencies acting largely in isolation from one another. The Drug Enforcement Agency focuses on controlling narcotics; the

Food and Drug Administration concentrates on stopping counterfeit pharmaceuticals; the Department of Energy targets dual-use components of weapons of mass destruction; and the State Department limits conventional weapons flows to name but a few. These organizations are all short on resources, are highly overworked, are evaluated using divergent metrics by Congress, and are unable to develop the interagency responses necessary to disrupt the increasingly interconnected illicit enterprises they are charged with fighting.

Studies aimed at anticipating the evolution of TOC emphasize the need to understand the cultures and sub-cultures that yield and shield organized crime (Miklaucic and Brewer 2013). In addition, enhanced awareness of the political and economic incubators for criminal enterprises are needed. Facilitating the development of appropriate precautions or countermeasures by law enforcement agencies requires anticipating the long-term risk management strategies of criminal enterprises.

Recent empirical research on drug trafficking networks in Central and South America, confirms that illicit networks are not only composed of the expected unlawful social agents but also include critical “gray agents” (Salcedo-Albaran and Salamaca 2012). Gray agents are defined as social agents with conflicting organizational and functional roles. Examples are public servants, political actors, or security specialists who also promote criminal interests. Such agents are said to engage in preference falsification driven by their divergent, and mutually incompatible, commitments. As a result, interactions with gray agents produce different social relationships than those seen amidst the typical confrontation between bright (i.e., lawful) and dark (i.e., unlawful) social agents (Salcedo-Albaran and Salamaca 2012). These unexpected interactions contribute to the already high level of complexity found in TOC-infused systems. This naturally leads to a discussion of complex adaptive systems.

The complex adaptive system used in our case study is that of worldwide TOC network connections to local gangs. We plan to apply the atomic and molecular system dynamics model generation approaches discussed earlier to the TOC control problem.

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