Artificial Societies Enabling Multidisciplinary Policy Evaluation – A Health Policy Example

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ABSTRACT

Complex problem situations are characterized by heterogeneous components that are interrelated in various, often highly non-linear ways. Unexpected properties can emerge, possibly resulting in unintended consequences. Side effects also result from well-intentioned policies. Policies intended to address such complex problems are therefore predominantly reactive, ad hoc, and narrowly focused on treating consequences rather than the root causes and interconnected structural factors that drive the issue. Using a computational support tool allows us to evaluate multi-criteria and multi-objective decisions holistically; provide immersive feedback to policy makers; identify policies that address the issues without creating unintended consequences; and make policy makers aware of emerging and potentially negative side effects.

Artificial societies deliver this capability. They advance the agent-based modeling paradigm by using social science research to integrate human and social factors, utilizing three main components: (1) individual agents reflecting demographics and attributes of interest, (2) the situated environment with its infrastructure and social determinants, and (3) the social networks in which an individual is engaged. Policies are regulating the constraints under which the individuals can act by enabling or disabling certain behavior. The resulting artificial society becomes the common model for experts from all relevant disciplines.

We developed an artificial society for the evaluation of health policies regarding the opioid crises to demonstrate this capability. The resulting simulation has more than 500,000 agents in 250,000 households plus additional infrastructure components. We use this use case as an example for the application of this new class of computational decision support tools for multi-criteria, multi-value decisions in complex domains.

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INTRODUCTION

In their foundational paper on policy evaluation using simulation, Gilbert et al. (2018) state that "where the costs or risks associated with a policy change are high, and the context is complex, it is not only common sense to use policy modeling to inform decision making, but it would be unethical not to." However, few publications address the issue in a way that addresses all the issues policy makers are faced with, such as the following:

- Complexity is changing the rules of evaluation and optimization. Complex problems are no longer solvable by applying methods based on reductionism and may even require an approach beyond systems thinking, particularly when emergent behavior results from complexity (Diallo et al., 2018).
- Focusing on a single point optimized solution is not necessarily the best option, as the system is changing through adaption by individuals towards better solutions, which results in "dancing landscapes" (Page, 2009), so that robust solutions are preferred.
- Additionally, decisions in complex systems have side effects that may quickly become as important as the intended effects. Addressing them in the decision process requires multiple criteria decisions as well as multiple objective decisions. Supporting methods recently have been compiled in Ezell et al. (2021).
- Many policy decisions will touch multiple expert domains, so that cross-disciplinary approaches are needed. Experts from these various domains must be brought together to contribute to the formulation of the model to be used for the computational decision support activity (Tolk et al., 2021a).

Policies intended to address such complex problems are therefore in danger to become predominantly reactive, ad hoc, and narrowly focused on treating consequences rather than the root causes and interconnected structural factors that drive the issue. To avoid this, the computational decision support tool must take the complexity into account and provide realistic prognosis based on the inputs of experts from relevant disciplines. The computational decision support tool must represent the policy relevant heterogeneous components and their relations, including information that can be exchanged, and the individuals need to be placed in a situated synthetic environment that represents relevant constraints. All this needs to be instantiated with realistic data describing the problem domain.

Artificial societies deliver the required capabilities for policy evaluation. They advance the agent-based modeling paradigm by using social science research to integrate human and social factors, utilizing three main components:

(1) individual agents reflecting demographics and attributes of interest,
(2) the situated environment with its infrastructure and social determinants, and
(3) the social networks in which an individual is engaged.

To evaluate a policy, it is implemented as a set of regulating constraints under which the individuals can act by enabling or disabling certain behavior. Agent behaviors are derived from subject matter expert inputs. Agents may choose to ignore guidelines and constraints, and the social groups they are embedded in may support such behavior. The resulting artificial society becomes the common model for experts from all relevant disciplines, allowing to provide input and compare the heterogeneous views and metrics (Tolk et al., 2018). This paper describes the components of an artificial society when being used as the core of a computational decision support tool for the evaluation of policies. We also provide an example from the healthcare domain demonstrating the feasibility of the proposed framework.

A FRAMEWORK FOR A COMPUTATIONAL DECISION SUPPORT TOOL ENABLING POLICY EVALUATION

The artificial society simulation described builds the core of the framework. However, to be useful, the simulation must be embedded into a framework that helps obtain the required data, including preparing these data for use in the simulation. The framework also supports conducting the experiments and presenting the results to the decision maker. Within this section, we will first discuss artificial societies in more detail, then describe the types of data needed to instantiate and calibrate an artificial society, next we will discuss how we handle the design of experiments, and then look at the presentation of results.

Artificial Societies

The use of the agent-based paradigm in the domain of computational social science is well established (Epstein & Axtell, 1996) and was only recently reemphasized in (Davis et al., 2019). In their call for action to the community of artificial societies and social simulation experts, Squazzoni and colleagues emphasized the need to integrate human and social behavior into computational support models when addressing the COVID-19 pandemic (Squazzoni, et al., 2020). Several leading research institutions provided such support, like the Argonne National Laboratory (Ozik et al., 2021) or the Center on Social and Economic Dynamics at the Brookings Institution (Parker & Epstein, 2011), just to name two examples. Figure 1 shows the three characteristics of artificial societies that will be explained in this section.

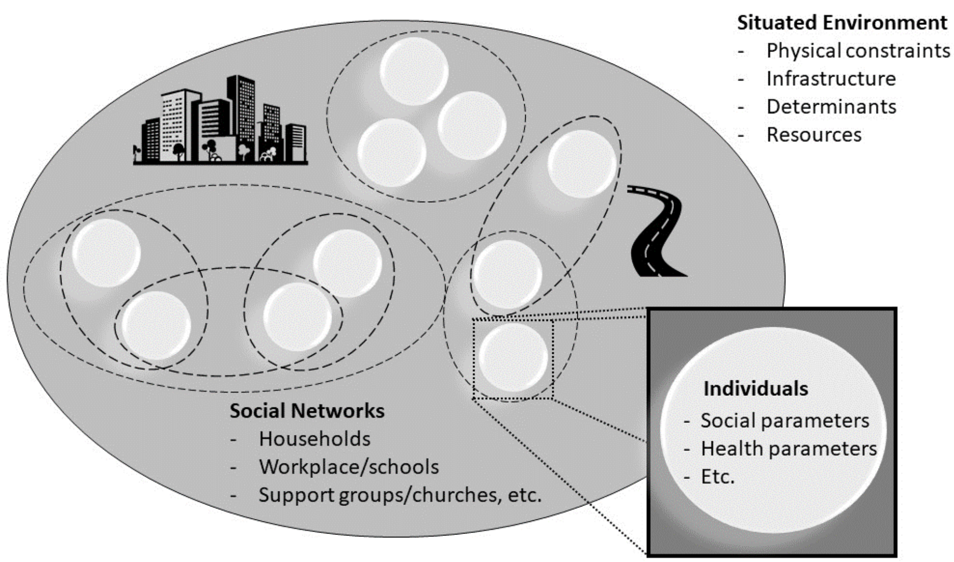

Figure 1: Artificial Societies with their individuals in their social networks within the situated environment

One of the characteristic attributes of artificial societies is that the individuals are socially capable agents. They are embedded into social groups, such as families, friends, work colleagues, etc., and take the inputs from and the values of these group into account when making decisions. The rules they follow are not only engineering based but are modeled using insight and guidance from the Humanities and Social Sciences. The characteristic attributes of individuals are captured as states within the representing agents. Depending on the problem domain, additional information important for an individual needs to be stored as well, as these support the decision process for the individual. They also have memories that guide their decisions.

The individuals can belong to multiple social groups or social networks with different, maybe even conflicting values, so that the decision-making process of agents can become a multi-criterion, multi-objective challenge itself. These social connections can be pivotal for many decisions and state changes. If an event occurs that is negative for an individual, being in a strong group that provides support can save an individual from making a choice with further negative consequence, e.g., having access to “life coaches” can help to stay on course. They are represented as dashed lines grouping individuals into various groups.

Finally, they are embedded into a synthetic situated environment, which provides hard constraints – such as physical barriers as well as access or lack thereof to needed resources – as well as soft constraints – such as norms and values, including existing policies and guidelines. Soft constraints can be ignored by the individuals, e.g., if they had bad prior experiences following a similar guideline or following a guideline from the same group of policy makers, or if they are part of a group that is opposed to these guidelines. The environment may also contain social environmental determinants that are important for the policy domain of interest, such as social determinants of health as exemplified by Mahamoud et al. (2013).

Data for Artificial Societies

To trust simulation results, not only good algorithms are needed, but the necessary data needs to be obtainable and aligned with the simulation assumptions as well. Artificial societies require a high variety of data. The first set of data needs to populate the characteristic attributes of individuals. As these individuals are socially capable agents, they need data capturing the general as well as the individual social behavior. As societies are home for many activities, the individual participants in such activities need to be defined, such as when and where people go to work, using what kind of transportation. Which schools or universities are attended by which students? Which shops are in the neighborhood providing which services, and who is using these services? When obtaining these data, there are two general challenges:

- The data are distributed over many heterogeneous data sources, which are not necessarily well aligned. They may differ in scope, resolution, and structure, requiring not only simple mapping, but often transformations of data into aggregates or disaggregating data, etc. The classic approaches of federated schemata can help, see, among others, Heimbigner and McLeod (1985).
- It is often necessary to augment real-world data with synthetic data. First, some data are not publicly available, too costly, or for other practical reasons not obtainable. If such data are needed for the simulation, synthetic data serves as a substitute. Second, the use of personal data is constrained by a variety of data laws and regulations, e.g., when data are part of Personal Identifying Information (PII), often making their use impractical. Third, the use of synthetic data allows for the generation of unobserved but still scientifically interesting constellations and initialization. The mathematical background and additional information are provided in Raghunathan (2021).

While finding the data needed to instantiate and calibrate the individuals is already challenging, the data for social networks and the behavior of agents representing the individuals is even harder to obtain. Often, the expertise of subject matter experts from the relevant domain is the only way to get these data. Sometimes, extensive literature research supported by artificial intelligence methods can lead to the generation of applicable rules and/or state changes based on peer reviewed documentation of specific knowledge. In addition, scripts and schedules triggering behavior like going to work, going to the mall, or visiting friends can be applied as well.

Validating the resulting instantiated and calibrated models is a challenging task, as the number of free parameters can easily become overwhelming. Troitzsch (2004) recommends a stepwise approach for calibration and validation of agent-based models applicable to artificial societies as well, starting with general questions in a prototypical setting to gain an understanding of the behavior and sensibility of the model. The focus of this first step lies on ensuring that the structure of the model is correct. Next, the simulation should be set in an empirical setting to reproduce observed behavior of the real system. The focus lies on calibrating the model by identifying appropriate parameter constellations. Lastly, the model can be applied to make predictions. Windrum, Fagiolo, and Moneta (2007) provide an overview of additionally applicable empirical validation methods, although research is ongoing.

While using simulation methods to address complex situations we learned that we cannot simulate what exactly will happen, but that we are still able to simulate what may happen in form of trends. In this context, trust in the simulation (Harper et al., 2021) and plausability of the approaches are often more important than the application of traditional validation methods as they grew outo fo the physics-based modeling realm. As a matter of practicality, engaging policy and decision makers as team members in the development of models and simulations rather than using these models only as means to generate reports for them, is good practice. Rouse and Serban (2014) observe that engaging decision makers in this development process results in them trusting the model more. The models become an integral part of the decision process, they are no longer just another tool.

Design of Experiments under Complexity

Complex problem situations are characterized by heterogeneous components that are interrelated in various, often highly non-linear ways, including feedback loops. Unexpected and sometimes even counterintuitive properties can emerge, resulting in likely unintended consequences. Additionally, side effects can lead to counter-developments negating the positive effects of policy choices.

As collecting all necessary data is not always possible, many model choices will depend on subject matter expert inputs and estimates rather than on empirical observations. The more complex a challenge is, the more experts from multiple disciplines are needed within the team to solve it. Page (2008) makes a strong argument that solving complex challenges requires diversity of opinions and methods. However, the experts in such diverse teams may not agree on values or value distribution for characteristic attributes, and they may even disagree on which attributes are truly characteristic. There will be disagreement on the effects of certain activities, the measures of merit and related metrics to be used to define success, and even the conceptual model underlying the artificial society itself may be subject of discussion. Within operations research, this class of challenges is called deep uncertainty, and the method to address those uncertainties is exploratory modeling and analysis (Kwakkel & Pruyt, 2013). Recommendations for process management of such multidisciplinary teams is given by Shults and Wildman (2020).

Extending the ideas presented by Tolk (2016), conducting sensitivity analysis is necessary, but not sufficient. Instead, an understanding of the topological structure of the solution space is needed, addressing the stability of the solution space even under adoption of new rules and behavior. It is pivotal to understand where the landscape is stable, and where it is going to “dance” as described by Page (2009). Exploratory modeling and analysis support this by not only modifying the free parameters, but all parameters as well as alternative structures. Even if certain rules cannot be validated by empirical observations, this approach allows us to understand how different behavior patterns will influence the result of the policy, understanding under which parameters the solution remains stable. The workbench described by Kwakkel (2017) provides a structure allowing us to plan for exploratory modeling and analysis.

Presentation of Results

Artificial societies provide a multitude of data under uncertainty. These data need to be presented to the decision maker in an understandable and actionable form. To make the insights of the simulation applicable for decision makers, they must clearly understand policy levers representing various policies and alternatives. Rouse (2021) proposes making the system immersive and interactive to become the “flight simulator for decision makers.” Haberlin and Page (2022) describe the use of large-scale, highly configurable visualization facilities. Placing the decision maker into such an interactive and immersive display results in understanding the solution space better and even experiencing possible effects and side effects of policies.

The use of dashboards, as they are used by decision makers to visualize real-world data for situational and option awareness, should be part of these presentations. But dashboards often fall short of visualizing uncertainties. These uncertainties are a vital part of the insights that can be provided using artificial societies, requiring us to augment the dashboards accordingly. Visual representation of uncertainties is a topic of ongoing research and requires that we continue to follow developments for the best support of communication of uncertainties and related risks to the decision maker.

AN EXAMPLE FROM THE HEALTHCARE DOMAIN

The following example has been presented at the Annual Research Meeting of the Academy Health (Tolk, et al., 2021b) and has been extended to allow broader applicability since then. We first present the use case followed by recent technological advances that address the challenges discussed in the first part of this paper.

Use Case: COVID-19 Policy Effects on the Opioid Crises in Washington, D.C.

In an internal research and development project, our team implemented an artificial society to evaluate policy effects on the opioid crises. The motivation for this effort, which started in 2019, is that every day more than 100 Americans die after overdosing on opioids. The total economic burden of prescription opioid misuse in the United States alone is

$78.5 billion a year (Florence et al., 2016). These issues have only been exacerbated by the current pandemic. As the Capital region provides good access to data needed to describe the problem domain, Washington, D.C., was chosen as the example region for this research effort.

The initial artificial society represents a subset of the individuals, households, and neighborhood attributes of the residents of Washington, D.C. The society represents the 169 census tracts and the eight wards of the District of Columbia. The main sources used to generate the individual and household agents, as well as their school and workplace locations, were RTI International's 2010 U.S. Synthetic Household Population™ Database (Wheaton, 2012) and Synthea™ (Walonoski, et al., 2018), a MITRE-developed open-source synthetic patient generator, which provided information on health records for synthetic individuals. These synthetic data sources were augmented with publicly available data sources, including the U.S. Census Bureau's American Community Survey (ACS); the U.S. Department of Health & Human Services' National Survey on Drug Use and Health (NSDUH); the Center for Disease Control and Prevention's (CDC) Social Vulnerability Index; and Pew Research Center's Religious Landscape Study. The resulting data are realistic and reflect the demography without giving private data away or violating other data rights.

The main characteristics of interest regarding the evaluation of effects of policies are the health states and social states the individuals are in. For opioid misuse, the literature survey resulted in five individual health states of interest: susceptible, opioid misuse, recovery, overdosed, and deceased. State changes are triggered by events that happen in the artificial society. Examples are the loss of a partner or job, but health-related events, such as sickness and pain, can lead to a state change as well. The likelihood of a state change is influenced by individual characteristics, social determinants of the environment, and characteristics of the social networks. These characteristics make up the social states an individual is in.

All modeled states, their transitions, and influencing factors are motivated by a literature review based on artificial intelligence extraction of these information (Source: https://curismeditor.co). We scanned 40 million research articles on substance abuse using the following search queries: "Dynamics of Substance Addiction and Recovery," "Dynamics of Opioid Addiction and Recovery," "Probability of Drug Addiction Recovery," "Opioid Addiction Peer Recovery Coaches," "Mathematical Models of Addiction," and "Markov Models of Disease Stages." Three journals appeared most frequently – *Harm Reduction Journal, International Journal of Mental Health System's,* and *BMC Psychiatry* – resulting in 250 highly vetted articles to identify research justifying our attributes, parameters, and state change options.

These articles supported identifying the relevant status information an individual may be in, but they did not support deriving transition probabilities between them, as the conditions for each study captured in the literature are rather disparate. Transition probabilities are an example of important attributes that require subject matter expert inputs and must be evaluated via exploratory modeling and analysis. In this use case, interviews with internal experts that were followed by an extended sensitivity analysis in the calibration phase determined the transition probabilities. The process followed the recommendations of Troitzsch (2004): The literature search determined the individual behavior, and the calibration steps ensured explainable behavior in groups that step-by-step grow up into the artificial society.

These steps resulted in the attributes required as well as state change probabilities that were developed in workshops with team members and implemented as an agent-based model within a situated synthetic environment. While most healthcare-related publications recognize the importance of the social determinants of health (SDOH) on opioid misuse, our literature review revealed that social networks (such as family, peers and friends, co-workers, and service providers, including social services, and law enforcement) are often just as important. We therefore reflected the SDOH in the situated environment for the agents and the social networks as relations between the agents.

The initial experiments instantiated slightly more than 5,000 individuals in approximately 2,500 households. They were configured and calibrated so that the artificial society represent proportionally the citizens of the eight wards of Washington, D.C. Based on the available data described above, a base policy was instantiated regulating the contact rate within social networks that reflected the situation of 2017, in which social support groups can be active but they are highly dependent on the social determinants. The D.C. Government's Opioid Dashboard provided the number of opioid-related emergency room visits and deaths. The calibration ensured that the number of agents observed reflected the expected number when compared with the empirical data captured in the D.C. Government's Opioid Dashboard. Once the calibration was done, two alternative policies were implemented, resulting in three simulation experiments.

- The results from the calibration provided the base case, reflecting the pre-pandemic state.
- The first alternative mirrored the situation of a lockdown, like that of the 2020 pandemic: no social contacts were supported.
- The second alternative increased the number of support groups in all wards. Social workers and support groups were increased.

The effects of the three policies can be compared via the simulation shown in Figure 2, in which we see the effect of absence (left side), presence (middle), and active support (right) from social networks on the proportion of the population experiencing opioid misuse in each ward.

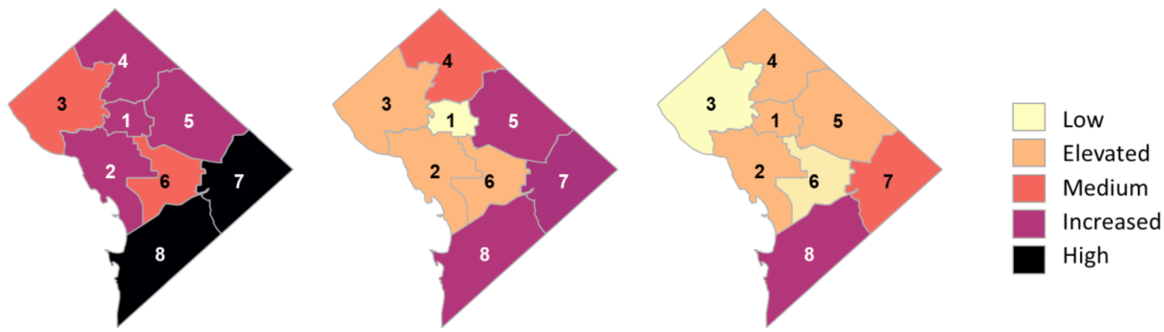

Figure 2: Simulation results showing effects of absence (left), presence (middle), and active support (right) from social networks

These results are not precise forecasts but show a trend. Nonetheless, they predict a significant increase of opioid misuse with the lack of social support groups, and a substantial decrease when such groups are supported. Such predictions were only possible due to the modeling of social networks as the third pillar beside individual parameters and social determinants of the situated environment. It also shows the potential to make decision makers aware of possible unintended consequences that now can be taken into consideration before they are observed in the real world once the policy is set in place in such a multifaceted and complex environment. In this use case, the prediction of an increase of opioid misuse under the circumstances of lockdowns was observed in reality as well (Mason et al., 2021).

Ongoing Technical Improvements

As the initial work showed the feasibility and value of the approach, the artificial society was technically improved. Also, the framework supporting the use was enhanced and transformed to open-source solutions as follows.

- The simulation engine was transitioned to Repast High Performance Computing (HPC), generating a fork of the original Argonne National Laboratory engine accessible via https://github.com/Repast/repast.hpc. This allowed us to grow the number of simulated entities significantly.
- The artificial society used the core of chiSIM (Macal, Collier, Ozik, Tatara, & Murphy, 2018), transitioned it from Chicago, IL, to Washington, DC, which resulted in *communitySIM*. In addition to changing the geospatial part, additional functionality was included as identified in the initial research work.
- Using the Apache family of open standards, the presentation of the results was moved into a configurable experience layer. Apache Kafka (https://kafka.apache.org/), Apache Druid (https://druid.apache.org/), and Apache Superset (https://superset.apache.org/) allow for streaming the data as needed, using a distributed data store, which now can be explored and visualized as requested by the decision maker.
- Finally, using the open-source containerization platform Docker (https://www.docker.com/) allows us to deploy these solutions to a variety of target platforms.

Figure 3 shows the resulting and currently used configuration: on the left side, the necessary data are obtained and prepared to be used in the simulation; the artificial society in the middle allows to create numerical insights into the dynamics of the artificial society; and the right side provides tool for the visualization of the results in an immersive and interactive form.

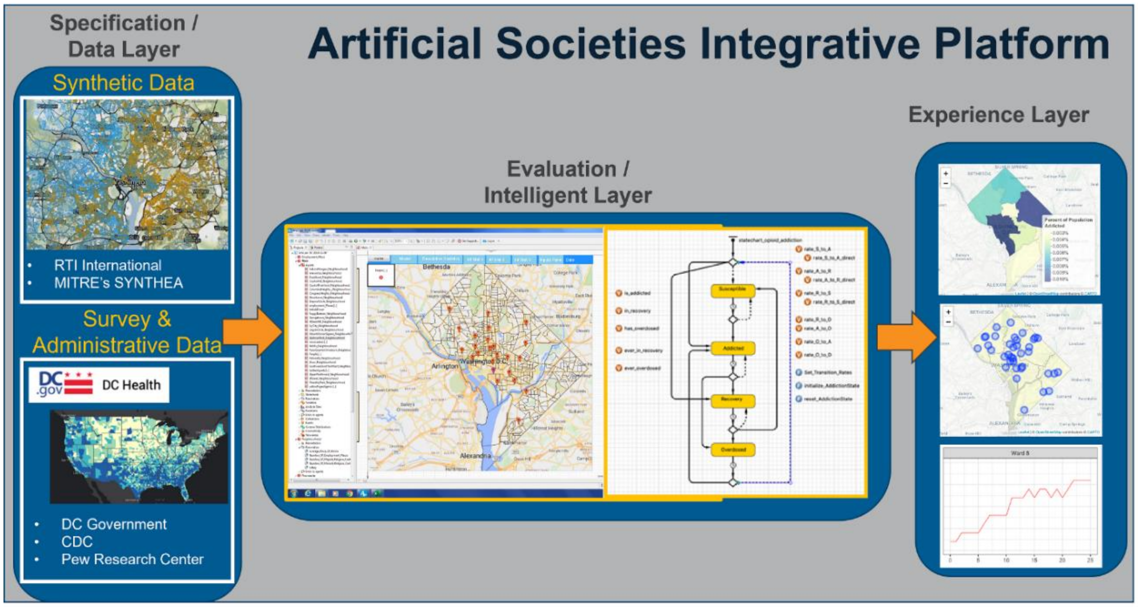

Figure 3: The artificial society within the framework of the computational decision support tool

The current computational decision support tool can use high-performance computers as well as personal computers. It currently supports the simulation of more than 560,000 individuals in 260,000 households, 200 schools, and 50,000 workplaces. It reflects the demographic and economic structure of the target population.

SUMMARY AND DISCUSSION

Policy and decision makers need computational decision support to better understand the complexity of the environment that they are working in, and respectively, the effects and side effects their policy decisions will have. The vast number of heterogeneous entities interrelated via multiple non-linear connections and feedback loops require adding new methods to the toolset utilized by decision makers so far. Artificial societies embedded into a data analytics framework that obtains and visualizes the data and supports design of experiments to address deep uncertainties support these methods. Policy effects in such environments are usually multifaceted, and many side effects may result in unintended consequences. Artificial societies can help us become aware of such effects early on and avoid them. The use case presented provides one example to demonstrate this capability. The technical improvements presented in this paper result in a capability that can help evaluate communities with more than 500,000 members, but the data challenge to initialize and calibrate such a solution can become enormous as well.

Depending on the research question of interest, data may have to be obtained from so many unaligned databases that manual mapping or the application of ad hoc heuristics are no longer feasible. Initial research on this topic, including aligning of real world and synthetic data, has been conducted, but more is needed. Furthermore, the application of exploratory modeling and analysis also increases the amount of data making up the results, so that it may become necessary to apply additional data analytics here as well.

As discussed earlier, artificial societies have been successfully applied in several domains. However, so far, the various applications were individual developments. With the increasing use, the question arises to what degree a common core capability may serve as a rapid start to different questions. Is the number of common attributes and entities in various applications sufficient to justify a common core, or is it more economic to develop a new system from scratch? Preliminary observations tend to suggest that particularly when a common open-source approach is utilized, as described in the technical improvement section, the use of a common core increases the productivity of teams, as they can focus earlier on problem domain research.

As discussed in (Diallo et al., 2018), complexity exists in the real world and must be understood by the decision makers. It is of little value trying to reduce the complexity within a solution that then no longer provides applicable advice for the original real-world problem which started the request for support. Within this paper, the use of artificial societies is motivated to better understand and govern complexity, allowing us to evaluate policy decision making under such complexity and deep uncertainty.

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