Growing People: Generating Realistic Populations and Explainable, Goal Directed Behavior

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ABSTRACT

Agent-based modeling and simulation is critical to answering key questions within the Intelligence Community and Department of Defense. Ranging from strategic defense planning to public health and disaster recovery, many use cases involve emergent behavior where the actions of a few individuals can affect the behavior of the whole. Having actionable findings necessitates accurately depicting individuals' motivations and decisions at scale. However, modelers often have limited access to open-source, accurate person-level data. To overcome this limitation and answer scenarios like these, we expand on known agent-based modeling capabilities to show geolocated, goal-directed behavior by synthetically representing a real population making real decisions.

Prior work to generate synthetic populations largely utilized aggregate distributions commonly found in census datasets. Other work shows the importance of personality in shaping realistic behavior but has yet to generate representative individual agent personality. Our work builds upon methods in the behavioral and computational sciences by generating a population from available aggregate data for a specific geographic region to model personality effects on agents' cognitive processes. Our goal is to better capture how the real-world population would respond to simulated scenarios. We detail how agents can be grown using representative aggregate data to guide that growth into realistic simulated entities. We generate agents using best-in-class methods within the Synthetic Reconstruction and Combinatorial Optimization classes. Last, we discuss those entities taking motivated actions unique to their geographic areas.

We developed the current methods in collaboration with the National Geospatial-Intelligence Agency (NGA). Our work reveals the impact that population realism lends to applications across the Intelligence Community and Department of Defense. Implications for national security include higher fidelity modeled outcomes that inform policy or decisions when it comes to a populace, interventions, or making policies.

ABOUT THE AUTHORS

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INTRODUCTION

Government and defense users collect human geographic data such as population surveys, demographics, and spatial relationships to inform sociopolitical decisions. These decisions often constitute interventions that affect the outcome of an ongoing or future scenario. However, decision makers lack the means to effectively operationalize static human geographic data into a framework suitable for scenario-based decision-making. Effective sociopolitical interventions are typically measured in terms of a population's aggregate response to the intervention. However, individuals ultimately make up the population and drive aggregate results. Our ability to project the outcome of an intervention is dependent on our ability to simulate emergent behaviors derived from individual decisions. To this end, we focus on generating representative synthetic populations from aggregate statistics and spatial data, to include generating new agent-level attributes such as behavioral characteristics.

Background

Our work can inform use cases critical to government and defense where understanding a population's behaviors, from the individual level to the aggregate whole, is paramount. These methods further provide a mechanism of operationalizing human geographic data into scenario-driven modeling and simulation to discover and understand emergent population-level behaviors that could better inform interventions and policy decisions.

Since our work produces anonymized representative members of a population, we can estimate how different types of individuals may respond in a scenario without the need to collect potentially private or identifying information. Even in cases where sensitive personal information is electively provided as a data source (such as individual surveys), data sanitization methods such as differential privacy could provide another layer of abstraction to gather macro-level statistics without retaining private information (NCSL, 2021).

Representing social group identities, power structures, and values within a synthetic population could provide a fundamental element of analysis for military planners. Intelligence preparation of the operational environment is a process used to analyze all relevant aspects of the subject environment; this includes political, military, economic, social, information, and infrastructure systems (Joint Chiefs of Staff, 2014). Societal intelligence preparation most often includes collecting general information about a population (e.g., income, religion, ethnicity) to inform qualitative decision-support frameworks. Synthetic populations could provide military planners a means to generate previously unknown social attributes in their operating environments to support statistical modeling and improve decision-support tools.

Human geographic information depicting the environment, communities, and cultural attributes aids civil support activities such as humanitarian assistance and disaster relief. In many cases, users may infer from this information behaviors such as how notional subgroup members would respond to a particular policy or humanitarian objective. Simulation-based decision aids would enable policy makers and disaster response authorities to visualize the range of behavioral responses to scenarios of interest, identify unexpected emergent behaviors, and inform more effective interventions. Similarly, agent classes within a synthetic population could represent social archetypes that warfighters, diplomats, and humanitarians encounter in real-world operating environments. Users could infer ethnographic conclusions about these archetypes without extensive direct contact with the target population and develop narratives as the corpus of social information grows. Users can then iteratively verify findings through simulation and conduct quality sampling from direct interactions.

Prior Work

To generate synthetic population data, prior work often samples from aggregate distributions to recreate those distributions (Simple Integrated Land Use Orchestrator, 2020; Urban Data Science Toolkit, 2018; Ye et al., 2009). Building on this approach, one difficulty we address is extracting individual variable distributions of specific categories from a combined dataset. Prior work on the impact of personality demonstrates that it affects realistic behavioral outcomes. These examples largely focus on individual personality traits affecting areas of an action space, parts of a framework (such as the belief-desire-intention model), or specific scenario outcomes (Ahrndt et al., 2015). We are extending prior methods by generating data unique to geographic areas at the person level, expanding on realistic person-level data, and utilizing the full personality vector to drive decisions.

Current Work

Our goal is to generate geographically realistic synthetic people with actionable motivations and show how that realism further propagates to population-level outcomes. We start with explaining how to generate or *grow* agents. These demographic and behavioral attributes make up the roots of the synthetic person. Building on the generated base of a population of people, we explain the branching path from personality to basic needs to actions (such as going to geographic points of interest to fulfill a need). Last, we detail ongoing work to implement and iterate on this functionality as general models used in specific scenarios.

GENERATION

We used best-in-class methods to generate population data. Multiple works have generated populations from the ground up using such methods as Iterative Proportional Fitting (IPF) and Iterative Proportional Updating (IPU) with U.S. census data (Simple Integrated Land Use Orchestrator, 2020; Urban Data Science Toolkit, 2018; Ye et al., 2009), similarly to our current work. Monte Carlo microsimulation (Moeckel et al., 2003) is another method used in data generation, though it relies on microdata. Our work integrates several of these methods to iteratively build the population's attributes.

Generation Methods

Synthetic person-entity generation is a three-step process. First, we sampled base entity attributes for race, sex, and age from aggregate distributions found within U.S. census data (American Community Survey, 2018). Further attributes were then added by sampling from distinct joint probability distributions for specific race, sex, and age combinations. We derived these joint probability distributions using one of two techniques depending on the nature of the underlying datasets used. The most common technique involved combining two or more univariate distributions using IPF. For example, we defined the distribution of occupational groups as a two-dimensional matrix with marginal distributions set to the proportions of employment by age group and occupation category by race. We then used IPF to determine the values of individual cells by balancing the sum of their values across columns and rows such that the marginal distributions were maintained. To *seed* the matrix, we utilized the national distribution of occupations by age groups from the Bureau of Labor of Statistics to initialize cell values.

The second technique was utilized when it was necessary to extract the individual distributions of specific categories from a combined dataset of ordinal values. This was accomplished by developing a custom algorithm that was calibrated using differential evolution that exploited median values and category counts to *untangle* the individual distributions from one another.

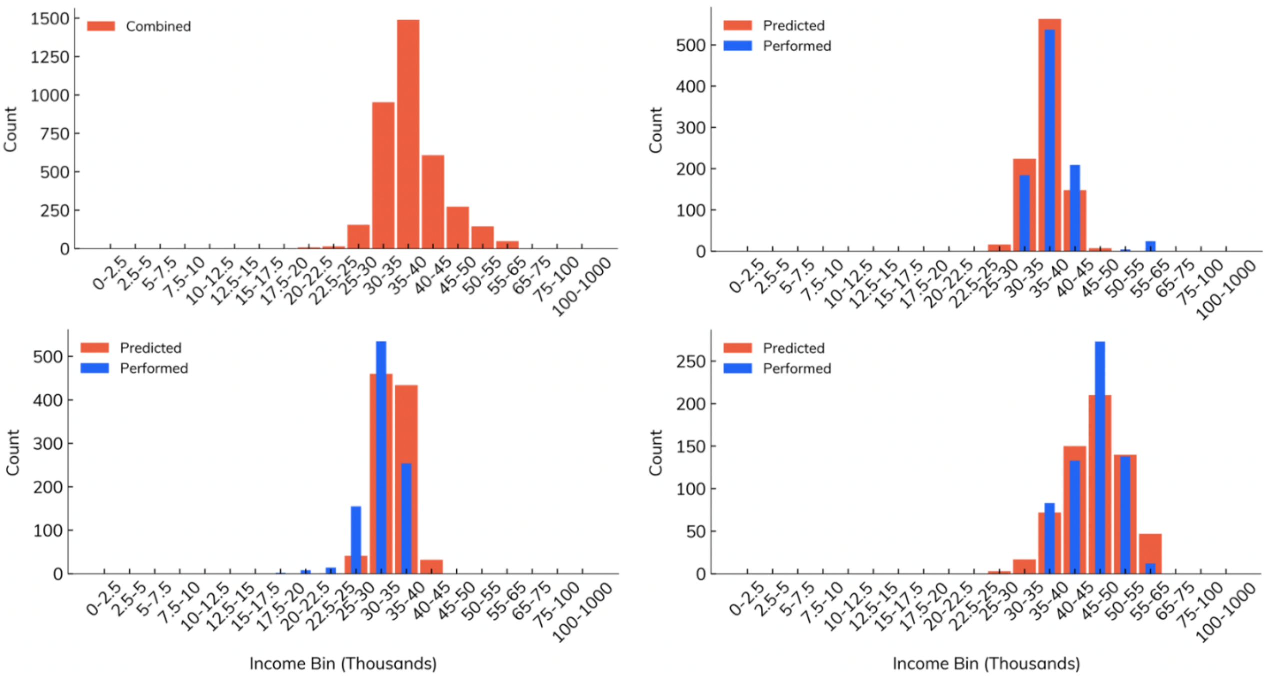


Figure 1. Tangled and untangled distributions using synthetic data. Combined or *tangled* distribution of incomes across occupational groups (upper left); untangled distributions for three income ranges (upper right and bottom charts). In the untangled charts, orange represents the actual generated distribution and blue represents the predicted distribution to show how the algorithm is performing.

For example, there are census datasets that provide the distribution of income groups and the median salary and total number of members in each occupational group for each race. Our algorithm untangled the individual distribution of income groups for each occupational category from the combined set by using the median salary and total number of population members employed in each occupational group. The graphs in Figure 1 depict a combined distribution and multiple untangled distributions.

Our ongoing person-entity generation work makes use of Monte Carlo methods on univariate census distributions to assign head of household status based on education, age, sex, and race. Household status is prerequisite to placing agents in house locations. The final step in the population generation process considers the disposition of entities that represent points of interest such as homes, schools, and places of work to further refine population member attributes; this work in progress utilizes location data derived from Google Maps, Open Street Map, and commercial satellite imagery.

With a base synthetic population built, we expanded it by generating outward to personality parameters and actions to show the end-to-end process for growing people. Figure 2 illustrates how the attributes build on each other from the base population to behavioral attributes.

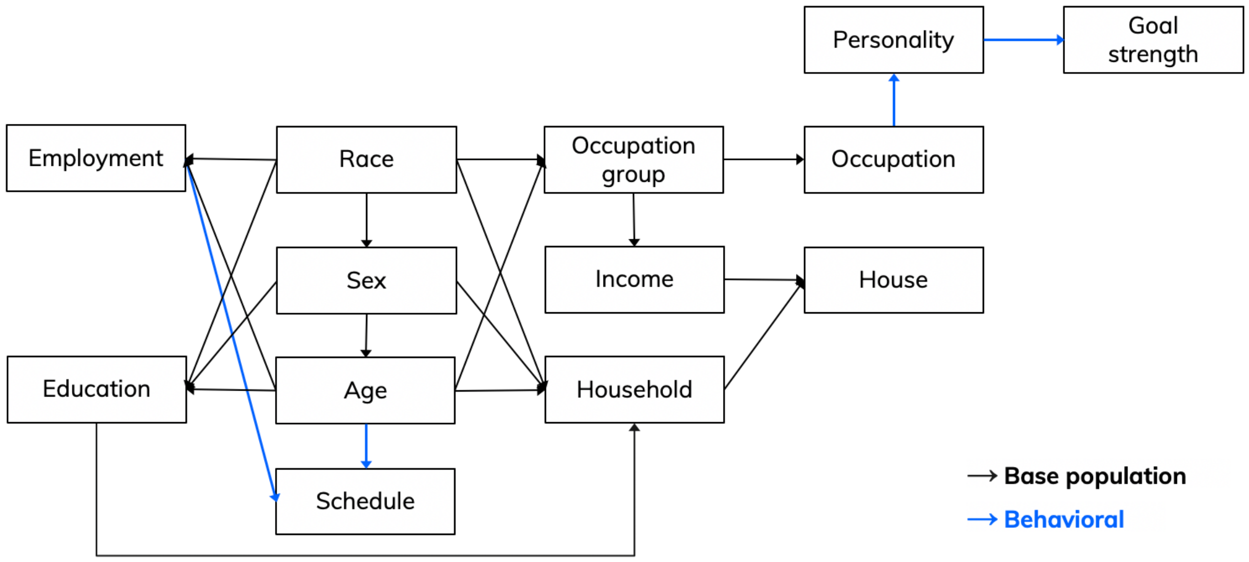


Figure 2. Attribute generator dependencies

BEHAVIOR

The impetus for people to travel and to interact with others stems from cognition, providing individualistic flow and movement. Building on the generated base population, we explored personality traits as a cognitive basis for basic needs, personality-driven goal strength for choosing actions, and generated a starting point for a realistic pattern of life based on demographics. Figure 3 depicts how these concepts build.

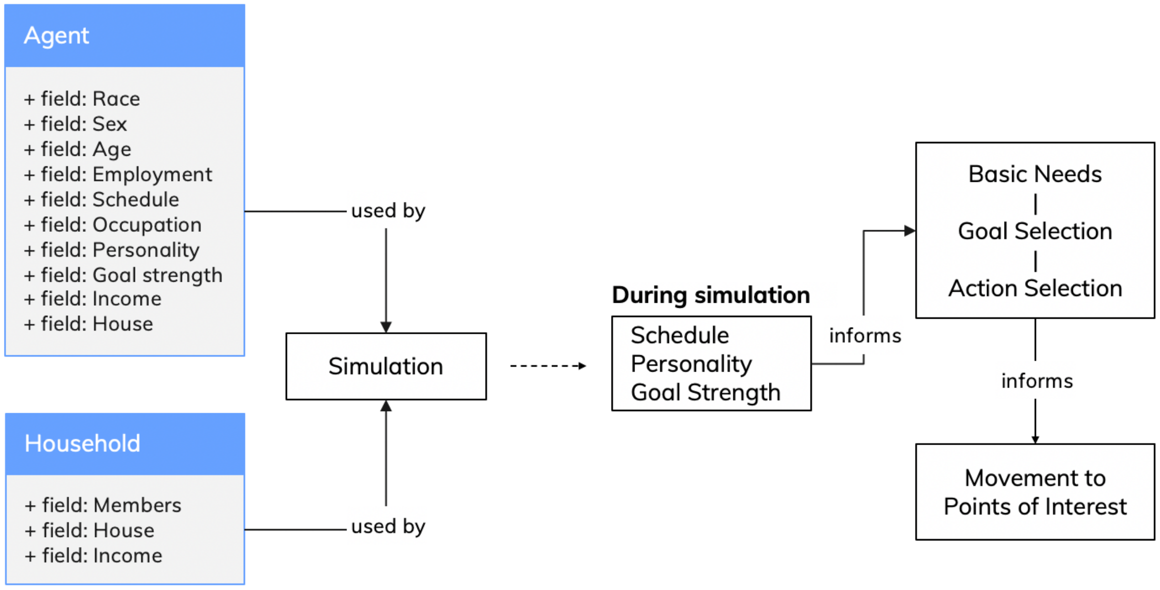


Figure 3. Concepts building from base population data to individual outcomes

We used the Five Factor Model (FFM) or OCEAN theory of personality. This theory represents the traits Openness, Conscientiousness, Extroversion, Agreeableness, and Neuroticism. Researchers prefer the FFM for several reasons. Importantly, given the FFM's acceptance within psychological work, researchers often integrate and extend FFM findings such as with Schwartz' personal values (Parks-Leduc et al., 2015), Murray's needs (Costa & McCrae, 1988), and Kern et al.'s profession profiles (2019). This research base provides richer access to findings. We considered the benefit of reducing complexity by assigning agents personality types. However, prior work on personality typologies (even using the FFM) is mixed in how reliably and globally those types can be identified (Gerlach et al., 2018). We found that choosing to implement agents' five OCEAN traits as percentiles grants us an information space from which to build an extensible cognitive model.

We chose occupation as a basis on which to generate personality because it is an accessible life choice. Interest in the effect of personality on occupation dates to Holland's theory of career choice (1959) suggesting personality can be inferred from vocational interests. Research has built on this idea by clearly relating OCEAN traits to these typologies (Barrick et al., 2003) and finding distinct profession profiles clustered by personality traits and personal values (Kern et al., 2019).

Behavioral Methods

Taking a synthetically generated population for a geographic area, we used occupation as the input to derive agents' personality (the five OCEAN traits). Starting with an agent's occupation, it is compared to occupations clustered by personality (Kern et al., 2019). We applied fuzzy string matching by using Levenshtein distance (SeatGeek, 2020) and word stemming to calculate differences between strings. If highly similar matches were not found between occupation titles, the process utilized additional context of alternate job titles (synonymous job titles used in workplaces; O*NET, 2015) to find an acceptable match within a profession cluster. With these as reference data, the process sampled agents' personality vectors from the professional cluster their job falls within.

People have motivations driving them to actions; these motivations provide the basis for why agents do things. Having a motivation component in a cognitive model is central to driving decision-making that produces realistic behavior. We term these motivations *basic needs*, and examples include safety needs, physiological needs, and social needs. Sun (2009) draws on Murray's needs (Murray, 1938) to represent basic needs. Following in this vein of work, we structured our motivations as beginning with foundational basic needs that are each linked to multiple explicit goals from which agents choose an action (i.e., basic need → goal → action). These basic needs were the motivational starting point, but to use those to enact goals, they required a relationship back to what is driving them. We used personality traits to further generate values for pursuing goals.

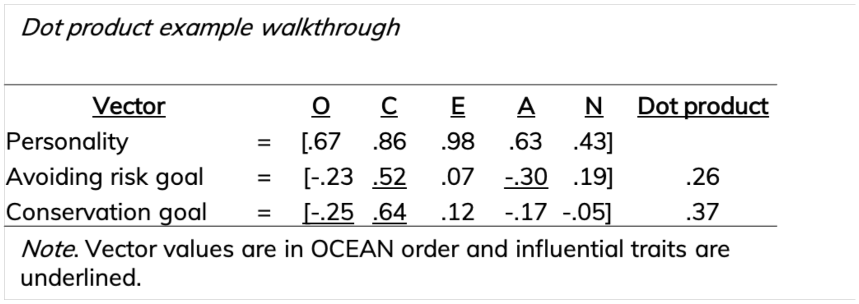
Our approach was similar to Sun and Wilson's (2014) approach of mapping empirical work that links motivational measures to the FFM of personality back to the basic needs and goals we use to have agents enact actions. We used Costa and McCrae's work (1988) linking the FFM and needs-based behavior.

Using this approach, we derived a data table of correlational data relating each goal to each OCEAN trait; this table describes how strongly a goal is related to each personality trait. To decide on a course of action in line with an agent's most pressing basic need (ex: safety needs), the goals' vectors related to OCEAN traits (from the data table) and the agent's personality vector (five OCEAN percentiles) are used to calculate a dot product. Safety has multiple goals that meet this need, so the dot product for each goal is calculated for which goal receives the highest priority. This dot product represents personality-driven goal strength and measures how similar two vectors are or how well they travel together. In the calculation, each product receives directionality for how strongly the OCEAN trait factors into the goal. The products retain a higher value for which traits are more important. Summing the products produces an overall value of goal strength. See an example walkthrough next for going from a basic need (ex: Safety) through calculation to goal and action selections:

- Basic needs are referenced for priority (state of how high they rank).
- The Safety need ranks the highest and is selected for action.
- Safety's goals go through a calculation of:
  - Score = goal's dot product × utility
  - Utility = environmental policies in the simulation are meant to adjust utility by setting priorities for classes of actions or for particular goals.

- Dot product calculation in Table 1 (vector values are in OCEAN order).
- Policy where illness prevention measures are adopted (e.g., wearing face masks to avoid risk) = 1.5
    - Preference avoiding risk = **.26** × 1.5 = 0.39
    - Preference conservation = **.37** × 1 = 0.37
    - Avoiding risk is the most relevant for the agent's preferences and environmental state.
- Agent adopts actions or states in line with this goal such as wearing a mask to avoid illness, avoiding visiting new places, or other relevant actions mapped to this goal (as supported by research).
- After completing an action, an agent's basic need tracker is decremented such that the basic need's tracker is lower.

Table 1



Dot product example walkthrough

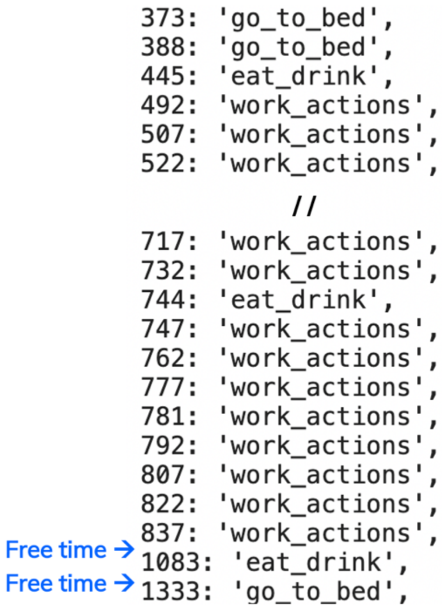
Vector		O	C	E	A	N	Dot product
Personality	=	[.67	.86	.98	.63	.43]	
Avoiding risk goal	=	[-.23	.52	.07	-.30	.19]	.26
Conservation goal	=	[-.25	.64	.12	-.17	-.05]	.37

Note. Vector values are in OCEAN order and influential traits are underlined.

Agents higher in conscientiousness had a higher goal strength for a goal such as avoiding risk. Assuming an agent had to choose between pursuing multiple goals, the dot product was the differentiating calculation between which goal took precedence. From there, multiple actions were mapped to a goal and one was carried out. This process represents goal-directed behavior. The intent of mapping from a high level (basic needs) down to an action space is to have an ontologically extensible cognitive model in which our future work can add domain or general action sets to the action space to answer specific scenarios.

We designed a flexible scheduler to partially populate agents' schedules as a starting point for a pattern of life. We generated a simple structure based on a series of *person types* where agents were defined orthogonally according to employment status and age; for instance, school-age agents are those between ages 5 to 18 years, and employed adults are over 18 years old and have an employed status. The purpose of these general types was to populate a realistic structure of time use including work, school, or free time as well as nourishment and sleep. School-age agents for the most part do not require work shifts as part of a normal schedule while employed adults often do not require attending class and studying as part of a full-time schedule. We utilized free time blocks and interruptions in a starting schedule to initiate a decision-making process in which agents selected individual actions they were driven toward.

Figure 4 shows a sample of a schedule where time is in minutes in a day and individual actions are scheduled in 15-minute increments. This truncated code sample for an employed adult shows how we used static intervals for this scheduler iteration and how we bound actions to time while leaving free time slots where agents made decisions. School-age agents or unemployed adults received different intervals.



```
373: 'go_to_bed',
388: 'go_to_bed',
445: 'eat_drink',
492: 'work_actions',
507: 'work_actions',
522: 'work_actions',

        //

717: 'work_actions',
732: 'work_actions',
744: 'eat_drink',
747: 'work_actions',
762: 'work_actions',
777: 'work_actions',
781: 'work_actions',
792: 'work_actions',
807: 'work_actions',
822: 'work_actions',
837: 'work_actions',
1083: 'eat_drink',
1333: 'go_to_bed',
```

Figure 4. A sample generated schedule with intervals and free time blocks.

This work provided the first iteration in which we created agents' initial scheduling and allowed decision-making to occur. Details around scheduling and decision-making that are currently in progress include basic need rates of decrement per need when an action fulfills it as well as the rate of incrementing each need such that its priority rises for agents. With this framework, basic needs can be conceptualized as bars that rise in priority and deplete when they are addressed.

DISCUSSION

Implications and Challenges

There are multiple implications from our current work. Generators require a minimal level of data to run. This enables population generation to proceed for each attribute where some generators may be available at differing levels of fidelity (with high being more data-rich or detailed). We used a lower level of generator fidelity for occupations where agents representatively received one of five U.S. occupational groups as represented in the census; this generator represented lower fidelity because more population statistics are needed to generate individual level jobs, which would enable a higher fidelity, or detailed, generator (e.g., “Construction Manager” from membership in the “Management Occupations” group). Further, we used open-source data in our current work. This approach facilitates trust in the methods used to represent people accurately and in drawing conclusions based on that data without ethical concerns for data privacy. In particular, our methods did not require person-level data to have an accurate representation of people in an area, whether it was a higher or lower fidelity.

One limitation of using occupation to derive personality is that systems around working differ in other regions of the world. Our current method works for Western societies, but we anticipate this model would need to be adapted for societies that have different occupational structures, mobility, and values regarding the importance of job choices.

One challenge in our approach is the reliance on accurate population summary statistics for the timeframe of the simulation. While some level of forward propagation is possible, dated census and human geographical information could reduce the reliability of forecasted results. This challenge could be a prevalent issue in many parts of the world that lack regular population surveying, are geographically hard-to-reach, or are conflict areas (which present higher time and financial requirements for accurate data collection). Barring access, research must often make use of dated statistics. Regarding this challenge, differential privacy approaches could provide significant value in generating anonymized statistics. We could apply this approach to sanitize and aggregate publicly available social media data to extract socio-behavioral attitudes in online statements and further inform agent behavior. For example, Operational Code extracted via the Verbs in Context System (VICS) has provided insight into the belief systems of political leaders (Walker et al., 2003).

Future work

A limitation of our current approach is complexity in incorporating the full personality vector and more variable time use into agent decisions. Future iteration to incorporate both areas into agent decision-making will utilize time use data such that agents’ schedules can be approximately filled based on how the country generally spends time across activity categories (OECD, 2020). Our work is ongoing in being able to thoroughly describe single entity statuses and agent decision points. By logging complex interactions in the simulation and visualizing this information, our future work aims to interrogate and visualize singular agents’ decision processes beginning with having a basic need, seeing the calculations made to pursue a goal, and selected actions and points of interest that fulfill it.

Future entity generation work will include extending attributes of the base population. Additional generation work will include agents’ immediate and extended social networks to understand the propagation of influence via social circles. We are interested in generating connections for each agent representing physical proximity and closeness in relationships. Several important relationship types (e.g., family, friend, and co-worker) further operationalize closeness of relationship to that person and will help drive agent interactions.

Our team continues model implementation to build scenarios addressing relevant use cases. This work entails translating our generators and models into a simulation runtime we are operating in Python using common packages such as NumPy. We are pursuing use cases where the success of an intervention strategy is measured in aggregate but hinges on individual choices. For example, the success of COVID-19 vaccination rates could be measured as the percent of the total population vaccinated in an area over time. Ultimately the decision to receive a vaccination is an individual choice informed by personal beliefs and often reinforced by social circles. In our current and future work, personality traits and social networks generated from demographics could inform the likelihood of pertinent personal beliefs and where researchers would geographically be more likely to see high vaccination rates. Increasing the vaccination rate in a region may require interventions like targeted outreach to inform subsets of the population about the benefits of the desired health objective. By understanding the beliefs of the target audience and how they can be reinforced by social circles, outreach such as information campaigns may be better tailored towards a particular policy goal (increasing the rate of immunization).

CONCLUSION

The impact of this work includes generator re-use and extends to driving defense community data collection requests. Reusing or adapting generators for population attributes can facilitate rapid development of a synthetic population in an area to develop scenarios for exploring mission critical questions and possible intervention outcomes. Our work facilitates growing datasets of people for this purpose where comprehensive data on potentially impactful agent attributes do not exist. This ability to represent previously unknown attributes may shed light on which attributes are most influential on outcomes, which in turn can prioritize intelligence collection.

Generators may depend on linked attributes in order to synthetize population data, thereby identifying data gaps in building a population. The use of generators can reveal these gaps in being able to understand a population and drive data collection requests as a result. Such requests could lead to government-led data collection campaigns to assist in increasing the availability and frequency of updated statistics over regions of interest. Crowd-sourced data collection, open-source, and the rise of commercial remote sensing provide opportunities to increase data gathering. Macro-level simulations could inform these data collection campaigns by assisting in the prioritization of data required to effectively maintain or update key attributes for agents. Informing these key attributes will enable modelers and policy makers to simulate key national security questions over regions, enabling an environment in which users can synthetically represent the involved populations to interrogate past situations, understand present conditions and sentiment, and explore future scenarios.

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