

Large-Language Agent-based Network Dynamic (LAND) model for Social Simulation

Lynnette Hui Xian Ng^{1,2} and Kathleen M. Carley^{1*}

¹ Carnegie Mellon University, Pittsburgh PA 15213, USA

² Defence Science and Technology Agency, Singapore
lynnetteng@cmu.edu, kathleen.carley@cs.cmu.edu

Abstract. Currently, there are three main paradigms that are used for modeling societies: agent-based models, large-language models and network dynamic models. This paper argues that these three traditions should converge rather than compete. We describe the Large-language Agent-based Network Dynamic (LAND) model, a framework in which the network-dynamic modeling supplies the interaction topology, agent-based modeling supplies the behavioral dynamics and large-language models supply the language and content generation. We also describe how the LAND model can be used as a pre-deployment policy testbed, and some open challenges and research agendas.

Keywords: agent based modeling · large-language models · network dynamic models

1 Introduction

Consider a scenario where a policymaker is trying to design and decide on appropriate interventions to combat a harmful narrative spread on social media platforms. Some questions that could be asked would be: How far would the narrative potentially spread? Can I use automated bot interventions to combat the narrative spread? How many bots and what types of bots should I use to combat the spread? Answering any of these questions with more than intuition requires the ability to generate counterfactual social data, in order to ask what would have happened to a narrative’s spread under different sets of moderation and intervention mechanisms. Beyond that, sometimes it is also intractable and unethical to run such interventions directly on the live population, because such

* This material is based upon work supported by the Scalable Technologies for Social Cybersecurity, U.S. Army (W911NF20D0002), the Minerva-Multi-Level Models of Covert Online Information Campaigns, Office of Naval Research (N000142112765), the Threat Assessment Techniques for Digital Data, Office of Naval Research (N000142412414), and the MURI: Persuasion, Identity & Morality in Social-Cyber Environments (N000142112749), Office of Naval Research. The views and conclusions contained in this document are those of the authors and should not be interpreted as representing official policies, either expressed or implied by the Office of Naval Research, U.S. Army or the U.S. government.

an intervention in itself would also change the discourse and the structure of the digital ecosystem [13].

Three modeling traditions have each answered part of the problem. Agent-based models (ABMs) generate the emergent, bottom-up macro-patterns like polarization, cascades, tipping points, that arise from simple local rules. BotSim, for instance, models the spread of conspiratorial belief across a population of rule-based agents and shows how deliberately placing a small number of counter-messaging bots can shift the trajectory of belief adoption, without a single agent [18]. However, an ABM agent updates a scalar state; it does not speak in natural language like we humans do, thus miss out on conversational realism. Network-dynamic modeling (NDM) represents the structural scaffolding on who can reach whom, and how far apart the agents are. [4] destabilization analysis models an organization as a dynamic network and identifies which individuals to remove to fragment communication fastest, showing that the technique’s predictive power is on the interaction relationship between agents, i.e. who is connected to whom, not what is said. However, the DNA modeling technique typically treats the flow across the network scaffolding as a number rather than language. Then, generative artificial intelligence allowed the creation of Large-language Model (LLM) agents, which could generate fluent, persona-conditioned text. But a dialogue between two or multiple LLM-agents usually have no governed topology and no interaction protocol.

We argue that the way forward is the convergence of these three modeling traditions. We describe the Large-language Agent-based network Dynamic (LAND) model. The LAND model is a framework in which network-dynamic modeling supplies the agent-agent interaction topology, agent-based modeling supplies the micro behavioral dynamics of each agent, and LLMs supply the language and content generation. With such a convergence, who can talk to whom, what governs their behavior, and what they actually say, are all answered within a single, jointly designed simulation.

2 Three Modeling Traditions

2.1 Agent-Based Models

Agent-based modeling (ABM) specifies the micro-level behavior that an agent has, and observes how that behavior, repeated across many interacting agents, creates emergent macro-level patterns that no single agent intended.

The field’s canonical demonstrations established a durable lesson: that complex, unplanned collective outcomes can emerge from individually simple behavioral rules. For example, Schelling’s segregation model showed that a mild individual preference not to be a small minority in one’s immediate neighborhood produces, in aggregate, residential segregation that no single agent intended [23]. Epstein and Axtell’s Sugarscape extended this logic into a fuller artificial society, in which agents following local rules of movement, trade and reproduction generated population-level dynamics like wealth inequality, migration and

group formation [9]. Macal and North’s tutorial work formalized the agent-based modeling method as a population of heterogeneous, bounded-rational agents interacting within an environment and generating system-level patterns through local interactions [14]. Miller and Page situate the ABM technique within the broader study of complex adaptive systems, where non-linear interactions among many components generate emergent behavior that classical equilibrium models miss [16]. Macy and Willer’s “from factors to actors” argument re-frames the ABM methodology as a shift in method itself: rather than modeling how variables relate to one another, ABM models how autonomous decision-making units as agents generate the aggregate pattern from the bottom up [15].

This bottom-up strength is also this tradition’s limitation. ABMs require the modeler to enumerate, in advance, every rule that an agent might need. This produces the well-known problem of equifinality, in which many different, but equally plausible parameter combinations would produce the same macro-level pattern and undermine a single causal story. More fundamentally, an ABM agent does not speak; it updates a state variable. Much of our social interaction is conducted through natural language discourse, this modeling tradition with no linguistic capability cannot represent the discursive content of the interactions it aims to explain.

2.2 Network Dynamic Modeling

Network dynamic modeling (NDM) specifies whom an agent can reach, and through with structural position [3]. Treating a network’s topology as an evolving state variable rather than a static backdrop reveals that network structure is frequently a dominant determinant of a system’s dynamics. Barabasi and Albert established that many real-world networks are scale-free, and their degree distributions are generated by the preferential attachment mechanism, which explains why a small number of highly connected hub nodes can dominate information diffusion across a network [1]. Granovetter’s threshold models of collective behavior show that a cascade like a riot, a fad or a bank run, takes off or fizzles depends less on the average disposition of the population than on the distribution of the individual thresholds and the order in which the agents are exposed to prior adopters [12]. Carley’s constructural model goes a step further, arguing that a network’s structure and the cognition and behavior of agents embedded in it are not separable: knowledge diffuses along social ties, and those same ties strengthen, weaken or dissolve as a consequence of the interaction that agent-agent knowledge exchange produces, so that networks and behavior co-evolve rather than one simply determining the other [5]. Community detection methods further show that networks divide into densely connected clusters with comparatively sparse ties between them, so that information may circulate efficiently within a community while diffusing slow across community boundaries [10].

The NDM’s structural realism comes at the same cost as ABM’s behavioral realism: what flows across the network is almost modeled as a scalar, like an opinion value or a binary adoption state, not a natural language utterance. A network-dynamic model can predict that a claim will reach a hub node quickly,

but it cannot say how that hub node will phrase its endorsement, or whether its stance favors the claim.

2.3 Large-Language Models Agents

Large-Language Models (LLM) agents fill the gap that ABM and NDM leave open: the capacity to generate and interpret natural language. Past work constructed an LLM-driven “social simulacra” that could populate prototype social platform with plausible synthetic user behavior, including undesirable behavior such as harassment, well enough to let designers pre-test moderation rules before implementation on a real community **citation**. Argyle et al. showed that under carefully constructed conditioning, LLMs can exhibit algorithmic fidelity, in which their outputs vary with a persona’s demographic and political attributes that is tractable to how real human subgroups respond to survey items **citation**. This makes LLM agents plausible, though imperfect, proxies for costly human-subjects research. Later generative-agent architecture extended this further by giving agents a memory stream and a periodic reflection step, so that an agent’s apparent goals emerge from accumulated experience rather than a static objective stated once at initialization **citation**.

What LLM agents cannot supply on their own is the governance of their coordinated state. An LLM agent has no fixed decision-theoretic objective; what looks like goal-directed behavior is pattern-matching conditioned on a persona description **citation**. Without an explicit interaction protocol, LLM-agents that are left to converse produce dialogue, not a bounded social system. A persona, a network position and an interaction protocol, together, are what turns a language model into a social agent; otherwise, the result is a conversation, not a simulation. The interaction protocol can be provided by the ABM, and the network positionality can be provided by the NDM.

3 The LAND Model

The Large-Language Agent-Based Network-Dynamic (LAND) model is an agent-based model whose agents are built using large language models and interact within a dynamic network environment. Network dynamic modeling (NDM) supplies the interaction topology, agent-based modeling (ABM) supplies the behavioral dynamics and large-language modeling (LLM) supplies the conversational realism. No single modeling tradition covers every dimension; the LAND model is a union of the three feature sets rather than a fourth, competing method. Table 1 summarizes how the three parent traditions complement one another along the dimensions that a social simulation must capture.

Within this scaffold, a LAND simulation decomposes naturally into three interacting submodels: an ABM submodel that specifies behavioral rules governing interactions, a network-dynamic submodel specifying the evolving structure of who can interact with whom, and an LLM-agent submodel, governed by

Feature	Agent-Based	Network-Dynamic	Large-Language
Heterogeneous agents	X	X	X
Communication	Numerical representations	Interactions	Words
Relational structure		X	
Rich cognition and reasoning	X		X
Context-sensitive behavior	half		X
Information via network structure		X	
Emergence	X		

Table 1: Comparison of the three modeling traditions that the LAND model architecture unifies

a probabilistic natural language process conditioned on persona, memory and conversational context rather than the traditional utility function.

Concretely, the ABM layer specifies what an agent does: its behavioral heuristics for whether or not the agent acts, and the action that the agent would take on. The NDM specifies whom the agent can view and reach, and through which structural position, formalizing the relational scaffolding that ABMs typically leave implicit. The LLM layer then adds the conversational realism of generating natural language messages that neither NDM nor ABM can provide. Where an ABM’s unit of analysis is the individual agent, and NDM’s unit of analysis is the relational tie between agents, the LAND model’s unit of analysis is the message: the utterance that an agent produces, conditioned on its LLM-based persona, its network position and the accumulated history of what it and its neighbors have said.

This convergence produces a specific theoretical shift relative to each parent tradition. Against classical ABMs, the LAND model replaces the exhaustive rule enumeration with behavioral plausibility. Instead of hand-coding every threshold or payoff or heuristic that an agent might need, the LLM component improvises a contextually plausible response to situations that the modeler did not explicitly anticipate, though at the cost of introducing hallucination as a new failure mode. Against NDMs, the LAND model turns the network from a passive conduit for scalar updates into a lived environment, where influence and diffusion happen through language that agents reason over and remember. Against LLM multi-agent systems, the LAND model imposes governed interaction, where the ABM and NDM layers jointly determine who may say something to whom and under what behavioral constraints so that the resulting dialogue is bounded by an explicit social structure rather than emerging from an unconstrained agent-to-agent chat.

There are a few instances of implementation of LAND models in social simulation. OASIS scales LLM-driven social simulation to one million agents **citations**, and AgentSociety couples generative agents with urban-scale behavioral data to study daily life and societal dynamics **citations**. These two examples show that the convergence of the multiple modeling traditions are technically tractable at scale. Validation of such models, though, have been considerably smaller in scale. (author?) [6] found that LLM-generated social networks can be structurally realistic in aggregate, while systematically overestimating political homophily relative to real populations. However, some work found that LLM-based agents in a network-dynamic setting does not necessarily mirror the interaction structure of real social media communications, unless there are specific network-based constraints. This governed-interaction requirement is an instance of a broader argument that agentic artificial-intelligent systems operating inside social environments need social theory as a structural prior - formalized as strategic heterogeneity, networked-constrained dependence, co-evolution and distributional instability assumptions [21].

3.1 Verification and Validation

Verification and validation of a LAND model differs slightly from its traditions, mainly because each submodel must be independently verified. The study of verification and validation of each submodel in the context of the LAND simulation is a subject warranting further scrutiny and research.

Verification asks whether the model was built right, and in accordance to the specifications of the intended design and research question. Agent-level verification confirms individual behavioral and textual fidelity. For LLM-agents, frameworks like PersonaGym can be used to evaluate persona agents along dimensions including consistency, action justification and linguistic habit [22]. Model-level verification confirms that the network topology, scheduling and interaction rules match the simulation’s specification. Finally, output-level verification confirms that the resulting aggregate patterns are the ones that the simulation purpose requires.

Validation asks whether the right model was built. What counts as sufficient validation depends entirely on the simulation’s purpose. A model built to train human analysts to recognize influence operations needs to reproduce a platform’s visibility and exposure rules with high fidelity, while a LAND model built for the theoretical exploration of a single mechanism can abstract exposure to one uniform probability. This purpose-driven validation should be built into every LAND simulation from the start, rather than treating validation as an afterthought, and is the methodological discipline that would achieve a successful simulation fit for purpose.

A LAND model can be used as a pre-deployment policy testbed. That is, a reproducible, controllable environment in which a policy (whether it be a social policy or an agent-based methodological policy), or a counter-intervention can be tested against a synthetic population before it is trialed on a real one. This

is the same logic that motivated agent-based modeling in domains where live experimentation on human populations is impossible [11, 8].

An example of a LAND simulation is the AuraSight simulation, which populates a single platform-mediated information environment with four persona types – ordinary fans, journalistic organizations, automated bot accounts and dredgers (opportunistic amplifiers who recirculate their own content by latching onto whatever hashtag is trending). This scenario allows the development of temporal narrative analysis techniques, tracing how competing narrative frames rise and fall as they propagate across a semantic network of co-occurring hashtags. Such an analysis would be useful in studying in-group narrative alignment in situations such as protests and riots [19]. The AuraSight scenario also allows teaching and application of influence maneuver taxonomies, such as the BEND framework [2], which has been used to characterize such maneuvers in conflict and digital diplomacy situations [17]. Applied inside a LAND simulation rather than to purely archival data, the same methodology allows us to ask counterfactual questions that archival analysis cannot: how would the narrative contest unfolded under a different network topology? How would different mix of automated accounts affect the influence outcomes?

Another example where a LAND model can be used is to a simulation scenario that evaluates whether deliberately deployed useful bots can mitigate the formation of echo chambers [18]. In this scenario, the LAND model is an intervention testbed, letting a designer trial a counter-messaging strategy of bot placement, persona and posting cadence against a full synthetic network before deciding whether such a bot should be deployed on a live platform. Such a simulation would provide the evidentiary basis for deployment and mitigation of digital harms such as echo chambers and polarization.

4 Open Challenges and a Research Agenda

We elaborate on six open problems that stand between the current formulation of LAND models and the LAND models that a policymaker can use as a source of evidence.

1. Standardized benchmarks. Social simulation currently have no agreed reference scenarios or standard metric suite against which a LAND model’s output can be compared, so most of the current validation still rests on face validity rather than a shared quantitative standard. Without such benchmarks, comparing LAND models built by different research groups, and comparing the output of a LAND model against data collected about a real-world event remains inherently ad-hoc.
2. Interpretability of failure. The stochastic, black-box nature of LLM inference makes it difficult to diagnose why a simulation produced an implausible dynamic: whether the fault lies at the agent level (i.e., a mis-specified persona), the model level (i.e., an interaction rule producing unintended dynamics), or the output level (i.e., a mismatch with the target phenomenon). We need to

develop diagnostic tooling to localize failure as a precondition for trusting the LAND models results.

3. Reproducibility conventions. With the mixture of probabilistic formulations in all three sub-models of the LAND model, a LAND simulation’s results are inherently distributional rather than deterministic. Thus, we need to have shared conventions, like how many replications, which seeds, or which summary statistics, are required for reporting and comparing distributional results across studies.
4. Persona bias and drift. The LLM-agents constructed in LAND models inherit the demographic and linguistic skew of their training data [20]. Thus, they can drift away from their assigned characteristics over the course of a long interaction [7]. We need to be mindful of these two problems when constructing and evaluating LAND models, otherwise we risk quietly encoding a non-representative population into a simulation whose results are then read as though they were representative.

5 Conclusion

Agent-based models gave social simulations the ability to model how complex social patterns emerge from simple micro-level local rules. Network science established that the interactions and relationships between individuals matter more than any individual rule. Large language models allowed agents in a social simulation to actually converse in natural language akin to the real world. The Large-language Agent-based Network Dynamic (LAND) model is our proposal for combining these three modeling techniques into a single simulation methodology. We hope that this framework would give the social simulation community a shared vocabulary for designing and validating the next generation of policy-relevant social simulations.

Bibliography

- [1] Albert, R., Barabási, A.L.: Topology of evolving networks: local events and universality. *Physical review letters* **85**(24), 5234 (2000)
- [2] Carley, K.M.: Social cybersecurity: an emerging science. *Computational and mathematical organization theory* **26**(4), 365–381 (2020)
- [3] Carley, K.M., Diesner, J., Reminga, J., Tsvetovat, M.: Toward an interoperable dynamic network analysis toolkit. *Decision Support Systems* **43**(4), 1324–1347 (2007)
- [4] Carley, K.M., Lee, J.S., Krackhardt, D.: Destabilizing networks. *Connections* **24**(3), 79–92 (2002)
- [5] Carley, K.M., Martin, M.K., Hirshman, B.R.: The etiology of social change. *Topics in Cognitive Science* **1**(4), 621–650 (2009)
- [6] Chang, S., Chaszczewicz, A., Wang, E., Josifovska, M., Pierson, E., Leskovec, J.: Llms generate structurally realistic social networks but overestimate political homophily. In: *Proceedings of the International AAAI Conference on Web and Social Media*. vol. 19, pp. 341–371 (2025)
- [7] Choi, J., Hong, Y., Kim, M., Kim, B.: Examining identity drift in conversations of llm agents. *arXiv preprint arXiv:2412.00804* (2024)
- [8] Conte, R., Paolucci, M.: On agent-based modeling and computational social science. *Frontiers in psychology* **5**, 668 (2014)
- [9] Epstein, J.M., Axtell, R.: *Growing artificial societies: social science from the bottom up*. Brookings Institution Press (1996)
- [10] Fortunato, S., et al.: *Community detection in graphs* (2010)
- [11] Gotts, N.M., Polhill, J.G., Law, A.N.R.: Agent-based simulation in the study of social dilemmas. *Artificial Intelligence Review* **19**(1), 3–92 (2003)
- [12] Granovetter, M.: Threshold models of collective behavior. *American journal of sociology* **83**(6), 1420–1443 (1978)
- [13] Kramer, A.D., Guillory, J.E., Hancock, J.T.: Experimental evidence of massive-scale emotional contagion through social networks. *Proceedings of the National Academy of Sciences* **111**(24), 8788–8790 (2014)
- [14] Macal, C.M., North, M.J.: Tutorial on agent-based modeling and simulation. In: *Proceedings of the Winter Simulation Conference, 2005*. pp. 14–pp. IEEE (2005)
- [15] Macy, M.W., Willer, R.: From factors to actors: Computational sociology and agent-based modeling. *Annual review of sociology* **28**(1), 143–166 (2002)
- [16] Miller, J.H., Page, S.E.: *Complex adaptive systems: an introduction to computational models of social life*. Princeton University Press (2008)
- [17] Ng, L.H.X., Carley, K.M.: Deflating the chinese balloon: types of twitter bots in us-china balloon incident. *EPJ Data Science* **12**(1), 63 (2023)
- [18] Ng, L.H.X., Carley, K.M.: Botsim: Mitigating the formation of conspiratorial societies with useful bots. *Journal of Artificial Societies and Social Simulation* **29**(1), 4 (2026)

- [19] Ng, L.H.X., Cruickshank, I.J., Carley, K.M.: Coordinating narratives framework for cross-platform analysis in the 2021 us capitol riots. *Computational and Mathematical Organization Theory* **29**(3), 470–486 (2023)
- [20] Ng, L.H.X., Cruickshank, I.J., Lee, R.: Examining the influence of political bias on large language model performance in stance classification. In: *Proceedings of the International AAAI Conference on Web and Social Media*. vol. 19, pp. 1315–1328 (2025)
- [21] Ng, L.H.X., Cruickshank, I.J., Lim, A.X.W., Carley, K.M.: Social theory should be a structural prior for agentic ai: A formal framework for multi-agent social systems. *arXiv preprint arXiv:2605.07069* (2026)
- [22] Samuel, V., Zou, H.P., Zhou, Y., Chaudhari, S., Kalyan, A., Rajpurohit, T., Deshpande, A., Narasimhan, K.R., Murahari, V.: Personagym: Evaluating persona agents and llms. In: *EMNLP (Findings)*. pp. 6999–7022 (2025)
- [23] Schelling, T.C.: Dynamic models of segregation. *Journal of mathematical sociology* **1**(2), 143–186 (1971)