A Multi-agent Simulation Model on Individual Cognitive Structures and Collaboration in Sciences

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Abstract. This research designs, implements and tests a multi agent simulation model to study knowledge diffusion in scientific communities. It differs from existing studies in the literature as it primarily focuses on incorporating social network perspective while modeling agent-agent interactions. Additionally, it designs various knowledge creation and diffusion mechanisms that may take place during these interactions. Implemented model serves to experiment and examine how knowledge may be diffused in a field of science and what collaboration structures may emerge over time paralleling or leading to specified diffusion mechanisms. Role of cognitive similarities and dissimilarities on agent's incentive to pick a collaborator, as well as, at modeling outcome of collaborations is analyzed. Experiment results hint that in scenarios where agents are inclined to collaborate with cognitively dissimilar agents, then resulting collaboration structure rather mimics co-authorship relations seen within a research center. On the other hand, when cognitive similarity leads the incentives to pick a collaborator, then resulting co-authorship rather mimics network structures observed within domain of a journal in a field.

Keywords: Collaboration; Cognitive Structures; Knowledge Diffusion; Co-authorship

Motivation

The research takes a multi agent perspective while simulating knowledge diffusion mechanism in science. Multi agent systems are systems that are composed of a large number of autonomous agents that are capable of interacting with each other. Here, being autonomous is not to control each individual agent by a central mechanism, but having embedded decision taking logic within the design of each agents actions, where they are able to make decisions in order to accomplish individual tasks (Wooldridge, 2009).

In a science network, if two scientists work on the same paper, then they are considered to be connected (Newman, 2004). The social interaction linkage between them is a possible channel for knowledge diffusion. In our model, each academic is considered as an agent that is capable of working with other academics, choosing whom to work with and what subject to work on. A semantic network is assumed to represent the knowledge of each individual scientist. The set of keywords, which is driven from publications of a scientist, forms the node set of the individual semantic network. The semantic relations, namely the links, in between the keywords in the set are established by their co-occurrence on a published article.

There is a set of challenges, which frames our research question. The challenges are (i) incorporating a dynamic social network perspective while modeling interactions in between agents, (ii) designing, simulating and examining various knowledge creation and diffusion mechanisms as the outcomes of agent-agent interactions.

The first challenge addresses a problem within multi-agent modeling research area. Computational simulation of social systems falls short at covering dense and multitude interactions in between actors. Majority of agent-agent interactions are implicitly and limitedly modeled via agents interactions using environmental variables. This limitation is partly due complexities at agent-agent interactions and mainly due to lack of empirically validated interaction mechanisms. In this work, we borrow and adopt models from social network literature. More specifically, we examine co-authorship networks and empirically validated interaction models within the field.

In the second challenge, we take a socio-cognitive approach. We model and exploit cognitive structure of each agent both at the incentives of individuals to select other agents to collaborate and at modeling the outcome of resulting interactions. Namely, agents purposefully interact to create and transfer new knowledge.

In addition to challenges mentioned above there are several implementation challenges to be addressed for the simulation model. First of all, not all agents in the population interact with each other at each run and preferences of interaction cannot be uniformly random. In the model, those ones who decide to collaborate compute the set of candidate collaborators autonomously. An agent's current knowledge space, and his/her ego network are taken into consideration at incentives to collaborate. For instance, literature suggests that repetition of joint collaborations follows a power law distribution (Morris and Goldstein, 2007; Guo et al., 2008) mimicking power law distribution of individual publication productivity known as Lotka's Law (Lotka, 1926). Likewise, propensity to collaborate with collaborator of an existing co-author is incorporated adopting transitivity property of social ties (Wellman, 1988). Another empirically validated model of social tie formation mechanism that is adopted is "preferential attachment". It is known that in a complex social network probability of a node to have a new connection is proportional to the connections it already has (Barabasi, 2002; Newman, 2003). At each round of the simulation each agent independently determines a candidate set of collaborators. This candidate set is formed employing above-mentioned mechanisms.

A second implementation challenge is how to incorporate knowledge of individual agents. Dynamic social network mechanism does not take actual knowledge space of individual into consideration. In other words, knowledge space of individuals does not play a direct role on the interactions. Besides, while social interaction mechanisms hint whom to pick to collaborate it does not explain outcome of interactions. It is necessary to come up with empirically validated and sound models to represent what knowledge will be exchanged as the outcome of such social interactions.

Literature suggests that there are two competing social mechanism which may help to consider cognitive structure of individuals on the preferences of collaborators. They are 'cognitive distinctiveness' and 'cognitive similarity' (Carley, 1990). Cognitive distinctiveness or cognitive similarity of two agents is measured by comparing their knowledge bases. For a pair of agents when the distinctiveness is high then there are more possibilities for them to learn from each other. If their knowledge bases overlaps widely, the knowledge they can get from each other is limited (Carley, 1991). However it is known that people, in some cases, tend to interact with people they are similar to. This is known as homophily (McPherson et.al, 2001). The experiments are devised to observe impact of these two competing models.

Methodology

Methods incorporated within this study, in general, derives upon multi-agent simulation of social and economic systems and dynamic social network studies. Validity of developed model is tested using empiric data.

Every author is represented as an agent. Each agent has its own individual memory, where its knowledge base and its co-authorship history is kept and updated throughout the simulation. Knowledge base of an agent is formed by set of keywords based on agent's publication records. This set of keywords is interrelated to each other. It is represented by a symmetric matrix. The matrix is a representation of cognitive structure of an agent. The entries of the matrix encode co-occurrence frequency of respective keywords. Co-authorship memory of an agent is a set of authors with whom the agent worked with on a publication.

Set of all the keywords that are gathered from all of the publications is represented as a weighted graph. If two keywords belong to the same publication, then they have a connection and weight of the connection is the number of the times they are used together. When entire set of publications for all agents is considered, then this graph is the cognitive structure of the entire network and it will be represented as an environmental component in the simulation.

It is certain that real agents learn from each other via collaboration, but this is not the only way of learning new things. They also learn from their readings, the workshops they attend and many other resources, etc. In order to represent all such various source of knowledge accumulation by agents, knowledge injection method is used. At each year, a set of new keywords will be added to the cognitive structure of entire population. A probabilistic model is adopted to update cognitive structures after injection of new keywords to the set. Betweenness centrality of existing keywords is used. The higher betweenness of a keyword, the higher chance it receives a new link.

As of simulation platform RePast toolkit is used. Python programming language and libraries as well as R programming and statistical tools are used to analyze and visualize outputs of experiments. RePast is agent based simulation framework created by Social Science Research Computing, University of Chicago (North and Macal, 2007).

Primary data that is used for initialization and validation of the simulation is retrieved from publication records. It covers management sciences related bibliographic entries in Turkey. The set spans entire period of Turkish Republic from 1923 up to 2008 and covers scientific articles. The initial population of agents and co-authorship ties in between them and knowledge space of each agent is initialized using aforementioned data. Each run of the simulation corresponds to one year in real life. Author(s), year and title fields of each entry are used to form initial agent population and cognitive map of each agent as well as co-authorship ties. For instance, for one set of experiments, while publication records of 1990-2000 is used to initialize simulation, data on subsequent years are used to compare and contrast it with output of experiments.

Results

Results from our initial experiments hint that in scenarios where agents are inclined to collaborate with cognitively dissimilar agents, then resulting collaboration structure rather mimics co-authorship relations seen within a research center. On the other hand, when cognitive similarity leads the incentives to pick a collaborator, then resulting co-authorship rather mimics network structures observed within domain of a journal in a field.

Future Work

A large set of experiments are to be conducted to fully verify and validate our initial results as well as to discuss challenges addressed above.

There are a set of additional implementation challenges, which will be addressed and attempted. They are (i) how to model when and in what circumstances multiple co-authorship occurs; (ii) and how to specify knowledge content of collaboration. Cognitive structures of interacting dyads will be studied while addressing these questions. Besides, (iii) at each run, not only new knowledge pieces but also new agents will be injected to the simulation. Knowledge base of those new agents will be composed of partially by a subset of keywords that is already in the current set and partially by new keywords that is not in the set. This approach will mimic arrival of new scientists in a field.

References

- Axtell R. (2006). The end of the beginning for Multi Agent Systems Social Sciences. In Agent-based Modelling and Simulation in the Social and Human Sciences, D. Phan and F.

Amblard (eds) GEMAS Studies in Social Analysis Series, Bardwell Press.

- Barabasi, A. L., H. Jeong, Z. Neda, E. Ravasz, A. Schubert, and T. Vicsek (2002). Evolution of the social network of scientific collaborations. Physica A: Statistical Mechanics and its Applications 311 (3-4), 590–614.
- Brafman, R.I. and M. Tennenholtz. (1997). Modelling agents as qualitative decision makers. Artificial Intelligence 94 (1-2), 217-268.
- Batty, M and Jiang, B (1999) Multi-agent simulation: new approaches to exploring space-time dynamics in GIS. Centre for Advanced Spatial Analysis (UCL), London, UK.
- Carley, K. (1990). Group stability: A socio-cognitive approach. Advances in Group Processes 7, 1–44.
- Carley, K. (1991). A theory of group stability. American Sociological Review 56, 331–354.
- Chen, S.H. and Chie, B.T. (2008). Lottery markets design, micro-structure, and macro behavior: An ACE approach. Journal of Economic Behavior and Organization 67(2): 463-480.
- Cohen,P.R. and H.J. levesque. (1990). Intention is choice with commitment. Artificial Intelligence, Vol. 42, 213-261.
- Dignum, F., (2012) Agents for games and simulations. Autonomous Agents and Multi-Agent Systems, 24 (2), 217-220.
- De Weerdt, Mathijs M., Zhang, Yingqian and Tomas Klos (2012). Multiagent task allocation in social networks, Autonomous Agents and Multi-Agent Systems, 25 (1), 46-86.
- Drogoul, Alexis, Diane Vanbergue and Thomas MeurisseLecture, (2003). Multi-agent Based Simulation: Where Are the Agents?, Notes in Computer Science, Volume 2581/2003, 43-49.
- Epstein, J. and R. Axtell,(1996). Growing Artificial Societies: Social Science from the Bottom Up, Washington, D.C., MIT Press.
- Granovetter, M. (1985). On the Embeddedness of Social Life, American Sociological Review
- Guo, H., Kretschmer, H., and Liu, Z. (2008). Distribution of co-author pairs' frequencies of the Journal of Information Technology. COLLNET Journal of Scientometrics and Information Managment, 2, 73-81.
- Gulyas, Laszlo (2005), "A Generative Model of Power Law Distributions with Optimizing Agents with Constrained Information Access", European Conference on Complex Systems.
- Ilachinski A. (2004). Artificial War, Multiagent-Based Simulation of Combat, World Scientific Publishing.
- Karagiannis, P., George Vouros, Kostas Stergiou and Nikolaos Samaras, (2012). Overlay networks for task allocation and coordination in large-scale networks of cooperative agents, Autonomous Agents and Multi-Agent Systems, 24 (1), 26-68.
- Kubera, Y., Philippe Mathieu and Sebastien Picault, (2011). IODA: an interaction-oriented approach for multi-agent based simulations, Autonomous Agents and Multi-Agent Systems, 23 (3), 303-343.
- Koskinen, J. and T. Snijders, (2007). Bayesian Inference for Dynamic Social Network Data, Journal of Statistical Planning and Inference 137.
- Lotka, A.J., (1926). The frequency distribution of scientific production. Journal of the Washington Academy of Science, 16, 317-323.
- Lorenz, J. and Battiston, S., (2008). Systemic risk in a network fragility model analyzed with probability density evolution of persistent random walks. Networks and Heterogeneous Media vol. 3, pp. 185- 200.
- Lux, T. and M. Marchesi, (1999). Scaling and Criticality in a Stochastic Multi-Agent Model of a Financial Market. Nature, 397, 498-500.

- Neruda, Roman and Gerd Beuster, (2006). Description and Generation of Computational Agents. In Knowledge Science, Engineering and Management, Lecture Notes in Computer Science, Volume 4092/2006, 318-329.
- Niazi, M. and A. Hussain, (2009). Agent Based Tools for Modeling and Simulation of Self-Organization in Peer-to-Peer, Ad-Hoc and other Complex Networks, Feature Issue, IEEE Communications Magazine.47 No.3, March 2009, 163-173.
- Mansury, Yuri and Gulyás, László (2007), "The Emergence of Zipf's Law in a System of Cities: An Agent-Based Simulation Approach", Journal of Economic Dynamics and Control, 31, 7: 2438-2460.
- McPherson, Miller; Smith-Lovin, Lynn and James M. Cook. (2001). Birds of a Feather: Homophily in Social Networks, Annula Review of Sociology 27, 415-444.
- Morris, S.A., & Goldstein, M.L. (2007). Manifestation of research teams in journal literature: a growth model of papers, authors, collaboration, coauthorship, weak ties, and Lotka's law. Journal of the American Society for Information Science and Technology, 58(12), 1764-1782.
- Moore,R.C., (1985). A formal theory of knowledge and action. In Formal Theories of the Commonsense World, ed. J.R. Hobbs and R.C. Moore, Ablex.
- Newman, M. *E. J.* (2003). The structure and function of complex networks. SIAM Review.
- *Newman, M. E. J.* (*2004*). Fast algorithm for detecting community *structure* in networks. Phys. Rev. E 69 (6)
- North, Michael J. and Macal, Charles. (2007). Managing Business Complexity: Discovering Strategic Solutions with Agent-Based Modeling and Simulation. Oxford Press.
- Ricci, A. Michele Piunti and Mirko Viroli, (2011). Environment programming in multi-agent systems: an artifact-based perspective. Autonomous Agents and Multi-Agent Systems, 23 (2), 158-192.
- Siebers, Peer-Olaf, Charles M. Macal, Jeremy Garnett, David Buxton, and Michael Pidd. (2010). Discrete-Event Simulation is Dead, Long Live Agent-Based Simulation!. Journal of Simulation 4 (3). 204-210.
- Shoham,Y. (1993). Agent-oriented programming. Artificial Intelligence, Vol. 60, 1993. p.51-92.
- Weidlich, W. and G. Haag, (1983). Concepts and Methods of a Quantitative Sociology, Berlin: Springer.
- Wellman, B. (1988). Social Structures a Network Approach, Chapter Structural analysis: from method and metaphor to theory and substance, pp. 19–61. Cambridge University Press.
- Wooldridge, M. (2009). Introduction to Multi-agent Systems. John Wiley & Sons.
- Yongqin Gao and Greg Madey, Towards understanding: A study of the SourceForge.net community using modeling and simulation, Agent-Directed Simulation (ADS'07) - Part of the 2007 Spring Simulation Multiconference (SpringSim'07), The Society for Modeling and Simulation International (SCS), Norfolk, VA, USA, March 25- 29, 2007, pp-145-150.
- Younger S.M. (2003). Discrete Agent Simulations of the Effect of Simple Social Structures on the Benefits of Resource Sharing, Journal of Artificial Societies and Social Simulation, 6 (3).
- Ziparo, V. A., L. Iocchi, Pedro U. Lima, D. Nardi and P. F. Palamara, (2011). A framework for collaboration and coordination in multi-robot systems, Autonomous Agents and Multi-Agent Systems, 23 (3), 344-383.
- Zhuang,Enyu, Chen, Guanrong and Feng, Gang. (2011). A network model of knowledge accumulation through diffusion and upgrade. Physica A, Volume 390, Issue 13, p. 2582-2592.