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Towards a Smart(er) Social Science using high-dimensional continuous-time trajectories from the Open Dynamic Interaction Networks (ODIN) platform

Bilal Khan
Department of Sociology
University of Nebraska-Lincoln
Lincoln, Nebraska, USA
bkhan2@unl.edu

Kirk Dombrowski
Department of Sociology
University of Nebraska-Lincoln
Lincoln, Nebraska, USA
kdombrowski2@unl.edu

Alekhya Bellam
Social Network Research Group
University of Nebraska-Lincoln
Lincoln, Nebraska, USA
alekhyab505@gmail.com

Gisela Font Sayeras
Social Network Research Group
University of Nebraska-Lincoln
Lincoln, Nebraska, USA
gfontsayeras@gmail.com

Kin Pi
Social Network Research Group
University of Nebraska-Lincoln
Lincoln, Nebraska, USA
kinlampi@gmail.com

Devan Crawford
REACH Lab
University of Nebraska-Lincoln
Lincoln, Nebraska, USA
dcrawford3@unl.edu

Patrick Habecker
REACH Lab
University of Nebraska-Lincoln
Lincoln, Nebraska, USA
phabecker2@unl.edu

Maisha Jauernig
Social Network Research Group
University of Nebraska-Lincoln
Lincoln, Nebraska, USA
mjauernig2@unl.edu

Abstract—In this paper, we describe Open Dynamic Interaction Networks (ODIN), a software platform designed to move the social, behavioral, and public health sciences toward a new investigative paradigm. ODIN enables us to collect and analyze rich, contextual continuous-time data on both personal change and interpersonal interaction. It achieves this by supporting dynamic delivery of questions based on the currently sensed context of each participant. The ODIN system extends beyond static (or even stepwise dynamic) graph-theoretic renderings of social life and individual behavior by considering "social relationship" to be measured in terms of high-dimensional continuous-time trajectories. The system is designed to be extensible, allowing seamless incorporation of new sensors, and correspondingly sophisticated compound rules by which contexts of interest may be specified. As such, ODIN opens the door for a "smarter" social science based on continuous contextual data, and a "smarter" data science that is reflective and sociologically informed.

Keywords—social network analysis, dynamic networks, longitudinal networks, temporal networks contextual survey, adaptive survey, ecological momentary assessment

I. Introduction

Invoking the distinction between an involuntary blink, a conspiratorial wink, and a satirical grimace, anthropologist Clifford Geertz reminded us that what people think they are doing ought to matter a lot in our understanding of what they are doing. Geertz's notion of "thick description" contrasts the recent rash of "thin" scientific analysis. Thin analysis is content to apply "machine learning" to "big data", presuming that the world operates by laws of "social physics". Criticism of these assumptions is common, and yet falls largely on deaf ears. Maintaining a commitment to the "meaning" of social-scientific data is increasingly difficult in large part because, to date, we lack the means for wide-scale, rapid, contextual and reflective data collection.

Traditional social network analysis (SNA) views human interactions as occurring over largely stable networks or sets of social connections.[1,2] This perspective allows SNA theorists to draw on graph theory as a basis for highly sophisticated social network analysis strategies.[3–5] Case in point is the development of Exponential Random Graph Modeling (ERGM),[6–9] which views social networks as formal logit-like statistical models whose weighted components are understood as the "logic" underlying link structure.[10]

The treatment of social network modeling in SIENA[11] follows a complementary approach. Here, models of *network change* are estimated using observations of the extant ties in a network at two different time points. With such data in hand, network change is simulated as a Markov process that influences individual actor states ("attributes") as well as the ties between actors.[6,12] Modelers select from a range of network-related mechanisms that could account for change within the network. They fit the mechanisms by simulating the network forward from time 1 to find parameter values that yield networks similar to those observed at time 2. The advantage of this approach is that it simultaneously accounts for both changes in network ties and actor states, and distinguishes attribute-changing "peer influence" from link-changing "homophily" dynamics.[7,13]

The ERGM and SIENA modeling approaches advanced our understanding of the process of individual and social change. In fact, the *network metaphor* for social interaction is largely invisible even as it grows immensely popular. However, at their root both approaches assume that the "observed" network is essentially stable, and the linking relationships are glossed as "equivalent" and "discrete".[8,9] Hidden in this process is that "network ties" in ERGM, SIENA—and SNA more generally—implicitly stand for ongoing relationships, which are themselves a selective abstraction of the more fluid world of interpersonal interaction. While the sedimentation of long term interactions into links allows network researchers to work with human relationships in a form that ordinary people find meaningful and substantive, a full picture of the richness and temporality

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