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Choices in networks: a research framework

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Abstract
Networks are ubiquitous in life, structuring options available for choice and influencing their relative attractiveness. In this article, we propose an integration of network science and choice theory beyond merely incorporating metrics from one area into models of the other. We posit a typology and framework for "network-choice models" that highlight the distinct ways choices occur in and influence networked environments, as well as two specific feedback processes that guide their mutual interaction, *emergent valuation* and *contingent options*. In so doing, we discuss examples, data sources, methodological challenges, anticipated benefits, and research pathways to fully interweave network and choice models.

Keywords Choice models · Networks · Decision theory · Computational social science · Marketing · Data science

1 Introduction

Many critical life decisions are intrinsically situated in networks: forming a social circle, evaluating housing options, and seeking a romantic partner all transpire in networked environments with interdependencies among decision-makers and/or alternatives. Networks are also endemic to contemporary business practice, where consumers mutually interact through firm platforms: collaboration tools (e.g., Dropbox, Google Drive), communications (WhatsApp, Skype), transport (Uber, Lyft), lodging (HomeAway, Flipkey), retailing (Amazon, Alibaba), and payment (PayPal, Venmo), among others. Consumer networks enable firms to leverage "social multipliers"—for

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example, running effective referral campaigns—and growing the network increases member value for interactive services like dating sites and multiplayer games.

Owing to recent data and methodological advances, choice modeling has begun to accommodate the impact, structure, and constraints of networks. Analogously, while network models accommodate "generative" accounts of node connection (e.g., preferential attachment, triadic closure), these await fuller integration into utility-driven "decision processes" common in choice modeling. We propose a framework for combining choice theory with network modeling, specifically in problem domains that, like marketing and sociology, naturally encompass them both. Such a synthesis is enabled by suitably granular information—often disintermediated, large-scale online activity data—and computational power that allow researchers to capture interrelations between choices and networks, especially their mutual feedback and co-evolution.

We argue that models representing complex and/or goal-directed decision processes can and should incorporate network structure. To that end, we postulate a typology for *network-choice models*—processes that combine a network with a choice scenario—suggesting potential implications and insights beyond merely extracting information derived from one approach and inputting it to the other.

2 Definitions and prior research

To delineate network-choice models requires first defining their components: what is a network and what is a choice? To set terminology, we follow Newman (2003), that a network is "a set of items, which we will call vertices or sometimes nodes, with connections between them, called edges." As per Louviere et al. (2000, §1.3), "choice" can encompass a chain of activities, starting with awareness, amassing attribute information, constructing a "choice set," then selecting among them. In regard to networks, specifically, "choices" can refer to individuals' decisions regarding social connections or tie formation (which have implications for network structure), as well as "asocial" (e.g., economic or informational) decisions played out in a network context. Greater detail about types of choices especially pertinent for network-choice modeling appears in the next section. The balance of this section provides an overview of literature in marketing, social science, and network theory relevant to situating the proposed framework.

2.1 Networked choice effects in marketing

A comprehensive review of network effects in marketing contexts is beyond our scope. We refer the reader to the pioneering work of Webster and Morrison (2004)—particularly regarding summary network metrics—and detailed summaries in Rand and Rust (2011), Kiesling et al. (2012), and Wang et al. (2013). That said, networks have been implicated in vast swaths of business practice, including customer relationship management (CRM), new product diffusion and adoption, positioning, organizational structure, consumers' personal / professional contacts, information acquisition and word-of-mouth (WOM), "viral" marketing, and online community participation.

An overarching theme in this article is that assessing the effects of interventions or marketing activities in networked environments requires a detailed understanding of *how participants' actions affect one another*. This is exemplified by Ascarza et al. (2017), who found communication between targeted and directly connected customers increased a telecommunications CRM campaign's effectiveness by 28%. This *passive, non-incentivized* social influence contrasts with seeded marketing communications (where proselytizing is explicitly encouraged; Chae et al. 2017) or referral campaigns, e.g., Gmail's initial restriction to existing users' invitees (Hinz et al. 2011). Because actions aimed at targeted customers may also indirectly impact non-targeted connections, forecasts and counterfactuals ignoring network-generated "spillover" may systematically misestimate managerial or policy actions.

Network metrics as covariates Although networks can be distilled into various summary metrics (e.g., density, centrality) for incorporation into choice models, this can falter when choices are interdependent, i.e., when opportunities and payoffs depend on others' activities. This specific insufficiency has long been recognized. Webster and Morrison (2004) underscore that marketing studies typically gather network member characteristics (e.g., network size, interaction frequency, relationship type), concluding "such information is useful but limited in determining how the structure of a network affects network members." This is because such metrics omit or average over critical information about *who (or what) one is connected to*: their characteristics, past behavior, their own connections, and trajectory forecasts (Overgoor et al. 2019).

2.2 Incorporating network information into choice theory

Prior research incorporating networks into choice models—notably Manski's (1993, 2009) seminal "reflection problem" typology—have not fully encompassed the scope of this research space. Noting that "incorporating these social effects into discrete choice models is non-trivial," Maness et al. (2015) build upon Manski's typology by specifying "payoff functions" for choice alternatives, combining individual-level characteristics, endogenous and contextual influence mechanisms, and social contact metrics. This line of work differs from ours in its focus on social influence and bypassing how choice sets are *structured*, i.e., situated in networked environments where not all choices are universally available (e.g., although social pressure can encourage public transportation, it may be inaccessible). Future research can and should build on Maness et al.'s (Maness et al. 2015; Table 1) characterization to study network and choice-set-specific influences, such as portfolios, goals, dyadic exchange, and cognitive constraints, to which we later return.

Our forthcoming framework builds on the dual premises that networks can evolve as a function of choices, and social factors can affect both choice sets and decision rules. That is, we focus on two distinct forms of choice of especial interest to marketers and policy-makers: *whom to connect with* (endogenous network structure and the "link prediction problem"; Martínez et al. 2016) and, more critically, *off-network choices* where opportunities are constrained or characteristics and preferences are shaped both by the existing network and what others are doing.

Table 1 A broad typography for choices in networks

How choice interfaces with network	Network's role in defining choice set	
	Structured	Unstructured
Creates	Membership stores; dating pay sites; hierarchical organizations; social networking	Friend and linkage requests
Navigates	Curricular; multi-stage travel; referral programs	e-Commerce sites; online streaming services
Influenced by	Word-of-mouth; seeding campaigns; choice of collaboration tools	Product reviews; neighbors' service choices

2.3 Incorporating choice modeling into network science

Analogously, network scientists have devised methods to understand network structure by accommodating covariate types typical of choice models. Broadly speaking, these fall into three general classes; while all focus on relationships between covariates and network structural properties, models in the first class explicitly focus on estimation, while those in the second and third are more explanatory and exploratory.

The first domain includes *exponential random graph models* (ERGMs) and *stochastic actor models* (SAMs). ERGMs (Lusher et al. 2013) are probabilistic models relating a (social) network's link structure to available node covariates. ERGMs have been used to investigate preferences (e.g., potential mates' ethnicity; Lewis 2013), but have several well-known shortcomings (Cranmer and Desmarais 2011) including a simplified and "localized" behavioral theory. SAMs (Snijders et al. 2010) are statistical models for network dynamics, "driven by actors" whose latent utility functions can incorporate network structure, actor characteristics, and dyadic node covariates. While SAMs provide an individual-choice perspective on longitudinal network dynamics (not present in cross-sectional ERGMs), they have not integrated behavioral constructs from the choice modeling literature, or incorporated nonlocal social influence variables.

In the second domain lie *network growth and rewiring models*. Growth models posit network formation via the sequential addition of nodes that form or rewire links based on node degree preferences (Price 1965; Barabási and Albert 1999), reciprocity, triadic closure, homophily, and mixtures of preference and restricted choice sets (e.g., Jackson and Rogers' 2007 "strangers and friends-of-friends"). Methods in this class are rarely presumed to correspond to human-centered goals or decision processes. Overgoor et al. (2019) view new edges as connection "decisions" made by a focal node based on other available nodes' covariates; this reframing allows rigorous assessment of nodal features and linkage mechanisms, incorporating decades of choice modeling research into network science, to which we return in the Conclusion.

The third domain includes *microsimulation and agent-based models* (ABMs) that explore situations where feedback occurs between individuals' behavior and their environment (Bruch and Atwell 2015). ABMs have seen wide application—in marketing (Rand and Rust 2011), public policy, epidemiology, and throughout social science—illuminating how the same decision may lead to different outcomes depending on network structure (e.g., Centola 2018). ABMs and models in this class more broadly take agents' behaviors (i.e., decision rules) as inputs and emphasize their aggregate implications, rather than inferring them from data. Kiesling et al. (2012) discuss how diffusion processes can be viewed as ABMs; e.g., the Bass (1969) model's fully interconnected population with homogeneous decision rules.

We note in closing a key distinction regarding "choice processes." Specifically, in network science, choice processes are statistical tendencies for node linkage based on features of network topology (e.g., homophily, reciprocity, triadic closure). By contrast, in choice theory, they typically encompass the decision-maker's overarching problem, detailed covariate information, and selection rules reflected in individual-level parameters suitable for forecasting or counterfactual analysis.

3 Research framework

To better understand the interplay between choices and networks, the vast body of prior research in cognate disciplines—economics, marketing, sociology, network science proper—can be situated relative to the sorts of choices involved, and how they are influenced or constrained by the network. Table 1 broadly characterizes the problem space along these two dimensions: how the choice *interfaces* with the network (rows), and whether the network *structures* the space of options (columns). We discuss these dimensions in turn, but note that neither is perfectly exclusive: several of Table 1's examples might conceivably fall into other cells, as marketing, policy, and consumers often interoperate in multiple ways concurrently. The two dimensions are nonetheless helpful in conceptualizing the problem space and potential for dedicated methodology.

Choices *create* networks (row 1) when they generate (or delete) explicit linkages, thus potentially altering the network itself, for example, "connecting" on Facebook or LinkedIn. Such choices can involve where to situate in a novel network, whom to contact in an existing one, or even whom to invite in.

By contrast, choices that *navigate* a network do not explicitly alter it, but are embedded in a network structure that is traversed. This feature is common to many decision scenarios, the canonical generic illustration being that traveling from A to C requires passing through B. Typical examples include choosing courses as prerequisites for future ones satisfying degree requirements, reaching "distal" consumers through targeted referral programs, and charting a career path, which involves training, internship, etc. In such cases, nodes may be fully "viewable" (as in course selection) or not; the key distinction is that attaining various end-states requires routing through the network itself.

Lastly, choices can *be influenced by* networks when choices themselves are not networked, but decision-makers are, thereby affecting their decision processes. Word-of-mouth is a classic route for consumer inter-influence—information traverses the network, affecting purchases *outside* the network—e.g., music streaming services (Apple, Spotify) reporting "what your friends are listening to."

While marketers are interested in all three choice types, understanding or predicting social network interlinkages is less an end than a means: accounting for dyadic interactions and influence (Gilly et al. 1998). By contrast, choices *influenced by* or *navigated through* a network—particularly decisions about products, services, and venues—are critical throughout management and economics.

The second dimension (columns) in Table 1 concerns whether vital aspects of the choice scenario are "structured" (or constrained) by the network. In particular, networks can determine whether decision-makers are aware of particular choices or if those choices are available to them. To revisit our prior examples, the mere act of contacting someone on LinkedIn or Facebook is not restricted ("structured") by the network itself, but the ability to extensively interact with them is regulated or fully determined by network position. In marketing, referral programs (Hinz et al. 2011) and "seeding campaigns" explicitly leverage network structure: messages and inducements cannot be passed along by people unknown to the downstream target. Similarly, colleagues can only settle on a collaboration tool if both agree to the choice; by contrast, a neighbor's choice of lawn service may be influenced by yours, but is in no way constrained by it. The pivotal point is that individuals differ in their connections (friends, family), which in turn affect awareness, availability, and consideration of various options.

The last column of Table 1 highlights situations where individuals' choices are informed or affected—but not explicitly constrained—by a network, and thus termed "unstructured." For example, the vast majority of online purchases, though potentially influenced by others' choices, do not depend on personal connections or specific paths through an interlinked e-commerce site. Similarly, product reviews or "star ratings" (e.g., Amazon or IMDB), while conveying others' purchase activity and evaluations, do not operate via a specific network pathway. In such cases, all decision-makers can access the same opportunities, information, and/or influences based on the prior choices of others, although they may weigh these heterogeneously. We view the first column of Table 1, then—where networks not only sway, but at least partially constrain—as the area most ripe for novel methodology.

Figure 1 provides one way of visualizing Table 1's networked-choice scenarios in greater granularity. Specifically, it highlights how such choices shape, or are shaped by, network interactions. Network-choice effects can manifest in any of the five "outcome" boxes; we highlight which outcomes are primarily associated with which choice types and the major direction of (causal) influence. First, for choices that "create" (or modify) the network, causal arrows run from the choice to the network. By contrast, in the remaining cases—when in-network choices "navigate" or out-of-network choices "are influenced by" the network—causal arrows run from the network to the decision process.

In this last case ("influence"), the network can impact decision processes in three distinct ways that accord with choice model components, through (1) the decision-maker's choice set, (2) the decision-maker's preferences, and (3) the attributes of

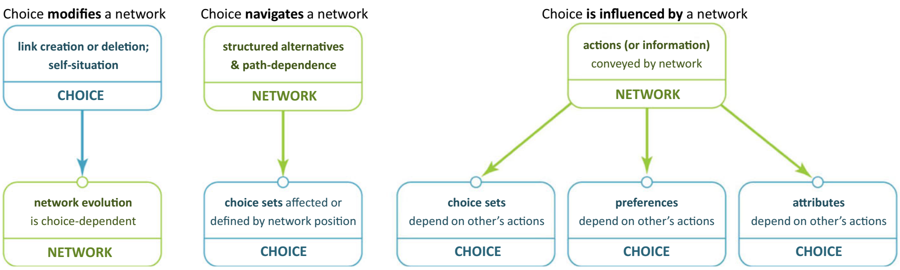

Fig. 1 Graphical framework for network-choice models

available options. As a concrete example, imagine a friend mentions they had purchased their first electronic vehicle (EV). This information can cause EVs to enter your choice set (they may never have otherwise), for economy and environmental impact to become higher-valued attributes, or start-up costs for this EV model to appear lower, since the friend can supply vital information.

We have thus far emphasized how network-choice processes operate for a single decision-maker. However, with multiple decision-makers within the same network, one person's decisions may "feed back" to affect the choices of others. For example, my desire to connect with someone on LinkedIn—thus creating a network tie (Table 1, upper left cell)—may be a function of the number of contacts that person already has, but my decision to link adds to their connections. Such feedback between individuals' choices and network environment features is "cross-cutting": it can occur in any choice scenarios outlined in Table 1. Below we highlight two primary forms of feedback.

3.1 Emergent valuation

In many real-world settings, relative option desirability is shaped by the choices of others. Baseball legend Yogi Berra's aphorism "No one goes to that restaurant anymore; it's too crowded" simultaneously highlights an option's baseline desirability and diminished utility due to popularity. Major routes may involve congestion (a negative) or allow carpooling efficiencies (a positive). In such cases, even if networks were fixed and decision-makers had perfect information about their structure, option *payoffs* depend on others' choices, which are emergent and can differ stochastically from realization to realization.

Emergent valuation encompasses the sorts of classic social influence discussed by Manski (1993, 2009) and Maness et al. (2015), but is considerably broader, incorporating not only signaling, conformity (etc.), but *any change in valuation induced by the choices (actions) of others*. As but one example, a consumer's network can provide information that leaves alternatives' "utilities" fixed, but alters the nature of the choice process itself, e.g., reducing acceptable choice set size, or causing more conjunctive evaluation. Relative to Table 1, a choice can modify or navigate a network to make certain end states easier for others to reach (and therefore more desirable) or a choice made by someone linked to us—as in the aforementioned EV example—can affect our own choice set composition, preference strengths, or attribute values.

3.2 Contingent options

As previously discussed, individuals' differences in connections can affect what options are available to them, which they seriously consider, or their decision processes. But, importantly, what options are available may also *change* over time owing to choices made by others (e.g., someone purchases the last concert ticket), or by financial or environmental changes. The key here is that the *availability*, as opposed to *desirability*, of a particular option may depend on others' choices.

Contingent options also operate across the spectrum of networked-choice scenarios of Table 1. In the case of curricular choice ("navigating" a network), students can only enroll in particular courses if seats are available. Similarly, in online dating, mate-seekers may be unable to cognitively juggle more than 3–4 correspondences each week. So, a decision to respond to a message—a choice "creating" a network—may depend on how many others they have recently received. In both scenarios, others' choices can alter opportunities or options available to the decision-maker.

4 Discussion: Methods and further directions

Everyday and major life choices occur in networked settings, raising a host of research questions regarding measurement, influence, and intervention requiring specific inferential and forecasting capabilities. Prominent among these are estimating "preferences," given the network and decisions made (e.g., how much one values a particular Twitter follower); designing behavioral interventions (e.g., nudges encouraging families to exercise together); and, above all, performing counterfactual analyses (e.g., where experiments are impracticable, like building a new road).

The array of specific research issues addressable in such a setting is vast, defying full characterization, yet some examples readily suggest themselves. For example, *endogenous dynamics*: how do actors' preferences co-evolve as functions of others' choices or network changes and how might they be parsimoniously modeled? Such problems are intrinsically high-dimensional, suggesting research on scalable inference, how forward-looking or "deep" such models need to be (Seshadri et al. 2019), goal pursuit (Swait et al. 2018), and "flattening" network topology (Braun and Bonfrer 2011). And, most broadly, there is design: transport networks, information seeding, shopping site architectures, referral programs, and occupational training sequences must all take account of (heterogeneous) routing and preferences, and how arguably endogenous, socially influenced actions affect network structure, future choices, and their interplay.

4.1 Methods

Measuring the (causal) effects of social interactions is notoriously difficult, due to intrinsic confounding of contagion—a network effect marketers and policy-makers seek to leverage—and homophily (Shalizi and Thomas 2011), as well as endogenous group formation, correlated unobservables, and simultaneity (Hartmann et al. 2008), the last often requiring analyst-imposed exclusion restriction. For example, millennials tend to use ride-sharing services, but this could be because they are differentially urban (increased availability), their neighbors do (conformity), they perceive it as efficient (individual preferences), or their social circle does (signaling or activity-sharing). A practical concern is taking such scenarios to data, which can require jointly estimating choice model parameters and network evolution, the latter notoriously challenging without experimental manipulation. For example, one potential data source is observed user behavior on the network, but observed choices may be a misleading indicator of latent preferences if the network strongly constrains choice sets; e.g., each user has few available routes. A possible remedy is to fuse such data with a choice experiment (e.g., Louviere et al. 1999; Feit et al. 2010) where users choose among hypothetical routes. Another involves field experiments manipulating the network and/or choice environment directly, e.g., closing roads and adding tolls.

Intermarrying choice models and network science raises substantial measurement problems, but also the ability to extend approaches in the econometric literature (Brock and

Durlauf 2001; Durlauf and Ioannides 2010). Among these are link prediction (e.g., future associations between nodes), the role of missing data, structural impediments (e.g., lack of critical covariates), offline covariate and outcome information (e.g., real-world interactions), and selectivity (who is in the network vs. not, e.g., dating sites). Similarly, modeling the “choice” to influence—deliberately or inadvertently—others in a network has particular implications for communications, e.g., seeding, referral, and “viral” marketing.

However, the most critical and potentially fruitful methodological issues raised by our framework concerns the role of networks—both through emergent valuation and contingent options—in *affecting choice processes*. Yet heterogeneous decision rules can be elusive to extract from data (Hauser et al. 2010) even in non-networked settings. As per Overgoor et al. (2019), network linkage can be analyzed at manageable computational cost via binary discrete choice methods assuming choices are independent (modulo covariates); however, one may be seeking a “manageable” number of total ties, or a portfolio with sufficient variety, calling to question the decision-maker’s presumed expected utility specification. The model-builder’s task is determining critical structures and relationships, then capturing them parametrically (or nonparametrically), along with errors, preference heterogeneity, and appropriate dynamics. Though challenging, accurately capturing choice processes, network formation, and their mutual interactions is critical in any interconnected system where decision-makers’ actions affect one another: failing to do so raises the specter of systematically mis-estimating the effects of inducements or policy interventions.

Opportunities and insights gleaned from considering choice in networked contexts extend beyond human decision processes. Network perspectives have critically advanced understanding of emerging group structure and decision-making in the natural world, from microbes to insects to primates (Fewell 2003). However, this work has rarely incorporated the sorts of cognitively-nuanced choice models developed in transportation, quantitative marketing, and behavioral decision theory. Such a connection, facilitated by network-choice models, may illuminate how organisms’ strategies and behaviors are both shaped by and shape larger scale social structures (Fefferman and Ng 2007) in the purely human sphere and beyond.

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