3.4 Cognitive Network Modeling as a Basis for Characterizing Human Communication Dynamics and Belief Contagion in Technology Adoption

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Clayton Hutto
Georgia Tech Research Institute
Clayton.Hutto@GTRI.GaTech.edu

Erica Briscoe
Georgia Tech Research Institute
Erica.Briscoe@GTRI.GaTech.edu

Ethan Trewhitt
Georgia Tech Research Institute
Ethan.Trewhitt@GTRI.GaTech.edu

Abstract. Societal level macro models of social behavior do not sufficiently capture nuances needed to adequately represent the dynamics of person-to-person interactions. Likewise, individual agent level micro models have limited scalability – even minute parameter changes can drastically affect a model's response characteristics. This work presents an approach that uses agent-based modeling to represent detailed intra- and inter-personal interactions, as well as a system dynamics model to integrate societal-level influences via reciprocating functions. A Cognitive Network Model (CNM) is proposed as a method of quantitatively characterizing cognitive mechanisms at the intra-individual level. To capture the rich dynamics of interpersonal communication for the propagation of beliefs and attitudes, a Socio-Cognitive Network Model (SCNM) is presented. The SCNM uses socio-cognitive tie strength to regulate how agents influence–and are influenced by–one another's beliefs during social interactions. We then present experimental results which support the use of this network analytical approach, and we discuss its applicability towards characterizing and understanding human information processing.

1.0 INTRODUCTION

The idea of a social network has been attracting interest from researchers in the social and behavioral sciences since the turn of the twentieth century when social theorist George Simmel discussed the implications of individuals' affiliations with groups of others (which he called social circles) [1].The notion of investigating relationships among entities, and the capability for describing the patterns and regularities of these relationships with precise formal definitions, is indeed appealing. The presence of regularities and patterns in relationships is referred to as structure, and quantities that measure structure are called structural variables[2].Based on the mathematical concepts associated with graph theory, the network perspective characterizes relationships in terms of nodes and ties. Nodes are the individual actors (e.g., people or organizations) which are tied (or linked) by one or more specific types of interdependent connections such as friendship, kinship, common interest, financial exchange, or information transfer, for example. Social network analysis is more than just a methodological approach, a convenient vocabulary, or intuitive metaphor for discussing social and behavioral relationships. The network analysis perspective presents a theoretical alternative to the assumption of independent social actors – an assumption that is prevalent in previous sociological and psychological research. The network perspective offers a common framework for testing theories about structured social relationships, and provides a means to precisely characterize important social concepts with explicit formal definitions (see the introductory chapters of [2] for a brief overview).

Unfortunately, as its name implies, the majority of social network research has focused almost exclusively on social structures. Furthermore, much of this research conveys a static, rather than dynamic, social structure. These static views of social structure tend to marginalize the role of social and cultural transmissions described by Tomasello (i.e., the passing of knowledge via multi-generational history, as well as personal ontogeny, c.f., [3]) when studying human social-cognition interactions. Static network views also poorly capture the situated nature of cognition as put forth by Lave (i.e., dynamically evolving cognition that both influences – and is influenced by – the contextual situation, c.f., [4], [5]).Finally, many of these views do not specify how changes to society occur relative to the individuals' cognition and behavior.

The remainder of this paper is organized as follows: first, we present the Cognitive Network Model (CNM) as a framework for quantitatively characterizing individuals' belief systems as a network of interrelated proposition nodes, with each node having specified quantitative parameters. Next, we present the Socio-Cognitive Network Model (SCNM), which is intended to capture the effects of interpersonal communication and influence on individuals' Belief Networks (BNs) during person-to-person interactions. We then present some preliminary results of computational modeling and simulation studies of the CNM and SCNM, using *technology adoption* as a domain of demonstration. Finally, we discuss how this multilevel modeling approach helps to bridge the divide between micro- and macro- models of human behavior (c.f., [6], [7]), as well as the social and cognitive perspectives of human communication dynamics.

2.0 THE COGNITIVE NETWORK MODEL

The Cognitive Network Model (CNM) is a computational modeling approach to characterize specific cognitive mechanisms associated with human social-cultural information processing at the individual agent level. Similar to Carley's conception of constructuralism [8], the fundamental tenet of CNM is the application of network precepts and analysis techniques as a basis for characterizing and understanding human information processing resulting from the diffusion of information. In essence, CNM represents human information processing in terms of the emergent interactions of a set of parameters associated with beliefs. Thus, beliefs are the foundational element of cognitive network modeling.

2.1 Beliefs: Propositions and Parameters

Beliefs are often represented as propositions and can be thought of as subjective probability estimates of an object having a particular attribute [9], [10].In the network perspective, belief propositions are represented as network nodes, with links representing relationships such as correlations between the propositions. In the CNM approach, a belief proposition is described as a pairing of cognitive concepts. For example, the proposition "raisins are healthy" pairs the concept of "raisin" with "healthy". The human agent assigns a subjective value of perceived truth to the proposition in order to reflect that individual's level of agreement with the proposition. To represent beliefs, and to provide insight into how to predict the effect of new information, CNM represents beliefs through three main quantitative parameters: veracity, epsilon, and defense (see Figure 1).

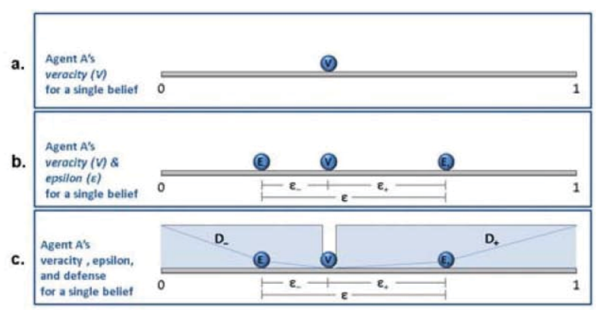

Figure 1: a. *Veracity (V)* is the quantitative parameter in CNM that captures an agent's level of acceptance or rejection in the "degree of truth" of a belief proposition; b. *Epsilon (ε)* captures the interval limits on either side of current veracity for which new or alternative values of veracity may be most readily accepted; c. *Defense (D)* reflects the degree of resistance to adoption of alternative veracity values for a given belief proposition.

Veracity (V).Veracity indicates an agent's level of acceptance or rejection in the "degree of truth" of a belief proposition(Figure 1a).Quantitatively, veracity is represented as a value between 0 and 1, where 0 indicates the agent believes the proposition is not true at all (proposition is completely rejected), and 1 indicates complete belief in the truth of the proposition (proposition is completely accepted).This quantitative characterization of the veracity of the belief overlaps quite well with existing characterizations of beliefs represented as propositions with a subjective probability of being correct [9], [10].

Epsilon (ε).Epsilon captures the interval limits on either side of current veracity for which new values of veracity may be most readily adopted(Figure 1b).For a given belief proposition, new values of veracity might be based on information received from an external source such as another agent, contextual evidence, or personal experience. Epsilon is derived from literature based on bounded confidence models of belief formation (c.f.,[11-13]), and is a quantitative construct that captures the qualitative concept of certainty (or conversely, uncertainty) for a selected belief proposition. Epsilon also accounts for the qualitative construct of *social proof* (c.f., [14]), the phenomena whereby individuals rely more heavily on interpersonal social influence in conditions of uncertainty. Quantitatively, ε+ is the magnitude of the distance between V and the upper boundary limit; ε- is the magnitude of the distance between V and the lower boundary limit. Epsilon may not be uniform in each direction; changes in veracity may be more readily adopted for one direction versus the other.

Defense (D).Defense can be thought of as the degree of resistance to adoption of alternative beliefs (Figure 1c). Quantitatively, defense is a value between 0 and 1, where 0 indicates a weak strength of defense value (i.e., weak resistance to adopting new veracity values), and 1 indicates a strong defense (high resistance, or intolerance).If an agent's defense of the belief is low, differing or conflicting information is less likely to be rejected outright without first modifying one or more belief parameters. Thus, the defense value affects the degree to which an existing belief is amenable to change via (a) adjusting epsilon, (b) adjusting the strength of veracity, (c) adjusting the strength of the defense, or (d) a combination of belief parameter adjustments. The defense parameter accounts for the qualitative construct of cognitive consistency (or conversely, cognitive dissonance – see [15]) within the belief network, and is the mechanism by which the CNM is able to model both rational and irrational cognitive behavior.

Cognitive network modeling is then a matter of (a) selecting the beliefs of interest to represent a structured belief system for the chosen domain (termed a Belief Network, BN, described in the next section), (b) defining the relevant agent-specific belief parameter values (V, ε, and D) for each belief represented in the BN, and (c) describing the governing functions for dependencies between beliefs as well as the role of other intra-personal influences (e.g., age, gender).

2.2 The Belief Network

The Belief Network (BN) is conceptualized according to principles familiar to areas of graph theory and network science: vertices represent individual belief propositions, and edges represent connections/relationships between those beliefs; they are usually weighted and may be either directed or undirected (see [16] for an introduction to graph theory and networks).The BN is the collection of all of the relevant belief propositions for the selected domain (with their associated parameters) held by an individual agent. For example, the BN used as a domain of demonstration in the current effort (see Figure 2) was derived from research literature on the Unified Theory of Acceptance and Use of Technology (UTAUT)[17] that integrates eight of the most prominent theoretical models of technology adoption. Figure 2 depicts the BN containing belief propositions related to performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), voluntariness of use (VoU), behavioral intentions (BI), usage behavior (UB) based on usage experience, and perceptions of trust and power status of another agent as an information source:

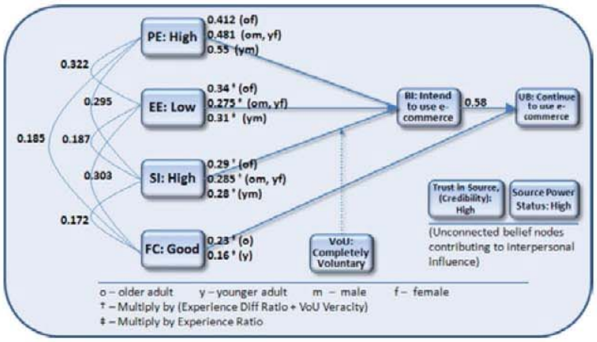

Figure 2: Conceptual rendering of the agent belief network for adoption of technology (e.g., e-commerce), as derived from [17].

From this framework, it follows that CNM is able to capture the concept of culture by adjusting one or more of the following in the BN: (1) the relative strengths of individual belief parameters for belief nodes determined to be culturally germane, (2) the weighted magnitude of the BN edges, and/or (3) the relationships defining the intra-network and external influence governing functions (more on these governing functions in the SCNM discussion, below).Likewise, the BN belief parameters and edge weights can also be initialized according to expected “roles” or “norms”. For example, in a model of technology adoption, we might categorize population segments according to Rogers’ description of the diffusion of innovations [18], whereby individuals’ BN are stochastically drawn from population “types” such as innovators, early adopters, early majority, late majority, laggards, and luddites. It is recognized that an individual human agent’s BN (representing cognition) interacts with other, non-cognitive personal determinants such as personality, transient affective states (moods), biological factors (e.g., age, gender), and personal history or experiences (e.g., education, work). Although not detailed herein, they are considered an integral part of the CNM, and need to be notionally represented in the agent based model. However, it should be noted that the agent-based computational model used for the research described in this paper only partially accounts for these individual differences.

If beliefs are conceived as subjective valuations of the degree of acceptance or rejection of information (propositions), then the model needs to support changes to targeted belief propositions resulting from interpersonal influence. This may be accomplished either through shifts in strength of veracity of the belief (“raisins actually are not very healthy”), shifts in epsilon surrounding the veracity of the belief (“I’m no longer certain how healthy raisons really are”), or changes in the strength of the defense of the belief (“If I trust someone as a credible source of new information, I may not resist adopting their view that raisins are unhealthy”). Thus, the belief parameters of veracity, epsilon, and defense are the mechanisms by which cognitive network modeling quantitatively characterizes many of the processes associated with human information processing. These processes are discussed in further detail in the context of interpersonal interactions within the Socio-Cognitive Network Model, described next.

3.0 THE SOCIO-COGNITIVE NETWORK MODEL

The Socio-Cognitive Network Model (SCNM) extends the representation of belief propositions into communication patterns that exist between agents. At the SCNM level, network vertices are individual human agents, and network edges are the cognitive and social ties between them. Socio-cognitive network modeling is extremely relevant to the study of human communication dynamics and interpersonal interactions: just as the BN does not function in isolation within an individual agent, neither do agents act in isolation – a number of social and environmental factors interact with the agent to affect the agent’s cognition. For the purposes of this paper, we focus on factors of interpersonal influence as a moderator of belief propagation in social networks. Specifically, within the SCNM, interpersonal influence is captured by a variable called the Socio-Cognitive Influence Power (SCIP). The SCIP is a critical index of an agent-node within the SCNM, as it indicates the influence power of an adjacent agent *j* over the current agent *i*. As an extension of Granovetter's notion of *tie strength* [19], the SCIP index is determined by considering the relative strength of ties along four dimensions (see Table 1):

Table 1: Four Dimensions of Socio-Cognitive Influence Power (SCIP) index.

1. ***Structural dimension***: relative patterns of vertex and edge relationships with regards to network structure (c.f., [20-26])
2. ***Cognitive dimension***: relative agreement of Belief Network parameters between agents
3. ***Interaction dimension***: relative interaction intensity (i.e., frequency, type/medium, and quality – c.f., [19], [26-34])
4. ***Social dimension***: relative perception of the strength of the social relationship (e.g., trust, credibility, and emotional support [35]; social distance [36] or status similarity [37]; and power status [38]).

For the sake of space, we limit the current discourse to discussions primarily regarding the cognitive dimension. A central premise of SCNM is that the strength of the cognitive ties (degree of similarity between agents' BNs) will affect the degree to which agents influence–and are influenced by–one another's beliefs during social interactions. By representing the relevant beliefs for a given domain, as well as the governing functions associated with the modification of those beliefs, the proposed multi-level model can monitor the changes in adoption or rejection of belief propositions (both at the individual and at the aggregate levels) to determine the effects of information as it propagates through the social network. For example, during interpersonal interactions, the belief parameters can be dynamically adjusted according to certain interpersonal influence factors. This dynamic adjustment is determined via heuristic algorithms which use condition-based governing functions for interpersonal interactions (see Figure 3).

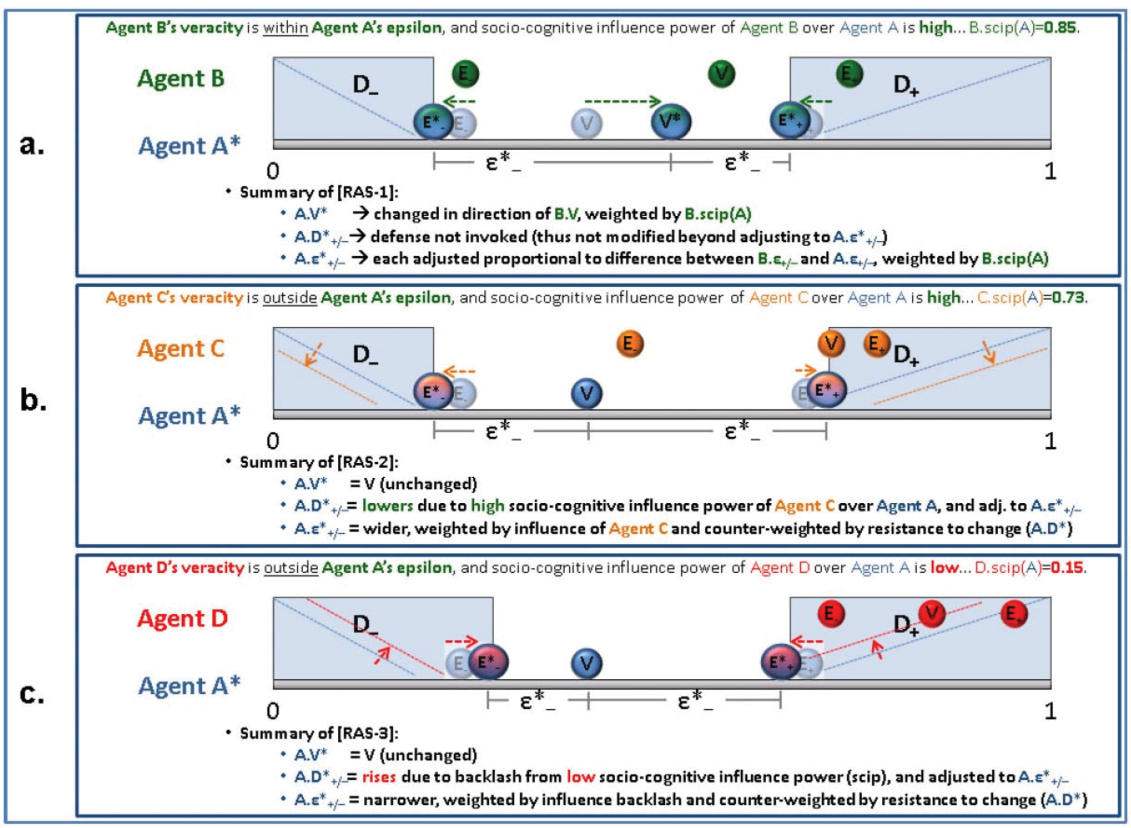

Figure 3: Notional illustrations of example governing functions (reconciliation algorithm sets, or RASs) for the acceptance or rejection of belief propositions during interpersonal interactions.

Figure 3a shows the situation where Agent B is presenting the case for a more extreme veracity value for a selected belief proposition. The proposed veracity is within Agent A's epsilon (i.e., the zone of ready adoption – simulated in this case as the most extreme condition where the defense is not invoked at all [value is 0.0], indicating no resistance to adopting the proposed veracity), and Agent B's SCIP over Agent A is high (0.85).Thus, Agent B influences Agent A to adopt a more extreme veracity value for the belief proposition.

Next, Figure 3b illustrates the situation where Agent B is again attempting to convince Agent A to adopt a more extreme veracity value for a selected belief proposition. This time, the proposed veracity position is just outside Agent A's epsilon, thus the defense parameter is invoked. Agent B does not successfully get Agent A to adopt the more extreme veracity during this interaction. However, because Agent B is a trusted source (SCIP of Agent B over Agent A is high, 0.73), Agent B is successful at making Agent A less confident, less certain about the belief proposition, and lowering Agent A's resistance to change (both of which will make it easier to influence Agent A on subsequent interactions).

Finally, Figure 3c depicts the interesting situation where an attempt by Agent B to influence Agent A actually *backfires* such that the consequence is that the interaction has the opposite effect of what is desired. This occurs in the SCNM as a result of Agent B attempting to convince Agent A to adopt a very extreme veracity position for a selected belief proposition, but not only is the proposed veracity position outside Agent A's epsilon (thus invoking the defense parameter), but Agent B is perceived as being untrustworthy or cognitively dissimilar (SCIP of Agent B over Agent A is low, 0.15) that Agent A actually entrenches in their own belief. Agent A becomes more certain of his own veracity position (i.e., epsilon narrows, perhaps due to Agent A explaining why he thinks his position is actually superior, or describing shortfalls or other reasons for inferiority of Agent B's position). Agent A's defense (resistance to change) also increases. These will make it even more difficult for Agent B to influence Agent A on subsequent interactions.

4.0 PRELIMINARY RESULTS

Using the Unified Theory of Acceptance and Use of Technology (UTAUT) [17] as the basis for developing the relevant BN (see Figure 2), as well as a number of notional governing functions (some of which are described above), we demonstrate the how the CNM and SCNM models collectively account for a number of phenomena noted in the diffusion literature. Figure 4 illustrates the relationships between the CNM parameters of defense and epsilon (aggregated for all beliefs in the BN for each agent) to the adoption rate of a particular technology (i.e., e-commerce) in a computer simulation study. The relationship shows a general trend in the direction that would be expected according to the CNM concepts – those agents with lower defense and wider epsilon are the "easiest" to influence and were thus the earliest adopters. As defense rises, and as the epsilon range becomes narrower, agents become more "difficult" to influence, thus taking longer to adopt.

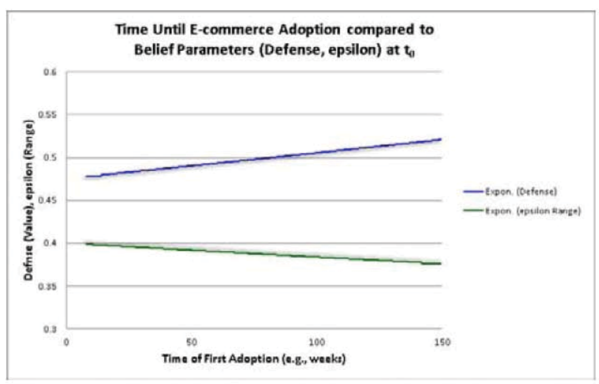

Figure 4: Depicts the relationships between the CNM parameters of Defense and Epsilon (aggregated for all beliefs in the BN for each agent) to the time of adoption of a technology.

Also, Figure 5 illustrates the distinctive processes related to Rogers' first and second stages of diffusion of innovations [18]. The first stage is the diffusion of awareness of new information (exposure to alternative belief propositions); the second stage reflects the influence processes where by individuals are persuaded to adopt:

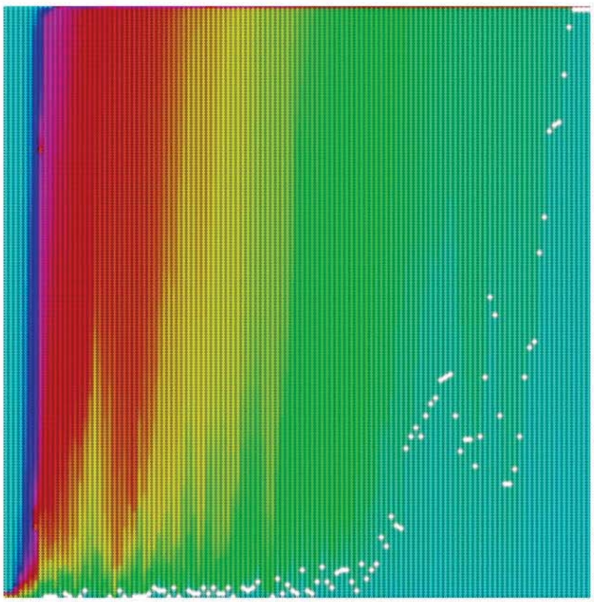

Figure 5: Illustration of the distinctive processes of awareness of new information (alternative belief propositions) and the pursausion process to adopt those alternative views.The horizontal axis represents time while the vertical axis represents individual acceptance. White indicates the transition point at which all subsequent persons have adopted.

5.0 DISCUSSION AND FUTURE WORK

Cognitively motivated theories have the potential for providing a framework that can be used to explain a wide variety of social phenomena. For the most part, however, many models of social behavior have historically been remiss in incorporating cognitive models [8], [39].This work has presented an approach that uses a multi-level model that exchanges relevant information across representational scales in order to demonstrate the pairing of theoretically grounded models of human cognition with those that account for the influence of interpersonal interactions. The Cognitive Network Model (CNM) and Socio-Cognitive Network Model (SCNM) is the first and second levels of what is to become a multi-scaled modeling approach that helps to narrow the gap. The proposed models are intended to provide a means of describing and explaining specific processes related to the propagation of information across communication and social networks. A specific issue that this model intendeds to explain is the occurrence of a backfire effect, where a communication causes a reaction that is an opposite direction of the intended influence (e.g., [40]).

The proposed representation scheme is currently being refined and validated by comparing to ‘real-world’ data that exists in the domain of technology adoption as well as in human experimentation on belief propagation. These experiments are designed to test a number of hypotheses which emerge from the CNM and SCNM characterization of belief propagation and interpersonal influence. In addition, we intend to incorporate other important metrics into the network models, including other relevant agent-factors, e.g. the emotional intensity of a communication and biological differences in age and gender.

6.0 CONCLUSION

This paper has presented a multi-scale network perspective approach using a framework for representing the beliefs of an individual (represented in an agent-model) as well as the communication and influence on those beliefs by the individual’s social interaction. While this work is still in its infancy, we anticipate that planned experiments will provide a validation and refinement of the model that will then allow it to make predictions of human behavior.

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