



Learning Nonlinear Decision Making

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Final Report**

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AFOSR Project Final Report

Project Title: Learning Nonlinear Decision Making

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Summary of Project

To advance the science of decision-making as it pertains to how people learn to make decisions and how this process can be captured computationally, we specifically addressed the challenge of how nonlinear decisions can be learned from data, experience, and even interactions with other decision-makers. Nonlinear thinking is a prized ability we, humans, have that is ubiquitously applied across any and all domains when the problems are challenging, and known solutions or ways of addressing the problems all fail to provide an adequate solution – e.g., All available choices are bad choices, must we settle for the least bad one? The ability to discover a new choice has been called being nonlinear, innovative, intuitive, emergent, or “outside-the-box.” It is well-documented that humans can often excel at such thinking in situations when there is a scarcity/overflow of data, significant uncertainty, and numerous contradictions in what is known or provided. However, how this could be replicated computationally for a machine was not fully addressed or understood in previous research. We took an intuitive approach, simply called perspectives, that treated each piece of data and information intuitively as a point-of-view for one or more entities described by the piece but did not require a predefined “dictionary” or ontology that explicitly related the pieces together. It was the latter which has been an open problem in areas such as big data where attributes in data must have predefined mappings and relationships before any analyses can begin. Instead, as points-of-views, we could consider the myriad possible relationships dynamically and combine them together to define a space of many different possible models; and then algorithmically optimize the collection to arrive at a canonical answer model. What is most interesting is that non-linearity naturally arises out of this merging since the canonical model is itself the mechanism for inferring decisions. Perspectives is combined with the second tenet of our approach: transformations. Intuitively, transformations capture changes in perceptions, memory, and goals not just due to the addition of new information or influences (endogenous and exogenous), but also due to the multiple tasks a decision-maker must handle some of which entail complex interactions. So, drawing inspiration for solving one task while in the process of solving a completely different task is an ultimate element of transformation.

Our goal was to research and develop a rigorous and comprehensive computation and cognitive framework to understanding and capturing how non-linear decision making occurs and how we can learn them. More specifically, our objectives were as follows:

- Mathematically define the computational formalism and cognitive process to serve as the basis for non-linearity in decision-making needed to derive rigorous necessary and sufficient conditions and properties that determines the overall capabilities and limits of such an approach.
- Develop and define the formalism for multiple entity decision-making interaction and learning focusing on conditions and properties arising in non-linearity of entity decisions.
- Derive and develop algorithms for explainability and transparency – the ability to explain how a given prediction/computation/learned model is arrived at from the initial conditions and over time
- Define and design synthetic testbeds representing non-linear decision-making situations in order to develop quantitative measures to determine the efficacy of our underlying computational model.
- Implement proof-of-concept prototype(s) with synthetic test-case(s).
- Apply our framework to explore real-world non-linear decision-making in commander’s decision-making, problem solving, and/or intelligence analysis – using case-studies as well as identifying opportunities for human subject studies to further enhance our understanding of this phenomenon.

In what follows, we briefly describe some of our major research contributions towards this effort.

1. Automatic Detection of Emergence in Complex Decision-Making

We developed a mathematical framework of nonlinear decision-making for an individual within a collection of individuals who can potentially interact with one another – allowing us to formally differentiate nonlinear from linear. Our approach identified and formally defined how emergent decisions arise through information fusion and its impacts on decision-making and opinion formation.

Complex systems usually consist of multiple subsystems, whose nonlinear interactions can cause unpredictable and disastrous outcomes. However, it is intractable to analyze all possible outcomes in complex systems directly due to the combinatorial nature of this problem. Extant analysis approaches often build separate models for all subsystems and make conclusions about the entire system by linearly aggregating individual analysis results. This approach, although simple, cannot model emergence of complex systems.

This is complicated by the fact that the information (including decisions and opinions) can be contradictory across different sources. Thus, we demonstrated that typical approaches to resolving this such as employing ensemble methods fails to detect or even account for emergence.

We intuitively defined emergence in complex systems as follows: Given some target variable, we query its state on the subsystem models (potentially learned from corresponding datasets) and simply group their opinions into majority and minority sets. Then we observe its state at the entire/overall system level. If its true state (observed over the entire system) is different from the majority opinion given by the subsystems, we consider this situation as emergent. This concept is similar to the ones given by predictive approaches where emergence arises when it cannot be predicted even by individuals who possess thorough knowledge of the parts of this system.

As such, based on the existence of majority and minority opinions, we can define emergence as composed of four types. If all subsystems form a unanimous opinion, and the true result differs from it, we call it Type 1 emergence. If both majority and minority opinions exist, but the true result differs from both opinions, we call it Type 2 emergence. If both majority and minority opinions exist, and the true result is consistent with the minority opinion, we call it Type 3 emergence. If only minority opinions exist, but the true result differs from all minority opinions, we call it Type 4 emergence. This emergence definition is complete for a complex system with an arbitrary number of subsystems, if each subsystem can provide a valid opinion about the queried target.

Our approach to modeling and detecting emergence in complex systems according to our proposed definition of emergence is as follows: We first learn subsystem dynamics using Bayesian Knowledge Bases (BKBs) from observations on each subsystem. Then we fuse these subsystem BKBs together which accounts for interactions among subsystems in a probabilistically and structurally sound manner. Lastly, we perform reason (belief updating) on the fused BKB (FBKB) to detect emergence in this complex system. The entire framework, which consists of learning, fusing, and reasoning blocks, is named as the Bayesian Knowledge Fusion for Complex System (BKFCFS).

Experiments on synthetic datasets show that our proposed method can detect emergence over extant approaches. We also demonstrated that our approach can still adequately detect emergence when our algorithm is limited to polynomial time complexity for all three phases of learning, fusion, and reasoning through approximation. In summary, whereas ensemble methods are unable to detect emergence, our BKBFCS is capable of recognizing this nonlinear situation.

Papers: [Santos & Zhao, 2017][Zhao & Santos, 2019][Zhao, 2019]

2. Double Transition Model of Decision-Making Interactions and Opinion Formation

Our approach for representing decision-making builds upon a mathematical model called the *Double Transition Model (DTM)* that captures the *underlying process* of how opinions/decisions are formed/made and change for an individual both endogenously (retrospection) and exogenously when new knowledge is accepted from the external environment. In particular, an individual faces a sequence of different tasks (or episodes) $\{t_1, t_2, t_3, t_4, t_5\}$, each with different subsequences of environmental and internal changes caused by the (task-interleaved) actions taken by the individual:

$$\{\langle a_1^1, s_1 \rangle, \langle a_1^2, s_2 \rangle, \langle a_2^1, s_3 \rangle, \langle a_1^3, s_4 \rangle, \langle a_2^2, s_5 \rangle, \langle a_3^1, s_4 \rangle, \langle a_1^4, s_4 \rangle, \dots, \langle a_5^{m_5}, s_n \rangle\}$$

where a_j^k is the k^{th} action for task j and s_l is the individual's state (knowledge, beliefs, experiences, etc.) after l actions taken. The decision process behind task t_1 is

$$\{\langle a_1^1, s_1 \rangle, \langle a_1^2, s_2 \rangle, \langle a_1^3, s_4 \rangle, \langle a_1^4, s_4 \rangle\}.$$

Given the various types of changes/dynamics required, the model is formulated based on the concept of *transformations*. Changes to an individual's (sub-)taskings, state, goals, inferencing mechanism, action choices, etc. are considered transformations of components represented in the DTM (**Error! Reference source not found.**). A DTM consists of two sub-models: a *query transition graph (QTG)* and a *memory transition graph (MTG)*. Simply put, the QTG embodies the different decisions and decision sequences that must be made in satisfying the tasks/episodes. Which decision to be made is in essence a query to be answered by the individual and the QTG reflects changes to the query over time. As a complement, the MTG embodies the changes in the memory of the individual as actions are taken over time. At any given time, the states of the QTG + MTG determines the answer (decision) taken by the individual. Actions (internal and external) derived from the decision result in transformations in one or both graphs. As such, the decision processes for the tasks is simply the simultaneous (cross-product) transition "walk" through the QTG and MTG. The space of possible walks is rich and provides a flexible yet rigorous computational model.

Prior results demonstrated DTMs to be capable of networked decision-making. We briefly describe a simple networked decision problem in an opinion formation task between two people as follows:

Two agents, e_1 and e_2 , are exchanging influents with each other guided by their respective goals. At each time step, agent e_1 needs to decide an action to take.

The goal for agent e_i can be defined as

$$\lim_{t \rightarrow +\infty} \{\gamma_i | o_i^{t+1} - o_i^t | + \zeta_i | o_i^{t+1} - o_j^{t+1} |\} = 0$$

where o_i^t is the opinion for agent e_i at time t , $i \neq j$, and $\gamma_i, \zeta_i \in [0,1]$ are control parameters. The first term¹ represents the degree of opinion change from time t to $t + 1$ for e_i while the second term represents the gap in the two agents' opinions at time $t + 1$.

The goals cover the two possible ways to reduce the gap between two agents: one by moving e_1 's opinion towards e_2 's and the other way of moving e_2 's opinion towards e_1 's. What are the meanings of the two parameters γ_1 and γ_2 ? Intuitively, they are values on a *malleability-idealism scale* from 0 to 1 representing an agent's willingness to change its own opinion; while parameters ζ_1 and ζ_2 are on a *passivity-activism scale* from 0 to 1 representing an agent's eagerness for reaching a consensus. The higher the malleability-idealism score is, the more idealistic an agent is (i.e., more unwilling to change its opinion).

¹ Replacing o_i^t by o_i^w where $w = 0$ or $w < t$ directly reflects the desire to revert to their original or an earlier opinion.

The higher the passivity-activism score is, the more active an agent is (i.e., more eager to reach a consensus). The goal is used to assess how desirable each transition between states is for an agent.

Through simulation, a number of differentiable two agent situations could be distinguished in a simple hypothetical problem as follows:

Problem Setting: We want to train advocates at Dartmouth College to be proficient at convincing others to believe it is a great university. We have materials about different universities, but unfortunately cannot recruit too many people to practice with that have a wide variety of beliefs and behaviors.

Target Questions: What type of advocate is best? How critical is representative training?

The primary take away of this study is the ability of DTMs to capture how the underlying opinions/beliefs change through interaction and especially how they change when faced with a stream of “different” agent-partners to interact with.

Papers: [Yu & Santos, 2016][Santos et al., 2018][Russell & Santos, 2019][Santos et al., 2019][Santos & Nyanhongo, 2019]

3. A Failure of Collective Intelligence

We examined the impact of social influence on collective intelligence which can cause the divergence of individual decisions from the expected collective decision (a form of emergence). An important area of collective intelligence is the modeling and prediction of national election, which has historically encountered spectacular failures. While experts have provided various explanations, this work posited that such influence among different types of voters to be the primary reason. The 2015 UK Election was taken as a case study, demonstrating that such influence is intrinsic to collective intelligence. We then proposed a social influence-based prediction model to remedy these failures. Experiments demonstrated that our model can account for the existence of such social influence.

Papers: [Zhao & Santos, 2018][Zhao, 2019]

Publications [4 journal articles, 1 book chapter, 8 conference papers, 1 PhD Thesis]
[The publications below were supported in full or in part by this project.]

Li, Deqing and Santos, Eugene, Jr., “Discriminating Deception from Truth and Misinformation: An Intent-level Approach,” *Journal of Experimental and Theoretical Artificial Intelligence*, 2019. DOI: 10.1080/0952813X.2019.1652354

Russell, Jacob and Santos, Eugene, Jr., “Explaining Reward Functions in Markov Decision Processes,” *Proceedings of the 32nd International FLAIRS Conference*, 56-61, Sarasota, FL, 2019.

Santos, Eugene, Jr., "Cost-Based Temporal Reasoning," *Information Sciences* **482**, 392-418, 2019.

Santos, Eugene, Jr., Kim, Keum Joo, Russell, Jacob, Nguyen, Hien, Veenhuis, Luke, Boparai, Ramnjit, and De Guelle, Luke, "Analysis of Computational Models to Describe Individual Decision-Making Process," to appear in *Proceedings of the IEEE/WIC/ACM International Conference on Web Intelligence (WI 2019)*, Thessaloniki, Greece, 2019.

Santos, Eugene, Jr., Nguyen, Hien, Kim, Keum Joo, Russell, Jacob A., Hyde, Gregory M., Veenhuis, Luke J., Boparai, Ramnjit S., De Guelle, Luke T., and Mac, Hung Vu, "A Contextual Decision-Making Framework," in *Computational Context: The Value, Theory and Application of Context with AI* (Eds. W. Lawless, R. Mittu, and D. Sofge), 253-286, CRC Press, 2018.

Santos, Eugene, Jr., Nguyen, Hien, Nyanhongo, Clement, Hyde, Gregory, Kim, Keumjoo, and Russell, Jacob, "A Decision-Making Framework for Agents in Complex Environments," *Proceedings of 14th International Naturalistic Decision Making Conference*, 176-181, San Francisco, CA, 2019.

Santos, Eugene, Jr. and Nyanhongo, Clement, "A Contextual-based Framework for Opinion Formation," *Proceedings of the 32nd International FLAIRS Conference*, 62-67, Sarasota, FL, 2019.

Santos, Eugene, Jr. and Zhao, Yan, "Automatic Emergence Detection in Complex Systems," *Complexity*, vol. **2017**, Article ID 3460919, 24 pages, 2017. DOI:10.1155/2017/3460919

Santos, Eunice E., Santos, Eugene, Jr., Korah, John, Thompson, Jeremy E., Zhao, Yan, Murugappan, Vairavan, and Russell, Jacob, "Modeling Social Resilience in Communities," *IEEE Transactions on Computational Social Systems* **5(1)**, 186-199, 2018.

Yakaboski, Chase and Santos, Eugene, Jr., "Bayesian Knowledge Base Distance-based Tuning," *Proceedings of the IEEE/WIC/ACM International Conference on Web Intelligence (WI 2018)*, 64-72, Santiago, Chile, 2018.

Yu, Fei and Santos, Eugene, Jr., "On Modeling the Interplay between Opinion Change and Formation," *Proceedings of the 29th International FLAIRS Conference*, 140-145, Key Largo, FL, 2016.

Zhao, Yan and Santos, Eugene, Jr., "A Failure of Collective Intelligence," *Proceedings of the IEEE/WIC/ACM International Conference on Web Intelligence (WI 2018)*, 361-366, Santiago, Chile, 2018.

Zhao, Yan and Santos, Eugene, Jr., "Emergence in Multiagent Systems," *Proceedings of the 32nd International FLAIRS Conference*, 144-147, Sarasota, FL, 2019.

Zhao, Yan, "Emergence in Collective Intelligence," Doctoral Dissertation, Thayer School of Engineering, Dartmouth College, 2019.

Personnel Supported

Dr. Eugene Santos Jr.
Dr. Keum Joo Kim

Graduate Students –
Yan Zhao (completed PhD 2019)
Jeremy Thompson (doctoral candidate)
Jacob Russell (doctoral candidate)
Clement Nyanhongo
Chase Yakaboski

Interactions & Transitions

"Nonlinear Decision Making and Emergent Behavior," Invited Speaker, Workshop on Interdisciplinary Challenges to Intelligent Systems, Intelligence Systems Center, Johns Hopkins University Applied Physics Laboratory (APL), Baltimore, MD, 2015.

"Adversary Intent Inferencing for Predictive Analytics," Keynote Speaker, NATO IST-145 Specialists' Meeting, Sibiu, Romania, 2017.

"Learning Behavior and Decision Processes: Cognitive Style vs. Bias and Deception," Invited Speaker, JASON 2018 Summer Study on Bias in Machine Learning, La Jolla, CA, 2018.

"Computational Intent," Lunch and Learn Seminar, Duke University, Durham, NC, 2019.

Transitioned research to multiple SBIR and STTR proposals during FY 18-19.

Major Award

2016 (Santos) AAAS Fellow "for distinguished contributions to the field of information and decision sciences, particularly for computational modeling of decision-making under uncertainty with application to human behavior modeling."