EDITORIAL

Special Issue on Learning Complex Couplings and Interactions

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Our natural, living, social, economic, and cultural worlds are becoming increasingly complex, forming ubiquitous complex systems.[1–3] While there are often various system complexities[4–6] embedded in such complex systems, each of them essentially involves multifaceted and intricate coupling relationships and interactions within and between system elements, entities, behaviors, subsystems, and environments, as well as their dynamics and evolution.

Here, *couplings and interactions* broadly refer to "any relationships and connections (for instance, cooccurrence, neighborhood, dependency, linkage, correlation, or causality) between two or more aspects, such as object, object class, object property (variable), process, fact and state of affairs, or other types of entities or properties (such as learners and learned results) appearing or produced prior to, during and after a target process (such as a learning task)" (Definition 2.1[7]). *Couplings* also refer to "both well-explored relationships such as cooccurrence, neighborhood, dependency, linkage, correlation, and causality, and poorly explored and rarely studied ones such as sophisticated cultural and religious connections and influence." In complex systems, couplings and *interactions* also reflect the relationships between factors related to technical, business (domain-specific), and environmental (including socio-cultural and economic) aspects.[8] Such couplings and interactions may be present in any types, granularities, directions, orders, and hierarchies, and evolve over time and system developments.[7,8]

Deeply characterizing, representing, and analyzing complex couplings and interactions is foundational for understanding, quantifying, and managing complex systems and developing their problem-solving solutions. Effective modeling of complex couplings and interactions in complex data, behaviors, and systems has the potential to directly understand the core nature and challenges of complex problems and is critical for building next-generation intelligent theories and systems and improving machine intelligence and intelligent system design.

The state-of-the-art progress made in new-generation artificial intelligence, deep learning, and data-driven scientific discovery (or simply data science) presents new opportunities and lays paramount theoretical and technical foundations to "quantify" and further "learn" the couplings and interactions in complex systems. Complex systems are data intensive. The data describes their entities, subsystems, behaviors, states, dynamics, environments, as well as inbuilt explicit and implicit, local and global, static and dynamic, subjective, and objective couplings and interactions both within a system and between the system and its environments. Many new scientific opportunities and challenges emerge during the capture, creation, storage, search, sharing, analysis, visualization, and management of complex interactions and couplings.[1,7] These drive interesting research topics on learning complex couplings and interactions in complex systems.

There are many interesting topics, problems, and opportunities to be explored in learning complex couplings and interactions in complex systems. Examples are probabilistic and stochastic modeling of coupling and interaction uncertainty and dependency; representation learning of complex couplings and interactions; coupling learning of complex relations, interactions, and networks and their dynamics; interaction learning of activities, behaviors, events, processes, and their sequences, networks, and dynamics; learning couplings and interactions in hybrid intelligent systems and problems; representing, analyzing, and managing interaction networks; learning natural, online, social, economic, cultural, and political couplings and

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interactions; learning real-time, dynamic, high-dimensional, heterogeneous, large-scale, and sparse couplings, dependencies, and interactions; deep learning of complex couplings and interactions in big data and complex behaviors; explainable learning of complex couplings and interactions; large-scale simulation of complex couplings and interactions; visual analytics and visualization of complex couplings and interactions; impactful applications and tools for modeling complex couplings and interactions; and human understandable explanations of complex couplings and interactions.

In the past decade, significant progress has made on learning complex couplings and interactions.[8,9] Examples of progress and open issues are coupling and interaction representation, coupled representation, coupling and interaction based metric learning, similarity learning, and various media-based coupling, and interaction learning, such as non-IID data learning, networking analysis, interaction network modeling, textual coupling learning, multimedia coupling learning, multimodal coupling learning, heterogeneous coupling learning, cross-model and cross-domain coupling learning, coupled behavior analysis, and coupling shallow and deep learning.[7–13]

This special issue on learning complex couplings and interactions aims to encourage deep research in the above areas and beyond, with a focus on the latest advancements in modeling complex couplings and interactions in big data, complex behaviors, and systems. Seven articles were competitively selected. Below, we briefly introduce them.

1. "Concept Representation by Learning Explicit and Implicit Concept Couplings" proposes a neural coupled concept representation (CoupledCR) framework and its instantiation: a coupled concept embedding (CCE) model. CCE first learns two types of explicit couplings from concept cooccurrences and hyperlink relations, respectively, and then learns a type of high-level implicit couplings between these two types of explicit couplings.
2. "Differentially Private Collaborative Coupling Learning for Recommender Systems" introduces a distributed collaborative coupling learning system with differential privacy, which defends against the adversary who has gained full knowledge of the training mechanism and the access to the model trained collaboratively with a privacy-utility tradeoff.
3. "Conformity: A Path-Aware Homophily Measure for Node-Attributed Networks" introduces a novel measure, Conformity, to provide a node-centric quantification of assortative mixing patterns. Differently from the other measures, Conformity is designed to be path-aware and allow for a more detailed evaluation of the impact that nodes at different degrees of separations have on the homophilic embeddedness of a target.
4. "CoTrRank: Trust Ranking on Twitter" develops a trust evaluation method to model users and tweets separately in two networks that are coupled with each other by interactions. They provide mapping functions to map the statistical numbers of actions of users/tweets to trust values that indicate their relevant trust degrees.
5. "SEPN: A Sequential Engagement Based Academic Performance Prediction Model" proposes a sequential engagement-based academic performance prediction network (SEPN) consisting of two main components: engagement detector and sequential predictor to leverage the advantages of convolutional neural network (CNN) in detecting student engagement patterns and adopt the structure of long short-term memory to learn the interactions between the engagement feature spaces and demographic features.
6. "Optimal Finite-Horizon Perturbation Policy for Inference of Gene Regulatory Networks" focuses on the partial-observability of genes state by using the signal model of partially observed Boolean dynamical systems (POBDS).
7. "An Efficient Solution to Detect Common Topologies in Money Launderings Based on Coupling and Connection" introduces eight common topologies based on coupling and connection from simple to much more complicated structures to solve various kinds of problems concerning money laundering in the real world, and proposes an efficient solution based on graph and subgraph isomorphism and distance measurement to detect money laundering behavior.

Last but not least, we express our sincere gratitude to the Editor-in-Chief, Professor Venkatramanan Subrahmanian and the *Intelligent Systems* team for their support of this special issue. We hope this special issue would be helpful to encourage deeper thinking and exploration of "computing" and "managing" complex couplings and interactions in complex systems and novel strategies and designs for building complex intelligent systems.

REFERENCES

1. L. Cao, *Metasynthetic Computing and Engineering of Complex Systems*. London, U.K.: Springer, 2015.
2. X. Qian, J. Yu, and R. Dai, "A new discipline of science—The study of open complex giant system and its methodology," *Chinese J. Syst. Eng. Electron.*, vol. 4, no. 2, pp. 2–12, 1993.
3. C. Gros, *Complex and Adaptive Dynamical Systems: A Primer* (4th ed.). Cham, Switzerland: Springer, 2015
4. M. Mitchell, *Complexity: A Guided Tour*. New York, NY, USA: Oxford Univ. Press, 2011.
5. M. Waldrop, *Complexity: The Emerging Science at the Edge of Order and Chaos*. New York, NY, USA: Simon & Schuster, 1992.
6. J. H. Holland, *Signals and Boundaries: Building Blocks for Complex Adaptive Systems*. Cambridge, MA, USA: The MIT Press, 2014.
7. L. Cao, "Coupling learning of complex interactions," *J. Inf. Process. Manage.*, vol. 51, no. 2, pp. 167–186, 2015.
8. "Coupling and interaction learning," 2021. [Online]. Available: https://datasciences.org/coupling-learning/
9. "Non-IID learning of complex data and behaviors," 2021. [Online]. Available: https://www.ijcai19.org/tutorials.html
10. C. Wang, C. H. Chi, Z. She, L. Cao, and B. Stantic, "Coupled clustering ensemble by exploring data interdependence," *ACM Trans. Knowl. Discovery Data*, vol. 12, no. 6, 2018, Art. no. 63.
11. C. Zhu, L. Cao, and J. Yin, "Unsupervised heterogeneous coupling learning for categorical representation," *IEEE Trans. Pattern Anal. Mach. Intell.*, to be published.
12. P. Battaglia *et al.*, "Interaction networks for learning about objects, relations and physics," in *Proc. Adv. Neural Inf. Process. Syst.*, 2016, pp. 1–12.
13. H. Crane and W. Dempsey, "Edge exchangeable models for interaction networks," *J. Amer. Statist. Assoc.*, vol. 113, no. 523, pp. 1311–1326, 2018.