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Opinion

Data-knowledge co-driven innovations in engineering and management

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Modern intelligent engineering and management scenarios require advanced data utilization methodologies. Here, we propose and discuss data-knowledge co-driven innovations that could address emerging challenges, and we advocate for the adoption of interdisciplinary methodologies in numerous engineering and management applications.

Introduction

Increasing integration of advanced AI-based systems with manufacturing and operations management promises more efficient, refined, and environmentally friendly processes than before (see Tang and Meng[1]), but challenges to successful adoption remain.

With the rapid advance of AI research, pure data-driven models show great potential for solving tasks across engineering and management practices. Indeed, the 2024 Nobel Prize in Physics went to AI pioneers for their foundational discoveries and inventions that enable machine learning with artificial neural networks. Recent technological innovations in large language models—such as ChatGPT, LLaMA, and Sora—have demonstrated remarkable competence in question answering, text comprehension, and image or video generation tasks. These pure data-driven models, however, are unlikely to be reliable for high-stakes decisions, as they are considered black boxes with little explainability or accountability.[2] Recent commentaries on the "AI bubble" have also criticized generative AI for "too much spend, too little benefit," given the great vision to revolutionize every industry and the chatbots that are actually delivered, which sometimes make things up.[3]

Given these issues, we question whether current AI tools can deal with crucial industrial, decision-making, or management applications that generate real economic value. Also, we argue that pure data-driven methodologies will always be limited due to biased knowledge extracted or distilled from ill-formed datasets or outliers. Hence, in this opinion, we argue that the future lies in developing models that include explicit knowledge-driven modules that complement and address the limitations and drawbacks of pure data-driven methodologies. The term "knowledge" here can refer to various guided constraints, such as physical rules, human expertise, evidence, and neurological indicators. We believe these top-down data-knowledge co-driven model designs can improve model explainability and accountability and can expand our understanding of engineering and management research frontiers.

Data-knowledge co-driven framework

In Figure 1, we summarize the literature and outline a data-knowledge co-driven framework to address various engineering and management tasks intelligently and innovatively. We outline four conceptual steps or processes: data generation, knowledge discovery, model integration, and application. Below, we discuss different types of modeling methods embodying this concept.

Physics-informed methods

These kinds of methods embed physical or mathematical constraints into data-driven model structures, thereby reducing counterfactual outliers at the application step. By introducing reasonable physical constraints, the integrated model leverages the advantages of both physical and data-driven models, resulting in better model interpretability and reproducibility.

A plausible example would be physics-informed neural networks, in which a variety of explicit physical rules and formulations from the real world—such as inertia, momentum, gravity, kinematics, and spatial or temporal continuity—can be easily implemented as model constraints to neural networks (see Saibene et al.[4]). A simple implementation method would be calculating the training loss from both the employed physical model and the data-driven neural networks and then constructing a comprehensive loss function and training the model by minimizing the overall loss.[5] In this way, both physical knowledge and data patterns could simultaneously guide the proposed model and generate more reliable and informed model outputs.

Moreover, "physical information" is not limited to pure physical rules and can be extended to algebraic, geometric, topological, and other laws that can act as computable constraints to data-driven models. Incorporating these fundamental mathematical rules, tools, and methods can guarantee or preserve mathematical principles in the learning process.

Physics-informed methods can be used to deal with many engineering and management tasks where physical constraints are known. Typical application scenarios include a spectrum of industrial manufacturing processes and engineering practices, such as intelligent perception, estimation, prediction, and feedback control. Specifically, physics-based features make derived models good at solving partial differential equations, and they are believed to perform well in discovering hidden physics and tackling high-dimensional problems.[6]

Expert-system-embedded methods

These kinds of methods actively discover and store human prior knowledge or professional experience in a particular field to imitate the decision-making process of human experts. The implicit knowledge from domain experts can be represented by certain knowledge representations or

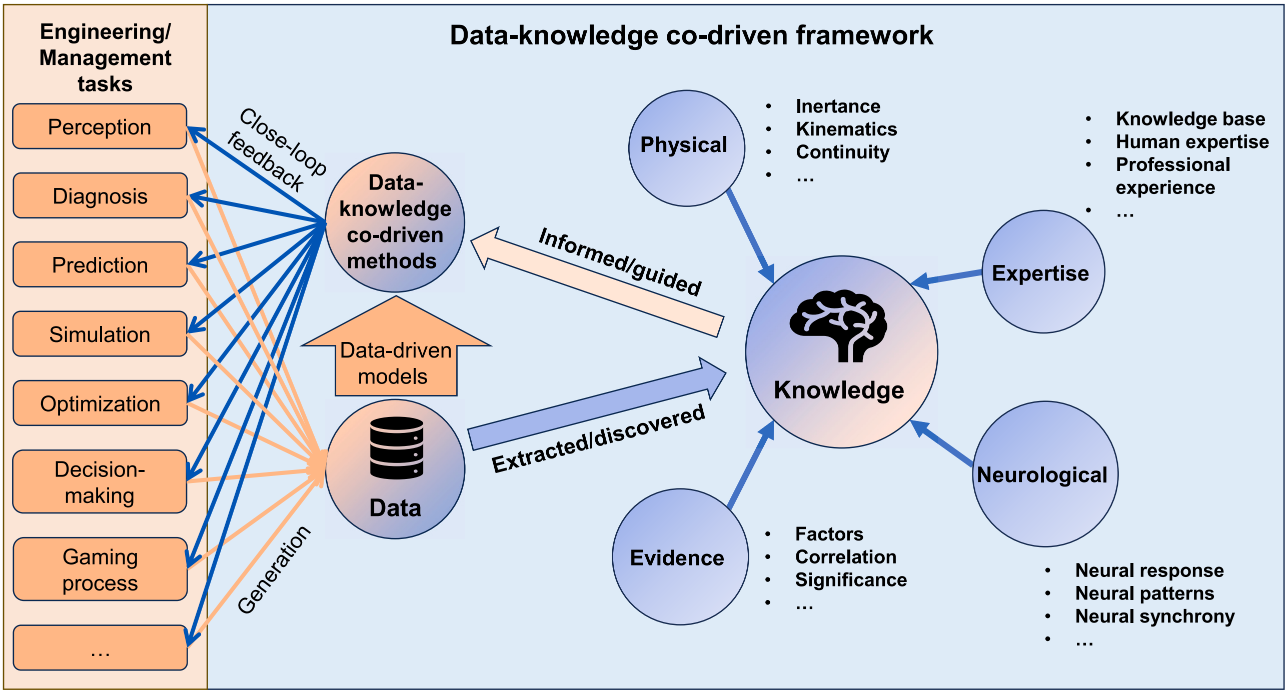

Figure 1. Data-knowledge co-driven framework
Four stages were concluded on according to data utilization and knowledge feedback. (1) Data generation: data streams can be generated from various engineering or management tasks, such as perception, diagnosis, prediction, and simulation. (2) Knowledge discovery: a spectrum of knowledge can be discovered from data, such as physical rules, evidence, expertise, and neurological patterns. (3) Model integration: the discovered knowledge can be employed to inform and guide the data-driven models and integrate them into data-knowledge co-driven methods. (4) Application: the proposed methods can be used to control or regulate the task through closed-loop feedback, which holds the merits of both data-driven models and knowledge-guided methods.

knowledge reasoning methods (i.e., knowledge engineering or knowledge graph-based research) to solve complicated problems. Expert-knowledge-embedded systems not only aid users with specific know-how but also support, complement, and even substitute for human experts.[4]

Though specific system structures may vary, most expert systems include a knowledge base and an inference engine as major components. The knowledge base acquires and stores necessary expert knowledge in a specific domain to solve a targeted problem and is the key basis for the system's performance. Hence, abundant and high-quality expert knowledge is essential. The inference engine mainly uses forward chaining and backward chaining methods to utilize the logic or rules from the knowledge base. The forward chaining method finds matched policies or assertions in the knowledge base and employs conflict-resolution strategies to search and distinguish the best ones to execute. The backward chaining method starts with a defined target and actively searches for a set of rules or logic that can lead to targeted conclusions.

Expert-system-embedded methods are mainly applied to decision-making scenarios where professional human expertise and knowledge are needed. Combining advanced computing algorithms and human expertise, these methods can crystallize collective behavioral trends, make decisions or recommendations, or manage potential risks, especially in domains such as management, manufacturing, and health care.

Evidence-based methods

These kinds of methods scientifically organize data and find explicit or implicit data correlations at the knowledge discovery step to improve decisions. Unlike physics-informed or expert-system-embedded methods, evidence-based methods actively gather scientifically proven information and generate knowledge that was previously unknown and cannot be discovered by professional experience only. In general, evidence-based methods aim to find the most suitable solutions when various tangled options with pros and cons are available from extensive documented trials.

We borrow this idea from the well-established concept of evidence-based medicine, which aims to combine the best research evidence, clinical expertise, and patient concerns to generate effective and personalized treatment decisions. This research paradigm can harness the knowledge gained from all relevant information available and accessible in a multidisciplinary manner.[7] In view of the engineering and management research domains, optimization and decision-making tasks are not always straightforward: there are often dozens of possible options, and each of them has unclear pros and cons.[8] To ensure every decision is made based on the best available knowledge from previous practice, "gold standard" evidence could be concluded from multiple randomized controlled trials or meta-analysis results complying with certain inclusion criteria.

Evidence-based methods are mainly applied to complicated optimization or decision-making tasks where explicit rules or human expertise are unavailable. In these cases, the knowledge of intervention mechanisms can only be discovered from previous experimental data, preferably compared with controlled experiments to verify results. Though methods of this kind are mainly applied in medical research, they have great potential to address various challenging problems in engineering or management disciplines, where input-output correlations can only be found in practice.

Neuro-informed methods

These kinds of methods investigate the activation patterns of human neurological signatures when executing tasks, discover neural information processing pipelines, and build subsequent biomimetic human-like models at either the model integration or the application step. These neurological signatures can be sampled at the data generation step by electroencephalogram (EEG), magnetoencephalogram, functional magnetic resonance imaging, functional near-infrared spectroscopy, etc. By describing the human cognition or decision-making process at the neurological level, neuro-informed methods reveal how the human brain functions cognitively and why people make certain decisions.

To vividly illustrate this idea, we would like to cite our study on human-like driving behavior cognition of autonomous vehicles (AVs)[9] as an example. We aimed to endow AVs with an understanding of human-like driving behavior that may ultimately let them coexist peacefully and efficiently with human-driven vehicles. We investigated the EEG responses of human drivers while watching first-person driving scenarios and discovered hierarchical patterns of neural activity in the temporal lobes that underlie driving behavior. A human-like driving semantics model was subsequently built in a neuro-informed manner, employing neural information processing pipelines similar to those discussed above. The proposed model imitated human cognitive functions while driving and was shown to have the ability to address long-term contextual dependency of driving behaviors. While neuro-informed methods have mainly been applied to tasks where humans interact or communicate with machines, the neurological patterns of other species have also been investigated and used to generate interesting bio-inspired AI methodologies. For instance, the *Drosophila* learning system was incorporated into AI systems to improve adaptability for continual learning,[10] as these AI systems have shown strong merits in balancing memory stability with learning plasticity by employing multiple learning modules.

We regard neuro-informed methods as new research frontiers that actively integrate biologically plausible knowledge into data-knowledge co-driven frameworks. Various neuromorphic computing architectures and applications have validated the efficiency of neuro-informed AI methodologies (see, e.g., Pedersen et al.[11]). Intrinsically, as the neural network itself was designed to mimic real neural functions, investigating neuro-informed AI may also benefit future AI designs and overcome current model-induced drawbacks.[12] Due to their biologically plausible characteristics, these methods can upgrade pure data-driven models with higher interpretability and adaptivity[13] and can ultimately make machines and humans understandable to each other. Hence, they may reduce reliance on or even supersede human labor in some tasks that focus heavily on perception, cognition, decision-making, cooperation, and human-machine interaction.

Challenges and outlooks

Numerous data streams are continuously generated in engineering and management applications. How to best utilize them is a profound question. From these data streams, we can learn and define explicit knowledge-based models to supervise data-driven models. Compared with using pure data-driven methodologies, integrating explicit knowledge can accelerate model optimization, reduce confounding outputs, and improve model accountability.

Though there will be much work required in defining and modeling knowledge in specific engineering or management scenarios, this research is worthy of being conducted to identify real data patterns and understand implicit mechanisms. These innovative explorations are crucial for harnessing closed-loop feedback in various applications or practices and moving forward engineering and management research frontiers as well as for ultimately realizing the economic promise of AI-based systems.

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DECLARATION OF INTERESTS

Y.X. serves on the advisory board of *Patterns*.

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