Perspective

ChatGPT Chats on Computational Experiments: From Interactive Intelligence to Imaginative Intelligence for Design of Artificial Societies and Optimization of Foundational Models

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POWERED by the rapid development of Internet, the penetration of the Internet of Things, the emergence of big data, and the rise of social media, more and more complex systems are exhibiting the characteristics of social, physical, and information fusion. These systems are known as cyber-physical-social systems (CPSS) [1], [2]. These CPSS face unprecedented challenges in design, analysis, management, control and integration due to their involvement with human and social factors [3], [4]. To cope with this challenge, there are two main approaches to CPSS research:

1) Data driven analysis method. Regard complex systems as black boxes, focus on the relationship between inputs and outputs, without modeling and analyzing the complex processes within the system. In the practical application, complex systems tend to be replaced by statistical models based on data and intelligent algorithms, such as convolutional neural network (CNN), recurrent neural networks (RNN), foundation models, etc. The latest ChatGPT (chat generative pre-trained transformer) is a typical example of this approach.

2) Knowledge driven analysis method. According to the principle of "simple consistency", the complex system in practice can be recognized, understood and analyzed by designing and restoring the structure and function of each system component. The computational experiments method is a representative method [5]. Starting from the micro-scale, it cultivates an "artificial society" of the real system in the cyber world. Then, a variety of experiments can be conducted to identify the causal relationship between intervention variables and system emergence to realize the interpretation, understanding, guidance and regulation of macro phenomena.

Both the two methods have advantages and disadvantages when analyzing complex systems. The knowledge modeling method can effectively capture the essential characteristics and principal contradictions of the system, obtaining an effective model structure. However, due to the limited cognitive ability at the time, it can be challenging to accurately describe the operation and evolution mechanism of complex systems. In contrast, data modeling method has advanced by leaps and bounds over the years. The advantage of data modeling is that it can automatically acquire the information and knowledge hidden in the data. But, it heavily relies on the quantity and quality of data samples, and conducting an in-depth analysis and interpretation of the system mechanism can be difficult. As shown in Fig. 1, the difference of the two methods can be visually represented by the "cognitive gap" [6]. Integrating different research methods may provide a solution to bridge the "cognitive gap".

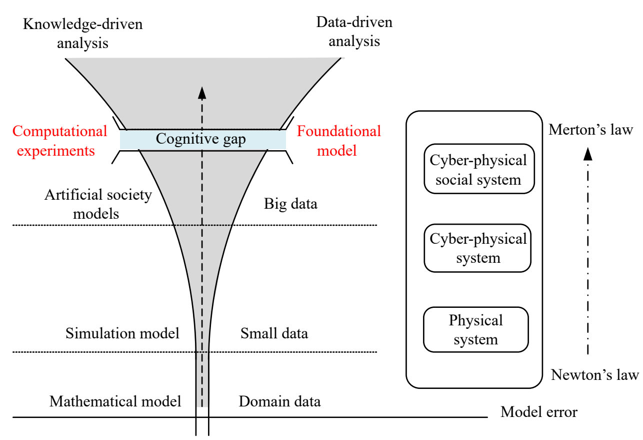

Fig. 1. The "cognitive gap" between data-driven analysis and knowledge-driven analysis.

This paper will address two main issues: Firstly, it will explore how ChatGPT can be utilized to improve computational experiments, particularly in the construction of artificial society models. Currently, the manual design of such models poses a significant challenge to the

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widespread adoption of computational experiments. However, ChatGPT, as the infrastructure of artificial intelligence generated content (AIGC), has the potential to facilitate the automatic generation of these models. Therefore, leveraging ChatGPT to enhance the computational experiments method shows great promise. Secondly, this paper will investigate how computational experiments can be used to improve ChatGPT. While ChatGPT is adept at automatically processing human-like events, it struggles with the problem of causal reasoning in complex systems. Computational experiments, on the other hand, excel at algorithmizing counterfactuals and prescribing results. Therefore, utilizing computational experiments to bolster ChatGPT's performance is a valuable area of inquiry.

What is computational experiments?

Restricted by methodology, economy, law, ethics and other elements, traditional experimental methods may not be applicable for studying such complex systems. In 2004, Wang [7] formally proposed the ACP (artificial systems + computational experiments + parallel execution) method, which emphasizes the use of computational means to study complex systems. As shown in Fig. 2, this approach involves abstracting a software-defined model corresponding to the real system − the artificial system. Through online learning, offline computing, virtual-real interaction, etc., the artificial system becomes a "social laboratory" that can be experimented on and provides "reference", "prediction" and "guidance" for the operation of the actual system. The parallel system adopts the view of "multi-worlds", meaning that when modeling complex systems, the model is no longer evaluated solely based on its degree of approximation to the real system, but instead, it is regarded as an alternative form and another possible implementation of the real complex system. The computational experiments method provides a digital and computational method for quantitative analysis of complex systems.

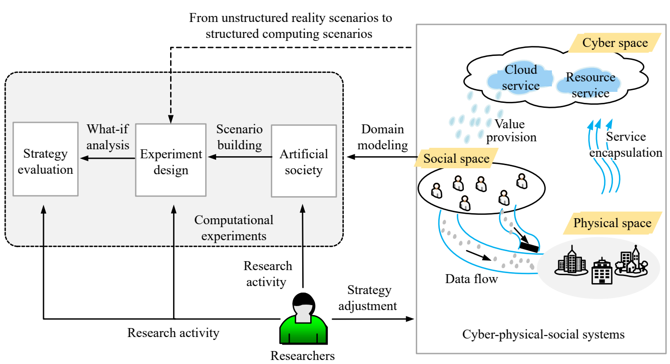

Fig. 2. Schematic diagram of the computational experiments method.

In 2020, "*Computational Experiments Method for Complex Systems − Principles, Models and Cases*" was published, marking the gradual maturation of this method [8]. In addition, [5] provides a comprehensive review of the development status and future challenges of computational experiments method. As a scientific research methodology, computational experiments have been applied to systems that pose high risks, high costs or are impossible to test directly in reality. Nevertheless, the application of computational experiments method also exposes some challenges, including the design and verification of computational model, the design and analysis of computational experiments, and so on. Addressing these challenges will clear the obstacles for the further application of computational experiments.

What is ChatGPT?

Recently, OpenAI's ChatGPT has become a popular search, rekindling enthusiasm for AI among the tech community and the public. ChatGPT represents a significant improvement over past publicly available chatbots, as it is able to engage in daily conversations and acquire knowledge relatively reliably. Moreover, It can assist with writing documents and codes based on requirements provided by humans, and even correct errors in text or bugs in code. In essence, ChatGPT is the integrator of Transformer, GPT and relevant technologies [9]−[11]. In terms of technological innovation, ChatGPT can be summarized as three points:

1) General foundation models

In the field of natural language processing (NLP) research, there are hundreds of tasks, including text classification, information extraction, text understanding, etc., each requiring its own model and framework trained on specific data and made available to everyone. The emergence of "Foundation model" has promoted a shift in AI research paradigm [11]. ChatGPT has demonstrated that it is now possible to pursue the ideal large language models (LLM) directly, with characteristics mainly manifested in two aspects: a) LLM should have a strong ability of autonomous learning and be capable of automatically learning all the knowledge points contained in the massive data without human intervention, while flexibly applying the knowledge to solve practical problems. LLM can be viewed as an implicit knowledge map embodied by model parameters. b) LLM should be able to solve problems in any subdomain of NLP, not just limited domains, and should even be able to respond to problems in domains other than NLP. As such, future research trends will focus on constructing this ideal LLM rather than solving specific problems in one domain.

2) Interactive and linguistic intelligence

The primary objective of ChatGPT is to generate responses based on user input, while aligning with the inherent goals of the language model, which aim to predict the most likely next word in a given context. However, ChatGPT goes beyond this by generating responses that are satisfactory to humans. To endow AI with human-like communication capabilities, ChatGPT was trained using reinforcement learning with human-in-the-loop, 40 human labelers to be exact [12]. Traditional chatbots can be seen as a cyber-physical systems (CPS), in which computing (or networking) resources are tightly integrated and coordinated with physical resources. Now, ChatGPT has evolved into a human-in-the-loop system (i.e., CPSS), which integrates human preferences in an organic and subtle manner to enable efficient and effective system operation [10].

3) Imaginitive intelligence based on emergent Ability

The LLM model possesses an "emergent ability" that is dependent on the scale of its parameters. When the model′s parameters fail to reach a certain threshold, it is unable to effectively solve certain tasks, which is evident in its poor performance and random selection of answers. However, there is a sudden increase in its effectiveness for such tasks when its size exceeds a certain threshold. This is remarkable because it suggests that while LLM may currently struggle with certain tasks or lack the ability to solve them altogether, expanding the model may eventually unlock this ability [13]. The important source of open creativity in LLM is the diffusion model [14]. By integrating massive pre-training data and introducing randomness into the model, unimaginable creativity can be generated. Imaginitive Intelligence may also play a crucial role in further enhancing ChatGPT's reasoning capabilities.

ChatGPT for computational experiments

Artificial society modeling serves as the foundation for conducting computational experiments [5], [15] and [16]. To create a computational model that is logically sound and accurate, it is necessary to simplify and abstract the complex behaviors and phenomena found in real social systems. In the case of complex systems like CPSS, significant amounts of digital content are required to support the construction of an artificial society model. Manual design and development cannot meet this demand. Therefore, leveraging ChatGPT's AI generated content (AIGC) capabilities to aid in the automated design and generation of artificial society models has emerged as a promising research direction in this field. AIGC's abundant creative resources and capabilities are poised to revolutionize the way artificial societies are currently constructed.

As shown in Fig. 3, ChatGPT has powerful intelligent- assisted programming capabilities that promote the design of computational experiments, which consists of three parts: 1) Generation of intelligent agent. The intelligent agent can be an "agent" or a "digital

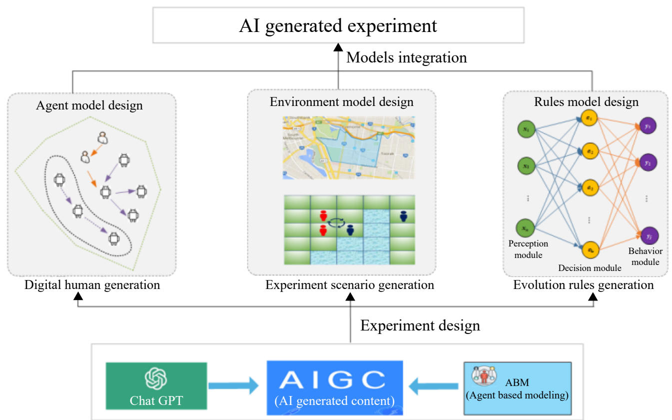

Fig. 3. The generation of computational experiments based on ChatGPT.

human". These modeled agent or digital humans are created as code through AIGC technology, which can present various human-like characteristics such as heterogeneity, bounded rationality, and learning evolution. 2) Generation of virtual environments. It includes both physical environment and social environment. Model as a service (MaaS), which combines knowledge modeling and data modeling, has gradually become the underlying infrastructure for building environment models. 3) Generation of evolution rules. It is used to describe the whole life cycle process from experiment design to artificial society operation, including the interaction and updating rules between agents, environments, agents and environments. These rules can be either mappings of real social rules or hypothetical rules that are artificially assumed.

In traditional experiment design, the operating logic resembles the deterministic function in mathematics. To be more specific, it treats the experimental process as a transformation of multiple inputs (usually a combination) into one or more observable response variables. The focus of traditional experimental design is on selecting an effective subset from a vast space of possible values, using methods such as orthogonal design and Latin hypercube designs. Nonetheless, complex systems like CPSS involve human and social factors, resulting in uncertain value space and making it difficult to select effective subsets. ChatGPT's operating logic is not based on classical functions but rather resembles probability functions. In AI-assisted design, samples are drawn from a probability distribution centered around the expected result. This approach may lead to random biases and inaccurate results but significantly improves efficiency. Moreover, the "way of thinking" of AI is more divergent, making it more suitable for designing uncertain experimental scenes in CPSS.

Computational experiments for ChatGPT

ChatGPT is primarily a language output generation system that learns patterns of content from various sources such as the web and books. What's remarkable about ChatGPT is its ability to produce human-like output ranging from short phrases to entire chapters. While ChatGPT is currently adept at automating human-like category events, not everything useful follows a human-like pattern, especially, particularly in complex systems. ChatGPT is still powerless in the face of uncertain events that occurred in complex systems. Still, the amount of data available for some major emergencies is always insufficient. As we move forward, it is crucial to address the weaknesses of ChatGPT to further improve its capabilities [17]. Hence, the use of computational experiments is the optimal approach to aid ChatGPT in answering complex causality questions.

As shown in Fig. 4, a symbiotic dynamic feedback system can be established between computational experiments and ChatGPT. Computational experiments accurately describe the reasoning challenges that ChatGPT encounters in artificial societies and consider knowledge as a means of reconstructing interdependence in artificial systems. Real-world issues can be abstracted into virtual space models, and computational experiments can be conducted. The enormous simulation analysis data generated can be utilized as the dynamic input for ChatGPT, which can continually update its model. ChapGPT can continuously optimize and revise the experiment design under the guidance of users, so as to dig out deeper causal relationship, and provide "reference", "prediction" and "guidance" for dealing with possible situations. On this basis, the system can

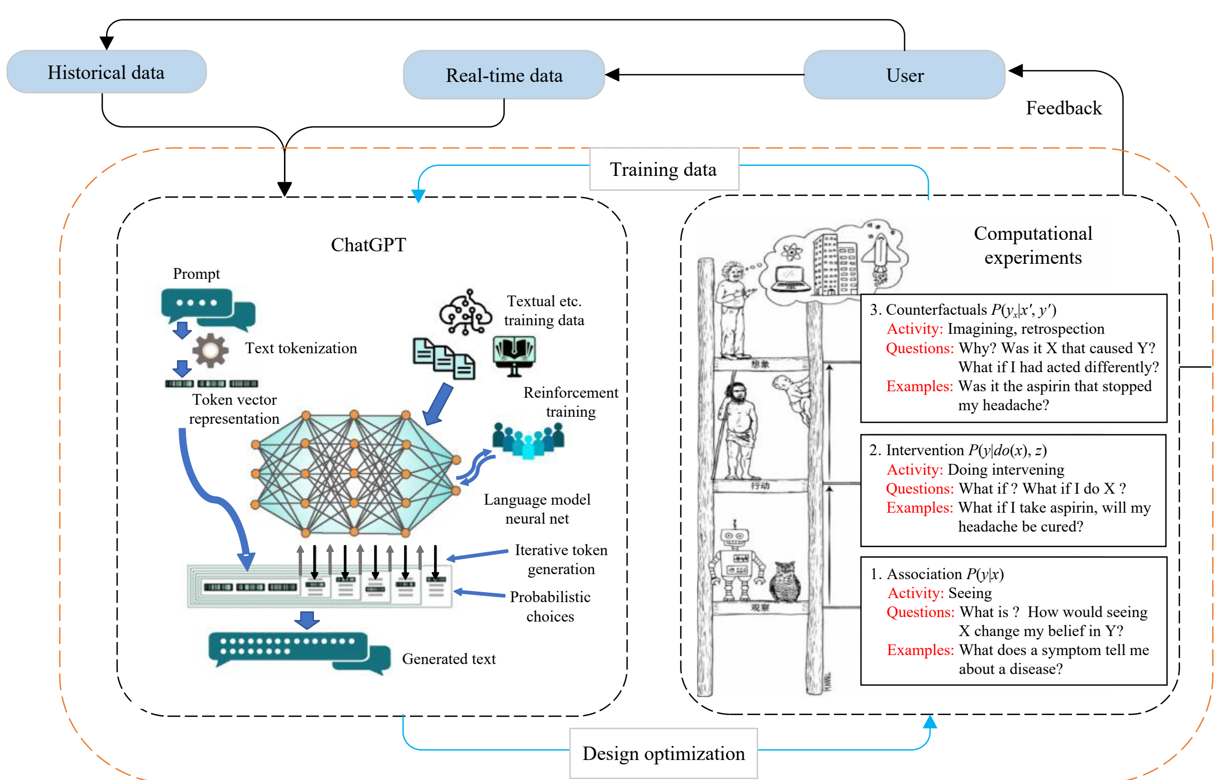

Fig. 4. The improvement of ChatGPT based on computational experiments.

iterate in this feedback loop until it converges [18].

ChatGPT belongs to "behavior modeling" or "behavior description" to a certain degree. Its primary function is to represent the world and does not involve the control or management of the real world. In this regard, computational experiments belong to "target modeling" or "target description". Their function is to calculate the world, emphasizing how to construct "scenarios" in which events occur, develop, transform and evolve, and evaluate the effects of different coping strategies. They form a running process that integrates the behavior model and the goal model, which can improve ChatGPT's complex reasoning ability in three aspects [19]: 1) Black-box analysis (What happened): This involves summarizing and sorting out experimental data to understand the changing rules between influencing factors and response variables. 2) Behavior analysis (How it happened): This involves describing the dynamic behavior of Agent and analyze the occurrence and development process of event chain. 3) Mechanism analysis (why it happened): This involves obtaining the causality between the scenarios reflected in the evolution of the event chain.

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