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Editorial

Special Issue "Artificial Intelligence in Complex Networks"

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1. Introduction

Artificial intelligence (AI) in complex networks has made revolutionary breakthroughs in this century, and AI-driven methods are being increasingly integrated into different scientific research [1–3]. The scientific research of complex networks can be traced back to two aspects. Firstly, the main mathematical subjects of graph theory and statistical physics. One of the major breakthroughs in graph theory is the idea of random graph theory. Complex topologies arise from simple random rules. Random graph theory is often used in conjunction with percolation theory to describe random network modeling. Secondly, complex systems and statistical physics gave birth to a few important theoretical models, such as the Ising model [4–8], mean-field theory, nonequilibrium thermodynamics and dissipative structure theory, synergetic theory, and self-spinning glass model [8,9].

Moreover, AI plays a crucial role in improving the performance of network dynamics, key node mining, community detection, and recommendation behaviors in complex networks [10,11]. The social impact of artificial intelligence is becoming increasingly prominent. On the one hand, as the core force of a new round of scientific and technological revolution and industrial reform, artificial intelligence is promoting the upgrading of traditional industries, driving the rapid development of an "unmanned economy", and having a positive impact on people's livelihoods, such as intelligent transportation, smart homes, and intelligent medical care. On the other hand, issues such as personal information and privacy protection, intellectual property rights of AI-created content, possible discrimination and bias of AI systems, traffic regulations for driverless systems, and the scientific and technological ethics of brain–computer interfaces and human–machine symbiosis, have emerged and need to be urgently provided with solutions [12–15].

Despite the transformative potential of AI in complex networks, there are challenges such as data privacy, user privacy protection, data sample scarcity and diverse network structure, and so on. As these technologies continue to evolve, addressing these issues is paramount for ensuring their responsible and ethical implementation. In the future, further developments in AI technologies are expected to refine and expand their applications in social networks, social computing, transportation and finance networks, large model applications, etc.

2. An Overview of the Published Articles

Complex network theory is widely used in the field of artificial intelligence, and key node identification is the core technology of complex network theory research, which has been highly concerned by the academic community. Many scholars have conducted in-depth research on academic problems such as the identification of critical nodes or the ranking of node importance in complex networks, and have achieved a large number of research results (contributions 1, 4, 7, 10).

A community in a network is a set of nodes that are highly connected to each other, unlike other nodes in the network, which have relatively random and scattered relationships. A key role of community detection algorithms is that they can be used to extract

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useful information from the network. The biggest challenge for community detection is that the community structure is not universally defined (contributions 3, 5, 19).

As the most central component of the personalized recommendation system, the efficiency of the recommendation algorithm directly affects the performance of the entire recommendation system. More mature recommendation algorithms include content-based, collaborative filtering, and other algorithms. Although these algorithms have been widely used, there are still many areas to be improved. The recommendation algorithm based on complex network theory is a good attempt, and it is also one of the current research hotspots (contributions 9, 11, 12, 16).

The data modeling, image processing, object detection and optimization methods of artificial intelligence technology have all been widely used (contributions 2, 6, 8, 13, 14, 15, 17, 18, 20).

There are two main ways to predict information propagation in complex networks. One is feature-based methods; these methods rely on users to manually extract features, such as the content features of the information, the timing features of the current propagation, the structural features, and the user characteristics on the propagation path. Based on these features, a regression algorithm is used to predict the number of retweets. The effects of these kinds of methods depend heavily on the extraction of features. For different problems, users need to extract appropriate features according to their own experiences. The second category is the generative algorithm, which designs a model to simulate the mechanism of information diffusion, tries to retain the main characteristics of information diffusion in the model, and then uses the model to calculate the spread range of each piece of information in the future.

These papers were received from Europe and Asia, with a number combining the expertise of researchers from different countries and even different continents. Finally, we are particularly pleased with the breadth of authors, topics, techniques, and findings that can be found within this Special Issue, “Artificial Intelligence in Complex Networks”.

3. Conclusions and Future Perspectives

With the publication of the present Special Issue, we hope to contribute to better links being formed between artificial intelligence and complex networks; as such, we have selected original works aimed at including key node identification, community detection, recommendation systems, object detection, data processing, and optimal decision algorithms in complex networks. Due to its interdisciplinary and complexity characteristics, the study of complex networks involves the knowledge and theoretical bases of many disciplines, especially those of system science, statistical physics, mathematics, computer and information science, etc. The commonly used analysis methods and tools include graph theory, combinatorics, matrix theory, probability theory, stochastic process, optimization theory, genetic algorithms, etc. The main research methods of complex networks are based on graph theory and its methods, and have achieved gratifying results.

Conflicts of Interest: The authors declare no conflicts of interest.

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