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Article

Collaborative Natural and Artificial Intelligence: A Multilayer Network Interpretation

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Abstract: The revolutionary idea of complementary intelligence involves a unique strategy in which artificial intelligence (AI) works with human cognitive abilities embodied by natural intelligence (NI), creating a harmonious partnership instead of engaging in a competitive relationship. This innovative concept can potentially revolutionize how we approach scientific research and discovery. This cutting-edge process capitalizes on pooling the vast information from various distinct and autonomous sources to generate forecasts that frequently outshine human perspectives by significant margins, leading to groundbreaking advancements in scientific development based on hybrid intelligence. Multilayer networks extend traditional network theory to adjacent layers linked through copula nodes. Artificial intelligence, with its retrieval capacity to collect and interpret big data, sharply increases the number of nodes and their linking interpretation. This process, amplified by multilayer networks, dramatically improves the scalability of the networked ecosystem. Multilayer networks can represent NI and AI in complementary hyperplanes, connecting them with copula nodes and edge properties. Thus, it is possible to measure the interaction of NI and AI, assessing their scalable value co-creation properties. This study examines the interaction of NI and AI with an innovative and multidisciplinary approach. A theoretical framework of these related concepts precedes practical insights for possible applications in future research.

Keywords: network theory; nodes; edges; scalability; hybrid intelligence; complementary intelligence; value co-creation; power laws

1. Introduction

The concept of complementary (hybrid) intelligence, a strategy where artificial intelligence (AI) augments human cognitive capabilities rather than competing with them, is gaining traction. This innovative approach harnesses the collective knowledge of diverse and independent sources to make predictions that often surpass human insights by years, marking significant milestones in scientific progress. The potential of AI to revolutionize scientific discovery is not just promising, but it is crucial for the future of scientific research. It also underscores the urgent need for collaboration between artificial and natural intelligence, an essential partnership for revolutionary discoveries and progressions that we, as a scientific community, are responsible for fostering. This collaboration is not just beneficial but necessary for the future of scientific research.

Moreover, information-theoretic methodologies unveil the inner workings of neural networks by simplifying them into more understandable forms devoid of hidden layers, thereby boosting overall performance and yielding weights akin to linear correlation coefficients between inputs and outputs.

A novel network-flow model for artificial neural networks (ANN) has emerged. Unlike traditional multilayer architectures, this model does not depend on a multilayer structure, providing a broader framework. It maintains the accomplishments of conventional multilayer ANNs while

potentially revealing more universal characteristics. This model is not just a new development but an exciting one that ignites anticipation about the future of AI.

By amalgamating these diverse strategies, AI can sidestep the cognitive biases inherent in the scientific community, producing hypotheses that supplement human intelligence and enrich collective human knowledge. This pattern fosters innovative potential, empowering us as part of a larger scientific community. This comprehensive understanding of multilayer networks underscores the extraordinary capabilities of AI when it is engineered to collaborate harmoniously with natural intelligence, ultimately leading to revolutionary discoveries and progressions.

Artificial and organic intelligence complement each other by utilizing their strengths to solve intricate issues and amplify human skills. In natural intelligence, which manifests in the brains of animals and humans, proficiency is evident in rapid learning, broad generalization abilities, autonomy, and creativity owing to its highly organized structure and self-arranged network patterns known as net fragments. These net fragments facilitate swift learning and effective generalization from minimal examples. The structured regularity inherent in natural intelligence enables it to efficiently connect abstract objectives with real-world scenarios, bridging the gap seamlessly.

AI excels in handling vast amounts of data, pattern recognition, and process optimization, particularly valuable in domains like pharmaceutical discovery. AI's strengths in these areas reassure us of its potential to significantly impact scientific research and discovery. The potential of AI is not just promising, but it is crucial for the future of scientific research. AI models can swiftly produce replicable imitations of natural substances, enhancing molecular design efficiency and expediting the discovery of new medicinal applications.

However, AI's reliance on symbolic and verbal representations limits its adaptability in the unpredictable and complex real world, where natural intelligence's holistic perception and comprehension play a vital role. This awareness of AI's challenges is crucial for future research and development in complementary intelligence, and these challenges make the concept of complementary intelligence so important.

Moreover, despite AI's ability to boost speed and efficacy, it faces limitations inherent in digital technologies and often displays an overly reductionist approach. By merging the computational prowess of AI with the adaptive, creative, and holistic problem-solving capabilities of natural intelligence, we can forge more resilient and versatile systems capable of addressing a wider array of challenges.

This fusion enhances human capacities, empowering individuals to navigate and acclimate to rapidly evolving environments more efficiently. Furthermore, it leverages AI's strengths in data processing and optimization to bolster and enrich the decision-making processes of natural intelligence.

Multilayer networks (Aleta & Moreno, 2019; Berlingerio et al., 2013; Kivelä et al., 2014), also known as multiplex networks or networks of networks, are complex systems where nodes connect following different types of interactions, represented as layers. This framework allows for a more nuanced representation of real-world systems than single-layer networks. This canvas enables connections between nodes across different layers and representing various interactions.

2. Literature Review

To consider the following references in a consistent pattern that illustrates the current literature, we can organize them into a structured framework. This review will highlight how each work contributes to understanding complementary intelligence systems using copula functions. Below is a possible framework for Complementary Intelligence Systems (AI + NI) Using Copula Functions:

1. Foundational Theories and Methods

Copula Theory: Nelsen (2006) provides a comprehensive introduction to copula functions, which are essential for modeling dependencies between variables in multivariate distributions. **Joe**

(1997) explores multivariate models and the concepts of dependence, providing the mathematical foundation for linking NI and AI layers via copula nodes.

Explainable AI: Samek et al. (2017) discuss methods for making AI decisions transparent and interpretable, which is crucial for integrating human cognitive insights into AI systems. **Montavon et al. (2018)** review the techniques for interpreting deep neural networks, highlighting the approaches that enhance human-AI collaboration.

2. Neural Networks and Multilayer Networks

Goodfellow et al. (2016) illustrate a comprehensive guide to deep learning techniques, providing the theoretical and practical knowledge required to build multilayer AI networks. **LeCun et al. (2015)** overview deep learning advancements, underscoring AI's potential to learn complex patterns that human insights can complement.

3. Human-AI Collaboration

Dellermann et al. (2019) propose a taxonomy for designing hybrid intelligence systems, emphasizing the collaboration between humans and AI. **Horvitz (2016)** discusses AI's implications for the future of work, highlighting the importance of creating systems where AI and human intelligence complement each other.

4. Optimization Techniques

Bottou (2010) explores stochastic gradient descent (SGD) for large-scale machine learning, providing methods to optimize neural networks effectively. **Kingma & Ba (2014)** introduce the Adam optimization algorithm, widely used for training deep neural networks, including those in complementary intelligence systems.

5. Human Cognitive Processes and AI

Kahneman (2011) examines human cognitive processes, offering insights into how humans think and make decisions. These insights can inform the design of complementary AI systems. **Anderson & Lebiere (1998)** present a theory of human cognition to model the human layers in a complementary intelligence system.

The copula theory provides the mathematical foundation for linking NI and AI layers. Explainable AI techniques ensure that the AI decisions are interpretable, facilitating effective human-AI collaboration. Neural network and optimization techniques allow us to build and train sophisticated AI models, while insights from human cognitive processes ensure these models can work synergistically with human intelligence.

This structured approach highlights the interconnectedness of these diverse fields and illustrates the current literature's comprehensive and multidisciplinary nature.

This study represents an advancement in the current literature since it examines the links between NI and AI using a multilayer network ecosystem where copula nodes pollinate both layers, scaling them up and improving the overall value with win-win propositions.

3. Multilayer Networks and AI

Understanding the mathematical properties of these networks, such as degree distribution, clustering coefficient, modularity, inter-layer connectivity, path length, efficiency, robustness, and resilience, provides valuable insights into several features and practical applications. The formulation of these properties falls beyond the scope of this introductory paper and can be found in many quoted references, starting from Bianconi, 2018.

These properties inspire applications, according to which new nodes, extracted from big data/IoT, are collected and stored in the cloud, being validated – if necessary – by blockchains, eventually undergoing artificial intelligence (AI) interpretation (Abiodun et al., 2018) that adds value to the whole ecosystem, establishing new linking edges among the larger node datasets. Multilayer

networks further improve the scalability of the connected ecosystems, already ignited by AI multiplication of nodes and edges (Wang et al., 2015).

AI can analyze multilayer networks more efficiently than traditional methods, identifying patterns and anomalies that may not be apparent to human analysts. For instance, machine learning algorithms (Chen et al., 2017) can predict the evolution of these networks or identify key influencers within them.

Kumar & Thakur (2012) have surveyed advanced applications of neural networks and artificial intelligence.

The interaction of AI with multilayer networks can lead to significant improvements in information gains:

- a) **Advanced Analytics and Pattern Recognition:** AI, particularly machine learning (ML) algorithms, can uncover complex patterns and interactions within and across the network layers that might not be apparent through traditional analysis methods.
- b) **Enhanced Prediction Models:** AI can improve the accuracy and efficiency of predictive models in multilayer networks by learning from large datasets, identifying significant features, and adapting to changes in the system dynamics (Boccaletti et al., 2014; De Domenico et al., 2021).
- c) **Automated Network Optimization:** AI techniques can automatically optimize network configurations for better performance, resilience, or efficiency, considering the multilayer nature of the network.
- d) **Dynamic Network Adaptation:** AI-driven systems can monitor multilayer networks in real-time and dynamically adapt to changes, optimizing network performance and mitigating potential issues before they become critical.
- e) **Improved Data Integration and Processing:** AI can enhance the capability to integrate and process data from different layers, enabling more effective decision-making and insights generation.
- f) **Personalized Recommendations and Services:** In multilayer networks representing social or economic systems (Dickison et al., 2016), AI can provide customized recommendations or services by analyzing interconnected data layers (e.g., user preferences, social relationships, and transaction histories).

Within this framework, the research question of this study (synthetically represented in Figure 1) investigates how AI and NI interact with multilayer networks, igniting a scalable interpretation of the ecosystems linked by interlayer copula nodes. The purpose is to start a new research stream where on-field experts (physics, mathematicians, IT specialists, etc.) can investigate specific aspects of this broad and somewhat superficial presentation with mathematical models and practical solutions for different fields.

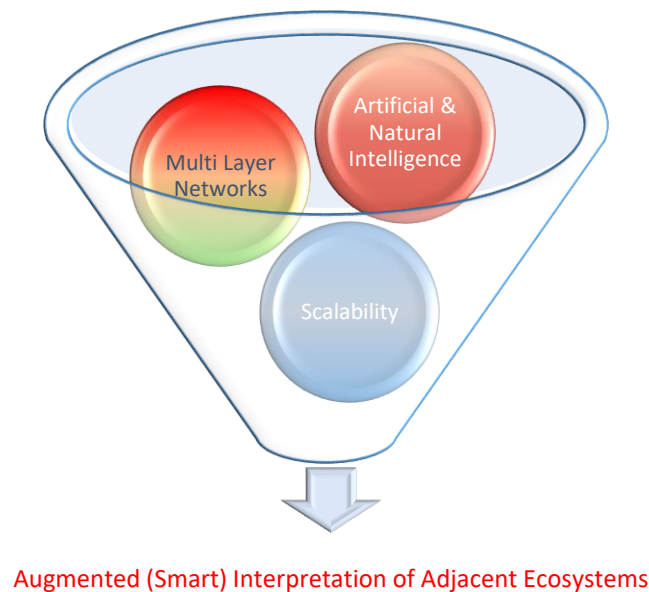


Figure 1. Interaction of Multilayer Networks and AI to produce Scalable Interpretation of Adjacent Ecosystems.

Multilayer networks (Bianconi, 2018) undergo several topographic and mathematical properties shortly recalled in this Section and linked to AI applications.

The literature on multilayer networks inspires the practical patterns illustrated in Table 1.

The following table represents the core part of this introductory paper, which aims to introduce some of the main properties of multilayer networks linked to AI interpretation. This somewhat holistic (but superficial) introduction seeks to provide more comprehensive insights backed by mathematical formulations (not introduced in this preliminary analysis, just for simplicity), graphs, and practical insights.

A synthetic representation of connected concepts, referring to networks and their multilayer extensions, is reported in Appendix A.

4. Enhancing Multilayer Networks with AI

The application of AI in analyzing and optimizing multilayer networks represents a powerful tool for enhancing their design and functionality. As AI techniques become more sophisticated, their ability to understand, predict, and influence the dynamics of complex networks will become increasingly vital across various domains, from technological and biological systems to social and economic networks.

This synergy between AI and multilayer networks advances our understanding of complex systems and opens new avenues for innovation in network-based applications.

In particular, AI links the intangible chain, schematically represented by sourcing information (IoT and big data, warehoused in fog or cloud databases, validated with blockchains, and eventually interpreted with natural intelligence, as briefly schematized in Figure 2.

With AI, the Hermeneutics in Augmented Multilayer Hyperplanes are enhanced by the connecting abilities of AI that introduce new nodes and additional edges, as synthetically shown in Figure 3.

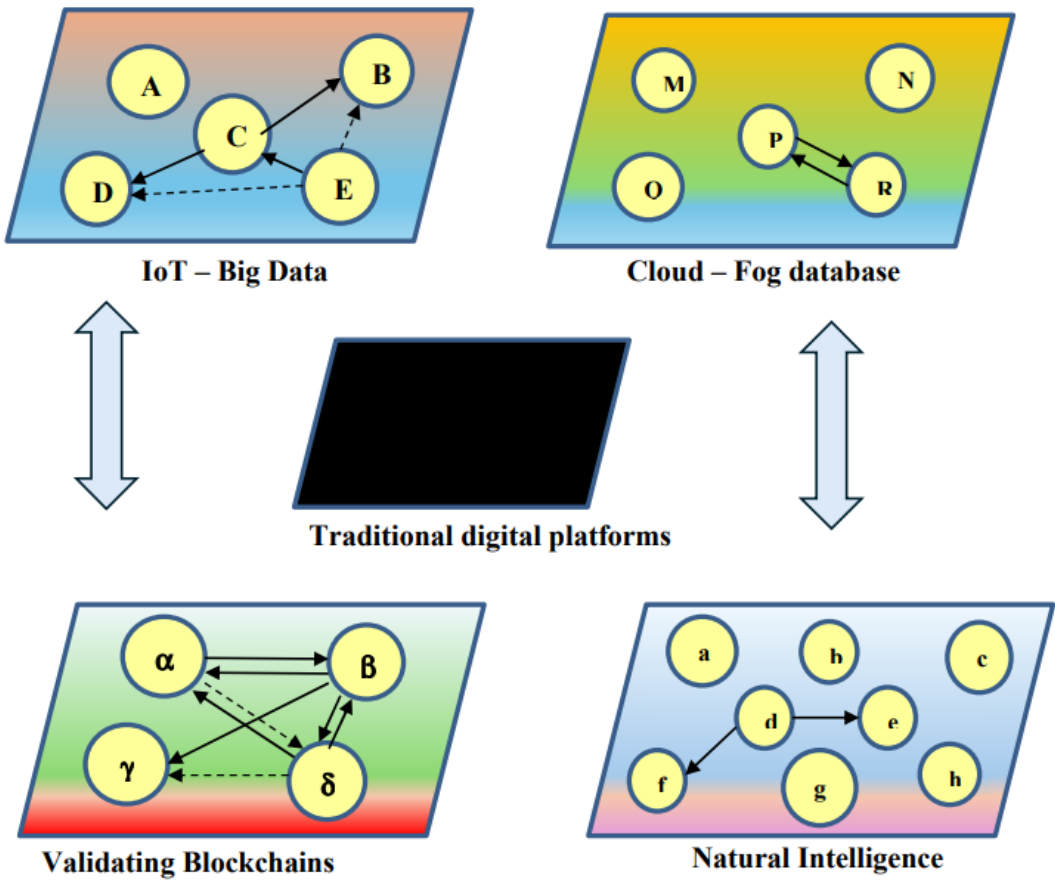


Figure 2. Natural Intelligence Hermeneutics in Standard Networked Ecosystems.

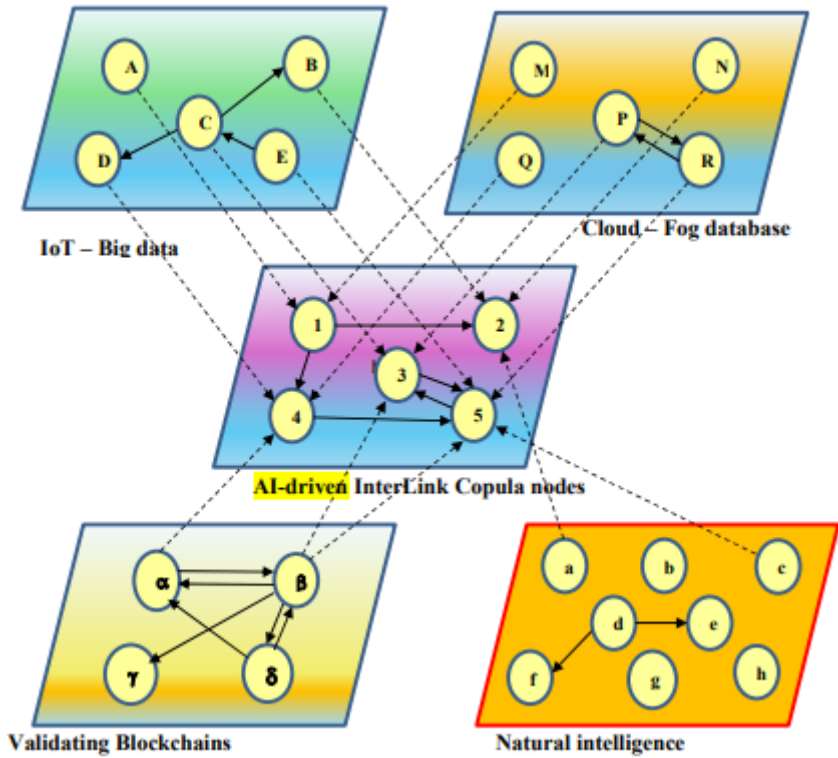


Figure 3. Artificial Intelligence Hermeneutics in Augmented Multilayer Hyperplanes.

5. Scalable Power Laws

The impact of scalable power laws, especially when ignited by AI within multilayer networks, presents a fascinating intersection of network theory, big data analytics, and AI. Scalable power laws in this context refer to the relationships between elements in a network that can expand or scale predictably, often described by a mathematical power law distribution. The integration of AI significantly amplifies the capabilities and potential applications of these networks, with impacts across various dimensions:

A) Enhanced Network Efficiency and Scalability

- **Complex Network Management:** AI's capability to interpret and manage big data allows for more efficient handling of complex, multilayer networks. As networks grow in size and complexity, AI can automate optimizing network paths and connections, leading to more efficient data flow and reduced bottlenecks.
- **Scalability:** Using scalable power laws, combined with AI, means that networks can grow more efficiently. AI algorithms can predict how networks expand and dynamically adjust resources to meet demand without compromising performance, ensuring that the network can scale up or down as needed.

B) Improved Data Analysis and Decision Making

- **Data Interpretation:** AI enhances the ability to analyze data across different network layers, uncovering patterns that may not be visible through traditional analysis methods. This can lead to better decision-making, as AI can provide insights based on a comprehensive view of the networked ecosystem.
- **Predictive Analytics:** Integrating AI with multilayer networks enables predictive analytics of future network states based on current data. This capability is crucial for anticipating and mitigating potential issues before they impact the network.

C) Broader Practical Applications

- **Healthcare:** In healthcare, multilayer networks combined with AI can improve patient outcomes by integrating and analyzing data across various healthcare providers, research databases, and patient records, allowing for personalized and timely medical interventions.
- **Smart Cities:** For smart cities, AI-driven multilayer networks can optimize traffic flow, energy distribution, and emergency services by analyzing and responding to data from many sensors and sources in real time.

D) Challenges and Considerations

- **Privacy and Security:** As networks become more interconnected and data-driven, the potential for privacy breaches and security threats increases. Ensuring the security of multilayer networks and the privacy of the data they handle is a significant challenge.
- **Complexity and Governance:** The increased complexity of AI-driven multilayer networks raises questions about governance, accountability, and control. Developing frameworks for the ethical and effective management of these networks is crucial.

The impact of scalable power laws, fueled by AI, on multilayer networks, is profound, offering enhanced efficiency, scalability, and a wide range of practical applications. However, these advancements also bring privacy, security, and governance challenges, which need careful consideration and management. Future research in this area will likely address these challenges while exploring new applications and ways to maximize the benefits of AI-driven multilayer networks.

6. How do Copula Functions Foster AI-NI Integration?

Copula functions play a crucial role in integrating artificial and natural intelligence. They serve as the bridge connecting the two, allowing for the seamless exchange of information and creating a unified intelligence system that leverages the strengths of both AI and NI.

They offer a robust framework for modeling and simulating the relationships between multiple variables, essential for making accurate predictions and informed decisions. Incorporating copulas enables linking multivariate distribution functions with their one-dimensional marginal distributions, eliminating the necessity to assume multivariate normality or independence across dimensions. This adaptability proves especially advantageous in AI applications dealing with intricate, high-dimensional datasets.

An example is the Neural Copula technique, which utilizes a hierarchical unsupervised neural network to estimate both the marginal and copula functions through the solution of differential equations. This approach creates smooth and analytically expressible copulas that surpass traditional methods in effectively fitting complex distributions. Moreover, models based on copulas, like the Khoudraji-Liebscher copula functions, have demonstrated superior performance in predicting phenomena such as rainfall interception, showcasing their practical value in environmental modeling by yielding lower root mean square error (RMSE) and mean absolute error (MAE) values.

Incorporating copulas into AI systems also enhances their capability to aggregate univariate uncertainty representations into a multivariate framework, accommodating diverse forms of imprecision and dependencies like belief functions and necessity functions. Additionally, copula-based universal integrals expand the scope of these functions to finite universes, thereby amplifying their usefulness in discrete data scenarios often encountered in AI applications. In summary, using copula functions within AI-NI integration furnishes a potent instrument for capturing and representing complex dependencies, ultimately leading to the development of more precise and dependable AI systems.

7. A Mathematical Interpretation of Copula Nodes

Copula functions are a potent instrument in statistics and machine learning. They capture the intricate web of relationships between various random variables. These Copula nodes, operating via Copula functions, present a sturdy foundation for depicting dependencies across numerous variables, ultimately facilitating the development of adaptable and robust statistical and machine-learning models.

This separation allows for a more nuanced and precise control over the interrelationships among variables, enhancing the overall understanding and manipulation of complex data patterns.

1. Copula Functions

1. Multilayer Network Structure

A multilayer network \mathcal{G} can be represented as a tuple $\mathcal{G} = (V, E, L)$ where:

- V is the set of nodes.
- E is the set of edges, which may differ across layers.
- L is the set of layers.

Each layer $l \in L$ represents a different type of interaction or relationship. Nodes can belong to one or multiple layers, and edges within each layer can capture different types of dependencies.

2. Copula Nodes in Multilayer Networks

In this context, copula nodes illustrate the dependencies between the various network layers. Specifically, copula functions can link the distribution of node attributes or interactions across layers, allowing for a more holistic modeling of the network's structure.

3. Mathematical Framework

Consider a multilayer network where we have n layers, each representing different interactions among the same set of nodes. Let $X_i^{(l)}$ represent the attribute of node i in layer l . The dependency between the attributes of nodes across layers can be modeled using a copula function.

Sklar's Theorem in Multilayer Networks

For each node i , let $F_i^{(l)}$ be the marginal distribution of $X_i^{(l)}$ in layer l . According to Sklar's theorem, there exists a copula function C_i such that the joint distribution of $X_i^{(1)}, X_i^{(2)}, \dots, X_i^{(n)}$ is given by:

$$F_i(x_i^{(1)}, x_i^{(2)}, \dots, x_i^{(n)}) = C_i(F_i^{(1)}(x_i^{(1)}), F_i^{(2)}(x_i^{(2)}), \dots, F_i^{(n)}(x_i^{(n)}))$$

This allows us to decouple the marginal distributions of attributes in each layer from their dependency structure.

Copula Density in Multilayer Networks

The copula density function c_i can be derived as:

$$c_i(u_i^{(1)}, u_i^{(2)}, \dots, u_i^{(n)}) = \frac{\partial^n C_i(u_i^{(1)}, u_i^{(2)}, \dots, u_i^{(n)})}{\partial u_i^{(1)} \partial u_i^{(2)} \dots \partial u_i^{(n)}}$$

where $u_i^{(l)} = F_i^{(l)}(x_i^{(l)})$ are the uniform marginals.

The joint density function of the node attributes across layers is then:

$$f_i(x_i^{(1)}, x_i^{(2)}, \dots, x_i^{(n)}) = c_i(F_i^{(1)}(x_i^{(1)}), F_i^{(2)}(x_i^{(2)}), \dots, F_i^{(n)}(x_i^{(n)})) \cdot f_i^{(1)}(x_i^{(1)}) \cdot f_i^{(2)}(x_i^{(2)}) \dots f_i^{(n)}(x_i^{(n)})$$

4. Applications to Natural Intelligence and AI

Each layer uniquely showcases diverse dimensions like cognitive functions, interpersonal dynamics, and AI decision-making mechanisms in the intricate web of a multilayer network that connects natural and artificial intelligence realms. Nestled within these layers are copula nodes that skillfully grasp the intricate dependencies between these facets, offering a profound understanding of the complicated dance between human intellect and the workings of AI systems.

An example scenario may consider a multilayer network with three layers:

- **Layer 1:** Cognitive processes of humans (e.g., problem-solving abilities).
- **Layer 2:** Social human interactions (e.g., communication patterns).
- **Layer 3:** AI system interactions (e.g., recommendations or decisions made by AI).

Let $X_i^{(1)}, X_i^{(2)}$, and $X_i^{(3)}$ be the respective attributes of node i (e.g., a person or AI agent) in these layers. The copula function C_i models the dependency between these attributes across layers.

By implementing suitable copula models, we can delve into the intricate connections between an individual's cognitive functions and interpersonal dynamics, further exploring how interactions with artificial intelligence shape these dynamics. Unraveling these complex relationships can pave the way for a deeper understanding of how AI systems can be seamlessly integrated with human behavior, ultimately fostering a synergy that boosts collaborative intelligence to unprecedented levels of efficacy and innovation.

Copula nodes in multilayer networks provide a powerful mathematical framework for modeling and understanding complex dependencies across interactions and relationships. By applying copula

functions, we can decouple marginal distributions from dependency structures, allowing for a more flexible and comprehensive analysis of how natural intelligence and AI interact within a multilayer network.

This approach illustrates integrating human cognitive and social processes with AI systems, fostering enhanced collaborative intelligence.

8. Adjacent Multilayer Networks with Copula Nodes That Link NI and AI Layers

To understand the properties and mathematical formulations of adjacent multilayer networks connected by copula nodes that link natural intelligence layers with AI layers, it is important first to detect the key components and then consider their mathematical representations.

The Key Components of Multilayer Networks are represented by:

- Natural Intelligence (NI) Layers: These layers represent human cognitive processes and decision-making.
- Artificial Intelligence (AI) Layers: These layers represent artificial neural networks or machine learning models.

Copula Nodes are functions that couple multivariate distribution functions to their one-dimensional marginal distribution functions. In this context, copula nodes link the outputs of NI layers to AI layers, capturing the dependency structure between them.

The properties of multilayer networks linked through copula nodes include:

- a) Interconnectedness: The copula nodes facilitate the transfer of information between NI and AI layers, ensuring the integration of NI into AI processing and vice versa.
- b) Dependency Modeling: Copula nodes capture the dependency between the outputs of NI and AI layers, allowing for more nuanced and accurate modeling of joint distributions.
- c) Layer-wise Interactions: Each layer in NI can be connected to multiple layers in AI through copula nodes, allowing for complex interactions and information flow.

The mathematical formulations are:

1. Multilayer Network Representation:

Let's denote the output of the i -th layer of the NI network as \mathbf{y}_i^{NI} and the output of the j -th layer of the AI network as \mathbf{y}_j^{AI} .

2. Copula Function:

A copula C that links the outputs of these layers can be defined such that:

$$H(\mathbf{y}_i^{NI}, \mathbf{y}_j^{AI}) = C(F_i^{NI}(\mathbf{y}_i^{NI}), F_j^{AI}(\mathbf{y}_j^{AI}))$$

where:

- H is the joint cumulative distribution function (CDF) of \mathbf{y}_i^{NI} and \mathbf{y}_j^{AI} .
- F_i^{NI} and F_j^{AI} are the marginal CDFs of \mathbf{y}_i^{NI} and \mathbf{y}_j^{AI} , respectively.

3. Dependency Structure:

The copula function captures the dependency structure between the NI and AI layers. Common choices for copulas include Gaussian copulas, t-copulas, Clayton copulas, and Gumbel copulas, each modeling a different type of dependency structure.

4. Layer-wise Backpropagation:

To train this interconnected network, we need to consider the gradient flow through the copula nodes. The gradient of a loss function L with respect to the parameters of the NI and AI layers can be computed using the chain rule, taking into account the copula dependencies:

For the i -th NI layer:

$$\frac{\partial L}{\partial \theta_i^{NI}} = \frac{\partial L}{\partial \mathbf{y}_i^{NI}} \cdot \frac{\partial \mathbf{y}_i^{NI}}{\partial \theta_i^{NI}}$$

For the j -th AI layer:

$$\frac{\partial L}{\partial \theta_j^{AI}} = \frac{\partial L}{\partial \mathbf{y}_j^{AI}} \cdot \frac{\partial \mathbf{y}_j^{AI}}{\partial \theta_j^{AI}}$$

The gradients $\frac{\partial L}{\partial \mathbf{y}_i^{NI}}$ and $\frac{\partial L}{\partial \mathbf{y}_j^{AI}}$ need to incorporate the effect of the copula function.

5. Optimization:

Such a network can be optimized using stochastic gradient descent (SGD) or variants. The copula-induced dependencies are considered during the gradient update steps, ensuring the optimization process's robustness. The properties of adjacent multilayer networks connected by copula nodes involve the ability to model dependencies between human cognitive processes and AI models, allowing for complementary intelligence. The mathematical formulation includes defining copula functions to link the outputs of NI and AI layers and incorporating these dependencies into the gradient-based training process of the network. This approach leverages the strengths of both natural and artificial intelligence, potentially leading to more robust and insightful predictive models.

A graphical representation of potential multilayer networks that connect NI and AI through copula nodes can be tentatively illustrated in Figure 4.

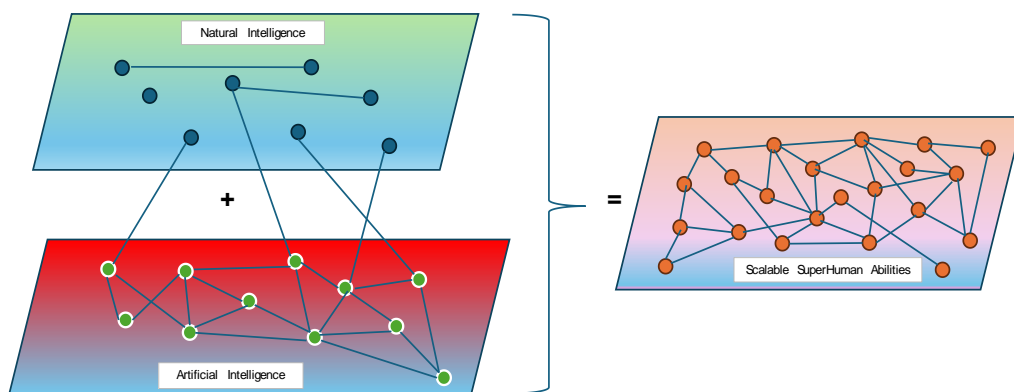


Figure 4. Multilayer Networks Connecting Natural and Artificial Intelligence.

9. Hybrid (Complementary) Intelligence

Collaboratively merging AI and NI, referred to as Complementary Intelligence (CI), heralds a transformative paradigm shift in which AI and NI harmonize synergistically rather than engaging in competition. This harmonious and cooperative strategy has the potential to propel groundbreaking advancements in scientific research and problem-solving by harnessing the distinct strengths of both

entities. AI's remarkable capability to analyze vast volumes of data complements human intuition and contextual comprehension, resulting in more precise predictions and profound insights.

This amalgamation, known as Hybrid Intelligence, merges AI's computational prowess with human ingenuity, intuition, and ethical discernment, elevating overall performance to new heights. The interaction between AI and NI in intricate multilayer networks is based on intermediary copula nodes and edge characteristics that facilitate dynamic collaboration and knowledge exchange.

This conceptual framework provides a more nuanced insight into how AI and NI can collaboratively create value on a scalable level, amplifying each other's contributions and engendering innovative perspectives. Moreover, delving into interdisciplinary realms that bridge disciplines such as cognitive science, computer science, and philosophy can yield fresh viewpoints on CI, nurturing a comprehensive and interconnected approach to integrating AI and NI.

Adhering to principles of responsible and ethical AI utilization in creative endeavors, as delineated in the proposed "fundamental laws of generative AI," ensures that this partnership upholds human values and moral principles, thereby averting the propagation of harmful content and fostering a promising future for creativity and AI.

While initial implementations of collaborative intelligence are predominantly in the prototyping phase, they have showcased the potential for enhancing efficiency, fostering creativity, and ensuring safety across diverse sectors, including healthcare, emergency response, and knowledge-based tasks.

By amalgamating insights from diverse origins and synthesizing AI-driven and human-generated data, we can attain a more thorough and precise comprehension of complex challenges, propelling the boundaries of scientific knowledge and problem-solving to unprecedented advancement.

10. Discussion and Conclusion

The study explores the win-win propositions for NI and AI in a multilayer network ecosystem, showing that copula nodes are crucial in scaling up and improving the overall value.

Copula functions bridge artificial and natural intelligence for seamless information exchange. The neural Copula technique uses an unsupervised neural network to estimate copula functions. Khoudraji-Liebscher copula functions show superior performance in predicting phenomena. Copulas in AI systems aggregate uncertainty representations into the multivariate framework.

Examining the links between NI and AI advances the existing literature. Future research can accurately model dependencies between variables in various fields using copula functions. Copula nodes allow researchers to create flexible statistical and ML models with a clear understanding of dependencies. Separating marginal behavior from dependencies provides a deeper understanding and manipulation of multivariate distributions. Using copula nodes gives researchers a robust framework for developing advanced statistical models.

The network layers provide a framework for understanding how human intelligence and AI systems interact. These nodes offer a way to study the interconnectedness of cognitive processes, social interactions, and AI decision-making. By examining these connections, a deeper understanding of how natural intelligence and AI can impact each other is achieved.

Fitting copula models can analyze relationships between cognitive processes, social interactions, and AI. Copula functions allow for a comprehensive analysis of how human and AI interactions intertwine. The integration of mental and social processes with AI fosters collaborative intelligence. The properties and formulations of networks linking natural intelligence and AI layers are explored.

The copula nodes are crucial in capturing the dependency structure between different layers. By connecting the outputs of various layers, copula nodes help understand the dependency relationships. Understanding the role of copula nodes is essential for analyzing the relationships within neural networks. Incorporating copula nodes enhances the modeling of intricate dependencies within the network architecture.

The copula nodes act as bridges, facilitating the transfer of insights between natural intelligence and artificial intelligence layers, enhancing the overall network's interconnectedness. Different copula choices, such as Gaussian, t-copulas, Clayton copulas, and Gumbel copulas, are utilized to

model diverse dependency structures between the outputs of natural intelligence and artificial intelligence layers. The network's optimization process, including stochastic gradient descent, incorporates copula-induced dependencies between NI and AI layers, ensuring the robustness of the optimization process and enhancing the network's performance.

The interconnected multilayer networks, linked by copula nodes, enable the modeling of dependencies between human cognitive processes and AI models, leveraging the strengths of both natural and artificial intelligence for more insightful predictive models.

The interaction of AI with multilayer networks represents a pioneering approach to enhancing how we understand and leverage information gains within complex systems. By incorporating various types of interactions across different layers, multilayer networks provide a richer and more nuanced representation of real-world systems than traditional single-layer networks. While offering a more detailed view, this complexity requires advanced analytical methods to unlock its full potential.

AI, especially machine learning algorithms, plays a critical role in this context by offering the computational power and sophistication needed to analyze these complex networks efficiently. Here are several ways in which the interaction of AI with multilayer networks leads to significant improvements in information gains:

- a) **Predictive Analytics:** AI algorithms can process vast amounts of data from multilayer networks to predict future network evolution. This predictive capability is vital for various applications, from anticipating social media trends to forecasting the spread of diseases within interconnected populations.
- b) **Anomaly Detection:** AI is adept at identifying patterns and deviations from these patterns within data. In multilayer networks, this means being able to spot anomalies or unexpected behavior across different layers, which could indicate issues like system failures, fraud, or emerging social phenomena.
- c) **Optimized Connectivity and Robustness:** Through analyzing network properties such as inter-layer connectivity and path length, AI can suggest optimizations that improve the efficiency and resilience of these networks. This could lead to more robust telecommunications, transportation, and energy distribution infrastructures.
- d) **Enhanced Interpretation and Decision-Making:** AI's ability to interpret complex datasets from multilayer networks adds significant value by providing actionable insights. This can inform better decision-making in urban planning, environmental management, and public health, among other fields.
- e) **Scalability and Dynamic Adaptation:** As new nodes are added to the network, AI can help manage the increased complexity, ensuring the network scales effectively. This is particularly important in fast-evolving systems like IoT devices or large-scale social networks.
- f) **Security and Trust:** Integrating blockchain technologies for validating new nodes and transactions within multilayer networks introduces additional protection and trust. AI can enhance these aspects by detecting potential security breaches and ensuring the integrity of the blockchain.
- g) **Interdisciplinary Innovation:** The insights gained from AI analysis of multilayer networks can drive innovation across disciplines, from enhancing social network analysis to improving the efficiency of transportation systems and even advancing the study of neural networks in biology.

In conclusion, the under-investigated interaction between AI and multilayer networks opens new research and practical avenues for understanding complex and interrelated ecosystems. This synergy not only advances scientific and technical knowledge but also has interdisciplinary practical implications (see, for instance, Rawat et al., 2018; Rana et al., 2018).

Appendix A. Multilayer Network Properties and AI Interactions

Multilayer networks – properties	AI interactions
Architecture / Design / model complexity / random graphs / Small word and growing networks	<p>Architecture / Design</p> <p>AI impacts the architecture and design of multilayer networks by optimizing network structures for better performance and efficiency. For example, AI algorithms can suggest the optimal number of layers or connections needed to achieve desired outcomes, such as minimizing latency or maximizing throughput. In designing resilient networks, AI can simulate different failure scenarios to ensure robustness against attacks or malfunctions.</p> <p>Model Complexity</p> <p>AI helps in managing the complexity of models used to represent multilayer networks. These networks' sheer scale and intricacy can overwhelm traditional modeling techniques. Machine learning models, especially those involving deep learning, can handle high-dimensional data and uncover complex inter-layer interactions that simpler models cannot. This enables more accurate predictions and insights into network behavior.</p> <p>Random Graphs</p> <p>AI can provide new ways to analyze and interpret these models in the context of random graphs used to model the randomness in network connections. For instance, AI techniques can detect patterns or structures within random graphs that might signify underlying processes or influences affecting the network. This can be particularly useful in understanding the robustness and vulnerability of multilayer networks to various types of failures or attacks.</p> <p>Small-World Networks</p> <p>Small-world networks have high clustering and short path lengths. AI can play a significant role in identifying and analyzing these networks, which often appear in social networks, brain networks, and other biological systems. Machine learning algorithms can uncover the small-world properties in large datasets, helping researchers understand the efficiency of information transfer within these networks and the implications for dynamics like spreading processes.</p> <p>Growing Networks</p> <p>Growing networks, which evolve by adding new nodes and connections, are common in many real-world scenarios. AI techniques are essential for modeling and predicting the growth patterns of these networks. For example, AI can help understand how social networks expand or how new connections in a transportation system might affect overall network efficiency and resilience.</p>
Complex networks / scale-free networks	<p>Complex Networks</p> <p>Complex networks have intricate connection patterns between nodes, including features like high clustering, small-world properties, and community structure. AI impacts the study and application of complex networks in several ways:</p> <ol style="list-style-type: none">Pattern Detection and Analysis: AI algorithms, especially those based on deep learning, are adept at identifying patterns within large and complex datasets that human analysts might miss. This capability is crucial for understanding the underlying structure and dynamics of complex networks, which often display non-trivial patterns of connectivity and interaction.

	<div><div><div>2. Predictive Modeling: AI can predict the evolution of complex networks over time, including how nodes and links might change. This ability is vital for anticipating future network states and preparing for potential challenges, such as congestion in communication networks or spreading misinformation in social networks.</div><div>3. Optimization: AI techniques can help optimize networks for various criteria, such as improving efficiency, robustness, or attack resilience. By simulating different configurations and analyzing the outcomes, AI can guide the design of more effective network architectures.</div></div><div>Scale-Free Networks<p>Scale-free networks are a type of complex network characterized by a power-law distribution of node connectivity, meaning a few nodes have a very high degree of connections while most have relatively few. This property emerges from many real-world networks, including the Internet, biological, and social networks. AI's impact on scale-free networks includes:</p><div><div>a) Understanding Growth Mechanisms: AI models, particularly those incorporating elements of evolutionary algorithms or reinforcement learning, can simulate the growth processes of scale-free networks. This understanding can reveal how certain nodes become highly connected hubs and the implications for network dynamics and resilience.</div><div>b) Robustness and Attack Tolerance: Scale-free networks are known for their robustness against random failures but vulnerability to targeted attacks on high-degree nodes. AI can analyze these networks to identify critical nodes and suggest strategies to protect the network or ensure faster recovery from attacks.</div><div>c) Network Evolution Prediction: AI can forecast how scale-free networks will evolve, identifying potential new hubs or predicting how interventions might alter the network's structure. This predictive power is essential for managing the growth and health of social networks, technological networks, and biological systems.</div></div></div></div>
Degree correlation, degree sequence, average degree, aggregated degree, and degree distribution / multilayer degree	<div>Degree Correlation<p>Degree correlation refers to the tendency of nodes in a network to connect with other nodes with similar (or dissimilar) connections. AI, especially through predictive modeling and pattern recognition, can analyze degree correlations to uncover the underlying organizational principles of networks. This analysis helps understand how network structure influences its resilience and dynamics, such as the spread of information or diseases.</p></div> <div>Degree Sequence<p>The degree sequence is a list of degrees of all nodes in the network, usually sorted in non-increasing order. AI can analyze degree sequences to classify networks, predict evolution, and understand network robustness. Machine learning models can identify patterns in degree sequences that are indicative of specific network types or properties, enabling more effective network design and intervention strategies.</p></div> <div>Average Degree<p>The average degree of a network is a simple yet important metric indicating the average number of connections per node. AI techniques can help analyze how the average degree influences network dynamics, such as connectivity and the efficiency of information or epidemic spreading. AI can also predict changes in the average degree as networks grow or evolve, aiding in network planning and management.</p></div>

	<p>Aggregated Degree</p> <p>In multilayer networks, the aggregated degree combines the degrees of nodes across all layers, providing a holistic measure of node connectivity. AI can analyze aggregated degrees to understand the multifaceted nature of node importance and influence in multilayer networks. This insight is crucial for applications ranging from infrastructure resilience planning to targeted marketing strategies.</p> <p>Degree Distribution</p> <p>Degree distribution, the probability distribution of degrees over the entire network, helps characterize the network's structure (e.g., scale-free or random). AI models, which handle complex, high-dimensional data, can analyze degree distributions to infer network models and predict network behavior under various conditions.</p> <p>Multilayer Degree</p> <p>The multilayer degree extends the concept of degree to multilayer networks, considering the connections of a node across different layers. AI's role is pivotal in analyzing multilayer degrees to uncover the roles and influences of nodes in a more nuanced way than single-layer analyses allow. This capability is vital for understanding complex systems like social networks, where individuals engage in different interactions, or transportation systems, where various modes of transport are interconnected.</p>
Overlaps, multi-links, and multi-degrees	<p>Overlaps</p> <p>Overlaps in multilayer networks refer to nodes or links present in multiple layers of the network, indicating a degree of redundancy or multiplexity in relationships. AI, especially machine learning techniques, can analyze these overlaps to uncover insights into the resilience and robustness of networks and the multifunctionality of certain nodes or links. For instance, overlaps might indicate strong ties between individuals in social networks, while in transportation networks, they could highlight critical infrastructure serving multiple functions. AI can help quantify and optimize these overlaps for better network performance and resilience.</p> <p>Multi-links</p> <p>Multi-links are connections between the same set of nodes across different layers of a multilayer network. These links can carry various interactions or relationships, adding to the network's complexity. AI methods are crucial for analyzing multi-links to understand how different types of relationships interact and influence overall network dynamics. This analysis can reveal how information or influence flows across different layers and how disruptions in one layer might affect others. By applying network analysis algorithms and machine learning models, AI can identify critical multi-links and suggest strategies to leverage or protect them.</p> <p>Multi-degrees</p> <p>The concept of multi-degree extends the node degree to multilayer networks by considering a node's connections across all layers. This measure provides a more comprehensive view of a node's importance or centrality in the network. AI techniques can analyze multi-degree distributions to identify key nodes that play crucial roles across multiple network layers. For example, nodes with high multi-degrees in biological networks might be essential genes or proteins that participate in multiple pathways. In social networks, they could represent influential individuals engaged in various social</p>

	<p>circles. AI's capability to handle complex, high-dimensional data makes it possible to efficiently analyze multi-degrees and their impact on network structure and dynamics.</p>
Scalability / efficiency / modularity / performance	<p>Scalability</p> <ul style="list-style-type: none">• AI and Scalability: AI contributes to multilayer networks' scalability (Moro-Visconti et al., 2023) by enabling adaptive and dynamic network analysis and management. Through predictive modeling and real-time data analysis, AI systems can anticipate network growth and adapt to changes efficiently. This capability is crucial for maintaining network functionality and quality of service as the number of nodes, layers, and connections increases.• Optimization Algorithms: Machine learning algorithms can optimize routing, resource allocation, and layer integration strategies, ensuring that the network scales effectively without a significant loss in performance or increase in complexity. <p>Efficiency</p> <ul style="list-style-type: none">• Network Efficiency Analysis: AI techniques help analyze and enhance the efficiency of multilayer networks by identifying optimal paths for data transmission, minimizing latency, and reducing resource wastage. AI can optimize cross-layer interactions by analyzing data from various network layers, enhancing overall network efficiency.• Energy Consumption: AI also significantly reduces energy consumption through smart routing and node activation strategies, contributing to more sustainable network operations. <p>Modularity</p> <ul style="list-style-type: none">• Enhancing Network Modularity: AI algorithms detect and enhance modularity within multilayer networks, which is the degree to which the network can be divided into clearly defined, densely interconnected modules or communities. This is particularly important for networks where high modularity can improve resilience and functionality.• Community Detection: AI-driven community detection algorithms can uncover modular structures within multilayer networks, aiding in understanding network dynamics and identifying critical nodes or clusters that are pivotal for the network's integrity and performance. <p>Performance</p> <ul style="list-style-type: none">• Performance Optimization: AI techniques optimize the performance of multilayer networks by continuously monitoring network states and adjusting parameters to maintain or enhance the quality of service. This includes balancing load across layers, predicting and mitigating potential failures, and optimizing data flow.• Predictive Maintenance: Utilizing AI for predictive maintenance helps identify potential issues before they occur, minimize downtime, and maintain optimal network performance.
Path length / Shortest distance / navigability	<p>Path Length</p> <ul style="list-style-type: none">• AI and Path Length Analysis: AI techniques, particularly graph neural networks and other machine learning models, are adept at analyzing the path lengths within multilayer networks. By efficiently processing large datasets, AI can identify average path lengths across different layers, uncovering insights into the network's overall connectivity and efficiency. This analysis is vital for understanding the "small-world" phenomena in complex networks, where short path lengths indicate high interconnectedness.• Optimization: AI algorithms can also suggest network modifications to reduce average path lengths, enhancing information flow and making the network more efficient. <p>Shortest Distance</p>

	<ul style="list-style-type: none">• Shortest Path Calculation: AI significantly enhances the capability to calculate shortest paths in multilayer networks by employing sophisticated algorithms that account for multiple layers' unique constraints and opportunities. This is crucial in logistics and transportation planning applications, where finding the most efficient routes impacts cost and time.• Dynamic Routing: Through real-time data analysis and predictive modeling, AI systems can dynamically adjust routes or suggest alternative paths to navigate around congestion, failures, or other disruptions in the network, ensuring optimal distances under varying conditions. <p>Navigability</p> <ul style="list-style-type: none">• Improving Navigability with AI: AI enhances the navigability of multilayer networks by analyzing complex patterns of connectivity and suggesting strategies to enhance cross-layer interaction. This might involve optimizing link placement or adjusting node roles based on their importance across different layers.• Navigation Algorithms: AI-driven algorithms, such as reinforcement learning, are particularly effective at developing strategies for navigating multilayer networks. These algorithms can learn from experience, optimizing navigation strategies over time to adapt to changes in the network structure or usage patterns.
Dynamics (Robustness / resilience / percolation / Epidemic Spreading versus Immunization / Diffusion / Random Walks / Synchroniza- tion)	<p>Robustness and Resilience</p> <ul style="list-style-type: none">• Predictive Modeling and Simulation: AI models can simulate various attack or failure scenarios to assess the robustness and resilience of multilayer networks. By predicting the network's response to node or link failures, AI helps identify vulnerabilities and develop strategies to mitigate potential impacts.• Optimization Strategies: AI algorithms can optimize network structures and configurations to enhance their robustness and resilience. This includes strategies for redundancy, diversifying connections, and adaptive network reconfiguration in response to failures. <p>Percolation</p> <ul style="list-style-type: none">• Threshold Analysis: AI can analyze percolation thresholds in multilayer networks, determining the critical points at which a small change can significantly impact network connectivity. This analysis is crucial for understanding how networks maintain their integrity and functionality.• Network Design: Using AI to understand percolation properties, network designers can create more resilient architectures that are less susceptible to cascading failures or abrupt collapses. <p>Epidemic Spreading versus Immunization</p> <ul style="list-style-type: none">• Predictive Analytics: AI models, especially those incorporating temporal and spatial data, can predict the spread of epidemics across multilayer networks. These models help identify potential hotspots and the impact of various intervention strategies.• Optimization of Immunization Strategies: AI algorithms can identify optimal strategies for vaccine distribution or targeted interventions that minimize the spread of an epidemic while considering resource constraints and network dynamics. <p>Diffusion</p> <ul style="list-style-type: none">• Modeling and Optimization: AI can model diffusion processes across multilayer networks, whether related to information, innovations, or behaviors. Machine learning algorithms can optimize these diffusion processes, enhancing the effectiveness of marketing campaigns, information dissemination, or behavior change initiatives. <p>Random Walks</p>

	<ul style="list-style-type: none">• Analysis and Application: AI techniques analyze random walks in multilayer networks, which have applications ranging from search algorithms to understanding transport processes. AI can optimize these processes, improving search efficiency or resource distribution. <p>Synchronization</p> <ul style="list-style-type: none">• Synchronization Dynamics: AI helps in studying synchronization phenomena in multilayer networks, which is crucial for systems that require coordinated functioning, such as power grids or neural networks (Mocanu et al., 2018). Machine learning models can predict synchronization stability and identify parameters that enhance or disrupt synchronized states.
Network Control / bias	<p>Network Control</p> <ul style="list-style-type: none">• Optimization of Control Strategies: AI, particularly through machine learning and control theory, enables the development of sophisticated control strategies for multilayer networks. These strategies can dynamically adjust to changing network conditions, optimizing for performance, resilience, or efficiency based on real-time data analysis. AI algorithms can identify key control nodes (drivers) critical for influencing the network's behavior or state, enabling more effective interventions.• Adaptive Control Systems: AI facilitates the creation of adaptive control systems that can learn and evolve, improving their ability to manage complex multilayer networks under uncertainty. This is particularly important for networks that undergo frequent changes or are subject to external disturbances.• Predictive Control: Leveraging predictive models, AI can forecast potential network issues before they occur, allowing for preemptive control actions to prevent cascading failures or optimize network performance. This predictive capability is crucial for maintaining stability and efficiency in dynamic and complex network environments. <p>Bias</p> <ul style="list-style-type: none">• Detection and Analysis of Bias: AI tools can help identify and analyze biases present within multilayer networks, whether arising from structural properties, data representation, or algorithmic decision-making. Bias in multilayer networks can lead to skewed outcomes, unfairness, or inefficiency, particularly in networks that underpin social, economic, or technological systems.• Mitigating Bias: Once identified, AI algorithms can be employed to alleviate bias in multilayer networks. This may involve adjusting the network structure, re-weighting connections, or employing fairness-aware machine learning algorithms to reduce bias in decision-making processes.• Understanding Bias Propagation: AI can also study how biases might propagate across layers in a multilayer network, affecting the network's overall behavior and outcomes. This understanding is crucial for designing effective interventions across the entire network rather than addressing bias in a piecemeal or layer-specific manner.
Data Learning and Generaliza-tion	<p>Data Learning</p> <ul style="list-style-type: none">• Feature Extraction and Representation Learning: AI excels at extracting features and learning representations of data that capture the essence of complex relationships within multilayer networks, particularly through deep learning techniques. This capability is critical for analyzing networks where different layers may contain vastly different types of information, such as social

	<p>networks with layers representing various forms of interaction (e.g., friendships, professional relationships, interests).</p> <ul style="list-style-type: none">• Cross-layer Correlation and Integration: AI methods enable the identification of correlations and interactions across layers, learning integrated representations that reflect the multifaceted nature of real-world systems. Cross-layer learning is essential for understanding how different data dimensions interact, affecting overall network behavior and outcomes.• Predictive Modeling: By leveraging the rich, layered data within multilayer networks, AI algorithms can build predictive models that are more accurate and robust. These models can forecast future network states, predict node behavior, or identify potential network evolutions based on comprehensive learning from all data layers. <p>Generalization</p> <ul style="list-style-type: none">• Transfer Learning and Generalization Across Networks: AI techniques, particularly those involving transfer learning, enable models trained on one multilayer network to be applied to another, potentially unrelated network. This capability is crucial for generalizing learned insights across different domains or systems, reducing the need for extensive retraining, and allowing for more efficient deployment of AI solutions.• Robustness to Data Variability: AI models trained to understand and interpret multilayer networks are often more robust to variability and noise within data. This robustness improves the generalization capabilities of these models, ensuring they remain effective even as the network grows or changes.• Understanding Systemic Properties: AI's ability to learn from and generalize across multilayer networks aids in uncovering systemic properties and principles that govern network behavior. This understanding can lead to more universal theories and models of network dynamics, applicable across a range of disciplines and applications.
Clustering coefficients, communities	<p>Clustering Coefficients</p> <ul style="list-style-type: none">• Enhanced Analysis: AI techniques, especially those involving graph neural networks (GNNs) and other deep learning models, can analyze the clustering coefficients in multilayer networks more effectively than traditional methods. The clustering coefficient, which measures the degree to which nodes in a network tend to cluster together, can be crucial for understanding the network's local structural properties. AI can identify nuances in clustering patterns across different layers, providing insights into how these local structures influence overall network behavior.• Prediction and Optimization: AI models can predict changes in the clustering coefficients as networks evolve, helping to optimize network growth or restructuring for desired outcomes, such as improved resilience or enhanced communication efficiency. By understanding how modifications to one layer affect clustering in others, AI-driven strategies can improve network properties globally. <p>Communities</p> <ul style="list-style-type: none">• Community Detection: AI excels at detecting communities within multilayer networks, where communities are groups of nodes more densely connected than the rest of the network. Machine learning algorithms, including unsupervised learning techniques, can uncover community structures that might not be apparent when considering each layer in isolation. This capability is

	<p>essential for understanding the multifaceted nature of real-world networks, from social networks to biological systems.</p> <ul style="list-style-type: none">• Cross-Layer Community Analysis: AI methods can analyze how communities extend across or differ between layers, providing a holistic view of the network's structure and function. This cross-layer analysis helps understand complex dynamics, such as how information or disease spreads across different relationships or interactions.• Dynamic Community Evolution: AI can also track and predict the evolution of communities over time, identifying emerging trends, shifts in community structure, or the formation of new communities. This dynamic analysis is crucial for networks subject to rapid changes, enabling timely interventions or adjustments to maintain network health and performance.
Causality links (directed /undirected networks)	<p>Causality Detection and Analysis</p> <ul style="list-style-type: none">• Advanced Analytics: through machine learning models and statistical analysis tools, AI provides advanced capabilities for detecting and analyzing causality links in multilayer networks. This includes distinguishing between correlation and causation, identifying directional influences, and understanding how these relationships vary across different layers or contexts within the network.• Pattern Recognition: AI algorithms are particularly adept at pattern recognition, allowing them to uncover subtle, causal relationships within large and complex datasets that may not be immediately apparent through traditional analytical methods. This capability is invaluable in multilayer networks, where the sheer volume of interactions and the complexity of interlayer dynamics make manual analysis impractical. <p>Directed and Undirected Networks</p> <ul style="list-style-type: none">• Handling Directed Links: In directed networks, where links have a clear direction indicating the influence flow, AI can help model and predict the dynamics of influence spread, information dissemination, or contagion. By analyzing these directed causality links, AI can provide insights into the mechanisms driving network behavior, identify key influencer nodes, and suggest interventions to enhance or inhibit specific outcomes.• Analyzing Undirected Networks: For undirected networks, AI can assist in inferring directionality and potential causal relationships from data patterns, even when the direction of influence is not explicitly provided. Techniques such as Granger causality in time-series data, applied within a network context, can reveal directional influences based on temporal sequences of events. <p>Enhancing Understanding of Multilayer Networks</p> <ul style="list-style-type: none">• Cross-Layer Influence Mapping: AI is crucial in mapping how causal influences propagate across different layers of a multilayer network. This understanding is critical for systems where interactions within one layer can significantly impact outcomes in another, such as in socio-technical systems, ecological networks, or complex financial systems.• Predictive Modeling: By incorporating causality links into predictive models, AI enhances the accuracy and reliability of forecasts related to network dynamics. This includes predicting the spread of information, the impact of interventions on public health, or the stability of financial markets.• Intervention Strategies: Understanding causality links enables the development of more effective intervention strategies. AI-driven analysis can identify leverage points within the

	<p>network where targeted actions can lead to desired outcomes, optimize resource allocation, or prevent undesirable events.</p>
Centralities (Eigenvector; Katz; PageRank; betweenness; communica- bility; nodes versatility ...)	<p>Eigenvector Centrality</p> <ul style="list-style-type: none">• Enhanced Computation and Interpretation: AI models can efficiently compute Eigenvector centrality, which measures a node's influence based on the principle that connections to high-scoring nodes contribute more to the score of the node in question. AI can help identify key influencers within multilayer networks, considering the multiplex nature of connections. <p>Katz Centrality</p> <ul style="list-style-type: none">• Scaling Analysis: Katz centrality extends Eigenvector centrality by introducing a factor that accounts for the total number of walks between pairs of nodes, attenuated by the length of the walk. AI techniques can scale the computation of Katz centrality for large multilayer networks, providing insights into node influence that incorporates direct and indirect connections across layers. <p>PageRank</p> <ul style="list-style-type: none">• Cross-Layer Influence: Originally designed for ranking web pages, PageRank can be adapted to multilayer networks with AI's help to evaluate the importance of nodes considering the unique structure of these networks. AI can modify the PageRank algorithm to account for the heterogeneity of connections and their different strengths across layers, identifying key nodes that facilitate information or resource flow. <p>Betweenness Centrality</p> <ul style="list-style-type: none">• Dynamic Network Analysis: Betweenness centrality measures the extent to which a node lies on the shortest path between other nodes. AI algorithms can dynamically calculate betweenness centrality in evolving multilayer networks, highlighting nodes that act as critical bridges or bottlenecks for the flow of information or resources. <p>Communicability</p> <ul style="list-style-type: none">• Complex Patterns Identification: Communicability extends the concept of connectivity by considering all paths linking two nodes, weighted by their lengths. AI can uncover complex patterns of communicability in multilayer networks, identifying potential channels for efficient communication or the spread of processes like diseases or information. <p>Node Versatility</p> <ul style="list-style-type: none">• Multilayer Role Identification: Node versatility measures a node's ability to connect across different network layers, highlighting its role in integrating or segregating different types of interactions. AI can analyze nodes' versatility to understand their function in connecting disparate network regions or layers, facilitating the design of interventions to enhance network integration or resilience.
Inter-layer connectivity and interdependence / Replica nodes / Orphan (uncorrelated)	<p>Inter-layer Connectivity and Interdependence</p> <ul style="list-style-type: none">• Understanding and Optimization: AI techniques, particularly machine learning models, are adept at analyzing the intricate connectivity patterns and the dependencies between layers in a multilayer network. By understanding these relationships, AI can help optimize network structure for resilience, efficiency, or other desired outcomes. For example, AI can predict how changes in one layer might affect another, enabling proactive adjustments to network configurations.

Networks	<ul style="list-style-type: none">• Dynamic Analysis: AI models facilitate dynamic analysis of inter-layer connectivity, providing insights into how these connections evolve. This is crucial for networks subject to rapid changes, such as technological or social networks, where the interdependencies between different types of interactions can significantly influence overall network behavior. <p>Replica Nodes</p> <ul style="list-style-type: none">• Identification and Management: Replica nodes, which represent the same entity across different layers, are critical for understanding nodes' multifaceted roles and influences within multilayer networks. AI can identify and analyze these replica nodes, assessing their centrality and influence across layers. This insight is vital for identifying key influencers in social networks, optimizing resource allocation in infrastructural networks, or understanding gene regulation networks in biology.• Cross-layer Influence: AI techniques enable the study of how replica nodes facilitate or hinder the flow of information, resources, or influence across layers. This includes analyzing the role of replica nodes in spreading processes, resilience against failures, and the integration of functionalities across a network. <p>Orphan (Uncorrelated) Networks</p> <ul style="list-style-type: none">• Analysis and Integration: Orphan networks, which lack direct correspondence or correlation with other layers in a multilayer system, pose unique challenges for analysis and integration. AI can help uncover hidden correlations or indirect relationships between orphan networks and different layers, integrating disparate data sources and enhancing understanding of complex systems.• Handling Uncorrelated Data: AI, especially unsupervised learning and pattern recognition techniques, is instrumental in deriving value from uncorrelated networks. By identifying patterns, anomalies, or emergent properties within these networks, AI contributes to a more comprehensive view of the multilayer system.• Predictive Insights: Even without direct inter-layer connections, AI can predict the impact of changes or interventions in one network on the dynamics of orphan networks. This predictive capability is essential for decision-making and strategy development in complex environments.
Nodes and Edges Creation and loops	<p>Nodes and Edges Creation</p> <ul style="list-style-type: none">• Automated Network Growth: AI can automate the process of network growth by identifying patterns, needs, or opportunities for new nodes and edges. For instance, in social networks, AI algorithms can suggest potential new connections based on common interests, mutual friends, or other relevant criteria. In transportation or logistics networks, AI can identify the need for new routes or connections to optimize efficiency or reduce congestion.• Optimization: AI techniques optimize the creation of nodes and edges, ensuring that new additions enhance the network's overall functionality, resilience, or performance. This might involve complex decision-making processes where the benefits of adding new nodes and connections are weighed against potential drawbacks, such as increased complexity or maintenance costs.• Predictive Modeling: AI models can predict where and when new nodes and edges (Pang et al., 2019) are necessary within a network based on trends, growth patterns, or changing conditions. This predictive capacity allows for proactive network planning and adaptation, ensuring networks remain efficient and effective.

	<p>Loops</p> <ul style="list-style-type: none">• Loop Detection and Analysis: Loops in networks can have significant implications for network dynamics, such as creating redundancy, influencing information flow, or affecting network stability. AI algorithms are adept at identifying loops within multilayer networks, analyzing their impact, and determining whether they enhance or hinder the network's intended functions.• Loop Optimization: In some cases, loops are desirable for redundancy and resilience, while in others, they may represent inefficiencies. AI can help optimize the presence of loops in a network, ensuring that they serve a beneficial purpose, such as improving robustness or providing more effective information dissemination.• Dynamic Adjustment: AI-driven systems can dynamically adjust the creation or elimination of loops in response to network changes or evolving requirements. This dynamic adjustment is crucial for maintaining optimal network performance, especially in rapidly changing environments like telecommunications or traffic networks.
Temporal multilayer Networks /Synchroni- zation / Disconti- nuity / Pattern formation	<p>Temporal Multilayer Networks</p> <ul style="list-style-type: none">• Dynamic Analysis and Prediction: AI and machine learning models that process sequential data (e.g., recurrent neural networks and Long Short-Term Memory networks) can analyze temporal changes in multilayer networks. This enables the prediction of future network states, the identification of growth patterns, and the anticipation of potential network disruptions or emergent behaviors.• Adaptive Network Models: AI facilitates the development of adaptive models that can adjust to the temporal evolution of multilayer networks, ensuring analyses and decisions remain relevant as the network changes. This adaptability is key for managing networks in real-time, allowing for the adjustment of strategies in response to detected changes or predictions. <p>Synchronization</p> <ul style="list-style-type: none">• Enhancing Synchronization: In networks where synchronization of processes across layers or nodes is crucial (such as power grids, communication networks, or biological systems), AI can optimize synchronization mechanisms. By analyzing timing and interactions across the network, AI algorithms can identify optimal pathways and configurations that promote effective synchronization.• Predicting Synchronization Failures: AI can also predict and detect synchronization failures, critical for preventing systemic failures in networks relying on coordinated timing. Early detection enables preemptive adjustments to restore or maintain synchronization. <p>Discontinuity</p> <ul style="list-style-type: none">• Detection and Management: Discontinuities, or abrupt changes in network structure or function, can significantly impact network performance and stability. AI models are adept at detecting these changes, analyzing their implications, and suggesting interventions to mitigate adverse effects or leverage positive ones. This capability is crucial for maintaining network integrity and functionality. <p>Pattern Formation</p> <ul style="list-style-type: none">• Identification and Analysis: AI excels at identifying and analyzing patterns in data, including those within temporal multilayer networks. This includes recognizing recurring structures, behaviors, or anomalies that signify underlying processes or emerging challenges within the network.

	<ul style="list-style-type: none">● Guiding Network Evolution: By understanding pattern formation within these networks, AI can guide network evolution in beneficial directions, suggesting where new connections might be needed or identifying potential inefficiencies or vulnerabilities within the network's structure.
Multilayer Network Communities / consensus clustering	<p>Multilayer Network Communities</p> <ul style="list-style-type: none">● Detection and Analysis: AI excels at identifying communities within multilayer networks, particularly through machine learning algorithms such as graph neural networks (GNNs) and community detection algorithms. These communities may differ significantly across layers, reflecting the multifaceted nature of nodes' roles and interactions. AI can analyze these communities to understand their structure, dynamics, and roles in the overall network functionality.● Dynamic Community Tracking: For temporal multilayer networks, AI can track the evolution of communities over time, identifying how they grow, shrink, merge, or split. This dynamic tracking is essential for understanding how network structures and node relationships evolve, providing insights into the changing nature of the network.● Interlayer Community Integration: AI techniques help understand how communities are integrated or segregated across different network layers. This analysis is crucial for uncovering complex interdependencies and interactions that can influence network behavior on a global scale. <p>Consensus Clustering</p> <ul style="list-style-type: none">● Improved Cluster Quality: By applying consensus clustering techniques, AI can integrate multiple clustering results from different layers or clustering algorithms to produce a more robust and representative understanding of the network's structure. This approach helps mitigate the biases or limitations of individual clustering methods, leading to more accurate and meaningful community detection.● Cross-layer Consensus: AI algorithms are particularly useful in finding a consensus among clustering results across multiple layers, which is challenging due to the heterogeneity and complexity of multilayer networks. This consensus can reveal new insights into how similar structures or communities persist across different interactions or relationships.● Noise Reduction and Stability Enhancement: Consensus clustering, facilitated by AI, helps reduce noise and enhance the stability of clustering results. This is particularly important in complex networks where data variability and the presence of outliers can significantly impact the quality of clustering. AI-driven consensus clustering can identify the core structure of the network that is more resilient to such variations.
Similarity Indexes (based on Information Theory)	<p>Enhanced Similarity Analysis</p> <ul style="list-style-type: none">● Automated Similarity Detection: AI, particularly machine learning techniques, can automate calculating similarity indexes across the layers of a multilayer network. This automation is crucial for large-scale networks where manual analysis is impractical due to the data volume and the interactions' complexity.● Deep Learning for Complex Patterns: Deep learning models, including unsupervised learning techniques, can uncover complex patterns in data that are not readily apparent. These models can analyze multilayer networks to identify similarities and differences between layers or within a layer based on the information content of nodes and their connections.

	<p>Improved Understanding of Network Structure</p> <ul style="list-style-type: none">• Information-Theoretic Measures: AI algorithms can apply information-theoretic measures to assess the similarity and divergence between network layers. These measures help understand the amount of shared information between layers, revealing the underlying structure and function of the network. For example, calculating the Mutual Information between layers can indicate how much knowledge of one layer reduces uncertainty about another.• Cross-layer Interaction Analysis: By leveraging similarity indexes, AI can analyze how interactions in one layer relate to those in another, providing insights into the interlayer dependencies and how they influence overall network behavior. This analysis is crucial for understanding the flow of information or the spread of processes (e.g., diseases, rumors) across a multilayer network. <p>Optimization and Network Design</p> <ul style="list-style-type: none">• Network Optimization: Understanding the similarities and differences between layers, as informed by similarity indexes, can guide the optimization of network structures for enhanced performance, resilience, or efficiency. AI-driven analysis can suggest modifications to network design, such as strengthening or pruning connections, to optimize information flow or robustness based on the desired network properties.• Predictive Modeling: AI models can use similarity indexes as features or inputs to predict future states of the network, potential points of failure, or the outcomes of interventions. This predictive capability is vital for proactive network management and decision-making.
Multilayer Network Modelling	<p>Enhanced Modeling Capabilities</p> <ul style="list-style-type: none">• Complex Pattern Recognition: AI algorithms, especially those in machine learning and deep learning, excel at identifying complex patterns and relationships within and across the layers of multilayer networks. This capability is crucial for accurately modeling the interactions and dependencies that define the network's behavior.• Predictive Modeling: AI enables the development of predictive models that can forecast the evolution of multilayer networks over time. These models can predict how changes in one layer might affect others, allowing for proactive adjustments and decision-making.• Automated Model Optimization: AI techniques can automate optimizing network models and adjusting parameters to improve accuracy, efficiency, or other desired outcomes. This optimization can involve refining the structure of the network model or tuning the algorithms used for analysis and prediction. <p>Improved Analysis and Decision-Making</p> <ul style="list-style-type: none">• Cross-layer Analysis: AI facilitates comprehensive cross-layer analysis, enabling a holistic understanding of multilayer networks. By analyzing how layers interact and influence each other, AI helps to uncover insights that would be difficult to obtain through traditional methods focused on single-layer analysis.• Dynamic Behavior Analysis: AI enhances the ability to model and analyze dynamic behaviors within multilayer networks. This includes understanding how information spread, contagion, or failure propagation moves through and between layers.• Decision Support: AI-driven models provide valuable decision support, helping stakeholders to identify key nodes or links, evaluate the potential impact of interventions, and develop strategies for network management and optimization.

	<p>Novel Insights and Discoveries</p> <ul style="list-style-type: none">• Uncovering Hidden Structures: AI can reveal hidden structures and patterns in multilayer networks that are not immediately apparent. This might include identifying communities that span multiple layers or detecting anomalies that indicate disruptions or opportunities for intervention.• Interdisciplinary Applications: The advancements in multilayer network modeling powered by AI have significant implications across various fields, including epidemiology, sociology, transportation, telecommunications, and ecology. This cross-disciplinary impact facilitates novel insights and fosters innovation in understanding complex systems.• Scalability: AI models, particularly those leveraging parallel processing and scalable algorithms (Sen et al., 2023), can handle the increased size and complexity of multilayer networks more efficiently than traditional modeling approaches. This scalability is essential for analyzing large-scale networks in real-world applications.
Game theoretical approaches	<p>Strategic Modeling and Optimization</p> <ul style="list-style-type: none">• Learning-Based Strategy Development: AI algorithms, especially those employing reinforcement learning, enable agents within a multilayer network to develop and evolve their strategies based on past interactions and outcomes. This learning capability allows for optimizing strategy over time, adapting to changes in the network's structure or the strategies of other agents.• Prediction of Strategic Outcomes: AI models predict the outcomes of strategic interactions in multilayer networks, considering the complex interdependencies and the multitude of strategies available to agents. This predictive capability is crucial for understanding potential future states of the network and for planning interventions or policies to guide the network toward desired outcomes. <p>Enhanced Analysis of Network Dynamics</p> <ul style="list-style-type: none">• Analyzing Equilibrium States: AI can help identify equilibrium states in multilayer network games, where no agent is incentivized to change their strategy unilaterally. By efficiently analyzing the vast space of possible strategies and interactions, AI assists in understanding the conditions under which networks stabilize and how these conditions can be influenced.• Complexity Reduction: Game theoretical models of multilayer networks can become exceedingly complex, especially as the number of layers and agents increases. AI techniques can simplify these models without losing essential information, making it feasible to analyze and derive insights from complex multilayer strategic interactions. <p>Improved Understanding of Cooperative and Competitive Behaviors</p> <ul style="list-style-type: none">• Cooperation and Competition Analysis: In multilayer networks, agents may engage in cooperative and competitive behaviors, depending on the context and objectives. AI can dissect these interactions, identifying underlying patterns and strategies that promote cooperation or competition. This analysis is particularly valuable in networks where cooperation among agents in one layer might conflict with competitive dynamics in another.• Network Design and Policy Making: By applying game-theoretical approaches with AI, stakeholders can design network policies or interventions that encourage desirable behaviors among agents. AI-driven simulations and models can evaluate the potential impacts of these

	<p>policies, ensuring they align with overall objectives such as maximizing network efficiency, resilience, or fairness.</p> <p>Facilitating Multidisciplinary Applications</p> <ul style="list-style-type: none">• Broad Applicability: The combination of game theory and AI in analyzing multilayer networks finds relevance across various fields, from economics and sociology to biology and engineering. This multidisciplinary impact allows for transferring insights and methodologies between fields, fostering innovation and a deeper understanding of complex systems.
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