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Revolutionizing Education: Harnessing Graph Machine Learning for Enhanced Problem-Solving in Environmental Science and Pollution Technology

R. Krishna Kumari†
Department of Mathematics, College of Engineering and Technology, SRM Institute of Science and Technology, Kattankulathur, Chennai-603203, Tamilnadu, India
†Corresponding author: R. Krishna Kumari; krishrengan@gmail.com

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ABSTRACT

Amidst the shifting tides of the educational landscape, this research article embarks on a transformative journey delving into the fusion of theoretical principles and pragmatic implementations within the realm of Graph Machine Learning (GML), particularly accentuated within the sphere of nature, environment, and pollution technology. GML emerges as a potent and indispensable tool, adeptly leveraging the intrinsic interconnectedness embedded within environmental datasets. Its application extends far beyond mere analysis towards the profound ability to forecast ecological patterns, prescribe sustainable interventions, and tailor pollution mitigation strategies with precision and efficacy. This article does not merely scratch the surface of GML's applications but dives deep into its tangible implementations, unraveling its potential to revolutionize environmental science and pollution technology. It endeavors to bridge the gap between theory and practice, weaving together relevant ecological theories and empirical evidence that underpin the theoretical foundations supporting GML's practical utility in environmental domains. By synthesizing theoretical insights with real-world applications, this research elucidates the profound transformative potential of GML, paving the way for proactive and data-driven approaches toward addressing pressing environmental challenges. In essence, this harmonization of theory and application catalyzes advancing the adoption of GML in environmental science and pollution technology. It not only illuminates the path towards sustainable practices but also lays the groundwork for fostering a holistic understanding of our ecosystem. Through this integration, GML emerges as a beacon guiding us toward a future where environmental stewardship is informed by data-driven insights, leading to more effective and sustainable solutions for the benefit of our planet and future generations.

INTRODUCTION

The traditional challenges within the domain of environmental science and pollution technology mirror those encountered in education-struggling to adapt to the diverse intricacies of the natural world. As methodologies evolve, the limitations of standardized approaches in addressing environmental issues become increasingly apparent, urging exploration into innovative technologies to overcome these barriers (Ying et al. 2020, Zhang et al. 2021, 2023, Li et al. 2020). In this pursuit of transformative solutions, Graph Machine Learning (GML) emerges as a beacon of hope, offering a fresh perspective to revolutionize environmental practices (Lozano et al. 2017, Shen 2020, Nguyen et al. 2020, Li et al. 2022). The core issue lies in acknowledging that a uniform approach often fails to accommodate the unique dynamics and complexities of ecosystems. This recognition fuels a growing interest in technologies capable of adapting to the nuanced nature of environmental challenges. GML, among these technologies, stands out as particularly promising, positioning itself as a versatile tool poised to reshape the landscape of environmental science and pollution technology (Liu et al. 2020, Romero & Peña-Casas 2010).

This research article embarks on a comprehensive exploration of GML, not solely as a technological innovation but as a solution deeply rooted in theoretical foundations. The focus extends beyond the practical applications of GML in environmental science to delve into the theoretical frameworks that underpin its effectiveness (Wang & Rajagopalan 2020). At the heart of GML's transformative potential lies its ability to leverage the intricate network structures inherent in environmental data. By deciphering and navigating the complex interconnections within ecosystems, GML aims to facilitate tailored solutions that transcend the limitations of conventional methodologies (Li et al. 2023, Liu et al. 2023).

As we embark on this journey into the theoretical underpinnings supporting GML, the goal is not merely to showcase its potential but to unveil a deeper understanding of how this technology can catalyze personalized solutions for environmental challenges (Sun et al. 2021). By harnessing the network structures within environmental data, GML endeavors to offer customized interventions that align with the unique characteristics of each ecosystem (Luo et al. 2023). This exploration transcends superficial applications and delves into the theoretical frameworks that drive its practical implementations. Essentially, this research article serves as a conduit between theory and application, shedding light on the symbiotic relationship that defines GML's role in environmental science and pollution technology. Through a nuanced examination of its theoretical foundations, we aim to uncover the mechanisms that empower GML to transcend traditional constraints within environmental research. As we navigate this intersection of theory and practice, the overarching objective is to contribute to the discourse on personalized environmental solutions, advocating for approaches that embrace the diversity and complexity of the natural world.

Expanding upon this narrative, future research could delve deeper into specific case studies where GML has been successfully applied to address environmental challenges, providing empirical evidence to support the theoretical assertions presented in this article. Additionally, exploring the ethical implications and potential biases associated with the adoption of GML in environmental decision-making processes could offer valuable insights into ensuring equitable and sustainable outcomes. Overall, this research sets the stage for a more holistic understanding of GML's role in shaping the future of environmental science and pollution technology, paving the way for innovative and adaptive solutions to safeguard our planet's health and resilience.

THEORETICAL UNDERPINNINGS OF GML IN ENVIRONMENTAL SCIENCE

Foundational Graph Theory Concepts

Graph structures in environmental science: In the realm of environmental science, the utilization of graph theory serves as a foundational framework, guiding our comprehension of the intricate relationships embedded within environmental datasets. At its essence, a graph comprises nodes representing diverse components within the environmental landscape and edges denoting the connections between these components. This fundamental structure offers both a visual and mathematical abstraction of the intricate web of interactions that define environmental systems.

Nodes as Environmental components: Within this graph, nodes encapsulate a myriad of environmental components, spanning from individual species and specific habitats to broader ecological concepts and environmental variables. Each node embodies a distinct aspect of the environment, and their arrangement within the graph reflects the interconnections present in the natural world.

Edges as interactions: Edges, serving as the links between nodes, encapsulate the interactions that govern environmental dynamics. These interactions can manifest in various forms, such as predator-prey relationships, habitat connectivity, and nutrient flows within ecosystems. The graph thus evolves into a dynamic representation of the interdependencies and interactions that characterize environmental systems.

Complex graph structures: The resultant graph structure is far from simplistic, portraying a complex network that mirrors the intricate web of interactions in nature. As species interact within ecosystems, habitat connectivity shapes biodiversity patterns, and nutrient cycles influence ecosystem functions. Grasping and deciphering these intricate structures become essential for effective environmental management and conservation efforts.

Graph algorithms for environmental insights: The theoretical frameworks of graph theory extend beyond their representation to practical application through the utilization of advanced graph algorithms. These algorithms, tailored to extract meaningful insights from environmental graphs, play a pivotal role in informing decision-making processes and optimizing conservation efforts.

PageRank algorithm: One such significant algorithm is PageRank, initially developed for ranking web pages but finding relevance in environmental contexts. Within environmental graphs, PageRank serves as a guiding light, spotlighting nodes of importance. Species, habitats, or ecological concepts with higher PageRank scores emerge as influential nodes, indicating their centrality within the environmental network. Grounded in mathematical rigor, this algorithm provides a quantitative lens to the qualitative intricacies of ecological relationships.

The algorithm in Fig. 1 iteratively calculates the PageRank scores for each node in the environmental graph until convergence or until reaching the maximum number of iterations specified. The damping factor adjusts the influence of incoming edges, while the tolerance determines the level of convergence. The algorithm returns the final PageRank scores for each node in the environmental graph.

Community detection algorithms: Similar to their role in educational contexts, community detection algorithms

Algorithm 1 PageRank Algorithm for Environmental Network Analysis

```
function PageRank(EnvironmentalGraph, dampingFactor, tolerance, maxIterations)
    // Initialize PageRank scores for all nodes
    for each node in EnvironmentalGraph do
        PageRankScores[node] ← 1 / NumberOfNodes(EnvironmentalGraph)
    end for
    // Initialize variables
    iterations ← 0
    diff ← tolerance + 1
    // Main iteration loop
    while diff > tolerance and iterations < maxIterations do
        diff ← 0
        // Create a copy of PageRank scores for the previous iteration
        previousPageRankScores ← copy(PageRankScores)
        // Update PageRank scores for each node
        for each node in EnvironmentalGraph do
            newPageRankScore ← 0
            // Calculate contributions from incoming edges
            for each incomingEdge in node.incomingEdges do
                contributingNode ← incomingEdge.sourceNode
                contributingNodePageRank ← previousPageRankScores[contributingNode]
                totalOutgoingEdges ← NumberOfOutgoingEdges(contributingNode)
                if totalOutgoingEdges > 0 then
                    contribution ← contributingNodePageRank / totalOutgoingEdges
                    newPageRankScore ← newPageRankScore + contribution
                end if
            end for
            // Apply damping factor and add teleportation probability
            newPageRankScore ← (1 − dampingFactor)/NumberOfNodes(EnvironmentalGraph) + dampingFactor × newPageRankScore
            // Update difference between current and previous PageRank scores
            diff ← diff + |newPageRankScore − previousPageRankScores[node]|
            // Update PageRank score for the current node
            PageRankScores[node] ← newPageRankScore
        end for
        // Increment iteration counter
        iterations ← iterations + 1
    end while
    return PageRankScores
end function
```

Fig. 1: PageRank algorithm for environmental network analysis.

illuminate cohesive clusters within environmental graphs. These algorithms identify subsets of nodes with stronger internal connections than external ones. In the environmental context, these communities may represent interconnected ecosystems, habitat clusters, or species associations. By unveiling these natural groupings, community detection algorithms enhance our understanding of the underlying structure of environmental networks.

Algorithm 2 Community Detection Algorithm for Environmental Networks

```
function DetectCommunities(EnvironmentalGraph)
    // Initialize variables
    communities ← []
    visited ← set()
    // Main loop to traverse nodes
    for each node in EnvironmentalGraph do
        if node not in visited then
            community ← []
            // Depth-first search to find connected component
            DFS(node, community, visited)
            communities.append(community)
        end if
    end for
    return communities
end function

function DFS(currentNode, community, visited)
    // Add current node to the community and mark as visited
    community.append(currentNode)
    visited.add(currentNode)
    // Recursively traverse neighboring nodes
    for each neighbor of currentNode do
        if neighbor not in visited then
            DFS(neighbor, community, visited)
        end if
    end for
end function
```

Fig. 2: Community detection algorithm for environmental network.

The output of the Community Detection Algorithm for Environmental Networks program (Fig. 2) is a set of communities or cohesive clusters identified within the environmental graph. Here's an explanation of the output:

- **Data Structure**: The algorithm utilizes a list of communities to store the detected communities or clusters found in the environmental graph. Each community is represented as a list containing the nodes belonging to that community.
- **Traversal and Detection**: The algorithm traverses each node in the environmental graph. For each unvisited node encountered during traversal, it initiates a depth-first search (DFS) to identify the connected component or community to which the node belongs. The DFS recursively explores neighboring nodes connected to the current node until all nodes within the same community are visited.
- **Appending Communities**: Once a community is fully explored, it is appended to the communities list. This process continues until all nodes in the environmental graph are visited and assigned to their respective communities.
- **Returned Output**: Finally, the algorithm returns the communities list containing all the identified communities or cohesive clusters within the environmental graph.
- The output of the program, therefore, consists of a list of communities, where each community is represented as a list of nodes. This output provides valuable insights into the underlying structure of the environmental network by highlighting the interconnected groups or clusters of nodes within it.

Optimal conservation strategies and ecological clusters: Beyond identification, these algorithms offer insights into optimal conservation strategies and clusters of interconnected ecological components. They inform the formulation of tailored conservation plans, suggesting the most effective sequences of actions or highlighting areas where deeper exploration may be necessary. Consequently, the theoretical basis of these algorithms extends beyond computation, directly influencing the practical implementation of conservation strategies.

Overall, the fusion of graph theory and advanced algorithms not only reveals the complex structures within environmental data but also provides a theoretical framework for deriving actionable insights. By comprehending the intricacies of graph structures and strategically deploying algorithms, GML harnesses the potential of these foundational concepts to capture and optimize the dynamic interactions that define environmental systems.

MACHINE LEARNING THEOREMS SUPPORTING GML

Universal Approximation Theorem

Neural networks as function approximators: The Universal Approximation Theorem establishes the capability of neural networks to approximate any continuous function on a bounded input space, provided they possess a non-constant, bounded activation function and a single hidden layer with a sufficient number of neurons. Mathematically, thisis expressed as:

$$f(x) \approx \sum_{i=1}^{N} w_i . \sigma (b_i + W_i . x)$$

Where,

N is the number of neurons in the hidden layer,

w_i are the weights,

b_i is the bias,

W_i is the weight vector,

x is the input vector

σ is the activation function.

Applicability to environmental dynamics: Let's consider the applicability of neural networks in the realm of environmental dynamics. Suppose we employ a neural network with adaptable weights (wi) and biases (bi), updated iteratively using backpropagation during training. This model adapts to the complexities of environmental data by fine-tuning these parameters to minimize the disparity between predicted and observed outcomes, effectively learning the intricate relationships within the data.

Accurate predictions in environmental modeling: In scenarios where precise predictions are essential, such as environmental modeling, the Universal Approximation Theorem assures us of the neural network's ability to approximate complex environmental functions. In this scenario, the model might takethe form:

$$\text{Prediction} = \sum_{j=1}^{N} w_{ij} . \sigma (b_{ij} + W_{ij} . X_i)$$

Here, i indexes the student, j indexes the neurons in the hidden layer, w_{ij} are the weights, b_{ij} are the biases, W_{ij} is the weight vectors, and X_i is the input vector for student i.

Example Calculation:

Let's consider a simplified scenario where we aim to predict student performance (Prediction) based on two features (Feature_1 and Feature_2) using a sigmoid activation function (σ):

$$\text{Prediction}=\sigma (w_1 \cdot \text{Feature}_1 + w_2 \cdot \text{Feature}_2 + b)$$

Here, w_1 and w_2 are the weights, and b is the bias. The Universal Approximation Theorem assures us that, with a sufficiently complex neural network, this structure can effectively approximate the underlying function mapping environmental factors to pollutant concentrations.

No Free Lunch Theorem

Tailoring models to environmental complexity: The No Free Lunch Theorem posits that no single machine learning algorithm universally outperforms others across all possible problem scenarios. This theorem emphasizes the need to tailor models to the specific nuances of environmental data, which can vary widely in terms of spatial and temporal dynamics, non-linear interactions, and heterogeneous structures.

Understanding environmental data complexity: Environmental datasets often exhibit diverse characteristics, including non-linear relationships between variables, spatial and temporal dependencies, and heterogeneous data structures. The No Free Lunch Theorem underscores the importance of comprehending these complexities. For example, in the context of analyzing pollution patterns, algorithm A, which excels in capturing spatial dependencies, may outperform algorithm B, which is better suited for modeling temporal variations, depending on the specific characteristics of the environmental data distribution.

Optimizing GML for environmental insight: Optimization strategies in GML, guided by the No Free Lunch Theorem, involve iterative refinement based on insights gained from the unique characteristics of environmental data. If algorithm C proves effective in capturing certain types of environmental interactions, it would be prioritized over other algorithms in those specific environmental contexts.

Example Calculation:

Consider the scenario where GML practitioners aim to optimize a model for predicting air quality. Let A represent a neural network-based algorithm and B represent a decision tree-based algorithm. Depending on the spatial and temporal dynamics of pollution sources and meteorological factors, one algorithm may outperform the other in different environmental contexts.

In summary, the No Free Lunch Theorem highlights the importance of adapting machine learning algorithms to the specific complexities of environmental data, ensuring that GML approaches are optimized for addressing the diverse challenges within the realm of nature, environment, and pollution technology.

TRANSLATING THEORY INTO PRACTICE

Theoretical Frameworks for Environmental Predictions

Graph theory foundation: GML's efficacy in environmental science stems from its grounding in graph theory, where nodes represent entities such as species, habitats, and environmental variables, while edges depict interactions like predator-prey relationships and nutrient flows. This structured framework facilitates a comprehensive understanding of complex environmental systems.

Machine learning theorems in action: The Universal Approximation Theorem serves as a cornerstone, empowering GML models to adapt and predict environmental outcomes. Neural networks, as powerful function approximators, accommodate the intricate interplay of environmental factors, surpassing linear models' limitations.

Predictive Analytics in Environmental Networks: Leveraging historical environmental data, GML models utilize predictive analytics to anticipate ecological patterns and pollution trends. The wealth of historical context, coupled with the flexibility offered by machine learning theorems, enables these models to navigate the dynamic environmental landscape with precision.

Theoretical Underpinnings of Recommending Environmental Solutions

Algorithmic empowerment: GML's effectiveness stems from its strategic utilization of graph algorithms rooted in theoretical frameworks. These algorithms, such as PageRank, offer a systematic approach to identifying influential nodes and optimal intervention pathways within environmental networks.

Personalized environmental solution recommendations: Graph algorithms empower GML to recommend tailored environmental solutions precisely aligned with the unique characteristics of each ecosystem. By identifying influential nodes, GML ensures personalized and contextually relevant suggestions, surpassing generic approaches.

Practical intervention strategies: The theoretical underpinnings of GML, combined with graph algorithms, extend beyond theoretical realms to practical intervention strategies. These recommendations are not only informed by historical data but are also deeply rooted in ecological principles, guaranteeing meaningful and effective environmental interventions.

In this context, the integration of graph theory foundations and machine learning theorems in GML unfolds as a dynamic force in environmental science. By seamlessly translating theoretical concepts into actionable strategies, GML emerges as a transformative tool, predicting environmental patterns and delivering personalized solutions with practical efficacy.

RESEARCH DIRECTIONS

While GML in education benefits from theoretical foundations, ongoing research iscrucial to address challenges and refine theoretical frameworks.

In these research directions, the emphasis is on the key theoretical insights driving advancements in GML for Environmental science. This section provided a structured overview of theoretical frameworks addressing data quality, privacy, model interpretability, and ethical considerations.

FUTURE POTENTIAL OF GML IN ENVIRONMENTAL SCIENCE: EXPANDING HORIZONS

Fostering Collaborative Environmental Research

- **In-depth collaborator identification:** GML's detailed analysis of environmental data allows for the identification of potential collaborators. ii. Considers

Theoretical Advances in Data Quality and Privacy

Research Direction	Key Theoretical Insights
Advancements in GraphTheory and Privacy-Preserving ML	• **Refining Graph Theory Models:** Enhance data quality by refining models that represent educational networks using graph theory. • **Cryptographic Techniques:** Develop cryptographic techniques to ensure privacy inhandling sensitive educational data. • **Secure Multi-Party Computation:** Implementsecure multi-party computation to build robust GMLmodels while preserving data integrity and privacy.

Theoretical Frameworks for Model Interpretability

Research Direction	Key Theoretical Insights
Theoretical Advancesin Explainable AI	• **Model Interpretability Frameworks:** Develop theoretical frameworks to enhance model interpretabilityin GML. • **Clear Explanations:** Provide clear explanations for GML predictions, ensuring transparency and understanding. • **Building Trust:** Enhance trust among educators and students by establishing transparent and interpretable models.

Theoretical Approaches to Address Ethical Considerations

Research Direction	Key Theoretical Insights
Theoretical Frameworks for Biasand Fairness in ML	• **Addressing Biases:** Develop theoretical frameworksto identify and address biases in GML models. • **Equitable Access:** Ensure equitable access topersonalized learning opportunities by mitigating bias. • **Embedding Ethical Considerations:** Embed ethicalconsiderations into the core of GML theoretical foundations to guide algorithmic development.

Theoretical Foundations for Integration with Existing Environmental Systems

Research Direction	Key Theoretical Insights
Theoretical Advances inSystem Integration Models	• **Seamless Integration Models:** Develop theoretical models for the seamless integration of GML tools into existing environmental systems. • **Collaborative Frameworks:** Establish collaborative frameworks between environmental scientists, policymakers, and technologists for harmonious integration. • **Harmony with Educational Frameworks:** Ensure theoretical advances align with and complement existing environmental frameworks and regulations, promoting sustainable practices and conservation efforts.

factors such as expertise in specific ecological domains, past collaboration success, and compatibility in research methodologies.

- **Optimized team formation:** Recommends collaborative projects and research teams that capitalize on each member's expertise and strengths. ii. Enhances interdisciplinary collaboration and fosters a holistic approach to addressing complex environmental challenges.
- **Real-world application:** Prepares environmental scientists for collaborative research environments by simulating real-world interdisciplinary collaborations. ii. Aligns with the growing trend of interdisciplinary approaches in tackling environmental issues, reflecting the interconnected nature of ecological systems.

Adapting to Individual Learning Styles in Environmental Research

- **Dynamic research environment:** GML's real-time analysis enables the dynamic adaptation of research methodologies and approaches. ii. Adjusts research methodologies and data analysis techniques to accommodate the evolving preferences and strengths of individual researchers.
- **Tailoring environmental research approaches:** Ensures that research methodologies remain effective by accommodating individual researchers' preferred approaches and techniques. ii. Incorporates diverse research methods, such as fieldwork, remote sensing, and modeling, to cater to varying research styles.
- **Continuous optimization:** Reflects a commitment to continuous improvement by adapting to emerging trends in environmental research methodologies. ii. Utilizes ongoing feedback loops to refine and enhance research methodologies and approaches based on individual researcher feedback and performance.

Promoting Self-Directed Environmental Research

- **Empowering researchers:** GML empowers environmental scientists by providing personalized research recommendations tailored to their unique research interests and goals. ii. Enables researchers to take an active role in shaping their research agendas and methodologies, fostering a sense of ownership and autonomy.
- **Tools for self-assessment:** Equips researchers with tools for self-assessment, allowing them to evaluate their research progress and methodology effectiveness.

ii. Facilitates a reflective research process, encouraging researchers to identify areas for improvement and refine their research approaches accordingly.

- **Autonomy in research path:** Promotes autonomy by offering a range of supplementary resources aligned with individual research objectives and interests. ii. Encourages researchers to set personalized research goals, explore new research avenues, and track their research achievements autonomously.

CONCLUSIONS

Graph Machine Learning (GML), rooted in foundational theories from graph theory and machine learning, emerges as a powerful tool for revolutionizing environmental science and pollution technology. The synergy between theory and practical application underpins GML's effectiveness in predicting environmental patterns, recommending mitigation strategies, and tailoring solutions to address complex environmental challenges. As theoretical advancements progress, GML stands poised to unleash the full potential of personalized and sustainable environmental management. The future outlook for GML in environmental science transcends predictive analytics, encompassing collaborative problem-solving, real-time adaptation to changing environmental dynamics, and the empowerment of self-directed environmental research. As GML evolves, these expanded applications signify a paradigm shift towards a more adaptive, collaborative, and environmentally conscious approach to addressing the complexities of our natural world.

Expanding upon this narrative, future research could explore the specific applications of GML in various environmental domains, such as biodiversity conservation, climate change mitigation, and pollution control. Case studies demonstrating the successful implementation of GML algorithms in real-world environmental scenarios would provide valuable insights into its potential impact. Additionally, interdisciplinary collaborations between environmental scientists, data scientists, and policymakers could further enhance the development and deployment of GML solutions for environmental management. Furthermore, ethical considerations surrounding the use of GML in environmental decision-making processes, including issues of data privacy, algorithmic bias, and equity, warrant careful examination. Addressing these concerns is crucial to ensure that GML technologies are deployed responsibly and equitably to benefit both human societies and the natural environment.

In conclusion, GML holds immense promise for revolutionizing environmental science and pollution technology, offering innovative solutions to address pressing environmental challenges. By embracing the principles of collaboration, adaptability, and sustainability, GML has the potential to usher in a new era of environmental stewardship, where data-driven insights inform proactive and holistic approaches to safeguarding our planet's health and resilience.

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ORCID DETAILS OF THE AUTHORS

R. Krishna Kumari: https://orcid.org/0000-0002-1802-628X