Why Does It Look like this? Introducing a Preliminary Framework for Explainable Graph Drawing (XGD)

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Keywords: Explainable Artificial Intelligence, Graph Drawing, Network Visualization.

Abstract: The discipline of Explainable Artificial Intelligence (XAI) enhances the transparency and trustworthiness of AI models by providing human-readable interpretable explanations for AI-driven decisions. The recent introduction of AI-accelerated techniques to the graph drawing community brings the challenge of comprehending the black-box ML and AI outputs when suggesting a layout for a specific graph - a problem we dub Explainable Graph Drawing (XGD). As a first step in addressing this challenge, this paper introduces a preliminary framework to match existing XAI methods to present and future AI approaches in graph drawing. This supports researchers in framing the used AI algorithm in XAI literature and helps in selecting the appropriate explanation method. We apply our approach on a chosen AI technique for graph drawing and present our findings. Finally, we discuss future perspectives and opportunities for explainable graph drawing.

1 INTRODUCTION

AI influence in visualization is growing, automating and simplifying aspects of the visualization design process. Recently, AI algorithms were introduced in Graph Drawing (GD) - that is the discipline of generating geometric representations of network data. AI supports the construction of layouts for nodes and edges by optimizing factors such as nearest neighbors, space-filling curves, and repulsive and attractive forces (Wang et al., 2020; Wang et al., 2023; Yan et al., 2022; Cao et al., 2022). However, one of the concerns that is usually expressed when discussing the use of AI in visualization and data analysis in general, is how to *trust* the results (Elzen et al., 2023). Trust can come from comprehending how the AI-powered results were generated, providing the user with sufficient means to comprehend the reasons behind the algorithm output.

XAI aims to make AI systems transparent and understandable, enhancing trustworthiness by providing detailed explanations of AI processes (Barredo Arrieta et al., 2020). In graph analysis, XAI could provide human-readable explanations, aiding in validating and understanding AI-driven insights. Popular XAI methods, such as Local Interpretable Model-agnostic Explanations (LIME), Shapley Additive Explanations (SHAP), and Layer-wise Relevance Propagation (LRP), offer flexible, interpretable methods that clarify AI predictions (Ribeiro et al., 2016; Ribeiro et al., 2018; Simonyan et al., 2014). While XAI facilitates the understanding and elucidation of AI methodologies, deciding which XAI method to use in each specific analysis context remains an open and challenging issue, as many aspects are involved and selecting an appropriate method is non-trivial.

We seek to bridge the gap between AI models in GD and XAI techniques and address the challenge of supporting users in "opening the black box" of AI-accelerated GD methods, with the help of currently existing XAI techniques. Therefore, the paper introduces a preliminary framework that identifies and organizes key dimensions of XAI in GD, derived from literature review. These dimensions include explanation aspects, verification approaches, and user- and task-related features (Miksch and Aigner, 2014). By identifying and categorizing these dimensions, our goal is to outline how existing XAI methods can be applied to improve the understanding of AI reasoning in the context of GD (Gobbo et al., 2022). To demonstrate the utility of the framework, we apply it to a

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Çela, K., van den Elzen, S., van Wijk, J. and Arleo, A.
Why Does It Look like this? Introducing a Preliminary Framework for Explainable Graph Drawing (XGD).
DOI: 10.5220/0013111100003912

In *Proceedings of the 20th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications (VISIGRAPP 2025) - Volume 1: GRAPP, HUCAPP and IVAPP*, pages 851-858
ISBN: 978-989-758-728-3; ISSN: 2184-4321

case study (Kwon et al., 2019), mapping the identified dimensions to corresponding XAI methods. Through this analysis, we explore how XAI techniques can support transparency and trust in AI-accelerated GD methods. We include a reflection about the value of XAI in GD and expansion opportunities for our framework.

2 LITERATURE REVIEW

In this section, we present a succinct summary of the current state of the art and of the related literature that also acted as an inspiration for our work.

Understanding Human-AI Interaction. The foundational elements of XAI strategies can be categorized along two dimensions: explaining approaches (or *explainers*) and verification methods. An explainer is identified as an XAI method used to explain the output of the AI model while considering the given input. On the other hand, we use verification methods to ensure that users correctly understood the explanation presented to them, therefore ensuring its success. Gobbo and El-Assady (Gobbo et al., 2022) identify the key attributes of these two dimensions and discuss how they are quite diverse and encompass aspects such as the *task* (action carried out through the explanation), the type of *data* employed, the combination of media and language (*medium*), the way in which blocks are connected (*path*), the type of navigation and exploration allowed (*exploration*), the target *user*, and the usage and fruition scenarios (*scenario*) (Gobbo et al., 2022). The explanation process in XAI has been investigated in the work by El-Assady et al. (El-Assady et al., 2019). This process is as a sequence of phases, consisting of explanation and verification blocks. Each block employs a specific medium and strategy for explanation or verification. These blocks are interconnected through pathways, which can be linear or iterative, allowing the building blocks to be visited once or multiple times. Pathways also define the type of navigation, which can be either guided or open for exploration. In this model, mediums such as verbal explanations, visualizations, and multimedia are used for effective communication in regards to the data (Gobbo et al., 2022). Holter and El-Assady (Holter and El-Assady, 2024) expand on this by proposing a design space for human-AI collaboration, organized into three categories: Agency (who controls the analysis), Interaction (communication between human and AI), and Adaptation (how they learn from each other).

Explanation Approaches. Arrieta et al. (Barredo Arrieta et al., 2020) discuss various types of explanation approaches in XAI and how they cater to different aspects (text, visual, local, by example, by simplification, feature relevance). Spinner et al. (Spinner et al., 2020) propose a framework for interactive and explainable machine learning that enables users to (1) understand machine learning models; (2) diagnose model limitations using different explainable AI methods; as well as (3) refine and optimize the models. It discusses types of explainers, both single and multi-model. Model-specific and model-agnostic (single), provide insights into individual model states, either by delving into the model's internal structure (specific) or by treating the model as a black box (agnostic) (Ribeiro et al., 2018). Multi-model explainers offer a broader perspective by allowing for comparative analysis across different model states, aiding in model selection and refinement. Spinner et al. (Spinner et al., 2020) also analyze the level-abstraction-dependency properties and explain how each of them contribute to the model of the explainer. The **level** property refers to the data coverage by the explainer ('local' or 'global'). The **abstraction** dimension concerns the model coverage, which is divided into 'low' and 'high' abstraction. The **dependency** aspect specifies the necessary inputs for the explainer to function and it can involve dependencies on data, model specifics, or domain knowledge.

AI in Graph Drawing. AI has been introduced in graph drawing recently, but proved to be an already fruitful and thriving combination. There are several applications of deep learning in the context of end-to-end graph drawing, including (but not limited to) *DL4GD* (Giovannangeli et al., 2021; Giovannangeli et al., 2024), *DeepGD* (Wang et al., 2020), *Deep4GD* (Wang et al., 2023), DeepFD (for generating force-directed layouts of large graphs) (Cao et al., 2022), GRAPHULY (Yan et al., 2022). Tiezzi et al. (Tiezzi et al., 2024) build on graph neural network research to propose graph neural *drawers*. Optimization methods that produce a layout by iteratively improving on a set of aesthetic criteria expressed as differentiable function using, e.g., gradient descent (as in the paper by Ahmed et al. (Ahmed et al., 2022)), have been explored as well.

Assessment. From our analysis, we identify two key points. First, while there is significant interest in applying AI to graph drawing, most studies focus solely on optimizing layout quality metrics and evaluate the results *post-hoc*, without exploring *why* specific embeddings are produced. Second, visualization research increasingly seeks to deepen understanding of AI recommendations. This paper aims to raising awareness on XGD and encourage on expanding the research at the intersection of XAI and GD.

3 A FRAMEWORK FOR XGD

In this section, we present and discuss our categorization of the dimensions of AI-accelerated graph layout methods. The methodology is illustrated in Figure 1.

Our work on this categorization started with a comprehensive review of the literature to examine the state-of-the-art of XAI and AI methods in GD. This exploration was guided by the question: "How are XAI methods constructed and how do they work in the context of GD?" This process informed the foundational elements of our framework and was further inspired by prior works (Gobbo et al., 2022; Spinner et al., 2020). Specifically, Gobbo et al.(Gobbo et al., 2022) influenced the identification of our framework's main "building blocks" (explanation and verification strategies), while Spinner et al.(Spinner et al., 2020) provided insights into categorizing explainer models and their characteristics.

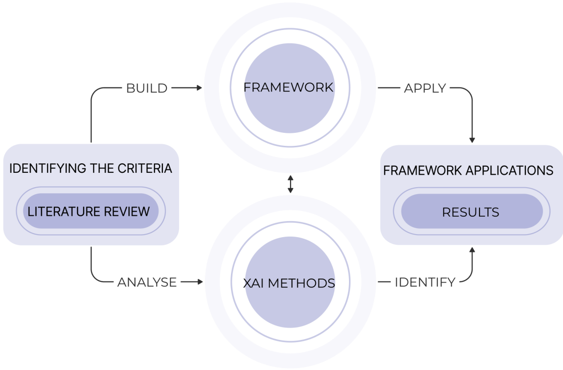

Figure 1: An illustration of the methodology approach that guided the research and evaluation process of this paper. Once the components building the framework were identified during the research phase, they were then used to build the framework as well as analyze XAI methods. The built framework was applied to a selected AI GD technique to select an appropriate XAI method.

3.1 Conceptual Framework Layout

The presented framework serves as both a strategic guide and a practical tool, helping to navigate the complexities of selecting appropriate XAI methods for specific GD challenges. At a high-level, it is divided into two main branches that represent the foundational blocks of our framework (see Figure 2). The first is the **Explanation**: within this block we include the type of reasoning strategy used to explain the AI result (*inductive*, *deductive*, *contrastive*). The second is **Verification**. Under this branch we include the methods used for ensuring that users understood the explanation (*flipped classroom*, *reproduction*, *transfer*). We describe and detail both of these dimensions in the following.

3.2 Explanation

By explanation, we mean the process of making something clear or understandable by describing its cause, purpose, and underlying mechanisms. The explanation could be further categorized into *strategy*, *approach*, and *model*.

3.2.1 Strategy

Within our framework, we define explanation strategies as follows. *Inductive* strategies break down complex structures into clear, manageable parts and provide illustrative examples and metaphors to enhance understanding (top-down). Notable examples include approaches such as Divide and Conquer, Depth First Breadth First, Teaching by Categories, Simplification and many others as presented in Figure 2. *Deductive* strategies, on the other hand, aggregate graph components, offer detailed and high-level explanations, and narrate the decision-making process to reveal the AI model's logic (bottom-up). *Contrastive* strategies explain the task at hand by highlighting differences between alternative outcomes or decisions, focusing on why a specific result was chosen over others, and providing clarity through comparisons.

Attributes. Explanation strategies are defined by various attributes, which facilitate the AI-user interaction (Gobbo et al., 2022; El-Assady et al., 2019). The type of *data* employed in the system, the target *user*, and the *task* to be carried out through the explanation, all together form what we later refer to as Data-Users-Tasks triangle, present by (Miksch and Aigner, 2014). We also consider the combination of media and language adopted (*medium*), the way in which the building blocks are connected (*path*) and navigated (*exploration*), the usage *scenarios*, and the specialized area of application (*domain*) as additional building blocks attributes.

Data, Users, Tasks. We also integrated the Data-Users-Tasks triangle (Miksch and Aigner, 2014) in our attributes list, as these three aspects focus on critical elements considered in the final visualization design. The technical expertise of the intended user and domain-specific knowledge, are pivotal in choosing an XAI or visualization method that is both understandable and applicable. The selection of an XAI method is also influenced by the nature of the task. The complexity of the task, the nature of decision-making it involves, and the required explanation detail vary; complex tasks may need detailed, feature-

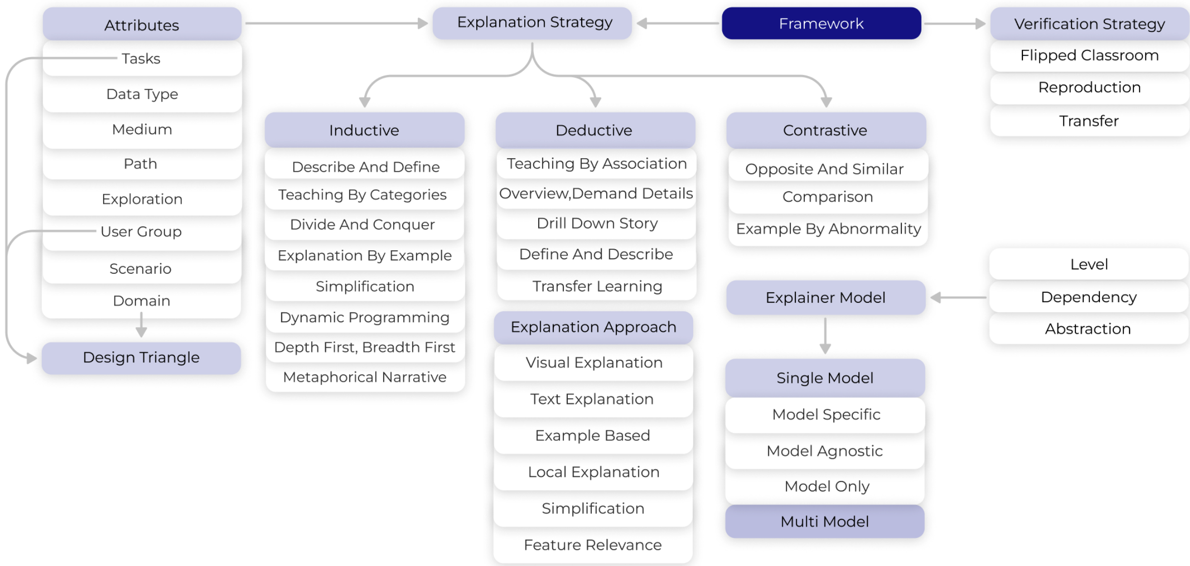

Figure 2: Extended overview of the framework, composed of the two building blocks, the attributes (including the design triangle), explanation approach, explainer model and the level-abstraction-dependency relationship.

specific explanations, whereas simpler tasks might only necessitate a basic understanding of the decision process. In the context of XGD, the audience might include data scientists, network analysts, and domain experts; the tasks are more tailored to understanding the reasons behind a network embedding given a specific parameter selection applied to a GD algorithm.

Medium, Path, Exploration, Scenario. Attributes such as the *medium*, encompass the combination of media and language, the *path* explains the method by which blocks are interconnected, the *exploration* explains the type of navigation permitted, and the usage and application contexts describes the *scenario* (Gobbo et al., 2022; El-Assady et al., 2019).

Domain. The choice of XAI method is heavily influenced by the domain in which it is applied. For example, healthcare prioritizes accuracy and interpretability, while finance may focus on regulatory compliance, influencing the selection process based on the type of data and decision criticality inherent to the domain (Miksch and Aigner, 2014). Therefore, physicians and nurses require detailed, clinically relevant explanations, while patients benefit from simpler, accessible insights (Miksch and Aigner, 2014). Similarly, in GD, the XAI method must cater to the varying needs of network analysts, data scientists, and domain-specific experts, ensuring that the explanations provided by the XAI methods are appropriate for the intended audience, relevant to the domain, and suitable for the specific tasks at hand.

3.2.2 Approach

Explanation approaches include *text explanations* (generating text to explain AI model decisions), *visualizations* (graphical representations), *local explanations* (explaining specific decisions or aspects of the AI model, not the entire model), *example-based explanations* (examples to illustrate how the AI model functions or makes decisions), *simplifications* (creates a simpler model that approximates a more complex behavior), and *feature relevance* (explains the importance of different features) (Barredo Arrieta et al., 2020). These explanation approaches are particularly suited for the context of GD, addressing various aspects in focus and complexity.

For instance, text explanations aim to simplify and articulate the decision-making process of AI models. For example, when a user clicks on a node, a text-based explanation could clarify its placement by describing the influence of its connectivity, degree, or proximity to other nodes. Similarly, visualizations make it easier to interpret complex relationships within a graph by presenting them in an intuitive, graphical form—such as heatmaps highlighting feature importance or diagrams depicting structural relationships. *Example-based explanations* can offer users relatable scenarios, demonstrating how changes in inputs (e.g., adding or removing edges) affect the resulting layout. *Simplifications* address the need for interpretability by approximating the behavior of complex graphs with simpler surrogate models. For instance, a linear regression model might be used to approximate how edge crossings are minimized in a graph layout, providing an easy-to-follow explanation for a technically complex process. *Feature relevance* provides a deeper, more technical insight into how specific graph attributes (e.g., node degree, edge weights, clustering coefficients) influence the layout process. *Local explanations* are particularly useful for tasks requiring granular insights, such as justifying the placement of an individual node or cluster, while *example-based explanations* can offer users relatable scenarios, demonstrating how changes in inputs (e.g., adding or removing edges) affect the resulting layout. Depending on the specific task and audience, certain explanation approaches may prove more effective than others.

Level-Abstraction-Dependency Decision Parameters. Another key element of the framework are the level-abstraction-dependency decision parameters. By incorporating these three dimensions, the framework gains precision in selecting the appropriate XAI methods. The abstraction level and user perspective from the design triangle mentioned above are crucial in determining the depth of detail needed in the explanations for explainable GD.

Global explainability methods such as Partial Dependence Plots (PDP) provide a broad view of how features affect a model's output, which is valuable for stakeholders needing a general understanding of what drives model decisions in graph layouts (Spinner et al., 2020). Conversely, *Local* explainability methods like LIME (Ribeiro et al., 2016) or SHAP (Lundberg and Lee, 2017) focus on individual predictions and are essential in fields like telecommunications or bioinformatics where detailed explanations for specific graph structures are necessary.

Abstraction in XAI, which determines how detailed or simplified explanations should be, must match the user's expertise and the complexity of the task. For example, graph models used by network analysts may require more detailed explanations, whereas those for the general public or non-experts should be more simplified.

The *dependency* aspect in XAI addresses how explanations consider feature interdependencies in data, domain and model. Methods like SHAP account for interactions between features, which is important in GD models where these interactions significantly influence the layout.

3.2.3 Model

A model is identified as an XAI method used to explain the output of the AI model while considering the given input. Identifying components like the user-domain-task and the level-abstraction-dependency relationships in the framework aids in selecting the appropriate explainer model, as outlined in Section 2. We categorize explainers as *single* and *multi-model*, following the description in the paper by Spinner et al. (Spinner et al., 2020).

Single-model explainers (model-agnostic and model-specific) focus on understanding and refining a single model by analyzing its inputs, outputs, and internal mechanisms. In the context of GD, single-model explainers can help dissect and improve individual graph layout algorithms by providing in-depth analyses of how specific inputs influence the graph structure. In explainable GD, model-agnostic explainers can provide general insights into the effectiveness of the layout without needing to understand the algorithm's inner workings (remaining in a black-box nature), whereas model-specific explainers can offer detailed explanations on how specific layout algorithms operate. For GD, architecture-focused explainers can provide insights into the computational processes behind the layout generation.

Multi-model explainers are valuable for conducting comparative analyses between different model states, helping to choose the best configuration or understand varied parameter effects. For GD, this is particularly useful in comparing different graph layout algorithms to determine which provides the most accurate or visually appealing representations for specific datasets.

3.3 Verification

Our second fundamental block of this framework is verification. It is a critical step following the explanation of an AI method, because it ensures that users not only receive the explanation, but also genuinely understand it and can act on it. This process builds trust and confidence in the AI system by validating that the user has understood how the model works and how decisions are made. Without verification, there is a risk that users may misinterpret explanations, leading to incorrect conclusions or ineffective use of the AI's insights. We include *reproduction*, *transfer*, and *flipped classroom* as three distinct methods of verification in the framework. In a reproduction set, users are asked to reproduce the models output, but when using transfer in verifying, it is crucial that they are able to apply the model in a similar set of inputs that result in a valuable and correct output. Apart from these two methods, flipped classroom works in a slightly different way, where the users are now the explainers of the model.

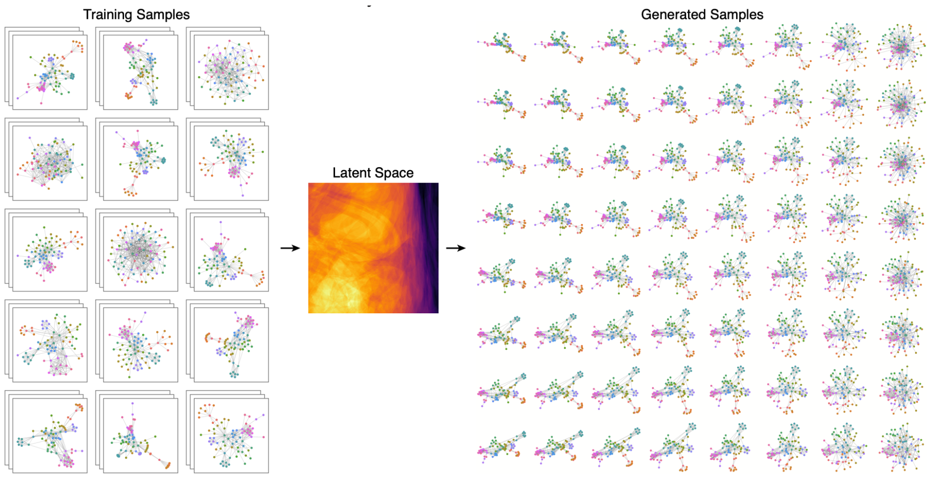

Figure 3: Figure from the paper by Kwon and Ma (Kwon et al., 2019). Within the grid of generated samples (right side of the picture), smooth transitions between the different layouts can be seen. The color mapping of the latent space represents the shape-based metric (Eades et al., 2017) of the generated samples.

4 FRAMEWORK APPLICATION

We apply our framework to a GD paper with AI elements, breaking it down along its dimensions. We introduce three well-known and highly used methods: LIME, SHAP, and LRP. Then, we discuss which of the three mentioned XAI methods could be feasible considering the characteristics of the dimensions as highlighted by the XGD framework.

Foreword. LIME, SHAP, and LRP are distinct XAI methods, all with unique characteristics (Alicioglu and Sun, 2022). LIME uses a surrogate model, sampling data points around an example, and learning a linear model to highlight local feature importances. SHAP, based on Shapley values and game theory, calculates the contribution of each feature to the final prediction. LRP uses backward propagation to assign relevance scores, specifying feature importances (Alicioglu and Sun, 2022). The primary distinction is their approach: LIME uses linear approximation, SHAP employs a game-theoretic method, and LRP uses backward propagation.

Analysis and Discussion. We apply our XGD framework to a paper by Kwon and Ma (Kwon et al., 2019) about an innovative approach of deep learning in the context of GD. The selection criteria for this paper was the innovative approach in deep learning methods concerning GD. Deep learning automates and optimizes tasks by reducing dependency on existing algorithms, learning graph features autonomously, and once trained these models generate layouts faster compared to traditional approaches, with similar quality metrics. We use our framework to evaluate how SHAP, LRP, and LIME fit as XAI methods for this technique.

The paper introduces a deep generative model for GD, shown in Figure 3. This model aims to alleviate the labor-intensive and time-consuming process of graph layout design, which is often a trial-and-error method for users. The study presents an encoder-decoder architecture to learn from a collection of graph layout examples, which then enables the generation of new, diverse layouts. The model generates a 2D latent space of different layouts for the users to explore, making it more intuitive and less reliant on user expertise or manual tweaking of parameters.

The breakdown of the technique along the dimensions of our framework is illustrated in Table 1. Since the variational autoencoder generates layouts based on encoded graph attributes, we suggest SHAP as appropriate for local feature importance explanations. SHAP aims to show how individual node or edge attributes (such as node centrality or connectivity) impact their positions in the final layout by analyzing how much each feature contributes to a particular layout decision. The task, one of the attributes in the framework, would be to help users understand why certain nodes are placed together or why certain graph attributes are emphasized in the layout.

As far as global explanations go, LRP could potentially enable the back-tracing through the Graph Neural Network (GNN) encoded layers to highlight how different parts of the graph structure are processed and how this affects the latent representation. Considering these observations, the framework component that could have the most weight in determining the XAI method is the Data-Users-Tasks aspects (see Section 3.2.1). Depending on the expertise and the

Table 1: Results of analyzing the paper based on the components specified in the framework.

Dimension	Paper Analysis
Explanation Strategy	detailed layer-wise relevance scores that trace the contributions of input features through the neural network categorizing and summing the contributions across layers (SHAP or LRP would help to distinguish the impact of different graph characteristics on the layout) simplifying the understanding of complex neural network models by breaking down the relevance of each feature layer by layer
Verification Strategy	examine the relevance scores assigned to each feature in a transparent manner, allowing for interactive exploration of the contributions that specific graph features make to the final layout - reproduction of results
Attributes	detailed understanding and diagnosis of neural network behaviors by providing a granular breakdown of feature relevance primarily for users with technical expertise highly effective for models that use tabular data to represent graph properties and visual data for graph layouts using iterative exploration, important for refining and understanding deep generative models
Design Triangle	intricate data structures and high-dimensional inputs suitable for domains that require detailed layer-wise analysis, such as bioinformatics and social network analysis most effective for users with a solid understanding of neural networks
Decision Parameters	local and global explanations both detailed and high-level insights into the decision-making process explain how specific elements of the encoder-decoder architecture and the learned latent space representations impact the final graph layouts
Model	single-model predictions, model-specific
Approach	visual tools to map relevance scores across the network layers (SHAP would use waterfall plots to present the input significance of each feature in regards to the output) textual explanations, help in illustrating specific examples and simplifying the understanding of the model's behavior

task in hand, one would choose between SHAP and LRP for experts of the field and LIME for text and visual explanations for novice readers to explain the described AI technique.

The paper by Kwon and Ma (Kwon et al., 2019) provides a tool intended for users who are primarily **researchers** or **practitioners** in GD and visualization, with varying degrees of focus on interpretability. Local explanation is required to explain the individual graph features and node placements, while global explanation is necessary to understand the overall process of layout generation. When determining the suitable XAI method, the focus is an expert audience familiar with GD. Therefore, **SHAP** appears to be an effective XAI method for the GD model explored, due to its ability to provide consistent, locally accurate explanations, but also global explanations. As the technique described in the paper dynamically generates graph structures, SHAP could break down the contributions of each node or edge. This step-by-step reasoning captures the complexity of the paper processes, providing users with understandable explanations. In our view, SHAP would provide a flexible and intuitive framework for interpreting how the model generates graph layouts.

As for LIME and LRP, our framework categorized the former as more appropriate for a non-expert audience, which is not the case, and the latter best suited for global explanations, rather than local. Therefore, considering the nature of GD and the importance of graph features, and that we were able to identify ways on how SHAP could provide global explanations, SHAP was concluded to be our XAI recommendation for this technique.

5 CONCLUSION

In this paper, we introduce a preliminary framework that identifies and organizes the relevant dimensions of XAI applied to GD. These dimensions encompass key features of XAI methods and the context in which they are applied, providing a structured foundation for understanding the interactions between AI and GD. By analyzing these dimensions, the framework offers insights into how existing XAI methods can support the interpretation of AI-driven decisions in GD. We apply our method on a deep learning GD technique, and then matching our findings with three popular XAI methods, specifically LIME, SHAP, and LRP.

The goal of this paper is to raise awareness about the XGD challenge, providing a first interpretation of a complex puzzle. Our proposed dimensions are based on observations of the literature, which require further validation and experimentation. There are several questions left to answer: how expressive and comprehensive is our framework?

The potential returns of this research include better techniques to *explain* AI applications in GD, identifying unique requirements and challenges in each domain. Avenues for future work include expanding and detailing the presented framework to expand its applicability beyond the drawing of simple graphs, enabling to tackle dynamic and multi-faceted networks. Also, we could develop concrete instances of systems that use AI for graph drawing and provide explanations. Evaluation of these can teach us what the contribution of XGD could be in practice. Furthermore, expanding the valuation on different techniques could lead to the creation of design guidelines for XAI method selection, ultimately contributing to the broader goal of enhancing AI interpretability and trustworthiness of AI for GD.

REFERENCES

Ahmed, R., De Luca, F., Devkota, S., Kobourov, S., and Li, M. (2022). Multicriteria scalable graph drawing via stochastic gradient descent, $(sgd)^2$(sgd)2. *IEEE Transactions on Visualization and Computer Graphics*, 28(6):2388–2399.

Alicioglu, G. and Sun, B. (2022). A survey of visual analytics for explainable artificial intelligence methods. *Computers & Graphics*, 102:502–520.

Barredo Arrieta, A., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., Garcia, S., Gil-Lopez, S., Molina, D., Benjamins, R., Chatila, R., and Herrera, F. (2020). Explainable artificial intelligence (xai): Concepts, taxonomies, opportunities and challenges toward responsible ai. *Information Fusion*, 58:82–115.

Cao, J., Li, M., Chen, X., Wen, M., Tian, Y., Wu, B., and Cheung, S.-C. (2022). Deepfd: automated fault diagnosis and localization for deep learning programs. In *Proceedings of the 44th International Conference on Software Engineering*, page 573–585. Association for Computing Machinery.

Eades, P., Hong, S.-H., Nguyen, A., and Klein, K. (2017). Shape-based quality metrics for large graph visualization. *Journal of Graph Algorithms and Applications*, 21(1):29–53.

El-Assady, M., Jentner, W., Kehlbeck, R., Schlegel, U., Sevastjanova, R., Sperrle, F., Spinner, T., and Keim, D. (2019). Towards explainable artificial intelligence: Structuring the processes of explanations. In *HCML Workshop at CHI'19*, Glasgow, UK.

Elzen, S. v. d., Andrienko, G., Andrienko, N., Fisher, B. D., Martins, R. M., Peltonen, J., Telea, A. C., and Verleysen, M. (2023). The flow of trust: A visualization framework to externalize, explore, and explain trust in ml applications. *IEEE Computer Graphics and Applications*, 43(2):78–88.

Giovannangeli, L., Lalanne, F., Auber, D., Giot, R., and Bourqui, R. (2021). Deep neural network for drawing networks, $(dnn)^2$. In Purchase, H. C. and Rutter, I., editors, *Graph Drawing and Network Visualization*, pages 375–390, Cham.

Giovannangeli, L., Lalanne, F., Auber, D., Giot, R., and Bourqui, R. (2024). Toward efficient deep learning for graph drawing (dl4gd). *IEEE Transactions on Visualization and Computer Graphics*, 30(2):1516–1532.

Gobbo, B., Elli, T., Hinrichs, U., and El-Assady, M. (2022). xai-primer.com — a visual ideation space of interactive explainers. In *Extended Abstracts of the 2022 CHI Conference on Human Factors in Computing Systems*, CHI EA '22, New York, NY, USA. Association for Computing Machinery.

Holter, S. and El-Assady, M. (2024). Deconstructing human-ai collaboration: Agency, interaction, and adaptation. *Computer Graphics Forum*, 43(3). Manuscript received; accepted. The final version available at Eurographics.

Kwon, O.-H., Crnovrsanin, T., and Ma, K.-L. (2019). A deep generative model for graph layout. In *IEEE Pacific Visualization Symposium (PacificVis)*, pages 96–100, Bangkok, Thailand. IEEE.

Lundberg, S. M. and Lee, S. (2017). A unified approach to interpreting model predictions. In *Proceedings of the 31st International Conference on Neural Information Processing Systems (NIPS'17)*, pages 4768–4777, Red Hook, NY, USA. Curran Associates Inc.

Miksch, S. and Aigner, W. (2014). A matter of time: Applying a data–users–tasks design triangle to visual analytics of time-oriented data. *Computers & Graphics*, 38:286–290.

Ribeiro, M. T., Singh, S., and Guestrin, C. (2016). "why should i trust you?" explaining the predictions of any classifier. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pages 1135–1144, San Francisco, CA, USA. ACM.

Ribeiro, M. T., Singh, S., and Guestrin, C. (2018). Anchors: High-precision model-agnostic explanations. In *Proceedings of the Thirty-Second AAAI Conference on Artificial Intelligence (AAAI-18)*. AAAI.

Simonyan, K., Vedaldi, A., and Zisserman, A. (2014). Deep inside convolutional networks: Visualising image classification models and saliency maps. *arXiv preprint arXiv:1312.6034*.

Spinner, T., Schlegel, U., Schäfer, H., and El-Assady, M. (2020). explainer: A visual analytics framework for interactive and explainable machine learning. *IEEE Transactions on Visualization and Computer Graphics*, 26(1):1064–1074.

Tiezzi, M., Ciravegna, G., and Gori, M. (2024). Graph neural networks for graph drawing. *IEEE Transactions on Neural Networks and Learning Systems*, 35(4):4668–4681.

Wang, X., Yen, K., Hu, Y., and Shen, H.-W. (2023). Smartgd: A gan-based graph drawing framework for diverse aesthetic goals. *IEEE Transactions on Visualization and Computer Graphics*, pages 1–12.

Wang, Y., Jin, Z., Wang, Q., Cui, W., Ma, T., and Qu, H. (2020). Deepdrawing: A deep learning approach to graph drawing. *IEEE Transactions on Visualization and Computer Graphics*, 26(1):676–686.

Yan, K., Zhao, T., and Yang, M. (2022). Graphuly: Graph u-nets-based multi-level graph layout. *IEICE Transactions on Information and Systems*, E105.D(12):2135–2138.