Charitha Vadamala

Prof. Anna Baynes

CSC173 Data visualization-section 1

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Background Literature Review

"Deep Drawing: A deep learning approach to graph drawing."

1. **What is the major contribution of this paper?**

   The major contribution of this paper is the development of DeepDrawing, a novel graph-LSTM-based approach for graph drawing. The approach treats graph drawing as a learning and prediction problem. Given a graph drawing dataset, DeepDrawing is trained to learn a graph drawing style and can then generate graph drawings with similar characteristics. To the best of the authors' knowledge, this is the first application of deep learning to graph drawing (Wang et al. 677)

2. **How did they analyze the effects of their work?'**

   The authors conducted both qualitative and quantitative evaluations on three types of graphs (grid graphs, star graphs, and general graphs with good community structures) and four types of drawings (grid layout, star layout, ForceAtlas2, and PivotMDS). They assessed the speed, efficiency, and effectiveness of DeepDrawing for graph drawing. They also compared DeepDrawing's ability to preserve the original graph drawing style to that of a general LSTM-based method.

3. **What 2 questions do you have for the author(s)?**

   a. Given the good results obtained with DeepDrawing, could the method be extended or adapted to handle dynamic graphs, which often depend on the temporal correlation between adjacent time stamps?
   b. While DeepDrawing has proven effective for smaller graphs with 20-50 nodes, how would the system handle larger, more complex networks? Is there a plan to conduct future evaluations on larger graph structures?

4. **How does your work on the mini-challenges relate to this paper?**

   My work on the mini-challenges involved using a graph-based approach to visualize connections between entities and identify probable illegal activity. The work presented in this paper could enhance my work by providing a machine learning-based approach to graph drawing. Instead of manually analyzing and visualizing the graph, I could train a model like DeepDrawing to learn the characteristics of legal and illegal entities. This could potentially make the process of identifying illegal activities more efficient and effective.

"Key-node-separated graph clustering and layouts for human relationship graph visualization."

1. **What is the major contribution of this paper?**

   The major contribution of this paper is the development and validation of a novel approach to explore and visualize key nodes and their adjacent relations in large and complex networks. Specifically, the authors designed a technique for graph-clustering and layout that significantly improves the visibility of key nodes and their connections, as compared to other common techniques like modularity clustering (Itoh et al. 36). The technique was applied and validated on two diverse datasets, one on academic coauthorship and the other on Twitter communications, demonstrating its versatility.

2. **How did they analyze the effects of their work?'**

   The authors analyzed the effects of their work both qualitatively and quantitatively. They performed experiments with their approach using two different datasets and compared the results with those from other standard techniques. They quantified their results by looking at the number of inside cluster edges and the computation time. They also conducted a subjective user evaluation with 13 university students (Itoh et al. 38), who compared the visualization results from the authors' technique and the common techniques.

3. **What 2 questions do you have for the author(s)?**

   a. What measures were taken to ensure the subjectivity introduced during keyword selection (for creating feature vectors) does not bias the results significantly?
   b. Given that key nodes were identified based on their high degree of connections, how would your technique work on networks where key nodes aren't necessarily the most connected?

4. **How does your work on the mini-challenges relate to this paper?**

   My work on the mini-challenges seems to align well with this paper. Like the authors, I was working with large, complex networks, though my focus is on illegal fishing activities. The technique detailed in the paper would likely prove useful for my challenge. I could apply their method to my data to improve visualization and potentially identify other entities involved in illegal fishing. The graph-clustering and layout method they proposed would help in visualizing not only the immediate nodes but also the second degree nodes, just like I did. It could further assist in identifying patterns and relationships that might be indicative of illegal activities.

"Graph drawing by stochastic gradient descent."

1. **What is the major contribution of this paper?**

The major contribution of this paper is the presentation and validation of a new method to minimize the energy function, or "stress," in force-directed graph drawing. This is achieved by applying stochastic gradient descent (SGD), moving a single pair of vertices at a time. The authors provide evidence that SGD consistently reaches lower stress levels faster than majorization without requiring a specific initialization. The paper also illustrates how the properties of SGD make it easier to generate constrained layouts than previous methods, and how SGD can be applied in the sparse stress approximation of Ortmann et al., allowing the algorithm to scale up to larger graphs.

2. **How did they analyze the effects of their work?'**

The authors analyzed the effects of their work through a series of experiments. They compared the performance of SGD to majorization, demonstrating faster convergence to lower stress levels using SGD. They also conducted experiments on real-world applications to illustrate the benefits of SGD in handling unique properties including constrained layouts and scalability to large graphs.

3. **What 2 questions do you have for the author(s)?**

    a. You mention that SGD can struggle with local minima, for instance, in the case of the 'dwt_2680' which is susceptible to twisting in the middle. Could you provide more insight into how this issue can be resolved without adversely affecting other cases?
    b. You mention the possibility of overshooting as a solution, with the risk of divergence and poorer local minima. How might adaptive annealing be used in combination with overshooting to optimize performance?

4. **How does your work on the mini-challenges relate to this paper?**

The research described in this paper has significant implications for the work I did on the mini-challenges. The method proposed by the authors, using stochastic gradient descent (SGD) to reduce stress and create visual representations of graphs, can be directly applied to the visualization of our large, complex network of entities involved in fishing activities. By applying SGD to my task, I could potentially uncover more effective and efficient ways to identify and visualize entities that are involved in illegal fishing. It might also make it easier to visualize and understand the complex relationships and the impact of different entities within the fishing industry.

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"Exemplar-based layout fine-tuning for node-link diagrams."

1. **What is the major contribution of this paper?**

   The major contribution of this paper is the design and evaluation of a novel layout fine-tuning technique for node-link diagrams, which allows for the adjustment of a group of substructures in a batching mode based on an exemplar provided by the user. This is achieved through a three-step process involving the representation, retrieval, and morphing of substructures. The paper also introduces an efficient modification-transfer algorithm (Pan et al. 1657) that can transfer fine-tuned results of an exemplar substructure to other topologically similar substructures. Additionally, a user interface was developed to facilitate these processes.

2. **How did they analyze the effects of their work?'**

   The authors analyzed the effects of their work through a combination of quantitative comparisons, case studies, and a within-participant user study. The quantitative comparisons used benchmark datasets and focused on the accuracy of graph matching results, showing that their approach performed better than others. The case studies demonstrated the application of their approach on different datasets and layouts, while the user study involved participants fine-tuning structures in different modes, which revealed that their approach reduced or eliminated laborious interactions.

3. **What 2 questions do you have for the author(s)?**

   a. What are the potential applications of this work outside of the contexts discussed in the case studies?
   b. Given the large-scale networks the approach can handle, how well does the method scale for networks with millions of nodes and edges?

4. **How does your work on the mini-challenges relate to this paper?**

   My work on the mini-challenge 1 aligns well with this paper, as it also involves the visualization of node-link diagrams, albeit for the specific purpose of identifying entities involved in illegal fishing. This paper's novel layout fine-tuning technique could enhance my current process by facilitating the adjustment of a group of substructures based on an exemplar, possibly making it easier to identify and analyze suspected entities and their connections. The ability to transfer modifications from an exemplar to similar substructures could potentially improve my ability to detect patterns of illegal activity across the network.

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"A deep generative model for graph layout."

1. **What is the major contribution of this paper?**

   The major contribution of this paper is the development of a novel approach to graph visualization using deep generative models. The authors designed an encoder-decoder architecture to learn a generative model from a collection of example layouts. This encoder-decoder model represents training examples in a latent space and generates new layouts from this latent space. This provides a more intuitive and systematic way for users to visualize a graph in diverse layouts, circumventing the time-consuming trial-and-error process traditionally involved in graph layout design. The new approach allows users to generate layouts that satisfy their requirements without expert knowledge of layout methods.

2. **How did they analyze the effects of their work?'**

   The authors analyzed the effects of their work through both quantitative and qualitative evaluations of the generated layouts. These evaluations showed that their model is capable of learning and generalizing abstract concepts of graph layouts, instead of merely memorizing training examples. They also demonstrated that their model can generate new layouts faster than existing methods, and the generated layouts are spatially stable, making them easier for users to compare.

3. **What 2 questions do you have for the author(s)?**

   a. While your research presents an innovative approach to graph visualization, could you elaborate on potential methods to enhance the interpretability of each dimension in the latent space?

   b. The paper mentions that the model does not generalize across different graphs and different layouts, requiring a new model for each graph. Could you discuss potential advancements or strategies that might help overcome this limitation in the future?

4. **How does your work on the mini-challenges relate to this paper?**

   The work on the mini-challenges greatly relates to this paper. Specifically, the paper is focused on the usage of AI & ML algorithms to analyze complex patterns within large datasets. This is parallel to the mini-challenge where I have to identify patterns for entities involved in illegal fishing. Moreover, the methods utilized during MC1, including identifying immediate and second-degree nodes, and applying degree analysis and link weight analysis, are in essence, techniques of data analysis. These techniques align with the paper's thematic focus on employing AI for data exploration and analysis

Works Cited

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