Leveraging Large Language Models for Automated Causal Loop Diagram Generation: Enhancing System Dynamics Modeling through Curated Prompting Techniques

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Extended Abstract:

The increasing complexity of socio-technical systems demands sophisticated tools for understanding and managing these systems effectively. System Dynamics (SD) provides a framework for analyzing such systems by formalizing causal structures and using simulations to diagnose and address problematic behaviors. Over the past seven decades, SD has evolved significantly, especially with advancements in computational tools that simplify model building and simulation. However, core processes like constructing Causal Loop Diagrams (CLDs) remain labor-intensive and manual, posing challenges for modelers, particularly novices (Deutsch et al., 2024; Lane, 2008).

While contemporary SD tools have become more sophisticated, the manual process of translating dynamic hypotheses into CLDs remains a bottleneck. CLDs are critical in SD as they depict the feedback structure underlying system behaviors, but their construction is prone to errors such as over-aggregation, mislabeling of loop polarities, and speculative inferences without full simulation models. Recent advancements in Generative AI, particularly Large Language Models (LLMs), offer promising solutions to these challenges by automating aspects of SD model development (Ghaffarzadegan et al., 2024; Hosseinichimeh et al., 2024). Previous studies have demonstrated the potential of LLMs in research, decision-making simulations, and even in generating graphical representations from text, although the accuracy and efficiency of these methods are still under exploration.

This paper introduces a novel method for automating the translation of dynamic hypotheses into CLDs using LLMs, guided by curated prompting techniques (Liu et al., 2021). The approach leverages LLMs' emergent capabilities in causal reasoning to discern relationships between variables from text and translate these into CLDs (Chowdhery et al., 2022). We developed a dataset of high-quality dynamic hypothesis and CLD pairs from published SD textbooks (Sweeney & Meadows, 2010; Sterman, 2000; Ford, 1999), which served as the basis for training and testing the LLMs. Experiments were conducted using four different prompting techniques, and the generated CLDs were evaluated against those created by expert modelers, serving as the ground truth.

The LLM-generated CLDs demonstrated a promising level of accuracy in replicating expert-generated diagrams, particularly when few-shot prompting techniques were applied. The results highlight the potential of LLMs to significantly reduce the time and effort required to develop CLDs, making the modeling process more accessible to novices and potentially accelerating the model development process in general.

Our findings suggest that the automation of CLD creation using LLMs could be a valuable addition to the SD toolkit. This approach not only aids novice modelers by reducing the complexity of model building but also opens up new avenues for automating more sophisticated tasks, such as the development of complex CLDs and executable simulation models. The ability of LLMs to perform causal reasoning also presents significant implications for real-world applications in analyzing complex systems, including economic, social, and environmental domains.

This research introduces a approach to automating CLD creation in SD using LLMs. By automating the translation of text into CLDs, this method has the potential to streamline model development, enhance accessibility for novice modelers, and eventually automate more complex aspects of SD modeling. The demonstrated tool, available at https://cldgenerator.azurewebsites.net/ offers a practical implementation of this approach, with future research aimed at expanding its capabilities to more complex and fully executable models. This work contributes to the evolving field of SD by integrating cutting-edge AI technologies into its methodology, with far-reaching implications for the analysis of complex systems.

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