Challenges in Visualizing Complex Causality Characteristics

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ABSTRACT

This poster paper examines current methods of visualizing causality and their limitations. Causality is important for providing explanations especially when using computational models to understand complex systems structure and behavior, and what happens when change occurs in the system. There are many properties of causality that need to be considered and made visible, but current causality visualization methods are limited in expressions, scale, dimensionality and do not provide sufficient support for user tasks such as "what-if" and "how-to' questions, or in supporting groups considering multiple scenarios. There are many challenges to be discussed.

Keywords: Causality, Visualization design, Graph visual analytics, Graph analytics,

1 INTRODUCTION

To encourage discussion, this poster paper examines current methods of visualizing causality and suggests areas to improve to work with richer representations of systems that include causality.

There is increasing use of computational models to represent and understand the structural and dynamic properties of causality in complex systems. Example modeling methods include Bayesian models of political influence, probabilistic graphical models [17], Petri net models of sequential processes, system-dynamics models of infrastructure process flows, agent-based models of social behavior [16], statistical models (e.g. economics, biochemical reactions [5], correlation-based causality [20] and influence diagrams [1]. In these models, causality operates through modeled action and outcome relationships. While there are a variety of computational methods, we can consider the common properties of causality with which visual expressions can establish a consistent way of working with causality.

2 ABOUT CAUSALITY

Causal relationships are important for providing an explanation to users of the reasons for predicted observations of changes and phenomena. Causality is a way of understanding systems and sub-systems, how they operate dynamically, what their characteristics are, and which forces are responsible for changes. There is a large field of philosophy on causality including Aristotle and David Hume fundamentals, but from an engineering perspective, causality is a mechanism that connects system interactions with subsequent observations. Pearl's unifying theory of causality uses probabilistic structural causal models to answer questions about the direct and indirect effects of interventions [17]. In understanding the causal connection from action to effect, there is an important role for visualization.

3 USER TASKS IN WORKING WITH CAUSALITY

Decision-makers, planners and analysts need to first understand complex systems, including their structure and dynamics, then to work with simulations of those systems to comprehend "what if"scenarios. As part of sense-making, people ask "why?" questions to understand observed behavior. Answers to "what if" questions can help decision-makers weigh the pros and cons of specific actions. Intervention and counter-factual reasoning is supported via "if this were true" reasoning. Finding answers requires tracing causality chains and characteristics as people examine what factors caused variables to exhibit specific behaviors. Visualization is essential for answering all these questions, for tracing complex causality, and for illustrating characteristics of causality such as prioritized leverage points in the "causal landscape" [15].

Group participatory discourse and debate, while comparing options and building shared understanding, is part of the decision-making process when developing a plan to intervene in a complex system [14]. Many diverse perspectives need to be shared to improve causal decision-making models, and to produce insights into predicted system dynamics. Visualization has a role in supporting groups of people working with these models.

4 PROPERTIES OF CAUSALITY TO VISUALIZE

In working with models of systems, there are numerous properties of causality relevant for visualization. The system description includes structure such as objects (i.e. entities with attributes and values), relationships to other objects, and causal links from object actions to effects (i.e. changes in structure or values). The system description has scale. It can be a small or large system, and there can be a simple or detailed description. Causal links in the systems have direction, strength and certainty [1][2]. Causality has agency (i.e. the entity performing an action) and the agency has characteristics (e.g. membership of a political, social or economic sub-system). Causality also has both polarity (e.g. positive, negative influence), and valence (i.e. the influence supports or opposes the purpose of an intervention(s). Causality also has characteristic patterns as shown in Figure 1 [7][10].

Causality can be deterministic, or probabilistic with varying levels of likelihood. Probabilistic graphical models encode belief propagation. Hard or soft evidence on states of variables, allows inference of current states, or reasoning about potential effects.

Causality also occurs in a temporal context. Events and behavior occur over time with delays, concurrency, non-linear behavior, variable time series, events that are episodes of behavior and change, etc.

Amplification	C increases the effect A -> B
Damping	C decreases the effect A -> B
Prevention	C blocks A -> B
Mutual	A -> B and B -> A
Domino	A -> B -> C -> D ... continues
Cyclical	A -> B -> C -> A ... repeats
Feedback	A -> B -> A -> B ... repeats

Figure 1: Patterns of causation can help interpret complex causality.

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5 CURRENT CAUSALITY VISUALIZATIONS AND LIMITATIONS

Causal relationships are typically represented using a directed acyclic graph (DAG), with labeled nodes linked by arrows representing simple if-then relationships. For graph attributes, methods have not progressed much beyond combining directed arrows, color, transparency and size (width of edge, diameter of node). See Figure 2. Tapered directed edges have been found to perform better than arrows [11]. Evaluations have shown width is preferred over color for "strength", and for certainty, using brightness and fuzziness showed higher accuracy and understandability than dashed lines [1][8]. Current work often uses datasets that are smaller (e.g. 20 to 400 nodes) [5], and the number of properties displayed are fewer. High dimensional graph attributes (i.e. multiple node/edge properties) require multivariate graph visualization but higher dimensions are a representation challenge [9]. Additional attributes must be seen without increasing clutter.

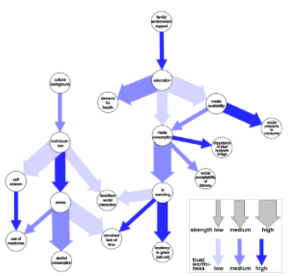

Fig. 2. Too simple causality [2].

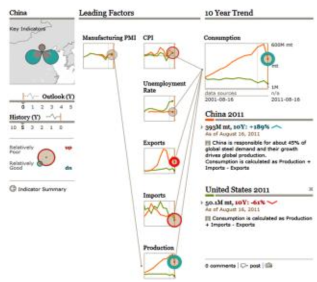

Fig 3. Linked visible behaviours [13].

A recent causal graph reasoning tool, tightly integrated with conditional dependence methods, uses only limited color encodings. Green/red arrows for edge polarity, and blue/yellow for node variable type (categorical, numerical). Edge color transparency encodes amount of change exerted by the cause onto the effect. A stronger effect is more visible. It remains a challenge to visualize additional attributes (e.g. test statistics), and to compare model scenarios and their attributes [20].

Representing complexity while also enabling people to see higher order patterns is a significant challenge. Another recent tool, ReactionFlow, uses novel gradient-filled sets of arcs to show causal pathways and feedback loops [5]. Linked Visible Behaviors in Figure 3 shows non-linear linked time series variables with multiple scenario comparison but is limited in the number of variables concurrently displayed.

Causality has been represented using animation and interaction [6]. Additional exploratory thinking has examined expressive animations for some causal characteristics listed in Figure 1 [22] but animation sequences have issues due to human attention/distraction and weak short term memory [Wickens 2013]. Static methods provide better ability to reason with the information [23]. Static diagrams offer access at any time as the user builds their mental model of comprehension. However, animations of continuously repeating loops show promise for encoding graph attributes [12]. Looping motion methods were found to be effective for highlighting long complex graph paths when tracing [21]. But in general, dynamic graphs (either animation or timeline-based) have not been investigated for use with causality, and scalability and working with high dimensional data remain a challenge [3].

While there are a wide variety of graph layouts [19], not many beyond force-directed or hierarchical have been applied to causality. Semantic anchoring layouts or user defined "semantic substrates", which are efficient for scalability and understanding [18], have not been used for understanding and working with causality.

6 CONCLUSION

Current causality visualization methods are limited in expressions, scale, dimensionality and do not provide sufficient support for user tasks. For example, visual support for discourse on causal alternatives and "what-if" questions remains lacking. Efficient visibility into computational models and results is required for using causality models as a cognitive tool for thinking. There are many challenges and opportunities to be discussed.

Next steps include imagining concepts for expressive causality and developing prototypes to evaluate with representative users.

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