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CAUSAL INFLUENCE DIAGRAMS

Causal influence diagrams (a.k.a causal loop diagrams) are one of the important tools used by system dynamists to model the dynamic feedback relationships among the components of a complex system. A system is said to be complex if (1) it has a large number of parts (or variables, agents, individuals, components); (2) there are many interrelationships or interactions among the parts of the system; (3) the parts produce combined effects (synergies) that are not easily foreseen and may often be novel or surprising (chaotic) to the observer; in other words, if there exists an emergent global dynamics resulting from the actions of its parts rather than being imposed by an external or a central agent.

Complex systems are pervasive in our lives: the human nervous system, an ant colony, the climate system, ecosystems, economic systems such as the global economy, the Earth systems, epidemics (e.g., HIV, malaria), the stock market, energy market, meteorological systems, transportation systems, social systems (e.g., family groups, sports teams, legislative bodies), political parties, governments, supply-chain systems, management of multi-national corporations, wars against insurgencies, and health-care legislations are all examples of complex systems. Due to their emergent behavior, complex systems cannot be understood by inspection or intuition; to deal with them intelligently one needs a set of *tools* to describe, analyze, and model them in order to be able to manipulate certain of their output parameters with minimum unintended consequences.

System dynamicists use causal influence diagrams to serve as preliminary sketches of causal hypothesis during model development of a complex system. Causal influence diagrams are also used to elicit and capture mental models of individuals about a complex system or to simplify illustration of a model to communicate the important feedbacks that are believed to be responsible for a complex system or a problem.

Nearly every professional, whether it is a physician, biologist, biomedical engineer, agronomist, ecologist, pharmacologist, economist, politician, or a stock-market speculator, encounters complex systems and have to make decisions concerning how to interact with it or formulate policies about it. Thus, understanding complex systems is a highly valued competency in many decision-making and problem-solving task domains such as STEM. As a consequence, the tools by system dynamicists to understand complex systems, such as the causal influence diagramming, is relevant to many educational technology applications.

Causal influence diagramming has the potential to effectively facilitate learning of complex systems and complex problem-solving competencies because: (1) it serves as a knowledge representation tool that could externally represent a learner's problem space; (2) it enables problem solvers to be system thinkers and forces them to view the problem holistically by identifying all the key factors that play important roles in the solution of the problem and the interrelationships among these factors; (3) it can be used as the basis of a method to assess progress of learning to continuously track the development of learners' conceptual understanding of complex systems and their development of complex problem-solving competencies.

Anatomy of a Causal Influence Diagram

Suppose that you are studying an epidemic, during which a sharply increasing number of people become ill. The crisis reaches a climax and then returns to a low rate. During your observations, let's assume that you make the following hypotheses:

(1) The infectious birds infect vulnerable people who then contract the disease and become contagious;

(2) The contagious people are bitten by clean mosquitoes, which after a while become infectious and transfer the disease to other vulnerable birds and people;

(3) The humans who recover from this epidemic remain immune for life.

Your assumptions can be modeled by a causal influence diagram (Figure 1) as a dynamic hypothesis of this epidemic.

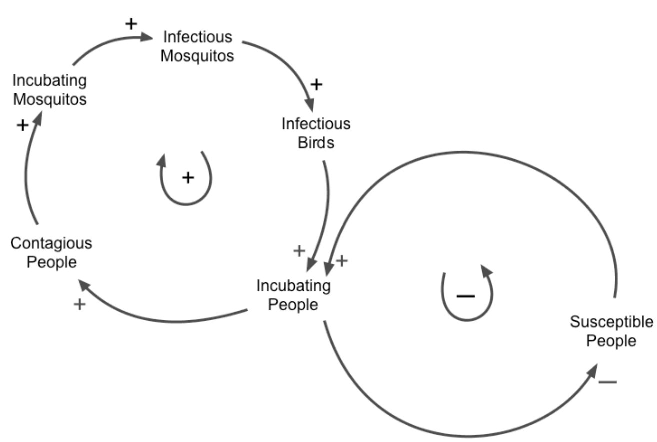

Figure 1. Sample causal influence diagram of an epidemic

As illustrated in Figure 1, a causal influence diagram consists of arrows denoting the causal links among system variables. Each causal link is assigned a polarity, either positive (+) or negative (–) to indicate how the dependent variable changes when the independent variable changes. A positive link indicates a *direct* relationship; in other words, if the cause increases the effect also increases or if the cause decreases the effect also decreases. For example, in Figure 1, an increase in the number of contagious people means an increase in the number of incubating mosquitos above what it would otherwise have been.

On the other hand, a negative link indicates an *inverse* causal relationship; in other words, if the cause increases the value of the effect decreases or vice versa. For instance, in Figure 1, an increase in the number of incubating people means the number of susceptible people will fall below what it would otherwise have been.

In a causal influence diagram, important feedback loops are highlighted by a loop identifier, which shows whether a loop is a positive (reinforcing) or negative (balancing) feedback loop. For instance, in Figure 1, there are two main feedback loops; the first one on the left is a positive feedback loop while the other one on the right is a negative feedback loop. Note that the loop identifier in the middle circulates in the same direction as the loop to which it corresponds.

In a positive feedback process, a variable continually feeds back upon itself to reinforce its own growth or collapse. Several familiar phrases characterize the phenomenon of positive feedback. For example, the *snowball effect* relates the growth of certain ideas to the growth of a snowball as it rolls down a mountainside; as a rolling snowball picks up snow, its mass and circumference increases, which causes the snowball to grow even faster. The phrase *vicious cycle* is also synonymous for positive feedback loop. In a vicious cycle, a worsening of one element in a causal chain brings about further degradation of the element. Conversely, in a vicious cycle, positive changes in a system element trigger further improvement. The viciousness of a positive feedback system depends on whether the elements of the loop mutually deteriorate or mutually improve.

On the other hand, negative feedback loop is characterized by a goal-directed behavior. If the current level of the variable of interest is above the goal, then the loop structure pushes its value down, while if the current level is below the goal, the loop structure pushes its value up. Such terms as self-governing, self-regulating, self-equilibrating, homeostatic, or adaptive – all implying the presence of a goal – define negative feedback loop or systems.

When a positive and a negative loop are combined, as in Figure 1, a variety of patterns are possible. For instance, it is possible that a positive feedback loop leads to early exponential growth, but then, after a delay, a negative feedback loop comes to dominate the behavior of the system.

Causal influence diagrams are well suited to represent interdependencies and feedback process of a complex problem situation. However, causal influence diagrams also suffer from a number of limitations. One of the most important limitations of causal diagrams is in their inability to capture the stock and flow structure of systems, which are the two central concepts of system dynamics theory. Hence, following the creation of a causal influence diagram, system dynamicists typically transform it into a stock-and-flow model, which include mathematical equations to represent the stocks (i.e., accumulators), flow rates, variables, and any constraints that may be assumed to govern the system. In this way, the simpler causal influence diagram is elaborated and transformed into the basis for a mathematically driven simulation model that can be manipulated to test overall system behavior when certain variables in the model are changed.

Implications for Learning, Complex Problem-Solving, & Assessment

As remarked earlier, understanding complex systems is a highly valued competency in many decision-making and problem task domains, such as STEM; however, as shown Dietrich Dörner, there are seven common problems people have when dealing with complex systems: (1) Failure to state and prioritize specific goals; (2) failure to reprioritize as events change; (3) failure to anticipate side effects and long-term consequences; (4) failure to gather the right amount of system information; (5) failure to realize that actions often have delayed consequences, leading to overcorrection and possible instability when the result of an action do not occur at once; (6) failure to construct suitably complex models of the system or situation; and (7) failure to monitor progress and reevaluate input actions. Part of these failures stem from our education system, which trains individuals for simple- and well-structured problem solving that has a single viable solution. As an alternative, scholars such as Dietrich Dörner and Peter Senge stress the importance of complex systems thinking for effective complex problem solving.

A causal influence diagram supports a holistic view of a complex system in a single representation that depicts the dynamic interrelationships among problem constituents, delayed effects, and the feedback loops affecting the overall system behavior. Hence, causal influence diagrams can be useful in facilitating complex systems thinking and supporting learning and instruction as argued by scholars such as Marcelo Milrad, J. Michael Spector, and Pål Davidsen. There are two ways of using causal influence diagrams to support learning and complex problem solving: (1) learning with models and (2) learning by modeling. Learning with models has been shown as an effective method for teaching complex science systems by scholars like John J. Clement and Deniz Eseryel. In this instructional strategy, learners could be provided by the causal influence diagram of a complex system and are asked to articulate on the dynamic interrelationships among system components or how the overall system would behave if certain system components are manipulated. Another learning-with-models strategy could be to provide learners with a causal influence diagram and to ask them to create their own digital stories to answer a particular problem scenario, such as “How does climate change influence ecosystem over time?” The complete model is revealed step-by-step as the annotated causal relationships are accompanied with corresponding parts of the story. Causal influence diagrams can also be used as an effective cognitive regulation scaffold during complex problem solving as shown by Deniz Eseryel. For instance, during inquiry learning, learners can be provided with the causal influence model of the underlying complex system as they try to interpret the findings of their hypothesis-testing to formulate new hypothesis.

Learning by modeling has also been shown to facilitate effective complex problem solving competencies and lead to deeper understanding of complex systems. In this type of instruction, a learner could be provided with a complex problem scenario that requires in-depth understanding of a complex system. Asking the learners to depict the text-based complex problem scenario as a causal influence diagram is the initial step in learning by modeling.

However, there is no need to introduce the technical jargon of causal influence diagrams or to train learners on developing causal influence diagrams. Rather, it is sufficient to simply present the problem situation and asking the learners to (a) indicate key factors influencing the problem situation, (b) describe each factor; (c) indicate how those factors are interrelated by drawing arrows from cause-to-effect; and (d) describe those relationships. In several studies, even 6th grade students are shown to be able to construct annotated causal influence diagrams with these simple instructions. The learner could then be asked to reflect upon the diagram to come up with effective solution of the complex problem individually and then discuss their solution approaches in a small group or as the whole class. As shown by Deniz Eseryel, such implementation of learning-by-modeling strategies could lead to positive far transfer of complex problem-solving competencies to other domains in as quickly as 3-weeks. In addition, she showed that the instructional strategy of learning-by-modeling is more effective as a cognitive regulation scaffold when compared with the strategy of learning-from-models as the problem scenarios increase in complexity.

Causal influence diagramming has also been adapted by several educational researchers, including J. Michael Spector, Tiffany A. Koszalka and Deniz Eseryel, as an alternative method for assessing progress of learning in complex task domains. Continuous tracking of a learner's causal influence diagram of a complex system can be compared with that of a domain expert to assess whether the instructional intervention is facilitating desired conceptual changes or whether particular misconceptions in students mental models are preventing their learning. Such immediate and continuous feedback could help teachers introduce just-in-time information to address apparent misconceptions or to modify the design of the instructional intervention to bring about desired changes in learners' mental models.

Deniz Eseryel

See also Adaptive Learning Software and Platforms; Assessing Learning in Simulation-Based Environments; Assessment of Problem Solving and Higher Order Thinking; Games to Promote Inquiry Learning; Formative Assessment; Learning Analytics; Learning by Modeling; Learning with Models; Learning with Simulations; Management Flight Simulations; Model-Based Approaches; Problem- and Project-based Learning with Technology; Simulation-Based Learning; System Dynamics, Modeling, Tools for Modeling and Simulation.

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