A brief introduction to complexity science and human-centric dynamical systems

The emerging science of complexity deals with complete systems formed by the interaction of agents (people, resources, animals, etc.), who are interdependent and can co-evolve in their environment. That is to say that the interactions and characteristics of the individuals are dynamic and subject to change, which then alter the system itself, often in unpredictable ways.

Human-centric complex systems are often best modeled as interconnected nodes in the form of networks, where each vertex represents a person or resource at a single point in time. These are dynamical systems by virtue of varying initial conditions, non-linear processes, individual learning, and interaction among agents. Consequently, these systems operate far from equilibrium, co-evolve in their eco-systems, and display emergent outcomes.

System Processes

Systems are often defined as functional entities that begin with a set of initial inputs or conditions. They are often designed to enable their participants to engage in personal goal-directed behavior that may or may not be cooperative with other members. Additionally, there may be overarching organizational, economic, or social goals that are expected to emerge from the system operating as intended.

One example is the transportation infrastructure within a city and those who utilize it. This represents a collection of people, equipment, streets, rules, and resources. Agents may operate their own vehicles or choose alternate transportation to achieve their personal goals (e.g. getting to a workplace), while employers and cities simultaneously benefit from economic outcomes.

Classical Systems

Complex adaptive systems are described as far from equilibrium to emphasize a number of unique characteristics and differentiate their behavior from more traditional, deterministic models of performance. In contrast, the variables in classical design, (e.g. cost, specifications, and reliability) are considered to be known or knowable and they are typically measured or monitored to ensure specified performance. The classical approach is also reductionistic where large systems can be broken down for modular analysis and described in terms of sequential processes. In turn, these smaller activities are amenable to traditional analysis such as Monte Carlo simulation and Markov processes, and a variety of statistical techniques.

In classical analytics, variables that are not accounted for in system performance may be classified as noise, acts of god, catastrophic, or serendipitous outcomes. Significant effort is often exerted to remove these uncertainties from system operation, but the alternative is to monetize those outcomes by purchasing insurance, developing production alternatives (e.g. cross-training, backup machinery, extra stock, etc.), or contractually limiting liability. This approach also forces standardization to supplant judgment in highly skilled individuals and places a strong paper trail requirement to ensure the processes are in compliance. Consequently, the cost, relative effectiveness, and efficiency of these methods are seldom measured in their entirety and even more difficult to predict in advance.

Complex Systems

Not all problems and processes are complex enough for the application of complexity theory. Many well-defined and historically validated processes operate successfully within a constrained environment with accepted externalities. However, certain classes of problems are inadequately addressed in the classical domain. These include:

- Large, loosely specified activities (e.g. driving to work with other traffic)
- Situations where individual or interactive performance drives success
- Systems that highly impact or are significantly affected by the environment
- Situations where the problem is rapidly evolving (e.g. forest fire fighting)
- Where innovation and new or novel solutions are needed

- When regulations are co-evolving with new technologies or ideologies
- Many others

These examples illustrate how complexity science embraces all the messiness of human behavior by voiding the assumption that people are interchangeable “resources” when they are trained for specific tasks. Human agents come to the party with individual experiences, varying knowledge, different interpersonal skills and capabilities to learn. The interaction of individuals with their environments often spur complexity because the environment is dynamical and evolves at a local level, creating different pathways that especially effect iterative and recursive work.

A New Math

Edward Deming first applied statistical processes to automobile manufacturing in Japan by applying Shewhart charts for workers to measure machined components for quality purposes. He defined normal variation as the capability of a machine to produce specified parts and, separately, defined special variation as a cause of error that can be predicted and prevented. The Shewhart charts focused on serially progressive dimensional changes that are consistent with tool wear. This allowed machinists to replace worn tools before the parts were made defective.

These classical statistics work very well under conditions such as these where the requirements are well specified, easily measurable and take advantage of the law of large numbers. In other words, where the distribution is known to be normally distributed over the entire population when caused by random error.

A new math is required for complex systems that are far from equilibrium. Analytics based on Gaussian or similar statistical distributions don’t apply because the humans being measured along with the situational structure are changing and co-evolving with the system. Using the prior example for illustration, - how would an individual’s performance and perhaps larger system objectives be measured if a traffic accident blocked the main path to work? Traffic jams, black swans, avalanche events, and other unpredictable and non-linear events are incorporated rather than avoided in a complex systems analysis. Consequently, the mathematical starting point for a complexity approach is to utilize network graph theory and develop a variety of vertices to model specific functions. The network itself must also be designed to accurately reflect the actual system and incorporate the externalities of the ecosystem. This work has been in development for the last couple of decades and has gained significant momentum with the development of large computer networks.

My Work and Interests

Scholars often talk about their work as the intersection of two topics. My two are ***human cognition*** and ***outcome prediction.*** Cognition has been a topic of renewed interest as computer scientists have pursued artificial intelligence and computer-augmented cognition. Such work may offer future benefits to people to overcome several forms of bounded rationality and make better life choices. This is especially salient now when technology offers many new options while increasing the complexity of many common life functions.

A common refrain is that weather forecasters never get it right, but in reality, the success of weather prediction has increased dramatically over recent years as more advanced computer models are applied to predicting weather changes. Weather is the prototypical complex system that requires a constant feed of new data to make daily predictions while simultaneously evaluating global patterns to make longer term predictions.

In many ways, systems that are driven by human behavior are much more challenging than weather prediction, but also have the potential to yield huge benefits across many different applications. In a separate report, I will outline a complexity approach toward dynamical system analytics where un-coordinated human action is the driving force that predicts incremental system level evolution.