With Behaviors Like These in Complex Systems, Who Needs Mechanisms?

A new study of complex systems supports a growing trend that focuses more on analyzing a system's collective behavior rather than on trying to uncover the underlying interaction mechanisms.

By **Daniele Marinazzo**

When observing a flock of starlings swirling through the sky in perfect coordination—a phenomenon known as murmuration—we witness the elegant interplay of individual actions creating collective behavior. In trying to understand these mesmerizing patterns, researchers can isolate simple rules based on an individual bird's field of vision and distance to its neighbors, but there's always a question of whether the model is really capturing the processes behind the bird interactions (Fig. **1**). The problem is a general one in complex systems research, and it comes down to distinguishing mechanisms (the rules governing interactions) from behaviors (the observable patterns that emerge).

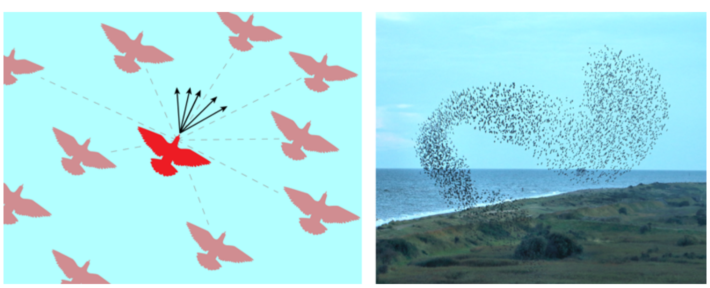

Figure 1: In bird flocks, each bird chooses its motion based on the separation distance and flight orientation of its neighbors (left). These simple rules can produce complex patterns, such as the "murmurations" of starlings (right). New research explores how mechanisms (individual rules) relate to behaviors (collective patterns) in networks that represent complex systems.
Credit: APS/Alan Stonebraker; Airwolfhound

A good way to study mechanisms versus behaviors is through representative networks of interacting individuals, or nodes. Traditionally, researchers have focused on pairwise interactions, but many systems also include higher-order interactions between multiple nodes. What impact these higher-order mechanisms have on behaviors has been unclear. Thomas Robiglio from the Central European University in Vienna and colleagues have now addressed this issue by considering networks with higher-order interactions and evaluating the resulting behaviors in terms of statistical dependencies between the node values [**1**]. The researchers identified higher-order behavioral signatures that—unlike their pairwise counterparts—revealed the presence of higher-order mechanisms. Their findings open new ways for distinguishing between mechanisms and behaviors when studying complex systems [**2**]—a distinction that is crucial when approaching inference across network science, neuroscience, social sciences, and beyond.

The traditional approach to understanding complex systems, however, often blurs this distinction, treating behaviors as proxies for the underlying mechanisms. In neuroscience, for instance, researchers often criticize functional connectivity (statistical dependencies between brain regions) as an improper stand-in for actual neural pathways. This problem of treating behaviors as proxies for mechanisms has been described in terms of the famous logical fallacy of confusing the map with the territory [**3**].

The inference problem lies at the heart of this muddling: Researchers typically observe behaviors but not mechanisms. When they measure correlations or more sophisticated statistical dependencies, they're probing for potential underlying mechanisms following some hypotheses. However, the relationship between mechanisms and behaviors is complex and often nonintuitive. Multiple different mechanisms can produce identical behaviors, and simple mechanisms can generate complex behaviors (and vice versa). This many-to-many mapping presents a fundamental challenge for scientific inquiry.

Robiglio and colleagues addressed a part of this challenge by focusing on higher-order mechanisms in large networks, where nodes are connected through a set of interactions. As the interactions are higher-order ones, the mechanistic links are represented not by pairwise lines but by multiconnection polygons (called simplicial complexes). The researchers considered two representative networks: one that deals with magnetic spins (a higher-order Ising model) and another that tracks the spread of ideas (a so-called social contagion model). The team ran simulations for both cases and observed the patterns of statistical dependencies that emerged.

To analyze the results, Robiglio and colleagues used a measure based on the entropy of multivariate distributions, called dynamical O-information [**4**]. With this measure they could quantify the extent to which the observed patterns were due to higher-order mechanisms. This was particularly evident for statistical synergy—where information about a system of three variables can only be recovered by considering all elements together. An example of synergistic behavior is a frustrated spin system, a magnetic arrangement where competing interactions between neighboring spins make it impossible for all pairs to simultaneously achieve their preferred relative orientation.

The researchers showed that the synergistic signatures—identified through the dynamical O-information measure—could not be detected using traditional pairwise methods such as correlations and mutual information. Importantly, as the strength of higher-order mechanisms increased, so did the synergistic behavior, but in a complex, nonlinear relationship that varied between systems. This relationship provides new guidance in how to use higher-order statistical dependencies—such as the dynamical O-information—to study complex dynamical systems in the presence of higher-order mechanisms.

There's also a lesson here for the traditional approach that would try to extract the underlying mechanisms from the observed pairwise behaviors. Robiglio and colleagues showed that this strategy can lead to unexplained statistical dependencies, which are often called "spurious" correlations. Yet, if we truly embrace the study of behaviors on their own terms, recognizing the inherent limitations of our methods, then no behavior is truly spurious. The problem is not with the unexplained behaviors but with an insistence on reconstructing the complete set of interaction mechanisms—often an impossible task. In fact, accurate predictions can often be made without full knowledge of the mechanisms. For example, it has been shown that the collective dynamics in some interaction networks can be predicted even without knowing all the interactions [**5**]. Similarly, social triangles (a friend of a friend is my friend) can be explained with a simplified set of interactions [**6**]. Rather than trying to force a mechanical interpretation on a system, a better focus would be on identifying the behavioral signatures that constrain possible mechanisms.

It's crucial to emphasize, however, that mechanisms remain indispensable for predicting how a system will respond to a perturbation or to an intervention. For example, how birds flock in low visibility (foggy) conditions or how ideas spread as new forms of communication develop. While behaviors may be sufficient for prediction in some cases, understanding causal mechanisms—through the development of mechanism-based (generative) models—becomes essential when designing interventions or control strategies. This balance between studying behaviors for prediction and mechanisms for intervention represents a more nuanced approach than simply favoring one over the other.

This balanced approach connects closely with the statistical inference perspective, which assumes that the actual network structure is hidden and must be reconstructed from observables [**7**]. This perspective treats the inferred model as the crucial link between data and abstraction, allowing us to articulate prior knowledge and test hypotheses in a formal framework. By embracing the different levels of complexity—the often unobservable target properties, the observables and their dependencies, and the statistical inference model—we can more fully appreciate the dancing flocks that we encounter in our scientific forays.

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