a pair of Weyl points with opposite chirality will be linked in momentum space by an arc of surface states called a Fermi arc (Fig. 1c). So far, most studies of Weyl systems have focused on the measurement of the Fermi arc — a hallmark of Weyl fermions.

Huber and colleagues designed a 3D artificial magnetic field that is applied to an acoustic Weyl structure. When subjected to a magnetic field, Weyl fermions can exhibit chiral Landau levels (Fig. 1d): the zeroth-order Landau level is no longer flat, but has a linear dispersion determined by the chirality of the Weyl point and the direction of the magnetic field. These chiral Landau levels are another hallmark of Weyl fermions, but are extremely difficult to observe directly in condensed-matter systems.

In Huber and colleagues' experiment, the artificial magnetic field was constructed by engineering the unit cell of a previously designed acoustic Weyl structure such that the Weyl points were moved along a specific direction in momentum space[4]. Sound waves propagating parallel to the artificial magnetic field have a unidirectional behaviour, possessing either a positive or negative group velocity depending on the chirality of the Weyl points. Moreover, by applying a Fourier transform to the measured acoustic field, the dispersions of the chiral Landau levels were measured directly.

It is interesting that Landau levels are now audible, but limitations still exist. For example, loss is ubiquitous in acoustic systems. This issue is more severe in Huber and colleagues' experiment as it involves acoustic bulk transport in a 3D structure. Also, both experiments only work for low-frequency sound and it is currently unclear how to push the frequency into the ultrasound and even hypersound regimes. Nevertheless, these experiments have opened avenues for future exploration. The acoustic Landau levels possessing a high density of states provide the possibility of enhancing sound emission and nonlinear wave mixing, which may further lead to novel acoustic lasers. It is also exciting that many theoretically predicted phenomena, such as the chiral magnetic effect and the chiral vortical effect, are now possible with acoustic waves.

By sharing the Landau levels for electrons, light and now sound, one can envision more complex functionalities being engineered on a single chip. Indeed, in modern optomechanical circuits, acoustic waves are used to bridge the gap between electronics (the acoustic frequency can match the working frequency of a central processing unit (CPU) and wireless communication) and photonics (the acoustic wavelength can be comparable to that of light). In the future, with the help of acoustic Landau levels, we may see a chip integrating the electronic states of the quantum Hall effect and the photonic states of topological lasers. ❐

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Published online: 5 March 2019
https://doi.org/10.1038/s41567-019-0479-7

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NETWORK SCIENCE

Propagation patterns unravelled

From disease proliferation to cell functioning, spreading dynamics on networks impact many collective phenomena. The joint contributions of the interaction structure and local dynamics have now been disentangled, revealing three distinct types of spreading pattern.

Marc Timme and Jan Nagler

In a cell, changes in the abundance of one protein generate transient alterations of activity patterns throughout its biochemical reaction network. Analogously, following a local outbreak, infectious diseases may spread to distant places as a result of human travel. In these distributed networked systems, a change that has occurred earlier at a given location affects other units — here, the abundance of one cellular component or a local human population — only after an induced signal has propagated across the network. The joint time evolution of the signals at all units yields a variety of complex spatiotemporal patterns. Yet, key collective properties of these modes of transient dynamics remain unknown. Now, writing in *Nature Physics*, Chittaranjan Hens and co-workers have revealed how the intrinsic dynamics of the units and of their interactions, as well as the topology of the interaction network, all participate in giving rise to qualitatively different types of spatiotemporal network pattern in response to localized changes[1]. In the future, such insights might help to predict, contain or enhance signals spreading in networked dynamical systems.

Transient collective dynamics induced by local changes play a key role in a broad range of complex systems. The timing and strength of a received spreading signal are of particular importance. For instance, spatiotemporal patterns of spreading signals may determine the mode of operation of subcellular dynamics, lead to congested or free-flowing vehicle traffic, govern how diseases spread and whether power grids exhibit cascades of infrastructure outages. Understanding transient dynamics of networks also constitutes a topical mathematical problem, mainly because of the absence of any systematic theory for network transients from the perspective of dynamical systems.

Hens et al. combined numerical and mathematical analyses of a range of model dynamics and network topologies to reveal

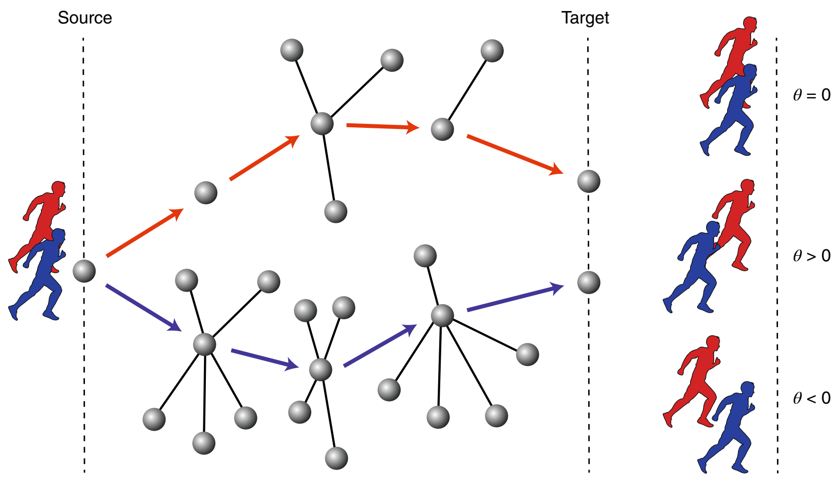

Fig. 1 | Different types of transient signal propagation. Two signals (represented by the red and blue runners) propagate on a network from a common source to their individual targets. If the network response dynamics is distance-driven ($\theta = 0$), the signals will arrive simultaneously because they travel the same distance (top). For degree-driven dynamics (middle), due to the slowly responding hubs along the blue path, the blue signal will be delayed ($\theta > 0$). For composite dynamics (bottom), the red signal may be delayed ($\theta < 0$).

that many networked systems propagate transient signals in one of only few modes. These modes were found to emerge from a delicate interplay between the influences of the nonlinear dynamics of (and among) the units, and the topology of their interactions. For example, some combinations of dynamics and topologies yield what the authors call distance-driven propagation, others yield degree-driven propagation (Fig. 1).

For distance-driven propagation, the arrival time at one unit of a signal originating from another is largely determined by the length of the path covered by the signal. In particular, a unit's degree — the number of its neighbours — as well as global properties of the topology hardly influence the pattern of signal arrival times in the network.

In contrast, for degree-driven propagation, the type of topology of the network dramatically influences the distribution of arrival times. They are all of the same order of magnitude in entirely random (Erdős–Rényi) networks, whereas for networks with broad degree distributions (that is, a large range in the number of neighbours of each unit), arrival times vary over several orders of magnitude. Intriguingly, signals may even arrive earlier at units that are more distant from the source — if distance is measured in terms of the number of intermediate units visited on the network.

The analysis by Hens et al. paves the way towards estimating an effective, temporal distance measure between any two units by linking the scaling behaviour across the fastest shortest path between them to properties of local dynamics for a given model. Compared with effective distance measures often considered in previous works, the authors' measure for temporal distance more closely integrates both topological and dynamical properties of a networked system.

The work of Hens et al. naturally complements recent progress on the analysis of spreading patterns in networks. For instance, one study heuristically defined an effective distance indicator to reveal the origin of globally spreading contagion processes[2]. Recently, a systematic approximation scheme[3] consolidated such heuristics for a class of stochastic spreading processes. Also, experimental data from electric grids were analysed to understand how frequency fluctuations caused by wind power feed-in propagate through a network[4].

At the same time, the purely deterministic spreading governed by ordinary differential equations, the case studied by Hens et al., is not fully understood even in the simplest linear setting. Recent analytical work[5] proposed a complementary perspective, where normalized deterministic state trajectories are analysed as if they were probability distributions. Considering the effective expectation values of these distributions at individual units yields a signal's travel time and intensity as an explicit function of the global interaction structure and local dynamics.

The work of Hens et al. advances our understanding by providing a framework for classifying signal propagation patterns into characteristic types based on the combinations of network topologies and local dynamics. It also provides mechanistic insights that may help to predict these patterns. Yet many questions remain unanswered. Hens et al. considered propagating patterns induced by 'frozen' local changes of the state variable of one unit. Other works[2–5] equally have focused on one specific class of settings. However, the fundamental theoretical challenge of fully grasping transient spreading in real-world systems requires consideration of the combinations of deterministic and stochastic dynamics, as well as systems where local changes are themselves time-dependent and distributed.

Additionally, even for a given single observable, it still remains unclear how to identify the features of real-world spreading data with the highest predictive power. Techniques from machine learning may be helpful, but keeping track of the choice of the observables is at least equally important. This requires mathematical predictions to be framed according to the conditions under which the natural and artificial networks around us reveal themselves.

There is much work ahead to fill these gaps. It will require the bridging of different disciplines through collaborations with researchers with complementary expertise. It's time to spread the news to our colleagues. ❐

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Published online: 28 January 2019
https://doi.org/10.1038/s41567-019-0424-9

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