Decoupled states, hypergraphs, and Dragon Kings Ground state











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Structure and function of interdependent networks



Each network is a complex system with emergent behaviors

Behaviors not predicted a priori from the constituent equations of motion.



pattern formation.

Phase transitions "Tipping points"

Where is the complexity?

Statistical

Physics

In the network structure?

In the nodal dynamics?

In both!



Node complexity

Control theory and non-linear dynamics

Today's topics:

Decoupled synchronized states

- Interplay of nodal dynamics and network structure
- **Cluster synchronization on hypergraphs**
 - Systems with higher-order coupling, beyond dyadic
 - The projection onto dyadic matrices is sufficient for analyzing full synchronization, but not cluster synchronization.
 - Formulation in terms of node- and edge-clusters.

Cascading dynamics on oscillator networks

• The BTW sandpile model meets Kuramoto

Decoupled states: Phase-amplitude oscillators

Ground state

Nanoelectro θ membrane, with a "Duffing"-like non-linearity







Described by slow-time envelope dynamics Ai(t)





Experimental collaboration with Micheal Roukes and Matt Matheny at Caltech

ARO MURI No. W911NF-13-1-0340



8-node of ring NEMs oscillators



Decoupled NN with emergent NNN order

Interplay of nodal dynamics and coupling structure lead to decoupled states on ring of N=4m, $m \in \mathbb{Z}$.



Average |A_i|=1

Emergent couplings of higher order



Physical connection NN Kuramoto-Sakaguchi coupling Biharmonic phase coupling NNN Kuramoto-Sakaguchi coupling Triadic phase coupling

Matheny et al., "Exotic states in a simple network of nanoelectromechanical oscillators", *Science*, 363, March 8, 2019.

Linear stability calculations

Symmetry subgroups of nodal dynamics and coupling structure constrain the Jacobian:



Ring of $4m, m \in \mathbb{Z}$



$$D_{k} = \frac{1}{2} \begin{bmatrix} -1 & -\beta(1-\zeta^{-k})\sin\psi & 0 & \beta(1-\zeta^{-k})\cos\psi \\ \beta(1-\zeta^{k})\sin\psi & -1 & \beta(1-\zeta^{k})\cos\psi & 0 \\ 4\alpha & -\beta(1-\zeta^{-k})\cos\psi & 0 & -\beta(1-\zeta^{-k})\sin\psi \\ -\beta(1-\zeta^{k})\cos\psi & 4\alpha & \beta(1-\zeta^{k})\sin\psi & 0 \end{bmatrix}$$

- Unstable for phase-only oscillators.
- Stable for phase-amplitude oscillators.
- Although average $|A_i| = 1$, fluctuations are necessary to stabilize the system!

Emenheiser, et al., arXiv:2010.09131

Admissibility and stability of decoupled states in general

PHYSICAL REVIEW RESEARCH 2, 043261 (2020)

Decoupled synchronized states in networks of linearly coupled limit cycle oscillators

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(Received 26 June 2020; accepted 27 October 2020; published 19 November 2020)





Hypergraphs – beyond dyadic coupling



 Hypergraph coupling: Hyperedges representing higher-order interactions (dyadic, triadic, etc.)

Challenge: Hyperedges of all order contribute to the dynamics and the stability calculations.

Example higher-order interactions:

- Chemical reactions
- Co-authorship networks

Cluster synchronization on hypergraphs

Anastasiya Salova, R.D., arXiv:2101.05464

Anastasiya Salova, R.D., arXiv:2107.13712



Cluster synchronization:

Nodes can be divided up into distinct groups where the dynamical trajectories within a group are identical, but distinct from all the other groups.

2 cluster state

The hypergraph may support multiple states



- How do we find the admissible clusters?
- How do we calculate their stability properties?

Hypergraph: Incidence matrices of all orders



Incidence matrices

$$[I^{(m)}]_{i,e} = 1$$
 if $e \in \mathcal{E}_i^{(m)}$

(Can equivalently formulate in terms of adjacency tensors A^(m)) e.g., Battiston et al., *Phys. Reports* 2020.

Node evolution:

$$\dot{x}_i = F(x_i) + \sum_{m=2}^d \sigma^{(m)} \sum_{e \in \mathcal{E}^{(m)}} [I^{(m)}]_{i,e} G^{(m)}(x_i, x_{e \setminus i})$$

Dyadic projection of the hypergraph

Projecting the interactions for each order *m* onto a dyadic adjacency matrix

$$\mathcal{A}^{(m)} = I^{(m)} [I^{(m)}]^T - \mathcal{D}^{(m)}$$

where $[\mathcal{D}^{(m)}]_{ii} = \sum_j I^{(m)}_{ij}$

Useful in analyzing the admissibility and stability of full synchronization:

- Gambuzza, et al., *Nature Communications* 12(1), 2021.
- Lucas, et al., Phys. Rev. Research 2:033410, 2020.
- Carletti, et al., J of Phys: Complexity 1(3):035006, 2020.
- Ferraz de Arruda et al., *Communications Physics*, 4(1), 2021.

But not sufficient for more complex dynamics like cluster synchronization on general hypergraphs:

The projection is not always unique

Two non-isomorphic hypergraphs (with only triadic interactions)



Distinct dynamical processes:

Same projection, $\mathcal{A}^{(3)}$





Symmetries of the projection versus the hypergraph

Structural symmetries of the system (orbital partitions) let us determine many of the admissible states.

Not all the symmetries of the projection (b) are symmetries of the original hypergraph (a)



The solution – organize by edge clusters



For *K*-cluster state

Node clusters: C_1 to C_K Node cluster trajectories: s_1 to s_K



For each order m there are K_m different edge clusters

Edge clusters: $C_1^{(m)}$ to $C_{Km}^{(m)}$ for each order m Edge cluster trajectories:

$$s_{C_1^{(m)}}, s_{C_2^{(m)}}, \dots, s_{C_{K_m}^{(m)}}$$

Admissible patterns of cluster synchronization

Equitable partitions of node and edge clusters:

The partition is equitable if each node in a given node cluster gets the same input from each edge cluster over all edge orders





External equitable partitions if Laplacianlike coupling

Stability calculations

Instead of defining one single projection A^(m) for each order m, define a projected adjacency matrix **for each** edge cluster of order m>2

$$\mathcal{A}_k^{(m)} = I_k^{(m)} [I_k^{(m)}]^T - \mathcal{D}_k^{(m)}$$

k denotes the k-th, m-th order edge cluster





Stability calculations

Jacobian organized by edge-clusters and their trajectories

$$\delta \dot{x} = \left(\sum_{k=1}^{K} E_k \otimes JF(s_k) - \sum_{m=2}^{d} \sigma^{(m)} \cdot \left[\sum_{k=1}^{K_m} \sum_{l \in \{C_k^{(m)}\}} \sum_{p \in \{C_k^{(m)} \setminus l\}} E_l \mathcal{A}_k^{(m)} E_p \otimes JG^{(m)}(s_l, s_p, s_{C_k^{(m)} \setminus l, p}) + \sum_{k=1}^{K_m} \sum_{l \in \{C_k^{(m)}\}} E_l \mathcal{D}_k^{(m)} \otimes JG^{(m)}(s_l, s_{C_k^{(m)} \setminus l})\right] \right) \delta x.$$

 E_j – cluster indicator matrix for which nodes are in node cluster j.

All node clusters (first term) and all edge clusters of all orders (second term) contribute to linear stability calculation.

Stability calculations, cont

Simultaneously block-diagonalizing this set of matrices block-diagonalizes the Jacobian.

$$\{E_1, ..., E_K, \mathcal{A}^{(2)}, \mathcal{A}^{(3)}_1, ..., \mathcal{A}^{(3)}_{K_3}, ..., \mathcal{A}^{(d)}_1, ..., \mathcal{A}^{(d)}_{K_d}\}$$



Example: Layered hypergraph (multiple edge types)



Anastasiya Salova, R.D., arXiv:2101.05464

Anastasiya Salova, R.D., arXiv:2107.13712

https://github.com/asalova/hypergraph-cluster-sync

Oscillator networks exhibit cascading failures



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BTW sandpile model used to model power grid and brain networks

Self-organized criticality

Bak-Tang-Wiesenfeld PRL 1987: self-organized criticality

Sandpile model on networks

- Start with a network
- Drop <u>units of load</u> () randomly on nodes
- Each node has a threshold. Here = degree.
- Load on a node ≥ threshold
 ⇒ node topples, moves load to neighbors



Sandpile models on networks

- Start with a network
- Drop <u>units of load</u>) randomly on nodes
- Each node has a threshold. Here = degree.
- Load on a node ≥ threshold
 ⇒ node topples, moves load to neighbors
- Neighbors may topple. Etc.
 Cascade (or avalanche) of topplings.



Power-law distribution of avalanche sizes, $P(s) \sim s^{-3/2}$

Self-organized criticality

Power law tails (Universal behavior)

Extreme events often referred to as "Black Swans"

This scaling behavior is robust on networks. (Goh et al. PRL 03, Phys. A 2004/2005, PRE 2005. PLRGs with $2 < \gamma < 3$ not mean-field.)

Power law tails seem to characterize the sizes of electrical blackouts, financial fluctuations, neuronal avalanches, earthquakes, landslides, overspill in water reservoirs, forest fires and solar flares.

- [1] I. Dobson, B. A. Carreras, V. E. Lynch, and D. E. Newman, Chaos 17, 026103 (2007).
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- [13] P. Bak, C. Tang, and K. Wiesenfeld, Phys. Rev. Lett. 59, 381 (1987).

SOC in power grids and the brain?



Image © extremetech



Image © Forbes

But this neglects the oscillatory nature of the nodes!

Sandpile cascades on oscillator networks: the BTW model meets Kuramoto

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arXiv:2112.00104

Initial goal: Leverage interaction to maximize synchronization and minimize large cascades.



Guram Mikaberidze

Oscillator dynamics: The Kuramoto model



Coupled BTW-KM dynamics. Each node has:

- Phase ϕ_i (KM)
- Capacity c_i (BTW)
- Load s_i (BTW)

Coupled BTW-KM

BTW sandpile ⇒ Kuramoto

Kuramoto ⇒ BTW sandpile



BTW -> KM

• If a node topples during a cascade its phase is reset at random at the end of the cascade.

KM -> BTW

- Assume a node out-of-sync with its neighbors is more vulnerable so lower its capacity to hold load.
 - This creates *endogenous* cascade seeds.

Explicit dynamical rules

Rules of the model

1. **KM:** KM runs for time interval ΔT :

$$\dot{\phi}_i(t) = \omega + k \sum_{j \in \mathcal{N}_i} \sin(\phi_j(t) - \phi_i(t))$$

2. **KM** \rightarrow **BTW:** Update SP capacities:

$$c_i = c^0 - \alpha (l - r_i)$$

- 3. BTW: Add unit load to SP and cascade
- 4. BTW→KM: Randomize phases of toppled nodes
 - Infinite separation of time scales: cascades are infinitely faster
 - Uniform oscillator frequencies (for now)

Emergent periodic oscillations

3-regular random graphs

- *r(t)* is the Kuramoto order parameter
- S is the total load on the system



Emergent 3-phase oscillations



Cascade size distribution in each of the three phases



Self-amplifying cascades kick off a DK

At the tipping point, a large cascade desynchronizes many nodes, causing an even larger cascade at the next step.



Exponential growth in subsequent size: "cascade of cascades"



Beyond "Black Swans" -> Dragon Kings



Poorly understood, massive events caused by nonlinear amplifying mechanisms. (Introduced by D. Sornette, 2009.)

Dragon Kings

- Bubbles in financial markets; sizes of cities; failures in engineered systems & nuclear accidents, etc.
- Self-amplifying mechanism, endogenous nature
- Far more likely than Black Swans and equally massive
- Theory in its infancy:
 - Conjecture: needs
 homogeneous elements with
 large coupling
- Dragon kings have predictability



Analytic calculations



$$(S_{\mathrm{TP}}, r_{\mathrm{TP}}) = \left(\frac{\lfloor c^0 - \alpha(l-1) \rfloor N d}{2(d-1)}, 1\right)$$

(1) The location of the tipping point



Next steps 1: Different coupling from BTW to Kuramoto

Let oscillator frequency depend inversely on load – more load spins slower

Natural frequency varies with load (motivation: power grid with inertia)

- 1. **KM:** KM runs for time period ΔT : $\dot{\phi}_i(t) = \omega_i + k \sum_{j \in \mathcal{N}_i} \sin(\phi_j(t) - \phi_i(t))$
- 2. **KM**→**BTW:** Update SP capacities:

$$c_i = c_i^0 - \alpha(l - r_{(i)})$$

- 3. **BTW:** Add unit load to SP and cascade.
- **4. BTW**→**KM**: Update KM intrinsic frequencies:

$$\omega_i = \omega_i^0 + \beta s_i$$



Next steps 1: Different coupling from BTW to Kuramoto

- Local sync drives capacities higher
- Higher capacity which causes higher dispersion in frequencies
- Frequency dispersion destabilizes the synchrony.



Next steps 2: Theory of Dragon Kings

Dragon Kings as an absorbing-state phase transition. Slow driving and small dissipation cause self-organized DK cycles.



Self-organization around a (a) 1st order and a (b) second order phase transition.



More opportunities?

- Complex co-evolving networks:
 - New phenomena & emergent timescales
 - Long-time oscillations opportunity to self-organize (e.g., betawaves in neuronal networks, correlations among generators in the power grid).
 - Modeling layered networks with inhibitory and excitatory layers (e.g., the visual cortex)

• Distributed control:

- How are existing sandpile control schemes disrupted by the oscillatory degree of freedom?
- Interventions to nodal frequencies for sandpile control (e.g., explosive sync reveals interplay of nodal frequency distribution and network topology).

Conclusions/Opportunities

Interplay of nodal dynamics and network structure

• Decoupled synchronized states

Hypergraph dynamics:

- Higher order interactions
- Organizing by edge clusters organizes calculations and simplifies stability calculations.

Cascades on oscillator networks

• Coupling the oscillatory and cascading dynamics leads to new emergent behaviors and emergent timescales.