Latent Geometry Driven Network Automata for Complex Network Dismantling

Thomas Adler, Marco Grassia, Ziheng Liao,
Giuseppe Mangioni, Carlo V. Cannistraci

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Department of
Electrical electronic and computer engineering

Tsinghua University

CCNI
Center for Complex Network Intelligence
复杂网络智能中心

What do these events have in common?

METRO

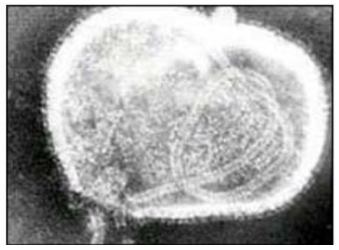
Ryanair warns 100,000 passengers will have flights cancelled next week: 'Needless disruption'

FRANCE 24

Court jails leaders of Belgian Islamic State group terrorist cell

Alert over Hong Kong 'super-flu'

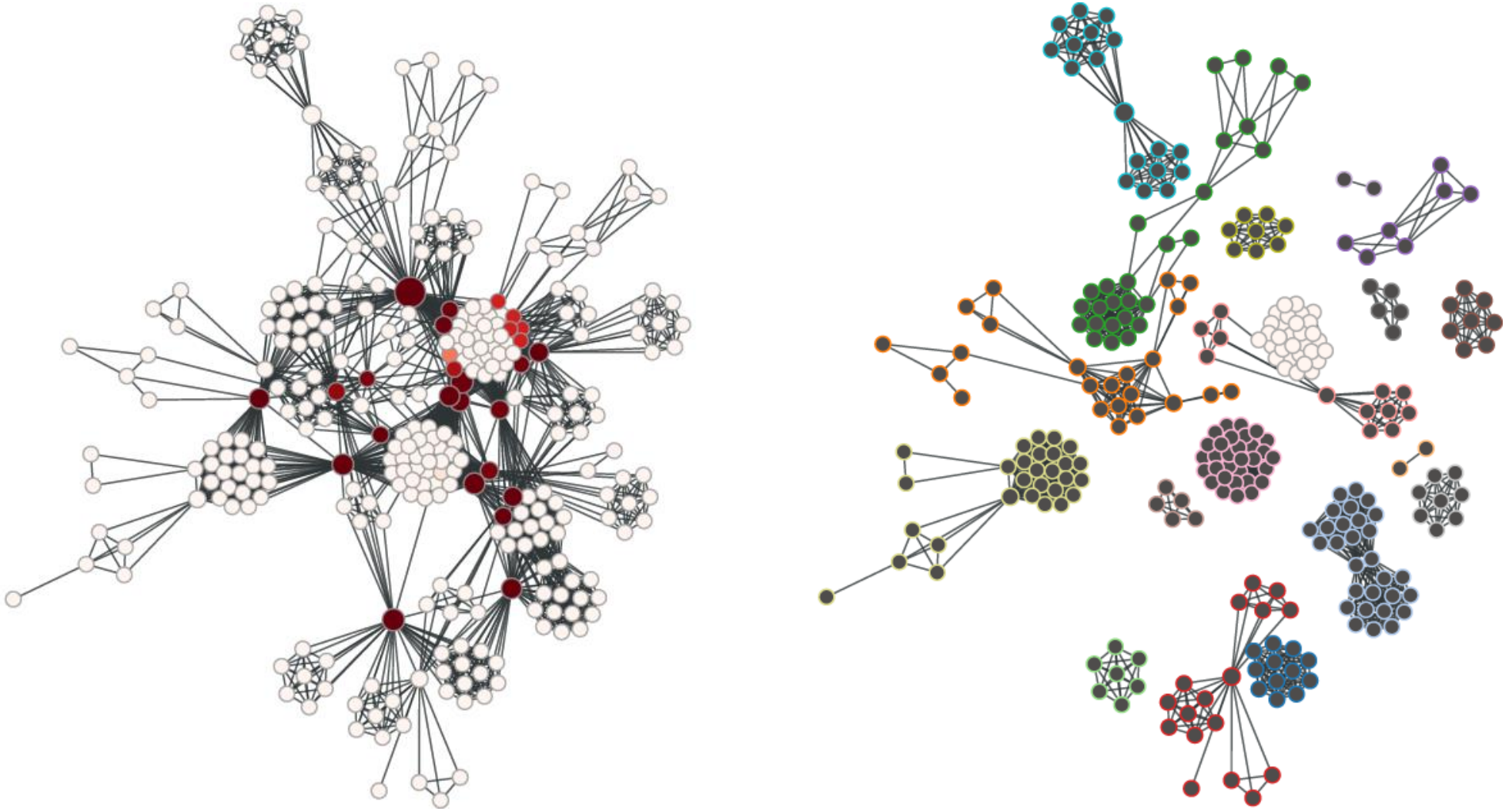
BBC NEWS



What do these events have in common?

- **Networks**
- **Disruptions**
- **Loss of functionality**
- **Network was “attacked” → Network Dismantling**

What is network dismantling?



Grassia, M., De Domenico, M. & Mangioni, G. Machine learning dismantling and early-warning signals of disintegration in complex systems. Nat Commun 12, 5190 (2021).

Why would we want to dismantle a network?

“Knowing others is intelligence; knowing yourself is true wisdom”

老子-Lao Zi

Why would we want to dismantle a network?

- Improve the robustness of your own network

- Not all networks are desirable (epidemic, criminal)

Challenges of efficient dismantling

- NP-hard problem – no known algorithm can efficiently dismantle very large networks
- Large solution space (2^N)
- Non-linear dependencies
- Structural complexity of real-world networks

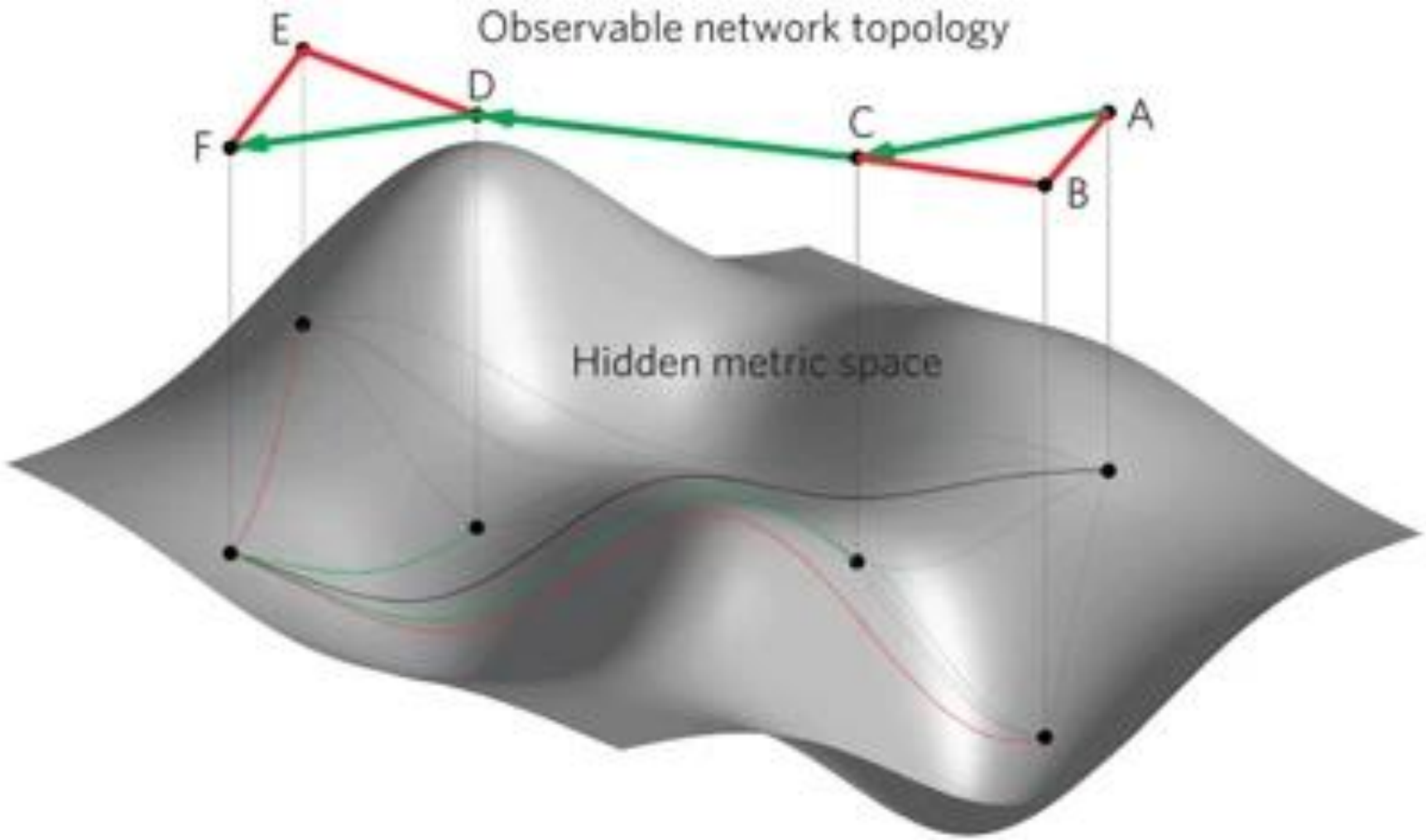
Previous dismantling methods are not ideal…

- Global centrality measures
- Machine Learning based
- Inefficient for very large networks

…but most importantly…

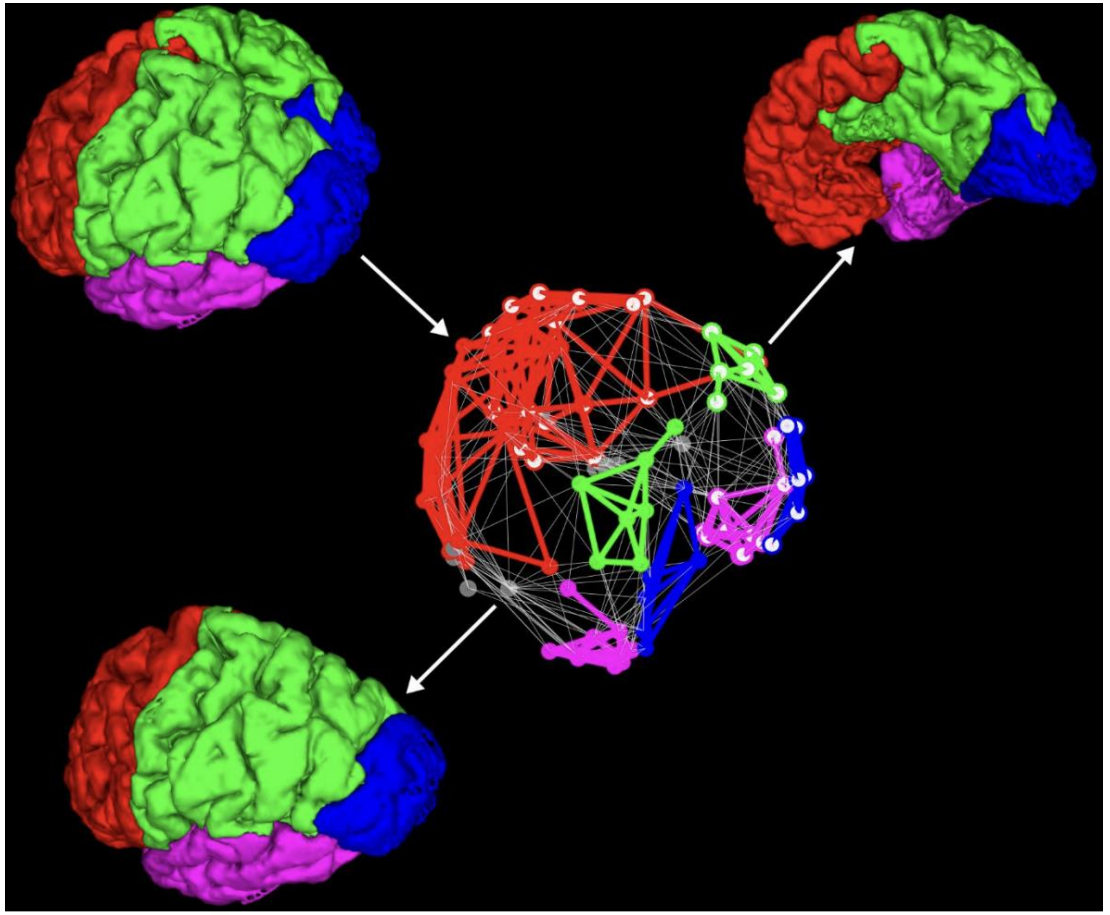
They only use the topology, not the (**latent**) **geometry** of the network!

What is the latent geometry?



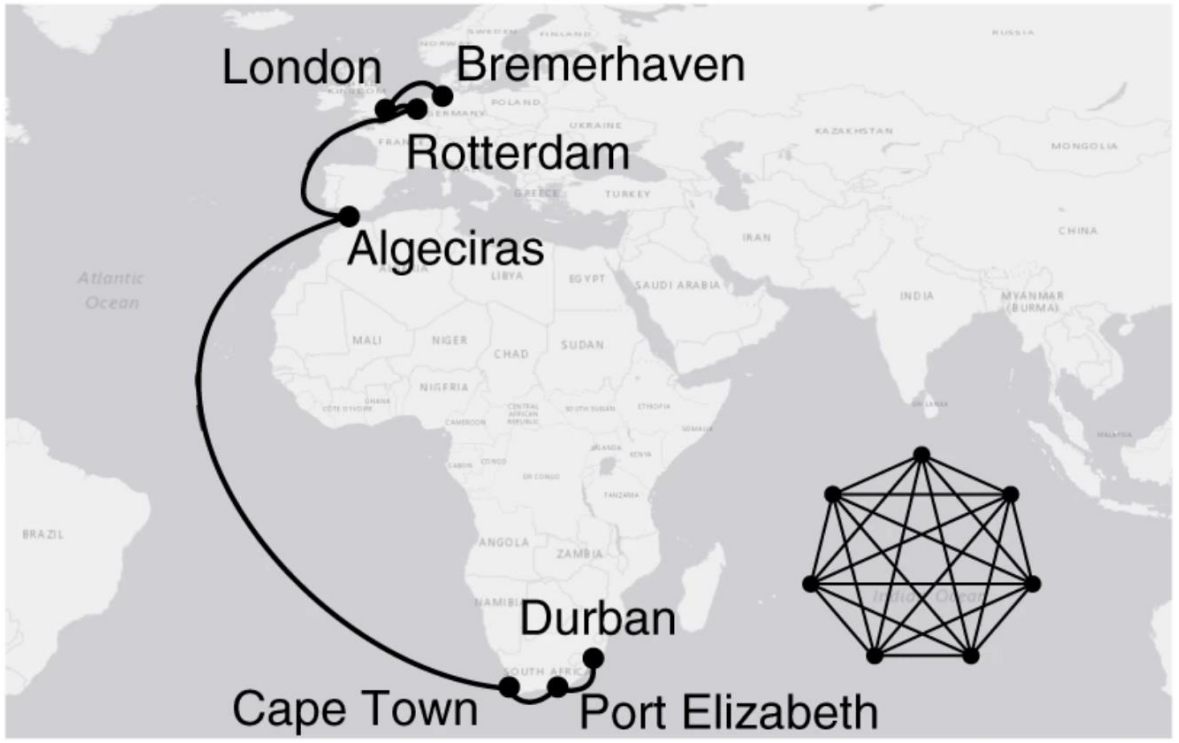
*Boguñá, M., Krioukov, D. & Claffy, K. Navigability of complex networks. Nature Phys **5**, 74–80 (2009).*

Complex networks have a latent geometry, including the brain…



Cacciola, A., Muscoloni, A., Narula, V., Calamuneri, A., Nigro, S., Mayer, E. A., ... & Cannistraci, C. V. (2017). Coalescent embedding in the hyperbolic space unsupervisedly discloses the hidden geometry of the brain.

…and the global shipping network…



Xu, M., Pan, Q., Muscoloni, A. et al. Modular gateway-ness connectivity and structural core organization in maritime network science. Nat Commun 11, 2849 (2020).

...and can explain efficient navigation...

Article | Published: 16 November 2008

Navigability of complex networks

Marián Boguñá, Dmitri Krioukov & K. C. Claffy

Nature Physics **5**, 74–80 (2009) | Cite this article

Hyperbolic geometry of complex networks

Dmitri Krioukov[1], Fragkiskos Papadopoulos[2], Maksim Kitsak[1], Amin Vahdat[3], and Marián Boguñá[4]

Show more

Phys. Rev. E **82**, 036106 – **Published 9 September, 2010**

LETTER | NEUROSCIENCE |

Navigability evaluation of complex networks by greedy routing efficiency

Alessandro Muscoloni and Carlo Vittorio Cannistraci Authors Info & Affiliations

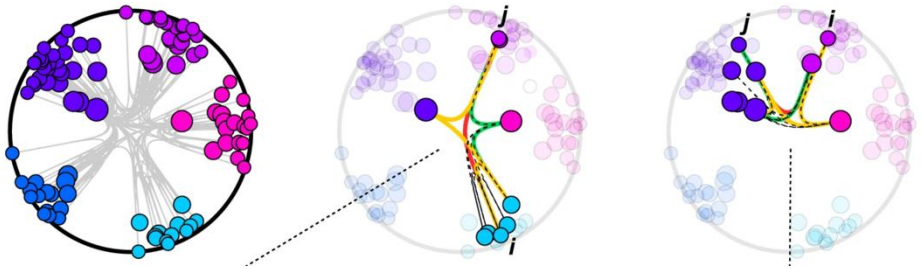
January 10, 2019 | 116 (5) 1468-1469 | https://doi.org/10.1073/pnas.1817880116

Brief Communication | Published: 24 August 2000

Navigation in a small world

Jon M. Kleinberg

Nature **406**, 845 (2000) | Cite this article



Cannistraci, C.V., Muscoloni, A. Geometrical congruence, greedy navigability and myopic transfer in complex networks and brain connectomes. Nat Commun 13, 7308 (2022).

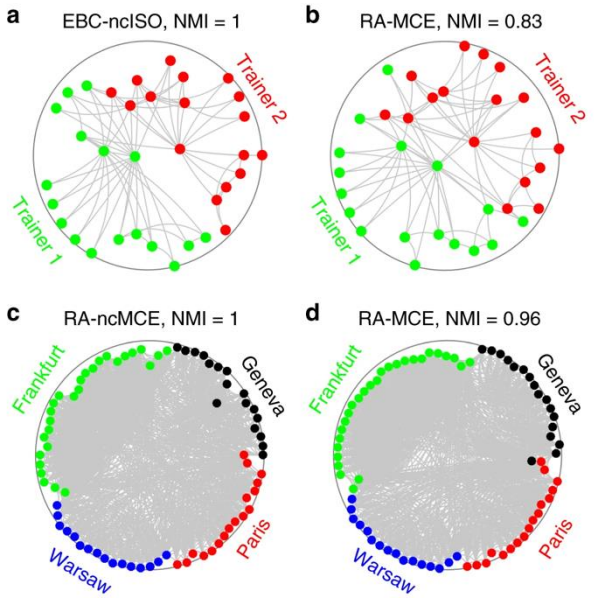
...community detection...

Article | Open access | Published: 29 April 2015

Emergence of Soft Communities from Geometric Preferential Attachment

Konstantin Zuev, Marián Boguñá, Ginestra Bianconi & Dmitri Krioukov

Scientific Reports **5**, Article number: 9421 (2015) | Cite this article



PAPER • OPEN ACCESS

Leveraging the nonuniform PSO network model as a benchmark for performance evaluation in community detection and link prediction

Muscoloni Alessandro and Cannistraci Carlo Vittorio

Published 15 June 2018 • © 2018 The Author(s). Published by IOP Publishing Ltd on behalf of Deutsche Physikalische Gesellschaft

New Journal of Physics, Volume 20, June 2018

Article | Open access | Published: 20 November 2017

Machine learning meets complex networks via coalescent embedding in the hyperbolic space

Alessandro Muscoloni, Josephine Maria Thomas, Sara Ciucci, Ginestra Bianconi & Carlo Vittorio Cannistraci ✉

Nature Communications **8**, Article number: 1615 (2017) | Cite this article

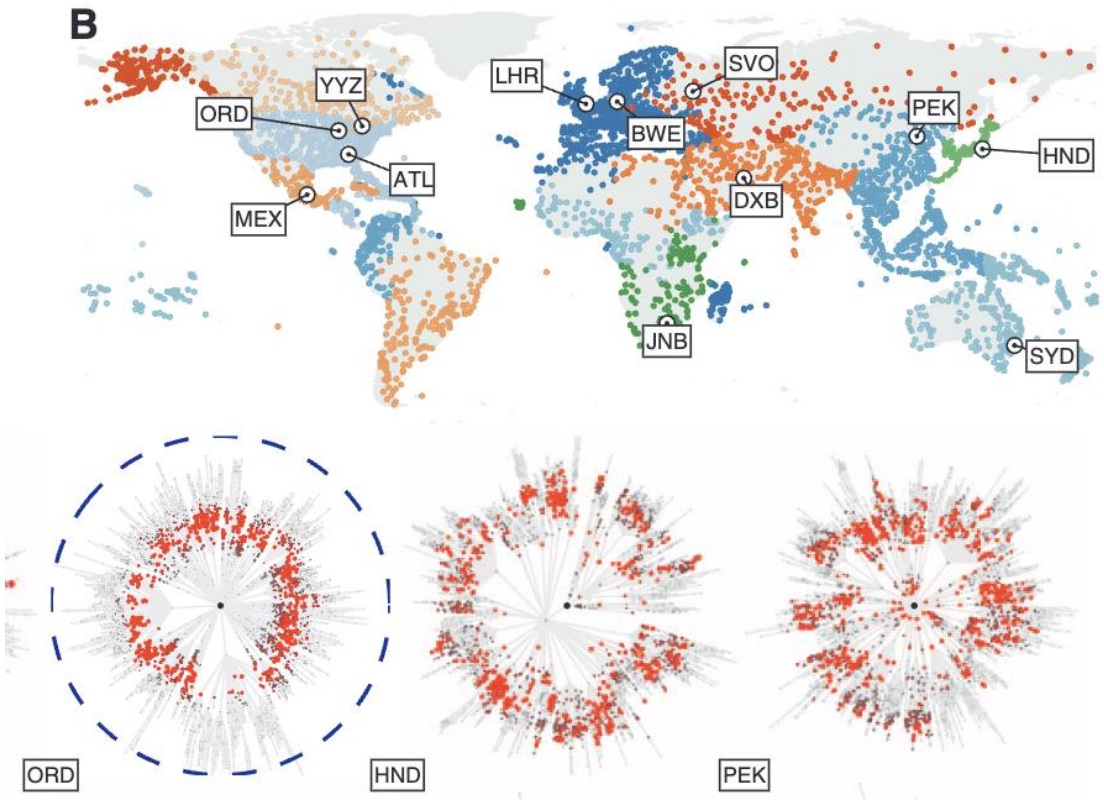
*Muscoloni, A., Thomas, J.M., Ciucci, S. et al. Machine learning meets complex networks via coalescent embedding in the hyperbolic space. Nat Commun **8**, 1615 (2017).*

...and even contagion spread

The Hidden Geometry of Complex, Network-Driven Contagion Phenomena

DIRK BROCKMANN AND DIRK HELBING Authors Info & Affiliations

SCIENCE • 13 Dec 2013 • Vol 342, Issue 6164 • pp. 1337-1342 • DOI: 10.1126/science.1245200



Dirk Brockmann, Dirk Helbing ,The Hidden Geometry of Complex, Network-Driven Contagion Phenomena.Science342,1337-1342(2013).

Isn’t the latent geometry…well…**hidden**?

Yes…but there are ways to estimate it

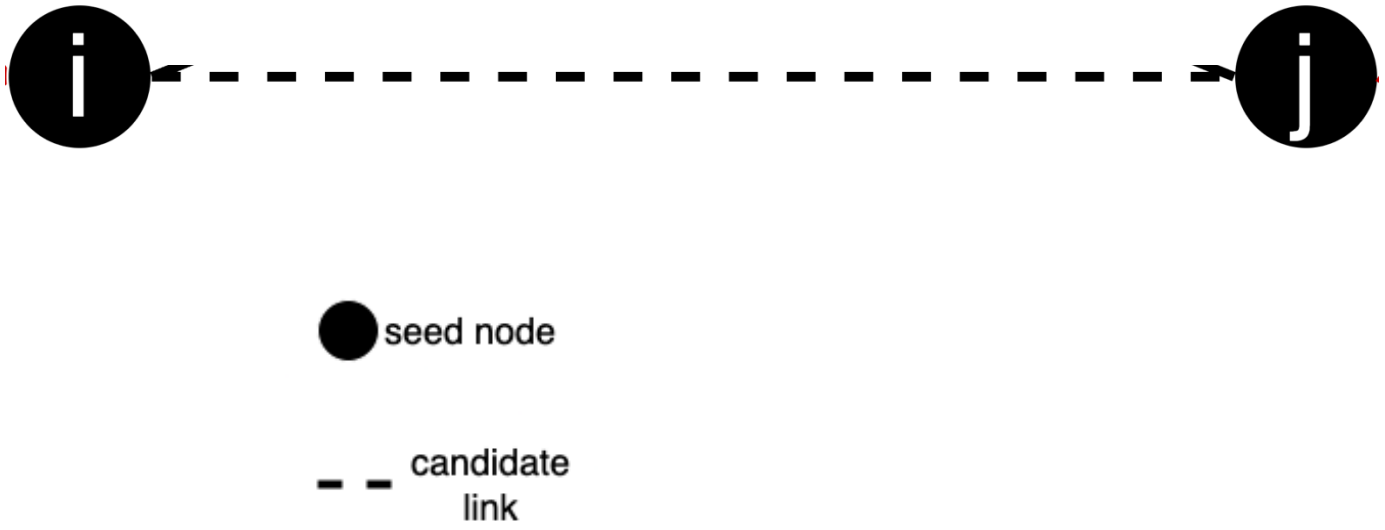
…with the Repulsion Attraction rule 2 (**RA2**)

- Estimate the **distance** between two linked nodes in a hidden metric space, representing a latent geometry
- **Network automata** because it uses local information
- Successful at network embedding and community detection

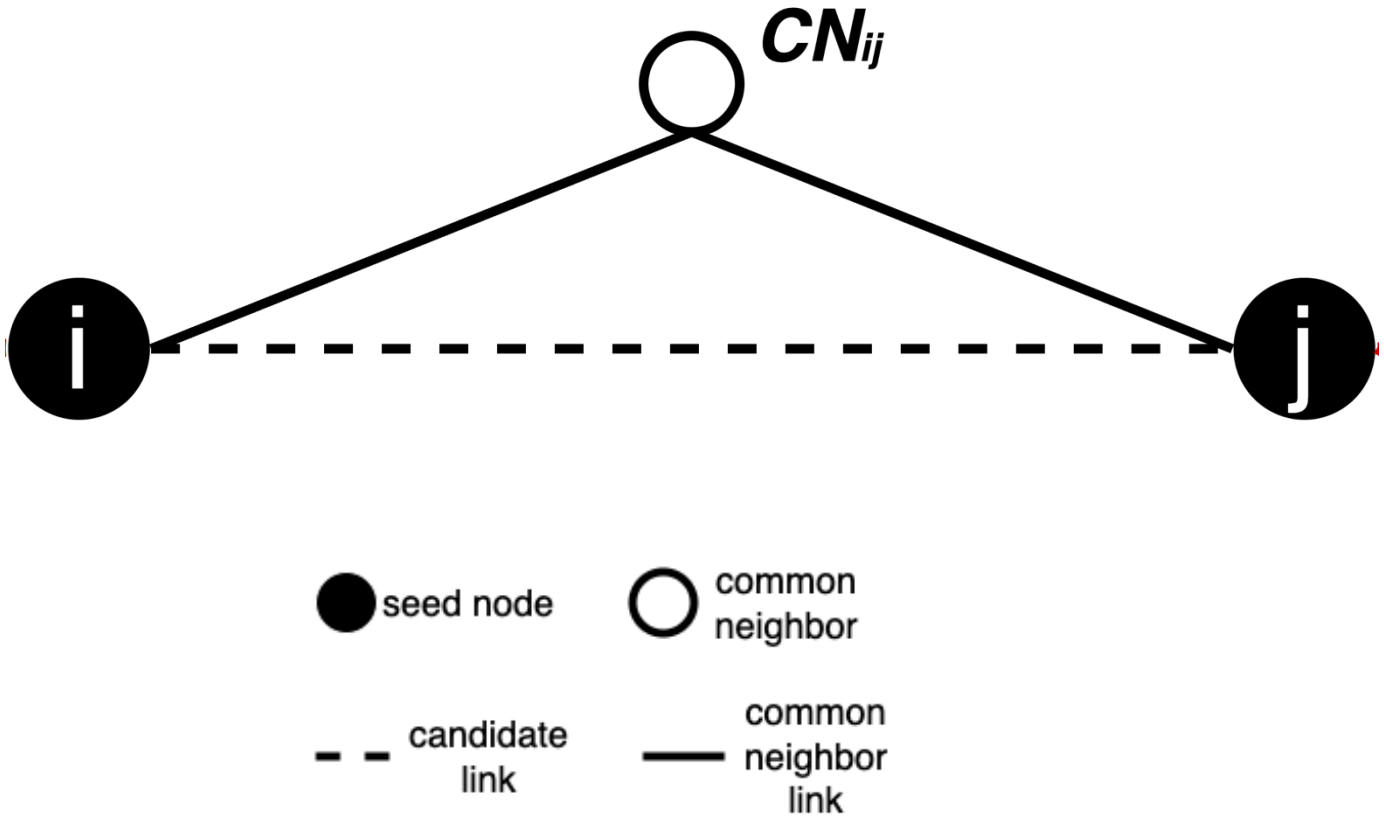
→ network dismantling?

*Muscoloni, A., Thomas, J.M., Ciucci, S. et al. Machine learning meets complex networks via coalescent embedding in the hyperbolic space. Nat Commun **8**, 1615 (2017).*

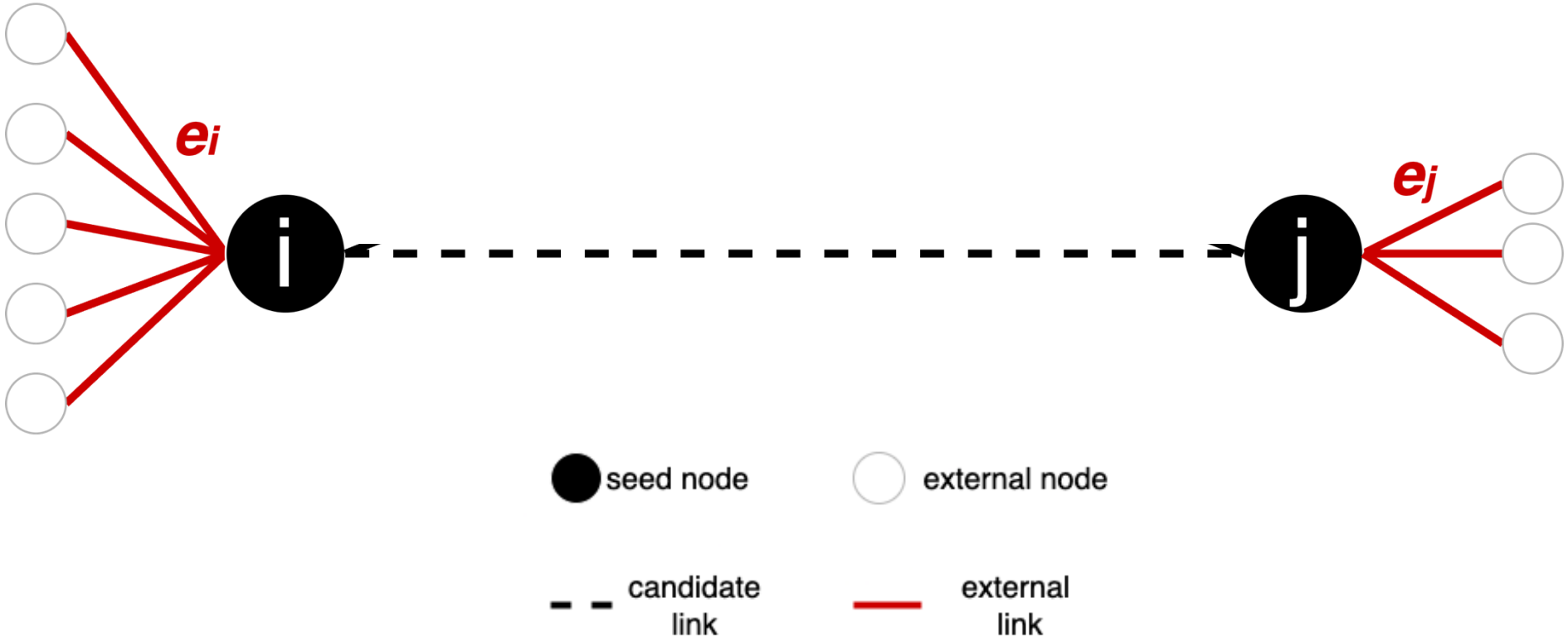
Goal: Assign a weight to an edge→ distance



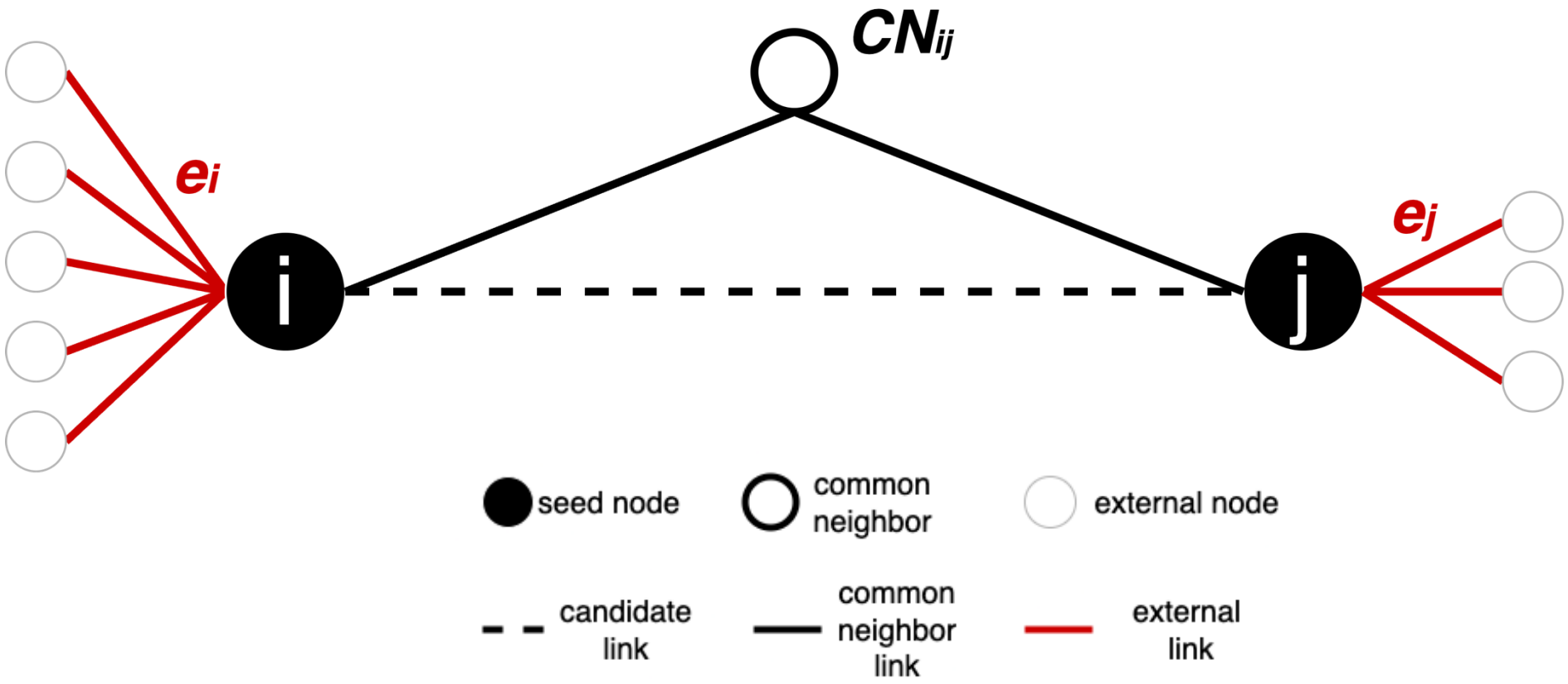
Common Neighbors: **Attraction**



External Links: **Repulsion**

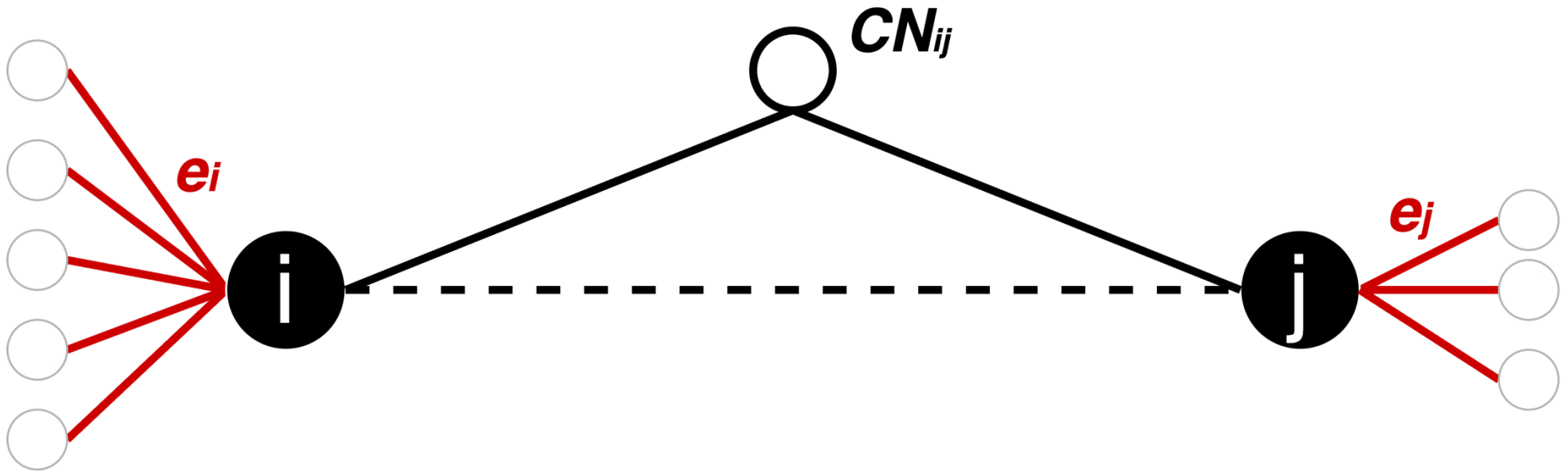


Repulsion Attraction



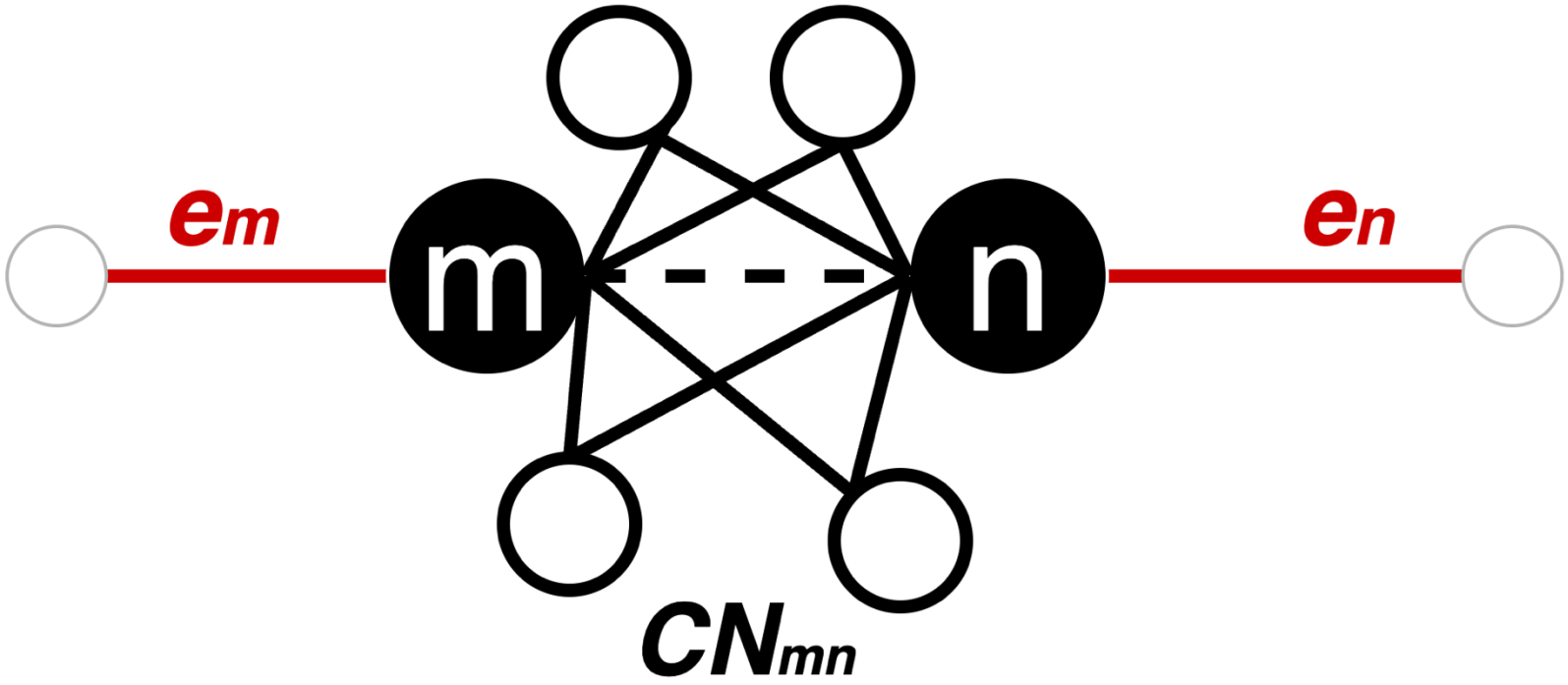
$$\nu_{ij}^{RA2} = \frac{1 + e_i + e_j + e_i e_j}{1 + CN_{ij}}$$

These nodes are far apart…

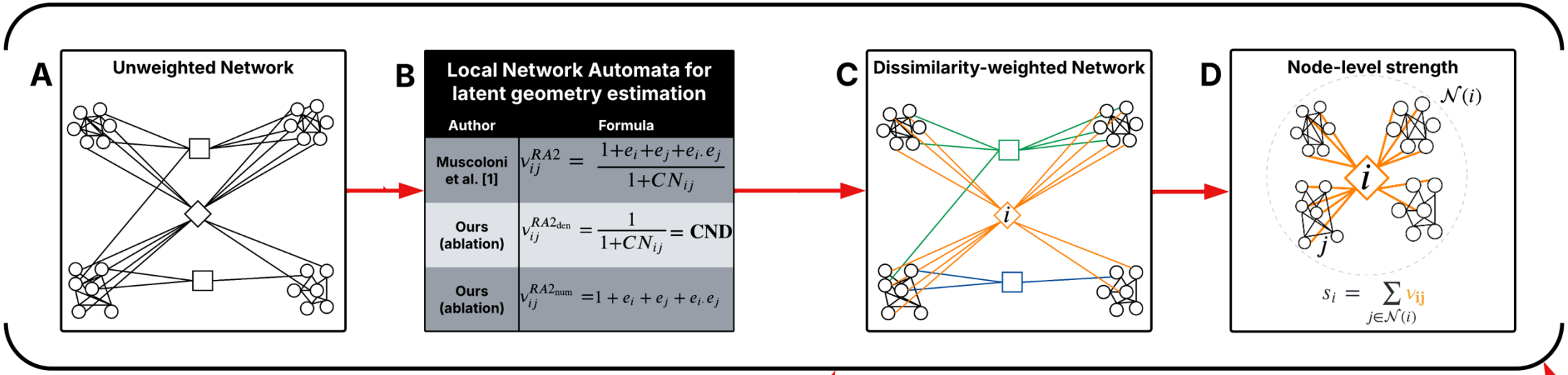


$$\nu_{ij}^{RA2} = \frac{1 + e_i + e_j + e_i e_j}{1 + CN_{ij}}$$

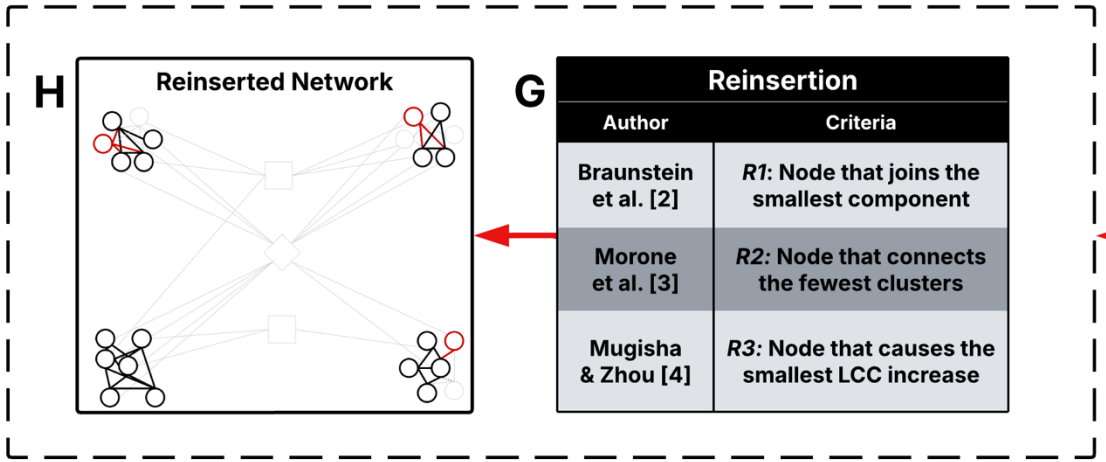
…those are closer to each other

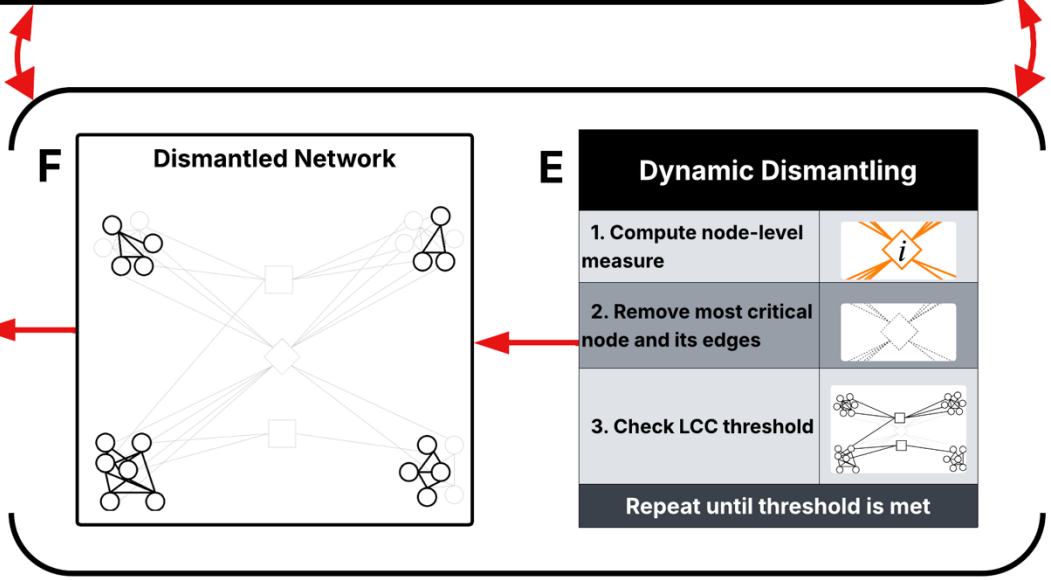


Latent Geometry Driven Network Automata

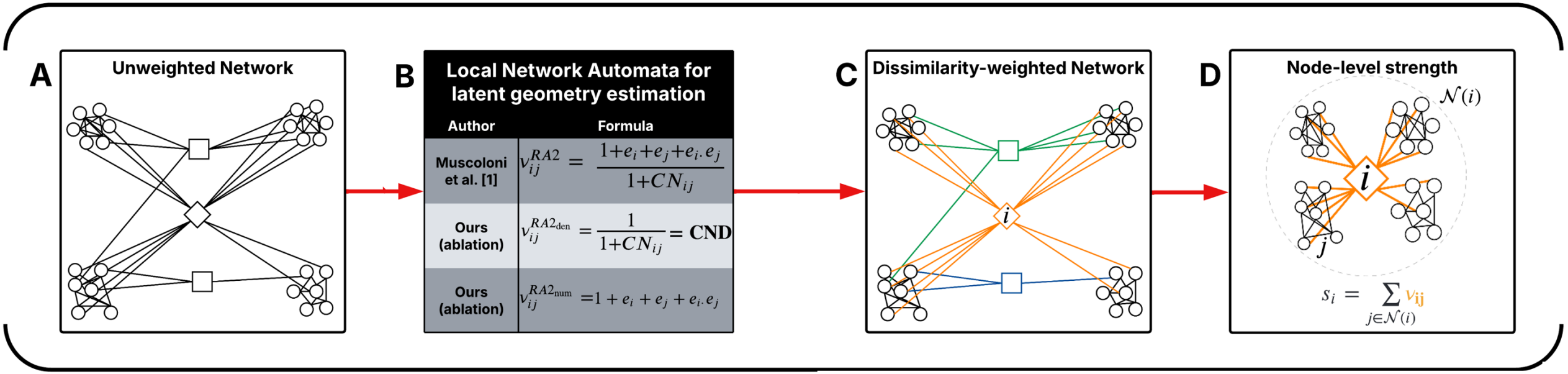


Optional



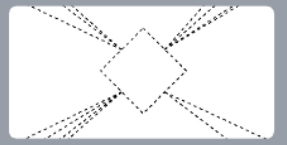
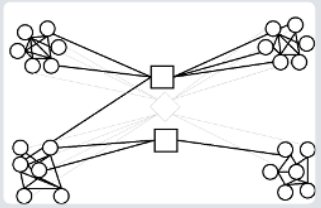


Estimate the latent geometry with network automata rules…



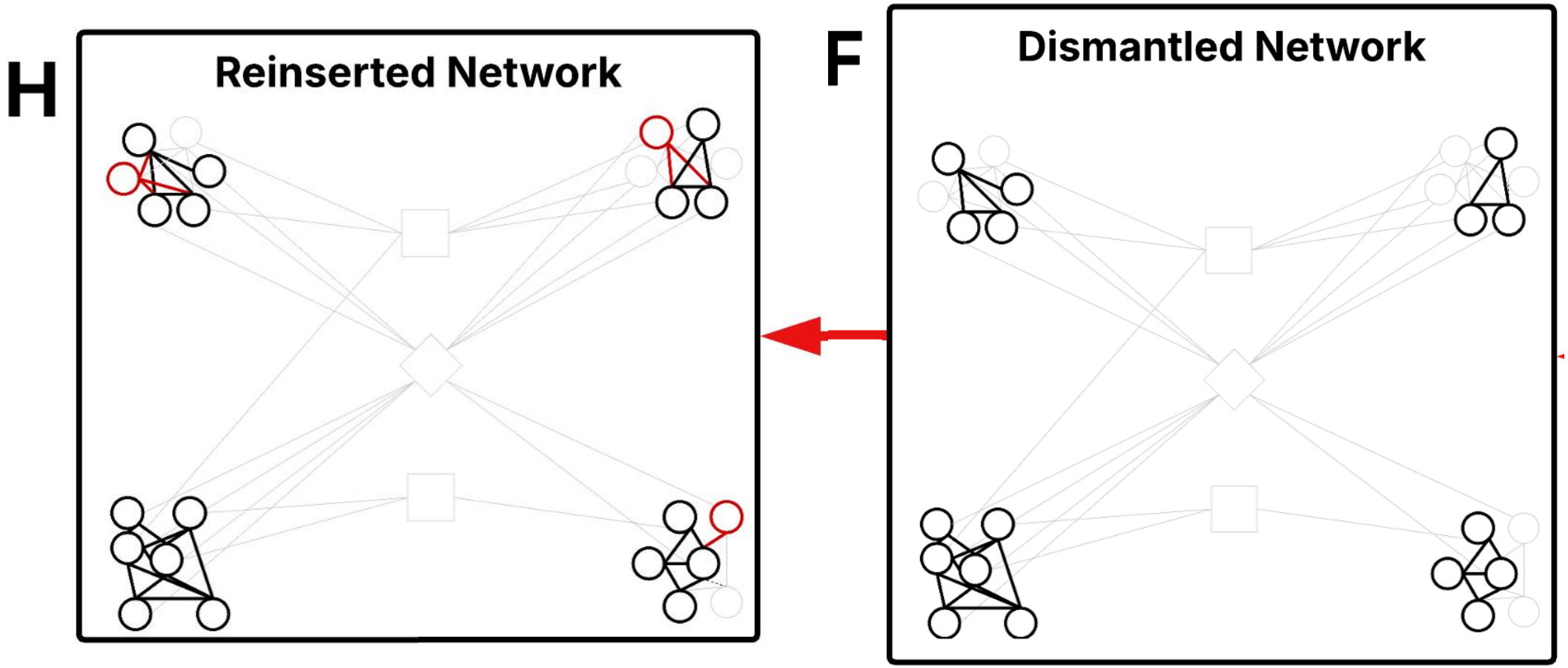
...use it for dismantling...

E

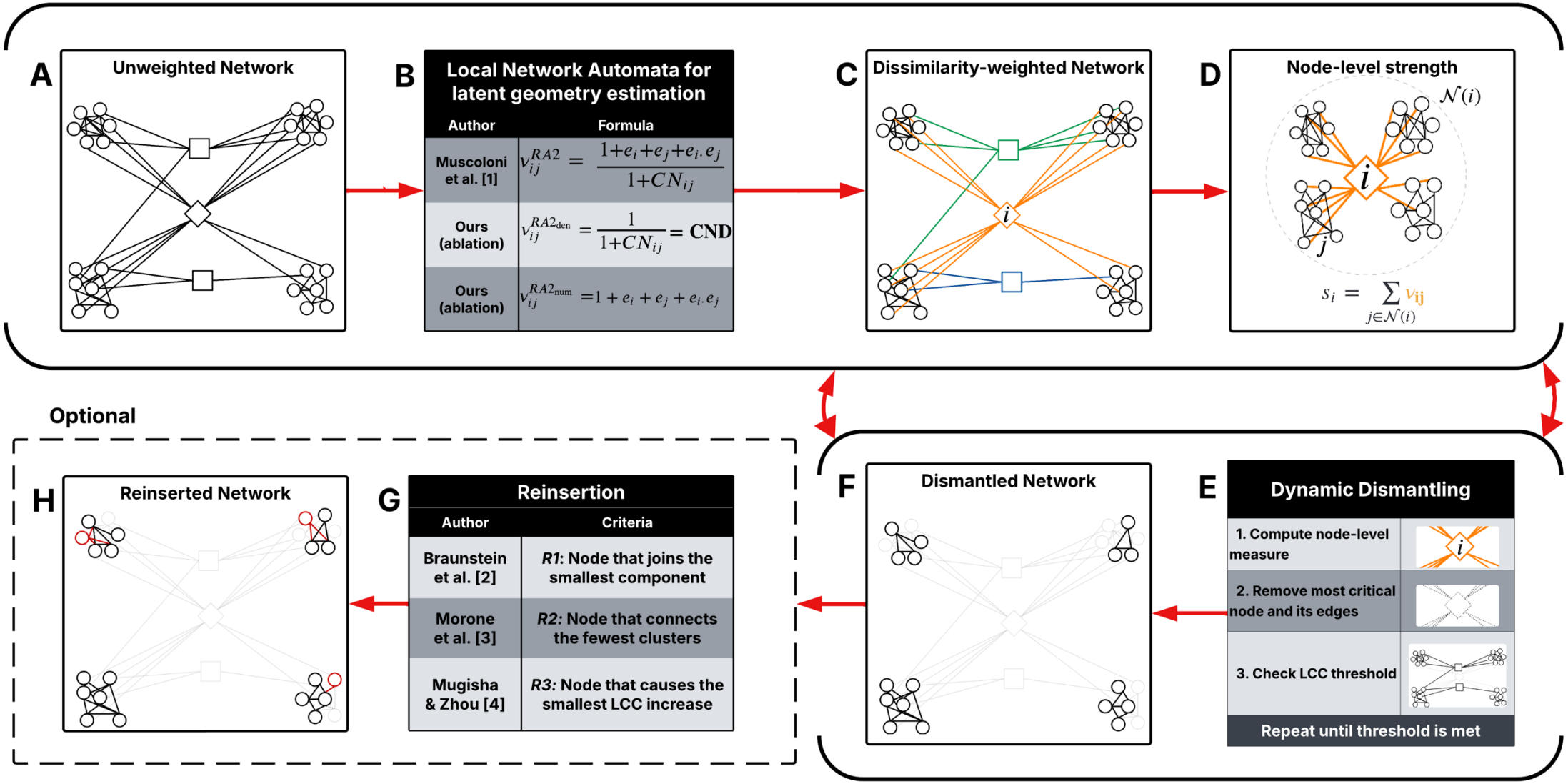
Dynamic Dismantling	
1. Compute node-level measure	
2. Remove most critical node and its edges	
3. Check LCC threshold	
Repeat until threshold is met	

LCC: Largest Connected Component

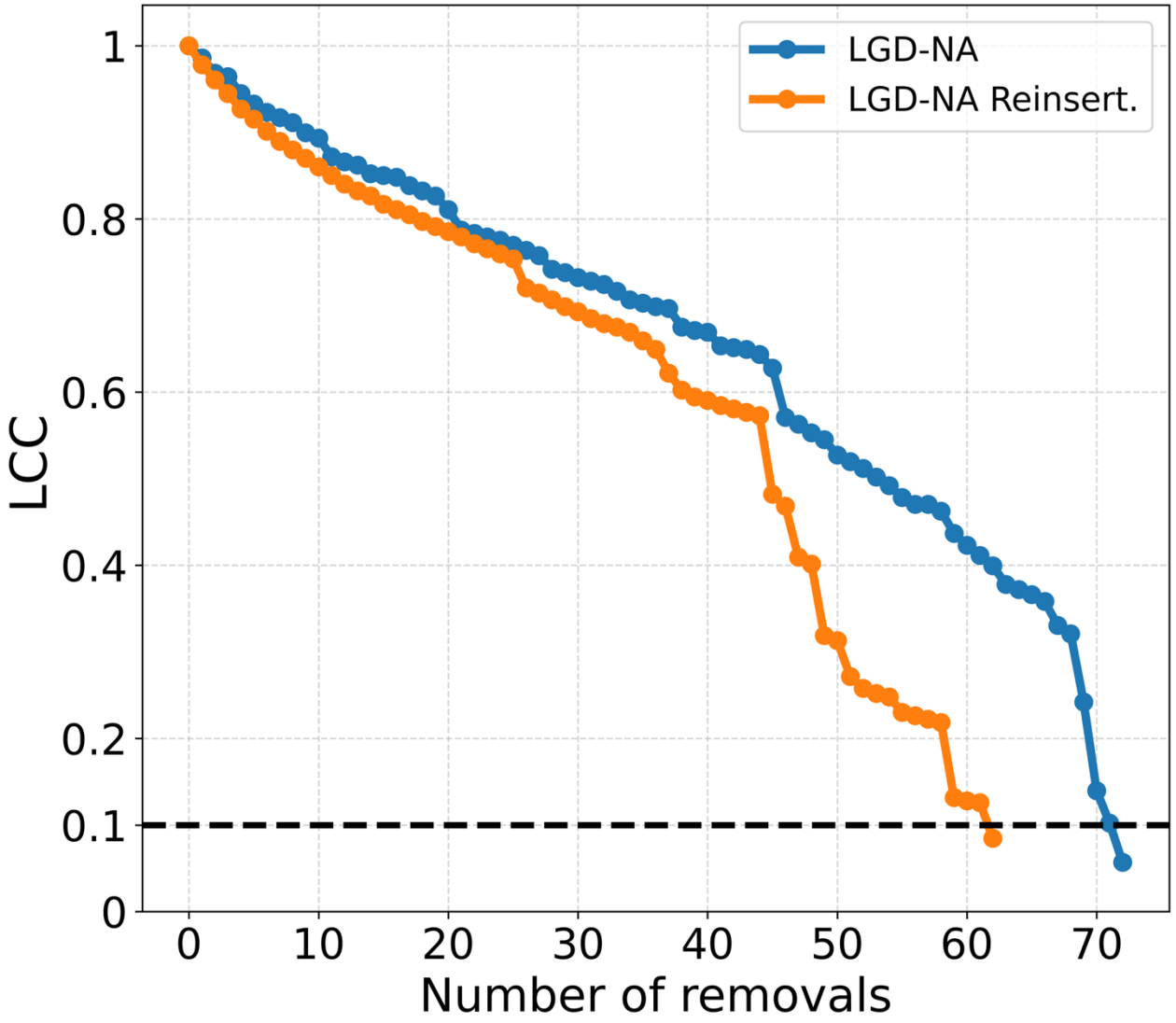
… and optionally reinsert some nodes



LGD-NA


A
Unweighted Network
B
Local Network Automata for latent geometry estimation
Author
Formula
Muscoloni et al. [1]
$\nu_{ij}^{RA2} = \frac{1+e_i+e_j+e_i.e_j}{1+CN_{ij}}$
Ours (ablation)
$\nu_{ij}^{RA2_{den}} = \frac{1}{1+CN_{ij}} = CND$
Ours (ablation)
$\nu_{ij}^{RA2_{num}} = 1+e_i+e_j+e_i.e_j$
C
Dissimilarity-weighted Network
D
Node-level strength
$\mathcal{N}(i)$
$s_i = \sum_{j \in \mathcal{N}(i)} \nu_{ij}$
Optional
H
Reinserted Network
G
Reinsertion
Author
Criteria
Braunstein et al. [2]
R1: Node that joins the smallest component
Morone et al. [3]
R2: Node that connects the fewest clusters
Mugisha & Zhou [4]
R3: Node that causes the smallest LCC increase
F
Dismantled Network
E
Dynamic Dismantling
1. Compute node-level measure
2. Remove most critical node and its edges
3. Check LCC threshold
Repeat until threshold is met

How do we evaluate a dismantling method?



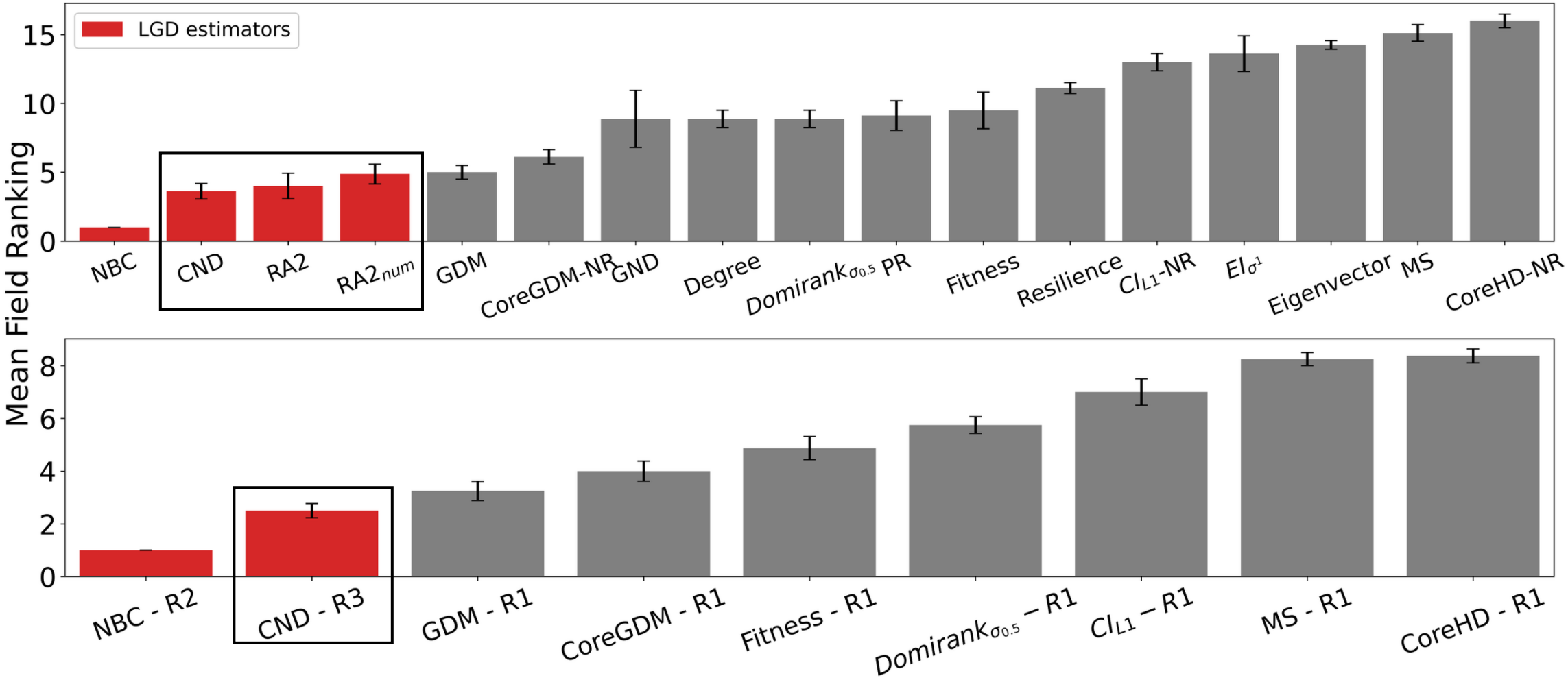
We test on the largest collection of real-world networks for dismantling...

Algorithm	Year	Networks	Ref.
Collective Influence (CI)	2016	2	Morone et al. (2016)
CoreHD	2016	12	Zdeborová et al. (2016)
Explosive Immunization (EI)	2016	5	Clusella et al. (2016)
Min-Sum (MS)	2016	2	Braunstein et al. (2016)
GND	2019	10	Ren et al. (2019)
Resilience Centrality	2020	4	Zhang et al. (2020)
GDM	2021	57	Grassia et al. (2021)
CoreGDM	2023	15	Grassia & Mangioni (2023)
Domirank Centrality	2024	6	Engsig et al. (2024)
Fitness Centrality	2025	5	Servedio et al. (2025)
LGD-NA	**2025**	**1,475**	**Ours**

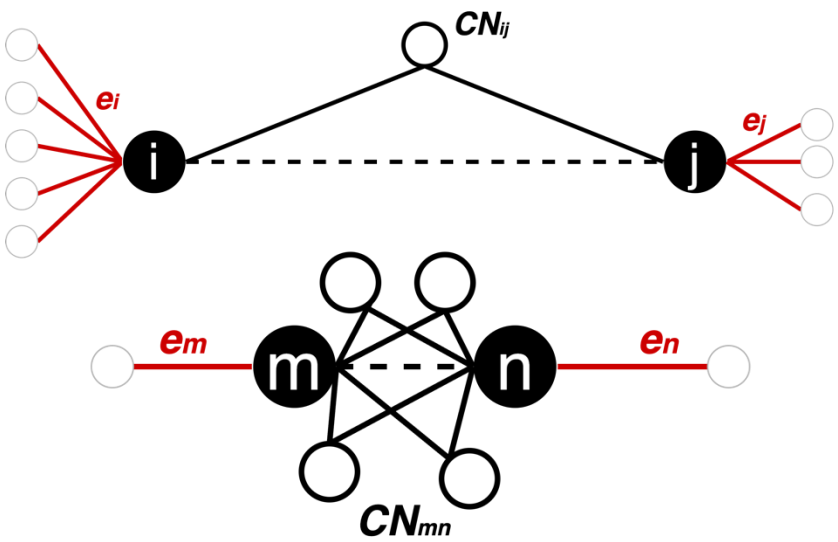
...and the most diverse

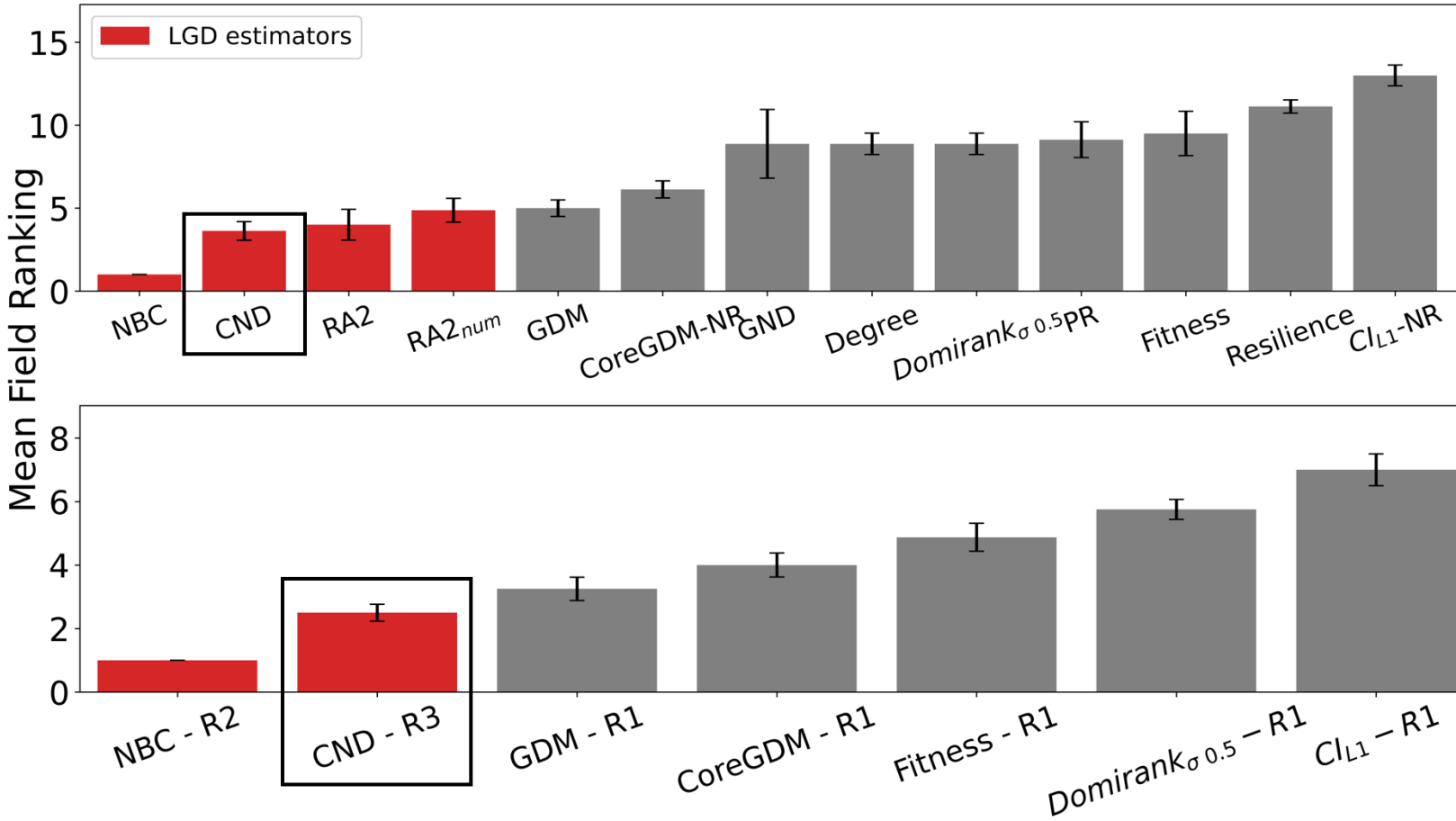
Field	Subfields	Types	Networks
Biomolecular	5	PPI, Genetic, Metabolic, Molecular, Transcription	27
Brain	1	Connectome	529
Covert	2	Covert, Terrorist	89
Foodweb	1	Foodweb	71
Infrastructure	7	Flight, Nautical, Power grid, Rail, Road, Subway, Trade	314
Internet	1	Internet	206
Misc	8	Citation, Copurchasing, Game, Hiring, Lexical, Phone call, Software, Vote	38
Social	7	Coauthorship, Collaboration, Contact, Email, Friendship, Social network, Trust	201
Total	**32**		**1,475**

LGD-NA outperforms all other algorithms

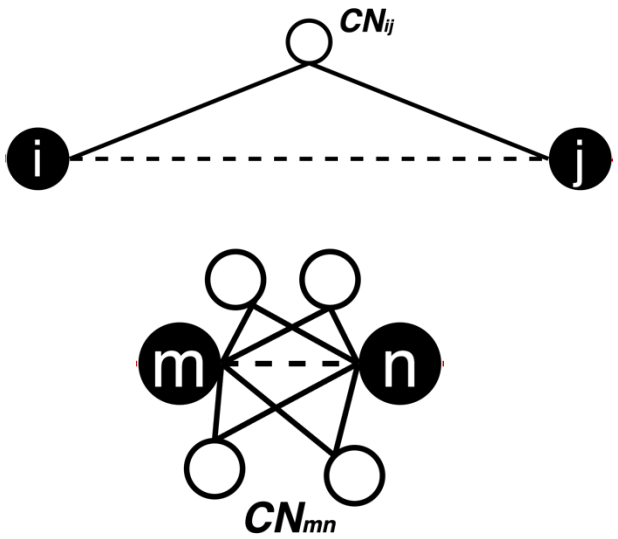


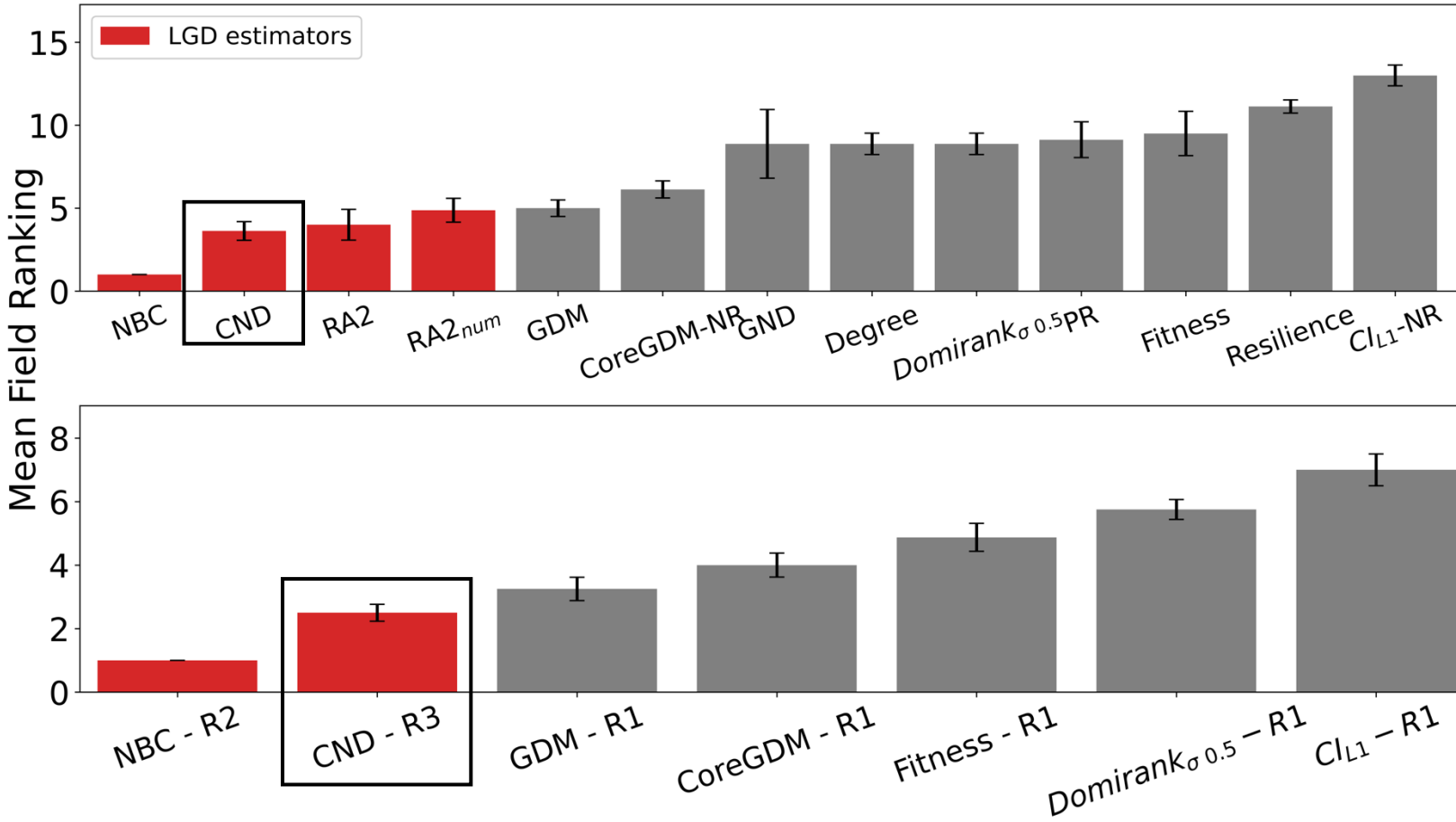
And the simplest local measure works the best…





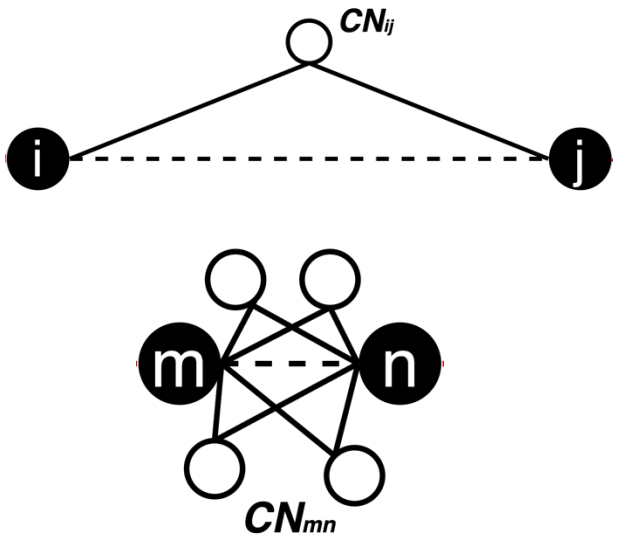
Common Neighbor Dissimilarity - **CND**

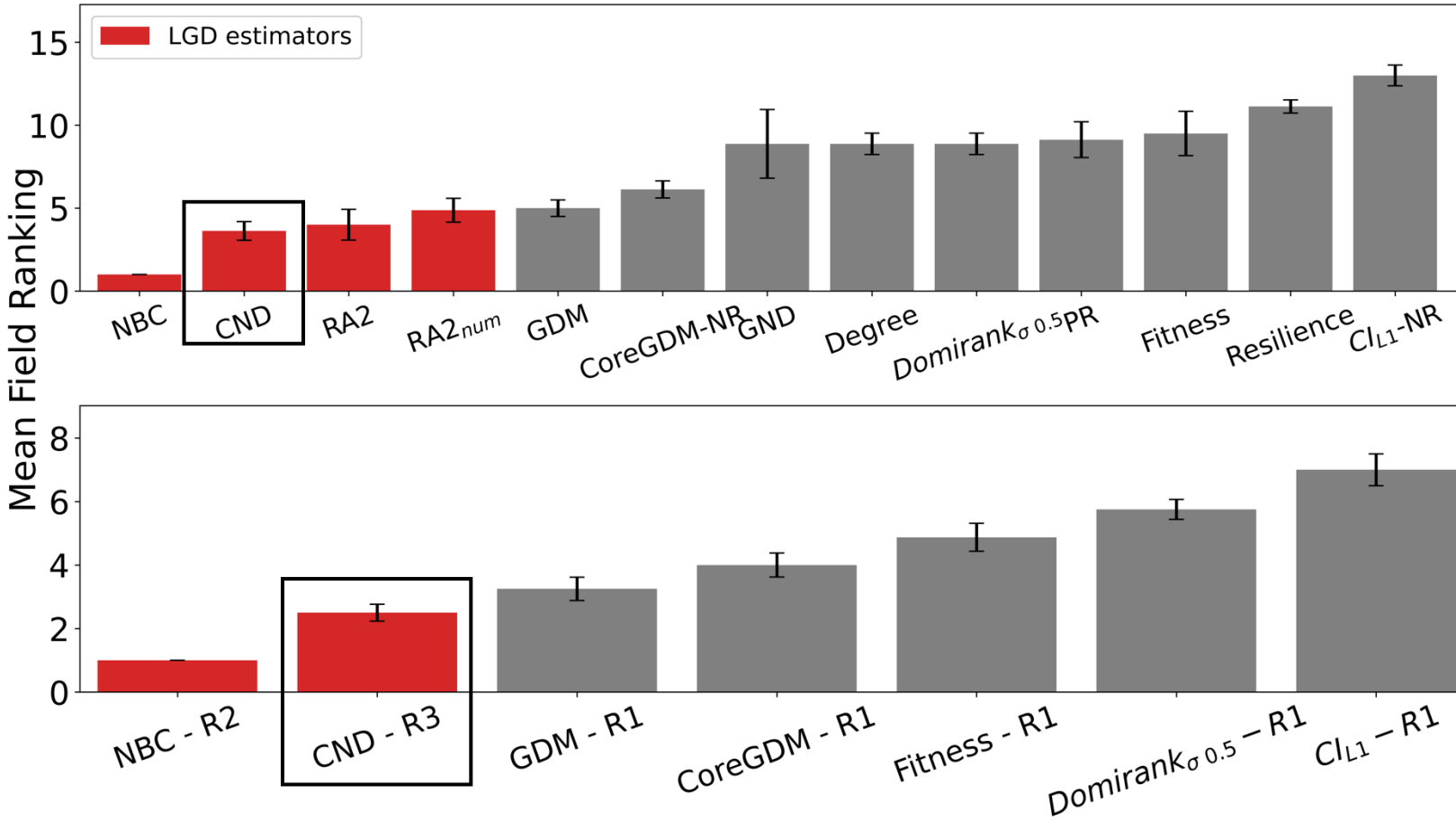




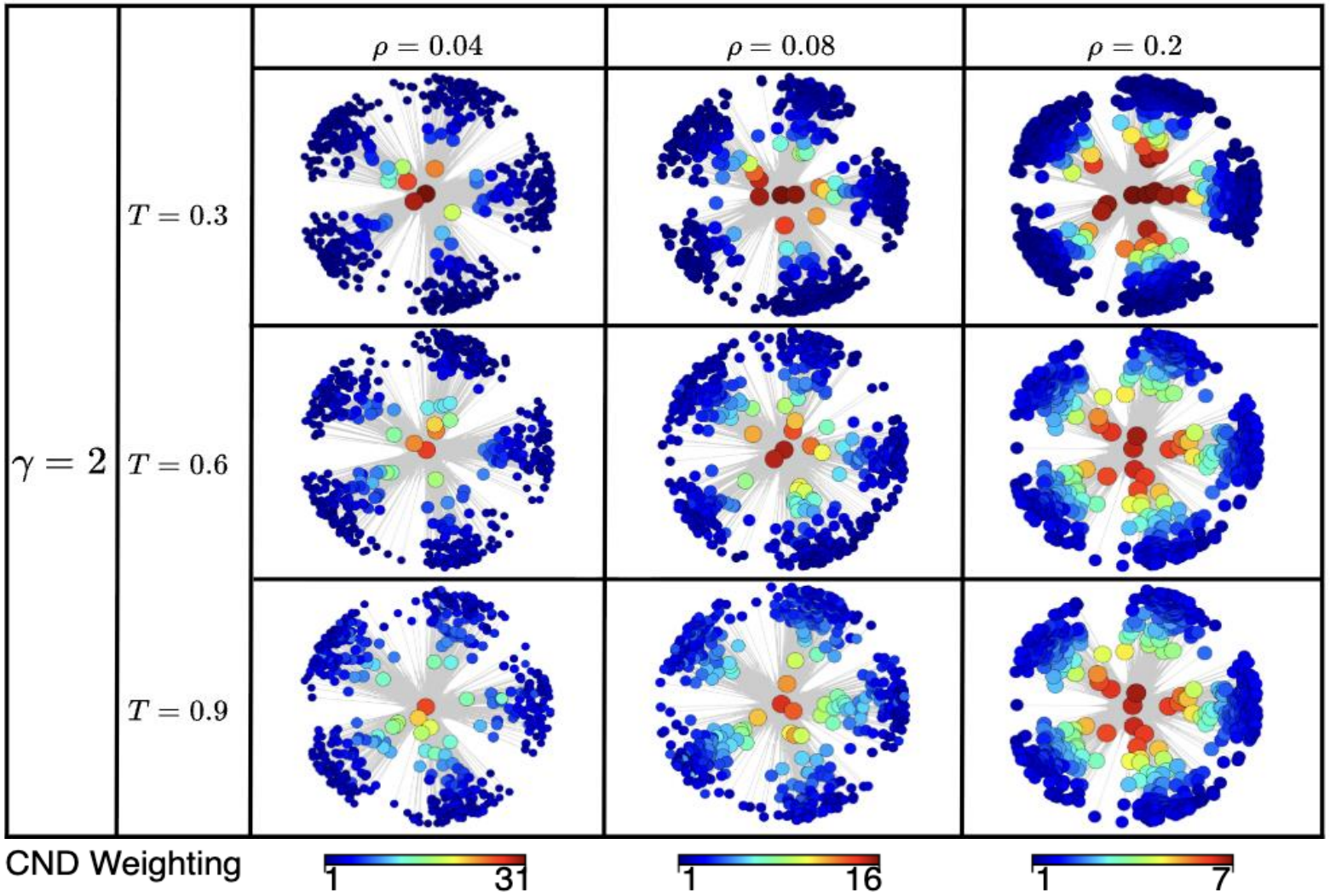
Common Neighbor Dissimilarity - **CND**

$$\nu_{ij}^{CND} = \frac{1}{1 + CN_{ij}}$$

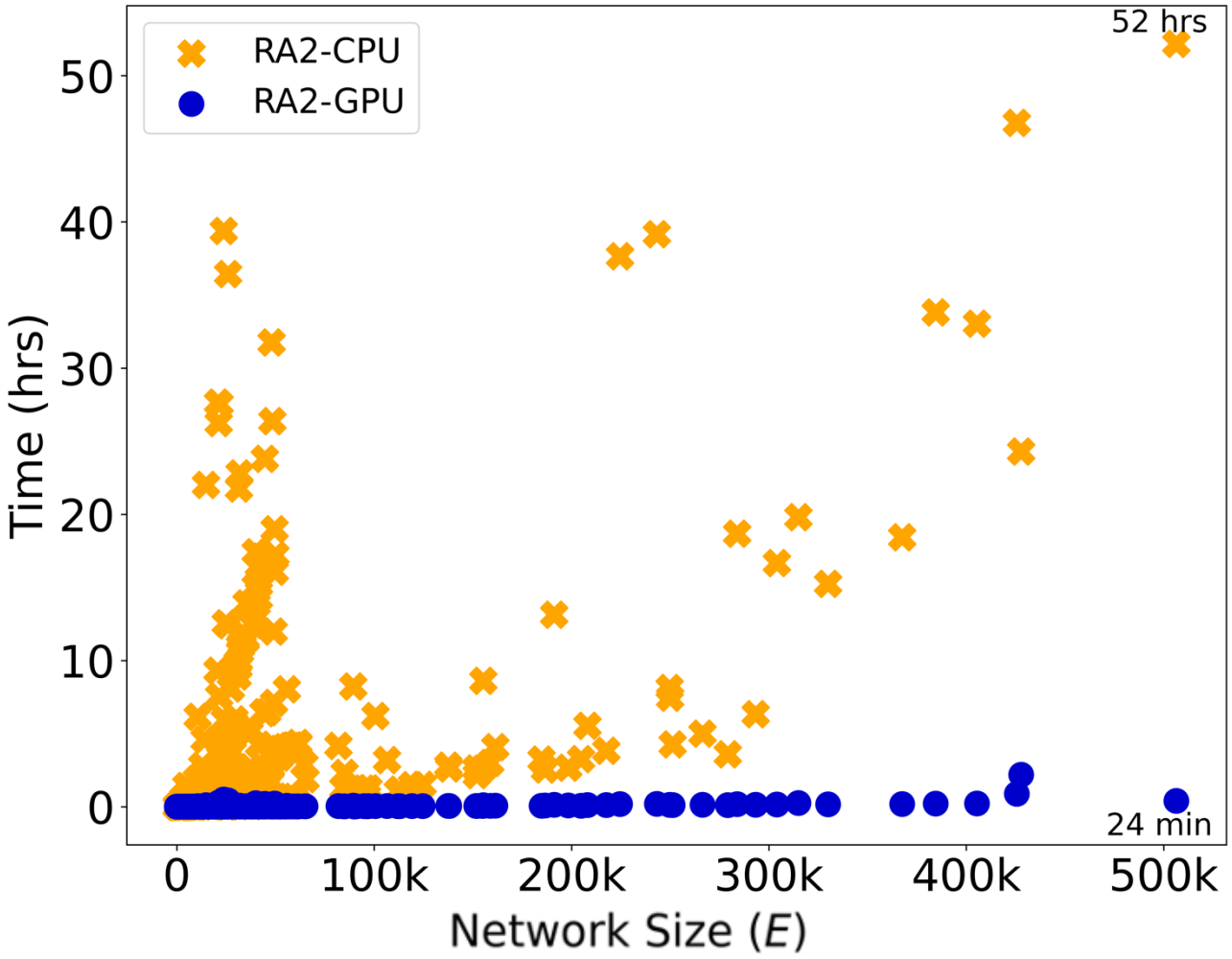


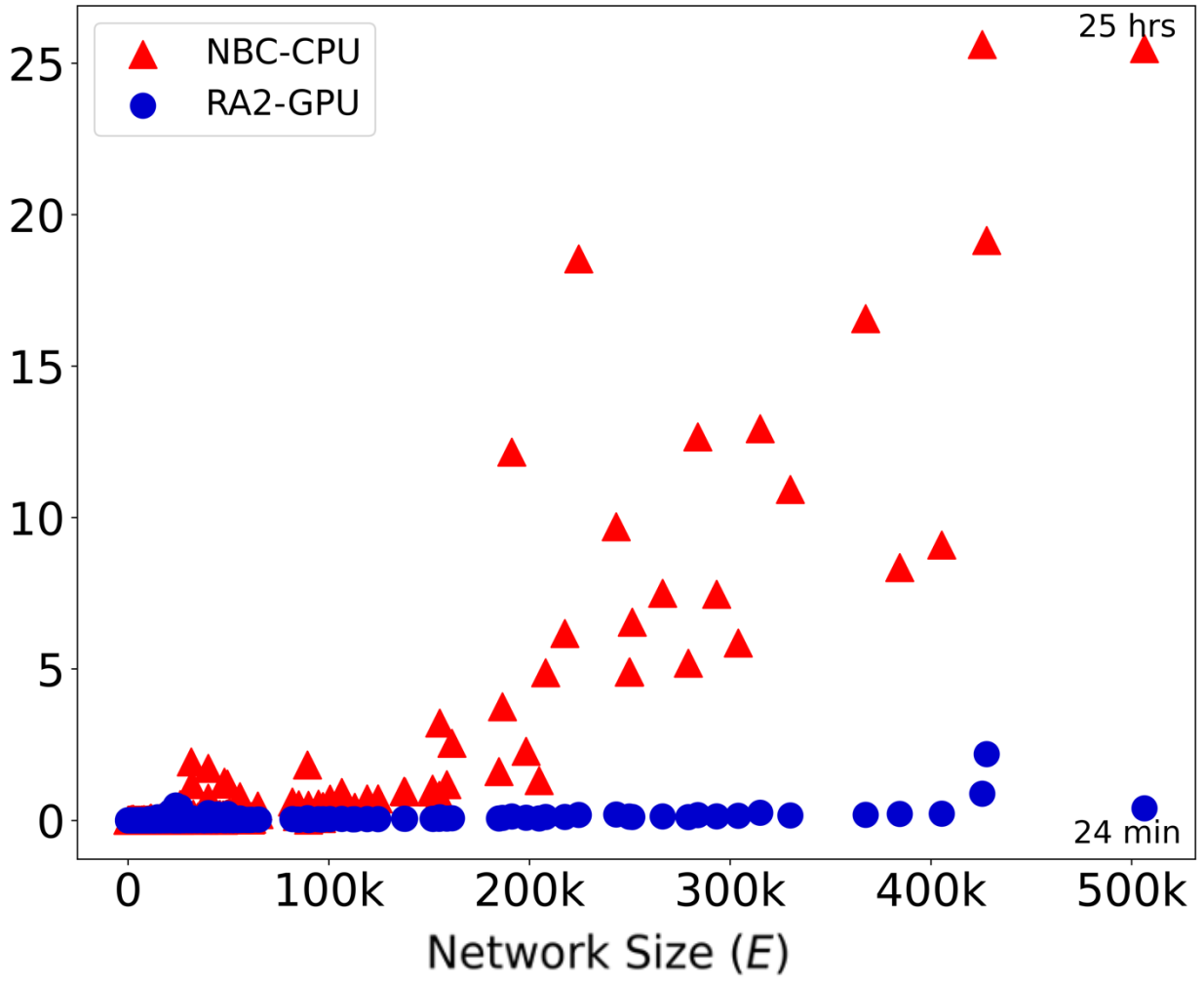


We confirm that our latent-geometry measures do identify geometrically central nodes

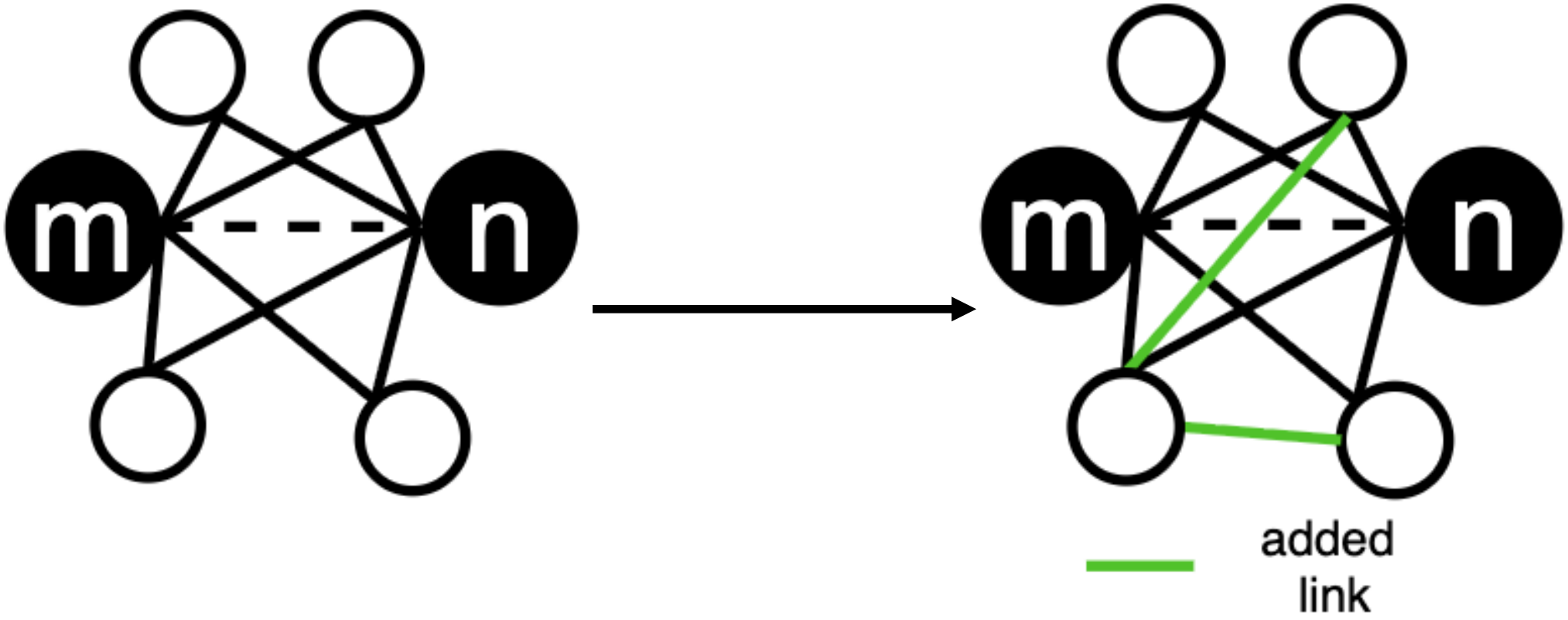


Matrix multiplication enables GPU acceleration for larger networks

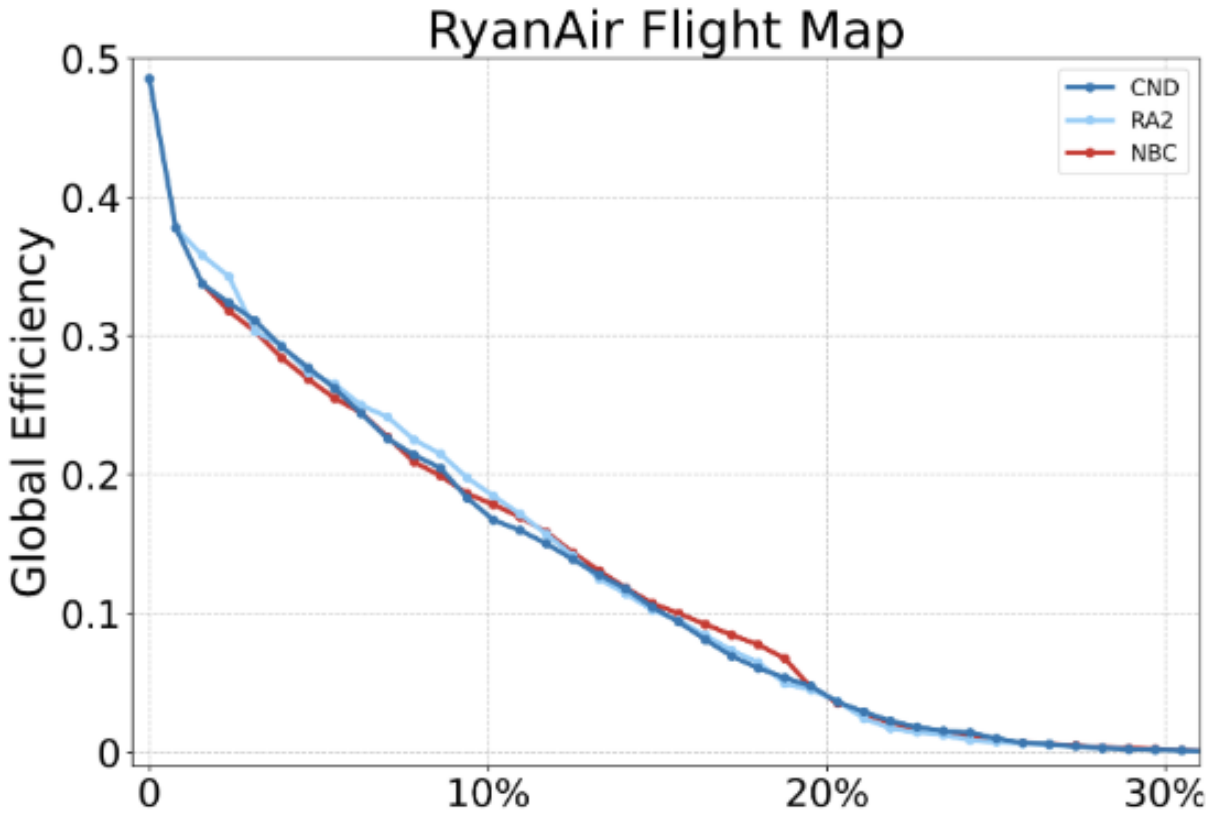


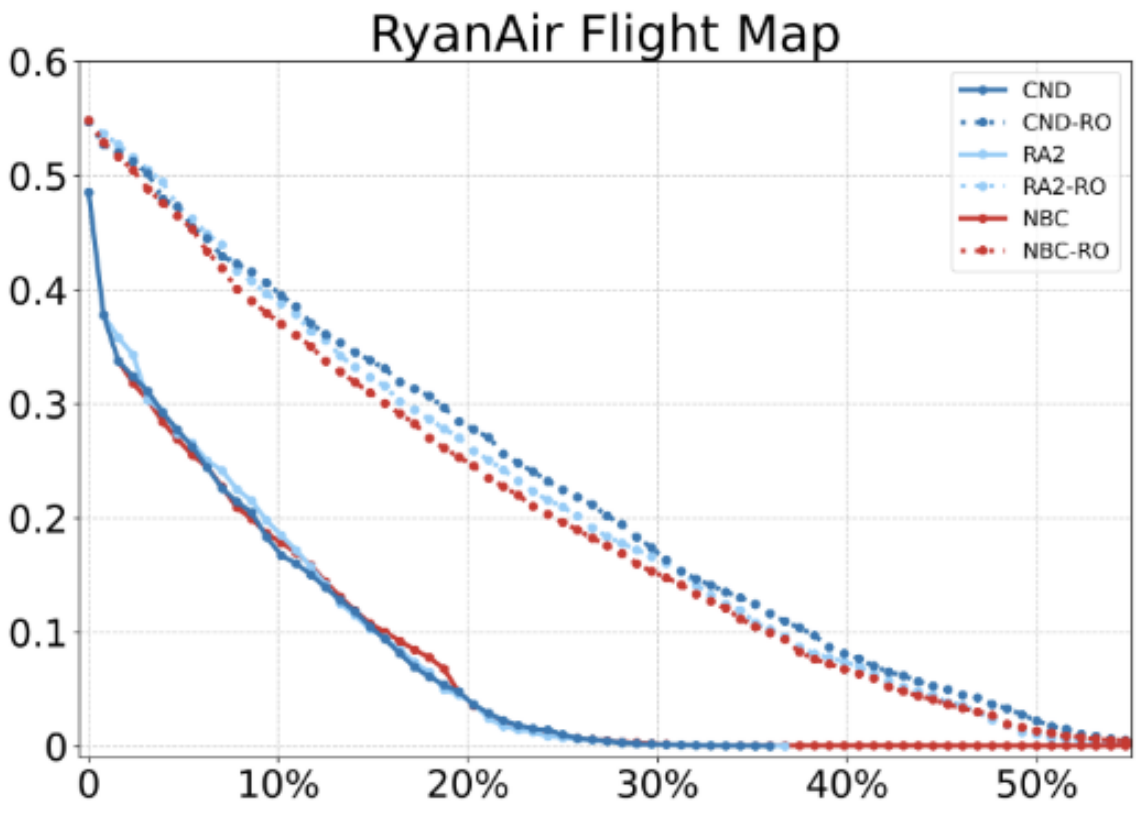


Our measures even enable us to engineer network robustness

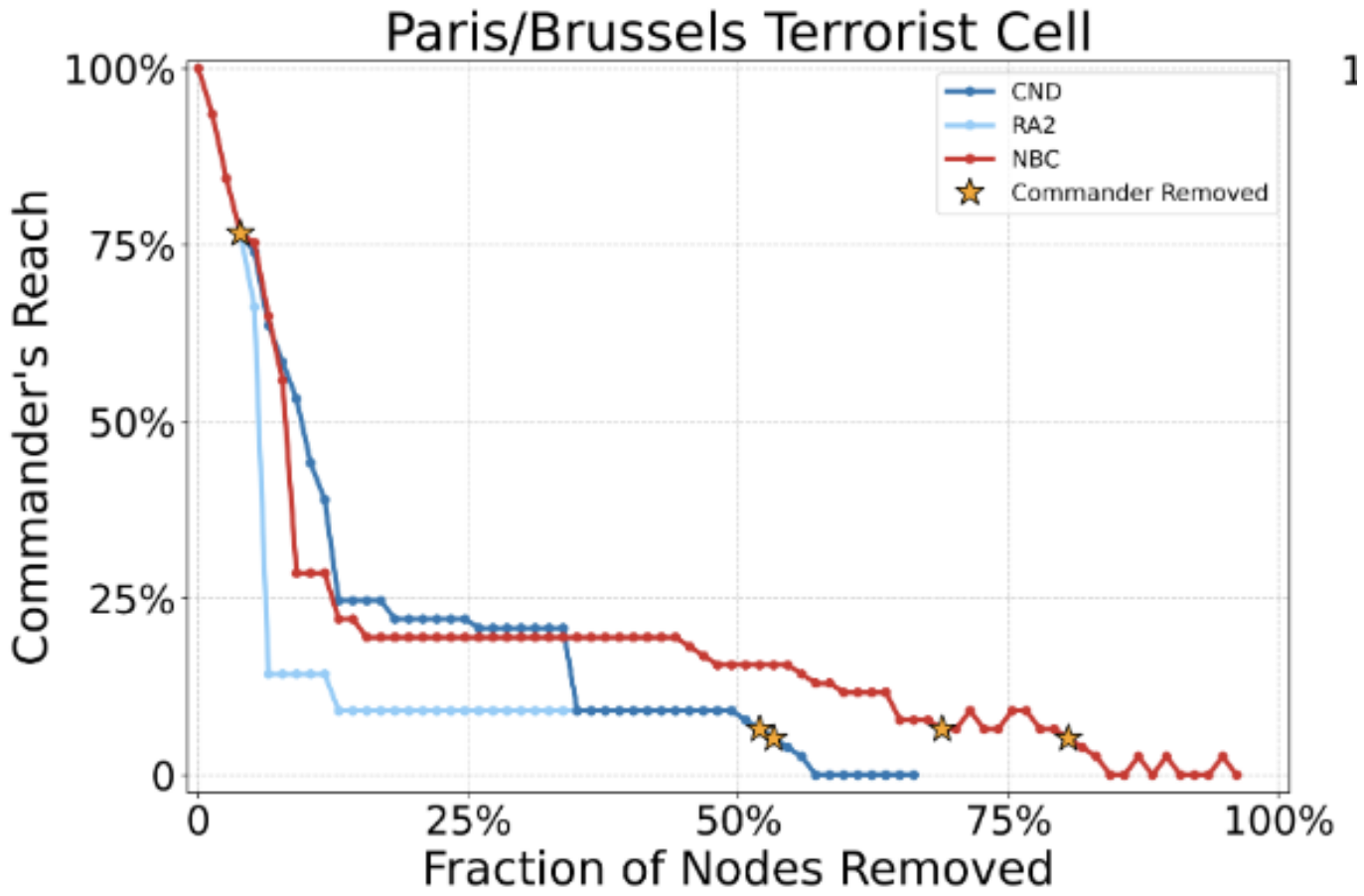


Our measures even enable us to engineer network robustness





LGD-NA Dismantling to use cases



Limitations

- Dual-use of network dismantling → method to engineer network robustness

- Directed networks → tested

Future Work

- Weighted networks
- Combining local and global geometry information
- Edge dismantling
- Explainable AI (XAI) for "perturbation experiments”

Thank you to our team!

Thomas Adler

CCNI, Tsinghua University

thomas0299@gmail.com

Marco Grassia

University of Catania

marco.grassia@unict.it

Ziheng Liao

CCNI, Tsinghua University

lzhalpha@gmail.com

Giuseppe Mangioni

University of Catania

giuseppe.mangioni@unict.it

Carlo V. Cannistraci

CCNI, Tsinghua University

kalokagathos.agon@gmail.com