Latent Geometry-Driven Network Automata for Complex Network Dismantling

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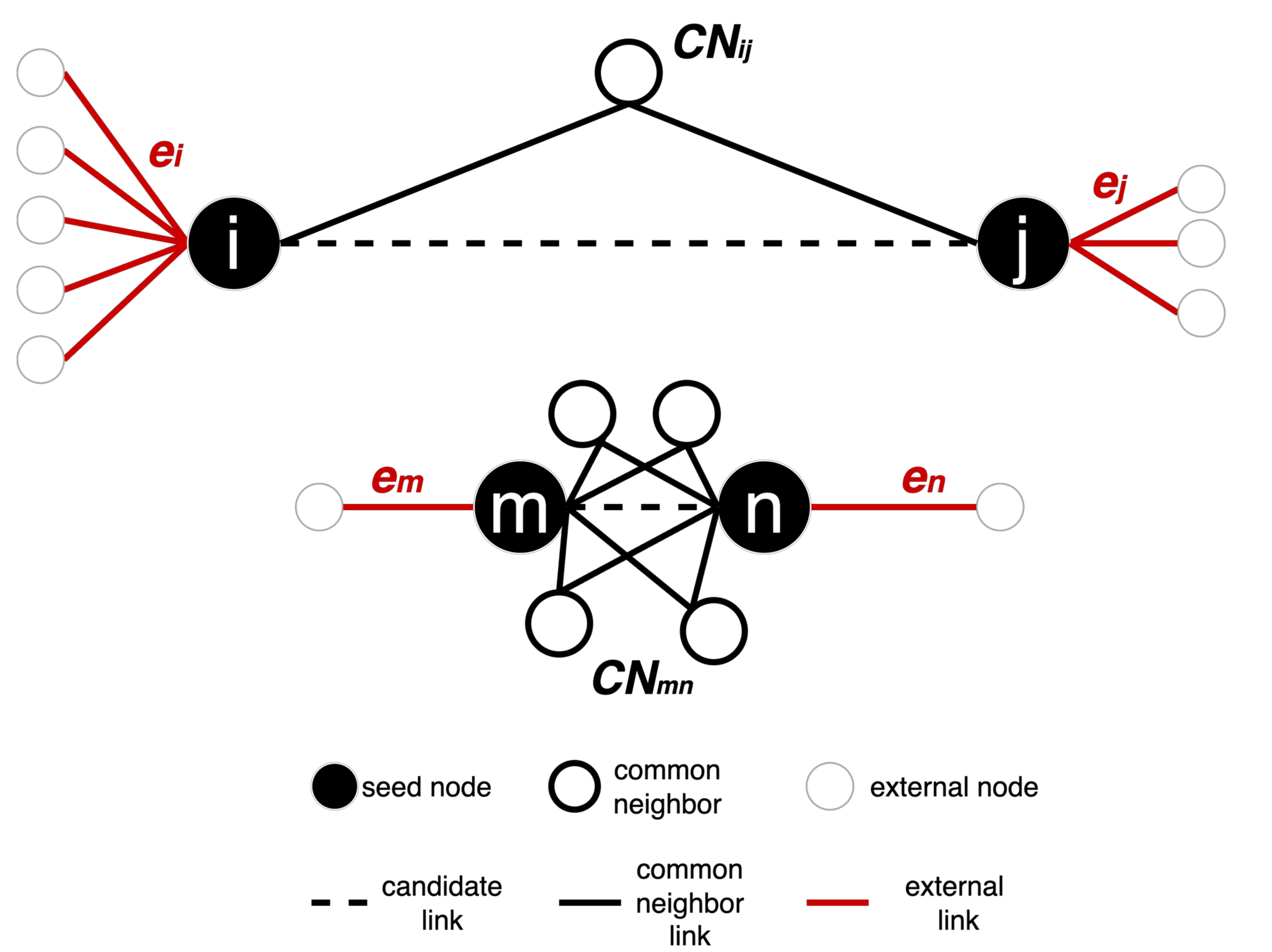
Network Dismantling

- Find the minimal set of nodes to **disconnect a network** and hurt its functionality.
- Why? Improve desirable networks and hurt undesirable ones.
- NP-hard problem – **complex system**
- Previous methods either rely on global information, use machine learning, are inefficient, or don't work well.

Latent-Geometry Estimators

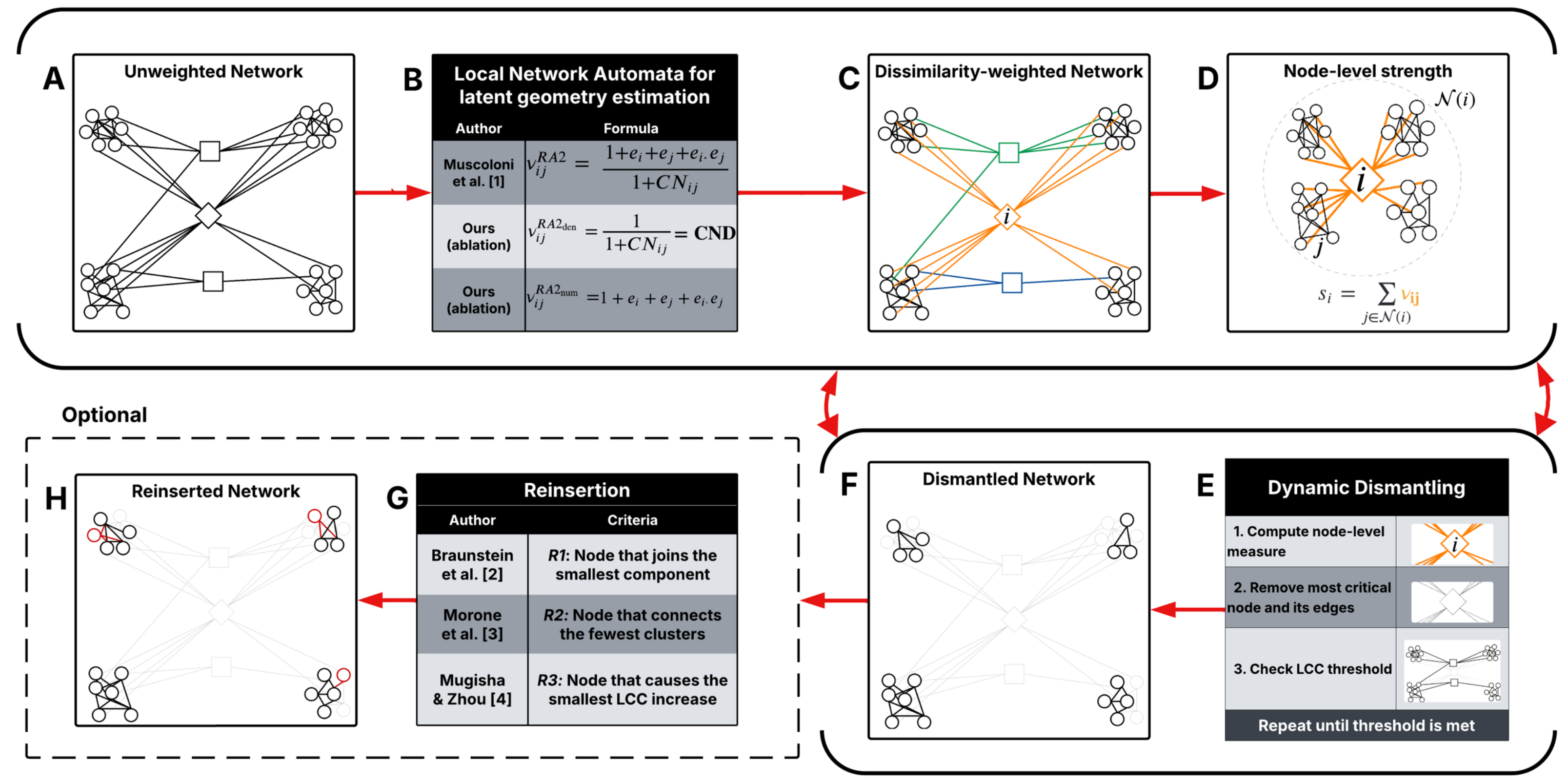
- The latent geometry is the **underlying hidden metric space** from which the observed topology is constructed.
- This latent geometry has been shown to explain efficient navigation, community detection, and contagion spread.
- We use the **Repulsion Attraction rule 2** and its variants to approximate **effective link distances** between interacting nodes.
- Assigning geometric distances to links enables us to **identify nodes that connect far-apart regions** in the underlying geometric space.
- As a **Network Automata,** it only uses local information.



Repulsion Attraction rule 2 (RA2). Seed nodes are shown in black; common neighbors (*CN*) are shown in white with a black border, and external nodes are white with a grey border. The dashed line is the edge that is being assigned a weight. External links e denote the number of edges connecting a node to nodes outside its CN set, here in red. In black, the links to common neighbors.

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

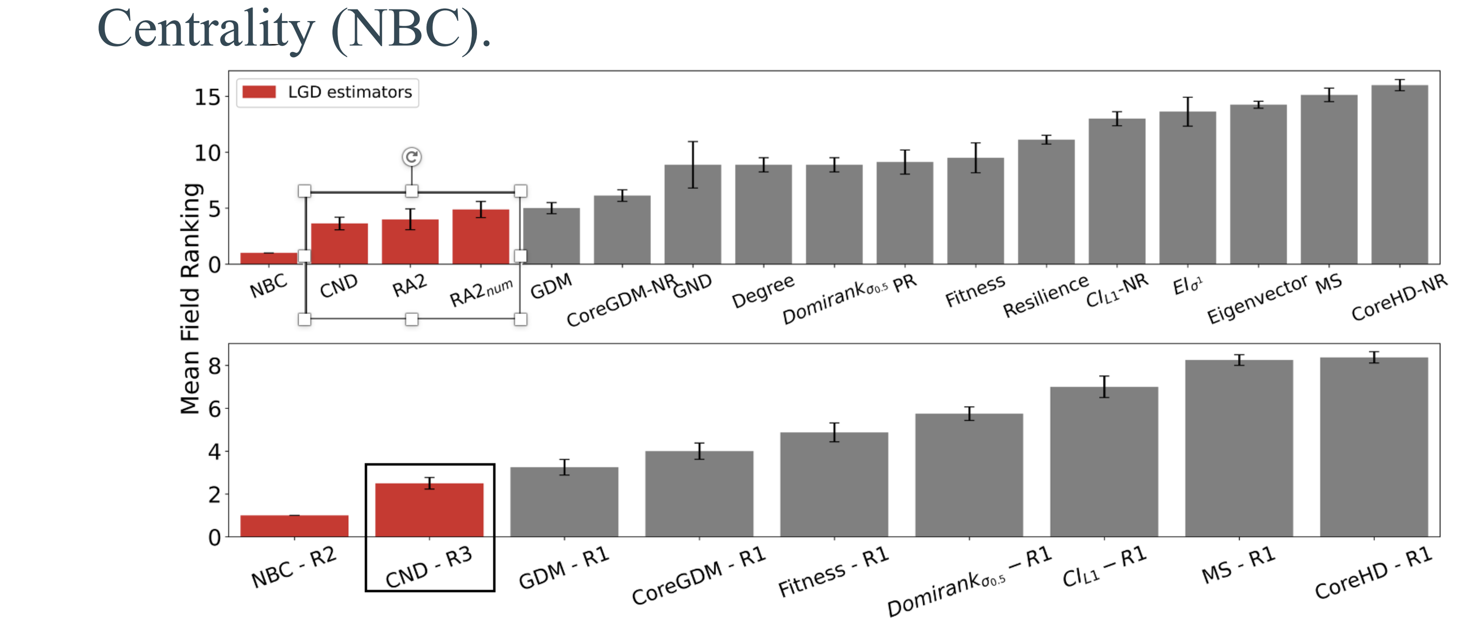
Latent Geometry-Driven Network Automata



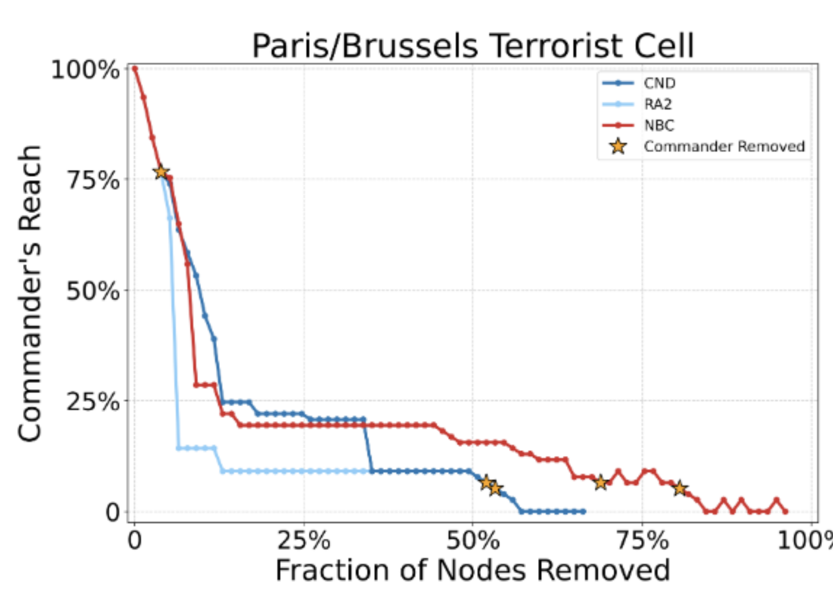
LGD Network Automata framework. **A**: Begin with an unweighted and undirected network. **B**: Estimate latent geometry by assigning a weight ν_{ij} to each edge between nodes i and j using local latent geometry estimators. **C**: Construct a dissimilarity-weighted network based on these weights. **D**: Compute node strength as the sum of geometric weights to all neighbors in $N(i)$: $s_i = \sum_{j \in N(i)} \nu_{ij}$ **E–F**: Perform dynamic dismantling by iteratively computing node strengths, removing the node with the highest s_i and its edges, and checking whether the normalized size of the largest connected component (LCC) has dropped below a threshold. **G–H** (optional): Reinsert dismantled nodes using a selected reinsertion method.

Experiments

- Validated on most extensive dataset for network dismantling: **1,475 real-world networks across 32 complex systems** domains (PPI, power grids, brain connectomes, and road maps).
- LGD-NA outperforms all other algorithms, except for Betweenness Centrality (NBC).



Network Dismantling. Mean field ranking for each dismantling method without reinsertion ($n = 1{,}296$; upper) and with reinsertion ($n = 1{,}237$; lower), for dynamic dismantling. In the lower panel, a subset of the best-performing methods from each category is paired with their respective best performing reinsertion strategy. Methods based on latent geometry are shown in red. NR denotes variants where the original reinsertion step was disabled. Error bars indicate the standard error of the mean.



Dismantling of Terrorist Cell. The plot shows the drop in Commander's Reach, defined as the percentage of operatives able to communicate with at least one of the three key commanders, as a function of the fraction of nodes removed. The star represents a commander being eliminated. Plot includes RA2, CND, and NBC.

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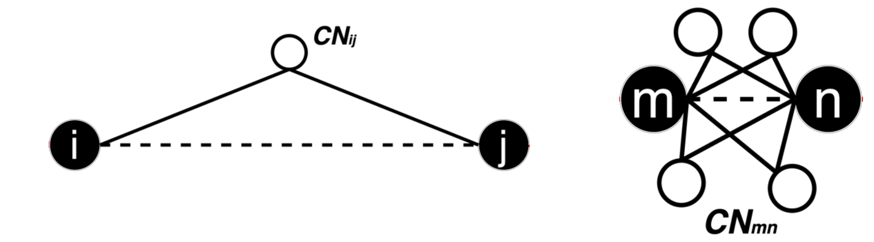
Common Neighbor Dissimilarity (CND)

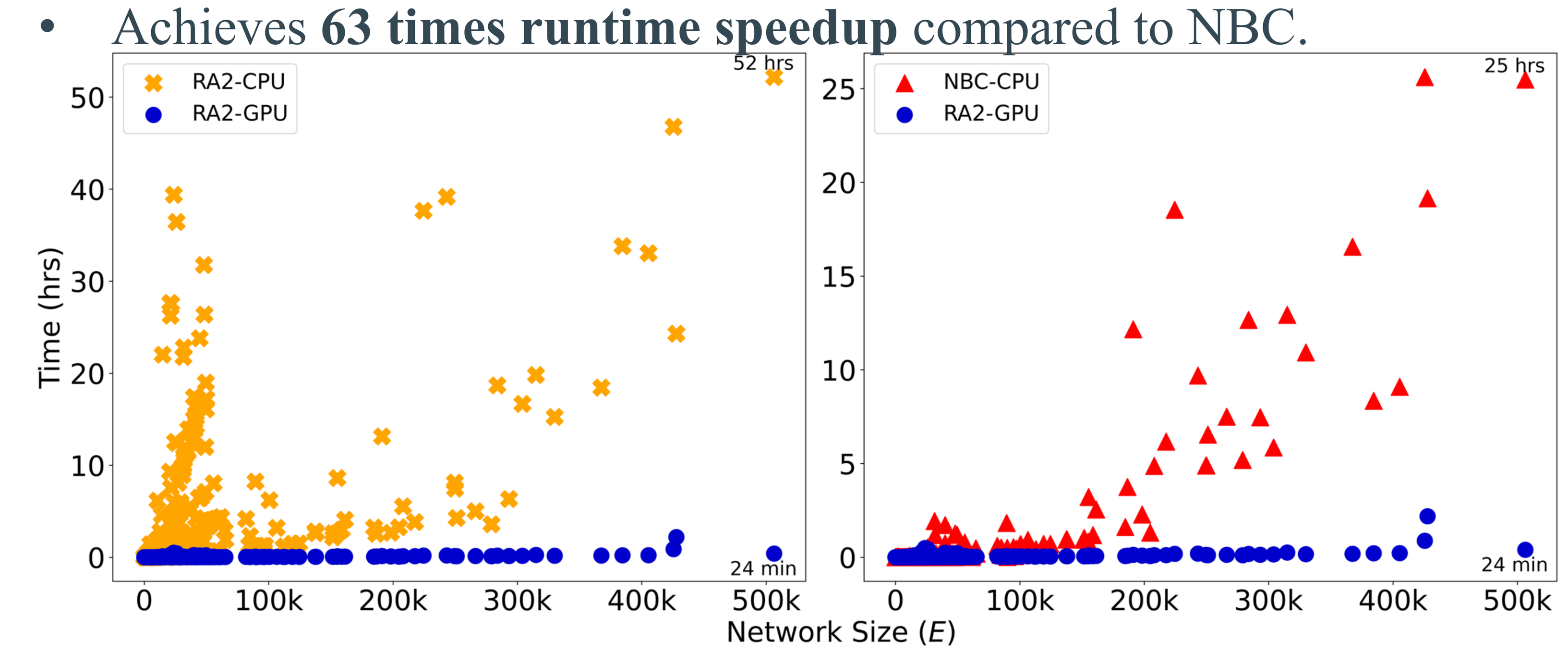
- **Simples local measure works the best**, solely based on Common Neighbors.

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



GPU Acceleration

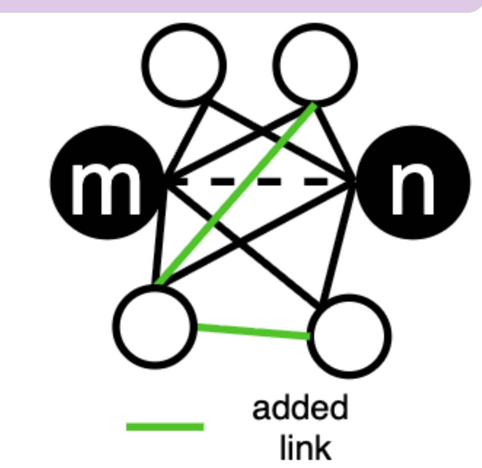
- Implemented **matrix multiplication enabling GPU acceleration** for larger networks.
- Achieves **63 times runtime speedup** compared to NBC.



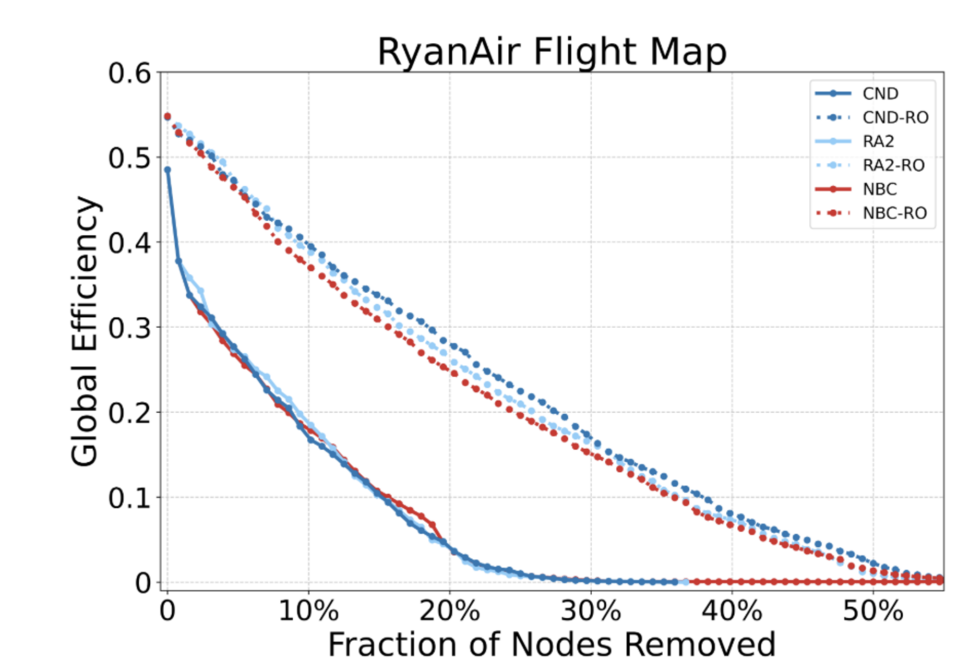
GPU acceleration of RA2. Runtime (in hours) is plotted against network size, measured by the number of edges, E, for dynamic dismantling. The annotated time indicates the runtime for the largest network. Evaluated on networks of up to 23,000 nodes and 507,000 edges ($n = 1{,}475$).

Engineering Network Robustness

- The explainability of our method enables us to **engineer a more robust network**.
- Simply add a few links between the common neighbors of the seed nodes of links with high distance.
- This connects far-away regions in the hidden geometric space.



Engineering robustness of real-world networks. Dismantling curve on the original (solid) and reinforced networks (dashed). The right panel shows the Global Efficiency of a flight map. Both as a function of the fraction of nodes removed. Plot includes RA2, CND, and NBC.



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