

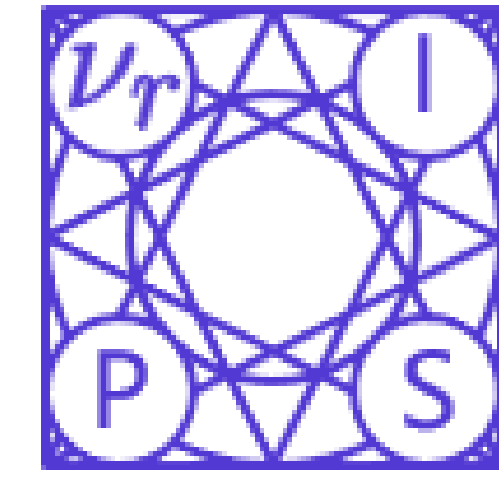


REM: From Structural Entropy To Community Structure Deception

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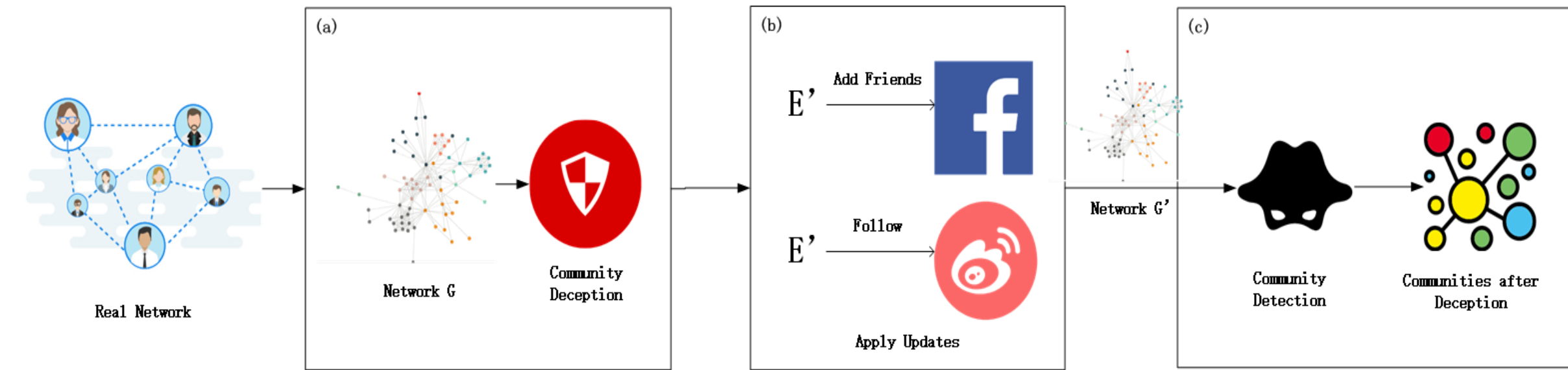
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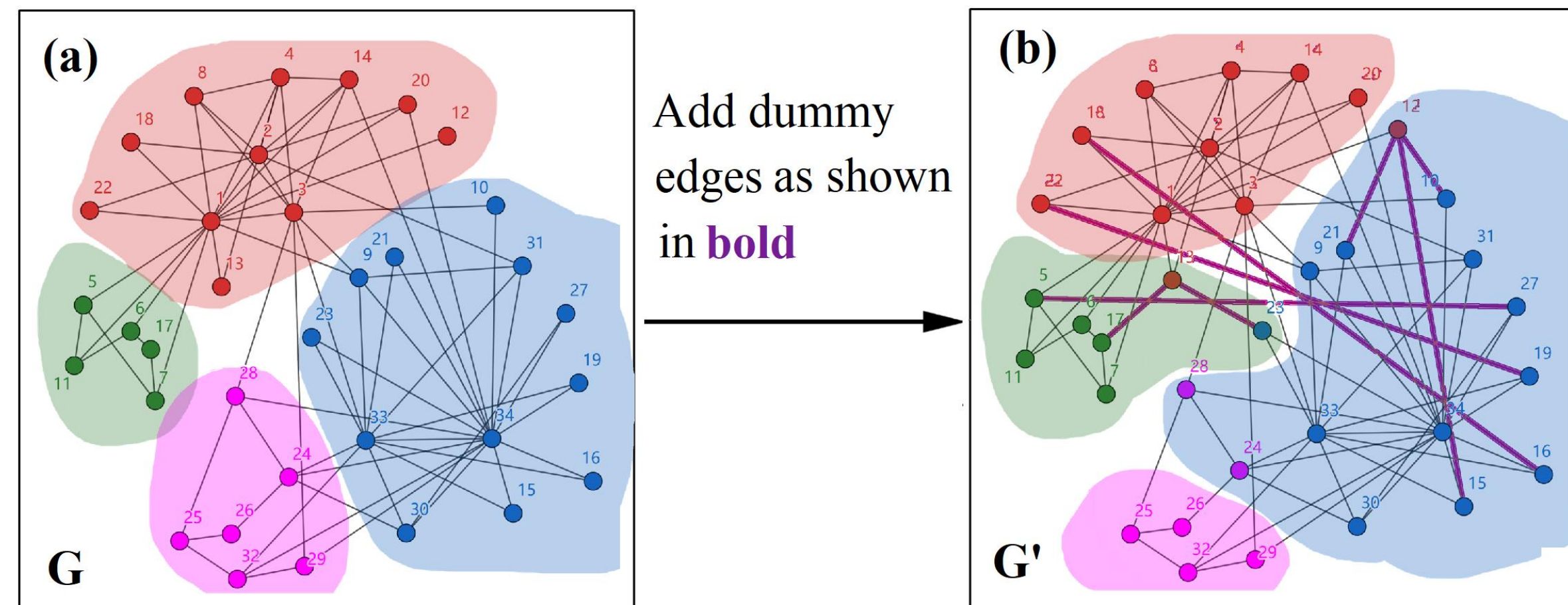
Background

The disclosure of the users' community affiliations leads to privacy leak. This raises the problem of **community structure deception (CSD)**, which asks for ways to minimally modify the network so that a given community structure maximally hides itself from community detection algorithms.



Problem Formulation

- A social network \rightarrow An undirected connected graph $G = (V, E)$.
- The community structure \rightarrow a partition $P = \{X_1, X_2, \dots, X_L\}$ of V .
- obfuscating $P \rightarrow$ by adding a number of “dummy edges”.



We measure the similarity between P and P' by three metrics:

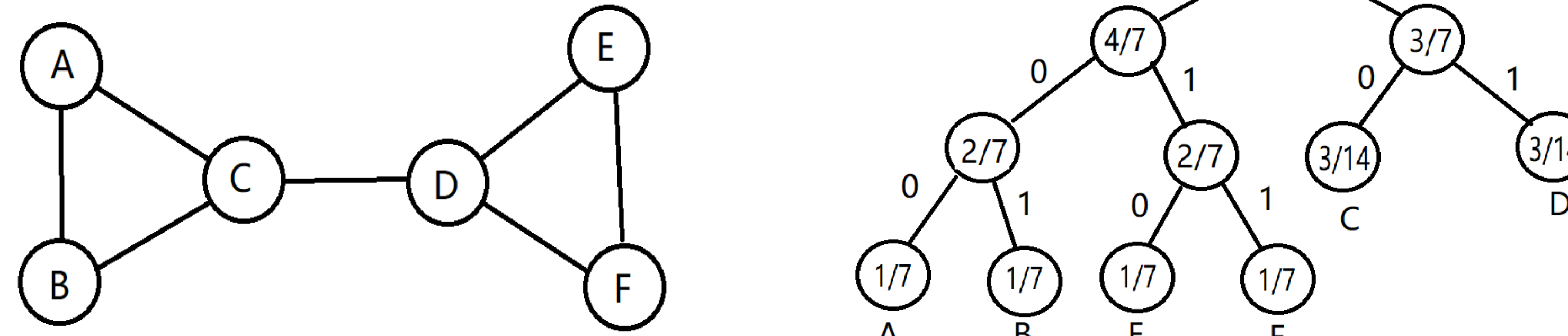
- $J(P, P')$: J is **jaccard index**
- $D(P, P')$: D is **normalized mutual information**
- $R(P, P')$: R is the **recall**

Residual Entropy-based CSD

Definition 1. (Shannon entropy) $\mathcal{H}(G)$ captures the average number of bits needed to encode the n vertices in a lossless way:

$$\mathcal{H}(G) := -\sum_{i=1}^{|V|} \frac{d_i}{2|E|} \log_2 \frac{d_i}{2|E|},$$

where d_i is the degree of vertex i .

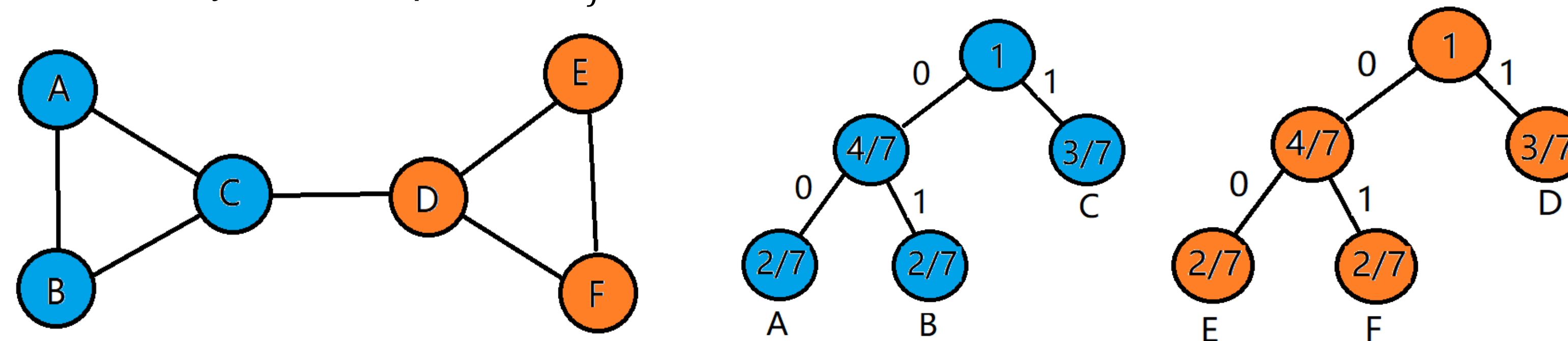


A: 000 B: 001 C: 10 D: 11 E: 010 F: 011 $\mathcal{H}(G) = 5.11$

Definition 2. The structural entropy of G relative to P is:

$$\mathcal{H}_P(G) := -\sum_{j=1}^L \frac{v_j}{2|E|} \mathcal{H}(G \upharpoonright X_j) - \frac{g_j}{2|E|} \log_2 \frac{v_j}{2|E|},$$

where the subgraph $G \upharpoonright X_j$ is **induced by X_j** and g_j denotes the number of edges with exactly one end point in X_j .



A: 00 B: 01 C: 1 D: 1 E: 00 F: 01 $\mathcal{H}_P(G) = 3.40$

Definition 3. The normalized residual entropy of P is

$$\rho_P(G) := (\mathcal{H}(G) - \mathcal{H}_P(G)) / \mathcal{H}(G).$$

REM: Algorithm and optimization

Theorem 1. There exists a critical non-edge $\{u, v\}$ is RE-minimizing.

Theorem 2. Examining the critical edges implements in $\mathcal{O}(L|V|)$.

Algorithm 1: An efficient REM deceptor

Input: Graph $G = (V, E)$, $\mathcal{P} = \{X_1, X_2, \dots, X_L\}$

Output: A non-edge $\{u^*, v^*\}$

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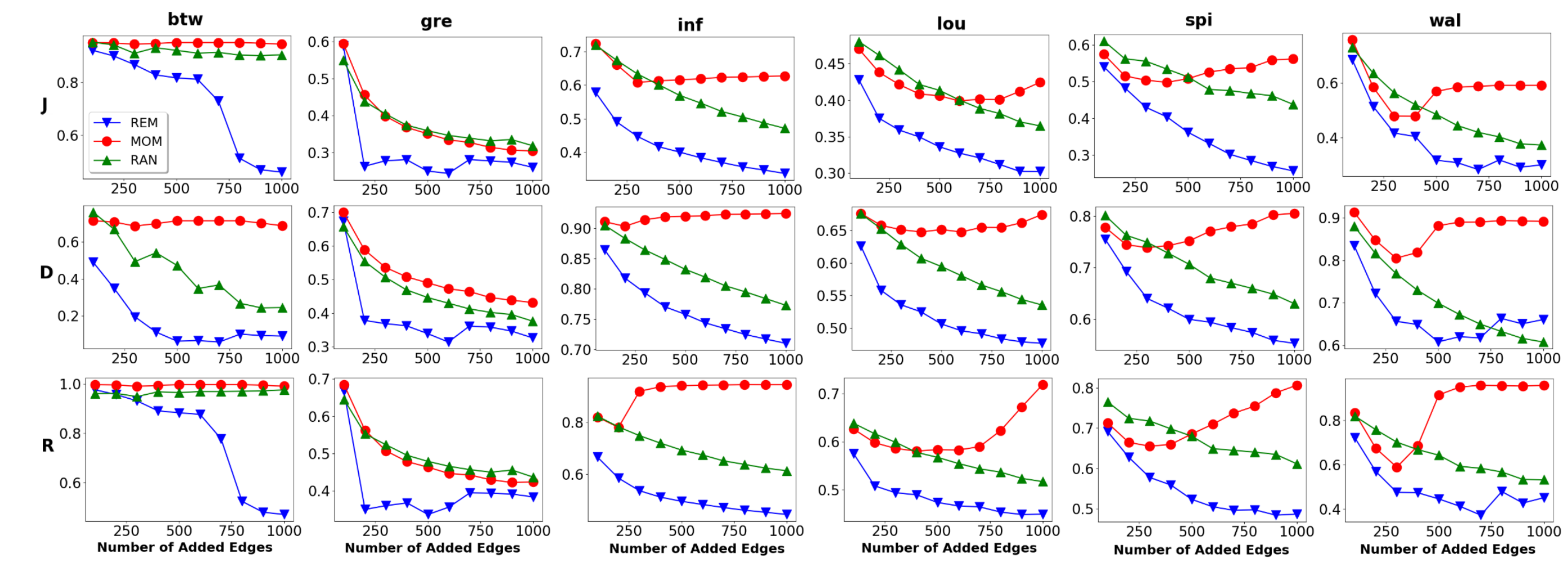
1 Initialize  $\rho^* \leftarrow 1$ ;
2 for  $s \leftarrow 1$  to  $L$  and  $t \leftarrow s$  to  $L$  do
3   if  $X_s \times X_t$  contains no non-edge then
4     continue;
5   for all critical non-edge  $\{u, v\}$  in  $X_s \times X_t$  do
6     Set  $\rho_{u,v} \leftarrow (\mathcal{H}(G \oplus \{u, v\}) - \mathcal{H}_P(G \oplus \{u, v\})) / \mathcal{H}(G \oplus \{u, v\})$ ;
7     if  $\rho_{u,v} < \rho^*$  then
8       Set  $\rho^* \leftarrow \rho_{u,v}$ ,  $u^* \leftarrow u$ , and  $v^* \leftarrow v$ ;
9 return  $\{u^*, v^*\}$ ;
```

A crude implementation runs in $\mathcal{O}(|V|^2)$ time. We present an $\mathcal{O}(L|V|)$ -implementation by only examining the critical edges.

Experiments

Dataset: 9 real-world networks. **Adversary:** $\{btw, gre, inf, lou, spi, wal\}$.

Evaluation: 3 metrics, $\{J, D, R\}$. **Benchmark:** $\{MOM, RAN\}$.



The preservation of the data after applying REM:

Dataset	$ E' $	Jaccard	Clustering coefficient	Mean shortest path length	10% Pagerank	10% Betweenness
Dol	10	$1 \rightarrow 0.44$	$0.308 \rightarrow 0.298$	$3.357 \rightarrow 2.996$	$1 \rightarrow 0.833$	$1 \rightarrow 0.833$
Jaz	250	$1 \rightarrow 0.48$	$0.520 \rightarrow 0.498$	$2.23 \rightarrow 2.070$	$1 \rightarrow 0.895$	$1 \rightarrow 0.842$
Eml	100	$1 \rightarrow 0.39$	$0.166 \rightarrow 0.166$	$3.606 \rightarrow 3.577$	$1 \rightarrow 0.991$	$1 \rightarrow 0.982$
PGP	400	$1 \rightarrow 0.45$	$0.378 \rightarrow 0.377$	$7.485 \rightarrow 7.279$	$1 \rightarrow 0.979$	$1 \rightarrow 0.930$
CAI	1000	$1 \rightarrow 0.49$	$0.007 \rightarrow 0.007$	$3.875 \rightarrow 3.869$	$1 \rightarrow 0.983$	$1 \rightarrow 0.977$
Bri	1000	$1 \rightarrow 0.44$	$0.111 \rightarrow 0.111$	$4.858 \rightarrow 4.854$	$1 \rightarrow 0.993$	$1 \rightarrow 0.971$

Conclusions

- Utilize community based structural entropy to the CSD problem
- Propose a residual minimization (REM) algorithm.
- Reduce search space to critical edges to optimize REM.
- validate the performance of our algorithm.