Multiscale Evolutionary Perturbation Attack on Community Detection

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Abstract—Community detection, aiming to group nodes based on their connections, plays an important role in network analysis, since communities, treated as meta-nodes, allow us to create a large-scale map of a network to simplify its analysis. However, for privacy reasons, we may want to prevent communities from being discovered in certain cases, leading to the topics on community deception. In this paper, we formalize this community detection attack problem in three scales, including global attack (macroscale), target community attack (mesoscale) and target node attack (microscale). We treat this as an optimization problem and further propose a novel Evolutionary Perturbation Attack (EPA) method, where we generate adversarial networks to realize the community detection attack. Numerical experiments validate that our EPA can successfully attack network community algorithms in all three scales, i.e., hide target nodes or communities and further disturb the community structure of the whole network by only changing a small fraction of links. By comparison, our EPA behaves better than a number of baseline attack methods on six synthetic networks and three real-world networks. More interestingly, although our EPA is based on the louvain algorithm, it is also effective on attacking other community detection algorithms, validating its good transferability.

Index Terms—Social network, community detection, community deception, privacy protection, genetic algorithm.

1 INTRODUCTION

Natural network consists of many nodes and links, which captures certain relationship in real world and is often used as a mathematical representation for a variety of complex systems, such as social systems [1]–[4], transportation systems [5], [6] and supply chain systems [7], [8], etc. Many real-world networks can be divided into communities, with the nodes within the same communities connected densely, while those across different communities connected sparsely [9]. The revealed community structure can not only present the close relationship among the nodes inside a certain community, but may also indicate that these nodes tend to share common properties or play similar roles in the respective fields [10]. Analyzing community structure in a network thus can help to better understand the interactions inter- and intra- close groups of nodes in the network, which is the exact reason why new community detection algorithms are continuously proposed and widely used in a large number of areas.

Community detection algorithms are designed to divide the network into partitions of dense regions which correspond to strong related entities. Evaluating the effectiveness of these algorithms has been a controversial problem until Newman proposed the modularity Q [11], [12]. The proposal of modularity makes the problem of non-overlapping community detection unprecedented developed. A bunch of modularity optimization algorithms were subsequently proposed, some of which are based on splitting or aggregation [13]–[16], while many others use optimization algorithms to maximizes the modular Q, such as annealing [17], Particle Swarm Optimization (PSO) [18], external optimization [19] and spectral optimization [20]. These algorithms translate community detection into an optimization problem and try to find the optimal community division by maximizing certain fitness. In addition, there are also community detection algorithms based on information theory [21]–[24] and label propagation [25]–[27]. The former believes that data flow can be compressed with regular code, such as random walk model. The main idea is that the probability of wandering to the nodes in the same group is much greater than those in different groups; while the latter updates each node label to its most frequent neighbor label through iteration, which was widely used due to its simplicity and high efficiency.

However, on one hand, people may not want their social information, such as communities, as a part of privacy to be discovered by certain algorithms; on the other hand, a lot of graph-based models, e.g., graph-based recommenders, need to integrate community detection to improve their efficiency, especially for those relatively large systems. The normal operation of such systems thus may rely on the robustness of community detection algorithm. These bring up a problem: how to attack community detection algorithms or defense against such attacks? Since different links play different roles in keeping the community structure of a network, the community detection algorithms could be significantly disturbed by only changing a small fraction of links. In this paper, we focus on the attack part, and seek the maximum community change by rewiring minimal number of links, which can help to judge which links are most vulnerable and thus also provides insights for the defense part in order to keep the community structure.

There are some attack strategies to disturb network algorithms [31]–[34], but few studies related to community
detection attack. Nagaraja [28] first introduced a community hiding problem, where they added links based on centrality values. Waniek et al. [29] proposed a heuristic rewiring method to hide a community, by deleting the links within the same communities while adding the links across different communities. Because the links are randomly selected, the method is of relatively low effectiveness. And they also propose the concept of individual hiding, as a way to avoid an influential node being highlighted by three centrality measures (i.e., degree, closeness, betweenness). Valeria et al. [30] proposed a deception score to evaluate the effect of community deception, which takes the accuracy and recall of community detection into account, as well as the reachability of target community. The essence of this score is that the target community is expected to be divided into more new communities and each new community contains less percentage of target nodes. However, this may lead to the following two problems: first, it encourages more communities which might make the attack less concealed; second, when the number of communities is set to be constant, it can’t guide the nodes from the target community to the optimal community to achieve better attack capacity. Quite recently, Chen et al. [35] proposed Q-Attack based on Genetic Algorithm (GA) and modularity, for the first time, to disturb the overall modular structure of a network.

Generally, we think there are following three types of community detection attacks of different scales.

- **Global attack (macroscale):** This attack is to achieve maximum community changes of the whole network by rewiring minimal number of links.
- **Target community attack (mesoscale):** This attack is also known as community deception, which is to hide one specific community by rewiring minimal number of links that are connected to at least one node in the community.
- **Target node attack (microscale):** This attack is to make target node belong to different communities by rewiring the minimal number of links around it. Note that our target node attack is different from the individual hiding proposed by Waniek et al. [29], since the latter has nothing to do with community detection.

In this paper, we formalize the community detection attack problem and present an Evolutionary Perturbation Attack (EPA) algorithm to attack community detection algorithms in three scales, i.e., macroscale (network), mesoscale (community) and microscale (node). The main differences between our method and the previous attack algorithms are summarized in TABLE 1. Moreover, we use a series of metrics to evaluate the attack results obtained by different attack methods on several real datasets. In particular, we make the following main contributions.

- To the best of our knowledge, this is the first time to formalize the problem of community detection attack into three scales, i.e., macroscale (network), mesoscale (community) and microscale (node).
- We propose a novel EPA algorithm to attack community detection, which is capable of generating approximate optimal adversarial network with the minimal number of rewired links to launch all the three scales of attacks. We compare our EPA with other baseline attack methods on several synthetic networks and real-world networks, and find that EPA behaves the best in most cases, achieving the state-of-the-art results.
- We use GA to solve the optimization problem in EPA algorithm, and meanwhile introduce network structural properties including betweenness and the shortest path lengths between pairwise nodes into the mutation process to accelerate the convergence rate, making it faster to obtain the approximate optimal solution.
- We find that our EPA has outstanding transferability, i.e., the adversarial network generated by EPA against the louvain algorithm (LOU) can also be used to successfully fool other community detection algorithms.

The rest of paper is organized as follows. In Sec. 2, we formalize the problem of community detection attack and introduce our EPA method in details. Then, we compare the attack effects by utilizing EPA and other attack methods on a number of synthetic networks and real-world networks in Sec. 3 where we further use a variety of community detection algorithms to verify the transferability of EPA. Finally, we conclude the paper and highlight future research directions in Sec. 4.

### TABLE 1: Comparison with the existent approaches.

| Approach     | Scale of Attack | Way to Change Network | Budget Required |
|--------------|-----------------|-----------------------|-----------------|
| Nagaraja     | Mesoscale       | Addition              | Yes             |
| Waniek et al.| Mesoscale       | Rewiring              | Yes             |
| Fionda et al.| Mesoscale       | Rewiring              | Yes             |
| Our EPA      | Macroscale & Mesoscale & Microscale | Rewiring & Addition | No              |

**Definition 1 (Adversarial network).** Denoting the original network $G=(V, E)$ as the target, the adversarial attack selects some key links to construct an adversarial perturbation network $\hat{G}=(V, \hat{E}, \omega)$, where $\omega_{uv} \in \{-1, 0, 1\}$ is the weight on the $E_{uv}$. Adversarial network $\hat{G}=(V, \hat{E}),$
generated by adding adversarial perturbation on the original network, is defined as
\[
\tilde{E}_{uv} = E_{uv} + \omega_{uv} \tilde{E}_{uv}.
\] (1)

**Problem 1 (Global Attack).** Given a network \( G=(V,E) \), generate an adversarial network \( \tilde{G}=(\tilde{V},\tilde{E}) \) via attack strategy to make community detection method \( \varphi \) fail with budget \( \beta \). \( \tilde{G} \) is divided into communities \( \tilde{C} = \{\tilde{C}_1, \tilde{C}_2, \ldots, \tilde{C}_r\} \) by using the same community detection algorithm. Furthermore, \( E^+ \) (resp., \( E^- \)) denotes a set of link additions (resp., deletions) and the global attack is realized by solving the optimization problem:
\[
\arg \max \{ \phi(C, \tilde{C}, E, E^+, E^-, \beta) \},
\] (2)
where \( \beta = |E^+| = |E^-| \), meaning that we only consider the rewiring operation for global attack, and \( \tilde{E} = (E \cup E^+) \setminus E^- \). Since the links are rewired globally, we have
\[
E^+ \subseteq \{(u,v) : u \in V \land v \in V, (u,v) \notin E\},
\] (3)
\[
E^- \subseteq \{(u,v) : u \in V \land v \in V, (u,v) \in E\}.
\] (4)

**Problem 2 (Target Community Attack).** Given a target community \( C_i \subseteq C \), which is obtained by community detection method \( \varphi \) on the original network \( G \). After target community attack, \( C_i \) cannot be detected by \( \varphi \), i.e., in the adversarial network \( \tilde{G} \), the nodes in \( C_i \) belong to a set of new communities, denoted by \( \tilde{C} = \{\tilde{C}_1, \tilde{C}_2, \ldots, \tilde{C}_r\} \subseteq \tilde{C} \), with \( \tilde{C}_j \cap \tilde{C}_i \neq \emptyset, \forall j \in [1, r] \), which is realized by solving the optimization problem:
\[
\arg \max \{ \phi(C_i, \tilde{C}, E, E^+, E^-, \beta) \}.
\] (5)

Here, we still consider the rewiring process and thus have \( \beta = |E^+| = |E^-| \), \( \tilde{E} = (E \cup E^+) \setminus E^- \). In order to hide community \( C_i \), it would be best to disconnect the links inside the community while add connections between the nodes in \( C_i \) and those in other communities, thus we have
\[
E^+ \subseteq \{(u,v) : u \in C_i \oplus \tilde{C}_i, (u,v) \notin E\},
\] (6)
\[
E^- \subseteq \{(u,v) : u \in C_i \land \tilde{C}_i, (u,v) \in E\}.
\] (7)

**Problem 3 (Target Node Attack).** Given a target node \( t \), suppose it belongs to community \( C_i \) in the original network \( G \), while it belongs to \( \tilde{C}_i \) in the adversarial network \( \tilde{G} \), then the target node attack is realized by solving the optimization problem:
\[
\arg \max \{ \delta \times \mu(E, \tilde{E}, E^+, E^-, \beta) \},
\] (8)
\[
\delta = \begin{cases} 
1 & \frac{|\tilde{C}_i \cap C_i|}{|\tilde{C}_i|} < \epsilon \\
0 & \text{else}
\end{cases}
\] (9)
where \( \mu \) is the function to measure the amount of network change. \( \epsilon \in [0,1] \) is a predefined threshold, based on which we determine whether communities \( C_i \) and \( \tilde{C}_i \) are close to each other or not. We think the attack is successful only when these two communities are relatively different from each other. Similarly , we still have \( \beta = |E^+| = |E^-| \) and \( \tilde{E} = (E \cup E^+) \setminus E^- \). To make the attack more effective, at this time, we rewire links around the target node \( t \), thus we have
\[
E^+ \subseteq \{(u,t) : u \in V, (u,t) \notin E\},
\] (10)
\[
E^- \subseteq \{(u,t) : u \in V, (u,t) \in E\}.
\] (11)
TABLE 2: The definitions of main symbols.

| Symbol | Definition |
|--------|------------|
| $n$    | The number of nodes in network |
| $m/m_t$ | The number of links in network/target community |
| $\beta$ | The budget which is the number of rewired links |
| $\theta$ | The maximum number of rewired links |
| $C_i/C_j$ | The communities before/after the attack |
| $M_i/M_t$ | The number of nodes in new/original community $C_i$ |
| $m_{i,j}/m_{i,j}$ | The number of community $C_i$’s nodes which originally belong/not belong to the target community $C_j$ |
| $E_M/E_M$ | The entropy of new/target communities |
| $N_i/N_b$ | The number of communities in the control/test group |
| $O_i$ | The $i$-th chromosome of the population |
| $(.)_{O_i}$ | The value under the attack represented by $O_i$ |

The function $\phi$ in Eqs. (2) and (3) is used to evaluate the attack gain, which will be specialized in Sec. 2.3. Note that the attack gain consists of two parts: the budget $\beta$, defined as the number of rewired links, and the attack effect. As we can see, the overall attack effect generally increases as the budget $\beta$ grows, as a result, it is our focus to improve the attack gain with only limited budget $\beta$.

These indicate that community detection attack can always be represented as an optimization problem, which could be well solved by evolutionary computing methods, such as Genetic Algorithm (GA). In this paper, we propose a GA based Evolutionary Perturbation Attack (EPA) for community detection. In order to make the GA more suitable for finding appropriate attack strategy, we use rewired link ID as genes on the chromosome instead of binary coding, which can effectively reduce the storage space of the population. Considering that the number of rewired links is also a variable here, we adopt a strategy called *unequal crossover* to make the length of chromosome changeable during the crossover process. Moreover, a novel search mechanism based on network structural properties, including betweenness and the shortest path lengths between pairwise nodes, is introduced in the mutation process to accelerate the convergence of GA, making it faster to obtain the approximate optimal solution.

In particular, our EPA is established in four stages, including initialization, evaluation, crossover and mutation, which will be introduced one by one in the following. The flowchart of EPA is shown in Fig. 1, and the main symbols used in this paper are listed in TABLE 2 for convenience.

### 2.2 Initialization

First, we directly use the ID of rewired link as the gene of chromosome to facilitate the evolving. Specifically, we create the indexes for existing links and nonexistent links and treat them as link deletion and addition genes, respectively.

To make the attack more concealed, we set the number of deleted links equal to that of added links, so that the total number of links in the network keeps constant. Denote the threshold of the number of rewired links by $\theta$ and the chromosome by $O_i$ with the budget $\beta \in [1, \theta]$. We thus have

$$O_i = (A_i, B_i) = (a_i^1, a_i^2, \ldots, a_i^{\beta}, b_i^1, b_i^2, \ldots, b_i^{\beta}),$$

where $O_i$, with the index $i \in [1, P]$, represents the $i$-th chromosome in population and $P$ is the population size of GA. $A_i$ and $B_i$ represent the sets of link addition and deletion links, respectively, in chromosome $O_i$, with the element $a_i^j$ (or $b_i^j$) being the index of a node pair which are disconnected (or connected). The link change $\omega_{uv}$ between two nodes $u$ and $v$, represented by chromosome $O_i$, is thus calculated by

$$\omega_{uv} = \begin{cases} 1 & \text{Index}(u, v) \in A_i, \\ -1 & \text{Index}(u, v) \in B_i, \\ 0 & \text{otherwise} \end{cases},$$

where Index($u, v$) is the function to obtain the index of a node pair $(u, v)$. An illustration to explain how chromosomes are coded and initialized is shown in Fig. 2.

Note that, to make the target node attack more effectively, instead of initializing randomly, we first select a target community randomly, then we preferentially delete the links between the target node and those not belonging to the target community, while establish links between the target node and those in the target community. If all nodes in the target community are connected to the target node, then we randomly select another target community and repeat the above steps.
2.3 Evaluation

2.3.1 Fitness Function
Each chromosome corresponds to an attack strategy. After encoding the attack strategies, we then need to evaluate the attack effect of each strategy using some fitness function. Note that the entropy is maximized when each new community consists of nodes uniformly from many different real communities. Since the uniform distribution emphasized by entropy makes the overall accuracy and recall as low as possible, we thus think it’s an appropriate metric to evaluate the attack effect. For the global attack or target community attack, their fitness functions follow the same general form, represented by

$$\phi_i = \Psi(d'|O_i) \times X(C, \hat{C}|O_i)$$

(14)

which consists of two parts: the attenuation function $\Psi \in [0, 1]$ and the attack effect evaluation function $X$. $\Psi$ is a monotonic decreasing function of $d'|O_i$, with $d'$ being the normalization of $d$ which represents the degree change after the attack represented by chromosome $O_i$. $X$ is the function to evaluate the attack effect based on entropy, and the terms $C$ and $\hat{C}|O_i$ denote the community detection results before and after the attack, respectively. For the target node attack, however, since the attack effect is binary, i.e., either success or failure, the fitness function only contains the first part, i.e., the change of target node degree.

2.3.2 Attenuation Function

In order to perform the attack with limited budget $\beta$, we use the exponential decay function as our attenuation function, described as follows:

$$\Psi(d'|O_i) = \exp(c \times d')|O_i$$

(15)

where $d' = d/m$ ($m$ is the number of links in the whole network) for global attack while $d = d/m_1$ ($m_1$ is the number of links in the target community) for target community attack; and $c$ is a constant that controls the decay speed. For a network of $n$ nodes, the degrees of all nodes before and after the attack are denoted by $D = \{d_1, d_2, \cdots, d_n\}$ and $\hat{D} = \{\hat{d}_1, \hat{d}_2, \cdots, \hat{d}_n\}$, respectively. Then, the distance $d$ between them is calculated by

$$d = \frac{1}{n} \sum_{i=1}^{n} |d_i - \hat{d}_i|,$$

(16)

where $d_i$ and $\hat{d}_i$ are the degrees of node $i$ before and after the attack, respectively. Note that when adding and deleting links on totally different nodes, the degree distance $d$ tends to be equal to the number of rewired links divided by the number of nodes. However, if we delete a link around a node whenever we add a link to it, its degree will not change, and thus the degree distance must be equal to 0 all the time. In this study, the latter is considered more concealed and thus is preferred according to Eq. (15).

2.3.3 Attack Effect

Given a confusion matrix $M$ with each element $m_{ij}$ representing the number of the shared nodes between the original community $C_i$ and the new community $\hat{C}_j$, we define the function $X$ to evaluate the attack effect:

$$X(C, \hat{C}|O_i) = (E'_{Me} + E'_{Mm})|O_i,$$

(17)

where $E'_{Me}$ and $E'_{Mm}$ are the normalized entropy of $M_e$ and $M_m$, and thus $X$ must be in the range of $[0, 2]$. Suppose $E_{Me}$ and $E_{Mm}$ are the entropy of new communities and target communities, which are obtained by considering the row vectors and column vectors of $M$, respectively. Suppose the matrix $M$ dimension is $N_a \times N_b$, with $N_a$ and $N_b$ being the numbers of communities in control group (i.e., real community number) and test group (i.e., community number detected by certain community detection algorithm after the attack), respectively, the maximum values of $E_{Me}$ (resp., $E_{Mm}$) $E_{M}$ are obtained when the values of each row (resp., column) are equal. In this case, the calculation of $E_{Me}$ and $E_{Mm}$ is simplified to

$$\max E_{Me} = -\sum_{i=1}^{N_a} \frac{M_e(i)}{n} \log_2 \frac{1}{N_b} \times N_b = \log_2 N_b,$$

(18)

$$\max E_{Mm} = -\sum_{i=1}^{N_b} \frac{M_m(i)}{n} \log_2 \frac{1}{N_a} \times N_a = \log_2 N_a,$$

(19)

where $n$ is the number of nodes in network. $M_e$ and $M_m$ represent the numbers of nodes in new and original community $C_i$, respectively.

For global attack, the entropy for new communities and that for target communities $E_{Me}$ and $E_{Mm}$ can be calculated by

$$E_{Me} = -\sum_{i=1}^{N_a} \sum_{j=1}^{N_b} M_e(i,j) \log_2 \frac{m_{ij}}{M_i},$$

(20)

$$E_{Mm} = -\sum_{i=1}^{N_b} \sum_{j=1}^{N_a} M_m(i,j) \log_2 \frac{m_{ij}}{M_j},$$

(21)

where $m_{ij}$ is the number of nodes in new community $C_i$ that originally belong to community $C_j$.

Suppose all the communities keep exactly the same after the attack, we have $E_{Me} = E_{Mm} = 0$. With Eq. (18) we can conclude that $E_{Me}$ and $E_{Mm}$ must be in the range of $[0, \log_2 N_a]$ and $[0, \log_2 N_b]$, respectively. Therefore, based on Eq. (14) and Eq. (17), the fitness of $O_i$ for global attack is defined as

$$\phi_i = \Psi(d'|O_i) \times \left(\frac{E_{Me}}{\log_2 N_b} + \frac{E_{Mm}}{\log_2 N_a}\right)|O_i.$$

(22)

For target community attack, here we limit that any added or deleted link must be connected to at least one node in the target community, which greatly reduces the searching space of solutions. In this case, $M$ is an $N_a \times 2$ matrix with element $m_{ij}$ (resp., $\hat{m}_{ij}$) being the number of nodes in community $C_i$ that originally belong (resp., don’t belong) to target community $C_j$. For target community $C_j$, $E_{Me}$ and $E_{Mm}$ are defined as

$$E_{Me} = -\sum_{i=1}^{N_a} \frac{M_e(i)}{n} \log_2 \frac{m_{ij}}{M_i} + \frac{\hat{m}_{ij}}{M_i} \log_2 \frac{\hat{m}_{ij}}{M_i},$$

(23)

$$E_{Mm} = -\sum_{j=1}^{N_b} \frac{m_{ij}}{M_j} \log_2 \frac{\hat{m}_{ij}}{M_j}.$$ (24)

Based on the above definitions, we always have $\hat{m}_{ij} = M_i - m_{ij}$. The remaining variables are defined the same as those in Eq. (20) and Eq. (21).
Similarly, with Eq. (18) we can conclude that $E_{M_r}$ and $E_{M_s}$ must be in the range of $[0,1]$ and $[0, \log_2 N_a]$, respectively. Therefore, the fitness of $O_i$ for target community attack is defined as

$$
\phi_i = \Psi(d') \times (E_{M_r} + \frac{E_{M_s}}{\log_2 N_a}).
$$

(25)

It should be noted that our fitness function based on entropy is somewhat similar to the deception score $H$ mentioned in [20], i.e., both of them have a tendency to spread more nodes of the target community into more communities. The main difference is that by using normalization, in our method, the number of new communities will not be too large, making the attack more concealed.

Finally, for target node attack, it is quite easy to hide a node by rewiring links. In this study, however, we try to hide a node by only adding links to the target node. We believe that adding, rather than deleting, certain links are much more convenient for social network users. For target node $t$, the fitness of chromosome $O_i$ thus is calculated by

$$
\phi_i = \begin{cases} 
\frac{d_t}{d_t + \beta |O_i|} & \text{successful attack} \\
0 & \text{otherwise}
\end{cases},
$$

(26)

where $d_t$ is the degree of target node $t$ before the attack and $\beta |O_i|$ is the length of chromosome $O_i$. Thus, $d_t + \beta |O_i|$ is the degree of the target node after the attack represented by $O_i$.

For any kind of attack, after evaluating each individual in GA, we further use roulette selection method to select offspring. If the fitness of each individual in the population is $\phi_i \ (i = 1, 2, \ldots, M)$ and the size of the population is $M$, the selection probability of individual $O_i$ is calculated by

$$
P(O_i) = \frac{\phi_i}{\sum_{j=1}^{M} \phi_j}.
$$

(27)

2.4 Crossover

Traditionally, the length of chromosomes is set the same and is fixed throughout the evolution in GA. Here, we prefer to use non-equal crossover, where the length of chromosomes can change in the process of crossover, so that we can find the optimal solution with the smallest budget $\beta$, which is described by the following steps.

1) Choose two chromosomes $O_i$ and $O_j$ and form two subsets $E_i=\{A^E_i, B^E_i\} \subseteq O_i$ and $E_j=\{A^E_j, B^E_j\} \subseteq O_j$ by removing the identical elements that are considered nonexchangeable, where $A^E_i$ (or $A^E_j$) and $B^E_i$ (or $B^E_j$) are the exchangeable gene sets of addition and deletion, respectively, in chromosomes $O_i$ (or $O_j$).

2) Calculate the lengths of $A^E_j$, $B^E_j$, $A^E_i$ and $B^E_i$, and denote them by $l^E_A$, $l^E_B$, $l^E_{1A}$ and $l^E_{1B}$, respectively.

3) Generate two random integers $r_i$ and $r_j$ in the intervals $[1, \min(l^E_{1A}, l^E_{1B})]$ and $[1, \min(l^E_A, l^E_B)]$, respectively.

4) Suppose the numbers of rewired links by chromosomes $O_i$ and $O_j$ are $\beta_i$ and $\beta_j$, respectively, and the threshold is $\theta$. If $\beta_i - r_i + r_j$ or $\beta_j + r_i - r_j \notin [1, \theta]$, go to step 3; otherwise, go to step 5.

5) Select $r_i$ addition and deletion genes, respectively, from $O_i$, and select $r_j$ addition and deletion genes, respectively, from $O_j$; exchange the genes selected from $O_i$ with those selected from $O_j$, to generate two new chromosomes $O_i$ and $O_j$.

The whole process of crossover is shown in Fig. 3.

2.5 Mutation

Here, we further utilize the structural information around pairwise nodes as heuristic information to accelerate the searching process of GA.

For link addition, two nodes are of less similarity if the network distance (or the shortest path length) between them is relatively long. Therefore, in order to make the attack more effective, it is better to add the links between pairwise nodes of longer distance. Suppose the distance between a pair of disconnected nodes $i$ and $j$ is $\lambda_{ij}$, then the probability that a link addition gene to create a link between these two nodes is generated by mutation is defined as

$$
P(a_k) = \frac{\lambda_{ij}}{\sum_{(i,j) \notin E} \lambda_{ij}}.
$$

(28)
where \( a_{ij} \) is the index of the pair of nodes \((i, j)\).

For link deletion, the links inside communities always have lower betweenness than those across different communities. Therefore, in order to make the attack more effective, it is better to delete the links of lower betweenness. Given a link with its index \( b_k \), its betweenness is calculated by

\[
C_b(b_k) = \sum_{s, t \in V} \frac{\sigma(s, t | b_k)}{\sigma(s, t)},
\]

(29)

where \( V \) is the node set in the network, \( \sigma(s, t) \) represents the total number of shortest paths between nodes \( s \) and \( t \), and \( \sigma(s, t | b_k) \) represents the number of shortest paths through the link. Then, the probability that a link deletion gene to the link is generated by mutation is defined as

\[
P(b_k) = \frac{1}{\sum_{k=1}^m \frac{1}{C_b(b_k)}},
\]

(30)

where \( m \) is the total number of links in the network.

3 Experiments

In this part, we will perform the three kinds of attacks on several synthetic networks and real-world networks. For global attack, we first compare our EPA with three heuristic algorithms under different budgets \( \beta \), and we also design the experiment to show the ability of EPA to find the optimal budget. For target community attack, we first use EPA to get the optimal budget and then compare EPA with the other algorithms under this budget. For target node attack, we select some representative nodes as targets. For each experiment, we run 10 times and record the mean result. Our experimental environment consists of i7-8700 3.2GHz (CPU), GTX 1050Ti 4GB (GPU), 16GB memory and Windows 10.

3.1 Datasets

To evaluate the attack effect of EPA, we use three community detection algorithms, i.e., greedy (GRE) [13], Infomap Algorithm (INF) [21] and Louvain (LOU) [36] on the six synthetic networks and three real networks, described as follows, with their basic properties presented in TABLE 3 and TABLE 4 respectively. The descriptions of parameters for generating a synthetic network are listed in TABLE 5 for convenience.

- **The synthetic networks** [37]: These networks are generated by LFR benchmark, all of which are undirected and unweighted networks.
- **The USA college football (Football)** [14]: This network represents the matches between American football teams during the season of 2000.
- **Email-Eu-core network (Email)** [38]: The network represents the emails between members of a large European research institution.
- **Political blogs (Pol.Blogs)** [39]: This network represents the political leaning collected from blog directories.

In experiments, we only consider undirected networks and remove the isolated nodes from data sets since they are meaningless in community detection. The three community detection algorithms we adopt are also briefly introduced as follows to make the paper self-contained.

- **GRE [13]**: Each node is considered as a separate community initially and the communities are fused in the direction of maximum increment of modularity \( Q \).
- **INF [21]**: It’s an information theory based algorithm which strive to compress the average description length for a random walk.
- **LOU [36]**: This is a modularity based algorithm which can generate a hierarchical community structure by compressing the communities continuously.

3.2 Baseline Attack Methods

Inspired by various community detection algorithms, we use the following four heuristic attack methods as the baselines for global attack.

- **A_G**: A GA based method where the modularity \( Q \) is used to design the fitness function [35].
- **A_S**: Rather than using the entropy-based fitness function, here we use the average of deception score [30] as the fitness function and the rest is the same as EPA.
- **A_B**: Deleting the links with the highest betweenness centrality, while adding the links between the nodes with the longest distance.
- **A_D**: Deleting the links with the largest sum of degrees of their terminal nodes, while adding the links between the nodes with the longest distance.

For target community attack, we use the safeness based deception algorithm \( D_s \) [30] and random algorithm \( D_r \) [29] as the baseline attack methods, which can effectively hide the target community against different community detection algorithms, and they are briefly introduced as follows.

- **D_s**: Both link addition and deletion aim to maximize the safeness of target community defined in [30].

### TABLE 3: The basic properties of the six synthetic networks.

| Network   | N   | k   | \( \text{max } k \) | \( \mu \) | \( \text{min } c \) | \( \text{max } c \) |
|-----------|-----|-----|---------------------|-------|-----------------|-----------------|
| N-1000-\( \mu \)-0.3 | 1000 | 10  | 50                  | 0.3   | 50              | 100             |
| N-1000-\( \mu \)-0.5 | 1000 | 10  | 50                  | 0.5   | 50              | 100             |
| N-3000-\( \mu \)-0.3 | 1000 | 10  | 50                  | 0.3   | 100             | 200             |
| N-3000-\( \mu \)-0.5 | 1000 | 10  | 50                  | 0.5   | 100             | 200             |
| N-5000-\( \mu \)-0.3 | 15   | 100 | 100                 | 0.3   | 100             | 200             |
| N-5000-\( \mu \)-0.5 | 15   | 100 | 100                 | 0.5   | 100             | 200             |

### TABLE 4: The basic properties of the three networks.

| Network         | \#Nodes | \#Links | \#Communities |
|-----------------|---------|---------|---------------|
| Football        | 115     | 613     | 12            |
| Email           | 1005    | 25571   | 42            |
| Pol.Blogs       | 1490    | 19090   | 2             |

### TABLE 5: The meaning of parameters in synthetic networks.

| Parameter   | Meaning                                      |
|-------------|----------------------------------------------|
| \( m \)     | total number of links in the network         |
| \( \sigma(s, t) \) | total number of shortest paths between nodes \( s \) and \( t \) |
| \( \sigma(s, t | b_k) \) | number of shortest paths through the link |
| \( P(b_k) \) | probability of a link deletion gene to the link |
| \( C_b(b_k) \) | betweenness of a link with its index \( b_k \) |
| \( N \)     | number of nodes                              |
| \( k \)     | average degree                               |
| \( \text{max } k \) | maximum degree                              |
| \( \mu \)   | mixing parameter                             |
| \( \text{min } c \) | minimum community size                       |
| \( \text{max } c \) | maximum community size                       |
• $D_w$: This method randomly adds links inter different communities while deletes links intra communities.

For target node attack, we propose a heuristic algorithm $D$, which randomly add links between target node and the nodes in other communities.

3.3 Performance Metrics

In order to verify the effectiveness of our EPA, we compare it with other baseline attack methods by using a series of metrics.

For global attack, we use Normalized Mutual Information (NMI) and Adjusted Rand Index (ARI) to evaluate the community detection results. Then, we further evaluate the attack effects by comparing their values before and after attacks. In particular, NMI and ARI are defined as attack effects by comparing their values before and after community detection results. Then, we further evaluate the

\[
\text{NMI} = \frac{-2 \sum_{i=1}^{N} \sum_{j=1}^{N} m_{ij} \log \left( \frac{m_{ij}}{nm_i n_j} \right)}{\sum_{i=1}^{N} m_i \log \left( \frac{m_i}{M} \right) + \sum_{j=1}^{N} m_j \log \left( \frac{m_j}{M} \right)},
\]

(31)

\[
\text{ARI} = \frac{\sum j \left( m_{ij} \right) - \left[ \sum \left( M_i \right) \sum \left( M_j \right) / \binom{n}{2} \right]}{\frac{1}{2} \left[ \sum \left( M_i \right)^2 + \sum \left( M_j \right)^2 \right] - \left[ \sum \left( M_i \right) \sum \left( M_j \right) / \binom{n}{2} \right]},
\]

(32)

where $M_i$ and $M_j$ are the sums over row $i$ and column $j$, respectively. $N_d$ and $N_b$ are the numbers of communities in control group (i.e., real community number) and test group (i.e., community number detected by certain community detection algorithm), respectively.

For target community attack, in addition to the fitness, we also use the deception score $H$ [30] to evaluate the attack effect, which is defined as

\[
H = \left[ 1 - \frac{|S(C)| - 1}{|C| - 1} \right] \times \frac{1}{2} \left( 1 - \max(R) + \frac{1}{2} (1 - P) \right),
\]

(33)

where $|S(C)|$ is the number of connected components in the subgraph induced by the members in $C$. $\bar{P}$ and $R$ are the mean precision and recall rate, respectively.

For target node attack, we just use the percentage of target node degree increment in the attack to evaluate the results.

3.4 Experimental Results

3.4.1 Global Attack

In global attack, we fix the budget and rewire $k\%$ of links to compare our EPA with four baseline methods including $A_Q$, $A_S$, $A_B$ and $A_D$. We choose LOU as the basic community detection algorithm, and meanwhile we also use the GRE and INF algorithms to verify the black-box attack effect. The population used in the experiment is 100, the maximum number of iterations is 200, the crossover and mutation rates are 0.6 and 0.1, respectively. TABLE 6 [30] presents the community detection results before attack.

The community detection results, in terms of NMI and ARI, on different datasets obtained by various community detection algorithms, after the attacks by EPA and the four baseline attack methods for various percentages of rewired links, are presented in Fig. 4. Generally, we can find that, our EPA has the best attack effect on each performance metric, i.e., leading to smaller NMI and ARI, in most cases.

More specifically, we find that EPA performs especially well on Pol.Blogs network, i.e., rewiring 4% links can decrease both NMI and ARI to near 0.3. This may be because LOU performs quite well in revealing the community structure of this network, and meanwhile this network is also easy to be disturbed since the connections are much sparse. In fact, none of the attack methods performs well on LFR generated networks with small mixing parameter, i.e., NMI and ARI still keep relatively high after any kind of attack, since the communities of these networks are relatively dense and thus are easier to be detected. Indeed, for larger mixing parameter, all attacks behave better, leading to smaller NMI and ARI. By comparison, EPA outperforms all the others on synthetic networks, no matter for large or small mixing parameters. Besides, we can also find that white-box attack (LOU) behaves better than black-box attacks (GRE and INF), which is quite intuitive since all the attack methods here are based on the LOU algorithm. More interestingly, by comparison, the communities detected by INF are relatively robust than those detected by GRE, under the attack of LOU based EPA. This may be because both GRE and LOU are modulearity-based algorithms, while INF is based on information theory.

Now, let’s focus on the influence of the attenuation factor $c$ which controls the degree that the budget $\beta$ penalizes the fitness and ultimately controls the optimal budget generate by EPA. We thus compare the attack results under different values of $c$, and fix the other parameters. For each value, we run the experiment 10 times and report the mean results in TABLE 7 [29], where we can see that as $c$ increases from 3 to 6, the final budget generated by EPA significantly decreases with a little bit sacrifice of attack effects, i.e., NMI and ARI increases slightly as $c$ increases. We thus suggest to use relatively large value of $c$ if we want to get a more concealed attack, while use relatively small value of $c$ if the optimal attack effect is pursued.

3.4.2 Target Community Attack

Target community attack is also known as community deception. As an example, we visualize the attack effect of our EPA on the Dolphin network using t-SNE algorithm [40], as shown in Fig. 5. Here, we compare EPA with safeness based deception algorithm $D_s$ [30] and random algorithm $D_w$ [29]. In order to make fair comparison, we fix the budget $\beta$ for each algorithm, i.e., we first use our EPA to find the optimal budget and then use it as the input of $D_s$ and $D_w$. Again, we record the mean values of fitness and deception.

| Network | GRE | INF | LOU |
|---------|-----|-----|-----|
| Football | 0.73 | 0.49 | 0.92 |
| Email | 0.45 | 0.16 | 0.68 |
| Pol.Blog | 0.69 | 0.79 | 0.52 |
| N-1000-µ=0.3 | 0.73 | 0.54 | 0.97 |
| N-1000-µ=0.5 | 0.37 | 0.19 | 0.78 |
| N-3000-µ=0.3 | 0.63 | 0.34 | 0.96 |
| N-3000-µ=0.5 | 0.28 | 0.14 | 0.71 |
| N-5000-µ=0.3 | 0.75 | 0.44 | 1.00 |
| N-5000-µ=0.5 | 0.42 | 0.15 | 0.95 |

TABLE 6: The community detection results before attack.
Fig. 4: The attack effects, reflected by the change of NMI and ARI, obtained by EPA and the four baseline attack methods by rewiring k% of links, with k varies from 1 to 5, for the three real-world networks and six synthetic networks. Darker colors represent better attack performances and the best performance of each k is shown in red box.

TABLE 7: The global attack results obtained by EPA under various attenuation factor c.

| Network    | c=3  | c=4  | c=5  | c=6  |
|------------|------|------|------|------|
| Football   |      |      |      |      |
| β NMI      |    12.8 | 0.76 | 0.53 | 10.6 | 0.77 | 0.54 | 8.6  |
| ARI        |      |      |      |      |
| NMI        | 0.77 | 0.54 | 8.6  | 0.77 | 0.55 | 7.8  | 0.78 | 0.57 |
| Email      |      |      |      |      |
| β NMI      |    566.6 | 0.48 | 0.22 | 506.4 | 0.49 | 0.23 | 134.5 |
| ARI        |      |      |      |      |
| NMI        | 0.49 | 0.23 | 134.5 | 0.51 | 0.25 | 113.7 | 0.53 | 0.26 |
| Pol.Blogs  |      |      |      |      |
| β NMI      | 1947.1 | 0.33 | 0.35 | 1690.9 | 0.34 | 0.35 | 1172.8 |
| ARI        |      |      |      |      |
| NMI        | 0.34 | 0.35 | 1172.8 | 0.37 | 0.36 | 1125.5 | 0.38 | 0.39 |

score H for all detected communities with at least 10 nodes on each network, as presented in TABLE 8. Note that here, for synthetic networks, we only give the results of INF and LOU algorithms, since GRE is of high time complexity and thus is quite time-consuming on networks including more than thousands of nodes, especially we need to attack each community in a network.

We find that, again, our EPA behaves significantly better, in terms of much higher fitness and deception score H, than both Ds and Dsw. And such results are quite robust. For instance, for the Football network, it seems that Ds and Dsw lose their attack effects on INF and LOU, i.e., the values of Fitness and H are quite small by comparing with those on GRE, as presented in TABLE 8. However, by using our EPA, their values still keep relatively large for all the three community detection algorithms, indicating that EPA is effective in both white-box and black-box situations. Moreover, it seems that the synthetic networks with smaller mixing parameters µ always have lower fitness in the corresponding cases. The reason may be that the networks of smaller µ tend
more important in various applications. In particular, we first rank the nodes in each network based on their degree and betweenness, from large to small, respectively. Then, in addition to selecting the two nodes with the largest degree and betweenness, respectively, as the target nodes, we also sum the two orders for each node and choose the top one as our another target node. We name these three target nodes addition to selecting the two nodes with the largest degree and betweenness, respectively. Finally, we compare EPA with the $D_r$ algorithm that randomly adds links between target nodes and the nodes in different communities.

The percentages of degree increment in the attack for different strategies are presented in TABLE 10-TABLE 11. We can find that, in general, EPA performs significantly better than $D_r$, in terms of smaller percentage of degree increment, especially in the football network. Moreover, the bridge nodes of large betweenness are relatively easy to be attacked, since the neighbors of bridge nodes are always distributed in different communities, making them quite sensitive to link changes. On the contrary, it’s relatively difficult to hide a node with both high degree and betweenness, since as hub nodes, a much large number of links always need to be added to change their communities. Note that, for real-world networks, based on EPA, the number of added links is much smaller than the degree of target nodes, indicating our method performs well in target node attack.

4 Conclusions

In this paper, we propose a novel Evolutionary Perturbation Attack (EPA) method, based on Genetic Algorithm (GA), to disturb community detection algorithms in three scales,
from local to global, by only changing a small fraction of links. In particular, we design a non-equal crossover strategy to treat the length of chromosome as a variable and naturally integrate it into GA; and we also integrate the network structural information, such as network distance and betweenness, into the algorithm to guide the search so as to find the better optimal attack strategy more quickly.

Numerical experiments on six synthetic networks and three real-world validate the effectiveness and trasferability of our EPA method on attacking various community detection algorithms, i.e., by comparing with other attack methods of different scales, EPA behaves the best in most cases, achieving the state-of-the-art attack effects.

In the future, we will expand this work in the following three directions. First, we will propose new network coding methods and also utilize more network structural properties to improve the efficiency of EPA; second, we will try to integrate network embedding and deep learning graph models to improve the attack performance; third, we will do more experiments on more various networks, and further check the effectiveness of our EPA on the downstream algorithms based on community detection, to see the potential influence of EPA on many real applications.

**Acknowledgments**

The authors would like to thank all the members in the IVSN Research Group, Zhejiang University of Technology for the valuable discussion about the ideas and technical details presented in this paper.

This research was supported by Zhejiang Provincial Natural Science Foundation of China (LY19F020025, LR19F030001), Major Special Funding for Science and Technology Innovation 2025 in Ningbo (2018B10063), National Natural Science Foundation of China (61502423, 61973273, 61572439), “Key Technologies, System and Application of Cyberspace Big Search” Major Scientific Research Project of Zhejiang Lab (2019DH0ZX01).

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**Table 11: Target node attack on synthetic networks.**

| dataset | Node | INF | Lou |
|---------|------|-----|-----|
| EPA | $D_1$ | EPA | $D_1$ |
| 1000-0.3 | $T_1$ | 67% | 336% | 53% | 406% |
| 1000-0.5 | $T_1$ | 64% | 412% | 43% | 349% |
| 1000-0.5 | $T_1$ | 70% | 409% | 55% | 445% |
| 3000-0.3 | $T_1$ | 43% | 385% | 53% | 227% |
| 3000-0.5 | $T_1$ | 46% | 320% | 22% | 58% |
| 3000-0.5 | $T_1$ | 29% | 265% | 28% | 117% |
| 5000-0.3 | $T_1$ | 142% | 340% | 40% | 625% |
| 5000-0.5 | $T_1$ | 114% | 408% | 47% | 522% |
| 5000-0.5 | $T_1$ | 194% | 493% | 54% | 596% |
| 5000-0.5 | $T_1$ | 242% | 302% | 16% | 138% |
| 5000-0.5 | $T_1$ | 60% | 279% | 8% | 19% |
| 5000-0.5 | $T_1$ | 78% | 321% | 16% | 26% |

| 1000-0.3 | $T_1$ | 86% | 518% | 55% | 706% |
| 1000-0.5 | $T_1$ | 70% | 558% | 52% | 653% |
| 1000-0.5 | $T_1$ | 108% | 672% | 83% | 815% |
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