CRIME: Community Rewiring for Influence and Masking Entities in Social Networks (Student Abstract)

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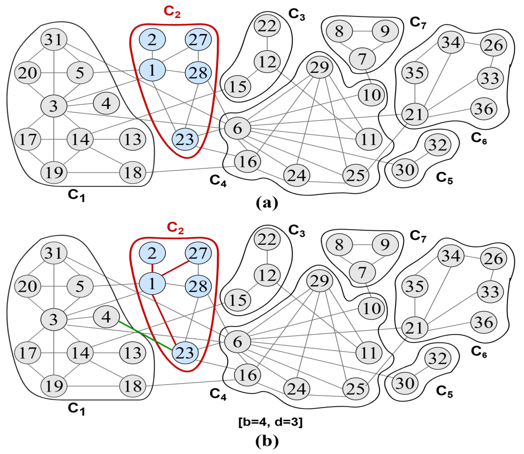
Abstract

In social networks, revealing the structure of communities can expose sensitive groups to detection. Traditional approaches, such as DICE, attempt to hide these communities by randomly rewiring links, but this strategy is often inefficient and insecure. We propose an efficient heuristic method called CRIME *(Community Rewiring for Influence and Masking Entities)* to address this challenge. CRIME removes the most influential internal links, measured by edge-betweenness centrality, and adds external links with the least betweenness centrality. Experiments on real-world networks demonstrate that CRIME hides targeted communities more effectively than DICE, and also achieves faster execution and improves hiding effectiveness by up to 99.8%.

The CRIME Algorithm

Let $G = (\mathcal{V}, \mathcal{E})$ represent a social network, where $\mathcal{V}$ is the set of nodes (i.e., users) and $\mathcal{E}$ is the set of edges (i.e., connections between the users) in G. We know a *community* is a subset of nodes $\mathcal{C} \subseteq \mathcal{V}$, where the nodes within $\mathcal{C}$ are more densely connected to each other than to the nodes outside of $\mathcal{C}$. A *targeted community*, denoted as $\mathcal{C}^{(T)} \subseteq \mathcal{V}$, is a connected subgraph where the number of nodes is the median community size in the network. In an online social network such as Facebook, a median community spreading misinformation can propagate it faster than other groups. The median community acts as a bridge between highly influential and weakly connected communities, thereby reducing bias toward extremes. Hence, the median community is often chosen as an effective medium for spreading information on social media. However, if the median community follows a random uniform connection and disconnection process, weak connections may also be removed. As a result, the median community cann't be secured and requires more time to remain hidden, making detection more challenging. The state-of-the-art algorithm for hiding a median community within a social network is DICE (Waniek et al. 2018). While DICE randomly creates and removes connections, CRIME disconnects the most influential internal links of the mastermind and reconnects them with less influential external nodes. This allows the target community to be secured in less time. CRIME first identify the targeted community T_c in G. Then detects a set of communities $\mathcal{S}_c = \{C_1, C_2, \ldots\}$, such that $\bigcup_i C_i \subseteq G$, using the *Louvain community detection algorithm* (Traag, Waltman, and Van Eck 2019). The Louvain algorithm is chosen for its effectiveness in reliably identifying tightly-knit groups within networks. Next, CRIME selects the community whose size (i.e., number of nodes) is the median among all community sizes in $\mathcal{S}_c$, and this is referred to as the *targeted community* T_c (Waniek et al. 2018). In Figure1, CRIME detects the communities $C_1, C_2, \ldots, C_7$, and among them, community $C_2 = \{1, 2, 23, 27, 28\}$ has the median size. In this case, CRIME identifies C_2 as the targeted community because its size lies at the median of the community size distribution. Next, CRIME determines the set of internal links $\mathcal{IL}^{\dagger}$ from the targeted community C_T (cf. Line 2 in Algorithm 1). In Figure 1, CRIME identifies the internal links as $(1, 23), (1, 28), (1, 27), (1, 2), (23, 28), (27, 28)$, which represent all the connections among nodes within the targeted community C_T (cf. Line 3 in Algorithm 1). If two or more values are equal, CRIME selects one of them at random. The edge-betweenness centrality (EBC) values corresponding to each internal link in C_2 are presented in Table 1. Next,



(a)

[b=4, d=3]

(b)

Figure 1: Executing CRIME on the 9/11 terrorist network. In Figure (b) red links indicate the disconnected internal links and green links represent new connections between less influential external nodes.

$IL^\dagger$	$1,2$	$1,23$	$1,27$	$1,28$	$23,28$	$27,28$
EBC	0.4	0.25	0.25	0.2	0.15	0.15

Table 1: Edge-betweenness Centrality value for each internal link in C_2

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Algorithm 1: CRIME Heuristic
Input: A graph $G = (V, E)$, the number of iterations $iter$, the number of connection and disconnection links $b$ and the number of disconnection links $d$ and $m$ is the top most internal links used in each iteration.
Output: Rank of the target community $C_T$ .
1: Identify the set of communities $\mathcal{S}_C$ in $G$ using Louvain community detection algorithm.
2: Identify the target community $C_T$ in the graph $G$.
3: Determine the set of Internal links ($\mathcal{IL}^\dagger$) from targeted community $C_T$.
4: Determine the set of External nodes ($\mathcal{EX}^\dagger$) from outside of targeted community $C_T$.
5: for $k \leftarrow 1$ to $iter$ do
6:     Find the top $m$ most Internal links $1 \leq m \leq |IL_{max}|$ and disconnect $d \leq b$ internal links from within $C_T$. Reconnect $(b - d)$ external nodes with $C_T$ to $(b - d)$ external nodes from outside of $C_T$ based on betweenness centrality.
7:     Remove these $m$ internal links from $IL^\dagger$.
8: end for
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CRIME determines the set of external nodes $\mathcal{EX}^\dagger$ connected to the targeted community C_T (cf. Line 4 in Algorithm 1). These external nodes are outside of targeted community C_T, but are directly connected to its members.

From $\mathcal{IL}^\dagger$, the top m most influential internal links IL_{max} are selected based on their edge-betweenness centrality (EBC) values, where $1 \leq m \leq |\mathcal{IL}^\dagger|$ (cf. Line 6 in Algorithm 1). CRIME operates iteratively (cf. Lines 5–7 in Algorithm 1), selecting the top m internal links in each iteration. In our example, we set $d = 3$, which means CRIME disconnects three internal links within the targeted community T_c to weaken the internal structure. Then, creates $b - d$ new external links between the members of T_c and the external nodes to strengthen their external connectivity. Here, b denotes budget, which defines the total number of connections and disconnection process, and d represents the number of internal links to be removed. This strategy reduces the internal cohesiveness of the targeted community and increases its connections with the outside, making it more difficult for community detection algorithms to identify C_T as a distinct group. In initial (Figure 1(a)), the targeted community $C_2 = \{1, 2, 23, 27, 28\}$ is shown with its internal structure highlighted in red. In Figure 1(b), when $b = 4$ and $d = 3$, CRIME removes the internal links $(1, 2)$, $(1, 23)$, and $(1, 27)$ (in red) and adds one external link $(4, 23)$ (in green), linking node 23 to an external node. This approach prioritizes the removal of internal links with most influence and the addition of links to the least influential external nodes. In case of a tie (i.e., when multiple links have the same EBC value or BC value), one is selected at random.

Experiments and Discussion

To evaluate CRIME, we analyze centrality values in table 2 shows results for CRIME and DICE on the real-world networks. Compared to DICE, CRIME reduces the time to execution by 0.05 seconds on Bali, 0.17 seconds on Madrid, 0.06 seconds on WTC, and 28569 seconds for Facebook. In contrast, DICE operates on uniformly random, leading to more computationally expensive operations.

Met.	**Algo.**	**Bali**	**Madrid**	**WTC**	**Facebook**
DC	DICE	5.9	2.21	2.4	143.40
	CRIME	5.8	0.86	2.4	142.18
CC	DICE	0.58	0.17	0.26	0.27
	CRIME	0.53	0.04	0.24	0.27
BC	DICE	0.19	0.03	0.10	0.0002
	CRIME	0.11	6×10^{-5}	0.09	0.0001
PR	DICE	0.06	0.02	0.02	0.0003
	CRIME	0.05	0.01	0.02	0.0003
Time	DICE	0.14	0.89	0.19	180024
	CRIME	0.05	0.17	0.06	28569

Table 2: Comparison of DICE and CRIME heuristics across different networks where, b = 4 and d = 3.

CRIME achieves for Bali, CRIME achieves a DC value that is 1.69%, a CC value that is 8.62%, a BC value that is 42.10%, and a PR value that is 16.70% lower than those of DICE. For Madrid, CRIME achieves a DC value that is 61.10%, a CC value that is 76.50%, a BC value that is 99.80%, and a PR value that is 33.30% lower than those of DICE. For WTC, CRIME achieves a DC value that is the same as DICE, while the CC value is 7.70%, the BC value is 10.00% lower, and the PR value remains the same. For Facebook, CRIME achieves a DC value that is 0.85% lower, a CC value that is the same, a BC value that is 50.00% lower, and a PR value that is the same as those of DICE. In summary, CRIME consistently achieves lower degree centrality (DC), closeness centrality (CC), betweenness centrality (BC), and pagerank centrality (PR) values compared to DICE, except in CC and PR values for WTC and Facebook. The reduction in DC, CC, BC, and PR values achieved by DICE makes it more difficult for investigators to trace the targeted community.

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