Slow poisoning and destruction of networks: edge proximity and its implications for biological and infrastructure networks

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There have been many studies on malicious targeting of network nodes using degree, betweenness etc. We propose a new network metric, edge proximity, $P_e$, which demonstrates the importance of specific edges in a network, hitherto not captured by existing network metrics. Effects of removing edges with high $P_e$ might initially seem inconspicuous but is eventually shown to be very harmful for the network. When compared to existing strategies, removal of edges by $P_e$, leads to remarkable increase of diameter and average path length in real and random networks till the first disconnection and beyond. $P_e$ can be consistently used to rupture the network into two nearly equal parts, thus presenting a very potent strategy to greatly harm a network. Targeting by $P_e$ causes notable efficiency loss in US and European power grid. $P_e$ identifies proteins with essential cellular functions in protein-protein interaction networks. It pinpoints regulatory neural connections and important portions of the neural and brain networks respectively. Energy flow interactions identified by $P_e$ form the backbone of long food web chains. Finally, we scrutinize the potential of $P_e$ in edge controllability dynamics of directed networks.

Considerable research has been done on importance of various metrics in complex networks [1][3]. Importance of nodes and remarkable effects of their targeted removal using various network metrics like betweenness or degree is now well-known. In comparison, role of edges has received lesser attention [4][6]. In this context, one may ask if it is possible to prognose situations where not even a single node is pruned from the network for a long time and yet tremendous damage is inflicted on it by selectively targeting specific edges. Indeed, as we show here, such a process might initially appear inconspicuous or even deceptively innocuous. Using a simple metric, which we call edge proximity, $P_e$, we are able to identify specific edges whose removal can slowly poison networks and silently wreak havoc in them. Furthermore, we show that $P_e$ can be used to design strategies to consistently rupture networks into two nearly equal parts. Thus, this could eventually be far more destructive than currently available strategies for targeting network edges including those where rapid disconnection can be achieved due to detachment of small subgraphs from the parent network.

The most well known edge based measure, edge betweenness or $B_e$, attempts to capture frequency of an edge lying on the shortest path between all pairs of vertices in a network [4][5]. Edges with highest $B_e$ values are most likely to lie between subgraphs, rather than inside them. Thus, targeting by node or edge betweenness ensures rapid disconnection of networks by small number of deletions [7][8].

Herein, we introduce a new edge based network metric, edge proximity, $P_e$. $P_e$ of an edge, $e$, is the inverse of the sum of its shortest distance $d(e, f)$, with every other edge, $f$, in a connected network, $G(V,E), V,E$ denote the set of nodes and edges respectively in $G$. $N = |V|$ and $M = |E|$ are the total number of nodes and edges in $G$ respectively. Thus,

$$P_e = \frac{M - 1}{\sum_{f} d(e,f)} \quad (1)$$

$P_e$ lends clues as to how close each edge is to every other edge in $G$ through shortest paths between them.

Average shortest path length, $L_G$, is the average of all the shortest path lengths between any pair of nodes of $G$ and is defined as,

$$L_G = \frac{1}{N(N-1)} \sum_{s,t \in V; s \neq t} d(s,t) \quad (2)$$

Diameter of $G$ is defined as,

$$D = \max(d(s,t)), \forall s,t \in V; s \neq t \quad (3)$$

d($s,t$) being the shortest path from $s$ to $t$. From the definition of $L_G$ and $D$ it is clear that $L_G$ and $D$ become infinite when $G$ becomes disconnected.

When edges are targeted by $B_e$, the damage done to the network in form of increase in average path length, $L_G$, and diameter, $D$, might initially seem to be higher. However, we observe here that $P_e$ helps in identifying those crucial edges of the network whose deletions ensure the highest increase of $L_G$ and $D$ in $G$ (or its largest giant connected component), when compared to other methods of edge deletion. This appears to be true for both the first disconnection and beyond. In fact, when targeting by $P_e$ no node is disconnected from the network for a very long time. Here, we study the effect of various edge deletion strategies on real-world undirected networks like EU and US power grids and protein-protein interaction networks of $S.\ ceriseiae$ and $E.\ coli$ till the first disconnection. We also scrutinise the effect of these strategies, long after the first disconnection (till only about 30% of
the edges remain in the largest connected component), on various models like Erdős-Rényi (ER) 9, Barabasi-Albert (BA) 10 and Small-world (SW) 11 12 networks. We also study a variety of directed biological networks, namely the macaque brain network, the C. elegans neural network, and a number of food webs. We find that in each case $\mathcal{P}_e$ successfully provides meaningful biological information.

There have been lots of studies on disconnection of networks by malicious targeting. However, it is obvious that significant damage would be caused to the network when each disconnection causes the network to rupture into two nearly equal parts rather than when a small chunk is disconnected from a network. We demonstrate that $\mathcal{P}_e$ can be remarkably successful in consistently achieving this, when compared to other methods of edge removal.

An edge with higher $\mathcal{P}_e$ should possess the potential to reach many other edges of directed networks. Of late, there has been considerable research on node controllability of directed networks and a number of food webs. We find that in the original graph $G$, as done here for $\mathcal{P}_e$ might be a good way to compute the value of a type-II edge based measure. The computation time for a type-II measures in which $L(G)$ is used might be slightly higher than a type-I measure.

We investigate a number of edge deletion strategies which affect $L_G$ and $D$ of the largest connected component in $G$. The strategies adopted here consist of independently deleting successive edges: (i) with $\text{max}(\mathcal{P}_e)$, (ii) with $\text{max}(B_e)$, (iii) connected to node with highest degree in $G$ [$\text{max}(K_e)$], and, (iv) purely at random $(R_e)$. To illustrate further, we construct four identical copies of $G(V, E)$: $G_1(V, E_1), i \in \{1, 2, 3, 4\}$. We then remove the edge with $\text{max}(\mathcal{P}_e)$, $\text{max}(B_e)$, $\text{max}(K_e)$, $e \in E_i, i \in \{1, 2, 3\}$, from $G_1, G_2, G_3$ respectively. In case there is more than one edge with $\text{max}(\mathcal{P}_e)$, $\text{max}(B_e)$ and $\text{max}(K_e)$, we randomly choose one among them. We re-calculate values of $\mathcal{P}_e, B_e$ and $K_e$, $e \in E_i, i \in \{1, 2, 3\}$; for $G_1, G_2, G_3$ respectively. For all real-world networks studied here, we repeat this removal and recalculation process, until the first node is disconnected. In $G_4$, edges are always deleted randomly.

We test these strategies for power grid network (PGN) of European Union 16 and USA 17 by recording changes in $L_G$ and $D$ till the first node is disconnected from them. As shown in Fig. 2 deletion of edges using $B_e$ might initially have a strong effect over increase of $D$ (and also $L_G$). Random edge deletion strategy does not show significant increase in $D$ and $L_G$ in PGNs. Similarly, targeting by $\text{max}(K_e)$ does not show significant increase in $D$ and $L_G$, at least for the US PGN. The most striking increase in $D$ and $L_G$ is however seen for successive deletions using $\text{max}(\mathcal{P}_e)$. Thus $\mathcal{P}_e$ suggests the importance of specific edges which might be crucial as damage to them seems to affect $\eta$; $L_G$ and $D$ significantly in PGNs.

We also calculate efficiency, $\eta$, which is an average of the inverse of all shortest path lengths between any pair of nodes in $G$. 18

$$\eta = \frac{1}{N(N-1)} \sum_{s,t \in V; s \neq t} \frac{1}{d(s,t)} \quad (4)$$

Both EU and US PGN becomes disconnected by small number of random edge deletions with insignificant loss of $\eta$. Notably, connectedness is still maintained for both EU and US PGN when targeted by $\text{max}(K_e)$. However, maximum loss of $\eta_L$ (and increase of $D$ and $L_G$) is observed here, when edges are targeted by $\text{max}(\mathcal{P}_e)$. Of course, loss of $\eta_L$ for EU power grid is comparable for

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**Fig. 1.** Construction of directed line graph $L(G)$ from $G$. The first step for creating $L(G)$ is that every node in $L(G)$ represents an edge in the original graph $G$. An edge is drawn between any two nodes in $L(G)$ if the corresponding edges in $G$ share a common node. For directed graphs, an edge in $L(G)$ represents a directed path of length 2 in $G$. Each node of $L(G)$ is an edge of $G$. Thus, $\mathcal{P}_e, e \in E$ can be obtained from closeness centrality of corresponding node in $L(G)$.
be broken into two nearly equal parts at each disconnection rather than having a small part disconnected from the network. As demonstrated in Fig. 3 for Barabási-Albert [10], Erdős-Rényi [9] and Small-World networks [11], targeting by $P_e$ can be a remarkably successful way to consistently achieve this outcome.

We test the effect of all the four aforementioned strategies on protein-protein interaction networks (PPIN). Especially, we scrutinise the biological significance of edges with highest $P_e$ and $B_e$. For this purpose, we calculate

$$Z(Q) = \frac{Q - \mu(Q)}{\sigma(Q)}, \; Q \in \{P_e, B_e\}.$$  \hspace{1cm} (5)$$

$\mu(Q)$ and $\sigma(Q)$ are the mean and standard deviation of the $Q$ distribution. For consistency, we restrict ourselves to the top $2\%$ of edges with $Z(Q) \geq 1$. First, we observe effect of edge deletion in the largest connected component of PPIN of $S. \text{cerevisiae}$ [20] and $E. \text{coli}$ [21] till first disconnection. Removal of interactions by $P_e$, value increases $L_Q$ and $D$ of PPINs, the most as shown in Fig. 2 (c) & (d). In $E. \text{coli}$ PPIN, an essential protein, $60 \text{kDa}$ chaperonin is consistently present at an end of $Z(P_e) \geq 1$ edges. This $60 \text{kDa}$ protein exhibits a specific stress dependent co-expression with its connected proteins via these $Z(P_e) \geq 1$ edges [22], alike date hubs [23].

Tropic interactions and energy flow directions in a food web network are represented by directed edges from prey to predators [24]. Cascade of extinction and role of keystone species is well documented depending on the species or node based approach of food web network [25, 26]. Tropic interactions or edge based approach might be beneficial for identifying important interactions in the food web network. Herein, we analyze three Coral reef food webs of Cayman Island, Cuba and Jamaica [27] and four food web networks from South Florida Ecosystems [29, 30]. $B_e$ and $P_e$ identify different sets of edges for these food webs. The root interactions of the dominator tree of corresponding food webs [25, 31] are considered to be important interactions of primary consumers with producers or interactions with outside environment. These are located at initial positions of long food chains. Removal of those interactions may lead to secondary extinction of many species [25] or may stop sending input energy inside the food webs from outer environment [29, 30]. $P_e$ seems to identify these root interactions correctly. $Z(P_e) \geq 1$ include such interactions like primary consumers interacting with planktonic bacteria, phytoplancton, macrophytes or the environmental input to primary producers and epiphytes. $B_e$ identifies other interactions between keystone species such as Diadema, Bivalves, Vertebrate Detritus, Meso-invertebrates, Bivalves etc [23, 28, 32, 33] successfully. Thus, many food chains pass through $Z(B_e) \geq 1$ edges and their removal might hamper many tropic interactions [28]. But, as shown here afterwards, these may

$\max(K_e)$ and $\max(P_e)$ strategies.

As shown in Fig. 4 for Erdős-Rényi (ER), Barabási-Albert (BA) and Small-World (SW) networks, we keep deleting edges even after the first node disconnection, until the largest giant component contains only about $30\%$ of the original edges. We do not proceed with further edge deletions when there are only $30\%$ of edges in the largest connected component of the network. This is because in a very small graph $P_e$ loses its meaning as most edges are very close to each other. Of course, difference in behaviour between ER and BA networks is observed only when $m_0 > 1$ is chosen for BA networks [10], leading to non-zero clustering in the latter.

Great harm can be caused to a network if it can

FIG. 2. $D_S = D/D_0$ of the giant component versus fraction of edges deleted, $m$, using different types of successive edge deletions strategies before first node disconnection of (a) EU & (b) US Power Grid networks, and, (c) $E. \text{coli}$ & (d) $S. \text{cerevisiae}$ PPIN. $D_0$ is the diameter of the original network. Increase of $D_S$ versus $m$ is initially higher for $B_e$ but is eventually highest for $P_e$. $L_Q$ versus $m$ curves show similar behaviour.

FIG. 3. Loss of efficiency $\eta_L = \eta/\eta_0$ versus fraction of edges deleted, $m$, for different strategies of (a) EU and (b) US power grid networks where $\eta_0$ is the efficiency of the original network.
These are basically ring motors and interneurons associates RME, AIB, RIA, RIF, AIM and AEV synapses. Functionally and structurally important synapses, we are able to reconstruct of electron microscopy [37]. To detect network. The connectivity data has been obtained from networks are rather well studied in case of network from original network, where various synapses are represented by edges. Functional and structural aspects of neural connectivity is 0 SW [11], initially every node has 4 neighbours and probability of edge rewiring is 0.2; for BA m₀ = 2 in (c) and m₀ = 3 in (d) respectively. For SW (e, f) initially every node has 5 and 4 neighbours respectively and probability of edge rewiring is 0.3 and 0.2 respectively. D₅ fluctuates most in ER networks due to larger number of disconnections.

There has been significant activity in detecting emergent behavioral patterns from networks of interconnected neurons, where various synapses are represented by edges. Functional and structural aspects of neural networks are rather well studied in case of C. elegans network. The connectivity data has been obtained from reconstruction of electron microscopy [37]. To detect functionally and structurally important synapses, we analyze the network using $P_e$ and $B_e$. $Z(B_e) ≥ 1$ identifies RME, AIB, RIA, RIF, AIM and AEV synapses. These are basically ring motors and interneurons associated with thermotaxis and backward movement [38][40]. However, $Z(P_e) ≥ 1$ identifies various synapses of AVEL which are solely associated with backward movement of

not be the driven edges under switchboard dynamics [15]; unlike $Z(P_e) ≥ 1$ edges.

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C. elegans [38].

We also study the brain network of macaque monkeys formed from collation of connectivity data on the macaque brain (CoCoMac datasets), where neural fibers connecting different portions of brain are represented by directed edges [11]. Analyzing all neural connections by $B_e$ and $P_e$, we find that two rather different types of edges in hierarchical information processing pathways are identified by these two metrics. $Z(B_e) ≥ 1$ identifies interactions which are essentially localized in the intermediate regions of the brain like prefrontal cortex [12]. Interestingly, $Z(P_e) ≥ 1$ corresponds to various connections from cortex to thalamus, frontal lobe and temporal lobe, which are the starting interactions of longer information processing pathways from cortex to other region of brain [12].

Finally, under switchboard dynamics (SBD) of edge controllability, each node is conceived as acting similar to a small switchboard like device [13]. Nodes map the input signals of the inbound edges to the outbound edges.
Fig. 1 depicts an example akin to Ref. [15]. Maximum matching algorithm is used on the line graph, $L(G)$ constructed from the original network $G = G(V,E)$ for identifying all possible sets of driven edges, $E^* = \{E'_i : i \in \mathbb{Z}_+\}$, in $G$ under SBD; $E'_i \subset E$. We calculate $P_e$ and $B_e$, $e \in E$ in Fig. 1. Intuitively, edges with higher $P_e$ could be driven edges for edge controllability under SBD. This is consistent with Table I where $P_e > 0$ for $E'_i \in E'$. $E'_2 = \{(2,6), (3,2), (6,3)\}$ also shows $P_e > 0$, thus raising the possibility of whether $E'_2 \in E'$? However, $E'_2 \in E_f$, where $\{E_f\}$ denotes all sets of edges participating in feedback loops of $G$. Thus, $E'_i \in \{E_f\}$, $i \in \mathbb{Z}_+ \Rightarrow E'_i \notin E'$, because if $E'_i \in \{E_f\}$, $E'_i$ is self-controllable. Again either $(2,3)$ or $(6,4)$ is not a good driven edge because these edges can control only themselves. We observe that $P_e = 0$ for them. This proof-of-concept example illustrates the potential utility of $P_e$ to act as an index of edge control centrality of individual edges under SBD.

It should be noted that the role played by $P_e$ would become increasingly prominent with increase in $N$. As aforementioned, for very small networks $P_e$ becomes irrelevant because most edges are rather close to each other. As with almost any other network metric, its importance would be rather limited for denser graphs.

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