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How to exploit structural properties of dynamic networks to detect nodes with high temporal closeness

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Abstract

The ability to detect important nodes in temporal networks has been investigated lately. This has been a challenge on both the theoretical aspects as well as computational ones. In this study we propose and evaluate different strategies to detect nodes that have high temporal closeness.

Keywords : *Temporal closeness, Sampling, Approximation, Dynamic network*

1 Introduction and definitions

Evaluating the importance of nodes in complex networks has been an interesting question for a long time. Several measures of importance have been introduced, such as degree, closeness or betweenness centrality. As complex networks have grown in size, approximation methods have been introduced. One of the first method to approximate centrality was introduced in [6]. They consider k source nodes selected randomly, from which they compute the shortest-paths with all other nodes of the network. Since then, several methods have been proposed to help selecting the source nodes [4] or the target nodes [8] in order to reduce the computation required to estimate the closeness and betweenness centrality. Those studies all consider a single and static network. However, most of real application involve networks whose structure evolves with time. This led the community to propose adaptation of centrality metrics to assess the importance of nodes through time [7, 11]. This temporal dimension makes the computation more demanding, making methods for approximating centrality metrics even more essential. In this study, we study how structural properties of dynamic networks can be exploited to detect nodes that have a high *temporal closeness centrality* [7].

More precisely, let $G = (V, E)$ be a dynamic network composed of a set V of nodes and a set E of temporal links of the form (u, v, t) where $u, v \in V$ and t is a timestamp. A temporal path from u to v starting at time t_s is given by a sequence of links $(u, v_0, t_0), (v_0, v_1, t_1), \dots, (v_{k-1}, v, t_k)$ such that $t_0 > t_s$ and, for all $i, i = 0..k-1, t_i < t_{i+1}$.

Such a path is a *shortest path* if it has the least duration ($t_k - t_s$) among all paths from u to v starting at time t_s . The (*temporal*) *distance* from u to v at time t_s is then the duration of such a shortest path (denoted $d_{t_s}(u, v)$)¹. Following the classical definition of the closeness of a node in a static network, the *temporal closeness* of a node u at time t is defined by:

$$C_t(u) = \sum_{v \neq u} \frac{1}{d_t(u, v)}$$

It measures the importance of node u at time t in the dynamic network. In order to assess what nodes are important at time t , one can rank the nodes according to their temporal closeness at time t and consider for instance the top 25% rankings. This enables in turn to compute for each node u its total duration spent in the top 25% rankings (denoted by $Dur_{top}(u)$). It measures the *global* importance of node u in G . The purpose of the present study is to propose strategies to detect which nodes are globally important without relying on the exact computation of the temporal closeness of all nodes at all time instant.

2 Strategies and results

In order to detect globally important nodes, we propose to first compute global properties of the nodes that can easily be extracted either from the aggregated graph $G_A = (V, E_A)$ (with $E_A = \{(u, v) | \exists t, (u, v, t) \in E\}$) or from an analysis of the temporal activity. For every node u , we compute its closeness centrality $CC(u)$, its degree centrality $DC(u)$ and its number of links $NL(u)$ – all computed on G_A – as well as its duration of activity $DU(u)$ ² and its average inter-contact duration time $LD(u)$ ³. Then we propose:

Parameter based strategy (P_1/P_2): we consider the rankings given by mixing the importance measured by P_1 and P_2 defined by: $R(u) = \alpha \times \mathbf{rank}(P_1(u)) + (1 - \alpha) \times \mathbf{rank}(P_2(u))$ with $\alpha \in [0 : 1]$ ⁴ and where $\mathbf{rank}(P)$ is the rank provided by property P .

Parameterless strategy (PS): we only take into account the number of links and the duration of activity: $R(u) = \mathbf{rank}(NL(u) \times DU(u))$.

In order to assess the relevance of each strategy (and for any α), we compute the number of nodes correctly detected as important⁵ in the top k nodes (for $k \in [1..n]$) and denote this vector as the *hit rate* vector. The hit rate vector of a perfect strategy would then be equal to $[1, 2, \dots, n]$. From these vectors we can compute the distance between any strategy and the perfect strategy and normalize it by the worse case strategy. Formally, we define the score of a strategy by: $score(S) = 1 - \frac{distance(perfect_strategy, S)}{distance(perfect_strategy, worse_case)}$

Figure 1 shows the scores for all the strategies (with different values for α) when applied on nine datasets whose characteristics are provided in Table 1. We observe that in most cases $NL/DU, DU/LD$ and PS score higher than other combinations as well as any pure static centralities. They are much closer to a perfect strategy or ground truth than any

¹ $d_{t_s}(u, v) = \infty$ if there is no path between u and v .

²the difference between that last and the first activity.

³the average time between two consecutive links involving u .

⁴note that $\alpha = 1$ implies that only P_1 is considered.

⁵we consider the exact computation of the temporal closeness as the ground truth.

Datasets	Type	#Nodes	#Edges	Duration	Ref
Enron	Email	151	47 088	3 years	[10]
Radoslaw	Email	168	82 876	9 months	[9]
DNC	Email	1891	39 264	2.6 years	[1]
HashTags	Social Network	3 048	100 429	22 days	-
Facebook	Social Network	8 977	66 153	1 year	[12]
Article Tags	Social Network	2902	571 877	10 years	-
Reality Mining	Movement	96	1 M	9 month	[5]
Taxi Rome	Movement	158	241 736	1 day	[3]
Primary	Movement	242	125 773	1.5 days	[2]

TAB. 1: Dataset, Type, Number of nodes, Number of links, Duration

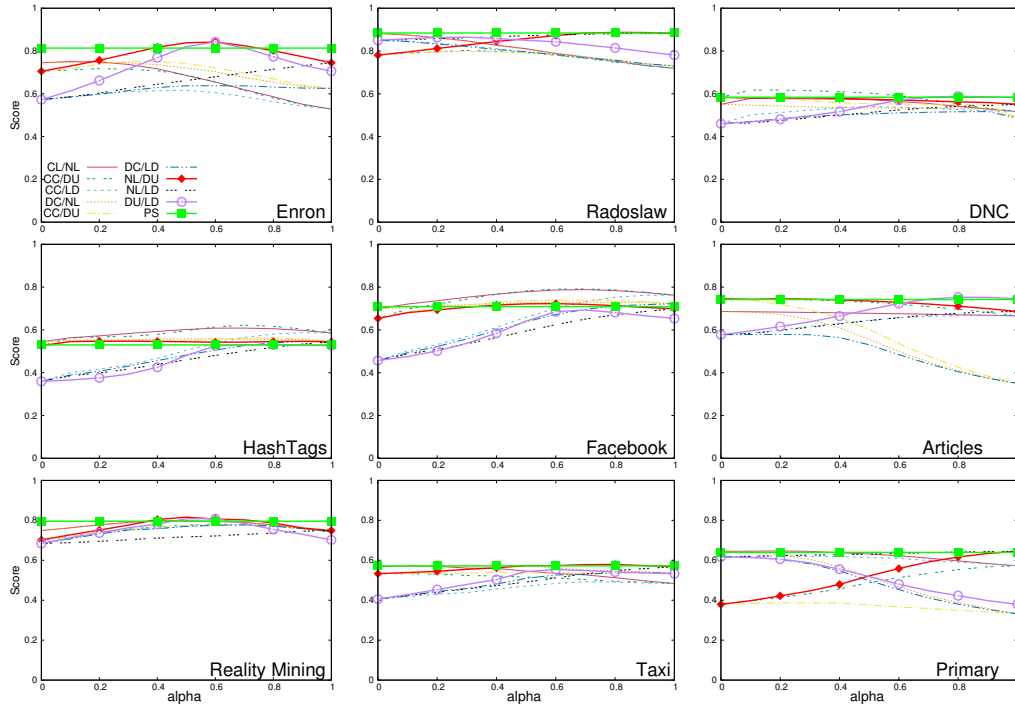


FIG. 1: Score for each strategy on the nine datasets

other strategies. In addition, we can observe that datasets of same nature lead to similar α value for the best strategies.

3 Conclusions

In this study we proposed different strategies that rely on global characteristics of nodes to detect nodes with high temporal closeness centrality. In most cases, three strategies present the best results. They all take into account temporal properties of the nodes.

This work is a first step to adapt recent technics [6, 4, 8] to approximate the importance of nodes in dynamics networks.

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