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k-Cliques mining in dynamic social networks based on triadic formal concept analysis

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ABSTRACT

Internet of Things (IoT), an emerging computing paradigm which interconnects various ubiquitous things is facilitating the advancement of computational intelligence. This paper aims at investigating the computation intelligence extraction approach with focus on the dynamic k-clique mining that is an important issue in social network analysis. The k-clique detection problem as one of the fundamental problems in computer science, can assist us to understand the organization style and behavioral patterns of users in social networks. However, real social networks usually evolve over time and it remains a challenge to efficiently detect the k-cliques from dynamic social networks. To address this challenge, this paper proposes an efficient k-clique dynamic detection theorem based on triadic formal concept analysis (TFCA) with completed mathematical proof. With this proposed detection theorem, we prove that the k-cliques detection problem is equivalent to finding the explicit k-cliques generated from k-triadic equiconcepts plus the implicit k-cliques derived from its high-order triadic equiconcepts. Theoretical analysis and experimental results illustrate that the proposed detection algorithm is efficient for finding the k-cliques and exploring the dynamic characteristics of the sub-structures in social networks.

1. Introduction

Internet of Things (IoT), one of the latest and the fastest growing technologies on the Internet which is composed of a huge number of intelligence communicating 'things', allows people in social space and things in cyber and physical spaces to be connected anytime, anywhere: (1) allows objects to have their own social networks; (2) allows humans to form their social networks according to social interactions; (3) allows people and objects to have more information interaction and to form a heterogeneous social network. Based on the features of IoT, it is normally defined as a dynamic global network infrastructure with self-configuring capabilities [1]. In order to obtain the potential computation intelligence and services from IoT, efficient exploration of the IoT network infrastructure is required. Social network analysis, especially the topological structure mining within social network, can provide an insight into the structural characteristics of the IoT and extract the computational intelligence from IoT. Therefore, this paper aims at exploiting the computation intelligence extraction approach with focus on the dynamic k-clique mining.

A social network can be represented with multiple nodes (*i.e.*, users) and edges which indicates the social interactions. Normally, a social network is mathematically formalized as a graph $G=(V,E)$ where V denotes the set of vertices and E denotes the set of relationships between vertices. From the dynamic point of view, the social networks contain two types, *i.e.*, static social networks and dynamic social networks. Clique as a very common structure in social networks, which is composed of the set of vertices as well as the reciprocal relationships among them, reflects the social behavior and its social features among users. Therefore, clique detection is playing an important role in various applications, such as social recommendation [2], network routing [3], community detection [6], content modeling [7], and finding the frequently occurring patterns in protein structures [8]. For instance, in an online social learning network, finding the collaborative teams with the required number of learners for completing some given assignments is one of the cases of clique detection.

The rapid development of wireless network technologies and wide usage of mobile devices facilitate a change of the life mode of

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social network. It is transforming from static web-based social network to dynamic mobile social network. Therefore, given a dynamic social network, finding the interesting vertices or sub-graph structures from dynamic social networks is a great challenge. To address this challenge, many researchers attempt to investigate the topological structure of the dynamic social network. Born and Kerbosch [4] firstly provided an algorithm for finding all cliques in an undirected graph. With a dynamic graph, Stix [5] proposed algorithms to track all maximal cliques in a fully dynamic graph. Palla et al. [9] utilized a local and restrictive approach for finding overlapping cliques of predefined size in consecutive time steps. Falkowski et al. [10] proposed an intuitive approach to identify static communities in each snapshot using the Girvan–Newman algorithm [16] and then contract those into a community graph and apply the Girvan–Newman algorithm once more to find dynamic communities. Tantipathananandh et al. [11] detected the dynamic communities by using a social cost model. The proposed approach that is a classic two-step algorithm that is firstly to apply any algorithm for inferring static communities to obtain partitions in groups and then to apply the algorithms to obtain dynamic communities. Takaffoli et al. [12] presented a framework for modeling and detecting community evolution in social networks, where a series of significant events was defined for each community. A community matching algorithm was also proposed to efficiently identify and track similar communities over time.

Different from the existing algorithms on communities evolution mining in dynamic social network, we adopt the triadic formal concept analysis methodology for discovering the k-cliques as well as exploring the dynamic features of sub-graph structures. The main contributions of this paper are summarized as follows:

- (*Triadic formal context construction*) Due to the dynamical features of social networks, we incorporate the advantages of triadic formal concept analysis into social networks and then characterize the dynamic social graph as the triadic formal context. We regard each vertex in a social network as both objects and attributes, and the timestamps as the conditions. A binary relation between the objects and attributes according to the social interactions at time t is defined. Then, a triadic formal context is constructed from the dynamic social network by Modified Adjacency Matrix. Formally, it is represented as a quadruple $TFC(G_t) = (V, V, T, I)$, $t = 1, 2, \ldots, T$.
- (*TFCA-based k-cliques detection*) We propose a TFCA-based k-clique detection approach. First, we prove that k-clique detection problem is equivalent to finding the explicit k-cliques generated from k-triadic equiconcepts plus the implicit k-cliques derived from the its high-order triadic equiconcepts. Then, a corresponding detection algorithm is devised based on the proposed theorem.
- (*Evaluation of proposed approach*) We conduct the experiments on a real social networking dataset for validating the effectiveness of the proposed approach. The experimental results demonstrate that the proposed algorithm can achieve the high precision and recall of k-cliques for the dynamic social networks. In addition, some interesting sub-graph structures, named constant k-cliques and frequent k-cliques are additionally discovered, and the performance of frequent k-cliques detection is also evaluated. The experimental results demonstrate that the proposed algorithm can obtain more frequent k-cliques from dynamic social networks.

The remainder of this paper is structured as follows. Section 2 presents the related work. The problem definition and solution framework for k-cliques detection in dynamic social network are proposed in Section 3. Section 4 introduces the adopted methodology of triadic formal concept analysis. The dynamic detection approach and algorithm of k-cliques are explored in Section 5. Section 6 presents the experimental results and evaluation. Section 7 concludes this paper.

2. Related work

Identifying the maximum cliques or all the cliques from a graph has been widely investigated in the fields of Web, digital libraries, data mining and bio-informatics [13]. At present, the research on clique detection contains two types: k-clique detection, k-clique communities detection [9,14]. The pioneering work on k-clique community detection method is the Clique Percolation Method (CPM) which defines a model of rolling a k-clique template [9]. But CPM did not propose the object function to quantitatively qualify the clustering results. Ostergard et al. [15] presented a new algorithm for finding a maximum clique in an arbitrary graph. This new algorithm improves on old methods for several types of graphs, including sparse, random graphs and graphs with certain combinatorial properties. Kumpula et al. [16] proposed an efficient approach Sequential Clique Percolation (SCP) for k-clique community detection. Although SCP can detect communities on weighted networks, it cannot generate k-clique communities for each possible k in a single execution. Additionally, some extended cliques' detection is also carried out [17,18]. Traag and Bruggeman [17] adopted the concept of modularity to detect communities in complex social networks with both positive and negative links. Our previous work [18] firstly addressed the k-balanced trusted cliques detection in signed social networks.

Considering the dynamical features of networks, Duan et al. [19] proposed incremental k-clique clustering algorithms based on local DFS (depth first search) forest updating technique. Further, Wu et al. [20] improved the above incremental k-clique algorithm and devised an incremental community detection method based on Locality-Sensitive Hashing (LSH). Their method can efficiently and effectively detect the communities in dynamic social tagging systems. However, the aforementioned approaches only concentrate on the given sub-graph structures' mining but not other extended structures. This research work also takes the time into account in dynamic social networks and presents the k-cliques detection based on triadic formal concept analysis. It not only can identify the required k-cliques, but also can reveal the other special sub-structures, such as frequent k-cliques and constant k-cliques. Therefore, our approach is more flexible and easy to implement.

3. Problem definition and solution framework

This section firstly revisits the preliminaries on clique and k-clique. Then, the problem of k-cliques detection in dynamic social network is formally defined. Additionally, a solution framework of the addressed problem is presented.

3.1. Problem definition

As the preliminaries, the definitions of clique and k-clique are provided as follows [18]:

Definition 1 (*clique*). Let $G = (V, E)$ be an undirected graph. A clique in G is a subset $S \subset V$ such that for any two vertices $v_j, v_j \in S$ there exists an edge $(v_i, v_j) \in E$.

Definition 2 (*k-clique*). Let $G = (V, E)$ be an undirected graph. A k-clique in G is a subset $S \subset V$ and $|S| = k$ such that for any two vertices $v_1, v_2 \in S$ there exists an edge $(v_1, v_2) \in E$. Formally,

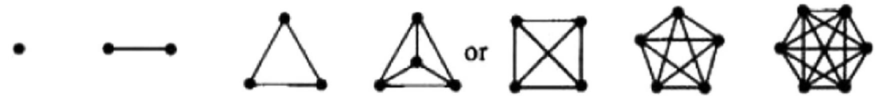


Fig. 1. Cliques with 1, 2, 3, 4, 5 and 6 vertices.

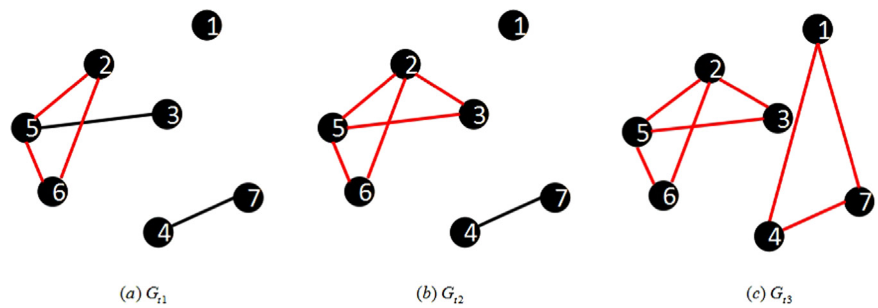


Fig. 2. A dynamic social network $g = \langle G_{t1}, G_{t2}, G_{t3}\rangle$.

a k-clique is represented with a pair $(\{v_1, v_2, \ldots, v_k\}, \{v_1, v_2, \ldots, v_k\})$.

Fig. 1 presents an example of k-clique $(k = 1, 2, \ldots, 6)$. The clique structure, where there must be an edge for each pair of vertices, shows many restrictions in real life modeling.

Problem 1 (*k-Cliques detection in dynamic social network*). Given a dynamic social network $G_t = (V, E_t)(t = 1, 2, \ldots, T)$ where node set V denotes entities in the social network and edge set $E_t = ((u, v)|u, v \in V)$ denotes relationships between entities at time t. Once the parameter k is given, the k-clique detection problem is to find all k-cliques at different time t.

To clearly understand our research problems, a toy example of 3-clique detection in a dynamic social network $g = \langle G_{t1}, G_{t2}, G_{t3}\rangle$ is given in Fig. 2.

Obviously, Fig. 2 presents a dynamic evolving procedure of a social network including 7 users. Fig. 2(a) is the topology of a social network G_{t1}, only one 3-clique $(\{2, 5, 6\}, \{2, 5, 6\})$ can be identified. At the next time slot, two 3-cliques $(\{2, 5, 6\}, \{2, 5, 6\})$, $(\{2, 3, 5\}, \{2, 3, 5\})$ are detected from G_{t2} as shown in Fig. 2(b). Similarly, three 3-cliques $(\{2, 5, 6\}, \{2, 5, 6\})$, $(\{2, 3, 5\}, \{2, 3, 5\})$, $(\{1, 4, 7\}, \{1, 4, 7\})$ are easily founded in Fig. 2(c).

3.2. Solution framework

This paper aims to detect the k-cliques from dynamic social networks and bridge the connection between social networks and triadic formal concept analysis (TFCA) as shown in Fig. 3, then a dynamic detection theorem of k-cliques is presented.

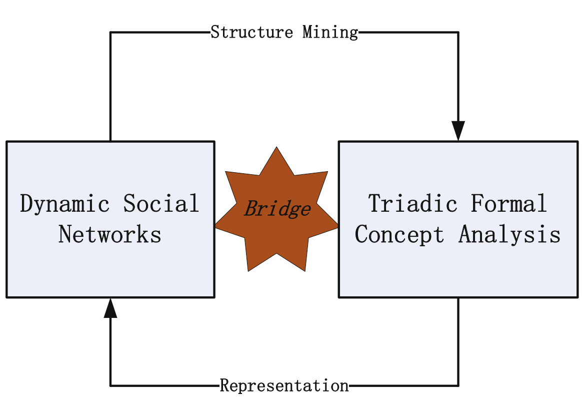


Fig. 3. Conceptual solution architecture.

As can be seen from Fig. 3, the topology of dynamic social network structure can be represented with triadic formal context that is a core definition of triadic formal concept analysis. Also, the properties of the triadic concept can reflect the sub-structure (*e.g.*, k-clique) of the given social network [22]. Therefore, the novelty of the proposed theorem is that clique detection in dynamic social network is equivalent to detecting the triadic equiconcepts that will be defined in the next section.

The proposed solution framework contains three key technical steps:

1. constructing the triadic formal context from an input graph;
2. detecting the explicit cliques generated from the triadic equiconcepts and the implicit k-cliques derived from high-order triadic equiconcepts;
3. combining the explicit and implicit k-cliques into the query output.

4. Triadic formal concept analysis

Aiming at implementing the solution framework addressed in the previous section, this section presents the methodology about Triadic Formal Concept Analysis (TFCA) which we adopt in this paper. Firstly, the definition of triadic context is formally provided. Then, three concept-forming operators are introduced for inducing the triadic concept. Finally, an example of healthcare system is given for revealing the generation procedure of triadic concepts.

Definition 3 (*Triadic context*). A triadic context is formally represented as a quadruple $\langle O, A, C, I\rangle$ where O, A and C are non-empty sets, and I is a ternary relation between O, A and C, i.e., $I \subseteq O \times A \times C$. Here, O, A and C indicate the sets of objects, attributes and conditions, respectively; I is interpreted as the incidence relation. Therefore, $\langle o, a, c\rangle \subseteq I$ can be interpreted as: object o has attribute a under condition c. In this case, we say that o, a, c are related by I.

Note that the triadic context can be also represented with "0" and "1" table just like a binary formal context. In order to introduce the triadic concept, a given triadic context can be projected into three 2-dimensional space which corresponds to three projected formal contexts (A, C, I_X), (O, C, I_B), (O, A, I_D), where $(a, c) \subseteq I_X$ indicates there exists a relationship $(x, a, c) \subset I$ for $x \subseteq X$. The following concept-forming operators (CFOs) are presented in Definitions 4–6.

Definition 4. Suppose (O, A, C, I) be a triadic context, $X \subseteq O$, for $B \subseteq A$, $D \subseteq C$, two concept-forming operators induced by the projected formal context (A, C, I_X) are formally defined as follows:

$$B^{(X,,)} = \{c \subseteq C | \forall a \in B, (a, c) \in I_X\}$$
$$D^{(X,,)} = \{a \subseteq A | \forall c \in D, (a, c) \in I_X\} \quad (1)$$

Definition 5. Suppose (O, A, C, I) be a triadic context, $B \subseteq A$, for $X \subseteq O$, $D \subseteq C$, two concept-forming operators induced by the projected formal context (O, C, I_B) are formally defined as follows:

$$X^{(,B,)} = \{c \subseteq C | \forall x \in X, (x, c) \in I_B\}$$
$$D^{(,B,)} = \{x \subseteq O | \forall c \in D, (x, c) \in I_B\} \quad (2)$$

Definition 6. Suppose (O, A, C, I) be a triadic context, $D \subseteq C$, for $X \subseteq O$, $B \subseteq A$, two concept-forming operators induced by the projected formal context (O, A, I_D) are formally defined as follows:

$$X^{(,,D)} = \{a \subseteq A | \forall x \in X, (x, a) \in I_D\}$$
$$D^{(,,D)} = \{x \subseteq O | \forall a \in B, (x, a) \in I_D\} \quad (3)$$

After the introduction of concept-forming operators under three projected formal contexts, a triadic concept is formally defined as follows:

Definition 7 (*Triadic concept*). Suppose (O, A, C, I) be a triadic context, for $X \subseteq O, B \subseteq A, D \subseteq C$, if $B = D^{(X,,)}$, $D = B^{(X,,)}$, $X = B^{(,,D)}$, $B = X^{(,,D)}$, then a triple (X, B, D) is called as a triadic concept of the triadic context (O, A, C, I), where X, B and D refers to the "extent", "intent", and "condition", respectively.

To better understand the above definitions about triadic context as well as the extraction procedure of triadic concepts, an illustrative example is provided as follows:

Example 1. Table 1 shows a triadic context (O, A, C, I) about a healthcare information system, $x_,$, x_2, x_3 are three objectives, i.e., patient A, patient B, patient C; a_1, a_2, a_3 are three attributes that correspond to respiratory efficiency, liver function, and renal function; c_1, c_2, c_3 indicate three conditions, i.e., hospital-1, hospital-2, hospital-3; where "1" denotes the normal state and "0" denotes the abnormal state for physical check.

According to Definition 7, the following 13 triadic concepts are easily obtained:

$TC_1 = (\{x_1, x_2, x_3\}, \{a_2\}, \{c_3\})$, $TC_2 = (\{x_1, x_2, x_3\}, \{a_3\}, \{c_2\})$,
$TC_3 = (\{x_2\}, \{a_1, a_2, a_3\}, \{c_3\})$, $TC_4 = (\{x_3\}, \{a_1, a_2, a_3\}, \{c_2\})$,
$TC_5 = (\{x_1\}, \{a_2, a_3\}, \{c_1, c_2, c_3\})$, $TC_6 = (\{x_1, x_3\}, \{a_2\}, \{c_1, c_2, c_3\})$,
$TC_7 = (\{x_1, x_2\}, \{a_3\}, \{c_1, c_2, c_3\})$, $TC_8 = (\{x_2\}, \{a_1, a_3\}, \{c_1, c_2, c_3\})$,
$TC_9 = (\{x_2, x_3\}, \{a_1\}, \{c_1, c_2\})$, $TC_{10} = (\{x_3\}, \{a_1, a_2\}, \{c_1, c_2\})$,
$TC_{11} = (\{\varnothing\}, \{a_1, a_2, a_3\}, \{c_1, c_2, c_3\})$, $TC_{12} = (\{x_1, x_2, x_3\}, \{\varnothing\}, \{c_1, c_2, c_3\})$,
$TC_{13} = (\{x_1, x_2, x_3\}, \{a_1, a_2, a_3\}, \{\varnothing\})$.

Table 1
A triadic formal context (O, A, C, I).

Patient	c1			c2			c3		
	a1	a2	a3	a1	a2	a3	a1	a2	a3
x1	0	1	1	0	1	1	0	1	1
x2	1	0	1	1	0	1	1	1	1
x3	1	1	0	1	1	1	0	1	0

As matter of fact, each triadic concept reflects its own semantics, such as triadic concept TC_2 is interpreted as "*The patients A,B, and C's renal function are normal under checked in hospital-3*".

5. Detection of *k*-cliques in dynamic social networks

This section provides a novel detection approach of cliques using Triadic Formal Concept Analysis (TFCA) theory. Inspired by the good properties of triadic formal concept analysis and dynamical feature of social network, (1) we firstly construct a triadic formal context of a dynamic social network which is composed of a sequence of undirected graph $g = \langle G_1, G_2, \ldots, G_T\rangle$; (2) then, we define a new concept called "*triadic equiconcept*" which has the same extent and intent for finding the cliques; (3) finally, a generic dynamical detection algorithm based on TFCA for finding cliques is presented.

5.1. Triadic formal context construction

For a given dynamic social network g, a triadic formal context can be constructed according to our previous work [18] and Definition 3. Specifically, the basic idea of the construction approach is that a Modified Adjacency Matrix of a graph $G_t = (V, E_t)$ at time t is represented as a triadic formal context $TFC(G_t) = (V, V, T, I)$, in which I indicates the binary relationship between two vertices, i.e., for any $v_i, v_j \in V$, $I(v_i, v_j) = 1$ if $(v_i, v_j) \in E$ otherwise, $I(v_i, v_j) = 0$. As a special case, we limit $I(v_i, v_i) = 1$ for any $i \in \{1, 2, \ldots, n\}$ as well as $t \in \{1, 2, \ldots, T\}$, obviously, $TFC(G) = (V, V, T, I)$ is a special triadic formal context because its sets of objects and attributes are the same. That is to say, the vertices in $G_t (t = 1, 2, \ldots, T)$ are regarded as the objectives and attributes, the edges in $G_t (t = 1, 2, \ldots, T)$ are viewed as the binary relationship between objective and attribute, and timestamp t is a condition.

Example 2. Let us take Fig. 2 as an example with a dynamic social network $g = \langle G_{t1}, G_{t2}, G_{t3}\rangle$, the triadic formal context of g is constructed as shown in Table 2 based on the above approach.

5.2. Triadic equiconcept

According to our previous research finding about the equivalence theorem of clique and equiconcept, this section extends that theorem and presents a novel concept called *triadic equiconcept* which is able to assist us for identifying the cliques structure from social networks.

Definition 8 (*Triadic equiconcept*). For a triadic formal context $\Gamma = (O, A, C, I)$, for $X \subseteq O, B \subseteq A, D \subseteq C$, if $B = D^{(X,,)}$, $D = B^{(X,,)}$, $X = B^{(,,D)}$, $B = X^{(,,D)}$ and $X = B$, then a triple (X, B, D) is called as a triadic equiconcept where X is called the extent of the triadic equiconcept, B is called the intent of the triadic equiconcept. And let $TE(\Gamma)$ denotes the set of all triadic equiconcepts with respect to triadic formal context Γ.

Definition 9 (*k-Triadic equiconcept*). For a triadic formal context $\Gamma = (O, A, C, I)$, for $X \subseteq O, B \subseteq A, D \subseteq C$, if $B = D^{(X,,)}$, $D = B^{(X,,)}$, $X = B^{(,,D)}$, $B = X^{(,,D)}$ and $X = B$ and $|X| = |B| = k$, then a triple (X, B, D) is called as a k-triadic equiconcept where X is called the extent of the k-triadic equiconcept, B is called the intent of the k-triadic equiconcept. And let $KTE(\Gamma)$ denotes the set of all k-triadic equiconcepts with respect to triadic formal context Γ. Besides, $K^iTE(\Gamma)$ denotes the set of all $(k + i)$-triadic equiconcepts

Table 2
The constructed triadic formal context of g: $TFC(g) = (V, V, T, I)$.

Vertex	t_1							t_2							t_3						
	v_1	v_2	v_3	v_4	v_5	v_6	v_7	v_1	v_2	v_3	v_4	v_5	v_6	v_7	v_1	v_2	v_3	v_4	v_5	v_6	v_7
v_1	1	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	1	0	0	1
v_2	0	1	0	0	1	1	0	0	1	1	0	1	1	0	0	1	1	0	1	1	0
v_3	0	0	1	0	1	0	0	0	1	1	0	1	0	0	0	1	1	0	1	0	0
v_4	0	0	0	1	0	0	1	0	0	0	1	0	0	1	1	0	0	1	0	0	1
v_5	0	1	1	0	1	1	0	0	1	1	0	1	1	0	0	1	1	0	1	1	0
v_6	0	1	0	0	1	1	0	0	1	0	0	1	1	0	0	1	0	0	1	1	0
v_7	0	0	0	1	0	0	1	0	0	0	1	0	0	1	1	0	0	1	0	0	1

$(i = 1, 2, \ldots, n)$ with respect to triadic formal context Γ.

5.3. Dynamical detection of k-cliques based on TFCA

This section is devoted on investigating an intrinsic equivalent relationship between cliques detection and triadic concepts and bridging the connection between dynamic social network and TFCA.

Based on our previous work [18], the following detection theorem for finding the k-cliques from dynamic social networks is derived.

Theorem 1. *Given a dynamic social network $g = \langle G_1, G_2, \ldots, G_T \rangle$, the k-cliques detection problem $P_{k-clique}(g)$ is equivalent to finding the k-triadic equiconepts $KTE(TFC(G_t))$ as well as the remaining k-triadic equiconepts derived from high-order triadic equiconcepts,*[1] *i.e., $(k+1)$-triadic equiconcepts, $(k+2)$-triadic equiconcepts, …, (M)-triadic equiconcepts $(M > k)$. M is the number of maximum extent or intent of maximum triadic equiconcepts. This theorem is formally represented mathematically,*

$$P_{k-clique}(g) \equiv \bigcup_{t=1}^{T} KTE(TFC(G_t)) \bigcup Derived(K^iTE(TFC(G_t))) \quad (4)$$

Proof. According to the above theorem, the k-cliques detection problem $P_{k-clique}(g)$ is equivalent to the problem of finding the k-triadic equiconcepts $P_{KTE(TFC(G_t))}$ that is composed of basic k-triadic equiconcepts $KTE(TFC(G_t))$ and the derived k-cliques from $K^iTE(TFC(G_t))$. Hence, we should prove it toward two directions: (1) $P_{k-clique}(g) \Rightarrow P_{KTE(TFC(G_t))}$ and (2) $P_{k-clique}(g) \Leftarrow P_{KTE(TFC(G_t))}$

- $(P_{k-clique}(g) \Rightarrow P_{KTE(TFC(G_t))})$: Given a dynamic social network g, a k-clique in G_t contains vertices $v_1, v_2, \ldots, v_k$, for any two vertices v_i, v_j, there exists an edge between them. Since a k-clique is a subgraph, we can easily construct the triadic formal context via Modified Adjacency Matrix. Obviously, the triadic formal context of a k-clique is a matrix of ones. We can extract a special such kind of concept $(\{v_1, v_2, \ldots, v_k\}, \{v_1, v_2, \ldots, v_k\})$ from this triadic formal context which satisfies $X{=}B$, X is the extent of this special concept, and B is the intent of this special concept. This special concept is actually a k-Triadic Equiconcept. In addition, the derived k-Triadic Equiconcept also satisfies the same extent and intent. Similarly, as the time elapses, all the k-Triadic Equiconcepts are obtained. Therefore, $P_{k-clique}(g) \Rightarrow P_{KTE(TFC(G_t))}$.
- $(P_{k-clique} \Leftarrow P_{KEC(FC(G))})$: Due to Definition 9, we know that all extracted k-triadic equiconcepts $KTE(TFC(G_t)) = \{(X_i^t, B_i^t) | i = 1, 2, \ldots, r;\ t = 1, 2, \ldots, T\}$ and r is the number of k-equiconcepts with respect to the triadic formal context $TFC(G_t)$ at time t;

Here, (X_i^t, B_i^t) is the i^{th} k-triadic equiconcept at time t, X_i^t is the extent of the i^{th} k-Triadic Equiconcept at time t and B_i^t is the intent of the i^{th} k-triadic equiconcept at time t and $|X_i| = |B_i| = k$. In a triadic formal context of dynamic social network g, both X_i^t and B_i^t are consisted of subset of vertices, *i.e.*, $X_i^t = \{v_1, v_2 \ldots, v_k\}$. Since X_i^t and B_i^t is one of k-triadic equiconcepts, it means vertices in X_i^t are connected with vertices in B_i^t at time t. Hence, we can obtain a subgraph (k-clique) based on the association between X_i^t and B_i^t. For $i = 1, 2, \cdots, r$ and $t = 1, 2, \cdots, T$, we can obtain all k-cliques from g. Consequently, $P_{k-clique}(g) \Leftarrow P_{KTE(TFC(G_t))}$.

Since we have already proved that $P_{k-clique}(g) \Rightarrow P_{KTE(TFC(G_t))}$ and $P_{k-clique}(g) \Leftarrow P_{KTE(TFC(G_t))}$, then $P_{k-clique}(g) \equiv P_{KTE(TFC(G_t))}$ holds. □

Example 3. Given a dynamic social network $g = \langle G_{t1}, G_{t2}, G_{t3} \rangle$ as shown in Fig. 2, the 2-cliques are easily detected from the two aspects:

1. detecting the explicit 2-cliques according to its 2-triadic equiconcepts, i.e., $(\{3, 5\}, \{3, 5\}, t_1)$, $(\{4, 7\}, \{4, 7\}, t_1)$, $(\{4, 7\}, \{4, 7\}, t_2)$, three explicit 2-cliques are discovered.
2. deriving the implicit 2-cliques from the high-order triadic equiconcepts $(\{2, 5, 6\}, \{2, 5, 6\}, t_1)$, $(\{2, 5, 6\}, \{2, 5, 6\}, t_2)$, $(\{2, 3, 5\}, \{2, 3, 5\}, t_2)$, $(\{2, 5, 6\}, \{2, 5, 6\}, t_3)$, $(\{2, 3, 5\}, \{2, 3, 5\}, t_3)$, $(\{1, 4, 7\}, \{1, 4, 7\}, t_3)$,

According to Theorem 1, 2-cliques are derived as follows: $(\{2, 5\}, \{2, 5\}, t_1)$, $(\{2, 6\}, \{2, 6\}, t_1)$, $(\{5, 6\}, \{5, 6\}, t_1)$, $(\{2, 5\}, \{2, 5\}, t_2)$, $(\{2, 6\}, \{2, 6\}, t_2)$, $(\{5, 6\}, \{5, 6\}, t_2)$, $(\{2, 3\}, \{2, 3\}, t_2)$, $(\{2, 5\}, \{2, 5\}, t_2)$, $(\{3, 5\}, \{3, 5\}, t_2)$, $(\{2, 5\}, \{2, 5\}, t_3)$, $(\{2, 6\}, \{2, 6\}, t_3)$, $(\{5, 6\}, \{5, 6\}, t_3)$, $(\{2, 3\}, \{2, 3\}, t_3)$, $(\{2, 5\}, \{2, 5\}, t_3)$, $(\{3, 5\}, \{3, 5\}, t_3)$, $(\{1, 4\}, \{1, 4\}, t_3)$, $(\{1, 7\}, \{1, 7\}, t_3)$, $(\{4, 7\}, \{4, 7\}, t_3)$.

However, the above triples are not triadic concepts that cannot satisfy Definition 7. In summary, for a 2-cliques detection problem from a dynamic social network, the detection results are the union of explicit and implicit 2-cliques.

From the dynamic point of view, the critical purposes of detection of k-cliques in dynamic social network are not only to identify the k-cliques but also able to reveal the dynamic characteristics of k-cliques.

Corollary 1. *For a triadic formal context $TFC(G_t) = (V, V, T, I) | (t = 1, 2, \ldots, T)$ of a dynamic social network g and a threshold $\theta \in [1, |T|]$, the detected k-clique (X, B) is called frequent k-cliques if $\sum_{t=1}^{T} sign(t) \geq \theta$, where $sign(t) = 1$ if $X_i^t = B_i^t = X = B$, otherwise $sign(t) = 0$.*

Based on the above corollary and extreme setting values of θ, the following property is induced.

Property 1. *In Corollary 1, when threshold $\theta = |T|$, this type of k-clique exists in the dynamic social network during the graph*

[1] High-order triadic equiconcepts refers to the triadic equiconcepts that have more vertices compared to current triadic equiconcept.

involving. We call this type special k-clique as constant k-clique.

Example 4. Continue the Example 3, if $\theta = 2$ and $k=3$, it is easily to obtain 2 frequent 3-cliques, i.e., ({2,3,5},{2,3,5}), ({2,5,6},{2,5,6}). In particular, if $\theta = 3$ and $k=2$, there exist 5 constant 2-cliques, i.e., ({2,5},{2,5}), ({2,6},{2,6}), ({5,6},{5,6}), ({3,5},{3,5}), ({4,7},{4,7}).

Note that the semantic of frequent k-cliques and constant k-cliques is very useful for understanding the social interactions and community features in the dynamic social networks. For example, the constant k-cliques structure in mobile social networks reflects the stable social relationships. In another word, the mobile users in k-cliques have frequent social interactions. Therefore, some recommendation services, information propagation and social marketing can be carried out by the virtue of this special structures.

5.4. Algorithm and complexity analysis

This section mainly provides the k-clique dynamic detection algorithm as shown in Algorithm 1 for finding the k-cliques from a dynamic social network. In addition, the complexity of the proposed algorithm is also analyzed.

Algorithm 1 works as follows: initially, a graph G and parameter k are inputs of whole algorithm; then, we initialize a set of k-cliques with Q (Line 1). After the initialization of algorithm, it goes into the triadic formal context construction and triadic concepts generation codes part (Lines 2–5). Lines 6–9 find the explicit k-cliques by inserting the k-triadic equiconcepts (X,B) into Q. The implicit k-cliques are derived from other high-order k-triadic equiconcepts and are inserted into Q (Lines 10–14).

Algorithm 1. k-Clique dynamic detection algorithm.

Require:
$g = \langle G_{t1}, G_{t2}, \ldots, G_T \rangle$;
Parameter k;
Ensure:
Set of k-Cliques Q
1: Initialize $Q = \varnothing$
2: ***begin***
3: Construct a triadic formal context $TFC(G_t)|t = 1, 2, \ldots, T$ by Section 5.1
4: Mining all triadic concepts $TC(TFC(G_t))$
5: ***end***
6: ***for*** each concept $(X, B, D) \in TC(TFC(G_t))$
7: ***begin***
8: ***if*** $|X| = |B| = k$
9: $Q \leftarrow Q \cup (X, B)$
10: ***for*** $i = k + 1$ ***to*** M ***do***
11: ***begin***
12: $Q \leftarrow Q \cup Derived((X_i, B_i))$
13: ***end***
14: ***end***

The complexity of the above algorithm is analyzed in terms of time factor, *i.e.*, time complexity analysis. Clearly, the time is mainly consumed by the following three aspects: (1) the triadic formal context construction, since there exist $|T|$ matrix operations when a triadic formal context is constructed, the time complexity is $\Theta(|T| \times |V|^3)$; (2) mining the triadic formal concepts, the time complexity analysis is similar to our previous work [22], *i.e.*, time complexity equals to $\Theta(|V|^2 \times L)$ (L indicates the total number of concepts); (3) deriving the implicit k-cliques, the time complexity is evaluated as $\Theta\left(\sum_{i=k+1}^{M} C(i, k)\right)$. To summary, the time complexity of algorithm is $\Theta\left(|T| \times |V|^3 + |V|^2 \times L + \sum_{i=k+1}^{M} C(i, k)\right)$.

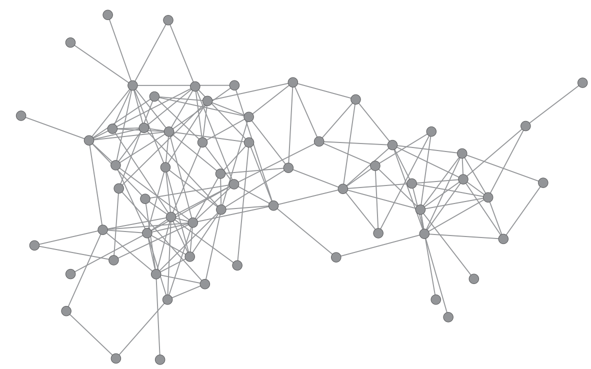


Fig. 4. The visualization of Dolphin living network.

6. Experiments

This section is going to demonstrate an application of dynamic k-cliques detection. All algorithms are implemented in JAVA language and executed on an Intel core i7-2600K processor, 3.4GHZ, 8 GB RAM computer.

6.1. Data set and configurations

We adopt the Dolphin Living Networks (Dolphin) dataset[2] that is a classical dataset on the social network of frequent associations between 62 dolphins in a community living off Doubtful sound, New Zealand. This graph contains 62 vertices and 159 edges as shown in Fig. 4. To characterize the dynamic of this graph, the timestamps are marked one by one in terms of month. In another words, this dynamic graph reflects the dynamical relationships between dolphins. For example, one dolphin D_i has no relationship with D_j on *March*, but they gradually establish the relationship on *September* through frequent social interactions. Of course, the existing relationship between D_m and D_n on *May* might disappear on *October*.

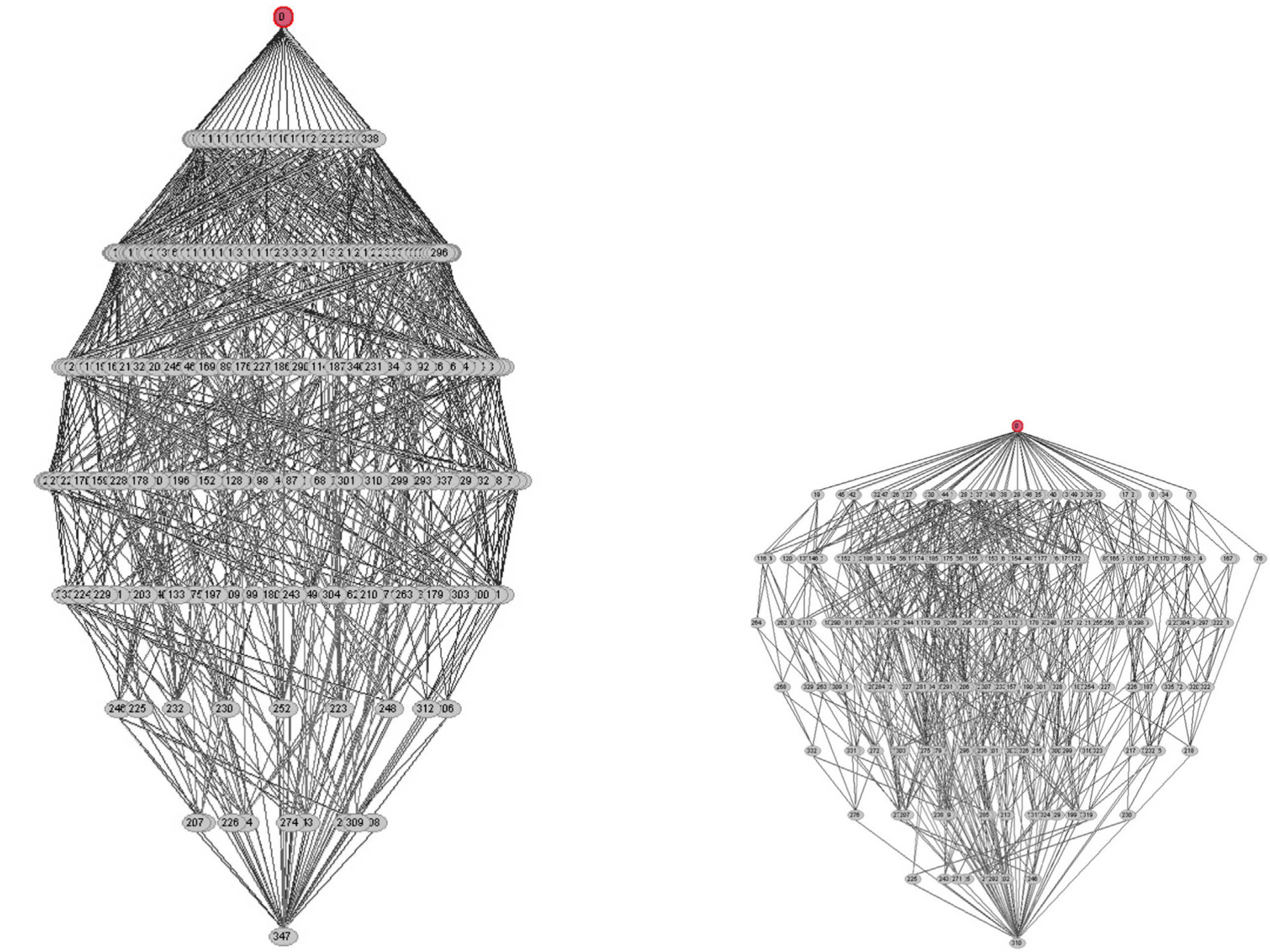
Fig. 5 shows the dynamical visualization of concept lattices at time t_1 and t_2. With this dynamic social network, we execute a series of detection on the corresponding graph according to different setting of k as well as threshold θ from t_1 to t_5. Without loss of generality, we choose the k ranged from 3 to 5 with 1 step, *i.e.*, $k = \{3, 4, 5\}$ and the θ ranged from 1 to 5 with 1 step *i.e.*, $\theta = \{1, 2, 3, 4, 5\}$, for the evaluation of the frequent k-cliques mining. For the better visualization of the k-cliques mining performance, the threshold value θ is scaled as $\{0.02, 0.04, 0.06, 0.08, 0.1\}$, for example, 3/50=0.06.

6.2. Results

This section mainly evaluates the proposed approach with two important metrics: precision/recall ratio of k-cliques detection. The experiments are conducted on different time stamps in the experimental dataset. For a given parameter k and time t, a set of k-cliques are obtained, the corresponding precision and recall ratio are defined as follows:

- *Precision* is the ratio of the number of relevant k-cliques in the

[2] https://networkdata.ics.uci.edu/data.php?id=6



(a) Concept Lattice at Time t_1

(b) Concept Lattice at Time t_2

Fig. 5. The dynamical visualization of concept lattices on different time.

detection results to the total number of k-cliques obtained by that detection.

- *Recall* is the ratio of the number of relevant k-cliques in the detection results to the total number of existing relevant k-cliques.
- *F1-score* is used to evaluate how well each algorithm can find the k-cliques from a graph by fitting the *Precision* and *Recall*, denoted as $F1 = \frac{2 * Precision * Recall}{Precision + Recall}$.

The precision of the proposed detection algorithm is measured with various k at different time as shown in Table 3 and Fig. 6(a). Clearly, the detection precision of k-cliques increases as the k increases. In particular, the precision reaches the 100% when we try to find out the 5-cliques. Similarly, the recall of the proposed algorithm in Table 4 and Fig. 6(b) increases in general as the time elapses. Also, the recall of the detection algorithm achieves 100% when k=5. Additionally, we also evaluate the proposed algorithm with various k in terms of F1-score that is used to evaluate how well each algorithm can find the k-cliques from a social network. Fig. 7 reports that the proposed algorithm can discover the k-cliques efficiently especially the cliques with a larger k.

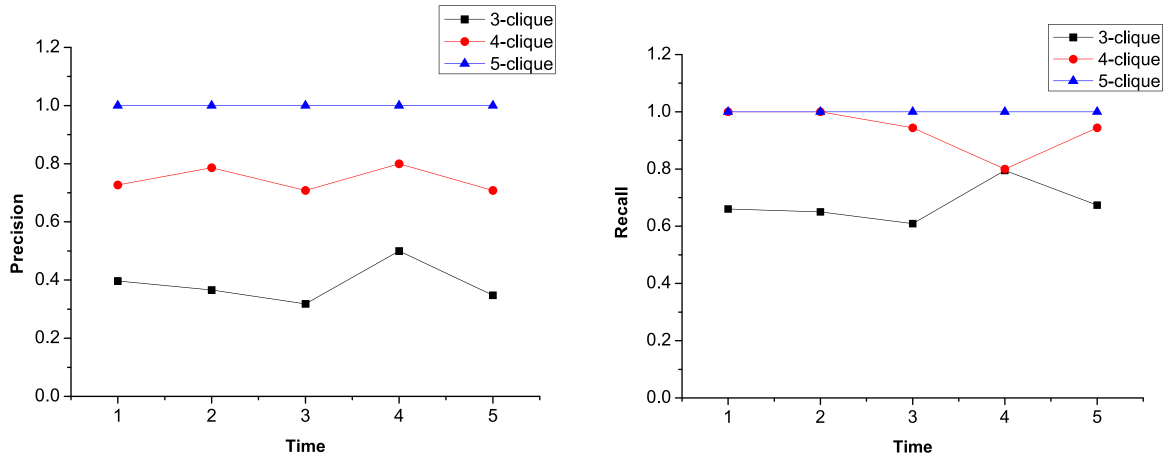
Table 3
The precision of algorithm at different time.

k	t_1	t_2	t_3	t_4	t_5
3	31/78	26/71	28/88	35/70	31/89
4	16/22	11/14	17/24	8/10	17/24
5	3/3	3/3	1/1	2/2	1/1

6.3. Results, discussions and new findings

According to the above experiment evaluation and analysis, it is obvious to conclude the following statements: the unique feature of the TFCA-based k-cliques detection approach is that it can easily find out the k-cliques via constructed detection index—*k-Triadic Equiconcept*. The proposed algorithm represents a high feasibility as well as robustness.

During the k-cliques dynamic detection on the time line, we found that some special sub-graph structures such as constant k-cliques and frequent k-cliques always existing in the dynamic social network. By comparing the detected k-cliques at different time, we can easily to get 26 constant 3-cliques, 8 constant 4-cliques, and 1 constant 5-clique respectively. In



(a) (b)

Fig. 6. k-cliques detection precision and recall with the proposed algorithm. (a) The precision of the proposed algorithm with various k at different time. (b) The recall ratio of the proposed algorithm with various k at different time.

Table 4
The recall of algorithm at different time.

k	t_1	t_2	t_3	t_4	t_5
3	31/47	26/40	28/46	35/44	31/46
4	16/16	11/11	17/18	8/10	17/18
5	3/3	3/3	1/1	2/2	1/1

other words, the topological structure of these constant k-cliques never changes during the evolving of the social networks, and the relationships among the dolphins are quite steady.

In most real-life applications, such as the targeted social marketing and social collaborations, the constraints of constant k-cliques are too harsh. Therefore, devising a flexible mining mechanism of k-cliques is becoming very important. To this end, inspired by the idea of [21], we evaluate the mining performance of frequent k-cliques in terms of various thresholds.

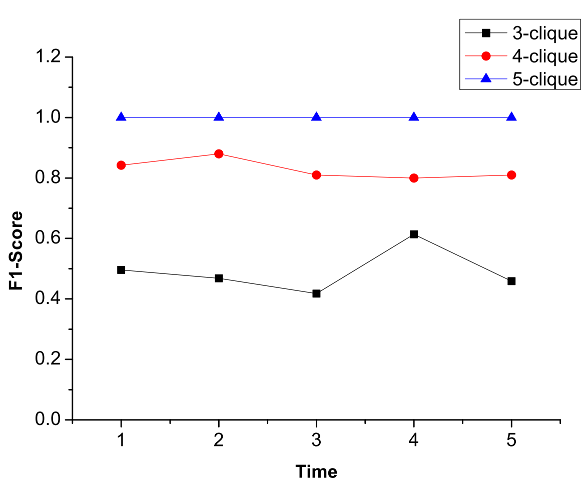


Fig. 7. k-Cliques detection F1-score of the proposed algorithm with various k at different time.

Similarly, the precision of the proposed detection algorithm is also measured with various thresholds θ at different time as shown in Table 5 and Fig. 8(a).

As can be seen from Fig. 8(a), the precision decreases as the threshold θ increases. That is to say, the higher of constraint for the frequent k-cliques is, the lower of detection precision is. Meanwhile, the recall of the proposed algorithm in Table 6 and Fig. 8(b) decreases as the threshold increases. Importantly, we found that there is no k-cliques ($k \geq 6$) since the elements on the rightmost column are 0.

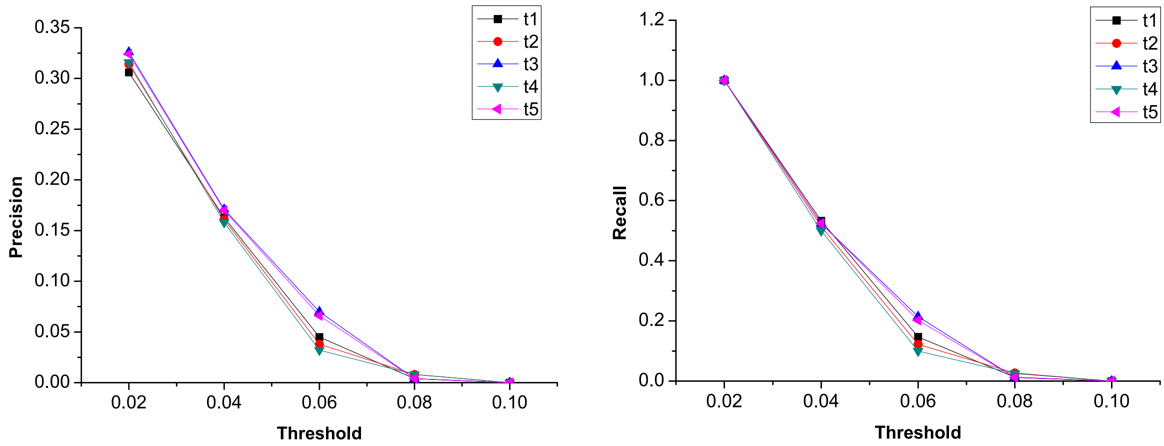
Fig. 9 shows that the proposed algorithm can discover more frequent k-cliques efficiently.

7. Conclusions

This paper aims to identify the k-cliques in dynamic social networks for extracting the computational intelligence from IoT and enhancing the interconnections between the intelligence communicating things of IoT. We propose an efficient k-cliques dynamic detection algorithm based on Triadic Formal Concept Analysis (TFCA). To devise proposed detection algorithm, we firstly provide a solution for the triadic formal context construction of a social network by using Modified Adjacency Matrix. Then, it is proved that the k-cliques detection problem is equivalent to finding the k-triadic equiconcepts whose number of elements equals to k. Additionally, two new concepts of frequent k-clique and constant k-clique are defined for revealing more practical community intelligence in various applications. We evaluate the proposed algorithm on k-cliques

Table 5
The precision of algorithm at different time for various thresholds.

Time	0.02	0.04	0.06	0.08	0.1
t_1	75/245	40/245	11/245	1/245	0
t_2	74/236	38/236	9/236	2/236	0
t_3	84/258	44/258	18/258	1/258	0
t_4	80/253	40/253	8/253	2/253	0
t_5	84/259	44/259	17/259	1/259	0



(a) (b)

Fig. 8. Frequent k-cliques detection precision and recall of the proposed algorithm. (a) The precision of the proposed algorithm with various k at different time. (b) The recall ratio of the proposed algorithm with various k at different time.

Table 6
The recall of algorithm at different time for various thresholds.

Time	0.02	0.04	0.06	0.08	0.1
t_1	75/75	40/75	11/75	1/75	0
t_2	74/74	38/74	9/74	2/74	0
t_3	84/84	44/84	18/84	1/84	0
t_4	80/80	40/80	8/80	2/80	0
t_5	84/84	44/84	17/84	1/84	0

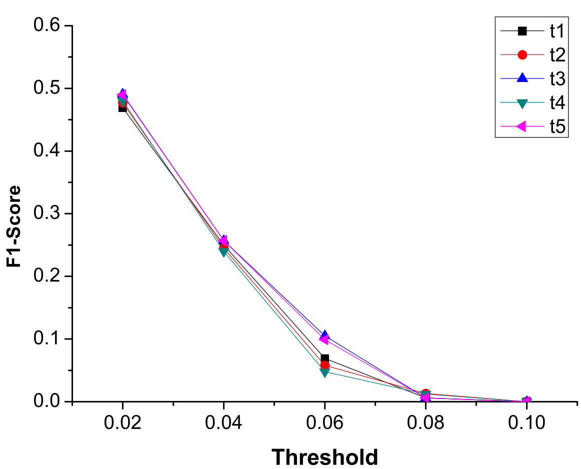


Fig. 9. Frequent k-cliques detection F1-score of the proposed algorithm with various k at different time.

and frequent k-cliques detection from the aspects of precision, recall and F1-score, respectively. Experimental results show that the proposed algorithm has a high feasibility and robustness for detecting the k-cliques as well as frequent k-cliques in social networks.

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