# Evolutionary Spatiotemporal Community Discovery in Dynamic Weighted Networks

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## Abstract

Detecting evolving communities in dynamic weighted networks are significant for understanding the evolutionary patterns of complex networks. However, it is difficult and challenging for traditional approaches to extract evolving communities with notable significance from dense and large dynamic complex networks, because most of communities are still so dense and large that we could not observe directly the detailed evolving sub-structures. In this paper, a novel approach is proposed to extract overlapping evolutionary spatiotemporal communities in large, dense and dynamic weighted networks. Evolutionary spatiotemporal communities can not only show the evolutionary of nodes and edges in a certain period clearly, but also contain weight vectors with similar evolving trend. Experiments on the global trading network show that the proposed approach can discover more sophisticated evolving patterns and properties which hide in those seemingly stable community structures.

**Keywords:** Link community, Weighted complex network, Community evolution, Biclustering

## 1 Introduction

Community detection plays a key role in complex network analysis. Traditional community detection approaches are mainly restricted in finding static community structures, such as spectral method based on modularity matrix [1], GN [2], hierarchical clustering [3], Bayesian approach [4] and so on. These methods show good results for static community detection.

However, in many real networks, not only the complex network structure may evolve over time, but also the structure of communities does as well. Moreover, for weighted networks, the evolving patterns of weighted communities show more sophisticated behaviors, which evolve at two dimensions simultaneously: the topological structure and weight values. For instance, in trading networks, nodes represent different states, and weighted edges reflect the trading relationship by total exports or imports between two countries in one year. Countries select their trading partners in part based on their political relations with the home state, suggesting that the trade–conflict relationship runs in both directions [5]. A trading community is a group of states that trade with each other significantly more than they trade with states outside the community. The trading relationship evolves over time and the value of trade fluctuates over time also. After a period of time, some countries may decrease the value of trade for political or economic conflict reasons, or quit the community in a certain extreme case even. That means, besides of the structure of a community may evolve, the fluctuation of edge weights is also another important type of evolving patterns in complex networks.

Therefore, an increasing number of researchers pay more attention to detect dynamic network communities so as to discover and understand the evolving mechanism of complex networks.

In general, there are mainly two kinds of community detection methods.

One category is to find nodes-community. Community is defined as a group of nodes in unweighted networks, where the nodes in a community have higher degrees and those between different communities have lower density [6]. Most of community detection algorithms aim to find this kind of communities and focus on finding how the nodes evolve in a community. Communities in complex networks often are overlapping, in which some nodes and edges are shared by several communities. Palla et al. [7] designed a novel algorithm CFinder based on clique percolation to extract overlapping unweighted communities at each time step, then trace and compare the structure evolving between time $t$ and $t+1$. Takaffoli et al. [8] introduced an algorithm to detect similar communities over time in social networks. Guo et al. [9] developed an algorithm to detect evolutionary communities in dynamic weighted networks. They used the sum of weight value of a node at timestep $t$ as

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the node degree, and then define the weighted modularity of a community. The dynamic communities can be extracted by expanding or merging communities via evaluating the weighted modularity.

On the contrary, the other category is to detect link community. Ahn et. al. [10] proposed the concept of link community for the first time. A link community is considered to be a set of closely interrelated links. Ahn et. al. proposed a partition algorithm to detect link communities based on an objective function measuring the link density inside communities. Some evolutionary clustering algorithms are introduced to discover stable and consistent communities [11-12]. These evolutionary clustering methods considered faithful communities should not dramatically from one timestep to the next time step. Liu et al. [13] designed an algorithm to detect link communities in weighted dynamic networks, and detect overlapping communities by mapping link communities to node communities.

Other helpful works include overlapping community detection based on density peaks [14], locality optimization or multi-objective optimization [15]. Ma et al. [16] proposed an efficient overlapping community detection algorithm named LED (Loop Edges Delete), which converts structural similarity between vertices to weights of network, and then use Structural Clustering method to detect overlapping communities. Rong et al. [17] proposed a K+-isomorphism method to partition the subgraphs into some similar-subgraph-clusters, and find preserved structures of communities which are isomorphic to each other. Other interesting methods include weighted-spectral clustering [18] and two-level evolutionary algorithm [19], and so on. Qu et al. [20] design a novel method to mine multi-level subgraphs so as to monitor the architecture evolving of heterogeneous wireless communication networks. Liu et al. [21] designed a prediction model based on an optimized Kernel-based Extreme Learning Machine algorithm, then proposed a speculative approach to improve the spatial–temporal efficiency. Dong et al. [22] proposed an anonymous social network framework which considering anonymous users and privacy-preserving [23-25].

These methods mentioned above have some common weakness. First, they do not discuss the communities in directed networks. Although some methods believe their models can be extended into directed networks, there are still some problems which need to be solved for communities with directed edges. Second, these methods focus on the nodes density, but omit those weighted edges which also evolve over time. Those algorithms detecting weighted link community do not consider edges' evolving behaviors even. They just take node's weigh value as a new kind of node density via weighted sum operation. However, in some real-world networks, take the trading network as an example, the link weight values reflect the relationship strength be-tween two states. The trade links (edges) may keep for many years, and the community structure looks like stable, while in fact, the total exports or imports between some states are fluctuating dramatically. From the view of a community, could we still put these edges with increasing weight and those with decreasing weight into the same community without any hesitation?

Inspired by link communities [10] and biclustering [26] algorithms, we propose a novel method focusing on detecting link communities with evolving weight values from dynamic weighted and directed networks.

The remainder of this paper is organized as follows. In Section 2, we describe some concepts and definitions related to the evolutionary community detection. Section 3 proposes a two-stage community detection algorithm. Then Section 4 demonstrates the experiment setting and the results of spatiotemporal community detection. Finally, Section 5 is the conclusion.

## 2 Problem Formulation

To facilitate our elaborations, some fundamental concepts and notations are introduced as follow.

### 2.1 Dynamic weighted networks

Let $G_t$ = ($V_t$, $E_t$) be a network snapshot at time $t$, where $V_t = \{V_t^1, V_t^2, ..., V_t^N\}$ is the set of vertices in the network snapshot $G_t$, and $E_t$ is the set of weighted edges. A dynamic weighted network can be denoted as a sequence of subgraph $G_t$, $G = \{G_1, G_2, ..., G_t, ..., G_{|T|}\}$, where $T$ is the set of time steps, $t \in |T|$.

If at least one $G_t$ is a weighted network, the whole weighted network G can be denoted as $G$ = ($E$, $T$), where $E$ is the set of all of edges between vertex $v_i$ and $v_j$. There is mapping $E \times T \rightarrow W_{ET}$, $W_{ET} = (w_{ij}^t) = (e_k^t), e_k \in E$.

### 2.2 Spatiotemporal Community

Ahn et al. [10] proposed the concept of link community in unweighted dynamicnetwork. A dynamic network can be denoted as a set of communities $C_t = \{C_t^1, C_t^2, ..., C_t^n\}$ at time t, where $C_t^1 \cap C_t^j = \phi, i \neq j$, which means there is no any nodes belonging to two different communities simultaneously. The original link community is defined as none-overlapping community. A link community is still a static sub-network at a timestep t. We have to trace the topological structure so as to observe which nodes and edges have joined or left a community at a period of time. Moreover, the concept of link community neglects the evolving behaviors of edge weights in a community over times.

Here, we propose Spatiotemporal Community to describe the evolutionary of a community from both of the perspectives of space and time simultaneously.

Let $C\{C^m, T^n, W'\}$ be a dynamic link community in a weighted network, where time interval $T^n = [t_s, t_e]$, start time step $t_s \in T$ and $t_e \in T$, $G^m$ is a subgraph, $S(\cdot)$ is a similar function, $W'$ is a sub-matrix of the community's weight matrix in time interval $T^n$.

Intuitively, if $S(W') \le \delta$, where $\delta$ is a similarity threshold, then community C is a spatiotemporal community.

That means, a spatiotemporal community is such a community with well-connected nodes and similar temporal evolving weight vectors of edges.

### 2.3 Mean Squared Residue

Cheng et al. [26] introduced a quality function called mean squared residue score to measure the coherence of genes and conditions in a sub-matrix of a DNA array. This measure then was applied to similar pattern clustering [27], factor graphs [28], and deep Convolutional Neural Networks analysis [29], and other various application domains [30].

The mean squared residue score H of data matrix $A_{IJ}$ is defined as

$$H(A_{IJ}) = \frac{1}{|I||J|}\sum_{i\in I, j\in J}(w_{ij} - w_{iJ} - w_{Ij} + w_{IJ})^2 \quad \textbf{(1)}$$

where

$$w_{iJ} = \frac{1}{|J|}\sum_{j\in J} w_{ij}, \quad w_{Ij} = \frac{1}{|I|}\sum_{i\in I} w_{ij},$$

$$w_{IJ} = \frac{1}{|I||J|}\sum_{i\in I, j\in J} w_{ij} = \frac{1}{|I|}\sum_{i\in I} w_{iJ} = \frac{1}{|J|}\sum_{j\in J} w_{Ij}.$$

The matrix element $w_{ij} \in A_{ij}$, I and J are the subset of rows and columns respectively, the |I| and |J| are the number of rows and the number of columns in a subset. Small mean squared residue score indicates the uniform fluctuation of data vectors. We will use this measure to define our similar function of subgraphs.

## 3 Problem Solution

In this subsection, we propose a community detection algorithm, which consists of two main stages: (1) biclustering dynamic weighted network in order to obtain spatiotemporal sub-networks with similar evolving trend, (2) extracting overlapping communities in spatiotemporal sub-networks.

### 3.1 Bipartite Weighted Graph Matrix

We denote a dynamic weighted network $G = \{G_1, G_2, ..., G_t, ..., G_{|T|}\}$ as one bipartite graph $G_B = (E, T)$. As Figure 1. Shows, the time set $T$ is one part, and the set of all of weighted edges $E$ is another part. If an edge vertex $e_i$ appear in time vertex $t_k$, then link edge $e_i$ and time $t_k$. Therefore, a series of weighted graph can be put into the same data matrix no matter the network is directed or undirected (Figure 2(a)). The different columns in the data matrix correspond to different subgraphs $G_t$ in $G$.

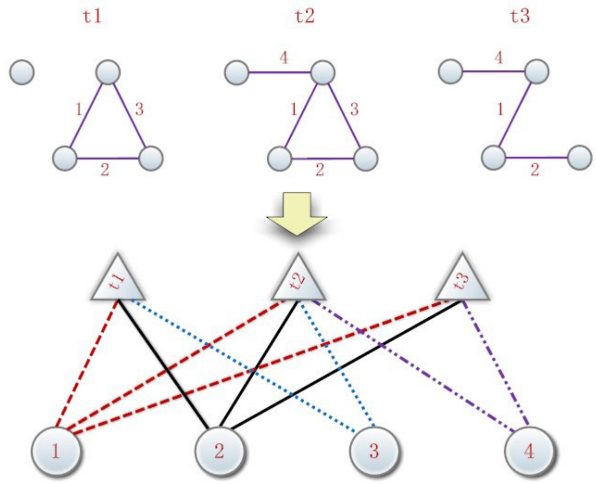
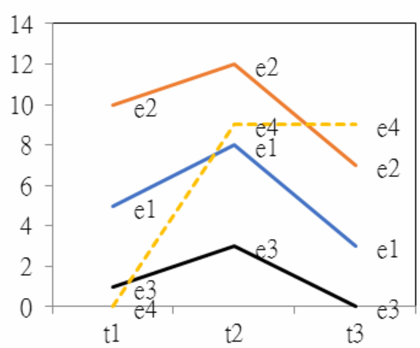



**Figure 1.** Transform dynamic subgraphs into a bipartite graph

Figure 2(a) is the bipartite graph weight matrix of a dynamic network. In Figure 2(b), from time *t1* to *t3*, the weight vectors of edge *e1*, *e2* and *e3* show similar evolving trend, and *e4* is different in trend with other edges apparently. The edge *e1, e2* and *e3* can be put into a bicluster based on mean squared residue score.

| | t1 | t2 | t3 |
|---|---|---|---|
| e1 | 5 | 8 | 3 |
| e2 | 10 | 12 | 7 |
| e3 | 1 | 3 | 0 |
| e4 | 0 | 9 | 9 |

(a) Weight matrix




(b) Trend similar patterns

**Figure 2.** Bipartite weighted graph matrix and similar patterns

### 3.2 Extracting Temporal Similar Sub-graphs

Here, we define the temporal similar sub-graph based on mean squared residue score.

Let $V_{ij} = \{A_1, A_2, ..., A_t, ..., A_{|J|}\}$ be a sub matrix of the bipartite graph matrix, where the column vector $A_t = (e_{1t}, e_{2t}, ..., e_{it}, ..., e_{|I|t})'$, I is a subset of edges, $I \subseteq E, t \in J, J$ is a subset of time step, $J \subseteq T$, the similar score is

$$\text{Score}(A_t, A_{t+1}) = \frac{1}{|I|}\sum_{i \in I}(e_{i,t+1} - e_{i,t} - e_{I,t+1} + e_{I,t}) \quad \textbf{(2)}$$

where $e_{I,t} = \frac{1}{|I|}\sum_{i \in I} e_{i,t}$.

If the similarity Score $(A_t, A_{t+1})$ is less than a threshold $\delta$, the pattern $(A_t, A_{t+1})$ is a temporal similar sub-graphs pattern.

A consecutive of temporal similar sub-graphs can construct a spatiotemporal network with similar evolving trend.

Given a spatiotemporal network $G_{IJ} \subseteq G_B(E, T)$, $I \subseteq E, J \subseteq T, |J| > 2,$ a threshold $\delta > 0$, Score $(A_{IJ}) < \delta$, where

$$\text{Score}(A_{IJ}) = \frac{1}{|J|-1}\sum_{i \in I}^{|J|-1} \text{Score}(A_j, A_{j+1}) \quad \textbf{(3)}$$

According to the definition above, biclustering in a bipartite weighted graph matrix is equivalent to extracting the maximum edge bicliques, which is a NP-complete problem [31]. We propose a biclustering algorithm to extract temporal similar subgraphs. The detail of the clustering algorithm is described in algorithm 1.

### 3.3 Extracting Overlapping Communities

We use bipartite graph to describe spatiotemporal sub-networks (Figure 3), and then propose a method to detect communities based on clique percolation method (CPM) [7].

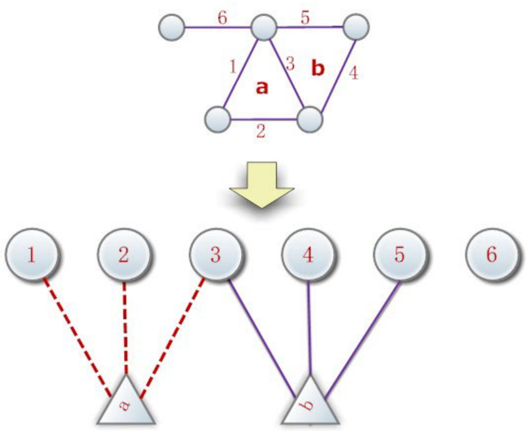



**Figure 3.** Extracting cliques from bipartite graph

**Algorithm 1:** Extracting Temporal Similar Sub-graphs

**Input**: Bipartite graph matrix, threshold $\delta$
**Output**: all temporal similar sub-graphs
**begin**
  **foreach** $t \in T$ **do**
    sort all $(A_t, A_{t+1})$ by ascendence;
    initial each edge as a cluster $C_i^t \leftarrow \{(e_{i,t}, e_{i,t+1})\}$;
  **end**
  **foreach** $t \in T$ **do**
    /* expand one row into $C_i^t$ */
    **foreach** $C_i^t$ **do**
      **if** $score(C_i^t \cup C_{i+1}^t) < \delta$
      $and\ score(C_i^t \cup C_{i+1}^t) \leq score(C_{i+1}^t \cup C_{i+2}^t)$ **then**
        $C_i^t \leftarrow C_i^t \cup C_{i+1}^t$
      **end**
      /* expand one column into $C_i^t$ */
      **if** $score(C_i^{t,t+1}) < \delta$ **then**
        $C_i^t \leftarrow C_i^{t,t+1}$
      **else**
        $reslut\_set.append(C_i^t)$
      **end**
    **end**
  **end**
  return $result\_set$;
**end**

k-cliques are defined as fully connected subgraphs of k vertices. If two k-cliques share k-1 vertices, these two cliques are adjacent. A k-clique-community is defined as the union of all k-cliques that can be reached from each other through a series of adjacent k-cliques [7].

The basic features of such communities are that their node members can be reached through well connected subgraphs, and thus the communities may overlap because of sharing nodes with each other.

In this stage, the biclustering results in first stage, spatiotemporal sub-networks, are treated as unweighted and undirected networks. As we can see in Figure 3, the 3-clique a and b are inserted into a bipartite graph. Each clique is a vertex in the graph, and every edge consisting of the clique are linked with their clique vertex.

The outline of the community detecting algorithm is shown in Algorithm 2.

**Algorithm 2:** Extracting Overlapping Communities

**Input**: Temporal Similar Sub-graphs
**Output**: all spatiotemporal communities
**repeat**
  Once a $k-clique$ is detected in a spatiotemporal sub-network;
  Insert it into a bipartite graph;
**until** *no new* $k-clique$ *are detected*;
**repeat**
  Start from one $k-clique$, construct adjacent $k-cliquechain$ till no adjacent $k-clique$ is found, which is called the maximal $k-clique$ connected subgraph;
**until** *every* $k-clique$ *are visited*;
return the maximal k-clique connected subgraphs as spatiotemporal communities;

# 4 Experimental Results

In this subsection, we use a real dataset to evaluate and validate the effectiveness of our method.

## 4.1 Global Trading Network

These data provide estimates of trade flows between independent states (1948-2000) and GDP per capita of independent states (1950-2000) [32]. We use the export data, which include 1158458 records, corresponding to the total export between different countries in the world from 1948 to 2000. This dataset covers many political crises and financial crises, such as the financial crisis in Asia in 1997.

In our experiment, the original export network data are converted into a bipartite graph of 5361 weight vectors with 53 years. Figure 4 shows the clustering coefficient (the upper line) and the network density of the global trading network. These two measurements indicate the network is evolving over time, and become more and more dense. Figure 4 also shows the global economic connections are becoming closer.

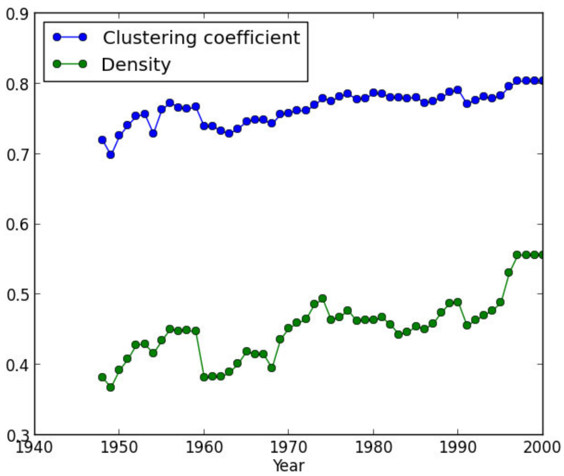



**Figure 4.** The clustering coefficient and density in 1948-2000

## 4.2 Results Analysis

When the clique k is set as 10, threshold δ=0, we obtained 198 spatiotemporal communities. Some results are shown in Figure 5. A spatiotemporal community is shown as two graphs, a topological structure and a line figure.

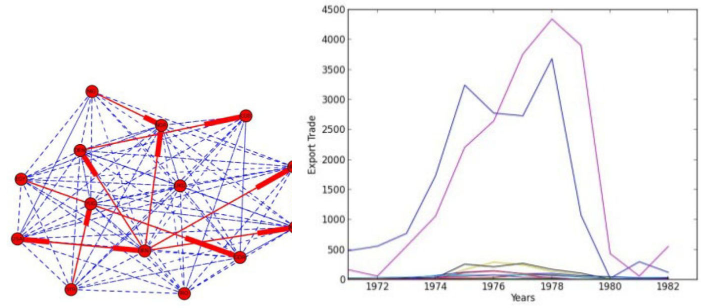
In Figure 5, the upper graphs are the topological structures of communities, whose solid lines with arrows (the red lines) are those edges with similar evolving trend and similar score is less than the threshold. The line figure next to communities' structure show the evolving trends of their edges' weight vectors over time. In a line figure, each line represents an edge vector in a certain time interval. If a line's value declines to zero, it means the edge disappears at a timestamp, such as in Figure 5a, 5b, and 5c. Take the community 189 as instance, which shows some countries export to China and China export to Philippines from year 1991 to 2000. As we know, a critical financial crisis broke out in Asia in 1997. We can find that in that period, the export to China witnessed a slight fluctuation when the financial crisis of Asia breaking out, whereas the export USA to Mexico (the uppermost line in Figure5d) kept a rapid increasing.

In Community_195, we can see the total exports experienced a rapid decline in from 1997 to about 1998, then the lines climbed slowly. These countries include South Korea, Iceland, Brazil, Paraguay, Netherland, German, and so on. While in the Community _193, some of the total exports of these countries underwent dramatic decreases from 1996 in advance. It seems that they forecasted the crisis. These lines include Venezuela to Cuba, Hungary to Mexico, and so on. However, when the financial crisis broke out, their exports increased sharply. They tell us that even in financial crisis, someone still could find a chance to make much money. The Community_189 confirmed my assert. In this community, we can find USA to Mexico, the highest line, and China to Australia, China to Sweden, to China Singapore, and so on.

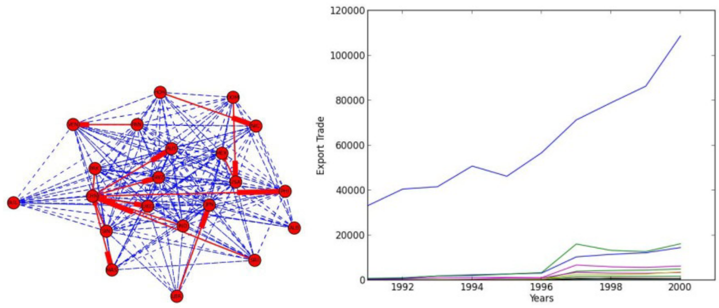
Comparing with the results of literature [5], the spatiotemporal communities extracted by our method are no longer limited in the same geographical area, but crossing intercontinental area, for example including European countries and Asian countries in a same community, and are more suitable for revealing the temporal evolving mechanism. That is because the similarity of two edges is measured by vector similarity, not the distance of two nodes.

# 5 Conclusion

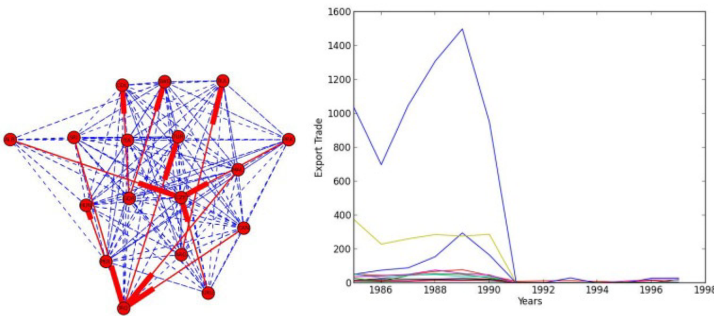
In this paper, we propose a method to detect evolutionary spatiotemporal communities in dynamic weighted networks. This kind of communities can discover the evolving behaviors simultaneously at two dimensions: structure and edge weights when communities are changing with time passing. In addition, our method could be directly applied to directed networks without any modification. The advantages of a spatiotemporal community lie in: (1) it is more suitable for large and dense networks, and the results can be visualized clearly; (2) the evolutionary patterns in structure and weight vectors can be discovered simultaneously. Our experimental results also demonstrate evolutionary spatiotemporal communities can discovery more sophisticated evolving information than traditional communities.



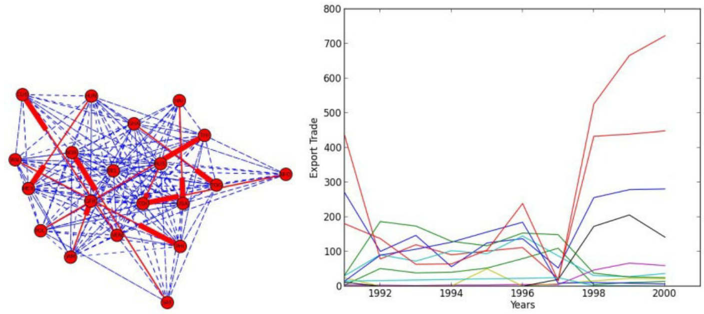

a. Community_15, year 1971 to 1982



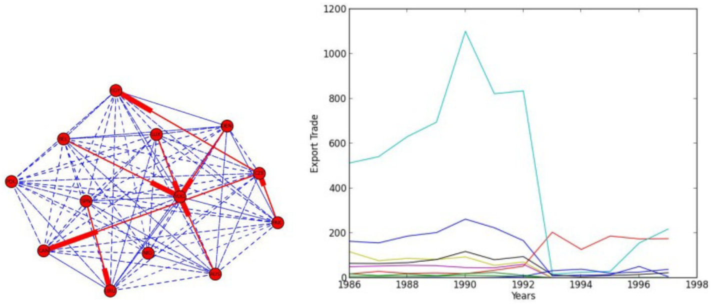

d. Community_189, year 1991 to 2000



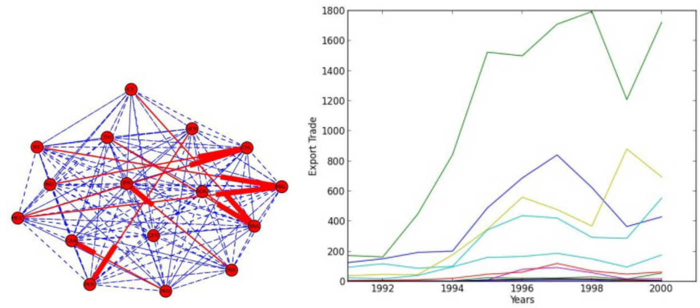

b. Community_108, year 1985 to 1997




e. Community _193, year 1991 to 2000




c. Community _133, year 1986 to 1997




f. Community _195, year 1991 to 2000

**Figure 5.** Some spatiotemporal communities results

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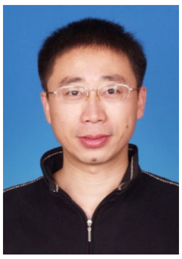
## Biographies



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