









## GROUP EVOLUTION DISCOVERY

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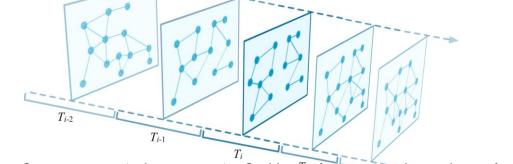
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Group extraction and their evolution are among the topics which arouse the greatest interest in the SNA domain. However, while the group extraction methods in social networks are developed very dynamically, the methods of **group evolution discovery are still 'uncharted territory'**. In recent years, only few methods for tracking changes of social groups have been proposed [2,3,5,6]. Therefore we present the new method for the group evolution discovery called **GED**.

## 1. Temporal Social Network and Events in Group Evolution

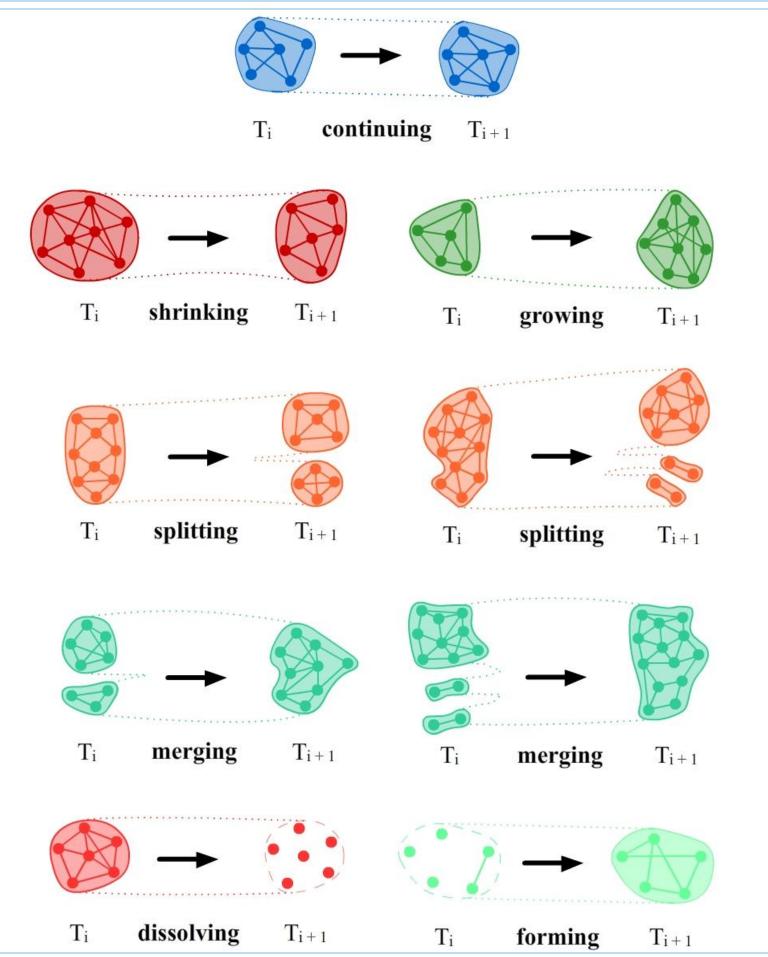
**Temporal social network** *TSN*: is a list of succeeding timeframes (time windows) *T*. Each timeframe is in fact one social network SN(V,E) where V – is a set of vertices and E is a set of directed edges  $\langle x,y \rangle : x,y \in V$ ,  $x \neq y$ 

$$TSN = \langle T_1, T_2, ..., T_m \rangle, m \in N$$
  
 $T_i = SN_i(V_i, E_i), i = 1, 2, ..., m$   
 $E_i = \langle x, y \rangle : x, y \in V_i, x \neq y \quad i = 1, 2, ..., m$ 



Evolution of a social community can be represented by a sequence of events (changes) following reach other in the successive timeframes within the *TSN*. Possible **events in social group evolution** are:

- 1. **Continuing** (stagnation) two following groups are identical or differ only a little (size remain the same).
- 2. *Shrinking* some nodes have left the group, making its size smaller than in the previous time window.
- 3. **Growing** some new nodes have joined the group, making its size bigger than in the previous time window.
- 4. **Splitting** the group splits into 2 or more groups in the next time window when few groups from  $T_{i+1}$  consist of members of one group from  $T_i$ . Two types of splitting: (1) *equal* the contribution of the groups in The split group is almost the same and (2) *unequal* one of the groups has much greater contribution in the split group, which for this one group the event might be similar to shrinking.
- 5. **Merging** merging several other groups when one group from  $T_{i+1}$  consist of two or more groups from the previous time  $T_i$ . Merge might be (1) *equal* the contribution of the groups in the merged group is almost the same, or (2) unequal one of the groups has much greater contribution into the merged group (for the biggest group the merging might be similar to growing).
- 6. **Dissolving** a group ends its life and does not occur in the next time window.
- 7. **Forming** a group which has not existed in the previous time  $T_i$  appears in  $T_{i+1}$ . A group can be inactive over several timeframes it is treated as dissolving of the first group and forming again of the, second, new one.



## 2. The Inclusion Measure

Key component of *GED* - a **new measure** called *inclusion*. It allows to evaluate the inclusion of one group in another:

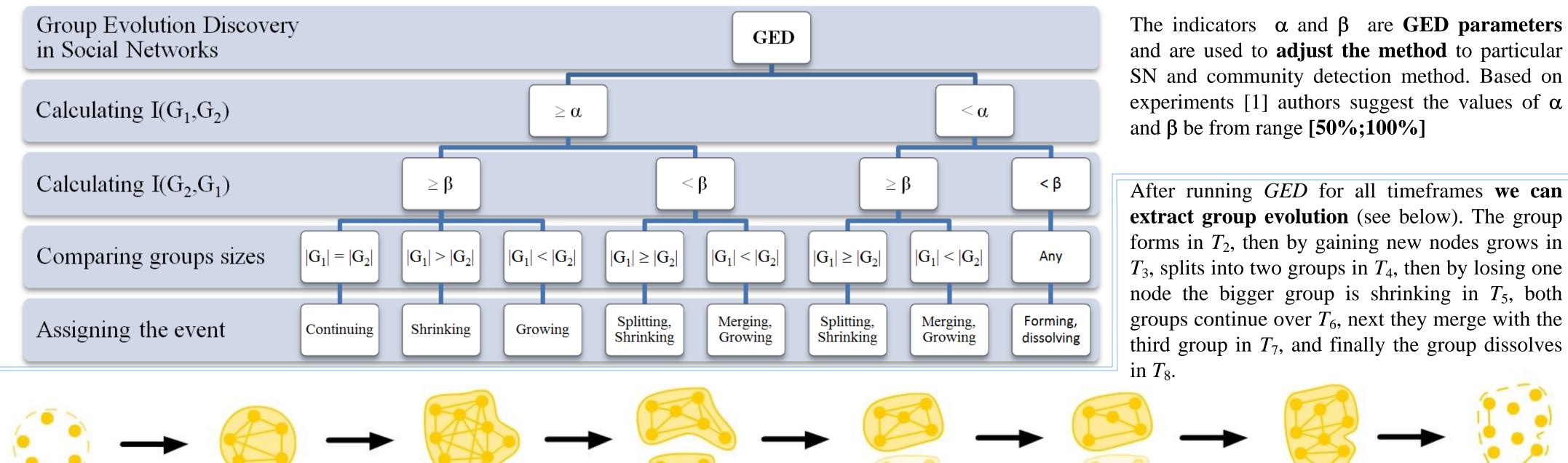
$$I(G_{1},G_{2}) = \underbrace{\frac{|G_{1} \cap G_{2}|}{|G_{1}|}}_{group quantity} \cdot \underbrace{\frac{\sum_{x \in (G_{1} \cap G_{2})} SP_{G_{1}}(x)}{\sum_{x \in (G_{1})} SP_{G_{1}}(x)}}_{SP_{G_{1}}(x)}$$

The GED method, to match two groups from consecutive timeframes takes into consideration both, the **quantity and quality** of the group members. The **quantity** is reflected by the first part of the *inclusion* measure, i.e. what portion of  $G_1$  members is shared by  $G_2$ , whereas the **quality** is expressed by the second part of the *inclusion* measure, namely what contribution of important members of  $G_1$  is shared by  $G_2$ . It provides a balance between the groups, which contain many of the less important members and groups with only few but key members. To indicate user importance one of the centrality measures may be used. For this presentation we have utilized SP measure [4].

## 3. GED – Group Evolution Discovery Method

**Input:** Groups in TSN are extracted by **any community detection** algorithm for each timeframe  $T_i$ . Calculated any **user importance measure**.

- 1. For each pair  $\langle G_1, G_2 \rangle$  in timeframes  $T_i$  and  $T_{i+1}$  inclusion of  $G_1$  in  $G_2$  and  $G_2$  in  $G_1$  is computed.
- 2. Based on **inclusion and size** of two groups one type of event may be assigned:
  - a. **Continuing**:  $I(G_1, G_2) > \alpha$  and  $I(G_2, G_1) > \beta$  and  $|G_1| = |G_2|$
  - b. Shrinking:  $I(G_1, G_2) > \alpha$  and  $I(G_2, G_1) > \beta$  and  $|G_1| > |G_2|$  OR  $|I(G_1, G_2)| < \alpha$  and  $|G_2, G_1| > \beta$  and  $|G_1| > |G_2|$  and there is only one matching event between  $|G_2|$  and all groups in  $|G_1| > |G_2|$
  - c. **Growing**:  $I(G_1, G_2) > \alpha$  and  $I(G_2, G_1) > \beta$  and  $|G_1| < |G_2|$  OR  $I(G_1, G_2) > \alpha$  and  $I(G_2, G_1) < \beta$  and  $|G_1| > |G_2|$  and there is only one matching event between  $G_1$  and all groups in the next time window  $T_{i+1}$
  - d. **Splitting**:  $I(G_1, G_2) < \alpha$  and  $I(G_2, G_1) > \beta$  and  $|G_1| > |G_2|$  and there is more than one match (matching events) between  $G_2$  and all groups in the previous time window  $T_i$
  - e. **Merging**:  $I(G_1, G_2) > \alpha$  and  $I(G_2, G_1) < \beta$  and  $|G_1| > |G_2|$  and there is more than one match (matching events) between  $G_1$  and all groups in the next time window  $T_{i+1}$
  - *f.* **Dissolving**: for  $G_1$  in  $T_i$  and each group  $G_2$  in  $T_{i+1}$   $I(G_1, G_2) < 10\%$  and  $I(G_2, G_1) < 10\%$
  - *g. Forming*: for  $G_2$  in  $T_{i+1}$  and each group  $G_1$  in  $T_i$   $I(G_1, G_2) < 10\%$  and  $I(G_2, G_1) < 10\%$



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growing

 $T_3$ 

splitting

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- 5 Palla, G., Barabási, A.L., and Vicsek, T. Quantifying social group evolution. Nature 446, (2007), 664-667.
  6 Sun J., Papadimitriou S., Yu P., Faloutsos C, GraphScope: Parameter-free Mining of Large Time-evolving Graphs

forming

Acknowledgments.

continuing

 $T_5$ 

shrinking

 $T_6$ 

merging

dissolving