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Top Leaders Community Detection Approach in Information Networks

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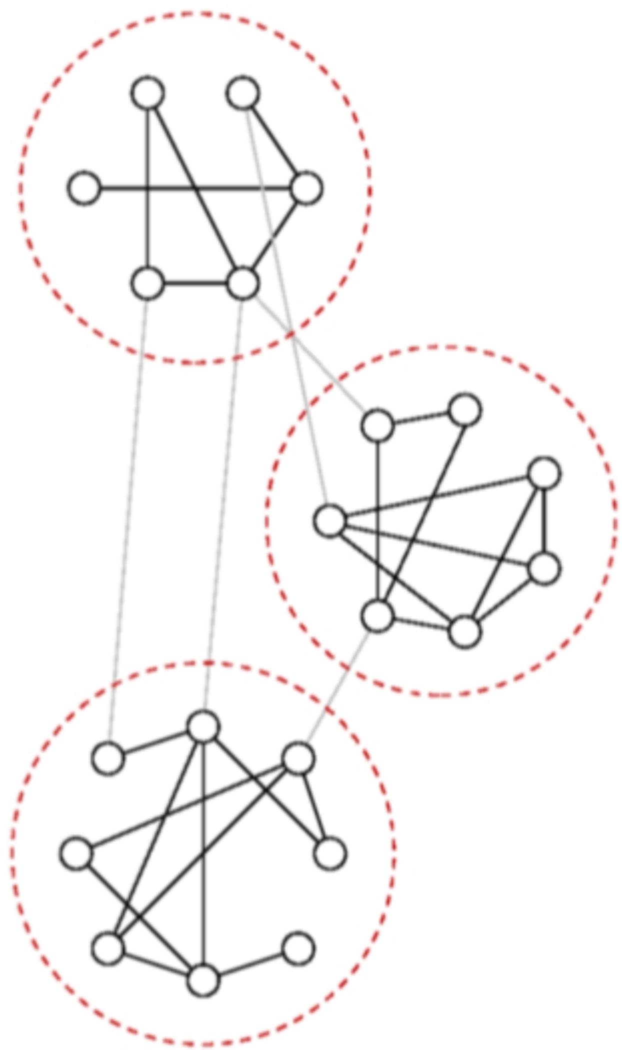
What is Community Structure?

- *Community structure* denotes the existence of densely connected groups of nodes, with only sparser connections between groups.
- Many social networks share the property of a community structure, e.g., WWW, tele-communication networks, academic collaboration networks, friendship networks, etc.



Many similarities with data **Clustering**

Outline

- Introduction
- Some related work
  - Graph Partitioning, Modularity Q and others
- Top Leaders
  - Problem Definition
  - Associating nodes to Leaders
  - Initialization of the leaders
  - Experiments
- Conclusions

Introduction

- A new Approach for Finding Communities in the Networks
  - Densely connected nodes with sparse connections outside the group

- Community: set of followers congregating around a potential leader

- Algorithm: similar in spirit to k-means
  - starts by identifying promising leaders in the network
  - iteratively until convergence
    - assembles followers to their closest leaders to form communities
    - finds new leaders in each group around which to gather followers again

Related Work

- Graph partitioning and spectral clustering approaches
  - dividing the network into groups with (roughly) equal size, while minimizing the number of edges that run between vertices in different groups
- Q-modularity by Newman 2004
  - measure of the quality of a particular division of a network
- CFinder by Palla et al. 2005
  - community: union of complete subgraphs of size k
  - k between 3 and 5: very effective on real networks
- SCAN by Xu et al. 2007
  - nodes that are structurally reachable from each other are grouped together in the same community

Problem Definition

- Finding leaders and their followers in the network to form the communities
- Leader: The central/influential node
- Community: Set of followers surrounding a leader
- Assigning followers to closest leader based on the intersection of their neighborhoud

Top Leaders Approach

A leader is the most central member in a community

Algorithm 1 Top Leaders algorithm

Input: A social network G, and k the number of desired communities

```
initialize k leaders
repeat
    {finding communities}
    for all Node n ∈ G do
        if n ∉ leaders then
            associate n to a leader {Algorithm 2}
        end if
    end for
    {updating leaders}
    for all l ∈ leaders do
        l ← arg max_{n∈Community(l)} Centrality(n)
    end for
until there is no change in the leaders
```

Associating Nodes to Leaders

Algorithm 2 Associate n to its leader

Input: Social network G, node n, set of k leaders

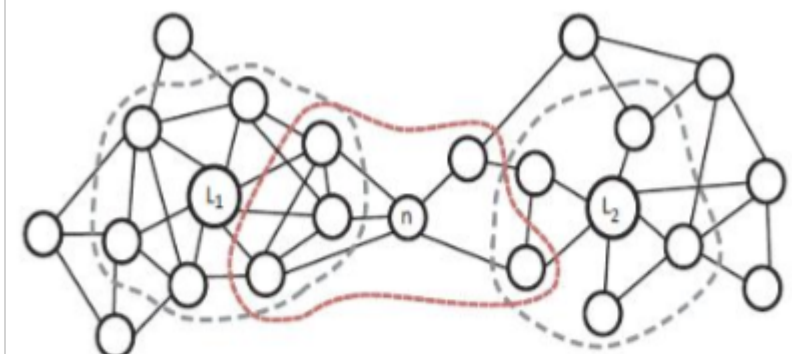
depth $\leftarrow$ 1
CanList $\leftarrow$ leaders
repeat

$$\text{CanList} \leftarrow \underset{\substack{c \in CandList \wedge \\ |\aleph(n_1,d) \cap \aleph(n_2,d)| > \gamma}}{\arg\max} |\aleph(n_1,d) \cap \aleph(n_2,d)|$$

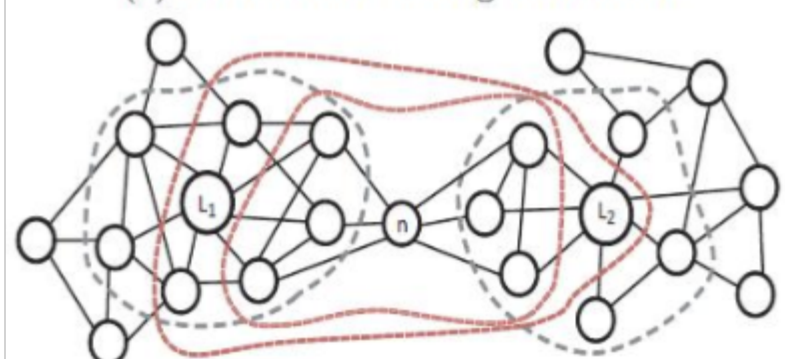
depth $\leftarrow$ depth+1
until $|\text{CanList}| \leq 1 \vee \text{depth} > \delta$

if $|\text{CanList}| = 0$ **then** {No candidate leader}
associate n as an outlier
else if $|\text{CanList}| > 1$ **then** {Many candidates}
associate n as a hub
else {Only one candidate leader in CanList}
associate n to CanList
end if

Community membership of the nodes is association of followers to nearby leaders



(a) Intersection of neighbourhoods



(b) Expanding Neighbourhoods

Top Leaders Approach

A leader is the most central member in a community

Algorithm 1 Top Leaders algorithm

Input: A social network G, and k the number of desired communities

initialize k leaders
repeat
  {finding communities}
  for all Node n $\in$ G **do**
    if n $\notin$ leaders **then**
      associate n to a leader {Algorithm 2}
    end if
  end for
  {updating leaders}
  for all l $\in$ leaders **do**
    l $\leftarrow \arg\max_{n \in Community(l)} Centrality(n)$
  end for
until there is no change in the leaders

Initialization Methods

Wrong leaders may get stuck in a bad local optimum

- Naïve Initialization
  - random selection of k nodes from the network
- Top Global Leaders
  - k most central nodes in the network
- Top Leaders & not Direct Neighbour
  - the k most central nodes that are not directly connected to each other
  - avoid choosing two correct leaders that are directly connected but truly in different communities
- Top leaders & Few Neighbours in Common
  - based on intersections, similar to followers association

Experiments and Datasets

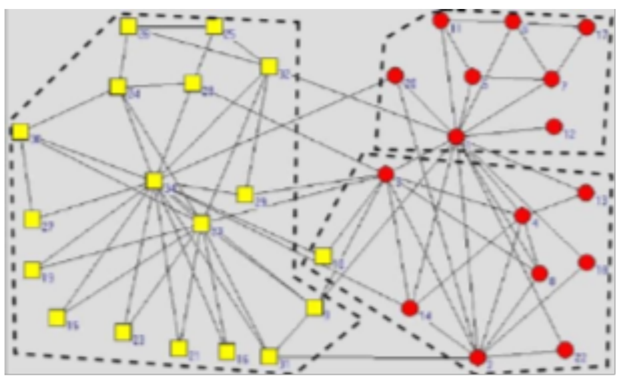
Competitors

- three of other well-known community detection methods
  - SCAN (KDD 2007), CFinder (Nature 2005) and FastModularity (2004)

Datasets

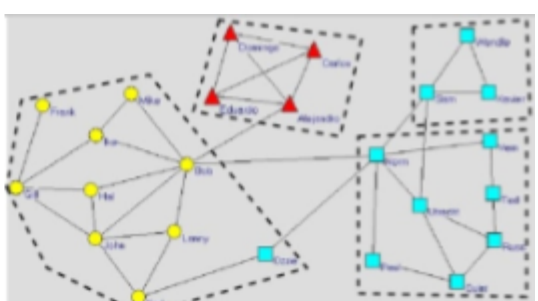
- Karate-Club dataset

34 nodes in 2 communities



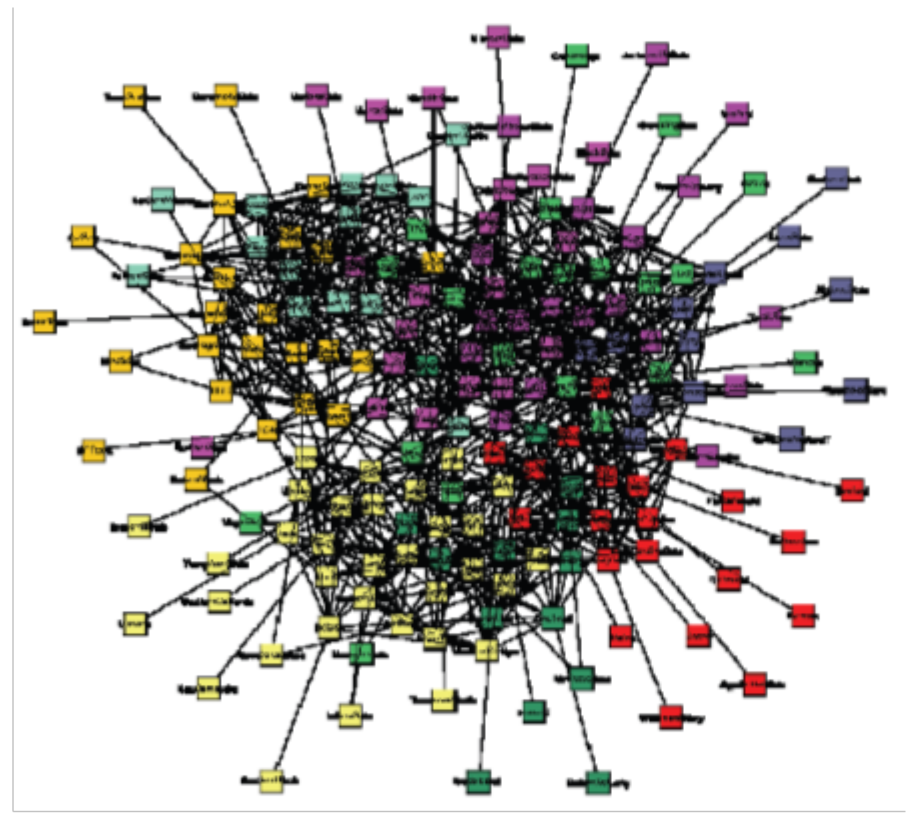
- Sawmill Strike dataset

24 nodes in 3 communities



- Football dataset

180 nodes in 11 communities



Evaluation Metrics

- Comparing with Ground Truth
  - Purity
    - the number of correctly assigned nodes divided by the total number of nodes. **0 (no agreement at all) to 1 (full agreement)**.
  - Adjusted Rand Index (ARI)
    - penalizes false negatives and false positives. **-1 (no agreement at all) and 1 (full agreement), 0 (no better than random)**

- Modularity
  - how well the edges fall within the detected communities compared to a randomized network. **0 (no different than a randomized network), > 0.3 (good partition)**

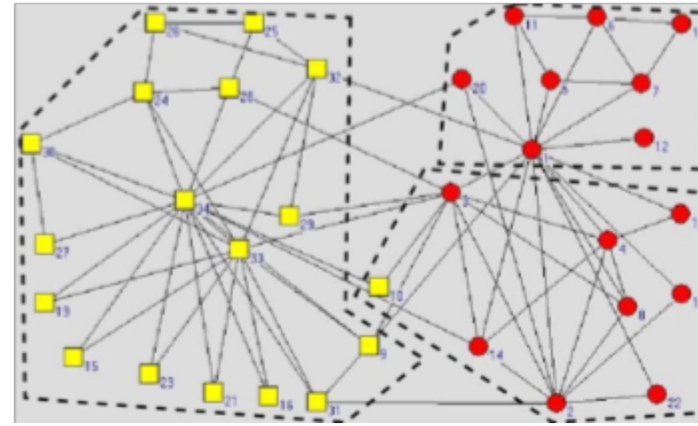
Comparing Initialization Methods

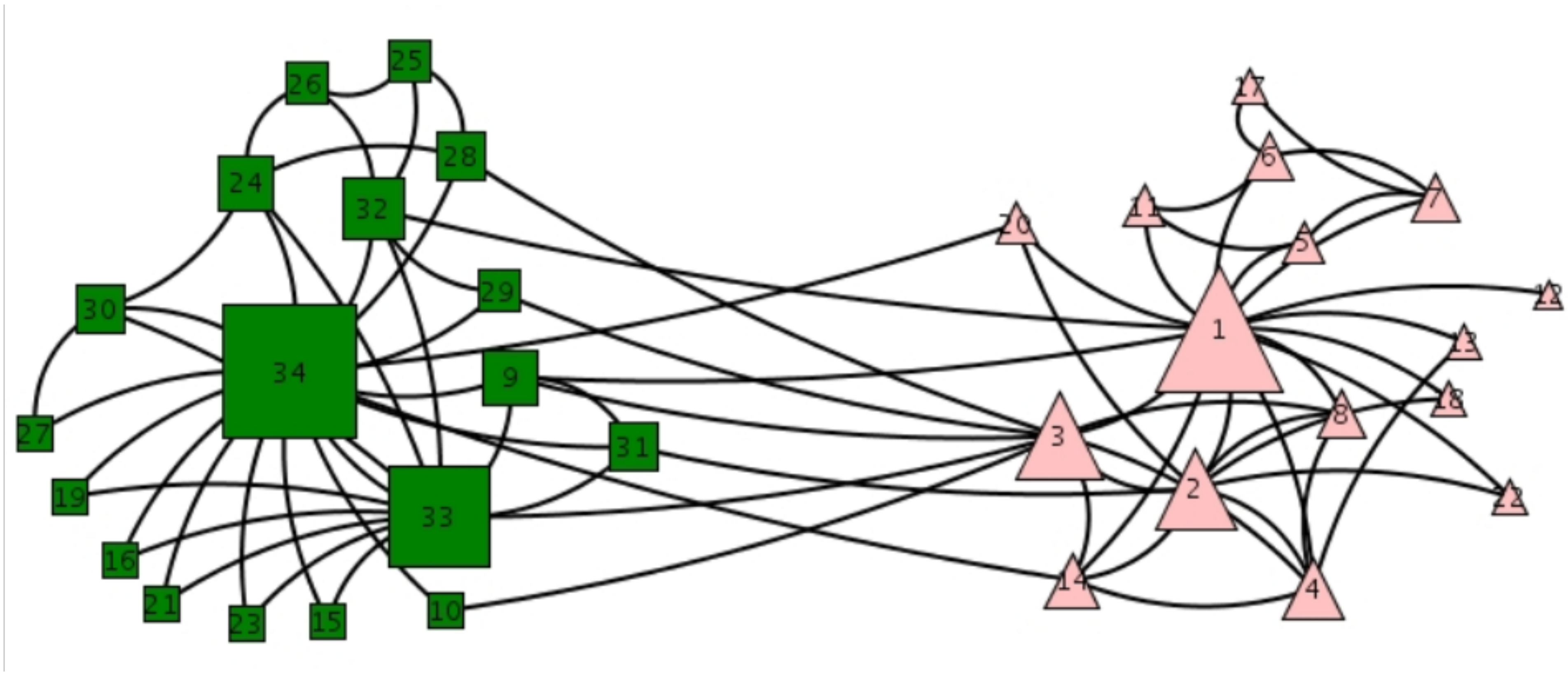
- Naïve
- Top Global Leaders (TGL)
- Top Leaders & not Direct Neighbour (TL&NDN)
- Top Leaders & Few Neighbours in Common (TL&FNiC)

method	dataset	ARI	purity	Q
Naïve	Karate	$.80 \pm .33$	$.90 \pm .20$	$.28 \pm .13$
	Strike	$.59 \pm .25$	$.81 \pm .13$	$.41 \pm .12$
	Football	$.39 \pm .12$	$.66 \pm .08$	$.27 \pm .07$
TGL	Karate	1.0	1.0	0.37
	Strike	1.0	1.0	.54
	Football	.83	.88	.43
TL&NDN	Karate	1.0	1.0	0.37
	Strike	1.0	1.0	.54
	Football	.78	.88	.42
TL&FNiC	Karate	1.0	1.0	0.37
	Strike	1.0	1.0	.54
	Football	.98	.97	.51

Visualized Results

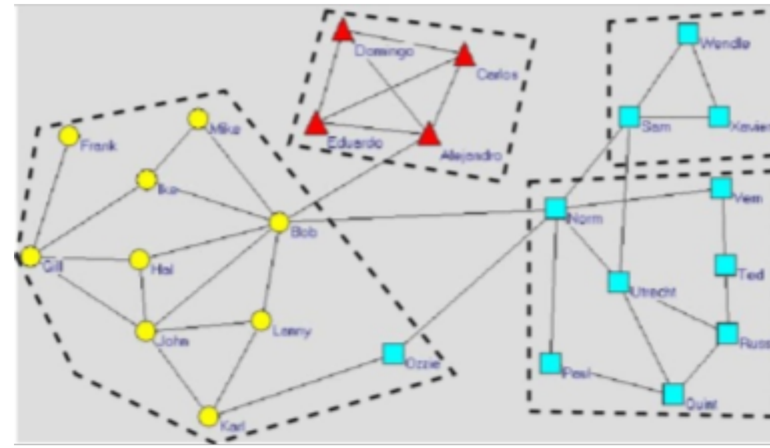
Karate Club

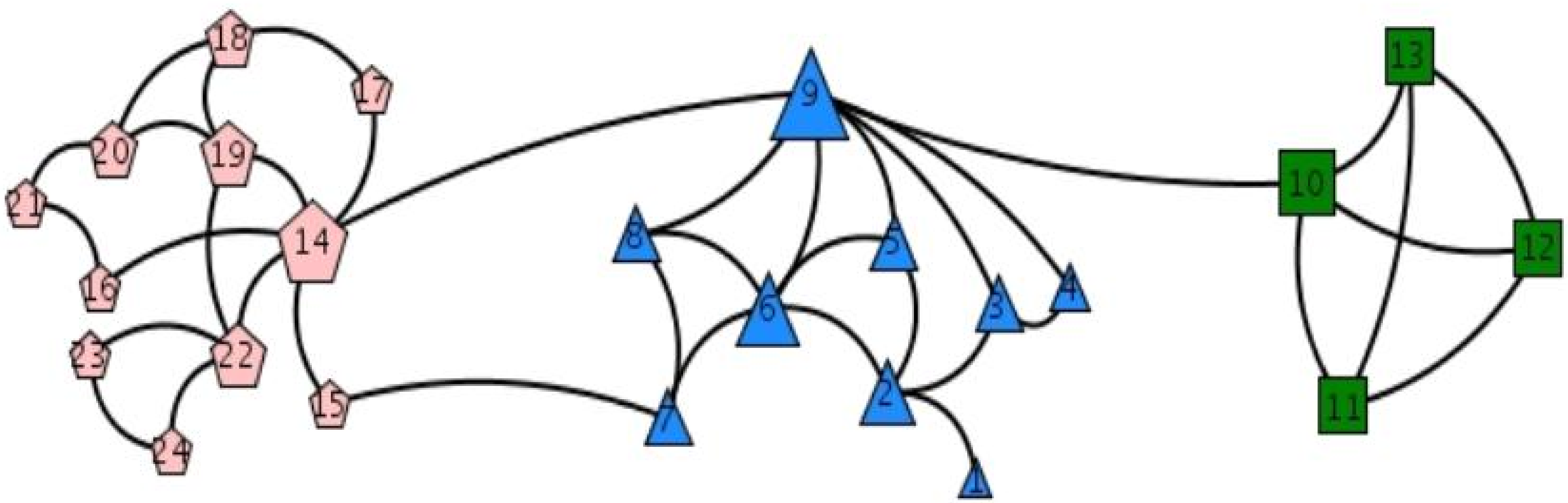




Visualized Results

Strike

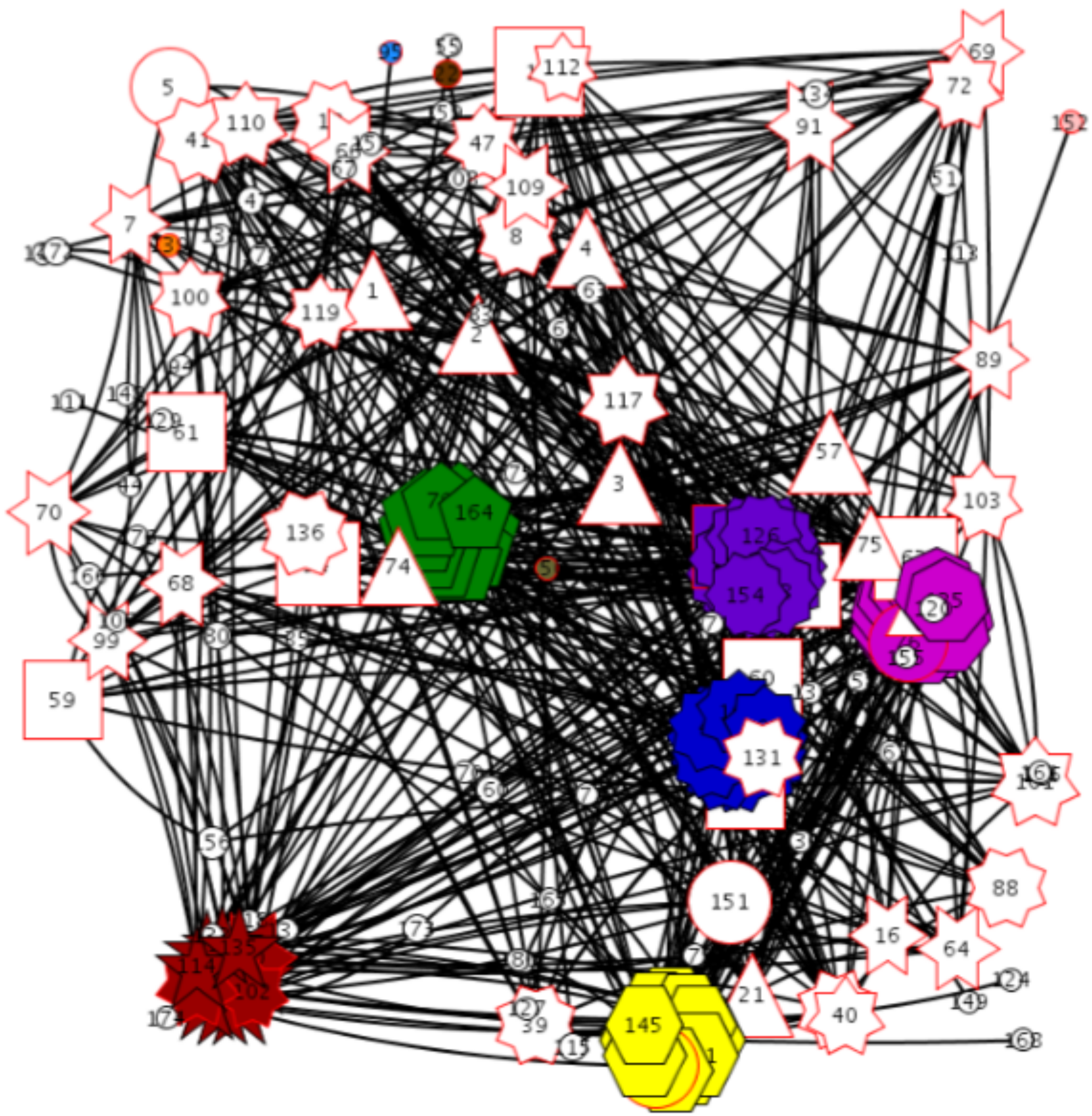




Visualized Results

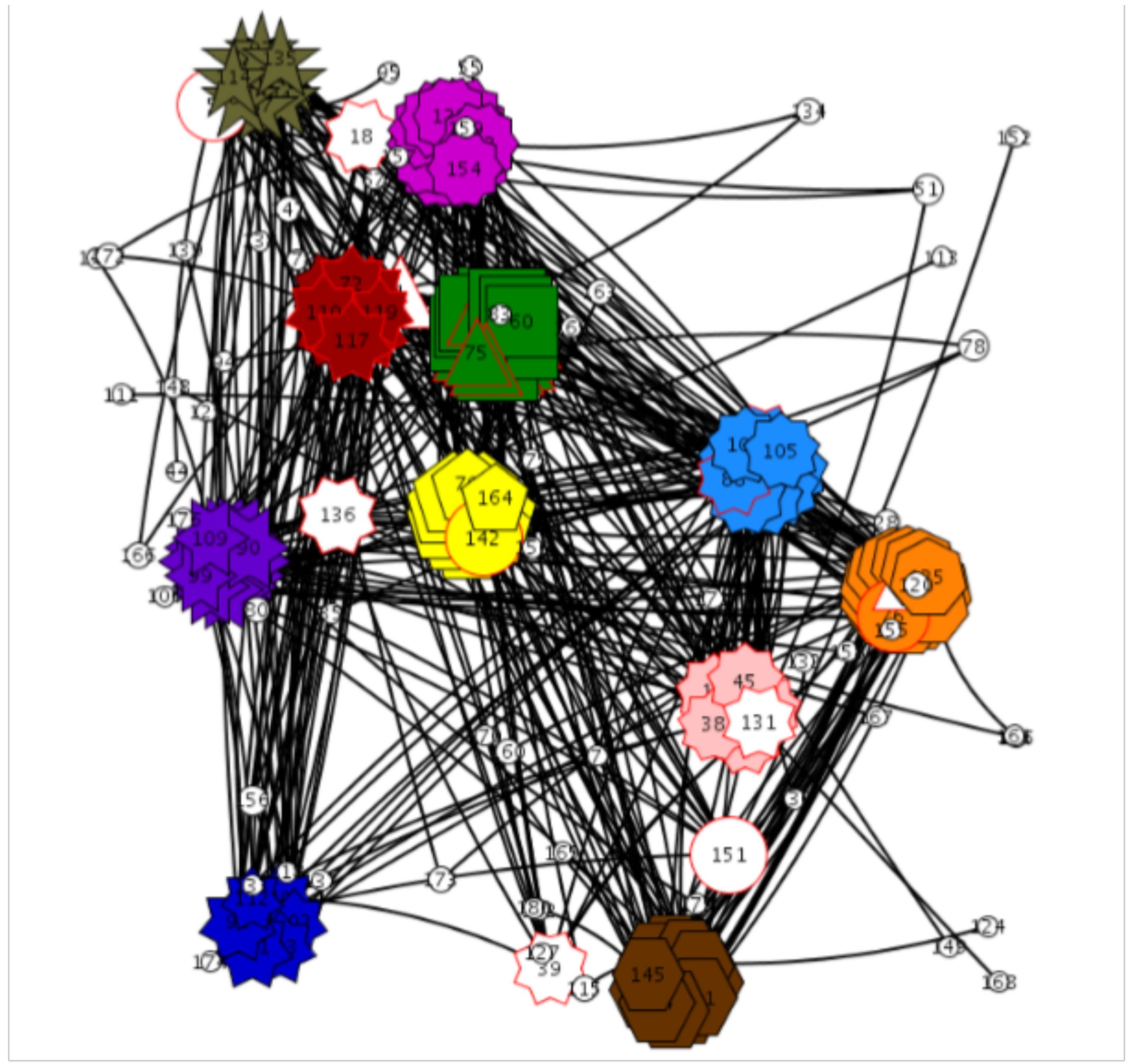
Football, Naïve Initialization

ARI: 0.8±0.3



Visualized Results
Football, Top Global Leaders

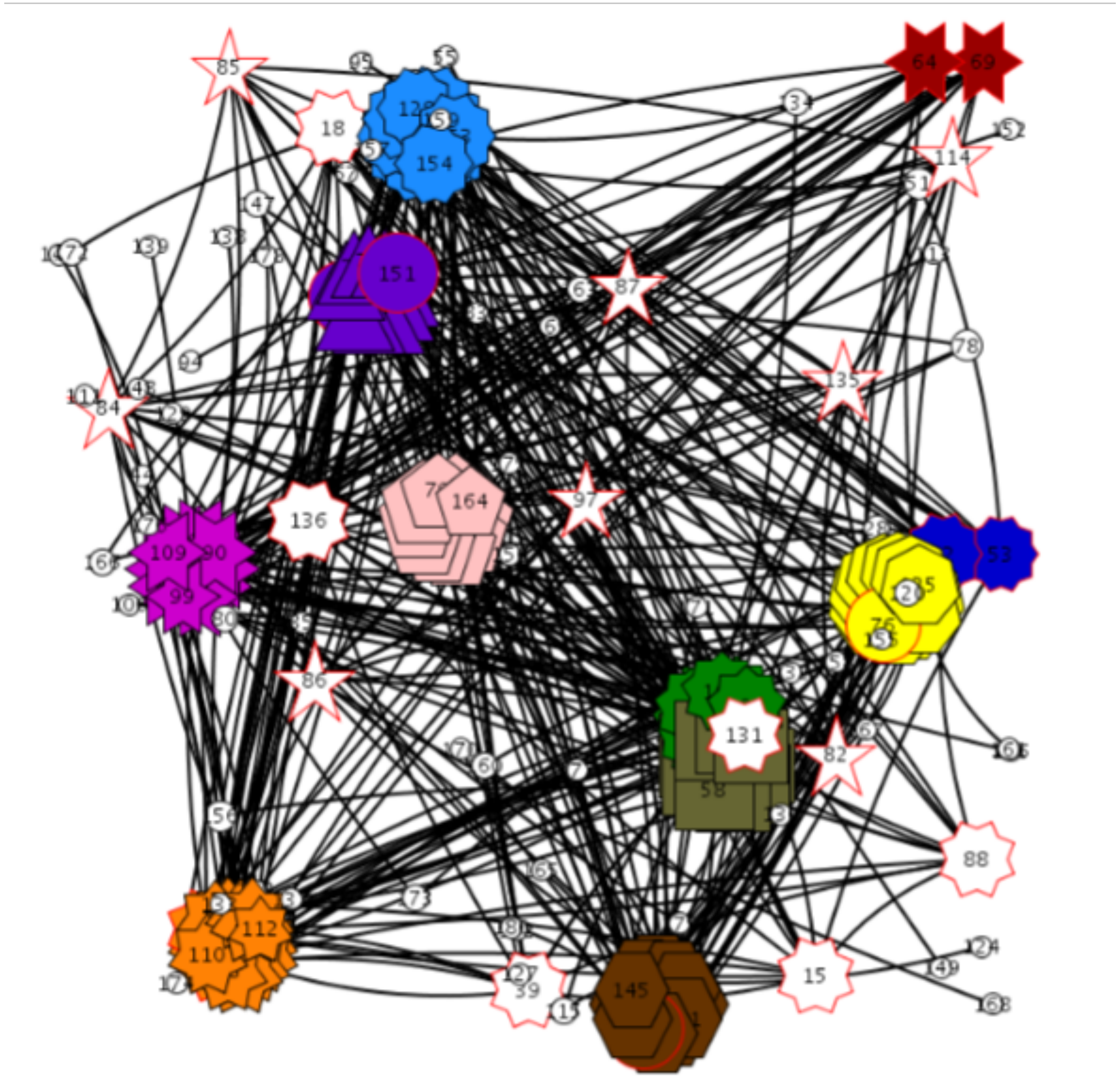
ARI: 0.83



Visualized Results

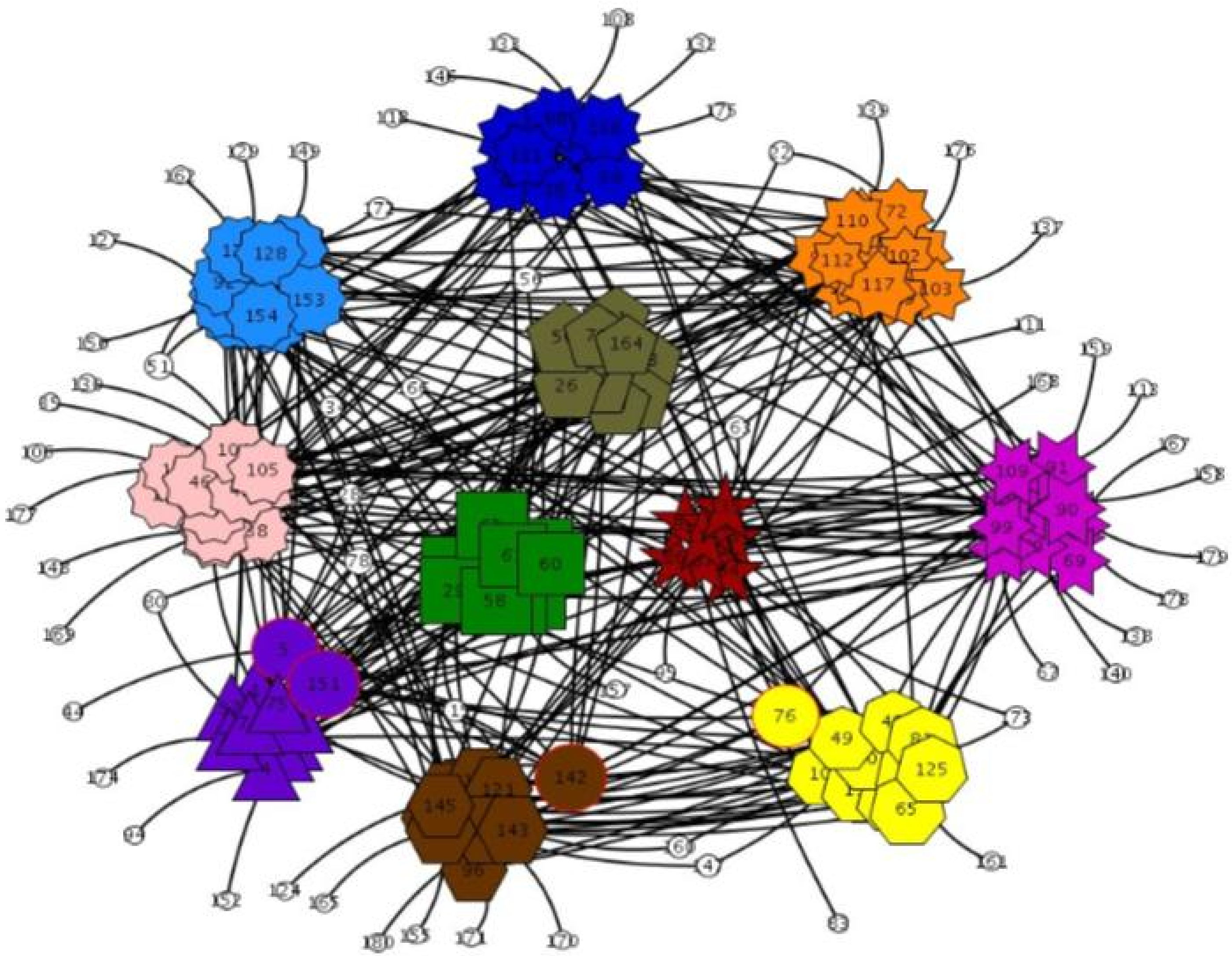
Football, TL & Not Direct Neighbour

ARI: 0.78



Visualized Results
Football, TL & Few Neighbour in Common

ARI: 0.98



Comparing with other approaches

- Given the correct initial k, TopLeaders always provides the best result.
- The other methods do not always find the correct k but even when seeded to Top Leaders, our approach improved the quality of the found communities based on ARI.

dataset	method	k	ARI	purity	Q
Karate 2 groups	fastModularity	3	.680	.970	.380
	cFinder	3	.705	.065	.182
	TopLeader(3)		**.838**	1.0	.374
	SCAN	4	.314	.764	.312
	TopLeader(4)		**.788**	1.0	.361
	TopLeader(2)		1.0	1.0	.371
Strike 3 groups	fastModularity	4	.664	.958	.555
	TopLeader(4)		**.935**	1.0	.532
	cFinder	6	.348	1.0	.485
	TopLeader(6)		**.609**	1.0	.457
	SCAN	3	.848	.958	.547
	TopLeader(3)		**1.0**	1.0	0.548
Football 11 groups	fastModularity	7	.206	.427	.567
	TopLeader(7)		**.637**	.783	.394
	cFinder	12	.983	.913	.532
	TopLeader(12)		**.993**	.977	.511
	SCAN	11	1.0	1.0	.501
	TopLeader(11)		.988	.977	.513

Conclusion

- A novel algorithm to mine communities, which assigns nodes to leaders of communities and selects the leaders of communities iteratively.
- Effective in discovering communities and also in identifying outliers in a network.
- Requires k, the number of desired communities as input. However, it is possible to obtain k after running other contenders and provide the number of discovered communities to our algorithm;
    - Our experimental results showed that communities obtained in this way are more accurate than the original discovered communities even if the used method detected wrong number of communities.

- **Questions?**