Game Theoretic Approach to Measure Social Capital

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High Level View of this Presentation

When we consider *Games* and *(Social or Economic) Networks*, largely there are two types:

- **Type 1 Games:** Here game theoretic models are designed on a given (social or economic) network. This class of games is also called as *games on networks*.
  - Network will NOT change during the course of the game
  - Examples: Congestion games, Clustering games, etc.
- **Type 2 Games:** Here game theoretic models are designed on a dynamic or evolving (social or economic) network.
  - Network structure will change during the course of the game. That is, the set of nodes or edges possibly change.
  - Examples: Network formation games, dynamic network games, etc.

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High Level View of this Presentation (Cont.)

The one line take away of this presentation is to use (cooperative) game theoretic models for accurate design of centrality measures in (social or economic) networks.

T.P. Michalak, Stefano Moretti, Ramasuri Narayanam, Oskar Skibski, Piotr Szczepanski, Talal Rahwan, Michael Wooldridge. A New Approach to Measure Social Capital using Game-Theoretic Techniques. ACM SIGecom Exchanges:14(1), 95-100, 2015.

Outline of the Presentation

1. **Social Network Analysis**
2. Centrality Measures
3. Social Capital
4. Game Theoretic Centrality Design
5. Summary and Concluding Remarks

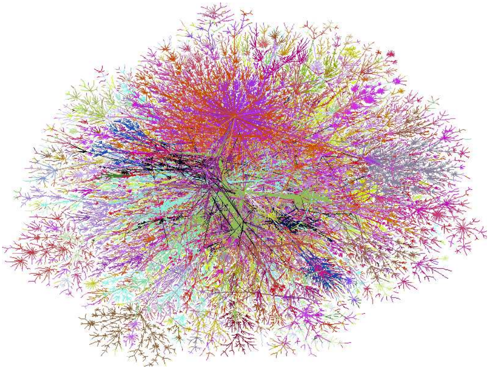
Social Networks: Introduction

Social networks are ubiquitous and have many applications:

- For targeted advertising
- Monetizing user activities on on-line communities
- Job finding through personal contacts
- Predicting future events
- E-commerce and e-business
- For Propagating trusts in web communities
- ...

M.S. Granovetter. The Strength of Weak Ties. American Journal of Sociology, 1973.

Example 1: Web Graph

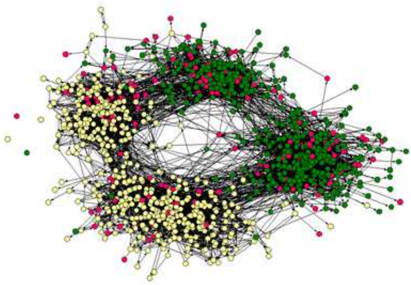


Nodes: Static web pages
Edges: Hyper-links

Reference: Prabhakar Raghavan. Graph Structure of the Web: A Survey. In Proceedings of LATIN, pages 123-125, 2000.

Example 2: Friendship Networks

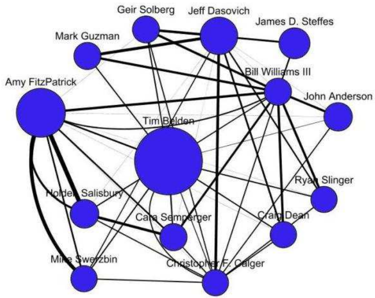
Friendship Network



Nodes: Friends
Edges: Friendship

Reference: Moody 2001

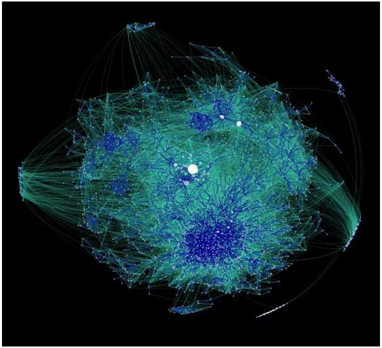
Subgraph of Email Network



Nodes: Individuals
Edges: Email Communication

Reference: Schall 2009

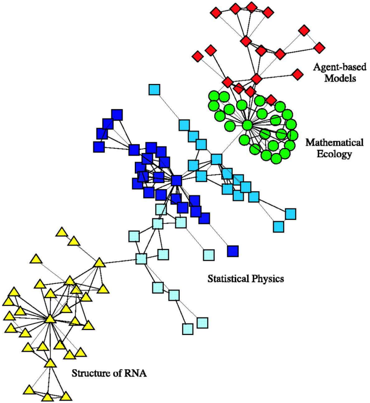
Example 3: Weblog Networks



Nodes: Blogs
Edges: Links

Reference: Hurst 2007

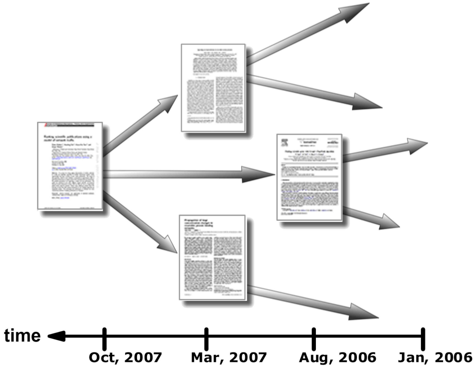
Example 4: Co-authorship Networks



Nodes: Scientists   Edges: Co-authorship

Reference: M.E.J. Newman. Coauthorship networks and patterns of scientific collaboration. PNAS, 101(1):5200-5205, 2004

Example 5: Citation Networks



Nodes: Journals Edges: Citation

Reference: http://eigenfactor.org/

Social Networks - Definition

- *Social Network:* A social system made up of individuals and interactions among these individuals
- Represented using graphs
  - Nodes - Friends, Publications, Authors, Organizations, Blogs, etc.
  - Edges - Friendship, Citation, Co-authorship, Collaboration, Links, etc.

S.Wasserman and K. Faust. Social Network Analysis. Cambridge University Press, Cambridge, 1994

Social Network Analysis (SNA)

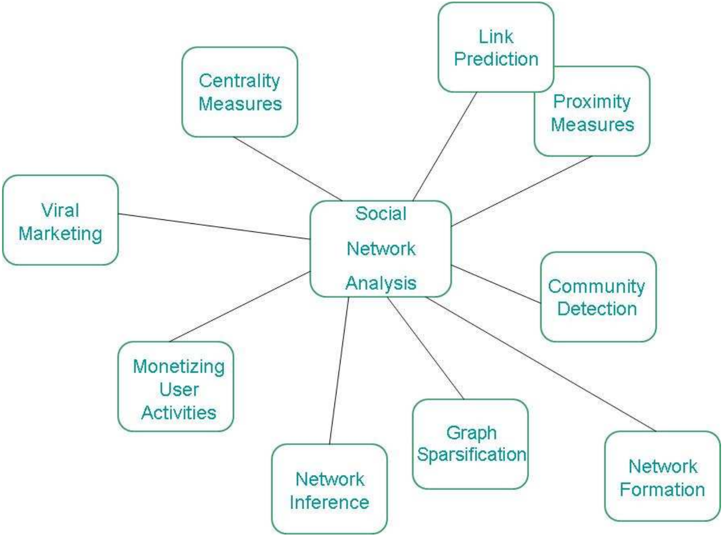
- Social network analysis (SNA) is the process of investigating social structures in terms of nodes and edges by using network and graph theories.
  - shortest paths, dense communities, diameter of the network, etc.

- Two principal categories:
  - **Node/Edge Centric Analysis:**
    - Centrality measures such as degree, betweeneness, stress, closeness
    - Anomaly detection
    - Link prediction, etc.
  - **Network Centric Analysis:**
    - Community detection
    - Graph visualization and summarization
    - Frequent subgraph discovery
    - Generative models, etc.

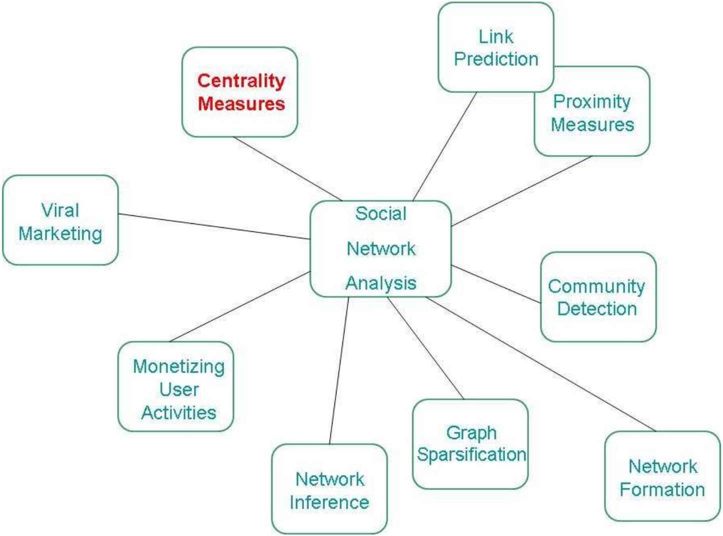
Why is SNA Important?

- To understand complex connectivity and communication patterns among individuals in the network
- To determine the structure of networks
- To determine influential individuals in social networks
- To understand how social network evolve
- To determine outliers in social networks
- To design effective viral marketing campaigns for targeted advertising
- ...

Social Networks: Some Key Topics



Social Networks: Some Key Topics



Centrality Measures

- Significant amount of attention in the analysis of social networks is devoted to understand the centrality measures
- A centrality measure essentially ranks nodes/edges in a given network based on either their positional power or their influence over the network;
- Some well known centrality measures:
  - Degree centrality
  - Closeness centrality
  - Clustering coefficient
  - Betweenness centrality
  - Eigenvector centrality, etc.

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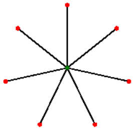

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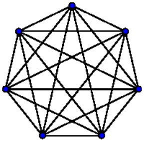

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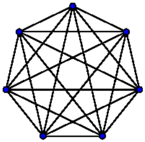
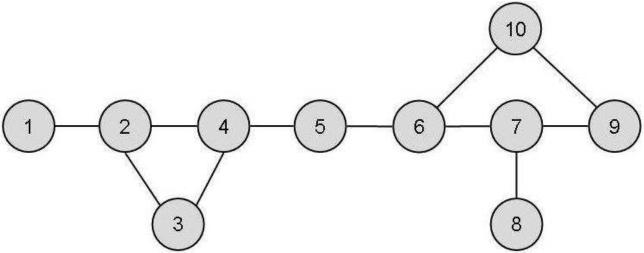


Degree Centrality

- **Degree Centrality:** The degree of a node in a undirected and unweighted graph is the number of nodes in its immediate neighborhood.
    - Rank nodes based on the degree of the nodes in the network
    - Freeman, L. C. (1979). Centrality in social networks: Conceptual clarification. Social Networks, 1(3), 215-239
    - Degree centrality (and its variants) are used to determine influential seed sets in viral marketing through social networks

Degree Centrality (Cont.)

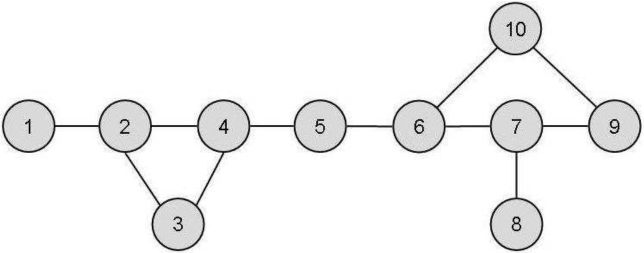


Degree Centrality										
Node	1	2	3	4	5	6	7	8	9	10
Value	1	3	2	3	2	3	3	1	2	2
Rank	9	1	5	1	5	1	1	9	5	5

Closeness Centrality

- The farness of a node is defined as the sum of its shortest distances to all other nodes;
- The closeness centrality of a node is defined as the inverse of its farness;
- The more central a node is in the network, the lower its total distance to all other nodes.

Closeness Centrality (Cont.)

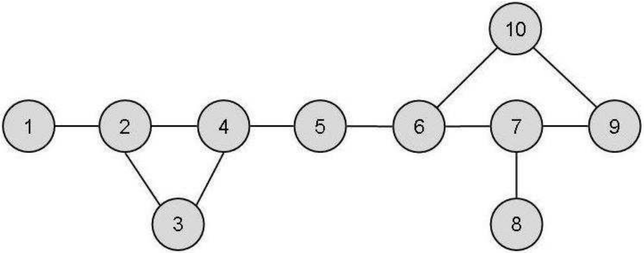


Closeness Centrality										
Node	1	2	3	4	5	6	7	8	9	10
Value	$\frac{1}{34}$	$\frac{1}{26}$	$\frac{1}{27}$	$\frac{1}{21}$	$\frac{1}{19}$	$\frac{1}{19}$	$\frac{1}{23}$	$\frac{1}{31}$	$\frac{1}{29}$	$\frac{1}{25}$
Rank	10	6	7	3	1	1	4	9	8	5

Clustering Coefficient

- It measures how dense is the neighborhood of a node.
- The clustering coefficient of a node is the proportion of links between the vertices within its neighborhood divided by the number of links that could possibly exist between them.
- D. J. Watts and S. Strogatz. Collective dynamics of 'small-world' networks. Nature 393 (6684): 440442 , 1998.
- Clustering coefficient is used to design network formation models

Clustering Coefficient (Cont.)



Clustering Coefficient										
Node	1	2	3	4	5	6	7	8	9	10
Value	0	$\frac{1}{3}$	1	$\frac{1}{3}$	0	0	0	0	0	0
Rank	3	2	1	2	3	3	3	3	3	3

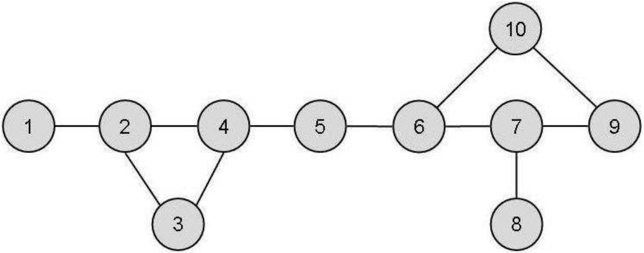
Betweeness Centrality

- **Between Centrality:** Vertices that have a high probability to occur on a randomly chosen shortest path between two randomly chosen nodes have a high betweenness.
  - Formally, betweenness of a node v is given by

$$C_B(v) = \sum_{s \neq v \neq t} \frac{\sigma_{s,t}(v)}{\sigma_{s,t}}$$

    where $\sigma_{s,t}(v)$ is the number of shortest paths from s to t that pass through v and $\sigma_{s,t}$ is the number of shortest paths from s to t.
  - L. Freeman. A set of measures of centrality based upon betweenness. Sociometry, 1977.
  - Betweenness centrality is used to determine communities in social netwoks (Reference: Girvan and Newman (2002)).

Betweenness Centrality (Cont.)



Betweenness Centrality										
Node	1	2	3	4	5	6	7	8	9	10
Value	0	8	0	18	20	21	11	0	1	6
Rank	8	5	8	3	2	1	4	8	7	6

A Simple Observation

ID	Degree Centrality	Closeness Centrality	Clustering Centrality	Betweenness Centrality	Eigenvector Centrality
1	9	10	3	8	9
2	1	6	2	5	2
3	5	7	1	8	3
4	1	3	2	3	1
5	5	1	3	2	5
6	1	1	3	1	3
7	1	4	3	4	6
8	9	9	3	8	10
9	5	8	3	7	8
10	5	5	3	6	7

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Social Capital

- Social capital a fundamental concept in sociology literature
- Social capital can be thought of the value that individuals and groups in a social system derive using the links/connections and shared values in social system
- The first approach conceives of social capital as a value/quality of groups
- The second approach conceives of social capital as the value/quality of an individuals social connections

S.P. Borgatti, C. Jones, and M.G. Everett. Network measures of social capital. CONNECTIONS 21(2), 1998.

Social Capital (Cont.)

- The value of social capital (for both groups and individuals) can be determined either internally or externally
- This immediately leads to three different forms of social capital:
  - The value of each individual is determined using the connections with others (First Form of Social Capital)
  - The value of each group is determined using the connections among themselves only (Second Form of Social Capital)
  - The value of each group is determined using the connections that the group members have outside of it (Third Form of Social Capital)

Classical Measures of Social Capital

- Measures for First Form of Social Capital: Degree centrality, Closeness centrality, Clustering Coefficient, Betweenness centrality, etc.
- Measures for Second Form of Social Capital: Average distance, Maximum distance, etc.
- Measures for Third Form of Social Capital: Group degree, Group closeness, Group betweenness, etc.

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Limitations of Classical Approach

- The common phenomenon of these standard centrality measures is that they assess the importance of each node by focusing only on the role played by that node itself.
- *Such an approach is inadequate to capture the synergies that may occur if the functioning of nodes as groups is considered.*

Motivating Scenario 1

- **Between Centrality:** Vertices that have a high probability to occur on a randomly chosen shortest path between two randomly chosen nodes have a high betweenness.
  - Formally, betweenness of a node v is given by

$$C_B(v) = \sum_{s \neq v \neq t} \frac{\sigma_{s,t}(v)}{\sigma_{s,t}}$$

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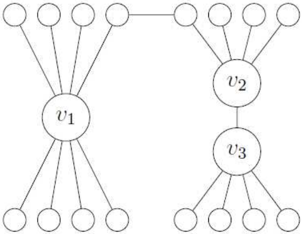
  - Betweenness centrality is used to determine communities in social netwoks (Reference: Girvan and Newman (2002)).

Motivating Scenario 1 (Cont.)

- **Group Betweenness Centrality** of a set of nodes $S \subseteq V$ is defined as:

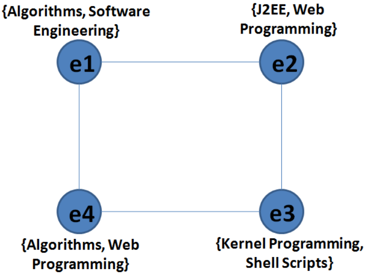
$$c_{gb}(S) = \sum_{s,t \in V \setminus S} \frac{\sigma_{st}(S)}{\sigma_{st}},$$

  where $\sigma_{st}(S)$ is the number of shortest paths from s to t passing through at least one node in S.
- For any arbitrary set $S \subseteq V$ is, in general, equal to the sum of the betweenness centralities of the nodes in S (Szczepanski *et. al.* (Artificial Intelligence 2016)).



Motivating Scenario 2

- Consider four employees $\{e_1, e_2, e_3, e_4\}$ along with their skills and collaboraiton graph



- Consider three projects with requirements as follows:
  $P_1 = \{algorithms\}$, $P_2 = \{J2EE\}$,
  $P_3 = \{J2EETechnologies, SoftwareEngineering\}$, and
  $P_4 = \{KernalProgramming, SoftwareEngineering\}$.

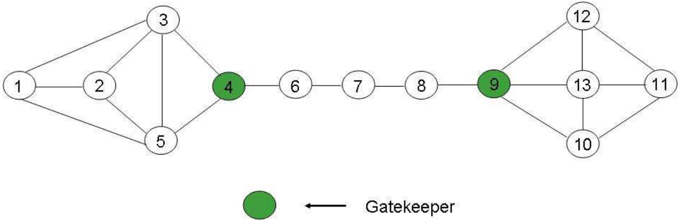
Motivating Scenario 2 (Cont.)

- Any team of employees to perform project *should be connected in the graph*
- Now we derive the values of the following coalitions:
  - $v(\{e_1\}) = 1$ (as employee e_1 can perform only P_1),
  - $v(\{e_2\}) = 1$ (as employee e_2 can perform only P_2),
  - $v(\{e_1, e_2\}) = 3$ (as employees together can perform P_1, P_2, P_3),
  - $V(\{e_1, e_3\}) = 0$ (as it is a disconnected team).
- **Observation:** *The value of a group of employees is NOT the same as the sum of values of the individual employees in that group.*

Motivating Scenario 3

- We consider a network of individuals (such as social network of the buyers) or a network of objects (such as intranet of a company);
- Assume that certain unwanted process may attack a node uniformly at random and then starts spreading over the network effecting the function of all reachable nodes/individuals;
- We have some limited budget to reach out at most k nodes;
- The problem is which k nodes that we should target to minimize the expected number of the nodes that receive the misinformation.

Motivating Scenario 3: Example (k = 2)



Centrality Measure	Rank 1	Rank 2
Degree	9	3,5,10,11,12,13
Closeness	7	6,8
Betweenness	7	6,8
Clustering Coefficient	10,11,12,13	9
EigenVector	1,2,10,11,12,13	3,5
PageRank	9	3,5

Game Theory based Centrality Design

- The classical approach to centrality in networks tries to come up with a value for a node by just focusing on that node itself
- Cooperative game theory based approach to design centrality measures on networks takes a sophisticated approach where
  - It attaches a value for each possible coalition of nodes in the network,
  - Then it derives the values for each node by using a solution concept (such as Shapley value), and
  - These values for nodes can be used to construct the ranking of the nodes.
- Game theory approach can take into account the synergies that are possible with groups of nodes as opposed to the classical approach to design centrality metrics

Case Study: Connectivity Games in Social Networks

- Let $G = (V, E)$ be a graph where $V(G)$ is the set of vertices and $E(G)$ is the set of edges
- Let $\mathcal{C}(G)$ be the set of connected coalitions (or connected sub-graphs)
- *Connectivity Game:* Consider the following cooperative game $(V(G), \upsilon)$ where:

$$\upsilon(C) = \begin{cases} f(C, G) & \text{if } C \in \mathcal{C}(G) \\ 0 & \text{otherwise.} \end{cases}$$

Special Case: (0,1)-Connectivity Games

- Consider a cooperative game $(V(G), v)$ where:

$$v(C) = \begin{cases} 1 & \text{if } C \in \mathcal{C}(G) \\ 0 & \text{otherwise.} \end{cases}$$

- In these settings, it is interesting to determine the most influential vertices (or nodes) in the graph.

Application to Terrorist Networks

- It is key for security agencies to design efficient techniques to identify who plays crucial role within a terrorist network
- Several techniques based on social network analysis including centrality metrics such as degree, closeness and betweenness have been proposed to investigate such networks
- Analyst's Notebook 8 is a software tool that is widely used by Law-Enforcement and Intelligence agencies
- However, these existing tools and techniques often unable to capture the complex nature of these terrorist networks

Application to Terrorist Networks (Cont.)

- To address the above inadequacies, Lindelauf *et al.* proposed

$$f(C) = \frac{|E(C)|}{\sum_{e \in E(C)} w_e}$$

- Lindelauf *et al.* worked with the above form of characteristic form to derive a ranking of the nodes based the Shapley values of the nodes

- The goal of any centrality metric is to form a ranking of nodes

- Thus Shapley value based approach is used to design a centrality metric in networks

Application to Team Formation Games

- Consider a social network of agents where edges represent the collaboration strength among these agents
- Each agent has a set of skills
- There is a task to be completed which has a set of desired skills
- We assume that any two disconnected agents cannot collaborate efficiently
- We call a *team of agents satisfies the task* if the set of skills of these agents satisfies the set of desired skills of the task
- Our goal is to rank the agents based on their ability to form an efficient team
- *Team Formation Game:* Here the characteristic function is defined as follows:

$$v(C) = \begin{cases} \text{Num of missing skills} & \text{if } C \in \mathcal{C}(G) \\ 0 & \text{otherwise.} \end{cases}$$

Key Aspect

- In this setting, we have values defined for coalitions of the players
- Then, it is interesting to derive the Shapley values of the individual nodes
- Computational aspects of deriving the Shapley values of the nodes in connectivity games is addressed by Michalak *et. al.* (IJCAI 2013).

Analysis of Marginal Contributions

The marginal contribution of node $v_i \in V$ to a coalition $C \subseteq V \setminus \{v_i\}$:

(a) Node v_i can join a *connected* coalition $C \in \mathcal{C}$ and the resulting coalition is also *connected*, *i.e.*, $C \cup \{v_i\} \in \mathcal{C}$.
$mc_i(C) = \nu_f(C \cup \{v_i\}) - \nu_f(C) = f(C \cup \{v_i\}) - f(C)$

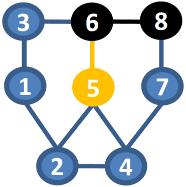
(b) Node v_i can join a *disconnected* coalition $C \in \tilde{\mathcal{C}}$ and the resulting coalition becomes *connected*, *i.e.*, $C \cup \{v_i\} \in \mathcal{C}$.
$mc_i(C) = \nu_f(C \cup \{v_i\}) - \nu_f(C) = f(C \cup \{v_i\})$

(c) Node v_i can join a *connected* coalition $C \in \tilde{\mathcal{C}}$ and the resulting coalition becomes *disconnected*, *i.e.*, $C \cup \{v_i\} \in \tilde{\mathcal{C}}$.
$mc_i(C) = \nu_f(C \cup \{v_i\}) - \nu_f(C) = -f(C)$

(d) Node v_i can join a *disconnected* coalition $C \in \tilde{\mathcal{C}}$ and the resulting coalition remains *disconnected*, *i.e.*, $C \cup \{v_i\} \in \tilde{\mathcal{C}}$:
$mc_i(C) = \nu_f(C \cup \{v_i\}) - \nu_f(C\imath)) = 0$

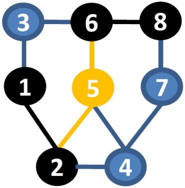
Analysis of Marginal Contributions (Cont.)

(a)



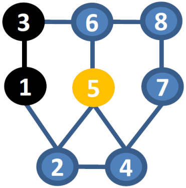
$$mc_5(\{v_6, v_8\}) = f(\{v_5, v_6, v_8\}) - f(\{v_6, v_8\})$$

(b)



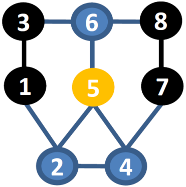
$$mc_5\left(\left\{\begin{matrix}v_1, v_2\\ v_6, v_8\end{matrix}\right\}\right) = f\left(\left\{\begin{matrix}v_1, v_2, v_5\\ v_6, v_8\end{matrix}\right\}\right)$$

(c)



$$mc_5(\{v_1, v_3\}) = -f(\{v_1, v_3\})$$

(d)



$$mc_5(\{v_1, v_3, v_7, v_8\}) = 0$$

General Purpose Algorithm

- Both connected and disconnected coalitions play a crucial role when computing the Shapley value
- Let $N(C)$ be the set of neighbors of nodes in C
- Running time of this general purpose algorithm is: $O(|V| + |E|)2^{|V|}$

- *Reference:* Tomasz P. Michalak, Talal Rahwan, Piotr L. Szczepanski, Oskar Skibski, Ramasuri Narayanam, Nicholas R. Jennings, Michael J. Wooldridge: Computational Analysis of Connectivity Games with Applications to the Investigation of Terrorist Networks. IJCAI 2013.

General Purpose Algorithm (Cont.)

Algorithm 1: GeneralSV Algorithm for the SV

Input: Graph $G = (V, E)$ and characteristic function ν_f

Output: Shapley Value, $SV_i(\nu_f)$, for each node $v_i \in V$

- **foreach** $v_i \in V$ **do**
  - $SV_i(\nu_f) \leftarrow 0;$
- **foreach** $C \in 2^V$ **do**
  - $CheckConnectedness(C);$
  - **if** $C \in \mathcal{C}$ **then**
    - **foreach** $v_i \in \mathcal{N}(C)$ **do**
      - $SV_i(\nu_f) \leftarrow SV_i(\nu_f) + \xi_C(\nu_f(C \cup \{v_i\}) - \nu_f(C))$
    - **foreach** $v_i \notin \mathcal{N}(C)$ **do**
      - $SV_i(\nu_f) \leftarrow SV_i(\nu_f) - \xi_C \nu_f(C)$
  - **else**
    - **foreach** $v_i \in \mathcal{N}(C)$ **do**
      - $CheckConnectedness(C \cup \{v_i\})$
      - **if** $C \cup \{v_i\} \in \mathcal{C}$ **then**
        - $SV_i(\nu_f) \leftarrow SV_i(\nu_f) + \xi_C \nu_f(C \cup \{v_i\})$

Outline of the Presentation

1. Social Network Analysis
2. Social Capital
3. Game Theoretic Centrality Design
4. **Summary and Concluding Remarks**

Summary of the Talk

- Gave brief introduction to *social network analysis* and in particular *centrality measures*
- Looked at the classical notion of *social capital* and the methods of measuring social capital
- Presented the *game theoretic approach of designing centrality measures* with the help of several motivating settings

Key References of this Talk

- S.Wasserman and K. Faust. Social Network Analysis. Cambridge University Press, Cambridge, 1994.
- Ramasuri Narayanam, Yadati Narahari: A Shapley Value-Based Approach to Discover Influential Nodes in Social Networks. IEEE T. Automation Science and Engineering 8(1): 130-147 (2011).
- Ramasuri Narayanam, Oskar Skibski, Hemank Lamba, Tomasz P. Michalak: A Shapley Value-based Approach to Determine Gatekeepers in Social Networks with Applications. ECAI 2014: 651-656.
- Piotr L. Szczepanski, Tomasz P. Michalak, Talal Rahwan: Efficient algorithms for game-theoretic betweenness centrality. Artif. Intell. 231: 39-63 (2016).
- Tomasz P. Michalak, Stefano Moretti, Ramasuri Narayanam, Oskar Skibski, Piotr Szczepanski, Talal Rahwan, Michael Wooldridge. A New Approach to Measure Social Capital using Game-Theoretic Techniques. To appear in SIGEcom Exchanges, 2015.
- Tomasz P. Michalak, Talal Rahwan, Piotr L. Szczepanski, Oskar Skibski, Ramasuri Narayanam, Nicholas R. Jennings, Michael J. Wooldridge: Computational Analysis of Connectivity Games with Applications to the Investigation of Terrorist Networks. IJCAI 2013.

Some Important Text Books

- D. Easley and J. Kleinberg. Networks, Crowds, and Markets. Cambridge University Press, 2010.
- M.E.J. Newman. Networks: An Introduction. Oxford University Press, 2010.
- M.O. Jackson. Social and Economic Networks. Princeton University Press, 2008.
- U. Brandes and T. Erlebach. Network Analysis: Methodological Foundations. Springer-Verlag Berlin Heidelberg, 2005.

Network Dataset Repositories

- Jure Leskovec: http://snap.stanford.edu/data/index.html
- MEJ Newman: http://www-personal.umich.edu/m̃ejn/netdata
- Albert L. Barabasi: http://www.nd.edu/ñetworks/resources.htm
- NIST Data Sets: http://math.nist.gov/R̃Pozo/complex_datasets.html
- MPI Data Sets: http://socialnetworks.mpi-sws.org/
- ...

Software Tools for Network Analysis

- Gephi (Graph exploration and manipulation software)
- Pajek (Analysis and Visualization of Large Scale Networks)
- UCINET (Social Network Analysis tool)
- CFinder (Finding and visualizing communities)
- GraphStream (Dynamic graph library)
- Graphviz (Graph vizualisation software)
- Refer to Wikipedia for more information (http://en.wikipedia.org/wiki/Social_network_analysis_software)

A List of Important Conferences

- ACM Conference on Electronic Commerce (ACM EC)
- Workshop on Internet and Network Economics (WINE)
- ACM SIGKDD
- WSDM
- ACM Internet Measurement Conference (ACM IMC)
- CIKM
- ACM SIGCOMM
- Innovations in Computer Science (ICS)
- AAMAS
- AAAI
- IJCAI
- . . .

A List of Important Journals

- American Journal of Sociology
- Social Networks
- Physical Review E
- Data Mining and Knowledge Discovery
- ACM Transactions on Internet Technology
- IEEE Transactions on Knowledge and Data Engineering
- Games and Economic Behavior
- ...

THANK YOU