Meerkat

SSRM: Structural Social Role Mining for Dynamic Social Networks

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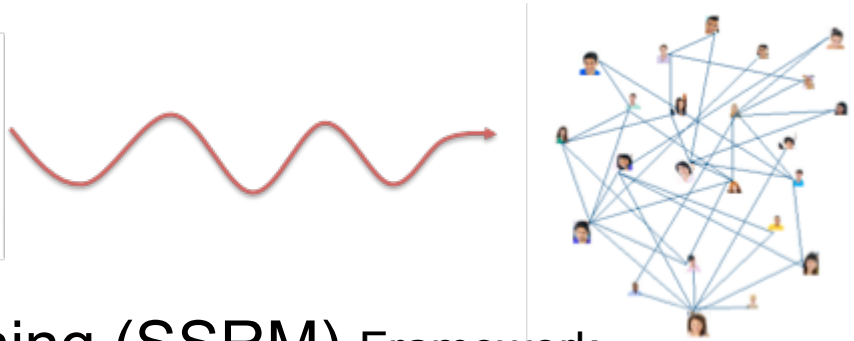
Motivation

- Role: an important concept
  - Used for studying many social issues
- Defining the concept of role in network science.
- Define roles?
- Detect roles?
- What we get by roles in SNs.
  - Changes?
  - Effects?
- Many attempts to study:
  - Influential people
  - Influence/belief propagators
  - Trustworthy individuals
  - expert
  - …

Problem Definition

Society → Graph → Social Network



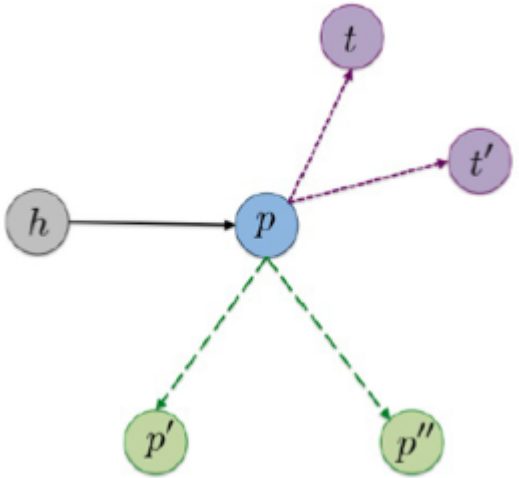
- **S**tructural **S**ocial **R**ole **M**ining (SSRM) Framework
  - General Framework
  - Study roles and their effects
    - define roles
    - methods to identify roles

Background

- Definitions of Role
  - “A node role is a subjective characterization of the part it plays in a network structure.”(Scripps, Tan, Esfahanian 2007)
  - “Rights and duties attached to a given status.” (Goffman 1959)
  - Social Role: set of factors in an individual’s behaviours (Golder and Donath 2004)
    - Skills
    - Privileges
    - Responsibilities
  - The mixture of allowances and constraints, combined with the choices the individual as part of a social structure (Golder and Donath 2004)

Background

- Role Theory (Biddle 1968)
  - Integrate works of role
  - Role theory:
    - Functional role theory
    - Structural role theory
      - A mathematical model
      - Task: set of jobs toward a goal
      - Position: title in the social structure
      - Person: set of attributes
    - Organizational role theory
    - Cognitive role theory



Related Work

- Explicit vs. non-explicit roles (Forestier, Stavrianou, Velcin, Zighed 2012)
  - Non-explicit
  - Explicit e.g. expert

- Identify expert in Java forums (Zhang, Ackerman, Adamic, WWW 2007)
  - # replies posted (# answers)
  - # people replied to (# indegree)

- Identify influentials in blogs (Agarwal, Liu, Tang, Yu, WSDM 2008)

Related Work

- Roles in online discussion forums (Golder and Donath 2004)
  - Celebrity
  - Newbie
  - Lurker
  - Flamer, troll, ranter
- Community-based roles (Scripps, Tan, Esfahanian, SNA-KDD 2007)
  - Community-metric
    - Based on cliques
  - roles
    - Ambassador
    - Big fish
    - Loner
    - Bridges

Contributions

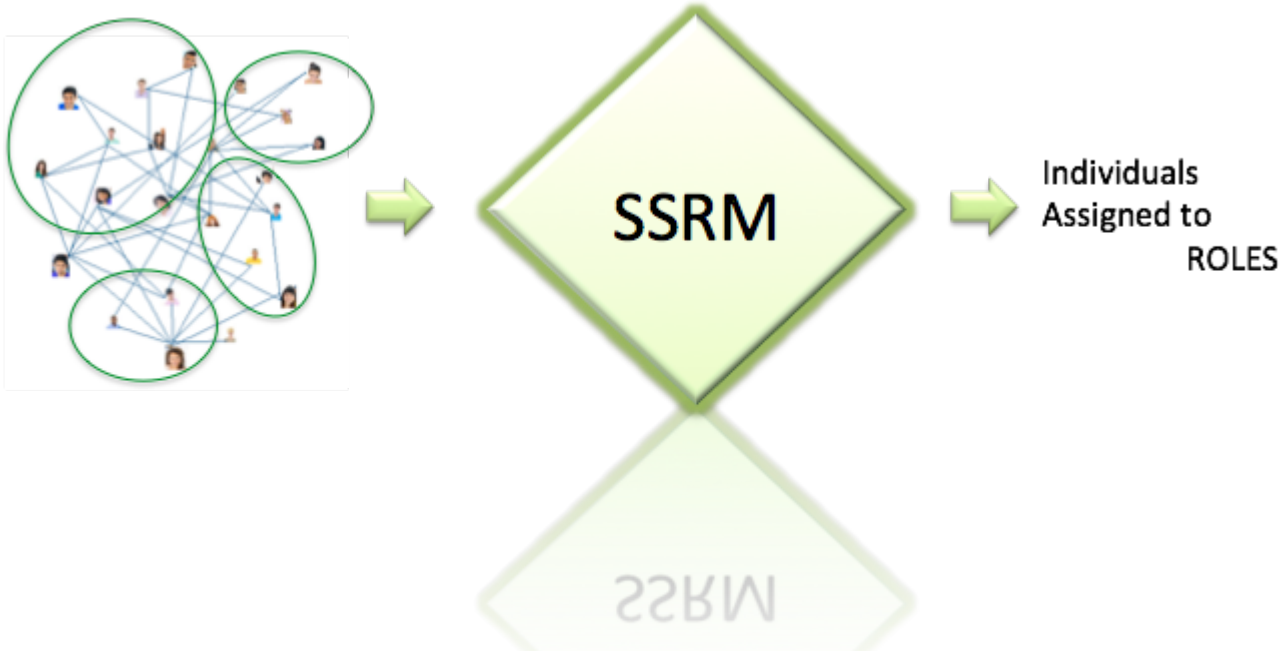
- Defining a set of roles
  - Context dependent
  - Based on social facts
- Studying patterns of role changes
- Show the mutual relation
  - Role change
  - Community events
- Define new measure
  - LBC
  - CBC
- Compare BC, CBC, and LBC

SSRM Framework

- Structural Social Role Mining
  - Structural: structural properties of the network
  - Social Role: roles of individuals in social networks
  - Mining: defining and extracting

- Two fundamental assumptions:
  1. *Role-taking* behaviour
  2. Existence of *communities*

SSRM Framework



SSRM Roles Definition

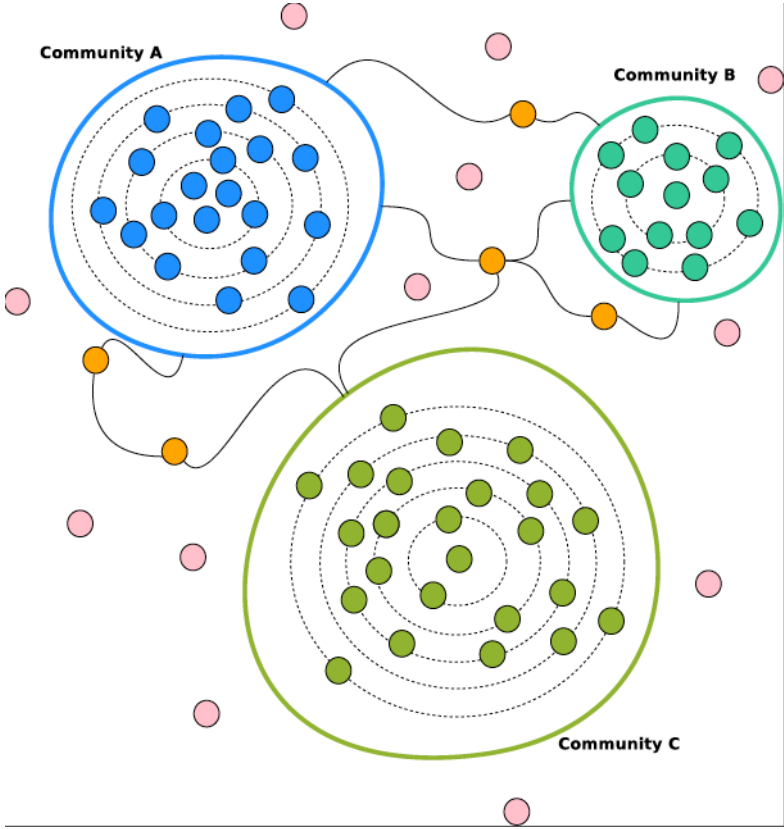
- Set of fundamental roles
  - Based on real sociological observations
- [definition2.] Leader

  important individual in a community
- [definition3.] Outermost

  least significant individual in a community
- [definition4.] Outsider

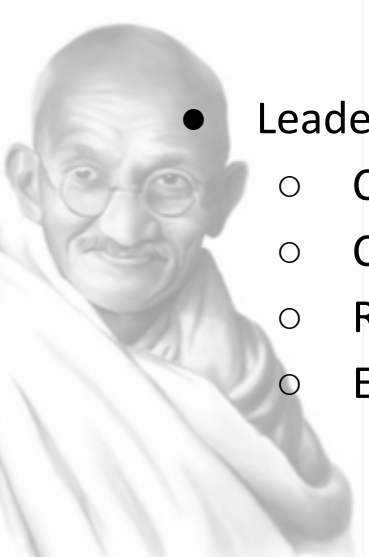
  does not belong to any community
- [definition5.] Mediator

  important individual in connecting multiple communities.
  - Inclusive mediator
  - Exclusive mediator (also outsider)



SSRM Role Identification

- Outlier
  - Not affiliated with a community.

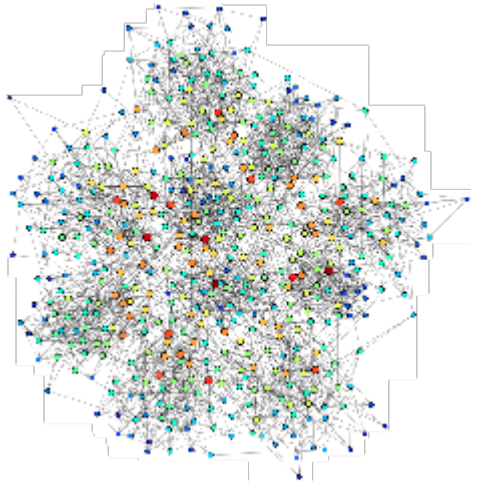


- Leader & Outermost
  - Choose a metric (M), i.e. a centrality measure
  - Compute node scores
  - Rank nodes
  - Extract leaders and outermosts

http://www.fansshare.com/gallery/photos/11157799/gandhi-wallpaper-wallpaper/

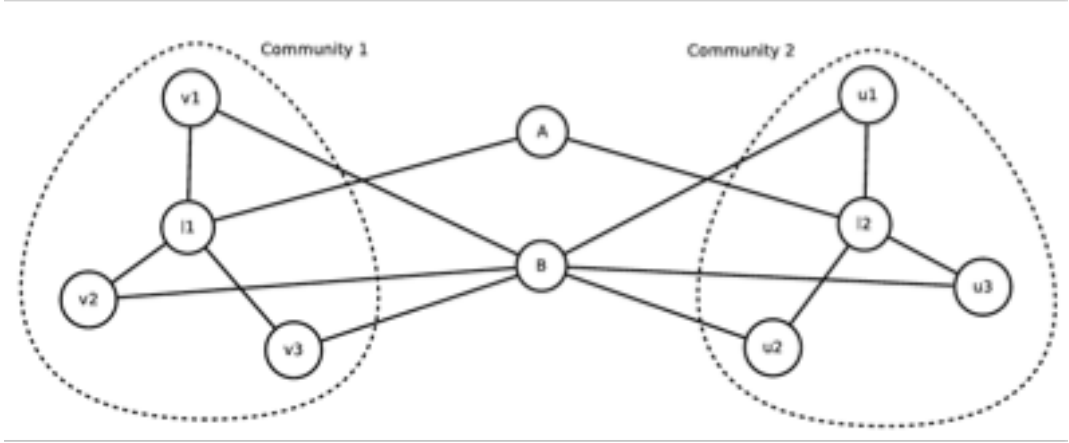
SSRM Role Identification

- Mediator
  - Connects multiple communities
  - How to measure?
  - MedExtractor



- Betweenness Centrality (BC)?
  - Define new measure:
    - Leader Betweenness Centrality (**LBC**)
    - Community betweenness Centrality (**CBC**)

SSRM Role Identification (mediator)



$$LBC(A) = 1$$
$$LBC(B, v_1, v_2, v_3, u_1, u_2, u_3) = 0$$

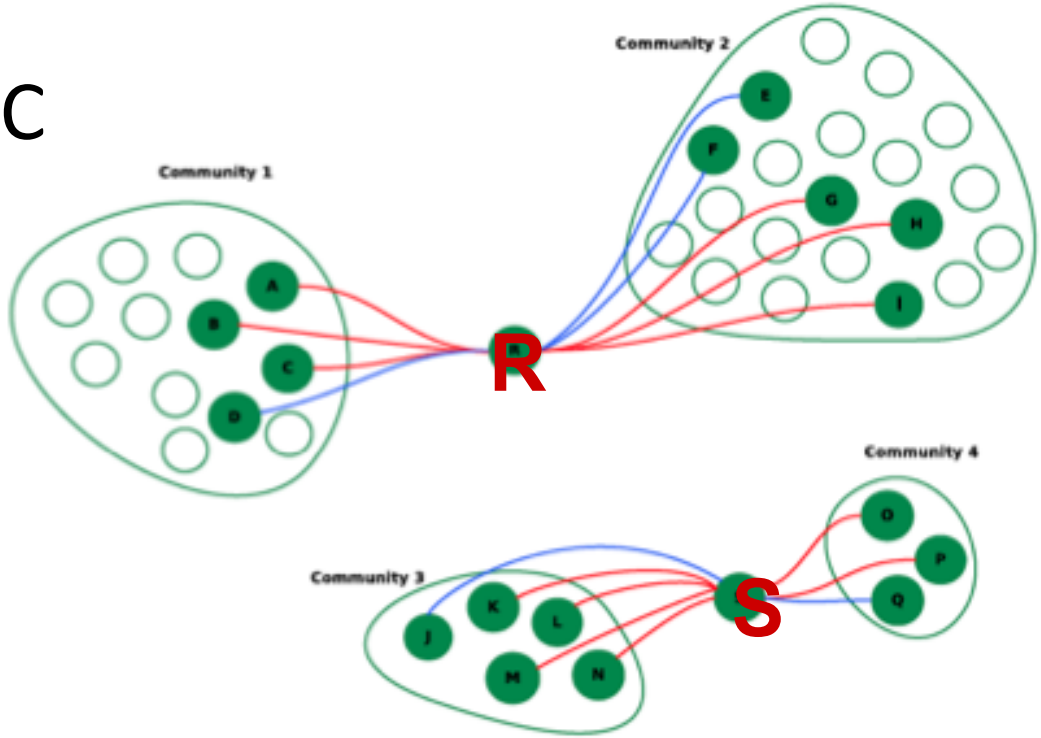
$$CBC(A) = 7$$
$$CBC(B) = 27$$
$$CBC(v_1, v_2, v_3, u_1, u_2, u_3) = 3$$
$$CBC(l_1, l_2) = 3.$$

SSRM Role Identification (mediator)

- Discussion on CBC

$$CBC(R) = 11$$

$$CBC(S) = 9$$

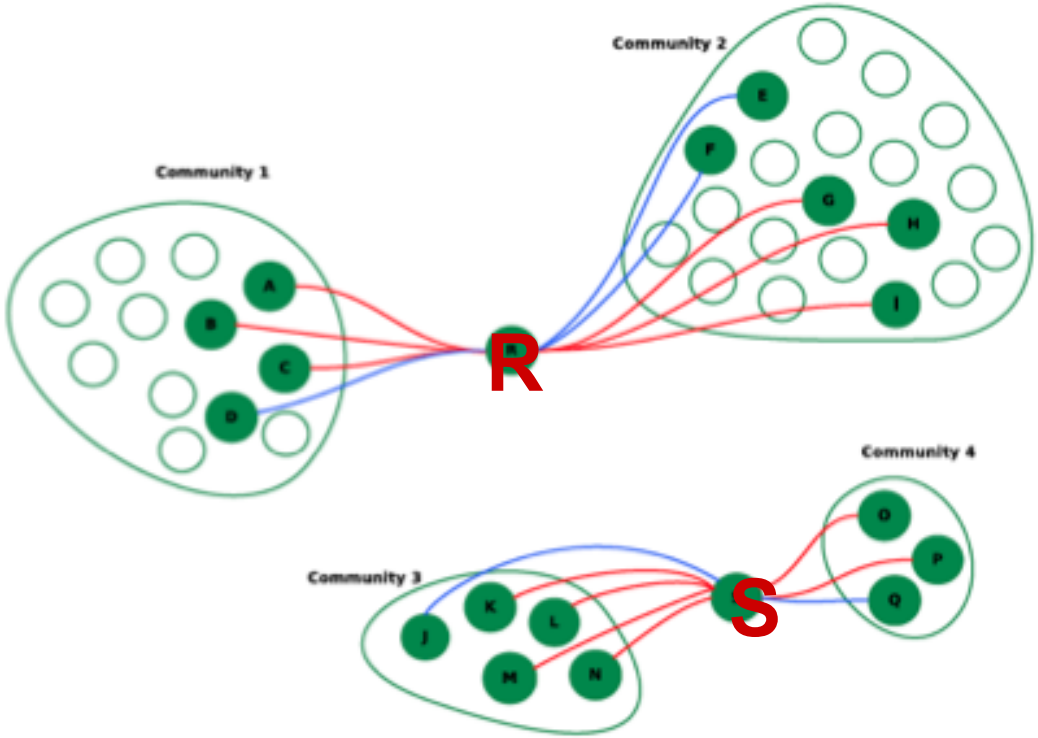


SSRM Role Identification (mediator)

- Normalized CBC

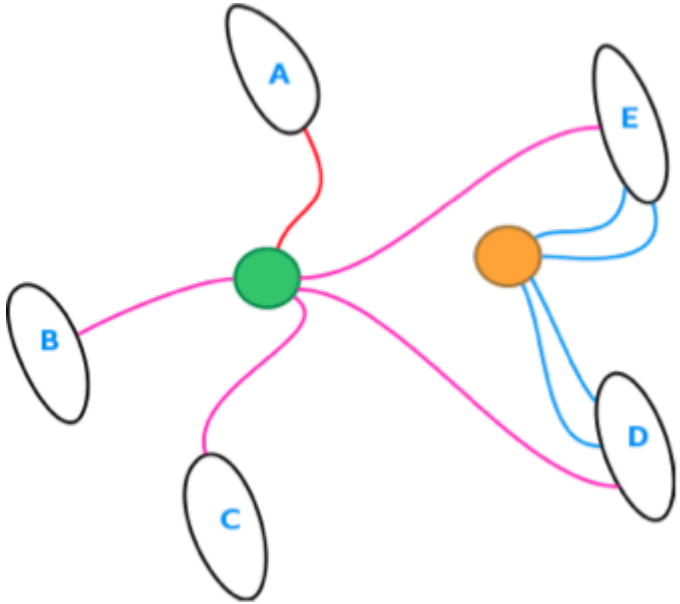
$$NCBC(R) = \frac{11}{12}$$

$$NCBC(S) = \frac{9}{3}$$



SSRM Role Identification (measures)

- variety of communities connected through a node:
  - Diversity Score
    - DS_count(v)
    - DS_pair(v)

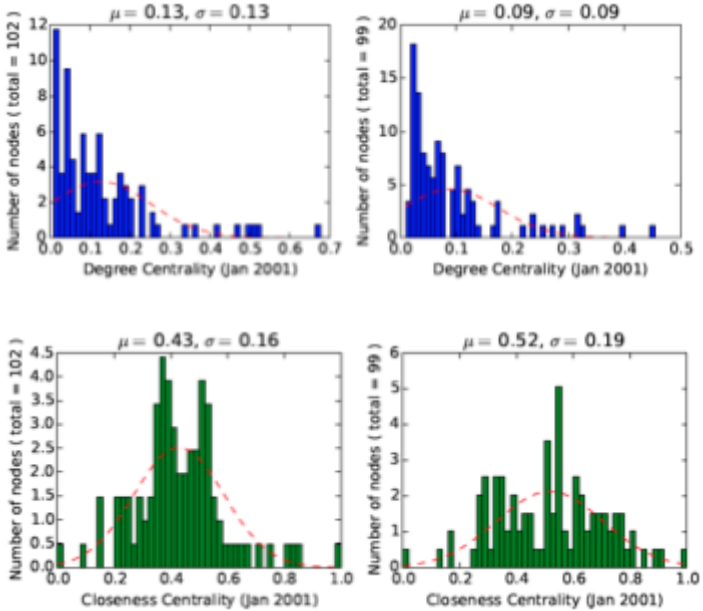


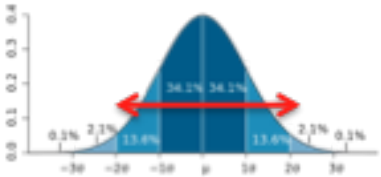
Case Study: DataSet intro.

- Enron Email Dataset
  - Real email dataset
  - From Enron Corp.
  - Released by FERC in 2002
  - Investigations on Enron Scandal
- Enron Communication Network
  - Emails in 2001 in each month
  - 12 timeframes
  - Total 285 nodes, 23559 edges
  - At least one email in each month: an edge
  - Unweighted, undirected
  - Communities found by Local Community Mining Alg. (Chen, Zaiane, and Goebel 2009)

Case Study: Enron

- Identifying Leaders and Outermosts
  - Candidate metrics:
    - degree centrality
    - closeness centrality

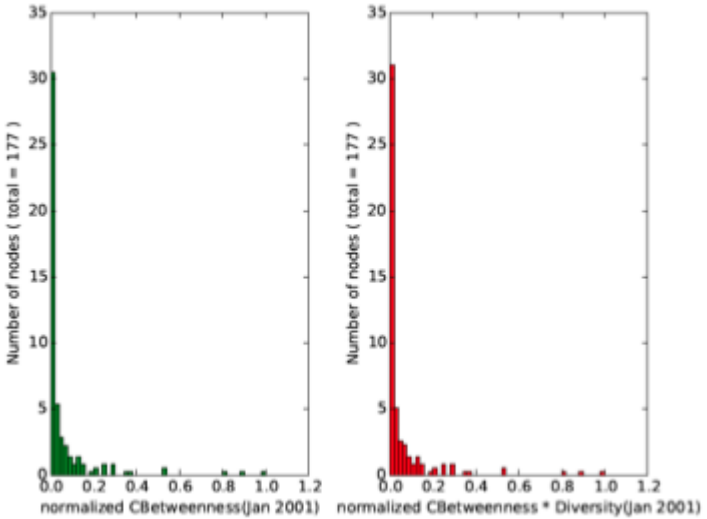




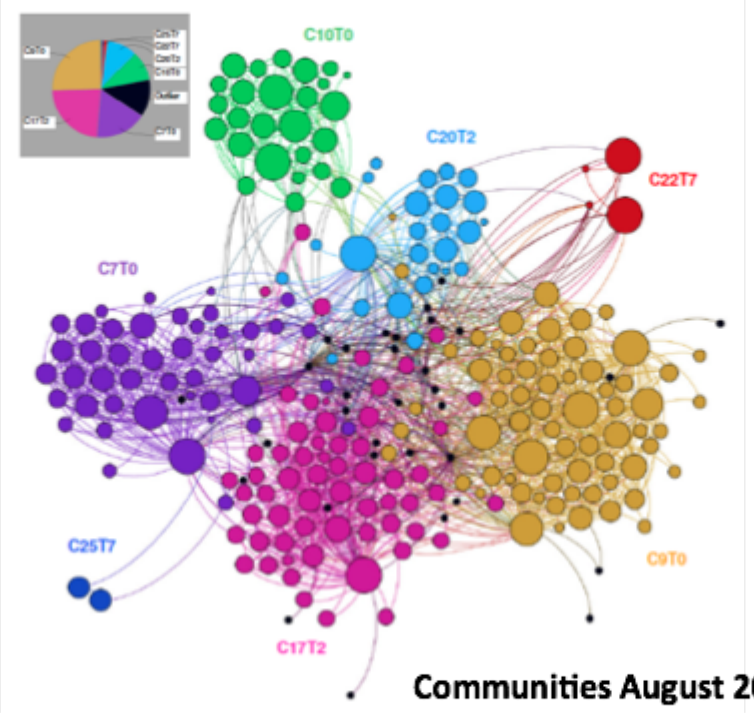
- $M(v) > \mu+2\sigma \rightarrow$ leader
- $M(v) < \mu-2\sigma \rightarrow$ outermost

Case Study: Enron

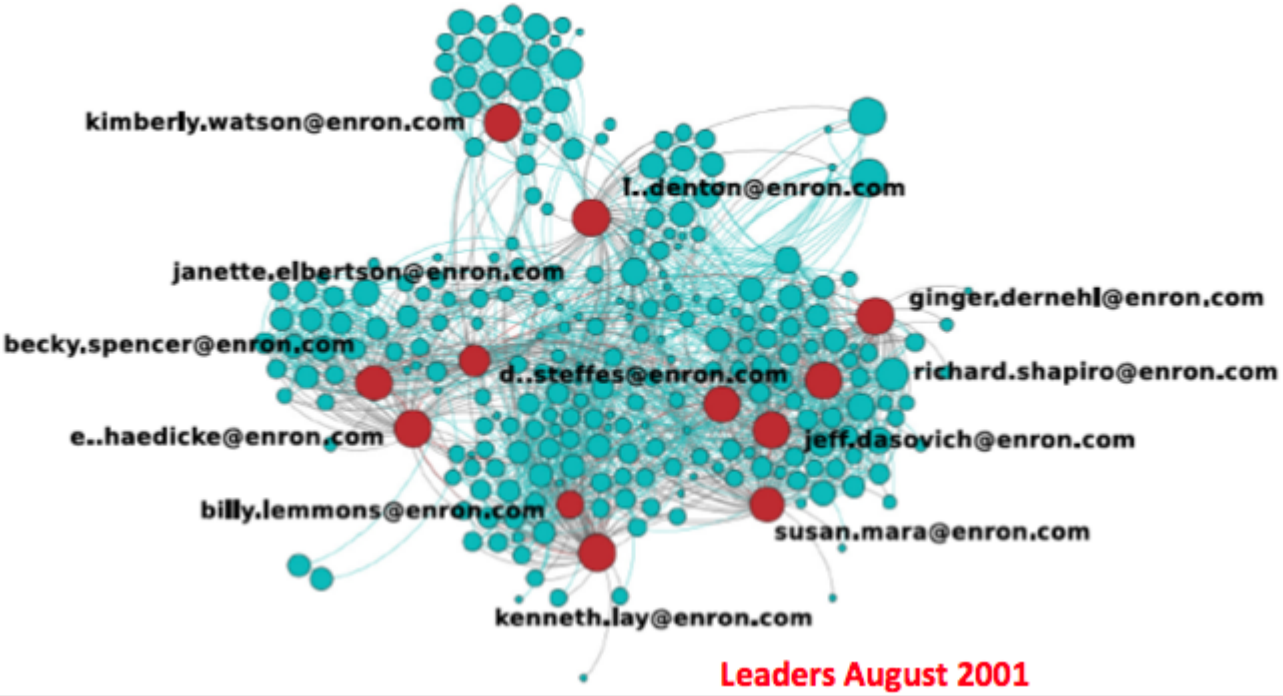
- Identifying Mediators
  - MediatorScore(v) = NCBC(v) * DS(v)
  - More like power law
  - Use **MedExtractor** Algorithm
  - Use **distribution properties**
    - Gaps
    - 80-20 rule



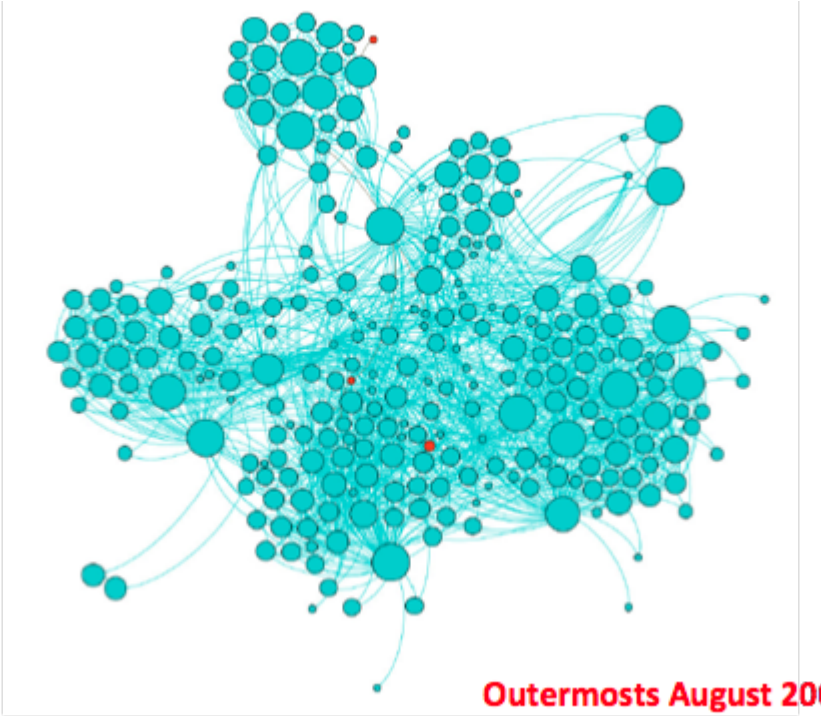
Case Study: Enron Results



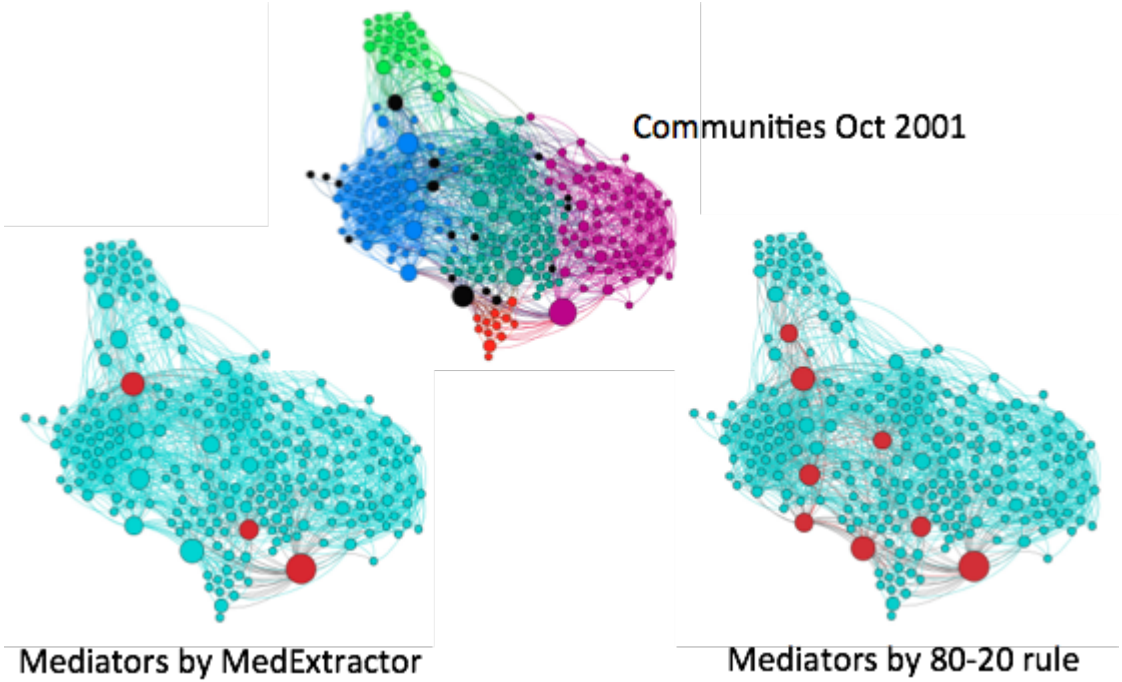
Case Study: Enron Results



Case Study: Enron Results



Case Study: Enron Results



Case Study: Enron Results

Leader → Important Position

email	*position*
tana.jones@enron.com	Senior Legal Specialist
jeff.dasovich@enron.com	Executive/Director for State Government Affairs
james.steffes@enron.com	Vice President
richard.shapiro@enron.com	VP regulatory affairs (Enron'stop lobbyist)
d..steffes@enron.com	*James Steffes*
marie.heard@enron.com	Lawyer
louise.kitchen@enron.com	President of Enron Online
susan.mara@enron.com	California director of Regulatory Affairs
mary.hain@enron.com	In house Lawyer
janel.guerrero@enron.com	An employee in government affairs department
john.lavorato@enron.com	CEO, Enron America
alan.comnes@enron.com	Director Government and Regulatory Affairs
billy.lemmons@enron.com	Vice President
steven.kean@enron.com	VP and Chief of staff
lynn.blair@enron.com	Manager
e..haedicke@enron.com	Managing director, Legal
kate.symes@enron.com	Trader
audrey.robertson@enron.com	Transwestern Pipeline Company

Table1. Leaders found in the Enron communication network and their position in the organization.

Case Study: Enron Results

Mediator → Critical position

email	*position*
jeff.dasovich@enron.com	Executive/Director for State Government Affairs
cheryl.johnson@enron.com	Minority Counsel
rhonda.denton@enron.com	Lawyer
l..denton@enron.com	Lawyer
tim.belden@enron.com	Head of Enron's West Coast Trading Desk in Portland Oregon
shelley.corman@enron.com	VP, regulatory affairs
susan.scott@enron.com	Assistant trader
kam.keiser@enron.com	Employee
l..nicolay@enron.com	Senior Director Regulatory Affairs
kenneth.lay@enron.com	CEO, Chairman
d..steffes@enron.com	Vice President
veronica.espinoza@enron.com	Staff of credit risk management
janel.guerrero@enron.com	An employee in government affairs department
outlook.team@enron.com	*mailing list*
scott.neal@enron.com	VP, Trader
k..allen@enron.com	Managing director
bob.ambrocik@enron.co	Manager - Enterprise Storage and Backup Team

Table2. Mediators found in the Enron communication network and their position in the organization.

Case Study: Enron Results [Role Change]

- Important Roles in SSRM
  - Leader
  - Mediator

- Interesting role changes
  - Outsider/outermost → leader/mediator
  - Leader/mediator → outsider/outermost

Case Study: Results [Role Change]

- # of times being a leader
- Constant leader
- Leader in first timeframes
- Leader when present
- Degree of leadership

	Jan-01	Feb-01	Mar-01	Apr-01	May-01	Jun-01	Jul-01	Aug-01	Sep-01	Oct-01	Nov-01	Dec-01	
jeff.dasovich@enron.com	0	0.91	0.97	1	0.91	0.86	1	1	0.94	0	0	0	8
tana.jones@enron.com	1	1	1	1	1	0	0	0	0.89	1	0	0	7
james.steffes@enron.com	0.82	1	0.85	0.73	1	0.79	0	0			0		6
richard.shapiro@enron.com	0						0.82	1	0.99	1	0.86	0.87	6
d..steffes@enron.com	0							0.98	0.94	0.96	1	0.85	5
marie.heard@enron.com	0						1	0	1	0.94	1	0.78	5
becky.spencer@enron.com	0			0.98	0	1	1	0.96	0	0	0	0	4
louise.kitchen@enron.com	0								1	0.73	1	1	4
ginger.dernehl@enron.com	1	0	0	0	0.86	0	0	1	0	0	0	0.87	4
susan.mara@enron.com	0					0.9	0.79	0.91	0.94	0	0	0	4
kathryn.sheppard@enron.com	0								1	1	1	1	4
alan.comnes@enron.com	0		0.84	0	0	1	0	0	0.92	0	0	0	3
mary.hain@enron.com	0.84	0.92	1	0	0								3
janel.guerrero@enron.com	0			0.73	0	0	0	0	0	1	0	1	3
john.lavorato@enron.com	0			1	1	0	0	0	0	0	0.91	0	3

Table3. Leader role change in the Enron communication network.

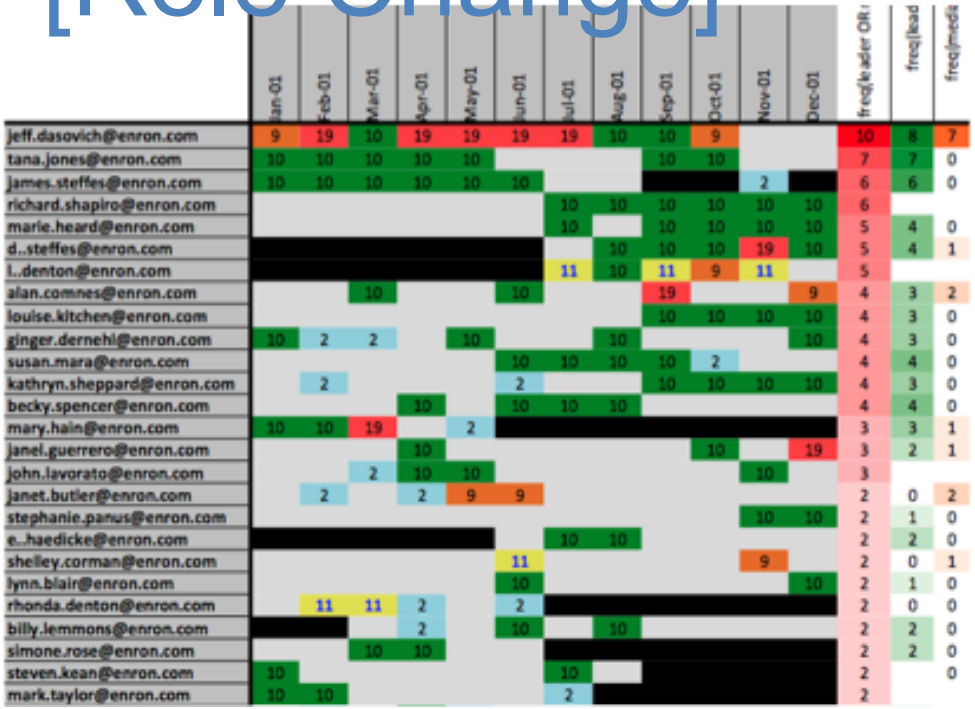
Case Study: Enron Results [Role Change]

- Freq. of being mediator
- Degree of mediator-ship
- # of mediators in timeframes
- When mediators are stronger?

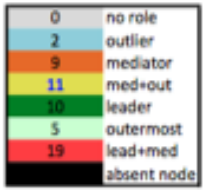
	Jan-01	Feb-01	Mar-01	Apr-01	May-01	Jun-01	Jul-01	Aug-01	Sep-01	Oct-01	Nov-01	Dec-01	
jeff.dasovich@enron.com	0.043	0.069	0	0.218	0.252	0.264	0.791	0	0	0.114	0	0	7
l..denton@enron.com							0.547	0	0.083	0.144	0.139	0	4
alan.comnes@enron.com	0								0.095	0	0	0.114	2
rhonda.denton@enron.com	0	0.113	0.634	0	0	0							2
janet.butler@enron.com	0				0.588	0.272	0	0	0	0	0	0	2
shelley.corman@enron.com	0					0.236	0	0	0	0	0.097	0	2
cheryl.johnson@enron.com	0						0.335	0	0	0	0	0	1
susan.scott@enron.com	0			0.285	0	0	0	0	0				1
kam.keiser@enron.com	0							0.486	0	0	0	0	1
l..nicolay@enron.com	0								0.046	0	0	0	1
stanley.horton@enron.com	0				0.144	0	0	0	0	0	0	0	1
mark.frevert@enron.com	0		0.135	0	0	0	0	0	0	0	0	0	1
kenneth.lay@enron.com	0							1	0	0	0	0	1
tim.belden@enron.com	0											0.126	1
mary.hain@enron.com	0		0.512	0	0								1
d..steffes@enron.com	0										0.091	0	1
janel.guerrero@enron.com	0											0.095	1
deshonda.hamilton@enron.com	0		0.463	0	0								1
outlook.team@enron.com	0			0.197	0	0	0	0					1
stephanie.miller@enron.com	0						0.16	0	0	0	0	0	1
k..allen@enron.com	0						0.424	0	0	0	0	0	1
bob.ambrocik@enron.com										0.073			1

Table4. Mediator role change in the Enron communication network.

Case Study: Enron Results [Role Change]



	Jan-01	Feb-01	Mar-01	Apr-01	May-01	Jun-01	Jul-01	Aug-01	Sep-01	Oct-01	Nov-01	Dec-01	freq(leader OR	freq(lead	freq(media
jeff.dasovich@enron.com	9	19	10	19	19	19	19	10	10	9			10	8	7
tana.jones@enron.com	10	10	10	10	10				10	10			7	7	0
james.steffes@enron.com	10	10	10	10	10	10					2		6	6	0
richard.shapiro@enron.com							10	10	10	10	10	10	6		
marie.heard@enron.com							10		10	10	10	10	5	4	0
d..steffes@enron.com								10	10	10	19	10	5	4	1
l..denton@enron.com							11	10	11	9	11		5		
alan.comnes@enron.com			10			10			19			9	4	3	2
louise.kitchen@enron.com									10	10	10	10	4	3	0
ginger.dernehl@enron.com	10	2	2		10			10				10	4	3	0
susan.mara@enron.com						10	10	10	10	2			4	4	0
kathryn.sheppard@enron.com		2				2			10	10	10	10	4	3	0
becky.spencer@enron.com				10		10	10	10					4	4	0
mary.hain@enron.com	10	10	19		2								3	3	1
janel.guerrero@enron.com				10						10		19	3	2	1
john.lavorato@enron.com			2	10	10						10		3		
janet.butler@enron.com		2		2	9	9							2	0	2
stephanie.panus@enron.com											10	10	2	1	0
e..haedicke@enron.com							10	10					2	2	0
shelley.corman@enron.com						11					9		2	0	1
lynn.blair@enron.com						10						10	2	1	0
rhonda.denton@enron.com		11	11	2		2							2	0	0
billy.lemmons@enron.com				2		10		10					2	2	0
simone.rose@enron.com			10	10									2	2	0
steven.kean@enron.com	10						10						2		0
mark.taylor@enron.com	10	10					2						2		



- Interesting role-change patterns
- Timeframe when role-change happens

Table5. All role change in the Enron communication network.

Case Study: Community Events

- An example of events in a social network
  - Community events (Takaffoli, Sangi, Fagnan, Zaiane 2011)
    - Survive
    - Split
    - Merge
    - Dissolve

Case Study: Role-Event Relation

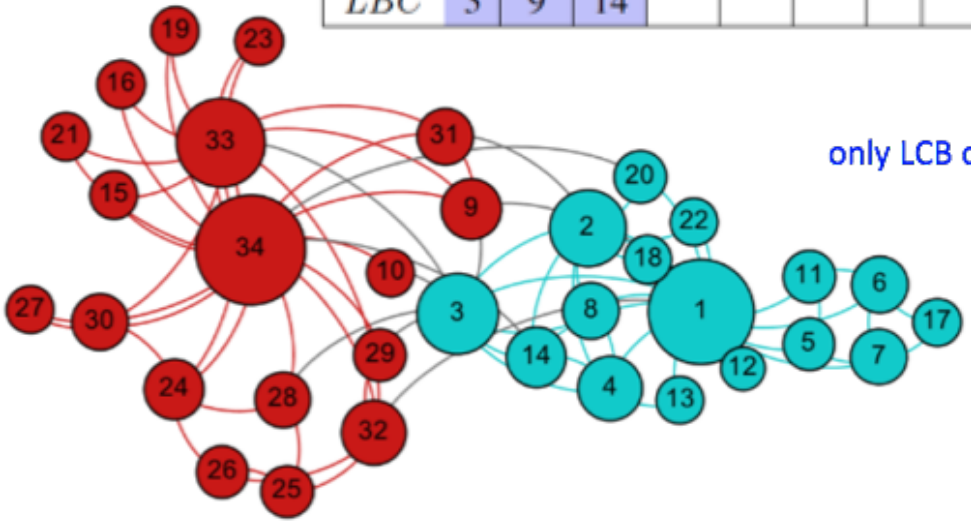
t	$source(t-1)$	$result(t)$	$event$	$email$	$role_{t-2}$	$role_{t-1}$	$role_t$	com_{t-2}	com_{t-1}	com_t
1	C7T0	C17T1	split	tamara.black@enron.com	null	-	leader	null	C7T0	C17T1
2	C7T0	C7T0	split	mark.taylor@enron.com	leader	leader	-	C7T0	C7T0	C7T0
3	C7T0	C7T0	survive	tana.jones@enron.com	leader	leader	leader	C7T0	C7T0	C7T0
4	C7T0	C7T0	split	becky.spencer@enron.com	-	leader	-	C7T0	C7T0	C7T0
5	C7T0	C7T0	survive	janette.elbertson@enron.com	outsider	outsider	leader	-1	-1	C7T0
6	C7T0	C7T0	merge	e..haedicke@enron.com	null	-	leader	null	C7T0	C7T0
6	C7T0	C7T0	merge	becky.spencer@enron.com	-	leader	leader	C7T0	C7T0	C7T0
6	C7T0	C7T0	merge	janette.elbertson@enron.com	outsider	leader	-	-	C7T0	C7T0
6	C7T0	C11T6	split	marie.heard@enron.com	-	-	leader	C7T0	C7T0	C11T6
6	C7T0	C11T6	split	cheryl.johnson@enron.com	-	-	mediator	C7T0	C7T0	C11T6
6	C7T0	C7T0	split	becky.spencer@enron.com	-	leader	leader	C7T0	C7T0	C7T0
6	C7T0	C7T0	split	janette.elbertson@enron.com	outsider	leader	-	-	C7T0	C7T0
6	C7T0	C7T0	survive	janette.elbertson@enron.com	outsider	leader	-	-	C7T0	C7T0
7	C7T0	C7T0	merge	e..haedicke@enron.com	-	leader	leader	C7T0	C7T0	C7T0
7	C7T0	C7T0	merge	deb.korkmas@enron.com	-	leader	-	C7T0	C7T0	C7T0

Table6. role change – community events in the Enron communication network.

Case Study: BC vs. CBC vs. LBC

- Karate Club Network

BC	1	34	33	3	32	9	2	14	20	7	6	28	24	31	4	26	30	25	29	10
CBC	1	3	34	33	14	32	2	28	9	31	7	20	6	4	24	10	30	25	27	22
LBC	3	9	14																	



only LCB can clearly find mediators

Case Study: BC vs. CBC vs. LBC

BC	*CBC*	*LBC*
sally.beck@enron.com	l..denton@enron.com	jeff.dasovich@enron.com
jeff.dasovich@enron.com	jeff.dasovich@enron.com	tim.belden@enron.com
l..denton@enron.com	tim.belden@enron.com	l..denton@enron.com
l..nicolay@enron.com	alan.comnes@enron.com	s..bradford@enron.com
d..steffes@enron.com	l..nicolay@enron.com	mike.grigsby@enron.com
louise.kitchen@enron.com	bob.ambrocik@enron.com	john.lavorato@enron.com
bob.ambrocik@enron.com	louise.kitchen@enron.com	b..sanders@enron.com
richard.shapiro@enron.com	nancy.bagot@enron.com	l..nicolay@enron.com
j..kean@enron.com	d..steffes@enron.com	danny.mccarty@enron.com
tim.belden@enron.com	shelley.corman@enron.com	stanley.horton@enron.com
fraisy.george@enron.com	b..sanders@enron.com	alan.comnes@enron.com
joannie.williamson@enron.com	susan.lindberg@enron.com	fran.chang@enron.com
s..bradford@enron.com	sally.beck@enron.com	drew.fossum@enron.com
nancy.bagot@enron.com	bill.williams@enron.com	brian.redmond@enron.com
b..sanders@enron.com	john.lavorato@enron.com	janette.elbertson@enron.com
veronica.espinoza@enron.com	john.buchanan@enron.com	edward.sacks@enron.com
janel.guerrero@enron.com	janet.butler@enron.com	robert.badeer@enron.com
e..haedicke@enron.com	sarah.novosel@enron.com	jeff.richter@enron.com
shelley.corman@enron.com	j..kean@enron.com	louise.kitchen@enron.com
alan.comnes@enron.com	drew.fossum@enron.com	dave.perrino@enron.com

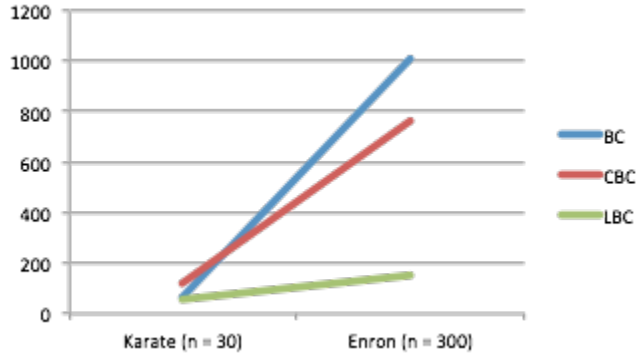
Table7. Top-20 nodes in the Enron communication network in Oct 2001.

Case Study: BC vs. CBC vs. LBC

	BC, CBC	BC, LBC	CBC, LBC
Karate Club	0.94	0.58	0.62
Enron	0.90	0.63	0.72

Table8. Spearman correlation between BC, CBC, and LBC.

Case Study: BC vs. CBC vs. LBC



	t_{BC}	t_{CBC}	t_{LBC}	t_{BC}/t_{CBC}
karate club (34 nodes)	64_{ms}	118_{ms}	57_{ms}	0.54
Enron Oct. 2001 (228 nodes)	1012_{ms}	762_{ms}	152_{ms}	1.33

Table9. Average running time for computing BC, CBC, and LBC.

Conclusion

1. Proposed a framework for defining and tracking structural roles

2. Investigated these roles over time in real dataset showing the correlation of their changes with the changes in the community structure of the network

3. proposed new metrics based on the community structure for detecting structural roles

Future work

- Dynamic Roles (temporal)
- Methodologies to study changes of roles.
- Methodologies to study effect of roles on the structure of the underlying network.

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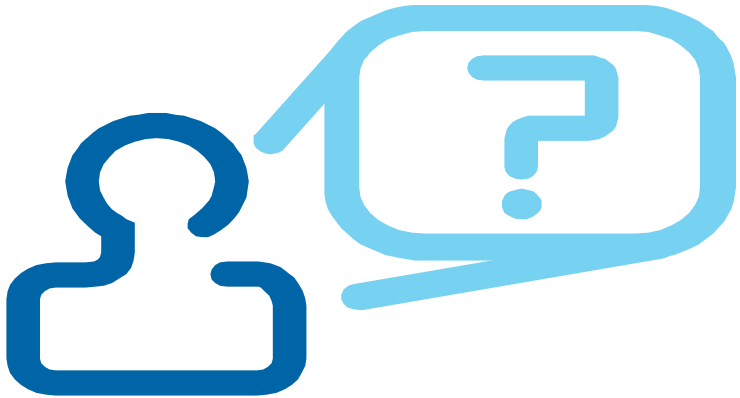
Thank You



Extra

SSRM Framework: Mediator Identification

$$LPath = \{l | l \in ShortestPath(a, b) \wedge a \in leaderSet(c_i) \wedge b \in leaderSet(c_j)\}$$

LBetweenness Centrality

$$LBC(v) = \sum_{p \in LPath} I_l(p, v)$$

$$I_l(p, v) = \begin{cases} 1 : v \text{ resides on } p \\ 0 : o.w. \end{cases}$$

SSRM Framework: Mediator Identification

CBetweenness Centrality

$$CBC(v) = \frac{1}{2}\sum_{c_i}\sum_{c_j \neq c_i} I_c(p_{c_i,c_j}, v): \quad \textit{for undirected networks,}$$

$$\sum_{c_i}\sum_{c_j \neq c_i} I_c(p_{c_i,c_j}, v): \quad \textit{for directed networks.}$$

$$I_c(p_{c_i,c_j}, v) = \begin{cases} 1 : v \ \textit{resides on} \ p_{c_i,c_j} \\ 0 : o.w. \end{cases}$$

$$p_{c_i,c_j} = \{p | p \in AllShortestPath \wedge start(p) \in c_i \wedge end(p) \in c_j\}$$

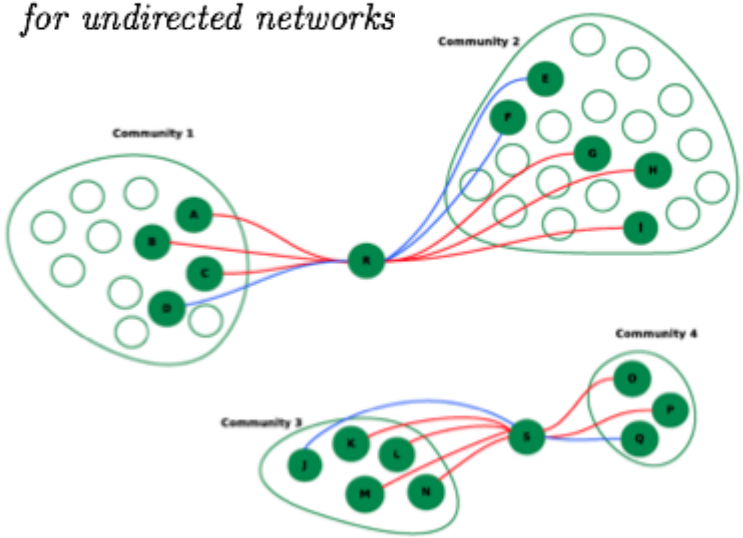
SSRM Framework: Mediator Identification

- Normalized-CBC (NCBC)

$$NCBC(v) = \frac{1}{2}\sum_{c_i}\sum_{c_j \neq c_i}\frac{I_c(p_{c_i,c_j}, v)}{min(size(c_i), size(c_j))} \quad for\ undirected\ networks$$

$$NCBC(R) = \frac{11}{12}$$

$$NCBC(S) = \frac{9}{3}$$



SSRM Framework: MedExtractor

Algorithm 1 MedExtractor: Find Mediators from SortedList based on their Mediacy Score

```
1: procedure ExtractMediators(Graph G, OrderedList L)
2:     ▷G is the graph associated with a network
3:     ▷L is descending OrderedList containing nodes of the network sorted based on their
   mediacy score.
4:     mediatorSet = {}                          ▷ set of selected nodes as mediators
5:     connectedComs = {}      ▷ set of communities connected to eachother by nodes in
   mediatorSet
6:     while connectedComs.size < G.CommunityCount do
7:         n ← L.top()
8:         for all Community c ∈ n.incedentCommunities() do
9:             if c ∉ connectedComs then
10:                Add n to mediatorSet
11:                Add c to connectedComs
12:            end if
13:        end for
14:        L.remove(n)
15:    end while
16: end procedure
```

Outline

Introduction

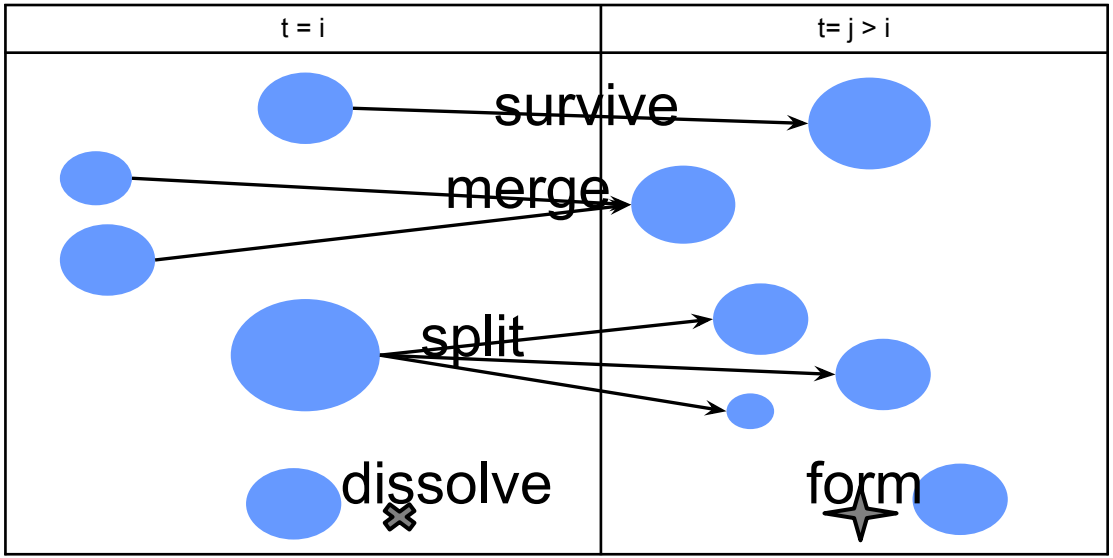
…

Experiment

Conclusion

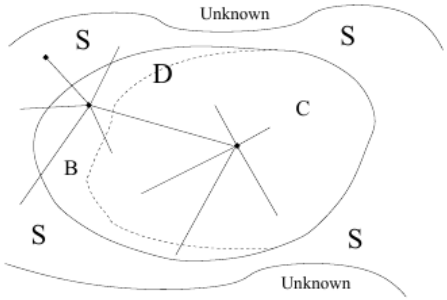
MODEC Framework (CASON 2011)

- Critical events are used to characterize the evolution of communities.



L-metric Community Mining

- Based on regions D,C,B,S



- L-metric
  - $L = \frac{\text{community internal relation}}{\text{community external relation}} = \frac{\text{average internal degree of nodes in D}}{\text{average external degree of nodes in B}}$
- Start from one node
- Add neighbours if L-metric increases

Experiment

- Enron Email Dataset
  - Year 2001 with 285 nodes , 23559 edges, and monthly snapshots
- Dynamic community mining
  - Incremental L-metric
  - Independent L-metric (CASoN 2011)
  - FacetNet (NIPS 2005)

- Incorporate Topic Extraction for the Discovered Communities
  - Apply KEA to produce a list of the keywords discussed within each community
  - Consider the 10 most frequent keywords of each community as its topic