Community and Role Model

Zhongjing Yu

Outline

Role model: Role is a important factor to model for detect behavior or detect community.

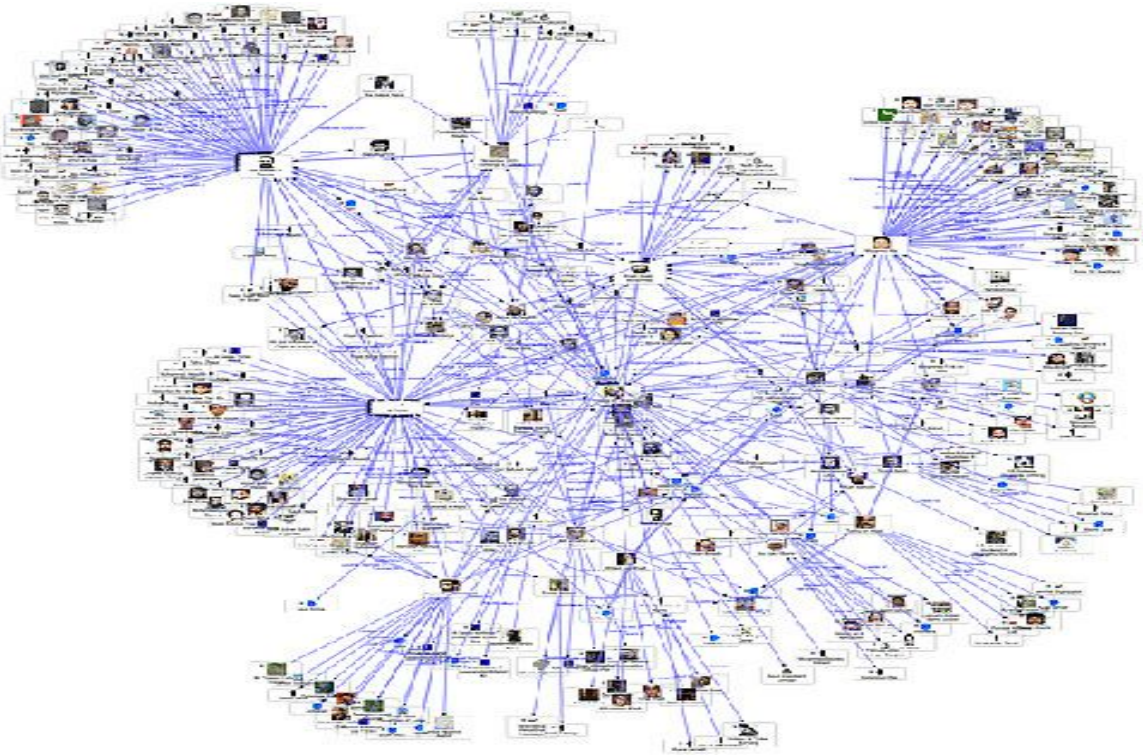
- Firstly , introduce a model to identify roles and application of the model.
- Secondly , introduce a Probabilistic Community and Role Model ,which consider role and other factors are significant to model.

(SSRM：Structural Social Role Mining for Dynamic Social Networks, Probabilistic Community and Role Model for Social Networks)

SSRM：Structural Social Role Mining for Dynamic Social Networks

Afra Abnar, Mansoureh Takaffoli,
Reihaneh Rabbany, Osmar R. Zaiane

Background:



Structure of role model exists in a social network and each individuals play various of roles

Outline

- Target: identify roles in social networks
- Analysis some kinds of roles
- How to identify

  which measure adapted

  C-Betweenness

  L-Betweenness

  MedExtractor algorithm
- Experiment

Target: identify roles in social networks

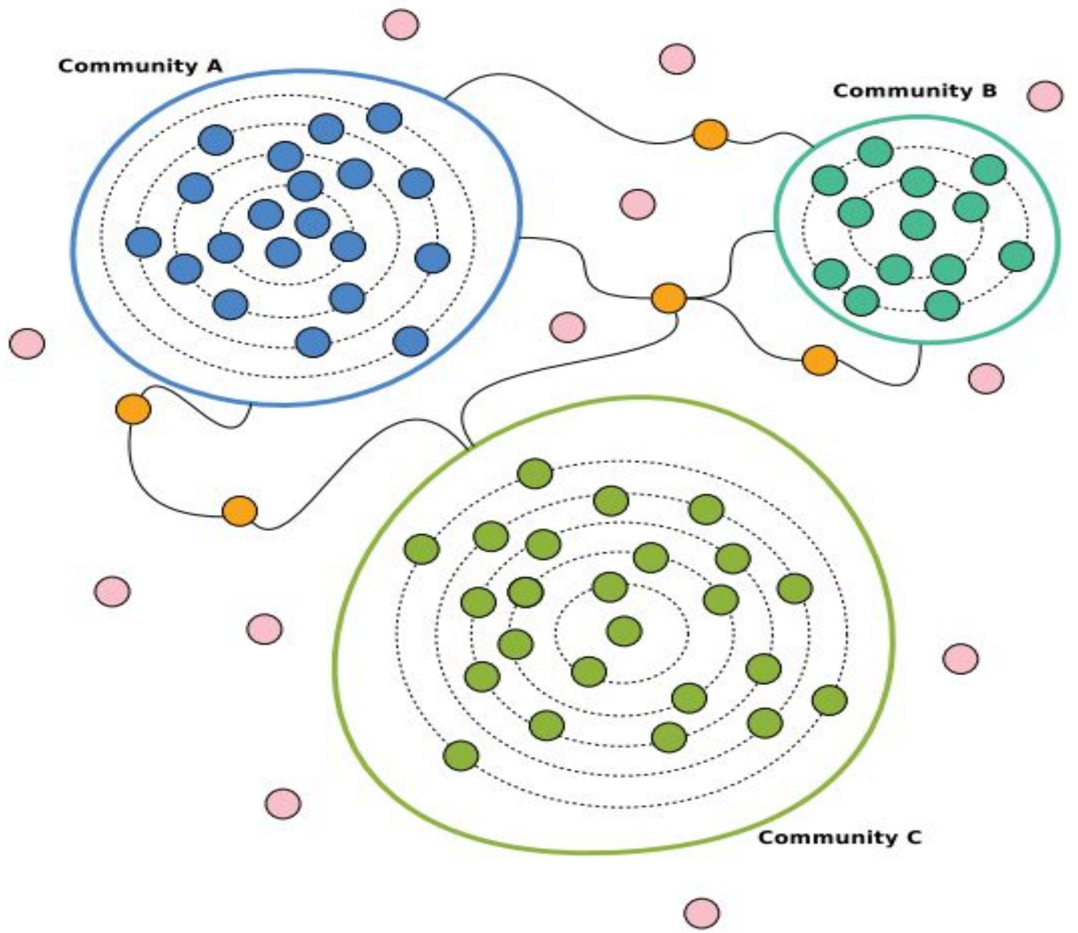
condition:

- The SSRM framework is built up two characteristic of human societies, given structural properties:

❖ role-taking behavier of the individuals with each other （edges）

❖ A social network is considered only structural properties of nodes(nodes)

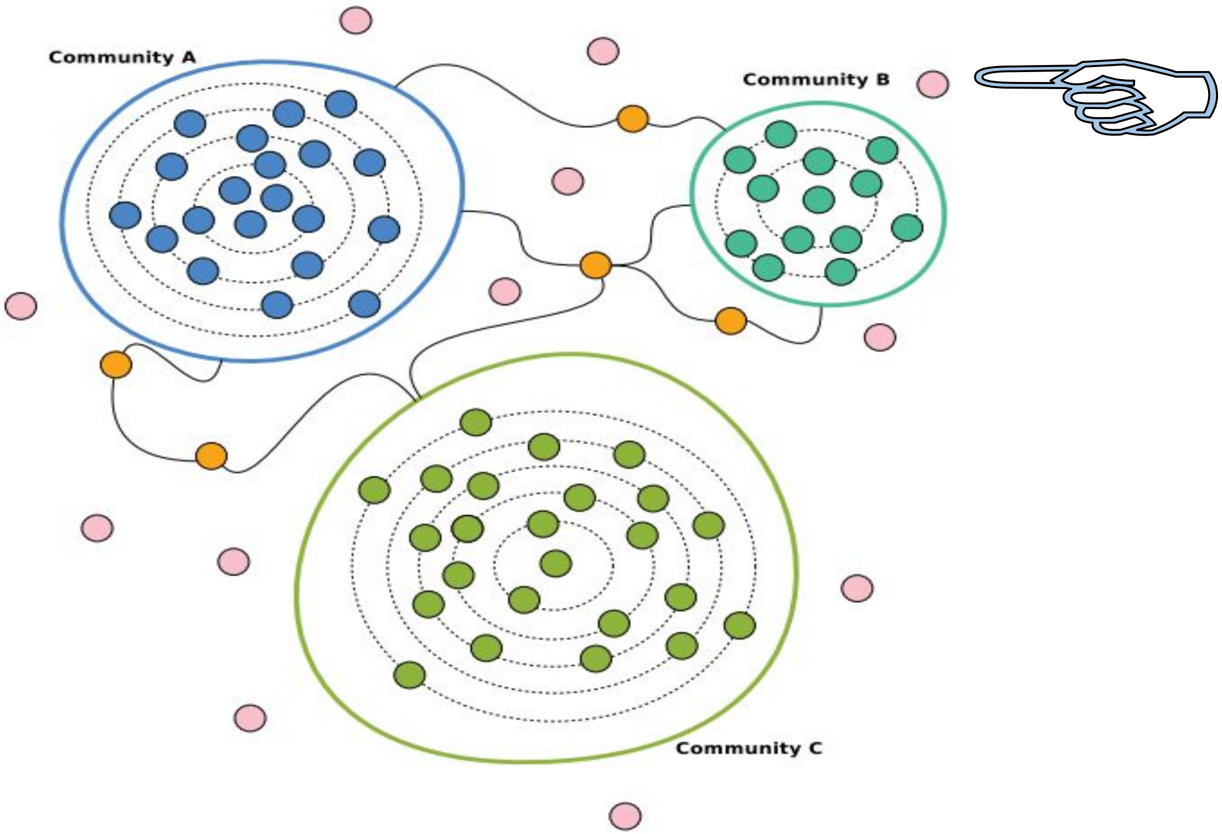
Analysis



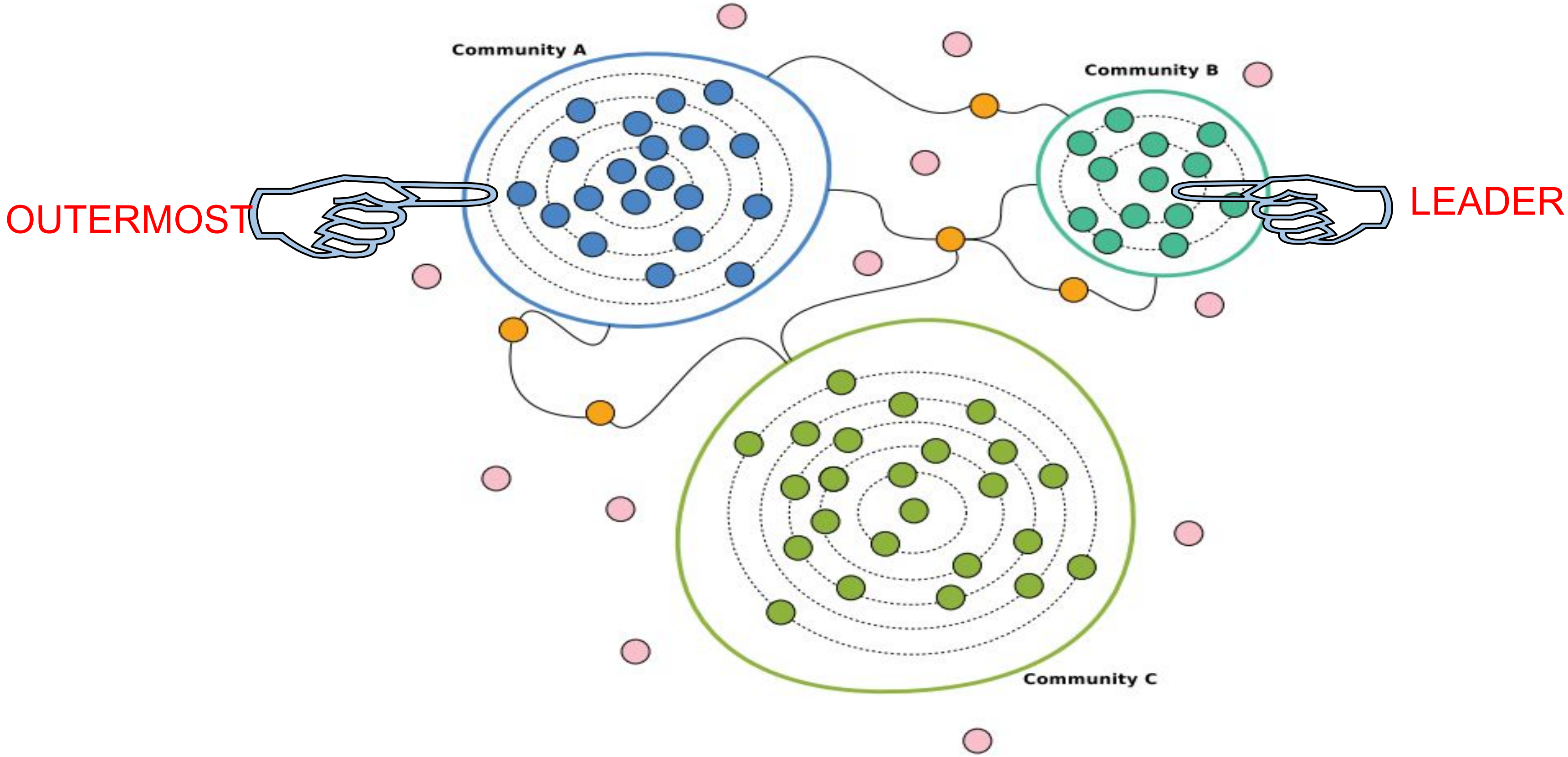
- LEADERS:important nodes in a community
- OUTERMOSTS:least significant individuals
- MEDIATORS:connect different communities
- OUTSIDERS:no affiliate to any one community

How to identify

❖ OUTSIDER members not belong to any community



- LEADER (a) adapts an appropriate measure M is used to score the members of the community;(b) the probability ditribution function(pdf) for the importance scores is estimated.
- OUTERMOST members are identified in contrast to the leaders.



Measure

- degree centrality:
- closeness centrality:
  - Closeness centrality of a node u is the reciprocal of the sum of the shortest path distances from u to all n−1 other nodes. Since the sum of distances depends on the number of nodes in the graph, closeness is normalized by the sum of minimum possible distances n−1

$$C(u) = \frac{n-1}{\sum_{v=1}^{n-1} d(v,u)},$$

where d(v,u) is the shortest-path distance between v and u , and n is the number of nodes in the graph.

-------NetworkX

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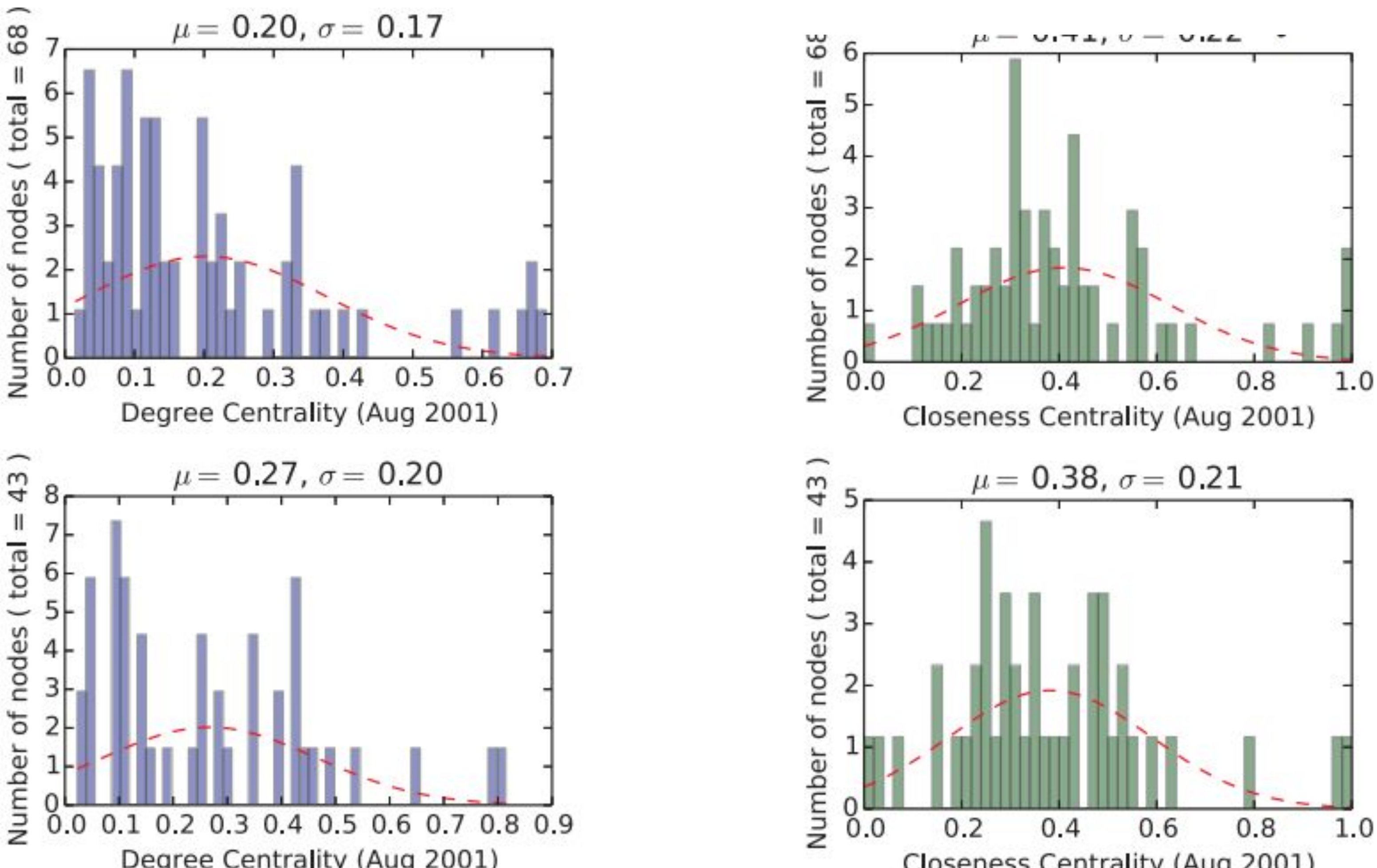
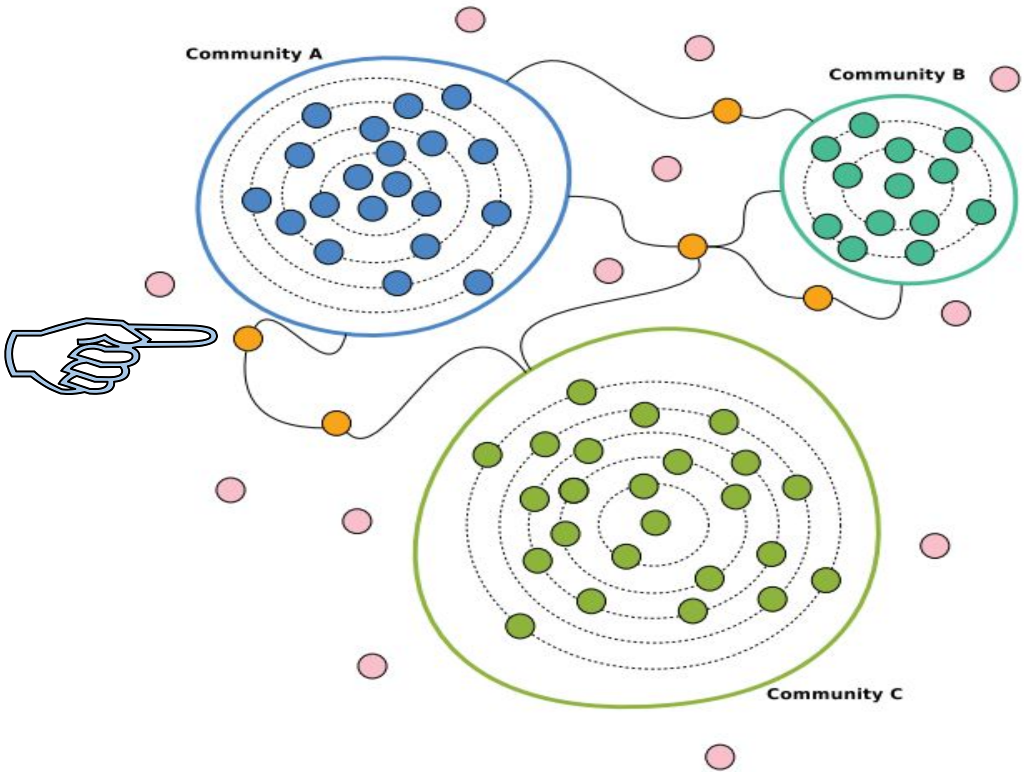

$\mu = 0.20$, $\sigma = 0.17$
Number of nodes (total = 68)
Degree Centrality (Aug 2001)
Number of nodes (total = 6
Closeness Centrality (Aug 2001)
$\mu = 0.27$, $\sigma = 0.20$
Number of nodes (total = 43)
Degree Centrality (Aug 2001)
$\mu = 0.38$, $\sigma = 0.21$
Number of nodes (total = 43)
Closeness Centrality (Aug 2001)

- MEDIATOR: Commonly-used **betweenness centrality** ranks nodes based to the number of shortest paths that pass through the nodes.

MEDIATOR



Betweenness centrality

C-Betweenness counts the numbers of shortest paths beween *different communities* that pass through a node.

- s_p and e_p denote the start point and end point of the shirtest path p
- c_v return community that node v belongs to.
- the set of all shortest paths that *connect different communities* as

$$CPaths = \{p \mid c_{s_p} \neq c_{e_p}\}$$

- $I_p(p, v)$ return 1 if node v resides on path p ,and 0 otherwise.
- C-Betweenness of node v is defined as:

$$CBC(v) = \frac{1}{2} \sum_{p \in CPaths} I_p(p, v)$$

L-Betweenness denotes noly the shortest paths between leaders of *different communities*.

- *leaderSet(c)*： the set of leaders of community *c,* then consider *LPath* as:

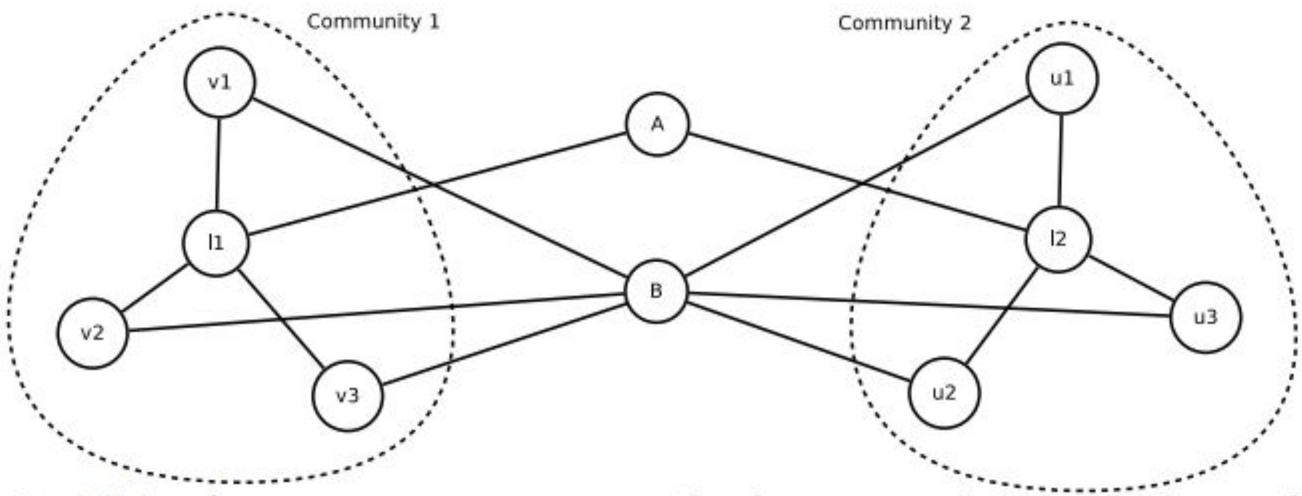
$$LPaths = \{p \in CPaths \mid \exists c_i, c_j : s_p \in leaderSet(c_i) \wedge e_p \in leaderSet(c_j)\}$$

- *L-Betweenness* of a node *v* ,*LBC(v)* is defined as:

$$LBC(v) = \frac{1}{2} \sum_{p \in LPath} I_p(p, v)$$

(2 is omitted for directed graph)

C-Betweenness score, L-Betweenness score



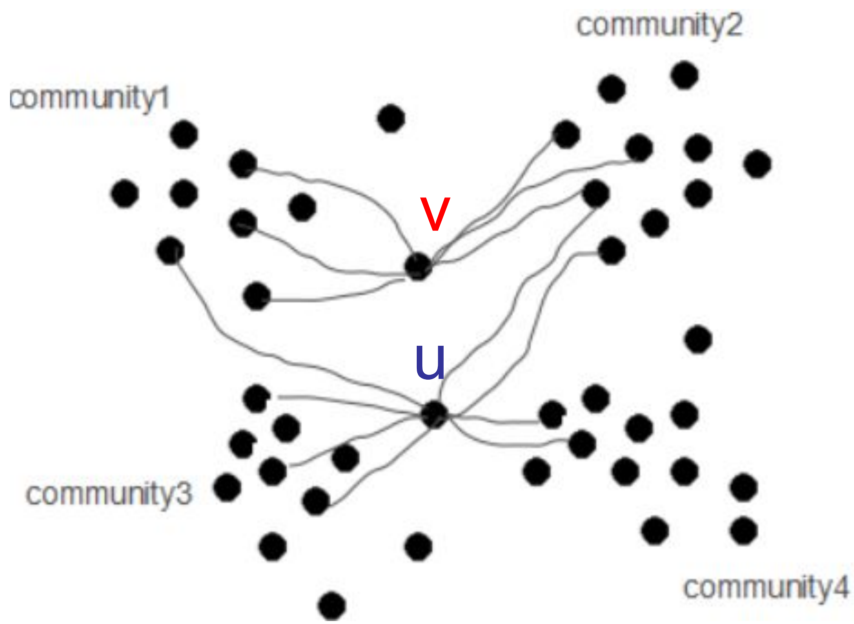
This figure presents a synthetic network consisting of two communities.Leaders of two communities(l_1 and l_2) are connected to the node A,while other nodes are all connected to node B.Computing LBC and CBC for all nodes of the graph,the results are as follows:LBC(A) = 1, LBC(B)= 0, CBC(A) = 7,CBC(B) = 12, $\forall i$:CBC(v_i) = CBC(u_i) = 6 ,and CBC(l_1) = CBC(l_2) = 3

which is more important ,for A, B ?

the measure is not sufficient.

Question and new notions

the CBC values of two nodes are same .



considering the number of distinct communities related with the mediator,there come up with the notion of **diversity score**.

Define two various for the diversity score: DS_{count} ,DS_{pair}

DS_{count} is defined as *the number* of *distinct communities* connected through a node.
let $I_d(c_i,v)$ return 1 if $\exists p \in CPaths : s_p \in c_i \wedge v \in p$. and DS_{coun} as follows:

$$DS_{count}(v) = \frac{1}{2}\sum_{c_i} I_d(c_i, v) \quad \text{for undirected networks.}$$

(division by 2 is omitted for directed graphs.)

DS_{pair} count **pairs of communities** that have at least one shortest path between their mumbers passing through node *v.$I_d(c_i,c_j,v)$* ,return 1 if

$$\exists p \in CPaths : s_p \in c_i \wedge e_p \in c_j \wedge v \in p.$$

$$DS_{pair}(v) = \frac{1}{2} \sum_{c_i} \sum_{c_j \neq c_i} I_d(c_i, c_j, v)$$

in this papper,it propose *MedExtractor* algorithm to identify ranked nodes connecting the max number of communities as mediators

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

```
procedure ExtractMediators (Graph G, OrderedList L)
    ▷G is the graph associated with a network
    ▷L is descending OrderedList containing nodes of the network sorted based on their mediacy score.
    mediatorSet = {}            ▷ set of selected nodes as mediators
    connectedComs = {}          ▷ set of communities connected to eachother by nodes in mediatorSet
    while connectedComs.size < G.CommunityCount do
        n ← L.top()
        for all Community c ∈ n.incedentCommunities() do
            if c ∉ connectedComs then
                Add n to mediatorSet
                Add c to connectedComs
            end if
        end for
        L.remove(n)
    end while
end procedure
```

Choosing a Centrality Measure:

the probability of finding more prominent mediators between larger communities is higher in comparison to the smaller communities.

- **normalized CBC as follows:**

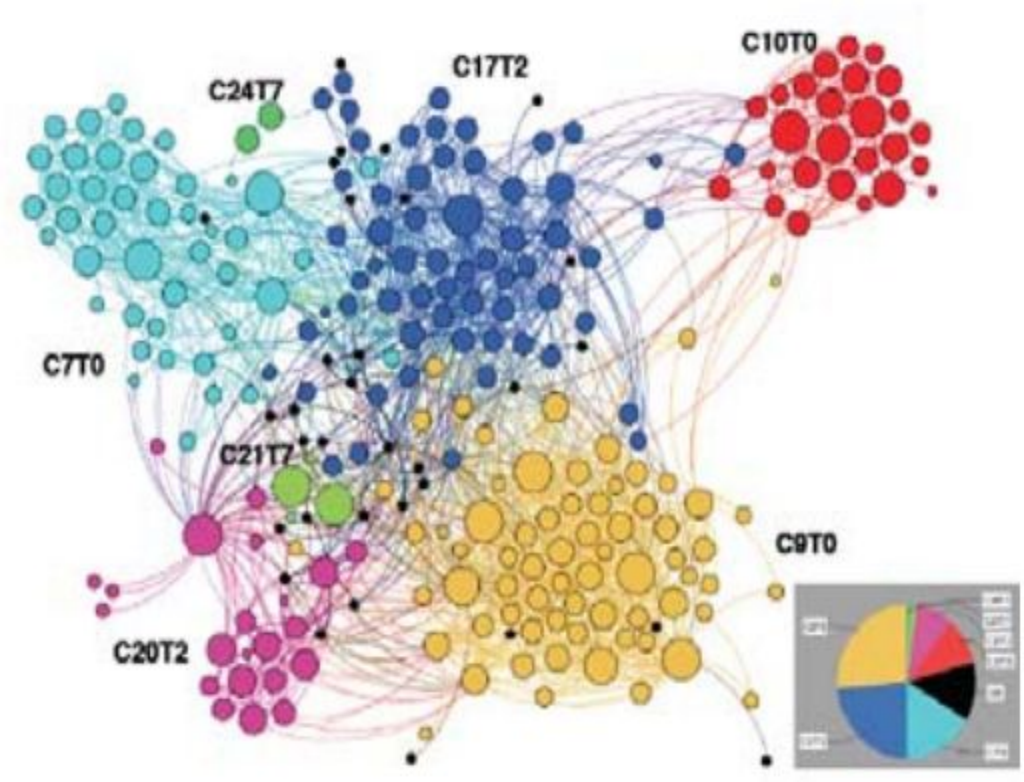
$$NBC(v) = \frac{1}{2} \sum_{p \in CPaths} \frac{I_p(p, v)}{min(|c_{s_p}|, |c_{e_p}|)}$$

- **define mediator score:**

$$MS(v) = NCB(v) \times DS_{count}(v).$$

Experiment

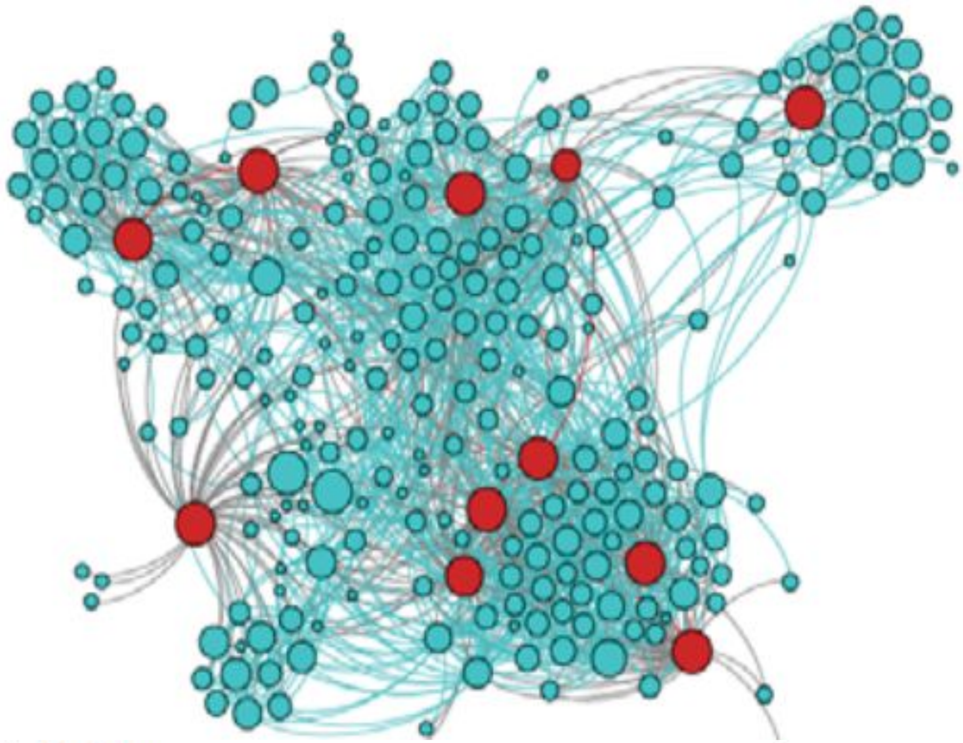
Outsiders



(a)

communities within the Enron email network in August 2001 .Colors represent communities except for black that represents outsiders.Size of a node shows its centrality in its community

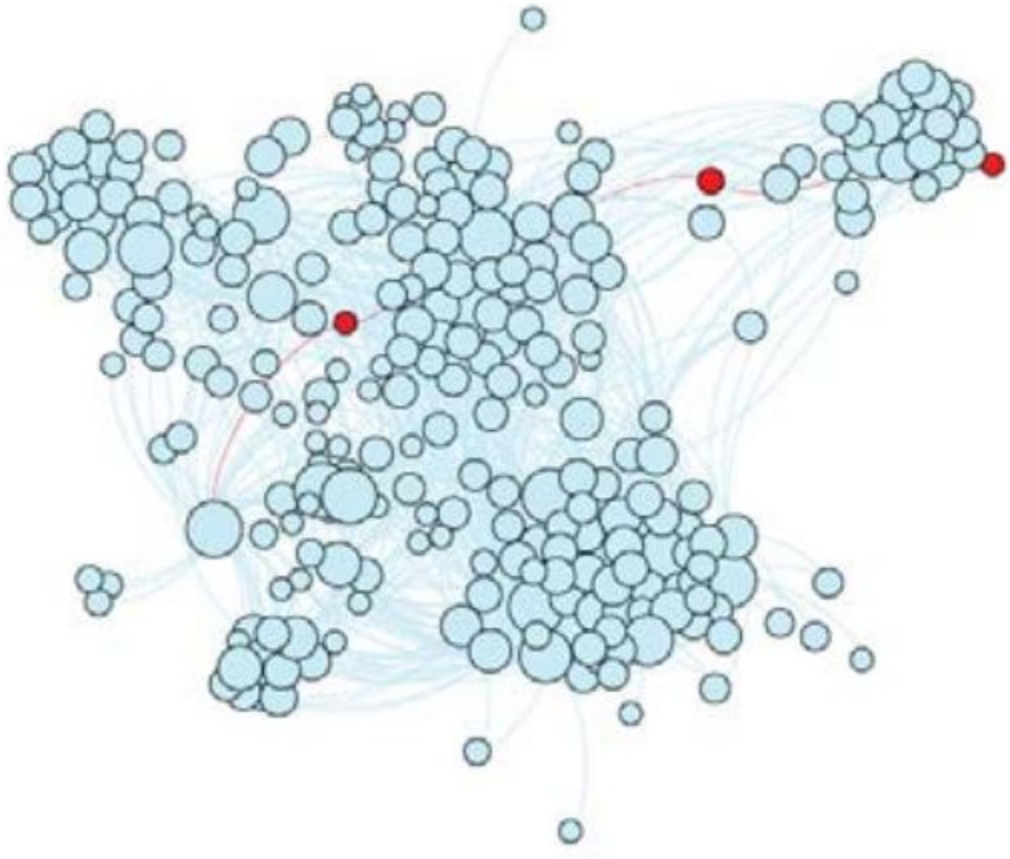
Leaders:



Email	Community	Position
jeff.dasovich@enron.com	C9T0	Executive/Director for State Government Affairs
giger.dernehl@enron.com	C9T0	
richard.shapiro@enron.com	C9T0	VP regulatory affairs (Enron's top lobbyist)
kimberly.watson@enron.com	C10T0	Director
d..steffes@enron.com	C9T0	Vice President
kenneth.lay@enron.com	C17T2	CEO, chairman, and chief executive officer
e..haedicke@enron.com	C7T0	Managing director
susan.mara@enron.com	C9T0	California director of Regulatory Affairs
billy.lemmons@enron.com	C17T2	Vice President
becky.spencer@enron.com	C7T0	
l..denton@enron.com	C20T2	Lawyer

TABLE I: Leaders of the network shown in Figure 5b, their community affiliation and position in the Enron organization

Outermost



(c)

outermosts showed in red,just two communities have nodes serving as outermosts.From right to left, outermosts are Ava Garcia (probably an assistant according to the body of some emails),Shirley Crenshaw (probably an assistant), and Leslie Reves a module manager.

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	
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

- Changes of nodes serving as leaders in the Enron dataset

	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
Number of mediators in each timeframe	1	2	4	3	3	3	5	2	3	3	3	3	

Changes of nodes serving as mediators in Ernon dataset

conclusion

In this papper, SSRM was proposed to analyze social networks, based on taking behavior of people,considering the existence of community structures.and it indeed identified outsiders ,outermosts, mediators, and leaders and found interestiong information about the people associated with nodes having the role of a leader or a mediator.it applied to detect the behavior of node in social networks.

However , we usually don't know the structure of social network,but we want to model and consider influence of roles, attributes and so on.

Probabilistic Community and Role Model for Social Networks

Yu Han and Jie Tang

Outline

- Introduction
- Main idea
- Analysis
- Formulation and Define
- Model Description
- Experiments

Introduction

- There are not only visible elements , but also invisible elements to affect the structure of social network
- Recovery the structure of social network through many samples

Question:

People's behaviors not only depend on their own attributes, but also on their neighbors and communities.

How to model to capture the intrinsic relations between all these element?

How to use a social network model to handle issues such as community detection and behavior prediction?

Main Idea

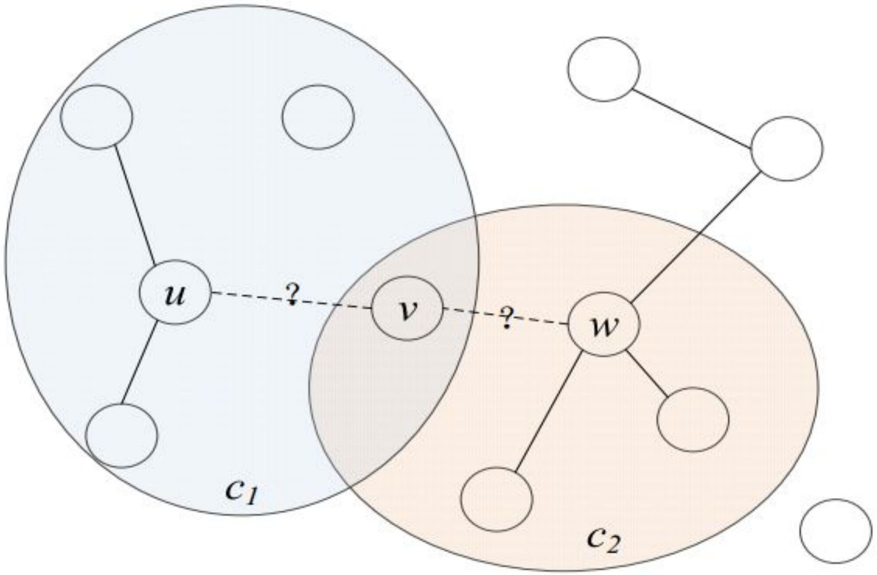
- Propose a unified probabilistic framework,the Community Role Model(CRM), to model a social network.CRM incorporates all the information of modes and edges that form a social network. the methods based on Gibbs sampling and an EM algorithm.

Gibbs sampling or a Gibbs sampler is a Markov chain Monte Carlo (MCMC) algorithm for obtaining a sequence of observations which are approximated from a specified multivariate probability distribution (i.e. from the joint probability distribution of two or more random variables), when direct sampling is difficult. --------------wikipedia

- CRM can be used not noly to represent a social network ,but also to handle various application problems with better performance than a baseline model, without any modification to model.

Analysis

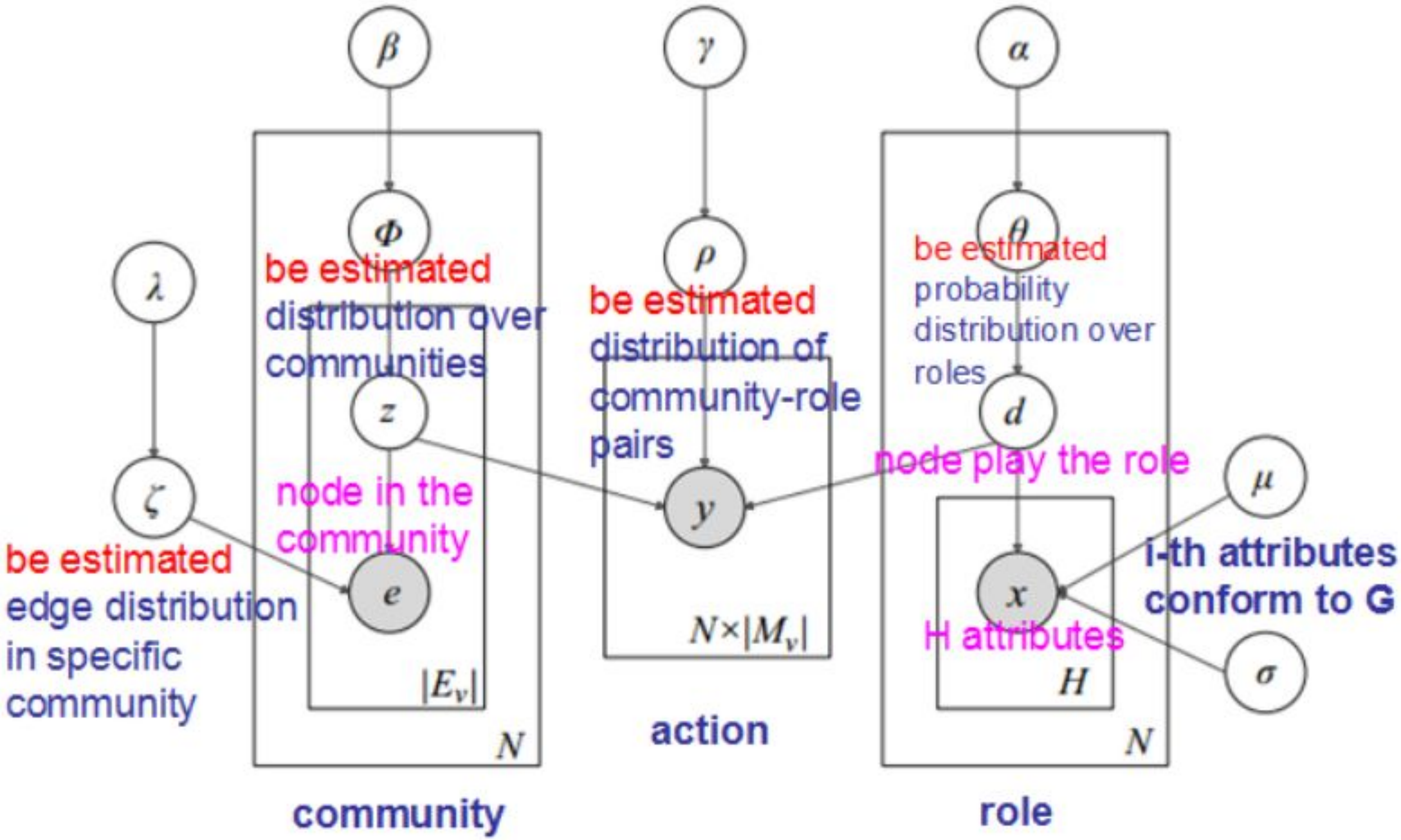
- Community



which probability is higher ?

Each node may belong to several communities,and whether it has a link to other nodes might depend on the communities to which it belongs. Thus we assume that each node has **a distribution over the communities**

- Role
  - Each node has many attributes . we can classify the node into clusters,and each cluster can be regarded as a role that nodes play.
  - The attributes of each role satisfy a specific distribution such as Gaussian distribution.Each node has a distribution over roles
- Action
  - Most nodes tend to take similar actions with nodes in the same community.
  - Moreover, whether a node takes an action may also depend on the role it plays.
  - Consider the distribution that the node has over both communities and roles



be estimated
distribution over communities
be estimated
distribution of community-role pairs
be estimated
probability distribution over roles
node play the role
node in the community
be estimated
edge distribution in specific community
i-th attributes conform to G
H attributes
community
action
role

Formulation and Define

- Structure of a social network: $G=(V,E,X)$
- Users(nodes): V , $|V|=N$
- Edges: E ,an $N*N$ matrix,with each element $e_{v,u}=0$ or 1 indicating whether user vhas a link to user u.
- The set of edges that associate with v :
- Notation X : $N * H$, H is the number of all attributes

and element $x_h^{(v)} \in X$ denotes the h-th attribute of user v E_v

- **Community**:A social network consists of multiple communities, denoted as c = [1,2,...,C].Each community has a multinomial distribution over all pair (u,v),denoted as ς .in communityc, subject to $\sum_{v,u} \varsigma_{u,v}{}^{(c)} = 1$

- **Node Distribution over Communities**: $\phi_c^{(v)}$ denotes the probability for v to be located in c.and is subject to

$$\sum_c \phi_c^{(v)} = 1$$

- **Role:** a node may play multiple different roles, denotes as r=[1,2,...,R],Each role has a set of parameters for the distribution the attributes conform to. Here we use Gussian distribution. if a node plays role r,its h-th attribute conforms to $N(u_{r,h}, \sigma^2_{r,h})$

- Nodes Distribution over Roles:each node has a multinominal distribution over roles, which is denoted as θ , $\theta_r^{(v)}$:the probability for v to play role r and is subject to $\sum_r \theta_r^{(v)} = 1$
- Action: For different kinds of social networks ,actions take different forms. $y_m^{(v)}$ denote a repost action of user v.and set t=0 as the start point.During time period [0,T],there are M messages posted by the user that v follows. $y_m^{(v)} = 0$ or 1 to denote whether v reposts the m-th message during a reasonable time period [0,T'].
- Community-Role Pair:whether a node would take an action depends on the communities and the role it play.

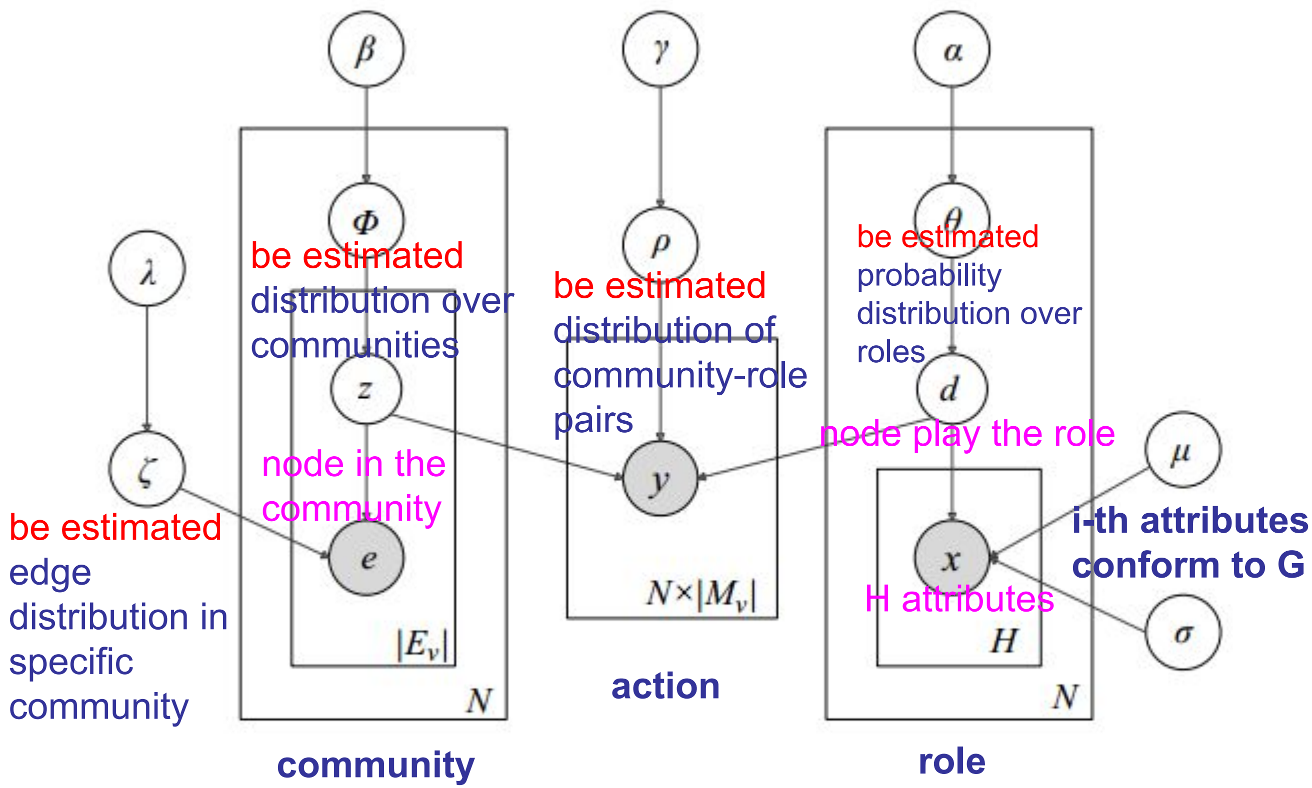
  ρ :the distribution of community-role pairs over action.

  $\rho^{\tau,r}$:the probability for $y_m = 1$,where τ=1($c_u \neq c_v$).

  that the "community" in "community-role pair" represents whether the node and its target belong to the same community

Model Description

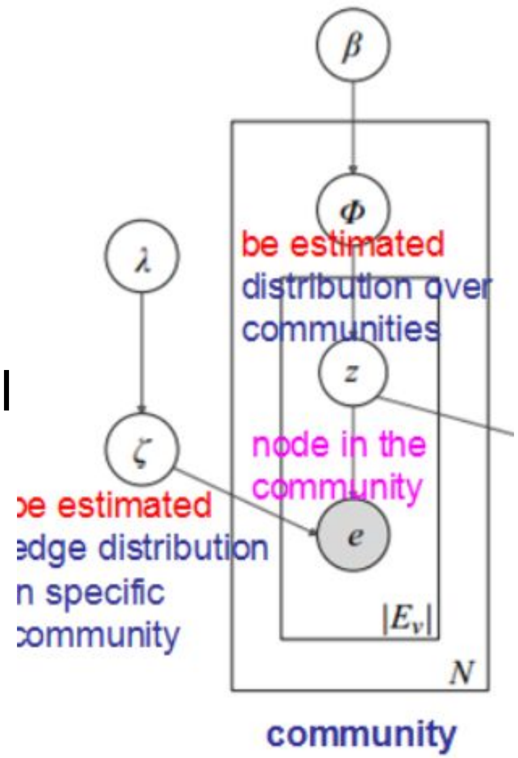
- Goal:devise a probabilistic generative model, CRM, to represent a social network
- CRM assumes that a social network can be generated through three processes,every process based on edges,node attributes, and actions



Edge

For each node v in graph:

1. Draw ς from Dirichlet(λ);
2. Draw a ϕ_v from Dirichlet(β) prior;
3. For each edge $e_{v,i}$
   - Draw a community $z_{v,i} = c$ from multinomial distribution
   - Draw an edge $e_{v,i}$ from a multinomial $\varsigma^{(c)}$ specific to community c.



The distribution of the edge E is as:

$$p(E|\beta,\lambda) = \int p(\zeta|\lambda) \prod_v \int p(\phi_v|\beta) \cdot \prod_{|E_v|} \sum_{z_{v,i}} p(z_{v,i}|\phi_v) p(e_v|z_{v,i},\zeta) d\phi_v d\zeta. \quad (1)$$

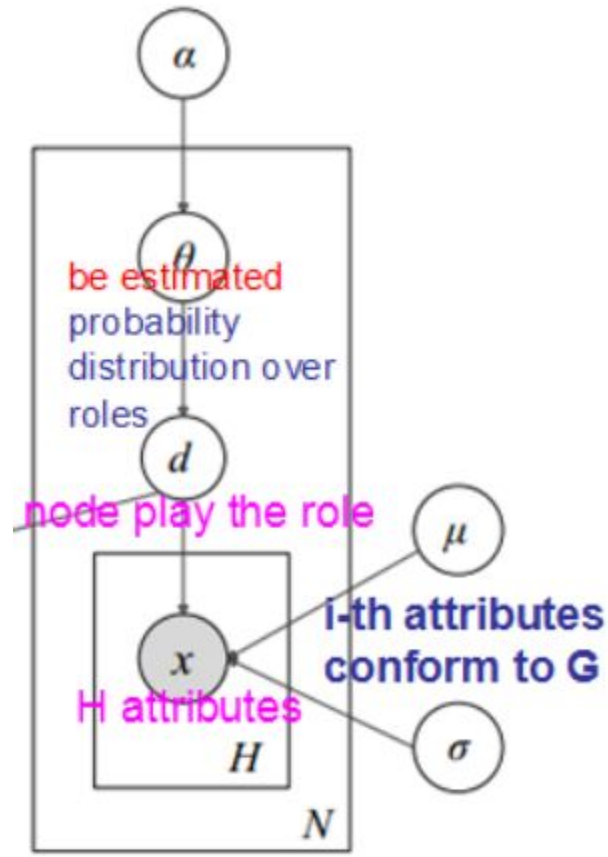
Node

For **each node** v in graph:

1. Draw θ_v from Dirichlet(α) prior;
2. Draw a role $d_v = r$ from multinomial distribution θ_v
3. For each attribute of v, draw a value $x_h^{(r)} \sim G(u_{r,h}, \sigma_{r,h}^2)$

The joint distribution of attributes X is defined as :

$$p(X|\alpha,\mu,\sigma) = \prod_v \int p(\theta_v|\alpha) \cdot \sum_{d_v} p(d_v|\theta_v) \prod_h p(x_h^{(v)}|d_v,\mu_{r,k},\sigma_{r,k}) d\theta_v . \quad (2)$$

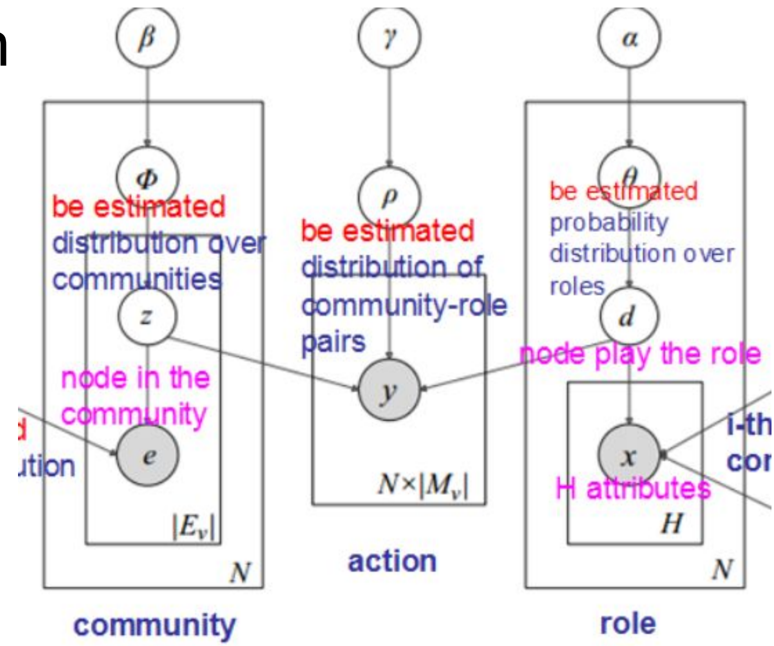


role

Actions

1. Draw ρ from Dirichlet(γ) prior;
2. Draw a community c_v for v from ϕ_v ;
3. Draw a community c_u for u, which post the message m,from ϕ_u
4. Draw a role r form θ_v ;
5. Draw $y_m \sim Bernoulli(\rho^{\tau,r})$

The joint distribution fo actions Y is defined as:



$$p(Y|\gamma,\phi,\theta) = \int p(\rho_{\tau,r}) \prod_v \sum_\tau \sum_r p(r|\theta_v)p(\tau|\phi_v)p(y_m^{(v)}|\rho_{\tau,r})d\rho_{\tau,r}. \quad (3)$$

Inference and Parameters Estimation

- Using Gibbs sampling to estimate ς and ϕ
- The posterior probability of $z_{v,i}$ is calculated by

$$p(z_{v,i} = c|\mathbf{z}_{-v,-i}, E) \propto \frac{n_{-v,-i,c}^{(v)} + \beta}{|E_v| + |C|\beta} \frac{n_{-v,-i,c}^{(e)} + \lambda}{n_{-v,-i,\cdot}^{(e)} + |E|\lambda}. \quad (4)$$

- Parameters ς and ϕ can be estimated by:

$$\phi_{v,c} = \frac{n_{v,c} + \beta}{|E_v| + |C|\beta}, \quad (5)$$

$$\zeta_{c,e} = \frac{n_{c,e} + \lambda}{n_c + |E|\lambda}. \quad (6)$$

- The likehood of X can be written as:

$$\mathcal{L} = \prod_{v} \prod_{h} \sum_{d_v} \frac{\theta_{v,r}}{\sqrt{2\pi}\sigma_{r,h}} e^{-\frac{(x_{v,h}-\mu_{r,h})^2}{2\sigma_{r,h}^2}}. \qquad (7)$$

- E-step,estimate the h-th item of θ given the current parameters by:

$$\theta_{v,r} = \frac{\prod_h (2\pi)^{-\frac{1}{2}} \sigma_{r,h}^{-1} e^{-\frac{(x_{v,h}-\mu_{r,h})^2}{2\sigma_{r,h}^2}}}{\sum_{d_v} \prod_h (2\pi)^{-\frac{1}{2}} \sigma_{r,h}^{-1} e^{-\frac{(x_{v,h}-\mu_{r,h})^2}{2\sigma_{r,h}^2}}}. \qquad (8)$$

- M-step,update parameters u and σ

$$\mu_{r,h} = \frac{\sum_v \theta_{v,r} x_{v,h}}{\sum_v \theta v, r},$$

$$\sigma_{r,h} = \sqrt{\frac{\sum_v \theta_{v,r}(x_{v,h} - \mu_{r,h})^2}{\sum_v \theta_{v,r}}}.$$

- Only need to estimate ρ ,because θ and ϕ have been estimated.

$$p(a_v = \tau, d_v = r | a_{-v}, r_{-v}, \mathbf{y}) \propto (\phi_v \phi_v^T) \theta_v \frac{n_{-v,-m,\tau,r} + \gamma}{|M| + 2|H|\gamma}. \tag{11}$$

- And parameters can be estimated by :

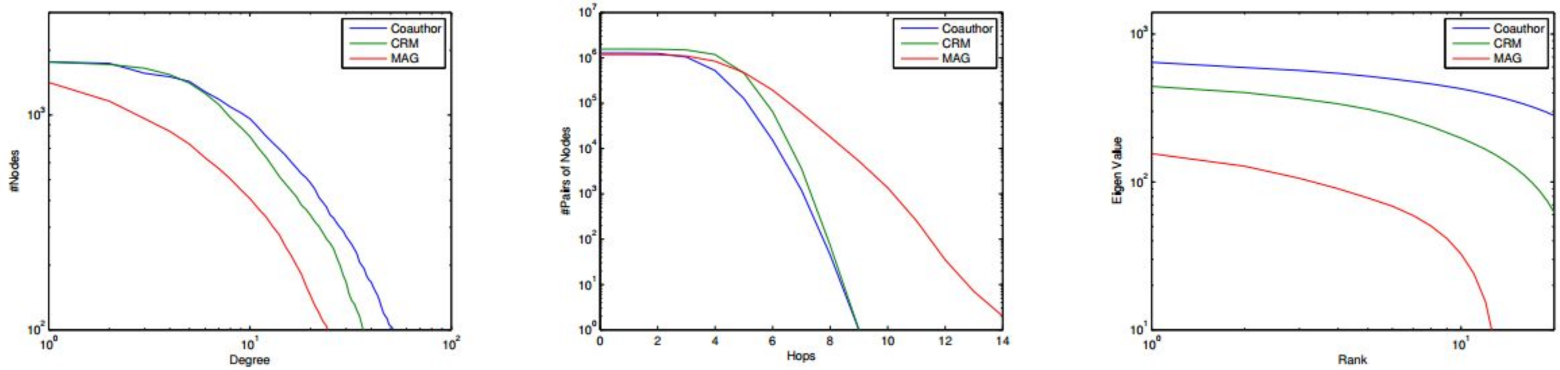
$$\rho = \frac{n_{v,m,\tau,r} + \gamma}{|M| + 2|H|\gamma}. \tag{12}$$

Experiments

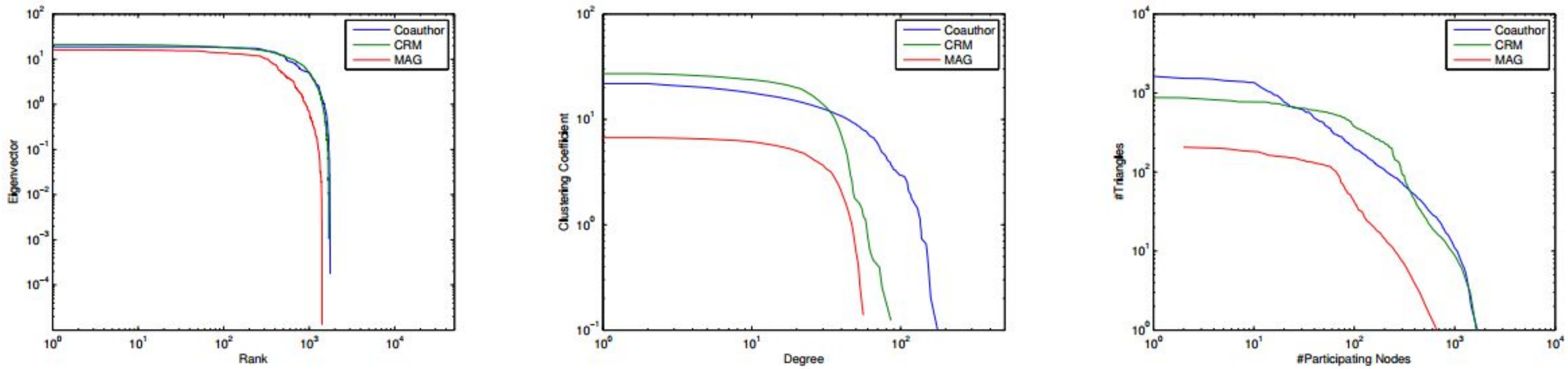
- Parameters ς represent communities discovered by CRM
- Parameters ρ can be used to predict user's actions
- Structure recovery.

Structure recovery

- Comparing with real data, MAG[1].



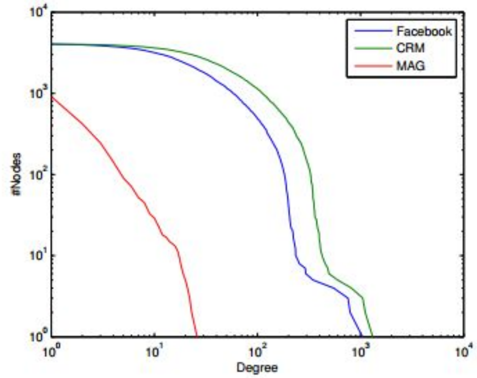
(a) Degree (b) Pairs of Nodes (c) Eigenvalues



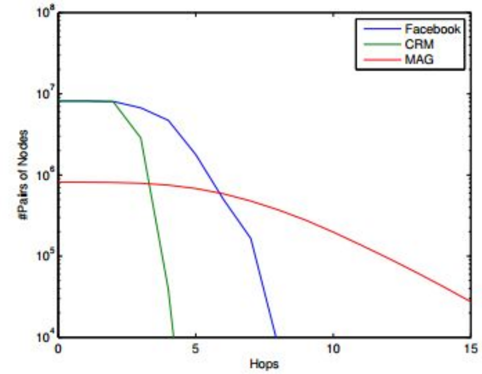
(d) Eigenvector (e) Clustering Coefficient (f) Triangle Participation Ratio

Metric values of the Coauthor network and the two networks generated by CRM and MAG.CRM outperforms MAG for every metric

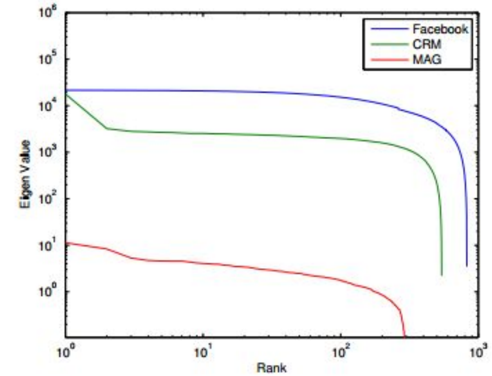
1.M. Kim and J. Leskovec. Modeling social networks with node attributes using the multiplicative attribute graph model. arXiv preprint arXiv:1106.5053, 2011



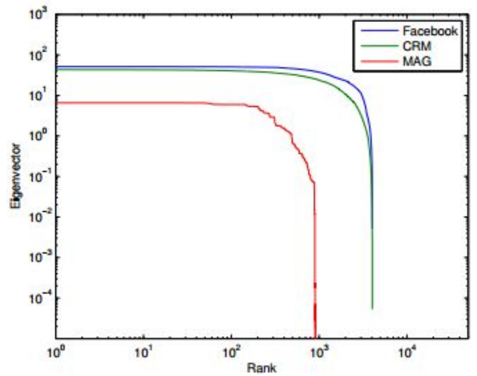
(a) Degree



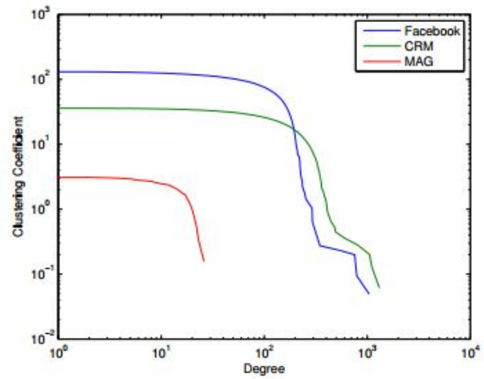
(b) Pairs of Nodes



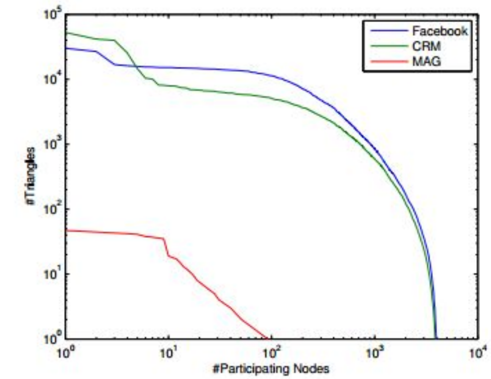
(c) Eigenvalues



(d) Eigenvector



(e) Clustering Coefficient



(f) Triangle Participation Ratio

Metric values of the Facebook network and the two networks generated by CRM and MAG.CRM outperforms MAG for every metric

Behavior Prediction

Classifies users into three roles:opinion leader, structrual hole spanner, and ordinary users.Whether a user reposts a message greatly depends on the role it plays(ρ :a node would take an action depends on the communities and the role it play. action mean that a reposted action of a node).

Date set	Method	Precision	Recall	F1-measure	AUC
Coauthor	SVM	**0.8838(0.1725)**	0.5562(0.3183)	0.6827(0.2054)	0.7360(0.1111)
	SMO	0.8647(0.1218)	0.8142(0.1260)	0.8387(0.1138)	0.9218(0.0366)
	LR	0.8668(0.1242)	0.8292(0.1022)	0.8476(0.1016)	0.9642(0.0196)
	NB	0.8183(0.1830)	0.8115(0.1444)	0.8149(0.1549)	0.9417(0.0335)
	RBF	0.8552(0.1058)	0.8353(0.1165)	0.8451(0.1081)	0.9477(0.0271)
	C4.5	0.8328(0.0518)	0.8015(0.1286)	0.8169(0.1478)	0.9065(0.1165)
	CRM	0.8562(0.1490)	**0.8630(0.0598)**	**0.8596(0.1013)**	**0.9800(0.0199)**
Weibo	SVM	0.5067(0.1405)	0.5027(0.1185)	0.5047(0.1150)	0.6068(0.1113)
	SMO	0.5074(0.1464)	0.5209(0.1099)	0.5141(0.1271)	0.6145(0.0363)
	LR	0.5199(0.1306)	0.5469(0.1073)	0.5331(0.1157)	0.6330(0.0377)
	NB	0.5112(0.1245)	0.5692(0.1083)	0.5386(0.1172)	0.6397(0.0394)
	RBF	0.5225(0.1361)	0.4679(0.1117)	0.4937(0.1217)	0.5945(0.0085)
	C4.5	0.5237(0.1367)	0.5322(0.1114)	0.5279(0.1211)	0.6271(0.1083)
	CRM	**0.7017(0.1300)**	**0.7305(0.1079)**	**0.7158(0.1149)**	**0.8174(0.0233)**

Average prediction performance of different methods on the Coauthor and Weibo detasets.The numbers enclosed in brackets are standard deviations

Behavior Prediction

CRM achieves much better performance than other methods.

Data Sets	Precision	Recall	F1-measure	AUC
Coauthor	0.37%	13.76%	7.04%	9.45%
Weibo	36.22%	40.14%	38.14%	32.08%

Improvement shown by CRM over SVM,SMO,LR,NB,RBF,and C4.5 in terms of precision,recall, F1-measure,and AUC

community detection

detect community with parameters ς

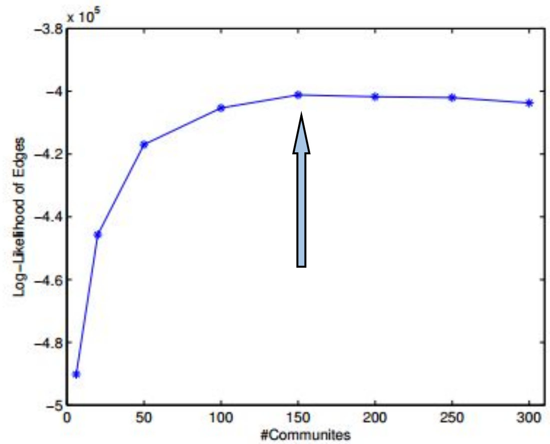
- We must decide the number of communities C before detecting communities with CRM.
- The probability ς of a edge in different communities is different .compute the sums of log-likelihood for edges and action with :

$$\mathcal{L}(edges) = \sum_{i=1}^{|E|} \ln p(e_i), \tag{13}$$

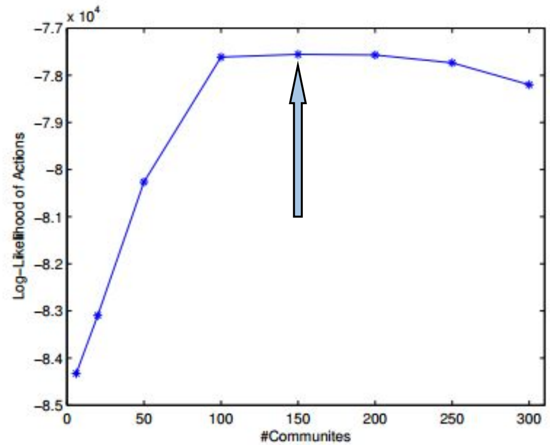
$$\mathcal{L}(actions) = \sum_{i=1}^{|Y|} \ln p(y_i). \tag{14}$$

❖ c=150 may be the best choice .

❖ Through the training of the model,we obtain the community distribution over node



(a) Sum of log-likelihood of edges changes with C



(b) Sum of log-likelihood of actions changes with C

conclusion

- Know how to model a social network through many samples,capturing its information,including structure recovery ,behavior prediction
- Applying CRM to real-world datasets,and obtain better performance .

the end , thanks