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Role-aware Conformity Influence Modeling and Analysis in Social Networks

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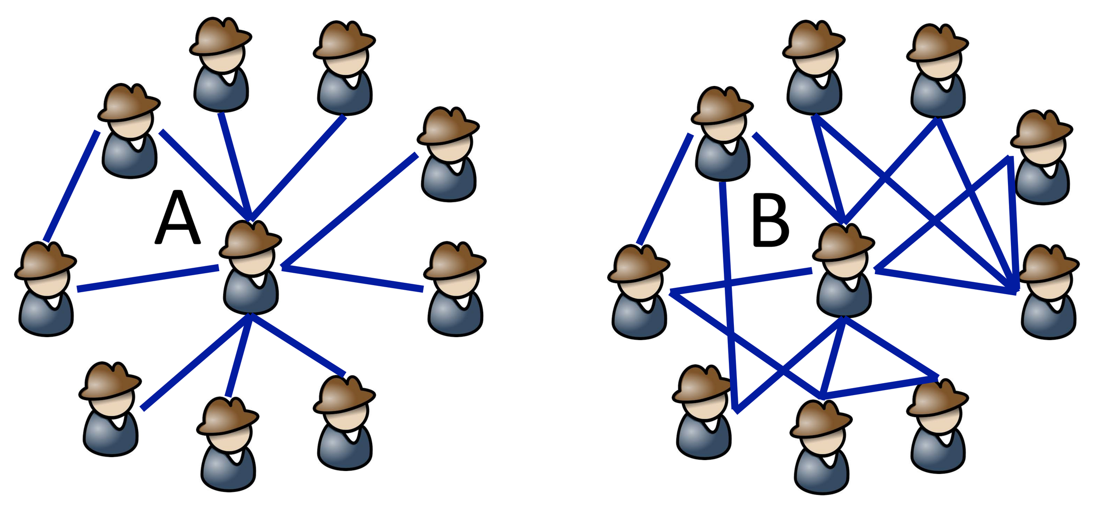
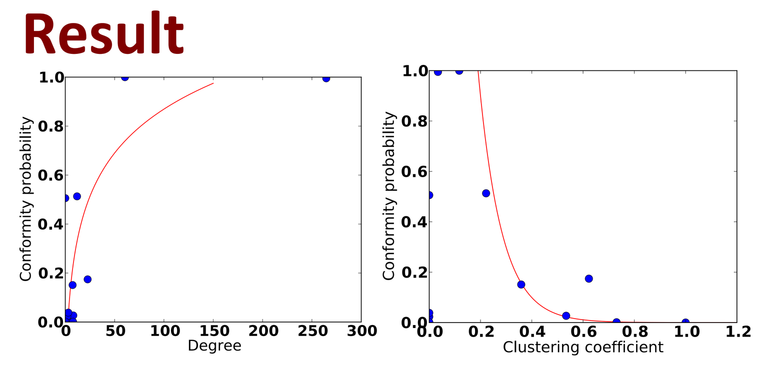
1. Problem



Question: Who is more likely to conform to others, A or B?

Result



The persons with higher degree and lower clustering coefficient are more likely to conform to others.

2. Prediction

- Data Set: We select eight domains from computer science, and collect papers (title, authors, citation relationships) from the well-known journals/conferences in the domain. 231,728 papers, 269,508 authors, and 347,735 citations.
- Prediction Task: predict whether a user will write a given word in her paper title in a given time period.
- Baseline Methods:
  - PLSA : ignore conformity tendency.
  - CIM : conformity tendency is learned for each person.
  - RCM(our method): conformity tendency is learned for each role.

Method	P@5	MAP	AUC
PLSA	17.49	8.49	78.85
CTM	21.75	11.31	85.13
RCM	24.36	12.07	85.95

3. Formalize Conformity Influence

Conformity Theory [Bernheim 1994]

- Everyone in a group express her own individuality.
- Yet, even individualists pursue somewhat for status (esteem or popularity) and change their choices toward the social norm.

Utility Function

Intrinsic utility + conformity utility

$$f(y_i) = (1-\lambda_i)\, d(y_i, \hat{y}_i) + \lambda_i \sum_{j \in N(i)} d(y_i, y_j)$$

- y_i : a binary value to represent whether a user v_i adopts an action or not.
- $\hat{y}_i$: the intrinsic preferred selection of user v_i.
- N(i) : neighbors of v_i at the time when v_i makes the decision.
- d(.,.) : a metric that gives a utility of 1 when two decisions are the same, and 0 otherwise.
- λ_i : the conformity tendency of user v_i.

Nash Equilibria

There exists Nash equilibria if all users in a network make the decisions for a given action according to the utility function.

Proof:

1. When there is only one user in a network, the proof is straightforward.
2. When there are two users in a network,
   - If their intrinsic preferences are the same, a Nash equilibrium exists because they will make the same decision.
   - If their intrinsic preferences are different, λ determines the final selection.
     - λ < 0.5 , a Nash equilibrium exists because they will select their own preferences respectively.
     - λ > 0.5 , two Nash equilibria exist because they will both select the intrinsic preference $\hat{y}_1$ or $\hat{y}_2$.
3. We use induction method to prove if a Nash equilibrium exists in a k-network, a Nash equilibrium will definitely exist in any (k+1)-network.
   - The general idea is to investigate whether the neighbors of v_{k+1} will change their decisions when v_{k+1} joined a k-network that has already arrived at a Nash equilibrium.

4. Measure Conformity Influence

Utility Function Extension

- To solve data sparsity problem in real applications, we extend the utility function by incorporating role and topic.
  - **Role r** : Conformity tendency is different for persons with different roles.
  - **Topic z** : Conformity tendency is different on actions with different topics.
  - Binary action y_i is extended to a set of actions {w}.
- When in role r, the utility function of v_i taking an action w is :

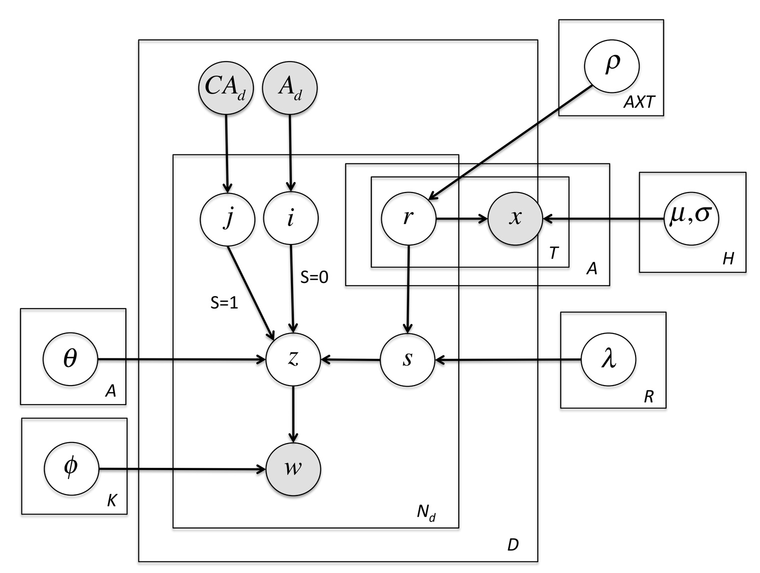
Intrinsic utility + conformity utility

$$\gamma_{i,r}^{w} = \left[(1-\lambda_r) \sum_{z=1}^{K} \theta_i^z \phi_z^w + \lambda_r \frac{1}{|N_i|} \sum_{j \in N_i} \sum_{z=1}^{K} \theta_j^z \phi_z^w \right]$$

- θ_i^z : the probability of user v_i choosing topic z.
- ϕ_z^w : the probability of taking action w under topic z.
- λ_r : the conformity tendency of role r.

Model Intuition

- The first part models the generation of individual attributes **x**.
  - For an attribute, we first draw a role from a multinomial distribution, and then draw x from a normal distribution with respect to r.



- The second part models the total utility of generating all the actions **w**.
  - For an action, we first toss a coin s with distribution Bern(λ_r). Then, if s = 1, w is determined by individual's intrinsic topic distribution. Otherwise, w is influenced by the neighbors' topic distributions.

Model Learning

- To estimate λ_r , i.e., the conformity over role.
- By maximizing the likelihood of generating both the individual attributes and the actions.

$$\mathcal{L}_1 = \prod_{i=1}^{A} \prod_{t=1}^{T} \prod_{h=1}^{H} \sum_{r=1}^{R} \frac{\rho_{i,t}^r}{\sqrt{2\pi\sigma_{r,h}^2}} \exp\left[-\frac{(x_{i,t,h} - \mu_{r,h})^2}{2\sigma_{r,h}^2} \right] \quad \mathcal{L}_2 = \prod_{d,w} \sum_{i \in A_d} \frac{\sum_{r=1}^{R} \rho_{i,t}^r \gamma_{r,i}^w}{|A_d|}$$

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