Uncovering Groups via Heterogeneous Interaction Analysis

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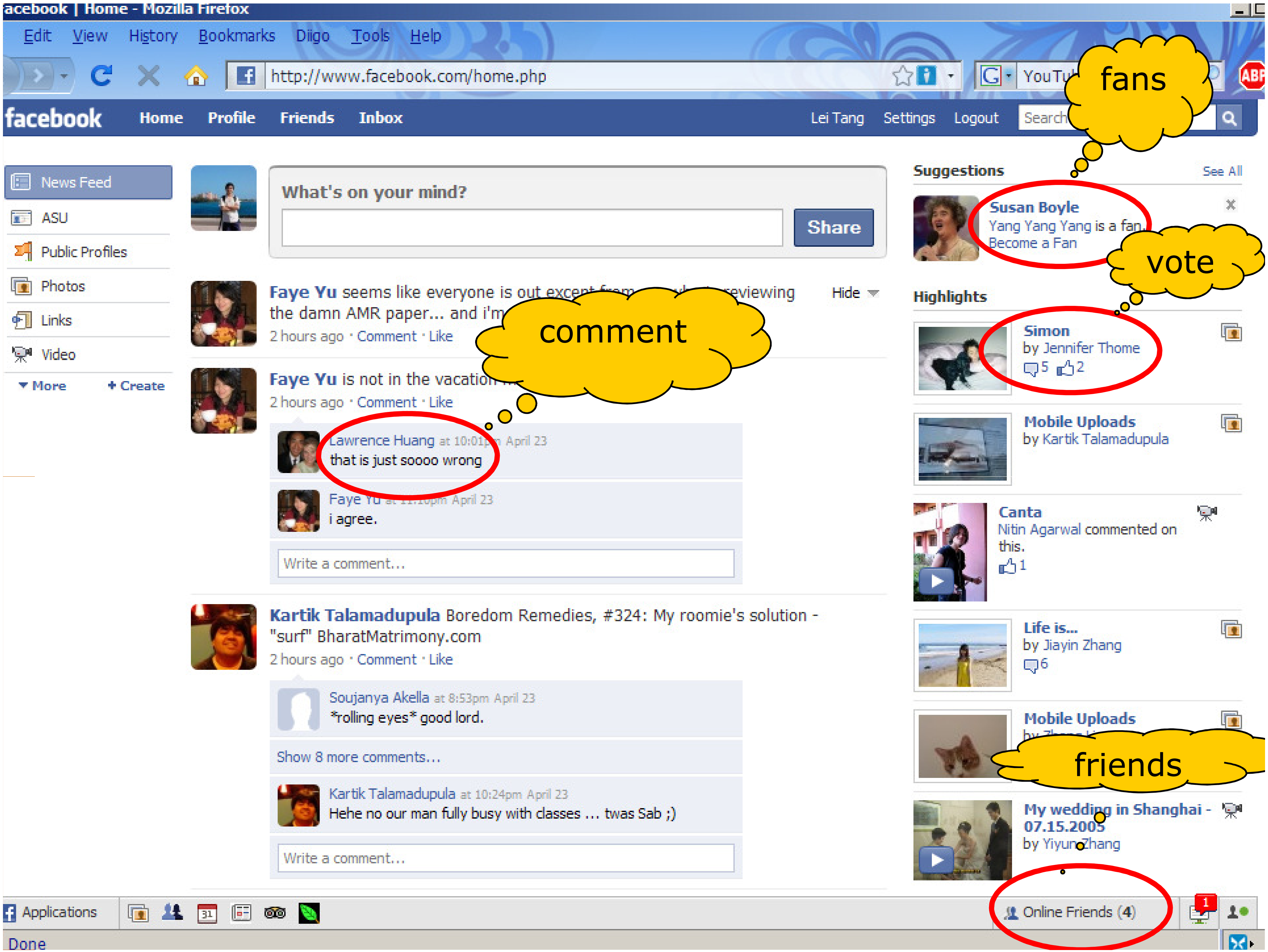

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Applications
Online Friends (4)
Done

Multi-Dimensional Network

- Different behaviors lead to heterogeneous Interactions

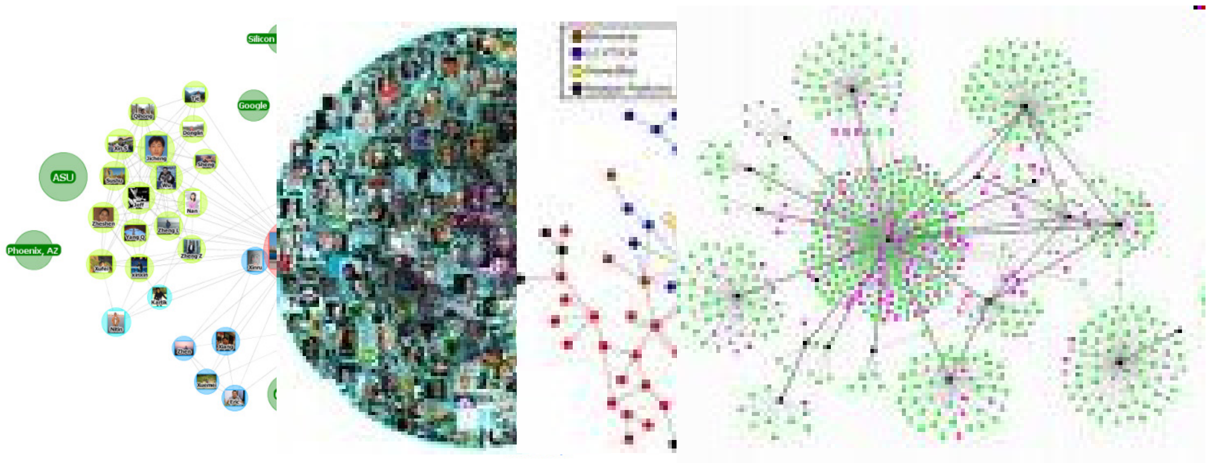
Contacts/friends

Tagging on Social Content

Fans/Subscriptions

Response to Social Content

…………………



Network of Multiple Dimensions

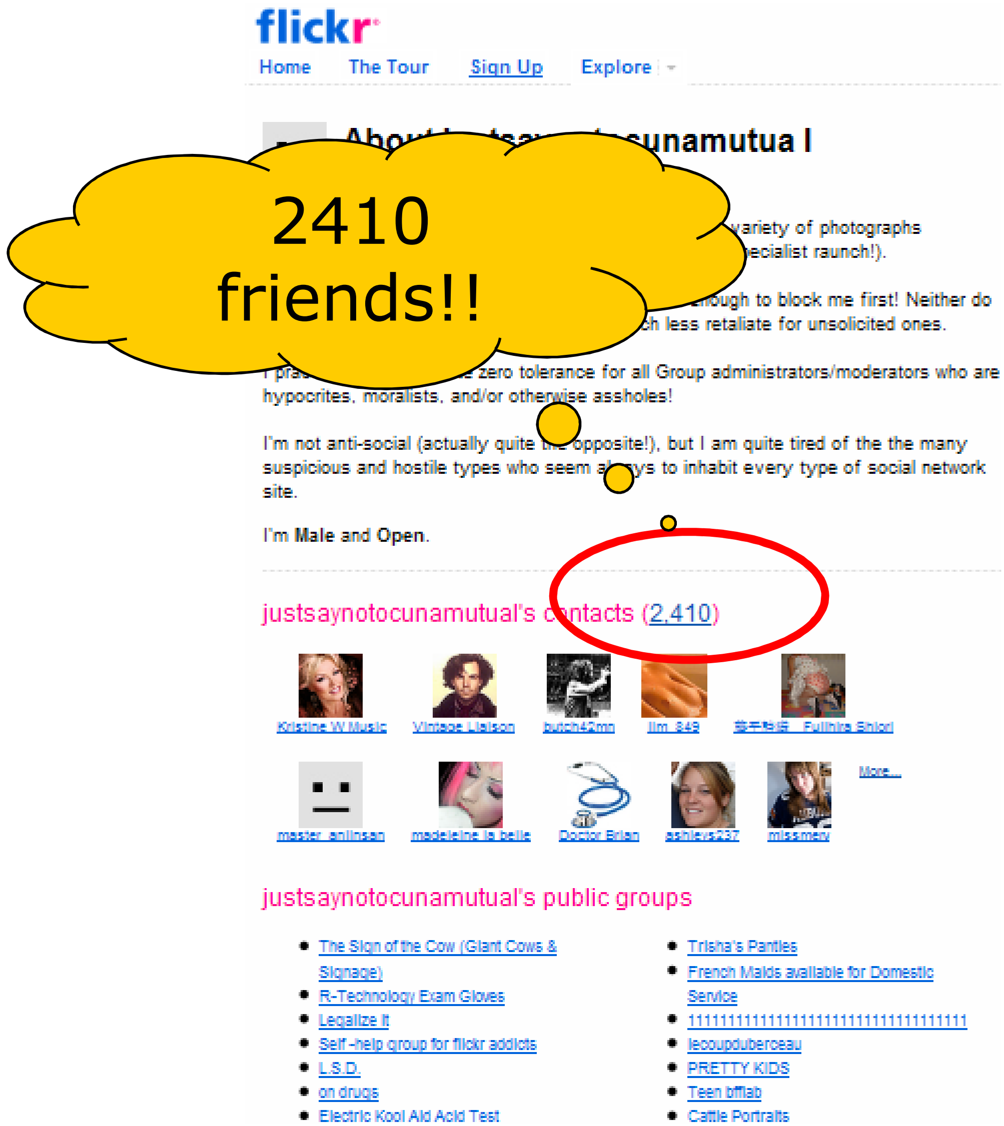
Heterogeneous Interaction Analysis

- A latent community structure is shared in a multi-dimensional network
  - E.g. a group sharing similar interest

- Goal: *Find out the shared community structure by integrating the interactions at different dimensions*

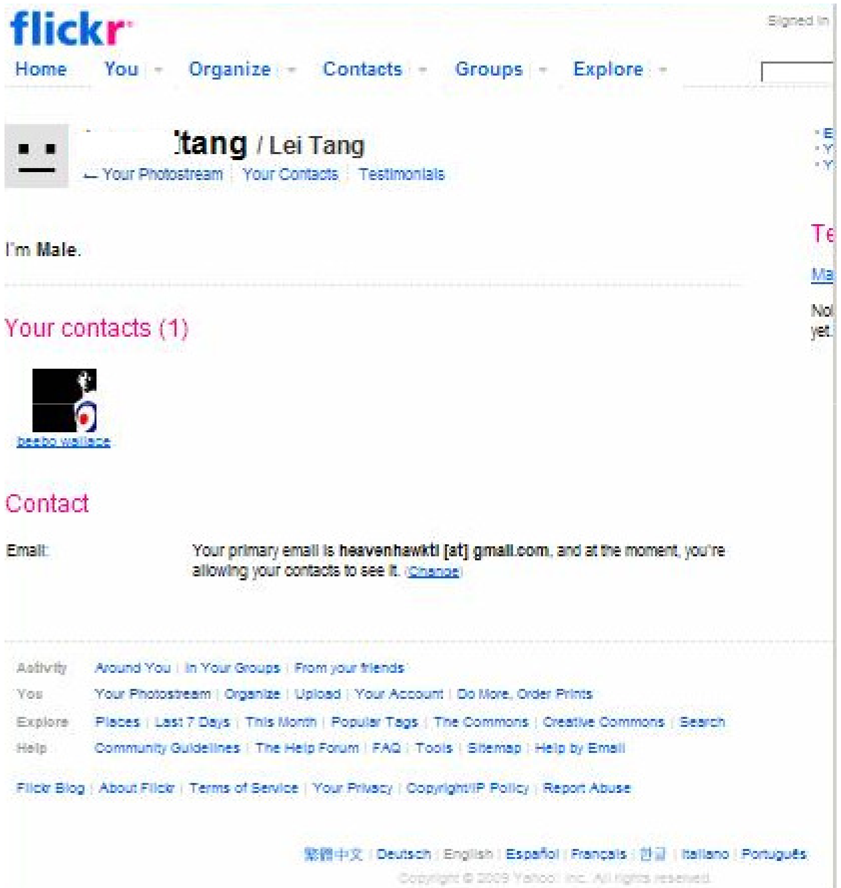
Why not just friends network?

- Too many friends?



Why not just friends network?

- Too many friends?
- Too few friends?
- Friends network tells limited info for some users
- Interaction at other dimensions might help



Recap of Modularity

- **Modularity**: A measure that compares the within group interaction with uniform random graph *with the same node degree distribution*

- In a network of m edges, for two nodes with degree d_i and d_j, respectively, the expected number of edges between them:

$$d_i d_j / 2m$$

- The connection strength in a group: $\sum_{i \in C, j \in C} A_{ij} - d_i d_j / 2m$

- To partition the network into multiple groups, we maximize

$$\frac{1}{2m} \sum_{C} \sum_{i \in C, j \in C} A_{ij} - d_i d_j / 2m$$

Modularity Matrix

- Modularity can be formulated in a matrix form

$$Q = \frac{1}{2m} Tr(S^T B S)$$

- B is the modularity matrix

$$B_{ij} = A_{ij} - d_i d_j / 2m$$

- With spectral relaxation, S corresponds to the top eigenvectors of the modularity matrix B

Modularity in M-D Networks

- Average Modularity Maximization (AMM)
  - Average the network interaction of different dimensions

$$\bar{A} = \frac{1}{D}(A_1 + A_2 + \cdots + A_D)$$

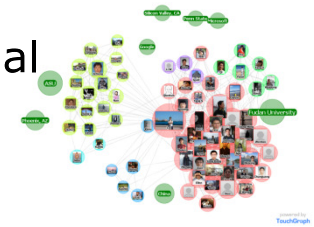
- Total Modularity Maximization (TMM)
  - the total sum of modularity at different dimensions

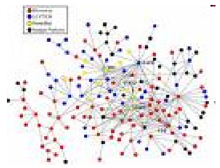
$$\max(Q_1 + Q_2 + \cdots + Q_D)$$

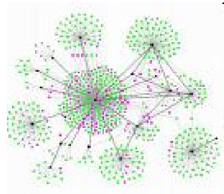
- Potential Cons
  - Not sure whether the interaction or modularity of different dimensions are comparable
  - Can be sensitive to networks of noisy dimensions

Principal Modularity Maximization

Multi-Dimensional Networks







Extract Structural Features via Modularity Maximization

Denoise the interaction at each dimension

- These structural features are not necessarily similar, but are highly correlated.

- Transform these features into a shared space such that their correlation is maximized.

- Solution: Generalized Canonical Correlation Analysis (CCA)

Canonical Correlation Analysis

$$R(i,j) = (S_i w_i)^T (S_j w_j) = w_i^T (S_i^T S_j) w_j = w_i^T C_{ij} w_j$$

$$\max \quad \sum_{i=1}^{d} \sum_{j=1}^{d} w_i^T C_{ij} w_j$$

$$s.t. \quad \sum_{i=1}^{d} w_i^T C_{ii} w_i = 1$$

$\Rightarrow$

$$\begin{bmatrix} C_{11} & C_{12} & \cdots & C_{1d} \\ C_{21} & C_{22} & \cdots & C_{2d} \\ \vdots & \vdots & \ddots & \vdots \\ C_{d1} & C_{d2} & \cdots & C_{dd} \end{bmatrix} \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_d \end{bmatrix} = \lambda \begin{bmatrix} C_{11} & 0 & \cdots & 0 \\ 0 & C_{22} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & C_{dd} \end{bmatrix} \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_d \end{bmatrix}$$

$$C_{11} = S_1^T S_1 = I$$
$$C_{22} = S_2^T S_2 = I$$
....

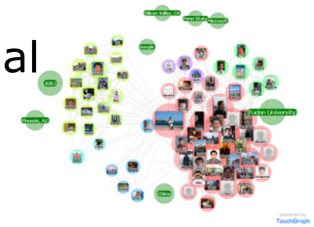
$\Downarrow$

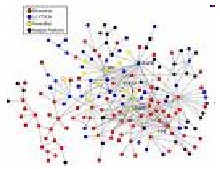
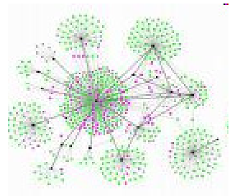
Principal Component Analysis (PCA)

eigvenvector of the covariance matrix

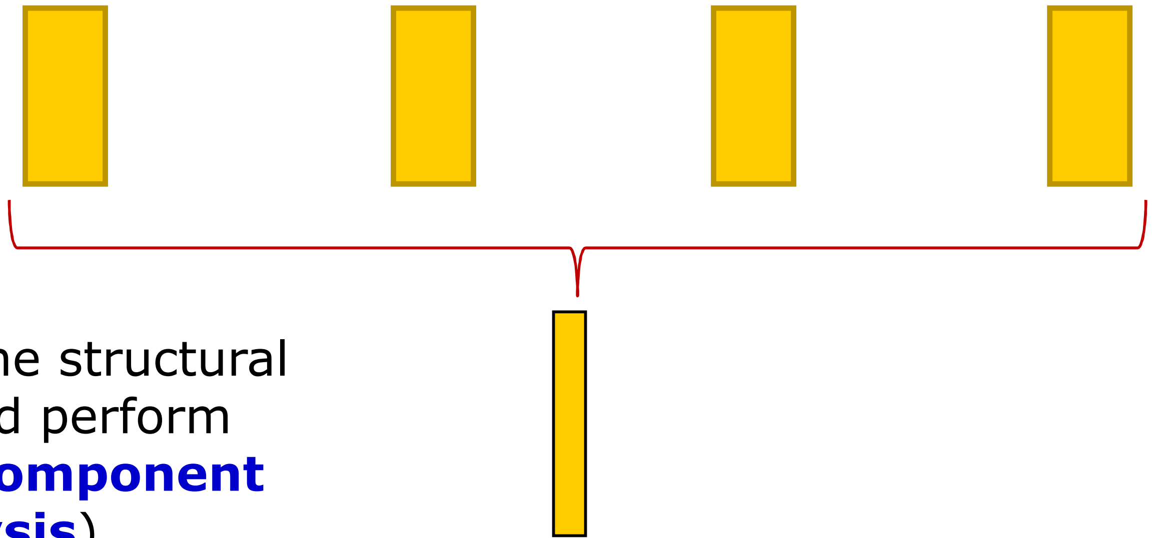
Principal Modularity Maximization

Multi-Dimensional Networks



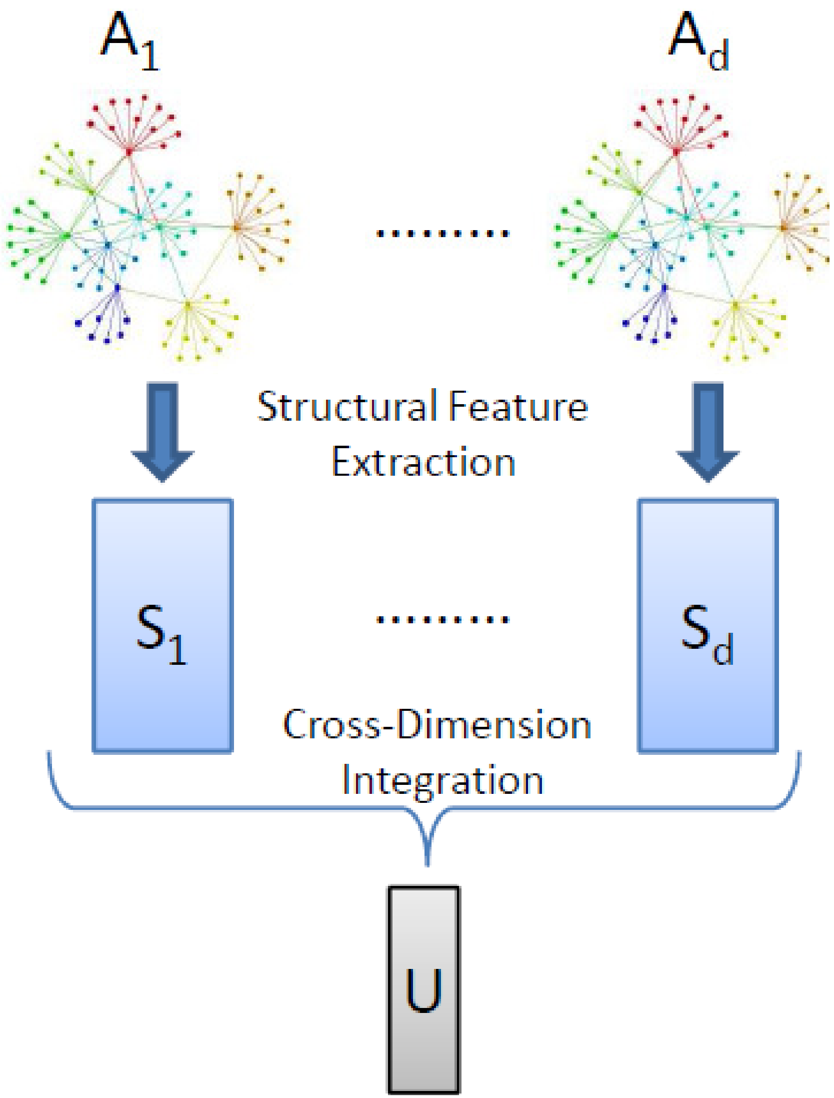



Extract Structural Features via Modularity Maximization



Combine all the structural features and perform **Principal Component Analysis**)

Overview of PMM



PMM Algorithm

- **Given:** a multi-dimensional network
- **Output:** shared group structure

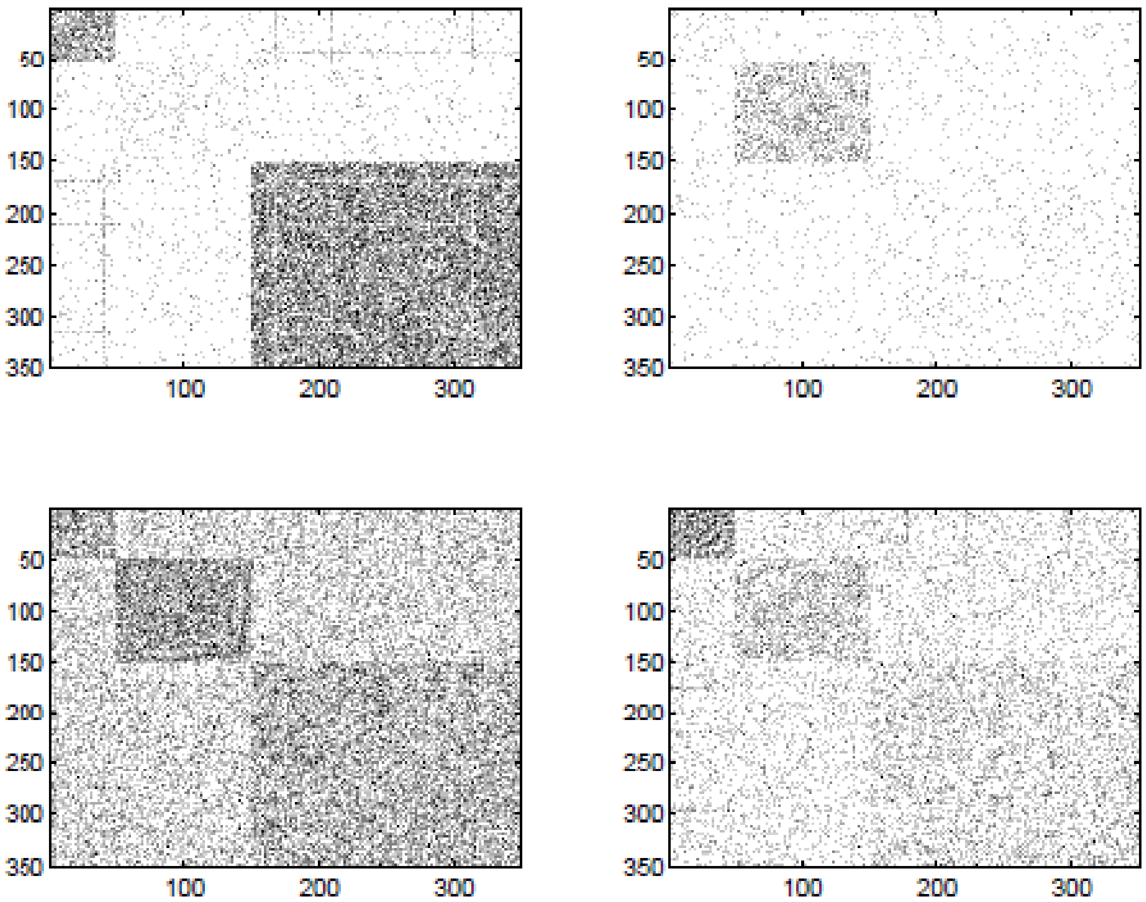
- **Algorithm:**
  - Phase I: Extract structural features from each dimension of the network
  - Phase II: Combine all the extracted features of each dimension and perform PCA
  - Apply K-means to obtain the discrete partition

Experiments

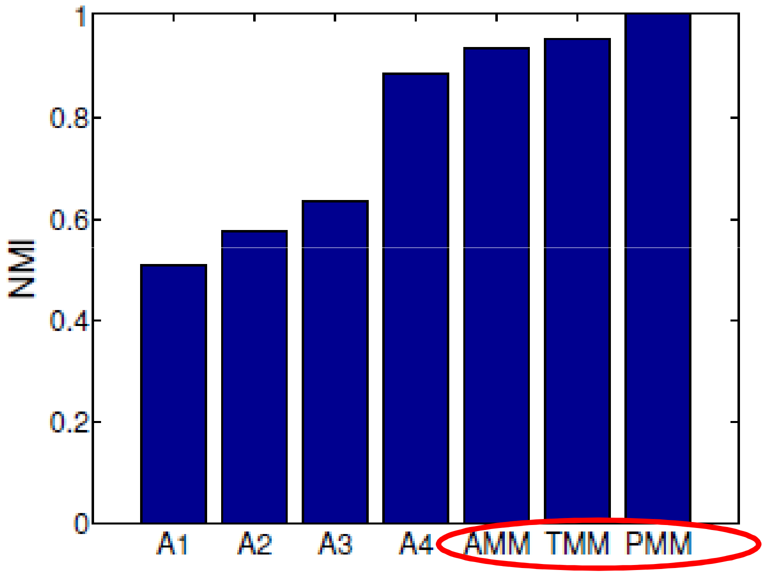
- Compare different community detection strategies
  - AMM, TMM, PMM
  - Modularity maximization on a single dimension
- Verify the sensitivity to noise for different methods
- Data Sets
  - Synthetic Data
    - controlled noise and ground truth information
  - Real-World Data
    - collected from YouTube

Synthetic Data

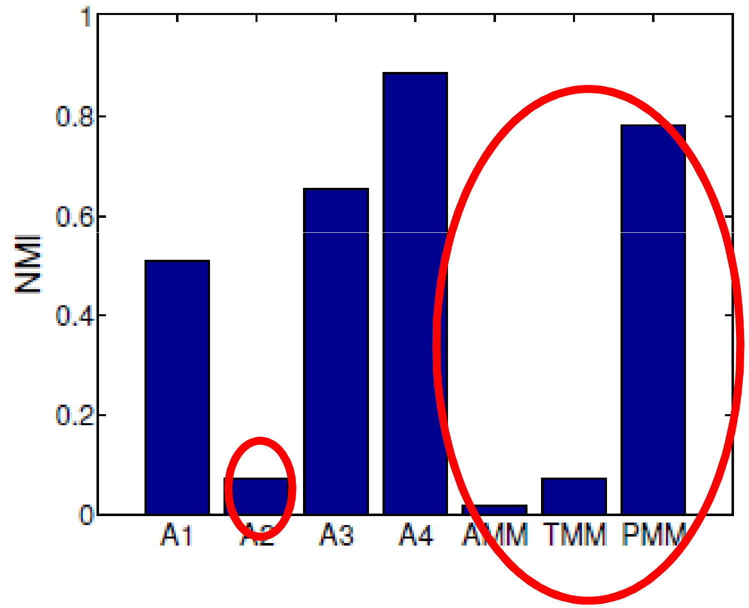
- 4 dimensions, 3 communities
- 50, 100, 150 members respectively



Performance on Synthetic Data



Small Noise



Substantial Noise
in one dimension

Average Performance

Table 1: Average Performance Over 100 Runs

	Strategy	Performance
	A_1	0.7237 ± 0.1924
Single-Dimensional	A_2	0.6798 ± 0.1888
	A_3	0.6672 ± 0.1848
	A_4	0.6906 ± 0.1976
	AMM	0.7946 ± 0.1623
Multi-Dimensional	TMM	0.9157 ± 0.1137
	PMM	$\mathbf{0.9351 \pm 0.1059}$

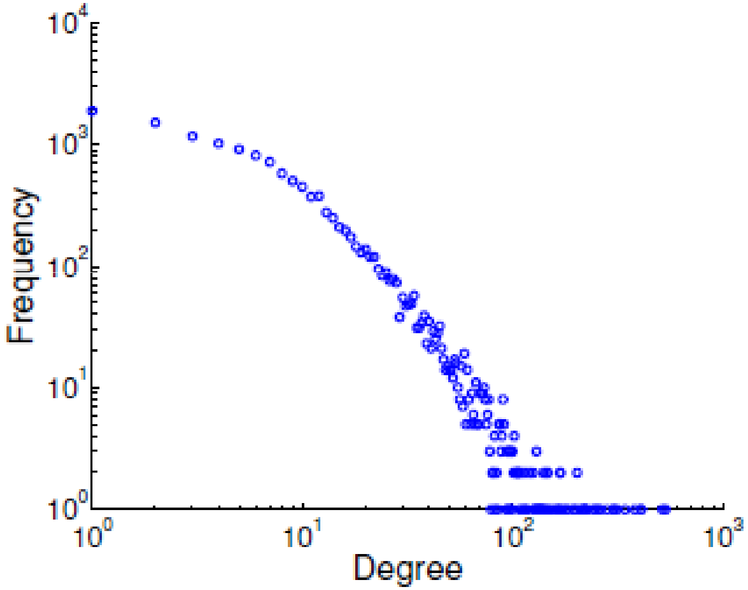
Single < AMM < TMM < PMM

PMM: Low Variance

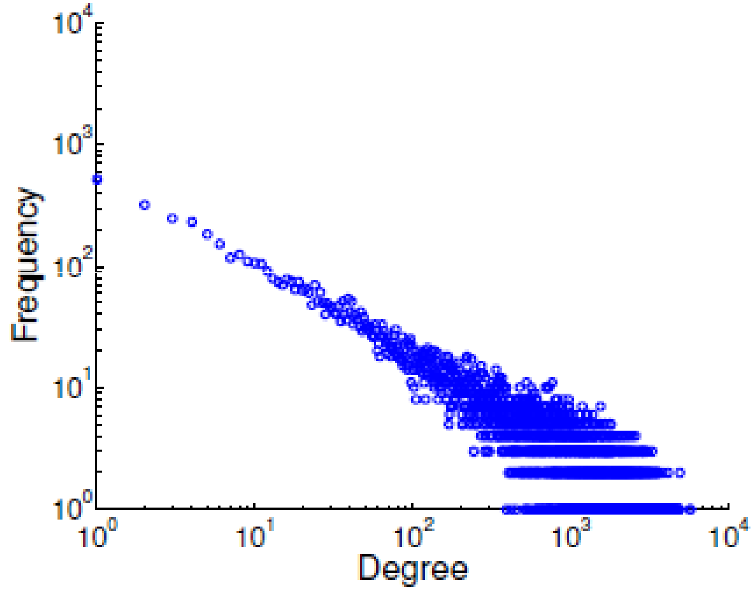
YouTube Data

- Collect contact network, subscription network, and users' favorite videos
- Crawl 30,522 user profiles reaching in total 848,003 users and 1,299, 642 favorite videos
- 15,088 active users
- Construct a 5-dimensional network
  - Contact
  - Share Contacts
  - Share subscription
  - Followed by the same set of people
  - Share favorite videos

Degree Distribution



(a) Contact Network



(b) Favorite Network

Evaluation on Real-World Data

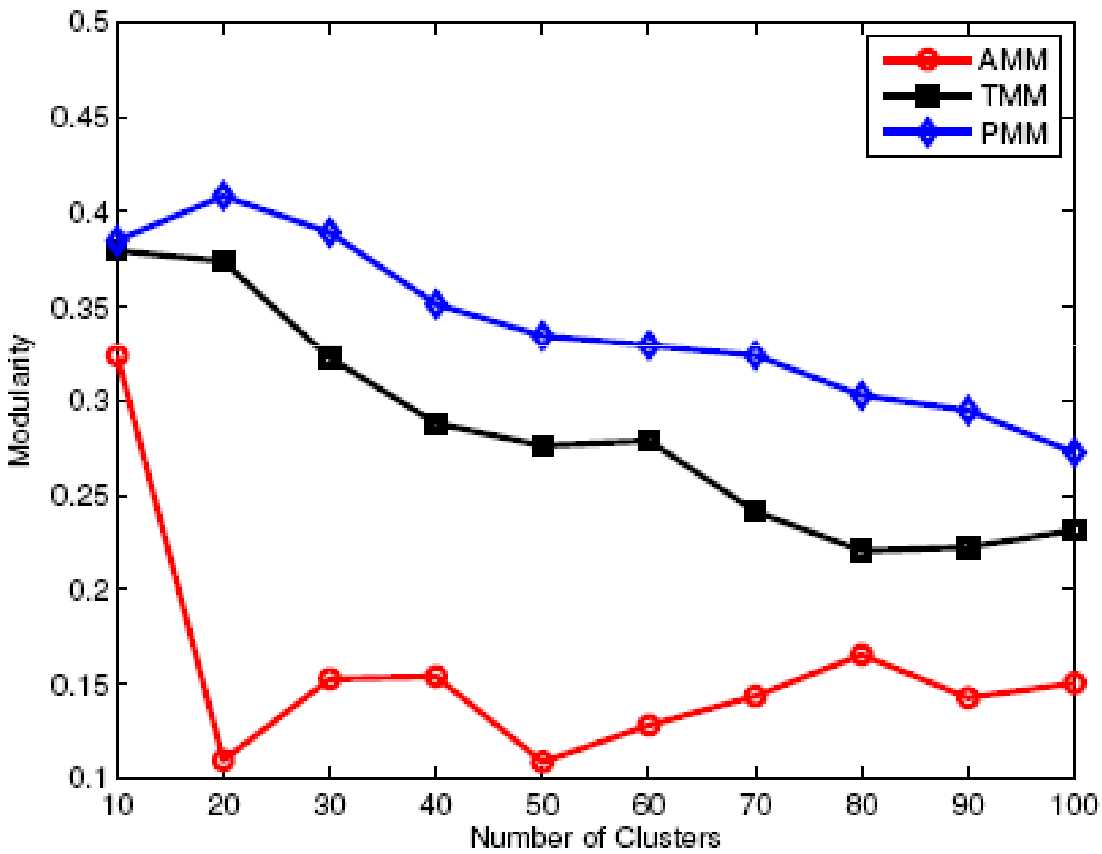
- Challenges
  - No ground truth
  - Need a smart way to do the comparative study
- Evaluation -- Cross Dimension Validation
  - Follow the idea of cross validation
  - For a network of *D* dimensions
    - learn the community structure from (*D-1*) dimensions
    - evaluate it on the remaining dimension in terms of modularity

Performance on YouTube Data

Methods	A_1	A_2	A_3	A_4	A_5
A_1	—	.0007	.0008	.0008	.0002
A_2	.1548	—	.0133	.0361	.0076
A_3	.0712	.0275	—	.0446	.0140
A_4	.0584	.0569	.0186	—	.0108
A_5	.0314	.0135	.0095	.0180	—
AMM	.1096	.0001	.0018	.0053	.0070
TMM	.3740	.1856	.1246	.1800	.0706
PMM	**.4085**	**.2063**	**.1307**	**.1844**	**.0947**

- PMM tends to be the winner

PMM compared with AMM & TMM



AMM < TMM < PMM

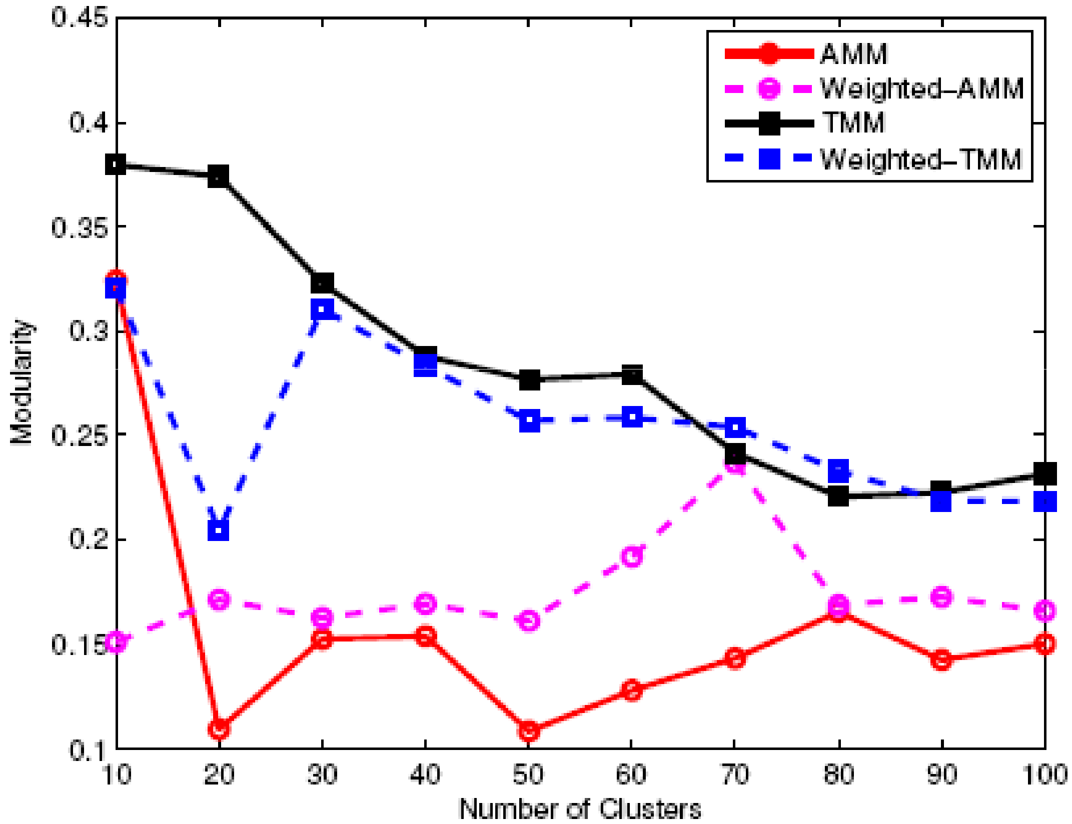
Conclusions & Future Work

- Networks in social media are multi-dimensional and noisy
- Propose an effective Principal Modularity Maximization to extract the shared group structure
  - Extract Structural Features via Modularity Maximization
  - Perform Cross-Dimensional Integration via PCA
- Can be applied similarly to other spectral clustering methods
- Future Work:
  - Determine whether two network dimensions share the same community structure?
  - Need to remove noisy interaction dimensions?
  - One actor assigned to multiple different groups?
  - Scalability?

Acknowledgments

- Thanks to the sponsorship of AFOSR and ONR.

Weighted AMM & TMM



Assigning a proper weight to each dimension is not easy!