UIC

Community Detection for Emerging Networks

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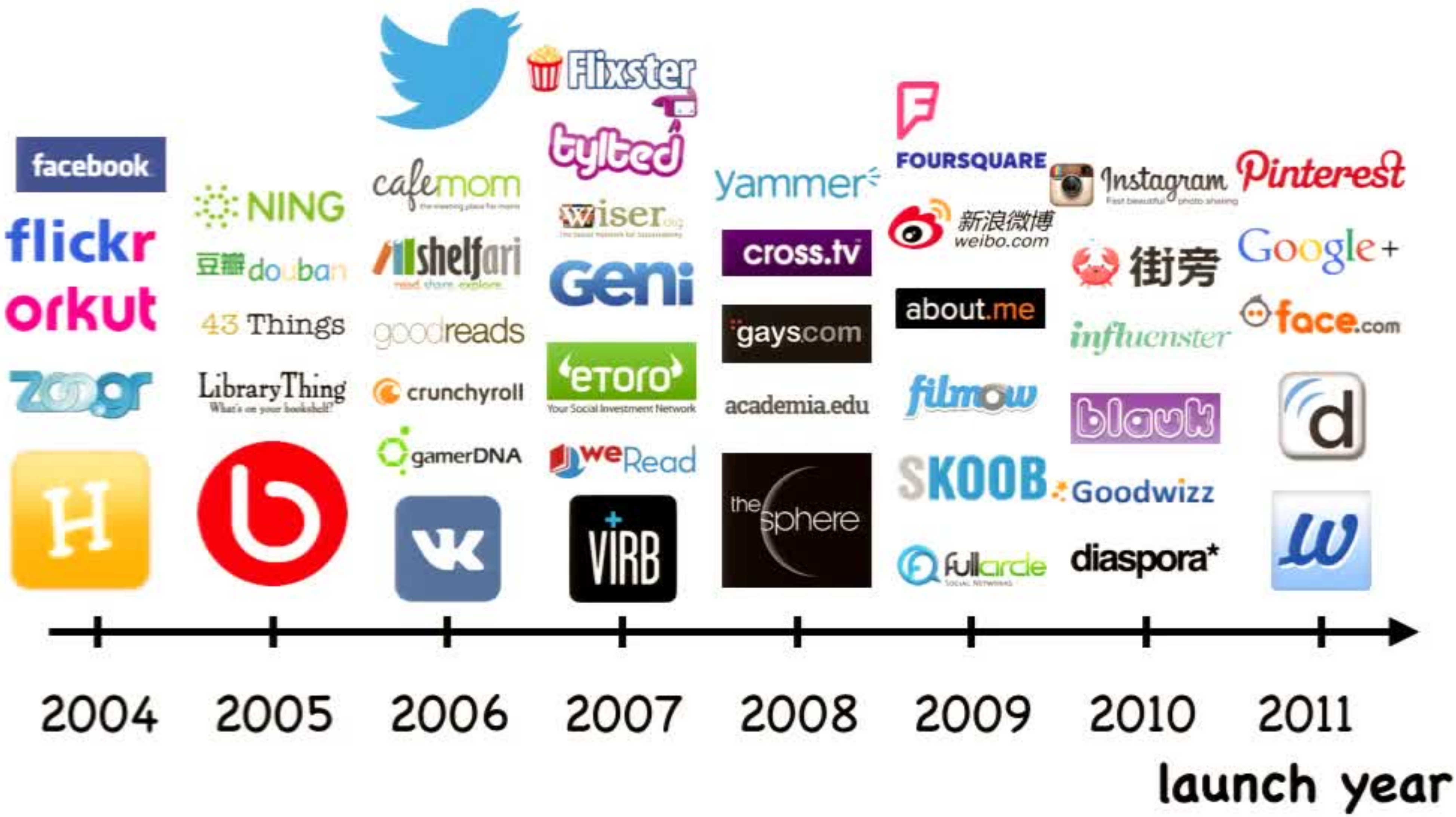
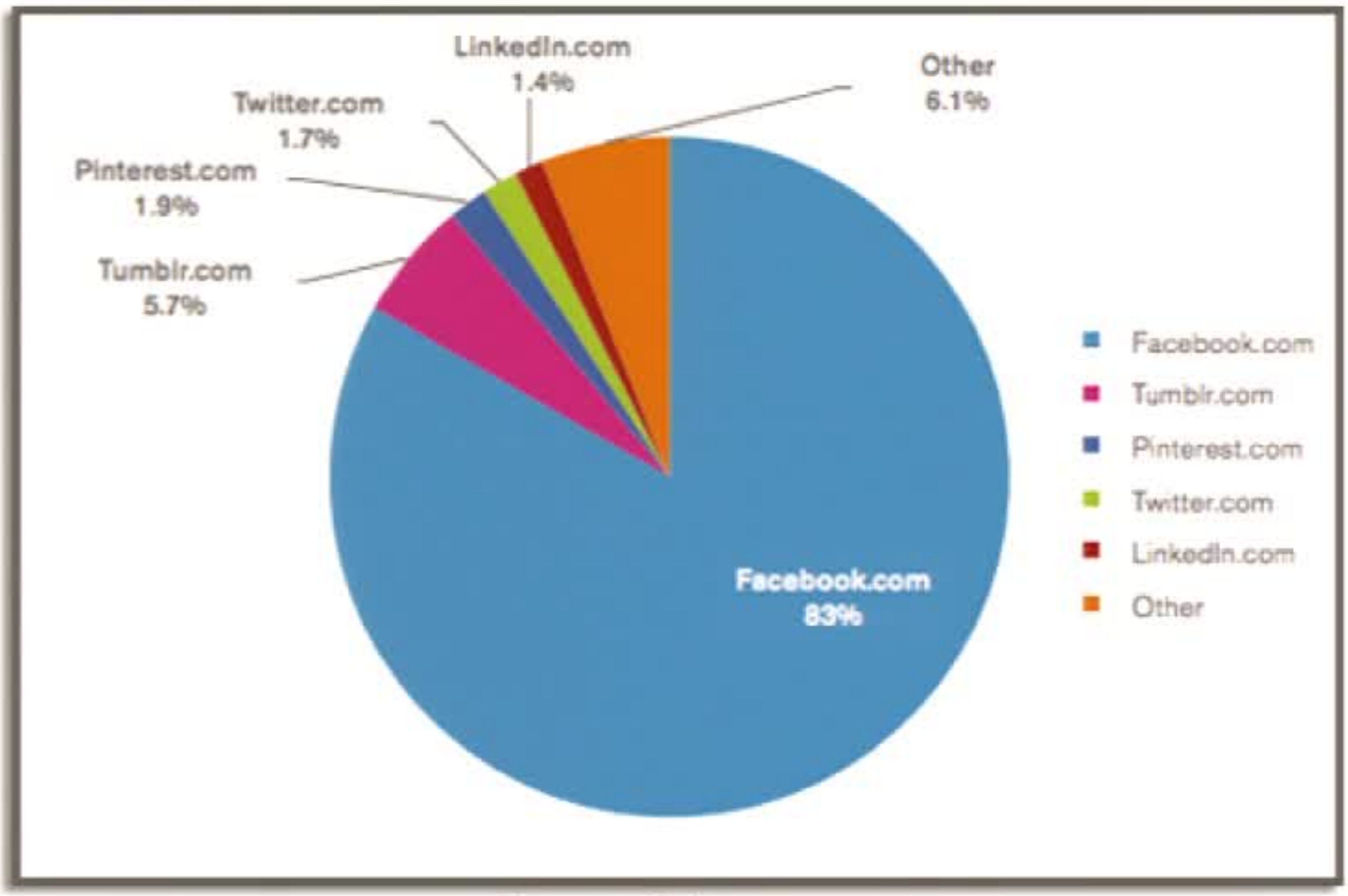
New Social Networks Emerge Every Year



http://en.wikipedia.org/wiki/List_of_social_networking_websites

Emerging Networks Attract Limited Usages



Share of time spent

Emerging Networks Contains Sparse Information

Emerging Network
Community Detection

Emerging Networks Contains Sparse Information

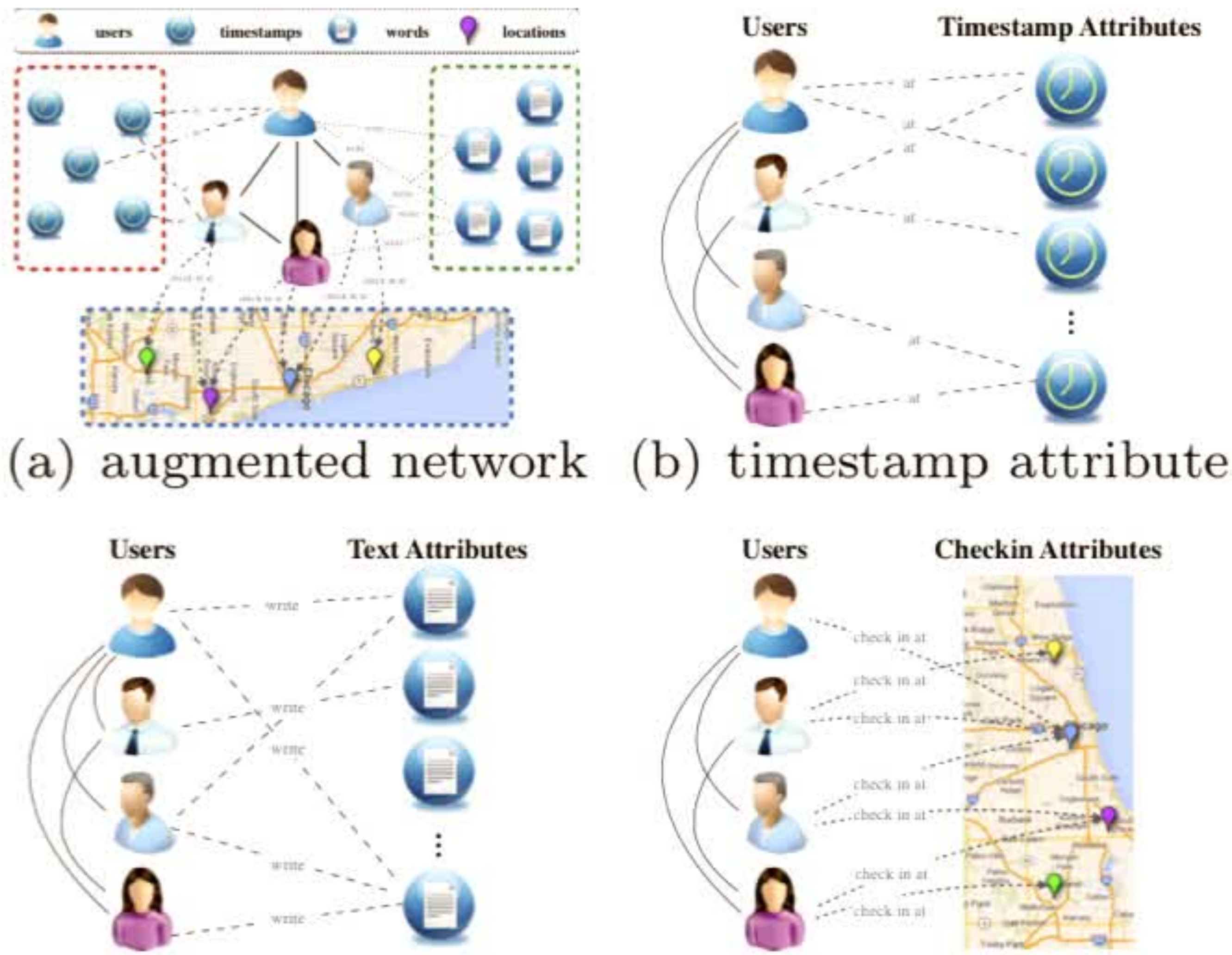
Emerging Network
Community Detection

Hard to calculate effective closeness measures among users due to the sparse information

closeness measures among users:
Intimacy

Challenge 1: Information Sparsity Problem

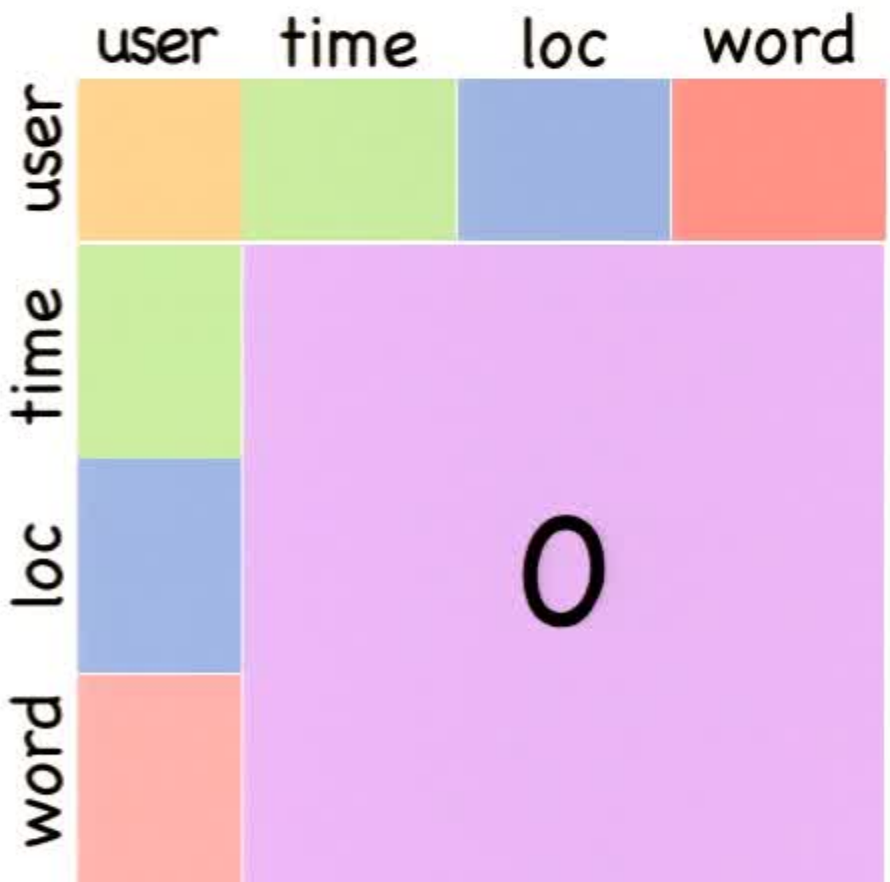
- Solution: use both Link and Attribute information



(a) augmented network (b) timestamp attribute

(c) text attribute (d) checkin attribute

Intimacy Calculation with both Connection and Attribute Information

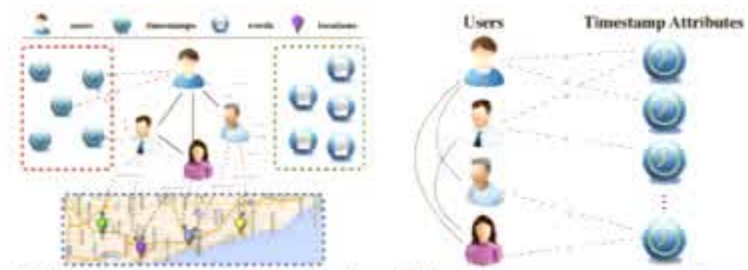


network transitional matrix

weighted normalized adjacency matrices

(1) among users

(2) between users and attributes

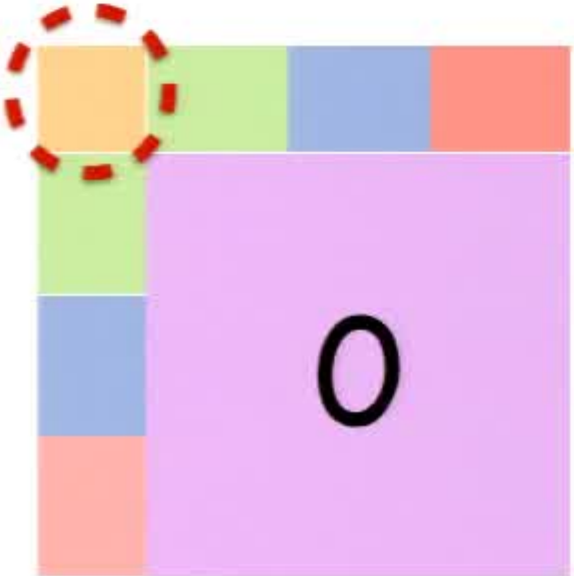


(a) augmented network (b) timestamp attribute

(c) text attribute (d) checkin attribute

$$\tilde{\mathbf{Q}}_{aug} = \begin{bmatrix} \tilde{\mathbf{Q}} & \tilde{\mathbf{R}} \\ \tilde{\mathbf{S}} & \mathbf{0} \end{bmatrix}$$

Intimacy Calculation with both Connection and Attribute Information



$$\left(\mathbf{I} + \alpha \tilde{\mathbf{Q}}_{aug}\right)^{\tau}$$

high-dimensional
stationary network transitional matrix

we only care about the intimacy matrix among users (lower dimension)

$$\underline{\tilde{\mathbf{H}}_{aug}} = \left(\mathbf{I} + \alpha \tilde{\mathbf{Q}}_{aug}\right)^{\tau} \underline{(1:|\mathcal{V}|, 1:|\mathcal{V}|)}$$

intimacy matrix
among users

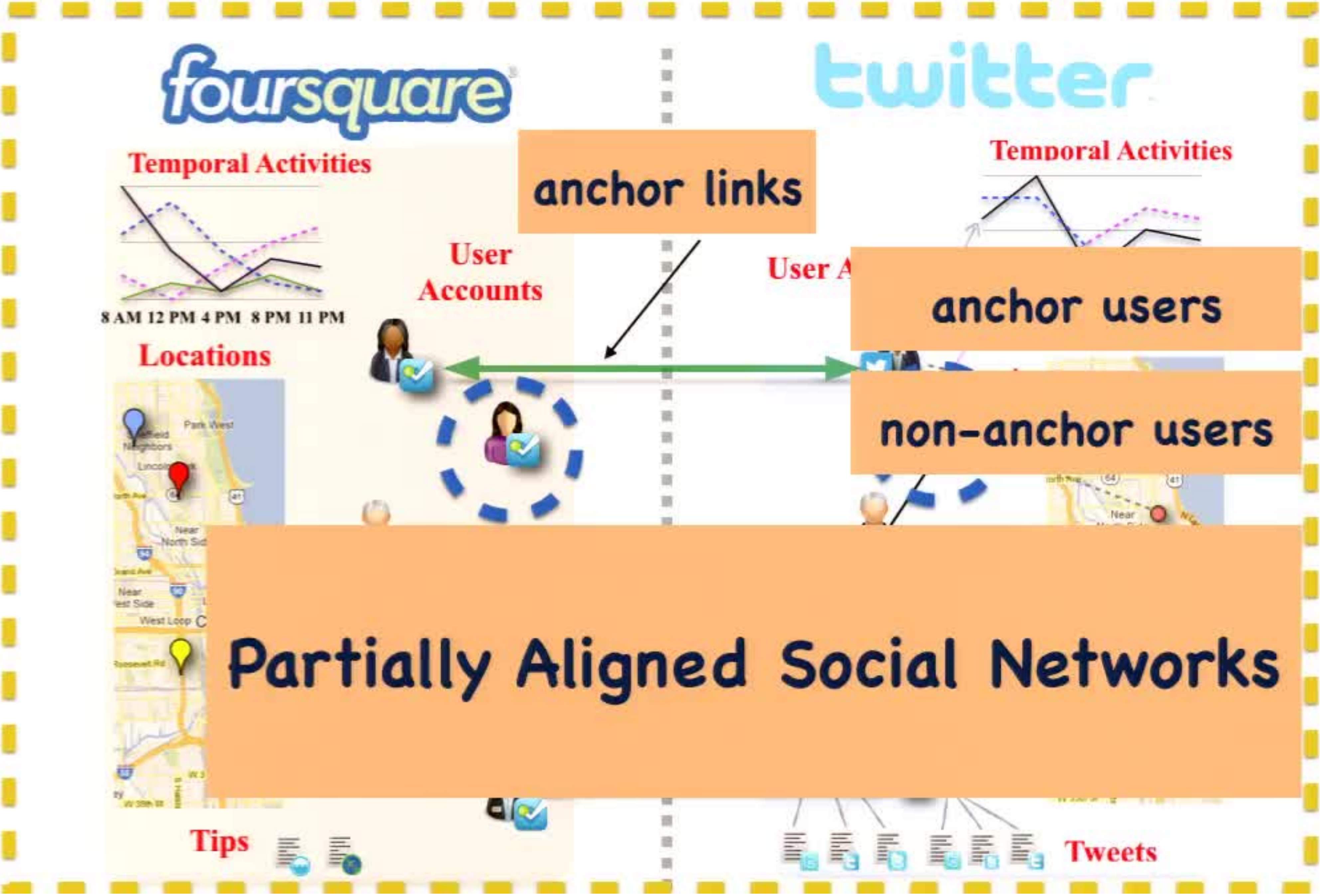
sub-matrix
at the upper left corner

Challenge 2: Cold Start Community Detection

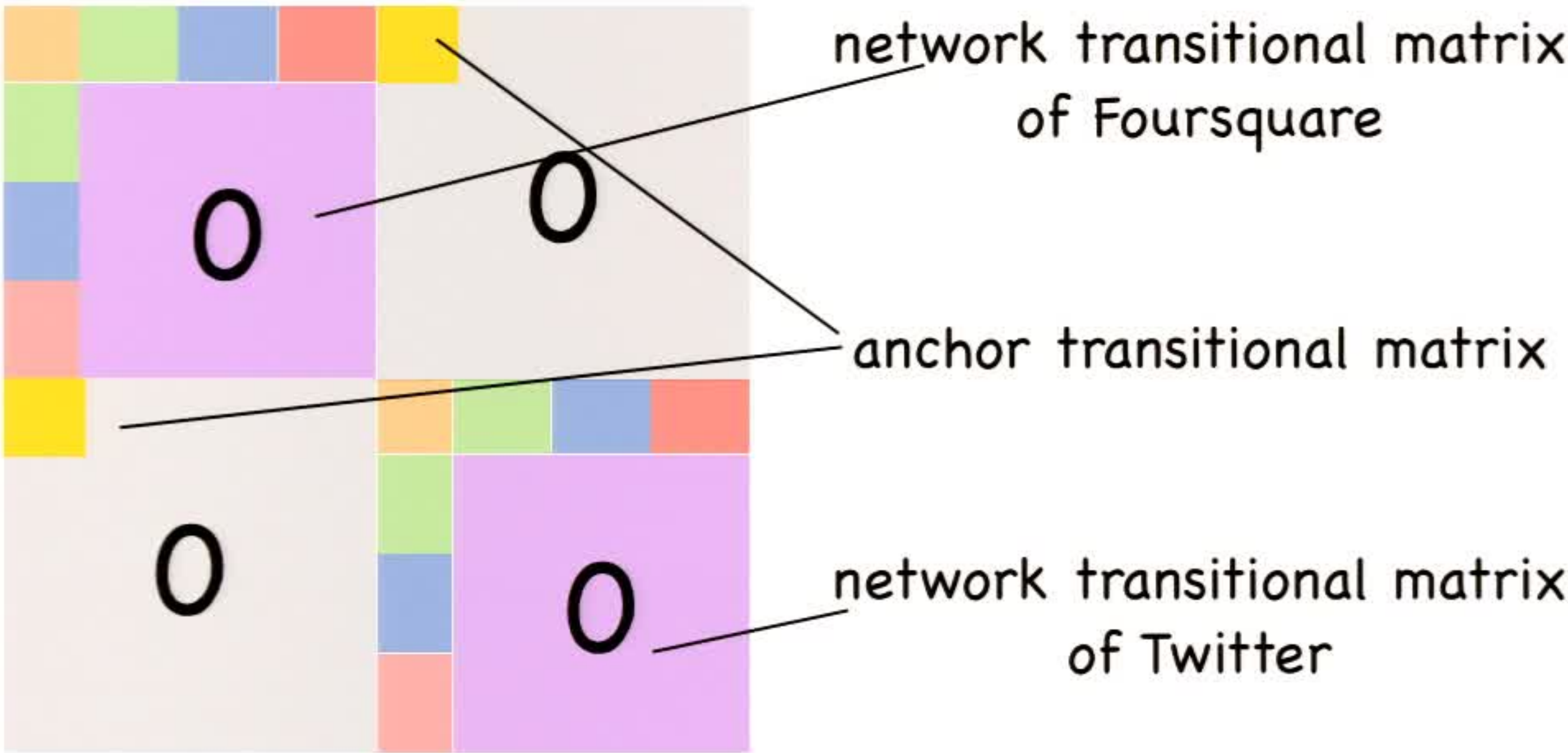
Emerging Network Community Detection

A special case: Cold Start Community Detection (no social activities exist at all)

Users use multiple social networks simultaneously



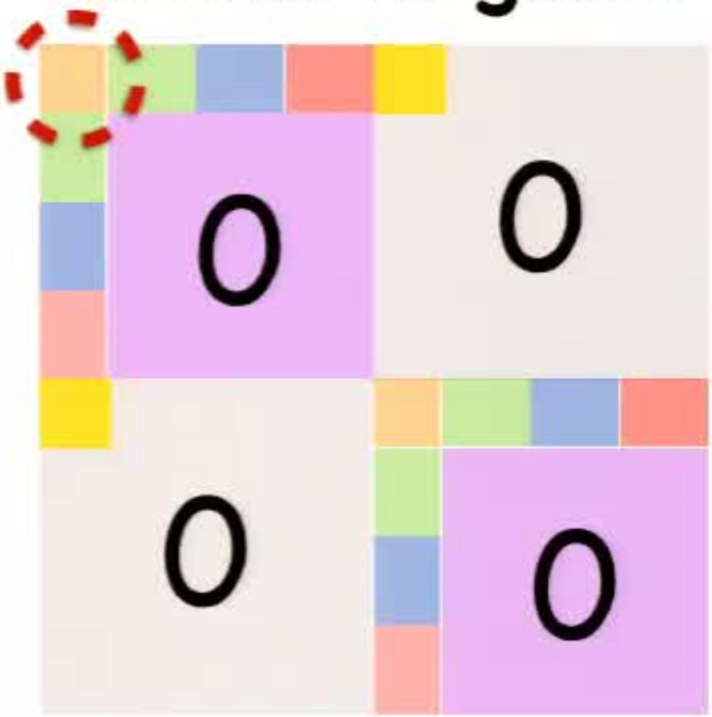
Intimacy Calculation with Information across Aligned Networks



$$\bar{\mathbf{Q}}_{align} = \begin{bmatrix} \bar{\mathbf{Q}}^t_{aug} & \bar{\mathbf{T}}^{t,s} \\ \bar{\mathbf{T}}^{s,t} & \bar{\mathbf{Q}}^s_{aug} \end{bmatrix}$$

weighted aligned network transitional matrix

Intimacy Calculation with Information across Aligned Networks



$$(\mathbf{I} + \alpha \bar{\mathbf{Q}}_{align})^{\tau}$$

high-dimensional
stationary aligned
network transitional matrix

we only care about the intimacy matrix among users (lower dimension)

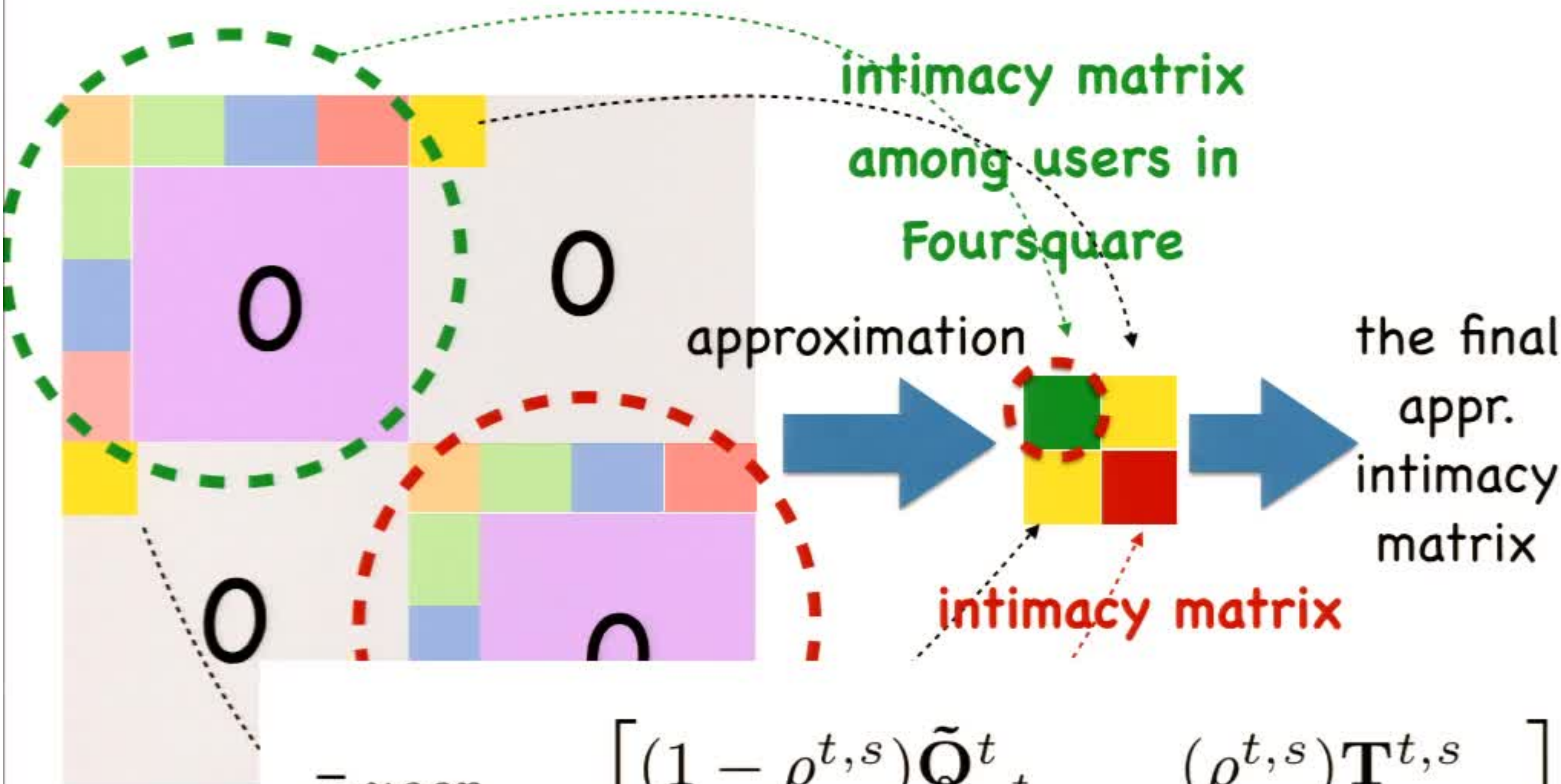
$$\bar{\mathbf{H}}_{align} = (\mathbf{I} + \alpha \bar{\mathbf{Q}}_{align})^{\tau}(1 : |\mathcal{V}^t|, 1 : |\mathcal{V}^t|)$$

intimacy matrix among users in Foursquare

sub-matrix at the upper left corner

Challenge 3: High Time and Space Costs

Solution: Approximated Intimacy Calculation



$$\bar{\mathbf{Q}}^{user}_{align} = \begin{bmatrix} (1-\rho^{t,s})\tilde{\mathbf{Q}}^{t}_{\tau^t} & (\rho^{t,s})\mathbf{T}^{t,s} \\ (\rho^{s,t})\mathbf{T}^{s,t} & (1-\rho^{s,t})\tilde{\mathbf{Q}}^{s}_{\tau^s} \end{bmatrix}$$

Clustering based on Intimacy Matrix

$$\min_{\mathbf{U},\mathbf{V}} \left\| \bar{\mathbf{H}}_{align} - \mathbf{U}\mathbf{V}\mathbf{U}^T \right\|_F^2 + \theta \left\| \mathbf{U} \right\|_F^2 + \beta \left\| \mathbf{V} \right\|_F^2,$$

$$s.t., \mathbf{U} \geq \mathbf{0}, \mathbf{V} \geq \mathbf{0},$$

where $\mathbf{U}$ is the latent feature vectors, $\mathbf{V}$ stores the correlation among rows of $\mathbf{U}$, θ and β are the weights of $\|\mathbf{U}\|_F^2$, $\|\mathbf{V}\|_F^2$ respectively.

The latent feature vectors in $\mathbf{U}$ can be used to detect communities in some traditional clustering methods, e.g., Kmeans [3].

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Parameter Adjustment: weights of different information types and sources

Experiments

- Dataset

Table 1: Properties of the Heterogeneous Networks

		network	
	property	**Twitter**	**Foursquare**
# node	user	5,223	5,392
	tweet/tip	9,490,707	48,756
	location	297,182	38,921
# link	friend/follow	164,920	76,972
	write	9,490,707	48,756
	locate	615,515	48,756

anchor links: 3,388

Experiments

- Comparison Methods
  - CADE-A (Exact intimacy matrix based CAD with parameter Adjustment)
  - CADA-A (Approximated intimacy matrix based CAD with parameter Adjustment)
  - CADE (Exact intimacy matrix based CAD)
  - CADA (Approximated intimacy matrix based CAD)
  - SINFL (Social Influence-based clustering)
  - NCUT (Normalized Cut)
  - KMEANS

Experiments

- Evaluation Metrics

  - *normalized Davies-Bouldin index*: $ndbi(\mathcal{C}) = \frac{1}{K}\sum_{i=1}^{K} \min_{j\neq i} \frac{d(c_i,c_j)+d(c_j,c_i)}{\sigma_i+\sigma_j+d(c_i,c_j)+d(c_j,c_i)}$, where c_i is the centroid of $U_i \in \mathcal{C}$, $d(c_i, c_j)$ is the distance between c_i and c_j, σ_i denotes the average distance between items in U_i and centroid c_i [23].
  - *Silhouette*: Let $a(u) = \frac{1}{|U_i|-1}\sum_{v\in U_i, v\neq u} d(u,v)$ and $b(u) = \min_{j, j\neq i}\left(\frac{1}{|U_j|}\sum_{v\in U_j} d(u,v)\right)$, the *Silhouette index* is defined to be $silhouette(\mathcal{C}) = \frac{1}{K}\sum_{i=1}^{K}(\frac{1}{|U_i|}\sum_{u\in U_i}\frac{b(u)-a(u)}{\max\{a(u),b(u)\}})$ [9].
  - *Entropy*: $E(\mathcal{C}) = -\sum_{i=1}^{K} P(i)\log P(i)$, where $P(i) = \frac{|U_i|}{|\mathcal{V}|}$ [23].

Ex

performance of methods using approximated intimacy scores is close to the one with the exact intimacy scores

measure	methods	Information Sampling Rate 0.0	0.1	0.2	0.3	0.4	0.5
ndbi	CADE-A	**0.954**	**0.959**	**0.966**	**0.969**	**0.968**	**0.972**
	CADA-A	0.917	0.922	0.923	0.925	0.938	0.946
	CADE	0.938	0.944	0.949	0.949	0.954	0.957
	CADA	0.914	0.914	0.918	0.923	0.932	0.936
	SINFL	-	0.881	0.889	0.901	0.907	0.913
	NCUT	-	0.864	0.870	0.889	0.889	0.893
	KMEANS	-	0.842	0.859	0.881	0.886	0.887

Expe parameter adjustment step helps

Table 2: Community Detection Result o

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Exp

our proposed methods can overcome the cold start problem very well

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Ex

methods with approximated intimacy matrix can save lots of space and time

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Table 3: Space and time costs in calculating $\bar{\mathbf{H}}_{align}$.

emerging network	cost	method: **exact**	**approx.**
Foursquare	space cost(MB)	19526	1627
	time cost(s)	65996.17	6499.97

Summary

- Problem Studied: Emerging Network Community Detection & Cold Start Community Detection
- Calculate the Intimacy scores among users in the emerging network with both Connection and Attribute information across Partially Aligned Networks.
- To lower the time and space cost: Approximated Intimacy Calculation

Q & A

Summary

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- Calculate the **Intimacy** scores among users in the emerging network with both **Connection** and **Attribute** information across **Partially Aligned Networks**.
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Experiment Results

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Anchor Links across Networks