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Semi-supervised Clustering in Attributed Heterogeneous Information Networks

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Introduction

- Attributed heterogeneous information network (AHIN)

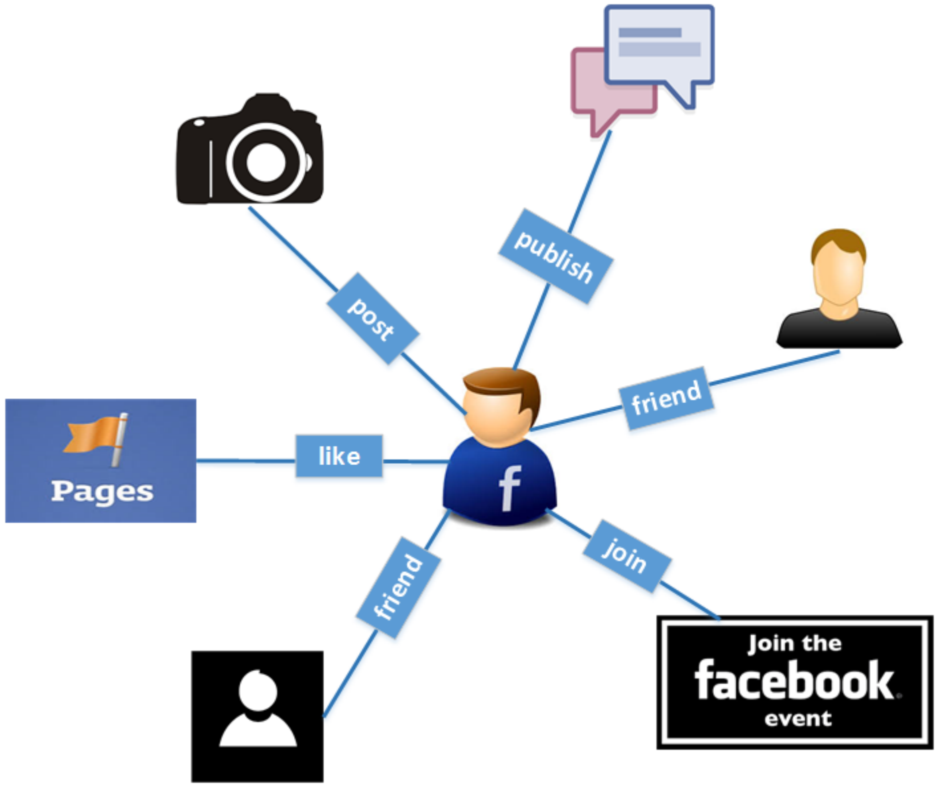
□ Heterogeneous information network
  - ○ multiple types of objects
  - ○ different types of links

□ Object attributes

□ Example: Facebook Open Graph

○ objects: users, pages, photos, events, etc.

○ attributes:
  - users (gender, age, school, etc.),
  - photo (lat-long, date/time)



Meta-path

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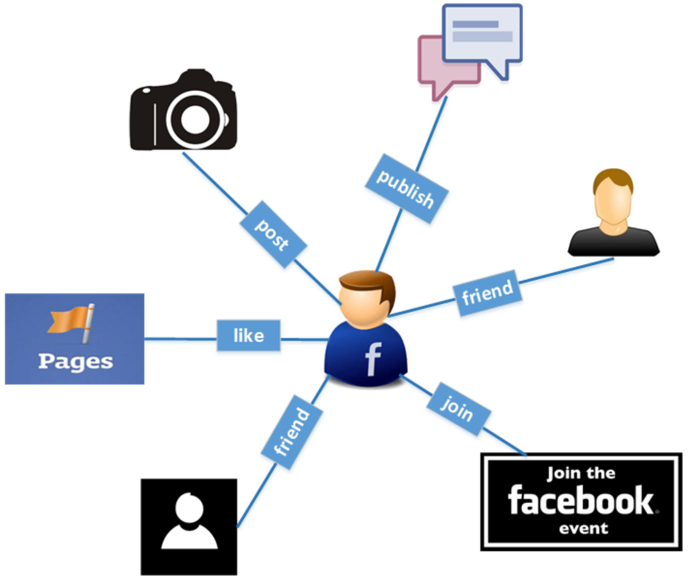
- A meta-path is a sequence of object types that expresses a relation between objects
- Example: Facebook Open Graph

□ objects: users (U), product pages (P), etc.



- UPU: user-page-user (two users like the same product page)
- UUU: user-user-user (two users have a common friend)

Challenge

- Why clustering in attributed heterogeneous information networks?
- Link-based similarity
  - simple network distance measure (eg: random walk)
  - meta-path based measure (eg: PathSim)
- Attribute-based similarity
- **Challenge1: how to aggregate various types of similarities?**

Challenge

- Not all the attributes and meta-paths are useful
- Automatic process to select best attributes and meta-paths
- User can provide guidance to supervise the clustering
- **Challenge2: how to automatically perform the selection?**

Related Work

	without supervision			supervision		
	attribute	link	both	attribute	link	both
homogeneous	k-means, Ncuts	METIS, AGM, BigClam	CODICIL, CESNA, SA-Cluster	Spectral-learning, SS-Kernel-kmeans	label propagation	FocusCO
heterogeneous		RankClus, NetClus, SI-Cluster	GenClus		PathSelClus, SemiRPClus	**SCHAIN**

Attribute-based similarity

- Suppose x_u has attribute vector f_u, x_v has attribute vector f_u

$$S_A(x_u, x_v) = \sum_{j=1}^{|A_i|} (\omega_j \cdot sim(f_{uj}, f_{vj})),$$

- sim() can be any standard similarity function defined over the j-th attribute

Link-based similarity

- An effective meta-path based measure: PathSim
- Each meta path P_j defines a similarity measure S_{P_j}
- Suppose we have m meta paths, then $$S_L = \sum_{j=1}^{m} \lambda_j S_{P_j}$$
- To combine attribute-based and link-based similarity, we have:

$$S = \alpha S_A + (1-\alpha) S_L$$

Supervision constraints

- Must-link set M and cannot-link set C (user supervision)
- To measure the clustering quality,

1. How similar intra-cluster and inter-cluster objects are?
2. How well the cluster agrees with the supervision constraints?

- we use normalized cuts to be the measure

- **reward** object pairs in M which are clustered in the same cluster
- **penalize** objects pairs in C which are clustered in the same cluster

$$\mathcal{J}(\boldsymbol{\lambda}, \boldsymbol{\omega}, \{C_r\}_{r=1}^k) = \sum_{r=1}^{k} \frac{links(C_r, \mathcal{X}_i \backslash C_r)}{links(C_r, \mathcal{X}_i)}$$

Ncuts

Reward

$$- \sum_{r=1}^{k} \sum_{\substack{(x_u, x_v) \in \mathcal{M} \\ L(x_u) = L(x_v) = r}} \frac{S(x_u, x_v)}{links(C_r, \mathcal{X}_i)} \quad (4)$$

penalty

$$+ \sum_{r=1}^{k} \sum_{\substack{(x_u, x_v) \in \mathcal{C} \\ L(x_u) = L(x_v) = r}} \frac{S(x_u, x_v)}{links(C_r, \mathcal{X}_i)},$$

- Our goal is to minimize J

$$\mathcal{J}(\boldsymbol{\lambda}, \boldsymbol{\omega}, \{\boldsymbol{z}_r\}_{r=1}^{k}) = \sum_{r=1}^{k} \frac{\boldsymbol{z}_r^T (D - S - \mathcal{W} \circ S) \boldsymbol{z}_r}{\boldsymbol{z}_r^T D \boldsymbol{z}_r} + \gamma(||\boldsymbol{\lambda}||^2 + ||\boldsymbol{\omega}||^2). \tag{6}$$

- Constraints:

$$\sum_{r=1}^{k} \boldsymbol{z}_r(u) = 1$$

$$\boldsymbol{z}_r(u) \in \{0, 1\}$$

$$\sum_{j=1}^{|\mathcal{PS}|} \lambda_j = 1$$

$$\sum_{l=1}^{|A_i|} \omega_l = 1$$

$$\lambda_j \geq 0$$

$$\omega_l \geq 0$$

Optimization

- An iterative method
  - Optimize $\{z_r\}_{r=1}^{k}$ given λ and ω
    - Transform into spectral clustering optimization problem
  - Optimize λ and ω given $\{z_r\}_{r=1}^{k}$
    - Transform into a non-linear fractional programming problem

Experiment

- Task1: Yelp-Business

❑ businesses (B), cities (C), users (U) and categories (T)

❑ business attributes: lat-long, review count, quality star and lot

❑ meta-paths = {BCB (two businesses are in the same city), BUB (two businesses have the same customer), BTB (two businesses are of the same category)}

❑ clustering objective: to cluster businesses by geographical state

Experiment

- Task2: Yelp-Restaurant

❑ restaurants (B), reviews (R), users (U) and keywords (K)

❑ restaurant attributes: service, reserve, review count, quality star and lot

❑ meta-paths = {BRURB (two restaurants have reviews written by the same customer), BRKRB (two restaurants have reviews with the same keyword)}

❑ clustering objective: to cluster restaurants by category

Experiment

- Task3: DBLP

❑ authors (A), papers (P) and terms (T)

❑ author attributes: published paper count to CIKM, KDD,VLDB and SIGIR

❑ meta-paths = {APA (co-authorship), APAPA (two authors publish papers with the same coauthor), APTPA (two authors publish papers with the same keyword)}

❑ clustering objective: to cluster authors by research interests

Clustering quality

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Table 2: NMI comparison on Yelp-Restaurant

	Attribute-only		Link-only			Attribute+Link	SCHAIN Variants		
% seeds	SL	SNcuts	GNetMine	PathSelClus	SemiRPClus	FocusCO	SCHAIN-RWR	SCHAIN-NL	SCHAIN
5%	0.225	0.185	0.284	0.564	0.142	0.088	0.427	0.628	**0.689**
10%	0.258	0.188	0.332	0.610	0.134	0.087	0.429	0.635	**0.707**
15%	0.416	0.192	0.367	0.627	0.136	0.095	0.433	0.655	**0.725**
20%	0.425	0.198	0.379	0.635	0.132	0.087	0.426	0.678	**0.738**
25%	0.437	0.251	0.392	0.637	0.136	0.090	0.436	0.689	**0.744**

Weight learning

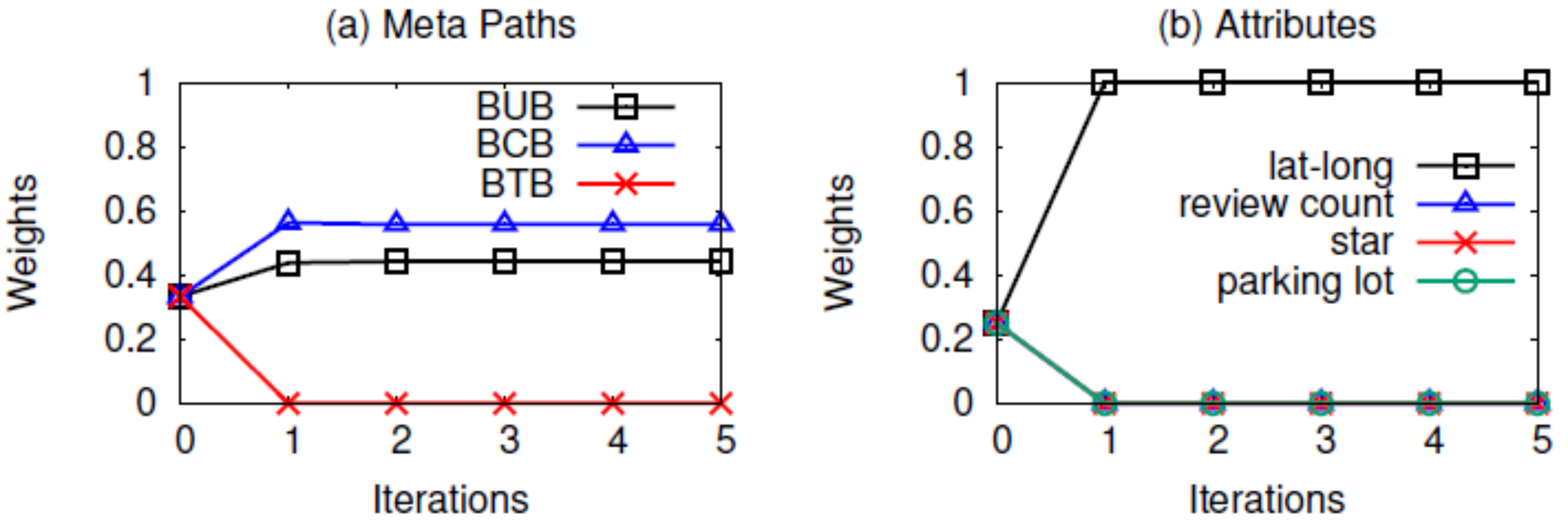

Figure 2: Weight learning on Yelp-Business

Weight learning

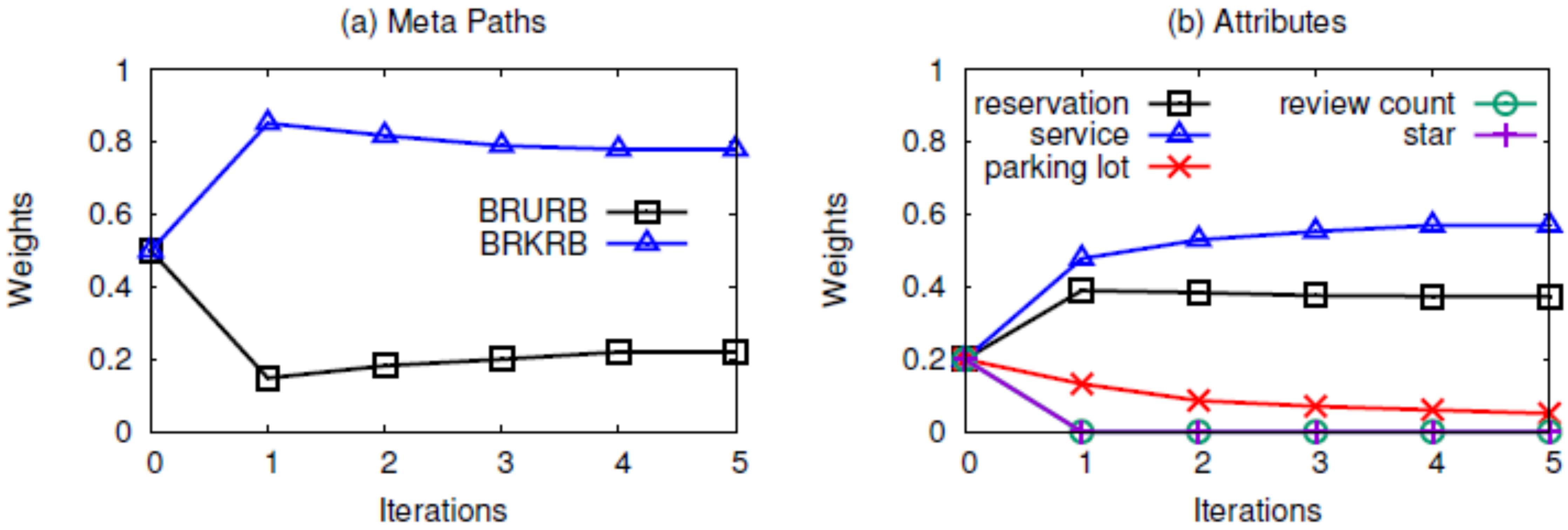

Figure 3: Weight learning on Yelp-Restaurant

Weight learning

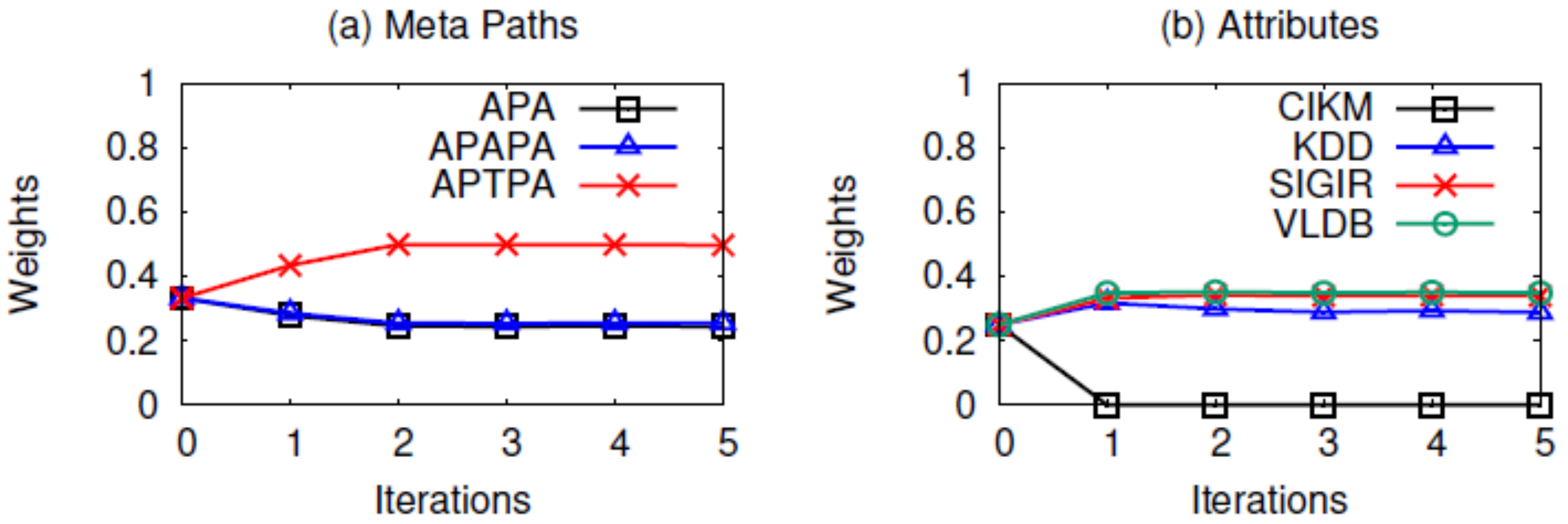

Figure 4: Weight learning on DBLP

Convergence analysis

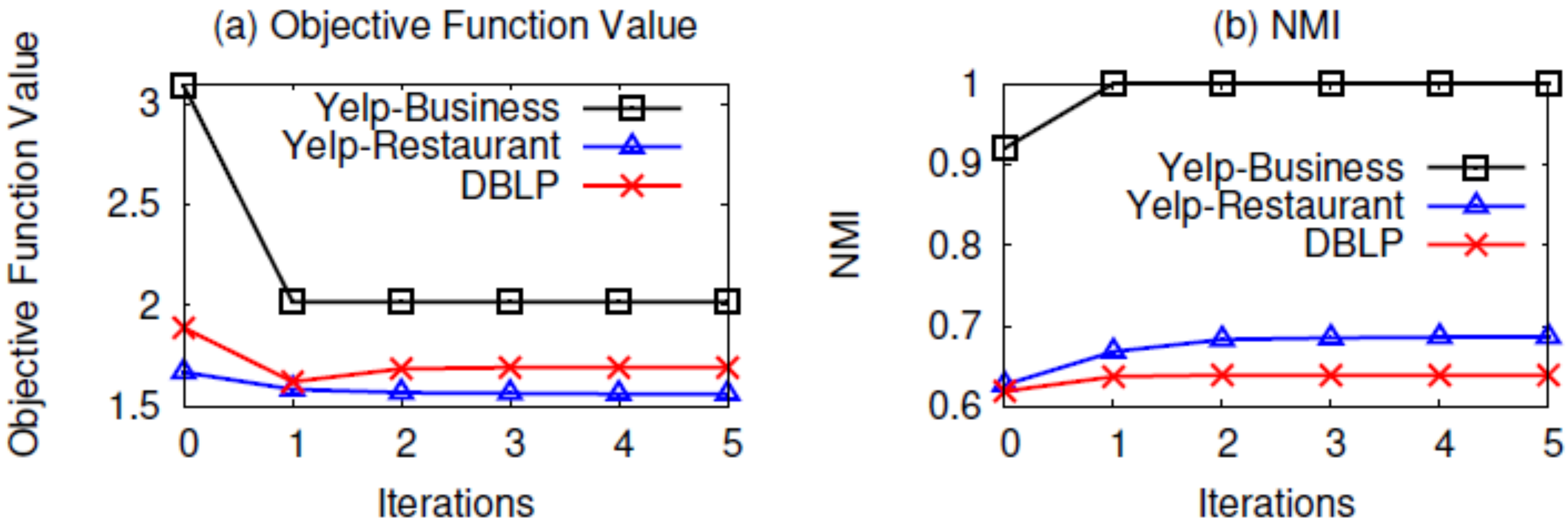

Figure 5: Convergence analysis

Conclusion

- We studied semi-supervised clustering in AHINs
- We proposed a novel algorithm SCHAIN which considers both object attributes and meta-paths
- We experimentally proves the usefulness of SCHAIN

Thank you!