Weighted Micro-Clustering :

Application to Community Detection in Large-Scale

Our Goal

• Detecting communities from undirected graphs **with vertex attributes**.

Our Results

• Simple and scalable soft-clustering method based on Micro-Clustering [T.Uno+ 15] for detecting communities from undirected graphs with vertex attributes

- Propose the new algorithm by extending Microclustering [T. Uno+ 15] to accept weighted graphs
- Apply our method to large-scale co-purchasing networks of real online auction data (YAHUOKU!)

Our Method : Weighted Micro-Clustering

Vertices represent buyers, and if two buyers buy products from almost the same sellers, their vertices are adjacent. **True class:** 3rd level categories of items user purchased **User attributes :** 2nd level categories of items user purchased

Algorithm

1. Compose a co-purchasing graph $G = (V, E)$ from data.

1. Partition vertices by associating users with their most frequently purchased item categories. 2. Measure NMI and Purity scores between the set of users in communities $\Omega = \{w_1, \ldots, w_M\}$ and in the true class $C = \{c_1, \ldots, c_L\}$

Books Magazines Literature

Novels

SF

Cookbooks

Japanese

French

• Communities are vertices which probably share common properties and/or play similar roles Within the graph [S. Fortunato 08].

2. Compose a polished graph $G_w = (V, E_w)$ from G where $E_w = \{(u, v) \mid \left| \sin_w(u, v) > \theta, \left| \left| N(u) \cap N(v) \right| > 0, (u, v) \in E \right\},\right.$ $sim_w(u, v) = \frac{\sum_{n \in N(u) \cap N(v)} \min (J(\mathbf{u}, \mathbf{n}), J(\mathbf{v}, \mathbf{n}))}{\sum_{v \in N(v)} \max (J(\mathbf{u}, \mathbf{n}), J(\mathbf{v}, \mathbf{n}))}$

Experiments

Data : Co-purchasing graph data from YAHUOKU!

YAHOO!

Results

• Results of BOOKS data

Evaluation

3. Enumerate maximal cliques from the polished graph *Gw*

Traditional methods

- 1. Propagation-based methods [C.D. Manning+ 08], [P. Judea+ 82] etc.
- 2. Modularity-based methods [V. Blondel+ 08], [M. Girvan+ 02] etc.
- 3. Clique-based methods [T. Uno+ 15], [G. Palla+ 05] etc.

$$
NMI(\Omega, C) = \frac{-2\sum_{m=1}^{M} \sum_{l=1}^{L} \frac{|w_m \cap c_l|}{S} \log \frac{S|w_m \cap c_l|}{|w_m||c_l|}}{\sum_{m=1}^{M} \frac{|w_m|}{S} \log \frac{|w_m|}{S} + \sum_{l=1}^{L} \frac{|c_l|}{S} \log \frac{|c_l|}{S}}
$$

purity(Ω, C) = $\frac{1}{S} \sum_{m} \max_{l} |w_m \cap c_l|$ where $S = |\bigcup_{\omega \in \Omega} w|$

 $J(\mathbf{u},\mathbf{v})$ is a similarity between vectors. For example $J(\mathbf{u}, \mathbf{v}) = \frac{\sum_{i=1}^{n} \min (\mathbf{u_i}, \mathbf{v_i})}{\sum_{i=1}^{n} \max (\mathbf{u_i}, \mathbf{v_i})}$ (Generalized jaccard index)

 \mathbf{u}, \mathbf{v} : the attribute vectors of u, v , respectively. u_i, v_i : the *i*th element of the vector u, v , respectively.

NMI (Normalized Mutual Information)

Purity Scores

Conclusion

- Our method takes account of both the graph structure and their vertex attributes.
- Our method outperforms previous methods.

