Music Recommendation by Unified Hypergraph: Combining Social Media Information and Music Content

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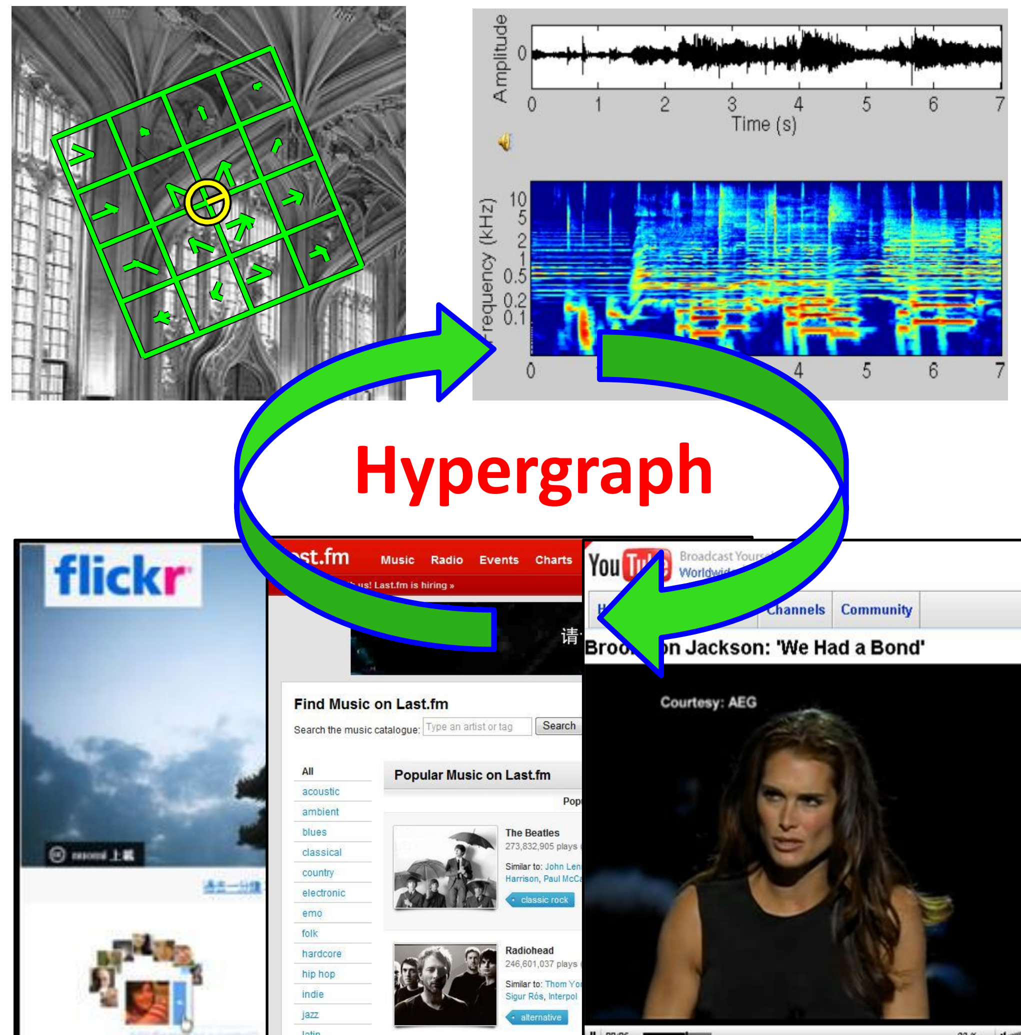
Multi-type Media Fusion

- Content analysis
  - text
  - Image
  - Audio
  - Video
  - ……
- Social analysis
  - Friendship
  - Interest group
  - Resource collection
  - Tag
  - ……

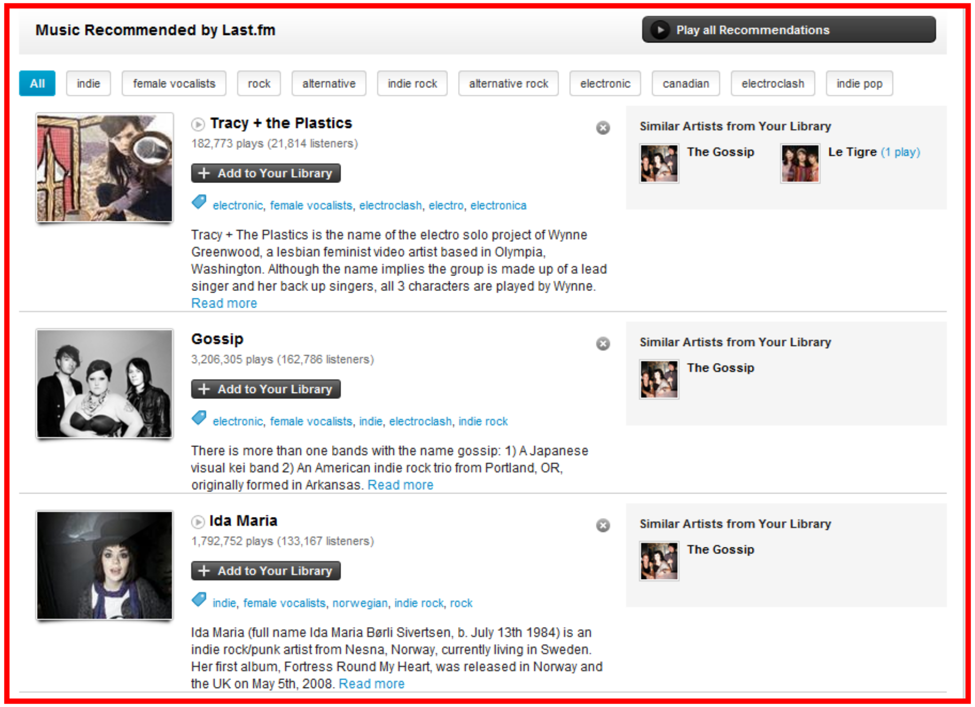


Outlines

- Music Recommendation
- Social media information
- Unified Hypergraph Model
- Music Recommendation on Hypergraph (MRH)
- Experimental results

Music Recommendation

- We have huge amount of music available in music social communities
- It is difficult to find music we would potentially like
- Music Recommendation is needed!

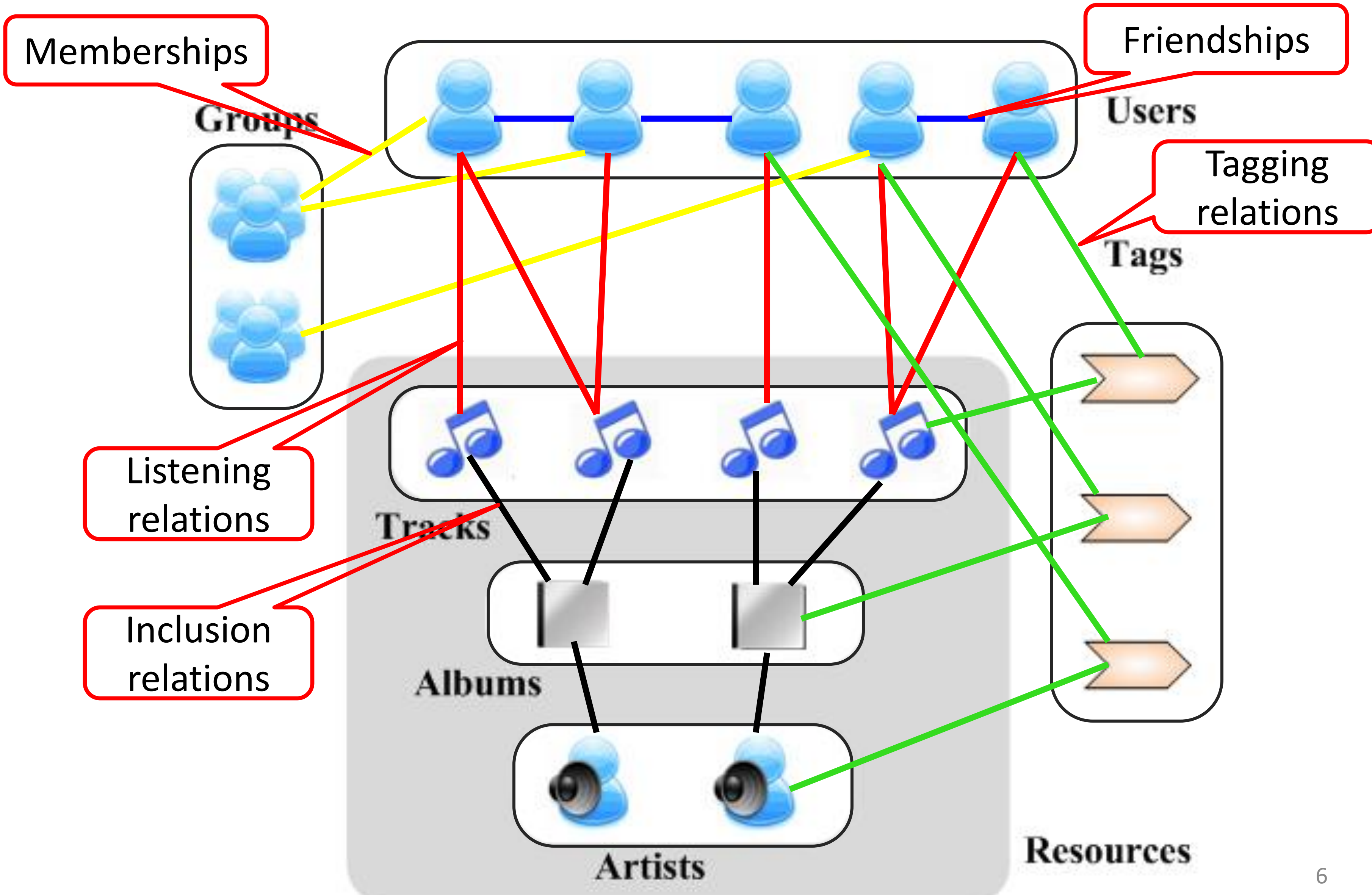


Recommended music by the Last.fm.

Traditional Music Recommendation

- Traditional music recommendation methods only utilize limited kinds of social information
  - Collaborative Filtering (CF) only uses rating information
  - Acoustic-based method only utilizes acoustic features
  - Hybrid method just combines these two

Social Media Information in Last.fm



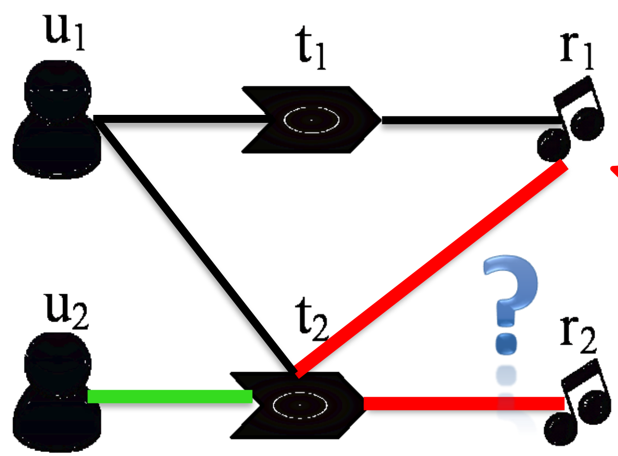
Social Media Information

- The rich social media information is valuable for music recommendation.
  - To build the users' preference profiles.
  - To predict users' interests from their friends.
  - To recommend music tracks by albums or artists.
  - …

How About Graph Model?

- Use traditional graph to model social media information but fail to keep high-order relations in social media information

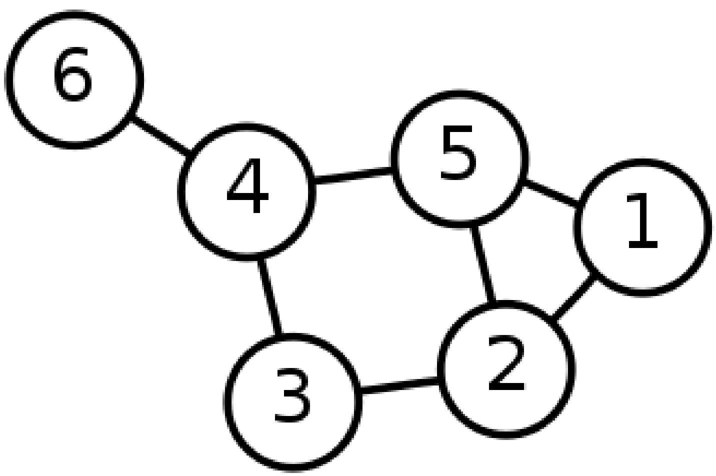
(u_1, t_1, r_1)
(u_1, t_2, r_2)
(u_2, t_2, r_1)

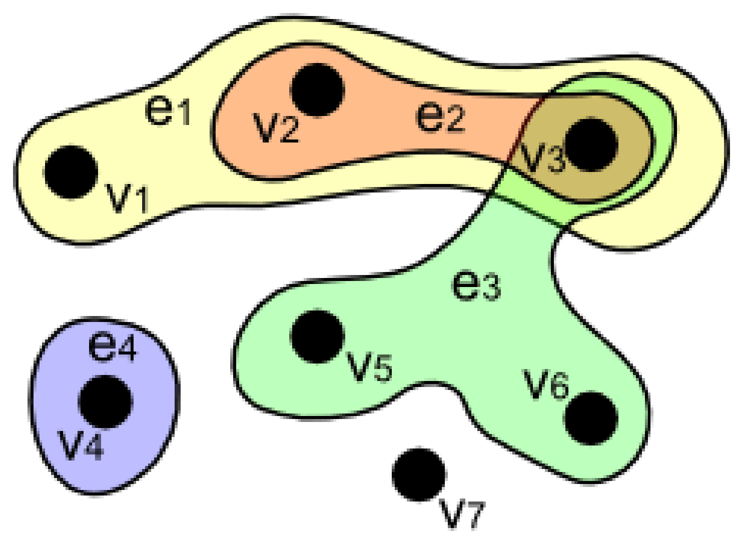


It is unclear whether u_2 bookmarks r_1, r_2, or both.

Unified Hypergraph Model

- Using a unified hypergraph to model multi-type objects and the high-order relations
  - Each edge in a hypergraph, called a hyperedge, is an arbitrary non-empty subset of the vertex set
  - Modeling each high-order relation by a hyperedge, so hypergraphs can capture high-order relations naturally





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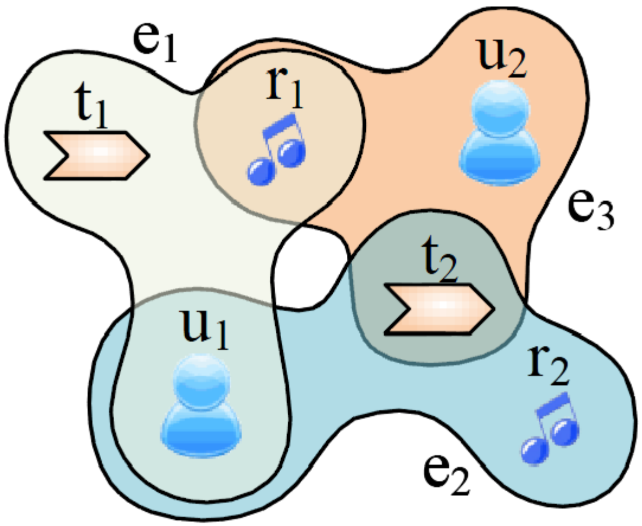
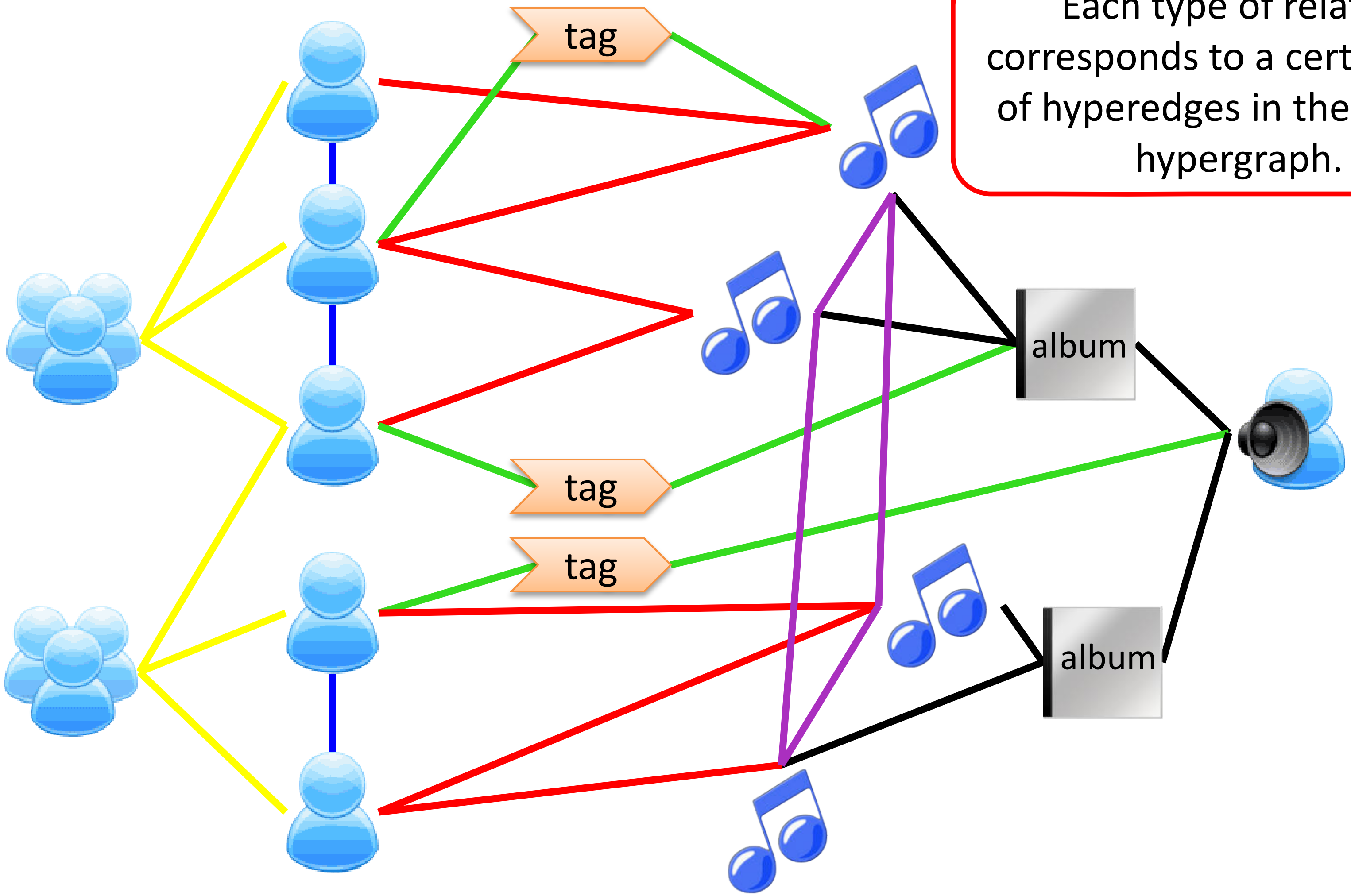


The high-order relations among the three types of objects can be naturally represented as triples.

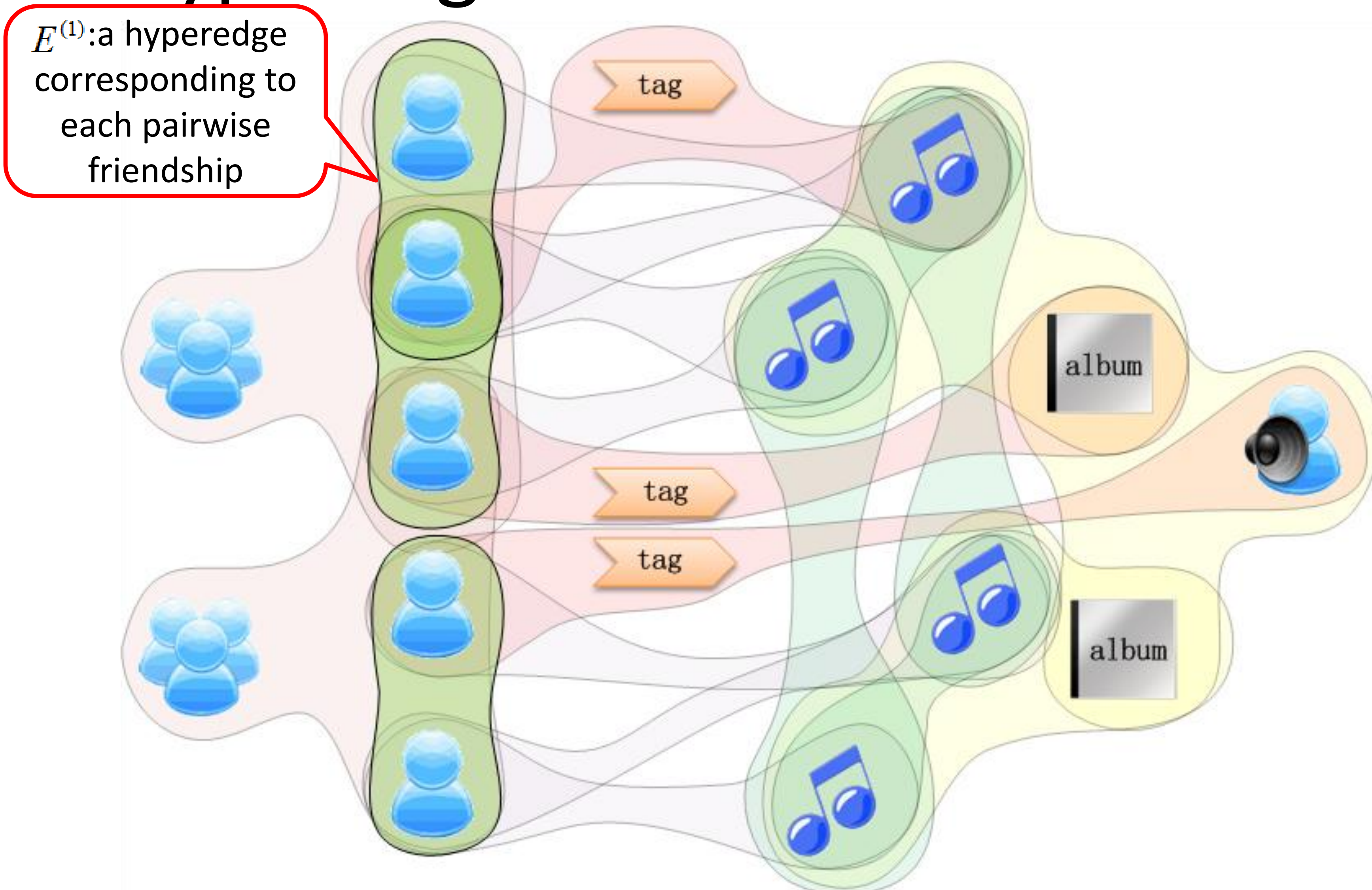
Unified Hypergraph Construction



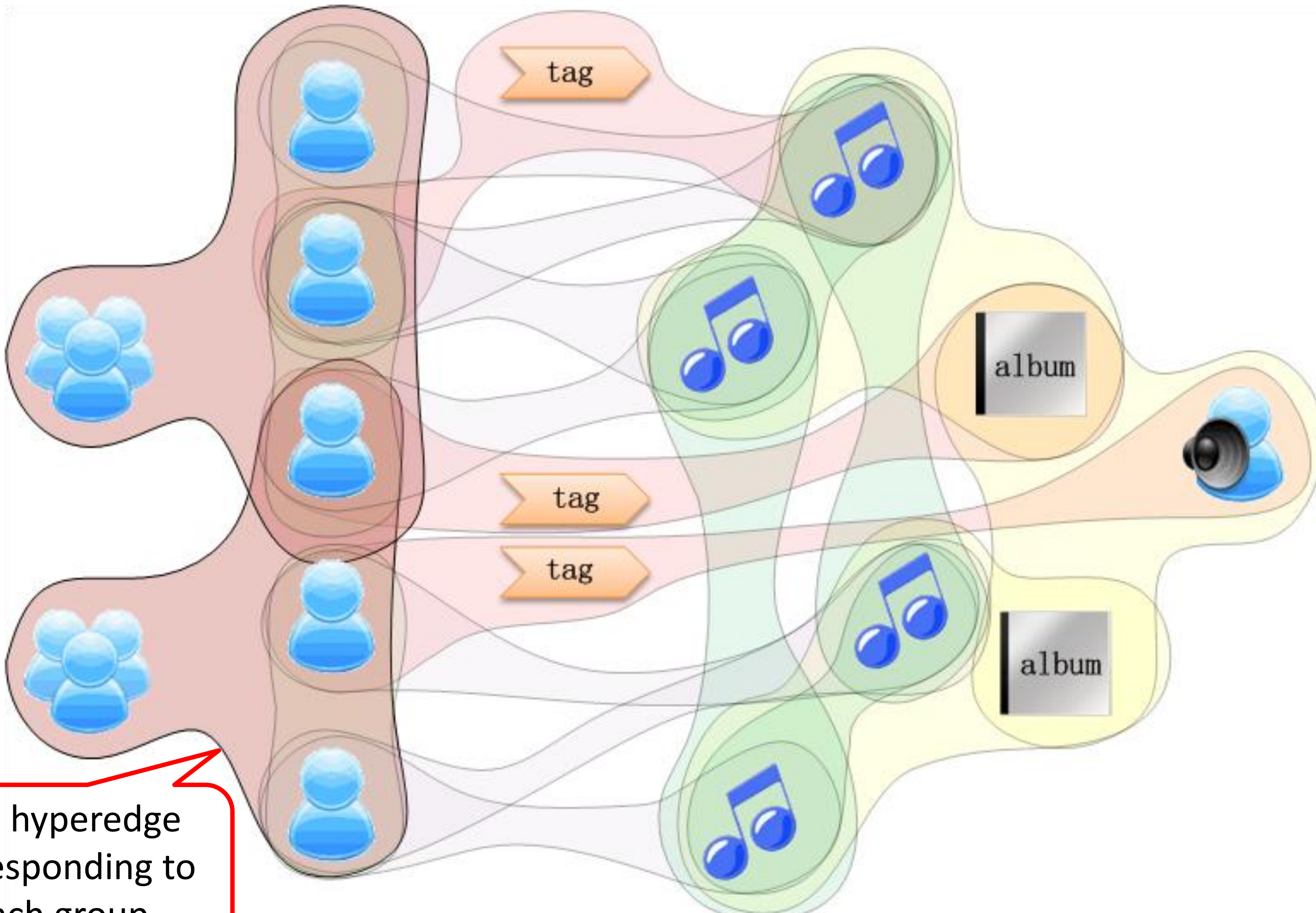
Each type of relation corresponds to a certain type of hyperedges in the unified hypergraph.

The six types of objects form the vertex set of the unified hypergraph.

Hyperedges Construction Details

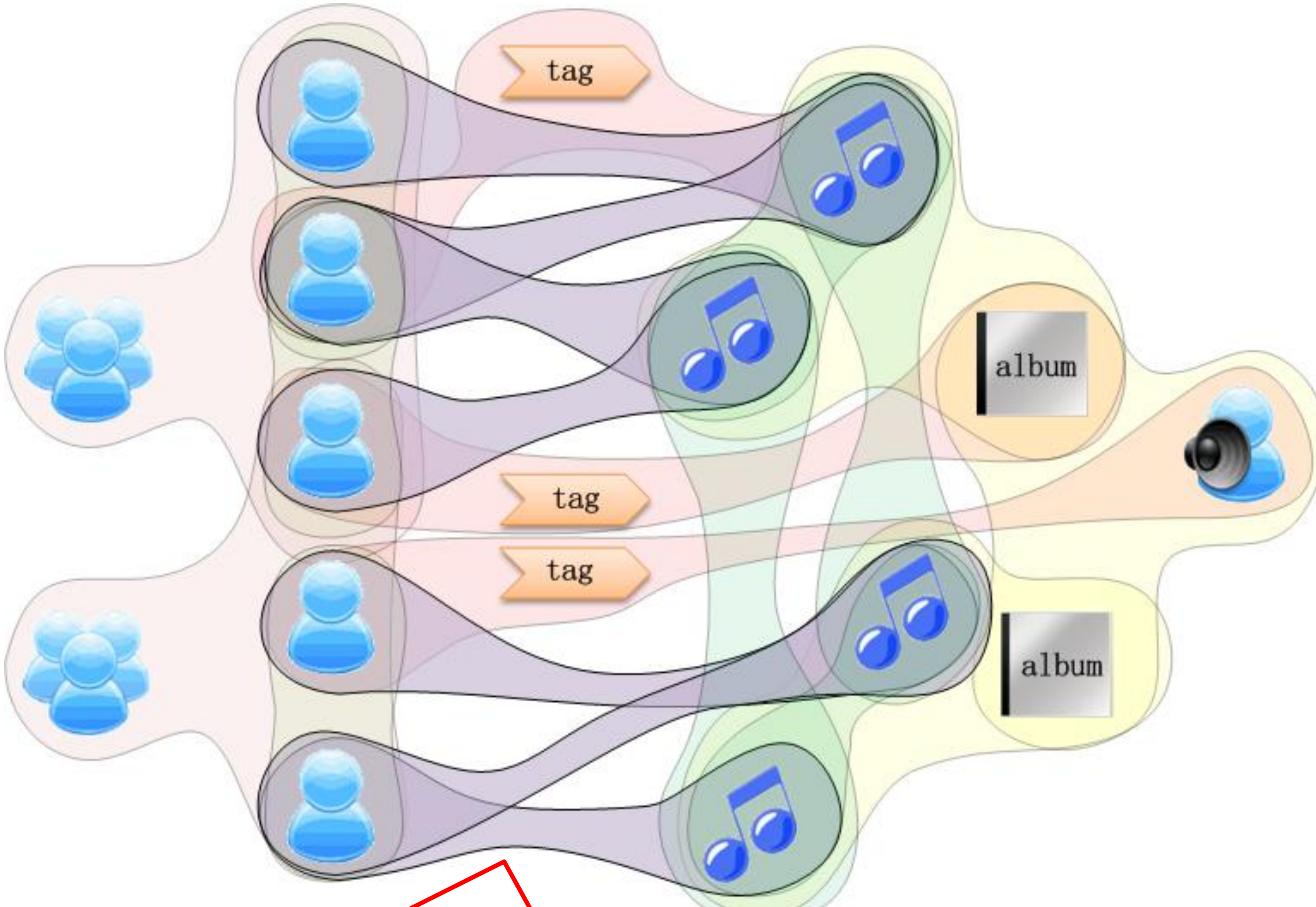


Hyperedges Construction Details



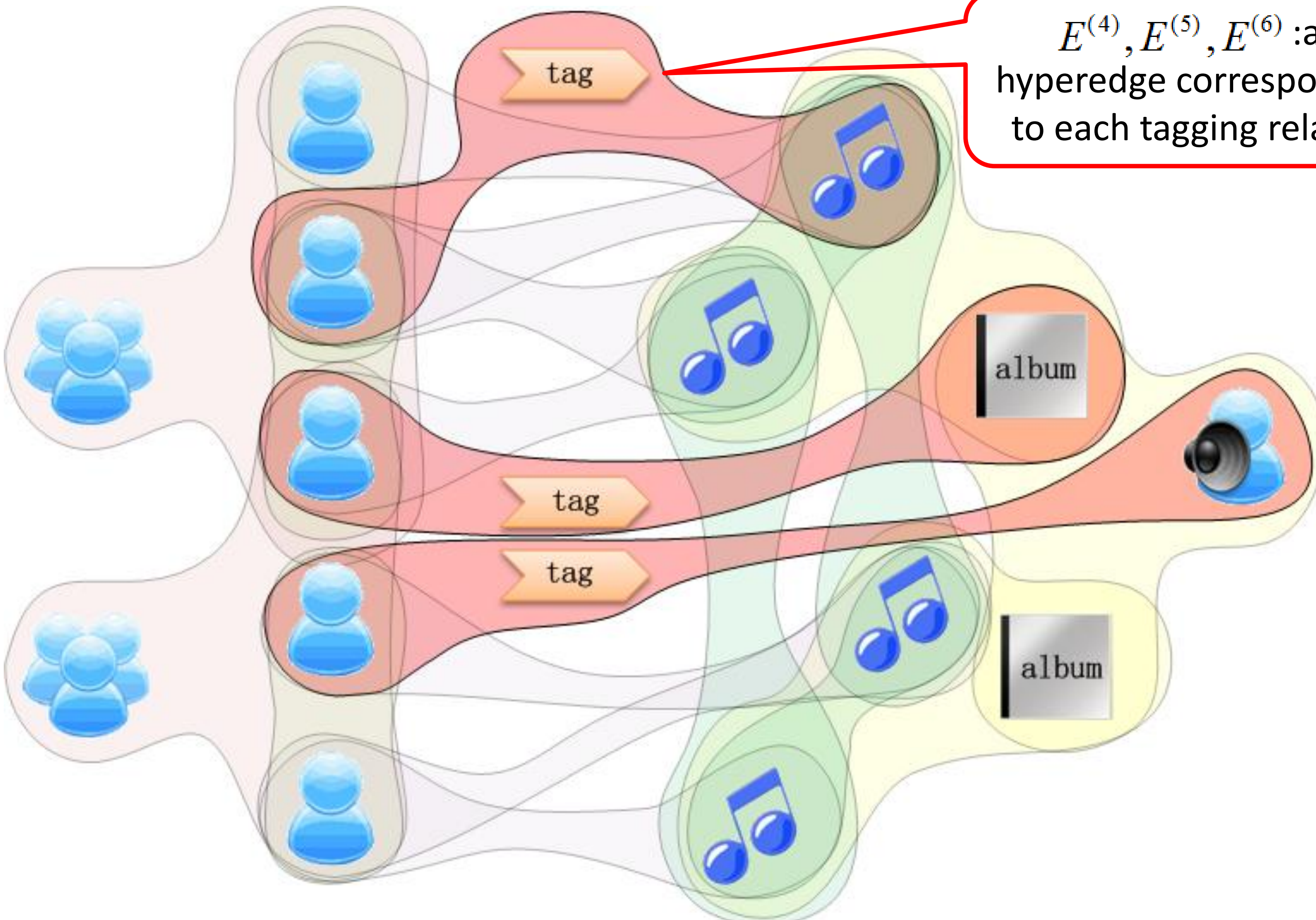
$E^{(2)}$:a hyperedge corresponding to each group

Hyperedges Construction Details



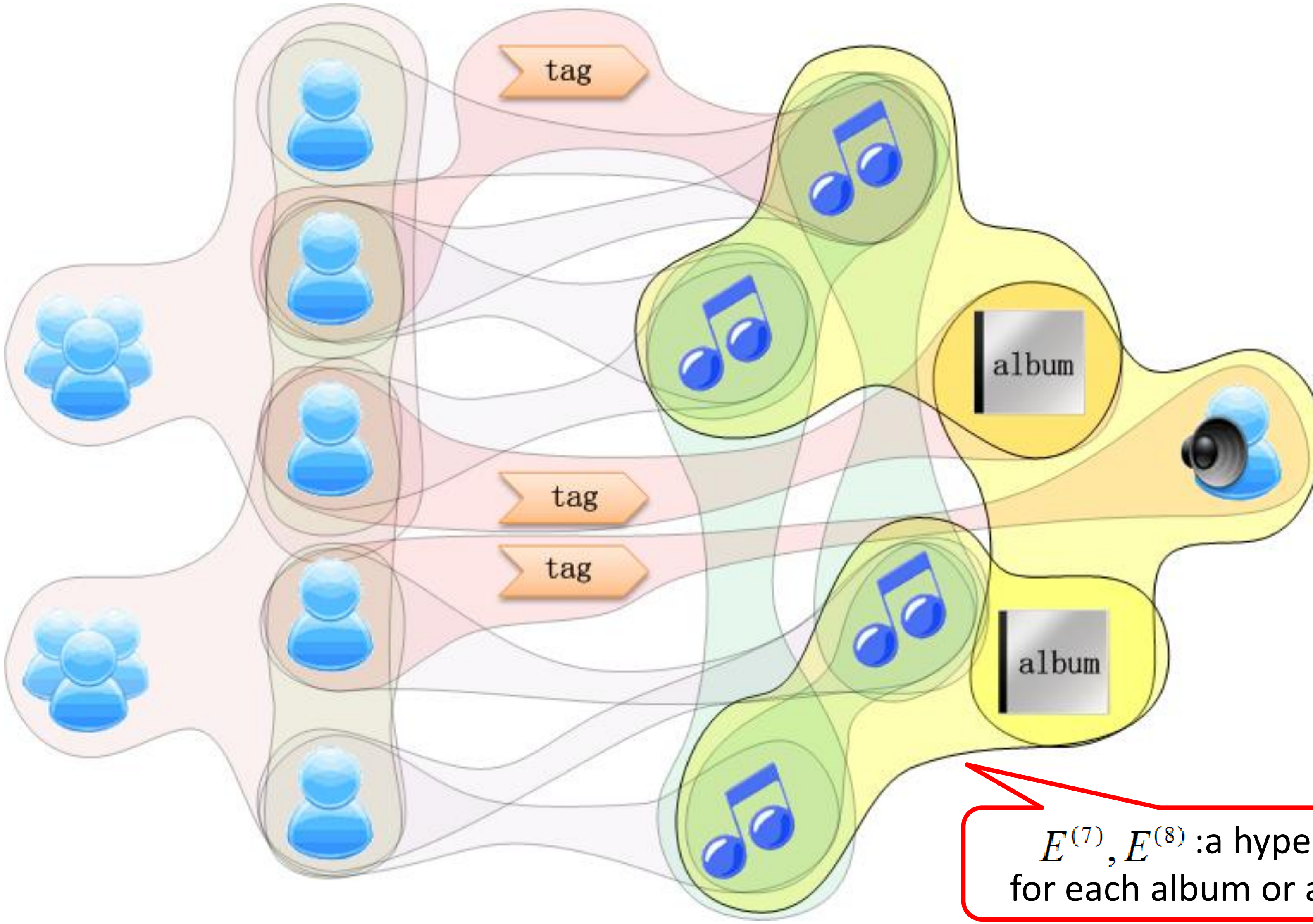
$E^{(3)}$: a hyperedge for each user-track listening relation

Hyperedges Construction Details



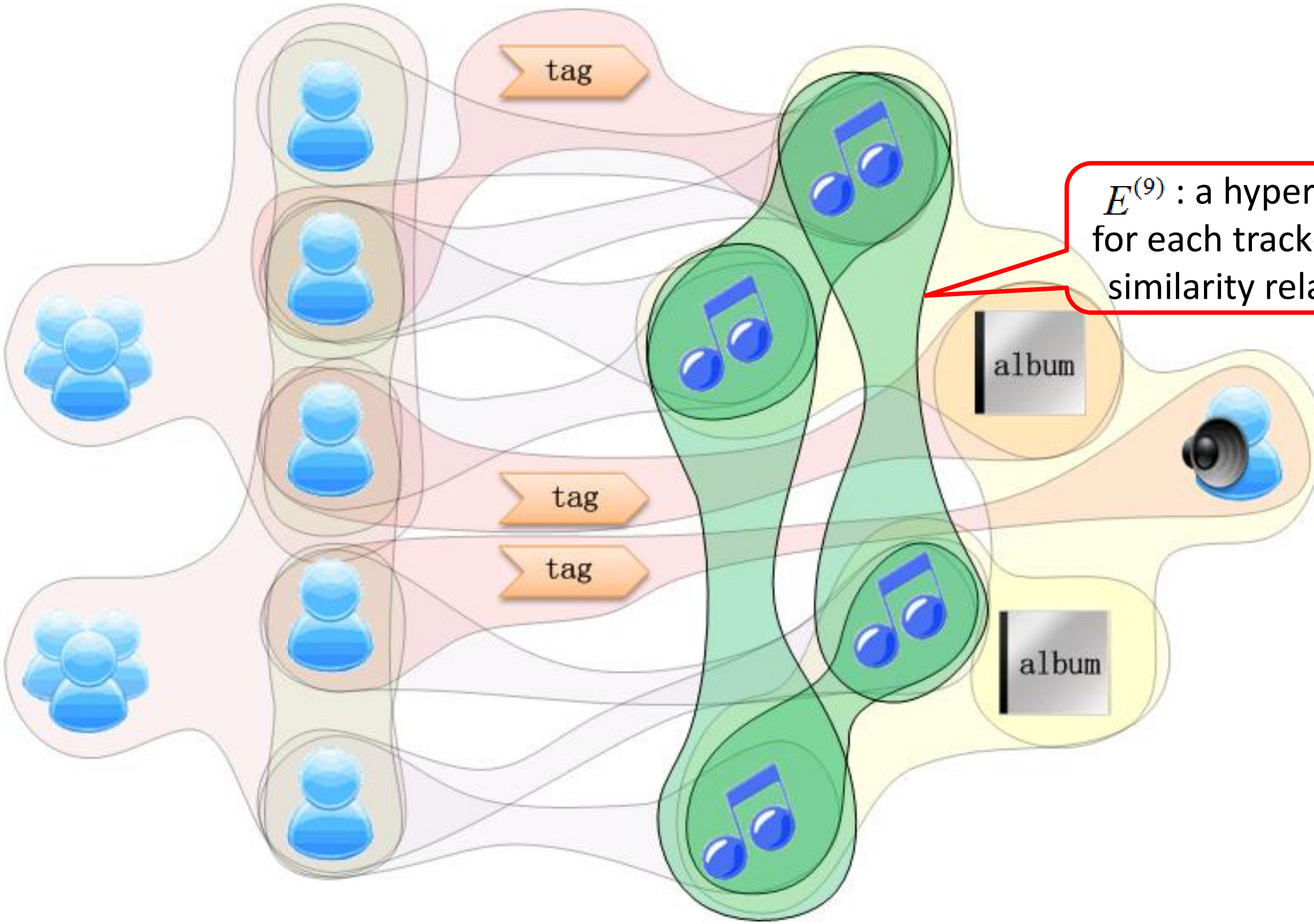
$E^{(4)}, E^{(5)}, E^{(6)}$:a hyperedge corresponding to each tagging relation

Hyperedges Construction Details



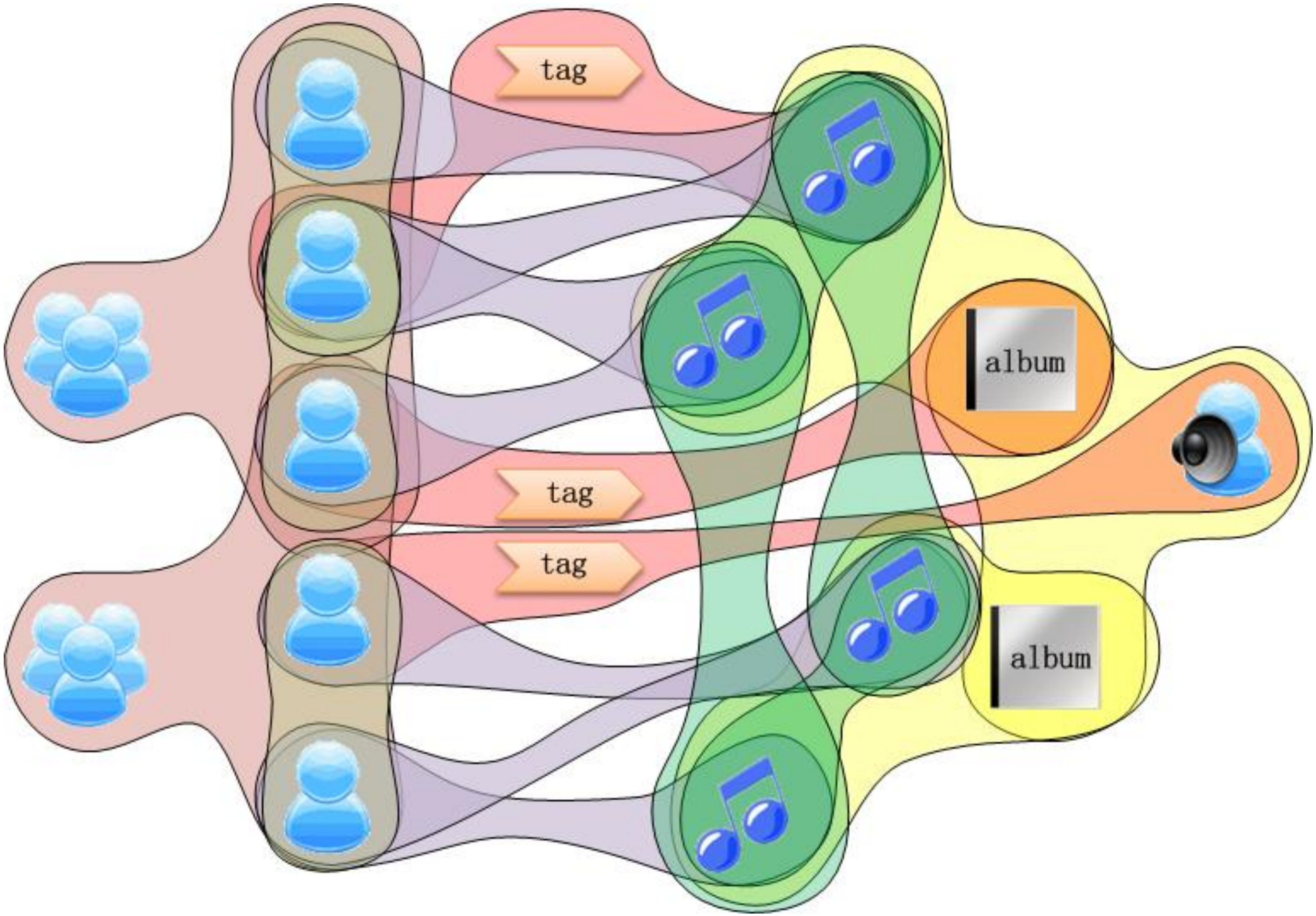
$E^{(7)}, E^{(8)}$:a hyperedge for each album or artist

Hyperedges Construction Details

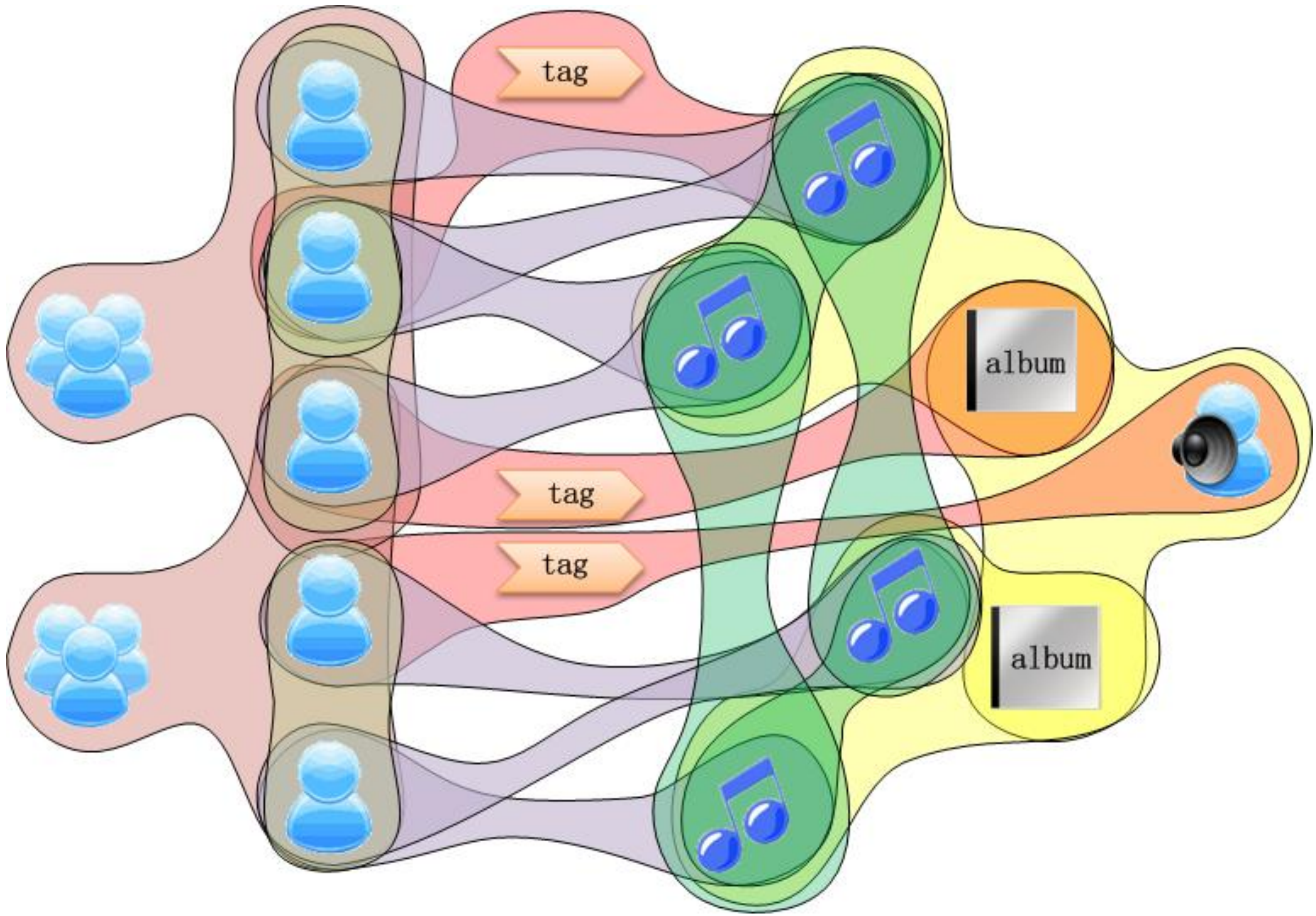


$E^{(9)}$: a hyperedge for each track-track similarity relation

Hyperedges Construction Details



Ranking on Unified Hypergraph



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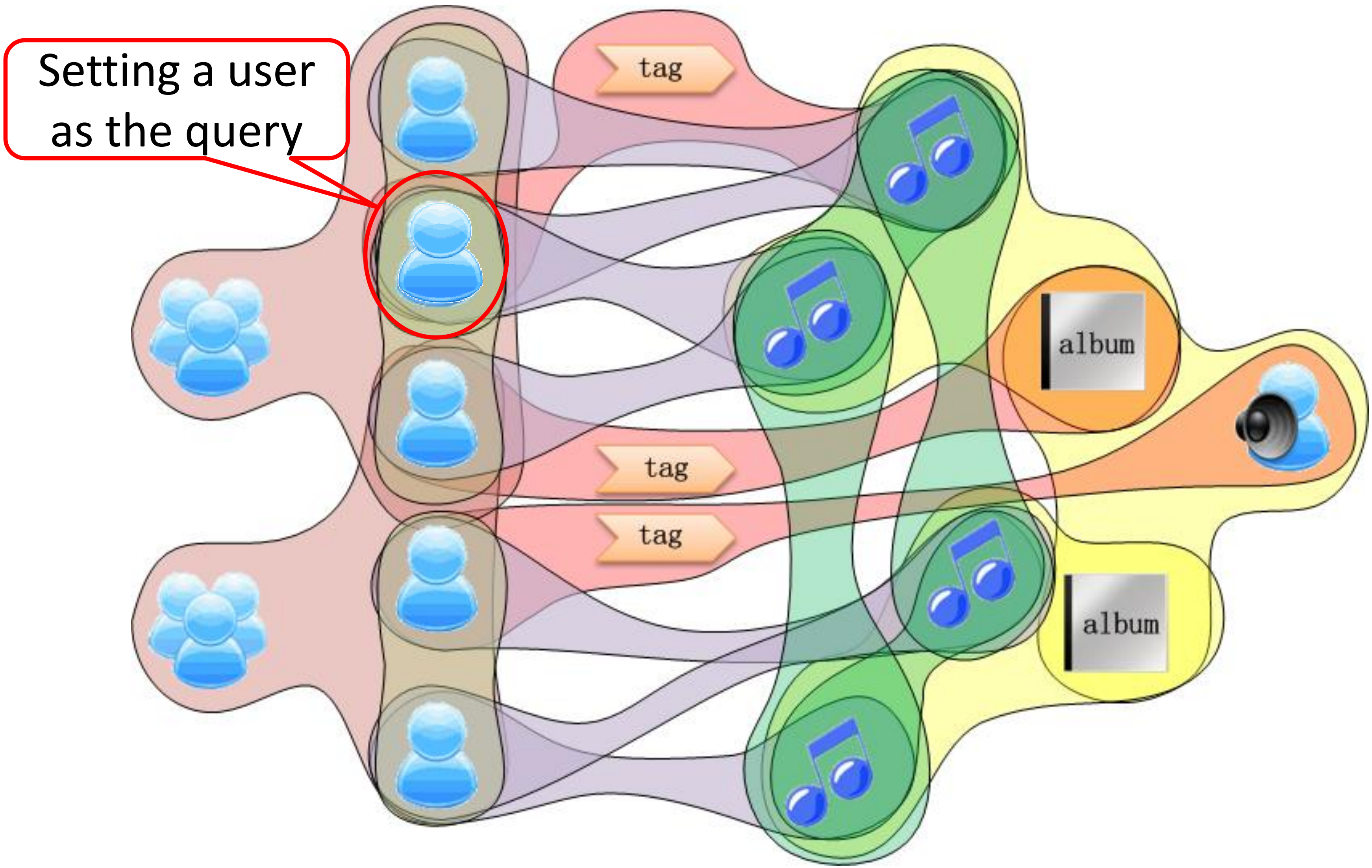

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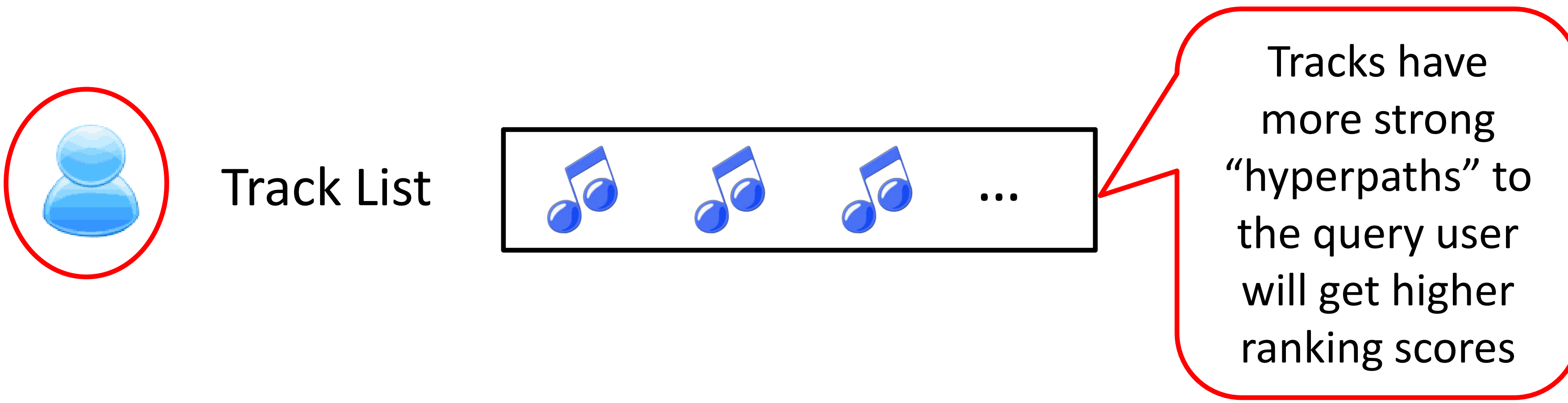


Notation

- A unified hypergraph $G(V, E, w)$
- ***H*** : Vertex-hyperedge incidence matrix
- $\delta(e)$: the degree of a hyperedge
- $d(v)$: the degree of a vertex

$$
\begin{aligned}
d(v) &= \sum_{e \in E} w(e) h(v, e), \\
\delta(e) &= \sum_{v \in V} h(v, e).
\end{aligned}
$$

- $\boldsymbol{D}_v$, $\boldsymbol{D}_e$ and ***W*** : diagonal matrices consisting of hyperedge degrees, vertex degrees and hyperedge weights

The Regularization Framework

$$Q(\mathbf{f}) = \frac{1}{2}\sum_{i,j=1}^{|V|}\sum_{e\in E_h}\frac{w(e)h(v_i,e)h(v_j,e)}{\delta(e)}\left\|\frac{f_i}{\sqrt{d(v_i)}}-\frac{f_j}{\sqrt{d(v_j)}}\right\|^2$$

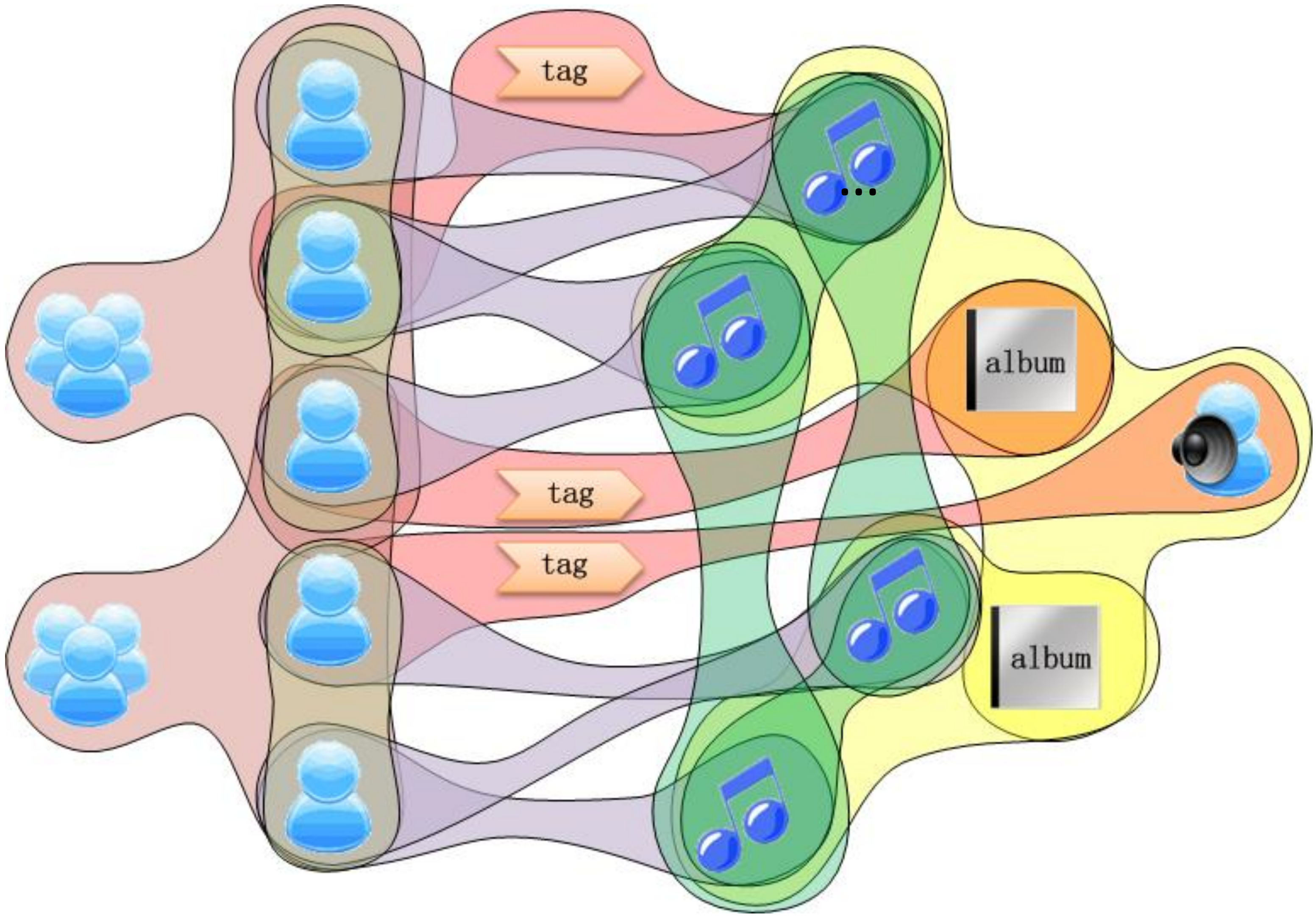
$$+\mu\sum_{i=1}^{|V|}\|f_i-y_i\|^2,$$

$$\mathbf{f}^* = \arg\min_{\mathbf{f}} Q(\mathbf{f}).$$

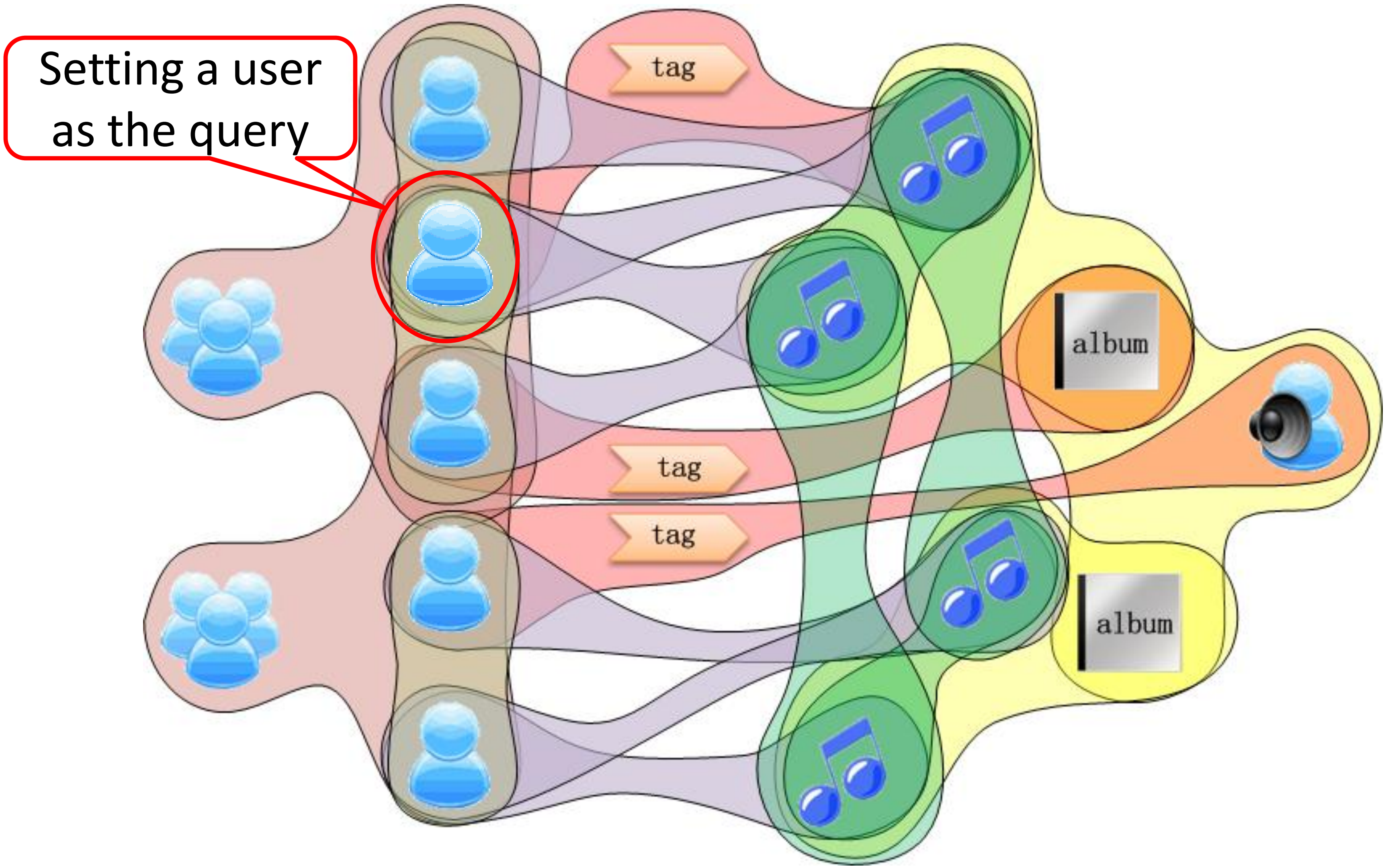
$$\mathbf{A} = \mathbf{D}_v^{-1/2}\mathbf{H}\mathbf{W}\mathbf{D}_e^{-1}\mathbf{H}^T\mathbf{D}_v^{-1/2}. \qquad \alpha = 1/(1+\mu).$$

$$\mathbf{f}^* = \left(\mathbf{I}-\alpha\mathbf{A}\right)^{-1}\mathbf{y}.$$

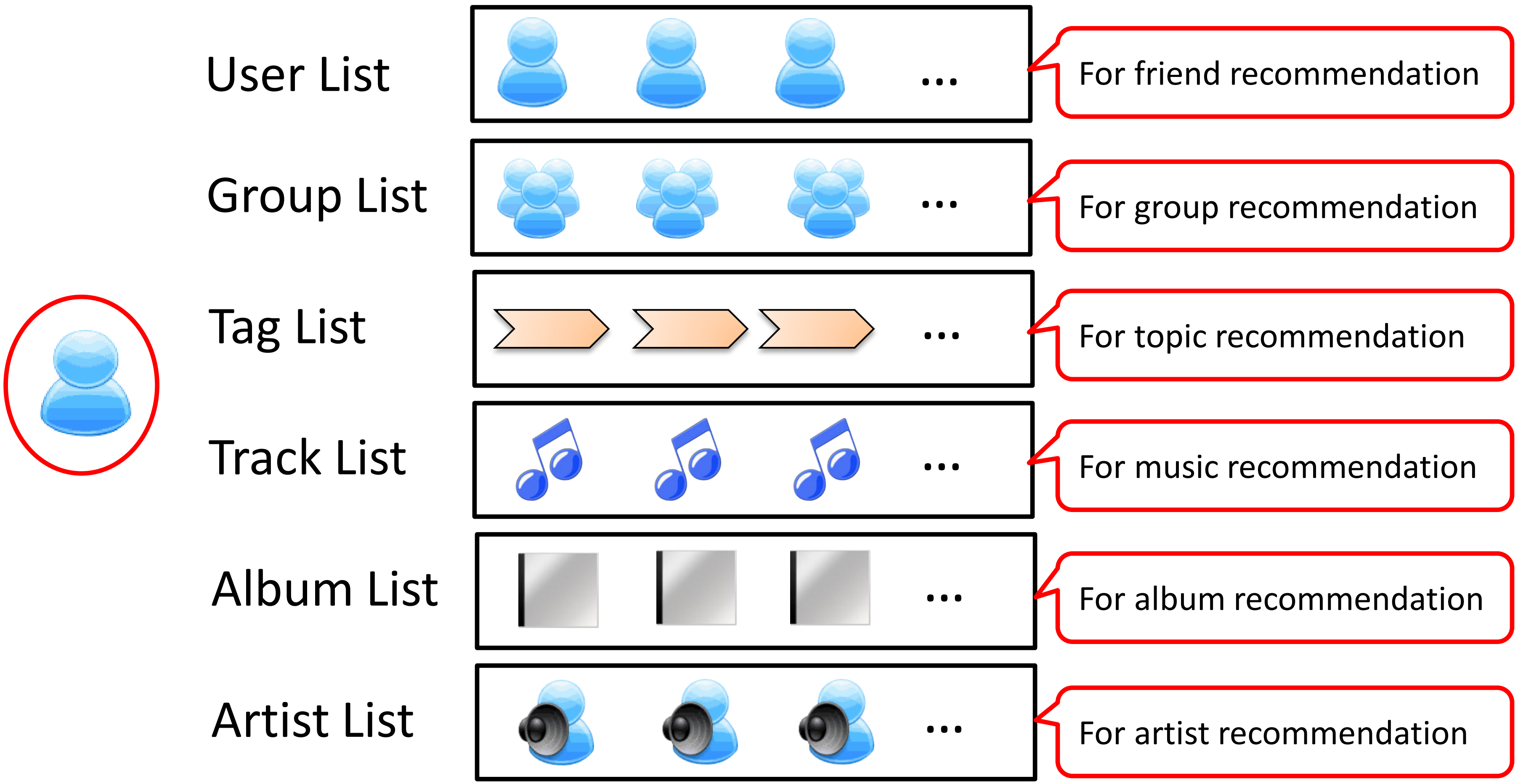
General Ranking Framework



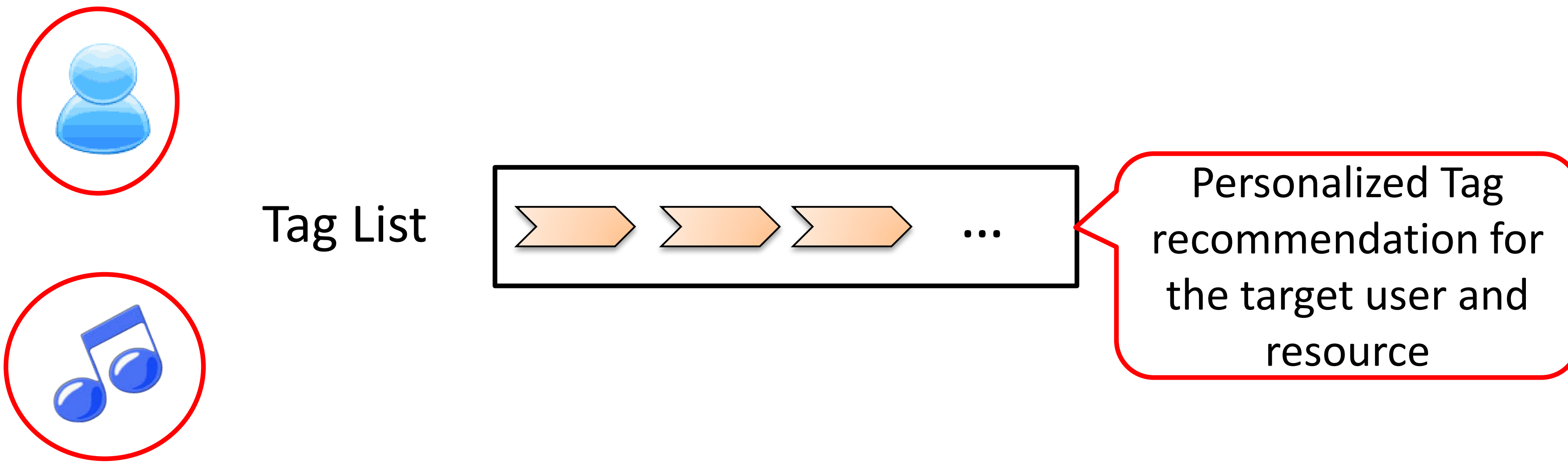
General Ranking Framework



General Ranking Framework



Personalized Tag Recommendation



Compared Algorithms

Algorithms		Information Used
User-based Collaborative Filtering (CF)		R_3
Acoustic-based music recommendation (AB)		R_3, R_9
Ranking on Unified Graph (RUG)		R_1, R_2, R_3, R_4, R_5, R_6, R_7, R_8, R_9
Our proposed music recommendation on Hypergraph method (MRH)	MRH-hybrid	R_3, R_9
	MRH-social	R_1, R_2, R_3, R_4, R_5, R_6, R_7, R_8
	MRH	R_1, R_2, R_3, R_4, R_5, R_6, R_7, R_8, R_9

- **R_1**: friendship relations
- **R_2**: membership relations
- **R_3**: listening relations
- **R_4**: tagging relations on tracks
- **R_5**: tagging relations on albums
- **R_6**: tagging relations on artists
- **R_7**: track-album inclusion relations
- **R_8**: album-artist inclusion relations
- **R_9**: similarities between tracks

Performance Comparison

Comparison of recommendation algorithms in terms of MAP and F1.

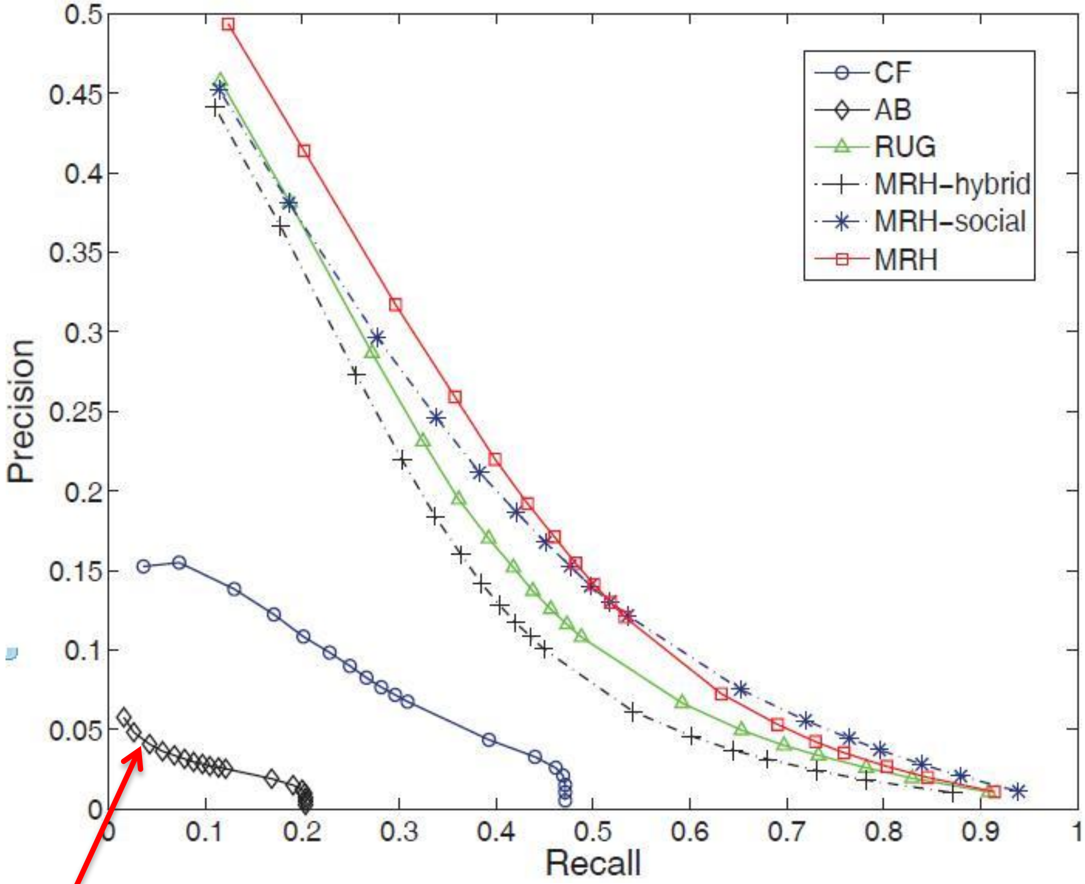
	MAP	F1@5	F1@10	F1@20	F1@30	F1@50	F1@70	F1@100	F1@200
CF	0.1632	0.0557	0.0929	0.1243	0.1329	0.1294	0.1197	0.1064	0.0765
AB	0.0762	0.0226	0.0303	0.0377	0.0403	0.0421	0.0415	0.0401	0.0334
RUG	0.2626	0.1729	0.2323	0.2587	0.2516	0.2237	0.1988	0.1701	0.1169
MRH-hybrid	0.2470	0.1653	0.2224	0.2451	0.2377	0.2099	0.1855	0.1581	0.1076
MRH-social	0.2755	0.1705	0.2311	0.2654	0.2660	0.2440	0.2202	**0.1906**	**0.1318***
MRH	**0.2948***	**0.1855***	**0.2510***	**0.2839***	**0.2799***	**0.2509***	**0.2227**	0.1892	0.1270

Comparison of recommendation algorithms in terms of NDCG.

	NDCG@5	NDCG@10	NDCG@30	NDCG@50	NDCG@70	NDCG@100	NDCG@200
CF	0.1522	0.1713	0.2519	0.2987	0.3278	0.3579	0.4120
AB	0.0733	0.0820	0.1241	0.1532	0.1749	0.2027	0.2556
RUG	0.4849	0.4318	0.3826	0.4109	0.4345	0.4587	0.5037
MRH-hybrid	0.4587	0.4091	0.3640	0.3911	0.4124	0.4346	0.4753
MRH-social	0.4759	0.4268	0.3866	0.4197	0.4480	0.4763	0.5264
MRH	**0.5192***	**0.4650***	**0.4174***	**0.4484***	**0.4740***	**0.4987***	**0.5419***

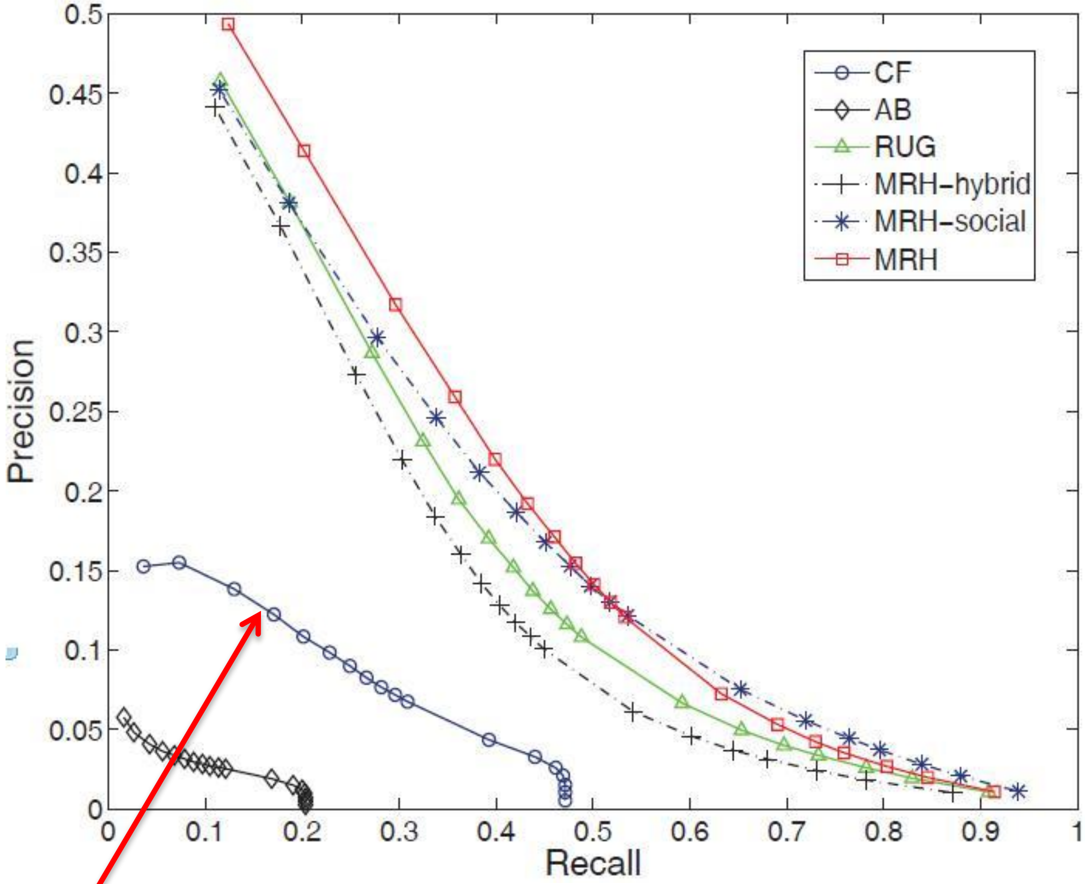
It is clear that our proposed algorithm significantly outperforms the other recommendation algorithms

Precision-Recall Curves



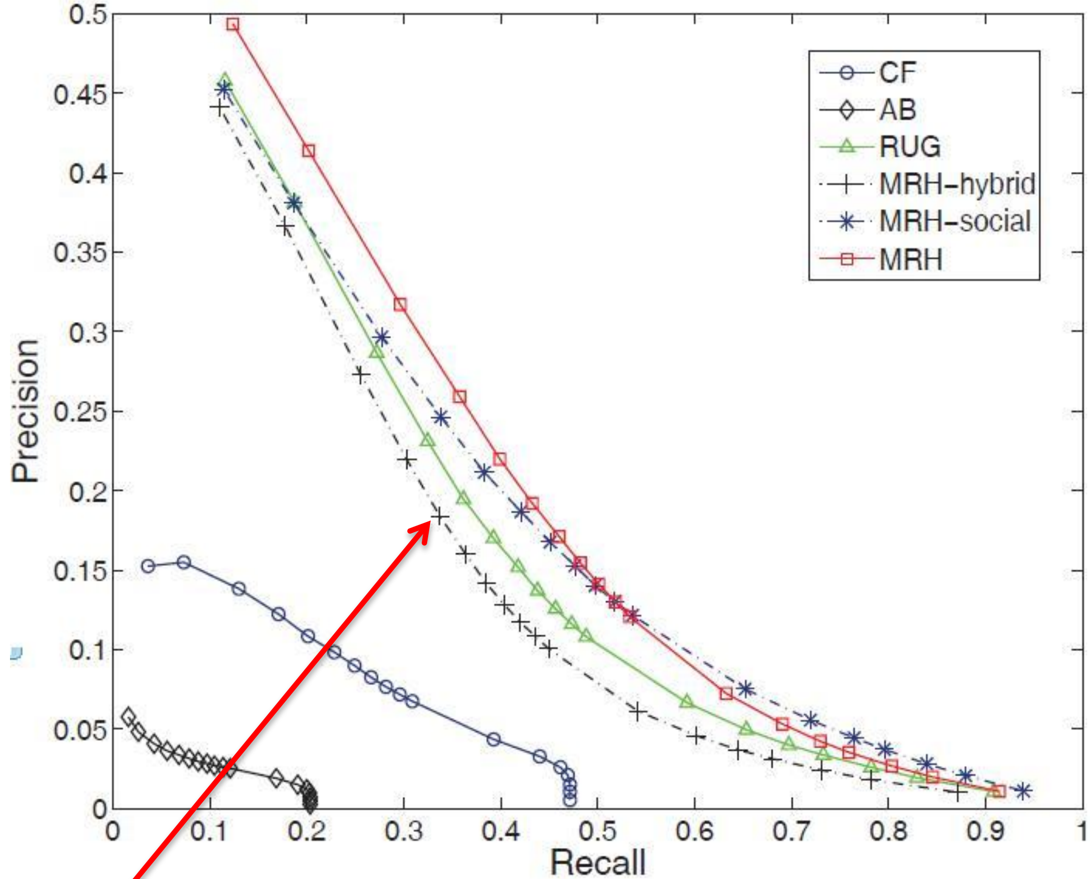
Acoustic-based (AB) method works worst. That is because acoustic-based method incurs the semantic gap and similarities based on acoustic content are not always consistent with human knowledge

Precision-Recall Curves



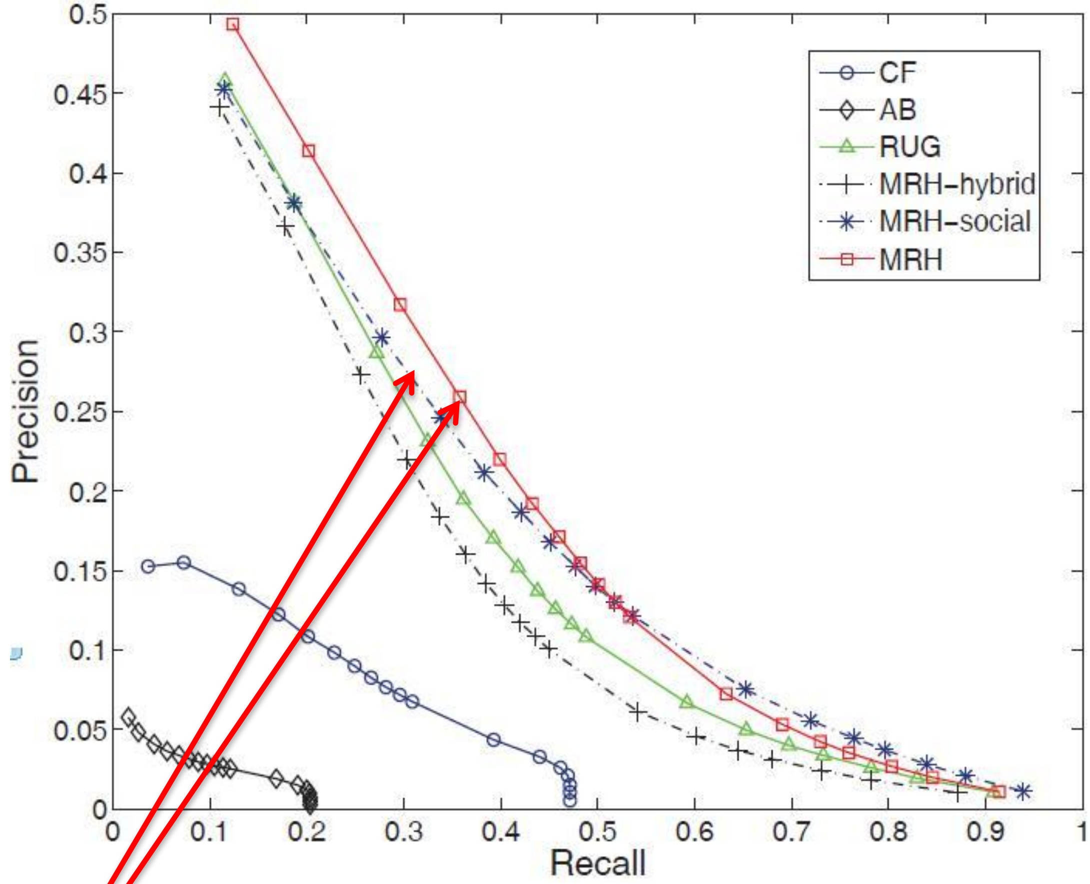
CF algorithm does not work well too. This is probably because the user-track matrix in our data set is highly sparse

Precision-Recall Curves



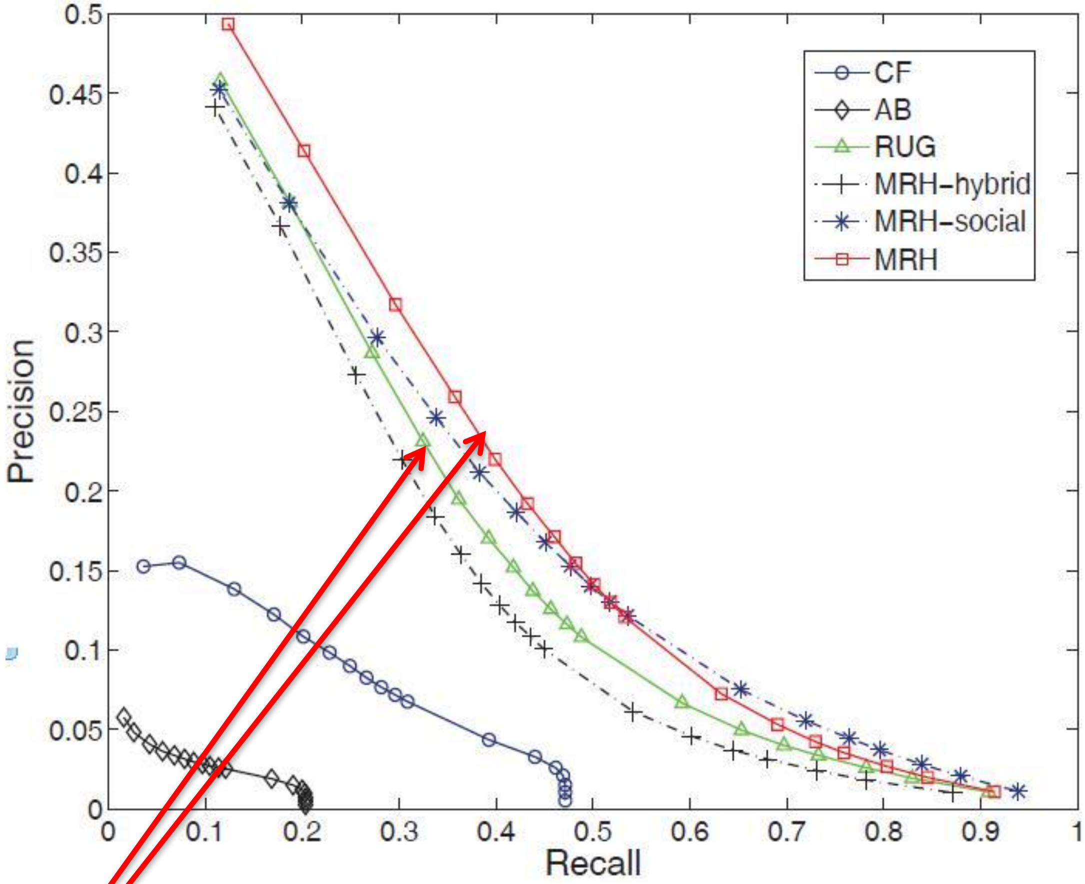
Our proposed method alleviates these problems. MRH-hybrid only uses similarity relations among music tracks and listening relations, but it works much better than AB and CF

Precision-Recall Curves



Comparing to MRH-social, MRH uses similarity relations among tracks additionally. We find that using this acoustic information can improve the recommendation result, especially when we only care top ranking music tracks.

Precision-Recall Curves



The superiority of MRH over RUG indicates that the hypergraph is indeed a better choice for modeling complex relations in social media information

Conclusion

- We use the unified hypergraph model to fuse multi-type media, includes multi-type social media information and music content.
  - ➢Social media information is very useful for music recommendation.
  - ➢Hypergraphs can accurately capture the high-order relations among various types of objects.

Thank You !