

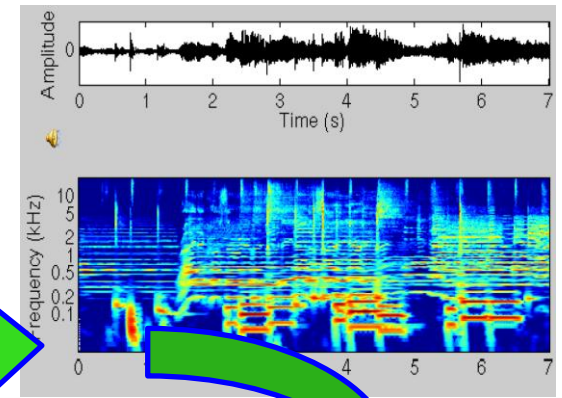
Music Recommendation by Unified Hypergraph: Combining Social Media Information and Music Content

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Multi-type Media Fusion

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

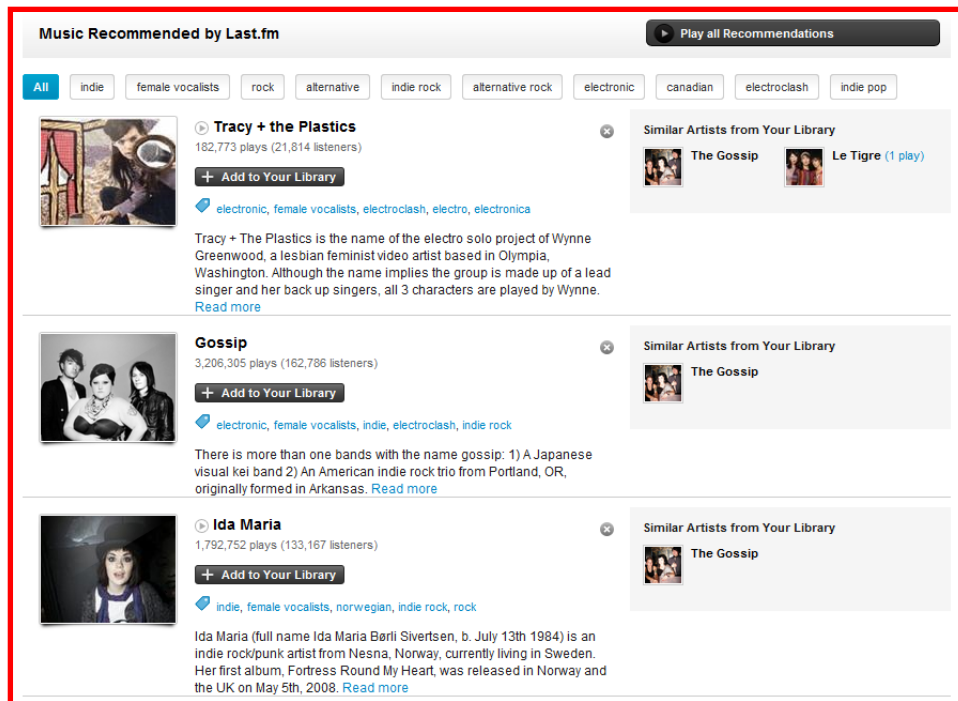


Outlines

- 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!**



The screenshot displays the 'Music Recommended by Last.fm' interface. At the top, there is a search bar and a 'Play all Recommendations' button. Below this, a row of genre tags includes 'All', 'indie', 'female vocalists', 'rock', 'alternative', 'indie rock', 'alternative rock', 'electronic', 'canadian', 'electroclash', and 'indie pop'. The main content area features three music recommendations, each with an album cover, artist name, play count, a 'Add to Your Library' button, genre tags, a brief description, and a 'Read more' link. To the right of each recommendation is a 'Similar Artists from Your Library' section with a close button and one or more artist suggestions.

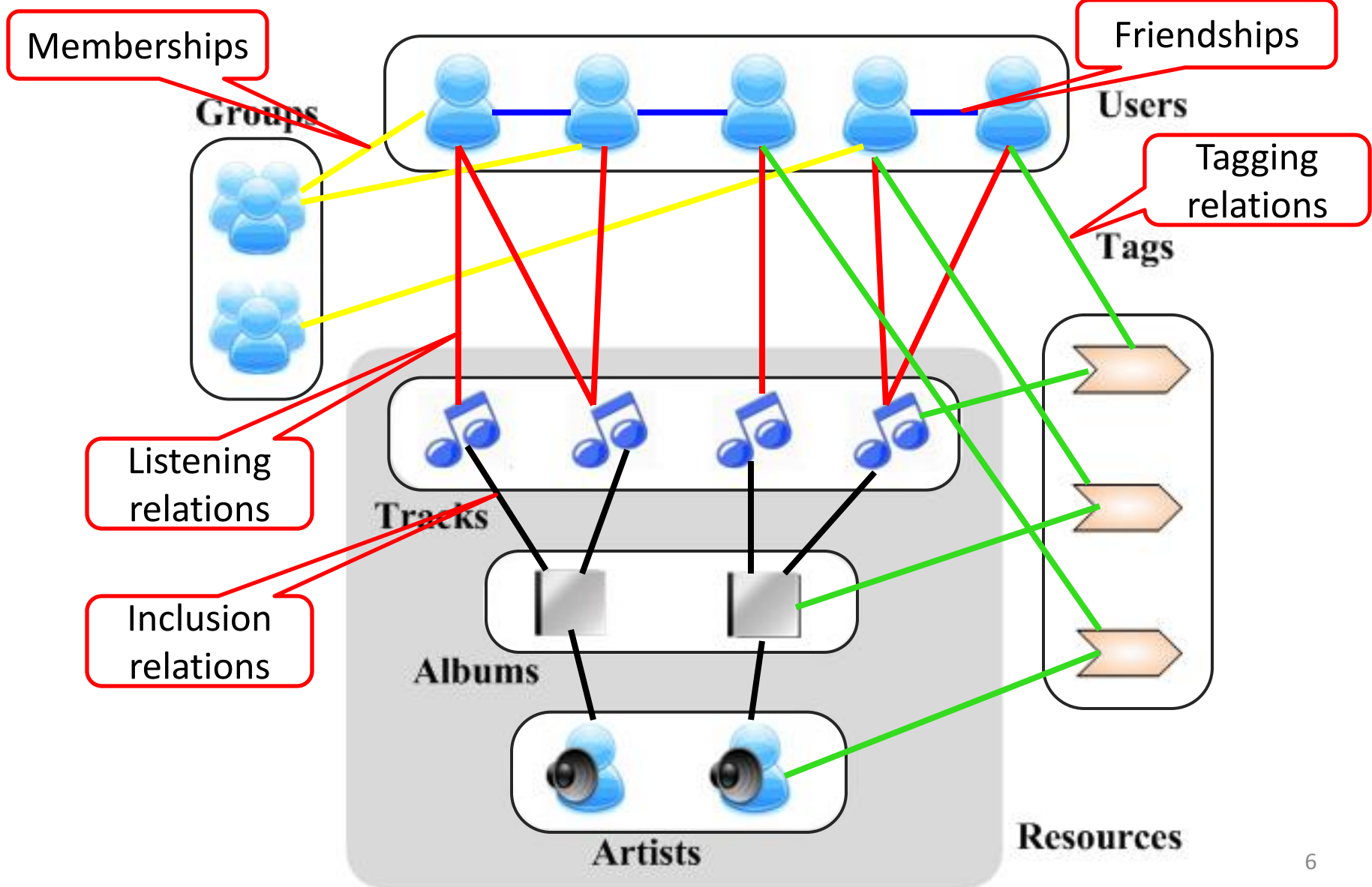
- Tracy + the Plastics**: 182,773 plays (21,814 listeners). Genres: electronic, female vocalists, electroclash, electro, electronica. Description: Tracy + The Plastics is the name of the electro solo project of Wynne Greenwood, a lesbian feminist video artist based in Olympia, Washington. Although the name implies the group is made up of a lead singer and her back up singers, all 3 characters are played by Wynne. [Read more](#)
- Gossip**: 3,206,305 plays (162,786 listeners). Genres: electronic, female vocalists, indie, electroclash, indie rock. Description: There is more than one bands with the name gossip: 1) A Japanese visual kei band 2) An American indie rock trio from Portland, OR, originally formed in Arkansas. [Read more](#)
- Ida Maria**: 1,792,752 plays (133,167 listeners). Genres: indie, female vocalists, norwegian, indie rock, rock. Description: Ida Maria (full name Ida Maria Børli Sivertsen, b. July 13th 1984) is an indie rock/punk artist from Nesna, Norway, currently living in Sweden. Her first album, Fortress Round My Heart, was released in Norway and the UK on May 5th, 2008. [Read more](#)

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

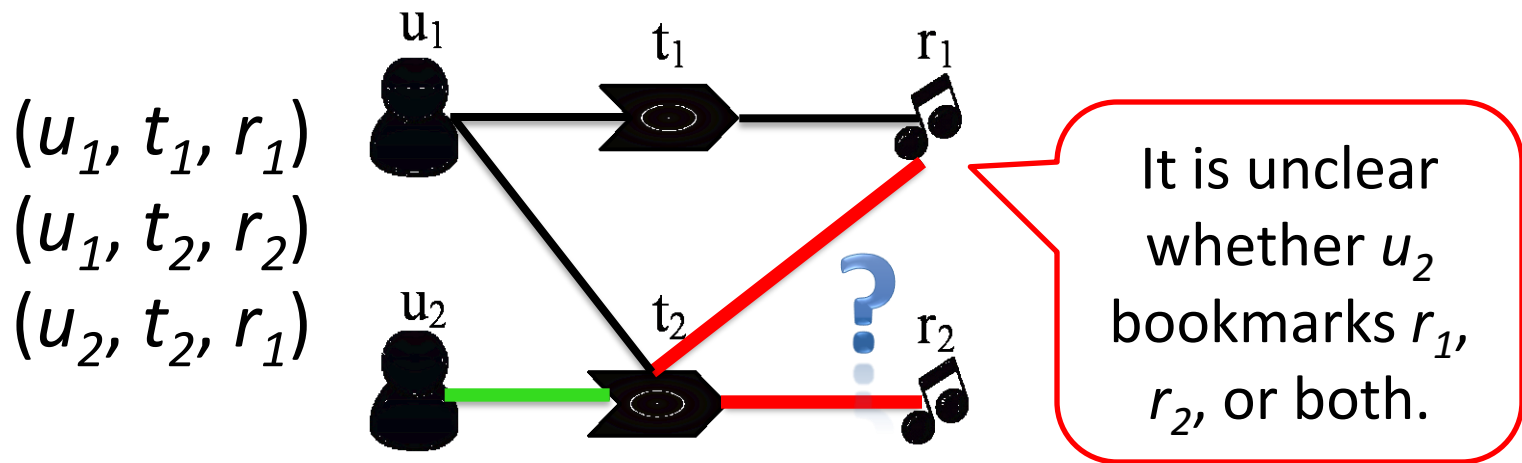


Social Media Information

- 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.
 - ...

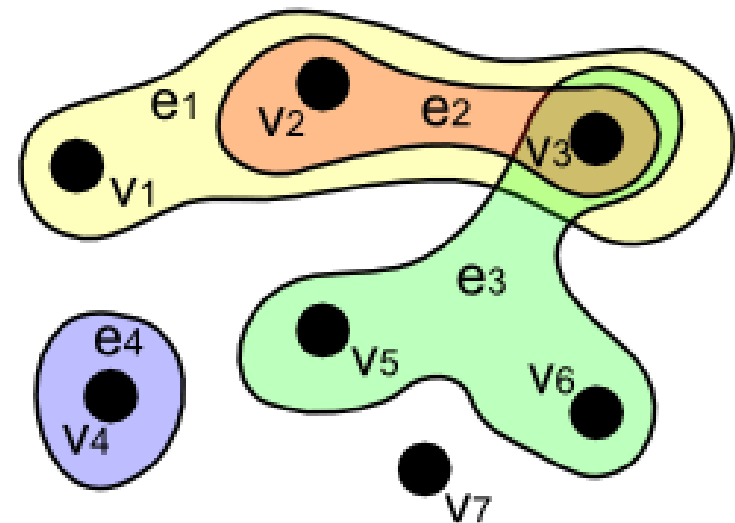
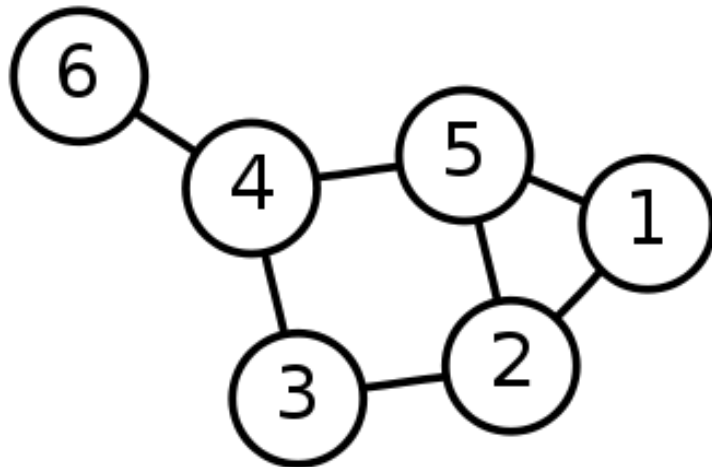
How About Graph Model?

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



Unified Hypergraph Model

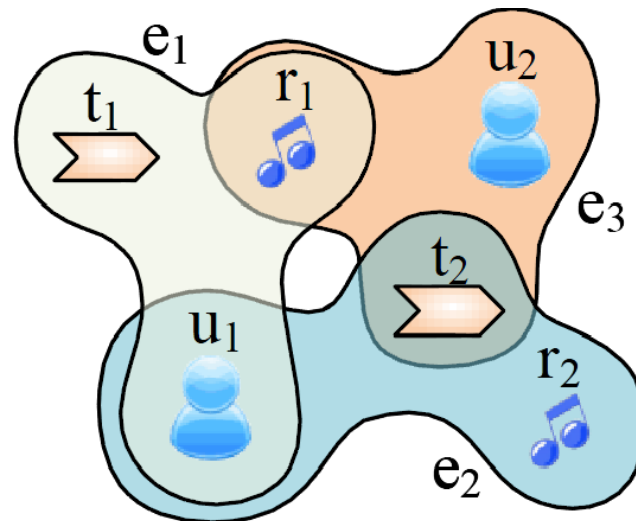
- Using a unified hypergraph to model multi-type objects and the high-order relations
 - Each edge in a hypergraph, called a hyperedge, is an arbitrary non-empty subset of the vertex set
 - Modeling each high-order relation by a hyperedge, so hypergraphs can capture high-order relations naturally



Unified Hypergraph Model

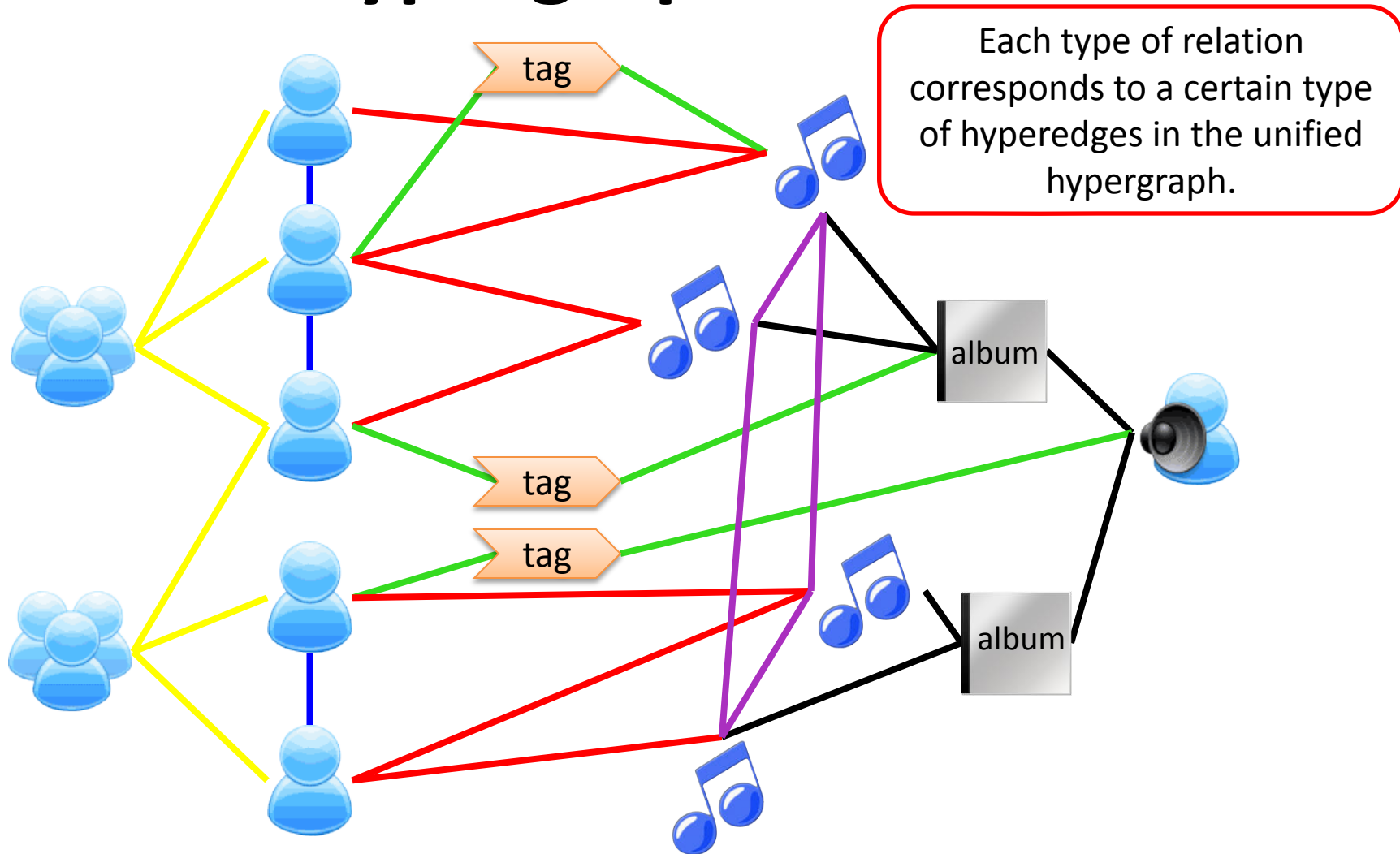
- Using a unified hypergraph to model multi-type objects and the high-order relations
 - Each edge in a hypergraph, called a hyperedge, is an arbitrary non-empty subset of the vertex set
 - Modeling each high-order relation by a hyperedge, so hypergraphs can capture high-order relations naturally

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



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

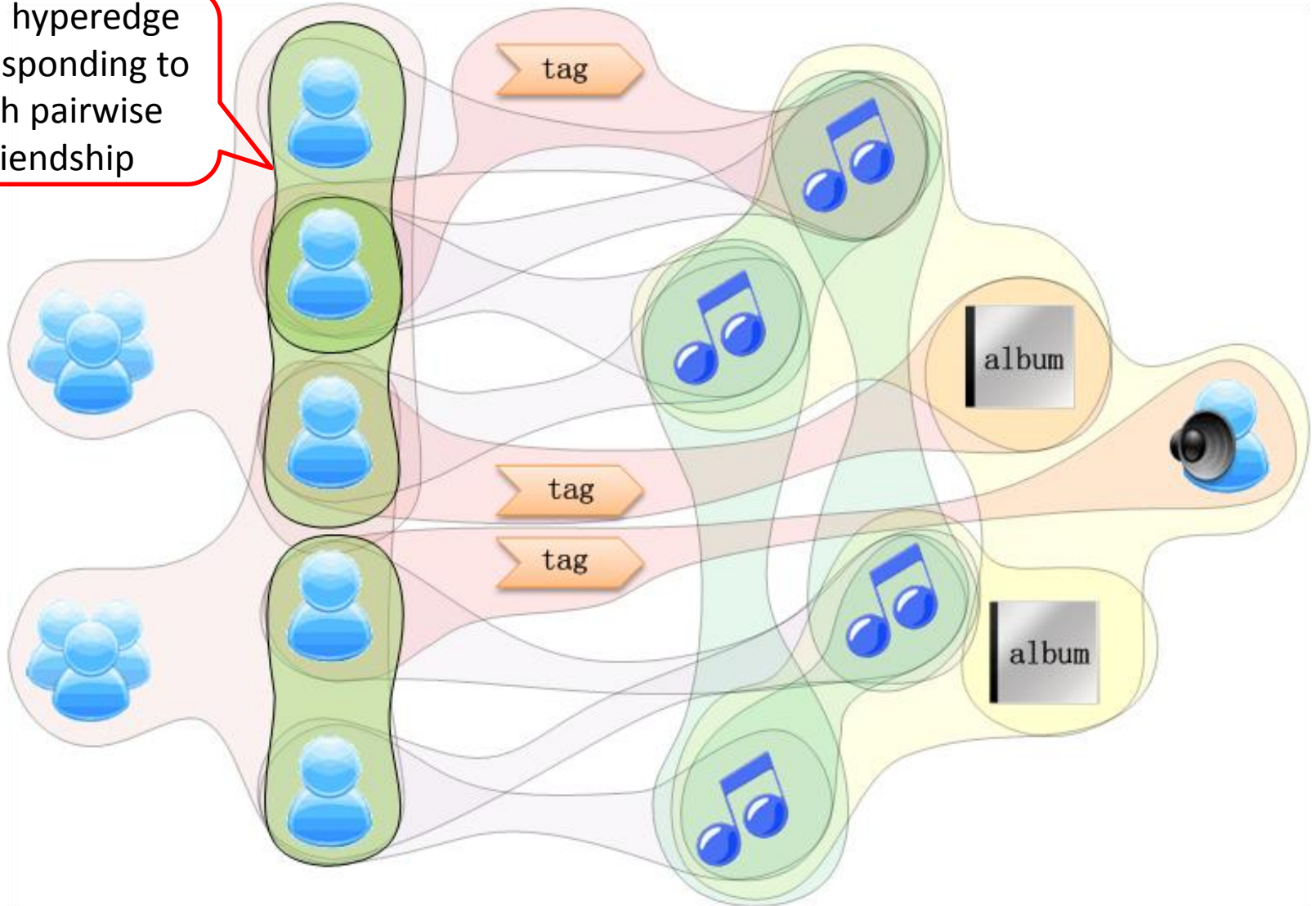
Unified Hypergraph Construction



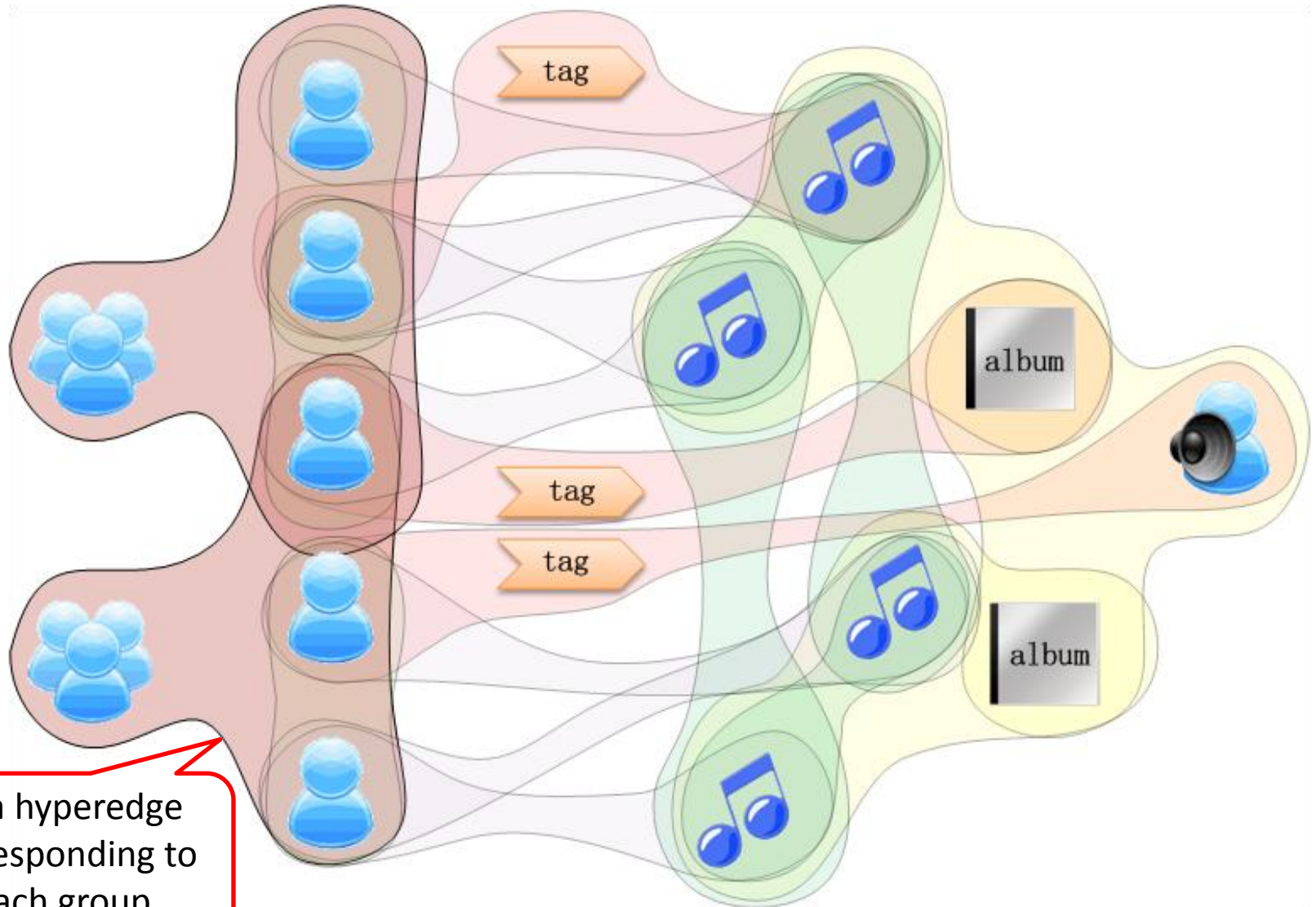
The six types of objects form the vertex set of the unified hypergraph.

Hyperedges Construction Details

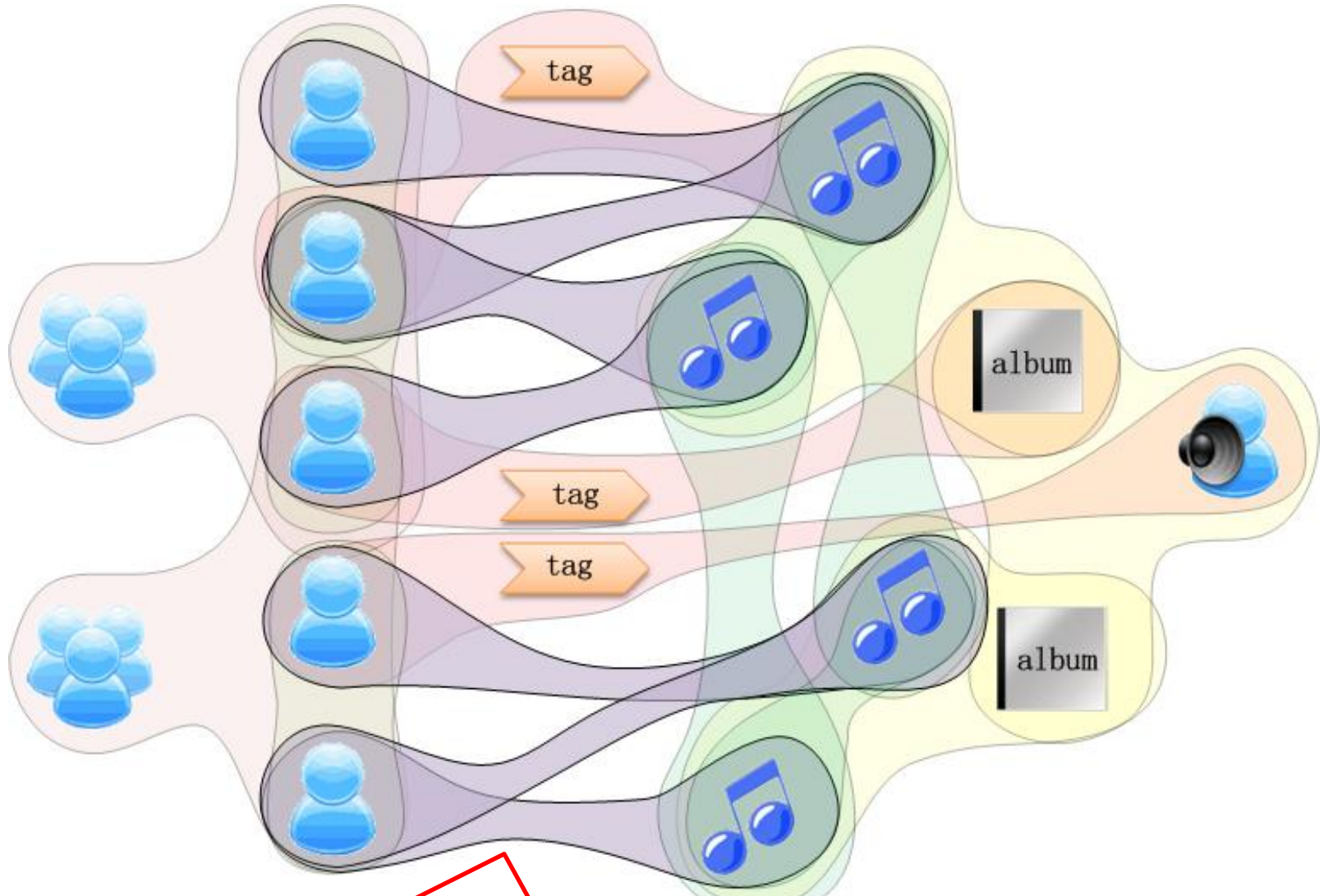
$E^{(1)}$: a hyperedge corresponding to each pairwise friendship



Hyperedges Construction Details

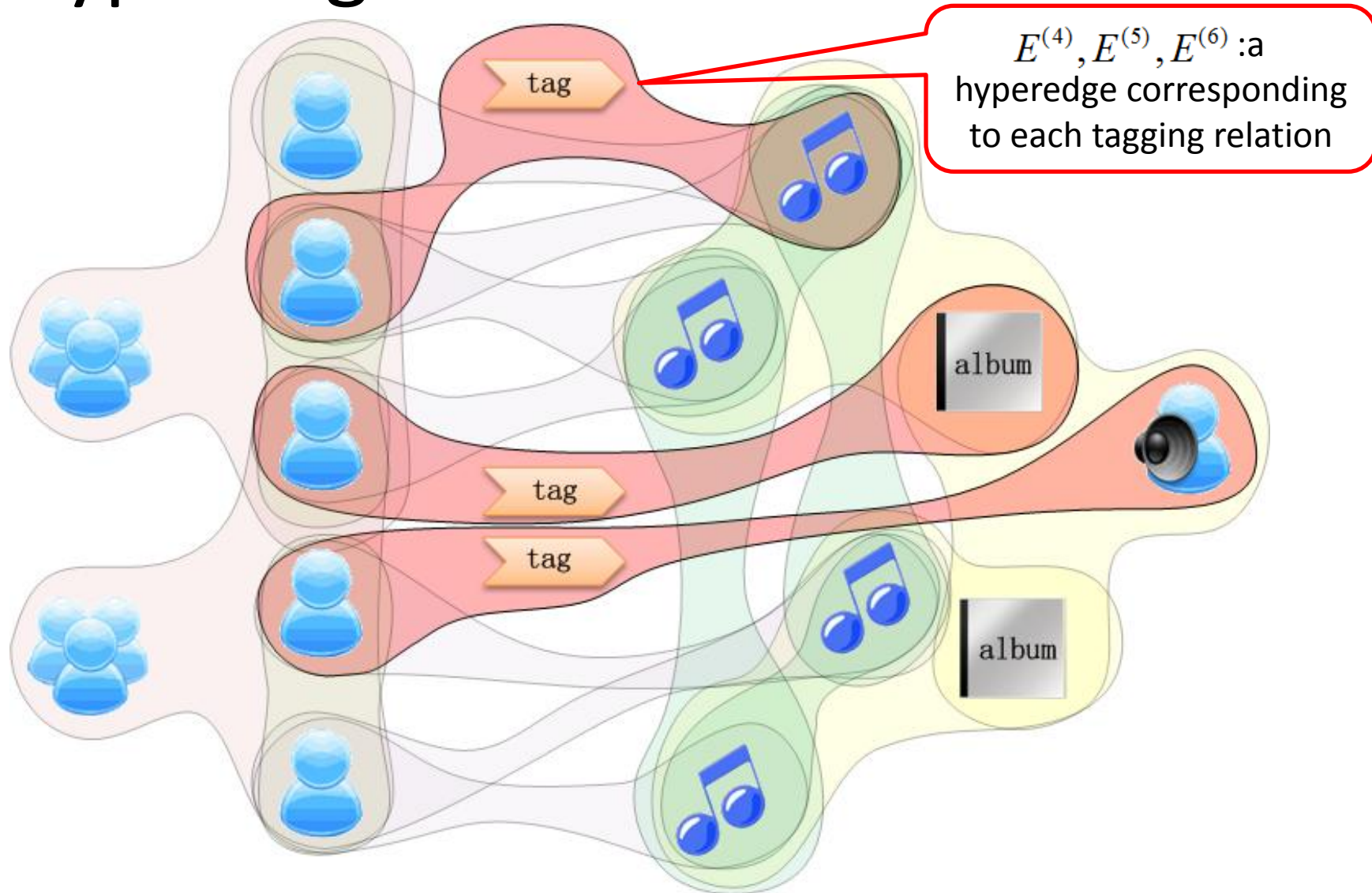


Hyperedges Construction Details

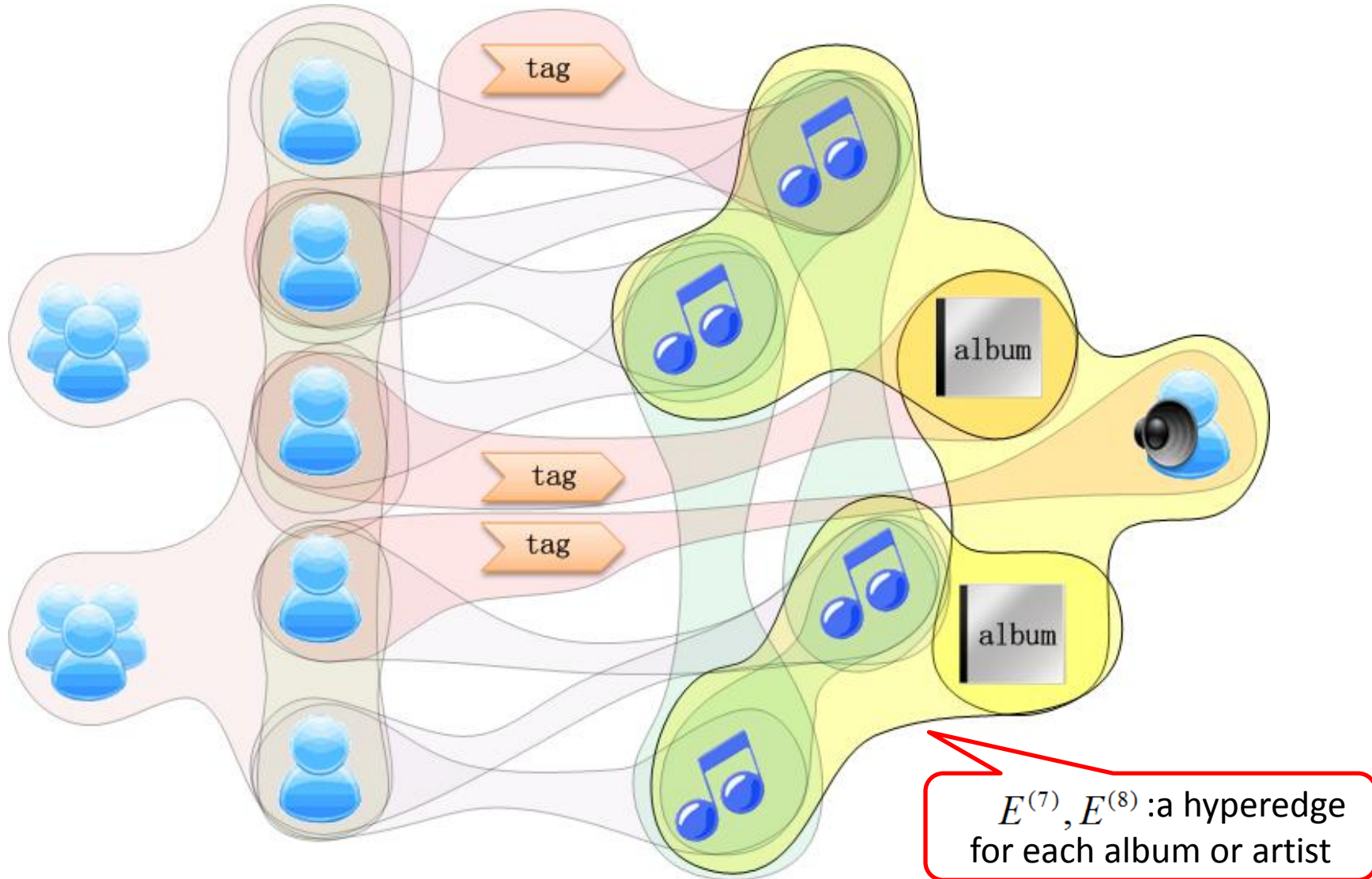


$E^{(3)}$: a hyperedge for each user-track listening relation

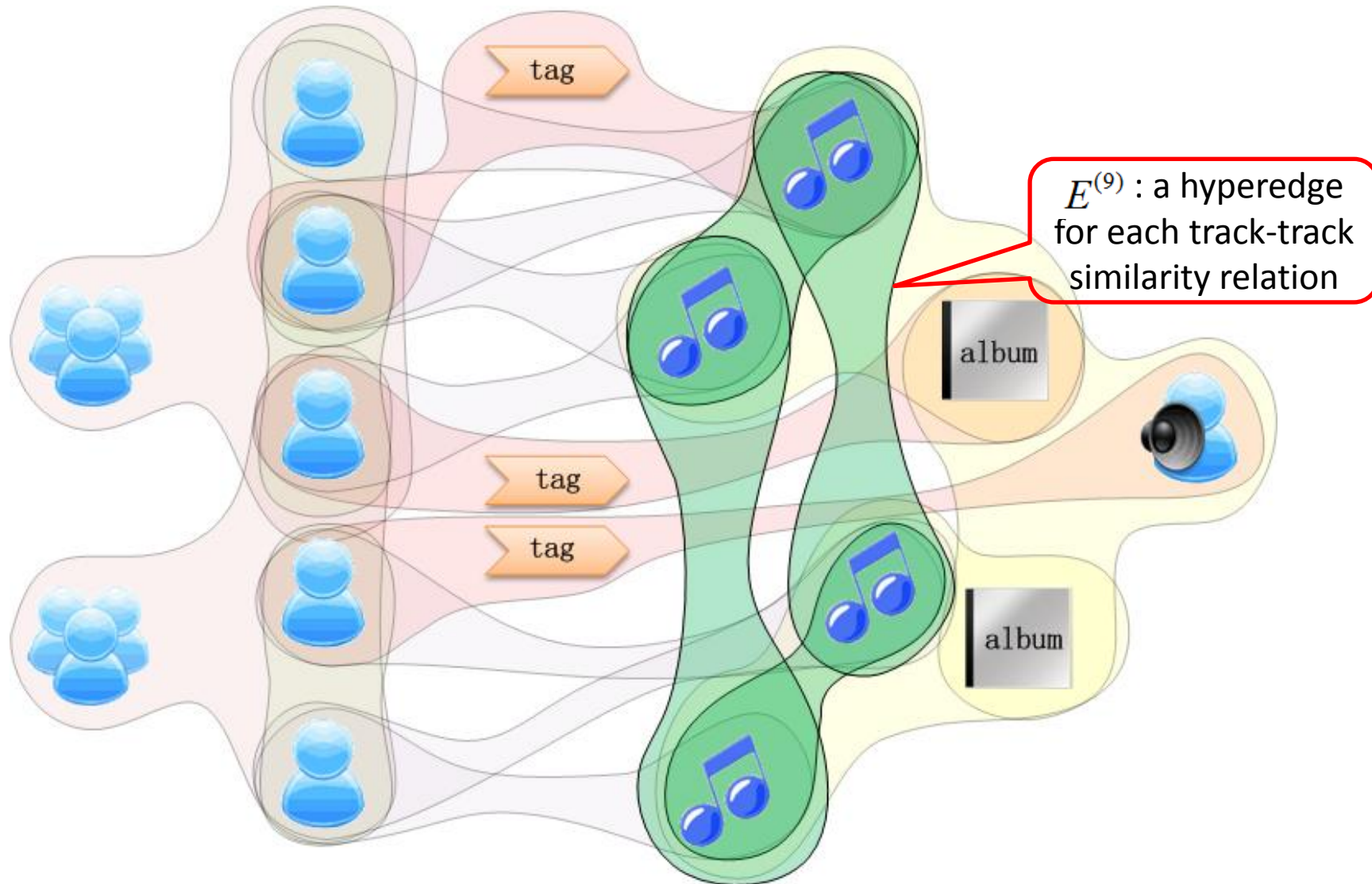
Hyperedges Construction Details



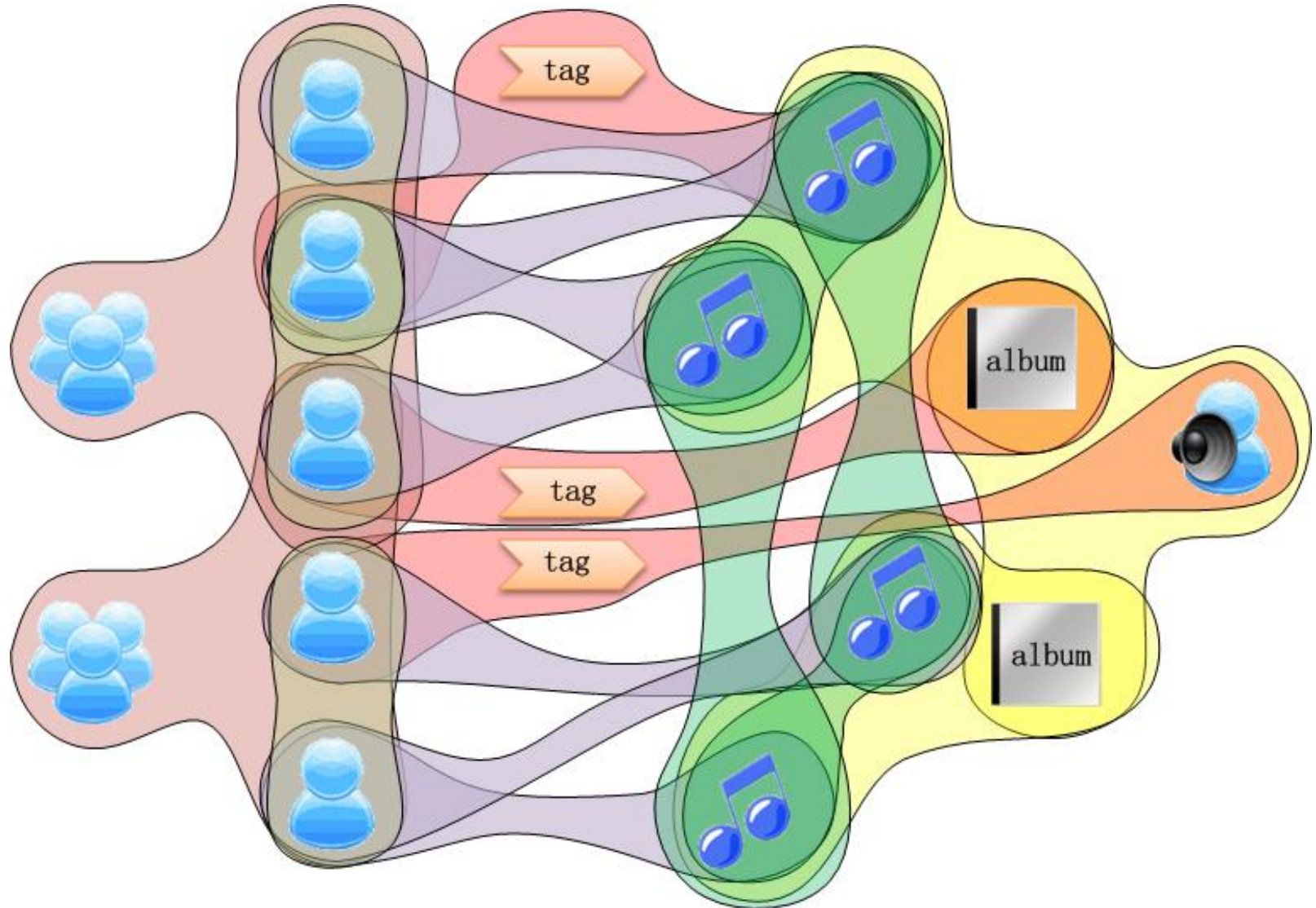
Hyperedges Construction Details



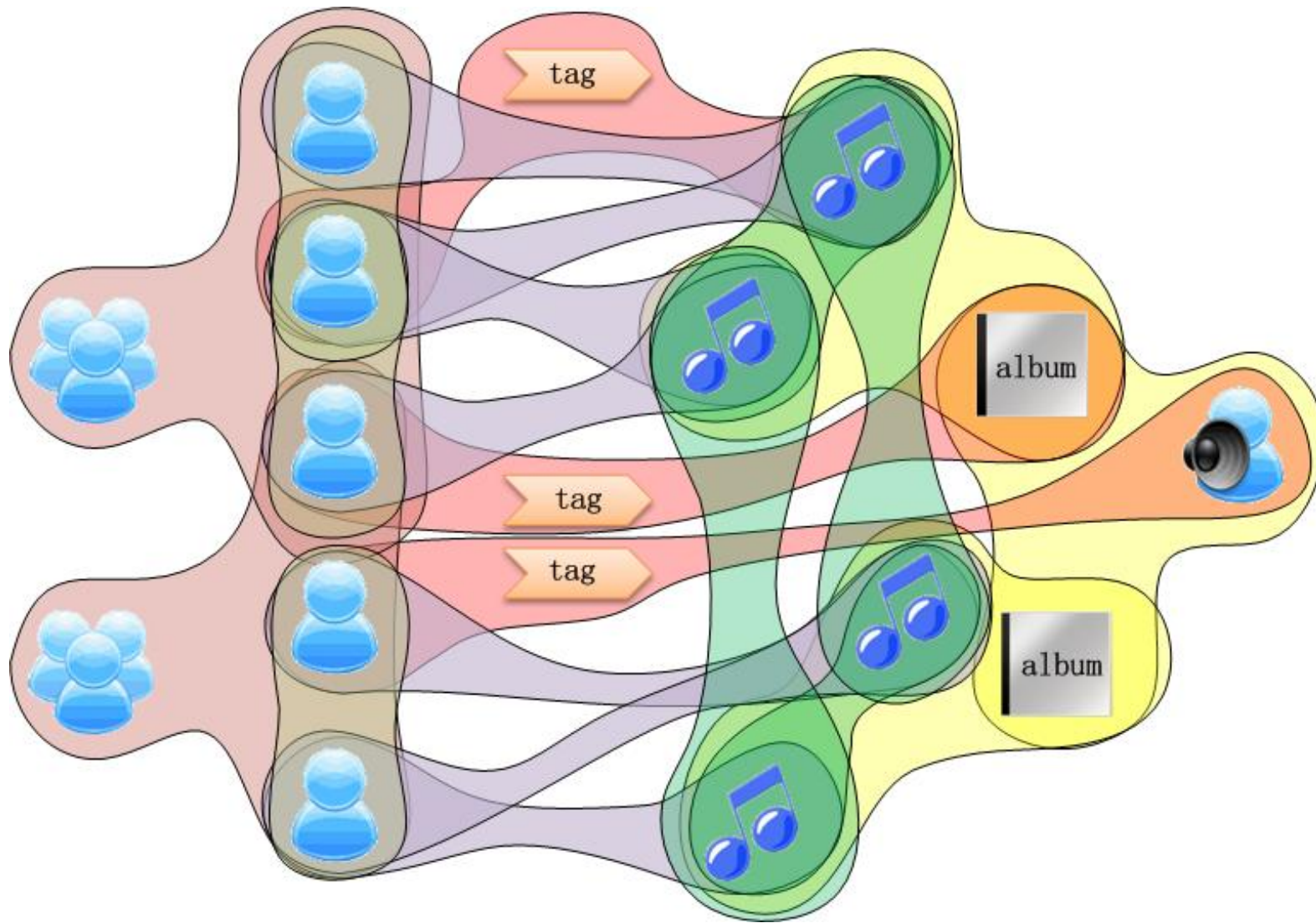
Hyperedges Construction Details



Hyperedges Construction Details

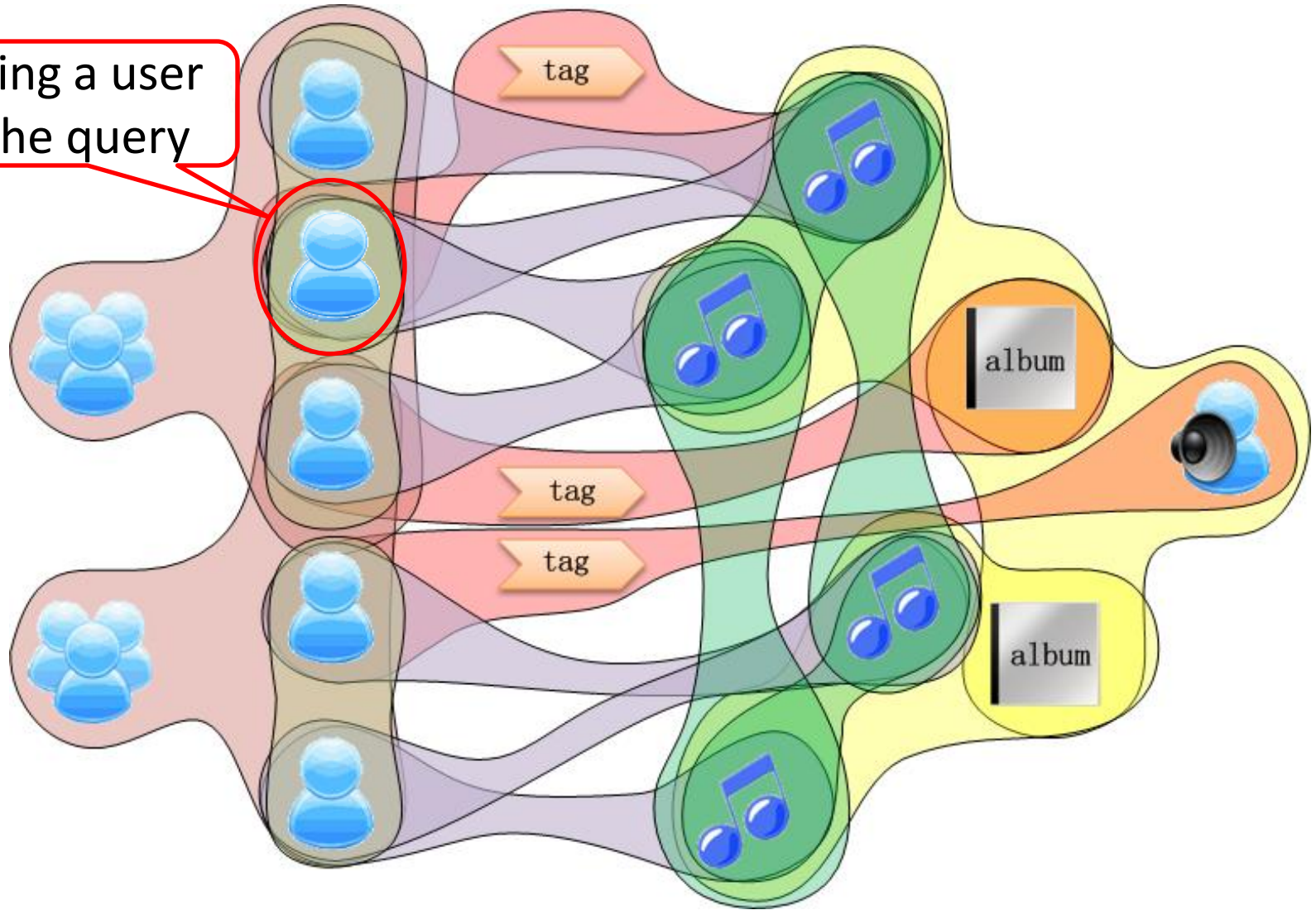


Ranking on Unified Hypergraph



Ranking on Unified Hypergraph

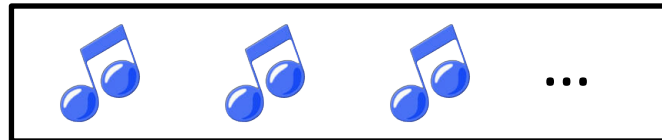
Setting a user
as the query



Ranking on Unified Hypergraph



Track List



Tracks have more strong “hyperpaths” to the query user will get higher ranking scores

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

$$d(v) = \sum_{e \in E} w(e)h(v, e),$$

$$\delta(e) = \sum_{v \in V} h(v, e).$$

- D_v , D_e and W : diagonal matrices consisting of hyperedge degrees, vertex degrees and hyperedge weights

The Regularization Framework

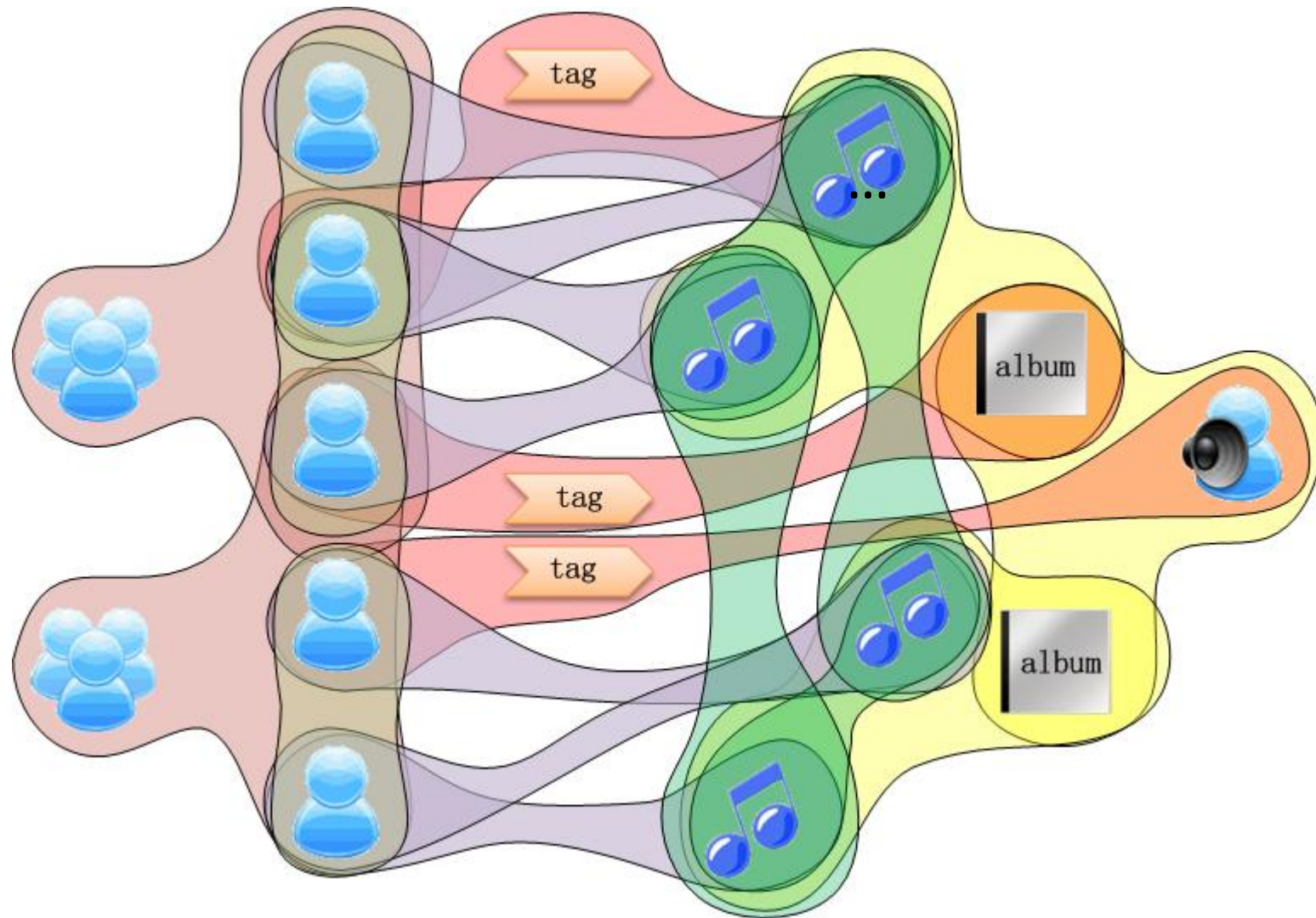
$$Q(\mathbf{f}) = \frac{1}{2} \sum_{i,j=1}^{|V|} \sum_{e \in E_h} \frac{w(e)h(v_i, e)h(v_j, e)}{\delta(e)} \left\| \frac{f_i}{\sqrt{d(v_i)}} - \frac{f_j}{\sqrt{d(v_j)}} \right\|^2 + \mu \sum_{i=1}^{|V|} \|f_i - y_i\|^2,$$

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

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

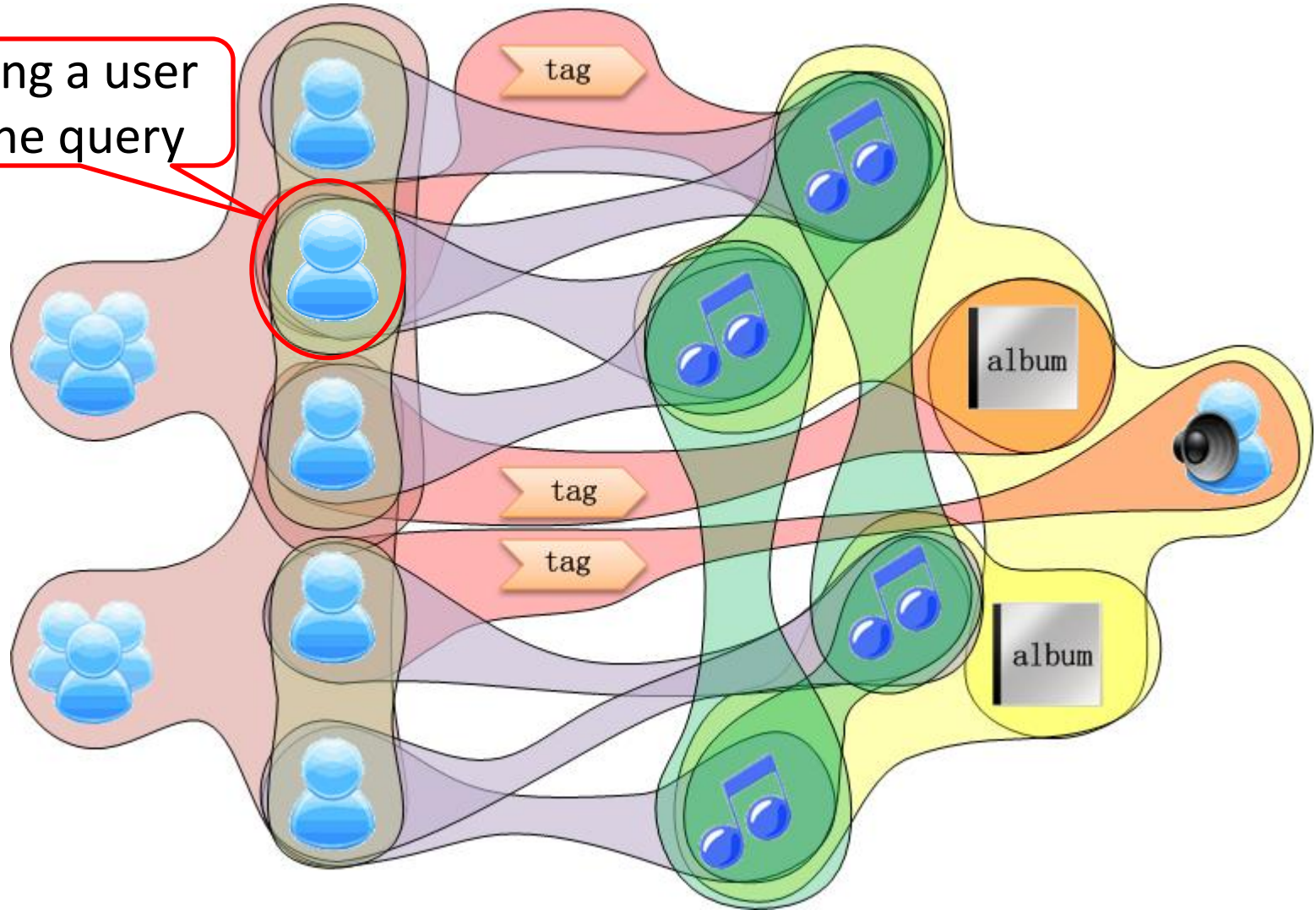
$$\mathbf{f}^* = (\mathbf{I} - \alpha \mathbf{A})^{-1} \mathbf{y}.$$

General Ranking Framework

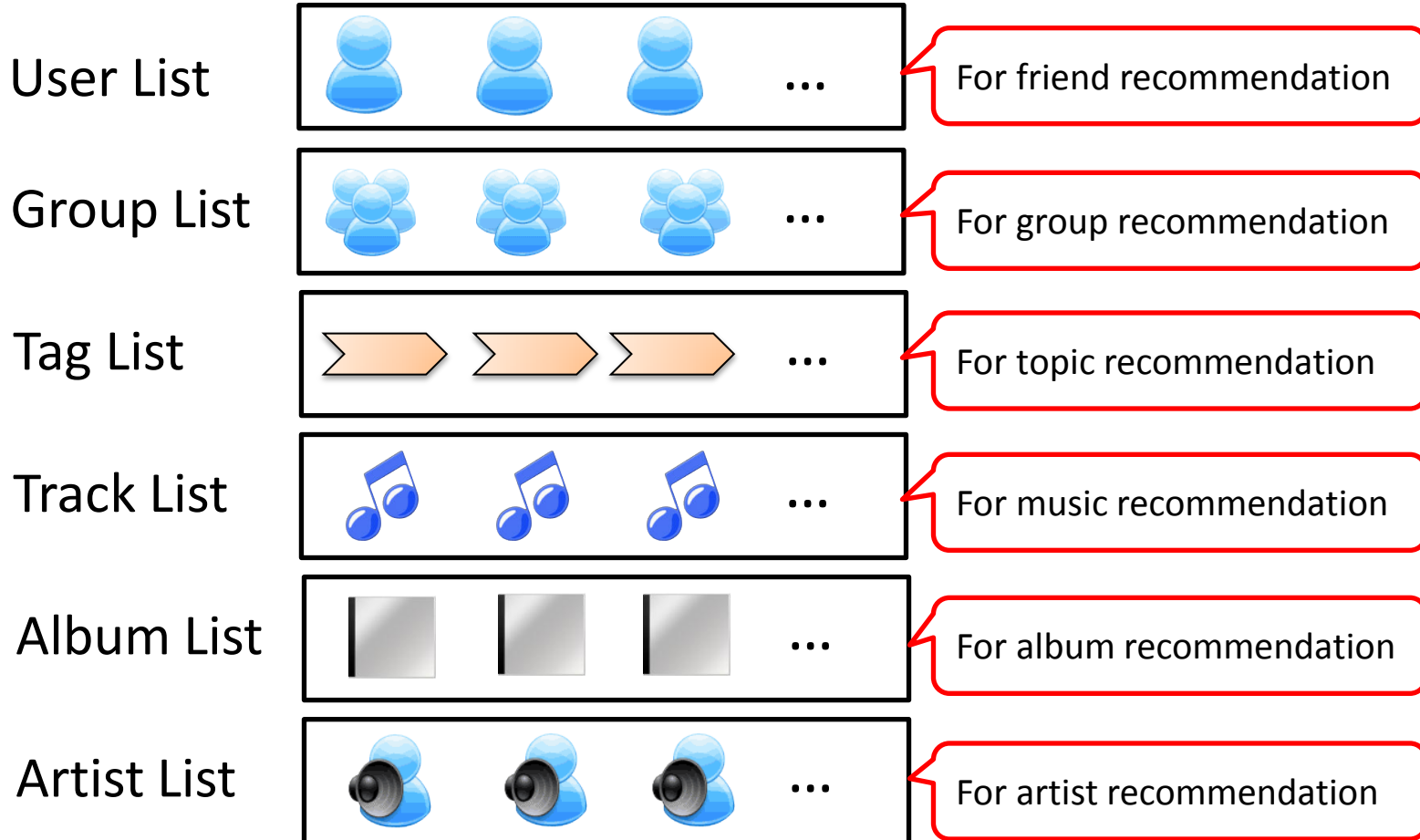


General Ranking Framework

Setting a user
as the query



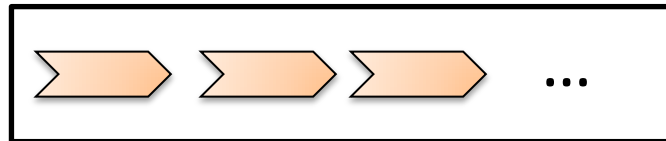
General Ranking Framework



Personalized Tag Recommendation



Tag List



Personalized Tag recommendation for the target user and resource



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.

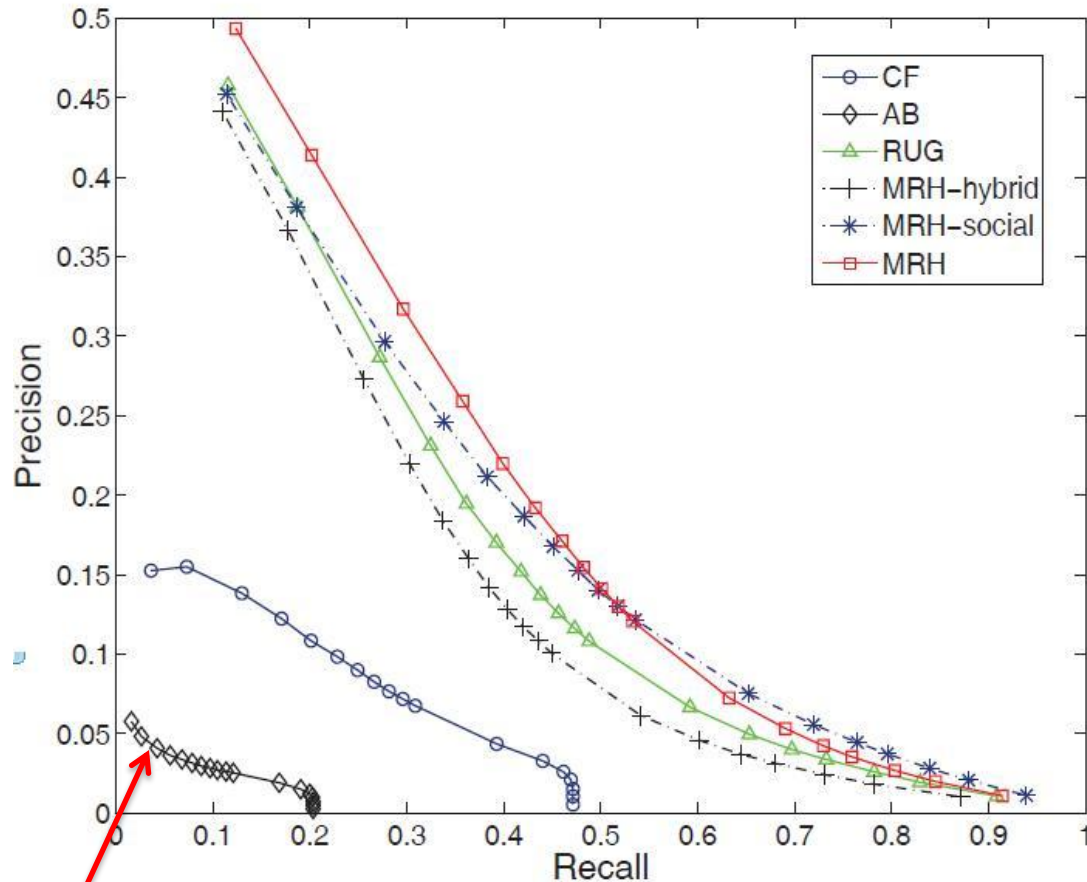
	MAP	F1@5	F1@10	F1@20	F1@30	F1@50	F1@70	F1@100	F1@200
CF	0.1632	0.0557	0.0929	0.1243	0.1329	0.1294	0.1197	0.1064	0.0765
AB	0.0762	0.0226	0.0303	0.0377	0.0403	0.0421	0.0415	0.0401	0.0334
RUG	0.2626	0.1729	0.2323	0.2587	0.2516	0.2237	0.1988	0.1701	0.1169
MRH-hybrid	0.2470	0.1653	0.2224	0.2451	0.2377	0.2099	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*

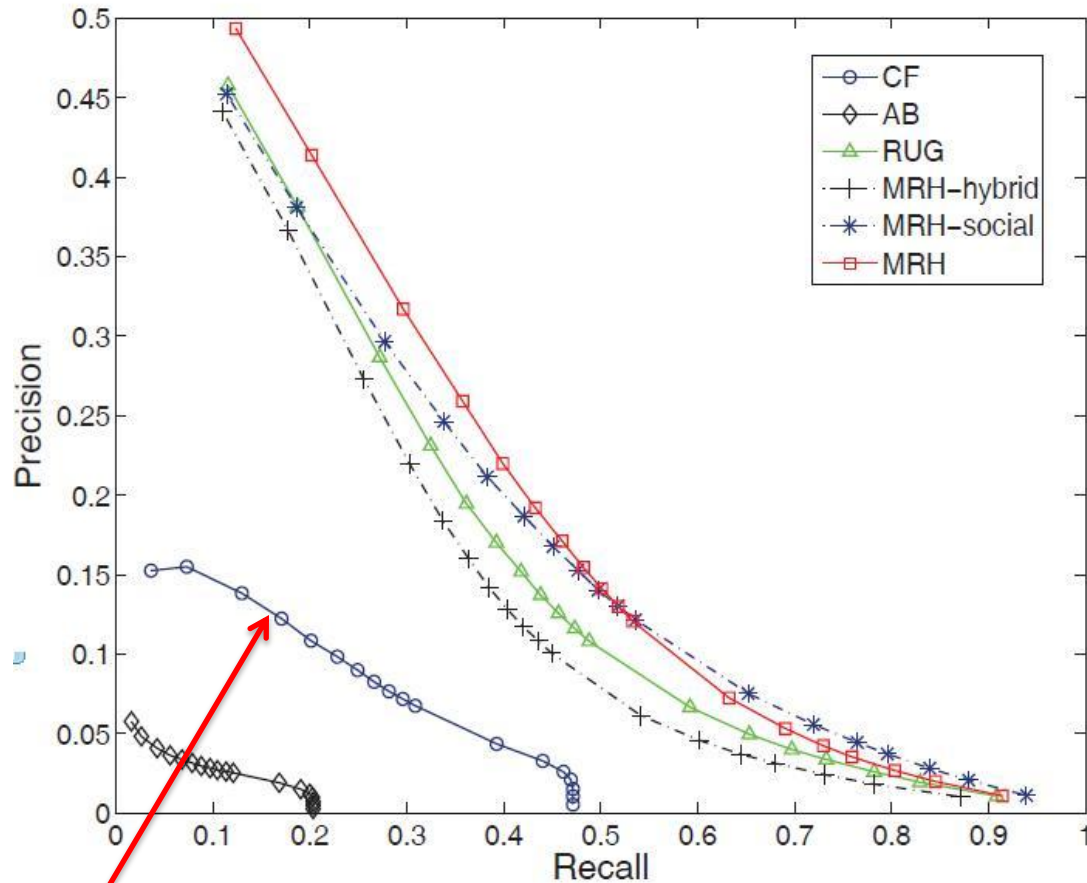
It is clear that our proposed algorithm significantly outperforms the other recommendation algorithms

Precision-Recall Curves



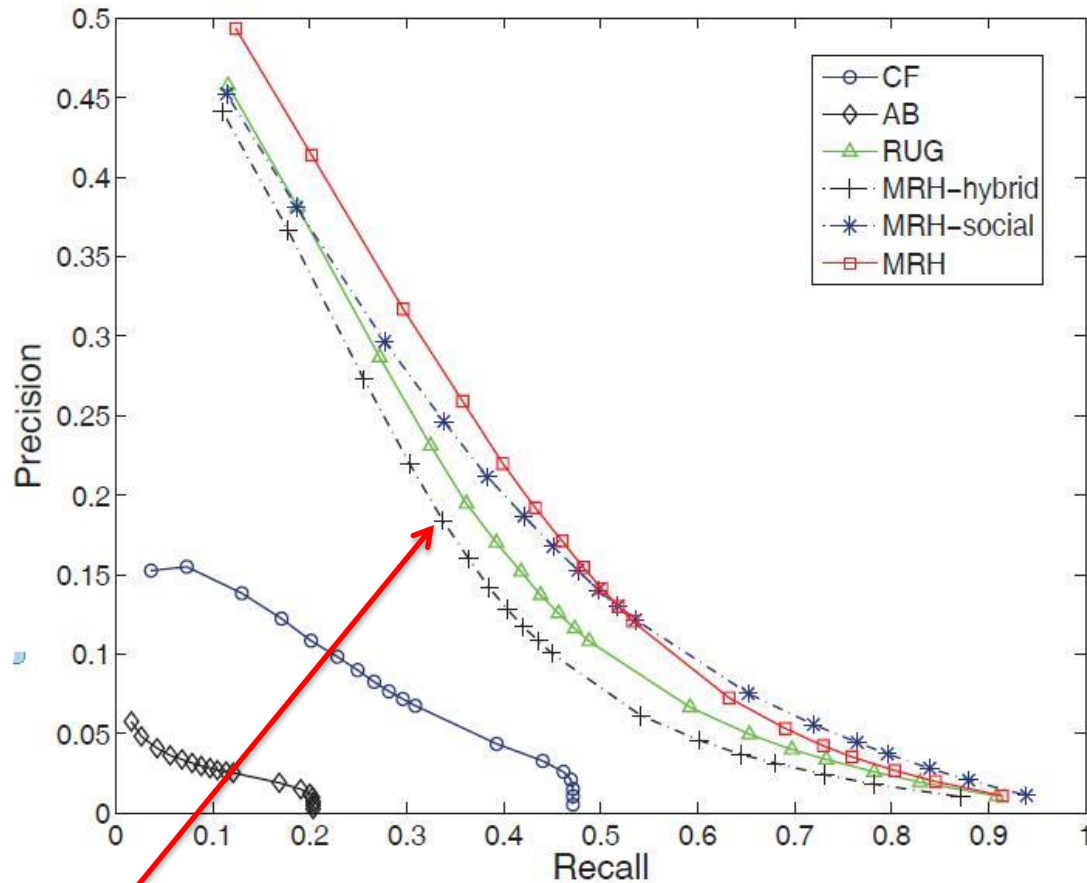
Acoustic-based (AB) method works worst. That is because acoustic-based method incurs the semantic gap and similarities based on acoustic content are not always consistent with human knowledge

Precision-Recall Curves



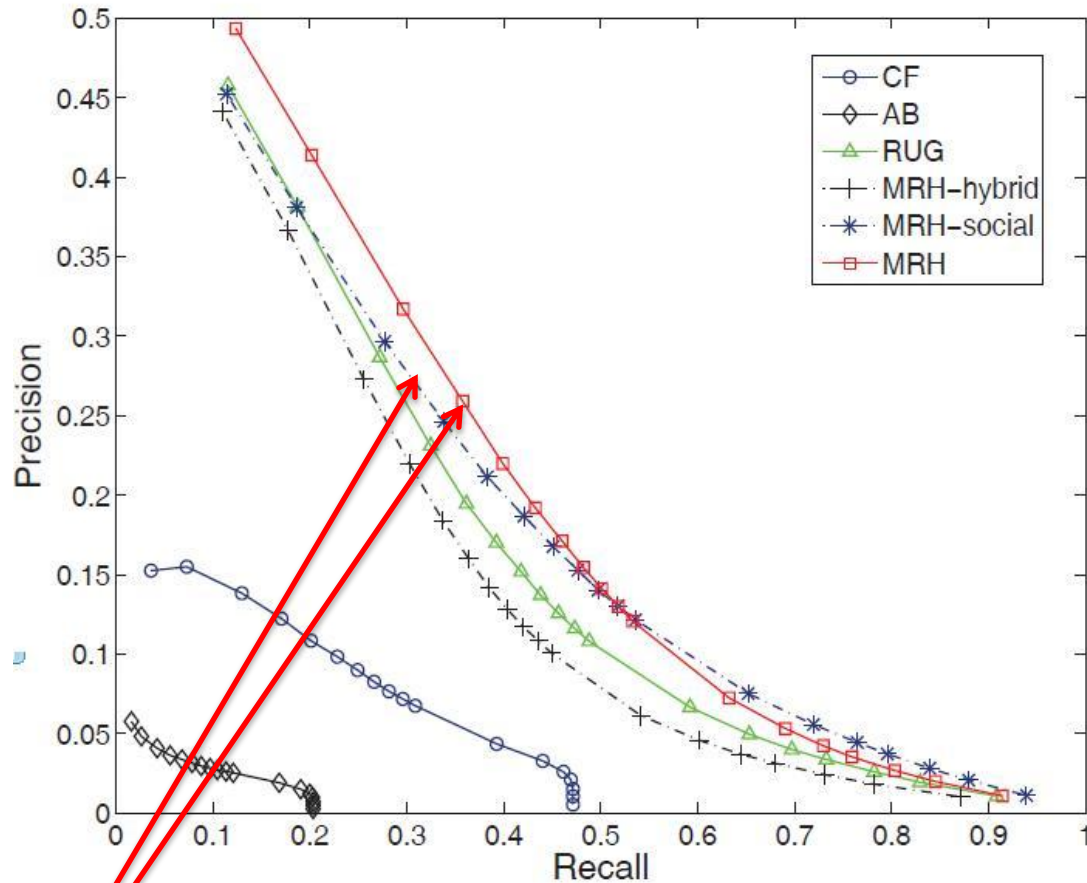
CF algorithm does not work well too. This is probably because the user-track matrix in our data set is highly sparse

Precision-Recall Curves



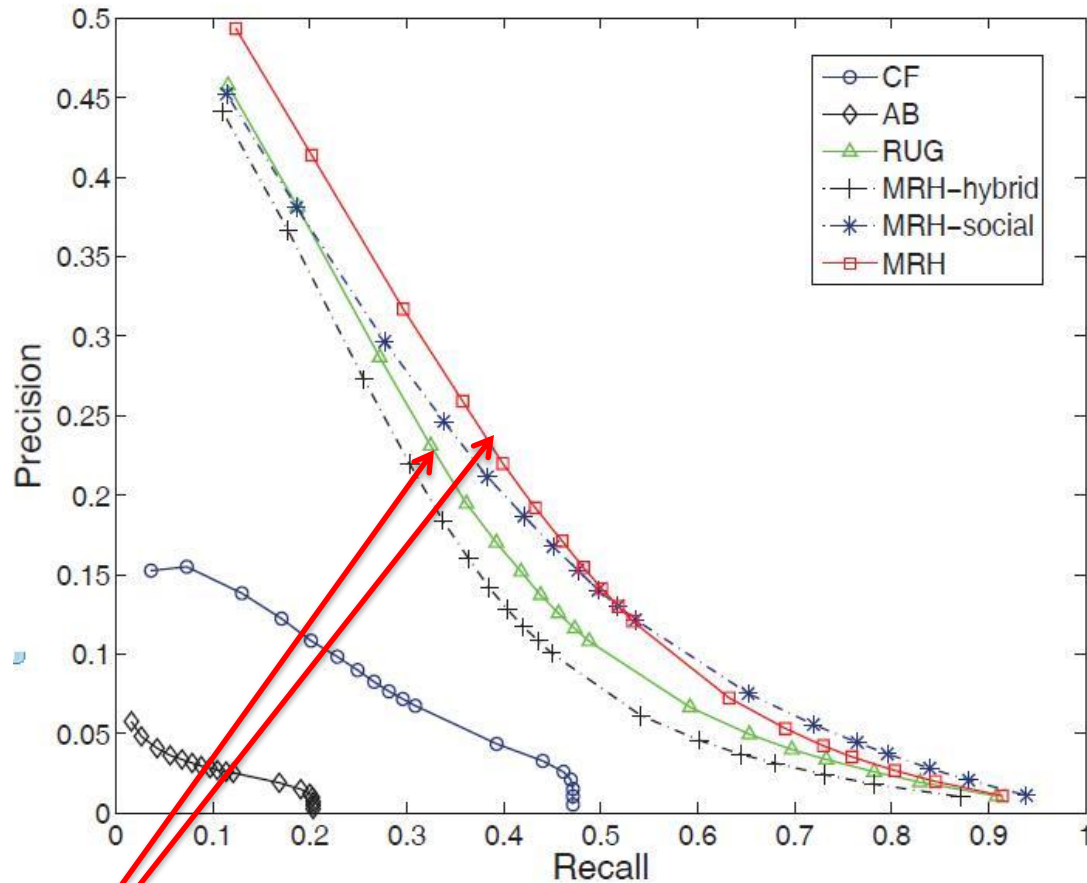
Our proposed method alleviates these problems. MRH-hybrid only uses similarity relations among music tracks and listening relations, but it works much better than AB and CF

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 !