ConsRec: Learning Consensus Behind Interactions for Group Recommendation

WWW'2023 Social Network and Graph Algorithms Track Paper

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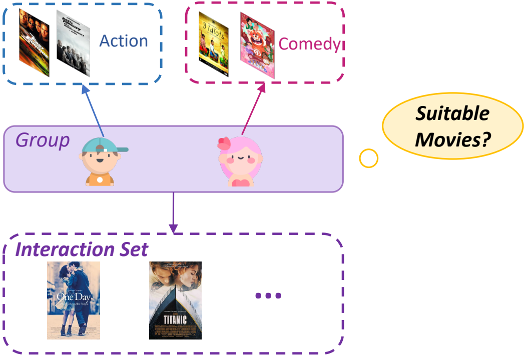
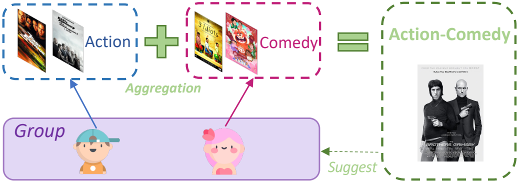
Group Recommendation

- **Task Definition:** based on user-/group-behavioral history, and user-group affiliations, suggesting items for a group



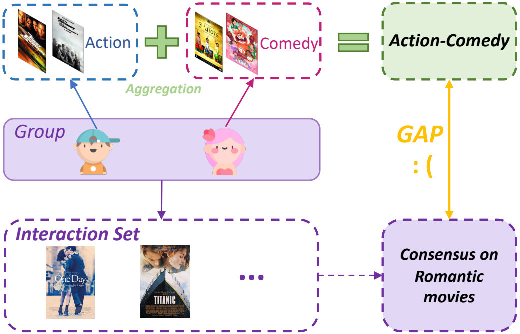
Aggregation-based

- **Practice:** Applying aggregation strategy across members' interests to estimate group preferences



Aggregation-based

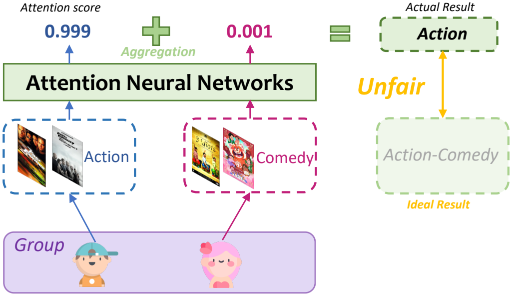
- **Practice:** Applying aggregation strategy across members' interests to estimate group preferences
- **Drawbacks:**
  - **Gap between aggregation and actual consensus**



Existing Methods

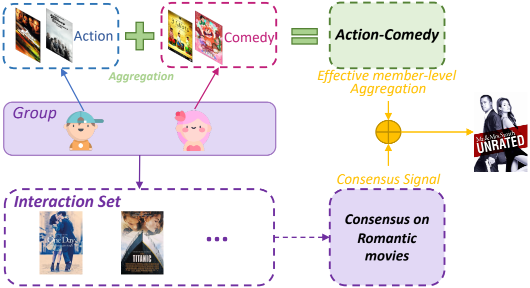
Aggregation-based

- **Practice:** Applying aggregation strategy across members' interests to estimate group preferences
- **Drawbacks:**
  - Gap between aggregation and actual consensus
  - **Unfair aggregation**



ConsRec

- Mine consensus information behind group interactions for better capturing interests
- Alleviate unfair issue on member-level aggregation
- Combine them to realize better recommending results



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2 Methodology

Group Recommendation

Sets: $\mathcal{U} = \{u_1, u_2, ..., u_M\}$, $\mathcal{I} = \{i_1, i_2, ..., i_N\}$, and $\mathcal{G} = \{g_1, g_2, ..., g_K\}$ denote the sets of users, items, and groups, respectively.

Interactions: There are two types of observed interactions among $\mathcal{U}$, $\mathcal{I}$, and $\mathcal{G}$, namely, group-item interactions $\mathbf{Y} \in \mathbb{R}^{K\times N}$ and user-item interactions $\mathbf{R} \in \mathbb{R}^{M\times N}$.

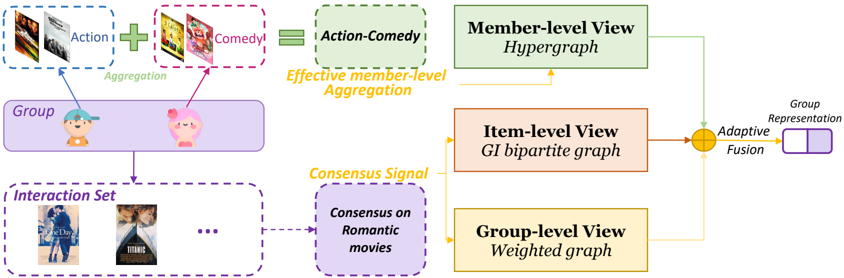
Task: The t-th group $g_t \in \mathcal{G}$ consists of a set of user members $\mathcal{G}_t = \{u_1, u_2, ..., u_s, ..., u_{|\mathcal{G}_t|}\}$ where $u_s \in \mathcal{U}$ and $|\mathcal{G}_t|$ is the size of $\mathcal{G}_t$. Then, given a target group g_t, the group recommendation task is defined as recommending items that g_t may be interested in.

Embedding: Maintain three embedding tables $\mathbf{U} \in \mathbb{R}^{M\times d}$, $\mathbf{I} \in \mathbb{R}^{N\times d}$, and $\mathbf{G} \in \mathbb{R}^{K\times d}$.

ConsRec Overview

2 Methodology

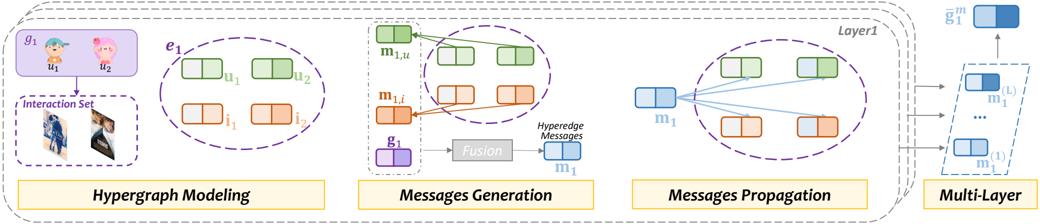
- Multi-view Modeling
  - Member-level: realize better aggregation
  - Item/Group-level: capture consensus information (*i.e.*, item-side interests and inherent properties)
- Adaptive Fusion to generate final groups' representations for prediction



Construct a hypergraph G^m and employ Hypergraph Neural Networks for aggregation

- Hypergraph Construction: each group is modeled as a hyperedge and connect its members' and interacted items' nodes
- Hypregraph Propagation: fuse item-side, member-side, and inherent features to generate messages for propagation; stack multiple layers
- Result: obtain groups' member-level aggregation $\overline{\mathbf{G}}^m$

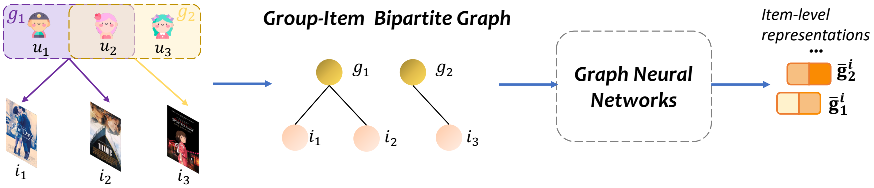
$$[\overline{\mathbf{G}}^m, \overline{\mathbf{I}}, \overline{\mathbf{U}}] = \textbf{HyperGNN}([\mathbf{G}, \mathbf{U}, \mathbf{I}]; G^m)$$



Item-level View

Construct a group-item bipartite graph G^i and mine groups' item-side interests

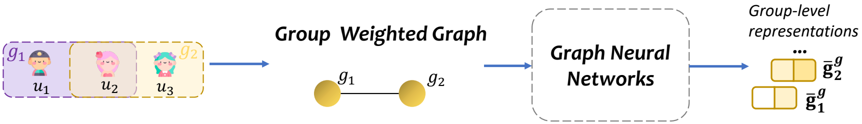
- Via GNN, groups' representations can obtain interacted items' features, reflecting consensus information
- Result: obtain groups' item-level representation $\overline{\mathbf{G}}^i$ $([\overline{\mathbf{G}}^i, \overline{\mathbf{I}}^i] = \text{GNN}([\mathbf{G}, \mathbf{I}]; G^i))$



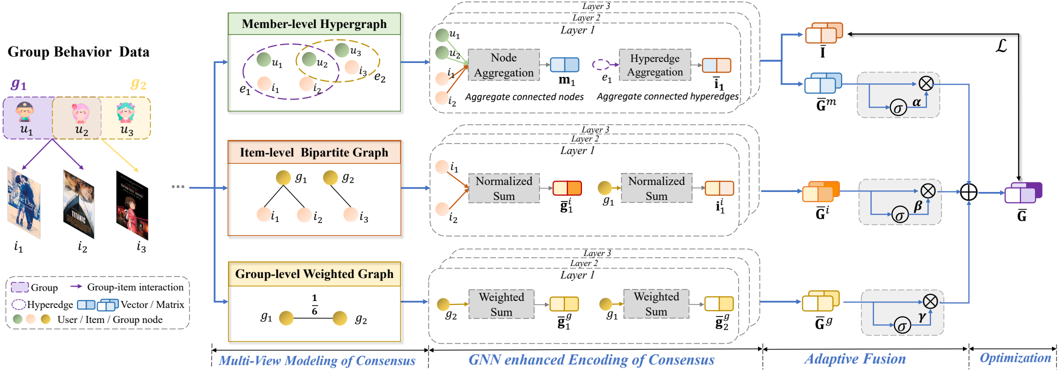
Group-level View

Construct a group weighted graph G^g where similar groups are connected and can reinforce each others' representations

- Groups carry interent features, connecting similar groups can help propagate such signals and capture consensus information
- Result: obtain groups' group-level representation $\overline{\mathbf{G}}^g$ ($\overline{\mathbf{G}}^g = \mathrm{GNN}(\mathbf{G}; G^g)$)



Adaptively fuse three views to generate final groups' representations, together with items' representations, for optimization and prediction.



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Experimental Setup

- **Datasets**

Dataset	#Users	#Items	#Groups	#U-I interactions	#G-I interactions
Mafengwo	5,275	1,513	995	39,761	3,595
CAMRa2011	602	7,710	290	116,344	145,068

- **Baselines:**
  - Non-Personalized: Popularity
  - Classical neural network-based: NCF
  - Attentive aggregation-based: AGREE
  - Hypergraph-enhanced: HyperGroup, HCR
  - Self-supervised learning-enhanced: GroupIM, $\mathbf{S}^2$-HHGR, and CubeRec
- **Evaluation Metrics:** HitRatio, NDCG@K

Overall Performance

3 Experiments

Table 2: Performance comparison of all methods on group recommendation task in terms of HR@K and NDCG@K.

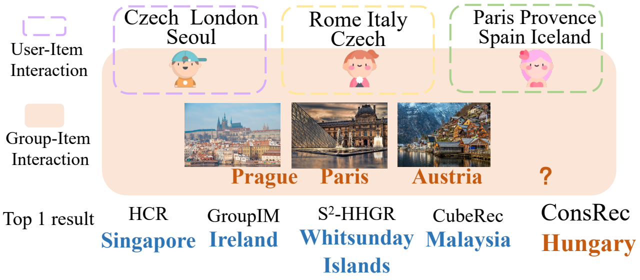
Dataset	Metric	Pop	NCF	AGREE	HyperGroup	HCR	GroupIM	S^2-HHGR	CubeRec	**ConsRec**
Mafengwo	HR@5	0.3115	0.4701	0.4729	0.5739	0.7759	0.7377	0.7568	0.8613	**0.8844**
	HR@10	0.4251	0.6269	0.6321	0.6482	0.8503	0.8161	0.7779	0.9025	**0.9156**
	NDCG@5	0.2169	0.3657	0.3694	0.4777	0.6611	0.6078	0.7322	0.7574	**0.7692**
	NDCG@10	0.2537	0.4141	0.4203	0.5018	0.6852	0.6330	0.7391	0.7708	**0.7794**
CAMRa2011	HR@5	0.4324	0.5803	0.5879	0.5890	0.5883	**0.6552**	0.6062	0.6400	0.6407
	HR@10	0.5793	0.7693	0.7789	0.7986	0.7821	**0.8407**	0.7903	0.8207	0.8248
	NDCG@5	0.2825	0.3896	0.3933	0.3856	0.4044	0.4310	0.3853	0.4346	**0.4358**
	NDCG@10	0.3302	0.4448	0.4530	0.4538	0.4670	0.4914	0.4453	0.4935	**0.4945**

Table 3: Performance comparison of all methods on user recommendation task in terms of HR@K and NDCG@K.

Dataset	Metric	Pop	NCF	AGREE	HyperGroup	HCR	GroupIM	S^2-HHGR	CubeRec	**ConsRec**
Mafengwo	HR@5	0.4047	0.6363	0.6357	0.7235	0.7571	0.1608	0.6380	0.1847	**0.7725**
	HR@10	0.4971	0.7417	0.7403	0.7759	0.8290	0.2497	0.7520	0.3734	**0.8404**
	NDCG@5	0.2876	0.5432	0.5481	0.6722	0.6703	0.1134	0.4637	0.1099	**0.6884**
	NDCG@10	0.3172	0.5733	0.5738	0.6894	0.6937	0.1420	0.5006	0.1708	**0.7107**
CAMRa2011	HR@5	0.4624	0.6119	0.6196	0.5728	0.6262	0.6113	0.6153	0.5754	**0.6774**
	HR@10	0.6026	0.7894	0.7897	0.7601	0.7924	0.7771	0.8173	0.7827	**0.8412**
	NDCG@5	0.3104	0.4018	0.4098	0.4410	0.4195	0.4064	0.3978	0.3751	**0.4568**
	NDCG@10	0.3560	0.4535	0.4627	0.5016	0.4734	0.4606	0.4641	0.4428	**0.5104**

Case Study

Both the group and members like European cities. ConsRec captures this consensus can suggests Hungary that hits the ground truth.



- **Paper Title: ConsRec: Learning Consensus Behind Interactions for Group Recommendation**
- **Code:** https://github.com/FDUDSDE/WWW2023ConsRec
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