ConsRec: Learning Consensus Behind Interactions for Group Recommendation

Xixi Wu
21210240043@m.fudan.edu.cn
Shanghai Key Laboratory of Data Science, School of Computer Science, Fudan University
Shanghai, China

Yun Xiong*
yunx@fudan.edu.cn
Shanghai Key Laboratory of Data Science, School of Computer Science, Fudan University
Shanghai, China

Yao Zhang
yaozhang@fudan.edu.cn
Shanghai Key Laboratory of Data Science, School of Computer Science, Fudan University
Shanghai, China

Yizhu Jiao
yizhuj2@illinois.edu
University of Illinois at Urbana-Champaign
IL, USA

Jiawei Zhang
jiawei@ifmlab.org
IFM Lab, Department of Computer Science, University of California, Davis
CA, USA

Yangyong Zhu
yyzhu@fudan.edu.cn
Shanghai Key Laboratory of Data Science, School of Computer Science, Fudan University
Shanghai, China

Philip S. Yu
psyu@uic.edu
University of Illinois at Chicago
IL, USA

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Code: https://github.com/FDUDSDE/WWW2023ConsRec

Reported by liang li

Motivation

Details:

- Existing information aggregation lacks a holistic group-level consideration, failing to capture the consensus information.
- Besides, their specific aggregation strategies either suffer from high computational costs or become too coarse-grained to make precise predictions.

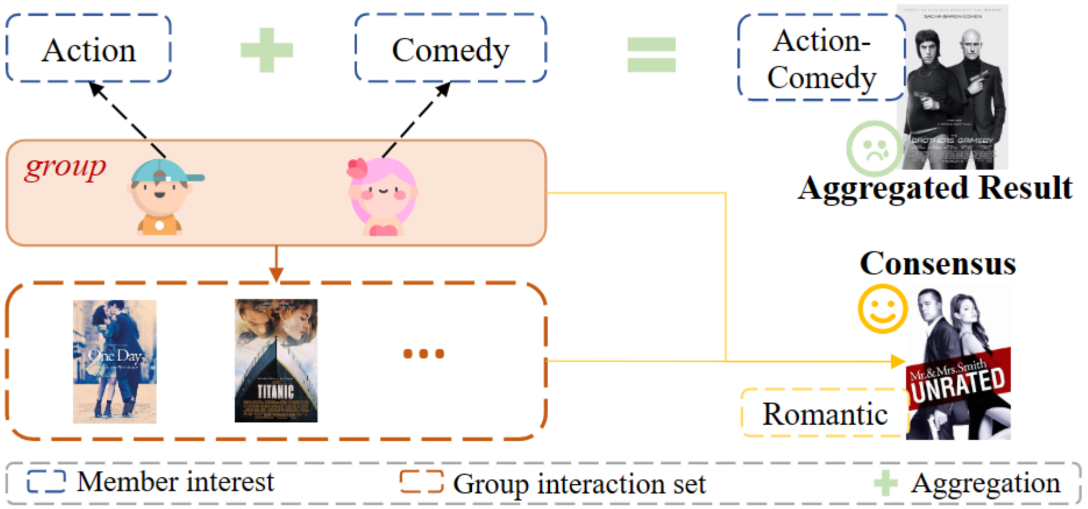


Figure 1: An illustrative example of the gap between aggregated result and group's consensus. Merely aggregating diverse members' interests lacks the holistic consideration of the group's overall taste, failing to capture the consensus.

Problem Statement

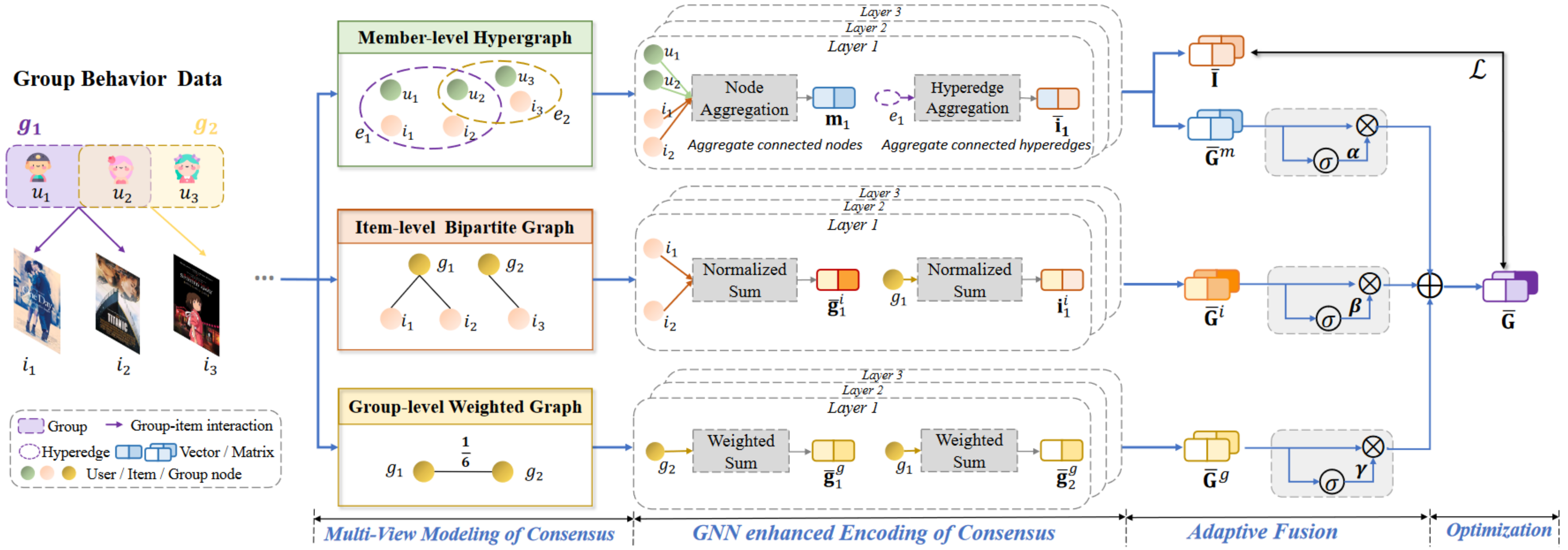


Figure 2: ConsRec Overview. We construct three distinct views for consensus modeling and adopt specific graph neural networks for representation learning. We further integrate these view-specific representations for group-item prediction.

Problem Statement

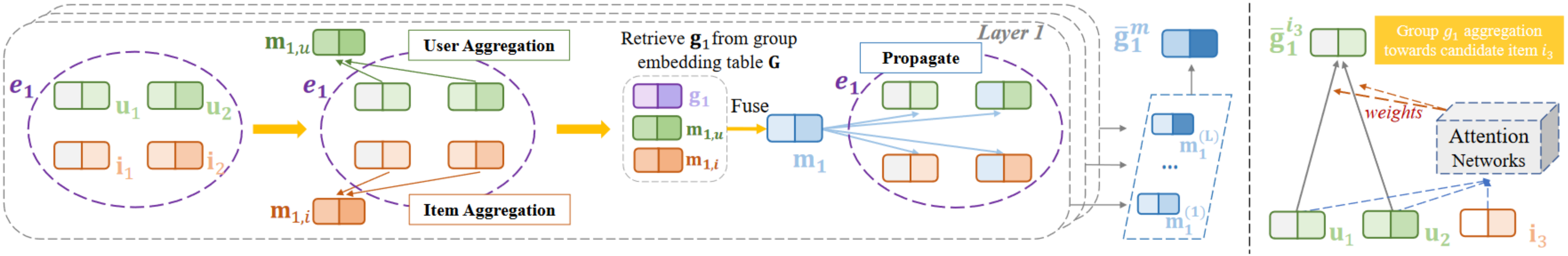


Figure 3: Comparison between our hypergraph learning-based aggregation (left) and the commonly adopted attentive aggregation (right). Ours wins in efficiency, fairness, and expressiveness with details explained in Section 4.2.2.

$\mathbf{Y} \in \mathbb{R}^{K \times N}$ Group-item interaction matrix

$\mathcal{U} = \{u_1, u_2, ..., u_M\}$

$\mathbf{R} \in \mathbb{R}^{M \times N}$ User-item interaction matrix

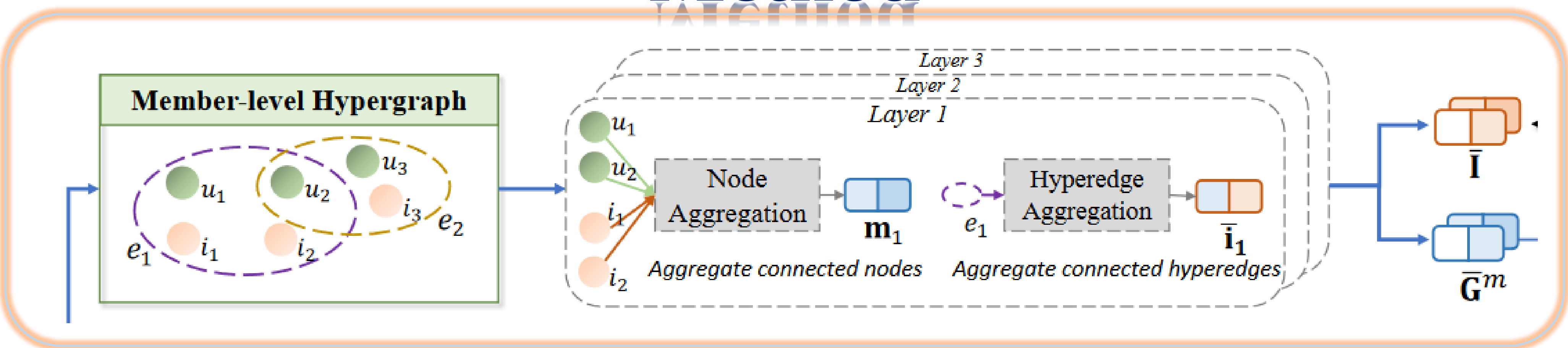
$\mathcal{I} = \{i_1, i_2, ..., i_N\}$

$\mathcal{G}_t = \{u_1, u_2, ..., u_s, ..., u_{|\mathcal{G}_t|}\}$

$\mathcal{G} = \{g_1, g_2, ..., g_K\}$

$\mathcal{Y}_t = \{i_1, i_2, ..., i_j, ..., i_{|\mathcal{Y}_t|}\}$

Method



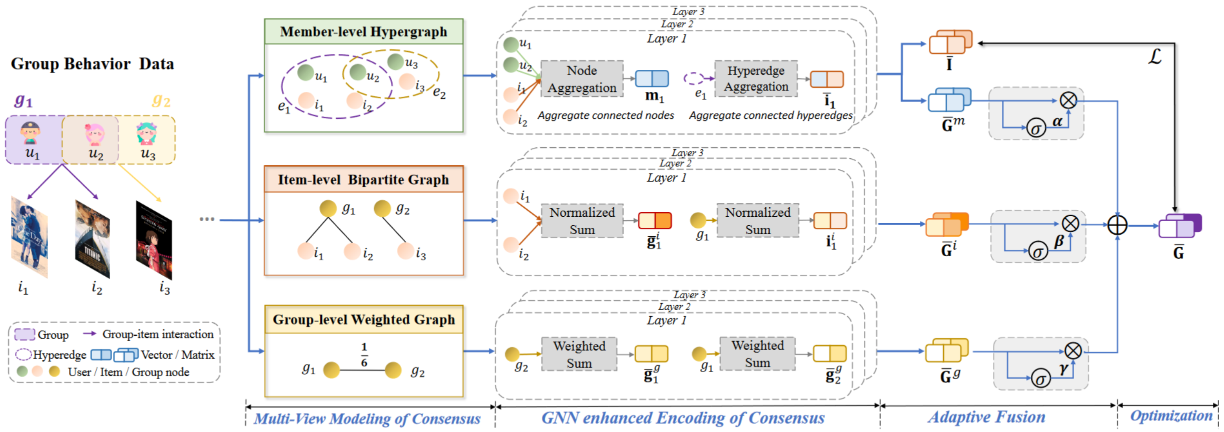


Figure 2: ConsRec Overview. We construct three distinct views for consensus modeling and adopt specific graph neural networks for representation learning. We further integrate these view-specific representations for group-item prediction.

$$G^m = (\mathcal{V}^m, \mathcal{E}^m, \mathbf{H}^m) \qquad \mathcal{V}^m = \mathcal{U} \cup \mathcal{I}$$

$$\mathcal{E}^m = \mathcal{G} \qquad \mathbf{H}^m \in \mathbb{R}^{|\mathcal{V}^m| \times |\mathcal{E}^m|}$$

$$\mathbf{m}_{e,u} = \mathrm{AGG}_{node}(\{\mathbf{u}_s | u_s \in \mathcal{G}_e\})$$

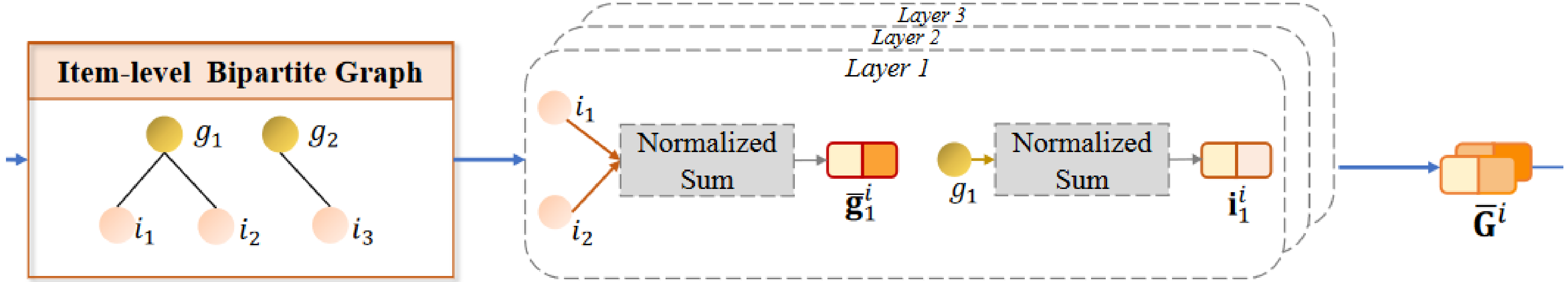
$$\mathbf{m}_{e,i} = \mathrm{AGG}_{node}(\{\mathbf{i}_j | i_j \in \mathcal{Y}_e\})$$

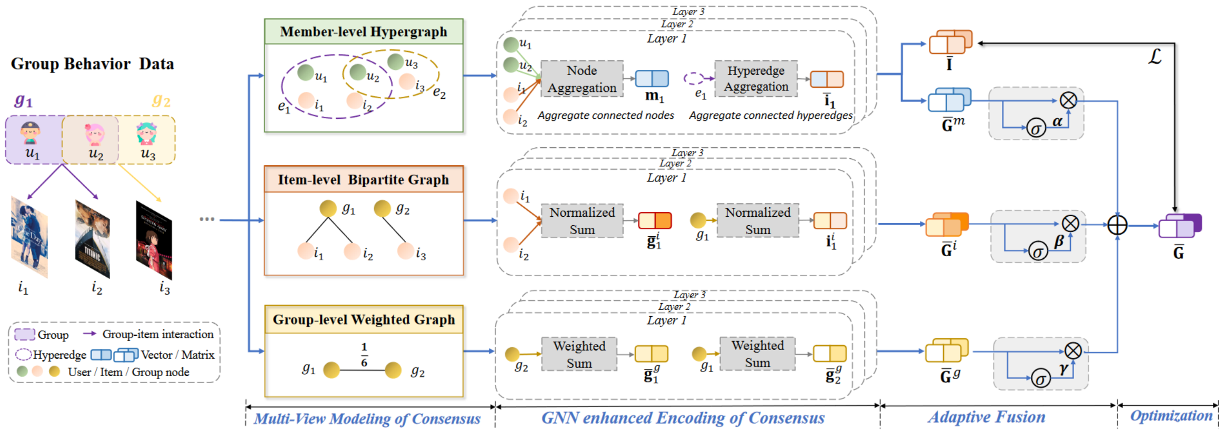
$$\mathbf{m}_e = \mathrm{CONCAT}(\mathbf{m}_{e,u}\ ,\ \mathbf{m}_{e,i}\ ,\ \mathbf{m}_{e,i} \odot \mathbf{g}_e)\mathbf{W}^f, \tag{1}$$

$$\bar{\mathbf{i}}_j = \mathrm{AGG}_{he}(\{\mathbf{m}_e | e \in \mathcal{E}_j\}), \tag{2}$$

$$\bar{\mathbf{g}}_e^m = \frac{1}{L+1}\sum_{l=0}^{L}\mathbf{m}_e^{(l)}, \qquad \bar{\mathbf{i}}_j = \frac{1}{L+1}\sum_{l=0}^{L}\mathbf{i}_j^{(l)},$$

Method





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$$G^i = (\mathcal{V}^i, \mathcal{E}^i, \mathrm{A}^i) \qquad \mathcal{V}^i = \mathcal{G} \cup \mathcal{I}$$

$$\mathcal{E}^i = \{(g_t, i_j) | g_t \in \mathcal{G}, i_j \in \mathcal{I}, \mathrm{Y}(t, j) = 1\}$$

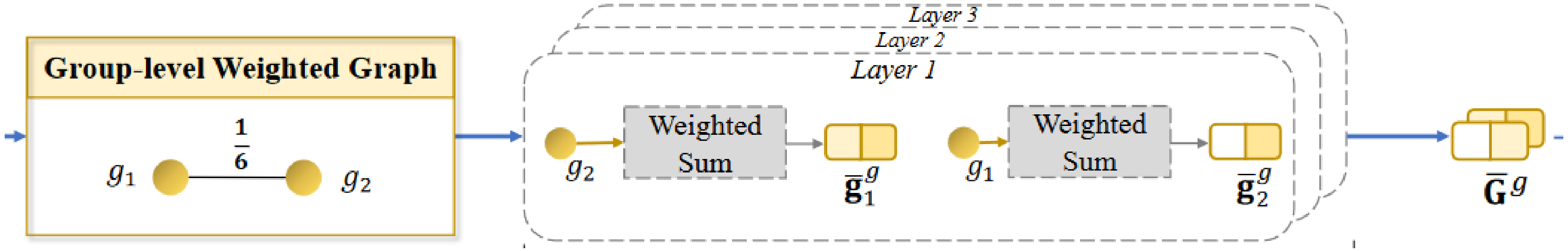
$$\mathrm{A}^i \in \mathbb{R}^{(K+N)\times(K+N)}$$

$$\mathrm{E} = \begin{bmatrix} \mathrm{G} \\ \mathrm{I} \end{bmatrix} \qquad \mathrm{A}^i = \begin{bmatrix} 0 & \mathrm{Y} \\ \mathrm{Y}^{\mathrm{T}} & 0 \end{bmatrix}$$

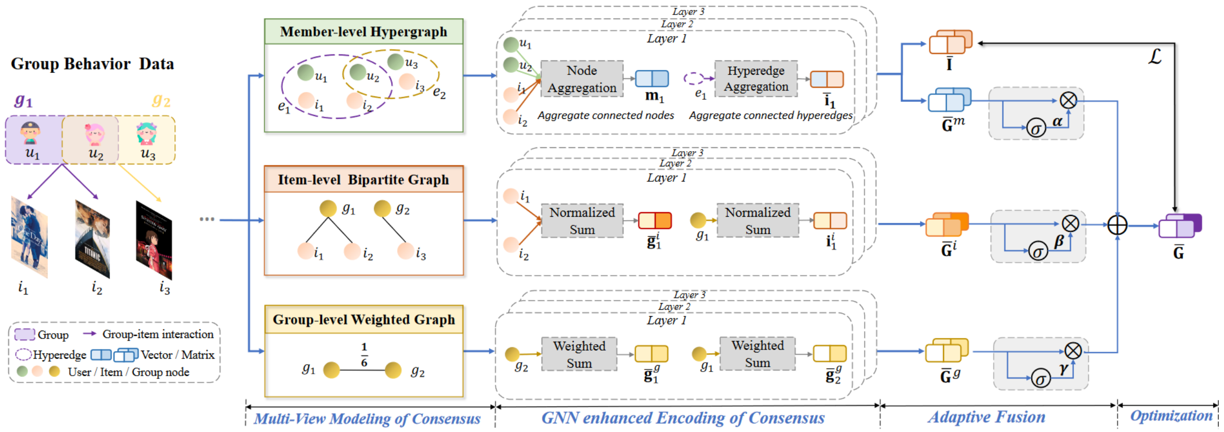
$$\mathrm{E}^{(l+1)} = \mathrm{D}^{-\frac{1}{2}} \mathrm{A}^i \mathrm{D}^{-\frac{1}{2}} \mathrm{E}^{(l)}, \tag{3}$$

$$\overline{\mathrm{E}} = \frac{1}{L+1} \sum_{l=0}^{L} \mathrm{E}^{(l)} = \begin{bmatrix} \overline{\mathrm{G}}^i \\ \overline{\mathrm{I}}^i \end{bmatrix}$$

Method



$$\mathcal{E}^g = \{(g_p, g_q) | g_p, g_q \in \mathcal{G}, |\mathcal{G}_p \cap \mathcal{G}_q| \geq 1 \text{or } |\mathcal{Y}_p \cap \mathcal{Y}_q| \geq 1\}$$



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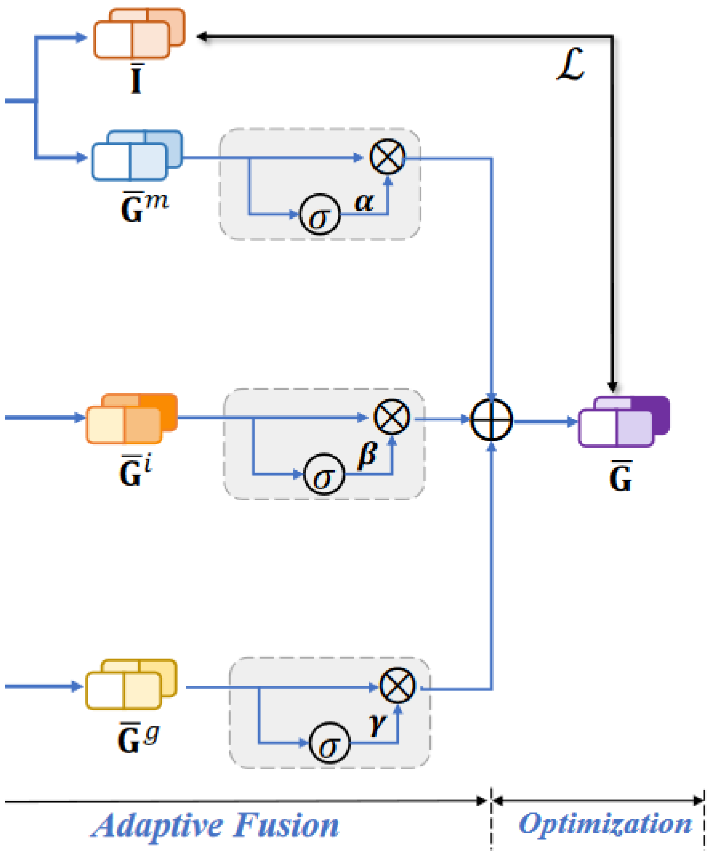
$$G^g = (\mathcal{V}^g, \mathcal{E}^g, A^g) \qquad \mathcal{V}^g = \mathcal{G}$$

$$A^g(p,q) = \frac{|\mathcal{G}_p \cap \mathcal{G}_q| + |\mathcal{Y}_p \cap \mathcal{Y}_q|}{|\mathcal{G}_p \cup \mathcal{G}_q| + |\mathcal{Y}_p \cup \mathcal{Y}_q|}$$

$$\overline{G}^g = \frac{1}{L+1} \sum_{l=0}^{L} G^{(l)}$$

Method



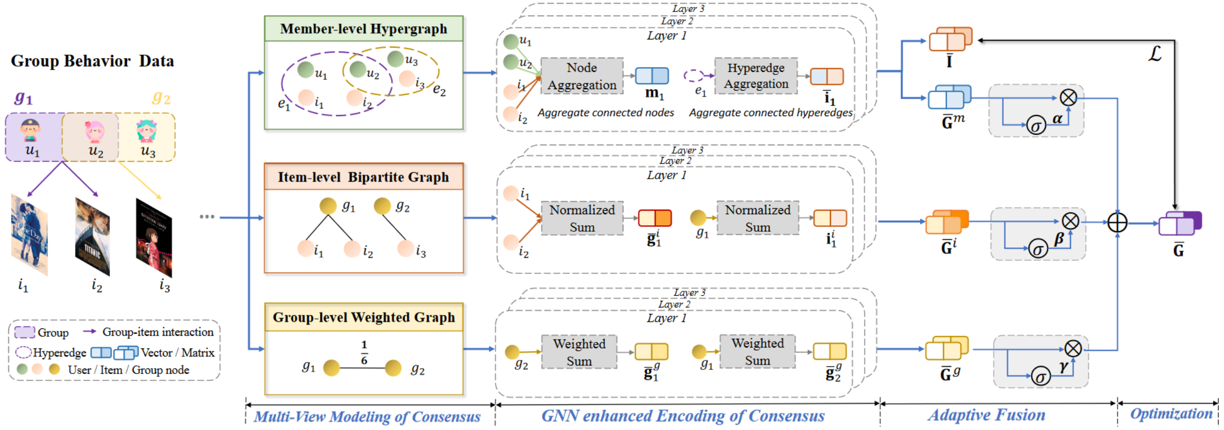


Figure 2: ConsRec Overview. We construct three distinct views for consensus modeling and adopt specific graph neural networks for representation learning. We further integrate these view-specific representations for group-item prediction.

$$\boldsymbol{\alpha} = \sigma(\overline{\mathbf{G}}^m \mathbf{W}^m),\ \boldsymbol{\beta} = \sigma(\overline{\mathbf{G}}^i \mathbf{W}^i),\ \text{and}\ \boldsymbol{\gamma} = \sigma(\overline{\mathbf{G}}^g \mathbf{W}^g)$$

$$\overline{\mathbf{G}} = \boldsymbol{\alpha}\overline{\mathbf{G}}^m + \boldsymbol{\beta}\overline{\mathbf{G}}^i + \boldsymbol{\gamma}\overline{\mathbf{G}}^g, \qquad (4)$$

$$\mathcal{L}_{group} = -\sum_{g_t \in \mathcal{G}} \frac{1}{|\mathcal{D}_{g_t}|} \sum_{(j,j') \in \mathcal{D}_{g_t}} \ln \sigma(\hat{y}_{tj} - \hat{y}_{tj'}), \qquad (5) \qquad \hat{y}_{tj} = \mathbf{MLP}(\bar{\mathbf{g}}_t \odot \bar{\mathbf{i}}_j)$$

$$\mathcal{L}_{user} = -\sum_{u_s \in \mathcal{U}} \frac{1}{|\mathcal{D}_{u_s}|} \sum_{(j,j') \in \mathcal{D}_{u_s}} \ln \sigma(\hat{r}_{sj} - \hat{r}_{sj'}), \qquad (6) \qquad \hat{r}_{sj} = \mathbf{MLP}(\mathbf{u}_s \odot \mathbf{i}_j)$$

$$\mathcal{L} = \mathcal{L}_{group} + \mathcal{L}_{user}$$

Experiments

Table 1: Statistics of 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

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	<u>0.8613</u>	**0.8844**
	HR@10	0.4251	0.6269	0.6321	0.6482	0.8503	0.8161	0.7779	<u>0.9025</u>	**0.9156**
	NDCG@5	0.2169	0.3657	0.3694	0.4777	0.6611	0.6078	0.7322	<u>0.7574</u>	**0.7692**
	NDCG@10	0.2537	0.4141	0.4203	0.5018	0.6852	0.6330	0.7391	<u>0.7708</u>	**0.7794**
CAMRa2011	HR@5	0.4324	0.5803	0.5879	0.5890	0.5883	**0.6552**	0.6062	0.6400	<u>0.6407</u>
	HR@10	0.5793	0.7693	0.7789	0.7986	0.7821	**0.8407**	0.7903	0.8207	<u>0.8248</u>
	NDCG@5	0.2825	0.3896	0.3933	0.3856	0.4044	0.4310	0.3853	<u>0.4346</u>	**0.4358**
	NDCG@10	0.3302	0.4448	0.4530	0.4538	0.4670	0.4914	0.4453	<u>0.4935</u>	**0.4945**

Experiments

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	<u>0.7571</u>	0.1608	0.6380	0.1847	**0.7725**
	HR@10	0.4971	0.7417	0.7403	0.7759	<u>0.8290</u>	0.2497	0.7520	0.3734	**0.8404**
	NDCG@5	0.2876	0.5432	0.5481	0.6722	<u>0.6703</u>	0.1134	0.4637	0.1099	**0.6884**
	NDCG@10	0.3172	0.5733	0.5738	0.6894	<u>0.6937</u>	0.1420	0.5006	0.1708	**0.7107**
CAMRa2011	HR@5	0.4624	0.6119	0.6196	0.5728	<u>0.6262</u>	0.6113	0.6153	0.5754	**0.6774**
	HR@10	0.6026	0.7894	0.7897	0.7601	0.7924	0.7771	<u>0.8173</u>	0.7827	**0.8412**
	NDCG@5	0.3104	0.4018	0.4098	<u>0.4410</u>	0.4195	0.4064	0.3978	0.3751	**0.4568**
	NDCG@10	0.3560	0.4535	0.4627	<u>0.5016</u>	0.4734	0.4606	0.4641	0.4428	**0.5104**

Experiments

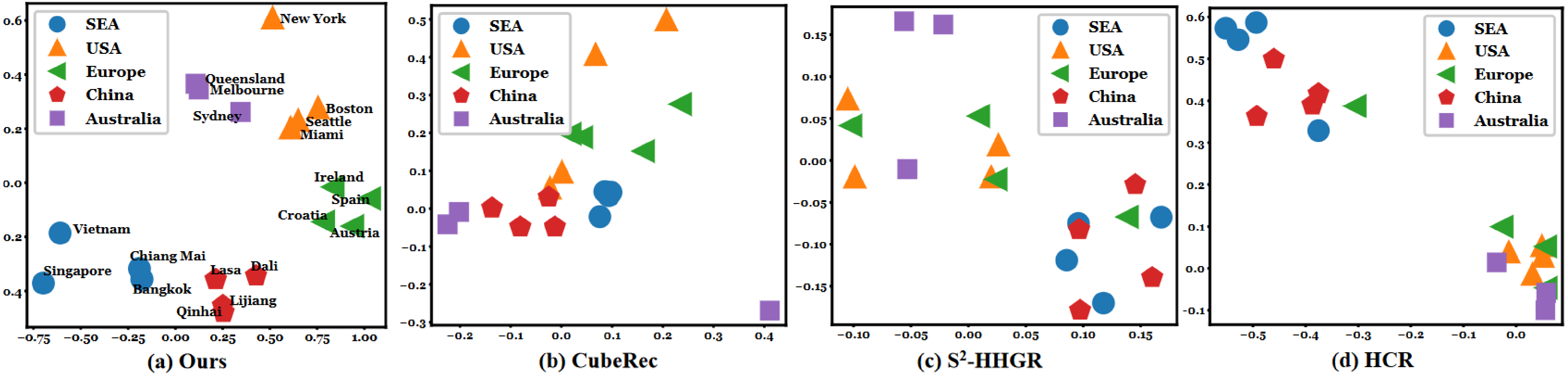


Figure 4: Visualization of learned item embeddings. We plot two dimensions of item representations on Mafengwo-S. ConsRec learns the latent properties of items as geographically similar items are close to each other in the embedding space.

Experiments

Table 4: Ablation study on different views with group recommendation results reported. "w/o. M", "w/o. I", and "w/o. G" refer to the variant that eliminates the member-level, item-item, and group-level view, respectively.

Dataset	Metric	w/o. M	w/o. I	w/o. G	**Full**
Mafengwo	HR@5	0.8201	0.8704	0.8593	**0.8844**
	HR@10	0.8724	0.9075	0.9005	**0.9156**
	NDCG@5	0.7021	0.7597	0.7376	**0.7692**
	NDCG@10	0.7192	0.7718	0. 7510	**0.7794**

Table 5: Performance comparison on group recommendation task on Mafengwo-S dataset.

Metric	HCR	GroupIM	S^2-HHGR	CubeRec	**ConsRec**
HR@5	0.4845	0.5824	0.5928	<u>0.6237</u>	**0.6409**
HR@10	0.6099	<u>0.6959</u>	0.6546	0.6873	**0.6993**
NDCG@5	0.3947	0.4591	0.5348	<u>0.5357</u>	**0.5447**
NDCG@10	0.4353	0.4983	0.5545	<u>0.5567</u>	**0.5642**

Experiments

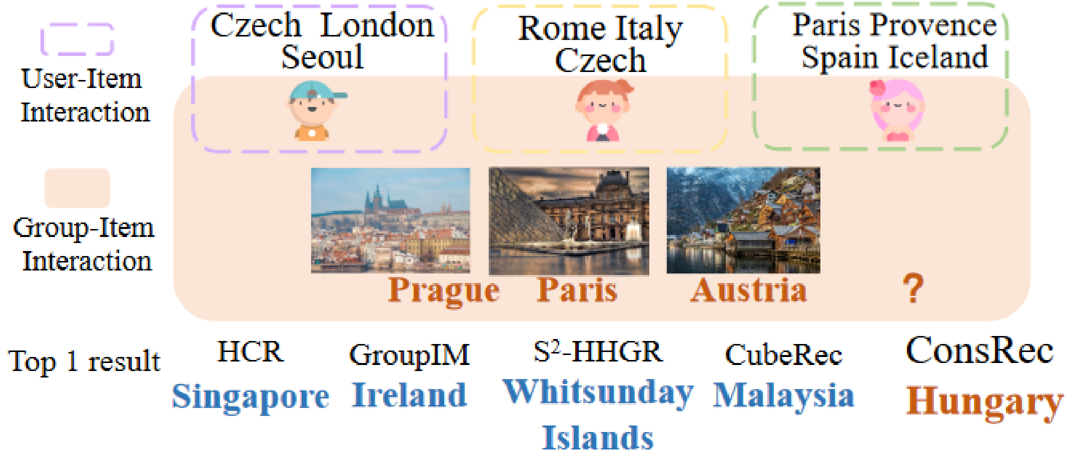


Figure 5: Case study on Mafengwo-S. Both the group and its members have visited European cities. ConsRec captures this consensus and suggests Hungary that hits the ground truth. On the contrary, HCR, GroupIM, S^2-HHGR, and CubeRec are biased by one member's interests towards Iceland and recommend unsatisfying islands or coastal cities.

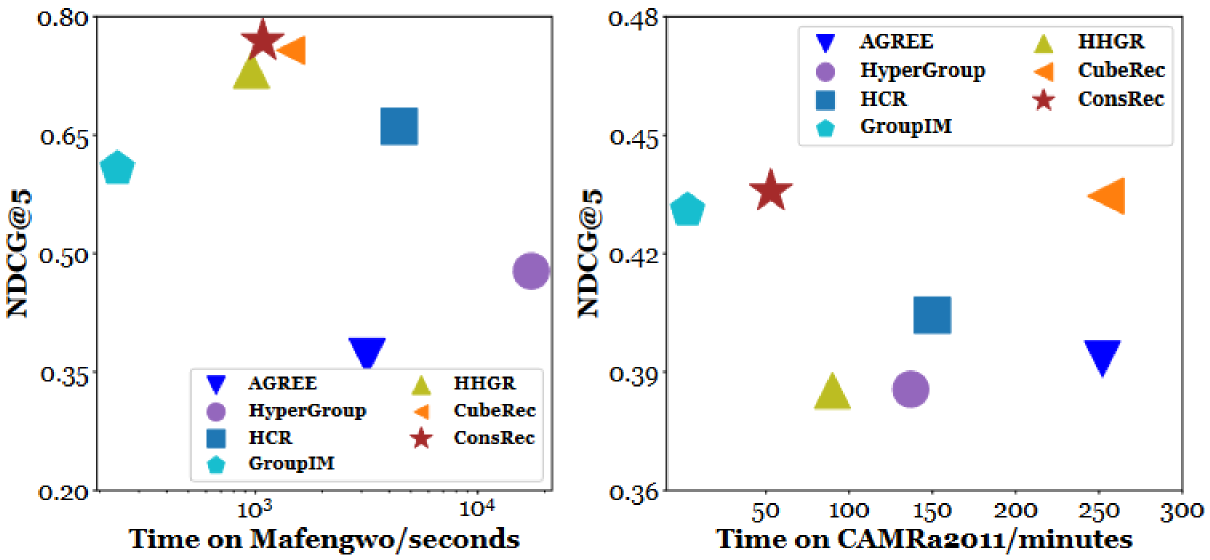


Figure 6: Efficiency Study

Thanks