Towards Better Utilization of Multiple Views for Bundle Recommendation

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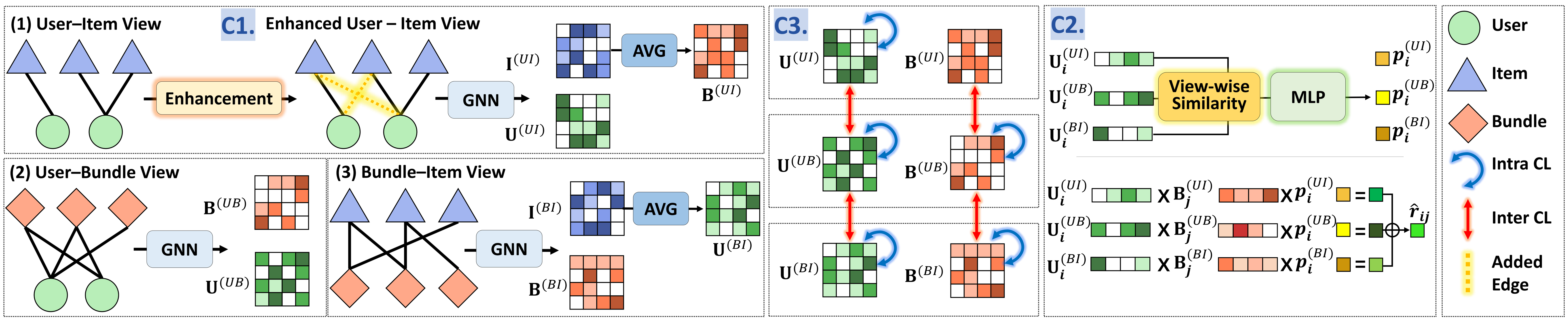


Summary

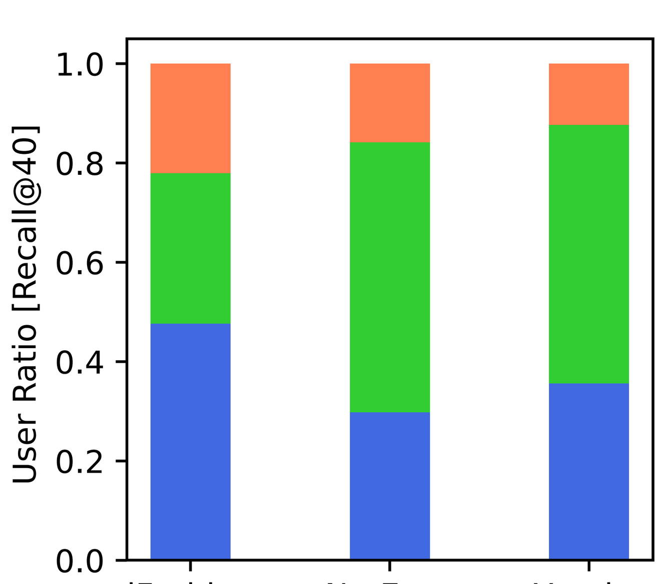
- **Goal:** to recommend suitable bundles to users, leveraging three different types (i.e., user-bundle interaction, user-item interaction, bundle-item affiliation) of information (or views).
- **Observations:**
  - The best input combination of the views varies across target users.
  - The User-Item view is the least effective view as the input for message passing of GNN-based models.
- **Proposed Method: PET**
  - A novel bundle recommendation model.
  - Focus on the synergy of the three types of information through:
    (1) User-Item view enhancement
    (2) Personalized view weighting
    (3) Two pronged contrastive learning
- **Experiments**
  - PET outperforms the competitors up to 39.26%↑ accuracy.

Background: Bundle Recommendation

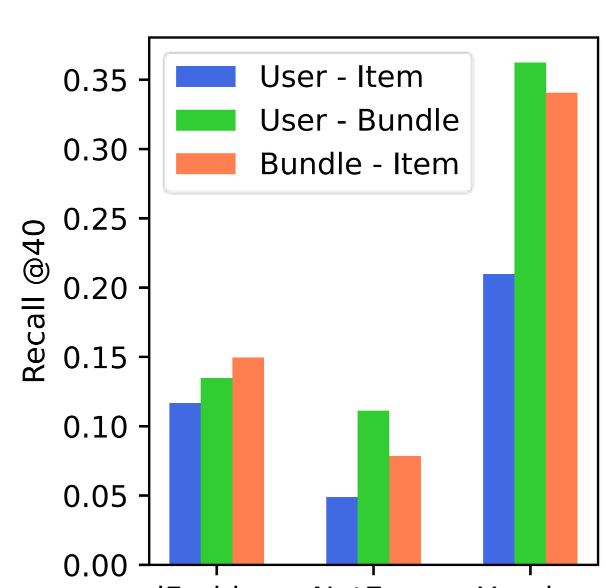
- **Bundle** is a set of items.
  - E.g., playlists in music streaming platforms, fashion outfits in online shopping, combo meals in food delivery services.
- **Objective of bundle recommendation** is to recommend suitable bundles to users.
- **Bundle recommender systems** typically use GNNs to learn user and bundle representations (embeddings) from the *user-item*($\mathbf{A}^{(UI)}$), *user-bundle*($\mathbf{A}^{(UB)}$), *bundle-item*($\mathbf{A}^{(BI)}$) *interactions.*
- **Key Concepts**
  - **Main view** is the one for which we learn embeddings by **applying the GNN message passing** on it.
  - **Sub view** is used to **pool the embeddings** from the main view to obtain user or bundle embeddings, if necessary.
    - Utilizing (U-I) as the main view, we utilize (B-I) view as the sub view to obtain bundle embeddings by pooling item embeddings.
    - Utilizing (B-I) as the main view, we utilize (U-I) view as the sub view to obtain user embeddings by pooling item embeddings.

Observations

- **[Observation 1] One size does not fit all.**
  - The best input combination of the views for bundle recommendation varies across target users.
- **[Observation 2] User-Item view is least effective as the main view .**
  - Message passing on user-item interactions results in the lowest performance across all datasets.



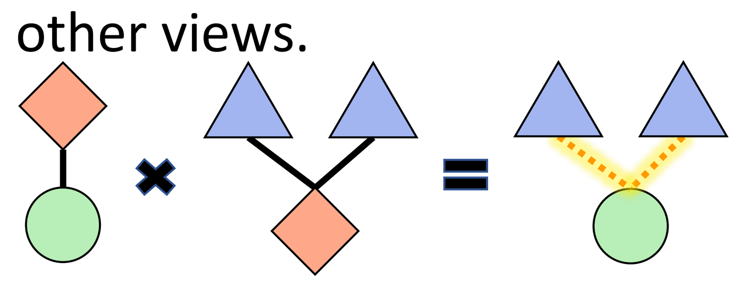
Observation 1



Observation 2

Proposed Method: PET

- **PET: P**ersonalized view weighting with data **E**nhancement **T**wo-pronged Contrast.
  - **C1. U-I Enhanced view representation**
    - **Goal:** To address the relative weakness of the U-I view (O2).
    - Enhance it by integrating extra user-item interactions derived from other views.



  - **C2. Personalized view weighting**
    - **Goal:** To address "no single view is optimal for all users" (O1).
    - Compute the importance of each view, personalized for each user.
  - **C3. Two-pronged contrastive learning**
    - **Goal:** To enhance user and bundle representations under limited number of interactions.
    - **Intra-CL**: contrastive learning within each view.
    - **Inter-CL**: contrastive learning between different views.

Experimental Results

- **RQ1. Accuracy: PET** outperforms SOTA bundle recommender systems.

Datasets	iFashion		NetEase		Youshu	
Metrics	Recall@20	NDCG@20	Recall@20	NDCG@20	Recall@20	NDCG@20
BPRMF	0.0882	0.0647	0.0677	0.0363	0.2660	0.1532
LightGCN	0.0957	0.0707	0.0751	0.0397	0.2750	0.1622
MIDGN	0.0694	0.0500	0.0680	0.0358	0.2688	0.1562
BundleGT	0.0981	0.0726	0.0913	0.0481	0.2927	0.1745
CrossCBR	0.1308	0.1004	0.0901	0.0485	0.2831	0.1689
MultiCBR	0.1863	0.1569	0.0928	0.0509	0.2932	0.1732
PET	**0.2532**	**0.2185**	**0.0978**	**0.0528**	**0.3052**	**0.1804**
Improvement	35.91%	39.26%	5.39%	3.73%	4.09%	3.38%

Datasets	iFashion		NetEase		Youshu	
Metrics	Recall@40	NDCG@40	Recall@40	NDCG@40	Recall@40	NDCG@40
BPRMF	0.1347	0.0612	0.1082	0.0469	0.3691	0.1835
LightGCN	0.1439	0.0876	0.1184	0.0508	0.3757	0.1859
MIDGN	0.1091	0.0640	0.1075	0.0460	0.3696	0.1836
BundleGT	0.1471	0.0898	0.1394	0.0607	0.3964	0.2028
CrossCBR	0.1888	0.1209	0.1372	0.0609	0.3843	0.1968
MultiCBR	0.2475	0.1779	0.1391	0.0631	0.3968	0.2012
PET	**0.3220**	**0.2429**	**0.1459**	**0.0655**	**0.4103**	**0.2095**
Improvement	30.10%	36.54%	4.66%	3.80%	3.40%	3.30%

- **RQ2. Ablation study**: All key components of **PET** are effective.

Datasets	iFashion		NetEase		Youshu	
Metrics	R@40	N@40	R@40	N@40	R@40	N@40
PET-E.	0.3161	0.2420	0.1413	0.0638	0.4081	**0.2092**
PET-P.	0.3215	0.2427	0.1406	0.0636	0.4011	0.2030
PET-I.	0.2917	0.2209	0.1393	0.0629	0.4028	0.2056
PET	**0.3220**	**0.2429**	**0.1459**	**0.0655**	**0.4103**	0.2090

- **RQ3. Effect of personalization**: View weights are indeed **personalized**.