MIC: Model-agnostic Integrated Cross-channel Recommender

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Contents

CONTENTS

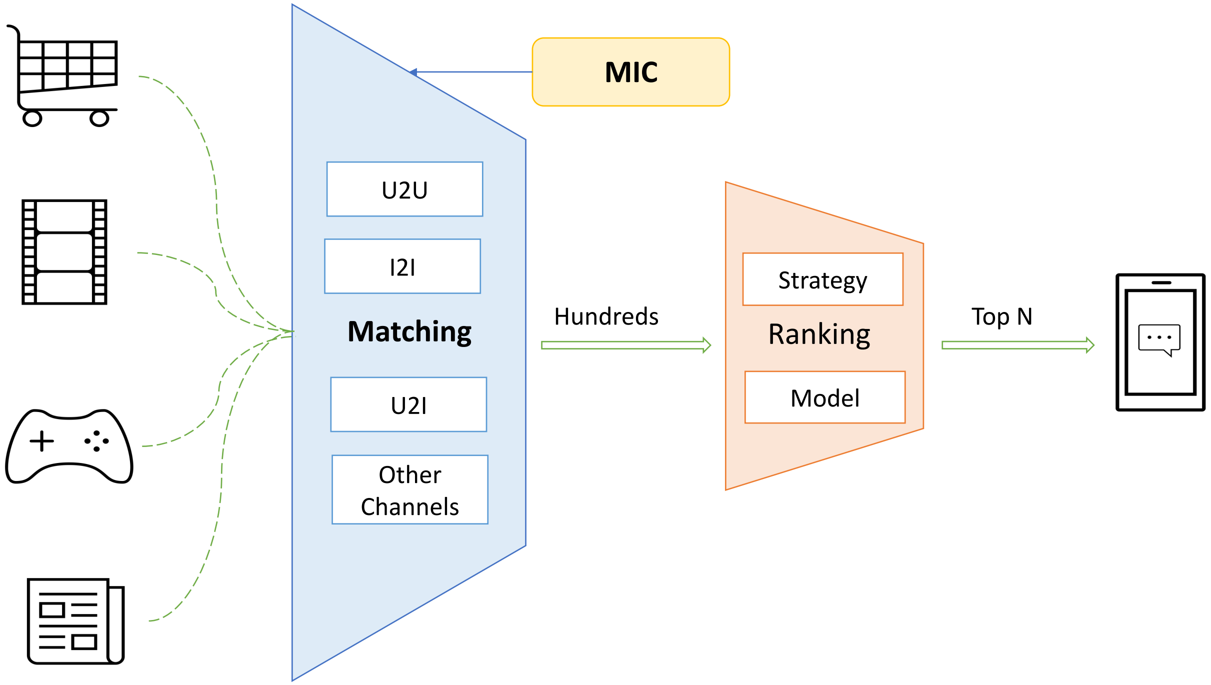
MIC-Multi-Channel Background

Pre-defined retrieval channels

- User-CF (U2U)
- Item-CF (I2I)
- Embedding-based Retrieval (U2I)

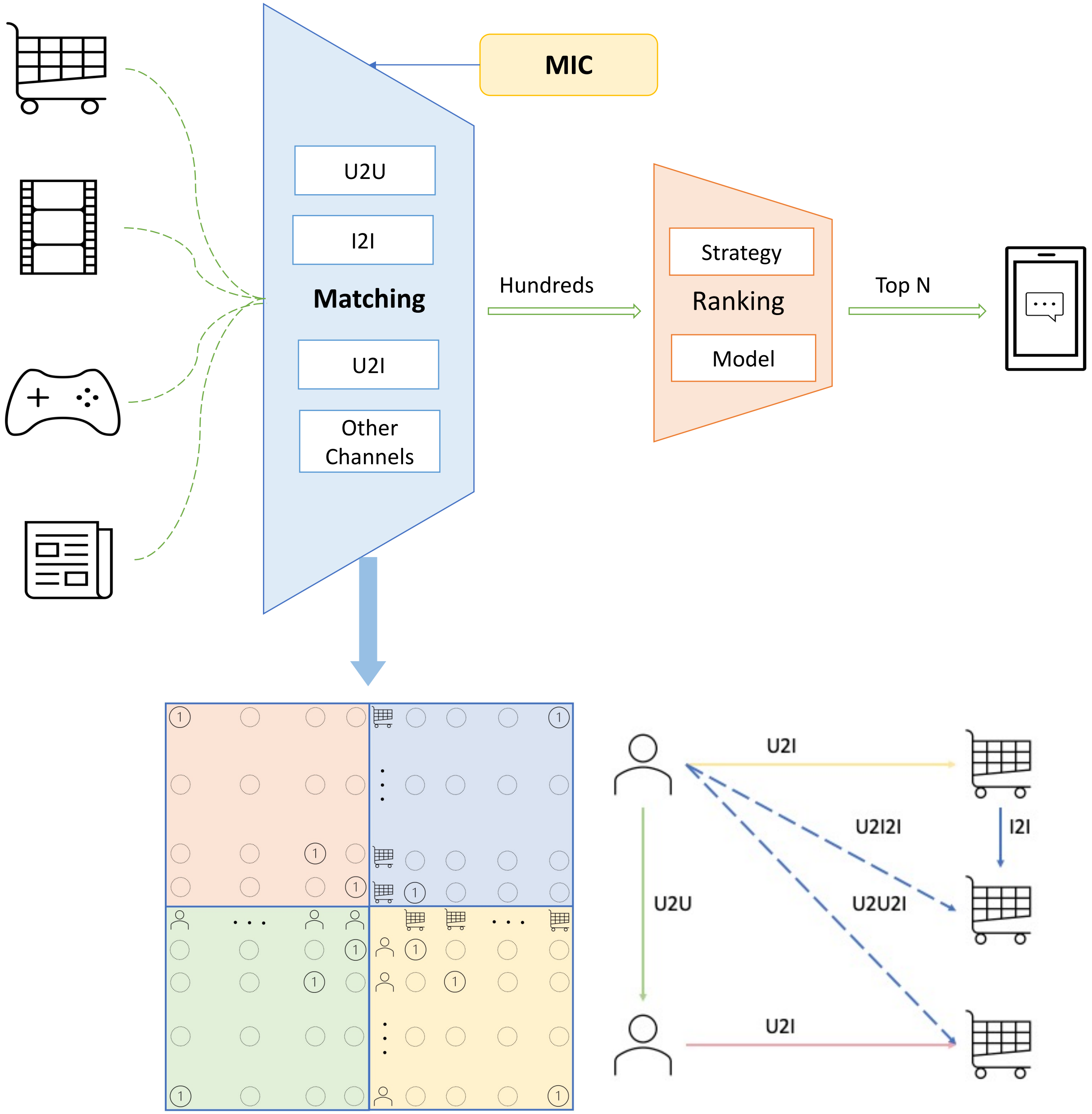
Limited correlation between users and items which solely entail from partial information of latent interactions

MIC-Multi-Channel Background



A typical two-stage recommender system including matching and ranking stage: MIC can be applied in the matching stage.

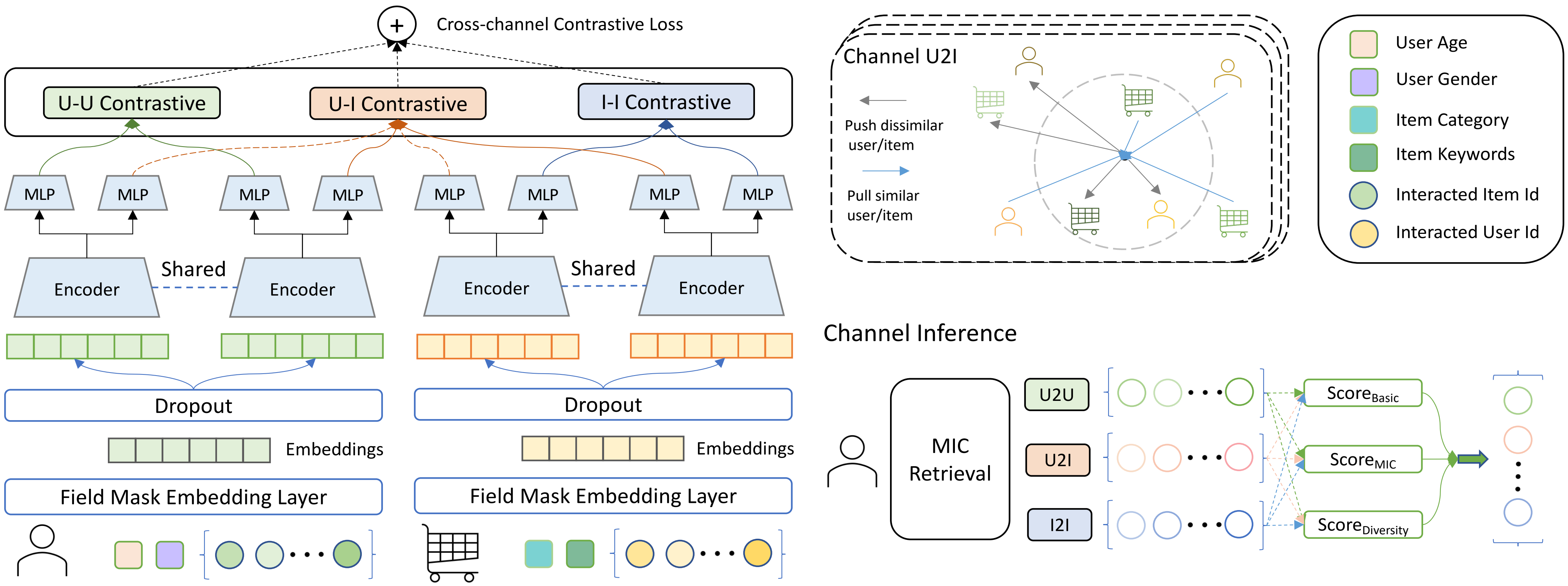
MIC-Multi-Channel Background



A typical two-stage recommender system including matching and ranking stage: MIC can be applied in the matching stage.

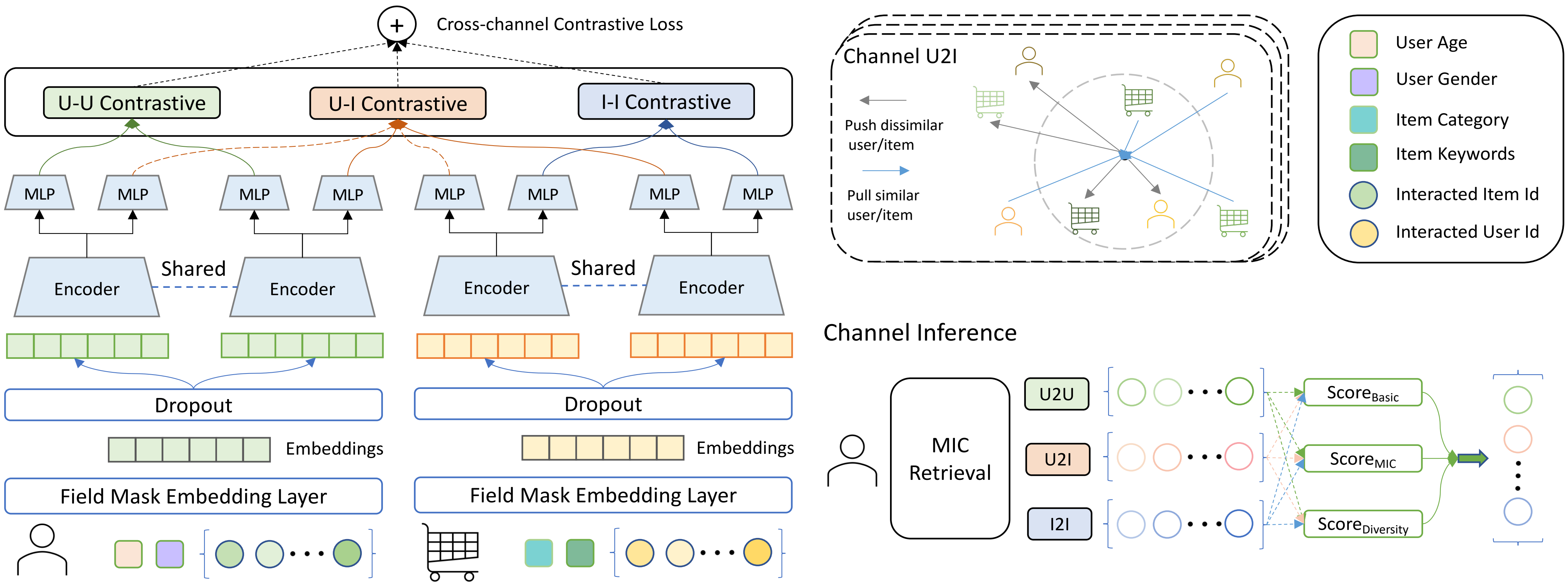
Multiple retrieval paths among users and items: including U2I, I2I, U2U, U2U2I, U2I2I.

MIC-Model Architecture



Overview of model-agnostic integrated cross-channel recommender (MIC)

MIC-Model Architecture



Overview of model-agnostic integrated cross-channel recommender (MIC)

$$\mathcal{L}_{uv} = -\log\frac{\exp(\mathrm{sim}(u,v_i)/\tau)}{\sum_{\substack{j=1\\ j\neq i}}^{N}\exp(\mathrm{sim}(u,\tilde{v_j})/\tau)} - \log\frac{\exp(\mathrm{sim}(v,u_i)/\tau)}{\sum_{\substack{j=1\\ j\neq i}}^{N}\exp(\mathrm{sim}(v,\tilde{u_j})/\tau)}$$

$$\mathcal{L}_{uu} = -\log\frac{\exp(\mathrm{sim}(u_k,\tilde{u_k})/\tau)}{\sum_{\substack{j=1\\ j\neq k}}^{N}\exp(\mathrm{sim}(u_k,u_j)/\tau)}$$

$$\mathcal{L}_{vv} = -\log\frac{\exp(\mathrm{sim}(v,\tilde{v_i})/\tau)}{\sum_{\substack{j=1\\ j\neq i}}^{N}\exp(\mathrm{sim}(v,v_j)/\tau)}$$

$$\mathcal{L}_{basic} = -\frac{1}{N}\sum_{i}[y_i\log\hat{y}_i + (1-y_i\log(1-\hat{y}_i))]$$

$$\mathcal{L} = \lambda\mathcal{L}_{basic} + (1-\lambda)(\mathcal{L}_{uv} + \mathcal{L}_{vv} + \mathcal{L}_{uu})$$

$$Score_{Basic}(v_i) = p(\overrightarrow{e_{v_i}}, \vec{u}), Score_{MIC}(v_i) = \frac{exp(s_i)}{\sum_{j\in|V_C|} exp(s_j)}$$

$$g(i,j) = \delta(C(i)! = C(j)), Score_{Div}(v_i) = \sum_{i\in V_C}\sum_{j\in V_C} g(i,j)$$

$$Score = Score_{Basic} + \lambda_{mic}Score_{MIC}(v_i) + \lambda_{div}Score_{Div}(v_i)$$

MIC-Multi-Channel Experiments

We conduct experiments to investigate the following research questions:

- Research Question 1 (RQ1): How does MIC perform on large public recommendation datasets (Book, Taobao, Movielens, Steam)?
- Research Question 2 (RQ2): How does MIC perform in realword News Recommendations System?
- Research Question 3 (RQ3): Are different components and losses essential in MIC?
- Research Question 4 (RQ4): How does MIC alleviate the seesaw phenomenon between retrieval accuracy and diversity: Can MIC achieve high retrieval accuracy and diversity simultaneously?
- Research Question 5 (RQ5): How does contrastive learning modules (UU,UI,II) help improve the embedding space and recall performance for corresponding U2U, U2I, I2I channel?

MIC-Model Experiments Dataset and Competitors

Performances on:
- Amazon Book,
- Taobao
- Movielens
- Steam.

Dataset	users	items	interactions
Amazon Books	459,133	313,966	8,898,041
Steam	2,567,538	15,474	7,793,069
Taobao	976,779	1,708,530	85,384,110
MovieLens-1M	6,040.	3,900	1,000,209

Competitors
- Retrieval Baseline
  - YoutubeDNN, Gru4Rec, ComiRec
- MIC as Plugin
- MIC Variants

MIC-Model Experiments of Public Datasets

RQ1

Gain represents the performance gain of X +MIC vs vanilla X model.

Datasets	@N	Metrics	Baselines			X+MIC					
			DNN	Gru4Rec	ComiRec	DNN	**Gain**	Gru4Rec	**Gain**	ComiRec	**Gain**
Amazon Book	@20	Recall	5.608	5.877	6.634	5.934	**5.81%**	6.0141	**2.33%**	7.457	**12.41%**
		NDCG	5.371	5.835	6.023	5.836	**8.66%**	5.992	**2.69%**	6.195	**2.86%**
		Hit Rate	12.291	12.545	13.423	12.828	**4.37%**	12.997	**3.60%**	15.124	**12.67%**
	@50	Recall	8.885	8.908	10.2574	9.3066	**4.75%**	9.411	**5.65%**	11.55	**10.90%**
		NDCG	6.594	6.915	7.217	7.077	**7.32%**	7.105	**2.75%**	7.889	**9.31%**
		Hit Rate	18.709	18.949	19.231	19.373	**3.55%**	19.535	**3.09%**	22.790	**18.51%**
Taobao	@20	Recall	3.319	4.132	5.065	3.531	**6.39%**	4.442	**7.50%**	5.642	**11.39%**
		NDCG	12.493	15.449	19.324	13.481	**7.91%**	17.995	**16.48%**	21.221	**9.82%**
		Hit Rate	28.417	32.033	38.429	29.592	**4.13%**	36.661	**14.45%**	41.878	**8.97%**
	@50	Recall	5.075	6.118	7.115	5.278	**4.00%**	6.377	**4.23%**	7.861	**10.48%**
		NDCG	14.263	16.084	20.635	15.187	**6.48%**	18.999	**18.12%**	22.509	**9.08%**
		Hit Rate	39.31	42.114	48.094	40.324	**2.58%**	45.551	**8.16%**	51.607	**7.30%**
Movielens	@20	Recall	12.251	12.993	13.001	12.508	**2.10%**	13.012	**0.15%**	13.322	**2.47%**
		NDCG	36.249	37.033	37.207	36.898	**1.79%**	37.603	**1.54%**	38.186	**2.63%**
		Hit Rate	71.688	72.344	73.772	73.841	**3.00%**	74.308	**2.71%**	76.551	**3.77%**
	@50	Recall	23.028	24.447	25.043	23.875	**3.68%**	25.003	**2.27%**	25.927	**3.53%**
		NDCG	38.756	39.888	41.099	40.003	**3.22%**	41.309	**3.56%**	42.109	**2.46%**
		Hit Rate	87.245	89.705	90.138	88.907	**1.90%**	90.111	**0.45%**	91.391	**1.39%**
Steam	@20	Recall	2.901	2.672	2.753	3.117	**7.45%**	2.839	**6.25%**	3.009	**9.30%**
		NDCG	4.702	4.557	5.284	4.992	**6.17%**	5.703	**25.15%**	5.503	**4.14%**
		Hit Rate	10.308	9.928	11.044	10.554	**2.39%**	10.422	**4.98%**	11.333	**2.62%**
	@50	Recall	3.671	4.432	5.021	4.288	**16.81%**	4.775	**7.74%**	5.123	**2.03%**
		NDCG	5.077	4.997	6.23	5.779	**13.83%**	5.413	**8.32%**	6.671	**7.08%**
		Hit Rate	12.031	11.089	13.149	12.608	**4.80%**	12.307	**10.98%**	14.388	**9.42%**

MIC-Model Experiments of Online A/B Results

RQ2

Main Page Clicked Rec Video

Rec More Videos

A/B App:
- Tencent News

A/B Time:
- 2021/10/01 to 2021/10/15

#Scenario	EPV ratio	Average Play Percentage ↑	Average Duration ↑	Average Viewed Video ↑
Video Recommendation	25.00%	+3.51%	+1.26%	+1.85%

MIC-Model Experiments of Ablations

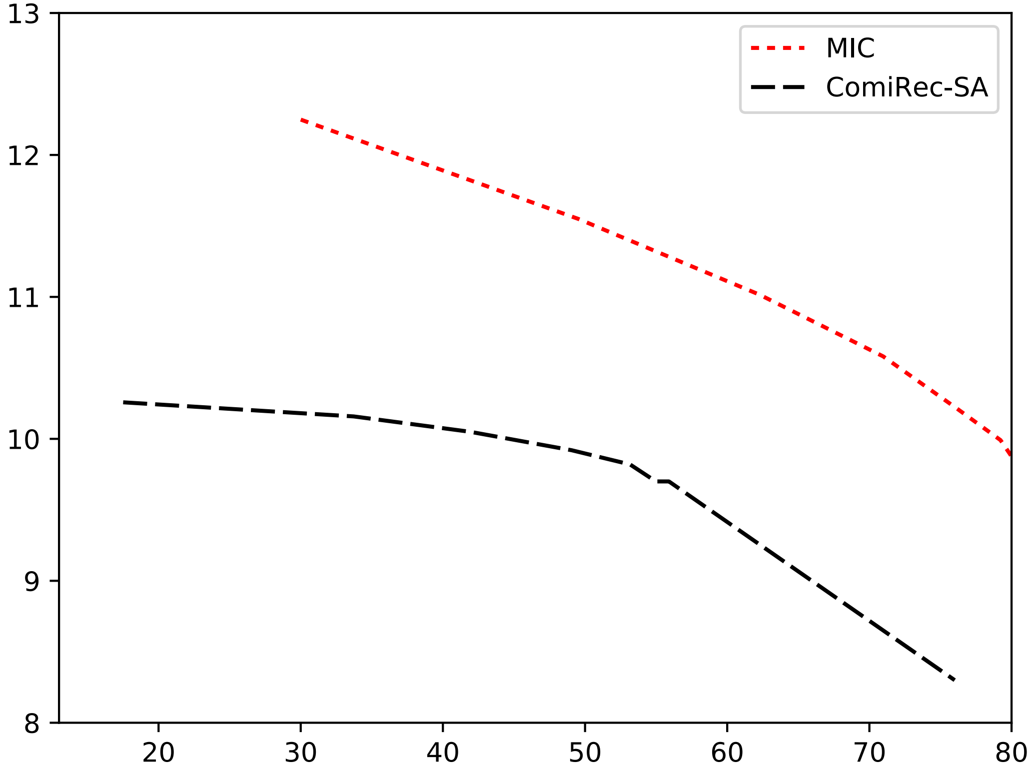
RQ3

Modules	Settings	Recall	NDCG	Hit Rate	Diverstiy
	Full Model	11.554	7.889	22.790	49.511
Contrastive Loss	-UU	10.556	7.689	21.132	44.021
	-UI	10.347	6.462	21.273	42.483
	-II	11.096	7.089	22.668	46.796
	-Perturbation	8.415	5.346	16.590	34.188
	-Mining	10.176	6.098	20.727	41.983
Inference Channel	-U2U channel	11.148	7.688	22.076	45.478
	-U2I channel	11.484	7.825	22.571	45.603
	-I2I channel	11.316	7,758	22.443	41.709

MIC Variants over ComiRec on Amazon Book

MIC-Model Retrieval Accuracy and Diversity Balance

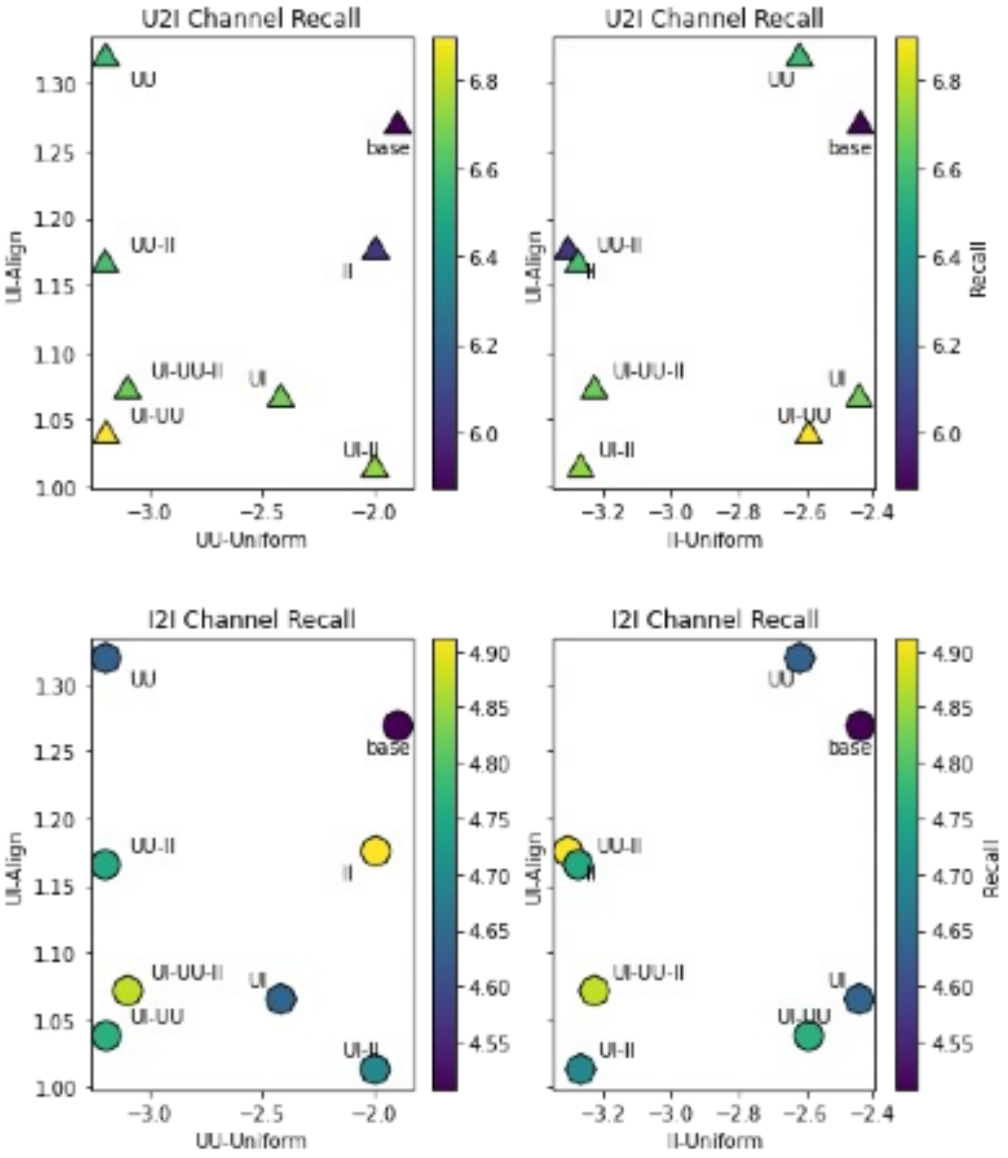
RQ4

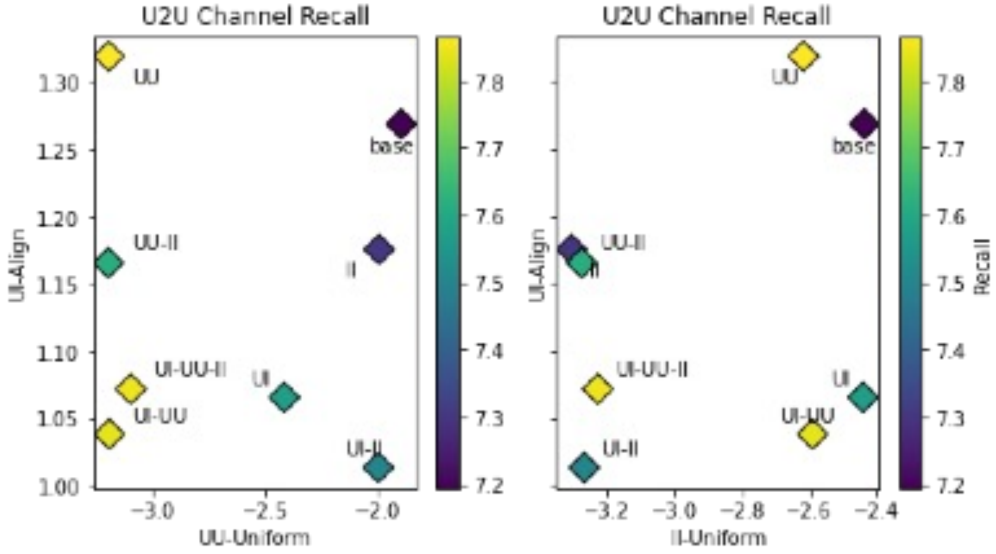


Retrieval Accuracy and Diversity Balance

MIC-Model Qualitative Results

RQ5





Visualization of User and Item Representation in U2I, U2U and I2I channel over Alignment and Uniformity Metrics of UI-Align, UU-Uniform and II Uniform and Recall Performance

Conclusion

- We formulate the matching stage of recommendation as connecting user and item from multiple channels and propose a model-agnostic MIC architecture based on integrated cross-channel user and item representation learning techniques.
- We address the aforementioned long-standing challenges in recommendation in a unified manner via a cross-channel contrastive aggregation mechanism. MIC mitigates the uncertainty of co-evolving user-item correlations and alleviates the seesaw effect between retrieval accuracy and diversity. To the best of our knowledge, this is the first work that proves it is possible to simultaneously utilize U2I, U2U, and U2I channels to improve retrieval accuracy and diversity.
- Compared with the existing method, MIC shows superior effectiveness and efficiency performance on four public datasets. MIC can also be incorporated into other matching stage recommenders to boost their performance.
- We deployed MIC on the Tencent News platform, the satisfactory online A/B test results on million-scale users and items confirm the efficiency and effectiveness of MIC practically.

Thank you!