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# A Contrastive Framework with User, Item and Review Alignment for Recommendation

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Paper

# Outline

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- ❑ **Introduction**
- ❑ Methodology
- ❑ Experiment
- ❑ Conclusion and Future Work

# Introduction

- Traditional CF-based model: Rely on user-item interaction data.
- Textual reviews contain useful semantic information


Review-aware recommendation limitation:

- Reviews are not universal (missing feature,…)
- Not integrate reviews into the user- item space

How to incorporates reviews into the core learning process?

# Challenges and present work

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Q1: How can we seamlessly integrate **reviews** into the **collaborative filtering** models, rather than merely employing them at the feature level?

⇒

We employ **review data** for **augmentation** within a **contrastive learning** framework to alleviate the sparsity of interaction data, since same user typically exhibits consistent reviewing patterns.

Q2: How can we align **user**, **item** and **review** representations in a shared **latent space** to ensure their consistency?

⇒

We propose another **contrastive strategy** to align the **user**, **item** and **review-based** representations. We seek to maximize the agreement between user's representations and theirs review.

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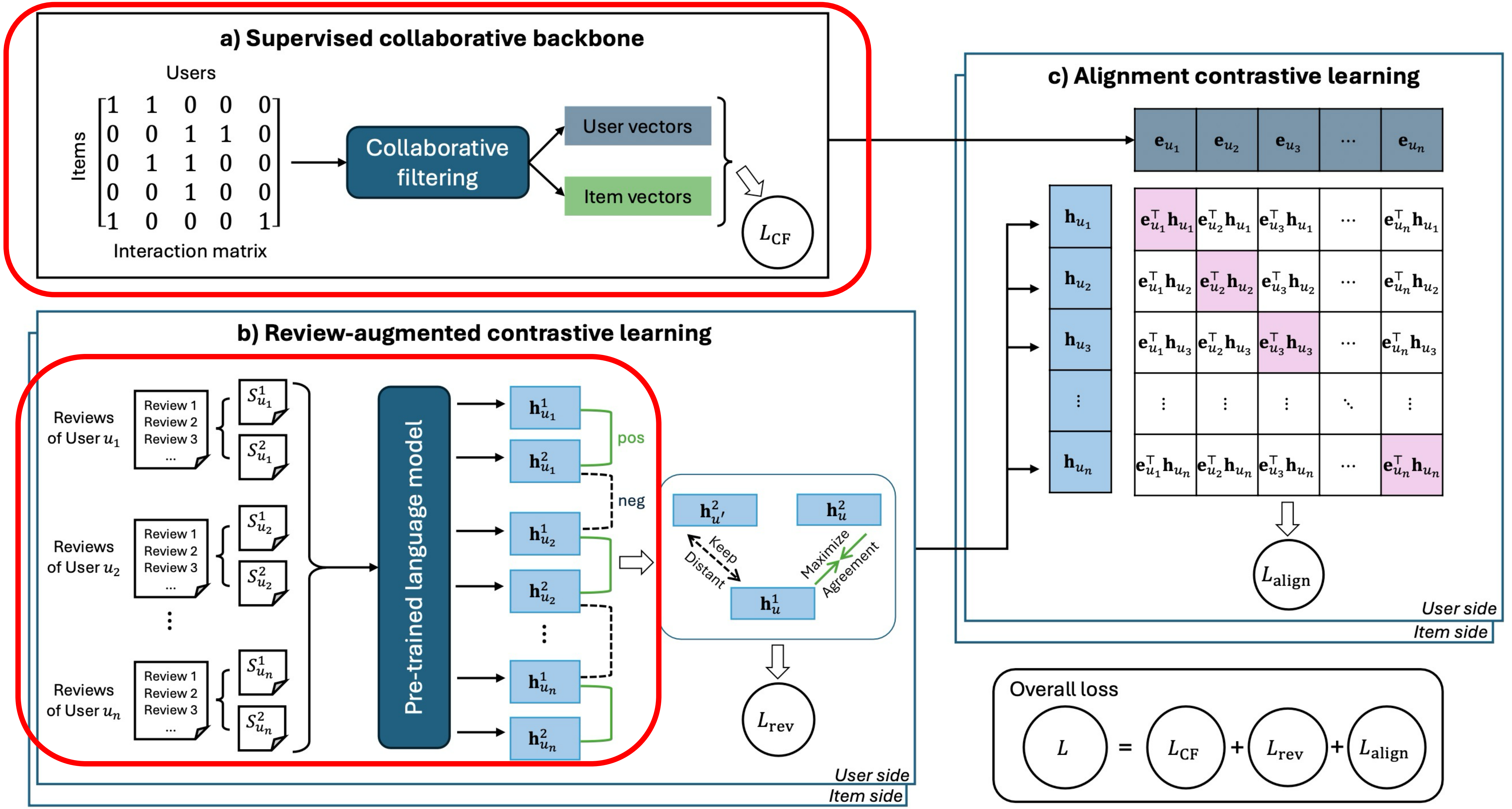
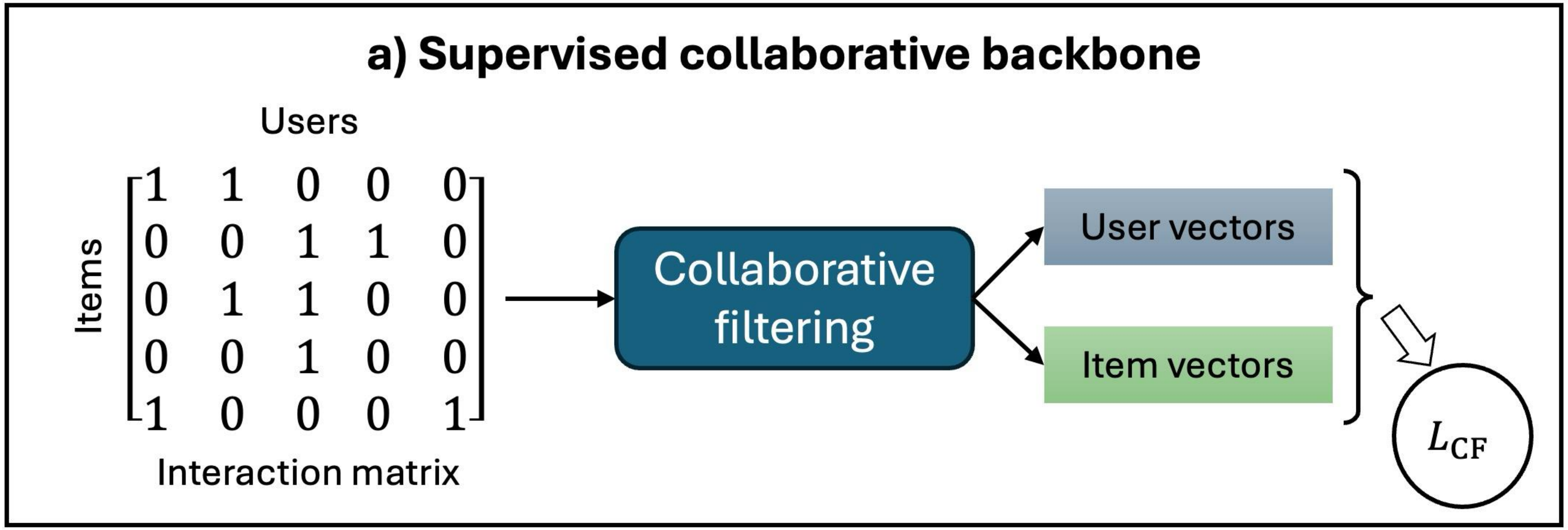
# Overall framework of ReCAFR



# Supervised collaborative backbone






$$y_{u,i} = \begin{cases} 1, & u \text{ has an observed interaction with } i, \\ 0, & \text{otherwise.} \end{cases} \Longrightarrow L_{\mathrm{CF}} = \sum_{(u,i,j)\in O} -\ln \sigma(\hat{y}_{u,i} - \hat{y}_{u,j}),$$

# Review-augmented contrastive learning

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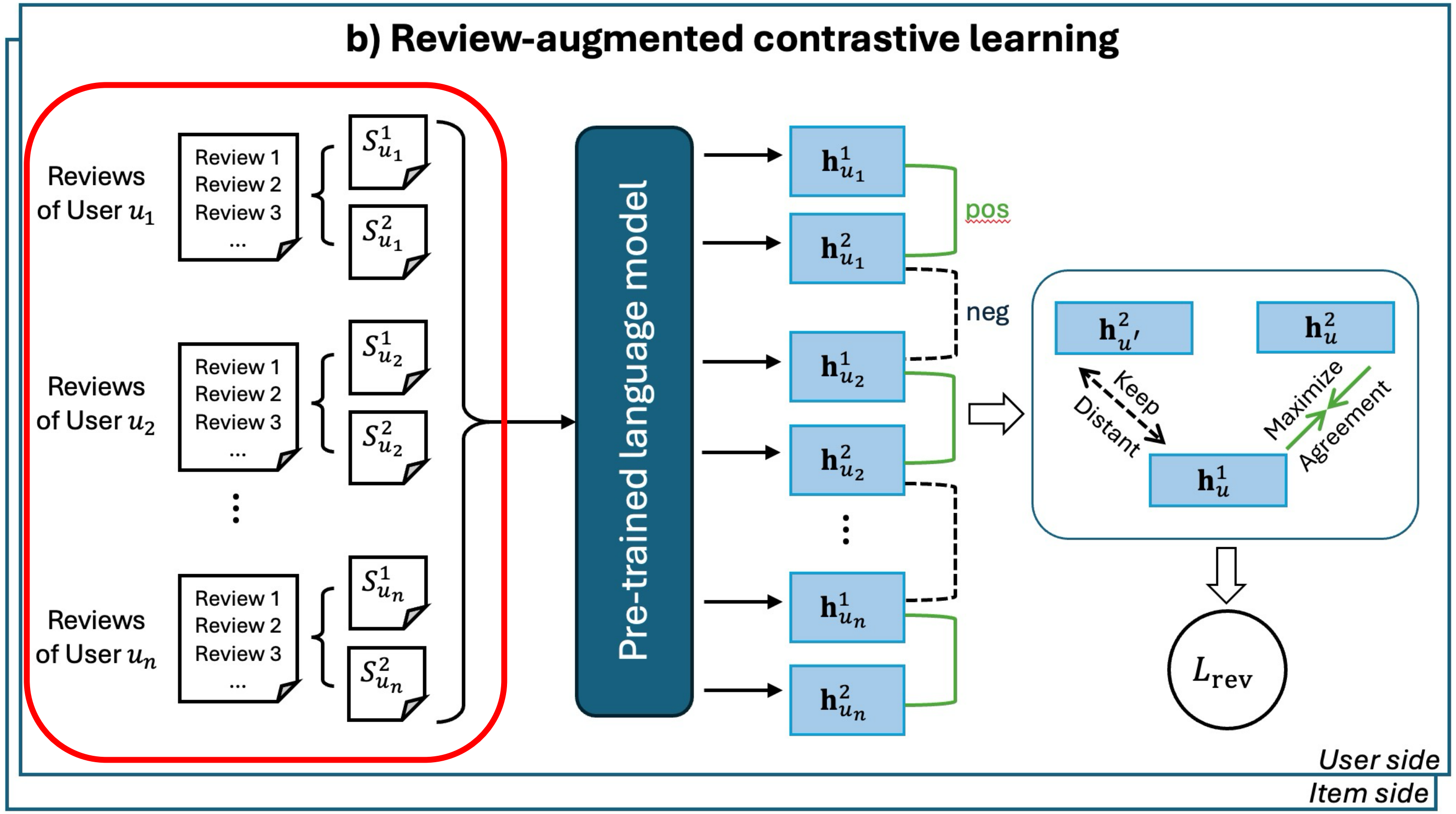


User 1 has 10 reviews:

1. “I wasn't sure what to expect, but this book completely exceeded my expectations.”
2. “The writing style is engaging, making it hard to put down.”
3. “Some chapters felt a bit repetitive, but overall, it was a great read.”
4. “I loved how the author used real-life examples to illustrate key points.”
5. “The pacing was perfect, keeping me interested from start to finish.”
6. “I wish there were more details about the main character’s backstory.”
7. “This book has completely changed how I think about this topic.”
8. “There were a few typos, but they didn’t take away from the overall experience.”
9. “I would highly recommend this to anyone interested in personal development.”
10. “Looking forward to reading more from this author in the future”

$S^1_{u_1}$: Random 5 from 10 reviews above

$S^1_{u_1}$: Remaining reviews

# Review-augmented contrastive learning

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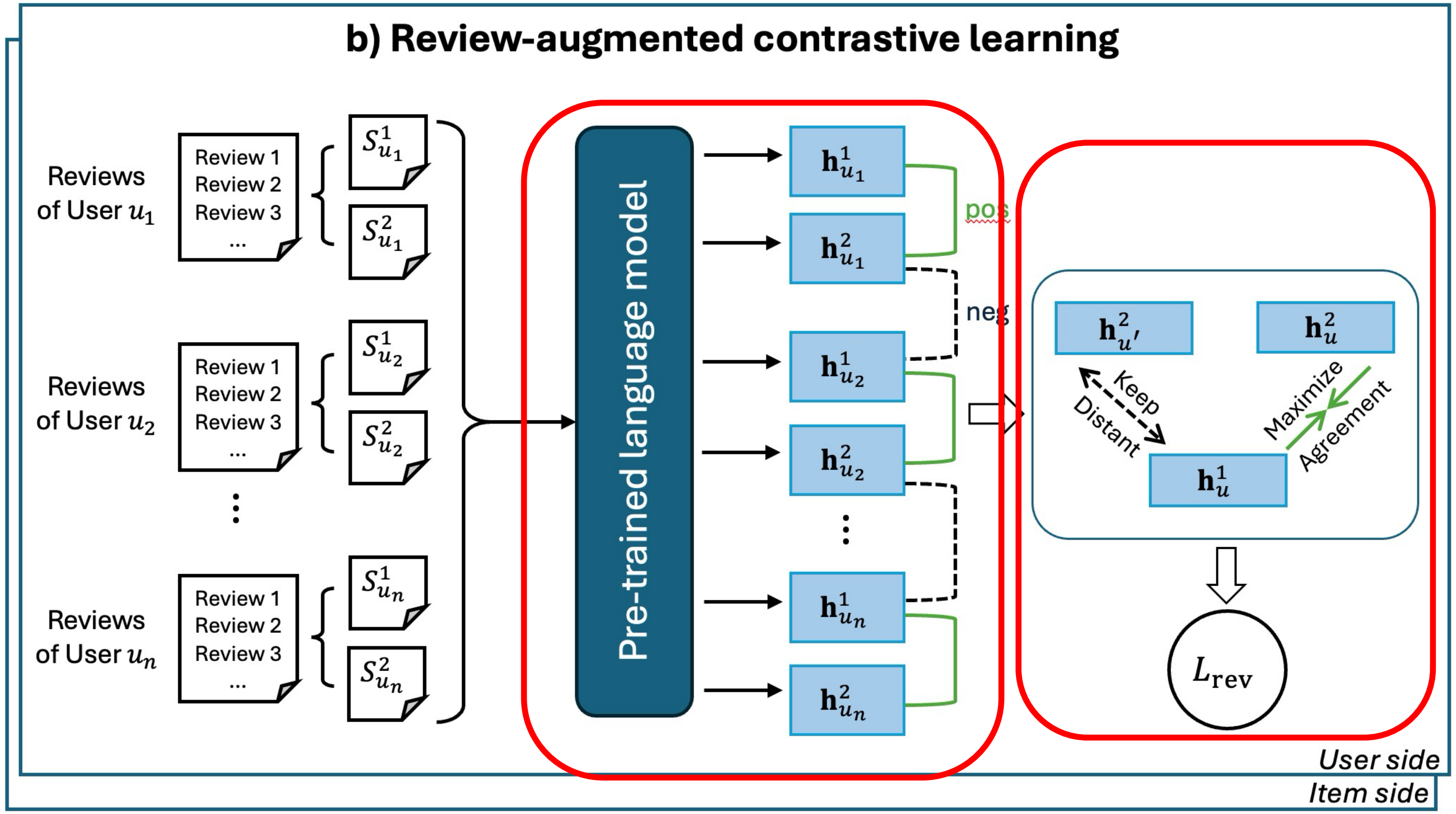


- View-level representation for each sampled view:

$$\mathbf{h}_u^k = \text{MEAN}(\{f(s) \mid s \in S_u^k\}),$$
$$\mathbf{h}_i^k = \text{MEAN}(\{f(s) \mid s \in S_i^k\}).$$

- We then adopt the InfoNCE[1] loss:

$$L_{\text{rev}}^{\text{user}} = \sum_{u \in U} -\log \frac{\exp(\text{sim}(\mathbf{h}_u^1, \mathbf{h}_u^2)/\tau)}{\sum_{u' \in U} \exp(\text{sim}(\mathbf{h}_u^1, \mathbf{h}_{u'}^2)/\tau))},$$
$$L_{\text{rev}}^{\text{item}} = \sum_{i \in I} -\log \frac{\exp(\text{sim}(\mathbf{h}_i^1, \mathbf{h}_i^2)/\tau)}{\sum_{i' \in I} \exp(\text{sim}(\mathbf{h}_i^1, \mathbf{h}_{i'}^2)/\tau))},$$

[1] Aaron van den Oord, Yazhe Li, and Oriol Vinyals. 2018. Representation learning with contrastive predictive coding. arXiv preprint arXiv:1807.03748 (2018).

# Alignment contrastive learning

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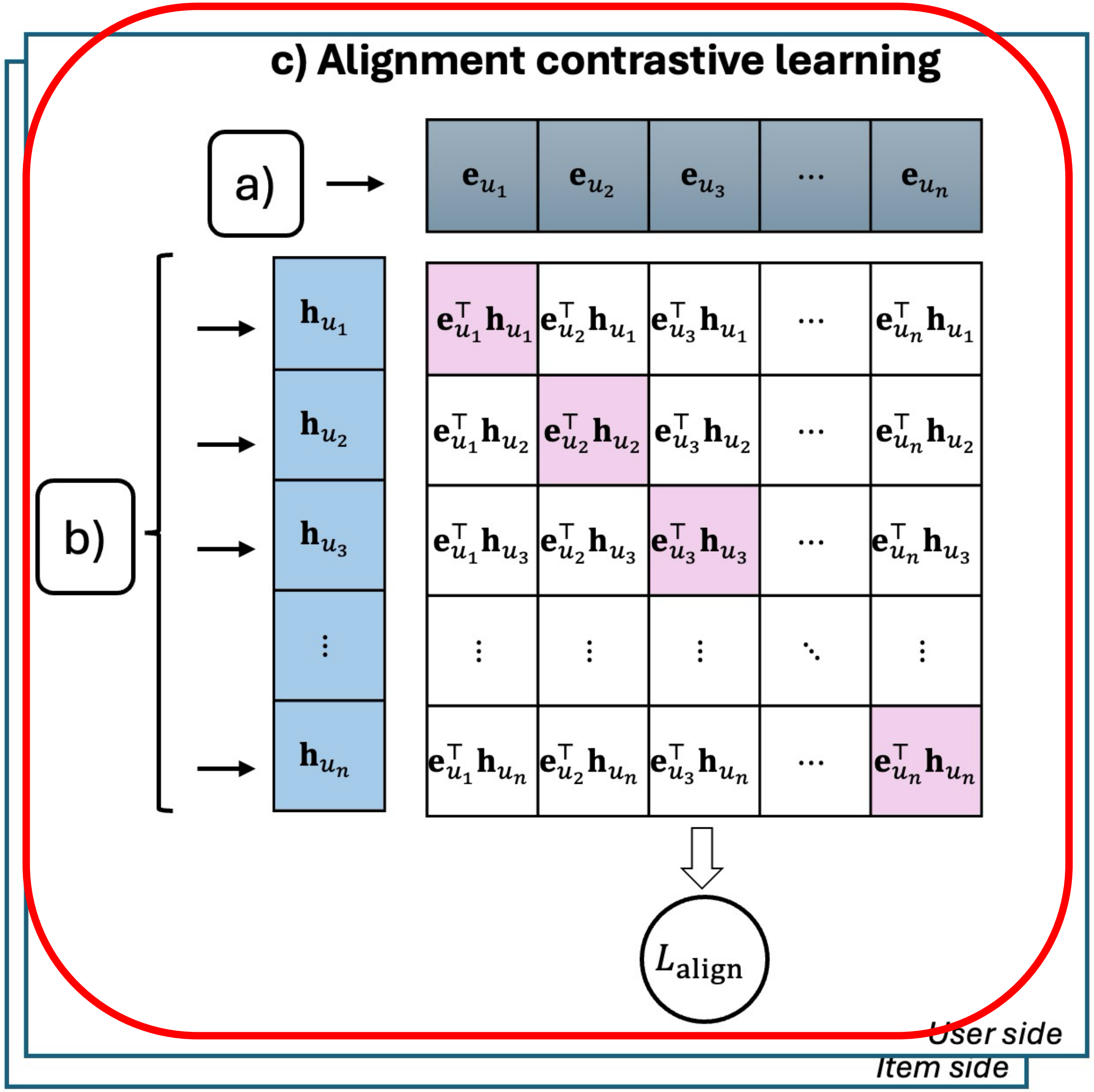


- Align user, item and review representations.
- Maximize the agreement between the representations of the same user or item:

$$L_{\text{align}}^{\text{user}} = \sum_{u \in U} -\log \frac{\exp(\text{sim}(\mathbf{e}_u, \mathbf{h}_u)/\tau)}{\sum_{u' \in U} \exp(\text{sim}(\mathbf{e}_u, \mathbf{h}_{u'}))/\tau))},$$

$$L_{\text{align}}^{\text{item}} = \sum_{i \in I} -\log \frac{\exp(\text{sim}(\mathbf{e}_i, \mathbf{h}_i)/\tau)}{\sum_{i' \in I} \exp(\text{sim}(\mathbf{e}_i, \mathbf{h}_{i'}))/\tau))},$$

Training objectives:

$$L = L_{\text{CF}} + \lambda_1 \left(L_{\text{rev}}^{\text{user}} + L_{\text{rev}}^{\text{item}}\right) + \lambda_2 \left(L_{\text{align}}^{\text{user}} + L_{\text{align}}^{\text{item}}\right) + \lambda_3 \|\Theta\|_2^2,$$

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# Datasets

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Table 1: Statistics of the datasets.

| Dataset | #User | #Items | # Interactions | # Reviews | Density |
|---|---|---|---|---|---|
| Kindle | 365,687 | 356,888 | 3,348,523 | 3,327,676 | .003% |
| Book | 500,000 | 678,705 | 11,417,323 | 11,266,408 | .003% |
| Beauty | 6,119 | 5,082 | 23,291 | 22,257 | .075% |
| Yelp | 22,450 | 17,213 | 606,123 | 601,512 | .157% |

- Kindle, Book and Beauty are 3 Amazon [2] review datasets
- Yelp [3] is subset of Yelp's businesses, reviews, and user data

[2] https://jmcauley.ucsd.edu/data/amazon/
[3] https://www.yelp.com/dataset/

# Comparison to baselines w/o review data

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| | Kindle | | | Book | | | Beauty | | | Yelp | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Methods** | Recall@5 | Prec@5 | NDCG@5 | Recall@5 | Prec@5 | NDCG@5 | Recall@5 | Prec@5 | NDCG@5 | Recall@5 | Prec@5 | NDCG@5 |
| BPR | .0203±.0003 | .0223±.0008 | .0242±.0005 | .0142±.0009 | .0227±.0006 | .0236±.0001 | .0264±.0007 | .0272±.0009 | .0310±.0003 | .0109±.0006 | .0157±.0007 | .0166±.0002 |
| ReCAFR+BPR | **.0226**±.0001 | **.0241**±.0009 | **.0245**±.0001 | **.0143**±.0002 | **.0228**±.0001 | **.0237**±.0008 | **.0277**±.0003 | **.0287**±.0002 | **.0313**±.0008 | **.0115**±.0008 | **.0162**±.0004 | **.0169**±.0004 |
| LightGCN | .0232±.0001 | .0253±.0007 | .0281±.0001 | .0152±.0005 | .0244±.0001 | .0254±.0006 | .0254±.0008 | .0261±.0005 | .0298±.0000 | .0112±.0006 | .0159±.0004 | .0168±.0002 |
| ReCAFR+LightGCN | **.0243**±.0005 | **.0265**±.0009 | **.0293**±.0001 | **.0187**±.0005 | **.0299**±.0002 | **.0311**±.0001 | **.0266**±.0006 | **.0276**±.0004 | **.0300**±.0006 | **.0125**±.0006 | **.0168**±.0002 | **.0175±.0005** |
| SGL | .0237±.0006 | **.0259**±.0007 | .0286±.0007 | .0169±.0001 | .0270±.0008 | .0281±.0005 | .0269±.0002 | **.0276**±.0009 | .0316±.0008 | .0101±.0004 | .0143±.0001 | .0151±.0004 |
| ReCAFR+SGL | **.0242**±.0009 | .0257±.0005 | **.0291**±.0005 | **.0171**±.0006 | **.0274**±.0007 | **.0285**±.0007 | **.0276**±.0007 | .0273±.0004 | **.0319**±.0009 | **.0106**±.0001 | **.0148**±.0008 | **.0158**±.0001 |
| DirectAU | .0255±.0009 | .0271±.0003 | .0309±.0007 | .0167±.0009 | .0269±.0007 | .0281±.0009 | .0298±.0007 | .0284±.0007 | .0338±.0006 | **.0124**±.0009 | .0161±.0008 | .0169±.0005 |
| ReCAFR+DirectAU | **.0262**±.0000 | **.0273**±.0006 | **.0317**±.0009 | **.0172**±.0006 | **.0271**±.0006 | **.0285**±.0007 | **.0301**±.0008 | **.0286**±.0008 | **.0341**±.0007 | .0121±.0006 | **.0179**±.0001 | **.0172**±.0008 |
| SimGCL | .0253±.0002 | .0277±.0004 | **.0306**±.0003 | .0180±.0007 | .0289±.0006 | .0301±.0007 | .0288±.0000 | .0295±.0002 | .0339±.0007 | .0145±.0001 | .0181±.0002 | .0188±.0002 |
| ReCAFR+SimGCL | **.0269**±.0002 | **.0285**±.0001 | .0302±.0003 | **.0184**±.0003 | **.0295**±.0006 | **.0307**±.0001 | **.0296**±.0007 | **.0304**±.0005 | **.0365**±.0001 | **.0155**±.0007 | **.0191**±.0009 | **.0202**±.0004 |

We generally observe better performance when each backbone recommender is integrated with ReCAFR than when it is not.

Contrastive methods leverage self-supervised signals to learn inherent properties within the interaction data.

# Comparison to review-based baselines

| Method | Kindle | | | Book | | | Beauty | | | Yelp | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Using all available reviews** | | | | | | | | | | | | |
| | Recall@5 | Prec@5 | NDCG@5 | Recall@5 | Prec@5 | NDCG@5 | Recall@5 | Prec@5 | NDCG@5 | Recall@5 | Prec@5 | NDCG@5 |
| NARRE | .0238±.0009 | .0235±.0005 | .0269±.0007 | .0160±.0008 | .0257±.0003 | .0266±.0001 | .0266±.0006 | .0276±.0002 | .0303±.0009 | .0129±.0002 | .0182±.0009 | .0171±.0006 |
| RGCL | .0242±.0006 | .0264±.0009 | .0292±.0001 | .0183±.0003 | .0293±.0003 | .0305±.0003 | .0269±.0006 | .0279±.0002 | .0325±.0004 | .0142±.0002 | .0189±.0006 | .0196±.0005 |
| RMCL | .0236±.0008 | .0259±.0006 | .0288±.0001 | .0172±.0003 | .0286±.0001 | .0294±.0009 | .0273±.0006 | .0265±.0006 | .0315±.0004 | .0144±.0007 | .0186±.0003 | .0192±.0006 |
| ReCAFR+SimGCL | **.0269**±.0004 | **.0285**±.0008 | **.0302±.0003** | **.0184**±.0005 | **.0295**±.0005 | **.0307±.0003** | **.0296**±.0003 | **.0304**±.0001 | **.0365**±.0008 | **.0155**±.0009 | **.0191**±.0008 | **.0202**±.0007 |
| **Removing 30% of the reviews** | | | | | | | | | | | | |
| | Recall@5 | Prec@5 | NDCG@5 | Recall@5 | Prec@5 | NDCG@5 | Recall@5 | Prec@5 | NDCG@5 | Recall@5 | Prec@5 | NDCG@5 |
| NARRE | .0206±.0007 | .0229±.0009 | .0213±.0008 | .0141±.0005 | .0214±.0008 | .0211±.0006 | .0239±.0007 | .0261±.0007 | .0240±.0006 | .0102±.0006 | .0145±.0005 | .0140±.0007 |
| RGCL | .0215±.0009 | .0238±.0004 | .0216±.0009 | .0152±.0002 | .0258±.0009 | .0273±.0006 | .0247±.0005 | .0274±.0008 | .0248±.0008 | .0109±.0001 | .0152±.0005 | .0156±.0001 |
| RMCL | .0226±.0007 | .0248±.0002 | .0211±.0005 | .0163±.0005 | .0247±.0003 | .0259±.0001 | .0251±.0001 | .0279±.0006 | .0264±.0008 | .0116±.0005 | .0163±.0004 | .0148±.0005 |
| ReCAFR+SimGCL | **.0241**±.0007 | **.0254**±.0005 | **.0279**±.0007 | **.0171**±.0001 | **.0261**±.0005 | **.0295**±.0004 | **.0274**±.0008 | **.0289**±.0009 | **.0329**±.0006 | **.0121**±.0005 | **.0175**±.0005 | **.0184**±.0001 |

- ReCAFR outperforms in all cases, showing the advantage of integrating reviews with collaborative filtering within a unified space can more effectively mitigate the sparsity of interaction data.
- When 30% of the reviews are removed, all methods experience a performance drop; ReCAFR tends to be more robust.

# Experiments

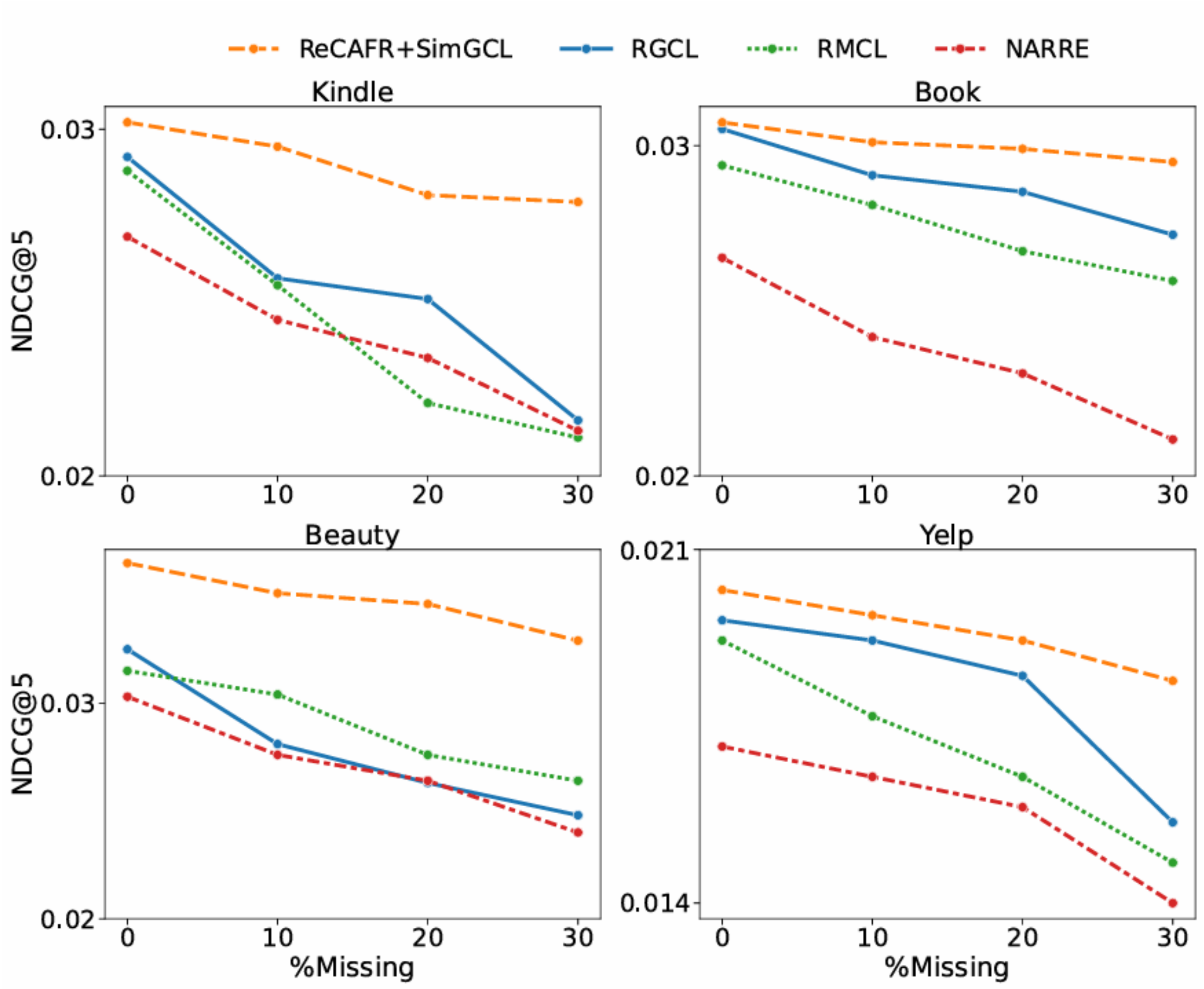


**Figure 3: Impact of missing reviews.**

**Table 4: Ablation study on ReCAFR, reporting NDCG@5.**

| Variants | Kindle | Book | Beauty | Yelp |
|---|---|---|---|---|
| ReCAFR+SimGCL | **.0302** | **.0307** | **.0365** | **.0202** |
| w/o text emb. init. | .0294 | .0286 | .0351 | .0199 |
| w/o user CL | .0281 | .0281 | .0346 | .0186 |
| w/o item CL | .0276 | .0284 | .0331 | .0182 |

You will serve as an assistant to help me determine which types of books a specific user is likely to enjoy.
I will provide you with information about books that the user has purchased, as well as his or her review of that book.
Here are the instructions:
1. Each purchased book will be described in JSON format, with the following attributes:
{ "title": "the title of the book", (if there is no title, I will set this value to "None")
"description": "a description of what types of users will like this book",
"review": "the user's review on the book" (if there is no review, I will set this value to "None")}
2. The information I will give you:
PURCHASED ITEMS: a JSON string describing the item that the user has purchased.

**Requirements:**
1. Please provide your decision in JSON format, following this structure:
{ "summarization": "A summarization of what types of books this user is likely to enjoy" (if you are unable to summarize it, please set this value to "None")
"reasoning": "briefly explain your reasoning for the summarization}
2. Please ensure that the "summarization" is no longer than 100 words.
3. The "reasoning" has no word limits.
4. Do not provided any other text outside the JSON string.

***Instruction***

{"title": "The Mythic Guide to Characters: Writing Characters Who Enchant and Inspire",
"description": "The Mythic Guide to Characters is, in short, a remarkable book. It's intelligent and insightful but at the same time easily approachable and user friendly..."
"review": "The Mythic Guide to Characters is a well-organized effort to assist writers, especially those early in their careers, in creating strong and varied characters..."}

***Input Prompt***

{ "summarization": "This user is likely to enjoy books focused on writing and character development, particularly those aimed at helping aspiring writers improve their craft.",
"reasoning": "The user praised 'The Mythic Guide to Characters' for its organizational structure and practical advice for early-career writers, indicating a strong interest in writing as a form of expression. The appreciation for examples from popular works suggests a desire for relatable references and a focus on character creation. This aligns with an enjoyment for instructional and insightful literature that aids in the writing process."}

***Generated from LLM***

**Figure 5: Review enhancement using LLMs, illustrated with the Book dataset.**

**Table 5: Demonstration of ReCAFR with LLM-enhanced reviews on the Beauty dataset.**

| Methods | Recall@5 | Prec@5 | NDCG@5 |
|---|---|---|---|
| BPR | .0264 | .0272 | .0310 |
| ReCAFR+BPR | **.0277** | .0287 | .0313 |
| ReCAFR+BPR (LLM) | .0269 | **.0289** | **.0315** |
| LightGCN | .0254 | .0261 | .0298 |
| ReCAFR+LightGCN | .0266 | .0276 | .0300 |
| ReCAFR+LightGCN (LLM) | **.0269** | **.0277** | **.0311** |
| DirectAU | .0298 | .0284 | .0338 |
| ReCAFR+DirectAU | .0301 | .0286 | .0341 |
| ReCAFR+DirectAU (LLM) | **.0306** | **.0295** | **.0349** |
| SimGCL | .0288 | .0295 | .0338 |
| ReCAFR+SimGCL | .0296 | .0304 | .0365 |
| ReCAFR+SimGCL (LLM) | **.0298** | **.0313** | **.0376** |

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# Conclusion

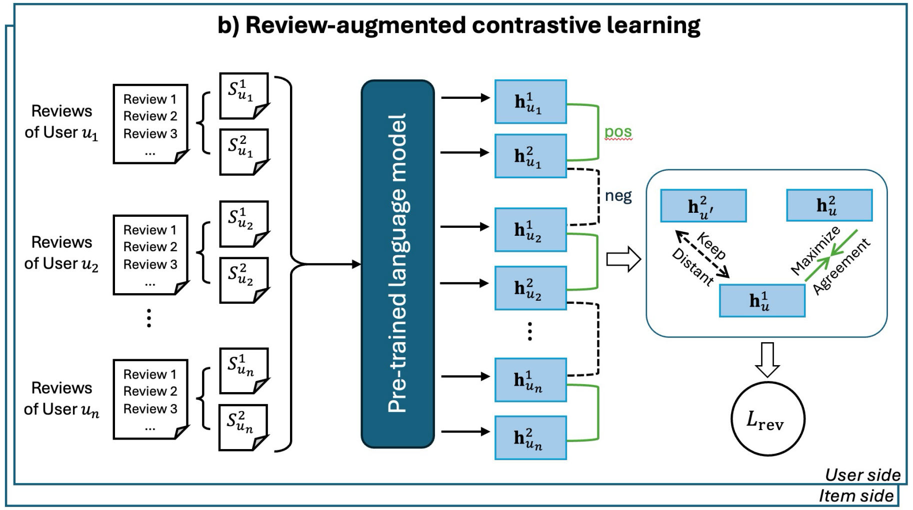


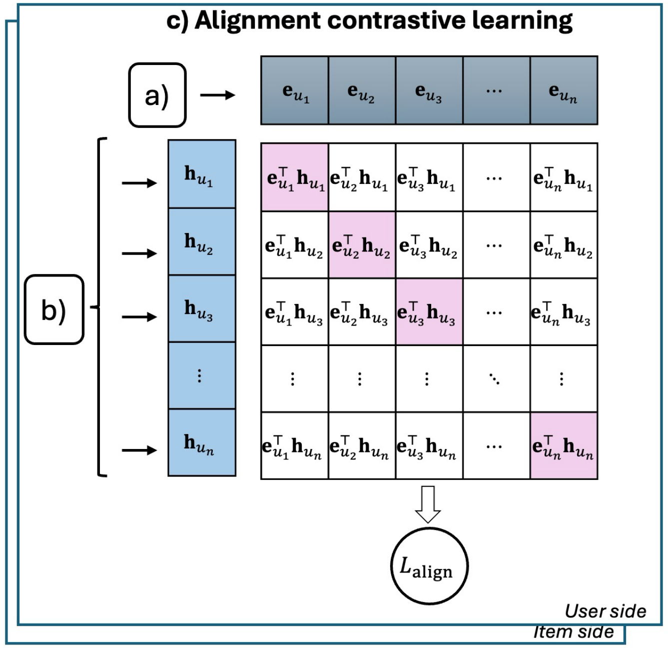
**Key contributions:**

- Addressed the problem of inherent in treating review data merely as **features**.
- Propose ReCAFR, not only employs review data for augmentation to mitigate the **sparsity problem** but also aligns the tripartite representations to improve **robustness**.

**Limitations & future works:**

- More modalities could be considered.
- Analysis of different LMs




Paper