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Empowering Retrieval-based Conversational Recommendation with Contrasting User Preferences

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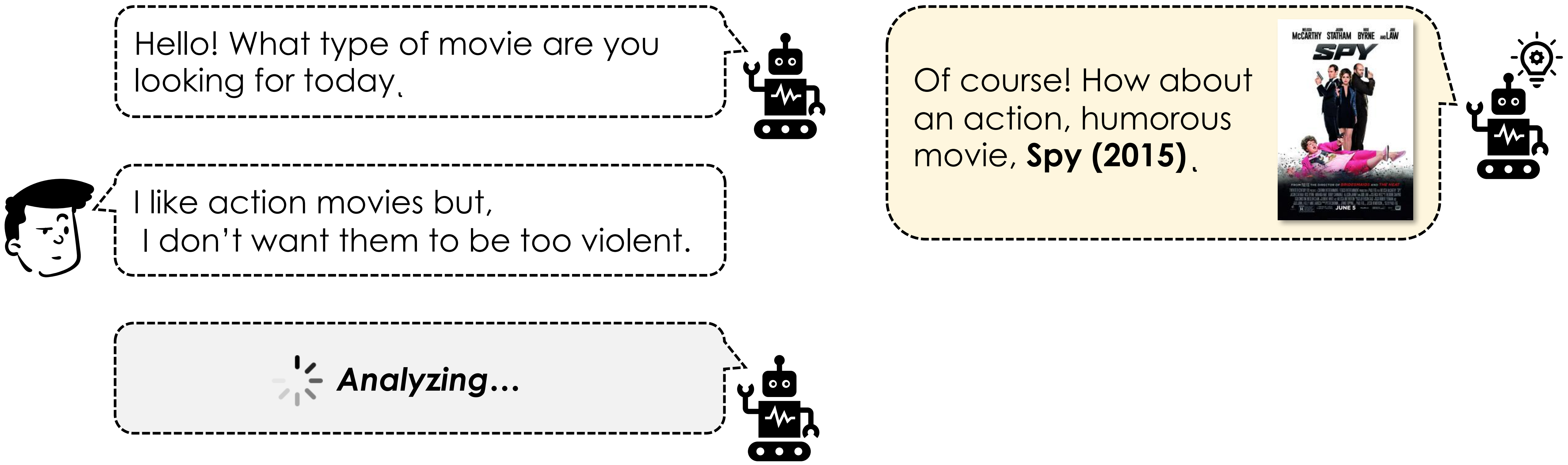
Introduction

- Conversational Recommender Systems (CRSs)
- Limitations of Existing Methods
- Challenges: Contrasting Preferences
- Key Contributions

Task: Conversational Recommender Systems (CRSs)

- **CRSs provide personalized recommendations by understanding users' intentions through multi-turn interactions.**



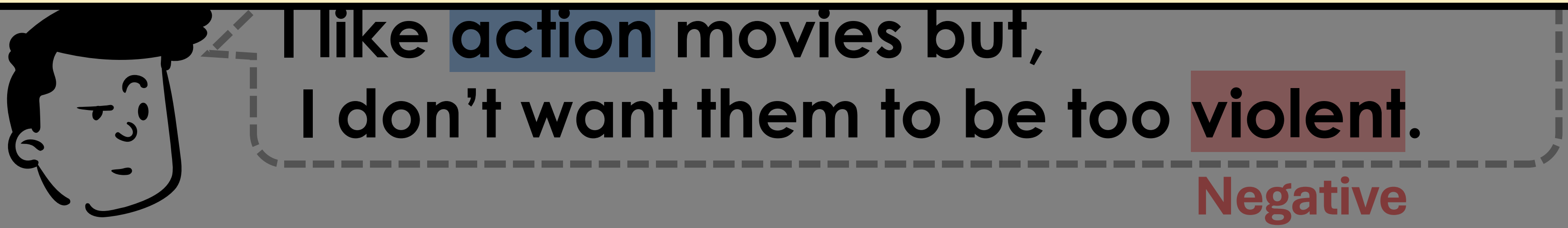
Task: Conversational Recommender Systems (CRSs)

- **Accurately capturing diverse sentiments—both positive and negative—is essential.**
  - This reflects opposing intentions!

Task: Conversational Recommender Systems (CRSs)

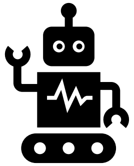
- **Accurately capturing diverse sentiments—both positive and negative—is essential.**
  - This reflects opposing intentions!

User's opposing intentions in dialogue, namely *contrasting preference*



Limitations of Existing Methods

- Most existing methods **overlook the complex relationship** between the user, item, and contrasting preferences.

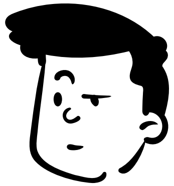


Hello! What type of movie are you looking for today?

Positive

I like action movies but,
I don't want them to be too violent.

Negative



Kill Bill (2003)

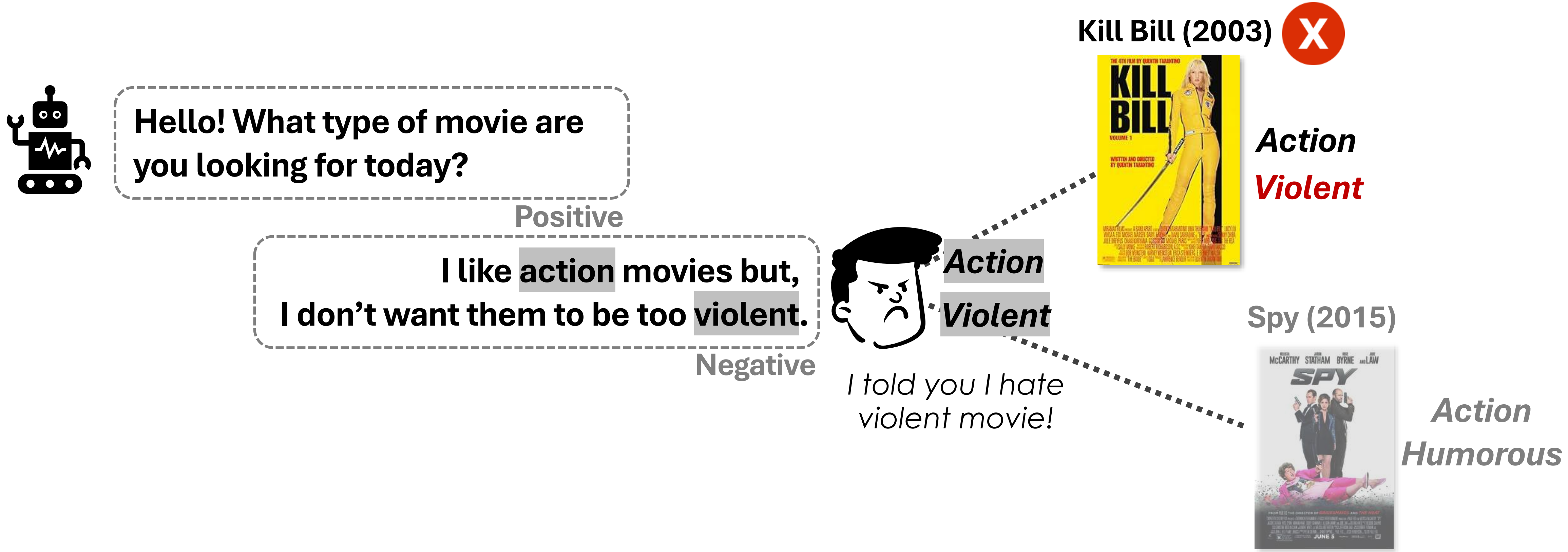
Action
Violent

Spy (2015)

Action
Humorous

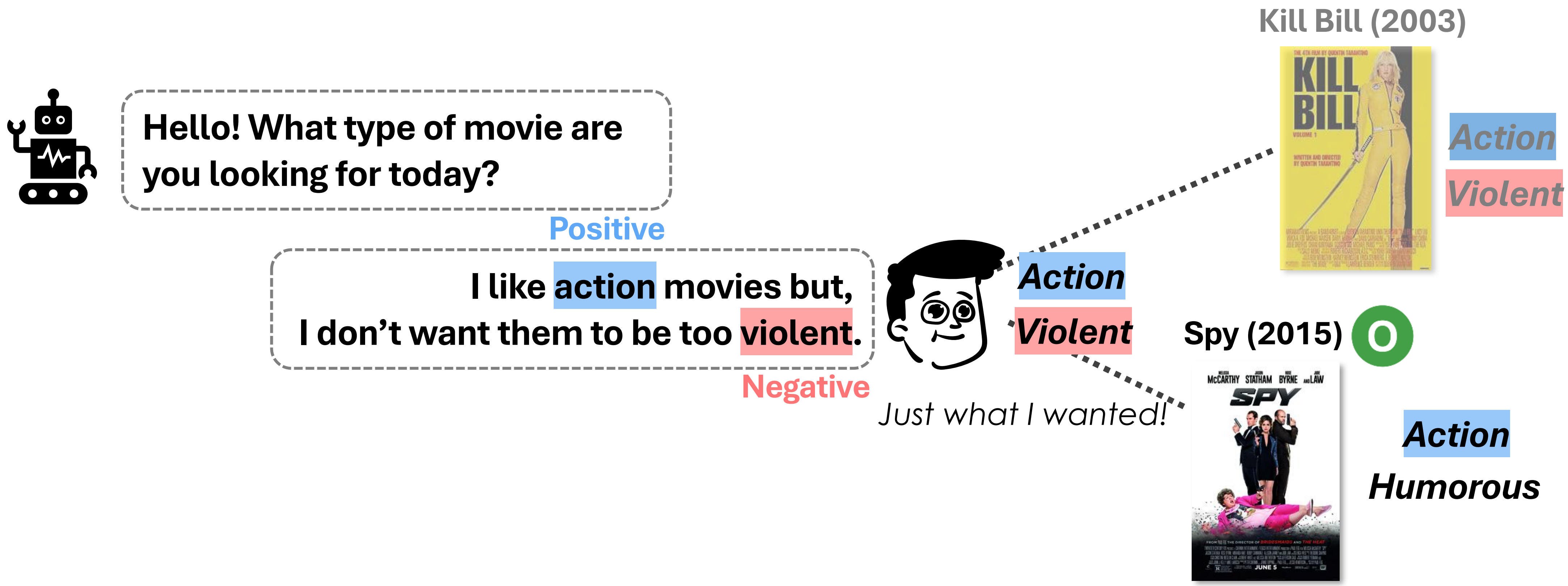
Limitations of Existing Methods

- **Most existing methods overlook the complex relationship between the user, item, and contrasting preferences.**
  - All this information is aggregated in a single representation.



Our Solution

- **We represent contrasting preferences as distinct vectors.**
  - Explicitly representing and modeling the user, item, and contrasting preferences enables more accurate recommendations that reflect the user's intent.



Our Solution

We devised CONTRASTING USER PREFERENCE EXPANSION AND LEARNING (CORAL), which extracts and learns contrasting preferences.

Challenge 1.
How do we extract contrasting user preferences from the conversation?

Method 1.
Contrasting Preference Expansion

Challenge 2.
How do we learn the relationship between the contrasting preferences and the user/item?

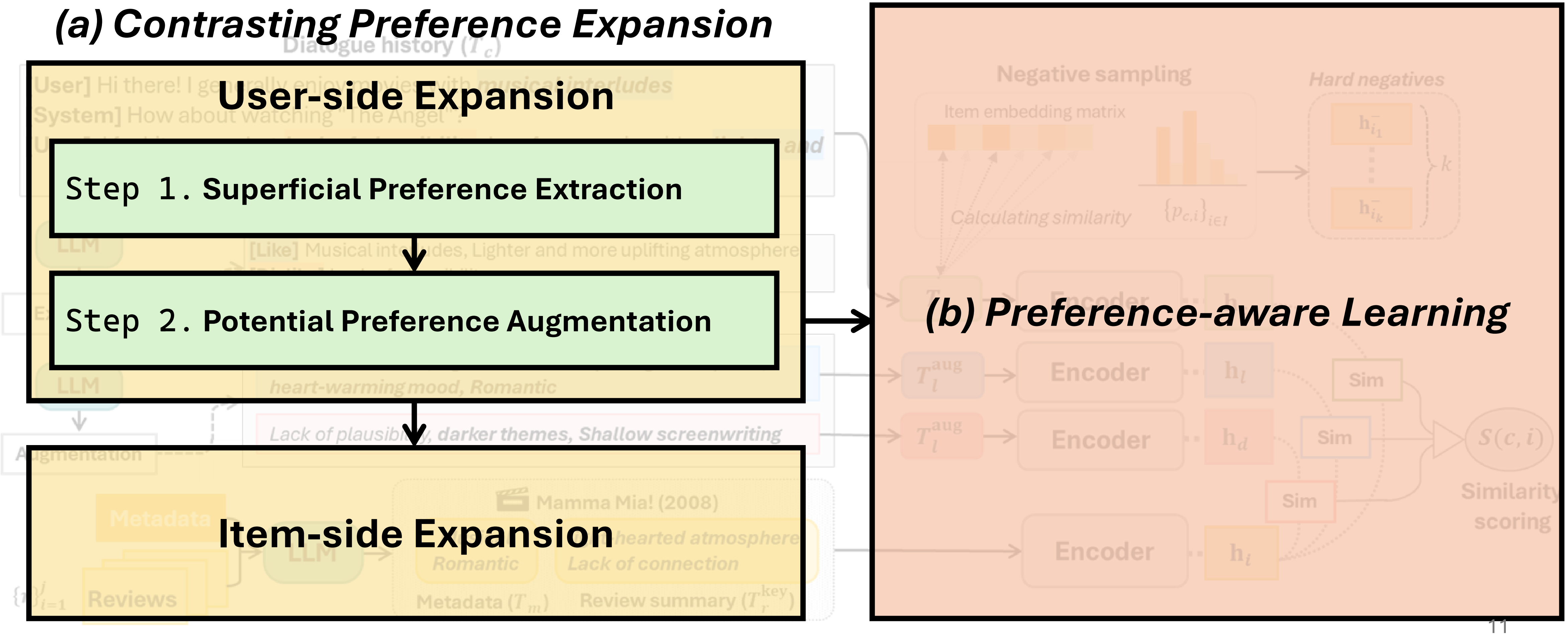
Method 2.
Preference-aware Learning

Proposed Method

- Overview of CORAL 🪸
- Contrasting Preference Expansion
- Preference-aware Learning

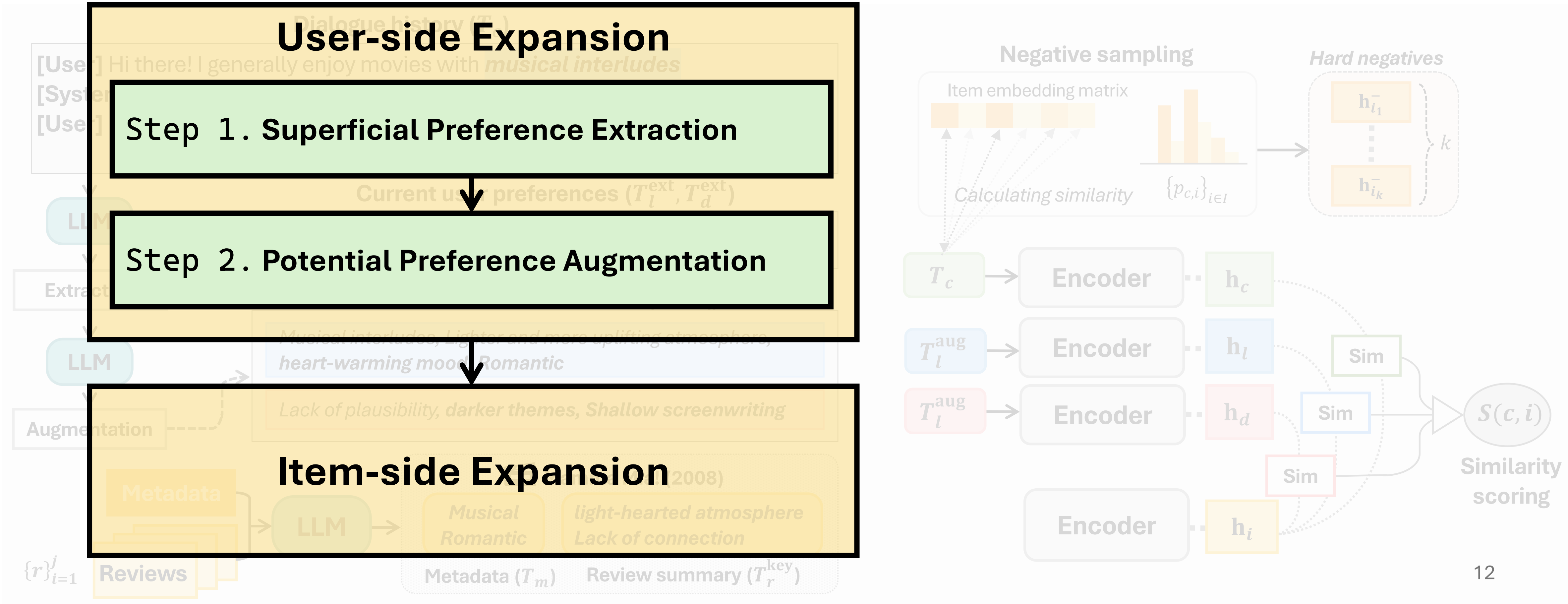
Overview of CORAL

CORAL (a) extracts and (b) learns contrasting preferences.



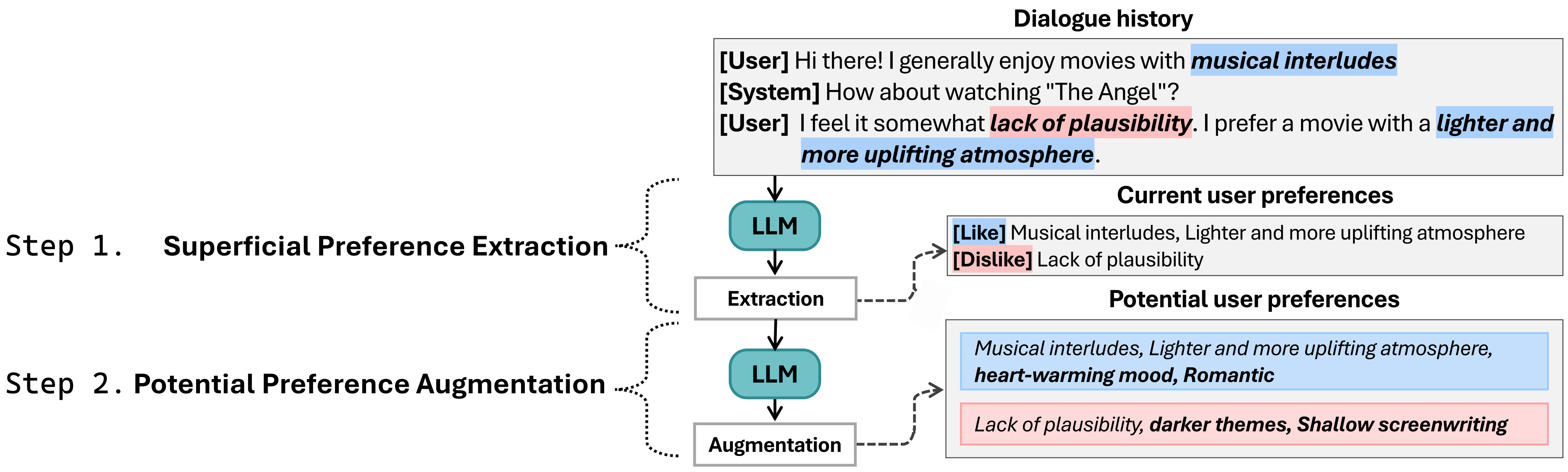
Contrasting Preference Expansion

- Extract **superficial contrasting preferences** from dialogue history/review.
- Expand **potential preferences** via LLMs' reasoning abilities.



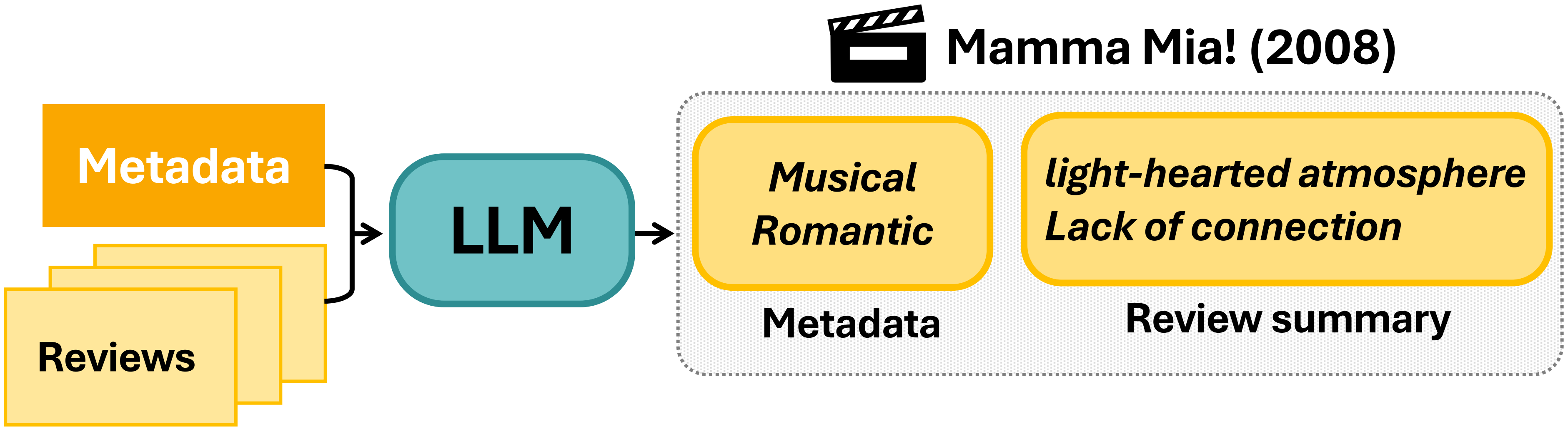
Contrasting Preference Expansion

- **User-side expansion** distinguishes and infers user preferences embedded in the dialogues



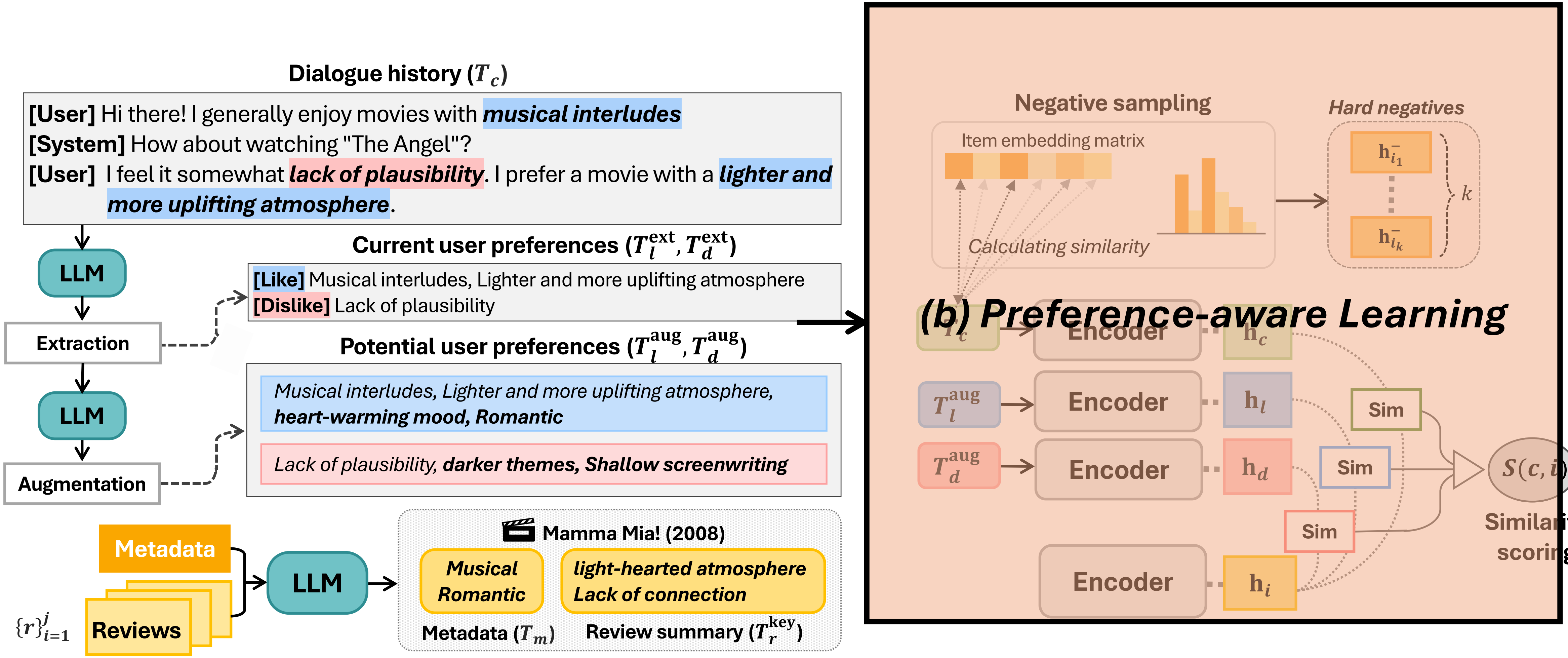
Contrasting Preference Expansion

- **Item-side expansion** enhance the representation of an item using review summary.
  - The metadata lacks sufficient information about user preferences.
  - It can connect user conversations with item metadata using review data.



Preference-aware Learning

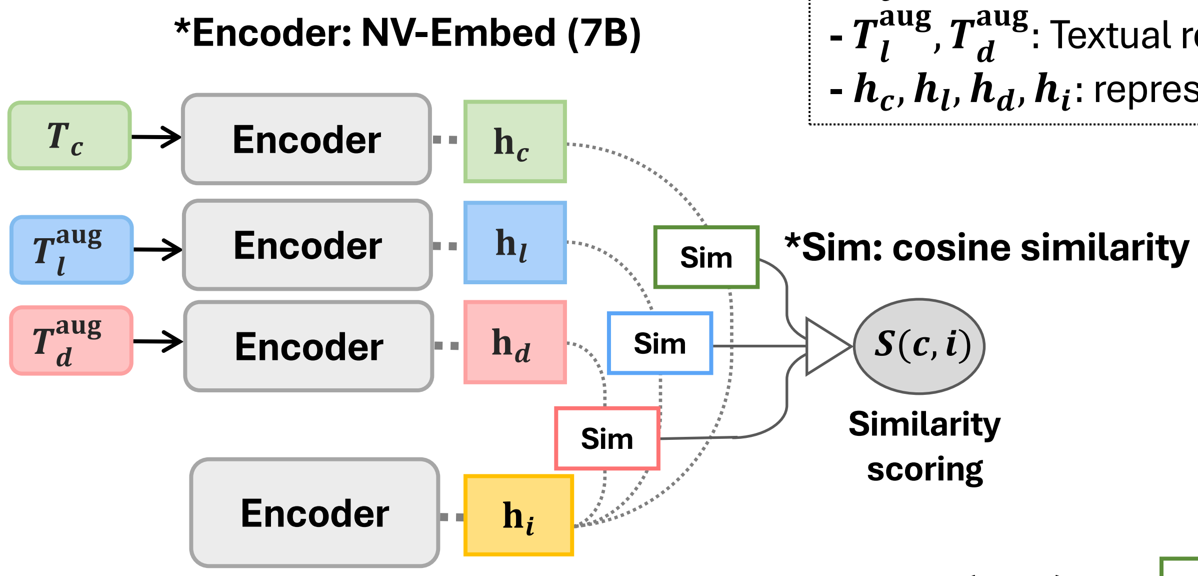
- **Explicitly represent these preferences separately from the conversation and learn the relationship between them.**



Preference-aware Learning

- **Preference modeling** explicitly represent preferences and conversation separately, and engage them in item scoring directly.

- T_c: Textual representation of dialogue history
- T_l^{aug}, T_d^{aug}: Textual representations of the augmented like/dislike preferences
- h_c, h_l, h_d, h_i: representation obtained after passing through the encoder



$$S(c, i) = \boxed{\text{Sim}} + \alpha \cdot \boxed{\text{Sim}} - \beta \cdot \boxed{\text{Sim}}$$

Conversation-item *Like pref.-item* *Dislike pref.-item*

Experiments

- Experimental Setting
- Overall Performance
- Case Study

Experimental Setting ①: Dataset

- **We use three well-known public English movie recommendation conversation datasets**
  - **PEARL**, **INSPIRED**, and **ReDial**

Dataset	#Dial.	#Items	#Likes	#Dislikes
PEARL	57,159	9,685	9.59	5.97
INSPIRED	1,997	1,058	11.09	5.65
REDIAL	31,089	5,896	10.99	1.00

#Dial. : the number of dialogues.

#Items: the number of items

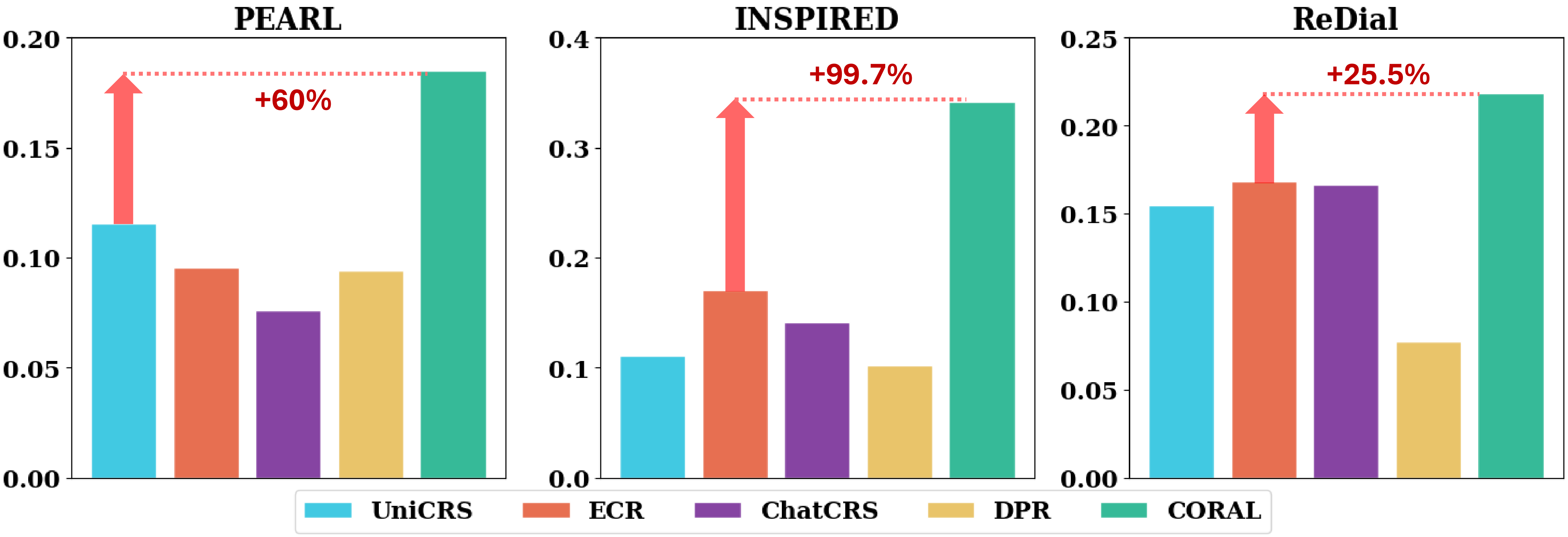
#Likes, #Dislikes: The average counts of the like and dislike preference after the augmentation stage, respectively.

Experimental Setting ②: Baselines

(1) Traditional CRS	UniCRS	A model built on DialoGPT (117M)with prompt tuning
	RevCore	Categorizes user sentiments regarding entities as either positive or negative
	ECR	Identifies nine distinct emotional responses regarding entities.
(2) LLM-based CRS	Zero-shot	Recommends solely based on dialogue history and internal knowledge items.
	ChatCRS	Enhances the domain knowledge of LLM through a knowledge graph
(3) Retrieval-based CRS	BM25	Ranks item by term relevance from a static index
	DPR	Retrieves items based on the similarity with dense vectors of the dialogue context (BERT-base (110M))

Key Results

- CORAL 🪸 achieves state-of-the-art performance over existing methods in three benchmark datasets, improving **up to 99.7% in Recall@10**



Key Results: Ablation Study on INSPIRED

- **Effect of Like/Dislike preferences**

Variant	R@10	R@50	N@10	N@50
CORAL	**0.3481**	0.5667	**0.1827**	**0.2297**
w/o ***Like, Dislike***	0.3248	**0.5767**	0.1668	0.2226
w/o ***Review***	0.3167	0.5348	0.1710	0.2193
w/o ***Like, Dislike, Review***	0.2948	0.5633	0.1595	0.2196

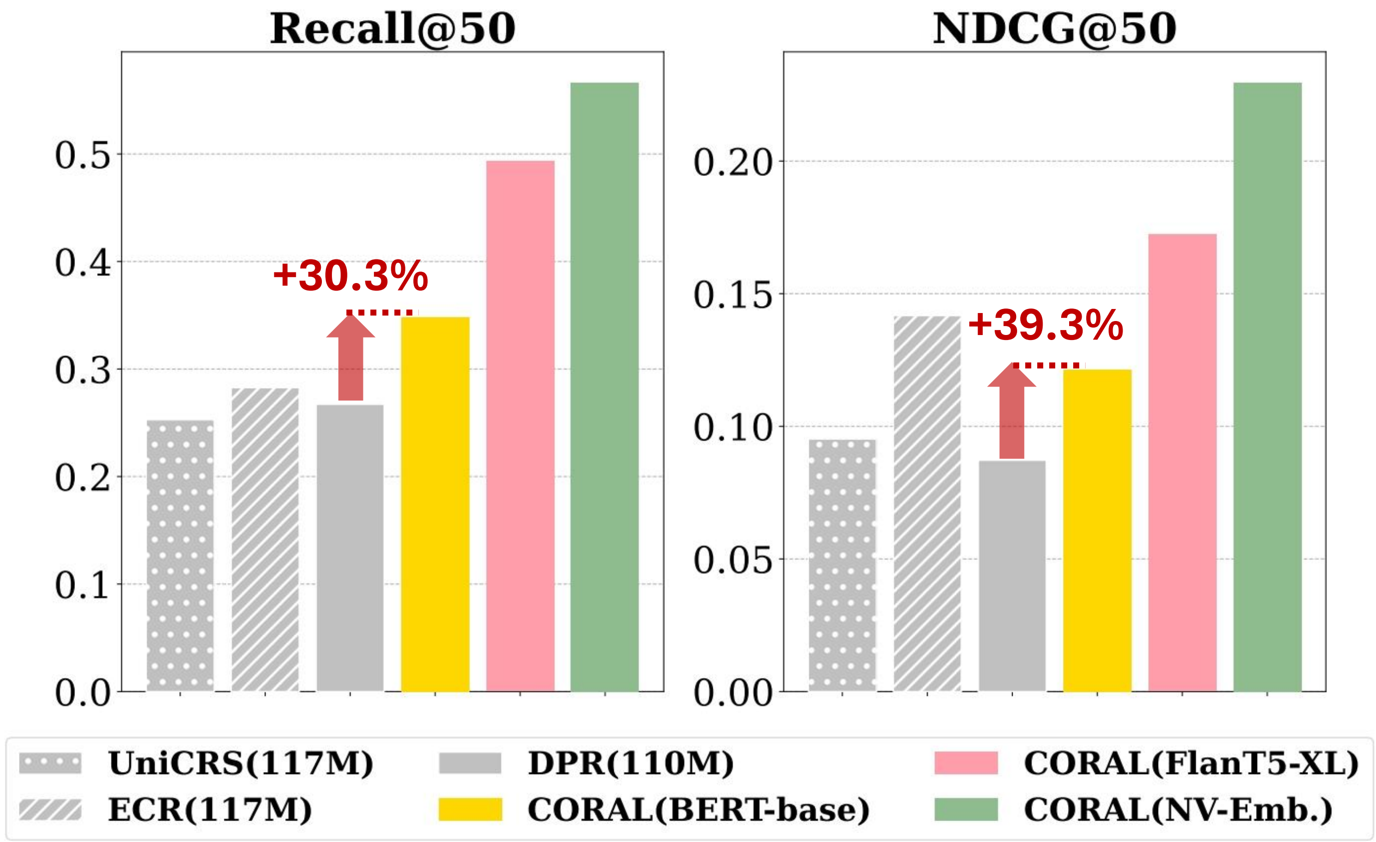
- **Effect of Preference-aware Learning**

Variant		R@10	R@50	N@10	N@50
w/o ***Negative sampling***	w/ ***PL***	**0.2974**	**0.5692**	**0.1520**	**0.2115**
	w/o ***PL***	0.1847	0.3616	0.1107	0.1491

** PL: Preference-aware Learning*

Key Results: Performance by Model Size

- CORAL 🪸 significantly improves performance even with a relatively small model.



**DPR: CORAL w/o preference-aware learning*

Case Study

- **CORAL effectively captures contrasting preferences to improve recommendations and enhance explainability.**

I'm generally a fan of movies that have a lot of tension and build-up, as well as ones that portray society and real-life characters in an engaging way

...

I appreciate films that have a more detailed and realistic portrayal of events

User's utterances

[Like]

real-life characters in an engaging way,

psychological thrillers & dramas

Immersive sound design

[Dislike]

unrealistic events

over-the-top action sequences

Contrasting preferences

Title: Sicario (2015)

Genre: Cop Drama, Drug, Crime, Action, Mystery, Thriller

[Review Summary]

Realistic feel

Immersive atmosphere

Intense and engaging

Amazing sound design

Item metadata & summary

Conclusion

- **We propose a novel retrieval-based CRS framework that extracts and learns contrasting preferences.**
  - **CO**ntrasting user p**R**eference exp**A**nsion and **L**earning (**CORAL**),

- **CORAL addresses contrasting preferences by**
  - distinguishing and enhancing contrasting preferences into like/dislike.
  - learning the relationship between conversation, preferences, and items directly.

- **CORAL achieves the best performance with existing CRS models on PEARL, INSPIRED, and REDAIL, improving up to 99.72% in Recall@10.**

Thank you!
Any question?

Email: hjkook@g.skku.edu

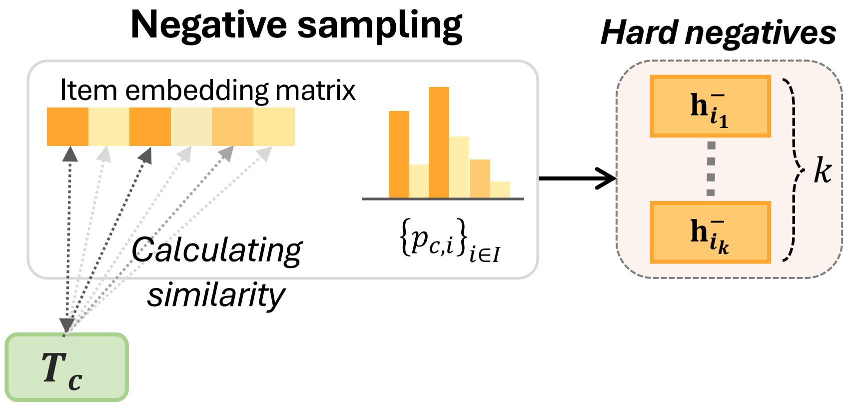
Code: https://github.com/kookeej/CORAL.git

Paper

Code

Appendix: Negative Sampling

- **Hard negative sampling** differentiate samples that are challenging to predict based on conversation alone with contrasting preferences.



- Calculate the similarity between $\mathbf{h}_c$ and all item embeddings.
- Apply *softmax* to convert the similarity scores into a probability distribution.

- **Loss function**

$$\mathcal{L} = -\log \frac{\exp(S(c, i^+)/\tau)}{\sum_{i \in \mathcal{I}_c^-} \exp(S(c, i)/\tau)}$$

where i^+ is the positive item of c, $\mathcal{I}_c^-$ is a set of k negative items, and τ is a hyperparameter to adjust the temperature.

Appendix: Overall Performance

Model		Traditional CRS			LLM-based CRS		Retrieval-based CRS			Gain
Dataset	Metric	RevCore	UniCRS	ECR	Zero-shot	ChatCRS	BM25	DPR	CORAL	
PEARL	R@10	0.0268	<u>0.1156</u>	0.0957	0.0767	0.0763	0.0026	0.0940	**0.1851***	60.07%
	R@50	0.0898	<u>0.2624</u>	0.2373	0.1129	0.1168	0.0123	0.2206	**0.3619***	37.94%
	N@10	0.0132	<u>0.0642</u>	0.0501	0.0468	0.0462	0.0014	0.0502	**0.1125***	75.17%
	N@50	0.0266	<u>0.0958</u>	0.0806	0.0560	0.0565	0.0033	0.0777	**0.1511***	57.74%
INSPIRED	R@10	0.0948	0.1113	<u>0.1711</u>	0.1436	0.1410	0.0429	0.1019	**0.3417***	99.72%
	R@50	<u>0.3344</u>	0.2528	0.2826	0.2436	0.2436	0.1210	0.2672	**0.5632***	68.45%
	N@10	0.0509	0.0642	<u>0.1077</u>	0.0927	0.0806	0.0202	0.0512	**0.1772***	64.52%
	N@50	0.1041	0.0952	<u>0.1417</u>	0.1175	0.1071	0.0373	0.0872	**0.2255***	59.07%
REDIAL	R@10	<u>0.1739</u>	0.1549	0.1685	0.1670	0.1666	0.0373	0.0774	**0.2182***	25.48%
	R@50	0.3034	0.3540	<u>0.3793</u>	0.2783	0.2824	0.0300	0.2138	**0.4741***	25.23%
	N@10	<u>0.1053</u>	0.0776	0.0805	0.0937	0.0893	0.0032	0.0403	**0.1128***	7.10%
	N@50	<u>0.1337</u>	0.1215	0.1293	0.1226	0.1191	0.0083	0.0713	**0.1724***	28.96%

Table 2: Overall performance. The best and second-best are **bold** and <u>underlined</u>. Gain measures the difference between CORAL and the best competitive baseline. '*' indicates statistically significant improvement ($p < 0.01$) for a paired t-test of CORAL compared to the best baseline, as conducted across 5 experiments.

Appendix: Ablation Study

	Dataset		INSPIRED			
	Variants		R@10	R@50	N@10	N@50
	CORAL		**0.3481**	0.5667	**0.1827**	**0.2297**
Effect of Like/Dislike preference	w/o ***Like, Dislike***		0.3248	**0.5767**	0.1668	0.2226
	w/o ***Review***		0.3167	0.5348	0.1710	0.2193
	w/o ***Like, Dislike, Review***		0.2948	0.5633	0.1595	0.2196
Effect of Potential preference	w/o ***Augmentation***		0.3016	0.5379	0.1663	0.2202
Effect of Preference-aware learning	w/o ***NS***	w/ ***PL***	0.2974	0.5692	0.1520	0.2115
		w/o ***PL***	0.1847	0.3616	0.1107	0.1491

- *NS: Negative sampling*
- *PL: Preference-aware Learning*

Appendix: Zero-shot Performance

Dataset		PEARL				INSPIRED				REDIAL			
Retriever	L, D	R@10	R@50	N@10	N@50	R@10	R@50	N@10	N@50	R@10	R@50	N@10	N@50
BM25	w/o	0.0053	0.0269	0.0031	0.0076	0.0390	0.1486	0.0216	0.0444	0.0091	0.0361	0.0044	0.0104
	w/	**0.0079**	**0.0340**	**0.0045**	**0.0099**	**0.0448**	**0.1714**	**0.0297**	**0.0580**	**0.0235**	**0.0704**	**0.0113**	**0.0219**
BERT	w/o	**0.0040**	0.0203	**0.0015**	0.0049	0.0057	0.0410	0.0017	0.0100	0.0069	0.0270	0.0039	0.0084
	w/	0.0031	**0.0225**	**0.0015**	**0.0056**	**0.0086**	**0.0648**	**0.0032**	**0.0152**	**0.0087**	**0.0302**	**0.0048**	**0.0096**
NV-Emb.	w/o	0.0454	0.1323	0.0210	0.0397	0.1648	0.3943	0.0856	0.1374	0.0767	0.1885	0.0368	0.0613
	w/	**0.0569**	**0.1508**	**0.0286**	**0.0489**	**0.2276**	**0.4048**	**0.1140**	**0.1538**	**0.0872**	**0.2190**	**0.0408**	**0.0711**

Table 3: The zero-shot performance of various language models depending on the presence or absence of the user's potential preference. L and D mean T_l^{aug} and T_d^{aug}, respectively.

Appendix: Performance depending on the LLM utilized for Contrasting Preference Expansion

Dataset	INSPIRED			
Model	R@10	R@50	N@10	N@50
UniCRS	0.1113	0.2528	0.0642	0.0952
ECR	0.1711	0.2826	0.1077	0.1417
CORAL $_{\text{w/o } L,D,R}$	0.2948	0.5633	0.1595	0.2196
CORAL $_{\text{Mistral}}$	0.3162	0.5410	0.1809	0.2326
CORAL $_{\text{gpt-4o-mini}}$	0.3417	0.5632	0.1772	0.2255

Table 7: Performance depending on the LLM utilized for Contrasting Preference Expansion. L, D and R denote T_l^{aug}, T_d^{aug}, and T_r^{key}, respectively.

Appendix: Zero-shot Performance for Preference Input Variant

Dataset	Input info.	R@10	R@50	N@10	N@50	Avg. Gain(%)
PEARL	C	0.0476	0.1230	0.0229	0.0395	-
	C, L	0.0560	0.1349	0.0303	0.0474	**19.91%**
	C, D	0.0481	0.1349	0.0224	0.0415	**3.40%**
	C, L, D	0.0573	0.1481	0.0311	0.0504	**26.05%**
INSPIRED	C	0.1837	0.4133	0.1038	0.1545	-
	C, L	0.2103	0.3949	0.1133	0.1534	**4.62%**
	C, D	0.2000	0.4154	0.1064	0.1527	**2.68%**
	C, L, D	0.2205	0.4205	0.1166	0.1597	**9.37%**
REDIAL	$C,$	0.0887	0.2067	0.0383	0.0640	-
	C, L	0.0954	0.2325	0.0415	0.0710	**9.83%**
	C, D	0.0910	0.2129	0.0400	0.0665	**3.48%**
	C, L, D	0.0986	0.2431	0.0427	0.0735	**13.78%**

Table 5: Zero-shot performance for preference input variant. C, L, and D denote T_c, T_l^{aug}, and T_d^{aug}, respectively.

Appendix: Ablation study on BERT

Dataset	INSPIRED				REDIAL			
Variants	R@10	R@50	N@10	N@50	R@10	R@50	N@10	N@50
CORAL	**0.1219**	**0.3714**	0.0625	**0.1173**	**0.0856**	0.2255	**0.0446**	**0.0765**
w/o *L*, *D*	0.0962	0.3429	0.0429	0.0968	0.0775	**0.2287**	0.0407	0.0754
w/o *R*	0.1133	0.2695	**0.0752**	0.1103	0.0749	0.2052	0.0405	0.0702
w/o *L*, *D*, *R*	0.0876	0.3010	0.0450	0.0967	0.0764	0.2231	0.0403	0.0738
w/o *Neg.*	0.0867	0.2629	0.0371	0.0757	0.0725	0.2151	0.0375	0.0697
w/o *PL*	0.1076	0.2467	0.0516	0.0832	0.0774	0.2138	0.0403	0.0713

Table 6: Ablation study of CORAL in INSPIRED and REDIAL on BERT. The best scores are in **bold**. L, D and R denote T_l^{aug}, T_d^{aug}, and T_r^{key}, respectively. Also, *Neg.* and *PL* mean potential hard negative sampling and preference-aware learning, respectively.