Neighborhood-Based Collaborative Filtering for **Conversational Recommendation**

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https://github.com/zhouhanxie/neighborhood-based-CF-for-CRS

(1) Introduction -

- Challenge in Conversational Recommender Systems (CRS)
- CRS need to handle complex, knowledge-intensive user queries > We leverage existing dialogue data to recommend items based
- > Existing methods rely on external knowledge bases or LLMs, which can be resource-intensive and have practical limitations

Neighborhood-Based Collaborative Filtering (NBCRS)

on similar past queries without external knowledge bases or large models

(2) Proposed Method: NBCRS

Key Ideas

- > Retrieve similar dialogue contexts from training data
- Recommend items frequently associated with these contexts
- \blacktriangleright (Optional) Train a scoring model p(item|query) to incorporate the scores further



Start

YES

I have no issue serving LLM (13B+) in terms of speed/cost/copyright & LLM has knowledge about my items (e.g.

movies)

(3) Experiments

Datasets

Dataset	Total Movies	N. Train Samples	N. Test Samples			
Inspired	1506	731	211			
Redial	6476	8929	4288			
Reddit	29705	39928	19438			
Table 1: Statistics of the Datasets						

Overall Performance (see the paper for full-table)

Model	Setting	Inspired Recall@20	Reddit Recall@20	Redial Recall@20
KGSF	Sft+KG	9.17 0.39	8.90 0.49	17.05 0.01
UniCRS	Sft+KG	18.59 0.12	9.79 0.50	27.12 0.28
Popularity	-	11.3 2.19	2.21 0.10	6.01 0.36
FISM	Sft	13.45 0.49	6.51 0.48	8.24 0.46
Gemma-2B	Zero-Shot	4.74 1.47	2.89 0.12	5.78 0.36
	Sft	2.37 1.05	3.49 0.13	5.11 0.33
Vicuna-7B	Zero-Shot	11.37 2.20	6.06 0.17	13.67 0.52
	Sft	10.43 2.11	7.18 0.18	13.67 0.52
NBCRS	Zero-Shot	14.69 2.44	14.08 0.24	16.34 0.56
	NB	16.11 2.23	15.52 0.25	16.58 0.54
	MB	1.42 0.81	13.62 0.24	14.80 0.54
	N+M	15.16 0.21	<u>15.58</u> 0.26	16.86 0.57

Table 3: Performance of models across datasets with standard errors. The reported numbers are percentages. Best performance excluding and including knowledge-graph-enhanced models are bolded and <u>underlined</u>, respectively.

Further Analysis



(4) Conclusion

Contributions

- Introduced a simple vet effective method for CRS: NBCRS
- > Demonstrated that NBCRS can match or exceed the performance of larger, resource-intensive methods

When to Use NBCRS?

This decision tree is mainly depicting *classes* of models, do double check and don't miss out the SOTA! Curated AUG 24.

[1] Neighborhood Based Collaborative Filtering for Conversational Recommendation, RecSys 24

[2] Large Language Model as Zero-shot Conversational Recommender, CIKM 23

[3] Reindex-Then-Adapt: Improving Large Language Models for Conversational Recommendation, Arxiv Preprint 24

[4] Towards Unified Conversational Recommender Systems via Knowled Enhanced Prompt Learning, KDD 22

[5] CRSLab: An Open-Source Toolkit for Building Conversational Recommender System, ACL Demos 21



NO