A Worrying Reproducibility Study of Intent-Aware Recommendation Models

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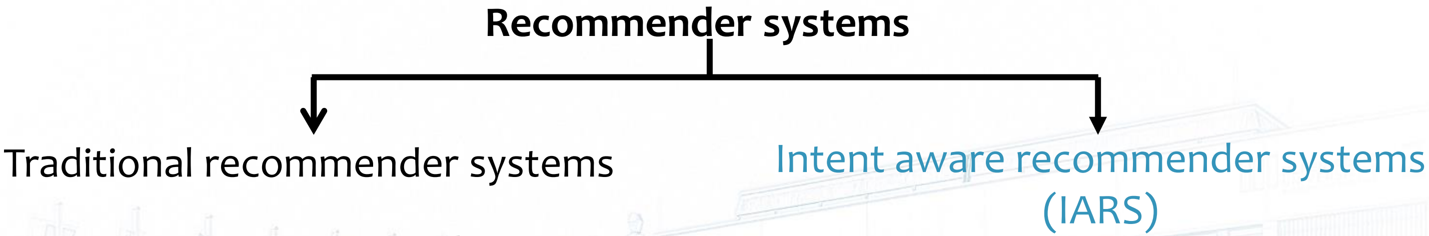
Introduction and Motivation



Recommender systems

Traditional recommender systems

Intent aware recommender systems (IARS)

- ❑ **Intent aware recommender systems**
  - Analyze the user's current needs or situational context to provide more relevant recommendations
  - Developed for sequential and top-N recommender systems [1, 2, 3]
  - Examples: browsing YouTube content at home vs. at the office [4]
- ❑ **From a technical point of view**
  - Most research papers on IARS are based on neural models [1]
  - Assume multiple underlying intents behind a user-item interaction
  - Key neural architectures: Graph neural networks (GNN), Graph contrastive learning, Attention mechanism, etc.

Reproducibility Crisis

- ❑ Due to the increased sophistication of complex models, one can imagine their superiority over simpler models
  - However, the literature work presents a different picture
    - Studies [5, 6] demonstrate the superiority of simpler models over top-N recommenders like NeuMF and ConvMF
    - Another recent study [7] shows similar results for GNN-based session-based recommender systems
    - Another study [8] shows shared artifacts are insufficient to reproduce reported results in a paper
- ❑ Various factors [5, 7] contribute to this “virtual progress”, such as comparing only one family of algorithms (neural models), poorly tuned baseline models, etc.

Research Questions

❑ From the literature review, we observe that the performance of complex algorithms is quite limited

❑ However, we want to know whether this pattern is still persistent in the emerging and promising area of IARS. Therefore, we have formulated two research questions:

- Can the reported results of published papers be reproduced using the provided artifacts, such as source code and other relevant information?
- How could the simpler models be compared with complex models?

Research Methodology

❑ **Identification of IARS papers**

1. Queried Google Scholar and IEEE Xplore for papers containing the terms ‘intent’ or ‘intent awareness’ along with the keywords ‘recommend’
2. Identified 88 papers and retained those proposing a top-N model, published in the last four years in A* venues or top journals
3. Thirteen papers met this criteria

❑ **Baselines:** Chose six baseline models, which showed good performance in the previous reproducibility studies [6, 7, 8]

- ItemKNN
- RP$^3\beta$
- and others

❑ **Evaluation methodology:** Simpler models are compared with IARS under the same configuration used in the published papers [6]

Results (1/3)

□ RQ1: Can the reported results of published papers be reproduced using the provided artifacts, such as source code and other relevant information?

□ Here are the findings our study

- Practice of sharing reproducibility packages: 7 out of 13 (~53%)
- Reproducibility packages in working condition: 5 out of 13 (~38%)
- Reproducibility packages with reproducible results: 3 out of 13 (~23%)

List of papers with working reproducibility packages

SR.NO.	Title	Venue	Is it reproducible
1	Disentangled Graph Collaborative Filtering (DGCF) [9]	SIGIR ’20	✓
2	Learning Intents behind Interactions with Knowledge Graph for Recommendation (KGIN) [10]	WWW ’20	×
3	Intent Disentanglement and Feature Self-supervision for Novel Recommendation (IDS4NR) [11]	IEEE TKDE ‘22	×
4	Disentangled Contrastive Collaborative Filtering (DCCF) [12]	SIGIR ’23	✓
5	Bilateral Intent-guided Graph Collaborative Filtering (BIGCF) [13]	SIGIR ‘24	✓

Results (2/3)

❑ RQ2: How could the simpler models be compared with complex models?

❑ Here are the key findings of the experiments

- On all accuracy measures, the simpler models outperform all IARS
- In one case, the KGIN model outperforms the simpler models on Recall@20 for the Last.fm dataset. However, in this case, we observe a severe data leakage issue in the shared train-test splits
- For the DCCF and BIGCF models, the authors used an unusual recommendation list length, such as 40, without providing a valid reason
- We found no single winner among the simpler models. However, ItemKNN and $RP^3\beta$ demonstrate competitive performance

Results (3/3)

- ❑ What is about computational complexity?

- ❑ We measure the training time (T-time) and prediction time (P-time) of the KGIN and the simpler models for the largest Alibaba iFashion dataset
  - The Alibaba iFashion dataset is significantly smaller than the Netflix Prize dataset (100M), which was released 15 years ago
  - KGIN takes 1 day and 8 hours per iteration on **GPU**, with several iterations required for hyperparameter tuning
  - ItemKNN, which performs best on this dataset, requires only 2 minutes on **CPU** to build the lookup tables
  - In terms of P-time, KGIN model is also 50% slower than ItemkNN

Alibaba iFashion dataset	
Users	114, 000
Items	30,000
Interactions	1.7M

Conclusions

- ❑ Reproducibility challenges in recommender systems keep returning, even after fifteen years
  - While one might assume that the reproducibility should be high, particularly in top-rank venues, but our findings suggest otherwise
  - None of examined papers share the code of baselines, data preprocessing, etc., to ensure full reproducibility
  - Sometimes, authors are unresponsive when approached for guidance
  - Lastly, we are not against research on complex algorithms. Many studies have shown their effectiveness in computer vision and NLP , however:
    - The current progress in IARS is limited
    - Need to avoid reoccurring methodological issues, such as data leakage
    - Encourage researchers to share their source code for proposed and baseline models to ensure full reproducibility

Thank you for your attention

SCAN ME to access the source code

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