Unveiling the Potential of Recommender Systems through Multi-Objective Metrics*

Discussion Paper

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Abstract

Current recommender systems (RSs) prioritize accuracy, often neglecting aspects like diversity and fairness. This single-metric approach overlooks valuable trade-offs between different qualities. We propose a multi-objective evaluation using Pareto optimality and ***Quality Indicators*** **(QI)** of Pareto frontiers to consider all model configurations simultaneously across multiple perspectives. This approach reveals a more comprehensive picture of RS performance, potentially leading to a reevaluation of existing methods. Code and data are available at https://github.com/sisinflab/RecMOE.

Keywords

Recommender System, Multi-Objective Evaluation, Pareto optimality

1. Introduction

The success of Recommender Systems (RSs) is often measured by their ability to accurately predict a user's preferences and suggest relevant items. However, beyond-accuracy metrics like diversity [2], novelty [3, 4], and fairness [5, 6] have been proposed. While beyond-accuracy metrics have gained momentum, accuracy is still prioritized [7, 8, 9]. Figure 1 shows the normalized performance of baselines on the Goodreads dataset, selecting the best hyper-parameters for each metric. Selecting the best model solely based on accuracy limits consideration of beyond-accuracy performance. A Pareto-optimal configuration improves at least one objective without hurting others, forming the Pareto frontier [10, 11]. We propose introducing ***Quality Indicators*** (QIs) [12] to RSs, providing a quantitative evaluation of Pareto frontiers from different perspectives [13]. Our contributions are (i) Showing the negative impact of prioritizing accuracy and motivating multi-objective evaluation; (ii) Computing Pareto frontiers for hyper-parameter settings of models on public datasets in multi-objective scenarios. (iii) Enhancing multi-objective evaluation by utilizing QIs to comprehensively analyze recommendation models.

2. Quality Indicators

In this Section, we present the Quality Indicators (QIs) to assess the Pareto frontiers corresponding to an RS model. They can be classified according to the quality they assess.

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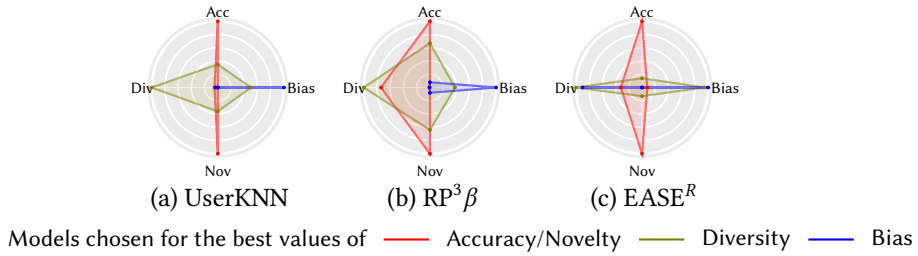


Figure 1: Kiviat diagrams indicating the performance of the models on the Goodreads dataset. The models are selected according to different metrics for each objective. Higher means better.

Spread QI. The QIs for Spread indicate the range of the Pareto-optimal solutions on the Pareto frontier. For our study, we use the Maximum Spread (MS) [14]. Specifically, this spread indicator measures the range of a Pareto frontier by considering the maximum extent of each objective. The higher the value, the better the extensiveness of the curve.

Uniformity QI. The uniformity of a Pareto frontier provides information about the distribution of the solutions. A higher uniformity of the curve denotes that the solutions are less dispersed, while a low uniformity indicates more diversity within the set. Specifically, we employ the Spacing metric (SP) [15] that measures the variation in the Manhattan distances between the Pareto-optimal solutions. The lower the value, the more concentrated the solutions are on the Pareto frontier. However, an $SP = 0$ indicates that all the solutions could be equidistant.

Cardinality QI. Given K generic solutions belonging to the set B, the QIs for cardinality determine the proportion of Pareto-optimal solutions in this set. Specifically, the Error Ratio (ER) [16] is defined as $ER(B) = \frac{\sum_{b \in B} e(b)}{K}$ with $e(b) = 1$ if b is a Pareto-optimal solution, 0 otherwise. A higher ER value indicates greater Pareto-optimal solutions in the set B.

All quality aspects QI. The QIs included in this category provide insights into the spread, uniformity, and cardinality of the Pareto frontiers simultaneously. Among them, the Hypervolume (HV) [17] is a volume-based QI that measures the volume of the objective function space dominated by the Pareto frontier. The larger the hypervolume, the better the solution set is.

3. Experiments

We aim to answer two research questions: **RQ1**: *To what extent can the models provide Pareto-optimal configurations? Are these configurations uniformly distributed, or are they dispersed enhancing diverse solutions to the trade-off?* **RQ2**: *Which model has the Pareto frontier that simultaneously offers better solutions on multiple metrics?*

Datasets. We select three different datasets to cover several domains. Specifically, we use *Amazon Music* (music), *Goodreads* [18] (books), and *Movielens1M* [19] (movies).

Baselines and Hyper-parameters Settings Exploration. We train five recommendation algorithms, i.e., EASE^R [20], MultiVAE [21], LightGCN [22], RP$^3\beta$ [23], and UserKNN [24]. We train 32 hyper-parameter values combinations of each model by using Elliot [25].

Metrics. We assess the baselines' performance under several perspectives. We compute nDCG, Precision, and Recall for the accuracy of recommendations. From the final user point of view, we evaluate the diversity (with Gini index [26] and Item Coverage) and novelty (with EPC and

Table 1
QIs of the Pareto frontiers results for the identified scenarios. The arrow indicates the descending or ascending order for the best solution. SP has no specific order of solutions, since its interpretation is strictly connected with the MS indicator. C counts how many solutions lay on the Pareto frontier.

	Model	Objectives									
		Accuracy / Novelty / Diversity					Accuracy / Bias				
		HV↑	ER↑	MS↑	SP	C↑	HV↑	ER↑	MS↑	SP	C↑
Amazon Music	EASE^R	**0.00095**	**0.46875**	0.24986	0.01476	**15**	0.01355	**0.43750**	0.11886	0.00669	**14**
	UserKNN	0.00082	0.34375	**0.29452**	0.00496	11	0.01448	0.34375	**0.17871**	0.00980	11
	LightGCN	0.00051	0.06250	0.01335	0.00000	2	0.00835	0.03125	0.00000	0.00000	1
	MultiVAE	0.00022	0.12500	0.09656	0.01738	4	0.00468	0.15625	0.05629	0.00351	5
	RP$^3\beta$	0.00039	0.18750	0.20753	0.05888	6	**0.03489**	0.21875	0.11336	0.01173	7
Goodreads	EASE^R	0.00074	**0.59375**	0.09910	0.00227	**19**	0.00439	0.65625	0.09433	0.00214	21
	UserKNN	**0.00110**	0.31250	**0.19889**	0.01287	10	0.02267	**0.71875**	**0.48042**	0.01471	**23**
	LightGCN	0.00051	0.18750	0.06743	0.00783	6	0.00696	0.18750	0.09180	0.01536	6
	MultiVAE	0.00043	0.06250	0.05022	0.00000	2	0.00521	0.06250	0.01827	0.00000	2
	RP$^3\beta$	0.00083	0.12500	0.05584	0.01213	4	**0.05544**	0.28125	0.29529	0.02657	9
Movielens1M	EASE^R	0.00865	**0.68750**	0.09833	0.00446	**22**	0.00281	**0.65625**	0.06001	0.00196	**21**
	UserKNN	**0.01296**	0.28125	**0.30929**	0.03641	9	0.08191	0.50000	0.52723	0.01810	16
	LightGCN	0.00807	0.18750	0.01012	0.00287	6	0.00974	0.15625	0.00617	0.00181	5
	MultiVAE	0.01216	0.21875	0.03419	0.00427	7	0.01639	0.18750	0.02528	0.00293	6
	RP$^3\beta$	0.00839	0.06250	0.03796	0.00000	2	**0.14014**	0.46875	**0.86913**	0.03228	15

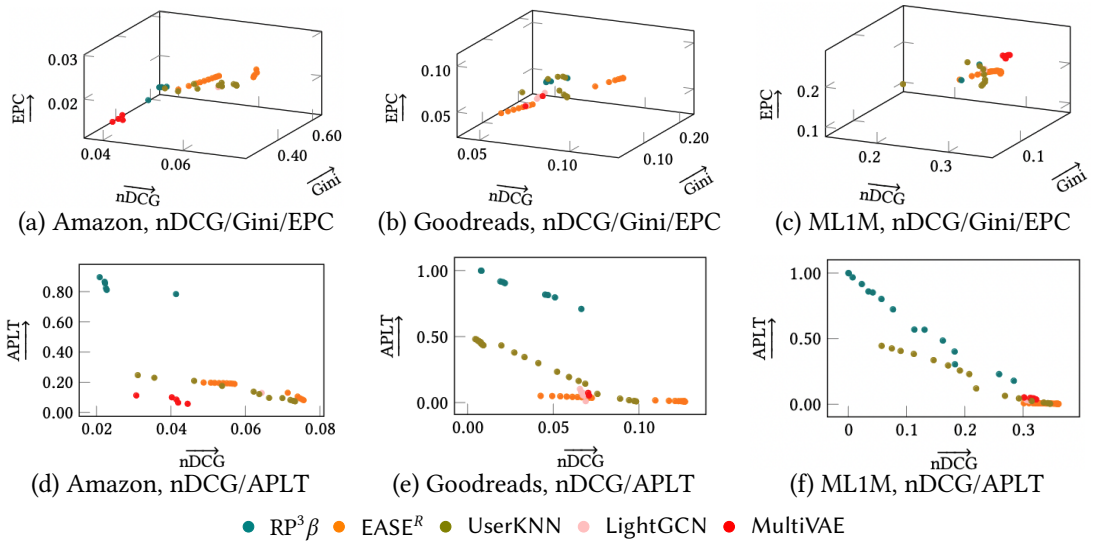
EFD [3]). Finally, we measure the popularity bias of the recommendations with APLT [27] – the greater, the better – and ARP [26] – the less, the better. All these metrics refer to cutoff 10.

Multi-Objective Evaluation Methodology. We obtain Pareto frontiers for each recommender system (RS) baseline using the metrics described in Section 2. Each hyper-parameter setting represents a solution in the objective space. We identify the Pareto-optimal configurations for each baseline, forming their respective Pareto frontiers. We evaluate these frontiers using QIs under two scenarios: 1) user-centered (accuracy, diversity, novelty) and 2) accuracy vs. algorithmic bias. Figure 2 shows the resulting Pareto frontiers.

3.1. Results and Discussion

While EASE^R and UserKNN provide the most accurate recommendations, beyond-accuracy metrics paint a different picture. By observing Figure 2, UserKNN exhibits better diversity than EASE^R. Finally, RP$^3\beta$ consistently outperforms its competitors in addressing the popularity bias. We delve into a multi-objective evaluation using QIs on Pareto frontiers. Here, we examine the distribution of Pareto-optimal configurations and performance on all quality metrics.

Distribution of Pareto-optimal configurations. The Error Ratio (ER), Maximum Spread (MS), and Spacing metric (SP) values in Table 1 unveil interesting insights into the distribution of Pareto-optimal configurations for each model. In the nDCG/APLT scenario for the Movielens1M dataset, for instance: 1) UserKNN exhibits a wide range of solutions with good dispersion across the Pareto frontier, indicating its ability to offer various well-balanced trade-offs between accuracy and algorithmic bias; 2) EASE^R, while offering a high number of solutions on the frontier, they tend to be concentrated in a limited area, suggesting a lack of diversity in the achievable trade-offs; 3) RP$^3\beta$ strikes a good balance between the number of solutions, their dispersion, and the ability to provide various trade-offs between accuracy and bias. This is reflected in its high ER, MS, and SP values. Similar trends are observed for the other datasets



(a) Amazon, nDCG/Gini/EPC (b) Goodreads, nDCG/Gini/EPC (c) ML1M, nDCG/Gini/EPC

(d) Amazon, nDCG/APLT (e) Goodreads, nDCG/APLT (f) ML1M, nDCG/APLT

Figure 2: Pareto optimal solutions plots for Amazon Music, Goodreads, and MovieLens1M. The first row refers to the nDCG/Gini/EPC scenario, and the second row refers to the nDCG/APLT scenario. The arrows indicate the optimal directions.

(see Figures 2f - 2e). When examining the user-centric scenario (nDCG/Gini/EPC), UserKNN again excels, offering well-diversified solutions across all datasets (see Figures 2a - 2c).

Performance on all quality metrics. In response to RQ2, we can utilize the Hypervolume (HV) measure. HV evaluates the performance of models from multiple objectives simultaneously, as shown in Table 1. By considering the cardinality and dispersion of the Pareto-optimal solutions and the dominance among the Pareto frontiers, HV provides us with valuable insights. The higher the volume or area under the frontier, the greater the HV. The results show that UserKNN outperforms the other models by achieving the best or second-best values of HV for all datasets and scenarios. This result indicates that UserKNN generates an extensive and diversified Pareto frontier while performing well across all metrics. While EASE^R has the highest value of HV for the Amazon Music dataset in the user-centred scenario, it does not dominate or get dominated in the remaining cases. This result highlights the model's limited reliance on accounting for multiple metrics. LightGCN shows no distinctive trends, while MultiVAE's HV decreases when dealing with sparser datasets. RP$^3\beta$ confirms its capability in managing the nDCG/APLT trade-off by achieving the highest values of HV and visual dominance of its Pareto frontiers against the others in Figures 2d, 2e, and 2f.

4. Conclusion and Future Work

Our multi-objective evaluation with Quality Indicators reveals new insights into recommender systems (RSs). While EASE^R exhibits high accuracy, UserKNN emerges as a strong contender offering diverse solutions across multiple objectives. Additionally, RP$^3\beta$ proved to be highly effective in the accuracy/algorithmic bias scenario.

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