Understanding Diversity in Session-Based Recommendation

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ABSTRACT

Current session-based recommender systems (SBRSs) mainly focus on maximizing recommendation accuracy, while few studies have been devoted to improve diversity beyond accuracy. Meanwhile, it is unclear how the accuracy-oriented SBRSs perform in terms of diversity. Besides, the asserted "trade-off" relationship between accuracy and diversity has been increasingly questioned in the literature. Towards the aforementioned issues, we conduct a holistic study to particularly examine the recommendation performance of representative SBRSs w.r.t. both accuracy and diversity, striving for better understanding the diversity-related issues for SBRSs and providing guidance on designing diversified SBRSs. Particularly, for a fair and thorough comparison, we deliberately select state-of-the-art non-neural, deep neural, and diversified SBRSs, by covering more scenarios with appropriate experimental setups, e.g., representative datasets, evaluation metrics, and hyper-parameter optimization technique. Our empirical results unveil that: 1) non-diversified methods can also obtain satisfying performance on diversity, which might even surpass diversified ones; and 2) the relationship between accuracy and diversity is quite complex. Besides the "trade-off" relationship, they might be positively correlated with each other, that is, having a same-trend (win-win or lose-lose) relationship, which varies across different methods and datasets. Additionally, we further identify three possible influential factors on diversity in SBRSs (i.e., granularity of item categorization, session diversity of datasets, and length of recommendation lists).

Keywords recommender systems · session-based recommendation · diversification · diversified recommendation

1 Introduction

Session-based recommender systems (SBRSs) have become popular for capturing short-term and dynamic user preferences, and thus providing more timely and accurate recommendations, which are sensitive to the evolution of session contexts [1, 2]. Existing SBRSs strive to deploy complex models such as deep neural networks to improve the recommendation accuracy by learning a user's short-term preference from the most recent session. For example, GRU4Rec [3] adopts recurrent neural networks with gated recurrent units (GRU) to capture the sequential behaviors in a session, while NARM [4] and STAMP [5] further adopt attention mechanism to learn a user's main interest (purpose).

To capture more complex item relationship, SR-GNN [6] and GC-SAN [7] import graph neural networks (GNNs) based on item graph constructed from the corresponding session to learn more accurate item embeddings. Besides the current session graph, GCE-GNN [8] also constructs a global graph from all sessions.

However, the above popular and representative state-of-the-art SBRSs ignore to consider diversity, which has been recognized, beyond accuracy, as a key factor in satisfying users' diversified demands [9] and promoting enterprises' sales [10]. It is widely known that, those RSs and SBRSs that only seek to improve recommendation accuracy, would lead to overemphasizing dominant interests (e.g. categories) and weakening minor interests for every user [11]. More seriously, diversity bias will cause filter bubbles considering the iterative or closed feedback loop in RSs [12, 13].

To this end, diversified RSs aim to provide more diverse recommendation lists, which can be mainly divided into three categories: post-processing heuristic methods [14, 11], determinantal point process (DPP) methods [15, 16, 17] and end-to-end learning methods [18, 10]. However, there are few diversified SBRSs, and to the best of our knowledge, only three representative ones are retrieved, i.e., MCPRN [19], ComiRec [20] and IDSR [21]. MCPRN and ComiRec both assume the existence of multiple purposes instead of only one main purpose in a session, whilst IDSR jointly considers both item relevance and diversity by optimizing on a weighted loss function. These three diversified SBRSs argue that they have more appropriately involved diversity in contrast to those previous approaches, but *they neglect to moderately compare with other representative SBRSs in terms of accuracy and diversity*. For example, ComiRec is not compared to baselines regarding the diversity metrics, whereas MCPRN merely compares with some deep neural methods w.r.t. both accuracy and diversity metrics, but not with traditional non-neural methods.

Meanwhile, several diversified RSs adopt a "trade-off" hyper-parameter [14, 15, 21] to combine relevance score and diversification score. Due to such kind of model design, accuracy and diversity are more likely to show accuracy-diversity trade-off in related models. However, it seems unfair to conclude accuracy-diversity absolute trade-off, as "common sense" holds. Besides, other studies [22, 18] treat accuracy and diversity as conflicting goals, which consistently convey the kind of message that improvements on diversity can only be achieved at the expense of accuracy. In contrast, there are also some explorations [16] unveiling that, considering diversity adapted to user demands, which are mined from users' historical diversified logs, might facilitate the recommendation performance for both accuracy and diversity. In this case, whether there is a trade-off relationship, or others, between accuracy and diversity needs a further thorough exploration. Moreover, which kinds of factors do lead to diversity difference besides model design, is under-explored.

On the other hand, there are quite a set of surveys on SBRSs [23, 24, 1, 2], for the sake of elaborating algorithms and their evaluations, including the measurements of diversity and accuracy. For example, Quadrana et al. [24] propose that evaluations on SBRSs should jointly consider several quality factors (e.g., accuracy and diversity). Ludewig et al. [23] further compare some SBRSs (e.g., FPMC, GRU4Rec) w.r.t. various measures like accuracy and coverage. Although previous surveys empirically state that a fair and thorough evaluation across different approaches should consider more metrics (e.g., diversity) beyond accuracy, they ignore to specifically explore the model performance on diversity, and are also lack of a well understanding on the relationship between accuracy and diversity. Moreover, a fair comparison regarding both accuracy and diversity on the representative SBRSs, including "non-diversified" (i.e., accuracy-oriented, e.g., NARM and GCE-GNN) and diversified deep neural based SBRSs (e.g., IDSR), and traditional non-neural methods (e.g., ItemKNN [25], FPMC) are still in the blank.

Towards the aforementioned issues, we conduct a holistic study to particularly examine the recommendation performance of representative SBRSs with regard to both accuracy and diversity, aiming to better understand the relationship between accuracy and diversity of different SBRSs across different scenarios, as well as the factors affecting model performance on diversity. The main contributions of this work are summarized as follows.

- We have thoroughly compared the recommendation performance among state-of-the-art non-diversified and diversified SBRSs on commonly-used datasets across different domains (including e-commerce and music) from accuracy, diversity, and a jointly-considered metric on both accuracy and diversity, which has greatly filled the research gaps in existing surveys.
- We have deeply explored the experimental results to check the complex relationship, besides "trade-off" one, between accuracy and diversity, from both inter- and intra-model perspectives.
- We have further investigated the influential factors on diversity performance besides the complex model designs, including granularity of item categorization, session diversity of datasets, and length of recommendation lists.

2 Related work

Our study is related to three primary areas: session-based recommendation, diversified studies for traditional and session-based recommendation scenarios, and surveys on SBRSs. The three areas are detailed as below. Additionally,

we also highlight some concepts that are relevant yet different from our research scope (e.g., Individual Diversity and Fairness).

2.1 Session-Based Recommendation

The methods on SBRSs can be simply drawn into two groups: traditional non-neural methods and deep neural ones. Representative traditional methods includes but not limited to Item-KNN [25], BPR-MF [26], FPMC [27] and SKNN [28]. Specifically, Item-KNN is an item-to-item method which measures cosine similarity of every two items according to the training set. BPR-MF is a Matrix Factorization (MF) method which optimizes a pairwise ranking loss function via SGD. FPMC further combines MF with Markov Chain (MC) to better deal with sequential relationship between items. Generally, these methods aim at predicting next actions for users but are not designed especially for session-based scenarios with anonymous users [23]. Besides, they cannot well address the item relationships in relatively longer sequences. In addition, compared with Item-KNN, Session-based KNN (SKNN) [28, 23] considers session-level similarity instead of only item-level similarity, and thus is capable of capturing best information for more accurate session-based recommendation. In particular, for each session, SKNN samples k most similar past sessions in the training data. However, the SKNN does not consider the order of the items (sequential information) in a session when using the Jaccard index or cosine similarity as the distance measure. Therefore, some SKNN-variants are raised (e.g., V-SKNN [23] and STAN [29]) to better consider sequential and temporal information.

On the contrary, deep neural networks are capable of utilizing a much longer sequence for better prediction [30, 31]. For instance, GRU4Rec [3] is the first to apply recurrent neural network to capture the long-term dependency in a session. Quite a few extended variants of GRU4Rec have been proposed. For example, Improved GRU4Rec [30] obtains better recommendation performance by designing new data augmentation technique. Hidasi et al. [31] design novel ranking loss function and negative sampling method to enhance the effectiveness of GRU4Rec without sacrificing efficiency. NARM [4] further deploys an attention mechanism to model the similarity score between previous items and the last item, and thus captures the main purpose in the session. Later, STAMP [5] uses simple MLP networks and an attentive net to capture both users' general interests and current interests.

However, the above methods always model single-way transitions between consecutive items and neglect the transitions among the contexts (i.e., other items in the session) [32]. To overcome the limitation, GNN-based methods have been designed in recent years. For example, SR-GNN [6] imports GNNs to generate more accurate item embedding vectors from the session graph. Similar to SR-GNN, GC-SAN [7] replaces the simple attention network with self-attention to capture long-range dependencies by explicitly attending to all the positions. TAGNN [33] uses target-aware attention such that the learned session representation vector varies with different target items. Furthermore, GCE-GNN [8] learns it over both the current session graph and all-session graph.

It is worth noting that, the aforementioned traditional and deep neural SBRSs are all accuracy-oriented methods, ignoring to consider diversity. This may cause filter bubbles given the iterative or closed feedback loop in RSs [12, 13], thus failing to meet users' diversified demand and decreasing user engagement.

2.2 Diversified Recommendation

Diversity can be viewed at individual or aggregate levels in RSs. Individual diversity depicts the dispersion of recommendation lists, whilst aggregate diversity refers to dispersion from the RS perspective. Our paper mainly focuses on individual diversity, that is, we explore diversity at individual level if not particularly indicated.

Towards individual diversity in traditional recommendation scenarios, Carbonell et al. [14] propose the Maximal Marginal Relevance (MMR) to greedily select an item with the local highest combination of similarity score to the query and dissimilarity score to selected documents at earlier ranks. Inspired from dissimilarity score in MMR, some studies [34, 35] define diversification on explicit aspects (categories) or sub-queries. Steck [11] uses the historical interest distribution as calibration to capture minor interests. Furthermore, Chen et al. [15] provide a better relevance-diversity trade-off using DPP in recommendation. The essential characteristic of DPP is that it assigns higher probability to sets of items that are diverse from each other [36]. Based on the fast greedy inference algorithm [15], some recent studies [16, 17] employ DPP to improve diversity for different recommendation tasks. However, the above heuristic or DPP-based models are two-stage ones, which consider the diversity in the second stage by re-ranking items ordered by relevance in the first stage. Only several studies [18, 10] are end-to-end ones, that is, jointly optimizing diversity and accuracy by one model. Note that the above studies are for traditional recommendation tasks, rather than anonymous session-based scenarios.

To the best of our knowledge, for session-based recommendation, there are only three end-to-end diversified works, i.e., MCPRN [19], ComiRec [20], and IDSR [21]. In particular, MCPRN uses mixture-channel purpose routing networks to

guide the multi-purpose learning, while ComiRec explores two methods, namely dynamic routing method and self-attentive method, as multi-interest extraction module. MCPRN and ComiRec both use multiple session representations to capture diversified preferences, which can implicitly satisfy diversified user demand. On the contrary, IDSR explicitly constructs set diversity and achieves end-to-end recommendation guided by the intent-aware diversity promoting (IDP) loss. The final user preference towards an item is a combination of the relevance score and diversification score, weighted by a "trade-off hyper-parameter" (as defined in IDSR) controlling the balance between accuracy and diversity. However, as we have discussed, whether there is other kind of relationship, in addition to trade-off, between accuracy and diversity, and how diversified methods perform compared to other non-diversified SBRSs on diversity, are both under-explored.

2.3 Surveys on SBRSs

There are some surveys (including empirical ones) on SBRSs [23, 24, 1, 2]. For example, Quadrana et al. [24] propose a categorization of recommendation tasks, and discuss approaches for sequence-aware recommender systems where SBRSs is one type of them. Meanwhile, they argue that empirical evaluations should consider multiple quality factors, e.g., accuracy and diversity. Ludewig et al. [23] present an in-depth experimental performance comparison of several SBRSs (FPMC, GRU4Rec, and some simpler methods like Item-KNN) on evaluation measures (e.g., accuracy and aggregate diversity). Fang et al. [1] design a categorization of existing SBRSs in terms of behavioral session types, summarize and empirically demonstrate the key factors affecting the performance of deep neural SBRSs in terms of accuracy-related metrics. Wang et al. [2] generally define the problems in SBRSs, and further summarize different data characteristics and challenges of SBRSs.

However, these surveys mainly strive to guide future research by providing an overall picture of existing studies on SBRSs. Although some of them might have considered the evaluation issues, or conducted some form of empirical evaluations to compare different models, they generally ignore to specifically explore the model performance on diversity, and thoroughly compare representative SBRSs in terms of both accuracy and diversity. This, consequently, leads to an insufficient understanding on the relationship between accuracy and diversity. Our study aims to address these issues with an appropriate empirical design.

2.4 Discussions on Relevant yet Different Concepts

Session-Based Recommender Systems (SBRSs) vs. Sequential Recommender Systems (SRSs) SBRSs and SRSs are built on session data and sequence data, respectively, while they are often gotten mixed up by some readers since both of them consider the sequential information of interactions [2]. In academia, SRSs are typically operationalized as the task of predicting the next user action [23] based on user sequence data. That is, a single sequence data contains all historical, time-ordered logs for a given user, e.g., his/her item viewing and purchase activities on an e-commerce shop, or listening history on a music streaming site. On the contrary, as we have defined, SBRSs commonly consider anonymous sessions where user information (including identities) is unknown. Besides, different from the relatively longer user sequences in SRSs, a session usally contains fewer interactions and is bounded in a shorter time window [2], e.g., one-day [23] or 30-minutes [37]. Our paper focuses on session-based recommendation which recommends the Top-N list for next-item prediction. Therefore, some popular SRSs (e.g., SASRec [38] and BERT4Rec [39]) are out of our research scope, and thus are not included in Baselines.

Individual Diversity vs. Aggregate Diversity Diversity can be viewed at individual or aggregate levels in RSs. Specifically, individual diversity depicts the dispersion of recommendation lists, whilst aggregate diversity refers to dispersion from the RS perspective [40]. That is to say, the individual diversity is for recommended items to each individual user regardless of other users, but the aggregate diversity is for all recommended items across all users, which mainly considers overall product variety and sales concentration (e.g., Coverage [41]). For example, some studies [41, 42] utilize long-tail (less popular or frequent) items to further improve aggregate diversity. Besides, some works [43, 44] dealing with popularity bias also contribute to higher aggregate diversity. Importantly, aggregate and individual diversity are not necessarily correlated. For example, a system can recommend the same set of highly diverse items to everyone and thus obtains higher individual diversity, which does not lead to high aggregate diversity. Our paper focuses on individual diversity, that is, we explore diversity at individual level if not particularly indicated.

Diversity vs. Fairness Fairness in recommendations is built on notions of inclusion, non-discrimination, and justice [45]. There are also two-fold of fairness-related studies: individual fairness and group fairness. The former emphasizes the requirement that similar individuals are expected to be treated similarly, while the latter one, also known as statistical parity, considers the requirement that demographics of those receiving a particular positive (or negative) outcome, for example, a positive or negative classification, are identical [46, 47]. The statistical parity (group fairness)

in recommendation is stated as a property of a collection of items which is easily-confused with individual diversity. For example, statistical parity requires that the distribution of results across genders regarding a task is the same as the whole population (e.g., 10% women and 90% men for job applicants). Although a fairer algorithm will preserve more similar gender ratio, but it is not always the case that fairness and diversity objectives are in agreement [47]. Determining conditions under which fairness leads to diversity, and diversity leads to fairness, is an open research question that asks for further investigation [47]. Our paper focuses on the accuracy and individual diversity performance and explore their relationship in SBRSs.

3 Experimental Settings

Instead of only evaluating recommendation accuracy, we further explore diversity in the session-based scenario. Towards a fair study to draw convincing results, we aim to cover more scenarios with appropriate experimental setups. Specifically, we select representative datasets across different domains, including e-commerce and music (Section 3.1); we moderately choose three types of session-based methods for comparison, namely traditional non-neural methods, state-of-the-art deep neural methods, and two diversified ones (Section 3.2); and we take a comprehensive set of accuracy- and diversity-related indicators (Section 3.3). Accordingly, we conduct extensive experiments to answer three key research questions (RQs):

- RQ1: How do representative SBRSs of different types perform in terms of accuracy and diversity metrics?
- **RQ2**: Whether there is a "trade-off" relationship between accuracy and diversity? Is there any other one between them?
- RQ3: Which kinds of factors will influence diversity performance of SBRSs, besides various model designs?

3.1 Datasets and Preprocessing

We delicately select four representative public datasets for the experimental purpose. They are three e-commerce datasets (i.e., Diginetica¹, Retailrocket², Tmall³) with item category information and one music dataset (i.e., Nowplaying⁴) with artist information.

- **Diginetica** comes from CIKM Cup 2016 and includes user e-commerce search engine sessions with its own 'SessionId'. Note that we only use the 'view' data.
- **Retailrocket** collects users' interaction behavior in the e-commerce website over 4.5 months. We also only explore interactions of 'view' type, and partition user history into sessions in every 30-minute interval following [37].
- **Tmall** comes from the IJCAI-15 competition and contains anonymous shopping logs on Tmall. We adopt interactions of 'buy' and 'view' action-types, and partition user history into sessions by day following [23]. Since the original datasets are quite large, we select 1/16 sessions as sampling inspired by fractions of Yoochoose [4].
- **Nowplaying** tracks users' current listening from music-related tweets. Ludewig et al. [23] publicize the processed version⁵ with 'SessionId'. We use 'ArtistId' as the category information to distinguish different music for simplicity by following the previous studies (e.g., [48] uses region information to represent category on the POI dataset Gowalla).

For data preprocessing, following [4, 5, 6], to filter noisy data, we drop sessions of length 1 and items occuring less than 5 times. We set the most recent data (a week) as the test set whilst the other sessions as the training set. Besides, we further filter out items appearing in the test set but not in the training set. The statistics of these four datasets after preprocessing are shown in Table 1. It should be noted that sequence splitting preprocess [4] is necessary if a recommendation model is not trained in session-parallel manner [3]. Sequence splitting preprocess refers to that, for a session sequence $S = [i_1, i_2, \ldots, i_n]$, we can generate n-1 sub-sequences $([i_1], i_2), ([i_1, i_2], i_3), \ldots, ([i_1, \ldots, i_{n-1}], i_n)$ for training.

https://competitions.codalab.org/competitions/11161#learn_the_details-overview.

²https://www.kaggle.com/retailrocket/ecommerce-dataset.

https://tianchi.aliyun.com/dataset/dataDetail?dataId=42.

⁴https://zenodo.org/record/2594483#.YdfMgxNBy8U.

⁵www.dropbox.com/sh/dbzmtq4zhzbj5o9/AACldzQWbw-igKjcPTBI6ZPAa?dl=0

Table 1: Statistics of Datasets (Note: # train and #test represent the number of sessions before sequence splitting preprocess).

Dataset	Diginetica	Retailrocket	Tmall	Nowplaying
# interactions	993,483	1,082,246	1,505,683	1,227,583
# train	186,670	294,629	188,756	144,356
# test	18,101	12,206	51,894	1,680
# items	43,097	48,893	96,182	60,622
# categories	995	944	822	11,558
avg. len.	4.8504	3.5253	6.0775	8.4056

3.2 Baseline Models

To explore the recommendation performance on accuracy and diversity, we select three categories of popular and representative baseline models for session-based recommendation: *traditional non-neural methods*, *deep neural methods*, and *deep diversified methods*.

Traditional Non-neural Methods

- POP always recommends top ranking items based on popularity in the training set.
- S-POP recommends top frequent items of the current session, which differs from POP using global popularity values. Ties are broken up using global popularity values.
- Item-KNN [25] is an item-to-item model which measures cosine similarity of every two items regarding sessions in the training data. For a session, it recommends the most similar items to the last item of the session.
- **BPR-MF** [26] optimizes a pairwise ranking loss on Matrix Factorization (MF) method. It further averages items' feature vectors in the session as its feature vector.
- FPMC [27] is a sequential method based on MF and first-order MC. To adapt to anonymous session-based recommendation, it drops user latent representations.

Deep Neural Methods

- **GRU4Rec** [3] is an RNN-based model which utilizes session-parallel mini-batch training process and also adopts pairwise ranking loss function.
- NARM [4] is an RNN-based model with an attention mechanism to capture the main purpose from the hidden states and combine it with the last hidden vector as the final representation to generate recommendations.
- **STAMP** [5] employs attention layers directly on item representation instead of the output of RNN encoder then captures the user's long-term preference from session context, and the short-term interest according to a session's last item.
- **SR-GNN** [6] employs a gated GNN layer to obtain item embeddings and then applies an attention mechanism to compute the session representations.
- GC-SAN [7] is quite similar to SR-GNN, except it uses Self-Attention Network (SAN) to learn session representations.
- GCE-GNN [8] constructs both current session (local) graph and global graph to get session- and global-level item embeddings. Then, position-aware attention is adopted to fuse reversed position information to obtain the final session representation.

Deep Diversified Methods

- MCPRN [19] models users' multiple purposes (instead of only main purpose as NARM) in a session. It further uses target-aware attention to combine those learned multiple purposes to get the final representation. As claimed in the original paper, MCPRN can boost both accuracy and diversity.
- **IDSR** [21] is the first end-to-end deep neural network based method that jointly considers diversity and accuracy for SBRSs. It presents a novel loss function to guide model training in terms of both accuracy and diversity, where hyper-parameter *λ* is adopted to balance the relevance score and diversification score.

3.3 Evaluation Metrics

For an exhaustive evaluation, we adopt the following metrics related to accuracy, diversity, or both. A higher value of each metric indicates better performance. Specifically, to evaluate accuracy [4, 6, 8], we adopt HR (Hit Rate), MRR (Mean Reciprocal Rank), and NDCG (Normalized Discounted Cumulative Gain). In particular, **HR** measures whether a ground-truth item is contained in the Top-N Recommended List (abbreviated as RL, and N is the length of the RL); **MRR** measures whether a correctly predicted item ranks ahead in the RL; and **NDCG** rewards each hit based on its position in the RL.

Towards diversity, we choose ILD (Intra-List Distance) [49, 20, 21], Entropy [19, 18], and Diversity Score [10]. To be specific, **ILD** measures the average distance between every pair of items in RL where d_{ij} denotes the euclidean distance between the respective embeddings (e.g., one-hot encoding) of categories that items i and j belong to,

$$ILD = \frac{\sum_{(i,j)\in RL} d_{ij}}{|RL| \times (|RL| - 1)};$$
(1)

Entropy measures the entropy of item category distribution in the RL. The more dispersed category distribution is, the more diverse the RL is; and **Diversity Score** (shorted as **DS**) is calculated by the number of interacted/recommended categories divided by number of interacted/recommended items.

Furthermore, we adopt **F-score** [49] as an aggregative indicator which jointly considers both accuracy and diversity. Here, F-score is computed as the Harmonic mean of accuracy metric (i.e., HR) and diversity metric (i.e., ILD),

$$F-score = \frac{2 HR \times ILD}{HR + ILD}.$$
 (2)

A higher F-score implies that the corresponding model has a more comprehensive strength with regard to both accuracy and diversity.

3.4 Hyper-parameters Setup

For deep models, we use the Adam optimizer. We tune hyper-parameters of all baseline models on a validation set which is the most recent data (last week) of every training set.

Noted that different baselines have different hyper-parameters, where the most common ones include item embedding dimension, dimension of latent vector, learning rate, the size of mini-batch, and the number of epochs. Considering a fair comparison, we use the Bayesian TPE [50] of Hyperopt⁶ framework to tune all hyper-parameters of baselines on all datasets, which has proven to be a more intelligent and effective technique compared to grid and random search, especially for deep methods (having more hyper-parameters) [51]. The detailed optimal hyper-parameter settings by Hyperopt of the baselines are shown in Table 2. The exceptions are made on that we set both item embedding dimension and mini-batch size as 100 (consistent with the original paper setting) for GCE-GNN due to memory space limits. Similarly, we set the mini-batch size as 50 for MCPRN. Besides, IDSR is the only method that strives to balance and improve accuracy and diversity (two objectives) simultaneously with hyper-parameter λ . Thus, for IDSR, we set λ as $\{0.2, 0.5, 0.8\}$ on every dataset, which can be treated as three variants of IDSR.

We have integrated all the codes with PyTorch framework, except for IDSR that we adopt its original code in TensorFlow version⁷ with an early-stopping mechanism. We will publicize our codes upon acceptance.

4 Experimental Results

In this section, we present our experimental results to answer the raised three research questions (RQs).

4.1 Overall Comparisons (RQ1)

Experimental results of the selected baselines on the four real-world datasets are respectively presented in Tables 4-7, where the best result under each metric is highlighted in boldface and the runner-up is underlined⁸. The best results are marked with '*' which demonstrates it outperforms the runner-up at 95% confidence level in t-test for means of paired two sample. Note that the results are measured as an average of 5 times with the best hyper-parameter settings.

⁶https://github.com/hyperopt/hyperopt

⁷https://bitbucket.org/WanyuChen/idsr/

⁸We can get similar results concerning baselines of different scenarios with N=5, which are not mentioned in the main paper.

Table 2: The Optimal Hyper-parameter Settings by Bayesian TPE of Hyperopt.

Model	Hyper-parameter	Digi*	Retail*	Tmall	Now*	Searching Space	Description
Item-KNN	-alpha	0.9270	0.7100	0.8514	0.9074	U(0.1,1)	Balance for normalizing items' supports
	-item_*_dim	300	100	200	150	[min = 100, max = 300, step = 50]	the dimension of item embedding
BPR-MF	-lr	0.01	0.01	0.001	0.001	[0.001, 0.005, 0.01, 0.05]	learning rate
DLK-MIL	-batch_size	64	64	512	512	[64, 128, 256, 512]	the size for mini-batch
	-epochs	20	20	40	15	[min = 10, max = 40, step = 5]	the number of epochs
	-item_*_dim	250	100	200	250	[min = 100, max = 300, step = 50]	
FPMC	-lr	0.005	0.001	0.001	0.005	[0.001, 0.005, 0.01, 0.05]	
	-batch_size	256	256	512	512	[64, 128, 256, 512]	
	-epochs	30	10	40	40	[min = 10, max = 40, step = 5]	
	-item_*_dim	150	300	300	100	[min = 100, max = 300, step = 50]	
	-lr	0.05	0.01 256	0.05 64	0.01	[0.001, 0.005, 0.01, 0.05]	
	-batch_size -epochs	256 25	30	30	512 35	$ \begin{bmatrix} 64, 128, 256, 512 \\ min = 10, max = 40, step = 5 \end{bmatrix} $	
GRU4Rec	-hidden_size	50	200	150	200	[min = 10, max = 40, step = 5] [min = 50, max = 200, step = 50]	the dimension of latent vector
	-n_layers	1	1	130	1	[ntin = 50, max = 200, step = 50] [1, 2, 3]	the number of layers in RNN
	-dropout_input	0.3123	0.1073	0.3697	0.1407	$\mathcal{U}(0.1,1)$	dropout rate
	-dropout_hidden	0.2946	0.1311	0.6618	0.4170	$\mathcal{U}(0.1,1)$	dropout rate
	-item_*_dim	200	100	250	150	[min = 100, max = 300, step = 50]	dropout rate
	-lr	0.001	0.001	0.005	0.001	[0.001, 0.005, 0.01, 0.05]	
374 D3 6	-batch_size	512	512	256	512	[64, 128, 256, 512]	
NARM	-epochs	35	40	25	10	[min = 10, max = 40, step = 5]	
	-hidden_size	50	150	150	150	[min = 50, max = 200, step = 50]	
	-n_layers	1	1	1	2	[1, 2, 3]	
	-item_*_dim	100	100	150	200	[min = 100, max = 300, step = 50]	
STAMP	-lr	0.001	0.001	0.01	0.001	[0.001, 0.005, 0.01, 0.05]	
SIAMI	-batch_size	128	512	256	128	[64, 128, 256, 512]	
	-epochs	35	20	35	15	[min = 10, max = 40, step = 5]	
	-item_*_dim	300	150	150	200	[min = 100, max = 300, step = 50]	
	-lr	0.005	0.005	0.005	0.005	[0.001, 0.005, 0.01, 0.05]	
SR-GNN	-batch_size	256	256	128	512	[64, 128, 256, 512]	
	-epochs	25	20	15	10	[min = 10, max = 40, step = 5]	
	-step	1 250	150	3 150	300	[1,2,3]	gnn propogation steps
	-item_*_dim -lr	250 0.001	150 0.001	0.005	0.001	[min = 100, max = 300, step = 50] [0.001, 0.005, 0.01, 0.05]	
	-batch_size	512	512	256	256	[64, 128, 256, 512]	
GC-SAN	-epochs	25	40	10	30	[min = 10, max = 40, step = 5]	
	-epochs -weight	0.4	0.4	0.4	0.4	$\begin{bmatrix} mth = 10, max = 40, step = 5 \\ [0.4, 0.6, 0.8] \end{bmatrix}$	weight factor (in combined embedding)
	-blocks	3	4	1	3	[1, 2, 3, 4]	the number of stacked self-attention blocks
	-item_*_dim	250	100	100	100	[100]	are number of statement serious stocks
	-lr	0.001	0.001	0.005	0.001	[0.001, 0.005]	
	-batch_size	128	100	100	100	[100]	
GCE-GNN	-epochs	10	30	20	30	[min = 10, max = 30, step = 5]	
	-n_iter	1	1	2	1	[1,2]	the number of hop
	-dropout_gcn	0.4	0.4	0.2	0.0	[0, 0.2, 0.4, 0.6, 0.8]	dropout rate
	-dropout_local	0.5	0.0	0.0	0.0	[0, 0.5]	dropout rate
	-item_*_dim	150	150	100	200	[min = 100, max = 200, step = 50]	dimension of item embedding/latent vector
	-lr	0.005	0.005	0.005	0.005	[0.005, 0.01, 0.05]	
MCPRN	-batch_size	256	50	50	50	[50]	
	-epochs	15	30	25	15	[min = 10, max = 40, step = 5]	
	-tau	1	0.01	0.01	0.1	[0.01, 0.1, 1, 10]	temperature parameter in softmax
	-purposes	1	4	1	3		The number of channels
						ow* for Nowplaying, item_*_dim for ite	m_embedding_dim.
Remark	2. Omit the hyper-					O (original softing) in CCE CNIN 11-	tab siza as 50 in MCDDN avaant Diai*
	Due to memory The page arms	official T	nem_"_di	ni, baich_	size as 10	0 (original setting) in GCE-GNN, and ba pping. Tune $\lambda_e \in [0.1, 1]$ and set it as 1 f	for four datasets
	T. IDSK uses OWI	ometai It	711201 LIOM	Coue with	carry-810	pping. Tune $\wedge_e \in [0.1, 1]$ and set it as 1.1	oi ioui ualastis.

	Accuracy	Rank	Diversity	Rank	F-score	Rank
POP	10	15	311	3	5	15
S-POP	127	10	295	5	75	6
Item-KNN	186	7	69	13	48	12
BPR-MF	96	13	176	8	37	13
FPMC	42	14	192	7	16	14
GRU4Rec	124	12	311	4	61	11
NARM	334	2	43	14	75	7
STAMP	295	4	129	10	85	4
SR-GNN	272	5	91	12	73	8
GC-SAN	303	3	113	11	88	2
GCE-GNN	370	1	1	15	63	9
MCPRN	194	6	176	9	62	10
IDSR(λ =0.2)	125	11	360	1	86	3
IDSR(λ =0.5)	179	8	322	2	93	1
IDSR(λ =0.8)	178	9	246	6	78	5

Table 3: Borda Count and Corresponding Rank of Baselines On Accuracy, Diversity and F-score.

We further adopt a Borda count [52] ranked voting scheme to aggregate our experimental results on the four datasets, for better overall comparisons. Specifically, for these baselines (15 in all), on each dataset in terms of each metric regarding a specific Top-N recommendation list ($N = \{5, 10, 20\}$), the first-ranked one receives 14 points, and the last-ranked one gains 0 points. We consider every such scenario as a vote. For each baseline, we aggregate all ranking points regarding accuracy metrics (NDCG, MRR, and HR) as Accuracy points, while those for diversity metrics (ILD, Entropy and DS) as Diversity points. We then rank these baselines regarding Accuracy, Diversity and F-score points, respectively, considering that more points refer to better performance. The results are shown in Table 3.

4.1.1 Performance on Recommendation Accuracy

As shown in Tables 4-7, the performance of different approaches on recommendation accuracy is measured via NDCG@N, MRR@N, and HR@N ($N=\{10,20\}$). From the results in Tables 3-7, several interesting observations are noted.

(1) Regarding recommendation accuracy, deep neural methods generally outperform traditional non-neural methods, except that Item-KNN performs the best on Tmall. The deep diversified methods (i.e., MCPRN and IDSR with $\lambda = \{0.2, 0.5, 0.8\}$ respectively) perform worse than the accuracy-oriented deep methods in most cases, but better than traditional ones. (2) Among traditional non-neural methods, the performance of S-POP and Item-KNN could be within the same order of magnitudes with that of deep neural methods, except for S-POP on Tmall. However, MF-based method like BPR-MF, performing quite well in traditional RSs, gains relatively worse accuracy in SBRSs. (3) In regard to the six (accuracy-oriented) deep neural methods, GCE-GNN, which further considers global graph instead of only session graph like other GNN-based models (GC-SAN and SR-GNN), achieves the best performance in all scenarios. NARM using vanilla attention ranks second in most scenarios (except on Tmall), which, however, has lower computational complexity than GCE-GNN. (4) Of the two diversified methods, IDSR (with some λ) can defeat MCPRN in most scenarios, except on Tmall (see Tables 4-7); whereas, the overall performance of MCPRN exceeds that of IDSR (see Table 3). Besides, the performance of IDSR w.r.t. accuracy metrics generally improves with the increase of λ value (except on Retailrocket), conforming to the intuition of trade-off hyper-parameter in model design.

4.1.2 Performance on Recommendation Diversity

As shown in Tables 4-7, the performance of different approaches on recommendation diversity is measured via ILD@N, Entropy@N, and DS@N ($N = \{10, 20\}$). Based on Tables 3-7, we gain three observations.

(1) Regarding recommendation diversity, the diversified method, IDSR ($\lambda=0.2$) performs the best as it ranks first on Diginetica and Retailrocket or second on Nowplaying, except that IDSR ($\lambda=0.5$) performs better on Tmall. Besides, non-neural methods (POP and S-POP), and accuracy-oriented deep method (GRU4Rec), though not being specifically designed for diversity purpose, obtain a relatively better performance than other baselines, which is comparable to IDSR. (2) The accuracy-oriented deep methods (except GRU4Rec), especially GCE-GNN and NARM, usually perform far behind other baselines w.r.t. recommendation diversity. (3) The two deep diversified methods beat the accuracy-oriented deep methods. MCPRN, though being worse than IDSR, outperforms other accuracy-oriented SBRSs in most cases.

Table 4: Model Performance on Diginetica. * denotes the best model significantly outperforms the runner-up using a paired t-test (p-value < 0.05).

Model	Ñ.	NDCG	MRR	3R	Ξ	H		D	Entropy	opy	Q	S	F-score	ore
	@10	@ 20	@10	@20	@10	@ 20	@ 10	@ 20	@10	@ 20	@10	@20	@10	@20
POP	0.0025	0.0027	0.0017	0.0018	0.0052	0.0061	1.1314	1.2256	2.0464	2.6826	0.5000	0.5333	0.0055	0.0067
S-POP	0.1625	0.1630	0.1475	0.1476	0.2083	0.2100	1.1147	1.1914	2.1088	2.5454	0.5326	0.4891	0.2152	0.2274
Item-KNN	0.1313	0.1438	0.0999	0.1036	0.2343	0.2814	0.1653	0.2247	0.2852	0.4353	0.1562	0.1376	0.0375	0.0635
BPR-MF	0.0799	0.0954	0.0618	0.0661	0.1397	0.2012	0.5334	0.5799	0.9490	1.2148	0.2871	0.2159	0.0676	0.1061
FPMC	0.0787	0.0954	0.0592	0.0638	0.1428	0.2094	0.5566	0.5968	1.0143	1.2854	0.3035	0.2282	0.0554	0.0904
GRU4Rec	0.1220	0.1396	0.0938	0.0987	0.2141	0.2837	0.8351	0.9126	1.7810	2.4512	0.5406	0.5255	0.0970	0.1635
NARM	0.3191	0.3468	0.2578	0.2654	0.5162	0.6256	0.1811	0.2519	0.3047	0.5037	0.1575	0.1182	0.0921	0.1645
STAMP	0.3143	0.3385	0.2558	0.2624	0.5018	0.5973	0.2704	0.3923	0.4781	0.8410	0.1977	0.1783	0.1381	0.2491
SR-GNN	0.2971	0.3247	0.2371	0.2447	0.4905	0.5995	0.2435	0.3385	0.4222	0.7060	0.1836	0.1527	0.1226	0.2162
GC-SAN	0.3013	0.3264	0.2450	0.2520	0.4818	0.5809	0.2855	0.4014	0.5048	0.8556	0.2020	0.1774	0.1308	0.2376
GCE-GNN	0.3458^*	0.3723^*	0.2876^*	0.2950^*	0.5324^*	0.6373^*	0.1124	0.1623	0.1825	0.3096	0.1328	0.0892	0.0627	0.1145
MCPRN	0.2321	0.2610	0.1858	0.1938	0.3829	0.4972	0.2671	0.3394	0.4651	0.7106	0.1935	0.1556	0.1100	0.1867
$IDSR(\lambda = 0.2)$	0.1677	0.1973	0.1435	0.1517	0.2521	0.3686	1.3108^*	1.2460	2.8540^*	3.3085^*	0.8127^*	0.6760^*	0.2829	0.4025
$IDSR(\lambda = 0.5)$	0.2230	0.2547	0.1806	0.1893	0.3633	0.4886	0.7996	0.7531	1.5522	1.7468	0.4433	0.3401	0.2600	0.3607
$IDSR(\lambda = 0.8)$	0.2681	0.2958	0.2140	0.2217	0.4438	0.5532	0.4105	0.4635	0.7464	1.0110	0.2593	0.2090	0.1814	0.2688

Table 5: Model Performance on Retailrocket. * denotes the best model significantly outperforms the runner-up using a paired t-test (p-value ≤ 0.05).

Model	N N	NDCG	M	MRR	H	HR	IL	D	Entropy	dc	D	S	F-s	F-score
	@10	@20	@10	@20	@10	@20	@10	@20	@10	@20	@10	@20	@10	@20
POP	0.0047	0.0052	0.0026	0.0027	0.0121	0.0141	1.2571	1.3334	2.4464	3.1899	0.6000	0.6667	0.0135	0.0161
S-POP	0.3078	0.3086	0.2912	0.2915	0.3581	0.3612	1.2164	1.2664	2.4831	3.0547	0.6463	0.6545	0.3995^*	0.4103
Item-KNN	0.1522	0.1598	0.1236	0.1258	0.2440	0.2729	0.6498	0.7460	1.2110	1.5946	0.3481	0.3427	0.1422	0.1871
BPR-MF	0.1195	0.1309	0.1000	0.1031	0.1827	0.2278	0.7872	0.8395	1.4468	1.8447	0.3896	0.3094	0.1323	0.1811
FPMC	0.0787	0.0918	0.0610	0.0645	0.1368	0.1885	0.7473	0.8068	1.3664	1.7411	0.3739	0.2912	0.0871	0.1361
GRU4Rec	0.2380	0.2511	0.2039	0.2075	0.3467	0.3984	1.0513	1.1498	2.2385	3.1506	0.6303	0.6348	0.3075	0.3984
NARM	0.3582	0.3765	0.3105	0.3156	0.5102	0.5826	0.4736	0.5723	0.8401	1.2350	0.2646	0.2269	0.2451	0.3432
STAMP	0.3451	0.3619	0.3012	0.3058	0.4847	0.5510	0.5192	0.6375	0.9529	1.4289	0.2936	0.2641	0.2504	0.3554
SR-GNN	0.3291	0.3489	0.2829	0.2883	0.4769	0.5549	0.4811	0.5874	0.8595	1.2737	0.2713	0.2370	0.2390	0.3423
GC-SAN	0.3330	0.3491	0.2909	0.2954	0.4669	0.5308	0.5457	0.6660	1.0001	1.4960	0.3045	0.2756	0.2449	0.3489
GCE-GNN	0.3834^*	0.4024^*	0.3355^*	0.3408^*	0.5359^*	0.6110^*	0.3631	0.4439	0.6122	0.8992	0.2120	0.1697	0.2121	0.2996
MCPRN	0.2276	0.2409	0.2011	0.2047	0.3128	0.3653	0.7383	0.8098	1.4441	1.9635	0.4118	0.3677	0.2154	0.2766
$IDSR(\lambda = 0.2)$	0.2211	0.2459	0.1983	0.2051	0.3000	0.3979	1.2962	1.2267	2.9170	3.4360	0.8332	0.7091	0.3363	0.4351
$IDSR(\lambda = 0.5)$	0.2494	0.2787	0.2254	0.2334	0.3292	0.4452	1.2677	1.1668	2.7634	3.1378	0.7695	0.6274	0.3652	0.4752^*
$IDSR(\lambda = 0.8)$	0.2192	0.2360	0.1870	0.1916	0.3238	0.3902	0.8265	0.8628	1.7779	2.2918	0.5005	0.4340	0.2430	0.3159

Table 6: Model Performance on Tmall. * denotes the best model significantly outperforms the runner-up using a paired t-test (p-value ≤ 0.05).

ore	@20	0.0082	0.0044	0.0573	0.0259	0.0105	0.0109	0.0642	0.0481	0.0574	0.0674	0.0744	0.0326	0.0112	0.0186	0.0327
F-score	@10	0.0063	0.0021	0.0442	0.0168	0.0061	0.0075	0.0386	0.0292	0.0355	0.0408	0.0443	0.0193	0.0061	0.0100	0.0192
S	@20	0.6000	0.6075	0.4219	0.3805	0.3883	0.7603	0.3778	0.4494	0.4308	0.3861	0.3345	0.4679	0.7123	0.7335	0.6773
D	@10	0.7000	0.6660	0.4546	0.4852	0.4921	0.8407	0.4689	0.5428	0.5190	0.4754	0.4161	0.5686	0.7912	0.8451	0.8108
.oby	@ 20	3.0566	2.9665	2.0452	2.3219	2.4328	3.7410	2.2625	2.5806	2.4823	2.3003	2.0340	2.6437	3.6406	3.6509	3.4530
Entr	@10	2.7219	2.5332	1.6790	1.8716	1.9524	2.9584	1.7760	2.0375	1.9468	1.8019	1.5691	2.1139	2.8553	2.9744	2.8725
Q	@ 20	1.3199	1.2763	0.9593	1.0350	1.0969	1.3517	1.0085	1.0959	1.0661	1.0202	0.9326	1.1042	1.3468	1.3395	1.2969
II	@10	1.3199	1.2447	0.8888	0.9963	1.0539	1.3415	0.9453	1.0449	1.0090	0.9568	0.8571	1.0661	1.3274	1.3483	1.3175
<u>۳</u>	@20	0.0072	0.0039	0.0655	0.0279	0.0108	0.0097	0.0720	0.0511	0.0619	0.0747	0.0886^*	0.0354	0.0098	0.0165	0.0303
H	@10	0.0055	0.0018	0.0551	0.0186	9900.0	0.0068	0.0476	0.0336	0.0417	0.0499	0.0594	0.0225	0.0054	0.0089	0.0179
KR.	@ 20	0.0012	0.0004	0.0259^*	0.0075	0.0028	0.0032	0.0191	0.0133	0.0178	0.0206	0.0207	0.0084	0.0039	0.0050	0.0063
MF	@10	0.0011	0.0003	0.0251^*	0.0069	0.0025	0.0030	0.0174	0.0121	0.0164	0.0189	0.0187	0.0075	0.0036	0.0045	0.0054
). J.C	@20	0.0025	0.0012	0.0349	0.0119	0.0044	0.0046	0.0306	0.0215	0.0274	0.0324	0.0355	0.0142	0.0051	0.0074	0.0114
NDCG	@10	0.0021	0.0006	0.0321^*	0.0096	0.0034	0.0039	0.0244	0.0171	0.0223	0.0261	0.0282	0.0110	0.0040	0.0055	0.0083
Model		POP	S-POP	Item-KNN	BPR-MF	FPMC	GRU4Rec	NARM	STAMP	SR-GNN	GC-SAN	GCE-GNN	MCPRN	$IDSR(\lambda = 0.2)$	$IDSR(\lambda = 0.5)$	$IDSR(\lambda = 0.8)$

Table 7: Model Performance on Nowplaying. * denotes the best model significantly outperforms the runner-up using a paired t-test (p-value ≤ 0.05).

	./		J				J		I	0		1	./	
Model		D)	M	MRR	H	R	П	Q,	Entr	opy	П	SC	F-s	F-score
	@10	@20	@10	@20	@10	@20	@10	@20	@10	@ 20	@10	@20	@10	@20
POP	0.0111	0.0111	0.0064	0.0064	0.0266	0.0266	1.4142	1.4142^{*}	3.3219	3.9069	1.0000	1.0000^{*}	0.0311	0.0311
S-POP	0.1051	0.1067	0.0860	0.0864	0.1683	0.1744	1.2504	1.3107	2.8207	3.4678	0.8354	6098.0	0.1517	0.1877
Item-KNN	0.1118	0.1213	0.0848	0.0876	0.2003	0.2364	0.8879	0.9518	1.9073	2.3448	0.5716	0.5624	0.11111	0.1535
BPR-MF	0.0392	0.0460	0.0322	0.0341	0.0622	0.0893	1.3080	1.3298	2.8665	3.6625	0.8132	0.7427	0.0673	0.1001
FPMC	0.0298	0.0339	0.0250	0.0261	0.0458	0.0621	1.3176	1.3355	2.8701	3.6481	0.8081	0.7311	0.0506	0.0701
GRU4Rec	0.0249	0.0275	0.0225	0.0233	0.0326	0.0432	1.3820	1.3948	3.1797	4.1663	0.9422	0.9402	0.0370	0.0499
NARM	0.1162	0.1320	0.0964	0.1007	0.1810	0.2438	1.1584	1.2095	2.4929	3.2648	0.7132	0.6638	0.1608	0.2376
STAMP	0.1170	0.1300	0.0982	0.1017	0.1785	0.2300	1.2241	1.2686	2.6837	3.5309	0.7749	0.7421	0.1703	0.2367
SR-GNN	0.1160	0.1311	0960.0	0.1001	0.1818	0.2415	1.1985	1.2446	2.6096	3.4242	0.7512	0.7112	0.1686	0.2432
GC-SAN	0.1182	0.1307	0.1016	0.1050	0.1725	0.2220	1.2160	1.2611	2.6557	3.4900	0.7651	0.7292	0.1625	0.2268
GCE-GNN	0.1293^*	0.1480^*	0.1038^*	0.1090^*	0.2130^*	0.2870^*	1.0471	1.1264	2.2147	2.9912	0.6367	0.6065	0.1707	0.2616^*
MCPRN	0.0521	0.0640	0.0401	0.0432	0.0922	0.1394	1.2330	1.2684	2.7035	3.5214	0.7790	0.7368	0.0900	0.1428
$IDSR(\lambda = 0.2)$	0.0481	0.0586	0.0447	0.0476	0.0602	0.1018	1.4000	1.3872	3.2393	4.1021	0.9608	0.9131	0.0700	0.1167
$IDSR(\lambda = 0.5)$	0.0548	0.0693	0.0493	0.0532	0.0738	0.1318	1.3635	1.3533	3.0846	3.9018	0.9001	0.8487	0.0830	0.1467
$IDSR(\lambda = 0.8)$	0.0628	0.0769	0.0521	0.0559	0.0993	0.1552	1.3670	1.3358	3.1101	3.8045	0.9141	0.8186	0.1124	0.1719

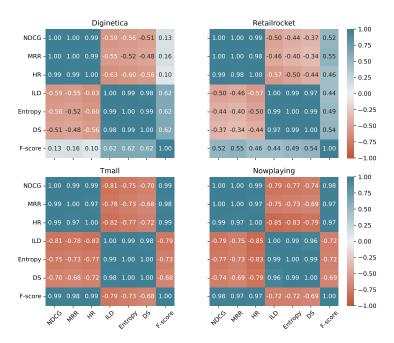


Figure 1: Pearson Correlation Coefficient of Metrics on Every Dataset. Each value is calculated given two corresponding arrays by concatenating Top-10 performance of all baselines on the respective dataset.

Moreover, the performance of IDSR on recommendation diversity decreases with the increase of λ (except on Tmall dataset), which is also consistent with the trade-off hyper-parameter's intuition.

4.1.3 Comprehensive Performance

By following the idea of [49], in order to more thoroughly and fairly assess session-based algorithms from both accuracy and diversity perspectives, we have compared them in terms of F-score (see Equation 2). It should be noted that we can compute the Harmonic mean of any two combinations where one comes from accuracy group (i.e., HR, MRR, and NDCG) and the other from diversity group (i.e., ILD, Entropy, and DS). As can be seen from Tables 4-7 and Figure 1, the metrics within the same group are positively correlated with each other. Thus, for evaluating the comprehensive performance, we particularly select the most popular one from each group respectively, i.e., HR and ILD, to calculate the F-score. As shown in Tables 3-7, we have the following observations regarding the F-score.

(1) Among the non-neural methods, POP, although it performs quite well on diversity, ranks the last in most scenarios w.r.t. the comprehensive performance except on Tmall. Nevertheless, S-POP, which far exceeds POP on accuracy due to its particular design for session situation, ranks the first of the five traditional methods except on Tmall. (2) Generally speaking, deep neural methods (including the diversified ones) obtain better comprehensive performance than non-neural traditional methods, where IDSR is the winner on Diginetica and Retailrocket, and GCE-GNN ranks first on Tmall and Nowplaying. Interestingly, the former one ranks first regarding diversity metric on those two datasets, whilst the latter one is the winner on accuracy. Overall, IDSR ($\lambda = 0.5$) ranks the first (see Table 3). (3) For the diversified methods, IDSR (with some λ) consistently outperforms MCPRN, except on Tmall dataset. Besides, MCPRN underperforms other deep neural methods.

To conclude, from the above results, we can see that, (1) accuracy-oriented approaches (e.g., GC-SAN, STAMP), although not particularly designed for diversity purpose, can achieve a satisfying balance between accuracy and diversity, and thus gain better comprehensive performance. And, the deep diversified method, although emphasizing more on diversity, can outperform traditional non-neural methods on recommendation accuracy. Particularly, IDSR performs the best in terms of comprehensive performance due to its relatively satisfactory results on both metrics; and (2) the performance of different approaches regarding accuracy, diversity and F-score varies across the four datasets, which will be detailed in the following subsections.

4.2 Accuracy-Diversity Relationship (RQ2)

Accuracy-Diversity Trade-off (Dilemma) [22, 18] refers to that the performance improvement on diversity can only be taken place at the expense of recommendation accuracy and vice versa. Inspired by the intuition, most of the diversified recommendation methods further design a trade-off hyper-parameter to combine relevance score (for accuracy) and diversification score, e.g., [14, 15, 21]. Particularly, IDSR clearly shows such kind of dilemma on accuracy and diversity (accuracy improves and simultaneously diversity decreases when $\lambda = 0.2 \rightarrow 0.5 \rightarrow 0.8$) as shown in Tables 4 and 7. However, we can also see that, although equipped with such trade-off design, IDSR fails to prove the trade-off relationship on Retailrocket and Tmall, where a lose-lose relationship can be found between diversity and accuracy in Table 5 ($\lambda = 0.5 \rightarrow 0.8$), and a win-win one is present in Table 6 ($\lambda = 0.2 \rightarrow 0.5$).

To further analyze, the win-win relationship can be obtained by properly mining user preferences. On a dataset where user preferences are more diversified, it is more likely to view the same-trend for both accuracy and diversity. In this case, blindly pursuing diversity will make accuracy deteriorate. On the contrary, recommendation accuracy can be maintained or even boosted if personalized diversity is reasonably considered [16]. For example, as shown in Tables 4-7, POP and S-POP always provide well-diversified recommendations due to popularity selection. By better fusing personalized user preference regarding every session, S-POP obtains much better accuracy while only sacrificing little performance on diversity compared to POP, thus achieving win-win compared with other traditional methods on Diginetica and Retailrocket.

In summary, the relationship between accuracy and diversity is quite complex and mixed. Besides the "trade-off" relationship, they might be positively correlated with each other, that is, possessing a same-trend (win-win or lose-lose). Such as the model design (like IDSR), characteristics of datasets (representing different domains/scenarios) might be probably another reason leading to varied observed relationship between diversity and accuracy.

Next, we seek to deeply explore the varied relationship from the inter- and intra-model views. From the inter-model view, as observed in Tables 4-7, besides the aforementioned same-trend cases, GRU4Rec gains better accuracy and diversity than FPMC and BPR-MF on Diginetica and Retailrocket, and so is the STAMP to SR-GNN. The trade-off relationship occurs more commonly, especially for deep neural methods with promising accuracy performance. With accuracy as the main objective, they often show the dilemma on increasing accuracy with the decrease of diversity, e.g., GCE-GNN ranks the first place in terms of accuracy but the last one on diversity. Besides, with regard to datasets, the same-trend relationship is more common for every model on Retailrocket. To dig more, we calculate the Pearson Correlation Coefficients among the seven adopted metrics by gathering all baselines' performance (@10) on each dataset. As presented in Figure 1, overall, the trade-off relationship is dominating between accuracy and diversity, as the correlation between every metric in accuracy group and diversity group is negative. However, the trade-off relationship is the weakest on Retailrocket (with smallest absolute values of negative coefficients), followed by the second weakest of Diginetica, compared to the other two datasets. This possibly explains why we can view more same-trend cases on Retailrocket and Diginetica.

From the intra-model view, for further analysis, we also calculate the Pearson Correlation Coefficient among the seven metrics (@10) regarding each baseline by gathering their performance in terms of every metric on the four datasets. The results are depicted in Figure 2, where the trade-off relationship is relatively weaker on BPR-MF, FPMC, GRU4Rec and IDSR ($\lambda = \{0.2, 0.5\}$) (with smaller absolute values of negative coefficients) compared to other baselines. On a finer granularity level, we further explore each method on every dataset (see Figure 39). We note that the relationship between accuracy and diversity regarding every method varies across different datasets, where the same-trend relationship (positive coefficients) also can be observed.

To sum up, from the inter- and intra-model perspectives, it is revealed that, besides the trade-off relationship, same-trend one does exist across different datasets and methods.

4.3 Influential Factors of Diversity (RQ3)

Based on the above analysis, we seek to further identify the possible influential factors, besides the complex model designs, that could improve diversity in SBRSs, with the goal of providing guidance towards better diversified SBRSs. In particular, we mainly discuss three factors: granularity of item categorization, session diversity of datasets, and length of recommendation lists.

 $^{^9}$ Here, we only show the results of FPMC and IDSR ($\lambda=0.5$) on three datasets, and other results are consistent with the conclusion.

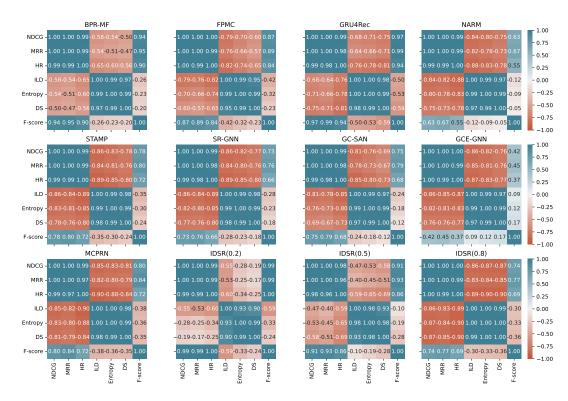


Figure 2: Pearson Correlation Coefficient of Metrics Regarding Different Baselines. Each value is calculated given two corresponding arrays by concatenating Top-10 performance of each baseline on all the datasets.

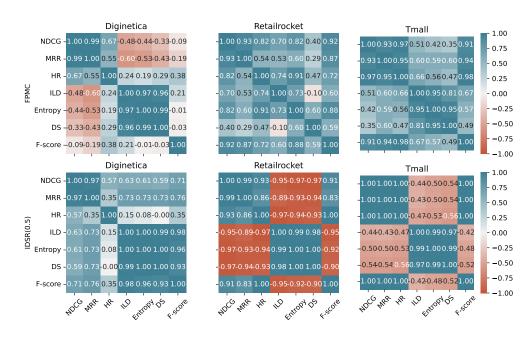


Figure 3: Pearson Correlation Coefficient of Metrics for Different Baselines on Every Dataset. Each value is calculated given two arrays by concatenating Top-10 performance (running 5 times) of each baseline on each dataset.

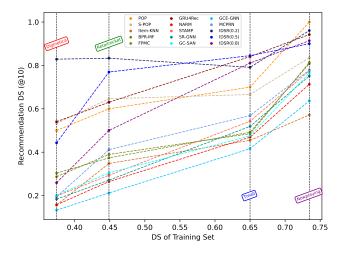


Figure 4: The Influence of Session Diversity of Datasets.

4.3.1 Granularity of Item Categorization

Most of the popular diversity metrics (e.g., ILD and Entropy) are calculated via item category information. In this view, towards the same Top-N recommendation list, higher diversity is inclined to be obtained on finer granularity of item categorization, that is, having a larger number of categories and more levels of hierarchy.

As shown in Table 1, the number of categories on Diginetica, Retailrocket, Tmall, and Nowplaying is 995, 944, 822, and 11,558 respectively. Meanwhile, as can be seen in Tables 4-7, the diversity performance gaps among baselines are decreasing as the number of categories increases across the four datasets (see Figure 4, and its explanation is deferred to Section 4.3.2). For example, w.r.t DS@10, the variance of all baselines is 0.0360 on Diginetica, but 0.0133 on Nowplaying. It implies that the improvement on the performance gap (w.r.t. DS@10) of worse-performing method (e.g., GCE-GNN) over that of better one (e.g., IDSR($\lambda=0.2$)) on Nowplaying (|0.6367-0.9608|=0.3241) compared to that on Diginetica (|0.1328-0.8127|=0.6799) is attributed to the finer-grained item category instead of the model design per se. Therefore, it should be kept alert that performance improvement of methods (measured via category-based diversity metrics) on finer-granularity scenario does not necessarily guarantee a better model, and user-perceived diversity [53] is recommended to be involved in diversified recommendation studies.

4.3.2 Session Diversity of Datasets

We plot the diversity performance (i.e., DS@10) of each baseline on every of the four datasets in Figure 4, where the x-axis represents DS of the corresponding dataset's training set. The DS of training set on Diginetica, Retailrocket, Tmall, and Nowplaying is 0.3741, 0.4488, 0.6500, and 0.7345 respectively, and a larger value means that user sessions are more diverse regarding corresponding training set. It should be noted that, since Diginetica, Retailrocket, and Tmall have similar number of categories, the aforementioned granularity level of item categorization on diversity performance can be conditionally ignored. From Figure 4, we can conclude that the diversity performance is positively correlated with the session diversity of input datasets, which is consistent across baselines. This suggests that a model inclines to generate more diversified recommendation for historically more diversified sessions. The results are quite similar to personalized diversity according to every historical session [40].

4.3.3 Length of Recommendation Lists

Figures 5(a)-5(c) plot the diversity performance of every baseline in terms of ILD, Entropy and DS respectively, regarding varied length of recommendation lists $(N = \{5, 20\})$.

First, we can see that from low diversity scenario (Diginetica) to high diversity one (Nowplaying), for every baseline, its diversity performance with regard to each diversity metric increases, further validating the positive correlation between diversity performance and session diversity of datasets (as discussed in Section 4.3.2). Second, when $N=10\to 20$, the diversity performance w.r.t. ILD (or Entropy) for every baseline is consistently increasing as depicted in Figure 5(a), whereas that regarding DS decreases in Figure 5(c). This implies that ILD (or Entropy) is positively associated with the length of the recommendation list N within a model, while that on DS is on the opposite, that is, negatively correlated

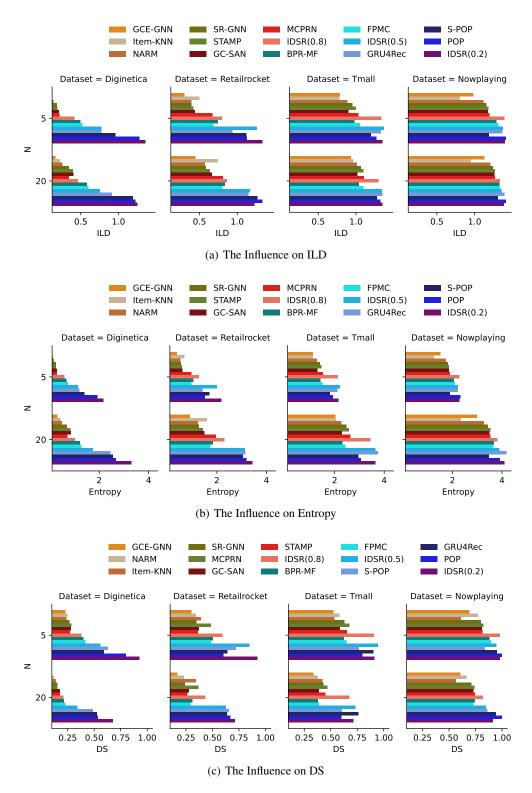


Figure 5: The Influence of Length of Recommendation Lists.

with N. This might be caused by, that when N increases, more unique categories are likely to occur and thus pair-wise diversity metric (ILD) and category distribution (Entropy) also tend to grow. However, DS removes the bias from length of recommendation list by dropping its effect (with appropriate design). In this case, DS will decrease if the increasing rate of new categories is lower than that of N.

In conclusion, ILD and Entropy suffers from the length bias of recommendation list, whereas DS moderately address this issue. Since in real scenarios, user sessions are mostly of different lengths, diversity metrics like DS are more suitable than those like ILD and Entropy for capturing diversity preference of variable-length sessions. That is to say, we may consider to design diversity-related objective aligned with DS-style metrics.

5 Conclusion

Towards better understanding on diversified recommendation, we have conducted extensive experiments to evaluate 15 state-of-the-art SBRSs with regard to accuracy, diversity and comprehensive performance on four representative datasets. Our experimental findings show that, for accuracy, deep neural methods perform significantly better than traditional non-neural methods, where GCE-GNN ranks the first place. For diversity, IDSR performs consistently well, proving the effectiveness of its diversity module. Meanwhile, non-diversified methods, POP, S-POP and GRU4Rec also gain satisfying performance w.r.t. diversity metrics, implying that non-diversified methods can still maintain a promising diversity performance. Our empirical analysis also unveil that the relationship between accuracy and diversity is quite complex and mixed. Besides the "trade-off" relationship, they might be positively correlated with each other, that is, having a same-trend (win-win or lose-lose) relationship, which does exist across different methods and datasets. We have also identified three possible influential factors, besides the complex model design, that can be capable of improving diversity in SBRSs: granularity of item categorization, session diversity of datasets, and length of recommendation lists. We further offer an intuitive idea for better model-designs based on the relationships of item embeddings of different categories.

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