

# Session-aware Recommendation: A Surprising Quest for the State-of-the-art

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## Abstract

Recommender systems are designed to help users in situations of information overload. In recent years, we observed increased interest in session-based recommendation scenarios, where the problem is to make item suggestions to users based only on interactions observed in an ongoing session. However, in cases where interactions from previous user sessions are available, the recommendations can be personalized according to the users' long-term preferences, a process called *session-aware* recommendation. Today, research in this area is scattered and many existing works only compare *session-aware* with *session-based* models. This makes it challenging to understand what represents the state-of-the-art. To close this research gap, we benchmarked recent session-aware algorithms against each other and against a number of session-based recommendation algorithms and trivial extensions thereof. Our comparison, to some surprise, revealed that (i) simple techniques based on nearest neighbors consistently outperform recent neural techniques and that (ii) session-aware models were mostly not better than approaches that do not use long-term preference information. Our work therefore not only points to potential methodological issues where new methods are compared to weak baselines, but also indicates that there remains a huge potential for more sophisticated session-aware recommendation algorithms.

*Keywords:*

Session-aware Recommendation, Evaluation, Reproducibility

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## 1. Introduction

Recommender systems (RS) are used on many modern e-commerce and media streaming sites, where they are a proven means to help users find items of interest in situations of information overload. One reason for the success of RS lies in their ability to *personalize* the item suggestions based on the preferences and observed past behavior of the individual users. Historically, researchers have therefore strongly focused on situations where information about the long-term preferences of users is available, e.g., in the form of item ratings. Only in recent years, more focus was put on the problem of *session-based* recommendation, where the system has to deal with anonymous users and has to base its recommendations only on a small number of observed interactions in an ongoing session.

Due to the practical relevance of this problem, a variety of technical approaches to session-based recommendation were proposed in the past few years, in particular ones based on deep learning (neural) techniques<sup>1</sup>. Implicitly, these methods try to make recommendations by guessing the user's short-term intent or situational context only from the currently observed

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<sup>1</sup>See [26] for a comparison of such approaches.

interactions. However, while it is well known that the current intents and context may strongly determine which items are relevant in the given situation [2, 18], information about long-term preferences of users, if available, should not be ignored. In particular, the consideration of such information allows us to make *personalized* session-based recommendations, a process which is also called *session-aware* recommendation [32].

Session-aware recommendation problems are recently receiving increased interest. Today, the research literature is however still scattered, which makes it difficult to understand what represents the state-of-the-art in the field. One particular problem in that context is that existing works do not use a consistent set of baseline algorithms in their performance comparisons. Some works, for example, mainly compare *session-aware* models with *session-based* ones, i.e., with algorithms that do not consider long-term preference information, e.g., GRU4Rec [13]. Several other works use *sequential* recommendation algorithms, e.g., FOSSIL [11], as a baseline. These are algorithms that consider the sequence of the events, but are usually designed for settings where the input is a time-stamped user-item rating matrix and not a sequential log of observed interactions. Only in a few works, previous session-aware algorithms are considered in the evaluations. One example is the method by [31], which uses the HGRU method by [33] as a baseline. Finally, almost all works include some trivial baselines, e.g., the recommendation of popular items in a session.

With this work, our goal is to close the research gap regarding the state-of-the-art in session-aware recommendation. For this purpose, we have conducted extensive experimental evaluations in which we compared five recent neural models for *session-aware* recommendation with (i) a set of existing neural and non-neural approaches to *session-based* recommendation, and (ii) trivial extensions of the session-based techniques that, e.g., make use of reminders [18] or consider interactions happening immediately before the ongoing session. Regarding the baseline techniques, we in particular considered methods based on nearest neighbors techniques, which previously proved to be very competitive in session-based recommendation scenarios [27]. All investigated techniques were compared by extending the evaluation framework shared in [25]. For reproducibility purposes, we share all data and code used in the experiments online<sup>2</sup>, including the code for data preprocessing, hyperparameter optimization, and measuring.

The results of our investigations are more than surprising. In the majority of cases, and on all three datasets, trivial extensions of existing *session-based* algorithms were the best-performing techniques. In many cases, even plain session-based techniques, and in particular ones based on nearest-neighbor techniques, outperform recent session-aware models even though they do not consider the available long-term preference information for personalization. With our work, we therefore provide new baselines that should be considered in future works on session-aware recommendation. On a more general level, these observations also point to potential methodological issues, where new models are compared to baselines that are either not properly optimized or too weak for the given task. Similar observations were previously made in the field of information retrieval, e.g., [3, 48] and in recommender systems [36, 7].

On a more positive note, our evaluations suggest that there is a huge potential to be tapped by more sophisticated (neural) algorithms that combine short-term and long-term preference signals for session-aware recommendation. An important prerequisite for progress in this area however lies in an increased level of reproducibility of published research. A side observation of our research is that despite some positive developments in recent years, where researchers increasingly share their code on public repositories, it in many cases still remains challenging to reproduce existing works.

The paper is organized as follows. In Section 2, we discuss relevant previous works Section 3 describes our research methodology in more detail with respect to the compared algorithms,

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<sup>2</sup><https://www.dropbox.com/sh/h3dr9ejum0piw6/AACJbrVydQJORMR0necKnNTNa?dl=0>

evaluation protocol, and performance measures. The results of our experiments are reported in Section 4. The paper ends with an outlook on future works.

## 2. Previous Work

Historically, recommender systems research focused strongly on the problem of rating prediction given a user-item rating matrix, a setting which is also known as the “matrix completion” problem [37]. In this original collaborative filtering problem setting, the order of the ratings or the time when they were provided were not considered in the algorithms. Soon, however, it turned out that these aspects can matter, leading to the development of *time-aware* recommender systems [5], e.g., in the form of the *timeSVD++* algorithm as used in the Netflix Prize [21].

Ten years after the Netflix Prize, the focus of research has mostly shifted from rating prediction to settings where only implicit feedback signals by users (e.g., purchase or item-view events) are available. Moreover, instead of considering the user-item matrix as the main input, recent research more often focuses on settings where the main input to a recommendation algorithm are time-ordered logs of recorded user interactions. The family of approaches that relies on such types of inputs are referred to as *sequence-aware* recommender systems [32].

Within this class of sequence-aware recommender systems, we can differentiate between three main categories of problem settings and algorithmic approaches.

- *Sequential Recommender Systems*: Unlike the other types of sequence-aware approaches discussed here, these systems are rooted in the tradition of relying on a user-item rating matrix as an input. The particularity here is that the sequence of events is extracted from such a matrix, and the goal usually is to predict the next user action (e.g., the next POI that a user will visit), given the entire preference profile of the user.
- *Session-based Recommender Systems*: The input to these systems are time-ordered logs of recorded user interactions, where the interactions are grouped into *sessions*. Such a session could, for example, correspond to a listening session on a music service, or a shopping session on an e-commerce site. One particularity of such approaches is that users are anonymous, which is a common problem on websites that deal with first-time users or users that are not logged in. The prediction task in this setting is to predict the next user action, given only the interactions of the ongoing session. Today, session-based recommendation is a highly active research area due to its practical relevance.
- *Session-aware Recommender Systems*: This category is also referred to as *personalized session-based recommender systems*. It is identical to session-based recommendation in that the user actions are grouped into session. Also the prediction goal is identical. However, in this problem setting, users are not anonymous, i.e., one can also leverage information about past user sessions when predicting the next interaction for the current session.

Unfortunately, the terminology in the literature is not entirely consistent. In this work, we will therefore use the categorization and terminology as described above to avoid confusion. Next, we review the main technical approaches in each category.

*Sequential Recommendation Approaches*. Early and comparably simple approaches in this category were based on Markov models, e.g., [29]. Later on, more sophisticated approaches emerged which, for example, combined the advantages of matrix factorization techniques with sequence modeling approaches. Rendle et al. [35], for example, proposed the Factorized Personalized

Markov Chain (FPMC) approach as an early method for next-item recommendations in e-commerce settings, where user interactions are represented as a three dimensional tensor (user, current item, next-item). Kabbur et al. [19] later proposed FISM, a method based on an item-item factorization. FISM was later combined with factorized Markov chains to incorporate sequential information into the FOSSIL model [10].

In recent years, several sequential recommender systems based on neural networks were developed. Kang and McAuley [20], for example, proposed SASREC (self-attention based sequential model), a method that allows to capture long-term semantics like an RNN, but, using an attention mechanism, makes its predictions based on relatively few actions (like Markov Chain approaches). Most recently, Sun et al. [41] proposed BERT4REC, which employs a deep bidirectional self-attention mechanism to model user behavior sequences. In the CASER method, finally, Tang and Wang [43] embed a sequence of recent items into latent spaces as an “image” in time and learn sequential patterns as local features of the image using convolutional filters.

In this present work, we do not consider this class of algorithms in our performance comparison, because these methods, in their original designs, do not consider the concept of a session in the input data. While it is in principle possible to apply these methods in a particular way for session-based recommendation problems, a previous evaluation shows that sequential approaches are often not competitive with techniques that were specifically designed for the problem setting. Specifically, the evaluation presented in [25] included a number of sequential approaches, namely FPMC, MC, SMF, BPR-MF, FISM, and FOSSIL.<sup>3</sup> Their findings showed that *(i)* these approaches either are generally not competitive in this setting or only lead to competitive results in a few specific cases and *(ii)* that nearest neighbor recommenders outperform them in terms of prediction accuracy.

*Session-based Recommendation Approaches.* While there exist some earlier works on session-based recommendation, e.g., in the context of website navigation support and e-commerce [28, 40], research on this topic started to considerably grow only in the mid-2010s. These developments were particularly spurred by the release of datasets in the context of machine learning competitions, e.g., at ACM RecSys 2015. At around the same time, deep learning methods were increasingly applied for recommendation problems in general. One of the first deep learning approaches to session-based recommendation was GRU4REC [13], which is based on Recurrent Neural Networks. Later on, various other types of neural architectures were explored, including attention mechanisms [23, 24], convolutional neural networks [50], graph neural networks [46] or hybrid architectures, e.g., [44].

Recent work however indicates that in many cases much simpler methods can achieve similar or even higher performance levels than today’s deep learning models. Most recently, Ludewig et al. [27] benchmarked several of the mentioned neural methods against session-based algorithms that, for example, rely on nearest-neighbor techniques. Quite interestingly, their analyses and similar previous works [8, 25] not only show the strong performance of conceptually simple techniques, but also revealed that two of the earlier neural methods, GRU4REC and NARM, often perform better than more recent complex techniques. In the performance comparison in this present work on session-aware recommendation, we include several techniques for session-based recommendation as baselines. This allows us to assess the added value of considering long-term preference information compared to a situation where such information is not available or leveraged.

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<sup>3</sup>[13], FPMC: Factorized Personalized Markov Chains [35], MC: Markov Chains [29], SMF: Session-based Matrix Factorization [25], BPR-MF: Bayesian Personalized Ranking [34], FISM: Factored Item Similarity Models [19], FOSSIL: FactOried Sequential Prediction with Item SIMilarity ModeLs [10].

*Session-aware Recommendation Approaches.* The literature on session-aware recommendation is still quite sparse. An early approach is discussed in [18]. One main goal of their work was to understand the relative importance of short-term user intents when visiting an e-commerce site compared to the long-term preference model. Their analyses, which were based on a large but private e-commerce dataset, emphasized the importance of considering the most recent observed user behavior when recommending. Furthermore, it also turned out that *reminding* users of items that they have viewed before can be beneficial, both in terms of accuracy measures and business metrics.

While the work in [18] relied on deep learning for the final predictions in one of their models, the core of the proposed technical approach was based on feature engineering and the use of side information about the items to recommend. One of the earliest “pure” deep learning techniques for session-aware recommendation was proposed by [33]. Technically, the authors base their work on GRU4REC, and they use an additional GRU layer to model information across sessions, resulting in a model called HGRU4REC. Their analyses show that incorporating long-term preferences in that way can be favorable, i.e., HGRU4REC was outperforming an early version of GRU4REC in their experiments.

In the same year, Ruocco et al. [38] proposed the IIRNN model. Like HGRU4REC, this model uses an RNN architecture and extends a session-based technique to model inter-session and intra-session information. Like in the case of HGRU4REC, the authors investigate the value of considering long-term preference information by comparing their method to session-based techniques. RNNs were later on also used in the NSAR model [30] to encode session patterns in combination with user embeddings to represent long-term user preferences across sessions. In their experiments, the authors not only compare their model to session-based techniques, but also to HGRU4REC as a representative of a session-aware approach.

A number of neural architectures other than RNNs were proposed in recent years. Hu et al. [15], for example, combine the inter-session and intra-session context with a joint context encoder for item prediction in the NCSF approach. In the SHAN model [49], in contrast, the authors leverage a two-layer hierarchical attention network to model short-term and long-term users’ interests. In the SWIWO [14] approach, the authors apply language modeling techniques to recommender systems. The main idea is that items can be seen as words, hence, predicting a relevant word based on context is equivalent to recommending a relevant item according to the current session. Finally, Cai and Hu [4] proposed the SAMR method, which leverages a topic-based probabilistic model to define the users’ listening behavior.

In our present work, we benchmark five of these recent session-aware methods with session-based techniques and extensions thereof. Unlike most previous works, which compare a newly-proposed session-aware model with previous session-based ones, our work allows us to compare session-aware methods against each other. We describe our research methodology next.

### 3. Research Methodology

In this section, we describe which algorithms we selected for inclusion in our comparison and we provide details about the experimental configuration in terms of the evaluation protocol and the used datasets. As mentioned, all datasets and code used in the experiments are shared online to ensure reproducibility.

#### 3.1. Compared Algorithms

In our experiments, we compare neural session-aware algorithms with a number of baselines. Details about the algorithms are provided next.

### 3.1.1. Neural Session-Aware Algorithms

We identified five recent neural approaches that we included in our comparison: HGRU4REC, IIRNN, SHAN, NCSF and NSAR.

- HGRU4REC: This method [33] is based on the GRU4REC algorithm. To model the interactions of a user within a session, it utilizes RNNs based on a single GRU layer. By adding an extra GRU layer, it models information across user sessions.
- IIRNN: This method [38] extends an RNN session-based recommender, called intra-session RNN, by using a second RNN that is called inter-session RNN. The intra-session RNN is the same as in the GRU4REC model. The inter-session RNN learns from the user’s recent sessions and feeds the information to the intra-session RNN: at the beginning of every session, the final output of the inter-session RNN initializes the hidden state of the intra-session RNN.
- SHAN: This model [49] uses a two-layer hierarchical attention network to learn a hybrid representation for each user that combines the long-term and short-term preferences. It first embeds sparse user and item inputs into low-dimensional dense vectors. The long-term user representation is a weighted sum over the embeddings of items in the long-term item set. By learning the weights, the first attention layer learns user long-term preferences. The second attention layer outputs the final user representation by combining user long-term and the embeddings of items in the short-term item set.
- NCSF: This session-aware neural method [15] includes three parts: (i) the historical session encoder to represent the inter-session context, (ii) the current session encoder to represent the intra-session context, and (iii) the joint context encoder to integrate the information of the intra-session context and the inter-session context for item prediction.
- NSAR: This method [31] utilizes RNNs to encode session patterns (short-term user preferences) and user embeddings to represent long-term user preferences across sessions. It integrates user long-term preferences with session patterns using different strategies. User embeddings can be integrated with either input or output of the session RNNs. Moreover, with the help of a gating mechanism, the contribution of each component can be fixed or adaptive.

To avoid a bias in the algorithm selection, we applied the following procedure to identify algorithms for inclusion in our experiments. An initial set of candidate works was retrieved through a search on Google Scholar using search terms like “session-aware recommendation” or “personalized session-based recommendation”. We then inspected the returned results to see if the papers fulfilled our inclusion criteria. Besides being actually a work on session-aware recommendation according to the above definition, we required that the source code of the method was publicly available and could be integrated into our Python-based evaluation framework<sup>4</sup>. Moreover, we only considered papers that had undergone a peer review process, i.e., we did not include non-reviewed preprints. Finally, only works were included that did not consider side information, e.g., about the items. As a result of this last constraint, we did not include recent works like proposed by [42] for the domain of news recommendation.

In Table 3.1.1, we show to which baselines the selected neural approaches were compared in their original publications. Note that in this table only the last two rows, HGRU4REC and SWIWO represent session-aware techniques. Our analysis furthermore shows that researchers use

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<sup>4</sup>The methods proposed in [4] and [14] were for example not considered because their implementation was not based on Python.

a variety of baselines in their experiments, which contributes to the difficulty of understanding what represents the state of the art.

### 3.1.2. Neural and Non-Neural Session-based Baselines

We selected the baselines according to the results of [27]. Note that while GRU4REC and NARM are not the most recent neural methods, the analysis in [27] showed that they are highly competitive among the neural models for different datasets.

- GRU4REC: This neural model [13] employs RNNs based on Gated Recurrent Units (GRU) [6] for the session-based recommendation task. It introduces several modifications, including a ranking loss function, to classic RNNs to adapt it for the recommendation task in the session-based setting. By improving the loss function and applying further refinements, the authors later improved the model [12]. We include the latest version of GRU4REC in our experiments.
- NARM: This model [23] extends GRU4REC. It utilizes a hybrid encoder with an attention mechanism to model the sequential behavior of users and capture their main purpose in the ongoing session. The combination of them represents the session. A bi-linear matching scheme computes the recommendation scores of each candidate item based on this unified session representation.
- SR: The “Sequential Rules” method, proposed in [25], extends the simple “Association Rules” technique and counts pairwise item co-occurrences in the training sessions. It considers the order of the items in a session as well as the distance between them while scoring items to make the recommendation list.
- VSKNN: This nearest-neighbor baseline for session-based recommendation was proposed in [25], and it is based on the SKNN method [17]. It first finds past sessions that contain the same items as the current session. The recommendation list is then generated with ranked items of the most similar sessions. This method considers the order of the items while computing both session similarities and item scores. Moreover, it applies the Inverse-Document-Frequency (IDF) weighting scheme to emphasize on less popular items.
- STAN: The “Sequence and Time Aware Neighborhood” method is proposed in [8]. It improves SKNN by considering three additional factors for making recommendations: (i) the recency of an item in the current session, (ii) the recency of a past session w.r.t. the current session, and (iii) the distance of a recommendable item w.r.t. a shared item in the neighboring session.
- VSTAN: This nearest-neighbor session-based recommendation algorithm combines all the extensions to SKNN from STAN and VSKNN in a single approach; proposed in [27].

### 3.1.3. Extensions of Session-based Baselines

We experimented with three simple ways of extending session-based algorithms in a way that they consider past preference information, when available.

- EXTEND – *Extending the current session with recent interactions*: In case there is little information available about the ongoing session, e.g., when only a few first clicks are recorded, we extend the current session with interactions that we observed in the previous sessions of the user.

Table 1: Overview of the baseline techniques that each neural session-aware approach was originally compared to. The methods are ordered chronologically by the date of publication. The marks (✗) indicate which baselines were used in the comparison.

	Method				
	HGRU4REC	IIRNN	SHAN	NCSF	NSAR
MR		✗			
POP		✗	✗	✗	
PPOP	✗				
IKNN	✗	✗		✗	
BPR-MF		✗	✗		✗
FPMC			✗	✗	
FOSSIL			✗		
GRU4REC	✗	✗		✗	✗
GRU4REC2				✗	✗
BPR-GRU4REC2					✗
HRM			✗		
CASER					✗
HGRU4REC					✗
SWIWO				✗	

MR: most recent interacted item; POP: most popular item in the dataset; PPOP: most popular item for the user; IKNN: Item-based kNN [13]; BPR-MF: Bayesian Personalized Ranking [34]; FPMC: Factorized Personalized Markov Chains [35]; FOSSIL: FactOried Sequential Prediction with Item SIilarity ModeLs [10]; GRU4REC: [13]; GRU4REC2: the improved version of the GRU4REC model [12]; HRM: Hierarchical Representation Model [45]; CASER: Convolutional Sequence Embedding Recommendation Model [43]; BPR-GRU4REC2: a baseline proposed in [31] that merges the rankings returned by BPR-MF and GRU4REC2 following the proposed framework in [16] for session-aware setting; HGRU4REC: [33]; SWIWO: [14].



- **BOOST** – *Emphasizing previously seen items*: In some domains, repeated interactions with already seen or consumed items is not uncommon. We apply a simple “boosting” approach to slightly increase the scores computed by an underlying algorithm, when an item has appeared previously in the interaction history.
- **REMIN**D – *Applying reminding techniques*: In [18], the authors proposed more sophisticated “reminder” techniques to emphasize items the user has seen before. We considered two strategies that were inspired by [18] in our evaluations.

**EXTEND**. We implemented the following specific strategy. First, we choose a value for the “desired session length”  $d$ , which is a hyperparameter to be determined on the validation set. In case an ongoing session has fewer interactions than  $d$ , we extend the current session with previous interactions from the same user until the session length  $d$  is reached or no more previous interactions exist. The extension is done by simply prepending the elements of previous interactions to the current session in the order they appeared in the log.

**BOOST**. This simple approach in principle can be applied to any algorithm that returns scores. Methods like SR and VSKNN, for example, return scores as described in [25] based on item co-occurrences and the positions of the co-occurring items. In our experiments, we used a hyperparameter  $b$  as a boost factor. Technically, we look up each item that is recommended by the underlying method and check if it occurred in the interaction history of the current user at least once. In case the item appeared previously in the history, we increase the original score by  $b$  %.

**REMIN**D. Different reminding strategies were proposed in [18]. Here, we tested two alternative ways to select items to consider as reminders. More complex variations are possible, but in the context of this work we are mainly interested if reminders are helpful in general in our experiment setup.

The most trivial selection strategy for reminders is based on *interaction recency*, i.e., we consider the last few items before the current session and sort them by timestamp in decreasing order, i.e., the most recent item comes first. Duplicates are removed from the list. An alternative approach proposed in [18] is based on *session similarity*. Here, we first look for past sessions of the current user that are most similar to the current one. We collect items from those past similar sessions until a defined threshold and then sort the items by *interaction frequency*, i.e., how often we observed each item in past few sessions of the user. The choice of the selection strategy and the number of previous or similar sessions to consider are hyperparameters to tune.

After having created the list of potential reminders, we retain only the first  $r$  elements, which is again a hyperparameter. These  $r$  elements are then combined with the top- $n$  elements returned by the underlying method by substituting the last  $r$  elements of the top- $n$  list with the reminders. Other, more elaborate techniques, as described in [18], are of course possible.

### 3.2. Datasets

We conducted our evaluations using public datasets from three different domains: e-commerce, music, and social media.

- **RETAIL**: A dataset published by the e-commerce personalization company *Retail Rocket*. It covers user interactions with a real-world e-commerce website for 4.5 months.
- **LASTFM**: A music dataset that contains the entire listening history of almost 1,000 users over around five years. The dataset was retrieved from the online music service *Last.fm*<sup>5</sup>.

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<sup>5</sup><https://www.last.fm/>

- *XING*: A dataset published in the context of the ACM RecSys 2016 Challenge that contains interactions of job postings on career-oriented social networking site *XING* for about three months. It contains a fraction of *XING* users and job postings, and the data is enriched with artificial users for privacy reasons. The interactions include four types of actions: *click*, *bookmark*, *reply*, and *delete*. We filtered out all interactions of type *delete* from the dataset for our evaluation, as done in [33], because they are considered as negative interactions.

For each dataset, we first partitioned the log into sessions by applying a commonly used 30-minute user inactivity threshold. We kept multiple interactions with the same item in one session because repeated recommendations can help as reminders [18, 22]. Many previous works on session-aware recommendation use a single training-test split of the whole dataset or a sample of it for evaluation. Evaluating on only one split of data is risky because of possible random effects. We therefore split each dataset into five contiguous subsets by time and averaged the results across slices as done in [27]. Moreover, to have about the same number of events for each dataset, we skipped the first 500 days of the LASTFM dataset.

Following common practice in the field, we then further pre-processed each slice as follows. We first removed items with less than five interactions in the slice. Then, we removed sessions that contain only one event. For the LASTFM dataset, we also removed sessions with more than 20 events<sup>6</sup>. Finally, we filtered out users with less than three sessions. Table 2 shows the average characteristics of the slices for each dataset after the pre-processing phase.

Table 2: Characteristics of the datasets. The values are averaged over all five slices.

	Events	Users	Sessions	Items	Sessions per User	Actions per Session
RETAIL	45,378	1,400	7,198	10,424	5.15	6.28
XING	333,625	13,533	59,318	61,006	4.38	5.62
LASTFM	750,276	658	94,818	107,134	144.61	7.92

### 3.3. Evaluation Protocol and Metrics

*Creation of Training, Validation, and Test Splits.* Since we are given user-IDs for the sessions, we are able to apply a user-wise data splitting approach. Specifically, like in [31, 33, 30, 9, 47], we use the last session of each user as test data. The second-to-last session is used as validation data to tune the parameters in our experiments, see also [31, 47, 30]. The remaining sessions are considered as training data. This splitting approach provides the advantage of assessing the performance for users with different numbers of sessions in their history. We finally filter out the items from validation and test sets of each five slices that did not appear in the training set of that slice.

*Target Item Selection.* We apply the procedure that is commonly used also in session-based recommendation, e.g., in [13] and many other works. Specifically, we iteratively reveal each item after the other in the test session and do the evaluation after each item. We apply this approach as it reflects the most realistic user behavior in a session. Following previous works [25, 26, 27], we consider two evaluation scenarios. In one case, we only consider the immediate next item in the test session as a ground truth. In the other, more realistic case, all upcoming items in the test session are considered as relevant items.

<sup>6</sup>The dataset contains a number of very long sessions with dozens of listening events, and the probability that users *actively* listened to tracks for many hours seems low. Therefore, we only considered the first 20 elements, which corresponds to a listening session about 1.5 hours for the case of pop music, see also [30, 38] for similar approaches.

*Accuracy Metrics.* We use standard classification and ranking measures to evaluate the accuracy performance of the recommendation algorithms. We measure the performance in two different ways, as done in [27], according to the target item selection approach. First, when we consider only the immediate next item as the target item, the used corresponding metrics are the Hit Rate (HR) and Mean Reciprocal Rank (MRR). Second, when all items of the current session are assumed to be relevant to the user, we consider all the remaining items of an ongoing session as the target item. The used accuracy metrics are Precision, Recall, and Mean Average Precision (MAP).

*Coverage and Popularity Bias Metrics.* It is well known that factors other than accuracy can effect the performance of a recommendation algorithm in practice [39]. In this work, we consider *coverage* and the tendency of an algorithm to focus on popular items (*popularity bias*) as relevant factors. *Coverage* tells us how many items actually ever appear in the top-n lists of users. This measure, which is also known as “aggregate diversity” [1], gives us some indication how strongly personalized the recommendations of an algorithm are. A strong popularity bias, on the other hand, indicates that an algorithm is not focusing much on the long-tail of the item catalog, which can be desirable in practice. We calculated the *popularity bias* as done in [25]. Specifically, we average the popularity scores of all recommended items. These popularity scores are computed by counting how often each item appears in the training set. To bound their values between 0 and 1, we applied min-max normalization.

*Hyperparameter Optimization.* To obtain reliable results, we systematically and automatically tuned all hyperparameters for each algorithm and dataset. Technically, we applied a random hyperparameter optimization procedure with 100 iterations to optimize MRR@20 as done, e.g., in [25]<sup>7</sup>. For NARM, we however only ran 50 iterations as this method has a smaller set of hyperparameters. For SHAN, we only ran 9 hyperparameter configurations since they cover all possible value combinations according to the original paper<sup>8</sup>. For each dataset, we used the slice with the most number of events to tune hyperparameters.

## 4. Results

Table 3, Table 4 and Table 5 show the results of our performance comparison of neural and non-neural methods, ordered by the values obtained for the MAP@20 metric. Here, we correspondingly report the values obtained by applying a cut-off threshold of 20. We performed additional experiments using alternative cut-off lengths (5 and 10). The rankings of the algorithms for those other cut-off values were generally in line with those observed at list length 20. Non-neural methods are highlighted with a light gray background in the tables. Neural session-*based* methods have a gray background. Session-*aware* techniques finally have a dark gray background.

Note that we do not report all possible combinations of the proposed extensions discussed in Section 3.1.3 for the sake of conciseness.

- EXTEND and BOOST: We only report the combined effects of these extensions, and we denote the extended method by appending the postfix “\_EB” (extend and boost) to the algorithm name, e.g., VSKNN\_EB. The reason is that the effectiveness of the individual extensions varied across algorithms, but combining the methods in almost all cases led to

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<sup>7</sup>We also tried MAP@20 as the optimization target for some approaches, but this did not lead to a different ranking of the algorithms in terms of accuracy.

<sup>8</sup>We unsuccessfully contacted the authors regarding the hyperparameter spaces.

the highest performance improvements<sup>9</sup>. For the neural methods, GRU4REC and NARM, these extensions did not lead to positive effects in our initial experiments, which is why we do not report the results here.

- Extensions for neighborhood-based methods: We only report the results when extending VSKNN as a representative, because this method is usually performing very well. For the alternative neighborhood-based methods, STAN and VSTAN, the results are similar, i.e., the extensions lead to slight increases in accuracy.
- We denote algorithm variants that were extended with the reminder technique with the postfix “\_REMINDER”. Note that it is not meaningful to incorporate the reminder extensions to *session-aware* methods, as these models should already be able to implicitly leverage the long-term preference information.

In Table 3 to Table 5, the highest obtained values per dataset are printed in bold. Note that in our analysis we focus on the performance comparison between non-neural methods and neural session-aware recommendation techniques. Therefore, we underline the highest value that is obtained by the other family of algorithms. Stars indicate significant differences ( $p < 0.05$ ) according to a Kruskal–Wallis test between all the models and a Wilcoxon signed-rank test between the best-performing techniques from either category (non-neural or neural session-aware recommendation methods).

Table 3: Results of the performance comparison on the RETAIL dataset with the focus on the comparison between **simple (non-neural)** methods and **session-aware** ones. The best results for each metric are highlighted in bold font. The next best results for algorithms from the other category (either simple methods or session-aware ones) are underlined. Non-neural methods are highlighted in light gray, session-based ones in gray and session-aware ones in dark gray.

Metrics	MAP@20	P@20	R@20	HR@20	MRR@20	COV@20	POP@20
RETAIL							
VSKNN_EB_REMINDER	<b>*0.0338</b>	<b>0.0749</b>	<b>*0.5109</b>	<b>*0.6955</b>	0.4172	<b>*0.8647</b>	0.0549
VSKNN_EB	0.0331	0.0723	0.4976	0.6831	0.4164	0.8517	0.0537
VSKNN_REMINDER	0.0323	0.0726	0.5004	0.6858	0.4186	0.8423	0.0484
STAN	0.0311	0.0680	0.4837	0.6747	<b>*0.4411</b>	0.7818	0.0582
VSTAN	0.0310	0.0675	0.4825	0.6745	0.4397	0.7947	0.0580
VSKNN	0.0303	0.0669	0.4646	0.6476	0.4164	0.8055	<u>0.0469</u>
GRU4REC_REMINDER	0.0296	0.0658	0.4831	0.6686	0.4224	0.9141	0.0416
NARM_REMINDER	0.0281	0.0635	0.4626	0.6249	0.3560	0.7800	0.0609
GRU4REC	0.0272	0.0576	0.4367	0.6172	0.4196	0.9059	0.0394
SR_REMINDER	0.0258	0.0596	0.4373	0.5900	0.3349	0.7829	0.0543
SR_B_REMINDER	0.0258	0.0596	0.4371	0.5899	0.3441	0.7777	0.0538
NARM	0.0252	0.0542	0.4086	0.5650	0.3566	0.7620	0.0622
IIRNN	<u>0.0239</u>	<u>0.0524</u>	<u>0.3775</u>	0.5108	0.3190	<u>0.7709</u>	0.0689
HGRU4REC	0.0226	0.0485	0.3681	<u>0.5165</u>	<u>0.3296</u>	0.7502	<b>0.0425</b>
NCSF	0.0217	0.0468	0.3625	0.5042	0.3120	0.6871	0.0967
SR	0.0213	0.0460	0.3477	0.4847	0.3265	0.7186	0.0528
SR_B	0.0213	0.0458	0.3467	0.4833	0.3356	0.7125	0.0522
SHAN	0.0205	0.0451	0.3448	0.4498	0.2673	0.3406	0.1276
NSAR	0.0169	0.0370	0.2830	0.3702	0.2160	0.5813	0.0671

<sup>9</sup>Note that for the SR method, only boosting was applied, because extending the session is not applicable for this algorithm which by design only considers the last interaction in a session.

Table 4: Results of the performance comparison on the LASTFM dataset with the focus on the comparison between **simple (non-neural)** methods and **session-aware** ones. The best results for each metric are highlighted in bold font. The next best results for algorithms from the other category (either simple methods or session-aware ones) are underlined. Non-neural methods are highlighted in light gray, **session-based** ones in gray and **session-aware** ones in dark gray.

Metrics	MAP@20	P@20	R@20	HR@20	MRR@20	COV@20	POP@20
LASTFM							
VSKNN_EB_REMINDER	<b>*0.0494</b>	<b>*0.1013</b>	<b>*0.4297</b>	<b>*0.5423</b>	0.1773	0.4935	0.0504
VSKNN_EB	0.0493	<b>*0.1003</b>	0.4248	0.5383	0.1771	0.5053	0.0499
VSKNN_REMINDER	0.0479	0.0983	0.4186	0.5316	0.1730	0.4972	0.0487
VSKNN	0.0474	0.0964	0.4104	0.5227	0.1725	0.5091	<u>0.0479</u>
STAN	0.0400	0.0856	0.3760	0.5012	0.1886	0.5067	0.0557
VSTAN	0.0394	0.0852	0.3791	0.5100	0.1935	<u>0.5115</u>	0.0555
SR_B_REMINDER	0.0361	0.0804	0.3532	0.4772	<b>0.3496</b>	0.4654	0.0556
SR_B	0.0359	0.0778	0.3408	0.4622	0.3487	0.5010	0.0549
SR	0.0348	0.0765	0.3383	0.4615	0.3350	0.4982	0.0544
SR_REMINDER	0.0345	0.0781	0.3470	0.4738	0.3359	0.4656	0.0553
IIRNN	<u>0.0311</u>	<u>0.0724</u>	<u>0.3270</u>	<u>0.4729</u>	<u>0.3491</u>	0.4443	0.0732
GRU4REC	0.0307	0.0701	0.3175	0.4681	0.3342	0.5124	0.0468
GRU4REC_REMINDER	0.0306	0.0724	0.3271	0.4768	0.3345	0.4614	0.0495
NSAR	0.0280	0.0675	0.3044	0.4350	0.2906	0.4937	0.0483
NARM_REMINDER	0.0274	0.0675	0.3084	0.4594	0.3189	0.4557	0.0627
NARM	0.0272	0.0658	0.3002	0.4510	0.3192	0.4748	0.0633
NCSF	0.0219	0.0556	0.2639	0.4393	0.2434	0.4875	0.0712
HGRU4REC	0.0208	0.0517	0.2464	0.4206	0.3167	<b>*0.5647</b>	<b>0.0404</b>
SHAN	0.0072	0.0223	0.0920	0.1149	0.0345	0.0824	0.1640

#### 4.1. Accuracy Results

We can summarize the accuracy results for the individual datasets as follows.

*RETAIL*. Quite surprisingly, simple nearest-neighbor recommenders win on all the accuracy measures on this dataset, with VSKNN and STAN being the best-performing methods. Moreover, the simple extensions of the session-based algorithms further improve their accuracy performance in most cases.

Probably even more surprising is that we find the *session-aware* methods at the very end of the performance ranking. This means that they are actually outperformed by methods which do not consider any long-term preference information at all. Among the neural methods, the earliest method, GRU4REC, achieves the best results. Also in this case, the reminder extension is effective, leading to a small performance improvement.

The best results in the class of neural *session-aware* recommendation algorithms are achieved by IIRNN and HGRU4REC. These two methods are, however, the earliest proposed session-aware recommendation methods in this comparison. Differently from the original paper, HGRU4REC is not able to outperform the last version of GRU4REC on this dataset.

*LASTFM*. The picture for this dataset is similar, with non-neural approaches leading to the best results. Again, the simple extensions lead to additional performance gains. Like in some previous works, the SR method is sometimes working quite well on the MRR measure. While session-aware methods can again be mostly found at the bottom of the list, the IIRNN method is at least able to outperform the neural session-based methods.

*XING*. Similar patterns are also found for the XING dataset, with neighborhood based methods leading to the best results, the extensions resulting in performance improvements, and

Table 5: Results of the performance comparison on the XING dataset with the focus on the comparison between **simple (non-neural)** methods and **session-aware** ones. The best results for each metric are highlighted in bold font. The next best results for algorithms from the other category (either simple methods or session-aware ones) are underlined. Non-neural methods are highlighted in light gray, session-based ones in gray and session-aware ones in dark gray.

Metrics	MAP@20	P@20	R@20	HR@20	MRR@20	COV@20	POP@20
XING							
VSKNN_EB_REMINDER	<b>*0.0166</b>	<b>*0.0440</b>	<b>*0.2775</b>	<b>*0.4232</b>	0.2663	<b>*0.9526</b>	0.0333
VSKNN_REMINDER	0.0160	0.0428	0.2727	0.4177	0.2626	0.9526	0.0330
VSKNN_EB	0.0148	0.0377	0.2410	0.3896	0.2644	0.9199	0.0311
NARM_REMINDER	0.0141	0.0387	0.2502	0.3767	0.2034	0.8759	0.0463
GRU4REC_REMINDER	0.0141	0.0382	0.2541	0.3977	0.2681	0.9440	0.0304
VSKNN	0.0139	0.0357	0.2312	0.3783	0.2605	0.9193	<u>0.0305</u>
VSTAN	0.0138	0.0353	0.2368	0.3890	<b>*0.2747</b>	0.8996	0.0353
STAN	0.0137	0.0352	0.2367	0.3887	0.2734	0.8950	0.0386
SR_B_REMINDER	0.0122	0.0341	0.2166	0.3184	0.1726	0.8935	0.0366
SR_REMINDER	0.0121	0.0339	0.2160	0.3178	0.1676	0.8934	0.0366
NARM	0.0117	0.0304	0.2031	0.3320	0.2035	0.8252	0.0480
GRU4REC	0.0113	0.0284	0.2007	0.3454	0.2653	0.9174	0.0270
NCSF	<u>0.0101</u>	<u>0.0262</u>	<u>0.1800</u>	<u>0.2982</u>	<u>0.1706</u>	0.7885	0.0683
SR_B	0.0092	0.0238	0.1568	0.2534	0.1682	0.8280	0.0321
SR	0.0092	0.0238	0.1567	0.2532	0.1633	0.8279	0.0321
NSAR	0.0086	0.0229	0.1449	0.2013	0.0968	0.8268	0.0361
HGRU4REC	0.0081	0.0203	0.1464	0.2524	0.1681	<u>0.8474</u>	<b>0.0296</b>
IIRNN	0.0072	0.0185	0.1274	0.2046	0.1254	0.8387	0.0484
SHAN	0.0051	0.0151	0.0932	0.1231	0.0503	0.2673	0.1329

session-aware techniques being outperformed by all other methods. Among the session-aware recommendation methods, this time NCSF achieves the best accuracy results. Note that the reminders help to improve the performance of neural session-based techniques (GRU4REC, NARM) to an extent that they sometimes outperform the nearest-neighbor techniques. However, when the extensions are also considered for the neighborhood-based techniques, their accuracy results are again much higher than for the neural techniques.

*Summary and Additional Observations.* Table 6 summarizes Table 3, Table 4 and Table 5, by reporting the best performing approaches on the individual datasets. Overall, we can see that VSKNN\_EB\_REMINDER largely dominates across the datasets and measures, and this method should therefore be considered as a baseline in future performance comparisons. As a side observation, we see that the ranking of the neural algorithms is often not correlated with the publication year of the methods, i.e., newer methods are not consistently better than older ones.

#### 4.2. Coverage and Popularity

Table 3, Table 4 and Table 5 also report the values of *popularity bias* and *coverage* of the algorithms. We can make the following observations.

*Popularity Bias.* GRU4REC and HGRU4REC consistently have the lowest tendency to recommend popular items. SHAN, in contrast, in many cases exhibits much higher *popularity bias* values than other methods. The neighborhood-based approaches are often in the middle. They are therefore not focusing on popular items more than neural approaches in general. The session-aware extensions of the session-based recommendation methods in most cases lead to a higher *popularity bias*.

Table 6: Best performing approaches for each dataset and each accuracy metric. Algorithms that were significantly better than the best algorithms from the other category (either **neural** or **non-neural**) are marked with **\***.

Datasets	RETAIL	LASTFM	XING
MAP@20	*VSKNN_EB_REMINDER	*VSKNN_EB_REMINDER	*VSKNN_EB_REMINDER
P@20	VSKNN_EB_REMINDER	*VSKNN_EB_REMINDER/VSKNN_EB	*VSKNN_EB_REMINDER
R@20	*VSKNN_EB_REMINDER	*VSKNN_EB_REMINDER	*VSKNN_EB_REMINDER
HR@20	*VSKNN_EB_REMINDER	*VSKNN_EB_REMINDER	*VSKNN_EB_REMINDER
MRR@20	*STAN	SR_B_REMINDER	*VSTAN

*Coverage.* SHAN consistently has the lowest *coverage* value across all datasets. In other words, it has the highest tendency to recommend the same set of items to different users. This sets the algorithm apart from all other techniques. The coverage values of most other techniques are often not too far apart, the difference between nearest-neighbor algorithms and neural algorithms is often small, and no consistent pattern can be found here. What can be observed is that the achieved level of coverage and the ranking of the algorithms in this respect seems to depend on the datasets.

## 5. Conclusions

Our in-depth empirical investigation of five recent neural approaches to session-aware recommendation has revealed that these methods, contrary to the claims in the respective papers, are not effective at leveraging long-term preference information for improved recommendations. According to our experiments, these methods are almost consistently outperformed by methods that only consider the very last ongoing session to make recommendations. Furthermore, our analyses showed that non-neural methods based on nearest neighbors can lead to better performance results than ones based on deep learning, as was also often observed for session-based recommendation previously in [27].

We speculate that these phenomena are largely due to methodological issues in recommender systems research. The main problems in this context are that researchers either compare their methods to baselines that are too weak in general or that they do not invest sufficient effort in fine-tuning the baselines. Recent works in more traditional recommendation setups showed that even papers that are published in highly-reputed conferences face this issue of “phantom progress” [7, 36]. Our investigations also showed that researchers use a variety of different baselines to demonstrate the superiority of their method, which makes it difficult to understand what represents the state-of-the-art. Our experiments suggest that session-based nearest-neighbor methods should be considered as baselines in future work.

To avoid such methodological issues in the future, we provide an open-source framework for the evaluation of session-aware recommendation algorithms. Relying on such a framework, which also has defined procedures for dataset pre-processing, data splitting, hyperparameter optimization and measuring should not only increase the reproducibility of newly published works but also help avoiding methodological mistakes as observed, e.g., in [7].

On a more positive note, our findings suggest that there are many opportunities for the development of better neural and non-neural methods for session-aware recommendation problems. We in particular believe that it is promising to look at repeating patterns, seasonal effects, or trends in the data. Moreover, the incorporation of side information (e.g., category information about items) as well as contextual information should help to further improve the prediction performance of new algorithms.

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## Appendix A. Hyperparameter ranges and optimal values

Table A.7: Hyperparameter space for simple methods.

Algorithm	Fixed Hyperparameter Values	Hyperparameter	Type	Range	Steps
SR		steps	Integer	2 - 14	13
			Integer	15 - 30	4
		weighting	Categorical	linear, div, quadratic, log	
SR_REMINDER	remind_strategy = recency remind_mode = end	remind_sessions_num	Integer	1 - 10	10
		reminders_num (r)	Integer	1 - 5	5
SR_B		steps	Integer	2 - 14	13
			Integer	15 - 30	4
		weighting	Categorical	linear, div, quadratic, log	
		boost_own_sessions (b)	Real	0.1-3.9	20
SR_B_REMINDER	remind_strategy = recency remind_mode = end	remind_sessions_num	Integer	1 - 10	10
		reminders_num (r)	Integer	1 - 5	5
VSKNN		k	Integer	50, 100, 500, 1000, 1500	
		sample_size	Integer	500, 1000, 2500, 5000, 10000	
		weighting	Categorical	same, div, linear, quadratic, log	
		weighting_score	Categorical	same, div, linear, quadratic, log	
		idf_weighting	Boolean, Integer	False, 1, 2, 5, 10	
VSKNN_REMINDER	remind_mode = end	remind_strategy	Categorical	recency, session_similarity	
		remind_sessions_num	Integer	1 - 10	10
		reminders_num (r)	Integer	1 - 5	5
VSKNN_EB		k	Integer	50, 100, 500, 1000, 1500	
		sample_size	Integer	500, 1000, 2500, 5000, 10000	
		weighting	Categorical	same, div, linear, quadratic, log	
		weighting_score	Categorical	same, div, linear, quadratic, log	
		idf_weighting	Boolean, Integer	False, 1, 2, 5, 10	
		extend_session_length (d)	Integer	1 - 25	25
VSKNN_EB_REMINDER	remind_strategy = recency remind_mode = end	boost_own_sessions (b)	Real	0.1 - 3.9	20
		remind_strategy	Categorical	recency, session_similarity	
		remind_sessions_num	Integer	1 - 10	10
		reminders_num (r)	Integer	1 - 5	5
STAN		k	Integer	100, 200, 500, 1000, 1500, 2000	
		sample_size	Integer	1000, 2500, 5000, 10000	
		lambda_spw	Real	0.00001, 0.4525, 0.905, 1.81, 3.62, 7.24	
		lambda_snh	Real	2.5, 5, 10, 20, 40, 80, 100	
VSTAN		lambda_inh	Real	0.00001, 0.4525, 0.905, 1.81, 3.62, 7.24	
		k	Integer	100, 200, 500, 1000, 1500, 2000	
		sample_size	Integer	1000, 2500, 5000, 10000	
		similarity	Categorical	cosine, vec	
		lambda_spw	Real	0.00001, 0.4525, 0.905, 1.81, 3.62, 7.24	
		lambda_snh	Real	2.5, 5, 10, 20, 40, 80, 100	
		lambda_inh	Real	0.00001, 0.4525, 0.905, 1.81, 3.62, 7.24	
		lambda_ipw	Real	0.00001, 0.4525, 0.905, 1.81, 3.62, 7.24	
lambda_idf	Boolean, Integer	False, 1, 2, 5, 10			

Table A.8: Hyperparameter search space for neural methods.

Algorithm	Fixed Hyperparameter Values	Hyperparameter	Type	Range	Steps
GRU4REC	layer_size = 100	learning_rate	Real	0.01 - 0.1	10
		momentum	Real	0.1 - 0.5	5
		loss	Real	0 - 0.9	10
		final_act	Categorical	bpr-max, top1-max	
		dropout_p_hidden	Categorical	elu-0.5, linear	
		constrained_embedding	Real	0 - 0.9	10
GRU4REC_REMINDER	remind_strategy = recency remind_mode = end	remind_sessions_num	Integer	1 - 10	10
		reminders_num	Integer	1 - 5	5
NARM	epochs = 20 layer_size = 100	factors	Integer	50, 100	
		learning_rate	Real	0.01-0.001	10
NARM_REMINDER	remind_strategy = recency remind_mode = end	remind_sessions_num	Real	0.001-0.0001	10
		reminders_num	Integer	1 - 5	5
HGRU4REC	session_layers = 100 user_layers = 100 loss = top1 (as in the original paper)	user_propagation_mode	Categorical	init, all	
		learning_rate	Real	0.01-0.1	10
		momentum	Real	0.1-0.5	5
		final_activation	Real	0 - 0.9	10
		dropout_p_hidden_usr	Categorical	linear, relu, tanh	
		dropout_p_hidden_ses	Real	0 - 0.9	10
		dropout_p_init	Real	0 - 0.9	10
		batch_size	Integer	50, 100	
HIRNN	max_epoch = 100 for RETAIL and LASTFM max_epoch = 20 for XING	dropout_pkeep	Real	0.1 - 1	10
		learning_rate	Real	0.01 - 0.001	10
		embedding_size	Real	0.001 - 0.0001	10
		max_session_representations	Integer	50, 100	
		use_last_hidden_state	Integer	1, 5, 10, 15, 20	
SHAN	global_dimension = 100 epochs = 100 (as in the original paper)	lambda_uv	Boolean	True, False	
		lambda_a	Real	0.01, 0.001, 0.0001	
NCSF		max_nb_his_sess	Integer	1, 10, 50	
		att_alpha	Real	0, 1, 2, 5, 10	
		window_sz	Real	0.01, 0.1, 1, 10	10
NSAR	epochs = 20 keep_pr = 0.25 (as in the original paper) batch_size = 64 for RETAIL and LASTFM (as in the original paper) batch_size = 32 for XING because of out of memory error	learning_rate	Integer	1 - 10	
		hidden_units	Real	0.001 - 0.01	10
			Real	0.01 - 0.05	5
			Integer	50, 100	

Table A.9: Optimal hyperparameters for simple methods.

Algorithm	Hyperparameter	RETAIL	LASTFM	XING
SR	steps	15	8	25
	weighting	quadratic	quadratic	quadratic
SR_REMINDER	steps	15	8	25
	weighting	quadratic	quadratic	quadratic
	remind_sessions_num	9	1	10
	reminders_num	5	5	5
SR_B	steps	12	20	30
	weighting	quadratic	quadratic	quadratic
	boost_own_sessions (b)	3.1	3.1	1.9
SR_B_REMINDER	steps	12	20	30
	weighting	quadratic	quadratic	quadratic
	boost_own_sessions (b)	3.1	3.1	1.9
	remind_sessions_num	2	3	4
	reminders_num	5	5	5
VSKNN	k	50	50	100
	sample_size	500	500	500
	weighting	log	quadratic	log
	weighting_score	linear	quadratic	quadratic
	idf_weighting	10	5	10
VSKNN_REMINDER	k	50	50	100
	sample_size	500	500	500
	weighting	log	quadratic	log
	weighting_score	linear	quadratic	quadratic
	idf_weighting	10	5	10
	remind_strategy	recency	session_similarity	recency
	remind_sessions_num	2	5	6
	reminders_num	5	5	5
VSKNN_EB	k	1500	50	1500
	sample_size	1000	500	10000
	weighting	log	quadratic	log
	weighting_score	linear	quadratic	quadratic
	idf_weighting	1	1	10
	extend_session_length (d)	8	3	1
	boost_own_sessions (b)	0.1	2.5	3.5
VSKNN_EB_REMINDER	k	1500	50	1500
	sample_size	1000	500	10000
	weighting	log	quadratic	log
	weighting_score	linear	quadratic	quadratic
	idf_weighting	1	1	10
	extend_session_length (d)	8	3	1
	boost_own_sessions (b)	0.1	2.5	3.5
	remind_strategy	session_similarity	session_similarity	recency
	remind_sessions_num	5	8	5
reminders_num	5	3	5	
STAN	k	1500	100	100
	sample_size	2500	10000	10000
	lambda_spw	0.905	0.00001	0.4525
	lambda_snh	100	80	80
	lambda_inh	0.4525	3.62	0.4525
VSTAN	k	200	1000	1500
	sample_size	5000	5000	10000
	similarity	vec	cosine	cosine
	lambda_spw	1.810	1.81	3.620
	lambda_snh	40	100	20
	lambda_inh	0.905	1.81	0.453
	lambda_ipw	0.905	0.000	0.453
	lambda_idf	False	False	10

Table A.10: Optimal hyperparameters for neural methods.

Algorithm	Hyperparameter	RETAIL	LASTFM	XING
GRU4REC	learning_rate	0.08	0.04	0.05
	momentum	0.1	0.1	0.6
	loss	top1-max	bpr-max	top1-max
	final_act	linear	linear	elu-0.5
	dropout_p_hidden	0.7	0	0.8
	constrained_embedding	True	False	True
GRU4REC_REMINDER	learning_rate	0.08	0.04	0.05
	momentum	0.1	0.1	0.6
	loss	top1-max	bpr-max	top1-max
	final_act	linear	linear	elu-0.5
	dropout_p_hidden	0.7	0	0.8
	constrained_embedding	True	False	True
	remind_sessions_num	8	4	10
reminders_num	4	5	5	
NARM	factors	50	100	100
	learning_rate	0.01	0.007	0.007
NARM_REMINDER	factors	50	100	100
	learning_rate	0.01	0.007	0.007
	remind_sessions_num	1	10	2
	reminders_num	5	2	5
HGRU4REC	user_propagation_mode	all	all	all
	learning_rate	0.06	0.09	0.08
	momentum	0.3	0.5	0.6
	final_act	linear	linear	tanh
	dropout_p_hidden_usr	0.4	0.7	0.8
	dropout_p_hidden_ses	0.3	0.1	0
	dropout_p_init	0.4	0.3	0.6
	batch_size	50	50	100
HIRNN	dropout_pkeep	0.4	0.6	0.6
	learning_rate	0.002	0.001	0.002
	embedding_size	100	100	100
	max_session_representations	15	20	1
	use_last_hidden_state	False	True	False
SHAN	lambda_uv	0.01	0.01	0.01
	lambda_a	1	10	1
NCSF	max_nb_his_sess	5	0	0
	att_alpha	10	1	10
	window_sz	2	1	2
NSAR	learning_rate	0.01	0.003	0.004
	hidden_units	100	100	100