Prospective Preference Enhanced Mixed Attentive Model for Session-based Recommendation

Bo Peng, Member, IEEE, Chang-Yu Tai, Srinivasan Parthasarathy, Member, IEEE, and Xia Ning*, Member, IEEE

Abstract—Session-based recommendation aims to generate recommendations for the next item of users’ interest based on a given session. In this manuscript, we develop prospective preference enhanced mixed attentive model (P²MAM) to generate session-based recommendations using two important factors: temporal patterns and estimates of users’ prospective preferences. Unlike existing methods, P²MAM models the temporal patterns using a light-weight while effective position-sensitive attention mechanism. In P²MAM, we also leverage the estimate of users’ prospective preferences to signify important items, and generate better recommendations. Our experimental results demonstrate that P²MAM models significantly outperform the state-of-the-art methods in six benchmark datasets, with an improvement as much as 19.2%. In addition, our run-time performance comparison demonstrates that during testing, P²MAM models are much more efficient than the best baseline method, with a significant average speedup of 47.7 folds.

Index Terms—session-based recommendation, recommender system, attention mechanism

1 INTRODUCTION

Session-based recommendation aims to generate recommendations for the next item of users’ interest based on a given session (i.e., a sequence of items chronologically ordered according to user interactions in a short-time period). It has been drawing increasing attention from the research community due to its wide applications in online shopping [1], [2], music streaming [3] and tourist planning [4], among others. With the prosperity of deep learning, many deep models, particularly based on recurrent neural networks (RNNs) [5] and graph neural networks (GNNs) [6] have been developed for session-based recommendation, and have demonstrated the state-of-the-art performance. These methods primarily model the temporal patterns (e.g., transitions, recency patterns, etc.) in sessions, but are not always effective in modeling other important factors that are indicative of the next item. In addition, existing methods primarily model the temporal patterns using gated recurrent units (GRUs) [7]. However, considering the notorious sparse nature of session-based recommendation datasets, as shown in the literature [5], the complicated GRUs may not be well-learned and could degrade the performance. Due to its recurrent essence, GRUs also suffer from limited parallelizability and poor interpretability.

To mitigate the limitations of existing methods, in this manuscript, we develop prospective preference enhanced mixed attentive model, denoted as P²MAM, for session-based recommendation. In P²MAM, different from existing methods, we model the temporal patterns using a novel position-sensitive attention mechanism, which is light-weight, fully parallelizable, and could enable better interpretability over GRUs. Besides the temporal patterns, we also leverage the estimate of users’ prospective preferences for better recommendation. Users’ prospective preferences is another important factor for recommendation. Intuitively, if we would have known beforehand that the user is going to watch action movies next (i.e., prospective preference), we could generate better recommendations by learning her/his preference from action movies instead of comedy movies in her/his watching history. We conducted an analysis to empirically verify that users’ prospective preferences could signify important items, and thus, improve the recommendation performance as in the Discussion Section. The results reveal that conditioned on the prospective preferences, we could learn indicative attention weights over items, and enable superior performance. However, in practice, users’ prospective preferences are usually intractable. Thus, in P²MAM, we explicitly estimate the prospective preferences, and learn attention weights based on the estimate to boost the recommendation performance.

With different combinations of the two factors (i.e., temporal patterns and the estimate of users’ prospective preferences), P²MAM has three variants: P²MAM-O, P²MAM-P and P²MAM-O-P. P²MAM-O models temporal patterns using a novel position-sensitive attention mechanism. P²MAM-P leverages the estimate of users’ prospective preferences to weigh items and generate recommendations. P²MAM-O-P explicitly leverages the two factors for better recommendation.

We compare P²MAM with five state-of-the-art baseline methods on six benchmark session-based recommendation datasets.
Our experimental results demonstrate that \texttt{P2MAM} significantly outperforms the state-of-the-art methods on all the datasets, with an improvement of up to 19.2%. The results also show that on most of the datasets, the two factors are mutually strengthened, and could enable superior performance when used together. We also conduct a comprehensive analysis to verify the effectiveness of different components in \texttt{P2MAM}. The results show that with the position embeddings, our position-sensitive attention mechanism could effectively capture the temporal patterns in the datasets, and on most of the datasets, our learning-based prospective preference estimate strategy could be more effective than recency-based strategies. Moreover, we conduct run-time performance analysis, and find that \texttt{P2MAM} is much more efficient than the best baseline method with an average speedup of 47.7 folds over the six datasets.

Our major contributions are summarized as follows:

- We develop a novel session-based recommendation method \texttt{P2MAM}, which leverages both the temporal patterns and estimates of users’ prospective preferences for recommendation.
- \texttt{P2MAM} significantly outperforms five state-of-the-art methods on six benchmark datasets (Section 6.1).
- Our analysis demonstrates the importance of modeling the position information for session-based recommendation (Section 6.5).
- The experimental results show that our learning-based prospective preference estimate strategy is more effective than the existing recency-based strategy (Section 6.6).
- Our analysis shows that the learned attention weights in \texttt{P2MAM} could capture the temporal patterns in the data (Section 6.7).
- Our analysis verifies that users’ prospective preferences could signify important items, and benefit recommendations (Section 7).
- For reproducibility purposes, we release our source code on GitHub \footnote{https://github.com/ninglab/P2MAM} and report the hyper parameters in the Appendix.

## 2 Related Work

### 2.1 Session-based Recommendation

In the last few years, numerous session-based recommendation methods have been developed, particularly using Markov Chains (MCs), attention mechanisms and neural networks such as RNNs and GNNs, etc. MCs-based methods \cite{9} use MCs to capture the transitions among items for recommendation. For example, Rendle et al. \cite{9} employs a first-order MC to generate recommendations based on the transitions of the last item in each session. Attention-based methods \cite{1, 10} model the importance of items for the recommendation. For example, Liu et al. \cite{10} developed a short-term attention priority model (STAMP), which adapts a gate mechanism to capture users’ short-term preferences. Recently, RNNs-based methods such as GRU4Rec+ \cite{11} and NARM \cite{1} have been developed to model the temporal patterns among items primarily using GRUs.

GNNs-based methods are also extensively developed for the session-based recommendation. Wu et al. \cite{2} converted sessions to direct graphs, and developed a GNNs-based model (SR-GNN) to generate recommendations based on the graph structures. Qiu et al. \cite{12} re-examined the importance of item ordering in session-based recommendations and developed a GNN-based model (FGNN), which included self-loop for each node in graphs to better capture users’ short-term preferences. Chen et al. \cite{4} showed that the widely used directed graph representations cannot fully preserve the sequential information in sessions. To mitigate this problem, they converted sessions to multigraphs, and developed a GNNs-based model (LESSR) to generate recommendations. Xia et al. \cite{3} developed hyper graph-based model (DHGN), which leverages hyper graphs and hyper graph convolutional networks to capture the high-order information among items.

### 2.2 Sequential Recommendation

Sequential recommendation aims to generate recommendations for the next items of users’ interest based on users’ historical interactions. It is closely related to session-based recommendation except that in sequential recommendation, we could access users’ historical interactions in a long-time period (e.g., months). In the last few years, neural networks (e.g., RNNs) and attention mechanisms have been extensively employed in sequential recommendation methods. For example, RNNs-based methods such as User-based RNNs \cite{13} incorporate user characteristics into GRUs for personalized recommendation. Skip-gram-based methods \cite{14} leverage the skip-gram model \cite{15} to capture the co-occurrence among items in a time window. Recently, Convolutional Neural Networks (CNNs) are also adapted for sequential recommendation. Tang et al. \cite{16} developed a CNNs-based model, which uses multiple convolutional filters to model the synergies \cite{17} among items. Yuan et al. \cite{18} developed another CNN-based generative model NextItRec to better capture the long-term dependencies in sequential recommendation. Besides CNNs, attention-based methods \cite{19, 20, 21} are also developed for sequential recommendation. Kang et al. \cite{19} developed a self-attention based model, which adapts the self-attention to better model users’ long-term preferences. Sun et al. \cite{20} further developed a bidirectional self-attention based model to improve the representational power of item embeddings.

## 3 Definitions and Notations

In this manuscript, we tackle the recommendation problem that given an anonymous session, we recommend the next item of users’ interest in the session. An anonymous session
Specifically, following Vaswani et al. [19], we use a constant zero vector as the embedding of padded empty items. Previous work [19], [21], [22], we use a constant zero vector as the embedding of padded empty items.

In P^2MAM, different from other methods, we develop a novel position-sensitive attention mechanism to model the temporal patterns, and generate predictions of users’ preferences accordingly. Specifically, we use a dot-product attention mechanism as follows:

\[
C = E + P, \quad \alpha = \text{softmax} \left( \frac{Q^T C}{\sqrt{d}} \right), \quad h^e = \alpha C, \tag{3}
\]

where \( C \) combines items embeddings and position embeddings in the session, and \( c_i \) is the \( i \)-th row in \( C \), \( \alpha \) is a vector of attention weights, \( q \in \mathbb{R}^{1 \times d} \) is a learnable vector shared by all the sessions, and \( h^e \) is the position-sensitive preference prediction.

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is a learnable projection matrix shared by all the heads, and $h^p \in \mathbb{R}^{1 \times d}$ is the prospective preference enhanced preference prediction. The intuition of our strategy (i.e., $P^2E$) is that we learn predictive attention weights based on the estimate of users’ prospective preferences. As will be shown in Section 4.4.3 this strategy could significantly improve the recommendation performance. Note that $P^2E$ serves as a general strategy that is adaptable to other estimates of users' prospective preferences. We also tried the dot-product attention as in PS but empirically found that it produces inferior performance.

4.4 Recommendation Scores in $P^2MAM$

In $P^2MAM$, we calculate recommendation scores based on the predictions of users’ preferences (i.e., $h^o$ and $h^p$). Specifically, we develop three different methods to calculate the scores. Based on the scores, the items with the top-$k$ largest scores will be recommended.

4.4.1 Scores based on temporal patterns ($P^2MAM-O$)

Similarly to existing methods [1], [2], we calculate the recommendation scores based on the temporal patterns as follows:

$$\hat{r} = \text{softmax}(h^o V^\top),$$

(5)

where $\hat{r}$ is a vector of recommendation scores over candidate items, $V$ is the item embedding matrix (Section 4.1), and the softmax function is employed to normalize the scores to be into the range $[0, 1]$. We denote this $P^2MAM$ variant as $P^2MAM-O$.

4.4.2 Scores based on users’ prospective preferences ($P^2MAM-P$)

In $P^2MAM$, we could also generate recommendations from the prospective preference enhanced preference prediction $h^p$ as follows:

$$\hat{r} = \text{softmax}(h^p V^\top).$$

(6)

We denote this $P^2MAM$ variant as $P^2MAM-P$.

4.4.3 Scores based on temporal patterns and users’ prospective preferences ($P^2MAM-O-P$)

The two preference predictions (i.e., $h^o$ and $h^p$) could be mutually strengthened and might enable better performance when used together. Following this motivation, we also calculate recommendation scores using both $h^o$ and $h^p$ as follows:

$$\hat{r} = \text{softmax}((h^o + h^p) V^\top),$$

(7)

where we sum $h^o$ and $h^p$ for the recommendation. We denote the $P^2MAM$ variant using both $h^o$ and $h^p$ as $P^2MAM-O-P$.

4.5 Network Training

Following the literature [2], [4], [10], we adapt the cross-entropy loss to minimize the negative log likelihood of correctly recommending the ground-truth next item as follows:

$$\min_\Theta \sum_{i=1}^{\lvert T \rvert} -r_i \log(r_i^\top),$$

(8)

where $T$ is the set of all the training sessions, $r_i$ is a one-hot vector in which the dimension $j$ is 1 if item $j$ is the ground-truth next item in the $i$-th training session or 0 otherwise, $r_i$ is the vector of recommendation scores for the $i$-th training session, and $\Theta$ is the set of learnable parameters (e.g., $V$, $P$, and $W$). All the learnable parameters are randomly initialized, and are optimized in an end-to-end manner. We use this objective to optimize all the $P^2MAM$ variants (i.e., $P^2MAM-O$, $P^2MAM-P$ and $P^2MAM-O-P$).

5 MATERIALS

5.1 Baseline Methods

We compare $P^2MAM$ with the five state-of-the-art baseline methods:

- POP [2] recommends the most popular items of each session.
- NARM [1] employs GRUs and attention mechanisms to model the temporal patterns for the recommendation.
- SR-GNN [2] transforms sessions into directed graphs, and employs GNNs to model complex transitions in sessions.
- LESSR [4] transforms sessions into directed multigraphs and generates recommendations using GNNs.
- DHCN [3] transforms sessions into hypergraphs and generates recommendations using a hypergraph convolutional network.

Note that DHCN and LESSR have been compared against a comprehensive set of other methods including GRU4Rec+ [11], STAMP [10] and FGNN [12], and have outperformed those methods. Thus, we compare $P^2MAM$ with DHCN and LESSR instead of the methods that they have outperformed. For all the baseline methods, we use the implementations provided by their authors (Section A in Appendix).

5.2 Datasets

We compare $P^2MAM$ with the baseline methods in the following benchmark datasets that are widely used in the literature [1], [2], [4]:

- Diginetica (DG) is from the CIKM Cup 2016, and contains anonymized browsing logs and transactions. Following the literature [1], [2], [4], we only use the transaction data in our experiments.
- Yoochoose (YOC) is from the RecSys Challenge 2015 containing sessions of user clicks within 6 months.
- Gowalla (GA) is a point-of-interests dataset and includes user-venue check-in records with timestamps.
- Lastfm (LF) is a dataset collecting streams of music listening events in the Last.fm. Following the literature [4], we focus on the music artist recommendation in our experiments.
- Nowplaying (NP) is another dataset describing the music listening events of users.
- Tmall (TH) is from the IJCAI-15 competition, and it includes anonymized shopping logs on the online retail platform Tmall.

2.  http://cikm2016.cs.iupui.edu/cikm-cup
3.  http://2015.recsyschallenge.com/challenge.html
4.  https://snap.stanford.edu/data/loc-gowalla.html
5.  http://oceina.net/MusicRecommendationDataset/lastfm-1K.html
6.  http://dbis-nowplaying.uibk.ac.at/#nowplaying
7.  https://tianchi.aliyun.com/dataset/dataDetail?dataId=42
Following the literature [1], [2], [3], [4], for GA, we only keep the top 30,000 most popular locations, and view the check-in records in one day as a session [4], [8]. For LF, we only keep the top 40,000 most popular artists, and view the listening events in 8 hours as a session [4]. For all the datasets, we filter out sessions of length one and items appearing less than five times over all the sessions.

5.3 Experimental Protocol

5.3.1 Training and testing Sets
Following the literature [2], [3], [4], we generate the training and testing sets as follows: for DG, NP and TM, we use the sessions in the last week as the testing set, and all the other sessions as the training set. For YC, we use the sessions in the last day as the testing set. For the other sessions, following that in Li et al. [1], we use the last (i.e., most recent) 1/64 of them for training. For GA and LF, we use the last (i.e., most recent) 20% of all the sessions for testing, and all the other sessions for training.

Following the literature [1], [2], [3], [4], we augment the data to enrich the training and testing data. Specifically, for each original training and testing session $S = \{s_1, s_2, \ldots, s_{|S|}\}$, we split it to $\{s_1, s_2\}, \{s_1, s_2, s_3\}, \ldots, \{s_1, s_2, \ldots, s_{|S|-1}\}$ and $\{s_1, \ldots, s_{|S|}\}$, and use all the resulted sessions as the augmented sessions for training and testing. The key statistics of the original and augmented datasets are presented in Table 2. Note that, we transform the data to enrich the training and testing data. Specifically, for each session $S$, the recall@$k$ is 1 if $s_{|S|+1}$ is among the top $k$ of the recommendation list, or 0 otherwise. Note that in next item recommendation, recall@$k$ is the most popular evaluation metric. It is also called precision@$k$ and HR@$k$ as in the literature [3].

- MRR@$k$ is the mean reciprocal rank of the correctly recommended item, and is 0 if the ground-truth next item is not in the top-$k$ of the recommendation list. MRR@$k$ is widely used in the literature [1], [2], [3], [4], [10] as a rank-aware evaluation metric for session-based recommendation.

- NDCG@$k$ is the normalized discounted cumulative gain for the top-$k$ ranking, and is another widely used rank-aware metric [16], [19], [26]. Different from MRR@$k$ that only focuses on the very top ranked items (e.g., top-1) [27], NDCG@$k$ effectively measures models’ performance in ranking the top-$k$ items, and thus, might be a better metric for evaluating recommendation methods in some scenarios. Follow the literature [16]. In our experiments, the gain indicates whether the ground-truth next item is recommended (i.e., gain is 1) or not (i.e., gain is 0).

For all the evaluation metrics, we report the average results over all the testing sessions in the experiments. We also statistically test the significance of the performance difference among different methods via a standard paired $t$-test at 95% confidence level.

6 Experimental Results

6.1 Overall Performance Comparison
Table 3 presents the overall performance of different methods at recall@$k$, MRR@$k$ and NDCG@$k$ in recommending the next item. Due to the space limit, we do not present the results on recall@$5$, MRR@$5$ and NDCG@$5$. However, we observed a similar trend on these metrics. Table 3 shows that overall, $P^2$-MAM (i.e., $P^2$-MAM-D, $P^2$-MAM-P and $P^2$-MAM-O-P) is the best performing method on the six benchmark datasets. In terms of recall@$10$ and recall@$20$, $P^2$-MAM achieves the best performance on all the six datasets, with significant average improvement of 4.2% and 5.5%, respectively, compared to the best baseline method at each dataset. Note that in session-based recommendation, improvement of above 1% is generally considered as significant [2]. At MRR@$2$, $P^2$-MAM also achieves competitive performance over the baseline methods. For example, on DG and GA, $P^2$-MAM achieves statistically significant improvement of 2.7% and 1.9% at MRR@$10$ and MRR@$20$, respectively. On YC and TM, $P^2$-MAM achieves the second best performance at MRR@$10$ and MRR@$20$. We found a similar trend at NDCG@$k$. For example, in terms of NDCG@$10$, $P^2$-MAM substantially outperforms the baseline methods on DG and GA; at NDCG@$20$, $P^2$-MAM is the best method on four out of six datasets except YC and LF. These results demonstrate the strong recommendation performance of $P^2$-MAM. We notice that on YC, LF and TM, at MRR@$10$ and MRR@$20$, $P^2$-MAM appears considerably worse than the baseline methods (e.g., LESSR). These results indicate that on certain datasets, even though $P^2$-MAM may be less effective than the baseline methods on ranking the ground-truth next items on the very top (e.g., top-1), $P^2$-MAM is still on average more effective on recommending the correct items among on top.

### Table 2: Dataset Statistics

| dataset | #items | #train | #test length | #aug train | #aug test | aug len |
|---------|--------|--------|--------------|------------|-----------|--------|
| DG      | 42,596 | 188,636| 15,955       | 4.8        | 716,835   | 60,194 | 4.90 |
| YC      | 17,597 | 124,472| 15,237       | 4.2        | 394,802   | 55,424 | 6.14 |
| GA      | 29,510 | 234,403| 57,492       | 3.8        | 675,561   | 155,332| 4.32 |
| LF      | 38,615 | 260,780| 64,763       | 11.7       | 2,837,644| 672,519| 9.16 |
| NP      | 60,416 | 128,077| 14,479       | 7.4        | 825,304   | 89,824 | 6.53 |
| TM      | 40,727 | 65,206 | 1,027        | 6.69       | 351,268   | 25,898 | 8.01 |

In this table, #item is the number of items. The columns #train, #test, and length correspond to the number of training sessions, the number of testing sessions, and the average length of sessions, respectively, before the augmentation. The columns #aug train, #aug test and ‘aug len’ correspond to that after the augmentation.
6.2 Comparison among $P^2$MAM Variants

As shown in Table 3, among the three variants of $P^2$MAM, $P^2$MAM-O-P has the best performance overall. In terms of recall@10, $P^2$MAM-O-P outperforms the other variants on YC, GA and LF, and achieves the second best performance on the other three datasets. In terms of recall@20, $P^2$MAM-O-P is the best method at four out of six datasets except DG and NP. We found a similar trend at MRR@k and NDCG@k. For example, in terms of NDCG@10 and NDCG@20, $P^2$MAM achieves significant improvement over the other variants on three out of six datasets (i.e., YC, GA and LF). On the other three datasets, $P^2$MAM is still ranked as the second best method.

Compared to $P^2$MAM-O, $P^2$MAM-O-P learns attention weights conditioned on the estimate of users’ prospective preferences (i.e., $P^2E$), while $P^2$MAM-O does not have this strategy. The superior performance of $P^2$MAM-O-P over $P^2$MAM-O on four out of six datasets indicates that on most of the datasets, incorporating the estimate of prospective preferences could enable better recommendations. Compared to $P^2$MAM-P, $P^2$MAM-O-P generates recommendations using the preference predictions from temporal patterns (i.e., $h^s$) and users’ prospective preferences (i.e., $h^p$), while $P^2$MAM-P only use $h^s$ to generate recommendations. The strong improvement of $P^2$MAM-O-P compared to $P^2$MAM-P indicates that when used together, the two preference predictions could reinforce each other and improve the recommendation performance. We notice that on DG and NP, the performance of $P^2$MAM-O-P is slightly worse than that of $P^2$MAM-O at recall@20. This might be due to that as will be shown in Section 6.3.5 in certain datasets (e.g., DG and NP), the temporal patterns are highly strong, and could undermine the learning process. As a result, incorporating the $P^2E$ component may not improve the recommendation performance.

| method       | recall@k | MRR@k    | NDCG@k |
|--------------|----------|----------|--------|
| PDP          | 0.0085   | 0.0078   | 0.0221 |
| BARN         | 0.4049   | 0.5401   | 0.1751 |
| SR-GNN       | 0.3783   | 0.5097   | 0.1629 |
| LESSR        | 0.0400   | 0.5321   | 0.1765 |
| DHCM         | 0.4058   | 0.5400   | 0.1708 |
| $P^2$MAM-O   | 0.4148   | 0.5500   | 0.1817 |
| $P^2$MAM-P   | 0.4028   | 0.5354   | 0.1749 |
| $P^2$MAM-O-P | 0.4120   | 0.5474   | 0.1805 |

For each dataset, the best performance among our proposed methods (e.g., $P^2$MAM-O-P) is in bold, the best performance among the baseline methods is underlined, and the overall best performance is indicated by a dagger (i.e., †). The row “improv” presents the percentage improvement of the best performing variant of $P^2$MAM (bold) over the best performing baseline methods (underlined). The ∗ indicates that the improvement is statistically significant at 95% confidence level.

6.4 Comparison with Graph-based Methods

Graph-based methods [2], [3], [12] are extensively developed for session-based recommendation, and have been demonstrated the state-of-the-art performance. However, as shown in Table 3, $P^2$MAM-O-P as a sequence-based method, significantly outperforms the state-of-the-art graph-based methods (i.e., SR-GNN, LESSR, DHCM) on the benchmark datasets. For example, $P^2$MAM-O-P achieves significant improvement compared to the state-of-the-art graph-based methods at both recall@10 and recall@20 on all the datasets. Graph-based methods convert sessions to directed graphs or hyper graphs, and learn the complex temporal patterns [2] leveraging the graph structure (i.e., topology). However, the graphs are constructed based on some assumptions by design such as an item should link to all the subsequent
items [4]. Such assumptions may introduce noises or unnecessary/unrealistic relations in the graphs. Meanwhile, the sparse nature of recommendation datasets, and thus of the graphs, may not support the complicated learning of GNN-based models very well. The superior performance of P^2MAM-0-P over graph-based methods signifies that the sequence representation could be more effective than graphs for the recommendation.

6.5 Analysis on Position Embeddings

We conduct an analysis to verify the importance of position embeddings in P^2MAM. Specifically, in P^2MAM, we remove the position embeddings (i.e., P) in Equation 3 and Equation 4 and calculate the attention weights using item embeddings (i.e., E) only. We denote P^2MAM without position embeddings as P^2MAM\PE, and report the performance of P^2MAM and P^2MAM\PE in Table 4. Due to the space limit, we do not present the performance of P^2MAM-P but we observed a similar trend in P^2MAM-P.

As presented in Table 4 without position embeddings, the performance of P^2MAM\PE and P^2MAM-0-P\PE degrades significantly on four out of six datasets (i.e., DG, YC, GA and NP). For example, on DG and YC, P^2MAM-0-P\PE underperforms P^2MAM-0-P at 3.8% and 5.5%, respectively. Recall that in P^2MAM, we learn position embeddings to incorporate the position information into the model, and better model the temporal patterns. These results demonstrate the importance of the position information for session-based recommendation. These results also reveal that the temporal patterns on the four datasets (e.g., DG and NP) are strong, and explain the similar performance of P^2MAM-0 and P^2MAM-0-P on DG and NP as discussed in Section 6.2. We also notice that on LF and TM, P^2MAM-0-PE and P^2MAM-0-P\PE still achieve performance similar to that with position embeddings. For example, on LF, P^2MAM-0-P\PE achieves 0.2449 at recall@20, and P^2MAM-0-P achieves 0.2454 (difference: 0.2%). Similarly, on TM, at recall@20, the performance of P^2MAM-0-P\PE and P^2MAM-0-P is 0.3468 and 0.3438, respectively (difference: 0.9%). As will be shown in Section 6.7 on some datasets (e.g., LF), the position information may not be crucial for the recommendation. Therefore, on these datasets, without position embeddings, the model could still achieve similar performance.

6.6 Prospective Preference Estimate Analysis

In P^2MAM, we leverage the position-sensitive preference prediction (i.e., h^o) from PS (Section 4.2) as the estimate of users’ prospective preferences (Section 4.3). We notice that in the literature [2], [10], [19], another strategy is to estimate the users’ prospective preferences from the last item in each session. This strategy is based on the recency assumption [2], [10] that the most recently interacted item could be a highly strong indicator of the next item of users’ interest. We conduct an analysis to empirically compare the two strategies in P^2MAM-0-P. Specifically, in Equation 4 instead of h^o, we use the embeddings of the last item and its position in each session (i.e., v_{n-1} + p_{n}) to calculate the attention weights, and denote the resulted variant as LAST-0-P. Table 5 presents the performance of P^2MAM-0-P and LAST-0-P. Similarly to that in P^2MAM-0-P, we tune hyper parameters for LAST-0-P using grid search, and report the results from the identified best performing hyper parameters. As presented in Table 5, overall P^2MAM-0-P achieves considerable improvement compared to LAST-0-P on four out of six datasets (i.e., DG, GA, LF and TM). At recall@5, recall@10 and recall@20, on average, P^2MAM-0-P achieves significant improvement of 3.5%, 3.4% and 3.5%, respectively, over LAST-0-P. We find a similar trend at MRR@k and NDCG@k.

For example, in terms of MRR@5 and NDCG@5, on the four datasets, P^2MAM-0-P still significantly outperforms LAST-0-P with an average improvement of 4.9% and 4.4%, respectively. The primary difference between P^2MAM-0-P and LAST-0-P is that P^2MAM-0-P uses a learning-based method to estimate users’ prospective preferences in a data-driven manner, while LAST-0-P generates the estimate based on the recency assumption. The above results indicate that on most of the datasets, data driven-based estimate is more effective than recency-based estimate. We also notice that on YC and NP, the performance of P^2MAM-0-P is competitive with that of LAST-0-P. For example, on YC, the performance difference between P^2MAM-0-P and LAST-0-P is 0.2% and 0.1% at recall@20 and MRR@20, respectively. On NP, the difference at recall@20 is also as small as 0.5%. As shown in the literature [10], some datasets such as YC have strong recency patterns. The similar results between P^2MAM-0-P and LAST-0-P on YC and NP, indicate that on datasets with strong recency patterns, our learning-based strategy may implicitly capture the patterns, and still produce competitive results.

6.7 Attention Weight Analysis

We conduct an analysis to evaluate the attention weights learned in P^2MAM-0-P. Particularly, we represent the attention weights learned in PS (Section 4.2) over corresponding session positions in Figure 2. Due to the space limit we only present the results on YC and LF but we have similar results on the other datasets. In Figure 2, the y-axis corresponds to the session length; the x-axis corresponds to the last n positions of a session of length n (n = 1, · · · , 8). Due to the space limit we only present the weights in augmented
testing sessions with at most 8 items, which represent 82.2% and 57.4% of all the testing sessions in YC and LF, respectively. We observed a similar trend in the longer sessions as that in Figure 2.

Figure 2a and 2b present the attention weight distribution from PS with and without position embeddings (i.e., \(PE\)), respectively, on YC. Similarly, Figure 2c and 2d present the distributions on LF. Comparing Figure 2a and Figure 2b, we notice that on YC, the attention weights on the last item of sessions (i.e., diagonal in the Figure) are significantly higher than those in the earlier ones. This weight distribution is consistent with the recency pattern on YC as shown in the literature [10], and demonstrates that with the position embeddings, PS could accurately capture the recency patterns in YC. Figure 2b shows that without position embeddings, the attention weights from PS do not show considerable difference over positions, revealing that without position embeddings, the attention mechanism cannot differentiate positions. The comparison between Figure 2a and Figure 2b further demonstrates the importance of position embeddings in P²MAM.

Comparing Figure 2a and Figure 2c, we find that on YC, the weights follow the recency pattern, while on LF, the second last item has higher weights than the last one. This result implies that the recency assumption may not always hold, and our learning-based method (i.e., PS) could be more effective than the existing recency-based method in estimating prospective preferences (Section 6.6). Comparing Figure 2c and Figure 2d, we notice that without position embeddings, on sessions with more than 4 items, the weight distribution in Figure 2d is still similar with that in Figure 2c. This result reveals that on this dataset, the position information may not be critical, and also supports the similar performance of P²MAM and P²MAM \(\text{\textbackslash}PE\) on LF as discussed in Section 6.5.

### 6.8 Analysis on Cosine Similarities

We conduct an analysis to verify if P²MAM truly learns predictive preferences from the data. Specifically, we calculate the cosine similarities between the preference predictions (i.e., \(h^p\) and \(h^p\)) and the item embeddings on the six datasets, and present the results in Table 6. For P²MAM-O/P²MAM-P, we calculate similarities between \(h^p\) and item embeddings. For P²MAM-D-P, since we calculate recommendation scores using \(h^p + h^o\) (Equation 7), we use \(h^p + h^o\) to calculate the similarities. Table 6 shows that in P²MAM-O, P²MAM-P and P²MAM-D-P, compared to the average similarities among all the items, the similarities between the predictions and the ground-truth next item is significantly higher. This result reveals that P²MAM could learn to capture users’ true preferences from the data.
preferences could signify the important items, and thus, we conduct an experiment to verify that users’ prospective preferences. As a result, we will not lose crucial information when the most recent few items are effective in learning users’ preferences, which could significantly affect the user experience and thus revenue. As presented in Table 7, the run-time performance of P2MAM-D-P is substantially better than that of DHCN on all the datasets. Specifically, on average, P2MAM-D-P is 47.7 times faster than DHCN. The superior run-time performance of P2MAM-D-P over DHCN demonstrates that while generating high-quality recommendations, P2MAM could enable lower latency in real time, and thus could significantly improve the user experience.

### 6.10 Parameter Study

We conduct a parameter study to assess how the length of the transformed sequence (i.e., \( n \)) affect the recommendation performance on the widely used DG, YC, GA and LF datasets. Particularly, on each dataset, we change \( n \) and fix the other hyper parameters as the best performing ones during hyper parameter tuning, and report the performance at recall@20 on augmented testing sessions in Figure 3. As shown in Figure 3 on DG, YC and GA, the performance increases significantly as \( n \) increases when \( n < 5 \), while when \( n \geq 5 \), incorporating earlier items in the session will not considerably improve the performance. Similarly on LF, the performance becomes stable when \( n \geq 10 \). These results reveal that on session-based recommendation datasets, only the most recent few items are effective in learning users’ preferences. As a result, we will not loss crucial information in P2MAM by using only the last \( n \) items (Section 4.1) for the recommendation.

### 7 Discussion

We conduct an experiment to verify that users’ prospective preferences could signify the important items, and thus, benefit the recommendation. Specifically, we develop a method, denoted as ORACLE, which learns attention weights conditioned on the ground-truth next item (i.e., \( s_{|S|+1} \), the true preference). In ORACLE, we generate recommendations in the same way as that in P2MAM-D-P except that in the dot-product attention (Equation 3), we remove the position embeddings (i.e., \( P \)) and replace \( q \) with \( v_{s_{|S|+1}} \) (i.e., embedding of \( s_{|S|+1} \)). We empirically compare ORACLE with another method, denoted as MEAN, which uses a mean pooling to equally weigh items in the session. We report the results of ORACLE and MEAN on the six datasets in Table 8.

As shown in Table 8, ORACLE significantly outperforms MEAN in all the datasets. For example, in terms of recall@5, MRR@5 and NDCG@5, compared to MEAN, on average, ORACLE achieves significant improvement of 68.6%, 100.7% and 89.5%, respectively. The superior performance of ORACLE over MEAN shows that the learned attention weights in ORACLE are effective, and further reveals that users’ prospective preferences could indicate important items. These results motivate us to estimate the prospective preferences, and weigh items conditioned on the estimate as in \( P^E \) (Section 4.3).

We notice that on TM, MEAN outperforms P2MAM and all the baseline methods (Table 3). Previous work [17] suggests that on some extremely sparse recommendation datasets, the attention-based methods may not be well-learned, and underperform simple mean pooling-based method (i.e., MEAN). TM with the smallest training set and a large number of items is extremely sparse. Therefore, MEAN could outperform P2MAM and all the baseline methods on this dataset. However, on all the other datasets, P2MAM significantly outperforms MEAN, which reveals that on most of the datasets, P2MAM could learn well, and thus, enable better performance.

### 8 Conclusions

In this manuscript, we presented novel P2MAM models that conduct session-based recommendations using two important factors: temporal patterns and estimates of users’ prospective preferences. Our experimental results in comparison with five state-of-the-art baseline methods on the six benchmark datasets demonstrate that P2MAM significantly improves the recommendation performance.
outperforms the baseline methods with an improvement of up to 19.2%. The results also reveal that on most of the datasets, the two factors could reinforce each other, and enable superior performance. Our analysis on position embeddings signifies the importance of explicitly modeling the position information for session-based recommendation. Our analysis on prospective preference estimate strategies demonstrates that on most of the datasets, our learning-based strategy is more effective than the existing recency-based strategy. Our analysis on the learned attention weights shows that with position embeddings, P$^2$MAM could effectively capture the temporal patterns (e.g., recency patterns). Our results in run-time performance comparison show that P$^2$MAM is much more efficient than the best baseline method DHCN (47.7 average speedup). Our analysis on users’ prospective preferences demonstrates that the prospective preferences could signify important items, and thus, benefit the recommendation.

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APPENDIX A
REPRODUCIBILITY
We implement P$^2$MAM in python 3.7.3 with PyTorch 1.4.0.
We use Adam optimizer with learning rate 1e-3 on all the datasets for P$^2$MAM variants (i.e., P$^2$MAM-D, P$^2$MAM-P and P$^2$MAM-O-P). We initialize all the learnable parameters using the default initialization methods in PyTorch. The source code and processed data is available on GitHub. For all the methods, during the grid search, we initially search the hyper parameters in a search range. If the hyper parameter yields the best performance on the boundary of the search range, we will extend the search range, if applicable, until a value in the middle yields the best performance. Table 9 presents the hyper parameters used for all the methods.

For P$^2$MAM and LAST-O-P, the initially search range for the embedding dimension $d$, the length of transformed sequence $n$ and the number of heads $h$ is $\{32, 64, 128\}$, $\{10, 15, 20\}$ and $\{1, 2, 4\}$, respectively.

For NARM, we initially search $d$ and the learning rate $lr$ from $\{32, 64, 128\}$ and $\{1e-4, 1e-3\}$, respectively.

For SR-GNN, we initially search $d$, $lr$ and the weight decay factor $\lambda$ from $\{32, 64, 128\}$, $\{1e-4, 1e-3\}$ and $\{1e-5, 1e-4, 1e-3\}$, respectively.

For LESSR, we initially search $d$, $lr$ and the number of GNN layers $l$ from $\{32, 64, 128\}$, $\{1e-4, 1e-3\}$ and $\{1, 2, 3, 4, 5\}$, respectively.

For DHCN, we initially search $d$ and the factor for the self-supervision $\beta$ from $\{32, 64, 128\}$ and $\{1e-4, 1e-3, 1e-2\}$, respectively. We use the default number of GNN layers (i.e., 3) due to the fact that the original paper of DHCN shows that DHCN is not sensitive to this hyper parameter, and it is very expensive to tune hyper parameters for DHCN (Section 6.9).

REFERENCES
[1] J. Li, P. Ren, Z. Chen, Z. Ren, T. Lian, and J. Ma, “Neural attentive session-based recommendation,” in Proceedings of the 2017 ACM on Conference on Information and Knowledge Management, 2017, pp. 1419–1428.
[2] S. Wu, Y. Tang, Y. Zhu, L. Wang, X. Xie, and T. Tan, “Session-based recommendation with graph neural networks,” in Proceedings of the AAAI Conference on Artificial Intelligence, 2019, pp. 346–353.
[3] X. Xia, H. Yin, J. Yu, Q. Wang, L. Cui, and X. Zhang, “Self-supervised hypergraph convolutional networks for session-based recommendation,” arXiv preprint arXiv:2012.06852, 2020.
[4] T. Chen and R. C.-W. Wong, “Handling information loss of graph neural networks for session-based recommendation,” in Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, 2020, pp. 1172–1180.
[5] A. Shersitsky, “Fundamentals of recurrent neural network (rnn) and long short-term memory (lstm) network,” Physica D: Nonlinear Phenomena, vol. 404, p. 132006, 2020.
[6] J. Zhou, G. Cui, S. Hu, Z. Zhang, C. Yang, Z. Liu, L. Wang, C. Li, and M. Sun, “Graph neural networks: A review of methods and applications,” AI Open, vol. 1, pp. 57–81, 2020.
[7] J. Chung, C. Gulcehre, K. Cho, and Y. Bengio, “Empirical evaluation of gated recurrent neural networks on sequence modeling,” arXiv preprint arXiv:1412.3555, 2014.
[8] B. Peng, Z. Ren, S. Parthasarathy, and X. Ning, “M2: Mixed models with preferences, popularities and transitions for next-basket recommendation,” arXiv preprint arXiv:2004.01646, 2020.
[9] S. Rendle, C. Freudenthaler, and L. Schmidt-Thieme, “Factorizing personalized markov chains for next-basket recommendation,” ser. WWW '10, 2010, p. 811–820.
[10] Q. Liu, Y. Zeng, R. Mokhosi, and H. Zhang, “Stamp: short-term attention/memory priority model for session-based recommendation,” in Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, 2018, pp. 1831–1839.
[11] B. Hidasi and A. Karatzoglou, “Recurrent neural networks with top-k gains for session-based recommendations,” in Proceedings of the 27th ACM international conference on information and knowledge management, 2018, pp. 843–852.
[12] R. Qiu, J. Li, Z. Huang, and H. Yin, “Rethinking the item order in session-based recommendation with graph neural networks,” in Proceedings of the 28th ACM International Conference on Information and Knowledge Management, 2019, pp. 579–588.
[13] T. Donkers, B. Loepp, and J. Ziegler, “Sequential user-based current neural network recommendations,” in Proceedings of the Eleventh ACM Conference on Recommender Systems, ser. RecSys '17, 2017, p. 152–160.
[14] F. Vasile, E. Smirnova, and A. Conneau, “Meta-prod2vec: Product embeddings using side-information for recommendation,” in Proceedings of the 10th ACM Conference on Recommender Systems, 2016, pp. 225–232.
[15] T. Mikolov, I. Sutskever, K. Chen, G. S. Corrado, and J. Dean, “Distributed representations of words and phrases and their compositionality,” Advances in neural information processing systems, vol. 26, 2013.
[16] J. Tang and K. Wang, “Personalized top-n sequential recommendation via convolutional sequence embedding,” in Proceedings of the Eleventh ACM International Conference on Web Search and Data Mining, 2018, pp. 565–573.
[17] B. Peng, Z. Ren, S. Parthasarathy, and X. Ning, “Hm: hybrid associations models for sequential recommendation,” IEEE Transactions on Knowledge and Data Engineering, 2021.
[18] F. Yuan, A. Karatzoglou, I. Arapakis, J. M. Jose, and X. He, “A simple convolutional generative network for next item recommendation,” in Proceedings of the Twelfth ACM International Conference on Web Search and Data Mining, 2019, pp. 582–590.
[19] J. Li, P. Ren, Z. Chen, Z. Ren, T. Lian, and J. Ma, “Neural attentive session-based recommendation,” In Proceedings of the 2017 ACM on Conference on Information and Knowledge Management, 2017, pp. 1419–1428.
[20] S. Wu, Y. Tang, Y. Zhu, L. Wang, X. Xie, and T. Tan, “Session-based recommendation with graph neural networks,” In Proceedings of the AAAI Conference on Artificial Intelligence, 2019, pp. 346–353.
[21] X. Xia, H. Yin, J. Yu, Q. Wang, L. Cui, and X. Zhang, “Self-supervised hypergraph convolutional networks for session-based recommendation,” arXiv preprint arXiv:2012.06852, 2020.
[22] T. Chen and R. C.-W. Wong, “Handling information loss of graph neural networks for session-based recommendation,” In Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, 2020, pp. 1172–1180.
TABLE 9: Best Hyper Parameters for P^2MAM, LAST-O-P and Baseline Methods

| Dataset | P^2MAM-O | P^2MAM-O-P | LAST-O-P | NARM | SR-GNN | LESSR | DHCN |
|---------|----------|-----------|---------|------|--------|-------|------|
|         | d  n  b  | d  n  b  | d  lr  | d  lr  | d  lr  | d  lr  | d  β  |
| DG      | 128 10 128 15 8 | 128 10 4 64 | 1e-3 | 32 1e-3 | 1e-6 | 32 2e-3 | 3 128 5e-3 |
| YC      | 128 7 128 8 8 | 128 20 2 64 | 1e-3 | 128 1e-3 | 0.0 | 32 1e-3 | 2 128 1e-4 |
| GA      | 128 10 128 15 8 | 128 10 4 64 | 1e-3 | 128 1e-3 | 1e-6 | 32 1e-3 | 2 128 1e-3 |
| LF      | 128 10 128 20 2 | 128 20 1 128 1e-3 | 128 5e-4 | 0.0 | 128 1e-3 | 4 128 1e-5 |
| NP      | 128 9 128 8 4 | 128 20 4 64 | 1e-3 | 128 5e-4 | 1e-6 | 32 2e-3 | 3 128 1e-3 |
| TM      | 128 15 128 10 4 | 128 20 4 128 1e-4 | 96 1e-3 | 1e-6 | 128 5e-4 | 2 64 5e-5 |

In this table, in P^2MAM, d, n and b are the dimension of the hidden representation, length of the transformed session and the number of heads. In NARM, SR-GNN and LESSR, d is the dimension of the hidden representation and lr is the learning rate. In SR-GNN, λ is the weight decay factor. In LESSR, t is the number of GNN layers, and in DHCN, β is the factor for the self-supervision.

[19] W.-C. Kang and J. McAuley, “Self-attentive sequential recommendation,” in 2018 IEEE International Conference on Data Mining (ICDM). IEEE, 2018, pp. 197–206.

[20] F. Sun, J. Liu, J. Wu, C. Pei, X. Lin, W. Ou, and P. Jiang, “BerTrec: Sequential recommendation with bidirectional encoder representations from transformer,” in Proceedings of the 28th ACM international conference on information and knowledge management, 2019, pp. 1441–1450.

[21] Z. Fan, Z. Liu, S. Wang, L. Zheng, and P. S. Yu, “Modeling sequences as distributions with uncertainty for sequential recommendation,” in Proceedings of the 30th ACM International Conference on Information & Knowledge Management, 2021, pp. 3019–3023.

[22] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. Kaiser, and I. Polosukhin, “Attention is all you need,” in Advances in neural information processing systems, 2017, pp. 5998–6008.

[23] Y. Li, D. Tarlow, M. Brockschmidt, and R. Zemel, “Gated graph sequence neural networks,” arXiv preprint arXiv:1511.05493, 2015.

[24] B.-J. Hou and Z.-H. Zhou, “Learning with interpretable structure from gated rnn,” IEEE transactions on neural networks and learning systems, pp. 2267–2279, 2020.

[25] C. Xu, P. Zhao, Y. Liu, V. S. Sheng, J. Xu, F. Zhuang, J. Fang, and X. Zhou, “Graph contextualized self-attention network for session-based recommendation.” in IJCAI, 2019, pp. 3940–3946.

[26] Z. Fan, Z. Liu, J. Zhang, Y. Xiong, L. Zheng, and P. S. Yu, “Continuous-time sequential recommendation with temporal graph collaborative transformer,” in Proceedings of the 30th ACM International Conference on Information & Knowledge Management, 2021, pp. 433–442.

[27] Y. Wu, M. Mukunoki, T. Funatomi, M. Minoh, and S. Lao, “Optimizing mean reciprocal rank for person re-identification,” in 2011 8th IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS). IEEE, 2011, pp. 408–413.

Xia Ning received her Ph.D. degree from the Department of Computer Science & Engineering, University of Minnesota, Twin Cities, in 2012. She is currently an Associate Professor at the Biomedical Informatics Department, and the Computer Science and Engineering Department, The Ohio State University. Her research is on data mining, machine learning and artificial intelligence with applications in recommender systems, drug discovery and medical informatics.

Bo Peng received his M.S. degree from the Department of Computer and Information Science, Indiana University–Purdue University, Indianapolis, in 2019. He is currently a Ph.D. student at the Computer Science and Engineering Department, The Ohio State University. His research interests include machine learning, data mining and their applications in recommender systems and graph mining.

Chang-Yu Tai received his M.S. degree from the Department of Chemistry, National Taiwan University, in 2018. He is currently an M.S. student at the Computer Science and Engineering Department, The Ohio State University. His research interests include deep learning applications in natural language processing and recommender systems.

Srinivasan Parthasarathy received his Ph.D. degree from the Department of Computer Science, University of Rochester, Rochester, in 1999. He is currently a Professor at the Computer Science and Engineering Department, and the Biomedical Informatics Department, The Ohio State University. His research is on high performance data analytics, graph analytics and network science, and machine learning and database systems.