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Attribute-aware Diversification for Sequential Recommendations

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ABSTRACT
Users prefer diverse recommendations over homogeneous ones. However, most previous work on Sequential Recommenders does not consider diversity, and strives for maximum accuracy, resulting in homogeneous recommendations. In this paper, we consider both accuracy and diversity by presenting an Attribute-aware Diversifying Sequential Recommender (ADSR). Specifically, ADSR utilizes available attribute information when modeling a user’s sequential behavior to simultaneously learn the user’s most likely item to interact with, and their preference of attributes. Then, ADSR diversifies the recommended items based on the predicted preference for certain attributes. Experiments on two benchmark datasets demonstrate that ADSR can effectively provide diverse recommendations while maintaining accuracy.

CCS CONCEPTS
• Information systems → Recommender systems.

KEYWORDS
Sequential recommendation, Attribute-aware diversification

1 INTRODUCTION
Recommender Systems (RSs) are widely used to help users find items they are interested in. Traditional RSs such as Collaborative Filtering and Matrix Factorization \cite{9} provide recommendations using a decomposition of a user-item interaction matrix. These approaches do not take the order of interactions into account and fail to capture the users’ evolving preferences. Sequential Recommenders (SRs) have attracted a lot of attention, as they can exploit the order of interactions \cite{8}. In industry, SRs allow e-commerce retailers to provide recommendations to users, based on their sequence of interactions and have proven to be very effective \cite{6–8}.

Side information in SRs, e.g., item attributes (category, genre, etc.), has proven to be useful for capturing user preferences. E.g., Bai et al. \cite{2} use available item attributes to make their model attribute-aware by obtaining a unified representation from items and their attributes. And Chen et al. \cite{5} use item attributes to infer users’ future intention, allowing them to do intent-aware recommendation. However, the focus of these methods lies on increasing performance in terms of accuracy only, resulting in homogeneous recommendations. Moreover, diversity is an important metric to consider as it has been shown that users prefer diverse search results opposed to highly accurate, but redundant ones \cite{3, 10}.

We propose to use item-attribute information to diversify SRs. For instance, if we know that a user enjoys \textit{documentaries} and \textit{thrillers}, and this user is in search of films about “Artificial Intelligence” (AI), they are likely interested in both a \textit{documentary} about AI and in a \textit{thriller} where general AI achieves world domination. Genre information and preferences can be used to present diverse recommendations related to AI, collectively covering multiple genres. To this end, we present an Attribute-aware Diversifying Sequential Recommender (ADSR), which considers both accuracy and diversity while generating the list of recommendations.

The ADSR consists of three modules: an Attribute-aware Encoder (AE), an Attribute Predictor (AP), and an Attribute-aware Diversifying Decoder (ADD). The AE models the sequence of item interactions and the sequence of item-attributes. The AP learns and predicts the user’s preference on attribute level. Finally, the ADD incrementally generates diversified recommendations by using the predictions from the AP and trading off accuracy and diversity.

The AE and AP both make predictions and are therefore optimized in a multi-task learning paradigm \cite{4}. We carry out experiments on two benchmark datasets. The results demonstrate that ADSR benefits from modeling and predicting item attributes, and can provide attribute-aware diversified recommendations while preserving accuracy.

To sum up, the contributions of this work are as follows:
• We propose ADSR, which is one of the first to address diverse recommendations for SRs.
• We devise AP and ADD modules to generate attribute-aware diversified recommendations by jointly optimizing item recommendation and item attribute prediction as an auxiliary task.

2 Attribute-aware Diversifying Sequential Recommender (ADSR)
Given user \textit{u} with behavior sequence \(S_u = \{v_1, \ldots, v_T\}\) and corresponding item attribute sequence \(S_c = \{c_1, \ldots, c_T\}\), where \(v_t\) is the item \textit{u} interacts with at time step \textit{t}, and \(c_t\) is the attribute of \(v_t\), we aim to create a diversified list of recommendations \(R_L\). Formally, let \(P(c_t \mid S_c, S_u)\) be the importance of \(c_t\) based on the sequences and let \(P(R_L \mid S_u, S_c, c_t)\) be the probability of recommending \(R_L\) conditioned that \(c_t\) is the user’s preferred attribute.

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Then, we find \( R_L \) by maximizing \( P(R_L | S_v, S_c) \), defined as:

\[
P(R_L | S_v, S_c) = \prod_{j=1}^{|C|} P(R_L | S_v, S_c, c_j) P(c_j | S_v, S_c),
\]

Optimising \( P(R_L | S_v, S_c) \) directly is difficult due to the large search space [1]. Therefore, we propose to generate \( R_L \) iteratively, by appending the item with the highest score \( S(v_i) \) to \( R_L \) at each time step, similar to [1, 3]:

\[
S(v_i) = \lambda_v \cdot S_{rel}(v_i) + (1 - \lambda_v) \cdot S_{div}(v_i),
\]

where \( S_{rel}(v_i) \) is the relevance score for item \( v_i \) (see §2.1), and \( S_{div}(v_i) \) is the attribute-aware diversity score (see §2.3). The hyper-parameter \( \lambda_v \) is used to balance \( S_{rel} \) and \( S_{div} \), giving control over the accuracy and diversity of the trained model.

We propose ADSR to model \( S_{rel}(v_i) \) and \( S_{div}(v_i) \), as shown in Figure 1. The Attribute-aware Encoder (AE) models the input sequences \( S_c, S_v \) to get \( h_v \) and \( h_c \), respectively. Next, the Attribute Predictor (AP) predicts the next item attribute distribution \( P(c | S_v, S_c) \). Finally, the Attribute-aware Diversifying Decoder (ADD) uses these outputs to generate the diversified list \( R_L \).

### 2.1 Attribute-aware Encoder

First, the sequence of attributes is encoded using a bidirectional RNN with GRU-cells [7]. The input of this GRU is a sequence of item attribute embeddings concatenated with the item embeddings: \( \{p_1, p_2, \ldots, p_T\} \) where \( p_t = [v_t; v_t] \in \mathbb{R}^{d_e + d_v} \). The output of the GRU are hidden representations \( \{h_{v1}, h_{v2}, \ldots, h_{vT}\} \) where \( h_{v_i} \in \mathbb{R}^{2d_{cav}} \). Then, a second bidirectional RNN is used to get the representation for the sequence of item interactions. The input to this encoder is the concatenation of the item embeddings and the hidden states: \( q_t = [v_t; h_{v_t}] \), yielding \( \{h_{v1}, h_{v2}, \ldots, h_{vT}\} \in \mathbb{R}^{2d_{cav}} \).

Next, we employ additive attention to get the global preference \( f_v \) and \( f_c \), capturing the complete sequences, as follows:

\[
f_v = \sum_{j=1}^{T} \alpha_{T_j} h_{vT_j}
\]

\[
\alpha_{T_j} = \text{softmax} \left( W_p \tanh(W_q h_{vT_j} + W_k h_{cT_j}) \right),
\]

where matrices \( W_q, W_k \) are used to transform \( h \) into a latent space, and \( W_p \in \mathbb{R}^{2d_{cav} \times 1} \) is used to get the attention weights. \( f_c \) is calculated as in Eq. 3 using the attention weights \( \alpha_{T_j} \) obtained for \( f_v \). Finally, AE calculates the relevance score as:

\[
S_{rel}(v_i) = P(v_i | S_v, S_c) = \frac{\exp(g^T v_i)}{\sum_{j=1}^{|V|} \exp(g^T v_j)},
\]

where \( g = [f_v; c_t] \in \mathbb{R}^d \) and \( \tilde{c}_{T+1} = \sum c_i P(c_i | S_v, S_c) \cdot c_i \) is the weighted average item attribute based on AP’s predicted attribute preference. For clarity, the loss induced by AE \( L_{AE} \) is described in Section 2.4.

### 2.2 Attribute Predictor

The AP is of great importance to our model. The output \( P(c | S_v, S_c) \) is used by the AE to determine item relevance, and by the Attribute-aware Diversifying Decoder (ADD) (Sec. 2.3) to diversify the recommendations. The AP predicts \( P(c | S_v, S_c) \) with a small neural network. The input is the concatenation of the global preference: \([f_v, f_c] \). In doing so, the AP exploits features from both encoders when making the prediction. The AP consists of a hidden layer, with Batch Normalisation and ReLU activation, followed by the output layer activated with a sigmoid function. This prediction task is an auxiliary task, with an additional loss \( L_{AP} \) (see Section 2.4).

### 2.3 Attribute-aware Diversifying Decoder

The ADD is responsible for generating the diversified list of recommendations \( R_L \). Inspired by IA-Select, a method used in web search [1], we incrementally extend \( R_L \) by selecting at each step the item with the highest score (Eq. 2), i.e., \( v_i^* = \arg \max_{v_i} S(v_i) \). Specifically, at each step the ADD calculates \( S_{div} \) using \( P(c | S_v, S_c) \), obtained from the AP, as initial estimation of importance per category \( U \):

\[
S_{div}(v_i) = \sum_{j=1}^{|C|} U(c_j | S_v, S_c, R_L) \ (1 - V(v_i | c_j)),
\]

where \( V(v_i | c_j) \) represents the value of \( v_i \) in context of \( c_j \), and is 1 if \( v_i \) belongs to category \( c_j \) and 0 else. After each step, we update \( U(c_j | S_v, S_c, R_L) \) to reflect the newly added item to \( R_L \) by:

\[
U(c_j | S_v, S_c, R_L \cup \{v_i\}^*) = \text{softmax} \left[ (1 - V(v_i | c_j)) \ U(c_j | S_v, S_c, R_L) \right].
\]

### 2.4 Losses

The loss \( L_{AE} \) calculated for the AE is the Cross-Entropy Loss.

\[
L_{AE} = - \frac{1}{|V|} \sum_{i=1}^{|V|} y_i \log P(v_i | S_v, S_c)
\]

\[
y_i = 1 \text{ if } v_i = v_{T+1}, \ 0 \text{ else, where } v_{T+1} \text{ is the target.}
\]
Table 1: Dataset statistics after pre-processing.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>#Users</th>
<th>#Items</th>
<th>#Train seq.</th>
<th>#Valid seq.</th>
<th>#Test seq.</th>
<th>#Attributes</th>
</tr>
</thead>
<tbody>
<tr>
<td>ML1M</td>
<td>6,041</td>
<td>3,261</td>
<td>784,309</td>
<td>93,929</td>
<td>97,871</td>
<td>18</td>
</tr>
<tr>
<td>TMall</td>
<td>31,855</td>
<td>58,344</td>
<td>698,081</td>
<td>54,706</td>
<td>54,705</td>
<td>71</td>
</tr>
</tbody>
</table>

To calculate $L_{AP}$, the Binary Cross-Entropy Loss is used, allowing for multi-labeled targets:

$$L_{AP} = -\frac{1}{|C|} \sum_{i=1}^{C} y_i \log P(c_i | S_v, S_c) + (1-y_i) \log (1 - P(c_i | S_v, S_c))$$  \hfill (8)

where $y_i = 1$ if $c_i = c_{T+1}$, else 0, where $c_{T+1}$ is the target.

Then, to form the final loss used to optimize ADSR ($L_{ADSR}$), the two losses are interpolated with balancing parameter $\lambda_{MT}$:

$$L_{ADSR} = \lambda_{MT} \cdot L_{AE} + (1-\lambda_{MT}) \cdot L_{AP}. \hfill (9)$$

3 EXPERIMENTAL SETUP

We seek to answer the following questions in our experiments:

(RQ1) Where does the improvement of ADSR come from? What are the effects of the AE, AP and ADD modules? (See §4.1.) (RQ2) What is the performance of ADSR compared with non-attribute-aware diversity methods? (See §4.2.) (RQ3) How does the trade-off parameter $\lambda_{a}$ affect the performance of ADSR? (See §4.3.)

3.1 Datasets

We evaluate ADSR on the following real-world datasets:

- MovieLens-1M,\(^1\) which contains 1 million ratings from 6K users over 4K movies. Movies belong to at least one of 18 genres.
- TMall,\(^2\) which is an e-commerce dataset containing 44.5M user interactions over 24M items belonging to one of 72 categories. We use the “buy” interactions only.

Genre and category are used as item attribute. Multi-labeled genres are handled by summing the embeddings.\(^3\) Both datasets are filtered from users and items with less than 20 interactions. Per sequence, the first 80% is used as training set. The 20% is filtered from sequences with unseen items and halved to form the validation and test sets. The final inputs are sliding windows of size 10 [6] (10th item as target). Statistics after processing are reported in Table 1.

3.2 Evaluation metrics

Following [6-8], we measure accuracy of the model using $MRR@k$ and $Recall@k$. Predictions made by the AP for multi-labeled targets are considered correct if one of the active labels is predicted. To measure diversity, we use Intra-List Diversity (ILD) [10]:

$$ILD(R_L) = \frac{2}{|R_L| \cdot (|R_L| - 1)} \sum_{i \in R_L} \sum_{j \in R_L \setminus i} d(i, j),$$  \hfill (10)

where $d(i, j)$ is the euclidean distance between the one-hot-encoded item attributes of $v_i$ and $v_j$. A second diversity measure is used where the number of unique attributes in the recommended list is counted, we refer to this as discrete diversity ($Dis$).

\(^1\)https://grouplens.org/datasets/movielens/1m
\(^2\)https://tianchi.aliyun.com/dataset/dataDetail?dataId=53
\(^3\)In this work, a single genre/category is used as attribute, but ADSR can be modified to use other/multiple attributes (or contexts) using e.g. embedding summation.

3.3 Models for comparison

A number of SR methods have been proposed in the last few years. We do not compare with them because: (1) improving recommendation accuracy is out of the scope of this paper; and (2) many are not directly comparable due to the use of different model architectures. Therefore, we construct/select baselines that are fair (use the same information, similar architectures, etc.) to compare with:

- Base Sequential Recommender (BSR) uses only $S_{c}$ to generate hidden representations. Then, BSR applies additive attention to get the global preference, used to generate $R_{L}$, similar to NARM [7].
- Attribute-aware Neural Attentive Model (ANAM) incorporates attribute information and applies attention to the hidden representations, similar to ANAM [2]. We have adapted it to do SR rather than next-basket recommendation, and modified it to be similar to our own variants. The core principles remain the same, both apply attention to a unified representation based on $S_{c}$.
- Multi Task Attribute-aware Sequential Recommender (MTASR) extends ANAM to predict the attribute preference, and to use the weighted attribute embedding to predict $R_{L}$. This model can be regarded as a special case of ADSR with $\lambda_{a} = 1$.
- ANAM+MMR is ANAM with the Maximal Marginal Relevance reranking algorithm by Carbonell and Goldstein [3], trading off relevance and diversity by selecting $v^*$ by:

$$v^* = \arg \max_{v_{i} \in V \setminus R_{L}} \delta(v_{i}) + (1 - \lambda) \min_{v_{j} \in R_{L}} d(i, j),$$  \hfill (11)

where $V$ are all items not in $R_{L}$ and $d(i, j)$ is the same as in Eq. 10. This model does not have the AP module, so it cannot do attribute-aware diversification based on preference. Besides ANAM+Maximal Marginal Relevance (MMR), none of the methods listed considers diversity when recommending items. ADSR learns attribute preferences to provide an attribute-aware diversified list of recommendations.

3.4 Implementation details

For a fair comparison, we use the same settings for all models. We set $d_v = d_c = d_{GRU} = 128$. Embeddings are initialized using the Xavier method. Dropout is applied to the embeddings and hidden representations with $p = 0.5$. We use the Adam optimizer with learning rate 0.01, batches of 1024 samples for 60 epochs. $f_c$ is projected to $d_c$ by one linear layer in the case of BSR and ANAM. A bilinear mapping is used to combine and project $f_v$ and $f_c$ in MTASR and ADSR. The best model is selected by MRR and Recall on the validation set.\(^4\)

4 EXPERIMENTAL RESULTS

4.1 Ablation study

To answer (RQ1) and to show the effectiveness of the AE, AP and ADD modules, we compare the results of variations of ADSR, as shown in Table 2. BSR is ADSR without all three modules (no attribute information is used). Further, ANAM is ADSR without AP and ADD, and MTASR is ADSR without ADD.

First, the AE is effective. This is demonstrated by the fact that ANAM outperforms BSR on both datasets, showing that modeling attribute information significantly improves performance. Second,
the AP further enhances performance of the model, as MTASR outperforms ANAM. This shows that learning attribute preference with the AP brings a significant improvement to the model. Third, the ADD significantly improves diversity without hurting accuracy. This claim is supported by the fact that ADSR outperforms MTASR on both diversity metrics. MTASR outperforms ADSR in terms of MRR and Recall, which is expected as diversity is increased by trading off relevance, where MTASR is equal to ADSR with $\lambda_s=1$. However, the trade-off is advantageous, as gains in diversity are made of 39% and 14% over BSR in ILD@10 and Dis@10, with a reduction of merely 1.24% in MRR@10 and 3.29% in Recall@10.

### 4.2 Comparison with non-attribute-aware diversity methods

To answer (RQ3), we compare ADSR with ANAM+MMR. By incorporating MMR into ANAM, ANAM+MMR is able to provide diversified recommendations. From Table 2 we see that ADSR is able to provide more diverse recommendations on both datasets. On ML1M, ADSR significantly outperforms ANAM+MMR on all metrics, while increasing diversity: ADSR is more effective at diversifying results, showing increases of 9.98% over ANAM+MMR in terms of Dis@10 and ILD@10, while yielding higher MRR and Recall. On TMall, ADSR is best at diversifying results, showing increases of 9.98% and 9.03% over ANAM+MMR in terms of Dis@10 and ILD@10, and gains of 16.46% and 11.69% in Dis@20 and ILD@20. However, ADSR yields lower accuracy than ANAM and ANAM+MMR, which is likely due to the high sparsity of TMall and the larger attribute space, making it harder for the AP to correctly predict attributes.

### 4.3 Effect of the trade-off hyperparameter $\lambda_s$

To answer (RQ3), we vary $\lambda_s$ from 0.0 to 1.0 and investigate the effect it has on accuracy and diversity (for brevity, we chose a single metric of each type; see Figure 2). When $\lambda_s=0$, it maximizes diversity only, and does this successfully, yielding the maximum diversity possible on both datasets. On TMall, very low values of $\lambda_s$ are required to diversify results as the item space is much larger, resulting in very small values for $S_{div}$. Clearly, $S_{div}$ only affects item selection when it is weighed much heavier than $S_{sp}$. Finally, Figure 2 shows that diversity decays slower than accuracy increases, meaning that ADSR can effectively achieve a large gain in diversity for a small loss of accuracy.

### References