AMER: Automatic Behavior Modeling and Interaction Exploration in Recommender System

Pengyu Zhao*, Kecheng Xiao*, Yuanxing Zhang*, Kaigui Bian and Wei Yan
School of EECS, Peking University, Beijing, China
{pengyuzhao, kecheng, longo, bkg, w}@pku.edu.cn

Abstract
User behavior and feature interactions are crucial in deep learning-based recommender systems. There has been a diverse set of behavior modeling and interaction exploration methods in the literature. Nevertheless, the design of task-aware recommender systems still requires feature engineering and architecture engineering from domain experts. In this work, we introduce AMER, namely Automatic behavior Modeling and interaction Exploration in Recommender systems with Neural Architecture Search (NAS). The core contributions of AMER include the three-stage search space and the tailored three-step searching pipeline. In the first step, AMER searches for residual blocks that incorporate commonly used operations in the block-wise search space of stage 1 to model sequential patterns in user behavior. In the second step, it progressively investigates useful low-order and high-order feature interactions in the non-sequential interaction space of stage 2. Finally, an aggregation multi-layer perceptron (MLP) with shortcut connection is selected from flexible dimension settings of stage 3 to combine features extracted from the previous steps. For efficient and effective NAS, AMER employs the one-shot random search in all three steps. Further analysis reveals that AMER’s search space could cover most of the representative behavior extraction and interaction investigation methods, which demonstrates the universality of our design. The extensive experimental results over various scenarios reveal that AMER could outperform competitive baselines with elaborate feature engineering and architecture engineering, indicating both effectiveness and robustness of the proposed method.

1 Introduction
Recommender system is responsible for presenting items that match users’ interests from a large number of candidates, which has become an essential part of today’s online E-commerce websites and content platform. Facing the increasing number of users, items, and user-item interactions, more and more real-world applications [11, 84] resort to powerful deep learning models to discover personalized content. Two mainstream issues have been receiving widespread attention: Behavior modeling [26, 32, 67, 84] probes into capturing user’s diverse and dynamic interest from historical behaviors with neural network models; Interaction exploration [18, 39, 52, 70] investigates interactions among different feature fields to reinforce multi-layer perceptron (MLP) and provide intuitive conjunction evidence for recommendation. Though achieved prevailing success [11, 84], existing methods are only suitable for specific scenarios due to their intrinsic advantages and limitations. Hence, architecture engineering to model user behaviors and feature engineering to exploit attribute interactions are two fundamental challenges for developing appropriate recommender systems in different scenarios.

Specifically, among the methods for encoding user’s behaviors, recurrent neural network (RNN) [26, 27] is hard to preserve long-term behavioral dependencies even though employing gated memory cells [9, 28]. Convolutional neural network (CNN) [67, 80] is capable of learning local feature combinations yet it relies on a wide kernel, deep network or global pooling to distinguish long-term interests. Although the attention mechanism [2] is able to directly aggregate features from entire

*Equal contribution.
Figure 1: The three-stage search space and three-step searching pipeline of AMER. AMER searches for choice blocks of dynamic depth, feature interactions and aggregation MLP (three layers as an example) in Steps 1-3.

historical behaviors, additional recurrent models are still necessary for modeling the evolving user’s preferences, potentially incurring the drawbacks of RNNs. Self-attention is recently popular in modeling various long-term behaviors, but it is hard to be deployed in real-time applications that require fast inference with limited resources. Regarding the methods for interaction exploration, vanilla MLP implicitly models high-order interactions while missing the low-order information. Linear regression (LR), factorization machine (FM) and product-based neural network (PNN) introduce low-order feature interactions from input categorical features. On top of that, DCN and xDeepFM further involve compressed high-order interactions in the networks. However, all the above methods either require hand-crafted features or simply enumerate all interactions of bounded degree which may introduce noise in the final result. Some latest attempts find useful interactions with AutoML, whereas they either explore a small subset of cross features in LR or merely evaluate low-order interactions in FM.

Recently, neural architecture search (NAS) paradigm is proposed to automatically design neural networks by searching task-specific and data-oriented optimal architecture from the search space, thereby mitigating the human efforts. NAS has demonstrated great success in various tasks of computer vision and neural language processing. However, little attention has been paid to recommendation. In this paper, we introduce AMER for Automatic behavior Modeling on the user’s sequential history as well as low-order and high-order interaction Exploration on the categorical features in the Recommender system. The key contributions of AMER are the novel search space that covers most of representative recommendation models and the customized three-step searching pipeline matching the three stages in the backbone architecture. In the first step, AMER finds the appropriate network from block-wise search space of stage 1 to extract sequential features based on user behaviors, where each block has various choices of normalization, layer and activation operations. In the second step, AMER generates useful low-order and high-order features interactions from the non-sequential interaction space of stage 2, and finally AMER searches for aggregation MLP from MLP space of stage 3 with Squeeze-and-Excitation (SE) shortcut to combine the search results with raw input. To find the appropriate architecture in the search space, AMER introduces the one-shot strategy, strictly FairNAS, in all three steps and adopts the competitive random search on the trained one-shot model to conduct efficient and effective architecture search. The experimental results over various recommendation scenarios show that our automatic paradigms consistently achieve state-of-the-art performance despite the influence of multiple runs and could even outperform the strongest baselines with elaborate manual design, indicating both effectiveness and robustness of AMER’s search space and searching pipeline.

2 AMER

In this section, we describe the search space and searching pipeline of AMER. We first introduce the three-stage backbone model and the corresponding operation sets. Then, we detail the three-step one-shot searching pipeline for efficient and effective architecture search. Finally, we discuss the relationship between AMER and representative recommender systems, and show that AMER is able to cover most of these methods.

2.1 A.1 Backbone Architecture in AMER’s Search Space

As illustrated in Fig[1], the child networks in AMER’s search space share the same backbone architecture, which consists of the following aspects.
Stage 0: Feature Representation and Embedding. In the common recommendation tasks, the input features are usually collected in a multi-field categorical form. Generally, there are three basic elements in the data instances: user profile, item profile and context profile. User profile represents the user’s personal information and can be expressed by a tuple of multiple fields, e.g., ("User ID", "User Attributes", etc). Analogously, item profile and context profile can be represented by ("Item ID", "Item Attributes", etc) and ("Time", "Place", etc). Based on the basic elements, AMER segregates the features into two groups: (1) The sequential features denote the historical user’s behaviors, which can be represented by a list of behavior elements. Each behavior element contains the corresponding item profile and the optional context profile. (2) Non-sequential features depict the attribute information of current recommendation, including user profile and instant context profile. In the click-through rate (CTR) prediction task, the target item profile should also be involved in non-sequential features. Conforming to the existing methods [27, 84], AMER transforms the data instances into high-dimensional sparse vectors via one-hot or multi-hot encoding. Specifically, if the field is univalent, it will be converted to one-hot vector; if the field is multivalent, it will be encoded as a multi-hot vector. Therefore, the encoding of each data instance can be formally illustrated as:

\[
x = [x^a, x^b] = [x^a_1, x^a_2, ..., x^a_N, x^b_1, ..., x^b_T],
\]

where \( x^a = [x^a_1, x^a_2, ..., x^a_N] \) denotes \( N \) encoded vectors of non-sequential feature fields, while \( x^b = [x^b_1, x^b_2, ..., x^b_T] \) represents the encoded sequential behavior elements of length \( T \), where each behavior element \( x^b_i = [x^b_{i,1}, x^b_{i,2}, ..., x^b_{i,N_b}] \) is grouped in \( N_b \) categorical fields of the same dimension.

As the input features are high-dimensional sparse vectors, AMER compresses the features to low dimensional dense real-value vectors via embedding layer. Assume the number of unique features is \( F \). AMER creates embedding matrix \( E \in \mathbb{R}^{F \times K} \), where each embedding vector has dimension of \( K \). The embedding process follows the embedding lookup mechanism: If the field is univalent, the field embedding is the feature encoding; If the field is multivalent, the field encoding is the sum of feature embedding. Therefore, the embedding of data instances can be represented by:

\[
e = [e^a, e^b] = [e^a_1, e^a_2, ..., e^a_N, e^b_1, e^b_2, ..., e^b_T]
\]

where \( e^a_i \in \mathbb{R}^K \) is the field embedding of \( x^a_i \), and \( e^b_i = [e^b_{i,1}, e^b_{i,2}, ..., e^b_{i,N_b}] \in \mathbb{R}^{N_b \times K} \) is the concatenation of the field embedding in \( x^b_i = [x^b_{i,1}, x^b_{i,2}, ..., x^b_{i,N_b}] \).

Stage 1: Behavior Modeling on Sequential Features. To extract the sequential representation from user’s behavior, AMER introduces a block-wise macro search space to model sequential patterns based on grouped behavioral embedding \( H^b_0 = [e^b_{1,1}, e^b_{1,2}, ..., e^b_{1,T}] + [e^b_{2,1}, e^b_{2,2}, ..., e^b_{2,T}] + ... + [e^b_{N_b,1}, e^b_{N_b,2}, ..., e^b_{N_b,T}] \in \mathbb{R}^{T \times N_b \times K} \). The behavior modeling networks in the search space are constructed by stacking a fixed number of \( L_b \) residual blocks, where the \( l \)-th block receives the hidden state \( H^b_{l-1} \) from the previous block as input and produces new hidden state \( H^b_l \) of the same dimension. Each block consists of three consecutive operations, i.e., normalization, layer and activation, which are selected from the corresponding operation sets. Therefore, the hidden state of layer \( l \in [1, ..., L_b] \) can be represented by:

\[
H^b_l = \text{Act}^b_l(\text{Layer}^b_l(\text{Norm}^b_l(H^b_{l-1}))) + H^b_{l-1},
\]

where \( \text{Act}^b_l \), \( \text{Layer}^b_l \) and \( \text{Norm}^b_l \) are the selected normalization, layer and activation operations. As the fully connected networks can only handle fixed-length inputs, AMER compresses the final hidden states into fixed dimension via sequence-level sum pooling: \( h^b_{pool} = \sum_{i=1}^{T} h^b_{l_b,i} \), where \( h^b_{l_b,i} \in \mathbb{R}^{N_b \times K} \) denotes the \( i \)-th element in \( H^b_{l_b} \). Moreover, to extract the current interest of user, the last hidden state \( h^b_{l_b,T} \) is also included in the result. Besides, when recommender systems have access to target item under scenarios like CTR prediction, AMER adopts an attention mechanism to extract a target-aware representation from the sequential features: \( h^b_{att} = \sum_{i=1}^{T} a_i h^b_{l_b,i} \), where \( a_i \) is computed by local activation unit [84] between \( h^b_{l_b,i} \) and target item embedding. Then, the combined result \( h^b = [h^b_{pool}, h^b_{l_b,T}, h^b_{att}] \) is served as the sequential representation of behavior modeling.

Stage 2: Interaction Exploration on Non-sequential Features. Learning effective feature interactions is crucial for many recommender systems. The widely-used methods [8, 18, 39] mainly require manual feature engineering to extract useful interactions or exhaustively enumerate implicit and explicit interactions of bounded degrees. Different from those methods, AMER automatically explores a small number \( M \) of beneficial interactions \( p^i = [p^i_1, p^i_2, ..., p^i_M] \) from the interaction search space that contains all low-order and high-order interactions among the non-sequential features. Each interaction has the same dimension as non-sequential embedding, i.e., \( p^i \in \mathbb{R}^K, i \in [1, 2, ..., M] \).
As described in the backbone model, the child networks in AMER comprise behavior modeling 
where \( \sigma \) is the sigmoid function. The explored interactions and sequential representation as input: \( h_{l_0}^c = [e_1^c, e_2^c, \ldots, e_N^c, p_1^c, p_2^c, \ldots, p_M^c, h_{pool}^c, h_{act}^c, h_{l_{i-1}}^c]^T \). Assume MLP exploits \( L_c \) hidden layers to implicitly capture high-order feature interactions. AMER searches for hidden layer sizes and activation functions in the MLP. The forward process of hidden layer \( l \in [1, 2, \ldots, L_c] \) can be depicted as:

\[
h_l^c = Act_l^c(W_l^c h_{l-1}^c + b_l^c),
\]

where \( h_l^c \), \( W_l^c \), \( b_l^c \) and \( Act_l^c \) are the output, weight, bias, and activation function of the \( l \)-th layer. Meanwhile, inspired by the bypath in recommendation models [8, 18], AMER introduces a dense connection on feature embedding and extracted interactions \( Q^e \), where \( Q^e = [(e_1^e)^T, \ldots, (e_N^e)^T, (p_1^e)^T, \ldots, (p_M^e)^T]_c^T \in \mathbb{R}^{(M+N) \times K} \). The dimension of \( Q^e \) is several times higher than \( h_{l_{i-1}}^c \), AMER compresses the bypath into a representation of lower dimension. Particularly, AMER employs SE module with 1.0 expansion ratio to recalibrate the features in the compressed feature. The gated units in SE module \( a^{se} = [a_1^{se}, a_2^{se}, \ldots, a_{M+N}^{se}]^T \) are computed by:

\[
a^{se} = \sigma(W_2^{se} ReLU(W_1^{se} Q^e v)),
\]

where \( v \in \mathbb{R}^{K \times 1} \) is applied for linear projection on \( Q^e \). \( \text{ReLU}, \sigma \) represent ReLU and sigmoid activations for gating control and \( W_1^{se}, W_2^{se} \) are weight matrices in fully-connected layers. Then, AMER performs weighted sum pooling on the interactions to generate compressed feature \( h^{se} = \sum_{i=1}^{M+N} a_i^{se} q_i^{se} \), where \( q_i^{se} \) is the \( i \)-th element in \( Q^e \). After that, \( h^{se} \) is concatenated with the hidden feature \( h_{l_{i-1}}^c \) as the final representation \( h^c = [h_{l_{i-1}}^c, h^{se}]^T \).

**Loss Function.** For CTR prediction, AMER minimizes binary log loss for optimization:

\[
L = - \frac{1}{|S|} \sum_{(x, y) \in S} [y \log \sigma(w^T h^c) + (1 - y) \log (1 - \sigma(w^T h^c))],
\]

where \( \sigma(w^T h^c) \) is the predicted CTR score, and \( S \) is the training set with \( x \) as the input and \( y \in \{0, 1\} \) as the click label. For retrieval or next-item prediction task, AMER adopts the sampled binary cross entropy loss as the objective function to approximate the softmax cross entropy loss:

\[
L = - \frac{1}{|S|} \sum_{(x, i) \in S} [\log \sigma(e_i^T W h^c) + \sum_{j \in I_i} \log (1 - \sigma(e_j^T W h^c))],
\]

where \( \sigma(e_i^T W h^c) \) is the relevance score between item \( i \) and hidden representation, and \( S \) is the training set of input \( x \) and target item id \( i \). \( I_i \) denotes the set of the sampled negative items.

### 2.2 Choice Sets of Different Stages

As described in the backbone model, the child networks in AMER comprise behavior modeling stage, interaction exploration stage and aggregation stage, where in each stage the models will select corresponding residual blocks, feature interactions and MLP settings respectively from the choice sets. In the following, we will describe each component in the search space.

**Choice Blocks in Stage 1.** In order to cover the existing sequence modeling methods, AMER proposes the choice blocks to search various normalization, layer and activation operations in the network. Specifically, AMER collects the normalization set of \{Layer normalization [11], None\} and activation set of \{ReLU, GeLU [25], Swish [54], Identity\} which are commonly used in the existing methods. Regarding the layer operations, AMER introduces four categories of candidate layers, namely convolutional layers, recurrent layers, pooling layers and attention layers to identify sequential patterns. The convolutional layers are all one-dimension, including standard convolution with kernel size in \{1, 3\} and dilated convolution with kernel size \{3, 5, 7\}. The pooling layers consists of average pooling and max pooling with kernel size 3. Both convolutional and pooling layers are of stride 1 with SAME padding to maintain the spatial size. Bi-directional GRU (Bi-GRU) [9] is employed as the recurrent layer as it is faster than Bi-LSTM [28] without loss of precision while 2-head and 4-head bi-directional self attentions [68] are also introduced for better sequence modeling. In addition, when the target item is included in the input, the layer operation set associates the attention layer that attends to each sequence position from target item [84]. Besides, zero operation is also applied to drop redundant layers and implicitly allow for dynamic depth of network.
Choice Interactions in Stage 2. The existing methods adopt Hadamard product \[ \odot \], inner product \[ \prod \], bilinear functions \[ \langle \rangle \] and cross product \[ \times \] for feature interactions. Hadamard product calculates the element-wise product among the feature embedding, which can be exploited by both MLP and skip connection. The inner product can be seen as a simple form of Hadamard product that is compressed by sum pooling. Bilinear function extends Hadamard product by learning fine-grained interactions but introduces extra parameters in the interactions. Besides, bilinear function cannot handle high-order interactions and does not exhibit superiority over non-parameterized Hadamard product when combining with MLP. Although cross product can yield more flexible feature interactions, it can only be used in the wide part \[ \mathbb{E} \], because the corresponding embedding will exponentially explode in the order of features meanwhile can not be well trained due to the low frequency of occurrence. Therefore, AMER chooses Hadamard products as interaction functions due to its expressive power and flexibility. The interaction search space includes all low-order and high-order Hadamard interactions, and an interaction of order \( r \) can be computed by \( e_{i_1}^a \odot e_{i_2}^a \odot \cdots \odot e_{i_r}^a \). where \( \odot \) denotes Hadamard product and \( e_{i_1}^a, e_{i_2}^a, \ldots, e_{i_r}^a \) are selected from \( \mathbb{E} \).

Choice MLPs in Stage 3. As MLP settings can also affect the final recommendation result, AMER searches for the dimension of hidden layers as well as the activation functions in the aggregation MLP. Assume the dimension of \( h_0^a \) is \( K_0 \). The hidden layer dimensions of MLP are chosen from \( \{0.1, 0.2, \ldots, 1.0\} \) of \( K_0 \) while ensuring monotonically non-increasing following the common network design principle. The activation functions are selected from \{ReLU, Swish, Identity, Dice [84]\}.

2.3 Three-step One-shot Searching Pipeline

One-shot NAS in AMER. Recent approaches [4, 50] introduce efficient one-shot weight-sharing paradigm in NAS to boost search efficiency, where all child networks share the weights of common operations in a single one-shot model that subsumes every possible architecture from the search space, and thus training one architecture implicitly trains the relevant sub-structures. Though diverse complex searching algorithms [5, 7, 10, 13] have been coupled with one-shot NAS, recent studies [4, 12, 37] reveal that the primitive random search with one-shot strategy is a surprisingly competitive baseline compared to gradient-based methods such as DARTS [44] and SNAS [76] or RL-based methods like ENAS [50]. Therefore, we employ one-shot random search in AMER for efficient and effective architecture search. Specifically, one-shot model is first trained via random sampling within the search space. Then, an appropriate number of candidate architectures are randomly selected and evaluated on a small number of mini-batches of validation set to find the appropriate architecture as the final result. In order to obtain the correct ranking between one-shot model and child networks, AMER modularizes the searching process into three steps matching the three stages in the backbone model according to [38, 61], meanwhile ensuring the adequacy and fairness of one-shot model-training to alleviate representation shift caused by weight sharing [10, 79]. For strict fairness among architectures, FairNAS [10] is introduced to train the shared weights of one-shot models, where all candidate operations in each layer are uniformly sampled and activated per gradient update. Moreover, one-shot model is evaluated at every training epoch on a small subset of validation instances to determine the convergence time for adequate training and avoid overfitting.

Step 1: Sequential Model Search. In the first step, AMER selects the best performed sequential model from the choice blocks, as shown in Fig 1. To decouple behavior modeling from interaction exploration and aggregation MLP, AMER uses a pre-defined MLP to combine sequential representation \( h^b \) and \( e^a \) during architecture search. After one-shot model training, AMER randomly samples several sequential models for evaluation on the validation set, and then selects top architectures for further evaluation. It is worth emphasizing that one-shot model weights can directly initialize the child networks in step 1 because the training protocols of model architectures and datasets are the same for one-shot model and child networks, which is in contrast to most existing methods [44, 62, 75, 79] that adopt proxy task for one-shot model training. The inherited model weight can accelerate the training process of selected child networks to compensate for the search cost.

Step 2: Interaction Exploration. In the second step, AMER introduces sequential model-based optimization (SMBO) algorithm [12, 43] to search for low-order and high-order interactions on non-sequential features by progressively increasing the order of interactions. The interaction set \( P^\omega \) is initialized with non-sequential features \( \mathbb{E}^\omega \), and then updated by several rounds of evolution as illustrated in Fig 1. (a) First, the candidates in \( P^\omega \) intersect with all possible non-sequential fields from \( \mathbb{E}^\omega \) via Hadamard product to mutate for higher-order interactions and expand current interaction set to \( P^{\omega'} \). (b) Then, all intersections in \( P^{\omega'} \) are trained by one-shot NAS and evaluated on the validation set. (c) Afterwards, only top \( k \) interactions with the highest validation fitness in \( P^{\omega'} \) are retained in
with learnable variables or all-ones vector to generate the prediction score jointly with MLP hidden AMER. Specifically, the choice blocks of stage 1 include all layers, activations and normalizations in we focus on two main parts of these methods, i.e., behavior modeling and interaction exploration.

3 Experiments

3.1 Experiment Setup

Datasets. We introduce three types of datasets to evaluate AMER in various scenarios, namely sequential datasets, non-sequential datasets and hybrid datasets. (1) The sequential datasets only present sequential behaviors to examine step 1 sequential modeling, and the training is based on the next-item prediction of Eqn. (7). Sequential datasets include Amazon Beauty [49] and Steam [32].
(2) The non-sequential datasets involve benchmarking Criteo and Avazu datasets, which only include non-sequential categorical features for CTR prediction to verify the step 2 interaction exploration and step 3 MLP investigation. (3) The hybrid dataset is employed to test all three steps in AMER. We refer to Alimama CTR dataset [16] that comprises both sequential and non-sequential data for comprehensive comparison. Preprocessings of these datasets follow the common practice as in [63, 41] and [16] respectively. Details and availability of datasets can be found in Appendix B.

**Evaluation Metrics.** To quantify the performance of sequential models, we use HR (Hit Ratio) and NDCG (Normalized Discounted Cumulative Gain) in sequential datasets. To avoid heavy computation on evaluating all items for each user, we follow the common settings [24, 34] that randomly sample 100 negative items to construct the candidate item set for evaluation. For non-sequential and hybrid datasets, we use standard metrics of AUC (Area Under ROC Curve) and log loss.

**Baseline Methods.** To show the effectiveness, we compare AMER with various representative baseline methods. For the sequential baselines, we introduce POP, BPR [57], GRU4Rec+ [26], STAMP [45], NARM [36], Caser [67], NextItNet [80], SRGNN [74] and BERT4Rec [63] for comparison. Regarding the non-sequential baselines, we compare AMER with DNN [11], Wide & Deep [8], DeepFM [18], IPNN [51], DCN [70], xDeepFM [59], FibiNet [31], AutoCross (on Wide & Deep) [47] and AutoFIS (on DeepFM) [41]. Finally, we exploit the mentioned DNN, Wide & Deep and DeepFM in hybrid experiment and further introduce DIN [84], DIEN [83] and DSIN [16] as more competitive baselines. More details about the baseline methods are shown in Appendix C.

### 3.2 Implementation Details

We use Adam optimizer [33] to train AMER and baseline methods in all experiments. For one-shot model searching, we employ single cosine schedule [46] during training period, and select top-5 results from the randomly sampled 2000 child models for further evaluation in step 1 and step 3. The convolutional layers, recurrent layers, linear layers and embedding are initialized with He [20], orthogonal [60], xavier [17] and 0.05 uniform initializers respectively. For sequential datasets, we use embedding size $K$ of 128, and the maximum sequence length $T$ of 15 for Beauty and 25 for Steam. The batch size is set to 512 with 1e-6 L2 regularization for all models. The layer number $L_b$ of AMER is set to 6 to cover representative recommendation methods and one-shot model is trained with learning rate of 1e-3 for 4000 epochs on Beauty. 2000 epochs on Steam under 1:1 negative sampling rate. After one-shot model training, AMER fine-tunes the selected models with a smaller learning rate of 1e-6. For non-sequential datasets, the batch size is set to 4096, and embedding size is set to 5 for Criteo and 40 for Avazu. The interaction exploration evolves for 4 rounds, which is trained by 1e-4 learning rate for 30 epochs in total, with pre-defined MLP of [200×3] for Criteo and [500×5] for Avazu [18, 52]. At each round, 50 interactions are retained and finally top-15 interactions are chosen as the result. Following MLP settings in step 2, the maximum MLP of step 3 is set to 3 layers and 5 layers on Criteo and Avazu for clipping. The one-shot MLP and the final derived model are both trained by 1e-3 for evaluation. For Alimama dataset, the batch size is set to 1024 for all methods with embedding size of 4 and maximum sequence length of 50 [16]. During step 1, $L_b$ is set to 3 and one-shot model is trained for 15 epochs. In steps 2 and 3, AMER conducts the same interaction exploration and MLP investigation as non-sequential datasets despite the base MLP is set to [200, 80] and only top-5 interactions are reserved in the final model. The one-shot models and derived model are trained with 1e-5 learning rate, and one-shot weights are used to initialize the weights of derived model. By conforming to [37, 44, 61], we run AMER for 4 times on all datasets and report the metrics across 4 runs as the final results. More implementation details can be found in Appendix D.
Table 3: Ablation study on the aggregation MLP.

| Model                                      | Criteo AUC | Log Loss | Avazu AUC | Log Loss |
|--------------------------------------------|------------|----------|-----------|----------|
| MLP (DNN)                                  | 0.7983     | 0.4549   | 0.7746    | 0.3831   |
| MLP + MLP Interaction                       | 0.8021     | 0.4492   | 0.7789    | 0.3801   |
| MLP + FM Interaction (DeepFM + AMER-I)     | 0.8024     | 0.4491   | 0.7791    | 0.3799   |
| MLP + MLP Interaction + FM Interaction     | 0.8041     | 0.4488   | 0.7795    | 0.3795   |
| MLP + MLP Interaction + SE Interaction (AMER-2) | 0.8030     | 0.4486   | 0.7798    | 0.3794   |
| Searched MLP + MLP Interaction + SE Interaction (AMER-23) | 0.8034     | 0.4482   | 0.7802    | 0.3792   |

Table 4: Comparison with representative methods on the hybrid dataset.

| Model       | DNN    | Wide & Deep | DeepFM  | DIN    | DIEN   | DSIN   | AMER-1   | AMER-12  | AMER-123  |
|-------------|--------|-------------|---------|--------|--------|--------|----------|----------|----------|
| AUC         | 0.6304 | 0.6313      | 0.6320  | 0.6341 | 0.6344 | 0.6352 | 0.6357 ± 0.0001 | 0.6359 ± 0.0003 | 0.6383 ± 0.0004 |

3.3 Performance on Sequential Datasets

Tab. 1 summarizes the results of AMER and baseline methods on Beauty and Steam datasets. It is obvious that all baseline methods including the powerful BERT4Rec and NextItNet can not dominate both datasets, which empirically justifies that the best architecture is usually task-aware in sequential modeling. Owing to the effectiveness and robustness of AMER’s search space and the tailored one-shot searching pipeline, AMER-1 (only performs step 1 sequential modeling) achieves state-of-the-art performance over all metrics under multiple runs. Moreover, the best found architectures present stable and prominent performance compared to the baseline methods with well-designed architecture engineering, indicating the strength of AMER as well as the capability of searching better models from stage 1 search space. The selected architectures can be found in Appendix E.1.

3.4 Performance on Non-sequential Datasets

Comparison with Baseline Methods. We compare AMER with other interaction exploration methods on non-sequential datasets, and show the results in Tab. 2. It can be observed that DeepFM + AMER-I (DeepFM with interactions explored by AMER) consistently surpasses competitive hand-crafted baselines (xDeepFM, FibiNet) and AutoML-based baselines (AutoCross, AutoFIS) on different tasks over multiple runs, validating the efficacy of interaction exploration module in AMER. Moreover, our method gains remarkable improvement over DeepFM + AMER-I when combining searched interactions with backbone model of AMER (AMER-2) and aggregation MLP investigation (AMER-23), which verifies both the design of SE connection and the importance of MLP search. The searched interactions and MLPs can be found in Appendix E.2.

Ablation Study on Architecture of Aggregation MLP. In order to analyze the origin of model improvement, we investigate the influence of different parts in the aggregation MLP and present the average results in Tab. 3. We first show the impact of combining strategies of explored interactions. It is obvious that interactions applied to deep MLP (MLP interaction) and wide FM (FM interaction) bring orthogonal improvement on vanilla DNN, indicating that both combining strategies can contribute to the recommendation. Additionally, SE interaction (AMER-2) and MLP search (AMER-23) further boost the performance of MLP, which supports the design of backbone architecture in AMER.

3.5 Performance on Hybrid Dataset

Tab. 4 depicts the results on Alimama dataset. AMER-1 (step 1 on base model) presents competitive performance with the promising empirical architectures DIEN and DSIN. Furthermore, a significant improvement can be observed when combining AMER-1 with searched interactions (AMER-12) and MLP (AMER-123). An interest point on Alimama dataset is that compared to sequential modeling and interaction exploration, the MLP search significantly contributes to the final results. Together with the previous experimental results, it can be concluded that all three stages / steps in AMER are essential and effective for high-quality recommendation. The search results are shown in Appendix E.3.

4 Conclusion

In this paper, we introduce AMER for automatic behavior modeling and interaction exploration in recommender systems to relieve the human efforts from feature engineering and architecture engineering. Owing to the three-stage search space and the matched three-step one-shot searching pipeline, AMER covers most of representative recommendation models and outperforms the competitive methods in various scenarios, demonstrating both effectiveness and robustness of the proposed method.
Appendix A: Comparison between AMER and Representative Methods

In Appendix A, we conduct a detailed analysis of the representative recommender systems and show that these methods can be obtained in AMER’s search space.

A.1 Behavior Modeling

The existing behavior modeling methods can be categorized into RNN-based, CNN-based, Transformer-based methods and mixed methods.

- RNN-based methods \cite{27, 26, 53, 73} mainly apply LSTM or GRU layers to extract sequential representations, which can be covered by recurrent blocks in AMER.

- CNN-based methods apply convolutional layers on the sequential representations. Caser \cite{67} introduces horizontal and vertical convolutions by sliding windows on the sequential embedding and applies max pooling over the extracted feature maps for compression. However, sequence-level pooling on one hidden convolution layer is hard to capture complex relations in the sequence. NextItNet \cite{80} utilizes stacked residual blocks of dilated convolution, which can be roughly regarded as special cases as the sequential modeling in AMER because both dilated convolution and standard $1 \times 1$ convolution are included in the stage 1 search space.

- Transformer-based methods, e.g., ATRank \cite{82}, SASRec \cite{32}, and BERT4Rec \cite{63} introduce self-attention layers and point-wise feedforward layers to capture long-term semantics, which are the same as the stack of multi-head attention layers and $1 \times 1$ convolutions in the choice blocks.

- Mixed methods such as DIEN \cite{83} and DSIN \cite{16} employ the mixture of the above-mentioned layers, which potentially take advantages of these operations from various aspects. DIEN introduces GRU + AUGRU to capture interest evolving in the user behavior. DSIN employs self-attention + Bi-LSTM to model inner and intra relationship in the multiple historical sessions. Both DIEN and DSIN (if neglecting the session division) can be approximated by sequences of layer operations in AMER, i.e., \{Bi-GRU, Attention from Target, Bi-GRU\} and \{4-Head Attention, 1 $\times$ 1 Conv, Bi-GRU\} respectively.

Upon the behavior modeling, these methods either extract the last hidden state \cite{27, 32}, or employ pooling layer \cite{67} and attention layer from target \cite{84, 83} to compress the sequential hidden states into a fixed-length representation, which are all comprised by stage 1 behavior modeling of AMER.

A.2 Interaction Exploration

In Sec.2, we have declared that AMER can cover all feature interactions and interaction-combining strategies in the representative interaction exploration methods. For a more formal and intuitive comparison, we develop the computation process of similarity scores in representative recommender systems and AMER, and show that all compared methods can be explicitly or implicitly included in AMER’s search space. Following the existing symbol usage, $x^a$ and $e^a$ denote the non-sequential input features and corresponding field embeddings. For convenience of representation, we use $p^a$ to represent both investigated interactions and enumerated bounded-degree interactions of various types, including cross-product interactions, bilinear interactions and Hadamard-product interactions (inner-product interaction can be expressed as a special form of Hadamard-product interaction, i.e., $1^T p^a_i$, where $p^a_i$ represents a Hadamard-product interaction) according to the related literature. We use $a$ to denote the vector of weighted scores of interactions and embeddings computed by cross network \cite{70}, compressed interaction network (CIN) \cite{39}, or attention module \cite{41, 75}. The bias in the MLP layers is omitted for convenience. We compare AMER (stage 2 and 3) with representative methods of LR, FM \cite{56}, AFM \cite{75}, DNN \cite{11}, Wide & Deep \cite{8}, AutoCross \cite{47} (Wide & Deep version), NFM \cite{23}, DeepFM \cite{18}, DCN \cite{70}, xDeepFM \cite{39}, AutoFIS \cite{41}, FNN \cite{52} and FibitNet \cite{31} (SE feature interactions implicitly included in $p^a$). The similarity scores of these methods can be...
B.1 Sequential datasets

In Appendix B, we introduce three types of datasets to evaluate AMER on various scenarios, namely sequential datasets, non-sequential datasets and hybrid dataset. Table 5-7 show the statistics of the datasets included in AMER’s search space.

Table 5: Statistics of the sequential datasets.

|        | # User | # Item | Min. Length | Max. Length | Avg. Length | Density |
|--------|--------|--------|-------------|-------------|-------------|---------|
| Beauty | 22,363 | 12,101 | 5           | 204         | 8.876       | 0.07%   |
| Steam  | 281,210| 11,961 | 5           | 1,226       | 12.391      | 0.10%   |
The sequential datasets are proposed to evaluate the stage 1 behavior modeling in AMER, which only include sequential behavior of each user and the training is based on next-item prediction with Eqn. (7):

- Amazon is composed of reviews and metadata from Amazon.com [48], where data instances are categorized into separate datasets according to product category. In this paper, we use the category of “Beauty” for evaluation.
- Steam is introduced by [32] which contains millions of review information from Steam video game platform.

Following the common practice [24, 32], the reviews in the datasets are treated as implicit feedbacks. We group data instances by users and sort them according to the timestamps. The users and items with less than 5 feedbacks are removed from datasets. The leave-one-out strategy is adopted for partitioning [24, 32, 63], where for each user the last two actions are treated as validation set and test set, and the remaining actions are used for training.

### B.2 Non-sequential Datasets

| Dataset | # Train Instances | # Test Instances | Fields | Prop. of Click |
|---------|------------------|-----------------|--------|----------------|
| Criteo  | 41,256,555       | 4,584,062       | 39     | 25.62%         |
| Avazu   | 32,343,173       | 8,085,794       | 24     | 16.98%         |

The non-sequential datasets only include non-sequential categorical features for CTR prediction to verify the interaction exploration and aggregation MLP investigation:

- Criteo contains 7 days of click-through data, which is widely used for CTR prediction benchmarking. There are 26 anonymous categorical fields and 13 continuous fields in Criteo dataset. The continuous fields are normalized to [-1,1] and only used for MLP input while categorical fields are applied to both MLP and shortcut connection as well as the interaction exploration module in AMER and baseline methods. The dataset is randomly split into two parts while maintaining the label distribution: 90% is for training and the rest is for testing. Besides, 10% of the training set is used for validation.
- Avazu consists of 11 days of online ad click-through data. Each data instance includes 24 categorical fields that represent profiles of a single ad impression. We randomly split the dataset into two parts, where 80% is for training and the rest is for testing. Same as Criteo dataset, 10% of the training set is used for validation.

### B.3 Hybrid Dataset

| # Users | # Sparse Feature | # Dense Feature | (cate_id, brand) Avg. Seq. Length | # Train Traces | # Test Traces | Prop. of Click |
|---------|------------------|----------------|----------------------------------|----------------|---------------|----------------|
| 265,443 | 15               | 1              | 1,027,443                        | 46.31          | 5,544,213     | 660,694        | 0.0514         |

The hybrid dataset contains data of all formats mentioned in Sec. 2, so that it is used for comprehensive comparison in all three-stage pipeline of AMER: Alimama provides 26 million records of ad display / click logs in 8 days, where for each user it keeps track of 200 recent shopping behaviors in 22 days. The logs in the first 7 days are used for training set and the logs in the last day are treated as the test set. There are 15 sparse features, including user profile, user’s sequential behaviors, and context profile. The dimension of these features ranges from 3 to 309,449. There is 1 dense feature of “price” which has been normalized to [-1,1]. We randomly sampled 25% of the dataset, which remains 6,204,907 data instances [16]. We use 5% of the training set as validation in the architecture search.

---

2http://jmcauley.ucsd.edu/data/amazon/
3https://cseweb.ucsd.edu/~jmcauley/datasets.html#steam_data
4http://labs.criteo.com/downloads/download-terabyte-click-logs/
5http://www.kaggle.com/c/avazu-ctr-prediction
6https://tianchi.aliyun.com/dataset/dataDetail?dataId=56
and model selection. As there are many users that do not have any records of sequential behaviors, we assign a special tag to the behavior sequences of these users to avoid the sequential blocks executing on vacant inputs.

Appendix C: Baseline Methods

In Appendix C, we introduce the sequential, non-sequential and hybrid baseline methods used for comparison.

C.1 Sequential Baselines

To evaluate AMER on the sequential datasets, we prepare several baselines to compare with our design. We carefully categorize the state-of-the-art sequential recommender systems, and select representative methods for each category to report the performance in the limited pages of the paper. Since other sequential recommendation methods have been outperformed on the similar datasets by the selected baselines, we omit comparison against them.

- POP is the simplest baseline which only recommends the most popular items with the highest number of interactions from the candidate set (also used for evaluating the complexity of datasets);
- BPR [57] is a legacy method for matrix factorization from implicit feedback and is optimized by a pairwise ranking loss. We use BPR to represent the family of matrix factorization-based methods [24, 49].
- GRU4Rec+ [26] is an improved version of GRU4Rec, which utilizes delicately-designed loss function and sampling strategy to train GRU model. GRU4Rec+ can be seen as the representative of the RNN-based sequential recommender systems, such as GRU4REC [27], EvoRNN [3], etc.
- STAMP [45] simultaneously captures user’s long-term general interests and short-term current interests with attention module on MLP. STAMP is a typical sequential recommender system without RNN or CNN, representing the MF-based sequential recommender system such as FPMC [58] and TransRec [22].
- NARM [36] uses global GRU encoder to extract sequential behavior, and captures the user’s main purpose with the attention mechanism on local GRU encoder. Regarding the local GRU encoder, the latest 3 items are used for Beauty dataset and the latest 5 items are used for Steam dataset. NARM is a representative for the combination of attention and recurrent neural network.
- Caser [67] is a CNN-based recommender system. It applies horizontal and vertical convolutional operations on the embedding matrix for sequential representation. For Beauty dataset, the number of channel in the vertical convolutions is set to 5 and in the horizontal convolutions is set to 2. For Steam dataset, the number of channel in the vertical convolutions is set to 8 and in the horizontal convolutions is set to 3. To ensure a fair comparison, we modify the concatenation of $d$-dimension embedding in the original design of Caser (as introduced in Eqn. (10) in [67]), and replace by summation, to avoid the unfair use of the embedding with double dimension.
- NextItNet [80] employs residual blocks of dilated convolutions to increase receptive fields and model both short- and long-range item dependencies on user behaviors. We set the kernel size to be 3, and leverage five dilated convolutional layers with dilation 1, 2, 1, 2, 2. NextItNet represents the algorithms that employ dilation convolutions and residual blocks.
- SRGNN [74] applies GNN to generate item representations and then encodes global and current user interests using an attention network. We use the Gated-GNN to learn the item embeddings, add regularization of all parameters with weight 1e-6, and set the initial learning rate to 1e-7 to avoid the gradient explosion of the recurrent unit. SRGNN is the classical implementation to use GNN on recommendation, which represents the GNN-based recommender system such as GCSAN [77], GraphRec [15] and PinSage [78].
- BERT4Rec [63] adopts BERT to learn bi-directional representations of sequences by predicting masked items in the context. The transformer is set to have 2 layers with 4 heads. The dropout rate is set to 0.5 on inputs, 0.2 on feed-forward network after multi-heads and convolutions, to prevent overfitting. BERT4Rec is a successful transplant of Transformer to recommendation, which is on behalf of Transformer-based recommender systems including SASREC [32], MBTREC [61], BST [6], etc.
The model-relevant hyper-parameters and initializations are either following the recommended settings in the corresponding papers or tuned by the grid search on the validation sets. For those models using uni-directional structures (e.g., GRU4REC and NextItNet), we train them by either predicting the next-item at each position given the sequences or the same training process as AMER. Then, we report the best result of them. For those models using bi-directional structures, we employ the same training process as AMER.

C.2 Non-sequential Baselines

The non-sequential baselines include representative interaction exploration methods in deep learning recommender systems. MLP [11] and Wide & Deep [8] are early attempts of deep learning recommender systems. DeepFM [18], DCN [70] and xDeepFM [39] enumerate interactions of bounded degrees and combine the feature interactions with MLP via shortcut connection while IPNN [51] and FibiNet [31] directly apply interactions to MLP. AutoCross [47] and AutoFIS [41] are the recently-proposed AutoML-oriented methods, which automatically find the useful cross features for linear part or important weighted interactions in FM.

- MLP [11] is the base model with embeddings as input. MLP learns implicit interactions among the features.
- Wide & Deep [8] extends DNN by introducing wide part of linear regression on the input features to learn both high-order and low-order interactions. Wide part and deep part are jointly trained in Wide & Deep.
- DeepFM [18] replaces the linear regression in Wide & Deep with the FM module.
- IPNN [51] combines the inner product of feature interactions with raw feature embeddings as MLP input.
- DCN [70] proposes cross network to comprise explicit bit-wise interactions of bounded degrees. The compressed interactions and MLP output are concatenated and then fed to the last linear layer to generate prediction score.
- xDeepFM [39] designs compressed interaction network to replace cross network in DCN by enumerating vector-wise interactions via Hadamard product. Linear regression is also used for shortcut connection as DeepFM.
- FibiNet [31] employs SENET [29] to learn importance of embeddings, and then generates bilinear interactions on both SE and original feature embeddings as the input of MLP. The linear regression is also used in FibiNet.
- AutoCross [47] learns useful high-order cross feature interactions on a tree-structured space with beam search and successive mini-batch gradient descent. The explored interactions are exploited in linear part of Wide & Deep.
- AutoFIS [41] identifies important feature interactions in the FM model with differentiable architecture search [44], and keeps the architecture parameters as attention weights for the corresponding interactions. The generated interactions are applied to FM module in DeepFM.

To ensure fair comparison, the base MLP of all baseline methods is set to the same as the pre-defined MLP in AMER, i.e., [200 × 3] for Criteo [18] and [500 × 5] for Avazu [52] with ReLU activation. Besides, CIN is set to 256 / 128 layers for Criteo / Avazu in xDeepFM. The training is based on the CTR prediction of Eqn. (6) for all methods.

C.3 Hybrid Baselines

The hybrid baselines include the common DNN [11], Wide & Deep [8], DeepFM [18] and the more competitive methods of DIN [84], DIEN [83], DSIN [16].

- MLP [11] is usually introduced as base model in CTR prediction. It utilizes sum pooling on the users’ historical behavior embedding, and then concatenates the results with other non-sequential feature embedding of user profile, context profile and target item / ad profile as the input of MLP to generate final prediction score.
- Wide & Deep [8] additionally adds linear regression on non-sequential features to the output of MLP base model.
- DeepFM [18] replaces the wide part in Wide & Deep with FM.
• DIN \cite{84} extends base model by using attention mechanism on the user behavior with respect to target item to adaptively learn diversity characteristic of user interests.

• DIEN \cite{83} enhances DIN by using GRU and AUGRU module to extract user’s evolving interests, where an auxiliary loss is employed as a regularization term to make hidden states more expressive.

• DSIN \cite{16} further investigates the homogeneity and heterogeneity in the user behavior, and models the user interests through intra-session self-attention layer and inter-session Bi-LSTM layer. The sequential behaviors are split into sessions by 30 minute intervals, and each session remains at most 10 behaviors.

The MLP model of all baseline methods is fixed to \([200, 80]\), while the activation is set to Dice in DIN and DIEN and set to ReLU in other methods. The training is based on the CTR prediction of Eqn. (6) for all methods.

**Appendix D: Implementation Details**

In Appendix D, we introduce the implementation details of AMER and baseline methods, including the common settings and the selection of hyper-parameters in sequential, non-sequential and hybrid datasets.

• For **sequential datasets**, we fix the maximum sequence length as 15 for Beauty and 25 for Steam. The baseline methods and AMER are trained by Adam optimization \cite{33} with batch size of 512. During training, the sequences are randomly clipped (with at least one item) and the next 5 items are taken as the positive items. Meanwhile, we randomly sample 5 items that the user has not interacted with as negative items. The embedding and the self attentions are initialized uniformly in \([-0.05, 0.05]\), while the convolutional block and the GRU block are initialized by He initialization \cite{21} and orthogonal initialization \cite{60} respectively. We apply grid-search to find the best choices of the hyper parameters in AMER and baseline methods. We search the embedding size from \{64, 96, 128, 160, 192\} and find that when the embedding size is greater than 128, the performance of most of the baselines would not further increased and the compared models even become hard to reach convergence. Therefore, we fix the embedding size as 128 for all models in stage 1. We also examine the impact of initial learning rate and regularizer for all methods from candidate set \{1e-3, 1e-4, 3e-5, 1e-5\} and \{1e-3, 1e-4, 1e-5, 1e-6\} respectively. High learning rate may cause premature convergence or overfitting, while low learning rate leads to slow convergence of the model. Meanwhile we attempt to add dropout to the input and hidden layers of sequential models from \{0, 0.1, 0.2, 0.3, 0.4, 0.5\}.

• For **non-sequential datasets**, we use embedding size of 5 for Criteo and 40 for Avazu datasets. The batch size is set to 4096 and xavier initialization \cite{17} is used for initializing the hidden layers of MLP. Similar as the candidate sets in sequential datasets, the learning rate and L2 regularizer are chosen from \{1e-3, 1e-4, 3e-5, 1e-5\} and \{1e-3, 1e-4, 1e-5, 1e-6\} respectively. Meanwhile, we use grid search to select dropout rate from \{0, 0.1, 0.2, 0.3, 0.4, 0.5\} for both MLP input and hidden layers.

• For **hybrid dataset** of Alimama, we use embedding size of 4 \cite{16} , batch size of 1024 and maximum sequence length of 50 for all methods. Same as the previous datasets, the convolutional layers, recurrent layers, linear layers and embeddings are initialized with He, orthogonal, xavier and uniform initializers respectively, and then optimized by Adam optimization. We also search for the learning rate, L2 regularization and dropout rate for the MLP input from the candidate sets via grid search.

**Appendix E: Searched Blocks/Interactions/MLPs and Experimental Results**

In Appendix E, we show the searched sequential blocks, feature interactions and aggregation MLPs of AMER and the corresponding experimental results in the 4 runs.

**E.1 Sequential Datasets**

Tab.\,\,8 summarizes the searched blocks on the sequential datasets with the corresponding experimental results. Apparently, though the maximal number of layers is set to 6, all searched architectures over the 4 runs for each dataset contains three to five layers (i.e., at least one “Zero” in each searched
E.2 Non-sequential Datasets

Tab. 9 depicts the searched interactions as well as the pre-defined / searched MLP of AMER-2 and AMER-23 on the non-sequential datasets. Though AMER could search high-order interactions, most of the searched interactions (best-performing interactions) are in second-order while some pairs of features never form appropriate interactions to be selected by the one-shot model according to the statistics. This observation attributes to the automatic recognition of the feasible interactions with appropriate order by the one-shot searching, potentially relieving the effort of manual feature engineering. Moreover, it can be found that some interactions, e.g., (C6, C13), (C13, C26) in Criteo and (C15, C18), (device_conn_type, C18) in Avazu, are shared across different runs, which verifies the robustness of AMER over multiple runs. Regarding the aggregation MLP, we notice that AMER-23 tends to select MLPs of higher dimension in the bottom layers and lower dimension in the top layers, which is more reasonable for the neural network design as opposed to the hand-crafted settings in [18, 52]. The adaptive design of MLP further improves the performance on the non-sequential datasets, indicating the effective and efficient one-shot searching of AMER. Besides, compared to the novel activations of Swish and Dice, AMER prefers ReLU and Identity in the searched MLP, which demonstrates that using all ReLUs as the activation functions might be a good starting point for MLP design.

E.3 Hybrid Dataset

Tab. 10 demonstrates the searched architectures on the hybrid dataset. Regarding step 1, we can see that AMER automatically raises the best searched blocks with two or three active layers based on the sequential data. As the item profiles and non-sequential feature fields in Alimama is quite different from Beauty and Steam, the searched blocks are distinct from the results on the sequential datasets. Moreover, it can be observed that the searched blocks all include one non-parameterized operation of average pooling or dummy layer of zero, indicating that the shallow sequential models might be optimal for this dataset. Therefore, compared to the empirical state-of-the-art CTR prediction models such as DIEN and DSIN, the searched blocks contribute more to the AUC metric. Besides, although the “attention from target” operation is involved in Alimama, we find that it does not help improve the AUC result. Regarding step 2, the searched interactions contain both second-order and third-order interactions. Though there are fewer non-sequential sparse features in Alimama dataset compared to Avazu and Criteo, the searched interactions can slightly but consistently improve the performance upon the searched blocks. The correlation within the searched interactions may enhance the interpretability of the prediction. Regarding step 3, the searched aggregation MLP tends to select the layers with lower dimension activated by ReLU. This decision significantly upgrades the performance on the CTR prediction task, with fewer parameters compared to the models by manual architecture engineering. The prominent performance of the low-dimension MLP enlightens us that a proper MLP could boost the learning capability of a specific architecture, and one-shot searching is able to acquire the best settings of the MLP. The above observations verify the practicability and efficiency of all three stages and steps of the proposed AMER.

Appendix F: Discussion on One-shot Model

The one-shot strategy has been widely used for accelerating the architecture search. In most of the existing literature, the one-shot NAS is only applied to find the best model in the search space, and then the derived model is re-trained from scratch. In AMER, we find an interesting phenomenon in the one-shot model, especially for step 1 behavior modeling. Specifically, we find out that fine-tuning
the derived model with the one-shot model weights can achieve better performance than directly re-training the derived model with random initialization as mentioned in Appendix D.

We first guess that the performance improvement of fine-tuning may be caused by the use of embedding. Compared to the computer vision tasks which take the fixed image pixels as input, the shared trainable embedding in recommender system would get appropriate and adequate training in the one-shot model and thus promote the recommendation quality. However, if we only initialize the derived model with the trained embedding, the resulting model could not attain the similar high performance with the fine-tuned model. This result indicates that the layer parameters and embedding parameters are highly coupled in the one-shot model. In this case, we speculate that this phenomenon may be universal in the one-shot NAS, yet it tends to be ignored as most of the existing methods either use the proxy models and datasets to improve the efficiency of architecture search [4, 44, 72, 76] or do not exhaustively train the one-shot model as it is hard to converge on large datasets like ImageNet [10, 19]. Hence, these methods hardly witness this phenomenon due to the discrepancy between the training protocols of one-shot model and the derived model. In contrast, the proposed AMER fills the discrepancy by performing one-shot training on the same model and dataset as the derived model, and the training process does not stop until convergence. Hence, the fine-tuned model can achieve better performance than the stand-alone model from derivation. Moreover, the recently proposed HM-NAS (ICCVW’19) also supports our hypothesis, which applies fine-tuning on the one-shot model weights for CIFAR-10 and ImageNet datasets and outperforms the derived model that re-trains from scratch with random initialization.

In addition, the recommendation model usually suffers from the overfitting problem. The one-shot training, which is equivalent to adding large drop-path on the supernet, can be considered as introducing an extra regularization on the model training. Therefore, it helps prevent / delay the appearance of overfitting meanwhile guaranteeing the sufficient training of the network. We observe that under similar training settings, one-shot training presents later overfitting epoch compared to re-training the derived models from scratch. The observation is consistent with our argument.

The above discussions are our speculation based on the experimental results, while we may not affirm whether this problem will appear in other scenarios. We hope that our work can be regarded as the evidence for the strength of one-shot model weights, and more outstanding works will be carried out to study and analyze this interesting phenomenon.
Table 8: Searched blocks and corresponding experimental results of behavior modeling (AMER-1) on Beauty and Steam over 4 runs. Each block $i$ denotes the residual block of $i$-th layer, which is represented by either a tuple of (layer operation, activation operation, normalization operation) or a “Zero” operation (skip this layer).

| Dataset | Run ID | Searched Blocks                                                                 | HR@1 | HR@5 | NDCG@5 |
|---------|--------|--------------------------------------------------------------------------------|------|------|--------|
| Beauty  | 1      | Block 1: (1×5 Dconv, GeLU, LayerNorm) Block 2: (1×5 Dconv, Identity, None) Block 3: Zero Block 4: (1×7 Dconv, Identity, None) Block 5: Zero Block 6: (1×7 Dconv, Identity, None) | 0.164 | 0.345 | 0.260  |
|         | 2      | Block 1: (4-Head Attention, Swish, LayerNorm) Block 2: (2-Head Attention, GeLU, LayerNorm) Block 3: (4-Head Attention, Identity, LayerNorm) Block 4: Zero Block 5: (Bi-GRU, Swish, LayerNorm) Block 6: (1×3 Dconv, Swish, None) | 0.153 | 0.337 | 0.254  |
|         | 3      | Block 1: (1×3 Conv, ReLU, LayerNorm) Block 2: Zero Block 3: Zero Block 4: (4-Head Attention, Identity, LayerNorm) Block 5: (4-Head Attention, Swish, LayerNorm) Block 6: (1×3 Dconv, Swish, None) | 0.159 | 0.341 | 0.255  |
|         | 4      | Block 1: (2-Head Attention, Swish, LayerNorm) Block 2: (4-Head Attention, Swish, LayerNorm) Block 3: (1×3 Dconv, ReLU, None) Block 4: (Bi-GRU, Swish, LayerNorm) Block 5: Zero Block 6: (Bi-GRU, Swish, None) | 0.158 | 0.341 | 0.256  |
| Steam   | 1      | Block 1: Zero Block 2: (4-Head Attention, Swish, LayerNorm) Block 3: (2-Head Attention, Identity, LayerNorm) Block 4: Zero Block 5: (1×5 Dconv, GeLU, None) Block 6: (1×5 Dconv, GeLU, None) | 0.339 | 0.682 | 0.517  |
|         | 2      | Block 1: (2-Head Attention, GelU, LayerNorm) Block 2: Zero Block 3: (4-Head Attention, Identity, LayerNorm) Block 4: Zero Block 5: Zero Block 6: (Bi-GRU, Identity, None) | 0.339 | 0.683 | 0.519  |
|         | 3      | Block 1: (1×1 Conv, GelU, None) Block 2: (1×3 Conv, ReLU, LayerNorm) Block 3: (4-Head Attention, ReLU, LayerNorm) Block 4: (2-Head Attention, GelU, None) Block 5: Zero Block 6: (2-Head Attention, Swish, None) | 0.337 | 0.681 | 0.517  |
|         | 4      | Block 1: Zero Block 2: (1×7 Dconv, GeLU, LayerNorm) Block 3: Zero Block 4: (4-Head Attention, Swish, None) Block 5: (2-Head Attention, Swish, None) Block 6: (1×5 Dconv, ReLU, None) | 0.335 | 0.678 | 0.515  |
Table 9: Searched interactions, MLPs and corresponding experimental results of interaction exploration (AMER-2) and additional aggregation MLP investigation (AMER-23) on Criteo and Avazu over 4 runs. Each interaction is represented by a tuple of non-sequential feature fields. Each MLP includes a list of hidden layers, where each hidden layer is represented by a tuple of (hidden size, activation operation).

| Dataset | Run ID | Searched Interactions | Model | MLP | AUC | Log Loss |
|---------|--------|-----------------------|-------|-----|-----|----------|
| Criteo  | 1      | [(C10, C13), (C13, C26), (C15, C24), (C15, C20), (C1, C21), (C15, C19), (C4, C16), (C2, C15), (C7, C19), (C21, C26), (C19, C24), (C15, C19), (C14, C23), (C3, C6), (C10, C16), (200, ReLU), (80, ReLU)] | AMER-2 | [(200, ReLU), (200, ReLU), (200, ReLU)] | 0.629 | 0.4487 |
|         | 2      | [(C15, C18), (device_conn_type, C18), (app_category, device_type), (site_category, C18), (app_domain, device_id), (day, app_category), (day, device_model)] | AMER-2 | [(200, ReLU), (200, ReLU), (200, ReLU)] | 0.779 | 0.4487 |
|         | 3      | [(device_conn_type, C18), (C1, C21), (site_domain, device_conn_type), (day, C1), (site_id, C21), (app_category, device_type), (site_category, device_id), (weekday, site_id), (site_id, C17), (device_id, C15)] | AMER-2 | [(200, ReLU), (200, ReLU), (200, ReLU)] | 0.803 | 0.4480 |
|         | 4      | [(device_conn_type, C18), (C15, C18), (C1, C21), (device_id, C16), (banner_pos, app_id), (C1, C15), (app_id, device_id), (app_domain, device_id), (weekday, site_id), (site_id, C18), (C18, C19), (site_id, C17), (app_domain, device_id), (C15, C24), (C12, C16), (C12, C13), (C6, C11), (C2, C13), (C15, C20)] | AMER-2 | [(200, ReLU), (200, ReLU), (200, ReLU)] | 0.802 | 0.4490 |
| Avazu   | 1      | [(C15, C18), (device_conn_type, C18), (app_category, device_type), (site_category, C18), (app_domain, device_id), (day, app_category), (day, device_model)] | AMER-2 | [(200, ReLU), (200, ReLU), (200, ReLU)] | 0.779 | 0.3794 |
|         | 2      | [(device_conn_type, C18), (C1, C21), (site_domain, device_conn_type), (day, C1), (site_id, C21), (app_category, device_type), (site_category, device_id), (weekday, site_id), (site_id, C18), (C18, C19), (site_id, C17), (app_domain, device_id), (C15, C24), (C12, C16), (C12, C13), (C6, C11), (C2, C13), (C15, C20)] | AMER-2 | [(200, ReLU), (200, ReLU), (200, ReLU)] | 0.779 | 0.3793 |
|         | 3      | [(device_conn_type, C18), (C1, C21), (device_id, C16), (banner_pos, app_id), (C1, C15), (app_id, device_id), (app_domain, device_id), (weekday, site_id), (site_id, C18), (C18, C19), (site_id, C17), (app_domain, device_id), (C15, C24), (C12, C16), (C12, C13), (C6, C11), (C2, C13), (C15, C20)] | AMER-2 | [(200, ReLU), (200, ReLU), (200, ReLU)] | 0.780 | 0.3793 |
|         | 4      | [(device_conn_type, C18), (C15, C18), (C1, C21), (device_id, C16), (banner_pos, app_id), (C1, C15), (app_id, device_id), (app_domain, device_id), (weekday, site_id), (site_id, C18), (C18, C19), (site_id, C17), (app_domain, device_id), (C15, C24), (C12, C16), (C12, C13), (C6, C11), (C2, C13), (C15, C20)] | AMER-2 | [(200, ReLU), (200, ReLU), (200, ReLU)] | 0.780 | 0.3790 |

Table 10: Searched blocks, interactions, MLPs and corresponding experimental results of behavior modeling (AMER-1), additional interaction exploration (AMER-12) and further aggregation MLP investigation (AMER-123) on Alimama over 4 runs. Each block i denotes the residual block of i-th layer, which is represented by a “Zero” layer (skip this layer). Each interaction is represented by a tuple of non-sequential feature fields. Each MLP includes a list of hidden layers, where each hidden layer is represented by a tuple of (hidden size, activation operation).

| Run ID | Searched Blocks | Searched Interactions | Model | MLP | AUC |
|--------|----------------|----------------------|-------|-----|-----|
| 1      | Block 1: (1×7 Dconv, Swish, None) | [(F08, F11), (F04, F10), (F06, F11), (F07, F09, F10), (F05, F06, F11)] | AMER-1 | [(200, ReLU), (80, ReLU)] | 0.638 |
|        | Block 2: (Zero) | None | AMER-12 | [(200, ReLU), (80, ReLU)] | 0.6362 |
|        | Block 3: (1×5 Dconv, Identity, LayerNorm) | None | AMER-123 | [(42, ReLU), (10, ReLU)] | 0.6387 |
| 2      | Block 1: (1×3 Dconv, Identity, None) | [(F04, F10), (F06, F08), (F06, F07, F11), (F03, F08, F11), (F05, F06, F11)] | AMER-1 | [(200, ReLU), (80, ReLU)] | 0.6357 |
|        | Block 2: (Bi-GRU, ReLU, LayerNorm) | None | AMER-12 | [(200, ReLU), (80, ReLU)] | 0.6357 |
|        | Block 3: (1×3 AvgPool, Identity, None) | None | AMER-123 | [(42, ReLU), (10, ReLU)] | 0.6383 |
| 3      | Block 1: (2-Head Attention, GeLU, None) | [(F08, F10), (F06, F08), (F06, F07, F11), (F03, F08, F11), (F05, F06, F11)] | AMER-1 | [(200, ReLU), (80, ReLU)] | 0.6356 |
|        | Block 2: (Bi-GRU, ReLU, LayerNorm) | None | AMER-12 | [(200, ReLU), (80, ReLU)] | 0.6357 |
|        | Block 3: (1×3 AvgPool, Identity, None) | None | AMER-123 | [(42, ReLU), (10, ReLU)] | 0.6383 |
| 4      | Block 1: Zero | [(F08, F11), (F07, F10), (F04, F06, F10), (F06, F11)] | AMER-1 | [(200, ReLU), (80, ReLU)] | 0.6358 |
|        | Block 2: (1×5 Dconv, ReLU, None) | None | AMER-12 | [(200, ReLU), (80, ReLU)] | 0.6361 |
|        | Block 3: (Bi-GRU, Identity, LayerNorm) | None | AMER-123 | [(42, ReLU), (10, ReLU)] | 0.6385 |
Broader Impact

In this paper, we introduce AMER for automatic behavior modeling and interaction exploration in the deep learning based recommender systems.

Applicability in various recommendation scenarios. AMER follows the automatic paradigm of neural architecture search and thus mitigates a lot of human efforts from heavy feature engineering and architecture engineering. The search space of AMER covers most of the mainstream methods, and AMER employs an effective and efficient one-shot random searching pipeline. Hence, AMER can be directly applied to various recommendation scenarios such as next-item recommendation, CTR prediction, and even other recommendation tasks that have not been mentioned in this paper. Only little fine-tuning operation is required to surpass competitive baseline methods, which would surely save the cost of manually trying the methods involved in the search space.

Competitive baseline in industry. We believe that the most important societal implication of AMER is that it can be used as a very competitive baseline method in the industrial scenarios. The engineers could first employ AMER to search for a competitive model as baseline for the recommendation tasks and then conducts manually feature engineering or architecture engineering to improve the performance based on the search result. Moreover, the searched interactions can provide interpretability in the recommendation, which is also critical from both business perspective and application perspective in the industry scenarios.

Potential risks of automation. While AMER has achieved state-of-the-art performance on various datasets, the traditional hand-crafted modeling is still important, since it can help engineers realize intuition on the recommender system and is more relevant to the industrial tasks. Therefore, the abuse of automatic search may be detrimental to the intensive study of recommender system, especially in terms of interpretability, modeling intuition and task-aware analysis, thereby inhibiting the long-term development of this area. Meanwhile, as AMER belongs to the family of neural architecture search, the risks can also be arisen from the choice of random seeds in both training and searching periods. Even though the empirical study reveals that the random seeds only have little influence on the final recommendation quality, it may still introduce uncertainty when applied in the real-world applications so that searching over multiple runs may be an appropriate compensation for this problem.

Suggestions for extending AMER and future works. In this paper, we only involve the most common settings of the existing literature, and thus the searched model may be sub-optimal for certain tasks. We would suggest that the engineers who would like to implement AMER in their applications carefully customize the search space, including candidate layer, activation and normalization operations in the sequential modeling, and the interaction function in the aggregation MLP. Moreover, if the computation cost and search cost are not very crucial, it is also recommended to sample more candidates in the random search or employ evolutionary algorithm on the one-shot model which proves to be more robust and effective in architecture search. We also encourage future work to complement AMER with other hyper-parameter optimization methods for automatically tuning learning rate, weight decay and regularization to achieve more automation in the recommendation.

References

[1] Jimmy Lei Ba, Jamie Ryan Kiros, and Geoffrey E Hinton. Layer normalization. arXiv preprint arXiv:1607.06450, 2016.
[2] Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. Neural machine translation by jointly learning to align and translate. In ICLR, 2015.
[3] Francois Belletti, Minmin Chen, and Ed H Chi. Quantifying long range dependence in language and user behavior to improve rnns. In SIGKDD, 2019.
[4] Gabriel Bender, Pieter-Jan Kindermans, Barret Zoph, Vijay Vasudevan, and Quoc Le. Understanding and simplifying one-shot architecture search. In International Conference on Machine Learning, pages 550–559, 2018.
[5] Han Cai, Ligeng Zhu, and Song Han. Proxylessnas: Direct neural architecture search on target task and hardware. In ICLR, 2019.
[6] Qiwei Chen, Huan Zhao, Wei Li, Pipei Huang, and Wenwu Ou. Behavior sequence transformer for e-commerce recommendation in alibaba. In Proceedings of the 1st International Workshop on Deep Learning Practice for High-Dimensional Sparse Data, pages 1–4, 2019.
[7] Yukang Chen, Tong Yang, Xiangyu Zhang, Gaofeng Meng, Xinyu Xiao, and Jian Sun. Detnas: Backbone search for object detection. In Advances in Neural Information Processing Systems, pages 6638–6648, 2019.
[8] Heng-Tze Cheng, Levent Koc, Jeremiah Harmsen, Tal Shaked, Tushar Chandra, Hrishi Aradhye, Glen Anderson, Greg Corrado, Wei Chai, Mustafa Ispir, et al. Wide & deep learning for recommender systems. In Proceedings of the 1st workshop on deep learning for recommender systems, pages 7–10, 2016.

[9] Kyunghyun Cho, Bart van Merriënboer, Caglar Gulcehre, Dzmitry Bahdanau, Fethi Bougares, Holger Schwenk, and Yoshua Bengio. Learning phrase representations using rnn encoder–decoder for statistical machine translation. In Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 1724–1734, 2014.

[10] Xiangxiang Chu, Bo Zhang, Ruijun Xu, and Jixiang Li. Fairnas: Rethinking evaluation fairness of weight sharing neural architecture search. arXiv preprint arXiv:1907.01845, 2019.

[11] Paul Covington, Jay Adams, and Emre Sargin. Deep neural networks for youtube recommendations. In Proceedings of the 10th ACM conference on recommender systems, pages 191–198, 2016.

[12] Jin-Dong Dong, An-Chieh Cheng, Da-Cheng Juan, Wei Wei, and Min Sun. Dpp-net: Device-aware progressive search for pareto-optimal neural architectures. In Proceedings of the European Conference on Computer Vision (ECCV), pages 517–531, 2018.

[13] Xuanyi Dong and Yi Yang. Network pruning via transformable architecture search. In Advances in Neural Information Processing Systems, pages 759–770, 2019.

[14] Xuanyi Dong and Yi Yang. Nas-bench-102: Extending the scope of reproducible neural architecture search. In ICLR, 2020.

[15] Wenqi Fan, Yao Ma, Qing Li, Yuan He, Eric Zhao, Jiliang Tang, and Dawei Yin. Graph neural networks for social recommendation. In The World Wide Web Conference, pages 417–426, 2019.

[16] Yufei Feng, Fuyu Lv, Weichen Shen, Menghan Wang, Fei Sun, Yu Zhu, and Keping Yang. Deep session interest network for click-through rate prediction. In Proceedings of the 28th International Joint Conference on Artificial Intelligence, pages 2301–2307. AAAI Press, 2019.

[17] Xavier Glorot and Yoshua Bengio. Understanding the difficulty of training deep feedforward neural networks. In Proceedings of the thirteenth international conference on artificial intelligence and statistics, pages 249–256, 2010.

[18] Huifeng Guo, Ruiming Tang, Yunming Ye, Zhenguo Li, and Xiuqiang He. Deepfm: a factorization-machine based neural network for ctr prediction. In Proceedings of the 26th International Joint Conference on Artificial Intelligence, pages 1725–1731, 2017.

[19] Zichao Guo, Xiangyu Zhang, Haoyuan Mu, Wen Heng, Zechun Liu, Yichen Wei, and Jian Sun. Single path one-shot neural architecture search with uniform sampling. arXiv preprint arXiv:1904.00420, 2019.

[20] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Delving deep into rectifiers: Surpassing human-level performance on imagenet classification. In Proceedings of the IEEE international conference on computer vision, pages 1026–1034, 2015.

[21] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Delving deep into rectifiers: Surpassing human-level performance on imagenet classification. In 2015 IEEE International Conference on Computer Vision (ICCV), 2016.

[22] Ruining He, Wang Cheng Kang, and Julian Mcauley. Translation-based recommendation. In Eleventh Acm Conference on Recommender Systems, 2017.

[23] Xiangnan He and Tat-Seng Chua. Neural factorization machines for sparse predictive analytics. In Proceedings of the 40th International ACM SIGIR conference on Research and Development in Information Retrieval, pages 355–364, 2017.

[24] Xiangnan He, Lizi Liao, Hanwang Zhang, Liqiang Nie, Xia Hu, and Tat-Seng Chua. Neural collaborative filtering. In Proceedings of the 26th International Conference on World Wide Web, pages 173–182. International World Wide Web Conferences Steering Committee, 2017.

[25] Dan Hendrycks and Kevin Gimpel. Bridging nonlinearities and stochastic regularizers with gaussian error linear units. 2016.

[26] Balázs Hidasi and Alexandros 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, pages 843–852. ACM, 2018.

[27] Balázs Hidasi, Alexandros Karatzoglou, Linas Baltrunas, and D Tikk. Session-based recommendations with recurrent neural networks. In 4th International Conference on Learning Representations, ICLR 2016, 2016.
[28] Sepp Hochreiter and Jürgen Schmidhuber. Long short-term memory. Neural computation, 9(8):1735–1780, 1997.

[29] Jie Hu, Li Shen, and Gang Sun. Squeeze-and-excitation networks. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 7132–7141, 2018.

[30] Yifan Hu, Yehuda Koren, and Chris Volinsky. Collaborative filtering for implicit feedback datasets. In 2008 Eighth IEEE International Conference on Data Mining, pages 263–272. Ieee, 2008.

[31] Tongwen Huang, Zhiqi Zhang, and Junlin Zhang. Fibenet: combining feature importance and bilinear feature interaction for click-through rate prediction. In Proceedings of the 13th ACM Conference on Recommender Systems, pages 169–177, 2019.

[32] Wang-Cheng Kang and Julian McAuley. Self-attentive sequential recommendation. In 2018 IEEE International Conference on Data Mining (ICDM), pages 197–206. IEEE, 2018.

[33] Diederik P Kingma and Jimmy Ba. Adam: A method for stochastic optimization. In ICLR, 2015.

[34] Yehuda Koren. Factorization meets the neighborhood: a multifaceted collaborative filtering model. In Proceedings of the 14th ACM SIGKDD international conference on Knowledge discovery and data mining, pages 426–434, 2008.

[35] Yehuda Koren, Robert Bell, and Chris Volinsky. Matrix factorization techniques for recommender systems. Computer, 42(8):30–37, 2009.

[36] Jing Li, Pengjie Ren, Zhumin Chen, Zhaochun Ren, Tao Lian, and Jun Ma. Neural attentive session-based recommendation. In Proceedings of the 2017 ACM on Conference on Information & Knowledge Management, pages 1419–1428. ACM, 2017.

[37] Liam Li and Ameet Talwalkar. Random search and reproducibility for neural architecture search. In Proceedings of the Thirty-Fifth Conference on Uncertainty in Artificial Intelligence, UAI, 2019.

[38] Xiang Li, Chen Lin, Chuming Li, Ming Sun, Wei Wu, Junjie Yan, and Wanli Ouyang. Improving one-shot nas by suppressing the posterior fading. arXiv preprint arXiv:1910.02543, 2019.

[39] Jianxun Lian, Xiaohuan Zhou, Fuzheng Zhang, Zhongxia Chen, Xing Xie, and Guangzhong Sun. Xdeepfm: Combining explicit and implicit feature interactions for recommender systems. In Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, pages 1754–1763, 2018.

[40] Greg Linden, Brent Smith, and Jeremy York. Amazon.com recommendations: Item-to-item collaborative filtering. IEEE Internet computing, 7(1):76–80, 2003.

[41] Bin Liu, Chenxu Zhu, Guilin Li, Weinan Zhang, Jincai Lai, Ruiming Tang, Xiupiang He, Zhenguo Li, and Yong Yu. Autoafs: Automatic feature interaction selection in factorization models for click-through rate prediction. arXiv preprint arXiv:2003.11235, 2020.

[42] Chenxi Liu, Liang-Chieh Chen, Florian Schroff, Hartwig Adam, Wei Hua, Alan L Yuille, and Li Fei-Fei. Auto-deeplab: Hierarchical neural architecture search for semantic image segmentation. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 82–92, 2019.

[43] Chenxi Liu, Barret Zoph, Maxim Neumann, Jonathon Shlens, Wei Hua, Li-Jia Li, Li Fei-Fei, Alan Yuille, Jonathan Huang, and Kevin Murphy. Progressive neural architecture search. In Proceedings of the European Conference on Computer Vision (ECCV), pages 19–34, 2018.

[44] Hanxiao Liu, Karen Simonyan, and Yiming Yang. Darts: Differentiable architecture search. In ICLR, 2019.

[45] Qiao Liu, Yifu Zeng, Refuoe Mokhosi, and Haibin Zhang. Stump: short-term attention/memory priority model for session-based recommendation. In Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, pages 1831–1839, 2018.

[46] Ilya Loshchilov and Frank Hutter. Sgdr: Stochastic gradient descent with warm restarts. In ICLR, 2017.

[47] Yuanfei Luo, Mengshuo Wang, Hao Zhou, Quanming Yao, Wei-Wei Tu, Yuqiang Chen, Wenyuan Dai, and Qiang Yang. Autocross: Automatic feature crossing for tabular data in real-world applications. In Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, pages 1936–1945, 2019.

[48] Julian McAuley, Christopher Targett, Qi Mfeng Shi, and Anton Van Den Hengel. Image-based recommendations on styles and substitutes. In Proceedings of the 38th International ACM SIGIR Conference on Research and Development in Information Retrieval, pages 43–52, 2015.
[49] Andriy Mnih and Ruslan R Salakhutdinov. Probabilistic matrix factorization. In Advances in neural information processing systems, pages 1257–1264, 2008.

[50] Hieu Pham, Melody Guan, Barret Zoph, Quoc Le, and Jeff Dean. Efficient neural architecture search via parameters sharing. In International Conference on Machine Learning, pages 4095–4104, 2018.

[51] Yanru Qu, Han Cai, Kan Ren, Weinan Zhang, Yong Yu, Ying Wen, and Jun Wang. Product-based neural networks for user response prediction. In 2016 IEEE 16th International Conference on Data Mining (ICDM), pages 1149–1154. IEEE, 2016.

[52] Yanru Qu, Bohui Fang, Weinan Zhang, Ruiming Tang, Minzhe Niu, Huifeng Guo, Yong Yu, and Xiuqiang He. Product-based neural networks for user response prediction over multi-field categorical data. ACM Transactions on Information Systems (TOIS), 37(1):1–35, 2018.

[53] Massimo Quadrana, Alexandros Karatzoglou, Balázs Hidasi, and Paolo Cremonesi. Personalizing session-based recommendations with hierarchical recurrent neural networks. In Proceedings of the Eleventh ACM Conference on Recommender Systems, pages 130–137, 2017.

[54] Prajit Ramachandran, Barret Zoph, and Quoc V Le. Searching for activation functions. arXiv preprint arXiv:1710.05941, 2017.

[55] Esteban Real, Alok Aggarwal, Yanping Huang, and Quoc V Le. Regularized evolution for image classifier architecture search. In Proceedings of the aaai conference on artificial intelligence, volume 33, pages 4780–4789, 2019.

[56] Steffen Rendle. Factorization machines. In 2010 IEEE International Conference on Data Mining, pages 995–1000. IEEE, 2010.

[57] Steffen Rendle, Christoph Freudenthaler, Zeno Gantner, and Lars Schmidt-Thieme. Bpr: Bayesian personalized ranking from implicit feedback. In Proceedings of the twenty-fifth conference on uncertainty in artificial intelligence, pages 452–461. AUAI Press, 2009.

[58] Steffen Rendle, Christoph Freudenthaler, and Lars Schmidt-Thieme. Factorizing personalized markov chains for next-basket recommendation. In Proceedings of the 19th international conference on World wide web, pages 811–820, 2010.

[59] Badrul Sarwar, George Karypis, Joseph Konstan, and John Riedl. Item-based collaborative filtering recommendation algorithms. In Proceedings of the 10th international conference on World Wide Web, pages 285–295, 2001.

[60] Andrew M Saxe, James L McClelland, and Surya Ganguli. Exact solutions to the nonlinear dynamics of learning in deep linear neural networks. In ICLR, 2014.

[61] Christian Sciuto, Kaicheng Yu, Martin Jaggi, Claudiu Musat, and Mathieu Salzmann. Evaluating the search phase of neural architecture search. In ICLR, 2020.

[62] David So, Quoc Le, and Chen Liang. The evolved transformer. In International Conference on Machine Learning, pages 5877–5886, 2019.

[63] Fei Sun, Jun Liu, Jian Wu, Changhua Pei, Xiao Lin, Wenwu Ou, and Peng Jiang. Bert4rec: Sequential recommendation with bidirectional encoder representations from transformer. In Proceedings of the 28th ACM International Conference on Information and Knowledge Management, pages 1441–1450, 2019.

[64] Mingxing Tan, Bo Chen, Ruoming Pang, Vijay Vasudevan, Mark Sandler, Andrew Howard, and Quoc V Le. Mnasnet: Platform-aware neural architecture search for mobile. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 2820–2828, 2019.

[65] Mingxing Tan and Quoc Le. Efficientnet: Rethinking model scaling for convolutional neural networks. In International Conference on Machine Learning, pages 6105–6114, 2019.

[66] Mingxing Tan, Ruoming Pang, and Quoc V Le. Efficientdet: Scalable and efficient object detection. In Proceedings of the IEEE conference on computer vision and pattern recognition, 2020.

[67] Jiaxi Tang and Ke Wang. Personalized top-n sequential recommendation via convolutional sequence embedding. In Proceedings of the Eleventh ACM International Conference on Web Search and Data Mining, pages 565–573, 2018.

[68] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Lukasz Kaiser, and Illia Polosukhin. Attention is all you need. In Advances in neural information processing systems, pages 5998–6008, 2017.
[69] Alvin Wan, Xiaoliang Dai, Peizhao Zhang, Zijian He, Yuandong Tian, Saining Xie, Bichen Wu, Matthew Yu, Tao Xu, Kan Chen, et al. Fbnetv2: Differentiable neural architecture search for spatial and channel dimensions. In Proceedings of the IEEE conference on computer vision and pattern recognition, 2020.

[70] Ruoxi Wang, Bin Fu, Gang Fu, and Mingliang Wang. Deep & cross network for ad click predictions. In Proceedings of the ADKDD'17, pages 1–7. 2017.

[71] Yujing Wang, Yaming Yang, Yiren Chen, Jing Bai, Ce Zhang, Guinan Su, Xiaoyu Kou, Yunhai Tong, Mao Yang, and Lidong Zhou. Textnas: A neural architecture search space tailored for text representation. In AAAI, 2020.

[72] Bichen Wu, Xiaoliang Dai, Peizhao Zhang, Yanghan Wang, Fei Sun, Yiming Wu, Yuandong Tian, Peter Vajda, Yangqing Jia, and Kurt Keutzer. Fbnet: Hardware-aware efficient convnet design via differentiable neural architecture search. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 10734–10742, 2019.

[73] Chao-Yuan Wu, Amr Ahmed, Alex Beutel, Alexander J Smola, and How Jing. Recurrent recommender networks. In Proceedings of the tenth ACM international conference on web search and data mining, pages 495–503, 2017.

[74] Shu Wu, Yuyuan Tang, Yanqiao Zhu, Liang Wang, Xing Xie, and Tieniu Tan. Session-based recommendation with graph neural networks. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 33, pages 346–353, 2019.

[75] Jun Xiao, Hao Ye, Xiangnan He, Hanwang Zhang, Fei Wu, and Tat-Seng Chua. Attentional factorization machines: learning the weight of feature interactions via attention networks. In Proceedings of the 26th International Joint Conference on Artificial Intelligence, pages 3119–3125, 2017.

[76] Sirui Xie, Hehui Zheng, Chunxiao Liu, and Liang Lin. Snas: stochastic neural architecture search. In ICLR, 2019.

[77] Chengfeng Xu, Pengpeng Zhao, Yanchi Liu, Victor S Sheng, Jiajie Xu, Fuzhen Zhuang, Junhua Fang, and Xiaofang Zhou. Graph contextualized self-attention network for session-based recommendation. In Proc. 28th Int. Joint Conf. Artif. Intell.(IJCAI), pages 3940–3949, 2019.

[78] Rex Ying, Ruining He, Kaifeng Chen, Pong Eksombatchai, William L Hamilton, and Jure Leskovec. Graph convolutional neural networks for web-scale recommender systems. In Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, pages 974–983, 2018.

[79] Kaicheng Yu, Rene Ranftl, and Mathieu Salzmann. How to train your super-net: An analysis of training heuristics in weight-sharing nas. arXiv preprint arXiv:2003.04276, 2020.

[80] Fajie Yuan, Alexandros Karatzoglou, Ioannis Arapakis, Joemon M Jose, and Xiangnan He. A simple convolutional generative network for next item recommendation. In Proceedings of the Twelfth ACM International Conference on Web Search and Data Mining, pages 582–590, 2019.

[81] Yuanxing Zhang, Pengyu Zhao, Yushuo Guan, Lin Chen, Kaigui Bian, Lingyang Song, Bin Cui, and Xiaoming Li. Preference-aware mask for session-based recommendation with bidirectional transformer. In ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pages 3412–3416. IEEE, 2020.

[82] Chang Zhou, Jinze Bai, Junshuai Song, Xiaofei Liu, Zhengchao Zhao, Xiusi Chen, and Jun Gao. Atrank: An attention-based user behavior modeling framework for recommendation. In Thirty-Second AAAI Conference on Artificial Intelligence, 2018.

[83] Guorui Zhou, Na Mou, Ying Fan, Qi Pi, Weijie Bian, Chang Zhou, Xiaocheng Zhu, and Kun Gai. Deep interest evolution network for click-through rate prediction. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 33, pages 5941–5948, 2019.

[84] Guorui Zhou, Xiaocheng Zhu, Chenru Song, Ying Fan, Han Zhu, Xiao Ma, Yanghui Yan, Junqi Jin, Han Li, and Kun Gai. Deep interest network for click-through rate prediction. In Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, pages 1059–1068, 2018.

[85] Barret Zoph and Quoc V Le. Neural architecture search with reinforcement learning. In ICLR, 2017.

[86] Barret Zoph, Vijay Vasudevan, Jonathon Shlens, and Quoc V Le. Learning transferable architectures for scalable image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 8697–8710, 2018.